**EPISODE 53**

[INTRODUCTION]

**[0:00:10.5] SG:** 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.

The show you're about to hear is part of a series of shows recorded in San Francisco at the Artificial Intelligence Conference which was hosted by our friends at O'Riley and Intel Nervana. In addition to their support for the vent itself, Intel Nervana is also our sponsor for this series of podcasts from the event.

A huge thanks to them for their continued support of this show. Make sure you check out my interview with Naveen Rao, VP and GM of Intel's AI products group and Scott Apeland, director of Intel's developer network which you can find at twimlai.com/talk/51. At the AI Conference, Intel Nervana announced a dev cloud. A cloud hosted hardware and software platform for learning, sandboxing and accelerating the development of AI solutions.

The dev cloud will be available to 200,000 developers, researchers, academics and startups via the Intel Nervana AI Academy this month. For more information on the dev cloud or the AI Academy, visit intelnervana.com/devcloud for machine intelligence. In our talk, we take a super deep dive on the mathematical underpinnings of TDA and its practical application in software. Nerd alert!

All right, on to the show.

[INTERVIEW]

**[0:01:45.5] SG:** Hey everyone, I am here at the O'Riley and Intel Nervana AI Conference and I've got the pleasure to be seated here with Gunnar Carlsson who is the president of IASDI, welcome Gunnar.

 

**[0:02:04.4] GC:** Thank you, great to be here.

**[0:02:05.9] SC:** Absolutely, great to have you. Why don't we start with having you tell us a little bit about your background and your areas of research.

**[0:02:14.6] GC:** I come from an academic background with my PHD in mathematics and for the first 20, 25 years of my career, worked very much in pure mathematics. Over time, I started to become more interested in how could we apply things that we were doing in the pure math side, in a shorter timeframe because often times, the applications have a very long time to go.

I tried to do some things more quickly and my main area within mathematics is topology which is the study of shape and a generalized sense where I can talk about shapes and higher dimensions and so, I wanted to apply that to the study of large and complex data.

It turned out, it led to a lot of things, basically big career change, it wasn't just a little hobby thing, we found that it was a very hot topic both for the national science foundation and DARPA, the research arm or the innovation arm within DOD. In the middle of that, we spun out a company, IASDI Incorporated which is sort of commercializing the ideas coming out of there and other things as well.

That's kind of where we are, I live in the Stanford campus and math professor at Stanford or retired math professor at Stanford I should say. There I've got you know, three grown kids who are in the area.

**[0:03:30.3] SC:** Awesome, sound like a busy guy.

**[0:03:32.0] GC:** Busy guy but I don't want to not be busy, right?

**[0:03:35.5] SC:** Yeah, absolutely. Let's talk a little bit about topological data analysis and topology in general which was a topic of tutorial that you did here at the conference today. You mentioned the study of shapes, the first thing that comes to my mind is like high school geometry and trigonometry. I imagine it gets a lot more interesting when you're talking about higher dimensions and lots of data.

**[0:03:56.9] GC:** It is, on the other hand, sometimes what you can do is get very simple, you know, small representations of complex data sets by the things, the simple things that you mentioned.

**[0:04:05.9] SC:** Okay. What we do is we represent a data by network model. When you think about mathematical modeling, one often thinks about algebra, things about equations, things about various kinds of equations and so forth.

**[0:04:21.0] GC:** Maybe, one should try to model data by something else, maybe something with the richer output than just equations and for us, the output of our models is a network in a computer science sense that is nodes and edges. It turns out to be a very useful compressed representations and data sets for many different applications.

**[0:04:40.8] SC:** Interesting, when you say network and nodes and edges, I think of graphs, is this graph theory we're talking about?

**[0:04:48.1] GC:** Well, one can view it in that way but you know, a lot of times graph theory deals with very nitty, gritty local discussions and degree and so forth. This is sometimes thinking of it as a higher dimensional shape. For example, you know, a graph with four nodes and might actually code it tetrahedron rather than just its edges and so we kind of think in those terms.

