EPISODE 105

[INTRODUCTION]

[0:00:10.4] SC: Hello and welcome to another episode of TWiML Talk, the podcasts write 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 hows. 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 this 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 build Cozmo, the cutest little computer vision powered robot.

Lighthouse whose smart home security camera combines 3D sensing with deep learning and NLP. Intel, whose is using the single shot, multi-box images 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 U.S., and last but not least, Aeriel.ai, who applies sophisticated analytics to Wi-Fi signals to enable some really interesting home automation and healthcare applications.

Now, as of 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 web cam 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 show, I'd 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 like to watch.

Look for my conversation with Intel's Andy Keller and Emile Chin-Dickey earlier in this series for an in-depth discussion about this project and be sure to visit ai.intel.com where you'll find Andy's technical blog post on the topic.

Now, about today show. In this episode, I'm joined by Stuart Feffer, cofounder and CEO of Reality AI, which provides tools and services for engineers working with sensors and signals; and Brady Tsai, business development manager a Koito, which develops automotive lighting solutions for car manufacturers. Stuart and Brady join me at CES a few weeks ago after they announced a partnership to bring the adaptive driving beam, ADB, headlights to North America. Brady explains what exactly ADB technology is and how it works, while Stuart walks me through the technical aspects not only of this partnership, but of the reality AI platform as a whole.

Now, on to the show.

[INTERVIEW]

[0:04:33.4] SC: Hey everyone! We are here at CES, and I am with Stuart Feffer of Reality AI and Brady Tsai of Koito. Stuart and Brady, welcome to this week in machine learning and AI.

[0:04:47.7] SF: Hi.

[0:04:48.4] BT: Hi.

[0:04:49.1] SC: It is great to have you guys here, and thanks for braving the driving rain and horrendous traffic at CES to make it here.

[0:04:58.3] SF: It is a phenomenon. That's for sure.

[0:05:00.2] SC: It is definitely a spectacle. Why don't we get started by having the two of you guys introduce yourselves and tell us a little bit about your background and kind of how you got to what you're up to nowadays?

[0:05:13.2] SF: Yeah. Sure. Yeah, I'm Stuart Feffer and I'm a cofounder and CEO of Reality AI, and we are an AI startup. I'm sure you have a lot of them on these podcast. Our focus is a little different than most, I think. We are very much focused on problems related to sensors and signals, and we are not deep learning. We use a different set of approaches that are very much grounded in signal processing math, and I'm sure we'll talk about that.

We're at here at CES with a one of our customers, Koito, also known in the United States as North American Lighting, and they're making a product announcement that features our technology.

[0:05:56.2] SC: Nice. Brady?

[0:05:58.1] BT: Hi, I'm Brady. I'm a business development manager with NAL and Koito. I work in a Silicon Valley lab, which is based in San Jose. Just to give you a brief introduction of Koito. Koito is a tier-1 supplier for automotive lighting and we are the supplier for major OEMs, such as like Honda, Toyota and Ford. There is a product called ADP. That's where we work with Stuart, Reality AI, try to bring the AI into automotive lightings.

[0:06:34.2] SC: It's called ADP?

[0:06:35.6] BT: ADB.

[0:06:36.2] SC: Okay.

[0:06:37.3] SF: Adaptive Driving Beam.

[0:06:38.6] SC: ADB, Adaptive Driving Beam, and tell me a little bit about what's the main idea there.

[0:06:46.3] SC: Yeah. Go ahead, Brady.

[0:06:46.9] BT: Yeah. Adaptive Driving Beam, it's a vehicle lighting mechanism where it allows a user to have high beam always on, but in order to do that, we don't want to blind the incoming traffic or the traffic in front of you. So now that all the headlights and taillights are based on LEDs, that allows us to turn on and off a section of our headlights. In order to know which section to shut off, we have, first, to be able to detect the vehicle in front of us, and that's where AI technology comes in.

[0:07:35.0] SC: What sensors do you assume or require on the vehicle in order to be able to do that. I'm imagining, if we're talking about technology, that's going to be available in a near term. We're not expecting every car to have lidar on it.

[0:07:50.0] BT: Right. So for the ADB purpose, we only need camera.

[0:07:54.8] SC: Okay. All right, cool.

