Demystifying Machine Learning

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Hello and welcome to CapTech Trends, a place where we meet with thought leaders and subject matter experts to discuss emerging technology, design, and project methodology. I'm your host Vinnie Schoenfelder, Principal and Chief Technology Officer at CapTech Consulting. Today, we're focusing on machine learning and artificial intelligence. It's a really fun topic. We're going to get into how people define these differently, talk about some different use cases, and how you can leverage them within your own organization. It is interesting stuff, but it's also a bit complicated. That's why I brought in some heavy hitters, I have with me Tom Stella, a Managing Director at CapTech, and Gabrielle Baum, a Director at CapTech. Both are thought leaders in this space frequently speaking and writing on these and related topics. I'm really happy to have you both, welcome.

Gabriella Baum
Thanks, Vinnie. Excited to be here.

Tom Estella
Yes, this should be great.

Vinnie Schoenfelder
Great. So, one of the things I wanted to start with is the difference between AI, artificial intelligence, and machine learning itself between those two labels/definitions, and then maybe go deeper into machine learning and how people define even that differently. So, Gabriella, why don't we start with you?

Gabriella Baum
Sure, I think it's a great place to start because a lot of people define it differently. I'm sure even in today's conversation, Tom will have a slightly different definition. So, anytime you're talking about machine learning or AI, it's really important to level set on how you define it before you go into that conversation. So, for today I think of artificial intelligence as a really broad term, it means a lot of things, and it's really focused on computers mimicking human intelligence, and that can take a variety of forms and implementations. Think of machine learning as a subset of AI (of artificial intelligence). And machine learning, as the name suggests, is machines learning from experience. So, it's being able to feed a machine a dataset and allowing it to learn from that data to extract patterns and use those patterns to make predictions and draw inferences that can be used in future decision making.

Vinnie Schoenfelder
Tom, would you add anything to that?

Tom Estella
I think Gabriella hit the nail on the head with a lot of that. So, machine learning is a subset of AI and it's the subset that allows for the machine to learn from the dataset and create new algorithms that can help us make decisions better.

Vinnie Schoenfelder
You know, I'd like your feedback on this: when I think about it, I think of people who have years and years of experience in SQL – either directly or indirectly writing reports, using Excel, getting different datasets, drilling in – that's all very deterministic. We know what fields we're looking at, we know what questions we want to ask it, and we get answers that are definably true, right? And then you get in the machine learning and it's probabilistic. You're looking at the interaction between fields and elements that maybe you didn't know had relationships. And it's not deterministic. It's only probably 80%, 90%, 85%, whatever it is likely, as opposed to deterministic. So, I think there's a paradigm shift people have to go through in order to really get the full understanding of the benefit of machine learning. Am I accurate on that? And if so, how do you get people through that divide?

Tom Estella
So, you are accurate. When we talk about machine learning and AI, it really depends, it's all probabilistic. So, at best you have 90, 95% of the time that your answer is correct. If you need to be a 100% right, if it's something that's that important, analytics and AI is probably not the right answer. But when 95% accuracy or 90% accuracy is okay, that's when we're starting to work with this. But to your point of probabilistic and looking at the data, the most important part is to start with a business problem. So, although it's not deterministic in terms of 100%, we have to really have a clearly defined business problem to start the process.

Gabriella Baum
I think it's a good point. When you are starting to try to solve a problem – it doesn't matter if you're trying to use traditional SQL or machine learning to solve it – understanding what is the necessary outcome and how often does it have to be accurate. And if it's a life or death situation, if you're trying to figure, does this person have this diagnosis or not? Then to Tom's point, you know, maybe machine learning isn't the right solution. It can help, it might be a first point in the decision-making process, but it shouldn't be your final point. If it's something where every single time you see temperature over 102 degrees, then you want to diagnose

this other thing. Then again, that's going to be a very different implementation. That is something that a very simple rules-based engine could solve. You don't necessarily need machine learning for that. So really understanding in the early design phase of a project, "what is the business problem?" as Tom said, but also "what is the necessary solution? How accurate does it have to be?" And that will help you determine if machine learning or AI is right for this business problem. It doesn't work for everything.

