**EPISODE 86**

[INTRODUCTION]

**[0:00:10.4] SC:** Hello and welcome to another episode of TWIML talk. The podcast where I interview interesting people doing interesting things and machine learning and artificial intelligence. I'm your host Sam Charrington.

This week on the podcast, we're featuring a series of conversations from the AWS reinvent conference in Las Vegas. I had a great time at this event, getting caught up on the new machine learning and AI products and services, announced by AWS and its partners. If you missed the news coming out of reinvent and want to know more about what one of the biggest AI platform providers is up to, make sure you check out Monday's show.

TWIML talk number 83, a round table discussion I held with Dave McCurry and Laurence Chung. We cover all of AWS's most important news including the New Sage Maker, Deep Lens, recognition video, transcription, Alexa for business, Green Grass ML imprints and more. This week, we're also running a special listener appreciation contest to celebrate hitting one million listens here on the podcast.

To thank you all for being so awesome. Tweet to us using the hashtag #twiml1mil to enter. Every entry gets a fly TWIML 1 Mil sticker, plus a chance to win a limited run T shirt commemorating the occasion. We'll be digging into the magic TWIML swag bag and giving away some other mystery prizes as well so you definitely don't want to miss this. If you're not on twitter or you want more ways to enter, visit twimlyai.com/twiml1mil for the full rundown.

Before we dive in, I'd like to thank our good friends over at Intel Nirvana for their sponsorship of this podcast and our reinvent series. One of the big announcement at reinvent this year was the release of Amazon Deep Lens, a fully programmable deep learning enabled, wireless video camera designed to help developers learn and experiment with AI, both in the cloud and at the edge.

Deep Lens is powered by an intel atom X5 processor which delivers up to 100 gigaflops of processing power to onboard applications. To learn more about deep lens and the other interesting things intel's been up to in the AI space, check out intelnirvana.com.

Okay, in this episode, we're joined by Chris Adzima. Senior information analyst for the Washington County's Sheriff's Department. Chris join me to discuss his very interesting use case for AWS recognition. Their image object detection system which he uses to help his agency identify criminal suspects in the Portland area by matching photos to mug shots.

We discuss how bias affects the work he's doing and how they tried to remove it from their process as well as what his next steps are with the recognition services. This was a pretty interesting discussion and I'm sure you'll enjoy it. Now, on to the show.

[INTERVIEW]

**[0:03:18.7] SC:** All right everyone, I am here at the AWS Movement Conference and I've got the pleasure of being seated with Chris Adzima. Chris is a senior information system's analyst with the Washington county sheriff's office and Washington County if you don't know is in the Portland area, is that right Chris?

**[0:03:34.2] CA:** That's right.

**[0:03:35.0] SC:** Chris, welcome to This Week In Machine Learning and AI.

**[0:03:37.4] CA:** Thanks for having me.

**[0:03:39.1] SC:** It's great to have you here, I am looking forward to learning a little bit about the talk that you gave yesterday. What was the topic of that one?

**[0:03:46.2] CA:** It was called the Unusual Suspects and essentially, it is about how I used AWS recognition to attempt to identify unknown suspects who committed crimes. What I used is previous booking photos or mug shots to upload to recognition, create a collection and now we can search surveillance footage or pictures taken by eye witnesses against those booking photos and attempt to identify those people based on if they had stayed in our jail.

**[0:04:20.9] SC:** Wow. Before we get into that, why don't we spend a little of time having you share with us a little bit about your background and how you got interested in the machine learning and AI stuff to begin with?

**[0:04:32.3] CA:** Sure. I have a pretty extensive background, it goes back about 15 years now where I started at eBay working in fraud detection and there we utilized machine learning, I didn't ever make any models because I'm not a data scientist but I utilized the models to detect things like people taking over accounts or posting fraudulent items.

