EPISODE 59

[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 in machine learning and artificial intelligence. I'm your host, Sam Charrington.

We are back with our third show this week and the 3rd in our autonomous vehicle series. My guest this time is Katie Driggs Campbell, postdoc in the Intelligence Systems Lab at Stanford University's Department of Aeronautics and Astronautics. Katie joins us to discuss her research into human behavioral modelling and control systems for self-driving vehicles.

Katie also gives us some insight into her process for collecting training data, how social nuances comes into play for self-driving cars and more. Our autonomous vehicle series is supported by Mighty AI and I'd like to take a brief moment to thank them for their support. Mighty AI helps companies working in the autonomous vehicle market, create training and validation data sets to support computer vision. Their platform combines guaranteed accuracy with scale and expertise and includes annotation software, consulting and manage services, proprietary machine learning and a global community of pre-qualified annotators.

If you haven't caught my interview with their CEO Daryn Nakhuda, which was the first show in this series, please be sure to check it out at twimlai.com/talk/57 and of course, be sure to visit them at www.mty.ai to learn more and follow them on Twitter @mighty_ai. Before we jump in, if you're in New York City next week, we hope you'll join us at the NYU Future Labs AI Summit.

As you may remember we attended the Inaugural Summit back in April. This year's event features more great speakers including Corinna Cortes, Head of Research at Google New York. Davide Venturelli, Science Operations Manager at NASA Ames Quantum AI Lab, and Dennis Mortensen, CEO and founder of startup, x.ai. For the event homepage, visit aisummit2017.futurelabs.nyc and for 25% off of all tickets, use the code “twiml25”.

And, now on to the show.

[INTERVIEW]

[0:02:12.3] SC: All right everyone, I am on the line with Katie Driggs Campbell. Katie is a postdoc at Standford in the Intelligence Systems Laboratory in the Department of Aeronautics and Astronautics.

Katie, welcome to This Week in Machine Learning and AI.

[00:02:52] KC: Thanks for having me.

[00:02:55] SC: I am really looking forward to this conversation. So, as you know, we are kind of in the midst of a series of podcast on Autonomous Vehicles and usually we end up talking to folks that are in CS or, you know, Electrical Engineering or other disciplines. But, you are out of the department of, again, Aeronautics and Astronautics and so, I'm really looking forward to digging into the connection between that and Autonomous Vehicles. I guess a good way to start is to have you tell us a little bit about your background and your path to what you're doing now.

[00:03:32] KC: Yeah, yeah, sure. So I'll tell you a little bit about, I guess how I ultimately ended up in the Aerospace Department. So, I started out in Electrical Engineering, actually. So, I got — I did my undergraduate in Arizona State University but I was really interested in Control Systems and ultimately, robotics. So, I was really interested on how we can control and interact ultimately with people. So, when I applied to grad school, I applied to mostly Robotics Programs.

So, then I ended up at UC Berkeley where I worked with Ruzena Bajcsy in Robotics, and that was in Electrical Engineering and Computer Science. So, I slowly shifted to Computer Science and that's I guess when I first started working on Intelligent Vehicles. So, when we first got started on this, this was, you know, 6 some years ago so Autonomous Vehicles weren't — I guess, they hadn't really quite hit the road. So we were actually working at -

[00:04:25] SC: No pun intended

[00:04:25] KC: Exactly, exactly, we were actually working on semi-autonomous vehicles and we found that the big problem with semi-autonomous vehicles was, how do you model the human? So, we start to think about how we can model the human, how we can design control systems to keep people safe. So, we thought a lot about texting while driving, how different environmental influences will affect your driving abilities and how we can ultimately, you know, design active safety systems to keep you safe. And, slowly over the years this shifted to autonomous vehicles like everyone else.

