UNITED STATES PATENT AND TRADEMARK OFFICE

BEFORE THE PATENT TRIAL AND APPEAL BOARD

TESLA, INC.,

Petitioner,

v.

AUTONOMOUS DEVICES LLC,

Patent Owner

Case IPR2023-01054

U.S. Patent 10,452,974

Deposition of ELI SABER, PH.D.,

Conducted Remotely

Thursday, May 16, 2024

8:32 a.m.

Reported by: Matthew Goldstein, RMR, CRR

DIGITAL EVIDENCE GROUP

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TESLA 1016
Tesla, Inc. v. Autonomous Devices LLC
IPR2023-01172

Deposition of ELI SABER, PH.D., conducted remotely:

Pursuant to Notice, before Matthew Goldstein, RMR, CRR, Notary Public in and for the State of Maryland.

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C O N T E N T S

EXAMINATION OF ELI SABER, PH.D.	PAGE
By MR. KHAN	5

E X H I B I T S

EXHIBIT		PAGE
Exhibit 1004	United States Patent No. 9,604,359 B1	159
Exhibit 1001	United States Patent No. 10,452,974 B1	8
Exhibit 2007	Declaration of Dr. Eli Saber, Ph.D.	8
Exhibit 2015	Curriculum Vitae of Dr. Eli Saber	9

P R O C E E D I N G S

Whereupon,

ELI SABER, PH.D.,

being first duly sworn or affirmed to testify to the truth, the whole truth, and nothing but the truth, was examined and testified as follows:

EXAMINATION BY COUNSEL FOR THE PETITIONER

BY MR. KHAN:

Q. Good morning, again.

A. Good morning.

Q. Well, thank you for making yourself available today. I understand you have a sharp cutoff at 5 o'clock. So I'll do my best to finish before then. I think most likely we will.

Given our start time, we may take a few breaks here and there. When you do need a break, please let me know.

MR. KHAN: And same thing for Matt and Arvind, if there's a break, just please let me know.

BY MR. KHAN:

Q. I'll just request that you give me a

few minutes heads-up notice so I can finish up that line of questioning.

Does that work for you?

A. That works fine.

Q. Great.

And when we do take those breaks, you understand you're not allowed to discuss the substance of your testimony today with opposing counsel?

A. I do.

Q. And if you are approached by anyone at any point during the cross-examination today regarding your testimony or any feedback or anything, will you let me know?

A. Of course.

Q. Thank you.

And, again, giving the timing, we may take a lunch break in between. I'm happy to give an extended lunch break as needed.

Do you agree that we are here today to discuss your declaration which was submitted as Exhibit 2007 in IPR proceeding IPR2023-01054,

which relates to U.S. Patent No. 10,452,974?

A. I do.

Q. For purposes of brevity, I'll refer to the patent at issue as the '974 patent.

Is that okay?

A. That's perfectly fine.

Q. Do you understand that your testimony today is sworn testimony taken under oath?

A. I do.

Q. And you understand that your oath you're taking is as solemn as the oath you would be taking if you were testifying at trial in court?

A. I do.

Q. Do you understand that the deposition testimony today can be used at a trial and subsequent briefs in this proceeding?

A. I do.

Q. Are you taking any medicine that would prevent you from answering the questions completely and truthfully to the best of your ability?

A. No, I'm not.

Q. Is there anything else that would prevent you from answering the questions completely and truthfully to the best of your ability today?

A. No.

Q. Do you have a clean copy of the '974 patent, which is Exhibit 1001, and your declaration, which is Exhibit 2007, with you today?

A. I do.

Q. Okay.

A. But I also ask you to drop it in the chat box.

Q. Sure.

A. Have you dropped it?

Q. I am in the process right now.

(Exhibit 1001 was marked for identification and attached to the transcript.)

(Exhibit 2007 was marked for identification and attached to the transcript.)

BY MR. KHAN:

Q. You should see the first document

loading pretty soon. Let me know when you have that or you see that.

A. I do. Just one second.

I received the '974 document.

Q. Okay. The other one will take a little bit longer. It's your declaration. So you should be seeing it pretty soon.

A. Do you want me to go ahead -- I received it. Do you want me to go ahead and open them?

Q. Yes, please. Thank you.

And while we're at it, I'll also put your CV, which is Exhibit 2015, here in the chat.

A. Thank you.

(Exhibit 2015 was marked for identification and attached to the transcript.)

BY MR. KHAN:

Q. You can let me know when you have the three open.

A. I have all three of them open.

Q. Fantastic.

Okay. So just a few questions on your background. Did you obtain your bachelor's in

1988 and your Ph.D. in 1996?

A. That is correct.

Q. Did your Ph.D. or graduate research involve applying machine learning techniques?

A. To some extent, yes.

Q. Can you explain how?

A. Sure.

So my research was about -- if you look at the title of my dissertation, automatic image annotation and query by example using color shape and texture information. So, essentially, what we were doing at the time, we were building a system, we called it Voogle, kind of like a visual Google in a sense.

And the system was supposed to -- you should be able to present the system with an image, to show the system an image of a car, and it should be able to go into a database of images or videos and search for that particular object based on shape, color, and texture information in a series of images.

You know, the idea behind it is if you

went to Disney World, for instance, on a vacation and you collected 10,000 images or something and you came back home, you put them all in a database, can you query them and search them, and so on in a visual manner by giving examples to the computer and have the computer go find what it's looking for.

So that's the essence of the work in a short, brief summary.

Q. And which part of this involved machine learning?

A. Well, in a sense, the color and the shape. Mostly the shape one involved more machine learning than the color.

Q. When you say the color and the shape involved machine learning, could you just clarify what you mean by that?

A. Well, I mean, with the color stuff, we were looking at examples. For instance, we were looking at there are what we call memory colors, say, you know, people's skin, green grass, blue sky is something you would remember. And memory

color, you typically don't think of grass as red, for instance.

So if you were showed the computer a texture of a grass or a piece of grass, you know, an example of a piece of grass, could the computer go search the database and find this piece of grass based on the color information. So we designed some algorithms to do that, to do the searching.

The same thing with shape, for instance, a car, if you were able to provide the computer with a template of a car, this is what a car shape looks like, a sedan or an SUV or something, can the computer go segment the images, you know, do some segmentations and, say, frame by frame in a video or just regular images, segment the images, separate different things, and locate that shape, which may be a collection of multiple regions.

Because when you segment a car, you know, the glass is, let's say, white, the car is red, the tires are black, so if you segment based on color, you have multiple regions. You still

have to combine them in the hierarchical object description to say this is the root node of a car in a sense and then match to that object.

Q. You mentioned segmentation. Is that required to do the comparison here? You have to break out a picture and compare the segments, or can you compare kind of images as a whole one-to-one kind of thing?

MR. JAIRAM: Objection; form.

THE WITNESS: Essentially, it depends a little bit of what exactly you're looking for, but segmentation is usually the underlying foundation for a lot of the algorithms. You'll need to separate the images into a variety of regions, typically.

Sometimes people do foreground/background segmentations. Sometimes people do, you know, multi-object segmentations. So you need to have some understanding of the objects in the image to do the queries. Otherwise, you're probably doing, like, a brute force type of approach.

BY MR. KHAN:

Q. What happens when there's only one object in an image?

A. Well, you would still segment that frame in a sense. You would find that object. You might create -- you know, if a hierarchical representation of the object, you might create a root node that says this is the object and then sub nodes under it that would say these are the tires and this is the windows and this is the fenders or whatever.

So you have the pieces of the object under, let's say, the parent root node, if you wish. And that would be your object versus the background in the scene.

Q. And how does the computer know that there's a particular object in a picture -- an image, sorry?

A. Well, you would have to use some type of a template. You would have to say, for instance, I'm looking for an object that has this kind of shape. So you'd have to provide a template --

you'd have a database of -- like a training set, if you wish, a database of templates.

You might say, here's a shape of what a car looks like. It's shaped in this fashion. So as the computer is searching the image, it's looking for regions or a combination of regions that might match that particular shape, depending on what shape matching algorithms you were using.

Q. And just so I understand, and once the machine is trained -- let's just use your example of a car. The machine understands that a certain type of car has to have a certain type of shape. What does it do with that information? Does it store it, like, in a library, or what does it do with that information?

A. Yeah, you would --

MR. JAIRAM: Objection; form.

THE WITNESS: Yeah, you would basically -- I mean, if you're looking at the single image, for instance, the single frame of video and you have segmented this frame for the very first time, let's say, and you have a bunch

of regions and the car may be ten regions.

And as you search that image for a car and you've provided this shape and it happens to find those ten regions put together match that shape, you would have a record of that.

So now you have, like, an accompanying record in a sense of the image stored in a database with that image, like some type of a connection or a correlation that would indicate that this particular, you know, group of ten regions matches that particular template. So the next time you search that image, you have some prior knowledge.

BY MR. KHAN:

Q. So is this -- the shape, it's essentially -- is it, like, a certain type of pixel orientation? How does it determine the -- how does the computer determine the shape?

A. Well --

MR. JAIRAM: Objection; form.

THE WITNESS: -- it's essentially the boundary -- one way to look at the shape is the

boundary of the cohesive region. So you're looking at regions that have to be neighboring, for instance, and you have a boundary of those regions or the subregions. Those boundaries would define, in a sense, the shape.

You do have to be cognizant of the scale variations and, you know, rotations and translations. Typically, translations are easier, but rotations in the image plane are much easier than rotations in and out of the image plane.

BY MR. KHAN:

Q. So in storing this information, once the computer learns to associate a shape with a certain object, so the certain shape, for example, associated with a car --

A. Yep.

Q. -- then in its database it stores that shape information along with a label, such as this is a car; is that correct?

MR. JAIRAM: Objection; form.

THE WITNESS: I mean, more or less, yes. I mean, your -- general summary, yes.

BY MR. KHAN:

Q. And along with that information there could be additional information such as a scalability factor or perhaps variations in color?

MR. JAIRAM: Objection; form.

THE WITNESS: Yeah, I mean, it would recognize, you know, these group of regions is the car. If you do some color matching on that, you would say, okay, this is a red car.

So as you search, you will learn more and you augment, in a sense, your database. So you would create a root node it, for instance, for where the car is and put under that root node the subregions of the car. And each of them would have, you know, a proper kind of metadata-type things. It would say, you know, this has the color red and the tires are black and, you know, et cetera.

BY MR. KHAN:

Q. And this whole machine learning algorithm that we're just discussing, this is part of your Ph.D. thesis?

A. Yes. This was part of my Ph.D. work, and you could see that published in my CV. So if you go to my CV -- I'm just going to hit the journal papers, but if you'll look at the first five journal papers, the ones that are labeled 35 through 39, and the corresponding conference papers, those published the work directly from my Ph.D. work.

And then after that, you know, once I completed my Ph.D., I started working with a student, Yaowu Xu, who you see named in the remaining papers after that. That continued a lot of this work until he graduated.

Q. On page 11 of your CV, you also have a list of patents, patent applications, and publications; is that right?

A. That is correct.

Q. So there's a list of 12 --

A. Yeah.

Q. -- documents; is that right?

A. That is correct.

Q. Were you involved in the prosecution

work for these patents in any way?

MR. JAIRAM: Objection; form.

THE WITNESS: I don't know what you mean by "prosecution work." I was involved in providing the attorney with the technical aspects of the patents. You know, the ones at Xerox -- that were done at Xerox, you know, Xerox has attorneys that would handle all the legal stuff of the patents. You know, we provide the technical stuff.

So they would sit with us on multiple meetings and they would ask all the technical details and read any papers that we might have put together that weren't published yet and et cetera, you know, write flowcharts.

And we walk them through all the technical stuff, and then they would follow up with the patent office and do all the legal stuff that needs to be done, you know, write the claims, for instance, and that type of thing and prosecute the patent, as you would say, to achieve the patent.

MR. JAIRAM: I'll caution the witness not to reveal the substance of any third-party confidential information, including any confidential information of Xerox or any other party.

BY MR. KHAN:

Q. Are you familiar with the term "office action"?

A. I am, yes.

Q. Did you work on any office action responses for any of the patent applications that you were named an inventor for?

A. No, I have not. You know, the attorneys would come back to us and ask additional questions. It's probably related, you know, to some responses that they would receive. So it's not just one meeting, and you're done. So it's kind of an iterative -- collaborative and iterative process. But they would come back and ask questions, and then we'd provide more details as needed.

Q. Okay. Now, you mentioned you were at

Xerox. You were at Xerox for about 16 years; is that correct?

A. That is correct.

Q. Is it fair to say that was one place where you were for the longest part of your career?

A. No, that would not be correct.

Q. Which other place have you been longer than your period at Xerox?

A. So I started at RIT in 1998 as an adjunct faculty. If you look at my CV, you would notice I was an adjunct faculty at the University of Rochester -- well, I would say a part-time faculty at the University of Rochester, because I had also research funding together with the faculty there and I had teaching responsibilities, versus at RIT I was just an adjunct faculty, because I didn't have any research responsibilities.

So I started at RIT in 1998 as an adjunct faculty. And in 2004, I joined full-time as faculty. And today we're 2024. So my

full-time period, in this August it would be 20 years, and obviously before that, I've had six years or so of adjunct.

Q. And at the time you were at Xerox, were you teaching full-time?

A. No. When I was working for Xerox, I was working for Xerox full-time, and I was teaching part-time at the University of Rochester and teaching part-time at the Rochester Institute of Technology.

At the U of R, I also had a research grant with a Professor Murat Tekalp. We had a GOALI -- NSF GOALI grant, which is essentially the grants they would give to somebody where you have a faculty from a university, a representative from industry, that was me, and a student that's being guided by both the faculty and the industry personnel.

Q. During the course of your education or subsequent professional experience, did you learn how to code?

A. Oh, yes. Oh, yes, most of the stuff

that I coded at the time -- well, initially, I learned to code in Fortran, because I guess I'm getting older these days, but I learned to code in Fortran in the '80s. In the '90's, I learned to code in C and then C++ and MATLAB, because these became much more available at the university settings.

I continued to code a lot with MATLAB for my coursework and some of my research, but the coursework a lot of times, you know, you want to demonstrate something for the students or create an algorithm or show how something would take place.

MATLAB is a really great place to do that, because, one, it has all the supporting functions underneath it. You don't have to create, you know, a least squared algorithm and create multiplication or whatever. All those functions are available. They're well organized. It's free to all students and faculty. So students can access it freely. They don't have to download and do stuff.

Q. How many languages would you say you know?

A. You mean computer languages?

Q. Sorry, computer languages.

A. Yes. So I used to know Fortran. It's been a long time since I've coded in Fortran. I actually started coding in basic, excuse me, back at my engineering science part -- degree. So I used to know basic, probably don't know it much anymore.

I used to know Fortran -- or have coded in Fortran. C and C++ are the primary ones I have used over the years, as I was doing my Ph.D. work and subsequent to that. But then, also, we use MATLAB more extensively, because it's available for us freely at the university.

MR. JAIRAM: And may I suggest, Dr. Saber, if you refer to any technical acronyms, such as Fortran, MATLAB, et cetera, please spell it out to ease it for the court reporter?

THE WITNESS: Okay.

BY MR. KHAN:

Q. Dr. Saber, do you know that the petitioner in this case is Tesla?

A. Is what?

Q. Tesla?

A. Yes.

Q. I'm sorry, can you give me a moment, please?

A. Sure, take your time.

(Recess from the record.)

BY MR. KHAN:

Q. So I asked you whether you know that the petitioner in this case is Tesla?

A. Yes.

Q. Do you own a Tesla vehicle?

A. No, I do not.

Q. Is there a reason you do not?

A. I like, actually, trucks, believe it or not. So I own a Dodge Ram 1500, and then I -- you will probably never find me driving a car. I haven't driven a car since 2010.

Q. I see.

A few moments ago we were talking about your patents. Are there specific ones that are related to machine learning?

MR. JAIRAM: Objection; form.

THE WITNESS: Let me take a peek here for a second.

The one that has to do with Unsupervised Color Image Segmentation by Dynamic Color Gradient Thresholding has -- well, it's not exactly machine learning, but it has some of the fundamentals that you would use for, you know, a machine learning immigrate.

The one on Image Segmentation using Dynamic Color Gradient Threshold would also have, you know, the fundamental pieces that we would be using. I mean, these were basically algorithms that we used in some of our machine learning work.

BY MR. KHAN:

Q. Just to be clear, you're referring to Items 4 and 5 in your patent list on page 11 of your CV?

A. I'm referring to -- sorry, I think -- I

was referring to 5 and 7, but 4 provides a different methodology of doing the similar thing, because we were doing multi-resolution. You know, this way you can take large images and work as a pyramid.

And the last one that HP filed, so the one -- No. 1, 2, 3, I think, were filed by HP. I was doing some work for HP on a number of grants. HP funded my lab for a number of years. Those were filed by HP.

The last one obviously has to do with CNN, convolutional neural networks. I don't know what the status of that is from HP. I don't know -- I haven't followed up on it.

Q. I wanted to turn to Exhibit 2007, which is your declaration. And if you could, please, let me know when you have that in front of you.

A. I have my declaration in front of me.

Q. And can you turn to paragraph 32?

A. Yes, just one second.

Yes, I'm at paragraph 32.

Q. In paragraph 32, you refer to a person

of ordinary skill in the art; is that right?

A. Yes.

Q. For purposes of our discussion, I'll refer to person of ordinary skill in the art as a POSITA.

Is that okay?

A. That's fantastic. Thank you.

Q. So who is a POSITA?

A. Well, as you see in paragraph 32, this is kind of the legal description of a POSITA. And in my declaration on page 16, we define the POSITA for this particular declaration. When you hear me flip, I have a hard copy here in front of me that counsel has provided.

Q. I'll just repeat my question.

Who is a POSITA?

A. Well, as you see in paragraph 32, that's the legal definition of a POSITA. I understand it's a person of ordinary skill -- having ordinary skill in the art may be defined by factors, such as the levels of education and experience of the inventor or other persons actively involved in the

field, the type of problems encountered in the field, prior art solutions to those problems, you know, rapidity with which innovations are made and sophistication of the technology.

So that's the legal definition, to my understanding. Obviously, I'm not a lawyer, but that's the legal definition that I was provided for a POSITA.

Q. So in paragraph 32, I understand you mentioned the factors that you used to define a POSITA.

A. Right.

Q. But it doesn't tell me who a POSITA is. For example, you have factors of levels of education or types of problems encountered in the field, but you haven't specified what those types of problems are.

So, again, who is a POSITA?

A. So if you go to page 16 of my declaration, on paragraph 45, it defines the POSITA for this particular declaration. You know, in that paragraph we call him a POSA, but I'm sure

it's the same thing.

So the definition that I've used is I believe a person of ordinary skill in the art at the time of the alleged invention would have had at least a bachelor's degree in electrical engineering, computer engineering, computer science, systems engineering, or a similar technical field with at least three years of experience in the fields of computer vision, image video processing, and/or machine learning.

And, obviously, there's an alternative, one, if you have a master's. So that defines, in a sense, the POSITA for this declaration.

Q. This definition was -- sorry, was this definition something that you developed?

A. I don't remember exactly how this definition came about, but this definition obviously is something that I follow -- you know, we collaboratively developed and followed.

Q. When you comment on what would have been or what would not have been obvious to a POSITA, what's the criteria you use to make your

conclusion?

A. Well, obviously, I've been working in the field for many years. I worked with engineers, colleagues, students, professionals of various types. So -- and I've worked with people that are experts in the field. I've worked with people that are practitioners in the field and at variety levels.

So I'm well-versed in the knowledge of the field and what a person of ordinary skill in the art would know at the time of the invention.

Q. How does someone like yourself who received a bachelor's and master's in the '90's understand what would have been obvious to a POSITA in the year 2016?

A. Well, I received my bachelor's, master's, and doctorate, you know, obviously, as you know, in the late '80s and '90's. And I've been -- since that time, I've been teaching in the field, doing research in the field.

You know, I started teaching in the field in 1997, as my first teaching assignment at

the University of Rochester, and also had a grant with Professor Tekalp from U of R.

I started teaching at RIT in 1998, as an adjunct faculty, as I mentioned earlier. And I've worked in this field ever since. I mean, we've done a lot of work in various aspects of this field.

We've had multiple grants from the Department of Defense, I think five of them, if my memory serves me right. I've had multiple grants from Hewlett Packard and other industrial partners to do a variety of different things. So I've worked in this field for many, many years.

Q. You mentioned that a POSITA would have a bachelor's degree in electrical engineering, computer engineering, computer science, systems engineering, or a similar technical field with at least three years of experience; is that correct?

A. That's correct.

Q. Of the students that you have had who achieved a bachelor's degree and obtained three years of experience, are you in touch with

any one of them?

A. Well, some of them, obviously, worked for me doing an MS/Ph.D. So they got their bachelor's, and then they worked under me doing an MS/Ph.D. type of work with me. Some of them went to industry, like HP and others.

The ones that have -- you know, that I've worked with, professionals from HP, not just my students, but others that also -- at different paces of their careers. Some of them were on let's say the first five years of their career, so to speak. Others were more advanced in their careers.

So I've worked with a variety of different engine- -- at Xerox, for instance, I've hired engineers. You know, towards the end of my career at Xerox, I was a senior scientist and manager. So I've hired engineers of various -- you know, various degrees.

Some had a BS in engine science. Others had a BS in electrical engineering. And, you know, I've coached them and obviously mentored

them. So I'm very familiar with, you know, their knowledge.

MR. KHAN: Matthew, we're joined by Nicholas Stephens. He might be joining in and out today. He's a colleague of mine at Fish & Richardson. We both represent petitioner, just for the record.

BY MR. KHAN:

Q. Dr. Saber, you mentioned that you have some of your students doing MS after your -- after their bachelor's.

Does that MS take more than three years?

A. Well, it depends sometimes on the student. Occasionally, some do. Most usually complete in two years or so. Occasionally, a student will spill into the three-year format. And once they complete the MS, you know, some of them have taken my advice and gone on for a Ph.D. at RIT and continued from there.

I also think that that POSITA definition here is I think very much similar definition to what Tesla had in their petition, if I'm not

mistaken.

Q. So why did you think that experience in computer vision, image video processing, and/or machine learning is necessary for a POSITA?

A. Well, I mean, if you think about the field of, let's say, autonomous driving, you have the vehicle. The vehicle has sensors on it. Those sensors can be LiDAR, it could be cameras. You know, cameras and LiDAR are probably the primary most used sensors.

Cameras acquire imagery. So that imagery has to be analyzed for the vehicle, obviously, to properly operate. And you could acquire imagery from all around the vehicle. So it has to be analyzed in the proper context of where you are in the vehicle, and it has to be analyzed so you know what's in the front, what is in the back type of thing.

So you need a lot of computer vision techniques to be able to handle all that analysis in, obviously, a realtime situation, if you're driving.

You need image and video processing knowledge because you're going to be acquiring videos, not still images. You're going to be acquiring frames of videos at, say, 30 frames a second. So you'll need a lot of tracking knowledge and video type of knowledge.

And you need machine learning knowledge because you're going to be making decisions on, you know, what the vehicle should do within a limited amount of time. That has to be done in near-realtime or realtime-type situations.

So you have to have some way of absorbing all this imagery, dissecting what's important, and providing, you know, output to the vehicle so the vehicle can do what needs to be done. So you have to have some control knowledge of how to control the vehicle, you know, start, stop, move, turn, et cetera.

Q. Did you write the declaration yourself?

A. So, typically, I usually -- obviously, I read the patents and the prior art in the petition in this case very carefully. I have discussions,

obviously, with counsel.

I provide a first draft for the declaration, and then it becomes a collaborative and iterative effort between myself and counsel until the final document is finalized. I review that extremely carefully. I read every word of the document and I approve it and I sign it.

Q. So I -- my question was not what you typically did. It was specifically for this particular declaration.

For this particular declaration, did you write the first draft?

A. I wrote the first draft of this declaration, that is correct.

Q. And then you engaged in the back-and-forth process with opposing counsel?

A. It's a collaborative -- as I mentioned, it's a collaborative and iterative effort, you know, back and forth.

MR. JAIRAM: I'll instruct the witness not to reveal the substance of any privileged communications with counsel.

BY MR. KHAN:

Q. Are you familiar with the term "claim construction"?

A. Obviously, I'm not an attorney, but yes, I am familiar with the term.

Q. What does that mean to you? Sorry, I should be clear, what does claim construction mean to you?

A. Well -- so if -- so if you go to paragraph 55 of my declarations, that defines claim construction.

Q. And what is the definition of "claim construction"?

A. Well, as you can see on the first sentence of paragraph 55, I understand that claim terms are typically given their ordinary and customary meaning as would have been understood by a POSITA at the time of the alleged invention.

Q. Are you involved in the co-pending district court proceedings for this patent?

A. I don't believe so, no. I'm just involved in the IPR process.

Q. Now, in your declaration, you offered a construction for the term "connection"; is that correct?

A. That is correct.

Q. And how did you develop this construction?

A. Well, as you can see in paragraph 55, the second sentence is what I've applied, obviously. In considering the meaning of the claims, I also understand that one must consider the claim language, the specification, prosecution history, and the knowledge of a POSITA at the relevant time.

So if you look at paragraph 57 of my declaration, I provide my opinion. So it says, in my opinion, in the context of Claim 7 of the '974 patent, including in light of the claims, specifications, drawings, and obviously prosecution history of this patent, a connection should be construed as a relationship that includes a link. And that's supported by the claims, the specs, the drawings, and the intrinsic

record as a whole.

Q. Can you explain to me how you applied the prosecution history in developing your construction for the term "connection"?

A. Well, I mean, I've looked at the prosecution history, I looked at the '974 patent, I looked at the specification, I looked at the drawings, not just one document. I looked at the claims to try to understand what does the owner of the patent mean with the term "connection" and, based on that, generated this construction.

Q. Can you tell me which part of the prosecution history informed your opinion on what the construction for "connection" should be?

A. I don't remember off the top of my head, sitting here today. It's been a while. I don't remember off the top of my head. But I looked at all those things I just mentioned.

Q. Is it fair to say that whatever information you considered in developing your construction for the term "connection" was cited in paragraphs 56 to 62 of your declaration?

A. Well, I mean, obviously, this is the summary in a sense of how this was arrived at and explained here. But I certainly looked at the claims by the patents. I looked at the specifications, the drawings of the patent itself.

As I mentioned, the prosecution history and my knowledge of the word "connection" and what does it entail in this particular setting. And based on that, we -- that -- you know, that definition came about.

Q. Is it correct to say that in paragraphs 56 to 62, you did not have a single citation to the prosecution history?

A. I don't recall. I would have to check all those, but I don't recall off the top of my head. I would have to check.

Q. It's about seven paragraphs. You can check, and then you can let me know.

(Witness peruses the exhibit.)

THE WITNESS: Yes, I do not see a direct citation to the prosecution history in paragraphs 57 to 62.

BY MR. KHAN:

Q. So I just wanted to understand. In paragraph 55, you noted that you must consider the prosecution history in formulating your construction, but in paragraphs 56 to 62, when you adopted -- or when you specified your construction, you did not include any mention of the prosecution history; is that correct?

A. I hear some discussion in the background.

So I did not include a citation to the prosecution history in those paragraphs, but obviously, I included many citations to the patent itself and where -- in each of the paragraphs, you know, where the knowledge came about.

Q. We've hit the one-hour mark. So maybe we can take a short break here. How does ten minutes sound to you?

A. It sounds fine to me.

MR. JAIRAM: Dr. Saber, do you want to do five minutes so that we can make sure that we, like, you know, get everything done in the time

frame? We can do ten if you want, but I suggest doing five for the breaks to keep things moving along.

THE WITNESS: It's up to counsel. I'm happy to take five. I'm happy to take ten, as long as we're done by 5 o'clock.

MR. KHAN: Yeah. Well, I think we'll be fine. We can take a ten-minute break. And we can come back at 9:40?

THE WITNESS: 9:40. I have 9:30 on my clock. I'll be back in my seat at 9:40.

MR. KHAN: Thank you.

THE WITNESS: Thank you very much.

(Recess from the record.)

BY MR. KHAN:

Q. Dr. Saber, can we turn to Exhibit 1001, which is the '974 patent? When you have that open, can you let me know, please?

A. Yes, I have that open.

Q. How would you describe the '974 patent?

MR. JAIRAM: Objection; form.

THE WITNESS: Well, it's a long patent.

So it's -- but as you obviously can see, if you look at the title of the patent and the abstract of the patent, it provides a decent description. And I also have a description in my declaration, a brief description in the declaration.

BY MR. KHAN:

Q. Can you turn to Figure 1, please. And just let me know when you're there.

A. Figure 1.

Q. Figure 1 of the '974 patent.

A. Yes, sir.

Q. Can you describe to me your understanding of Figure 1?

A. Well, obviously, Figure 1 provides an overview, essentially, of the invention. It provides kind of an overview, like, where you would follow a block diagram or, you know, an architectural kind of block diagram of the invention.

The description on the patent of the figure says it's "a block diagram of a Computing Device 70 that can provide processing capabilities

used in some of the disclosed embodiments."

Q. Do you believe that the '974 patent has an alleged innovative feature?

A. Of course.

Q. Which block in Figure 1 has that innovative feature, whatever that may be?

A. Well, it's not -- you can't point to a single block, because it's obviously integrated knowledge. So it's not just in a single block. I mean, you have a human machine interface in block 23. You have memory in block 16.

You know, I/O devices are probably not going to have some of that stuff, but you have a processor there that's going to have software that's going to do a variety of things that the patent describes.

You have storage, where you have, you know, the information that's being stored, the connections that we're talking about, the correlations, the mixed knowledge base. So it's not in a single box of that figure or architectural diagram.

Q. Can you tell me which boxes it is in?

A. I'm sorry?

Q. Can you tell me which boxes the innovative features are in?

MR. JAIRAM: Objection; form.

THE WITNESS: As I mentioned to you, you know, it's not in a specific box of these boxes. I mean, it's -- you know, the invention, obviously, you have algorithms, you have knowledge base. So it's not in a single one of these boxes. It's going to be, you know, dependent on what piece of it is going to be in various places of these boxes.

BY MR. KHAN:

Q. The display device 21, is there something different that this display device does, compared to other display devices?

A. Probably not in a display device. I mean, I'm assuming it's just a -- you know, it's a display device like we have here. So it's going to be -- it's going to display some of the connectivity and stuff.

There may be interfaces there, like a graphical user interface that's being displayed. So it's -- you know, you can't say well, this box has and this box has not. This is just an overall architecture diagram. But the invention will probably be -- will have pieces on all the boxes.

