EPISODE 64

[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.

I'd like to start off this show by sending out a huge thank you to everyone listening. We've dropped a ton of great interviews over the past few weeks, and through your dedication we continue to see a growing, outpouring of feedback, comments and shares with each release. If you're a regular listener but don't' normally send in feedback, we'd really love to hear from you. So please head on over to Apple Podcast of wherever you listen and leave us a review.

A five-star review is of course appreciated, but what's most important is that your voice is heard. It lets us know what you like or what you feel we can improve on and it also lets those looking for a new machine learning and AI podcast know that they should join the TWiML Community.

Speaking of community, the details of our next TWiML Online Meet Up have been posted. On Tuesday, November 14th at 3 p.m. Pacific Time, we'll be joined by Kevin Tee, who'll be presenting his paper; Active Preference Learning for Personalized Portfolio Construction.

If you're already registered for the meet up you should have received an invitation with all the details. If you still need to register, head on over to twimlai.com/meetup to do so. We hope to see you there.

Now, as some of you may know, we spent a few days last week in New York City hosted by our great friends at NYU Future Labs. About six months ago we covered their Inaugural AI Summit, an event they hosted to showcase the startups and the first batch of their AI NexusLab program as well as the impressive AI talent in the New York City ecosystem.

We were more than excited when we found out they would be having a second summit so soon. This time we had the pleasure of interviewing the four startups of the second AI NexusLab batch, Mt. Cleverest, bite.ai, SecondMind and Bowtie Labs. We also interviewed a bunch of the speakers from the event and we'll be sharing those discussions over the upcoming weeks.

In this show, I speak with Ron Fisher and Mike Wang who, along with Vivek Sudarsan, founded Bowtie Labs, a 24/7 AI-based receptionist designed to help businesses in the beauty, wellness and fitness industries increase retail conversion rates.

I've talked with a few startups in the conversational space recently and one common theme seems to be quickly outgrowing commercial conversational platforms. Ron and Mike shared their own experiences with this decisions and shared some of the challenges they're trying to overcome with their own ML models as well as some of the techniques they use to make their system as robust and responsive as possible.

[INTERVIEW]

[0:03:12.1] SC: All right everyone. I am at NYU Future Labs and I am with the cofounders of Bowtie, Ron Fisher and Mike Wang. Ron and Mike, welcome to this week in machine learning and AI.

[0:03:23.4] RF: Thank you very much.

[0:03:24.0] MW: Thank you.

[0:03:25.4] SC: Why don't we get started with having you, Ron, tell us a little bit about your background and how you got to get involved in Bowtie.

[0:03:33.0] RF: Sure. It's definitely been a long and winding road. After college I served in the Israeli Army for three years basically and did the digital strategy there and helped build out the new media. So that was definitely my beginnings in terms of working with technology. After that, I worked in Nielsen for five years and then finally got my MBA at Cornell Tech where I met Mike, and my cofounder also came from Nielsen, so we had already known each other and then the three of us formed this team as a part of our final semester where we are tasked with basically working on any problem we want and if we wanted to continue that work after, spinout as a real company.

[0:04:09.0] SC: Oh, wow! How about you, Mike?

[0:04:11.1] MW: I graduated from Cornell undergrad where I studied computer science, and that's where I really found my interest in sort of machine learning and AI in that field. Following that, I actually went directly to Cornell Tech for grad school and that's where I met these guys and we formed the team and I think we have a really balanced skillset and it's been an amazing journey so far with them.

[0:04:36.9] SC: Nice. Awesome! Bowtie — What does Bowtie do besides having an awesome robot logo sticker?

[0:04:43.0] RF: Yes. Actually, that robot has been retired.

[0:04:45.9] SC: Oh, really?

[0:04:46.5] RF: Yeah. Things change very quickly in a startup. It's a 24/7 AI receptionist. It's currently focused on beauty, wellness and fitness businesses, so anything from like a high-end beauty salon to like a chain of gym, yoga studios, things like that. It operates on the web and through texting, and if you call any of the businesses and nobody answers, then the AI receptionist will instantly text you back. It can convert people before they have a chance to move on to another business.

[0:05:12.0] SC: Okay. How does that work?