We're still — the human had a huge impact, so we're still thinking about how people either interact with autonomy in the vehicle or how the autonomous vehicle can interact with other people or human drivers on the road around them. That's sort of how I slowly shifted into autonomous vehicles. Yeah, so then I finished my PhD and I started working in an Aerospace Lab so we're the AI section of the Aerospace Department here, and so the lab that I work in is famous for air flight and collision avoidance systems, actually.

[00:05:28] SC: Okay

[00:05:27] KC: Yeah, so think about how we can design safety systems for planes which isn't all that different from vehicles, actually. So, the lab I'm in is actually, mostly funded by vehicle companies and working on autonomous vehicles and decision making for vehicles. So it's, sort of, a different than maybe what you might expect from an Aerospace Department but a lot of the systems are pretty similar.

[00:05:51] SC: I Imagine that's - that Aerospace Departments have been working on this problem of, you know, auto pilot when it comes from, you know, piloting a plane and, you know, space programs, some things like that have been trying to have autonomous or semi-autonomous remote vehicles on, you know, like the lunar lander, things like that. I Imagine there's - that there's quite a history in Aeronautics and Aerospace Departments around this kind of work, is that the case?

[00:06:20] KC: Yes, yes, definitely. So, I've heard Aerospace is described as the department that is, or studies the system of systems which is exactly what Autonomous Vehicles are, it's exactly what planes are, but it's really thinking about how all these different components and pilots and autonomy and all these things gonna fit together. So yeah, definitely and exactly what you said; there's a long, long history of dealing with automation in the Aerospace Industry, so it really is sort of, fits nicely into a lot of the same paradigm.

[00:06:48] SC: Awesome, awesome. So, what's your research focus there?

[00:06:52] KC: So, here I'm currently working on generally Autonomous Vehicles. So a lot of what I've been doing is the decision making and control. So, how can we use things like, deep learning to come up with very human-like decisions?

[00:07:07] SC: Okay

[00:07:07] KC: And how then do we use these, sort of, perhaps, not the most trustworthy systems like deep learning can be? How can we design that robust controllers to execute these decisions? So, how do we still get some of the robustness from the more traditional learning control techniques while using in this more advanced AI tool?

[00:07:24] SC: Hmmm. What do you mean when you say “human-like driving?”

[00:07:31] KC: Right, so I think, well personally when I think about autonomous vehicles hitting or coming on to the road relatively soon — sorry, no more puns. We need to think about how they'll integrate with the human drivers that are currently on the road. We can't expect that there's going to be, you know, homogeneous autonomous vehicles anytime soon.

So, the need to be able to interact with other humans on the road and the other humans on the road need to be able to interact with that autonomous vehicle. So, you can't have the autonomous vehicle doing things that are unexpected even if they might be optimal in some sense. That needs to be optimal in the social context that it will be driving in.

[00:08:08] SC: And, so responding to erratic Saint Louis or New York drivers also the ones that I know the best but I'm sure everyone has their, I guess, probably wherever you are the drivers that you hate.

[00:08:21] KC: Yup, yup, California stops

[00:08:22] SC: Exactly, exactly. So you mentioned that and then you also mentioned an aspect of the research that is — so, you know, we're doing all these things to build up this deep learning models and then I, you know, maybe we think about the deep learning models as directly controlling things but it sounds like you're suggesting that a big part of your research is, "Well, maybe if we put some other stuff between the deep learning models and a drive by wire systems, you know, we can get better results?"

[00:08:54] KC: Yes, yes, and I think from my perspective, it's really important. You can really prove things about how the deep learning and the decision making that comes from these learning are - how they're going to function. I think it is important that you have, sort of, some more reliable method for actually executing these maneuvers making sure that's very safe and interpretable even.

[00:09:17] SC: So, can you maybe walk us through, you know, some of the specifics about the research and, you know, in each of these camps? I guess we can start with, you know, what are all of the research challenges associated with autonomous vehicles interacting with human-driven vehicles?

