Advanced AI PM Course - AI Strategy - YouTube
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Transcript:
(00:03) all right welcome everyone session number three of the advanced AI PM course today I'm particularly excited because today um we are actually able to have the guest that um we were going to have less time um but before I introduce her I wanted to thank everyone for the offline messages and um and engaging with the content um I'd love to hear what people thought of Google collab and I know that some people felt a bit uncomfortable uh I know some people loved it I know some other people this I'm not going to say
(00:37) the name person messaged me and said oh I would never want to be a data scientist or a machine learning engineer and I get it like I used to be one in I I switched right so um so we were able to shift the schedule a bit in order to accommodate the change that happened last time um so just so you know you're not going to miss out on any session so um I promised you and Amazon senior machine learning engineer that is coming um the next two sessions so we shifted things over um but with no further Ado I want to tell you a story about how I met
(01:12) our amazing speaker we have today and the theme of today is um I want you to hear from an AI product executive so we're all there are a lot of leaders there are a lot of you know heads of product and so on but it's a whole level next to say that you're an executive and the person I'm about to introduce to you is someone that is is a mentor is a friend and someone I really admire but the way I met her is actually really really interesting um many many years ago I was interviewing for this super
(01:44) role at meta um and you know there was a whole interview panel and the last person of this panel was this woman that I'll introduce to you now and we had the best discussion like it was amazing and I met her and I was so inspired by her um I did not get the job I did not get the job but to my surprise after a few years she just sent me a friend request on Facebook and I was I was amazed because I really enjoyed the conversation I had with her and now we're actually friends um colleagues we support each other and because we
(02:18) support each other um she has agreed to come give a talk to this group um but just let me give you some information on her amazing background um so Natalia and she's already in the um joined Microsoft uh in May 2008 and then she was a group product manager in 2010 so she was a group product manager in 2010 okay like the thing this real and then she was director of product management um and Samsung and she was actually the founder of a company that got acquired by Samsung that was back um in 2012 and then she was director of
(02:56) product management and machine learning in Salesforce back in 2016 and then she was working um in as an executive at Facebook as an AI product lead and that's where I met her um but yeah as part of um this course I I really wanted to tap on my network and bring you the best there is and I'm just so excited um she has agreed to come she actually gave a talk on the previous cohort as well and everyone in the comments said okay this was the best thing so um with no further Ado I'd love to introduce everyone to you to Natalia
(03:32) um and she has prepared some amazing content for you please feel free to raise your virtual hand for questions and write in the chat um but yeah here we go Natalia welcome thank you for joining us again hi thank you for having me I'm really excited to be here today um as merily mentioned my name is Natalia thank you for being here um yeah to kick things off actually I'd love to know where everyone is while I set up my screen real fast and Natalia we are going to do a meet up in the Bay Area and I will

(04:07) invite you there because there are like 30 people in the Bay Area so it would be it would be great if you joined us there too all right can you see my screen yep chat okay let's see where are we wow London Berkeley Denver Bristol San Francisco Canada we have people from all over amazing Texas denk incred Bangalore people are everywhere Zur we have a bunch of people in Europe Romania hello hello everyone well I am in let's see make sure Meno Park um I'm I'm in Melo Park and uh that's that's where I'm
(04:50) located uh thanks everyone for sharing your location uh so as merily uh mentioned I've been in AI product before it was AI product um in the early days of Microsoft being search when we're fiercely competing with Google um and it's just really fascinating how the field has evolved over time I want to start us off with a little story um and the story is based on based on reality so uh let's let's let's do some story time um so imagine it's it's morning it's 6:00 a.m.
(05:40) you wake up you've had a long sleepless night uh and you need to quickly embark on your one and a half hour commute to make it to the 8:30 a.m. inperson meeting with your SVP this by the way as I mentioned true story so your uh your assignment you will be presenting the next big AI project uh as it happens in Bay area and I'm sure other places in the world as well the daily traffic to San Francisco from Peninsula imagine you live in Peninsula which is down south uh where a lot of people live and commute to San Francisco
(06:22) the traffic is an unpredictable nightmare worst case it could take you two hours your SVP is uh pedantic and judges people on their appearance likes to have everything neat and uh and very well uh organized and and perfect um and yet he schedules an 8 a. meeting um he is also very Stern uh again you had trouble sleeping last night uh so you start to present there's your traffic true story is a SVP he's got his morning coffee so you start to present uh and the SVP looks very unconvinced um in particular he drives home the point that
(07:17) the AI prototype is not producing the exact same results when he gives it specific input why is this happening um the quality of your product is bad in his opinion and why do the recommendations not make sense uh the SVP is really into Gulf uh so he's expecting recommendations that are personalized to him and his taste uh but instead this is what he gets he gets women's frilly uh ice skates so uh the SVP is aggressively questioning your work you start to stutter your perplexed you feel unappreciated um and again the cycle
(08:05) continues you have you're having a hard time with this job uh review ends on a sour note um I wanted to debug this this situation uh why did this happen I'd love you know i' love your your opinions you guys want to give give me a little bit of feedback why why these things happen Evan uh I mean the thing the difference in expectations almost you know if you're presenting one thing that doesn't match up with not fully understanding the svp's expectations and then presenting something that doesn't match it is going
(08:44) to lead to a challenging conversation exactly and as often happens there's so many things happening um we're we're all very busy lack of communication through diff stages model is still learning um there's not enough time or we perceive that there's not enough time to do this alignment the plan wasn't socialized before from the beginning yeah so let's break it up into you know how this could have gone better and why we just didn't work hard enough maybe maybe but probably it's
(09:24) communication CP is Too Proud to admit they don't understand exactly so I want to provide you with a framework for uh for for dealing for preventing things like this uh let's see so one oops set context and expectations so here's a three-part framework for how you prevent uh these types of situations and then I'll I'll go and and deep dive into each particular thing so one

um as Evan mentioned set context and expectations two a lot of times we don't have the right culture in the organization for AI
(10:05) products um we are used to uh the type of product development where you just go through the product cycle you develop something once and then you ship it with AI really need more of an experimental culture where you try things time and time over again and you iterate into the right product so you really need an experimental culture and you need to to your leadership why this is important his daughter used his browser in the cookie this is true this could have happened um this happens a a lot of times is uh the just misund
(10:45) understanding of how the product works um and then the other one is you need to really get the Buy in beforehand um there was a comment earlier around we didn't work hard enough it's you know it it really really a lot of times is more about slowing everything down as a product leader really kind of having a backbone to push back against your leadership and saying hey um you know this is going too fast you don't have the right expectations we need more time you need to have a set of tip a set of things that you sort of
(11:24) push push everything back and reset the expectations and resetting expectations for AI products is so crucial um even even working in a very AI mature organization like meta really the more you move up in management the more it is about managing expectations and managing your leadership um and you just you have to figure out ways to align with with them um so one how do you set a context and and expectations so the nature of AI is it's probabilistic meaning just because you make the same requests you may not get
(12:11) the same answer it um it's not something where you can uh just it build it once and be done you have to keep iterating you have to keep getting data you have to get get data the very first time and then you have to keep data and you have to keep improving it um but the reality is that you're always going to have some amount of um AI results be wrong you're always going to have some sort of false positives it's always about a game of thresholds and so it's important for leadership to internalize this um llms are famous for
(12:58) different answers each time exactly so I think this is something that people don't understand um both on the user side as well as on the leadership side uh secondly AI development is iterative um again there's this whole life cycle where you have to get the data you have to design and develop validation and testing approve and deploy Monitor and optimize and you have to do it all over again and the particular story uh that I told you guys and in that example what happened was that the company really worked on a six- month
(13:37) ship cycle Enterprise company uh you know get it out once and you're done and that was the expectation with AI you have to set the expectation with leadership H and you really have to manage the user expectations around how the product is created and really the magic of AI product management is matching the technology with the user need and you have to iterate into it and have to get there over time and in order to do that the whole AI life cycle is um really its own animal and uh you have all these stages
(14:25) that you have to continuously keep going through prototypes are easy but putting things in production isn't and I think this is where a lot of times we get into trouble um especially with all of the generative AI stuff it's like look AI can do all these cool things but we forget again that in order to make a prototype a reality there are so many different pieces that need to go into place um and as more and more leadership is asking for AI strategy for generative AI products it's really important to reset
(15:06) the expectations and let them know that um prototype is one thing and building a product is something different I'll give you an example of this so again um generative AI is really hot

right now and everyone's getting excited about everything that it can do um people want to integrate it into their products they want to improve workflows they want to build new things the reality is that if you're using a large language model it's exorbitantly expensive a prototype is cheap you can easily use apis and hack
(15:45) something together but the cost of inference is so big that it's really uh you know it starts to get very infeasible to build and put into production and so costs are going down over time but it's something that we have to wait catch up we have to like figure out all the tooling around large language models which famously is the wild west right now I mean i' I'd go back and say that all of AI development is a wild west there is um there are so many different platforms tools um it's it's not something that is
(16:24) as mature as the um sort of more traditional software development this is something I ran into meta very often uh even a company as mature as meta has so many different platforms there so many different tools and if you're trying to do something companywide in a centralized fashion it is really difficult um uh let's go on to the second piece of this so again I'm going to stress set context and and um and expectations as a aipm leader that's the key thing you have to nail for all of your work you
(17:02) can save yourself a whole bunch of trouble and hard work uh if uh if you manage expectations with your manager with your leadership with your team it really uh have to put in a concerted effort to do that correctly secondly it's really important to Foster an experimental culture um what does this mean to bring break this down um you can you can carve out time to build experiments uh but what you don't want to do is just make it a free-for-all for your team you want to uh make sure that there are outcomes and that the work
(17:49) experimental work is productive so uh I'll give you another example from my time at meta I work very often with a research organization the research or organization has a free-for-all working on AI building AI they they want to do they just are so excited about the technology they're very excited about writing papers they're really excited about advancements you know one of the problems we ran into them is it's not clear what all of the research does for products and so in working with a research organization for each product
(18:26) it's really important to align on outcomes that are important to the business um and each experiment needs to have a clear line uh back to how it benefits the product and how it benefits the business and so in the very beginning even if you're giving people free reign too experiments make sure that the work is actually useful for your product and your business and it's not just a bunch of play that doesn't go anywhere because eventually um eventually that comes back and bites the organization and in this time of
(19:08) layoffs and efficiency first thing that goes are you know the parts of the organization that don't uh deliver any clear business value it's okay to fail on your experiments but make sure you're clear about what you learn and how it um applies to actual product product and business out out comes and just clarifying that writing it down in itself is enough second part is time box your experimentation so you can experiment you can have free reign but be very clear around like how long you have for that and how how much it's okay
(19:47) to experiment um because you do have other priorities and things you have to do uh third be Scrappy so I mentioned working with larg language models apis are really cheap they're really good for experiments um you can get away with that you don't have to build your AI from the bottom up uh and dive directly into building an AI product use what's there off the shelf see what's cheap pretend that you're a startup without any resources even if you're in a big organization to save yourself

(20:27) time third uh get Buy in beforehand how do you get Buy in beforehand it's easy to say I think you know as with anything all these things are easy to say hard to do how do you make sure that your leadership has the right expectations that by the time you get into that meeting um you you go in without fear and you know you go in knowing what to expect and you're not in this like frenzied State uh where you can't sleep but night um so some tips uh communicate business value I'll I'll come back to the
(21:07) question let me quickly go through this one um communicate business so again make sure that in the example uh story that I gave you we were talking about a prototype uh but it wasn't clear What that particular product or prototype was going to do for the business it was like a cute prototype that was being shown to the SVP but what does this mean for the business if you think about it from an svp's point of view what they want like their goal is to run a successful business unit and so they have certain
(21:45) metrics that they have to deliver on and make sure that your prototype actually moves those metrics is important for them um assemble your entourage of Champions so going into each one of these meetings uh it's really important for to to have an agreement beforehand with your engineering manager with other leaders on the team that they're going to support you and back you up in the presentation uh that you're giving it's not you should never feel like you're alone presenting it it should be you or
(22:19) the face of the team and your uh your team should be there to back you up so have an agreement beforehand um and then C send previews an updates to leadership well ahead of time um that way you know if uh they're saying something and you have a mismatch of expectations you should remind them in a friendly way that uh this was already shared in an email um that you tried to get their attention um try to get as much clarification and feedback beforehand um so those are those are my tips um let me go back to
(22:55) some of these questions so um Alicia says can can you talk about time boxing what kind of metrics are you looking for to gain confidence on being able to ship into production or when you need to go back and revisit the strategy usually we get rushed to push things out so time boxing depends on what kind of ship Cycles your company has um a lot of times Enterprise companies will ship once or twice a year so you have to figure out how to align to whatever the the um sorry I hope you guys can see we have like some crying in the background um we
(23:36) you you have to again align with whatever your organizational expectations are um in terms of what kind of metrics are you looking for to gain confidence metrics come from each so in my experience each business um usually has some top level business goals that they're going after um it it you know it depends what is the business model of the company and the product that you're working on so you really have to kind of level up and think of it from an SCP point of view like what are those business metrics um are you selling ads
(24:14) are you selling an Enterprise product do you need to have customers who are paying and not churning do you need to have user growth and engagement you really have to think about doing that in the context of your company and then your organization and then think about it from a product and the more you can demonstrate um how your product and work directly impacts those top goals for the company the more successful you can be and more you can celebrate it um when do you need to go back and revisit the strategy well it depends on
(24:50) what kind of results you're getting from your your prototyping um you you know take the time that you need to ship and break it up work with your engineering to break it up into iterations of the experiment um and then see how how much do you have the data you need I mean there's so many variables here you kind of have to be step through them in a very

structured way and check off all the boxes to make sure that that everything is um is aligned to the point where you can hit those expectations one of the
(25:22) things we're going to be talking about next is why do AI products fail so we'll cover some of that there um but you know I I I would encourage everyone just sit down and come up with a very intentional plan of how to do this in a very organized way in a stepbystep uh fashion do you use figma or make videos to show what's possible in meta I don't use figma I don't use videos do you make road maps in Meo and update there honestly road maps we just did Google Docs and um yeah I don't right we didn't use miror
(26:00) or anything like that it was very much which doesn't mean that other teams at meta didn't we had a lot of freedom so each team kind of used whatever tools they wanted uh let's see can you give a few examples of metrics kpis related to the kind of experiments you mentioned are those experimental kpis accuracy Etc or do you want to focus on business related ones user growth Etc um so some examples of kpis let me think um one of the projects we did was uh click was smart keyboard in arvr um and so the idea is you have a virtual
(26:45) Smart Keyboard where you have to kind of um type things in and um what we wanted to do was make sure that we had people use our suggestions as you type um more frequently than the prior model and we knew that they were accurate because people um were choosing those suggestions um we had a model in the background that generated this and and added to um the acceptance of those um suggestions um there's a lot of questions I'm going to take this last one and then I want to open it up I want to open it up
(27:26) for your maybe your stories or or suggest if somebody wants to share can you talk about how you help researchers others TI let's see uh researchers others ties tie to business value um you again you as a product manager it's your job to know the business metrics in and out and it's your job to go and explain to researchers what people need uh what your customers need so a lot of working with researchers is actually bringing them up to speed around your point of view and what people need and so for example one of the effective
(28:13) techniques in getting researchers involved is to pull them into customer conversations pull them into user research to get them excited and motivated about Building Product and I have to say not all researchers will care or want to build products um so you have to kind of pick who you work with um nille do you maybe want to uh it might be easier do you wanna do you wanna yeah yeah right so um uh so I I work at Amazon part of uh group who uses machine learning for uh a Last Mile Logistics uh and like we service a whole
(28:58) number of like internal customers with this technology and sometimes what I found is um the further away some teams might be from this technology um they may not fully appreciate the problem probabilistic nature of this so it's like expecting Perfection or expecting all the time correct or the you know uh uh the uh expected outcome and these are like you know short meetings and there's lot of stakeholders so I found it like difficult to explain the probabilistic nature of AI in a short time frame right
(29:38) like and and to do it in a like you know of course like respectful way not repeating something they may already know um so I'm just wondering like kind of you mentioned before one of the points is hey the nature of the space is probabilistic experimental I'm wondering if you've had kind of similar experiences or kind of best practices how to manage those uh let's say knowledge gaps and how to address it in a those kind of instances yeah um let me make sure I understand your your situation it sounds
(30:11) like you're working with another group that doesn't have that perspective and so doesn't understand right you're dealing with yeah yeah I think you know one of the big um I would say

