

1 UNITED STATES PATENT AND TRADEMARK OFFICE
2
3 BEFORE THE PATENT TRIAL AND APPEAL BOARD

4 TESLA, INC.

5 Petitioner,

6 v.

7 PERCEPTIVE AUTOMATA LLC

8 Patent Owner.

9
10 Case No. IPR2025-01573
Patent 10,614,344

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

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

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

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

17 *****
18 REMOTE ORAL DEPOSITION OF
19 DR. ELI SABER, PH.D.
AUGUST 11, 2026
20 VOLUME 1

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

1 cause on August 11, 2026, from 8:09 a.m. to
2 3:07 p.m., before Mendy A. Schneider, CSR,
3 RPR, in and for the State of Texas, recorded
4 by machine shorthand, remotely at the offices
5 of MENDY SCHNEIDER, LLC, The Woodlands,
6 Texas, pursuant to the Federal Rules of Civil
7 Procedure and the provisions stated on the
8 record or attached hereto; that the
9 deposition shall be read and signed before.
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(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.)

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

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

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

15 DR. ELI SABER, PH.D.,
16 having been first duly sworn, testified as
17 follows:

18 THE WITNESS: Can you hear me
19 well?

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

1 Barazesh for Petitioner Tesla.

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

6 MR. SPEEGLE: Great.

7 EXAMINATION

8 BY MR. SPEEGLE:

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

11 A. Yes. Eli Saber.

12 Q. Thank you, Dr. Saber.

13 And you understand that you are
14 under oath today?

15 A. I do.

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

18 A. I do.

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

21 A. Yes, I have.

22 Q. How many times have you been

1 deposed before?

2 A. About 37 times, I think.

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

6 Is that all right?

7 A. That would be fantastic. Thank
8 you.

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

14 Is that okay?

15 A. Yes. Fantastic.

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

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

21 Q. Great.

22 And is there any reason that

1 you cannot testify fully and accurately
2 today?

3 A. No.

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

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

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

11 A. I'm located in my home office.

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

14 A. No, there's not.

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

18 A. Absolutely.

19 Q. And are you on a laptop today?

20 A. No. I'm on a desktop.

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

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

3 Q. Okay.

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

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

9 A. Absolutely.

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

13 A. No, I do not.

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

17 A. I will. I will surely do so.

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

20 A. I do.

21 Q. And what documents do you have
22 with you?

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

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

8 Q. Great.

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

12 A. No, sir.

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

16 A. Absolutely.

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

20 A. That is correct.

21 Q. And let me clarify.

22 When I say "this case," you

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

3 A. Yes, I do.

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

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

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

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

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

17 A. I did, sir.

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

21 (Marked Saber Exhibit No. 1.)

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

1 it?

2 (BY MR. SPEEGLE)

3 Q. Yes. And I'll designate that
4 as Exhibit 1. And can you let me know if
5 you've seen Exhibit 1.

6 A. Yeah. Let me go ahead and open
7 it. Give me one moment.

8 Yes. That's my declaration.

9 Q. Great.

10 And that's your declaration for
11 Patent No. 10,614,344, right?

12 A. That's correct.

13 Q. Okay. Let's look at the
14 document in the Chat that starts with the 2
15 dash.

16 (Marked Saber Exhibit No. 2.)

17 A. Yes, sir.

18 (BY MR. SPEEGLE)

19 Q. Have you seen -- I'll designate
20 this as Exhibit 2.

21 Have you seen Exhibit 2 before?

22 A. Yes. That's my declaration.

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

4 A. That is correct.

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

9 (Marked Saber Exhibit No. 3.)

10 A. I do.

11 (BY MR. SPEEGLE)

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

14 Have you seen Exhibit 3 before?

15 A. Yes, I have.

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

19 A. That's correct.

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

1 A. I do.

2 (Marked Saber Exhibit No. 4.)

3 (BY MR. SPEEGLE)

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

6 Have you seen Exhibit 4 before?

7 A. Yes, I have.

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

11 A. That is correct.

12 Q. All right. One more. Let's
13 turn to the document beginning with the
14 5 dash.

15 (Marked Saber Exhibit No. 5.)

16 (BY MR. SPEEGLE)

17 Q. Let me know when you have that
18 open.

19 A. I do.

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

22 Have you seen Exhibit 5 before?

1 A. Yes, I have.

2 Q. And Exhibit 5 is your
3 declaration with respect to 11,520,346; is
4 that right?

5 A. That is correct.

6 Q. All right. And Exhibits 1
7 through 5 are the five declarations that
8 you're being deposed on today; is that
9 correct?

10 A. That is correct.

11 Q. All right. My first question
12 on these is: Are you aware of any mistakes
13 or corrections that you need to make in any
14 of the five declarations that are designated
15 as Exhibits 1 through 5?

16 A. There is some minor typos here
17 and there. I'll point them out as we get
18 into the declarations and the paragraphs.

19 Q. Okay. All right. Can you turn
20 to the document that begins with the 6 dash?

21 A. Yes, sir.

22 Q. And have you seen -- and I'll

1 designate this as Exhibit 6.

2 (Marked Saber Exhibit No. 6.)

3 (BY MR. SPEEGLE)

4 Q. Have you seen Exhibit 6 before?

5 A. Yes, I have.

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

8 A. That is correct.

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

11 A. Yes, sir.

12 Q. I'll designate this as
13 Exhibit 7.

14 (Marked Saber Exhibit No. 7.)

15 (BY MR. SPEEGLE)

16 Q. And have you seen Exhibit 7
17 before?

18 A. I have.

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

21 A. That is correct.

22 Q. All right. Let's go to the

1 next one, the document beginning with the
2 8 dash.

3 A. Yes, sir.

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

6 (Marked Saber Exhibit No. 8.)

7 (BY MR. SPEEGLE)

8 Q. Have you seen Exhibit 8 before?

9 A. Yes, I have.

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

12 A. That's correct.

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

16 (Marked Saber Exhibit No. 9.)

17 A. I do.

18 (BY MR. SPEEGLE)

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

21 Have you seen Exhibit 9 before?

22 A. Yes, I have.

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

3 A. That is correct.

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

7 A. I do.

8 (Marked Saber Exhibit No. 10.)

9 (BY MR. SPEEGLE)

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

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

14 A. That is correct.

15 Q. Great.

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

20 A. That is correct.

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

1 familiar with those three patents, right?

2 A. Yes, sir.

3 Q. And that's the -- the
4 '344 patent, the '889 patent, and the
5 '046 patent?

6 A. Correct.

7 Q. You understand that these
8 patents are related to each other?

9 A. Yes.

10 Q. Okay. And that means that they
11 have a shared specification; is that right?

12 A. Yes.

13 Q. Okay. So if I ask you a
14 question about something that's with
15 specification of -- of any one of those
16 patents, that same material is going to be in
17 the other two of those three patents, right?

18 MR. GINNINGS: Objection; form.

19 A. I mean, generally speaking,
20 that's the idea, but the -- obviously, the
21 claims are different, so we would have to
22 address it on -- on an element-by-element and

1 claim-by-claim basis.

2 (BY MR. SPEEGLE)

3 Q. Sure.

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

8 A. Yes.

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

11 MR. GINNINGS: Objection to
12 form.

13 A. Yes.

14 (BY MR. SPEEGLE)

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

17 A. You said -- you said
18 62/822,269, correct?

19 Q. Yes.

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

1 February 6.

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

5 Do you see that?

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

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

10 A. Yes, I see that, sir.

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

13 A. I see that.

14 Q. Does that tell you that the
15 '346 patent claims priority back to the
16 provisional No. 62/822,269?

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

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

22 A. Yes, sir.

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

3 A. Yes, sir.

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

6 A. Yes, sir.

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

10 A. You are correct.

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

15 A. I mean, generally speaking,
16 yeah.

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

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

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

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

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

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

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

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

20 A. '344.

21 Q. Yes, this is Exhibit 1, your
22 '344 declaration.

1 A. Yes, sir.

2 Q. And I would like you to direct
3 you to Paragraph 30, which is on Page 10.

4 A. Yes, sir.

5 Q. And here, it's talking about
6 the legal standard that you applied for your
7 declarations, right?

8 A. That is correct.

9 Q. And counsel for Perceptive
10 provided you the legal standard that you used
11 in each of your declarations, right?

12 A. That is correct.

13 Q. You reviewed the patent owner's
14 responses that Perceptive submitted in each
15 of these IPR proceedings?

16 A. Yes.

17 Q. Are you aware of any
18 divergences between Perceptive's responses
19 and the positions taken in your declarations?

20 A. Not off the top of my head.

21 Q. Okay. Go up to Paragraph 7 of
22 your declaration, the '344 declaration, which

1 is, again, Exhibit 1.

2 And this is listing some of
3 your credentials, correct?

4 A. Yes, sir.

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

8 A. Yes, sir.

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

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

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

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

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

4 Q. For imaging science. Great.

5 A. Correct.

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

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

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

12 Q. I believe it's on Page 8.

13 A. Yes, sir.

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

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

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

22 It looks like Dr. Janet's

1 declaration. But it's being downloaded.

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

7 Do you see that?

8 A. I do.

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

12 A. That is correct.

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

15 A. That is correct.

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

19 A. Paragraph 52, yes, sir.

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

1 A. Yes, sir.

2 Q. Okay. And that's a -- the
3 definition of a person of ordinary skill in
4 the art provided by Dr. Janet?

5 A. Yes, sir.

6 Q. And you've agreed with the
7 definition of a personal of ordinary skill in
8 the art provided by Dr. Janet in these
9 matters?

10 MR. GINNINGS: Objection; form.

11 A. Well, as I state in
12 Paragraph 53, just below this paragraph, that
13 for the purposes of providing my opinions in
14 connection with this declaration, I did
15 not -- I do not dispute Dr. Janet's
16 definition of a POSITA.

17 (BY MR. SPEEGLE)

18 Q. Okay. Now, you have a -- the
19 next sentence in Paragraph 53 says, I note
20 that Dr. Janet offers this definition as of
21 July 5, 2017, even though he opines that the
22 challenged claims of the '344 patent are not

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

3 (Discussion off the record.)

4 (BY MR. SPEEGLE)

5 Q. Let me try that again.

6 However, I note that Dr. Janet
7 offers this definition as of July 5, 2017,
8 even though he opines that the challenged
9 claims of the '344 patent are not entitled to
10 a priority date earlier than December 4,
11 2017.

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

14 A. You read it correctly.

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

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

22 Q. Is there any material impact on

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

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

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

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

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

17 Q. Are you able to still review
18 the document?

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

1 point.

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

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

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

12 And have you seen Exhibit 11
13 before?

14 (Marked Saber Exhibit No. 11.)

15 A. Yes, I have.

16 (BY MR. SPEEGLE)

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

20 A. That is correct.

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

1 beginning of the section titled Background
2 and Qualifications.

3 Do you see that?

4 A. I'm getting there.

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

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

10 MR. GINNINGS: Yeah.

11 A. I am there, sir.

12 (BY MR. SPEEGLE)

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

16 A. Yes, sir.

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

19 A. Yes, sir.

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

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

7 Q. Okay.

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

11 Q. You have reviewed his
12 credentials, right?

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

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

1 matter?

2 MR. GINNINGS: Objection; form.

3 A. I wasn't asked to provide any
4 opinions on Dr. Janet's expert or expertise.
5 (BY MR. SPEEGLE)

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

8 MR. GINNINGS: Objection to
9 form.

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

15 (BY MR. SPEEGLE)

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

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

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

5 A. That is correct.

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

12 A. Yes.

13 Q. -- right?

14 A. You read that correctly.

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

22 MR. GINNINGS: Objection to

1 form.

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

7 (BY MR. SPEEGLE)

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

12 MR. GINNINGS: Objection; form
13 and scope.

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

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

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

8 (BY MR. SPEEGLE)

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

14 MR. GINNINGS: Objection to
15 form and scope.

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

22

1 (BY MR. SPEEGLE)

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

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

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

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

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

18 MR. GINNINGS: Objection; form
19 and scope.

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

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

5 (BY MR. SPEEGLE)

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

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

14 Q. Sir, are you testifying now --

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

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

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

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

7 Q. I'm sorry.

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

10 (BY MR. SPEEGLE)

11 Q. It's a pretty simple question.
12 Did Perceptive's counsel ask
13 you to adopt Dr. Janet's definition of
14 POSITA?

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

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

22 A. So as I've told you,

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

10 (BY MR. SPEEGLE)

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

15 A. Yes, sir. Yes, sir.

16 Q. In your list of exhibits
17 considered, it goes 1001, 1002, 1003, 1004,
18 1005, 1006, and then it jumps to 1010.

19 Do you see that?

20 A. Yes, sir, I do.

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

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

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

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

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

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

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

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

19 A. Well, I mean --

20 MR. GINNINGS: Objection; form.

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

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

7 (BY MR. SPEEGLE)

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

11 MR. GINNINGS: Objection to
12 form.

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

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

1 (BY MR. SPEEGLE)

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

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

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

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

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

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

1 Q. Okay. So Exhibit 1007 of
2 Tesla's IPR petition on the '344 patent is
3 the original provisional application for the
4 '344 patent.

5 Have you reviewed that
6 provisional application?

7 MR. GINNINGS: Objection to
8 form.

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

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

17 (BY MR. SPEEGLE)

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

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

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

3 (Speaking simultaneously.)

4 A. Exhibit 6 of what you
5 submitted?

6 (BY MR. SPEEGLE)

7 Q. Correct.

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

10 Q. Correct.

11 A. Okay. What about it?

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

16 Let me know when you're there.

17 A. Yes. I'm there.

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

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

22 Q. Correct.

1 A. That -- that's what it states.

2 That's what it states, yes.

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

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

9 A. Yes.

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

13 MR. GINNINGS: Objection to
14 form.

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

18 So if you look at my
19 Paragraph 27, I've been asked to consider the
20 time of the invention of the claim -- the
21 challenged claims to be around December 4,
22 2017, which I understand is the filing date

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

4 (BY MR. SPEEGLE)

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

7 A. Oh.

8 Q. I'm just asking about material
9 that you considered in rendering your
10 opinions about the scope and meaning of the
11 '344 patent.

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

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

17 (BY MR. SPEEGLE)

18 Q. I'm sorry, please continue.

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

1 one you just read, which was filed on July 5,
2 2017.

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

6 Q. Are you done?

7 A. And --

8 Q. Sorry.

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

14 So that was my assignment.

15 Q. Thank you, Dr. Saber.

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

19 A. That is correct.

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

1 application, right?

2 MR. GINNINGS: Objection to
3 form.

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

9 So you don't read the claims in
10 a vacuum. So when I read the claims of the
11 '344, I'm reading that in light of the
12 specification described in the '344, the
13 prosecution history of the '344, the
14 intrinsic and potentially extrinsic evidence
15 as well.

16 (BY MR. SPEEGLE)

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

20 MR. GINNINGS: Objection to
21 form.

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

1 you mean by "failed." No, I did not do so.

2 (BY MR. SPEEGLE)

3 Q. You failed to consider the
4 provisional application which was
5 incorporated by reference into the '344
6 patent?

7 MR. GINNINGS: Objection to
8 form.

9 A. That is not correct.

10 (BY MR. SPEEGLE)

11 Q. Is the '344 -- is the -- sorry.
12 Is the provisional application,
13 which is Exhibit 1007, and the '344 patent
14 application listed on your materials
15 considered?

16 A. No, it is not, because it's not
17 cited in my declaration. It's just mentioned
18 in that paragraph that you see on
19 Paragraph 28.

20 Q. Paragraph 26 says, In forming
21 my opinions expressed in this declaration, I
22 considered the following materials.

1 Right?

2 A. That is correct. You read that
3 correct.

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

6 A. You read that correctly, sir.

7 Q. Is Paragraph 26 accurate?

8 A. Yes.

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

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

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

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

1 I've looked at them and considered them.

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

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

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

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

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

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

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

6 (BY MR. SPEEGLE)

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

11 THE WITNESS: Makes sense. All
12 right.

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

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

16 (BY MR. SPEEGLE)

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

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

1 of machine learning?

2 A. Very much. Yes.

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

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

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

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

17 A. '889. Okay.

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

22 A. Which paragraph?

1 Q. 110.

2 A. Paragraph 110.

3 Q. Are you there?

4 A. Yes.

5 Q. Okay. I would like for you to
6 read for the record two sentences from this
7 paragraph that begin with the -- the last
8 sentence on Page 50, which starts with the
9 words "in essence" and then continues on the
10 next sentence that starts on Page 51, "the
11 model."

12 Could you read those for the
13 record, please?

14 A. All right. Let me locate it.
15 This is, okay, eight or ten lines down.

16 So we are in declaration for
17 the '889, Paragraph 110.

18 The sentence you asked me to
19 read, it says, In essence, supervised machine
20 learning - as described and primarily
21 utilized in Cox for face classification - is
22 a type of machine learning in which a model

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

4 Q. Thank you.

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

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

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

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

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

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

9 A. Starting with the word "the
10 model"?

11 Q. Yes.

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

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

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

4 A. Sure.

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

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

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

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

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

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

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

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

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

5 Q. A desk data test?

6 A. Test.

7 Q. Test data set. Okay.

8 A. Yes.

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

13 A. Sure.

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

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

22 The difference between them

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

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

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

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

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

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

1 Q. Mr. --

2 (Speaking simultaneously.)

3 (BY MR. SPEEGLE)

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

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

10 A. Correct.

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

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

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

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

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

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

11 Q. Okay.

12 A. Ideally speaking, obviously.

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

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

19 And this, again, is from your
20 '889 declaration, which is Exhibit 3.

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

1 starting with "Nearly every"?

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

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

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

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

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

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

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

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

13 A. '344 declaration?

14 Q. Yes.

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

17 Yes, what about it?

18 Q. Sir, are you at Paragraph 97?

19 A. Getting there. Yes.

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

1 Do you see that?

2 A. Yes.

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

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

13 Q. Thank you.

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

17 A. That is correct.

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

1 MR. GINNINGS: Objection; form.

2 A. Could you repeat the question,
3 sir?

4 (BY MR. SPEEGLE)

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

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

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

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

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

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

11 MR. GINNINGS: Objection; form.

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

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

1 wouldn't be able to do that immediately.

2 (BY MR. SPEEGLE)

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

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

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

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

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

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

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

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

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

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

1 seen before.

2 Q. Got it.

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

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

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

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

22 Do I want to do dropouts? Do I

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

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

9 Generalization is good.
10 Overfitting is bad.

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

15 A. '579 declaration.

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

19 A. Yeah, that's an interesting
20 one.

21 Yes, sir.

22 Q. Okay. And can you read the --

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

4 A. Yes.

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

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

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

1 classes.

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

6 So there is what's called the
7 class conditional probability density
8 function, probability of X given class. And
9 there is what's called the posterior
10 probability, what's probability of the class
11 given X.

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

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

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

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

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

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

21 Q. Yeah, this is very helpful.

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

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

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

11 Is -- is that basically --

12 A. That's generally the idea.

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

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

22 What's the a priori? It's more

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

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

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

12 Q. Okay.

13 A. And that comes originally from
14 the radar theory.

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

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

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

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

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

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

22 A. Yes. It's a fun conversation

1 besides.

2 Q. Absolutely.

3 All right. So if our labels
4 are, you know, whether a pedestrian will
5 cross the street or wait at a stop sign, you
6 would classify -- those could be your
7 classes, and you could have a 70 percent, you
8 know, probability of crossing the street,
9 30 percent probability of waiting on the
10 side, and the model would say, okay, we're
11 going to classify this as -- as crossing the
12 street. Right?

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

18 Q. Okay.

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

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

3 Q. Okay.

4 A. That's the idea.

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

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

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

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

22 So I am going to compute that

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

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

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

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

16 A. Sometimes what?

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

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

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

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

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

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

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

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

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

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

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

15 You still have to also know the
16 a priori probability.

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

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

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

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

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

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

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

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

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

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

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

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

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

7 That's the histogram.

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

14 If I were to take the 10 and
15 divide it by the total 20 and the 5 and
16 divide it by the total 20, I would get what's
17 called the probability histogram because it's
18 now all percentage, right? It's .5 of A and
19 1 -- whatever .25 of B, et cetera.

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

1 continuous.

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

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

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

15 Q. Okay. Yeah.

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

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

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

4 So if -- if my model predicts a
5 60 percent for sky, what does that mean for
6 the probability density? Is that saying like
7 60 percent of the labelers would have been
8 sky, or what is this saying?

