EPISODE 56

[INTRODUCTION]

[0:00:10.3] SC: Hello and welcome to another episode of TWiML Talk, the podcast where I interview interesting people doing interesting things in machine learning in artificial intelligence. I'm your host, Sam Charrington.

I'd like to start out by sending a huge thanks to everyone who took the time out to listen to AI Conference San Francisco series this past week and for all the feedback and comments. We are so glad you enjoyed it. From now through the end of the year we will be releasing a ton of great interviews and we're really looking forward to your continued thoughts and feedback. Be sure to reach out to us via @twimlai on Twitter of Facebook or via the show notes page for each episode.

Next up, I'd like to take a second to tell you about our sponsor, Nexosis, and thank them for sponsoring this week's show. Nexosis is a company focused on providing easy access to machine learning. The Nexosis machine learning API meets developers where they're at regardless of their mastery of data science so they can start putting up predictive applications immediately in their preferred language.

It's as simple as loading your data and selecting the type of problem you want to solve. Their automated platform trains and selects the bets model fit for your data and then outputs predictions. Get your free API key and discover how to start leveraging machine learning in your next project at nexosis.com/twiml. That's nexosis.com/twiml. Head on over, check them out and be sure to let them know who sent you.

In a few weeks we'll be back in New York City for the NYU Future Labs AI Summit. Now, as some of you may remember, we held our very first TWiML Happy Hour our last visit to New York and it was amazing. We had a really nice mix of listeners and conference attendees come out which inspired us to go even bigger this time, and that is just what we did. We're excited to present the AI Apocalypse and Killer Robots Halloween Social. Yup, on October 30th, hang out with us as we're joined by Dr. Seth Baum, Executive Director of the Global Catastrophic

Institute, and Shane Hobel, founder of Mountain Scout Survival School as we discussed your most pressing questions about extreme AI. The discussion will be interactive and this will be our very first live podcast recording and we couldn't be more excited.

This event is being produced in conjunction with our good friends over at Tech 2025. For ticket info and more details about the show, visit twimlai.com/halloween, and over on the show notes page you'll find a discount code for 25% off registration for the NYU Future Labs AI Summit.

Finally, about today's show. A few weeks ago I sat down with James Guszcza, U.S. chief data scientist at Deloitte Consulting, to talk about human factors and machine intelligence. James was in San Francisco to give a talk at the AI Conference on why AI needs human-centered design. We had an amazing conversation in which we explored the many reasons why the human element is so important in machine learning and AI along with useful ways to build algorithms and models that reflect that human element while weeding out things like group think and biases. James and I had a really great conversation and I'm sure you're going to enjoy it.

Now, on to the show.

[INTERVIEW]

[0:03:55.4] SC: All right everyone. I am here at the AI Conference in San Francisco and I'm here with James Guszcza, and James is the U.S. chief data scientist with Deloitte Consulting and he's going to be speaking later today actually on topics that you've heard me allude to here on the podcast a number of times; human factors in artificial intelligence, and so I'm really looking forward to diving into this conversation with you, James. Welcome to the podcast.

[0:04:22.2] JG: Thank you very much. I'm happy to be here.

[0:04:23.7] SC: Absolutely. Why don't we get started by having you tell us a little bit about your background?

[0:04:29.6] JG: You want to hear my checkered past.

[0:04:30.5] SC: I want to hear your checkered past. Yeah. In fact I saw in your bio that you've got a Ph.D. in the philosophy of science.

[0:04:39.1] JG: Yeah, I know it's a cliché. Yeah, I have a Ph.D. in philosophy from University of Chicago. I'm a very intellectually curious person. Actually, when I entered philosophy, what I thought I was going to study was artificial intelligence.

[0:04:51.6] SC: Really?

[0:04:52.2] JG: Yeah. I'm a very old person. This is back in the early 90s, and back then artificial intelligence was talked about. A lot of people are connectionists, Jerry Fodor and so on and so on. I almost went to University of Pittsburgh, which had a lot of types with Carnegie Mellon University and one of the strongest philosophy of science programs in the country is at Pitt, right down the street from CMU. I really thought I'm going to do artificial intelligence.

Long story, I changed my mind. I went to the University of Chicago and I got a Ph.D. in philosophy, but I focused more in philosophy of physics, and especially the way statistics is used in physics. This is all my way of saying I studied free unemployment. I always joke that philosophy is the Greek word that means pre-unemployment.

It was wonderful. It was some of the best years of my life. I love Chicago. I love the University of Chicago. I loved what I studied. It was fabulous, but I needed a way to make a living. This is back in the early 2000s, late 90s, I was thinking through the various options. I thought, "Well, I'm a humanities guy, go to law school." I'm not going to do that. I'm doing kind of scientific stuff. I can go to Wall Street, right? I could do the whole options thing, which is very sexy back then. I didn't think it would culturally work for me. I just didn't think — I actually landed a job. I went off for the interview. I just didn't enjoy it, so I didn't do it. I went for the fame and fortune and glamour of becoming an actuary.

[0:06:04.8] SC: Okay.

