Speaker 1:

This is IT Visionaries, your number one source for actual insights and exclusive interviews with CIOs, CTOs, and CSOs, and many more. I'm your host, Albert Chou, a former CIO, former sales VP, and now podcast host.

Speaker 2:

A typical way of doing things is data analyst would spend weeks or months to figure out this data, like why something change. What Sisu does is we have developed this machine learning algorithm so we could actually tell you what impacts your KPI within minutes. That's really the [inaudible 00:00:35] essence of Sisu, that we can tell you why something changed across this huge dimension space within minutes that generally takes hours, weeks, or months to get that data out.

Speaker 1:

Data, it's a valuable tool that businesses use to point them towards what is and isn't working in an operation. What if technology existed that could not only identify what is happening but why? That's the Holy Grail, that's what everyone's looking for. Today's guest is Jigar Desai, SVP of Engineering at Sisu. That's S-I-S-U. It's a data tool that uses automated analytics to help companies determine why certain KPIs and KPI changes occur. Before landing at Sisu, Jigar's engineering experience included leadership roles in major companies like eBay, PayPal, and Facebook. And on this episode, Jigar explains why groundbreaking technology behind Sisu's data intelligence engine, how its implementation process works. He even tells us why this very podcast could benefit from its use. Listen in.

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Jigar Desai, welcome to the show.

Speaker 2:

Thank you, Albert. Pretty excited to be on this show.

Speaker 1:

Listen, the marketers are very good at marketing, but sometimes, I'm not going to lie, I don't really know what they're saying. There's a lot of companies in this space. If you could, Jigar, can you tell us what is Sisu and what do you guys do?

Speaker 2:

As you started with, Sisu is the decision intelligence tool. Now, there is a lot of jargon here in terms of what does it actually do. I generally explain it to an example. Let's say you're an e-commerce company and you are worried about your KPIs, like what is your average order size or how are my customers doing? Lot of companies have a lot of data about all of this. E-commerce company would have petabytes of data on how user activities are happening, but whenever there is a question about, "Why is my average order size going up?" or "Why is my cart size going down?" they actually get into some manual way of figuring things out.

A typical way of doing things is data analysts would spend weeks or months to figure out this data, like why something change. What Sisu does is we have developed this machine learning algorithms so we could actually tell you what impacts your KPI within minutes. That's our really [inaudible 00:03:25] essence of Sisu, that we can tell you why something changed across this huge dimension space within minutes that generally takes hours, weeks, or months to get that data out.

Speaker 1:

Okay, so I'm getting a little bit fired up because this is something that we at Mission have been looking for. I've been in e-commerce, and I know my customers back then were looking for it. I've been in social media management, I've been in software for a while, that thing you just said, that simple three little word, why, right? I think data has historically been very good identifying what is happening. No one actually knows why anything happens or they didn't use to know or it wasn't clearly obvious right out the gate. You already mentioned data analysts. If anyone goes and looks at the job requisitions at a big company, you'll see tons of analyst jobs. A lot of people are in charge of figuring out why anything happens.

I got a question for you. What is unique or what are you building at Sisu that is able to do this? Because one of the things I used to always think about that it's still true is a lot of times why something has happened doesn't necessarily give enough signal. There's not enough signal to demonstrate why something is changing. And so, I used to think it was going to be standard deviations away from the norm, like if you noticed a two standard deviation away from norm pattern in certain data variables that something was happening there, but it was really hard to track. Give me an idea how... I know you can't give away everything, but give us an idea of how you're able to mathematically or using software technology figure out the why of something, why it's happening.

Speaker 2:

It would be good to share some context. Sisu originated from our founder's work at Stanford. Peter was an assistant professor at Stanford, and he was working on this particular project about, "Hey, we have a lot of data to explain what but very little to explain why." Our roots in terms of technology, they're based in statistical ML. So you can imagine a typical e-commerce scenario where you have, let's say, 300 columns or 300 dimensions. The dimensions could be geolocation, it could be customer age, it could be the type of product, and things like that. When you have a high dimensional space and then each of this dimension has certain values, like geolocation could be all the states within the United States or it could be Canada and much of other countries, in a high dimensional space, a combination of those dimension and values can be very large. It could be millions of combinations.