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

11 Q. Okay.

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

16 Q. Okay.

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

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

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

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

8 I may get a .6. What about the
9 other class given that sample? I may get a
10 .2.

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

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

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

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

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

15 A. Yes. You would need that.

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

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

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

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

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

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

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

22 Q. Okay. So what does it mean if

1 for a -- a model to have a, you know, a -- a
2 60 percent confidence in a given class? What
3 does that mean in terms of -- of the model's
4 analysis? Like what -- what is that saying?

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

7 You're speaking somewhat of a
8 foreign language.

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

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

12 Q. Well, let me --

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

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

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

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

1 set, right?

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

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

13 Q. Correct.

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

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

1 content?

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

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

14 There's a lot of skill in
15 making, you know, these -- first of all, how
16 you design a network, you know, do I want
17 5 layers, 10 layers, 15 layers?

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

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

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

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

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

12 A. That's an interesting question.
13 And the answer is you will need -- I mean,
14 obviously we were teaching neural nets in the
15 '90s. So I know -- I know people see machine
16 learning today and they're, you know, excited
17 about it, of course.

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

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

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

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

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

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

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

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

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

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

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

22 So it's not just a slam dunk.

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

3 It's not quite that case.

4 Q. Okay.

5 A. Nothing happens like that in
6 machine learning.

7 Q. Now, what about backpropagation
8 algorithms specifically?

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

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

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

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

22 The idea behind backpropagation

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

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

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

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

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

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

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

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

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

14 Q. Interesting.

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

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

22 So you use a batch size. Let's

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

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

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

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

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

21 But are you familiar with the
22 term "softmax"?

1 A. Of course.

2 Q. What is a softmax?

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

9 Q. Okay.

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

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

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

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

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

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

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

11 Let's say if you use a sigmoid
12 activation function, that output is going to
13 be between 0 and 1, but it's not going to add
14 up to 1 because they can come out to be .6,
15 .5, and .2.

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

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

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

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

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

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

12 Q. And that's --

13 (Speaking simultaneously.)

14 A. That's where softmax comes in.

15 (BY MR. SPEEGLE)

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

18 A. Yeah.

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

22 A. Yeah. Turn it into a

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

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

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

8 Q. All right.

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

13 THE WITNESS: Fantastic.

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

15 (BY MR. SPEEGLE)

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

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

21 A. Yes, I do.

22 Q. And I'll directly to

1 Paragraph 62 of your declaration.

2 A. You said Paragraph 62?

3 Q. Yes.

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

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

8 A. Yes.

9 Q. And you applied the plain and
10 ordinary meaning of all terms in the
11 '344 patent?

12 A. Yes.

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

15 A. No, I applied plain and
16 ordinary meaning.

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

19 A. That's correct.

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

1 you to Paragraph 56 of that declaration.

2 A. Yes, sir.

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

6 A. That's correct.

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

9 A. That is correct.

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

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

15 A. You said 59?

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

18 A. Yes.

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

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

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

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

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

8 Sorry about that.

9 So if you take a look at the
10 '046 patent, and obviously read through the
11 patent and the claims and et cetera, when you
12 read the claims clearly in light of the
13 specification as we discussed earlier, the
14 patent is referring -- when they're saying
15 "user," they're talking about a road user,
16 and that's the context of what -- how "user"
17 is being utilized in the patent.

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

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

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

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

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

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

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

13 A. Yes. I see that.

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

18 Do you see that?

19 A. Yes.

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

1 predict the state of mind of a road user
2 pictured in the stimulus, the predicted
3 statistics are therefore a prediction of the
4 aggregate judgment of human observers of the
5 state of mind of the pictured road user and
6 thus an indirect prediction of the actual
7 state of mind of the road user.

8 Do you see that?

9 A. You read it correctly.

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

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

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

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

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

2 A. Okay.

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

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

16 Do you see that?

17 A. Yes.

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

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

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

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

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

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

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

1 have different meanings.

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

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

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

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

16 A. Yes. Yes, sir.

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

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

22 Q. Okay. This is not referring to

1 a road user, right?

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

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

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

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

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

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

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

22 Q. And am I right that in

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

4 A. You are correct.

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

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

11 Q. Okay.

12 A. Yes.

13 Q. All right. I want to ask you
14 about a specific claim limitation in the '889
15 patent. So if you scroll up, you'll see
16 there is a -- a list of the claims in the
17 '889 patent.

18 Do you see that?

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

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

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

3 A. Okay.

4 Q. And do you see that?

5 A. I do. Give me one moment.

6 Yes.

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

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

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

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

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

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

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

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

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

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

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

6 What is a statistic?

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

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

19 A. '344.

20 Q. Exhibit 6.

21 A. Yes, sir.

22 Q. And if you'd scroll down to the

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

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

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

8 Do you see that?

9 A. Yes.

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

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

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

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

22 So the applicable statistical

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

5 So that's what that output
6 statistical summary is.

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

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

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

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

22 Q. And is that any different from

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

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

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

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

16 Q. Well, let me ask --

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

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

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

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

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

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

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

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

1 between summary statistics and statistical
2 summaries?

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

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

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

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

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

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

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

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

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

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

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

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

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

1 that.

2 It's not done in a vacuum.

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

7 A. Yes. Yes.

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

12 A. On the word what?

13 Q. "Statistical summary."

14 A. "Statistical summary."

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

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

19 A. Yes. "Statistical" space
20 "summary."

21 And I see what looks like one
22 of seven.

1 Q. Is it seven or nine?

2 A. Nine. Sorry. I'm -- I'm not
3 able, I guess, to read it. It's so small.

4 Q. All good.

5 A. Yeah. Hang on a second. I
6 want to make sure.

7 So, yes, it's one of nine.
8 Sorry.

9 Q. And if you want to click
10 through those nine hits, can you confirm for
11 me that all nine of those hits appear in the
12 claims of the '344 patent?

13 A. That is correct.

14 Q. Okay. Now, did you interpret
15 the phrase "statistical summary" in the
16 claims of the '344 patent in view of the
17 passage we described earlier that's at
18 Column 6, Lines 1 through 36?

19 A. I think you're mixing apples
20 and oranges a little bit. Because the
21 passage we described earlier, if my memory
22 serves me right, was on the '046. So it's

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

3 Q. Yeah.

4 A. So --

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

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

13 So what we were looking at
14 before was the '889; now we're looking at the
15 '344 in Column 6, which starts with "In
16 step 210." It's pretty similar language to
17 what you see in the '046 and the '889 for
18 that same type of thing.

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

22 A. Yes.

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

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

8 Q. And so you -- you interpreted
9 the statistical summary in the claims of the
10 '344 consistent with the summary statistics
11 described in the specification of the '344.
12 Is that fair?

13 A. Generally speaking, yes.

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

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

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

1 terms of certain parameters associated with
2 the statistics, such as the content of a
3 response, a time associated with entering a
4 response, and a position of an eye of a human
5 observer associated with the response.

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

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

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

13 A. What do you mean?

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

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

1 observer.

2 Q. Okay.

3 A. That could potentially be
4 important.

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

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

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

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

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

22 But there's other examples that

1 do other things.

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

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

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

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

22 A. What -- what do you mean?

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

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

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

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

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

1 summarizing the content of those annotations,
2 right?

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

9 Q. Okay.

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

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

14 Am I understanding the -- the
15 '344 patent right, that the -- the verb in
16 this phrase is "characterizing"?

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

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

1 "providing."

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

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

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

17 And it's predicting an output
18 statistical summary characterizing a
19 distribution of user responses expected to be
20 received responsive to presenting the sensor
21 data to a plurality of users.

22 So as if I took that sensor

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

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

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

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

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

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

4 A. Paragraph 110, '344 dec?

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

7 A. Yes.

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

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

22 You see that?

1 A. Yes.

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

8 A. Incorrectly, but yes.

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

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

15 A. That is correct.

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

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

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

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

7 A. Yes.

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

13 MR. GINNINGS: Objection to
14 form.

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

18 (BY MR. SPEEGLE)

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

22 A. Well, depending on the context

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

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

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

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

15 A. Yes.

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

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

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

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

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

8 MR. GINNINGS: Objection to
9 form.

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

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

21 So the claims are claiming that
22 particular thing.

1 (BY MR. SPEEGLE)

2 Q. Is it --

3 (Speaking simultaneously.)

4 (BY MR. SPEEGLE)

5 Q. I'm sorry, are you done?

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

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

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

22 So statistical summary that's

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

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

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

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

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

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

1 the eye position of human annotators?

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

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

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

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

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

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

22 And the sensor data is

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

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

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

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

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

1 responses. Is that right?

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

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

9 Q. Okay.

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

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

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

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

22 A. Well, the output of the model

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

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

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

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

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

13 Q. How --

14 A. It's --

15 Q. How is that different?

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

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

1 and we had sky, skin, and grass?

2 A. Yes.

3 Q. And you said it could be 10,
4 30, 60?

5 A. Yeah.

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

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

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

22 Q. Okay.

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

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

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

11 So -- and -- and --

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

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

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

20 Q. Okay.

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

1 no such thing as two-sentence explanation.

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

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

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

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

1 Q. Yeah. So I want to direct you
2 to Column 12, Lines 53 through 60 of the
3 '344 patent.

4 Can you go up to there?

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

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

10 A. Yes. It says, Because these
11 summary statistics characterize the
12 distribution of human responses that predict
13 the state of the mind of the road user
14 pictured in the stimulus, the predicted
15 statistics are therefore a prediction of the
16 aggregate judgment of human observers of a
17 state of mind of a pictured road user and
18 thus an indirect prediction of the actual
19 state of mind of the road user.

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

22 Q. Okay. And so how is this --

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

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

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

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

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

1 probability.

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

8 Q. All right. Let's turn to the
9 '046 patent.

10 A. '046. Yes, sir.

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

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

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

22 I'm happy to take a break now,

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

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

5 MR. GINNINGS: Yeah. Sure.

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

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

9 (BY MR. SPEEGLE)

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

12 So can you get your copy of the
13 '046 up in front of you. I think it's
14 Exhibit 7.

15 A. Yes, sir.

16 Q. And we had been discussing
17 before the break the claim language from the
18 '344 patent concerning a statistical summary.

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

22 Can you -- can you read the

1 claim limitation starting there?

2 A. Column 15, Line 54?

3 Q. Yes.

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

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

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

17 Q. Okay. Now, with regards to the
18 '344 patent, we had been discussing what the
19 phrase "characterizing a distribution" means.

20 And I would ask if you would
21 confirm that that language is not used in the
22 '046 claim limitation that you just read,

1 right?

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

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

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

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

10 A. Correct.

11 (Speaking simultaneously.)

12 (Discussion off the record.)

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

15 (BY MR. SPEEGLE)

16 Q. Thank you.

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

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

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

1 be, right?

2 A. Yes, examples, obviously.

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

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

8 Q. I would like for you to read
9 it.

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

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

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

1 that an example of a state of mind in the
2 '046 patent is whether a pedestrian is likely
3 to cross a street?

4 A. That's an example, yes.

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

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

10 A. Dependent claim 7, yes.

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

14 It says, The
15 computer-implemented method of claim 1,
16 wherein the summary statistics is associated
17 with at least one of the content of a
18 response, a time associated with entering a
19 response, and a position of an eye of a human
20 observer associated with the response, the
21 position being measured with respect to a
22 display associated with the image.

1 You see that?

2 A. You read it correctly.

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

6 MR. GINNINGS: Objection to
7 form.

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

11 (BY MR. SPEEGLE)

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

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

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

7 A. I mean, claim 7 is dependent on
8 claim 1, so it's narrowing the limitation of
9 claim 1, but claim 1 doesn't have that
10 limitation.

11 Q. Right. But claim 1 would
12 include that as an example of summary
13 statistics, right?

14 A. Yes. Generally speaking, yes.

15 Q. Okay.

16 A. That's one example of several.

17 Q. Let me direct you to
18 Paragraph 217.

19 A. Of what?

20 Q. I'm sorry, this is of your '046
21 declaration.

22 A. Paragraph 217?

1 Q. Yes.

2 A. Okay. Let me get there.

3 Paragraph 217, yes, sir.

4 Q. Can you read the second
5 sentence of Paragraph 217?

6 A. A POSITA reading the challenged
7 claims would read the summary statistics,
8 quote/unquote, in this element as referring
9 to the same summary statistics,
10 quote/unquote, in elements 1[b-iii]/[b-iv],
11 8[b-iii]/[b-iv], and 15[b-iii]/[b-iv].

12 Q. Okay. And what is the -- what
13 is the meaning of this sentence here?

14 A. Well, this sentence is
15 referring -- I mean, we are now talking
16 about -- if you look above Paragraph 215, we
17 are talking about element 1[c].

18 And if you look at the claims,
19 element 1[c] says, Training and model using
20 the training data, the model configured to
21 receive an input image showing a user and
22 predict summary statistics describing a state

1 of mind of the user in the image.

2 So that's what the claim
3 element is in this case, right, that we're
4 talking about.

5 So the summary statistic that's
6 referred to in this claim is the same summary
7 statistic that you're talking about in
8 claim 1[b-iii], et cetera.

9 Q. Okay.

10 A. So 1[b-iii] would be the
11 generating summary statistic limitation,
12 which is a couple of lines above it.

13 Q. Okay. So it's your
14 understanding that the -- the summary
15 statistics that are output of the model are
16 the same summary statistics that are used in
17 training?

18 A. Well, I mean, if you look at
19 the claim and the way the claim is written or
20 constructed, you see that generating -- the
21 first generating on Line 44 of the claim.

22 So that first generating has

1 three -- three or four sub pieces under it.
2 There is a generating sending, receiving,
3 generating and storing. Right?

4 So all of those are kind of
5 under that big generating on Line 44. So the
6 generating training data from plurality of
7 images and then it says the generating
8 comprising for each image.

9 And it lists sending,
10 receiving, generating, and storing. Those
11 are the 1[b-i], [ii], [iii], and [iv].

12 So -- so the generating summary
13 statistics describing the state of mind on
14 Line 54 is the same generating -- the summary
15 statistics we're talking about here in -- in
16 the training element -- claim element.

17 Q. Is that accurate, that the --
18 the model will output the same statistics
19 that it is trained on?

20 A. Well, I think you're
21 misunderstanding the word "same." Same
22 doesn't mean it's the exact mathematical

1 equivalent. It's just the same entity.

2 So the training and model using
3 the training data, the model configured to
4 receive an input image showing a user and
5 predict summary statistics.

6 So you've trained the model to
7 essentially predict summary statistics and
8 the way you've trained it using the previous
9 human annotator stuff that you did before in
10 the previous limitation.

11 So it's going to generate
12 summary statistics. It doesn't mean it's the
13 exact same numbers, but that's what it's
14 generating.

15 Q. So your declaration in
16 Paragraph 2017 [verbatim], when you say a
17 POSITA reading the challenged claims would
18 read the summary statistics in this element
19 as referring to the same summary statistics
20 in Elements 1[b] and et cetera, you don't
21 mean literally the same, you just mean kind
22 of similar?

1 A. I mean, the same entity, not
2 the same values. Like, you know, if I have a
3 training example for my machine learning,
4 let's say my training example the output
5 should be .3.

6 And I've trained my -- my
7 machine learning model. When I show a
8 example, it may not give me exactly .3. It
9 might be .31 or .32, because obviously the
10 model isn't perfect.

11 So it's going to predict a
12 probability. It's not going to be perfectly
13 exactly what I trained it on.

14 But it's the same entity. So
15 it's predicting a summary statistic. It
16 doesn't mean the exact numbers are exactly
17 the -- so the word "same" here isn't relating
18 to the exact numbers of what's being
19 predicted.

20 It's the entity that's being
21 predicted.

22 Q. What do you mean by "entity"?

1 A. Well, the summary statistics
2 that's being predicted.

3 Q. I apologize, because I know it
4 probably -- it probably feels like I'm being
5 needlessly repetitive, but I generally don't
6 understand what you mean when you say it's
7 the same statistics but it's not the same
8 statistics.

9 A. It's predicting summary
10 statistics. That doesn't mean the numbers
11 are exactly the same as if a human create --
12 so a human might create -- let me give you an
13 example.

14 A human might create a
15 histogram. Right? I might create a
16 histogram, and then I will have a
17 machine-learning algorithm. I give it data
18 and it creates a histogram.

19 Both are creating histograms.
20 It doesn't mean that both histograms are
21 exactly the same values. Right?

22 They're both creating a

1 histogram and hopefully it will be ideally
2 very, very close, but you can't examine the
3 machine learning model to create the exact
4 same histogram as a set of human observers,
5 let's say.

6 Q. Okay.

7 A. A hundred percent.

8 Q. We've talked a bit about
9 others, multiple different examples in the
10 '046 patent about things that can be
11 statistical summaries or summary statistics.

12 Are -- are you saying that the
13 use of summary statistics in the [c] element
14 has to be the same kind of one of those
15 examples as whatever summary statistics was
16 used in the [b] elements?

17 A. Well, the summary statistics of
18 the [c] element are going to be -- basically
19 predict so many statistics that describe a
20 state of mind of the user.

21 As long as they describe a
22 state of mind of the user, then [c] element

1 has been met.

2 Q. So they don't have to be the
3 same kind of summary statistics as in the
4 [b] element?

5 A. Well, the [b-iv] -- [b-iii]
6 element describes -- they're summary
7 statistic describing the state of mind of the
8 user.

9 So as long as they describe the
10 state of mind of the user, then it met the
11 [b-iii] element.

12 Q. Okay. And if it -- if there
13 was an example where the [b-iii] element was
14 met by describing the statement of user, you
15 know, with the histogram and then the
16 [c] element was describing the state of the
17 user with a distribution, would you -- would
18 you say that the claims are satisfied?

19 A. Well, as long as the summary
20 statistics describe the state of mind of the
21 user in the image, that element is satisfied.

22 Q. Okay. So you don't actually

1 have to be the same kind of statistics?

2 A. I think you're mixing up the
3 word "same" here. The "same" just means that
4 it's summary statistics that's describing the
5 state of mind of a -- of the user and the
6 image.

7 So it's not, for instance --
8 the 1[c] doesn't describe, for instance, the
9 color of grass in my backyard.

10 Q. So let me -- let me just go two
11 sentences further in Paragraph 217 to see
12 help -- if this helps clear this up.

13 You say, A POSITA would not
14 interpret the challenged claims to recite
15 generating one set of summary statistics in
16 the "[b]" elements but having a model
17 configured to predict a different set of
18 summary statistics.

19 What do you mean by "set of
20 summary statistics" in this sentence?

21 A. Well, I mean if you -- for
22 instance, in the [b] element if you

1 created -- let's say your summary -- I'm
2 making -- making this as an example.

3 If you create a histogram and
4 computed the mean and variance and, I don't
5 know, the -- the -- the spread of that
6 histogram, that might be a set of summary
7 statistics.

8 So the [b] elements of the
9 challenged claims are part of generating the
10 training data.

11 And the [c] element recite --
12 you're training the model using the training
13 data.

14 So if you're training the model
15 using the training data, you would expect
16 that the model would predict the similar set
17 of stuff as your training data.

18 Now, it doesn't mean the
19 numbers are exactly the same. It's just
20 you're predicting a similar set.

21 Q. Okay. You understand that
22 patent claims don't have to recite every --

1 everything that's used in the invention,
2 right?

3 A. I mean, I'm not an attorney.

4 Q. Let me -- let me say it this
5 way: The '046 patent does not require that
6 the training data only use summary statistics
7 for training, right?

8 A. I mean, it -- it states what
9 it's doing, right? I don't understand what
10 you're asking.

11 Q. Okay. Do -- can you tell me
12 one way or the other whether the '046 patent
13 requires that the model only use summary
14 statistics for training?

15 A. I don't understand what you
16 mean by --

17 Q. Okay.

18 A. -- "only use summary statistics
19 for training."

20 I mean, it talks about
21 generating summary statistics, describing the
22 state of mind of the user and the image. And

1 then you're training the model using the
2 training data that you just created.

3 Q. Okay. And as somebody who has
4 opined about the scope of claim 1 in the
5 '046 patent, can you tell me about whether
6 claim 1 of the '046 patent requires that the
7 model only be trained with summary statistics
8 recited in the element [b]?

9 A. Well, I mean, if you look at
10 the way the claim is constructed, so if you
11 go back to Line 44, it says "generating
12 training data from the plurality of images."
13 So -- and then it talks about how that's
14 done.

