EPISODE 104

[INTRODUCTION]

[0:00:10.8] SC: Hello and welcome to another episode of TWiML Talk, the podcast where I interview interesting people doing interesting things in machine learning and artificial intelligence. I'm your host, Sam Charrington.

Contest alert. This week we have a jam-packed intro, including a new contest we're launching, so please bear with me. You don't want to miss this one. First, a bit about this week's shows; as you may know, I spent a few days at CES earlier this month. While there, I spoke with a bunch of folks applying AI in the consumer electronics industry and I'm including you in those conversations via these series of shows.

Stay tuned as we explore some of the very cool ways that machine learning and AI are being used to enhance our everyday lives. This includes work being done at Anki, who built Cozmo, the cutest little computer vision powered robot. Lighthouse, who's smart home security camera combines 3-D sensing with deep learning and NLP. Intel, who is using the single-shot multi-box image detection algorithm to personalize video feeds for the Ferrari Challenge North America.

Firstbeat, a company whose machine learning algorithms analyze your heartbeat data to provide personalized insights into stress, exercise and sleep patterns. Reality AI and Koito, who have partnered to bring machine learning based adaptive driving beams, or automatically adjusting high beams to the US. Last but not least, Aerial.ai who applies sophisticated analytics to Wi-Fi signals to enable some really interesting home automation and healthcare applications.

Now as if six amazing interviews wasn't enough, a few of these companies have been so kind as to provide us with products for you, the TWiML community. In keeping with the theme of the series, our contest will be a little different this time. To enter, we want to hear from you about the role AI is playing in your home and personal life and where you see it going.

Just head on over to twimlai.com/myaicontest, fire up your webcam or smartphone camera and tell us your story in two minutes or less. We'll post the videos to YouTube and the video with the most likes wins their choice of great prizes, including an Anki Cozmo, a Lighthouse smart home camera and more. Submissions will be taken until February 11th and voting will remain open until February 18th. Good luck.

Before we dive into today's show, I like to thank our friends at Intel AI for their continued support of this podcast. Intel was extremely active at this year's CES, with a bunch of AI, autonomous driving and VR-related announcements.

One of the more interesting partnerships they announced was a collaboration with the Ferrari Challenge North America race series. Along with the folks at Ferrari Challenge, Intel AI aspires to make the race viewing experience more personalized, by using deep computer vision to detect and monitor individual race cars via camera feeds, and allow viewers to choose the specific car's feeds that they'd like to watch.

You'll learn much more about this application in today's show, which features Intel's Andy Keller and Emile Chin-Dickey. Andy is a deep learning data scientist at Intel and Emile Chin-Dickey is senior manager of marketing partnerships at the company.

In this show, Emile gives us a high-level overview of the Ferrari Challenge Partnership and the goals of the collaboration. Andy and I then dive into the various machine learning aspects of this project, including how the training data was collected, the techniques they used to perform fine-grain object detection in the video streams, how they built the analytics platform, some of their remaining challenges and more.

Now, on to the show.

[INTERVIEW]

[0:04:15.5] SC: All right, everyone. We are here at CES. I have the pleasure of being seated with Andy Keller, who is a deep learning data scientist at Intel, and Emile Chin-Dickey who is a senior manager of marketing partnerships at Intel. We've got an opportunity to chat about one of the cool announcements that was made, was it yesterday or today? It was announced yesterday and then more fully announced today? I'm going to keep you in suspense for just a little bit longer and actually ask these guys to introduce themselves. Then we'll get into what that announcement was.

Why don't we start with you, Andy?

[0:04:53.7] AK: Yeah. Thanks for having me. I'm a deep learning data scientist at Intel. I started at Nirvana before the acquisition working as an intern, doing some of the same object localization stuff that we're using for this soon-to-be-announced project. Specifically I was implementing some other models, like faster RCNN.

[0:05:21.2] SC: Like what?

[0:05:21.9] AK: Faster RCNN. More recently, I've moved to more similar work that I did for my masters at UCSD, which is natural language processing and dialogue systems and question-answer systems. Now I am started fulltime after finishing my degree and love being here.

[0:05:50.5] SC: Awesome. Emile?

[0:05:53.0] ECD: My name is Emile Chin-Dickey. I joined last year the artificial intelligence products group at Intel. I'm responsible for marketing partnerships. What that means is that I work with our partner companies to showcase both partner technologies, as well as Intel technologies showcasing our efforts in artificial intelligence.