Yeah, it is graph theory in some sense that in the sense that we studied graphs. I would say that we do it in a way that's different from what is usually meant by graph theory in the math side. It's more of what's meant by shape and topology on the topology side of math if that makes sense.

**[0:05:25.9] SC:** Okay. How does this all play into machine learning?

**[0:05:30.3] GC:** One of the big things about machine learning is that it's great but many people including people like regulators, like MD's, you know, all the people that one might want to use it with, often regard it as a block box.

They regard it as something which although it seems to produce good answers, they can't put their head around, understand where it came from and that means that sometimes there's some difficulty in you know, making use of it for those reasons.

We view ourselves, we view the topological data analysis as you know, a part of the growing area of machine learning, you know, we believe that it produces richer models than just simply classifiers or linear regression models that come out or clustering that comes out of machine learning and so you know, it's augmenting and helping machine learning develop over time. That's how we view it.

**[0:06:23.8] SC:** Okay, I heard a couple of things in there, I heard one, that the models are richer and I'd like you to explain or elaborate on why that is but I also heard that you suggest that this approach, the taking things from a topological perspective aids in explain ability and that's a huge issue for the constituencies that you mentioned.

But also, you know a business that's going to depend on machine learning or artificial intelligence, whatever we want to call it, you know, they want more than just to box set it, right? You know, kind of walk us through the next level of what TDA is all about and how it lends itself to achieving those goals for machine learning.

**[0:07:08.1] GC:** Let me talk about an example, you know, for the explainability part for the learning. Let me say by the way, what we produce, we produce a network, it can be viewed as a map of your data in a sense. You know, for us, we're working with a bank that had failed the stress test thing, sea crest stress testing process two years in a row, they had failed it in part, most part because they had produced machine learning models in which you know.

Which were predictive but which were not understandable that is to say they came as a large vector of numbers vector eco-efficiencies if you like and regulators couldn't understand.

**[0:07:47.6] SC:** The stress testing processes, the bank basically has to say, I've got this much reserve based on my risk and I've got to justify that some kind of way and they produced this model but they couldn't explain what the model was doing to justify it.

 

**[0:08:01.0] GC:** That's right, it wasn't explainable enough, that's correct. For us, now, the model was actually based on a lot of features, a lot of macroeconomic and other kind of global economic indicators.

We built one of our models on that and within that model, we found several hotspots for a coronation with revenue in a business unit. More than one, and so for each one of those, we might adjoin one or two features from each of those hot spots of those groups.

Let me say, the hotspot itself turns out to be a large collection of you know, these economic indicators but they were understandable to the regulators. We tell them, look, we have a model with four features, okay?

First of all, a much small, then each feature is representative of some class of features which are recognizable as similar or related by regulators. That is what we would call an understandable model, low dimensional and annotation in terms of a group for each one of the features.

**[0:09:08.3] SC:** Okay, I've got some questions. You started out by saying you built, you were talking about their model and you said you built a model on that. Did you build your model on their model or on their –

**[0:09:19.6] GC:** No, sorry, we're building separate models.

**[0:09:21.8] SC:** On their data?

**[0:09:22.3] GC:** building, you know, yes, on their data but not on their model, that's right, we're building, we involved many hundreds or even thousands of variables, you know, ours is a small number of variables and each one is understood as being representative of a class of indicators all over strong correlation.

**[0:09:41.5] SC:** Yeah. It almost sounds like what you're doing is you're like semantically clustering the features and kind of ranking the features in their relevance to the prediction.

**[0:09:54.6] GC:** That's correct. Here's the interesting feature in this, you might say, "well, why don't you just take all the features and find the ones that are the most correlated? You know, why do you need a – "

Well, the reason is that, features are perhaps correlated with revenue for different reasons. You have different groups of things which are correlated in different ways. If you put them all together, you know, you don't get nearly the same kind of explain ability as you do when you have separated them out and understand that each one is representative of a particular class of things that are similar. That's the key thing there.

