Episode 66: Working with Data Scientists with Lauren Burke

Rashmi (03:10):

Welcome to Women in Product, Lauren. We are very, very excited to have you here on a very different topic today.

Lauren (03:42):

Yeah, thank you, Rashmi. I'm so excited to be joining you both.

Rashmi (03:46):

Yeah, so when we are thinking about building products, especially products with ai, there is yet another cross-functional persona that we closely very closely interface with, which are the data scientists, and hence this episode is all about understanding their role and what really a successful collaboration between a PM and a data scientist looks like. And we are really excited to explore more around this topic with you. And let's begin with understanding your background then. How did you get interested in data science? And you are a podcast host too, right?

Lauren (04:25):

Yes, I am a part of an organization called Women in Analytics, and I host the women in analytics after hours podcast where we just talked to women in the space about what they do, the cool impact they're making and how they got there. But for me, I've always really loved math and then problem solving as well. I always was someone that asked probably the annoying child the why, why, why? Because I wanted to know why it worked that way, why it was set up that way, why we were doing this this way. And when you think about it, the reasoning behind that is actually data. And so I kept down this path. I studied math, I took some computer science classes and at my college we do a senior thesis around a topic of our choice that relates to our major. And I chose to do it on a large scale optimization of a road trip through every US national park.

And I use machine learning techniques combined with math. And during that whole process, it really just solidified how much I enjoyed working through the process of starting with some data, starting with the question we want to answer, and figuring out through the process of exploring that data, figuring out what key things we need to consider, and eventually getting to some solution where that data is able to answer some question for us or improve something. And so after I graduated, I was able to take that project in, kind of have a really great way to showcase, I've done data science work, and that took me to my first role, a more junior role in retail. And then two years after that I moved over to CoverMyMeds in a data science role and a little bit in the product data science space.

Rashmi (06:22):

That's such an interesting project to think about how do you optimize all the national parks within us? That is so interesting, Lauren. And one of the things that I've been very curious about, which our audience would really appreciate I think, is what's a day in the life of a data scientist? Can you walk us through how your day looks like as a product data scientist?

Lauren (06:49):

And so it'll look different for every data scientist based on your company, your industry, even the team you're on. But for me, I am tied to one of our products and so am really focused on deeply understanding what we can do there in the more predictive sense. So when I say product data science, a lot of it ties into thinking of the user. And when you think of the user in the healthcare space, you have a lot more than just one type of user. You have patients, you have providers like your doctors, your physicians, your nurse practitioners, you have people on the pharmacy side, you have people on the payer side, the insurance companies, you have pharmaceutical companies. And what you can do with data science in that environment, which is really exciting, is kind of try and figure out how you can take that really large amount of data you have in the healthcare space and try and understand how you can improve the process for everyone.

And then at the end of the day, improve the patient experience and get them their medication faster. But for kind of the day to day, there's always a lot of meetings, a lot of understanding what's next, what we could be doing. I do some stuff on the strategy side, so kind of scoping out and trying to understand, alright, here's what our problems are right now, here's what the requests we're getting are, here's what we would solve if we could solve it with something like data science. And then trying to look at the kind of deeper pieces of that and say all well, do we have usable data that can be used to apply a data science approach to this? Talking to stakeholders and understanding, alright, what key assumptions, what caveats, what other things we need to understand? Are there any edge cases, how we are measuring this and trying to understand if we're successful in this endeavor and is that still matching with what we started out doing or do we need to reframe? And then other than that, some coding. So I work mostly in Python sometimes just doing data exploration. So I always love visualizing data just even for myself mostly, I don't have a Tableau license, you don't want to see what I can do in Tableau. It's not great.

And then a lot of it is along the way also kind of delivering little bits and pieces of the data science process to say like, all right, here's what we set out to do. Here's what we figured out. Here's what we can either continue down this path or maybe we need to change our minds. And so in the product data science sense, I think it's a little more of a faster pace between data science back to looking at what we have data science back to looking at what we have. And in that sense, the people that make data science successful are not just data scientists, it's your stakeholders in the product space as well. And so you really are partnering much more closely, I think.