[0:06:05.0] JG: I didn't know what that meant back then, but I assume that actuarial science meant data science, and it didn't, but now kind of does. There's a weird way in which actuaries were the original data scientist. There's a weird way in which my first data science program, or project, which I did at the Allstate Research Center in Menlo Park, California. There's a weird way in which that was actually artificial intelligence. I didn't think of it at the time, but I basically — You could think of credit score as a sort of an early example of AI in the sense that Kris Hammond from the Narrative Science in northwestern talks about, which is that it's not so much AI from folks through a technical lens, but functionally it's AI, because we used to have this whole profession called bank loan officers, and that was like a lot of people. That was their job as bank loan officers.

It turns out that went out the window when we use algorithms to make lending decisions. I can get into this. There are a lot of reasons why that makes a lot of sense. Some of it is on the data side and some of it is on the human cognition side.

[0:07:03.7] SC: A lot of reasons why what aspect of this makes a lot of sense.

[0:07:06.0] JG: There's a lot of reasons why — And that was an early case where algorithms outperformed human judgment and the use of algorithms kind of like shrunk as a certain part of the workforce, right?

[0:07:19.3] SC: And so is this contested? Like that feels intuitively obvious to me that this is a fundamentally data-based decision and if you can accurately characterize a person or a situation in data, which we are able to do now, then algorithms are going to do a pretty good job with this over golf in relationships and some of the things that we think of as the past lives of the loan officer.

[0:07:43.6] JG: Absolutely, and I would say, "Yes, but." I think this kind of gets a little bit —

[0:07:47.3] SC: The "Yes, but," is always the interesting part.

[0:07:49.1] JG: Yeah, absolutely. Exactly. This is sort of — It kind of gets at one aspect of what I'm going to be talking about in my talk this afternoon, which is that unaided judgment is notoriously unreliable when it comes to making judgments and decisions. If the listeners have read things like Daniel Kahneman; *Thinking, Fast and Slow,* or *Nudge* by Thaler and Sunstein, or *Kluge,* by Gary Marcus, the cognitive scientist. We realized that our brains evolved — They were optimized by evolution for a certain kind of environment outrunning predators in the Savannah or whatever it was.

[0:08:21.2] SC: I'm also thinking, *Predictively Irrational* by Dan Ariely.

[0:08:23.5] JG: There's some other popularization of this whole thing. Exactly. The reason pop classic in my opinion is *Thinking, Fast and Slow* by Kahneman. That should be in every machine learner's shelf in my opinion. This is kind of like the complements of machine learning in my opinion.

Yeah, those same sort of mental heuristics that service well in kind of everyday life, they don't service so well when we put on a suit and sit on a board room and try to decide, "Should I acquire this company?"
"Should I admit this student to the university?" "How should I treat this patient?" Does this person get the loan or not?" There can be all sorts of advices creeping in. This is the theme of *Predictively Irrational* and *Thinking, Fast and Slow.*

Kahneman talks about — He calls them the miracles and the flaws of unaided judgment. That's a paraphrase. The miracle is that most of the decisions we make in day-to-day life are what you'd call thinking fast. Just like effortless, they come automatically. We kind of tell the story and the story kind of works. In these kind of mission-critical cases where it's more like, "Is this person going to commit a crime?" or "Is this person going to pay back the loan?" or "Is this person going to crash his car?" or "Does this person have the disease?" That's why we really need help from algorithms.

That's kind of like one half of the story. I think another one of the topics that we've all known about for decades, but it's really becoming — It's coming to the fore, is the need to make sure we reflect societal values in these algorithms at the same time.

When I was at Allstate doing this, it's kind of an interesting story. I wasn't building a credit scoring algorithm for Allstate because they were underwriting loans. It's because they're selling insurance contracts. It turns out the credit is hugely predictive of who's going to crash their car, or have like a water homeowners claims. We can get into that. It's a very interesting story about why is the data subjective in that way.

We're also very interested in the legal doctrine of disparate impacts. Even if we didn't put a protected class in the algorithm, there could be unintended consequence or the algorithm could have systematically different scores for different groups of people, like by income or whatever it is, or urban rule, or race, or gender or whatever it is. We don't want that.

It's very interesting, because these same early conversations are now reflected in the larger scale in the world of AI, but early on, I would get into these conversations with other quants, back then they're actuaries. Back then we called it machine learning, to answer your question, or data mining. That's what we called it back then. KDD was around back then, so we called it data mining.

The actuaries would say, "This is just ridiculous. We just want to come up with the actuarially fair price. Everybody should be charged insurance that reflects their risk." But that might be a limited perspective. There might be other perspectives that legitimately should constrain models. What is the way to kind of optimize models? Is it the kind of a metric of we're going to make this prediction with the greatest out of sample accuracy or is it subject to this, that and the other constrain? Some of those constrains are societal in nature. Some of those constrains are what we are calling human factors in nature. There are some cases where maybe it's a really complex risk. Maybe I'm trying to underwrite a very complex loan or a very complex insurance contract or a very complex medical diagnosis or a judge making a parole decision. We don't necessarily wanted to simply turn that over to a machine, right? We don't just want to automate it away, take humans out of the loop. Rather what we want to do is we want to kind of take the best of both worlds and say, "Well, the machines are good in one way. They can weigh together 400 factors better than we can get it for. Oh, by the way, do it the same way before lunch and after lunch, versus after lunch, which we don't do."