Vinnie Schoenfelder

It seems ideal for things that you can test and learn from as well – advertising campaigns, pricing, those types of things. So, as we bring those up, it's kind of a good place to move this to. So, within the industries we serve and the clients you're speaking to, what are some of the top use cases? How are people using this?

Gabriella Baum

So, I can go first. I think it differs by industry a little bit, but there's definitely a lot of similarities in the types of applications that we see. So, one of the biggest ones that I've been a part of is around personalizing the customer experience. And we see this in our day-to-day lives. So, think about Amazon, I think a lot of people are doing online shopping right now. I go to Amazon, I'm looking for a specific product, and because of past purchases that I've made or past products that I've looked at, it's all linked to my account, and they make recommendations of other products that I might like. And you don't know how many times I'll see a recommended product that I didn't even know existed or that I needed, but I ended up purchasing it. And that's one of the great ways that you can see machine learning in practice is through those recommender systems.

You see it with Netflix as well. So, based on the videos and TV shows and movies that you've watched, it will recommend other things that you might like. And I would say at least 50% of the things that I end up watching on Netflix are things that have been recommended to me through the algorithm that it has. And that's all machine learning behind the scenes, making those predictions based on what you've looked at and what other people that it classifies as similar to you have also looked at. So, I think that's a really great application where it can really lead to a better personalized experience.

Vinnie Schoenfelder

So, before we go into other use cases, I want to jump into this one because recommender systems have been around before machine learning was prominent, right? They called them "intelligence systems" or "smart systems," where I know if you're looking for a Toyota Corolla, you might also like a Honda Civic, right? It was kind of prescriptive in that way. Or, if you like "Stranger Things," you might also like this other science fiction type show. So, how is machine learning being more accurate or providing more value to these recommendations than just those intelligence systems? Tom, do you have a thought on that?

Tom Estella
Yeah, so they have been around for years, right? So forever, we've been saying if someone likes a Honda, they'd probably like a Toyota. The difference is that this is actually looking at the action afterwards, taking that into consideration, and making a new decision on the next pass. So, if we think Honda is associated to Toyota, in that example, over time if we see a trend from Hondas more in line with the Nissan, the machine learns that, and starts to pick up secondary and tertiary items that may make it more likely that you're getting more likely to purchase a Nissan and give a recommendation, instead of having hardened rules that stick and stay there for the life of the product.

Vinnie Schoenfelder
So, your rules will only be as good as they were when you first coded them, and they may actually get worse over time. Whereas, the machine learning is set up to constantly improve itself?

Tom Estella
That's exactly right.

Vinnie Schoenfelder
Okay, I interrupted you Gabriella. You started with recommender systems. What are some other top use cases?

Gabriella Baum
Yeah, another one that we see a lot, and this reaches across industries, is being able to detect anomaly. So, in the insurance industry, this could be detecting fraudulent claims; in the healthcare industry, the same type of thing, being able to identify things that look out of the norm. In financial services, you see it a lot in anti-money laundering or even fraud detection on your credit card. So, I know I'll get alerts from Chase saying, did you really purchase this? If it's from a store that maybe I've never shopped at, or it's a strange amount that could be potentially incorrect. And so, those are all different ways that you can leverage machine learning, to identify based on patterns, things that look skewed or outside of the norm.

Vinnie Schoenfelder

And again, we had this before machine learning, right? But it wasn't as accurate, it wasn't improving over time. So, you were frustrating your customers more. Every time they went to the beach and bought something out across state lines. You know, I remember 10 years ago traveling with my family and every time we crossed the state line, you couldn't buy gas until you called the bank up and said you were really there. So, from a customer experience perspective, brand loyalty perspective, brand affinity perspective, these are the sort of hidden things that you don't know why necessarily you're so close to your bank, but it's these types of actions or behaviors, or the lack of the negative behaviors, that really improve that experience. Tom, do you have any other use cases as well?