[0:06:19.8] SC: In fact, there is one of these partnerships that Intel CEO Brian Krzanich announced at his CES keynote last night. It's a partnership with Ferrari Racing. I think for me thinking back to Brian's keynote, it was a little surprising for me. I guess, I exist in this AI level and I expected it to be just pure AI consumer devices stuff, but Intel as a company is way more all-in into this virtual reality and immersive experience than I knew.

I didn't know anything about Intel's efforts around True VR and the other virtual reality plays and the immersive experience that he talked about. It's everything from outfitting the Olympics that are coming up. You guys built a studio, like a volumetric studio and there was a partnership with Paramount Theaters announced.

There was a ton of discussion around, like how you would use the stuff in sports. Then one of the partnerships that was announced in that context was this partnership with Ferrari. Tell us a little bit about that partnership and what you're hoping to achieve with it.

[0:07:46.1] AK: Yeah. What was announced was a three-year partnership with Ferrari Challenge. Ferrari Challenge is a race series put on by Ferrari. It takes place in different regions. We're specifically partnering with the North America team. One of the areas that we're applying artificial intelligence to the race stream, so that's basically applying AI techniques around single shot detection and fine-grain classification to recognize the cars that are being captured in each of the camera feeds.

Then the intent is to use that as metadata to curate camera feeds for viewers that are specific to each car, or driver. Basically a fan could pick their favorite driver and we could deliver a curative feed specific to that driver as they make their way around the entire track.

[0:08:50.0] SC: As I understand it, it's not just today, but today the – all of the folks that are broadcasting a race, like the Ferrari challenge, they're all operating off of the same feed, like everybody gets the same feed. Is that how it's working today?

[0:09:07.6] AK: Yeah. If you think of a traditional race broadcast, or a more typical race broadcast, you have a director's cut of the action. Normally, the feed is focused on the first three or four cars in the race. If your favorite driver is not among those couple cars then you may not actually see too much of them during a broadcast.

We noticed that people's consumption of media is changing and we expect that there is no reason why that shouldn't change for motorsports broadcast as well. This basically puts more choice in the hands of the fan to get a more tailored, customized viewing experience.

[0:10:00.8] SC: How would I configure my feed? Is this something that – is this being delivered from the – a live stream and I'm choosing a car, or something like that? Or what's the experience of tailoring the feed?

[0:10:17.6] AK: Yeah. The intention is that there should be a stream that would be broadcast live over an app, or a website. Yeah, exactly what you said, you could pick your favorite driver and get that tailored, that tailored stream according to that driver.

[0:10:36.5] SC: This isn't being done by just putting traditional cameras around the track.

[0:10:43.0] AK: Yeah. There's two components. We're using drones to capture the race footage. That actually adds a rather dramatic element to the race experience, if you will. These are not fix point cameras. Then the notion is that you can apply these recognition techniques to each of those camera feeds, so that at any given point in time you know exactly which cars are showing up and which camera feeds. With that information, you can tailor that stream to a end user and viewer.

[0:11:19.4] SC: Interesting. How many drones are going to be flying around the Ferrari Challenge when this thing is running?

[0:11:25.9] AK: Yeah. It's somewhat a function of the track configuration length. For starters, we're looking at between five and six drones, and we'll go from there.

[0:11:37.9] SC: Are the drones mostly fixed and each one covers an area of the track, or are they following the cars or something?

[0:11:49.1] AK: Yeah. They're not fixed in one location. They have more like a territory, if you will, that they'll cover.

[0:11:58.7] SC: You may see them zipping around the territory?

[0:12:01.9] AK: Yeah, they'll be moving around. Yeah, exactly.

[0:12:05.3] SC: I was talking to someone on your team yesterday about this at the keynote, or like before the keynote and we're going to talk a little bit about the AI elements and challenges associated with this. Just thinking about even the – this day and age you've got to be capturing 4K, 8K streams off of a drone and getting those down to someplace where you got to – I mean, there's a ton of stuff that keeping the drones in the air is a challenge. A ton of technical challenges here. Really, really interesting.

Maybe it is a good segway to actually talk about some of the AI stuff. Andy, this is where some of your work has come in. Maybe tell us a little bit about the underlying AI technologies and what the primary goals are for the project that you work on.