At the same time, they don't have common sense, whereas humans have common sense. They understand ethics. They understand the strategic goals of the organization. They understand societal values, legal constraints, whatever it is, public relations, whatever it is.

Figuring out how to marry the best of both worlds, that's part of what I mean by design. You know what I mean?

[0:12:11.7] SC: Yeah.

[0:12:12.9] JG: It's like one analogy I've made for a long time is that — Yeah, these algorithms do replace humans in certain tasks. I always talk about credit scores in the early example of artificial intelligence. For some types of loans or risks or medical diagnosis or whatever, you just kind of like turn the algorithm on, it will make a smart decision. It might be wrong a part of the time, but maybe the losses are acceptable for whatever reason.

In other cases, you just can't do that, and so it's more like there's this art to somehow blending the machine indication with a human judgment, and that's always fascinated me. That's been more of the late motif of my work at Deloitte since leaving Allstate. At Allstate we're doing a lot of big data, personal insurance. Allstate is the second or third largest insurance carrier in the country, so they had all these big data and you could do a lot of these kind of like, "Oh, I'll just have this algorithm. It will spit out a price. Boom! There's your price." It's automation.

When I joined Deloitte, there's a lot more work for smaller medium-size companies or organizations that want to use data to make more complex decisions. This idea of blending algorithmic indications with human judgment became much more of an issue.

I only came to appreciate this gradually as I was working in Deloitte. I started off as a pure quant. I was just interested in the math, and I still am. I love it. That's the geeky side of me, but there's also this kind of side where I'm just fascinated by the way it's used in organizations. I'm just interested in like you need organizational buy-in. You need to reflect domain knowledge and institutional knowledge in the data, the design of the algorithm. You need to think upfront about how is the algorithm going to be used in the organization. Who's going to be using it? Who are our stakeholders? If you get all those things wrong and if you don't plan for them upfront, I won't guarantee it, but I will bet money you'll get a negative ROI on your analytics projects. That's why I become obsessed by this, and I think the same exact issues arise now that we're in the age of AI.

[0:14:07.3] SC: Yeah. One of the things that struck me as interesting in hearing you tell the story about the work you did at Allstate in particular was it sounded like you were very aware at that time about issues that I think of in many ways is like only now kind of finding contemporary voice, right?

[0:14:30.5] JG: You're right.

[0:14:32.3] SC: Bias and algorithmic bias. In fact just last night — Just last night, Pedro Domingos tweeted, true fact, algorithms cannot discriminate. I replied, "How do we define algorithm? What are we talking about here?"

[0:14:51.1] JG: Exactly, yeah.

[0:14:52.4] SC: In that lens, it's like this is a new issue. We're just gearing up to fight this fight, but it sounds like you're grappling with this way back when and not just thinking about it, but the impression I'm getting from the way you described was that the organization had a consciousness around it. Talk more about this.

[0:15:14.6] JG: Yeah. It completely is. I'd love to talk a little bit more about pro-social uses of big data. I have kind of like a little mantra on that. This is one of those things where — Ben Franklin had this idea of doing well by doing good. I don't want to make any grand claims from my employers or anything like that, but it's in an organization's enlightened self-interest to think in the long term. Maybe in the short term you can just throw out whatever model you want, but they're smart enough to realize that if there're unintended consequences, it will come back to bite them later on. It doesn't make any sense, right?

[0:15:49.3] SC: Since all organizations are self-interested, does that mean that some are more enlightened than others?

[0:15:54.0] JG: I think some are more enlightened. It's clear. Something else we could tangent, we could talk about group think. Think about all of the organizations or both private and public sector organizations or governments that make catastrophically bad decisions — This is another interesting thing, like are organizations people? Well, no. They're people that comprise organizations. Organizations can act as if they're rational or not, or they're enlightened or not. Sometimes what happens is you'll meet a lot of very well-meaning people in an organization, but they kind of have to self-sensor and even if they think there's something that's not quite right, they have to kind of either self-sensor or maybe they just get into this habit of believing their elders or their superiors, because —

[0:16:37.5] SC: Drinking the Kool-Aid.

[0:16:38.3] JG: Drinking the Kool-Aid, yeah. This is called group think, right? It's like the absolute of collective intelligence, which is what data science should be all about. That was a tangent, but I think —

[0:16:47.4] SC: This recognition, was it purely internal or was it driven by regulatory frameworks or fear of —

[0:16:54.3] JG: I don't want to be grandiose.