What we do is we calculate impact of all of those combinations on a KPI. For example, your average order size went up overall, but it went up because in Washington there was a campaign and people started buying ski gear early on rather than waiting for winter to arrive. That actually changed your average order size. Now, that's like a needle in haystack, you have to really figure it out. Washington, a particular city in Washington, and a particular age group is impacting this average order size. What we do is, using statistical ML, we figured out the impact created by each of these combinations, and then we surface the top combinations that actually are impacting a particular KPI. So out of a hundred million combinations, we'll show you the first thousand and tell you that these are likely the reasons why your KPI move up or down.

Speaker 1:

How fast can that occur?

Speaker 2:

We can process hundreds of millions of combinations within minutes. The reason we can do it is multiple. One is we are very optimized for this kind of calculation. Any kind of false discovery rate, statistical significance that we tried to derive, we've optimized those algorithms. And second, we can actually scale out. So we can use multiple nodes and multiple computer and storage to get this results much faster. So yes, we can do hundreds of million of combinations within minutes in a case which I just described, which is a typical scenario for Sisu to go after.

Speaker 1:

When you just mentioned that commerce example, I do recall working with different commerce companies. You'd have your, let's say, Monday or Tuesday weekly meeting to talk about sales demand in the last week, and then you would forecast your demand planning for the next week. All the while, the current week, no one really talked about the current week because you couldn't do anything about it.

Speaker 2:

That's right.

Speaker 1:

Give me an idea of what are people discovering because there's a lot of companies that claim that they can provide insights from data, and I think most buyers of this type of software have gotten more advanced so they're going to want some level of proof of concept to be like, "If your tool cannot find something that I don't know already, then it's probably not going to be worth it." I remember five years ago McKinsey did a study that said, "Hey, most big data projects return less than 50% of the cost of implementing the project."

I know that that's changed now because, of course, the technology's improved. But give us an idea of some of the stories or some of the things that you've heard of businesses when they first implement this or the first POC when they were just discovering things that they just otherwise couldn't figure out, or maybe by the time they did figure it out, it was too late to do something about it, like you mentioned, that demand change. For example, if there was a seasonal demand or a weather based demand, if the weather pattern's gone, obviously the demand is gone. I didn't know if you had any stories or examples.

Speaker 2:

My favorite example was about a food company, actually a large pizza chain. They were using Sisu as a POC, and they were trying to figure out how is the sales per store looking. They were comparing different locations and figuring out why is one location not doing better than the other location. There were lots of dimensions in a pizza place. You have a location, you have time of the week.

Speaker 1:

Sure.

Speaker 2:

It could be other factors like weather, like you maybe in Michigan and your pizza sales dip because it's too hot versus in California. When they actually put lot of these things into Sisu, what they figured out is one of the ingredients was changed. The vendor was supplying that ingredient into that particular store was different than other stores. That was one of the factors why things started dropping after that change happened. So we could detect that there was a change, and that was one of the drivers of why the sales actually dropped.

This is something happened before I joined Sisu, but I've heard this example many times. But I think another typical example would be e-commerce space where there are a whole bunch of dimensions. I was giving you example on particular types of campaigns or particular types of product types. It's very difficult to really figure out a particular combination that is driving things up and down. By the way, the first factor is generally easy to figure out, so if there is clearly a location, it's easy to even visualize this in charts.

Speaker 1:

Sure.

Speaker 2:

But when it is a combination of things, when we say this is the location plus that's the age group plus this is the particular product act, that's actually moving your KPI up and down. So when your dimensions grow from single dimensions to multiple factors, it becomes very hard problem to do it manually. Lots of our fintech clients and e-commerce clients are feeding us maybe hundreds of dimensions, and that's where this insight actually comes up pretty easily in Sisu.

By the way, I think keep in mind, sometimes these are obvious insights. So what we do is we also give them a way to suppress obvious insights. For example, seasonality as you were mentioning or if you're a fintech company, volatility of the stock market. Of course, it's going to impact your results, but you can say, "I want to see impact outside of that volatility-

Speaker 1:

Oh that's cool.

Speaker 2:

... and can you show me that?"

