

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

3
4 MICROSOFT CORPORATION,

5 Petitioner,

6 v.

7 REALD SPARK, LLC,

8 Patent Owner.
9

10 Case IPR2023-01046

11 Patent No. 10,740,985
12

13
14 VIRTUAL VIDEOCONFERENCE DEPOSITION OF
15 ELI SABER, PH.D., VOLUME I
16

17 Wednesday, June 5, 2024

18 Remotely Testifying from Webster, New York
19

20
21
22 Stenographically Reported By:

23 Hanna Kim, CLR, CSR No. 13083

24 Job No. 6730451
25

Page 1

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14

15 Virtual videoconference deposition of ELI
16 SABER, PH.D., Volume I, taken on behalf of the
17 Petitioner, on Wednesday, June 5, 2024, remotely
18 testifying from Webster, New York, upon the
19 stipulations of counsel thereof, before Hanna Kim,
20 CLR, Certified Shorthand Reporter, No. 13083.
21
22
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25

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(IPR Exhibits were not attached and included in the transcript per instruction of Counsel.)

1 Remotely Testifying from Webster, New York

2 Wednesday, June 5, 2024

3 8:01 a.m., Eastern Daylight Time

4 --000--

5
6 ELI SABER, PH.D.,

7 having been duly administered an oath over
8 videoconference as stipulated by all counsel, was
9 examined and testified as follows:

10
11 EXAMINATION

12 BY MR. STEIN:

13 Q. Okay. Good morning, Dr. Saber.

14 A. Good morning to you.

15 Q. So I think you know this, but I'll go
16 through a little bit of the framework for the
17 deposition. And so just bear with me for a couple
18 sort of default questions.

19 A. Sure.

20 Q. We're here today to discuss your testimony
21 in IPR2023-01046.

22 Is that -- is that your understanding?

23 A. That is my understanding.

24 Q. And just to keep things easy, is it okay
25 with you if I just refer to that by the shorthand of

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1 "the IPR" or "the proceeding"?

2 Is that okay with you?

3 A. That would be fine.

4 Q. Okay. And the -- the patent that we're
5 discussing today, that's U.S. Patent Number
6 10,740,985. And, again, just to kind of keep things
7 simple, if I just call that "the '985 patent" or
8 "the patent," will you -- will you know what I'm
9 referring to?

10 A. I will.

11 Q. Okay. And today I'm -- I'm here
12 representing the Petitioner Microsoft in the IPR.

13 Do you understand that?

14 A. I do.

15 Q. And even though you're testifying
16 virtually today, do you understand that the
17 testimony you give under oath here is subject to the
18 same penalty of perjury as if you were testifying in
19 a courtroom?

20 A. I understand that, yes.

21 Q. And are you -- are you in your home? Are
22 you in an office? Where -- where are you today?

23 A. I'm in my home office.

24 Q. Okay. I will assume that you understand
25 each of the questions I ask, unless you explicitly

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1 tell me otherwise.

2 Is that -- is that fair?

3 A. That's fair.

4 Q. And is -- is there anything that would
5 prevent you from thinking clearly and testifying
6 truthfully today?

7 A. No.

8 Q. Okay. And in terms of sort of breaking up
9 the questioning, because I know it can get to be a
10 long day, is it okay with you -- we'll -- we'll try
11 about once an hour, but if we're sort of in the
12 middle of a line of questioning, hopefully we can go
13 a little bit over, but -- but just let me know. I
14 don't -- I don't want to go too long if you -- if
15 you want to break.

16 A. That would be fine.

17 Q. Okay. And you -- you also understand that
18 you're not to discuss your testimony with counsel
19 during breaks; is that right?

20 A. I -- I understand that, yes.

21 Q. Okay. And in this proceeding, the IPR,
22 you've submitted more than one declaration; is
23 that -- is that right?

24 A. That is correct.

25 Q. And the first one, that would be

1 Exhibit 2001, and the second one, that's
2 Exhibit 2008.

3 Is that right?

4 A. I'm assuming you're right, yes.

5 (Previously marked IPR Exhibit 2001 was
6 referenced.)

7 (Previously marked IPR Exhibit 2008 was
8 referenced.)

9 BY MR. STEIN:

10 Q. Okay. Do -- do you have copies of those
11 declarations in front of you?

12 A. I have -- yes, I have copies.

13 Q. So what -- what are the exhibit numbers
14 that you have on them?

15 A. The first one says RealD Exhibit 2001.
16 The second one actually doesn't have an exhibit
17 number on it, but I assume you are correct. It's
18 2000- -- it's -- it's 2008.

19 (Interruption in audio/video.)

20 THE COURT REPORTER: I didn't hear the
21 last number, Dr. Saber.

22 THE WITNESS: It's 2000- -- it's Exhibit
23 2008.

24 THE COURT REPORTER: Counsel, may we go
25 off the record real quick for a quick audio

1 adjustment?

2 MR. STEIN: Sure.

3 MS. MAURI: Yes.

4 (Off the record.)

5 MR. STEIN: Let's go.

6 BY MR. STEIN:

7 Q. Okay. So, Dr. Saber, you also told me
8 that you're in your home office today; is that
9 correct?

10 A. That is correct.

11 Q. Is there anyone in the room with you
12 today?

13 A. No, there is not.

14 Q. And you said that you have some materials
15 with you, so whi- -- which materials do you have in
16 the room with you?

17 A. Counsel has sent me binders of all the
18 exhibits in this particular case. I have the
19 declarations in front of me.

20 Q. Do you have any handwritten notes on those
21 materials that you have in the room with you?

22 A. No, I do not. They're clean copies.

23 Q. Okay. And did you spend time preparing
24 for today's deposition?

25 A. I have.

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1 Q. Approximately how -- how much time did you
2 spend preparing?

3 A. Off the top of my head, I don't remember.
4 Probably somewhere around eight hours or so, eight
5 to ten hours.

6 Q. And -- and what materials did you look at
7 in preparing for today's deposition?

8 A. Well, I looked at my declarations. I
9 looked at the patent, obviously, the prior arts, and
10 materials.

11 Q. Any- -- anything else?

12 A. I don't recall off the top of my head, but
13 those are the primary ones.

14 Q. Okay. So your -- your declarations and
15 the -- the -- the '985 patent, I think you said.
16 And you said the references.

17 So when you -- when you refer to the
18 references, what are you referring to?

19 A. The Ganin reference, the Chalom reference,
20 the Aslan reference. I might have looked at some of
21 the other exhibits quickly as they're cite- -- as
22 they're cited in my declaration.

23 Q. Okay. Did you take any notes while you
24 were preparing for your deposition today?

25 A. No, I did not.

1 Q. And in the room, do you -- do you have any
2 open lines of communication with your counsel, any
3 text message threads or any chat windows or anything
4 like that?

5 A. No, I do not.

6 Q. What -- what do you have open, your -- are
7 you on a laptop or a desktop?

8 A. I'm on a desktop, and I don't have
9 anything open except this Zoom meeting and a blank
10 folder to drop stuff in when you put it in the chat
11 box.

12 Q. Okay. So you had a dissertation in
13 conjunction with your Ph.D.; is that -- is that
14 correct?

15 A. That is correct. And I would assume you
16 will give me a copy of my CV?

17 Q. So in conjunction with that dissertation,
18 did you -- did you make any use of machine learning?

19 A. Yes. In my dissertation I did quite a bit
20 of work on pattern recognition and machine learning.

21 THE COURT REPORTER: Of what recognition
22 and machine learning?

23 THE WITNESS: Pattern -- of pattern
24 recognition and machine learning.

25 BY MR. STEIN:

1 Q. What's -- what's the difference between
2 pattern recognition and machine learning?

3 A. Excuse me. Well, I mean, there are --
4 there's a lot of commonalities between them. The --
5 the focus -- a lot of -- the focus of my
6 dissertation was more in -- in the areas of
7 annotation and segmentation and classification. So
8 in the areas of color and shape recognition.

9 So you use some of the pattern recognition
10 algorithms in doing the machine learning to
11 essentially recognize objects or -- or templates and
12 images and -- and video frames.

13 Q. And do the -- do those pattern recognition
14 algorithms that you said are similar to machine
15 learning, did they make use of an objective
16 function?

17 A. Some do, yes.

18 Q. So which -- which types of pattern
19 recognition algorithms might make use of an
20 objective function?

21 A. Well, obviously when you're doing shape
22 matching or you're doing face recognition or face
23 detection, you would use objective functions to try
24 to determine whether the match -- how good the match
25 is or to train the algorithms or the -- you know,

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1 the -- the -- the methodology that you're working
2 with.

3 Q. Did you use one objective function to
4 train more than one pattern recognition algorithm?

5 A. I don't remember off the top of my head
6 what exactly was used. We're talking in the '90s
7 now, so it's 30-plus years ago.

8 Q. What about just thinking about sort of the
9 pre-2017 time frame? Is that something that a -- a
10 skilled person in this field could have done, make
11 use of one objective function to train multiple
12 algorithms?

13 A. You could. I mean, it -- it depends a
14 lot -- I mean, you're -- you're asking me a
15 question -- a very, very broad question. It depends
16 a lot on the context, the application, what's being
17 done. You have to be more specific.

18 Q. Yeah, sure.

19 Let -- let's talk specifically about the
20 pattern recognition algorithms you mentioned in
21 conjunction with your dissertation.

22 So before 2017, would those have been
23 something that a skilled artisan in this field could
24 have used one objective function to train multiple
25 of those pattern recognition algorithms?

1 MS. MAURI: Objection. Form.

2 THE WITNESS: I -- I'm -- I'm not sure
3 what you are asking. I mean, you're asking a very
4 big question, and I'm not exactly sure what you are
5 asking.

6 BY MR. STEIN:

7 Q. Okay. So what -- what's unclear --
8 (Interruption in audio/video.)

9 THE COURT REPORTER: Oh, one second.

10 THE WITNESS: I'm sorry.

11 You have to be more specific, sir, about
12 what you're asking exactly.

13 BY MR. STEIN:

14 Q. Sure. So what -- what's the ambiguity
15 that you see in the question?

16 A. Well --

17 MS. MAURI: Objection to form.

18 THE WITNESS: -- again, you're asking a
19 very big question, and I'm not -- I don't understand
20 what you are asking about.

21 Do you have something specific about my
22 dissertation that you want to ask about?

23 BY MR. STEIN:

24 Q. So when I asked you before, did you tell
25 me that your dissertation made use of pattern

1 recognition algorithms? Is that fair?

2 A. Yes.

3 Q. And do you understand what an "objective
4 function" is?

5 A. Yes.

6 Q. So putting those two things together, can
7 you tell me whether, before 2017, you could have
8 made use of one objective function to train multiple
9 of those pattern recognition algorithms that you
10 would have described in your dissertation?

11 MS. MAURI: Objection. Form.

12 THE WITNESS: I mean, it -- it's hard to
13 say what you could have done. I mean, I can tell
14 you if you have specific questions about my
15 dissertation, but I -- I'm not -- I'm not here to
16 answer hypothetical questions.

17 Do you have something specific about my
18 dissertation that you'd like me to answer?

19 BY MR. STEIN:

20 Q. Yeah, I'd just like to answer the question
21 I propose [verbatim].

22 So we talked about the fact that you
23 remember having pattern recognition algorithms in
24 your dissertation. You also indicated that you
25 know -- you understand what an objective function

1 is.

2 So I -- I think you should be able to
3 answer the question, which just puts those two
4 things together.

5 The -- the question is just, is that a
6 possibility -- let's frame it that way -- is it a
7 possibility that you could have used one objective
8 function to train multiple of those pattern
9 recognition algorithms in the context of your
10 dissertation?

11 MS. MAURI: Objection. Form.

12 THE WITNESS: Well, again, you're asking a
13 very big question, and it's -- it's hard to answer
14 the question in a general sense like this.

15 Is there something specific about my
16 dissertation that you'd like to ask about?

17 Like I've -- we've done some work on
18 color. We've done some work on shape. So I'm happy
19 to answer something specific, but general, big
20 umbrella questions like that are very difficult to
21 answer, what could like be done, what would have
22 been done, what should have been done.

23 BY MR. STEIN:

24 Q. Okay. So let -- let's talk about color.
25 So tell -- tell me about the work you did on color.

1 MS. MAURI: Objection to form.

2 THE WITNESS: Well, the work we have done
3 on -- on -- on color is essentially trying to
4 recognize, one, memory colors, like your skin
5 colors, sky colors, you know, blue skies, green
6 grass, and recognize that in images and video
7 frames, be able to recognize that and distinguish it
8 from other colors in the frames. So that's one
9 piece of the work.

10 The other piece of the work had to do with
11 segmentation algorithms that would be based on color
12 and/or, you know, shape information, and -- and
13 sometimes texture.

14 BY MR. STEIN:

15 Q. And you -- it looks like you had some
16 industry experience at Xerox; is that -- is that
17 correct?

18 A. That is correct.

19 Q. And you were there -- it looks like you
20 were -- you were pretty successful there; is that --
21 is that fair?

22 MS. MAURI: Objection to form.

23 THE WITNESS: Yes, I was -- I was -- I was
24 there for 16 years, and I was very successful and
25 well recognized.

1 BY MR. STEIN:

2 Q. Yeah, what -- what made you leave sort of
3 that kind of successful career path?

4 A. Excuse me.

5 MS. MAURI: Objection to form.

6 THE WITNESS: Will -- will you repeat the
7 question, please.

8 BY MR. STEIN:

9 Q. Sure.

10 Yeah, I was just wondering, so the career
11 at Xerox, which, like you said, appears pretty
12 successful, why -- why leave that industry career?

13 MS. MAURI: Same objection.

14 THE WITNESS: Well, as you have noticed
15 from my CV, I was at Xerox -- I joined Xerox in
16 1998, and I left in 2004.

17 Simultaneously, when I finished my Ph.D.
18 in 1996, I was asked by University of Rochester in
19 1997 if I would be a -- kind of a part-time faculty
20 where I would teach coursework for them, generally
21 at the graduate level and sometimes at the
22 undergraduate level.

23 And then I also acquired an NSF GOALI
24 grant together with Professor Murat Tekalp, who was
25 a full-time faculty at the time.

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1 Now, the GOALI grant is kind of a -- a --
2 an NSF program. I don't know if it still exists
3 at -- at the -- at this time. But it's an NSF
4 program that brings in an industry researcher
5 together with a faculty and a student. So it's kind
6 of like a triangle of three.

7 So I -- I was at U of R as a part-time
8 faculty --

9 (Interruption in the audio/video.)

10 THE COURT REPORTER: I was at the? I
11 didn't hear you. I was at the?

12 THE WITNESS: I was at the University of
13 Rochester as a part-time faculty from 1997 to 2004.

14 At the same time, on 1998, RIT asked if I
15 would be an adjunct faculty -- the Rochester
16 Institute of Technology, RIT, asked if I would be an
17 adjunct faculty and teach courseworks [verbatim] for
18 them as well. So I did that from 1998 to 2004.

19 And so in -- in that time period I was
20 working full-time at Xerox and teaching in two
21 academic institutions kind of part time during, you
22 know, afternoons, evenings.

23 So I -- I discovered that I enjoyed the
24 academic environment a lot more and wanted the
25 autonomy and just, you know, the freedoms of

1 basically being in the academic environment. So
2 I've [verbatim] decided to leave Xerox in 2004 and
3 join academia full time.

4 BY MR. STEIN:

5 Q. You got sick of being micromanaged by the
6 Xerox guys, huh?

7 A. Well, I mean, I -- I wanted --
8 obviously -- I enjoyed the academic environment. I
9 enjoyed the freedoms of, you know, the teachings,
10 the research, working with students, you know,
11 traveling to conferences, and working with other
12 colleagues and kind of doing my own direction, so to
13 speak.

14 So I -- I was -- you know, Xerox has been
15 a very good company. I've -- I've enjoyed my time
16 there as well. And I learned a lot by working
17 there.

18 Q. You also indicate that you -- it looks
19 like you have some experience with "deep
20 learning/artificial intelligence for object
21 detection" [as read] --

22 THE COURT REPORTER: Can you slow down,
23 Counsel, please.

24 MR. STEIN: Okay.

25 BY MR. STEIN:

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1 Q. It also looks like you have some
2 experience with "deep learning/artificial
3 intelligence for object detection and tracking
4 purposes." [As read]

5 Is that -- is that correct?

6 A. That is correct.

7 Q. So what is deep learning?

8 A. Well, I mean, generally speaking --
9 obviously it's a very big question and it's a very
10 big area. But, generally speaking, you're
11 constructing large networks that may have multiple
12 layers and, you know, a depth of variety of layers
13 and could be components of different layers.

14 Q. And -- and what's "a layer"? Is that a
15 machine learning algorithm?

16 A. Well, in -- in -- in the learn- -- in
17 the -- you know, in the deep learning or machine
18 learning technology, it would be -- a layer would be
19 like a -- you know, a collection, for instance, of
20 nodes in a fully connected neural network would be
21 considered a layer or, you know, a set of
22 convolutional layers would be considered a layer.

23 Q. A set of convolutional layers would be
24 considered a layer or a set of convolutional layers
25 would be considered a machine learning algorithm?

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1 MS. MAURI: Objection. Form.

2 THE WITNESS: So a -- a set of
3 convolutional, for instance, maps, if you would,
4 let's say a -- a -- a set of convolutional maps
5 together with, let's say, pulling or something,
6 would be considered a layer.

7 And then you may repeat that, you know,
8 10, 15 times depending on the application that you
9 are doing.

10 BY MR. STEIN:

11 Q. And then if that -- if that becomes a
12 convolutional neural network, that's a machine
13 learning algorithm?

14 MS. MAURI: Objection. Form.

15 THE WITNESS: Well, it depen- -- I would
16 have to see the details. I can't answer off the top
17 of my head what it becomes. We'd have to see
18 exactly what is being done with that algorithm.

19 BY MR. STEIN:

20 Q. And you also mentioned artificial
21 intelligence, and I also see the term "machine
22 learnings."

23 Can you tell me about the difference
24 between the term "machine learning" as compared to
25 the term "artificial intelligence" in the pre-2017

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1 timeframe?

2 MS. MAURI: Objection to form.

3 THE WITNESS: Well, I mean, it -- it's a
4 very big question that you're asking. But, you
5 know, machine learning might be, you know, perhaps a
6 little bit on the smaller scale, so to speak.

7 Artificial intelligence is a very big
8 umbrella that covers a lot of things.

9 Machine learning is essentially part of
10 that umbrella, if you would. You know, you'd have
11 the same neural network that's trained to do facial
12 recognition or object detection or object tracking.
13 You know, that would be considered part of machine
14 learning, to accomplish something. If I'm looking
15 for, you know, circumstances or activities or
16 something, part of my artificial intelligence, you
17 know, methodology.

18 BY MR. STEIN:

19 Q. Are you familiar with lookup tables?

20 (Interruption in audio/video.)

21 THE COURT REPORTER: Oh, excuse me.

22 THE WITNESS: I'm sorry? Excuse me.

23 BY MR. STEIN:

24 Q. Are you familiar with lookup tables?

25 A. Oh, yes.

1 Q. Is a lookup table a machine learning
2 algorithm?

3 A. Well, lookup tables would be --
4 essentially you could put that as part of a machine
5 learning algorithm. It's essentially a way to speed
6 up the processing.

7 I mean, we use lookup tables on -- in
8 color -- color engineering at Xerox quite a bit to
9 do rendering of documents to print. And lookup
10 tables are a way to speed up the process in a sense,
11 you know, once you have trained the algorithms or,
12 you know, created the methodology that you want to
13 create.

14 Q. And you al- -- it looks like you're also
15 advising Ph.D. and master students in some areas of
16 machine learning or artificial intelligence
17 applications; is that accurate?

18 A. That is accurate. Yes, I have -- we
19 have -- I have two people --

20 Q. And what -- what are the models?

21 (Simultaneous speaking.)

22 (Interruption in audio/video.)

23 THE COURT REPORTER: I'm sorry, I didn't
24 hear the question.

25 Counsel, I didn't hear the question.

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1 There were too many people speaking.

2 THE WITNESS: I didn't hear the question.

3 BY MR. STEIN:

4 Q. Yeah, we'll have to -- we'll have to try
5 to both pause, Dr. Saber. My -- my apologies there,
6 but I -- I think you were continuing to answer the
7 question. So why -- why don't you continue and then
8 I can ask again.

9 A. No. Please go ahead and ask your
10 question.

11 Q. Okay. What kinds of machine learning
12 models are your students researching currently?

13 MS. MAURI: Objection to form.

14 THE WITNESS: So currently we are working
15 on a Department of Defense grant from the National
16 Geospatial-Intellig- -- the Intelligence Agency on
17 object recognition and tracking in multimodal
18 imagery.

19 BY MR. STEIN:

20 Q. Is that sort of for military applications?
21 What kind of objects are you trying to track?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: Well, they don't tell us
24 what they're going to apply it for. The grant is
25 about tracking and, you know, recognition --

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1 detection and recognition tracking in essentially
2 multimodal imagery.

3 It -- you know, it's -- it's -- you know,
4 it's a general type of work. You know, the National
5 Geospatial doesn't tell us how they're going to use
6 that work or what they're going to use it for. But
7 you would think they'll be interested in, you know,
8 the aspects of military applications or surveillance
9 applications.

10 BY MR. STEIN:

11 Q. And what sorts of architectures have
12 your -- have your students attempted so far for
13 that -- in conjunction with that grant we were just
14 discussing?

15 A. Well, a lot of convolutional -- CNN,
16 convolutional neural nets. So when I say "CNN," I
17 mean a convolutional neural net. So convolutional
18 neural nets typically are used extensively with
19 imagery because of their, you know, value in the
20 sense. They -- they -- they work very well with
21 images. And usually that is followed by fully
22 connected neural nets to do the classifications and
23 recognitions that you're trying to do based on, you
24 know, how you've portrayed your application.

25 Q. Any -- any other types of architectures

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1 besides CNN?

2 MS. MAURI: Objection. Form.

3 THE WITNESS: Well, that's generally what
4 we're working on now, is using the CNNs together
5 with the fully connected neural nets. So that's
6 generally our architecture right now. Obviously,
7 multiple layers and all this kind of thing.

8 BY MR. STEIN:

9 Q. And -- and under what circumstances would
10 you use a CNN instead of a fully connected neural
11 net?

12 MS. MAURI: Objection. Form.

13 THE WITNESS: Well, that's a good
14 question, and it's a very big question. But CNNs
15 are typically -- the convolutional type of networks
16 are typ- -- typically very well suited for imagery
17 because you're using one convolutional kernel, or if
18 you selected convolutional kernels to -- to perform
19 the convolution. And those are usually limited in
20 terms of, you know, maybe it's a five by five or
21 seven by seven. So they have a limited amount of
22 parameters compared to a fully connected neural net
23 that may have thousands of weights and parameters.
24 So th- -- there are -- there are tradeoffs between
25 them.

1 But with images, we usually like to start
2 with some kind of CNNs. And when I say
3 "convolutional," obviously, they do
4 cross-correlation, not convolution. But they call
5 them convolutional neural nets.

6 BY MR. STEIN:

7 Q. Yeah. Talk to me more about that. So --
8 so what's a convolution, and how does that relate to
9 a cross-correlation?

10 A. Well, a convolutional would be, if I'm
11 doing a convolution on an image, for instance, and
12 I'm using a five by five kernel, if you look at the
13 equation, you would need to flip the kernel twice
14 and then drag it across the image, so to speak, to
15 perform the convolution. And, you know, it's --
16 it'll be like -- in the one-dimensional world, it'll
17 be like HKXN minus K. So your --

18 THE COURT REPORTER: I'm sorry, Dr. Saber,
19 could you slow down, please.

20 THE WITNESS: Yes.

21 THE COURT REPORTER: The --

22 THE WITNESS: So in the one-dimensional
23 world, it would be like having XKHN [verbatim] minus
24 K. And so, you're flipping the kernel and dragging
25 it across the image as you're performing your

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1 convolution.

2 Cross-correlation would be done without
3 the flipping, so you would just drag it across the
4 image directly to do that correlation.

5 And obviously the two will be the same if
6 the kernel is symmetric. So flipping the kernel
7 twice results in the same five by five. Then the
8 two are symmetric, then the kernel is symmetric and
9 the two will result in pretty much the same answer.
10 BY MR. STEIN:

11 Q. And -- and what is -- what is the kernel
12 that -- that you're referring to?

13 A. A kernel would be like your -- a five by
14 five by -- template that you have designed perhaps
15 to find, let's say, edge detection. You're doing --
16 (Interruption in audio/video.)