[0:16:55.8] SC: Do you have a sense for —

[0:16:56.1] JG: I do have a sense. I don't want to be grandiose. Insurance is very heavily regulated. It's regulated, the state level in fact. It's not just one agency. It's 50 agencies in the United States. It's a rare case where it's actually more heavily regulated in the U.S. than it is in Europe. They absolutely — In fact part of the reasons why my employer wanted to build — I hope the statute of limitations applies here. I think one of the reasons they want to build this thing in-house is that they actually wanted to have control over the details of the model. They want to be able to make sure that, "No, we're getting this exactly right." Maybe you can't use medical bankruptcies in this state. We're not. We can prove it, because this is algorithm. Whereas if we bought some black box off-the-self thing, we're not sure we've lifted that regulation in the thing.

Of course, regulations are in attempt to reflect societal values. The ultimate thing is you want to reflect societal values in the algorithms, and regulations are kind of a halfway house. I'm speaking philosophically from a mental perspective, but I think that's what's going on here.

That's the game. The companies want to make sure they're using algorithms to run their processes more efficiently. In the case of Allstate, we wanted to — It's the oldest game in the book. You want to be able to come up with a more accurate price for a risk.

The logic of credit scoring and insurance is we all know that 16-year-old male motorcycles are bad drivers, or probably — I should riskier than average drivers perhaps. Riskier than perhaps a middle-aged female station wagon driver perhaps. If you can find the 16-year-old male motorcycle driver who's also present at the chess club, subscribes to Martha Steward Living Magazine and has a good credit score, he's probably a good risk. If you can collect all those good credit scores of 16-year-old male motorcycle drivers, you can kind of give them a lower rate, because they are actually a better risk than might appear on the surface. That means the other companies who don't have credit score have to charge more for the 16-year-old male motorcycle drivers, and this is kind of adverse selection spiral. That's the kind of like economic logic for doing — This is why insurances are very early adopter of big data, data mining analytics. That's subject to constrain.

If you just did kind of a crows sourcing competition, come up with the best segmentation thing, unless you've prepared the data yourself and unless you're very careful about auditing that algorithm, you're not sure that that reflects these regulatory constraints which are reflected to societal values or not.

Another thing, crowd sourcing would be bad in this context and just saying you have to kind of take that into account. You're optimizing more than one thing, not just [inaudible 0:19:23.6] accuracy, but these other things too. I think there are a lot of companies, that it's not just regulation. They just want to do the right thing.

Actually, Richard Thaler, who's one of my heroes, he's the father of behavioral economics at the University of Chicago Business School. He tweeted about — I won't say which company it is, but it's an airline that kind of fixed its fees for flights out of Miami at a fairly low rate to help people escape the storm, even though they could have done surge pricing. Thaler would say that just kind of goes against the grain of human psychology. We have these things that Adam Smith called moral sentiments, which we call ethics now. That just doesn't feel right.

Even though from a technical classical economics, homo-economic is rational, profit maximizing perspective, they should charge $4,000 for a flight to Atlanta from Miami, but they didn't. Thaler is saying it's because they're thinking in the longer term. In that case it wasn't regulation, it was just like we're playing the long game. There were other companies that did jack up the prices, and that's really interesting actually, because maybe the case — I don't know, I'm speculating, but that may have been unbridled algorithmic thinking. It maybe that —Like a pricing algorithm. It's quite possible that some of these competitors did do surge pricing, because it's kind of like — The algorithm is just kind of calling the shots.

[0:20:44.3] SC: That's what the algorithms usually do.

[0:20:46.0] JG: Absolutely. Right. This is like a really nice case where it's sort of like parallel, I think, to the insurance case, except it wasn't due to regulation. It was just more due to like customer lifetime value. You don't want to alienate people. People just aren't going to remember things like this.

It's like our customers —

[0:20:59.9] SC: But does the algorithm — The algorithm would have to have a pretty long life cycle to pick up on that customer lifetime value piece.

[0:21:08.7] JG: Yeah. That's kind of the point.

[0:21:11.4] SC: That suggests that it's more likely there was human in the loop there.

[0:21:14.6] JG: Precisely. That's exactly the point. It's like we can kind of speculate about singularities. We can kind of speculate and have fun conversations about when are we going to reach artificial and general intelligence. We have like a robot that can like use commonsense and price it both to optimize things, but also — Okay, but that's not happening any time soon, right? These are machine learning algorithms. They're essentially like statistical models on steroids basically. Deep learning models are like logistic regression models on steroids that create their own features.

That's what we got, and that's great. It's really, really powerful. As you're suggesting, I think what it implies is that we want to have humans that have common sense reasoning to keep the models in check. What that implies is that the people that — I'm going to quote an economist here named John Kay, "The people that understand —"

[0:22:00.0] SC: Don't do too much of that on this podcast though.

[0:22:02.4] JG: Why?

[0:22:02.2] SC: I'm just joking.

[0:22:05.2] JG: Sorry. [inaudible 0:22:05.2] the economist? Yeah, I know. It's a big turnoff. John Kay was my favorite — I think he's retired, but he's my favorite columnist in the Financial Times. He used to be an Oxford economist, I think, or one business school or something. He was asked 10 years ago to diagnose — Somebody asked him the question in the aftermath of the financial crisis, "Why is it that all these models built by Harvard, Cambridge, MIT, Quants failed so badly?"

