

Pursuant to the Eastern District of Texas Local Patent Rule 3.3 and the Court's Second Amended Docket Control Order (ECF 52), Defendant Tesla, Inc. ("Tesla" or "Defendant") provides these Invalidity Contentions to Plaintiff Perceptive Automata LLC, ("Perceptive" or "Plaintiff") for the claims asserted in Plaintiffs' Disclosure of Asserted Claims and Infringement Contentions ("Infringement Contentions").

Tesla's Invalidity Contentions include the accompanying claims charts concerning U.S. Patent No. 10,614,344 (the "'344 Patent"), U.S. Patent No. 11,126,889 (the "'889 Patent"), U.S. Patent No. 11,467,579 (the "'579 Patent"), U.S. Patent No. 11,520,346 (the "'346 Patent"), and U.S. Patent No. 11,753,046 (the "'046 Patent").

I. PRELIMINARY STATEMENT AND RESERVATION OF RIGHTS

Plaintiff asserts that Tesla infringes the following patents and claims: claims 1-22 of the '344 Patent, claims 1-9 and 11-19 of the '889 Patent, claims 1-20 of the '579 Patent, claims 1-23 of the '346 Patent, and claims 1-19 of the '046 Patent (collectively, "Asserted Claims"). As further detailed in and supported by these Invalidity Contentions, Tesla contends that each of the Asserted Claims is invalid under at least 35 U.S.C. §§ 101, 102, 103, and/or 112.

Based on this disclosure of the Asserted Claims, Tesla does not provide any contentions regarding any claims not asserted in Plaintiff's Infringement Contentions. To the extent that the Court permits Plaintiff to assert additional claims against Tesla and/or to amend its infringement contentions, Tesla reserves the right to further modify, amend, or supplement these invalidity contentions accordingly – for example, to show the invalidity and/or ineligibility of any such newly Asserted Claims.

These Invalidity Contentions do not constitute an admission that any accused products infringe the Asserted Patents. These Invalidity Contentions should not be deemed to be related to the non-infringement positions that Tesla may advance in this action. Tesla's Invalidity

Contentions are made in addition to, and/or in the alternative to, Tesla's non-infringement positions. As such, these contentions should not be interpreted to rely upon, or in any way affect, the non-infringement arguments Tesla makes in this case.

Tesla further reserves the right to amend or supplement these Invalidity Contentions in view of any of (for example) the Court's construction of terms and phrases recited in one or more of the Asserted Claims; additional information obtained during discovery (including any additional prior art references Tesla identifies); additional infringement theories put forth by Plaintiff during fact and/or expert discovery (to the extent permitted by the Court); any findings as to the priority dates of the Asserted Claims; and/or positions that Plaintiff, its fact witnesses, or its expert witnesses may take in the course of this litigation. Tesla further reserves the right to supplement its accompanying document productions with additional prior art documents, information, testimony, prior art systems and related documentation, and/or software or hardware code, including information provided by third parties after the date of service of these Invalidity Contentions.

Prior art not included in these Invalidity Contentions, whether known or not known to Tesla, may become relevant and Tesla reserves the right to add more prior art to these contentions during the course of this litigation. Because discovery is ongoing, Tesla anticipates that additional prior art and invalidity bases may be found. As one example, Tesla is currently unaware of the extent, if any, to which Plaintiff will contend that limitations of the Asserted Claims are not disclosed in the prior art identified in these Invalidity Contentions. Accordingly, Tesla reserves the right to identify other references that disclose the allegedly missing limitations of the claims of the Asserted Patents, to the extent Plaintiff identifies any such allegedly missing limitations. Additionally, Tesla's investigation and analysis of the prior art is continuing, and

thus Tesla reserves the right to supplement, amend, and/or revise the information provided herein as Tesla conducts further investigation and/or analysis, including identifying, charting, and relying on additional references. As an example, in view of likely third-party discovery that will be taken, Tesla reserves the right to present additional items of prior art identified in view of third-party discovery or further investigation, and to assert contentions of invalidity based on such information. For example, Tesla has issued subpoenas (and may issue further subpoenas) to third parties believed to have knowledge, documents, and/or other evidence concerning invalidity of one or more of the Asserted Claims.

Tesla may further rely on inventor admissions concerning the scope or state of the prior art relevant to the Asserted Claims, the patent prosecution histories of the Asserted Patents or related patents and/or patent applications (including the prior art cited therein), any deposition or trial testimony (*e.g.*, testimony from the named inventors on the Asserted Patents), and the papers filed and any evidence produced or submitted by Plaintiffs in connection with these cases or other related litigation. Tesla reserves the right to contend that one or more of the Asserted Claims are invalid for incorrect inventorship, in the event Tesla obtains evidence that one or more of the named inventors did not invent the subject matter in the Asserted Claims.

Further, consistent with the Court's Docket Control Order (D.I. 52), Tesla provides these Invalidity Contentions before the parties have begun the claim construction process. The citation and discussion of the prior art herein and in the accompanying exhibits are not intended to reflect Tesla's claim construction positions, which will be disclosed in due course in accordance with the Docket Control Order (D.I. 52). Instead, Tesla's Invalidity Contentions as set forth herein and in the accompanying exhibits may reflect Plaintiff's apparent claim constructions based on

its Infringement Contentions. For the avoidance of doubt, Tesla disagrees with Plaintiff's apparent claim constructions and does not adopt them by serving these Invalidity Contentions.

Additionally, Plaintiff has not identified its contentions regarding the level of ordinary skill in the art for any of the Asserted Patents. Thus, Tesla has based its Invalidity Contentions on the level of skill in the art apparent from the face of the Asserted Patents. For the avoidance of doubt, Tesla contends that the Asserted Claims are invalid for the reasons set forth in their Invalidity Contentions under any plausible definition of the level of ordinary skill for each of the Asserted Patents. Nevertheless, Tesla reserves the right to amend or supplement these Invalidity Contentions in response to any position taken by Plaintiffs as to the level of ordinary skill in the art applicable to a given Asserted Patent.

The references identified in these Invalidity Contentions, which include the attached claim charts, disclose the elements of the Asserted Claims explicitly and/or inherently, render those elements alone or in combination obvious to those of ordinary skill, and show the state of the art in the relevant time frame. References identified in these Invalidity Contentions, as well as the "References Cited" on the face of the Asserted Patents and the patents cited within the body of the Asserted Patents, may be used to illustrate, but not limit the scope of, the state of the art to which the Asserted Patents pertain (i.e., at a time prior to the date of alleged inventions of the Asserted Claims of the Asserted Patents). Moreover, Tesla reserves the ability to rely on later-identified sources of information, including but not limited to witness testimony and other discovery, to establish the state of the art in the relevant time frame pertaining to the Asserted Patents.

In addition to the positions and prior art identified in these Invalidity Contentions (including the accompanying claim charts), Tesla also incorporates by reference all invalidity

contentions and subject matter eligibility contentions, prior art, and invalidity claim charts (including, without limitation, all anticipation positions, obviousness positions, indefiniteness positions, written description positions, and non-enablement positions) concerning one or more of the Asserted Patents, that are disclosed at any time. This includes without limitation disclosures in previous or related litigation, in United States Patent & Trademark Office (“USPTO”) proceedings, by the Plaintiff, by any other parties accused of patent infringement by the Plaintiff, or by the named inventors or any individuals associated with the prosecution and/or any form of post-grant review or reexamination of the Asserted Patents. For example, Tesla identifies, as prior art upon which it may rely to show the invalidity of the Asserted Claims, the prior art references disclosed by parties in any other litigation or proceedings (including *inter partes* review and/or reexamination proceedings) involving one or more of the Asserted Patents, any patent related to any of the Asserted Patents, and/or any other patent claiming priority to the Asserted Patents.

To the extent Tesla has stipulated or stipulates in the future that it will not pursue certain invalidity grounds in these actions concerning patent claims subject to instituted *inter partes* review proceedings, Tesla will abide by those stipulations, and nothing in these contentions should be read as suggesting otherwise. Rather, these contentions are intended to put Plaintiff on notice of the grounds of invalidity that Tesla may assert in this action, including because the conditions of any relevant stipulation are not met (*e.g.*, if the corresponding *inter partes* review is not instituted) or because the grounds fall outside the scope of such stipulations.

The Invalidity Contentions are based on the priority dates set forth in the Infringement Contentions. However, the Federal Circuit has clearly stated that there is no presumption that a given patent is entitled to the priority date of a provisional application to which it claims priority. *Dynamic Drinkware, LLC v. National Graphics, Inc.*, 800 F.3d 1375, 1380 (Fed. Circ. 2015).

Perceptive bears the burden to establish that a provisional provides written description support under 35 U.S.C. §112(a) for each Challenged Claim. *Chiron Corp. v. Genentech, Inc.*, 363 F.3d 1247, 1253 (Fed. Cir. 2004); *New Railhead Mfg., L.L.C. v. Vermeer Mfg. Co.*, 298 F.3d 1290, 1294-95 (Fed. Cir. 2002). This means Perceptive must show that the specification “describe[s] the invention sufficiently to convey to a person of skill in the art that the patentee had possession of the claimed invention at the time of the application[.]” *Lizardtech, Inc. v. Earth Resource Mapping, Inc.*, 424 F.3d 1336, 1345 (Fed. Cir. 2005).

Perceptive has not shown that any of the Asserted Patents are entitled to an earlier priority date than their filing date. In particular, Plaintiff contends that “the ’344, ’889, and ’046 patents are entitled to a priority date at least as early as July 5, 2017,” but the provisional application filed on July 5, 2017 does not support all claim limitations for those patents. Tesla reserves the right to amend these Invalidity Contentions upon Plaintiff’s assertion of any other priority dates or the Court’s (or other competent jurisdiction’s) determination of the correct priority dates of the Asserted Claims.

As described below, the Asserted Patents are invalid as obvious under § 103. A POSITA would have had numerous motivations to combine the identified prior art references discussed below. For example, as the United States Supreme Court held in *KSR*, “[t]he combination of familiar elements according to known methods is likely to be obvious when it does no more than yield predictable results.” 550 U.S. at 416. The Supreme Court further held that, “[w]hen a work is available in one field of endeavor, design incentives and other market forces can prompt variations of it, either in the same field or a different one. If a person of ordinary skill can implement a predictable variation, § 103 likely bars its patentability. For the same reason, if a technique has been used to improve one device, and a person of ordinary skill in the art would

recognize that it would improve similar devices in the same way, using the technique is obvious unless its actual application is beyond his or her skill. . . .” *Id.* at 417. Accordingly, a person of skill in the art would have been motivated to combine or adapt known or familiar methods in the art.

One or more combinations of the prior art references identified below would have been apparent because these references would have been combined using: known methods to yield predictable results; known techniques in the same way; a simple substitution of one known, equivalent element for another to obtain predictable results; and/or a teaching, suggestion, or motivation in the prior art generally. In addition, it would have been obvious to try combining the prior art references identified below because there were only a finite number of predictable solutions and/or because known work in one field of endeavor prompted variations based on predictable design incentives and/or market forces either in the same field or a different one. Furthermore, the combination of the prior art references identified below would have been obvious because the combination represents the known potential options with a reasonable expectation of success.

Additional evidence that there would have been a motivation to combine the prior art references identified below includes the interrelated teachings of multiple prior art references; the effects of demands known to the design community or present in the marketplace; the existence of a known problem for which there was an obvious solution encompassed by the asserted claim; the existence of a known need or problem in the field of endeavor at the time of the invention(s); and the background knowledge that would have been possessed by a person having ordinary skill in the art.

Thus, the motivation to combine the teachings of the prior art references disclosed herein is found in the references themselves and: (1) the nature of the problem being solved; (2) the express, implied and inherent teachings of the prior art; (3) the knowledge of persons of ordinary skill in the art; (4) the predictable results obtained in combining the different elements of the prior art; (5) the predictable results obtained in simple substitution of one known element for another; (6) the use of a known technique to improve similar devices, methods, or products in the same way; (7) the predictable results obtained in applying a known technique to a known device, method, or product ready for improvement; (8) the finite number of identified predictable solutions that had a reasonable expectation of success; and (9) known work in various technological fields that could be applied to the same or different technological fields based on design incentives or other market forces.

Accordingly, the teaching, suggestion, or motivation to modify or combine the references in the manner claimed can be found in the explicit and/or implicit teachings of the references and the prior art as a whole, the general knowledge of those skilled in the art, including knowledge of trends in the field, and knowledge that the art is of special interest or importance in the field.

Much of the art identified below and in the attached Exhibits reflects common knowledge and the state of the art prior to the filing date of the Asserted Patents and/or at the time the alleged invention was made. In many instances where a particular contention calls for, or requires, combining references, any one of a number of references can be combined. The inclusion of certain example combinations herein does not exclude other combinations, as there are many possible combinations of the references listed herein.

II. INVALIDITY UNDER 35 U.S.C. §§ 102, 103

The following contentions are subject to revision and amendment pursuant to Federal Rule of Civil Procedure 26(e) and the Orders of record in this matter to the extent appropriate, *e.g.*, in

light of further investigation and discovery regarding these defenses, the Court's construction of the claims at issue, and/or review and analysis of expert witnesses. Tesla offers these Invalidity Contentions in response to Plaintiff's Infringement Contentions and without prejudice to any position it may ultimately take as to any claim construction issues.

As detailed below and in the attached claim charts, the concepts disclosed and claimed in the Asserted Patents are not new. Rather, the concepts have been disclosed and actively practiced by others prior to the claimed priority date. The prior art includes various documents, systems, products, patents and inventions that separately and together render the Asserted Claims invalid. Tesla asserts that at least the prior art listed below, individually or in combination, invalidates the Asserted Claims. In particular, Tesla provides below prior art that anticipates and/or renders obvious the Asserted Claims of the Asserted Patents. The identification of prior art below is not exhaustive, and Tesla's production contains additional references that render the Asserted Claims invalid. Although Tesla provides prior art for each Asserted Patent, Tesla reserves the right to rely on any of the prior art listed in its Invalidity Contentions, even if it is not listed under a specific Asserted Patent for anticipation and/or obviousness. Tesla reserves the right to rely on any permutation of combination of prior art listed in its Invalidity Contentions, even if the combination is not expressly stated in the Invalidity Contentions. Tesla reserves the right to rely upon both the listed and unlisted references, as well as other art that may become known and/or relevant during the course of this or related litigation.

The attached exhibits provide detailed claim charts for the Asserted Patents. The claim charts show where each claim limitation may be found in the particular reference being charted. For those references for which detailed claim charts are not provided in the aforementioned exhibits, those additional prior art references are otherwise pertinent to the invalidity of the

Asserted Patents, either alone or in combination with other references. At this time, Tesla may not provide claim charts for each of these additional references, for any of a variety of reasons, such as: because the references are cited in conjunction with primary references for which charts have already been provided and are cited therein, because the references have similar disclosure to the prior art references for which invalidity charts have been provided, because the references may be used to show the state of the art, and/or because Tesla's investigation of the references is ongoing. Tesla reserves the right to rely on the uncharted references, for example, to address claim construction, findings regarding the priority date of the claims, and/or positions that Plaintiff or expert witnesses may take in the future concerning infringement and/or invalidity issues.

The references cited herein disclose the limitations of the Asserted Claims explicitly or inherently, and/or they may be relied upon to demonstrate how the state of the art in the relevant time frame invalidates each asserted patent claim. In the context of the knowledge of a person of ordinary skill in the art, each reference's disclosure applies in the context of both anticipation and obviousness. Therefore, any suggested single reference obviousness positions and obviousness combinations are provided in the alternative to Tesla's anticipation contentions and are not to be construed to suggest that any reference included in the combinations is somehow deficient or is not by itself anticipatory. Further, the combinations listed herein are exemplary and not exhaustive. There are many possible invalidating combinations of the references listed herein, and it is not practical, at this early stage, to identify and list all potentially relevant combinations without the benefit of further factual investigation and the Court's claim construction.

Tesla not only relies upon the prior art disclosed herein, but also on any commercial embodiments and accompanying literature of the various assignees that correspond to the respective disclosures found within the prior art disclosed herein. The assignees' various and

respective commercial embodiments and/or corresponding literature anticipate and/or render obvious the claims of the Asserted Patents for at least the reasons disclosed in these Invalidity Contentions and claim charts, as well as for other independent reasons found within the commercial embodiments and corresponding literature. Tesla also reserves the right to rely on related patents, published applications, foreign patents or publications, and other patent documents as necessary to establish prior art status or clarify the disclosures cited.

Further, in addition to the detailed bases for invalidity that Tesla provides below, Tesla contends that an analysis of secondary considerations further supports the view that each of the Asserted Claims is invalid as obvious. For example, evidence of simultaneous invention may be considered as a secondary consideration providing indicia of obviousness. *Geo M Martin Co. v. Alliance Machine Sys. Int'l LLC*, 618 F.3d 1294, 1304-05 (Fed. Cir. 2010). Tesla's Invalidity Contentions show that many companies and individuals had developed or were simultaneously developing the features claimed in the Asserted Patents. Tesla reserves the right to rely on any of the prior art references identified below as evidence of simultaneous invention and that the claimed invention is the product of ordinary mechanical or engineering skill.

Plaintiff has not identified any evidence supporting any secondary considerations showing that the asserted claims are non-obviousness. For example, Plaintiff has not identified any evidence that it, or any predecessor in interest of the Asserted Patents, has developed a commercially successful product embodying the claimed subject matter of these patents. Plaintiff has also provided no evidence that the Asserted Patents were directed to long felt, unresolved needs. On the contrary, the Asserted Patents addressed problems that had been handled successfully in the prior art. Additionally, and as outlined herein and in the attached exhibits, numerous prior art references anticipate the Asserted Claims of the Asserted Patents, so failure by

others cannot be cited as a secondary consideration in favor of non-obviousness. Plaintiff also has not presented any evidence to suggest that others in the industry copied or praised the alleged inventions of the Asserted Patents. At the time of the alleged invention of the Asserted Patents, those in the art would not have been skeptical of the general approach or idea disclosed therein. To the contrary, the general ideas – e.g., using human-labeled data and sensor input to train a computer program – were already in existence for as long as engineers have been in the process of developing self-driving vehicles. None of the ideas claimed in the asserted patents were patentable by the time the applicants filed their patent applications. People of ordinary skill in the art would have regarded the disclosures and matter claimed in the Asserted Patents as obvious.

Tesla reserves all rights to respond to any secondary considerations of non-obviousness raised by Plaintiff, including by updating, modifying, and/or adding to these Invalidity Contentions. Tesla also reserves the right to affirmatively rely on secondary considerations of obviousness to the extent necessary and appropriate.

A. The '344 Patent

Pursuant to Patent Rule 3-3 and subject to Tesla's reservations of rights in these Invalidity Contentions, at least the prior art listed below, individually or in combination, invalidates the Asserted Claims of the '344 Patent. Exhibits A-1 through A-24 provide detailed claim charts showing where each claim limitation may be found in certain references listed below, either expressly or inherently as the reference would be understood by a person having ordinary skill in the art. For those references for which detailed claim charts are not provided, those additional prior art references are otherwise pertinent to the invalidity of the '344 Patent, either alone or in combination with other references.

The prior art references, systems, and products listed below and in the accompanying claim chart exhibits may be relied upon for certain limitations, state of the art, and background of the art;

indicia of obviousness; as evidence of the level of skill in the art at the time of the filing of the Patents-in-Suit; and/or in support of assertions that it is proper to combine certain prior art references in certain ways.

Tesla also incorporates by reference each and every prior art reference of record in the prosecution of the Patents-in-Suit and patents or patent applications related to the Patents-in-Suit, the prior art referred to in the specifications of the Patents-in-Suit, as well as the prior art identified in any USPTO proceedings involving any of the Patents-in-Suit.

1. Bases for Anticipation and/or Obviousness

Each prior art reference identified in Exhibits A-1 through A-27 expressly, implicitly, or inherently anticipates and/or renders obvious the Asserted Claims of the '344 Patent, either alone or in combination with other prior art references (*e.g.*, other references identified below) or the knowledge of the person of ordinary skill in the art at the time of the alleged invention. In the table below, Tesla identifies a non-exhaustive list of prior art references that, alone or in combination, anticipate and/or render obvious the Asserted Claims of the '344 Patent.

Exhibit	Patent No. or Title (Primary Inventor/Author)	Date of Issuance or Publication
Ex. A-1	U.S. Patent No. 10,496,901 ("Ross")	Dec. 3, 2019 (Filed Aug. 17, 2016)
Ex. A-2	WO2014/210334 ("Cox")	Dec. 31, 2014
Ex. A-3	U.S. Patent No. 10,733,506 ("Ogale")	Aug. 4, 2020 (Filed Dec. 14, 2016)
Ex. A-4	U.S. Patent No. 9,766,626 ("Zhu")	May 30, 2019 (Filed Nov. 27, 2017)
Ex. A-5	U.S. Patent No. 10,007,269 ("Gray")	Jun. 26, 2018
Ex. A-6	U.S. Pat. Pub. No. 2017/0099200 ("Ellenbogen")	Apr. 6, 2017 (Filed Oct. 6, 2016)
Ex. A-7	U.S. Pat. Pub. No. 2019/0072966 ("Zhang")	Mar. 7, 2019 (Filed Nov. 7, 2017)
Ex. A-8	U.S. Pat. Pub. No. 2018/0373980 ("Huval")	Dec. 27, 2018 (Filed Jun. 27, 2017)

Ex. A-9	Schneemann, “Context-based Detection of Pedestrian Crossing Intention for Autonomous Driving in Urban Environments” (“Schneemann”)	Oct. 2016
Ex. A-10	Quintero, “Pedestrian Path Prediction using Body Language Traits” (“Quintero”)	Jun. 2014
Ex. A-11	Keller, “Will the Pedestrian Cross? A Study on Pedestrian Path Prediction” (“Keller”)	Apr. 2014
Ex. A-12	Furuhashi, “Estimation of Street Crossing Intention from a Pedestrian’s Posture on a Sidewalk Using Multiple Image Frames” (“Furuhashi”)	2011
Ex. A-13	Kooij, “Analysis of pedestrian dynamics from a vehicle perspective” (“Kooij”)	Jun. 2014
Ex. A-14	Kohler, “Early Detection of the Pedestrian’s Intention to Cross the Street” (“Kohler”)	Oct. 25, 2012
Ex. A-15	Volz, “A data-driven approach for pedestrian intention estimation” 2016 (“Volz 1”)	Nov. 2016
Ex. A-16	Volz, “Feature Relevance Estimation for Learning Pedestrian Behavior at Crosswalks” (“Volz 2”)	2015
Ex. A-17	Schneider, “Pedestrian Path Prediction with Recursive Bayesian Filters: A Comparative Study” (“Schneider”)	2013
Ex. A-18	Karasev, “Intent-Aware Long-Term Prediction of Pedestrian Motion” (“Karasev”)	May 2016
Ex. A-19	U.S. Patent No. 9,632,502 (“Levinson”)	Apr. 25, 2017 (Filed Nov. 5, 2015)
Ex. A-20	Bhattacharyya, “Long-Term On-Board Prediction of People in Traffic Scenes under Uncertainty” (“Bhattacharyya”)	Nov. 24, 2017

The Asserted Claims of the '344 Patent are also invalid under 35 U.S.C. § 102(a) and (b) because the subject matter was known by others, publicly used, and on sale in the United States before it was purportedly invented and more than one year before the priority date of the Asserted Claim. Additionally, the Asserted Claim because any purported invention was made in this country by another who had not abandoned, suppressed, or concealed the purported invention. For example, the foregoing patents and publications are evidence of such prior art systems and inventions. As such, the following systems are prior art under 35 U.S.C. § 102:

Exhibit	System Prior Art
Ex. A-21	Tesla – Autopilot HW1
Ex. A-22	Tesla – Autopilot HW2
Ex. A-23	Daimler/ Mercedes
Ex. A-24	Waymo
Ex. A-25	iMotions
Ex. A-26	TestMyBrain.com
Ex. A-27	Zoox

The accompanying claim charts (Exhibits A-1 through A-27) set forth example bases for anticipation and obviousness, identifying where each reference discloses, alone or in combination with other references, each limitation of the Asserted Claims of the '344 Patent on a limitation-by-limitation basis. Tesla's claim charts are exemplary and not exhaustive.

2. Obviousness Combinations

Subject to Tesla's reservation of rights, Tesla contends that all of the prior art references, as identified above and described in the charts attached as Exhibits A-1 through A-27 by themselves anticipate the Asserted Claims of the '344 Patent in accordance with 35 U.S.C. § 102 and/or render the Asserted Claim of the '344 Patent obvious under 35 U.S.C. § 103, as more specifically noted in the attached charts. The cited portions of the prior art references are examples and representative of the content of the prior art references, and should be understood in the context of the reference as a whole, as understood by one of ordinary skill in the art. To the extent a cited prior art reference is deemed not to anticipate or render obvious a claim as noted in the attached charts for failing to teach or suggest one or more limitations of that claim, that claim would nonetheless have been obvious to one of ordinary skill in the art at the time of the invention by the combination of the cited prior art reference with one or more other prior art references and/or common knowledge disclosing the missing claim limitations. For example, any of the references

listed above, to the extent it does not explicitly or inherently disclose any limitation, could be combined with any one or more of the other references listed above which discloses that limitation. Tesla reserves the right to supplement the obviousness arguments using any references listed above, or any references that may become known to Tesla during the course of discovery.

In the table below, Tesla further identifies exemplary combinations of prior art that render the Asserted Claims of the '344 Patent obvious:

Primary Reference	Secondary Reference	Claim
Ross	Cox	1, 2, 5, 6, 10, 11, 14, 15 19
	Ogale	1, 2, 10, 11, 19
	Schneemann	1, 10, 19
	Gray	2, 11
	Ellenbogen	1, 2, 10, 11, 19
	Zhang	1, 10, 19
	Keller	5, 14
	Volz 1	2, 11
	Volz 2	1, 10, 19
	Huval	2, 11
	Bhattacharyya	1, 2, 6, 10, 11, 15, 19
	One or more of Cox, Ogale, Schneemann, Gray, Ellenbogen, Zhang, Keller, Volz 1, Volz 2, and/or Huval, Bhattacharyya	1, 2, 5, 6, 10, 11, 14, 15, 19
Cox	Ross	1, 3, 4, 8, 9, 10, 12, 13, 17, 18, 19, 21, 22
	Ogale	1, 3, 10, 12, 19
	Zhu	1, 3, 4, 8, 9, 10, 12, 13, 17, 18, 19, 21, 22
	Gray	1, 3, 10, 12, 19
	Schneemann	1, 4, 8, 10, 13, 17, 19, 21
	Quintero	4, 13
	Zhang	1, 4, 8, 10, 13, 17, 19, 21
	Huval	1, 3, 10, 12, 19, 21
	Keller	1, 3, 4, 8, 10, 12, 13, 17, 19, 21

Primary Reference	Secondary Reference	Claim
	Furuhashi	1, 3, 4, 8, 10, 12, 13, 17, 19, 21
	Kooij	1, 3, 10, 12, 19
	Kohler	1, 4, 10, 13, 19
	Volz 1	1, 3, 4, 8, 9, 10, 12, 13, 17, 18, 19, 21, 22
	Volz 2	1, 3, 4, 8, 10, 12, 13, 17, 19, 21
	Schneider	1, 3, 10, 12, 19
	Karasev	1, 3, 10, 12, 19
	Levinson	1, 3, 10, 12, 19
	Zoox	1, 3, 10, 12, 19
	Waymo	1, 3, 4, 8, 9, 10, 12, 13, 17, 18, 19, 21, 22
	Bhattacharyya	1, 3, 4, 8, 10, 12, 13, 17, 19, 21
	One or more of Ross, Ogale Zhu, Gray, Schneemann Quintero, Zhang, Huval, Keller, Furuhashi, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Waymo, Levinson, Zoox, and/or Bhattacharyya	1, 3, 4, 8, 9, 10, 12, 13, 17, 18, 19, 21, 22
Ogale	Ross	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Cox	5, 6, 7, 14, 15, 16, 20
	Schneemann	4, 7, 8, 13, 16, 17, 20
	Quintero	4, 7, 13, 16, 20
	Zhu	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Zhang	4, 8, 13, 17, 21
	Ellenbogen	7, 16, 20
	Keller	4, 5, 7, 8, 13, 14, 16, 17, 20, 21
	Furuhashi	4, 7, 8, 13, 16, 17, 20, 21
	Kohler	4, 13
	Volz 1	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Volz 2	4, 7, 8, 13, 16, 17, 20, 21

Primary Reference	Secondary Reference	Claim
	Bhattacharyya	4, 6, 7, 8, 13, 15, 16, 17, 20, 21
	Waymo	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	One or more of Ross, Coz, Schneemann, Quintero, Zhu, Zheng, Ellenbogen, Keller, Furuhashi, Kohler, Volz 1, Volz 2, and/or Bhattacharyya	4, 5, 6, 7, 8, 9, 13, 14, 15, 16, 17, 18, 20, 21, 22
Schneemann	Ross	1, 3, 9, 10, 12, 18, 19, 22
	Cox	2, 5, 6, 11, 14, 15
	Ogale	1, 2, 3, 10, 11, 12, 19
	Zhu	1, 3, 9, 10, 12, 18, 19, 22
	Ellenbogen	2, 11
	Kohler	1, 10, 19
	Gray	1, 2, 3, 10, 11, 12, 19
	Zhang	1, 10, 19
	Huval	1, 2, 3, 10, 19, 11, 12
	Keller	1, 3, 5, 10, 19, 12, 14
	Furuhashi	1, 3, 10, 12, 19
	Kooij	1, 3, 10, 19, 12
	Volz 1	1, 2, 3, 9, 10, 11, 12, 18, 19, 22
	Volz 2	1, 3, 10, 19, 12
	Schneider	1, 3, 10, 19, 12
	Karasev	1, 3, 10, 19, 12
	Zoox	1, 3, 10, 12, 19
	Levinson	1, 3, 10, 12, 19
	Waymo	1, 3, 9, 10, 12, 18, 19, 22
	Bhattacharyya	2, 3, 6, 11, 12, 15
	One or more of Ross, Cox, Ogale, Zhu, Ellenbogen, Kohler, Gray, Zhang, Huval, Keller, Furuhashi, Kooij, Volz 1, Volz 2, Schneider, Karasev, Zoox, Levinson, Waymo, and/or Bhattacharyya	1, 2, 3, 5, 6, 9, 10, 11, 12, 18, 19, 22
Zhu	Cox	1, 2, 5, 6, 10, 11, 14, 15, 19
	Ogale	1, 2, 10, 11, 19
	Gray	2, 11
	Schneemann	1, 10, 19

Primary Reference	Secondary Reference	Claim
	Ellenbogen	1, 2, 10, 11, 19
	Zhang	1, 10, 19
	Huval	2, 11
	Keller	5, 14
	Volz 1	2, 11
	Volz 2	1, 10, 19
	Bhattacharyya	1, 2, 6, 10, 11, 15, 19
	One or more of Cox, Ogale, Schneemann, Ellenbogen, Zhang, Huval, Keller, Volz 1, Volz 2, and/or Bhattacharyya	1, 2, 5, 6, 10, 11, 14, 15, 19
Gray	Ross	4, 7, 8, 9, 13, 16, 17, 18, 22
	Cox	1, 5, 6, 7, 10, 14, 15, 16, 19, 20
	Ogale	1, 10, 19
	Schneemann	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21
	Quintero	4, 7, 13, 16
	Ellenbogen	1, 7, 10, 16, 19, 20
	Zhu	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Zhang	1, 4, 8, 10, 13, 17, 19, 21
	Keller	4, 5, 7, 8, 13, 14, 16, 17, 20, 21
	Furuhashi	4, 7, 8, 13, 16, 17, 20, 21
	Kohler	4, 13
	Volz 1	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Volz 2	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21
	Waymo	4, 7, 8, 9, 13, 16, 17, 18, 22
	Bhattacharyya	1, 4, 6, 7, 8, 10, 13, 15, 16, 18, 19, 20, 21
	One or more of Ross, Cox, Ogale, Schneemann, Quintero, Ellenbogen, Zhu, Zhang, Keller, Furuhashi, Kohler, Volz 1, Volz 2, Waymo, and/or Bhattacharyya	1, 4, 5, 6, 7, 8, 9, 10, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22
Zhang	Ross	3, 7, 9, 12, 16, 18, 20, 22
	Cox	2, 5, 6, 7, 11, 14, 15, 16, 20
	Ogale	2, 3, 11, 12

Primary Reference	Secondary Reference	Claim
	Schneemann	7, 16, 20
	Quintero	7, 16, 20
	Zhu	3, 7, 9, 12, 16, 18, 20, 22
	Gray	2, 3, 11, 12
	Ellenbogen	2, 7, 11, 16, 20
	Huval	2, 3, 11, 12
	Keller	3, 5, 7, 12, 16, 20
	Furuhashi	3, 7, 12, 16, 20
	Kooij	3, 12
	Volz 1	2, 3, 7, 9, 11, 12, 16, 18, 20, 22
	Volz 2	3, 7, 12, 16, 20
	Schneider	3, 12
	Karasev	3, 12
	Levinson	3, 12
	Zoox	3, 12
	Waymo	3, 7, 9, 12, 16, 18, 20, 22
	Bhattacharyya	2, 3, 6, 7, 11, 12, 15, 16, 20
	One or more of Ross, Cox, Ogale, Schneemann, Quintero, Zhu, Gray, Ellenbogen, Huval, Keller, Furuhashi, Kooij, Volz 1, Volz 2, Schneider, Karasev, Levinson, Zoox, Waymo, and/or Bhattacharyya	2, 3, 5, 6, 7, 9, 11, 12, 14, 15, 16, 18, 20, 22
Huval	Ross	4, 7, 8, 9, 13, 16, 17, 18, 22
	Cox	1, 5, 6, 7, 10, 14, 15, 16, 19
	Ogale	1, 10, 19
	Schneemann	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21
	Ellenbogen	1, 7, 10, 16, 19
	Quintero	4, 7, 13, 16
	Zhu	4, 7, 8, 9, 13, 16, 17, 18, 20, 21
	Zhang	1, 4, 8, 10, 13, 17, 19, 21
	Keller	4, 5, 7, 8, 13, 14, 16, 17, 20, 21
	Furuhashi	4, 7, 8, 13, 16, 17, 20, 21
	Kohler	4, 13
	Volz 1	4, 7, 8, 9, 13, 16, 17, 18, 20, 21
	Volz 2	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21

Primary Reference	Secondary Reference	Claim
	Waymo	4, 7, 8, 9, 13, 16, 17, 18, 22
	Bhattacharyya	1, 3, 6, 7, 10, 12, 15, 16, 19, 20
	One or more of Ross, Cox, Ogale, Schneemann, Quintero, Zhu, Gray, Ellenbogen, Huval, Keller, Furuhashi, Kooij, Volz 1, Volz 2, Schneider, Karasev, Waymo, and/or Bhattacharyya	1, 2, 3, 5, 6, 7, 8, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 21, 22
Keller	Ross	9, 18, 22
	Cox	1, 2, 6, 10, 11, 15, 19
	Ogale	1, 2, 10, 11, 19
	Schneemann	1, 10, 19
	Gray	2, 11
	Ellenbogen	1, 2, 10[, 11, 19
	Huval	2, 11
	Zhang	1, 10, 19
	Zhu	9, 18, 22
	Volz 1	2, 9, 11, 18, 22
	Volz 2	1, 10, 19
	Bhattacharyya	1, 2, 6, 10, 11, 15, 19
	Waymo	9, 18, 22
	One or more of Ross, Cox, Ogale, Schneemann, Gray, Ellenbogen, Huval, Zhang, Zhu, Volz 1, Volz 2, Bhattacharyya, and/or Waymo	1, 2, 6, 9, 10, 11, 15, 18, 19, 22
Furuhashi	Ross	1, 9, 10, 18, 19, 22
	Cox	1, 2, 5, 6, 10, 11, 14, 15, 19
	Ogale	1, 2, 10, 11, 19
	Schneemann	1, 10, 19
	Zhu	1, 9, 10, 18, 19, 22
	Gray	1, 2, 10, 11, 10, 19,
	Zhang	1, 10, 19
	Ellenbogen	1, 2, 10, 11, 19
	Huval	1, 2, 10, 11, 19
	Keller	1, 5, 10, 14, 19
	Volz 1	2, 9, 11, 18, 22
	Volz 2	1, 10, 19
	Schneider	1, 10, 19
	Karasev	1, 10, 19

Primary Reference	Secondary Reference	Claim
	Levinson	1, 10, 19
	Bhattacharyya	1, 2, 6, 10, 11, 15, 19
	Zoox	1, 10, 19
	Waymo	1, 9, 10, 18, 19, 22
	One or more of Ross, Cox, Ogale, Schneemann, Zhu, Gray, Zhang, Ellenbogen, Huval, Keller, Volz 1, Volz 2, Schneider, Karasev, Levinson, Bhattacharyya, Zoox, and/or Waymo	1, 2, 5, 6, 9, 10, 11, 14, 15, 19, 22
Waymo	Ross	9, 18, 22
	Cox	2, 5, 6, 11, 14, 15
	Test My Brain	2, 5, 6, 11, 14, 15
	Ogale	2, 11
	Gray	2, 11
	Ellenbogen	2, 11
	Keller	5, 14
	Zhu	9, 18
	Huval	2, 11
	Volz 1	2, 9, 11, 18, 22
	iMotions	2, 5, 6, 9, 11, 15, 18, 22
	Bhattacharyya	2, 6, 11, 15
	One or more of Ross, Cox, Test My brain, Ogale, Gray, Ellenbogen, Keller, Zhu, Huval, Volz 1, iMotions, and/or Bhattacharyya	2, 5, 6, 9, 11, 14, 15, 18, 22
Autopilot HW2	Ross	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Cox	1, 2, 5, 6, 7, 10, 11, 14, 15, 16, 19, 20
	Test My Brain	1, 2, 5, 6, 7, 10, 11, 14, 15, 16, 19, 20
	Ogale	1, 2, 10, 11, 19
	Schneemann	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21
	Quintero	4, 7, 13, 16
	Zhu	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Gray	2, 11
	Ellenbogen	1, 2, 7, 10, 11, 16, 19, 20
	Zhang	1, 4, 8, 10, 13, 17, 19, 21
	Huval	2, 11

Primary Reference	Secondary Reference	Claim
	Keller	4, 5, 7, 8, 13, 14, 16, 17, 20, 21
	Furuhashi	4, 7, 8, 13, 16, 17, 20, 21
	Kohler	4, 13
	Volz 1	2, 4, 7, 8, 9, 11, 13, 16, 17, 18, 20, 21, 22
	Volz 2	4, 7, 8, 13, 16, 17
	iMotions	1, 2, 5, 6, 7, 9, 10, 11, 15, 16, 18, 19, 22
	Waymo	4, 7, 8, 9, 13, 16, 17, 18, 20, 21, 22
	Bhattacharyya	1, 2, 6, 7, 8, 10, 11, 15, 16, 17, 19, 20, 21
	One or more of Ross, Cox, Test My Brain, Ogale, Schneemann, Quintero, Zhu, Gray, Ellenbogen, Zhang, Huval, Keller, Furuhashi, Kohler, Volz 1, Volz 2, iMotions, Waymo, and/or Bhattacharyya	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 14, 15, 16, 19, 20, 21, 22
Autopilot HW1	Ross	1, 4, 7, 8, 9, 10, 13, 16, 17, 18, 19, 22
	Cox	1, 2, 5, 6, 7, 10, 11, 14, 15, 16, 19
	Test My Brain	1, 2, 5, 6, 7, 10, 11, 14, 15, 16, 19
	Ogale	1, 2, 10, 11, 19
	Schneemann	1, 4, 7, 8, 10, 13, 16, 17 19
	Quintero	4, 7, 13, 16
	Zhu	1, 4, 7, 8, 9, 10, 13, 16, 17, 18, 19, 22
	Gray	1, 2, 10, 11, 19
	Ellenbogen	1, 2, 7, 10, 11, 16, 19
	Zhang	1, 4, 8, 10, 13, 17, 19, 21
	Huval	1, 2, 10, 11, 19
	Keller	1, 4, 5, 7, 8, 10, 13, 14, 16, 17, 19, 20, 21
	Furuhashi	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21
	Kooij	1, 10, 19
	Kohler	1, 4, 10, 13, 19
	Volz 1	1, 2, 4, 7, 8, 9, 10, 11, 13, 16, 17, 18, 19, 20, 21, 22

Primary Reference	Secondary Reference	Claim
	Volz 2	1, 4, 7, 8, 10, 13, 16, 17, 19, 20, 21
	iMotions	1, 2, 5, 6, 7, 9, 10, 11, 15, 16, 18, 19, 20, 22
	Levinson	1, 10, 19
	Zoox	1, 10, 19
	Waymo	1, 4, 7, 8, 9, 10, 13, 16, 17, 18, 19, 22
	Bhattacharyya	1, 2, 7, 8, 10, 11, 16, 17, 19, 20, 21
	One or more of Ross, Cox, Test My Brain, Ogale, Schneemann, Quintero, Zhu, Gray, Ellenbogen, Zhang, Huval, Keller, Furuhashi, Kooij, Kohler, Volz 1, Volz 2, iMotions, Levinson, Zoox, Waymo, and/or Bhattacharyya	1, 2, 4, 7, 8, 9, 10, 11, 13, 14, 16, 17, 19, 20, 21, 22
Mercedes	Ross	9, 18, 22
	Cox	1, 2, 6, 10, 11, 15, 19
	Test My Brain	1, 2, 6, 10, 11, 15, 19
	Ogale	1, 2, 10, 11, 19
	Schneemann	1, 10, 19
	Gray	2, 11
	Ellenbogen	1, 2, 10, 11, 19
	Huval	2, 11
	Zhang	1, 10, 19
	Zhu	9, 18, 22
	Volz 1	2, 9, 11, 18, 22
	Volz 2	1, 10, 19
	iMotions	1, 2, 6, 9, 11, 15, 18, 22
	Waymo	9, 18, 22
	Bhattacharyya	1, 2, 6, 10, 11, 15, 19
	One or more of Ross, Cox, Test My Brain, Ogale, Schneemann, Gray, Ellenbogen, Huval, Zhang, Zhu, Volz 1, Volz 2, Waymo, and/or iMotions	1, 2, 6, 9, 10, 11, 15, 18, 19, 22

3. Motivation to Combine and Reasonable Expectation of Success

With respect to the '344 Patent, the prior art identified above demonstrates the scope and content of the prior art. As detailed in Exhibits A-1 through A-27, the prior art included each limitation recited in the Asserted Claims of the '344 Patent. To the extent a cited prior art reference is deemed not to anticipate a claim, the only difference between the claimed invention and the prior art is the lack of actual combination of the elements in a single prior art reference. However, a Person of Ordinary Skill in the Art ("POSITA") would have been motivated to combine each of the above prior art references.

For example, many of the above-identified references (Ross, Ogale, Schneemann, Zhu, Gray, Zhang, Huval, Keller, Furuhashi, Waymo, Autopilot HW2, Autopilot HW1, Mercedes, Quintero, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Levinson, Bhattacharyya, and Zoox) are all related to motor vehicles. These references constitute analogous art within the same field of endeavor—specifically, automotive design and engineering—and address the same or substantially similar technical problems regarding vehicle operation and subsystem integration. A POSITA would naturally consult these references when seeking to improve vehicle performance or functionality. Here, because Ross, Ogale, Schneemann, Zhu, Gray, Zhang, Huval, Keller, Furuhashi, Waymo, Autopilot HW2, Autopilot HW1, Mercedes, Quintero, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Levinson, Bhattacharyya, and Zoox all reside within the automotive domain, the barrier to combination is exceedingly low. A POSITA would recognize that the teachings of each such reference are compatible with (or could be adapted to be compatible with) other references related to motor vehicles. The combination of these references related to motor vehicles also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar elements to perform their primary functions. And, driven by the perpetual market

pressure in the automotive industry to enhance safety, efficiency, and user experience, a POSITA would have been motivated to combine the specific features of each of Ross, Ogale, Schneemann, Zhu, Gray, Zhang, Huval, Keller, Furuhashi, Waymo, Autopilot HW2, Autopilot HW1, Mercedes, Quintero, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Levinson, Bhattacharyya, and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of an automobile, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As a further example, many of the above references relate more specifically to autonomous driving (e.g., Ross, Ogale, Zhu, Gray, Zhang, Huval, Schneemann, Karasev, Waymo, Autopilot HW1, Autopilot HW1, Levinson, and Zoox). These references constitute analogous art within the same field of endeavor—specifically, the development of automated driving systems using sensors—and address the same or substantially similar technical problems regarding object detection, environmental perception, and real-time decision making. A POSITA would naturally consult these references when seeking to improve the reliability or safety of an autonomous driving feature. Here, because Ross, Ogale, Zhu, Gray, Zhang, Huval, Schneemann, Karasev, Waymo, Autopilot HW1, Autopilot HW1, Levinson, and Zoox all involve descriptions of autonomous vehicle architectures, the barrier to combination is exceedingly low. For example, a POSITA would recognize that the sensing or control teachings of each such reference are compatible with the processing or navigation modules of other references related to autonomous driving. The combination of references relating to autonomous driving also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar algorithms and hardware to perform their primary functions. And, driven by the industry competition to achieve higher levels

of autonomy (e.g., for SAE Levels 3-5) and the necessity to eliminate human error, a POSITA would have been motivated to combine the specific features of each of Ross, Ogale, Zhu, Gray, Zhang, Huval, Schneemann, Karasev, Waymo, Autopilot HW1, Autopilot HW2, Levinson, and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of a self-driving platform, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As another example, many of the above identified references (Ross, Cox, Ogale, Zhu, Gray, Ellenbogen, Zhang, Huval, Schneemann, Quintero, Keller, Furuhashi, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Waymo, Autopilot HW1, Autopilot HW2, iMotions, Bhattacharyya and Test My Brain) are all related to the development and training of machine learning models, including supervised learning techniques. These references constitute analogous art within the same field of endeavor—specifically, artificial intelligence and data annotation—and address the same or substantially similar technical problems regarding model accuracy, ground truth verification, and the reduction of prediction error. A POSITA would naturally consult these references when seeking to improve the performance of a neural network or statistical model through high-quality supervision. Here, because Ross, Cox, Ogale, Zhu, Gray, Ellenbogen, Zhang, Huval, Schneemann, Quintero, Keller, Furuhashi, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Waymo, Autopilot HW1, Autopilot HW2, iMotions, Bhattacharyya, and Test My Brain all relate to data-driven algorithm development, the barrier to combination is exceedingly low. A POSITA would recognize that the human-labeled datasets or annotation interfaces of each such reference are compatible with (or could be adapted to be compatible with) the training pipelines and loss functions disclosed in other references related to machine learning. The combination of

these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar training loops to perform their primary functions. And, driven by the market pressure in the artificial intelligence industry to maximize inference accuracy and leverage human validation for edge cases, a POSITA would have been motivated to combine the specific features of each of Ross, Cox, Ogale, Zhu, Gray, Ellenbogen, Zhang, Huval, Schneemann, Quintero, Keller, Furuhashi, Kooij, Kohler, Volz 1, Volz 2, Schneider, Karasev, Waymo, Autopilot HW1, Autopilot HW2, iMotions, Bhattacharyya, and Test My Brain. Specifically, the use of human-generated ground truth labels to calibrate or refine model weights is a foundational practice in the art, making the aggregation of these teachings a matter of routine optimization. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known supervised learning solutions within the standard constraints of a predictive system, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As an additional example, many of the above identified references (Cox, Ellenbogen, Huval, iMotions, and Test My Brain) are all related to techniques and interfaces for generating training data. These references constitute analogous art within the same field of endeavor—specifically, the creation and management of ground truth datasets for machine learning—and address the same or substantially similar technical problems regarding annotator efficiency, labeling precision, and the workflow for verifying training data. A POSITA would naturally consult these references when seeking to streamline the process of generating high-quality inputs for a model. Here, because Cox, Ellenbogen, Huval, iMotions, and Test My Brain all reside within the specific domain of human-computer interaction for data entry, the barrier to combination is exceedingly low. A POSITA would recognize that the graphical user interfaces, bounding box

tools, or segmentation brushes of each such reference are compatible with (or could be adapted to be compatible with) the data export formats or workflow management systems of other references related to dataset generation. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar UI elements to perform their primary functions. And, driven by the perpetual market pressure in the machine learning industry to alleviate the data bottleneck in model development and minimize the cost of human supervision, a POSITA would have been motivated to combine the specific features of each of Cox, Ellenbogen, Huval, iMotions, and Test My Brain. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known productivity solutions within the standard constraints of a data pipeline, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

Below, Tesla has provided several additional illustrative examples of the motivations that a POSITA would have had to combine certain of the prior art references in Exhibits A-1 through A-27. The inclusion of certain example combinations herein does not exclude other combinations based on the claim charts attached hereto, as there are many possible combinations of the references listed herein, and it is not practical, particularly at this early stage prior to further factual investigation and claim construction proceedings, to identify and list all potentially relevant combinations. Instead, in many instances where a particular contention calls for, or requires, combining references, any one of a number of references can be combined. As such, these motivations to combine apply equally to the combination of a primary reference to one secondary reference, and the combination of a primary reference to multiple secondary references.