17 THE COURT REPORTER: What detection?

18 THE WITNESS: Edge detection. Or you're
19 looking to find corners in images or something like
20 that. You would design a -- a five by five or a
21 seven by seven kernel to look for these features.

22 BY MR. STEIN:

23 Q. And you mentioned -- when we were talking
24 about convolutions and cross-correlation, you
25 mentioned parameters.

1 So talk -- talk to me about parameters in
2 the context of machine learning algorithms.

3 MS. MAURI: Objection. Form.

4 THE WITNESS: Well, the kernel has
5 parameters. So if you have a five by five kernel,
6 you have a 25 parameters that you would have to
7 train as part of your training process. In the
8 fully connected neural net, you essentially have
9 biases and weights that connect, let's say, one
10 node -- node to the next nodes, et cetera.

11 So those would be your, you know -- your
12 in -- in-network parameters. Your biases, the same
13 weights in that network. There's obviously hyper
14 parameters as well that are part of the training
15 that you would have to train as well.

16 BY MR. STEIN:

17 Q. What -- what are hyper parameters?

18 A. It'd be like, for instance, a
19 regularization parameter or a gradient decent --

20 (Interruption in audio/video.)

21 THE COURT REPORTER: What decent? Coun --
22 Doctor --

23 THE WITNESS: A gradient.

24 THE COURT REPORTER: Gradient.

25 THE WITNESS: A gradient. I'd be like a

1 gradient decent, for instance, parameter that you
2 want to train to slow down the decent in a sense or
3 speed it up. A regularization parameter that you
4 would want to train if you're doing regularization,
5 that kind of thing.

6 BY MR. STEIN:

7 Q. And what -- what kind of tradeoffs are
8 involved with choosing sort of the number of
9 parameters and selection of hyper parameters?

10 A. There are many tradeoffs. And usually
11 the -- the time it takes to train, the size of the
12 training database that you have, how long you're
13 going to train, how many epoch [verbatim] you're
14 going to train is the objective function convex or
15 not. There are many -- many dis- -- many
16 discussions here.

17 Q. And -- and would those tradeoffs have been
18 something that a person of skill in the art would've
19 known about in the pre-2017 timeframe?

20 A. Well, a person working in the machine
21 learning area would know -- would know basically
22 about -- you know, fully connected networks would
23 know about CNNs and, you know, learning how to train
24 these networks.

25 Q. And in the pre-2017 timeframe, would they

1 have known about the teacher/student architecture?

2 A. Well, I'm not sure what you mean. You'd
3 have to be more application specific. So you -- you
4 know, this is a very general question. You have to
5 be very -- you know, what is the application and
6 whether that makes sense to the application. It --

7 Q. So --

8 A. -- it depends what's -- what's going on
9 with the application that you're doing.

10 Q. Okay. So are -- are you familiar with the
11 pre-2017 timeframe and the perspective that a person
12 of ordinary skill in the art would have had in that
13 timeframe?

14 A. Yes.

15 MS. MAURI: Objection. Form.

16 BY MR. STEIN:

17 Q. And are you familiar with what a
18 teacher/student architecture is?

19 MS. MAURI: Objection. Form.

20 THE WITNESS: Again, yes, I am familiar
21 with -- with what a -- what that architecture is.

22 BY MR. STEIN:

23 Q. Okay. So, again, putting those two things
24 together, your familiarity with how a skill --
25 person of skill in the art would've known in this

1 timeframe and your familiarity with teacher/student
2 architecture, would that person have known of the
3 teacher/student architecture in the pre-2017
4 timeframe?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: Well, generally speaking,
7 you know, obviously such an architecture might be
8 known -- it would be known, but that's not what
9 we're talking about here.

10 What I'm saying is, it depends on the
11 context of the application. You know, so you're
12 asking a very general question. And I'm trying to
13 tell you, it depends on the context of the
14 application, and it's not something trivial to do as
15 this -- you know, integrate multiple networks
16 together. So it depends a lot on what the
17 application [verbatim].

18 You have to be more specific. You're
19 asking very general questions, and you have to be
20 more specific with your questions.

21 BY MR. STEIN:

22 Q. Okay. Well, just -- let's just start with
23 the general question and then let's drill down. So
24 just the general question of not -- not specific to
25 any context, but was there general knowledge in the

1 pre-2017 timeframe for the person of ordinary skill
2 in the art that a teacher/student architecture was
3 one option for implementing machine learning
4 algorithms?

5 MS. MAURI: Objection. Asked and
6 answered.

7 THE WITNESS: I've already answered that
8 question for you, and my answer isn't going to
9 change as you ask it multiple times. It depends on
10 the application of what you are trying to do. The
11 devil is in the details.

12 So what is the application, what are the
13 specifics of the application, does it make sense in
14 a given application. That -- all of those have to
15 be understood. I would have to look at what the
16 application is and understand those scenarios before
17 I can answer such a big blanket question like that.
18 BY MR. STEIN:

19 Q. Yeah. Okay. You did not answer my
20 question.

21 MR. STEIN: And -- and, Jennifer, if you
22 keep instructing him how to answer, we'll have to go
23 to the Board.

24 MS. MAURI: I did not instruct him how to
25 answer.

1 (Simultaneous speaking.)

2 (Interruption in audio/video.)

3 THE COURT REPORTER: One person at a time,
4 please.

5 MR. STEIN: Let's continue. Well, if you
6 get -- you get one-word objections, Jennifer. And
7 if you do otherwise, we'll -- we'll talk to the
8 Board.

9 MS. MAURI: Sure. You know, I'll -- I'll
10 point you to the fact that you made the exact same
11 objection in Dr. Karam's depo. So I -- you know,
12 what's -- what's good for the goose is good for the
13 other counsel.

14 But please continue.

15 BY MR. STEIN:

16 Q. Yeah. So you're familiar with the image
17 classification, Dr. Saber?

18 A. I am.

19 Q. So if we reasked that same question about
20 the -- the knowledge in the pre-2017 timeframe of
21 whether a skilled artisan would've been aware of the
22 teacher/student architecture in the context of image
23 classification, is that something they would have
24 known about?

25 MS. MAURI: Same objection.

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1 THE WITNESS: I mean, you -- again, I'm --
2 you're asking a very general question, and I'm
3 trying to tell you that the devil is in details. I
4 would have to know what the image classification
5 application you're talking about, take a look and
6 see the construction of the architecture, does it
7 make sense in that particular architecture or not.

8 So, you know, this is -- this is not a --
9 this is not a -- a simple question to answer, and I
10 think your -- your question is too general and not
11 specific enough.

12 BY MR. STEIN:

13 Q. Are -- are you familiar with the '985
14 patent?

15 A. Yes, I am.

16 Q. Does the '985 patent, the claims of the
17 patent, do they cover a teacher/student
18 architecture?

19 A. Well, which claim are you referring in the
20 '985 patent, let's be specific. I -- I don't want
21 to answer general blanket questions. Let's be
22 specific on what you're asking. And if -- could you
23 please upload the '985 patent.

24 Q. Well, have you reviewed the patent, and do
25 you recall what's described in the patent?

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1 MS. MAURI: Objection. Form.

2 THE WITNESS: I don't have the patent
3 memorized, sir. So would you please upload the
4 patent to the chat box.

5 BY MR. STEIN:

6 Q. I'll -- I'll -- I'll do that when we get
7 there, Dr. Saber, for sure. But let's -- let's move
8 along for now.

9 So is there a difference between what a
10 machine learning model is and what a machine
11 learning algorithm is?

12 MS. MAURI: Objection. Form.

13 THE WITNESS: Well, generally speaking --
14 I mean, again, you're asking very general questions,
15 and it's going to -- it depends a lot on the
16 application. But generally speaking, you have a
17 model that models the architecture that you want
18 to -- to -- to -- you know, to -- you know, to model
19 in a sense. You have a model that models the
20 architecture of your application. And then you have
21 al- -- you design an algorithm that may, you know,
22 to try to do the training of this particular model.
23 And what -- you know, what -- what type of gradient
24 decent algorithms you're going to use.

25 So the algorithm is kind of like the

1 building blocks in a sense to train your overall
2 model. But you'd have some kind of a model that
3 would model the architecture that you are trying
4 to -- to fill your application.

5 BY MR. STEIN:

6 Q. So a machine learning model and a machine
7 learning algorithm are two different things?

8 MS. MAURI: Objection. Form.

9 THE WITNESS: Well, depends -- again,
10 depends on the application. Sometimes people refer
11 to them, you know, in different meanings. But you
12 have to put something specific. So you have to show
13 me something specific, and I'm happy to answer a
14 question when I see something specific.

15 The devil is in the details.

16 BY MR. STEIN:

17 Q. What's the difference between a machine
18 learning model and a machine learning architecture?

19 MS. MAURI: Objection. Form.

20 THE WITNESS: So, again, people sometimes
21 refer to that in the same -- in the same breath, in
22 a sense. You know, the architecture usually would
23 refer to how you've put this thing together. The
24 model may be, you know, I'm going to use CNNs or
25 something. So it depends a lot on the architecture

1 or the application.

2 You have to be more specific in your
3 questions. You -- your general questions are hard
4 to answer, off the top like that without being
5 specific to what is the application.

6 The devil here is in the details.

7 BY MR. STEIN:

8 Q. Yeah, you've repeated that a lot. You
9 call everything general.

10 Let's look at Paragraph 42.

11 You said you have your declaration in
12 front of you, Exhibit 2008.

13 Do you have that?

14 A. Yes. Can -- can you upload that to the
15 chat box as well, please.

16 Q. Don't -- don't you have it written --
17 don't you have a printed copy in front of you?

18 A. Yes, but I would like to have a virtual
19 copy as well.

20 Q. All right.

21 THE COURT REPORTER: Counsel, may we go
22 off the record real quick?

23 MR. STEIN: Sure.

24 MS. MAURI: Yes.

25 (Discussion off the record.)

1 THE COURT REPORTER: We are back on.

2 BY MR. STEIN:

3 Q. Okay. So, Dr. Saber, we've e-mailed you a
4 copy of -- and -- and everybody at the depo, a copy
5 of Exhibit 2008, even though you have a printed copy
6 in front of you.

7 But if you'd turn to Paragraph 42, please,
8 it's on page 15. And actually, go -- go ahead to
9 page 16. It's the last sentence in the paragraph,
10 and it starts with "Put another way."

11 Just let me know when you see that.

12 A. I got --

13 Q. Dr. Saber, are you -- are you referring to
14 the printed copy after you just made me e-mail
15 everyone the exhibits?

16 A. I'm looking at the -- I'm looking at the
17 electronic copy right now.

18 Q. I see.

19 A. So "Put another way, a machine learning
20 algorithm is a computer model that trains itself to
21 perform a specific task by using training data."

22 That sentence?

23 Q. Yeah. That sentence.

24 A. Yes.

25 Q. And do you -- do you remember when we were

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1 talking about whether if there's a difference
2 between sort of a -- a machine learning model and a
3 machine learning algorithm? Do you remember that
4 discussion?

5 A. Yes.

6 Q. So in -- in this sentence, you say a
7 machine learning algorithm is a computer model. So
8 are you using those two terms interchangeably, an
9 algorithm includes a computer model?

10 A. Well, you have to look at the context of
11 the paragraph, obviously. And -- and we are trying
12 to describe it here in layman terms. So you have to
13 look at the context of the paragraph itself. So
14 it's not just a sentence out of context. And I
15 think that's what you're doing, is taking a sentence
16 out of context.

17 Q. Okay. Tell -- tell me about the context
18 and how it makes a difference in whether a mach- --
19 whether you understand a machine learning algorithm
20 and a machine learning model to be the same or
21 different. Tell -- tell me about how the context
22 makes it different in Paragraph 42.

23 A. Well, if you look at the paragraph from
24 the start, you see I'm trying to describe it in --
25 in layman terms in a sense. So I'm -- we're stating

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1 that "machine learning is a subfield of artificial
2 intelligence and relates to the capability of a
3 machine --

4 THE COURT REPORTER: I'm sorry, Doctor --
5 Dr. Saber, you have to please slow down and read
6 into the record slowly. Please.

7 THE WITNESS: Okay. So in -- in
8 Paragraph 42, we are describing, essentially in
9 layman terms, so it's just like an overview in a
10 sense, of machine learning and, you know, how you
11 would apply that in the context of facial
12 recognition, for instance. So it -- it's -- it's a
13 general description in a sense. This is not, you
14 know, a specific technical detailed description
15 of -- of, you know, the details.

16 BY MR. STEIN:

17 Q. Sure. Is -- is -- in the pre-2017
18 timeframe, would a neural network have been
19 understood by a POSITA as an example of a machine
20 learning algorithm?

21 A. Well, a neural network obviously would --
22 you would have a -- a series of layers. So it
23 provides an architecture for machine learning. And
24 it would also as you apply inputs, let's say to the
25 neural network and you process things through the

1 neural network, so it obviously has an algorithm of
2 processing the information from input to output.

3 Q. So -- so was that a yes, in the pre-2017
4 timeframe, a neural network would have been
5 understood to a POSITA to be a machine learning
6 algorithm; is that fair?

7 A. Well --

8 MS. MAURI: Objection. Form.

9 THE WITNESS: Again, I mean, you're asking
10 very general questions in a sense. And I've just
11 explained to you, a -- a neural network -- you know,
12 let's say we're looking at a fully connected neural
13 network. So you have a series of layers, a series
14 of nodes in each layer, and you have connectivity
15 between these layers. So when you provide an input
16 to the network, the network processes that input and
17 produces a corresponding output. So that's in -- in
18 layman [verbatim] term, it's essentially a quick
19 summary.

20 BY MR. STEIN:

21 Q. In the pre-2017 timeframe, is it your
22 testimony that a neural network was not a machine
23 learning algorithm?

24 MS. MAURI: Objection. Form.

25 THE WITNESS: That's not what I said.

1 BY MR. STEIN:

2 Q. Now, let's turn to Paragraph 26 of your
3 declaration, Exhibit 2008.

4 A. Paragraph 26?

5 Q. Yeah, 2-6 on page 9 of Exhibit 2008.

6 A. Yes. So I'm looking at Paragraph 26.

7 Q. Okay. Do you see in the -- sort of in the
8 middle of that Paragraph 26, you say, "Thus, it is
9 not necessary to look at any other claim to
10 determine what an independent claim covers."

11 Do you see that?

12 A. Yes.

13 Q. Is that still your testimony today?

14 MS. MAURI: Objection. Form.

15 THE WITNESS: Well, I'm -- I'm not an
16 attorney. I'm not here -- I'm not here to provide
17 legal, you know, advice in a sense. But that's my
18 understanding of an independent claim.

19 BY MR. STEIN:

20 Q. So to -- to understand what an independent
21 claim covers, you do not need to look at a dependent
22 claim; is that correct?

23 MS. MAURI: Objection. Form.

24 BY MR. STEIN:

25 Q. You said, right, you do not -- it is not

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1 necessary to look at any other claim; that's what
2 you said?

3 A. Well, yes, that's what the sentence says.
4 But, I mean, obviously, you're looking at the
5 independent claim as -- as a whole to understand
6 what is being claimed. But you -- you read that in
7 the context obviously of the specification and, you
8 know, the other claims in the patent and so on. So
9 it's not just a point in a vacuum.

10 Q. Okay. So it's not necessary to look at
11 any other claim, but it's not just a point in a
12 vacuum, and you would look at the specification and
13 other things. So that's what -- that's your
14 understanding of -- of the law?

15 MS. MAURI: Objection. Form.

16 THE WITNESS: Again, I'm not an attorney.
17 So I'm not here to provide legal advice. But it is
18 my understanding that when you're reading a claim,
19 you're going to look at the claim as a whole, and
20 you're going to read that in the light of the
21 specification, and -- and you'll -- potentially
22 other claims and -- and what's being described in
23 the figures in the patent. So it's -- it's not just
24 a point in vacuum [verbatim].

25 BY MR. STEIN:

1 Q. Okay. Let's go to Paragraph 24. Just a
2 little bit above on the same page 9 in your
3 declaration, Exhibit 2008.

4 Do you see in -- in this Paragraph 24, you
5 talk about the perspective of a POSITA, and you
6 indicate that you've -- throughout your -- this
7 declaration, you address issues from the perspective
8 of a POSITA.

9 Is that correct?

10 A. You read -- well, the paragraph says that
11 "I have been asked to address the issues from the
12 perspective of a POSITA." A POSITA is a person of
13 ordinary skill in the art, in the field of the
14 '985 patent.

15 Q. And -- and do you remember when we were
16 discussing Paragraph 42, and you -- you were
17 answering my question and saying, oh, that -- that's
18 about a layman. So are there certain paragraphs in
19 here that are from the perspective of a layman and
20 other ones that are perspective [verbatim] of a
21 POSITA? And how do I know when you're talking about
22 one or the other?

23 MS. MAURI: Objection. Form.

24 THE WITNESS: Again, you know, I
25 have addressed -- so obviously, some of these

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1 descriptions are general just to give a background
2 to what we are talking about here. But I have
3 addressed the issues in this declaration and my
4 opinions from the perspective of a POSITA in the
5 field of the '985 patent.

6 BY MR. STEIN:

7 Q. But you -- but you have a handful of
8 paragraphs that are from the perspective of a
9 layman. Is a layman a POSITA?

10 MS. MAURI: Objection. Form.

11 THE WITNESS: Again, I have addressed
12 in -- I mean, you're looking at a single paragraph
13 and essentially taking it out of context. Some
14 paragraphs are a little bit of overview to provide
15 some description of things. Others are more
16 specific to the details. But I've tried to address
17 in this declaration everything from the eyes of a
18 POSITA.

19 BY MR. STEIN:

20 Q. Except for Paragraph 42, which you said
21 was from the eyes of a layman; right?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: Again, that's not what's
24 being addressed in that paragraph. I think you're
25 taking the words out of context.

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1 BY MR. STEIN:

2 Q. So Paragraph 42 is from the perspective of
3 a POSITA?

4 MS. MAURI: Objection. Form.

5 THE WITNESS: As I've already answered to
6 you, I've addressed in this declaration, as that
7 sentence says, I've been asked to address the issues
8 from the perspective of a POSITA. And I have done
9 so throughout this declaration. Now, some
10 descriptions are more general to just kind of give
11 a -- you know, a context so to speak or a general
12 description. But in this declaration, things have
13 been addressed from the eyes of a POSITA.

14 BY MR. STEIN:

15 Q. Let's go one page earlier, so Paragraph
16 22, which is on page 8 of your declaration,
17 Exhibit 2008.

18 In that paragraph, in the middle of
19 Paragraph 22, you mention "two to three years of
20 experience in machine learning and/or pattern
21 recognition."

22 Do you see that passage?

23 A. Yes.

24 Q. So is it your testimony that a POSITA
25 could qualify if they only had experience with

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1 pattern recognition, two to three years of
2 experience with pattern recognition?

3 MS. MAURI: Objection. Form.

4 THE WITNESS: Well, in the right areas of
5 pattern recognition as it pertains to machine
6 learning.

7 BY MR. STEIN:

8 Q. Did you state that in paragraph 22, or did
9 you state "including approximately two to three
10 years of experience in machine" --

11 THE COURT REPORTER: Counsel, can you slow
12 down if you're reading into the record, please.

13 BY MR. STEIN:

14 Q. -- "including approximately two to three
15 years of experience in machine learning and/or
16 pattern recognition"?

17 Did you mention anything about context in
18 Paragraph 22? I'm just asking about Paragraph 22.

19 MS. MAURI: Objection to form.

20 THE WITNESS: Well, the sentence you read
21 there, you read that correctly, but that's the
22 intent, is you're -- you know, if you, for instance,
23 open a book on pattern recognition -- let's just
24 talk about it as -- as an example.

25 If you look at, for -- for instance,

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1 Theodoridis and Koutroumbas, which is a famous book
2 on pattern recognition, you obviously see a lot of
3 neural net discussions there and a lot of things
4 that are related to machine learning.

5 So there's a lot of similarities, a lot of
6 intersections, and a lot of commonalities between
7 those two areas. And that's essentially what's
8 being said here.

9 BY MR. STEIN:

10 Q. So in the -- in the con- -- in
11 Paragraph 22, what's the proper context of the
12 pattern recognition experience that a POSITA would
13 need to qualify under your definition?

14 A. Well, you have to have worked in the area
15 of -- in the pattern recognition area and --
16 obviously related to machine learning experience --
17 things are related to the machine learning
18 experience of the pattern recognition area.

19 Q. Let's go to Paragraph 40, which is on page
20 14 of your declaration, Exhibit 2008. And just --
21 if you could just indicate to me when you've gotten
22 there.

23 Paragraph 4-0 on page 14, 1-4.

24 A. I am there, and I am reading the
25 paragraph.

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1 Q. Okay. Do you see you -- you mention a
2 term -- I know this -- this is your understanding of
3 the law, but I'm going to ask you some questions so
4 I know how you understand the law.

5 So in that paragraph you mention the term
6 "articulated reasoning." What -- what does
7 "articulated reasoning" mean to you?

8 A. Well, you have to provide some
9 descriptions, some technical details, some -- some
10 reasoning behind your assessment.

11 Q. And what would be a "nonarticulated
12 reasoning"?

13 MS. MAURI: Objection to form.

14 THE WITNESS: Just perhaps a statement.
15 Like if you said, you know, the sky is brown, it's
16 just a statement -- you know, a conclusory statement
17 in a sense or a statement without some support or
18 some description, some technical definitions, some
19 details.

20 BY MR. STEIN:

21 Q. And you -- in the -- and a couple of words
22 after that, "articulated reasoning with some
23 rational underpinning."

24 So what -- what would be articulated
25 reasoning without some rational underpinning?

1 MS. MAURI: Objection. Form.

2 THE WITNESS: So, again, I mean, you --
3 you might say, for instance, something is obvious
4 because of this or this, but -- you provide an
5 articulation, but you don't provide the details or
6 why would this be the specific details or why
7 it's -- it's the case.

8 So you -- you know, the rational
9 underpinning kind of provides like what is the
10 details, you know, does it make sense to -- to make
11 this particular, you know, connection or whatever.
12 BY MR. STEIN:

13 Q. And let's continue. So then you say, "I
14 understand that there may be no rational
15 underpinning to support the legal conclusion of
16 obviousness where systems are already complete." [As
17 read]

18 So what -- what is an "already complete"
19 system?

20 A. Well, I mean, again, you're asking very
21 general questions. You know, I'm not an attorney.
22 I'm not here to provide legal definitions.

23 You know, I may have a complete system
24 that may have all the pieces in place that you are
25 trying to do an obvious analysis on with relation to

1 some prior art, so...

2 Q. So did you write this declaration,
3 Dr. Saber?

4 A. I -- I have a process that works for me
5 very well. I usually provide the first draft of
6 this declaration, and then it's a collaborative and
7 iterative process between myself and counsel to
8 arrive at the final document.

9 Q. And the final document in Paragraph 40
10 includes the statement "systems are already
11 complete."

12 So is it your testimony today that you
13 can't tell me what that means?

14 MS. MAURI: Objection. Form.

15 THE WITNESS: I think I already told you
16 what that means.

17 BY MR. STEIN:

18 Q. So I asked you previously -- I'm reading
19 from the transcript -- So what is an already
20 complete system? Your answer was, Well, I mean,
21 again, you're asking very general questions. You
22 know I'm not an attorney. I'm not here to provide
23 legal definitions. You know, I might have a
24 complete system that -- that you're trying to do in
25 an obvious analysis on in relation to some prior

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1 art.

2 So is that what you're referring to me as
3 having been your answer of what a complete system
4 is?

5 A. Well, as I tried to tell you earlier,
6 I'm -- obviously I'm not an attorney and I'm not
7 trying -- trying to provide legal advice here.

8 But if you have a complete system, you
9 have all the components of the system. So you have
10 a complete system that is in -- existing in patent X
11 and you're trying to provide validity or invalidity
12 analysis in comparison to some obvious prior art.

13 So that's essentially what it's talking
14 about.

15 So the -- it -- so the sentence says -- I
16 think you're taking things out of context a little
17 bit. That sentence says, "I understand that there
18 may be no rational underpinning to support the legal
19 conclusion of obviousness where systems are already
20 complete and the party challenging validity seeks to
21 mix and match components, which each exist in its
22 separate systems, from these complete systems."