Quay was direct to the point so [inaudible 0:22:31.7] said, "The problem was that the people that understood the math, that understand the world, the people that understood the world and understand the math." I think that's another kind of case of where we need to kind of like — I can't remember who said this, but I heard a very nice quote the other day that a really good data scientist needs a kind of communication empathy ability to be able to kind of talk to the people that understand the world not just to reflect their knowledge in the data, but also to reflect just the kind of like strategic goals, the societal values, the longitude. We don't want to alienate our customers. All those kinds of things. You know what I mean?

[0:23:07.7] SC: Interesting. This is all kind of background for your talk. How do you organize your talk? Did you have a list of human factors that an organization needs to consider?

[0:23:18.7] JG: Oh, no. It's nothing bad. Cut and dry. Honestly, nothing about me is like that. My background is philosophy, so I always kind of go back to first principles. I'm really just thinking about what are algorithms good at. Why do we have algorithms? What are their limitations? What are ways of overcoming those limitations?

Yeah, I do have some ideas for where we kind of need to inject sort of like extra statistical or extra machine learning or extra computer — Beyond computer science principles into what we're doing? These are all examples that I've been giving.

The way I structure the talk — Should we get into that now?

[0:23:55.2] SC: Yeah, sure.

[0:23:55.8] JG: The way I structured the talk is — Actually, I'm quoting someone I know a little bit, Kris Hammond at Northwestern University at Narrative Science. He's someone I greatly admire actually. He and I overlapped at the University of Chicago. I was getting my Ph.D. in philosophy when he's a computer science professor there. He's now at Northwestern doing really innovative stuff and he's also the chief scientist or chief science officer for narrative science, the natural language generation company.

Here's this really nice way of thinking about AI. We shouldn't think of AI in terms of the underlying technology. We should really think about AI in terms of like what is its function. What are we trying to achieve here? "Oh, well we're trying to automate this process. Humans are really bad at this. They fall asleep in the wheel. Let's have AI that drives for them, or let's just have AI that kind of recognizes their face when they're getting drowsy, the [inaudible 0:24:43.6] to software, like Rana el Kalioub, and then kind of nudges that and maybe turns the radio up or something.

[0:24:50.5] SC: Gives you the punch.

[0:24:51.7] JG: Whatever it is, a nudge or a punch. That's the goal. Some of these things can be done through robotic process automation, which is not even data-driven. This was like kind of logic. Some can be done through deep learning. Yeah, sure. If you upload my photograph into Facebook, it will say that's a picture of George Clooney, which is a pretty good guess, right? Joke.

That's automation and that is also the augmentation side of things, which I want to talk about too. That's kind of like the large structure. Start off with Kris Hammond, talk about the fact that when we talk about AI, it should be kind of like a functional thing, not a tech first thing. It's not just about deep learning. It's not just about machine learning. It's really building computer algorithms that do things that worthy to be done by humans they'd be considered intelligent. That's kind of Kris Hammond channeling John McCarthy at Dartmouth in 1956. He's one of the founding fathers of AI. Very smart, kind of like operational definition, and I like it. As a consultant, because I'm really a consultant first. I'm a consultant who happens to be a data scientist or the data scientist who happens to work in a consulting firm.

As someone who really believes that he's a consultant, I think that's just a really great way of thinking about it, because I've seen the hype cycles come and go, but over and over and over again I see that the organizations and the leaders who kind of take a tech first view of this stuff, it tends to get a lot of attention and buzz early on, but it doesn't really produce the value downstream.

Whereas if you start with kind of like a problem-centric view first and kind of reverse engineer from there, what do I want? You're more likely to succeed, and it's likely to be a more efficient elegant and frankly cost-effective solution with less risk.

[0:26:25.4] SC: And in many cases, a lot simpler than the thing that you would have done if you were just following a shiny object.

[0:26:30.2] JG: Yes, exactly. Again, old school I'll do some more old quotes. Someone who's sort of an informal mentor of mine at the University of Chicago was a very prominent Bayesian econometrician named Arnold Zellner, and he had a concept called sophisticated simplicity. It's sophisticatedly simple, the idea is that you start off with a simple model, and if it works done. If it doesn't work, you just gradually add structure until it does work, and then you just stop. You don't start with most the complicated things that makes you seem like most smart or impressive or macho, right?

I think an analogous comment could be made about artificial intelligence. Kris was kind of making this point the other day in his tutorial, which I just loved. He said, “If all you need is robotic process automation, do it.” What’s the downside? Just do it. You don’t even need big data for that. You just need smart consultant and programmers and you’ll just save a lot of money and there’s very little downside risk.

[0:27:25.1] SC: Let me ask you about do you do a lot of — You’ve brought up RPA a couple of times.

[0:27:29.8] JG: Yeah, it’s part of the family of AI. Yeah.

[0:27:32.0] SC: I’m just curious your perspective on this. I’ll jump to the question. The question is can you provide for me specific proof point examples where people are doing RPA that suggest that RPA is more than a rebranding of BPM.