Q. What's the human machine interface 23 in Figure 1?

A. Well, I mean, it is described in the patent. So if you look at the patent, on Column 58 of the patent, it will describe the human machine interface that you were asking about.

So it states there in Column 58, Computing Device 70, which is the device of this whole figure here, via bus 5, which you see that bus going across the figure -- sorry, I read the wrong line. This was a mistake. Let me back up.

Computing Device 70 may also include -- I'm reading the wrong line again. One second.

So Computing Device 70 may also include Human interface -- machine interface 23, which is

what you're asking about, such as a keyboard, a pointing device, a mouse, a touchscreen, joystick, remote controller, and/or other input device.

And then there's -- in other implementations, it discusses more the Human-machine interface.

Q. Thank you.

Can you turn to Figure 2 of the '974 patent?

A. Yes.

Q. What's your understanding of Figure 2?

Well, sorry, what's your understanding of what Figure 2 depicts?

A. Well, let's look at the description in the patent. So if you look at the patent itself, so the patent states, Figure 2 illustrates an embodiment of Device 98. So -- and that's what it labels there, Device 98 -- comprising unit for learning and/or Using a Device's Circumstances for Autonomous Device Operation. And it calls that a DCADO Unit 100. Essentially, that's one of their devices.

Q. Is device 98 in Figure 2 the same as device 70 in Figure 1?

A. Well, it's not the same as device 70. Device 70 is the overall kind of description, in a sense an overall architectural diagram, you know, a block diagram, as we discussed.

Device 98 kind of talks about the pieces that have to do with, you know, the learning and/or using a device's circumstances for autonomous device operation. So it's talking specific about that piece of it. It's not something you can pick up and drop into the other piece.

Q. So is device 98 not the same as device 70 in Figure 1?

A. Well, device 70, as I said, in Figure 1, provides the processing capabilities used in some of the disclosed embodiments. It's just a block diagram that kind of gives you the overall processing capabilities of the disclosed embodiments in this particular patent.

Device 98 focuses more on the autonomous

device operation unit, as I described.

Q. Are there any embodiments that are implemented by the device in Figure 2 -- device 98 in Figure 2 that -- I'm sorry.

Are there certain embodiments in device 70 in Figure 1 that are not implemented in device 98 in Figure 2?

A. And I'm not sure what you're asking. I mean, device 98 in Figure 2 talks about -- you know, illustrates an embodiment -- Figure 2 illustrates an embodiment of device 98 comprising a unit for learning and/or using a device's circumstances for autonomous device operation. So it talks about one embodiment.

Q. I understand that. I guess what I'm trying to understand is whether Figure -- device 98 in Figure 2 is the same or different from device 70 in Figure 1. And I haven't got an answer from you.

So, I mean, can you indicate, is device 70 the same or different than device 98?

A. Well, I just described to you what they

are. Device 70 provides a block diagram of a computing device. So this is a block diagram, and it talks about the processing capabilities. So, essentially, it lays out a bit of the hardware kind of description of this computing device in a sense.

You know, it talks about the I/O ports, the processor, memory. So it lays out in a sense the hardware type of description as a block diagram architecture.

Device 98 talks more about an embodiment for learning and/or using a device's circumstances. So device 98 gets into one of his embodiments of this particular invention.

Q. So I can appreciate the description of each one of these devices that you're providing, but that was not my question. My question was not asking you to describe these devices.

The question was: Is device 98 in Figure 2 the same or different than device 70 in Figure 1?

A. Well, they're different functionality.

I mean, device 70 is a block diagram architecture of essentially laying out the hardware as one would use in a system.

Device 98 is talking more about this DCADO unit that the inventor has proposed. So they're not -- they don't define the same things.

Q. Thank you.

So you mentioned the D-C-A-D-O. I'll refer to that as DCADO, if that's okay.

Is that okay?

A. Yeah, that's fine.

Q. Thank you.

What is the DCADO unit used for?

A. Well, as you can see from the figure, right, it provides all the pieces, right. In this particular embodiment we're talking about, it provides the pieces that you would need for autonomous driving.

Q. And when you say the pieces that you would need for autonomous driving, you're referring to things like machine learning and training; is that correct?

A. Well, all the fundamental pieces. Like, if you look at Column 66 of the patent, it starts to describe referring to Figure 2. And it describes the DCADO unit that is illustrated in Figure 2. It talks about the various pieces of it.

Q. What does the artificial intelligence unit 110 do?

A. Well, just what it says. I mean, that's where probably -- that's where his artificial intelligence, say algorithms or whatever, are comprised. So if you look, for instance -- so if you look on Column 67, starting at line, say, 14 or so, you can see a description of the artificial intelligence unit. And it's a long description. So I'm not going to read all of it, but it starts on line 67. There's a good description starting on line, say, 13, 14.

Q. The artificial intelligence unit is connected to the object processing unit 93 in Figure 2.

Do you see that?

A. Yes.

Q. What does the object processing unit 93 do?

A. So if you look at Figure 3A to 3E, it kind of provides some high-level descriptions of various sensors that feed into the object processing units. So you have sensors, like, you know, a camera, microphone, et cetera, feed into the object processing unit. Sorry.

And if you look at Column 71, so Column 71 starts to describe the object processing unit. And starting at line 38, it talks about the description of the object processing unit.

Q. Going back to the DCADO unit, the DCADO unit has a modification interface 130.

What does a modification interface do?

A. So if you look at Column 139 of the patent, starting on line 64, it describes the modification interface. And there's also a description on line -- on Column 140, starting on line 42.

Q. So -- and I've asked you a few different

components and you've pointed to me in the spec where they're mentioned, but, you know, I can read the spec. I would like to understand what your understanding is.

So can you tell me what your understanding of the modification interface 130 is?

A. So if you look at Column 139, for instance, towards the bottom, it says, "Modification Interface 130 comprises the functionality for modifying execution and/or functionality of Application Program 18, Processor 11," et cetera.

On Column 140, starting at line 9 or 8, Modification Interface comprises the functionality to access, modify, and/or perform other manipulations on runtime, engine/environment, virtual machine, operating machine, et cetera, compiler, et cetera, et cetera.

And later on, it will say, comprise the functionality to access, modify, or perform other manipulations. Essentially, that's the purpose of

it.

Q. So in systems such as the one in the '974 patent, when, as you just described, there is a modification of the execution and/or functionality of application programs, how is such modification implemented?

A. Well, some will be implemented in hardware. Some will be implemented in software. So it depends on, you know, how the system essentially is designed. Some of them could be implemented in hardware, some software.

Q. And so when you are -- when we're talking about -- and maybe I should clarify my question. We're talking about specifically Column 140, where it's talking about modification involving modifying execution and/or functionality of application program. That's what you had just mentioned earlier.

How is the application program execution functionality modified?

MR. JAIRAM: Objection; form. Objection; scope.

THE WITNESS: I'm not sure I understand what you're asking.

BY MR. KHAN:

Q. Well, what I'm asking is that Column 140 -- just an explanation of what this means really. In Column 140 you just pointed to is talking about the modification interface comprises the functionality for modifying execution and/or functionality of application program 18, that's in Column 140, lines 1 through 3 which you had just pointed me to and I'm trying to understand better what that means and what that would entail. So that's what I'm asking.

What does modify -- how does the modifying of the execution functionality of application program actually accomplished?

A. Well, if you look at that same column, starting at line, let's say, 35, you'll see, "Modification Interface 130 comprises the functionality to access, create, delete, modify, and/or perform other manipulations on values, variables, parameters, and/or other data or

information."

Then the next line will say, Modification Interface comprises any features, functionalities, and embodiment of Acquisition Interface 120, and vice versa, and other disclosed functionalities.

So, essentially, the modification interface has the functionality, I'm reading at line 35, to access, create, delete, modify, and/or perform other manipulations on values, variables, and parameters.

So you have an application program that has values, variables, parameters, and the modification interface will go in and make a change and say, you know, I see a person running quickly to my car, you know, it's going to hit the car or do something.

So it will change variables, modify, you know, parameters in the application program to make the proper changes.

Q. And these changes occur during the course of machine learning; is that correct?

MR. JAIRAM: Objection; form.

THE WITNESS: Well, I think your question is extremely broad, and I'm not sure I understand what you mean. But you typically have machine learning algorithms. You have a training, essentially, dataset. In a typical machine learning application, you have training datasets, you have test datasets.

So I'm not sure what you're asking. I'm not sure what your question is about.

BY MR. KHAN:

Q. I'll try to be a little clearer to the extent I can so hopefully it will be helpful.

Is it correct that the DCADO unit is a unit for learning and/or using a device's circumstances?

MR. JAIRAM: Objection; form.

THE WITNESS: So let's be precise and accurate. Let's look at the description. So if you look at Figure 2 description, it says, "illustrates an embodiment of Device 98 comprising Unit for Learning and/or Using a Device's

Circumstances for Autonomous Device Operation."

So that's the precise description.

BY MR. KHAN:

Q. Okay. That wasn't my question. Again, I'm going to ask you to answer the question specifically.

Is it correct that the DCADO unit is a unit for learning and/or using a device's circumstances?

MR. JAIRAM: Objection; form.

THE WITNESS: That's -- I mean, if you look at Figure 2 description, I think I have answered your question. So you have a device 98 comprising unit for learning and/or using a device's circumstances for autonomous device operation. So it's using the device's circumstances for autonomous operation.

So I'm not sure I understand your question, but that's the description.

BY MR. KHAN:

Q. Well, I'm asking you about learning and/or so using a device's circumstances, and your

response does not indicate -- in your response you're saying it's using a device's circumstances for autonomous operations. You're not answering the question. And I can repeat the question.

Is it correct that the DCADO unit is a unit for learning and/or using a device's circumstances?

A. I think I've answered your question.

Q. You haven't, and I can ask it again.

A. I mean, if we go back to Column 66, that's the starting description of Figure 2, it describes the DCADO unit comprises interconnected AI, Artificial Intelligence Unit, et cetera, et cetera. So it describes the DCADO unit, which is this whole Figure 2 that we're talking about.

So, obviously, it's going to do all these pieces that you see in this diagram in Figure 2. It's got a Human-machine interface. It's got an object processing unit. It's got sensors. It's got an AI unit.

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

Q. Okay. We can move on. We can go back,

actually, to modification interface. You had pointed me to the description of the modification interface in Column 140, I believe it was lines 26 to 30, where it states, "Modification Interface comprises the functionality to access, create, delete, modify, and/or perform other manipulations on functions, methods, procedures, routines, subroutines, and/or other elements of Application Program 18"; is that correct?

A. What was the column you just mentioned?

Q. Column 140, approximately lines 26 to 30.

A. Column 140. Yes. So -- yes, this is the description. I mean, it describes it, obviously, starting -- the description starts on Column 139, on line 64, and goes into Column 40. But, yes.

Q. So can you give me one example of the functionality of deleting function, method, or procedure of application program 18?

A. Are you reading?

Q. It's that same section. I'm just asking

for an example of the description.

A. So can you point me to which line are you reading so we can be on the same page?

Q. Yeah, it's, again, lines 26 to 30, Column 140, with the same --

A. Okay.

Q. Yeah. You see it says, to access, create, delete, modify, and/or perform other manipulations on functions, methods, procedures, et cetera, of application program 18.

So I was looking at that and trying to understand that better, and I was asking if you could give an example of when some -- you know, there's a deleting of a function method procedure routine of application program 18?

A. Well, I mean --

MR. JAIRAM: Objection; form.

THE WITNESS: I mean, you're asking a very obviously general question. You would have to look at the software carefully. But generally speaking, and I'm speaking now in very general terms, I mean, let's say you have an application

program that's -- maybe it's slowing down the vehicle.

So you have a program that's going to slow down the vehicle and come to a stop, let's just say. And that program is slowing it too abruptly, so where the -- potentially a passenger sitting in the car is being rocked forward too fast or something.

Then, obviously, this modification interface, as you do some training, you would access those variables, and you would say, okay, put it slower, a slower time constant on this. Let's slow down so the deceleration is being slowed down so you're not rocking the person inside or you're not accelerating abruptly from where you are.

So you're modifying, i.e., the function, perhaps. Maybe you put a filter on some of these variables or, you know, time charts or you're deleting perhaps one and putting a whole new one or you're accessing some of the variable time constants or whatever and you're changing them,

you're slowing things down so you don't overshoot, that type of thing. So those are some examples.

BY MR. KHAN:

Q. Thank you. I appreciate that.

A. You're welcome.

Q. You mentioned the example of a car and a passenger sitting in the car. When a car is traveling on a new road that may not be, you know, on the driving app, road map, how does the system learning modify its knowledge of the road structure?

A. I --

MR. JAIRAM: Objection; form.

THE WITNESS: I'm not sure I follow your question, sir.

BY MR. KHAN:

Q. So in your last example you talked about a car traveling on a road, coming to a stop sign, something like that.

A. Yes.

Q. So I'm just asking, going along with that example, when you have a car, let's say the

car is now on a road that's not there in the application map, right --

A. So you have a car on a road that it is not part of any of the maps in the car?

Q. That's right. That's right.

Does the application then -- if it's, like, a mapping application, does it update its records to reflect that there's a new road here?

MR. JAIRAM: Objection; form. Objection; scope.

THE WITNESS: Well, I'm not sure exactly what you're asking. But you're obviously asking a very hypothetical question, and it's very hard to constrain all the details. So I will try to give you some answers with the understanding that you're asking a very open-ended, a very hypothetical question that's essentially -- you know, it's hard to constrain all the pieces.

But if you put a car on a road that the car has never seen before and the road doesn't exist in the road application map of the vehicle, the vehicle would have to rely on its sensors at

that point, just like you would if you were -- if you were to pick me up and put me in Johannesburg, South Africa, where I've never been and put me on a road there that I've never seen before.

So the car would have to rely on its sensors, cameras, Lidars, et cetera, to do the automation, you know, to do the driving. So you'll have to ingest the videos and/or information from all the sensors, process that in realtime, and provide controls to the vehicle.

You know, obviously, there are some things you would use from its machine learning, you know, artificial intelligence unit, but you will need to do realtime processing of sensors right then and there.

So I'm not sure about -- if this is addressing what you're asking, but you're asking a very open-ended, hypothetical question that's -- without knowing all the constraints, without knowing all the pieces, without seeing the road, it's hard to answer such questions like that.

BY MR. KHAN:

Q. Thanks for the explanation.

In what circumstances does the modification interface 130 access the functions, methods, procedures, routines of the application program 18?

A. I'm not sure I could answer that question without -- you know, you'd have to go through the code specifically to really answer exactly in what circumstances that happens.

But I would assume you'd have access to the application programs, you know, on a regular basis, because you have to be able to interact. You're doing this in realtime in a sense. You have to be able to interact with those application programs readily.

Q. And when the system is -- I'm sorry, when the modification interface is accessing this application program, does that involve accessing the corresponding memory locations of the application program?

A. Well, it's got to access -- see, if you

look and see -- I'm going back to 140, Column 140, the lines that you mentioned, lines 26 to 30. So Modification Interface comprises a functionality to access, create, delete, modify, and/or perform other manipulations on functions, methods, procedures, routines, subroutines, and/or other elements of Application Program.

So it has the capability to do all these things. Now, does it do that every single time, every single one of them? It depends on what's -- what it's seeing, what it's receiving, what's the input. But it has the ability to do all these things.

Q. Yeah, and I'm actually just asking -- you know, given that you're the expert, I'm asking what the -- exactly this disclosure, how it would be done and what it means. And that's why I had asked earlier about, you know, deleting.

And now I'm asking about access. Like, how does it do the accessing; right? We can just stick to the sentence, right, and that's fine. I'm trying to understand how this is done.

So in the context of the '974 patent, right, nothing abstract, nothing -- like in the context of the '974 patent, when we're talking about the modification interface accessing the function methods of the procedures, et cetera, as noted in lines 26 to 30 of Column 140, right, of the application program, how is that done. And I'm just trying to understand that.

So is this access done? Is it done -- my previous question was: Is it done by referencing memory locations that are -- correspond to application program 18, or is there something else?

So if you could explain -- the question here, to be clear, is: How is the accessing, as noted in lines 27 of Column 140, how is that access done?

A. Well, to answer this question very specifically, how is it done, you would have to look at the software, you know, exactly and/or the hardware design to really answer that.

But I will give you a generic answer,

you know, not the exact specific how, but a generic answer. You know, the modification interface, let's assume -- I'm making assumptions here.

So we'll assume that the modification interface is a software program that is handling this -- all these type of things. So it's kind of like an overall programming, you know, software application here.

It would have to access the variables in the application program. It would have to access various memory locations there. It would have to access, you know, some of the classes and different things to be able to make changes and delete and modify stuff.

It would have to access some of the functions and provide, you know -- because the functions will have input variables. It would have to update the values of all these input variables so the functions can then process that information.

So it has to have -- be able to do all

this. So it's got to access all these different things for it to be able to provide the proper input into the application programs.

Q. And, again, that list of verbs, access, create, delete, modify, and perform -- there's also perform. And I'm referencing lines 26 to 30, Column 140, the '974 patent.

When the patent talks about the modification interface performing these functions, methods, of the application program 18, does that include performing the instructions -- the instruction sets that are also part of the disclosure in the '974 patent?

A. Well, it's performing other manipulations on functions, methods, procedures, routines, subroutines. So it's going to perform, you know, manipulations there. It may, you know, change case. For instance, if you see this, do this or -- you know, you're familiar with C, probably. You have like this case -- case-case type of calls. So it's going to affect some of that. So it's going to perform these type of

manipulations on functions.

There may be multiple functions that do a specific item. It's going to select which one of these functions should be run in a sense. There may be calls within the functions that, you know, use -- and I'm being generic now and making assumptions and being hypothetical and really just providing a simplistic example here.

But, you know, for instance, it may say, well, why don't we use a least square algorithm instead of an absolute value algorithm to do this and that.

So it's going to depend a lot on what's being -- what it's seeing and what's being done. It's very hard to answer such generic questions, very hypothetical.

Q. Well, just to be clear, there's no hypothetical here, because I'm just asking you to explain what the patent means when it's making these statements. And this is within the context of the '974 patent.

I'm not providing any hypothetical here.

I'm just asking you to explain, based on your knowledge as an expert, how these things are done or what they mean, right. I'm just pointing to the same statement.

And so along those lines, when we're talking about performing, deleting, or creating, modifying these functions, methods, procedures, routines, subroutines, and other elements of the application program, would this involve modifying, deleting, adding instruction sets, as well, that are part of this application program 18?

A. Well, it will involve whatever is needed to obviously perform the activity that's being programmed by the software -- you know, that's put forth by the hardware and/or program by the software of this particular application.

Q. Did these instruction sets that might be stored as part of the functions of an application program, are they typically stored in a memory location associated with the application program?

A. Well, I mean, for instance, if you look at -- if you look at that same column, 140, let's

go to line 42.

For instance, you can see it talks about various techniques for modifying, execution or functionality of the application program, processor, et cetera. Some aspects, some of the previously described techniques and/or tools can be utilized. Code instrumentation, for instance, may involve inserting additional code, overwriting or rewriting existing code, and/or branching to separate segments of code.

So it has to be able to access all these different locations to do these type of things. So code is typically stored, you know, in memory locations and/or hard drives somewhere in this particular application. It's got to be able to access that in the appropriate timing for the activity that you're doing.

Q. I see.

So along the lines of what it says here, lines 45 to 51 in Column 140, the addition of code or overwriting or rewriting existing code would be part of the modification performed by the

modification interface --

A. Yeah. Yes, I mean, obviously, that's what it describes. It gives you a little example, like, Device1.moveLeft type of thing or whatever. So you have some example -- a small example there.

But it has to be able to access whatever the application that's being accessed and do these type of things to effect the situation at hand. Because you can't possibly program every possible situation you're going to see out there in the world. So it has to make decisions more or less on the fly.

Q. I see.

Can I ask you to turn to Column 80, line 50, of the '974 patent?

A. Column 80, line 50.

Q. If you can let me know when you're there.

A. I am there.

Q. Could you read that sentence starting at line 50?

A. Yes. So referring now to the DCADO

Unit 100, DCADO Unit 100 comprises any hardware, programs, or a combination thereof.

Q. Based on this sentence, is it your understanding that in some cases the DCADO unit can be just hardware?

A. The DCADO unit comprises any hardware, programs, or a combination thereof. So it would -- it has obviously hardware. It's got to have memories and processing units and so on. It's got to have software programs that are going to do the various things, and you're going to be able to change those on the fly in a sense, you know, make changes to those. And it's got to have a combination between them to be able to do what it needs to do.

Q. So is your understanding of this statement that the DCADO unit must have a combination of hardware and programs?

A. It comprises any hardware, programs, or a combination thereof. So it's got to have the proper hardware, the proper software, and combinations of those where it's needed.

Q. So you just said "and a combination where needed." Does that sentence say "and" or "or"?

A. Well, it specifically says "or a combination thereof." But, you know, you have to understand, I mean, this unit has -- it's got to have hardware, it's got to have programs that are functioning onto this hardware, and obviously a combination was needed to do what it needs to do.

Q. And when you say it must have hardware, can you point to me where in the patent it says that it must have hardware?

A. Well, this is a pretty large patent. I mean, I can do some searching if you want, but obviously, it says it comprises any hardware, programs, or a combination thereof. So it has all those pieces. It has the ability to have all those pieces.

Q. So does it have all the pieces or the ability to have all those pieces?

MR. JAIRAM: Objection; form.

THE WITNESS: I guess I'm not sure what

you're asking, but the DCADO unit that we're talking about here comprises any hardware, programs, or a combination thereof. So it has hardware, it has programs, and combinations is needed.

BY MR. KHAN:

Q. Okay. We're hitting about the one-hour mark. So we can take another ten-minute break. That would be great.

Does that work for you?

A. That works fine for me.

Q. Great.

MR. KHAN: If that's okay with everyone else, then we'll see you back at 10:50 a.m., okay, Eastern.

THE WITNESS: Thank you very much.

(Recess from the record.)

BY MR. KHAN:

Q. Dr. Saber, can you turn to Figures 4A and 4B of the '974 patent. And let me know when you're there, please.

A. Yes, I have Figure 4A and 4B in front of

me.

Q. Great.

In your words, can you describe what's depicted in Figures 4A and 4B?

A. Well, if you go to Column 79 of the patent, it talks about the description in 4A. And Column 80 talks about the description in 4B.

So if you take a look at the figure, as he's describing, so you see it's an example in Figure 4A, you have an object 615a, which is -- in this case is a cat -- it looks like a cat. Object may be detected at a distance of 6 meters from the device. It shows a bearing angle, and it provides a description. So do you want me to read the section on 4A, or is this sufficient?

Q. Well, the question was to describe Figures 4A and 4B in your words. I'm familiar with the patent. I've read the patent. So, you know, when I ask those questions, I'd appreciate -- of course, answer how you'd like, but if you can answer in your own words when asked, that would be great, instead of reading

from the patent, because I think we've all done that already.

So in future, if I ask you that, then please note that what I'm asking is not to, you know, read off of the patent, just to describe in your own words what your opinions are.

A. I would like to be as precise and accurate for the deposition, and that's why I think it's important to look at them. So it's a very precise description and not just a generic thing.

Q. Yeah, I can understand that. I appreciate that.

A. Sure.

Q. Thank you.

Would you agree that in Figure 4A, there's three objects -- I'm sorry, there's -- the device 98 detects three objects, which is the -- object 615a, b, and c; is that right?

A. That would be correct, yes.

Q. And object 615c is a person, 615a is a cat, 615b is a tree; is that correct?

A. That is correct.

Q. How does the device know that the person, 615c, is John Doe?

A. Well, I mean, in this diagram they just have a label there so they can refer to it. But this is -- I mean, for this particular figure, this is just a label there so you can refer to it.

You know, now, if you look at the description here, it describes basically -- in the patent, it says, Object 16C [sic] is also detected. Object 16C may be recognized as a person. Object 16C may be identified as John Doe.

So you would have to have, obviously, the proper object tracking and recognition algorithms to recognize a person and facial recognition to determine that person is John Doe.

Q. So I guess I'm asking exactly about this object tracking and recognition algorithms that you've referred to in your answer.

How does that work? Can you explain to me in the context of the '974 patent, how is that object recognition and tracking performed so that

the system can determine that this person is John Doe?

A. Well, it talks about that a little bit earlier. So if you go to Column 75, for instance.

If you look at the top of Column 75, even a little bit earlier, but 75 I think will be a good place to start just for the discussion and the question that you asked.

So if you look at Column 75, starting at the beginning, you have a picture recognition techniques, analyze features, lines, edges, ridges, corners, et cetera.

A few lines below that, he refers to artificial intelligence unit 110. I'm on line 10 now. Line 11 talks about facial recognition techniques that would obviously do facial recognitions. Line 17, some aspects, facial recognition techniques and/or tools involve identifying and/or analyzing facial features. So you're looking at a variety of facial features to be able to obviously recognize the person.

So you have to have appropriate facial

recognition techniques that can do this.

Q. I see.

And so putting that disclosure that you just pointed to in the frame of Figure 4A, for instance, the system performs object recognition and determines that there's an object that matches the -- I guess the records related to a John Doe, and, therefore, it identifies that person -- that object as John Doe; is that right?

A. So you cut out a little bit, but you obviously -- the device has to recognize there is an object. So you have object detection. Then you have object recognition. So you're going to detect the object. There is an object over here. You have to recognize this is a human, cat, tree, whatever. Because some objects move, others don't. Like a tree hopefully is not moving.

But the person may be walking across a crosswalk. So there's object recognition in terms of recognizing this is a person versus another, you know, vehicle or something.

And then there's also the recognition of

if it is a person, is this John Doe? And then there's -- obviously, it would be tracking where you would track that object throughout the frames.

So in this case, you know, you're recognizing John Doe. So you have to have facial recognition and something in your database that says this is John Doe.

Q. And then is it fair to say then that this information, the data that's recognized, is then stored as part of a collection of object representations that you see in Figure 4B?

A. Well, if you look at the description in Figure 4B, I'm looking at Column 80, starting at line 16. And if you look at that, it's referring to object processing unit 93. And that's the label that you see on Figure 4B of that big -- that largest box there, object processing unit.

And within that, you have a collection of object representations, and those are essentially -- if you look at the description, starting on line 16, you have object processing unit may generate -- may create or generate

collection of object representations. And he gives a bunch of examples of that.

And he gives an instance -- for instance, you talked about the cat, you have a type, you have a distance, and so on. So you have descriptions of each of the objects in these object representations.

Q. So when an image, such as the one shown in Figure 4A, is processed in the '974 system, the system will determine that there's these three objects and then add in the collection of object representations the data corresponding to these objects. And that data is in the form of, for example, the object representation shown in Figure 4B.

Did I get that right?

A. Well, close. I mean, you obviously identify an object. You would create an object representation with various categories. He gives an example here of the type, the distance, the bearing.

But, obviously, the example continues --

he also states -- line 34, Column 80, also states, any number of object representations and/or other elements or information can be included in collection of object representation.

So, you know, you identified a cat. You might want to say, you know, the size of the cat or where it is located in the frame of the video. You know, there's other pieces that you would need for you to track that particular object through the video that you're collecting.

Q. In the object representation, we see that the labels of John Doe, cat, tree, they're captured in that stored object representation. Let's just say you come across another cat --

A. Yeah.

Q. -- you know, you're having a stream of pictures. How does the system figure out whether it's the same cat or a different cat?

A. Well, you obviously have to do object detection. So you have a video -- let's say you're capturing a video. So I'm talking now a little bit hypothetically speaking.

You're capturing a video with your camera. There's two cats out there, one on the right side, one on the left side. So they're in different spatial locations in the video. Cat 1 is, you know, on bearing angle whatever, 56 degrees. And cat 2 is at bearing angle 287 degrees.

So they're at two different locations in the video. They have two different motions. Maybe the sizes are different. So you would have to capture that information.

Q. I see.

So you have this video, let's say images coming in from a video. And initially you have these three objects, as shown in Figure 4A. And maybe in a subsequent image there's another cat, and so the object -- the collection of object representations would then be updated or modified to include the description of the additional cat once it enters the images.

And so the object representations would include, for example, a label of cat 1 at a

distance of 6 meters at a bearing 56 degrees angle, and then another object representation with a label of, for example, cat 2 and a distance varying corresponding to the location of cat 2; is that right?

A. That's generally correct, yes. You would have obviously different representation for each of the objects dynamically through the system.

Q. Could I ask you to turn to Figure 32, please, of the '974 patent?

And please let me know when you're there.

A. Yes, I am there.

Q. Figure 32, Step 9105, that step says that there's a "receiving a first collection of object representations."

Do you see that?

A. Yes.

Q. What are object representations?

A. Well, we just described that earlier. We just talked about that a few minutes ago in the

other Figure 4B.

Q. Okay. I see.

And so the collection of object representations is that collection that we see in Figure 4B, is that --

A. Yeah, go ahead. Sorry, I --

Q. Yeah, so I just want to clarify.

So one example of receiving a first collection of object representations would be when we receive data that is similar to what was shown in Figure 4B; is that correct?

A. Yeah, I mean, that's what it says. If you look at Figure 4B, Item 525, it says, collection of object representations, and it gives three examples.

Q. And then Step 9110 says, "receiving a first one or more instruction sets for operating a device."

Do you see that?

A. I do.

Q. How is this receiving in Step 9110 accomplished?

A. What do you mean how is it accomplished?

Q. How does it receive the sets for operating a device?

A. Well, it has, obviously, instruction sets. You've done some training. You've created some instruction sets. Those instruction sets are in the system. So all you're doing the training as we speak, and you're creating instruction set. It depends on what the application is.

Q. So the instruction sets are a result of the training; is that right?

A. Well, yeah, you would -- I mean, you're doing some type of training, and you are creating, you know, instruction sets as a result of your training.

Q. And there would be -- I'm sorry, were you finished or --

A. Yeah, I'm not sure I understand what you're asking, but you have -- you know, as you do some training, you provide -- you receive instruction sets. You create instruction sets.

Q. And is there generally just one type of

training, or can there be multiple types of trainings?

A. Well, such a big generic question. Obviously, you have different ways of doing training, depending on the activity that's being trained.

Q. In the context of the '974 patent, is the device performing one type of training or multiple types of training?

A. Well, I mean, it's going to perform training, obviously, dependent on different types of objects that we're talking about here.

Q. Can you clarify that? I just want to understand. You said that it performs training depending on different types of objects.

So does that mean that the training for a cat would be different from the training of a person?