Exemplary Motivations for Combining Ross and Cox

A POSITA, following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox’s “statistical learning,” e.g., because using statistical methods and outputs would have been known to help reduce risks, and “in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect.” Cox at [0035]; *see also* Cox at [0027]-[0035]. A POSITA would also have looked to Cox to train Ross’s perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. Cox describes its training model as a neural network or other described supervised learning models, e.g., “any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression.” Cox at [0060]. Further, a POSITA would have found it obvious to reduce the risk involved with training Ross’s method of detecting objects and maneuvering autonomous vehicles by looking to Cox’s statistical methods, including statistical data associated with response data. Specifically, a POSITA would be motivated to look to Cox’s teachings of the parameters including psychometric data (including responses times) and eye tracking. Cox at [0019]-[0021], [0063]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Ross, to look to basic statistical concepts. For example, a POSITA would have found it obvious to implement ranges and averages for response times, taught in Cox. Cox [0029].

Exemplary Motivations for Combining Ross and Ogale

A POSITA, following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Ogale’s “human-labeled training data” e.g.,

because using statistical methods and outputs, and verifying data related to human responses with human labeling would have been known to help reduce risks since “[h]uman-labeled training data tends to be more accurate than the auto-labeled training data.” Ogale at 3:29-48, 6:51-7:12. A POSITA would also have been motivated to look to different methods to train and execute Ross’s predictions for intended future action, including Ogale’s generation of “human-labeled training data,” e.g., to improve the accuracy of the data input to statistical summaries. Ogale at 3:29-48, 6:51-7:12. Further, a POSITA would have looked to Ogale to train Ross’s perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. For example, Ogale teaches that neural networks can be used with autonomous vehicles for object classification and output prediction. Ogale at 1:11-2:9.

Exemplary Motivations for Combining Ross and Schneemann

A POSITA, following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Schneemann’s statistical methods applied to human responses regarding intent e.g., because using statistical methods and outputs would have been known to help reduce risks and obtaining human responses are what the method is trying to mimic. Schneemann at 2246 (“we developed a label tool, which asks the human observer to rate if a pedestrian has a principal aim to cross the street”). In addition, a POSITA would have been motivated to look to different methods to train and execute Ross’s predictions for intended future action, including Schneemann’s generation of a table with the distribution of labels, which represents a statistical summary of expected user responses. Schneemann at 2246.

Exemplary Motivations for Combining Ross and Gray

A POSITA would have looked to Gray to train Ross’s perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. For example, Gray teaches that its model “can be a convolution neural network.” Gray at 10:12-31.

Exemplary Motivations for Combining Ross and Ellenbogen

A POSITA following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Ellenbogen’s creation of composite outputs and composite confidences, e.g., because using statistical methods and outputs would have been known to help reduce risks. Ellenbogen at [0056]. A POSITA would also have looked to Ellenbogen to train Ross’s perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems, such as Ellenbogen’s deep neural network or convolution neural network. Ellenbogen at [0136].

Exemplary Motivations for Combining Ross and Zhang

A POSITA following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Zhang’s training data “labeled using human labelers,” because a POSITA would understand human responses to be what the neural network is designed to mimic. Zhang at [0051], [0053]. And a POSITA would have been motivated to look to different methods to train and execute Ross’s predictions for intended future action, including Zhang’s generation of predicted trajectories, which represents a statistical summary of expected user responses. Zhang at [0054].

Exemplary Motivations for Combining Ross and Keller

A POSITA would have found it obvious to reduce the risk involved with training Ross's method of detecting objects and maneuvering autonomous vehicles by looking to Keller's "manual labeling [of] pedestrian shapes in the images." Keller at 501

Exemplary Motivations for Combining Ross and Volz 1

A POSITA would have looked to Volz 1 to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems, such as the neural network architectures described in Volz 1. Volz 1 at 3-4.

Exemplary Motivations for Combining Ross and Volz 2

A POSITA, following Ross's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Volz 2's identification of pedestrian action and calculating an accuracy by percentage to improve the accuracy of Ross's method. Volz 2 at 857. In addition, a POSITA would have been motivated to look to different methods to train and execute Ross's predictions for intended future action, including Volz 2's generation of accuracy of predictions, which represents a statistical summary of expected user responses. Volz 2 at 857.

Exemplary Motivations for Combining Ross and Huval

A POSITA would have looked to Huval to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. For example, Huval describes, not only feedback provided by human annotators, but passing data through a neural network. Huval at [0010].

Exemplary Motivations to Combine Ross and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics such means of predictive distributions to improve Ross' determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Ross already outputs predictions road user intent, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Ross' pedestrian intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Cox and Ross (or Waymo)

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include inputting sensor data from autonomous vehicles, as taught in Ross (or Waymo), for object recognition. Ross at 7:57-8:31 ("the detection system 170 may include lasers, sonar, radar, cameras and/or any other detection devices that record data which may be processed by computing device 110"). A POSITA would have understood that Cox's description of classifying "query objects" would easily be applied to the context of objects on the road, particularly when Cox's techniques are implemented for autonomous driving and that a POSITA would be motivated to look to Ross's (or Waymo's) determination of "road user's intent" for this. Ross at 8:13-40. A POSITA would have found it obvious to use the trained data described in Cox to aid in the operation of an autonomous vehicle on the road. A POSITA would have been further motivated to look to Ross

(or Waymo), which describes using similar identification methods to maneuver a vehicle, to aid in this implementation. Ross at 9:13-65, 16:23-41.

Exemplary Motivations for Combining Cox and Ogale

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include inputting sensor data from autonomous vehicles for object recognition, and would have been motivated to look to different specific, known methods to train and execute Cox's method of classifying objects, and would have been motivated to combine Cox's techniques with Ogale's explanations of how it uses sensor data to implement similar methods for object detection, "including vehicles, pedestrians, bicyclists, or lane markers." Ogale at 4:34-42, 4:48-5:30. A POSITA would have further understood that Cox's description of classifying "query objects" would easily be applied to the context of objects on the road, particularly when Cox's techniques are implemented for autonomous driving, which a POSITA would have also found to be an obvious use of Cox's methods. A POSITA would have been motivated to combine Cox's classification of objects with Ogale's teachings of training a neural network with human-labeled output layer" and providing "the human-labeled output layer to a planning subsystem of the vehicle" as well as using object predictions to "make fully-autonomous or semi-autonomous driving decisions" to aid in this implementation, e.g., for increased driving safety. Ogale at 2:63-3:48, 5:66-6:7 (using object predictions "to make fully-autonomous or semi-autonomous driving decisions); *see also id.* at 6:51-7:12, 11:10-18.

Exemplary Motivations for Combining Cox and Zhu

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include

inputting sensor data from autonomous vehicles for object recognition, and would be motivated to look to Zhu's teachings of using sensors "to identify, track and predict the movements of pedestrians, bicycles, other vehicles, or objects on the roadway" to implement this. Zhu at 7:23-7:28. A POSITA would have further understood that Cox's description of classifying "query objects" would easily be applied to the context of objects on the road, particularly when Cox's techniques are implemented for autonomous driving, which a POSITA would have also found to be an obvious use of Cox's methods, and that a POSITA would be motivated to look to Zhu's teachings of using the computer "to take particular actions in response to the predicted actions of surrounding objects" to implement this. Zhu at 8:26-50. A POSITA would have been motivated to use Cox's identification and prediction methods to identify objects on the road as well as potential actions of said road users and to predict intentions of these road users as well as awareness of the road user of autonomous vehicles, and would have been motivated by Zhu to fill in details. Zhu at 9:65-10:20.

Exemplary Motivations for Combining Cox and Gray

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include inputting sensor data, as taught in Gray, from autonomous vehicles for object recognition. Gray at 8:12-8:24. A POSITA would have further understood that Cox's description of classifying "query objects" would easily be applied to the context of objects on the road, particularly when Cox's techniques are implemented for autonomous driving, which a POSITA would have also found to be an obvious use of Cox's methods, and would have been motivated to look to Gray's "training images" from vehicles to implement this. Gray at 9:60-10:2, 23:11-44.

Exemplary Motivations for Combining Cox and Schneemann

A POSITA would have been motivated to look to different specific, known methods to train and execute Cox’s method of classifying objects, including Schneemann’s generation of tables “show[ing] the distribution of the labels in [its] data set,” which represents a statistical summary of expected user responses. Schneemann at 2246. A POSITA would have been motivated to use Cox’s identification and prediction methods to identify potential actions of road users and to predict intentions of these road users, and would have been motivated to look to Schneemann, which uses similar training methods, to fill in these details, including using a “label tool, which asks the human observer to rate if a pedestrian has a principal aim to cross the street.” Schneemann at 2244.

Exemplary Motivations for Combining Cox and Quintero

A POSITA would have found it obvious to use the identification method taught in Cox to identify actions, such as staying in place, changing lanes, or crossing a street. For example, Cox would have found it obvious to combine Cox with Quintero, which both describe predicting behavior, to fill in details on the specifics of pedestrian behavior. Quintero at 321.

Exemplary Motivations for Combining Cox and Zhang

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include inputting sensor data from autonomous vehicles, such as taught in Zhang, for object recognition, and would have been motivated to look to different specific, known methods to train and execute Cox’s method of classifying objects. Zhang at [0058]. A POSITA would have further understood that Cox’s description of classifying “query objects” would easily be applied to the context of objects on the road, particularly when Cox’s techniques are implemented for autonomous driving, which a POSITA would have also found to be an obvious use of Cox’s methods. Specifically, a

POSITA would have been motivated to combine Zhang's description of training images relating to traffic and teachings of predicting trajectories, with Cox's detailed classification techniques. See Zhang at [0047], [0054]. A POSITA would have been motivated to use Cox's identification and prediction methods to improve the training taught in Zhang, which points to identifying potential actions of road users and predicting intentions of these road users. Zhang at [0051], [0058]. Furthermore, a POSITA would have been motivated to combine Cox's training techniques with Zhang's specific applications to a vehicle and details on how to make practical use of the training techniques. Zhang at [0058].

Exemplary Motivations for Combining Cox and Huval

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, could include inputting sensor data from autonomous vehicles for object recognition, as better described in Huval, and would have been motivated to look to different specific, known methods to train and execute Cox's method of classifying objects, such as those taught in Huval. Huval at [0018], [0021]-[0022]. A POSITA would have further understood that Cox's description of classifying "query objects" would easily be applied to the context of objects on the road, and would have been motivated to combine Cox's methods with Huval's specific application to the road. Huval at [0018].

Exemplary Motivations for Combining Cox and Keller

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include inputting sensor data from autonomous vehicles, such as taught by Keller, for object recognition, and would have been motivated to look to Keller for further implementation details. Keller at 494.

A POSITA would have further understood that Cox’s description of classifying “query objects” would easily be applied to the context of objects on the road, particularly when Cox’s techniques are implemented for autonomous driving, which a POSITA would have also found to be an obvious use of Cox’s methods. A POSITA would have been motivated to combine Cox’s detailed learning methods with Keller’s application to a vehicle to provide for a practical application of Cox, including improving the safety of a vehicle. Keller at 494, 505 (pointing to “advanced pedestrian path prediction” to “perform emergency vehicle maneuvers”). A POSITA would have been motivated to use Cox’s identification and prediction methods to identify objects on the road as well as potential actions of said road users and to predict intentions of these road users, and would have been motivated to Keller’s explanations of the specific context of pedestrian path prediction to implement Cox’s methods. Keller at 494 (describing prediction of a crossing pedestrian for purposes of increased road safety).

Exemplary Motivations for Combining Cox and Furuhashi

A POSITA would have further understood that Cox’s description of classifying “query objects” would easily be applied to the context of objects on the road, particularly when Cox’s techniques are implemented for autonomous driving, and would have been motivated to combine Cox’s classification methods with Furuhashi’s specific road context for a practical application of Cox’s methods. Furuhashi at 18. A POSITA would have been motivated to use Cox’s identification and prediction methods to identify objects on the road as well as potential actions of said road users and to predict intentions of these road users, specifically pedestrians, as taught in Furuhashi, for increased road safety. Furuhashi at 18.

Exemplary Motivations for Combining Cox and Kooij

A POSITA would have understood that Cox’s description of classifying “query objects” would easily be applied to the context of objects on the road, particularly when Cox’s techniques are implemented for autonomous driving. For example, a POSITA would have found it obvious to combine Cox’s classification techniques with Kooij’s description of predicting pedestrian trajectories to provide a practical application of Cox and improve the method, and thus improve the safety, described in Kooij. Kooij at 1448. A POSITA would have further found it obvious to use the identification method taught in Cox to identify objects on the road, including any or all of a pedestrian, a cyclist, or a motor vehicle, as taught by Kooij. Kooij at 1448.

Exemplary Motivations for Combining Cox and Kohler

A POSITA would have understood that Cox’s description of classifying “query objects” would easily be applied to the context of objects on the road, particularly when Cox’s techniques are implemented for autonomous driving. Specifically, a POSITA would have been motivated to combine Cox’s teachings of classification techniques with Kohler’s teachings of applying learned models to pedestrian prediction, especially to increase road user safety. Kohler at 2. A POSITA would have found it obvious to use the identification method taught in Cox to identify actions, such as staying in place, changing lanes, or crossing a street, as taught in Kohler. Kohler at 2.

Exemplary Motivations for Combining Cox and Volz 1

A POSITA would have further understood that Cox’s description of classifying “query objects” would easily be applied to the context of objects on the road, particularly when Cox’s techniques are implemented for autonomous driving, as taught by Volz 1. Volz 1 at 5. A POSITA would have been motivated to combine Cox’s classifying techniques with Volz 1’s similar classifying techniques in the specific context of pedestrians and cars. A POSITA would have been motivated to use Cox’s identification and prediction methods to identify objects on the road as

well as potential actions of said road users and to predict intentions of these road users as well as awareness of the road user of the autonomous vehicle, and would have been motivated to look to Volz 1 for more details on how to perform this specific implementation, especially in light of Volz 1's explanation that "[p]redicting the movement of arbitrary objects is a crucial part of automated driving systems." Volz 1.

Exemplary Motivations for Combining Cox and Volz 2

A POSITA would have further understood that Cox's description of classifying "query objects" would easily be applied to the context of objects on the road, particularly when Cox's techniques are implemented for autonomous driving, as taught by Volz 2. A POSITA would have been motivated to combine Cox and Volz 2, which both describe classification and learning techniques. Volz 2 at 857. A POSITA would have been motivated to look to different specific, known methods to train and execute Cox's method of classifying objects, including Volz 2's generation of a "labeled dataset," which represents a statistical summary of expected user responses. Volz 2 at 856. A POSITA would have been motivated to use Cox's identification and prediction methods to identify objects on the road as well as potential actions of said road users and to predict intentions of these road users, as taught in Volz 2, since both references employ training technique and Volz 2 is a practical application of techniques taught in Cox. Volz 2 at 854.

Exemplary Motivations for Combining Cox and Schneider

A POSITA would have understood that a natural implementation of the machine learning techniques taught in Cox, especially with regard to mimicking human reactions, would include inputting sensor data from autonomous vehicles for object recognition. A POSITA would have been motivated to use the techniques taught in Cox in the context of pedestrian path prediction taught in Schneider, at least to improve road safety with regard to intelligent vehicles. Schneider

at 174. A POSITA would have found it obvious to use the identification method taught in Cox to identify objects on the road, including any or all of a pedestrian, a cyclist, or a motor vehicle, and would have been motivated to look to Schneider for details of this practical application. Schneider at 179-80.

Exemplary Motivations for Combining Cox and Karasev

A POSITA would have found it obvious to use the identification method taught in Cox to detect and classify external objects on a road, such as pedestrians, bicyclists, dogs, and other vehicles. A POSITA would have been motivated to apply Cox's training methods with Karasev's goal of estimating pedestrian motion and path. Karasev at 2546.

Exemplary Motivations for Combining Cox and Levinson (or Zoox)

A POSITA would have found it obvious to use the identification method taught in Cox to identify objects on the road, including any or all of a pedestrian, a cyclist, or a motor vehicle. A POSITA would have been motivated to apply Cox's training methods with Levinson's (or Zoox's) goals of classifying and tracking external objects to estimate the likelihood of collision. Levinson at 8:62-9:30, 12:17-53.

Exemplary Motivations to Combine Cox and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teachings implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to expand upon the scenarios that Cox is able to predict. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Cox already outputs a prediction of a state of mind of a person in an image, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. Bhattacharyya at 1-4.

Exemplary Motivations for Combining Ogale with Ross (or Waymo)

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street. For example, a POSITA would look Ross’s (or Waymo’s) descriptions of identifying actions of road users since both references have the same aim of improving pedestrian safety. Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Ross’s (or Waymo’s) description of predicted trajectories of a pedestrian, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. A POSITA would be further motivated to look to Ross’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle and awareness of a road user of an autonomous vehicle to better generate Ogale’s object predictions. Ross at 4:33-46, 15:22-27.

Exemplary Motivations for Combining Ogale with Cox

Ogale describes “a human-labeled output layer that predicts how a human would identify objects in the projections of input sensor data.” Ogale at 3:22-48. A POSITA would be motivated to look at Cox to fill in details on analysis of this human input, including Cox’s description of human annotators. Cox at [0019]-[0021]. Ogale teaches generating projections from input sensor data, suggesting a use of statistical data. A POSITA would find it obvious for the projections to use general statistical concepts, such as those taught in Cox. Cox at [0029]. For example, Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Cox’s

description of analyzing psychophysics and other stimulus, which represent the state of mind of a road user, to aid in Ogale's prediction of future action. *See Cox at [0019]-[0021].*

Exemplary Motivations for Combining Ogale with Schneemann

Ogale teaches "each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers.." Ogale at 4:34-42. A POSITA would have understood that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Schneemann, which presents similar methods and goals towards identifying pedestrians. Schneemann at 2244. Ogale teaches generating "an object prediction as an output...[including] a region of space that is likely to be occupied by an object." Ogale at Abstract. A POSITA would find it obvious to use Schneemann's description of pedestrian crossing intention, which represents the state of mind of a road user, to aid in Ogale's prediction of future action. Schneemann at 2244. A POSITA would be motivated to look to Schneemann's teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale's object predictions. Schneemann at 2243.

Exemplary Motivations for Combining Ogale with Quintero

Ogale teaches "each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers.." Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Quintero, which similarly analyzes pedestrian behavior, including analyzing pedestrian body language. Quintero at 321. Ogale teaches generating "an object prediction as an output...[including] a region of space that is likely to be occupied by an object." Ogale at Abstract. A POSITA would find it obvious to

use Quintero’s description of pedestrian body language, which hints at the state of mind of a road user, to aid in Ogale’s prediction of future action. Quintero at 317.

Exemplary Motivations for Combining Ogale with Zhu

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Zhu, which similarly looks to predicting pedestrian movement. *See* Zhu at 9:65-10:20. Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Zhu’s description of pedestrian intent, such as whether to cross the street, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Zhu at 10:47-11:42. A POSITA would be motivated to look to Zhu’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle and awareness of a road use of an autonomous vehicle to better generate Ogale’s object predictions. Zhu at 10:47-11:42.

Exemplary Motivations for Combining Ogale with Zhang

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Zhang. Zhang at [0051]. A POSITA would be motivated to look to Zhang’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions. Zhang at [0058].

Exemplary Motivations for Combining Ogale with Ellenbogen

Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Ellenbogen’s description of determining suspicious behavior, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Ellenbogen at [0057]. A POSITA would have been motivated to combine Ogale with Ellenbogen since both intend to improve a computer’s ability to detect and mimic human behavior. *Id.*

Exemplary Motivations for Combining Ogale with Keller

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Keller. Keller at 494. Ogale describes “a human-labeled output layer that predicts how a human would identify objects in the projections of input sensor data.” Ogale at 3:22-48. A POSITA would be motivated to look at Keller to fill in details on analysis of this human input, including Keller’s description of using manual input. Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Keller’s description of path prediction of a pedestrian who may or may not cross a road, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Keller at 494. A POSITA would be motivated to look to Keller’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions. Keller at 494.

Exemplary Motivations for Combining Ogale with Furuhashi

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Furuhashi, which similarly teaches pedestrian prediction. Furuhashi at 18. Ogale teaches generating “an object prediction as an output....[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Furuhashi’s description of predicting pedestrian intention from posture, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Furuhashi at 18. A POSITA would be motivated to look to Furuhashi’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions. Furuhashi at 18.

Exemplary Motivations for Combining Ogale with Kohler

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Kohler, which similarly addresses prediction of a pedestrian path. Kohler at 2.

Exemplary Motivations for Combining Ogale with Volz 1

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught by Volz 1, which similarly focuses on predicting pedestrian motion and behavior. Volz 1 at 2. Ogale teaches generating “an

object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Volz 1’s description of pedestrian body language to predict behavior, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Volz 1 at 3. A POSITA would be motivated to look to Volz 1’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions. Volz 1 at 3. For example, A POSITA would be motivated to look to Volz 1’s teachings of predicting awareness of the road user of the autonomous vehicle to better generate Ogale’s object predictions. Volz 1 at 3 (looking at head orientation to predict pedestrian action).

Exemplary Motivations for Combining Ogale with Volz 2

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object...[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Volz 2, which similarly focuses on using computers to predict pedestrian action. Volz 2 at 854 Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Volz 2’s description of “pedestrians’ intentions,” which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Volz 2 at 854. A POSITA would be motivated to look to Volz 2’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions. Volz 2 at 856.

Exemplary Motivations to Combine Ogale and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Ogale is able to determine future subject motion, such as whether pedestrian will stay in place or cross a street. Bhattacharyya at 1-4.

Exemplary Motivations for Combining Schneemann with Ross (or Waymo)

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Ross's (or Waymo's) "perception system." Ross at 7:57-8:31. A POSITA would be motivated to look to Ross's (or Waymo's) description of predicted trajectories of a road user to better represent Schneemann's detection of pedestrians crossing streets. Ross at 9:13-40. A POSITA would be motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Ross (or Waymo) to find details on how to perform this control. Ross at 16:23-41.

Exemplary Motivations for Combining Schneemann with Cox

A POSITA would be motivated to look to Cox for details or different variations of known supervised learning based models to use to implement Schneemann's method for training a learning algorithm. Cox at [0060]. A POSITA would further be motivated to look at Cox's description of human input, as well as its details regarding statistical methods to improve the data input and analysis used in Schneemann's method. Cox at [0019]-[0021], [0029], [0063].

Exemplary Motivations for Combining Schneemann with Ogale

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Ogale's teachings of on-board sensors, which detect objects on the road. Ogale at 4:34-5:30. A POSITA would have been

motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Ogale to find details on how to perform this control. Ogale at 5:66-6:7. A POSITA would be further motivated, given Schneemann's intention to improve awareness of an autonomous vehicle, to look to Ogale for more details on specific neural networks and for specific objects, such as pedestrians on the road. Ogale at 1:22-2:9, 11:10-18.

Exemplary Motivations for Combining Schneemann with Zhu

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Zhu's teachings of sensor data, also in a vehicle. Zhu at 7:23-7:28. A POSITA would be motivated to look to Zhu's description of using sensors to track and predict movement of pedestrians to better represent Schneemann's detection of pedestrians crossing streets. Zhu at 7:23-7:28, 10:47-11:22 ("Autonomous vehicle then accesses database 137 to determine whether pedestrians, in that situation, are likely to cross the street before vehicle 620 completes its right-hand turn.") A POSITA would be motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Zhu to find details on how to perform this control. Zhu 8:26-50.

Exemplary Motivations for Combining Schneemann with Ellenbogen

A POSITA would be motivated to improve Schneemann's computer method of detection with Ellenbogen's description of specific neural networks. Ellenbogen at [0136].

Exemplary Motivations for Combining Schneemann with Kohler

A POSITA would be motivated to look to Kohler's description of pedestrian location using a bounding box to better represent Schneemann's detection of pedestrians crossing streets. Kohler at 2.

Exemplary Motivations for Combining Schneemann with Gray

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Gray's teachings of collision avoidance systems and object identification (for training) to better improve automotive safety. Gray at 8:12-8:24, 9:60-10:2, 23:11-44. A POSITA would be motivated to look to Gray's details regarding specific neural networks and identification of vehicles, pedestrians, and cyclists to improve Schneemann's road detection. Gray at 1:63-66, 10:12-31. A POSITA would be motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Gray to find details on how to perform this control. Gray at 2:34-2:42, 12:45-56.

Exemplary Motivations for Combining Schneemann with Zhang

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Zhang's teachings of a "prediction-based trajectory planning module" that uses "vehicle sensor subsystems," to better improve object detection. Zhang at [0058]. A POSITA would have been motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Zhang to find details on how to perform this control. *See* Zhang at [0058].

Exemplary Motivations for Combining Schneemann with Huval

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Huval's teachings of giving a

computer access to LIDAR data to improve its sensor use. Huval at [0021]-[0022]. A POSITA would be motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Huval to find details on how to perform this control. Huval at [0018]. For example, A POSITA would be motivated to look to Huval for details or different variations of known supervised learning-based models to use to implement Schneemann's method for training a learning algorithm. Huval at [0010].

Exemplary Motivations for Combining Schneemann with Keller

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Keller's teachings of using stereo vision data and detecting objects on the road. Keller at 494, 496. A POSITA would be motivated to implement Schneemann's predictions of pedestrian street crossing to better control an autonomous vehicle, and would be motivated to look to Keller to find details on how to perform this control. Keller at 505. A POSITA would further be motivated to combine Schneemann with Keller to provide further details as to what the object on the road is and the possibility of movement of that object. Keller at 494.

Exemplary Motivations for Combining Schneemann with Furuhashi

A POSITA would be motivated to look to Furuhashi's description of evaluating pedestrian posture as it concerns intent to cross a street to better represent Schneemann's detection of pedestrians crossing streets. *See* Furuhashi at 18.

Exemplary Motivations for Combining Schneemann with Kooij

A POSITA would be motivated to look to Kooij's description of collecting a dataset of pedestrian trajectories to better represent Schneemann's detection of pedestrians crossing streets. *See* Kooij at 1448.

Exemplary Motivations for Combining Schneemann with Volz 1

A POSITA would be motivated to look to Volz 1's description of collecting data related to pedestrians to better represent Schneemann's detection of pedestrians crossing streets. Volz 1 at 5. A POSITA would be motivated to look to Volz 1 for details or different variations of known supervised learning-based models to use to implement Schneemann's method for training a learning algorithm. *See* Volz 1 at 3-4. A POSITA would find it obvious that one aspect of Schneemann's prediction of a pedestrian's intention to cross a street could include awareness of a road user to an autonomous vehicle, as described in Volz 1. Volz 1 at 3 (using head orientation to "determine the pedestrians situational awareness").

Exemplary Motivations for Combining Schneemann with Volz 2

A POSITA would be motivated to look to Volz 2's description of learning "the behavior of pedestrians at crosswalks" to better represent Schneemann's detection of pedestrians crossing streets. *See* Volz 2 at 854, 856.

Exemplary Motivations for Combining Schneemann with Schneider

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Schneider's similar teachings of images "recorded with a stereo camera system...mounted behind the windshield of a vehicle" to better detect pedestrians. Schneider at 179-80.

Exemplary Motivations for Combining Schneemann with Karasev

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Karasev's teachings of creating a model describing pedestrian motion, which would serve Schneemann's purpose of using an on-board camera. Karasev at 2546.

Exemplary Motivations for Combining Schneemann and Levinson (or Zoox)

A POSITA would be motivated to combine Schneemann's teachings of capturing data with an "on-board mono camera" on an autonomous vehicle with Levinson's (or Zoox's) methods for classifying and tracking objects on the road, including any or all of a pedestrian, a cyclist, or a motor vehicle. A POSITA would have been motivated to apply Levinson's (or Zoox's) methods of classifying and tracking external objects to implement Schneemann's predictions of pedestrian street crossing to estimate the likelihood of collision. Levinson at 8:62-9:30, 12:17-53.

Exemplary Motivations to Combine Schneemann and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teachings implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Schneemann's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Schneemann already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Schneemann is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Schneemann's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Zhu with Cox

A POSITA would have found it obvious to supplement Zhu's description of "a library of rules of what objects will do in various situations" that "may begin as a human built set of rules"

or “may begin as a rules learned from vehicle observation and have humans examine the rules and improve them manually” with teachings of making these predictions a distribution of user responses expected to be received when presented with sensor data, at least as a common and efficient way to analyze data. A POSITA would have been motivated to look to Cox’s description of neural networks to implement Zhu’s teachings that it’s behavior prediction model “may be accomplished by, for example, tools and techniques of machine learning.” Specifically, a POSITA would have understood that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. Cox describes its training model as a neural network or other described supervised learning models, e.g., “any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression.” Cox at [0060]. A POSITA would have found it obvious to turn Zhu’s “human built” “library of rules” into statistical data based on human responses, such as the answers to the “set of queries posed to a crowd” taught by Cox. Cox at [0035]; *see also id.* at [0027]-[0035]. A POSITA would have found it obvious to use basic statistical concepts, as taught in Cox, to build its rules based on human responses. Cox at [0019]-[0021], [0063].

Exemplary Motivations for Combining Zhu with Ogale

A POSITA would have found it obvious to supplement Zhu’s description of “a library of rules of what objects will do in various situations” that “may begin as a human built set of rules” or “may begin as a rules learned from vehicle observation and have humans examine the rules and improve them manually” with teachings of making these predictions a distribution of user responses expected to be received when presented with sensor data, such as is taught in Ogale at least as a common and effective way to analyze data. Ogale at 3:29-48, 6:51-7:12 (“Co-training

allows the system to combine the benefits of highly-accurate, but limited human-labeled data with less-accurate, but more voluminous auto-labeled data”). Furthermore, a POSITA would be motivated to combine Zhu’s trained model with Ogale’s description of neural networks to implement Zhu’s teachings that it’s behavior prediction model “may be accomplished by, for example, tools and techniques of machine learning.” Ogale at 1:11-2:9

Exemplary Motivations for Combining Zhu with Gray

A POSITA would have been motivated to look to Gray’s description of a “convolution neural network” to implement Zhu’s teachings that it’s behavior prediction model “may be accomplished by, for example, tools and techniques of machine learning.” Zhu at 9:67-10:20; Gray at 10:12-31.

Exemplary Motivations for Combining Zhu with Schneemann

A POSITA would have found it obvious to supplement Zhu’s description of “a library of rules of what objects will do in various situations” that “may begin as a human built set of rules” or “may begin as a rules learned from vehicle observation and have humans examine the rules and improve them manually” with teachings of making these predictions a distribution of user responses expected to be received when presented with sensor data, at least as a common and effective way to analyze data. Zhu at 8:26-50. A POSITA would have been motivated to improve Zhu’s behavior prediction model with Schneemann’s analysis of its labels, in part because Zhu points to machine learning as a way to accomplish its behavior prediction model. Zhu 9:67-10:20; Schneemann at 2246.

Exemplary Motivations for Combining Zhu with Ellenbogen

Zhu would have found it obvious to supplement Zhu’s description of “a library of rules of what objects will do in various situations” that “may begin as a human built set of rules” or “may

begin as a rules learned from vehicle observation and have humans examine the rules and improve them manually” with teachings of making these predictions a distribution of user responses expected to be received when presented with sensor data, at least as a common and efficient way to analyze data. Zhu at 8:26-50. A POSITA would have been motivated to look to Ellenbogen’s description of “gathering of human intelligence” to implement Zhu’s teachings that it’s behavior prediction model “may be accomplished by, for example, tools and techniques of machine learning.” Ellenbogen at [0056]-[0057], [0136]. A POSITA would have further been motivated to combine Zhu’s set of rules with the machine learning techniques found in Ellenbogen. Ellenbogen at [0136].

Exemplary Motivations for Combining Zhu with Zhang

A POSITA would have found it obvious to supplement Zhu’s description of “a library of rules of what objects will do in various situations” that “may begin as a human built set of rules” or “may begin as a rules learned from vehicle observation and have humans examine the rules and improve them manually” with teachings of making these predictions a distribution of user responses expected to be received when presented with sensor data, at least as a common and effective way to analyze data. Zhu at 8:26-50. For example, a POSITA would have been motivated to combine Zhu’s rules with Zhang’s training data that “can be labeled using human labelers” and then used to predict trajectories. Zhang at [0053].

Exemplary Motivations for Combining Zhu with Huval

A POSITA would have been motivated to look to Huval’s description of training a neural network to implement Zhu’s teachings that it’s behavior prediction model “may be accomplished by, for example, tools and techniques of machine learning.” Zhu at 8:46-50; *see also* Huval at

[0010]. A POSITA would have found it obvious to combine Zhu and Huval, which both use computers to generate predictions regarding vehicles. Zhu at 7:23-7:28, Huval at [0008]-[0010].

Exemplary Motivations for Combining Zhu with Keller

A POSITA would have found it obvious to turn Zhu's "human built" "library of rules" into statistical data based on human responses, such as the "GT locations of the pedestrians in the world [that] where obtained by manual labeling the pedestrian shapes in the images" taught by Keller. Keller at 501.

Exemplary Motivations for Combining Zhu with Volz 1

A POSITA would have been motivated to look to Volz's description of neural network architectures to implement Zhu's teachings that it's behavior prediction model "may be accomplished by, for example, tools and techniques of machine learning." Volz 1 at 3-4.

Exemplary Motivations for Combining Zhu with Volz 2

Zhu would have found it obvious to supplement Zhu's description of "a library of rules of what objects will do in various situations" that "may begin as a human built set of rules" or "may begin as a rules learned from vehicle observation and have humans examine the rules and improve them manually" with teachings of making these predictions a distribution of user responses expected to be received when presented with sensor data, as taught by Volz 1, at least as a common and effective way to analyze data. Zhu at 8:26-50; Volz 2 at 856-57 (using a labeled dataset to predict pedestrian behavior).

Exemplary Motivations to Combine Zhu and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Zhu's determination of future subject motion.

Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Zhu already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Zhu is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Zhu's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Gray with Ross (or Waymo)

A POSITA would have been motivated to look to Ross (or Waymo) to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Ross at 9:41-65. A POSITA would have been motivated to look to Ross (or Waymo) and its "intent models" to predict the state of mind of a user, denote a user's intent to step into the path of a vehicle, or be aware of an autonomous vehicle to better determine likelihoods of collisions. Ross at 4:33-46, 9:13-40, 15:22-27

Exemplary Motivations for Combining Gray with Cox

A POSITA would have been motivated to look to Cox to provide additional details on how to present summary statistics of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. Cox at [0035], [0027]-[0035]. A POSITA would have been motivated to look to Cox to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such

as thorough statistical data, whose parameters include at least the content of response, as taught by Cox. Cox at [0019]-[0021], [0063]. A POSITA would have found it obvious to use basic statistical concepts, as taught in Cox, to determine likelihoods of collisions. Cox at [0029]. A POSITA would have also been motivated to look to Cox to predict the state of mind of a user to better determine likelihoods of collisions, a goal of Gray. Cox at [0016].

Exemplary Motivations for Combining Gray with Ogale

A POSITA would have been motivated to look to Ogale to provide additional details on how to present summary statistics of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. A POSITA would have been motivated to look to Ogale to provide additional details on how to present a statistical summary data of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. Ogale at 3:29-48, 6:51-7:12

Exemplary Motivations for Combining Gray with Schneemann

A POSITA would have been motivated to look to Schneemann to provide additional details on how to present summary statistics of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. Schneemann at 2246. A POSITA would have been motivated to look to Schneemann to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Schneemann at 2244. A POSITA would have been motivated to look to Schneemann to predict the state of mind of a user to better determine likelihoods of collisions. Schneemann at 2244. A POSITA would further have been motivated to look to Schneemann to predict the intention of a

road user to step into the path of an autonomous vehicle to better determine likelihoods of collisions. Schneemann at 2243.

Exemplary Motivations for Combining Gray with Quintero

A POSITA would have been motivated to look to Quintero to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Quintero at 321. A POSITA would have been motivated to look to Quintero to predict the state of mind of a user to better determine likelihoods of collisions. Quintero at 317.

Exemplary Motivations for Combining Gray with Ellenbogen

A POSITA would have been motivated to look to Ellenbogen to provide additional details on how to present summary statistics of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. Ellenbogen at [0056] (describing queries and a "gathering of human intelligence"), [0136]. A POSITA would have been motivated to look to Ellenbogen to predict the state of mind of a user to better determine likelihoods of collisions. Ellenbogen at [0057].

Exemplary Motivations for Combining Gray with Zhu

A POSITA would have been motivated to look to Zhu to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street, as demonstrated by Zhu's prediction of pedestrian and vehicle movement. Zhu at 9:65-10:20. A POSITA would have been motivated to look to Zhu to predict the state of mind of a user to better determine likelihoods of collisions. Zhu at 10:47-11:22 (evaluating how a pedestrian perceives their surroundings in determining whether they are likely to cross). A POSITA would have been

motivated to look to Zhu to predict the intention of a road user to step into the path of an autonomous vehicle to better determine likelihoods of collisions. Zhu at 9:67-10:20. (predicting potential collisions and likely paths of vehicles). A POSITA would have been further motivated to look to Zhu to predict user the awareness of a road user of an autonomous vehicle to better determine likelihoods of collisions. Zhu at 10:47-11:22 (evaluating how a pedestrian perceives their surroundings in determining whether they are likely to cross).

Exemplary Motivations for Combining Gray with Zhang

A POSITA would have been motivated to look to Zhang to provide additional details on how to present summary statistics and other data of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. Zhang at [0051], [0053]. A POSITA would have been further motivated to look to Zhang to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Zhang at [0051] (labeling heading and direction of travel). A POSITA would have further been motivated to look to Zhang to predict the intention of a road user to step into the path of an autonomous vehicle to better determine likelihoods of collisions. Zhang at [0058] (predicting trajectories).

Exemplary Motivations for Combining Gray with Keller

A POSITA would have been motivated to look to Keller to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Keller at 494 (path prediction). A POSITA would have been motivated to look to Keller to predict the state of mind of a user to better determine likelihoods of collisions. A POSITA would have been motivated to

look to Keller to predict the intention of a road user to step into the path of an autonomous vehicle to better determine likelihoods of collisions. Keller at 494 (describing path prediction).

Exemplary Motivations for Combining Gray with Furuhashi

A POSITA would have been motivated to look to Furuhashi to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Furuhashi at 18 (predicting pedestrian intent, in part based on posture). A POSITA would have been motivated to look to Furuhashi to predict the state of mind of a user to better determine likelihoods of collisions. *Id.* A POSITA would have been motivated to look to Furuhashi to predict the intention of a road user to step into the path of an autonomous vehicle to better determine likelihoods of collisions. *Id.*

Exemplary Motivations for Combining Gray with Kohler

A POSITA would have been motivated to look to Kohler to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Kohler at 2 (“predicting whether a pedestrian is likely to enter a lane”).

Exemplary Motivations for Combining Gray with Volz 1

A POSITA would have been motivated to look to Volz 1 to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Volz 1 at 2 (“Predicting the movement of arbitrary objects is a crucial part of automated driving systems”). A POSITA would have been motivated to look to Volz 1 to predict the state of mind of a user to better determine likelihoods of collisions. *Id.* A POSITA would have similarly been motivated to

look to Volz 1 to predict the intention of a road user to step into the path of an autonomous vehicle and to predict the awareness of the pedestrian to better determine likelihoods of collisions. Volz 1 at 3 (looking at body language and head orientation for a more sophisticated approach).

Exemplary Motivations for Combining Gray with Volz 2

A POSITA would have been motivated to look to Volz 2 to provide additional details on how to present summary statistics and statistical data of the drivable space and likelihoods of collision determined using Gray's model, especially since it is trained using human input to label regions of images. Volz 2 at 856 (describing using a labeled dataset). A POSITA would have further been motivated to look to Volz 2 to provide additional details on the specifics on how to determine the likelihood of a collision, as taught in Gray, such as by determining whether an object will stay in place, change lanes, or cross a street. Volz 2 at 854. A POSITA would have been motivated to look to Volz 2 for more details on what is included in user responses and predicted intentions to further improve determinations of intent and awareness of a pedestrian to improve Gray's model. Volz 2 at 854.

Exemplary Motivations to Combine Gray and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Gray's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Gray already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Gray is able to determine future subject motion.

Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Gray's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Zhang with Ross (or Waymo)

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Ross (or Waymo) for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its calculation of planned trajectory. Ross at 4:33-46, 9:13-65, 15:22-27.

Exemplary Motivations for Combining Zhang with Cox

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have found it obvious to combine Zhang's trajectory calculations with Cox's detailed teachings of learning-based models to improve Zhang's trajectory calculations. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. Cox describes its training model as a neural network or other described supervised learning models, e.g., "any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression." Cox at [0060].

Exemplary Motivations for Combining Zhang with Ogale

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Similarly, Ogale describes a method of maneuvering an autonomous vehicle. *See*

Ogale at 4:34-42. A POSITA would have been motivated to look to Ogale for more details on what is included in a statistical summary and what type of neural network may be used and to further improve determinations of intent and awareness of a pedestrian to improve Zhang's predictions. Ogale at 1:11-2:9, 3:29-48, 6:51-7:12.

Exemplary Motivations for Combining Zhang with Schneemann

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Schneemann, which uses similar training methods to those presented by Zhang, to fill in details, including using a "label tool, which asks the human observer to rate if a pedestrian has a principal aim to cross the street," which indicates a state of mind of a user. Schneemann at 2244.

Exemplary Motivations for Combining Zhang with Quintero

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Quintero for more details on what is included in user responses and predicted state of mind (based on body language) and to further improve determinations of intent and awareness of a pedestrian to improve Zhang's predicted trajectory. Quintero at 321.

Exemplary Motivations for Combining Zhang with Zhu

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Zhu for more details on what is included in user response and state of mind, intentions, and awareness of a road user, to further improve determinations of intent and awareness of a pedestrian to improve Zhang's trajectory prediction. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Zhang with Gray

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Similarly, Gray describes a method of detecting objects near an autonomous vehicle. *See* Gray at 9:53-66. A POSITA would have been motivated to look to Gray for more details on potential neural networks to use for training and analysis to further improve Zhang's trajectory prediction, which prediction would be aided by a better understanding of objects around the vehicle. Gray 10:12-31.

Exemplary Motivations for Combining Zhang with Ellenbogen

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Ellenbogen describes a method of classifying sensor data. *See* Ellenbogen at [0006]. A POSITA would have been motivated to look to Ellenbogen for more details on statistical output, specific neural networks, and predicted state of mind to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ellenbogen at [0056], [0136].

Exemplary Motivations for Combining Zhang with Huval

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Similarly, Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Huval to find more details regarding machine learning models to further improve determinations of intent and awareness of a pedestrian to improve Zhang's trajectory predictions. Huval at [0010].

Exemplary Motivations for Combining Zhang with Keller

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Similarly, Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Keller for more

details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a pedestrian to improve Zhang's vehicle trajectory prediction, as this would allow the trajectory to work around pedestrians. Keller at 494.

Exemplary Motivations for Combining Zhang with Furuhashi

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Furuhashi describes a method of predicting pedestrian intention. *See* Furuhashi at 17. A POSITA would have been motivated to look to Furuhashi for more details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a pedestrian to improve Zhang's trajectory prediction. Furuhashi at 18.

Exemplary Motivations for Combining Zhang with Kooij

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Kooij describes a method of capturing and analyzing data from a vehicle on the road. *See* Kooij. A POSITA would have been motivated to look to Kooij for more details on gathering and using sensor data to further improve determinations of intent and awareness of a pedestrian to improve Zhang's trajectory prediction. Kooij at 1448.

Exemplary Motivations for Combining Zhang with Volz 1

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Volz 1 describes a method of analyzing and predicting pedestrian movement in and around a road. *See* Volz 1 at Abstract. A POSITA would have been motivated to look to Volz 1 for more details on neural networks as well as what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to anticipate pedestrian movement and thereby improve Zhang's trajectory prediction. Volz 1 at 2, 3-4.

Exemplary Motivations for Combining Zhang with Volz 2

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. Volz 2 describes a method of using sensors and artificial intelligence to analyze pedestrian behavior. *See* Volz 2 at 856. A POSITA would have been motivated to look to Volz 2 for more details on what is included in user responses and predicted intentions to further improve determinations of intent and awareness of a pedestrian to anticipate pedestrian movement and thereby improve Zhang's trajectory prediction. Volz 2 at 854.

Exemplary Motivations for Combining Zhang with Schneider

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have found it obvious to use the identification method taught in Schneider to identify objects on the road, including any or all of a pedestrian, a cyclist, or a motor vehicle, and would have been motivated to look to Schneider for details of this practical application. Schneider at 179-80.

Exemplary Motivations for Combining Zhang with Karasev

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to apply Karasev's goal of estimating pedestrian motion and path with Zhang's goal of predicting trajectory of a vehicle to anticipate pedestrian movement and thereby improve Zhang's trajectory prediction. Karasev at 2546.

Exemplary Motivations for Combining Zhang and Levinson (or Zoox)

Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to apply Levinson's (or Zoox's) methods for classifying and tracking external objects such as pedestrians, cyclists, a motor vehicles to Zhang's goal of predicting trajectory of a vehicle to anticipate pedestrian movement and thereby improve Zhang's trajectory prediction. Levinson at 8:62-9:30, 12:17-53.