23 Q. Let's go back -- remember we were talking
24 about convolutional neural networks earlier?

25 A. Yes.

1 Q. Could you tell me what are the components
2 of a convolutional neural network?

3 MS. MAURI: Objection to form.

4 THE WITNESS: Well, generally speaking,
5 and I'm speaking in general now, it's -- you know,
6 you would have to -- to put one in front of me
7 specifically so we can talk about the details.

8 But, generally speaking, you have
9 convolutional portion of the network. You have, you
10 know, essentially sections where the convolution is
11 being done. You typically have some kind of pooling
12 or -- and then you have some type of activations in
13 a sense.

14 So usually those are the main -- the
15 prime -- the main -- some of the main components of
16 a convolutional neural net. So you have
17 convolutional essentially pieces that are happening.
18 You have pooling. You have activation.

19 THE COURT REPORTER: Dr. Saber, are you
20 saying "pooling" or "polling"?

21 THE WITNESS: Pooling, P-O-O-L-I-N-G, like
22 a pool. Pooling.

23 BY MR. STEIN:

24 Q. So you mentioned -- you said
25 "convolutional essentially pieces are happening."

1 Talk to me about what that means, pie- --
2 what are "convolutional pieces"?

3 MS. MAURI: Objection. Form.

4 THE WITNESS: So you have an input image,
5 let's say, as an example. You have an input image.
6 You have a kernel. You're going to perform a
7 convolutional net image.

8 So that convolution takes place on the
9 image and outputs an output as part of the
10 convolution process of the CNN. So you have an
11 output from the -- from the convolution of -- of
12 performing the convolution.

13 BY MR. STEIN:

14 Q. I'm going to introduce a new exhibit here,
15 and I'm going to e-mail it, as we discussed a bit
16 ago.

17 A. Please do.

18 Q. Give me a moment, please.

19 MR. STEIN: So this will be Exhibit 1059,
20 Hanna.

21 (Previously marked IPR Exhibit 1059 was
22 referenced.)

23 MR. STEIN: And I'm e-mailing it to
24 everybody that's in the depo.

25 Okay. This is a new exhibit.

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1 Okay. I've just e-mailed it.

2 So, Dr. Saber, Jennifer, Hanna, if you can
3 just confirm when it's received, then -- then we can
4 continue.

5 THE COURT REPORTER: May we go off the
6 record while we do that, please.

7 MR. STEIN: Okay.

8 MS. MAURI: No. I think we should stay on
9 the record to allow -- to accurately reflect the
10 time that's being spent.

11 MR. STEIN: Well, not --

12 THE COURT REPORTER: I just can't -- I
13 just can't press two buttons, Counsel, just letting
14 you know.

15 MS. MAURI: Okay. Well, we can -- we can
16 pause until it's received. I'll agree to go off the
17 record 'til it's received.

18 MR. STEIN: Yeah, it's not -- I mean,
19 I'd -- Jennifer, I'd -- I'd prefer to just keep
20 going quickly. You guys asked for this e-mail
21 thing, so...

22 MS. MAURI: Well, you just mentioned this
23 is a new exhibit, so how are you anticipating having
24 him review a brand-new exhibit without sending it to
25 him?

1 MR. STEIN: I did send it.
2 THE WITNESS: I have received the exhibit.
3 MR. STEIN: Okay.
4 MS. MAURI: I have as well.
5 MR. STEIN: Okay.
6 THE WITNESS: Hanna?
7 THE COURT REPORTER: Yes. Thank you.
8 (Off the record.)
9 MR. STEIN: Okay. Let's go back on the
10 record, please.
11 BY MR. STEIN:
12 Q. So we're back on the record after
13 e-mailing Exhibit 1059, a new exhibit in the IPR.
14 So, Dr. Saber, do you have Exhibit 1059 up
15 on your screen, which is U.S. Patent Number
16 11,523,004?
17 A. Yes, I do.
18 Q. And does your name appear on this patent,
19 "Eli Saber, Rochester, New York" [as read], under
20 Item 72 in the left-hand column on the first page?
21 A. Yes, it does.
22 Q. So you're an inventor on this patent,
23 11,523,004?
24 A. Yes, I am.
25 Q. And what -- what is the title of this

1 patent?

2 A. The title of the patent is "PART
3 REPLACEMENT PREDICTIONS USING CONVOLUTIONAL NEURAL
4 NETWORKS."

5 Q. So is the -- is the convolutional neural
6 network that you describe in this patent, is that an
7 example of a machine learning algorithm?

8 MS. MAURI: Objection. Form.

9 THE WITNESS: Well, generally speaking,
10 CNNs usually are part of a machine learning
11 algorithm.

12 BY MR. STEIN:

13 Q. Let's look at Column 3 of Exhibit 1059,
14 Dr. Saber.

15 A. Column 3?

16 Q. Yeah.

17 A. I'm there, sir.

18 Q. But do you see here in your patent you're
19 just -- you're indicating that "The manner by which
20 the convolutional neural network model is applied is
21 not limited"? That's Column 3, Lines 1 to 2.

22 A. Yes, I see that -- you read that sentence
23 correctly.

24 Q. And what -- what does that sentence mean?

25 MS. MAURI: Objection. Form.

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1 THE WITNESS: Well, I mean, we would have
2 to read through this patent. You're taking, again,
3 a sentence out of context, and I haven't looked at
4 this patent in a long time. So I -- I wouldn't be
5 able to answer to you off the top of my head without
6 having to study the patent in details. It's been a
7 while since I've looked at this.

8 BY MR. STEIN:

9 Q. And then if we go to Column 4 [verbatim],
10 you indicate "This model may be used on images with
11 no preprocessing such that a raw image received by
12 the communications interface 15 may be directly
13 processed." [As read]

14 What's a "raw image"?

15 MS. MAURI: Objection. Form.

16 THE WITNESS: Well, I -- I don't know
17 where you're reading from, sir, so you're going to
18 have to help me.

19 BY MR. STEIN:

20 Q. Column 3, Line 4, as I said at the
21 beginning of the question.

22 A. Because you just said "Column 4" in --
23 when you started your question, if I'm not mistaken.

24 Q. I meant -- sorry, I meant Line 4, then.
25 My apologies.

1 A. Yes, what about that sentence?

2 Q. What's a "raw image"?

3 A. Well, let's say you've taken an image with
4 your camera and you haven't done any gamma
5 corrections or you haven't done any, you know,
6 histogram equalization or any kind preprocessing on
7 the image. You haven't done any --

8 (Interruption in audio/video.)

9 THE COURT REPORTER: I'm sorry. Excuse
10 me. Dr. Saber, you're audio just cut out, so I
11 have:

12 Answer: "Well, let's say you've taken an
13 image with your camera and you haven't
14 done any gamma corrections or you haven't
15 done any histogram equalization, any."

16 THE WITNESS: So you haven't done any
17 preprocessing. You know, maybe noise, you know,
18 suppression or something. So you haven't done any
19 kind of a preprocessing on the image. Generally
20 speaking, we refer to that as a raw image. So it's
21 just strictly taken by the camera without any
22 manipulation of the image.

23 BY MR. STEIN:

24 Q. And continuing on in Column 3 of
25 Exhibit 1059 at Line 10, you mention "a training

1 dataset having 64,000 training images."

2 Do you see that phrase?

3 A. Yes.

4 Q. Is "a training dataset having 64,000
5 training images" a large training dataset or a small
6 training dataset?

7 MS. MAURI: Objection. Form.

8 THE WITNESS: Well, you know, it depends
9 on your perspective in a sense. Nowadays this would
10 be more on the smaller -- small training dataset.

11 Back in those days, it was, perspective
12 speaking, a much larger dataset. But in today's
13 environment, it would probably be a small dataset.

14 BY MR. STEIN:

15 Q. So if you were to kind of bring this
16 convolutional neural net up to modern times with --
17 with a larger training set, would that make it more
18 accurate?

19 MS. MAURI: Objection. Form.

20 THE WITNESS: Again, you're asking
21 hypothetical questions. And the training -- I would
22 have to see what your training dataset looked like
23 first, and what are you adding? You know, are you
24 adding things that are dependent, independent? How
25 are you augmenting this training dataset?

1 It's not a question that you can just
2 answer.

3 But, generally speaking, if you're adding
4 more training data into the training dataset --
5 you're augmenting your dataset -- there has to be
6 some independent information coming in; otherwise,
7 it's already contained in the training dataset.

8 So it depends -- I -- I would have to see
9 your dataset and look at the -- how you're
10 augmenting it.

11 BY MR. STEIN:

12 Q. And -- and what if I was using this
13 convolutional neural network to classify or identify
14 people's noses and I trained it on 250,000 training
15 images of dog faces, would that be a good training
16 dataset for the purpose of the model I've proposed
17 in this hypothetical?

18 MS. MAURI: Objection. Form.

19 THE WITNESS: I missed half of your
20 question. You cut out, sir, on my end.

21 BY MR. STEIN:

22 Q. Okay. I'll read it again.

23 What if I was using this convolutional
24 neural network from your patent, Exhibit 1059, to
25 classify or identify people's noses and I trained it

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1 on 250,000 training images of dog faces, would that
2 be a good training dataset for the purpose of the
3 model I proposed in this hypothetical?

4 MS. MAURI: Same objection.

5 THE WITNESS: Obviously -- well, generally
6 speaking, it would not be a good -- you -- you would
7 have to have -- the training set has to have some
8 indication of what you are -- you know, what are you
9 targeting.

10 So that would not be a -- a -- a good
11 training dataset for, you know, identifying people
12 [verbatim] noses, as you put it. But, again, I --
13 it's hypothetical questions. We have -- I have to
14 see the details, what exactly you're trying to do.
15 It's hard to answer things on a blanket setting like
16 that.

17 BY MR. STEIN:

18 Q. But is it fair to say that merely having a
19 larger training dataset in the pre-2017 timeframe
20 would not always improve accuracy?

21 MS. MAURI: Objection to form.

22 THE WITNESS: Well, "always" is al- --
23 obvious- -- obviously a -- a -- a -- a tough thing
24 to imply.

25 So if you increase your data -- training

1 dataset, you don't generally increase accuracy just
2 by increasing it numberwise. You have to do some
3 intelligent work in increasing it. It's not just
4 adding stuff.

5 BY MR. STEIN:

6 Q. Okay. I -- I think it might be -- would
7 you like a break, Dr. Saber? I may have gone a
8 little over an hour, so I apologize --

9 A. Yeah.

10 Q. -- for that. But if --

11 A. No problem. I'll -- I'll -- is it five
12 minutes or ten minutes? What's good for you?

13 THE COURT REPORTER: May we go off the
14 record to discuss?

15 MR. STEIN: Sure.

16 MS. MAURI: Yes.

17 (Short recess taken.)

18 MR. STEIN: All set.

19 BY MR. STEIN:

20 Q. Okay. So, Dr. Saber, we were talking
21 about Exhibit 1059. I'm trying to recall exactly
22 where we were at.

23 And so going -- going back to the front
24 page, I recall you told me that the title was "PART
25 REPLACEMENT PREDICTIONS USING CONVOLUTIONAL NEURAL

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1 NETWORKS."

2 Is that correct?

3 A. You read that correctly.

4 Q. So why -- why would this system need to
5 use multiple convolutional neural networks?

6 MS. MAURI: Objection. Form.

7 THE WITNESS: I haven't looked at this
8 patent in quite a while, so I wouldn't be able to
9 answer questions for you off the top of my head. I
10 would have to sit down and study it to give you the
11 details.

12 But typically you would use multiple
13 layers to refine things a little bit or, you know,
14 get more refinement on some of the features or --
15 that you're trying to -- you know, to come -- to,
16 you know, recognize in a sense.

17 But I haven't read this patent in quite a
18 while. I would have to sit down and study it before
19 I can answer specific questions about it.

20 BY MR. STEIN:

21 Q. And do you re- -- do you recall if this
22 patent discloses the structure of the convolutional
23 neural network being described?

24 MS. MAURI: Objection. Form.

25 THE WITNESS: I don't remember off the top

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1 of my head. This was several years back as you see.
2 I don't remember off the top of my head. Without
3 looking -- without reading the patent in detail, it
4 would be hard for me to answer specific questions.

5 BY MR. STEIN:

6 Q. And the -- the convo- -- convolutional
7 neural network -- if you look at Column 4 of
8 Exhibit 1059 at Line 36, for a second --

9 A. Column 4, Line 36, yes.

10 Q. Column 4, Line 36, yeah.

11 -- do you see the term there? We've
12 talked about convolutional neural network, but you
13 use this other term called "convolutional neural
14 network model."

15 So I'm wondering what's the difference
16 between a "convolutional neural network" and a
17 "convolutional neural network model"?

18 A. I -- I -- I think we're getting into
19 semantics, sir, a little bit, and you're asking
20 questions that aren't really relevant here. You're
21 getting into semantics.

22 Obviously this is referring to the model
23 of the -- what is being proposed here. But, again,
24 I can't answer specific questions about this patent
25 without reading it in detail. And it's been several

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1 years since this was published.

2 Q. So is that a phrase that you would use,
3 "convolutional neural network model"? Is that a
4 common phrase?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: It -- it depends on the
7 context of what you're trying -- what you're
8 describing or -- so I -- I'd have to know the
9 context. I would have to know the details. I'd
10 have to see the application. It's hard to answer
11 general questions without context.

12 BY MR. STEIN:

13 Q. And do you recall if in this patent,
14 Exhibit 1059, you describe an ability to substitute
15 in other types of machine learning models besides
16 the convolutional neural network?

17 MS. MAURI: Objection. Form.

18 THE WITNESS: Again, sir, I haven't looked
19 at this patent in several years. I would need to
20 sit down and study it before I can answer questions
21 for you specific to what is being described in this
22 patent.

23 BY MR. STEIN:

24 Q. We took a break about five minutes ago.
25 Did you have any conversations with your counsel

1 during that break?

2 A. No, I did not.

3 Q. What did you do during the break?

4 A. Just relaxed. Had a drink of water.

5 Q. Let's look at Column 3 of Exhibit 1059 at
6 Line 57. Just let me know when you get there. It
7 starts with "Although the present."

8 A. Yes. I see Column 3, Line 57 to, say, 62.

9 Q. Yeah.

10 Yeah, so what's -- what's being stated in
11 that passage, Column 3, Line 57 to Line 62, of
12 Exhibit 1059?

13 A. Yeah.

14 Q. What is being stated there?

15 A. Well, it says, "Although the present
16 examples use a convolutional neural network model to
17 analyze the images, other artificial intelligence or
18 machine learning models may be used."

19 Q. And then it continues; right? "For
20 example, other model may include support vector
21 machines, random forest trees, Naïve Bayes
22 classifiers, recurring neural networks, and other
23 types of neural networks."

24 Is that correct?

25 A. You read that sentence correctly.

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1 Q. So is it -- is it fair that -- in -- in
2 your own patent, you've said that it's -- it's
3 possible to swap out one type of machine learning
4 algorithm for another?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: Again, this say "may include
7 support vector machines," et cetera, but, again, you
8 have to look at the specifics -- the devil is in the
9 details. You have to look at the specifics. What
10 exactly is being done, how it's being done, and
11 whether it makes sense or not.

12 So -- and I haven't looked at this patent
13 in many years, so I can't answer the questions
14 specifically to this patent without taking the time
15 to study it.

16 BY MR. STEIN:

17 Q. How much time would you need to study it?

18 A. I don't know. I would have to read
19 through it carefully. Go back through the de- --
20 the diagrams and details. It's not -- it's not a
21 few minutes.

22 Q. A few hours, like 12 hours, or how long?

23 A. I -- I -- I don't know at this point. I
24 would have to read it and see what it's about and
25 then -- take my time into reading it, and then I'll

1 be able to answer questions about it.

2 Q. Did you read it before it was filed?

3 A. Ye- -- yes, I read it before it was filed,
4 but that was many years ago. I mean, this thing --
5 this thing was filed -- it says PCT filed in 2018.
6 So it -- it's many years ago.

7 Q. So would a -- would something maybe that
8 you filed in sort of 2024 or the end of 2023, is
9 that something you'd have a better recollection of?

10 MS. MAURI: Objection. Form.

11 THE WITNESS: I work on a lot of stuff,
12 sir. I teach courses. I work on multiple cases.
13 It's hard to remember everything off the top of your
14 head. I wish I could, but I can't.

15 BY MR. STEIN:

16 Q. Yeah. Yeah.

17 A. So I would -- you'd have to show me what
18 it is you want me to look at. I would tell you
19 whether I can answer or I -- I would need to time to
20 study the material to provide --

21 Q. Sir --

22 A. -- for that particular material.

23 (Simultaneous speaking.)

24 (Interruption in audio/video.)

25 THE COURT REPORTER: "To provide"? I

1 didn't hear you. Your audio cut out.

2 THE WITNESS: To provide a specific --

3 THE COURT REPORTER: I'm sorry --

4 THE WITNESS: -- to provide a specific --
5 to provide a specific answer to the material that
6 you are asking about.

7 BY MR. STEIN:

8 Q. Okay. Turn- -- turning back to
9 Exhibit 1059, Column 3, Line 59, you -- you
10 emphasized a moment ago the word "may."

11 Do you recall pointing me to the
12 word "may" in that -- in that sentence there?

13 A. Yes.

14 Q. So what does the word "may" mean?

15 A. Well, again, I would -- I would have to
16 study this in detail to answer specific questions
17 about it. But what it's suggesting here is that
18 depending on how you structure your model, you may
19 be able to use support vector machines to get to the
20 same answer or not.

21 But I would have to study this
22 specifically to give you specific answers.

23 Q. What are some of the advantages to support
24 vector machines as compared to convolutional neural
25 networks before 2017?

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1 A. Well, support vector machines typically
2 tackle classification-type situations that you
3 would -- you would essentially either tag on or
4 attach to a back end of a convolutional neural
5 network in a sense.

6 So you have a convolutional neural network
7 that may be connected -- a fully connected neural
8 network that may be structured as a support vector
9 machine, or you could use that directly on the
10 application depending what the application is.

11 So you're asking, again, general
12 questions. The devil is in the details. I would
13 need to see specifically what the application is,
14 how this is being done, and then I can answer your
15 questions.

16 Q. And what -- what about a convolutional
17 neural network as compared to a random forest tree,
18 what are some of the advantages and disadvantages of
19 those two before 2017?

20 A. Well, I mean, a convolutional neural
21 network is going to perform convolutions. A random
22 forest classifier or random forest trees is going to
23 define a set of features and define different ways
24 of, you know, handling the classification through a
25 variety of, let's say, trees, different ways of

1 structuring the classification.

2 So I -- I would need to see the details.
3 I would have -- it's hard to answer questions --
4 general generic questions like that.

5 Q. Is a random forest tree a kind of
6 algorithm?

7 A. Yeah, it -- it's essentially a
8 classifying -- it's a classifier type, obviously,
9 algorithm that you would use to do classifications
10 in a sense, most -- mostly used for classifications.

11 Q. And a -- a person of skill in the art
12 would have known that a random forest tree was a
13 machine learning algorithm before 2017; is that --
14 is that fair?

15 MS. MAURI: Objection. Form.

16 THE WITNESS: Well, again, I mean, it's --
17 it's used in the community for classification
18 purposes.

19 BY MR. STEIN:

20 Q. Okay. What -- what about the
21 term "knowledge distillation," are you familiar with
22 that term?

23 A. Well, it's -- it's a very large term. So,
24 you know, I would have to see the details to answer
25 specifics.

1 Q. Do you recall referring to knowledge
2 distillation as a prominent approach earlier this
3 year?

4 MS. MAURI: Objection. Form.

5 THE WITNESS: I -- I don't recall off the
6 top of my head --

7 BY MR. STEIN:

8 Q. Sure.

9 A. -- what I said earlier this year. You
10 would have to -- is there something specific in my
11 declaration that you're referring to?

12 Q. Let's take a look. I will send around
13 another exhibit.

14 So this is marked -- going to be marked as
15 Exhibit 1-0-6-0, 1060. Just bear with me for a
16 minute, and I will send it.

17 If -- if you could just confirm again,
18 Dr. Saber and Jennifer, when you have it, then
19 I'll -- I'll wait to continue.

20 (Previously marked IPR Exhibit 1060 was
21 referenced.)

22 THE WITNESS: I do have the exhibit.

23 MR. STEIN: Okay. Jennifer, do you have
24 it as well?

25 MS. MAURI: Not quite yet.

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1 MR. STEIN: Okay.

2 MS. MAURI: I am -- I'm clicking refresh
3 as much as I can.

4 MR. STEIN: Okay.

5 MS. MAURI: There it is. I have it now.
6 Thank you for your patience.

7 MR. STEIN: Sure.

8 This is Exhibit 1060.

9 BY MR. STEIN:

10 Q. So, Dr. Saber, if you could open up
11 Exhibit 1060 on your computer. You recall a moment
12 ago I asked you a question. But before I get there,
13 do you -- do you see your name in the front page of
14 this paper, "Eli Saber, Senior Member, IEEE"?

15 A. Yes, I do.

16 Q. So you're -- you're an author on this
17 paper?

18 A. I am.

19 Q. And it looks like this is a fairly recent
20 paper. In the left-hand side, it's got a date stamp
21 of 15th, January 2024.

22 Is that what it says?

23 A. That is correct.

24 Q. So -- and going back to what I had
25 mentioned earlier, I -- I asked you if you recalled

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1 earlier this year, specifically January, indicating
2 that a prominent approach is knowledge distillation.

3 So if I can direct you to page 2 of your
4 paper, in the "RELATED WORK" Section II, the second
5 sentence.

6 A. Yes, I see that sentence.

7 Q. So what did you mean when you said "a
8 prominent approach is knowledge" -- well, strike
9 that.

10 What is knowledge distillation?

11 A. Well, specific to this paper, I would have
12 to sit down and read this paper. It's been a while
13 since, obviously, I've looked at it. So I would
14 have to read this more carefully to be able to give
15 you any details about it.

16 I mean, this is just talking in general
17 terms. Like, you know, distilling knowledge in a
18 sense or capturing certain knowledge.

19 Q. Well, it continues; right? "A prominent
20 approach" -- and you called it prominent, so I'm a
21 little surprised you're being so resistant to
22 answer. But "A prominent approach is knowledge
23 distillation, where a large, accurate model (the
24 teacher) guides a smaller model (the student) by an
25 appropriate transfer of knowledge."

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1 So does it look as quite as general as
2 you're saying? Aren't -- aren't you saying
3 something specific about what knowledge distillation
4 is?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: Well, again, it's -- it's --
7 I mean, this is is a general sentence there, that --
8 you know, the devil is usually in the details.
9 The -- it's an application specific type of thing.
10 So I would have to see details before I can answer
11 specific questions. This is just a general
12 sentence.

13 BY MR. STEIN:

14 Q. So if one -- if one of your students --
15 you -- you teach classes at your university; right?

16 A. I do.

17 Q. If one of your students asked you,
18 Professor Saber, I'm super confused. You know, I've
19 been wracking my head against the wall on this. I
20 just can't figure out what knowledge distillation
21 is. Your answer would be, I'm sorry, that's a super
22 general question, I would have to have context, I
23 can't answer you.

24 You -- you can't just give me an answer as
25 to what your understanding of knowledge distillation

1 is? Assuming -- just assume I'm one of your
2 students, and I don't know what this is.

3 MS. MAURI: Objection. Form.

4 THE WITNESS: So, again -- so, again, you
5 would have -- I mean, I would have to ask the
6 student about the details. You know, can you show
7 me where specifically this wording has popped up.
8 You know, what is it that you're specifically asking
9 about. So --

10 (Interruption in audio/video.)

11 THE COURT REPORTER: Excuse me.
12 Dr. Saber, your audio -- your audio cut out.

13 THE WITNESS: So maybe get a paper of what
14 the stud- -- student is refer -- what book he's
15 looking at. So this is what I would need to help
16 him -- help him or her understand what -- what are
17 we referring about.

18 BY MR. STEIN:

19 Q. Okay. And -- and what if they handed you
20 this paper that I've handed you, Exhibit 1060, and
21 said, Dr. Saber, in the second sentence of your
22 Section II, you say, "A prominent approach is
23 knowledge distillation." Then you provide an
24 example that references a teacher and a student.

25 And the question is simply, Professor

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1 Saber, could you just explain to me a little bit
2 more about what this is because I'm just having
3 trouble understanding what it is. You would still
4 say I can't -- I'm sorry, student, I -- I still
5 can't answer your question?