[0:07:57.0] SF: ADB, by the way, it's available today. Brady, this is a live product. It's on the road in Japan and —

[0:08:03.9] BT: Yes. It's been widely used in Japan, also in Europe, and its coming to North America in a very short period of time.

[0:08:12.7] SC: Okay.

[0:08:13.6] SF: What we've been doing, what we've been showing today, starting today at CES, is the next generation of ADB. The existing iteration is based more on traditional machine vision techniques, which is great. It works pretty well, but it is prone to some false positives, and the idea here is to use AI to reduce the false positive rate so that the — We got to be able to tell the difference between a headlight and a stoplight or a bright vending machine, that's not a truck, that type of thing. So the idea is to refine the prediction and deliver a more accurate prediction using that machine learning.

[0:09:01.7] SC: What is it about the traditional techniques that lends itself to the false positives?

[0:09:08.3] SF: Traditional machine vision techniques without getting into the specifics of what Koito's current product does, because we can't really do that, but these kind of traditional machine vision, like template matching. They very good in constrained environments where you don't have a great deal of variation in target and background. That's when they tend to perform best.

Pattern matching, machine vision techniques are great, say, on an assembly line where you are doing quality control. But out in that dynamic real-world where you have a lot more variation both in your target and in the background against which you're trying to separate that target. Well, you start to come up against the limitations of the technique.

One of the main constraints here though is we're not talking about an autonomous vehicle necessarily. This is a product that's going to go on regular cars starting in — They're available, as I said — As Brady was saying, they're available in Japan and Europe today and in the United States 2019 or 2020, something like that.

It's got to fit within a certain price point. You can't have an expensive processing brick just turning the high beams on and off. It doesn't work as a product. So the challenging bit here is not just accomplishing the detection using machine learning and suppressing false positives where you need false positives suppressed. The real challenge is doing that and then delivering that prediction in a form that can run on cheap hardware that meets the price point requirements of the product.

[0:10:49.2] SC: And this is cheap hardware that is presumably mounted within the lens, within the light —

[0:10:56.0] SF: In the headlight assembly. Inside the headlight assembly. That's exactly right. So it's got to — You can't make the car to much more expensive. You could make it only is more expensive as people perceive value and being able to turn their high beams on and off automatically.

Okay. We're doing more than just turning high beams on and off automatically as Brady was saying. We're actually tracking vehicles leaving the high beams always on, and tracking that vehicle that's in front of you where that's oncoming as it moves across the field of vision so that he's selectively blocked out, but you could still see animals, pedestrians or other things that are peripheral to that.

[0:11:37.0] SC: This is resonating really strongly with me, because while I normally live in a city environment over the holidays, I was in a moral environment and made frequent use of the high beams, and when you depend on the high beams and then you turn them off because there's oncoming traffic collecting lights. It's just like, "Where am i?" It's like it's totally dark." So I can relate to wanting to just — A, as cars get more complex, they're going to have more knobs and stuff and one less thing the worry about would be great, but there's — If you can have — You can offer me visibility into kind of my field of view even while oncoming cars are approaching, that sounds like a great proposition and one that will increase safety.

Tell me a little bit about some of the technology that goes into making this happen.

[0:12:32.0] SF: Yeah, sure. On the sensing side, which is our contribution. Koito, North American Lighting, they're the headlight experts, and in terms of controlling the beam and shaping the beam and figuring out exactly how to adapt the beam to the driving patterns, that's their area of expertise for sure.

Our area of expertise is sending the car in front so that in delivering that location of the car to their control mechanism so that it can appropriately adapt. So it knows where the car is a. It could do the calculations it needs to do to figure out what to do with those LEDs.

[0:13:08.3] SC: So you give them like vector a of angles and distances, for example?

[0:13:12.7] SF: Basically, it's very similar to what you would see in an ADAS system, the sort of collision avoidance system for autonomous vehicles where you see bounding boxes on cars, pedestrians, that kind of thing. It's a very similar sort of output. That's our contribution to this, is the sensing piece.

I think I mentioned in the introduction, Reality AI, our approach to machine learning is a little different. We're not using deep learning. Deep learning unfortunately would probably require more compute power than we can afford on that control unit.

[0:13:52.1] SC: Even on the inference side alone?

[0:13:54.3] SF: Yeah. So our approach, in general, to machine learning is we spend a lot of energy on the feature engineering, and we take us signal processing based approach and we have a process that looks through 200, 300 different feature types and computes each of them, test them and predicts which ones are going to be best for any given situation.