Back then, it was very interesting to me and I kind of grew up with that as part of my background. When I moved into public service, I started working at the sheriff's office, I wanted to bring some of that interest into the sheriff's office and so I started looking at ways we could utilize machine learning or anything like that in order to help our deputies do their job.

One of the biggest areas of opportunity was the fact that we have all of this videos, all of these pictures of people who committed crimes that we can't identify. We also have all of this pictures of people who have been booked into our jail.

I thought, there's got to be a way that we can marry those two situations and come up with a very interesting way to solve that problem and so that's kind of where – how I grew up and got interested into it.

**[0:05:51.7] SC:** Okay, great. Is this the first machine learning project that you've done at the sheriff's office?

**[0:05:59.3] CA:** Yes, this is the first one, we started looking into other machine learning things and we're slowly getting into other things like crime detection and by crime detection, I don't mean somebody, one specific person committing a crime, I mean –

**[0:06:17.0] SC:** Minority Report?

**[0:06:18.2] CA:** Not like Minority Report, no. More specifically like, we noticed that as crime happens in one area, it migrates to another area over time. We can utilize that data to predict that there's a possibility that a crime is going to occur in an area subsequent or bordering. Therefore, we can send out patrols to that area, not to attempt to catch the person but to attempt to prevent the crime from happening in the first place. Because that's honestly what our goal is, right?

We don't' want to catch the people doing the crime, we want the people to not do the crime in the first place, that's what our hopes are for that.

**[0:06:53.5] SC:** An application like that is essentially like you know, how you got this fleet of cars and officers and other vehicles, how do you deploy them?

**[0:07:02.8] CA:** Right. How do you put them in the areas that are going to get the most prevention for where they are.

**[0:07:10.8] SC:** Okay. How long have you been at the sheriff's office?

**[0:07:14.9] CA:** Just about two years now. In fact, is it the $29^{th}$?

**[0:07:18.9] SC:** It is the $29^{th}$.

**[0:07:19.8] CA:** Yes, it will be two years tomorrow.

**[0:07:21.6] SC:** Wow, happy anniversary. I guess I'm curious, Did the – you know, you used Amazon's recognition product to do this first application. To what degree did having access to this, via an API as supposed to needing to build your own models, contribute to your ability to actually do it?

**[0:07:48.7] CA:** 100%.

**[0:07:50.4] SC:** I guess I kind of knew the answer to that question but –

 

**[0:07:53.9] CA:** I'm not a data scientist. I don't know how any of the stuff works in the back end. I'm okay with that. What it really did was allowed me, somebody who is very big into coding, I know how to code. Now, I'm able to utilize these machine learnings, these deep learning techniques to help me do my job and I didn't have to engage a data scientist, I didn't have to even know the model, I just took – was able to tie into an API and utilize their model that they already built.

It has been immensely beneficial because of that.

**[0:08:29.6] SC:** Can you talk a little bit about your process for developing the system?

**[0:08:34.7] CA:** Yeah. In my talk yesterday, I talked about how quickly this happened, right around this time last year, at Reinvent the announced recognition and by mid-November, sorry, mid-December, I had had a prototype up and running already. Basically.

**[0:08:53.8] SC:** That's incredible.

**[0:08:54.8] CA:** Yeah, it was really amazing, once I found out a recognition existed and I did a quick, I think it only took me about a day to go in and read the documentation because it's not an overly complicated API. I think there's only something like 20 calls.

**[0:09:10.7] SC:** Okay.

**[0:09:10.9] CA:** In total. Once I read the documentation. I was able to go in and realize that okay, the first thing I need to do is get my mug shots available to recognition, uploaded 300,000 mug shots into best three. I did it manually, I didn't realize there was an API I could use, this was when I was really green with AWS.

Literally, I used the web for my drag and drop, 300,000 increments of a thousand.