[0:05:13.8] RF: Let's say like, Morgan, finds a cool salon on Yelp. She calls it up, nobody answers. She's frustrated. She wants to blow up. She will now call another business. Now, she calls a salon, nobody answers, and then our AI receptionist texts her instantly, says, "Hey, it's Lily from Bowtie Salon. How can I help you?" Then Morgan was like, "Oh! She just texted back. I love a blow out today at 3 p.m." Then they go back and forth by messaging to input the appointment.

[0:05:40.7] SC: What percentage of the inbound calls are coming from mobile nowadays? Do you get a pretty high hit rate on that?

[0:05:46.9] MW: Yeah. I would say almost all the inbound calls are coming from mobile. I don't have an exact number, but we're able to text back the vast majority of users. Sometimes we see like someone calling from a landline, but that's actually in the low minority.

[0:06:01.8] SC: Interesting. I've been familiar with some kind of these appointment scheduling kind of apps, and then you have like your x.ai, Amy kind of thing, and you guys are brining that together. Is that a good way to think about this?

[0:06:15.3] RF: Yeah. We're kind of like business to business to consumer in a sense. We're giving them a toolset that they get deployed to their customer base.

[0:06:23.5] SC: Okay. Interesting. How does it all work?

[0:06:28.0] MW: Yeah, great question. All the texting, we use Twilio for the SMS stuff. We also do web chat, which we have our own little plugin that sits on their website. That's typically where customers first find out about us or contact the bot.

[0:06:44.8] SC: Is it plugged in to Facebook Messenger or is it a standalone bot on the page?

[0:06:51.0] MW: Yeah. We do have Facebook Messenger as a third channel. We have web chat, which typically sits on their website. You can think of like Intercom or like Drift as an example what that might look like. Then SMS is where we reach out to customers who call and nobody answers. Those are the sort of three channels that we're working in right now.

What happens is that when a customer sends us a message, we do two things; we extract the intent of the customer. So what are they looking to do? Some people are looking to book an appointment right away. Other people are just looking for prices or what time are you guys open? We classify their intent and then we extract the entities, relevant entities in the message to figure out like, "Okay. Who are they trying to book with? What are they trying to book? What time do they want to come in?" Then if there's anything missing, then we follow up and say like, "Hey, I got that you want a haircut. Did you want a men's cut or a women's cut and who do you want it with and when do you want to come in?" and so forth.

[0:07:45.3] SC: Interesting. How did you select the particular vertical that you're going after or at least starting with?

[0:07:52.8] RF: Originally, we wanted to do — We're very passionate about chat bots. We're talking about predictive assistance and we knew that were a lot of companies attacking the enterprise side of the problem and we said that it'd be really cool to do some sort of like self-service platform to be able to provide this to business in mass similar to what MailChimp does with email. This was before Facebook opened up the platform for Messenger and like before it kind of like superheated up while we were still in school. We actually originally were like, "Okay. What is a business that people interact with every day?" We're like, "What do people do every day? They eat."

We started in food, because none of us have any experience really in like beauty, wellness or fitness. Then eventually, once we launched across 25 restaurants in New York, we felt like we weren't really solving a problem. While it was like iteratively better, it wasn't like 10 times better and in that sense we're kind of fighting an uphill battle.

During our time in an accelerator already after school we said, "We believe in the underlying thesis of Bowtie, which is that like apps are becoming increasingly relevant, like 65% of users download zero new apps a month," and that all these types of businesses, like local businesses and things like that are filled pumping money into apps that nobody really wants. Then we spoke to a bunch of different people who did research and then basically like after a few conversations, one of which was with like a beauty expert in our accelerator, CEO of VIVE at the time, Alanna Gregory, and we said, "You know, we're considering the beauty space." Then she's like, "Yeah. I don't know. Let me think about it." Two days later she's like, "No." She's like, "This is a real issue for this sector." Then after doing our own research, we found a variety of reasons why it really made sense to actually dive in and apply the technology to them.

[0:09:36.6] SC: Okay. What kind of response have you received? Generally, these kind of mom and pop shops for lack of a better term, like they are historically really difficult to gain traction in for startups. What are you doing to try to overcome that?