6 MS. MAURI: Objection. Form.

7 THE WITNESS: I would certainly ask the
8 student to leave the paper with me. I would take
9 some time to read through it so I can give him an
10 acc- -- him or her an accurate answer. So this is a
11 general, obviously, sentence that's taken out of
12 context of an entire paper. So I would have to read
13 what they're talking about specifically and then try
14 to understand what exactly they're asking, and I'm
15 happy to answer their question. But I would need
16 context. I would need -- you know, I may take --

17 BY MR. STEIN:

18 Q. Okay.

19 A. -- time to read the paper ahead of time to
20 do that.

21 Q. So without context, and I don't know what
22 context you're talking about, but you can't tell me
23 what knowledge distillation is without some
24 amorphous context?

25 MS. MAURI: Objection to form.

1 THE WITNESS: Again, I said to you -- I
2 mean, generally speaking, you're -- you're talking
3 in general knowledge distillation, obviously,
4 distilling knowledge or acquiring knowledge perhaps
5 from whatever application that you're looking at.
6 But to answer specific questions about it,
7 especially with regards to a paper, I would need to
8 study that and give you accurate answers, especially
9 in a deposition.

10 BY MR. STEIN:

11 Q. Right. But I -- yeah. Okay.

12 So let's look -- so you -- you have a
13 bunch of sort of end notes on this paper. Right?
14 The numbers that appear within brackets, are those
15 referred to as end notes?

16 A. I don't know -- I don't know what you mean
17 by "end notes." Can you be specific on what you're
18 referring to?

19 Q. Sure. So that -- that sentence that you
20 refuse to answer my question, "A prominent approach
21 is knowledge distillation," that ends with "[11]."

22 Do you see that?

23 A. Yes.

24 MS. MAURI: Objection. Form.

25 BY MR. STEIN:

1 Q. What's -- what does the Number 11 refer
2 to?

3 A. It refers to the citation at the end of
4 the paper. So if you go to page 10 or at the end of
5 the paper --

6 Q. Mm-hmm.

7 A. -- it refers to, those are citation
8 numbers. To cite a certain reference that we are
9 citing to.

10 Q. Okay. And if we go there, so page --
11 you -- page 10 it looks like of Exhibit 1060, and if
12 we go to Number 11, what -- what do we find?

13 A. Well, it's -- it's citing a paper that
14 appears to have been written by G. Hinton, O.
15 Vinyals, and J. Dean. And it's called "Distilling
16 the knowledge in a neural network." And then its
17 publication shows it's published in 2015.

18 Q. So what -- what does that mean that it was
19 published in 2015? Does that -- does that mean that
20 people of skill in the art would have been able to
21 find that paper and -- and read its contents?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: It appeared at -- in this
24 preprint in 2015, and it gives you a number that you
25 can go find it.

1 BY MR. STEIN:

2 Q. So this -- this knowledge distillation,
3 which you constantly keep calling general and won't
4 answer, does this citation in 11 -- does this mean
5 that whatever that is, which you won't tell me what
6 it is, that was known in 2015?

7 MS. MAURI: Objection. Form.

8 THE WITNESS: Well, again, you're asking
9 very general questions. So we'd have to read the
10 paper specifically to tell you what is known in that
11 paper, what the authors are addressing. It -- it's
12 hard to answer very big general generic questions
13 like that.

14 BY MR. STEIN:

15 Q. You -- you mention in your declaration --
16 let's go to Exhibit 2008. There's a course -- a new
17 course you mention that you're designing for your
18 university. Do you -- I'll find it, but do you know
19 what I'm referring to?

20 A. On which paragraph are you referring to?

21 Q. Para- -- Paragraph 14 on page 4 of your
22 declaration.

23 A. Page 4. Yes.

24 Q. And you -- you have some kind of typo in
25 here, so I'm not exactly sure what you meant. But

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1 you say "I am currently to developing" -- I don't
2 know what that means -- "a graduate course titled."
3 [As read] And then you have a title.

4 Do you see that?

5 A. Yes, it should say "I am currently
6 developing." The "to" is a typo.

7 Q. I see. Who made that typo, you or your
8 counsel?

9 MS. MAURI: Objection.

10 THE WITNESS: I don't -- like I said, I --
11 I've written the first draft, and there's been
12 collaborations and iterative process. So I -- I
13 don't recall off the top of my head.

14 BY MR. STEIN:

15 Q. Okay. So as part of that course,
16 "Advanced Neural Networks and Deep Learning:
17 Theory, Mathematics and Algorithms," do you cover
18 anything about knowledge distillation in that
19 course?

20 A. No. I -- I didn't talk specifically about
21 that subject matter. That course was about
22 essentially introduction to the field of obviously
23 machine learning or -- and, you know, advanced
24 neural networks and deep learning. Talks about, you
25 know -- gets into the mathematics of a -- gradient

1 techniques, regression, et cetera.

2 I don't think the topic of knowledge
3 distillation was part of that fi- -- first offering.

4 Q. And when I -- when I asked you whether you
5 taught knowledge distillation in that class, you
6 understood what I was referring to; didn't you?

7 A. Well, I -- all I'm saying is the words
8 "knowledge distillation" aren't -- I don't remember
9 those being part of the class exactly specifically.
10 That's what I'm referring to. But the class
11 obviously is talking about advanced neural nets and
12 deep learning.

13 Q. And -- and do you know what a
14 teacher/student architecture is?

15 A. Yeah, I mean, generally speaking, yes.
16 And, obviously, I would need to see the details, but
17 yes, generally speaking, yes.

18 Q. And in -- in the pre-2017 timeframe,
19 what -- what is a teacher/student architecture?

20 MS. MAURI: Objection. Form.

21 THE WITNESS: Well, again, I mean, you --
22 you have essentially a -- an architecture that
23 provides perhaps a -- an in-depth knowledge in a
24 sense or an in-depth training or an in-depth, you
25 know, a set of algorithms. And the other

1 architecture might be a slightly smaller
2 architecture or a slightly more efficient
3 architecture in a sense.

4 It -- it depends on the application. I
5 would have to see what application you're referring
6 to or whether it makes sense in that application or
7 not.

8 BY MR. STEIN:

9 Q. Let's look at -- I'd like to go back to
10 Exhibit 1060, your -- your paper from just a couple
11 of months ago that you don't remember. If you look
12 at --

13 MS. MAURI: Objection.

14 MR. STEIN: -- the first page -- you've
15 got to let me finish the question before you object.
16 If you look at the first page --

17 MS. MAURI: I don't think you're making --
18 (Interruption in audio/video.)

19 THE COURT REPORTER: One person -- wait.
20 Counsel, I can't take two people. Please start
21 over.

22 BY MR. STEIN:

23 Q. So turning to Exhibit 1060, Dr. Saber, on
24 page 1, do you see there's something called an
25 "Impact Statement" in the second paragraph in the

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1 left-hand column?

2 A. Yes, I do.

3 Q. And then it -- it describes "The rapid
4 proliferation of edge computing and Internet of
5 Things devices demands lightweight yet efficient
6 machine learning models."

7 So do -- are you able to tell me what a
8 lightweight yet efficient machine learning model is?

9 A. Well, again, you're asking very general
10 questions. It depends a lot on the applications and
11 the context. But typically, a lightweight one would
12 be something with, say, less layers or less nodes
13 per layers. So it's more, you know, a -- it's -- it
14 still does the job, but it's a bit more
15 computationally efficient perhaps.

16 And -- and gets, you know, the -- the
17 high -- you know, close enough to the highest
18 accuracy but may not be needed to have highest -- so
19 it depends on the application --

20 (Interruption in audio/video.)

21 THE COURT REPORTER: But may not need? I
22 didn't hear you.

23 THE WITNESS: You may not need the highest
24 accuracy possible. You may -- you know, it depends
25 a lot on the application. I mean, again, you're

1 asking very generic and general questions and -- and
2 the details -- you know, the devil is in the
3 details, usually.

4 BY MR. STEIN:

5 Q. Okay. Let's go to the next sentence. You
6 say, "Current Convolutional Neural Networks (CNNs),
7 while powerful, are often too resource-intensive for
8 these applications."

9 What -- what is -- what makes something
10 too resource-intensive?

11 A. Well, if you have, for instance -- I mean,
12 this is one example, obviously.

13 If you have, for instance, many layers,
14 you're doing, you know, a variety of convolutions,
15 many layers. And obviously, you have to train all
16 that. So that makes it resource-intensive.

17 Q. And what does it mean -- the next
18 sentence, "Our proposed Dynamic Parameter Rank
19 Pruning method automates the compression of CNNs
20 during training."

21 So how do you -- how do you perform
22 compression during training of a CNN?

23 A. So, again, you're asking me questions
24 about a paper that was published six months ago.
25 And I would have to sit down and read the paper

1 carefully to be able to answer specific questions
2 about the paper. So I don't want to answer general
3 questions without having the specifics about the
4 paper, and it's been several months since I looked
5 at this paper.

6 Q. What additional -- what did you say? What
7 additional specifics about the paper would you need
8 to be able to answer a question about that impact
9 statement at the beginning?

10 MS. MAURI: Objection. Form.

11 THE WITNESS: Well, I mean, I would have
12 to read the paper in detail just so I can -- so I
13 can recollect what is in the paper and what -- what
14 we're proposing exactly, how we did -- how this was
15 done. So I -- you know, the devil's in the details.
16 I would have to read this carefully before answering
17 specific questions about it.

18 BY MR. STEIN:

19 Q. Let's continue. So under the
20 "INTRODUCTION" section in Exhibit 1060, you see the
21 terminal sentence of that section "Although these
22 large-scale models"?

23 A. I don't.

24 Q. Okay. It's the right -- so the first page
25 of Exhibit 1060, the right-hand column under the

1 section titled "INTRODUCTION," there's a full
2 paragraph. And if you look at the last sentence of
3 that full paragraph under the "INTRODUCTION"
4 section, it starts with "Although these large-scale
5 models."

6 A. First paragraph; right?

7 Q. Yeah. The terminal sentence of the first
8 paragraph. Yeah.

9 A. Yes, yes. So I -- I see the sentence.
10 "Although these large-scale models..." [As read]

11 Q. Yeah. What's -- what's a large-scale
12 model in the pre-2017 timeframe? Reminding you that
13 you said in your declaration, Exhibit 2008, that
14 you're familiar with the perspective of a POSITA in
15 that time period.

16 MS. MAURI: Objection. Form.

17 THE WITNESS: I mean, just what it says,
18 "large-scale models." You have a lot of layers, a
19 lot of depth in a given layer. So they're --
20 they're large models that try to model whatever the
21 application that you're trying to model. So I --
22 I'm not sure what you're asking.

23 BY MR. STEIN:

24 Q. What makes those viable in computer vision
25 applications? Is that -- what's the reason why

1 they're viable in those applications, computer
2 vision?

3 A. Well, it's -- obviously, if you -- for
4 instance, I mean, you're doing facial recognition or
5 whatever object tracking, the CNN-type models are
6 very viable because they capture the imagery.
7 They -- you know, imagery has redundancy in it.
8 Right? Imagery -- video imagery has spatial
9 redundancy to it, has temporal redundancy to it --

10 (Interruption in audio/video.)

11 THE COURT REPORTER: Can you say the last
12 part again, Doctor. Video imagery has?

13 THE WITNESS: So video imagery has spatial
14 redundancy to it, has temporal redundancy to it.
15 And the CNN-type models usually are very effective
16 in capturing those redundancies.

17 BY MR. STEIN:

18 Q. And then it looks like at the end of that
19 sentence, Exhibit 1060, it says, "Those large-scale
20 models pose challenges in environments with limited
21 training examples or comp-" -- "computational
22 resources such as remote sensing and edge
23 computing." [As read]

24 Do you know what remote sensing and edge
25 computing are?

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1 MS. MAURI: Objection. Form.

2 THE WITNESS: Well, yes, I mean, remote
3 sensing is typically, you know, you're trying --
4 you're trying to, you know, let's say, sense an
5 environment from an airplane, for instance, where
6 you're capturing multimodal imagery. So you are
7 capturing, you know, lidar imagery, video imagery,
8 and there's lots of that imagery. So these
9 obviously pose a lot of challenges in these type of
10 environments.

11 BY MR. STEIN:

12 Q. And why do those types of environments,
13 remote sensing and edge computing, have limited
14 training examples or computational resources?

15 MS. MAURI: Objection. Form.

16 THE WITNESS: Well, they're -- you know,
17 you don't -- you don't -- you don't have as much
18 publicly available databases in those environments
19 as you do in other environments. You know, for
20 instance, the Department of Defense has classified
21 databases in these type of environments. Because
22 it -- you know, it costs more money to collect --
23 you know, you have to run an airplane, collect
24 stuff, so there isn't as widely distributed of a
25 databases [verbatim] in that environment than you

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1 have in, say, the regular multimedia type
2 environment.

3 BY MR. STEIN:

4 Q. Okay. I'd like to turn to the '985 patent
5 for a minute. And do you -- are you able to
6 reference what's in front of you? Or would -- would
7 you like me to e-mail that one as well?

8 A. Please do e-mail it.

9 Q. Sure. While I'm -- while I'm getting
10 there, I'm going to be referring to Claim 1.

11 Do you remember Claim 1 of the '985
12 patent?

13 A. I will -- I will take a look at it when I
14 have it, so it's in front of me.

15 Q. Do you have it in paper form in front of
16 you right now?

17 A. I do. I have it in paper form.

18 Q. And was that one of the exhibits you told
19 me you reviewed in preparing for this deposition?

20 A. I have.

21 Q. But -- but, again, consistent with a lot
22 of your answers today, you -- you still refuse to
23 answer questions on materials you've reviewed very
24 recently; is that right?

25 MS. MAURI: Objection. Argumentative.

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1 THE WITNESS: I think your conclusion is
2 incorrect, sir.

3 BY MR. STEIN:

4 Q. Okay. I mean, it'll be your credibility
5 that the Board evaluates. It'd be easier if you
6 just answer the questions. They're not very
7 complicated.

8 MS. MAURI: Objection. Argumentative.

9 BY MR. STEIN:

10 Q. Here's the exhibit, Dr. Saber. It should
11 come through in a minute. When it does come
12 through, if you could pull up Column 26 of
13 Exhibit 1001, starting around Line 31, that's where
14 Claim 1 shows up.

15 (Previously marked IPR Exhibit 1001 was
16 referenced.)

17 A. I am there. I have it open up in front of
18 me.

19 Q. Okay. Are you able to tell me --

20 MS. MAURI: I -- I'm still waiting for it
21 on my end. Sorry.

22 MR. STEIN: Okay.

23 Jennifer, do you really not have a copy of
24 Exhibit 1001, the patent in front of you already?

25 MS. MAURI: I do not have a copy of

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1 Exhibit 1001 in front of me, but it just arrived.

2 MR. STEIN: That's shocking.

3 BY MR. STEIN:

4 Q. Okay. So Exhibit 1001, at Column 26,
5 Dr. Saber. It sounds like you're already there;
6 right?

7 A. I am there, sir.

8 Q. Okay. So if you could just take a look at
9 that claim or, you know, whatever recollection
10 you're able to recall having, you know, reviewed
11 this recently like you told me, does this Claim 1 --
12 does this cover a teacher/student architecture?

13 MS. MAURI: Objection. Form.

14 THE WITNESS: I'm not sure what you're
15 asking. We can walk through the claim elements, and
16 that's what it covers.

17 BY MR. STEIN:

18 Q. Okay.

19 A. The elements -- the claim elements are
20 described there in Claim 1.

21 Q. So if I -- if I handed you a Microsoft
22 product, and I told you it had a teacher/student
23 architecture, would you not be able to tell me
24 whether that practice is this claim or not?

25 MS. MAURI: Objection. Form.

1 THE WITNESS: I -- I would have to see the
2 product -- okay, you're asking a general question,
3 sir, that's hard to answer. I would have to see the
4 products, see the specifics, see what the
5 application's about, how it is done, what are the
6 technical details behind it. It's very hard to
7 answer generic public -- generic blanket type
8 questions like that.

9 BY MR. STEIN:

10 Q. Okay. So looking at Claim 1, moving past
11 the receiving training data steps that appear,
12 Column 26, Lines 34 to 44, if you could turn to the
13 operations that appear on Line 45 of Column 26,
14 "using a first machine learning algorithm."

15 Do you see that?

16 A. I -- I do.

17 Q. Okay. So that first machine learning
18 algorithm, could that be a teacher algorithm in a
19 student/teacher architected machine learning
20 algorithm?

21 A. Well, again, you -- you have to show me
22 what is it that you're doing, whether it makes sense
23 if it is or it isn't. You -- I would have to see
24 the specifics.

25 Q. Sure. Sure.

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1 So go -- go ahead and please read, you
2 know, Column 26, Line 45 to Column 26, Line 57 and,
3 you know, please let me know if that could be a
4 teacher/student architecture in which the first
5 machine learning algorithm is the teacher and the
6 second machine learning algorithm is the student.

7 A. So, again, you would have to show me what
8 the architecture that you're talking about so
9 what -- so that we can be specific.

10 Q. The --

11 A. It's hard to answer, you know, generic
12 blanket questions like that.

13 Q. Could you -- just let me know, Dr. Saber,
14 what's generic about this particular question?

15 So I'm pointing you to the specific claim
16 language, which says "using a first machine learning
17 algorithm...using a second machine learning
18 algorithm" [as read], are you saying that the claim
19 language is generic? Because I'm only asking you
20 about the claim language.

21 A. So that's not what I understood your
22 question to be asking. But if you're ask- -- asking
23 about the specific claim language here, the claim
24 language obviously clearly states you're "using a
25 first machine learning algorithm to generate first

1 reference data using the training data," and it goes
2 on from there.

3 So your first machine learning algorithm
4 is being used to generate first reference data that
5 comprises editing instructions and -- for adjusting,
6 obviously, a digital representation of the head
7 region.

8 Q. Yeah.

9 So with -- so does that define an
10 architecture to you, what's recited in Column 26,
11 Lines [verbatim] 45, to Column 26, Line 57, of
12 Exhibit 1001? Does that define an architecture or
13 not?

14 MS. MAURI: Object to form.

15 THE WITNESS: It defines a -- it defines a
16 first machine learning algorithm and a second
17 machine learning algorithm and what they are doing.
18 BY MR. STEIN:

19 Q. So is -- is that an architecture, or is
20 that not an architecture?

21 A. The word "architecture" is not mentioned
22 there. This -- it defines what the specific of each
23 machine learning algorithm is -- is designed to do.

24 Q. So let's look at the language -- so within
25 those two clauses, "using a first machine learning

1 algorithm..." [as read], then you'll see it says
2 "for a range of possible digital representations of
3 the head region."

4 Do you see that around Line 48 --
5 Column 26, Line 48 of Exhibit 1001, 48 to 49?

6 A. I do.

7 Q. And then if we go inside of the "using a
8 second machine learning algorithm" clause that
9 begins at Column 26, Line 50, of Exhibit 1001, and
10 go all the way to Lines 56 to 57, do you see it says
11 the same language, "for a range of possible digital
12 representations of the head region"?

13 A. Yes.

14 So what is your question?

15 Q. So those two recitations of a range of
16 possible representations of the head region, could
17 those be the same possible digital representations
18 of the head region or must they be different
19 possible digital representations of the head region?

20 A. So what it's stating is it's the
21 digital -- for adjusting the digital represen- -- so
22 using the first machine learning algorithm -- I'm
23 talking about the first one right now -- so for
24 adjusting the digital representation of a head
25 region for a range of possible digital

1 representations of the head region.

2 So you're going to make an adjustment of
3 the digital representation of the head region in
4 that -- you know, for a possible range of them.

5 And then the second machine learning
6 algorithm is going to also -- has the capability of
7 making an adjustment of the digital representation
8 of the head region for a -- for a range of possible
9 digital representations of the head region.

10 So I -- I'm not sure what you're asking.
11 The -- each of them is capable of making this
12 adjustment of the digital representation.

13 Q. Yeah, I want -- I want to focus on -- and
14 I -- I want to be clear as I possibly can because I
15 see we're struggling here.

16 So Column 26, Line [verbatim] 48 to 49,
17 has a phrase, right, "for a range of possible
18 digital representations of the head region"?

19 And then could you just confirm for me
20 that at Column 26, Lines 56 to 57, we see that exact
21 same phrase, "for a range of possible digital
22 representations of the head region?"

23 Can we agree on that? We see the same
24 phrase twice; right?

25 A. Yes, you read that correctly.

1 Q. So when we see that same phrase recited
2 twice, does that mean that the editing instructions
3 that are part of the first reference data have to
4 cover the same range of possible digital
5 representations of the head region or a different
6 range as compared to the editing instructions for
7 the second reference data that we see recited
8 immediately thereafter?

9 MS. MAURI: Objection. Form.

10 THE WITNESS: I'm not sure -- well, I
11 think you're taking this out of context, and you're
12 mixing apples and oranges in this description and
13 pulling this sentence out of context.

14 BY MR. STEIN:

15 Q. Okay.

16 A. So you're adjusting the digital
17 representation of a head region for a range of
18 possible digital representations of the head region.
19 So you have a range of possibilities.

20 You're making an -- that adjustment within
21 that range of possibilities, you know, and the first
22 machine learning algorithm has the ability to make
23 that adjustment in those range of possibilities.

24 And the second machine learning algorithm
25 has also the ability to make the adjustment of the

1 digital representation for a -- for a range of
2 possible digital representations.

3 Q. Okay. Yeah. So I -- I would just like to
4 try and compare -- I -- I think your statement is
5 consistent with mine.

6 So those range of possibilities between
7 the editing instructions associated with the first
8 reference data and the editing instructions
9 associated with the second -- second reference data,
10 those range of possible digi- -- digital
11 representations that you just talked to me about for
12 the two different reference data, do they need to be
13 the same ranges or different ranges?

14 MS. MAURI: Objection. Form.

15 THE WITNESS: Yeah, it's essentially -- I
16 don't -- I don't understand what you're asking. I
17 think you're mixing apples and oranges, and I'm not
18 sure what you're asking.

19 But each -- each algorithm can have a
20 certain range that you make the adjustments. I --
21 I'm not sure what you're asking. I think you're
22 mixing apples and oranges and taking things out of
23 context.

24 BY MR. STEIN:

25 Q. So let's just read. So -- yeah, I -- I

1 hope I'm being as clear as possible, but you -- you
2 just a few moments ago told me the first machine
3 learning al- -- algorithm has the ability to make
4 that adjustment in those range of possibilities.

5 You then said and the second machine
6 learning algorithm also has the ability to make the
7 adjustment of the digital representation for a range
8 of possible digital representation.

9 So you just told me the first MLA and the
10 second MLA, they can adjust across a range of
11 possible digital representations.

12 Is that -- is that fair?

13 A. Yes, the first MLA can adjust the digital
14 representation of a head region for a range of
15 possible digital representations.

16 And the second MLA can also do -- adjust
17 the digital representation of a head region for a
18 range of possible digital representations.

19 So you have a range for each of them to
20 make the adjustments in.

21 Q. Okay. Is it -- so I guess -- here's
22 another way to frame my question.

23 Is it possible for you to compare the
24 ranges for those two different machine learning
25 algorithms, or is that not possible?

1 A. I'm not sure what you're asking. What do
2 you mean "compare the ranges"? I don't -- I don't
3 know what you're talking about.

4 Q. Well, you -- here's what you just said.
5 You said, So you have a range for each of them to
6 make the adjustments in.

7 So the range that you are referring to in
8 your answer for the first MLA and the second MLA,
9 can you compare those? Are those ranges the same,
10 or are they different?

11 A. I'm not sure I -- I apologize, but I'm not
12 sure what you are asking. You have a range of
13 adjustment with the first MLA. You can adjust the
14 head region over a given range, maybe plus or minus
15 30 degrees or whatever. I'm making these numbers
16 up.

17 But you can adjust it over a given range,
18 and you can adjust the second one over a given
19 range. It depends on how you obviously design them.
20 But I'm not sure what you're asking.

21 Q. So just -- let's just try one more time.
22 So -- so you -- you just told me -- again, I'm just
23 reading what you told me, Dr. Saber. I'm -- I'm --
24 I don't think these are very complicated.

25 But you said, You can adjust it over a

1 range, and you can adjust the second one over a
2 given range.

3 So you have told me in your answer that
4 the first machine learning algorithm is associated
5 with some range. The second machine -- machine
6 learning algorithm is also associated with some
7 range.

8 Can we just pause there and ask if
9 we're -- are we aligned on that? They have -- they
10 each have some range; right?