A. Well, I mean, if I'm doing -- let's say I'm doing training for facial recognition. So, obviously, I'm going to be training -- I'm not going to be using a cat to train on human facial

recognition. I'm going to be using faces of, let's say, humans. You might interject other things there to see if the system can do things accurately.

So if I'm training on, for instance, recognizing the shape of an animal, my training database is going to be -- has different sets of, you know, training imagery. It's such a big topic. It's hard to define what you're asking. But training has to be customized or tailored to what you are trying to train.

Q. Okay. Just so I can understand, maybe in the context of this somewhat relatable example, I guess. In the context of, for instance, security situations, you mentioned facial recognition. So I could go to one camera and there could be a facial recognition algorithm that's performed and that data is used for training.

So then when I go to another airport and they also perform a facial recognition. As a result of the training of the first camera, the

system -- the security system would be able to determine that I'm the same person; is that right?

A. I think you're mixing up --

MR. JAIRAM: Objection to form.

THE WITNESS: I think you're mixing up a lot of things. It's kind of hard to follow what you're saying. But let's say, for instance -- I'll give you an example.

Say, for instance, I have a company with 100 employees, and, obviously, they all look different. And I want to train a camera system to open the door when only one of my employees show up.

Okay. So I have pictures of the 100 employees. I may have pictures of profiles versus head on versus different angles and slightly different scales, perhaps. I have all these pictures in, say, some kind of what we call a training database.

So then I will train my neural network or my machine learning algorithm, I would construct an algorithm with neural nets and

multiple layers, whatever, CNN, whatever you construct. You're going to train that algorithm on all these various imageries, and then you're going to provide images that are these people, as well as others, to test on. Because if there's somebody that's not your employee, it shouldn't open the door, right.

So you're going to test it on unknown subjects, and you're going to test it on your employees. You have perhaps a test database and you determine its level of accuracy and you tweak and make changes.

So the training will take place on, you know, whatever -- in this case, the facial recognition that you're trying to do. So when an employee walks up to the door, the camera now executing -- you're not training anymore. You're just executing now.

It will see the employee walking up. It will take a snapshot, let's say, or take a look at the video, track the person as they're coming towards the door, and then do facial recognition

and say, yes, this is Tom, open the door, and this is an unknown, don't open the door. So this is kind of a simplified illustration, example type of thing.

BY MR. KHAN:

Q. I see.

And so in that example, let's go with that example, the training is, I guess, data that's related to the facial features of your employee and then the instruction set would, for instance, be if the facial scan matches whatever is in the database, then allow the door to open, and if it doesn't, then don't allow the door to open?

A. So that would be, you know, obviously, a simplified illustrative example, but, yeah, that's the idea. So you have facial pictures of your employees at various angles and scales and so on. You've trained this neural network to recognize them.

So now when a person walks up, the neural network is going to run facial recognition

on that person. It's going to say, that's Tom. Then the computer system is going to say, yep, this is one of our employees, unlock the door, take a picture of the person walking in, maybe they have a suitcase in their hand, whatever.

I mean, you have an instruction set that you want -- the company wants to follow in the right protocol for that employee.

Now, if somebody comes in -- comes over that's not an employee, maybe they're holding a weapon or whatever, then you're going to see that person, you're going to determine they're holding a weapon, and maybe the instruction says, call 911, they're holding a weapon.

So, yes, you have instruction sets that you're going to do dependent on what you see in this particular illustrative generic example.

Q. And let's say I grow some facial hair -- or sorry, let's say your employee grows some facial hair and comes in the following day. Would that additional facial hair then be part of the training data for that particular employee so that

in future when that employee again grows some facial hair, that it still matched to that employee?

MR. JAIRAM: Objection; form.

THE WITNESS: Again, I mean, we're still talking in this illustrative hypothetical type of example. But typically, when you're doing facial recognition, you kind of weight the recognition algorithms to more of the center of the face.

Like, you know, I could -- you could shave your entire head, right. So all your hair has disappeared. You know, you could obviously grow a beard, as you have mentioned.

So the outside portion of your face, which is generally referring to your hair on your head and your beard and so on, are very easy to change. But the interior part of your face, your eyes, your nose, your mouth, and the location of those, you know, require plastic surgery to change. So they're much more difficult to do.

So you typically weight facial recognition algorithms on more the inside -- let's

say, the inside two-third of the face. If you look at the face as an ellipse, for instance, you're looking at the inside two-third of that face as the heavier weighting versus the outside of the face.

Now, if you still don't recognize the person because your algorithms were not -- you know, let's say they're wearing sunglasses that are very strong, and you can't see the eyes. Then you would just say, I don't recognize this person, and the door doesn't open. And then the person would have to call security, and security would have to say, You need to remove your glasses and come again.

You know, so things of that sort. I mean, it's not -- obviously, these systems are not 100 percent perfect.

BY MR. KHAN:

Q. And the images that you obtained for the employee as part of the training or part of the collection of the object representations, does that have to be from one camera, or can it be from

multiple cameras?

A. Well, it can be -- it can be from multiple cameras. It's typically -- and you do some type of what you call feature normalization. So you have to do some type of -- because the picture could be taken on a sunny day. The next day it's a shady day or whatever. So you have to do some type of normalizations. It's not just a straight ingestion of it. And, two, there's dynamic updating.

You know, like the employee obviously gets older, right, year after year after year. You're not going to use the same picture from 25 years ago. If you looked at me 25 years ago, I had a full head of hair when I joined RIT. So things change over time.

So as the employee continues to come, right, you continue to update -- you know, you're collecting imagery from that employee. You may set a certain update cycle in a sense in your database and continue to update that. You know, for different objects, the cycle will be

different.

Q. I see.

And then the instruction sets -- going back to Step 9110, Figure 32, the instruction sets that are received, who are these -- or where or who are these instruction sets received from?

A. So your system -- you know, you've done some training -- you know, in the case of the employee walking into the company, as we've been talking, you've done some training, and you've determined that Tom is an employee. You've done some face recognition. And then you've created an instruction set that basically says, Open the door for Tom when he's coming in.

But maybe John is an employee in a wheelchair. So -- and let's say that particular door has steps, but there's a different door where that particular person in a wheelchair can roll across the ramp. So for that person, you're going to open a different door.

So there's a different instruction set for John, we know John is in a wheelchair. So

open door 2 instead of door 1. So the instruction set would be tailored, you know, to the objects in a sense or the circumstance that's taking place.

Q. That tailoring that you're talking about, is that what's referred to in Step 9115 as the "correlating"?

A. I mean, generally speaking, yes, that's obviously correlating the instruction set with the collection of object representation.

Q. And so who -- again, I guess who provides instruction sets? Is it, like, the employer or, you know, an organization of the building? Like who is providing the -- this feature says, receiving a first one -- sorry, this Step 9110 says, "receiving a first one or more instruction sets for operating a device."

Where is the instruction set being received from?

A. Well, I mean, I'm going to give you a generic answer. Typically, the instruction sets would be created as part of the training. So you would, you know, create that as part of the

training and obviously modify them as part of the training.

Q. Okay. Thanks.

I can appreciate that, but my question, though, is: Where is the instruction sets being received from?

A. That's what I said. When you're doing the training for what other activity that you're doing, you are going to create some instruction sets for that particular training. So if I see a person walking in a crosswalk while the car is coming up a crosswalk, you are going to provide certain instruction sets so that would take place to do what needs to be done.

Q. And who is doing the providing?

A. Well, as part of your training, that could be done by some human interaction. It could also be done with the machine -- you know, artificial intelligence algorithms. You're asking me a very generic question. It depends on the particular thing that you're doing.

Q. I'm just trying to understand the figure

and what it entails. So, you know, any explanation you can provide is helpful. Thanks.

You know, with respect to -- you know, you mentioned that there's -- you mentioned that the instruction sets are created as part of the training. And so these instruction sets, can they be different for different objects and different for -- I'm sorry, let me ask one question at a time.

The instruction sets that are created, can they be different for the different objects?

A. I mean, generally speaking, yes, of course. I mean, you have different objects. You know, the instruction sets would be different -- could be different. It depends on -- it's hard to answer that. But, you know, if I have a person walking in a crosswalk versus an incoming vehicle coming from the other side and -- you know, the instruction sets would be different.

Q. And can the instruction sets be different depending on the sensor that's being used to obtain the image?

A. Well, I mean, if you're capturing, let's say, imagery with a camera versus you're capturing LiDAR information with a sensor, the instructions -- or you're doing multimodal, so you have camera and LiDAR and, you know, other sensors, yeah, the instruction sets would have to accommodate whatever the input that you have.

Q. And moving to Step 9115, when the object representations are correlated to the instruction sets, what does the system do to correlate the object representations with the instruction sets?

A. Well, that would be, in essence, the part of your training, right. So if you have a person walking in a crosswalk and you would like the car to come to a stop so you don't run over the person, so you have imagery that show a person coming through the crosswalk, you've done some object recognition in tracking, et cetera, and you've defined that basically situation, you now have to define instruction sets for the vehicle to slow down and come to a stop so that the person can, you know, clear the crosswalk.

And you would correlate that circumstance of a person walking through a crosswalk with the vehicle coming to a -- you know, slowing down and potentially coming to a stop, depending on where it's at in relation to the crosswalk.

Q. But is that something like a -- in terms of implementation, does that look like an if-then statement, sort of, like, if certain circumstances are there, then perform operation X?

A. Well, it's not quite that. I mean, that's what -- you know, you have a machine learning neural net. It's not an if-then set of instructions. It's more of you have machine learning algorithms that are going to have -- you've trained the algorithm, let's say supervised learning, you've trained the algorithm. You provide a set of input imagery, and the algorithm will do something.

And you basically say, This is what I would like you to do. You did this. You really should do this. So you define an error, you know,

we call that a loss function or a cost function. You quantify the difference between them. You essentially back propagate that difference through the network. You update all the potential parameters and hyperparameters of the network, and then you continue the training process. You provide another sequence.

And then you keep this up for a while. You know, training could take several hours, days sometimes, depending on what you're doing, what you're training, until you have a satisfactory situation with the accuracy that you're looking for.

And if you don't have enough data, you need to get more data and so on and so forth. So there's a lot to it. You're, I think, oversimplifying it extensively.

Q. Yeah, pardon my lack of experience in the area. So maybe my questions will be oversimplified, but bear with me while I can, please.

You mentioned sometimes this case of --

you know, you might have in some cases hours of data, in some cases not so much. And I suppose in situations like security systems maybe that are monitoring certain premises, you can have hours of data that are being recorded.

A. Yeah.

Q. And in these sets of situations when you have so much data and volume, what does the system do in terms of training storage when, you know, there's no more space left for the data?

A. Well, you obviously have to organize the data. I mean, you, for instance -- I'm going to take a billion image of me and put that in your database. You know, you're going to take enough images of me so you can -- so the accuracy of your training is beyond the point where you want it.

Let's say I'm looking for 99 percent accuracy or 95 percent accuracy, right. And I find that ten images of me will provide 95 percent accuracy of me when I walk up to the camera. Then I may store 10 or 15 images. I'm not going to store a thousand images.

You know, and the same thing with the video collections, you know. If you have -- you're not going to store a billion videos of people walking in crosswalks. You're going to store enough -- you're going to -- this is what we call data augmentation. You're going to have enough data to ensure an accuracy that you're willing to accept for this particular application. And each application is different.

Like the employees walking in the company, the accuracy doesn't have to be that high. Because the worse that can happen is, No, I'm not going to open the door for you, and you'll have to call security and security will come over and open the door once they verify you're an employee.

But if this is a medical imaging application where you may be doing a spinal surgery, you can't afford a 95 percent accuracy. You know, you may have to have 99.9 or better than any possible doctor can possibly do.

So it depends on the application how you

would approach the storage of the data and how much of the data and how frequent of the data and how dynamically do you update the data and you retrain.

Q. So this part I wanted to get a little bit more detail in terms of better understanding the storage and the training of -- and the storage of training data.

When you get an image and it's being stored for training purposes, what exactly is stored? Is it, like, pixel values? Is it shape and size?

What is the information that's stored?

A. I think you should take my course at RIT.

Q. You know, one day I might, but if you give --

A. Yes, I have an advanced graduate course on this that would teach you all these aspect of it.

But, typically, in images -- let's say we're looking at images, facial recognition.

You're going to store pictures of Eli. And, you know, you may take a head shot. You may take a shot at this angle, that angle. You're going to store enough pictures.

And each picture, obviously, is going to be in color, let's say. So it's got an RGB component to it. Each RGB has a value of pixel between 0 and 255. And you have images, you know, mug shots of me at various angles, maybe even all the way around your head.

So you may store -- depending on the accuracy that you're looking for, you're going to store images. You may store images with tilted heads or, you know, where the head is tilted one way or the other, tilted backward or forward. That's called rotations in and out of the image plane, when it's tilted backward and forward or right and left. Or if I'm tilting this way, those are rotations within the image plane that are much easier to handle than rotations in and out of the image plane.

So you're going to store -- you know,

you might start by storing, let's say, three or four or five mug shots of me. And then when you do your training, you'll discover that, you know, it's not -- it's not generalizing.

You know, when I say "generalizing" for a network means does the network -- if I would have you shown a network, a database that it's never seen, would it perform at the same accuracy as my training. So that's what we call generalizing.

So if I collect three or four pictures of me and then all these other people and the accuracy is only 67 percent, it's not doing it, then I have to change some network parameters.

I may add more layers. I may have more nodes per layers. I may change the convolutional aspect of the network. And if it's still not doing it, then I have to do maybe data augmentation.

And I may say, well, instead of having four pictures per person, let's go to six. We're going to get more precision, more resolution on

the angles, you know, more rotations.

So you start to augment your dataset until you get the training accuracy that you're looking for or you're happy with on your training dataset. Then at that point you test that on a test dataset, which you have of these people that you've never trained on, to see if they generalize it.

Will it get the accuracy on the test dataset at the same value as the accuracy of the training dataset? If the answer is yes, then you're doing a great job. If the answer is no, then you need to do changes to your training.

You should take my course at RIT.

Q. It sounds fascinating.

So the -- when you're taking a bunch of these pictures, and you mentioned like the subject might be at different angles, like tilting backward or straight or, you know, a side face or front face. Those pictures are then -- I guess there's a label that's assigned to them, this is front face or this is tilted, and then that is

stored?

A. You can.

Q. Okay.

A. I mean, you don't really -- it depends on the objective. If your objective is to recognize a person, as long as you have different pictures of it -- of the person on the database you trained on and I arrived to the door -- let's say I'm that person and I'm talking to my friend as I'm walking to the door, so I'm slightly on an angle. The camera is able to pick me up and say, Yes, this is Dr. Saber, then you're successful.

Q. Yeah.

A. The camera picks you up and says, I don't know who that is, then you're not so successful.

Q. Yeah, I mean, is there a way to understand -- for the system to know, for instance, whether this is the front of my face, or this is the front of my face?

A. Yeah, I mean, you can train that. You can train that to say, okay, these are profiles,

pictures versus frontal pictures. You can train all of that.

Q. I see.

And so when you are -- I forgot the exact term you used, but once you've done some training, you test it again, so sort of a -- I guess a test database, and you see what the results are. If it's good enough, then you know you're good. If it's not good enough, then you have to augment; is that right?

A. Well, you may have to do other things, but typically, we do three -- there's three things that are done. There's a training database; there's a validation database, typically, and there's a test database. And there are ways of doing all these things, you know, what we call, you know, like different ways of capturing randomly samples from the database.

But let's -- without getting into those details, so you have a training database. Let's say I have 100,000 images in that database of my employees, you know, a thousand per employee, and

I have 100 of them.

And then you have a validation database that has pictures of those employees, but not the same ones from the training database.

And then you have a test database that also has pictures from your employees, but not the same one in the other two databases.

So they're basically three distinct databases. You do your training on the training database. So you -- you know, you do the various things you want to do to the network on your training database.

You then use the validation database to tweak the hyperparameters. You know, you want more regularization or you want smaller regularization parameter, you want different nodes, you want to do a dropout, whatever. You fiddle around with the parameters of the network. You use the validation database to validate each of these parameters to find the right one.

Finally, when you're done, you say, okay, now I'm ready -- and you keep an accuracy

value, right. You keep, you know, with your best training. Finally, when you've tweaked everything, your accuracy is 95 percent.

Then you go to your test database. You say, okay, here's a database the network has never seen. Put that into the network and give me, you know, the accuracy measurements.

And if the accuracy comes out to be 95 percent, then you've done a great job. If the accuracy comes out to be 10 percent, then obviously your network isn't generalizing properly to data it hasn't seen. You need to make changes.

That could be data augmentation. That could be different ways of training. That could be selecting differently randomly from the database. It could be feature normalization, upfront you're not doing -- it could be normalizing at every layer in the network. It could be changing templates of the CNN algorithms. There's a lot of things you have to do -- you could do.

Q. I see. And --

A. This is a big, big area, sir. That's why I have one course on this, advanced. You know, it's a course for MS -- second-year MS and first-year Ph.D. students that RIT actually asked me to create. So we created part one. I'm in the process of creating part two for this particular course. Part one was just taught this spring, and then I'm in the process of creating part two.

This goes through all the mathematics, every details of supervised learning and all the pieces of it and gets into the math, like going into the back propagation algorithms, all the mathematics of it, every step. So a graduate student, like a Ph.D. student, can pick that up, learn, and then go and create original research.

Q. Yeah. I mean, I'm sure your students are not going to be bored any day. So this is really cool stuff. It's very interesting.

You know, just to follow up on that, one of the things I'm not clear about, if you could explain is, when these images are obtained, how does the system know which memory locations to go

to?

So, for example, there's, you know, subject X, right, that John Doe we saw in Figure 4A. How does the system know which locations in the memory to go to for John Doe and update the information on John Doe?

MR. JAIRAM: Objection; scope.

THE WITNESS: Well, I'm not sure exactly what you're asking, but if I'm creating the employees thing that we're talking about, you're going to create some type of database, and you have a structure in that database. So you're going to put employee A in, let's say, folder A, employee B in folder B, employee C in folder C.

And employee A, I have ten pictures of, employee B, I only have five, and employee C, I have 15. So you're going to have some organization of how your data is organized. It could be as simple as dumping it all in one big database or more of a structured database. It depends on your application and the complexity of the application.

BY MR. KHAN:

Q. So using the example that you're saying, let's just say you're an organization with 100 employees, and so you have presumably some images for your 100 employees. Now, let's say that you want to update the training, your training the images for employee John Doe, right.

Then does the system know, for instance, okay, there are certain memory allocated for John Doe, so I need to go to that memory and update it? Is that kind of how it works?

A. It depends on how you've structured the data -- how you designed and structured the database for your system. So if, for instance, your database is, let's say, a set of folders and subfolders. So John Doe has a subfolder. Tom X has a different subfolder.

So John Doe's subfolder has 10 images of John Doe. If that's not enough for your training and you acquired three more, you're going to put those in the John Doe folder, and now you have 13.

So it could be as simple as something

like that, where you have allocated different memory locations to different people. It could also be interconnected, depending on the application that you're looking at. So it's not a simple thing to do. It depends on how -- what the application is, how the database is structured, et cetera.

Q. So what happens when the allocated memory for these images is filled up? So let's say you've -- you have a certain amount of space, it's already used up. Then do you have to delete stuff and then add the new stuff -- so I should be more clear, I'm sorry. Let me rephrase that.

When you're running out of memory when you're training these systems, and you may now have memory to update your training database, then what does the training database do? Does it remove data that's stored in the training base to add the new data?

MR. JAIRAM: Objection; form. Objection; scope.

THE WITNESS: Well, memory is cheap

these days, just buy more memory. You know, if your disk drive is, you know, I don't know 1 trillion or 1 terabyte and it's not big enough, you get another one.

BY MR. KHAN:

Q. Yeah, I understand that, but, you know do you --

A. If your disk drive is limited, then you do some what we call pruning. So you will -- if I have 50 pictures of John Doe and they're all front pictures and I'll pick the best ten and I remove the rest.

Q. I see.

So you would select information -- you would be -- essentially, you'd filter out the new information, you wouldn't add it, and you'd keep the old information and you'd filter out the new information?

A. That's not what I said. So --

Q. Okay.

A. -- if I have 100 pictures of John Doe in my database, okay, and 30 of those pictures are

just straight on John Doe, so there's 30 of them. It's really redundant, and I find that in my training if I were to remove 25 of those 30, my accuracy hasn't changed.

So I get 95 percent accuracy in recognizing John Doe with only five of the 30 or 30 of the 30, then obviously the other 25 are redundant. So I would remove the other 25 and store them somewhere else for now and just keep the five.

So this is sometimes what we call principal component analysis. So you try to do some analysis on your database to remove situations that are 100 percent redundant or have a high degree of redundancy that you don't need because that could speed up your training process.

But with today's memory being so cheap and disk space being so cheap, typically, that's not a big problem. The problem is the time to train more so than the storage.

Q. And what do you do with training information that is out of date? So let's see

just say, for example, there's a vehicle -- there's a road, and that road is now -- you know, doesn't exist anymore. There's a building, that building doesn't exist anymore.

What happens in those situations for the training data?

MR. JAIRAM: Objection; form. Objection; scope.

THE WITNESS: Well, you would potentially prune some of that out. Like, you know, I look different today than I looked 40 years ago. So, you know, my -- a picture of me 40 years ago may not be as relevant to recognize me today, right. So you would prune some of that out or make dynamic updates to your database.

So every so often you may have to do some retraining. You have to collect new data and update. You know, do you ever see the Google car or whatever driving around and taking pictures of the streets or whatever, doing some updates?

A new neighborhood comes in, it's not on Google Maps and, you know, they send a car around

and it kind of takes pictures and then all of a sudden it shows up on Google Maps.

So you have to do some -- I mean, it's not a perfect science. You have to do some updates over time. You have to add things and delete things and prune things.

There are some things that remain more constant, like somebody walking in a crosswalk. Crosswalks are still going to be there, say, ten years from now. So those are more of a constant. But if a street no longer exists, for instance, or a type of object no longer exists, then that would change.

BY MR. KHAN:

Q. Right. Okay. Yeah, I think that's conceptually easier to understand, that you have, for example, a Google vehicle moving around, it captures some images.

Now, let's say there's a new building around the corner. It will then go to the database -- the training database, modify it by adding information about that building --

A. Yeah.

Q. -- and then the whole sort of Google Maps' database updates, and whenever you see the road, then you can see the picture of that building?

A. Yeah, I mean, you know, you have to continuously make updates. And obviously as you -- as vehicles drive autonomously and you have more of that database, obviously, you're collecting information. So that database can be dynamically updated on a regular basis.

Q. Okay. We are close to lunchtime now. So -- and we've been just about an hour. So if it's all right, I suggest maybe a 45-minute break for lunch.

Does that work?

A. It works for me. So I will be back in my chair at 12:45 Eastern.

Q. Excellent.

MR. JAIRAM: Okay.

MR. KHAN: Thank you.

(Recess from the record.)

BY MR. KHAN:

Q. Dr. Saber, thanks.

During the lunchtime, did you have any contact with counsel for Autonomous Devices?

A. No, I have not.

Q. Great.

Before the break, we were discussing Figure 32 of the '974 patent.

A. Yes.

Q. If you don't mind going back there, we'll sort of continue where we left off.

A. No, no problem.

Q. Great.

And for this conversation, I might jump between Figure 32 and 33.

Do you agree the first two steps are essentially identical?

A. Yes.

Q. In Figure 32, Step 9125 and 9130, there's a receiving of new collection of object representations and comparing the new collection with the first collection of object

representations.

Do you see that?

A. Yes.

Q. Okay.

A. It says 9125 and 9130?

Q. Yes, that's right.

A. Yeah.

Q. What does the system do when it's comparing the collection of object representations -- the two collection of object representations?

A. Well, it's going to, obviously, do some comparisons. Let me take you to that section.

So if you go to Column 154, starting at line 42, it discusses this particular step.

Q. So my understanding is lines 42 onwards, beginning with line 44, it states, "Comparing one collection of object representations with another collection of object representations may include comparing at least a portion of one collection of object representations with at least a portion of the other collection"?

A. Yes.

Q. Do you see that?

A. Yes.

Q. Yeah, so I guess that's my question, is how does it do the comparing?

A. Well, it depends a little bit on the object, obviously, and it depends what kind of object it is. But if you'll continue reading there, it's going to give you some description. You know, like on line 54, it will say, "comparing of object representations may include comparing one or more object properties of one object representation with one or more object properties of another object representation."

For instance, I'm looking at the shape of a cat, and I'm comparing the shape of a cat from object one with the shape of the cat from object two to see if both shapes are very similar or not. So you're looking at object properties and/or elements of a particular object.

Q. In Figure 33, there is a similar receiving Step 9220.

Do you see that?

A. 9220 is the method. 9205 is the receiving.

Q. No, in Step 9220, there's receiving a new collection.

A. Oh, yes.

Q. That's the same as Step 9125 in Figure 32?

A. Yes, they both state, "receiving a new collection of object representations." So they both state the same exact thing.

Q. Yeah. And Figure 33, Step 9225 that follows Step 9220, there's an anticipating step, anticipating the instructions --

A. Yes.

Q. -- based on at least a partial match.

Can you explain to me how that is implemented? How do you anticipate the instructions based on the partial match?

A. So if you go to Column 159, it obviously talks about that step of anticipating based on at least a partial match. And, essentially, what

it's referring to here is if you have a partial -- let's say you have a collection of images of which the object has been tracked into in your training database, and you receive a new collection of object representation. And the old collection, for instance, had -- you know, I'm giving you here an example.

The old collection, for instance, was taken on the street in -- I don't know, in downtown Beijing, and a new collection may be taken in a different street somewhere else where some of the background might be different, but the object -- objects may be the same or similar.

You have a partial match of objects, which then you can anticipate. I see a crosswalk. I see a person walking in the crosswalk, and whether they're walking in the crosswalk in Beijing or in downtown Nashville, your reaction should be the same.

So if you've been trained on the object that's walking through the crosswalk in Beijing, you would anticipate when you see the object

walking across the crosswalk in Nashville to perform the proper instruction, which would be, obviously, slow down and stop. It's just kind of an illustration in a sense or, you know, a simplification of this description.

Q. We talked about the -- based on at least the partial match between the two object collections. So that at least a partial match, that would include matches between some of the objects in object representations or all of the object representations; is that right?

A. I didn't understand your question.

Q. The step of comparing the two object collections --

A. Yes.

Q. -- or collections of objects -- I'm sorry, the step of comparing the collection of object representations, right --

A. Yes.

Q. -- and determining whether there's at least a partial match between the --

A. Yes.

Q. -- two collection of object representations --

A. Yes.

Q. -- that could encompass a match of some of the object representations in the two collections or all of the object representations in the two collections; is that right?

A. We have at least a partial match. So you could have a partial match of the object because -- I mean, there are different situations. You have a person walking in a crosswalk. The background is downtown Washington, D.C. You have another person walking in a crosswalk and the background in Nashville.

So there are different backgrounds, but the partial matching would recognize the person walking in the crosswalk. Even though the backgrounds don't match, the object representation in the situation does match.

Now, if you happen to get a person walking in the same exact -- downtown in Nashville in the same exact crosswalk, then the matching

will be a lot higher. Typically, ideally you would probably never get an exact full match, but you'll be very high.

Q. Yeah. And so these comparisons involve comparing like -- comparing an entire image or portions of the image; right?

A. Or collection of images. I mean, you're going to have typically a series of video frames. So you're comparing not just a single image, but you're comparing -- you're finding the object, you're identifying the object, you're tracking the object in the video frames, and you're comparing to whatever you've been trained on. So the comparisons usually are done on the video frames.

Q. I see.

A. It's not just a single image comparison is what I'm saying.

Q. I see.

And then in response to determining that there's a partial match, the system will execute the first one or more instruction sets that are correlated with that first collection of object

representations. That's Step 9140 and Step 9230 in Figure 32 and 33.

Do you see that?

A. Yes, you read it directly.

Q. Okay. So how does it perform this execution? What does the system have to do to figure out which -- how to execute these instruction sets?

A. So, again, I'll give you a simplistic example here just to illustrate. So if you had a person walking through the crosswalk that you've trained your vehicle to come to a stop on and that person was 6'5 tall. Okay.

And today I have a person that's 4 foot 3, walking through the crosswalk in Nashville versus the training was done, let's say, in Rochester, New York. Okay. So the training was done in Rochester, New York, on a 6'5 person. I have a person walking through in Nashville, and they're 4'6 or whatever.

So that's receiving a new collection of object representation. So you've segmented the

video, you found the object, you've tracked it, all this type of thing. You compared the new collection of object representation with the first collection. So you've compared that with what your training has been done and you've recognized that this is a crosswalk and there's a person walking in the crosswalk.

You've created a partial match. So you understand that this is a crosswalk circumstance situation. You now execute the instructions that you've been trained on in Rochester here in Nashville, because you expect that the vehicle comes to a stop regardless whether a person is 4'3 or 6'5.

So you would execute the instructions. So you would let the vehicle know that you need to come to a stop. Now, the vehicle might be 600 feet away, the vehicle might be 10 meters away, the vehicle might be 60 meters away. So you have to adjust, obviously, that appropriately to where the vehicle is in relation to this crosswalk.

Q. What's the difference between executing the instruction sets and performing operations defined by the instruction sets?

A. Where --

Q. That's the Steps 9140 and Step 9145 in Figure 32, Step 9230 and 9235 in Figure 33.

A. So if you look at Column 158, starting at line 26, it describes obviously the Step 9145. And if you read through this section, it says the one or more operations may be performed in response to the aforementioned executing, which is obviously mentioned in the previous step.

So, essentially, the operations are kind of like subsections, if you would, or subpieces of the entire instruction, because you may not need the entire instruction.

You know, in our illustration example, for instance, the person may be walking in the crosswalk, but the car is 60 meters away. So you don't need to come to a full stop. You can execute the instruction of slowing down. So the operation is slowing down and slowly decelerating

and et cetera.

And as you're paying attention to the crosswalk, the person has cleared the crosswalk so you now can proceed without having to come to a complete stop. So the instruction may have all of those pieces in it, all these different operations, but you don't have to execute them all for every situation.

Excuse me for one minute. I'm just going to mute my audio because I'm hearing noise from upstairs. Just one second.

Q. Sure.

A. I'm sorry, please go ahead.

Q. No problem.

A. I think there's some phone calls going on upstairs.

Q. Can you turn to Figure 17, please, in the '974 patent?

And let me know when you're there, please.

A. Yeah, one second.

Yes, sir, I am there.