[00:09:38] KC: Yeah, sure. So, I think one of the really big problems is that you basically - you can model people but every model is only going to or it's going to have places where it fails. So, coming up with a way to balance, you know, a general model of how people typically behave while still capturing sort of, the crazy things that people also do is a really hard problem. Because you get something like you're either not accounting for it, the places where you really need to be safe. So, when people do something really unexpected or maybe do something kind of crazy, but then the flip side you'll be overconservative if you only model those things. So, you still want to be able to get to your destination, so there's some balance between, you know, being safe and actually driving normally. So, figuring out how to balance that in an intelligent way is really, really difficult.

[00:10:32] SC: And, what's the general approach to that, that you've taken in your research?

[00:10:36] KC: So, the general approach that I've taken is trying to do something like switching maneuvers. So, if you have - you try and detect basically when people are starting to deviate from the normal sort of, expected behaviors. If you have a typical model of how people behave, you can use that for the most part, but you have to always be aware and always be monitoring people for when they start, as I said, deviating. So, you look for, sort of like, the anomaly driver and then you can start saying, "Okay, this person's acting a little bit weird, I'm going to be more conservative around this driver.

[00:11:05] SC: Hmmm. What does it even mean to have a model of how people behave? like, I guess I think of, I think of the stuff that I've seen, you know, around deep learning is maybe like a lower level, you know, kind of lower level models or capturing lower level, you know, ideas about how to interact, how a vehicle might interact with the world. Is there also a part of the system that is, you know, trying to capture at large, like the behavior of people?

[00:11:37] KC: Yes, so at least in my work there is. Yes, so a lot of my PhD work was coming up with general models of how people behave. So, how do you take all these big data sets and come up with models that are useful from that. So, yeah basically-

[00:11:53] SC: So, what are some examples of things that you can get a model to, that you can kind of, capture in a model about a person's behavior with regard to driving in particular?

[00:12:03] KC: So, in driving in particular, we've really been thinking about lane changing behaviors. So, it's a pretty common maneuver and it's pretty easy to find examples of. So, in this work we've been thinking about how people respond to merging behaviors, so if you try to cut someone off, how are they likely to respond? If you want to execute a maneuver, what sort of, cues do you need to send to that person to make sure that they will actually let you in if the gap is not big enough? So, how do you sort of, handle these, like, social nuances in your emotion and then your trajectory planning.

[00:12:37] SC: Okay, what's the general approach you've taken to address that kind of thing? like, is it changes to the way you model? or is it, you know, set of heuristics that you kind of build around the model? or are you injecting things into the system otherwise?

[00:12:53] KC: Right, so in this original work for modeling how people behave and how people respond, we were really trying to think about how we can come up with a robust prediction, so we actually came up with a new modeling method to capture these behaviors in a sort of, a more general fashion. So, instead of thinking about trying to predict a person by guessing their exact trajectory. We start to think about how we can come up with basically, sets that they might follow. So, we think of an area that they might enter, basically. So, when you start thinking about things in terms of set behavior instead of just an exact trajectory, you get a much more robust prediction. So, you might be off a little bit but you'll still capture the general behavior and this is, sort of, where - what I was mentioning before with bouncing being overconservative and being quite precise kind of, comes in.

So, when you start basically, reducing the uncertainty in your prediction, you will shrink this set down to something that's smaller and more precise, but if you're more uncertain or you start detecting some anomalies, you can grow this set out and capture more of the uncertainty and that will just automatically influence how you change. So, if you basically, take this sets and incorporate them into your low level controller that is planning and trying to keep you in safe regions, this will, sort of, automatically be captured by that.

[00:14:06] SC: And, in this work, is - does the set represent - are you evaluating the set in terms of, kind of, you know, in or out? oR likelihood of in or out? or are you looking at, like, geographic regions as probabilistic fields that are maybe more continuous?