**[0:10:31.2] SC:** I get the example and I kind of get what you're doing but still, how do you explain the TDA part of that, like at the next level of detail, what are you doing or how does it work?

**[0:10:43.4] GC:** Yeah, let me tell you, again, this may get a little geeky but let's go ahead and try it anyway.

**[0:10:48.9] SC:** We love geeky.

**[0:10:49.4] GC:** We love geeky, all right. You know, the starting point for us is always a data set equipped with a similarity measure of some kind. We encode that as actually a distance function mathematical sense which is an abstraction of ordinary distance that we have in a plane or in space.

**[0:11:06.0] SC:** Is your distance function something that might be like your error function or is it distance of the, you know, your rose or your points within the data set itself.

**[0:11:17.6] GC:** If distance is one road to another, you know, normal thing, supposing that it were – that we really only had two coordinates, you know, two features. Then my rows would be vectors with two entries and I could compute their distance regarding them as being in a plane and that distance would be, that would be a perfectly good distance that we could work with.

**[0:11:40.5] SC:** Right.

**[0:11:41.8] GC:** Now, the thing is that often times for you know, for different phenomenon with more features, by the way, those formulas for distance and dimension too, they extend to any number of dimension. If I have a spreadsheet with numbers, it doesn't matter whether I got five or 10 or even a thousand fields, it's off good, you can go ahead and compute with it.

Supposing that you're in a situation instead, you know, like you hire in the study of genetics where you have long sequences in an alphabet of symbols. You know, what you might do is you might take the two sequences and say, "well how many spots do they differ in?" Keep a count of that.

That is a distance of similarity measure as well. That's one that when we're using that context, in fact, you know, for us, there's sort of many different choices, these distance functions, there's libraries of them and so on.

You know, I've just given you kind of two important ones, the first one we call, the nuclei general, second one would be called hamming. Cold correlation, angle and cosign and so one, there's a lot of variety of them but the idea is always to get at some notion of similarity of data points.

The distance is small, we regarded data points as similar and if they're far apart, we regard them as dissimilar.

**[0:12:54.2] SC:** Maybe let's take this back to your example with the bank, you know, given a data set that consists of macro-economic factors and transactions perhaps and portfolios and the like, what does the distance mean in that context?

**[0:13:11.6] GC:** All those things are, there are numbers, there are, this is really just a spreadsheet. I could do the Euclidian distance there, I think there's a variant on Euclidian distance which is called, you know, variance normalized euclidian which means that if you've got some variables that have much larger range than others, you might want to make those ranges the same so that the one variable doesn't swamp the others.

 

Fundamentally, it would be the first one that I talk about, you know, be the notion of Euclidian, yeah.

**[0:13:37.1] SC:** I guess, maybe the question that I'm asking is, does a Euclidian distance or any distance I guess in the general case have like a semantic meaning in a highly – high dimensional data set or is it just the distance between points in a data set?

**[0:13:56.3] GC:** You know, it's not that one justifies it in terms of semantics or theory. But what one observes is that you know, it does typically coincide with one's notion of similarity. If it does not, then you know, maybe this is a data set for which some other metric or distance is more useable.

**[0:14:16.6] SC:** Okay.

**[0:14:16.7] GC:** Again, it's more what you actually see in the data, it's not about the theory that says, "yes, this is the one you want to use."

**[0:14:25.1] SC:** Okay, got it. You define this distance metric and apply it to the data and then what?

**[0:14:31.2] GC:** Now, what we want to do is, well, we have a projection of the data set which I won't go into detail on that. Basically what we do is we find, we've been the data set into overlapping bins. We do that in a systematic way and it has to do with a projection of some kind.

Once that's done, we perform a clustering step within each of those bins, each cluster is now made the node of a network and we connect to nodes if they share data point. You know, that's the short version of it. It's a kind of what we call partial clustering.

