UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.

Petitioner,

v.

PERCEPTIVE AUTOMATA LLC

Patent Owner.

Case No. IPR2025-01573
Patent 10,614,344

Case No. IPR2025-01574
Patent 11,126,889

Case No. IPR2025-01575
Patent 11,753,046

Case No. IPR2025-01576
Patent 11,467,579

Case No. IPR2025-01577
Patent 11,520,346

****

REMOTE ORAL DEPOSITION OF
DR. ELI SABER, PH.D.
AUGUST 11, 2026
VOLUME 1

****

REMOTE ORAL DEPOSITION of DR. ELI SABER, PH.D., produced as a witness at the instance of the Petitioner, and duly sworn, was taken in the above-styled and numbered

cause on August 11, 2026, from 8:09 a.m. to 3:07 p.m., before Mendy A. Schneider, CSR, RPR, in and for the State of Texas, recorded by machine shorthand, remotely at the offices of MENDY SCHNEIDER, LLC, The Woodlands, Texas, pursuant to the Federal Rules of Civil Procedure and the provisions stated on the record or attached hereto; that the deposition shall be read and signed before.

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Janet Declaration

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SABER EXHIBIT NO. 13 185
Ross Patent No. 10,496,091

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SABER EXHIBIT NO. 15 196
Zhang Patent

SABER EXHIBIT NO. 16 210
Ellenbogen Prior Art Reference

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Huval Patent

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Declaration of Dr. Janet

(REPORTER'S NOTE: All quotations from exhibits are reflected in the manner in which they were read into the record and do not necessarily denote an exact quote from the document.)

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THE REPORTER: The attorneys participating in this deposition acknowledge that I am not physically present in the deposition room and that I will be reporting this deposition remotely.

They further acknowledge that in lieu of an oath administered in person, I will administer the oath remotely.

The parties and their counsel consent to this arrangement and waive any objections to this manner of reporting.

DR. ELI SABER, PH.D.,

having been first duly sworn, testified as follows:

THE WITNESS: Can you hear me well?

MR. SPEEGLE: Yes. Thank you. This is Mark Speegle for Petitioner Tesla. And with me is also Ellyar

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Barazesh for Petitioner Tesla.

MR. GINNINGS: And good morning. Austin Ginnings from Nelson Bumgardner Conroy on behalf of the patent owner.

MR. SPEEGLE: Great.

EXAMINATION

BY MR. SPEEGLE:

Q. Can you please state your full name and record -- full name for the record?

A. Yes. Eli Saber.

Q. Thank you, Dr. Saber.

And you understand that you are under oath today?

A. I do.

Q. And your testimony is the same as if you were sitting in a courtroom?

A. I do.

Q. Now, have you been deposed before, Dr. Saber?

A. Yes, I have.

Q. How many times have you been

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deposed before?

A. About 37 times, I think.

Q. Okay. I'm sure you're familiar with the rules, but I'm going to go over them briefly just so we're on the same page.

Is that all right?

A. That would be fantastic. Thank you.

Q. Okay. So, first, because the court reporter is transcribing everything that we're saying, it's important that we both wait until the other one finishes before you start talking.

Is that okay?

A. Yes. Fantastic.

Q. Okay. And will you please let me know if you do not understand any of my questions?

A. Of course. I'll be happy to do so.

Q. Great.

And is there any reason that

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you cannot testify fully and accurately today?

A. No.

Q. And where are you located physically for this deposition?

A. I'm located in Webster, New York, where life is worth living. They used to -- they used to say that.

Q. Are you located in your home or in an office?

A. I'm located in my home office.

Q. Okay. Is there anyone else in the room with you today?

A. No, there's not.

Q. Okay. Will you let me know if anyone else comes into the room during the deposition?

A. Absolutely.

Q. And are you on a laptop today?

A. No. I'm on a desktop.

Q. Okay. And what windows do you have open on your desktop right now?

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A. Just this Zoom window. That's it.

Q. Okay.

A. And a folder -- the folder where I put the downloads in.

Q. Okay. Will you let me know if any other windows open up on your -- on your desktop during the deposition?

A. Absolutely.

Q. And do you have any other electronic devices with you in the -- in the room where you're at?

A. No, I do not.

Q. Okay. Will you let me know if anyone attempts to contact you while we're taking the deposition?

A. I will. I will surely do so.

Q. Okay. And I understand you have some documents with you. Is that right?

A. I do.

Q. And what documents do you have with you?

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A. I have five binders that counsel has sent that have clean hard copies of the exhibits that have been filed with my declaration.

And I have the electronic copies, it looks like ten of them, that you have asked me to download.

Q. Great.

Do you have any -- any notes or -- or markings on the -- on the documents in the binders?

A. No, sir.

Q. And will you let me know if you reference any of the physical documents during your deposition testimony?

A. Absolutely.

Q. All right. So you were retained by Patent Owner Perceptive Automata in this case, right?

A. That is correct.

Q. And let me clarify.

When I say "this case," you

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understand that this is an IPR proceeding for five different cases; is that right?

A. Yes, I do.

Q. Okay. And I'm going to read those IPR numbers just for the record.

We have IPR2025-1573, IPR2025-01574, IPR2025-01575, IPR2025-01576, and IPR2025-01577.

Does that align with your understanding of the IPRs that we're addressing today?

A. Sounds about right. I assume you read them correctly, so...

Q. All right. And you provided a declaration in each of those five IPRs, right?

A. I did, sir.

Q. Okay. And can I get you to look at what was provided in the -- in the Chat as -- it has a 1 dash beginning in it.

(Marked Saber Exhibit No. 1.)

A. Yeah, it says 1 - 344. Is that

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it?
(BY MR. SPEEGLE)
Q. Yes. And I'll designate that as Exhibit 1. And can you let me know if you've seen Exhibit 1.
A. Yeah. Let me go ahead and open it. Give me one moment.
Yes. That's my declaration.
Q. Great.
And that's your declaration for Patent No. 10,614,344, right?
A. That's correct.
Q. Okay. Let's look at the document in the Chat that starts with the 2 dash.
(Marked Saber Exhibit No. 2.)
A. Yes, sir.
(BY MR. SPEEGLE)
Q. Have you seen -- I'll designate this as Exhibit 2.
Have you seen Exhibit 2 before?
A. Yes. That's my declaration.

Q. And Exhibit 2 is your declaration with respect to Patent No. 11,753,046; is that right?

A. That is correct.

Q. All right. Let's turn to the third one. This is the document beginning with the 3 dash. Let me know when you have that open.

(Marked Saber Exhibit No. 3.)

A. I do.

(BY MR. SPEEGLE)

Q. Okay. And I'll designate this as Exhibit 3.

Have you seen Exhibit 3 before?

A. Yes, I have.

Q. And Exhibit 3 is your declaration with respect to Patent No. 11,126,889, right?

A. That's correct.

Q. All right. And let's turn to the document beginning with 4 dash. Let me know when you have that open.

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A. I do.

(Marked Saber Exhibit No. 4.)

(BY MR. SPEEGLE)

Q. Okay. And I'm going to designate this document as Exhibit 4.

Have you seen Exhibit 4 before?

A. Yes, I have.

Q. And is Exhibit 4 your declaration with respect to Patent No. 11,467,579?

A. That is correct.

Q. All right. One more. Let's turn to the document beginning with the 5 dash.

(Marked Saber Exhibit No. 5.)

(BY MR. SPEEGLE)

Q. Let me know when you have that open.

A. I do.

Q. And have you -- and I'll designate this as Exhibit 5.

Have you seen Exhibit 5 before?

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A. Yes, I have.
Q. And Exhibit 5 is your declaration with respect to 11,520,346; is that right?
A. That is correct.
Q. All right. And Exhibits 1 through 5 are the five declarations that you're being deposed on today; is that correct?
A. That is correct.
Q. All right. My first question on these is: Are you aware of any mistakes or corrections that you need to make in any of the five declarations that are designated as Exhibits 1 through 5?
A. There is some minor typos here and there. I'll point them out as we get into the declarations and the paragraphs.
Q. Okay. All right. Can you turn to the document that begins with the 6 dash?
A. Yes, sir.
Q. And have you seen -- and I'll

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designate this as Exhibit 6.

(Marked Saber Exhibit No. 6.)

(BY MR. SPEEGLE)

Q. Have you seen Exhibit 6 before?

A. Yes, I have.

Q. And this is U.S. Patent No. 10,614,344, right?

A. That is correct.

Q. All right. Let's turn to the document beginning with the 7 dash.

A. Yes, sir.

Q. I'll designate this as Exhibit 7.

(Marked Saber Exhibit No. 7.)

(BY MR. SPEEGLE)

Q. And have you seen Exhibit 7 before?

A. I have.

Q. And this is U.S. Patent No. 11,753,046, right?

A. That is correct.

Q. All right. Let's go to the

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next one, the document beginning with the 8 dash.

A. Yes, sir.

Q. Have you -- and I'll designate this as Exhibit 8.

(Marked Saber Exhibit No. 8.)

(BY MR. SPEEGLE)

Q. Have you seen Exhibit 8 before?

A. Yes, I have.

Q. And Exhibit 8 is U.S. Patent No. 11,126,889, right?

A. That's correct.

Q. All right. Let's turn to the document beginning 9 dash. Let me know when you've got that open.

(Marked Saber Exhibit No. 9.)

A. I do.

(BY MR. SPEEGLE)

Q. And have you seen -- and I'll designate this as Exhibit 9.

Have you seen Exhibit 9 before?

A. Yes, I have.

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Q. And Exhibit 9 is U.S. Patent No. 11,467,579, right?

A. That is correct.

Q. All right. And then let's turn to the document beginning with the 10 dash. Let me know when you've got that open.

A. I do.

(Marked Saber Exhibit No. 10.)

(BY MR. SPEEGLE)

Q. And I'll designate this document as Exhibit 10.

Exhibit 10 is a copy of U.S. Patent No. 11,520,346, right?

A. That is correct.

Q. Great.

All right. And Exhibits 6 through 10 are the five patents that are the subjects of each one of your corresponding declarations; is that right?

A. That is correct.

Q. Okay. Now, three of these patents that are Exhibit 6, 7, and 8, you

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familiar with those three patents, right?
A. Yes, sir.
Q. And that's the -- the '344 patent, the '889 patent, and the '046 patent?
A. Correct.
Q. You understand that these patents are related to each other?
A. Yes.
Q. Okay. And that means that they have a shared specification; is that right?
A. Yes.
Q. Okay. So if I ask you a question about something that's with specification of -- of any one of those patents, that same material is going to be in the other two of those three patents, right?
MR. GINNINGS: Objection; form.
A. I mean, generally speaking, that's the idea, but the -- obviously, the claims are different, so we would have to address it on -- on an element-by-element and

claim-by-claim basis.

(BY MR. SPEEGLE)

Q. Sure.

Okay. And Exhibits 9 and 10, which are the '579 and the '346 patent, those two patents claim back to a shared provisional application, right?

A. Yes.

Q. They both claim priority back to provisional 62/822,269; is that right?

MR. GINNINGS: Objection to form.

A. Yes.

(BY MR. SPEEGLE)

Q. All right. Let me just ask you some general questions.

A. You said -- you said 62/822,269, correct?

Q. Yes.

A. Yeah. I -- I assume so. I mean, there's another one there also, provisional application 62/802,151 filed on

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February 6.

Q. Okay. If you look at Exhibit 10 on the left-hand side, there's a -- a 60 in parentheses.

Do you see that?

A. The right-hand side. Exhibit 10, right-hand side.

Q. I'm sorry. Left-hand side. Left-hand side of Page 1 of Exhibit 10.

A. Yes, I see that, sir.

Q. And right next to the 60 it says, Provisional application No. 62/822,269?

A. I see that.

Q. Does that tell you that the '346 patent claims priority back to the provisional No. 62/822,269?

A. Yes. The -- what I was pointing out, there's a comma. There's provisional application as well next to it.

Q. Right. And the -- if you turn to Exhibit 9.

A. Yes, sir.

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Q. And you see on the left-hand side, the same spot, there's another 60?

A. Yes, sir.

Q. And it lists two provisional applications after that 60?

A. Yes, sir.

Q. And the first one, provisional application No. 62/822,269, that's the same number we just saw on Exhibit 10, right?

A. You are correct.

Q. All right. And that tells you that the '579 patent and the '346 patent claim priority back to a shared provisional application, right?

A. I mean, generally speaking, yeah.

Q. Okay. All right. I -- so I'm going to ask a little -- a few questions about the preparation of your declaration.

And I understand that you may need to listen to your counsel's privilege objections on this. I'm not trying to get

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into privileged material. I'm just trying to understand some basics about preparation. So listen carefully to my questions, and wait for counsel to object if needed.

My first question is: Did you personally prepare the first draft of each of your declarations?

A. Yes, I -- I typically prepare the first draft of each of my declarations.

Q. Okay. I assume that there was a revision -- a revision process back and forth between you and counsel after that first draft?

A. It's a collaborative and intuitive effort between me and counsel to arrive at the final draft.

Q. Okay. And let's look at your declaration on the '344 patent, which is Exhibit 1.

A. '344.

Q. Yes, this is Exhibit 1, your '344 declaration.

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A. Yes, sir.
Q. And I would like you to direct you to Paragraph 30, which is on Page 10.
A. Yes, sir.
Q. And here, it's talking about the legal standard that you applied for your declarations, right?
A. That is correct.
Q. And counsel for Perceptive provided you the legal standard that you used in each of your declarations, right?
A. That is correct.
Q. You reviewed the patent owner's responses that Perceptive submitted in each of these IPR proceedings?
A. Yes.
Q. Are you aware of any divergences between Perceptive's responses and the positions taken in your declarations?
A. Not off the top of my head.
Q. Okay. Go up to Paragraph 7 of your declaration, the '344 declaration, which

is, again, Exhibit 1.

And this is listing some of your credentials, correct?

A. Yes, sir.

Q. And you were a professor at the Rochester Institute of Technology; is that correct?

A. Yes, sir.

Q. Okay. And you teach courses in advance neural networks and pattern recognition?

A. Yes. I have an appointment -- my primary appointment is in the electrical engineering department. And I taught a variety of different courses there.

But I do have a second appointment in the Center for Imaging Science. I've taught a variety of courses. I think they're listed later on in the -- in the paragraphs.

Q. Sir, can you say again, what is your second appointment?

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A. I have a second appointment as an extended faculty in the Center for Imaging Science at RIT.

Q. For imaging science. Great.

A. Correct.

Q. If you turn and look at -- I lost it.

You have a list of materials considered in your declaration, right?

A. That is correct. I am opening the hard copy in front of me as well.

Q. I believe it's on Page 8.

A. Yes, sir.

Q. I'm going to drop into the Chat another document that begins with an 11 dash. And let me know when you've got that open.

A. It's not allowing me to download it yet, so it might still be loading.

Oh, there it is. It's still trying to download it.

It looks like Dr. Janet's

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declaration. But it's being downloaded.

Q. Okay. Well, while it's downloading, I'll just direct you to Page 8 of your declaration, which is, again, Exhibit 1 and the materials considered, Paragraph 26.

Do you see that?

A. I do.

Q. And you considered the declaration of Dr. Janet in preparing your declaration?

A. That is correct.

Q. And that's true for each of the five IPRs?

A. That is correct.

Q. Okay. Can you turn to Paragraph 52 of your declaration. Let me know when you've got that in front of you.

A. Paragraph 52, yes, sir.

Q. And that's an excerpt that you have in your declaration from the -- from the declaration of Dr. Janet, right?

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A. Yes, sir.
Q. Okay. And that's a -- the definition of a person of ordinary skill in the art provided by Dr. Janet?
A. Yes, sir.
Q. And you've agreed with the definition of a personal of ordinary skill in the art provided by Dr. Janet in these matters?
MR. GINNINGS: Objection; form.
A. Well, as I state in Paragraph 53, just below this paragraph, that for the purposes of providing my opinions in connection with this declaration, I did not -- I do not dispute Dr. Janet's definition of a POSITA.
(BY MR. SPEEGLE)
Q. Okay. Now, you have a -- the next sentence in Paragraph 53 says, I note that Dr. Janet offers this definition as of July 5, 2017, even though he opines that the challenged claims of the '344 patent are not

entitled to a priority date earlier than December 4, 2017.

(Discussion off the record.)

(BY MR. SPEEGLE)

Q. Let me try that again.

However, I note that Dr. Janet offers this definition as of July 5, 2017, even though he opines that the challenged claims of the '344 patent are not entitled to a priority date earlier than December 4, 2017.

Is that an accurate recitation of what's in your declaration?

A. You read it correctly.

Q. Is there any material difference to any of your opinions whether or not the definition of a POSITA is considered as of July 2017 or December 2017?

A. I'm sorry, I didn't understand your question. You cut out for a second. Would you repeat, please.

Q. Is there any material impact on

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your opinions or analysis in this case based on the definition of a POSITA referring to July 2017 versus December 2017?

A. Not that I can think of off the top of my head.

Q. Okay. Has that document that begins with an 11 come through the Chat for you?

A. Yes, but I'm not -- somehow, for whatever reason, it's not downloading. It just opens in the Chat directly, but it doesn't download. I don't know why.

The other ones gave me a download icon to download. This one just opens in the Chat box, but it doesn't allow me to download it.

Q. Are you able to still review the document?

A. Yeah, I can open it. I can open it and see it. I just can't download it for whatever reason, but that's okay. We'll -- we'll -- I can deal with it at this

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point.

Q. Okay. I just have a couple of questions about it.

A. I believe it's probably -- it's probably in the notes here. I think the exhibit's here anyway if I need to in the hard copies.

Q. Okay. If you turn to Page 7 of -- well, let me start off this way. I'm going to designate the document that begins with an 11 as Exhibit 11.

And have you seen Exhibit 11 before?

(Marked Saber Exhibit No. 11.)

A. Yes, I have.

(BY MR. SPEEGLE)

Q. And Exhibit 11 is the declaration of Dr. Jason Janet in the '344 IPR, right?

A. That is correct.

Q. Okay. And if you turn to Page 7 of Exhibit 11, you'll see the

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beginning of the section titled Background and Qualifications.

Do you see that?

A. I'm getting there.

MR. GINNINGS: You want PDF Page 7 or numbered Page 7, just so I'm clear?

MR. SPEEGLE: Sorry. PDF Page 7, which is numbered Page 1.

MR. GINNINGS: Yeah.

A. I am there, sir.

(BY MR. SPEEGLE)

Q. Okay. You see beginning at Paragraph 2, the section beginning Background and Qualifications for Dr. Janet?

A. Yes, sir.

Q. And you've reviewed Dr. Janet's qualifications before?

A. Yes, sir.

Q. Do you have any -- any issue or question about whether Dr. Janet is qualified to serve as an expert in this matter?

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A. I did not consider that and wasn't asked to provide any opinions on whether Dr. Janet, you know, can -- is -- meets the definition of a POSITA or is an expert in this matter, wasn't asked to provide any opinions on that.

Q. Okay.

A. I was just asked to review his declaration in rendering obviously my opinions and analysis.

Q. You have reviewed his credentials, right?

A. I have reviewed his credentials. I reviewed his declaration, but I wasn't asked to provide any opinions on his credentials or whether, you know, he meets the POSITA requirements.

Q. So my question was about whether he's qualified to serve as an expert in this matter, do you have -- do you have -- based on his credentials, would you have any qualms about him serving as an expert in this

matter?

MR. GINNINGS: Objection; form.

A. I wasn't asked to provide any opinions on Dr. Janet's expert or expertise.

(BY MR. SPEEGLE)

Q. Okay. Are you able to answer my question?

MR. GINNINGS: Objection to form.

A. Again, I wasn't -- I wasn't asked to provide any opinions. I would have to obviously, you know, investigate that. I was asked to provide -- to review his declaration and that's what I did.

(BY MR. SPEEGLE)

Q. Okay. Well, you have a definition of a POSITA in your -- I think you're referring to in your Exhibit 1 declaration, right?

A. That is correct. It's Paragraph 52, which I believe was adopted from Dr. Janet's declaration.

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Q. Okay. And you understand that the second -- there's two alternative ways to qualify as a POSITA in the definition -- that's in Paragraph 52; is that right?

A. That is correct.

Q. And the second prong of it is master's degree in electrical engineering, computer engineering, and computer science or equivalent coursework with a focus in computer vision, autonomous vehicles, and/or machine learning --

A. Yes.

Q. -- right?

A. You read that correctly.

Q. And you would agree with me that in Paragraph 3 of Dr. Janet's declaration, which is Exhibit 11, it recites that he has a master's degree of integrated manufacturing systems and a Ph.D. in electrical and computer engineering from North Carolina State; is that right?

MR. GINNINGS: Objection to

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form.

A. You read that -- you read -- Paragraph 3 does recite a master's of integrated manufacturing systems and a Ph.D. in electrical and computer engineering from NC -- NCSU.

(BY MR. SPEEGLE)

Q. Okay. So you would agree that at least as of 1998 Dr. Janet qualified as a POSITA under the definition you agreed to in Paragraph 52?

MR. GINNINGS: Objection; form and scope.

A. Well, as I mentioned to you earlier, if you look at the definition, first of all, it says a master's degree in electrical engineering, computer engineering, computer science, or equivalent coursework, with a focus in computer vision, autonomous vehicles, and/or machine learning.

So it's -- it's got a focus to it as well.

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And as I said to you earlier, I was not asked to provide any analysis on Dr. Janet's qualifications or definition of a POSITA. I was asked to adopt the definition of a POSITA that you see there directly in my analysis. Review his declaration, his analysis, and adopt that definition.

(BY MR. SPEEGLE)

Q. Okay. Are you able to tell me if a Ph.D. in computer engineering is equivalent of coursework to or a master's degree in computer science and computer engineering?

MR. GINNINGS: Objection to form and scope.

A. Again, I -- as I mentioned to you, I was not asked to provide any opinions on Dr. Janet's qualifications or his definition about POSITA. I was just asked to adopt that definition in my analysis, and that's what I've done.

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(BY MR. SPEEGLE)

Q. Who asked you to adopt that position in your analysis?

A. Well, obviously, Dr. Janet has provided the definition of a POSITA in his declaration.

I -- you know, as you see in Paragraph 53, for the purpose of providing my opinions, I did not dispute that definition of a POSITA. And I've utilized that in my analysis.

Q. I think in your last answer you said, I was just asked to adopt that definition in my analysis.

And my question is: Who asked you to adopt that definition in your analysis?

MR. GINNINGS: Objection; form and scope.

A. I mean, just -- just working with counsel, you know, I -- I read his definition of a POSITA. And for the purpose

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of providing my opinions in connection with this declaration, I did not dispute that definition of a POSITA. So I -- I utilized that definition in my analysis.

(BY MR. SPEEGLE)

Q. You testified three questions ago that you were asked to adopt that definition of a POSITA. Is that true?

A. Well, I meant -- I meant by reading his declaration and the definition of the POSITA that Dr. Janet has put forth in his declaration, I utilized that definition in my analysis.

Q. Sir, are you testifying now --

A. I mean, obviously, working with counsel I utilized that definition in my -- in my analysis.

Q. Did -- did Perceptive's counsel ask you to adopt Dr. Janet's definition?

A. I -- as I just mentioned to you, I mean, I've read -- had read his definition of a POSITA. And as it says in

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Paragraph 53, for the purposes of my opinions in connection with this declaration, I did not dispute Dr. Janet's definition. I wasn't asked to provide any opinions on whether -- on any details of Dr. Janet or any qualifications of Dr. Janet.

Q. I'm sorry.

MR. SPEEGLE: I'm going to move to strike as nonresponsive.

(BY MR. SPEEGLE)

Q. It's a pretty simple question.

Did Perceptive's counsel ask you to adopt Dr. Janet's definition of POSITA?

MR. GINNINGS: I'm going to object to form and scope.

And you're argumentative with the witness. I'm going to ask you to move on from this question, Mr. Speegle. You've asked it four times, and he's answered it each time.

A. So as I've told you,

Mr. Speegle, I read Dr. Janet's declaration. I read his definition of a POSITA. And for the purposes of providing my opinions in connection with this declaration, I did not dispute that definition. And I -- and I utilized that in my analysis. I wasn't asked to render any opinions on Dr. Janet's qualifications or whether he meets the definition of a POSITA.

(BY MR. SPEEGLE)

Q. I want to turn back to the materials considered paragraph -- which is I believe it's Paragraph 26 of your declaration. It starts on Page 8.

A. Yes, sir. Yes, sir.

Q. In your list of exhibits considered, it goes 1001, 1002, 1003, 1004, 1005, 1006, and then it jumps to 1010.

Do you see that?

A. Yes, sir, I do.

Q. So you did not consider Exhibits 1007 through -9, right?

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A. Not that I recall off the top of my head.

Q. Why did you not consider all of the exhibits submitted with Tesla's petition?

A. Well, I considered the ones that are relevant to my analysis.

Q. If you didn't review them, how did you decide if they were relevant?

A. I'm not sure I understand your question.

Q. Well, I ask why did you not consider all of the exhibits submitted with Tesla's petition. And I understood you said, I considered the ones that are relevant to my analysis.

And my follow-up question was: If you didn't review them, how did you know they were not relevant?

A. Well, I mean --

MR. GINNINGS: Objection; form.

A. -- I think you misunderstood my -- my position. I mean, I obviously took

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a peek at what they are. I do have -- I did receive an -- the entire pleadings and the scans of everything. So I looked at what they all are, and I've -- the ones that I put in my declarations are the ones that I've relied on in rendering my opinions.