[00:14:26] KC: Right, right. So, a little bit of both. So we - the ultimate or the effort of this model is a - something like confident interpoles. So, you get this, sort of, strict boundaries and the probability associated with these different, basically, level sets of trajectories, so it's a little bit of both. So, once you've picked what confidence in a role you would like to pick, you have a strict set. And you can basically, evaluate this by in or out, but you can also look at this as a basically, as series of confident intervals, so then you get something like imperical distribution back out.

[00:14:59] SC: Okay, okay. When you're implementing this in a lane changing context, is it, I guess I'm trying to picture the - I guess dimensionalities overloaded but, like, if you - are you thinking about it from a perspective of a car and like, the lane ahead? You know, how many feet from the vehicle, another vehicle is likely to intrude on? So, like a two-dimensional kind of interaction? Or is it more three-dimensional interaction where you are thinking about the distance between your car and your lane and the other car in the other lane, as well as where it might intrude into your lane?

[00:15:43] KC: That's a great question. So, in most of the work that I've been doing, I've been looking at basically a set of three-vehicle-interaction. So, if you think about predicting the vehicle that you want to merge in front of, you can think about the influences of that vehicle basically, being what your actions will be in a vehicle in front of them. So, I've been, sort of, looking at that network, but we can expand this out by, sort of, looking at things like clusters of behaviors, if you think about different vehicles, sort of, inserting more influence [inaudible + 00:16:14] you can think about how this, sort of, generally happens by looking at clusters of behaviors. So, if there's more vehicles, you can basically do a look up and you get more clusters or similar clusters, similar situations and by the similarity metric you can expand this out to more vehicles and larger networks, some things like that.

[00:16:31] SC: Okay, yeah I've seen some interesting videos of how a driver behavior and I think even autonomous vehicle interactions with drivers where, you know, the vehicle isn't given a certain level of aggressiveness it will just get stuck, like, it cannot execute a lane change until there's, you know, there's this need that you're describing for the vehicle to, you know, not just be able to anticipate human behavior but to start to emulate human behavior because like signaling to going to another lane isn't just, you know, putting on the blinkers it's also like starting to go into the other lane.

[00:17:13] KC: Exactly, exactly. I was talking to someone in L.A. about this and they said if you turn your blink around that is a cue for the other driver to just speed up. So, you don't just want that.

[00:17:24] SC: Right, right. So, you've got this ability to kind of, predict other drivers' behaviors and when they're likely to enter your lane and you can kind of, expand that to multiple vehicles, what's the next step. How do you, kind of, build on that to create a more robust system?

[00:17:45] KC: Right, so now that we have a good model of our environment, if we believe this is a good model of our environment. So, the next layer that we were thinking about is, “How can we safely execute, sort of, high level decisions?" And this is where we start using deep learning. So, if we have a good representation of the environment, we want to think about, "Should I execute a lane change? Will this help me achieve my goal? And also, there is some we wanted to see if we could capture things like, sort of, implicit rules. So, there are some rules that aren't necessarily captured by the letter of the law, so like, intersections, there is a strict ordering that happens so if one vehicle comes first, they get to pass through. There's some yielding rules, but people don't always follow these rules and there's somewhat uncertainty in these rules.

So, we've been using deep learning and simulation to try and capture some of these sort of, nuance behaviors to come up with these, sort of, high-level decisions like, what high-level actions should I give? So, this high-level actions can be things like, execute a lane change or go ahead and move through the intersection now. And, so we've been doing with, as I mentioned, deep learning. But deep learning, in and of itself, is not very trustworthy. So, s lot of what we've been doing is trying to think about how we can develop new tools and new warning algorithms to try and make these systems more than give some insight to the confidence of the system. So, can we determine when are deep learning algorithm is uncertain about it's decision. And, if we know when it's uncertain we can decide whether now we should listen to it or not.

[00:19:13] SC: In this example, what's the training data?

[00:19:15] KC: So, in this example, we've been putting a lot of effort into coming up with good simulated traffic models. So we can basically train in simulation and then transfer it to real vehicle, which is a whole another problem that we're also working at.