We don't apply clustering to the whole data set, we apply it to a bunch of pieces and those produce points for a network or nodes for a network. Makes sense?

**[0:15:16.8] SC:** It does, it almost, it makes me think of a number of things. Things like word embeddings, that makes me think of things like I don't even know what – I don't remember the general terminology for it but there is a company called Cortical or Numento, they do something similar to word embeddings, kind of evokes that for me but it also evokes for me like a convolution on neural net where you're like windowing your bins or kind of like your convolution of windows that you're moving across your image.

**[0:15:48.6] GC:** It is a little bit, I think actually I think there are a lot of connections with that, we're just starting to develop those now, you know, it's slightly different, it goes through a part of this whole TDA business which we haven't talked about which is about measuring shape through what's called persistent homology.

You know, this is a very kind of – it's always been regarded as the most esoteric part of mathematics for reasons that are kind of quite necessary to it but nevertheless, it's very powerful, it allows you to measure shape, it allows you to say, "look, is there a loop in our data? Is there a sphere in your data? You know, are there connected components here?" All those kinds of things that we think about, it allows you to actually measure those in a formal way.

**[0:16:32.8] SC:** This last step you describe, you're taking your bins and I heard that it's a windowing kind of effect.

**[0:16:40.8] GC:** Key that the bins be overlapping in this case, that not that there'd be disjoint, it's to overlapping because we want the clusters to have the ability to overlap so we can draw edges between them, you know?

**[0:16:50.3] SC:** Okay. Tell me what you do with your distance metric once you have these bins?

**[0:16:57.0] GC:** Actually, that's how we use – we only use the distance metric so as to be able to get the bins. As it perform clustering within the bins.

**[0:17:04.5] SC:** Got it.

**[0:17:05.3] GC:** Once I've performed cluster within the bins, you know, at this point, I can, for the time being, shelve the metric and say look, the representation I'm interested in which can be thought off as a generalized VEN diagram if you like, you know, it's this network model and this network model is something that we now want to examine.

**[0:17:21.8] SC:** Okay. All right, let's talk a little bit more about that examination process, that sounds like that's what's next.

**[0:17:28.0] GC:** That's right. Let me say by the way, first of all, what I'm going to describe is sort of the way to sort of interact with the model. You know, visually and on a screen and so on. One can also interact with it programmatically and that's what it wants to do to build applications ultimately.

You know, for some kind of manual data analysis, what one does is one puts a network on a screen through a layout algorithm and now there's lots of things that capabilities that you have, you're able to select parts of the network the way you would in photoshop or illustrator and once I do that, I can make that into a set of data points because the nodes correspond the collections of data points.

**[0:18:06.8] SC:** Okay.

**[0:18:07.9] GC:** Now I have new sets that I can either perform other analysis on or I can ask for their explanation that is to say, what is – what are the features that characterize the sub set. That's done in an appropriate mathematical and statistical sense.

You know, there are some choices on that but we made one particular choice.

**[0:18:28.2] SC:** What's that choice?

**[0:18:29.5] GC:** The choice is -  well, the main thing is that we're decided, we're selecting, we have distributions on the group of a particular variable on the groups and the question is, to choose those variables which are maximally different in terms of a so called call Smirnoff distance in distributions.

 

I'm just saying, I think there are other notions of distance on distributions one could use, sort of list those but.

**[0:18:54.1] SC:** When you say you've made that choice, you mean, in a given use case, you've selected one of many or the company's approach?

**[0:19:01.3] GC:** The company's approach is that one.

**[0:19:02.6] SC:** Got it, okay.

**[0:19:04.8] GC:** It tends to do a good job of maximizing the distance for the class of problems that you're going after.