15 So the -- the generating of
16 training data is done by sending the image to
17 plurality of human observers, they're
18 receiving input from the observers,
19 generating summary statistics that describe
20 the state of mind, and storing that in
21 association with the image as part of the
22 training data.

1 So to complete the training,
2 it's doing all these four steps, which you
3 call 1[b-i], 1[b-ii], 1[b-iii] and 1[b-iv].

4 And then it goes on to say,
5 well, I'm training now a model using that
6 training data that has antecedent in
7 generating training data, on Line 44.

8 So that -- the training data is
9 the training data on Line 44 that you just
10 got done creating with those steps.

11 Q. And is it your opinion that the
12 training the model referenced in Line 59 of
13 Column 15 must be the only training that the
14 model receives in order to practice claim 1
15 of the '046 patent?

16 A. I don't know what you mean by
17 "must be the" -- you're training -- what it
18 says -- the claim element says training a
19 model using the training data.

20 So you're going to use the
21 training data that you created from Lines 44
22 to 58. You created all that data, and you

1 associate it with the image. So each image
2 you associated some training data with it.
3 That's kind of your training data set in a
4 sense.

5 So now you're training the
6 model using the training data that you just
7 created.

8 Q. Okay. Now, a --

9 A. That's how -- that's how I
10 would read it.

11 Q. And so would you say that
12 claim 1 of the '046 patent does not cover a
13 model that is trained on the training data
14 described at Line 44 in addition to other
15 training data that is not listed in claim 1?

16 A. Well, I mean, when you read
17 element 1[c], it says training and model
18 using the training data.

19 So the training data is
20 referring to training data on Line 44, which
21 was created using those steps of sending and
22 receiving, generating and storing.

1 So the plain ordinary meaning
2 would be, I'm training the model using the
3 training data that I just created.

4 Q. Okay. And because you're
5 interpreting claim 1 of the '046 patent to be
6 limited to only training on the training data
7 described in Line 44, is that why you reached
8 the conclusion that the summary statistics in
9 Line 61 of claim 1 must be the same summary
10 statistics as described in Line 54, claim 1?

11 MR. GINNINGS: Objection to
12 form.

13 A. Well, I mean, again, I guess I
14 think we're talking a little bit, perhaps,
15 past each other on this.

16 Again, the same doesn't mean
17 the exact same numbers, you're -- you're just
18 predicting summary statistics describing --
19 as long as the summary statistics describing
20 the state of mind of the user in the image,
21 as long as you predicted that, you've met the
22 claim limitation.

1 (BY MR. SPEEGLE)

2 Q. All right. Let's -- let's turn
3 to the '889 patent.

4 A. '889.

5 Q. Which is Exhibit 8 to the
6 deposition.

7 A. Give me one moment. Let me get
8 it opened.

9 Yes, sir.

10 Q. All right. And if you want to
11 look at claim 1, which is on Column 15,
12 beginning at Line 32, let me know when you're
13 there.

14 A. Claim 1 of the '889?

15 Q. Yes.

16 A. Beginning on Line 32. I am
17 there.

18 Q. Now, I think we covered this
19 before lunch.

20 But just to confirm, you did
21 not apply any construction for any terms
22 in -- in the '889 patent, you only used the

1 plain and ordinary meaning; is that right?

2 A. That is correct.

3 Q. Okay. And can you read the
4 claim limitation that starts on Line 46,
5 Column 15, toward "generating."

6 A. Yeah. That's limitation, I
7 think, 1[c], right?

8 Yeah, so it's generating a
9 training data set comprising summary
10 statistics of user [verbatim] responses
11 describing the state of minds of road users
12 displayed in the plurality of images.

13 Q. And is the use of "state of
14 minds" in claim 1 of the '889 patent the same
15 as "state of minds" as we discussed it in the
16 '046 patent?

17 A. Well, I mean, it -- it's
18 described in the specification of the '889.
19 So however it's described there, it's what it
20 is.

21 Q. Okay. Let's go back up to
22 Column 6 of the '889. And I direct you

1 specifically to Lines 18 through 22.

2 A. Yes.

3 Q. And this is the same passage
4 describing summary statistics that we've read
5 for the '344 and '046 as well?

6 A. Generally speaking, yes. I
7 mean, I don't know if the exact wording is
8 exactly the same, but the general idea is
9 there.

10 Q. Okay. Is it fair to say the
11 general idea of summary statistics and
12 statistical summary is the same across the
13 three patents, in your view?

14 A. Well, generally speaking, it's
15 obviously described in this particular step,
16 but I think the language is very -- very
17 similar.

18 Q. Okay. Okay. I want to spend a
19 little bit of time going through in the '046,
20 '889, and '344 declarations and understanding
21 which limitations you're saying are missing
22 from the prior art versus those ones that you

1 haven't opined about or disputed in your
2 declarations.

3 Is that okay?

4 A. Sure.

5 Q. All right. So let's start with
6 the '344 declaration. And I think it's
7 probably easiest to start with the table of
8 contents in that.

9 A. Yes. I was just going to say
10 that's probably the easiest way.

11 Q. And I tell you what, while
12 we're doing this, I am going to put two more
13 documents in the Chat.

14 Can you see the documents
15 beginning 12 dash and 13 dash that I've added
16 in the Chat?

17 A. Yes. You've added Cox and
18 Ross.

19 Q. Yeah. So I'll -- I'll go ahead
20 and introduce what -- the document that
21 begins 12 dash as Exhibit 12 in your
22 deposition.

1 (Marked Saber Exhibit No. 12.)

2 (BY MR. SPEEGLE)

3 Q. Have you seen Exhibit 12
4 before?

5 A. Hang on a second. Let me just
6 download them so I'm looking at the same
7 thing you're looking. It's taking a minute
8 to download so give me one moment here.

9 (Marked Saber Exhibit No. 13.)

10 A. Okay. So I have 12 and I have
11 13.

12 (BY MR. SPEEGLE)

13 Q. Okay. And so the document
14 beginning 12 dash, which has been designated
15 as Exhibit 12, do you recognize Exhibit 12?

16 A. Yes.

17 Q. And what is Exhibit 12?

18 A. It's the Cox document.

19 Q. And this is the Cox prior art
20 reference that's an exhibit to each of the
21 five IPRs?

22 A. Yes. I don't know if this is

1 all five, but, yes, it's -- it's the Cox
2 document.

3 Q. Okay. And whether it's in all
4 of them or most of them, there's only one Cox
5 reference, right?

6 A. Yes. That's correct.

7 Q. Okay. So similar questions for
8 the document that begins 13 dash, which I'll
9 introduce as Exhibit 13.

10 Have you seen Exhibit 13
11 before?

12 A. Yes. That's the Ross document
13 that's in most of them. Same Ross document,
14 the only one.

15 Q. Okay. All right. So turning
16 back to the table of contents for your '344
17 declaration, let me know when you have that
18 in front of me [verbatim].

19 A. All right. One moment here.
20 Yes. I'm at the table of content.

21 Q. Okay. And "Ground 1" at the
22 bottom of the first page of the table of

1 contents is identified as "Ross and Cox."

2 Do you see that?

3 A. Yes.

4 Q. And it looks like under
5 Ground 1 you disputed -- it's your opinion
6 that Ross and Cox do not teach element 1[b],
7 10[b], 19[b], and then elements 1[c], 10[c],
8 and 19[c]. Is that right?

9 A. That's correct.

10 Q. And that's the same element in
11 three different independent claims, right?

12 A. Yes.

13 Q. And I think you have that
14 element in the heading in parentheses right
15 there starting, "providing."

16 A. I'm sorry.

17 Q. I'm just confirming that the --
18 the element 1[b], 10[b], and 19[b], which is
19 the same, that also appears in the heading in
20 the parentheses and quoted there in the table
21 of contents?

22 A. That's correct. That's the

1 element itself, yes.

2 Q. Okay.

3 A. The quotes are starting with
4 "providing" and ending with "object."

5 Q. Got it and so the -- for the
6 [b] element and the [c] element from each
7 independent claim are the two elements that
8 you believe are missing from the combination
9 of Ross and Cox compared to the '344 patent,
10 right?

11 A. These are the ones I opined on,
12 yes.

13 Q. And you didn't opine about any
14 other claim elements potentially being
15 missing in the '344 patent?

16 A. I did not provide any opinions
17 on the other ones.

18 Q. Okay. Let's scroll down to
19 Ground 2.

20 A. Yes, sir.

21 Q. And Ground 2 involves another
22 reference called Ogale, right?

1 A. Yes, sir.

2 Q. And I will add what's
3 Document 14 dash to the Chat. Let me know
4 when you have that.

5 A. I see it in the Chat. Let me
6 download it. This one doesn't give me a
7 download button. That's interesting. Let me
8 see if I can download it. It's still
9 downloading.

10 Q. Well, I tell you what, let's go
11 back and I'll ask you some questions about
12 Ground 1 and we can come back to Ground 2.
13 Let's look at Paragraph 89 of your
14 declaration.

15 A. '344 declaration?

16 Q. Yes. This is your
17 '344 declaration, Paragraph 89. I'm
18 interested in the last sentence, which is on
19 the top of numbered Page 37.

20 A. Okay.

21 Q. And that last sentence says,
22 And nowhere do Tesla and Dr. Janet discuss

1 any modifications to Ross in view of Cox.

2 Do you see that sentence?

3 A. Yes.

4 Q. Is that sentence accurate in
5 your view today?

6 A. Yes.

7 Q. Okay. Can we turn back to
8 Exhibit 11, which is Dr. Janet's declaration
9 from the '344 patent?

10 A. '344, Dr. Janet.

11 Q. Yeah. Exhibit 11.

12 A. Yes. I have it open.

13 Q. Okay. Can you go to PDF
14 Page 39, numbered page 33.

15 A. PDF Page 39, which talks about
16 motivation and combine.

17 Q. Yes, Paragraph 80.

18 A. Yes, sir.

19 Q. Okay. And the first sentence
20 there says, In my opinion, a POSITA would
21 have been motivated to combine Ross and Cox
22 such that Ross's intent model is a supervised

1 learning model that is trained with human
2 annotated image data, as taught by Cox.

3 Do you see that sentence?

4 A. I do.

5 Q. Now, you just said that Tesla
6 and Dr. Janet did not discuss any
7 modifications to Ross in view of Cox.

8 And my question to you is: Why
9 is Paragraph 80 not a discussion of changes
10 to Ross in view of Cox?

11 A. Well, that's just a generic
12 sentence. I mean, I could tell you I'm going
13 to take my Dodge Ram and put the missile
14 engine on it to have it orbit the moon.
15 That's -- I mean, that's just a generic
16 sentence.

17 Where are the technical details
18 of that? That's just generic.

19 Q. Okay. So you're -- you don't
20 dispute that there are proposed modifications
21 to Ross in view of Cox, it's just your
22 position they're not sufficiently described;

1 is that right?

2 A. This is not a modification.
3 This is just a generic sentence that
4 basically says, I can take my Dodge Ram and
5 put an airplane engine in it.

6 I mean, anybody can make that
7 statement. I want -- what I'm referring to
8 here is discuss any modifications to Ross in
9 view of Cox.

10 Like what are you planning?
11 How are you planning to modify Ross in view
12 of Cox?

13 Like what is missing when you
14 read Ross compared to the claims that we are
15 discussing here?

16 What is Ross missing that's in
17 the claims that Ross doesn't have that a
18 POSITA would look forward to Cox and say, Oh,
19 okay, I'm going to go grab this thing from
20 Cox and somehow modify Ross and how I'm going
21 to do that.

22 So it's not just, oh, I'm just

1 going to put those two together, there you
2 have it.

3 That's not a modification.

4 That's -- that's a conclusory statement
5 without any rationale underpinning, so to
6 speak.

7 Q. Okay. So you don't think that
8 using a human annotated image data as taught
9 by Cox is a modification?

10 A. No. You have to provide
11 what -- how you're going to do that. I mean,
12 Ross talks about intent. Has nothing to do
13 with face -- face detection.

14 Cox talks about face detection
15 labeled imagery. What -- what -- what are
16 you going to -- to put -- what human
17 annotated image data are you going to take
18 from Cox and put into Ross? What are you
19 talking about?

20 Anybody can make this
21 statement. A kindergartner can make the
22 statement. I want to know what are the

1 technical details that we're talking about
2 here.

3 Q. Okay. Before we go further
4 here, did the exhibit -- or the document with
5 14 dash download on your end?

6 A. Yes, sir, it did.

7 Q. Okay. Can you -- I'll
8 designate this as Exhibit 14.

9 (Marked Saber Exhibit No. 14.)
10 (BY MR. SPEEGLE)

11 Q. Can you let me know if you've
12 seen Exhibit 14?

13 A. Yes, I have, the Ogale prior
14 art, which is, I think, mentioned only in one
15 of them.

16 Q. Okay.

17 A. A mistake.

18 Q. And this is the Ogale reference
19 that's used in Ground 2 on the '344 patent?

20 A. That is correct.

21 Q. Okay. And going back to your
22 table of contents in your '344 declaration.

1 A. Okay. Yes, sir.

2 Q. And am I right that the -- the
3 only limitations that you dispute for
4 Ground 2 are the same ones that you disputed
5 for Ground 1?

6 A. That is correct.

7 Q. Let me introduce
8 Document 15 dash. And let me know when you
9 have this one.

10 A. Okay. Let me go ahead and
11 download it. I see it in the Chat. It's
12 being downloaded. It's still being
13 downloaded, so I think the server is a little
14 slow on the --

15 Q. Well, I tell you, I can go
16 ahead and ask you my questions about it.

17 This is -- looking at your
18 table of contents, you also opined about
19 Ground 3 in the '344 IPR; is that right?

20 A. That is correct. And I do have
21 the document downloaded at this time, sir.

22 Q. Okay. So the Document 15 dash,

1 I'll exhibit -- I'll identify as Exhibit 15.

2 (Marked Saber Exhibit No. 15.)

3 (BY MR. SPEEGLE)

4 Q. And have you seen Exhibit 15
5 before?

6 A. Yes, I have.

7 Q. And what is Exhibit 15?

8 A. It's the Zhang prior art
9 reference that's referenced in this IPR, and
10 I think only in this IPR.

11 Q. Okay. So the Zhang reference
12 is the reference used in Ground 3 of the
13 '344 IPR, right?

14 A. That is correct, sir.

15 Q. And it looks like in your table
16 of contents you identified the two same
17 missing elements that you dispute, and that
18 is the [b] element and [c] element; is that
19 right?

20 A. You are correct, sir.

21 Q. Let's look at Paragraph 131 of
22 your declaration. This is your '344

1 declaration still.

2 So you say here that,

3 Regardless of which data is used, Zhang does
4 not teach or suggest that its model predicts
5 what users' response [verbatim] or labels to
6 the image data would be. Instead, Zhang
7 makes clear that what its model predicts are
8 "vehicle or object trajectories."

9 You see that?

10 A. One second.

11 Yeah. Okay. I see the
12 sentence. Starting with the third sentence,
13 correct?

14 Q. Yes.

15 A. "Regardless," yep, I see that.

16 Q. Now, if the -- if the model is
17 predicting vehicle or object trajectories,
18 that means it was trained on labels of
19 vehicles or object trajectories, right?

20 A. Give me one second here.

21 Yeah. What was your question
22 again, sir?

1 Q. If the model in Zhang is
2 predicting vehicle or object trajectories,
3 that means it was trained on labels
4 reflecting vehicle or object trajectories,
5 right?

6 A. That would be generally the
7 idea, although you can predict trajectories
8 without -- by just doing, you know, video
9 segmentation and motion estimation.

10 Q. Okay. If the vehicle or object
11 trajectories are what users were labeling,
12 isn't it true that by Zhang predicting those
13 vehicle object trajectories, it is project --
14 it is predicting what humans would have
15 labeled the image -- instance or input as,
16 right?

17 A. No. You're mixing two
18 different -- apples and -- you're mixing
19 apples and oranges.

20 Q. Okay. I'm trying to understand
21 your -- your position on this.

22 A. Well, predicting a trajectory

1 has nothing to do with summary statistics of
2 user responses to what a user sees in the
3 image.

4 So if I'm predicting a
5 trajectory and I'm using, let's say, video
6 segmentation on frames and I see a car moving
7 in the next -- in the last ten frames and I
8 predict the car is going to be here in the
9 next frame, that has nothing to do with user
10 responses looking at that image and saying, I
11 think I see the cyclist over here, I think
12 it's going to do a U-turn.

13 So predicted trajectory of an
14 object is not the same thing as statistical
15 summary of user responses, which is what the
16 '344 is targeting.

17 Q. Okay. And I know there's
18 layers to unpeel there with the -- with the
19 statistical summary question, but let me just
20 try to understand one part of that.

21 If Zhang has human labels of
22 trajectories and the model is predicting

1 trajectories, is it fair to say that the
2 model is predicting what the label would have
3 been?

4 A. If a human has gone in and
5 labeled a video frame with a potential
6 trajectory and your model is being trained to
7 predict ideally that trajectory, so ideally
8 speaking, the model is trying to predict a
9 trajectory that has nothing to do with the
10 statistical summary that describes the
11 distribution of user responses.

12 Q. I was understanding you until
13 you started talking about statistical
14 summary.

15 So I -- I understand there's a
16 separate disagreement about statistical
17 summary, and I absolutely will follow up on
18 that question here in a minute, but I want to
19 try to understand this first part.

20 So let me ask it again. And
21 without getting into the question of whether
22 or not any of this counts as a summary

1 statistic or statistical summary, if Zhang
2 has human labels of trajectories and the
3 model is predicting trajectories, is it fair
4 to say the model is predicting what the label
5 would have been?

6 A. That -- the model is trying to
7 predict what -- potentially what a label
8 would have been.

9 And, again, I mean, you're --
10 you're looking at this section, which is
11 talking about Zhang and addressing
12 element 1[b] and 10[b] and 19[b] of the
13 claim, which has to do with predicting
14 output, statistical summary, characterizing,
15 et cetera, et cetera, et cetera.

16 So the context of what we're
17 talking about here is regarding that claim
18 element.

19 Q. Okay. So I think I'm
20 understanding what you're saying, so let me
21 say it back to make sure I'm tracking you.

22 That the dispute here is not

1 about whether the model is predicting what a
2 human labeler would say; the dispute is
3 whether that prediction is in the form of a
4 summary statistic.

5 Is that -- is that a fair
6 understanding of where -- where the
7 disconnect is?

8 A. Yeah, I mean, as I'm saying in
9 Paragraph 131, Zhang doesn't teach that its
10 model predicts anything about what user
11 responses would be. It's predicting a
12 trajectory.

13 I mean, if you look at Zhang,
14 you know, the title, "Prediction-Based System
15 and Method for Trajectory Planning of
16 Autonomous Devices." So it's predicting a
17 trajectory.

18 It has nothing to do with user
19 responses as to if a user looking at an
20 object in the image and trying to -- you
21 know, trying to -- you know, a statistical
22 summary of that. The two are distinct

1 entities.

2 Q. Yeah. I -- I think I
3 understand it. I was just trying to sort
4 through whether the difference -- what --
5 which part of the claim language we're
6 disagreeing about. And I think I understand
7 now that there's not a dispute that the model
8 is going to try to match what the human
9 labelers put in. The dispute is whether what
10 is being predicted counts as a summary
11 statistic.

12 A. That's the main dispute, but we
13 also -- we'd have to look at Zhang to see
14 exactly what's being annotated.

15 Q. Yeah. If you want to -- if you
16 want to close that loop, I'm happy to direct
17 you to Paragraph 51 of Zhang where it talks
18 about this.

19 Again, I don't know if I have a
20 question about it, but if you want to look at
21 it, you can.

22 But we can move on. We don't

1 have to keep spinning our wheels here.

2 All right. Let's look at the
3 '046 declaration and talk about where the
4 disputes are in that one.

5 So can you let me know when you
6 have the table of contents from the '046 in
7 front of you?

8 A. Just give me one second.

9 MR. GINNINGS: And, Counsel,
10 it's fine if you want to -- if you
11 want to cover this. I know we're
12 coming up on another hour here. I
13 mean, if you've got a few more
14 minutes, that's fine. But, you know,
15 if we want -- if you're going to dive
16 into something longer, then maybe we
17 should take a break now.