(BY MR. SPEEGLE)

Q. So you did, in fact, review additional exhibits that are not listed on your materials considered?

MR. GINNINGS: Objection to form.

A. Well, again, as I mentioned, I received the entire pleadings -- an entire folder that has all the pleadings that were filed with this IPR. And I've looked -- I've looked at all of them to see what they are, but I've -- the ones I relied on in rendering my analysis, I put those in my declaration.

Those are the ones that I relied on in rendering the analysis that you see in this declaration.

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(BY MR. SPEEGLE)

Q. All right. When you say "took a peek at them," what do you mean?

A. Well, I mean, I -- I -- I can -- I can open every one of them and take a look and see what they are, right? I've received a huge PDF -- you know, a huge folder of all of them. So I can open and see what they are.

And the ones that I've put in my declarations are the ones that I relied on in rendering my opinions or I cited to in rendering my opinions.

Q. But you did review every exhibit that was submitted with Tesla's IPR?

A. Yeah. I've looked at them. I've looked at the ones -- I've looked at them. Some -- some I've reviewed more than others, but I've looked at them.

But the point is, the ones that I've utilized to render my analysis are here in this declaration.

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Q. Okay. So Exhibit 1007 of Tesla's IPR petition on the '344 patent is the original provisional application for the '344 patent.

Have you reviewed that provisional application?

MR. GINNINGS: Objection to form.

A. As I mentioned, I've looked at it. I didn't -- was there -- is there something in my declaration that you are asking about?

Because my opinions are in my declaration. I didn't render any opinions on the provisional application, as far as I remember.

(BY MR. SPEEGLE)

Q. So let me direct you to Exhibit 6, which is the '344 patent.

A. Exhibit 6. I don't know what you're -- what numbering are we looking at here? The 1001?

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Q. No. I'm sorry. This is -- this is Deposition Exhibit 6.

(Speaking simultaneously.)

A. Exhibit 6 of what you submitted?

(BY MR. SPEEGLE)

Q. Correct.

A. This morning. Okay. Which is the patent itself?

Q. Correct.

A. Okay. What about it?

Q. And if you turn to PDF Page 14, which is the first page of text, there's a section at the beginning which refers to the cross-reference to related applications.

Let me know when you're there.

A. Yes. I'm there.

Q. Okay. And the '344 patent incorporates by reference U.S. Provisional Application No. 62/528,771, right?

A. 528,771, is that what you said?

Q. Correct.

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A. That -- that's what it states. That's what it states, yes.

Q. So the provisional application is part of the '344 patent application -- or sorry, let me strike that.

U.S. Provisional Application No. 62/528,771 is incorporated by reference into the '344 patent, right?

A. Yes.

Q. And you did not rely on the provisional application or consider it in rendering your opinions in this matter?

MR. GINNINGS: Objection to form.

A. So if you look at my declaration on Paragraph 27 and 28, that's what I was asked to consider and analyze.

So if you look at my Paragraph 27, I've been asked to consider the time of the invention of the claim -- the challenged claims to be around December 4, 2017, which I understand is the filing date

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of the earliest nonprovisional patent application to which the '344 patent claims priority.

(BY MR. SPEEGLE)

Q. I'm not asking you about priority dates.

A. Oh.

Q. I'm just asking about material that you considered in rendering your opinions about the scope and meaning of the '344 patent.

MR. GINNINGS: Mr. Speegle, Dr. Saber was still in the middle of his answer.

A. Yeah, I'm trying to answer your question, sir.

(BY MR. SPEEGLE)

Q. I'm sorry, please continue.

A. If you look at Paragraph 28 of my declaration, you see it says, I understand that the '344 also claims priority to U.S. Patent Application 528,771, which is the

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one you just read, which was filed on July 5, 2017.

And then my opinions here do not differ whether the time of the invention of the challenged claims is July or December.

Q. Are you done?

A. And --

Q. Sorry.

A. -- for the sake of clarity, I was -- I have been asked to assume that all of the references relied upon by Tesla in support of this IPR petition are prior art to the challenged claims of the '344.

So that was my assignment.

Q. Thank you, Dr. Saber.

In the course of your opinions on the '344 patent, you interpret claim terms within the claims of the '344 patent, right?

A. That is correct.

Q. And when interpreting the claims of the '344 patent, you did not consider or rely on the provisional

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application, right?

MR. GINNINGS: Objection to form.

A. Well, as you are, I'm sure, well aware, you read the claims in light of the specification, the prosecution history, the intrinsic and sometimes extrinsic evidence as well.

So you don't read the claims in a vacuum. So when I read the claims of the '344, I'm reading that in light of the specification described in the '344, the prosecution history of the '344, the intrinsic and potentially extrinsic evidence as well.

(BY MR. SPEEGLE)

Q. But you failed to consider some of the specification and prosecution history, right?

MR. GINNINGS: Objection to form.

A. I'm not sure what you -- what

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you mean by "failed." No, I did not do so.
(BY MR. SPEEGLE)
Q. You failed to consider the provisional application which was incorporated by reference into the '344 patent?
MR. GINNINGS: Objection to form.
A. That is not correct.
(BY MR. SPEEGLE)
Q. Is the '344 -- is the -- sorry.
Is the provisional application, which is Exhibit 1007, and the '344 patent application listed on your materials considered?
A. No, it is not, because it's not cited in my declaration. It's just mentioned in that paragraph that you see on Paragraph 28.
Q. Paragraph 26 says, In forming my opinions expressed in this declaration, I considered the following materials.

Right?

A. That is correct. You read that correct.

Q. Paragraph 20 -- I'm sorry, were you finished?

A. You read that correctly, sir.

Q. Is Paragraph 26 accurate?

A. Yes.

Q. And the provisional application that led to the '344 patent is not included on your materials considered list?

A. I didn't cite to it in my declaration, no. The -- the list of materials that you see here are the ones that I've cited to in my declaration.

Q. Well, is there -- is there a distinction you're making between citing and considering?

A. Well, as I mentioned to you, I've received an entire folder of -- of all the exhibits that were filed in this proceeding -- in all five proceedings, which

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I've looked at them and considered them.

But the ones that I've relied on in rendering my opinions and I cited to are in my declaration.

Q. Okay. Did Perceptive's counsel give you any guidance about what documents to rely on in your declaration?

MR. GINNINGS: I'm going to object here. And to the extent that the question calls for, you know, your communications with counsel, Dr. Saber, I instruct you not to answer the question.

If there's any way you can answer the question without doing so, you're free to do so.

A. I've been working on this case, sir, since -- I want to say off the top of my head I think it was April time frame. I don't remember what conversations have taken place between then and now between me and counsel.

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And if I did, I wouldn't be able to tell you here in this deposition.

Just a question, Mr. Speegle. Do you plan on taking breaks on the hour or what -- what works in your timeline?

(BY MR. SPEEGLE)

Q. We can take a break now. I generally try to break every hour and this is -- we've been going about an hour, so this is a fine time for a break.

THE WITNESS: Makes sense. All right.

(Break from 8:55 a.m. to 9:00 a.m.)

MR. SPEEGLE: We can go back on the record.

(BY MR. SPEEGLE)

Q. All right. Dr. Saber, I would like to switch gears here a little bit and ask you about some of the general technology related to this case.

Are you familiar with the concept of supervised learning in the context

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of machine learning?

A. Very much. Yes.

Q. Would you -- would you agree with me that the -- the patents at issue in this case are -- are related to supervised learning?

A. Generally speaking, yes, but obviously the devil is in the details when you start looking at every sentence and every description, the general idea.

Q. Okay. So I want to direct you now to your declaration in the '579 matter -- I'm sorry -- the '889 matter, which I believe is your Exhibit 3 for this deposition.

Let me know when you've got that in front of you.

A. '889. Okay.

Q. I'm going to direct you specifically to Paragraph 110, so let me know when you can turn to there. It's on PDF Page 54, which is numbered Page 50.

A. Which paragraph?

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Q. 110.
A. Paragraph 110.
Q. Are you there?
A. Yes.
Q. Okay. I would like for you to read for the record two sentences from this paragraph that begin with the -- the last sentence on Page 50, which starts with the words "in essence" and then continues on the next sentence that starts on Page 51, "the model."
Could you read those for the record, please?
A. All right. Let me locate it. This is, okay, eight or ten lines down.
So we are in declaration for the '889, Paragraph 110.
The sentence you asked me to read, it says, In essence, supervised machine learning - as described and primarily utilized in Cox for face classification - is a type of machine learning in which a model

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is trained using specifically labeled data, where each input is paired with a known and appropriately labeled output or target value.

Q. Thank you.

And I -- can you just explain a little bit what you mean in this sentence when you say each input is paired with a known and appropriately labeled output or target value?

A. Well, as you're doing -- I mean, when you do supervised machine learning, you typically have a series of samples or examples in your database.

And for each of those examples, you have a ground truth that either was labeled by a human observer or some other way, but you have the ground truth that basically says this is where the entity is or this is where whatever it is that you're looking at is.

So that's called -- usually referred to as labeled data.

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So the input, your example in your data set, you know, training data set, would be paired with a particular labeled data. So you can use that in your supervised machine learning to train the algorithm.

Q. Okay. And then can you continue on and read that next sentence in Paragraph 110.

A. Starting with the word "the model"?

Q. Yes.

A. So the next sentence in Paragraph 110 of Declaration '889 says, The model learns the relationship between the training inputs and outputs by minimizing prediction errors during training via the use of properly designed loss functions, enabling it to generalize and make accurate predictions on new, unseen data for classification purposes as disclosed in Cox.

Q. Can you just explain what that -- that sentence means a little bit

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more? And, again, I'm referring just generally to supervised machine learning, not Cox in specific?

A. Sure.

So as you, I'm sure, understand, you're putting together the supervised machine learning the same neural network. That network is blank to start with, so you have to train the -- you know, the weight and the -- you know, the hyperparameters and all the variables of that network.

So what you do is you present the training inputs and you present the output that goes with that input that you know is the ground truth.

So here's my input, here's what I expect to see for that particular input.

Obviously, the model is going to give you something because you initialize it to start with. The model is going to give you something.

The output of the model -- the difference between the output of the model and what you want it to give you, the ground truth, is typically captured using via some type of a loss function that's designed specifically for the supervised machine learning system, you know, that you're doing.

So you capture that difference, and then through backpropagation algorithms you backpropagate the error using, you know, Gradient descent algorithms.

And I'm -- I'm obviously summarizing extensively, but -- for this discussion.

So you backpropagate the error through the network and make updates for the weights and hyperparameters, et cetera, and you continue the training, example after example after example, until you're fairly satisfied that the model is generalizing properly and not overfitting to the noise in the training data.

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And then you, obviously, test that on a -- what we call -- typically we have three data sets: A training data set, a validation data set, and a test data set.

Q. A desk data test?

A. Test.

Q. Test data set. Okay.

A. Yes.

Q. Okay. And you talked about a loss function. And can you explain a little bit more what the loss function is trying to capture?

A. Sure.

So a loss function, I mean, I'll give you an example just for the sake of discussion here and illustration. Think of it as means square error.

So I'm looking at the error between what I want, the ground truth, and what I am -- what the model is predicting, the output of the model.

The difference between them

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constitute an error. So if my loss function is a means square error, then I'm subtracting the two and the square of that becomes the error. If, you know, MSE is the loss function.

If I'm using absolute, you know, maximum absolute distance, it will be a different loss function or cross-entropy or, you know, there -- there are different ones. Hinge loss, et cetera.

Q. Okay. And so you're -- you're trying to minimize the difference from the -- the labels that were put into the training to begin with?

A. I mean, ideally speaking, you want the model to predict exactly the ground truth that you have.

So if I give you the -- show this example, I want you to predict exactly my ground truth.

So if you can do that, then the error would be zero.

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Q. Mr. --

(Speaking simultaneously.)

(BY MR. SPEEGLE)

Q. I'm sorry, didn't mean to cut you off.

To make sure I'm following what you're saying, the ground truth in this context could be labels provided by human annotators or from another source?

A. Correct.

Q. So if you had human label data and you train the model on it, the model is going to make predictions that hopefully align with what the human label data was that was put in after training?

A. As much as possible. Obviously, nothing is perfect.

But, yes, the idea is I have -- the training data set is typically a data set that consists of training examples in some way of having those examples labeled in a supervised type situation.

Now, that labeling could be done automatically by another network. It could be done mostly, you know, by human annotators, but that's the idea.

Q. Okay. So it's being pushed towards whatever your labels are?

A. Yeah. So you're trying to train the network to predict basically an output that is close to the ground truth as possible.

Q. Okay.

A. Ideally speaking, obviously.

Q. So there's -- and I want to go back to Paragraph 110 in your declaration.

And this time I want to scroll up a little bit to the second sentence in Paragraph 110 that starts with "nearly every."

And this, again, is from your '889 declaration, which is Exhibit 3.

Could you read that paragraph -- I'm sorry. That sentence

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starting with "Nearly every"?

A. Yes. So, Nearly every machine learning system (and especially those that are intended for use in autonomous vehicles) including supervised learning systems -- supervised machine learning systems as disclosed in Cox aspire to "human-like" performance.

Q. What do you mean by "aspire to 'human-like' performance"?

A. Well, typically -- I mean, obviously, there are always exceptions. But typically, the human annotator or, you know, if -- if you show me an image and ask me to do a segmentation of the image, the human annotator is usually more accurate -- can do a more accurate type segmentation than just as standard algorithm.

You know, when it comes to image understanding or video understanding, humans are usually, you know, much better at it, generally speaking, than a computer.

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So you want the machine -- so since the ground truth is created by human annotators, and that reflects what you want the system to be, you're looking for basically the system to try to mimic as much human-like performance as possible.

Q. Okay. I'm going to switch back to your '344 declaration, which is Exhibit 1.

And I'm going to direct you to Paragraph 97 in that.

Can you let me know when you get to Paragraph 97?

A. '344 declaration?

Q. Yes.

A. One moment. Just taking a minute to open.

Yes, what about it?

Q. Sir, are you at Paragraph 97?

A. Getting there. Yes.

Q. Okay. And about halfway down there's a sentence that says, While Ross does not expressly state...

Do you see that?

A. Yes.

Q. Could you please read that sentence for the record?

A. While Ross does not expressly state the purpose of training the model with this data, a POSITA would have known that the purpose of using annotated training data to train Ross's model (or any machine learning model) is to make the model's predictions consistent with the annotations in the training data.

Q. Thank you.

And POSITA is an acronym for person of skill -- ordinary skill in the art, right?

A. That is correct.

Q. Okay. So why would a POSITA know that the purpose of using annotated training data to train Ross's model is to make the predictions consistent with the annotations in the training data?

MR. GINNINGS: Objection; form.

A. Could you repeat the question, sir?

(BY MR. SPEEGLE)

Q. Let me -- I mean, I can strike and ask a different question.

Can you just explain more about what you mean about what a POSITA would understand here?

A. I mean, the purpose of the general -- I mean, the general idea or the general purpose of the supervised learning model is for you to create a model that's going to predict what you're training -- you know, ideally speaking you have a set of training data that's labeled.

So I have a training example, let's say I'm doing area segmentation or face detection, I have a training -- training set of data where a human annotator has gone through and found all the faces in that particular image and -- and labeled them.

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So that kind of constitutes your ground truth. And the objective of the model would be to try to come as close to that ground truth as possible. Ideally speaking, of course.

Q. And is it your understanding that this is something that would have been well-known in the prior art to a POSITA, at least as of the time that the '344 patent was filed?

MR. GINNINGS: Objection; form.

A. Well, I mean, the concept is generally when -- you know, well-known, but the point is the devil is always in the details of how it's done and how the training is done, and that's not a -- a turnkey operation.

So it's -- there's a lot of details in how to train the model because you're looking for the model to generalize and not overfit. And that's not a trivial thing to do. You know, a generic person

wouldn't be able to do that immediately.

(BY MR. SPEEGLE)

Q. What do you mean by "generalize and not overfit"?

A. So when you have training data, you have limited amount of data. You know, let's say 10,000 images or 20,000 or whatever. You have a limited amount of data.

So with that limited amount of data, you're trying to train a neural network to respond -- you know, to -- to create basically, you know, outputs that are very similar to what you're -- you know, what you're looking for.

So -- now, if I show you a new image that's not in the training data that the network has not seen, will it make the right prediction or will it base -- that's called generalizing.

So will the network generalize based on -- from that new image that you haven't seen as a network, will it make the

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correct, you know, output? Will it get the correct output from -- from that image? That's called generalizing.

Or during your training, did you just overfit to the noise in the data? Because the data you have training -- training images, they have obviously noise in them.

So if you don't train your network correctly, you could just be overfitting -- so, basically, you're -- you -- you fudged the network to fit the training data exactly.

Think of it as -- you know, as a layman term. You've -- you fudged it to fit the training data. And when you show it a new image, it doesn't know what to do with it or it gets it wrong.

So that's called you've overfit because you -- all it does is just gives you what the training data says and it doesn't generalize to an example that you haven't

seen before.

Q. Got it.

And when you say you fudged it, is that something that would happen during how you set up backpropagation?

A. Well, it's done -- typically it depends on how you do the training. Because that's why I say the -- there's a skill in doing training.

It's not just I give the network a bunch of training images, I push a button, and go have some coffee and come back and there it is. Right? That's not how it works.

So there is a skill in how you do the training. You know, do I want to do, you know, backpropagation on every sequence on every example, the one where I do batch training, do a set of -- a set of 10 or 20 or 30 or 50 or 100 and then do the backpropagation?

Do I want to do dropouts? Do I

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want to, you know, sample different things? Do I want to change the initialization starting point?

There's a lot of -- you know, do I want to do regularization? There's a lot of things that go into how you train the network so you can get it to generalize and not overfit.

Generalization is good. Overfitting is bad.

Q. Okay. All right. I apologize for jumping around between your declarations so much, but could you now go to the Exhibit 4, which is your '579 declaration.

A. '579 declaration.

Q. Yes. And I'm going to be directing you to Paragraph 54 when you -- when you have that open.

A. Yeah, that's an interesting one.

Yes, sir.

Q. Okay. And can you read the --

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the last sentence on Page 21 of Paragraph 54. And that's number paged 21. It starts, A PNN...

A. Yes.

A PNN -- and PNN refers to probabilistic neural network. So a PNN, a probabilistic neural network, is a kernel-based classifier derived from Bayesian decision theory that estimates the probability density function for each class using Parzen windows or similar style estimations and classifies new observations according to the maximum -- sorry -- maximum posterior probability without iterative weight optimization.

Q. What does "classifies new observations according to the maximum posterior probability" mean?

A. Okay. So if you think about -- let's say I'm doing a classification. I have three classes, skin, sky, and grass. Okay. I want to classify an example between those

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classes.

So for each of these classes, I have a probability density function. That may be Gaussian, may be some other function. Let's just say it's Gaussian for now.

So there is what's called the class conditional probability density function, probability of X given class. And there is what's called the posterior probability, what's probability of the class given X.

So if I show you a sample X, what's a probability of that sample belonging to skin versus sky versus grass. That's called the posterior probability, probability of class given this sample.

Now, obviously, you want to maximize that because if it -- if the sample is closer to skin, the maximum posterior probability would show that the skin is the best, you know, classification for this particular example.

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So that's usually done by -- by what's called Bayesian optimizations. So typically -- if you go back to your probability book and have a look at Bayesian optimization, you'll see the maximum posterior probability or like probability of class given X.

Let's just say the classes are A, B, and C. So probability of A given X is equal to probability of X given A times probability of A divided by probability of X. That's called the Bayesian Decision Theory equation.

So you want to maximize that based on given a sample that your -- that's unknown for its classification. You want to say, okay, does it belong to the skin class, the sky class, or the grass class.

I'm talking about color, and I'm just giving an example here.

Q. Yeah, this is very helpful.

So I'm -- I'm sure I'm not

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following you as well as one of your students would, but I'm doing the best that -- to unpack the examples here, you have, you know, an image that's maybe just a little square of color.

If it's green, it's going to have a very high probability for grass. If it's pink, it will have a high probability for skin. And, you know, if it's blue, it will have a high probability for sky.

Is -- is that basically --

A. That's generally the idea.

So when you do -- when you do the Bayesian thing, you've got to say what's the probability of the class A given the sample X. It's equal to the probability of X given class.

That's your probability density function for the class that you have, your Gaussian, let's say, times probability of the class.

What's the a priori? It's more

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likely for the class to be this versus this versus this versus this. That's called the a priori probability. Divided, what's the probability of the sample?

So typically the probability of the sample is the same across all three of them. So you -- it's like dividing by .5 for all three of them.

So you can ignore the denominator, but the numerator is where the maximization happens.

Q. Okay.

A. And that comes originally from the radar theory.

Q. Okay. So when you say it's going to classify according to maximum posterior probabilities, you know, if you say, okay, I've got 70 percent that I think this is sky, 20 percent that I think this is grass, and 10 percent that I think this is skin, that's going to be classified as -- as sky, right?

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A. Yeah, which everyone has. So when you compute the posterior probability, you're going to say what's the probability of A given X, where A is the class, let's say, of skin. What's the probability of B given X? What's the probability of C given X?

And all these will have numbers and obviously between 0 and 1. And the one with the highest probability, that would be your maximum.

So you would say, okay, it's -- it's more likely to be in that class with the one that has the highest probability. That's called the maximum posterior probability.

Q. Okay. And I want to start bringing us back to the technology in this case.

But just to be clear, everything you've talking about so far is just generally background information about supervised learning, right?

A. Yes. It's a fun conversation

besides.

Q. Absolutely.

All right. So if our labels are, you know, whether a pedestrian will cross the street or wait at a stop sign, you would classify -- those could be your classes, and you could have a 70 percent, you know, probability of crossing the street, 30 percent probability of waiting on the side, and the model would say, okay, we're going to classify this as -- as crossing the street. Right?

A. I mean, generally speaking, but obviously the devil is in the details. And when we get into the details, we, you know -- but the idea is you want to put the sample in the most likely class that it should be at.

Q. Okay.

A. That's how -- that's why -- why you compute the posterior probability. And then the maximum of them is where you assign the sample to be. Now, that doesn't mean

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it's a hundred percent correct. You know, you could still make errors.

Q. Okay.

A. That's the idea.

Q. And these classes are still going to be defined by whatever the labels were in your training data, right?

So if your labels are sky, skin, grass, that's what you'll classify it as. If your labels are cross the street, wait at the sign, car, that's how it would be classified. Right?

A. Well, if we go to the skin, sky, and grass example that I gave you, I mean, in this case you're doing a classification.

So I receive a new sample, whether it's a pixel or a block of pixels. And I'm looking to see is this block of pixels skin colored, sky colored, or grass colored, right.

So I am going to compute that

probability, that posterior probability for that particular sample and then place it with a class that has the highest posterior probability.

That's the idea of, you know, classification using Bayesian Decision Theory.

So as that sentence says, you will need to estimate the probability density function for each class. So those don't just don't appear, you -- you still have to work to estimate those.

Q. Okay. Now, sometimes the training levels are themselves generated by machines, right?

A. Sometimes what?

Q. Training labels used to train a neural network can be generated by a machine?

A. Sometimes, yeah. I mean, you know, you could do some -- some with audit in quarters [phonetic] or whatever, yes. Sometimes you could do that.

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But, generally speaking, they're mostly humans. But you could train a machine to generate labels as well or -- or use the size of the space, like audit in quarters [phonetic] do.

Q. And when we say labels are generated by humans, that means that some human looked at a picture or a video and applied a label or otherwise classified the image manually; is that right?

A. So, for instance, you know, if I'm looking at an image and I'm doing a classification between skin, sky, and grass, so I show a human annotator an image and I say, Okay, circle for me -- you know, label 1 the sections of the image that are skin colored, label 2 the ones that are, you know, sky, and label 3 the ones that are grass.

That's, you know, typically one example of doing it.

Q. Okay. And when we're talking about this kind of classification, the -- to

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determine what has the maximum posterior probability, the probability of each class has to be calculated and considered, right?

A. Yes. So the probability density function of each class, so you would have to -- I mean, obviously, you would have to get that from training data.

So you would have to look at the color space of skin and say where the pixels typically fall in the color space.

And when you look at a series of examples, you know, 10,000 or whatever, you would develop a probability density function for that particular class.

You still have to also know the a priori probability.

Because that class, you know, for instance -- what I mean by that is let's say I'm showing you 10,000 images, but they're all shot, for instance -- they're all shot, let's say, in the middle of a city. Okay? Shanghai on the street. So how likely

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there would be any grass in those images, right? It's mostly going to be skin and maybe sky.

So the a priori in that case is mostly skin, right? More likely to be skin because in the middle of Shanghai on the street I would assume -- let's assume there's no grass.

It also depends on where the training set was done. That's why you would like a diversified training set. Not one, you know, that's shot in a, you know, biased manner, so to speak.

Q. Where does that a priori probability come from? Is it provided by human supervisors?

A. Well, you would have to estimate it. You would have compute it and estimate it.

And hopefully based also on your training data set and how diversified that data set is.

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So if I stood, for instance, in your garage and I took a thousand images of your garage, that's not a thousand diversified images, right? That's just like having five or ten. Because they're all pretty much the same thing. Just because you duplicate an image 10,000 times, it doesn't mean you get new knowledge, right?

So that's where you want your training data set to be as diversified as possible.

Q. Okay. So you used a phrase earlier, I want to make sure I'm understanding. You said you will need to estimate the probability density function for each class.

Can you explain a little more what a "probability density function" is?

A. Yes. So if you go to the Papoulis book on probability, I'm sure Papoulis will be happy to give you a very good explanation.