**[0:19:09.8] SC:** It does, we find the explained capabilities were quite useful and works well.

**[0:19:13.6] GC:** Okay. Anyway, that's something one can do with it, you can actually color by quantities of interest so if I'm interested in things like revenue or survival or whatever it is, I can color a node by the average value of quantity for each of the data points and so, that becomes quite informative and often what you see in the network is, collections of hot spots.

You know, some value's high and more than one place. It turns out that they're different, they're high there for different reasons often and that's what's quite why the network is so informative. Because otherwise you would just take and you aggregate, you would study this quantity and since – you know, putting together all the different ways in which that thing is high.

You can't understand it. You can't make sense of it in a way that you can when it's split out like that.

**[0:20:02.5] SC:** You mentioned that that's this kind of add hoc interaction with the model. It's just one way to interact with the model but the way you describe that makes me think of used cases like forensic types of used cases like I associate with a company like Palantir. Do you overlap with them in the types of used cases you go after?

**[0:20:24.2] GC:** Yeah, so I think the answer is we don't fully know and the connection we know. I mean what they're doing is just sort of searching data that comes as a network, you know what I mean? Whereas in our case we are actually saying, "Well actually all data can be represented as networks and it provides a compression. I actually think there are connections there between those things that could make things efficient but we would want to speak to them because I don't have firm ideas in mind.

**[0:20:49.8] SC:** Do you tend to find yourself pursuing a lot of forensic types of used cases or?

**[0:20:54.7] GC:** You know at the moment, we have been focusing on health care and financial services. We are moving back into government in various ways and so we may very well hit that.

**[0:21:05.8] SC:** Okay, so we talked a little bit about this, the ways that you can interact with this network that's created out of the data. How else can you use this models?

**[0:21:14.6] GC:** So you know another thing that one can do is supposed that you have a linear regression or predictive model, most likely it's gotten by optimizing something, some kind of arrow function but it's probably also not perfect. It's probably also the case that there are some areas within your dataset, some particular phenomena that happen that maybe there are some systematic errors that happen. You know you can't correct them within your own model.

And within the features that you've got but what it allows us to do is it allows us to say, "Let's take a network and let's color it by that model air". Maybe we'll find some hot spots for model air and maybe I will try to correct around those hot spots by adding features somehow. So that's another point I would put it under the general heading of model diagnosis and model improvement. So that's another situation.

**[0:22:03.1] SC:** Interesting. You mentioned health care, what are some of the used cases in health care?

**[0:22:07.1] GC:** So we have something called a clinical variation management which helps study both finding new and optimizing care paths for particular procedures as well as tracking it here instantly. We have a population health kind of application that is working on trying to understand trends and population health. Who is going to go to the 5% group who are the most expensive? Who is on track to go bad and how can we improve their chances?

So that's a couple of things, there are some on the financial side as well. We work with hospitals as well as payers, providers as well as payers in the health care side.

**[0:22:46.1] SC:** Can you maybe just to tie all the terminology together maybe pick one of those examples and walk us through what the data tend to look like, what the clusters might represent, what are some of the findings that someone might see?

**[0:23:03.0] GC:** Yeah, so let's talk about the clinical variation management for example. So the data there consists basically at all the events that happened during the course of someone's stay. Say for some particular surgical procedure like knee replacement, like bowel surgery and so forth and so what one can then do is one needs to put on that set of things, some appropriate similarity measure and that this dysfunction and that turns out to be quite a tricky interesting problem.

Probably the key part in the solving that problem and that ultimately it produces for us then sort of a consensus care pass. Maybe if you care pass that are very good and one consensus together with some explanations to what are the key features that differentiate that from others.

**[0:23:48.3] SC:** So it's almost allowing you to identify which outcomes or which features of the care if you will or kind of correlated with success or maybe where some outliers are and the features might be what drugs are administered, what doses are administered when are they administered, things like that?

**[0:24:09.4] GC:** That's exactly right and just to give you a sense of how it could work in one's situation, when hospital systems are deciding on care pass, what they usually do is they get together the people, the smartest people that they consider who are working on this and they get together in a room and they discuss it out and ultimately come to some kind of answer about what it should be. They cut the problems with that model.