tools and my toolbox is to find people who in in in um that other organization and find to find people who get your point of view who may be the leaders on that team uh and sometimes leaders in the team are not people who you expect uh there might be somebody they might be secret leaders of the team like they may not have the
(30:52) title but they're actually very influential and so they I mean definitely you know start with can you get the leadership of that team to understand and help help you educate them on where you're coming from like that is a Surefire way to to deal with this if you can't get to the leadership sometimes what you have to do is identify who are the influential sort of secret leaders in that team that don't necessarily have the title or um you know they're not they're influential but don't you know don't have like
(31:29) management um responsibilities or something like that and then I would use them and work through them to educate the rest of that organization and that team so you don't feel like you're doing it by yourself because if you're doing it by yourself it might feel like an uphill battle and it could cause a lot of conflict you kind of need to have your inside people uh like I was one of my one of my suggestions is assemble your Entre Char of Champions you know can you get one person who's influential
(32:01) whether they're a formally in a leadership role or an informally in a leadership role sometimes people who are formally in a leadership role are actually less powerful than people who have informal leadership and influence and so I'd say like take some time to get you know Intel on that organization talk to people in that organization grab coffee to figure out who are those people that you can leverage uh to explain your point of view you who understand where you're coming from who understand um what it means to build Ai
(32:34) and get them to to help you with this uh rather than going at it alone and feeling like you're in a kind of um you know adversarial relationship with that other team that's my yeah yeah that's helpful thank you Nat you're welcome uh let's take a few more questions nikil is Ram do you want to uh speak likely because they're used to working with standard software yes um how do you send previews and updates to leadership J Julian do you w to uh elaborate on your question a little bit Yeah so um in my company uh what's
(33:16) happening is obviously there's a lot of experimentation happening uh several teams are depending on um I'm building a platform for everyone to be able to build uh these products the generative AI products and platform as a product on its own has a lot of its own challenges and sometimes things go down things things are apis are up or or DBS go down but do we like these it feels like there are too nitty-gritty technical details to go and update your leadership about uh but like do I talk about like I have
(33:51) a bi-weekly newsletter uh but do I talk about it there so that you know everybody gets it like we are working on on this it it it will fail I'm very open in that newsletter uh kind of like a open letter to everyone like you know this is happening but this is stay tuned for the launches this is up and running or do I do you know these small detailed emails like great question this is fantastic question and one of the big lessons I had in the last I don't know maybe like six years of my career and that's the power of framing your work so
(34:27) um I think the really the the problem that you're looking at here is how do you you're doing so much work you're down on the ground and you have to figure out how to frame this from a leadership perspective in a way that they get it and the way to do that is you really have to you have to elevate the technical details and connect them with the user and the product and again you know if you think about it from from a leader leaders point of view the more you can internalize their view the more successful you're going to be as an as a

(35:02) leader and the more you can kind of you know rise up in the organization and what you have to understand is if you're an executive you're running multiple businesses and multiple products right how does your part fit in for them what is you know what is your part of the puzzle if you give them too much technical detail on the ground they're just going to be confused and frustrated so you really have to take that and again figure out how to tie it to the kind of metrics that they care about in the business value and then say like
(35:37) look we're moving these metrics this is the user problems you really have to elevate it to that level kind of it might feel like you're dumbing it down but you're just giving them the kind of perspective that they need and then back it up with all the details and give them all the work so they know that look there's all the stuff happening but this is one of the major problems like at meta we had this constantly we because we have a very Bottoms Up culture where um the engineering teams were empowered
(36:05) to do a lot of projects on their own but I think a lot of failure that I I saw uh you know from from a lot of people was the inability so what I'd say is like figure out how to frame it and you know maybe talk to your marketing person or somebody like that who who doesn't understand the Deep technical details finds somebody uh who understands more of like the language and the the selling part of it it's almost like you have to Market your work to the executives get their feedback and and play around until
(36:38) you figure out the framing in a way that um that resonates with the leadership but that is fundamentally the key to working well with leadership you have to figure out what is their point of view and what is the kind of language um that they speak um Swami uh you've been you've had your hand up for a while go ahead thank you I think you you already answered some of the questions I was just wondering for an organization that's trying to break into AI um so in other words there's not a explicit you
(37:10) know we are using AI as a commitment say meta and the large larger technology organizations um can you layer an additional tip on on top of that because again business values understanding the SVP point of view business metrics you already answered but I just want to say why AI in this context be helpful great question so let me just make sure I understand you're you're buil you're bringing in Ai and you want to justify it and make sure that it fits in is that kind of your what your question is so um you know the only introduction
(37:47) to AI that many smaller organizations have is all the LMS and all the the generative AI tools that they're playing with uh but the the imagination to apply it in in a specific product and increase value and so on is is is sort of limit is is emerging so how do you spark that imagination in this context yeah I mean the easy way to spark their imagination is is to show them prototypes and that's a double-edged sword right because it could be the shiny new thing that everybody wants to to to chase but it
(38:20) may not actually be U meaningful to your business so your job as an AI product leader is to actually make sure that you have a valid case for for for for AI and that it's the right fit like a lot of times like we're so AI crazy um people want to chase it as a shiny shiny uh object but it doesn't actually add value so I'd say you know it's kind of on you to build that case for why it's um it's something you should invest in um and the problem you know you can have a prototype again it's a double-edged
(38:55) sword it looks Shiny People people get excited about it but then building the AI is a completely different Endeavor that's actually very resource intensive um and that requires a big commitment so you know you could start with a prototype give people excited but you have to really balance that very carefully with setting the expectations that a you need to iterate into this

slowly and then once you you you're convinced that it's going to meaningfully make an impact to your business and your product then you have
(39:27) to really work with your engineering team to lay out the plan and be very realistic around What It Takes and what it's going to cost because it's going to cost you people it's going to cost you you know compute it's going to be infrastru I mean it gets complicated very quickly so be very careful about what you promise and how you manage how you manage all of that um I have some tips for that actually the next subject I want to talk about is why AI products fail um and I think uh some of the upcoming stuff uh hopefully I can give
(40:00) you a framework to make sure that you know you go into it um confidently in a way that you know you make sure you check off all these boxes over time uh and eventually get to a point where you have successful AI product okay I'm gonna take a few more questions you have to um move on to the next one um let's see Rebecca was next let's do five more minutes uh Rebecca are you there hi can you see me and hear me yes hi so actually exactly what you were talking about and maybe you're going to answer
(40:35) this within the next section because it's kind of a followup to what you were discussing you know I have a valid case and I am you know I've got those success metrics defined and I know what it is that we're going to do in terms of prototyping to prove out that this um is going to add value it's just something that is you know going to be hardcoded for you know its initial release how do you and we are planning like I am planning to iterate slowly in terms of the next phase like going from that iterative slowly like
(41:11) sort of like first prototype to investing in AI resources because it is intensive what are the types of thresholds that you look for to sort of like bring your leadership along that says like hey now is the time that's worth the scaling up and the investing to like move to that next phase because that like I I hear everything that you're talking about I just that is the one area that I'm struggling how to bridge for my organization yeah I think that's the million-dollar question and you nailed
(41:42) it and my answer is GNA be it depends and it's an art and this is where there's no one you know specific answer it really you know you have to call it you may not always have data you may have to literally go with your gut on whether this thing is going to work and take the chances what I will say is you know as somebody in product and somebody you know the more you grow it's really about managing the Optics of how this thing go I've seen people work on projects AI project completely fail right and yet
(42:20) they get the trust of the leadership and they get promoted so like one it's an art there's no exact answer to your question it's really about managing the expectations over time and working closely with your leadership and your engineering Partners to see how you know how well things are going and is this thing going to work and then doing experiments with your customers like one of the big reasons AI product I mean we're going to get into this I'll give you examples is like you need to have
(42:52) feedback from users and customers and as you get more feedback it gets better and better and better over time and in the beginning phases it's very hard to know right because you just don't have that feedback from your users yet but the way that AI products work is the more people use it the better it gets if you build it right that's what's going to happen and so again my answer is like focus on on that communication on the expectation on the Optics you know and then do the best you can with the product um you
(43:24) can't you can't fullprof that in any Point okay two more questions and then um I got to go into the next one whoops uh let's see I think Abe you're next he good morning uh thank you

Natalia I just have a question I mean you've been in in in Salesforce in um meta and you know you could argue one's in consumer the other one's more business um so assuming you sign up for the concept that some organizations are set up to sort of of realize the value of AI more than others how would you assess
(44:02) organizationally um what to look for in terms of hey this company is organizationally uh whether it's incentives whether it's leadership capabilities more likely to set up for for success in adopting a technology like like uh AI what what would you look for um to assess their Readiness yeah I mean the first thing I'd look for is data right like the first thing I'd say is you have to have a clear data story around how you're going to get data for your AI um do you have the data is it available the problem with a lot of
(44:41) organizations particularly with Enterprise softwares it was just not built in a way that you can get data easily and it's siloed and it's like all across the different departments and so start with that um and start out by figuring out what is your data story where are you going to get it how are you gonna how are you going to build that I mean I'll I have a great example of where this failed in a company where you wouldn't expect it would fail like even very mature organizations I'll give
(45:11) you an example I was talking somebody at at Adobe theyve doing fabulous work with generative AI like amazing one of the things they have is one of the problems they have is like they're the kind of comp they started out as as um a desktop company and as an artifact of how they started out they just don't have systems for instrumentation they don't record how people are using their products and this is a really big problem for them right so um I'll get into the details of the AI life cycle and really there's
(45:44) like a whole set of things you have to have set up um but you know I I i' say don't stop don't let any of this stuff stop you start small experiment maybe you don't need the whole infrastructure rure sometimes you don't need all the data maybe you can have a smaller high quality dat especially with generative AI like one of the big benefits of generative AI is you get a foundation model and then you can use your high quality data to fine-tune and use the power of those Foundation like this is
(46:13) why generative AI is such a big deal I think people don't understand this that well maybe you know you can do open source stuff I mean this is why you have to experiment um but usually start with the data that without the data you cannot uh you cannot move um so I'll get into some of this a bit later I'm going to take one more question and then I think we we should we should really move on to the next one t just go ahead great thanks Natalia I I wanted to ask a question about a problem that I'm
(46:41) running into as a platform PM really often and it's somewhat of a chicken and and the Egg problem of especially around pitching the buz business justification for a platform investment typically to obtain those learnings and valid Val those hypothesis you need some sort of modeling or infrastructure investment but then on the flip side in order to obtain that investment need to prove that business justification so I want to get your input on how to approach that kind of problem yeah this is a great question uh one of the really big
(47:16) challenges with building platforms is it takes a long time right and so the first thing uh I had this this great mentor who was a VP engineering VP at Google and I'm going to borrow his advice um his advice was if you're building a platform product shape your road map in a way where you can still build small wins that are visible and show momentum to your leadership so like you're building a platform is going to take a year and that's just the nature of the beast but can you find some things within all of that work that

(47:56) you can do faster that you can sort of you know use as your shiny object to show the leadership that you're moving along that you're actually providing business value um usually you can and there are things and and uh it it does two things like it it helps manage your expectations with your leadership and value and visibility but it also helps motivate your team if you if you can come up with those things um yeah I it you know the rest depends on the context of your particular situation but I I think this
(48:30) is like it's a big big challenge for and a lot of it depends on um you know the culture of the company and the leadership so then the next thing I'm going to advise is what I advised in in the prior uh question find your champion and Leadership that gets platforms because the problem is a lot of leadership doesn't get platforms they're not technical right find your like engineering leader in leadership who can help push and and build that relationship with them you know or find somebody who's influential but may not
(49:01) have like leadership position like that's that's the other trick I'd use um so those are the two tips two tips I I I'd offer um we're we're great discussion I love your questions thank you all um I'm gonna I'm going to go into the next part which I think will also uh be helpful for a lot of the stuff which is around uh AI failures so can you guys see okay I think you should all be able to see my slides this is so meant to be humorous but basically these are all of the AI all the fails the robot
(49:38) fails um from Boston Dynamics um so here's some crazy statistic for you um why are AI failures are a big deal so it turns out that um 85% of machine learning projects fail according to Gartner um again this is because all this stuff is is uh is pretty complicated to build um and has been really the case I think now again the reason why people are so excited about generative AI is because foundation with Foundation models um you can cut a lot of this uh and and just leverage the foundation models um and not have to always build everything from
(50:24) the ground up so that is the the the secret that nobody's talking about is the power of generative AI Foundation models is you can fine-tune them and not always start from scratch um because normally with AI we've always had to start everything from scratch and build out the infrastructure every single time now you might be able to piggy piggyback um on some of some of the foundation models um so um I want to uh quick quick exercise write down at least one potential reason why AI fails um and then towards towards the end we we'll
(50:59) get back into it um just write it down think about it um and then we we'll discuss a bit later so you know as I like to I always think about um Anna Karenina which is a book from toll store that he had this quote all happy families are alike each unhappy family is unhappy in its own way uh the point of this you know a all AI products uh that are successful are are alike but each fail in its own way so there's multiple ways that you can fail there's no end to the reasons why AI products fail um from people's stuff to
(51:40) infrastructure to data to user expect I mean there's so many ways but I'm going to pick my top five so this is in no way meant to be comprehensive but it's I think the top five reasons why AI uh fails so drum roll uh here we go one your product doesn't meet user expectations so we touched on this a little bit in the the prior discussion but basically you know the threshold of accuracy is such that it's just not good user experience for people um you have user need you have things that the pro the product promises
(52:20) but it doesn't it doesn't meet user expectations so you have to really have this happy date in the vend diagram where you hit the intersection of user need and product promises um so case study uh here is an example of a voice recognition software that was used in England where basically in order to go through a toll a Tunnel toll the person had to speak into a phone uh to

communicate with the speech to text speech to text classic AI natural language processing problem this person had to speak into the phone
(53:01) 103 times before the system actually recognized that they were going to pay so this an example of a time where it was such a horrible failure I mean it really made the news iPhone auto correct so this is a really interesting one I'm sure we've all been there um it's uh you know headline it's Ru ruining my life users complain Apple's textt feature is atrocious this is really unusual actually if you think about it apple is a big company right they have some of the top AI talent in the world what is
(53:38) going on why is Apple failing um on its auto correct which should you know be a fairly straightforward we've had Auto suggest forever um I I built Auto suggest at eBay back in like 2011 um Google's had it forever this is very standard feature uh what is going on and you know Apple's the big company that has been the most silent um on its AI strategy well it turns out interesting story um this is you know this is from um uh an article by a publication called the information that gives some of the inner gossip of what's going on at Apple
(54:25) and it's it's an article specifically about Siri but it really gives us an insight into the organizational issues at Apple that are correct causing problems with its AI so Dandrea is this guy who joined from Google he went to Apple goal was simple enough improve Apple's use of data with the goal of making eii products better but it turns out that apple on likee Amazon and Google does not do as thorough of a job of collecting and analyzing data from users of their products and part of the reason for this is the internal culture
(55:02) of protecting people's privacy and this this culture um you know again great thing to do uh but but one of the in interesting uh incentive side effects of the culture of protecting people's privacy is that Apple did not do a good job of collecting prod like metrics and usage data about its AI products like Auto suggest and Siri and so they just never built out the internal tools that are required to measure and analyze the usage of their AI systems because there was a contingent internally that just
(55:40) like really was very protective of the AI privacy the privacy of its users and so this is really telling like you really have to keep track of how people are using the data and you use that usage data over time to make your product better if you're not doing that your product is going to fail and again this is why you know it's so expensive to build AI products you really need the structure where you're constantly collecting usage data and feeding it into your AI product and it gets better and better and better over time this is
(56:17) why Google search is so awesome or you know and arguable now but like it's why it's been so successful at least um so many engineers at Apple are in the dark about details as basic as how many people are using their products uh and how often they're using it this is crazy like if you come from meta or Apple or Google it is the very unexpected thing about you would not think that that is the case from Apple but that's fundamentally like why they're having some of this stuff um two failure to operationalize the AI life
(56:51) cycle so I think as as we kind of noted before a lot of companies have a very traditional approach to uh development where you do it once you're done you get it out there's a whole life cycle there this is the AI life cycle data training design develop it's the circular thing um you validate test approve and deploy monitor optimize you do it all over again and you have to keep doing it um so um yeah I I think yeah they they fixed a correct um so oops and actually as part of this there's a whole um other thing around
(57:34) data sourcing if they have infrastructure experimentations organizational expectations mlops is really big um and this is uh the idea that um you really have to have good practices

around your machine learning products and you have to have visibility into each each of the stages um and so that in itself is a whole process and by the way like once you get the AI product out into out into the wild you have to really monitor it because you could have drift it could it could work great today and then a few months down the line you could um see
(58:16) data drift and it it stops functioning or you have some unexpected data come in that it ruins everything um test AI I think this one is really really kind of difficult but you know it just starts with even a clear objective function clear metrics s surprising and shocking how people don't have this um do you need more data to keep improving your model uh and product and have you done an AI system so let me introduce you guys if you've never heard of it before um something called an AI System card so AI System card is kind of
(58:53) like a report card of how your AI is doing and I'm a big proponent of this um I actually worked on a team at meta that um put this out into the world and the idea behind an AI System card is that you provide uh transparency around your product um let me see what happened I had a slide around it uh okay maybe I will send it out back um after this is done for some reason it got deleted but um the whole idea of an a System card is it really provides a report card of like what is your AI product supposed to do
(59:30) and what you did to evaluate it uh and make sure that it's um fair that it's transparent that it's accountable so if you had to justify your AI to um Regulators which is um something that's been talked about a lot like what would you put out into the world how would you explain to people how your AI Works um um that that's the idea behind an AI System card and again I'll I'll send more information later I accidentally deleted the slide on that one um here's oops here's here's another
(1:00:08) one so this is a really interesting one um you don't have human feedback uh when you're building your AI so what I mean by this is like you need lots and lots of labeled data to refine your AI so you can think of the initial product that that you build as sort of like this this monster and then the more you refine it with labeled data with human feedback the cuter and nicer it gets um so this picture is actually from training of the jet chat GPT model um so GPT they start out you know stage one is unsupervised learning where you take
(1:00:47) basically indiscriminate data from the internet and you just have this monster uh supervised finetuning is where you start adding some feedback from humans and it gets gets nicer and then they refine it uh by using reinforcement learning from Human feedback where they have a model that literally ranks how good a response is um and it they put a smiley face on on the AI and again I think this is one of the dirty secrets of building AI products you really need human lbook data uh to make it make it good and I think
(1:01:24) one one of the things people don't realize is that success of Chad GPT is in large part due to a large volume of people who literally wrote example responses and these were highly paid Highly Educated people who knew how to write well and they hired lots of these people they spent you know I don't lots of money on them and that's why it worked um and the reason this is you know I've talked to lots of friends in Industry who or we're building like major AI products at Amazon and other companies we as AI product uh managers
(1:02:03) and leaders always get pushed back from engineering on using uh using humans to refine our AI products this has happened to me time and time over again and so you really have to go and work with your team and convince your engineering team that like you have to invest in human feedback to give it that smiley face and to really make it ready for prime time um and so I I've personally been in a lot of those battles so uh I have the chatbot uh craze of 2016 because a lot of the early chatbots you know were dumb and did not