[0:14:23.7] SC: What are the sensor that you have available? I'm assuming you don't have access to vehicle sensors. It's only the sensors in the headlight assembly and this is maybe a camera or are there other [inaudible 0:14:35.8]?

[0:14:36.0] SF: On this case, we're working with a camera. I mean, it's certainly conceivable that in the future other sensors might be in play, but at the moment it's purely camera-based. Our technology is not camera specific. If I'm going to be candid, I would actually say image-based things is probably our weakest area.

In the image-based things where we tend to be strongest is in problems that can be reduced to a question of texture. If you're doing object recognition, you want to know, "That thing over there, is that a pedestrian or a person on a bicycle?" That's a good deep learning problem, object recognition. Deep learning is good at that and it requires compute, but it can do it.

Our stuff tends to work much better on texture-based problems, and in fact that's the way in which we approach this with the headlight detection and the false-positive suppression, is looking at spatial relationships between pixels of different colors inside of a decision window. It's just a different way of going about it.

Now, the fact is our stuff is much more widely used, and we do we do some things with images, and they're texture-based, but sound, vibration, accelerometer, electrical signals, those are really a sweeter spot for us most of the time and we are getting ready to launch a couple of things with Koito that will involve other types of sensors beyond cameras as well. Different kind of product, different kind of use.

[0:16:13.1] SC: When you say your stuff, what are we talking about here? Is it some hardware that goes in the headlight assembly? Is it some algorithms? Is it IP? Is it services?

[0:16:25.0] SF: Sure. The headlight is Koito's product. What Reality AI offers is a tool for the R&D engineer to create that product. By our stuff, what I mean is the algorithms and the application that allows an engineer to use those algorithms, to expose the algorithms to data and generate detection code, which can then be either hung in the cloud if it's cloud-based application or pulled out of the of that cloud-based environment, pulled into the IDE for an embedded environment and then run in the embedded target, which is how Koito plans to use this.

[0:17:13.9] SC: Maybe tell me a little bit about the — Can you tell me about kind of the experience of your engineers working with this technology. Do your — I'm imagining that your engineers don't typically have machine learning and AI expertise or am I wrong about that?

[0:17:32.2] BT: Right. So as a lighting company, most of our effort is on optics and mechanical and how to control the head in the headlights. We are now experiencing in putting sensors or more computing embedded system in our headlamps. We're quite excited to be able to work with Reality AI and then to try to find possibility to put sensors into headlamps and try to make it a smarter headlights and rear lights.

[0:18:09.9] SC: So the platform — Do you refer to it as a platform or a toolkit?

[0:18:15.1] SF: Yeah, we call it a toolkit or an application even.

[0:18:18.0] SC: So it’s kind of like an SDK that’s got some built-in — How is the —

[0:18:23.5] SF: Think of it as a code generation application. This is a podcast, so I can’t pull up a demonstration, but think of this as a toolset where you can provide examples of what you're looking for. In the case of what we’re doing with Koito, what those are, here are images where this is — This over here is A, the taillight of a car that we’re following and we want to block out. We don't want to a blind. Right next to it over there, that's a reflection off of a stop sign, so that's a counterexample. I don't count that as a headlight. That red light off in the distance, that's a stoplight. Don't count that either. That’s our input. We have snippets of images taken by the camera, and with some labels on them that tell us what they are.

In our application, we can load it with these examples and run, first, the process we call AI explore. AI explore does the feature engineering. It's a machine learning driven process. You could almost think of it as an expert system, but it isn't really, but what it will do is go through and to try to identify an optimized feature set, which can then be exposed to a machine learning algorithm, which could be in SVM, it could be your neural network.

We can pick that based on what's the most appropriate form of output for what the customer, what Koito needs for their technical requirements for the product. I mean, your audience is all about machine learning and AI, so I'm sure you and they and they know that when you have the right feature set, your choice of algorithm becomes much less important. If you have good, really solid features that separate — That give you a good separation between classes, well, heck almost any algorithm will find what you're looking for.

So that's really what the point of our application is, is to do that feature engineering and identify the most optimized features possible such that we can then use the lightest touch machine learning possible and therefore delivered prediction code that is as compact and computationally efficient as possible.