 

You maybe haven't found all the best people who are doing this procedure, maybe you haven't chosen exactly the right group and in a way, it is also the case that when people are sort of arguing things out in a room sometimes it's the strongest personality rather than the strongest case that comes out. So there is all sorts of issues with that.

**[0:24:49.1] SC:** I also think there's implicit versus explicit knowledge right? I mean there could just be things that some people do and they don't really realize that they're doing it different from the other doctors and so they don't know to argue it.

**[0:25:01.1] GC:** Exactly and then so in fact that was what happened for us with one of our customers was exactly some of that. We found that for one surgical procedure, there was a group a small group out in the periphery of the system that people hadn't really observed so much but they were doing something that had good improved effect on length of stay and so that was sound. That was quite an important contribution to them. So even just in terms of the search thing like that, it was quite useful that way.

**[0:25:32.8] SC:** Interesting. So if someone wants to learn more about this, it sounds like topology is an interesting place to start is there a canonical paper or reference or something like that?

**[0:25:45.7] GC:** Yeah, well why I knew that of course, if you go to study topology you'll be involved for years before you get there application. So I wouldn't necessary – I mean one could certainly read some things about it but what I would say is, first of all our company has a lot of a stuff on its website basically sort of knowledge center with a lot of technical papers and somewhat less technical as well. So I would recommend reading survey paper route as oppose to taking a textbook and chugging through.

Because this is a newly developing subject and so there are some textbooks in this persistent homology side that I talked about but the general notion of topological modelling, you know I think we have a lot of stuff on our web on it's won but yeah, actually come to think of it on here we do have my colleague FX Campion, Francis Campion and I have written a book which is called M*achine Intelligence for Health Care* and so it's available on Amazon and I recommend it.

It's got the first half, it's kind of discussion of this mathematical modeling and then the second half is specifically how does this work in health care. So I would recommend it.

**[0:26:53.5] SC:** Okay, that sounds really interesting yeah and did you elaborate on persistent homology or did we?

**[0:27:01.3] GC:** Let me just say that it is a very interesting way of detecting shape features, certain kinds of shaped features in data and as it is on the pure math side, it detects feature in regular spaces. Spaces with complete information and where you got the whole thing. It can be used in two ways. One way is that it can be used as a way of recognizing what the overall organization of the data set is. Did we found for example, in studying some image processing data sets.

That the frequently occurring phenomena in three by three patches are aligned around one circumstance of circle and a slightly higher level of understanding around the mathematical object called the climb bottle which was very interesting for us. We used it for understanding image compression and also texture recognition. So it was quite interesting. The second thing though is that it can be used and this I think is going to be a much more rapid application.

Is where it gets used to generate features in unstructured data. So when you have data that is complicated and that somehow carries a notion of distance on it like molecules where the atoms can be regarded as the points and the distance has to do with the bonds then you can attach the so-called persistence barcodes to those points and that's quite useful in organizing and understanding those kind of unstructured databases. The databases of unstructured data.

**[0:28:30.1] SC:** Interesting. You mentioned earlier and I saw it on the description of your session as well something that I think is related to this identifying loops in data. What does that even mean, loops in data?

**[0:28:45.5] GC:** Well imagine I had a fly, imagine that you had a picture, you see your data. Supposed the data is actually in 2D and supposing that you've got a bunch of dots. So the data is a bunch of dots and it looks like it's kind of surrounding like it's a circle. We see it as a circle.

**[0:29:02.1] SC:** Right so something like a clustering algorithm doesn't really know how to do it very well but you can identify this higher order primitive that hey, this is like a geometrical primitive essentially.