Rashmi (10:03):

Right. No, I think there's so much to peel in with what you said. I think it definitely seems so interesting with everything that you described there, Lauren, and we'll get to a lot of those in more details. With all of this that you described, what do you think are the most exciting aspect of being a data scientist for you? And what is it that something that you're not really a big fan of off?

Lauren (10:30):

Yeah, so I find data really exciting because it's an opportunity for you to dig into something and figure out that why. I've always really loved the problem solving piece of things. And a lot of times with data, you have a lot of untapped data or you can look into the data to tell you what to do next, let it guide the way. So I love just how much it allows me to be creative and just kind of exploring and continually learning on the side because there's new techniques and new technologies continually coming out. I don't know, I don't think there's really a part of it I don't like as much. I think sometimes projects can take very, very long, so it's hard not to get bogged down with that and see the light at the end of the tunnel. But yeah, overall I do find it pretty exciting.

Rashmi (11:26):

Yeah, no, loved how you talked about, there's the untapped data, but again, another side of it is let the data guide you to the problem there. Love the way you just mentioned that. And with the event of gen ai, especially since the last one year or so, do you think the role of the data scientist has evolved itself as well?

Lauren (11:50):

Yeah, so data scientist as a title is something that is honestly a little bit vague. So if you were to ask me and ask someone else and ask a room full of 10 data scientists, their individual roles would be likely so different just based on their industry or the team they're on.

Lauren (14:02):

I do think there definitely is a difference in role just depending on who your stakeholders are or who your clients are. So sometimes you as a data scientist can be mostly client facing. So you can be working with your stakeholders as a data scientist are directly on the client side. So that's who you are connecting with, that's who you are providing deliverables to, that's who you're kind of scoping out use cases with. And then maybe on the other side, you really are mostly just communicating internally. And so that could be a different approach just depending on the technical level of the people you are working with as stakeholders. If you're at a larger company that is a very data-driven technology forward company, you might be working with people who understand the data science process and the work you do a little bit more thoroughly versus if you're working with people who are mostly on the business side, you might have to figure out how you should be presenting certain things to everyone just so that everyone stays on the same page.

Rashmi (15:17):

Yeah, that's a great distinction I think. And how do you stay updated with all of these latest trends going on, right? I mean, by the time I feel I get on top of a topic, there's already another one out there waiting or a couple waiting there for me. How do you stay updated with these?

Lauren (15:37):

Yeah, I think one of the fun things is right now, gen AI has been the hype. So a lot of it has just been continually building on gen AI and seeing what we can do in specific areas. But like you mentioned earlier, I do host our podcast, which is a really great way to just connect with other people in this space. And every time I host an episode, I'm meeting with someone that I learn something new from because we're talking about their industry or their role or their background. And a lot of times if they're in an industry different from what I'm familiar with in the healthcare space or the retail space, they might be doing something working with data that's a little bit different. And so I'm learning something through that. I also listen to other podcasts. I love to attend meetups and conferences. There's a couple of Slack groups I love to go to for just what's the latest happening in trends. One is locally optimistic and one is data angels. And then on top of that, I just kind of follow people on LinkedIn who are around the AI data, data product space. Because a lot of times that's also how you can see just get a general pulse on the industry.

Rashmi (16:52):

Yeah, completely agree. Especially when you're talking to new people and inviting them on your podcast. I think that's how even I've learned quite a lot as well. So I shared the same as well here. Moving on from a little more into what you initially talked about use cases and you see the problems out there, how do you come up with some of the use cases there and for experimentation, how do you start that process? And is there any involvement with the product managers at that stage or tell us a little more about that.