Exemplary Motivations to Combine Zhang and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Zhang is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Zhang's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Huval with Ross (or Waymo)

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would find it obvious to use Ross's (or Waymo's) description of predicted trajectories of a pedestrian, which represents the state of mind of a road user, to aid in Huval's calculations and control relating to a road vehicle. A POSITA would be further motivated to look to Ross's (or Waymo's) teachings of predicting intention of a road user to move into the path of the autonomous vehicle and awareness of a road user of an autonomous vehicle to improve the safety of Huval's method. Ross at 4:33-46, 15:22-27.

Exemplary Motivations for Combining Huval with Cox

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Cox to provide additional details on how to present summary statistics after implanting Huval's trained model. Cox at [0035], [0027]-[0035]. A POSITA would have been motivated to look to Cox to provide additional details on the specifics on how to train a model for an autonomous vehicle, as taught in Huval, such as thorough statistical data, whose parameters include at least the content of response, as taught by Cox. Cox at [0019]-[0021], [0063]. A POSITA would have found it obvious to use basic statistical concepts,

as taught in Cox, to determine accuracy of Huval's models. Cox at [0029]. A POSITA would have also been motivated to look to Cox to predict the state of mind of a user to better determine drive autonomous vehicles. Cox at [0016].

Exemplary Motivations for Combining Huval with Ogale

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Ogale describes a method of maneuvering an autonomous vehicle. *See* Ogale at 4:34-42. A POSITA would have been motivated to look to Ogale for more details on what is included in a statistical summary and what type of neural network may be used and to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Ogale at 1:11-2:9, 3:29-48, 6:51-7:12.

Exemplary Motivations for Combining Huval with Schneemann

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Similarly, Schneemann describes a method of capturing data on a vehicle and classifying this data. *See* Schneemann. A POSITA would have been motivated to look to Schneemann for more details on what is included in a statistical summary and what is included in user responses, as well as to improve on methods of determining state of mind and intent of a pedestrian to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Schneemann at 2244, 2246.

Exemplary Motivations for Combining Huval with Ellenbogen

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Ellenbogen describes a method of classifying sensor data. *See* Ellenbogen at [0006]. A

POSITA would have been motivated to look to Ellenbogen for more details on statistical output, specific neural networks, and predicted state of mind to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Ellenbogen at [0056], [0136].

Exemplary Motivations for Combining Huval with Quintero

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Quintero describes a method of identifying pedestrians. *See* Quintero. A POSITA would have been motivated to look to Quintero for more details on what is included in user responses and predicted state of mind (based on body language) and to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Quintero at 321.

Exemplary Motivations for Combining Huval with Zhu

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Zhu describes a method of maneuvering an autonomous vehicle. *See* Zhu 11:35-11:60. A POSITA would have been motivated to look to Zhu for more details on what is included in user response and state of mind, intentions, and awareness of a road user, to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Huval with Zhang

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Similarly, Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Zhang for more details on what is included in user responses and to further improve determinations of intent and

awareness of a pedestrian to improve its driver assistance system. A POSITA would have been motivated to look to Zhang for more details on statistical output, specific neural networks, content of user responses, and predicted intentions of a pedestrian to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Zhang at [0051] [0053], [0058].

Exemplary Motivations for Combining Huval with Keller

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Also in the realm of road navigation and safety, Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Keller for more details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Keller at 494.

Exemplary Motivations for Combining Huval with Furuhashi

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Furuhashi describes a method of predicting pedestrian intention. *See* Furuhashi at 17. A POSITA would have been motivated to look to Furuhashi for more details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Furuhashi at 18.

Exemplary Motivations for Combining Huval with Kohler

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Also in the realm of road navigation and safety, Kohler describes a method of detecting

pedestrians in and around a road. *See* Kohler at Abstract. A POSITA would have been motivated to look to Kohler to further understand details related to what is included in a user response. Kohler at 2 (“In this paper we focus on scenarios, where a pedestrian stands at the pavement and decides to enter the lane.”)

Exemplary Motivations for Combining Huval with Volz 1

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Volz 1 describes a method of analyzing and predicting pedestrian movement in and around a road. *See* Volz 1 at Abstract. A POSITA would have been motivated to look to Volz 1 for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval’s method of navigating an autonomous vehicle using artificial intelligence. Volz 1 at 2, 3-4.

Exemplary Motivations for Combining Huval with Volz 2

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Volz 2 describes a method of using sensors and artificial intelligence to analyze pedestrian behavior. *See* Volz 2 at 856. A POSITA would have been motivated to look to Volz 2 for more details on what is included in user responses as well as more details regarding statistical methods and predicted intentions to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Volz 2 at 854, 857.

Exemplary Motivations to Combine Huval and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya’s teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Huval’s determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Huval

already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Huval is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Huval's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Keller with Ross (or Waymo)

Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. Similarly, Ross (or Waymo) describes a method of maneuvering a vehicle. *See* Ross at 1:30-2:53. A POSITA would have been motivated to look to Ross for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its vehicle safety system. Ross at 4:33-46, 9:13-65, 15:22-27.

Exemplary Motivations for Combining Keller with Cox

Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Cox's teachings of obtaining responses feedback from users presented with sensor data as input to generate Keller's statistical summary of predicted motion based on input, particularly since Keller describes observed motion. A POSITA would have been motivated, based on Keller's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Cox. Specifically, a POSITA would have understood that a user would be likely to use a supervised learning based model for training the perception, prediction,

and/or maneuvering systems. Cox describes its training model as a neural network or other described supervised learning models, e.g., “any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression.” Cox at [0060]. A POSITA would have further been motivated by Keller’s teachings of computing median object motion and extracting orientation histograms to look to Cox’s teachings of statistical concepts. *Id.*

Exemplary Motivations for Combining Keller with Ogale

Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Ogale’s teachings of obtaining responses feedback from users presented with sensor data as input to generate Keller’s statistical summary of predicted motion based on input, particularly since Keller describes observed motion. Ogale at 3:29-48, 6:51-7:12. A POSITA would have been motivated, based on Keller’s teaching of using its method on an “intelligent vehicle,” to fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Ogale. Ogale at 1:11-2:9.

Exemplary Motivations for Combining Keller with Schneemann

Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Schneemann’s teachings of obtaining responses feedback from users presented with sensor data as input to generate Keller’s statistical summary of predicted motion based on input, particularly since Keller describes observed motion. Schneemann at 2246 (“we developed a label tool, which asks the human observer to rate if a pedestrian has a principal aim to cross the street.”).

Exemplary Motivations for Combining Keller with Gray

A POSITA would have been motivated, based on Keller's teaching of using its method on an "intelligent vehicle," to fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Gray. Gray at 10:12-31.

Exemplary Motivations for Combining Keller with Ellenbogen

A POSITA would have been motivated to look to Ellenbogen's teachings of obtaining responses feedback from users presented with sensor data as input to generate Keller's statistical summary of predicted motion based on input, particularly since Keller describes observed motion. Ellenbogen at [0056] ("The current subject matter can coordinate use and gathering of human intelligence, including performing quality, efficiency, latency, confidence measures in real-time of the agents"), 25:42-59. A POSITA would have been motivated, based on Keller's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Ellenbogen. Ellenbogen at [0136].

Exemplary Motivations for Combining Keller with Huval

A POSITA would have been motivated, based on Keller's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Huval, which also involves vehicles that rely heavily on computer systems. Huval at [0010].

Exemplary Motivations for Combining Keller with Zhang

Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. In a similar vein, Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Zhang for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. A

POSITA would have been motivated to look to Zhang for more details on statistical output, specific neural networks, content of user responses, and predicted intentions of a pedestrian to further improve determinations of intent and awareness of a pedestrian, particularly since Keller describes observed motion. Zhang at [0051] [0053], [0058].

Exemplary Motivations for Combining Keller with Zhu

Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated by Keller's teachings of predicting motion of a pedestrian to look to Zhu for its teachings of awareness of a road user to improve the prediction. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Keller with Volz 1

A POSITA would have been motivated, based on Keller's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Volz 1. Volz 1 at 3-4. A POSITA would have been motivated by Keller's teachings of predicting motion of a pedestrian to look to Volz 1 for its teachings of awareness of a road user to improve the prediction. Volz 1 at 2.

Exemplary Motivations for Combining Keller with Volz 2

A POSITA would have been motivated to look to Volz 2's teachings of obtaining responses feedback from users presented with sensor data as input to generate Keller's statistical summary of predicted motion based on input, particularly since Keller describes observed motion. *See* Volz 2 at 856. A POSITA would have been motivated to look to Volz 2's teachings of obtaining responses feedback from users presented with sensor data as input to generate Keller's statistical summary of predicted motion based on input, particularly since Keller describes observed motion. Volz 2 at 854.

Exemplary Motivations to Combine Keller and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Keller's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Keller already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Keller is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Keller's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Furuhashi with Ross (or Waymo)

A POSITA would have found it obvious to combine use Furuhashi's method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught in Ross (or Waymo). Ross at 1:30-2:53. A POSITA would be motivated based on Furuhashi's teachings of applying the method to a moving vehicle and its description of pedestrian protection being implemented in the field of "advanced driver assistance systems" to look to methods of further controlling the vehicle, as taught in Ross (or Waymo). Ross at 1:30-2:53. A POSITA would have been motivated by Furuhashi's teaching of starting to cross the street and "abort[ing] it and then cross[ing] after the vehicle had passed" to look to Ross's (or Waymo's) teaching of determining pedestrian awareness of a vehicle to improve the overall Furuhashi's

overall goal of determining a pedestrian's intent to cross the street. Ross at 4:33-46, 9:13-65, 15:22-27.

Exemplary Motivations for Combining Furuhashi with Cox

A POSITA would have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user responses of intent, such as taught in Cox, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street. Cox at [0019]-[0021], [0027]-[0035], [0063]. A POSITA would have been motivated by Furuhashi's goal of improving pedestrian detection to look to different known supervised learning models, such as those taught in Cox, to improve the calculations already taught in Furuhashi. Cox at [0016], [0029], [0060]. Specifically, a POSITA would understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. Cox describes its training model as a neural network or other described supervised learning models, e.g., "any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression." Cox at [0060]. A POSITA would have further been motivated by Furuhashi's goal of improving pedestrian detection to improve the accuracy of the conclusions reached through Furuhashi's probability calculations to use common statistical methods, such as those taught in Cox. Cox at [0029].

Exemplary Motivations for Combining Furuhashi with Ogale

A POSITA would have found it obvious to combine use Furuhashi's method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught in Ogale. A POSITA would have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user

responses of intent, such as taught in Ogale, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street. Ogale at 1:11-2:9, 3:29-48, 6:51-7:12. A POSITA would be motivated based on Furuhashi's teachings of applying the method to a moving vehicle and its description of pedestrian protection being implemented in the field of "advanced driver assistance systems" to look to methods of further controlling the vehicle, as taught in Ogale. Ogale at 5:66-6:7.

Exemplary Motivations for Combining Furuhashi with Schneemann

A POSITA would have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user responses of intent, such as taught in Schneemann, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street, especially since Furuhashi teaches using statistical methods to calculate probability. Schneemann at 2244, 2246.

Exemplary Motivations for Combining Furuhashi with Zhu

A POSITA would have found it obvious to combine use Furuhashi's method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught in Zhu. Zhu 11:35-11:60. A POSITA would further be motivated based on Furuhashi's teachings of applying the method to a moving vehicle and its description of pedestrian protection being implemented in the field of "advanced driver assistance systems" to look to methods of further controlling the vehicle, as taught in Zhu. Zhu 11:35-11:60. A POSITA would have been motivated by Furuhashi's teaching of starting to cross the street and "abort[ing] it and then cross[ing] after the vehicle had passed" to look to Zhu's teaching of determining pedestrian awareness of a vehicle to improve the overall Furuhashi's overall goal of determining a pedestrian's intent to cross the street. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Furuhashi with Gray

A POSITA would have found it obvious to combine use Furuhashi's method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught in Gray. Gray at 9:53-66. A POSITA would further be motivated based on Furuhashi's teachings of applying the method to a moving vehicle and its description of pedestrian protection being implemented in the field of "advanced driver assistance systems" to look to methods of further controlling the vehicle, as taught in Gray. Gray at 9:53-66 A POSITA would have been motivated by Furuhashi's goal of improving pedestrian detection to look to different known supervised learning models, such as those taught in Gray, to improve the calculations already taught in Furuhashi. *See* Furuhashi at 17-18.

Exemplary Motivations for Combining Furuhashi with Zhang

A POSITA would have found it obvious to combine use Furuhashi's method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught in Zhang. Zhang at [0014]-[0016]. A POSITA would further have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user responses of intent, such as taught in Zhang, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street. Zhang at [0014]-[0016]. A POSITA would have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user responses of intent, such as taught in Zhang, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street, especially since Furuhashi teaches using statistical methods to calculate probability. Zhang at [0051] [0053], [0058]. A POSITA would be motivated based on Furuhashi's teachings of applying the method to a moving vehicle and its description of pedestrian

protection being implemented in the field of “advanced driver assistance systems” to look to methods of further controlling the vehicle, as taught in Zhang. *See* Zhang at [0014]-[0016]

Exemplary Motivations for Combining Furuhashi with Ellenbogen

A POSITA would have been motivated by Furuhashi’s teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user responses of intent, such as taught in Ellenbogen, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street. Ellenbogen at [0056], [0136]. A POSITA would further have been motivated by Furuhashi’s goal of improving pedestrian detection to look to different known supervised learning models, such as those taught in Ellenbogen, to improve the calculations already taught in Furuhashi. Ellenbogen at [0056], [0136].

Exemplary Motivations for Combining Furuhashi with Huval

A POSITA would have found it obvious to combine use Furuhashi’s method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught in Huval. Huval at [0010]. A POSITA would be motivated based on Furuhashi’s teachings of applying the method to a moving vehicle and its description of pedestrian protection being implemented in the field of “advanced driver assistance systems” to look to methods of further controlling the vehicle, as taught in Huval. Huval at [0018]. A POSITA would have been motivated by Furuhashi’s goal of improving pedestrian detection to look to different known supervised learning models, such as those taught in Huval, to improve the calculations already taught in Furuhashi. Huval at [0010].

Exemplary Motivations for Combining Furuhashi with Keller

A POSITA would have found it obvious to combine Furuhashi’s method of data capture and prediction of intention of a pedestrian to aid in the movement of autonomous vehicles as taught

in Keller. Keller at 494. A POSITA would be motivated based on Furuhashi's teachings of applying the method to a moving vehicle and its description of pedestrian protection being implemented in the field of "advanced driver assistance systems" to look to methods of further controlling the vehicle, as taught in Keller. Keller at 505. A POSITA would have been motivated by Furuhashi's goal of improving pedestrian detection to train and validate data by obtaining user responses, such as taught in Keller. *See* Furuhashi at 17.

Exemplary Motivations for Combining Furuhashi with Volz 1

A POSITA would have been motivated by Furuhashi's goal of improving pedestrian detection to look to different known supervised learning models, such as those taught in Volz 1, to improve the calculations already taught in Furuhashi. Volz 1 at 3-4. A POSITA would have been motivated by Furuhashi's teaching of starting to cross the street and "abort[ing] it and then cross[ing] after the vehicle had passed" to look to Volz 1's teaching of determining pedestrian awareness of a vehicle to improve the overall Furuhashi's overall goal of determining a pedestrian's intent to cross the street. Volz 1 at 2.

Exemplary Motivations for Combining Furuhashi with Volz 2

A POSITA would have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of collecting user responses of intent, such as taught in Volz 2, to improve the accuracy of making the determination of whether a pedestrian intends to cross a street, especially since Furuhashi teaches using statistical methods to calculate probability. Volz 2 at 854, 856.

Exemplary Motivations for Combining Furuhashi and Levinson (or Zoox)

A POSITA would have been motivated by Furuhashi's teachings and ultimate goal of determining pedestrian intent to cross a road to look to teachings of classifying and tracking

external objects on a road as described by Levinson (or Zoox) to estimate the likelihood of collision. Levinson at 8:62-9:30, 12:17-53.

Exemplary Motivations to Combine Furuhashi and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Furuhashi's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Furuhashi already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Furuhashi is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Furuhashi's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Waymo with Ross

A POSITA would be motivated to, in addition to its blind spot detection, which helps Waymo understand whether a vehicle is aware of it, look to Ross to teach predicting awareness of pedestrians and others on the road to improve road safety. Specifically, a POSITA would have been motivated to look to Ross for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve road safety. Ross at 4:33-46, 9:13-65, 15:22-27.

Exemplary Motivations for Combining Waymo with Cox

A POSITA would be motivated by Waymo's description of Machine Learning techniques (e.g., deep neural networks) and their importance to autonomous cars to look to other references, such as Cox, for more details regarding details of specific machine learning techniques, so as to improve the safety of self-driving cars. Cox at [0060]. A POSITA would be motivated by Waymo's statistical calculations to look for other techniques for improving the accuracy of the statistics, such as through associating the statistical data with a parameter of user responses, such as taught in Cox. Cox at [0016], [0029], [0060]. A POSITA would further be motivated by Waymo's statistical calculations to look for other techniques for improving the accuracy of the statistics, such as through looking to teachings of general statistical concepts, such as taught in Cox. Cox at [0029].

Exemplary Motivations for Combining Waymo with Test My Brain

A POSITA would be motivated by Waymo's description of Machine Learning techniques (e.g., deep neural networks) and their importance to autonomous cars to look to other references, such as Test My Brain, for more details regarding details of specific machine learning techniques, so as to improve the safety of self-driving cars. Ex. A-26 at elements 1[a]-1[c]. A POSITA would be motivated by Waymo's statistical calculations to look for other techniques for improving the accuracy of the statistics, such as through associating the statistical data with a parameter of user responses, such as taught in Test My Brain. Ex. A-26 at elements 1[a]-1[c]. A POSITA would further be motivated by Waymo's statistical calculations to look for other techniques for improving the accuracy of the statistics, such as through looking to teachings of general statistical concepts, such as taught in Test My Brain. Ex. A-26 at elements 1[a]-1[c].

Exemplary Motivations for Combining Waymo with Ogale

A POSITA would be motivated by Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as Ogale, for more details regarding details of those machine learning techniques, so as to improve the safety of self-driving cars. Ogale at 1:11-2:9

Exemplary Motivations for Combining Waymo with Gray

A POSITA would be motivated by Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as Gray, for more details regarding details of those machine learning techniques, so as to improve the safety of self-driving cars. Gray at 9:53-66.

Exemplary Motivations for Combining Waymo with Ellenbogen

A POSITA would be motivated by Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as Ellenbogen, for more details regarding details of those machine learning techniques, so as to improve the safety of self-driving cars. Ellenbogen at [0136].

Exemplary Motivations for Combining Waymo with Keller

A POSITA would have been motivated to combine Waymo with Keller because Waymo embodies and Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Keller for more details on what is included in user responses to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Keller at 494.

Exemplary Motivations for Combining Waymo with Zhu

A POSITA would have been motivated to combine Waymo with Zhu because Waymo embodies and Zhu describes a method of maneuvering an autonomous vehicle. *See* Zhu 11:35-

11:60. A POSITA would have been motivated to look to Zhu for more details on what is included in user response and state of mind, intentions, and awareness of a road user, to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Waymo with Huval

A POSITA would be motivated by Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as Huval, for more details regarding details of those machine learning techniques, so as to improve the safety of self-driving cars. Huval at [0010].

Exemplary Motivations for Combining Waymo with Volz 1

A POSITA would be motivated by Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as Volz 1, for more details regarding details of those machine learning techniques, so as to improve the safety of self-driving cars. Volz 1 at 2, 3-4.

Exemplary Motivations for Combining Waymo with iMotions

A POSITA would be motivated by Waymo's description of Machine Learning techniques (e.g., deep neural networks) and their importance to autonomous cars to look to other references, such as iMotions, for more details regarding details of specific machine learning techniques, so as to improve the safety of self-driving cars. Ex. A-25 at elements 1[a]-1[c]. A POSITA would be motivated by Waymo's statistical calculations to look for other techniques for improving the accuracy of the statistics, such as through associating the statistical data with a parameter of user responses, such as taught in iMotions. Ex. A-25 at elements 1[a]-1[c]. A POSITA would further be motivated by Waymo's statistical calculations to look for other techniques for improving the

accuracy of the statistics, such as through looking to teachings of general statistical concepts, such as taught in iMotions. Ex. A-25 at elements 1[a]-1[c].

Exemplary Motivations to Combine Waymo and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Waymo's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Waymo already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Waymo is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Waymo's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Autopilot HW2 with Ross (or Waymo)

A POSITA would have been motivated to combine Autopilot HW2 with Ross (or Waymo) because Autopilot HW2 embodies and Ross (or Waymo) describes a method of maneuvering a vehicle. *See* Ross at 1:30-2:53. A POSITA would have been motivated to look to Ross (or Waymo) for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ross at 4:33-46, 9:13-65, 15:22-27.

Exemplary Motivations for Combining Autopilot HW2 with Cox

A POSITA would have been motivated to combine Autopilot HW1 and Cox's method of generating training data. *See* Cox at [0007]. A POSITA would have been motivated to look to Cox for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Cox at [0019]-[0021], [0027]-[0035], [0063]. A POSITA would further have been motivated to combine the system of Autopilot HW2 with the teachings of Cox regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW2's recognition and maneuvering system. Cox at [0016], [0029], [0060].

Exemplary Motivations for Combining Autopilot HW2 with Test My Brain

A POSITA would have been motivated to combine Autopilot HW1 and Test My Brain's method of generating training data. Ex. A-26 at elements 1[a]-1[c]. A POSITA would have been motivated to look to Test My Brain for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ex. A-26 at elements 1[a]-1[c]. A POSITA would further have been motivated to combine the system of Autopilot HW2 with the teachings of Test My Brain regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW2's recognition and maneuvering system. Ex. A-26 at elements 1[a]-1[c].

Exemplary Motivations for Combining Autopilot HW2 with Ogale

A POSITA would have been motivated to combine Autopilot HW2 with Ogale because Autopilot 2 embodies and Ogale describes a method of maneuvering an autonomous vehicle. *See* Ogale at 4:34-42. A POSITA would have been motivated to look to Ogale for more details on what is included in a statistical summary and what type of neural network may be used and to further

improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ogale at 1:11-2:9, 3:29-48, 6:51-7:12.

Exemplary Motivations for Combining Autopilot HW2 with Schneemann

A POSITA would have been motivated to combine Autopilot HW2 embodies and Schneemann describes a method of capturing data on a vehicle and classifying this data. See Schneemann. A POSITA would have been motivated to look to Schneemann for more details on what is included in a statistical summary and what is included in user responses, as well as to improve on methods of determining state of mind and intent of a pedestrian to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Schneemann at 2244, 2246.

Exemplary Motivations for Combining Autopilot HW2 with Quintero

A POSITA would have been motivated to combine Autopilot HW2 with Quintero because Autopilot HW2 embodies and Quintero describes a method of identifying pedestrians. See Quintero. A POSITA would have been motivated to look to Quintero for more details on what is included in user responses and predicted state of mind (based on body language) and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Quintero at 321.

Exemplary Motivations for Combining Autopilot HW2 with Zhu

A POSITA would have been motivated to combine Autopilot HW2 with Zhu because Autopilot HW2 embodies and Zhu describes a method of maneuvering an autonomous vehicle. See Zhu 11:35-11:60. A POSITA would have been motivated to look to Zhu for more details on what is included in user response and state of mind, intentions, and awareness of a road user, to

further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Autopilot HW2 with Gray

A POSITA would have been motivated to combine Autopilot HW2 with Gray because Autopilot HW2 embodies and Gray describes a method of detecting objects near an autonomous vehicle. *See* Gray at 9:53-66. A POSITA would have been motivated to look to Gray for more details on potential neural networks to use for training and analysis to further improve its driver assistance system. *Id.*

Exemplary Motivations for Combining Autopilot HW2 with Ellenbogen

A POSITA would have been motivated to combine Autopilot HW2 with Ellenbogen because Autopilot HW2 embodies and Ellenbogen describes a method of classifying sensor data. *See* Ellenbogen at [0006]. A POSITA would have been motivated to look to Ellenbogen for more details on statistical output, specific neural networks, and predicted state of mind to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ellenbogen at [0056], [0136].

Exemplary Motivations for Combining Autopilot HW2 with Zhang

A POSITA would have been motivated to combine Autopilot HW2 with Zhang because Autopilot HW2 embodies and Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Zhang for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. A POSITA would have been motivated to look to Zhang for more details on statistical output, specific neural networks, content of user responses , and predicted intentions of a pedestrian to further improve determinations of

intent and awareness of a pedestrian to improve its driver assistance system. Zhang at [0051], [0053], [0058].

Exemplary Motivations for Combining Autopilot HW2 with Huval

A POSITA would have been motivated to combine Autopilot HW2 with Huval because Autopilot HW2 embodies and Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Huval to find more details regarding machine learning models to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Huval at [0010].

Exemplary Motivations for Combining Autopilot HW2 with iMotions

A POSITA would have been motivated to combine Autopilot HW1 with iMotions' described method of training data. *See* Ex. A-25 at elements 1[a]-1[c]. A POSITA would have been motivated to look to iMotions for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ex. A-25 at elements 1[a]-1[c]. A POSITA would further have been motivated to combine the system of Autopilot HW2 with the teachings of iMotions regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW2's recognition and maneuvering system. Ex. A-25 at elements 1[a]-1[c].

Exemplary Motivations for Combining Autopilot HW2 with Keller

A POSITA would have been motivated to combine Autopilot HW2 with Keller because Autopilot HW2 embodies and Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Keller for more details on what is included in user responses and predicted state of mind and to further

improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Keller at 494.

Exemplary Motivations for Combining Autopilot HW2 with Furuhashi

A POSITA would have been motivated to combine Autopilot HW2 with Furuhashi because Autopilot HW2 embodies and Furuhashi describes a method of predicting pedestrian intention. *See* Furuhashi at 17. A POSITA would have been motivated to look to Furuhashi for more details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Furuhashi at 18.

Exemplary Motivations for Combining Autopilot HW2 with Kohler

A POSITA would have been motivated to combine Autopilot HW2 with Kohler because Autopilot HW2 embodies and Kohler describes a method of detecting pedestrians in and around a road. *See* Kohler at Abstract. A POSITA would have been motivated to look to Kohler to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Kohler at 2.

Exemplary Motivations for Combining Autopilot HW2 with Volz 1

A POSITA would have been motivated to combine Autopilot HW2 with Volz 1 because Autopilot HW2 embodies and Volz 1 describes a method of analyzing and predicting pedestrian movement in and around a road. *See* Volz 1 at Abstract. A POSITA would have been motivated to look to Volz 1 for more details on neural networks as well as what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Volz 1 at 2, 3-4.

Exemplary Motivations for Combining Autopilot HW2 with Volz 2

A POSITA would have been motivated to combine Autopilot HW2 with Volz 2 because Autopilot HW2 embodies and Volz 2 describes a method of using sensors and artificial intelligence to analyze pedestrian behavior. *See* Volz 2 at 856. A POSITA would have been motivated to look to Volz 2 for more details on what is included in user responses and predicted intentions to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Volz 2 at 854.

Exemplary Motivations to Combine Autopilot HW2 with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Autopilot HW2's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Autopilot HW2 already outputs a determination of future subject motion and location, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Autopilot HW2 is able to determine future subject motion and position. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Autopilot HW2's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Autopilot HW1 with Ross (or Waymo)

A POSITA would have been motivated to combine Autopilot HW1 with Ross (or Waymo) because Autopilot HW1 embodies and Ross (or Waymo) describes a method of maneuvering a vehicle. *See* Ross at 1:30-2:53. A POSITA would have been motivated to look to Ross (or Waymo)

for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ross at 4:33-46, 9:13-65, 15:22-27. A POSITA would further be motivated to look to Ross for its teachings regarding capturing and using real-time data. Ross at 7:57-8:31.

Exemplary Motivations for Combining Autopilot HW1 with Cox

A POSITA would have been motivated to combine Autopilot HW1 with Cox, which describes a method of training data. *See* Cox at [0007]. A POSITA would have been motivated to look to Cox for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Cox at [0019]-[0021], [0027]-[0035], [0063]. A POSITA would further have been motivated to combine the system of Autopilot HW1 with the teachings of Cox regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW1's recognition and maneuvering system. Cox at [0016], [0029], [0060]. A POSITA would further be motivated to look to Cox for its teachings regarding capturing and using real-time data. Cox at [0007].

Exemplary Motivations for Combining Autopilot HW1 with Test My Brain

A POSITA would have been motivated to combine Autopilot HW1 with Test My Brain, which describes a method of training data. Ex. A-26 at elements 1[a]-1[c]. A POSITA would have been motivated to look to Test My Brain for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ex. A-26 at elements 1[a]-1[c]. A POSITA would further have been motivated to combine the system of Autopilot HW1 with the teachings of Test My Brain regarding specific of state of mind, neural networks and statistical

methods to improve Autopilot HW1's recognition and maneuvering system. Ex. A-26 at elements 1[a]-1[c]. A POSITA would further be motivated to look to Test My Brain for its teachings regarding capturing and using real-time data.

Exemplary Motivations for Combining Autopilot HW1 with Ogale

A POSITA would have been motivated to combine Autopilot HW1 with Ogale because Autopilot 2 embodies and Ogale describes a method of maneuvering an autonomous vehicle. *See* Ogale at 4:34-42. A POSITA would have been motivated to look to Ogale for more details on what is included in a statistical summary and what type of neural network may be used and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ogale at 1:11-2:9, 3:29-48, 6:51-7:12. A POSITA would further be motivated to look to Ogale for its teachings regarding capturing and using real-time data. Ogale at 4:34-5:30.

Exemplary Motivations for Combining Autopilot HW1 with Schneemann

A POSITA would have been motivated to combine Autopilot HW1 embodies and Schneemann describes a method of capturing data on a vehicle and classifying this data. *See* Schneemann. A POSITA would have been motivated to look to Schneemann for more details on what is included in a statistical summary and what is included in user responses, as well as to improve on methods of determining state of mind and intent of a pedestrian to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Schneemann at 2244, 2246. A POSITA would further be motivated to look to Schneemann for its teachings regarding capturing and using real-time data. Schneemann at 2244.

Exemplary Motivations for Combining Autopilot HW1 with Quintero

A POSITA would have been motivated to combine Autopilot HW1 with Quintero because Autopilot HW1 embodies and Quintero describes a method of identifying pedestrians. *See*

Quintero. A POSITA would have been motivated to look to Quintero for more details on what is included in user responses and predicted state of mind (based on body language) and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Quintero at 321.

Exemplary Motivations for Combining Autopilot HW1 with Zhu

A POSITA would have been motivated to combine Autopilot HW1 with Zhu because Autopilot HW1 embodies and Zhu describes a method of maneuvering an autonomous vehicle. *See* Zhu 11:35-11:60. A POSITA would have been motivated to look to Zhu for more details on what is included in user response and state of mind, intentions, and awareness of a road user, to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Zhu at 9:65-10:20, 10:47-11:22. A POSITA would further be motivated to look to Zhu for its teachings regarding capturing and using real-time data. Zhu at 7:23-7:28.

Exemplary Motivations for Combining Autopilot HW1 with Gray

A POSITA would have been motivated to combine Autopilot HW1 with Gray because Autopilot HW1 embodies and Gray describes a method of detecting objects near an autonomous vehicle. *See* Gray at 9:53-66. A POSITA would have been motivated to look to Gray for more details on potential neural networks to use for training and analysis to further improve its driver assistance system. A POSITA would further be motivated to look to Gray for its teachings regarding capturing and using real-time data. Gray 10:12-31.

Exemplary Motivations for Combining Autopilot HW1 with Ellenbogen

A POSITA would have been motivated to combine Autopilot HW1 with Ellenbogen because Autopilot HW1 embodies and Ellenbogen describes a method of classifying sensor data. *See* Ellenbogen at [0006]. A POSITA would have been motivated to look to Ellenbogen for more

details on statistical output, specific neural networks, and predicted state of mind to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ellenbogen at [0056], [0136]. A POSITA would further be motivated to look to Ellenbogen for its teachings regarding capturing and using real-time data. Ellenbogen at [0006].

Exemplary Motivations for Combining Autopilot HW1 with Zhang

A POSITA would have been motivated to combine Autopilot HW1 with Zhang because Autopilot HW1 embodies and Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Zhang for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. A POSITA would have been motivated to look to Zhang for more details on statistical output, specific neural networks, content of user responses, and predicted intentions of a pedestrian to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Zhang at [0051], [0053], [0058]. A POSITA would further be motivated to look to Zhang for its teachings regarding capturing and using real-time data. Zhang at [0058].

Exemplary Motivations for Combining Autopilot HW1 with Huval

A POSITA would have been motivated to combine Autopilot HW1 with Huval because Autopilot HW1 embodies and Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Huval to find more details regarding machine learning models to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Huval at [0010]. A POSITA would further be motivated to look to Huval for its teachings regarding capturing and using real-time data. Huval at [0018].

Exemplary Motivations for Combining Autopilot HW1 with Keller

A POSITA would have been motivated to combine Autopilot HW1 with Keller because Autopilot HW1 embodies and Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Keller for more details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Keller at 494. A POSITA would further be motivated to look to Keller for its teachings regarding capturing and using real-time data. Keller at 496.

Exemplary Motivations for Combining Autopilot HW1 with Furuhashi

A POSITA would have been motivated to combine Autopilot HW1 with Furuhashi because Autopilot HW1 embodies and Furuhashi describes a method of predicting pedestrian intention. *See* Furuhashi at 17. A POSITA would have been motivated to look to Furuhashi for more details on what is included in user responses and predicted state of mind and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Furuhashi at 18. A POSITA would further be motivated to look to Furuhashi for its teachings regarding capturing and using real-time data. Furuhashi at 18.

Exemplary Motivations for Combining Autopilot HW1 with Kooij

A POSITA would have been motivated to combine Autopilot HW1 with Kooij because Autopilot HW1 embodies and Kooij describes a method of capturing and analyzing data from a vehicle on the road. *See* Kooij. A POSITA would have been motivated to look to Kooij for more details on gathering and using sensor data to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Kooij at 1448.

Exemplary Motivations for Combining Autopilot HW1 with Kohler

A POSITA would have been motivated to combine Autopilot HW1 with Kohler because Autopilot HW1 embodies and Kohler describes a method of detecting pedestrians in and around a road. *See Kohler at Abstract.* A POSITA would have been motivated to look to Kohler to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Kohler at 2 (“In this paper we focus on scenarios, where a pedestrian stands at the pavement and decides to enter the lane.”). A POSITA would further be motivated to look to Kohler for its teachings regarding capturing and using real-time data. Kohler at 2.

Exemplary Motivations for Combining Autopilot HW1 with Volz 1

A POSITA would have been motivated to combine Autopilot HW1 with Volz 1 because Autopilot HW1 embodies and Volz 1 describes a method of analyzing and predicting pedestrian movement in and around a road. *See Volz 1 at Abstract.* A POSITA would have been motivated to look to Volz 1 for more details on neural networks as well as what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Volz 1 at 2, 3-4. A POSITA would further be motivated to look to Volz 1 for its teachings regarding capturing and using real-time data. Volz 1 at 5.

Exemplary Motivations for Combining Autopilot HW1 with Volz 2

A POSITA would have been motivated to combine Autopilot HW1 with Volz 2 because Autopilot HW1 embodies and Volz 2 describes a method of using sensors and artificial intelligence to analyze pedestrian behavior. *See Volz 2 at 856.* A POSITA would have been motivated to look to Volz 2 for more details on what is included in user responses and predicted intentions to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Volz 2 at 854. A POSITA would further be motivated to look to Volz 2 for its teachings regarding capturing and using real-time data. Volz 2 at 856.

Exemplary Motivations for Combining Autopilot HW1 with iMotions

A POSITA would have been motivated to combine Autopilot HW1 embodies and iMotions describes a method of training data. Ex. A-25 at elements 1[a]-1[c]. A POSITA would have been motivated to look to iMotions for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ex. A-25 at elements 1[a]-1[c]. A POSITA would further have been motivated to combine the system of Autopilot HW1 with the teachings of iMotions regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW1's recognition and maneuvering system. Ex. A-25 at elements 1[a]-1[c]. A POSITA would further be motivated to look to iMotions for its teachings regarding capturing and using real-time data.

Exemplary Motivations for Combining Autopilot HW1 with Levinson

A POSITA would have been motivated to combine Autopilot HW1 with Levinson because Autopilot HW1 embodies and Levinson describes a method of determining a trajectory for an autonomous vehicle. *See* Levinson at 8:62-9:30, 12:17-53. A POSITA would further be motivated to look to Levinson for its teachings regarding classifying and tracking objects external to an autonomous vehicle. Levinson at 8:62-9:30.

Exemplary Motivations for Combining Autopilot HW1 with Zoox

A POSITA would have been motivated to combine Autopilot HW1 with Zoox because Autopilot HW1 embodies and Zoox describes a method of determining a trajectory for an autonomous vehicle. *See* Ex. A-27 at element 1[a]. A POSITA would further be motivated to look to Levinson for its teachings regarding classifying and tracking objects external to an autonomous vehicle. Levinson at 8:62-9:30.

Exemplary Motivations to Combine Autopilot HW1 and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Autopilot HW1's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Autopilot HW1 already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Autopilot HW1 is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Autopilot HW1's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Mercedes with Ross (or Waymo)

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. Ex. A-23 at elements 1[a]-1[c]. Similarly, Ross (or Waymo) describes a method of maneuvering a vehicle. *See* Ross at 1:30-2:53. A POSITA would have been motivated to look to Ross (or Waymo) for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its vehicle safety system. Ross at 4:33-46, 9:13-65, 15:22-27.

Exemplary Motivations for Combining Mercedes with Cox

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Ex. A-23 at elements 1[a]-1[c]. A POSITA would have been motivated to look to Cox's

teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes' statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. A POSITA would have been motivated, based on Mercedes' teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Cox. Specifically, a POSITA would have understood that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. Cox describes its training model as a neural network or other described supervised learning models, e.g., "any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression." Cox at [0060]. A POSITA would have further been motivated by Mercedes' teachings of computing median object motion and extracting orientation histograms to look to Cox's teachings of statistical concepts.

Exemplary Motivations for Combining Mercedes with Test My Brain

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Ex. A-23 at elements 1[a]-1[c]. A POSITA would have been motivated to look to Test My Brain's teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes' statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. A POSITA would have further been motivated by Mercedes' teachings of computing median object motion and extracting orientation histograms to look to Test My Brain's teachings of statistical concepts. Ex. A-26 at elements 1[a]-1[c]

Exemplary Motivations for Combining Mercedes with Ogale

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Ex. A-23 at elements 1[a]-1[c]. A POSITA would have been motivated to look to Ogale’s teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes’ statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. Ogale at 3:29-48, 6:51-7:12. A POSITA would have been motivated, based on Mercedes’ teaching of using its method on an “intelligent vehicle,” to fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Ogale. Ogale at 1:11-2:9.

Exemplary Motivations for Combining Mercedes with Schneemann

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Schneemann’s teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes’ statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. Schneemann at 2246 (“we developed a label tool, which asks the human observer to rate if a pedestrian has a principal aim to cross the street.”).

Exemplary Motivations for Combining Mercedes with Gray

A POSITA would have been motivated, based on Mercedes’ teaching of using its method on an “intelligent vehicle,” to fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Gray. Gray at 10:12-31.

Exemplary Motivations for Combining Mercedes with Ellenbogen

A POSITA would have been motivated to look to Ellenbogen’s teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes’ statistical summary of predicted motion based on input, particularly since Mercedes describes observed

motion. Ellenbogen at [0056] (“The current subject matter can coordinate use and gathering of human intelligence, including performing quality, efficiency, latency, confidence measures in real-time of the agents”), [0136]. A POSITA would have been motivated, based on Mercedes’ teaching of using its method on an “intelligent vehicle,” fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Ellenbogen. Ellenbogen at [0136].

Exemplary Motivations for Combining Mercedes with Huval

A POSITA would have been motivated, based on Mercedes’ teaching of using its method on an “intelligent vehicle,” fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Huval, which also involves vehicles that rely heavily on computer systems. Huval at [0010].

Exemplary Motivations for Combining Mercedes with Zhang

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Ex. A-23 at elements 1[a]-1[c]. In a similar vein, Zhang describes a method of planning a trajectory of an autonomous vehicle. *See* Zhang at [0014]-[0016]. A POSITA would have been motivated to look to Zhang for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. A POSITA would have been motivated to look to Zhang for more details on statistical output, specific neural networks, content of user responses, and predicted intentions of a pedestrian to further improve determinations of intent and awareness of a pedestrian, particularly since Mercedes describes observed motion. Zhang at [0051] [0053], [0058].

Exemplary Motivations for Combining Mercedes with Zhu

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated by Mercedes’ teachings of predicting

motion of a pedestrian to look to Zhu for its teachings of awareness of a road user to improve the prediction. Zhu at 9:65-10:20, 10:47-11:22.

Exemplary Motivations for Combining Mercedes with Volz 1

A POSITA would have been motivated, based on Mercedes's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Volz 1. Volz 1 at 3-4. A POSITA would have been motivated by Mercedes' teachings of predicting motion of a pedestrian to look to Volz 1 for its teachings of awareness of a road user to improve the prediction. Volz 1 at 2.

Exemplary Motivations for Combining Mercedes with Volz 2

A POSITA would have been motivated to look to Volz 2's teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes' statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. *See* Volz 2 at 856. A POSITA would have been motivated to look to Volz 2's teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes' statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. Volz 2 at 854.

Exemplary Motivations for Combining Mercedes with iMotions

Mercedes describes a method of using pedestrian recognition for a vehicle safety system. *See* Ex. A-23 at elements 1[a]-1[c]. A POSITA would have been motivated to look to iMotions' teachings of obtaining responses feedback from users presented with sensor data as input to generate Mercedes' statistical summary of predicted motion based on input, particularly since Mercedes describes observed motion. A POSITA would have been motivated, based on Mercedes' teaching of using its method on an "intelligent vehicle," fill in details of how to program these

vehicles by looking to teachings of neural networks, such as taught in iMotions. Specifically, a POSITA would have understood that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. A POSITA would have further been motivated by Mercedes' teachings of computing median object motion and extracting orientation histograms to look to iMotions' teachings of statistical concepts.

Exemplary Motivations to Combine Mercedes and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Mercedes's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Mercedes already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that prediction. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Mercedes is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Mercedes's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

B. The '889 Patent

Pursuant to Patent Rule 3-3 and subject to Tesla's reservations of rights in these Invalidity Contentions, at least the prior art listed below, individually or in combination, invalidates the Asserted Claims of the '889 Patent. Exhibits B-1 through B-28 provide detailed claim charts showing where each claim limitation may be found in certain references listed below, either expressly or inherently as the reference would be understood by a person having ordinary skill in

the art. For those references for which detailed claim charts are not provided, those additional prior art references are otherwise pertinent to the invalidity of the '889 Patent, either alone or in combination with other references.

The prior art references, systems, and products listed below and in the accompanying claim chart exhibits may be relied upon for certain limitations, state of the art, and background of the art; indicia of obviousness; as evidence of the level of skill in the art at the time of the filing of the Patents-in-Suit; and/or in support of assertions that it is proper to combine certain prior art references in certain ways.

Tesla also incorporates by reference each and every prior art reference of record in the prosecution of the Patents-in-Suit and patents or patent applications related to the Patents-in-Suit, the prior art referred to in the specifications of the Patents-in-Suit, as well as the prior art identified in any USPTO proceedings involving any of the Patents-in-Suit.

1. Bases for Anticipation and/or Obviousness

Each prior art reference identified in Exhibits B-1 through B-28 expressly, implicitly, or inherently anticipates and/or renders obvious the Asserted Claims of the '889 Patent, either alone or in combination with other prior art references (*e.g.*, other references identified above) or the knowledge of the person of ordinary skill in the art at the time of the alleged invention. In the table below, Tesla identifies a non-exhaustive list of prior art references that, alone or in combination, anticipate and/or render obvious the Asserted Claims of the '889 Patent.

Exhibit	Patent No. or Title (Primary Inventor/Author)	Date of Issuance or Publication
Ex. B-1	U.S. Patent No. 10,496901 ("Ross")	Dec. 3, 2019 (Filed Aug. 17, 2016)
Ex. B-2	U.S. Pat. Pub. No. 2018/0373980 ("Huval")	Dec. 27, 2018 (Filed Jun. 27, 2017)
Ex. B-3	U.S. Pat. Pub. No. 2016/0162456 ("Munro")	Jun. 9, 2016 (Filed Dec. 9, 2015)

Ex. B-4	WO2014/210334 (“Cox”)	Dec. 31, 2014
Ex. B-5	Schneemann, “Context-based Detection of Pedestrian Crossing Intention for Autonomous Driving in Urban Environments” (“Schneemann”)	2016
Ex. B-6	Quintero, “Pedestrian Path Prediction using Body Language Traits” (“Quintero”)	2014
Ex. B-7	U.S. Patent No. 10,733,506 (“Ogale”)	Aug. 4, 2020 (Filed Dec. 14, 2016)
Ex. B-8	U.S. Patent No. 9,766,626 (“Zhu”)	May 30, 2019 (Filed Nov. 27, 2017)
Ex. B-9	Furuhashi, “Estimation of Street Crossing Intention from a Pedestrian’s Posture on a Sidewalk Using Multiple Image Frames” (“Furuhashi”)	2011
Ex. B-10	Keller, “Will the Pedestrian Cross? A Study on Pedestrian Path Prediction” (“Keller”)	2014
Ex. B-11	Kohler, “Early Detection of the Pedestrian’s Intention to Cross the Street” (“Kohler”)	Oct. 25, 2012
Ex. B-12	U.S. Patent No. 10,007,269 (“Gray”)	Jun. 26, 2018
Ex. B-13	U.S. Pat. Pub. No. 2017/0099200 (“Ellenbogen”)	Apr. 6, 2017 (Filed Oct. 6, 2016)
Ex. B-14	U.S. Pat. Pub. No. 2019/0072966 (“Zhang”)	Mar. 7, 2019 (Filed Nov. 7, 2017)
Ex. B-15	Karasev, “Intent-Aware Long-Term Prediction of Pedestrian Motion” (“Karasev”)	2016
Ex. B-16	Volz, “A data-driven approach for pedestrian intention estimation” 2016 (“Volz 1”)	2016
Ex. B-17	Volz, “Feature Relevance Estimation for Learning Pedestrian Behavior at Crosswalks” (“Volz 2”)	2015
Ex. B-18	Bhattacharyya, “Long-Term On-Board Prediction of People in Traffic Scenes under Uncertainty” (“Bhattacharyya”)	Nov. 24, 2017
Ex. B-19	Schneider, “Pedestrian Path Prediction with Recursive Bayesian Filters: A Comparative Study” (“Schneider”)	2013
Ex. B-20	Kooij, “Analysis of pedestrian dynamics from a vehicle perspective” (“Kooij”)	Jun. 2014
Ex. B-21	U.S. Patent No. 9,632,502 (“Levinson”)	Apr. 25, 2017 (Filed Nov. 5, 2015)

The Asserted Claims of the '889 Patent are also invalid under 35 U.S.C. § 102(a) and (b) because the subject matter was known by others, publicly used, and on sale in the United States before it was purportedly invented and more than one year before the priority date of the Asserted Claim. Additionally, the Asserted Claim because any purported invention was made in this country by another who had not abandoned, suppressed, or concealed the purported invention. For example, the foregoing patents and publications are evidence of such prior art systems and inventions. As such, the following systems are prior art under 35 U.S.C. § 102:

Exhibit	System Prior Art
Ex. B-22	Tesla – Autopilot HW1
Ex. B-23	Tesla – Autopilot HW2
Ex. B-24	Daimler/ Mercedes
Ex. B-25	Waymo
Ex. B-26	iMotions
Ex. B-27	TestMyBrain.com
Ex. B-28	Zoox

The accompanying claim charts (Exhibits B-1 through B-28) set forth example bases for anticipation and obviousness, identifying where each reference discloses, alone or in combination with other references, each limitation of the Asserted Claims of the '889 Patent on a limitation-by-limitation basis. Tesla's claim charts are exemplary and not exhaustive.