[0:09:53.4] RF: We basically have a variety of techniques that we employ, whether that's drip emails or like cold calling, to trade shows, and what we found was that definitely the tradeshows is the most effective and it kind of draws the people who are looking for a new technology to begin with, and I think that that's been really helpful for us an they're also really happy, because we're the only ones who are providing this type of solution and it's a problem that they're very aware of that they have. So that being able to kind of deliver on something that they know is an issue, has been very helpful for us.

[0:10:23.7] SC: Okay.

[0:10:24.7] MW: One of the benefits about working with these types of business is that they pay attention to members and real improvement in their business. If you can prove that, say, where we can handle X% of their call volume or get them X-dollars in incremental revenue, that really resonates with them, because at the end of the day, even a small amount of incremental revenue can make a huge difference for these smaller shops.

In contrasting that with like consumer behavior where it's a lot more sort of up in the air, like, "This is fun to use. There're so many other alternatives." For us, it's like if we can really show them that it's going to materially improve their business, then that really resonates with them.

[0:11:09.9] SC: What are some of the biggest challenges you've faced from a machine learning and AI perspective and pulling these altogether?

[0:11:15.9] MW: Yeah. I would say, as you can imagine, the biggest challenge for us is that we started off with zero data, and so we really had to bootstrap the automation with like proprietary algorithms, just doing lots and lots of research into like what did people say, how did people say it, and sort of slowly collect enough data that we could start training a model and start to generalize a little bit. When you start doing this type of thing, you quickly realize that people say things in million different ways, like, “How many ways can you ask for a haircut?” You’d really be surprised how many ways you [inaudible 0:11:49.8] haircut.

There’s also so many other requests that we never would have thought of that someone might even text, like, “Do you guys offer organic products?” When we set out to build a system that could help people book appointments and reschedule and ask for prices or whatever, there’re a lot of things that we never considered where like requests that would be coming in. That is what makes the customer service space difficult in general if you’re trying to automate it. This is like the breadth of requests that come in.

That’s one of the reasons why we chose to start off in such a narrow vertical, is that it makes it vastly easier to handle those requests. Whereas if we wanted to — There’re a lot of companies out there, like ASAP and DigitalGenius who are trying to sort of augment or automate call centers and very generalized customer service, and that is a very, very difficult problem. So we’re trying to be a little bit more narrow.

[0:12:48.8] SC: Have you developed any particular kinds of tools or approaches for kind of starting to whittle down that long tail of requests or how do you handle that?

[0:13:01.2] MW: Yeah. The majority of requests that do come in are things that we’ve sort of collected over the past six months. To be honest, it’s a very manual process of like figuring out what a new request might be. You can get classic 80-20 really here. You can get 80% of those requests with like 20% of the work. The other 20% of the request might be sort of smaller random things.

What we do is whenever there’s something that we don’t understand, we mark that in our system. Then every once in a while we’d go through that list and pull out trends that we’re seeing. Initially, we didn’t realize that so many people would get to the end of a booking process and ask for the price, but we found that looking at our data and going back and saying like, “Okay. This is something that we now have to handle.”

There’s also a lot of requests that are like sort of specific to your business. Someone might be like, “Where do I park?” and that sort of thing. That’s another aspect that makes this difficult.

What we've done there is like created basically a custom FAQ system where business can go and enter in their own questions and answers. We use a mix of our own tools along with Microsoft Secure Native service to handle those like sort of more one-off questions and answers.

[0:14:25.7] SC: Okay. It sounds like you're not doing any human in the loop type of aspects of this where if a request comes in and it's not understood, it's kind of escalated to some [inaudible 0:14:36.7] that you or the customer is managing.

[0:14:42.8] MW: We actually do do that. If the bot doesn't understand something, then we pass it off to a human, and that's typically the business's existing customer support staff. That might be a receptionist or even our call center. Anything we don't understand, it gets passed off to a human. In terms of marking it in our system as something that we might want to handle in the future, that process is sort of difficult to automate, and that's something that we're working on. We even have sort of a dashboard that the business operators work in. We're planning on adding tools, and there, that would actually allow the operator to go highlight a sentence and say like, "This is something that the bot didn't get, but is a common request that we get." Then they could either add that to their FAQ automatically or sort of, like you said, escalate that to us and we would go work on it.