(1:02:45) actually take any human feedback into account and as a result did not um do as well of course now we're getting uh crazy good chat Bots because of foundation models but again you know the other dirty secret behind that is just tons of human feedback um fourth you don't understand your AI so you know like one of the big issues with um the the latest and greatest AI is it's deep learning and deep learning famously is a it's literally a black box so even for people who build it they don't understand it
(1:03:24) very well um they don't understand the system like we it gets so insanely complex like at meta I had we had thousands and thousands of models working together to build a product so it's a problem on a system level it's a problem on a Model level I you don't know why the model is giving certain results um and there's some interesting Solutions and like a whole whole set of research but I I encourage everyone to to focus on transparency the both the systems work and then for models there are libraries
(1:04:01) that will actually let you look inside the AI black box and debug some of that um one is called captum for pytorch but there's a whole slew of tools that I I encourage everyone to look into ah here's my system card so here's an example of a system card which is kind of like the report card for your for your AI um there's one from GPT 4 so I encourage everyone to to go check this one out they shipped one for Dolly to and what it is is really um it's a paper that explains and how they built it
(1:04:36) which is really interesting but it also explains what are all of the things they did to evaluate it and make sure that it's done well so it's it's it's a good example of uh how to do an AI product actually why is there a Content warning um there's a Content warning because uh it turns out um like let's say for Dolly people will will will really put in nasty things and to generate images that are in Savory um that's part of it for chat GPT people will ask questions that are potentially
(1:05:11) illegal around like how to make weapons and things like that so that's that's why there's a Content warning like Integrity you know back to like why do products fail um a lot of times your AI people may use your AI in a way that you're not expecting um and so I think it's really important to think through those use cases um those those Edge use cases where example here is providing illicit advice um Etc five your AI product does not treat all people equally um so what are examples of this well fairness um
(1:05:51) obviously there's a lot of kind of sexist AI products so an example might be um uh Dr Hansen study the patient chart carefully and then the AI may assume that it's a man um as opposed to a woman um the photos below are examples from mid Journey it assumes that product managers are men Engineers are men lawyers are men so it's this that's one one flavor of it um but it's here are some examples of failed product Amazon scrap secret AI recruiting tool that showed bias um Facebook researchers
(1:06:30) shut down AI Bots that went haywire um Twitter taught Microsoft AI chat but to be racist um these are all examples around fairness um bias that are really important to test on a question Ram can you hear me yes how do you differentiate between what might be an actual bias and the just inherent probabilistic nature that we talked about like sometimes the statistics are that males are more likely to be XYZ versus females now there may be bias in that like to the cause of that sure that's I think you can all accept that but as a statement
(1:07:09) on the surface it may be true that you know women are more likely to be X and then men are more likely to be y or whatever it is yeah I mean interest way to think about it um all of these systems depend on the kind of data that's being fed into it um you know this is where it gets gray and hazy and and weird and how do you even Define fairness which we could talk

about um I you know I would say this is where you have to get into the deep deep uh use cases and and figure out like okay you know it may be the case that today we don't have is it
(1:07:58) a it's kind of like a chicken and an egg problem we don't have CEOs that are women um but does that mean that we want our AI to always show men um it's kind of like a self self U fulfilling prophecy right and it it's one of these things that gets that gets weird and tricky um and it's kind of like a question of like well what what does it do versus what should it do and um what I say is we could argue about this um I think it gets into some funny societal issues and it gets very philosophical it goes into social
(1:08:35) science but uh ultimately what I'd say is like go back to what it means for your business and your product and who are your users and who are the people and you know is it what kind of an impact is it going to have like maybe it makes those predictions but is that a problem that you need to focus on like is it going to be really bad PR is it gonna like if if it gives that those kinds of results does it mean that women are GNA stop using your products like I would encourage you to you know we we can we could try and boil the ocean but
(1:09:08) When approaching these sorts of issues I think it's important to put them into B business context and tie them back into like well what is your product what are you selling who are your users what does it mean to and how does it impact them right like um so I I'd say you know it it it depends on the context that you're working with um and you have to tie it back to those things I will also say this like it's not free to do any of the responsible AI evaluation um it means putting resources it means doing evaluation so when
(1:09:45) considering you know how much you need to worry about all this stuff think about again what is your business who are your customers who are you selling to um again you can can easily Veer into philosophical discussions of fairness I know some teams that did that is horrible don't recommend it U but again tie it back to to your business metrics and uh how how it's going to impact the business a lot of times the perception and brand value is really hit by some of this so you have to go back and evaluate it and see what
(1:10:19) we can do time check 15 minutes left all right let me see what else I got um so top five reasons AI products fail not using not meeting user expectations this is the biggest one and the hardest one because it goes to building AI products is really an art um you do AI life cycle are wrong this is a really big one um no human feedback you don't spend time on labeled data hiring people to refine your your product uh you don't have you kind of lose track of what your AI is doing um both on assistance basis as well as
(1:10:55) model basis um and your AI product does not treat equally well and I'll give you one example for where AI product does not treat all people equally well is a really egregious business problem let's say you're a bank that uses AI to recommend whether somebody should get a loan or not it turns out that there was an example of um a lender that was not giving loans to people of color like this is a really big problem like that is something that absolutely has to get solved it is a horrible horrible thing
(1:11:31) for that particular product and business to do so there's an example all right I would love for you guys to share your top uh one or to three reasons of why AI products fail so please type that in using AI for the sake of VI yes shiny shiny product expectations and data yes mismatched expectations no data biased data set bad data yes doesn't fit business model dirty data bias data greedy boss all of these things um we're overusing AI this is so true um we often fail to find a golden ratio so really good comment from
(1:12:19) Daniel um yes I love using uxr to help uh give give a good balance of perspectives they're kind of like my secret weapon uh let's see what else no Market fit yes bad business

decisions multiple variables no one buy too hard confusing what can be done hyper expectations no offline testing yes all of these are really good slow internet yeah that's huge slow internet and target market that's a really interesting one there's now um on device AI um which is really promising for some of this stuff
(1:13:03) um pipeline meeting delivery constraints okay long time to Market and high cost yes all of these are excellent trying to rush yes okay excellent all right um excellent we have about 12 minutes left um I had planned I have a whole another section on AI strategy but I worry we not we may not be able to cover all of that uh what we could do is just spend more time talking through questions and and allocate that for discussions I honestly I honestly think
(1:14:08) um that there are so many questions and there will be so many questions I say because you've already addressed a lot of them I say let's just do a quick run of AI product strategy because you're the best person that can provide this information um but maybe before doing that we can also talk about um the little workshop we have coming up for Gen for business if that sounds uh good yeah so everyone we um so Natalia and I ran for the first time last time a little very very quick um Workshop is right here we actually opened up a
(1:14:40) second little cohort um just in case there's anyone interested in hearing more around the business perspective of gen not the product specifics um you can feel free to to R to this um all right so yeah Natalia I think I think the questions like it's unbelievable we're getting so many questions so I think we really if we want to um just spend five minutes quickly scanning through AI product stry would be great because people really really really um would love to learn about this um and then maybe we can have one or two questions
(1:15:14) um at the very very end would that sound okay yeah sounds good thank you yeah let's go through so AI it's product strategy is it's a really big topic we could do a whole whole session just on that but I will give you a brief uh I've done a lot of it uh so at meta um my my job was really to to figure out the AI product strategy for uh the company uh it was particularly focused around AI privacy and AI transparency and control but the really big challenge was um figuring out which product products
(1:15:54) to invest in because like imagine you're in my position you need to build out an AI strategy around like where do you need especially private you know to be careful around privacy for AI product like does that mean you should like focus on ads should you focus on news feed I mean meta has so many different products um and businesses Instagram WhatsApp Facebook app Etc so like this is one of the things that I did um and so I think the first thing start off with because um AI strategy like what does strategy even mean and just very simply
(1:16:31) to me strategy is just the path for you to uh realize your vision you have some sort of a vision for what your product and business uh should be on a longer term uh you know a longer term uh timeline so AI strategy is really thinking a few steps ahead uh around how do you get there and there's this famous um adage it's attributed to Churchill but I don't I'm actually not sure who it came from but like planning is indispensable plans are useless so just the process of putting together a strategy and thinking years ahead is
(1:17:11) really useful uh so that you're ready for whatever changes come your plans will change it doesn't mean you're going to do exactly what you said you know the way you map out your Str you change it over time but the whole process of putting it together um is in itself valuable and use useful and that's why um maybe in another time we could we could do the exercise of of putting one together but like you know I this this had come up before but uh AI is really expensive to build and so before you build your AI

(1:17:46) strategy take a step back and ask yourself do you even need an AI strategy can you can you get away with doing something that's much simpler and these are all the reasons why maybe you shouldn't always build AI um so I I'd encourage everyone to you know think carefully and ask the questions do we even need an AI strategy as you embark on building one um this particular thing is around um generative AI um but I think it can be applied in general so if you're building AI does it is it going to make business obsolete
(1:18:25) then you should probably go in is it a case where it can boost your business in Revenue like need to make an inest but you don't need to go all in will it help you gain a competitive Advantage so maybe there's some data that you have that's proprietary and you know you could build AI to set you apart and differentiate you and really take your business to the next level but maybe you make bets and you don't go all in and again maybe you don't need AI at all so be very mindful of that my AI strategy
(1:18:54) framework is you know sort of I like to break things up into steps and then I'll walk through these very quickly one again it sounds so obvious um and and pedestrian but understanding the problem and taking the time to understand that problem and pushing back against your leadership to make sure that you are solving the right problem not just being handed down something um I think is a step one two uh a lot of times you know we have the shiny shiny AI uh shiny ball uh but the tech may not be mature and it may not be
(1:19:36) a fit you may not have the infrastructure and all this stuff right three there are costs and tradeoffs costs in terms of building um building all the infra getting the data costs in terms of like you know launching everything going to Market hiring the right people what are the tradeoffs what are you uh what are you giving up by building particular AI um and investing in a strategy and so understand the problem again um does it align with company priorities is it big enough um are you under threat if your your company's under threat you
(1:20:15) absolutely have to do AI so for example um with generative AI all of the the stock asset compan are under serious threat okay I'll go through these quickly and I do have a write up of this uh for everyone I could share um Tech maturity fit user expectations Tex stack do you have that Tex stack in place do you have to build it and then do you know what are the risks around your AI um with respect to your business all right last one again costs how much is it going to cost and what else do you have to sacrifice so that's basic
(1:20:52) framework again I have have um a uh a write up of this that I'll I'll share um and with that I'm going to stop here and leave the next five minutes for questions perfect this has been great I'm getting messages and people are like thank you for bringing Natalia and she is awesome all right um so a couple of things I know there are so many questions um I do want to give the opportunity to someone that has not asked any question um I will upload the slides and Maven so please raise your virtual hand if you have a question and
(1:21:31) I am going to Peck not in order but from someone that has not speak before spoken before um just randomly because I want to give the opportunity for everyone um to have a voice so yeah please raise your viritual hand we can ask a question um but you know on a personal note um I have to say that it's just so exciting to see people like Natalia in executive positions um it's it's fantastic to see the kind of diverse background and experience um that she brings in and there are so many other people that are
(1:22:03) AI product leaders that are now finally um you know shining and and having the spotlight under them because this domain is finally um so so popular um all right well I am actually gonna give you a couple of minutes back so because there are no further questions um please reach out to me on Discord if there's anything targeted you'd like to ask Natalia um but

again thank you so much Natalia we could not appreciate more um your time I'm very very appreciative um to have a friend and a colleague um like you so
(1:22:35) really appreciate it thank you thank you thank you everyone I really enjoyed this and so good to hear all of the questions and learn from you about what you're doing um and the kind of problems that you're uh you're grappling with in your day-to-day so thank you so much all right thank you thank you take care bye bye

Live Model Training

Marily Nika
00:00:04
Perfect. Well, welcome. This is live session number 3 off our Aip. M. One on one course. So at this point we have gone through a lot of offline content and a lot online content. So
Marily Nika
00:00:19
today is kind of a different format. So the first 30 min is gonna be just an informal kind of discussion in QA. Where I wanna make sure to address any questions you have.
Marily Nika
00:00:30
Make sure to, you know. Take the discussion wherever you want it to go, really. And then at 9 Am. Pt. We're gonna have our guest speaker, which is a senior machine learning scientist at Alexa Amazon.
Marily Nika
00:00:44
and she will discuss how she works with Pms. And she will specifically discuss what she does on her day to day as a machine learning scientist.
Marily Nika
00:00:54
It's gonna be a live coding workshop. But it's gonna be for that perspective of a Pm. a lot of people find this very useful. But some people can get a bit intimidated in the sense that, you know. She will discuss a lot of things, and she'll get kind of
Marily Nika
00:01:10
technical enough.
Marily Nika
00:01:12
but I want you to get intimidated. I. The purpose of this session is for you to understand what your team is working on, and how they work
Marily Nika
00:01:21
for a product that you want created.
Marily Nika
00:01:25

So I feel like we're very honored to see decided to come again. And
Marily Nika
00:01:30
actually she has. We have added a lot of flying content in the Maison platform with introduction about Llm and python and more Google Club. So there's a lot of videos there, I can send you the link so that you can take a look. But
Marily Nika
00:01:48
she's amazing, and I encourage you to to fully take advantage. So the fact that she's coming and really listen in and ask any questions you have
Marily Nika
00:01:56
now seeing
Marily Nika
00:01:59
it. It was supposed to be 1 h so 9 to 10. But it looks like she has a lot of content, and I don't want to interrupt her, so I will let her go an hour and 15, or even an hour and 30 min. And if you have to go, that's only okay.
Marily Nika
00:02:14
But for my boot camp students we had a coaching session, anyway, after. So I may actually move the coaching session to another date, just because I want to make sure to give enough time to her because she has a lot of very interesting content to share. So let me share my screen
Marily Nika
00:02:31
and show you what that content looks like in case you are not familiar with the platform yet. So
Marily Nika
00:02:40
There we go.
Marily Nika
00:02:42
So this here is your portal, right? We've shared it before.
Marily Nika
00:02:48
and if you as you scroll
Marily Nika
00:02:52
all the way down. And, by the way, here's how you access the recordings of the previous sessions, you click here and I am gonna upload the slides so you'll be able to see slides here as well. But what I'm talking about is this, so she has sent us all this content just for you
Marily Nika
00:03:08
in case you wanna do more Google lab tutorials, python tutorials, Ml, tips and tricks. Cheat sheet, which is actually great. There is a video for the volusion of Lms that she has recorded for us subordinates sending an analysis, logistical regression, natural language processing. So I encourage you this and next week kind of pick it all in and go through it. I know it's a lot.