Lauren (17:30):

Yeah, I really like going around and just talking to people because I think we have so much insight into what we should be working on just by getting a group of people together who all will bring a little bit different perspective of what we should be focusing on or what the most urgent or things we should prioritize more are. So I kind of just like going around to people and figuring out, all right, what are the problems? Are there any ongoing requests from clients or users? Are there any ongoing concerns as well? Talking about the difference between traditional analytics versus data science and then showing with that potential, what would you do if you could solve anything? And then for anything that we're talking about as potential use cases, trying to always understand, alright, what's the value of this to the organization and to our users?

And if we don't solve this, is anything going to happen? And a lot of that is just talking about the potential. And then from that you can kind of start to bucket things into your, alright, we need to focus on this. We might not need to focus on this, but a lot of times I really like to focus on the quick wins because that's where you can add a lot of value, especially if it saves other people time. So automating something or if there's some reoccurring decision and we don't have data behind it, making sure that we build out an easy process to put data behind it so then people are as best informed as they can be when they're making a decision. And then I think when you just start to move on to more and more opportunities focusing on use cases that can be repeatable and are reproducible because that's what saves you time down the line.

Rashmi (20:05):

Could you walk us through the steps that you would take towards understanding what the use cases could be and towards experimentation and the outcome?

Lauren (20:16):

And so I actually gave a talk on something recently where I had these kind of use case building blocks set up. But yeah, so typically you start with a question or a challenge or a problem. This is something that people are suggesting needs solved or your users are telling you need solved or you're seeing in the data that there's a gap that you could fill and then that you have to make sure it aligns with the goals of your business. So if you invest time in this because it's going to take time, it's going to take resources, either technology resources or people resources, does that align with the goals? And then once you have that, you start to think about the people involved. So the user needs to be able to complete this in the way we want it to. What does it need to meet for those users?

And that can be anyone in the process that could be, alright, your client needs to have this sort of output, but the people who are internally creating this or maybe there's some automated process, what do they need to make sure that it works? And do we have the capability to meet all of those needs and continue on those paths? And then once we have that, we can go to our stakeholders and start gathering the context. And so when I say that stakeholders really are your partners in data science, I truly mean that because that is how you understand that you're on the right path and that you stay aligned in the process. And so you're talking about, alright, how do we connect this question with the business goals and the user needs? They might be the people more familiar with the users and they might be the ones that can kind of help you understand, alright, here's our key assumptions or caveats, here's this list of edge cases that we either need to focus more heavily on or we need to avoid at all costs.

And then once you have that, you as the practitioner go and see, alright, do we have data that we can use to make this happen? Is that data usable? Is it high quality? Is it the volume we need? If we're looking at users, is the population a accurate sample of what we need to be looking at? And once we have that, then we can move forward. If we don't have the usable data, we can't answer that question, so we need to reframe. But then once we do have that and all of those other pieces, then we talk about, alright, if we're going to do this, how do we know we did it correctly? And that's where we think about our success metrics and that's how we're going to measure success, how we are going to initially know we did this. And then if we have some sort of automated reporting, automated monitoring system, how we know that we are continually meeting the standard we set up to. And that varies by the use case, by the data we have, by the business goals to make sure we're aligned and meeting certain KPIs for instance. But that's kind of the process I go through building from the bottom layer to the top layer and each piece builds on each other and is very necessary.

Rashmi (23:25):

Yeah, I think you talked about a very important piece through the process. I just want to touch upon that part with respect to the data quality, so the accessibility of data and the data quality at that point, when you're evaluating that, is there kind of an interaction with the PMs? Is there a PM counterpart working with you on that aspect?

Lauren (23:48):

Yeah, I mean I definitely think part of it is you as the data practitioner going and exploring the data during the data exploration process, you are basically understanding the data more deeply, but also trying to figure out if there's anything that makes there a greater risk with using it to solve this particular problem. And so a lot of times, even maybe not just the PM side, but you might be connecting with other people in engineering, in user design, in if you have agents or people who are part of a certain workflow, understanding what goes into how they make a decision. And that is where you start to understand what the risk is of ignoring a certain situation or allowing something to go through and not taking that into consideration when you're building your model or a certain output. So yeah, when you're doing the data exploration stage, I definitely am always coming back to stakeholders and then together understanding, all right, here's what we found, it's all good news, or here's what we found. Here's some things we need to talk about and figure out, alright, how are we going to consider these things or do we need to bring someone else in that has more expertise in this particular area? But yes, it's definitely a very collaborative process,

Rashmi (25:16):

That'ss awesome. And in this process, do you think the PMs as your stakeholders as well, one of your stakeholders as well?