[0:20:56.9] SC: To what extent do the features that this tool spits out. Do they tend to be kind of intuitive features versus kind of artificial features, kind of mathematical combinations of the inputs that don't really have any intuitive interpretation?

[0:21:15.6] SF: Most of the time it's the latter.

[0:21:16.8] SC: The latter?

[0:21:17.0] SF: Yeah. So by the time someone gets to us, if it's a sound problem, for example, a vibration problem, by the time a customer gets to us, their engineers have already tried an FFT and put that into a neural net to see what would happen. If it was a problem was that easy to solve, they wouldn't be calling us in the first.

Look, our algorithm will check an FFT just to be in a couple of different flavors and a couple of different varieties to it just for completeness sake, but generally speaking, we're going to need to carve up that feature space is a very different way.

[0:21:53.8] SC: How do you do that?

[0:21:55.9] SF: We use mathematics you'd find in the literature under sparse coding, compressive sensing, that type of thing.

[0:22:03.8] SC: What are those things? What's sparse coding? What's compressive sensing?

[0:22:07.5] SF: I guess what we're doing is you could think of us as carving up time, frequency in a much more complex way than an FFT, which is using bands. And so it can be very responsive to things like transients and phase and those kinds of phenomena.

Now in the image kinds of problems, like we're dealing with here with ADB, that stuff isn't relevant, but it turns out when we use these same mathematics on images, what that basically translates to is a texture kind of relationship, and we tend to be good at finding textures and discontinuities in textures, but that's sort of a side — It's a side usage, which turns out to be very useful in certain cases, like with ADB. But our primary focus is more in that vibration, electrical signal, sound, lidar even.

[0:23:08.6] SC: So in the past when I've talked to folks who have — Or taking similar approaches to kind of automating feature engineering, there's — It's often a lot of like Monte Carlo type simulations and the kind of thing. Do you do that kind of stuff as well?

[0:23:26.3] SF: Yeah, not so much. We'll basically judge which feature set is the best. On the basis of — With feature sets that look promising according to our algorithm, we train a quick machine learning model on the subset of the training data. Do a quick K-fold analysis and we rank them on the basis of their performance into that K-fold. So it's a pretty straightforward accuracy-based ranking.

The other thing we do is we do generate a relative measure of the complexity of the feature computation because, again, our customers are by and large coming to us because they intend to deploy to an embedded target where compute is going to be a limited resource in their cycles or memory. So we'll give them a relative ranking of — If it's green and the bar is hardly filled in, well you can probably fit it on the cortex M3, M4, but if the bar is almost filled up and it's turned red, well, you're probably going to need server grade hardware to execute that particular model, and we basically make that engineering choice. Now, the engineer who is using this stuff can trade off computational complexity for accuracy in some cases.

[0:24:47.9] SC: I'm trying to wrap my heard around like the — So we get the problem. The problem is you've got limited computational capacity in a lot of these environments, and as exciting as deep learning is, it requires a significant compute capability even for the inference. But deep learning is exciting, because you don't have to do feature engineering. If you want to go the other way, you got to do some feature engineering, which is difficult manually. You guys automate it.

I'm trying to wrap my head around kind of the next level of detail, which is like if I wanted to build something like this, what are the things that I should be thinking of as a data scientist or an engineer, if I needed to build kind of automated feature engineering pipeline? Like understanding that there's proprietary IP and secret sauce and all that, what are the things that I should be thinking about?

[0:25:49.1] SF: Okay. The first case, the first thing I would say is that features are — Domain-specific isn't quite the right word. That's not what I'm going for.

[0:26:00.7] SC: There are classes of them or something like that?

[0:26:02.5] SF: Yeah. Our approach, the kinds of features we're going to try from soup to nuts are going to be the kinds of features that are relevant when you're talking about an input you could think of as a waveform in some way. Those kinds of features are going to be completely different than the kinds of features you would use if you're looking at business records of some sort, obviously.

Even with sound, the kinds of features we're looking at are not going to be same kinds of features you're going to want to use if you're building a competitor to Amazon Echo or Siri or Ok Google where the problem is natural language recognition. Our stuff isn't actually — The kinds of features we employ aren't actually very good at language recognition at all, but it's really good at machine hums.