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But the idea is think of a probability density function as a continuous histogram. You know, when you compute a histogram, right, you say, Okay, I have ten items of this kind and five items of that kind and three items of that kind, right?

That's the histogram.

Now, if I take each of those -- let's say I have 20 total items, and 10 of them are color red and 5 of them are color blue, 3 of them are color green, and 2 of them are color purple, that's 20. That's called a histogram.

If I were to take the 10 and divide it by the total 20 and the 5 and divide it by the total 20, I would get what's called the probability histogram because it's now all percentage, right? It's .5 of A and 1 -- whatever .25 of B, et cetera.

So that's typically a histogram, which is a discrete version of a probability density function which would be

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continuous.

So the XY -- you know, the -- the -- the plotting space would be continuous.

So if this was a two-dimensional, you know, Gaussian probability density function, the X and Y -- and this would be PXY. The X and Y would have continuous numbers, not discrete. And the PXY would be, you know, continuous quantity between 0 and 1.

But you've looked at, for instance, Gaussian distribution, right? Normal distribution.

Q. Okay. Yeah.

A. Yeah, that's typically a probability density function.

What -- generally what you've looked at is usually one dimensional, so you'll see the bell curve. But you can have a bell curve in two dimensional, three dimensional, four dimensional.

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Q. Okay. I'm trying to hold in my head what you're describing now and what you said earlier.

So if -- if my model predicts a 60 percent for sky, what does that mean for the probability density? Is that saying like 60 percent of the labelers would have been sky, or what is this saying?

A. I think you're mixing apples and oranges.

Q. Okay.

A. Maybe you want -- since we have a two-day deposition scenario, you might want to look at Papoulis tonight and do a little studying for tomorrow morning.

Q. Okay.

A. There's a difference between probability density function and posterior probability, which is a number.

So what's the probability of Class A given this sample. That number could be .6, right? Probabilities are always

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between 0 and 1, right? Even though people quote 110 percent, that's all nonsense, right? Probabilities are always between 0 and 1.

So the posterior probability is a single number. What's the probability of this -- this class given that sample?

I may get a .6. What about the other class given that sample? I may get a .2.

The probability density function is what are the -- how are the samples distributed in the class?

See what I'm saying? Like normal distribution. Like if you look at the -- I don't know -- a height of males in -- in, you know, in basketball, you know, in NBA or something, right? So they're not all 7-foot tall, right? There are some that are 7-foot 2, there are some that are 6.8, there are some that are 6.5, there are some that are 6.

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So that distribution of how many are in each different height, it's called the probability density function. There are probably none that are 2 feet tall, for instance, right? And probably none that are 10 feet tall, right?

So -- and, obviously, there's an average there. You know, maybe the average is 6.8. I mean, I don't know. I'm making these numbers up, but...

Q. Yeah. So am I to understand that the probability density function is an -- you know, an input or a step along the way to generating the posterior probability?

A. Yes. You would need that.

So if you look at the Bayesian equation -- and this is something you might went to look at, you know, tonight in preparing for tomorrow.

So if you look at the Bayesian equation, if you're searching for it or, you know, you go to ChatGPT or something, you'll

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find if you look at total probability in Bayes' theorem.

So you'll find that it's basically the posterior probability is equal, so probability A given sample X is equal to probability of X given A. That's the PDF. That's the probability density function. Times probability of A, that's the a priori probability of the class how -- how likely is this class to appear in this scenario.

If I'm Shanghai, how likely for me to have grass in an image? Probably near zero, right?

If I'm in Wyoming, how likely for me to have, you know, I don't know, asphalt, you know, in my park? Probably near zero, right.

And then divided by what's the probability of this sample theory because every sample has a probability of appearing, right, they're not all the same.

Q. Okay. So what does it mean if

for a -- a model to have a, you know, a -- a 60 percent confidence in a given class? What does that mean in terms of -- of the model's analysis? Like what -- what is that saying?

A. I'm not sure what you're asking.

You're speaking somewhat of a foreign language.

Q. Now, that's fine. I --

A. I'm not sure what you're asking, but --

Q. Well, let me --

A. -- the point is -- the point is you're trying to do a classification. Right?

So your objective is to find what is the most likely class for the sample that I have here in my hand.

Q. And those classifications are still based on the original human labels, right?

A. If that's how you generated them, yeah. I mean, you have a training data

set, right?

As I mentioned to you earlier, you have a training data set, you have a validation data set, and you have a test data set.

That's typically how the work is done. So you train using the training data set. You validate on the validation data set to make sure that it's generalizing and it's not overfitting and all this type of thing. And you may have to tweak hyperparameters and et cetera.

Q. Correct.

A. And then, ideally, you test on a test data set that the system has never seen and never used in the training or the validation.

Q. Is it -- is it the case that you -- you need to make a -- a training setup in an algorithm specific to the content that you're evaluating or can you use the same algorithm and training for different kinds of

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content?

A. I wish the later was true, but it's not the case. I mean, you can't use the same -- every -- every application is -- is specific -- you would have to design systems typically for each application fairly specifically.

Like you can't, for instance, say, Well, okay, I've trained the system here on classifying skin, sky, grass. I'm just going to pick it up and put it into a face classification scenario and it's just going to work. That doesn't work that way.

There's a lot of skill in making, you know, these -- first of all, how you design a network, you know, do I want 5 layers, 10 layers, 15 layers?

How deep is my network? How many neurons is per layer? What activation functions do I want to use?

What initializations do I want to start with? How large of a batch size do

I want to use? Do I want to use regularization or not?

I mean, there's a lot of decisions that you're going to have to make, because the space is enormous and you can't really figure out where the global minimum is. You can't see it. It's not liking have a parabola in 1D from your calculus board.

Q. Okay. What about hardware, do you need different hardware for different training applications?

A. That's an interesting question. And the answer is you will need -- I mean, obviously we were teaching neural nets in the '90s. So I know -- I know people see machine learning today and they're, you know, excited about it, of course.

I was teaching neural nets in the '90s. The only problems in the '90s, the computers weren't fast enough to be able to train on a database of 10,000 or 100,000 images. It would have taken four weeks.

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I mean, when I did my Ph.D., it was done on a SPARC 10. I mean, a SPARC 10 -- I mean, I don't know if you recall and I'm not sure when you graduated, but I got my Ph.D. in 1996.

A SPARC 10 probably has less power than your iPhone today. Right?

So if you -- if I had to sit down on a SPARC 10 and train, let's say, with a hundred thousand images, it would have probably taken two months to run that exercise. Right? That same exercise today is done in hours.

See what I mean? Like algorithms that I built in the '90s on segmentation -- I did a lot of work on segmentation for my Ph.D. work and I built a bunch of algorithms to segment images.

And when you run that algorithm in 1995, it would take, you know, four or five minutes to segment an image. That exact same code, when my students were running it

in the -- in the late 2000s, let's say 2008, it was done in seconds in the same code.

That's because the hardware got so much better. Like in video boards and all that stuff has come a long way and that's why you can train on very large -- millions of images in a database today.

Q. Okay. So it sounds like you can run the same algorithms on different pieces of hardware, it's just a question of how efficient they would run.

A. Well, I mean, generally speaking, yes, but some -- you know, you would have to obviously look at the hardware a little carefully because in some cases you may not be able to run it.

It just doesn't have enough power to -- like you can't host, for instance, 10,000 images in memory or whatever. There's just not enough space or not enough, you know, CPU power.

So it's not just a slam dunk.

It's not like I just pick it up here and drop it there, push the button and there it goes. It's not quite that case.

Q. Okay.

A. Nothing happens like that in machine learning.

Q. Now, what about backpropagation algorithms specifically?

Can you use the same backpropagation algorithm to train for different kinds of classes?

A. The algorithm structure is -- is essentially the same, but how you utilize it depends on your application. I don't know, do you know what backpropagation is?

Q. Oh, most of what I know about it you've probably said today.

A. Well, you might want to join my course that I teach in the spring on machine learning. I go over all the mathematics of it very carefully.

The idea behind backpropagation

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is the following. You know, I'm providing you with an example at the beginning -- you know, assume I have -- I put together a neural network with a bunch of layers in neurons.

And I provide an example as an input. I let -- I initialize all the way to an activation function. I put some initialization and I get an output.

Then I compare that output to my ground truth. And it's X far away. Right? Using some type of loss function.

So that difference now, I'll propagate that backwards using Gradient descent algorithms to update the weights, you know, in -- in the biases in all of these neurons.

So then I'm getting hopefully closer to the ideal global minimum, which almost always you never reach.

So -- so as you provide more examples, right, hopefully your weights are

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getting closer and closer to the ideal state, but you don't really know what an ideal state is. We don't know where that is.

So you have to start sometimes on the different initialization end points because, you know, the space is very large. Like you may have 10,000 weights. Right? And -- and, you know, 5,000 biases or -- the space is very -- it's not a one-dimensional space.

It's very large. So trying to search for that optimal point in that space is not a trivial problem.

Q. Interesting.

So is it fair to say the network itself does not know what it is predicting, it's just you minimizing the loss function?

A. Well, as you do -- as you use backpropagation back and forth, so you have what's called "feedforward backpropagation."

So you use a batch size. Let's

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say you pick a hundred samples. You do a feedforward. You collect all the stuff. You accumulate the adder [phonetic]. You backpropagate it. Do an update on all the weights and biases.

Then you pick the next batch, another hundred samples. Do the same thing again.

And you have to keep iterating, you know, epochs, you know, upon epochs to try to get it to converge to something. And you may have to provide different interpoints to see if you're getting the same thing and then test on the test data set to see if it generalizes.

So there's a lot of skill involved in how you do this. It's not just a turnkey operation.

Q. I'm going to shift to a different, probably related subject.

But are you familiar with the term "softmax"?

A. Of course.

Q. What is a softmax?

A. Well, if you look at some of the hinged -- like loss functions and you look at the -- what's called the max, you'll notice it's basically -- say, for instance, I told you max zero comma alpha. Right? So that function, if alpha is less than zero, then the value is zero.

If alpha is greater than zero, then you have, let's say, a linear -- let's say you have a linear, you know, growth.

So at the point zero, you have a discontinuity. You know, it -- it -- the derivative is discontinuous and that usually causes problems in Gradient descents because Gradient descents rely on derivatives. And if a derivative is discontinuous, it's problematic.

So you use what's called a "softmax function" to essentially provide a continuous equation to the discontinuous

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situation so that you can differentiate it, you know, in backpropagation.

So that's typically -- you know, we use that, you know, somewhat in algorithms.

And the other option is obviously on the output. Sometimes you apply a softmax so you can get some type of probabilities.

Q. Can you explain more about what you mean about that -- that other option?

A. So if I want my network to predict probabilities, right, those numbers have to be between 0 and 1. They can't just say 15, right?

So let's say the -- I have ten outputs or -- yeah, let's say I have ten outputs for my neural network and I provide an input and the output that comes out, those outputs -- and let's say those ten outputs represent -- well, let's make it easy. Let's say I have three outputs and the three

outputs represent the three classes of skin, sky, and grass.

So I present an example to my network. I want the output -- one of those three outputs to have, let's say, a high probability, hopefully, because I present you with the skin example. I want the skin output to have a very high probability and the other two to be very low. Because I can say that sample is skin.

So to get a probability on the output, not get a number like 15 or whatever, because probabilities are always between 0 and 1, you can apply a softmax function on the output layer to essentially turn that layer into a probability.

Q. So I'm a little confused now about why the model is spitting out numbers like 15 as a probability.

A. Well, it doesn't spit out 15 if you design it properly because you have a soft -- you know, when you create a model, if

this is a classification model and you have three classes, then you have three, let's say, output neurons, and those output neurons you set up as softmax function to make sure that the output is between 0 and 1 and when it adds up to 1. So it's got to also add up to 1, right, because otherwise it's not a probability.

Q. Okay.

A. So you have to design it properly. It's not just on its own.

If you don't put a softmax at the output, you just let the neurons do what they want, you could get a 15 and a minus 2. So, obviously, you have to design the network probably -- properly.

Q. So I -- I think -- I'm going to say this back to you so you make sure if I'm understanding it.

But that you can add a softmax to the output neurons of your model so that the outputs make sense as probabilities?

A. Yeah. You typically set up a softmax function on your, let's say, output layer.

Q. Okay. And if you did not set up that softmax layer, what did the outputs of your model represent?

A. I mean, they'll represent -- they'll have -- they'll have -- depends on how you set up the weights, what activation functions you use.

Let's say if you use a sigmoid activation function, that output is going to be between 0 and 1, but it's not going to add up to 1 because they can come out to be .6, .5, and .2.

If you set up, let's say, a ten function, you may have negative outputs.

So it depends on what the activation functions that you have utilized, you know, in your neural network are.

So that activation -- if you use, for instance, what's called the rail-U,

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it essentially basically is like a linear output when the -- when the value is positive and it's 0 when the value is negative. And that's a fairly popular you know, function, the rail-U.

So you could have values that are, you know, large, 15, 25, whatever.

So you want -- so if you want probabilities, you have to set up a proper layer at the output to give you a probability.

Q. And that's --

(Speaking simultaneously.)

A. That's where softmax comes in.

(BY MR. SPEEGLE)

Q. Okay. That's what the softmax does is it --

A. Yeah.

Q. -- it takes whatever the neuron output is and puts it into a sensible probability?

A. Yeah. Turn it into a

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probability. I mean, if you take my course in the spring, you'll see exactly how that works.

Q. Keep offering. I may take you up on it. I don't know.

A. Yes, I could -- I'm happy to come over to your law firm and teach it.

Q. All right.

MR. SPEEGLE: Probably a good time for a break. We've been going for about -- a little under an hour. Y'all good with a break now?

THE WITNESS: Fantastic.

(Break from 9:53 a.m. to 10:03 a.m.)

(BY MR. SPEEGLE)

Q. Okay. Dr. Saber, I would like to direct you to your '344 declaration, which is Exhibit 1 to this deposition.

Can you let me know when you've got that in front of you?

A. Yes, I do.

Q. And I'll directly to

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Paragraph 62 of your declaration.

A. You said Paragraph 62?

Q. Yes.

A. Okay. Sir, the paragraph that starts, "In my opinion"?

Q. Yes. And this is a paragraph regarding claiming construction, right?

A. Yes.

Q. And you applied the plain and ordinary meaning of all terms in the '344 patent?

A. Yes.

Q. Okay. So you do not provide any specific constructions for any terms?

A. No, I applied plain and ordinary meaning.

Q. Okay. And that includes for the term "statistical summary"?

A. That's correct.

Q. Okay. I'm going to ask you a similar question about your '046 declaration, which is Exhibit 2. And so I would direct

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you to Paragraph 56 of that declaration.

A. Yes, sir.

Q. And in the '046 declaration, you provided a construction for the term "user"; is that right?

A. That's correct.

Q. And you did not provide construction for any other term in the '046?

A. That is correct.

Q. Okay. I'll stay on this one for just a minute and ask you a little bit about your construction of "user."

Can you turn to Paragraph 59 of your '046 declaration?

A. You said 59?

Q. Yes, Paragraph 59 of Exhibit 2, which is your '046 declaration.

A. Yes.

Q. And can you read the first sentence of Paragraph 59 for me?

A. Based on my review of the '046 patent specification, there is no disclosure

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in the specification about the state of mind of a person that is not a road user.

Q. Okay. And -- and what do you mean by that?

A. Well, I mean, if you -- hold on a second. Something -- I clicked something here by mistake and my paragraph disappeared.

Sorry about that.

So if you take a look at the '046 patent, and obviously read through the patent and the claims and et cetera, when you read the claims clearly in light of the specification as we discussed earlier, the patent is referring -- when they're saying "user," they're talking about a road user, and that's the context of what -- how "user" is being utilized in the patent.

Q. Okay. Would you agree with me that the specification of the '046 patent refers separately to users and road users?

A. I -- I'm not sure what you're asking. Are you saying that the word "user"

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appears sometimes without "road user"? What exactly are you asking?

Q. Well, let me -- let me direct you to something specific.

So can you get Exhibit 7 to the deposition, which is the '046 patent in front of you?

A. Yes, I have the '046 patent in front of me.

Q. Okay. And can you turn to PDF Page 20, which should be Columns 13 and 14 of text.

A. Yes. I see that.

Q. Okay. Can you look at the -- if you look at the top of Column 13, the first full sentence starts with the word "because."

Do you see that?

A. Yes.

Q. Okay. And that sentence says, Because these summary statistics characterize the distribution of human responses that

predict the state of mind of a road user pictured in the stimulus, the predicted statistics are therefore a prediction of the aggregate judgment of human observers of the state of mind of the pictured road user and thus an indirect prediction of the actual state of mind of the road user.

Do you see that?

A. You read it correctly.

Q. Okay. And that's referring to "road user" as you are construing the term "user" by itself, right?

A. Yes, I mean, the -- as I mentioned to you earlier, the -- when you read the -- when you read the patent, you obviously read the -- the claims in light of the specification.

When it's referring in the claims to "user," that's talking about a road user.

Q. Well, I want to direct you to the bottom of Column 14 on this same page.

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And the -- a sentence that starts on Line 62.

A. Okay.

Q. Well, we can -- I'll -- I'll back up a little bit and just -- at the start of that paragraph.

It says, To provide for interaction with a user, the subject matter described herein can be implemented on a computer having a display device, e.g., a CRT (cathode ray tube) or LCD (liquid crystal display) monitor, for displaying information to the user and a keyboard and a pointing device, (e.g., a mouse or trackball), by which the user can provide input to the computer.

Do you see that?

A. Yes.

Q. And that did not refer to a road user, that just referred to a user by itself?

A. Yeah, I mean, this is talking about obviously a user that's using the

computer, a -- you know, the context obviously is important, but yes.

Q. So is it your understanding that when the specification refers to road users, it's talking about somebody out on a road like a car or a bicycle or pedestrian and when it just says users, it's using that term more generally?

A. Well, I think you're mixing a couple of things here. So obviously I'm analyzing the claims of the patent, right? I'm not just, you know, looking at the patent for enjoyment.

I'm analyzing the claims of the patent. And as I read the claims of the patent, that's the construction that I put in place for the word "user" in the claims of the patent given the context of the claims.

So with the -- the paragraph you just read is talking about a user on a computer. That we're -- obviously the word "user," depending on where you drop it, can

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have different meanings.

But we're talking about the claims here and reading those in light of the specification in the prosecution history, et cetera.

Q. I appreciate that. And I -- I'll ask you about the claims later. I'm just trying to understand the specification right now.

Let me direct you to Figure 2 of -- or specifically Figure 2A of the specification.

Can you let me know when you're at Figure 2A of the '046 patent? It's on PDF Page 4.

A. Yes. Yes, sir.

Q. And can you read what's in the bottom box of Figure 2A.

A. Apply model to other video data to generate a prediction of user behavior associated with the other video data.

Q. Okay. This is not referring to

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a road user, right?

A. Well, I mean, again, you're -- you have to read the -- the -- the specification in light of the context of what's going on.

So as I said to you earlier, when you read the claims, the claim construction is -- has to do with the claims and the use of the word "user" in the claims.

Q. Okay. My question is not about the claims yet. This is just about Figure 2A.

And can we agree that Figure 2A does not refer to a road user, right?

A. Yeah, this is talking about user behavior, yes.

Q. All right. Let's move on to your '889 declaration. I'll direct you to Paragraph 57 of that one.

A. '889, Paragraph 57. Just one moment. Okay.

Q. And am I right that in

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rendering your opinions on the '889 patent, you did not provide a construction for any terms in the '889 patent?

A. You are correct.

Q. You applied the plain and ordinary meaning of everything in the '889 patent?

A. That is correct, to -- well, I applied the plain and ordinary meaning to all -- of all terms of the challenged claims.

Q. Okay.

A. Yes.

Q. All right. I want to ask you about a specific claim limitation in the '889 patent. So if you scroll up, you'll see there is a -- a list of the claims in the '889 patent.

Do you see that?

A. Yes. Hang on. Let me find it. You said '889?

Q. Yes. Okay. And I'm looking at a page -- PDF Page 26, which is numbered

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Page 22, and the limitation at the top is 2[c].

A. Okay.

Q. And do you see that?

A. I do. Give me one moment. Yes.

Q. Can you read limitation 2[c] for me.

A. So this is '889 declaration, limitation 2[c].

Generating a training data set comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images.

Q. All right. What do the words "summary statistics" in this limitation mean to you?

A. Well, there is a description, obviously, in the patent itself about it. Let me open the patent itself. So I'm -- I'm looking at your '889 patent.

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And if you go to -- if you go to the patent '889, Column 6, starting at Line 8, there's a good description of summary statistics from Column 8 to roughly column -- I'm sorry -- Column 6, Line 8 to Line 43.

Q. Okay. This Column 6, Lines 8 through 43, repeatedly uses the phrase "summary statistics," right?

A. Well, it uses obviously the phrase "summary statistics." But it also -- if you look, for instance, at Line 18, it says, These summary statistics can characterize the human observer in terms of certain parameters associated with the statistics, such as the content of response, a time associated ... position ... parameters can also be associated with central tendency, variance, skew, kurtosis, scale, or histogram.

So also if you look at Line 27, it says the statistics can include a parameter that additionally or alternatively

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characterizes the movement of the human observers' eyes, et cetera, et cetera, et cetera.

Q. Okay. And let me ask an even simpler question.

What is a statistic?

A. Well, I mean, if you compute, for instance -- I mean, there are obviously various definitions that you can, you know -- a mean, for instance, if you copied an average, consider it a statistic, if you compute a variance, the cross-variance, a covariance, a correlation, a histogram, those are all, you know, within the umbrella of statistics, so to speak.

Q. Okay. And I know you opened up the '889 patent, but I would actually like to direct you to the '344 patent.

A. '344.

Q. Exhibit 6.

A. Yes, sir.

Q. And if you'd scroll down to the

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claims, which are on PDF Page 21, I want to ask you about Column 15, Line 35.

A. All right. I'm looking at the claims.

Q. Okay. And Column 15, Line 35, the '355 [verbatim] patent, claim 1, refers to statistical summary.

Do you see that?

A. Yes.

Q. Now, do you view the term "statistical summary" as equivalent to "summary statistics"?

A. Well, I mean, you've got to read the term as described in the claim and in the claim elements.

And so, for instance, if you look over here, this claim 1 that you're referring to is a method claim.

And if you look at Line 34, it says, and predicting an output statistical summary characterizing...

So the applicable statistical

summary characterizing a distribution of user responses expected to be received responsive to presenting the sensor data to a plurality of users.

So that's what that output statistical summary is.

Q. Do the words "statistical summary" by themselves impart any specific meaning to you?

A. Yeah, it's a statistical summary. So it's a summary -- it's -- it's got -- it's statistical. It's not classification. It's statistical, so it has to do with statistics and it's summary -- summarizing.

Q. What do you mean by -- I'm sorry.

A. It's statistical and it's summary. So it's -- there is some type of a statistical characterization and it's summarized.

Q. And is that any different from

what the words "summary statistics" would impart to you?

A. Well, I mean, you have to -- you know, one thing I've learned when I'm looking at claims and patents, the wording obviously has -- is very context dependent on the claims and how it's being structured in the claims.

So in this case, it's talking about an output statistical summary, which that output is from the out -- from the supervised learning-based model.

It's outputting a statistical summary that characterizes, et cetera, the rest of that sentence.

Q. Well, let me ask --

A. That's what it -- that's what it's targeting in this particular claim element.

Q. Yeah. Let me ask a question that hopefully might cut through some of this.

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Do any of your opinions in this case -- or in any of the five cases depend on a distinction between the words "summary statistics" and "statistical summary"?

A. Well, again, as I mentioned to you, my opinions are related directly to what's being disclosed or discussed in that patent and in the claims that I've analyzed in my declaration.

So when you read that claim, you read the claim in light of the specification, et cetera, and perform that analysis.

Now, when I go to a different patent, I read that claim relating to that specification.

And depending on what the claim element reads, you interpret it applying plain and ordinary meaning or apply construction as needed.

Q. Okay. So it's your opinion that a POSITA would make a distinction

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between summary statistics and statistical summaries?

A. Well, the POSITA would read the claim element and would interpret the claim element, in this case using plain and ordinary meaning.

And what -- what it is in -- in the case of the '344, that output statistical summary is referring to a characterization of a distribution of user responses, et cetera.

Any other claims, it has to do with what's being claimed there and how it's described.

So you apply plain and ordinary meaning to that. It's not just in a vacuum.

Q. Are you able to -- I mean, I understand that -- we'll talk about the claim limitations as a whole later, but I -- are you able to answer my question with respect to just the words "summary statistic" and "statistical summary" in isolation?

A. Well, I mean, words don't --

you know, you don't interpret words in isolation.

If I told you "bank," would you understand that to be an institution where you deposit money or will you understand it to be a river bank or would you understand it to be a snow bank.

So until I say something else, that "bank" could have different meanings.

So that's why each claim is specific to the patent and the -- and the specification that that claim is being, you know, described in. And you read it in light of that specification.

Q. Can you think of any examples where a statistical summary would be different from a summary statistic?

A. Not off the top of my head at this point.

But, again, you know, you read the claim elements in light of the specification and render an opinion based on

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that.

It's not done in a vacuum.

Q. All right. Dr. Saber, is the copy of the '344 patent that you have -- that you have that's identified as Exhibit 6, that's text searchable, right?

A. Yes. Yes.

Q. Can you do a text search on Exhibit 6 for the phrase "statistical summary," and let me know how many hits you have?

A. On the word what?

Q. "Statistical summary."

A. "Statistical summary."

So I'm doing a search on the words "statistical summary" together?