Speaker 1:

We'll use pizza as an example. I believe pizza deliveries during major sporting events goes up. It's quite obvious it goes up.

Speaker 2:

Exactly.

Speaker 1:

You're saying the tool can say, "This is a quite obvious insight. Let's remove this variable. Now let's see what's impacting us." And so, I'm just making something up, but being able to recognize, for example, that, let's say, mobile latency was the biggest factor for pizza sales because if people were waiting too long for the screen to render, they would choose another option. When you think about removing that, there's two things you said in your answer that I wanted you to explain a little more. There's one is really cool is you can remove obvious insights. So that will reset all the variables. But the next thing you said was you calculate and measure variables independently. But the big challenge and the big insight is when you find connected variables that are not obvious. How do you connect because you're testing them independently, how you make these connections?

That's pretty fascinating because there's... Well, 100%, it's probably got, they used to call them journey paths. There's probably like touchpoints or certain touchpoints of a customer journey path that in combination yields the highest best possible outcome. But these events might also be quite independent of each other, so how do you bring this together?

Speaker 2:

When we start calculating impact of these different factors, we go up to three factors or three or four combinations of things. In our engine, we actually look at things together. What we do is, let's say, you feed us hundreds of dimensions and there are millions of combinations, but those millions of combinations are based on three or four levels of factors. We work on those to figure out what is the statistical impact or significance those factors are bringing together, we don't just look at like, "Hey, volatility is one factor or just geolocation is another one. We would look at combination of two as well to actually calculate statistical significance.

Speaker 1:

Oh, wow.

Speaker 2:

That's how we actually get the results out. Now, we can only look at four or five factor combinations like that. Anything beyond that becomes computationally really expensive. We can give you a combination of saying, let's say, "This geolocation, this particular product type, and that age group is impacting your KPI." I think that's generally sufficient for any data analyst or KPI owner to get value out of it. If I just tell you that this particular geolocation, there is some activity there, the next question would be, "Tell me why." If you give you a drill down of two more factors, I think you have pretty much your answer that it's age group of 25 to 30 and it's actually a particular ski gear that's moving your average order size. That's pretty precise at that level. I do feel a combination of two or three factors, it becomes more precise or more actionable at that point in time.

Speaker 1:

I guess the next question is, for an audience who's not familiar with Jigar, I want to read some of the companies he's been a part of because the guy has quite an impressive resume of companies that you've been a part of. I'm going to pull this up right now on LinkedIn and let's take a look. You were at Facebook, you were at PayPal, and you were at eBay. So huge, huge tech companies. When you think about building this, how are you approaching engineering the solution because on one side there's clearly a heavy data science element?

One of the hardest things to do, and this is my opinion, I don't know, but one of the hardest things to do is to make something easy to understand out of something complicated. So the more complicated something is, the harder it is to explain it simply. We also know the modern customer, the modern user wants their answer fast. They want your insights fast, but they probably want a new layer, which I'm sure you're building, which is a recommendation layer. Give us an idea how you think about developing this because you certainly need core infrastructure to develop and process all this data in real time. You, of course, need data scientists and AI/ML experts to produce the answers. And then you probably need a UI/UX team that's extremely good at saying, "This is very difficult to understand. Change it to make it this easy to understand." Give us an idea how you're set up.

Speaker 2:

No, that's great. I think you also pretty much positioned it pretty well how we have built our team at Sisu. What we have is really three or four teams within engineering. There is a core ML team. These are set of researchers who are developing next gen ML algorithms or cutting edge ML algorithm, so key driving analysis, which is what I was talking about, answering the why question. But we also have developed algorithms like predictions, forecasting, trend detection. Bunch of other work is also in the flight.

The second part is we have developers who are building the app. This is the back end part of it, the database complexity, they build the business logic. And there's a third team that is doing the UI. You are absolutely right that our product is sometimes harder to understand. In fact, that's one of the journeys I'm going through personally as well that how do I simplify product for the masses. If you understand statistics pretty well and if you understand what subgroups mean, what facts mean, we show a lot of these details within our product. But a lot of times you're not a data scientist and you're not a data analyst. How do we show you details which is easy to understand? So that's where our UI layer comes in, which is much more visual. For example, one of our features is waterfall. Waterfall is our way of showing which factors are impacting your KPI and what is a mix shift in that, who's impacting what.