Q. Can you describe to me in your words what Figure 17 is showing?

A. So according to the patent, Figure 17 illustrates various artificial intelligence methods, systems, and/or models that can utilized in a DCADO unit. So it's essentially showing you different, you know, articulations of -- you know, you have Model A, Model B, Model C, Model D. It shows different interconnectivity of various, let's say, nodes in this AI unit.

Q. When you say "nodes," do you mean the circular structures 852, like we see in these models?

A. Yes. And you can see that on Column 103. If you go down to line 51, it will say, Node 52 can store any data, object, data structure, blah, blah, blah.

So it refers to it as node 52. And 853, obviously, is the connection.

Q. What do these nodes represent?

A. Well, if we look at Column 103, I'm on line, roughly, 46-ish. You can see it starts with

a little bit of description, As such, machine learning, knowledge structuring or representation, decision making, pattern recognition, and/or other AI functionality may include a network of nodes (also referred to as neurons) and connections similar to that of a brain.

So you use typical nodes, is usually what we use in neural nets. Sometimes people refer to them as neurons, sometimes people refer to them as nodes, but they're typically kind of a package where you hold various things. Like, you can have biases there, offsets, data structures. It depends on the design of your system, activation functions, et cetera.

In this case, the author says node 852 can store any data, object, data structure, and/or other item or reference thereto. And in the description after that -- so you can hold a data structure there, you know, object structure in a sense.

The next line, starting at line 53, may include a function for transforming or

manipulating the data. Typically, we call those sometimes activation functions. So input to the node maybe 45, and then you have a sigmoid that would be applied to the 45 or will give you some kind of an output.

And he gives examples of that. Like, on line 55, he'll say, Example of such transformation functions include mathematical transformations, et cetera.

Q. So that section you described is a little technically heavy. So I might ask some very basic questions, if that's okay.

This section, you know, it speaks to Model A, right, I think you were describing. This is a section in Column 103, lines 42 onwards --

A. Yeah.

Q. -- you were just referring to.

A. Yeah.

Q. It mentions here that the Model A, for instance -- in Model A, the disclosed artificially intelligent devices, systems, methods for learning and/or using a device's circumstances for

autonomous device operation may include a neural network (also referred to as artificial neural network).

And then I think early on you had mentioned something about the connections similar to that of a brain.

A. Well --

Q. Why are -- I guess just from a high-level perspective, why are these networks called neural networks?

A. I don't know. Was there a question there, sir? I guess --

Q. Oh, I'm sorry, you didn't hear my question?

A. No.

Q. My question was -- I'm sorry.

My question is: Why are these networks called neural networks?

A. Well, I mean, you have to go back way in history to, like, the first initial units which appeared, I think, I don't know, in the '40s or '50s or something. This is way back now. So

people were trying to look at the brain and connectivity of the brain and say, Can I create an artificial neural network that kind of re-creates or try to mimic this type of activity?

So there's some initial research on that, I think I forgot, in the '40s. And then there's the McCulloch cells and whatever. You know, I think McCulloch and Pitts or something published a paper many years back, maybe '40s or '50s. It's one of the initial papers on that. And, you know, how you would try to create some kind of artificial neural nets. So they adopted those names from back then.

Q. And is the idea of these, like, models that they created, so these nodes and connections is to kind of like mimic a model of what your higher brain might be thinking or processing this information.

Is that the general idea or something else?

A. Are you familiar with neural nets at all?

Q. Not too much; hence, my questions to you. So --

A. Maybe you should take my course.

But the idea is, you know, neural nets typically you have -- with artificial neural nets, you have a series of nodes. Each layer may contain a series of nodes, and the interconnectivity between the nodes is typically done in a nonlinear fashion.

Because if you were to do it all linearly, you can actually collapse the entire network to just two layers. You can show mathematically, and I have shown mathematically, that that could be the case. So you want some nonlinear connectivity between the layers of the neurons.

And supposedly, obviously with this nonlinear connectivity and all these different neurons, you can fit any particular space or any function in the space. So you can fit any nonlinear-type function. So if you had a nonlinear function of various kind, you can say,

well, if I add enough neurons, I can fit the nonlinearity of that function without having to create an equation.

You know, for instance, if you had a parabola, you know, Y equals AX squared would define a parabola. So you don't need to fit an equation to every point on the parabola, because Y equals X squared or, let's say, AX squared would define a parabola equation.

But if I give you a nonlinear function that has basically many different peaks and so on and so forth, you can't create a function -- an equation for that function; but if you add enough neurons, you can fit that function with the nonlinear description of the neural nets.

That's essentially one of their attraction, is the ability to fit to any nonlinearity in the space, which is not easily comprehended by equations; hence, the attraction.

Q. I see.

So the neural networks are a means of modeling the nonlinearity of a particular

situation.

Did I capture that right or --

A. Is that a question or a statement, sir?

Q. I'm trying to see if I captured that correctly or not.

A. Well, if you -- let's say, for instance, you've done an experiment, X and Y. You've collected points X and Y. And let's assume your points fit exactly on a straight line, perfect line. Then you don't need a neural net for this. You can just say, Y equals 2X plus 3 is the exact model for this experiment, right, because they fit perfectly on this line.

Well, that rarely ever happens in real life. You know, most of the things in real life and most of the systems are nonlinear in nature. So the responses are very nonlinear in nature. So you don't have an equation to fit this particular line. So now you have to try to fit every small portion of that function with some kind of equation. And people have done that with these lines or other things.

But one way to comprehend a nonlinearity and basically have an ability to manage a nonlinearity is through the use of neural nets, where you can allow the weighted connections between the neurons, as well as the content of each neurons, biases, offsets, whatever you put in there, to comprehend a nonlinearity of the space.

And as long as you have data on the input, training data on the input and corresponding output -- like, for instance, you say when I show you this, this is a cat. When I show you this, this is a dog.

So as long as you have that training dataset that is accurate in nature, you can hypothetically train the network and adjust these biases and these weighted connections and these activation functions and these hyperparameters to basically get the network to fit to the nonlinearity of the space. So that's typically the idea.

Now, sometimes it overfits, and that's what we call overfitting. Essentially, you're

fitting to the noise in the data, and you're not comprehending the model anymore. That's called overfitting.

Q. So thanks for the explanation.

I guess -- I still want to go back to my original question, which was: Why are these called neural networks?

I mean, why -- you know, you mentioned stuff about nonlinearities, I understand, but they're not called nonlinear networks or nonlinear models. They're called neural networks.

A. Yes.

Q. So why they chose neural networks?

A. Because you essentially create a neuron, a single neuron, which the neuron has -- if you look back in the 1940s or '50s -- and I'm drawing back on memory now from many years back, obviously, you know, where people have created the initial neuron cell. You know they had a cell, for instance, within some type of an activation like, let's say, a sigmoid activation or something of that sort or hard limiter.

So you have an input to that, there's some kind of bias, and the cell would give you an output. So that by itself, you call that a neuron or a node. Now, you're going to replicate that -- because one by itself cannot fit a high -- there's only so much one cell can fit. You can fit so much with -- especially if the cell, let's say, is a bias plus weight times input, times -- you know, going through an activation function.

So you can only fit so much nonlinearity with one cell. So then if you copy and paste the cell, now you have two cells, you can fit more nonlinearity. And if you copy and paste that more, you can fit more nonlinearity, and that's how you end up with a network, you know, multiple layers.

Now, in each layer you can actually duplicate the neuron, as well, so you have more flexibility per layer and connectivity to multiple layers, which essentially can fit higher and higher degrees of nonlinearity.

The problem with that is you also have

to have more time to train -- the bigger you make it, the more time it takes to train and get it to converge to what you're looking for.

Q. I see. Okay.

A. And the more data you need and the more iterations you need and the more time you need and -- bigger takes much more, usually.

Q. So these nodes are essentially models of, like, brain cells, like neurons; right? They're essentially models of that; is that right?

A. Well, they try to say that, but it's essentially more what we call artificial neural nets. So we don't really know exactly how a neuron in your brain exactly functions. You know, that's really not the interesting part of this. It's just you've created an artificial node that has a certain nonlinearity associated with it.

And that's essentially what McCulloch and Pitts initially tried to create with the initial cells. And then the Perceptron algorithms came about and added more to that and so on. There's a whole history of this of how these

things progressed.

Q. I see.

A. There's probably good tutorial papers on them. There's a tutorial paper by Lippmann in the signal -- IEEE Signal Processing Magazine that would give you a pretty good overview of some of the neural nets.

Q. Nice.

A. I think it's published in 1988, I think.

Q. Okay. Thank you. That's helpful.

And so these nodes are then -- they're connected by -- so they're associated with each other with some sort of relationship, and that relationship has this bias and weights that's specified by these connections; is that right?

A. Well, the connections -- the biases are typically within the node itself. So within the node, you have certain biases, perhaps certain offsets that you define for the node. And then you have a connectivity between the node and another node that you define. This could be a weighted connectivity. This could be some

function of one node to the other.

So you define what that connectivity is. It could be as simple as -- you know, a weighted connectivity could have more structure to it. It depends on how much training and stuff you want to do and how much data you have.

Because the more difficult you make the connectivity, the more parameters you add, the more you need to train and when you copy and paste that over an entire network.

So if two neurons are connected by one connection that has ten parameters and you copy and paste that 100 times, obviously, you're going to now have 1,000 parameters that you have to train. Yeah, so --

Q. And so how complex or simple the model is will also determine the complexity of the connection, as well; right?

A. Yeah, so the amount of layers -- the number of neurons per layer and the number of layers and that's the term -- you know, the term "deep learning"?

Deep learning, basically, you're getting more deeper -- more layers, right. Instead of just one layer or two layers, which we call, you know, shallow networks sometimes, I may have 50 layers.

So the more layers you add, the more nonlinearity and complexity you have, and the more difficult it is to train. Because as you back propagate the error using gradients, which is typically what we do, that -- as you back propagate through the layers, that gradient starts to vanish, because it's getting smaller and smaller. And pretty soon it's only .0001 by the time it gets to the first layer. So you would need to train many, many, many, many more iterations to get it to move anything.

So the more layers you add, the more complexity you're adding to the system. So you typically want to try to manage the complexity to the complexity of the problem.

Q. All right.

A. Yeah.

Q. Okay.

A. So if I'm recognizing apples from oranges, I don't need a 50-layer neural net with 500 nodes per layer to do that. You know, two layers with maybe ten nodes each may do it.

Q. Okay. Sorry, just give me a minute.

A. Take your time. I may step away for one minute. Is that okay?

Q. Yeah, that's fine.

A. Okay. Let me step away for one minute. I'll be back.

(Recess from the record.)

THE WITNESS: Okay, I'm back. Thank you.

BY MR. KHAN:

Q. The connections that we see in this -- in these models, are they -- in a particular model, so let's just say all the nodes -- sorry, all the connections in Model A, do they all have the same length, are they like -- yeah, do they all have the same length or is that -- sorry. Let me just stop there.

Does it have the same length?

A. Well, I don't know what you mean by length. These are not physical like you can't take a measuring stick and measure them. They're not -- they're virtual connections, right. They're not -- it's not like you have a node on the ground and 1 meter later you have another node and you just got to measure them. They're --

Q. I see.

A. Yeah.

Q. So it's more like they're -- when you say "virtual connections," do you mean, like, they're not actual, like, physical connections, but they're more like logical connections? It's like when you're going from one node to another?

A. Yeah, they're not like a string between the two nodes, right. They're -- so you know this node is connected to this other node, and there's some type of a function that connect those nodes. So it's not a physical -- you know, in the neural net, it's not a physical string. You know, this is not like a truss in a bridge, you know what I

mean.

Q. I see.

So even though, like, Model A, Model B, Model C, D, these are showing -- they're showing different lengths, but the length is not important. They might just be indicative of some type of a relationship between the different nodes that the connections are connecting?

A. Those are not length. They're different configurations.

Q. Okay.

A. So Model A could be what we call fully connected. A fully connected network means every node in layer I is connected to every node in layer I plus one. You don't have to have it fully connected. You can have certain connections not available or not needed. And you could also have connections that connect back on itself. So there are different ways of configuring them.

Q. I see.

A. Yeah, and then you can have feedback. And it's a very complicated subject. That's why I

have a two-course series on this at the graduate level with all the mathematics.

Q. Look out for my name one of these days. I might need to sign up.

Let's see. Okay. Maybe we will turn to the Grotmol reference. But we are coming up to the hour mark. So maybe it's a good time to take a short break. Would five minutes work for you?

A. It works fine for me.

Q. Okay.

MR. KHAN: Arvind, is five minutes is good for you?

MR. JAIRAM: Yes, thank you.

THE WITNESS: Should I turn to Grotmol?

MR. KHAN: Yeah, when we come back, we can turn to Grotmol. So maybe at 1:45, we can reconvene.

THE WITNESS: Perfect.

MR. KHAN: Okay.

THE WITNESS: I'll be back in my seat at 1:45.

MR. KHAN: Great.

(Recess from the record.)

(Exhibit 1004 was marked for identification and attached to the transcript.)

BY MR. KHAN:

Q. So while we were on break, I uploaded the Grotmol reference to the chat. If you'd like to open it that way, you can. Grotmol is Exhibit 1004 in this proceeding.

So please let me know when you have that open.

A. I am working on it.

Q. Great.

A. Okay. I have it open.

Q. Thank you.

And so Grotmol -- if you'd like to turn to Grotmol's Figure 1. Figure 1 -- oh, sorry, please let me know when you're there.

A. Yes, Figure 1, Grotmol.

Q. Great.

Figure 1 of Grotmol shows a robot 160 moving in direction 164, and there's a sensor component 166 that provides a view 168.

Do you agree with that?

A. Yes.

Q. And the sensor can include a camera; is that right?

A. Yes.

Q. And do you agree that the images obtained through this camera sensor would have data, including pixel values that are associated with objects and features in the frames and images captured by the camera sensor?

A. I'm not sure that I understood exactly your question.

Q. The question is basically the data that's captured by the camera, that data includes --

A. They're images.

Q. Yeah, the images.

A. So they're images captured by the camera. So they would basically be RGB images or gray scale images with pixel values, accordingly.

Q. Yeah.

A. Assuming it's a camera.

Q. Yeah.

And do you agree that Grotmol also discloses object recognition and classification?

A. Which section of Grotmol are you referring to?

Q. Well, I'm assuming you've reviewed Grotmol; is that correct?

A. Yes. I mean, Grotmol does talk about object recognition, but is there a specific section that you're referring to?

Q. Not at the moment. I might get into some more specifics right now, but I just wanted to see if at least we're on the same wavelength there that there is disclosure of object recognition and classification in Grotmol.

If it helps, I can also point to Column 9, lines 40 to 43 of Grotmol.

A. Yeah.

Q. Do you agree that it says there, "In one or more implementations, object recognition and/or classification may be implemented using a spiking neuron classifier..."?

A. Yeah.
Q. And can you turn to Figure 2?
A. Yes.
Q. And Figure 2 shows a number of features, specifically 1 to n?
A. Yes.
Q. That a part of the sensory context provided to predictor; is that right?
A. Yes.
Q. The features that are pointed to here, what are they referring to, Feature 1 to n?
A. Well, you know, it could be certain features.
Q. I'm sorry, are you done with your answer, or are you still continuing?
A. I'm not sure what you're asking. It could be, you know, features, you know, corners, or be detecting, you know, certain colors of certain pixels. Is there something specific that you're asking? I mean, yes, it says Features 1 through n.
Q. Okay. And these features are provided

in the Grotmol system for training purposes; is that right?

A. Yeah, presumably, training and/or operation purposes.

Q. On the point of features, could you turn to Figure 10A and 10B. Let me know when you're there.

A. 10A and 10B.

Q. Yeah.

A. Okay.

Q. Maybe we could start with Figure 10B.

In Figure 10B, you see that there's a box with feature extractors, and you see Feature extractor 1 to N?

A. Yes.

Q. And then there's a box, the Behavior 1, Adaptive controller 1; another one, Behavior 2, Adaptive controller 2.

Do you see that?

A. Yes. Yes.

Q. And then there's output 1 to output N.

Do you see that?

A. I do.

Q. Okay. Great.

What's the role of the adaptive controllers in Grotmol's system?

A. Well, he describes it a little bit with reference to Figure, you know, 4A, but it's a similar description. So if you look at Column 15, for instance, in Grotmol, he says, Figure 4A illustrates an implementation of adaptive control system 400.

So if you look at Figure 4A -- wait a minute. Yeah, this whole adaptive control system. So the adaptive control system may comprise a corrector, an adaptive predictor. So he has basically a description of it here.

There's also another description.

Q. Sorry, were you done with your answer, or are you --

A. Yeah, I mean, he describes it basically where I just mentioned. I'm going back there. Just give me one second.

So Figure 15 -- Column 15, as I said,

starting at line 18-ish or so, he describes, the adaptive control may comprise, you have a corrector. I mean, he's obviously talking about Figure 4A and Figure 4B later on, but...

So, essentially, you have a controller. You have basically an adaptive predictor, a combiner, and a controller robotic platform. And you have a learning process of the adaptive predictor.

And he talks about a supervised learning process, as we talked earlier, supervised learning, potentially enforcement learning. So that's the description that Grotmol offers.

Q. Okay. So these components you see in Figure 4A or 4B, these are the ones you would find in the adaptive controller in Figure 10B?

A. Generally speaking, yes. I mean, you would -- obviously, in the Figure 10B, it's showing you you have some user commands that you would provide. The controller is going to take on certain features. And then you have certain behaviors and then provide outputs. And you can

see in his Figure 4A, he gives a little bit of description of that.

Q. So Figure 10B, the adaptive controller, there's a line that goes diagonally across the adaptive controller, it says "user commands."

Do you see that?

A. Yes.

Q. And there's another one for adaptive controller 2, also have user commands; is that right?

A. Yes.

Q. And so these adaptive controllers can receive commands from different users and then have the outputs; is that right?

A. That's correct. I mean, you receive commands from different users to change a certain behavior or control a certain behavior or adjust it.

Q. And so in Figure 10A, you see, like, one adaptive controller behavior. In Figure 10B, you see two. In Figure 10C, you see N1s of these. That basically means that you can sort of have as

many adaptive controllers or a flexible number of adaptive controllers in Grotmol's system; is that right?

A. Yeah, that's the idea. So you have -- instead of just one big unit, you may have one unit that's dedicated to moving forward and backward, one unit dedicated to going right and left, you know. That's not what he says, but I'm just giving you an example of the idea.

Q. I'd just like to turn to Column 21, Grotmol, please. And let me know when you're there.

A. Column 21.

Q. 21, yes.

A. Yes, sir.

Q. Okay. Do you see Table 1, 2, and 3 there?

A. Yes.

Q. Okay. And right below Table 2, in lines 47, you see the sentence starting, "Training apparatus"?

A. Yes.

Q. Great.

At the end of that paragraph, there's line 50 to 55 talking about training and that depending on the type of robot, the task, state of training, and other information, the teacher may switch from one teaching mode to another one to teach a behavior that's in the most effective manner.

Do you see that?

A. I do.

Q. Okay. And so this training that's involved in Grotmol, it could vary depending on the type of robot; is that right?

A. Yeah, so it states, "Depending on one or more of the type of robot, the task, the state of training, and/or other information, the teacher may switch between one teaching mode to another..."

Q. I see.

So if you have one robot as one type of robot and there's another type of robot, you can configure them for different types of training and

the different modes; is that right?

A. Essentially. I mean, what's this saying? You know, if you have a robot, for instance, that has a higher resolution camera on it, another one that doesn't have a camera or it has, you know, maybe just LiDAR on it, you obviously can configure your training appropriately.

Q. And then in Table 3, we have a list. And Table 3 is in Column 22.

Do you see that?

A. I do.

Q. Okay. In that we have different modes. There's a control mode, listen mode, override mode, correct, an autonomous mode?

Do you see that?

A. I do.

Q. If it's not too much to ask, would you be able to give an example of when, like, a robot -- when a robot in Grotmol would perform each one of these modes or engage in these modes?

MR. JAIRAM: Objection; form.

THE WITNESS: Yeah, I'm not quite sure what exactly you're asking. But let's say I have a robot --

BY MR. KHAN:

Q. I'm sorry, I don't mean to interrupt. Can I clarify the question?

A. Please. Please do.

Q. Okay. Sure. Yeah, my apologies, it's probably not the clearest question.

So in Table 3, we see that there's a control mode. In the control mode, the action that is taken, it states, "Executes the action in accordance with the training input."

A. Yes.

Q. Okay.

A. Does not learn association.

Q. Yes.

And then we have a listen mode. In the listen mode, the robot executes the action in accordance with the training input?

A. Yes.

Q. And the difference between the control

and the listen mode is that in the control mode, the robot is not learning the association, but in the listen mode, it is learning the association; is that right?

A. Correct. You read it correctly.

Q. And then in the override mode, the robot executes the action in accordance with the training input and learns the association?

A. Yes.

Q. What's the difference in the listen and the override mode?

A. Well, in the listen mode, you have a training input, let's say, and you've provided some type of control to the robot. So the robot is going to execute the action in accordance with the training input, and it's going to learn that association.

Like when you see a table in front of you, slow down, come to a stop. So learn that. When you see an obstacle in front of you, when you see a table in front of you, whatever, come to a stop.

Override mode is you're going to override the action. Because the robot may be going, and it's going to hit the table. So perhaps the prior learning wasn't done 100 percent effective.

So you're going to provide an override and say, Well, you really need to stop before you hit the table about a meter away. I don't want you to stopping just 1 centimeter away. I want you stopping a meter away.

So you're going to override what the robot is doing, because the robot may stop 1 centimeter away or it may be stopping but speeding too abruptly and then going to come to a stop too abruptly. You're going to override that and provide additional -- different instructions.

Q. The override, can that happen by a user input?

A. Typically, that's what you provide. You provide an override input that essentially corrects the incorrect activity that the robot is doing. You're going to override that input and

correct it supposedly. So the next time the robot sees the table, it slows down, starts to slow down earlier, and stops 1 meter away instead of 1 centimeter away. There's a little description of that on Column 23.

So if you go to Column 23, Grotmol describes -- well, it starting, actually, in Column 22, and he goes through the descriptions. In the control mode -- the bottom of Column 22, it talks about the control mode. And then in Column 23, he talks about the listen mode.

And at the end of that, you see once enough examples have been provided and the robot has learned something, the override mode may be used. And then there's a description of the override mode starting at line 12 to, say, 22.

Q. So they -- going back to Table 3, there's a reference of the training input -- sorry, the description includes discussion of training input and the prediction.

And in the autonomous mode, the robot ignores the teaching input and executes an action

in accordance with the prediction.

When they refer to the prediction, what are they referring to?

A. What it predicts to what it's seeing. So if the robot is processing, let's say, imagery, it sees a table. So there's a prediction in its system based on what it has learned that when you see a table, you should start steering away from it. So it's being given basically -- so the systems of the robot are looking ahead in a sense of predicting what the next action is going to be.

Q. Is that prediction based on the training, as well?

A. Well, typically, yes.

Q. Could you turn to Column 33, please? And let me know when you're there.

A. Column 33?

Q. Yes.

A. Yeah, I'm there.

Q. Line 13 says, "Apparatus and methods for behavior undo during training of robots are disclosed herein..."

What does it mean by "behavior undo"?

A. If you go to Column 34, starting at line 18, it describes -- there's some capital UNDOS there, but it prescribes the undo. I mean, it probably -- a good description may be, if you look at line 22, "user indication may be used to trigger an UNDO operation. In some implementations, the UNDO operation may comprise loading of the previously saved configuration."

So -- and on line 32, you can see one or more undo indications may be utilized in order to remove multiple behaviors, basically correcting an erroneous behavior that you may have accidentally trained perhaps or erroneously trained.

Q. I see.

So you can implement an undo operation if you want to correct or remove certain behaviors of the robot; is that right?

A. Yeah, I mean, look at line 25, By loading at time t1 the configuration saved at time T0 less than t1, so a prior configuration, the robot controller effectively "forgets" what it

learned in time interval t0 to t1.

So you did something between t0 and t1, it wasn't effective, you didn't train the right behavior, you want to undo it and start again, essentially.

Q. I see.

And so then you could say -- you could load another configuration, and then that would effectively come in place of the configuration that's forgotten?

A. Well, you go back to a prior state, and then you will train from there. Kind of like you do when you're typing. You're typing text or say you created something and you cut and paste text and then you hit the undo. It just takes it away and brings you back to the previous configuration.

Q. Okay. I guess in this case -- in this case, when you're doing the undo operation, it loads the previously saved configuration, but forgets about it; is that right? That's at Column 34, lines 22 is 27?

A. I don't think you have it correct,

accurately. So you have a configuration up to time t0. Okay. So up to time t0 you have done some training. Let's say you have a configuration up to that time.

Between time t0 and time t1, you added some things. You told the robot to do a handstand. So between t0 and t1, the robot, instead of doing a handstand, fell on its face and broke the camera.

Then you're going to say, Well, I guess this didn't work. Let me undo this operation, go back to time zero, and I'm going to start over by doing something different, training it in a different way or putting safety guards in place so it doesn't break the camera while it's doing a handstand.

I'm exaggerating obviously, but...

Q. Yeah, I see.

So like in Column 34, lines 18 to 21, right before this, where it talks about high level that the software platform -- BrainOS software platform, it allows these multiple users to

selectively remove a learned behavior through the undo or time machine operation.

And that's what you're saying then, that once you're at a -- after time t0, if you ask the robot to do something and it doesn't do it properly, then you have the option to go back -- sorry, to undo the configuration; is that right?

A. More or less, yeah. Yes. To undo what you've done between t0 and t1 and go back to t0 and then restart over again with the training.

Q. I see.

And so the robot is constantly basically loading these different configurations based off of, you know, what may be -- so, yeah, sorry, let me correct.

So the robot is loading these configurations at different times; is that right?

A. Well, the robot is loading -- it depends on which mode it's in, but the robot is loading -- so if the robot is navigating forward, it sees a couch, and it hasn't been -- it's been trained on when it sees an obstacle to slow down and move to

the left, to the right, whatever, it's going to basically load that configuration and do what it's been trained to do. If there's never been any training, then obviously it's going to either come to a stop or hit the couch.

Q. Okay. So using -- sorry, I'm just reading your comments.

So using the example you gave with the couch, for instance, if the robot has a configuration that's been loaded, and when it comes up against a couch if that configuration says, you know, turn left, then it will turn left.

But, you know, let's say there's, like, water when you turn left, so it failed. And so you could then load another configuration and tell the robot to, well, when you come up to a couch turn right, so that the next time the robot approaches that couch, it will make a right turn because of that newly loaded configuration; is that right?

A. Well, close, but, I mean, like, if you look, for instance, at the -- look at Column 34,

towards the end of -- say between lines 28 and 36, 37. Do you see it says, By -- towards the end of that, let's say line 34, By a way of an illustration, pressing control plus Z in a MS Word may effectuate UNDO of successive edits.

So you would hit undo on your edits.

Similarly, providing a plurality of UNDO indicating -- it should say indications, but it's a typo -- may cause removal of multiple learned associations.

So you've taught the robot something up to t0. And between t0 and t1, you taught it something. Then between t1 and t2, you taught it more some more things. And between t2 and T3, you taught it some more things. And you discovered that it's failing, or it's not doing it right. You say, Okay, I'm going to go back to the beginning and start over again with my training.

So you're going to undo the t2 to t3, undo the t1 to t2, undo the t0 to t1, and then go back to t0 and say, Okay, I'm going to retrain it. I'm going to do it a little differently, or I'm

going to change the speed or whatever. So that's essentially what -- the idea behind it.

Q. I see.

And so with these different robots and users, you could have a situation where, according to Grotmol, you have a robot that -- one robot that comes up against this couch, makes a left turn, fails, another robot that makes a right turn but doesn't fail, and then by virtue of learning from each other, the first robot could then -- if it learns from the second robot, would then also make a right turn when it --

MR. JAIRAM: Objection --

BY MR. KHAN:

Q. -- reaches that couch the next time; is that right?

MR. JAIRAM: Objection; form. Objection; scope.

THE WITNESS: I think you're misunderstanding this whole operation. In Grotmol, there is one user training one robot in a sense. That configuration -- so I have a user

training a robot in one learning process. That configuration can be loaded on a second robot, but there's no mixed training of robots. That is not discussed at all.

So I have one user training one robot I can undo different things and retrain the robot and undo something and retrain the robot. And when I'm done, so to speak, I have some trained configuration of this robot. I can load that onto a second robot.

BY MR. KHAN:

Q. Can you point to me a disclosure in Grotmol that says only one user can train one robot?

A. Well, I mean, if you read the description of Grotmol, it's essentially that's what I was talking about.

Q. That's kind of what I'm asking, is can you point me to a disclosure in Grotmol that says only one user can train one robot?

A. So you can start -- you know, look at the background, for instance, Column 1, line 62,

63, "conventional approaches, given a task in which a user wants to train a robot to navigate along a path," and it talks about that. So that's starting with the background. So you can get an idea what Grotmol was trying to do with the motivation behind Grotmol.

So the user may first control the robot one time or multiple times to move along. And if you look at Column 10, starting on line 45, you see, In some implementations a user may train the system to switch between tasks based on sensory inputs.

And later on at line 50, it talks about a predictor may assign priorities, blah, blah, blah -- may assign priorities to the available tasks based on the sensory context. The priorities may be trained by the user via a corrector plus combiner scheme.

So later on in that same column, it talks about from the user, line 61.

Column 11, line 10, The user may correct the system by providing an indication as to which

task the system should be performing.

Line 17, In some context the user may want to signify.

Line 26, The user corrections may be processed.

I mean, it's clearly describing a user -- essentially, one user operating one device in one learning process and creating that learning activity.

Q. So your conclusion that Grotmol teaches one user per one robot is because in the description, Grotmol says "a user" when it's referring to the interaction with the training of the robot; is that right?

A. Well, Grotmol -- as I mentioned obviously in my analysis of the claims in my declaration, Grotmol discloses one user operating one device in one learning process. So you have one user, you're operating a device, you learn something, you operate that device, you learn something, and that learning -- that knowledge can be propagated onto a second robot.

But there's no description in Grotmol of multiple users operating multiple robots and having mixed knowledge of any kind. That is not discussed or disclosed in Grotmol. One user, one device, and one learning process.

Q. In these sections that you pointed to, does it say "one user"?

A. Well, it's talking a user, the user, a user, the user. I mean, we can keep going. You'll see that throughout Grotmol.

Q. So your conclusion that only one user is using the robot here portrayed is based on the explicit recitation of "a user" or "the user"?

A. No, my conclusion is based on reading Grotmol and obviously understanding what Grotmol is doing. Grotmol has one user operating one device in one learning process. And when you read the description of Grotmol and you read the specification carefully, you would come to that conclusion.