**[0:09:38.0] SC:** Ouch.

**[0:09:39.8] CA:** Into the web form. That took me about five days. Had I realized now that then what I know now about the API for S3, I would have just written the script and uploaded them that way, in fact, that's how we keep our mug shots up to date now, I have a daily script that runs, throws in them into S3 and index it.

**[0:09:57.0] SC:** Okay.

**[0:09:57.6] CA:** But.

**[0:09:58.5] SC:** At least your mug shots were digital.

**[0:10:00.3] CA:** Yeah, in the beginning, it was a manual process. Once I got those up into S3 though, I did write a script because then I knew that I could. Wrote a script to look through all 300,000, indexed them into recognition which is just one simple API call. Once they were indexed, I essentially had everything I needed to do to get up and running.

Once you have that collection, you can just do an API call to their search faces API and you send it the binary data from the image that you want to search from into the collection and it returns the results.

**[0:10:41.0] SC:** What are the images that you want to search from? What are those input images?

**[0:10:45.0] CA:** They come from a multiple different way. The web form that I created, we'll post them to S3 and then S3 will do the search that way. I'll then delete that one because we don't save any of the images we search for.

But then, I also have a mobile app, those will go directly into the API that way.

**[0:11:11.5] SC:** Those images though, are these like a surveillance video or is this like an office or in a street with your mobile app, taking a picture of someone or –

**[0:11:19.2] CA:** In my talk yesterday, I showed three different examples, one of them was from a surveillance, I don't know if people know this or not but there are surveillance cameras on those little self-checkout things and most of those departments stores. The surveillance camera from that. Yeah. That was a good hit.

**[0:11:36.8] SC:** Meaning like the credit card swipe or thing?

**[0:11:38.5] CA:** Well, it's not – the self-checkout's kiosks you know? The ones where you'd scan it yourself, in that case the guy was scanning the items but he didn't actually pay, he just put them back in the cart and walked out, made it seem like it was legitimate.

**[0:11:51.5] SC:** Okay.

**[0:11:52.8] CA:** We got a surveillance shot off of that, the second example I gave was actually a cellphone picture. An eye witness took a picture of somebody with their cellphone and then called the deputies. The deputies showed up and the deputy took a picture of the cellphone picture so it was like a second generation with all the glare on the phone and everything but recognition still found the face and ran that.

The third example which is the example that I am most pleased with was an artist rendition from an eye witness. Sketch. We ran a sketch through recognition and it pulled back a legitimate result.

**[0:12:33.1] SC:** Wow.

**[0:12:34.8] CA:** You know, when you say what we're running, we're running anything we can. If it has a face on it, it doesn't matter if it's a drawing or an image of an image of an image, we're trying. Because we want to identify these people.

**[0:12:49.7] SC:** How do you characterize the performance of recognition for your use case? Do you have specific ways you think about that?

**[0:13:03.0] CA:** As far as metrics go, not yet because it's still really early, it's only been a year since I even started and it's only been about six months that the deputies have been using it in full force. But I can tell you anecdotally, every single deputy, every single law enforcement officer has used this had said, "Wow, I can't believe that how good this is doing," and it's also difficult to quantify it because I'd love to get up here and say you know, this tool has led to x amount of convictions, right?

It doesn't quite work like that, right? The deputies use it as a tool, it's not their one and only thing they do. While a deputy might put something into the tool, get a result, it may or may not be the person in the picture but it could lead them to a relative.

With facial features being similar, you might get somebody's father return on the result, you go talk to the father, realize it was the son who was the person you're looking for. Is that a good hit for us? I don't know how to quantify that yet.

I can tell you that all of these situations have occurred so it's working well, everybody likes it and I think that's really all that matters when I'm putting the tool in the hands of a deputy, saving them time so that they can go out there and keep ourselves safe.

**[0:14:29.7] SC:** When you're thinking about it from the perspective of a developer or technologist using this service, how about the performance of recognition itself like have you – I guess you would have to – you put in an image, I guess you would want to know, what percent of the time you know is the image found when it's in the database? Do you track that?