18 MR. SPEEGLE: Okay. Well, I'm
19 just about to shift to the '046
20 patent.

21 Dr. Saber, if you have
22 something else you want to say about

1 Zhang, we can keep talking about Zhang
2 further or we could take a break here.

3 THE WITNESS: I think this is
4 a -- let's take a quick break. I
5 think that would be good. And five
6 minutes should be fine. I'll be
7 sitting at my desk at 1:35 Eastern.

8 MR. SPEEGLE: Okay. So we're
9 off the record at 11:30, 11:29.

10 (Break from 12:29 p.m. to 12:36 p.m.)

11 MR. SPEEGLE: All right. So
12 back on the record at 11:36 -- 12:36.

13 (BY MR. SPEEGLE)

14 Q. Okay. So I was going to ask
15 you about your opinions for the -- for the
16 '046 patent.

17 A. Yes, sir.

18 Q. Can you let me know when you
19 have the table of contents for your
20 '046 declaration in front of you?

21 A. I do have it in front of me.

22 Q. Okay. And looking at

1 Ground 1 --

2 A. Yes, sir.

3 Q. -- it looks like the
4 limitations where you have opined they're
5 missing from the Cox reference are 1[b-iii],
6 8[b-iii], 15[b-iii], 1[b-iv], 8[b-iv],
7 15[b-iv], and 1[c], 8[c], and 15[c]; is that
8 right?

9 A. That is correct.

10 Q. And scrolling down to Ground 2,
11 am I right that Ground 2 adds the Ross
12 reference in combination with Cox?

13 A. That's correct.

14 Q. And the -- the three disputes
15 are the same elements, the [b-iii], [b-iv],
16 and [c] elements?

17 A. That's correct.

18 Q. Now, Ground 3 -- Ground 3, I
19 believe, is just related to dependent claims.
20 And if you want to scroll down to
21 Paragraph 158 for more context, that's fine.

22 A. Yes.

1 Q. Okay. So the -- there's no
2 additional disputes with respect to Ground 3,
3 it just depends on the prior disputes
4 regarding the independent claims, right?

5 A. That's correct.

6 Q. Okay. And then Ground 4 is
7 based on the combination of Cox and Munro,
8 right?

9 A. Yes, sir.

10 Q. And I'm going to go ahead and
11 introduce two more exhibits. I know I
12 skipped one of these, so I'll go back and
13 get -- this is going to be the 16 dash and
14 17 dash exhibits. And let me know when you
15 have those come through.

16 A. I see them in the Chat. I'm
17 going to go ahead and download them now.

18 Q. It's going to take a minute for
19 them to download, so let me ask you a couple
20 more questions about Ground 1 while they
21 download.

22 Let's look at Page 32 of your

1 declaration, which is in Ground 1. And
2 there's a big heading C that I would like to
3 start at.

4 A. Yes, sir.

5 Q. All right. Now, this Section C
6 addresses the -- whether the Cox reference
7 discloses generating summary statistics
8 describing the state of mind of the user in
9 the image based on the received responses
10 from the plurality of human observers, right?

11 A. Yes. That's the 1[b-iii]
12 element that we talked about.

13 Q. And this section is organized
14 with several subheadings based on different
15 types of summary statistics that are
16 addressed by Tesla and Dr. Janet; is that
17 right?

18 A. That is correct.

19 Q. Okay. And the first one of
20 those, which begins with Paragraph 77 on
21 Page 33, is Psychometric Data, right?

22 A. Yes, sir.

1 Q. And then the next one, which
2 I've got to scroll down to, is on Page 37,
3 the Item-Response Curves.

4 A. Yes, sir.

5 Q. Okay. The next one is on
6 Page 39, and it's Human-Weighted Loss
7 Functions.

8 A. Yes, sir.

9 Q. And the last one is on Page 44,
10 and it's the End-of-Test Statistics, right?

11 A. That is correct.

12 Q. So those are the -- the four
13 different potential summary statistics that
14 are addressed in your declaration?

15 A. Yes, sir.

16 Q. Okay. Before I forget about
17 it, did the Document 16 and 17 come across in
18 your Chat?

19 A. Yes, they did.

20 Q. Okay. Can you let me know if
21 you've seen the document beginning 16 dash
22 before?

1 (Marked Saber Exhibit No. 16.)

2 A. Yes. That's the Ellenbogen
3 prior art reference.

4 (BY MR. SPEEGLE)

5 Q. Okay. I'm going to introduce
6 that 16 dash document as Exhibit 16.

7 And then can you let me know if
8 you've seen the document beginning 17 dash
9 before?

10 A. Yes, sir. That's the Munro
11 prior art reference.

12 (Marked Saber Exhibit No. 17.)

13 (BY MR. SPEEGLE)

14 Q. Okay. And I'll introduce that
15 document as Exhibit 17.

16 And to circle back to Ground 3
17 that we talked about briefly, that involves
18 the Ellenbogen reference, right?

19 A. Ground 3 of...

20 Q. Ground 3 of the '046.

21 A. '046. I'm sorry, ground -- you
22 said 3 or Ground 4?

1 Q. Ground 3 of the '046 is a
2 combination of Cox and Ellenbogen, right?

3 A. Yes.

4 Q. Okay. And Ground 4 is a
5 combination of Cox and Munro; is that right?

6 A. That is correct.

7 Q. And with respect to Ground 4,
8 I'm looking at the table of contents for your
9 '046 declaration again.

10 Am I right that it's the same
11 three limitations that are in dispute as the
12 [b-iii], [b-iv], and [c]?

13 A. That is correct.

14 Q. Okay. And then let's look at
15 Ground 5, which is a combination of
16 Ellenbogen and Munro, right?

17 A. That is correct.

18 Q. And, again, you've -- you've
19 disputed the same three limitations, that's
20 [b-iii], [b-iv], and [c]?

21 A. That is correct.

22 Q. All right. Now, I do want to

1 dig in a little bit more on -- on the
2 Ellenbogen ground here.

3 So could you turn to Page 85
4 of -- of your declaration that begins with
5 Paragraph 202.

6 A. Yes, sir.

7 Q. Now, as I've reviewed your
8 analysis in this Section B, I just want to
9 confirm that you don't have any opinions
10 about the content of Ellenbogen's composite
11 output, right?

12 A. I don't understand your
13 question.

14 Q. Well, do you understand the
15 combination of Ellenbogen and Munro that
16 Tesla and Janet -- Dr. Janet proposed?

17 A. Yes.

18 Q. And it involved modifying the
19 composite output of Ellenbogen in view of the
20 teachings of Munro, right?

21 A. Yes.

22 Q. And you opined in Paragraph 204

1 about the -- the content of the tallies
2 described in Munro, right?

3 A. Yes. I mean, Munro is about
4 natural language processing. It's a
5 completely different application than object
6 labeling of trajectories or anything else.

7 Q. I understand.

8 You have no opinions in your
9 declaration about the content of Ellenbogen's
10 composite output, right?

11 A. I mean, I -- I provided
12 opinions with regards to the claim elements
13 that I've analyzed. I mean, I don't
14 understand what you mean where you have no
15 opinions. I've provided opinions based on
16 the claim elements that I've analyzed.

17 Q. Sure. And I see your analysis
18 here about Munro's natural language
19 processing.

20 And I just don't see anything
21 here about the composite output in
22 Ellenbogen.

1 Now, I want to make sure I'm
2 not missing it or overlooking it, that you
3 did not discuss the composite output from
4 Ellenbogen in this section?

5 A. I may not have discussed it
6 specifically. But I'm -- obviously, I've
7 analyzed the claim element that we're talking
8 about here and why Tesla and Dr. Janet did
9 not meet that claim element.

10 Q. Okay. And do you have any
11 understanding about whether Ellenbogen has a
12 system that determines the sentiment of one
13 or more people?

14 A. Well, let's take a look at
15 Ellenbogen.

16 Okay. What was your question
17 about Ellenbogen?

18 Q. Yeah. The -- one of the tasks
19 described for this system in Ellenbogen is
20 determining the sentiment of one or more
21 people, right?

22 A. Generally speaking, yes. But

1 what -- what's the question?

2 Q. Okay. And that's not -- that's
3 a feature of Ellenbogen that you discussed in
4 your declaration?

5 A. I mean, I analyzed Ellenbogen
6 with regards to the claim elements that we're
7 discussing.

8 So whether it meets -- you
9 know, whether Dr. Janet's and Tesla's
10 analysis meets the claim element that we're
11 talking about...

12 Q. Okay. And the analysis you did
13 with that regard is reflected in your
14 declaration, right?

15 A. That is correct.

16 Q. All right. Let's turn to the
17 '889 patent. I'm also going to go ahead and
18 introduce another document in the Chat, which
19 is 18 dash.

20 (Marked Saber Exhibit No. 18.)

21 A. '889 patent. And you're
22 introducing another document, which I see and

1 I am going to download.

2 Download in progress.

3 (BY MR. SPEEGLE)

4 Q. While that's downloading, if
5 you look at the table of contents for your
6 '889 declaration, for Ground 1, am I right
7 that the Ground 1 is a combination of Huval
8 and Ross?

9 A. That is correct.

10 Q. And it looks like you've only
11 disputed one claim limitation with respect to
12 Ground 1; is that right?

13 A. That is correct.

14 Q. And that limitation is the
15 generating a training data set comprising
16 summary statistics of user responses
17 describing the state of minds of road users
18 displayed in the plurality of images as
19 recited in elements 1[c], 2[c], and 12[c]; is
20 that right?

21 A. That is correct.

22 Q. All right. Did

1 Document 18 dash come through for you?

2 A. Yes, it did.

3 Q. Okay. Have you seen 18 before?

4 A. I'm opening it now. Yes.

5 Q. Okay. What is the document
6 labeled 18 dash?

7 A. 18 is the Huval prior art
8 reference.

9 Q. Okay. So I will introduce this
10 as Exhibit 18 to the deposition. And, you
11 know, I want to ask a couple more questions
12 about this ground.

13 So am I right that in addition
14 to the -- the element 1[c], 2[c], 12[c] we
15 discussed, you also argued that a POSITA
16 would not have been motivated to combine
17 Huval and Ross in the manner Tesla and
18 Dr. Janet alleges; is that right?

19 A. That is correct.

20 You're talking about Ground 1,
21 correct?

22 Q. Correct.

1 A. Yes.

2 Q. Okay. Why don't you scroll
3 down to Paragraph 73 of your declaration,
4 which is Page 30. And this is your '889
5 declaration, to be clear.

6 MR. GINNINGS: Sorry. Which
7 paragraph again?

8 MR. SPEEGLE: 73.

9 THE WITNESS: Paragraph 73 of
10 the '889 declaration.

11 (BY MR. SPEEGLE)

12 Q. You have that in front of you?

13 A. Yes, I do.

14 Q. Okay. Now, I'm going to read
15 part of that first sentence that says, ... as
16 best I understand their theory, they proposed
17 to modify Huval such that the annotation
18 labels provided by human annotators (but not
19 the automated labels) be labels that identify
20 observed road user actions.

21 Did I read that right?

22 A. You did, yes, sir.

1 Q. Okay. What is your basis to
2 say that the automated labels would not be
3 modified?

4 A. Well, based on the description
5 from Dr. Janet's and Tesla's, Dr. Janet's
6 first combination.

7 Q. Okay. Does Dr. Janet say that
8 the automated labels are unmodified?

9 A. I mean, I would have to look at
10 Dr. Janet's declaration, but -- and I would
11 need you to download that, but that's -- I --
12 I don't remember exactly off the top of my
13 head, but I would -- I -- if I refer to it
14 that way, it probably wasn't specific.

15 I think it's Exhibit 1003 is
16 Dr. Janet; isn't that correct?

17 Q. Yes, I'm -- I'll introduce that
18 in just a second. I got to get it formatted
19 correctly here.

20 A. Sure.

21 And it looks like I'm referring
22 to Paragraph 72 of that declaration or

1 petition Paragraph 20.

2 Q. All right. Do you see
3 Exhibit 19 coming through?

4 A. I see Exhibit 19. I don't have
5 it yet.

6 Okay. So I -- it's still being
7 downloaded.

8 I do have it.

9 Q. Okay. And have you seen this
10 document beginning 19 dash before?

11 A. Yes, sir, I have.

12 Q. And what is the document
13 beginning as 19 dash?

14 (Marked Saber Exhibit No. 19.)

15 A. It's the declaration of
16 Dr. Janet with regards to the '889 patent.

17 (BY MR. SPEEGLE)

18 Q. All right. And I'll introduce
19 this as Exhibit 19.

20 And if you could, please, turn
21 to Paragraph 72 of Dr. Janet's declaration.

22 A. I am there, sir.

1 Q. Paragraph 72 is -- is -- does
2 not say anything about the automatic labels
3 in Huval, right?

4 A. That's correct. I mean, if you
5 look at the first bullet that I'm addressing
6 here, obviously, says, Huval's annotation
7 labels provided by human annotators -- these
8 are not the automated ones -- label observed
9 road user actions and image data captured by
10 vehicles, where such labeled actions
11 correspond to user -- road user intent.

12 And think that's what I
13 captured, it looks like, in my Paragraph 72.

14 Q. Okay.

15 A. It's interesting both of them
16 are Paragraph 72.

17 Q. Coincidence.

18 All right. I want to
19 understand a little bit more about the
20 relationship between the automatic labels and
21 the human labels in Huval.

22 So --

1 A. Okay.

2 Q. -- let's start by pulling up
3 Huval, which is Exhibit 18.

4 And let's look at Figure 1.

5 A. Yes, sir.

6 Q. So if you -- if you see
7 Figure 1, there's a training set on the top
8 right-hand corner.

9 Do you see that?

10 A. Yes, that's labeled S110.

11 Q. Right. And let's scroll down
12 to the body of Huval, and I direct you to
13 Paragraph 22 particularly.

14 A. Okay. Give me one moment.

15 Q. Actually I take it back, let's
16 look at Paragraph 21 first.

17 A. Yes, that's talking about the
18 training set.

19 Q. Yeah. And each -- and if you
20 read the first sentence of Paragraph 21, it
21 says, Block S110 of method S100 recites
22 accessing a training set including optical

1 images, wherein each optical image in the
2 training set includes a label linked to an
3 object represented in the optical image.

4 So this would be
5 manually-labeled data, right?

6 A. That's the assumption, yes.

7 Q. Yeah. So this would be the
8 data that Dr. Janet is proposing to modify so
9 that it would, you know, capture intents as
10 described in Ross, right?

11 A. What was your question again?

12 Q. Well, I just want to make sure
13 we're talking about the same thing, and I
14 want to make sure we're saying that the
15 Block S10 [verbatim] and the training data
16 which is labeled, that's -- that's the
17 original human annotated data that Dr. Janet
18 would be suggesting to change to -- in view
19 of Ross, right?

20 A. That's generically the idea,
21 yes.

22 Q. Okay. Now, let's talk about

1 what happens next in Huval. And we're going
2 to talk about Paragraph 23.

3 And, again, I don't have a good
4 way to -- if we were in a room together I
5 would have Figure 1 in one hand and the text
6 in the other hand so you can reference both.

7 If you can split your screen
8 and look at them both, it might be easier.

9 A. Yeah. I -- I have them up.

10 Q. Okay. All right. So at
11 Block S120 a model is trained based on this
12 label data, right?

13 A. That's the -- generically the
14 idea, right.

15 Q. Yeah. And when we talked
16 earlier about supervised learning models and
17 models that are trained with human label
18 data, the -- the model that's trained in S120
19 is going to be trained to predict what the
20 human labels are put into it, right?

21 A. That's generally the idea, yes.

22 Q. Okay. So a POSITA would

1 understand that the -- the outcome of
2 training Block S120 on modified data as
3 proposed by Janet would need to have a model
4 that also predicts intents as modified by
5 Ross, right?

6 MR. GINNINGS: Objection to
7 form.

8 A. I guess I'm not understanding
9 what your question is here. But I describe
10 the discrepancy in my paragraph.

11 So if you look at my
12 Paragraph 73, you see later on in the
13 paragraph it says -- I'm looking at Page 31,
14 Paragraph 73, maybe the third sentence or
15 something like that, second or third
16 sentence, see, it says, In my opinion, such a
17 modification would not make sense to a
18 POSITA, as it would result in a human
19 annotation relating to road user intent but
20 the automated annotations relating only to
21 the identification and location of objects in
22 the image ...

1 (BY MR. SPEEGLE)

2 Q. I understand.

3 A. You see, when you look at
4 Paragraph 23 of Huval, you see that?

5 Q. Yeah.

6 A. See where it says
7 Block S20 [verbatim] of the method S100
8 recites training a neural network, with the
9 training set, to identify objects in optical
10 images.

11 You see what I mean?

12 Q. It says "objects and
13 navigational actions," right?

14 A. Let's -- let's step back.

15 So Paragraph 23, first sentence
16 of Huval, Block S20 [verbatim] of the method
17 S100 recites training in neural network, with
18 the training set -- that is labeled S110 --
19 to identify objects in optical images.

20 Q. Right. And then the next
21 sentence --

22 A. Then it talks about -- the next

1 sentence says -- it says, Generally, in
2 Block S20 [verbatim] -- which is the neural
3 network you're referring to in the -- in the
4 figure -- the remote computer system can
5 implement machine learning techniques to
6 automatically develop a computational model
7 (or "neural network") -- right -- for
8 detecting and identifying (e.g., labeling,
9 classifying) localization objects, perception
10 objects, and navigational actions in optical
11 data...

12 You see what I mean?

13 So that's talking about if
14 you're looking at the frames of video or
15 images, it's identifying the object in the
16 image.

17 Q. Yeah.

18 A. That's what -- that's what the
19 automated system is doing.

20 Q. Well, let me ask you one more
21 question about Paragraph 23, then I'll get
22 back to where I was going before.

1 Oh, Paragraph 23 says that the
2 model is also for detecting and identifying
3 navigational actions.

4 Do you see that?

5 A. Yes.

6 Q. What are navigational actions?

7 A. Well, you identify the object.
8 And if I'm looking at the object from Frame 1
9 to Frame 2 to Frame 3 to Frame 4 to Frame 5,
10 I can see the object motion -- basically the
11 motion estimation of the object.

12 Q. Okay.

13 A. That's entirely different from
14 user predicting user intent.

15 Q. And you understand the
16 modification proposed here is to use
17 different data to train that neural network
18 in Block S120 so that it would include user
19 intents as taught by Ross, right?

20 A. Well, I mean, again, you're
21 proposing an idea, well, the question as how
22 you're going to do this.

1 You know, I can propose to you
2 that I'm going to install a jet engine in my
3 Dodge Ram and it's going to fly as of
4 tomorrow afternoon.

5 Q. Okay.

6 A. So that's the point. I mean,
7 it's -- you're proposing something without
8 any technical descriptions of how you're
9 going to do any of this, how you're going to
10 do any of this training, how you're going to
11 integrate it.

12 So --

13 Q. You think it would be beyond
14 the skill of a POSITA to use different data
15 to train the model S120?

16 A. As I explained to you earlier
17 with machine learning, training is a skill
18 set on its own because it's not like a -- a
19 cookbook recipe. You just say, Okay, I'm --
20 here's 50 elements I'm going to train with.
21 I just do boom, boom, boom, and there it is,
22 I have a tiramisu.

1 That's not how it works.

2 So there is a skill set in how
3 to conduct the training, how to set up the
4 data, what type of batches you're going to
5 use, what's the size of the network you're
6 going to use.

7 Are you going to conduct -- are
8 you going to use regularization or not?

9 How are you going to determine
10 if it's generalizing?

11 Are you going to utilize
12 multiple initialization point of entries?

13 Are you going to utilize
14 different descent trajectories?

15 There's a lot going on in a
16 training of a network. It's not like I
17 train, for instance, this network, I'm just
18 going to do the same thing with this other
19 network with a different data set. That's
20 not how it works.

21 Q. You don't think a POSITA could
22 figure this out?

1 A. No. It's not -- it's not that
2 simple.

3 Q. Okay.

4 A. It's not -- it's not that
5 simple. It requires -- I mean, you have to
6 sit down and study the data set, for example,
7 understand exactly what you need to do,
8 define what the structure of the network is.

9 You may have to add layers,
10 delete layers, add neurons, delete neurons,
11 change activation functions, change
12 regularization parameters, do a dropout, you
13 know, strategy.