11 MS. MAURI: Objection. Argumentative.

12 THE WITNESS: So, again -- and if you look
13 at the claim element, it says "for adjusting the
14 digital representation of the head region for a
15 range of possible digital representations of the
16 head region." So there's a range that it can adjust
17 in.

18 So, you know, as I said, maybe it's plus
19 or minus 30 degrees. I'm making this up, obviously,
20 just -- just to give you an example, an
21 illustration.

22 But there's a range of where you can make
23 the adjustment with the first MLA, and there is a
24 range where you can make the adjustment with the
25 second MLA.

1 BY MR. STEIN:

2 Q. Okay. So if -- if we take your example --
3 so let's say the first one, just -- just as an
4 example, it's plus or minus 30 degrees.

5 If that's the range for the first one,
6 does the second one also have to be plus or minus
7 30 degrees, or -- or may it be different?

8 A. It -- it -- it may be different. You
9 don't have to have the same range. It could be the
10 same range. It could be different range. It could
11 be more compact range. It could be more expanded
12 range. It depends how you design the application
13 and what you're trying to do with it.

14 Q. Okay. I want to turn to -- back to your
15 declaration, Exhibit 2008. If you could go to
16 Paragraph 45, please.

17 A. Yes.

18 Q. I'm going to turn to page 17 where
19 Paragraph 45 continues. Sort of in the middle of
20 page 17, the continuation of Paragraph 45 of
21 Exhibit 2008, do you see the sentence that begins
22 "Over time"?

23 A. Yes.

24 Q. And I'll -- I'll just read it.

25 "Over time, human programmers can tweak

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1 the model, change/adjust parameters, and/or supply
2 additional training data as needed to yield more
3 accurate results."

4 Have I read that sentence correctly?

5 A. You have read it correctly.

6 Q. What does it mean for a human programmer
7 to "tweak the model"?

8 A. Well, you [verbatim] obviously programming
9 the software in a sense, if we're talking about the
10 software here.

11 Let -- let's just -- as an example, if I'm
12 talking about software, so you -- you obviously can
13 tweak the model. You can add more nodes. You can
14 add more layers. You can, you know, make minor
15 changes in the model in a sense.

16 Q. And continuing, you all -- the same
17 sentence, "human programmers can change/adjust
18 parameters" [as read], what does that mean?

19 A. Well, let's say you're changing the
20 hyperparameters, so you're adjusting the
21 regularization parameters. You know, there's a lot
22 of parameters in the model. You know, gradient
23 descent parameters.

24 (Interruption in audio/video.)

25 THE COURT REPORTER: What -- what descent

1 parameters?

2 THE WITNESS: Gradient -- gradient descent
3 parameters.

4 BY MR. STEIN:

5 Q. And then the -- the last one, "human
6 programmers can supply additional training data" [as
7 read], what does that mean?

8 A. Just -- just what it says, you can provide
9 additional training data to your model.

10 Q. So that would be sort of the hypothetical
11 example I gave earlier where you supply a hundred
12 thousand images of dog faces to some sort of model?

13 MS. MAURI: Objection. Form.

14 THE WITNESS: Well, you have to pro- --
15 supply appropriate training data to your model.
16 It's not just randomly chosen stuff. You have to
17 provide -- if you're doing facial recognition, you
18 wouldn't provide, for instance, images of cars, you
19 know. You're generally going to provide images that
20 are related to the application that you're trying to
21 do at -- a- -- appropriate imagery.

22 BY MR. STEIN:

23 Q. And --

24 A. It's not just generic [verbatim].

25 Q. And in this same sentence that we've been

1 looking at, the three sort of options, "tweak the
2 model, change/adjust parameters, supply additional
3 training data" [as read], they're linked together by
4 an "and/or."

5 Do you see that?

6 A. Yes.

7 Q. Is that -- that understood to mean that
8 you can use all three of these or any one of these
9 to yield more accurate results? Is that your
10 intention?

11 A. That's my intention.

12 Q. And it -- is it always the case that for
13 any one of these it would yield more accurate
14 results; or, as you mentioned earlier, you need to
15 have sort of an appropriateness threshold for
16 yielding more accurate results, as you said, for the
17 training data?

18 A. I think your question's a little bit
19 convoluted, but I can make a change to a parameter
20 and yield less accurate results.

21 So it -- it obviously depends on the
22 application and what you're doing and how the change
23 is -- is -- but the idea behind it, generally
24 speaking, is you want to make changes to improve
25 accuracy or efficiency of a given model, but you can

1 make changes that would make the model worse.

2 Q. Sure.

3 Okay. So we'll take a -- I don't want to
4 run over on you again. So if you'd go to
5 Exhibit 2008, and you go to, you know, little Roman
6 numeral ii, which is titled "PATENT OWNER'S EXHIBIT
7 LIST," can you let me know when you're there?

8 A. Yes, I am there.

9 Q. So you've titled this "PATENT OWNER'S
10 EXHIBIT LIST," but do you see you have a whole bunch
11 of exhibits here that begin with 1-0 and then some
12 additional numerics?

13 A. Yes.

14 Q. So you -- you understand those to be
15 patent owner's exhibits?

16 A. I mean, I -- I -- I -- I don't know
17 exactly who's who exactly, but that sounds about
18 right, yes.

19 Q. Okay. And so Exhibit 1013, do you see
20 that sort of most of the way down the page?

21 A. 1013, yes.

22 Q. So would that have been an exhibit that
23 you reviewed?

24 A. I have reviewed these exhibits, yes.

25 Q. And then one final question, and then

1 we'll take a break.

2 So Exhibit 2008, page 5, the last sentence
3 of Exhibit -- sorry, Paragraph 14, this was a new
4 course we talked about earlier that you were
5 designing.

6 You mentioned that it's being taught for
7 the first time in spring 2024.

8 Did you end up teaching that course or
9 not?

10 A. Yes, I have.

11 Q. Okay.

12 MR. STEIN: With -- with that, I think we
13 can take a break. So we can go off the record and
14 talk about that, Hanna.

15 MS. MAURI: Okay.

16 (Short recess taken.)

17 MR. STEIN: Ready.

18 MS. MAURI: Ready when you guys are.

19 BY MR. STEIN:

20 Q. Okay. So, Dr. Saber, we just came back
21 from a -- about a 30-minute break or so.

22 What did you do during the break?

23 A. I had a quick lunch.

24 Q. Did you talk with your counsel during the
25 break?

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1 A. No, I have not.

2 Q. Any text messages from your counsel?

3 A. No.

4 Q. E-mails?

5 A. No.

6 Q. Okay. Let's go back. So before the break
7 we were talking about the '985 patent. So 1- -- I'd
8 like you to turn to the '985 patent; that's
9 Exhibit 1001.

10 A. Yes.

11 Q. So these -- the Claim -- Claim 1 that we
12 were looking at at Column 26, Line 31, the preamble
13 says, "A method of generating reference data." [As
14 read]

15 Do you see that?

16 (Interruption in audio/video.)

17 THE COURT REPORTER: "The preamble says"?
18 Excuse me. Could you please repeat.

19 BY MR. STEIN:

20 Q. The preamble says, "A method of generating
21 reference data." [As read]

22 Do you see that?

23 A. I do.

24 Q. Is reference data generated during
25 runtime, or is it generated during training?

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1 A. Excuse me.

2 So if you look at the element starting at
3 Line 45, it states, "using a first machine learning
4 algorithm to generate first reference data" -- so
5 that's the reference data we're talking about --
6 "using the training data." [As read]

7 So it's generating the reference data
8 using the training data.

9 Q. So it's a -- it's a training operation; is
10 that correct?

11 MS. MAURI: Objection to form.

12 THE WITNESS: Again, it's generating the
13 first reference data using the training data.

14 BY MR. STEIN:

15 Q. Well, when I'm asking questions about the
16 term "training," is that -- is that something you
17 understand in the context of Claim 1 of the '985
18 patent?

19 MS. MAURI: Objection. Form.

20 THE WITNESS: Yes, I do.

21 BY MR. STEIN:

22 Q. And when I use the term "runtime," is that
23 something you understand in the context of the '985
24 patent?

25 A. Generally speaking, yes. But you need to

1 be specific when you're asking your questions. So I
2 will ask you if I'm -- don't understand it.

3 Q. Okay. So when the -- when the claim says
4 "using a first machine learning algorithm to
5 generate first reference data," does that operation,
6 to generate first reference data, does that occur as
7 a training operation, or does that occur as a
8 runtime operation?

9 A. Well, if you continue reading that -- that
10 element that you just read, it says, "to generate
11 first reference data using the training data."

12 So it's using the training data to
13 generate the reference data.

14 And then the next part of that element
15 describes what the reference data is about.

16 Q. Okay. So let me rephrase the question.

17 When the claim says "using a first machine
18 learning algorithm to generate first reference data
19 using the training data," is that a training
20 operation, or is that a runtime operation?

21 A. It's -- would be -- it -- it would be --
22 it's using the training data to generate the
23 reference data. So it's during -- during the
24 training, it's using the training data to generate
25 the reference data.

1 Q. Okay. And if we look at the operation
2 that starts at Column 26, Line 50, "using a second
3 machine learning algorithm to generate second
4 reference data using the same training data as the
5 first machine learning algorithm," is that a
6 training operation, or is that a runtime operation?

7 A. Well, again, it's saying "using a second
8 machine learning algorithm to generate second
9 reference data," so that's different from the first
10 reference data, "using the same training data," that
11 is talking about in the previous one.

12 So you have training data. It's using the
13 same training data to generate the second reference
14 data.

15 Q. So that -- that operation, when you --
16 when you have training data that is using the same
17 training data to generate the second reference data
18 that -- that you just stated in your answer, is that
19 a training operation or a runtime operation?

20 A. Well, you -- you can't really put it in
21 those words. You're essentially using the training
22 data to generate the reference data.

23 So essentially, however you're doing it,
24 you're using the training data to generate the
25 reference data.

1 As long as you're using the training data
2 to generate the reference data, you're doing what
3 it's say- -- what it's stating.

4 Q. And one of the examples in the patent is
5 sort of using this reference data at runtime to
6 adjust somebody's eye gaze during a videoconference;
7 is that fair?

8 A. What part of the patent are you referring
9 to? Let's be specific.

10 Q. Sure.

11 I'm finding it for you. We'll come --
12 I'll come back to that.

13 So looking at the '985 patent, do you
14 recall if it discusses an objective function?

15 A. I don't remember if the word "objective
16 function" appear in the patent.

17 Q. And turn- -- turning back to Claim 1 of
18 the patent, that -- that Column 26 we've been
19 looking at in Exhibit 1001, does -- does Claim 1
20 reference an objective function?

21 A. Well, the words "objective functions" do
22 not -- are not printed on that page literally, but
23 obviously when you're doing the training, you have
24 to utilize some type -- you -- you need to utilize
25 some type of objective function to accomplish the

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1 training. Like the word --

2 Q. Could you --

3 A. Oh, go ahead.

4 Q. No, please -- please finish your answer.

5 I -- I didn't -- I thought you were com- -- I
6 thought you were finished.

7 A. No.

8 The words "objective function" aren't
9 printed literally on that page. But while you're
10 doing to training, you utilize some type of
11 objective function to accomplish the training.

12 Q. And would it be consistent with Claim 1
13 that you could utilize one objective function to
14 perform the training for the first and the second
15 machine learning algorithms?

16 A. I didn't hear the first part of your
17 question.

18 Q. Would it be consistent with Claim 1 in the
19 '985 patent that one objection -- objective function
20 could be utilized to perform the training for the
21 first and second machine learning algorithms?

22 A. Well, I'm -- I'm not sure. I mean, you
23 would have to show me what you're talking about in
24 details. You would need an objective function to
25 perform the training for the first machine learning

1 algorithm.

2 And you need an objective function to
3 perform the training for the second machine learning
4 algorithm.

5 You would have to show me equations or
6 whatever so I can say whether that would be
7 appropriate or not.

8 Q. Can you show me where in the patent it
9 says that you need, you know, different objective
10 functions for the two machine learning algorithms in
11 Claim 1?

12 MS. MAURI: Objection. Form.

13 THE WITNESS: Well, as I mentioned, the
14 word "objective" doesn't appear literally. But as
15 you are doing the training, you obviously will need
16 some type of objective function to hone in your
17 training, to -- to -- to essentially train the
18 network to accomplish what you're -- you know, the
19 supervised learning in a sense. So --

20 (Witness reviews.)

21 BY MR. STEIN:

22 Q. Just to confirm, Dr. Saber, are you
23 checking something? I don't want to ask when you're
24 still answering.

25 A. Yes, I'm checking to see -- so obviously

1 it talks in the patent about training extensively.

2 So if you look, for instance, at Column 7,
3 starting at Line 65 --

4 Q. Okay.

5 A. -- I think this is in -- this had been
6 referenced to Figure 3.

7 Q. Okay.

8 A. So you can see in -- starting on Line 65
9 is -- on -- on Column 7, it starts to talk about the
10 training input to the machine learning technique,
11 and it describes the two sets of images.

12 And on Column 8, it describes the input
13 images, starting at Line 6.

14 And then on Column 8, starting at Line 16,
15 it describes the output images.

16 Q. Is there anything else, Dr. Saber?

17 A. Yeah, so I'm waiting for your next
18 question, in a sense. So I'll get -- it
19 describes -- it describes the input images. It
20 describes the output images. And it describes the
21 steps of training going through Column 8 in the next
22 page.

23 Q. And -- in -- in Column 8 through the next
24 page, does it provide any guidance as to what the
25 objective function would be?

1 MS. MAURI: Objection. Form.

2 THE WITNESS: Well, again, I mean, you
3 would have to provide -- you would have to have --
4 it's understood, you know, with machine learning
5 that you have to have an appropriate objective
6 function designed to do the -- to do essentially the
7 training. I mean, that's part of the process, if
8 you would.

9 BY MR. STEIN:

10 Q. So you need at least one objective
11 function; is that right?

12 A. Well, you need to construct an appropriate
13 objective function to do the training. So it's not
14 just some random thing. It's an appropriate
15 objective function that you would utilize to do the
16 training to essentially map the input images to the
17 output image -- so you have a set of input images,
18 and you have the desired output image for the given
19 input image.

20 What you're trying to do is try to get the
21 network to find that output image, to generate that
22 output image when it sees that input image. So you
23 need to define an objective function that would help
24 essentially train the network to get to that level.
25 Otherwise, it'll just be a trial -- a trial and

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1 error, and would -- basically, you wouldn't have
2 conversions in a reasonable amount of time.

3 Q. So -- so in the '985 patent, you would
4 need at least one appropriate objective function; is
5 that phrase --

6 (Interruption in audio/video.)

7 THE COURT REPORTER: Could you repeat the
8 question. There was some audio...

9 BY MR. STEIN:

10 Q. Sure.

11 In the -- in the '985 patent, in the
12 claims, you would need at least one appropriate
13 objective function; is that more accurate?

14 MS. MAURI: Objection. Form.

15 THE WITNESS: Well, you need an
16 appropriately designed objective function for your
17 machine learning algorithm --

18 (Interruption in audio/video.)

19 THE COURT REPORTER: Dr. Saber, your audio
20 cut out.

21 THE WITNESS: Okay. Let me repeat.

22 So for the machine learning algorithms,
23 for machine learning algorithm 1, you need an
24 appropriately designed objective function to perform
25 the training that would result in an appropriate

1 designed MLA 1. And you would need an objective
2 function to perform the training for MLA 2, that
3 would result in appropriately designed MLA 2.

4 BY MR. STEIN:

5 Q. Could you show me where -- if you pointed
6 me to Column 8, can you show me where in the patent
7 it describes having an objective function for the
8 first machine learning algorithm and a different
9 objective function for the second machine learning
10 algorithm?

11 MS. MAURI: Objection. Form.

12 THE WITNESS: Well, I mean, if you read
13 the patent, it clearly describes two machine
14 learning algorithms. And, for instance, if you look
15 at Figure 14, you can see two machine learning
16 algorithms there in Figure 14 as an illustration, as
17 an embodiment of this patent.

18 So both of them are in the same input
19 training data 100 and then performing the
20 appropriate adjustments. So it would be understood
21 that you have to train those algorithms properly.
22 And then a POSITA would understand that, that you
23 would need an objective function to train the
24 algorithms.

25 BY MR. STEIN:

1 Q. So is your answer that the patent does not
2 say it, but that a POSITA reading, I guess you said
3 Figure 14, would be able to figure out that you need
4 these objective functions. Because you -- you
5 haven't pointed me to where in the patent it
6 actually says that.

7 A. Well --

8 MS. MAURI: Objection. Form.

9 THE WITNESS: -- as I mentioned to you
10 earlier, the word "objective function" doesn't
11 appear literally in the patent. I did a quick
12 search, and I don't see the word [verbatim]
13 "objective function" in the patent. But when you
14 read the description of the patent and you read the
15 training part of the patent, a POSITA would
16 understand that for you to accomplish the training,
17 you have to have an appropriately designed objective
18 function.

19 BY MR. STEIN:

20 Q. Could you look at Claim 11 on Column 27,
21 Line 52 of the patent.

22 Do you see where it says "the second
23 machine learning algorithm comprises one or more of
24 the following: A regression forest; regression
25 ferns, cluster centres, a lookup table, and

1 separable filter banks." [As written]

2 Do you see that?

3 A. I do.

4 Q. Is a lookup table a second machine
5 learning algorithm?

6 A. I think you're mixing concepts, sir. I
7 think you're mixing concepts tremendously.

8 Q. Okay. I -- I'm just reading Claim 11. So
9 what -- what does Claim 11 mean to you when it says
10 "the second machine learning algorithm comprises,"
11 and then it says a "lookup table"?

12 A. Well, it says "comprises." It's not -- it
13 does not say the machine learning algorithm is a
14 lookup table. It says comprises, one more -- more
15 of the following.

16 And so, you have a machine learning
17 algorithm that you have trained. And you may have
18 taken that training and incorporated it into a
19 lookup table to use for its speed and efficiency,
20 but --

21 (Interruption in audio/video.)

22 THE COURT REPORTER: What inefficiency?

23 THE WITNESS: For speed and efficiency.

24 MR. STEIN: Okay. I'm going to send the
25 Chalom reference to everyone for this thing. I

1 don't know why we're doing this.

2 BY MR. STEIN:

3 Q. And while we're waiting on that, let's
4 continue going on something else.

5 So you -- a couple of times today,
6 Dr. Saber, we've talked about something called a
7 teacher/student architecture; right?

8 A. Yes.

9 Q. Are you able to recall when -- when the
10 first time is that you would have heard about a
11 teacher/student architecture?

12 A. Not off the top of my head. I mean, I've
13 been working in this field for over 30 years.

14 Q. You think it was 30 years ago when you
15 first heard about it?

16 A. I -- I couldn't tell you off the top of my
17 head.

18 Q. 20 years ago?

19 A. Again, I couldn't tell you off the top of
20 my head. I did receive your document. I am going
21 to download it.

22 Q. Sure.

23 Could it have been last month was the
24 first time you heard about teacher/student
25 architecture?

1 A. No, it wasn't last month.

2 Q. Okay. So would it have been before 2017?

3 A. I mean, I don't recall off the top of my
4 head. And I've heard about it probably more than
5 once, but it -- it's been many years. I don't
6 remember exactly when --

7 Q. Sure --

8 A. -- and I don't want to give you an
9 inaccurate answer.

10 Q. Could it have been after 2017? It's
11 possible that was the first time you heard about
12 teacher/student architecture, it was after 2017?

13 A. No. It would have been definitely before
14 2017. It was -- it's -- it's not, you know,
15 something new.

16 Q. And -- and how many models does a
17 teacher/student architecture have?

18 MS. MAURI: Objection. Form.

19 THE WITNESS: I have no idea what you are
20 asking.

21 BY MR. STEIN:

22 Q. So do you -- do you know what a
23 teacher/student architecture is?

24 A. I do.

25 Q. So could you please describe it for me.

1 A. Well, again, it depends on the
2 application -- we've gone through this, sir,
3 already. It depends on the applications, how you've
4 constructed it. You would have to show me what the
5 application is, how it's constructed so I can opine
6 on it.

7 And generic open-ended questions like that
8 are not easy to answer because they're very generic,
9 they're very hypothetical, and there's no constraint
10 to them.

11 Q. Okay. Let's -- let's look at Paragraph 57
12 of your declaration, which is Exhibit 2008.

13 A. Paragraph 57?

14 Q. Yes. Could you please read that paragraph
15 and let me know if that might describe a
16 teacher/student architecture? Paragraph 57, on page
17 23 of your declaration, Exhibit 2008.

18 A. (Witness reviews.)
19 So what is your question?

20 Q. Yeah.
21 So I know a few times we've run into
22 roadblocks today where you're -- you're telling me
23 my questions are general. So I'm trying to do a
24 better job of, you know, pointing you to things in
25 your declaration and trying to ask the questions.

1 So looking at Paragraph 57 of your
2 declaration, does [verbatim] what's described there
3 apply to a teacher/student architecture?

4 A. What's described there applies to the
5 architecture of the '985 patent, and that -- that is
6 what it applies to. That applies to the
7 architecture of how the '985 patent is constructed.
8 The word [verbatim] "teacher/student" don't appear
9 in that patent.

10 Q. Well, let's -- let's try to break it
11 apart.

12 So in Paragraph 57 of your declaration,
13 Exhibit 2008, you state, "the first machine learning
14 algorithm may create its instructions using a
15 computationally intensive process to create highly
16 accurate results."

17 So, let's -- let's pause there.

18 Does that description apply to a teacher
19 model that might be used for an image classification
20 task?

21 MS. MAURI: Objection. Form.

22 THE WITNESS: Well, I -- again, you're --
23 you're asking very generic and general questions.
24 And I'm trying to answer -- I want to answer
25 specific questions with details and specificity and

1 accuracy.

2 And the '985 patent has two machine
3 learning algorithms, as you have said -- as you have
4 read there. One that's creating highly accurate
5 results. And the second one which can be fed to the
6 second machine learning algorithm to create
7 instructions using less complexity while still
8 arriving at highly accurate results. So that's
9 what's being described in the '985 patent. And I
10 think you're taking that out of context.

11 BY MR. STEIN:

12 Q. So you're -- you're -- you keep saying you
13 want to answer specific questions with details and
14 specificity and accuracy.

15 So let me -- let me just ask: When I --
16 when I point to this passage, "the mach- -- "first
17 machine learning algorithm may create its
18 instruction using a computationally intensive
19 process to create highly accurate results," what
20 additional specifics do you need in order to tell me
21 if that could apply to a teacher model for an image
22 classification task? What other specifics could I
23 offer to you?

24 A. Well, I would need to see what are you
25 doing, how you're structuring it, what application

1 is being done, what is exactly the structure of the
2 application, how the application is designed. I
3 mean, you're asking generic, hypothetical questions.

4 Q. Okay. So I'm -- I want to --

5 A. Out of context to what is being discussed
6 here.

7 Q. Okay. So my -- my question is
8 specifically about the '985 patent and that passage.

9 A. Yes.

10 Q. So that passage -- and to your point, how
11 you're structuring it, what application is being
12 done. I'm talking about the structure and the
13 application of the '985 patent. I'm talking about
14 your passage in Paragraph 57 and whether that
15 passage can apply to a teacher model having the
16 architecture and the structure of the '985 patent.
17 I'm using the '985 patent.

18 MS. MAURI: Objection. Form.

19 THE WITNESS: And, again, I'm answering to
20 you like -- you're -- you're taking one paragraph
21 out of a context out of a section. So the section
22 starts with overview of the '985. It describes the
23 patent itself. It talks about the de- -- some of
24 the details, provides an overview of the patent.
25 For instance, at Paragraph 56, we have a copy and

1 paste, Column 217 to 43, that describes the use of
2 the two machine learning algorithms, et cetera,
3 that's being described.

4 So you -- you're taking the sentence out
5 of context and trying to fit a round peg into a
6 square hole.

7 What's described in the patent is clear
8 about the use of the two machine learning algorithms
9 and how they're being utilized.

10 BY MR. STEIN:

11 Q. Okay. So that -- that entire description,
12 so we're -- we have no lack of context now, right,
13 we're talking about the whole passage in Paragraph
14 57. So -- so do we now have context? If I'm saying
15 it's the whole passage in Paragraph 57, do we now
16 have context?