Lauren (25:25):

Oh, absolutely. They have a stake in the process because they have a part in building the product or managing the product and making sure that that development of features or something new comes to fruition and does it successfully and correctly. And they're the most tied to the goals and the user needs. So they are absolutely critical in the process as a stakeholder.

Rashmi (25:49):

Got it. And when you're going through this process, when do you think that this is good enough when you're doing your experimentation and how do you come up with those decisions and those goals to say that, Hey, we can stop now, this is good enough for us to launch kind of a thing? I think that's probably the hardest and the most interesting part with AI products, I think, right?

Lauren (26:15):

Yes. And I think that through every data scientist works through something like that. I am such a heavy believer in the striving for that minimal viable product at first. And it doesn't have to be perfect, it has to work as well as you need it to. And so that means when you're developing a model, I could develop a model that's an ensemble, so a kind of combination of a hundred different models and get you a 98% accuracy, or I could build you a model that runs in 10 seconds instead of 10 days. And if that's at a 90% accuracy or a 95% accuracy, you're probably going to pick that lower side. And so everything else I mentioned a lot of the times is it's doing this together and figuring out, alright, if we're doing this, how accurate do we need it to be? Do we have a threshold of maybe we have false positives or false negatives we want to avoid?

And how high does our threshold need to be where we know we'll avoid that, but we're not adding on any additional kind of difficulties? It doesn't take a massive lift on the practitioner side, it doesn't need as much upkeep. The time to train it or run it doesn't take as long. So all of those little pieces come into play when you're kind of figuring out, alright, here's you, as the practitioner can say, alright, here's kind of what we can do. And then you talk through it together to say, alright, where's the good middle ground that meets our needs and just kind of makes it happen.

Rashmi (27:57):

That is so interesting. And sometimes does that change, at least in your experience initially you would've thought that, hey, this is what our MVP is and this is good enough. But through your experimentation process, has that also changed based on what you find and how have you been able to communicate that to the other stakeholders? What happens then?

Lauren (28:21):

Yeah, so I like to have a value first approach to communication, which basically means that if I'm telling you something and I am trying to say yes or no for one reason, want to have data to back it up. So in the training process, that's where things come out. You understand, alright, this is a better model for this particular case or with this kind of model or with this data set, we can't get an accuracy level over X number or we are starting to see that there's this bias within it and we need to work around that. Or maybe our sample size or the sample we have is allowing our model or causing our model to end up predicting something that doesn't align with either what we expected to see and we need to look into that. Or maybe it's showing us something new. So when you're coming back and trying to reset and say, alright, these measures of success, either we're on track towards those but we're not going to meet them.

Or we can reframe and say, alright, what else does success look like? Having data to back that up is your best friend as a data scientist. And another thing you can do with that is bringing value in incrementally. So trying to show, alright, the data science process, I went away and I did an exploration, I found out what features were most effective in determining this. And so when I bring that back to the stakeholder side, we can go through that together and say, alright, here's what we expected, here's new, here's what we need to change or we need to think about how we might change.

Rashmi ([30:11](#)):

That is so interesting. Thank you for describing that, Lauren, and definitely within this MVPN decision of what it should be and metrics around that. Have there been, obviously there are many different criteria that you would look at from a decision making. Have there been any financial implications as well during this process that you think about what's the cost of running this for one day versus I want to run this for a month in order to get the result after that? So could you talk a little bit about that?