14 There's a lot of stuff involved
15 here.

16 Q. So you don't think --

17 A. It's not like I can just put A
18 and B and I get C.

19 Q. You don't think a POSITA would
20 know how to train a neural network?

21 A. Generally speaking, I mean, the
22 idea a POSITA understands there is something

1 with training, but you still have -- there's
2 a skill set and each network is different in
3 how you train it.

4 Q. So you don't think a --

5 A. Just because -- just because
6 I'm training a neural network to generate --
7 to recognize apples, that doesn't mean I can
8 apply the same strategy to a neural network
9 and recognize faces.

10 Q. Is that something a POSITA
11 would know?

12 A. No. It's not something -- it's
13 not that simple.

14 Q. A POSITA wouldn't know that you
15 have to use different training techniques for
16 different types of classification models?

17 MR. GINNINGS: Objection to
18 form.

19 A. It's not just -- it's not about
20 knowing the different techniques. It's just
21 how would you use -- what would you do for
22 this particular network, because each network

1 is different.

2 And how you set up to train the
3 network is a skill set on its own, you know,
4 how many entry points you're going to use,
5 what type of training, how many epochs, how
6 long you're going to run this, what kind of
7 Gradient descent strategy you're going to
8 use.

9 There's a lot of stuff involved
10 here. This is not a simple I train on
11 apples, I can now train on faces.

12 I mean, what you're proposing
13 here and what Dr. Janet is proposing doesn't
14 make -- doesn't make sense.

15 You're basically saying I just
16 put A with B and therefore it comes out C.

17 If it was that easy, you know,
18 we would be, you know, automated --
19 automated -- autonomous vehicles would be
20 available today ten years ago.

21 (BY MR. SPEEGLE)

22 Q. You teach a course at RIT

1 called "Advance Neural Networks and Deep
2 Learning," right?

3 A. Yes, sir. That's part 1 and
4 I'm working on part 2, yes.

5 Q. Is that a graduate level
6 course?

7 A. I created -- I created the
8 course. And, yes, it's a graduate level
9 course. It's meant for MS -- second year MS,
10 first year Ph.D. students. And you have to
11 have a certain prerequisites to enter the
12 course.

13 Q. Okay. So somebody who gets a
14 master's degree from your school would have
15 taken that class?

16 A. A bachelor's or a master's, did
17 you say?

18 Q. Master's.

19 A. Well, it depends on their
20 interest, because somebody that is getting a
21 master's degree that's specializing in
22 controls wouldn't take that class.

1 Somebody that is getting a
2 master's degree that is focused on machine
3 learning would -- you know, would -- would
4 take the class.

5 Q. Okay.

6 A. It depends on what you're
7 specializing in for your master's. Somebody
8 who is specializing in hardware design
9 wouldn't take the class.

10 Q. What do you -- what do you
11 teach in that Advanced Neural Network Design
12 and Deep Learning class?

13 A. Well, I have -- I have a whole
14 outline I teach. I start by talking about
15 regression -- first of all, I give an
16 introduction to the field of neural nets.

17 Then I go through the
18 mathematical preliminaries. Then I go
19 through optimization techniques, Gradient
20 descent, you know, second -- you know, second
21 order derivatives, first order derivatives
22 type methods, and various ways of doing all

1 that.

2 Then I go into overview of
3 neural networks and, you know, what's the
4 difference between shallow and deep and set
5 the mathematical structure together.

6 And then I get into regression
7 techniques, classification techniques,
8 obviously for multilayer networks, et cetera,
9 and multidimensional situations, feature
10 selection, backpropagation algorithms, that
11 kind of thing.

12 Q. Does your -- does your Advanced
13 Neural Networks and Deep Learning class teach
14 your students how to train different neural
15 networks?

16 A. It talks about the training
17 strategies. It doesn't mean when you walk
18 out of there, you're going to learn to train
19 every network.

20 It talks about different
21 training strategies, but they don't all apply
22 to every network. Every network is a little

1 different depending on the data and what you
2 have.

3 Q. Do you feel like your class
4 prepares your students to get a job at a --
5 at a machine learning or artificial
6 intelligence company today?

7 A. Well, that's -- that's the
8 idea, is you would come out and have the
9 background to be able to, you know, work for
10 a company that does machine learning and --
11 and contribute.

12 Q. Yeah.

13 A. But there are still different
14 skill sets on how to use this on different
15 data.

16 Q. So one of your students would
17 be prepared to go work for a company that's
18 training models on different kinds of data,
19 right?

20 A. I mean, we provide you with a
21 background. You know, just like if you did a
22 hardware design, we teach you how to design

1 hardware.

2 That doesn't mean if you step
3 into NVIDIA, you get to design a board in ten
4 minutes just because you took a course on
5 hardware design.

6 You still have to determine
7 what are you trying to accomplish with this
8 new data, what type of data it is. Different
9 data has different design requirements.

10 So you still have to make
11 technical decisions on how to do the training
12 and what type of strategies of training to
13 apply to each different data set.

14 So I may -- I may have shown
15 you 50 different training strategies. You
16 can't -- you don't use all 50 on every time
17 you train.

18 I may use ten on this day on
19 this particular data set, a different set on
20 a different data set.

21 It depends on what the
22 application is. And some of this may be

1 iterative. You may have to try -- more or
2 less trial and error.

3 It's not -- it's not a -- you
4 know, there is no formula that says for this
5 problem use technique A, B, and C.

6 Q. How long you been teaching this
7 class at RIT?

8 A. Well, as I mentioned to you, we
9 were teaching neural nets in the '90s as part
10 of a class called "Pattern Recognition." So
11 I taught the course of Pattern Recognition --
12 well, I taught the course at U of R as well
13 as RIT.

14 At the U of R, I basically
15 continued teaching the course when I was
16 there as an adjunct faculty until 2004.
17 Didn't teach it every single semester, but I
18 taught it multiple times.

19 And at RIT, the course was
20 initially there in the early '80s, then it
21 was abandoned. I reinstated it. So I -- you
22 know, I restarted the course because, you

1 know, the faculty that was teaching it was
2 either retired or left the university.

3 So I reinstated the course,
4 reinstated the material, redeveloped
5 everything, and was teaching it, you know,
6 let's say, late '90s, early 2000s under the
7 heading of "Pattern Recognition."

8 So the Pattern Recognition
9 course had three bases to it, the
10 statistical, the structural, and the neural.

11 The statistical is what you
12 were asking about this morning, the Bayesian
13 and all that stuff.

14 And the neural net is what
15 we're talking about today.

16 So that kind of course evolved
17 a little bit.

18 But as machine learning start
19 to take on its own identity, so to speak,
20 where people started to talk about it as
21 machine learning instead of pattern
22 recognition, so we started to evolve some of

1 those courses.

2 So I decided to create a new
3 course on -- focus on just that and not
4 really talk about the structural and the
5 statistical part of pattern recognition.

6 We still teach that course,
7 except it's -- it's now focused a little
8 differently.

9 Q. Do you think one of your
10 students who has completed successfully your
11 Advanced Neural Net and Deep Learning course
12 would be able to train the model in Huval
13 using slightly modified data as taught by
14 Ross?

15 A. Well, like I said to you, they
16 would -- they -- they have the background,
17 but you still have to make some technical
18 decisions as you look at the data and start
19 the training. Because when you start the
20 training, you might find it's divergent, it's
21 not convergent.

22 So it's not -- it's not

1 generalizing and it's overfitting. So now
2 you have to change the training strategy, you
3 have to change the type of data you're
4 providing, the size of the batches you're
5 providing. The steps in the backpropagation,
6 how steep of a descent step you're going to
7 take.

8 There's a lot of variables
9 involved in this. It's not -- it's not just
10 turn the crank and there -- there comes a
11 term, it's okay.

12 Q. Okay. But those are all
13 challenges that you're preparing your
14 students to handle, right?

15 A. Well, we prepare the -- we
16 provide the student with a background. Just
17 like you provide a student with calculus,
18 that doesn't mean they can solve every
19 possible mathematical problem out there.
20 They understand the -- the background. They
21 now have to look at each problem and
22 understand, okay, formulate a technical

1 strategy for it and understand how to tackle
2 that particular problem. And the data set
3 that they have, all of that is basically very
4 problem and custom specific to the problem.

5 Q. Okay. So I know we had quite
6 a -- quite a long departure from Huval, but I
7 want to just try to bring it back to what
8 we've talked about in Figure 1 of Huval.

9 And maybe let's look at
10 Paragraph 31 of Huval.

11 A. Of Huval?

12 Q. Yeah.

13 And this is describing a
14 Block 132 of Figure 1 of Huval?

15 A. Yes, sir.

16 Q. The neural network is -- is
17 trained to identify -- apply automatic labels
18 to additional optical information, right?

19 A. Yeah. This is typically what
20 we call bounding boxes. So you're putting a
21 bounding box, so you see where it says there,
22 so block -- I'm -- I'm looking at

1 Paragraph 31 of Huval.

2 Block S132 recites passing the
3 first optical image through the neural
4 network to generate a first automated label
5 attributed to a first automatically-defined
6 location on the first optical image.

7 Q. Okay. And --

8 (Speaking simultaneously.)

9 A. That's the idea what you're
10 trying to do, is you're trying to define
11 where the object is in the image. And
12 typically that's done with block -- you know,
13 bounding boxes like you see -- if you look in
14 the figure, you see how they have like a
15 little bounding box. So it's kind of like
16 giving you the object is located roughly in
17 this area.

18 (BY MR. SPEEGLE)

19 Q. Yeah. And I just want to be
20 clear that the -- the generation of the
21 automatic labels is done by the neural
22 network that is trained based on human labels

1 in Block S110, right?

2 A. That's the general idea, yes.

3 So you want -- you want -- unless you train
4 the network, you want to be able to utilize
5 it.

6 Q. Okay.

7 A. Labeling the object, just like
8 we talked about in paragraph -- was it 23 or
9 earlier in that paragraph, yeah. Training --
10 Paragraph 23.

11 Q. All right. We can put aside
12 Huval.

13 I do want to ask a few more
14 questions about your '889 declaration. And
15 we -- we can go back to the table of contents
16 on this.

17 A. Sure. '889, table of contents.

18 Q. So we've talked about Ground 1.
19 And then Ground 2 adds the Cox reference,
20 right?

21 A. Yes.

22 Q. Okay.

1 A. Yes, Ground 1 is just Huval and
2 Ross.

3 Ground 2, Huval, Ross, and Cox.

4 Q. And the one element that you
5 disagree with for Ground 2 is the same as
6 what you disagreed with in Ground 1, right?

7 A. That is correct.

8 Q. Okay. And then if we turn to
9 Ground 3, that is for a combination of Huval,
10 Ross, and Munro; is that right?

11 A. That is correct.

12 Q. And it looks like you've
13 disputed some different limitations with
14 respect to Ground 3. Is that fair?

15 A. Yes, sir.

16 Q. Okay. So instead of disputing
17 limitation 1[c] you are now disputing
18 limitation 1[d], 2[d], and 12[d]. And then
19 1[f], 2[f], and 12[f]. Is that right?

20 A. That's correct.

21 Q. Okay. And then Ground 4, which
22 is a combination of Huval, Ross, Cox, and

1 Munro, again, you're no longer disputing
2 element 1[c] for this combination, right?

3 A. Yes, I'm disputing 1[d] and
4 1[f].

5 Q. Okay. And the same for the
6 parallel claims 2 and claim 12, right?

7 A. Yes, sir.

8 Q. Okay. All right. I know we're
9 a little bit faster than the last break, but
10 I'm about to shift gears back into summary
11 statistics again.

12 MR. SPEEGLE: Do you want -- do
13 you want to take a break now before I
14 do that?

15 THE WITNESS: Sure. Let's do
16 that. Let's take a five-minute maybe.

17 MR. SPEEGLE: Yeah.
18 Five-minute break sounds good.

19 (Break from 1:21 p.m. to 1:28 p.m.)

20 (BY MR. SPEEGLE)

21 Q. Okay. Let me ask you about
22 Paragraph 65 of your '889 declaration.

1 A. Paragraph 65, 889.

2 Yes, sir.

3 Q. Now, you say in here that --
4 well, I'm going to paraphrase. I'm not going
5 to quote it exactly.

6 But you said that Huval's
7 averaging does not constitute a summary
8 statistic; is that right?

9 A. That's correct. You have to
10 read that Paragraph 85 of Huval and
11 understand the technology that he's talking
12 about.

13 Q. Okay.

14 A. We can go to that if you would
15 like.

16 Q. Sure. We'll go there in just a
17 second, but before -- before we go on, just
18 read from here, and you -- you agreed earlier
19 that an average is a statistic, right?

20 A. Well, I mean, obviously, if I
21 compute an addition of five numbers and
22 divide by five, that gives me an average.

1 Q. Is that a statistic?

2 A. That would constitute, you
3 know, a statistic, but that's not what's
4 going on in Paragraph 85 of Huval.

5 Q. Okay. So -- and let's look at
6 Paragraph 85 of Huval.

7 A. Fantastic. Let's do it. One
8 of my favorite paragraphs.

9 Q. You know you're in the right
10 field when you have a favorite paragraph of a
11 patent.

12 A. Yes. When you wake up at
13 2:00 a.m. in the morning and think about it,
14 right?

15 Q. Okay. So --

16 A. Yes, sir.

17 Q. Paragraph 85 refers to an
18 average or otherwise combined responses; is
19 that right?

20 A. Yes, that's the language, but
21 that's not what it -- you have to understand
22 the technology underneath it to really

1 understand what he's saying here.

2 Q. Okay. What's your
3 interpretation of --

4 (Speaking simultaneously.)

5 (BY MR. SPEEGLE)

6 Q. What -- what's your
7 interpretation of what's -- what's going on
8 underneath?

9 A. See, take a look and see what
10 he says here.

11 So if you look at what Huval is
12 saying -- and let's just start -- first of
13 all, obviously, he's referring to Figure 1
14 and 3, correct? And label conflicts to other
15 human annotators. So he's talking about, you
16 know, distinguishing between label conflicts.

17 For example, he says -- where
18 I'm talking in probably second sentence in
19 the paragraph, ... remote computer system
20 can: serve an optical image, a manual label,
21 automated label for label conflict
22 resolution.

1 And then as you read a little
2 bit more below, it says, such as including
3 the human annotator who supplied the label
4 and receive manual confirmation of one of --
5 of one of the manual labels and the automated
6 labels, and average or otherwise combined
7 responses.

8 Then you notice it says there,
9 e.g., object types, label location,
10 activation times, and deactivation.

11 Do you see that?

12 Q. Yes.

13 A. Okay. So this wording of
14 "average" here, that doesn't mean you're
15 adding five numbers and dividing by five and
16 getting a statistical average.

17 Let me explain what I mean.

18 Let's suppose I -- I have two
19 humans or the human labeled this object as a
20 bicycle and the computer labeled that object
21 as a pedestrian. You are not going to add
22 that two and divide by two and say, Well,

1 there's your label, is it? That -- that's
2 not how it -- how you do a label conflict
3 resolution.

4 So what at that point you're
5 going to do is determine, okay, the human
6 labeler labeled the object as pedestrian,
7 which usually is more accurate in these type
8 of scenarios than the computer-automated
9 version, which might have labeled the object,
10 let's say, as a -- as a cyclist.

11 So then you're going to take
12 maybe a binary combination of the two or just
13 select the human label version as the
14 accurate one. You're not going to -- by
15 average, he doesn't mean I add the two and
16 divide by two. Because it wouldn't make
17 sense.

18 Same thing with label location.
19 So if I said to you the label is located --
20 the human labeler said, The label is located
21 here in the image, and the neural network
22 said, Well, no, it's not here, you're not

1 going to average the two and divide by two
2 because then you end up with junk.

3 So you're going to select which
4 of those two is the more accurate, you know,
5 label, which obviously, generally speaking,
6 it's the human annotators over the automated
7 version.

8 Same thing with activation
9 time. So activation time could mean infringe
10 a video -- let's say I have a hundred frames
11 of video. At frame 30, I see -- a human
12 annotator says, I see the cyclist showing up.

13 And frame 31, here he is, and
14 frame 32, 33, 34, et cetera, versus the
15 neural net automated one may say, Well, that
16 started at frame 33, not frame 31, or
17 starting at frame 34.

18 Well, you're not going to add
19 the two frames and divide by two. That
20 doesn't make any sense, because now you end
21 up with a number that doesn't -- is not a
22 frame.

1 So 31 plus 34 divided by 2 may
2 give you a decimal number. That's not --
3 that's not a frame number.

4 So the average that you see
5 here is mistakenly read by Dr. Janet and
6 Tesla to think it was just a statistical
7 average just because it says the word
8 "average."

9 That's basically a lack of
10 understanding of the technology that's being
11 assessed here.

12 Q. So why does it say "average"
13 and not pick the most accurate?

14 A. Well, I mean, people use
15 language, you know -- you know, average or
16 otherwise combined responses. You know,
17 people sometimes use language in a flexible
18 manner.

19 You know, it's -- I can't tell
20 you why Huval used that language.

21 But what I can tell you is
22 having done this many times and, you know,

1 I've developed segmentation algorithms, at
2 the time when I develop them were state of
3 the art in the world.

4 And we have a paper we
5 published to show we tested every possible
6 segmentation algorithm and showed that ours
7 were the best at the time.

8 I guarantee you that is not --
9 it's not a statistical average of any kind.
10 That doesn't make sense at all.

11 Q. So you think --

12 A. Otherwise combine makes sense.

13 Q. You think it's just a typo?

14 A. I mean, people -- like, you
15 know, people sometimes use language in a
16 flexible manner, right, just because, you
17 know, people do this all the time. Right?

18 They -- they use language in a
19 flexible manner. That doesn't mean it's
20 literally meaning I'm just going to divide --
21 add five numbers and divide by five, because
22 it doesn't make sense in doing object

1 labeling of any kind.

2 You never do that because it
3 doesn't -- what do you end up with? If you
4 average just like -- let's say three humans
5 came up with the person and the object is a
6 human. And one -- and a computer said two of
7 them came up with cyclists.

8 What do you do? Add the five
9 and divide by -- by five? What do you get?
10 Something between human and a cyclist?

11 Q. Could you, you know, correlate
12 the labels with different numerical values?

13 A. You don't do that because, I
14 mean, now you're taking away information. I
15 want to know the exact label of that object,
16 because that's what I'm trying to train the
17 neural network with.

18 See, I want -- I want ground
19 truth value, right? I want the most accurate
20 possible label. I don't want some averaging
21 of the label, because now I'm degenerating
22 the quality of the training data.

1 Q. Let me say I have no doubt that
2 the -- the Saber model will be superior to
3 the Huval model in every respect, but I'm
4 just trying the Huval model here.

5 Is there a way that they could
6 have, whether it's inferior or not,
7 attributed these activation times or the
8 object types to numbers and then numerically
9 average them to get a different weight for
10 their -- their weights?

11 A. No. It wouldn't make sense.

12 Q. Okay.

13 A. I mean, think about what's
14 being done here. Object -- if I told you the
15 object is located here versus the automated
16 system that says it's located here -- let's
17 suppose the two locations don't overlap at
18 all.

19 Let's just say I say it's
20 located in the right side of the image, and
21 then the neural net says it's located in the
22 left side in the image.

1 If you average the two
2 together, what do you get? It's -- neither
3 one now is correct.

4 What you get is a label that's
5 located in the middle of the image that
6 doesn't reflect either one of them. So
7 you've just -- what you did is you
8 degenerated the data and made it much poorer
9 quality training set, which then is going to
10 affect your neural network and come up with
11 junk.

12 Q. You --

13 A. You know the old atom -- or
14 idiom or whatever. Junk in/junk out. Right?
15 Garbage in/garbage out.

16 Q. I think I hear you. And I'm
17 not arguing on the quality for sure. I think
18 what you just described is still possible,
19 right, even if it's lower quality to, you
20 know, say if it's -- you got the right side,
21 the left side, you average it, you get the
22 middle?

1 A. You wouldn't do that. I mean,
2 it --

3 Q. Well, I might --

4 (Discussion off the record.)

5 A. So one is you wouldn't do that;
6 and two, Huval is not doing that.

7 (BY MR. SPEEGLE)

8 Q. Well, Huval says average. I
9 think what you're saying is he doesn't mean
10 average.

11 MR. GINNINGS: Objection; form.

12 A. Again, what I said to you is
13 the word "average" there is used in a
14 flexible manner just like people use words in
15 a flexible manner, you know, in different
16 context.