2. Obviousness Combinations

Subject to Tesla's reservation of rights, Tesla contends that all of the prior art references, as identified above and described in the charts attached as Exhibits B-1 through B-28 by themselves anticipate the Asserted Claims of the '889 Patent in accordance with 35 U.S.C. § 102 and/or render the Asserted Claim of the '889 Patent obvious under 35 U.S.C. § 103, as more

specifically noted in the attached charts. The cited portions of the prior art references are examples and representative of the content of the prior art references, and should be understood in the context of the reference as a whole, as understood by one of ordinary skill in the art. To the extent a cited prior art reference is deemed not to anticipate or render obvious a claim as noted in the attached charts for failing to teach or suggest one or more limitations of that claim, that claim would nonetheless have been obvious to one of ordinary skill in the art at the time of the invention by the combination of the cited prior art reference with one or more other prior art references and/or common knowledge disclosing the missing claim limitations. For example, any of the references listed above, to the extent it does not explicitly or inherently disclose any limitation, could be combined with any one or more of the other references listed above which discloses that limitation. Tesla reserves the right to supplement the obviousness arguments using any references listed above, or any references that may become known to Tesla during the course of discovery.

In the table below, Tesla further identifies exemplary combinations of prior art that render the Asserted Claims of the '889 Patent obvious:

Primary Reference	Secondary Reference	Claim
Ross	Huval	1, 2, 6, 7, 9, 11, 12, 16, 17, 19
	Cox	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Test My Brain	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Schneemann	1, 2, 6, 7, 12, 16, 17
	Ogale	4, 11, 14
	Keller	1, 2, 9, 12, 19
	Ellenbogen	1, 2, 11, 12
	Gray	11
	Zhang	1, 2, 12
	Waymo	1, 2, 4, 12, 14
	Volz 1	1, 2, 11, 12
	Kooij	1, 2, 12
	Munro	1, 2, 12
	Levinson	4, 14

Primary Reference	Secondary Reference	Claim
	Zoox	4, 14
	Bhattacharyya	1, 2, 9, 12, 19
	One or more of Huval, Coz, Test My Brain, Schneemann, Ogale, Keller, Ellenbogen, Gray, Zhang, Waymo, Volz 1, Kooij, Levinson, Zoox, and/or Bhattacharyya	1, 2, 4, 5, 7, 9, 11, 12, 15, 16, 17, 18, 19, 20
Huval	Ross	3, 13
	Cox	1, 2, 5, 8, 10, 12, 15, 18
	Test My Brain	1, 2, 5, 8, 10, 12, 15, 18
	Schneemann	3, 13
	Ogale	3, 13, 4, 14
	Zhu	3, 13
	Furuhashi	1, 2, 3, 12, 13
	Keller	3, 13
	Kohler	3, 13
	Ellenbogen	1, 2, 12
	Zhang	1, 2, 12
	Waymo	1, 2, 3, 4, 12, 13, 14
	Karasev	3, 13
	Volz 1	3, 13
	Volz 2	3, 13
	Schneider	3, 13
	Kooij	1, 2, 3, 12, 13
	Munro	1, 2, 12
	Levinson	4, 14
	Zoox	4, 14
	Bhattacharyya	1, 2, 3, 12, 13
	One or more of Ross, Cox, Test My Brain, Schneemann, Ogale, Zhu, Furuhashi, Keller, Kohler, Ellenbogen, Zhang, Waymo, Karasev, Volz 1, Volz 2, Schneider, Kooij, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 4, 5, 8, 10, 12, 13, 14, 15, 18
Ogale	Huval	1, 2, 6, 7, 9, 12, 16, 17, 19
	Cox	1, 2, 5, 7, 8, 10, 12, 15, 17, 18, 20
	Test My Brain	1, 2, 5, 7, 8, 10, 12, 15, 17, 18, 20
	Schneemann	1, 2, 6, 7, 12, 16, 17
	Keller	1, 2, 9, 12, 19

Primary Reference	Secondary Reference	Claim
	Ellenbogen	1, 2, 12
	Zhang	1, 2, 12
	Waymo	1, 2, 12
	Volz 1	1, 2, 12
	Kooij	1, 2, 12
	Munro	1, 2, 12
	Bhattacharyya	1, 2, 5, 9, 12, 19
	One or more of Huval, Cox, Schneemann, Keller, Ellenbogen, Zhang, Waymo, Volz 1, Kooij, Munro, Test My Brain, and/or Bhattacharyya	1, 2, 5, 6, 7, 8, 9, 12, 16, 17, 19
Waymo	Cox	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Test My Brain	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Huval	1, 2, 6, 7, 9, 11, 12, 17, 19
	Keller	9, 19
	Schneemann	6, 7, 16, 17
	iMotions	1, 2, 5, 6, 7, 12, 15, 16, 17
	Munro	1, 2, 12
	Bhattacharyya	1, 2, 9, 12, 19
	One or more of Cox, Test My Brain, Huval, Keller, Schneemann, iMotions, and/or Munro	1, 2, 5, 7, 8, 9, 10, 11, 12, 15, 16, 17, 18, 19, 20
Autopilot HW2	Kooij	1, 2, 3, 12, 13
	Huval	1, 2, 6, 7, 9, 11, 12, 16, 17, 19
	Cox	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Test My Brain	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	iMotions	1, 2, 5, 6, 7, 12, 15, 16, 17
	Munro	1, 2, 12
	Bhattacharyya	1, 2, 3, 5, 9, 11, 12, 13, 19
	One or more of Cox, Test My Brain, Huval, Keller, Schneemann, iMotions, Munro, and/or Bhattacharya	1, 2, 5, 7, 8, 9, 10, 11, 12, 15, 16, 17, 18, 19, 20
Autopilot HW1	Kooij	1, 2, 3, 12, 13
	Huval	1, 2, 6, 7, 9, 11, 12, 16, 17, 19
	Cox	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20,

Primary Reference	Secondary Reference	Claim
	Test My Brain	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	iMotions	1, 2, 5, 6, 7, 12, 15, 16, 17
	Munro	1, 2, 12
	Bhattacharyya	1, 2, 5, 9, 11, 12, 13, 19
	One or more of Kooij, Huval, Cox, Test My Brain, iMotions, Munro, and/or Bhattacharyya	1, 2, 3, 6, 7, 9, 11, 12, 13, 15, 16, 17, 18, 19, 20
Mercedes	Huval	1, 2, 6, 7, 9, 11, 12, 16, 17, 19
	Cox	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Test My Brain	1, 2, 5, 7, 8, 10, 11, 12, 15, 17, 18, 20
	Ogale	2, 4, 11, 14
	Ellenbogen	1, 2, 11, 12
	Gray	1, 2, 11, 12
	Zhang	1, 2, 12
	Waymo	1, 2, 4, 12, 14
	iMotions	1, 2, 5, 6, 7, 12, 15, 16, 17
	Munro	1, 2, 12
	Levinson	4, 14
	Zoos	4, 14
	Bhattacharyya	1, 2, 5, 9, 11, 12, 13, 19
	One or more of Huval, Cox, Test My Brain, Ogale, Ellenbogen, Gray, Zhang, Waymo, iMotions, Munro, Levinson, Zoos, and/or Bhattacharyya	1, 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20

3. Motivation to Combine and Reasonable Expectation of Success

With respect to the '889 Patent, the prior art identified above demonstrates the scope and content of the prior art. As detailed in Exhibits B-1 through B-28, the prior art included each limitation recited in the Asserted Claims of the '889 Patent. To the extent a cited prior art reference is deemed not to anticipate a claim, the only difference between the claimed invention and the prior art is the lack of actual combination of the elements in a single prior art reference. However,

a Person of Ordinary Skill in the Art (“POSITA”) would have been motivated to combine each of the above prior art references.

For example, many of the above-identified references (Ross, Huval, Schneemann, Quintero, Ogale, Zhu, Furuhashi, Keller, Kohler, Gray, Zhang, Karasev, Volz 1, Volz 2, Schneider, Autopilot HW1, Autopilot HW2, Mercedes, Waymo, Levinson, Bhattacharyya, and Zoox) are all related to motor vehicles. These references constitute analogous art within the same field of endeavor—specifically, automotive design and engineering—and address the same or substantially similar technical problems regarding vehicle operation and subsystem integration. A POSITA would naturally consult these references when seeking to improve vehicle performance or functionality. Here, because Ross, Huval, Schneemann, Quintero, Ogale, Zhu, Furuhashi, Keller, Kohler, Gray, Zhang, Karasev, Volz 1, Volz 2, Schneider, Autopilot HW1, Autopilot HW2, Mercedes, Waymo, Levinson, Bhattacharyya, and Zoox all reside within the automotive domain, the barrier to combination is exceedingly low. A POSITA would recognize that the teachings of each such reference are compatible with (or could be adapted to be compatible with) other references related to motor vehicles. The combination of these references related to motor vehicles also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar elements to perform their primary functions. And, driven by the perpetual market pressure in the automotive industry to enhance safety, efficiency, and user experience, a POSITA would have been motivated to combine the specific features of each of Ross, Huval, Schneemann, Quintero, Ogale, Zhu, Furuhashi, Keller, Kohler, Gray, Zhang, Karasev, Volz 1, Volz 2, Schneider, Autopilot HW1, Autopilot HW2, Mercedes, Waymo, Levinson, Bhattacharyya and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill

and creativity to implement known solutions within the standard constraints of an automobile, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As a further example, many of the above references relate more specifically to autonomous driving (e.g., Ross, Huval, Schneemann, Ogale, Zhu, Gray, Zhang, Karasev, Autopilot HW1, Autopilot HW1, Waymo, Levinson, and Zoox). These references constitute analogous art within the same field of endeavor—specifically, the development of automated driving systems using sensors—and address the same or substantially similar technical problems regarding object detection, environmental perception, and real-time decision making. A POSITA would naturally consult these references when seeking to improve the reliability or safety of an autonomous driving feature. Here, because Ross, Huval, Schneemann, Ogale, Zhu, Gray, Zhang, Karasev, Autopilot HW1, Autopilot HW1, Waymo, Levinson, and Zoox all involve descriptions of autonomous vehicle architectures, the barrier to combination is exceedingly low. For example, a POSITA would recognize that the sensing or control teachings of each such reference are compatible with the processing or navigation modules of other references related to autonomous driving. The combination of references relating to autonomous driving also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar algorithms and hardware to perform their primary functions. And, driven by the industry competition to achieve higher levels of autonomy (e.g., for SAE Levels 3-5) and the necessity to eliminate human error, a POSITA would have been motivated to combine the specific features of each of Ross, Huval, Schneemann, Ogale, Zhu, Gray, Zhang, Karasev, Autopilot HW1, Autopilot HW1, Waymo, Levinson, and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of a

self-driving platform, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As another example, many of the above identified references (Ross, Huval, Munro, Cox, Schneemann, Quintero, Ogale, Zhu, Furuhashi, Keller, Kohler, Gray, Ellenbogen, Zhang, Karasev, Volz 1, Volz 2, Schneider, Autopilot HW1, Autopilot HW2, Mercedes, Waymo, iMotions, Bhattacharyya, and Test My Brain) are all related to the development and training of machine learning models, including supervised learning techniques. These references constitute analogous art within the same field of endeavor—specifically, artificial intelligence and data annotation—and address the same or substantially similar technical problems regarding model accuracy, ground truth verification, and the reduction of prediction error. A POSITA would naturally consult these references when seeking to improve the performance of a neural network or statistical model through high-quality supervision. Here, because Ross, Huval, Munro, Cox, Schneemann, Quintero, Ogale, Zhu, Furuhashi, Keller, Kohler, Gray, Ellenbogen, Zhang, Karasev, Volz 1, Volz 2, Schneider, Autopilot HW1, Autopilot HW2, Mercedes, Waymo, iMotions, Bhattacharyya, and Test My Brain all relate to data-driven algorithm development, the barrier to combination is exceedingly low. A POSITA would recognize that the human-labeled datasets or annotation interfaces of each such reference are compatible with (or could be adapted to be compatible with) the training pipelines and loss functions disclosed in other references related to machine learning. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar training loops to perform their primary functions. And, driven by the market pressure in the artificial intelligence industry to maximize inference accuracy and leverage human validation for edge cases, a POSITA would have been motivated to combine the

specific features of each of Ross, Huval, Munro, Cox, Schneemann, Quintero, Ogale, Zhu, Furuhashi, Keller, Kohler, Gray, Ellenbogen, Zhang, Karasev, Volz 1, Volz 2, Schneider, Autopilot HW1, Autopilot HW2, Mercedes, Waymo, iMotions, Bhattacharyya, and Test My Brain. Specifically, the use of human-generated ground truth labels to calibrate or refine model weights is a foundational practice in the art, making the aggregation of these teachings a matter of routine optimization. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known supervised learning solutions within the standard constraints of a predictive system, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As an additional example, many of the above identified references (Huval, Cox, Ellenbogen, Test My Brain, and iMotions) are all related to techniques and interfaces for generating training data. These references constitute analogous art within the same field of endeavor—specifically, the creation and management of ground truth datasets for machine learning—and address the same or substantially similar technical problems regarding annotator efficiency, labeling precision, and the workflow for verifying training data. A POSITA would naturally consult these references when seeking to streamline the process of generating high-quality inputs for a model. Here, because Huval, Cox, Ellenbogen, Test My Brain, and iMotions all reside within the specific domain of human-computer interaction for data entry, the barrier to combination is exceedingly low. A POSITA would recognize that the graphical user interfaces, bounding box tools, or segmentation brushes of each such reference are compatible with (or could be adapted to be compatible with) the data export formats or workflow management systems of other references related to dataset generation. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of

a known technique to a piece of prior art ready for the improvement, utilizing familiar UI elements to perform their primary functions. And, driven by the perpetual market pressure in the machine learning industry to alleviate the data bottleneck in model development and minimize the cost of human supervision, a POSITA would have been motivated to combine the specific features of each of Huval, Cox, Ellenbogen, Test My Brain, and iMotions. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known productivity solutions within the standard constraints of a data pipeline, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

Below, Tesla has provided several additional illustrative examples of the motivations that a POSITA would have had to combine certain of the prior art references in Exhibits B-1 through B-28. The inclusion of certain example combinations herein does not exclude other combinations based on the claim charts attached hereto, as there are many possible combinations of the references listed herein, and it is not practical, particularly at this early stage prior to further factual investigation and claim construction proceedings, to identify and list all potentially relevant combinations. Instead, in many instances where a particular contention calls for, or requires, combining references, any one of a number of references can be combined. As such, these motivations to combine apply equally to the combination of a primary reference to one secondary reference, and the combination of a primary reference to multiple secondary references.

Exemplary Motivations for Combining Ross and Huval

A POSITA would have looked to Huval to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. For example, Huval describes, not only

feedback provided by human annotators, but passing data through a neural network. Huval at [0010].

Exemplary Motivations for Combining Ross and Cox (or Test My Brain)

A POSITA, following Ross's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox's (or Test My Brain's) "statistical learning," e.g., because using statistical methods and outputs would have been known to help reduce risks, and "in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect." Cox at [0035]. *See also* Cox at [0027]-[0035]. A POSITA would also have looked to Cox (or Test My Brain) to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. Cox (or Test My Brain) describes its training model as a neural network or other described supervised learning models, e.g., "any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression." Cox at [0060]. Further, a POSITA would have found it obvious to reduce the risk involved with training Ross's method of detecting objects and maneuvering autonomous vehicles by looking to Cox's (or Test My Brain's) statistical methods, including statistical data associated with response data. Specifically, a POSITA would be motivated to look to Cox's (or Test My Brain's) teachings of the parameters including psychometric data (including responses times) and eye tracking. Cox at [0019]-[0021], [0063]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Ross, to look to basic statistical

concepts. For example, a POSITA would have found it obvious to implement ranges and averages for response times, taught in Cox (or Test My Brain). Cox [0029].

Exemplary Motivations for Combining Ross and Schneemann

A POSITA, following Ross's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Schneemann's statistical methods applied to human responses regarding intent e.g., because using statistical methods and outputs would have been known to help reduce risks and obtaining human responses are what the method is trying to mimic. Schneemann at 2246 ("we developed a label tool, which asks the human observer to rate if a pedestrian has a principal aim to cross the street"). In addition, a POSITA would have been motivated to look to different methods to train and execute Ross's predictions for intended future action, including Schneemann's generation of a table with the distribution of labels, which represents a statistical summary of expected user responses. Schneemann at 2246.

Exemplary Motivations for Combining Ross and Ogale

A POSITA, following Ross's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Ogale's "human-labeled training data" e.g., because using statistical methods and outputs, and verifying data related to human responses with human labeling would have been known to help reduce risks since "[h]uman-labeled training data 127 tends to be more accurate than the auto-labeled training data." Ogale at 3:29-48, 6:51-7:12. A POSITA would also have been motivated to look to different methods to train and execute Ross's predictions for intended future action, including Ogale's generation of "human-labeled training data," e.g., to improve the accuracy of the data input to statistical summaries. Ogale at 3:29-48, 6:51-7:12. Further, a POSITA would have looked to Ogale to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would

understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. For example, Ogale teaches that neural networks can be used with autonomous vehicles for object classification and output prediction. Ogale at 1:11-2:9.

Exemplary Motivations for Combining Ross and Keller

A POSITA would have found it obvious to reduce the risk involved with training Ross's method of detecting objects and maneuvering autonomous vehicles by looking to Keller's "manual labeling [of] pedestrian shapes in the images." Keller at 501. A POSITA would have a reasonable expectation of success since it is merely swapping out a known part with another known part to achieve the predictable results suggested by Keller in the same field of endeavor. *See* Ross 1:30-54; Keller at 501.

Exemplary Motivations for Combining Ross and Ellenbogen

A POSITA following Ross's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Ellenbogen's creation of composite outputs and composite confidences, e.g., because using statistical methods and outputs would have been known to help reduce risks. Ellenbogen at [0056]. A POSITA would also have looked to Ellenbogen to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems, such as Ellenbogen's deep neural network or convolution neural network. Ellenbogen at [0136].

Exemplary Motivations for Combining Ross and Gray

A POSITA would have looked to Gray to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would

understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. For example, Gray teaches that its model “can be a convolution neural network.” Gray at 10:12-31. A POSITA would have a reasonable expectation of success since it is merely swapping out a known part with another known part to achieve the predictable results suggested by Gray in the same field of endeavor.

Exemplary Motivations for Combining Ross and Zhang

A POSITA following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Zhang’s training data “labeled using human labelers,” because a POSITA would understand human responses to be what the neural network is designed to mimic. Zhang at [0051], [0053]. And a POSITA would have been motivated to look to different methods to train and execute Ross’s predictions for intended future action, including Zhang’s generation of predicted trajectories, which represents a statistical summary of expected user responses. Zhang at [0054].

Exemplary Motivations for Combining Ross and Waymo

A POSITA, following Ross’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Waymo’s descriptions of its behavior prediction software and its Waymo Dataset, which included road scenes captured by its sensors, since using Waymo’s trained sensor data to train Ross’s model would be known to a POSITA to improve accuracy. In addition, a POSITA would have been motivated to look to different methods to train and execute Ross’s predictions for intended future action, including Waymo’s perception and behavior prediction models, since doing so would improve upon Ross’s methods with real-world data.

Exemplary Motivations for Combining Ross and Volz 1

A POSITA would have looked to Volz 1 to train Ross's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems, such as the neural network architectures described in Volz 1. Volz 1 at III.

Exemplary Motivations for Combining Ross and Kooij

A POSITA following Ross's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Kooij's teaching of extracting a dataset from images to be used for training of the system in order to improve real-world data used to more accurately maneuver it's autonomous vehicles, which Ross already teaches are run on a trained system. Kooij at 1446, 1448. A POSITA would have a reasonable expectation of success since it is merely swapping out a known part with another known part to achieve the predictable results suggested by Kooij.

Exemplary Motivations for Combining Ross with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Ross's training data. Munro simply provides implementation details specifying how Ross's predetermined list of actions is formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Ross with Levinson (or Zoox)

A POSITA would have been motivated to apply Levinson's (or Zoox's) identification of cyclists to Ross's detecting objects and maneuvering autonomous vehicles. Levinson (or Zoox) simply provides implementation details specifying policy criteria regarding navigation around

cyclists, which a POSITA would have found obvious to implement to improve the safety of Ross's model. Levinson at 18:35-49.

Exemplary Motivations for Combining Ross with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Ross' determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Ross already outputs a prediction of road user intent, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. Further, Bhattacharyya's model makes its prediction based on distributions of future bounding box sequences. A POSITA would have found it obvious to apply the same techniques to Ross to improve accurate detection and prediction of different road objects using bounding boxes. Bhattacharyya at 3-4, Fig. 2.

Exemplary Motivations for Combining Huval and Ross

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would find it obvious to use Ross's description of predicted trajectories of a pedestrian, which represents the state of mind of a road user, to aid in Huval's calculations and control relating to a road vehicle. A POSITA would be further motivated to look to Ross's teachings of predicting intention of a road user to move into the path of the autonomous vehicle and awareness of a road user of an autonomous vehicle to improve the safety of Huval's method. Ross at 4:33-46, 15:22-27.

Exemplary Motivations for Combining Huval and Cox (or Test My Brain)

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Cox (or Test My Brain) to provide

additional details on how to present summary statistics of the drivable space and likelihoods of collision determined using Huval's model, especially since it is trained using human input to label regions of images. Cox at [0035], [0027]-[0035]. A POSITA would have been motivated to look to Cox (or Test My Brain) to provide additional details on the specifics on how to perceive and track objects, as taught in Huval, such as thorough statistical data, whose parameters include at least the content of response, as taught by Cox (or Test My Brain). Cox at [0019]-[0021], [0063]. A POSITA would have also been motivated to look to Cox (or Test My Brain) to predict the state of mind of a user to safely navigate an autonomous vehicle in traffic. Cox at [0016].

Exemplary Motivations for Combining Huval and Schneemann

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would find it obvious to use Schneemann's description of predicted trajectories of a pedestrian, which represents the state of mind of a road user, to aid in Huval's calculations and control relating to a road vehicle. A POSITA would be further motivated to look to Ross's teachings of predicting intention of a road user to move into the path of the autonomous vehicle and awareness of a road user of an autonomous vehicle to improve the safety of Huval's method. Ross at 4:33-46, 15:22-27.

Exemplary Motivations for Combining Huval and Ogale

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would be motivated to look to Ogale's detailed descriptions of the data being input to its system to better prepare Huval's vehicle to interact with other vehicles and objects on the road.

Exemplary Motivations for Combining Huval and Zhu

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would be motivated to look to Zhu's detailed descriptions of the data being input to its system, including details regarding vehicle behavior, to better prepare Huval's vehicle to interact with other vehicles and objects, including pedestrians, on the road. Zhu at 9:65-10:20.

Exemplary Motivations for Combining Huval and Furuhashi

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would be motivated to improve Huval's described system by looking Furuhashi's teachings of collecting images for a dataset, including a pedestrian's intention to cross (i.e., their state of mind). Furuhashi at 18-19.

Exemplary Motivations for Combining Huval and Keller

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Keller's teachings of predicting pedestrian intention to improve the functioning and safety of Huval's described system. Keller at 494.

Exemplary Motivations for Combining Huval and Kohler

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Kohler's teachings of predicting pedestrian intention to improve the functioning and safety of Huval's described system. Kohler at 5.

Exemplary Motivations for Combining Huval and Ellenbogen

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Ellenbogen describes a method of classifying sensor data. *See* Ellenbogen at [0006]. A POSITA would have been motivated to look to Ellenbogen for more details on statistical output,

specific neural networks, and predicted state of mind to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Ellenbogen at [0056], [0136].

Exemplary Motivations for Combining Huval and Volz 1

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Volz 1 describes a method of analyzing and predicting pedestrian movement in and around a road. *See* Volz 1 at Abstract. A POSITA would have been motivated to look to Volz 1 for more details on what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve safety and Huval's method of navigating an autonomous vehicle using artificial intelligence. Volz 1 at 2, 3-4.

Exemplary Motivations for Combining Huval and Volz 2

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. Volz 2 describes a method of using sensors and artificial intelligence to analyze pedestrian behavior. *See* Volz 2 at 856. A POSITA would have been motivated to look to Volz 2 for more details on what is included in user responses as well as more details regarding statistical methods and predicted intentions to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Volz 2 at 854, 857.

Exemplary Motivations for Combining Huval and Schneider

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have found it obvious to use the identification method taught in Schneider to identify objects on the road, including any or all of a pedestrian, a cyclist, or a motor vehicle, and would have been motivated to look to Schneider for details of this practical application. A POSITA would have a reasonable expectation of success since it is merely swapping

out a known part with another known part to achieve the predictable results suggested by Schneider.

Exemplary Motivations for Combining Huval and Kooij

Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would be motivated to look to Kooij's description of collecting a dataset of pedestrian trajectories to better represent Ogales detection of pedestrians crossing streets. Kooij at 1448. For example, a POSITA would look to implement the machine learning methods to enhance its object prediction techniques by looking for ways to collecting data for machine learning. A POSITA would have a reasonable expectation of success since it is merely swapping out a known part (e.g., a dataset) with another known part (e.g., dataset collected by Kooij) to achieve the result of having more robust data as taught by Kooij that allegedly results in more accurate predictions in the use of artificial intelligence in the roadway.

Exemplary Motivations for Combining Huval with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Huval's training data. Munro simply provides implementation details specifying how Huval's labels are formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Huval with Levinson (or Zoox)

A POSITA would have been motivated to apply Levinson's (or Zoox's) identification of cyclists to Huval's method of using artificial intelligence for a road vehicle. Levinson (or Zoox) simply provides implementation details specifying policy criteria regarding navigation around

cyclists, which a POSITA would have found obvious to implement to improve the safety of Huval's model. Levinson at 18:35-49.

Exemplary Motivations for Combining Huval and Bhattacharyya

Huval describes a method of using artificial intelligence for a road vehicle. *See* Bhattacharyya at 3-4. A POSITA would have been motivated to look to Bhattacharyya's teachings of predicting pedestrian intention to improve the functioning and safety of Huval's described system. Kohler at 5.

Exemplary Motivations for Combining Ogale and Huval

Ogale describes "a human-labeled output layer that predicts how a human would identify objects in the projections of input sensor data." Ogale at 3:22-48. Ogale teaches generating projections from input sensor data, suggesting a use of statistical data to predict the presence and intent of roadway objects. A POSITA would have been motivated, based on Keller's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Huval, which also involves vehicles that rely heavily on computer systems. Huval at [0010].

Exemplary Motivations for Combining Ogale and Cox (or Test My Brain)

Ogale describes "a human-labeled output layer that predicts how a human would identify objects in the projections of input sensor data." Ogale at 3:22-48. A POSITA would be motivated to look at Cox (or Test My Brain) to fill in details on analysis of this human input, including Cox's (or Test My Brain's) description of human annotators. Cox at [0019]-[0021] Ogale teaches generating projections from input sensor data, suggesting a use of statistical data. A POSITA would find it obvious for the projections to use general statistical concepts, such as those taught in Cox (or Test My Brain). Cox at [0029]. For example, Ogale teaches generating "an object

prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Cox’s (or Test My Brain’s) description of analyzing psychophysics and other stimulus, which represent the state of mind of a road user, to aid in Ogale’s prediction of future action.

Exemplary Motivations for Combining Ogale and Schneemann

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Schneemann, which presents similar methods and goals towards identifying pedestrians. Schneemann at 2244. Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Schneemann’s description of pedestrian crossing intention, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Schneemann at 2244. A POSITA would be motivated to look to Schneemann’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions.

Exemplary Motivations for Combining Ogale and Furuhashi

Ogale teaches “each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers..” Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Furuhashi, which similarly teaches pedestrian prediction. Furuhashi at 18. Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.”

Ogale at Abstract. A POSITA would find it obvious to use Furuhashi's description of predicting pedestrian intention from posture, which represents the state of mind of a road user, to aid in Ogale's prediction of future action. *Id.* at 18. A POSITA would be motivated to look to Furuhashi's teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale's object predictions. *Id.* at 18.

Exemplary Motivations for Combining Ogale and Keller

Ogale teaches "each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers.." Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Keller. Keller at 494. Ogale describes "a human-labeled output layer that predicts how a human would identify objects in the projections of input sensor data." Ogale at 3:22-48. A POSITA would be motivated to look at Keller to fill in details on analysis of this human input, including Keller's description of using manual input. Ogale teaches generating "an object prediction as an output...[including] a region of space that is likely to be occupied by an object." Ogale at Abstract. A POSITA would find it obvious to use Keller's description of path prediction of a pedestrian who may or may not cross a road, which represents the state of mind of a road user, to aid in Ogale's prediction of future action. Keller at 494. A POSITA would be motivated to look to Keller's teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale's object predictions.

Exemplary Motivations for Combining Ogale and Ellenbogen

Ogale teaches generating "an object prediction as an output...[including] a region of space that is likely to be occupied by an object." Ogale at Abstract. A POSITA would find it obvious to

use Ellenbogen's description of determining suspicious, which represents the state of mind of a road user, to aid in Ogale's prediction of future action. Ellenbogen at [0057]. A POSITA would have been motivated to combine Ogale with Ellenbogen since both intend to improve a computer's ability to detect and mimic human behavior.

Exemplary Motivations for Combining Ogale and Zhang

Ogale teaches "each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers.." Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught in Zhang. Zhang at [0051]. A POSITA would be motivated to look to Zhang's teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale's object predictions. Zhang at [0058].

Exemplary Motivations for Combining Ogale and Waymo

A POSITA would be motivated by Ogale's disclosure of machine learning techniques in self driving cars and look to Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as the Waymo system to apply the machine learning techniques to improve the Waymo system as disclosed by Ogale. Ogale at 1:11-2:9.

Exemplary Motivations for Combining Ogale and Volz 1

Ogale teaches "each object prediction specif[ying] a region of space that is likely to be occupied by an object....[which object can include] vehicles, pedestrians, bicyclists, or lane markers.." Ogale at 4:34-42. A POSITA would understand that these objects could include an action of staying in place, changing lanes, or crossing a street, as taught by Volz 1, which similarly

focuses on predicting pedestrian motion and behavior. Volz 1 at 2. Ogale teaches generating “an object prediction as an output...[including] a region of space that is likely to be occupied by an object.” Ogale at Abstract. A POSITA would find it obvious to use Volz 1’s description of pedestrian body language to predict behavior, which represents the state of mind of a road user, to aid in Ogale’s prediction of future action. Volz 1 at 3. A POSITA would be motivated to look to Volz 1’s teachings of predicting intention of a road user to move into the path of the autonomous vehicle to better generate Ogale’s object predictions. Volz 1 at 3. For example, A POSITA would be motivated to look to Volz 1’s teachings of predicting awareness of the road user of the autonomous vehicle to better generate Ogale’s object predictions. Volz 1 at 3 (looking at head orientation to predict pedestrian action).

Exemplary Motivations for Combining Ogale and Kooij

A POSITA would be motivated to look to Kooij’s description of collecting a dataset of pedestrian trajectories to better represent Ogale’s detection of pedestrians crossing streets. Kooij at 1448. For example, a POSITA would look to implement the machine learning methods to enhance its object prediction techniques by looking for ways to collecting data for machine learning. A POSITA would have a reasonable expectation of success since it is merely swapping out a known part (e.g., a dataset) with another known part (e.g., dataset collected by Kooij) to achieve the result of having more robust data as taught by Kooij.

Exemplary Motivations for Combining Ogale with Munro

A POSITA would have been motivated to apply Munro’s data organization techniques to Ogale’s training data. Munro simply provides implementation details specifying how Ogale’s labels are formed, stored, and used for training, teaching that it would have included tallies of the

number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Ogale with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Ogale's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Ogale already outputs a prediction of a road object's future motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. Further, Bhattacharyya's model makes its prediction based on distributions of future bounding box sequences. A POSITA would have found it obvious to apply the same techniques to Ogale to improve accurate detection and prediction of different road objects using bounding boxes. Bhattacharyya at 3-4, Fig. 2.

Exemplary Motivations for Combining Waymo and Cox

A POSITA, following Waymo's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox's "statistical learning," e.g., because using statistical methods and outputs would have been known to help reduce risks, and "in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect." Cox at [0035]. See also Cox at [0027]-[0035]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Waymo, to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled data to determine more difficult situations to focus on in training. Cox at [0028].

Exemplary Motivations for Combining Waymo and Test My Brain

A POSITA, following Waymo's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Test My Brain's statistical learning because using statistical methods and outputs would have been known to help reduce risks. Ex. B-27 at elements 1[b]-1[d]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Waymo, to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled data to determine more difficult situations to focus on in training. Ex. B-27 at elements 1[b]-1[d].

Exemplary Motivations for Combining Waymo and Huval

A POSITA would be motivated by Waymo's description of Machine Learning techniques and their importance to autonomous cars to look to other references, such as Huval, for more details regarding details of those machine learning techniques, so as to improve the safety of self-driving cars. Huval at [0010].

Exemplary Motivations for Combining Waymo and Keller

A POSITA would have been motivated to combine Waymo with Keller because Waymo embodies and Keller describes a method of using pedestrian recognition for a vehicle safety system. *See* Keller at 494. A POSITA would have been motivated to look to Keller for more details on what is included in user responses to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Keller at 494.

Exemplary Motivations for Combining Waymo and Schneemann

A POSITA would have been motivated to combine Waymo's System to embody and Schneemann's disclosed method of capturing data on a vehicle and classifying this data. *See* Schneemann. A POSITA would have been motivated to look to Schneemann for more details on

what is included in a statistical summary and what is included in user responses, as well as to improve on methods of determining state of mind and intent of a pedestrian to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Schneemann at 2244, 2246. A POSITA would further be motivated to look to Schneemann for its teachings regarding capturing and using real-time data. Schneemann at 2244.

Exemplary Motivation to Combine Waymo with iMotions

A POSITA would have been motivated to adopt iMotions' technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Waymo's model to predict statistical outputs. Ex. B-26 at elements 1[b]-1[d]. A POSITA would have found this to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Waymo's model predictions.

Exemplary Motivations for Combining Waymo with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Waymo's training data. Munro simply provides implementation details specifying how Waymo's labels are formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Waymo with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Waymo's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Waymo already outputs a prediction of a road object's future motion, and Bhattacharyya simply expands

on that output by providing an uncertainty value associated with that motion. Further, Bhattacharyya's model makes its prediction based on distributions of future bounding box sequences. A POSITA would have found it obvious to apply the same techniques to Waymo to improve accurate detection and prediction of different road objects using bounding boxes. Bhattacharyya at 3-4, Fig. 2.

Exemplary Motivations for Combining Autopilot HW2 and Kooij

A POSITA would have been motivated to combine Autopilot HW2 with Kooij because Autopilot HW2 embodies and Kooij describes a method of capturing and analyzing data from a vehicle on the road. *See* Kooij. A POSITA would have been motivated to look to Kooij for more details on gathering and using sensor data to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Kooij at 1448.

Exemplary Motivations for Combining Autopilot HW2 and Cox

A POSITA would have been motivated to combine Autopilot HW1 embodies and Cox describes a method of training data. *See* Cox at [0007]. A POSITA would have been motivated to look to Cox for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Cox at [0019]-[0021], [0027]-[0035], [0063]. A POSITA would further have been motivated to combine the system of Autopilot HW2 with the teachings of Cox regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW2's recognition and maneuvering system. Cox at [0016], [0029], [0060].

Exemplary Motivations for Combining Autopilot HW2 and Test My Brain

A POSITA would have been motivated to combine Autopilot HW2 embodies and Test My Brain describes a method of collecting training data. *Ex.* B-27 at elements 1[b]-1[d]. A POSITA

would have been motivated to look to Test My Brain for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ex. B-27 at elements 1[b]-1[d]. A POSITA would further have been motivated to combine the system of Autopilot HW1 with the teachings of Test My Brain regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW2's recognition and maneuvering system. Ex. B-27 at elements 1[b]-1[d]. A POSITA would further be motivated to look to Test My Brain for its teachings regarding capturing and using real-time data.

Exemplary Motivations for Combining Autopilot HW2 and Huval

A POSITA would have been motivated to combine Autopilot HW2 with Huval because Autopilot HW2 embodies and Huval describes a method of using artificial intelligence for a road vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Huval to find more details regarding machine learning models to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Huval at [0010].

Exemplary Motivation to Combine Autopilot HW2 with iMotions

A POSITA would have been motivated to adopt iMotions' technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Autopilot HW2's model to predict statistical outputs. Ex. B-26 at elements 1[b]-1[d]. A POSITA would have found this to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Autopilot HW2's model predictions.

Exemplary Motivations for Combining Autopilot HW2 with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Autopilot HW2's training data. Munro simply provides implementation details specifying how

Autopilot HW2's labels are formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Autopilot HW2 with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Autopilot HW2's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Autopilot HW2 already outputs a prediction of a road object's future motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. Further, Bhattacharyya's model makes its prediction based on distributions of future bounding box sequences. A POSITA would have found it obvious to apply the same techniques to Autopilot HW2 to improve accurate detection and prediction of different road objects using bounding boxes. Bhattacharyya at 3-4, Fig. 2.

Exemplary Motivations for Combining Autopilot HW1 and Kooij

A POSITA would have been motivated to combine Autopilot HW1 with Kooij because Autopilot HW1 embodies and Kooij describes a method of capturing and analyzing data from a vehicle on the road. *See* Kooij. A POSITA would have been motivated to look to Kooij for more details on gathering and using sensor data to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Kooij at 1448.

Exemplary Motivations for Combining Autopilot HW1 and Huval

A POSITA would have been motivated to combine Autopilot HW1 with Huval because Autopilot HW1 embodies and Huval describes a method of using artificial intelligence for a road

vehicle. *See* Huval at [0008]. A POSITA would have been motivated to look to Huval to find more details regarding machine learning models to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Huval at [0010]. A POSITA would further be motivated to look to Huval for its teachings regarding capturing and using real-time data. Huval at [0021]-[0022]

Exemplary Motivations for Combining Autopilot HW1 and Cox

A POSITA would have been motivated to combine Autopilot HW1 embodies and Cox describes a method of training data. *See* Cox at [0007]. A POSITA would have been motivated to look to Cox for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Cox at [0019]-[0021], [0027]-[0035], [0063]. A POSITA would further have been motivated to combine the system of Autopilot HW1 with the teachings of Cox regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW1's recognition and maneuvering system. Cox at [0016], [0029], [0060]. A POSITA would further be motivated to look to Cox for its teachings regarding capturing and using real-time data. Cox at [0007].

Exemplary Motivations for Combining Autopilot HW1 and Test My Brain

A POSITA would have been motivated to combine Autopilot HW1 embodies and Test My Brain describes a method of collecting training data. Ex. B-27 at elements 1[b]-1[d]. A POSITA would have been motivated to look to Test My Brain for more details on generating a statistical summary and what is included in user responses and to further improve determinations of intent and awareness of a pedestrian to improve its driver assistance system. Ex. B-27 at elements 1[b]-1[d]. A POSITA would further have been motivated to combine the system of Autopilot HW1

with the teachings of Test My Brain regarding specific of state of mind, neural networks and statistical methods to improve Autopilot HW1's recognition and maneuvering system. Ex. B-27 at elements 1[b]-1[d]. A POSITA would further be motivated to look to Test My Brain for its teachings regarding capturing and using real-time data.

Exemplary Motivation to Combine Autopilot HW1 with iMotions

A POSITA would have been motivated to adopt iMotions' technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Autopilot HW1's model to predict statistical outputs. Ex. B-26 at elements 1[b]-1[d]. A POSITA would have found this to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Autopilot HW1's model predictions.

Exemplary Motivations for Combining Autopilot HW1 with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Autopilot HW1's training data. Munro simply provides implementation details specifying how Autopilot HW1's labels are formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Autopilot HW1 with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Autopilot HW1's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Autopilot HW1 already outputs a prediction of an objects future motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. Further,

Bhattacharyya's model makes its prediction based on distributions of future bounding box sequences. A POSITA would have found it obvious to apply the same techniques to Autopilot HW1 to improve accurate detection and prediction of different road objects using bounding boxes. Bhattacharyya at 3-4, Fig. 2.

Exemplary Motivations for Combining Mercedes with Huval

Ogale teaches generating projections from input sensor data, suggesting a use of statistical data to predict the presence and intent of roadway objects. A POSITA would have been motivated, based on Huval's teaching of using its method on an "intelligent vehicle," fill in details of how to program these vehicles by looking to teachings of neural networks, such as taught in Huval, which also involves vehicles that rely heavily on computer systems. Huval at [0010]. Further, a POSITA would have been motivated to utilize Huval's methods of collecting training data related to labeling actions of objects in various road scenes to provide more robust training data. Huval at [0036]-[0039].

Exemplary Motivations for Combining Mercedes with Cox

A POSITA, following Mercedes' method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox's "statistical learning," e.g., because using statistical methods and outputs would have been known to help reduce risks, and "in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect." Cox at [0035]. *See also* Cox at [0027]-[0035]. A POSITA would also have looked to Cox to train Mercedes' perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. Cox describes its training model as a neural

network or other described supervised learning models, e.g., “any form of supervised learning, including neural networks, boosting, bagging, random forests, nearest neighbor algorithms, naïve bay classifiers, density estimators, and other forms of statistical regression.” Cox at [0060]. Further, a POSITA would have found it obvious to reduce the risk involved with training Mercedes’ method of detecting objects and maneuvering autonomous vehicles by looking to Cox’s statistical methods, including statistical data associated with response data. Specifically, a POSITA would be motivated to look to Cox’s teachings of the parameters including psychometric data (including responses times) and eye tracking. Cox at [0019]-[0021], [0063]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Mercedes, to look to basic statistical concepts. For example, a POSITA would have found it obvious to implement ranges and averages for response times, taught in Cox. Cox [0029].

Exemplary Motivations for Combining Mercedes with Test My Brain

A POSITA, following Mercedes’ method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Test My Brain’s statistical learning because using statistical methods and outputs would have been known to help reduce risks. A POSITA would also have looked to Test My Brain to train Mercedes’ perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems. Test My Brain describes its training model as a neural network or other described supervised learning models. Further, a POSITA would have found it obvious to reduce the risk involved with training Mercedes’ method of detecting objects and maneuvering autonomous vehicles by looking to Test My Brain’s statistical methods, including statistical data associated with response data. Specifically, a POSITA would be

motivated to look to Test My Brain’s teachings of the parameters, which on information and belief include psychometric data (including responses times) and eye tracking. Ex. B-27 at elements 1[b]-1[d]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Mercedes, to look to basic statistical concepts. For example, a POSITA would have found it obvious to implement ranges and averages for response times, taught in Test My Brain. Ex. B-27 at elements 1[b]-1[d].

Exemplary Motivations for Combining Mercedes with Ogale

A POSITA, following Mercedes’ method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Ogale’s “human-labeled training data” e.g., because using statistical methods and outputs, and verifying data related to human responses with human labeling would have been known to help reduce risks since “[h]uman-labeled training data 127 tends to be more accurate than the auto-labeled training data.” Ogale at 3:29-48, 6:51-7:12. A POSITA would also have been motivated to look to different methods to train and execute Mercedes’ predictions for intended future action, including Ogale’s generation of “human-labeled training data,” e.g., to improve the accuracy of the data input to statistical summaries. Ogale at 3:29-48, 6:51-7:12. Further, a POSITA would have looked to Ogale to train Mercedes’ perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. For example, Ogale teaches that neural networks can be used with autonomous vehicles for object classification and output prediction. Ogale at 1:11-2:9.

Exemplary Motivations for Combining Mercedes with Ellenbogen

A POSITA following Mercedes' method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Ellenbogen's creation of composite outputs and composite confidences, e.g., because using statistical methods and outputs would have been known to help reduce risks. Ellenbogen at [0056]. A POSITA would also have looked to Ellenbogen to train Mercedes' perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning-based model for training the perception, prediction, and/or maneuvering systems, such as Ellenbogen's deep neural network or convolution neural network. Ellenbogen at [0136].

Exemplary Motivations for Combining Mercedes with Gray

A POSITA would have looked to Gray to train Mercedes perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. For example, Gray teaches that its model "can be a convolution neural network." Gray at 10:12-31. A POSITA would have a reasonable expectation of success since it is merely swapping out a known part with another known part to achieve the predictable results suggested by Gray in the same field of endeavor.

Exemplary Motivations for Combining Mercedes with Zhang

A POSITA following Mercedes' method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Zhang's training data "labeled using human labelers," because a POSITA would understand human responses to be what the neural network is designed to mimic. Zhang at [0051], [0053]. And a POSITA would have been motivated to look to different methods to train and execute Mercedes' predictions for intended

future action, including Zhang's generation of predicted trajectories, which represents a statistical summary of expected user responses. Zhang at [0054].

Exemplary Motivations for Combining Mercedes and Waymo

A POSITA, following Mercedes method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Waymo's descriptions of its behavior prediction software and its Waymo Dataset, which included road scenes captured by its sensors, since using Waymo's trained sensor data to train Mercedes' model would be known to a POSITA to improve accuracy. In addition, a POSITA would have been motivated to look to different methods to train and execute Mercedes' predictions for intended future action, including Waymo's perception and behavior prediction models, since doing so would improve upon Mercedes' methods with real-world data.

Exemplary Motivation to Combine Mercedes with iMotions

A POSITA would have been motivated to adopt iMotions' technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Mercedes' model to predict statistical outputs. Ex. B-26 at elements 1[b]-1[d]. A POSITA would have found this to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Mercedes' model predictions.

Exemplary Motivations for Combining Mercedes with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Mercedes' training data. Munro simply provides implementation details specifying how Mercedes' labels are formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132]-[0142].

Exemplary Motivations for Combining Mercedes with Levinson/Zoox

A POSITA would have been motivated to apply the teachings of Levinson/Zoox regarding the identification of cyclists to Mercedes' method of detecting objects and controlling vehicles to avoid collision. Levinson/Zoox simply provides implementation details specifying policy criteria regarding navigation around cyclists, which a POSITA would have found obvious to implement to improve the safety of Mercedes' collision-avoidance model. Levinson at 18:35-49.

Exemplary Motivations for Combining Mercedes with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics to improve Mercedes' determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Mercedes' already outputs a prediction of an objects future motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. Further, Bhattacharyya's model makes its prediction based on distributions of future bounding box sequences. A POSITA would have found it obvious to apply the same techniques to Mercedes to improve accurate detection and prediction of different road objects using bounding boxes. Bhattacharyya at 3-4, Fig. 2.