**[0:14:51.9] CA:** We did some benchmarking at the very beginning about that because we had images that were not mug shots but we knew those people and those images were – had been booked into our jail at some point. We created – I don't want to call it a blind case study but I didn't know which of the group had been in our jail and which of the group had not been in our jail.

I didn't know the identities of the people.

**[0:15:15.8] SC:** Okay.

**[0:15:18.8] CA:** One of the deputies sent me over about a hundred images. Of the images of the people who had been in our jail, I was able to correctly identify 75%. And of the people who had not been in our jail but results were returned, I was able to say that 50% of those people, I was able to say, "No, we don't have a good ID for these people."

About 50% of the people who had never been in our jail, I said, I think it's this person and it actually was. I think when it comes down to a 75% accuracy, saying that there's a 75% chance that if they had been booked in our jail, I'm going to be able to tell you who they are. That's tremendous.

**[0:16:01.3] SC:** Yeah, I think it's like what you said previously. It's a tool, right? If you think about it in that context and not like recognition is going to replace policing then it's helpful, right?

**[0:16:15.7] CA:** Exactly, giving the deputies as many tools as possible to go out and do their jobs is exactly what my job is and so, I don't necessarily want to do their job for them. Although I'd love to do their job but I don't necessarily want to do their job for them. I want them to have a tool that they cannot have to be sitting in behind the computer doing research, looking at thousands of mug shots that possibly fit.

Instead, they get a likely choice of five or six and they can go out and take action on those, follow up on leads as supposed to being tied to a computer.

**[0:16:59.8] SC:** Are there things that you need to think about as a developer when using these APIs that are different from the traditional ways you might develop applications?

**[0:17:11.8] CA:** As far as being in law enforcement, yes. I have to concern myself with different levels of data classification. For instance, there's laws that prevent us from sending images of juveniles over the internet without certain security in place. While those securities do exist with Amazon, I have to ensure that they are in place before I send a juvenile's image.

In that case, we just have a policy that we don't run recognition off of juvenile images. As far as just a regular old developer that I have been for a while now, thinking about these APIs, I have to think about them in a different way because kind of like what we were just talking about, the effectiveness of the API.

Usually, if you were to come with me and say this API is 75% effective. I wouldn't even look at it because that's just not beneficial but when you think about what it's doing and the fact that 75% beneficial is way better than 10% beneficial which is where we were at with you know, scraping through mug shots using a Boolean search essentially, it's way beneficial and that's something that you have to wrap your head around as a developer saying that don't just throw it out because you want to see in the high 99's.

**[0:18:40.9] SC:** Elaborate a little bit on the – what you were doing before?

**[0:18:44.3] CA:** Previous to having this recognition product in place, we had a web form where you would go in and you would type in demographics. Like, I'm looking for a male between the ages of 40 and 50, height of five foot 10, black hair, you know, down the list of anything that you can search for. It would then search for all of the inmates that meet those requirements and return thousands of mug shots that you would have to then search through by your eyes to determine.

**[0:19:17.9] SC:** Were those, that meta data was on manually –

**[0:19:22.7] CA:** Exactly. It's all based on when you get booked in? Ask you questions, how old are you. Sometimes we have all that information because they give us a driver's license and we can put all that in but in some cases it's all based on what the inmate tells us.

**[0:19:37.5] SC:** I can tell you that they for sure give us different names,

**[0:19:40.4] CA:** They for sure give us different birthdays. Yeah, it was very – well, it was somewhat accurate, it definitely did have a tilt to it because of incorrect entered data.

**[0:19:54.1] SC:** Okay, you get this list of your thousand search results and you know, for whatever reason, I guess it's TV but I am imagining these big binders of mug shots. You are not doing it like that anymore.

**[0:20:04.5] CA:** No, not anymore. Obviously before we had a website that the deputies could utilize, that is exactly how they did it and there was binders full of mug shots.