A waterfall is a real good visual way of understanding impact coming from different aspects to your KPI. But we are doing more of that where simplification on how we show our results matters a lot, and we are trying to more show it visually as well as combination of like NLP. If I show you something in natural language that, "Hey, this two factors impacted your KPI," rather than showing you some mathematical formula, that makes it easier for KPI owner to understand as well. So there is a simplification path going from being a statistical engine to more usable engine.

The second part I think you ask about recommendation. This is the next part, this is the next thing that we want to tackle. This is a pretty obvious question we get it from our customers. They are very appreciative that we were able to answer why. The next thing would be, "Well if you can actually look at the data and tell us why, can you also start predicting things?" For example, one of our customers was asking that you actually have lot of data on custom... they provided a lot of data on customer churn, which is great. What we were able to do based on that data, we started predicting which customer will churn in next six months, because our ML model was fine tuned on all the data they provided so we can now look forward three months or six months and say, "That particular customer is likely to churn. We have a confidence of around 60% that it's going to turn. You may want to pay an attention to that customer. You may want to throw some coupons or you want to run some campaigns to worry about this set of customers."

That's really the next step in terms of recommendations and predicting things so that it becomes more actionable insight rather than always just looking back historically what happened. This would be more like prevention of things from happening.

Speaker 1:

And then there's probably layers of optimization in there as well. One of the things that a lot of people that we've had in shipping and logistics come on this show and talk about, is exactly that, the logistics side of things. I like to use examples. A company like Amazon, so I used to sell games on Amazon, what I was surprised by was that they actually have data which they figured out. So if I ship, let's say, 1,000 games to Amazon, they will instantly disperse that inventory to locations that are closer to where they believe customers will order from. As orders pick up in a region, product will start moving there, not because it's been ordered, but because they believe the demand will continue. So they're always, I guess, rebalancing their inventories to make sure that if someone orders it that you get two-day shipping. So that's very much algorithmically-driven outcome. They have an algorithm that's pushing the supply chain.

Do you see that in your future? Is that something that you can see companies plugging systems into? Because that's going to be the next layer, right, is if you can make the recommendation that probably the next layer they're going to ask for is the automation, which is, "Why even ask me. You already figured this out. You know that if I move product A to location two, I will ship faster to customers. I want that to come true. So just go ahead and do it so I don't have an analyst doing it, like you do it." You see that, the next layer, which is recommendation that's going to lead to automation?

Speaker 2:

That's a good question. What I see is even in our existing tool when people are doing key driver analysis, they are trying to get an answer on their why questions. I do feel there is business context that is also important. I think you brought it up in our conversation as well. A lot of times we show them the facts, but when they look at it, they add business context they already have to understand why something is happening. Actually, to talk about Sisu, we say that, "Can we improve data analyst's life by speeding things up?" But we are not replacing data analysts by any means. Because we can shorten their time to insights by 80%, 90%, but the 10% of business context that bring it to table, that is what makes those insights actionable. So even if we now apply this recommendation or predictions, I do believe 100% automation would be very tough.

I think what we can do is provide a lot more proactive way of predicting things and recommendations, create what-if scenarios, but then somebody from having enough business context to make decisions on those what-if scenarios rather than us doing it automated behind the scenes. I do feel there is a human element, there is a business context that is super important. And while we can automate maybe 70, 80, 90% of everything they do, that 10 to 15% of business context is super important to make educated decisions and actionable insights out of it.

Speaker 1:

Well, I can see that completely because I was thinking about, oh yeah, because if we use that pizza example that we used during big sporting events, I don't know if the sporting calendars not in the Sisu database, then if it accidentally automates increase of supply chain orders of dough and cheese, the next week it's going to be overstocked, it's going to be a problem. So someone has to figure out and prevent that from happening.

What, for yourself, got you interested in this project because you know worked at some big companies. And based on the time spent at these different places, it looked like for the most part you worked at companies when they were established. This, it looks like your first startup or at least it's your first startup in some more than 10 years of development. What brought you here? What got you excited about the opportunity that was in front of you?