Lauren ([30:48](#)):

Yeah, and I think that's just one of the pieces that come into play when you're doing a model selection or even a use case selection, is looking at the potential value. So when you're looking at use cases, it helps to try and understand the expected value, expected benefit and expected data support. And so the expected value is what's going to change. So whether that's a financial benefit or whether that's some type of improvement to a process, something's going to perform faster, but maybe there is a little bit of financial cost, making sure you understand that the benefit of what's going to change, who is going to benefit, who's going to do things differently, who's going to have more time to do something else, then maybe that actually balances out some of that financial impact. And then looking at the data you have, so not just the data that's going into your model, but the data that's coming out of it that you can retroactively use to prove the value of your solution. So looking at not just the value you can provide, but seeing what impact is happening and whether the impact, whether the benefit outweighs the financial things you're considering.

Rashmi ([32:08](#)):

Makes sense. Totally makes sense. And one of the other questions I've always had when working with our data scientists, how do you think about training the models? There's so many models out there, so how do you, from your perspective, come up with suggestions, with respect to, hey, this is better for this versus this kind of model is better for this kind of a use case. How do you go about doing that at the backend per se? Because that's also a big part of your recommendation to solve a particular problem or to experiment.

Lauren (32:44):

Yes, absolutely. And so really similar to getting to the MVP, simplest is always simplest, is often what's going to be better. The world like Dunkin Donuts, the world runs on linear regression, logistic regression, the simplest effective models that we know they work, they're easy to put into place and they are right, they are kind of the standard for a reason. But a lot of times when you are on the practitioner side, you look at the data you have, is it more categorical? Is it numerical the size of the data, what type of prediction you're trying to output, whether the dataset is balanced. So maybe if you have two different outcomes, if it's unbalanced, you have 75% of one outcome and only 25% of the other. And all of those things, certain types of models are better or worse for different types of data or different types of situations.

And so sometimes you'll have multiple that could work in a particular situation. And that's when you go through the training process and you try and see, alright, what trade-offs are we making? We know this works better in this case, this works better. In this case we need to account for these false positives. We need to account for this edge case. If this feature comes into play, we need to weight it way more heavily because we know it has this impact and we're seeing that in the data. And then through your training process, you start to see, alright, of all of these that work, what also is kind of leaning towards that simplest solution then as well. If one has a 10 hour runtime for training, first one has a two minute runtime and the accuracy difference is a fraction of a percent, right? Then you already know which one's on the chopping block, right? So yeah, that's kind of the process of going through it.

Rashmi (34:42):

Yeah, I mean it's really great that you're talking about even in this case, the simplicity is what works a lot of times common sense and simplicity, how you extended that to the data scientist and the data science as well. Switching gears a little bit, I know we talked a little bit about working with the product managers according to you, what would be some of the really good qualities of a great product leader working with you as your counterpart where you thought this is such a perfect combination that we have, that we kind of understand from your perspective, tell us some of those good qualities or the qualities that a good PM should possess?

Lauren (35:30):

Yes, I love this one and luckily I've pretty much only worked with really amazing PMs who fit all of these qualifications, but being data-driven first and foremost. So letting data guide the way over opinion. So that could be letting data be what's going to tell us yes or no. Or when we have data that tells us the answer, we didn't want to hear being like, ah, alright, well I'm still willing to look at this in a different way. So that willingness then to reframe a problem if you need to reset your expectations. And then also that what I said earlier, knowing that your partners to data scientists in the process, so the information and perspective you provide on your side is very valuable. And then combining that with the perspective we have on our side is what keeps things moving. One thing, especially on the product side is when we are thinking of what we need to focus on, what's next, knowing that the data, really letting that guide the way, seeing what people are trying to do, seeing what our users are asking for because that's going to make the most impact. And that means we already have the data to explore this problem and then it's so much easier on our side and it's a quick win that everyone's happy with.

Rashmi (36:50):

Those are you articulated really well with some of those qualities. I think I have to go and check myself if I check check box across those. That was really good. And to flip the question, what kind of boundary should one draw between a PM and a data scientist where at some point you're like, I think I'll take care of it. I think this is my wheelhouse. So any suggestions on that front per se, Lauren?