17 A. Well, the section itself, right, starting
18 in Paragraph 47 and going obviously to Paragraph 67,
19 des- -- provide a description of what is being done
20 in the '985 patent and how the two machine learning
21 algorithms are -- are -- are designed and work
22 essentially together, in -- in a sense. So how
23 they're architected, how this architecture is --
24 is -- is done. Provides an overview of that.

25 What's the use of the first one? What's

1 the use of the second one? And you -- you're taking
2 one paragraph out of the context and trying to fit a
3 round peg in a square hole.

4 Q. All righty.

5 So let -- let's go to Exhibit 1005, which
6 I just e-mailed to you. If you could open that up,
7 please.

8 So this Exhibit 1005 that I've e-mailed to
9 you during the deposition per your counsel's
10 request, on the first page, could you let me know
11 what patent you're looking at?

12 A. I am looking at the U.S. 10,664,949, the
13 patent with inventor, Chalom, and titled, "EYE
14 CONTACT CORRECTION IN REAL TIME USING MACHINE
15 LEARNING."

16 (Previously marked IPR Exhibit 1005 was
17 referenced.)

18 BY MR. STEIN:

19 Q. So is this -- is this the Chalom reference
20 that you described -- the Chalom patent that you
21 describe in your declaration, Exhibit 2008?

22 A. It is.

23 Q. Okay. And if you -- if you look at the
24 figure that's on the front page of Chalom
25 Exhibit 1005, do you see there's an image at the

1 bottom?

2 A. Yes, I do see that.

3 Q. Okay. Is that the same image that appears
4 as Figure 3 in the Chalom patent, Exhibit 1005?

5 A. It is.

6 Q. And do you see that there's something
7 called a

8 "Random Forest Classifier 306"?

9 A. I do.

10 Q. So that Random Forest Classifier 306 is
11 not a -- a machine learning algorithm; is that
12 right?

13 A. I think you're mixing a lot of stuff, sir.
14 So that random force classifier is what was designed
15 to do the classification given Chalom's algorithms.
16 Given Chalom's, you know, architecture, in a sense,
17 Chalom has proposed a random forest classifier to do
18 the -- the feature classification and to get to the
19 end result.

20 Q. I'll just repeat the question.

21 So that Random Forest Classifier 306 that
22 we see in Figure 3, Chalom Exhibit 1005, that is not
23 a machine learning algorithm; is that correct?

24 MS. MAURI: Objection. Asked and
25 answered.

1 THE WITNESS: I -- I already answered your
2 question. I mean, you can look -- let's look at the
3 Figure 3 as a whole. So if you look at Figure 3,
4 you see there is -- 212 is an input image, that "II"
5 stands for "input image." So you have an input
6 image that you are doing face detection and facial
7 landmark detection on in 301.

8 And "FL" stands for "facial landmarks"
9 that you have acquired as a result of this 301,
10 which then you crop and resize. And then you have
11 essentially your eye region. So you -- you focused
12 on the eye region version -- portion of that image
13 because you might have an image that has -- like,
14 look at my background, it's got the towel behind it
15 and the door, and you want to adjust my head, not
16 the towel behind. So you focus on the eye region of
17 my -- of that image.

18 And then you have a feature generation,
19 Section 303, that does the feature generation. And
20 then the random forest classifier, we use the
21 feature sets, that FS 312, together with the
22 original image, it will do the classification. And
23 then provide -- it will look at the original image,
24 it will look at the feature sets that you created,
25 and it will provide the appropriate motion vectors.

1 And that's your "MVF," that you see there, the
2 motion vector field, which then is used together
3 with the original image.

4 The warp and integrate will then take
5 those motion vector fields, apply them to the
6 original image to get the ECCIs, the eye -- I think
7 corrected -- the eye con- -- you know, corrected
8 image, essentially.

9 BY MR. STEIN:

10 Q. That still hasn't answered my question.
11 But let's go to Column 10 of Chalom Exhibit 1005.

12 A. Column 10?

13 Q. Yep. Column 10.

14 A. Yes, sir.

15 Q. Do you see at Column 10, Line 61 of
16 Exhibit 1005, where it says, "such techniques may
17 provide for the application of different pretrained
18 models as an orientation or relative position
19 between camera 104 and display 102 may change."

20 Do you -- do you see that?

21 A. Yes.

22 Q. Does Chalom's reference to "different
23 pretrained models" refer to multiple machine
24 learning algorithms?

25 MS. MAURI: Objection. Form.

1 THE WITNESS: I -- I think you're taking
2 this out of context completely. I -- I don't know
3 what you're asking.

4 BY MR. STEIN:

5 Q. Just let me know what additional context I
6 could provide to help answer the question.

7 A. Look at the start of that paragraph. See,
8 this is talking about "reducing the histogram of
9 oriented gradient features and applying the
10 pretrained classifier to feature set to determine a
11 motion vector field." [As read]

12 So when you have an image that appears --
13 you are -- when you look at the -- the figure I just
14 went through with you, you -- if you look at Figure
15 3, you have an input image that's -- you've done the
16 face detection. You have facial landmarks. You
17 crop and resize, you focused on the eye region.

18 The next box that you see feature
19 generation, you're now essentially doing the
20 histogram of -- of gradient features, and you're
21 doing some feature reduction. Because you might
22 have thousands of features there, and you want the
23 more -- the higher confidence features or more
24 subset of those features to you -- to do the
25 classification because your random forest may not

1 comprehend, you know, 10,000 features. It may only
2 comprehend -- I'm making this up now, 500 features.

3 So you have to reduce that set to
4 something that is more reasonable to work with
5 and -- and has a higher accuracy of achieving the
6 result.

7 Q. Let's look at Column 3 of Chalom, Line 26.
8 And I'll -- I'll -- I'll read the full sentence.

9 "In" -- "In the offline training
10 component, a database of faces with a known gaze
11 angle may be used to train a machine learning system
12 that learns a model that may be used to predict
13 motion vectors that may adjust the input image to a
14 desired output image while running in real time."
15 [As read]

16 There were a few usages of the word "may"
17 in that passage, Dr. Saber.

18 Did you -- did you hear those and read
19 those?

20 A. Yeah, I heard those. Let me -- I'm
21 reading the sentence again.

22 (Witness reviews.)

23 Okay. So what is your question?

24 Q. Yeah. What -- what does the word "may"
25 mean in this sentence? Does it mean that what's

1 being recited after "may" is a required aspect, or
2 does it mean that it's something optional?

3 MS. MAURI: Objection. Form.

4 THE WITNESS: Well, I mean, you're getting
5 into semantics now. But the idea behind this is, in
6 the offline training, so you're training offline
7 essentially, component, a database of faces with a
8 known gaze angle. So you have a database of faces
9 where you have an input face and a corresponding
10 output face with a known gaze angle.

11 So you know the gaze of this face is ten
12 degrees -- I'm making this up now -- may be used to
13 train a machine learning system that learns the
14 model. And so, you're training this system that's
15 going to learn the model and then give you a
16 pretrained classifier that's going to be able to
17 take an input face at runtime and apply the
18 appropriate adjustments.

19 BY MR. STEIN:

20 Q. Let's try to unpack it. So just -- I'm --
21 I'm -- if -- I'm just trying to understand what the
22 word means here.

23 So it says -- for instance, on Column 3,
24 Line 29, it says, "that may adjust the input."

25 So, for instance, in that clause and the

1 larger context of this sentence, does that mean it
2 always adjusts the input, or it adjusts the input
3 sometimes but not all times. What does the
4 word "may" mean?

5 A. Well, let's suppose you had an input that
6 is -- the gaze has not changed. I'm looking exactly
7 at the camera, and I'm not -- my eyes aren't moving.
8 I'm looking exactly at the camera, just like I'm
9 doing right now. Then, you don't need to make any
10 gaze correction to that image. So if I give you
11 that training image as an input and the
12 corresponding output, which is exactly the same,
13 then in that case, no gaze correction is required.

14 But if I'm looking away, as I'm looking
15 away right now over there (indicating), and your
16 output image, you want to be looking at the camera,
17 then you obviously have to make some adjustment. So
18 it depends on what the images are and what is
19 happening.

20 Q. Okay. And let's go to Column 9, also as
21 Exhibit 1005 to Chalom. And looking at --

22 A. 9?

23 Q. Sorry, I got some feedback. Can you hear
24 me, Dr. Saber?

25 A. Yes. You said Column 9; correct?

1 Q. Yeah, yeah, yeah.

2 Column 9, Line 50.

3 A. Line 50.

4 Q. So it says, "The techniques discussed
5 herein may provide for high quality eye contact
6 correction in real time."

7 Again, looking at the word "may" and
8 consistent with our prior discussion just now, does
9 that mean it always has to have high quality eye
10 contact correction in realtime, or that it sometimes
11 does but not necessarily every time?

12 MS. MAURI: Objection. Form.

13 THE WITNESS: Well, I mean, again, you're
14 getting into semantics, and it's returning to
15 discuss about Figure 3. So it says -- it says there
16 starting, "Returning to Figure 3, any number of eye
17 contact corrected images may be generated such as a
18 video sequence of eye contact corrected images. The
19 techniques described herein may provide for high
20 quality eye contact correction in real time."

21 [As read]

22 So it's essentially saying, well, it may
23 provide for high quality eye contact correction, but
24 there may be some error also now and then. So
25 it's -- it's not saying it's going to do it 100

1 percent of the time every single time. So it says
2 it may provide for high quality eye contact
3 correction in realtime.

4 BY MR. STEIN:

5 Q. Okay. I want to jump, Dr. Saber, and then
6 maybe I'll take a quick break after one or two
7 questions here.

8 So on Ex- -- on Exhibit 2008, your
9 declaration, if you could go to Paragraph 54,
10 please.

11 A. 54?

12 Q. Yeah, Paragraph 54.

13 A. Yes, sir.

14 Q. Do you see on that page, if I could find
15 it, there's a sort of colored image we have there at
16 the top -- or at the bottom of Paragraph 54, but the
17 top of page 22, which is a continuation of that
18 paragraph.

19 Do you see the image?

20 A. There is an image on -- in page 21, and
21 there's an image on page 22. Which one are you
22 referring to?

23 Q. 22.

24 A. Okay. I do see it right above
25 Paragraph 55.

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1 Q. Yeah. So what do the arrows mean between
2 the boxes that we see in the image on page 22 of
3 your declaration?

4 MS. MAURI: Objection. Form.

5 THE WITNESS: What arrows are you
6 referring to?

7 BY MR. STEIN:

8 Q. So, for instance, in the -- there's an
9 "AUXD" box at the top with an arrow going to "EA1."
10 What -- what does the arrow signify?

11 A. Information is -- you know, if you look at
12 the patent itself, so...

13 (Witness reviews.)

14 So if you look at the patent on Line 65,
15 Column 3, it obviously gives you a title for that
16 figure, it -- it gives you a description of the
17 figure. It says, "Depicts data flow in an example
18 method of generating reference data." So it gives
19 you a data flow.

20 And starting on Column 16, Line 45, it
21 describes what's going on in that figure.

22 Q. Wha- -- what's going on for the box
23 labeled "MLA1" where there's two arrows, one going
24 to "LA1," one going to "ED1"?

25 What does that signify in that image that

1 we have on page 22 of your declaration,
2 Exhibit 2008?

3 MS. MAURI: Objection to form.

4 THE WITNESS: So MLA1 -- I mean, this is
5 obviously a block diagram; right? This is a
6 high-level block diagram.

7 So the ED1 stands for editing
8 instructions. So MLA1 is providing editing
9 instructions, so the flow to ED1. And I think LA is
10 selection instructions.

11 So you have data flow from LA -- MLA1,
12 essentially having selection instructions and
13 editing instructions; thus, LA1 and ED1.

14 BY MR. STEIN:

15 Q. And we see that ED1 appears to have an
16 arrow that goes to MLA2, but LA1 does not.

17 What does that mean? Why does one have an
18 arrow that go to MLA2 but one does not?

19 A. I -- you cut out a little bit. I did not
20 hear your question.

21 Q. Oh, okay.

22 So in that figure on the top of page 22 of
23 your declaration, we were talking about LA1 and ED1.
24 And I was asking, when we look at ED1 --

25 A. Yes.

1 Q. -- there's an arrow -- there's an arrow
2 going to MLA2, but if we look at LA1, we don't see
3 an arrow going to MLA2.

4 So I was just wondering, what's -- what's
5 the difference? Why does one have an arrow flowing
6 to MLA2 and the other does not? What does that
7 indicate?

8 A. Well, again, you're looking at a block
9 diagram, so it -- it is a high overview block
10 diagram.

11 So essentially what it's saying is -- and,
12 again, this is an overview -- the editing
13 instructions that MLA1 has generated are available
14 to MLA2 to utilize.

15 Q. And what about -- it doesn't look like LA1
16 has an arrow going to MLA2.

17 What's the significance of that?

18 A. Well, it's providing the editing
19 instruction to MLA2, and that's essentially part of
20 their process.

21 Q. And -- but I want to turn -- well, maybe
22 this is a good time for a quick break, actually.

23 MR. STEIN: So would five minutes -- so we
24 can go off the record, Hanna.

25 (Short recess taken.)

1 BY MR. STEIN:

2 Q. Okay. Dr. Saber, I'll ask you the same
3 question. So we just took a quick break.

4 Did you talk with your counsel at all
5 during the break?

6 A. No, I have not.

7 Q. Okay. I'm looking for something.

8 Okay. So I want -- I want to go back to
9 Claim 9 of the '985 patent, which we've looked at --
10 well, we looked at momentarily.

11 So column 27, Line 45.

12 THE COURT REPORTER: Could you repeat the
13 column?

14 MR. STEIN: Column 27, Line 45.

15 THE WITNESS: Yes. Well, I don't think we
16 have spoken about Claim 9. I think we spoke about
17 Claim 11.

18 BY MR. STEIN:

19 Q. Okay. So let's -- let's look at Claim 9,
20 then, anew. So Claim -- Claim 9 says, "the first
21 machine learning algorithm is of a different machine
22 learning algorithm type than the second machine
23 learning algorithm."

24 So why -- why might a POSITA want to use
25 two different types of machine learning algorithms

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1 in the '985 patent?

2 A. One, for more higher detailed -- the --
3 renderings, and another one, more efficient speed.

4 Q. And what if we look at some of the
5 examples in Claims [verbatim] 10 and then Claim 11,
6 for example?

7 So it looks like Claim 10 of the '985
8 patent says -- or one of the examples of the first
9 machine learning algorithm is a "generative
10 adversarial network," and one of the examples for
11 the second machine learning algorithm is a
12 "regression fern" [as read].

13 So why -- why would you choose a
14 generative adversarial network and a regression fern
15 together?

16 MS. MAURI: Objection. Form.

17 THE WITNESS: Well, a -- a -- a GAN
18 network is more extensive, more highly detailed,
19 generally speaking.

20 I -- regression ferns or, you know,
21 forests are a lot quicker and faster and easier,
22 especially if they're binary trees.

23 BY MR. STEIN:

24 Q. Is that -- is that also true of regression
25 forests?

1 A. Generally speaking, yes. I mean,
2 you're -- you know, if you -- if you have let's say
3 a -- a random forest classifier or regression
4 forest, you -- whether it's binary or not binary,
5 it's a lot easier than trying to, you know, develop
6 a GAN or something like that.

7 Q. What are -- what would be some of the
8 drawbacks with a re- -- regression fern in the
9 context of the '985 patent?

10 A. Well, you -- you'd have to be more
11 specific in terms, but, you know, you have
12 essentially a set of features you -- with the --
13 with the random -- with the forest classifiers, you
14 have certain trees that start with certain features
15 and then progress into the other features.

16 So there is a -- in essence, there's a
17 scheme or setup that's kind of engrained as part of
18 the random forest.

19 So if I started with Feature 1, then I
20 flow to Feature 2, and then maybe Feature 3, so
21 there's a --

22 THE COURT REPORTER: Slow down, please.

23 THE WITNESS: So if I started with
24 Feature 1 and I may flow, let's say, to Feature 2,
25 and then to Feature 3, so there's a little bit of

1 rigidity in a sense in the -- in the random forest
2 depending on the flow of how it's designed.

3 BY MR. STEIN:

4 Q. What is -- so you mentioned limited
5 rigidity in the random forest depending on the flow
6 of how it's designed.

7 What's -- what's "limited rigidity"?

8 MS. MAURI: Objection to form.

9 THE WITNESS: Essentially you may have,
10 for instance -- if you select Feature 1, then the
11 random forest, let's say -- you have Feature 1. You
12 now look at either Feature 2 or Feature 3.

13 And then if -- if you select Feature 2,
14 then you look at Feature 4 or Feature 5. So there's
15 a bit of a -- in -- in a sense, there's a -- there's
16 a structure to the tree that you would follow in the
17 random forest classifiers.

18 So you -- it's essentially a collection of
19 trees, and you would be following one of those trees
20 depending on what is the initial feature that you're
21 starting with.

22 So if I'm looking at the center of the
23 eyes as my first feature, then I follow from there.

24 If I'm looking at the tip of the nose as
25 my first feature, then I follow from there.

1 So there is a bit of a -- much less
2 flexibility with them than you would have, for
3 instance, in a -- some -- a neural net that's made
4 up of many layers and many nodes per layers.

5 MR. STEIN: Let me find my paper. Excuse
6 me.

7 BY MR. STEIN:

8 Q. Okay. Now, let's turn to Ganin for a
9 minute. So Paragraph 76 --

10 A. Could you, please, upload a copy of Ganin.

11 Q. Yeah, I -- I -- I'll make sure to do that,
12 but let -- let's just start with your declaration,
13 if you don't mind, and I'll -- I'll send Ganin in
14 the interim.

15 So are you at that paragraph of your
16 declaration, Dr. Saber? And I'll --

17 A. I didn't hear -- I didn't hear the
18 paragraph that you selected.

19 Q. Sure. 76, 7-6.

20 A. 7-6?

21 Q. Yes.

22 A. Okay. Yes, sir, I'm at Paragraph 76.

23 Q. So in here you're -- you're referring to
24 "CLAIM CONSTRUCTION"; right? And you refer to
25 something called "plain and ordinary meaning" [as

1 read].

2 Do you see that?

3 A. Yes.

4 Q. What -- what is a "plain and ordinary
5 meaning"?

6 A. Well, plain and ordinary meaning from the
7 eyes of a POSITA.

8 Q. Was that the answer, "plain and ordinary
9 meaning from the eyes of a POSITA"?

10 A. Yes.

11 Q. So what -- what does the word "plain" mean
12 in that phrase "plain and ordinary meaning"?

13 MS. MAURI: Objection to form.

14 THE WITNESS: Just what it says, plain and
15 ordinary meaning. I'm walking my dog. Plain and
16 ordinary meaning of --

17 BY MR. STEIN:

18 Q. So the -- are the words duplicative of
19 each other? Does plain mean something that ordinary
20 does not? Does ordinary mean something that plain
21 does not? What do -- what do they mean together as
22 compared to when they're on their own?

23 MS. MAURI: Objection. Form.

24 THE WITNESS: Again, I'm not -- I'm not a
25 legal attorney here. I'm not here to provide you

1 legal advice. But plain and ordinary meaning from
2 the eyes of POSITA. So I essentially applied the
3 plain and ordinary meaning of the words that I'm
4 reading from the eyes of a POSITA.

5 BY MR. STEIN:

6 Q. Now let's look at page 32 of your
7 declaration, just a little bit before the "CLAIM
8 CONSTRUCTION" paragraph we were just talking about.

9 Do you see there's a heading that says,
10 "Ganin does not disclose the use of a second machine
11 learning algorithm as claimed in Element 1[E]/18[E]
12 of the '985 Patent"?

13 A. That's after the "CLAIM CONSTRUCTION"
14 paragraph; correct?

15 Q. Yeah, yeah, after, correct, yeah.

16 A. See, I'm listening to you very carefully,
17 sir.

18 Q. Yeah, yeah, I see that, and I'm -- I'm a
19 little tired, so I've -- I've spoken off a little
20 bit. Thanks for catching that.

21 A. So we can always stop while you -- we're
22 ahead.

23 Q. I'll -- I'll survive.

24 Okay. So do you see --

25 A. Yes, I see Section X, and I see "Ground I:

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1 Ganin Does Not Anticipate," et cetera, et cetera, et
2 cetera.

3 Q. So in your -- in your declaration here --
4 I'm just flipping through -- is your -- is
5 the extent of your dispute as to Ganin limited to
6 Elements 1[E] and 18[E]? Are those the element --
7 the only elements that you say Ganin lacks?

8 MS. MAURI: Objection. Form.

9 THE WITNESS: Those are the elements I've
10 opined on in my declaration.

11 BY MR. STEIN:

12 Q. And did you -- did you opine on Ganin
13 missing any other elements, or is -- are your
14 opinions in your declaration as to Ganin limited to
15 1[E]/18[E]?

16 MS. MAURI: Objection. Form.

17 THE WITNESS: Those are the ones I opined
18 on. I wasn't asked to opine on any other elements.

19 BY MR. STEIN:

20 Q. So you haven't -- you haven't taken a
21 position in your declaration, Exhibit 2008, that
22 Ganin is missing any of the other elements of the
23 claims of the '985 patent; correct?

24 MS. MAURI: Objection. Form.

25 THE WITNESS: Again, I've opined -- the

1 ones I've opined on are in my declaration.

2 BY MR. STEIN:

3 Q. So let's look at Paragraph 85 in your
4 declaration, please. Oh, that's on page 36.

5 So feel -- feel free to read the paragraph
6 and just let me know when you finish, and then I --
7 I'd like to ask you a question about one of the
8 phrases in that paragraph. I just want to make sure
9 you have all the context.

10 A. (Witness reviews.)

11 Okay. So what is your question?

12 Q. So in the middle of Paragraph 85 of the
13 declaration, you'll see it -- it says -- there's a
14 sentence that begins with "Without these separate
15 and distinct training datasets." [As read]

16 Do you see that phrase?

17 A. I do.

18 Q. So it's your opinion that Ganin only has a
19 single training dataset?

20 A. That is correct, as disclosed in Ganin.

21 Q. Then let's go to Paragraph 82 of your
22 declaration on the -- one page earlier, page 35 of
23 Exhibit 2008.

24 A. Paragraph 82?

25 Q. 82.

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1 A. Yep.

2 Q. So what is this diagram that we see under
3 Paragraph 82 in your declaration, Exhibit 2008?

4 MS. MAURI: Objection to form.

5 THE WITNESS: That's just a high-level
6 illustration of essentially the steps -- the -- the
7 Step 1 module of Ganin, the Step 2. The coarse and
8 fine and -- module of Ganin.

9 BY MR. STEIN:

10 Q. So that image comes from Ganin?

11 MS. MAURI: Objection. Form.

12 THE WITNESS: What image? What image?

13 BY MR. STEIN:

14 Q. The image that appears in Paragraph 82,
15 does that image appear in Ganin?

16 A. Not to my knowledge, that it appears
17 exactly as were -- as were shown there in Ganin, but
18 Ganin does provide Figure 2 that gives kind of a
19 high-level diagram in a sense -- high-level block
20 diagram of Ganin.

21 Q. And then if we look at Paragraph 83, and I
22 believe you're referring to the -- the image that
23 you've -- you have below Paragraph 82, but you say,
24 "Between steps one and two, there is no completed
25 output, no highly-accurate corrected image."

1 Do you see that sentence in Paragraph 83
2 of your --

3 (Interruption in audio/video.)

4 THE WITNESS: Yes.

5 BY MR. STEIN:

6 Q. -- declaration, Exhibit 2008?

7 THE COURT REPORTER: One second. If you
8 can have the finished question and then the answer.
9 I didn't get part of the question. Please repeat.

10 Counsel, part of your question was cut
11 out.

12 MR. STEIN: Yeah, I was -- I was just --
13 yeah, I was just trying to reread, Hanna, to see
14 what was cut out.

15 BY MR. STEIN:

16 Q. Okay. So if we look at Paragraph 83, and
17 I believe you're referring to the image that you
18 have below Paragraph 82, you say, "Between steps one
19 and two, there is no completed output, no
20 highly-accurate corrected image."

21 Do you see that statement in Paragraph 83?

22 A. That's -- yes, I do.

23 Q. Does Claim 1 of the '985 patent require a
24 completed output between the training of its Machine
25 Learning Algorithm 1 and Machine Learning Algorithm

1 2?

2 A. I'm not -- I don't understand what you're
3 asking.

4 Q. So in -- in this Paragraph 83, you refer
5 to "completed output" -- "no completed output, no
6 highly-accurate corrected image."