**[0:20:14.2] SC:** Yeah, I think it is still like that on TV most days. I think on TV when they give what we call a six pack or a lineup card, it's still you know right there laid on the table where the guy points at the picture.

**[0:20:27.9] CA:** Yeah but it is one the computer now too.

**[0:20:29.7] SC:** Oh really?

**[0:20:30.0] CA:** Yeah so while it is very different than that it is actually very similar at the same time where yeah, you're just slogging through picture after picture and anybody who knows anything about like assembly line hypnosis or anything like that, after the fifth page you are not seeing those faces like you should anymore. You're just hoping that there is some huge mole on the guy's forehead or something because aside from that you're not going to see it.

**[0:20:57.4] SC:** Which is where you mention 10% accuracy rate before where that comes from.

**[0:21:04.5] CA:** Right.

**[0:21:06.4] SC:** So when I think about some of the issues associated with applying machine learning and AI, one of the things that comes up for me pretty quickly there some of the incidents and stories we've seen around. Just the bias that's injected into these types of algorithms and how that can play out in these which are really critical situations that involve human lives. What kind of – how do you think about that and what kind of experience have you had with those kinds of issues?

**[0:21:45.0] CA:** So luckily, I am happy to work for a sheriff who is very conscious about bias in policing well before any of the other counties were thinking about that. He was thinking about it and running reports to make sure that his deputies weren't bias. I have to say that all reports look good for us. So as far as personal or very specific to what I've done, I don't see it unfortunately to say that like this is how I would handle it or how we do handle it.

Fortunately we don't see it but I do keep that in mind because these algorithms do tend to have a little bit of bias and that bias is based on when the algorithms are trained, they tend to be trained by the developers. So the developers are going to – you know whoever developed it is going to have their ethnicity, their gender more likely to be detected than others. So those –

**[0:22:50.6] SC:** And is those specific effects, things that you've seen in your work with recognition?

**[0:22:55.0] CA:** I haven't necessarily seen a lot of, I don't know, what I would call a misidentity based on something that I would say that, "Oh this is definitely because this person is one ethnicity," but it's biased towards another ethnicity. I really haven't seen that much. That being said, we have come across a couple of situations where I would run, we would run an image through recognition and it would give us an ethnicity, the results would be an ethnicity that was contrary to what we personally thought just looking at the image. But in that case, we still haven't had a situation where we were in the proven wrong or right based on our previous things because we haven't identified that person.

**[0:23:40.3] SC:** Do you find that is it equally as effective in identifying woman in out of the pictures that you have identified or equally as effective in identifying all ethnicities or there are shifts and biases in that part?

**[0:23:59.4] CA:** I would say that when I see results that first if the results said it has multiple genders in that result set, I will see males put in with a picture of a female more than I will see females return when I give a picture of a male. So it definitely is more – I hate to use the word bias because I don't know how to say this except for that. When it is all said and done because it is just a tool that we've created, if it gives us five results of people who are completely off then we just sweep those results aside but yes –

**[0:24:40.9] SC:** And granted you know bias in some ways is a loaded term but –

**[0:24:46.5] CA:** Exactly and especially in my field.

**[0:24:48.1] SC:** Right but statistically you're – if we separate those kinds of issues that you are seeing where it is more likely to return male pictures than female pictures even when you give it a female picture for example.

**[0:25:03.5] CA:** Right and I find that I've almost looked at those results and saw that the results return - so if I give recognition of female picture and it returns five results and two of them are males, I find that those males tend to have more generic features. You know when you look at them, you don't see anything that stands out specifically and so that makes me wonder if those people's facial architecture is just simply generic in themselves and that's why they are getting returned.

I haven't delved deep enough into looking at their specific facial analysis which is one thing that recognition would allow me to do is that I could send that one picture through and it could tell me what it's likelihood of it being male-female, likelihood of it being one age group or another. I haven't really done that much of deep dive into those outliers that I have seen to see if maybe that's what it is, maybe the recognition thinks that this picture of a male is actually a picture of a female.