Lauren (37:36):

Yeah, so I think from the product manager versus the data scientist, if we're putting those in a box, the data scientist is the one who is taking the question and going to explore it and then bringing data back to the table. And the product manager can be the one bringing the question to the table and then going back and getting more perspectives or helping understand the problem and bringing that to the table. And I think that on the data science side, you do fall more in the technical side, but then you have a little bit of the business domain because you are the one communicating that back to the business side. But then on the product manager side, you're a little bit more on the business side, but you have the technical communication. And so that's where I feel like everyone's strengths lie and together you shouldn't have a lot of overlap, but you also shouldn't be doing each other's jobs because that probably is not the most productive way to do things.

Rashmi (38:41):

No, I think this reminds me of when we also work, when we work with the engineering, just take the why there and what the problem is and kind let them solve. You don't have to tell them how to implement that, which is their boundary. We will figure out the best way to solve the problem, but let's kind of discuss what the problem is in the first place. I think it reminded me of that. It seems very similar on the data scientist side as well, right?

Lauren (39:09):

Yeah. Yes. I would say trust that the people you're working with are the experts, are the people who know how to accomplish what you're asking them and they will then trust you to, on your side, accomplish what you might be asking, what they might be asking of you.

Rashmi (39:28):

Yeah, no, that's such a good feedback. I think especially when we have people probably who are now getting into the space of AI and working on problems and solutions. I think this is really helpful for them. And any frameworks or tools that you could share, Lauren, for a successful collaboration between the product and the data science teams?

Lauren (39:55):

I would say less of a framework for collaboration other than, I dunno, agile or having some sort of internal tool, but just I really love the principles of design thinking and using a design thinking approach to be what kind of guides the way you look at the work you're doing. It aligns really well with data science work. So it's user focused, it combines the needs of those users with the business requirements, the business goals, and then the possibilities with data science that you can provide. And I think many product managers are also very well versed in design thinking. And we also are going through this process and applying it in different ways, but that iterative process we go through going through those steps, we might not know that the other one is doing it, but I think that's something that really helps us work as effectively as possible and be considering everything we need to be considering.

Do we need a model? Is this even a data science problem? What are we asking each other? Trying to figure out, alright, here's the ideas, here's what we're saying, writing this down, is this what we actually need and or want? Is this what our users need? How is everyone going to be affected? How are we going to benefit? What are we going to be happy with? And I think having a framework like that, maybe not officially in place, but everyone knows that's the steps they're going through together. A lot of times we do that individually, but knowing and being more aware of the fact that this is the step we're on and this is what we're looking at trying to accomplish in this meeting, in this sprint, I think could be very valuable for collaboration.

Rashmi (41:53):

Yeah, no, that's such a good one actually. From a design thinking perspective, I completely agree with you. So many things you discover through that process that you might not know, I feel. And that comes well, that comes really well together from a step-by-step process. Actually, this question was not there here, but now it intrigues me to ask you. So when we think about our agile development process or design thinking with while you're building AI products with some of the things that you mentioned, how does this fit in? What are the extra steps that kind of fit in that needs to be done from a design thinking process? Now that you mentioned that Lauren?

Lauren (42:40):

Yeah, I don't think there's any extra steps, but I think if you're not using a design thinking process originally, it's very helpful because it helps you make sure that you're not missing anything. So some of the really core things I kind of mentioned briefly already, but I'll go back over, I think they're so important, but figuring out what you're actually trying to solve with ai, there is so much hype. There's so much like, alright, well we could use an LLM, we could use a massive deep neural network. But a lot of times then you should be asking, well, should we do we need this?

What's the benefit of this? Why can't we use that simpler solution? And then another piece is trying to figure out is this an AI problem? Do we just want to use AI for AI's sake or is this actually something that's going to benefit us?