[0:27:51.7] JG: I probably shouldn’t comment too much on that, because I’m not like one of our RPA experts. Maybe it is. It’s just like this is an idea that’s been around for a long time. It just makes eminent commonsense. I don’t really care what you call it so much, but just the idea of taking processes where somebody is doing something that’s just like routine and wrote boring spade-work. If you can just get a macro or a script to do that, why not do it?

That’s kind of like analogous to Zelman’s sophisticated simplicity. In a statistics thing it’s just like looking at the difference of two means is all I need and we can do bootstrapping, do it. In a business context, if all I need is to automate something that’s really, really [inaudible 0:28:30.3] and simple and spade-work, do it. You don’t need machine learning for that.

Kind of going up that kind of food chain of complexity, you just kind of want to start — I guess what I was getting at is you wanted to start with the problem and kind of back into the either technology or the data science or the machine learning, whatever it is that will solve the problem.

[0:28:50.9] SC: You mentioned automation and augmentation. Augmentation, what does that mean for you and how are you seeing folks who can value there?

[0:28:57.5] JG: I've seen folks gain value from augmentation in my whole career. I've been in Deloitte since 2001 and that's been one of the most common themes of what I've been doing. We've built algorithms that will automate things. Very often, we don't always work —

[0:29:11.3] SC: By augmentation are we talking about augmenting human intelligence?

[0:29:13.3] JG: Correct.

[0:29:14.2] SC: Okay. As supposed to data augmentation or some other flavor of augmentation.

[0:29:16.7] JG: Yeah, I'm talking about augmenting human intelligence. That vocabulary is somewhat new to me. I haven't always described what we do in those terms, but I like the vocabulary.

Early on, when we do our projects, for example, supposed we're working — Again, let's say we're working for an insurance company, but say it's a commercial insurance company. Instead of selling auto insurance, for example, they sell workers comp insurance. Now, there are fewer businesses to ensure in the world than there are cars. Businesses have fewer factors in common than cars do. Some are florists, some are hipster coffee shops, some are hospitals. That means you have few rows in your database and you have fewer columns, but you're trying to do something similar to what my first job was, which is you try to come up with a better price for the risk or underwriting decisions. Should I sell this person insurance or not? Should I sell your hipster coffee shop insurance or not?

That's a case where like what we've found just empirically through our data, through blind test validation, is that it would work pretty well in certain cases. That was an empirical question. It's partly empirical, partly strategic. It's like we'd have to work with a client to figure out what is the cutoff here or are we going to like stray through process these decisions or are these other decisions, we're just going to simply give it to an underwriter. Maybe we'll like rank order some things. We'll try to explain the underwriter what's going on here. We'll try to train the underwriter ahead of time to understand the premises of the models. If we don't do that, it's not just going to work.

This is like a very simple example of what we're calling human factors early on. I don't know if human factors is quite the right word, but it's some kind of like either a human-centered or an organization-centered design. I began to use the analogy Mr. Underwriter and Mrs. Underwriter. Just imagine that your eyes are myopic and so you go to the doctor and you get a pair of glasses. You can see better.

Daniel Kahneman and Dan Ariely and all these behavioral economists and psychologists teach us that our brains are myopic. Our brains have these biases heuristics that we used to make decisions. We have blurry mental vision. In these augmentation cases the algorithms are kind of like prosthesis. They're kind of like eyeglasses for the mind's eye. They just help de-bias our cognition.

Kind of getting that equation right with sort of the art towards science, and what fascinates me about it is that statistics is part of it, but not all of it. In business we've always called this kind of change management, this kind of goes into the change management rubric.

Frankly, right now, it's an art, but I like to think that it could become more of a science. I called this the last mile problem. We don't stop with an algorithmic output, we stop with a decision. In the case of automation, the computer makes a decision. It's saying, "I'm just going to send you this ad for this pair of shoes because I think you like these shoes."

The augmentation is more like, "I'm going to tell the doctor there's this probability of this person has this rare disease," but it's really the doctor's judgment call. I'm going to tell the doctor why the algorithm thinks this. Maybe it's an information retrieval system. IBM wants them to give some collateral information, but I'm going to give this to the doctor. This is one area where behavioral economics comes back again, is that behavioral economics teaches us that simply giving people information doesn't always result in the optimal decision. It's also the way you present information matters.

We've learned this in the last 30 or 40 years. This is the whole basis of the book *Nudge,* which is only 10 years old. We've really come to appreciate this a lot more. Behavioral economics is absolutely one way of thinking of this "human factors idea" or human centered-design idea.

I feel like we've been sort of like modeling though perhaps all these years, and it works. When I say modeling through, I mean it's more an art than a science. It's something that we've done for a long time, we've got better at overtime. We do it with our clients, but I'm intrigued with the idea that now that AI and machine learning is becoming such a business and societal trend, maybe there can be a new science emerging about this idea of human computer collaboration or human computer interaction.