Q. Yes, "statistical" space "summary."

A. Yes. "Statistical" space "summary."

And I see what looks like one of seven.

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Q. Is it seven or nine?
A. Nine. Sorry. I'm -- I'm not able, I guess, to read it. It's so small.
Q. All good.
A. Yeah. Hang on a second. I want to make sure.
So, yes, it's one of nine. Sorry.
Q. And if you want to click through those nine hits, can you confirm for me that all nine of those hits appear in the claims of the '344 patent?
A. That is correct.
Q. Okay. Now, did you interpret the phrase "statistical summary" in the claims of the '344 patent in view of the passage we described earlier that's at Column 6, Lines 1 through 36?
A. I think you're mixing apples and oranges a little bit. Because the passage we described earlier, if my memory serves me right, was on the '046. So it's

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pretty much the same package, but I just want to be sure for the record.

Q. Yeah.

A. So --

Q. It was the '889 patent we talked about earlier. This is -- and -- and you're right. Let's go look at -- let's just go look at Column 6, Lines 1 through 36 of the '344 patent.

A. Yeah. Which are obviously very similar language to the other one. I just want it to be clear for the record.

So what we were looking at before was the '889; now we're looking at the '344 in Column 6, which starts with "In step 210." It's pretty similar language to what you see in the '046 and the '889 for that same type of thing.

Q. Right. And this -- this passage of Column 6 describes summary statistics, right?

A. Yes.

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Q. And did this inform your interpretation of statistical summary in the claims of the '344 patent?

A. Yes. As I've read, obviously the '344 claims in light of the specification, you read obviously the entire specification and analyze it.

Q. And so you -- you interpreted the statistical summary in the claims of the '344 consistent with the summary statistics described in the specification of the '344. Is that fair?

A. Generally speaking, yes.

Q. Now, I think you read this on the '889 patent before, but I just want to refresh it on the '344 patent.

Can you read the sentence that starts at Line 11 of Column 6, "These summary statistics can characterize"?

A. Yes. So '344, Column 6, Line 11, These summary statistics can characterize the human observer responses in

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terms of certain parameters associated with the statistics, such as the 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.

Q. Now, one of these examples has to do with the position of a human eye, right?

A. Yeah. Obviously, that's an example.

Q. Do you have understanding of -- of how that embodiment would -- would work?

A. What do you mean?

Q. How -- how could the position of a human eye be used to characterize the -- the human observer response?

A. Well, potentially, I mean, if -- if I am labeling something on the image, you know, potentially on what I'm looking at at the image, so you have a camera looking at your face, you know, where -- where I'm looking at in the image, as a human

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observer.

Q. Okay.

A. That could potentially be important.

But, I mean -- but, obviously, these are examples. These are not -- so the claims -- you know, these are just examples.

Q. And do you -- do you agree that the claims cover these examples?

A. Well, I mean, obviously, the claims are more broad than just that, but these are examples of what a statistical summary could be. That doesn't mean that's all it is.

Q. Okay. So the -- a statistical summary can characterize a distribution of user responses based on the position of, you know, the eye of the human annotators, right?

A. Well, like I said, that's an example of -- you know, these are examples with the specifications providing.

But there's other examples that

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do other things.

You know, for instance, if you look at Line 20, also the statistics can include a parameter that additionally or alternatively characterizes a human -- you know, the movement of human observer's eyes.

You know, there's other examples. Like if you look down below, Line 28, In a further embodiment, the statistics stored in the database cover a large set of images of people on or near roads and are characterized in a number of different categories, such as pedestrian, drivers, et cetera, et cetera.

So these are different examples of, you know, what these type of things might be.

Q. Sure. Am I right that some of these examples of ways the summary statistics can describe the user responses don't actually include the user responses itself?

A. What -- what do you mean?

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Q. Well, if my summary statistics have to do with the position of an eye of a human observer, that's not going to actually say what the response of that human observer was, right?

A. Well, I mean, you're providing a statistical -- you know, a summary statistic of -- you know, let's say there was ten humans that looked at this image and you're summarizing their responses.

So that's where, for instance, histograms would come in, right? So you would summarize, you know, three of them looked over here and two of them looked over here.

So a histogram can provide the details so you know how many of them looked at the left side of the image versus the right side of the image as an example basically.

Q. Sure. But that example you just described does not involve actually

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summarizing the content of those annotations, right?

A. Well, obviously, it depends on what the summary statistic is. But in some cases you're summarizing a response time; in other cases, you're summarizing, you know -- like, you know, distribution of user responses.

Q. Okay.

A. So it depends on what you're summarizing.

Q. Okay. And you're using "summarizing" as a verb.

Am I understanding the -- the '344 patent right, that the -- the verb in this phrase is "characterizing"?

A. Well, if you look at the claim itself -- and let me make it a little bit bigger.

So if you look at the claim itself, so it says -- and I'm looking at the start -- the claim was starting with

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"providing."

So you see it says, Providing the sensor data as input to a supervised learning-based model.

So you're taking the sensor data that was collected in the previous 1[a], receiving, you're providing that sensor data as input to a supervised learning-based model. So now it's describing what that supervised learning-based model is going to do.

That supervised learning-based model is configured to receive an input sensor data displaying a particular object on the road, like a cyclist, a pedestrian. Right?

And it's 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.

So as if I took that sensor

data and showed it to ten users and they provided responses, your supervised machine learning model ideally should provide a -- you know, should provide an output statistical summary characterizing a distribution of user responses.

Q. Right. And an example in the specification about how summary statistics can characterize a distribution of user responses is by describing the position of the eyes of the human responses -- responders, right?

A. That's only one example. There are other examples where it's describing obviously the road users or state of mind. You know, there are different examples.

Q. But you would agree with me that the '344 patent is not limited to situations where the summary statistics actually reflect the user responses, right?

A. I don't -- I'm not sure I understand what you're saying.

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Q. Let me -- let me direct you somewhere else. Why don't you look at Paragraph 110 in your '344 declaration.

A. Paragraph 110, '344 dec?

Q. Yeah. This is Exhibit 1 to your deposition.

A. Yes.

Q. All right. In the -- I'll read this, and you can confirm if I get it right.

It says, In my opinion, Ross and Cox does not teach elements 1[b], 10[b], or 19[b] because, among other reasons, Ross does not teach or suggest how the "set of possible intents or hypotheses" or "associated likelihood values" are generated or what form they take, and neither of these items constitutes a "distribution of user responses" as required by the challenged claims because neither the set of intents/hypotheses or the likelihood of values is a distribution.

You see that?

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A. Yes.

Q. Now, you -- and just to add some context to it, you understand that the -- the set of possible intents or hypotheses and the associated likelihood values, that's what Dr. Janet and Tesla have identified as summary statistics, right?

A. Incorrectly, but yes.

Q. Okay. And you say that those alleged summary statistics are insufficient because they do not constitute a distribution of user responses.

Is that a fair characterization of what you say here in Paragraph 110?

A. That is correct.

Q. Now, you used the word "constitute." And I want to go back to claim -- the claim language we were looking at.

And -- and the word "constitute" is not in claim 1 of the '344 patent, right?

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A. Yeah. The word "constitute" does not appear exactly in the -- it's not printed on that -- in that claim, yes.

Q. Yeah. The -- the verb in the relevant sentence, which is on Column 15, Line 35, is "characterizing," right?

A. Yes.

Q. And we just looked at Column 6 of the '344 patent and they provided some examples of characterizing, which were very different from the word "constituting," right?

MR. GINNINGS: Objection to form.

A. I'm not sure what you mean, but I mean, the words say what they say in the patent.

(BY MR. SPEEGLE)

Q. Okay. Is it your opinion that "characterizing" and "constituting" mean the same thing?

A. Well, depending on the context

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that you're using, I mean, the wording, I mean, if you want to discuss -- if you have a specific sentence in mind, we can look at it.

But it -- you know, words are not obviously read in a vacuum. As I explained to you earlier, the word "bank," they're not read in a vacuum.

There -- there is a context of how the word is describing whatever is being read.

Q. Okay. And the sentence we read in Column 6 at Line 11 before says that the summary statistics can characterize the human observer responses --

A. Yes.

Q. -- in terms of certain parameters, right?

A. That's one example, yes. That's not all of it. Yeah, that's one example.

Q. What do you mean when you say "that's not all of it"?

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A. I mean, that's one -- the specification gives this as an example. There are other examples of summaries, you know, summary statistics.

Q. Okay. The '344 patent claims cover all of the examples in the specification, right?

MR. GINNINGS: Objection to form.

A. Well, if you read -- I mean, obviously the specifications describe examples, but what's claimed is -- is what the invention is. Right?

If I was taught one thing by attorneys, I suppose, see, the claims claim a certain thing. The claim -- so the claims are saying, I'm predicting an output statistical summary characterizing a distribution of user responses expected to be received, et cetera, et cetera.

So the claims are claiming that particular thing.

(BY MR. SPEEGLE)

Q. Is it --

(Speaking simultaneously.)

(BY MR. SPEEGLE)

Q. I'm sorry, are you done?

A. So the claims are claiming a certain -- this particular thing. So the claim -- the claims are saying we have an output statistical summary that characterizes the distribution of user responses.

So that output statistical summary has to characterize a distribution of user responses that would be expected to be received, responsive to presenting the sensor data to a plurality of users.

So if I took a sensor data, present it to a plurality of users and they provided responses and I were to create a distribution of those manually, my supervised system should be able -- should come up with the same idea or the same result.

So statistical summary that's

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being claimed here has to do with that particular set -- you know, information.

Q. And I'm -- I appreciate that information. That's very helpful. I'm just trying to understand how you interpreted that phrase "statistical summary characterizing a distribution."

And is it -- is it fair that your interpretation of characterizing means that the summary statistics have to actually include the distribution of user responses?

A. It's got to characterize -- it's got -- that statistical summary has to be -- has to characterize the distribution of user responses.

So I -- when I look at that summary, I should be able to get a pretty good understanding of the distribution of user responses.

Q. Could you get a pretty good understanding of the distribution of user responses by statistical summaries listing

the eye position of human annotators?

A. No. I don't -- I think you are misinterpreting the point here.

See, it's a good question, but you're misinterpreting the point.

See, you have to look at the entire claim of what's being claimed here. It's not -- you're not looking at one point or one sentence in a vacuum.

So you're receiving -- I mean, if you look at the claim, obviously it's a method claim, as you know.

You're receiving by a computing device associated with an autonomous vehicle operating on the road sensor data captured by the sensor installed on the autonomous vehicle.

So you have an autonomous vehicle, you have sensor on it, say a camera, and that sensor is capturing imagery on the road, and that's what you're receiving.

And the sensor data is

displaying an object on the road. It's not looking at, for instance, your garage to see if you -- you know, if you're organized in your garage.

It's looking at the -- you know, displaying an object on the road because it's on the vehicle and it's looking at an object on the road like a pedestrian, a cyclist, another car.

Then you're providing the sensor data as input supervised learning-based model. So the antecedent basis here is that sensor data is referring to sensor data on Line 27, et cetera.

So there is specific discussion here in the claim. It's not -- you're not just reading one sentence in a vacuum.

Q. Okay. And is it -- based on your read of the claims as a whole, you came to the conclusion that the claims require that the summary statistics give you a pretty good idea about the distribution of user

responses. Is that right?

A. To presenting a sensor data, so the users are looking at the sensor data. They're not looking at their pictures that they shot at Disney World. Right?

They're looking at the sensor data that was captured by the sensor that's mounted on the vehicle in claim 1[a].

Q. Okay.

A. And they're providing a response to that sensor data.

Q. And when you say "they," you mean the -- the hypothetical annotators?

A. They -- yeah, the -- the -- the users, right.

Q. Yeah. And that's -- and this may be where I was not following your summary of supervised learning earlier, but that's essentially the outputs of those models after they go through the softmax. Is that what we're talking about?

A. Well, the output of the model

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here -- I mean, what the model here is saying as -- see, if you look at 1[b], 1[b] says, Providing a sensor data as input to supervised learning-based model.

So you're going to take that sensor data that's captured by the sensor that's mounted on the vehicle, and you're going to give that to a supervised learning model.

Then the next part of 1[b] tells you what the model does with it. The model takes that sensor data as input and it's displaying a particular object on the road. It's not looking at your freezer to see if you have ice cream. It's displaying a particular object on the road like a pedestrian, a cyclist, et cetera. And predicting an output statistical summary that characterizes the distribution of user responses that you would expect to get when they look at that sensor data that's displaying an object on the road.

Q. Okay. I think what I'm trying to understand is the -- when you talk about predicting a distribution of user responses, is that different from the probability predictions as output of a softmax that you talked about in -- in general supervised machine learning context?

A. Yeah. I mean, in this case, it's predicting an output statistical summary that characterizes distribution of user responses. It's not just a probability of one or -- one or two or three classes.

Q. How --

A. It's --

Q. How is that different?

A. It's a -- it's -- it's different. I mean, having it -- how it's different? It's like how is a car different from a bicycle. They're different.

Q. Well, let me ask it this way: If I have a -- if I characterized -- I mean, you talked about the posterior probabilities

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and we had sky, skin, and grass?

A. Yes.

Q. And you said it could be 10, 30, 60?

A. Yeah.

Q. How is that different from saying if I had a hundred annotators, 10 would say skin, 30 would say grass, 60 would say sky?

A. Well, that could be the case. But the point is here you have an output statistical summary characterizing a distribution of user responses and not just -- so that statistical summary has to characterize the distribution, not just the output probability. It's got to basically -- I mean, when I give you the mean of the distribution, the variance, the covariances, you know, the spread.

So it's not just the probabilities boom, boom, boom.

Q. Okay.

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A. Characterizing the distribution is different from looking at the probability of a class.

Q. Okay. So the probabilities would be the same, but there's an extra characterizing layer. Is that what you're saying?

A. I -- I think you're -- you're misunderstanding the difference between distributions and probabilities.

So -- and -- and --

Q. Well, help me understand it. Help me understand it.

What is your two-sentence explanation for how these things are different?

A. There is no such thing as two-sentence explanation. There's a book called Papoulis.

Q. Okay.

A. On probabilities of random variables and stochastic processing. There's

no such thing as two-sentence explanation.

But a distribution is not the same thing as the probability. Like, if you look at the Bayes' theorem, probability of A given X, is the probability, is equal to probability of X given A, that's a distribution, times the probability of A, that's, again, a distribution, divided by probability of X, that's a probability. There is -- they're not the same thing.

Probability is a number, .6. A distribution is not the same thing as a probability.

You go on ChatGPT sometime this afternoon and say, Explain to me what a probability density function is and how is it different from a probability, I'm sure it will give you an explanation of that.

Or download Papoulis and just look at it. Like we talked earlier, a normal distribution. Remember what we said about that?

Q. Yeah. So I want to direct you to Column 12, Lines 53 through 60 of the '344 patent.

Can you go up to there?

A. Column 12, Lines 53 to 60 of the '344, yes.

Q. Yeah. Can you read that sentence that starts, "Because these summary statistics"?

A. Yes. It says, Because these summary statistics characterize the distribution of human responses that predict the state of the mind of the road user pictured in the stimulus, the predicted statistics are therefore a prediction of the aggregate judgment of human observers of a state of mind of a pictured road user and thus an indirect prediction of the actual state of mind of the road user.

That's exactly what I'm trying to explain to you.

Q. Okay. And so how is this --

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how is this related to what we were just describing about probabilities and distributions?

A. Well, you see where it says "Because these summary statistics characterize the distribution of human responses that predict the state of mind," so it's -- these summary statistics aren't just a single probability. They're characterizing the distribution of human responses.

Now, if you look at the claim, you see it says "statistical summary characterizing a distribution of user responses." It's not just a single probability. So it's characterizing a distribution.

So when you see those summary statistics, you should understand there's a distribution there. Like a -- say a normal probability density function.

So you're looking at a distribution, not a single number

probability.

And this explains further, the predicted statistics are therefore a prediction of the aggregate judgment. Because you have a hundred people looking at this, they all have different judgments. So you have to be able to comprehend all that.

Q. All right. Let's turn to the '046 patent.

A. '046. Yes, sir.

Let me state -- before we jump into the '046, let me ask you a couple of quick questions.

Is this a good time, one, for a break; and, two, do you want to do like a lunch at some point? What is your plan so I -- just so I have an idea?

MR. SPEEGLE: I thought you were going to ask me substantive questions for a minute. I was going to -- interesting questions.

I'm happy to take a break now,

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and we can do lunch now too. That's fine.

Austin, is this a good time for you to do lunch?

MR. GINNINGS: Yeah. Sure.

(Break from 10:56 a.m. to 11:33 a.m.)

MR. SPEEGLE: Back on the record at 11:33.

(BY MR. SPEEGLE)

Q. Dr. Saber, we were going to pivot and talk about the '046 patent.

So can you get your copy of the '046 up in front of you. I think it's Exhibit 7.

A. Yes, sir.

Q. And we had been discussing before the break the claim language from the '344 patent concerning a statistical summary.

And so I would like to direct you to what is Column 15, Line 54 of the -- of the '046 patent.

Can you -- can you read the

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claim limitation starting there?

A. Column 15, Line 54?

Q. Yes.

A. Okay. So the claim limitation there says, ... generating summary statistics -- statistics describing the state of mind of the user in the image based on the received responses from the plurality of human users, and ...

Q. And I think we discussed this previously, but just to confirm, you did not offer a construction for this claim limitation in your declaration?

A. I offered the construction for the '046 about the user, and that's the only construction that was offered.

Q. Okay. Now, with regards to the '344 patent, we had been discussing what the phrase "characterizing a distribution" means.

And I would ask if you would confirm that that language is not used in the '046 claim limitation that you just read,

right?

A. I don't see the word "characterizing" used in the '046, claim 1.

Q. And also doesn't refer to a distribution, does it?

A. I don't see the word "distribution" either in the claim.

Q. Okay. Now, it does talk about a -- a state of mind, right?

A. Correct.

(Speaking simultaneously.)

(Discussion off the record.)

A. Yes. It does talk about a state of mind of the user in the image.

(BY MR. SPEEGLE)

Q. Thank you.

Let's turn to Column 10, Lines 38 and 39 of the '046 patent.

A. Column 10, Lines 38 and 39. Yes, sir.

Q. And this is giving examples of what a state of mind of the road user might

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be, right?

A. Yes, examples, obviously.

Q. And the -- can you read what the examples of the state of mind are in Lines 38 and 39.

A. You're going to read it or you want me to read it?

Q. I would like for you to read it.

A. Okay. Okay. So I'm looking at Column 10, Line -- I'm going to start with Line 36.

This value may refer to the probability of the pictured human road user has given state of mind - e.g., that a pedestrian is likely to cross the street or that an oncoming vehicle is unlikely to be willing to yield to the vehicle containing the sensor if the vehicle containing the sensor needs to turn.

Q. And just to make sure I'm understanding what it says, would you agree

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that an example of a state of mind in the '046 patent is whether a pedestrian is likely to cross a street?

A. That's an example, yes.

Q. I want to direct you to dependent claim 7, which is on Column 16 of the '046 patent.

Can you let me know when you have that in front of you?

A. Dependent claim 7, yes.

Q. Just to have my own turn reading, I'll read this one before I ask questions about this.

It says, The computer-implemented method of claim 1, wherein the summary statistics is associated with at least one of the 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 image.

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You see that?

A. You read it correctly.

Q. Okay. And these are describing examples of what the summary statistics in claim 1 might be?

MR. GINNINGS: Objection to form.

A. Well, obviously, these are narrowing -- I mean, claim 7 is dependent on claim 1. So this is adding limitations.

(BY MR. SPEEGLE)

Q. Okay. And that list of examples in claim 7 regarding content of a response, time associated with entering a response, and position of an eye of a human observer, that's the same list of examples that we see in Column 6 of the specification around Lines 24 through 28, right?

A. Generally speaking, yeah, very similar language. But obviously always the devil is in the details, but, yes, generally speaking, very similar language.

Q. And does this passage in Column 6 of the '046 patent and the dependent claim 7 tell you that the summary statistics in claim 1 of the '046 can include, for example, the position of an eye of a human observer?

A. I mean, claim 7 is dependent on claim 1, so it's narrowing the limitation of claim 1, but claim 1 doesn't have that limitation.

Q. Right. But claim 1 would include that as an example of summary statistics, right?

A. Yes. Generally speaking, yes.

Q. Okay.

A. That's one example of several.

Q. Let me direct you to Paragraph 217.

A. Of what?

Q. I'm sorry, this is of your '046 declaration.

A. Paragraph 217?

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Q. Yes.

A. Okay. Let me get there. Paragraph 217, yes, sir.

Q. Can you read the second sentence of Paragraph 217?

A. A POSITA reading the challenged claims would read the summary statistics, quote/unquote, in this element as referring to the same summary statistics, quote/unquote, in elements 1[b-iii]/[b-iv], 8[b-iii]/[b-iv], and 15[b-iii]/[b-iv].

Q. Okay. And what is the -- what is the meaning of this sentence here?

A. Well, this sentence is referring -- I mean, we are now talking about -- if you look above Paragraph 215, we are talking about element 1[c].

And if you look at the claims, element 1[c] says, Training and model using the training data, the model configured to receive an input image showing a user and predict summary statistics describing a state

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of mind of the user in the image.

So that's what the claim element is in this case, right, that we're talking about.

So the summary statistic that's referred to in this claim is the same summary statistic that you're talking about in claim 1[b-iii], et cetera.

Q. Okay.

A. So 1[b-iii] would be the generating summary statistic limitation, which is a couple of lines above it.

Q. Okay. So it's your understanding that the -- the summary statistics that are output of the model are the same summary statistics that are used in training?

A. Well, I mean, if you look at the claim and the way the claim is written or constructed, you see that generating -- the first generating on Line 44 of the claim.

So that first generating has

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three -- three or four sub pieces under it. There is a generating sending, receiving, generating and storing. Right?

So all of those are kind of under that big generating on Line 44. So the generating training data from plurality of images and then it says the generating comprising for each image.

And it lists sending, receiving, generating, and storing. Those are the 1[b-i], [ii], [iii], and [iv].

So -- so the generating summary statistics describing the state of mind on Line 54 is the same generating -- the summary statistics we're talking about here in -- in the training element -- claim element.

Q. Is that accurate, that the -- the model will output the same statistics that it is trained on?

A. Well, I think you're misunderstanding the word "same." Same doesn't mean it's the exact mathematical

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equivalent. It's just the same entity.

So the training and model using the training data, the model configured to receive an input image showing a user and predict summary statistics.

So you've trained the model to essentially predict summary statistics and the way you've trained it using the previous human annotator stuff that you did before in the previous limitation.

So it's going to generate summary statistics. It doesn't mean it's the exact same numbers, but that's what it's generating.

Q. So your declaration in Paragraph 2017 [verbatim], when you say a POSITA reading the challenged claims would read the summary statistics in this element as referring to the same summary statistics in Elements 1[b] and et cetera, you don't mean literally the same, you just mean kind of similar?

A. I mean, the same entity, not the same values. Like, you know, if I have a training example for my machine learning, let's say my training example the output should be .3.

And I've trained my -- my machine learning model. When I show a example, it may not give me exactly .3. It might be .31 or .32, because obviously the model isn't perfect.

So it's going to predict a probability. It's not going to be perfectly exactly what I trained it on.

But it's the same entity. So it's predicting a summary statistic. It doesn't mean the exact numbers are exactly the -- so the word "same" here isn't relating to the exact numbers of what's being predicted.

It's the entity that's being predicted.

Q. What do you mean by "entity"?

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A. Well, the summary statistics that's being predicted.

Q. I apologize, because I know it probably -- it probably feels like I'm being needlessly repetitive, but I generally don't understand what you mean when you say it's the same statistics but it's not the same statistics.

A. It's predicting summary statistics. That doesn't mean the numbers are exactly the same as if a human create -- so a human might create -- let me give you an example.

A human might create a histogram. Right? I might create a histogram, and then I will have a machine-learning algorithm. I give it data and it creates a histogram.

Both are creating histograms. It doesn't mean that both histograms are exactly the same values. Right?

They're both creating a

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histogram and hopefully it will be ideally very, very close, but you can't examine the machine learning model to create the exact same histogram as a set of human observers, let's say.

Q. Okay.

A. A hundred percent.

Q. We've talked a bit about others, multiple different examples in the '046 patent about things that can be statistical summaries or summary statistics.

Are -- are you saying that the use of summary statistics in the [c] element has to be the same kind of one of those examples as whatever summary statistics was used in the [b] elements?

A. Well, the summary statistics of the [c] element are going to be -- basically predict so many statistics that describe a state of mind of the user.

As long as they describe a state of mind of the user, then [c] element

has been met.

Q. So they don't have to be the same kind of summary statistics as in the [b] element?

A. Well, the [b-iv] -- [b-iii] element describes -- they're summary statistic describing the state of mind of the user.

So as long as they describe the state of mind of the user, then it met the [b-iii] element.

Q. Okay. And if it -- if there was an example where the [b-iii] element was met by describing the statement of user, you know, with the histogram and then the [c] element was describing the state of the user with a distribution, would you -- would you say that the claims are satisfied?

A. Well, as long as the summary statistics describe the state of mind of the user in the image, that element is satisfied.

Q. Okay. So you don't actually

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have to be the same kind of statistics?

A. I think you're mixing up the word "same" here. The "same" just means that it's summary statistics that's describing the state of mind of a -- of the user and the image.