And right now there's so much hype around it that I think that is a hard one to answer just because you want to be able to use the fun ai, but then making sure, another thing is making sure what's in each other's heads is what we are going to provide and what we are actually focused on building. And that goes both ways. Making sure that when we're talking, we have a shared vocabulary, we are aligned on definitions. When we are looking at a value that has potential different options, we are focused on that single source of truth and understanding what this looks like to everyone is the same. And that's a big piece of it. And a lot of times that just means having more conversations and then the iterative process, having that willingness to change direction or reset your expectations or say, alright, we can't solve problem A, but we can solve problem B or we can solve problem A in a different way and we can still meet those needs and achieve those goals, but it looks differently.

And that willingness to do that together makes it so much simpler and makes it moves so much faster. And then another big piece is really the human-centered aspect. So trying to understand, alright, this model, is it going to be biased? Is it going to affect someone negatively? Is it going to affect someone positively? Is it going to affect someone way more positively than someone else? Or just understanding, alright, how is this going to benefit someone? What's going to improve for them? What processes will improve? And just going through that and being able to say, alright, we're trying to achieve this and here's the value that we think we will achieve and here's how we can prove that we've achieved that. And making sure that you're doing that at the beginning instead of at the end, because that saves you a lot of time.

Rashmi (45:33):

Yeah, no, that's so well said Lauren. You summarized it really well I think. And when we are talking about some of these, you mentioned about some of the ethical issues and risks and things. So in the process that you laid out initially, is this something you come up with during the process? Like beginning of the process, Hey, if you're doing this, this is the risk we see, or have you uncovered risks after the experimentation where I didn't expect that, but it looks like this is biased. Tell us a little more about that.

Lauren (46:08):

Yeah, so just like you said, it is totally both. So sometimes you're going in and you're saying, alright, we want to try and achieve this, but we were worried that this could be biased. Maybe you've tried to explore a similar use case in the past and that's why you know that there's risks you should be considering. Or maybe it's something that comes out of your exploration stage, maybe you see that the data is biased or maybe you see that you're missing a large part of your population that's not represented in the data and that could potentially leave basically a hole in your model that's going to be biased against them or just not be able to predict on that type of input data. And so yeah, it really is throughout the process, you're trying to understand even during the model training part, looking at how your model is performing versus how a different model is performing.

Making sure that any of those risks or those edge cases or just the things where you're like, Hey, that looks a little weird, we should talk that out. Or if you find some outlying data, not all outliers are bad. So understanding can we throw this out or Oh no, is this a really important edge case that we need to consider? And it just, I think gets a little bit more tricky the more with the specific data you're looking at. So if you're looking at data in an industry that's highly regulated like healthcare or financial companies or somewhere where you're trying to predict who gets a loan, the potential negative outcomes towards the end user, the end recipient who might not even know that they're being affected by this model just grows so immensely that you as the practitioner, you as the people putting the data, putting the AI solution in process are really the ones responsible for making sure that you're doing it correctly, ethically and responsibly.

Rashmi (48:11):

I think you kind of alluding towards the mindset I think, which the PMs work with you, that open mindset to change course when needed or rethink about it or take a different course when needed. I think that's probably a very important skill I think when you're working with the PMs, I guess, which I think you alluded to multiple times, right?

Lauren (48:34):

Yeah. I think, yeah, it's so much easier to, if everyone is willing to say, all right, that didn't work like what we thought, but we're going to look at this a different way. We're going to be flexible about it or trust the data and trust what we find in the data and say, alright, well it didn't answer the question in the way we hoped, but we still learned something that can help us in some way. So I guess try and stay on the optimistic side and doing that together is a lot easier than fighting each other on it.

Rashmi (49:05):

Completely agree on that. That's a lot of insights with closely working with the data scientists. Any last words to our PM audience or anything from your end?

Lauren (49:21):

Gosh, I always really like working with product managers. I think it's a really cool role and everyone I work with in a product manager role always has really interesting perspectives. So it's definitely a highlight of my day when I get to connect with people. And so yeah. Thank you guys for having me on. It was really great to talk with you and share some of what this looks like from the data science side.

Rashmi (49:48):

Yeah, absolutely. Thank you so much for your time. I think really enjoyed our conversation.