Tom Estella

I do, but to go back to that anomaly detection, I worked for an audit client for a long time and predicting when a transaction is likely to be fraudulent is another perfect use case for the anomaly detection. So, we're looking for something that looks odd and the machine learning aspect of it takes into consideration multiple tests and weights each of those tests to say which is the most important to understand whether or not this is a high-risk transaction.

But, to go away from that into another use case proactive maintenance, whether it's on cars, planes, or big machinery is another great use case. Understanding if a machine is working at its maximum capacity, if it's working efficiently, if it's likely to fail, and being able to proactively work on that machine so that it stays active and in use for a longer period of time, is just a great way to use machine learning, to make your make your team and your project more efficient.

Vinnie Schoenfelder

And again, I keep making this point, I think it's an important distinction. We had this before machine learning, like if a part is in a machine for more than three months, we know it's time to replace it. I mean, to the point, some cars have engineered obsolescence. We know the water pumps going to fail after 60,000 miles, right? But what we can learn with machine learning is, especially with IoT (Internet of Things) integrated with that, we know if it's running hotter, or if it's shaking more, or all of these little tiny details that we didn't know to look at, to your point. If we're looking at it post failure, we can start identifying pre-patterns to those failures.

Tom Estella

I have a great use case for that. So, we worked with large machinery that was in the mining space. So, if you think about these trucks that go into a mine that take a payload out of there that could be worth a half a million dollars per payload, there's a line of 15, 20 trucks that are waiting to get in there. What we found was that if you think about the temperature of the exhaust coming out and as there's multiple exhaust ways for it to exit the vehicle, if we looked at the ratio of the different exhausts, if that ratio changed, we could find failure within an engine, or within a piston of an engine, we could proactively not put that in the line so it doesn't block the mine, it doesn't block the rest of the trucks, and keep that line moving as we go to replace that one issue or problem. That could save millions and millions of dollars just in one application of that use of that use case.

Vinnie Schoenfelder
Yeah, that's great. Let's take that example and the other ones that you guys brought up and tie this back to AI, right? Because we're talking about both of these things. So, your definition in the beginning, I think it was you Gabriella that said machine learning is a subset of AI, and AI is a computer or machine performing a task normally performed by a human. So, in this last example, you went through Tom, I guess the machine learning is understanding when this failure might occur, that the AI component could be automatically setting up a service check, scheduling a mechanic, alerting the driver to shut the engine off – different behavioral things that normally people would do in that process to automate a system of responses. Do I have that correct?

Tom Estella
Yeah, so I think what we're talking about is a solution in general, so that the solution has more than just the machine learning or AI aspect of it. There are mechanics to that solution that not only do we know that something's about to fail or know that something's an anomaly, but we have an action that we can do to kind of take advantage of that knowledge.

Vinnie Schoenfelder
Yeah. But there's kind of post action versus action in the moment, right? So, if you think about collecting data from a plane after it lands, the terabytes of information and studying that and making some suggestions for the next flight; that's kind of after the event. Whereas a Tesla that's taking in – Is this a road sign? Is this a line on a highway? Is that a car breaking using that machine learning in the instant to act and behave on it? Those seem to be two pretty broadly different use cases.

Tom Estella
They are different use cases. So, the second one where they're both taking in that data, and whether it's the airplane or it's the Tesla, both can utilize that information to know what to do

next. I think the differentiation there, when the plane lands or we analyze that data, we look for new trends to find the next time we're in flight to say, "is there an action we need to take right away that we can leverage that information to leverage that knowledge at that time?" So, that secondary action is really more of the feedback loop to make the machine smarter so we know what to do next time, but the leveraging it is happening in real time.

Vinnie Schoenfelder

Yeah, got it. So, Tesla is doing the same thing as the plane is doing because as it's capturing driver data from everyone driving their cars, it's improving their models and downloading those at night when you're sleeping perhaps. So, when I think about AI – and we talked about some of these use cases in machine learning supporting it – I heard a good quote one time that AI is really good at targeting things that humans can do or recognize in a second or less. So, very complicated things are hard at this point for artificial intelligence, but simple things, repetitive things, they can do it exceedingly well. So, going back to the Tesla example, you know, seeing a stop sign is pretty obvious for the car. We can do that in less than a second, we know it's a to stop sign. But the machine learning doesn't get tired, it doesn't make that mistake.