[0:13:03.4] AK: Yeah. We thought a good place to start – we needed a foundation on which to build other analytics about all the drivers and the racing that was going on. All the cars do have telemetric data capturing units on the cars, but it's a challenge for us to actually get all that data for all the drivers. As you can imagine, it's a sensitive topic when you ask someone that you're directly competing against if you can have their data. What we –

[0:13:35.8] SC: These cars have like thousands of sensors on them.

[0:13:38.8] AK: Everything you can imagine, and temperature for air inside the tires, like everything.

[0:13:46.3] SC: One of your colleagues mentioned that the stakes – for those who aren't familiar with racing and I'm not super familiar with racing. Typically the difference between first and second place is like 100th of a second, did I get that right?

[0:14:01.8] AK: It's frequently very tiny.

[0:14:04.0] SC: Yeah. You were saying –

[0:14:07.3] AK: Little things like that make a big difference. Yeah, so that kind of stuff – I mean, we realized we needed something else to build some sort of analytics platform on. To start that, we really needed to be able to know, okay we're going to be using the video footage, we need to know which drivers we're looking at at any given at and we need to know where they are. We need to actually be able to localize them.

Obviously, the first thing that makes sense is some object detection, or object localization model, which can Dropboxes around all the cars on the track and then potentially classify them uniquely as who is in what car. As a starting point for that, we had tested out using models that were pre-trained on some other data sets and realize that – pretty quickly realize where you need to gather domain-specific data set. Just because like Emile mentioned, the drone footage is dramatic.

[0:15:14.5] SC: You don't find a lot of that out on YouTube.

[0:15:17.0] AK: Exactly.

[0:15:19.4] SC: What did you start with? What data sets did you try to train on initially?

[0:15:26.2] AK: Yeah. We were using the kiddie data set, which is one of the self-driving – early self-driving data sets. It has bounding boxes around all of the cars and you can build a basic car detector off of that, but it's all from the viewpoint of the dashboard of the car.

Some of those viewpoints apply from a drone, but a lot of our shots are really long distance and unique angles that we've never seen before in that data set. Those are our main driving factor in generating this new data set, which was a lot of the portion of beginning of this project.

[0:16:09.6] SC: In the typical race you'll have these five or six drones zipping around their territories capturing data of the field as a dozen, or two dozen cars typically?

[0:16:23.7] AK: Yeah. Somewhere around there.

[0:16:27.6] SC: For each of these drones instrumented with a camera and you're pulling down a feed and you're doing what otherwise might seem like a typical autonomous driving task, like putting bounty boxes around the cars that are in the – on the track.

The first step is build a model based on this kiddie set. Then that wasn't giving you the accuracy that you're looking for so you started building your own data set. Was this by running drones on top of race tracks, or –

[0:17:00.1] AK: Yeah, basically. We had a substantial amount of footage from across the entire 2017 season of recording from a bunch of drones at every single race. This was in 4K. We knew that a lot of these footage maybe wasn't as useful, so we needed to sort through that as a first step to generating a training set.

We had probably hundreds of hours of 4K footage and it was some of the data scientist jobs actually look through and find really high variance shots, shots with different [inaudible 0:17:41.7] and lighting, differences in size of the cars. Since these drones will move anywhere from 10 feet off the ground to a 100 feet off the ground, that really changes the appearance of the car and what the model is going to be able to learn. We really try to get as much variance as possible.

[0:18:00.3] SC: What was the approach to doing that? Was this something that was manually going through footage and hand annotating, or did you automated in some way?

[0:18:15.0] AK: We did have some of the cut from the live broadcast that was curated by the drone team, that was broadcast on the stream during the race. We knew a little bit of what shots to follow and what was the general – I mean, obviously they're at least going to have cars in the shot if it's in the broadcast. We're able to use those and then some amount of manually coming through unfortunately.

[0:18:45.6] SC: That wasn't the most exciting way that you spent time. With that, did you – the manual coming through, did you use some off the shelf tools to facilitate that?

[0:19:03.8] AK: Luckily, we were able to just write down timestamps and videos. Then I had written some scripts and FFmpeg is the default tool for –

[0:19:15.1] SC: To just snip out snippets and dump them in a drive or something like that.

[0:19:18.8] AK: Yeah. Once we had parsed through all those and extracted some percentage of the frames, we were able to send those off a labeling company and then provide them with a series of guidelines and helpful data sheets about each of the different cars that we wanted labeled since we had something close to 40 or 50 different cars, where some of them looked pretty similar. One of the larger challenges was making sure the labeling team was actually able to do their job correctly such the model itself was able to do it.