Q. Can you point to me anyplace in Grotmol that has one user, that recites explicitly one

user?

A. Well, I'm not sure the word "one user" is recited in Grotmol, but as I mentioned to you when you read -- when you read Grotmol, you would come to that conclusion. Grotmol has one user operating one device in one learning process.

Q. Can you point to me -- and, again, please just answer the question.

Can you point to me any place in Grotmol that recites only one user?

A. I don't --

Q. I'm sorry. I'm sorry, let me rephrase that.

Can you point to me anyplace in Grotmol that explicitly recites that only one user can use a robot?

A. I don't think those words explicitly are in Grotmol, but what I've said to you is when you read the context of Grotmol, you read the specification, you look at the drawings, you read the details, you understand what Grotmol is doing, you come to that conclusion. You have one user

operating one device in one training process or learning process.

Q. Okay. I think it's -- we just hit the one-hour mark. You want to take a five-minute break?

A. Sure, I'll be back in my seat at 1 -- at 2:50 Eastern.

Q. Okay.

(Recess from the record.)

MR. KHAN: I have no further questions. So the witness is yours.

MR. JAIRAM: Okay. Let's just go off the record, just take a five-minute break.

(Recess from the record.)

MR. JAIRAM: I have no questions. This concludes the deposition. Thank you.

Go off the record.

(Off the record at 3:16 p.m.)

STATE OF MARYLAND)

ss:

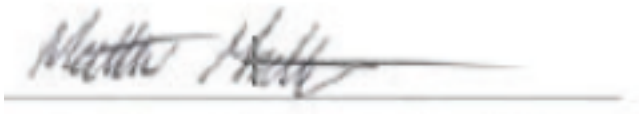
COUNTY OF MONTGOMERY)

I, Matthew Goldstein, Notary Public within and for the State of Maryland, do hereby certify:

That I reported the proceedings in the within entitled matter, and that the within transcript is a true record of said proceedings.

I further certify that I am not related to any of the parties to the action by blood or marriage, and that I am in no way interested in the outcome of this matter.

IN WITNESS WHEREOF, I have hereunto set my hand this 21st day of May, 2024.



Matthew Goldstein, RMR, CRR

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Case: Tesla, Inc. v. Autonomous Devices LLC
Date of deposition: May 16, 2024
Deponent: Eli Saber, Ph.D.

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Page No.	Line No.	Change

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A
a.m 1:17 80:14
ability 7:21 8:4 70:12 79:17,20 146:17 148:2
able 10:16,18 12:11 36:20 69:13,15 72:14 72:22 73:2 76:11,15 77:6 78:12,14 84:21 95:1 115:11 169:19
abruptly 65:6,15 172:14,15
absent 189:21
absolute 74:11
absorbing 37:13
abstract 45:2 71:2
accelerating 65:15
accept 110:8
access 24:21 56:16,21 58:20 59:9 63:5 64:7 65:11 69:4,11 69:22 70:4,19 71:9,17 72:10 72:11,13,16 73:1,4 76:11,16 77:6
accessed 77:7
accessing 65:21 69:18,19 70:20 71:4,15
accidentally 175:13
accommodate 106:7
accompanying 16:6
accomplished 58:16 91:22 92:1
accuracy 96:11 108:12 109:15 109:18,18,20 110:7,11,19 112:12 113:8 113:13 114:3,9 114:10 117:22 118:3,7,8,10 124:4,5
accurate 60:19 82:8 148:14
accurately 94:4 177:1
achieve 20:21
achieved 33:21
acknowledge 190:11
acquire 36:11,14
acquired 121:20
acquiring 37:2,4
Acquisition 59:4
acronyms 25:18
action 21:8,10 170:11,12,19 171:7,15 172:2 173:22 174:11 188:11
activation 141:14 142:2 148:17 149:20,21 150:9
actively 29:22
activity 75:13 76:17 93:5 104:8 144:4 172:21 184:9
actual 156:13
adaptive 163:17 163:18 164:3,9 164:12,13,14 165:2,6,8,16 166:3,5,8,12,20 167:1,2
add 87:11 113:15 122:12,19 123:16 126:5 146:1,13 153:8 154:6,17
added 151:21 177:5
adding 75:10 126:22 154:18
addition 76:20
additional 18:3 21:14 76:8 89:19 98:21 172:16
addressing 68:17
adjunct 22:11,12 22:17,21 23:3 33:4
adjust 137:20 148:15 166:17
adopted 43:6 144:12
advanced 34:12 111:18 119:2
advice 35:18
advise 189:12
advised 189:10
affect 73:21
affirmed 5:4
afford 110:19
aforementioned 138:11
Africa 68:3
ago 27:1 90:22 101:14,14 125:12,13
agree 6:20 82:16 128:16 160:1,6 161:2,19
ahead 9:8,9 91:6 139:13 174:10
AI 62:13,20 140:10 141:4
airport 94:20
algorithm 18:21 24:12,17 74:10 74:11 94:17 95:21,22 96:2 107:16,17,18
algorithms 12:8 13:13 15:8 27:16 47:9 54:11 60:5 83:15,18 99:9 99:22 100:7 104:19 107:15 118:19 119:12 151:20
alleged 31:4 39:18 46:3
allocated 121:9 122:1,8
allow 97:12,13 148:4
allowed 6:7 189:14
allows 177:22
alternative 31:11
amount 37:10 122:10 153:19
analysis 36:20 124:12,13 184:16
analyze 84:11
analyzed 36:12 36:15,17
analyzing 84:19
and/or 31:10 36:3 49:3,19 50:9 51:12 52:12 56:11,16 57:4,16 58:9,21 58:22 59:9 60:15,22 61:8 61:14,22 62:6 63:6,8 64:8 68:8 70:4,6 71:20 75:15 76:6,9,14 84:18 84:19 88:2 130:20 140:5 141:3,16 142:22 161:20 163:3 168:16 189:12
angle 81:13 89:5 89:6 90:2 112:3 112:3 115:11
angles 95:16 97:18 112:9 114:1,18
animal 94:6
annotation 10:10
answer 51:19 61:5 68:21 69:7 69:9 71:18,21 71:22 72:2 74:15 81:20,21 83:19 103:20 105:16 114:11 114:12 162:15 164:17 186:8
answered 61:13 62:8
answering 7:19 8:2 62:3
answers 67:15 190:15,17
anticipate 131:18 132:15,22
anticipating 131:13,14,21
anymore 25:10 96:17 125:3,4 149:2
anyplace 185:21 186:14
apologies 170:8
app 66:9
apparatus 167:21 174:20
APPEAL 1:3
appeared 143:21
apples 155:2
applicable 189:14
application 56:12 57:5,17,19 58:9 58:16 59:12,19 60:7 63:8,20 64:10,15,22 67:2,6,7,21 69:5,12,15,19 69:21 70:7 71:7 71:12 72:9,11 73:3,10 75:9,11 75:16,18,20

76:4,15 77:7 92:9 110:8,9,18 110:22 120:21 120:22 122:4,6
applications 19:15 21:11
applied 40:8 41:2 142:4
applying 10:4
appreciate 52:15 66:4 81:20 82:13 104:4
approach 13:22 111:1
approached 6:11
approaches 179:18 183:1
appropriate 76:16 84:22 190:14
appropriately 137:20 169:8
approve 38:7
approximately 63:11
architectural 45:18 46:22 50:5
architecture 48:5 52:10 53:1
area 108:19 119:1
arrived 42:2 115:8
art 29:1,4,20 30:2 31:3 32:11 37:21
articulations 140:7
artificial 54:7,10 54:14,19 62:13 68:13 84:14 104:19 140:4 143:2 144:3,12 145:5 151:12 151:16
artificially 142:20
Arvind 3:12 5:19 158:11
asked 26:12 55:22 70:18 81:22 84:8 119:4
asking 48:12 49:1 51:8 52:18 58:2,4,13 60:9 61:21 62:21 63:22 64:12,18 66:21 67:12,12 67:16 68:17,17 70:14,15,19 74:18 75:1 80:1 82:4 83:17 92:19 94:9 104:19 120:9 162:16,20 170:2 182:18
aspect 111:19 113:17
aspects 20:5 33:6 76:5 84:17
assign 183:14,15
assigned 114:21
assignment 32:22
associate 17:13
associated 17:15 75:20 151:17 152:12 160:8
association 170:16 171:2,3 171:8,17
associations 180:10
assume 69:11 72:3,5 147:8
assuming 47:19 160:22 161:6
assumptions 72:3 74:7
attached 8:18,20 9:15 159:3 190:16
attention 139:2
attorney 20:5 39:4
attorneys 20:8 21:13
attraction 146:17 146:19
audio 139:10
augment 18:11 114:2 116:10
augmentation 110:6 113:19 118:13
August 23:1
author 141:15
automatic 10:9
automation 68:7
autonomous 1:8 36:6 49:20 50:10,22 51:13 53:18,20 61:1 61:15,17 62:3 128:4 143:1 169:15 173:21 189:6 190:7 191:8
autonomously 127:8
available 5:12 24:6,19 25:15 157:17 183:15
Avenue 3:6
AX 146:5,8

B

b 4:6 82:19 120:14,14,16 140:8 157:3
B1 4:10,12
bachelor's 9:22 31:5 32:13,16 33:15,21 34:4 35:11
back 11:3 21:14 21:19 25:7 36:18 38:19 44:9,11 48:18 55:14 62:10,22 70:1 80:14 102:4 108:3 119:12 127:17 128:10 143:19 143:22 144:9 144:13 149:5 149:16,17,17 154:8,10 155:11,13 157:18 158:15 158:20 164:20 173:17 176:11 176:16 177:12 178:6,9 180:17 180:21 187:6
back-and-forth 38:16
background 9:22 14:15 43:10 132:12 134:12 134:14 182:22 183:4
backgrounds 134:15,18
backward 112:15 112:17 114:19 167:7
base 46:20 47:10 122:18
based 10:20 12:7 12:21 41:11 42:9 75:1 78:3 131:16,19,21 133:6 174:7,12 178:13 183:11 183:16 185:12 185:14
basic 25:7,9 142:12
basically 15:19 27:16 83:9 102:13 106:19 107:20 117:8 146:11 148:2 148:18 154:1 160:13,19 164:15,19 165:6 166:22 174:9 175:12 178:12 179:2
basis 69:13 127:11
bear 108:20
beard 99:13,16
bearing 81:13 87:21 89:5,6 90:1
beginning 84:10 129:17 180:18
BEHALF 3:2,11
behavior 163:16 163:17 166:17 166:17,20 168:7 174:21 175:1,13 176:4 178:1
behaviors 165:22 175:12,17
Beijing 132:10 132:18,21
believe 26:18 31:3 39:21 46:2 63:3
best 5:13 7:20 8:3 118:1 123:11
better 58:12 64:12 110:20 111:6
beyond 109:16
bias 150:2,8 152:14
biases 141:12 148:6,16 152:16,18
big 86:16 93:3 94:8 119:1,1 120:19 123:3 124:19 167:5
bigger 151:1,7
billion 109:13 110:3
bit 9:6 13:11 52:4 84:3,6 85:10 88:22 111:6

130:6 141:1 164:5 166:1
black 12:21 18:17
blah 140:17,17 140:17 183:14 183:14,15
block 45:17,18 45:21 46:5,8,9 46:11,11 50:6 50:18 52:1,2,9 53:1
blood 188:11
blue 11:21
BOARD 1:3
bored 119:17
bottom 56:9 173:9
boundaries 17:4
boundary 16:22 17:1,3
box 8:13 46:21 47:7 48:3,4 86:17 163:13 163:16 190:14
boxes 47:1,3,7,10 47:13 48:6
brain 141:6 143:6 144:1,2 144:17 151:9 151:14
BrainOS 177:21
branching 76:9
break 5:16,19 6:18,19 13:6 43:17 44:8 80:8 127:14 128:7 158:8 159:5 177:15 187:5 187:13
breaks 5:16 6:6 44:2
brevity 7:3
bridge 156:22
brief 11:9 45:5
briefs 7:16
brings 176:16
broad 60:3
broke 177:9
brute 13:21
BS 34:20,21
building 10:12 103:13 125:3,4 126:19,22 127:5
bunch 15:22 87:2 114:16
bus 48:16,17
buy 123:1

C

c 3:1 4:1 5:1 24:5 24:5 25:12,12 73:19 82:19 120:14,14,16 140:8 157:4
c/o 189:1
call 11:20 30:22 95:18 98:13 100:12 101:4 108:1 110:6,14 113:9 116:16 123:9 124:11 142:1 148:22 150:3 151:12 154:3 157:12 189:15
called 10:13 112:16 143:10 143:18 149:2,7 149:10,11
calls 49:20 73:21 74:5 139:15
camera 55:8 89:2 94:16,22 95:11 96:16 100:22 106:2,5 109:20 115:11,14 160:3,7,10,14 160:19,22 169:4,5 177:9 177:15
cameras 36:8,9 36:11 68:6 101:1,3
capabilities 45:22 50:17,20 52:3
capability 70:8
capital 175:3
capture 89:11 147:2
captured 88:13 147:4 160:10 160:14,18
captures 126:18
capturing 88:21 89:1 106:1,2 116:17
car 10:17 12:11 12:12,12,19,20 13:2 15:4,11,12 16:1,2 17:15,19 18:8,9,13,14 26:20,21 59:16 59:17 65:7 66:6 66:7,7,18,22 67:1,3,4,19,20 68:5 104:11 106:15 125:18 125:22 138:19
career 22:6 34:11 34:17
careers 34:10,13
carefully 37:22 38:6 64:20 185:19
case 1:11 26:3,13 37:22 73:18,20 81:11 86:4 96:14 102:8 108:22 141:15 145:14 176:17 176:18 189:6 190:7 191:8
case-case 73:20
cases 78:4 109:1 109:2
cat 81:11,11 82:22 85:15 87:4 88:5,6,12 88:14,18,18 89:4,6,16,19,22 90:3,4 93:17,22 130:16,16,17 148:11
categories 87:19
cats 89:2
cause 180:9
caution 21:1
cell 149:19,19 150:2,6,7,11,12
cells 144:7 150:12 151:9 151:20
center 99:9
centimeter 172:9 172:13 173:4
certain 15:11,12 16:16 17:14,14 51:5 101:20 104:13 107:9 109:4 121:9 122:10 151:17 152:18,18 157:16 162:12 162:18,19 165:21,21 166:16,17 175:17
certainly 42:3
certify 188:6,10
cetera 18:18 20:14 25:19 37:18 55:8 56:13,18,19,19 62:13,14 64:10 68:6 71:5 76:5 84:12 106:18 122:7 139:1 141:14 142:9
chair 127:18
change 59:15,18 73:18 78:12 99:17,20 101:16 113:14 113:16 126:13 166:16 181:1 191:11
changed 124:4
changes 59:20,21 72:14 78:13 96:12 114:13 118:12 190:16
changing 65:22 118:19
charts 65:19
chat 8:13 9:12 159:6
cheap 122:22 124:17,18
check 42:14,16 42:18 190:14
chose 149:13
circular 140:12
circumstance 103:3 107:2 137:9
circumstances 49:19 50:9 51:13 52:13 60:16 61:1,9,15 61:17,22 62:2,7 69:3,10 107:9 142:22
citation 42:13,21 43:11
citations 43:13
cited 41:21
claim 39:2,7,11 39:12,15 40:11 40:16
claims 20:19 40:10,17,22 41:9 42:4 184:16
clarify 11:16 57:13 91:7 93:13 170:6
classes 72:13
classification 161:3,15,21
classifier 161:22
clean 8:6
clear 27:19 39:7

71:15 74:17 106:22 119:20 122:13
cleared 139:3
clearer 60:12
clearest 170:9
clearly 184:6
clock 44:11
close 87:17 127:12 179:21
CNN 28:12 96:1 118:19
co-pending 39:19
coached 34:22
code 23:21 24:2,3 24:5,8 69:9 76:7,8,9,10,13 76:20,21
coded 24:1 25:6 25:11
coding 25:7
cognizant 17:6
cohesive 17:1
collaborative 21:18 38:3,17 38:18
collaboratively 31:19
collapse 145:11
colleague 35:5
colleagues 32:4
collect 113:11 125:17
collected 11:2 147:8
collecting 88:10 101:19 127:10
collection 12:18 86:10,18 87:1 87:11 88:4 89:17 90:16 91:3,4,9,14 100:21 103:9 128:20,21,22 129:9,10,18,19 129:20,22 131:5,10 132:2 132:4,5,8,10 133:17 134:1 135:7,22 136:21 137:3,4
collections 110:2 133:8,14,16 134:6,7
color 10:10,20 11:12,14,15,18 12:1,7,22 18:4 18:8,17 27:8,8 27:14 112:6
colors 11:20 162:18
column 48:11,14 54:2,13 55:10 55:11,17,20 56:8,14 57:15 58:5,6,10,17 62:10 63:3,10 63:11,13,16,16 64:5 70:1 71:6 71:16 73:7 75:22 76:20 77:14,16 81:5,7 84:4,5,9 86:13 88:1 129:14 131:20 138:7 140:15,21 142:15 161:17 164:7,22 167:10,13 169:10 173:5,6 173:8,9,11 174:15,17 175:2 176:21 177:19 179:22 182:22 183:9 183:19,21
combination 15:6 78:2,7,14 78:18,20 79:1,5 79:9,16 80:3
combinations 78:22 80:4
combine 13:1
combiner 165:7 183:18
come 21:14,19 44:9 65:4 88:14 100:14 101:17 106:15,21 110:14 136:12 137:17 138:20 139:4 158:15 171:19,21 172:14 176:9 179:4,16 185:19 186:5 186:22 189:11
comes 98:9,9,20 118:8,10 125:21 137:13 179:11 181:7
coming 66:18 89:14 96:21 102:14 104:12 105:18 106:17 107:3,4 158:6
commands 165:19 166:5,9 166:13,16
comment 31:20
comments 179:7
communications 38:22
company 95:9 98:7 102:9 110:11
compare 13:6,7
compared 47:17 137:2,4
comparing 128:21 129:9 129:17,20 130:5,10,11,16 133:13,17 135:5,5,9,10,12
comparison 13:5 135:16
comparisons 129:13 135:4 135:14
compiler 56:19
complete 35:15 35:17 139:5 189:10 190:15 190:17
completed 19:10
completely 7:20 8:3
complex 153:16
complexity 120:21 153:17 154:7,18,19,20
complicated 157:22
component 112:7 124:12 159:22
components 56:1 165:14
comprehend 148:1,7
comprehended 146:19
comprehending 149:2
comprise 56:20 164:13 165:2 175:8
comprised 54:12
comprises 56:10 56:15 58:8,19 59:3 62:12 63:5 70:3 78:1,6,19 79:15 80:2
comprising 49:18 51:11 60:21 61:14
computer 11:6,6 12:3,5,11,14 14:16 15:5 16:18 17:13 25:3,4 31:6,6,9 33:16,16 36:3 36:19 98:2
computing 45:21 48:15,19,21 52:2,5
conceptually 126:16
concludes 187:16
conclusion 32:1 184:10 185:11 185:14,20 186:5,22
conducted 1:15 2:1
conference 19:6
confidential 21:3 21:4
configuration 175:9,20,21 176:8,9,16,19 177:1,3 178:7 179:2,10,11,15 179:19 181:22 182:2,9
configurations 157:10 178:13 178:17
configure 168:22 169:7
configuring 157:19
connect 156:19 157:18
connected 54:20 152:12 153:11 156:18 157:13 157:13,14,16
connecting 157:8
connection 16:9 40:2,19 41:4,10 41:14,21 42:7 140:19 153:12 153:18
connections 46:19 141:5 143:5 144:15 148:4,16 152:15,16 155:16,19 156:5,12,13,14 157:8,16,18
connectivity 47:22 144:2 145:15,18

150:19 152:20 152:22 153:2,4 153:8
consent 189:22
consider 40:10 43:3
considered 41:20
considering 40:9
constant 65:12 126:8,11
constantly 178:12
constants 65:22
constrain 67:14 67:18
constraints 68:19
construct 95:22 96:2
construction 39:3,7,11,13 40:2,6 41:4,11 41:14,21 43:5,7
construed 40:20
contact 128:4
contain 145:7
content 148:5
context 36:15 40:16 71:1,3 74:20 83:21 93:7 94:13,14 162:7 183:16 184:2 186:19
continue 101:18 101:21 108:6 128:11 130:8
continued 19:12 24:8 35:19
continues 87:22 101:17
continuing 162:15
continuously 127:7
control 37:16,17 164:9,12,13 165:2 166:17 169:14 170:11 170:11,22 171:1,14 173:9 173:10 180:4 183:7
controller 49:3 163:17,18 165:5,7,16,20 166:3,5,9,20 175:22
controllers 164:4 166:12 167:1,2
controls 68:10
conventional 183:1
converge 151:3
conversation 128:14
convolutional 28:12 113:16
cool 119:18
copy 8:6 29:13 150:11,13 153:9,12 189:11
Copying 189:21
Copyright 189:20
corner 126:20
corners 84:12 162:17
correct 10:2 17:19 19:17,21 22:2,3,7 33:18 33:19 38:14 40:3,4 42:11 43:8 53:22 59:22 60:14 61:7 62:5 63:9 82:20,22 83:1 90:6 91:11 161:7 166:15 169:15 171:5 173:1 175:17 176:22 178:15 183:21 190:14 190:17
correcting 175:12
corrections 184:4
correctly 147:5 171:5
corrector 164:14 165:3 183:18
corrects 172:21
correlate 106:10 107:1
correlated 106:9 135:22
correlating 103:6 103:8
correlation 16:9
correlations 46:20
correspond 71:12
corresponding 19:6 69:20 87:12 90:4 148:10
cost 108:1
couch 178:21 179:5,9,11,16 179:18 181:7 181:15
counsel 5:7 6:9 29:14 38:1,4,16 38:22 44:4 128:4 189:12 189:13
COUNTY 188:3
course 6:15 23:19 46:4 59:22 81:20 105:13 111:14 111:18 114:14 119:2,3,7 145:3
coursework 24:9 24:10
court 7:12 25:20 39:20
create 14:6,7 18:12 24:11,17 24:18 58:20 59:9 63:5 64:8 70:4 73:5 86:22 87:18 92:21 103:22 104:9 119:5,15 120:11 144:2 144:11 146:3 146:12 149:14 151:19
created 92:5 102:12 103:21 105:5,10 119:5 137:8 144:15 149:18 151:16 176:14
creating 75:6 92:8,13 119:6,8 120:9 184:8
criteria 31:22
cross-examinat... 6:12
crosswalk 85:19 104:11,12 105:17 106:14 106:17,22 107:3,6 126:8 132:15,16,17 132:21 133:1 134:11,13,17 134:22 136:11 136:15 137:6,7 137:9,22 138:19 139:3,3
crosswalks 110:4 126:9
CRR 1:19 2:10 188:22
Curriculum 4:15
customary 39:17
customized 94:10
cut 85:10 176:14
cutoff 5:13
CV 9:12 19:2,3 19:14 22:11 27:21
cycle 101:20,22

D

D 5:1 140:8 157:4
D-C-A-D-O 53:8
D.C 1:21 3:8,17 134:12 189:4 190:3 191:3
data 58:22 86:9 87:12,13 91:10 94:18 97:8 98:22 108:14 108:15 109:2,5 109:8,10,12 110:6,7 111:1,2 111:2,3,8 113:18 118:12 118:13 120:18 121:13 122:18 122:19 125:6 125:17 140:16 140:16 141:12 141:16,16,18 142:1 148:8,9 149:1 151:5 153:6 160:8,13 160:14
database 10:18 11:4 12:6 15:1 15:2 16:8 17:17 18:11 86:6 94:7 95:19 96:10 97:12 101:21 109:14 113:7 115:7 116:7,13 116:14,15,18 116:20,21 117:2,4,5,10,12 117:13,19 118:4,5,16 120:11,12,20 120:20 121:14 121:15 122:6 122:16,17 123:22 124:13 125:15 126:21 126:21 127:3,9 127:10 132:4
databases 117:7 117:9

dataset 60:6 114:2,5,6,10,11 148:14
datasets 60:7,8
date 124:22 189:7 190:9,19 190:22 191:10 191:22
day 98:20 101:6 101:7,7 111:16 119:17 188:15
days 24:3 108:9 123:1 158:3
DCADO 49:21 53:5,9,13 54:4 55:14,14 60:14 61:7 62:5,12,14 77:22 78:1,4,6 78:17 80:1 140:6
decelerating 138:22
deceleration 65:13
decent 45:3
decision 141:3
decisions 37:8 77:11
declaration 4:13 6:21 8:8 9:6 28:16,18 29:11 29:12 30:20,21 31:13 37:19 38:3,10,11,14 40:1,15 41:22 45:4,5 184:17
declarations 39:10
dedicated 167:6 167:7
deep 153:22 154:1
deeper 154:2
Defense 33:9
define 17:5 29:11 30:10 53:6 94:9 106:20 107:22 146:6,9 152:19 152:21 153:2
defined 29:20 106:19 138:3
defines 30:20 31:12 39:10
definition 29:18 30:5,7 31:2,14 31:15,17,17 35:20,21 39:12 42:10
degree 25:8 31:5 33:15,21 124:15
degrees 34:19 89:6,7 90:1 150:21
delete 58:20 59:9 63:6 64:8 70:4 72:15 73:5 122:11 126:6
deleting 63:19 64:14 65:20 70:18 75:6,10
demonstrate 24:11
Department 33:9
depend 74:13
dependent 47:11 93:11 98:16
depending 15:7 93:5,15 105:21 107:5 108:10 112:11 122:3 168:4,12,14
depends 13:10 35:13 57:9 70:10 92:9 104:20 105:15 110:22 115:4 120:21 121:12 122:5 130:6,7 141:13 153:5 178:18
depicted 81:4
depicts 49:13
deponent 189:8 189:11,12
deposition 1:14 2:1 7:14 82:8 187:16 189:7 189:13 190:9 190:12 191:10
describe 44:20 45:12 48:11 52:18 54:3 55:11 81:3,16 82:5 140:1
described 48:9 51:1,22 57:3 76:6 90:21 142:10
describes 46:16 54:4 55:18 62:12,14 63:14 77:3 83:9 138:8 164:5,19 165:1 173:7 175:3
describing 81:9 142:14 184:6
description 13:2 29:10 45:3,4,5 45:20 49:14 50:4 52:5,9,15 54:14,15,17 55:13,20 60:19 60:20 61:2,12 61:19 62:11 63:2,14,15 64:1 81:6,7,14 82:10 83:9 86:12,20 89:19 130:9 133:5 141:1,18 146:15 164:7 164:15,16 165:13 166:2 173:4,15,19 175:5 182:16 184:12 185:1 185:18
descriptions 55:5 87:6 173:8
design 71:21 141:13
designed 12:8 57:10 121:13
detail 111:6
details 20:13 21:20 67:14 116:20 119:10 186:21
detect 85:14
detected 81:12 83:11
detecting 162:18
detection 85:12 88:20
detects 82:18
determine 16:17 16:18 83:16 84:1 87:10 95:2 96:11 98:12 153:17
determined 102:11
determines 85:6
determining 133:20 135:19
develop 40:5
developed 31:15 31:19
developing 41:3 41:20
device 45:22 47:15,16,18,20 48:15,15,19,21 49:2,3,17,18,20 50:1,2,3,4,7,10 50:14,15,16,22 51:1,3,3,6,7,9 51:11,13,17,18 51:21,21 52:1,2 52:5,11,13,19 52:20 53:1,4 60:21 61:1,13 61:15 81:13 82:18 83:2 85:11 91:18 92:3 93:8 103:16 143:1 184:7,18,19,20 185:5,17 186:6 187:1
device's 49:19 50:9 51:12 52:12 60:15,22 61:8,15,16,22 62:2,6 142:22
Device1.move... 77:4
devices 1:8 46:12 47:17 49:22 52:16,18 128:4 142:21 189:6 190:7 191:8
diagonally 166:4
diagram 45:17 45:18,21 46:22 48:5 50:5,6,19 52:1,2,10 53:1 62:17 83:4
difference 108:2 108:3 138:1 170:22 171:10
different 12:17 28:2 33:12 34:9 34:15 47:16 51:17,21 52:20 52:22 55:22 72:14 73:1 76:12 88:18 89:4,8,9,10 90:7 93:4,11,15 93:17 94:7 95:11,16,17 101:22 102:1 102:17,20,21 105:7,7,7,11,11 105:13,14,15 105:19,21 110:9 114:18 115:6 116:17 117:16 118:14 121:17 122:1,2 125:11 132:11 132:12 134:10 134:15 139:6 140:7,9 145:18

146:11 157:5,7 157:9,19 166:13,16 168:22 169:1 169:13 172:16 177:13,14 178:13,17 181:4 182:6
differently 118:15 180:22
difficult 99:20 153:7 154:8
Digital 1:20 189:19,20 190:1 191:1
direct 42:20
direction 159:21
directly 19:7 136:4
disappeared 99:12
disclosed 46:1 50:18,20 59:5 142:20 174:22 185:4
discloses 161:3 184:17
disclosure 70:16 73:13 85:3 161:14 182:12 182:19
discover 113:3
discovered 180:15
discuss 6:7,21
discussed 50:6 182:4 185:4
discusses 49:5 129:15
discussing 18:21 128:7
discussion 29:3 43:9 84:7 173:19
discussions 37:22
disk 123:2,8 124:18
Disney 11:1
display 47:15,16 47:17,18,20,21
displayed 48:2
dissecting 37:13
dissertation 10:9
distance 81:12 87:5,20 90:1,3
distinct 117:8
district 39:20
doctor 110:21
doctorate 32:17
document 8:22 9:4 38:5,7 41:8
documents 19:20
Dodge 26:19
Doe 83:3,12,16 84:2 85:7,9 86:1,5,7 88:12 120:3,5,6 121:7 121:10,16,19 121:21 123:10 123:21 124:1,6
Doe's 121:18
dog 148:12
doing 10:12 13:21 25:13 28:2,3,8 32:20 34:3,4 35:10 44:2 69:14 76:17 92:7,13 93:4,19,20 99:7 104:7,9,15,21 106:4 108:10 110:18 113:13 113:18 114:12 116:16 118:17 125:20 172:12 172:22 176:18 177:8,13,15 180:16 185:16 186:21
door 95:12 96:7 96:16,22 97:1,2 97:12,13 98:3 100:11 102:13 102:17,17,20 103:1,1 110:13 110:15 115:8 115:10
download 24:22
downtown 132:10,18 134:12,21
Dr 4:13,15 25:18 26:2 35:9 43:20 44:16 80:19 115:12 128:2
draft 38:2,12,13
drawing 149:16
drawings 40:18 40:22 41:8 42:5 186:20
drive 123:2,8 127:8
driven 26:21
drives 76:14
driving 26:20 36:6,22 53:18 53:20 66:9 68:7 125:19
drop 8:12 50:12
dropout 117:17
dropped 8:15
duly 5:4
dumping 120:19
duplicate 150:18
dynamic 27:8,14 101:10 125:15
dynamically 90:8 111:3 127:11