And that's why it's being returned but I can say that as far as age goes, I am a 35 year old guy and every single time I run my picture through it, it thinks I'm 50. So there's that and I think that if I maybe lost a beard and didn't have as much little grey hair maybe it wouldn't think of me as old but yeah.

**[0:26:34.3] SC:** Right, interesting. Are there – kind of continuing on the – are there ways – I am thinking the right way to get at this question. I am curious about again going back to the fact that recognition in a lot of ways is a black box for you right? Are there things that you are blind to as a developer that you might want to have more information about that you've run into?

**[0:27:06.1] CA:** Well obviously, I am pretty much blind to the entire recognition and how it works. I send it faces, it sends me results and I have no idea how it gets to be but I would like a way to, A, train recognition. It's not just for me you know? Not have them training my own collection but train it by some sort of feedback loop say that, “Indeed this was a good hit but indeed this wasn’t a good hit” so that it can get smarter. I’d love to see that.

I’d love to see a way for me to train it in different ways because while I only use one slice of recognition, there are other bits that would be hugely beneficial to us if they worked in the way we needed them. A great example of that is tattoo recognition, as well as a catalog of faces, we have a catalog of scars, marks and tattoos.

**[0:28:09.5] SC:** I’ve seen this on TV also.

**[0:28:11.3] CA:** Yes, this is on TV as well but you know on TV they are able to say, “Oh here is a picture of a skull tattoo and oh, here is him over here with his cool tattoo” that doesn’t exists in A, reality and B, in recognition it doesn’t, the API isn’t detailed enough to tell me this is a tattoo of a skull. It can say it’s a tattoo which is great but it would be even better if I could take all of my pictures of tattoos, feed them into the collections in recognition and then auto-tag those.

So that we could have a more standardized list of tattoos. So if recognition saw a skull, it would always return it as the same spelling of skull as the same –

**[0:29:05.9] SC:** To generate some kind of taxonomy of tattoos and –

**[0:29:08.6] CA:** Somebody would say skull, somebody may say crossbones, somebody may put an I in there somewhere. So we don’t have an easy way to textually search those for if a victim comes in and says their attacker had a skull tattoo on their chest, we could if we have recognition already auto-tagging these tattoos I could go in and search skull and get a list of everybody who has a skull tattoo on their chest that has been through our jail, possibly ID-ing them simply by knowing that they had a tattoo and that would be obviously immensely –

**[0:29:45.3] SC:** I could see how that would be powerful.

**[0:29:46.6] CA:** Powerful and I could tell you that I was watching a TV show a couple of days ago and they took a picture of a guy’s side of his head and they said, “Oh look at this guy’s ear. The ears are biometrically as identical to finger prints. So we are just going to take a picture of his ear and run that through ear recognition," I mean obviously if they could do that, I'd love recognition to do that. I brought that up because this is the thing I come across with the public is they assume we already can do this stuff.

They assume like when I talk about recognition with the citizens in our area, half of them didn't realize we couldn't do facial recognition before. They assume that when they send a picture to the news and say, "Could you help me identify this person?" that we have already done that part. Now luckily we have already done that part but before this year, it just didn't exist.

**[0:30:50.6] SC:** That's pretty funny, in my mind you are still going through these binders and things and the public thinks that you have Minority Report already established. That is interesting.

**[0:31:02.2] CA:** Exactly so that's another thing is I want to get us to the point where we are at where the citizens already think we are, right? So that when they watch TV they watches the TV show like APB and they see all of these stuff that doesn't exist yet that I can at least say, "Well I am working towards it. I am getting us there" and that's my goal.

**[0:31:26.5] SC:** And so what do you – what's next to get you there? Are you waiting for, are stuck waiting for recognition to build out all these features or is this like inspiration and justification for you to go find a data scientist department with or something like that? How do you proceed?