[0:19:58.4] SC: Do you have a sense for how long you spent on just this data collection and pre-labeling task?

[0:20:11.4] AK: The data collection itself, the recording of the video was over the entire 2017 race season, so I guess that maybe shouldn't be included. The curation of what we were going to divide to them, I would say happened over a week or two. We were able to get a couple different data scientist looking at it and people here.

[0:20:38.6] SC: You started with a hundred or so hours, I think you said. What was the size, like if you added up all the snippets that you sent on to get annotated, how many hours did you have off that?

[0:20:52.7] AK: It was close to I think one hour. Significantly less.

[0:20:57.1] SC: Very dense.

[0:21:00.3] AK: Yeah. After that, we obviously – because it's from frame-to-frame, there is really not that much difference. We were pulling something like maybe 10% of the frames, so that we can get more a variety with a lower number of frames since. Really every single frame is more effort for the labeling team and really trying to reduce that as much as possible.

[0:21:29.5] SC: Meaning you used 10% of the frames in the one hour of footage. Then you had this labeled by the labeling team. I would've imagine that you needed a lot more training examples to achieve acceptable performance on this. Were you using these examples in conjunction with the previous – or was this a transfer learning type of task, or did you train from scratch with these new examples?

[0:22:04.1] AK: Yeah. We ended up actually going straight from scratch. We tried to approximate the size of some of the other popular object detection data sets, like PASCAL VOC. That was our goal to begin with. Yeah, basically from scratch was a little bit challenging, but we realized we probably needed to do it that way just because of the uniqueness of this problem.

The fact that these cars are very small and we have 50 different classes, but they all look very similar, so it's more of a fine-grain classification problem, which a lot of these typical object detection data sets don't really cover.

[0:22:52.5] SC: Is it generally the case for these fine-grain types of object identification problems that you need less data than if you were training up coarse grain object detectors from scratch?

[0:23:11.9] AK: I don't know if I'd say less data. It depends on also how you develop the model. There are some future steps and some of the state of the art and fine grain detection that we're planning to implement where the old train on deep network and then chop off the top and add an SVM on top.

Then that was able to do a lot better at these tasks, where the features between the two classes are very similar, but there is boundary. Versus the traditional something with – something like what we use for SSD, whereas end-to-end neural network. I think for the end of end-case, you probably need about the same amount of data. We ended up having probably close to a thousand labels per car, maybe 2,000, which seemed to be similar to some of these other data sets.

Obviously some cars are more frequent than others and [inaudible 0:24:22.0] to do besides rebalancing afterwards. Yeah, it turned out to work pretty well thankfully.

[0:24:31.1] SC: Nice. What kind of model, like model approach, model architecture did you end up using and how did you arrive at that?

[0:24:42.5] ECD: Yeah. We ended up using a single shot multi-box detector, which I think Andres who was on your show a few weeks ago talking about the NASA project, they also used that for the creator detection. Because of some of the optimizations that we have and neon for Intel, that made sense on that front so we were able to get the live speed that we were looking for.

Then also, the general architecture itself, it's a one-shot – not one shot in a one-shot learning sense, but in the single shot, like it's a single architecture. You don't have a two-step process. Like faster RCNN has where first it proposes boxes and then it does the classification. This happens all at once. That is partially one of the reasons why it's significantly faster, which we liked. It also has feature maps of multiple different scales.

[0:25:48.7] SC: What does that mean?

[0:25:51.3] ECD: We have convolutional networks when they operate and you go up in higher layers, the feature maps continue to shrink down and down further. If we provide all of those to the end classifier, it's able to get the same object at a bunch of different resolutions. It's able to in the end basically means we're able to classify objects better at a lot of different scales; so small objects, big objects, which is really one of the main challenges of this problem in this data set.

[0:26:26.2] SC: You mentioned that one of the things that you looked at, or are looking at, or considered was doing a network where you chopped off the end of the network and replace it with NSVM. How far did you go down that path?

[0:26:42.5] ECD: We haven't gotten there at all yet. There is a lot of next steps they are looking into, I'm not sure how many I can discuss. Yeah, that's definitely something we're considering.

[0:26:58.4] SC: Okay. What are the outstanding challenges in trying to productionalize this? I always change whether I say productize, productionize, productionalize.

[0:27:12.9] ECD: It's a production.

[0:27:14.6] SC: Yeah. What's remaining for you to take on with this project?