E

E 3:1,1 4:1,6 5:1 5:1
earlier 33:4 57:18 70:18 84:4,6 90:21 165:11 173:3
early 143:4
ease 25:20
easier 17:8,9 112:20 126:16
easily 146:18
Eastern 80:15 127:18 187:7
easy 99:16
edges 84:11
edits 180:5,6
education 23:19 29:21 30:15
effect 77:8
effective 168:7 172:5 176:3
effectively 175:22 176:9
effectuate 180:5
effort 38:4,18
either 179:4
electrical 31:5 33:15 34:21
electronically 189:21
elements 63:8 70:7 75:8 88:3 130:20
Eli 1:14 2:1 4:2 4:13,15 5:3 112:1 189:1,8 190:8 191:9
ellipse 100:2
embodiment 49:17 51:10,11 51:14 52:11 53:16 59:4 60:21
embodiments 46:1 50:18,21 51:2,5 52:14
employee 96:6,16 96:19 97:10 98:8,10,19,22 99:1,3 100:20 101:11,17,19 102:9,11,15 110:16 116:22 120:13,14,14 120:15,16,16 121:7
employees 95:10 95:12,15 96:10 97:18 98:3 110:10 116:22 117:3,6 120:10 121:4,5
employer 103:12
encompass 134:4
encountered 30:1 30:15
enforcement 165:12
engage 169:21
engaged 38:15
engine 34:20
engine- 34:15
engine/environ... 56:17
engineering 25:8 31:6,6,7 33:15 33:16,17 34:21
engineers 32:4 34:16,18
ensure 110:7
entail 42:8 58:13
entails 105:1
enters 89:20
entire 99:11 135:5 138:15 138:16 145:11 153:10
entitled 188:8
equals 146:5,8 147:11
equation 146:3,7 146:9,13 147:18,21
equations 146:19
errata 189:13 190:16 191:6
erroneous 175:13
erroneously 175:14
error 107:22 154:9
especially 150:7
ESQUIRE 3:3,4 3:12,13
essence 11:8

106:12
essentially 10:11 13:10 16:16,21 23:13 45:15 49:21 52:4 53:2 56:22 57:10 59:7 60:6 67:17 86:20 108:3 123:15 128:17 131:22 138:13 140:6 146:16 148:22 149:14 150:20 151:8 151:10,12,18 165:5 169:2 172:20 176:5 181:2 182:16 184:7
et 18:18 20:14 25:19 37:18 55:8 56:13,18 56:19,19 62:13 62:13 64:10 68:6 71:5 76:5 84:12 106:18 122:7 139:1 141:14 142:9
Evidence 1:20 189:19,20 190:1 191:1
exact 72:1 116:5 131:11 134:21 134:22 135:2 147:11
exactly 13:11 27:9 31:16 67:11 69:10 70:16 71:20 83:17 111:10 120:8 147:9 151:13,14 160:11 170:2
exaggerating 177:17
EXAMINATI... 4:2 5:7
examined 5:6 190:12
example 10:10 12:5 15:10 17:14 30:14 63:18 64:1,13 66:6,17,22 74:8 77:3,5,5 81:9 87:14,20,22 89:22 90:3 91:8 94:13 95:8 97:3 97:7,8,16 98:17 99:7 120:2 121:2 125:1 126:17 132:7 136:10 138:17 142:7 167:9 169:19 179:8
examples 11:5,19 66:2 87:2 91:15 142:6 173:13
Excellent 127:19
excuse 25:7 139:9
execute 135:20 136:7 137:10 137:15 138:21 139:7 171:15
executes 170:12 170:19 171:7 173:22
executing 96:17 96:18 138:1,11
execution 56:11 57:4,16,19 58:9 58:15 76:3 136:6
exhibit 4:7,9,11 4:13,15 6:22 8:7,8,17,19 9:12,14 28:15 42:19 44:16 159:2,8
exist 67:21 125:3 125:4
existing 76:9,21
exists 126:11,12
expect 137:12
experience 23:20 29:21 31:9 33:18,22 36:2 108:18
experiment 147:7,12
expert 70:15 75:2
experts 32:6
explain 10:6 41:2 71:14 74:19 75:1 83:20 119:21 131:17
explained 42:3
explanation 58:5 69:2 105:2 149:4
explicit 185:13
explicitly 185:22 186:15,17
express 189:22
extended 6:19
extensively 25:15 108:17
extent 10:5 60:13
extractor 163:14
extractors 163:13
extremely 38:6 60:3
eyes 99:18 100:9

F

face 99:9,14,17 100:1,2,4,5 102:12 114:19 114:20,22 115:19,20 177:8
faces 94:1
facial 83:15 84:15,16,17,19 84:20,22 86:5 93:20,22 94:15 94:17,21 96:14 96:22 97:9,11 97:17,22 98:18 98:20,21 99:2,7 99:21 111:22
factor 18:4
factors 29:20 30:10,14
faculty 22:11,12 22:14,16,17,21 22:22 23:15,17 24:20 33:4
fail 181:9
failed 179:14
failing 180:16
fails 181:8
fair 22:4 41:19 86:8
familiar 21:7 35:1 39:2,5 73:19 81:17 144:21
fantastic 9:20 29:7
fascinating 114:15
fashion 15:4 145:9
fast 65:8
feature 46:3,6 101:4 103:14 118:16 162:11 163:13,13
features 47:4 59:3 84:11,19 84:20 97:9 160:9 162:4,10 162:13,17,20 162:22 163:5 165:21
feed 55:6,8
feedback 6:13 157:21
feet 137:18
fell 177:8
fenders 14:11
fiddle 117:18
field 30:1,2,16 31:8 32:3,6,7 32:10,20,20,22 33:5,7,13,17 36:6
fields 31:9
figure 45:7,9,10 45:13,14,21 46:5,21 48:8,16 48:17 49:8,11 49:13,16 50:1,2 50:15,16 51:3,4 51:6,7,9,10,16 51:17,18 52:20 52:21 53:14 54:3,5,21 55:4 60:20 61:12 62:11,15,18 80:22 81:8,10 82:16 83:6 85:4 86:11,13,16 87:9,15 88:17 89:15 90:10,15 91:1,5,11,13 102:4 104:22 120:4 128:8,15 128:19 130:21 131:8,12 136:2 136:7 138:6,6 139:17 140:2,3 159:16,16,18 159:20 162:2,4 163:6,11,12 164:6,8,11,22 165:4,4,15,16 165:18 166:1,3 166:19,20,21
Figures 80:19 81:4,17
filed 28:6,7,10
filled 122:9
filter 65:18 123:15,17
final 38:5
finalized 38:5
Finally 117:21 118:2
find 11:6 12:6 14:5 16:4 26:20 109:19 117:20 124:2 165:15

finding 135:10
fine 6:4 7:6 43:19 44:8 53:11 70:21 80:11 155:9 158:9
finish 5:13 6:1
finished 92:17
first 5:4 8:22 15:22 19:4 32:22 34:11 38:2,12,13 39:14 90:16 91:8,17 94:22 103:14,15 128:16,22 135:21,22 137:3 143:20 154:14 181:10 183:7
first-year 119:4
Fish 3:5 35:5
fit 145:19,20 146:1,6,14,17 147:9,12,18,19 148:18 150:5,6 150:6,10,12,14 150:20
fitting 149:1
five 19:5 33:9 34:11 43:21 44:2,5 113:2 120:16 124:6 124:10 158:8 158:11
five-minute 187:4,13
flexibility 150:19
flexible 167:1
flip 29:13
flowcharts 20:15
fly 77:12 78:12
focuses 50:22
folder 120:13,14 120:14 121:21
folders 121:15
follow 20:17 31:18 45:17 66:14 95:6 98:7 119:19
followed 28:14 31:19
following 98:20
follows 5:6 131:13
foot 136:15
forbidden 189:21
force 13:22
foregoing 190:12
foreground/ba... 13:17
forgets 175:22 176:20
forgot 116:4 144:6
forgotten 176:10
form 13:9 15:17 16:20 17:20 18:5 20:2 27:4 44:21 47:5 57:21 60:1,17 61:10 64:17 66:13 67:9 79:21 87:13 95:4 99:4 122:20 125:7 169:22 181:17
format 35:16
formulating 43:4
forth 38:19 75:15 108:15 146:12
Fortran 24:2,4 25:5,6,11,12,19
forward 65:7 112:15,17 167:6 178:20 189:13
found 137:1
foundation 13:12
four 113:2,11,21
frame 12:15,15 14:4 15:20,21 44:1 85:4 88:7
frames 37:4,4 86:3 135:8,12 135:14 160:9
free 24:20
freely 24:21 25:16
frequent 111:2
friend 115:9
front 28:17,18 29:13 36:17 80:22 114:20 114:22 115:19 115:20 123:10 171:18,20,21
frontal 116:1
full 101:15 135:2 138:20
full-time 22:21 23:1,5,7
fully 157:12,13 157:15
function 63:19 64:14 65:17 71:5 108:1,1 141:22 145:20 145:21,22 146:2,10,12,13 146:14 147:20 150:9 153:1 156:19
functionalities 59:4,6
functionality 52:22 56:11,12 56:15,21 57:5 57:16,20 58:8,9 58:15,20 59:8 63:5,19 70:3 76:4 141:4
functioning 79:8
functions 24:16 24:19 63:7 64:9 69:4 70:5 72:17 72:18,20 73:9 73:15 74:1,2,4 74:5 75:7,18 141:14 142:2,8 148:17 151:14
fundamental 27:15 54:1
fundamentals 27:10
funded 28:9
funding 22:15
further 187:10 188:10
future 82:3 99:1

G

G 5:1
general 17:22 64:19,21 144:19
generalize 114:7
generalizing 113:4,5,10 118:11
generally 64:20 90:6 92:22 99:15 103:7 105:12 165:17
generate 86:22 86:22
generated 41:11
generic 71:22 72:2 74:6,15 82:10 93:3 98:17 103:20 104:20
getting 24:3 116:19 154:1 154:12
give 5:22 6:18 23:14 26:7 63:18 64:13 67:14 71:22 95:8 103:19 111:17 118:6 130:9 136:9 142:4 146:10 150:2 152:6 155:6 164:21 169:19
given 5:15 39:16 70:15 174:9 183:1 190:15 190:17
gives 50:19 77:3 87:2,3,19 91:14 142:6 166:1
giving 6:17 11:5 132:6 167:9
glass 12:20
glasses 100:13
go 9:8,9 10:18 11:6 12:6,14 19:3 30:19 39:9 59:14 62:10,22 69:8 76:1 81:5 84:4 91:6 94:16 94:20 97:7 113:21 118:4 119:15,22 120:5 121:10 126:20 129:14 131:20 139:13 140:15 143:19 149:5 173:6 175:2 176:11 177:11 178:6,9 180:17,20 187:12,17
GOALI 23:13,13
goes 63:16 119:9 166:4 173:8
going 19:3 37:2,3 37:8 46:13,14 46:15 47:11,12 47:20,21 48:17 54:16 55:14 59:16 61:5 62:16 65:3 66:21 70:1 73:16,21,22 74:3,13 77:10 78:10,11 85:13 93:10,21,22 94:1,7 96:2,4,8 96:9 97:22 98:1 98:2,11,12,16 101:13 102:3 102:19 103:19 104:9,12

107:15 109:12 109:14,21 110:3,4,5,6,13 112:1,3,5,12,22 113:22 119:11 119:17 120:11 120:13,17 121:20 126:9 128:10 129:12 130:9 135:8 139:10,15 150:4,9 153:13 156:15 164:20 165:20 167:7 171:15,16 172:1,3,3,6,11 172:14,15,22 173:17 174:11 177:10,12 179:1,4 180:17 180:19,21,22 181:1 185:9
Goldstein 1:19 2:9 188:4,22
good 5:9,10 54:17 84:7 116:8,9,9 152:3 152:6 158:7,12 175:5
Google 10:13 125:18,22 126:2,17 127:3
governing 189:14
gradient 27:8,14 154:11
gradients 154:9
graduate 10:3 111:18 119:13 158:1
graduated 19:13
grant 23:12,13 33:1
grants 23:14 28:8 33:8,10
graphical 48:2
grass 11:21 12:1 12:4,4,5,7
gray 160:20
great 6:5 24:14 80:9,12 81:2,22 114:12 118:9 128:6,13 158:22 159:12 159:19 164:2 168:1
green 11:21
Grotmol 158:6 158:14,16 159:6,7,15,18 159:20 161:2,4 161:7,8,15,17 163:1 164:8 165:13 167:11 168:12 169:20 173:6 181:6,21 182:13,16,19 183:5,6 184:10 184:12,15,17 185:1,4,10,15 185:15,16,18 185:21 186:3,4 186:5,9,14,18 186:19,21
Grotmol's 159:16 164:4 167:2
ground 156:7
group 1:20 16:10 18:7 189:19,20 190:1 191:1
grow 98:18 99:13
grows 98:19 99:1
guards 177:14
guess 24:2 51:15 62:21 79:22 83:17 85:7 94:14 97:8 103:10 114:20 116:7 130:4 143:8,12 149:5 176:17 177:10
guided 23:17

H

H 4:6
hair 98:18,20,21 99:2,11,15 101:15
hand 77:8 98:5 188:15
handle 20:8 36:20 112:20
handling 72:6
handstand 177:7 177:8,16
happen 110:12 134:20 172:17
happens 14:2 16:3 69:10 122:8 125:5 147:14
happy 6:18 44:5 44:5 114:4
hard 29:13 67:13 67:18 68:21 74:15 76:14 94:9 95:6 105:15 149:22
hardware 52:4,9 53:2 57:8,11 71:21 75:15 78:1,5,6,8,18 78:19,21 79:7,8 79:10,12,15 80:2,4
he'll 142:7
head 41:15,17 42:16 95:16 99:11,16 101:15 112:2 112:10,14
heads 112:14
heads-up 6:1
hear 29:12 43:9 143:13
hearing 139:10
heavier 100:4
heavy 142:11
helpful 60:13 105:2 152:10
helps 161:16
hereunto 188:14
hesitate 189:15
Hewlett 33:11
hierarchical 13:1 14:6
high 110:12 124:15 135:3 150:5 177:20
high-level 55:5 143:9
higher 135:1 144:17 150:20 150:21 169:4
hired 34:16,18
history 40:12,19 41:3,6,13 42:6 42:13,21 43:4,8 43:12 143:20 151:22
hit 19:3 43:16 59:16 172:3,8 176:15 179:5 180:6 187:3
hitting 80:7
hold 141:11,18
holding 98:10,12 98:14
home 11:3
hopefully 60:13 85:17
hour 127:13 158:7
hours 108:9 109:1,4
HP 28:6,7,8,9,10 28:13 34:6,8
human 46:10 48:7,12,22 85:15 93:22 104:17
Human-machine 49:6 62:18
humans 94:2
hyperparamet... 108:5 117:14 148:17
hypothetical 67:13,17 68:18 74:7,16,18,22 99:6
hypothetically 88:22 148:15

I

i.e 65:17
I/O 46:12 52:7
idea 10:22 97:17 144:14,19 145:4 148:20 167:4,9 181:2 183:5
ideally 135:1
identical 128:17
identification 8:18,20 9:15 159:3
identified 83:12 88:5
identifies 85:8
identify 87:18
identifying 84:19 135:11
IEEE 152:5
if-then 107:8,13
ignores 173:22
illustrate 136:10
illustrated 54:4
illustrates 49:16 51:10,11 60:21 140:4 164:9
illustration 97:3 133:4 138:17 180:4
illustrative 97:16 98:17 99:6
image 10:9,17,17 13:20 14:3,18 15:5,20 16:2,7 16:8,12 17:9,10 27:8,13 31:9 36:3 37:1 87:8 89:16 105:22 109:13 111:9 112:16,19,21

135:5,6,9,16
imageries 96:3
imagery 36:11,12 36:14 37:13 94:8 101:19 106:2,16 107:18 174:5
images 10:18,21 11:2 12:14,16 12:16 13:7,14 28:4 37:3 89:13 89:20 96:4 100:19 109:15 109:19,21,22 111:21,22 112:8,13,13 116:21 119:21 121:4,7,18 122:9 126:18 132:2 135:7 160:6,9,16,17 160:18,19,20
imaging 110:17
immigrate 27:12
implement 175:16
implementation 107:8 164:9
implementations 49:5 161:20 175:8 183:10
implemented 51:3,6 57:6,7,8 57:11 131:18 161:21
important 37:14 82:9 157:6
include 43:7,11 48:19,21 73:11 89:19,22 129:19 130:11 133:9 141:4,22 142:8 143:1 160:3
included 43:13 88:3
includes 40:21 160:15 173:19
including 21:3 40:17 160:8 189:21
incoming 105:17
incorrect 172:21
indicate 16:9 51:20 62:1
indicating 180:8
indication 175:6 183:22
indications 175:11 180:8
indicative 157:6
industrial 33:11
industry 23:16 23:17 34:6
information 10:11,20 12:7 15:13,15 17:12 17:18 18:2,3 21:3,4 41:20 46:18 59:1 68:9 72:21 86:9 88:3 89:11 106:3 111:13 120:6 123:14,16,17 123:18 124:22 126:22 127:10 144:18 168:5 168:16
informed 41:13
ingest 68:8
ingestion 101:9
initial 143:20 144:5,10 149:19 151:20
initially 24:1 89:14 151:19
innovations 30:3
innovative 46:3,6 47:4
input 49:3 70:12 72:18,19 73:3 106:7 107:18 142:2 148:9,9 150:1,8 170:13 170:20 171:8 171:13,16 172:18,20,22 173:18,20,22
inputs 183:12
inserting 76:8
inside 65:15 99:22 100:1,3
instance 11:1,19 12:2,10 14:20 15:20 17:3 18:12 20:20 34:15 54:12 56:9 73:18 74:9 75:21 76:2,7 84:4 85:5 87:3 87:4 94:5,14 95:7,9 97:11 100:2 109:12 115:19 121:8 121:14 126:12 130:15 132:6,8 138:18 142:20 146:4 147:6 148:10 149:20 164:8 169:4 179:9,22 182:22
Institute 23:9
instruct 38:20
instruction 73:12 75:10,17 91:17 92:4,6,6,8,10 92:14,21,21 97:10 98:6,13 98:15 102:3,4,6 102:13,21 103:1,8,11,16 103:17,20 104:5,9,13 105:5,6,10,14 105:19,20 106:6,9,11,20 133:2 135:21 136:8 138:2,3 138:15,16,21 139:5
instructions 73:11 106:4 107:14 131:14 131:19 137:10 137:15 172:16
instrumentation 76:7
integrated 46:8
intelligence 54:7 54:11,15,19 62:13 68:13 84:14 104:19 140:4
intelligent 142:21
interact 69:13,15
interaction 104:17 184:13
interconnected 62:12 122:3
interconnectivity 140:9 145:8
interested 188:12
interesting 119:18 151:15
interface 46:10 48:2,7,12,22,22 49:6 55:15,16 55:19 56:6,10 56:15 58:7,19 59:3,5,8,14 62:18 63:1,3,4 65:10 69:4,18 70:3 71:4 72:3 72:6 73:9 77:1
interfaces 48:1
interior 99:17
interject 94:2
interrupt 170:5
interval 176:1
intrinsic 40:22
invention 31:4 32:11 39:18 45:15,19 47:8 48:5 52:14
inventor 21:12 29:22 53:5
involve 10:4 69:19 75:9,12 76:8 84:18 135:4
involved 11:10 11:13,16 19:22 20:4 29:22 39:19,22 168:12
involving 57:16
IPR 6:22 39:22
IPR2023-01054 1:11 6:22
issue 7:4
item 74:3 91:13 141:17
Items 27:20
iterations 151:6 154:16
iterative 21:18 21:19 38:4,18

J

JAIRAM 3:12 13:9 15:17 16:20 17:20 18:5 20:2 21:1 25:17 27:4 38:20 43:20 44:21 47:5 57:21 60:1,17 61:10 64:17 66:13 67:9 79:21 95:4 99:4 120:7 122:20 125:7 127:20 158:13 169:22 181:13,17 187:12,15
job 114:12 118:9
Johannesburg 68:2
John 83:3,12,16 84:1 85:7,9 86:1,5,7 88:12 102:15,22,22 120:3,5,6 121:7 121:10,16,18

121:19,21 123:10,21 124:1,6
joined 22:21 35:3 101:15
joining 35:4
journal 19:4,5
joystick 49:2
jump 128:14

K

K 3:15 189:3
keep 44:2 108:8 117:22 118:1 123:16 124:9 185:9
keyboard 49:1
KHAN 3:3 4:4 5:8,18,21 8:21 9:16 14:1 16:14 17:11 18:1,19 21:6 26:1,11 27:18 35:3,8 39:1 43:1 44:7 44:12,15 45:6 47:14 58:3 60:11 61:3,20 66:3,16 69:1 80:6,13,18 97:5 100:18 121:1 123:5 126:14 127:21 128:1 155:15 158:11 158:15,19,22 159:4 170:4 181:14 182:11 187:10
kind 10:13 13:7,8 14:21 18:15 21:18 29:10 45:16,18 50:4,7 50:19 52:5 55:5 72:7 95:6,18 97:3 99:8 121:11 126:1 130:7 133:3 138:13 141:10 142:5 144:3,12 144:16 145:22 147:20 150:2 176:12 182:18 185:3
know 5:17,20 6:14 9:1,17 10:22 11:21 12:4,14,20 13:18 14:6,16 16:10 17:7 18:7 18:15,16,17 19:9 20:3,6,7,9 20:15,19 21:13 21:15 24:10,17 25:2,5,9,9,11 26:2,12 27:11 27:15 28:3,12 28:14,17 30:3 30:21 31:18 32:11,17,18,21 34:7,16,19,22 35:1,17 36:9,17 37:9,14,17 38:19 42:9,18 43:15,22 44:18 45:8,17 46:12 46:18 47:7,8,11 47:19 48:3 50:5 50:8 51:10 52:7 55:8 56:2 57:9 59:15,16,19 64:13 65:19 66:8 67:18 68:7 68:11,13 69:8 69:12 70:15,18 71:20 72:1,2,8 72:13,17 73:17 73:17,19 74:6,9 75:14 76:13 77:17 78:13 79:5 80:20 81:19 82:5 83:2 83:8 85:21 86:4 88:5,6,8,16 89:5 90:12 92:14,19 94:8 96:14 97:15 99:10,12,19 100:8,15 101:11,18,21 102:7,8,22 103:2,12,22 104:18 105:1,3 105:3,14,16,18 106:5,22 107:4 107:12,22 108:9 109:1,9 109:14 110:1,2 110:20 111:16 112:2,8,14,22 113:3,5 114:1 114:19 115:15 115:18 116:8 116:16,17,22 117:10,14 118:1,7 119:3 119:19,22 120:2,4 121:8 123:1,2,2,6 125:2,11,12,18 125:22 127:6 130:10 132:6,9 133:4 137:16 138:17 139:19 140:7,7 141:19 142:13 143:11 143:21 144:8 144:11 145:4 146:4,5 147:15 149:8,18,19 150:8,15 151:13,14 153:3,21 154:4 155:4 156:2,17 156:20,21,22 159:9,17 162:12,17,17 162:18 163:6 164:6 167:8,11 169:3,6 174:16 178:14 179:12 179:13 182:21
knowing 68:19 68:20
knowledge 16:13 32:9 35:2 37:2 37:6,6,7,16 40:12 42:7 43:15 46:9,20 47:9 66:10 75:2 141:2 184:21 185:3

L

L.L.C 190:1
lab 28:9
label 17:18 83:5 83:7 86:16 89:22 90:3 114:21
labeled 19:5
labels 49:18 88:12
lack 108:18
language 40:11
languages 25:1,3 25:4
large 28:4 79:13
largest 86:17
late 32:18
lawyer 30:6
layer 118:18 145:6 150:17 150:19 153:20 154:3,14 155:4 157:14,15
layers 96:1 113:15,16 145:12,15 150:16,20 153:19,21 154:2,3,5,6,11 154:17 155:5
laying 53:2
lays 52:4,8
learn 18:10 23:20 119:15 170:16 171:16,19 184:19,20
learned 24:2,3,4 173:14 174:7 176:1 178:1 180:9
learning 10:4 11:11,14,16 18:20 27:3,10 27:11,17 31:10 36:4 37:7 49:19 50:8 51:12 52:12 53:21 59:22 60:5,7,15 60:22 61:8,14 61:21 62:6 66:10 68:12 95:21 107:13 107:15,17 119:10 141:2 142:21 153:22 154:1 165:8,10 165:12,12 171:2,3 172:4 181:9 182:1 184:8,8,18,21 185:5,17 186:6 187:2
learns 17:13 171:8 181:11
left 89:3 109:10 112:18 128:11 167:8 179:1,12 179:12,14 181:7
legal 20:8,18 29:10,18 30:5,7
length 155:20,21 156:1,3 157:5,9
lengths 157:5
let's 12:20 14:13 15:10,22 34:11 36:6 49:14 58:18 60:18,19 64:22 65:4,13 66:22 72:3 75:22 88:14,20 89:13 93:19 94:2 95:7 96:20 97:7 98:18,19

99:22 100:8 102:16 106:1 107:16 109:17 111:21 112:6 113:1,21 115:8 116:19,20 120:13 121:3,5 121:15 122:9 124:22 126:19 132:2 136:16 140:10 146:8 147:6,8 149:21 150:7 155:18 158:5 170:2 171:13 174:5 177:3 179:13 180:3 187:12
level 96:11 158:2 177:20
levels 29:21 30:14 32:8
library 15:14
LiDAR 36:8,9 106:3,5 169:6
Lidars 68:6
life 147:15,15
light 40:17
limited 37:10 123:8
limiter 149:22
line 6:2 48:18,20 54:13,17,18 55:12,18,20,21 56:14 58:18 59:2,9 63:16 64:2 76:1 77:15 77:16,21 84:14 84:15,17 86:14 86:21 88:1 129:15,17 130:10 138:8 140:15,22 141:21,21 142:7 147:9,10 147:13,19 165:1 166:4 168:3 173:16 174:20 175:3,6 175:10,19 180:3 182:22 183:9,13,20,21 184:2,4 191:11
linearly 145:11
lines 58:10 63:3 63:11 64:4 70:2 70:2 71:6,16 73:6 75:5 76:19 76:20 84:11,13 129:16 142:15 147:22 161:17 167:20 176:21 177:19 180:1
link 40:21
Lippmann 152:4
list 19:15,18 27:20 73:4 169:9
listen 169:14 170:18,19 171:1,3,10,12 173:11
little 9:5 13:11 60:12 77:3 84:3 84:6 85:10 88:22 111:5 130:6 141:1 142:11 164:5 166:1 173:4 180:22
LLC 1:8 189:6 190:7 191:1,8
load 176:8 179:2 179:15 182:9
loaded 179:10,19 182:2
loading 9:1 175:9 175:20 178:13 178:16,18,19
loads 176:19
locate 12:17
located 88:7
location 75:20 90:4 99:18
locations 69:20 71:11 72:12 76:12,14 89:4,8 119:22 120:5 122:2
logical 156:14
long 25:6 44:6,22 54:15 115:6 148:8,13
longer 9:6 22:8 126:11,12
longest 22:5
look 10:8 16:22 19:4 22:11 40:14 45:2 48:10 49:14,15 54:2,12,13 55:4 55:10,17 56:8 58:17 60:19,20 61:12 64:20 70:1 71:20 75:21,22 81:8 82:9 83:8 84:5 84:9 86:12,14 86:20 91:13 95:10 96:20 100:2 107:8 125:11 138:7 140:21 144:1 149:16 158:3 164:7,11 175:6 175:19 179:22 179:22 182:21 183:9 186:20
looked 41:5,6,7,7 41:8,17 42:3,4 101:14 125:11
looking 11:7,19 11:20 13:11 14:21 15:6,19 17:2 64:11 84:20 86:13 100:3 108:12 109:17 111:22 112:12 114:4 122:4 130:15 130:19 151:3 174:10
looks 12:13 15:4 81:11
loss 108:1
lot 13:13 19:12 24:8,10 33:6 36:19 37:5 74:13 95:6 108:16 118:20 135:1
lunch 6:18,19 127:15
lunchtime 127:12 128:3

M

M 1:21 190:2 191:2
machine 10:4 11:10,13,16 15:10,11 18:20 27:3,9,11,17 31:10 36:4 37:7 46:10 48:7,12 48:22 53:21 56:18,18 59:22 60:5,6 68:12 95:21 104:18 107:12,14 141:1 178:2
Magazine 152:5
Main 3:6
making 5:11 37:8 72:3 74:6,19 141:3
manage 148:2 154:19
manager 34:18
manipulating 142:1
manipulations 56:17,22 58:21 59:10 63:6 64:9 70:5 73:15,17 74:1
manner 11:5 168:8
map 66:9 67:2,21
mapping 67:7
maps 67:4 125:22 126:2
Maps' 127:3
mark 43:16 80:8 158:7 187:4
marked 8:17,19 9:14 159:2
marriage 188:12
Maryland 2:11 188:1,5
master's 31:12 32:13,17
match 13:3 15:7 16:4 131:16,19 131:22 132:14 133:7,8,21 134:4,8,9,18,19 135:2,20 137:8
matched 99:2
matches 16:11 85:6 97:11 133:9
matching 15:8 18:8 134:16,22
math 119:11
mathematical 142:8
mathematically 145:13,13
mathematics 119:9,13 158:2
MATLAB 24:5,8 24:14 25:15,19
Matt 5:18
matter 188:8,13 189:10
Matthew 1:19 2:9 35:3 188:4 188:22
MCCOMMAS 3:13
McCulloch 144:7 144:8 151:18
McKOOL 3:14 189:2
mean 11:17,18