I was in my car going up a two-lane road and I saw there's a truck in my lane and guy had a wood chipper and he was throwing logs in the back and a car was coming the other way and we both stopped beause now we can't get around the wood chipper. And we looked at the guy who was in control of the situation and he was doing hand motions I'd never seen before, one was like a "washie washie" with his left hand, and one was like "roll the film" with the other hand. And instantly me and the woman in the other car looked at him and looked at each other and had that look like this guy doesn't know what he's talking about. On our own, we're working this out, and then we started doing hand signals to figure out who's going to go. And when that's more than a second and Tesla's cameras and sensors aren't going to be able to do that for quite a while, right? So, I guess both of you talk about where you see the application of first of all, am I right? And it was kind of like a nice tidbit I picked up the second or less. But secondly, are you seeing people applying that logic? Are they stretching too far? Are they addressing the right issues? Gabriella, I'll let you jump in

Gabriella Baum

It's a great example, Vinnie. I think you're accurate in your definition of where machine learning works well, which is on repeatable tasks. So, the whole premise of machine learning is that you're using past data to make predictions about the future. So, if your past data doesn't mimic what's going to happen in the future, and if in reality, there's a lot of outliers that are inconsistent with the prior data, a machine is just not going to perform well in those situations. And that's when machine learning is not the right solution. Again, it doesn't work every single time, and I think that's really important to remember. There's so much hype around machine learning and AI where organizations feel like they have to use machine learning to have a competitive edge, and they try to force it for solutions that maybe don't warrant it, or maybe warrant a much simpler solution. And it's not worth the investment and the time and the people that would be required to build out a full machine learning application.

Vinnie Schoenfelder
That goes back to something you started with Tom, and I know you're passionate about, is know what you're trying to use it for and validate that that's a good use case.

Tom Estella
Yeah, that's right. You know, we talked about artificial intelligence and I like to think of that as advanced analytics, it's all of the probabilistic modeling that we're talking about. Within there, there's exactly what you're saying, machine learning, which is at one a second thing. We let the machine analyze each piece of data, find trends within there, and predict what we should be doing next. What's the best outcome or most likely best outcome that we do things?

The other side of AI is what I like to call "deep learning," right? So, there's machine learning where the machine does these quick analyses. And then there's deep learning where we can get a little deeper into understanding the patterns and recognizing those patterns within the data. I think there's use cases for both of these. On the machine learning side, when it's something that the data's changing quickly – whether it's hourly, daily, monthly, weekly – we can have the machine build new models almost immediately, we'll call it in a batch every two or three hours. We can have a new model that allows us to understand what's likely to happen because of that. When your data is very secure and stable and doesn't change over time, we might want to go a little deeper into that understanding of the data and do a more offline model build.

So, it's still using a machine, we're still using computers and advanced analytics and statistical programming, but we're understanding deeper within each piece of that information. Now, the downside to that is that we're not able to update that model as quickly. It's something that a person has to stand in and actually do that work, it may take a couple of weeks to actually implement. The upside is we probably get a little deeper extraction of information out of the data. So, there's different use cases for both of those, but they're both really important.

Vinnie Schoenfelder

So, we've talked about a lot of these systems existing pre-machine learning and the value that machine learning brings to them, what's changed? What made this possible? What are the recent advancements and technology like that that enable us to process this much data?

Gabriella Baum

I think that's a great point, machine learning is not new, advanced analytics is not new. This has been around for many, many decades. What is new is some of the technology advancements. So, if you think about what you need to build a machine learning solution, you need a lot of data and you need a lot of processing power. So, you can parse that data, analyze that data, and draw insights from that data and between the introduction of the internet. So much more information is becoming captured and readily available for analysis and advancements in cloud solutions where storage is a lot cheaper. So, you don't have to be as concerned about keeping and maintaining data without knowing if it's valuable. Computing is a lot easier to scale up and down. So, if you have a really large data set that you want to analyze, you don't have to go out and buy really expensive servers that are going to be able to support it. You can quickly stand up a virtual machine in AWS or Azure to analyze that data and then shut it back down. So, a lot of those technology advancements are really a driving force behind the advancements that we're seeing in machine learning and the adoption that we're seeing with it.