[0:15:30.0] SC: Is it your sense that something like that will be readily adopted by imagining a salon on our — I'm assuming you're going after not kind of these big chain salons, but like smaller shops. Are they going to want to even think about that?

[0:15:46.6] RF: We're going for both. We do have some bigger clients that are nationwide and they're easier to work with, but then they have their own technology issues, so they have like systems that they want us to integrate with. In terms of the smaller businesses, as long as you give them something at a mobile device, I actually do feel like they're pretty open to it, but they also have like a very low tolerance for error because of the fact that they're in the service business, so like you really have to nail it the first time.

[0:16:10.5] SC: Interesting. On the conversational side, did you start off on one of the commercial conversational platforms or did you roll your own? I'm thinking here things like api.ai and other things.

[0:16:23.4] MW: Yeah. We tried all those platforms out when we set out to do this initially and found that it was just too much of a black box. We have real clients using this product, then it really can't mess up on things that are like easily remedied if we had our own more customizable model and system.

[0:16:46.4] SC: What's an example of something that you found that messed up a lot on that given your own platform is easily remedied?

[0:16:52.9] MW: Yeah, definitely. For example, salon service is called single process. I had no idea that that existed before entering this space.

[0:17:03.4] SC: To me, I'm thinking versus multi-threaded. But its probably not anything. Right?

[0:17:08.1] MW: Single process is like two pretty common words together, and if you just piped in a sentence to an out of the box model that said like, "Can I come in for a single process next process?" It wouldn't recognize that as an entity, because —

[0:17:23.8] SC: The process is the entity and single is like —

[0:17:26.2] MW: Exactly. It's like a quantity. It might pick it up as a quantity process. It's like, "Is that even like a service or is it processes also a pretty general term?" What we found is that we really had to augment and customize a system to be able to work with even the most simple things in real production. That's actually very doable because we have a list of all the services that businesses have, and overtime we've sort of automated the process of creating aliases and different alternatives ways, people ask for things, and those are things that you just can't input in a blackbox model that you might find with .ai.

What we've found is that those things are good for like sort of a small talk kind of bot, or maybe something a little bit more geared towards one-off responses, like Q&A type of thing. In terms of having a full conversation and holding state and entities in the context of a very particular business and meeting very high accuracy to input the exact appointment that the user is asking for, that required a lot of more customization.

[0:18:37.3] SC: Okay. Tell me a little bit about the effort involved in building out that platform and what were some of the difficult decisions that you had to make and which way you ended up going on those.

[0:18:49.1] MW: Yeah, definitely. One of the big challenges was integrating into the businesses in the first place. We work with MINBODY businesses. MINDBODY is a scheduling platform that has fitness, beauty, wellness businesses. We use their API to sort of pull in the business's information when they onboard; their staff members, their services, their availability and so forth. What we found is that every single — Not every single business, but many of the businesses on those platforms have their menu structured or written out in a different way. They're like super messy, because when they're writing it out, all they need for it to do is for the receptionist to be able to click a dropdown and then find the service that the user is asking for on the phone and put it in an appointment.

When we are trying to automate that process, we have to be able to capture however a customer asks for it. We have to drill down to what specific service they're asking for. If they say laser hair removal, we need to be able to figure out if they're looking for laser hair removal on their chin or on their forearm, because those are all the specific services in the system.

Just importing and integrating into many business and sort of generalizing that process on top of automating the conversations has been a real challenge, because it doesn't come in as clean structured data where it's like, "Service one; name plus 10 ways of asking for it. Service two; name plus 10 ways of asking for it."

When we think about doing this in a scale, we not only have to develop sort of models for talking to the user back and forth, but also importing a business's menu data, structuring it and cleaning it up and not having to do that all manually.

[0:20:41.1] SC: Okay. Do your customers ever ask you about wanting to have input into kind of a personality, if you will, if they are bots. Whether they're formal or informal? Do you use a southern drawl in the text or something like that? Is that something that comes up?

[0:21:01.3] RF: Yeah. We've had some really weird requests, like one person wanted their AI to be an like AI dog. They want a bunch of dog references throughout this build model. Other times if it's like a larger brand, there's one that has like a global presence. They were very formal and they really wanted it to be like very fancy in their language. It's definitely always a back and forth between me saying that's fine and then Mike telling me that that could take like another 10 hours. Yes.