Speaker 2:

I started my career back in 1995 or something, and that was working for startups. Late '90s was crazy time, everybody was working for startup. I was just out of the college and I really wanted to work for smaller companies where I can really create impact. That's what actually lasted for at least eight or nine years before I jumped into eBay. The reason I switched my job to eBay is because in late '90s to early 2000, internet and scale actually became a reality. For example, back in 2003 or four, eBay and Yahoo were two companies that had tens of millions of users and they were facing very different problems than enterprise software. They were facing problems of scale. How do you serve 50 million users or how do you solve 100 million users? That got my attention. I really wanted to understand how to scale infrastructure to serve this many people. That's where I got into eBay. I spent 10 years building variety of products and infrastructure.

Then got an opportunity to work at PayPal, which was much more focused on payments, what does it mean to build reliable payment structure? So I learned a lot in there. And then Facebook was an incredible journey really supporting the data infrastructure at scale. Facebook captures a lot of data. We use this data in a variety of ways. How do you actually enable our internal users to get insights out of that data? What kind of tools do we need to provide at scale? Over time, this was my wish list that I wanted to go back to a startup. The reason I wanted to go back to a startup was impact and what you can do for the company is very different than working for a company that is a 100,000 people.

I always wanted to go back to my roots where I started, so I started looking for opportunity in the startup world. Sisu grabbed my attention because this is the problem I faced personally multiple times. I think you were mentioning the same thing in the beginning of the podcast. It's a very obvious question to ask why something happened, and we don't have great tools around it. That actually grabbed my attention, that how do you solve it? In fact, I asked the same questions you were asking me to my founders saying, "Well, how do you do it? It sounds magical to me." That's what got my attention, and I joined Sisu. I'm like, "This company has a lot of potential. We are solving deep problem, and this could actually address really a fundamental problem in the data space that we face today."

Speaker 1:

Yeah, the why. I mean, we get it all the time here at Mission. We are obviously in the creative space, but our sponsors do care very much about what every company that sponsors entertainment cares about, ratings. If we have a huge download week, they go, "Oh, why did that happen?" It's like, "I don't know." You would think certain things are obvious, right? Like you said, you got to back out the obvious. The obvious thing is, oh the new episode launched. So okay, we back that out. Then all of a sudden, every week looks similar to every other week but there's just a few more listens per episode. Now, when you culminate it, because we have so many episodes, you have a monster week, you have a big launch, and you have increased listenership across all episodes. But I have no data tools to tell me why was listenership up by 35% in a calendar week. How would the Sisu tool begin to investigate that? I'm curious.

Speaker 2:

What has happened in past 10 years is companies are capturing a lot of data. I'm pretty sure in your company, Mission, there is data available about your users, who's listening to the podcast, maybe certain age group, location, things like that. If you look at 2000s, we did not have enough data. If you look at now, there is a lot of data captured about all the user activities within an app. And that's true across the board, whether it is an e-commerce app, fintech, or it is a podcast app. We captured a lot of information about the users and about their activities.

What we do in Sisu, we have a concept called wide table. That means, give me one table with all of your dimensions in there. You can also add, of course, your metric in there. For example, in your case your metric is number of users for podcasts, that's what you care about. You want that to go up. And when it goes down, you want to actually get an answer why. So if you create this flat table with all of this dimensions around who's listening, what is their age group, what kind of podcast they listen every day, what is the geolocation, and if you feed this data in Sisu and suddenly if there is a trend change that you got 35% more users this week than last week, it'll start giving you a combination of things that draw that particular KPI.

One of the things that you need to do to make Sisu functional is give us all the data that you have captured so far, all the dimensions you have. We check the data that you provide us, [inaudible 00:28:28] the answers, we give it to you. For example, you provide us only geolocation then we give you really a vague answer that, "Yeah, I think somewhere in California people are listening more to your podcast." Not an actionable thing.

Speaker 1:

That's right. That's no why. "But why-

Speaker 2:

Exactly.

Speaker 1:

... because that's the next question. "Why are they listening in California?"

Speaker 2:

Yeah, if you add 10 more dimensions we can actually tell you what really happened behind the scene. We can actually create a lot more insights depending upon how good data is. Once you provide us this flat data, which is bunch of this columns around dimensions, we can actually be very creative in giving you answers on why. I think you should try it out for your data.