**[0:31:46.3] CA:** Many different ways, this is definitely not me sitting waiting for something to happen. This has really energized me and energized everybody on my team to go out and innovate and find new ways that we can assist the deputies and other law enforcement officers in doing their job. If it means that we know we want to do something and the only way we're going to be able to do it is finding a data scientist to partner with then we'll do that. If it means, you know, talking with Amazon over and over again until we get something into the product that we need then that's what it means.

If it means finding an interesting way to use another one of their machine learning tools that they didn't intend because I can honestly tell you all of the talks I've had with Amazon when they first put out recognition, nobody thought this would be great for recognizing criminals from mug shots.

But now that I do it, it's something that they absolutely think about the law enforcement application for all of their future machine learning stuff. Yeah, it's just going out there and trying to find interesting ways to use the things that we already have access to and possibly driving that thing into what we need it to be which is kind of what we've done with recognition.

Now, I won't take any credit for what the AWS guys do because they do great work and they do it on their own. I'm just saying that once they see that we have a use case there, they will take that into account and move for us.

**[0:33:20.3] SC:** When you think about the vast array of services that AWS offers or when you think about the array of machine learning and AI services that are offered by not only AWS but you know, google and Microsoft and a host of other players, are there, you know, do you have a kind of a short list of things that you're excited about? You know, tinkering with and putting the use in your – in the sheriff's office?

**[0:33:56.4] CA:** Absolutely. I mean, just this morning, the key note announced recognition for video. I don't even know if I'm going to wait till I get home to start playing with that. We have so much video in the way of surveillance of crimes in the way of video sent in by eye witnesses that we could utilize to determine who that person is and doing that thing.

Then there are other use cases that just quickly going through my head, you know, one of the things that recognition would possibly allow us to do is to determine intent, you know? Is somebody intending to do harm, is somebody intending to do somebody else harm, maybe there is a way to get notifications if a camera sees that.

Just many things I want to play around with that. There's the new – I think it's called Deep Lens which allows you to train a model based on what you show it, obviously, you can use that for anything from training it to determine products, to training it to determine I think they showed record labels, things like that.

I think I could train it to do better at finding the faces of people in those surveillance cameras or maybe like we were just talking about, maybe I can train it to do tattoo detection. That's something I want to play around with. Then they talked about – I can't remember the name of it now but the new –

They have a new machine learning platform that allows you to build the models without having to know anything about data science and so I'm going to play around with that obviously and see if I can get a model up and running and maybe like we were talking about predictive policing to know where to send deputies because of you know, maybe on the 4th of July we see a lot of illegal fireworks being set off in a certain area.

You get a notification, "Hey, why don't' you head over to that area?" That kind of thing. Lots of stuff I'm excited to play with.

**[0:36:08.0] SC:** Awesome. Well Chris, thanks so much for taking the time out to chat with me. I enjoyed learning a bit about your use case and you know, hearing about this kind of – dealing with AI services from a developer's perspective.

**[0:36:21.2] CA:** I enjoyed it too, thank you very much for having me.

[END OF INTERVIEW]

**[0:36:23.6] SC:** All right everyone, that's our show for today. Thanks so much for listening and for your continued feedback and support. For more information on Chris or any of the topics covered in this episode, head on over to twimlai.com/talk/86.

To follow along with the AWS reinvent series, visit twimlai.com/reinvent. To enter our TWIML 1 mil contest. Visit twimlai.com/twiml1mil. Of course, we'd be delighted to hear from you, either via a comment on the show notes page or via twitter to @twimlai or @samcharrington.

Thanks again to Intel Nirvana for their sponsorship of this series. To learn more about their role in Deep Lens and the other things they've been up to, visit intelnirvana.com. Of course, thanks once again to you for listening and catch you next time.

[END]

 