[00:19:32] SC: Okay, so, the simulated traffic data is, I mean, I'm envisioning like the video game Frogger. You just got all this traffic and you're - it's kind of moving at different speeds and is that higher? not literally, but is - are you just generally letting several lanes of traffic and how are you representing the vehicles in this training data set, for example?

[00:19:58] KC: Right, so there's a lot of work in the lab that I've been that goes in to coming up with good driver models for generating traffic. So, there's lots of really interesting work going on and actually using deep learning to mimic this driving behaviors so you could validate your autonomous vehicle. So, how do you generate these scenarios? How do you generate realistic behaviors? so then you can either train your system or just do some validation. So, if you just need to make sure it works, so you get some metric for how likely this should crash, you can use this validation tools to do that.

[00:20:34] SC: I'm still trying to visualize the training data set. Is it like, are you looking at a car as a like, a two-dimensional kind of representation of point or space or something like that? or are there some simplifying assumptions? or is it maybe more complex than that, you know, based on camera imagery or something?

[00:20:55] KC: So this ones, we are just using, we have a simulated light hour sensor so from our eco-vehicle. We basically just use this detection points, which are pretty similar to what we can extract from sensors on a real vehicle. So from the eco-vehicles perspective in simulation you basically just get something like a light hour image but projected down to just a 2D plane.

[00:21:19] SC: Okay, got it. So is it the 2D plane from above the vehicle or the 2D plane like looking ahead from a vehicle?

[00:21:27] KC: So, for us you can think of it as like, an occupancy grid so you can like look down at the world. Your vehicle's in the center of it. You get sort of, this distance around the vehicle thing.

[00:21:38] SC: Okay, okay. My next question was around the objective function like how did you construct the objective function for this model that you trained?

[00:21:45] KC: Right, so for these initial models to start, what we were using was a, some tools called imitation learning. So, we basically wanted to figure out how we can imitate a model or imitate some expert model. So we have some sort of expert behavior that we want to mimic. So this can be a human. for example. So we have some examples of how the human is going to behave or some example trajectories of this person driving. We basically want to try it and be as similar to this driver as possible or similar to this human. So mimicking the expert and training, and transferring this knowledge over to our, our novice or our deep learning algorithm.

[00:22:28] SC: Okay, so you've got your driver behavior model. You've trained deep learning model that can try to optimize an objective relative to some expert that it's imitating. What's next?

[00:22:43] KC: So then, once we have a model that can effectively mimic this high-level decisions, hopefully pretty well and hopefully in a safe way, that's when we started thinking about how can we actually implement this in our robust controller. So, we've been using some pretty standard tools from control, like model predictive control and robust control so we can take these high-level commands and turn them into trajectories that the vehicle that can follow quite smoothly.

So, basically using these commands or these high-level commands for deep learning. Now you can sort of, start thinking about different models and sort of, some of the differences between the simulation and the real world car, so you can sort of, extract the high-level information and execute it in the real vehicle. So it's actually what we're testing now so we're putting this on a real vehicle and testing all of that.

[00:23:31] SC: Nice, nice. You mentioned a couple of disciplines and control systems. Robust control and model something control?

[00:23:37] KC: Model predictive control.

[00:23:39] SC: Model predictive control. Can you walk us through what those are and the assumptions that they're making and what they're trying to accomplish?

[00:23:47] KC: Yeah, yeah. So at the heart of all what we do is model predictive control and in model predictive control — so basically using a model of your vehicle and the environment — it basically solves an optimization problem to give you an optimal trajectory over some finite time horizon. So say, two seconds in the future I'm going to play in the optimal trajectory to achieve my goal. Since this is just an optimization program, practically you can easily put in things like safety constraints, you can tune your trajectory so you have a smooth trajectory and basically by solving this problem you can come up with your optimal trajectory.