Can I give you one more example that's sort of like —

[0:33:20.7] SC: Please. Yes.

[0:33:21.6] JG: This is absolutely not a [inaudible 0:33:23.0] example. It's not a Deloitte example, but I find it incredibly thought provoking. It's more of a metaphor, but I think it's a very thought-provoking metaphor and it's a very nice way to think about sort of the future of work too, people being displaced by algorithms and so on.

Forgive me if you've heard this. Have you heard the story about freestyle chess?

[0:33:38.7] SC: No. I don't think so.

[0:33:39.9] JG: Good. Thank you. I like when people say no. I only learned them a few years ago myself. I actually read the article and I forgot it and then I reread it. I read an article in 2011 by Garry Kasparov, the chess grandmaster who's published in the New York Review of Books in 2011. He was talking about his own experiences being put out of work by IBM Deep Blue. This is a prequel to Watson, right? It's like there's a magazine cover called The Brain's Last Stand. The machine is vanquishing man. The chess master — Because that's identified with human intelligence. This is way back in '97, so like 20 years ago. I was like I just turned 12, I think. Kidding.

The turnout of the story was a lot more interesting than that. Kasparov actually invented a new game after he lost to Deep Blue called Advanced Chess. Advanced Chess would be instead of me playing human chess, it'd be Jim equipped with a laptop playing you equipped with a laptop.

It turns out that the same skills that enabled Kasprov to be good at traditional chess, he wasn't quite as good at freestyle chess or this advance chess concept.

Anyway, fast-forward to the year 2005, and I think a German website had an open game called freestyle chess, which is anybody around the world can enter. It can be Kasprov playing another grandmaster. It could be Kasprov plus teaming up with a number computer playing another grandmaster teamed up with another super computer. It could be anything. It turns out there's an upset victory. The team that won was two amateur chess players from New Hampshire, these two young guys working with three ordinary laptops equipped with three different chess programs. They won freestyle chess. They beat the grandmasters and the super computers and the grandmasters working with the super computers. Kasprov, when he wrote about in the New York Review of Books, he said — This is later called Kasprov's Law. It's a weak human plus an ordinary computer plus a better process of working together outperforms the grandmaster or the super computer or both plus an inferior process.

When I'm going to present this this afternoon, I'm going to circle the better process. That's what we need. When I read that for the second time — I'm a slow study. When I read this all these layer I realized, "Oh my God! That better process of the chess player working with a computer, that's just like what we would do in our consulting practice when we give a doctor, an underwriter, an admissions officer, a public sector case worker a list of cases saying, "Here. This will de-bias your judgment, but it's ultimately up to you, and we're going to help you do this. We're going to train you do it. We're going to train you to understand the algorithm. We're going to try to train you to understand its premises, its assumptions, the data it's based on, the variables and the models.

If you know the model contains variables one through 40, that you know factors 41, 42 and 43, and if you judge those to be really important and the algorithm doesn't know that, then you could override the algorithm, and that's okay, because you're using your brain. You're not just using Kahneman Thinking Fast, you're not using biases heuristics, you're using meta-cognition. You're using an intelligence to say, "Yeah, the computer is saying this, but I've also got this common sense of this other — I know this contextual factors. I'm going to override it and do this other thing. I could be wrong, but at least it's a principle decision.

When I talk about the freestyle chess, I'm not trying to make the claim that a human computer will always win chess. That's not my point. The point is that it's a very nice metaphor for this idea that the computer can do things that humans aren't good at, look at the decision tree of all these possible moves and all the implications that these moves downstream better than a human can, but the human has other kinds of capabilities.

Kasprov commented about these two guys who won freestyle chess, he said, "Their insight into looking deeply at what the computers were indicating really enabled them to kind of outperform the grandmasters to an inferior process. They actually had an insight into how the algorithms worked and developed kind of like an intuitive Spidy sense of for, "When I should trust this recommendation versus that recommendation?"

I just find it like a very nice metaphor for a real world professional making a mission critical judgment. It's called judgment on a known certainty with the help of an algorithm.

[0:37:44.8] SC: Yeah, it strikes me that the process in his characterization of this is it's kind of a load of vocabulary that has a bunch of individual things under it? There's like user interface. There's the things that we might traditionally think of as a process, like a set of steps there. As you mentioned, bank of experiences to fall back on on how have I been able to rely on the computer's advice historically. Have you done or seen any kind of work to kind of characterize this more granularly?

[0:38:23.2] JG: Yeah. You mean like exactly how do you pull off this better process? You mean what are the steps involved or the principles involved and so forth?

[0:38:30.3] SC: I think, ultimately, the goal is like as a business, if I can pick apart the pieces of what process means in this model that enable human plus computer to outperform expert. That kind of provides me a roadmap for, "Well, first, I need to make sure that my data is displayed in a way that is comprehensible for the computer, for example." Then I need to make sure that I've the tools available to interact with the systems, etc. I'm curious whether how evolve the thinking is there.