17 That average doesn't mean
18 you're adding up five labels and dividing by
19 five, because technically that wouldn't make
20 any sense and wouldn't make any sense in what
21 Huval is doing.

22 So anybody that reads it that

1 way has no understanding of how these systems
2 are done. And I'm sure Huval did not intend
3 it to be averaging and dividing by five.

4 (BY MR. SPEEGLE)

5 Q. Okay. Later in this
6 Paragraph 85, he mentions a binary
7 combination.

8 What's a binary combination?

9 A. An and, an or, an exclusive or,
10 that type of thing.

11 So if you had five humans, for
12 instance, that are saying this is a cyclist
13 and the automated system says it's a
14 pedestrian, then you would say, Okay, I'm
15 going to take those five and use that as
16 my -- you know, the five human responses.

17 Q. Okay.

18 A. So that's what makes sense, is
19 you're doing the proper combinations because
20 you want -- you know, think about what the
21 application here, is I want the very best
22 training data set possible with the very best

1 ground truth because that's what I want to
2 train my neural network with.

3 I'm not going to give my neural
4 network substandard data so then I have
5 degenerate type result.

6 Q. Now, I'm going to venture into
7 a little bit of math that I'm not a hundred
8 percent confident in, so I'll need your help
9 with it.

10 But I understand that when
11 models are actually trained on that data,
12 they used vectorized data; is that right?

13 A. Depends on the model. For
14 instance, if I'm doing -- are you familiar
15 with CNN, convolutional neural networks?

16 You don't use vector data,
17 because, if you did, you would basically --
18 an image -- if I were to show you an image --
19 and I do this example in my classes.

20 If I show you an image -- let's
21 say you took a picture at -- you're at Disney
22 World and you took a picture.

1 That picture is not just a
2 random selection of pixels. Right? It is a
3 cohesiveness in that picture. So when you
4 look at it, you see people, you see bicycles,
5 whatever.

6 If you were to vectorize that
7 image, if I were to take, let's say, the
8 first line and then put it in a vector and
9 then take the next line and put it in a
10 vector and vectorize the image and I show you
11 a vector, you would have no clue what's in
12 that image.

13 You just destroyed the
14 correlation that's in the image. And that's
15 why CNNs, you know, convolutional neural
16 networks, have been very effective in
17 analyzing imagery because they take
18 advantage, one, of the correlation in the
19 image; and two, you don't want to vectorize
20 the image because if you did, you would have
21 a huge input layer.

22 I mean, if the image is a 10 by

1 10 and you vectorize it, now you have a
2 hundred input layer to feed into your neural
3 network, which obviously images aren't 10 by
4 10. They're usually, say, 500 by 500 or
5 something. They're -- they're large.

6 So if you were to vectorize
7 that image, you would have a huge neural
8 network that would take hours to train. So
9 you don't want to do that. And that's why
10 CNNs don't do that.

11 Q. Okay.

12 A. Vectorization is only good for
13 classification type purposes, not necessarily
14 analyzing imagery in general.

15 Q. So when a CNN is being trained
16 on images, I understand that the -- the
17 images at some point are going to be
18 impacting numerical weights in the -- in the
19 model, right?

20 A. Well, the CNN -- if you're
21 using a CNN, you essentially have what we
22 call a kernel or a filter and that filter has

1 a certain size, let's say, a 5 by 5, which
2 you are passing over the image and doing
3 what's called convolution.

4 It actually does
5 cross-correlations in general, not
6 convolutions, but we call it convolution.

7 So -- and that's another
8 flexible use of technology. People call it a
9 convolution, but actually it doesn't do
10 convolution, it does cross-correlation.

11 So if you had to be --
12 accurately saying CNN, you should be saying
13 cross-correlation neural networks, not
14 convolution neural networks because they
15 don't do convolution.

16 But anyway, besides the point.

17 So you're -- you're training
18 the filter -- what you're trying to do is get
19 the right numbers for that kernel, and that's
20 what you're trying to train, as the kernel
21 that you're using for the cross-correlation,
22 so hopefully you can generate a set of

1 features from that image.

2 Q. Okay. What are the kinds of
3 models where you would use vectorized,
4 vectorized training data?

5 A. Typically more in
6 classification type models where you have
7 essentially a set of features, so you've got
8 some -- some objects or whatever you've
9 created -- you've -- you've gotten to a set
10 of features. Just like we do on the back end
11 of a CNN.

12 So we use a CNN up front. We
13 have a bunch of images. We do some filtering
14 and some basically pooling and activations,
15 et cetera, and we do that on a few layers,
16 say five layers for illustration purposes.

17 Now we have reduced that
18 imagery to a set of features which is a lot
19 smaller because you did some pooling.

20 By "pooling" means you're
21 subsampling the image in both directions. As
22 you're doing the convolution you're

1 subsampling the output.

2 So now you have a much smaller
3 set which you then vectorize.

4 If you're doing, for instance,
5 space recognition, you would vectorize at
6 that point and go into what's called a fully
7 connected neural network to do the
8 classification or the identification.

9 And, yes, this is Mark. And
10 yes, this is Eli. And Austin, so Austin
11 doesn't feel left out.

12 Q. Okay. And when you have a --
13 when you have vectorized training data, is it
14 more sensible to talk about averaging your
15 vectors?

16 A. And, again, I think you're
17 mixing apples and oranges because what you're
18 trying to do is fit the square peg in the
19 round hole.

20 So if my vector is the location
21 of the object in the image and I have another
22 vector which is another location of the

1 object in the image, I wouldn't average the
2 two because now you end up with junk because
3 now you're -- you have subpixel locations
4 instead of pixel locations.

5 So if I have a vector and it --
6 it has pixel locations to it, and I have
7 another vector that has different pixel
8 locations to it, and they're all integers and
9 I average the two, now I have decimal pixel
10 locations. It doesn't make sense for the
11 image.

12 So, you know, it -- it doesn't
13 make sense in these type of applications.

14 I mean, I understand your
15 motivation to get the average out of this to
16 work for you, but it doesn't work. This is
17 not what's being done in Huval, and it's not
18 what you would do. Any POSITA would know
19 that.

20 And by the way, that's my
21 favorite paragraph of Huval.

22 Q. You said, yeah. I see you get

1 fired up about it.

2 All right. So I'm going to
3 direct you back to your declaration, and this
4 is Paragraph 66.

5 And you say in Paragraph 66 of
6 your declaration --

7 A. '889 declaration, Paragraph 66,
8 for the record?

9 Q. Yes.

10 A. Okay.

11 Q. Do you have it in front of you?

12 A. I do, sir.

13 Q. In the last sentence, it says,
14 Nothing in the cited portions of Huval
15 describes --

16 THE REPORTER: Slow down for
17 me, please.

18 (BY MR. SPEEGLE)

19 Q. Nothing in the cited portions
20 of Huval describes computing a mean, median,
21 or mode of any figures.

22 Did I read that right?

1 A. You did.

2 Q. And am I understanding
3 correctly that -- that the basis for your
4 sentence here is that when Huval said
5 "averaging," he didn't really mean
6 "averaging"?

7 A. As I've --

8 MR. GINNINGS: Objection; form.

9 A. As I've explained to you for
10 the last 15 or 20 minutes, yes.

11 (BY MR. SPEEGLE)

12 Q. Okay.

13 A. This is nothing to do with
14 computing a mean. It's just a figure of
15 speech as being loosely used in -- in Huval,
16 just like you would do this in a lot of
17 times.

18 Q. All right.

19 A. I mean, if I said to you, I'm
20 running errands, does that mean I'm
21 running -- physically running outside and --
22 and -- no, "I'm running errands" means I'm

1 out there, you know, doing four or five
2 different activities. I'm not physically
3 running. You know, people use that as a
4 figure of speech, right?

5 Q. So you think it was just a
6 figure of speech when Huval said you could
7 average the responses?

8 A. Absolutely. I mean, you -- I
9 mean, any POSITA would understand this
10 technology, would know that this is not a
11 statistical mean of any kind. Because,
12 otherwise, it doesn't make sense, as I've
13 explained to you for the last 20 minutes.

14 Q. All right. Let's switch and
15 talk about the Ross reference. And which
16 is -- I think that's Exhibit 13.

17 A. Ross, yes. Another one of my
18 favorite.

19 Q. All right. So I want to direct
20 you to Column 3, Line 8 through 12. Let me
21 know when you're there.

22 A. Column 3, Lines 8 through 12.

1 Yes, sir.

2 Q. And do you see that sentence
3 that says, In one example, generating the
4 prediction of the intent includes generating
5 a set of predictions, wherein the set of
6 predictions includes the prediction of the
7 intent, and each given prediction of the set
8 of predictions identifies a next possible
9 action by the road user.

10 Do you see that?

11 A. Yes, I see.

12 Q. And what is your understanding
13 of what Ross is describing in this passage?

14 A. Well, I see, I mean, it's --
15 he's telling you, you're generating the
16 prediction of the intent, includes generating
17 a set of predictions.

18 So by a cyclist, I predict -- I
19 don't know -- is going to turn left. And the
20 next prediction, he's going to turn right or
21 she is going to turn left and turn right.

22 So generating a set of

1 predictions wherein the set of prediction
2 includes the prediction of the intent and
3 each given prediction of the separation
4 identifies a next possible action.

5 So predicting the intent and
6 the next possible action might be, well, he's
7 going to turn right versus turn left.

8 Q. Okay.

9 (Speaking simultaneously.)

10 A. As you know, Ross is about
11 predicting intents and behaviors.

12 (BY MR. SPEEGLE)

13 Q. Do you feel like that's
14 different from the '344 patent?

15 A. As I explain in my declaration,
16 yes.

17 Are we -- are we going to the
18 '344 now back?

19 (Speaking simultaneously.)

20 (BY MR. SPEEGLE)

21 Q. Let me talk to you about Ross.
22 We don't -- we don't need your declaration

1 right now.

2 A. Okay.

3 Q. Let's also look at Ross
4 Column 8, Lines 63 to 65.

5 A. Ross Column 8, Lines 63 to 65.

6 Q. Well, and if you want to read
7 the whole sentence, I'll back up to -- it
8 starts at Line 60, the part of the sentence
9 that I'm interested in is in the second half,
10 but why don't you just go read the whole --
11 whole sentence here?

12 A. Do you want me to read it out
13 loud.

14 Q. Yes, please.

15 A. Okay. So I'm at Column 8 --
16 Ross Column 8, Line 60.

17 As an example, given the
18 location, heading, speed, and other
19 characteristics included in the data from the
20 perception system 172, the behavior-time
21 models may provide a set of one or more
22 predictions for how the object could behave

1 for the predetermined period of time as well
2 as a corresponding likelihood value for each
3 prediction.

4 Q. My first question is: This
5 passage and the first passage you read
6 referred to a set of predictions, do you have
7 an understanding of what a set of predictions
8 would be in this context?

9 A. I think I've explained it to
10 you earlier, but I'll explain it again.

11 So I may predict for a road
12 user and, you know, looking at a road user I
13 may say, Well, he may be going left or it may
14 be going left, that's one prediction. It may
15 be going right, that's another prediction.
16 The two together form a set of predictions.

17 Q. Got it.

18 And there would -- the
19 probabilities of those options would add up
20 to one, right?

21 A. Well, if you -- if you're just
22 doing only two of them.

1 So if you made three
2 predictions, then you would -- that would be
3 slightly different, right? So you have the
4 probability of three add up to one. That
5 kind of thing.

6 Q. Right. So I guess however
7 many -- sorry. Let me say that again.

8 However many predictions you
9 have in your set, the cumulative probability
10 of all of those predictions together should
11 be one, right?

12 A. Well, you have a likelihood
13 value for each prediction. So that's the
14 idea. Yes.

15 Q. Okay.

16 A. It doesn't mean you're correct,
17 but that's the idea.

18 Q. And, sir, I'm going to jump
19 down to the last part of Column 8 going into
20 Column 9. I'll read this one.

21 It says, In this regard, the
22 prediction with the greatest likelihood value

1 may be the most likely to occur whereas with
2 predictions with lower likelihood values may
3 be less likely to occur.

4 A. Yes.

5 Q. Is this akin to the posterior
6 probability we discussed earlier?

7 A. Say again.

8 Q. Well, this is a selection of
9 the thing with the highest likelihood. And
10 it's reminding me of our conversation earlier
11 about posterior probability. And I -- so --

12 (Speaking simultaneously.)

13 A. That has nothing to do with
14 posterior probabilities.

15 (BY MR. SPEEGLE)

16 Q. Okay. How are they different?

17 A. Well, a posterior probability,
18 as I've explained to you -- and I'm assuming
19 if we meet tomorrow, I would invite you to
20 take a look at, say, Papoulis or ChatGPT just
21 to look at Bayes' theorem.

22 But posterior probability

1 requires the knowledge of the distribution of
2 the class.

3 So probability of A given my
4 sample X. Let's assume I have three classes,
5 A, B, and C. And I have -- I draw -- I have
6 one sample here in my hand.

7 Does it belong to -- let's say
8 I have three types of balls, a red ball,
9 green balls, and blue balls. And I just drew
10 one sample of random in my hand and then you
11 don't see the color.

12 What's the probability of that
13 sample being Class A, Class B, or Class C?

14 So what's the probability of A
15 given my sample? That's a posterior
16 probability.

17 For you to compute that, you
18 would need the class distribution. So you'd
19 need what's the probability of samples given
20 Class A.

21 That's a probability
22 distribution function, a probability density

1 function.

2 So you would need to know the
3 probability density function and the a priori
4 problem for you to compute the posterior
5 probability.

6 This is just the likelihood of
7 the prediction that Ross is predicting. Just
8 like a softmax type function, I make a
9 prediction and I give it a .7. I make
10 another prediction and it's .2 and another
11 prediction is .1.

12 So the likelihood predictions
13 has nothing to do with a posterior
14 probability in a sense because there is no
15 distribution here. There's no probability
16 density function.

17 Q. The way you said those things
18 together makes me think you intend them to be
19 related.

20 Are you saying to have a
21 distribution you need a probability density
22 function?

1 A. I think you're mixing up
2 several contexts. A probability density
3 function is a distribution. So think of it
4 as a histogram, but it's a continuous
5 histogram.

6 I'm simplifying, obviously,
7 oversimplifying.

8 But probability density
9 function, say a normal Gaussian distribution
10 for males that play in the NBA, right, so you
11 have mean and then you have a normal
12 distribution with a variance. You know, the
13 mean, let's say, is height 6.8 plus or minus
14 whatever, some inches.

15 So that's the probability
16 density function that describes the class and
17 the probability of different samples of
18 different values in the class.

19 So you need that to compute the
20 posterior probability using Bayes' theorem,
21 as I've explained to you earlier more than
22 once.

1 Q. Okay. So I guess when we're
2 talking about a set of predictions, you would
3 not call a set of predictions a distribution?

4 A. No.

5 Q. And why is that?

6 A. Because it isn't. I mean, a
7 distribution, essentially you would have to
8 know the class distribution to create a --
9 let's say a two-dimensional Gaussian or a
10 three-dimensional Gaussian or whatever.

11 It's distribution for the
12 different, you know, samples in the class in
13 a sense.

14 Q. So when you see the word
15 "distribution" in the '344 patent, you're
16 interpreting that -- I'm sorry, let me strike
17 that.

18 When you see the word
19 "distribution" in the claims of the '344
20 patent, you're interpreting that as a class
21 distribution?

22 A. Well, I mean, if you look at

1 the '344 -- let's go back and look at it so
2 we're saying the exact same things.

3 So if you look here at -- at
4 the '344, it says -- and I'm looking at claim
5 element 1[b], which has to do with this,
6 obviously.

7 So if you say -- see, it says
8 predicting an output statistical summary
9 characterizing a distribution of user
10 responses.

11 So you have a set of user
12 responded, a hundred, 200, whatever. Based
13 on all those responses, you've characterized
14 the distribution.

15 I'm making this up now. A
16 Gaussian -- a normal probability density
17 function, let's just say the distribution is
18 modeled by normal Gaussian.

19 So you have a Gaussian
20 probability density function with a mean and
21 covariances, et cetera. That's a
22 distribution of user responses in a sense.

1 Q. Okay. So your interpretation
2 of a distribution as used in the '344 patent
3 claims requires a -- a statistical
4 distribution like a Gaussian?

5 A. Well, the claim basically says
6 you have a statistical summary characterizing
7 a distribution of user responses.

8 So however that distribution is
9 modeled, you have a distribution of user
10 responses that are expected to be received
11 responsive to presenting the sensor data to a
12 variety of users.

13 Because different users will
14 have different opinions, right, or different
15 judgment on what they see?

16 Q. Okay. So to put this in terms
17 of Ross, your opinion is that the -- even if
18 the set of predictions described in Ross
19 covered distribution of possible future
20 outcomes, that's not sufficient for a
21 distribution in the terms of the '344 patent
22 because the '344 patent is specifically

1 referring to a distribution of hypothetical
2 user responses that would fall under
3 something like a Gaussian?

4 MR. GINNINGS: Objection to
5 form.

6 A. I have no idea what you're
7 saying. And Ross -- as I explained to you,
8 when you look at those paragraphs of Ross
9 that we have been talking about -- so both in
10 Column 8 and the previous one, which was
11 Column 3, right?

12 It's talking about a set of
13 predictions. There's no distribution here.
14 There's no discussion of a distribution. So
15 if you look at Column 3, it just says a set
16 of predictions, you know, include each of the
17 intent and possible action.

18 And if you go to Column 8 and
19 you look at what you read and you -- I read
20 and then you read, see, all it says is you
21 have a set of predictions and likelihood for
22 that prediction.

1 Think about it, you know, I
2 have a neural network with three outputs. I
3 make a prediction and I have a softmax layer
4 on the output. I make a prediction, so
5 output 1 .7, output 2 .2, and output 3 .1.

6 Turn left. Turn right. Go
7 straight.

8 So I just made three
9 predictions with three likelihood. So
10 clearly the .7 is the most likely scenario.
11 That's the greatest likelihood. That --
12 that's not a distribution of -- you know,
13 that's not a distribution of user responses,
14 first of all. It's just a prediction of a
15 network.

16 (BY MR. SPEEGLE)

17 Q. Okay.

18 A. It's certainly not a
19 statistical summary of a distribution of user
20 responses.

21 Q. Let's -- let me just make sure
22 I'm understanding what you're saying.

1 You're saying that if you have
2 a collection of potential predictions, each
3 with a different probability score, that is
4 not a distribution, right?

5 A. That is correct.

6 Q. Okay. Now, let's -- let's look
7 at what's in the '344 patent at --

8 A. One, it's not a distribution;
9 and two, it's not a distribution of user
10 responses.

11 Q. Okay. Let's look at Column 3,
12 Lines 58 through 67, of the '344 patent.

13 A. Column 3, Lines 58 to 67.

14 Q. Yeah.

15 A. Okay.

16 Q. And at the bottom -- and so
17 this is the last three lines there. It says,
18 The overall collection of scores on the
19 continuum comprises a distribution of scores.

20 A. There he goes. Yeah, exactly.

21 Q. Okay. Now, how is a
22 distribution of those scores different from a

1 distribution of probabilities that we were
2 talking about in Ross?

3 A. You see, obviously this is
4 talking about -- so if you step back in that
5 paragraph, so let's just take a look at it
6 step by step.

7 He says -- you see it says
8 human observers are presented with small
9 samples of video data.

10 So think of -- think about you
11 have a hundred human observers. They're each
12 sitting at a monitor. And you presented each
13 of them with three frames of video, okay,
14 that have been modified to focus the
15 observers on aspects of the samples.

16 So you're not just giving them
17 a random frame, you're giving them a frame,
18 you're basically telling them, Look over
19 here.

20 Okay? So you're just --
21 they're not just randomly looking at the
22 frame.

1 ... on aspects of the samples
2 most likely to be relevant to predicting
3 pedestrian ...

4 So you're showing them three
5 frames of video and traffic, and you're
6 pointing them to the pedestrian in the video,
7 right? So it's not just everywhere. You
8 point them to the pedestrian in the video,
9 and you're basically saying what do you think
10 that person is going to do.

11 ... or other driver behavior,
12 and to eliminate aspects which are not
13 relevant to predicting such behavior.

14 So you want them focused on the
15 road user that you're interested in.

16 Now, large sets of observers
17 are asked to score the samples of video data
18 on a continuum, so now you're asking them to
19 give them a score on a continuum, do you
20 think, you know, he's going to go right, go
21 left, whatever, do some scoring.