C. The '579 Patent

Pursuant to Patent Rule 3-3 and subject to Tesla's reservations of rights in these Invalidity Contentions, at least the prior art listed below, individually or in combination, invalidates the Asserted Claims of the '579 Patent. Exhibits C-1 through C-27 provide detailed claim charts showing where each claim limitation may be found in certain references listed below, either expressly or inherently as the reference would be understood by a person having ordinary skill in the art. For those references for which detailed claim charts are not provided, those additional

prior art references are otherwise pertinent to the invalidity of the '579 Patent, either alone or in combination with other references.

The prior art references, systems, and products listed below and in the accompanying claim chart exhibits may be relied upon for certain limitations, state of the art, and background of the art; indicia of obviousness; as evidence of the level of skill in the art at the time of the filing of the Patents-in-Suit; and/or in support of assertions that it is proper to combine certain prior art references in certain ways.

Tesla also incorporates by reference each and every prior art reference of record in the prosecution of the Patents-in-Suit and patents or patent applications related to the Patents-in-Suit, the prior art referred to in the specifications of the Patents-in-Suit, as well as the prior art identified in any USPTO proceedings involving any of the Patents-in-Suit.

1. Bases for Anticipation and/or Obviousness

Each prior art reference identified in Exhibits C-1 through C-27 expressly, implicitly, or inherently anticipates and/or renders obvious the Asserted Claims of the '579 Patent, either alone or in combination with other prior art references (*e.g.*, other references identified above) or the knowledge of the person of ordinary skill in the art at the time of the alleged invention. In the table below, Tesla identifies a non-exhaustive list of prior art references that, alone or in combination, anticipate and/or render obvious the Asserted Claims of the '579 Patent.

Exhibit	Patent No. or Title (Primary Inventor/Author)	Date of Issuance or Publication
Ex. C-1	U.S. Pat. No. 2019/0049970 ("Djuric")	Feb. 14, 2019 (Filed Sep. 5, 2018)
Ex. C-2	U.S. Pat. Pub. No. 2020/0160535 ("AA")	May 21, 2020 (Filed Nov. 15, 2018)
Ex. C-3	U.S. Pat. No. 10,496901 ("Ross")	Dec. 3, 2019 (Filed Aug. 17, 2016)
Ex. C-4	WO2014/210334 ("Cox")	Dec. 31, 2014

Ex. C-5	U.S. Pat. Pub. No. 2020/0110416 (“Hong”)	Apr. 9, 2020 (Filed Oct. 4, 2018)
Ex. C-6	U.S. Pat. Pub. No. 2019/0302767 (“Sapp”)	Oct. 3, 2019 (Filed Mar. 28, 2018)
Ex. C-7	U.S. Pat. Pub. No. 2019/0072966 (“Zhang”)	Mar. 7, 2019 (Filed Nov. 7, 2017)
Ex. C-8	U.S. Pat. Pub. No. 2018/0247200 (“Rolfe”)	Aug. 30, 2018
Ex. C-9	Djuric, “Motion Prediction of Traffic Actors for Autonomous Driving using Deep Convolution Networks,” (“Djuric 2”)	Aug. 17, 2018
Ex. C-10	Schneemann, “Context-based Detection of Pedestrian Crossing Intention for Autonomous Driving in Urban Environments” (“Schneemann”)	Oct. 2016
Ex. C-11	Furuhashi, “Estimation of Street Crossing Intention from a Pedestrian’s Posture on a Sidewalk Using Multiple Image Frames” (“Furuhashi”)	2011
Ex. C-12	Keller, “Will the Pedestrian Cross? A Study on Pedestrian Path Prediction” (“Keller”)	Apr. 2014
Ex. C-13	Kohler, “Early Detection of the Pedestrian’s Intention to Cross the Street” (“Kohler”)	Oct. 25, 2012
Ex. C-14	Quintero, “Pedestrian Path Prediction using Body Language Traits” (“Quintero”)	Jun. 2014
Ex. C-15	Volz, “A data-driven approach for pedestrian intention estimation” 2016 (“Volz 1”)	2016
Ex. C-16	Schneider, “Pedestrian Path Prediction with Recursive Bayesian Filters: A Comparative Study” (“Schneider”)	2013
Ex. C-17	Bhattacharyya, “Long-Term On-Board Prediction of People in Traffic Scenes under Uncertainty” (“Bhattacharyya”)	Jun. 20, 2018
Ex. C-18	Kooij, “Analysis of pedestrian dynamics from a vehicle perspective” (“Kooij”)	Jun. 2014
Ex. C-19	U.S. Patent No. 9,632,502 (“Levinson”)	Apr. 25, 2017 (Filed Nov. 5, 2015)

The Asserted Claims of the ’579 Patent are also invalid under 35 U.S.C. § 102(a) and (b) because the subject matter was known by others, publicly used, and on sale in the United States before it was purportedly invented and more than one year before the priority date of the Asserted Claim. Additionally, the Asserted Claim because any purported invention was made in this

country by another who had not abandoned, suppressed, or concealed the purported invention. For example, the foregoing patents and publications are evidence of such prior art systems and inventions. As such, the following systems are prior art under 35 U.S.C. § 102:

Exhibit	System Prior Art
Ex. C-20	Tesla – Hardware 1
Ex. C-21	Tesla – Hardware 2
Ex. C-22	Daimler/ Mercedes
Ex. C-23	Uber/Aurora
Ex. C-24	Waymo
Ex. C-25	iMotions
Ex. C-26	TestMyBrain.com
Ex. C-27	Zoox

The accompanying claim charts (Exhibits C-1 through C-27) set forth example bases for anticipation and obviousness, identifying where each reference discloses, alone or in combination with other references, each limitation of the Asserted Claims of the '579 Patent on a limitation-by-limitation basis. Tesla's claim charts are exemplary and not exhaustive.

2. Obviousness Combinations

Subject to Tesla's reservation of rights, Tesla contends that all of the prior art references, as identified above and described in the charts attached as Exhibits C-1 through C-27 by themselves anticipate the Asserted Claims of the '579 Patent in accordance with 35 U.S.C. § 102 and/or render the Asserted Claim of the '579 Patent obvious under 35 U.S.C. § 103, as more specifically noted in the attached charts. The cited portions of the prior art references are examples and representative of the content of the prior art references, and should be understood in the context of the reference as a whole, as understood by one of ordinary skill in the art. To the extent a cited prior art reference is deemed not to anticipate or render obvious a claim as noted in the attached

charts for failing to teach or suggest one or more limitations of that claim, that claim would nonetheless have been obvious to one of ordinary skill in the art at the time of the invention by the combination of the cited prior art reference with one or more other prior art references and/or common knowledge disclosing the missing claim limitations. For example, any of the references listed above, to the extent it does not explicitly or inherently disclose any limitation, could be combined with any one or more of the other references listed above which discloses that limitation. Tesla reserves the right to supplement the obviousness arguments using any references listed above, or any references that may become known to Tesla during the course of discovery.

In the table below, Tesla further identifies exemplary combinations of prior art that render the Asserted Claims of the '579 Patent obvious:

Primary Reference	Secondary Reference	Claim
Djuric	AA	1, 13, 20
	Cox	1, 2, 13, 14, 20
	Test My Brain	1, 2, 13, 14, 20
	Sapp	9
	Zhang	10
	Djuric 2 (and/or Uber)	1, 13, 20
	Keller	1, 13, 20
	Quintero	1, 13, 20
	Waymo	1, 9, 10, 13, 20
	Rolfe	3, 15
	Ross	7, 9
	Volz 1	1, 7, 8, 13, 20
	Levinson	9
	Zoox	9
	Bhattacharyya	8, 10
	One or more of AA, Cox, Test My Brain, Sapp, Zhang, Djuric 2(and/or Uber), Keller, Quintero, Waymo, Rolfe, Ross, Volz 1, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 7, 8, 9, 10, 13, 15, 20
AA	Djuric	1, 4, 5, 6, 8, 11, 12, 13, 16, 17, 18, 19, 20
	Ross	8, 9, 11, 19

Primary Reference	Secondary Reference	Claim
	Waymo	8, 9, 11, 19
	Cox	2, 4, 14, 16
	Test My Brain	2, 4, 14, 16
	Sapp	1, 8, 9, 11, 13, 19, 20
	Zhang	1, 8, 10, 13, 20
	Rolfe	3, 15
	Djuric 2 (and/or Uber)	8
	Schneemann	8
	Quintero	1, 13, 20
	Volz 1	8
	Levinson	1, 8, 9, 11, 13, 19, 20
	Zoox	1, 8, 9, 11, 13, 19, 20
	Bhattacharyya	1, 2, 4, 5, 6, 8, 10, 12, 13, 14, 16, 17, 18, 20
	One or more of Djuric, Ross, Waymo, Cox, Test My Brain, Sapp, Zhang, Rolfe, Djuric 2 (and/or Uber), Schneemann, Quintero, Volz 1, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 4, 5, 6, 8, 9, 10, 11, 12, 13, 14, 15, 16, 19, 20
Waymo	Djuric	1, 4, 5, 6, 12, 13, 16, 17, 18 20
	AA	1, 13, 20
	Ross	1, 13, 20
	Cox	2, 14
	Test My Brain	2, 14
	Rolfe	3, 15
	Djuric 2 (and/or Uber)	1, 13, 20
	iMotions	2, 14
	Levinson	1, 13, 20
	Zoox	1, 13, 20
	Bhattacharyya	1, 2, 5, 6, 12, 13, 14, 16, 17, 20
	One or more of Djuric, AA, Ross, Cox, Test My Brain, Rolfe, Djuric 2 (and/or Uber), iMotions, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 4, 5, 6, 12, 13, 14, 15, 16, 17, 20
Sapp	Djuric	1, 4, 5, 6, 12, 13, 16, 17, 18 20
	AA	1, 13, 20
	Ross	1, 13, 20
	Waymo	1, 13, 20
	Cox	1, 2, 4, 13, 14, 16, 20

Primary Reference	Secondary Reference	Claim
	Test My Brain	1, 2, 4, 13, 14, 16, 20
	Zhang	10
	Rolfe	3, 15
	Djuric 2 (and/or Uber)	1, 13, 20
	Keller	1, 13, 20
	Quintero	1, 13, 20
	Volz 1	1, 13, 20
	Bhattacharyya	1, 2, 5, 6, 10, 12, 13, 14, 16, 17, 18, 20
	One or more of Djuric, AA, Ross, Waymo, Cox, Test My Brain, Zhang, Rolfe, Djuric 2 (and/or Uber), Keller, Quintero, Volz 1, and/or Bhattacharyya	1, 2, 5, 6, 10, 12, 13, 14, 16, 17, 18, 20
Zhang	Djuric	1, 4, 5, 6, 11, 12, 13, 16, 17, 18 19, 20
	AA	1, 13, 20
	Ross	1, 9, 11, 13, 19, 20
	Cox	1, 2, 4, 13, 14, 16, 20
	Test My Brain	1, 2, 4, 13, 14, 16, 20
	Sapp	9, 11, 19
	Rolfe	3, 15
	Djuric 2 (and/or Uber)	1, 13, 20
	Keller	1, 13, 20
	Quintero	1, 13, 20
	Waymo	1, 9, 11, 13, 19, 20
	Volz 1	1, 7, 8, 13, 20
	Levinson	1, 13, 20
	Zoox	1, 9, 13, 11, 19, 20
	Bhattacharyya	1, 2, 4, 5, 12, 13, 14, 16, 17, 18, 20
	One or more of Djuric, AA, Ross, Cox, Test My Brain, Sapp, Rolfe, Djuric 2 (and/or Uber), Keller, Quintero, Waymo, Volz 1, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 4, 7, 8, 9, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20
Djuric 2 (and/or Uber)	Djuric	1, 3, 4, 5, 6, 11, 12, 13, 15, 16, 17, 18, 19, 20
	AA	1, 13, 20
	Ross	1, 13, 9, 11, 19, 20
	Cox	2, 4, 14, 16
	Test My Brain	2, 4, 14, 16

Primary Reference	Secondary Reference	Claim
	Sapp	1, 9, 11, 13, 19, 20
	Zhang	1, 10, 13, 20
	Rolfe	3, 15
	Quintero	1, 13, 20
	Waymo	1, 9, 10, 11, 13, 19, 20
	Autopilot HW2	11, 19
	Autopilot HW1	11, 19
	iMotions	1, 2, 9, 13, 14, 20
	Levinson	1, 9, 11, 13, 19, 20
	Zoox	1, 9, 11, 13, 19, 20
	Bhattacharyya	1, 2, 4, 5, 6, 10, 12, 13, 14, 16, 17, 18, 20
	One or more of Djuric, AA, Ross, Cox, Test My Brain, Sapp, Zhang, Rolfe, Quintero, Waymo, Autopilot HW2, Autopilot HW1, iMotions, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20
Mercedes	Djuric	1, 4, 5, 6, 12, 13, 16, 17, 18, 20
	Ross	1, 13, 20
	Waymo	1, 13, 20
	Cox	2, 4, 14, 16
	Test My Brain	2, 4, 14, 16
	Rolfe	3, 15
	Djuric 2 (and/or Uber)	1, 13, 20
	iMotions	1, 2, 7, 9, 13, 14, 20
	Levinson	1, 13, 20
	Zoox	1, 13, 20
	Bhattacharyya	1, 4, 5, 6, 12, 13, 16, 17, 18, 20
	One or more of Djuric, AA, Ross, Waymo, Cox, Test My Brain, Supp, Zhang, Rolfe, Quintero, Waymo, Autopilot HW2, Autopilot HW1, iMotions, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 4, 5, 6, 9, 10, 11, 12, 13, 15, 16, 19, 20

3. Motivation to Combine and Reasonable Expectation of Success

With respect to the '579 Patent, the prior art identified above demonstrates the scope and content of the prior art. As detailed in Exhibits C-1 through C-27, the prior art included each limitation recited in the Asserted Claims of the '579 Patent. To the extent a cited prior art reference is deemed not to anticipate a claim, the only difference between the claimed invention and the prior art is the lack of actual combination of the elements in a single prior art reference. However, a Person of Ordinary Skill in the Art ("POSITA") would have been motivated to combine each of the above prior art references.

For example, many of the above-identified references (Djuric, AA, Ross, Hong, Sapp, Zhang, Djuric 2, Schneemann, Furuhashi, Keller, Kohler, Quintero, Karasev, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, Levinson, Bhattacharyya, and Zoox) are all related to motor vehicles. These references constitute analogous art within the same field of endeavor—specifically, automotive design and engineering—and address the same or substantially similar technical problems regarding vehicle operation and subsystem integration. A POSITA would naturally consult these references when seeking to improve vehicle performance or functionality. Here, because Djuric, AA, Ross, Hong, Sapp, Zhang, Djuric 2, Schneemann, Furuhashi, Keller, Kohler, Quintero, Karasev, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, Levinson, Bhattacharyya, and Zoox all reside within the automotive domain, the barrier to combination is exceedingly low. A POSITA would recognize that the teachings of each such reference are compatible with (or could be adapted to be compatible with) other references related to motor vehicles. The combination of these references related to motor vehicles also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar elements to perform their primary functions. And, driven by the perpetual market

pressure in the automotive industry to enhance safety, efficiency, and user experience, a POSITA would have been motivated to combine the specific features of each of Djuric, AA, Ross, Hong, Sapp, Zhang, Djuric 2, Schneemann, Furuhashi, Keller, Kohler, Quintero, Karasev, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, Levinson, Bhattacharyya, and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of an automobile, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As a further example, many of the above references relate more specifically to autonomous driving (e.g., Djuric, AA, Ross, Hong, Sapp, Zhang, Djuric 2, Schneemann, Karasev, Autopilot HW1, Autopilot HW2, Uber, Waymo, Levinson, and Zoox). These references constitute analogous art within the same field of endeavor—specifically, the development of automated driving systems using sensors—and address the same or substantially similar technical problems regarding object detection, environmental perception, and real-time decision making. A POSITA would naturally consult these references when seeking to improve the reliability or safety of an autonomous driving feature. Here, because Djuric, AA, Ross, Hong, Sapp, Zhang, Djuric 2, Schneemann, Karasev, Autopilot HW1, Autopilot HW2, Uber, Waymo, Levinson, and Zoox all involve descriptions of autonomous vehicle architectures, the barrier to combination is exceedingly low. For example, a POSITA would recognize that the sensing or control teachings of each such reference are compatible with the processing or navigation modules of other references related to autonomous driving. The combination of references relating to autonomous driving also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar algorithms and hardware to perform their primary functions. And, driven by the industry

competition to achieve higher levels of autonomy (e.g., for SAE Levels 3-5) and the necessity to eliminate human error, a POSITA would have been motivated to combine the specific features of each of Djuric, AA, Ross, Hong, Sapp, Zhang, Djuric 2, Schneemann, Karasev, Autopilot HW1, Autopilot HW2, Uber, Waymo, Levinson, and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of a self-driving platform, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As another example, many of the above identified references (Djuric, AA, Ross, Cox, Hong, Sapp, Zhang, Rolfe, Djuric 2, Schneemann, Furuhashi, Keller, Kohler, Quintero, Karasev, Schneider, Kooij, Autopilot HW1, Autopilot HW1, Mercedes, Uber, Waymo, iMotions, Test My Brain, Bhattacharyya, and Zoox) are all related to the development and training of machine learning models, including supervised learning techniques. These references constitute analogous art within the same field of endeavor—specifically, artificial intelligence and data annotation—and address the same or substantially similar technical problems regarding model accuracy, ground truth verification, and the reduction of prediction error. A POSITA would naturally consult these references when seeking to improve the performance of a neural network or statistical model through high-quality supervision. Here, because Djuric, AA, Ross, Cox, Hong, Sapp, Zhang, Rolfe, Djuric 2, Schneemann, Furuhashi, Keller, Kohler, Quintero, Karasev, Schneider, Kooij, Autopilot HW1, Autopilot HW1, Mercedes, Uber, Waymo, iMotions, Test My Brain, Bhattacharyya, and Zoox all relate to data-driven algorithm development, the barrier to combination is exceedingly low. A POSITA would recognize that the human-labeled datasets or annotation interfaces of each such reference are compatible with (or could be adapted to be compatible with) the training pipelines and loss functions disclosed in other references related to

machine learning. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar training loops to perform their primary functions. And, driven by the market pressure in the artificial intelligence industry to maximize inference accuracy and leverage human validation for edge cases, a POSITA would have been motivated to combine the specific features of each of Djuric, AA, Ross, Cox, Hong, Sapp, Zhang, Rolfe, Djuric 2, Schneemann, Furuhashi, Keller, Kohler, Quintero, Karasev, Schneider, Kooij, Autopilot HW1, Autopilot HW1, Mercedes, Uber, Waymo, iMotions, Test My Brain, Bhattacharyya, and Zoox. Specifically, the use of human-generated ground truth labels to calibrate or refine model weights is a foundational practice in the art, making the aggregation of these teachings a matter of routine optimization. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known supervised learning solutions within the standard constraints of a predictive system, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

Below, Tesla has provided several additional illustrative examples of the motivations that a POSITA would have had to combine certain of the prior art references in Exhibits C-1 through C-27. The inclusion of certain example combinations herein does not exclude other combinations based on the claim charts attached hereto, as there are many possible combinations of the references listed herein, and it is not practical, particularly at this early stage prior to further factual investigation and claim construction proceedings, to identify and list all potentially relevant combinations. Instead, in many instances where a particular contention calls for, or requires, combining references, any one of a number of references can be combined. As such, these

motivations to combine apply equally to the combination of a primary reference to one secondary reference, and the combination of a primary reference to multiple secondary references.

Exemplary Motivations for Combining Djuric and AA

A POSITA would have been motivated to adopt AA's disclosure of a "probabilistic model" in Djuric, at least because Djuric teaches that its model may be a Bayesian network, and AA's disclosures regarding probabilistic model simply provide more implementation detail. AA at [0001], [0050]. A POSITA would also implement AA's "feature vector" stage to make Djuric's model more effective, as Djuric already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by AA. AA at [0034]-[0037].

Exemplary Motivations for Combining Djuric and Ross

A POSITA would have been further motivated to combine Ross with Djuric such that Djuric probabilistic neural network generates goal-based predictions using Djuric's goals and Ross's intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Djuric's use of goals with the prediction of intent and/or actions disclosed by Ross, which would expand the scenarios Djuric's model is capable of predicting.

Exemplary Motivations for Combining Djuric and Cox (or Test My Brain)

A POSITA would have been motivated to adopt Cox's (or Test My Brain's) disclosure of training and testing on feature vectors to improve Djuric's model performance by grouping features into neighborhoods before producing a set of final outputs of the probabilistic neural network. *See* Cox at [0039]. Further, a POSITA would have found it obvious to implement Cox's (or Test My Brain's) teaching of determining a mean accuracy of labels to determine which types of difficult training scenarios require more attentive analysis. *See* Cox at [0028].

Exemplary Motivations for Combining Djuric and Sapp

A POSITA, following Djuric’s method of extracting features from image data, would have looked to Sapp’s method of classifying attributes associated with road users “(e.g., whether the agent is looking down, whether the agent is paying attention, etc.)” in order to provide a safer model and improve prediction of road user movements. Sapp at [0009].

Exemplary Motivations for Combining Djuric and Zhang

A POSITA would have been motivated to look to different methods to train and execute Djuric’s predictions for intended future action of road users, including Zhang’s generation of predicted trajectories, which represents a statistical summary of expected user responses such as “short term driving goal[s].” Zhang at [0048], [0054].

Exemplary Motivations for Combining Djuric and Djuric 2 (and/or Uber)

A POSITA would have been motivated to implement Djuric 2’s (and/or Uber’s) “vector layer” to make Djuric’s model more effective, as Djuric already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Djuric 2 (and/or Uber). Djuric 2 at 4. Further, a POSITA would have been motivated to combine Djuric and Djuric 2 (and/or Uber) because they were invented/disclosed by the same individual.

Exemplary Motivations for Combining Djuric and Keller

A POSITA would have been motivated to apply feature vector generation as disclosed by Keller to make Djuric’s model more effective, as Djuric already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Keller. Keller at 499.

Exemplary Motivations for Combining Djuric and Quintero

A POSITA would have been motivated to “reduce the dimensionality of input data” by generating feature vectors as taught by Quintero to improve computing time for tracking and prediction tasks, thus making Djuric’s model more effective. Quintero at 320. Djuric already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Quintero.

Exemplary Motivations for Combining Djuric and Waymo

A POSITA would have been motivated to embed “semantic meaning” with objects captured in image data, as taught by Waymo, to improve the efficiency of Djuric’s model. Ex. C-24 at 1[a-ii], 1[a-iii]. Djuric already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Waymo.

Exemplary Motivations for Combining Djuric and Rolfe

A POSITA would have been motivated to combine Rolfe with Djuric to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data set in Djuric. Rolfe at [0086]. Djuric teaches that the model is trained so that “the negative log-likelihood of the training data set can be minimized.” Djuric at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details (already in the context of machine learning) that a POSITA could utilize to achieve the stated goal in Djuric.

Exemplary Motivations for Combining Djuric and Volz 1

A POSITA would have been motivated to combine Volz 1’s techniques of enhancing feature vectors using LiDAR based images to make Djuric’s model more effective as Djuric already inputs a LiDAR data set into the machine-learned model to predict trajectories of objects

around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Volz 1. Volz 1 at Abstract, 5. A POSITA would have been further motivated to combine Volz 1 with Djuric such that Djuric's probabilistic neural network generates goal-based predictions using Djuric's goals and Volz 1's predicted pedestrian intent. *Id.* A POSITA would have found it obvious to supplement Djuric's use of goals with the prediction of intent and/or actions disclosed by Volz 1, which would expand the scenarios Djuric's model is capable of predicting.

Exemplary Motivations for Combining Djuric and Levinson (or Zoox)

A POSITA would have been motivated to look to Levinson's (or Zoox's) method of classifying attributes associated with road users "(e.g., whether the agent is looking down, whether the agent is paying attention, etc.)" in order to provide a safer model and improve Djuric's prediction of road user movements. Ex. C-27 at claim 9.

Exemplary Motivations to Combine Djuric and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching of predicting future movements of pedestrians over long-time horizons, such as whether the pedestrian will cross a road, to Djuric's model to expand the scenarios Djuric's model is able to interpret. Bhattacharyya at 1.

Exemplary Motivations for Combining AA and Djuric

A POSITA would have been motivated to apply Djuric's teaching implementing supervised training techniques to predict confidence levels of different predicted paths for other vehicles to improve AA's determination of future subject motion. Djuric at [0034]. A POSITA would have found the combination straightforward, as AA already outputs a probability distribution of future subject motion, and Djuric simply expands on that output by providing

potential paths. A POSITA would have been further motivated to combine AA and Djuric such that AA's output includes a level of uncertainty, and use that uncertainty to improve the quality of predictions used to navigate the autonomous vehicle around the surrounding environment. Djuric at [0003], [0088]. A POSITA would also have been motivated to apply Djuric's "goal-based prediction[s]" in order to expand upon the scenarios in which AA is able to determine future subject motion. Djuric at [0081]. A POSITA would have been motivated to apply Djuric's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement AA's disclosure of controlling an autonomous vehicle based on a determined motion intent. Djuric at [0044]. Finally, a POSITA would have applied the various types of neural networks disclosed in Djuric to expand the potential models that could implement AA's motion intent determinations.

Exemplary Motivations for Combining AA and Ross (or Waymo)

A POSITA would have been motivated to combine Ross (or Waymo) with AA such that AA's probabilistic neural network generates motion intent using Ross's (or Waymo's) intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement AA's motion intents with the prediction of intent and/or actions disclosed by Ross (or Waymo), which would expand the scenarios AA's model is capable of predicting. A POSITA would have been motivated to apply Ross's (or Waymo's) explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement AA's disclosure of controlling an autonomous vehicle based on a determined motion intent. Ross at 6:49-59.

Exemplary Motivations for Combining AA and Cox (or Test My Brain)

A POSITA, following AA's method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox's (or Test My Brain's) "statistical learning," e.g., because using statistical methods and outputs would have been known to help reduce risks,

and “in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect.” Cox at [0035]. See also Cox at [0027]-[0035]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in AA, to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled data to determine more difficult situations to focus on in training. Cox at [0028].

Exemplary Motivations for Combining AA and Sapp

A POSITA would have been further motivated to combine Sapp with AA such that AA’s probabilistic neural network generates motion intent using Sapp’s intents or actions. *See* Sapp at [0068]. A POSITA would have found it obvious to supplement AA’s motion intents with the prediction of intent and/or actions disclosed by Sapp, which would expand the scenarios AA’s model is capable of predicting, such a user’s state of mind or a task a user plans on accomplishing. A POSITA would have been motivated to apply Sapp’s explicit disclosure regarding system controllers communicating with drive module systems to operate an autonomous vehicle to implement AA’s disclosure of controlling an autonomous vehicle based on a determined motion intent. Sapp at [0065].

Exemplary Motivations for Combining AA with Zhang

A POSITA would have been motivated to apply Zhang’s teaching implementing supervised training techniques to predict confidence levels of different predicted paths for other vehicles to improve AA’s determination of future subject motion. Zhang at [0058]. A POSITA would have found the combination straightforward, as AA already outputs a probability distribution of future subject motion, and Zhang simply expands on AA’s output by providing potential paths. Further, a POSITA would have been motivated to combine Zhang’s predicted

intentions and “short term driving goals” to expand the type of scenarios in which AA’s model is able to determine motion intent. Zhang at [0048].

Exemplary Motivations for Combining AA with Rolfe

A POSITA would have been motivated to combine Rolfe with Djuric to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data set in Djuric. Rolfe at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details that a POSITA could utilize to achieve generating improved training data in Djuric.

Exemplary Motivations for Combining AA with Djuric 2 (and/or Uber)

A POSITA would have been motivated to apply Djuric 2’s (and/or Uber’s) use of confidence levels to update AA’s determination of motion intent when unexpected events occur and expand the number of scenarios in which AA’s model is able to determine motion intent. Djuric 2 at 7.

Exemplary Motivations for Combining AA with Schneemann

A POSITA would have found it obvious to supplement AA’s motion intents with the prediction of intent and/or actions disclosed by Schneemann, such as predicting pedestrian intent to cross a road, which would expand the scenarios AA’s model is capable of predicting, such as whether a pedestrian intends to cross a road. Schneemann at 2243.

Exemplary Motivations for Combining AA with Quintero

A POSITA would have been motivated to apply techniques of determining pedestrian intent based on body position, as taught by Quintero, to better determine pedestrian motion intent and expand the scenarios AA’s model is capable of predicting. Quintero at 316.

Exemplary Motivations for Combining AA with Waymo

A POSITA would have been motivated to include Waymo's behavior prediction techniques, to better understand how people signal intentions and more accurately detect hidden context in sensor data to expand the scenarios AA's model is capable of predicting. Ex. C-24 at 1[a-ii], 1[a-iii].

Exemplary Motivations for Combining AA with Volz 1

A POSITA would have found it obvious to supplement AA's motion intents with the prediction of intent and/or actions disclosed by Volz 1, such as predicting pedestrian intent to cross a road, which would expand the scenarios AA's model is capable of predicting, such as whether a pedestrian intends to cross a road. Volz 1 at Abstract, 5.

Exemplary Motivations for Combining AA and Levinson (or Zoox)

A POSITA would have been further motivated to combine Levinson (or Zoox) with AA such that AA's probabilistic neural network generates motion intent using Levinson's (or Zoox's) intents or actions. *See* Ex. C-27 at 1[a-iii], claim 8, claim 11. A POSITA would have found it obvious to supplement AA's motion intents with the prediction of intent and/or actions disclosed by Levinson (or Zoox), which would expand the scenarios AA's model is capable of predicting, such as a user's state of mind or a task a user plans on accomplishing. A POSITA would have been motivated to apply Levinson's (or Zoox's) explicit disclosure regarding system controllers communicating with drive module systems to operate an autonomous vehicle to implement AA's disclosure of controlling an autonomous vehicle based on a determined motion intent. *See* Ex. C-27 at claim 9.

Exemplary Motivations to Combine AA and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of

pedestrians and related statistics to improve AA's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as AA already outputs a probability distribution of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which AA is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement AA's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Waymo and Djuric

A POSITA would have been motivated to adopt Djuric's disclosure of a probabilistic neural network to incorporate levels of uncertainty and confidence into the plurality of potential trajectories predicted by Waymo's behavior model. Djuric at [0089]-[0091]. A POSITA would have implemented those uncertainties and confidence levels to determine the best possible trajectory of the plurality of trajectories and navigate the autonomous vehicle accordingly. Djuric at [0021], [0035]. A POSITA would also have looked to Djuric to train Waymo's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. Djuric describes its training model as a neural networks or other described supervised learning models such as "convolutional neural networks, recurrent neural networks (e.g., long short-term memory recurrent neural networks), feed-forward neural networks, and/or other forms of neural networks." Djuric at [0053].

Exemplary Motivations for Combining Waymo and AA

A POSITA would have been motivated to adopt AA’s disclosure of a probabilistic neural network to incorporate levels of uncertainty and confidence into the plurality of potential trajectories predicted by Waymo’s behavior model. A POSITA would have recognized that implementing the probabilistic approach from AA would help Waymo “account for the uncertainty of future movements” and “account for the uncertainty of plausible future poses in predicting subject motion... in real-time.” AA at [0051]-[0052].

Exemplary Motivations for Combining Waymo and Cox

A POSITA, following Waymo’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox’s “statistical learning,” e.g., because using statistical methods and outputs would have been known to help reduce risks, and “in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect.” Cox at [0035]. See also Cox at [0027]-[0035]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Waymo, to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled data to determine more difficult situations to focus on in training. Cox at [0028].

Exemplary Motivations for Combining Waymo and Test My Brain

A POSITA, following Waymo’s method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Test My Brain’s “statistical learning” because using statistical methods and outputs would have been known to help reduce risks. Ex. C-26 at element 1[a-iii]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Waymo, to look to basic statistical concepts. For

example, a POSITA would have found it obvious to use mean values of accurately labeled data to determine more difficult situations to focus on in training.

Exemplary Motivations for Combining Waymo and Ross

A POSITA would have been motivated to combine Ross's teachings of navigating an autonomous vehicle based on likelihoods of predicted intents and trajectories, which would help Waymo account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Further, a POSITA would have been motivated to combine Waymo and Ross because Ross was applied for and is currently owned by Waymo, and implemented in Waymo's vehicles.

Exemplary Motivations for Combining Waymo and Rolfe

A POSITA would have been motivated to combine Rolfe with Waymo to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data used to train Waymo's models. Rolfe at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details that a POSITA could utilize to achieve generating improved training data in Waymo.

Exemplary Motivations for Combining Waymo and Djuric 2 (and/or Uber)

A POSITA would have been motivated to apply Djuric 2's (and/or Uber's) teachings of capturing uncertainty present in prediction data to reflect potentially unexpected situations and allow Waymo's vehicle to make more accurate predictions that account for less likely outcomes when data is "inherently noisy." Djuric 2 at 5, 7.

Exemplary Motivation to Combine Waymo with iMotions

A POSITA would have been motivated to adopt iMotions' technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Waymo's model to predict statistical outputs. Ex. C-25 at element 1[a-iii]. A POSITA would have found this

to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Waymo's model predictions. Further, a POSITA would have found it obvious to supplement Waymo's predictive model with the prediction of state of minds disclosed by iMotions, which would expand the model's predictive capabilities. Ex. C-25 at element 1[a-iii].

Exemplary Motivations for Combining Waymo and Levinson (or Zoox)

A POSITA would have been motivated to combine the teachings of Levinson (or Zoox) regarding selecting an autonomous vehicle trajectory based on a level of uncertainty associated with a current and future state of objects, which would help Waymo account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Levinson at 9:26-30. A POSITA would have been further motivated to apply the teachings of Levinson (or Zoox) regarding calculating trajectories as probabilistically-determined trajectories, which would help the Waymo autonomous vehicle avoid collisions. Levinson at 9:31-53.

Exemplary Motivations to Combine Waymo and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics such means of predictive distributions to improve Waymo's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Waymo already outputs a probability distribution of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Waymo is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the

potential models that could implement Waymo's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Sapp and Djuric

A POSITA would have been motivated to adopt Djuric's disclosure of a probabilistic neural network to incorporate levels of uncertainty and confidence into the plurality of potential trajectories predicted by Sapp's prediction model. Djuric at [0089]-[0091]. A POSITA would have implemented those uncertainties and confidence levels to determine the best possible trajectory of the plurality of trajectories and navigate the autonomous vehicle accordingly. Djuric at [0021], [0035]. A POSITA would also have looked to Djuric to train Sapp's perception, prediction, and maneuvering systems used to drive autonomous vehicles. Specifically, a POSITA would understand that a user would be likely to use a supervised learning based model for training the perception, prediction, and/or maneuvering systems. Djuric describes its training model as a neural networks or other described supervised learning models such as "convolutional neural networks, recurrent neural networks (e.g., long short-term memory recurrent neural networks), feed-forward neural networks, and/or other forms of neural networks." Djuric at [0053].

Exemplary Motivations for Combining Sapp and AA

A POSITA would have been motivated to adopt AA's disclosure of a probabilistic neural network to incorporate levels of uncertainty and confidence into the plurality of potential trajectories predicted by Sapp's behavior model. A POSITA would have recognized that implementing the probabilistic approach from AA would help Sapp "account for the uncertainty of future movements" and "account for the uncertainty of plausible future poses in predicting subject motion... in real-time." AA at [0051]-[0052].

Exemplary Motivations for Combining Sapp and Ross (or Waymo)

A POSITA would have been motivated to combine Ross’s (or Waymo’s) teachings of navigating an autonomous vehicle based on likelihoods of predicted intents and trajectories, which would help account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Ross at 16:23-41.

Exemplary Motivations for Combining Sapp and Cox (or Test My Brain)

A POSITA would have been motivated to adopt Cox’s (or Test My Brain’s) disclosure of training and testing on feature vectors to improve Sapp’s model performance by grouping features into neighborhoods before producing a set of final outputs of the probabilistic neural network. *See* Cox at [0039]. Further, a POSITA would have found it obvious to implement Cox’s (or Test My Brain’s) teaching of determining a mean accuracy and confidence levels of labels to determine which types of difficult training scenarios require more attentive analysis. *See* Cox at [0028].

Exemplary Motivations for Combining Sapp and Zhang

A POSITA would have been motivated to look to different methods to train and execute Sapp’s predictions for intended future action of road users, including Zhang’s generation of predicted trajectories, which represents a statistical summary of expected user responses such as “short term driving goal[s].” Zhang at [0048], [0054].

Exemplary Motivations for Combining Sapp and Rolfe

A POSITA would have been motivated to combine Rolfe with Sapp to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data used to train Sapp’s models. Rolfe at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details that a POSITA could utilize to achieve generating improved training data in Sapp.

Exemplary Motivations for Combining Sapp and Djuric 2 (and/or Uber)

A POSITA would have been motivated to implement Djuric 2's (and/or Uber's) "vector layer" to make Sapp's model more effective, as Sapp already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Djuric 2 (and/or Uber). Djuric 2 at 4. Moreover, a POSITA would have been motivated to apply Djuric 2's (and/or Uber's) teachings of capturing uncertainty present in prediction data to reflect potentially unexpected situations and allow Sapp's vehicle to make more accurate predictions that account for less likely outcomes when data is "inherently noisy." Djuric 2 at 5, 7.

Exemplary Motivations for Combining Sapp and Keller

A POSITA would have been motivated to apply feature vector generation as disclosed by Keller to make Sapp's model more effective, as Sapp already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Keller. Keller at 499.

Exemplary Motivations for Combining Sapp and Quintero

A POSITA would have been motivated to "reduce the dimensionality of input data" by generating feature vectors as taught by Quintero to improve computing time for tracking and prediction tasks, thus making Sapp's model more effective. Quintero at 320. Sapp already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Quintero.

Exemplary Motivations for Combining Sapp with Waymo

A POSITA would have been motivated to embed "semantic meaning" with objects captured in image data to improve the efficiency Zhang's model. Ex. C-24 at 1[a-ii], 1[a-iii]. Zhang

already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Waymo. Further, a POSITA would have looked to apply Waymo's behavioral prediction techniques to Zhang's model to better understand how people signal intentions and expand the scenarios Zhang's model is capable of predicting, such as determining awareness of road users or goals road users expect to achieve. Ex. C-24 at 1[a-ii], 1[a-iii].

Exemplary Motivations for Combining Sapp with Autopilot HW1

A POSITA would also have been motivated to apply Autopilot HW1's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Zhang's disclosure of controlling an autonomous vehicle based on a predicted trajectory. Ex. C-20 at element 1[e], claim 11.

Exemplary Motivations for Combining Sapp with Autopilot HW2

A POSITA would also have been motivated to apply Autopilot HW2's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Zhang's disclosure of controlling an autonomous vehicle based on a predicted trajectory. Ex. C-20 at element 1[e], claim 11.

Exemplary Motivations for Combining Sapp and Volz 1

A POSITA would have been motivated to combine Volz 1's techniques of enhancing feature vectors using LiDAR based images to make Sapp's model more effective as Sapp already inputs a sensor data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Volz 1. Volz 1 at Abstract, 5.

Exemplary Motivations to Combine Sapp and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics such means of predictive distributions to improve Sapp's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Sapp already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Sapp is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Sapp's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Zhang and Djuric

A POSITA would have been motivated to apply Djuric's teaching implementing supervised training techniques to predict confidence levels of different predicted paths for other vehicles to improve Zhang's determination of future trajectories. Djuric at [0034]. A POSITA would have been further motivated to combine Zhang and Djuric such that Zhang's output includes levels of uncertainty and confidence to improve the quality of predictions used to navigate the autonomous vehicle. Djuric at [0003], [0088]. A POSITA would also have been motivated to apply Djuric's "goal-based prediction[s]" in order to expand upon the scenarios in which Zhang is able to determine future subject motion. Djuric at [0081]. A POSITA would have been motivated to apply Djuric's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Zhang's disclosure of controlling an autonomous vehicle based on a

determined motion intent. Djuric at [0044]. Finally, a POSITA would have applied the various types of neural networks disclosed in Djuric to expand the potential models that could implement Zhang's motion intent determinations.

Exemplary Motivations for Combining Zhang and AA

A POSITA would have been motivated to adopt AA's disclosure of a probabilistic neural network to incorporate levels of uncertainty and confidence into the plurality of potential trajectories predicted by Zhang's trajectory prediction module. A POSITA would have recognized that implementing the probabilistic approach from AA would help Zhang "account for the uncertainty of future movements" and "account for the uncertainty of plausible future poses in predicting subject motion... in real-time." AA at [0051]-[0052].

Exemplary Motivations for Combining Zhang and Ross

A POSITA would have been motivated to combine Ross's teachings of navigating an autonomous vehicle based on likelihoods of predicted intents and trajectories, which would help Zhang account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Ross at 16:23-41. A POSITA would have been further motivated to combine Ross with Zhang such that Zhang's trajectory prediction module generates potential trajectories using Ross's intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Zhang's predicted trajectories with the prediction of intent and/or actions disclosed by Ross, which would expand the scenarios Zhang's model is capable of predicting. A POSITA would also have been motivated to apply Ross' explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Zhang's disclosure of controlling an autonomous vehicle based on a predicted trajectory. Ross at 6:49-59.

Exemplary Motivations for Combining Zhang and Cox (or Test My Brain)

A POSITA would have been motivated to adopt Cox's (or Test My Brain's) disclosure of training and testing on feature vectors to improve Zhang's model performance by grouping features into neighborhoods before producing a set of final outputs of predicted trajectories. *See* Cox at [0039]. Further, a POSITA would have found it obvious to implement Cox's (or Test My Brain's) teaching of determining a mean accuracy and confidence levels of labels to determine which types of difficult training scenarios require more attentive analysis. *See* Cox at [0028].

Exemplary Motivations for Combining Zhang and Sapp

A POSITA would have been further motivated to combine Sapp with Zhang such that Zhang's prediction model predicts future trajectories using Sapp's intents or actions. *See* Sapp at [0068]. A POSITA would have found it obvious to supplement Zhang's predicted trajectories with the prediction of intent and/or actions disclosed by Sapp, which would expand the scenarios Zhang's model is capable of predicting, such a user's state of mind or a task a user plans on accomplishing. A POSITA would have been motivated to apply Sapp's explicit disclosure regarding system controllers communicating with drive module systems to operate an autonomous vehicle to implement Zhang's disclosure of controlling an autonomous vehicle based on a determined motion intent. Sapp at [0065].

Exemplary Motivations for Combining Zhang and Rolfe

A POSITA would have been motivated to combine Rolfe with Zhang to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data used to train Zhang's models. Rolfe at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details that a POSITA could utilize to achieve generating improved training data in Zhang.

Exemplary Motivations for Combining Zhang and Djuric 2 (and/or Uber)

A POSITA would have been motivated to implement Djuric 2's (and/or Uber's) "vector layer" to make Zhang's model more effective, as Zhang already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Djuric 2 (and/or Uber). Djuric 2 at 4. Moreover, a POSITA would have been motivated to apply Djuric 2's (and/or Uber's) teachings of capturing uncertainty present in prediction data to reflect potentially unexpected situations and allow Zhang's vehicle to make more accurate predictions that account for less likely outcomes when data is "inherently noisy." Djuric 2 at 5, 7.

Exemplary Motivations for Combining Zhang and Keller

A POSITA would have been motivated to apply feature vector generation as disclosed by Keller to make Zhang's model more effective, as Zhang already inputs a data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Keller. Keller at 499.

Exemplary Motivations for Combining Zhang and Volz 1

A POSITA would have been motivated to combine Volz 1's techniques of enhancing feature vectors using LiDAR based images to make Zhang's model more effective as Zhang already inputs a sensor data set into the machine-learned model to predict trajectories of objects around the autonomous vehicle, and it would be straightforward to use this data to generate a feature vector as taught by Volz 1. Volz 1 at Abstract, 5.

Exemplary Motivations for Combining Zhang and Zoox

A POSITA would have been further motivated to combine Zoox with Zhang such that Zhang's prediction model predicts future trajectories using Zoox's intents or actions. *See* Ex. C-27 at element 1[d] and claim 9. A POSITA would have found it obvious to supplement Zhang's

predicted trajectories with the prediction of probabilistic intent and/or actions disclosed by Zoox, which would expand the scenarios Zhang's model is capable of predicting, such a user's state of mind or a task a user plans on accomplishing. *See* Ex. C-27 at element 1[d] and claim 9. A POSITA would have been further motivated to apply the teachings of Zoox regarding calculating trajectories as probabilistically-determined trajectories, which would help the Zhang autonomous vehicle avoid collisions. *See* Ex. C-27 at element 1[e]. A POSITA would have been motivated to apply Zoox's explicit disclosure regarding system controllers communicating with drive module systems to operate an autonomous vehicle to implement Zhang's disclosure of controlling an autonomous vehicle based on a determined motion intent. Ex. C-27 at claim 11.

Exemplary Motivations to Combine Zhang and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics such means of predictive distributions to improve Zhang's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Zhang already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Zhang is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Zhang's motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Djuric

A POSITA would have been motivated to apply Djuric's teaching implementing supervised training techniques to predict confidence levels of different predicted paths for other vehicles to improve Djuric 2's (and/or Uber's) predictions of future motions. Djuric at [0034]. A POSITA would have been further motivated to combine Djuric 2 (and/or Uber) and Djuric such that Djuric's output includes hidden context to improve the quality of predictions used to navigate the autonomous vehicle. Djuric at [0003], [0088]. A POSITA would also have been motivated to apply Djuric's "goal-based prediction[s]" in order to expand upon the scenarios in which Djuric 2 (and/or Uber) is able to determine future subject motion. Djuric at [0081]. Moreover, A POSITA would have been motivated to apply Djuric's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Djuric 2's (and/or Uber's) disclosure of controlling an autonomous vehicle based on a determined motion intent. Djuric at [0044]. A POSITA would have applied the various types of neural networks disclosed in Djuric to expand the potential models that could implement Djuric's motion intent determinations. As an additional reason, , a POSITA would have been motivated to combine Djuric and Djuric 2 (and/or Uber) because they were invented/disclosed by the same individual.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and AA

A POSITA would have been motivated to adopt AA's disclosure of a probabilistic neural network to incorporate levels of uncertainty and confidence into the plurality of potential trajectories predicted by Djuric 2's (and/or Uber's) trajectory prediction module. A POSITA would have recognized that implementing the probabilistic approach from AA would help Djuric 2 (and/or Uber) "account for the uncertainty of future movements" and "account for the uncertainty of plausible future poses in predicting subject motion... in real-time." AA at [0051]-[0052].