[0:26:56.1] SC: Okay. So you're doing — You probably have like — You're kind of doing different types of FFTs, different types of Windows, different types of —

[0:27:05.6] SF: Yeah. Again, we're check FFTs for completeness sake. We're more likely to be using sparse coding, compressing sensing and other kinds of more complex features sets.

[0:27:15.6] SC: I think it's [inaudible 0:27:15.7] So there's some set of algorithms that are particularly good at identifying either frequency components or something like that in this type of signal.

[0:27:26.9] SF: [inaudible 0:27:27.0] phase, frequency. Yeah.

[0:27:30.4] SC: So you're just kind of sweeping across those with different parameters and maybe there's some kind of grid searching or something like that that you're doing or randomized searching.

[0:27:39.8] SF: Something like that.

[0:27:40.5] SC: Or something like that in there.

[0:27:42.6] SF: Yeah. Something that we — It's guided, but there's still a fair amount of — We're going to try a spectrum of things and we try a spectrum of things and when we find a family of features that's promising, the algorithm will dive in and do more exploration within that promising family. Yeah, you kind of have the idea.

[0:28:02.4] SC: What's the origin of the kind of the company and the product?

[0:28:07.6] SF: Yeah, great question. So where this stuff really came from is, really, the other cofounder truthfully. I'm the business guy. My background is Wall Street. I've spent just enough time in math and physics and type of thing to be able to follow along. But the real genesis of this came from our other cofounder, Jeff Sieracki, and Jeff is our CTO. It turns out he's been my best friend since we were 13 years old.

But for the last, I guess, 10, 12 years or so before we started Reality AI, Jeff was doing contract R&D for U.S. Federal Government customers in military intelligence community. Always in this area of applying this new field of machine learning to complex signal processing, signal recognition problems, surveillance, target acquisition, that kind of thing.

And during that, developed a fairly comprehensive body of IP, and we have 10 patents awarded, 6 patents pending, most of which come from that period. But that's really where the expertise for this came from, and a couple of years ago when we decided to create reality AI, we took all of that IP out of the contracting entity [inaudible 0:29:31.8] used for those federal government customers. Everything that wasn't classified, wasn't subject to export control, because we don't want that. Anything that could be freely used commercially, we moved that intellectual property into a new company. We sunsetted the old thing that have been used for the defense contracting and we created Reality Analytics Inc., Reality AI, to apply this technology commercially.

We turned that into an application usable by an R&D engineer, version 1.0 of that came out in June of 2016. 2.0 is coming out in just a couple of weeks, and we've been adding customers, and automotive, probably our number one area right now. Followed very closely by industrial, and we also have a couple of consumer products, consumers that are doing interesting things.

[0:30:30.2] SC: So for industrial, this might be an industrial machinery supplier who wants to be able to do predictive maintenance and you just drop in the algorithms and — hum and kind of those kind of frequency-based —

[0:30:47.5] SF: Yeah, vibration and occasionally sound. Yeah. Even some of the automotive customers, by the way, are doing that same kind of thing, but on the vehicle. Yeah, the industrial customer are — It's always one form or another of figuring out when the wing and the jigger [inaudible 0:31:04.1].

[0:31:07.2] SC: Trying to make it — It's called the machine whisperer. There's always like the machine whisperer that knows when it sounds like this, you need to whack it here with a hammer four times or whatever.

[0:31:18.0] SF: You got it. Our approach commercially there is that we are generally working with the equipment makers, so that much like Koito who is building the smarts into the headlight. We are working with the industrial equipment makers, the pump makers, what have you, to build the smart into their equipment as supposed to some kind of aftermarket add-on.

[0:31:39.9] SC: It's interesting. I've asked several of the folks that I've talked to today, what kind of things have they learned trying to introduce artificial intelligence to consumer products, and universally the answer has a lot to do with the user experience. From the perspective the consumer, they don't really care about AI. This is like at the far end of that spectrum. Nobody, no one who's driving a car is even going to — Even if they know that, "Hey, I don't have to turn on my headlights, my high beams anymore." This is something that you just want to be invisible to them and just work.

That being said, have you — As a company, kind of learned anything about applying AI in these kind of situations?

[0:32:32.7] BT: Well.

[0:32:33.3] SF: It's still early days.