[0:27:22.7] ECD: Yeah. One of the big ones is the fact that the appearance of the cars isn't necessarily static in between races, or even in between days of a given race. A driver may change the color of their rims and their tires, or even completely change the wrap on their car, or crash the car and –

[0:27:46.5] SC: Snap on some different logos.

[0:27:48.8] ECD: Yeah, exactly. If we're trying to do a purely supervised one of these like just pound it with as much data as possible to learn, then that makes it a little more challenging.

[0:28:02.0] SC: Hard to keep up.

[0:28:02.8] ECD: Hard to keep up.

[0:28:06.5] SC: How do you address that?

[0:28:09.8] ECD: There is a couple ways. The way that we're thinking to address it at this point is we would like to be able to just during practice laps maybe take 5, 3, 4, 5 pictures of a given car. We can know when a car has changed appearance slightly. Then if we have a model that's able to learn to classify cars just based on that small support set, that is – that would be ideal.

There's some architectures out there that attempting to do this today and is in the one shot, few shot learning field. Stuff like matching networks, or some of the other meta learning techniques, I think are what we're going to be exploring in the immediate future.

[0:29:01.5] SC: How much have you dug into that stuff so far? One shot, few shot and meta learning are things that are on my list of things to dig into a bit more on the podcast this year. If you've learned about some of the stuff already, I'd love to get a sense for what you've seen out there and what you find interesting.

[0:29:24.1] ECD: Yeah. I saw a ton of interesting meta-learning talks this year at NIPS. A significant portion of them focused around this few shot learning idea. This seems like there's a lot of different ways to approach it and meta learning as a framework is pretty general. Some people were approaching it from the transfer learning perspective where you say, "Okay, we're actually going to design our optimization functions such that our goal is that we learn a set of parameters that with a single radiance that we're able to achieve a variety of different tasks." Achieve high-performance on a variety of different tasks, which is different than just optimized for a single specific task. I think that work is called mammal out of Berkeley.

That's something that I think is generally applicable to – I mean, obviously any model, which is cool. Then some stuff like the matching network where it's almost like a 10 years neighbors type approximation of classification where you say, "Okay, I'm going to give it five images of this type of dog and now show it a new dog. It's going to compare with these images that it knows and see which one is the closest." Then do some majority vote based on the class using that. The cool thing is that they're all kind of differentiable and not necessarily related to a specific data set. I think that is interesting.

[0:31:07.9] SC: The idea that you would have someone at the track who is – or I guess, it could be remotely, but someone who is looking at these live practice run videos and coming up with the – an annotated sample and shooting that. Are you then triggering an entire retrain of some model just before the race that sounds?

[0:31:35.7] ECD: We don't have to do that. That would be dangerous.

[0:31:39.9] SC: It sounds dangerous.

[0:31:42.0] ECD: I think we had discussed that before and we are like, "Well."

[0:31:45.3] SC: What could go wrong?

[0:31:47.8] ECD: What if it just doesn't finish training in that now? Yeah, so I think we want to have an interface where you can just draw, either click on the cars, or draw a couple of boxes around the cars. Our models will work as a general car detector from drone footage, regardless of how the appearance of the car changes. It should be as simple as just clicking on the new car over a series of frames and the boxes will already be there.

Hopefully if we use something like a matching network, those can just be cropped out and dumped into a directory and we actually don't have to do any retraining. The model uses those images as part of its inference procedure, which is the ideal scenario.

[0:32:40.9] SC: How is the model incorporating those images as part of the inference? You talked about the five images of the dog and getting a new one. Is it these annotated car images would be presumably the five images of the dog, but that's happening at inference time, not training time?

[0:33:04.5] ECD: Yeah. Maybe we have five images of every single car associated with that as the labels. This is a really rough overview of matching that, but they added some fancy stuff on top of this. Basically like a **[0:33:19.5]**, so all of those images, so maybe you have 10 different cars, so you have 15 in just total, they're all embedded with some learned embedding function, or just the mapping.

[0:33:32.8] SC: Embedding function into what space?

[0:33:36.9] ECD: Some lower dimensional – so you just have a fully connected neural network layer and then goes to some smaller space. You now features for all of those pictures. You also do the same mapping on your new input, then you can just compare through some distance metric or some similarity metric that new input and all of your 50 just loaded images. So these images were potentially never trained on. We're really just learning that embedding function.

Then once you compare and find, okay it's closest to these five, or these three, or these one, you can take a weighted combination of those classes. Then whichever class has the highest load is what you end up going with.