So it's not, for instance -- the 1[c] doesn't describe, for instance, the color of grass in my backyard.

Q. So let me -- let me just go two sentences further in Paragraph 217 to see help -- if this helps clear this up.

You say, A POSITA would not interpret the challenged claims to recite generating one set of summary statistics in the "[b]" elements but having a model configured to predict a different set of summary statistics.

What do you mean by "set of summary statistics" in this sentence?

A. Well, I mean if you -- for instance, in the [b] element if you

created -- let's say your summary -- I'm making -- making this as an example.

If you create a histogram and computed the mean and variance and, I don't know, the -- the -- the spread of that histogram, that might be a set of summary statistics.

So the [b] elements of the challenged claims are part of generating the training data.

And the [c] element recite -- you're training the model using the training data.

So if you're training the model using the training data, you would expect that the model would predict the similar set of stuff as your training data.

Now, it doesn't mean the numbers are exactly the same. It's just you're predicting a similar set.

Q. Okay. You understand that patent claims don't have to recite every --

everything that's used in the invention, right?

A. I mean, I'm not an attorney.

Q. Let me -- let me say it this way: The '046 patent does not require that the training data only use summary statistics for training, right?

A. I mean, it -- it states what it's doing, right? I don't understand what you're asking.

Q. Okay. Do -- can you tell me one way or the other whether the '046 patent requires that the model only use summary statistics for training?

A. I don't understand what you mean by --

Q. Okay.

A. -- "only use summary statistics for training."

I mean, it talks about generating summary statistics, describing the state of mind of the user and the image. And

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then you're training the model using the training data that you just created.

Q. Okay. And as somebody who has opined about the scope of claim 1 in the '046 patent, can you tell me about whether claim 1 of the '046 patent requires that the model only be trained with summary statistics recited in the element [b]?

A. Well, I mean, if you look at the way the claim is constructed, so if you go back to Line 44, it says "generating training data from the plurality of images." So -- and then it talks about how that's done.

So the -- the generating of training data is done by sending the image to plurality of human observers, they're receiving input from the observers, generating summary statistics that describe the state of mind, and storing that in association with the image as part of the training data.

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So to complete the training, it's doing all these four steps, which you call 1[b-i], 1[b-ii], 1[b-iii] and 1[b-iv].

And then it goes on to say, well, I'm training now a model using that training data that has antecedent in generating training data, on Line 44.

So that -- the training data is the training data on Line 44 that you just got done creating with those steps.

Q. And is it your opinion that the training the model referenced in Line 59 of Column 15 must be the only training that the model receives in order to practice claim 1 of the '046 patent?

A. I don't know what you mean by "must be the" -- you're training -- what it says -- the claim element says training a model using the training data.

So you're going to use the training data that you created from Lines 44 to 58. You created all that data, and you

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associate it with the image. So each image you associated some training data with it. That's kind of your training data set in a sense.

So now you're training the model using the training data that you just created.

Q. Okay. Now, a --

A. That's how -- that's how I would read it.

Q. And so would you say that claim 1 of the '046 patent does not cover a model that is trained on the training data described at Line 44 in addition to other training data that is not listed in claim 1?

A. Well, I mean, when you read element 1[c], it says training and model using the training data.

So the training data is referring to training data on Line 44, which was created using those steps of sending and receiving, generating and storing.

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So the plain ordinary meaning would be, I'm training the model using the training data that I just created.

Q. Okay. And because you're interpreting claim 1 of the '046 patent to be limited to only training on the training data described in Line 44, is that why you reached the conclusion that the summary statistics in Line 61 of claim 1 must be the same summary statistics as described in Line 54, claim 1?

MR. GINNINGS: Objection to form.

A. Well, I mean, again, I guess I think we're talking a little bit, perhaps, past each other on this.

Again, the same doesn't mean the exact same numbers, you're -- you're just predicting summary statistics describing -- as long as the summary statistics describing the state of mind of the user in the image, as long as you predicted that, you've met the claim limitation.

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(BY MR. SPEEGLE)

Q. All right. Let's -- let's turn to the '889 patent.

A. '889.

Q. Which is Exhibit 8 to the deposition.

A. Give me one moment. Let me get it opened.

Yes, sir.

Q. All right. And if you want to look at claim 1, which is on Column 15, beginning at Line 32, let me know when you're there.

A. Claim 1 of the '889?

Q. Yes.

A. Beginning on Line 32. I am there.

Q. Now, I think we covered this before lunch.

But just to confirm, you did not apply any construction for any terms in -- in the '889 patent, you only used the

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plain and ordinary meaning; is that right?

A. That is correct.

Q. Okay. And can you read the claim limitation that starts on Line 46, Column 15, toward "generating."

A. Yeah. That's limitation, I think, 1[c], right?

Yeah, so it's generating a training data set comprising summary statistics of user [verbatim] responses describing the state of minds of road users displayed in the plurality of images.

Q. And is the use of "state of minds" in claim 1 of the '889 patent the same as "state of minds" as we discussed it in the '046 patent?

A. Well, I mean, it -- it's described in the specification of the '889. So however it's described there, it's what it is.

Q. Okay. Let's go back up to Column 6 of the '889. And I direct you

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specifically to Lines 18 through 22.

A. Yes.

Q. And this is the same passage describing summary statistics that we've read for the '344 and '046 as well?

A. Generally speaking, yes. I mean, I don't know if the exact wording is exactly the same, but the general idea is there.

Q. Okay. Is it fair to say the general idea of summary statistics and statistical summary is the same across the three patents, in your view?

A. Well, generally speaking, it's obviously described in this particular step, but I think the language is very -- very similar.

Q. Okay. Okay. I want to spend a little bit of time going through in the '046, '889, and '344 declarations and understanding which limitations you're saying are missing from the prior art versus those ones that you

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haven't opined about or disputed in your declarations.

Is that okay?

A. Sure.

Q. All right. So let's start with the '344 declaration. And I think it's probably easiest to start with the table of contents in that.

A. Yes. I was just going to say that's probably the easiest way.

Q. And I tell you what, while we're doing this, I am going to put two more documents in the Chat.

Can you see the documents beginning 12 dash and 13 dash that I've added in the Chat?

A. Yes. You've added Cox and Ross.

Q. Yeah. So I'll -- I'll go ahead and introduce what -- the document that begins 12 dash as Exhibit 12 in your deposition.

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(Marked Saber Exhibit No. 12.)
(BY MR. SPEEGLE)
Q. Have you seen Exhibit 12 before?
A. Hang on a second. Let me just download them so I'm looking at the same thing you're looking. It's taking a minute to download so give me one moment here.
(Marked Saber Exhibit No. 13.)
A. Okay. So I have 12 and I have 13.
(BY MR. SPEEGLE)
Q. Okay. And so the document beginning 12 dash, which has been designated as Exhibit 12, do you recognize Exhibit 12?
A. Yes.
Q. And what is Exhibit 12?
A. It's the Cox document.
Q. And this is the Cox prior art reference that's an exhibit to each of the five IPRs?
A. Yes. I don't know if this is

all five, but, yes, it's -- it's the Cox document.

Q. Okay. And whether it's in all of them or most of them, there's only one Cox reference, right?

A. Yes. That's correct.

Q. Okay. So similar questions for the document that begins 13 dash, which I'll introduce as Exhibit 13.

Have you seen Exhibit 13 before?

A. Yes. That's the Ross document that's in most of them. Same Ross document, the only one.

Q. Okay. All right. So turning back to the table of contents for your '344 declaration, let me know when you have that in front of me [verbatim].

A. All right. One moment here. Yes. I'm at the table of content.

Q. Okay. And "Ground 1" at the bottom of the first page of the table of

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contents is identified as "Ross and Cox."
Do you see that?
A. Yes.
Q. And it looks like under Ground 1 you disputed -- it's your opinion that Ross and Cox do not teach element 1[b], 10[b], 19[b], and then elements 1[c], 10[c], and 19[c]. Is that right?
A. That's correct.
Q. And that's the same element in three different independent claims, right?
A. Yes.
Q. And I think you have that element in the heading in parentheses right there starting, "providing."
A. I'm sorry.
Q. I'm just confirming that the -- the element 1[b], 10[b], and 19[b], which is the same, that also appears in the heading in the parentheses and quoted there in the table of contents?
A. That's correct. That's the

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element itself, yes.

Q. Okay.

A. The quotes are starting with "providing" and ending with "object."

Q. Got it and so the -- for the [b] element and the [c] element from each independent claim are the two elements that you believe are missing from the combination of Ross and Cox compared to the '344 patent, right?

A. These are the ones I opined on, yes.

Q. And you didn't opine about any other claim elements potentially being missing in the '344 patent?

A. I did not provide any opinions on the other ones.

Q. Okay. Let's scroll down to Ground 2.

A. Yes, sir.

Q. And Ground 2 involves another reference called Ogale, right?

A. Yes, sir.
Q. And I will add what's Document 14 dash to the Chat. Let me know when you have that.
A. I see it in the Chat. Let me download it. This one doesn't give me a download button. That's interesting. Let me see if I can download it. It's still downloading.
Q. Well, I tell you what, let's go back and I'll ask you some questions about Ground 1 and we can come back to Ground 2. Let's look at Paragraph 89 of your declaration.
A. '344 declaration?
Q. Yes. This is your '344 declaration, Paragraph 89. I'm interested in the last sentence, which is on the top of numbered Page 37.
A. Okay.
Q. And that last sentence says, And nowhere do Tesla and Dr. Janet discuss

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any modifications to Ross in view of Cox.

Do you see that sentence?

A. Yes.

Q. Is that sentence accurate in your view today?

A. Yes.

Q. Okay. Can we turn back to Exhibit 11, which is Dr. Janet's declaration from the '344 patent?

A. '344, Dr. Janet.

Q. Yeah. Exhibit 11.

A. Yes. I have it open.

Q. Okay. Can you go to PDF Page 39, numbered page 33.

A. PDF Page 39, which talks about motivation and combine.

Q. Yes, Paragraph 80.

A. Yes, sir.

Q. Okay. And the first sentence there says, In my opinion, a POSITA would have been motivated to combine Ross and Cox such that Ross's intent model is a supervised

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learning model that is trained with human annotated image data, as taught by Cox.

Do you see that sentence?

A. I do.

Q. Now, you just said that Tesla and Dr. Janet did not discuss any modifications to Ross in view of Cox.

And my question to you is: Why is Paragraph 80 not a discussion of changes to Ross in view of Cox?

A. Well, that's just a generic sentence. I mean, I could tell you I'm going to take my Dodge Ram and put the missile engine on it to have it orbit the moon. That's -- I mean, that's just a generic sentence.

Where are the technical details of that? That's just generic.

Q. Okay. So you're -- you don't dispute that there are proposed modifications to Ross in view of Cox, it's just your position they're not sufficiently described;

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is that right?

A. This is not a modification. This is just a generic sentence that basically says, I can take my Dodge Ram and put an airplane engine in it.

I mean, anybody can make that statement. I want -- what I'm referring to here is discuss any modifications to Ross in view of Cox.

Like what are you planning? How are you planning to modify Ross in view of Cox?

Like what is missing when you read Ross compared to the claims that we are discussing here?

What is Ross missing that's in the claims that Ross doesn't have that a POSITA would look forward to Cox and say, Oh, okay, I'm going to go grab this thing from Cox and somehow modify Ross and how I'm going to do that.

So it's not just, oh, I'm just

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going to put those two together, there you have it.

That's not a modification. That's -- that's a conclusory statement without any rationale underpinning, so to speak.

Q. Okay. So you don't think that using a human annotated image data as taught by Cox is a modification?

A. No. You have to provide what -- how you're going to do that. I mean, Ross talks about intent. Has nothing to do with face -- face detection.

Cox talks about face detection labeled imagery. What -- what -- what are you going to -- to put -- what human annotated image data are you going to take from Cox and put into Ross? What are you talking about?

Anybody can make this statement. A kindergartner can make the statement. I want to know what are the

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technical details that we're talking about here.

Q. Okay. Before we go further here, did the exhibit -- or the document with 14 dash download on your end?

A. Yes, sir, it did.

Q. Okay. Can you -- I'll designate this as Exhibit 14.

(Marked Saber Exhibit No. 14.)

(BY MR. SPEEGLE)

Q. Can you let me know if you've seen Exhibit 14?

A. Yes, I have, the Ogale prior art, which is, I think, mentioned only in one of them.

Q. Okay.

A. A mistake.

Q. And this is the Ogale reference that's used in Ground 2 on the '344 patent?

A. That is correct.

Q. Okay. And going back to your table of contents in your '344 declaration.

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A. Okay. Yes, sir.

Q. And am I right that the -- the only limitations that you dispute for Ground 2 are the same ones that you disputed for Ground 1?

A. That is correct.

Q. Let me introduce Document 15 dash. And let me know when you have this one.

A. Okay. Let me go ahead and download it. I see it in the Chat. It's being downloaded. It's still being downloaded, so I think the server is a little slow on the --

Q. Well, I tell you, I can go ahead and ask you my questions about it.

This is -- looking at your table of contents, you also opined about Ground 3 in the '344 IPR; is that right?

A. That is correct. And I do have the document downloaded at this time, sir.

Q. Okay. So the Document 15 dash,

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I'll exhibit -- I'll identify as Exhibit 15.

(Marked Saber Exhibit No. 15.)

(BY MR. SPEEGLE)

Q. And have you seen Exhibit 15 before?

A. Yes, I have.

Q. And what is Exhibit 15?

A. It's the Zhang prior art reference that's referenced in this IPR, and I think only in this IPR.

Q. Okay. So the Zhang reference is the reference used in Ground 3 of the '344 IPR, right?

A. That is correct, sir.

Q. And it looks like in your table of contents you identified the two same missing elements that you dispute, and that is the [b] element and [c] element; is that right?

A. You are correct, sir.

Q. Let's look at Paragraph 131 of your declaration. This is your '344

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declaration still.

So you say here that, Regardless of which data is used, Zhang does not teach or suggest that its model predicts what users' response [verbatim] or labels to the image data would be. Instead, Zhang makes clear that what its model predicts are "vehicle or object trajectories."

You see that?

A. One second.

Yeah. Okay. I see the sentence. Starting with the third sentence, correct?

Q. Yes.

A. "Regardless," yep, I see that.

Q. Now, if the -- if the model is predicting vehicle or object trajectories, that means it was trained on labels of vehicles or object trajectories, right?

A. Give me one second here.

Yeah. What was your question again, sir?

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Q. If the model in Zhang is predicting vehicle or object trajectories, that means it was trained on labels reflecting vehicle or object trajectories, right?

A. That would be generally the idea, although you can predict trajectories without -- by just doing, you know, video segmentation and motion estimation.

Q. Okay. If the vehicle or object trajectories are what users were labeling, isn't it true that by Zhang predicting those vehicle object trajectories, it is project -- it is predicting what humans would have labeled the image -- instance or input as, right?

A. No. You're mixing two different -- apples and -- you're mixing apples and oranges.

Q. Okay. I'm trying to understand your -- your position on this.

A. Well, predicting a trajectory

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has nothing to do with summary statistics of user responses to what a user sees in the image.

So if I'm predicting a trajectory and I'm using, let's say, video segmentation on frames and I see a car moving in the next -- in the last ten frames and I predict the car is going to be here in the next frame, that has nothing to do with user responses looking at that image and saying, I think I see the cyclist over here, I think it's going to do a U-turn.

So predicted trajectory of an object is not the same thing as statistical summary of user responses, which is what the '344 is targeting.

Q. Okay. And I know there's layers to unpeel there with the -- with the statistical summary question, but let me just try to understand one part of that.

If Zhang has human labels of trajectories and the model is predicting

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trajectories, is it fair to say that the model is predicting what the label would have been?

A. If a human has gone in and labeled a video frame with a potential trajectory and your model is being trained to predict ideally that trajectory, so ideally speaking, the model is trying to predict a trajectory that has nothing to do with the statistical summary that describes the distribution of user responses.

Q. I was understanding you until you started talking about statistical summary.

So I -- I understand there's a separate disagreement about statistical summary, and I absolutely will follow up on that question here in a minute, but I want to try to understand this first part.

So let me ask it again. And without getting into the question of whether or not any of this counts as a summary

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statistic or statistical summary, if Zhang has human labels of trajectories and the model is predicting trajectories, is it fair to say the model is predicting what the label would have been?

A. That -- the model is trying to predict what -- potentially what a label would have been.

And, again, I mean, you're -- you're looking at this section, which is talking about Zhang and addressing element 1[b] and 10[b] and 19[b] of the claim, which has to do with predicting output, statistical summary, characterizing, et cetera, et cetera, et cetera.

So the context of what we're talking about here is regarding that claim element.

Q. Okay. So I think I'm understanding what you're saying, so let me say it back to make sure I'm tracking you.

That the dispute here is not

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about whether the model is predicting what a human labeler would say; the dispute is whether that prediction is in the form of a summary statistic.

Is that -- is that a fair understanding of where -- where the disconnect is?

A. Yeah, I mean, as I'm saying in Paragraph 131, Zhang doesn't teach that its model predicts anything about what user responses would be. It's predicting a trajectory.

I mean, if you look at Zhang, you know, the title, "Prediction-Based System and Method for Trajectory Planning of Autonomous Devices." So it's predicting a trajectory.

It has nothing to do with user responses as to if a user looking at an object in the image and trying to -- you know, trying to -- you know, a statistical summary of that. The two are distinct

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entities.

Q. Yeah. I -- I think I understand it. I was just trying to sort through whether the difference -- what -- which part of the claim language we're disagreeing about. And I think I understand now that there's not a dispute that the model is going to try to match what the human labelers put in. The dispute is whether what is being predicted counts as a summary statistic.

A. That's the main dispute, but we also -- we'd have to look at Zhang to see exactly what's being annotated.

Q. Yeah. If you want to -- if you want to close that loop, I'm happy to direct you to Paragraph 51 of Zhang where it talks about this.

Again, I don't know if I have a question about it, but if you want to look at it, you can.

But we can move on. We don't

have to keep spinning our wheels here.

All right. Let's look at the '046 declaration and talk about where the disputes are in that one.

So can you let me know when you have the table of contents from the '046 in front of you?

A. Just give me one second.

MR. GINNINGS: And, Counsel, it's fine if you want to -- if you want to cover this. I know we're coming up on another hour here. I mean, if you've got a few more minutes, that's fine. But, you know, if we want -- if you're going to dive into something longer, then maybe we should take a break now.

MR. SPEEGLE: Okay. Well, I'm just about to shift to the '046 patent.

Dr. Saber, if you have something else you want to say about

Zhang, we can keep talking about Zhang further or we could take a break here.

THE WITNESS: I think this is a -- let's take a quick break. I think that would be good. And five minutes should be fine. I'll be sitting at my desk at 1:35 Eastern.

MR. SPEEGLE: Okay. So we're off the record at 11:30, 11:29.

(Break from 12:29 p.m. to 12:36 p.m.)

MR. SPEEGLE: All right. So back on the record at 11:36 -- 12:36.

(BY MR. SPEEGLE)

Q. Okay. So I was going to ask you about your opinions for the -- for the '046 patent.

A. Yes, sir.

Q. Can you let me know when you have the table of contents for your '046 declaration in front of you?

A. I do have it in front of me.

Q. Okay. And looking at

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Ground 1 --

A. Yes, sir.

Q. -- it looks like the limitations where you have opined they're missing from the Cox reference are 1[b-iii], 8[b-iii], 15[b-iii], 1[b-iv], 8[b-iv], 15[b-iv], and 1[c], 8[c], and 15[c]; is that right?

A. That is correct.

Q. And scrolling down to Ground 2, am I right that Ground 2 adds the Ross reference in combination with Cox?

A. That's correct.

Q. And the -- the three disputes are the same elements, the [b-iii], [b-iv], and [c] elements?

A. That's correct.

Q. Now, Ground 3 -- Ground 3, I believe, is just related to dependent claims. And if you want to scroll down to Paragraph 158 for more context, that's fine.

A. Yes.

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Q. Okay. So the -- there's no additional disputes with respect to Ground 3, it just depends on the prior disputes regarding the independent claims, right?

A. That's correct.

Q. Okay. And then Ground 4 is based on the combination of Cox and Munro, right?

A. Yes, sir.

Q. And I'm going to go ahead and introduce two more exhibits. I know I skipped one of these, so I'll go back and get -- this is going to be the 16 dash and 17 dash exhibits. And let me know when you have those come through.

A. I see them in the Chat. I'm going to go ahead and download them now.

Q. It's going to take a minute for them to download, so let me ask you a couple more questions about Ground 1 while they download.

Let's look at Page 32 of your

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declaration, which is in Ground 1. And there's a big heading C that I would like to start at.

A. Yes, sir.

Q. All right. Now, this Section C addresses the -- whether the Cox reference discloses 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, right?

A. Yes. That's the 1[b-iii] element that we talked about.

Q. And this section is organized with several subheadings based on different types of summary statistics that are addressed by Tesla and Dr. Janet; is that right?

A. That is correct.

Q. Okay. And the first one of those, which begins with Paragraph 77 on Page 33, is Psychometric Data, right?

A. Yes, sir.

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Q. And then the next one, which I've got to scroll down to, is on Page 37, the Item-Response Curves.

A. Yes, sir.

Q. Okay. The next one is on Page 39, and it's Human-Weighted Loss Functions.

A. Yes, sir.

Q. And the last one is on Page 44, and it's the End-of-Test Statistics, right?

A. That is correct.

Q. So those are the -- the four different potential summary statistics that are addressed in your declaration?

A. Yes, sir.

Q. Okay. Before I forget about it, did the Document 16 and 17 come across in your Chat?

A. Yes, they did.

Q. Okay. Can you let me know if you've seen the document beginning 16 dash before?

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(Marked Saber Exhibit No. 16.)

A. Yes. That's the Ellenbogen prior art reference.

(BY MR. SPEEGLE)

Q. Okay. I'm going to introduce that 16 dash document as Exhibit 16.

And then can you let me know if you've seen the document beginning 17 dash before?

A. Yes, sir. That's the Munro prior art reference.

(Marked Saber Exhibit No. 17.)

(BY MR. SPEEGLE)

Q. Okay. And I'll introduce that document as Exhibit 17.

And to circle back to Ground 3 that we talked about briefly, that involves the Ellenbogen reference, right?

A. Ground 3 of...

Q. Ground 3 of the '046.

A. '046. I'm sorry, ground -- you said 3 or Ground 4?

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Q. Ground 3 of the '046 is a combination of Cox and Ellenbogen, right?
A. Yes.
Q. Okay. And Ground 4 is a combination of Cox and Munro; is that right?
A. That is correct.
Q. And with respect to Ground 4, I'm looking at the table of contents for your '046 declaration again.
Am I right that it's the same three limitations that are in dispute as the [b-iii], [b-iv], and [c]?
A. That is correct.
Q. Okay. And then let's look at Ground 5, which is a combination of Ellenbogen and Munro, right?
A. That is correct.
Q. And, again, you've -- you've disputed the same three limitations, that's [b-iii], [b-iv], and [c]?
A. That is correct.
Q. All right. Now, I do want to

dig in a little bit more on -- on the Ellenbogen ground here.

So could you turn to Page 85 of -- of your declaration that begins with Paragraph 202.

A. Yes, sir.

Q. Now, as I've reviewed your analysis in this Section B, I just want to confirm that you don't have any opinions about the content of Ellenbogen's composite output, right?

A. I don't understand your question.

Q. Well, do you understand the combination of Ellenbogen and Munro that Tesla and Janet -- Dr. Janet proposed?

A. Yes.

Q. And it involved modifying the composite output of Ellenbogen in view of the teachings of Munro, right?

A. Yes.

Q. And you opined in Paragraph 204

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about the -- the content of the tallies described in Munro, right?

A. Yes. I mean, Munro is about natural language processing. It's a completely different application than object labeling of trajectories or anything else.

Q. I understand.

You have no opinions in your declaration about the content of Ellenbogen's composite output, right?

A. I mean, I -- I provided opinions with regards to the claim elements that I've analyzed. I mean, I don't understand what you mean where you have no opinions. I've provided opinions based on the claim elements that I've analyzed.

Q. Sure. And I see your analysis here about Munro's national language processing.

And I just don't see anything here about the composite output in Ellenbogen.

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Now, I want to make sure I'm not missing it or overlooking it, that you did not discuss the composite output from Ellenbogen in this section?

A. I may not have discussed it specifically. But I'm -- obviously, I've analyzed the claim element that we're talking about here and why Tesla and Dr. Janet did not meet that claim element.

Q. Okay. And do you have any understanding about whether Ellenbogen has a system that determines the sentiment of one or more people?

A. Well, let's take a look at Ellenbogen.

Okay. What was your question about Ellenbogen?

Q. Yeah. The -- one of the tasks described for this system in Ellenbogen is determining the sentiment of one or more people, right?

A. Generally speaking, yes. But

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what -- what's the question?

Q. Okay. And that's not -- that's a feature of Ellenbogen that you discussed in your declaration?

A. I mean, I analyzed Ellenbogen with regards to the claim elements that we're discussing.

So whether it meets -- you know, whether Dr. Janet's and Tesla's analysis meets the claim element that we're talking about...

Q. Okay. And the analysis you did with that regard is reflected in your declaration, right?

A. That is correct.

Q. All right. Let's turn to the '889 patent. I'm also going to go ahead and introduce another document in the Chat, which is 18 dash.

(Marked Saber Exhibit No. 18.)

A. '889 patent. And you're introducing another document, which I see and

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I am going to download.

Download in progress.