Marily Nika
00:03:34
So yeah, today we'll discuss everything you need to know from a technical perspective. She's not gonna like. Please don't be overwhelmed or intimidated. The the work she will show you is not what you need to be doing, but it's what she will, she does once you works with pm, so it's more like understanding and empathizing for your scientists, if that makes sense.
Marily Nika
00:04:00
Alright. So we have 20 min. 25 min before she joins in, and I had a couple of slides. I wanted to go through with you, and we can kick off a little discussion. So
Marily Nika
00:04:14
the slides I wanted to kick off are if you, as an pm, have an idea about something you want to get created.
Marily Nika
00:04:22
You'll create your P. Id. Just like we talked about right. The next step is to add in your Pd the software engineer you'll be working with, and the research scientists that you'll be working with.
Marily Nika
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and they will add comments that will go through it. They will ask questions. They will tell you if something is absolutely not feasible. If something is feasible. And you will have kind of this live document
Marily Nika
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that's gonna go back and forth and back and forth until you all feel good about the scope of the project. So when the scope is ready, the scientist will take
Marily Nika
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the scope, and they will actually want to create a model that they can train just like we talk about with the data and data collection all these things.
Marily Nika
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they're not gonna reinvent the wheel. There are a lot of
Marily Nika
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algorithms that are ready for them to use. So being a machine learning engineer is kind of like figuring out which algorithm to use for which use case.
Marily Nika
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So let me give you an example here so that we can speak specifically. Let's say I'm at Pm. For spotify. And I wanna create a widget within the Ui. But you see that he's going to be recommending for me playlists and songs. That I should watch.
Marily Nika
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So I will write this up and appear the the whole behavior. What the widget looks like how many songs it has, and all this things. And I'll give it to my research scientists.
Marily Nika
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And then my research scientists will need to come up with an algorithm for recommendations.
Marily Nika
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Whenever you hear recommendations, there's an algorithm called collaborative filtering. It's a very standard kind of algorithm for this sort of thing. And
Marily Nika
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what this does is.
Marily Nika
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Let's see, we have person, A and person B, and person. A has a playlist person. B has a playlist.
Marily Nika
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It looks into this songs that you have on your playlist. Let's say you have 10 songs.
Marily Nika
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and then it looks at other people's songs in their playlists.
Marily Nika
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and they see the Delta. So let's say I have
Marily Nika
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10 songs in my playlist.
Marily Nika
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and then person B has 9 out of these 10 songs in their playlist, and then person C has 9 out of these 10 songs in their playlist. So they take the different one, the tenth that is not in your play that is not in their playlist, and it actually surfaces and recommends it
Marily Nika
00:06:48
so essentially. All this does, is it says, Oh, hey! People like you enjoy this. So you
Marily Nika
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should also enjoy it. And you take it and they surface it to you in the switches. So that's all. They do. So this algorithm find songs that fit your profile, that you have not listened to. Okay
Marily Nika
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and
Marily Nika
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And, by the way, this this was a simple example, imagine that this happens? At the same time for billions of playlists right?

Marily Nika
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And as a Pm, you have certain metrics that you wanna measure success with, for example, especially for streaming services. It's always listening time more than watch time. So you wanna make sure to maximize these.
Marily Nika
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And so what? The so the scientists will come up with this algorithm collaborative filtering, they'll develop it.
Marily Nika
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And they'll work with their software engineer to integrate this model. And this experience within software within spotify. Now, the next thing we're gonna do is we're gonna launch this feature, not to the entire population. We're gonna launch it to 1% of our population.
Marily Nika
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And we are going to be measuring reasoning time, which is our key.
Marily Nika
00:08:06
geometric.
Marily Nika
00:08:07
And we're not going to say, Okay, here's what.
Marily Nika
00:08:09
Listen! Average listening time per person.
Marily Nika
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that good surface. This widget looks like versus people that were not surfaced, this widget.
Marily Nika
00:08:19
and you will compare, and you will see, and you will essentially this hypothesis and say, Okay, my hobby hypothesis is for the high. If I have, yeah, if I have this widget that is, provide good recommendations and transitions for the users. They're more likely to keep staying in and keep listening to song. So it's it's maybe test. Absolutely.
Marily Nika
00:08:42
If you see that the using time is increased with your experiment, you will launch this to 2% of your population.
Marily Nika
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You will keep running with an experiment. If things still look favorable with the widget, you launched 5%,
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10%, 50%. And then a hundred. So this is kind of the process.

Marily Nika
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usually it can take like 2 weeks to round up to a hundred percent and you want to make sure everything is right. You want to make sure this makes sense.
Marily Nika
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Now let's say you've launched your widget and your listening time goes up, and it's all good
Marily Nika
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things. Don't stop there. Usually you will have some form of feedback that you will ask
Marily Nika
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your users that get servers this widget, and you will say, Hey, what do you think of the recommendations? Are they good? Are they bad? Or I think on it's an individual song. People can say, Hey, I love it, or I hate it all super good.
Marily Nika
00:09:42
So you will take the feedback that comes in.
Marily Nika
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and then you will have enough data to retrain the model. We train the algorithm so that you can surface even better recommendations.
Marily Nika
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So now there will be a point where you will have
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your standard widget that has the model, 2.1, and then you will have
Marily Nika
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an experimental version, which is model 2.2.
Marily Nika
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So now then, you will need to run another A B test where you compare the 2 different models with each other. So you learn you have your model. That's out there in the world. And then you have model 2.2 that you can open up to one of the 1% of all population you compare listening time, and so on. So, being an Ipm is full of these experiments like, I will go to work.
Marily Nika
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and I will have 10 of these that I need to monitor. And sometimes it's not that simple. Sometimes there are trade-offs like, Hey?
Marily Nika
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Least I think time is up. But people will pay less.
Marily Nika
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Or let me give you an amazing example that I asked as an interview question, actually, which is you're paying for Youtube.
Marily Nika
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And you see that comments are up.
Marily Nika
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But watch time is down.
Marily Nika
00:11:02
What do you do? Comments are up. What's them is down on Youtube. What on earth is happening there?
Marily Nika
00:11:09
So you will get things like that at your day to day life, and you will need to investigate and figure out what's happening and then figure out the right strategy. Right? you know, I'm not gonna give you the answer for the Youtube, because I want to. I want people to kind of think through it, because it's a very interesting question. And, as I said, like I,
Marily Nika
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I used to ask this
Marily Nika
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second. You say the cut of piggy occurs with scarf
Saket Tiwari
00:11:37
just to cut off of one participant watch the videos. So if it's early on and then they're leaving a comment, then the video quality is probably probably probably poor.
Saket Tiwari
00:11:46
That's where I was kind of going?
Marily Nika
00:11:48
Very, very good. Okay, actually, this is a great way to make consult. Let me ask the question properly. So
Marily Nika
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you are the Pm for Youtube. And one day you go to work and you realize that the amount of comments people leave in a video is 20% increased.
Marily Nika
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But the watch time is significantly decreased. You don't have any data. You just know that people just come and wait more and watch with less. Okay. we? We always ask it. Milo is asking, are the comments positive or negative? They have not. The composition has not changed at all, as opposed to what they used to be
Marily Nika

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before, like yesterday. James. Yep. So James says, let's look into internal and external factors. Okay.
Marily Nika
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So in order to tackle and interview your question like this. Obviously, you have all these suggestions right? But you need to take a step back and provide a little framework. So you need to say, hey? First of all, Mary, I wanna clarify what I understand, the metric, the exact metrics you're mentioning?
Marily Nika
00:12:56
I wanna understand exactly the question. What they try. What do I need to investigate? And then I'm gonna explore internal factors and maybe going on exactly work, cause analysis. Internal factors may be
Marily Nika
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it's the dashboard and tracking things properly.
Marily Nika
00:13:13
Is is there any other product cannabilizing our work that go launch?
Marily Nika
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Is. It's
Marily Nika
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a specific surface, like a patch that got released only for mobile phones, or only for tablets? External factors would be things like
Marily Nika
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Is there? Is that a war going on, or is it Christmas, or is it like a very special time of the year? Or, you know, was there an issue with credit cards and people can access our premium feature. No more things like that.
Marily Nika
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I love this. So did our competitor, releasing your feature. Amazing question. And no, no new feature from the competitor.
Marily Nika
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Is it an instance or a trend? Is this happening in particular? Geographic location? No, it's having it everywhere.
Marily Nika
00:14:04
I love this. I honestly are very curious to see who's gonna find what has happened? I love it. Recommendation videos. Is it a ui change? It's not a ui change.
Marily Nika
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Is it something caused by bots. Very good question, you know. Someone can learn some bots that just comments everywhere. But very good question. But no, that is not it released an AI feature that summarizes the video for you. Automates, comments. Very good. Nope, that's not either.
Marily Nika
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I wanted to see what's happening with other engagement metrics like shares and likes. Yep. Also the timing. When the comments happen. Okay.
Marily Nika
00:14:46
controversial comments has the algorithm changed users not liking recommendations, censorship. This is amazing. I love. It
Marily Nika
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updates by Youtube demography. Alright. we have a winner. We have a win there. The winner is Sean Peters.
Marily Nika
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Sean said. Hey, how about how about shorts versus regular video. So what happened there? And this is a real thing
Marily Nika
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shorts Youtube shorts lunch, which is short form videos. And one day they lunched and they broke all the metrics because shorts are like 1015, s videos. But people will comment a lot in them.
Marily Nika
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But watch time. The average watch time went from 5 min to boom, to never shrink, but the met, the comments were much more so. We're kind of like what is going on, what is happening. So well done, Shawn. That's exactly what happened. And
Marily Nika
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this is an excellent interview question, because
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if you don't go through the framework we discuss, there's just no way to figure out what on earth could be happening there. So you need to look into competitor launches. Yeah. But you also need to to look into a Jason lunches. And in these companies, it's such big, big
Marily Nika
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so many people working on the same product that you. You need to see who's launching what is happening. And so so
Marily Nika
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love it. Love the discussion. I have so many more of you. If you are interested.
Marily Nika

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Alright, that was fun. I have more. Yeah, we can. We can discuss that tomorrow. Okay.
Marily Nika
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so Sandy says, do Aipm typically own or assist with the right data collection or synthesizes the data required or the discussions on which attributes all the data to use for the role type or the Mpv, okay.
Marily Nika
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So once you scope out your project, you'll write your peer, D, you'll share it out. And then the Richard scientists will take that and they'll create their own design document. That's what it's called
Marily Nika
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in the design document. They will write how much data they feel, the need that at least minimum in order to have some meaningful model trained.
Marily Nika
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You are not gonna do the data collection. You do not
Marily Nika
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own that part.
Marily Nika
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but you will need to staff the team with a program manager. That will be the data collection program manager if you want
Marily Nika
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to. Indeed, collect data.
Marily Nika
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Now, it's interesting, because in some startups you'll need to do their collection as a Pm. Right? But in the big tech company that are orgs that run these things.
Marily Nika
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what you do still care about is to make sure.
Marily Nika
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You know you're the glue of all the departments, right? So you wanna make sure that the program manager knows exactly what the scientists need.
Marily Nika
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It's I mean, it's 2074 to this day, you know, communication between the Paris doesn't happen efficiently, and it's up to you to make sure
Marily Nika
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requirements are translated, and requirements from the scientists are translated in the right way. The program manager. Now, the problem manager doesn't really understand. Why we're doing this doesn't really understand exactly the importance of mood quality. So you want to make sure to include your PE program managers in the discussion so that they can know the importance of
Marily Nika
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high quality and exactly the type of data you need. So you assist in kind of the strategic level and in making sure that they know what they're doing and why
Marily Nika
00:18:30
I, in the beginning of my career.
Marily Nika
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11 years ago, I was a product product manager that engaged in active data collection.
Marily Nika
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So what did I do? I? Actually.
Marily Nika
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we had to collect speech data, okay, speech recognition people talking.
Marily Nika
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And
Marily Nika
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you know, they had the program manager had literally recording the recording app on the phone, and they would go out there and record people.
Marily Nika
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and then they would come back to the office and bring us
Marily Nika
00:19:04
50 devices. They will drop them off in my desk. And they would say, Okay, all the data is here.
Marily Nika
00:19:12
And I was kind of like. I have no idea who collected, whom. I don't know what they got asked.
Marily Nika
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how do I download on this? And how do I have any label as to like, what am I supposed to do? So what I did there is.
Marily Nika
00:19:27
I created a Prd. And I said, Hey, I am going to develop the simplest voice data collection app and I work. I grabbed one of one of the engineers and I said, Hey, I don't care about you eyes. All I want you to create is literally
Marily Nika

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a ui that has a record button. Sorry the ui that surfaces prompt.
Marily Nika
00:19:45
and then it has a record button. And once this happens, I want you to download automatically
Marily Nika
00:19:50
the audio and send it to this storage place.
Marily Nika
00:19:55
So we created that. And then what we did was in all these 60 devices I talked to you about. They had this app so they would go out there in the wild collecting data with that app.
Marily Nika
00:20:07
So the app was following in all the data in this storage.
Marily Nika
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And then what the program manager had to do is find vendors. To go through that data in the storage and clean it up, move it around, make sure it it meets the quality bar we need. But yeah, like as a Prof. Manager, you will need to hustle. But you need to be creative, right? If you wanna if you need to create an app, get out there and create an app.
Marily Nika
00:20:33
And I think these are the qualities you want to have as a product manager, which is to always come up with ideas, not be afraid to hustle, and when you see something that can have a product attached with please back to it.
Marily Nika
00:20:46
So
Marily Nika
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that's kind of what I've I've done in my area and was interested. Okay.
Marily Nika
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is an aip and responsible to define what inputs need to be considered to train the model, see? And an optimal output. No, not at all. This is is assigned this for so they will think about it. They will come up with it.
Marily Nika
00:21:06
They may discuss it with you.
Marily Nika
00:21:08
if it's something that's a bit more tangible like I was working, I told you for the A. R. Team at Google.
Marily Nika
00:21:16

If it's something more tangible, they will come to you. And they will say, Hey, we're taking as an input
Marily Nika
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like, what what the user sees from the camera. Specifically, if this is about exercising and running around, we wanna take as an input like the the weather cause, this is important.
Marily Nika
00:21:33
So depending on the experience you want to create, you might have an input. But typically, no, we do. Not defining what inputs need to be used.
Marily Nika
00:21:43
Mary, what is your view for blockchain technology. Please share your view on the Meta version. 3D gaming
Marily Nika
00:21:50
sandwich. You talked about blockchain maneuvers and gaming. Let's see, where do we begin. So I'll talk to you about the metaverse cause. I that was my most leading avatar within meda.
Marily Nika
00:22:02
I think that we are still 2, 3 years away from it, becoming mainstream, and people really embracing it
Marily Nika
00:22:11
and not afraid of it.
Marily Nika
00:22:13
I don't. I still don't think like, even in this group, right? Can you raise your virtual hand if you own a VR headsets
Marily Nika
00:22:22
like I don't think it's gonna be even 50% of the people. Let's see
Marily Nika
00:22:28
you own button. Use your son has 2, and that's awesome.
Marily Nika
00:22:34
So that's the thing. Once every once this becomes normalized to own a headset, and then to realize that
Marily Nika
00:22:43
your friends own it, too. And you can all collaboratively do something there. That shift. I think it's gonna take 2, 3 years now.
Marily Nika
00:22:51

There aren't enough experiences right now in there, like, sure, there's Beatsaver and all these fun games. Yes, but that's not. Gonna take it mainstream. So
Marily Nika
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in 2 3 years. There are experiences getting created that are amazing. the the codecabaters, which is what I was working on, which is going to be being able to see me just like this. It's gonna be game changer.
Marily Nika
00:23:13
But I think more. We're still 2, 3, 4 years away from it.
Marily Nika
00:23:19
3d gaming
Marily Nika
00:23:21
II do think that this you know, VR, and er is gonna make it more mainstream. But I don't think you know anything's gonna change to make it even more. Mainstream.
Marily Nika
00:23:34
Yeah. So these companies are trying to figure out good use cases, for we are for average consumers. And an amazing use case is collaboration and work
Marily Nika
00:23:42
right. The thing is, though, if you put this headset on right now, they have, like created this amazing virtual workstation. You can see all these different screens and all that stuff.
Marily Nika
00:23:52
but the hardware. The headset itself is heavy, and they will give you a headache after a while. So you see, there are like still fundamental things to solve before we need to think about how to make these things
Marily Nika
00:24:07
mainstream. So it's happening. It's slowly happening. But I don't think it has died or anything like that. I think it absolutely
Marily Nika
00:24:14
it's gonna work. We are
Marily Nika
00:24:17
a remote work like the used cases. Go to Hawaii and put that headset on, and you have your workstation there. You don't need anything else right? And not only that, you can also meet
Marily Nika
00:24:28
the people that you are working with. So it's I. Just I, personally am very passionate about it. But we're not there yet.
Marily Nika