Speaker 1:

Yeah, so you saying that started getting me thinking. Let's go back to the retail example. I think we all understand the retail business. Podcast business maybe people don't understand. The retail business thing, most people have a general concept of it. But as you were saying that I started thinking about, "Man, there's probably so many variables that's not even your data. I'll use an example. Let's say I'm a retailer. I will know my product data and my sales data, of course I'll know my web traffic data, but there's other data that I probably need to pump into you too which is my advertising data, where am I advertising, my print digital media data, my product release data. A good example is this. A retailer might only have a product SKU. For example, I have phone cases. And I might have a new phone case and I might have the colors and I know that stuff, but what I won't catalog, which I know most retailers don't catalog, is going to be the other things that went into that phone. It won't be in their database.

The phone case company might be using new materials, might be using a new build. They themselves might have changed their advertising campaign. That could influence total sales of phone cases across your retail operations. As you were saying that, I started thinking about not only is it your data, but sometimes the answer is probably in data that you have access to but you might not be tracking, like you're not measuring it. You know what I mean? If I'm a sales analyst and I haven't been measuring that, then I don't know to measure that. And so, I was thinking as you were saying that, "Yeah, you would probably need all these things to come true so that if you were retail you'd be like, "Hey, this region took off but also because these guys got this product first, this series one of this product with an advertising campaign and it all added together to better sales." I mean, that's a hypothetical scenario but piggybacking off what you said of all these other dimensions that maybe most businesses have access to but they might not be thinking about when they do their own analysis.

Speaker 2:

I think that's a really great point. What we do is we generally work with our customers when they use our tool and they say, "Well, these are some of the obvious facts we knew about." We would actually work with them to say, "Hey, what kind of dimensions have you captured? What kind of columns and data have you captured?" And maybe there is more. Maybe you want to join between these two tables and give us even that information. That's an ongoing thing. What we see, our customers, they start with certain data. They get some insights, but they want more insights, and they would ask us that, "Hey, what is the best way of getting this data into the tool as well?"

So generally, as I was talking about creating a large flat table which has all possible dimensions that you care about and you could add more dimensions as you find more data that you're captured, you can keep on getting better and better insights as you give us better data. Our tool adapts to this new set of information pretty well. It's almost like we start and said, "Okay, instead of looking at 100 columns, now I'm looking at 200 columns, and I can give you even better insights out of it."

What we generally tell is the good thing is most of this data these days is captured in some kind of data warehouse. Almost every sizeable SMB or enterprise companies, they would have some kind of data warehouse, and they've captured a lot of data. What we tell them is, "Make sure that you're giving us all of their data access rather than a small portion of data, because we can give you a much better insight." But this is an iterative process, and we generally work with our customers. If they hit a ceiling saying, "Well, this is a great insight but not actionable." And generally, it's less about our engine's capability, but it's more about what data is coming in and can they actually provide more dimensions so that we can actually provide better insights. So it's a cycle that goes on.

Speaker 1:

You saying this makes me think about the market opportunity for this data aggregation because this sounds like a... I mean, it's a big project. We've done it ourselves at Mission. So if we've done it, then we know that a big company's done it at even a bigger scale, which is of course all these data pools that currently don't connect into in one single place, how to bring it all together.

Jigar, it's been awesome having you on the show, talking stories, sharing stories of how businesses can use this, because I agree with you 100%, which is, a lot of times, a lot of these tools like this produce insights that are unfortunately a little bit obvious, but I love hearing the fact that you guys are pushing down the path to bring the non-obvious information to the forefront and doing it really fast. I can completely see how helpful that can be.

It was awesome having you on the show. But Jigar, before you go, it is time for the lightning round. The lightning round is brought to us by Salesforce platform, the number one cloud platform for digital transformation for every experience. This is where we ask you questions outside of the realm of work so our audience can get to know you a little better. Are you ready?

Speaker 2:

Sounds good.

Speaker 1:

All right. We're going to blend it a little bit this time around because I think I find your work quite fascinating. But question one, what is the most difficult IT problem you have solved in your career?