22 And the overall collection of

1 scores under continuum now comprises a
2 distribution of scores. Because out of the
3 hundred, maybe five of them -- let's make
4 this up, let's say the scores are 1 through
5 10. Five of them maybe out of the hundred,
6 maybe 50 will pick the 5, and 10 will pick 1,
7 and 6 will pick 2 or whatever.

8 So as they're scoring this,
9 you're creating a distribution of scores. So
10 it's essentially you're creating a histogram.
11 And if, obviously, you divide by the hundred,
12 you get a probability histogram, which is
13 modeling the probability density function.

14 Q. So you say that 50 of them will
15 pick 5 and 10 will pick 1 and 6 will pick 2,
16 that -- that represents the probability of
17 picking those numbers?

18 A. Well, you're going to turn then
19 to a probability, right, because if I had a
20 hundred users looking at that image and 50
21 out of those hundred picked 5, let's just
22 say, so 50 percent -- 50 divided by a hundred

1 is .5, so 50 percent of them picked 5.

2 And then if 30 of the hundred
3 picked 2, then .3 picked 2.

4 So you -- you turn that into,
5 obviously, a probability density function.

6 Q. The '344 patent doesn't
7 describe turning this into a probability
8 distribution function, does it?

9 A. Well, you're talking about the
10 overall collection of scores on the continuum
11 comprises a distribution of scores, so now
12 you have a distribution of scores.

13 The parameters of distribution
14 are then used to construct the target,
15 et cetera.

16 So you're computing parameters
17 of that distribution. So you're going to
18 basically look at it, look at its mean, its
19 variances, its cross-variances, correlations,
20 et cetera.

21 And they mention some of that
22 later on in that paragraph we've been talking

1 about, the summary statistics. You know,
2 you're looking at central tendency, variance,
3 skew, kurtosis, scale, histogram, more
4 two-dimensional distribution.

5 I'm looking at Column 6, Lines
6 24, 26 -- 24, 25. Sorry.

7 Q. If we're -- if we're talking
8 about a hundred responses and -- we have a
9 hundred total responses, 50 score 10,
10 30 score a 1, 20 score a 3, the score of 10
11 with 50 responses would have a higher
12 likelihood value. Is that fair?

13 A. I'm sorry. I didn't understand
14 what you're saying.

15 Q. So I'm imagining a distribution
16 here. We've got 50 -- 50 people who put down
17 10, 30 who put down 1, and 20 who put down 3.
18 Those are the only responses we got.

19 A. Yes.

20 Q. And so the 50 who put down a 10
21 means that 10 has the -- the higher
22 likelihood value, right?

1 A. Generally speaking, yes, that's
2 the case.

3 Yeah. Obviously, I mean,
4 that's a simplified illustration, what we're
5 talking about here, but yes.

6 Q. If you don't mind, could you
7 pull up the Ogale reference, which is
8 Exhibit 14?

9 A. Ogale. This is -- let me see.
10 Ogale, yes, sir.

11 Q. And the Ogale reference and the
12 Ross reference are both assigned to Waymo,
13 right?

14 A. I assume so, yeah.

15 Q. I mean, it says on top up
16 there. It says the applicant is Waymo for
17 each of them?

18 A. Yes. Ogale and Ross. Let me
19 see what the Ross one says.

20 Yeah. They're assigned to
21 Waymo.

22 Q. And you would agree that both

1 of these are related to sensor -- sensor data
2 processing for autonomous vehicles?

3 A. Well, I mean, that's obviously
4 generally the idea that they're targeting.
5 You know, Ross is targeting, you know,
6 behavior intent estimation, and Ogale is more
7 about object detection.

8 Q. So let me direct you to
9 Column 3, Lines 24 through 27 in Ogale.

10 A. Of Ogale. Column 3, Lines 24
11 and 27.

12 Yes.

13 Q. Okay. And it says, The
14 plurality of output layers includes: a
15 human-labeled output layer that predicts how
16 a human would identify objects in the
17 projections of input sensor data.

18 And then it goes on to list
19 other layers.

20 Do you see that?

21 A. Yes.

22 Q. Is it fair to say that Ogale

1 discloses having a machine learning model for
2 self-driving that predicts how humans would
3 have labeled data?

4 A. I mean, generally speaking,
5 that's the idea. But, obviously, the devil
6 is in the details. But, yes, I mean, it kind
7 of -- plurality of output layers include a
8 human-labeled output layer that predicts how
9 a human would identify objects in the
10 projections of the input sensor data.

11 So that human label output
12 layer is going to try to predict if I were to
13 go into the sensor data and identify the
14 object, the idea here is would that layer
15 give me the same identification.

16 Q. Okay. Now -- well, I'll move
17 on.

18 Let's talk about the Cox
19 reference.

20 A. Cox.

21 Q. Which is Exhibit 12.

22 A. Yes, sir.

1 What about it?

2 Q. You see the cover, it lists the
3 inventors of the Cox reference.

4 Do you see that?

5 A. Yes, sir.

6 Q. And the third inventor is
7 Samuel Anthony.

8 You see that?

9 A. I see that.

10 Q. Have you met Mr. Anthony?

11 A. No, I have not.

12 Q. You understand that Mr. Anthony
13 is the inventor on the challenged patents?

14 A. Yes, sir.

15 Q. Okay. Did you ask Perceptive
16 if you could speak with Mr. Anthony?

17 A. No.

18 Q. Why not?

19 A. Didn't need to.

20 Q. You didn't think that he might
21 have had more information about the
22 references or the patents?

1 A. No, I can read -- I can read
2 the patents. I know enough -- I have enough
3 expertise and experience in this field. I
4 can read the patents, and I can read the
5 analysis by Tesla and Dr. Janet and render my
6 own objective opinions.

7 Q. Okay. I believe you've opined
8 that the Cox reference, in your view, is not
9 applicable to driverless or semiautonomous
10 automobiles; is that right?

11 A. Generally speaking, that's the
12 idea, yes.

13 Q. Okay. I would like to direct
14 you to Paragraph 56 of Cox which is on PDF
15 Page 28.

16 A. And are we talking about --
17 which declaration now?

18 Q. Sorry. This is Paragraph 56 of
19 Cox.

20 A. Okay. Yes, but are you talking
21 with -- which declaration you have in mind?
22 Do you -- are you --

1 Q. At this point, it is relevant
2 to all of them.

3 A. Okay.

4 Q. So Paragraph 56 says that,
5 Embodiments of the present invention may be
6 directly applied to several important
7 domains ...

8 Do you see that?

9 A. I'm looking, yes.

10 Q. And then toward the bottom, it
11 says at Line 24, Important application areas
12 may also benefit from embodiments of the
13 invention, including ...

14 And then towards the end it
15 says, ... driverless/semiautonomous
16 automobiles ... Right?

17 A. Yes, I see that sentence.

18 Q. Do you disagree with the
19 statement in Cox that it may be applied to
20 several important domains and driverless and
21 semiautonomous automobiles are included?

22 A. Well, you have to really take

1 this in the proper context. I mean, for
2 instance, when we write a paper, we -- we
3 describe all the details and technical
4 content, et cetera, that in the future
5 directions sometimes it will say, Well, you
6 can apply this in these other areas.

7 You know, because some of it is
8 a little bit of marketing, so to speak.

9 You know, say, Well, okay,
10 here's my invention, and I can apply in all
11 these different things.

12 Well, this is a little bit more
13 of, I would say, marketing somewhat or
14 stretching a bit. There is obviously no
15 technical descriptions of any kind that show
16 how you would apply this to -- in all these
17 different areas. I mean, if you're going to
18 tell me, Well, okay, if I'm an autonomous
19 application and I give you an image and I
20 want to know what the face in the image is,
21 that might be a possibility.

22 But if you were going to tell

1 me, I'm going to use Cox to do autonomous
2 driving, that's not going to work.

3 So some of this is a little bit
4 of hand-waving, as you would -- you know,
5 putting it in gentle terms, marketing and
6 hand-waving.

7 Q. But fair to say you disagree
8 with the statement in Cox that it's
9 applicable to driverless and semiautonomous
10 automobiles?

11 A. As I mentioned, I mean, this is
12 what I would call marketing and hand-waving.
13 There's no technical description of any kind.
14 And the technical description that they
15 provide, when you look at their hinge loss
16 function, the human-rated loss function in
17 the application does not support, you know,
18 the generic statement.

19 There's no technical
20 description of how you would do that.

21 Q. I understand your point that
22 there's not a technical description here.

1 But I just -- on the face do
2 you agree with the statement in Cox or not?

3 A. I mean, as I said to you, I
4 mean, if you were going to tell me, well, in
5 this autonomous or semiautonomous driving
6 application I'm looking to do face detection,
7 in this particular image my application
8 requires to do face detection, then perhaps
9 Cox is somewhat applicable.

10 But as a generic statement like
11 this, you know, to me, you're just basically
12 hand-waving and, you know, marketing.

13 I don't -- I don't see any
14 technical details or any rational
15 underpinnings of how you would put this into
16 this application and make it work. So you're
17 hand-waving.

18 Q. I think you did say that if
19 your driverless or semiautonomous automobiles
20 needed to have some facial detection or
21 emotional recognition, Cox would be
22 applicable to that, right?

1 A. I mean, I'm saying if,
2 hypothetically speaking, you were to tell me
3 I need to do this, I mean, in an autonomous
4 situation, you don't need to do that.

5 I don't need to know where the
6 face is. I need to know where the pedestrian
7 is, or I don't care where the face is. I
8 just need to know they're here so I don't hit
9 them with the autonomous driving vehicle.

10 So the application isn't
11 typically concerned with face, because a lot
12 of times you can't see the face. The guy is
13 walking away from you. He's walking on the
14 side of the road away from you. You can't
15 see the face.

16 So this is just what I would
17 call flexible -- putting it in gentle terms,
18 flexible hand-waving and marketing.

19 There's no supporting evidence
20 of any kind that would show how this would be
21 directly applicable. Cox doesn't provide
22 anything that shows that.

1 Q. I know you're -- you're working
2 hard not to say you disagree with it, but
3 it's fair to say you kind of disagree with
4 it?

5 MR. GINNINGS: Objection to
6 form. Argumentative.

7 A. Well, I mean, like, look and
8 see what it says. In the discipline of human
9 biometrics, embodiments of the invention may
10 be applied to fingerprint verification,
11 fingerprint identification.

12 I -- I mean, there's a whole
13 collection of stuff that all have different
14 algorithms of how you would do this.

15 If this is the case where I
16 could solve all of these, my god, I'd adopt
17 this right away and have them do all the
18 stuff.

19 I mean, you know, again,
20 you're -- to me, you're just marketing and
21 hand-waving. You have no supporting
22 technical discussions or evidence of any kind

1 to show any of this works in any of these
2 applications.

3 (BY MR. SPEEGLE)

4 Q. Okay. Let's look at the end of
5 Paragraph 16, so this is on PDF Page 11 of
6 Cox. I'm looking at the last sentence.

7 A. Paragraph 16 of Cox, last
8 sentence, yes. Finally -- the sentence that
9 starts with "finally," correct?

10 Q. Correct. Do you want to read
11 that for the record?

12 A. Yeah. Cox says that finally in
13 application 145, which let me see what --
14 give me one moment here. I just want to see
15 what 145 is.

16 Okay. So if you look at
17 Figure 1A, they have object recognition as
18 145.

19 So, finally, in application
20 145, the system may be utilized to recognize
21 various other objects and images as shown.
22 The system may identify objects such as a

1 tree, a car, a bus, a building, and a street
2 in a given image.

3 Q. Would you agree with me that
4 it's relevant to self-driving cars to
5 identify objects such as a tree, a car, a
6 bus, a building, and a street?

7 A. I would agree that in
8 autonomous driving situations that would be
9 relevant. I don't agree that Cox has such an
10 algorithm that would do all this.

11 You would have to show me the
12 technical details of that. You've only
13 showed that you can do face detection with
14 it.

15 You haven't showed that you can
16 do all these other things. And they're
17 completely different from face detection.

18 I mean, faces have a certain
19 symmetry to them. Right? Your face -- if
20 you look in the mirror, there's a certain
21 symmetry. Your eyes aren't just randomly
22 located in your face. There's a certain

1 symmetry to the face that is very different.

2 Trees are completely different.

3 There's skinny trees. There's big trees.

4 There's tall trees. There's, you know,
5 different variety of branches and stuff.

6 You haven't really shown any of
7 that. That's just, again, I would say
8 hand-waving and marketing.

9 Q. Even though Cox says that's
10 applicable to driverless cars and even though
11 the inventor on Cox went on to start a
12 self-driving car startup and even though Cox
13 says that it can be used to identify things
14 like cars and buses and streets, you don't
15 think Cox is relevant to self-driving cars?

16 MR. GINNINGS: Objection to
17 form. Argumentative.

18 A. What I'm telling you is in this
19 reference that I have analyzed, Cox provides
20 no technical details to support any of these
21 statements to show that it would work in any
22 of these scenarios or how you would make that

1 happen. To me, that's just marketing and
2 hand-waving.

3 Because these things are very
4 different. Like a car is a very rigid
5 structure, like they're not flexible.

6 A tree is very flexible. A
7 tree waves in the wind. Right? They have
8 all different configurations, much more
9 difficult to recognize than, say, a car or a
10 bus or a building. Buildings have different,
11 you know, size, different poses.

12 So they're a lot different than
13 just a face on -- like if you look at the Cox
14 system, for instance, you'll see Figure 1A
15 and element 110.

16 You see you're looking straight
17 at a face. You're looking directly at the
18 frontal view of a face. That's very
19 different than a side view of an object on
20 the road with different, you know, perception
21 or different perspective.

22 So -- but I think that's just

1 hand-waving and marketing. There's no
2 technical support of any kind that tells me
3 how you would do that on these other objects.

4 (BY MR. SPEEGLE)

5 Q. All right. I want to ask you
6 about Paragraph 73 of your '046 declaration.
7 Could you get that in front of you?

8 A. Paragraph 73 of the '046 dec?

9 Q. Correct.

10 A. Yes, sir.

11 Q. Okay. And in Paragraph 73, you
12 say that -- in the last sentence, Nowhere
13 does -- I'm sorry, let me back up.

14 This is the second sentence.
15 It says, Instead, the images described in Cox
16 are of faces, and nowhere does Cox teach that
17 those faces are those of a road user (e.g., a
18 motorist, bicyclist, or pedestrian).

19 Did I read that right?

20 A. You read that correctly.

21 Q. How do you square that position
22 with what we just read in Paragraph 16 of Cox

1 that says the identified objects can be
2 motorists?

3 A. I'm sorry, you -- I missed
4 something. Say it again.

5 Q. Well, I'm just trying to -- I'm
6 trying to square what you -- what you say
7 here in Paragraph 73, that nowhere does Cox
8 teach that those faces are those of a road
9 user, e.g., a motorist, bicyclist, or
10 pedestrian, with what's in Cox that we read
11 at the end of Paragraph 16, that the system
12 may be utilized to recognize other objects
13 such as a tree, a car, a bus, a building, and
14 a street?

15 A. Like I told you, I mean, you
16 know, authors do this all the time in papers
17 and they probably do it all the time in
18 patents.

19 I've seen many patents in my
20 time. I've been doing consulting for
21 probably -- I don't know -- 20 years. I've
22 seen many patents in my time where they say

1 things. You know, saying it doesn't mean it
2 is.

3 It's like I told you, there's
4 nothing in Cox that describes how you would
5 take a frontal view face recognition system
6 like you would see in Cox and put it into
7 a -- I mean, look at the size of the faces
8 that you see in Cox in the imagery that Cox
9 provides.

10 If you look at the size of the
11 faces, they're very large. That's distinctly
12 different from an application where you're
13 doing autonomous driving where the face is
14 going to be a few pixels in a frame of video.

15 So assuming I'm driving down
16 the road and there's a person walking down
17 the street and that person is ten meters away
18 from me or whatever.

19 How big do you think that face
20 in the frame of my image is going to be? Few
21 pixels in the whole frame. Very different
22 from what Cox is talking about here.

1 So there's nothing technically
2 in Cox that tells me that what Cox is doing
3 is directly lift and drop into an autonomous
4 situation -- autonomous driving situation.

5 Q. Well, just to -- just to press
6 on that a little bit, if you look at -- let's
7 say -- this is Page 42 of Cox, which has
8 Figure 6.

9 A. Page 42 of Cox. Hang on a
10 second. PDF Page 42?

11 Q. Yes.

12 A. Yeah.

13 Q. And --

14 A. You see the size of the face?

15 Q. Yes.

16 And I believe what you were
17 just saying is that in self-driving
18 applications, for pedestrians the images of
19 faces are going to be very small and hard to
20 distinguish, right?

21 A. Well, do -- do this tonight
22 while -- while you're preparing for tomorrow.

1 Go out on the road, get in your car. As
2 you're driving down the street and when you
3 see a pedestrian, just take a picture with
4 your phone. Take a picture of that person
5 with your phone. Just stop the car for a
6 minute and take a picture.

7 And when you look at the
8 picture, tell me how many pixels do you think
9 that face is. Is it going to be the majority
10 of the image or a few? I would say you're
11 probably looking at 2 percent of the image,
12 if that.

13 Q. So is it fair to say that the
14 image quality for faces in this context would
15 be particularly low quality?

16 A. One, it may be low quality.
17 But it's not as much as the quality as it is
18 the size of the imagery as well.

19 Q. Yeah.

20 A. So if you're looking at a face
21 that's only, let's say -- of an image of,
22 let's say, 512 by 512, the face occupies a

1 12-by-12 block, that is a very small portion
2 of the image and a much more difficult
3 application to recognize the face than if the
4 face occupied 90 percent of the image, like
5 you'd see here in, let's say, number 600.

6 Q. Am I -- am I interpreting
7 figures 6A and 6B correctly to -- to convey
8 that the method in Cox is advantageous for
9 identifying pictures of faces with low
10 coherence or visibility?

11 A. With large -- one large -- you
12 know, the face is very large in the image.
13 So that -- that's a totally different
14 application than you would see in an
15 autonomous driving situation.

16 Like pure autonomously driving
17 down the road, you're not going to see a
18 coherence of .6 and .4. You know, you're not
19 going to see that. I mean, the camera you're
20 going to have on your vehicle isn't going to
21 have that kind of low quality.

22 If that's the case, your

1 vehicle isn't going to drive very far. So
2 you're not going to have that kind of low
3 quality.

4 What you're going to have is a
5 lot smaller face in the image.

6 And you're not trying to
7 recognize the face anyway. All you want to
8 know is there's a pedestrian there.

9 You know, when you're driving
10 down the road, you don't recognize faces.
11 You're not looking at faces of people. All
12 you care about is there's a pedestrian
13 walking down the road, I just don't want to
14 hit that person. You don't care what their
15 face is.

16 You know, and that could be
17 walking away from you, you can't see the face
18 at all, right?

19 If I'm a cyclist, like I do a
20 lot of cycling, I'm riding on the shoulder of
21 the road in the same direction of traffic.
22 You never see my face. I've got glasses on.

1 I've got a helmet on. You can't see my face
2 at all. All you care about is I'm a cyclist
3 on the shoulder, therefore you can't bring
4 your car on the shoulder. You know, they'll
5 avoid me.

6 It's totally different
7 applications.

8 Q. All right. We've been going
9 over an hour. I know that we are getting
10 towards the end of the time for today, so why
11 don't we take another break here, and then
12 we'll see what we got left for the day.

13 THE WITNESS: Fantastic.

14 (Break from 2:33 p.m. to 2:41 p.m.)

15 (BY MR. SPEEGLE)

16 Q. All right. Dr. Saber, let's go
17 look at Paragraph 76 of your -- well, sorry,
18 77 of your '046 declaration.

19 A. '046 declaration.

20 Q. Yes.

21 A. Paragraph 77.

22 Q. Yes.

1 Let me know when you have that
2 in front of you.

3 A. Yes, sir, that's the one about
4 psychometric data.

5 Q. Correct.

6 A. Okay. Yeah.

7 Q. I'm going to read the third
8 sentence there for the record.

9 Instead, as Cox makes clear,
10 its psychometric data, ... may include or
11 consist essentially of (i) response time for
12 classifying one or more features, (ii)
13 accuracy of feature classification, and/or
14 (iii) presentation time of one or more
15 training objects.