00:24:36
but the right steps have happened. And it's it's not gonna happen
Marily Nika
00:24:41
alright. So we'll says these things. More important have the main knowledge in the applied area and picking up the AI component as you go, or having AI knowledge and picking up the domain knowledge. Here you go. Wow, okay, this is an amazing question. Let's see.
Marily Nika
00:24:56
I think that right now.
Marily Nika
00:25:03
where the whole AI Pm domain is still
Marily Nika
00:25:07
getting created by some companies, you're better off having some domain knowledge.
Marily Nika
00:25:15
and then they all hire you there, and you'll pick up things as you go
Marily Nika
00:25:19
versus in 3, 4, or 5 years from now we're
Marily Nika
00:25:22
they will look into AI, and they will say, Okay, this person knows AI. They'll see your address.
Marily Nika
00:25:28
So right now, if you are an expert or have a niche or something. That's it. So every like I do coaching and every single person I quote. The first question I have for them is.
Marily Nika
00:25:38
Why is your niche?
Marily Nika
00:25:39
They're like, Oh, I'm a season. Pm, like, okay. Season. Pmu. In what? Like Whoa, I bring experiences to life.
Marily Nika
00:25:45
What experiences, you know. So I need you to find your niche, and then if you dig deep, you will say, Well, I've done these 3 or 4 things well, I guess.
Marily Nika
00:25:56
Fintech, and then I look into the version I'm like, yes, absolutely your Fintech. Pm, and you've had the AI component. So please find your niche.
Marily Nika
00:26:05

All these jobs you're finding in this awful market right now in the Pm. World. Have a
Marily Nika
00:26:13
niece that they're looking for
Marily Nika
00:26:15
recommendations, Fintech. Personalization. So we're not. We're far away from having the AI Pm. Generally's track. So please, if you have any search word, find it, and advertise yourself as that on Linkedin.
Marily Nika
00:26:31
This can be your passion.
Marily Nika
00:26:33
It's interesting because, I was at Google for like 7 or 8 years. And I was
Marily Nika
00:26:40
2, my needs was too specific. I was doing speech for 70 years.
Marily Nika
00:26:44
and companies will tell me. But can you do this other thing? Other thing being, you know, like vision, something like Jason, right? And it was very interesting to say, oh, I need to hide my niche
Marily Nika
00:26:55
that was back then. Now you need have a niche.
Marily Nika
00:27:00
and yes, and someone is asking. Yes, I do. Coaching. I have a link. You can book me for coaching anytime. We can do more contributors. We can make your regimen together.
Marily Nika
00:27:09
If you upgrade to the book. And we do group coaching sessions actually and for my goodcom students that are here, we're gonna cancel today's coaching session because we're gonna run over with our amazing machine learning scientists today.
Marily Nika
00:27:23
Okay, I am gonna answer one or 2 more questions. And then we're gonna hand it over to our scientist. Okay?
Marily Nika
00:27:30
So as a Pm. In payments company, what are your thoughts on the AI playing role in fraud and risk? I'm planning to propose, Jenny. I hackatham. Awesome idea, awesome, awesome, awesome, awesome.
Marily Nika
00:27:41

AI is excellent for fraud and risk. Of course you can detect any anomalies, and immediately flag things to you and your leadership like. If anything, I'd be shocked if they don't already have something like that.
Marily Nika
00:27:55
And yes, Jenny, I hack on sounds amazing, but
Marily Nika
00:27:59
it doesn't have to be Jim AI Hackham. It can be AI hack of them in the sense that you're like, okay. Well, I'm gonna figure out for them risk. And then, Jenny, I. So what are you gonna generate? Right?
Marily Nika
00:28:10
So AI is bigger than right. Yes, harsh, exactly, exactly. Exactly. So. Question.
Marily Nika
00:28:17
can you and niche be conversational? AI, instead of an industry-specific niche?
Marily Nika
00:28:22
Absolutely absolutely conversational. And AI is a huge deal right now.
Marily Nika
00:28:29
and it's very interesting, because all these people that we're working on, you know, 2,015 like Chatbots and figuring out. you know how to
Marily Nika
00:28:40
create this
Marily Nika
00:28:41
customer service that's automated. Now have become the experts in this right?
Marily Nika
00:28:48
I want to show you one more thing. So in my
Marily Nika
00:28:56
So I had have posted in my
Marily Nika
00:29:00
in my newsletter the different types via Ipms. Okay? And I have some interesting like, I encourage you to check this out. So you can have someone that's an AI infra platform. Pm, that manages infrastructures or platform.
Marily Nika
00:29:14
which is kind of the back end. But like it's a huge deal. A lot of people are hiring for platform pamps
Marily Nika

00:29:21
ranking as well for search results. Angie feeds. So companies like Yahoo, Google, are looking. Not just that with pinterest. I think they were looking for ranking.
Marily Nika
00:29:34
So 95 pm, so this is more like, what kind of content do my users want to see? And how do I work with sign this in order to generate this kind of content? Recommendations might be the most popular
Marily Nika
00:29:48
kind of area right now. And as you all know, I recently was interviewing cause I left Meta
Marily Nika
00:29:57
and I grew for a job that was about leaving the entire recommendations within the company, and
Marily Nika
00:30:04
the hiding monitor said, Hey, I have no idea how to do this. I need someone that knows I need someone that comes in and leads this because I don't know how to do it.
Marily Nika
00:30:12
So this is the dynamic. You see.
Marily Nika
00:30:14
the managers have no idea how to do this, so you'll come in. Say, yep, I got this this way. That's what you need to do.
Marily Nika
00:30:21
Responsible. AI privacy, huge deal ethical fairness, transparency bias prevention. Everyone will need someone like that
Marily Nika
00:30:31
personalization absolutely analytics. When we sessionally, I just like, we talk about computer vision security. Yeah, healthcare. So there's just so much in there, and the more specialized you are the better it's gonna be in this market.
Marily Nika
00:30:46
Alright.
Marily Nika
00:30:50
alright, yes. So
Marily Nika
00:30:52
I am going to upload all the slides in our portal now. What I would like to do. And I love all your questions. This is amazing.
Marily Nika
00:31:05

okay, I'll take this last question because it's interesting from Rafael. So Rafael says. I mean the Fintech Company. Now, AI is focused on business risk and fraud.
Marily Nika
00:31:15
I'm interested in AI for product. Do you have any suggestion on how to address it?
Marily Nika
00:31:21
Let's see.
Marily Nika
00:31:23
Well, you can create a little
Marily Nika
00:31:26
feature. Okay, so feature is kind of the right word for what you're looking for. Actually, you know what you should do. You should use my AI product to be team. That's what you should do. It is gonna come up with your ideas for you. I think that's that's exactly why I created it. So let me send you the link so that you can do this?
Marily Nika
00:31:45
Alright.
Marily Nika
00:31:46
These are amazing questions. And I see that our amazing research scientists has joined in. So what I would like to do is
Marily Nika
00:31:55
introduced here and then jump in. Okay.
Marily Nika
00:32:00
So what I talked to you about is when we as product managers come up with an idea on something. We wanna create like some sending an analyzer or anything like this.
Marily Nika
00:32:11
We'll write the peer knee. We'll share it with
Marily Nika
00:32:15
our research scientists team and software engineering team.
Marily Nika
00:32:19
the software engineering team. Let's start with them. What they will do is they will just take
Marily Nika
00:32:27
what was created by the scientists. They'll work with Ux, and they'll integrate the experience together.
Marily Nika
00:32:33

But when you work for the initiative science specifically.
Marily Nika
00:32:36
they will build a model that we'll provide the answer that will solve the problem that we're you're looking for.
Marily Nika
00:32:44
So she'll tell us how she works with Pm's. But essentially she'll take the requirements from a product perspective, and she'll translate it into a model.
Marily Nika
00:32:53
So what we will see today.
Marily Nika
00:32:56
what we will see today is how she works day-to-day to solve a problem
Marily Nika
00:33:03
did not get intimidated by the amount of code. You see, you're not gonna have to do this, but I want you to understand how she works
Marily Nika
00:33:11
day to day.
Marily Nika
00:33:12
and she actually will have an optional homework to give you, which I think is, gonna be great
Marily Nika
00:33:18
great, great, great opportunity for you to learn and ask her any questions. Okay, so I'll pass it on to her. If you have any questions, please keep typing in the chat.
Marily Nika
00:33:27
If you have any question which is like, Oh, God! I don't know. Idea what's happening. Please pause, take a step back and explain. Raise your virtual hand cause we want everyone to follow. Okay.
Marily Nika
00:33:39
So with no further ado, I want to introduce our fantastic machine learning scientist. Nicoletta, thank you. It's we're so happy to have you here again. Everyone is so excited to meet you
Marily Nika
00:33:53
and I'll let her take you from there. Please type in the chat questions.
Marily Nika
00:33:58
Raise your reach your hand if you're completely freaked out, which is totally fine. This is a one-on-one course. I want everyone to be comfortable. Alright, thanks. Take it away.
Nikoletta B

00:34:08
Okay. Hi, good morning, everyone. I'm happy to be here again. I always enjoy. Marilla is courses so as Marilyn mentioned today. we'll go over. Let me start sharing my screen. Actually, so that we have
Nikoletta B
00:34:22
my slides.
Okay, you can see my slides right?
Marily Nika
00:34:35
Yes.
Nikoletta B
00:34:37
get me.
Nikoletta B
00:34:40
Okay.
Nikoletta B
00:34:42
so what one I'm going to cover today. So as Marilyn mentioned, I want to have an idea a little bit of
Nikoletta B
00:34:51
what we have in our mind when working like on a problem. So and we will have the assignment in the end. And as Marilyn mentioned, it might sound a little bit too technical, too much coding, but this is mostly for a demonstration like to see, like all the steps that needs to happen. Let's say, in order to train the model, how you get the data, how you work on the data and how you evaluate your model. This is mostly like
Nikoletta B
00:35:20
as a demonstration, and there is also an optional exercise that you go over. But before we go into the demo part, I would like to share a little bit some information. Some basics on the terminology, on lands, language models. What is the language model? And some of these are in the workup, warm-up material
Nikoletta B
00:35:40
that was shared with you. But I want to make sure that we have a common ground. So we set the terminology straight. And you know, when we're talking about language models, you have some information about like the underlying technology. And then in the end. We will go over a little bit about the training paradigms, and this will lead us to the exercise in a smooth way. So let me start with.
Nikoletta B
00:36:08
II don't know if I can say the motivation. I'm pretty sure that all of you that are here are motivated, and you know, you are all interested in AI, especially after the boom, or even before. So your mind might look like this like you have all this gp, like models in your mind, and

Nikoletta B
00:36:28
but
Nikoletta B
00:36:30
before we'll go into the details of this I just want to share, like, just like the terminology. So you can see like here in this image. I have artificial intelligence, machine learning, deep learning type of science. And I'm pretty sure it's they are terms that you have
Nikoletta B
00:36:50
I used, and you know, ready. So what is artificial intelligence? So very simply, it's like, our effort to make machine seems like they are human, like, they have human intelligence. So and what do we mean by human intelligence? So
Nikoletta B
00:37:07
we want
Nikoletta B
00:37:09
systems that can be like, independent of the human that can feel like a human vision like a human, and exhibit human-like behaviors. And
Nikoletta B
00:37:21
the foundation of all these like. Now we are talking about AI and wept. We think that we are closer to this AI capability. Is the machine learning. So machine learning has been around for years. It's not something new, and this is the foundation. So it's the field of study. But
Nikoletta B
00:37:44
allow us to. I give this, the computer, the ability to learn without being explicitly programmed. And what I mean by that is like, I don't have to write down all the steps that like.
Nikoletta B
00:37:57
let's say, in order to do let's say, a simplistic task. You know. An addition. Or, you know, very simplistic. You have to tell to the computer. You take the first number, the second number, and then the addition operator. And you do this like very simplistic in machine learning, you just fit the data. And we will go into details about this later. You feed the data. And then you
Nikoletta B
00:38:23
the the the system. Lens, learns the task knows what to do.
Nikoletta B
00:38:29
A more is some field of machine learning. It's deep learning. Until you all know already that deep learning uses neural networks that has many, many layers, that that is the meaning of deep. So again, neural networks has been around for many, many years, but
Nikoletta B
00:38:47

due to like hardware limitations, they couldn't go that deep into all these complicated operations and computations. So now with Gpus, we have this capability. That's why we can start like a lot of layers and have all these big mobiles
Nikoletta B
00:39:05
and that are really powerful.
Nikoletta B
00:39:07
And you see here, from the from the email, so that all these fields go hand in hand with data science. So the common denominator for all this is the data. So we cannot do anything without data. We need to have some data that either we can annotate some data, we collect some data.
Nikoletta B
00:39:26
And somehow we have to create this data depending on the task. And this that can be a role like I'm structured.
Nikoletta B
00:39:34
Or it can be instructed data like date, like tables from databases. whatever you can think of depending on the field you are working on.
Nikoletta B
00:39:44
So I think if you have this picture on your mind, it's a good
Nikoletta B
00:39:49
you know, layout of the different fields, and how they are related together.
Nikoletta B
00:39:54
And then. Now I would like to go over a little bit further and talk about the history of AI.
Nikoletta B
00:40:02
And I want to say these from 2 main aspects, the one is emergence, which is actually the behavior of a system that is implicitly infused rather than explicitly constructed. And what I mean by this is like
Nikoletta B
00:40:21
what the what the the system is learning only so that we don't give it into input. But this is the mentioned feature of behavior.
Nikoletta B
00:40:30
and from the field homote of homogenization
Nikoletta B
00:40:34
which actually refers to all these
Nikoletta B
00:40:39
methodologies that come together in order to build these machine learning systems.