And the kind of cool thing about model predictive control is even though it's a finite time horizon, so it only works for about two seconds in the future whatever your finite time is. And it's an open loop trajectory. You basically take one step in the future and then you resolve the problem, so you resolve this trajectory or for this trajectory at each time step. And so by doing this receding horizon by sort of sliding along and constantly planning some time in the future, you actually approximate things like the infinite horizon so basically, the optimal control policy. So it's an open loop policy executed in that closed loop fraction.

[00:24:54] SC: I was recently reading some reviews of some of the production driver assistance like autonomous driver assistance, if you will, technology is like Cadillac has one, Mercedes has one obviously, Tesla, I forget the other one. I think it was Infinity that was in this article and they talked about how, you know, one of the things that they noticed was that for most of the assistance, I think Tesla was the only exception, like the car would basically bounce back and forth between the lane markers and I'm speculating a little bit but it sounds like what you're doing with model predictive control would tend to smooth out that kind of effect as opposed to, you know, maybe deriving a path straight out of a deep learning model. Like is that a reasonable kind of intuition about this or does it show up in other ways?

[00:25:51] KC: No that's exactly right. So by using this basically, constant smoothing and optimization technique you do come up with much smoother trajectories. It not only addresses things like the sort of jerky chattering, I guess that happens when you sort of oscillate between lanes, but it also helps for things like over shoots and things like that as well or jumping back and forth when you do things like turning. That usually it comes from common planning and techniques like that.

[00:26:17] SC: And now you're making me remember, you know, grad school control systems courses with light dampening and all of these other things that you need to think about to avoid, you know, over shooting and oscillation.

[00:26:31] KC: Yup, yup. Yeah, it's amazing how now that I'm implementing things on a real vehicle how all the original control systems is really coming back. Things I haven't thought about in like 10 years, yeah, are very important.

[00:26:41] SC: Nice, nice. So what are you seeing as you're trying to, you know go from these models to implementing them on a real vehicle? Are you finding that — are you surprised by anything or are there things that, you know, were working fine in simulation but needed to be tweaked as you moved to a real vehicle?

[00:27:01] KC: Yes. I think one of my favorite quotes was - or is, "Everything is doomed to work in simulation". So -

[00:27:10] SC: Nice.

[00:27:10] KC: We have all these by simulation tools but — and we think we have things working really well but a lot of it is, still has to be hand-tuned and it's amazing how some of these simple things or, especially when you kind of get caught up in a lot of the really cool stuff that's happening in AI. You think a lot of the really cool stuff comes out of the deep learning. But when you go to actually test things on the vehicle, so much of it comes down to this low level control, actually.

So it is kind of amazing how much time is actually spent on the, I guess, more traditional things. As you said like, the dampening and making sure everything is smooth and tuning cost functions and things like that. So, I think there's still a lot of work that has to go in to the end-to-end stuff to make sure it works well.

[00:27:54] SC: And is there kind of research into applying some of the ways we optimize machine learning to optimizing, you know, these control systems. Like, you know, can you think of can you apply like hyper-parameter optimization to these control systems to find the right dampening constants and all that kind of stuff? or is it - are the, you know, traditional techniques kind of, good enough there?

[00:28:23] KC: Yeah, so I think you can do some of those things. But again you still have this problem where you ultimately have to put all of this on a vehicle, you have to test it there and because you're testing on a real vehicle that is has a lot of very expensive equipment on it. So you have to be kind of careful with what you are willing to test and make sure you're very confident in this.

So you can't do a full, you know, cross-validation set on there unless you're confident that it's going to work really well. But, yeah, there's some work that we've been working in Robust reinforcement learning. So trying to do things like take into account some of the uncertainty that we think we might see or some of the things like model mismatch and trying to create basically make sure that our control systems and our deep learning algorithms are robust to these uncertainties. So, I think that should help it, but we'll see if that actually works or not when we actually go in to the real vehicle with that work.

[00:29:21] SC: Can you elaborate on that work a little bit more?