7 Do you -- do you understand what you were
8 referring to in Paragraph 83?

9 MS. MAURI: Objection. Form.

10 THE WITNESS: In Paragraph 83, I'm
11 discussing the illustration above as an illustration
12 talking about Ganin. So essentially Ganin has a
13 coarse module and then followed by a fine module and
14 then a light correction module.

15 So that's essentially what Ganin is doing
16 in its -- in its -- you know, in this description,
17 in what he discloses.

18 BY MR. STEIN:

19 Q. And that coarse module followed by the
20 fine module and the light correction module, those
21 are all part of one architecture, is that correct,
22 in Ganin?

23 A. That's what Ganin states, yes, and
24 discloses multiple times, as I've showed you in my
25 declaration.

1 Q. So let's look at Ganin. And I'd like to
2 draw your attention to Exhibit 1006 at page 4.

3 A. One second.

4 So Microsoft labeled page 4, which I think
5 is the same as -- yes.

6 Q. Correct.

7 So under Section 3 titled "The model" --

8 A. Yes.

9 Q. -- in the us -- sorry, second paragraph,
10 the second line from the end of that second
11 paragraph, do you see where it says, "All operations
12 outlined above are implemented in a single
13 feed-forward architecture and are trained jointly
14 end-to-end"?

15 A. I do.

16 Q. So when it -- when it's referring to the
17 "operations outlined above," is that referring to
18 the -- the fine module, the coarse module, and the
19 lightness correction neural network?

20 MS. MAURI: Objection. Form.

21 THE WITNESS: Yeah, "all operations
22 outlined above," it's referring to "All of the
23 operations outlined above are implemented in a
24 single feed-forward architecture" -- it's very
25 clear -- "and are trained jointly end-to-end."

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1 That's also very clear.

2 BY MR. STEIN:

3 Q. And when -- that acronym in Figure 2,
4 "Lightness correction NN," what does "NN" mean?

5 A. Neural network.

6 Q. Is a neural network a machine learning
7 algorithm?

8 A. I think you're taking the words out of
9 context here. So Ganin has a neural network for the
10 LCM, so you have essentially a set of layers or
11 whatever for the RC- -- LCM. And he has obviously a
12 coarse module and a fine module, but that's part of
13 a single architecture that's trained end to end, as
14 Ganin discloses very clearly.

15 And when you look at his -- when you read
16 through the paper and the equations and everything
17 else, it's very clear.

18 Q. And I would like to turn back to the '985
19 patent. And looking again at Claim 1, at Line 50,
20 when it says "using a second machine learning
21 algorithm to generate second reference data using
22 the same training data as the first machine learning
23 algorithm" -- do you see that?

24 A. I do.

25 Q. -- does that element of Claim 1 of the

1 '985 patent specify how the same training data must
2 be used by the second machine learning algorithm?

3 A. Well, it states that you are using the
4 same training data as the first machine learning
5 algorithm and the ref- -- the first reference data
6 generated by the machine learning algorithm.

7 So obviously you're reading that in
8 light -- and you read the claim as a whole, so you
9 have to look at the claim as a whole and in light of
10 what's described in the specification.

11 Q. Okay. So how -- how specifically is the
12 same training data used by the second machine
13 learning algorithm to generate second reference data
14 as recited in Claim 1 of the '985 patent?

15 A. Well, I mean, you would have to look at
16 the dis- -- disclosures in the '985 patent. But
17 it's clear in the claim element here that it's using
18 the same training data that is being provided to
19 both algorithms.

20 Like if you look, for instance, at the
21 example -- I'm looking at Figure 14 of the '985 as
22 an example. And, again, this is an example
23 embodiment, so you can see the training data labeled
24 100 is provided to MLA1 that you see on top and MLA2
25 that you see on the bottom.

1 So it's provided to Box 304 together with
2 101, which represent the first reference data that
3 comes out of MLA1. So both of those are provided to
4 MLA2.

5 Q. I -- I -- I understand it gets the same
6 training data.

7 What -- what I'm trying to ask, Dr. Saber,
8 is how does it use the training data? So are -- are
9 there different ways that you can use training data
10 in the context of machine learning algorithms, or is
11 there only one way you can use training data?

12 MS. MAURI: Objection to form.

13 THE WITNESS: So if you look at Column 3
14 of the '985, starting at Line 9 it provides a
15 description of receiving training data and what it
16 comprises of.

17 So that's essentially the first step, is
18 what is in the training data.

19 And this is obviously an illustra- -- an
20 example here.

21 But if you look at the sixth aspect on
22 Lines -- same column, Lines [verbatim] 26 or so, the
23 "sixth aspect of the present disclosure," so you can
24 see towards the bottom where it says -- and this is
25 one aspect of it, obviously.

1 I'm reading starting at Lines [verbatim]
2 38, "that the first machine learning algorithm was
3 trained to perform," so this is finishing the
4 discussion on the first one, "and training a second
5 machine learning algorithm using at least a subset
6 of the training data used to train the first machine
7 learning algorithm." [As read]

8 So you can provide the entire dataset.
9 You can provide a subset. So both options are
10 available.

11 BY MR. STEIN:

12 Q. So providing a subset of the training data
13 would sufficient -- be sufficient to be the same
14 training data recited in Claim 1 of the '985 patent?

15 A. Well, the claim states that you provide
16 training data. This is just one example of it.

17 Q. So were you -- were you able to find
18 anything in the patent that specifies how the same
19 training data, which you said can also be a subset,
20 is to be used by the second machine learning
21 algorithm?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: So there is a disclosure, I
24 mean, that's in -- this is talking about Figure 9.
25 So there's flexibility in the training data that's

1 being offered.

2 So if you look at the description on
3 Column 16, starting -- for Figure 9, starting at
4 Line 45, you see towards the end of that paragraph,
5 Line 63, it says, "Alternatively or additionally,
6 the training data may comprise an average absolute
7 or square difference between the adjusted image and
8 a target," et cetera, et cetera.

9 So it -- it provides different options for
10 training data, but the claim element states that
11 it's using the same training data.

12 BY MR. STEIN:

13 Q. I just want to go back.

14 So in Column 3, Line 39, you pointed me to
15 the statement here that says, "training a second
16 machine learning algorithm using at least a subset
17 of the training data used to train the first machine
18 learning algorithm." [As read]

19 Did you -- you pointed me to that section;
20 right?

21 A. Yes. That's --

22 Q. So that --

23 A. -- in Column 3; right?

24 Q. Gosh, I hope I said that right and didn't
25 misspeak again. I think I did. But, yes, it is

1 Column 3.

2 A. Yes, that's "According to a sixth aspect
3 of the present disclosure"; right?

4 Q. Okay. And is that an aspect that's
5 covered by Claim 1 of the '985 patent?

6 A. So Claim 1 states you're using the same
7 training data. So you have the same training data.
8 Now, how you use the data in your algorithms might
9 differ slightly, but you're using the same training
10 dataset in a sense.

11 Q. Okay. So I want -- I want to go back to
12 Ganin, Dr. Saber. That's Exhibit 1006?

13 A. Yes, sir.

14 Q. So you -- I just want to refresh. So you
15 told me -- we looked at, under Section 3 on page 4
16 of Exhibit 1006, that -- that reference to "single
17 feed-forward architecture" refers to the fine
18 warping module, the coarse warping module, and the
19 lightness correction neural network that we see in
20 Figure 2; right?

21 A. Yeah, it's a single feed-forward
22 architecture just like Ganin says.

23 Q. That -- that lightness correction neural
24 network, is that a separate machine learning
25 algorithm from the two-scale flow neural network?

1 MS. MAURI: Objection. Form.

2 THE WITNESS: I -- I don't know why you
3 would say that. It's -- it says "a single
4 feed-forward architecture." One single architecture
5 that's end to end -- that's trained jointly end to
6 end. I mean, the statement is very clear. You have
7 one architecture from end to end.

8 BY MR. STEIN:

9 Q. So we have two neural networks, right,
10 that we see in Figure 2, two-scale flow neural
11 network and lightness correction neural network?

12 MS. MAURI: Objection. Form.

13 THE WITNESS: I think you're -- you're
14 taking things out of context a little bit compared
15 to the '985 context.

16 So you're -- you're misplacing context.

17 MR. STEIN: Okay.

18 THE WITNESS: Just because you have -- it
19 says two something NN, that doesn't mean that's a
20 whole new machine learning algorithm on it -- by
21 it -- on its own.

22 So we -- we, you know, frequently have a
23 CNN, for instance, in front of a fully connected
24 neural network, and we call them CNN versus fully
25 connected. That doesn't mean they are two networks

1 that are trained separately, et cetera.

2 So what he has here is single architecture
3 from end to end, that's trained from end to end, as
4 he states clearly.

5 And each of -- each of the pieces has its
6 own kind of sub-module, so to speak, but it's a
7 single end-to-end architecture, and that's not the
8 same context as the '985.

9 BY MR. STEIN:

10 Q. I'm -- I'm just looking at Figure 2,
11 Dr. Saber. So Figure 2 says "2-scale flow neural
12 network" [as read]. Have I -- you've -- you've
13 accused me repeatedly of taking things out of
14 context. I'm just looking at Figure 2 of Ganin.

15 A. Okay.

16 Q. Do you see the text that says "2-scale
17 flow NN"? Do you see it?

18 A. I do.

19 Q. So I'm not taking anything out of context.
20 I'm just showing you the text in the figure. It
21 says "2-scale flow neural network." [As read]

22 Now I want to look -- look to the right of
23 that it. It says, "Lightness correction NN," does
24 it not?

25 A. You -- yes, it does.

1 Q. So that's lightness correction neural
2 network. So at this point, I'm not -- I'm not
3 taking anything out of context. I'm just reading
4 what's on the figure; right?

5 A. Yes. You read the figure correctly.

6 Q. So now is when I get to the question. So
7 we have two neural networks. Is that accurate for
8 your two -- it shows two neural networks?

9 A. Well, let's be accurate. It shows a --
10 let's be exactly accurate. It shows a two scale
11 flow NN, and it shows a lightness correction NN,
12 that's what it shows.

13 Q. Now, I want to look down in Ganin a little
14 bit. So could you go to page 17, please, of
15 Exhibit 1006, the Ganin -- Ganin reference.

16 A. 17?

17 Q. Page 17, yeah, please.

18 A. Yes, sir.

19 Q. So do you see it says at the bottom under
20 Appendix B.2, we now see a different word, it says
21 "lightness correction module." Is -- is Ganin
22 saying that the lightness correction module is the
23 same thing as we saw in Figure 2 that was listed as
24 "lightness correction neural network"?

25 A. Yes. That's what Ganin is referring to.

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1 Q. Now, on page 4 of Ganin, Exhibit 1006 --
2 and, again, I'm going to be looking at Section 3.
3 In that --

4 A. Yes, sir.

5 Q. -- that sentence at the bottom -- at the
6 end of that second paragraph under Section 3 of
7 Ganin, "All operations outlined above are
8 implemented in a single feed-forward architecture
9 and are trained jointly end-to-end." [As written]

10 I want focus on that last part. So
11 "trained jointly end-to-end."

12 Do you see that?

13 A. Yes.

14 Q. Could you train -- what -- strike that.
15 What -- what does "trained jointly
16 end-to-end" mean in the context of Ganin?

17 A. Just what it says. It's trained
18 jointly -- it's trained all together, end to end.
19 It's trained jointly, end to end.

20 Q. And joint -- what does -- the word
21 "jointly," though, has to sort of refer to at least
22 two different things; right? Otherwise, what are
23 you joining?

24 A. You --

25 MS. MAURI: Objection. Form.

1 THE WITNESS: So I mean, he's talking
2 about the operations, right, they're jointly, like
3 those -- the two scale flow NN, the lightness
4 correction NN, right, they're jointly trained
5 together end to end, as he states. And when you
6 read the paper, you look at the equations, and you
7 look at the figures, and it's clear that's what
8 Ganin is doing.

9 BY MR. STEIN:

10 Q. Okay. Let's look at Figure 10 of Ganin,
11 which appears on page 18 of Exhibit 1006, Dr. Saber.

12 A. Figure 10?

13 Q. Yeah, please.

14 A. Yes, sir.

15 Q. So at -- at the top in Ganin,
16 Exhibit 1006 -- actually, let's start with page 17.
17 Do you see that Appendix B sort of in the middle of
18 page 17 has a header called, "Details of the
19 proposed method"?

20 A. I do.

21 Q. And then it says, "Here we give a more
22 detailed architecture that we use in our gaze
23 correction system." [As read]

24 On page 17?

25 MS. MAURI: Counsel, did you e-mail this

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1 copy? I think I have a differently paginated
2 version than you do.

3 MR. STEIN: Yes, I did -- I did e-mail it,
4 Jennifer, just a moment ago. I think that's what
5 Dr. Saber is using.

6 BY MR. STEIN:

7 Q. Right, Dr. Saber?

8 A. Yes, sir. I downloaded your e-mail, and
9 you did not --

10 (Interruption in audio/video.)

11 THE COURT REPORTER: And you, what? I
12 didn't hear the last part.

13 THE WITNESS: And you did not read that
14 sentence correctly.

15 BY MR. STEIN:

16 Q. Oh, okay. So let me try again.

17 Page 17 of Exhibit 1006 says, "Here we
18 give a more detailed architecture" -- "a more
19 detailed view of the architecture" -- okay -- "that
20 we use in our gaze correction system." [As read]

21 So now -- now I've read it correctly;
22 right?

23 A. You're absolutely right, you have read it
24 correctly now.

25 Q. Okay. Thank you.

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1 So this -- this introduction here, this is
2 referring to that single feed-forward architecture
3 we talked about earlier; right?

4 A. It's providing a detailed view of the
5 architecture, yes. Single tense.

6 Q. And then let's look -- within the section
7 called Appendix B.1, the last sentence, it says "The
8 architectures" -- so now we're plural --

9 A. Yes.

10 Q. -- "of the two warping modules are same
11 (module" -- "(modulo the number of input maps) and
12 are shown in Figure 10(d). [As written]

13 So it -- does it not say here that an
14 architecture, that single feed-forward architecture,
15 can include multiple, plural, architectures? Is
16 that not what it's saying?

17 MS. MAURI: Objection. Form.

18 THE WITNESS: Well, you're taking a little
19 bit -- things a little bit out of context. So
20 essentially -- he could have used better wording,
21 but he's essentially referring -- if you look at the
22 next figure -- the next page, if you look at Figure
23 10(d), those are the convolutional layers that he's
24 utilizing in his high level pipeline and then in his
25 B and C.

1 BY MR. STEIN:

2 Q. Yeah.

3 A. So you see where it says "conv layer" in B
4 and "conv layer" in C? [As read]

5 Q. Mm-hmm.

6 A. That's essentially what he's referring to.
7 So they're part of the overall architecture.

8 Q. Okay. So there are -- there are multiple
9 architectures within that single feed-forward
10 architecture; right?

11 A. Well, the -- the choice of words is -- is
12 not -- is not ideal in the way it's stated here.
13 You have one single end-to-end architecture. And
14 you essentially have, I want to say, modules or
15 sublayers or sub-modules within that end-to-end
16 architecture. So those are not separate
17 architectures, in a sense, like he's using the word.
18 He -- I think he's using the word in two different
19 context [verbatim] here.

20 Q. Let's -- let's take a look at Figure 10(a)
21 together, Dr. Saber, on page 18. So if we look at
22 what's on 10(a), I'd -- I'd like you to help me
23 understand what we see in that figure. So if you'll
24 kind of talk me through that for a minute.

25 So do you see the image at the top, 10(a),

1 which is titled "High-level pipeline"?

2 A. Yes.

3 Q. So do you see that box that's colored in
4 green, and I -- it's kind of rhombus shaped, and
5 it -- it has the title, "input" in it?

6 A. Yes.

7 Q. So what -- what is the input in the
8 rhombus shaped box that we see in Figure 10(a) of
9 Ganin?

10 A. Your input image.

11 Q. And then what is the -- the "process half
12 X scale block," [as read] in Figure 10(a) that
13 appears as a blue rounded rectangle?

14 A. So the "process 0.5x space scale box,"
15 [as read] is what you see on B essentially that --
16 that whole diagram on B, essentially.

17 Q. And then what is the "process 1x space
18 scale" [as read] rounded rectangle box that we also
19 see in 10(a), the high-level pipeline of Ganin?

20 A. So the process 1x scale is what you're
21 essentially seeing in 1 -- in 10(c). You see it
22 says "1x-scale processing module"? So that's
23 essentially that -- that -- that box represents that
24 whole module.

25 Q. And -- and what's that -- I guess it's

1 kind of colored in a -- a dark pink I would call it.
2 But it's sort of a -- a triangle shaped geometric
3 structure pointing to the right of 10(a) in Ganin?

4 A. So that would be -- if I -- if you're --
5 you're referring to the word with "out" in it?

6 Q. No. I'm referring -- so starting from the
7 left, we have a green box, rhombus box labeled
8 "angle." Then below that a rhombus box tabled --
9 labeled "input." And then up above and to the
10 right, there's sort of a triangular geometric shape
11 pointing to the right --

12 A. Yeah.

13 Q. -- so what's -- what's that -- what's that
14 indicating?

15 A. So if you look at the legend that he's
16 provided -- that Ganin has provided, you can see on
17 the right side, there's that same structure and it
18 starts like a concatenate.

19 Q. And what -- what does a concatenate block
20 do?

21 A. Well, it's concatenating -- essentially --
22 'cause you have -- you know, you have the units that
23 you're -- you have the image, like an RGB image, for
24 instance, you have 16 units that talk about the
25 angle. So you're concatenating those together.

1 There is a description of that in Ganin.

2 So if you go on page 6 of Ganin --

3 Q. Okay.

4 A. -- and you look at the bottom, the very
5 last sentence.

6 Q. Yeah.

7 A. You see where it says, "Ultimately, the
8 input map stack consists of 33 maps" --

9 Q. Yes.

10 A. -- "RGB" -- which is your image -- "plus
11 16 angle embedding maps plus 14 feature point
12 embedding maps." [As read]

13 So that's essentially what he's
14 concatenating together to present to the network
15 down -- down the road -- you know, forward from
16 there.

17 Q. Okay. So after that, let's go back to
18 10(a) on page 18 of Exhibit 1006. So that input map
19 is going through that concatenater [verbatim] block
20 or operation? Tell me what the right term is. And
21 then it looks like there's two arrows that split.
22 One goes to the "process 0.5x space scale" [as read]
23 rounded rectangle and the other goes to another
24 block, and then to the "process 1x-" -- 1s -- x
25 space scale" [as read] rounded rectangle. So

1 what's -- what's happening there in terms of the
2 data that's moving to the half scale module and the
3 1x scale module?

4 A. So you look -- you see at 1C, 10 -- this
5 figure -- it's not 1C, sorry. Figure 10(c), you see
6 that's essentially a blowup of the "process 1x
7 scale."

8 Do you see that?

9 Q. Yeah.

10 A. And it receives as input as you see the
11 output from the concatenation. So that's
12 essentially your input maps. And it also receives
13 as input, the coarse flow that you see in the coarse
14 flow box there. So you see two boxes going in that
15 one -- going in 10(c). You have the input maps, and
16 you have the coarse flow.

17 So the coarse flow, if you go back to look
18 at 10(a), is what comes out of the .5. Do you see
19 that, where it says coarse flow, and it feeds into
20 the 1x?

21 Q. Yeah.

22 (Interruption in audio/video.)

23 THE COURT REPORTER: Wait, one second,
24 something got eaten up. Please repeat the last
25 sentence.

1 THE WITNESS: Yes. So the arrow on 10(a)
2 that comes out of the .5 -- the "process .5x scale,"
3 there's a down and to the right arrow that's labeled
4 "coarse flow." That goes into the 1x -- the
5 "process 1x" module, and that's the coarse flow that
6 you see in 10(c).

7 And then the input maps that you see in
8 10(c) is the output of the concatenation step that
9 is in 10(a) after the coarse out.

10 BY MR. STEIN:

11 Q. Okay. I'd like to turn back for a second
12 to your declaration.

13 Could you go to Paragraph 21, which is in
14 Exhibit 2008, please.

15 A. Paragraph 21?

16 Q. Yeah, yes, sir. Yeah, please.

17 A. In the section "POSITA"? [As read]

18 Q. Yes.

19 A. Okay.

20 Q. So there is -- you -- you state here in
21 Paragraph 21, "I understand that a person having
22 ordinary skill in the art may be defined by
23 factors." And then you -- you have factors listed
24 as sort of sub-elements, a, b, c, d, and e, in
25 Paragraph 21 of Exhibit 2008.

1 Do you see that?

2 A. I do.

3 Q. So I'm -- I'm wondering about sub-element
4 b here, which you've listed as "the types of
5 problems encountered in the field."

6 Do you see that one?

7 A. I do.

8 Q. And so, considering the time period that
9 you've outlined in your declaration, which in
10 Paragraph 22 you state as being, you know, August
11 2000 --

12 (Interruption in audio/video.)

13 THE COURT REPORTER: Excuse me, Mr. Stein,
14 your audio cut out.

15 MR. STEIN: Oh, okay.

16 BY MR. STEIN:

17 Q. All right.

18 So with -- with -- continued reference to
19 sub-element b in Paragraph 21, which states "the
20 types of problems encountered in the field,"
21 Dr. Saber, could you please tell me what types of
22 problems those were in the time period that you
23 delineate in Paragraph 24, which is August 2017 and
24 before?

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

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1 Q. Okay. So Paragraph 21, you -- you -- you
2 list out sub-elements of factors that define --

3 A. Yeah.

4 Q. -- yeah. And one of them is the types of
5 problems encountered in the field; right?

6 A. Yes.

7 Q. So are you able to tell me what the types
8 of problems encountered in this field are, the field
9 being what you articulate in Paragraph 22?

10 MS. MAURI: Objection. Form.

11 THE WITNESS: Well, we're talking about
12 basically here -- so if you look at Paragraph 22,
13 we're looking at that POSITA would have a bachelors
14 or masters degree in electrical engineering, et
15 cetera, or equivalent on-the-job training, including
16 approximately two to six years of experience in
17 machine learning and/or pattern recognition.

18 So you have experience in machine learning
19 in pattern recognition-type problems, you know,
20 facial recognition, object tracking, object
21 detection, object recognition, motion estimation,
22 you know, these kind [verbatim] of problems.

23 BY MR. STEIN:

24 Q. So you said "these kinds of problems"
25 after reading me Paragraph 22. So what -- what kind

1 of problems are you referring to? I -- I don't
2 understand.

3 MS. MAURI: Objection. Form.

4 THE WITNESS: Object detection, object
5 recognition, object tracking, facial recognition,
6 motion estimation, finding objects and images, that
7 kind of problems, you know, that -- the feature
8 selections. So you have experience in machine
9 learning in essentially how machine learning
10 applications or algorithms are structured. And you
11 have experience in the field of pattern recognition.
12 You know, object detection, that type of stuff.

13 BY MR. STEIN:

14 Q. Would one of those problems in the field
15 be how to make these types of machine learning
16 algorithms more efficient?

17 A. Yeah, I would expect so, yes. You -- I
18 mean, obviously, if you have experience in machine
19 learning, you would have experience in making --
20 designing them and making more efficient or
21 optimizing them in a sense.

22 Q. So, let's -- I want to go back to Chalom
23 for a little bit.

24 Okay. Okay. So if you could please go to
25 Exhibit 2008, which is your -- your dec- -- your

1 supplemental declaration. And take a look, please,
2 at Paragraph 106, which is on page 48 of
3 Exhibit 2008.

4 A. All right. You cut out. I didn't hear
5 the paragraph.

6 Q. Paragraph 106. 1-0-6 on page 48.

7 A. Yes, sir.

8 Q. So it -- in this paragraph, you talk about
9 "nothing in Chalom indicates it is inaccurate or
10 inefficient, so is there" -- "so there is no reason
11 to look at Aslan to fix this nonexistent problem."

12 Did I read that correctly?

13 A. Yes.

14 Q. In this field, though, even -- even when
15 you have somebody telling you that they have a
16 solution, is it not common to still look for further
17 improvements? Would you trust what people tell you
18 and just say, yeah, you -- you got the best solution
19 ever, nobody should look at this further, you know,
20 end -- end of story?

21 MS. MAURI: Objection. Form.

22 THE WITNESS: Well, it depends on the
23 application a little bit and what is being done. So
24 you have to show me something a little bit more
25 specific. I mean --

1 BY MR. STEIN:

2 Q. Well -- well, let me ask you, has -- have
3 your students ever come to you with a -- you know,
4 a -- a solution to one of your assignments, and --
5 and they said, hey, I've -- you know, Professor
6 Saber, I've got the best solution ever here. I
7 don't think we ever need to work on this again."