15:19 17:21,22 18:6 20:3 25:3 27:16 33:5 36:5 39:6,7 41:5,10 42:1 46:10 47:8 47:19 48:9 51:9 51:20 53:1 54:9 60:4 61:11 62:10 63:14 64:16,18,22 75:3,21 77:2 79:6,14 83:4,6 87:17 91:12 92:1,12 93:10 93:16,19 98:6 99:5 100:16 103:7,19 105:12,13 106:1 107:11 109:12 115:4 115:17,21 119:16 126:3 127:6 134:10 135:7 140:11 143:19 149:8 156:2,12 157:1 161:8 162:20 164:19 165:3 165:17 166:15 169:2 170:5 175:1,4,19 179:21 182:15 184:6 185:9
meaning 39:17 40:9
means 58:6,12 70:17 74:19 113:6 146:21 157:13 166:22
measure 156:4,8
measurements 118:7
measuring 156:4
medical 110:17
medicine 7:18
meeting 21:17
meetings 20:12
memories 78:9
memory 11:20 11:22 33:10 46:11 52:8 69:20 71:11 72:12 75:19 76:13 119:22 120:5 121:9,10 122:2,9,14,16 122:22 123:1 124:17 149:17
mention 43:7
mentioned 13:4 21:22 30:10 33:4,14 35:9 38:17 41:18 42:6 47:6 53:8 56:2 57:18 63:10 66:6 70:2 94:15 99:13 105:4,4 108:22 114:17 138:12 143:5 149:8 164:20 184:15 186:3
mentions 142:19
mentored 34:22
metadata-type 18:15
meter 156:7 172:8,10 173:3
meters 81:12 90:1 137:18,19 138:19
method 63:19 64:14 131:2
methodology 28:2
methods 63:7 64:9 69:5 70:5 71:5 73:10,15 75:7 140:5 142:21 174:20
microphone 55:8
mimic 144:4,16
mind 128:10
mine 35:5
minute 139:9 155:6,8,10 164:12
minutes 6:1 43:18,21 90:22 158:8,11
mistake 48:18
mistaken 36:1
misunderstand... 181:20
mixed 46:20 182:3 185:3
mixing 95:3,5
mode 168:6,17 169:14,14,15 169:15 170:11 170:11,18,19 171:1,1,3,6,11 171:12 172:1 173:9,10,11,14 173:16,21 178:19
model 140:8,8,8 140:8 142:14 142:19,20 144:16 147:12 149:2 153:16 155:18,19 157:3,3,4,12
modeling 146:22
models 140:5,13 144:14 149:11 151:8,10 155:17
modes 169:1,13 169:21,21
modification 55:15,16,19 56:6,10,15 57:4 57:6,15 58:7,19 59:3,7,14 63:1 63:2,4 65:9 69:4,18 70:3 71:4 72:2,5 73:9 76:22 77:1
modified 57:20 89:18
modify 56:16,21 58:14,20 59:9 59:18 63:6 64:8 66:10 70:4 72:15 73:5 104:1 126:21
modifying 56:11 57:16 58:8,15 65:17 75:7,9 76:3
moment 26:7 161:11
moments 27:1
monitoring 109:4
MONTGOME... 188:3
morning 5:9,10
motions 89:9
motivation 183:6
mouse 49:2
mouth 99:18
move 37:18 62:22 85:16 154:16 178:22 183:8
moving 44:2 85:17 106:8 126:17 159:21 167:6
MS/Ph.D 34:3,5
mug 112:9 113:2
multi-object 13:18
multi-resolution 28:3
multimodal 106:4
multiple 12:18 12:22 20:11 33:8,10 74:2 93:1,9 96:1 101:1,3 150:15 150:19 175:12 177:22 180:9 183:8 185:2,2
multiplication 24:18
Murat 23:12
mute 139:10

N

n 3:1 4:1,1 5:1 162:5,11,21 163:14,21
N1s 166:21
name 158:3 190:8 191:9
named 19:11 21:12
names 144:13
Nashville 132:18 133:1 134:14 134:21 136:16 136:19 137:12
nature 147:16,17 148:14
navigate 183:2
navigating 178:20
near-realtime 37:11
necessary 36:4
need 5:16 13:13 13:19 36:19 37:1,5,7 53:17 53:20 68:14 88:8 100:13 108:15 114:13 118:12 121:10 124:15 137:16 138:15,20 146:6 147:10 151:5,6,6 153:9 154:15 155:3 158:4 172:7
needed 6:19 21:21 75:12 78:22 79:2,9 80:5 157:17
needs 20:19 37:15 78:15 79:9 104:14
neighborhood 125:21

neighboring 17:2
net 107:13 147:10 155:3 156:21
nets 95:22 141:8 144:12,21 145:4,5 146:15 148:3 151:13 152:7
network 95:20 97:19,22 108:4 108:5 113:6,6,7 113:14,17 117:11,18 118:5,6,11,18 141:4 143:2,3 144:3 145:12 148:15,18 150:15 153:10 157:13
networks 28:12 143:9,10,17,18 146:21 149:7 149:10,11,13 154:4
neural 28:12 95:20,22 97:19 97:22 107:13 141:8 143:1,2 143:10,18 144:3,12,21 145:4,5 146:15 146:21 147:10 148:3 149:7,11 149:13 151:12 152:7 155:3 156:20
neuron 149:14,15 149:15,19 150:3,18 151:14 161:22
neurons 141:5,9 145:16,19 146:1,14 148:5 148:6 151:9 153:11,20
never 26:20 67:20 68:3,4 113:8 114:7 118:5 135:2 179:3
new 65:20 66:8 67:8 122:12,19 123:15,17 125:17,21 126:19 128:20 128:21 131:5,9 132:4,10 136:17,18,21 137:2
newly 179:19
Nice 152:8
Nicholas 3:4 35:4
node 13:2 14:8 14:13 18:12,13 140:16,18 141:15 142:3 150:4 151:16 152:17,18,19 152:20,21 153:1 156:6,7 156:15,18,18 157:14,14
nodes 14:9 113:16 117:17 140:10,11,20 141:4,7,10 144:15 145:6,7 145:8 151:8 152:11 155:4,5 155:18 156:17 156:19 157:7
noise 139:10 149:1
nonlinear 145:9 145:15,18,22 146:10,15 147:16,17 149:10,10
nonlinear-type 145:21
nonlinearities 149:9
nonlinearity 146:2,18,22 148:1,3,7,19 150:10,13,14 150:21 151:17 154:7
normalization 101:4 118:16
normalizations 101:8
normalizing 118:18
nose 99:18
Notary 2:10 188:4 190:22
note 82:4
noted 43:3 71:6 71:16 190:16
notice 2:9 6:1 22:12
noticing 189:13
noting 189:13
NSF 23:13
number 28:8,9 88:2 153:20,20 162:4 167:1
NW 1:21 3:15 189:3 190:2 191:2

O

O 4:1 5:1
o'clock 5:13 44:6
oath 7:8,10,11
object 10:19 13:1 13:3 14:3,5,7,8 14:12,14,17,21 17:14 54:20 55:2,6,9,11,13 62:19 81:10,11 82:19,21 83:10 83:11,12,14,18 83:22 85:5,6,9 85:12,12,13,14 85:14,19 86:3 86:10,15,17,19 86:21 87:1,7,11 87:14,18,18 88:2,4,9,11,13 88:19 89:17,17 89:21 90:2,17 90:20 91:3,9,14 100:21 103:9 106:8,11,18 126:12 128:20 128:22 129:9 129:10,18,19 129:21 130:7,8 130:11,12,12 130:13,14,17 130:18,19,20 131:10 132:3,5 132:13,20,22 133:7,10,11,13 133:18 134:1,5 134:6,9,18 135:10,11,12 135:22 136:22 137:1,3 140:16 141:16,19 161:3,9,14,20
Objection 13:9 15:17 16:20 17:20 18:5 20:2 27:4 44:21 47:5 57:21,22 60:1 60:17 61:10 64:17 66:13 67:9,10 79:21 95:4 99:4 120:7 122:20,21 125:7,8 169:22 181:13,17,18
objective 115:5,5
objects 13:20 82:17,18 85:16 87:6,11,13 89:15 90:8 93:12,15 101:22 103:2 105:7,11,13 132:13,14 133:10,16 160:9
obstacle 171:20 178:22
obtain 9:22 105:22
obtained 33:21 100:19 119:21 160:7
obvious 31:21 32:14
obviously 23:2 28:11 30:6 31:11,18 32:2 32:17 34:2,22 36:13,21 37:20 38:1 39:4 40:9 40:18 42:1 43:13 45:1,14 46:8 47:9 62:16 63:15 64:19 65:9 67:12 68:11 75:13 77:2 78:8 79:8 79:15 83:13 84:16,21 85:11 86:2 87:17,22 88:19 90:7 92:4 93:4,11,21 95:10 97:15 99:12 100:16 101:11 103:8 104:1 109:11 112:5 118:11 124:7 127:7,9 129:12 130:7 131:20 133:3 137:20 138:8 138:12 140:19 145:17 149:18 153:13 165:3 165:18 169:7 177:17 179:4 184:16 185:15
Occasionally 35:14,15
occur 59:21
offered 40:1
offers 165:13
office 1:1 20:18

21:7,10 189:11 189:15
offsets 141:12 148:6 152:19
oh 23:22,22 131:6 143:13 159:16
okay 7:5 8:11 9:5 9:21 18:9 21:22 25:21 29:6 53:9 53:10 61:4 62:22 64:6 65:11 80:7,13 80:14 91:2 94:12 95:14 104:3 115:3,22 117:22 118:5 121:9 123:20 123:22 126:15 127:12,20 129:4 136:5,13 136:17 142:12 151:4 152:10 155:1,6,8,10,13 157:11 158:5 158:10,19 159:13 162:22 163:10 164:2 165:14 167:16 167:19 168:11 169:13 170:8 170:15 176:17 177:2 179:6 180:17,21 187:3,8,12
old 123:17 132:5 132:8
older 24:3 101:12
once 15:9 17:12 19:9 35:17 89:20 110:15 116:5 173:12 178:4
one-hour 43:16 80:7 187:4
one-to-one 13:8
ones 19:5 20:6 25:12 27:2 34:7 117:4 165:15
onwards 129:16 142:15
open 9:9,18,19 44:18,19 95:12 96:7 97:1,2,12 97:14 100:11 102:13,20 103:1 110:13 110:15 159:7 159:10,13
open-ended 67:16 68:18
operate 36:13 184:20
operating 56:18 91:17 92:3 103:16 184:7 184:17,19 185:2,16 186:6 187:1
operation 49:20 50:10 51:1,13 61:1,16,17 107:10 138:22 143:1 163:4 175:7,8,16 176:18 177:11 178:2 181:20
operations 62:3 138:2,10,13 139:7
opinion 40:15,16 41:13
opinions 82:6
opposing 6:8 38:16
option 178:6 189:12,12
oranges 155:3
order 175:11
ordinary 29:1,4 29:19,19 31:3 32:10 39:16
organization 103:12 120:18 121:3
organize 109:11
organized 24:19 120:18
orientation 16:17
original 119:15 149:6 189:13
outcome 188:13
output 37:14 142:5 148:10 150:3 163:21 163:21
outputs 165:22 166:14
outside 99:14 100:4
overall 48:4 50:4 50:5,19 72:8
overfits 148:21
overfitting 148:22 149:3
override 169:14 171:6,11 172:1 172:2,6,11,15 172:17,20,22 173:14,16
overshoot 66:1
oversimplified 108:20
oversimplifying 108:17
overview 45:15 45:16 152:6
overwriting 76:8 76:21
owner 1:9 3:11 41:9

P

P 3:1,1 5:1
P.C 3:5,14 189:2
p.m 187:18
paces 34:10
package 141:11
Packard 33:11
page 4:2,7 19:14 27:20 29:11 30:19 64:3 189:13 190:6 191:11
pages 190:12
paper 144:9 152:4
papers 19:4,5,7 19:12 20:13 144:10 152:3
parabola 146:5,6 146:7,9
paragraph 28:19 28:21,22 29:9 29:17 30:9,20 30:22 39:10,15 40:7,14 43:3 168:2
paragraphs 41:22 42:12,17 42:22 43:5,12 43:14
parameter 117:16
parameters 58:22 59:11,13 59:19 108:5 113:14 117:18 117:20 153:8 153:12,14
pardon 108:18
parent 14:13
part 11:10 18:21 19:1 22:5 25:8 41:12 67:4 73:12 75:11,18 76:22 86:10 98:21 99:17 100:20,20 103:21,22 104:1,16 105:5 106:13 111:5 119:5,6,7,8 151:15 162:7
part-time 22:13 23:8,9
partial 131:16,19 131:22 132:1 132:14 133:7,8 133:21 134:8,9 134:16 135:20 137:8
particular 10:19 14:17 15:7 16:10,11 29:12 30:21 38:10,11 42:8 50:21 52:14 53:16 75:16 76:15 83:6 88:9 98:17 98:22 102:16 102:18 104:10 104:21 110:8 119:6 129:15 130:20 145:19 146:22 147:18 155:17
parties 188:11
partners 33:11
party 21:5
passenger 65:6 66:7
paste 150:11,13 153:9,13 176:14
patent 1:1,3,9,12 3:11 4:9,11 7:1 7:4,4 8:7 19:15 20:18,21,22 21:11 27:20 39:20 40:17,19 41:6,10 42:5 43:13 44:17,20 44:22 45:2,3,10 45:20 46:2,16 48:10,10,11 49:9,15,15,16 50:21 54:2 55:18 57:3 71:1 71:3 73:7,8,13 74:19,21 77:15 79:11,13 80:20 81:6,18,18 82:1 82:5 83:10,21 90:11 93:7

128:8 139:18 140:3
patents 19:15 20:1,6,9 27:2 37:21 42:4
path 183:3
pattern 141:3
paying 139:2
peaks 146:11
peek 27:5
people 13:16,18 32:5,7 96:4 110:4 113:12 114:6 122:2 141:8,9 144:1 147:21 149:18
people's 11:21
percent 100:17 109:17,18,19 110:19 113:13 118:3,9,10 124:5,14 172:4
Perceptron 151:20
perfect 100:17 126:4 147:9 158:18
perfectly 7:6 147:13
perform 56:16 56:21 58:21 59:10 63:6 64:8 70:4 73:5,6,16 73:22 75:13 93:10 94:21 107:10 113:8 133:2 136:5 169:20
performed 76:22 83:22 94:18 138:10
performing 73:9 73:11,14 75:6 93:8 138:2 184:1
performs 85:5 93:14
period 22:9 23:1 189:14
person 28:22 29:4,19 31:3 32:10 59:15 65:14 82:21 83:3,12,15,16 84:1,21 85:8,18 85:20 86:1 93:18 95:2 96:21 97:21 98:1,4,12 100:7 100:10,11 102:18,19 104:11 105:16 106:14,16,16 106:21 107:2 113:21 115:6,7 115:9 132:16 134:11,13,16 134:20 136:11 136:13,14,18 136:19 137:6 137:13 138:18 139:3
personnel 23:18
persons 29:22
perspective 143:9
peruses 42:19
petition 35:22 37:21
petitioner 1:6 3:2 5:7 26:3,13 35:6
Ph.D 1:14 2:1 4:2 4:14 5:3 10:1,3 18:22 19:1,8,10 25:13 35:18 119:4,14 189:1 189:8 190:8 191:9
phone 139:15
physical 156:3,13 156:20,21
pick 50:12 68:2 115:11 119:14 123:11
picks 115:14
picture 13:6 14:17 84:10 98:4 101:6,13 112:5 125:12 127:4
pictures 88:17 95:14,15,18 97:17 112:1,4 113:11,21 114:17,20 115:7 116:1,1 117:3,6 120:15 123:10,11,21 123:22 125:19 126:1
piece 12:4,5,6 47:12 50:11,13
pieces 14:12 27:15 48:6 50:7 53:15,17,19 54:1,5 62:17 67:18 68:20 79:17,18,19,20 88:8 119:11 139:6
Pitts 144:8 151:19
pixel 16:17 111:11 112:7 160:8,20
pixels 162:19
place 22:4,8 24:13,14 84:7 96:13 103:3 104:13 176:9 177:14 186:9
places 47:12
plane 17:9,10 112:17,19,21
plastic 99:19
platform 165:7 177:21,22
please 5:17,19 9:10 25:19 26:8 28:16 44:18 45:7 80:21 82:4 90:11,12 108:21 139:13 139:17,20 159:9,17 167:11 170:7,7 174:15 186:8 189:10,12,13 189:14
plurality 180:7
plus 147:11 150:8 157:15 180:4 183:18
point 6:12 46:7 64:2 68:1 79:11 109:16 114:5 146:7 161:16 163:5 182:12 182:19 185:21 186:7,9,14
pointed 56:1 58:6 58:11 63:2 85:4 162:10 185:6
pointing 49:2 75:3
points 147:8,9
portion 99:14 129:20,21 147:20
portions 135:6
portrayed 185:12
ports 52:7
POSA 30:22
POSITA 29:5,8 29:10,11,16,18 30:8,11,13,18 30:21 31:13,21 32:15 33:14 35:20 36:4 39:18 40:12
possible 77:9 110:21
possibly 77:9 110:21
potential 108:4
potentially 65:6 107:4 125:10 165:12
practitioners 32:7
precise 60:18 61:2 82:7,10
precision 113:22
predicting 174:11
prediction 173:20 174:1,2 174:6,12
predictor 162:8 164:14 165:6,9 183:14
predicts 174:4
premises 109:4
prescribes 175:4
present 10:16
pressing 180:4
presumably 121:4 163:3
pretty 9:1,7 79:13 152:6 154:13
prevent 7:19 8:2
previous 71:10 138:12 176:16
previously 76:6 175:9 176:19
primary 25:12 36:10
principal 124:12
prior 16:13 30:2 37:21 172:4 175:21 176:11
priorities 183:14 183:15,17
privileged 38:21
probably 13:21 21:15 25:9 26:20 36:9 46:12 47:18 48:6 54:10 73:20 135:2 152:3 170:9 175:5
problem 124:19

124:19 128:12 139:14 150:22 154:20
problems 30:1,2 30:15,17
procedure 63:20 64:14 189:14
procedures 63:7 64:9 69:5 70:6 71:5 73:15 75:7
proceed 139:4
proceeding 6:22 7:16 159:8
proceedings 39:20 188:7,9
process 8:16 21:19 38:16 39:22 68:9 72:20 108:6 119:6,8 124:16 165:8,11 182:1 184:8,18 185:5 185:17 186:6 187:1,2
processed 87:9 184:5
processing 31:10 36:3 37:1 45:22 50:17,20 52:3 54:20 55:2,7,9 55:11,13 62:19 68:14 78:9 86:15,17,21 144:17 152:5 174:5
processor 46:14 52:8 56:13 76:5
professional 23:20
professionals 32:4 34:8
Professor 23:12 33:2
profiles 95:15 115:22
program 56:12 57:17,19 58:10 58:16 59:12,19 63:9,20 64:10 64:15 65:1,3,5 69:6,19,21 70:7 71:7,12 72:6,11 73:10 75:9,11 75:15,19,20 76:4 77:9
programmed 75:14
programming 72:8
programs 57:5 69:12,16 73:3 78:2,7,10,18,19 79:7,16 80:3,4
progressed 152:1
propagate 108:3 154:9,11
propagated 184:22
propagation 119:12
proper 18:15 36:15 59:20 73:2 78:21,21 83:14 133:2
properly 36:13 118:11 178:6
properties 130:12,13,19
proposed 53:5
prosecute 20:20
prosecution 19:22 20:4 40:11,19 41:3,6 41:13 42:6,13 42:21 43:4,8,12
protocol 98:8
provide 12:11 14:22 20:9 21:20 38:2 40:15 45:22 68:10 72:17 73:2 92:20 96:4 104:12 105:2 107:18 108:7 109:19 165:20 165:22 172:6 172:16,19,20
provided 16:3 29:14 30:7 162:8,22 171:13 173:13
provides 28:1 45:3,14,16 50:17 52:1 53:15,17 55:5 81:13 103:11 159:22
providing 20:5 37:14 52:16 74:8,22 103:13 104:15 180:7 183:22
prune 125:10,14 126:6
pruning 123:9
Public 2:10 188:4
publications 19:16
published 19:2,7 20:14 144:9 152:9
purchased 189:11
purpose 56:22
purposes 7:3 29:3 111:10 163:1,4
Pursuant 2:9
put 9:11 11:3 16:4 18:13 20:13 65:12,18 67:19 68:2,3 75:14 109:13 118:6 120:13 121:20 148:6
putting 65:20 85:3 177:14
pyramid 28:5

Q

quantify 108:2
queries 13:20
query 10:10 11:4
question 29:15 38:8 52:17,17 52:19 57:14 60:3,10 61:4,5 61:13,19 62:4,4 62:8 64:19 66:15 67:13,17 68:18 69:8 71:10,14,18 81:16 84:8 93:3 104:4,20 105:8 130:4 133:12 143:11,14,16 143:17 147:3 149:6 160:12 160:13 170:6,9 186:8
questioning 6:2
questions 7:19 8:2 9:21 21:15 21:20 68:21 74:15 81:19 108:19 142:12 145:1 187:10 187:15 189:14 190:15,17
quickly 59:16
quite 107:11 170:1

R

R 3:1 5:1 23:11 33:2
Ram 26:19
ramp 102:19
randomly 116:18 118:15
rapidity 30:3
rarely 147:14
re-creates 144:3
reaches 181:15
reaction 132:18
read 20:13 37:21 38:6 48:17 54:16 56:2 77:20 81:14,18 82:5 136:4 138:9 171:5 182:15 185:17 185:18 186:4,4 186:19,19,20 190:11
readily 69:16
reading 48:20 59:8 63:21 64:3 81:22 130:8 179:7 185:14
ready 117:22 189:10
real 147:14,15
really 24:14 58:6 69:9 71:21 74:7 107:21 115:4 119:18 124:2 151:13,15 172:7
realtime 36:21 68:10,14 69:14
realtime-type 37:11
reason 26:17
recall 42:14,15
receive 21:16 91:10 92:2,20 132:4 166:13 166:15
received 9:4,8 32:13,16 102:5 102:6 103:18 104:6
receiving 70:11 90:16 91:8,16 91:21 103:14 103:15 128:20 130:22 131:3,4 131:9 136:21
Recess 26:10 44:14 80:17 127:22 155:12 159:1 187:9,14
recitation 185:13
recited 186:3

recites 185:22 186:10,15
recognition 83:14,16,18,22 84:10,15,18 85:1,5,13,19,22 86:6 93:20 94:1 94:16,17,21 96:15,22 97:22 99:8,8,22 102:12 106:18 111:22 141:3 161:3,9,15,20
recognitions 84:17
recognize 18:7 83:15 84:21 85:11,15 97:19 100:6,10 115:6 125:13 134:16
recognized 83:11 86:9 137:5
recognizing 85:20 86:5 94:6 124:6 155:2
reconvene 158:17
record 16:5,7 26:10 35:7 41:1 44:14 80:17 127:22 155:12 159:1 187:9,13 187:14,17,18 188:9
recorded 109:5 190:15,18
records 67:8 85:7
red 12:1,21 18:9 18:17
redundancy 124:15
redundant 124:2 124:8,14
refer 7:3 25:18 28:22 29:4 53:9 83:5,7 141:9,9 174:2
reference 141:17 158:6 159:6 164:6 173:18
referenced 189:10
referencing 71:11 73:6
referred 83:19 103:5 141:5 143:2
referring 27:19 27:22 28:1 53:21 54:3 77:22 86:14 99:15 132:1 142:17 161:5 161:10 162:11 174:3 184:13
refers 84:13 140:18
reflect 67:8
regarding 6:13
regardless 137:13
region 17:1
regions 12:18,22 13:14 15:6,6 16:1,1,4,11 17:2,4 18:7
regular 12:16 69:12 127:11
regularization 117:15,16
relatable 94:13
related 21:15 27:3 85:7 97:9 188:10
relates 7:1
relation 107:5 137:21
relationship 40:20 152:13 152:14 157:7
relevant 40:13 125:13
rely 67:22 68:5
remain 126:7
remaining 19:12
remember 11:22 31:16 41:15,17
remote 49:3
remotely 1:15 2:2
removal 180:9
remove 100:13 122:18 123:11 124:3,8,13 175:12,17 178:1
repeat 29:15 62:4
rephrase 122:13 186:12
replicate 150:4
reported 1:19 188:7
reporter 25:20
represent 35:6 140:20
representation 14:7 87:14,19 88:4,11,13 90:2 90:7 103:9 130:13,14 132:5 134:18 136:22 137:3 141:2
representations 86:11,19 87:1,7 87:12 88:2 89:18,21 90:17 90:20 91:4,9,14 100:21 106:9 106:11 128:21 129:1,10,11,18 129:19,21 130:11 131:10 133:10,11,18 134:2,5,6 136:1
representative 23:15
request 5:22
require 99:19
required 13:5
research 10:3,8 22:15,18 23:11 24:9 32:20 119:15 144:5
resolution 113:22 169:4
respect 105:3
response 62:1,1 135:19 138:11
responses 21:11 21:16 147:17
responsibilities 22:16,19
rest 123:12
restart 178:10
result 92:10,14 94:22
results 116:8
retrain 111:4 180:21 182:6,7
retraining 125:17
reveal 21:2 38:21
review 38:5 189:11
reviewed 161:6
rewriting 76:9,21
RGB 112:6,7 160:19
Richardson 3:5 35:6
ridges 84:12
right 8:16 19:16 19:20 29:1 30:12 33:10 53:15,15 67:2,5 67:5 68:15 70:20,21 71:2,6 75:3 82:19 85:9 87:16 89:3 90:5 92:11 95:2 96:7 98:8 99:11 101:12,18 106:13 109:18 112:18 116:10 117:20 118:1 120:3 121:7 125:14 126:15 127:14 129:6 133:11,18 134:7 135:6 142:14 147:2 147:12 151:9 151:10 152:15 153:18 154:2 154:21 156:5 156:17 160:4 161:12 162:8 163:2 166:10 166:14 167:3,7 167:19 168:13 169:1 171:4 175:18 176:3 176:20 177:20 178:7,17 179:1 179:17,18,20 180:16 181:8 181:12,16 184:14
RIT 22:10,17,20 33:3 35:19 101:15 111:15 114:14 119:4
RMR 1:19 2:10 188:22
road 66:8,9,10,18 67:1,3,8,19,20 67:21 68:4,20 125:2,2 127:4
robot 159:20 168:4,13,15,20 168:21,21 169:3,20,20 170:3,19 171:2 171:6,14,14 172:2,12,12,21 173:1,13,21 174:5,10 175:18,22 177:6,7 178:5 178:12,16,18 178:19,20 179:9,16,17 180:11 181:6,6 181:8,10,11,21

182:1,2,5,6,7,9 182:10,14,20 183:2,7 184:11 184:14,22 185:12 186:16
robotic 165:7
robots 174:21 181:4 182:3 185:2
Rochester 22:13 22:14 23:8,9 33:1 136:17,18 137:11
rocked 65:7
rocking 65:14
role 164:3
roll 102:18
root 13:2 14:8,13 18:12,13
rotations 17:7,9 17:10 112:16 112:19,20 114:1
roughly 140:22
routine 64:15
routines 63:7 69:5 70:6 73:16 75:8
Rules 189:14
run 74:4 97:22 106:15
running 59:15 122:14
runtime 56:17