(BY MR. SPEEGLE)

Q. While that's downloading, if you look at the table of contents for your '889 declaration, for Ground 1, am I right that the Ground 1 is a combination of Huval and Ross?

A. That is correct.

Q. And it looks like you've only disputed one claim limitation with respect to Ground 1; is that right?

A. That is correct.

Q. And that limitation is the generating a training data set comprising summary statistics of user responses describing the state of minds of road users displayed in the plurality of images as recited in elements 1[c], 2[c], and 12[c]; is that right?

A. That is correct.

Q. All right. Did

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Document 18 dash come through for you?

A. Yes, it did.

Q. Okay. Have you seen 18 before?

A. I'm opening it now. Yes.

Q. Okay. What is the document labeled 18 dash?

A. 18 is the Huval prior art reference.

Q. Okay. So I will introduce this as Exhibit 18 to the deposition. And, you know, I want to ask a couple more questions about this ground.

So am I right that in addition to the -- the element 1[c], 2[c], 12[c] we discussed, you also argued that a POSITA would not have been motivated to combine Huval and Ross in the manner Tesla and Dr. Janet alleges; is that right?

A. That is correct.

You're talking about Ground 1, correct?

Q. Correct.

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A. Yes.

Q. Okay. Why don't you scroll down to Paragraph 73 of your declaration, which is Page 30. And this is your '889 declaration, to be clear.

MR. GINNINGS: Sorry. Which paragraph again?

MR. SPEEGLE: 73.

THE WITNESS: Paragraph 73 of the '889 declaration.

(BY MR. SPEEGLE)

Q. You have that in front of you?

A. Yes, I do.

Q. Okay. Now, I'm going to read part of that first sentence that says, ... as best I understand their theory, they proposed to modify Huval such that the annotation labels provided by human annotators (but not the automated labels) be labels that identify observed road user actions.

Did I read that right?

A. You did, yes, sir.

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Q. Okay. What is your basis to say that the automated labels would not be modified?

A. Well, based on the description from Dr. Janet's and Tesla's, Dr. Janet's first combination.

Q. Okay. Does Dr. Janet say that the automated labels are unmodified?

A. I mean, I would have to look at Dr. Janet's declaration, but -- and I would need you to download that, but that's -- I -- I don't remember exactly off the top of my head, but I would -- I -- if I refer to it that way, it probably wasn't specific.

I think it's Exhibit 1003 is Dr. Janet; isn't that correct?

Q. Yes, I'm -- I'll introduce that in just a second. I got to get it formatted correctly here.

A. Sure.

And it looks like I'm referring to Paragraph 72 of that declaration or

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petition Paragraph 20.

Q. All right. Do you see Exhibit 19 coming through?

A. I see Exhibit 19. I don't have it yet.

Okay. So I -- it's still being downloaded.

I do have it.

Q. Okay. And have you seen this document beginning 19 dash before?

A. Yes, sir, I have.

Q. And what is the document beginning as 19 dash?

(Marked Saber Exhibit No. 19.)

A. It's the declaration of Dr. Janet with regards to the '889 patent.

(BY MR. SPEEGLE)

Q. All right. And I'll introduce this as Exhibit 19.

And if you could, please, turn to Paragraph 72 of Dr. Janet's declaration.

A. I am there, sir.

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Q. Paragraph 72 is -- is -- does not say anything about the automatic labels in Huval, right?

A. That's correct. I mean, if you look at the first bullet that I'm addressing here, obviously, says, Huval's annotation labels provided by human annotators -- these are not the automated ones -- label observed road user actions and image data captured by vehicles, where such labeled actions correspond to user -- road user intent.

And think that's what I captured, it looks like, in my Paragraph 72.

Q. Okay.

A. It's interesting both of them are Paragraph 72.

Q. Coincidence.

All right. I want to understand a little bit more about the relationship between the automatic labels and the human labels in Huval.

So --

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A. Okay.

Q. -- let's start by pulling up Huval, which is Exhibit 18.

And let's look at Figure 1.

A. Yes, sir.

Q. So if you -- if you see Figure 1, there's a training set on the top right-hand corner.

Do you see that?

A. Yes, that's labeled S110.

Q. Right. And let's scroll down to the body of Huval, and I direct you to Paragraph 22 particularly.

A. Okay. Give me one moment.

Q. Actually I take it back, let's look at Paragraph 21 first.

A. Yes, that's talking about the training set.

Q. Yeah. And each -- and if you read the first sentence of Paragraph 21, it says, Block S110 of method S100 recites accessing a training set including optical

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images, wherein each optical image in the training set includes a label linked to an object represented in the optical image.

So this would be manually-labeled data, right?

A. That's the assumption, yes.

Q. Yeah. So this would be the data that Dr. Janet is proposing to modify so that it would, you know, capture intents as described in Ross, right?

A. What was your question again?

Q. Well, I just want to make sure we're talking about the same thing, and I want to make sure we're saying that the Block S10 [verbatim] and the training data which is labeled, that's -- that's the original human annotated data that Dr. Janet would be suggesting to change to -- in view of Ross, right?

A. That's generically the idea, yes.

Q. Okay. Now, let's talk about

what happens next in Huval. And we're going to talk about Paragraph 23.

And, again, I don't have a good way to -- if we were in a room together I would have Figure 1 in one hand and the text in the other hand so you can reference both.

If you can split your screen and look at them both, it might be easier.

A. Yeah. I -- I have them up.

Q. Okay. All right. So at Block S120 a model is trained based on this label data, right?

A. That's the -- generically the idea, right.

Q. Yeah. And when we talked earlier about supervised learning models and models that are trained with human label data, the -- the model that's trained in S120 is going to be trained to predict what the human labels are put into it, right?

A. That's generally the idea, yes.

Q. Okay. So a POSITA would

understand that the -- the outcome of training Block S120 on modified data as proposed by Janet would need to have a model that also predicts intents as modified by Ross, right?

MR. GINNINGS: Objection to form.

A. I guess I'm not understanding what your question is here. But I describe the discrepancy in my paragraph.

So if you look at my Paragraph 73, you see later on in the paragraph it says -- I'm looking at Page 31, Paragraph 73, maybe the third sentence or something like that, second or third sentence, see, it says, In my opinion, such a modification would not make sense to a POSITA, as it would result in a human annotation relating to road user intent but the automated annotations relating only to the identification and location of objects in the image ...

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(BY MR. SPEEGLE)

Q. I understand.

A. You see, when you look at Paragraph 23 of Huval, you see that?

Q. Yeah.

A. See where it says Block S20 [verbatim] of the method S100 recites training a neural network, with the training set, to identify objects in optical images.

You see what I mean?

Q. It says "objects and navigational actions," right?

A. Let's -- let's step back.

So Paragraph 23, first sentence of Huval, Block S20 [verbatim] of the method S100 recites training in neural network, with the training set -- that is labeled S110 -- to identify objects in optical images.

Q. Right. And then the next sentence --

A. Then it talks about -- the next

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sentence says -- it says, Generally, in Block S20 [verbatim] -- which is the neural network you're referring to in the -- in the figure -- the remote computer system can implement machine learning techniques to automatically develop a computational model (or "neural network") -- right -- for detecting and identifying (e.g., labeling, classifying) localization objects, perception objects, and navigational actions in optical data...

You see what I mean?

So that's talking about if you're looking at the frames of video or images, it's identifying the object in the image.

Q. Yeah.

A. That's what -- that's what the automated system is doing.

Q. Well, let me ask you one more question about Paragraph 23, then I'll get back to where I was going before.

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Oh, Paragraph 23 says that the model is also for detecting and identifying navigational actions.

Do you see that?

A. Yes.

Q. What are navigational actions?

A. Well, you identify the object. And if I'm looking at the object from Frame 1 to Frame 2 to Frame 3 to Frame 4 to Frame 5, I can see the object motion -- basically the motion estimation of the object.

Q. Okay.

A. That's entirely different from user predicting user intent.

Q. And you understand the modification proposed here is to use different data to train that neural network in Block S120 so that it would include user intents as taught by Ross, right?

A. Well, I mean, again, you're proposing an idea, well, the question as how you're going to do this.

You know, I can propose to you that I'm going to install a jet engine in my Dodge Ram and it's going to fly as of tomorrow afternoon.

Q. Okay.

A. So that's the point. I mean, it's -- you're proposing something without any technical descriptions of how you're going to do any of this, how you're going to do any of this training, how you're going to integrate it.

So --

Q. You think it would be beyond the skill of a POSITA to use different data to train the model S120?

A. As I explained to you earlier with machine learning, training is a skill set on its own because it's not like a -- a cookbook recipe. You just say, Okay, I'm -- here's 50 elements I'm going to train with. I just do boom, boom, boom, and there it is, I have a tiramisu.

That's not how it works.

So there is a skill set in how to conduct the training, how to set up the data, what type of batches you're going to use, what's the size of the network you're going to use.

Are you going to conduct -- are you going to use regularization or not?

How are you going to determine if it's generalizing?

Are you going to utilize multiple initialization point of entries?

Are you going to utilize different descent trajectories?

There's a lot going on in a training of a network. It's not like I train, for instance, this network, I'm just going to do the same thing with this other network with a different data set. That's not how it works.

Q. You don't think a POSITA could figure this out?

A. No. It's not -- it's not that simple.

Q. Okay.

A. It's not -- it's not that simple. It requires -- I mean, you have to sit down and study the data set, for example, understand exactly what you need to do, define what the structure of the network is.

You may have to add layers, delete layers, add neurons, delete neurons, change activation functions, change regularization parameters, do a dropout, you know, strategy.

There's a lot of stuff involved here.

Q. So you don't think --

A. It's not like I can just put A and B and I get C.

Q. You don't think a POSITA would know how to train a neural network?

A. Generally speaking, I mean, the idea a POSITA understands there is something

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with training, but you still have -- there's a skill set and each network is different in how you train it.

Q. So you don't think a --

A. Just because -- just because I'm training a neural network to generate -- to recognize apples, that doesn't mean I can apply the same strategy to a neural network and recognize faces.

Q. Is that something a POSITA would know?

A. No. It's not something -- it's not that simple.

Q. A POSITA wouldn't know that you have to use different training techniques for different types of classification models?

MR. GINNINGS: Objection to form.

A. It's not just -- it's not about knowing the different techniques. It's just how would you use -- what would you do for this particular network, because each network

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is different.

And how you set up to train the network is a skill set on its own, you know, how many entry points you're going to use, what type of training, how many epochs, how long you're going to run this, what kind of Gradient descent strategy you're going to use.

There's a lot of stuff involved here. This is not a simple I train on apples, I can now train on faces.

I mean, what you're proposing here and what Dr. Janet is proposing doesn't make -- doesn't make sense.

You're basically saying I just put A with B and therefore it comes out C.

If it was that easy, you know, we would be, you know, automated -- automated -- autonomous vehicles would be available today ten years ago.

(BY MR. SPEEGLE)

Q. You teach a course at RIT

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called "Advance Neural Networks and Deep Learning," right?

A. Yes, sir. That's part 1 and I'm working on part 2, yes.

Q. Is that a graduate level course?

A. I created -- I created the course. And, yes, it's a graduate level course. It's meant for MS -- second year MS, first year Ph.D. students. And you have to have a certain prerequisites to enter the course.

Q. Okay. So somebody who gets a master's degree from your school would have taken that class?

A. A bachelor's or a master's, did you say?

Q. Master's.

A. Well, it depends on their interest, because somebody that is getting a master's degree that's specializing in controls wouldn't take that class.

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Somebody that is getting a master's degree that is focused on machine learning would -- you know, would -- would take the class.

Q. Okay.

A. It depends on what you're specializing in for your master's. Somebody who is specializing in hardware design wouldn't take the class.

Q. What do you -- what do you teach in that Advanced Neural Network Design and Deep Learning class?

A. Well, I have -- I have a whole outline I teach. I start by talking about regression -- first of all, I give an introduction to the field of neural nets.

Then I go through the mathematical preliminaries. Then I go through optimization techniques, Gradient descent, you know, second -- you know, second order derivatives, first order derivatives type methods, and various ways of doing all

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that.

Then I go into overview of neural networks and, you know, what's the difference between shallow and deep and set the mathematical structure together.

And then I get into regression techniques, classification techniques, obviously for multilayer networks, et cetera, and multidimensional situations, feature selection, backpropagation algorithms, that kind of thing.

Q. Does your -- does your Advanced Neural Networks and Deep Learning class teach your students how to train different neural networks?

A. It talks about the training strategies. It doesn't mean when you walk out of there, you're going to learn to train every network.

It talks about different training strategies, but they don't all apply to every network. Every network is a little

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different depending on the data and what you have.

Q. Do you feel like your class prepares your students to get a job at a -- at a machine learning or artificial intelligence company today?

A. Well, that's -- that's the idea, is you would come out and have the background to be able to, you know, work for a company that does machine learning and -- and contribute.

Q. Yeah.

A. But there are still different skill sets on how to use this on different data.

Q. So one of your students would be prepared to go work for a company that's training models on different kinds of data, right?

A. I mean, we provide you with a background. You know, just like if you did a hardware design, we teach you how to design

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hardware.

That doesn't mean if you step into NVIDIA, you get to design a board in ten minutes just because you took a course on hardware design.

You still have to determine what are you trying to accomplish with this new data, what type of data it is. Different data has different design requirements.

So you still have to make technical decisions on how to do the training and what type of strategies of training to apply to each different data set.

So I may -- I may have shown you 50 different training strategies. You can't -- you don't use all 50 on every time you train.

I may use ten on this day on this particular data set, a different set on a different data set.

It depends on what the application is. And some of this may be

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iterative. You may have to try -- more or less trial and error.

It's not -- it's not a -- you know, there is no formula that says for this problem use technique A, B, and C.

Q. How long you been teaching this class at RIT?

A. Well, as I mentioned to you, we were teaching neural nets in the '90s as part of a class called "Pattern Recognition." So I taught the course of Pattern Recognition -- well, I taught the course at U of R as well as RIT.

At the U of R, I basically continued teaching the course when I was there as an adjunct faculty until 2004. Didn't teach it every single semester, but I taught it multiple times.

And at RIT, the course was initially there in the early '80s, then it was abandoned. I reinstated it. So I -- you know, I restarted the course because, you

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know, the faculty that was teaching it was either retired or left the university.

So I reinstated the course, reinstated the material, redeveloped everything, and was teaching it, you know, let's say, late '90s, early 2000s under the heading of "Pattern Recognition."

So the Pattern Recognition course had three bases to it, the statistical, the structural, and the neural.

The statistical is what you were asking about this morning, the Bayesian and all that stuff.

And the neural net is what we're talking about today.

So that kind of course evolved a little bit.

But as machine learning start to take on its own identity, so to speak, where people started to talk about it as machine learning instead of pattern recognition, so we started to evolve some of

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those courses.

So I decided to create a new course on -- focus on just that and not really talk about the structural and the statistical part of pattern recognition.

We still teach that course, except it's -- it's now focused a little differently.

Q. Do you think one of your students who has completed successfully your Advanced Neural Net and Deep Learning course would be able to train the model in Huval using slightly modified data as taught by Ross?

A. Well, like I said to you, they would -- they -- they have the background, but you still have to make some technical decisions as you look at the data and start the training. Because when you start the training, you might find it's divergent, it's not convergent.

So it's not -- it's not

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generalizing and it's overfitting. So now you have to change the training strategy, you have to change the type of data you're providing, the size of the batches you're providing. The steps in the backpropagation, how steep of a descent step you're going to take.

There's a lot of variables involved in this. It's not -- it's not just turn the crank and there -- there comes a term, it's okay.

Q. Okay. But those are all challenges that you're preparing your students to handle, right?

A. Well, we prepare the -- we provide the student with a background. Just like you provide a student with calculus, that doesn't mean they can solve every possible mathematical problem out there. They understand the -- the background. They now have to look at each problem and understand, okay, formulate a technical

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strategy for it and understand how to tackle that particular problem. And the data set that they have, all of that is basically very problem and custom specific to the problem.

Q. Okay. So I know we had quite a -- quite a long departure from Huval, but I want to just try to bring it back to what we've talked about in Figure 1 of Huval.

And maybe let's look at Paragraph 31 of Huval.

A. Of Huval?

Q. Yeah.

And this is describing a Block 132 of Figure 1 of Huval?

A. Yes, sir.

Q. The neural network is -- is trained to identify -- apply automatic labels to additional optical information, right?

A. Yeah. This is typically what we call bounding boxes. So you're putting a bounding box, so you see where it says there, so block -- I'm -- I'm looking at

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Paragraph 31 of Huval.

Block S132 recites passing the first optical image through the neural network to generate a first automated label attributed to a first automatically-defined location on the first optical image.

Q. Okay. And --

(Speaking simultaneously.)

A. That's the idea what you're trying to do, is you're trying to define where the object is in the image. And typically that's done with block -- you know, bounding boxes like you see -- if you look in the figure, you see how they have like a little bounding box. So it's kind of like giving you the object is located roughly in this area.

(BY MR. SPEEGLE)

Q. Yeah. And I just want to be clear that the -- the generation of the automatic labels is done by the neural network that is trained based on human labels

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in Block S110, right?

A. That's the general idea, yes. So you want -- you want -- unless you train the network, you want to be able to utilize it.

Q. Okay.

A. Labeling the object, just like we talked about in paragraph -- was it 23 or earlier in that paragraph, yeah. Training -- Paragraph 23.

Q. All right. We can put aside Huval.

I do want to ask a few more questions about your '889 declaration. And we -- we can go back to the table of contents on this.

A. Sure. '889, table of contents.

Q. So we've talked about Ground 1. And then Ground 2 adds the Cox reference, right?

A. Yes.

Q. Okay.

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A. Yes, Ground 1 is just Huval and Ross.

Ground 2, Huval, Ross, and Cox.

Q. And the one element that you disagree with for Ground 2 is the same as what you disagreed with in Ground 1, right?

A. That is correct.

Q. Okay. And then if we turn to Ground 3, that is for a combination of Huval, Ross, and Munro; is that right?

A. That is correct.

Q. And it looks like you've disputed some different limitations with respect to Ground 3. Is that fair?

A. Yes, sir.

Q. Okay. So instead of disputing limitation 1[c] you are now disputing limitation 1[d], 2[d], and 12[d]. And then 1[f], 2[f], and 12[f]. Is that right?

A. That's correct.

Q. Okay. And then Ground 4, which is a combination of Huval, Ross, Cox, and

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Munro, again, you're no longer disputing element 1[c] for this combination, right?

A. Yes, I'm disputing 1[d] and 1[f].

Q. Okay. And the same for the parallel claims 2 and claim 12, right?

A. Yes, sir.

Q. Okay. All right. I know we're a little bit faster than the last break, but I'm about to shift gears back into summary statistics again.

MR. SPEEGLE: Do you want -- do you want to take a break now before I do that?

THE WITNESS: Sure. Let's do that. Let's take a five-minute maybe.

MR. SPEEGLE: Yeah.

Five-minute break sounds good.

(Break from 1:21 p.m. to 1:28 p.m.)

(BY MR. SPEEGLE)

Q. Okay. Let me ask you about Paragraph 65 of your '889 declaration.

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A. Paragraph 65, 889.

Yes, sir.

Q. Now, you say in here that -- well, I'm going to paraphrase. I'm not going to quote it exactly.

But you said that Huval's averaging does not constitute a summary statistic; is that right?

A. That's correct. You have to read that Paragraph 85 of Huval and understand the technology that he's talking about.

Q. Okay.

A. We can go to that if you would like.

Q. Sure. We'll go there in just a second, but before -- before we go on, just read from here, and you -- you agreed earlier that an average is a statistic, right?

A. Well, I mean, obviously, if I compute an addition of five numbers and divide by five, that gives me an average.

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Q. Is that a statistic?
A. That would constitute, you know, a statistic, but that's not what's going on in Paragraph 85 of Huval.
Q. Okay. So -- and let's look at Paragraph 85 of Huval.
A. Fantastic. Let's do it. One of my favorite paragraphs.
Q. You know you're in the right field when you have a favorite paragraph of a patent.
A. Yes. When you wake up at 2:00 a.m. in the morning and think about it, right?
Q. Okay. So --
A. Yes, sir.
Q. Paragraph 85 refers to an average or otherwise combined responses; is that right?
A. Yes, that's the language, but that's not what it -- you have to understand the technology underneath it to really

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understand what he's saying here.

Q. Okay. What's your interpretation of --

(Speaking simultaneously.)

(BY MR. SPEEGLE)

Q. What -- what's your interpretation of what's -- what's going on underneath?

A. See, take a look and see what he says here.

So if you look at what Huval is saying -- and let's just start -- first of all, obviously, he's referring to Figure 1 and 3, correct? And label conflicts to other human annotators. So he's talking about, you know, distinguishing between label conflicts.

For example, he says -- where I'm talking in probably second sentence in the paragraph, ... remote computer system can: serve an optical image, a manual label, automated label for label conflict resolution.

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And then as you read a little bit more below, it says, such as including the human annotator who supplied the label and receive manual confirmation of one of -- of one of the manual labels and the automated labels, and average or otherwise combined responses.

Then you notice it says there, e.g., object types, label location, activation times, and deactivation.

Do you see that?

Q. Yes.

A. Okay. So this wording of "average" here, that doesn't mean you're adding five numbers and dividing by five and getting a statistical average.

Let me explain what I mean.

Let's suppose I -- I have two humans or the human labeled this object as a bicycle and the computer labeled that object as a pedestrian. You are not going to add that two and divide by two and say, Well,

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there's your label, is it? That -- that's not how it -- how you do a label conflict resolution.

So what at that point you're going to do is determine, okay, the human labeler labeled the object as pedestrian, which usually is more accurate in these type of scenarios than the computer-automated version, which might have labeled the object, let's say, as a -- as a cyclist.

So then you're going to take maybe a binary combination of the two or just select the human label version as the accurate one. You're not going to -- by average, he doesn't mean I add the two and divide by two. Because it wouldn't make sense.

Same thing with label location. So if I said to you the label is located -- the human labeler said, The label is located here in the image, and the neural network said, Well, no, it's not here, you're not

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going to average the two and divide by two because then you end up with junk.

So you're going to select which of those two is the more accurate, you know, label, which obviously, generally speaking, it's the human annotators over the automated version.

Same thing with activation time. So activation time could mean infringe a video -- let's say I have a hundred frames of video. At frame 30, I see -- a human annotator says, I see the cyclist showing up.

And frame 31, here he is, and frame 32, 33, 34, et cetera, versus the neural net automated one may say, Well, that started at frame 33, not frame 31, or starting at frame 34.

Well, you're not going to add the two frames and divide by two. That doesn't make any sense, because now you end up with a number that doesn't -- is not a frame.

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So 31 plus 34 divided by 2 may give you a decimal number. That's not -- that's not a frame number.

So the average that you see here is mistakenly read by Dr. Janet and Tesla to think it was just a statistical average just because it says the word "average."

That's basically a lack of understanding of the technology that's being assessed here.

Q. So why does it say "average" and not pick the most accurate?

A. Well, I mean, people use language, you know -- you know, average or otherwise combined responses. You know, people sometimes use language in a flexible manner.

You know, it's -- I can't tell you why Huval used that language.

But what I can tell you is having done this many times and, you know,

I've developed segmentation algorithms, at the time when I develop them were state of the art in the world.

And we have a paper we published to show we tested every possible segmentation algorithm and showed that ours were the best at the time.

I guarantee you that is not -- it's not a statistical average of any kind. That doesn't make sense at all.

Q. So you think --

A. Otherwise combine makes sense.

Q. You think it's just a typo?

A. I mean, people -- like, you know, people sometimes use language in a flexible manner, right, just because, you know, people do this all the time. Right?

They -- they use language in a flexible manner. That doesn't mean it's literally meaning I'm just going to divide -- add five numbers and divide by five, because it doesn't make sense in doing object

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labeling of any kind.

You never do that because it doesn't -- what do you end up with? If you average just like -- let's say three humans came up with the person and the object is a human. And one -- and a computer said two of them came up with cyclists.

What do you do? Add the five and divide by -- by five? What do you get? Something between human and a cyclist?

Q. Could you, you know, correlate the labels with different numerical values?

A. You don't do that because, I mean, now you're taking away information. I want to know the exact label of that object, because that's what I'm trying to train the neural network with.

See, I want -- I want ground truth value, right? I want the most accurate possible label. I don't want some averaging of the label, because now I'm degenerating the quality of the training data.

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Q. Let me say I have no doubt that the -- the Saber model will be superior to the Huval model in every respect, but I'm just trying the Huval model here.

Is there a way that they could have, whether it's inferior or not, attributed these activation times or the object types to numbers and then numerically average them to get a different weight for their -- their weights?

A. No. It wouldn't make sense.

Q. Okay.

A. I mean, think about what's being done here. Object -- if I told you the object is located here versus the automated system that says it's located here -- let's suppose the two locations don't overlap at all.

Let's just say I say it's located in the right side of the image, and then the neural net says it's located in the left side in the image.

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If you average the two together, what do you get? It's -- neither one now is correct.

What you get is a label that's located in the middle of the image that doesn't reflect either one of them. So you've just -- what you did is you degenerated the data and made it much poorer quality training set, which then is going to affect your neural network and come up with junk.

Q. You --

A. You know the old atom -- or idiom or whatever. Junk in/junk out. Right? Garbage in/garbage out.

Q. I think I hear you. And I'm not arguing on the quality for sure. I think what you just described is still possible, right, even if it's lower quality to, you know, say if it's -- you got the right side, the left side, you average it, you get the middle?