8 Have you ever encountered that in your
9 entire career?

10 MS. MAURI: Objection. Form.

11 THE WITNESS: Well, I -- I can't think of
12 any instance at this point off the top of my head.

13 BY MR. STEIN:

14 Q. What about with any of your -- your
15 colleagues or your coauthors, have they ever come to
16 you and said, hey, Dr. Saber, or whatever friendly
17 term they use, we've -- we've got the best solution
18 ever here. This problem is solved, stop working,
19 we're done, completely solved?

20 MS. MAURI: Objection. Form.

21 THE WITNESS: I -- I think you're
22 exaggerating and really oversimplifying what's being
23 said here, but -- but I don't remember off the top
24 of my head conversations with colleagues.

25 BY MR. STEIN:

1 Q. I want to find --

2 (Interruption in audio/video.)

3 THE COURT REPORTER: I'm sorry, I didn't
4 hear you.

5 BY MR. STEIN:

6 Q. Sorry, I was muttering.

7 I want to find Chalom. So, Dr. Saber,
8 Exhibit 1005 at Column 15, please.

9 A. Yes, sir.

10 Q. All right.

11 Line 4, do you see where it states from
12 Lines 4 to 7 of Column 15 of Chalom, "Processing may
13 continue at Operation 1406 where the pretrained
14 classifier generated operation 1405 may be
15 compressed. The pretrained classifier may be
16 compressed using any suitable technique or
17 techniques." [As read]

18 So given your familiarity with the POSITA
19 at this time period, what would have been the
20 suitable technique or techniques that Chalom is
21 referring to at Column 15, Lines 4 to 7?

22 A. Well, you have to read the stuff
23 carefully. And see, if you look at -- I mean,
24 obviously, he's talking about Figure 14 here. So if
25 you look at Figure 14, for instance, that's a

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1 description that's being described here. And 1406
2 is the last box of Figure 14.

3 So you see where it says, "Compressed --
4 (Interruption in audio/video.)

5 THE COURT REPORTER: Could you say that a
6 little slower, Dr. Saber.

7 THE WITNESS: Sure.

8 You see in Figure 14, where it says,
9 "Compress Random Forest Classifier Based on
10 Parametrized Surface Fitting"?

11 Do you see that?

12 And it says that also in Chalom on
13 Lines -- so if you look at Lines --

14 (Interruption in audio/video.)

15 THE COURT REPORTER: Line, I didn't hear
16 you.

17 THE WITNESS: Line 7 to Line 9, you can
18 see it says "In an embodiment, the pretrained
19 classifier may be compressed based on parameterized
20 surface fitting."

21 Do you see that?

22 So essentially, I'll give you a simple
23 example. I can provide you with a line as a series
24 of points. I can create 1,000 points, 1,000 XY
25 points to show you an equal -- a line. Or I can

1 provide you of one equation of a line with a slope
2 and intercept that would represent all 1,000 of
3 those points with a small amount of error, assuming
4 the points aren't exactly all located on the line.

5 So one slope, one intercept would define
6 an equation of a line. That would represent, let's
7 say, 10,000 points. So instead of having to store
8 all 10,000 points, let's say, in a database or
9 lookup table or whatever, I can just store the slope
10 and intercept of that one line and essentially
11 accomplish the same thing.

12 So parameterized surface fitting is
13 this -- is -- is essentially a two or
14 three-dimensional version of that one-dimensional
15 example I just gave you.

16 BY MR. STEIN:

17 Q. And would parameterized surface fitting
18 have been the only example of a suitable compression
19 technique that a POSITA would have known at the --
20 at this time period?

21 A. Well, you would have to see how the random
22 forest classifier is designed. I mean, I -- I need
23 to get -- you have to show me more details of that.
24 But that is one suitable way to do it.

25 Q. And what would have been some other

1 suitable ways, considering that you're familiar with
2 the Chalom reference, and I'm referring specifically
3 to the details in architecture described in the
4 Chalom reference of which you've said you're
5 familiar?

6 A. So obviously, he's discussing here the
7 parameterized surface fitting as one approach of
8 the -- compressing this random forest classifier.
9 For his application, for the Chalom application, he
10 feels this is the appropriate compression
11 application.

12 But you could also, for instance, say,
13 well, I'm going to reduce a number of features.
14 Instead of using 10,000 features, I'm going to use
15 6,000. The -- the -- you know, I -- I may look at
16 all my features and rank them from the best to the
17 worst and cut off, let's say, the bottom 10 percent
18 or 20 percent and only use the top 80 percent or the
19 top 50 percent. So that's another form of
20 compression in a sense.

21 So it depends -- I have to see exactly
22 what you're talking about to tell you what would be
23 the best way to compress it.

24 Q. And -- and once the POSITA in this time
25 period, this pre-2017 timeframe, once the POSITA has

1 the details that you're asking for, and I'm -- I'm
2 referring specifically to Chalom, where would they
3 look to figure out the suitable technique or
4 techniques for compression?

5 MS. MAURI: Objection. Form.

6 THE WITNESS: Well, again, I mean, you
7 would have to look at your classifier, first of all,
8 and see, well, how large is this random forest
9 classifier that I'm -- that I've designed. You
10 would have to do some ablation studies to -- to
11 dec- -- to decide which features are more important.
12 So the -- there's some work to be done to get an
13 optimal compression.

14 BY MR. STEIN:

15 Q. And where -- where would the POSITA in
16 this time period, pre-2017, go to look to figure out
17 what that optimal compression would look like and
18 what the suitable technique or techniques might have
19 been?

20 MS. MAURI: Objection. Form.

21 THE WITNESS: Well, they may look at some
22 books, they may look at their ex- -- you know, based
23 on their experience and knowledge in the -- in the
24 field. So I -- I would -- you'd have to give me a
25 bit more specifics. You're -- you're -- you're

1 being very, very general again.

2 BY MR. STEIN:

3 Q. Let's look at Chalom -- find the piece.

4 So Chalom makes reference, for instance,
5 Exhibit 1005, Column 4, Lines 17 to 18. "For
6 example, the pretrained classifier may be a
7 pretrained random forest classifier."

8 What does -- what does it mean for
9 something to be pretrained?

10 A. Well, you're -- again, you're taking
11 sentences a little bit out of context here and
12 there. But if you go back to Column 3 and start
13 with, say, Line 21, you see where it says,
14 "embodiments may include a training component
15 (performed offline) and a real time component
16 (performed during implementation or run time) that
17 provides eye contact correction. In the offline
18 training component, a database of faces with a known
19 gaze angle may be used to train a machine learning
20 system that learns a model (e.g., a pretrained
21 classifier such as a random forest) that may be used
22 to predict motion vectors," et cetera, et cetera.
23 [As read]

24 Q. Par- -- Paragraph 71 of your declaration,
25 Dr. Saber, that's on page 29 of Exhibit 2008.

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1 A. Paragraph 71?

2 Q. Correct.

3 A. Yes.

4 Q. And then that last sentence of paragraph
5 71, "For example, if the camera is above the
6 display, one random forest model may be implemented
7 by the classifier, while if the camera is to the
8 left of the display, a different random forest model
9 may be implemented by the classifier."

10 So does that sentence in that paragraph
11 mean that Chalom discloses multiple different random
12 forest models?

13 MS. MAURI: Objection. Form.

14 THE WITNESS: Well, this is just providing
15 as an example -- so do you have -- you see that
16 you're -- you have to look at the whole paragraph as
17 a whole.

18 So Chalom teaches a single machine
19 learning algorithm that, as I said -- as I showed
20 you in the -- Column 3, it has an offline
21 potentially component and realtime component, the
22 offline training takes a database of faces, any
23 known gaze angle, and essentially trains the machine
24 learning algorithm.

25 That system includes a random forest

1 classifier, as you see in his diagram, like we
2 looked at Figure 3, for instance.

3 And if you look at Figure 8, it talks
4 about the training aspect of that random forest
5 classifier.

6 So, for instance, if the camera is above
7 the display, you would get a different gaze than if
8 the camera is to the left of the display and you
9 would have to apply a different portion of these
10 classifiers.

11 BY MR. STEIN:

12 Q. Is the random forest classifier in Chalom
13 a machine learning algorithm?

14 A. Well, it's of his machine learning
15 essentially --

16 (Interruption in audio/video.)

17 THE COURT REPORTER: Excuse me.

18 Dr. Saber, could you start the answer over again,
19 please.

20 THE WITNESS: Yes.

21 It's -- it's a portion of his essentially
22 architecture in a sense.

23 So if you look at Figure 3 of Chalom,
24 obviously there's an architecture there, diagram,
25 and -- well, let me call it the way it is.

1 So Figure 3 provides an example eye
2 contact correction module that Chalom has proposed
3 in the patent. And the random forest classifier
4 labeled 306 is a portion of that architecture.

5 BY MR. STEIN:

6 Q. And let's also look at Chalom, Column 10,
7 Line [verbatim] 10 to 14. "In other embodiments,
8 system 200 may include multiple contact correction
9 modules or contact correction module 20-" -- "204
10 may be capable of implementing eye contact" --

11 (Interruption in audio/video.)

12 THE COURT REPORTER: Counsel, could you
13 slow down, please.

14 BY MR. STEIN:

15 Q. "In other embodiments, system 200 may
16 include multiple contact correction modules or
17 contact correction module 204 may be capable of
18 implementing eye contact correction for multiple
19 orientations or relative positions between camera
20 104 and display 102."

21 Do you see that sentence, Dr. Saber?

22 A. Yes.

23 And this is referring -- you're talking
24 about now Figure 1 and Figure 2. So you see where
25 it starts on the previous column, 9, it says, "With

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1 a reference to Figure 1" [as read], and then it
2 continues the discussion on Column 10.

3 Q. Correct.

4 But right before that, Column 9, Line 48,
5 it's talking about Figure 3 and then Chalom reverts
6 to Figure 1.

7 And if we go back --

8 A. Yes.

9 Q. -- to Figure 3 and we look at -- we look
10 for that label, so Column 10, Lines 10 to 14, they
11 were referring to 204, right, which we see on Figure
12 3?

13 A. Yes.

14 Q. And you told me that 204 is an
15 architecture which can also be understood as a
16 machine learning algorithm; right?

17 A. Well, 204 is the -- I mean, the whole
18 diagram, Figure 3, is his eye correction module in a
19 sense. 204 is a portion of that module.

20 So if you look at Figure 2, he's got "Eye
21 Contact Correction," Label 204. And if you look at
22 203, he's got a big curly bracket that takes the
23 crop all the way down to the warp and calls it 204.
24 So he's essentially trying to map the two back and
25 forth.

1 Q. And what did you --

2 A. Keep -- go -- go ahead.

3 Q. No, no. I'm -- I'm sorry, Dr. Saber, I
4 don't want to interrupt you.

5 A. So if you look at, for instance, Figure 2,
6 you see where it says "FL," facial landmarks. And
7 you look at Figure 3, you'll see says "FL 214."
8 That's essentially the output of the curly bracket
9 on Figure 2 that says "301." That's your Figure 3,
10 301 bo- -- box.

11 So there is some e- -- e- -- essentially
12 correlation between the two diagrams. So he's
13 trying to basically connect the two diagrams, so
14 he's combined face detection and facial landmark
15 detection into one box on Figure 3. And he's
16 divided the eye contact module into multiple boxes
17 on Figure 3. But that's part -- all part of his
18 correction module all together.

19 Q. And that -- that module all together
20 you're saying is a machine learning algorithm; is
21 that correct?

22 MS. MAURI: Objection. Form.

23 THE WITNESS: Well, that's essentially --
24 well, Chalom's title is "EYE CONTACT CORRECTION IN
25 REAL TIME USING MACHINE LEARNING"; right? That's

1 the title of his patent.

2 BY MR. STEIN:

3 Q. So turning back to Column 10, Line 10 to
4 Lines 14 [verbatim], when Chalom says he can have
5 multiple contact correction -- correction modules,
6 is that a disclosure of multiple machine learning
7 algorithms in Chalom?

8 MS. MAURI: Objection. Form.

9 THE WITNESS: No, that's --
10 essentially what he's saying is you could have like
11 multiple modules, so I have, let's say -- I'm -- I'm
12 exaggerating and simplifying here.

13 So I can have a module that, for instance,
14 deal with 15 degrees to 10 degrees, and another
15 module maybe is from 10 degrees to 5 degrees.

16 So you could split them up if you want
17 that way, or you could have them all in one bigger
18 module, so to speak, for multiple orientations.

19 So he's essentially saying -- he's trying
20 to say, well, I can -- I can -- you can either split
21 them up or combine them together into one module.

22 But, again, when you look at Figure 3,
23 it's -- it's clear that random forest classifier
24 that he has as part of his Figure 3 module for eye
25 correction -- for eye -- you know, gaze correction.

1 MR. STEIN: I think we can take a quick
2 break. How about ten more minutes? Is that okay
3 for everyone?

4 MS. MAURI: Sure.

5 THE WITNESS: I have 4:27. I will be
6 sitting at my desk at 4:40.

7 Does that work?

8 MR. STEIN: Yes. Thank you, all.

9 (Short recess taken.)

10 MR. STEIN: Ready.

11 MS. MAURI: Ready.

12 BY MR. STEIN:

13 Q. Okay. Dr. Saber, now, I'd like to take a
14 look at the Aslan reference, which I know I'll need
15 to e-mail to you, which I will do right now. So
16 here comes Exhibit 1007. Does -- while I'm kind of
17 sending this, can you just confirm that Aslan a
18 reference you're familiar with, Dr. Saber?

19 A. Yes, I am.

20 (Previously marked IPR Exhibit 1007 was
21 referenced.)

22 BY MR. STEIN:

23 Q. Does -- does Aslan disclose a
24 teacher/student architecture?

25 A. Yes, it discloses a joint model

1 training -- it's a patent basically for joint model
2 training, and it provides a teacher/student
3 architecture.

4 Q. In your declaration, have you raised any
5 disputes as to whether Aslan qualifies as prior art
6 to the '985 patent?

7 MS. MAURI: Objection. Form.

8 BY MR. STEIN:

9 Q. I'm assuming you're just checking your
10 declaration, Dr. Saber. I just want to make sure of
11 the silence.

12 A. Yes, I'm checking my declaration. And I
13 did receive the Aslan's [verbatim] so let me go
14 ahead and download that.

15 What was your question again? Was it
16 whether Aslan is prior art?

17 Q. A little differently phrased. But in your
18 declaration, Exhibit 2008, did you raise any
19 disputes as to whether Aslan qualifies as prior art
20 to the '985 patent?

21 MS. MAURI: Objection. Form.

22 THE WITNESS: I -- I do not believe I
23 offered an opinion on Aslan as being prior art.

24 BY MR. STEIN:

25 Q. And you also didn't offer an opinion that

1 it's not prior art; is that correct?

2 A. I don't believe I've offered an opinion
3 either way. I -- I was not asked to provide such an
4 opinion.

5 Q. In your opinion, does Aslan show that
6 teacher student models were known before the '985
7 patent?

8 A. Well, the date of filing of Aslan shows it
9 as June 28, 2016. So that's when it was filed.

10 Q. Okay. And when -- what's the date on the
11 '985 patent? If you look at Exhibit 1001, is the
12 earliest date there August 10th, 2017?

13 A. Yes.

14 Q. So are you able to then say Aslan shows
15 that a teacher/student architecture was known before
16 the '985 patent?

17 A. I -- I wasn't asked to provide an opinion
18 as to whether Aslan is prior art to the '985 patent.
19 But Aslan does show a teacher/student architecture.

20 Q. And it shows a teacher/student
21 architecture that existed before the '985 patent,
22 given the dates you just explained to me; correct?

23 A. Again, I wasn't asked to provide an
24 opinion as when all things existed in the legal
25 world. The date on the patent shows June 28, 2016.

1 And it provides a teacher/student architecture.

2 Q. And the date that's on Aslan is earlier
3 than the date that's on the '985 patent; correct?

4 A. On its face -- again, I was not asked to
5 provide an opinion on this, but on its face, the
6 date filed of Aslan shows June 28, 2016. And the
7 provisional dates that you read shows August 8th or
8 10th, 2017.

9 Q. Thank you.

10 So I'd like to -- in Aslan, which is
11 Exhibit 1007, could you please direct your attention
12 to Paragraph 5.

13 A. Paragraph 5 of Aslan?

14 Q. Yeah. It's on page 10 of Exhibit 1007.

15 A. You said Paragraph 10?

16 Q. No, it -- page 10, Paragraph 5.

17 A. I'm sorry. Page 10, Paragraph 5?

18 Q. Yes.

19 A. Well that's on -- oh, page 10 -- I see,
20 page 10, the Microsoft label, page 10, not --

21 Q. Oh, yeah.

22 A. -- the patent?

23 Q. Yeah. I understand.

24 A. I'm sorry.

25 Q. No problem.

1 A. Thank you.

2 So, yes, I'm looking at Paragraph 5.

3 Q. Okay. So in the second sentence of
4 Paragraph 5, do you see how Aslan has in quotations
5 two terms, "parallel" and "sequential" training in
6 Paragraph 5 of Exhibit 1007?

7 A. Yes. I see those sequential -- I see
8 those quote "parallel," unquote, and "sequential,"
9 quote/unquote.

10 Q. Are you familiar with what parallel
11 training means?

12 A. Yes.

13 Q. So what -- what does parallel training
14 mean?

15 A. You would train two, essentially,
16 algorithms or two architectures in parallel.

17 Q. Could you -- could you train a neural
18 network in parallel with a random forest?

19 A. I think you're asking a very large
20 hypothetical questions [verbatim]. It -- it
21 depends on -- I have to see the application, the
22 details, what are you training, how you're training.
23 You know, which is like asking me --

24 (Interruption in audio/video.)

25 THE COURT REPORTER: I can't hear the

1 witness.

2 MR. STEIN: Yeah, we lost -- we lost you,
3 Dr. Saber, for a little bit there.

4 THE WITNESS: Oh, sorry.

5 So it -- I -- I would have to see the
6 application, the details, it depends on -- you know,
7 the devil is in the details, obviously.

8 BY MR. STEIN:

9 Q. So when you told me earlier after I asked
10 what does parallel training mean, you said you would
11 train two essentially algorithms or two
12 architectures in parallel.

13 So referring --

14 A. Yes.

15 Q. -- specifically to your answer, could you
16 please give me examples of the two algorithms or two
17 architectures that you were referring to?

18 (Interruption in audio/video.)

19 THE COURT REPORTER: I think the witness
20 is frozen.

21 MS. MAURI: I think he's frozen, as well.

22 MR. STEIN: Oh, shoot.

23 THE COURT REPORTER: May we go off the
24 record?

25 MS. MAURI: Yes.

1 (Off the record.)

2 THE COURT REPORTER: Okay. You're back
3 on.

4 MR. STEIN: Thank you.

5 So due to some unforeseen circumstances,
6 it seems like we need to postpone because Dr. Saber
7 no longer has internet access and has encountered
8 what appears to be some sort of power outage.

9 So -- so by agreement of counsel, and
10 hopefully Jennifer can say the same, it looks like
11 we'll -- we'll have to reconvene for about an hour
12 and a half and try to schedule that as soon as we
13 can and see -- see about any changes to the briefing
14 schedule, if we need them.

15 MS. MAURI: Just generally agree, but for
16 the clarity of the record, we've offered to continue
17 via telephone, which counsel is not willing to do at
18 this point. And given his unwillingness to continue
19 via telephone, then to complete the depo, we'd have
20 to do it at a future date.

21 MR. STEIN: Okay. I think we can go off
22 the record, Hanna.

23 (Proceedings concluded, 2:17 p.m., EDT, on
24 June 5, 2024.)
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JURAT

I, ELI SABER, PH.D., do hereby certify
under penalty of perjury that I have read the
foregoing transcript of my deposition taken remotely
via videoconference on Wednesday, June 5, 2024; that
I have made such corrections as appear noted herein
in ink, initialed by me; that my testimony as
contained herein, as corrected, is true and correct.

Dated this _____ day of _____, 2024,
at _____.

ELI SABER, PH.D.

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CERTIFICATE OF REPORTER

I, Hanna Kim, a Certified Shorthand Reporter, do hereby certify:

That prior to being examined, the witness in the foregoing proceedings was by me duly sworn to testify to the truth, the whole truth, and nothing but the truth;

That said proceedings were taken before me at the time and place therein set forth remotely via videoconference and were taken down by me in shorthand and thereafter transcribed into typewriting under my direction and supervision;

I further certify that I am neither counsel for, nor related to, any party to said proceedings, not in anywise interested in the outcome thereof.

Further, that if the foregoing pertains to the original transcript of a deposition in a federal case, before completion of the proceedings, review of the transcript [x] was [] was not requested.

In witness whereof, I have hereunto subscribed my name.

Dated: June 7, 2024.



Hanna Kim, CLR, CSR No. 13083

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Deponent: ELI SABER, PH.D.

[illegible]

EXPIRES: _____

1 JENNIFER MAURI, ESQ.

2 jmauri@mrllp.com

3 JUNE 7, 2024

4 RE: MICROSOFT CORPORATION vs. REALD SPARK, LLC

5 JUNE 5, 2024, ELI SABER, PH.D., VOLUME I, JOB NO. 6730451

6
7 The above-referenced transcript has been completed by
8 Veritext Legal Solutions and review of the transcript is being
9 handled as follows:

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11 — Per CA State Code (CCP 2025.520 (a)-(e)) - Contact Veritext
12 to schedule a time to review the original transcript at
13 a Veritext office.

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21 appearing counsel within the period of time determined at
22 the deposition or provided by the Code of Civil Procedure.

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2 Counsel - Original transcript to be released for signature
3 as determined at the deposition.

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15 the deposition or provided by the Federal Rules.

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18 requested before the completion of the deposition.

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California Code of Civil Procedure

Article 5. Transcript or Recording

Section 2025.520

(a) If the deposition testimony is stenographically recorded, the deposition officer shall send written notice to the deponent and to all parties attending the deposition when the Original transcript of the testimony for each session of the deposition is available for reading, correcting, and signing, unless the deponent and the attending parties agree on the record that the reading, correcting, and signing of the transcript of the testimony will be waived or that the reading, correcting, and signing of a transcript of the testimony will take place after the entire deposition has been concluded or at some other specific time.

(b) For 30 days following each notice under subdivision (a), unless the attending parties and the deponent agree on the record or otherwise in writing to a longer or shorter time period, the deponent may change the form or the substance of the answer to a question, and may either approve the transcript of the deposition by signing it, or

refuse to approve the transcript by not signing it.

(c) Alternatively, within this same period, the deponent may change the form or the substance of the answer to any question and may approve or refuse to approve the transcript by means of a letter to the deposition officer signed by the deponent which is mailed by certified or registered mail with return receipt requested. A copy of that letter shall be sent by first-class mail to all parties attending the deposition.

(d) For good cause shown, the court may shorten the 30-day period for making changes, approving, or refusing to approve the transcript.

(e) The deposition officer shall indicate on the original of the transcript, if the deponent has not already done so at the office of the deposition officer, any action taken by the deponent and indicate on the original of the transcript, the deponent's approval of, or failure or refusal to approve, the transcript. The deposition officer shall also notify in writing the parties attending the deposition of any changes which the deponent timely made in person.

(f) If the deponent fails or refuses to approve the transcript within the allotted period, the

deposition shall be given the same effect as though it had been approved, subject to any changes timely made by the deponent.

(g) Notwithstanding subdivision (f), on a seasonable motion to suppress the deposition, accompanied by a meet and confer declaration under Section 2016.040, the court may determine that the reasons given for the failure or refusal to approve the transcript require rejection of the deposition in whole or in part.

(h) The court shall impose a monetary sanction under Chapter 7 (commencing with Section 2023.010) against any party, person, or attorney who unsuccessfully makes or opposes a motion to suppress a deposition under this section, unless the court finds that the one subject to the sanction acted with substantial justification or that other circumstances make the imposition of the sanction unjust.

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Veritext Legal Solutions represents that the foregoing transcript is a true, correct and complete transcript of the colloquies, questions and answers as submitted by the deposition officer. Veritext Legal Solutions further represents that the attached exhibits, if any, are true, correct and complete documents as submitted by the deposition officer and/or attorneys in relation to this deposition and that the documents were processed in accordance with our litigation support and production standards.

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