Nikoletta B
00:40:46
And all these come from an amazing technical report that's done for the researchers.
Nikoletta B
00:40:53
put out. And II think it's the best history of AI I have seen, and I think if you have this in your mind you will have a better understanding of how things have progressed, and deeper knowledge of what's going on. Under the whole, I will not go much into details, but I think the information that I will share it will be enough. We don't have but many time either way. So around 90 s, like, we started talking about machine learning.
Nikoletta B
00:41:22
So you might have heard of algorithms like K-means or say Osbm or other forests.
Nikoletta B
00:41:29
So what was imagined there was the the how. So, as I mentioned earlier, we didn't give the the explicit algorithm. We just gave the data and then, some way for the for the system to work on the data, and then you had the result.
Nikoletta B
00:41:51
And in the homogenization space what was like consolidated what we also had to do to give with the data was the learning algorithm. So we had to pick
Nikoletta B
00:42:03
for the data we're having for the application. We're having what levin algorithm we're gonna use are we gonna use? Svm, are we gonna use random forest? So for example, if you had some data and you had categorical variables like.
Nikoletta B
00:42:17
something is positive negative neutral like this is kept in different categories. And at the same time you have. You had numbers like some ratings. 1, 2, 3, 4, 5.
Nikoletta B
00:42:32
So you have all these mixed type of features. You would probably go with a tree like approach like random forest. So I understand that based on the data and the task, if it's a classification or a regression.
Nikoletta B
00:42:45
you have to pick the learning algorithms, but just fit the data, and then you have to pick. I will solve this with, Madam Forest or Svm. Or K-means. If it's a unsupervised classroom
Nikoletta B
00:42:57
when we move to 2010. We started talking about deep learning,
Nikoletta B
00:43:05

and there again, as I mentioned, the common denominator is data. But what was emerging was the features. So we were feeding the system. Pro features, let's say in image processing, you have an image. So you have the pixel of of the image like the the RGB values
Nikoletta B
00:43:26
you. You were feeding this into the network. The network was, the the data was passing through all these deep layers and in order to do, let's say the classification task, if it's a cat or a dog.
Nikoletta B
00:43:40
and that you could see from the final layers of the network. What that.
Nikoletta B
00:43:44
what the network was is actually learning is like higher level features. And any months, let's say, where are the edges? So
Nikoletta B
00:43:55
in that sense we didn't save a model that here is the image. Here. Here are the edges. But the the network was able to learn this from the statistics of the day of the data.
Nikoletta B
00:44:07
And then what was the common denominator? What is a common denominator in this field? In group learning is the architecture. So as we in machine learning, we had to pick like Svm. Or whatever for deep learning, we have to pick the right architecture. So
Nikoletta B
00:44:25
if we were doing like image processing that I mentioned earlier, you would go with the
Nikoletta B
00:44:33
probably a Cnn architecture like the foundation. The the main architectural
Nikoletta B
00:44:40
component would be Cnn's. If you would go with text processing or Time Series processing. You would go with Rnn's or Lsdms.
Nikoletta B
00:44:52
And you know things were evolving like with you know, architectures like very specific for the task. So you see how things are progressing. We are going a little bit from
Nikoletta B
00:45:04
low level to a little bit higher level, from learning algorithms to architectures. You know, you know, we all know that we don't know exactly what is happening in this deep neural network what they are learning. But we get some hints right?
Nikoletta B
00:45:22
And in 2018 we have the foundation models.
Nikoletta B

00:45:27
and what is actually mentioned. There is
Nikoletta B
00:45:33
functionalities. Again, we're figuring some data, and when you you fit some day a lot of data actually to train this models but what is it mentioned is a functionality. So now you can interact with antiquity like models. And I know maybe you have had this term in context. So basically.
Nikoletta B
00:45:54
you just provide the prompt and a few examples. And you get the answer that you want. This is a functionality of these models. And what is the homogenization part is like
Nikoletta B
00:46:10
the model. So now we don't pick architectures, we actually pick a model. So if you're working like, if you're thinking on a generative AI space and on the Tpp space.
Nikoletta B
00:46:21
and you have a task, you might think, okay, what model should I pick? Should I pick this model or that model? And the differentiator in making this decision depends on a lot of things right? You know, ready that there are
Nikoletta B
00:46:34
open source models like llama
Nikoletta B
00:46:38
orca, whatever. And there are proprietary models that you have to pay like open, say, and so forth. So and there are a lot of differentiations like, when you have to pick like. How? What is the context window like? How much data you can fit in the prompt like. You cannot like this.
Nikoletta B
00:47:05
It gives you like how much memory the model has
Nikoletta B
00:47:08
or how what languages are supported like. Also, languages are supported, or just only English and a couple of languages. What data is trained on? What is the size of the model. Right? If you want to.
Nikoletta B
00:47:23
This models are really deep, so they come bigger and bigger sizes. So if you want to build a mobile application. You have to consider all these. And this goes hand in hand with latency. You want to get the response back
Nikoletta B
00:47:37
to the user quickly, and of course, the cost. If you're going, even, either you go with open source or proprietary models you have to take into account the cost, and we will cover this in more details in the advanced course. So but that. But just to have an idea, if you have this, you know,

schedule your mind that machine learning is how and the algorithms we are picking an algorithm for deep learning.
Nikoletta B
00:48:00
The features are imagined. And we have to pick an architecture and the found that from the foundation models we have functionalities, and we have to pick the model.
Nikoletta B
00:48:11
And then, just to mention that I know that everyone now is talking about like AI and models. But
Nikoletta B
00:48:21
you know these areas are not dead right? Like these are like, they are evolving into like one area is built on top of the other. It's founded on top of the other. And of course, when you have to make a decision. You have to be smart enough to pick the right algorithm or the right
Nikoletta B
00:48:39
approach for your problem. So there are still applications that you might not need the large language model for different reasons. You know, it's very costly, you know, or maybe you have a very simple task that doesn't require the functionality of the of the mobile, of the of the Gp. Like models. Right? So
Nikoletta B
00:48:59
I know that we are like in the in this area. But you have to remind yourselves that there are other things that we can still work on. So it's
Nikoletta B
00:49:10
the easy answer is like, Okay, we go with a Gp. And this solves our problem. But we have to be really careful. We don't want to like
Nikoletta B
00:49:18
certain mosquito with accounting right? We have to be very smart of on what we are working on, what we are picking.
Nikoletta B
00:49:28
And very briefly, because I mentioned what this is foundation models. Just to clarify basically foundation model, as we can see here is a model that is trained on lots of data. And this data can be text imaging speeds, structured data, or say the signals from set sensors, let's say self-driving car. So
Nikoletta B
00:49:50
driving cars. And then the good thing with this model is that because they are trained, though big amounts of data and to broad data, they can be adopted to different tasks like western answering
Nikoletta B
00:50:02
image captioning object, recognition, and so forth.
Nikoletta B

00:50:05
So large language models are indeed a foundation models, because they have all these properties.
Nikoletta B
00:50:15
they are trained on
Nikoletta B
00:50:17
lots of data like I could say, like the whole Internet, the textual form of the Internet.
Nikoletta B
00:50:23
and they have general purpose that can be used for many downstream applications.
Nikoletta B
00:50:28
and then I will not go over into details. I'm pretty sure you have interacted with Cpt like models already. But some of the applications that you might have tried out is like storage generation. We can provide a few words and have the Llm. I give you story or do machine translation
Nikoletta B
00:50:47
from one language to another to the other. Of course you have to make sure that the the Ln. Supports this language that you want to translate to. You can use it to write code you can give like the instruction I want the code in python that does this.
Nikoletta B
00:51:05
You can use it to generate very, something very specific, like, create a dialogue.
Nikoletta B
00:51:11
and you can just give the first 10, and then you can go it even further to summarize the dialogue. and you can see here, if you take a closer look, that in the summary the most important points for the dialogue are in here.
Nikoletta B
00:51:28
You can use it to generate images from text. If you're interacted with or tally, you can, you know, define a textual prompt, and then have the the images
Nikoletta B
00:51:44
and
Nikoletta B
00:51:46
again, you can combine language and vision, and have some kind of multimodal dialogue. So I don't know you have seen or heard about Google Gemini. This was the big model that was released by Google
Nikoletta B
00:52:01
couple like one month ago, maybe. So you can see here like that you can through some sketch, and then you have like in a piece of paper, and then you have the language model generate some

caption of what you are drawing, and you can build this app like to the C, and then you get, as we go, to get more and more information about what this
Nikoletta B
00:52:24
what is the doc and get more information about the doc? Like what you would do if you were opening
Nikoletta B
00:52:30
the Wikipedia Wikipedia article about tax. So you say, you know already there are a lot of capabilities.
Nikoletta B
00:52:37
What is also interesting is like that. You said some presentation of information is also supported, and it's very powerful. So I have here, like, have us certificate to summarize in a table format that
Nikoletta B
00:52:52
the co-hosts of Marilyn Marilla's Pm courses. You see, they are all this is like from another session. So you see here, everything is presented in a table format. Because this is what I ask. And if you are working with other data, you can also ask, like to generate graphs for you in order to, you know, see patterns or your data.
Nikoletta B
00:53:18
and then I can go even further and say, I add a description to the table, you see and do more and more requests.
Nikoletta B
00:53:27
So
Nikoletta B
00:53:30
**and just to mention here. Because I mentioned shades and presentation. Maybe you have noticed already. So when Jj. Came out, like all these models are trained on data, but they are**
Nikoletta B
00:53:45
fixed to the data they were trained on right? So if a model was built like 2 months ago. Yeah, it doesn't contain information about something that happened yesterday.
Nikoletta B
00:53:56
So what is happened. There are techniques in order to to
Nikoletta B
00:54:02
to take into account this misalignment in with respect to time. But if you go now to and you ask like a question that has to take information that the recent, like the the one I asked, you will see that. they integrated sets like a common sets in the in the Internet, like, what? When you were doing, Google sets. But now it's like being set because it's supported by Microsoft.
Nikoletta B

00:54:31
So so when you are asking something that is outside of the of the data, like
Nikoletta B
00:54:38
of the data that the Llm. Was trained on, you will see that the the interface. There's some big searches happening. So the information is gathered, and then this information are fed to the Llm. Under the hold. You don't notice this.
Nikoletta B
00:54:56
They are fed into the Llm. In a very specific way.
Nikoletta B
00:55:00
So this is like the context. And then the Llm. Can take this information and do what you're asking it to do like present the information, the right information, what you asked in the right format, and so forth.
Nikoletta B
00:55:15
and
Nikoletta B
00:55:16
just to point out. So
Nikoletta B
00:55:20
you know all these are generative models, right? They are trained to generate text, so, no matter what you put into the prompt, the Llm. Will generate something. So
Nikoletta B
00:55:33
you have to be very careful about the output like
Nikoletta B
00:55:37
it doesn't mean that it will be like 100% correct. So it's a model, right? But it's a good starting point. They are powerful enough. It's a good starting point like for
Nikoletta B
00:55:50
the things that you want to do. But and you could have you want to try. But still you have to be very careful. Because, you know, we have heard about combination. And all these issues with Llm. So
Nikoletta B
00:56:04
good starting point, a good tool to have, but always have in mind that not all the information are correct. Some cases they are 100, some cases there might be, and
Nikoletta B
00:56:17
entering.
Nikoletta B
00:56:19

I will go a little bit. This is like an image from another good paper. It is called Evolutionary Tree of Fellow Labs. So you see here, like all the different organizations that release different Ellen's and if you would want to go into details about like different models, I would not cover this here, because the part is not to say all the models, indeed, in details.
Nikoletta B
00:56:47
You see that there are open source and closed source like the the grade, are like open source. We can access them. Without having to pay. But I, what I want to point out here is like, basically that you see, you see, like oops.
Nikoletta B
00:57:04
Sorry. You see the timeline here that things started from 2,018
Nikoletta B
00:57:10
and you see, basically 4 main branches of models, like, I think this is a good categorization.
Nikoletta B
00:57:20
And the II think this is a good schematic, because again, you say that you know, things has been around and don't be underline. Technology has been around for many years.
Nikoletta B
00:57:32
It's not since, like 2020 a while, but that particular activity came out. But let me explain like a little bit about these plants. And so you see the first branch here, like the gray one that has fast X go to vac and glovey.
Nikoletta B
00:57:50
So this was the best the first models, big neural network based models that were used to learn embeddings. And by embeddings, we mean, like, for like text, these are based on text applications text. I had this in the world of warm up material. But basically
Nikoletta B
00:58:12
when you have a piece of text in order for the computer to process it, you have to transform you can some numbers, some vectors, some vector representation. And this is happening with a very principled way, with different techniques. And there are different ways to do so like these ones that you see here.
Nikoletta B
00:58:29
And once you have this eventic representation, then you can use these for your task.
Nikoletta B
00:58:36
Then there is another family of models, what is called encoder only models and you see here, Bert is the first one, and then, you see, it goes up to Electra from Stanford, and so forth. So
Nikoletta B
00:58:50

with encoded only mobiles this. This was the time like that. The transformer architecture has been released. All these large language models are using the transformer architecture. It's very specific. I will not go into details again. But there are. If you want to get into that.
Nikoletta B
00:59:10
There are some pointers
Nikoletta B
00:59:14
in the form of material but basically we started using, like the transformer architecture, like deep networks, and and then encode like the the text into some better bedding, or Albert the bedding, or
Nikoletta B
00:59:31
Roberta, and all these different, all these models have some differentiator like so Roberta is trained on more data. This is, you know, a distill version might be a distill version of that. But you get the point. You have some data, and you have to represent it in
Nikoletta B
00:59:48
and in an intermediate representation that the system understand. And then this is a powerful representation, because it has captured, like the most important information from the data that you fit into the network based on the statistics. And then, since all this information is stored in this eventings, we can use this embeddings
Nikoletta B
01:00:11
for other applications, for applications like for sentimental analysis or speech, classification or image classification. This is like for
Nikoletta B
01:00:23
if you go like to other modalities, but for text
Nikoletta B
01:00:27
like sentiment, analysis, the same translation, or whatever.
Nikoletta B
01:00:33
Then there is the encoder decoder models. So
Nikoletta B
01:00:40
so, as I mentioned, they coded model has only one module, which is the encoding you pass the information in, and this information is encoded to this representation
Nikoletta B
01:00:51
in the decoder only you have also, after the encoder you have another module, which is the decoder. And what is happening there is that you decode you take again. This is the needed representation that the encoder generated, and you transform it into a text again.
Nikoletta B
01:01:09

And this architecture came out from us in translation, where you have like text like in English, and then you have to transform it in, say Spanish or
Nikoletta B
01:01:19
Friends, or whatever. So you encode some intermediary presentation, and you decode it again in text.
Nikoletta B
01:01:27
and these are then called a decoder decoded models, and the last branch is a decoder only models. Where
Nikoletta B
01:01:39
I have already talked about the decoder. So you know, basically, you're feeding some data. And you're actually generating data in the end. So all these generative AI, all these models that you see, like Gemini, are basically decoded, only model. So you give some text in the input and you generate some text in the output.
Nikoletta B
01:02:02
So from the transformer architecture they have only the decoder part, not the encoder part. Are there any questions
Nikoletta B
01:02:17
Before I move on to the next.
Nikoletta B
01:02:24
Okay,
Marily Nika
01:02:28
let's see. There. There are some questions. But people answered with each other, which is amazing.
Marily Nika
01:02:36
okay, yeah. Well, that's actually there's one question. Harsha doesn't have a question. Go for Harsha.
Harsha Srivatsa
01:02:43
Hi, Nicoleta, thank you for the can you give some perspective of you talked about the evolution of AI to language large language models. Can you give some perspective of how innovation happened in data, storage databases as well as hardware? And how did that come about lock and step and make this
Harsha Srivatsa
01:03:03
you know, (202) 023-2024. The, you know, all the innovations that happen. So what I'm trying to get is you know, I mean what? What all pieces came together. So that you know, we have this fantastic technology today.
Nikoletta B

01:03:16
Oh, that's a very interesting question like II mentioned already, like, you know, that deep learning has been around. Le neural networks have been around like since
Nikoletta B
01:03:26
1915. If I remember correctly.
Nikoletta B
01:03:31
but they couldn't go that deep, right? And you know, like, we started using like more powerful machines like Gpus, different version. So we can. We could go into deep and again like the same with storage space, right like. Now we are talking about like back to databases where we can store, like
Nikoletta B
01:03:50
lots of data in a vector representation. And do this all you know log architectures. And so for rag solutions and so forth.
Nikoletta B
01:04:02
and you know, software and hardware go hand in hand. I can write like
Nikoletta B
01:04:09
something that you do. You need to transform it by? You need to be supported by like the hardware. So
Nikoletta B
01:04:15
just for some example, let's say so. What that came out? They started with. You're laughing. So you're you have some knowledge
Nikoletta B
01:04:25
about it, maybe
Nikoletta B
01:04:27
so when bed came out there were like different favor favors, like base lots, extra lads, whatever.
Nikoletta B
01:04:37
But then there were all these hardware limitations. Right? So they started compressing the models like doing software tests, techniques, distillations.
Nikoletta B
01:04:46
and this like, we're with less powerful, Gpus. We didn't have the gpus that we have now that we have, that we can go even with bigger parameters, bigger parameters.
Nikoletta B
01:04:57
Maybe you have seen, like all these graphs that shows like for the language models. Like as we go further, like the the number of parameters increase. So when you hear numbers big number of

parameters. You understand that. There you need more storage space. More memory, more powerful, Gpus, right?
Nikoletta B
01:05:19
And even now, in the Ellen space like, you'll see that there are different models of coming out
Nikoletta B
01:05:26
with different flavors. And still there are like hardware limitations like we. We have these powerful Gpus. But
Nikoletta B
01:05:34
you see that there is some innovation like in flash attention. So things are, you know, compressed.
Nikoletta B
01:05:41
you know. In handle better in memory. And things are, you know, more fo faster. Also, you don't need that many memory or quantization like so you don't need all this information or quantize the information. So
Nikoletta B
01:05:58
it's like you need to say, like, Where is your hardware? And you know that. So a lot of like, even in like, if you had that mixed trial, let's say, which is like a mixture of experts of Mistrial. These are all different techniques and different models that try to compensate some, either for hardware limitations
Nikoletta B
01:06:22
or like, you know, limitations in them. You know things that we want to do in the application space right? Like we don't want to have hallucinations, for example, or whatever, but they always go hand in hand. So it's it's a really interesting question. So in in every
Nikoletta B
01:06:40
area, and in every different time depending on where the hardware is and where is the requirement
Nikoletta B
01:06:47
things evolve like hand in hand. So I'm I'm I'm assuming like, if, like some more powerful Gpu came out more memory, the models will change again. But again, there will be some limitations. So that's the that's the thing that drives the innovation. So. But for the Lm space, now you can read papers where you have all this like even, you know, for transformers. It's very powerful to do this attention.
Nikoletta B
01:07:12
This is the most costly part. So there were, like, even before Lms techniques to
Nikoletta B
01:07:17

to have like different types of attention that is faster. They don't need that many memory in order to compensate for the hardware requirements. So I can give a lot of examples, but they get it gets too technical
Nikoletta B
01:07:31
but I don't know if you have some comment or you have some follow up question.
Nikoletta B
01:07:43
Marsha.
Harsha Srivatsa
01:07:48
Yeah, I mean, I mean, that was great, you know, trying to put together the different things. But I think the the focal point now is what is le limiting further advancements like, you know, data grows so exponentially every day. They say it grows so much so. How do we keep these foundation models lock in step and keep. You know. Keep
Harsha Srivatsa
01:08:13
keep it updated to the latest and greatest information. And and when you query, Chat Gp, how does it? How do we trust the fact that you know it is up to date, or let's say, you know, yesterday yesterday midnight's information. And and you know it it today, when I quit, it's you know, it gives
Harsha Srivatsa
01:08:31
best available information. So that's why I was trying to get at right? How how to put all the different confluence of technology that comes together and make this AI. Truly, you know, intelligent. So
Harsha Srivatsa
01:08:46
and it becomes a real innovation force.
Nikoletta B
01:08:51
Yeah, that's yeah. That's I. So now you're focusing more on the time aspect of things like how we, II understand, like information, are generated every day. So you have to. Have all these models keep up with the latest information. If they want them to be like powerful assistance. Right? So II alluded. I mentioned a little bit and
Nikoletta B
01:09:16
a little about this like now they are like integrated with sheds like the regular sets. And then we have, like we are talking about these. And the advanced course, like one of the main techniques, is like retrieval augmented documentation. So basically, you have the model that is trained like,
Nikoletta B
01:09:33
it's it's closed on the data that was trained on. But you can bring information, either specialized information or information related to time. and then bring them in as a context. But then, how you bring the same, what context to pick and like.
Nikoletta B