**[0:29:14.7] GC:** Exactly. That's exactly right and that's what we are trying to do. We're trying to mimic that fact. We know what a loop looks like but we don't know what it is our brain does to recognize that and so therefore you do this homology. So imagine that you are trying to understand how do you recognize a letter A from a letter B? The letter A has a loop and two legs and the B has two loops in it. So if you can find something that counts for you the number of loops you are going to be able to characterize a letter A from the letter B.

You'd be able to differentiate it and you'd be able to differentiate it in a way that's fun and independent, that's independent of the fact that you see it from an angle perhaps or that is sitting in the surface of a soccer ball. It's miraculously deformation. It's not sensitive to those deformations and that's what homology is.

**[0:30:06.8] SC:** That sounds promising but it also sounds, I guess, I think about it in a context of deep learning, right? Deep learning purist would say, "while you know, it's going to be a lot easier to just do tons and tons of data that have like all different kinds of B's you know? And A's.

Just let the network teach it" and I've had this conversation with some folks that specialize in deep learning around combining other approaches to create higher level insights with the deep learning and one of the answers is I'll just fill the data, add it and figure it out.

**[0:30:41.2] GC:** Sure of the course, what you find is that you know, they're adversarial approaches to that. You know, even for something as simple as M nest, the M nest data set which is of hand drawn numbers where you find that if you just mess with the background a little bit. In a way that you know, people wouldn't see the difference, people will see that you know, one is a one and a two is a two but it messes up the deep learner.

**[0:31:04.4] SC:** Yeah, absolutely.

 

**[0:31:05.9] GC:** That's a feature question, you see, it's doing a certain kind of overfitting is perhaps the wrong term but it's focusing on some features that have to do with the background that are not really relevant. To the extent that you can feed it features that are kind of background independent like that, then you're in good shape, that's what persistent homology is, a perfect tool for providing features to a deep learner because in fact.

The output of the persistence thing can be regarded as an image so it kind of fits directly into that.

**[0:31:38.6] SC:** Yeah, is this an application in theory and principle or are there demonstrable situations using M nest or some other data set that says persistent homology outperforms deep learning or has some cost benefit analysis relative to –

**[0:31:55.2] GC:** Well remember, it's not outperforming deep learning, it is feeding into deep learning and using it. The example I would point to is, we're using the persistent homology to create features that either replace the raw images or augment the raw images and then we're still using deep learning to learn.

**[0:32:13.2] SC:** That's correct, got it.

**[0:32:15.1] GC:** Now, again, most of this is sort of looking into the future however this exact thing has been carried out by a friend of mine or a colleague of mine at Michigan state Yu Wei Wei who has taken databases of molecules, candidates for drugs, you know, drug discovery.

Built persistence homology bar codes on them and then use those deep learning on those. Extremely successfully.

**[0:32:40.3] SC:** I'll ask you afterwards for the spelling of that name so we can –

**[0:32:42.9] GC:** Sure, I'll write it down for you.

**[0:32:44.3] SC:** Include it.

 

**[0:32:44.6] GC:** That's right.

**[0:32:45.9] SC:** Awesome, well that was great to have you here, I learned a ton and I feel like there's so much more to learn about this topic.

**[0:32:55.4] GC:** There's a lot to learn, I feel that way every day. Thanks very much, I enjoyed the conversation.

**[0:33:00.3] SC:** Great, thanks Gunnar, thank you.

[END OF INTERVIEW]

**[0:33:05.5] SG:** All right everyone, that's our show for today, thanks so much for listening and of course, for your ongoing feedback and support, for more information on Gunnar and any of the other topics covered in this episode, head on over to twimlai.com/talk/53. For the rest of this series, head over to twimlai.com/aisf2017, and please, please, please send us any questions or comments that you may have for us or our guests via Twitter @twimlai or @samcharrington or leave a comment on the show notes page.

There are a ton of great conferences coming up to the end of year. To stay up to date on which events we'll be attending and hopefully to meet us there, check out our new events page at twimlai.com/events. Thanks again for listening and catch you next time.

[END]