16 Do you see that?

17 A. You read it correctly.

18 Q. Then a couple of sentences
19 later you say, Likewise, the accuracy of the
20 feature classification by the annotator does
21 not describe the state of mind of any user in
22 the image, but is instead of a measure of the

1 correctness of the annotator's
2 classification.

3 You see that?

4 A. You read that correctly.

5 Q. Now, when I read "accuracy of
6 feature classification," that, to me, does
7 reflect what the correct classification is,
8 right?

9 A. So if, for instance, the
10 annotator selects this and says, This is a
11 cyclist, right? So you have an accuracy of
12 feature classification.

13 Or this is -- let's say I'm
14 doing face -- face detection, this is -- the
15 nose is a feature. I select the nose and
16 say, Here's where the nose is in the image.

17 That's an accuracy of feature
18 classification.

19 That doesn't describe the state
20 of mind of the road user that's in the image.

21 Q. Sure. What if the
22 classification was angry?

1 A. Still doesn't describe the
2 state of mind of the user. I mean, you have
3 to think about the application. The road
4 user -- the autonomous application is about
5 determining the context of these road users,
6 right? As I'm driving my car, I'm trying to
7 determine if that cyclist is going to jump in
8 front of me or not.

9 So --

10 Q. Your interpretation of state of
11 mind of the user in claims of the '046 patent
12 requires it to describe possible actions of a
13 road user?

14 A. Well, you're describing -- so
15 if you look at the '046, right, I'm
16 generating summary statistics that describe
17 the state of mind of the user in the image
18 based on the received responses.

19 So the -- the generating
20 here -- so I'm looking at 1[b-iii] of 1[b],
21 so 1[b] is generating training data from
22 plurality of images, the generating

1 comprising for each image.

2 So how this is generated is --
3 and then it explains. You're sending the
4 image, you're receiving, you're generating,
5 you're storing.

6 So you're generating summary
7 statistics that describe the state of mind of
8 the user. So you're not generating a
9 classification, you're generating summary
10 statistics that describe the state of mind of
11 the user in the image.

12 Q. And Cox suggests that there's
13 psychometric data that describes how
14 accurately the state of mind of users in the
15 image was described, right?

16 A. No, that's not correct. That's
17 not what the psychometric data is talking
18 about.

19 Q. So when Cox -- when Cox talks
20 about the accuracy of --

21 A. That's just --

22 Q. -- feature classification, what

1 does that mean to you?

2 A. So if -- if a user is going
3 into an image and selecting, let's say, nose,
4 okay, or selecting eye, so that's an accuracy
5 of feature classification. That is not the
6 same thing as summary statistics that
7 describe the state of mind of a road user.

8 Q. You understand the feature
9 classifications in Cox can include emotions,
10 right?

11 A. Well, I mean, Cox mentions
12 that. But, again, doesn't -- there's no
13 technical description in Cox of any of them.

14 All that Cox talked about is
15 face/no face classification. And if you look
16 at the equations that Cox is proposing and
17 use of the hinge loss functions and
18 et cetera, those are directed to face/no face
19 classification. It doesn't show any other
20 details technically of how you do these other
21 things.

22 Q. Even if it doesn't have the

1 technical details, it still says it can
2 identify emotions, right?

3 A. It -- it says that. But,
4 again, that's -- that's not the same thing as
5 statistical summary of the state of mind of
6 the road user in autonomous application.
7 It's entirely different.

8 Q. You're basing that on the fact
9 that Cox does not have what you consider
10 sufficient technical detail about the
11 identification of emotions?

12 A. Well, first of all, it's a
13 different concept completely.

14 And, second of all, Cox doesn't
15 have any technical details to show any of
16 that.

17 And when you look at Cox
18 equations, they don't support that.

19 Like, you know, your hinge loss
20 equation for instance, if you go to Cox and
21 look at -- go to Paragraph 35 of Cox. So if
22 you go to Paragraph 35 of Cox, so if you look

1 at that paragraph where it starts on
2 Page 19 -- PDF on Page 19 at the bottom,
3 that's my exhibit, I guess, Page 19 or
4 whatever.

5 So you see Cox is describing
6 his equations, and he says, One component --
7 so I'm at the bottom of Page 19.

8 One component of a
9 human-regularized maximum-margin kernel
10 machine is the addressing of the issue of the
11 loss function.

12 And he goes on to the next page
13 and describes the loss function.

14 And you see this is embodied by
15 the hinge loss function which is defined as
16 $\phi(z)$ is equal maximum $(0, 1-z)$.

17 Do you see that?

18 Q. Yeah.

19 A. Okay. That loss function is a
20 binary loss function. That loss function
21 doesn't work on emotions and other stuff,
22 which are -- that's his binary set of loss

1 function.

2 Because if you look at it --
3 and I can explain that to you, if you want.
4 Look --

5 Q. Well, let me just pause you
6 there real quick. And I just want to
7 reference what you said, was it has to be
8 binary.

9 And Cox describes a potential
10 binary emotional description, right?

11 MR. GINNINGS: Objection to
12 form.

13 (BY MR. SPEEGLE)

14 Q. Let's look at Paragraph 49 of
15 Cox, and I'll ask that question again.

16 A. Okay. What's Paragraph 49?

17 Q. Well, the -- the second
18 sentence of -- sorry -- the third sentence of
19 Paragraph 49 says, For instance, considering
20 the human face, it may be said that a woman
21 is beautiful, a man has black hair, or an
22 emotional state may be described as happy or

1 sad.

2 A. Yes.

3 Q. So you could -- you could use
4 the equation you just talked about to binary
5 separate things into happy and sad?

6 A. If you define it that way. But
7 the point I'm telling you is these equations
8 are limited to only binary classifications.

9 They wouldn't work in an
10 autonomous condition where you're talking
11 about summary statistics that describe a
12 state of mind of road users are not
13 necessarily binary.

14 Q. Okay.

15 A. Most likely not binary.

16 Q. Is the -- is the reason that
17 you don't think Cox discloses
18 element 1[b-iii] based on the fact that you
19 don't think Cox is applicable to autonomous
20 driving?

21 MR. GINNINGS: Objection to
22 form.

1 A. I mean, the equations that Cox
2 describes, if you look at a technical
3 description like that loss function I just
4 pointed you to, the hinge loss function,
5 that's designed for a binary type style
6 classification.

7 So if you look at $1 - Z$,
8 where Z is defined as Y times F of X , Y is
9 the ideal label plus 1 or minus 1 versus F of
10 X is the predicted output that the model is
11 going to predict.

12 And if the predicted output is
13 not the same as your label, then obviously
14 you get the minus 1 versus you get a plus 1.

15 So this is designed for a
16 binary style classification. A woman is
17 beautiful is not a binary style
18 classification.

19 So there are different levels
20 of potentially beauty, I would assume. So
21 that's not a binary style classification.

22 A man has black hair, I can

1 tell you over the last 20 years, the -- that
2 the evolution of my hair has changed
3 significantly. And that's also not a binary
4 classification.

5 Happy or sad is also not a
6 binary classification because, you know,
7 there's different levels of happiness and, I
8 would assume, sadness.

9 (BY MR. SPEEGLE)

10 Q. But you could set up a
11 classification model just to distinguish
12 between happy and sad, right?

13 MR. GINNINGS: Objection; form.

14 A. I mean, you -- you could set
15 something up, I would presume, but the point
16 is none of that would be relevant in the
17 autonomous driving situation because you
18 don't care whether the pedestrian is happy or
19 sad. You care about whether they're going to
20 go in the road or not.

21 (BY MR. SPEEGLE)

22 Q. So let me ask you a question.

1 I know you've opined that Cox -- or sorry,
2 strike that.

3 You've opined that the '046
4 patent should be limited to road users even
5 though the term "road users" is not used in
6 the claim, right?

7 A. Well, again, as I said to you
8 earlier in the morning when we talked about
9 this, you read the claim in light of the
10 specification, the prosecution history,
11 et cetera.

12 So when you read the claim,
13 it's clearly talking about a road user, not
14 just any generic thing. That's why the
15 construction was offered.

16 Q. I understand your position.
17 But if -- if -- let's say the -- the Patent
18 Office disagrees with you and the '046 patent
19 is not limited to autonomous driving
20 applications.

21 Would that change your opinion
22 about whether Cox discloses element 1[b-iii]

1 that we're talking about?

2 A. With all my due respect to the
3 Patent Office, that would not change my
4 position because I understand this
5 technology.

6 I -- you know, I've been
7 working in this field for years, probably
8 more so than anybody in the Patent Office, I
9 would assume.

10 And I -- you know, I've got a
11 lot of experience in both developing products
12 or algorithms as well as teaching and
13 developing coursework on this. I know this
14 technology.

15 Q. I'm sorry, I'm -- I'm not
16 trying to ask if you would change your
17 position and agree with the Patent Office.

18 I'm asking that if you assume
19 there was a legal determination made that the
20 patent is -- the '046 claims are not limited
21 to autonomous driving, you know, with that
22 assumption, do you have any arguments that

1 Cox still does not disclose element 1[b-iii]?

2 MR. GINNINGS: Objection to
3 form.

4 A. I mean, again, you're starting
5 to deal here in hypotheticals, and I don't
6 really like to deal in hypotheticals. So if
7 somehow some -- somehow somebody comes back
8 to me and says, Well, this is what the Patent
9 Office has defined user to be, blah blah
10 blah, and give me an exact definition of what
11 exactly they're talking about, I'll be happy
12 to sit down and do an analysis.

13 But I have to see the details.
14 I have to sit down, understand what they're
15 saying, why they're saying it, what's the
16 logic behind it. It's not just off-the-cuff
17 analysis.

18 (BY MR. SPEEGLE)

19 Q. Okay.

20 A. Reading the claims as they
21 stand today, it's -- to me, it's clear --
22 clear that they're talking about a road user.

1 Q. Okay. And you haven't done any
2 of the analysis you just discussed about
3 whether or not Cox would be applicable to the
4 '046 claim 1 in a scenario where the '046
5 claim 1 is not limited to road users. Fair?

6 MR. GINNINGS: Objection to
7 form.

8 A. I mean, I analyzed, obviously,
9 the claim based on reading the claim in light
10 of the specification, prosecution history,
11 et cetera, and rendered my opinions. And
12 that's what I stand behind.

13 (BY MR. SPEEGLE)

14 Q. Fair enough.

15 Okay. Would you agree with me
16 that an emotion is a state of mind?

17 MR. GINNINGS: Objection to
18 form.

19 A. Well, I mean, generic but
20 it's -- it's entirely different from what
21 we're talking about here for autonomous
22 driving.

1 So a state of mind of whether
2 I'm happy or sad is a very different
3 situation and different potential actions
4 from a pedestrian walking down the road and
5 is going to, you know, step into the
6 crosswalk, you know, randomly or something.

7 So, you know, there's -- I
8 mean, there -- technically there -- things
9 are very specific. It's not just, you know,
10 if it applies here, it applies there.

11 (BY MR. SPEEGLE)

12 Q. So you don't think we're
13 applying the plain and ordinary meaning of
14 state of mind in this case?

15 MR. GINNINGS: Objection to
16 form.

17 A. Well, again, if you look at the
18 '046 and you look at how the claims are
19 structured, you see it says generating
20 summary statistics describing the state of
21 mind of the user, which is via claim
22 construction road user, any image based on

1 the received responses from the plurality of
2 human observers.

3 So the summary statistics are
4 not describing the emotion on the face of the
5 user. They're describing the state of mind
6 of the road user in the image.

7 So that's what they're
8 describing. That's an entirely different
9 situation than me looking at a user and
10 describing whether they are smiling or, you
11 know, happy or sad.

12 (BY MR. SPEEGLE)

13 Q. So you don't think it's the
14 plain ordinary meaning of state of mind that
15 we're applying in the '046 patent?

16 MR. GINNINGS: Objection to
17 form.

18 A. I think I just answered your
19 question, but I'm more than happy to answer
20 it again.

21 See, if you look at the
22 claim con- -- the claim of the '046, it

1 clearly says, you know, my plain ordinary
2 meaning of that, generating summary
3 statistics.

4 So you have to generate summary
5 statistics. Not generating something else.
6 I'm generating -- not a classification. I'm
7 generating summary statistics that describe
8 the state of mind of the road user.

9 So if you look at my
10 construction and if you replace the word
11 "user" with "road user," so I'm describing --
12 the summary statistic is describing the state
13 of mind of the road user in the image.

14 (BY MR. SPEEGLE)

15 Q. Can you explain for me what the
16 phrase "describing the state of mind of a
17 road user" means to you?

18 A. Well, if you have to go back in
19 the patent and -- so if you go in the patent
20 and just search on state of mind...

21 So if you look at the '046 --
22 and I think you pointed to this earlier

1 yourself -- Column 10, Lines 34 to, say, 53,
2 you see somewhere -- Line 36, 37, you see it
3 says, This value may refer to the probability
4 of the pictured human road user has a given
5 state of mind, e.g., that a pedestrian is
6 likely to cross the street or that an
7 oncoming vehicle is likely to be willing to
8 yield to the vehicle containing the sensor,
9 et cetera.

10 So you're looking at
11 basically -- I mean, think about the
12 application here, right? I'm driving -- I'm
13 the autonomous vehicle going down the road.
14 I see a cyclist and I see a pedestrian and I
15 see an oncoming vehicle. I don't care
16 whether the pedestrian -- the pedestrian is
17 laughing or not, I just need to know are they
18 going to step in the street in front of me or
19 are they going to continue going where
20 they're going.

21 But if a pedestrian is standing
22 at the beginning of a crosswalk, are they

1 going to start to walk across the crosswalk
2 where I have to stop, or are they going to
3 stay there until my vehicle goes past?

4 So that's what I'm looking for
5 as an autonomous driver in the '046.

6 Q. So it sounds like some number
7 that qualifies as a summary statistic would
8 describe a state of mind of a road user if it
9 says how likely a pedestrian is to cross the
10 street. Is that fair?

11 A. However you quantify it, but
12 that's the idea is I want to know, you
13 know -- if you look -- if you read Lines 38,
14 you know, e.g., that a pedestrian is likely
15 to cross the street.

16 So let's say I see a pedestrian
17 at the top of a crosswalk, would that
18 pedestrian start walking across as I'm coming
19 down at 40 miles an hour, or are they going
20 to wait for me to go by?

21 Or the oncoming vehicle is
22 likely to -- you know, is likely to be

1 willing to yield to the vehicle coming --
2 containing the sensor.

3 So the oncoming vehicle is
4 coming, is it going to turn left in front of
5 me, or is it going to stop and wait for me to
6 go by?

7 That's the state of mind
8 that -- that the autonomous vehicle of the
9 '046 is trying to predict.

10 It doesn't care whether the
11 driver in the vehicle is smiling.

12 Q. Would you agree with me that's
13 a different interpretation of the phrase
14 "state of mind" than what a layperson on the
15 street might think?

16 A. Well, as I explained to you
17 earlier, and I think we've talked about this
18 a few times now, words mean different things
19 in a sentence.

20 So if I told you "bank," you
21 don't know whether I'm talking about an
22 institution where I deposit money or I'm

1 talking about the snow bank.

2 So it's not just the word by
3 itself. It's how is it read in the context
4 of what's being described.

5 So when you read the claim,
6 you're going to read the claim in light of
7 the specification. Otherwise, why have the
8 specification. Just have the claim.

9 Q. I'm certainly not criticizing
10 you for reading the specification.

11 I'm just asking in terms of the
12 word "state of mind," the meaning that you've
13 described here with reference to Column 10 is
14 different than I think if you went across the
15 street and just asked somebody at a coffee
16 shop what state of mind means, right?

17 MR. GINNINGS: Objection to
18 form.

19 A. I mean, clearly, you have to
20 read this in light -- I mean, you have to
21 read those claims and the claim elements and
22 write -- in light of the specification

1 that's -- that we have in front of us.

2 Just like if the word "bank"
3 appeared here, you would have to say, Okay,
4 is that -- is that a financial institution or
5 is that a snow bank or is that a river bank?
6 So you would have to look at the
7 specification and say, Okay, which one of
8 those three am I talking about?

9 If I just talk walked on the
10 street and said "bank," most people would
11 probably think about a -- a financial
12 institution, not necessarily a snow bank.

13 If you're in Texas, you
14 probably wouldn't think of a snow bank at
15 all, right?

16 (BY MR. SPEEGLE)

17 Q. I haven't seen a snow bank in a
18 long time.

19 A. Right. So -- exactly so...

20 Q. Okay. So I just want to be
21 clear here. When you say you're applying the
22 plain and ordinary meaning of the claims in

1 the '046, it's not the plain and ordinary
2 meaning like a person on the street would
3 think when you say these words, it's the
4 plain and ordinary meaning of a person of
5 ordinary skill in the art having read the
6 specification?

7 A. Yes, I mean, I'm looking at it
8 from the lens of a POSITA, not grabbing
9 generic John Doe on the street. I mean --

10 Q. Yeah. And those -- those
11 meanings are different, right?

12 A. Well, I mean, I'm looking at it
13 from the lens of a POSITA, a POSITA reading
14 this claim and reading the specification,
15 what would that POSITA interpretation mean.

16 Q. And that -- that answer is
17 different from what a person on the street
18 who might think happy as a state of mind
19 would think, right?

20 A. You know, it's irrelevant what
21 a person on the street thinks. I mean, you
22 analyze this, that's why we have a definition

1 of a POSITA, right? You put a definition of
2 a POSITA there to say, Okay, here's what I
3 expect a person ordinary skill in the art
4 looking at this to have.

5 That, for instance, you don't
6 see the definition says have a degree in
7 nursing or -- or a degree in psychology,
8 right? Because they wouldn't be a person of
9 ordinary skill in this art if they had a
10 degree in nursing.

11 So it has to be a person of
12 ordinary skill in the art, which -- which was
13 defined here as somebody that has a degree in
14 engineering or computer science, that has a
15 technical background and certain amount of
16 experience. It's not just a John Doe from
17 the street.

18 Q. All right. I know I've got a
19 little bit more time today, but I think I'm
20 going to wrap up for the day here anyway.

21 Before -- before I finish out,
22 Dr. Saber, is there anything from your

1 testimony today that you would like to change
2 or correct?

3 A. No, sir.

4 Q. Okay. And during the breaks
5 today, did you discuss the substance of your
6 testimony with anyone?

7 A. No, sir.

8 Q. Okay.

9 MR. SPEEGLE: Austin, I assume
10 you'll do redirect, if any, tomorrow?

11 MR. GINNINGS: Yeah.

12 MR. SPEEGLE: Okay. All right.
13 Well, I think we can go off the
14 record.

15 And, Mendy, if you want to give
16 us the final count from the day, we'll
17 be ready to start again tomorrow.

18 (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
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DR. ELI SABER, PH.D., VOLUME I

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

1 UNITED STATES PATENT AND TRADEMARK OFFICE

2
3 BEFORE THE PATENT TRIAL AND APPEAL BOARD

4 TESLA, INC.

5 Petitioner,

6 v.

7 PERCEPTIVE AUTOMATA LLC

8 Patent Owner.

9
10 Case No. IPR2025-01573
Patent 10,614,344

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

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

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

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

17 CERTIFICATE OF SHORTHAND REPORTER

18 I, Mendy A. Schneider Certified
19 Reporter within and for the State of Texas,
20 do hereby certify:

21 That DR. ELI SABER, PH.D., the
22 witness whose deposition is hereinbefore set

1 forth, was duly sworn by me before the
2 commencement of such deposition and that such
3 deposition was taken before me and is a true
4 record of the testimony given by such
5 witness.

6 I further certify that the adverse
7 party, PERCEPTIVE AUTOMATA LLC, was
8 represented by counsel at the deposition.

9 I further certify that the deposition
10 of DR. ELI SABER, PH.D., occurred remotely on
11 11th of August 2026, commencing at 8:09 a.m.
12 to 3:07 p.m.

13 I further certify the inspection,
14 reading and signing of said deposition was
15 not waived on the record by agreement of all
16 parties.

17 I further certify that I am not related
18 to any of the parties to this action by blood
19 or marriage, I am not employed by or an
20 attorney to any of the parties to this
21 action, and that I am in no way interested,
22 financially or otherwise, in the outcome of

1 this matter.

2 IN WITNESS WHEREOF, I have hereunto set
3 my hand this on the 21st of August, 2026.

4
5 *Mendy A. Schneider*
6 MENDY A. SCHNEIDER, CSR, RPR
7 Certification No.: 7761
8 Expiration Date: 1-31-2027
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