Vinnie Schoenfelder

Well, yeah, I don't have the numbers, but I saw an interesting article the other day, about the cost of a terabyte 20 years ago versus today. I mean, it's huge, right? It's, exponential, it's crazy how cheap storage is and how strong processing power is.

I kind of want to move the topic a bit and to talk about the pitfalls now. So, we've touched on what it is, the use cases – where are people getting it wrong, or what are some of the common characteristics of people that are struggling with getting machine learning to be successful in an organization?

Tom Estella

Yeah, I'll start with that. I really feel like there's two main ones, but I'll start with the first and that's for companies and organizations that are new to machine learning. They think of it as a silver bullet and they say, "what's the most complicated, difficult problem we have?" Let's try to solve it with a machine. Like anything else, if you try to jump in with both feet, a lot of times you can, you overshoot your pattern. And so, you don't get what you need. Start small, pick something that you can easily define, something that you understand exactly what the answer to the question should look like, and then allow the machine to learn that and do that for you. Then add onto it, pick one data set and say, “we're going to analyze this data set to predict this thing.” We can always add more data, we can always add more process.

The other piece I'm going to talk about – and we said this earlier – is to truly define what your business problem is and what you're trying to solve. Often, I find people are able to create these amazing statistical models that mathematically have an awesome aura about them, but they don't answer the actual business problem. So, organizations aren't able to leverage those to actually improve their efficiency or their effectiveness. So, making sure that you have a clearly defined business problem and starting small with your project, I think are two of the biggest steps for success.

Gabriella Baum

And I would add to that. I think another big one that I see is not having the right team. So, a lot of times people have a data scientist or organizations have a data scientist or a team of data scientists, but a machine learning implementation, thinking about getting a solution, an application in production, requires so much more than a data scientist. There's so much more to it than the model piece. And it's really important that you establish that cross functional team that encompasses the diversity of skills that you need early on in the life cycle of an implementation. So, you definitely need data scientists. You also need data engineers to help make the data available for the modeling. You need dev ops support to be able to automate and deploy all your code through the environments. You need a machine learning engineer or multiple machine learning engineers that can help with the consumption side. So, once the model output is available, how do you enable consumption of that? Are you integrating with a website? Are you feeding it to downstream sense systems? What does all that look like? And depending on the complexity, you might need scrum master project manager, product manager. There's a lot of roles that are involved in a team. And a lot of times people really just focus on the data science piece and that will get you only so far.

Vinnie Schoenfelder

I'm glad you brought up data engineering. One of the metrics I often look at is – it’s kind of like the 80/20 rule. When I talk to people doing machine learning, they have a data scientists and then they have six data engineers per data scientist. I forget the five V's of data: volume, veracity, velocity, wariety, and there's others. But getting your data straight – your data engineering as a prerequisite to machine learning – I think a lot of people miss that step. No one state is perfect, right? But they have some real data issues that they just miss; it's a gap. And then they go into machine learning and wonder why the results are or aren't good. So, for those listening, data engineering is totally a prerequisite to doing this right. Also, another interesting thing too: data scientists aren't data engineers and vice versa, right? People make that mistake cause they both have data in their names. And certainly, you can go from one role to the other you know, adding skillsets. But these are different roles in the organization.

Gabriella Baum

Yeah, I think that's good. And they typically have very different backgrounds. So, a lot of times data scientists come from statistical degrees, maybe even having PhDs – they're very mathematical – whereas data engineers traditionally are coming from more computer science a little bit more software engineering oriented. And so, a lot of times what you see is data scientists can develop really accurate models, but when it goes to building a production solution around it, the model, the code might not be optimized, it probably doesn't have logging, it doesn't have error handling. So, there's a lot of pieces that you'll have to work through in combination with those different resources that we talked about to be able to take a model and get it to a point that it can effectively meet your requirements in a production application.