01:09:49
What? How how big of a context you can give to the language model. That's another thing that you have to consider. So there are a lot of factors. Right? It's like.
Nikoletta B
01:09:59
what is the memory? What is the course like? And it boils down to your application right? What you are targeting for, like I'm assuming like for a health application
Nikoletta B
01:10:10
you cannot allow for mistakes or things like
Nikoletta B
01:10:14
you know
Nikoletta B
01:10:16
that could do harm to somebody. But like, if it's like a you know, a more chart like assistant. for, like very trivial tasks, I think, like, even from the
Nikoletta B
01:10:28
user perspective. I'm I'm fine. If I get an error right, it might be I'm using as well.
Nikoletta B
01:10:34
But yeah, that's these are techniques that. I mentioned one of the techniques. But it's it's an open open question
Harsha Srivatsa
01:10:43
in the near future. Do you see a scenario where techniques like rags and human human in the loop. You know, reinforcement
Harsha Srivatsa
01:10:51
doesn't become necessary at all. And you know, and and and AI systems are just self learning, self correcting and become you know, become very trustworthy. So right now II understand these techniques are required because of the limitations and because of the complexities. But do you see something like that? A truly.
Harsha Srivatsa
01:11:10
you know, are truly
Marily Nika
01:11:13
Hi, so sorry to interrupt, to interrupt? These are amazing questions and amazing discussion. But yeah, for the sake of time, we have so much wanted to go through. So let's take this offline. Nicola will be on discord as well. So feel free to tag her in the main chat. And she is gonna response. But yeah, let's move on. Because I just realized this. So thank you.
Nikoletta B
01:11:32

Thank you, Carson. We can continue offline on this call interesting question. Thank you so much. So I want to go over a little bit about what is happening under the hold, like, what are the main technologies? Because what I mentioned is like
Nikoletta B
01:11:50
all this innovation didn't happen overnight.
Nikoletta B
01:11:55
So that's a very quick schematic of machine learning algorithms. So you have, like a supervised learning unsupervised learning and reinforcement learning so unsupervised learning. It's a task driven. You have some data points, and you have some labels like, if it's like a good or bad review. If it's a cat or a dog, if it's like that person speaking, or that person speaking.
Nikoletta B
01:12:22
And basically, you have some, you fit this data to the network with the labels
Nikoletta B
01:12:28
and the network learns to
Nikoletta B
01:12:31
the task. And then you have a data point that you don't know the label, and you feed it to the network, and you'll get the answer if it's a dog or a cat, or maize speaking, or Marilyn speaking for unsupervised learning. This is completely data-driven.
Nikoletta B
01:12:50
You don't have. You have some data, and you don't know you don't have any labels. But you can run some algorithms like K-means or hierarchical clustering so that you can see how the data are in the space I like, you can see here that you have 2 different clusters so there are 2 different.
Nikoletta B
01:13:13
you know, patterns in the data. But you don't know what these problems are about. So it can be like you know
Nikoletta B
01:13:21
to different topics in text, or to different languages in states like German and France whatever.
Nikoletta B
01:13:31
And then there is a reinforcement learning. That you might have with Jp, but
Nikoletta B
01:13:39
It has been also around for a while. So in reinforcement learning. You have an agent interacting within with the environment and as the ancient interact with the environment, it gets some reward if the actions that it took is a good one or a bad one, and then based on the reward it adjusts its behavior.
Nikoletta B
01:13:59

So this is happening with reinforcement learning. There are specific algorithms with that enforcement plan. And there are also semi-supervised learning algorithms where you have both label them and label data. So you want to find out? The label of the data, but also,
Nikoletta B
01:14:18
you you, you have some structure in the data that you need to organize. So you resolve to some supervised learning algorithms.
Nikoletta B
01:14:28
very quickly. For supervised learning. 2 main problem regression problems and classification problem and the regression problems. The output is a continuous variable. So we have, let's say, the square footage of of a house and the price and based on that, we want to predict the price. So basically, we have to predict the number
Nikoletta B
01:14:56
and what we are trying to do here, let's say with linear regression, is to put
Nikoletta B
01:15:01
to find a line where has most of the points. We cannot fit the line to the points. Exactly. So. Then, when a new point comes in, we can see, okay, this point comes here in the line, and this must be the estimated price for classification again. We want to predict something, but we are predicting the discrete variable. So we want to predict this. If it's something a house or a townhouse like, good or bad, what I mentioned.
Nikoletta B
01:15:29
So basically, here, you see, maybe you have again
Nikoletta B
01:15:34
the the log size and the square footage. And you see how the data projected into space. And you can see now, if you have a new data point, you can see if it's like falls from this side or this side. So it's a house or a townhouse.
Nikoletta B
01:15:51
and
Nikoletta B
01:15:55
I hear very briefly, because we mentioned all these supervised, unsupervised, and reinforcement learning. And I mentioned, it's a foundation stone for
Nikoletta B
01:16:08
large language model sensitivity like models. Just to give you an idea. This is like a schematic of how Gp model was trained. And you see here that you have all this technologies that I mentioned, you have self supervised learning. So basically, you have
Nikoletta B
01:16:24

you feed the you train the large language model just fitting data. You don't need any labels. The model just have to predict the next world based on the previous world. Then you have some supervised learning tasks. Where? For example, you feed data and some label, let's say.
Nikoletta B
01:16:46
Here you have the prompt, I would say, explain reinforcement. Learning to six-year-old. You have someone labeling this data, and then you produce a model, a model that, given some data.
Nikoletta B
01:16:58
gives the output that you want based on the labels that you provided. There is also another model that is based on supervised learning that is used later for enforcement learning. So basically, you have some answers from the Gp, and then you have label labelers around these answers, what is the best to the worst one. And then you are building a reward model, and this model is predicting
Nikoletta B
01:17:28
If the answer that you get from the Lln is a good one or a bad one.
Nikoletta B
01:17:32
and this model is used here in enforcement learning, so that the model learns to. you know, improve itself, based on the report it gets from the reward model. So you see, what I mentioned earlier
Nikoletta B
01:17:47
is part is in this last language models.
Nikoletta B
01:17:55
and very briefly, I mentioned there already, what is a language model? I'm pretty sure you have interacted with language models even before so even when you were doing a simple shared some Google Google sets like, what is the weather? You see that it completes the next one. This comes from a language model. So basically, the language model is predicting the next word based on the previous words.
Nikoletta B
01:18:22
And if you want to see the like in a network schematic, you know, networks like this isn't the input. These are the hidden layers. I have some about this in the warm up material
Nikoletta B
01:18:33
you fit the input. It's input goes to a node. It passes through all the layers and you get the output probability for all the words that you have in the vocabulary like you have, like a vocabulary, let's say 50 k. Words. Your the network will produce a probability for all of these words, but then you will have to pick the right one, and the right one depends on the decoding the algorithm. So let's say, for simplicity to pick the largest probability
Nikoletta B
01:19:03
and the while language models are so powerful as I mentioned. But just to
Nikoletta B

01:19:14
say here in the sentence is that they are trained on lots of data and what they are picking from this data the statistics, like what the world comes next to the other. So then they can predict and you can make decisions if it's a sentiment. If a sentence is has a good syntax. If the semantics are right fact, some common sense. So
Nikoletta B
01:19:42
basically, the model predicts the likelihood of a sentence. So if you have a very correct grammatically syntactical sentence. The probability of this sentence will be high. But let's say you have like a sentence that it's like a word solid like there is no syntax you're expecting the probability will be would be low.
Nikoletta B
01:20:02
similar for the semantics, who cannot say that Parak only dogs are barking, because if you take all the text that you find in the Internet, like bark
Nikoletta B
01:20:11
we'll probably go next to had dogs, not to people, and similar for facts, and similar for common sense. So you see, like all, it's, it's a matter of statistics. Alright.
Nikoletta B
01:20:24
This is something that I mentioned earlier. It's like the the big book for the evolution of language model. Is this transformer architecture the same code? This is in the warm up material. If you want to go a little bit deeper into the details.
Nikoletta B
01:20:41
And now I will move on to the training paradigms. how again they involved over the years. So I will take as an example, like text classification
Nikoletta B
01:20:55
problem, where basically you are giving them the input text. And you have to produce. Let's say, we're talking about a sentiment classifier, something like that. It's a movie review is a positive negative or better.
Nikoletta B
01:21:07
And the first thing that needs to happen, as I mentioned earlier is to to extract some features or some embedding representation. So go from the numbers from the text to numbers.
Nikoletta B
01:21:20
and in the past there were like several supervised techniques. So you would use like, count vectorizer. So Dfid F to extract some features. And then we're using logistic regression, let's say, to do the task.
Nikoletta B
01:21:36
or later you could do this with a neural networks and train a neural network again.
Nikoletta B

01:21:44
you know, shoulder tasks. With
Nikoletta B
01:21:49
from 2017, when this transformer architecture was out, and you could train on lots of data the paradigm. But
Nikoletta B
01:21:59
dominated. Everything was pre-trained and fine tune.
Nikoletta B
01:22:03
So I mentioned earlier about bird these are pre-trained embedding. So what is happening here? You are you train the network on the language modeling task without labels. You're just hitting text. And the model has to predict the next word based on the previous world.
Nikoletta B
01:22:21
And then you have a powerful representation of all the text that the that you have said to the network representation in terms of language like the syntax, grammar, semantics, that I mentioned common sense. So you have, like this, contents, representation
Nikoletta B
01:22:38
and then, once you have disadvantage, let's say you have a task to do sentiment classification, which is a little bit more specific
since we have captured all the information about the language and the semantics.
Nikoletta B
01:22:53
You just need a cab. Not many label data. It's not that you need like the whole Internet, if I might say, and it's some label data in order to learn the specific task.
Nikoletta B
01:23:05
So basically, you are taking these embeddings.
Nikoletta B
01:23:08
you fill some label data and you train for a couple more epochs.
and you find from the date the the embeddings to to the task.
Nikoletta B
01:23:19
And this is pretending, and fine.
Nikoletta B
01:23:23
and let me go here. So just to have a visual of that fine tuning to is doing. Imagine you have like these sentences, and they are based on the embedding representation like you have trained this big model like the better beddings, and you projected into this space.
Nikoletta B
01:23:44

You see where the data points are found in the space. Then you get some labels like, if it's a negative or positive. If I just call, or the points based on the labels, you see that it's all over the place. So if you want to do the classification task. It's a card to find the plane
Nikoletta B
01:24:01
to separate these points right? They are all over the place. So what you're doing is like you're doing this fine-tuning where basically, you are adjusting this embeddings, you are, you know.
Nikoletta B
01:24:13
transforming them a little bit in order to have a representation like this. See? Like all the negative are in the top left corner, or the positive or in the right side. So now you can see that it's easier to find like this separating.
Nikoletta B
01:24:31
playing online in the studio space
Nikoletta B
01:24:35
to separate this point. So this is actually what is happening with fine tuning.
Nikoletta B
01:24:41
You have, like the first and pre representation, which is powerful. But then a specific task has, like specific labels. And you won't like to adjust your data a little bit in order to be able to solve the task
Nikoletta B
01:24:57
and going back
Nikoletta B
01:25:01
And what the the other training paradigm that
Nikoletta B
01:25:06
is now like the trend since 2019 is between prompt and predict. You have now the Ln like, model. And what you are doing is like, you do what is called prompting. So basically, when with generative models, what you are doing is like, you are not
Nikoletta B
01:25:29
changing the network. We are just try to fit the data to the network. Well, with this one they retrain and fine tune
Nikoletta B
01:25:38
you were feeding the data, and you were trying to change the model
Nikoletta B
01:25:44
based on the data. And with this one with the later one, this has shifted, the model is fixed.
Nikoletta B
01:25:53

But you are
Nikoletta B
01:25:54
changing your data. You're changing your prompt so that you book pick the right information from the model so that you make the model produce the right information
Nikoletta B
01:26:06
based on your task. And of course this doesn't mean that you're not doing any fine tuning with these models. You again. Not doing fine. You can do fine tuning but it's called instruction fine tuning for generative models, because the way you are keeping like the information to the model, it's like through instructions like.
Nikoletta B
01:26:28
and do they show that?
Nikoletta B
01:26:30
Okay. And III talked about this already. What is the trying just to have in mind like, I'm pretty sure you have about prompt engineering. And the first step
Nikoletta B
01:26:46
that you are doing with the language models. If you want to solve a task is to find the right prom I just want to mention, like why, this is important. And so, as you understand, like, let's say an example.
Nikoletta B
01:27:01
You have a physics question, right? You're asking the physics physics question. You understand that the the language model was trained on, loosely speaking, and the whole Internet. So it might have seen answers to a question from textbooks, from teachers like from phones or from students. So it will have the right answer to the question or their own answer to the question. So
Nikoletta B
01:27:28
if you are not specific in your prompt the model will generate something. The model doesn't know what information you want, right? So, depending on the statistics, it will generate something.
Nikoletta B
01:27:41
So if you want.
Nikoletta B
01:27:43
you have to be very specific in the prompt, let's say, and that's why they are saying also, to give a persona to your in your prompt like. You're a physics teacher, a teacher teaching high school. So you also implying, like the the level of complexity in the answer, answer this question right? So have this in mind like
Nikoletta B
01:28:06

on one hand, say it's easy with a prompt to generate something Vlm is guaranteed to generate something, but in order to be that Sa. In order to be like what you want. You have to be very specific in your phone and very careful
Nikoletta B
01:28:21
and be as explicit as possible about what you want. So you get the right information out to fit. And of course I will not go over into the hallucinations and face biases or other type of biases that you have to.
Nikoletta B
01:28:37
Be very careful about.
Nikoletta B
01:28:40
when you put this model into production. This is just to give you an idea of thinking about the prompt like. Imagine you have all the information, but you have to find the right information for your application.
Nikoletta B
01:28:53
And I will call now to the assignment.
Nikoletta B
01:29:02
let me stop sharing
Nikoletta B
01:29:05
to share Kim.
Nikoletta B
01:29:21
Okay.
Nikoletta B
01:29:31
how is the phone?
Marily Nika
01:29:35
I think. Let me see. Let me see? Yeah, I think it's good.
Nikoletta B
01:29:39
Okay? So for this, for this demo, we will do sentiment analysis with pre-trained teleense. So basically, what I mentioned earlier, we're gonna take some very type of bad things. Actually, we're gonna take this to bear, which is a more smaller version of that. And we will train on movie reviews, the Imp data set.
Nikoletta B
01:30:02
but not really. We will find tuning.
Nikoletta B
01:30:04