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A. You wouldn't do that. I mean, it --

Q. Well, I might --

(Discussion off the record.)

A. So one is you wouldn't do that; and two, Huval is not doing that.

(BY MR. SPEEGLE)

Q. Well, Huval says average. I think what you're saying is he doesn't mean average.

MR. GINNINGS: Objection; form.

A. Again, what I said to you is the word "average" there is used in a flexible manner just like people use words in a flexible manner, you know, in different context.

That average doesn't mean you're adding up five labels and dividing by five, because technically that wouldn't make any sense and wouldn't make any sense in what Huval is doing.

So anybody that reads it that

way has no understanding of how these systems are done. And I'm sure Huval did not intend it to be averaging and dividing by five.

(BY MR. SPEEGLE)

Q. Okay. Later in this Paragraph 85, he mentions a binary combination.

What's a binary combination?

A. An and, an or, an exclusive or, that type of thing.

So if you had five humans, for instance, that are saying this is a cyclist and the automated system says it's a pedestrian, then you would say, Okay, I'm going to take those five and use that as my -- you know, the five human responses.

Q. Okay.

A. So that's what makes sense, is you're doing the proper combinations because you want -- you know, think about what the application here, is I want the very best training data set possible with the very best

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ground truth because that's what I want to train my neural network with.

I'm not going to give my neural network substandard data so then I have degenerate type result.

Q. Now, I'm going to venture into a little bit of math that I'm not a hundred percent confident in, so I'll need your help with it.

But I understand that when models are actually trained on that data, they used vectorized data; is that right?

A. Depends on the model. For instance, if I'm doing -- are you familiar with CNN, convolutional neural networks?

You don't use vector data, because, if you did, you would basically -- an image -- if I were to show you an image -- and I do this example in my classes.

If I show you an image -- let's say you took a picture at -- you're at Disney World and you took a picture.

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That picture is not just a random selection of pixels. Right? It is a cohesiveness in that picture. So when you look at it, you see people, you see bicycles, whatever.

If you were to vectorize that image, if I were to take, let's say, the first line and then put it in a vector and then take the next line and put it in a vector and vectorize the image and I show you a vector, you would have no clue what's in that image.

You just destroyed the correlation that's in the image. And that's why CNNs, you know, convolutional neural networks, have been very effective in analyzing imagery because they take advantage, one, of the correlation in the image; and two, you don't want to vectorize the image because if you did, you would have a huge input layer.

I mean, if the image is a 10 by

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10 and you vectorize it, now you have a hundred input layer to feed into your neural network, which obviously images aren't 10 by 10. They're usually, say, 500 by 500 or something. They're -- they're large.

So if you were to vectorize that image, you would have a huge neural network that would take hours to train. So you don't want to do that. And that's why CNNs don't do that.

Q. Okay.

A. Vectorization is only good for classification type purposes, not necessarily analyzing imagery in general.

Q. So when a CNN is being trained on images, I understand that the -- the images at some point are going to be impacting numerical weights in the -- in the model, right?

A. Well, the CNN -- if you're using a CNN, you essentially have what we call a kernel or a filter and that filter has

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a certain size, let's say, a 5 by 5, which you are passing over the image and doing what's called convolution.

It actually does cross-correlations in general, not convolutions, but we call it convolution.

So -- and that's another flexible use of technology. People call it a convolution, but actually it doesn't do convolution, it does cross-correlation.

So if you had to be -- accurately saying CNN, you should be saying cross-correlation neural networks, not convolution neural networks because they don't do convolution.

But anyway, besides the point.

So you're -- you're training the filter -- what you're trying to do is get the right numbers for that kernel, and that's what you're trying to train, as the kernel that you're using for the cross-correlation, so hopefully you can generate a set of

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features from that image.

Q. Okay. What are the kinds of models where you would use vectorized, vectorized training data?

A. Typically more in classification type models where you have essentially a set of features, so you've got some -- some objects or whatever you've created -- you've -- you've gotten to a set of features. Just like we do on the back end of a CNN.

So we use a CNN up front. We have a bunch of images. We do some filtering and some basically pooling and activations, et cetera, and we do that on a few layers, say five layers for illustration purposes.

Now we have reduced that imagery to a set of features which is a lot smaller because you did some pooling.

By "pooling" means you're subsampling the image in both directions. As you're doing the convolution you're

subsampling the output.

So now you have a much smaller set which you then vectorize.

If you're doing, for instance, space recognition, you would vectorize at that point and go into what's called a fully connected neural network to do the classification or the identification.

And, yes, this is Mark. And yes, this is Eli. And Austin, so Austin doesn't feel left out.

Q. Okay. And when you have a -- when you have vectorized training data, is it more sensible to talk about averaging your vectors?

A. And, again, I think you're mixing apples and oranges because what you're trying to do is fit the square peg in the round hole.

So if my vector is the location of the object in the image and I have another vector which is another location of the

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object in the image, I wouldn't average the two because now you end up with junk because now you're -- you have subpixel locations instead of pixel locations.

So if I have a vector and it -- it has pixel locations to it, and I have another vector that has different pixel locations to it, and they're all integers and I average the two, now I have decimal pixel locations. It doesn't make sense for the image.

So, you know, it -- it doesn't make sense in these type of applications.

I mean, I understand your motivation to get the average out of this to work for you, but it doesn't work. This is not what's being done in Huval, and it's not what you would do. Any POSITA would know that.

And by the way, that's my favorite paragraph of Huval.

Q. You said, yeah. I see you get

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fired up about it.

All right. So I'm going to direct you back to your declaration, and this is Paragraph 66.

And you say in Paragraph 66 of your declaration --

A. '889 declaration, Paragraph 66, for the record?

Q. Yes.

A. Okay.

Q. Do you have it in front of you?

A. I do, sir.

Q. In the last sentence, it says, Nothing in the cited portions of Huval describes --

THE REPORTER: Slow down for me, please.

(BY MR. SPEEGLE)

Q. Nothing in the cited portions of Huval describes computing a mean, median, or mode of any figures.

Did I read that right?

A. You did.

Q. And am I understanding correctly that -- that the basis for your sentence here is that when Huval said "averaging," he didn't really mean "averaging"?

A. As I've --

MR. GINNINGS: Objection; form.

A. As I've explained to you for the last 15 or 20 minutes, yes.

(BY MR. SPEEGLE)

Q. Okay.

A. This is nothing to do with computing a mean. It's just a figure of speech as being loosely used in -- in Huval, just like you would do this in a lot of times.

Q. All right.

A. I mean, if I said to you, I'm running errands, does that mean I'm running -- physically running outside and -- and -- no, "I'm running errands" means I'm

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out there, you know, doing four or five different activities. I'm not physically running. You know, people use that as a figure of speech, right?

Q. So you think it was just a figure of speech when Huval said you could average the responses?

A. Absolutely. I mean, you -- I mean, any POSITA would understand this technology, would know that this is not a statistical mean of any kind. Because, otherwise, it doesn't make sense, as I've explained to you for the last 20 minutes.

Q. All right. Let's switch and talk about the Ross reference. And which is -- I think that's Exhibit 13.

A. Ross, yes. Another one of my favorite.

Q. All right. So I want to direct you to Column 3, Line 8 through 12. Let me know when you're there.

A. Column 3, Lines 8 through 12.

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Yes, sir.

Q. And do you see that sentence that says, In one example, generating the prediction of the intent includes generating a set of predictions, wherein the set of predictions includes the prediction of the intent, and each given prediction of the set of predictions identifies a next possible action by the road user.

Do you see that?

A. Yes, I see.

Q. And what is your understanding of what Ross is describing in this passage?

A. Well, I see, I mean, it's -- he's telling you, you're generating the prediction of the intent, includes generating a set of predictions.

So by a cyclist, I predict -- I don't know -- is going to turn left. And the next prediction, he's going to turn right or she is going to turn left and turn right.

So generating a set of

predictions wherein the set of prediction includes the prediction of the intent and each given prediction of the separation identifies a next possible action.

So predicting the intent and the next possible action might be, well, he's going to turn right versus turn left.

Q. Okay.

(Speaking simultaneously.)

A. As you know, Ross is about predicting intents and behaviors.

(BY MR. SPEEGLE)

Q. Do you feel like that's different from the '344 patent?

A. As I explain in my declaration, yes.

Are we -- are we going to the '344 now back?

(Speaking simultaneously.)

(BY MR. SPEEGLE)

Q. Let me talk to you about Ross. We don't -- we don't need your declaration

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right now.

A. Okay.

Q. Let's also look at Ross Column 8, Lines 63 to 65.

A. Ross Column 8, Lines 63 to 65.

Q. Well, and if you want to read the whole sentence, I'll back up to -- it starts at Line 60, the part of the sentence that I'm interested in is in the second half, but why don't you just go read the whole -- whole sentence here?

A. Do you want me to read it out loud.

Q. Yes, please.

A. Okay. So I'm at Column 8 -- Ross Column 8, Line 60.

As an example, given the location, heading, speed, and other characteristics included in the data from the perception system 172, the behavior-time models may provide a set of one or more predictions for how the object could behave

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for the predetermined period of time as well as a corresponding likelihood value for each prediction.

Q. My first question is: This passage and the first passage you read referred to a set of predictions, do you have an understanding of what a set of predictions would be in this context?

A. I think I've explained it to you earlier, but I'll explain it again.

So I may predict for a road user and, you know, looking at a road user I may say, Well, he may be going left or it may be going left, that's one prediction. It may be going right, that's another prediction. The two together form a set of predictions.

Q. Got it.

And there would -- the probabilities of those options would add up to one, right?

A. Well, if you -- if you're just doing only two of them.

So if you made three predictions, then you would -- that would be slightly different, right? So you have the probability of three add up to one. That kind of thing.

Q. Right. So I guess however many -- sorry. Let me say that again.

However many predictions you have in your set, the cumulative probability of all of those predictions together should be one, right?

A. Well, you have a likelihood value for each prediction. So that's the idea. Yes.

Q. Okay.

A. It doesn't mean you're correct, but that's the idea.

Q. And, sir, I'm going to jump down to the last part of Column 8 going into Column 9. I'll read this one.

It says, In this regard, the prediction with the greatest likelihood value

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may be the most likely to occur whereas with predictions with lower likelihood values may be less likely to occur.

A. Yes.

Q. Is this akin to the posterior probability we discussed earlier?

A. Say again.

Q. Well, this is a selection of the thing with the highest likelihood. And it's reminding me of our conversation earlier about posterior probability. And I -- so --

(Speaking simultaneously.)

A. That has nothing to do with posterior probabilities.

(BY MR. SPEEGLE)

Q. Okay. How are they different?

A. Well, a posterior probability, as I've explained to you -- and I'm assuming if we meet tomorrow, I would invite you to take a look at, say, Papoulis or ChatGPT just to look at Bayes' theorem.

But posterior probability

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requires the knowledge of the distribution of the class.

So probability of A given my sample X. Let's assume I have three classes, A, B, and C. And I have -- I draw -- I have one sample here in my hand.

Does it belong to -- let's say I have three types of balls, a red ball, green balls, and blue balls. And I just drew one sample of random in my hand and then you don't see the color.

What's the probability of that sample being Class A, Class B, or Class C?

So what's the probability of A given my sample? That's a posterior probability.

For you to compute that, you would need the class distribution. So you'd need what's the probability of samples given Class A.

That's a probability distribution function, a probability density

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function.

So you would need to know the probability density function and the a priori problem for you to compute the posterior probability.

This is just the likelihood of the prediction that Ross is predicting. Just like a softmax type function, I make a prediction and I give it a .7. I make another prediction and it's .2 and another prediction is .1.

So the likelihood predictions has nothing to do with a posterior probability in a sense because there is no distribution here. There's no probability density function.

Q. The way you said those things together makes me think you intend them to be related.

Are you saying to have a distribution you need a probability density function?

A. I think you're mixing up several contexts. A probability density function is a distribution. So think of it as a histogram, but it's a continuous histogram.

I'm simplifying, obviously, oversimplifying.

But probability density function, say a normal Gaussian distribution for males that play in the NBA, right, so you have mean and then you have a normal distribution with a variance. You know, the mean, let's say, is height 6.8 plus or minus whatever, some inches.

So that's the probability density function that describes the class and the probability of different samples of different values in the class.

So you need that to compute the posterior probability using Bayes' theorem, as I've explained to you earlier more than once.

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Q. Okay. So I guess when we're talking about a set of predictions, you would not call a set of predictions a distribution?

A. No.

Q. And why is that?

A. Because it isn't. I mean, a distribution, essentially you would have to know the class distribution to create a -- let's say a two-dimensional Gaussian or a three-dimensional Gaussian or whatever.

It's distribution for the different, you know, samples in the class in a sense.

Q. So when you see the word "distribution" in the '344 patent, you're interpreting that -- I'm sorry, let me strike that.

When you see the word "distribution" in the claims of the '344 patent, you're interpreting that as a class distribution?

A. Well, I mean, if you look at

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the '344 -- let's go back and look at it so we're saying the exact same things.

So if you look here at -- at the '344, it says -- and I'm looking at claim element 1[b], which has to do with this, obviously.

So if you say -- see, it says predicting an output statistical summary characterizing a distribution of user responses.

So you have a set of user responded, a hundred, 200, whatever. Based on all those responses, you've characterized the distribution.

I'm making this up now. A Gaussian -- a normal probability density function, let's just say the distribution is modeled by normal Gaussian.

So you have a Gaussian probability density function with a mean and covariances, et cetera. That's a distribution of user responses in a sense.

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Q. Okay. So your interpretation of a distribution as used in the '344 patent claims requires a -- a statistical distribution like a Gaussian?

A. Well, the claim basically says you have a statistical summary characterizing a distribution of user responses.

So however that distribution is modeled, you have a distribution of user responses that are expected to be received responsive to presenting the sensor data to a variety of users.

Because different users will have different opinions, right, or different judgment on what they see?

Q. Okay. So to put this in terms of Ross, your opinion is that the -- even if the set of predictions described in Ross covered distribution of possible future outcomes, that's not sufficient for a distribution in the terms of the '344 patent because the '344 patent is specifically

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referring to a distribution of hypothetical user responses that would fall under something like a Gaussian?

MR. GINNINGS: Objection to form.

A. I have no idea what you're saying. And Ross -- as I explained to you, when you look at those paragraphs of Ross that we have been talking about -- so both in Column 8 and the previous one, which was Column 3, right?

It's talking about a set of predictions. There's no distribution here. There's no discussion of a distribution. So if you look at Column 3, it just says a set of predictions, you know, include each of the intent and possible action.

And if you go to Column 8 and you look at what you read and you -- I read and then you read, see, all it says is you have a set of predictions and likelihood for that prediction.

Think about it, you know, I have a neural network with three outputs. I make a prediction and I have a softmax layer on the output. I make a prediction, so output 1 .7, output 2 .2, and output 3 .1.

Turn left. Turn right. Go straight.

So I just made three predictions with three likelihood. So clearly the .7 is the most likely scenario. That's the greatest likelihood. That -- that's not a distribution of -- you know, that's not a distribution of user responses, first of all. It's just a prediction of a network.

(BY MR. SPEEGLE)

Q. Okay.

A. It's certainly not a statistical summary of a distribution of user responses.

Q. Let's -- let me just make sure I'm understanding what you're saying.

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You're saying that if you have a collection of potential predictions, each with a different probability score, that is not a distribution, right?

A. That is correct.

Q. Okay. Now, let's -- let's look at what's in the '344 patent at --

A. One, it's not a distribution; and two, it's not a distribution of user responses.

Q. Okay. Let's look at Column 3, Lines 58 through 67, of the '344 patent.

A. Column 3, Lines 58 to 67.

Q. Yeah.

A. Okay.

Q. And at the bottom -- and so this is the last three lines there. It says, The overall collection of scores on the continuum comprises a distribution of scores.

A. There he goes. Yeah, exactly.

Q. Okay. Now, how is a distribution of those scores different from a

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distribution of probabilities that we were talking about in Ross?

A. You see, obviously this is talking about -- so if you step back in that paragraph, so let's just take a look at it step by step.

He says -- you see it says human observers are presented with small samples of video data.

So think of -- think about you have a hundred human observers. They're each sitting at a monitor. And you presented each of them with three frames of video, okay, that have been modified to focus the observers on aspects of the samples.

So you're not just giving them a random frame, you're giving them a frame, you're basically telling them, Look over here.

Okay? So you're just -- they're not just randomly looking at the frame.

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... on aspects of the samples most likely to be relevant to predicting pedestrian ...

So you're showing them three frames of video and traffic, and you're pointing them to the pedestrian in the video, right? So it's not just everywhere. You point them to the pedestrian in the video, and you're basically saying what do you think that person is going to do.

... or other driver behavior, and to eliminate aspects which are not relevant to predicting such behavior.

So you want them focused on the road user that you're interested in.

Now, large sets of observers are asked to score the samples of video data on a continuum, so now you're asking them to give them a score on a continuum, do you think, you know, he's going to go right, go left, whatever, do some scoring.

And the overall collection of

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scores under continuum now comprises a distribution of scores. Because out of the hundred, maybe five of them -- let's make this up, let's say the scores are 1 through 10. Five of them maybe out of the hundred, maybe 50 will pick the 5, and 10 will pick 1, and 6 will pick 2 or whatever.

So as they're scoring this, you're creating a distribution of scores. So it's essentially you're creating a histogram. And if, obviously, you divide by the hundred, you get a probability histogram, which is modeling the probability density function.

Q. So you say that 50 of them will pick 5 and 10 will pick 1 and 6 will pick 2, that -- that represents the probability of picking those numbers?

A. Well, you're going to turn then to a probability, right, because if I had a hundred users looking at that image and 50 out of those hundred picked 5, let's just say, so 50 percent -- 50 divided by a hundred

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is .5, so 50 percent of them picked 5.

And then if 30 of the hundred picked 2, then .3 picked 2.

So you -- you turn that into, obviously, a probability density function.

Q. The '344 patent doesn't describe turning this into a probability distribution function, does it?

A. Well, you're talking about the overall collection of scores on the continuum comprises a distribution of scores, so now you have a distribution of scores.

The parameters of distribution are then used to construct the target, et cetera.

So you're computing parameters of that distribution. So you're going to basically look at it, look at its mean, its variances, its cross-variances, correlations, et cetera.

And they mention some of that later on in that paragraph we've been talking

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about, the summary statistics. You know, you're looking at central tendency, variance, skew, kurtosis, scale, histogram, more two-dimensional distribution.

I'm looking at Column 6, Lines 24, 26 -- 24, 25. Sorry.

Q. If we're -- if we're talking about a hundred responses and -- we have a hundred total responses, 50 score 10, 30 score a 1, 20 score a 3, the score of 10 with 50 responses would have a higher likelihood value. Is that fair?

A. I'm sorry. I didn't understand what you're saying.

Q. So I'm imagining a distribution here. We've got 50 -- 50 people who put down 10, 30 who put down 1, and 20 who put down 3. Those are the only responses we got.

A. Yes.

Q. And so the 50 who put down a 10 means that 10 has the -- the higher likelihood value, right?

A. Generally speaking, yes, that's the case.

Yeah. Obviously, I mean, that's a simplified illustration, what we're talking about here, but yes.

Q. If you don't mind, could you pull up the Ogale reference, which is Exhibit 14?

A. Ogale. This is -- let me see. Ogale, yes, sir.

Q. And the Ogale reference and the Ross reference are both assigned to Waymo, right?

A. I assume so, yeah.

Q. I mean, it says on top up there. It says the applicant is Waymo for each of them?

A. Yes. Ogale and Ross. Let me see what the Ross one says.

Yeah. They're assigned to Waymo.

Q. And you would agree that both

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of these are related to sensor -- sensor data processing for autonomous vehicles?

A. Well, I mean, that's obviously generally the idea that they're targeting. You know, Ross is targeting, you know, behavior intent estimation, and Ogale is more about object detection.

Q. So let me direct you to Column 3, Lines 24 through 27 in Ogale.

A. Of Ogale. Column 3, Lines 24 and 27.

Yes.

Q. Okay. And it says, The plurality of output layers includes: a human-labeled output layer that predicts how a human would identify objects in the projections of input sensor data.

And then it goes on to list other layers.

Do you see that?

A. Yes.

Q. Is it fair to say that Ogale

discloses having a machine learning model for self-driving that predicts how humans would have labeled data?

A. I mean, generally speaking, that's the idea. But, obviously, the devil is in the details. But, yes, I mean, it kind of -- plurality of output layers include a human-labeled output layer that predicts how a human would identify objects in the projections of the input sensor data.

So that human label output layer is going to try to predict if I were to go into the sensor data and identify the object, the idea here is would that layer give me the same identification.

Q. Okay. Now -- well, I'll move on.

Let's talk about the Cox reference.

A. Cox.

Q. Which is Exhibit 12.

A. Yes, sir.

What about it?

Q. You see the cover, it lists the inventors of the Cox reference.

Do you see that?

A. Yes, sir.

Q. And the third inventor is Samuel Anthony.

You see that?

A. I see that.

Q. Have you met Mr. Anthony?

A. No, I have not.

Q. You understand that Mr. Anthony is the inventor on the challenged patents?

A. Yes, sir.

Q. Okay. Did you ask Perceptive if you could speak with Mr. Anthony?

A. No.

Q. Why not?

A. Didn't need to.

Q. You didn't think that he might have had more information about the references or the patents?

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A. No, I can read -- I can read the patents. I know enough -- I have enough expertise and experience in this field. I can read the patents, and I can read the analysis by Tesla and Dr. Janet and render my own objective opinions.

Q. Okay. I believe you've opined that the Cox reference, in your view, is not applicable to driverless or semiautonomous automobiles; is that right?

A. Generally speaking, that's the idea, yes.

Q. Okay. I would like to direct you to Paragraph 56 of Cox which is on PDF Page 28.

A. And are we talking about -- which declaration now?

Q. Sorry. This is Paragraph 56 of Cox.

A. Okay. Yes, but are you talking with -- which declaration you have in mind? Do you -- are you --

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Q. At this point, it is relevant to all of them.

A. Okay.

Q. So Paragraph 56 says that, Embodiments of the present invention may be directly applied to several important domains ...

Do you see that?

A. I'm looking, yes.

Q. And then toward the bottom, it says at Line 24, Important application areas may also benefit from embodiments of the invention, including ...

And then towards the end it says, ... driverless/semiautonomous automobiles ... Right?

A. Yes, I see that sentence.

Q. Do you disagree with the statement in Cox that it may be applied to several important domains and driverless and semiautonomous automobiles are included?

A. Well, you have to really take

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this in the proper context. I mean, for instance, when we write a paper, we -- we describe all the details and technical content, et cetera, that in the future directions sometimes it will say, Well, you can apply this in these other areas.

You know, because some of it is a little bit of marketing, so to speak.

You know, say, Well, okay, here's my invention, and I can apply in all these different things.

Well, this is a little bit more of, I would say, marketing somewhat or stretching a bit. There is obviously no technical descriptions of any kind that show how you would apply this to -- in all these different areas. I mean, if you're going to tell me, Well, okay, if I'm an autonomous application and I give you an image and I want to know what the face in the image is, that might be a possibility.

But if you were going to tell

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me, I'm going to use Cox to do autonomous driving, that's not going to work.

So some of this is a little bit of hand-waving, as you would -- you know, putting it in gentle terms, marketing and hand-waving.

Q. But fair to say you disagree with the statement in Cox that it's applicable to driverless and semiautonomous automobiles?

A. As I mentioned, I mean, this is what I would call marketing and hand-waving. There's no technical description of any kind. And the technical description that they provide, when you look at their hinge loss function, the human-rated loss function in the application does not support, you know, the generic statement.

There's no technical description of how you would do that.

Q. I understand your point that there's not a technical description here.

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But I just -- on the face do you agree with the statement in Cox or not?

A. I mean, as I said to you, I mean, if you were going to tell me, well, in this autonomous or semiautonomous driving application I'm looking to do face detection, in this particular image my application requires to do face detection, then perhaps Cox is somewhat applicable.

But as a generic statement like this, you know, to me, you're just basically hand-waving and, you know, marketing.

I don't -- I don't see any technical details or any rational underpinnings of how you would put this into this application and make it work. So you're hand-waving.

Q. I think you did say that if your driverless or semiautonomous automobiles needed to have some facial detection or emotional recognition, Cox would be applicable to that, right?

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A. I mean, I'm saying if, hypothetically speaking, you were to tell me I need to do this, I mean, in an autonomous situation, you don't need to do that.

I don't need to know where the face is. I need to know where the pedestrian is, or I don't care where the face is. I just need to know they're here so I don't hit them with the autonomous driving vehicle.

So the application isn't typically concerned with face, because a lot of times you can't see the face. The guy is walking away from you. He's walking on the side of the road away from you. You can't see the face.

So this is just what I would call flexible -- putting it in gentle terms, flexible hand-waving and marketing.

There's no supporting evidence of any kind that would show how this would be directly applicable. Cox doesn't provide anything that shows that.

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Q. I know you're -- you're working hard not to say you disagree with it, but it's fair to say you kind of disagree with it?

MR. GINNINGS: Objection to form. Argumentative.

A. Well, I mean, like, look and see what it says. In the discipline of human biometrics, embodiments of the invention may be applied to fingerprint verification, fingerprint identification.

I -- I mean, there's a whole collection of stuff that all have different algorithms of how you would do this.

If this is the case where I could solve all of these, my god, I'd adopt this right away and have them do all the stuff.

I mean, you know, again, you're -- to me, you're just marketing and hand-waving. You have no supporting technical discussions or evidence of any kind

to show any of this works in any of these applications.