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Ross

A POSITA would have been motivated to combine Ross's teachings of navigating an autonomous vehicle based on likelihoods of predicted intents and trajectories, which would help Djuric 2 (and/or Uber) account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Ross at 16:23-41. A POSITA would have been further motivated to combine Ross with Djuric 2 (and/or Uber) such that Djuric 2's (and/or Uber's) future path prediction module generates potential paths using Ross's intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Djuric 2's (and/or Uber's) future paths with the prediction of intent and/or actions disclosed by Ross, which would expand the scenarios Djuric 2's (and/or Uber's) model is capable of predicting. A POSITA would also have been motivated to apply Ross' explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Djuric 2's (and/or Uber's) disclosure of controlling an autonomous vehicle based on a predicted trajectory. Ross at 6:49-59.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Cox

A POSITA, following Djuric 2's (and/or Uber's) method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox's "statistical learning," e.g., because using statistical methods and outputs would have been known to help reduce risks, and "in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect." Cox at [0035]. *See also* Cox at [0027]-[0035]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Djuric 2 (and/or Uber), to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled

data and confidence levels of outputs to determine more difficult situations to focus on in training. Cox at [0028].

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Test My Brain

A POSITA, following Djuric 2's (and/or Uber's) method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Test My Brain's statistical learning because using statistical methods and outputs would have been known to help reduce risk. Ex. C-26 at element 1[a-iii]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Djuric 2 (and/or Uber), to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled data and confidence levels of outputs to determine more difficult situations to focus on in training.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Sapp

A POSITA would have been motivated to combine Djuric 2 (and/or Uber) with Sapp such that Djuric 2's (and/or Uber's) convolutional neural network generates predictions of object's future paths using Sapp's intent. *See* Sapp at [0068]. A POSITA would have found it obvious to supplement Djuric 2's (and/or Uber's) motion intents with the prediction of intent and/or actions disclosed by Sapp, which would expand the scenarios Djuric 2's (and/or Uber's) model is capable of predicting, such a user's state of mind or a task a user plans on accomplishing. A POSITA would have been motivated to apply Sapp's explicit disclosure regarding system controllers communicating with drive module systems to operate an autonomous vehicle to implement Djuric 2's (and/or Uber's) disclosure of controlling an autonomous vehicle based on a determined motion intent. Sapp at [0065].

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Zhang

A POSITA would have been motivated to apply Zhang's teaching implementing supervised training techniques to predict confidence levels of different predicted paths for other vehicles to improve Djuric 2's (and/or Uber's) determination of objects' future paths. Zhang at [0058]. A POSITA would have found the combination straightforward, as Djuric already outputs a distribution of objects' future paths, and Zhang simply expands on Djuric's output by providing confidence levels of those paths. Further, a POSITA would have been motivated to combine Zhang's predicted intentions and "short term driving goals" to expand the type of scenarios in which Djuric's model is able to determine future paths. Zhang at [0048].

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Rolfe

A POSITA would have been motivated to combine Rolfe with Djuric 2 (and/or Uber) to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data used to train Djuric 2's (and/or Uber's) models. Rolfe at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details that a POSITA could utilize to achieve generating improved training data in Djuric 2 (and/or Uber).

Exemplary Motivations for Combining Djuric 2 (and/or Uber) with Quintero

A POSITA would have been motivated to apply techniques of determining pedestrian intent based on body position, as taught by Quintero, to better determine pedestrian motion intent and expand the scenarios Djuric 2's (and/or Uber's) model is capable of predicting. Quintero at 316.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) with Waymo

A POSITA would have been motivated to include Waymo's behavior prediction techniques, to better understand how people signal intentions and more accurately detect hidden

context in sensor data to expand the scenarios Djuric 2's (and/or Uber's) model is capable of predicting. Ex. C-24 at 1[a-ii], 1[a-iii].

Exemplary Motivations to Combining Djuric 2 (and/or Uber) with Autopilot HW1

A POSITA would also have been motivated to apply Autopilot HW1's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Djuric 2's (and/or Uber's) disclosure of controlling an autonomous vehicle based on a predicted trajectory. Ex. C-20 at element 1[e], claim 11.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) with Autopilot HW2

A POSITA would also have been motivated to apply Autopilot HW2's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Djuric 2's (and/or Uber's) disclosure of controlling an autonomous vehicle based on a predicted trajectory. Ex. C-21 at element 1[e], claim 11.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Levinson (or Zoox)

A POSITA would have been motivated to combine Djuric 2 (and/or Uber) with Levinson (or Zoox) such that Djuric 2's (and/or Uber's) convolutional neural network generates predictions of an object's future paths using Levinson's (or Zoox's) intent. *See* Ex. C-27 at element 1[a-iii], claim 9. A POSITA would have found it obvious to supplement Djuric 2's (and/or Uber's) motion intents with the prediction of intent and/or actions disclosed by Levinson (or Zoox), which would expand the scenarios Djuric 2's (and/or Uber's) model is capable of predicting, such a user's state of mind or a task a user plans on accomplishing. *See* Ex. C-27 at element 1[a-iii], claim 9. A POSITA would have been motivated to apply Levinson's (or Zoox's) explicit disclosure regarding system controllers communicating with drive module systems to operate an autonomous vehicle

to implement Djuric 2's (and/or Uber's) disclosure of controlling an autonomous vehicle based on a determined motion intent. *See* Ex. C-27 at claim 11.

Exemplary Motivation to Combine Djuric 2 (and/or Uber) with iMotions

A POSITA would have been motivated to adopt iMotions' technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Djuric 2's (and/or Uber's) model to predict statistical outputs. Ex. C-25 at element 1[a-iii]. A POSITA would have found this to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Djuric 2's (and/or Uber's) model predictions. Further, a POSITA would have found it obvious to supplement Djuric 2's (and/or Uber's) predictive model with the prediction of state of minds disclosed by iMotions, which would expand the model's predictive capabilities. Ex. C-25 at element 1[a-iii].

Exemplary Motivations to Combine Djuric 2 (and/or Uber) and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics such means of predictive distributions to improve Djuric 2's (and/or Uber's) determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Djuric 2 (and/or Uber) already outputs a future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Djuric 2 (and/or Uber) is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Djuric 2's (and/or

Uber's) motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

Exemplary Motivations for Combining Mercedes with Djuric

A POSITA would have been motivated to apply Djuric's teaching implementing supervised training techniques to predict confidence and uncertainty levels of different predicted paths for other vehicles to improve Mercedes's determination of pedestrian intent. Djuric at [0034]. A POSITA would have been further motivated to combine Mercedes and Djuric such that the Mercedes model's output includes levels of uncertainty and confidence to improve the quality of predictions used to predict pedestrian movement and navigate an autonomous vehicle such that it maintains a safe distance from other objects. Djuric at [0003], [0088]. A POSITA would also have been motivated to apply Djuric's "goal-based prediction[s]" in order to expand upon the scenarios in which Mercedes is able to determine future subject motion. Djuric at [0081]. A POSITA would have been motivated to apply Djuric's explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Mercedes' disclosure of controlling an autonomous vehicle based on a determined motion intent. Djuric at [0044]. Finally, a POSITA would have applied the various types of neural networks disclosed in Djuric to expand the potential models that could implement Mercedes' motion intent determinations.

Exemplary Motivations for Combining Mercedes with Ross (or Waymo)

A POSITA would have been motivated to combine Ross's (or Waymo's) teachings of navigating an autonomous vehicle based on likelihoods of predicted intents and trajectories, which would help Mercedes account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Ross at 16:23-41. A POSITA would have been further motivated to combine Ross (or Waymo) with Mercedes such that Mercedes' future path prediction module generates

potential paths using Ross's (or Waymo's) intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Mercedes' future paths with the prediction of intent and/or actions disclosed by Ross (or Waymo), which would expand the scenarios Mercedes model is capable of predicting. A POSITA would also have been motivated to apply Ross's (or Waymo's) explicit disclosure regarding sending control signals to operate an autonomous vehicle to implement Mercedes' disclosure of controlling an vehicle based on a predicted trajectory of a pedestrian. Ross at 6:49-59.

Exemplary Motivations for Combining Mercedes with Cox

A POSITA, following Mercedes method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Cox's "statistical learning," e.g., because using statistical methods and outputs would have been known to help reduce risks, and "in any solution to a recognition problem there is some notion of risk involved that indicates the penalties incurred if a prediction is incorrect." Cox at [0035]. *See also* Cox at [0027]-[0035]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Mercedes, to look to basic statistical concepts. For example, a POSITA would have found it obvious to use mean values of accurately labeled data and confidence levels of outputs to determine more difficult situations to focus on in training. Cox at [0028].

Exemplary Motivations for Combining Mercedes with Test My Brain

A POSITA, following Mercedes method of detecting objects and maneuvering autonomous vehicles, would have been motivated to look to Test My Brain's statistical learning because using statistical methods and outputs would have been known to help reduce risks. Ex. C-26 at element 1[a-iii]. A POSITA would have found it obvious, in generating and/or training a system implementing the method taught in Mercedes, to look to basic statistical concepts. For

example, a POSITA would have found it obvious to use mean values of accurately labeled data and confidence levels of outputs to determine more difficult situations to focus on in training.

Exemplary Motivations for Combining Mercedes with Rolfe

A POSITA would have been motivated to combine Rolfe with Mercedes to use the disclosed ELBO techniques to minimize the negative log-likelihood of the training data used to train Mercedes models. Rolfe at [0086]. The disclosure of ELBO in Rolfe simply provides implementation details that a POSITA could utilize to achieve generating improved training data in Mercedes.

Exemplary Motivations for Combining Mercedes with Djuric 2 (and/or Uber)

A POSITA would have been motivated to apply Mercedes teachings of capturing uncertainty present in prediction data to reflect potentially unexpected situations and allow Mercedes' vehicle to make more accurate predictions that account for less likely outcomes when data is "inherently noisy." Djuric 2 at 5, 7.

Exemplary Motivation to Combine Mercedes with iMotions

A POSITA would have been motivated to adopt iMotions technique of generating training data, including statistics related to user inputs, to collect user labels of images and train Mercedes' model to predict statistical outputs. Ex. C-25 at element 1[a-iii]. A POSITA would have found this to be an obvious way to generate robust training data in an efficient manner and increase the accuracy of Mercedes' model predictions. Mercedes' predictive model with the prediction of state of minds disclosed by iMotions, which would expand the scenarios Mercedes' model is capable of predicting. Ex. C-25 at element 1[a-iii].

Exemplary Motivations for Combining Mercedes with Levinson/Zoox

A POSITA would have been motivated to combine the teachings of Levinson/Zoox regarding selecting an autonomous vehicle trajectory based on a level of uncertainty associated with a current and future state of objects, which would help Mercedes' model account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Levinson at 9:26-30. A POSITA would have been further motivated to apply the teachings of Levinson/Zoox regarding calculating trajectories as probabilistically-determined trajectories, which would help the Mercedes vehicle avoid collisions. Levinson at 9:31-53.

Exemplary Motivations to Combine Mercedes and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics such means of predictive distributions to improve Mercedes' determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Mercedes already outputs a prediction of future pedestrian motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion. A POSITA would also have been motivated to apply Bhattacharyya's techniques of anticipating pedestrian motion in order to expand upon the scenarios in which Mercedes is able to determine future subject motion. Bhattacharyya at 1-4. Finally, a POSITA would have applied the various types of neural networks disclosed in Bhattacharyya to expand the potential models that could implement Mercedes' motion intent determinations, such as Bayesian probability models and convolutional neural networks. Bhattacharyya at 3-5.

D. The '346 Patent

Pursuant to Patent Rule 3-3 and subject to Tesla's reservations of rights in these Invalidity Contentions, at least the prior art listed below, individually or in combination, invalidates the Asserted Claims of the '346 Patent. Exhibits D-1 through D-27 provide detailed claim charts

showing where each claim limitation may be found in certain references listed below, either expressly or inherently as the reference would be understood by a person having ordinary skill in the art. For those references for which detailed claim charts are not provided, those additional prior art references are otherwise pertinent to the invalidity of the '346 Patent, either alone or in combination with other references.

The prior art references, systems, and products listed below and in the accompanying claim chart exhibits may be relied upon for certain limitations, state of the art, and background of the art; indicia of obviousness; as evidence of the level of skill in the art at the time of the filing of the Patents-in-Suit; and/or in support of assertions that it is proper to combine certain prior art references in certain ways.

Tesla also incorporates by reference each and every prior art reference of record in the prosecution of the Patents-in-Suit and patents or patent applications related to the Patents-in-Suit, the prior art referred to in the specifications of the Patents-in-Suit, as well as the prior art identified in any USPTO proceedings involving any of the Patents-in-Suit.

1. Bases for Anticipation and/or Obviousness

Each prior art reference identified in Exhibits D-1 through D-27 expressly, implicitly, or inherently anticipates and/or renders obvious the Asserted Claims of the '346 Patent, either alone or in combination with other prior art references (*e.g.*, other references identified above) or the knowledge of the person of ordinary skill in the art at the time of the alleged invention. In the table below, Tesla identifies a non-exhaustive list of prior art references that, alone or in combination, anticipate and/or render obvious the Asserted Claims of the '346 Patent.

Exhibit	Patent No. or Title (Primary Inventor/Author)	Date of Issuance or Publication
Ex. D-1	U.S. Pat. No. 2019/0049970 ("Djuric")	Feb. 14, 2019 (Filed Sep. 5, 2018)

Ex. D-2	U.S. Pat. Pub. No. 2019/0164018 (“Zhu”)	May 30, 2019 (Filed Nov. 27, 2017)
Ex. D-3	U.S. Pat. No. 10,496901 (“Ross”)	Dec. 3, 2019 (Filed Aug. 17, 2016)
Ex. D-4	WO2014/210334 (“Cox”)	Dec. 31, 2014
Ex. D-5	U.S. Pat. Pub. No. 2019/0113920 (“Englard”)	Apr. 18, 2019 (Filed Oct. 2, 2018)
Ex. D-6	U.S. Pat. Pub. No. 2020/0110416 (“Hong”)	Apr. 9, 2020 (Filed Oct. 4, 2018)
Ex. D-7	U.S. Pat. Pub. No. 2021/0086795 (“Zhao”)	Mar. 25, 2021 (Filed May 31, 2018)
Ex. D-8	Quintero, “Pedestrian Path Prediction using Body Language Traits” (“Quintero”)	Jun. 2014
Ex. D-9	Karasev, “Intent-Aware Long-Term Prediction of Pedestrian Motion” (“Karasev”)	May 2016
Ex. D-10	Kohler, “Early Detection of the Pedestrian’s Intention to Cross the Street” (“Kohler”)	Oct. 25, 2012
Ex. D-11	Djuric, “Motion Prediction of Traffic Actors for Autonomous Driving using Deep Convolution Networks,” (“Djuric 2”)	Aug. 17, 2018
Ex. D-12	Schneemann, “Context-based Detection of Pedestrian Crossing Intention for Autonomous Driving in Urban Environments” (“Schneemann”)	Oct. 2016
Ex. D-13	Furuhashi, “Estimation of Street Crossing Intention from a Pedestrian’s Posture on a Sidewalk Using Multiple Image Frames” (“Furuhashi”)	2011
Ex. D-14	Keller, “Will the Pedestrian Cross? A Study on Pedestrian Path Prediction” (“Keller”)	Apr. 2014
Ex. D-15	Schneider, “Pedestrian Path Prediction with Recursive Bayesian Filters: A Comparative Study” (“Schneider”)	2013
Ex. D-16	Kooij, “Analysis of pedestrian dynamics from a vehicle perspective” (“Kooij”)	Jun. 2014
Ex. D-17	U.S. Patent No. 9,632,502 (“Levinson”)	Apr. 25, 2017 (Filed Nov. 5, 2015)
Ex. D-18	Bhattacharyya, “Long-Term On-Board Prediction of People in Traffic Scenes under Uncertainty” (“Bhattacharyya”)	Jun. 20, 2018
Ex. D-19	Volz, “A data-driven approach for pedestrian intention estimation” 2016 (“Volz 1”)	2016

The Asserted Claims of the '346 Patent are also invalid under 35 U.S.C. § 102(a) and (b) because the subject matter was known by others, publicly used, and on sale in the United States before it was purportedly invented and more than one year before the priority date of the Asserted Claim. Additionally, the Asserted Claim because any purported invention was made in this country by another who had not abandoned, suppressed, or concealed the purported invention. For example, the foregoing patents and publications are evidence of such prior art systems and inventions. As such, the following systems are prior art under 35 U.S.C. § 102:

Exhibit	System Prior Art
Ex. D-20	Tesla – Autopilot HW1
Ex. D-21	Tesla – Autopilot HW2
Ex. D-22	Daimler/ Mercedes
Ex. D-23	Uber/Aurora
Ex. D-24	Waymo
Ex. D-25	iMotions
Ex. D-26	TestMyBrain.com
Ex. D-27	Zoox

The accompanying claim charts (Exhibits D-1 through D-27) set forth example bases for anticipation and obviousness, identifying where each reference discloses, alone or in combination with other references, each limitation of the Asserted Claims of the '346 Patent on a limitation-by-limitation basis. Tesla's claim charts are exemplary and not exhaustive.

2. Obviousness Combinations

Subject to Tesla's reservation of rights, Tesla contends that all of the prior art references, as identified above and described in the charts attached as Exhibits D-1 through D-27 by themselves anticipate the Asserted Claims of the '346 Patent in accordance with 35 U.S.C. § 102

and/or render the Asserted Claim of the '346 Patent obvious under 35 U.S.C. § 103, as more specifically noted in the attached charts. The cited portions of the prior art references are examples and representative of the content of the prior art references, and should be understood in the context of the reference as a whole, as understood by one of ordinary skill in the art. To the extent a cited prior art reference is deemed not to anticipate or render obvious a claim as noted in the attached charts for failing to teach or suggest one or more limitations of that claim, that claim would nonetheless have been obvious to one of ordinary skill in the art at the time of the invention by the combination of the cited prior art reference with one or more other prior art references and/or common knowledge disclosing the missing claim limitations. For example, any of the references listed above, to the extent it does not explicitly or inherently disclose any limitation, could be combined with any one or more of the other references listed above which discloses that limitation. Tesla reserves the right to supplement the obviousness arguments using any references listed above, or any references that may become known to Tesla during the course of discovery.

In the table below, Tesla further identifies exemplary combinations of prior art that render the Asserted Claims of the '346 Patent obvious:

Primary Reference	Secondary Reference	Claim
Djuric	Zhu	1, 10, 19
	Ross	6, 15, 23
	Waymo	6, 15, 23
	Englard	1, 7, 10, 16, 19
	Hong	1, 7, 10, 16, 19
	Cox	1, 10, 19
	Test My Brain	1, 10, 19
	Zhao	1, 10, 19
	Djuric 2 (and/or Uber)	1, 7, 10, 16, 19
	Levinson	1, 10, 19
	Bhattacharyya	7, 16
	One or more of Zhu, Ross, Waymo, Englard, Hong, Cox, Test My Brain, Zhao, Djuric 2	1, 6, 7, 10, 15, 16, 19, 23

Primary Reference	Secondary Reference	Claim
	(and/or Uber), Levinson, and/or Bhattacharyya	
Englard	Djuric	1, 10, 19
	Cox	1, 10, 19
	Test My Brain	1, 10, 19
	Ross	1, 6, 10, 15, 19, 23
	Waymo	1, 6, 10, 15, 19
	Zhao	1, 10, 19
	Bhattacharyya	1, 10, 19
	One or more of Djuric, Cox, Test My Brain, Ross, Waymo, Zhao, and/or Bhattacharyya	1, 6, 10, 15, 19, 23
Zhao	Djuric	2, 3, 11, 12, 20, 21
	Ross	6, 15, 23
	Waymo	6, 15, 23
	Englard	1, 2, 3, 7, 10, 11, 12, 16, 19, 20, 21
	Hong	1, 2, 3, 7, 10, 11, 12, 16, 19, 20, 21
	Djuric 2 (and/or Uber)	7, 16
	Cox	1, 10, 19
	Test My Brain	1, 10, 19
	Bhattacharyya	7, 16
	One or more of Djuric, Ross, Waymo, Englard, Hong, Djuric 2 (and/or Uber), Cox, Test My Brain and/or Bhattacharyya	1, 2, 3, 6, 7, 10, 11, 12, 15, 16, 19, 20, 21, 23
Waymo	Djuric	2, 3, 11, 12, 20, 21
	Hong	1, 2, 3, 10, 11, 12, 19, 20, 21
	Englard	1, 2, 3, 10, 11, 12, 19, 20, 21
	Cox	1, 10, 19
	Test My Brain	1, 10, 19
	iMotions	1, 10, 19
	Levinson	1, 2, 3, 10, 11, 12, 19, 20, 21
	Zoox	1, 2, 3, 10, 11, 12, 19, 20, 21
	One or more of Djuric, Hong, Englard, Cox, Text My Brain, iMotions, Levinson, and/or Zoox	1, 2, 3, 10, 11, 12, 19, 20, 21
Hong	Djuric	1, 4, 10, 13, 19, 22
	Zhao	1, 10, 19
	Ross	4, 6, 13, 15, 23
	Waymo	4, 6, 13, 15, 23

Primary Reference	Secondary Reference	Claim
	Cox	1, 4, 10, 13, 19, 22
	Test My Brain	1, 4, 10, 13, 19, 22
	Englard	1, 4, 10, 13, 19, 22
	Zhao	1, 4, 10, 13, 19, 22
	Quintero	1, 10, 19
	Kohler	4, 13, 22
	Djuric 2 (and/or Uber)	4, 13, 22
	Volz 1	1, 10, 19
	Levinson	11, 10, 19
	Zoox	1, 10, 19
	Bhattacharyya	1, 4, 10, 13, 19, 22
	One or more of Djuric, Zhao, Ross, Waymo, Cox, Test My Brain, Englard, Zhao, Quintero, Kohler, Djuric 2 (and/or Uber), Volz 1, Levinson, Zoox, and/or Bhattacharyya	1, 4, 6, 10, 13, 15, 19, 22, 23
Djuric 2 (and/or Uber)	Djuric	1, 2, 3, 8, 10, 11, 12, 17, 19, 20, 21
	Zhu	1, 10, 19
	Ross	1, 6, 8, 10, 15, 17, 19, 23
	Waymo	1, 6, 8, 10, 15, 17, 19, 23
	Englard	1, 2, 3, 8, 10, 11, 12, 17, 19, 20, 21
	Hong	1, 2, 3, 8, 10, 11, 12, 17, 19, 20, 21
	Zhao	1, 8, 10, 17, 19
	Quintero	1, 10, 19
	Cox	1, 10, 19
	Test My Brain	1, 10, 19
	iMotions	1, 10, 19
	Volz 1	1, 10, 19
	Levinson	1, 10, 19
	Zoox	1, 2, 3, 8, 10, 11, 12, 17, 19, 20, 21
	Bhattacharyya	1, 10, 19
	One or more of Djuric, Zhu, Ross, Waymo, Englard, Hong, Zhao, Quintero, Cox, Test My Brain, iMotions, Volz 1, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 8, 10, 11, 12, 15, 17, 19, 20, 21, 23

Primary Reference	Secondary Reference	Claim
Mercedes	Djuric	1, 2, 3, 5, 8, 9, 10, 11, 12, 14, 17, 18, 19, 20, 21, 23
	Zhu	1, 10, 19
	Ross	5, 6, 8, 9, 14, 15, 17, 18, 23, 23
	Englard	1, 2, 3, 5, 8, 9, 10, 11, 12, 14, 17, 18, 19, 20, 21, 23
	Hong	1, 2, 3, 5, 8, 9, 10, 11, 12, 14, 17, 18, 19, 20, 21
	Zhao	1, 5, 8, 9, 10, 14, 17, 18, 19, 23
	Quintero	1, 10, 19
	Karasev	9, 18, 23
	Kohler	9, 18, 23
	Djuric 2 (and/or Uber)	1, 5, 9, 10, 14, 18, 19, 23
	Schneemann	1, 5, 10, 14, 19
	Furuhashi	1, 5, 10, 14, 19
	Waymo	1, 5, 6, 8, 9, 10, 14, 15, 17, 18, 19, 23
	Cox	1, 10, 19
	Test My Brain	1, 10, 19
	iMotions	1, 10, 19
	Volz 1	1, 10, 19
	Levinson	1, 10, 19
	Zoox	1 2, 3, 5, 8, 9, 10, 11, 12, 14, 17, 18, 19, 20, 21
	Bhattacharyya	7, 16
	One or more of Djuric, Zhu, Ross, Englard, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2 (and/or Uber), Schneemann, Furuhashi, Volz 1, Levinson, Zoox, and/or Bhattacharyya	1, 2, 3, 5, 6, 8, 9, 10, 11, 12, 14, 15, 17, 18, 19, 20, 21, 23

3. Motivation to Combine and Reasonable Expectation of Success

With respect to the '346 Patent, the prior art identified above demonstrates the scope and content of the prior art. As detailed in Exhibits D-1 through D-27, the prior art included each limitation recited in the Asserted Claims of the '346 Patent. To the extent a cited prior art reference is deemed not to anticipate a claim, the only difference between the claimed invention and the

prior art is the lack of actual combination of the elements in a single prior art reference. However, a Person of Ordinary Skill in the Art (“POSITA”) would have been motivated to combine each of the above prior art references.

For example, many of the above identified references (Djuric, Zhu, Ross, Englard, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2, Schneemann, Furuhashi, Keller, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, Levinson, Bhattacharyya, and Zoox) are all related to motor vehicles. These references constitute analogous art within the same field of endeavor—specifically, automotive design and engineering—and address the same or substantially similar technical problems regarding vehicle operation and subsystem integration. A POSITA would naturally consult these references when seeking to improve vehicle performance or functionality. Here, because Djuric, Zhu, Ross, Englard, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2, Schneemann, Furuhashi, Keller, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, Levinson, Bhattacharyya, and Zoox all reside within the automotive domain, the barrier to combination is exceedingly low. A POSITA would recognize that the teachings of each such reference are compatible with (or could be adapted to be compatible with) other references related to motor vehicles. The combination of these references related to motor vehicles also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar elements to perform their primary functions. And, driven by the perpetual market pressure in the automotive industry to enhance safety, efficiency, and user experience, a POSITA would have been motivated to combine the specific features of each of Djuric, Zhu, Ross, Englard, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2, Schneemann, Furuhashi, Keller, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, Levinson, Bhattacharyya, and

Zoox. Such combinations represents a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of an automobile, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As a further example, many of the above references relate more specifically to autonomous driving (e.g., Djuric, Zhu, Ross, Englard, Hong, Zhao, Karasev, Djuric 2, Schneemann, Autopilot HW1, Autopilot HW2, Uber, Waymo, Levinson, and Zoox). These references constitute analogous art within the same field of endeavor—specifically, the development of automated driving systems using sensors—and address the same or substantially similar technical problems regarding object detection, environmental perception, and real-time decision making. A POSITA would naturally consult these references when seeking to improve the reliability or safety of an autonomous driving feature. Here, because Djuric, Zhu, Ross, Englard, Hong, Zhao, Karasev, Djuric 2, Schneemann, Autopilot HW1, Autopilot HW2, Uber, Waymo, Levinson, and Zoox all involve descriptions of autonomous vehicle architectures, the barrier to combination is exceedingly low. For example, a POSITA would recognize that the sensing or control teachings of each such reference are compatible with the processing or navigation modules of other references related to autonomous driving. The combination of references relating to autonomous driving also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar algorithms and hardware to perform their primary functions. And, driven by the industry competition to achieve higher levels of autonomy (e.g., for SAE Levels 3-5) and the necessity to eliminate human error, a POSITA would have been motivated to combine the specific features of each of Djuric, Zhu, Ross, Englard, Hong, Zhao, Karasev, Djuric 2, Schneemann, Autopilot HW1, Autopilot HW2, Uber, Waymo, Levinson, and Zoox. Such combinations represent a common-

sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of a self-driving platform, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As another example, many of the above identified references (Djuric, Zhu, Ross, Cox, England, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2, Schneemann, Furuhashi, Keller, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, iMotions, Bhattacharyya, and Test My Brain) are all related to the development and training of machine learning models, including supervised learning techniques. These references constitute analogous art within the same field of endeavor—specifically, artificial intelligence and data annotation—and address the same or substantially similar technical problems regarding model accuracy, ground truth verification, and the reduction of prediction error. A POSITA would naturally consult these references when seeking to improve the performance of a neural network or statistical model through high-quality supervision. Here, because Djuric, Zhu, Ross, Cox, England, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2, Schneemann, Furuhashi, Keller, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, iMotions, Bhattacharyya, and Test My Brain all relate to data-driven algorithm development, the barrier to combination is exceedingly low. A POSITA would recognize that the human-labeled datasets or annotation interfaces of each such reference are compatible with (or could be adapted to be compatible with) the training pipelines and loss functions disclosed in other references related to machine learning. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar training loops to perform their primary functions. And, driven by the market pressure in the artificial intelligence industry to maximize inference accuracy and leverage human

validation for edge cases, a POSITA would have been motivated to combine the specific features of each of Djuric, Zhu, Ross, Cox, England, Hong, Zhao, Quintero, Karasev, Kohler, Djuric 2, Schneemann, Furuhashi, Keller, Schneider, Kooij, Autopilot HW1, Autopilot HW2, Mercedes, Uber, Waymo, iMotions, Bhattacharyya, and Test My Brain. Specifically, the use of human-generated ground truth labels to calibrate or refine model weights is a foundational practice in the art, making the aggregation of these teachings a matter of routine optimization. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known supervised learning solutions within the standard constraints of a predictive system, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As a further example, many of the above identified references (Djuric, Zhu, England, Zhao, Quintero, Waymo, Uber, Levinson, and Zoox) involve using LiDAR-based sensing and 3D point cloud data with autonomous vehicles. These references constitute analogous art within the same field of endeavor—specifically, using 3D environmental perception and spatial reconstruction. These references also address the same or substantially similar technical problems regarding depth estimation, obstacle classification, and the handling of sparse or unstructured geometric data. A POSITA would naturally consult these references when seeking to improve the accuracy or speed of an autonomous vehicle’s spatial mapping capabilities. Here, because Djuric, Zhu, England, Zhao, Quintero, Waymo, Uber, Levinson, and Zoox all reside within the specific domain of volumetric sensor data, the barrier to combination is exceedingly low. A POSITA would recognize that the point cloud data structures (e.g., x, y, z coordinates and intensity values) or scanning mechanisms of each such reference are compatible with (or could be adapted to be compatible with) the segmentation algorithms or voxelization techniques of other references related to 3D sensing. The combination of these references also yields predictable results. Consequently, the

integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar spatial data formats to perform their primary functions. And, driven by the perpetual market pressure in the autonomous vehicle industry to ensure robust operation in diverse lighting conditions and achieve precise distance measurements for safety, a POSITA would have been motivated to combine the specific features of each of Djuric, Zhu, England, Zhao, Quintero, Waymo, Uber, Levinson, and Zoox. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known perception solutions within the standard constraints of a real-time system, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

Below, Tesla has provided several additional illustrative examples of the motivations that a POSITA would have had to combine certain of the prior art references in Exhibits D-1 through D-27. The inclusion of certain example combinations herein does not exclude other combinations based on the claim charts attached hereto, as there are many possible combinations of the references listed herein, and it is not practical, particularly at this early stage prior to further factual investigation and claim construction proceedings, to identify and list all potentially relevant combinations. Instead, in many instances where a particular contention calls for, or requires, combining references, any one of a number of references can be combined. As such, these motivations to combine apply equally to the combination of a primary reference to one secondary reference, and the combination of a primary reference to multiple secondary references.

Exemplary Motivations for Combining Djuric and Zhu

A POSITA would have been motivated to use Zhu's teachings to further improve Djuric's object detection using LIDAR sensors and cameras. As taught by Zhu, combining the data allows objects and drivable road surfaces (i.e., where objects are not located in a road) to be detected. Zhu

at [0026], [0040]. This improves the navigation of Djuric's autonomous vehicle in relation to predicted trajectories. *Id.*

Exemplary Motivations for Combining Djuric and Ross (or Waymo)

A POSITA would have found it obvious to supplement Djuric's listed goals with the intents and/or actions disclosed by Ross (or Waymo) to expand Djuric's predictive capabilities, leading to more accurate predictions across a broader range of circumstances. Ross at 9:13-40.

Exemplary Motivations for Combining Djuric and England

A POSITA would have been motivated to use England's teachings to further improve object detection using LIDAR sensors and cameras. As taught by England, sensor data is divided into a grid, and England's model detects which cells of the grid are currently occupied by objects in the sensor data and which cells of the grid are currently expected to be occupied at one or more future instances. England at [0206]. Further, a POSITA would have applied England's teachings of determining "costs" corresponding to riskier locations for the autonomous vehicle to move in based on context in the sensor data that is interpreted by the model. England at [0153]. This improves the navigation of Djuric's autonomous vehicle in relation to predicted trajectories within a specific time interval.

Exemplary Motivations for Combining Djuric and Hong

A POSITA would have been motivated apply to Hong's teachings to further improve object detection using LIDAR sensors and cameras. As taught by Hong, a machine learning model can output heat maps representing probability predictions associated with an object's location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object's trajectory at a future time. Hong at [0015]-[0016]. Further, a POSITA would have applied Hong's teachings of "masking, covering, or otherwise removing predicted probabilities of

heat maps” based on context in the sensor data that is interpreted by the model. Hong at [0017]. This improves the navigation of Djuric’s autonomous vehicle in relation to predicted trajectories within a specific time interval.

Exemplary Motivations for Combining Djuric and Cox (or Test My Brain)

A POSITA would have been motivated to adopt Cox’s (or Test My Brain’s) disclosure of training and testing on feature vectors to improve Djuric’s model performance by grouping features into neighborhoods before producing a set of final outputs of the probabilistic neural network. *See* Cox at [0039]. Further, a POSITA would have found it obvious to implement Cox’s (or Test My Brain’s) teaching of determining a mean accuracy of labels to determine which types of difficult training scenarios require more attentive analysis. *See* Cox at [0028].

Exemplary Motivations for Combining Djuric and Zhao

A POSITA would have been motivated to apply Zhao’s teachings to further improve object detection using LIDAR sensors and cameras. As taught by Zhao, a machine learning model predicts trajectories associated with an object’s location within point cloud by combining a reference driveline and motion model of the object. Zhao at [0094], [0350]. This improves the navigation of Djuric’s autonomous vehicle in relation to the location accuracy of predicted trajectories.

Exemplary Motivations for Combining Djuric and Djuric 2 (and/or Uber)

A POSITA would have been motivated to apply Djuric 2’s (and/or Uber’s) teachings to further improve object detection using LIDAR sensors and cameras. As taught by Djuric 2 (and/or Uber), a machine learning model predicts object trajectories associated with a specific time within a 3D view of a rasterized 2D input image. Djuric 2 at 2, 4, 7. This improves the navigation of Djuric’s autonomous vehicle in relation to predicted trajectories within a specific time interval.

Exemplary Motivations for Combining Djuric and Levinson

A POSITA would have been motivated to apply Levinson's teachings of using blob tracking to track objects in image data and estimate motion. Levinson at 27:54-28:7, FIG. 26A. Because Djuric already teaches tracking and predicting trajectories for objects, a POSITA would have found it obvious to apply Levinson's teachings to improve object tracking and prediction accuracy.

Exemplary Motivations for Combining Djuric and Bhattacharyya

A POSITA would have applied Bhattacharyya's teachings of anticipating pedestrian movements over long-time horizons to Djuric's prediction model. Bhattacharyya at 1, 5-7, Fig. 4. The application of Bhattacharyya would have been obvious to a POSITA seeking to improve the accuracy of Djuric's model's predictions.

Exemplary Motivations for Combining Englard and Djuric

A POSITA would have looked to improve Englard's prediction model using Djuric's techniques of outputting a plurality of predicted trajectories for a given object based on information included in input image data such as locations, headings, and other state data and refining the predicted trajectory with additional data such as map data. Djuric at [0033]. This improves the navigation of Englard's autonomous vehicle in relation to predicted trajectories by considering multiple paths.

Exemplary Motivations for Combining Englard and Cox (or Test My Brain)

A POSITA would have been motivated to apply Cox's (or Test My Brain's) teachings of utilizing training data and related statistics to "model the pattern of the performance of [] human annotators" such that the model is capable of detecting hidden context of users, such as detecting human emotion or intention in an image. Cox at [0033]. A POSITA would expect this combination

to expand Englard's predictive capabilities, leading to more accurate predictions across a broader range of circumstances

Exemplary Motivations for Combining Englard and Ross (or Waymo)

A POSITA would have been motivated to combine Ross (or Waymo) with Englard such that Englard's prediction model predicts object movement using Ross's (or Waymo's) intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Englard's motion intents with the prediction of intent and/or actions disclosed by Ross (or Waymo) to expand Englard's predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Englard and Zhao

A POSITA would have been motivated to supplement Englard's model by adopting Zhao's teachings of predicting trajectories "based on one more, fewer, or other factors than the classification, the intention, and the reference driveline of the hypothesis." A POSITA would expect this combination to expand Englard's predictive capabilities, leading to more accurate predictions across a broader range of circumstances. Zhao at [0350].

Exemplary Motivations for Combining Englard and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics, such means of predictive distributions, to improve Englard's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Englard already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion.

Exemplary Motivations for Combining Zhao and Djuric

A POSITA would have been motivated to apply Djuric’s teachings of “goal-based prediction” including determining a plurality of “nominal pathways” and adjusting which pathway an object is likely to take based on information about the driver or object captured by the sensor data. Djuric at [0080]-[0081]. This improves the navigation of Zhao’s autonomous vehicle in relation to predicted trajectories by considering multiple paths and more information.

Exemplary Motivations for Combining Zhao and Ross (or Waymo)

A POSITA would have been motivated to combine Ross (or Waymo) with Zhao such that Zhao’s prediction model utilizes Ross’s (or Waymo’s) predicted intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Zhao’s motion intents with the predicted intent and/or actions disclosed by Ross (or Waymo) to expand Zhao’s predictive capabilities, leading to more accurate predictions across a broader range of circumstances

Exemplary Motivations for Combining Zhao and England

A POSITA would have been motivated to use England’s teachings to further improve object detection using LIDAR sensors and cameras. As taught by England, sensor data is divided into a grid and England’s model detects which cells of the grid are currently occupied by objects in the sensor data including which cells of the grid are currently expected to be occupied at one or more future instances. England at [0206]. Further, a POSITA would have applied England’s teachings of determining “costs” corresponding to riskier locations for the autonomous vehicle to move in based on context in the sensor data that is interpreted by the model. England at [0153]. This improves the navigation of Zhao’s autonomous vehicle in relation to predicted trajectories within a specific time interval, and adjusting predicted trajectories based on additional input information.

Exemplary Motivations for Combining Zhao and Hong

A POSITA would have been motivated apply to Hong’s teachings to further improve object detection using LIDAR sensors and cameras. As taught by Hong, a machine learning model can output heat maps representing probability predictions associated with an object’s location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object’s trajectory at a future time. Hong at [0015]-[0016]. Further, a POSITA would have applied Hong’s teachings of “masking, covering, or otherwise removing predicted probabilities of heat maps” based on context in the sensor data that is interpreted by the model. Hong at [0017]. This improves the navigation of Zhao’s autonomous vehicle in relation to predicted trajectories within a specific time interval, and adjusting predicted trajectories based on additional input information.

Exemplary Motivations for Combining Zhao and Djuric 2 (and/or Uber)

A POSITA would have been motivated to apply Djuric 2’s (and/or Uber’s) teachings to further improve object detection using LIDAR sensors and cameras. As taught by Djuric 2 (and/or Uber), a machine learning model predict trajectories associated with an object’s location at a specific time within a 3D view of a rasterized 2D input image. Djuric 2 at 2, 4, 7. This improves the navigation of Zhao’s autonomous vehicle in relation to predicted trajectories within a specific time interval.

Exemplary Motivations for Combining Zhao and Cox (or Test My Brain)

A POSITA would have been motivated to apply Cox’s (or Test My Brain’s) teachings of utilizing training data and related statistics to “model the pattern of the performance of [] human annotators” such that the model is capable of detecting hidden context of users, such as detecting human emotion or intention in an image. Cox at [0033]. A POSITA would expect this combination

to expand Zhao's predictive capabilities, leading to more accurate predictions across a broader range of circumstances

Exemplary Motivations for Combining Zhao and Bhattacharyya

A POSITA would have looked apply Bhattacharyya's teachings of anticipating pedestrian movements over long-time horizons to Zhao's prediction model. Bhattacharyya at 1, 5-7, Fig. 4. The application of Bhattacharyya would have been obvious to a POSITA seeking to improve the accuracy of Zhao's model's predictions.

Exemplary Motivations for Combining Waymo and Djuric

A POSITA would have been motivated to apply Djuric's teachings of "goal-based prediction" including determining a plurality of "nominal pathways" and adjusting which predicted pathway an object is likely to take based on information about the driver or object captured by the sensor data. Djuric at [0080]-[0081]. This improves the navigation of Waymo's autonomous vehicle in relation to predicted trajectories by considering multiple paths and adjusting based on additional output data from the model.

Exemplary Motivations for Combining Waymo and Hong

A POSITA would have been motivated apply Hong's teachings to further improve object detection using LIDAR sensors and cameras to Waymo. As taught by Hong, a machine learning model can output heat maps representing probability predictions associated with an object's location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object's trajectory at a future time. Hong at [0015]-[0016]. Further, a POSITA would have applied Hong's teachings of "masking, covering, or otherwise removing predicted probabilities of heat maps" based on context in the surrounding environment that is interpreted by the model. Hong at [0017]. This improves the navigation of Waymo's autonomous

vehicle in relation to predicted trajectories within a specific time interval and adjusting predicted trajectories.

Exemplary Motivations for Combining Waymo and England

A POSITA would have been motivated to use England's teachings to further improve object detection using LIDAR sensors and cameras. As taught by England, sensor data is divided into a grid, and England's model detects which cells of the grid are currently occupied by objects in the sensor data and which cells of the grid are currently expected to be occupied at one or more future instances. England at [0206]. Further, a POSITA would have applied England's teachings of determining "costs" corresponding to riskier locations for the autonomous vehicle to move in based on context in the surrounding environment that is interpreted by the model. England at [0153]. This improves the navigation of Waymo's autonomous vehicle in relation to predicted trajectories within a specific time interval and adjusting predicted trajectories.

Exemplary Motivations for Combining Waymo and Cox

A POSITA would have been motivated to apply Cox's teachings of utilizing training data and generating related statistics to "model the pattern of the performance of [] human annotators" such that the model is capable of detecting hidden context of users, such as detecting human emotion or intention in an image. Cox at [0033]. A POSITA would expect this combination to expand Waymo's predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Waymo and Test My Brain

A POSITA would have been motivated to apply Test My Brain's teachings of utilizing training data and generating related statistics. Ex. D-26 at elements 1[d-ii], 1[d-iii]. A POSITA

would expect this combination to expand Waymo's predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Waymo and iMotions

A POSITA would have been motivated to apply iMotions' teachings of utilizing training data and generating related statistics to train its model. Ex. D-25 at elements 1[d-ii], 1[d-iii]. A POSITA would expect this combination to expand Waymo's predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Waymo and Levinson (or Zoox)

A POSITA would have been motivated to combine the teachings of Levinson (or Zoox) regarding selecting an autonomous vehicle trajectory based on a level of uncertainty associated with a current and future state of objects, which would help Waymo account for uncertainty of potential future trajectories when navigating its autonomous vehicle. Levinson at 9:26-30. A POSITA would have been further motivated to apply the teachings of Levinson (or Zoox) regarding calculating trajectories as probabilistically-determined trajectories, which would help the Waymo autonomous vehicle avoid collisions. Levinson at 9:31-53.

Exemplary Motivations for Combining Waymo and Volz 1

A POSITA would have been motivated to supplement Waymo's model by adopting Volz 1's teachings of predicting trajectories based on "infer[ing] pedestrian crossing intentions." Volz 1 at Abstract, 5-6. A POSITA would expect this combination to expand Waymo's predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Hong and Djuric

A POSITA would have been motivated to apply Djuric's teachings of generating LIDAR point clouds associated with objects on the road. Djuric at [0022]. Hong already describes

generating a “heat map” including x and y coordinates associated with objects on the road, Djuric simply provides details on implementing this heat mat as a point cloud. Hong at [0015]-[0016]. Further, a POSITA would have looked to improve Hong’s prediction model using Djuric’s techniques of outputting a plurality of predicted trajectories for a given object based on information included in input sensor data including locations, headings, and other state data and refining the predicted trajectory with additional data such as map data. Djuric at [0033]. This improves the navigation of Hong’s autonomous vehicle in relation to predicted trajectories by considering multiple paths and more information. Moreover, a POSITA would have been motivated to apply Djuric’s “supervised training techniques” including the use of “labeled” input training data such that Hong’s model better mimics human driving decisions. Finally, a POSITA would have been motivated to adopt Djuric’s teachings of “nudg[ing] away from” pedestrians to “increase the distance between the vehicle and the predicted location(s) of the pedestrian” in order to increase overall safety of the operation of an autonomous vehicle. Djuric [0035].

Exemplary Motivations for Combining Hong and Zhu

A POSITA would have been motivated to apply Zhu’s teachings of generating LIDAR point clouds associated with objects on the road. Zhu at [0026]. Hong already describes generating a “heat map” including x and y coordinates associated with objects on the road, Zhu simply provides details on implementing this heat mat as a point cloud. Hong at [0015]-[0016].

Exemplary Motivations for Combining Hong and Ross (or Waymo)

A POSITA would have been motivated to combine Ross (or Waymo) with Hong such that Hong’s prediction system utilizes Ross’s (or Waymo’s) predicted intents or actions. *See* Ross at 1:55-2:13, 4:33-46. A POSITA would have found it obvious to supplement Hong’s predicted trajectories with the predicted intent and/or actions disclosed by Ross (or Waymo), to expand

Hong's predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Hong and Cox (or Test My Brain)

A POSITA would have been motivated to apply Cox's (or Test My Brain's) teachings of utilizing training data to "model the pattern of the performance of [] human annotators" such that the model is capable of detecting hidden context of users, such as detecting human emotion or intention in an image. Cox at [0033]. This expands Hong's predictive capabilities, leading to more accurate predictions across a broader range of circumstances. Further, Hong already discloses that its model may include "any type of machine learning" including "supervised learning." Hong at [0066]. Cox (or Test My Brain) simply provides details on how to implement supervised learning.

Exemplary Motivations for Combining Hong and England

A POSITA would have been motivated to apply England's teachings of generating LIDAR point clouds associated with objects on the road. England at [0086]-[0091]. Hong already describes generating a "heat map" including x and y coordinates associated with objects on the road, England simply provides details on implementing this heat map as a point cloud. Hong at [0015]-[0016]. Moreover, a POSITA would have been motivated to apply England's "supervised training technique" including the use of "labels, weights, or scores" such that Hong's model better mimics human driving decisions. England at [0074]-[0076]. Finally, a POSITA would have been motivated to adopt England's teaching of "staying at least some predetermined distance . . . away from a particular vehicle" to increase overall safety of the operation of an autonomous vehicle. England [0222].

Exemplary Motivations to Combine Hong and Zhao

A POSITA would have been motivated to apply Zhao's teachings of generating LIDAR point clouds associated with objects on the road. Zhao at [0094]. Hong already describes generating a "heat map" including x and y coordinates associated with objects on the road, Zhao simply provides details on implementing this heat mat as a point cloud. Hong at [0015]-[0016]. Moreover, a POSITA would have been motivated to supplement Hong's model by adopting Zhao's teachings of predicting trajectories "based on one more, fewer, or other factors than the classification, the intention, and the reference driveline of the hypothesis" to expand the scenarios Hong's model is capable of predicting. Zhao at [0350].