Tom Estella

I totally agree. I started 20 odd years ago on the data science side. I'm one of those math geeks that loves that part of it. But unfortunately, I've always had to do a lot of the data engineering myself. Now, I've learned SQL and I understand probably four or five other ways that I could work with the data and I can do it. I can get the data from this format to that format. But when we talk about an efficient inner join or an outer join, that's the data engineer's job. That's not my job and I'll try it, and if I need to do it during prototyping to actually score my model the first time, that's great, but we need a data engineer to actually make that an efficient job run so that it can run in production.

Vinnie Schoenfelder

Great. So, the last thing I wanted to go over was to get a little bit more specific, to go one level deeper, because this has been very conceptual, very good information, but I want to get down to actual tool names, platform names. So, I'm going to walk through what I see after hearing you guys talk to get started. And then you guys can give me some specifics. So, Tom, I'm going to start with you. Know what you want to do with it, clearly define what you want to do. That's the most important thing. Validate that it's a good approach and that you're not trying to do too much all those things you spoke about. But then how do you get traction? Do you hire the right person? Who do you hire for it? What platforms do you need? Are you go into Azure or Amazon? Are you doing it on prem? What are some of the tooling you would use? Let’s get specifics that people can have things to go Google later and look up dig into.

Tom Estella

So, there's a few questions there. So, I'll start with kind of where you started, which is how do you get started? And I think that does start with the business team. You probably need an advanced analytics or a ML engineer to help you understand what the problem is and how it can be solved; but you need to start by working with the business team to understand what problems they have and how the solution could be implemented. That's the first step in this; go through and actually do an evaluation of the business problems. You have the data that's available to solve that and start to put together a plan on how you would approach that. When it comes to the tooling, and I'm going to let Gabriella get a little deeper into this, but at this point, most big data solutions are going to have to need a cloud solution, whether it's Azure or AWS. For me there's not much of a preference for one of the other, they're pretty similar, but Gabriella could talk a little bit more about the actual tools within the systems.

Vinnie Schoenfelder

Yeah, Gabriella, we're gonna jump into that; but before we do to finish off your thought Tom, yes, we do have to know what problems to solve and work with the business. But you also have to have someone who has solved problems with machine learning in the past to know what are good candidates. Like, if we've never done machine learning before, we all start thinking what we could use it for, we're going to misapply it, right? So, what's that role? Who is the person who has that expertise to know what problems can and should be solved? Is it an evangelist, a czar?

Tom Estella

No, it's really a solution architect, right? It's someone who understands the machine learning process. Someone who's done this for a long time that has experience delivering these solutions that can start to look for some keywords or some key topics that help to decipher whether this is a good ML project or not. Things like, how often do I make this decision? If it's a decision I make once a month, I probably don't need a machine learning model for it. But if I make that decision once a minute, that's something I probably could use a machine learning model to make sure that we make that decision many times over the course of the day. If it's something that is a short-term solution, we're going to need to do this through COVID for the next two months, and then we don't need to do it anymore, we probably don't need to create a machine learning system to solve that question. We can tackle it in a differnt way in this two-month period. But if it's something we're gonna be doing for the next five years, well, we probably want to look into how we can automate that process, have the machine allow us to do it better.

Gabriella Baum
And I would expand on that and say that it shouldn't be just one person doing that. I think it's a team of people that you really need. You need that diverse knowledge within the organization. And one approach that I think works really well that I've seen is going through and creating a machine learning use case inventory. Think about all of the different ways that you could apply machine learning to improve your business, whether it's to save money, to optimize a process, to increase sales; it doesn't matter what the impact is. As long as it's impactful, capture all those use cases, capture information on if it's possible to implement it. You might have a great idea, but you don't have the right data. So, keep it on your backlog, but it's not going to be your first use case. And that's when you're going to work with a diverse group of business stakeholders to help prioritize and figure out what is the right place to start, well what is the right use case to start with? To Tom's point, don't pick the most complex one, pick a simple one to start with to kind of build some foundational skills, build out infrastructure, build out patterns, but having that full list of understanding where machine learning can improve your organization is really helpful to get yourself started.