[0:39:02.7] JG: Like I said, I would like it to be more of a science than it is, but I think what ends up happening is that it's a series of kind of like — What Simon called satisfying, where we make maybe not optimal decisions, but we kind of like look at the business context. Maybe it never will be a science. Maybe it will always be like a devil in the details kind of thing.

If it's a medical case, then the cases where you let the computer make an automatic decision, versus a human might be different depending on how many factors there are around. If you're in a poor country, it might not be optimal to have a doctor working with a computer. If the village has no doctors at all and it take a picture of a wound, do deep learning on it and upload it to the cloud and it comes back with like, "You don't need stitches," versus "you do need stiches," that's pretty good.

Ideally, we'd have a human in the loop. You know what I mean? It's always going to be like it's modeling through kind of thing. What is the cutoff? In some cases, like jurisprudence — I think Daniel Kahneman wrote about this actually a few years ago. He said the public would be shocked to hear that an algorithm was making decisions without the judge. Is that even constitutional? It might be kind of like — Just like ground unavoidable reasons why you always need to have a human in the loop.

I think that we are kind of gradually getting better at this stuff. People are coming up with better algorithms for explaining models. One of the — I'm probably going to get his name wrong, one of the speakers earlier on the conference, Carlos Guestrin from University of Boston.

[0:40:31.3] SC: Carlos Guestrin.

[0:40:31.7] JG: Yeah. He came up with the LIME algorithm for kind of explaining why does a deep learning model classify what it classifies. Conceptually, and I hate to say conceptually. It's much more sophisticated, but we've always done analogous things with our work. We would output not just a score saying the answer is 42. We'd say, "What does 42 mean and why this algorithm think it's 42?"

Every single score is contextualized with a set sort of like English language. Again, primitive natural language generation, but still, nevertheless, natural language generation. All these kinds of things we've been doing for a long time are getting refined. We've got better reason algorithms. We've got Kris Hammond's Natural Language Generation. We've got more advanced data visualization. Maybe we're going to come with better apps so that people — The emotional aspect of it is important.

John Whelan was speaking yesterday about the emotional quality of this kind of stuff. A nice comment he made was that people will choose a personal digital assistant even if it's less accurate. If it's more emotionally patient that will be pleasing to work with. Even just getting that right is something and that's something that my practice probably could get a little bit better at.

These are different aspects of the human factors. It's like some of it is helping us think better, but there's a lot of interesting neuroscience around emotions, and I think in the last 20 years sort of another kind of like headline that's kind of new to a lot of people including me is that emotions are not kind of like the Mr. Spock versus Captain Kirk thing that we all think of. It's not like emotions are sort of like the noise that clouds the static around rationality. It's more like emotions are sort of part and parcel of rationality.

[0:42:13.3] SC: They're pretty fundamental.

[0:42:14.6] JG: Yeah, it's a part and parcel.

[0:42:15.0] SC: That's a big part of what thinking fast, thinking slow. I always miss that out.

[0:42:18.9] JG: No. Thinking Fast and Slow, that's exactly right.

[0:42:20.8] SC: Yeah.

[0:42:21.5] JG: Also, the effect of computing stuff that Rana el Kaliouby was speaking about. That kind of relates, I think. That's effective computing. It was also effective neuroscience. One of the findings of effective neuroscience is that healthy emotions are important to rational decision making. They're not separate. That's an interesting kind of lens through which to look at this too. Again, these were all developing now so why it's such an exciting time to be working in this field.

I think the general idea is I think savvy people have always realized that when it comes to more complex decisions, you don't want turn over to an algorithm. Sure, we're surrounded by more big data now. Sure, algorithms are betting better. Sure, computing power is getting cheaper and cheaper. Sure, there will be more and more decisions that can be automated, but until we come up with this kind of singularity, which whatever.

[0:43:12.7] SC: Separate podcast.

[0:43:12.8] JG: Now, I don't want to say anytime soon. For a lot of decisions, we're going to need humans in the loop. We're going to need to kind of have a science of augmentation. This kind of freestyle X-idea, so freestyle insurance underwriting, freestyle medicine, or freestyle jurisprudence, freestyle university admissions. It's the algorithms helping de-bias the humans, but the humans kind of keeping the algorithms in check. Getting that balance right is — That's what I find fascinating. That's what kind of keeps us going.

[0:43:36.7] SC: That's fantastic. I'll mention since you mention Carlos Guestrin and Rana el Kaliouby, I'll note for folks that are listening that both of them have been on the podcast before. The fact, Carlos at the very first AI conference in New York, and Rana at the previous one in New York. This is the third one. Folks can find those on the website. Both great conversations. I really enjoy this conversation.

[0:44:07.5] JG: Likewise.

[0:44:08.8] SC: Thank you so much.

[0:44:08.8] JG: Thank you. Real pleasure.

[0:44:11.0] SC: Absolutely.

[END OF INTERVIEW]

[0:44:15.8] SC: All right everyone, that's our show for today. Thank you so much for listening, and of course for your ongoing feedback and support. For more information on James or any of the other topics we covered on this episode, head on over to twimlai.com/talk/56.

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Thanks again for listening, and catch you next time.

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