[00:29:21] KC: Yeah, sure. So we're building up with some tools in, from what's called Robust Adversarial Reinforcement Learning. So, in this framework the basic idea is if you have some uncertainties in your model or uncertainties in the environment, you can actually treat this as a game between two players. So if you have your controller, which is what you call the protagonist and your antagonist which is basically these disturbances or these uncertainties that are trying to sort of, perturb your model in a negative way.

So, if you basically treat this both as agents that you want to train a model for. You can train your protagonist to achieve some goal and then you can train your antagonist to basically get you to not achieve that goal. So by training these two basically your antagonist and your protagonist iteratively, you develop something that approximates a robust controller. So you have your ultimate system is able to handle things like uncertainty in your model because you've been training it against a adversarial uncertainty or disturbance. So, that's one way we're trying to deal with these model mismatches. We'll see how it works. I'll get back to you on that.

[00:30:31] SC: Yeah, yeah. Are you finding that there is a kind of a cultural mismatch between the folks that come from the traditional control systems perspective where, you know, you've got established practices and like well-defined, you know, guarantees or, you know, at least laws of physics to kind of rely on, you know, versus the, you know, folks that are more the deep learning camp where you're just kind of just throwing a bunch of data against the wall and, you know, this thing is miraculously training itself?

[00:31:11] KC: Yes. There's a huge cultural gap there. So, one of the things I'm trying to, is try and sort of, bridge that gap but I think there is just a - it's almost like they're speaking different languages. These two communities tend to get a little bit territorial in what they can and can't do. So, yes, in short.

[00:31:31] SC: Awesome. Well to close us out, are there, you know, what's next for you beyond you know getting your vehicle working? Not that, that's like a short task or a foregone conclusion. What are some of the other things on the horizon for you and your work?

[00:31:50] KC: Yeah, so some of the other things I've been thinking about is, thinking about autonomous vehicles at a little bit of a higher level or a broader perspective. So, some of the recent work that I'm just starting has been on how can you use autonomous vehicles and some of these tools from planning to do things like assist in evacuation and disaster responses? So, using some of these same tools to help there. I've been also been thinking about how you can start applying some of these tools to fleets so you can think about optimizing overall performance by making small changes on a minor level helping you do things when you have many, many vehicles all operating together.

[00:32:26] SC: And so, are these things like cooperative autonomy and swarming behaviors and the like?

[00:32:31] KC: Yeah, yeah. A little bit of that, so I think the evacuation planning is a little bit more of the cooperative side. For the fleet performance if you still have individual operators so if you think of like, a delivery fleet you still have an individual there driving the vehicle and making decisions. So how can you optimize, maybe their behaviors on a minor level and then have greater performance overall?

[00:32:53] SC: Interesting, interesting. So what's the best way for folks to learn more about your research or connect with you?

[**00:33:00] KC:** Yeah, you can find me on the Internet. So you can look at my website, so it's just Stanford.edu/~krdc/ or you can shoot me an email at krdc@stanford.edu.

[00:33:12] SC: Awesome, awesome. Well, Katie thank you so much for joining me to discuss this. This is really interesting research and I'm looking forward to keeping tabs on what you're up to.

[00:33:22] KC: Thanks, yeah, it's a great conversation, thank you for having me.

[00:33:24] SC: Thank you.

[END OF INTERVIEW]

[00:33:30] SC: Alright everyone that's our show for today. Thanks so much for listening and for your continued feedback and support. For more information on Katie or any of the topics covered in this episode, head on over to twimlai.com/talk/59. To follow along with the autonomous vehicle series visit twimlai.com/av2017. Of course, you can send along your feedback or questions via Twitter @twimlai or @samcharrington or just leave a comment on the shownotes page.

Thanks again to Mighty AI for their sponsorship of this series. Be sure to check out my interview with their co-founder and CEO, Daryn Nakhuda, at twimlai.com/talk/57 and take a look at what the company is up to at www.mty.ai.

Thanks again for listening and catch you next time.

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