Vinnie Schoenfelder
And I would add, educate the leaders and the people in the business that this is probabilistic, not deterministic, and workflows and processes are going to have to adapt to that aspect. It's a pretty serious thing people miss. Before we wrap up Gabriella, I wanted you to go a little deeper on some of the tools and platforms. Maybe pick like an ideal use case. If you went in and had a great, it doesn't have to be a particular client. Let's go ahead and just generalize it to like the last several projects you've been on. What are some of the tools and platforms that you would pick as a good reference architecture?

Gabriella Baum
So, I think one important thing to call out is that you can implement machine learning solutions on premise or in the cloud. And if you're in the cloud, every single major cloud provider has their own set of similar (although names slightly different and have slightly different features) services that you can use to accomplish this. So, I'm going to talk about AWS and Azure today, but recognize that if you're using Google cloud, there are options out there. If you're doing this on prem, that's also possible.

So, let's take a use case, let's say it's a retail client – and and we talked about Amazon before – they’re looking to build out a product recommendation algorithm. They want to be able to personalize recommendations of products to their customers. So, if we're working in Azure, you would need a storage layer, so you need a way to centralize and store your data. So, in Azure you could use Azure data lake store, which is pretty much a file system. If you're working in AWS, you can use S3 as your storage service; you really just need a place to store and organize your data in a structured manner. And you want it to be optimized for analytics, you're going to most likely have a lot of data. So, you need to make sure it's partitioned and organized in a way that you can consume that and process that data very quickly and efficiently. On top of your storage layer, you need a way to move low transformed data. So, there's an ETL or ELT component of every ML platform solution. In Azure data factory, is a tool I've used for this in AWS, glue is a common service that will support that as well. And then the piece that I think people are most interested in is the piece where you actually design, develop, deploy your models, right? So, where does the model itself live? How do you prototype a model? How do you structure that in production?

So, in Azure, there's quite a few different services you can use. One of my prior clients, we used Azure Databricks and found that to be really, really effective. So, it would be able to read the data from the storage layer, consume it, process it, do additional aggregations and then ultimately output a final model that was then called in real time. And AWS, again, multiple options there, sage maker is a service that we're using on one of my clients right now, which again, offers a whole suite of machine learning capabilities where your code is actually packaged as docker images. And you're able to deploy that. And that allows for a lot of reusability around your code, which is something really important to think about. You don't want to have to have each implementation require a lot of setup. So being able to reuse code enforces consistency, but also enables faster prototyping and development.

And then there's always going to be a consumption piece to it. So, thinking through once this model is out there, how are people consuming? It sometimes it's as simple as an output, like a file of score data, and someone is reviewing it, sometimes as being presented on a dashboard, sometimes it's interacting in real time, like you would have on a recommender system where it's interacting and embedded within a website. And so for those realtime pieces, there's an API layer often and Azure, we use Azure functions to be able to enable that integration so that, you know, when someone's looking at a product page, their inputs are automatically set to the model so that it could return the personalized recommended products for that individual. So again, there's a lot of different ways that you can do it. There's a lot of services that are available. It really is gonna depend on your specific preference in terms of the cloud provider, as well as the specific use case. And what are you trying to solve? And what's your SLA? And what is it that you're really trying to accomplish with this?

Vinnie Schoenfelder

That was great. Really good description of the full stack. And I wanted to stress the point that in this time of COVID – we did a couple of talks earlier about winning in the curves — this is the time to innovate. When things are going easy, you know, basically when you're on the straightaways, it's hard to overtake, but when you come into a hard corner, out breaking, out maneuvering, out accelerating your competition is how you make big gains.

So, if you're not deep into, or getting into, or prototyping machine learning know that your competitors are, and now's a great time to invest the time and resources to do it. And as Gabriella outlined, no better time in computing history to do this because so much of it is done on a platform level, both Amazon and Microsoft and Google, they have the tools set up for you. You can create these environments very quickly and get started. So, we're going to wrap up here. I ant to thank both Gabriella and Tom for joining, I think it was a great discussion. And for those listening, if you enjoyed this, please subscribe. We're going to try to keep these coming out weekly for the time being and see where that takes us, so thank you.