Speaker 2:

That would be EBay and PayPal were the same company. At some point in time they got split up into two, like two independent companies. One of the responsibilities I had was to separate infrastructure between these two companies. That was a pretty good experience because we could not get any of the sites impacted, like they have to be up and running. It's almost like changing machine while the plane is in the air and making sure that everything is taken care of. That was probably the most difficult project because it lasted for months and we could not have any downtime on either of these sites. So probably one of the most difficult projects I've taken on.

Speaker 1:

Who was a influential mentor you had in your career? Who got you really into software engineering, development, so on?

Speaker 2:

It's an incident that happened when I was in high school in India. W did not have computers back then, but my brother who was getting into college, one summer, he got a PC on a rent, just to try a few things out. Somehow there was a book, like basic book and there was a computer, and I got hooked onto it. I started writing some programs using that computer. That took me to this whole computer engineering path, and I've been fascinated ever since then, like what you can do with just a small device and your ideas about what you want to build around it. I think that has been a really influential factor for me. I don't think I would've got an exposed to the world of computer science so early on when I was 14 years old back in the country where computers were not available freely.

Speaker 1:

Now, I got to ask, what did that first app do? The first program you built, what did it do?

Speaker 2:

It was a simple program where you enter a date and it will tell you a day, what day it is, Monday, Tuesday, Wednesday. It takes care of leap year and it takes care of months and all of that. That was my first program.

Speaker 1:

Hey, I totally get it, man. Well, I think one of the fun parts about, I can age myself, it's fine, I was born in 1980, but literally PC computing became a thing at home. And remember, when you look back on it like, "Man, computers back in the day, they really couldn't do much." But it was always this idea that it was eliminating something that was hard. That's what probably always fascinated me is like-

Speaker 2:

Exactly.

Speaker 1:

... "This is hard. Can this be done faster?" So here we are today doing stuff extremely fast, but that's the whole point. It was just to answer a question that otherwise you had to get a calendar, back it up if you had one.

Speaker 2:

Absolutely. I somehow thought that was a good problem to solve, so that's what I went for.

Speaker 1:

That's it, that's it, it's all it needs to be. What's something you like to do outside of work?

Speaker 2:

You can see the books behind my chair.

Speaker 1:

I see a lot of books.

Speaker 2:

I like to read a lot. Generally I like to go for running or hiking, so that's how I clear up my thoughts. In weekend, you will see me either walking or hiking around. Those are the two activities I spend most of my time outside of work. And then I have a family, so that takes a significant time with two kids. I think I would say those three has taken all of my free time away.

Speaker 1:

Not a problem. Ma,. I got one last question for you. How old are your kids?

Speaker 2:

Oh, well, my son is 18 and my daughter is 14. So they're growing up.

Speaker 1:

Your son's in that age where for a lot of kids there's a period of time, obviously, in middle school and through most of your teenage years where you think your parents are not cool. And then you come around as you're getting older, you realize, "Wow, my parents really helped me out a lot." I got to ask, does your son think you're cool now?

Speaker 2:

So now he has gone to college, and he definitely thinks that I'm somewhat cool. Not completely cool.

Speaker 1:

There you go. That's it. That's it. Now, what about your middle, high school-aged, your other child, does she think you're cool?

Speaker 2:

She definitely thinks I'm cool. I think she hasn't hit that time when I'll become uncool again.

Speaker 1:

There you go. Hey, my son's 14. He's already telling me I'm a loser. I mean, it's okay. Jigar, it was awesome having you on the show. Thanks for sharing everything that you're doing at Sisu. I think what you're doing is exactly what people want to know, which is why is something happening. I think we all know what's happening, that's settled. Now we need to know why. I think that's an immensely helpful thing. I love the fact that you and the market of engineers in the AI ML space are chasing this goal. I wish you the best because if you guys make it happen, we certainly will use it at Mission because we do not know why certain weeks are better than others. We just don't know. I mean, outside the obvious, right? "Oh, the new episode's really popular. Okay, take that out. Now why?"

Speaker 2:

Thank you. This was awesome. Thank you for having me on.

Speaker 1:

Awesome. Thanks for joining us today on IT Visionaries.

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