[0:32:34.4] BT: Yeah. We're actually looking into possibility of embedding more sensors into headlights for autonomous driving as well, such as lidar and radars. After we — Right now, the [inaudible 0:32:48.6] factor of lidar is just too big to put into the lightings, but we're waiting for that size to shrink into a reasonable size so that we can put into the headlights.

[0:33:01.2] SC: Is the idea there that — Just that Koito would become a sensor provider to the OEM in addition to a lighting provider or it's somehow tied to lighting and the delivery of lighting?

[0:33:20.4] BT: I can't disclose that part yet, but we are looking into that kind of the possibility, also the possibility of doing some kind of an edge computing in headlights for autonomous driving.

[0:33:34.7] SC: Interesting.

[0:33:36.1] SF: The cool thing about what Koito is doing here is that because they provide — They're providing the headlights, the tail lights, the turn signals, that's their market. They own strategic real estate on the car. They have the placement on all of the corners, and if you want to place sensors to get the best possible field of view around the vehicle, where are you going to put them?

Plus these guys are — Since I've been standing next to them all day at CES in the booth, I've had a chance to hear them pitch, and being able to put these sensors in a form factor where it can standup to a carwash and whether — These guys are expert in creating electronics that are protected from the elements and can still see through.

That's actually — It turns out that as you sensor up a car, the real estate that their stuff owns and their ability to deliver it in a form factor that fits with a car's design that is protected from the elements, that could stand up to a power washing or whatever mother nature is going to throw at it, that's actually very, very important and something that the automotive industry looks to be only just beginning to grapple with as they start to think about the reality of making cars that are instrumented in this way.

[0:35:07.9] SC: Right. yeah I can imagine the modularity being — A lighting assembly is pretty plug and play relative to changing out something that's kind of built-in to the frame of the car, the sheet metal or something like that. It seems like a — I can see how it would be a strategic place to be.

Is this something that you envision becoming available like as an aftermarket type of thing or is it primarily you're going to market through the OEMs, the manufacturers?

[0:35:43.5] BT: Oh, you mean ADB?

[0:35:44.6] SC: Yeah.

[0:35:45.1] BT: Okay. I think right now in North America we're just waiting for the regulation to go through. I think sometimes in 2018 or 2019 frame, the regulation will go through and we can see vehicles on the street with ADB within two years.

[0:36:05.5] SC: And what's the nature of the regulation that is over this? Like the transportation, FTC has to —

[0:36:12.7] SF: Yeah, they have to approve everything.

[0:36:14.7] SC: Say that these high beams —

[0:36:16.8] SF: Safety.

[0:36:17.6] BT: Yeah. Apparently they have this kind of regulation in Japan already. So that's why you can see vehicle in Japan, they already have ADB embedded in cars.

[0:36:30.8] SC: This is already on the street in —

[0:36:32.3] BT: On a street. Yeah.

[0:36:32.9] SC: Oh, wow!

[0:36:33.8] SF: The first versions of ADB are on the street in Japan and Europe today.

[0:36:39.1] SC: It's interesting how much of this stuff — There's a lot of this stuff in this space, AI in general, that is behind regulation and then there's still even more of it that's like ahead of regulation, were never quite just right.

[0:36:55.6] SF: Yeah.

[0:36:57.3] SC: Yeah, it's been a great conversation. Any final parting words?

[0:37:02.9] SF: I always like to say — Because this is a machine learning audience, right? There's so much focus on deep learning for a lot of good reasons. I mean, deep learning is an incredibly powerful approach that has made progress on problems where very little progress has been in the long time before it. So I'm certainly not knocking deep learning in any way, shape or form relevant to a very wide class of issues, but it's not the only tool in the toolbox.

There are cases in — As I said in particular, edge cases, where you need real-time prediction at the edge in a product with a price point that it may not be the best tool.

[0:37:52.0] SC: So think broadly about your options as you're trying to solve real problems.

[0:37:55.3] SF: That's it, and for certain kinds of problems, we are one of those kinds of options. I think the statement is true generally.

[0:38:03.9] SC: Cool. We'll make sure to link to both your websites. I'm anxiously awaiting the automated high beams as well as the other aspects of the smarter car. Thank you both for taking the time to chat.

[0:38:20.1] BT: Thank you.

[0:38:20.5] SF: Thank you.

[END OF INTERVIEW]

[0:38:25.5] 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 Stuart, Brady or any of the topics covered in this episode, head on over to twimlai.com/talk/105.

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]