(BY MR. SPEEGLE)

Q. Okay. Let's look at the end of Paragraph 16, so this is on PDF Page 11 of Cox. I'm looking at the last sentence.

A. Paragraph 16 of Cox, last sentence, yes. Finally -- the sentence that starts with "finally," correct?

Q. Correct. Do you want to read that for the record?

A. Yeah. Cox says that finally in application 145, which let me see what -- give me one moment here. I just want to see what 145 is.

Okay. So if you look at Figure 1A, they have object recognition as 145.

So, finally, in application 145, the system may be utilized to recognize various other objects and images as shown. The system may identify objects such as a

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tree, a car, a bus, a building, and a street in a given image.

Q. Would you agree with me that it's relevant to self-driving cars to identify objects such as a tree, a car, a bus, a building, and a street?

A. I would agree that in autonomous driving situations that would be relevant. I don't agree that Cox has such an algorithm that would do all this.

You would have to show me the technical details of that. You've only showed that you can do face detection with it.

You haven't showed that you can do all these other things. And they're completely different from face detection.

I mean, faces have a certain symmetry to them. Right? Your face -- if you look in the mirror, there's a certain symmetry. Your eyes aren't just randomly located in your face. There's a certain

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symmetry to the face that is very different.

Trees are completely different. There's skinny trees. There's big trees. There's tall trees. There's, you know, different variety of branches and stuff.

You haven't really shown any of that. That's just, again, I would say hand-waving and marketing.

Q. Even though Cox says that's applicable to driverless cars and even though the inventor on Cox went on to start a self-driving car startup and even though Cox says that it can be used to identify things like cars and buses and streets, you don't think Cox is relevant to self-driving cars?

MR. GINNINGS: Objection to form. Argumentative.

A. What I'm telling you is in this reference that I have analyzed, Cox provides no technical details to support any of these statements to show that it would work in any of these scenarios or how you would make that

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happen. To me, that's just marketing and hand-waving.

Because these things are very different. Like a car is a very rigid structure, like they're not flexible.

A tree is very flexible. A tree waves in the wind. Right? They have all different configurations, much more difficult to recognize than, say, a car or a bus or a building. Buildings have different, you know, size, different poses.

So they're a lot different than just a face on -- like if you look at the Cox system, for instance, you'll see Figure 1A and element 110.

You see you're looking straight at a face. You're looking directly at the frontal view of a face. That's very different than a side view of an object on the road with different, you know, perception or different perspective.

So -- but I think that's just

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hand-waving and marketing. There's no technical support of any kind that tells me how you would do that on these other objects.

(BY MR. SPEEGLE)

Q. All right. I want to ask you about Paragraph 73 of your '046 declaration. Could you get that in front of you?

A. Paragraph 73 of the '046 dec?

Q. Correct.

A. Yes, sir.

Q. Okay. And in Paragraph 73, you say that -- in the last sentence, Nowhere does -- I'm sorry, let me back up.

This is the second sentence. It says, Instead, the images described in Cox are of faces, and nowhere does Cox teach that those faces are those of a road user (e.g., a motorist, bicyclist, or pedestrian).

Did I read that right?

A. You read that correctly.

Q. How do you square that position with what we just read in Paragraph 16 of Cox

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that says the identified objects can be motorists?

A. I'm sorry, you -- I missed something. Say it again.

Q. Well, I'm just trying to -- I'm trying to square what you -- what you say here in Paragraph 73, that nowhere does Cox teach that those faces are those of a road user, e.g., a motorist, bicyclist, or pedestrian, with what's in Cox that we read at the end of Paragraph 16, that the system may be utilized to recognize other objects such as a tree, a car, a bus, a building, and a street?

A. Like I told you, I mean, you know, authors do this all the time in papers and they probably do it all the time in patents.

I've seen many patents in my time. I've been doing consulting for probably -- I don't know -- 20 years. I've seen many patents in my time where they say

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things. You know, saying it doesn't mean it is.

It's like I told you, there's nothing in Cox that describes how you would take a frontal view face recognition system like you would see in Cox and put it into a -- I mean, look at the size of the faces that you see in Cox in the imagery that Cox provides.

If you look at the size of the faces, they're very large. That's distinctly different from an application where you're doing autonomous driving where the face is going to be a few pixels in a frame of video.

So assuming I'm driving down the road and there's a person walking down the street and that person is ten meters away from me or whatever.

How big do you think that face in the frame of my image is going to be? Few pixels in the whole frame. Very different from what Cox is talking about here.

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So there's nothing technically in Cox that tells me that what Cox is doing is directly lift and drop into an autonomous situation -- autonomous driving situation.

Q. Well, just to -- just to press on that a little bit, if you look at -- let's say -- this is Page 42 of Cox, which has Figure 6.

A. Page 42 of Cox. Hang on a second. PDF Page 42?

Q. Yes.

A. Yeah.

Q. And --

A. You see the size of the face?

Q. Yes.

And I believe what you were just saying is that in self-driving applications, for pedestrians the images of faces are going to be very small and hard to distinguish, right?

A. Well, do -- do this tonight while -- while you're preparing for tomorrow.

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Go out on the road, get in your car. As you're driving down the street and when you see a pedestrian, just take a picture with your phone. Take a picture of that person with your phone. Just stop the car for a minute and take a picture.

And when you look at the picture, tell me how many pixels do you think that face is. Is it going to be the majority of the image or a few? I would say you're probably looking at 2 percent of the image, if that.

Q. So is it fair to say that the image quality for faces in this context would be particularly low quality?

A. One, it may be low quality. But it's not as much as the quality as it is the size of the imagery as well.

Q. Yeah.

A. So if you're looking at a face that's only, let's say -- of an image of, let's say, 512 by 512, the face occupies a

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12-by-12 block, that is a very small portion of the image and a much more difficult application to recognize the face than if the face occupied 90 percent of the image, like you'd see here in, let's say, number 600.

Q. Am I -- am I interpreting figures 6A and 6B correctly to -- to convey that the method in Cox is advantageous for identifying pictures of faces with low coherence or visibility?

A. With large -- one large -- you know, the face is very large in the image. So that -- that's a totally different application than you would see in an autonomous driving situation.

Like pure autonomously driving down the road, you're not going to see a coherence of .6 and .4. You know, you're not going to see that. I mean, the camera you're going to have on your vehicle isn't going to have that kind of low quality.

If that's the case, your

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vehicle isn't going to drive very far. So you're not going to have that kind of low quality.

What you're going to have is a lot smaller face in the image.

And you're not trying to recognize the face anyway. All you want to know is there's a pedestrian there.

You know, when you're driving down the road, you don't recognize faces. You're not looking at faces of people. All you care about is there's a pedestrian walking down the road, I just don't want to hit that person. You don't care what their face is.

You know, and that could be walking away from you, you can't see the face at all, right?

If I'm a cyclist, like I do a lot of cycling, I'm riding on the shoulder of the road in the same direction of traffic. You never see my face. I've got glasses on.

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I've got a helmet on. You can't see my face at all. All you care about is I'm a cyclist on the shoulder, therefore you can't bring your car on the shoulder. You know, they'll avoid me.

It's totally different applications.

Q. All right. We've been going over an hour. I know that we are getting towards the end of the time for today, so why don't we take another break here, and then we'll see what we got left for the day.

THE WITNESS: Fantastic.

(Break from 2:33 p.m. to 2:41 p.m.)

(BY MR. SPEEGLE)

Q. All right. Dr. Saber, let's go look at Paragraph 76 of your -- well, sorry, 77 of your '046 declaration.

A. '046 declaration.

Q. Yes.

A. Paragraph 77.

Q. Yes.

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Let me know when you have that in front of you.

A. Yes, sir, that's the one about psychometric data.

Q. Correct.

A. Okay. Yeah.

Q. I'm going to read the third sentence there for the record.

Instead, as Cox makes clear, its psychometric data, ... may include or consist essentially of (i) response time for classifying one or more features, (ii) accuracy of feature classification, and/or (iii) presentation time of one or more training objects.

Do you see that?

A. You read it correctly.

Q. Then a couple of sentences later you say, Likewise, the accuracy of the feature classification by the annotator does not describe the state of mind of any user in the image, but is instead of a measure of the

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correctness of the annotator's classification.

You see that?

A. You read that correctly.

Q. Now, when I read "accuracy of feature classification," that, to me, does reflect what the correct classification is, right?

A. So if, for instance, the annotator selects this and says, This is a cyclist, right? So you have an accuracy of feature classification.

Or this is -- let's say I'm doing face -- face detection, this is -- the nose is a feature. I select the nose and say, Here's where the nose is in the image.

That's an accuracy of feature classification.

That doesn't describe the state of mind of the road user that's in the image.

Q. Sure. What if the classification was angry?

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A. Still doesn't describe the state of mind of the user. I mean, you have to think about the application. The road user -- the autonomous application is about determining the context of these road users, right? As I'm driving my car, I'm trying to determine if that cyclist is going to jump in front of me or not.

So --

Q. Your interpretation of state of mind of the user in claims of the '046 patent requires it to describe possible actions of a road user?

A. Well, you're describing -- so if you look at the '046, right, I'm generating summary statistics that describe the state of mind of the user in the image based on the received responses.

So the -- the generating here -- so I'm looking at 1[b-iii] of 1[b], so 1[b] is generating training data from plurality of images, the generating

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comprising for each image.

So how this is generated is -- and then it explains. You're sending the image, you're receiving, you're generating, you're storing.

So you're generating summary statistics that describe the state of mind of the user. So you're not generating a classification, you're generating summary statistics that describe the state of mind of the user in the image.

Q. And Cox suggests that there's psychometric data that describes how accurately the state of mind of users in the image was described, right?

A. No, that's not correct. That's not what the psychometric data is talking about.

Q. So when Cox -- when Cox talks about the accuracy of --

A. That's just --

Q. -- feature classification, what

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does that mean to you?

A. So if -- if a user is going into an image and selecting, let's say, nose, okay, or selecting eye, so that's an accuracy of feature classification. That is not the same thing as summary statistics that describe the state of mind of a road user.

Q. You understand the feature classifications in Cox can include emotions, right?

A. Well, I mean, Cox mentions that. But, again, doesn't -- there's no technical description in Cox of any of them.

All that Cox talked about is face/no face classification. And if you look at the equations that Cox is proposing and use of the hinge loss functions and et cetera, those are directed to face/no face classification. It doesn't show any other details technically of how you do these other things.

Q. Even if it doesn't have the

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technical details, it still says it can identify emotions, right?

A. It -- it says that. But, again, that's -- that's not the same thing as statistical summary of the state of mind of the road user in autonomous application. It's entirely different.

Q. You're basing that on the fact that Cox does not have what you consider sufficient technical detail about the identification of emotions?

A. Well, first of all, it's a different concept completely.

And, second of all, Cox doesn't have any technical details to show any of that.

And when you look at Cox equations, they don't support that.

Like, you know, your hinge loss equation for instance, if you go to Cox and look at -- go to Paragraph 35 of Cox. So if you go to Paragraph 35 of Cox, so if you look

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at that paragraph where it starts on Page 19 -- PDF on Page 19 at the bottom, that's my exhibit, I guess, Page 19 or whatever.

So you see Cox is describing his equations, and he says, One component -- so I'm at the bottom of Page 19.

One component of a human-regularized maximum-margin kernel machine is the addressing of the issue of the loss function.

And he goes on to the next page and describes the loss function.

And you see this is embodied by the hinge loss function which is defined as phi(z) is equal maximum (0,1-z).

Do you see that?

Q. Yeah.

A. Okay. That loss function is a binary loss function. That loss function doesn't work on emotions and other stuff, which are -- that's his binary set of loss

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function.

Because if you look at it -- and I can explain that to you, if you want. Look --

Q. Well, let me just pause you there real quick. And I just want to reference what you said, was it has to be binary.

And Cox describes a potential binary emotional description, right?

MR. GINNINGS: Objection to form.

(BY MR. SPEEGLE)

Q. Let's look at Paragraph 49 of Cox, and I'll ask that question again.

A. Okay. What's Paragraph 49?

Q. Well, the -- the second sentence of -- sorry -- the third sentence of Paragraph 49 says, For instance, considering the human face, it may be said that a woman is beautiful, a man has black hair, or an emotional state may be described as happy or

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sad.

A. Yes.

Q. So you could -- you could use the equation you just talked about to binary separate things into happy and sad?

A. If you define it that way. But the point I'm telling you is these equations are limited to only binary classifications.

They wouldn't work in an autonomous condition where you're talking about summary statistics that describe a state of mind of road users are not necessarily binary.

Q. Okay.

A. Most likely not binary.

Q. Is the -- is the reason that you don't think Cox discloses element 1[b-iii] based on the fact that you don't think Cox is applicable to autonomous driving?

MR. GINNINGS: Objection to form.

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A. I mean, the equations that Cox describes, if you look at a technical description like that loss function I just pointed you to, the hinge loss function, that's designed for a binary type style classification.

So if you look at 1 minus Z, where Z is defined as Y times F of X, Y is the ideal label plus 1 or minus 1 versus F of X is the predicted output that the model is going to predict.

And if the predicted output is not the same as your label, then obviously you get the minus 1 versus you get a plus 1.

So this is designed for a binary style classification. A woman is beautiful is not a binary style classification.

So there are different levels of potentially beauty, I would assume. So that's not a binary style classification.

A man has black hair, I can

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tell you over the last 20 years, the -- that the evolution of my hair has changed significantly. And that's also not a binary classification.

Happy or sad is also not a binary classification because, you know, there's different levels of happiness and, I would assume, sadness.

(BY MR. SPEEGLE)

Q. But you could set up a classification model just to distinguish between happy and sad, right?

MR. GINNINGS: Objection; form.

A. I mean, you -- you could set something up, I would presume, but the point is none of that would be relevant in the autonomous driving situation because you don't care whether the pedestrian is happy or sad. You care about whether they're going to go in the road or not.

(BY MR. SPEEGLE)

Q. So let me ask you a question.

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I know you've opined that Cox -- or sorry, strike that.

You've opined that the '046 patent should be limited to road users even though the term "road users" is not used in the claim, right?

A. Well, again, as I said to you earlier in the morning when we talked about this, you read the claim in light of the specification, the prosecution history, et cetera.

So when you read the claim, it's clearly talking about a road user, not just any generic thing. That's why the construction was offered.

Q. I understand your position. But if -- if -- let's say the -- the Patent Office disagrees with you and the '046 patent is not limited to autonomous driving applications.

Would that change your opinion about whether Cox discloses element 1[b-iii]

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that we're talking about?

A. With all my due respect to the Patent Office, that would not change my position because I understand this technology.

I -- you know, I've been working in this field for years, probably more so than anybody in the Patent Office, I would assume.

And I -- you know, I've got a lot of experience in both developing products or algorithms as well as teaching and developing coursework on this. I know this technology.

Q. I'm sorry, I'm -- I'm not trying to ask if you would change your position and agree with the Patent Office.

I'm asking that if you assume there was a legal determination made that the patent is -- the '046 claims are not limited to autonomous driving, you know, with that assumption, do you have any arguments that

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Cox still does not disclose element 1[b-iii]?

MR. GINNINGS: Objection to form.

A. I mean, again, you're starting to deal here in hypotheticals, and I don't really like to deal in hypotheticals. So if somehow some -- somehow somebody comes back to me and says, Well, this is what the Patent Office has defined user to be, blah blah blah, and give me an exact definition of what exactly they're talking about, I'll be happy to sit down and do an analysis.

But I have to see the details. I have to sit down, understand what they're saying, why they're saying it, what's the logic behind it. It's not just off-the-cuff analysis.

(BY MR. SPEEGLE)

Q. Okay.

A. Reading the claims as they stand today, it's -- to me, it's clear -- clear that they're talking about a road user.

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Q. Okay. And you haven't done any of the analysis you just discussed about whether or not Cox would be applicable to the '046 claim 1 in a scenario where the '046 claim 1 is not limited to road users. Fair?

MR. GINNINGS: Objection to form.

A. I mean, I analyzed, obviously, the claim based on reading the claim in light of the specification, prosecution history, et cetera, and rendered my opinions. And that's what I stand behind.

(BY MR. SPEEGLE)

Q. Fair enough.

Okay. Would you agree with me that an emotion is a state of mind?

MR. GINNINGS: Objection to form.

A. Well, I mean, generic but it's -- it's entirely different from what we're talking about here for autonomous driving.

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So a state of mind of whether I'm happy or sad is a very different situation and different potential actions from a pedestrian walking down the road and is going to, you know, step into the crosswalk, you know, randomly or something.

So, you know, there's -- I mean, there -- technically there -- things are very specific. It's not just, you know, if it applies here, it applies there.

(BY MR. SPEEGLE)

Q. So you don't think we're applying the plain and ordinary meaning of state of mind in this case?

MR. GINNINGS: Objection to form.

A. Well, again, if you look at the '046 and you look at how the claims are structured, you see it says generating summary statistics describing the state of mind of the user, which is via claim construction road user, any image based on

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the received responses from the plurality of human observers.

So the summary statistics are not describing the emotion on the face of the user. They're describing the state of mind of the road user in the image.

So that's what they're describing. That's an entirely different situation than me looking at a user and describing whether they are smiling or, you know, happy or sad.

(BY MR. SPEEGLE)

Q. So you don't think it's the plain ordinary meaning of state of mind that we're applying in the '046 patent?

MR. GINNINGS: Objection to form.

A. I think I just answered your question, but I'm more than happy to answer it again.

See, if you look at the claim con- -- the claim of the '046, it

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clearly says, you know, my plain ordinary meaning of that, generating summary statistics.

So you have to generate summary statistics. Not generating something else. I'm generating -- not a classification. I'm generating summary statistics that describe the state of mind of the road user.

So if you look at my construction and if you replace the word "user" with "road user," so I'm describing -- the summary statistic is describing the state of mind of the road user in the image.

(BY MR. SPEEGLE)

Q. Can you explain for me what the phrase "describing the state of mind of a road user" means to you?

A. Well, if you have to go back in the patent and -- so if you go in the patent and just search on state of mind...

So if you look at the '046 -- and I think you pointed to this earlier

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yourself -- Column 10, Lines 34 to, say, 53, you see somewhere -- Line 36, 37, you see it says, This value may refer to the probability of the pictured human road user has a given state of mind, e.g., that a pedestrian is likely to cross the street or that an oncoming vehicle is likely to be willing to yield to the vehicle containing the sensor, et cetera.

So you're looking at basically -- I mean, think about the application here, right? I'm driving -- I'm the autonomous vehicle going down the road. I see a cyclist and I see a pedestrian and I see an oncoming vehicle. I don't care whether the pedestrian -- the pedestrian is laughing or not, I just need to know are they going to step in the street in front of me or are they going to continue going where they're going.

But if a pedestrian is standing at the beginning of a crosswalk, are they

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going to start to walk across the crosswalk where I have to stop, or are they going to stay there until my vehicle goes past?

So that's what I'm looking for as an autonomous driver in the '046.

Q. So it sounds like some number that qualifies as a summary statistic would describe a state of mind of a road user if it says how likely a pedestrian is to cross the street. Is that fair?

A. However you quantify it, but that's the idea is I want to know, you know -- if you look -- if you read Lines 38, you know, e.g., that a pedestrian is likely to cross the street.

So let's say I see a pedestrian at the top of a crosswalk, would that pedestrian start walking across as I'm coming down at 40 miles an hour, or are they going to wait for me to go by?

Or the oncoming vehicle is likely to -- you know, is likely to be

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willing to yield to the vehicle coming -- containing the sensor.

So the oncoming vehicle is coming, is it going to turn left in front of me, or is it going to stop and wait for me to go by?

That's the state of mind that -- that the autonomous vehicle of the '046 is trying to predict.

It doesn't care whether the driver in the vehicle is smiling.

Q. Would you agree with me that's a different interpretation of the phrase "state of mind" than what a layperson on the street might think?

A. Well, as I explained to you earlier, and I think we've talked about this a few times now, words mean different things in a sentence.

So if I told you "bank," you don't know whether I'm talking about an institution where I deposit money or I'm

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talking about the snow bank.

So it's not just the word by itself. It's how is it read in the context of what's being described.

So when you read the claim, you're going to read the claim in light of the specification. Otherwise, why have the specification. Just have the claim.

Q. I'm certainly not criticizing you for reading the specification.

I'm just asking in terms of the word "state of mind," the meaning that you've described here with reference to Column 10 is different than I think if you went across the street and just asked somebody at a coffee shop what state of mind means, right?

MR. GINNINGS: Objection to form.

A. I mean, clearly, you have to read this in light -- I mean, you have to read those claims and the claim elements and write -- in light of the specification

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that's -- that we have in front of us.

Just like if the word "bank" appeared here, you would have to say, Okay, is that -- is that a financial institution or is that a snow bank or is that a river bank? So you would have to look at the specification and say, Okay, which one of those three am I talking about?

If I just talk walked on the street and said "bank," most people would probably think about a -- a financial institution, not necessarily a snow bank.

If you're in Texas, you probably wouldn't think of a snow bank at all, right?

(BY MR. SPEEGLE)

Q. I haven't seen a snow bank in a long time.

A. Right. So -- exactly so...

Q. Okay. So I just want to be clear here. When you say you're applying the plain and ordinary meaning of the claims in

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the '046, it's not the plain and ordinary meaning like a person on the street would think when you say these words, it's the plain and ordinary meaning of a person of ordinary skill in the art having read the specification?

A. Yes, I mean, I'm looking at it from the lens of a POSITA, not grabbing generic John Doe on the street. I mean --

Q. Yeah. And those -- those meanings are different, right?

A. Well, I mean, I'm looking at it from the lens of a POSITA, a POSITA reading this claim and reading the specification, what would that POSITA interpretation mean.

Q. And that -- that answer is different from what a person on the street who might think happy as a state of mind would think, right?

A. You know, it's irrelevant what a person on the street thinks. I mean, you analyze this, that's why we have a definition

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of a POSITA, right? You put a definition of a POSITA there to say, Okay, here's what I expect a person ordinary skill in the art looking at this to have.

That, for instance, you don't see the definition says have a degree in nursing or -- or a degree in psychology, right? Because they wouldn't be a person of ordinary skill in this art if they had a degree in nursing.

So it has to be a person of ordinary skill in the art, which -- which was defined here as somebody that has a degree in engineering or computer science, that has a technical background and certain amount of experience. It's not just a John Doe from the street.

Q. All right. I know I've got a little bit more time today, but I think I'm going to wrap up for the day here anyway.

Before -- before I finish out, Dr. Saber, is there anything from your

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testimony today that you would like to change or correct?

A. No, sir.

Q. Okay. And during the breaks today, did you discuss the substance of your testimony with anyone?

A. No, sir.

Q. Okay.

MR. SPEEGLE: Austin, I assume you'll do redirect, if any, tomorrow?

MR. GINNINGS: Yeah.

MR. SPEEGLE: Okay. All right. Well, I think we can go off the record.

And, Mendy, if you want to give us the final count from the day, we'll be ready to start again tomorrow.

(The deposition concluded at 3:07 p.m.)

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WITNESS CORRECTIONS AND SIGNATURE

Please indicate changes on this sheet of paper, giving the change, page number, line number and reason for the change. Please sign each page of changes.

PAGE/LINE	CORRECTION	REASON FOR CHANGE

DR. ELI SABER, PH.D., VOLUME 1

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S I G N A T U R E O F W I T N E S S

I, DR. ELI SABER, PH.D., solemnly swear or affirm under the pains and penalties of perjury that the foregoing pages contain a true and correct transcript of the testimony given by me at the time and place stated with the corrections, if any, and the reasons therefor noted on the foregoing correction page(s), and that I am signing this before a Notary Public.

_____
DR. ELI SABER, PH.D., VOLUME 1

STATE OF _____ *
COUNTY OF _____ *

SUBSCRIBED AND SWORN TO BEFORE ME BY DR. ELI SABER, PH.D. on this, the _____ day of _____, 2026.

_____
Notary Public, State of _____

My Commission Expires: _____

Job 644872

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UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.

Petitioner,

v.

PERCEPTIVE AUTOMATA LLC

Patent Owner.

Case No. IPR2025-01573
Patent 10,614,344

Case No. IPR2025-01574
Patent 11,126,889

Case No. IPR2025-01575
Patent 11,753,046

Case No. IPR2025-01576
Patent 11,467,579

Case No. IPR2025-01577
Patent 11,520,346

CERTIFICATE OF SHORTHAND REPORTER

I, Mendy A. Schneider Certified Reporter within and for the State of Texas, do hereby certify:

That DR. ELI SABER, PH.D., the witness whose deposition is hereinbefore set

forth, was duly sworn by me before the commencement of such deposition and that such deposition was taken before me and is a true record of the testimony given by such witness.

I further certify that the adverse party, PERCEPTIVE AUTOMATA LLC, was represented by counsel at the deposition.

I further certify that the deposition of DR. ELI SABER, PH.D., occurred remotely on 11th of August 2026, commencing at 8:09 a.m. to 3:07 p.m.

I further certify the inspection, reading and signing of said deposition was not waived on the record by agreement of all parties.

I further certify that I am not related to any of the parties to this action by blood or marriage, I am not employed by or an attorney to any of the parties to this action, and that I am in no way interested, financially or otherwise, in the outcome of

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this matter.

IN WITNESS WHEREOF, I have hereunto set my hand this on the 21st of August, 2026.

Mendy A. Schneider

MENDY A. SCHNEIDER, CSR, RPR
Certification No.: 7761
Expiration Date: 1-31-2027

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