[0:21:30.0] SC: How do those kinds of requests impact the system that you've built?

[0:21:34.4] MW: Yeah. The good thing is that a lot of those personality tweaks are just changes in copy in terms of the messages that we send out. What we have done is just created a bunch of different places in the conversation where the business can then go and tweak the message.

Around really core stuff, like, "This is your booking. Does it look right?" We don't want them to be able to tweak every single word, but what we do is like in the confirmation message, texts that the user gets when they've completed a booking, we might have a section at the bottom where the business can add anything they want there. If they have a cancellation policy that they need a highlight or if they have like special sort of — Something that they need to tell the user to not go suntan two weeks before the appointment or whatever, then they would put that there. We have a bunch of slots that they can modify.

[0:22:27.1] SC: Interesting. In terms of kind of the MLAI tech, having built up this platform from scratch, what are some of the toolkits and languages? What is the stack look like for you guys?

[0:22:43.4] MW: Yeah, definitely. We do everything in Python, and in my opinion the best language for data science or one of the best languages in general. We use SK-learn for a lot of the sort of out of the box models that we then we go and — For any model, really, most of the work goes into the feature engineering, feature selection, data cleaning, all that stuff that goes into it before actually doing the math and the regression or the classification behind it.

SK-learn, we use pretty extensively, and LTK is a great metro-language processing library that comes bundled with Python. We use that for a lot of like part of speech tagging, that type of thing. Then we use spaCy.io, which is another NLP library that can do like syntax, parsing at very high speeds compared to other more state of the art models that are a lot slower in terms of real-time parsing.

Yeah, we're experimenting right now with TensorFlow and some of the deep learning server, like word vectors and potentially looking into LSTMs for the entity recognition stuff. At this point, the data that we have isn't quite at the volume that you would need to do word vectors successfully, and we're still experimenting with that.

[0:24:06.0] SC: Okay. Awesome. What's next? What are some of the big things you're looking forward to on either the business or tech side or big challenges that you're looking to overcome?

[0:24:17.4] RF: Now, I think it's just about being able to like shrink down the testing phase for each of the clients that we work with, because of what I was saying with their low tolerance for error. We have like a huge influx of interest, because they are very excited about the whole idea and then they're expecting it to work 110% at a time. Just being able to make sure that we can basically give it to them and for it to launch and for them to be able to basically all have zero errors from the beginning, like ironing out that process, because now we're really scaling out the platform. I think that's the main issue for me at least in terms of what's next.

[0:24:52.8] SC: Anything to add, Mike?

[0:24:54.4] MW: Yeah, I would say I think basically scaling the onboarding process like we're on sort of getting at. Then also thinking about — This may be a little far off, but it's something that we started to think about is like expanding it to other verticals. How do we sort of transfer the models and the knowledge that we have from this particular vertical and make it more generalizable and make — If we get into real estate, that we won't have to bootstrap the automated conversations there like we did for this.

In that vein, there's going to be a lot of sort of how do we separate out the beauty-specific aspects of the model and maybe try to extract the appointment booking aspects and sort of try to generalize everything. That's something that we're thinking about a lot.

[0:25:41.5] SC: Awesome. Ron and Mike, thanks so much for taking the time to chat with us. I enjoyed learning about Bowtie.

[0:25:48.0] RF: Thank you.

[0:25:48.5] MW: Thank you.

[END OF INTERVIEW]

[0:25:53.2] SC: All right everyone, that's our show for today. Thanks so much for listening and for your continued feedback and support. For more information on Ron, Mike, Vivek, Bowtie Labs or any of the topics covered in this episode, head on over to twimlai.com/talk/64.

To follow along with the NYU Future Labs AI Summit Series which we'll be piping to your favorite podcather all week, visit twimlai.com/ainexuslab2. Of course, you can send along your feedback or questions via Twitter to @twimlai or @samcharrington or leave a comment right on the show notes page.

Thanks again to NYU Future Lab for the sponsorship of the show. For more information on the AI NexusLab program, visit futurelabs.nyc.

Of course, thanks again for listening, and catch you next time.

[END]