Exemplary Motivations to combine Hong and Quintero

A POSITA would have been motivated to apply Quintero's teachings of generating LIDAR point clouds associated with objects on the road. Quintero at 318. Hong already describes generating a "heat map" including x and y coordinates associated with objects on the road, Quintero simply provides details on implementing this heat mat as a point cloud. Hong at [0015]-[0016].

Exemplary Motivations to combine Hong and Kohler

A POSITA would have been motivated to combine Kohler with Hong such that Hong's prediction system utilizes Kohler's predicted pedestrian intents. Kohler at 4, Fig. 6. A POSITA would have found it obvious to supplement Hong's predicted trajectories with the predicted intent and/or actions disclosed by Kohler to expand Hong's predictive capabilities, leading to more accurate predictions across a broader range of circumstances

Exemplary Motivations to combine Hong and Djuric 2 (and/or Uber)

A POSITA would have been motivated to combine Djuric with Hong such that Hong's prediction system utilizes Djuric 2's (and/or Uber's) "uncertainty estimates" that "reflect

peculiarity of [] situations.” Djuric 2 at 7. A POSITA would have found it obvious to supplement Hong’s predicted trajectories with the uncertainty estimates disclosed by Djuric 2 (and/or Uber) to expand Hong’s predictive capabilities, leading to more accurate predictions across a broader range of circumstances, such as, for example, situations where a road user does not follow typical traffic rules. *Id.*

Exemplary Motivations for Combining Hong and Volz 1

A POSITA would have been motivated to apply Volz 1’s teachings to further improve object detecting using LIDAR sensors and cameras. For example, Volz 1 describes utilizing a “preprocessed point cloud” in determining hidden context indicating whether pedestrians will cross a crosswalk. Volz 1 at 1. It would have been obvious to a POSITA to improve Hong’s predictive capabilities by applying this method.

Exemplary Motivations for Combining Hong and Levinson (or Zoox)

A POSITA would have been motivated combine Hong with Levinson’s (or Zoox’s) teachings of segmenting LIDAR point clouds into 3D blobs associated with objects on the road. Levinson at 26:16-59. Hong already describes generating a “heat map” including x and y coordinates associated with objects on the road, Levinson (or Zoox) simply provides details on implementing the heat map of objects as a point cloud. Hong at [0015]-[0016]. Moreover, a POSITA would have been motivated to adopt Levinson’s (or Zoox’s) teaching of “maintaining a safety buffer” to increase overall safety of the operation of an autonomous vehicle. Levinson at 18:35-63. Further, a POSITA would have been motivated to combine Hong and Levinson (or Zoox) because both Hong and Levinson were applied for by Zoox, are assigned to Zoox, and are implemented in Zoox’s vehicles.

Exemplary Motivations for Combining Hong and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics, such means of predictive distributions, to improve Hong's determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Hong already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion.

Exemplary Motivations to combine Djuric 2 (and/or Uber) with Djuric

A POSITA would have been motivated to apply Djuric's teachings of generating LIDAR point clouds associated with objects on the road. Djuric at [0022]. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, Djuric simply provides details on implementing this as a point cloud. Djuric 2 at 2. Further, a POSITA would have looked to improve Djuric 2's (and/or Uber's) prediction model using Djuric's techniques of outputting a plurality of predicted trajectories for a given object based on information included in input sensor data including locations, headings, and other state data and refining the predicted trajectory with additional data such as map data. Djuric at [0033]. This improves the navigation of Djuric 2's (and/or Uber's) autonomous vehicle in relation to predicted trajectories by considering multiple paths and more information. Moreover, a POSITA would have been motivated to apply Djuric's "supervised training techniques" including the use of "labeled" input training data such that Djuric 2's (and/or Uber's) model better mimics human driving decisions. Additionally, a POSITA would have been motivated to adopt Djuric's teachings of "nudg[ing] away from" pedestrians to "increase the distance between the vehicle and the predicted location(s) of the pedestrian" in order to increase overall safety of the operation of an autonomous

vehicle. Djuric [0035]. Finally, a POSITA would have been motivated to apply Djuric's teachings of "goal-based prediction" including determining a plurality of "nominal pathways" and adjusting which predicted pathway an object is likely to take based on information about the driver or object captured by the sensor data. Djuric at [0080]-[0081]. This improves the navigation of Djuric 2's (and/or Uber's) autonomous vehicle in relation to predicted trajectories by considering multiple paths and adjusting based on additional output data from the model.

Exemplary Motivations to Combine Djuric 2 (and/or Uber) with Zhu

A POSITA would have been motivated to apply Zhu's teachings of generating LIDAR point clouds associated with objects on the road. Zhu at [0026]. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, Zhu simply provides details on implementing this as a point cloud. Djuric 2 at 2.

Exemplary Motivations to Combine Djuric 2 (and/or Uber) with Ross (or Waymo)

A POSITA would have found it obvious to supplement Djuric's (and/or Uber's) predictions with the intents and/or actions disclosed by Ross (or Waymo) to expand Djuric's (and/or Uber's) predictive capabilities, leading to more accurate predictions across a broader range of circumstances. Ross at 9:13-40. Further, a POSITA would have found it obvious to implement Djuric's (and/or Uber's) predictive model to navigate a vehicle by looking to Ross's (or Waymo's) disclosure of communication and vehicle control systems.

Exemplary Motivations to Combine Djuric 2 (and/or Uber) with England

A POSITA would have been motivated to use England's teachings to further improve object detection using LIDAR sensors and cameras. As taught by England, sensor data is divided into a grid and England's model detects which cells of the grid are currently occupied by objects in the sensor data including which cells of the grid are currently expected to be occupied at one or more

future instances. Englard at [0206]. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, Englard simply provides details on implementing this as a point cloud. Djuric 2 at 2. Further, a POSITA would have applied Englard's teachings of determining "costs" corresponding to riskier locations for the autonomous vehicle to move toward based on context in the sensor data that is interpreted by the model. Englard at [0153]. Moreover, a POSITA would have been motivated to apply Englard's "supervised training technique" including the use of "labels, weights, or scores" such that Djuric 2's (and/or Uber's) model better mimics human driving decisions. Englard at [0074]-[0076]. Finally, a POSITA would have been motivated to adopt Englard's teaching of "staying at least some predetermined distance . . . away from a particular vehicle" to increase overall safety of the operation of an autonomous vehicle. Englard [0222].

Exemplary Motivations to Combine Djuric 2 (and/or Uber) with Hong

A POSITA would have been motivated to apply Hong's teachings to further improve object detection using LIDAR sensors and cameras. As taught by Hong, a machine learning model can output heat maps representing probability predictions associated with an object's location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object's trajectory at a future time. Hong at [0015]-[0016]. Further, a POSITA would have applied Hong's teachings of "masking, covering, or otherwise removing predicted probabilities of heat maps" based on context in the surrounding environment that is interpreted by the model. Hong at [0017]. This improves the navigation of Djuric 2's (and/or Uber's) autonomous vehicle in relation to predicted trajectories within a specific time interval and adjusting predicted trajectories.

Exemplary Motivations to Combine Djuric 2 (and/or Uber) with Zhao

A POSITA would have been motivated to apply Zhao’s teachings of generating LIDAR point clouds associated with objects on the road. Zhao at [0094]. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, Zhao simply provides details on implementing this as a point cloud. Djuric 2 at 2. Moreover, a POSITA would have been motivated to supplement Djuric 2’s (and/or Uber’s) model by adopting Zhao’s teachings of predicting trajectories “based on one more, fewer, or other factors than the classification, the intention, and the reference driveline of the hypothesis” to expand the scenarios Djuric 2’s (and/or Uber’s) model is capable of predicting. Zhao at [0350].

Exemplary Motivations to Combine Djuric 2 (and/or Uber) with Quintero

A POSITA would have been motivated to apply Quintero’s teachings of generating LIDAR point clouds associated with objects on the road. Quintero at 318. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, Quintero simply provides details on implementing this as a point cloud. Djuric 2 at 2.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Cox

A POSITA would have been motivated to apply Cox’s teachings of utilizing training data and generating related statistics to “model the pattern of the performance of [] human annotators” such that the model is capable of detecting hidden context of users, such as detecting human emotion or intention in an image. Cox at [0033]. A POSITA would expect this combination to expand Djuric 2’s (and/or Uber’s) predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Test My Brain

A POSITA would have been motivated to apply Test My Brain’s teachings of utilizing training data and generating statistics. Ex. D-26. A POSITA would expect this combination to expand Djuric 2’s (and/or Uber’s) predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and iMotions

A POSITA would have been motivated to apply iMotions’ teachings of utilizing training data and generating statistics to train Djuric 2’s (and/or Uber’s) model. Ex. D-23 at elements 1[d-ii], 1[d-iii]. A POSITA would expect this combination to expand Djuric 2’s (and/or Uber’s) predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Volz 1

A POSITA would have been motivated to apply Volz 1’s teachings to further improve object detecting using LIDAR sensors and cameras. For example, Volz 1 describes utilizing a “preprocessed point cloud” in determining hidden context indicating whether pedestrians will cross a crosswalk. Volz 1 at 1. It would have been obvious to a POSITA to improve Djuric (and/or Uber’s) predictive capabilities by applying this method.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Levinson

A POSITA would have been motivated to combine Djuric 2 (and/or Uber) with Levinson’s teachings of segmenting LIDAR point clouds into 3D blobs associated with objects on the road. Levinson at 26:16-59. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, and Levinson simply provides details on implementing the image and LIDAR data as a point cloud. Hong at [0015]-[0016]. Moreover, a POSITA would have been motivated to adopt Levinson’s teaching of “maintaining a

safety buffer” to increase overall safety of the operation of an autonomous vehicle. Levinson at 18:35-63.

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Zoox

A POSITA would have been motivated to combine Djuric 2 (and/or Uber) with Zoox’s teachings to further improve object detection using LIDAR sensors and cameras and to segment LIDAR point clouds into 3D blobs associated with objects on the road. Ex. D-27 at element 1[b]. Djuric 2 (and/or Uber) already describes collecting sensor data using both cameras and LIDAR to rasterize 3D scenes into a 2D input image, and Zoox simply provides details on generating a point cloud with the sensor data. As further taught by Zoox, a machine learning model can output heat maps representing probability predictions associated with an object’s location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object’s trajectory at a future time. A POSITA would have applied Zoox’s teachings of “masking, covering, or otherwise removing predicted probabilities of heat maps” based on context in the surrounding environment that is interpreted by the model. Ex. D-27 at element 1[d-v] and claims 2, 3, 8. This improves the navigation of Djuric 2’s (and/or Uber’s) autonomous vehicle in relation to predicted trajectories within a specific time interval, and also enhances the adjustment of predicted trajectories. Moreover, a POSITA would have been motivated to adopt Zoox’s teaching of “maintaining a safety buffer” to increase overall safety of the operation of an autonomous vehicle. Ex. D-27 at element 1[e].

Exemplary Motivations for Combining Djuric 2 (and/or Uber) and Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya’s teaching implementing supervised training techniques to predict uncertainty level estimates of future motion of pedestrians and related statistics, such means of predictive distributions, to improve Djuric 2’s

(and/or Uber's) determination of future subject motion. Bhattacharyya at 1-4. A POSITA would have found the combination straightforward, as Djuric 2 (and/or Uber) already outputs a prediction of future subject motion, and Bhattacharyya simply expands on that output by providing an uncertainty value associated with that motion.

Exemplary Motivations to Combine Mercedes with Djuric

A POSITA would have been motivated to apply Djuric's teachings of generating LIDAR point clouds associated with objects on the road. Djuric at [0022]. Mercedes already describes detecting pedestrians in a "point system," Djuric simply provides details on implementing this as a point cloud. Ex. D-22 at element 1[b]. Further, a POSITA would have looked to improve Mercedes' prediction model using Djuric's techniques of outputting a plurality of predicted trajectories for a given object based on information included in input sensor data including locations, headings, and other state data and refining the predicted trajectory with additional data such as map data. Djuric at [0033]. This improves the navigation of Mercedes' vehicle in relation to predicted trajectories by considering multiple paths and more information. Additionally, a POSITA would have been motivated to adopt Djuric's teachings of "nudg[ing] away from" pedestrians to "increase the distance between the vehicle and the predicted location(s) of the pedestrian" in order to increase overall safety of the operation of an autonomous vehicle. Djuric [0035]. Finally, a POSITA would have been motivated to apply Djuric's teachings of "goal-based prediction" including determining a plurality of "nominal pathways" and adjusting which predicted pathway an object is likely to take based on information about the driver or object captured by the sensor data. Djuric at [0080]-[0081]. This improves the navigation of Mercedes' vehicle in relation to predicted trajectories by considering multiple paths and adjusting based on additional output data from the model.

Exemplary Motivations to Combine Mercedes with Zhu

A POSITA would have been motivated to use Zhu's teachings to further improve Mercedes' object detection using LIDAR sensors and cameras. As taught by Zhu, combining the data allows objects and drivable road surfaces (i.e., where objects are not located in a road) to be detected. Zhu at [0026], [0040]. This improves the navigation of Mercedes' autonomous vehicle in relation to predicted trajectories. *Id.*

Exemplary Motivations to Combine Mercedes with Ross

A POSITA would have found it obvious to supplement Mercedes' predictions with the intents and/or actions disclosed by Ross to expand Mercedes' predictive capabilities, leading to more accurate predictions across a broader range of circumstances. Ross at 9:13-40. Further, a POSITA would have found it obvious to implement Mercedes' predictive model to collect sensor data and navigate a vehicle by looking to Ross's disclosure of vehicle sensor, communication, and control systems. Ross at 5:12-6:67

Exemplary Motivations to Combine Mercedes with England

A POSITA would have been motivated to use England's teachings to further improve object detection using LIDAR sensors and cameras. As taught by England, sensor data is divided into a grid and England's model detects which cells of the grid are currently occupied by objects in the sensor data including which cells of the grid are currently expected to be occupied at one or more future instances. England at [0206]. Mercedes already describes detecting pedestrians in a "point system," England simply provides details on implementing this as a point cloud. Ex. D-22 at element 1[b]. Further, a POSITA would have applied England's teachings of determining "costs" corresponding to riskier locations for the autonomous vehicle to move toward based on context in the sensor data that is interpreted by the model. England at [0153]. Moreover, a POSITA would

have been motivated to apply Englard's "supervised training technique" including the use of "labels, weights, or scores" such that Mercedes' model better mimics human driving decisions. Englard at [0074]-[0076]. A POSITA would also have been motivated to adopt Englard's teaching of "staying at least some predetermined distance . . . away from a particular vehicle" to increase overall safety of the operation of an autonomous vehicle. Englard [0222]. Further, a POSITA would have found it obvious to implement Mercedes' predictive model to collect sensor data and navigate a vehicle by looking to Englard's disclosure of vehicle sensor, communication, and control systems. Englard at [0049], [0050], [0059], [0060].

Exemplary Motivations to Combine Mercedes with Hong

A POSITA would have been motivated to apply Hong's teachings to further improve object detection using LIDAR sensors and cameras. As taught by Hong, a machine learning model can output heat maps representing probability predictions associated with an object's location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object's trajectory at a future time. Hong at [0015]-[0016]. Further, a POSITA would have applied Hong's teachings of "masking, covering, or otherwise removing predicted probabilities of heat maps" based on context in the surrounding environment that is interpreted by the model. Hong at [0017]. This improves the navigation of Mercedes autonomous vehicle in relation to predicted trajectories within a specific time interval and adjusting predicted trajectories. Further, a POSITA would have found it obvious to implement Mercedes' predictive model to collect sensor data and navigate a vehicle by looking to Hong's disclosure of vehicle sensor, communication, and control systems. Hong at [0068], [0117]-[0119].

Exemplary Motivations to Combine Mercedes with Zhao

A POSITA would have been motivated to apply Zhao's teachings to further improve object detection using LIDAR sensors and cameras. As taught by Zhao, a machine learning model predicts trajectories associated with an object's location within point cloud by combining a reference driveline and motion model of the object. Zhao at [0094], [0350]. This improves the navigation of Mercedes' autonomous vehicle in relation to the location accuracy of predicted trajectories. Moreover, a POSITA would have been motivated to supplement Mercedes' model by adopting Zhao's teachings of predicting trajectories "based on one more, fewer, or other factors than the classification, the intention, and the reference driveline of the hypothesis" to expand the scenarios Mercedes' model is capable of predicting. Zhao at [0350]. Further, a POSITA would have found it obvious to implement Mercedes' predictive model to collect sensor data and navigate a vehicle by looking to Zhao's disclosure of vehicle sensor, communication, and control systems. Zhao at [0062]-[0064].

Exemplary Motivations to Combine Mercedes with Karasev

A POSITA would have been motivated to include several types of sensors, such as LIDAR and camera sensors disclosed by Karasev, to the Mercedes vehicle to improve the quality and amount of data that could be fed to Mercedes' predictive model. Karasev at 2547.

Exemplary Motivations to Combine Mercedes with Kohler

A POSITA would have been motivated to include several types of sensors, such as LIDAR and camera sensors disclosed by Kohler, to the Mercedes vehicle to improve the quality and amount of data that could be fed to Mercedes' predictive model. Kohler at 2, 5.

Exemplary Motivations to Combine Mercedes with Schneemann

A POSITA would have found it obvious to supplement Mercedes' predictions with the intents and/or actions disclosed by Schneemann to expand Mercedes' predictive capabilities,

leading to more accurate predictions across a broader range of circumstances. Schneemann at 2243.

Exemplary Motivations to Combine Mercedes with Furuhashi

A POSITA would have found it obvious to supplement Mercedes' predictions with the intents and/or actions disclosed by Furuhashi to expand Mercedes' predictive capabilities, leading to more accurate predictions across a broader range of circumstances. Furuhashi at 18-19.

Exemplary Motivations to Combine Mercedes with Waymo

A POSITA would have been motivated to apply Waymo's teachings to further improve object detection using LIDAR sensors and cameras. As taught by Waymo, a machine learning model predicts trajectories associated with an object's location within point cloud by combining a reference driveline and motion model of the object. Ex. D-24 at elements 1[b], 1[d-ii]-1[d-iv]. This improves the navigation of Mercedes' autonomous vehicle in relation to the location accuracy of predicted trajectories. Moreover, a POSITA would have been motivated to supplement Mercedes' model by adopting Waymo's teachings of predicting trajectories based on "hidden context, such as the meaning of hand signals of pedestrians on the road" to expand the scenarios Mercedes' model is capable of predicting. Ex. D-24 at elements 1[d-ii], 1[d-iii]. Further, a POSITA would have found it obvious to implement Mercedes' predictive model to collect sensor data and safely navigate a vehicle to maintain a safe distance from other objects by looking to Waymo's disclosure of vehicle sensor, communication, and control systems. Ex. D-24 at elements 1[Pre], 1[e].

Exemplary Motivations for Mercedes and Cox

A POSITA would have been motivated to apply Cox's teachings of utilizing training data and related statistics to "model the pattern of the performance of [] human annotators" such that

the model is capable of detecting hidden context of users, such as detecting human emotion or intention in an image. Cox at [0033]. A POSITA would expect this combination to expand Mercedes' predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Mercedes and Test My Brain.

A POSITA would have been motivated to apply Cox's teachings of utilizing training data and generating related statistics to train its model. Ex. D-26 at elements 1[d-ii], 1[d-iii]. A POSITA would expect this combination to expand Mercedes' predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Mercedes and iMotions

A POSITA would have been motivated to apply iMotions' teachings of utilizing training data and generating statistics to train its model. Ex. D-25 at elements 1[d-ii], 1[d-iii]. A POSITA would expect this combination to expand Mercedes' predictive capabilities, leading to more accurate predictions across a broader range of circumstances.

Exemplary Motivations for Combining Mercedes and Volz 1

A POSITA would have been motivated to apply Volz 1's teachings to further improve object detecting using LIDAR sensors and cameras. For example, Volz 1 describes utilizing a "preprocessed point cloud" in determining hidden context indicating whether pedestrians will cross a crosswalk. Volz 1 at 1. It would have been obvious to a POSITA to improve Mercedes' predictive capabilities by applying this method.

Exemplary Motivations for Combining Mercedes and Levinson

A POSITA would have been motivated to combine Mercedes with Levinson's teachings of capturing image data and segmenting LIDAR point clouds into 3D blobs associated with objects

on the road. Levinson at 26:16-59. Mercedes already describes collecting sensor data, and Levinson simply provides details on implementing sensor data as a point cloud. Moreover, a POSITA would have been motivated to adopt Levinson's teaching of "maintaining a safety buffer" to increase overall safety of the operation of an autonomous vehicle. Levinson at 18:35-63.

Exemplary Motivations for Combining Mercedes and Zoox

A POSITA would have been motivated to combine Mercedes with Zoox's teachings to further improve object detection using LIDAR sensors and cameras and to segment LIDAR point clouds into 3D blobs associated with objects on the road. Ex. D-27 at element 1[b]. Mercedes already describes collecting sensor data, and Zoox simply provides details on generating a point cloud with the sensor data. As further taught by Zoox, a machine learning model can output heat maps representing probability predictions associated with an object's location within a cell of the heat map, where the highest probability associated with a cell is a predicted point of the object's trajectory at a future time. A POSITA would have applied Zoox's teachings of "masking, covering, or otherwise removing predicted probabilities of heat maps" based on context in the surrounding environment that is interpreted by the model. Ex. D-27 at element 1[d-v] and claims 2, 3, 8, 9. This improves the control of Mercedes' vehicle in relation to predicted trajectories within a specific time interval, and also enhances the adjustment of predicted trajectories. Further, a POSITA would have found it obvious to implement Mercedes' predictive model to collect sensor data and navigate a vehicle by looking to Zoox's disclosure of vehicle sensor, communication, and control systems. Ex. D-27 at element 1[e], claim 8. Finally, a POSITA would have been motivated to adopt Zoox's teaching of "maintaining a safety buffer" to increase overall safety of the operation of an autonomous vehicle. Ex. D-27 at element 1[e].

Exemplary Motivations for Combining Mercedes and Bhattacharyya

A POSITA would have looked apply Bhattacharyya's teachings of anticipating pedestrian movements over long-time horizons to Mercedes' prediction model. Bhattacharyya at 1, 5-7, Fig. 4. The application of Bhattacharyya would have been obvious to a POSITA seeking to improve the accuracy of Mercedes' model's predictions.

E. The '046 Patent

Pursuant to Patent Rule 3-3 and subject to Tesla's reservations of rights in these Invalidity Contentions, at least the prior art listed below, individually or in combination, invalidates the Asserted Claims of the '046 Patent. Exhibits E-1 through E-26 provide detailed claim charts showing where each claim limitation may be found in certain references listed below, either expressly or inherently as the reference would be understood by a person having ordinary skill in the art. For those references for which detailed claim charts are not provided, those additional prior art references are otherwise pertinent to the invalidity of the '046 Patent, either alone or in combination with other references.

The prior art references, systems, and products listed below and in the accompanying claim chart exhibits may be relied upon for certain limitations, state of the art, and background of the art; indicia of obviousness; as evidence of the level of skill in the art at the time of the filing of the Patents-in-Suit; and/or in support of assertions that it is proper to combine certain prior art references in certain ways.

Tesla also incorporates by reference each and every prior art reference of record in the prosecution of the Patents-in-Suit and patents or patent applications related to the Patents-in-Suit, the prior art referred to in the specifications of the Patents-in-Suit, as well as the prior art identified in any USPTO proceedings involving any of the Patents-in-Suit.

1. Bases for Anticipation and/or Obviousness

Each prior art reference identified in Exhibits E-1 through E-26 expressly, implicitly, or inherently anticipates and/or renders obvious the Asserted Claims of the '046 Patent, either alone or in combination with other prior art references (*e.g.*, other references identified above) or the knowledge of the person of ordinary skill in the art at the time of the alleged invention. In the table below, Tesla identifies a non-exhaustive list of prior art references that, alone or in combination, anticipate and/or render obvious the Asserted Claims of the '046 Patent.

Exhibit	Patent No. or Title (Primary Inventor/Author)	Date of Issuance or Publication
Ex. E-1	WO2014/210334 (“Cox”)	Dec. 31, 2014
Ex. E-2	U.S. Patent Pub. No. 2017/0099200 (“Ellenbogen”)	Apr. 6, 2017 (Filed Oct. 6, 2016)
Ex. E-3	U.S. Pat. Pub. No. 2016/0162456 (“Munro”)	Jun. 9, 2016 (Filed Dec. 9, 2015)
Ex. E-4	U.S. Pat. No. 9,008,416 (“Movellan”)	Apr. 14, 2015 (Filed Feb. 10, 2014)
Ex. E-5	U.S. Pat. Pub. No. 2018/0373980 (“Huval”)	Dec. 27, 2018 (Filed Jun. 27, 2017)
Ex. E-6	Schneemann, “Context-based Detection of Pedestrian Crossing Intention for Autonomous Driving in Urban Environments” (“Schneemann”)	Oct. 2016
Ex. E-7	Furuhashi, “Estimation of Street Crossing Intention from a Pedestrian’s Posture on a Sidewalk Using Multiple Image Frames” (“Furuhashi”)	2011
Ex. E-8	Keller, “Will the Pedestrian Cross? A Study on Pedestrian Path Prediction” (“Keller”)	Apr. 2014
Ex. E-9	U.S. Pat. No. 2017/0238860 (“El”)	Aug. 24, 2017
Ex. E-10	Kohler, “Early Detection of the Pedestrian’s Intention to Cross the Street” (“Kohler”)	Oct. 25, 2012
Ex. E-11	U.S. Pat. No. 8,706,655 (“Rangarajan”)	Apr. 22, 2014
Ex. E-12	Kooij, “Analysis of pedestrian dynamics from a vehicle perspective” (“Kooij”)	Jun. 2014
Ex. E-13	Karasev, “Intent-Aware Long-Term Prediction of Pedestrian Motion” (“Karasev”)	May 2016

Ex. E-14	Schneider, “Pedestrian Path Prediction with Recursive Bayesian Filters: A Comparative Study” (“Schneider”)	2013
Ex. E-15	U.S. Patent No. 9,632,502 (“Levinson”)	Apr. 25, 2017 (Filed Nov. 5, 2015)
Ex. E-16	Quintero, “Pedestrian Path Prediction using Body Language Traits” (“Quintero”)	Jun. 2014
Ex. E-17	Volz, “A data-driven approach for pedestrian intention estimation” 2016 (“Volz 1”)	2016
Ex. E-18	Volz, “Feature Relevance Estimation for Learning Pedestrian Behavior at Crosswalks” (“Volz 2”)	2015
Ex. E-19	Bhattacharyya, “Long-Term On-Board Prediction of People in Traffic Scenes under Uncertainty” (“Bhattacharyya”)	Jun. 20, 2018

The Asserted Claims of the '046 Patent are also invalid under 35 U.S.C. § 102(a) and (b) because the subject matter was known by others, publicly used, and on sale in the United States before it was purportedly invented and more than one year before the priority date of the Asserted Claim. Additionally, the Asserted Claim because any purported invention was made in this country by another who had not abandoned, suppressed, or concealed the purported invention. For example, the foregoing patents and publications are evidence of such prior art systems and inventions. As such, the following systems are prior art under 35 U.S.C. § 102:

Exhibit	System Prior Art
Ex. E-20	Tesla – Autopilot HW1
Ex. E-21	Tesla – Autopilot HW2
Ex. E-22	Waymo
Ex. E-23	iMotions
Ex. E-24	TestMyBrain.com
Ex. E-25	Daimler/ Mercedes
Ex. E-26	Zoox

The accompanying claim charts (Exhibits E-1 through E-26) set forth example bases for anticipation and obviousness, identifying where each reference discloses, alone or in combination with other references, each limitation of the Asserted Claims of the '046 Patent on a limitation-by-limitation basis. Tesla's claim charts are exemplary and not exhaustive.

2. Obviousness Combinations

Subject to Tesla's reservation of rights, Tesla contends that all of the prior art references, as identified above and described in the charts attached as Exhibits E-1 through E-26 by themselves anticipate the Asserted Claims of the '046 Patent in accordance with 35 U.S.C. § 102 and/or render the Asserted Claim of the '046 Patent obvious under 35 U.S.C. § 103, as more specifically noted in the attached charts. The cited portions of the prior art references are examples and representative of the content of the prior art references, and should be understood in the context of the reference as a whole, as understood by one of ordinary skill in the art. To the extent a cited prior art reference is deemed not to anticipate or render obvious a claim as noted in the attached charts for failing to teach or suggest one or more limitations of that claim, that claim would nonetheless have been obvious to one of ordinary skill in the art at the time of the invention by the combination of the cited prior art reference with one or more other prior art references and/or common knowledge disclosing the missing claim limitations. For example, any of the references listed above, to the extent it does not explicitly or inherently disclose any limitation, could be combined with any one or more of the other references listed above which discloses that limitation. Tesla reserves the right to supplement the obviousness arguments using any references listed above, or any references that may become known to Tesla during the course of discovery.

In the table below, Tesla further identifies exemplary combinations of prior art that render the Asserted Claims of the '046 Patent obvious:

Primary Reference	Secondary Reference	Claim
Cox	Huval	3, 10, 17
	Movellan	5, 12, 19
	Schneemann	3, 5, 10, 12, 17, 19
	Furuhashi	3, 10, 17
	Keller	3, 10, 17
	Kohler	3, 10, 17
	Rangarajan	5, 12, 19
	iMotions	5, 12, 19
	Schneider	3, 10, 17
	Quintero	3, 10, 17
	Volz 1	3, 10, 17
	Volz 2	3, 10, 17
	Bhattacharyya	3, 10, 17
	Levinson	3, 10, 17
	Zoox	3, 10, 17
	One or more of Huval, Movellan, Schneemann, Furuhashi, Keller, Kohler, Rangarajan, iMotions, Schneider, Quintero, Volz 1, Volz 2, Bhattacharyya, Levinson, and/or Zoox	3, 5, 10, 12, 17, 19
Test My Brain	Huval	3, 10, 17
	Movellan	5, 12, 19
	Schneemann	3, 5, 10, 12, 17, 19
	Furuhashi	3, 10, 17
	Keller	3, 10, 17
	Kohler	3, 10, 17
	Rangarajan	5, 12, 19
	iMotions	5, 12, 19
	Schneider	3, 10, 17
	Bhattacharyya	3, 10, 17
	Quintero	3, 10, 17
	Volz 1	3, 10, 17
	Volz 2	3, 10, 17
	Levinson	3, 10, 17
	Zoox	3, 10, 17
	One or more of Huval, Movellan, Schneemann, Furuhashi, Keller, Kohler, Rangarajan, iMotions, Schneider, Quintero, Volz 1, Volz 2, Bhattacharyya, Levinson, and/or Zoox	3, 5, 10, 12, 17, 19

Primary Reference	Secondary Reference	Claim
Ellenbogen	Cox	2, 7, 9, 14, 16
	Test My Brain	2, 7, 9, 14, 16
	Huval	3, 10, 17
	Movellan	5, 12, 19
	Schneemann	3, 5, 10, 12, 17, 19
	Kohler	3, 10, 17
	Furuhashi	5, 12, 19
	Rangarajan	3, 10, 17
	Keller	3, 10, 17
	iMotions	5, 12, 19
	Schneider	3, 10, 17
	Bhattacharya	3, 10, 17
	Quintero	3, 10, 17
	Volz 1	3, 10, 17
	Volz 2	3, 10, 17
	Levinson	3, 10, 17
	Zoox	3, 10, 17
	One or more of Cox, Test My Brain, Huval, Movellan, Schneemann, Kohler, Furuhashi, Rangarajan, Keller, iMotions, Schneider, Quintero, Volz 1, Volz 2, Bhattacharyya, Levinson, and/or Zoox	3, 5, 10, 12, 17, 19
Movellan	Cox	1, 2, 6, 7, 8, 9, 13, 14, 15, 16
	Test My Brain	1, 2, 6, 7, 8, 9, 13, 14, 15, 16
	Ellenbogen	1, 6, 8, 13, 15
	Huval	1, 3, 6, 8, 10, 13, 15, 17
	Furuhashi	1, 3, 8, 10, 15, 17
	Schneemann	3, 10, 17
	Munro	1, 8, 15
	Keller	1, 3, 8, 10, 15, 17
	Kohler	2, 3, 9, 10, 17
	El	1, 6, 8, 13, 15
	iMotions	1, 6, 8, 13, 15
	Schneider	3, 10, 17
	Bhattacharyya	1, 3, 8, 10, 15, 17
	Quintero	1, 3, 8, 10, 15, 17
	Volz 1	1, 3, 8, 10, 15, 17
	Volz 2	1, 3, 8, 10, 15, 17
	Levinson	3, 10, 17
	Zoox	3, 10, 17

Primary Reference	Secondary Reference	Claim
	One or more of Cox, Test My Brain, Ellenbogen, Huval, Furuhashi, Schneemann, Munro, Keller, Kohler, El, iMotions, Schneider, Quintero, Volz 1, Volz 2, Bhattacharyya, Levinson, and/or Zoox	1, 2, 3, 6, 7, 8, 9, 10, 13, 14, 15, 16, 17
El	Cox	1, 2, 7, 8, 9, 14, 15, 16
	Test My Brain	1, 2, 7, 8, 9, 14, 15, 16
	Ellenbogen	1, 8, 15
	Munro	1, 8, 15
	Movellan	1, 5, 8, 12, 15, 19
	Huval	3, 10, 17
	Schneemann	1, 3, 5, 8, 10, 12, 15, 17, 19
	Rangarajan	1, 5, 8, 12, 15, 19
	Furuhashi	1, 3, 8, 10, 15, 17
	Keller	3, 10, 17
	Kohler	2, 3, 9, 10, 17
	iMotions	1, 5, 8, 12, 15, 19
	Schneider	3, 10, 17
	Bhattacharyya	3, 10, 17
	Quintero	3, 10, 17
	Volz 1	3, 10, 17
	Volz 2	3, 10, 17
	Levinson	3, 10, 17
	Zoox	3, 10, 17
	One or more of Cox, Test My Brain, Ellenbogen, Munro, Movellan, Huval, Schneemann, Rangarajan, Furuhashi, Keller, Kohler, iMotions, Schneider, Quintero, Volz 1, Volz 2, Bhattacharya, Levinson, and/or Zoox	1, 2, 3, 7, 8, 9, 10, 14, 15, 16, 17, 19
iMotions	Cox	2, 7, 9, 14, 16
	Test My Brain	2, 7, 9, 14, 16
	Huval	3, 10, 17
	Schneemann	3, 10, 17
	Furuhashi	3, 10, 17
	Keller	3, 10, 17
	Kohler	2, 3, 9, 10, 17
	Schneider	3, 10, 17

Primary Reference	Secondary Reference	Claim
	Bhattacharyya	3, 10, 17
	Quintero	3, 10, 17
	Volz 1	3, 10, 17
	Volz 2	3, 10, 17
	Levinson	3, 10, 17
	Zoox	3, 10, 17
	One or more of Cox, Test My Brain, Ellenbogen, Munro, Movellan, Huval, Schneemann, Rangarajan, Furuhashi, Keller, Kohler, iMotions, Schneider, Quintero, Volz 1, Volz 2, Bhattacharyya, Levinson, and/or Zoox	2, 3, 7, 9, 10, 16, 17
Daimler / Mercedes	Cox	1, 2, 7, 8, 9, 14, 15, 16
	Test My Brain	1, 2, 7, 8, 9, 14, 15, 16
	Cox and Test My Brain	1, 2, 7, 8, 9, 14, 15, 16

3. Motivation to Combine and Reasonable Expectation of Success

With respect to the '046 Patent, the prior art identified above demonstrates the scope and content of the prior art. As detailed in Exhibits E-1 through E-26, the prior art included each limitation recited in the Asserted Claims of the '046 Patent. To the extent a cited prior art reference is deemed not to anticipate a claim, the only difference between the claimed invention and the prior art is the lack of actual combination of the elements in a single prior art reference. However, a Person of Ordinary Skill in the Art (“POSITA”) would have been motivated to combine each of the above prior art references.

For example, many of the above identified references (Huval, Schneemann, Furuhashi, Keller, Kohler, Kooij, Karasev, Schneider, Levinson, Autopilot HW1, Autopilot HW2, Bhattacharyya, Zoox, and Waymo) are all related to motor vehicles. These references constitute analogous art within the same field of endeavor—specifically, automotive design and engineering—and address the same or substantially similar technical problems regarding vehicle

operation and subsystem integration. A POSITA would naturally consult these references when seeking to improve vehicle performance or functionality. Here, because Huval, Schneemann, Furuhashi, Keller, Kohler, Kooij, Karasev, Schneider, Levinson, Autopilot HW1, Autopilot HW2, Bhattacharyya, Zoox, and Waymo all reside within the automotive domain, the barrier to combination is exceedingly low. A POSITA would recognize that the teachings of each such reference are compatible with (or could be adapted to be compatible with) other references related to motor vehicles. The combination of these references related to motor vehicles also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar elements to perform their primary functions. And, driven by the perpetual market pressure in the automotive industry to enhance safety, efficiency, and user experience, a POSITA would have been motivated to combine the specific features of each of Huval, Schneemann, Furuhashi, Keller, Kohler, Kooij, Karasev, Schneider, Levinson, Autopilot HW1, Autopilot HW2, Bhattacharyya, Zoox, and Waymo. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of an automobile, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As a further example, many of the above references relate more specifically to autonomous driving (e.g., Huval, Schneemann, Karasev, Levinson, Autopilot HW1, Autopilot HW2, Zoox, and Waymo). These references constitute analogous art within the same field of endeavor—specifically, the development of automated driving systems using sensors—and address the same or substantially similar technical problems regarding object detection, environmental perception, and real-time decision making. A POSITA would naturally consult these references when seeking to improve the reliability or safety of an autonomous driving feature. Here, because Huval,

Schneemann, Karasev, Levinson, Autopilot HW1, Autopilot HW2, Zoox, and Waymo all involve descriptions of autonomous vehicle architectures, the barrier to combination is exceedingly low. For example, a POSITA would recognize that the sensing or control teachings of each such reference are compatible with the processing or navigation modules of other references related to autonomous driving. The combination of references relating to autonomous driving also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar algorithms and hardware to perform their primary functions. And, driven by the industry competition to achieve higher levels of autonomy (e.g., for SAE Levels 3-5) and the necessity to eliminate human error, a POSITA would have been motivated to combine the specific features of each of Huval, Schneemann, Karasev, Levinson, Autopilot HW1, Autopilot HW2, Zoox, and Waymo. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known solutions within the standard constraints of a self-driving platform, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As another example, many of the above identified references (Cox, Ellenbogen, Munro, Movellan, Huval, Schneeman, Furuhashi, Keller, El, Kohler, Rangarajan, Kooij, Karasev, Schneider, Autopilot HW1, Autopilot HW2, Waymo, iMotions, Bhattacharyya, and Test My Brain) are all related to the development and training of machine learning models, including supervised learning techniques. These references constitute analogous art within the same field of endeavor—specifically, artificial intelligence and data annotation—and address the same or substantially similar technical problems regarding model accuracy, ground truth verification, and the reduction of prediction error. A POSITA would naturally consult these references when seeking to improve the performance of a neural network or statistical model through high-quality

supervision. Here, because Cox, Ellenbogen, Munro, Movellan, Huval, Schneeman, Furuhashi, Keller, El, Kohler, Rangarajan, Kooij, Karasev, Schneider, Autopilot HW1, Autopilot HW2, Waymo, iMotions, Bhattacharyya, and Test My Brain all relate to data-driven algorithm development, the barrier to combination is exceedingly low. A POSITA would recognize that the human-labeled datasets or annotation interfaces of each such reference are compatible with (or could be adapted to be compatible with) the training pipelines and loss functions disclosed in other references related to machine learning. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar training loops to perform their primary functions. And, driven by the market pressure in the artificial intelligence industry to maximize inference accuracy and leverage human validation for edge cases, a POSITA would have been motivated to combine the specific features of each of Cox, Ellenbogen, Munro, Movellan, Huval, Schneeman, Furuhashi, Keller, El, Kohler, Rangarajan, Kooij, Karasev, Schneider, Autopilot HW1, Autopilot HW2, Waymo, iMotions, Bhattacharyya, and Test My Brain. Specifically, the use of human-generated ground truth labels to calibrate or refine model weights is a foundational practice in the art, making the aggregation of these teachings a matter of routine optimization. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known supervised learning solutions within the standard constraints of a predictive system, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

As an additional example, many of the above identified references (Cox, Test My Brain, Ellenbogen, Movellan, and iMotions) are all related to techniques and interfaces for generating training data. These references constitute analogous art within the same field of endeavor—

specifically, the creation and management of ground truth datasets for machine learning—and address the same or substantially similar technical problems regarding annotator efficiency, labeling precision, and the workflow for verifying training data. A POSITA would naturally consult these references when seeking to streamline the process of generating high-quality inputs for a model. Here, because Cox, Test My Brain, Ellenbogen, Movellan, and iMotions all reside within the specific domain of human-computer interaction for data entry, the barrier to combination is exceedingly low. A POSITA would recognize that the graphical user interfaces, bounding box tools, or segmentation brushes of each such reference are compatible with (or could be adapted to be compatible with) the data export formats or workflow management systems of other references related to dataset generation. The combination of these references also yields predictable results. Consequently, the integration of these references represents the application of a known technique to a piece of prior art ready for the improvement, utilizing familiar UI elements to perform their primary functions. And, driven by the perpetual market pressure in the machine learning industry to alleviate the data bottleneck in model development and minimize the cost of human supervision, a POSITA would have been motivated to combine the specific features of each of Cox, Test My Brain, Ellenbogen, Movellan, and iMotions. Such combinations represent a common-sense adaptation of existing technology, utilizing ordinary skill and creativity to implement known productivity solutions within the standard constraints of a data pipeline, thereby rendering the asserted claims invalid as obvious under 35 U.S.C. § 103.

Below, Tesla has provided several additional illustrative examples of the motivations that a POSITA would have had to combine certain of the prior art references in Exhibits E-1 through E-26. The inclusion of certain example combinations herein does not exclude other combinations based on the claim charts attached hereto, as there are many possible combinations of the

references listed herein, and it is not practical, particularly at this early stage prior to further factual investigation and claim construction proceedings, to identify and list all potentially relevant combinations. Instead, in many instances where a particular contention calls for, or requires, combining references, any one of a number of references can be combined. As such, these motivations to combine apply equally to the combination of a primary reference to one secondary reference, and the combination of a primary reference to multiple secondary references.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Huval

A POSITA would have been motivated to apply Huval's vehicle and pedestrian detection techniques to Cox's (and/or Test My Brain's) model to "detect and characterize dynamic objects," such as a pedestrian, based on a predicted state of mind. Huval at [0018]. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Movellan

Movellan describes asking observers to provide labels of training images based on how well the person in the image has replicated a certain emotion, such as "1. Looks nothing like it; 2. A poor attempt; 3. OK; 4. A pretty good attempt; 5. Incredibly good mimicking." Movellan at 7:10-14. A POSITA would have been motivated to combine such a rating system to label training data to train Cox's (and/or Test My Brain's) deep learning model scaled-based ratings would provide more robust training data.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Furuhashi

A POSITA would have been motivated to apply Furuhashi's pedestrian crossing prediction techniques to Cox's (and/or Test My Brain's) predictive model. Furuhashi at 18-19. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Keller

A POSITA would have been motivated to apply Keller's pedestrian crossing prediction techniques to Cox's (and/or Test My Brain's) predictive model. Keller at 494. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Schneemann

A POSITA would have been motivated to apply Schneemann's pedestrian crossing prediction techniques to Cox's (and/or Test My Brain's) predictive model. Schneemann at 2243. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities. Further a POSITA would have been motivated to adopt Schneemann's rating system in order to "allow the human observer to express possible uncertainties" and generate more robust training data. Schneemann at 2246.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Kohler

A POSITA would have been motivated to apply Kohler's pedestrian crossing prediction techniques to Cox's (and/or Test My Brain's) predictive model. Kohler at 4, Fig. 6. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Rangarajan

Rangarajan describes asking observers to provide labels of training images such as "3 out of 4, or 4 out of 5." Rangarajan at 7:33-7:49. A POSITA would have been motivated to combine such a rating system to label training data to train Cox's (and/or Test My Brain's) deep learning model scaled-based ratings would provide more robust training data.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with iMotions

On information and belief, iMotions teaches a POSITA to ask observers to provide labels of training images based on how well the person in the image has replicated a certain emotion, such as “1. Looks nothing like it; 2. A poor attempt; 3. OK; 4. A pretty good attempt; 5. Incredibly good mimicking.” A POSITA would have been motivated to combine such a rating system to label training data to train Cox’s (and/or Test My Brain’s) deep learning model scaled-based ratings would provide more robust training data.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Schneider

A POSITA would have been motivated to apply Schneider’s pedestrian crossing prediction techniques to Cox’s (and/or Test My Brain’s) predictive model. Schneider at 174. A POSITA would have found this to be an obvious way to expand Cox’s (and/or Test My Brain’s) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya’s pedestrian crossing prediction techniques to Cox’s (and/or Test My Brain’s) predictive model. Bhattacharyya at 1. A POSITA would have found this to be an obvious way to expand Cox’s (and/or Test My Brain’s) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Quintero

A POSITA would have been motivated to apply Quintero’s pedestrian crossing prediction techniques to Cox’s (and/or Test My Brain’s) predictive model. Quintero at Abstract, 318. A POSITA would have found this to be an obvious way to expand Cox’s (and/or Test My Brain’s) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Volz 1

A POSITA would have been motivated to apply Volz 1's pedestrian crossing prediction techniques to Cox's (and/or Test My Brain's) predictive model. Volz 1 at Abstract. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Volz 2

A POSITA would have been motivated to apply Volz 2's pedestrian crossing prediction techniques to Cox's (and/or Test My Brain's) predictive model. Volz 2 at 855. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities.

Exemplary Motivations to Combine Cox (and/or Test My Brain) with Levinson (or Zoox)

A POSITA would have been motivated to apply the dynamic object classification and tracking techniques of Levinson (or Zoox) to Cox's (and/or Test My Brain's) predictive model. Levinson at 11:61-12:12. A POSITA would have found this to be an obvious way to expand Cox's (and/or Test My Brain's) predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Cox (and/or Test My Brain)

A POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) techniques of generating "psychometric data" that summarizes how human annotators annotate training images to generate a more robust training dataset to train a model that better mimics human decisions. Cox at [0018]-[0020]. It would have been obvious to include such psychometric data in Ellenbogen's model improve the accuracy of predictions. Further, a POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) technique of degrading stimulus images before presenting them to human observers for labeling. Cox at [0014], [0064]. A POSITA would have

found it obvious that using degraded training images would provide better training data to train model to make accurate predictions with lower quality sensor data.