[0:34:29.5] SC: How does the train model interact with and inform this matching process that happens at inference time? Is it that in this model, like the model that you've trained the network is only doing object detection and then this matching processes doing the object identification? Or does having the trained model somehow informed the identification as well, but you've got this extra layer that refines it?

[0:35:01.2] ECD: Yeah. I think we could do it either way. We would like to be able to keep it as a single model just for speed reasons, but that's still in the research phase. An alternative is to have the SSD model just do the object detection and then have the – whatever additional network that we have on top does the few shot learning and classification notes of different cars. I think, yeah, a lot of these are things to explore in the near future.

[0:35:38.3] SC: You mentioned SSD a couple of time, what does SSD stand for?

[0:35:42.8] ECD: Sorry, it's the single-shot multi-box detector.

[0:35:45.9] SC: Got it. Single-shot multi-box detector. Right. Okay, as opposed to your hard drive.

[0:35:54.6] ECD: We have an implementation of SSD that's open source on the Neon Github repo. That's actually what we ended up using for this project, and it's pretty much just plug and play with a new data set and a little bit of teaming. We were able to achieve pretty good performance.

[0:36:14.1] SC: Nice. Now is the data set that you've – like are you publishing this data set or anything like that?

[0:36:23.6] ECD: Not at this point.

[0:36:24.6] SC: Okay. Or any of the models or anything like that, are you publishing them, or do you have technical blog post or something that folks can take a look at if they want to get more detail into like how you approach this problem?

[0:36:42.1] ECD: Yeah. We have a technical blog post that should be out, or will be coming out describing some of the data collection and the modeling procedure and pre-processing stuff that we used, as well as a little bit of the training. That should give people a pretty good idea.

[0:37:00.7]SC: Are there other types or classes of problem that you think that the same approach would lend itself to? Or do you think this is very custom to the unique challenges or having six drones flying around trying to identify formula racing car or Ferrari racing cars?

[0:37:23.9] ECD: Yeah, definitely. Even today here at CES at the booth, we had a lot of people coming up and saying, “Oh, this could work for this sport that I participate in.” We haven’t quite explored those areas in terms of partnerships or how that would work yet, but I think it’s definitely applicable to all sorts of different either broadcast races or sports, or just when there is a fast-moving object that it’s difficult for viewers to follow and it helps a lot to have some sort of either AI assistants or overlay or automatic broadcast control.

[0:38:02.9] SC: Andy, this project was just announced here. What are some of the other things that you’re working on?

[0:38:11.9] AK: Yeah. I’m working on obviously continuing this project and some of the optimization that I mentioned. My other work is more related like I said to what I had done my masters on, which is end-to-end question-answer systems and dialogue systems, using similar network topologies if you look at it squint and from a distance, stuff like memory networks. They’re a large part of my work. I’m really interested in memory augmented neural networks and the role that can play in not just question answering, but a bunch of different challenges.

[0:39:05.1] SC: Are memory networks and memory augmented networks, are these related to LSTMs and attention mechanisms and that kind of thing?

[0:39:14.9] AK: Yeah, very similar to attention. It’s typically the memory augmented network means it has some fixed readable memory that you can either load items into. For the case of the memory networks for question answering it will load in a story, like a text story of something that happened and then ask questions about that story. Similar to attention, the memory network will compare whatever its input is with all of the story that’s loaded in memory. Those are very similar.

[0:39:58.5] SC: Awesome. Well, thanks so much guys for taking the hike over in the rain and the traffic. It was great chatting with you and I enjoyed learning more about what you’re doing with the Ferrari Challenge.

[0:40:10.7] ECD: Absolutely. Thank you.

[0:40:11.4] AK: Thanks for having us.

[END OF INTERVIEW]

[0:40:16.3] SC: All right everyone, that's our show for today. Thanks so much for listening and for your continued feedback and support.

Remember, for your chance to win in our AI at home giveaway head on over to twimlai.com/myaicontest for complete details.

For more information on Andy, Emile, or any of the topics covered in this episode, head on over to twimlai.com/talk/104.

Thanks once again to Intel AI for their sponsorship of this series. To learn more about their partnership with Ferrari North America Challenge and the other things they've been up to, visit ai.intel.com.

Of course, we'd be delighted to hear from you either via a comment on the show notes page or via Twitter directly to me at @samcharrington, or to the show at @twimlai.

Thanks once again for listening and catch you next time.

[END]