S

S 3:1 4:1,6 5:1
Saber 1:14 2:1 4:2,13,16 5:3 25:18 26:2 35:9 43:20 44:16 80:19 115:12 128:2 189:1,8 190:8 191:9
safety 177:14
samples 116:18
satisfactory 108:11
saved 175:9,20 176:19
saw 120:3
saying 62:2 95:7 121:2 135:17 169:3 178:3
says 14:8 40:15 45:21 54:9 56:9 60:20 64:7 76:19 79:4,11 79:15 83:10 86:7 90:15 91:12,13,16 98:13 102:13 103:14,15 115:14 129:5 138:9 141:15 161:19 162:20 164:8 166:5 167:8 174:20 179:12 180:2 182:13,19 184:12
scalability 18:4
scale 17:6 160:20
scales 95:17 97:18
scan 97:11
scene 14:15
scheme 183:18
science 25:8 31:7 33:16 34:20 126:4
scientist 34:17
scope 57:22 67:10 120:7 122:21 125:8 181:18
search 10:19 11:4 12:6 16:2 16:12 18:10
searching 12:9 15:5 79:14
seat 44:11 158:20 187:6
second 9:3 27:6 28:20 37:5 40:8 48:20 139:11 139:21 164:21 181:11 182:2 182:10 184:22
second-year 119:3
section 63:22 81:15 129:13 138:9 142:10 142:13,15 161:4,10
sections 185:6
security 94:15 95:1 100:12,12 109:3 110:14 110:14
sedan 12:13
see 8:22 9:2 19:2 19:11 26:22 29:9,17 39:14 40:7 42:20 45:1 48:16 53:14 54:14,22 58:18 59:15 62:17 64:7 69:22 70:1 73:18 76:2,18 77:10,13 80:14 81:9 85:2 86:11 86:16 88:11 89:12 90:18 91:2,4,19 94:3 96:19 97:6 98:11,16 100:9 102:2 104:10 114:7 116:3,7 118:22 123:13 124:22 125:18 127:4,4 129:2 130:2,18 131:1 132:15,16,22 135:15,18 136:3 140:12 140:14,22 146:20 147:4 151:4 152:2 155:16 156:9 157:2,20 158:5 161:13 163:12 163:13,19,22 165:14 166:1,6 166:19,21,21 167:16,20 168:9,19 169:11,16 170:10 171:18 171:20,21 173:12 174:8 175:10,15 176:6 177:18 178:11 180:2 181:3 183:10 185:10
seeing 9:7 68:20 70:11 74:14 174:4
seen 67:20 68:4 113:8 118:6,12
sees 173:2 174:6 178:20,22
segment 12:14,16 12:19,21 14:4
segmentation 13:4,12 27:8,13
segmentations 12:15 13:17,18
segmented 15:21 136:22
segments 13:6 76:10
select 74:3 123:14
selected 189:12
selecting 118:15
selectively 178:1
send 125:22
senior 34:17
sense 10:14 11:12 13:3 14:5 16:7 17:5 18:11 31:13 42:2 50:5 52:6,8 69:14 74:4 78:12 101:20 103:3 133:4 141:20 174:10 181:22
sensor 105:21 106:3 159:21 160:3,7,10
sensors 36:7,8,10 55:6,7 62:20 67:22 68:6,9,14 106:6
sensory 162:7 183:11,16
sentence 39:15 40:8 70:21 77:20 78:3 79:2 167:20
separate 12:17 13:14 76:10
sequence 108:7
series 10:21 135:8 145:6,7 158:1
serves 33:10
set 15:1 92:8 97:10 98:6 101:20 102:13 102:21 103:2,8 103:17 107:13 107:18 121:15 188:14
sets 73:12 75:10 75:17 91:17 92:2,5,6,6,10 92:14,21,21 94:7 98:15 102:3,4,6 103:11,16,20 104:5,10,13 105:5,6,10,14 105:19,20 106:6,10,11,20 109:7 135:21 136:8 138:2,3
setting 42:8
settings 24:7
seven 42:17
shady 101:7
shallow 154:4

shape 10:10,20 11:13,13,15 12:10,12,17 14:22 15:3,7,8 15:12 16:3,5,15 16:18,22 17:5 17:13,14,18 94:6 111:11 130:15,16,17
shaped 15:4
shapes 130:18
sharp 5:12
shave 99:11
sheet 189:13 190:16 191:6
short 11:9 43:17 158:8
shot 112:2,3
shots 112:9 113:2
show 10:17 24:12 95:12 106:16 145:12 148:11 148:12
showed 12:3
showing 140:2,6 157:4,4 165:19
shown 87:8,14 89:15 91:10 113:7 145:13
shows 81:13 126:2 140:9 159:20 162:4
sic 83:10
side 89:3,3 105:18 114:19
sigmoid 142:3 149:21
sign 38:7 66:18 158:4 189:11 189:11
signal 152:5,5
signature 189:10 189:13 190:6 190:19 191:22
signed 189:13
signify 184:3
signing 189:12
similar 28:2 31:7 33:17 35:21 91:10 130:18 130:21 132:13 141:6 143:5 164:7
Similarly 180:7
simple 120:19 121:22 122:5 153:3,16
simplification 133:5
simplified 97:3 97:16
simplistic 74:8 136:9
Sincerely 189:18
single 15:20,20 42:12 46:8,9,21 47:10 70:9,10 135:9,16 149:15
sir 45:11 66:15 119:1 139:22 143:12 147:3 167:15
sit 20:11
sitting 41:16 65:7 66:7
situation 36:21 77:8,10 106:19 108:12 134:19 137:10 139:8 147:1 181:5
situations 37:11 94:15 109:3,7 124:14 125:5 134:10
six 23:3 113:21
size 88:6 111:12
sizes 89:10
skill 29:1,4,19,20 31:3 32:10
skin 11:21
sky 11:22
slightly 95:16 115:10
slow 65:4,13 106:21 133:3 171:19 173:2 178:22
slowed 65:14
slower 65:12,12
slowing 65:1,5 66:1 107:4 138:21,22
slowly 138:22
slows 173:2
small 77:5 147:19
smaller 117:15 154:12,13
SMITH 3:14 189:2
snapshot 96:20
software 46:14 57:8,11 64:20 71:20 72:6,8 75:14,16 78:10 78:21 177:21 177:21
solemn 7:11
solutions 30:2
somebody 23:14 96:6 98:9 126:8
somewhat 94:13
soon 9:1,7 154:13
sophistication 30:4
sorry 14:18 25:4 26:7 27:22 31:14 39:6 47:2 48:17 49:12 51:4 55:9 69:17 82:17 91:6 92:16 98:19 103:14 105:8 122:13 133:17 139:13 143:13 143:16 155:6 155:18,21 159:16 162:14 164:17 170:5 173:19 178:7 178:14 179:6 186:12,12
sort 100:15 107:9 116:6 127:2 128:11 149:22 152:13 166:22
sound 43:18
sounds 43:19 114:15
South 68:3
space 109:10 122:10 124:18 145:19,20 146:18 148:7 148:19
spatial 89:4
speak 34:12 92:8 182:8
speaking 64:21 64:21 88:22 103:7 105:12 165:17
speaks 142:13
spec 56:1,3
specific 27:2 47:7 50:11 72:1 74:3 161:9 162:19
specifically 38:9 57:14 61:6 69:9 71:19 79:4 162:5
specification 40:11 41:7 185:19 186:20
specifications 40:18 42:5
specifics 161:12
specified 30:16 43:6 152:15
specs 40:22
speed 124:16 181:1
speeding 172:14
spell 25:19
spiking 161:21
spill 35:16
spinal 110:18
spring 119:7
square 74:10
squared 24:17 146:5,8,8
ss 188:2
start 5:15 37:17 84:7 113:1 114:2 163:11 174:8 176:4 177:12 180:18 182:21
started 19:10 22:10,20 25:7 32:21 33:3
starting 54:13,17 55:12,18,20 56:14 58:18 62:11 63:15 77:20 84:9 86:13,21 129:14 138:7 141:21 165:1 167:20 173:7 173:16 175:2 183:4,9
starts 54:2,16 55:11 63:15 140:22 154:11 173:2
state 2:10 131:9 131:11 168:4 168:15 176:11 188:1,5
statement 75:4 78:17 107:9 147:3
statements 74:20
states 1:1 4:9,11 48:14 49:16 63:4 88:1,1 129:17 168:14 170:12
status 28:13
steering 174:8
step 90:15,15 91:16,21 102:4 103:5,15 106:8

119:13 128:19 129:15 130:22 131:4,7,12,13 131:13,21 133:13,17 136:1,1 138:5,6 138:8,12 155:7 155:10
Stephens 3:4 35:4
steps 102:17 128:16 138:5
stick 70:21 156:4
stop 37:18 65:4 66:18 106:15 106:21 107:5 133:3 136:12 137:13,17 138:20 139:5 155:22 171:19 171:22 172:7 172:12,15 179:5
stopping 172:9 172:10,13
stops 173:3
storage 46:17 109:9 111:1,7,7 124:20
store 15:14 109:21,22 110:3,5 112:1,4 112:11,13,13 112:22 124:9 140:16 141:16
stored 16:7 46:18 75:18,19 76:13 86:10 88:13 111:10,11,13 115:1 122:18
stores 17:17
storing 17:12 113:1
straight 101:9 114:19 124:1 147:9
stream 88:16
street 1:21 3:15 126:11 132:9 132:11 189:3 190:2 191:2
streets 125:20
string 156:16,21
strong 100:9
structure 66:11 120:12 140:17 141:16,19,19 153:4
structured 120:20 121:12 121:13 122:6
structures 140:12 141:12
structuring 141:2
STUART 3:13
student 19:11 23:16 35:14,16 119:14,14
students 24:11 24:20,21 32:4 33:20 34:9 35:10 119:4,16
stuff 11:18 20:8 20:10,17,18 23:22 24:22 46:13 47:22 72:15 119:18 122:12,12 149:9 153:5
sub 14:9
subfolder 121:16 121:17,18
subfolders 121:16
subject 114:17 120:3 157:22
subjects 96:9
submitted 6:21
subpieces 138:14
subregions 17:4 18:14
subroutines 63:8 70:6 73:16 75:8
subsections 138:14
subsequent 7:16 23:20 25:14 89:16
substance 6:8 21:2 38:21
successful 115:12 115:16
successive 180:5
sudden 126:2
sufficient 81:15
suggest 25:17 44:1 127:14
suitcase 98:5
Suite 1:21 3:7,16 189:3 190:2 191:2
summary 11:9 17:22 42:2
sunglasses 100:8
sunny 101:6
supervised 107:16 119:10 165:10,11
supported 40:21
supporting 24:15
suppose 109:2
supposed 10:15
supposedly 145:17 173:1
sure 8:14 10:7 26:9 30:22 43:21 51:8 58:1 60:3,9,10 61:18 62:21 66:14 67:11 68:16 69:7 79:22 82:14 92:18 119:16 120:8 139:12 160:11 162:16 170:1,8 186:2 187:6
surgery 99:19 110:19
SUV 12:13
SW 3:6
switch 168:6,17 183:11
sworn 5:4 7:8
system 10:12,15 10:16,17 53:3 57:9 66:9 69:17 84:1 85:5 87:9 87:10 88:17 90:9 92:7 94:3 95:1,1,11 98:2 102:7 106:10 109:8 115:18 119:22 120:4 121:8,14 129:8 135:20 136:6 141:13 154:18 163:1 164:4,10 164:12,13 167:2 174:7 183:11,22 184:1
systems 31:7 33:16 57:2 100:16 109:3 122:15 140:5 142:21 147:16 174:10

T

T 4:1,1,6
t0 175:21 176:1,2 177:2,2,5,7 178:4,9,9 180:12,12,20 180:21
t1 175:20,21 176:1,2 177:5,7 178:9 180:12 180:13,20,20
t2 180:13,14,19 180:20
t3 180:14,19
table 167:16,19 169:9,10 170:10 171:18 171:21 172:3,8 173:2,17 174:6 174:8
tailored 94:10 103:2
tailoring 103:4
take 5:15 6:6,18 9:5 24:12 26:9 27:5 28:4 35:12 43:17 44:5,5,8 80:8 81:8 96:13 96:20,20 98:4 104:13 108:9 109:13,14 111:14 112:2,2 114:14 129:13 145:3 155:7 156:4 158:7 165:20 187:4 187:13
taken 7:8 35:18 101:6 132:9,11 170:12
takes 126:1 151:2 151:7 176:15
talk 161:8
talked 66:17 87:4 90:22 133:6 165:11
talking 27:1 46:19 50:10 53:4,16 57:13 57:14,15 58:7 62:15 71:3 75:6 80:2 88:21 93:12 99:6 102:10 103:4 115:9 120:10 165:3 168:3 182:17 185:8
talks 50:7 51:9 51:14 52:3,7,11 54:5 55:12 73:8 76:2 81:6,7 84:3,15 131:21 165:10 173:10 173:11 177:20 183:3,13,20
tall 136:13

task 168:4,15 183:1 184:1
tasks 183:11,16
taught 119:7 180:11,12,13 180:15
teach 111:19 168:7
teacher 168:5,16
teaches 184:10
teaching 22:16 23:5,7,9 32:19 32:21,22 33:3 168:6,17 173:22
technical 20:5,9 20:12,17 25:18 31:8 33:17
technically 142:11
techniques 10:4 36:20 76:3,6 84:11,16,18 85:1
technology 23:10 30:4
Tekalp 23:12 33:2
tell 30:13 41:12 47:1,3 56:5 179:15
template 12:12 14:20,22 16:11
templates 15:2 118:19
ten 16:1,4,10 43:18 44:1,5 109:19 120:15 123:11 126:10 153:12 155:5
ten-minute 44:8 80:8
terabyte 123:3
term 21:7 39:2,5 40:2 41:4,10,21 116:5 153:21 153:21
terms 39:16 64:22 85:19 107:7 109:9 111:6
Tesla 1:5 26:3,5 26:13,15 35:22 189:6 190:7 191:8
test 60:8 96:5,8,9 96:10 114:5,6,9 116:6,7,15 117:5 118:4
testified 5:6
testify 5:4
testifying 7:12
testimony 6:8,13 7:7,8,15
text 176:13,14
texture 10:11,20 12:4
thank 5:11 6:16 9:10,13 29:7 44:12,13 49:7 53:7,12 66:4 80:16 82:15 127:21 152:10 155:13 158:13 159:14 187:16
thanks 69:2 104:3 105:2 128:2 149:4
thereof 78:2,7,20 79:5,16 80:3
thereto 141:17
thesis 18:22
thing 5:18 12:10 13:8 20:20 28:2 31:1 36:18 66:2 77:4 82:11 97:4 104:21 110:1 120:10 122:5 131:11 137:2
things 12:17 18:16 33:12 41:18 44:2 46:15 53:6,21 66:1 68:12 70:9 70:13 72:7,14 73:2 75:2 76:12 77:8 78:11 94:3 94:3 95:6 100:15 101:16 116:11,12,16 117:11 118:20 119:20 126:5,6 126:6,7 141:11 147:15,22 152:1 177:6 180:14,15 182:6
think 5:14 12:1 27:22 28:7 33:9 35:20,21 36:2,5 44:7 60:2 61:12 62:8 82:1,9 84:6 95:3,5 108:16 111:14 126:15 139:15 142:14 143:4 143:21 144:6,8 152:9,9 176:22 181:19 186:17 187:3
thinking 144:17
third-party 21:2
thousand 109:22 116:22
three 9:18,19 31:8 33:18,22 35:12 82:17,18 87:10 89:15 91:15 113:1,11 116:12,12 117:8 121:20
three-year 35:16
Threshold 27:14
Thresholding 27:9
Thursday 1:16
tilted 112:13,14 112:15,17 114:22
tilting 112:18 114:18
time 5:15 10:12 15:22 16:12 23:4 24:1 25:6 26:9 31:4 32:11 32:19 37:10 39:18 40:13 43:22 65:12,19 65:21 70:9 101:16 105:9 124:19 126:5 151:1,2,6 154:14 155:7 158:7 173:1 175:20,20 176:1 177:2,2,4 177:5,5,12 178:2,4 179:17 181:15 183:8 189:14
times 24:10 150:8,8 153:13 178:17 183:8
timing 6:17 76:16
tires 12:21 14:10 18:17
title 10:9 45:2
today 5:12 6:8,12 6:20 7:8,15 8:4 8:9 22:22 35:5 41:16 125:11 125:14 136:14
today's 124:17
told 177:6
Tom 97:1 98:1 102:11,14 121:16
tools 76:6 84:18
top 41:15,17 42:15 84:5
topic 94:9
touch 33:22
touchscreen 49:2
track 86:3 88:9 96:21
tracked 132:3 137:1
tracking 37:5 83:14,18,22 86:2 106:18 135:11
TRADEMARK 1:1
train 93:22 94:11 95:11,20 96:2 115:21,22 116:1 124:20 148:15 151:1,2 153:9,15 154:8 154:15 176:3 176:12 182:13 182:20 183:2 183:10
trained 15:10 93:6 97:19 107:16,17 114:7 115:8 132:20 135:13 136:12 137:11 175:14,14 178:21 179:3 182:8 183:17
training 15:1 53:22 60:5,7 65:10 92:5,7,11 92:13,15,20 93:1,5,8,9,11 93:14,16,17,20 93:21 94:5,6,8 94:10,19,22 95:19 96:13,17 97:8 98:22 100:20 102:8 102:10 103:21 104:1,2,8,10,16 105:6 106:13 108:6,9,11 109:9,16 111:7 111:8,10 113:3 113:9 114:3,4 114:11,13 116:6,13,20 117:4,9,9,12 118:2,14 121:6

121:6,19 122:15,16,17 122:18 124:3 124:16,21 125:6 126:21 132:3 136:16 136:17 137:5 148:9,13 153:5 163:1,3 167:20 168:3,5,11,16 168:22 169:7 170:13,20 171:8,13,16 173:18,20 174:13,21 177:3,13 178:10 179:4 180:18 181:21 182:1,3,5 184:13 187:1
trainings 93:2
transcript 8:18 8:20 9:15 159:3 188:9 189:10 189:11 190:12
transcription 190:15,17
transformation 142:7
transformations 142:8
transforming 141:22
translations 17:8 17:8
traveling 66:8,18
tree 82:22 85:15 85:17 88:12
trial 1:3 7:12,15
tried 151:19
trigger 175:7
trillion 123:3
trucks 26:18
true 188:9 190:14,16
truss 156:22
truth 5:5,5,6
truthfully 7:20 8:3
try 41:9 60:12 67:14 124:12 144:4,11 147:19 151:11 154:19
trying 51:16 58:11 64:11 70:22 71:8 94:11 96:15 104:22 144:1 147:4 183:5
turn 28:15,19 37:18 44:16 45:7 49:8 77:14 80:19 90:10 139:17 158:5 158:14,16 159:15 162:2 163:5 167:10 174:15 179:12 179:12,14,17 179:18 181:8,8 181:12
tutorial 152:3,4
tweak 96:11 117:14
tweaked 118:2
two 35:15 89:2,8 89:9 101:9 117:7 119:6,8 128:16 129:10 130:18 133:7 133:13 134:1,5 134:7 145:12 150:12 153:11 154:3 155:4 156:17 166:21
two-course 158:1
two-third 100:1,3
type 13:22 14:19 15:12,12 16:8 16:16 20:20 30:1 34:5 36:18 37:6 52:9 66:2 72:7 73:21,22 76:12 77:4,8 87:5,20 92:13 92:22 93:8 97:3 99:6 101:4,5,8 120:11 126:12 137:2 144:4 149:20 156:19 157:7 168:4,13 168:15,20,21 171:14
types 30:15,16 32:5 93:1,9,11 93:15 168:22
typical 60:6 141:7
typically 12:1 13:15 17:8 37:20 38:9 39:16 60:4 75:19 76:13 99:7,21 101:3 103:20 111:21 116:12,14 124:18 135:1,8 141:10 142:1 145:5,8 148:19 152:17 154:10 154:19 172:19 174:14
typing 176:13,13
typo 180:9

U

U 23:11 33:2
U.S 1:12 7:1
underlying 13:12
underneath 24:16
understand 5:12 6:7 7:7,10,14 15:9 29:18 30:9 32:14 39:15 40:10 41:9 43:2 51:15,16 56:3 58:1,12 60:4 61:18 64:12 70:22 71:8 79:6 82:12 92:18 93:14 94:12 104:22 115:18 123:6 126:16 133:12 137:9 149:9 186:21
understanding 13:19 30:6 45:13 49:11,12 56:4,6 67:15 78:4,16 111:6 129:16 185:15
understands 15:11
understood 39:17 160:11
undo 174:21 175:1,4,7,8,11 175:16 176:4 176:15,18 177:11 178:2,7 178:8 180:5,6,7 180:19,20,20 182:6,7
UNDOS 175:4
unit 49:18,21 51:1,12 53:5,13 54:4,8,15,19,20 55:2,9,12,13,14 55:15 60:14,15 60:22 61:7,8,14 62:5,6,12,13,14 62:19,20 68:13 78:1,1,4,6,17 79:6 80:1 84:14 86:15,17,22 140:6,10 167:5 167:6,7
United 1:1 4:9,11
units 55:7 78:9 143:20
university 22:12 22:14 23:8,15 24:6 25:16 33:1
unknown 96:8 97:2
unlock 98:3
Unsupervised 27:7
update 67:7 72:19 101:18 101:20,21 108:4 111:3 120:6 121:6,11 122:16 125:18
updated 89:18 127:11
updates 125:15 125:20 126:5 127:3,7
updating 101:10
upfront 118:17
uploaded 159:5
upstairs 139:11 139:16
use 14:19 15:10 25:14 27:11 31:22 53:3 68:12 74:6,10 101:13 117:13 117:19 141:7,8 148:3 186:15
user 48:2 165:19 166:5,9 172:17 175:6 181:21 181:22 182:5 182:13,20 183:2,7,10,17 183:20,21 184:2,4,7,7,11 184:12,17,19 185:4,7,8,8,9,9 185:11,13,13 185:16,22 186:1,2,5,10,15 186:22
users 166:13,16 177:22 181:5 185:2
USMAN 3:3
usually 13:12 35:14 37:20 135:14 141:7 151:7

utilized 76:7 140:5 175:11

V

v 1:7 189:6 190:7 191:8
vacation 11:1
validate 117:19
validation 116:14 117:2,13,19
value 74:11 112:7 114:10 118:1
values 58:21 59:10,13 72:19 111:11 160:8 160:20
vanish 154:12
variable 65:21
variables 58:22 59:10,13,18 65:11,19 72:10 72:18,20
variations 17:7 18:4
variety 13:14 32:8 33:12 34:14 46:15 84:20
various 32:5 33:6 34:18,19 47:12 54:5 55:6 72:12 76:3 78:11 87:19 96:3 97:18 112:9 117:10 140:4,9 141:11 145:22
vary 168:12
varying 90:4
vehicle 26:15 36:7,7,12,14,16 37:9,15,15,17 65:2,4 67:21,22 68:10 85:21 105:17 106:20 107:3 125:1 126:17 136:12 137:12,16,17 137:18,19,21
vehicles 127:8
verbs 73:4
verify 110:15
versa 59:5
versus 14:14 22:17 85:20 95:15,16 100:4 105:17 106:2 116:1 136:16
vice 59:5
video 12:16 15:21 31:10 36:3 37:1,6 88:7,10,20,21 89:1,4,9,13,14 96:21 110:2 135:8,12,14 137:1
videos 10:19 37:3 37:4 68:8 110:3
view 159:22
virtual 56:18 156:5,12
virtue 181:9
vision 31:9 36:3 36:19
visual 10:13 11:5
Vitae 4:15
volume 109:8
Voogle 10:13

W

wait 164:11
waive 189:12
walk 20:16 109:20
walking 85:18 96:19 98:4 102:9 104:11 105:17 106:14 107:2 110:4,10 115:10 126:8 132:16,17,21 133:1 134:11 134:13,17,21 136:11,15,19 137:7 138:18
walks 96:16 97:21
want 9:8,9 24:10 43:20 44:1 79:14 81:14 88:6 91:7 93:13 95:11 98:7 109:16 117:11 117:14,15,16 117:17 121:6 145:14 149:5 153:5 154:19 172:8,9 175:17 176:4 184:3 187:4
wanted 28:15 43:2 111:5 161:12
wants 98:7 183:2
Washington 1:21 3:8,17 134:12 189:4 190:3 191:3
wasn't 61:4 172:4 176:3
water 179:14
wavelength 161:13
way 16:22 20:1 28:4 37:12 112:10,15,18 115:17 143:19 143:22 148:1 159:7 177:14 180:3 188:12
ways 93:4 116:15 116:17 118:14 157:19
we'll 44:7 72:5 80:14 128:11
we're 9:11 18:21 22:22 35:3 44:6 46:19 53:16 57:12,14 62:15 71:3 75:5 80:1 80:7 93:12 99:5 111:22 113:21 120:10 161:13
we've 33:5,8 43:16 82:1 102:9 127:13
weapon 98:11,13 98:14
wearing 100:8
weight 99:8,21 150:8
weighted 148:4 148:16 152:22 153:3
weighting 100:4
weights 152:14
welcome 66:5
well-versed 32:9
went 11:1 34:5
weren't 20:14
wheelchair 102:16,18,22
WHEREOF 188:14
white 12:20
willing 110:8
windows 14:10
wish 14:14 15:2
witness 13:10 15:18 16:21 17:21 18:6 20:3 21:1 25:21 27:5 38:20 42:19,20 44:4,10,13,22 47:6 58:1 60:2 60:18 61:11 64:18 66:14 67:11 79:22 80:16 95:5 99:5 120:8 122:22 125:9 155:13 158:14,18,20 170:1 181:19 187:11 188:14 189:11 190:8 190:19 191:9
word 38:6 42:7 180:4 186:2
words 81:3,17,21 82:6 140:1 186:17
work 6:3 11:8 19:1,7,8,13 20:1,4 21:10 25:13 27:17 28:4,8 33:6 34:5 80:10 83:20 127:16 158:8 177:11
worked 32:3,5,6 33:5,13 34:2,4 34:8,14
working 19:10 23:6,7 32:2 159:11
works 6:4 80:11 121:11 127:17 158:9
world 11:1 77:11
worse 110:12
wouldn't 123:16
write 20:15,19 37:19 38:12
written 189:22
wrong 48:18,20
wrote 38:13

X

X 4:6 107:10 120:3 121:16 146:8 147:7,8
Xerox 20:6,7,7 21:4 22:1,1,9 23:4,6,7 34:15 34:17
Xu 19:11

Y

Y 146:5,7 147:7,8 147:11
Yaowu 19:11
yeah 15:16,18 18:6 19:19 44:7 53:11 64:4,7

70:14 77:2 82:12 88:15 91:6,7,12 92:12 92:18 97:16 106:6 108:18 109:6 115:13 115:17,21 119:16 123:6 126:15 127:1,6 129:7 130:4 131:12 135:4 139:21 142:16 142:18 153:15 153:19 154:22 155:9,20 156:10,16 157:21 158:15 160:17,21 161:1,18 162:1 163:3,9 164:12 164:19 167:4 168:14 170:1,8 174:19 175:19 177:18 178:8 178:14
year 32:15 101:12,12,12
years 22:1 23:2,3 25:13 28:9 31:8 32:3 33:13,18 33:22 34:11 35:12,15 101:14,14 125:12,13 126:10 144:9 149:17
yep 17:16 98:2
York 136:17,18

Z

Z 180:4
zero 177:12

0

0 112:8
0001 154:13

1

1 28:7 45:7,9,10 45:13,14 46:5 48:8 50:2,15,16 51:6,18 52:21 58:10 89:4,22 103:1 123:3,3 156:7 159:16 159:16,18,20 162:5,11,20 163:14,16,17 163:21 167:16 172:9,13 173:3 173:4 182:22 187:6
1,000 153:14
1:45 158:16,21
10 84:14 109:21 118:10 121:18 137:18 183:9 183:21
10,000 11:2
10,452,974 1:12 4:12 7:1
10:50 80:14
100 49:21 78:1,1 95:10,14 100:17 117:1 121:3,5 123:21 124:14 153:13 172:4
100,000 116:21
1000 3:6,7
1001 4:11 8:7,17 44:16
1004 4:9 159:2,8
103 140:15,21 142:15
10A 163:6,8 166:19
10B 163:6,8,11 163:12 165:16 165:18 166:3 166:20
10C 166:21
11 19:14 27:20 56:13 84:15 183:21
110 54:8 84:14
12 19:18 173:16
12:45 127:18
120 59:5
13 54:18 121:21 174:20
130 55:15 56:6,10 58:19 69:4
139 55:17 56:8 63:16
14 54:13,18
140 55:20 56:14 57:15 58:5,6,10 63:3,11,13 64:5 70:1,1 71:6,16 73:7 75:22 76:20
15 109:21 120:17 164:7,22,22
1500 26:19
154 129:14
158 138:7
159 4:9 131:20
16 1:16 22:1 29:11 30:19 46:11 86:14,21 189:7 190:9 191:10
160 159:20
164 159:21
166 159:22
168 159:22
16C 83:10,11,12
17 84:17 139:17 140:2,3 184:2
1730 1:21 190:2 191:2
18 56:12 58:10 63:9,20 64:10 64:15 69:6 71:12 73:10 75:11 175:3 177:19
18-ish 165:1
1940s 149:16
1988 10:1 152:9
1996 10:1
1997 32:22
1998 22:10,20 33:3
1999 3:15 189:3

2

2 28:7 49:8,11,13 49:16 50:1 51:3 51:4,7,9,10,17 52:20 54:3,5,21 60:20 61:12 62:11,15,18 89:6 90:3,4 103:1 162:2,4 163:17,18 166:9 167:16 167:19
2:50 187:7
20 23:2
20006 3:17 189:4
20024 3:8
20036 1:21 190:3 191:3
2004 22:21
2007 4:13 6:22 8:8,19 28:15
2010 26:21
2015 4:15 9:12,14
2016 32:15
202 1:22 190:4
202)-232-0646 189:15
202)232-0646 191:4
202.370.8324 3:18
202.626.6383 3:9
2024 1:16 22:22 188:15 189:7 189:20 190:9 191:10
21 47:15 167:10 167:13,14 177:19
21st 188:15
22 169:10 173:8,9 173:16 175:6 176:21
23 46:11 48:7,22 173:5,6,11
232-0646 1:22 190:4
25 101:14,14 124:3,7,8 175:19
255 112:8
26 63:3,11 64:4 70:2 71:6 73:6 138:8 184:4
27 71:16 176:21
28 180:1
287 89:7
2X 147:11

3

3 28:7 58:11 136:15 147:11 167:16 169:9 169:10 170:10 173:17
3:16 187:18
30 37:4 63:4,12 64:4 70:2 71:6 73:6 123:22 124:1,3,6,7,7
32 28:19,21,22 29:9,17 30:9 90:10,15 102:4 128:8,15,19 131:8 136:2 138:6 175:10
33 128:15 130:21 131:12 136:2 138:6 174:15 174:17
34 88:1 175:2 176:21 177:19 179:22 180:3
35 19:5 58:18 59:9
36 180:1
37 180:2
38 55:12
39 19:6

3A 55:4
3E 55:4

4

4 27:20 28:1 136:15
4'3 137:13
4'6 136:20
40 63:16 125:12 125:13 161:17
400 164:10
40s 143:21 144:6 144:9
42 55:21 76:1 129:15,16 142:15
43 161:17
44 129:17
45 30:20 76:20 142:3,4 183:9
45-minute 127:14
46-ish 140:22
47 167:20
4A 80:19,22 81:4 81:6,10,15,17 82:16 85:4 87:9 89:15 120:4 164:6,8,11 165:4,15 166:1
4B 80:20,22 81:4 81:7,17 86:11 86:13,16 87:15 91:1,5,11,13 165:4,15

5

5 4:4 5:13 27:20 28:1 44:6 48:16
50 77:15,16,21 123:10 154:4 168:3 183:13
50-layer 155:3
500 155:4
50s 143:22 144:10 149:16
51 76:20 140:15
52 140:16,18
525 91:13
53 141:21
54 130:10
55 39:10,15 40:7 43:3 142:7 168:3
56 41:22 42:12 43:5 89:6 90:1
57 40:14 42:22
58 48:11,14

6

6 81:12 90:1
6'5 136:13,18 137:14
60 137:19 138:19
600 3:16 137:18 189:3
61 183:20
615a 81:10 82:19 82:21
615b 82:22
615c 82:21 83:3
62 41:22 42:12,22 43:5 182:22
63 183:1
64 55:18 63:16
66 54:2 62:10
67 54:13,17 113:13

7

7 28:1 40:16
70 45:22 48:15,19 48:21 50:2,3,4 50:15,16 51:6 51:18,21 52:1 52:20 53:1
71 55:10,11
75 84:4,5,6,9
79 81:5

8

8 4:11,13 56:14
8:32 1:17
80 77:14,16 81:7 86:13 88:1
80s 24:4 32:18
812 1:21 190:2 191:2
852 140:12 141:15
853 140:18

9

9 4:15 56:14 161:17
9,604,359 4:10
9:30 44:10
9:40 44:9,10,11
90's 24:4 32:13 32:18
9105 90:15
911 98:14
9110 91:16,21 102:4 103:15
9115 103:5 106:8
9125 128:19 129:5 131:7
9130 128:19 129:5
9140 136:1 138:5
9145 138:5,8
9205 131:2
9220 130:22 131:2,4,13
9225 131:12
9230 136:1 138:6
9235 138:6
93 54:20 55:2 86:15
95 109:18,19 110:19 118:3,9 124:5
974 7:4 8:7 9:4 40:17 41:6 44:17,20 45:10 46:2 49:9 57:3 71:1,3 73:7,13 74:21 77:15 80:20 83:21 87:9 90:11 93:7 128:8 139:18
98 49:17,18 50:1 50:7,14,22 51:3 51:7,9,11,17,21 52:11,13,19 53:4 60:21 61:13 82:18
99 109:17
99.9 110:20