Exemplary Motivations to Combine Ellenbogen with Huval

A POSITA would have been motivated to apply Huval's vehicle and pedestrian detection techniques to Ellenbogen's model to "detect and characterize dynamic objects," such as a pedestrian, based on a predicted state of mind. Huval at [0018]. A POSITA would have found this to be an obvious way to expand Ellenbogen's predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Movellan

Movellan describes asking observers to provide labels of training images based on how well the person in the image has replicated a certain emotion, such as "1. Looks nothing like it; 2. A poor attempt; 3. OK; 4. A pretty good attempt; 5. Incredibly good mimicking." Movellan at 7:10-14. A POSITA would have been motivated to combine such a rating system to label training data to train Ellenbogen's deep learning model scaled-based ratings would provide more robust training data.

Exemplary Motivations to Combine Ellenbogen with Schneemann

A POSITA would have been motivated to apply Schneemann's pedestrian crossing prediction techniques to Ellenbogen's predictive model. Schneemann at 2243. A POSITA would have found this to be an obvious way to expand Ellenbogen's predictive capabilities. Further a POSITA would have been motivated to adopt Schneemann's rating system in order to "allow the human observer to express possible uncertainties" and generate more robust training data. Schneemann at 2246.

Exemplary Motivations to Combine Ellenbogen with Kohler

A POSITA would have been motivated to adopt Kohler’s technique of removing shadows to adjust the quality of training data to mimic indoor and outdoor scenes, and it would have been obvious to a POSITA that using training data in different environments would improve the outputs of a predictive model. Kohler at 2. Further, a POSITA would have been motivated to apply Kohler’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Kohler at 4, Fig. 6. A POSITA would have found this to be an obvious way to expand Ellenbogen’s predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Furuhashi

A POSITA would have been motivated to apply Furuhashi’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Furuhashi at 18-19. A POSITA would have found this to be an obvious way to expand Ellenbogen’s predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Rangarajan

Rangarajan describes asking observers to provide labels of training images such as “3 out of 4, or 4 out of 5.” Rangarajan at 7:33-7:49. A POSITA would have been motivated to combine such a rating system to label training data to train Ellenbogen’s deep learning model scaled-based ratings would provide more robust training data.

Exemplary Motivations to Combine Ellenbogen with Keller

A POSITA would have been motivated to apply Keller’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Keller at 494. A POSITA would have found this to be an obvious way to expand Ellenbogen’s predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with iMotions

On information and belief, iMotions teaches asking observers to provide labels of training images based on how well the person in the image has replicated a certain emotion, such as “1.

Looks nothing like it; 2. A poor attempt; 3. OK; 4. A pretty good attempt; 5. Incredibly good mimicking.” A POSITA would have been motivated to combine such a rating system to label training data to train Ellenbogen’s deep learning model scaled-based ratings would provide more robust training data.

Exemplary Motivations to Combine Ellenbogen with Schneider

A POSITA would have been motivated to apply Schneider’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Schneider at 174. A POSITA would have found this to be an obvious way to expand Ellenbogen’s predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Bhattacharyya at 1. A POSITA would have found this to be an obvious way to expand Ellenbogen predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Quintero

A POSITA would have been motivated to apply Quintero’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Quintero at Abstract, 318. A POSITA would have found this to be an obvious way to expand Ellenbogen’s predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Volz 1

A POSITA would have been motivated to apply Volz 1’s pedestrian crossing prediction techniques to Ellenbogen’s predictive model. Volz 1 at Abstract. A POSITA would have found this to be an obvious way to expand Ellenbogen’s predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Volz 2

A POSITA would have been motivated to apply Volz 2's pedestrian crossing prediction techniques to Ellenbogen's predictive model. Volz 2 at 855. A POSITA would have found this to be an obvious way to expand Ellenbogen's predictive capabilities.

Exemplary Motivations to Combine Ellenbogen with Levinson (or Zoox)

A POSITA would have been motivated to apply the dynamic object classification and tracking techniques of Levinson (or Zoox) to Ellenbogen's predictive model. Levinson at 11:61-12:12. A POSITA would have found this to be an obvious way to expand Ellenbogen's predictive capabilities.

Exemplary Motivations to Combine Movellan with Cox (and/or Test My Brain)

A POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) techniques of generating "psychometric data" that summarizes how human annotators annotate training images to generate a more robust training dataset to train a model that better mimics human decisions. Cox at [0018]-[0020]. It would have been obvious to include such psychometric data in Movellan's model to improve the accuracy of predictions. Further, a POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) technique of degrading stimulus images before presenting them to human observers for labeling. Cox at [0014], [0064]. A POSITA would have found it obvious that using degraded training images would provide better training data to train model to make accurate predictions with lower quality sensor data. Moreover, Cox (and/or Test My Brain) discloses that its model may be any form of supervised learning, including neural networks and random forests, and it would have been obvious to a POSITA to implement Movellan's prediction model as one of these forms of supervised learning models to increase model accuracy and efficiency. Cox at [0060].

Exemplary Motivations to Combine Movellan with Ellenbogen

Ellenbogen describes receiving labels and associated confidence measures when generating training data from human annotators to train its model to determine a confidence measure of its output. Ellenbogen at [0135]. A POSITA would have been motivated to apply this technique to Movellan so that its predictions better mimic the decisions of humans. Moreover, Ellenbogen discloses that its model may be any form of supervised learning, including convolutional neural networks, and it would have been obvious to a POSITA to implement Movellan's prediction model as one of these forms of supervised learning models to increase model accuracy and efficiency. Ellenbogen at [0136].

Exemplary Motivations to Combine Movellan with Huval

Huval describes human labelers confirming or correcting automatically generated labels and retraining its model using the updated labels to improve the accuracy of its road object detection and tracking system. It would have been obvious to a POSITA to apply this technique of reviewing automatically generated labels to improve Movellan's predictive model. Moreover, Huval discloses that its model may be a neural networks, and it would have been obvious to a POSITA to implement Movellan's prediction model as one of these forms of supervised learning models to increase model accuracy and efficiency. Huval at [0010].

Exemplary Motivations to Combine Movellan with Furuhashi

A POSITA would have been motivated to apply Furuhashi's pedestrian crossing prediction techniques to Movellan's predictive model. Furuhashi at 18-19. A POSITA would have found this to be an obvious way to expand Ellenbogen's predictive capabilities.

Exemplary Motivations to Combine Movellan with Schneemann

A POSITA would have been motivated to apply Schneemann's pedestrian crossing prediction techniques to Movellan's predictive model. Schneemann at 2243. A POSITA would

have found this to be an obvious way to expand Movellan's predictive capabilities. Further a POSITA would have been motivated to adopt Schneemann's rating system in order to "allow the human observer to express possible uncertainties" and generate more robust training data. Schneemann at 2246.

Exemplary Motivations to Combine Movellan with Munro

A POSITA would have been motivated to apply Munro's data organization techniques to Movellan's training data. Munro simply provides implementation details specifying how Movellan's annotator responses are formed, stored, and used for training, teaching that it would have included tallies of the number of annotators who classified a behavior or activity in an image as having various labels in their responses. Munro at [0132-0142].

Exemplary Motivations to Combine Movellan with Keller

A POSITA would have been motivated to apply Keller's pedestrian crossing prediction techniques to Movellan's predictive model. Keller at 494. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine Movellan with Kohler

A POSITA would have been motivated to adopt Kohler's technique of removing shadows to adjust the quality of training data to mimic indoor and outdoor scenes, and it would have been obvious to a POSITA that using training data in different environments would improve the outputs of a predictive model. Kohler at 2. Further, a POSITA would have been motivated to apply Kohler's pedestrian crossing prediction techniques to Movellan's predictive model. Kohler at 4, Fig. 6. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine Movellan with El

El describes generating histograms for training images including feature descriptors for areas of interest in the training images to generate more robust training data. El at [0096]. A POSITA would have been motivated to apply this technique to Movellan so that its predictions are more accurate. Moreover, El discloses that its model may a “random forests that use multiple learning algorithms to obtain better predictive performance,” and it would have been obvious to a POSITA to implement Movellan’s prediction model as one of these forms of supervised learning models to increase model accuracy and efficiency. El at [0078].

Exemplary Motivations to Combine Movellan with iMotions

The iMotions System discloses that the training image databases “contain statistics and normative distributions of all feature characteristics across respondents.” Ex. E-23 at elements 1[b-iii], 1[c]. It would have been obvious to a POSITA to apply such statistics to the training of Movellan to improve the predictive model’s accuracy and ensure it better mimics human decisions. Moreover, iMotions discloses that its model may use machine learning models such as neural networks, and it would have been obvious to a POSITA to implement Movellan’s prediction model as one of these forms of supervised learning models to increase model accuracy and efficiency. Ex. E-23 at elements 1[b-iii], 1[c].

Exemplary Motivations to Combine Movellan with Schneider

A POSITA would have been motivated to apply Schneider’s pedestrian crossing prediction techniques to Movellan’s predictive model. Schneider at 174. A POSITA would have found this to be an obvious way to expand Movellan’s predictive capabilities.

Exemplary Motivations to Combine Movellan with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's pedestrian crossing prediction techniques to Movellan's predictive model. Bhattacharyya at 1. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine Movellan with Quintero

A POSITA would have been motivated to apply Quintero's pedestrian crossing prediction techniques to Movellan's predictive model. Quintero at Abstract, 318. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine Movellan with Volz 1

A POSITA would have been motivated to apply Volz 1's pedestrian crossing prediction techniques to Movellan's predictive model. Volz 1 at Abstract. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine Movellan with Volz 2

A POSITA would have been motivated to apply Volz 2's pedestrian crossing prediction techniques to Movellan's predictive model. Volz 2 at 855. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine Movellan with Levinson (or Zoox)

A POSITA would have been motivated to apply the dynamic object classification and tracking techniques of Levinson (or Zoox) to Movellan's predictive model. Levinson at 11:61-12:12. A POSITA would have found this to be an obvious way to expand Movellan's predictive capabilities.

Exemplary Motivations to Combine El with Cox (and/or Test My Brain)

El describes human labelers labeling sample images and using those images to train a model to automatically code facial data from new image or video data. A POSITA would have

been motivated to apply Cox's (and/or Test My Brain's) techniques for collecting training data, including collecting psychometric data of human labelers, to El's system to facilitate the generation and storage of training data. Further, a POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) technique of degrading stimulus images before presenting them to human observers for labeling. Cox at [0014], [0064]. A POSITA would have found it obvious that using degraded training images would provide better training data to train model to make accurate predictions with lower quality sensor data.

Exemplary Motivations to Combine El with Ellenbogen

El describes human labelers labeling sample images and using those images to train a model to automatically code facial data from new image or video data. A POSITA would have been motivated to apply Ellenbogen's techniques for collecting training data, including collecting confidence measures of human labelers, to El's system to facilitate the generation and storage of training data. Ellenbogen at [0135].

Exemplary Motivations to Combine El with Munro

El describes human labelers labeling sample images and using those images to train a model to automatically code facial data from new image or video data. A POSITA would have found it obvious that training images need to be collected and stored and would have been motivated to do it using the techniques of Munro. Munro at [0061].

Exemplary Motivations to Combine El with Movellan

El describes human labelers labeling sample images and using those images to train a model to automatically code facial data from new image or video data. A POSITA would have been motivated to apply Movellan's techniques for collecting training data to El's system to facilitate the generation and storage of training data, such as sending training images to user

machines, asking a question regarding the image, and receiving ratings on a scale from 1-5. Movellan at 6:55-7:13.

Exemplary Motivations to Combine El with Huval

A POSITA would have been motivated to apply Huval's vehicle and pedestrian detection techniques to El's model to "detect and characterize dynamic objects," such as a pedestrian, based on a predicted state of mind. Huval at [0018]. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Schneemann

A POSITA would have been motivated to apply Schneemann's pedestrian crossing prediction techniques to El's predictive model. Schneemann at 2243. A POSITA would have found this to be an obvious way to expand El's predictive capabilities. Further a POSITA would have been motivated to adopt Schneemann's label collection and rating system in order to "allow the human observer to express possible uncertainties" and generate more robust training data. Schneemann at 2246.

Exemplary Motivations to Combine El with Rangarajan

Rangarajan describes asking observers to provide labels of training images such as "3 out of 4, or 4 out of 5." Rangarajan at 7:7-7:58. A POSITA would have been motivated to combine such a rating system to label and store training data to train Cox's (and/or Test My Brain's) deep learning model scaled-based ratings would provide more robust training data. *Id.*

Exemplary Motivations to Combine El with Furuhashi

El describes human labelers labeling sample images and using those images to train a model to automatically code facial data from new image or video data. A POSITA would have been motivated to apply Furuhashi's techniques for collecting training data to El's system to

facilitate the generation and storage of training data. Further, a POSITA would have been motivated to apply Furuhashi's pedestrian crossing prediction techniques to El's predictive model. Furuhashi at 18-19. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Keller

A POSITA would have been motivated to apply Keller's pedestrian crossing prediction techniques to El's predictive model. Keller at 494. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Kohler

A POSITA would have been motivated to adopt Kohler's technique of removing shadows to adjust the quality of training data to mimic indoor and outdoor scenes, and it would have been obvious to a POSITA that using training data in different environments would improve the outputs of a predictive model. Kohler at 2. Further, a POSITA would have been motivated to apply Keller's pedestrian crossing prediction techniques to El's predictive model. Keller at 494. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with iMotions

El describes human labelers labeling sample images and using those images to train a model to automatically code facial data from new image or video data. A POSITA would have been motivated to apply El's techniques for collecting training data to El's system to facilitate the generation and storage of training data, such as sending training images to user machines, asking a question regarding the image, and receiving ratings on a scale from 1-5. Ex. E-23 at claim 5.

Exemplary Motivations to Combine El with Schneider

A POSITA would have been motivated to apply Schneider's pedestrian crossing prediction techniques to El's predictive model. Schneider at 174. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's pedestrian crossing prediction techniques to El's predictive model. Bhattacharyya at 1. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Quintero

A POSITA would have been motivated to apply Quintero's pedestrian crossing prediction techniques to El's predictive model. Quintero at Abstract, 318. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Volz 1

A POSITA would have been motivated to apply Volz 1's pedestrian crossing prediction techniques to El's predictive model. Volz 1 at Abstract. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Volz 2

A POSITA would have been motivated to apply Volz 2's pedestrian crossing prediction techniques to El's predictive model. Volz 2 at 855. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine El with Levinson (or Zoox)

A POSITA would have been motivated to apply the dynamic object classification and tracking techniques of Levinson (or Zoox) to El's predictive model. Levinson at 11:61-12:12. A POSITA would have found this to be an obvious way to expand El's predictive capabilities.

Exemplary Motivations to Combine iMotion with Cox (and/or Test My Brain)

A POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) techniques of generating "psychometric data" that summarizes how human annotators annotate training images to generate a more robust training dataset to train a model that better mimics human decisions. Cox at [0018]-[0020]. It would have been obvious to include such psychometric data in iMotions' model improve the accuracy of predictions. Further, a POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) technique of degrading stimulus images before presenting them to human observers for labeling. Cox at [0014], [0064]. A POSITA would have found it obvious that using degraded training images would provide better training data to train model to make accurate predictions with lower quality sensor data.

Exemplary Motivations to Combine iMotion with Huval

A POSITA would have been motivated to apply Huval's vehicle and pedestrian detection techniques to iMotions' model to "detect and characterize dynamic objects," such as a pedestrian, based on a predicted state of mind. Huval at [0018]. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities

Exemplary Motivations to Combine iMotion with Schneemann

A POSITA would have been motivated to apply Schneemann's pedestrian crossing prediction techniques to iMotions' predictive model. Schneemann at 2243. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotion with Furuhashi

A POSITA would have been motivated to apply Furuhashi's pedestrian crossing prediction techniques to iMotions' predictive model. Furuhashi at 18-19. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities

Exemplary Motivations to Combine iMotion with Keller

A POSITA would have been motivated to apply Keller's pedestrian crossing prediction techniques to iMotions' predictive model. Keller at 494. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotion with Kohler

A POSITA would have been motivated to adopt Kohler's technique of removing shadows to adjust the quality of training data to mimic indoor and outdoor scenes, and it would have been obvious to a POSITA that using training data in different environments would improve the outputs of a predictive model. Kohler at 2. Further, a POSITA would have been motivated to apply Kohler's pedestrian crossing prediction techniques to iMotions' predictive model. Kohler at 4, Fig. 6. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotions with Schneider

A POSITA would have been motivated to apply Schneider's pedestrian crossing prediction techniques to iMotions' predictive model. Schneider at 174. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotions with Bhattacharyya

A POSITA would have been motivated to apply Bhattacharyya's pedestrian crossing prediction techniques to iMotions' predictive model. Bhattacharyya at 1. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotions with Quintero

A POSITA would have been motivated to apply Quintero's pedestrian crossing prediction techniques to iMotions' predictive model. Quintero at Abstract, 318. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotions with Volz 1

A POSITA would have been motivated to apply Volz 1's pedestrian crossing prediction techniques to iMotions' predictive model. Volz 1 at Abstract. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotions with Volz 2

A POSITA would have been motivated to apply Volz 2's pedestrian crossing prediction techniques to iMotions' predictive model. Volz 2 at 855. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine iMotions with Levinson (and/or Zoox)

A POSITA would have been motivated to apply the dynamic object classification and tracking techniques of Levinson/Zoox to iMotions' predictive model. Levinson at 11:61-12:12. A POSITA would have found this to be an obvious way to expand iMotions' predictive capabilities.

Exemplary Motivations to Combine Daimler / Mercedes with Cox (and/or Test My Brain)

A POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) techniques of generating "psychometric data" that summarizes how human annotators annotate training images to generate a more robust training dataset to train a model that better mimics human decisions. Cox at [0018]-[0020]. It would have been obvious to include such psychometric data in iMotions' model improve the accuracy of predictions. Further, a POSITA would have been motivated to adopt Cox's (and/or Test My Brain's) technique of degrading stimulus images before

presenting them to human observers for labeling. Cox at [0014], [0064]. A POSITA would have found it obvious that using degraded training images would provide better training data to train model to make accurate predictions with lower quality sensor data.

III. PATENTABLE SUBJECT MATTER

Tesla further asserts that certain of the Asserted Patents are ineligible for patent protection under 35 U.S.C. § 101. Tesla incorporates by reference its arguments regarding Subject Matter Eligibility in its Motion to Dismiss. ECF 30.

To be patentable subject matter under § 101, a claim must be directed to one of four eligible subject matter categories: “new and useful process, machine, manufacture, or composition of matter.” 35 U.S.C. § 101. “Claims that fall within one of the four subject matter categories may nevertheless be ineligible if they encompass laws of nature, physical phenomena, or abstract ideas.” *Digitech Image Techs., LLC v. Elecs. for Imaging, Inc.*, 758 F.3d 1344, 1350 (Fed. Cir. 2014) (citing *Diamond v. Chakrabarty*, 447 U.S. 303, 309 (1980)). The Supreme Court established a two-step test for deciding the subject matter eligibility of claims under § 101. *Alice Corp. Pty. Ltd. v. CLS Bank Int’l*, 134 S. Ct. 2347, 2355 (2014). First, the claims must be analyzed to determine whether they are drawn to one of the statutory exceptions. *Id.* Second, the elements of the claims must be viewed both individually and as an ordered combination to see if there is an “inventive concept.” *Id.* The mere fact that a claim recites or implies that an abstract idea is implemented using a general-purpose computer does not supply an inventive concept necessary to satisfy § 101. *See Elec. Power Grp., LLC v. Alstom S.A.*, 830 F.3d 1350, 1355 (Fed. Cir. 2016); *Alice*, 134 S. Ct. at 2357-59.

Based on Tesla’s investigation to date and currently-available information, the following patents are ineligible for patent protection.

A. The '344 Patent

The Asserted Claims of the '344 Patent are directed to ineligible subject matter under 35 U.S.C. § 101. More specifically the claims are directed to the abstract idea of using a machine learning model to drive a car. Moreover, the claims of the '344 Patent do nothing more than computerize the steps that every human driver has always performed: looking at a road, judging what other cars will do next, and driving accordingly. The claims include nothing more than functional, result-oriented steps (receiving data, providing data to model, executing model, controlling vehicle) on generic hardware. In this way, these “claims [] do no more than apply established methods of machine learning to a new data environment” (*e.g.*, to driving) and are therefore patent ineligible under Section 101. *Recentive Analytics, Inc. v. Fox Corp.*, 134 F.4th 1205, 1211 (Fed. Cir. 2025).

The chart below further illustrates how each element of Claim 1 corresponds to routine human activity. For purposes of Section 101 subject matter eligibility only, Claim 1 is representative of all claims of the '344 Patent.

Claim Limitation ('344 Patent – Claim 1)	Human Activity
[1.pre] A computer-implemented method comprising:	N/A
[1.a] receiving , by a computing device associated with an autonomous vehicle operating on a road, sensor data captured by a sensor installed on the autonomous vehicle, the sensor data displaying an object on the road;	Driver sees object on the road.
[1.b] providing the sensor data as input to a supervised learning based model , the supervised learning based model configured to receive an input sensor data displaying a particular object on a road and predicting an output statistical summary characterizing a distribution of user responses expected to be received responsive to presenting the sensor data to a plurality of users, the user responses associated with the particular object;	Driver interprets what is seen.

[1.c] executing the trained supervised learning based model to generate a statistical summary data characterizing a distribution of user responses expected to be received responsive to presenting the sensor data captured by the sensor installed on the autonomous vehicle to users; and	Driver predicts what object will do.
[1.d] controlling the operation of the autonomous vehicle on the road based on the generated statistical summary data.	Driver steers car based on prediction.

To the extent Claim 1 is not treated as representative of the dependent claims, no dependent claims in the '344 Patent materially impact the Section 101 analysis. Dependent claims 2 and 11 require that the recited model be one of a number of known types of models (e.g., a “simple neural network”). '344 Patent at 6:42-56 (listing, without further explanation, examples of supervised learning algorithms, including “any other supervised learning algorithm” capable of performing certain tasks); 11:37-44 (The algorithm may be any type of supervised learning algorithm capable of predicting a continuous label for a two or three dimensional input...). Claims 3 and 12 narrow the “object” on the road to some of the most common types of objects on the road, such as a motor vehicle. Claims 4 and 13 limit the content of the user response to “describe an action associated with the object,” but the content of the user response is printed matter with no relation to the substrate for the response. Claims 5, 6, 14 and 15 each further define the output of the model with a “parameter,” but the output of the model is printed matter. Similarly, the remaining dependent claims (7-9, 16-18, and 20-22) each describe additional predictions that the model may output, which again are printed matter, and reflect generic driving decisions such as identifying another driver’s state of mind, intention, or awareness.

Each element of the asserted claims is also conventional and well-understood in the prior art, as indicated in Exhibits A-1 through A-27.

Lastly, at least the following claim elements recite patent ineligible printed matter:

- 1[a], 10[a], 19[a] – “the sensor data displaying an object on the road”
- 1[b], 10[b], 19[b] – “input sensor data displaying a particular object on a road”
- 1[b], 10[b], 19[b] – “statistical summary characterizing a distribution of user responses expected to be received responsive to presenting the sensor data to a plurality of users”
- 1[c], 10[c], 19[c] – “statistical summary data characterizing a distribution of user responses expected to be received responsive to presenting the sensor data captured by the sensor installed on the autonomous vehicle to users”
- 4, 13 – “the user responses describe an action associated with the object, the action including one of the object staying in place, changing lanes, or crossing a street”
- 5, 14 – “the parameter including at least one of a content of a response, a time associated with entering a response, and a position of an eye of a human observer associated with the response, the position being measured with respect to a display associated with the user interface”
- 6, 15 – “the parameter is further associated with at least one of a central tendency, a variance, a skew, a kurtosis, a scale, and a histogram”
- 7, 16, 20 – “user responses describing a state of mind of a road user associated with the object”
- 8, 17, 21 – “user responses describing an intention of the road user to move into the path of the autonomous vehicle”
- 9, 18, 22 – “user responses describing awareness of the road user of the autonomous vehicle”

B. The '889 Patent

The Asserted Claims of the '889 Patent are directed to ineligible subject matter under 35 U.S.C. § 101. More specifically the claims are directed to the abstract idea of training and using a machine learning model to drive a car. Moreover, the claims of the '889 Patent do nothing more than computerize the steps that every human driver has always performed: learning to drive, looking at a road, judging what other cars will do next, and driving accordingly. The claims include nothing more than functional, result-oriented steps (receiving data, training a model with the data, executing model, controlling vehicle) on generic hardware. In this way, these “claims [] do no more than apply established methods of machine learning to a new data environment” (*e.g.*, to driving) and are therefore patent ineligible under Section 101. *Recentive*, 134 F.4th at 1211.

The chart below further illustrates how each element of Claim 2 corresponds to routine human activity. For purposes of Section 101 subject matter eligibility only, Claim 2 is representative of all claims of the '889 Patent.

Claim Limitation ('889 Patent - Claim 2)	Human Activity
[2.pre] A computer-implemented method for controlling an autonomous vehicle based on a predicted state of mind of road users in a scene captured by a camera of the autonomous vehicle, the method comprising:	N/A
[2.a] receiving a plurality of images displaying road scenes captured by one or more vehicles;	Driver receives driving examples.
[2.b] receiving a plurality of user responses , each user response describing a state of mind of a road user displayed in one or more images;	Driver receives descriptions of drivers in examples.
[2.c] generating a training dataset comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images;	Driver makes summary of what drivers do in examples.
[2.d] training , using the training dataset, a supervised learning based model configured to predict summary statistics describing a state of mind of a road user displayed in an input image;	Driver learns from summary.

[2.e] receiving , by an autonomous vehicle, a new image captured by a camera of the autonomous vehicle, the new image of a scene including a road user;	Driver drives and sees new driver on road.
[2.f] predicting , by the autonomous vehicle, using the supervised learning based model, summary statistics describing a state of mind of the road user in the new image; and	Driver predicts what new driver will do.
[2.g] controlling the autonomous vehicle based on the prediction of the supervised learning based model.	Driver steers based on prediction.

To the extent Claim 2 is not treated as representative of the dependent claims, no dependent claims in the '889 Patent materially impact the Section 101 analysis. Claims 3, 4, 13, and 14 describe the “road user” as a pedestrian or cyclist, and they further claim the road user’s predicted state of mind, which is both an abstract idea and printed matter. Claims 5 and 15 specify that the output printed matter (“summary statistics”) should be one of a number of known data groups, such as a histogram. *See* '889 Patent at 6:8-43 (providing no further explanation for how to generate summary statistics other than listing the names of statistical methods, implying the models were well known). Claims 6-10 and 16-20 all relate to collecting user responses to driving scenarios, which student drivers have done for years to prepare for driving exams. And claim 11 requires that the recited model be one of a number of known types of models (e.g., a “simple neural network”). *Id.* at 6:49-63 (providing a list of names of models, without further explanation); 11:42-49 (“The algorithm may be any type of supervised learning algorithm capable of predicting a continuous label...including but not limited to...”).

Each element of the asserted claims is also conventional and well-understood in the prior art, as indicated in Exhibits B-1 through B-28.

Lastly, the following claim elements recite patent ineligible printed matter:

- 1[Pre], 2[Pre], 12[Pre] – “a predicted state of mind of road users in a scene captured by a camera of the autonomous vehicle”

- 1[a], 2[a], 12[a] – “a plurality of images displaying road scenes”
- 1[b], 2[b], 12[b] – “a plurality of user responses, each user response describing a state of mind of a road user displayed in the one or more images”
- 1[c], 2[c], 12[c] – “summary statistics of user responses describing the state of minds of road users displayed in the plurality of images”
- 1[d], 2[d], 12[d] – “training dataset” and “summary statistics describing a state of mind of a road user displayed in an input image”
- 1[e], 2[e], 12[e] – “a new image of a scene including a road user”
- 1[f], 2[f], 12[f] – “summary statistics describing a state of mind of the road user in the new image”
- 3, 13 – “the road user in the input image [being] a pedestrian” and “the state of mind predicted by the supervised learning based model indicates whether the pedestrian is likely to perform an action, the action including one of: staying in place, or crossing a street”
- 4, 14 – “the road user in the input image [being] a cyclist” and “the state of mind predicted by the supervised learning based model indicates whether the cyclist is likely to cross a lane”
- 5, 15 – “the summary statistics comprises one or more of: a central tendency, a variance, a skew, a kurtosis, a scale, or a histogram”
- 6, 16 – “images including a road user” and “the user interface is configured to prompt the viewer to describe how the road user will act”
- 7, 17 – “stimulus comprising a set of images” and “user response describing the stimulus”

- 8, 18 – “subset of the image contained in a bounding box around the road user displayed in the image”
- 10, 20 – “an explicit response to a question asked via a user interface” and “an implicit data representing ... time taken to respond”

C. The '579 Patent

The Asserted Claims of the '579 Patent are directed to ineligible subject matter under 35 U.S.C. § 101. More specifically the claims are directed to the abstract idea of training and using a machine learning model to drive a car. Moreover, the claims of the '579 Patent do nothing more than computerize the steps that every human driver has always performed: learning to drive, looking at a road, judging what other cars will do next, and driving accordingly. The claims include nothing more than functional, result-oriented steps (receiving data, training a model with the data, executing model, controlling vehicle) on generic hardware. In this way, these “claims [] do no more than apply established methods of machine learning to a new data environment” (*e.g.*, to driving) and are therefore patent ineligible under Section 101. *Recentive*, 134 F.4th at 1211.

The chart below further illustrates how each element of Claim 1 corresponds to routine human activity. For purposes of Section 101 subject matter eligibility only, Claim 1 is representative of all claims of the '579 Patent.

Claim Limitation ('579 Patent - Claim 1)	Human Activity
[1.pre] A method for navigating autonomous vehicles, comprising:	N/A
[1.a] training a probabilistic neural network , the probabilistic neural network configured to perform steps comprising:	Driver learns how to drive
[1.a.1] receiving as input, an image of traffic , the image displaying a traffic entity belonging to the traffic,	Driver learns how to see traffic

[1.a.2] generating a feature vector for a plurality of features, the feature vector comprising values describing statistical distribution for each feature, and	Driver learns how to identify features of traffic
[1.a.3] generating output representing hidden context for the traffic entity, the output comprising a plurality of values, each value representing a likelihood of receiving a particular user response from a user presented with the image;	Driver learns how to identify what cars in traffic might do
[1.b] receiving a new image captured by a camera mounted on an autonomous vehicle navigating through traffic;	Driver sees road with traffic
[1.c] executing the probabilistic neural network to generate output representing hidden context for at least a traffic entity displayed in the new image;	Driver predicts what car in traffic will do
[1.d] determining a measure of uncertainty for each of the plurality of values; and	Driver decides how confident they are in prediction
[1.e] navigating the autonomous vehicle to avoid the traffic entity displayed in the new image, the navigation based on at least the measure of uncertainty generated by the probabilistic neural network.	Driver steers to avoid collision, based on prediction and confidence

To the extent Claim 1 is not treated as representative of the dependent claims, no dependent claims in the '579 Patent materially impact the Section 101 analysis. Claims 2 and 14 restrict the content of “values describing statistical distribution,” but the content of these “values” are printed matter. Claims 3 and 15 recite additional steps for the “training” based on two “pluralit[ies] of values,” but training a model is abstract under *Recentive*, and the content used to train the model is also printed matter. Similarly, claims 4 and 16 recite additional steps for “determining the measure of uncertainty” using “a plurality of samples” and “a confidence interval” for values, but this mathematical analysis is itself an abstract idea, and the underlying data used in the analysis is printed matter. Claims 5, 6, 17, and 18 recite a step of basic driving safety (maintaining a “threshold distance” away from other cars), based on printed matter (“the measure of uncertainty”). Claims 7-10 only restrict what the “hidden context” must represent — such as a “state of mind” or “awareness” of another driver — which is both an abstract idea and printed matter. Claims 11 and

19 add a trivial post-solution step of generating signals to control the car based on the recited steps, which is also something every human driver does when using a steering wheel to drive a car. And claim 12 merely requires that the recited probabilistic neural network be a known type of neural network: a “probabilistic convolutional neural network.”

Each element of the asserted claims is also conventional and well-understood in the prior art, as indicated in Exhibits C-1 through C-27.

Lastly, the following claim elements recite patent ineligible printed matter:

- 1[a-i], 13[a-i], 20[a-i] – “an image of traffic, the image displaying a traffic entity belonging to the traffic”
- 1[a-ii], 13[a-ii], 20[a-ii] – “the feature vector comprising values describing statistical distribution for each feature”
- 1[a-iii], 13[a-iii], 20[a-iii] – “output representing hidden context for the traffic entity, the output comprising a plurality of values, each value representing a likelihood of receiving a particular user response from a user presented with the image”
- 1[c], 13[c], 20[c] – “output representing hidden context for at least a traffic entity displayed in the new image”
- 2, 14 – “values describing statistical distribution for each feature comprise a mean value and a standard deviation for the feature”
- 3, 15 – “user responses obtained from users presented with images from a training dataset”
- 7 – “the hidden context represents a state of mind of a user represented by the traffic entity”

- 8 – “the hidden context represents a task that a user represented by the traffic entity is planning on accomplishing”
- 9 – “the hidden context represents a degree of awareness of the autonomous vehicle by a user represented by the traffic entity”
- 10 – “the hidden context represents a goal of a user represented by the traffic entity, wherein the user expects to achieve the goal within a threshold time interval”

D. The '346 Patent

The Asserted Claims of the '346 Patent are directed to ineligible subject matter under 35 U.S.C. § 101. More specifically the claims are directed to the abstract idea of using a machine learning model to drive a car. Moreover, the claims of the '346 Patent do nothing more than computerize the steps that every human driver has always performed: looking at a road, judging what other cars will do next, and driving accordingly. The claims include nothing more than functional, result-oriented steps (receiving data, providing data to model, executing model, controlling vehicle) on generic hardware. In this way, these “claims [] do no more than apply established methods of machine learning to a new data environment” (*e.g.*, to driving) and are therefore patent ineligible under Section 101. *Recentive*, 134 F.4th at 1211.

The chart below further illustrates how each element of Claim 1 corresponds to routine human activity. For purposes of Section 101 subject matter eligibility only, Claim 1 is representative of all claims of the '346 Patent.

Claim Limitation ('346 Patent - Claim 1)	Human Activity
[1.pre] A method comprising:	N/A
[1.a] receiving , by an autonomous vehicle, sensor data from sensors mounted on the autonomous vehicle, the sensor data comprising one or more images;	Driver sees road.

[1.b] generating a point cloud representation of the surroundings of the autonomous vehicle based on the sensor data;	Driver understands road.
[1.c] identifying , one or more traffic entities based on the sensor data, the traffic entities representing non-stationary objects in traffic in which the autonomous vehicle is driving;	Driver identifies cars on road.
[1.d.1] for each of the one or more traffic entities: determining one or more motion parameters describing movement of the traffic entity;	For each car...driver determines if car is moving.
[1.d.2] providing an image of the one or more images, the image showing the traffic entity as input to a machine learning model configured to receive an input image showing an input traffic entity and output summary statistics of expected human responses describing a hidden context of the input traffic entity shown in the input image;	...driver thinks about other car's goal.
[1.d.3] determining the hidden context of the traffic entity based on the output of the machine learning based model;	...driver determines other car's likely goal.
[1.d.4] determining a region of the point cloud where the traffic entity is expected to reach within a threshold time interval; and	...driver predicts where other car is currently heading.
[1.e] modifying the region based on the hidden context of the traffic entity; and	...driver predicts modified path based on likely goal of other car.
[1.f] navigating the autonomous vehicle so that the autonomous vehicle stays at least a threshold distance away from the modified region of each of the one or more traffic entities.	Driver steers to avoid the car.

To the extent Claim 1 is not treated as representative of the dependent claims, no dependent claims in the '346 Patent materially impact the Section 101 analysis. Claims 2, 3, 11, 12, 20, and 21 each describe predicting whether someone on the road will change the direction that they are moving (*e.g.*, “along the motion vector” or “opposite to the direction of the motion vector”), which is a routine step that human drivers perform constantly. Claims 4-7, 13-16, and 22-23 only restrict what the “hidden context” must represent — such as a “state of mind” or “awareness” of another driver — which is both an abstract idea and printed matter. Claims 8 and 17 add a trivial post-

solution step of generating signals to control the car based on the recited steps, which is also something every human driver does when using a steering wheel or changing speed. Claims 9 and 18 simply require capturing images with a camera — something entirely conventional — or alternatively the use of a lidar scan, which was also well-known before the '346 Patent. *See* '346 Patent at 1:36-38 (identifying as **background** to the claimed invention that “an autonomous vehicle may perceive the surroundings using camera images and lidar scans”).

Each element of the asserted claims is also conventional and well-understood in the prior art, as indicated in Exhibits D-1 through D-25.

Lastly, the following claim elements recite patent ineligible printed matter:

- 1[a], 10[a], 19[c] – “the sensor data comprising one or more images”
- 1[b], 10[b], 19[b] – “a point cloud representation of the surroundings of the autonomous vehicle”
- 1[d-i], 10[d-i], 19[d-i] – “motion parameters describing movement of the traffic entity”
- 1[d-ii], 10[d-ii], 19[d-ii] – “[the]/[an input] image showing [the]/[a] traffic entity,” “summary statistics of expected human responses describing a hidden context of the input traffic entity shown in the input image”
- 1[d-iv], 10[d-iv], 19[d-iv] – “a region of the point cloud where the traffic entity is expected to reach within a threshold time interval”
- Claims 4, 13 – “hidden context represents a state of mind of a user represented by the traffic entity”
- Claims 5, 14 – “hidden context represents a task that a user represented by the traffic entity is planning on accomplishing”

- Claims 6, 15 – “hidden context represents a degree of awareness of the autonomous vehicle by a user represented by the traffic entity”
- Claims 7, 16 – “hidden context represents a goal of a user represented by the traffic entity, wherein the user expects to achieve the goal within a threshold time interval”
- Claims 9 and 18 – “the sensor data represents one or more images captured by a camera mounted on the autonomous vehicle or a lidar scan captured by a lidar mounted on the autonomous vehicle”

E. The '046 Patent

The Asserted Claims of the '046 Patent are directed to ineligible subject matter under 35 U.S.C. § 101. More specifically the claims are directed to the abstract idea of training and using a machine learning model to drive a car. Moreover, the claims of the '046 Patent do nothing more than computerize the steps that every human driver has always performed: learning to drive, looking at a road, judging what other cars will do next, and driving accordingly. The claims include nothing more than functional, result-oriented steps (receiving data, training a model with the data, executing model, controlling vehicle) on generic hardware. In this way, these “claims [] do no more than apply established methods of machine learning to a new data environment” (*e.g.*, to driving) and are therefore patent ineligible under Section 101. *Recentive*, 134 F.4th at 1211.

The chart below further illustrates how each element of Claim 1 corresponds to routine human activity. For purposes of Section 101 subject matter eligibility only, Claim 1 is representative of all claims of the '046 Patent.

Claim Limitation ('046 Patent - Claim 1)	Human Activity
[1.pre] A computer-implemented method comprising:	N/A
[1.a] storing a plurality of images , each image displaying one or more users;	Collect examples

[1.b.1] generating training data from the plurality of images, the generating comprising, for each image: sending the image to a plurality of human observers , each human observer presented with a request to answer a question about a state of mind of a user in the image,	Teacher writes textbook by: Sending pictures to humans with question
[1.b.2] receiving , from each of the plurality of human observers, a response representing a judgment by the human observer of the state of mind of the user in the image,	Receiving responses from humans
[1.b.3] generating summary statistics describing the state of mind of the user in the image based on the received responses from the plurality of human observers, and	Tallying responses as statistics
[1.b.4] storing the summary statistics in association with the image as part of the training data;	Compiling statistics in a textbook
[1.c] training a model using the training data, the model configured to receive an input image showing a user and predict summary statistics describing a state of mind of the user in the input image; and	Student learns from textbook
[1.d] executing the trained model to predict a state of mind of a user in a new image.	Student makes prediction

To the extent Claim 1 is not treated as representative of the dependent claims, no dependent claims in the '046 Patent materially impact the Section 101 analysis. Claims 2 and 9 merely require altering images being sent to human observers, which is nothing more than abstract data manipulation, and moreover the content of the image is printed matter. Claims 3, 4, 10, 11, 17, and 18 each further claim a user's state of mind, which is both an abstract idea and printed matter. Claims 5, 12, and 19 require that a human observer provide "a rating on an ordinal scale," which is not inventive and remains printed matter. Claims 6 and 13 merely require that the recited model be one of a number of known types of models (e.g., a "simple neural network"). See '046 Patent at 11:52-59 (providing a basic list of potential models without further explanation, implying the listed models are well-known). Claims 7, 14 and 16 specify that the output printed matter

(“summary statistics”) should be associated with certain human responses (e.g., “a content of a response”), which is simply more data manipulation and printed matter.

Each element of the asserted claims is also conventional and well-understood in the prior art, as indicated in Exhibits E-1 through E-26.

Lastly, the following claim elements recite patent ineligible printed matter:

- 1[a], 8[a], 15[a] – “image displaying one or more users”
- 1[b-i], 8[b-i], 15[b-i] – “request to answer a question about a state of mind of a user in the image”
- 1[b-ii], 8[b-ii], 15[b-ii] – “response representing a judgment by the human observer of the state of mind of the user in the image”
- 1[b-iii], 8[b-iii], 15[b-iii] – “summary statistics describing the state of mind of the user in the image based on the received responses from the plurality of human observers”
- 1[c], 8[c], 15[c] – “input image showing a user” and “summary statistics describing a state of mind of the user in the input image”
- 1[d], 8[d], 15[d] – “a state of mind of a user in a new image”
- 3, 10, 17 – “the state of mind of the user in the image indicates whether the user is likely to perform a predetermined action”
- 4, 11, 18 – “the state of mind of the user in the image represents a measure of awareness of the user regarding an object”
- 5, 12, 19 – “the response from a human observer comprises a rating on an ordinal scale”

IV. INVALIDITY UNDER 35 U.S.C. § 112

The grounds identified below both individually and collectively render certain of the Asserted Claims invalid under the statutory requirements of § 112. By identifying certain claim language below, Tesla does not imply that such language is entitled to any patentable weight when comparing the claims as a whole to the prior art. Tesla's identifications are made based on Tesla's present understanding of the Asserted Claims and Plaintiff's apparent interpretation of these claims as reflected in its Infringement Contentions, and Tesla reserves the right to amend these identifications, including in response to claim constructions and claim interpretations that would render claim limitations not enabled, lacking in written description, or indefinite. To the extent a claim element is contained within an element identified below or encompass an element identified below, that claim element also renders the claim invalid under 35 U.S.C. § 112.

A. Lack of Enablement and Written Description

35 U.S.C. § 112 includes an enablement requirement: "The specification shall contain a written description . . . of the manner and process of making and using [the invention] in such full, clear, concise and exact terms as to enable any person skilled in the art to which it pertains, or with which it is most nearly connected, to make and use the same." 35 U.S.C. § 112 (a). To satisfy the enablement requirement, the disclosure "must teach those skilled in the art how to make and use the full scope of the claimed invention without 'undue experimentation.'" *Genentech, Inc. v. Novo Nordisk A/S*, 108 F.3d 1361, 1366 (Fed. Cir. 1997); *MagSil Corp. v. Hitachi Glob. Storage Techs., Inc.*, 687 F.3d 1377, 1381 (Fed. Cir. 2012); *Sitrick v. Dreamworks, LLC*, 516 F.3d 993, 999 (Fed. Cir. 2008). If a specification teaches away from a substantial portion of the claim or does not enable the full scope of the claim, there is no enablement. *AK Steel Corp. v. Sollac*, 344 F.3d 1234 (Fed. Cir. 2003); *see also MagSil Corp.*, 687 F.3d at 1383-84 (Fed. Cir. 2012).

35 U.S.C. § 112 further includes a written description requirement: “The specification shall contain a written description of the invention” 35 U.S.C. § 112 (a). “To satisfy the written description requirement, a patent applicant must convey with reasonable clarity to those skilled in the art that, as of the filing date sought, he or she was in possession of the invention.” *ICU Medical Inc. v. Alaris Medical Systems, Inc.*, 558 F.3d 1368, 1377 (Fed. Cir. 2009) (internal quotation marks and citations omitted); *see also Synthes USA, LLC v. Spinal Kinetics, Inc.*, 734 F.3d 1332, 1340 (Fed. Cir. 2013). “The test [for written description support] requires an objective inquiry into the four corners of the specification from the perspective of a person of ordinary skill in the art. Based on that inquiry, the specification must describe an invention understandable to that skilled artisan and show that the inventor actually invented the invention claimed.” *Ariad Pharms., Inc. v. Eli Lilly & Co.*, 598 F.3d 1336, 1351 (Fed. Cir. 2010) (en banc).

The specification must describe the claimed invention in sufficient detail so that a POSITA can recognize what is claimed. “The appearance of mere indistinct words in a specification or a claim, even an original claim, does not necessarily satisfy that requirement.” *University of Rochester v. G.D. Searle & Co.*, 358 F.3d 916, 923 (Fed. Cir. 2004) (internal quotation marks and citations omitted).

1. The '344 Patent

Especially in view of the expansive scope of these claim limitations that Plaintiff appears to take in its Infringement Contentions, at least the following claim terms or phrases of the '344 Patent are invalid for failing to adequately describe or enable under 35 U.S.C. § 112 (a) as indicated below:

Claims	Language
1, 10, 19	“controlling the operation of the autonomous vehicle on the road based on the generated statistical summary data”

Claim 1 of the '344 Patent is invalid under 35 U.S.C. § 112 (a) because there is very little disclosure on how to control a vehicle based on the predictions made by the machine learning model in the '344 Patent's specification. In fact, the specification only mentions control of the vehicle in the background, and only then when explaining that "autonomous vehicles may rely on methods that make decisions on how to control the vehicles by predicting 'motion vectors' of people near the vehicles." '344 Patent at 1:38-40.

2. The '889 Patent

Especially in view of the expansive scope of these claim limitations that Plaintiff appears to take in its Infringement Contentions, at least the following claim terms or phrases of the '889 Patent are invalid for failing to adequately describe or enable under 35 U.S.C. § 112 (a) as indicated below:

Claim	Language
1, 2, 12	"controlling the autonomous vehicle based on the prediction of the supervised learning based model"

Claim 1 of the '889 Patent is invalid under 35 U.S.C. § 112 (a) because there is very little disclosure on how to control a vehicle based on the predictions made by the machine learning model in the '889 Patent's specification. In fact, the specification only mentions control of the vehicle in the background, and only then when explaining that "autonomous driving vehicles may rely on methods that make decisions on how to control the vehicles by predicting 'motion vectors' of people near the vehicles." '344 Patent at 1:42-44.

**V. DOCUMENT PRODUCTION ACCOMPANYING INVALIDITY CONTENTIONS:
P.R. 3-4**

With these Invalidity Contentions, Tesla is also producing and/or making available for inspection the documents required under Local Patent Rule 3-4 and the Court's Docket Control Order. Tesla reserves the right to produce and rely on additional documents relating to the prior art or the accused products in view of, for example, additional information revealed during discovery regarding Plaintiff's allegations and/or amendments to Plaintiff's Infringement Contentions as discovery processes.

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Respectfully submitted,

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CERTIFICATE OF SERVICE

The undersigned hereby certifies that counsel of record who are deemed to have consented to electronic services are being served with a copy of this document on this 9th day of December 2025.

/s/ Roger Fulghum
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