So there is a warm up material with the Google Collab again. And Google collab tutorial, just to briefly say, just make sure to copy them
Nikoletta B
01:30:17
the notebook so that you can make changes. Also make sure that you will need
Nikoletta B
01:30:26
gpus for this task. Even though just for fine tuning, we are doing just a few iterations so maybe you will. You will have to train like like for 20 min, not like days, but still you will need gpus in terms of processing power and memory requirements. So make sure you go here and change the runtime type
Nikoletta B
01:30:52
and also check the resources in order to see how many resources you have available.
Nikoletta B
01:30:57
these are covered in the warm up, warm up material in more detail.
Nikoletta B
01:31:03
So the first thing that you have to do once you connect to your app time with Gpus, and everything is to install the dependencies we are. Gonna use the Transformers, library and datasets. Actually, all these packages would start from hagging phase. So hugging phases. A a library that has all these transformer based support and told models like better.
Nikoletta B
01:31:31
And you can do training fine-tuning inference with these models.
Nikoletta B
01:31:36
So you are installing the dependencies.
Nikoletta B
01:31:40
And then the first thing that you have to do is to load the data
Nikoletta B
01:31:48
oops, something we've enjoyed.
Nikoletta B
01:31:54
So as I mentioned that this data set is about movie reviews for my Mtv, so you have some text that you see here.
Nikoletta B
01:32:10
but has I love sci-fi blah, blah, blah blah! And then you have some label 0 one. If it's a positive or negative. And once you load the data, you see that you have, like the train and the test set.
Nikoletta B
01:32:23

So when you're a training model you have. You split the your data in train, validation and test set. So the train set is used to to fit the. It's the the larger portion of your data set, but you'll fit to the model in there in order to learn the task. So the simple parameters.
Nikoletta B
01:32:47
and the test set or the validation set, or the development set is used like during training in order to evaluate how well the model is is doing enhancing data. So the training data is used to train the model that
Nikoletta B
01:33:03
there's data. I used to evaluate the model on data that were not used for training. But still we're using this data to adjust like, let's say, parameters like the learning rate or the number of fat books.
Nikoletta B
01:33:16
so you need, you need 2 different tests. Alright.
Nikoletta B
01:33:21
And and then Once you, the data set is loaded. This is also all part of this dataset library. You don't have to do anything.
Nikoletta B
01:33:33
And then here, because the data set is like 25 k
Nikoletta B
01:33:38
samples for from train and test
Nikoletta B
01:33:42
just for the sake of the demo not gonna use like the 20 for the full data set. So what I'm doing here is basically dumb sample. I'm just taking
Nikoletta B
01:33:51
1,000 positive and 1,000 negative signals for train and test and then creating a small train and a small test for demo purposes.
Nikoletta B
01:34:03
And this is some constructed again this structure. No need to worry about this. So we loaded the data. We have them stored in these 2 variables for train and test
Nikoletta B
01:34:15
actually here. And then the first step that we need to do is to preprocess the data well. And the first processing step is that organization. So basically, this.
Nikoletta B
01:34:26

The first thing that happens is that the text is the word is split in sub words, and there are more information about this in the warm-up material. So, and when you hear in the Llm that the context window is like.
Nikoletta B
01:34:43
let's say.
Nikoletta B
01:34:44
24,000 tokens have in mind that tokens is a smaller fraction of words. If you go towards it would be smaller right? This number, because imagine the words are split into some words like smaller might be called small.
Nikoletta B
01:35:02
And then, yeah, like 2 different worlds. just a very simplistic example. There are different algorithms
Nikoletta B
01:35:10
that that that do this organization operation.
Nikoletta B
01:35:16
So here we're using the hugging phase library. So we are loading the tokenizer, and everything comes with a model. So we mentioned that we're gonna use the still bed as a model for via presentation
Nikoletta B
01:35:31
and when this
Nikoletta B
01:35:33
embeddings are trained are learned, a specific organizer is used. So you have to make sure that the model you're using is the same
Nikoletta B
01:35:43
for the tokenizer and for the model later. So your your you say that I'm gonna use the tokenizer for this little bird based on case.
Nikoletta B
01:35:55
So we are loading this. Then you you're just generating a function that actually runs this totalizer actually takes all them
Nikoletta B
01:36:06
the examples that you have in your data points and organizes them. And then I'm running this functions. Oops.
Oh.
Nikoletta B
01:36:21

okay, let me run this. So you see, you have to make sure that you run all the cells sequentially, I thought I had run this.
Nikoletta B
01:36:30
okay.
Nikoletta B
01:36:35
so I run this for the small data set. I'm not gonna run it for the the full data set because it will take around
12 min.
Nikoletta B
01:36:47
and then there is another function that is used for training in order to put collected data together based on the parties and that organization. No need to worry about that.
And then here you define the evaluation like, when the model is
Nikoletta B
01:37:07
this train. You're basically evaluating, based on accuracy, like, how
Nikoletta B
01:37:13
if the predictions that you get from the model are correct compared with the prediction predictions that you have in your
Nikoletta B
01:37:21
and your data.
Nikoletta B
01:37:25
This is not something that you have to worry. And now you start with a model training. This is just to to map that positive, like the the 0 and one to negative, positive, and vibrate vice versa. This is like for the
Nikoletta B
01:37:40
the Api that transformers need.
Nikoletta B
01:37:45
And again, now you're here. But this is the important part is where again, we are loading the model. You are loading a model for sequence classification from a pre-trained model, which is this model, and you specify that you have 2 labels, and these are like the mappings that I mentioned.
Nikoletta B
01:38:03
And you see again, you have the same name as the Tokenizer. This should be in power.
Nikoletta B
01:38:08
and I would be strong
in order to make sure that the mobile

Nikoletta B
01:38:12
behaves as expected. You get the identities.
Nikoletta B
01:38:18
And then because you, your, this model is pre-trained. But you're
Nikoletta B
01:38:23
have to do some fine tuning like exhaustive bedings to the same classification task you are doing like you have to specify some training arguments. So where this all this
Nikoletta B
01:38:38
by products of training will be so like here in this folder. What is the 11 grade? How the model? The model weights are adjusted like like
Nikoletta B
01:38:50
that? If it's a small
big learning grades. Since we're doing fine tuning, like the model is already trained. We call with a small learning grade like this one
Nikoletta B
01:39:00
the bad size, like when you're processing, you're doing training. You don't feed like we have, like 25 K at data points. You don't fit them all at once like these are bad. Small, you know, explained it to badges. And
Nikoletta B
01:39:13
the model is learn is learning like for the 16 boxes every time, and that's us
Nikoletta B
01:39:20
the number of training iboxes tool. And this again, because we are doing fine tuning. And when we are saying type of what apple, what is happening in a network is that?
Nikoletta B
01:39:29
it's how many times the model will see all the data points. So now with 2, this means that the model. We see the data points twice.
Nikoletta B
01:39:43
and if we are doing pre-training, this number should be large because we have to estimate the parameters from scratch. But now, since we have an initial representation, and we just want to shift the the embeddings a little bit.
Nikoletta B
01:39:57
we're just trying for a few members of 5 books.
Nikoletta B
01:40:00
2 is enough.

Nikoletta B
01:40:03
And the here, once you have defined the parameters. Then you've defined the object. You say that you're gonna do some training. So you need a trainer object. And I'm gonna use this model. This is the model that you loaded earlier.
Nikoletta B
01:40:19
And these are the training guards, arguments the
so forth.
Nikoletta B
01:40:27
And then I'm gonna train this model on this data. This is like for training. This is for evaluation. And you see here that we pass the variable that has that tokenized version of the data set based on that tokenize our model that we loaded there there.
Nikoletta B
01:40:44
And we say again that this is the tokenizer. And this is the data collateral, how the matches will gonna be built, and these are the metrics that we are gonna use. So you see, like, with this hugging phase library, it's a quite abstract like. It's easier to set up like a training training job. And then what you have to do is actually call the trainer with help. With that.
Nikoletta B
01:41:12
the train
function.
Nikoletta B
01:41:16
Okay, I'm not doing this?
Nikoletta B
01:41:18
so now, just 2 epochs. It's just a small dataset. It will not run for long. But, as you say, this training, you will see here the epochs and the training lows and the validation laws, the laws shows, how far is the prediction of the network from the actual label. So as you are training, you want to see the loss going down as the loss goes down, it means that the model is getting more accurate and predicting the the true label.
Nikoletta B
01:41:50
okay. and but you, because you are doing fine tuning you. I'm not. I didn't use much data. You will not see very big variations. But just to give you an idea.
Nikoletta B
01:42:05
So I have this training, and I will continue.
Nikoletta B
01:42:09
one thing that you have to do so one thing that you have to do is like in order to have access to the models and global models that you have trained so that you don't have to do train again.
Nikoletta B

01:42:22
you have to to mount a Google drive and there are instructions from how to do show, and there are also more details, instructions into the warm, warm up material
Nikoletta B
01:42:36
but this is a one time thing like not one time thing you have to do this every time you run the note.
Nikoletta B
01:42:43
But just to mention here you are using Zpus when you're doing training. So once you have trained the mobile, I suggest to save it, and then you can run as many inferences like, so that you can send save some of your Gpu.
Nikoletta B
01:43:03
Okay, and then, now you have trained your model. You have fine tune, your model to your task, and now you want to see how well it performs. Right?
Nikoletta B
01:43:13
So. And you have stored the models. And you see, like all these data, the the models.
Nikoletta B
01:43:20
what the training has generated, I will not go into details. It's for the to organizer the model and so forth.
Nikoletta B
01:43:29
So you have to load the models. Oops. Oh, I didn't do this, that's why.
Nikoletta B
01:43:36
And the
Nikoletta B
01:43:40
II you just need to do this step to give a logo group to access to Google trial.
Nikoletta B
01:43:52
okay. Oh, okay.
did it. Say, did it say.
Okay.
yeah, I had. I didn't run this. That's why this didn't run, because it was trying to load something that was not mapped
Nikoletta B
01:44:19
for the public lab to access it.
Nikoletta B
01:44:23

So we're using like the pipeline command. So basically, we're defining the task we are doing sentiment analysis. And we're using this model. And the, you see, this is our model. This is what we generated like the findings version of the model.
Nikoletta B
01:44:40
And we're using this organizer. This is a Max length. You you leave this as is goes with a model. So we cannot have
Nikoletta B
01:44:49
higher length in the input, because 512 training. So anything longer would be truncated.
Nikoletta B
01:44:58
And this is the bad size and the device it's like.
Nikoletta B
01:45:04
And you can have some text in the list like
the store reviews, and
Nikoletta B
01:45:11
you feed this to the pipe function and you get the label. So the first one is positive, and you see the score like that. The the model is quite confident that it is a positive review.
Nikoletta B
01:45:24
and this is a negative, if you like, which was not a masterpiece. And you say that the score is not that confident, but still it's on the high end, because you have the word masterpiece. But you also have the work. Not here. So
Nikoletta B
01:45:38
similar here.
Nikoletta B
01:45:42
But this is just to to do some you know.
Nikoletta B
01:45:48
Spot checking like, if you want to provide some examples with positive and negative content.
Nikoletta B
01:45:54
But usually what we are doing after training is we are evaluating the modeling in an enhancing data. So for the sake of demonstration, I was use the test set that was used for
Nikoletta B
01:46:11
when training the model to just like the learning grades and so forth. But you could have a different test set here.
Nikoletta B
01:46:21
So again, you just fit the the test data points in order to get the predictions.

This will run for a while.
Nikoletta B
01:46:33
this is just logistics in order to take the labels for positive and negative. So you make sure that you have for values of 0, you get negative and one. This is just representation.
Nikoletta B
01:46:50
And then you can specify. Get the accuracy, how accurate the model was. So it's 90%, which is code
Nikoletta B
01:47:00
all you can do the confusion matrix. You can see this display. You can see more detail. This diagonal shows, like the correct predictions, what is negative and was predicted negative, what is positive and was predicted positive. So you want all the numbers to fall in here and hold on 0 here for 100. So you see, here's something was negative and was predicted as positive.
Nikoletta B
01:47:28
and you can get a more different way of a classification report with precision. Recall and score.
Nikoletta B
01:47:35
that you see here. This is all python commands. Everything is easy. You just have to fit the true labels and the predicted labels, and you get all the numbers
Nikoletta B
01:47:46
and you get averages.
Nikoletta B
01:47:50
yeah, we get averages
for for precision recall, and the font score.
Nikoletta B
01:47:59
There are more details about this evaluation in the world warm up material
Nikoletta B
01:48:05
and
Nikoletta B
01:48:07
for the assignment for those who want to play a little bit with a notebook.
Nikoletta B
01:48:13
You! One thing that you can do is experiment with other rental lines I mentioned. But, we're using these still bird, which is a smaller version of bird you can try
Nikoletta B
01:48:27
the original bed. But again, like the base model. Don't go with large, because it will have like a lot of parameters, and we will need more time to train to be you or Roberta.

Nikoletta B
01:48:41
And you can do this and see how well the model
Nikoletta B
01:48:46
is performing
Nikoletta B
01:48:48
after fine tuning.
Nikoletta B
01:48:51
and you know, run again. So basically, you don't need to do anything. Just load the notebook and change the model
Nikoletta B
01:49:00
name in the tokenizer and in the model where the larger model. And again when you're doing pain inference. You don't need to change how the data handled
Nikoletta B
01:49:11
or anything
Nikoletta B
01:49:12
so this would be the first step and the
Nikoletta B
01:49:19
you shouldn't see any drop of performance, because these are larger models. They should behave
Nikoletta B
01:49:24
they should have better performance or the same. But again, we are still using a small version of the data set. Right? It's it's very just 2,000 data points. Is not that many?
Nikoletta B
01:49:40
and
another If you want to go a little bit deeper into the training, and how things are changing.
Nikoletta B
01:49:51
you can play with the training arguments and change the numbers epochs, but make sure that you keep the number loaded. Go to 100, like 2 or 5,
or the learning rate.
Nikoletta B
01:50:03
and before going here at least.
Nikoletta B
01:50:09
Maybe once you change the model and you train like the network class is with a small data set.
Nikoletta B

01:50:17
you can try to use the full dataset.
Nikoletta B
01:50:20
The whole 25 K samples. So
Nikoletta B
01:50:25
you have to specify here.
Nikoletta B
01:50:28
not the tokenized Imtb, small but tokenized Imtb, that you have here
Nikoletta B
01:50:34
a little bit further up.
Nikoletta B
01:50:36
tokenized I am to be
Nikoletta B
01:50:41
right? So you have. You have to make sure that you're on this. So you organize the full data set, and then you feed it
Nikoletta B
01:50:49
in your trainer that you want to train on on this data points. So if you do this, have in mind that the training operation will take longer, but then it will not take.
Nikoletta B
01:51:01
I think it takes around an hour, if I remember correctly, with Roberto Roberta
Nikoletta B
01:51:07
for the whole dataset, which is okay.
Nikoletta B
01:51:12
And you can say like, so you can have, like different evaluation, like different
results.
Nikoletta B
01:51:20
Like with, this different model small data set and then the large data set with the small and the bigger model
Nikoletta B
01:51:31
and I will stop here, and I know I know that we went over. Sorry about that. Thank you for your patience. But if there are people still online, I can take any questions.
Nikoletta B
01:51:48
You might have.

Marily Nika
01:51:52
Thank you. Thank you so much. That was a lot of meaningful content. Some someone asked and said, Hey, to to what extent are we involved in this process as aapm's? And the answer is.
Marily Nika
01:52:03
this is great, so that you can see what your partners are doing under day today, and what it means to train a you know, a model. And it's amazing to see these no Co tools while they're called tools. But this web web tools is just unbelievable. You should have seen what it was like 5, 10 years ago.
Marily Nika
01:52:23
Alright. So bob is asking, Is there a video and proper way to make and use a copy of colab?
Marily Nika
01:52:29
We have added tutorials in the Maven platform? Please check them out. It's what I showed early on in today's session.
Marily Nika
01:52:39
Any other questions for Nicole? Let that before we let here go, and she will be on discord as well.
Marily Nika
01:52:47
so you can. The way to ask your question is, go in the main channel, and at
Marily Nika
01:52:52
Nicole ask a question in the main channel, so that other people can benefit from it as well.
Marily Nika
01:52:58
Yeah, I'm looking at the questions. It's amazing, because people self answer to the questions. And it's amazing. Thank you harsh? Harsh! Your number one responder to questions. This is great. Alright.
Marily Nika
01:53:10
Let's hey? We're talking about responsible aipms, and this is great.
Marily Nika
01:53:17
yeah, let's
Marily Nika
01:53:19
one more question for Nicole. So alter is asking a great question about productionizing model.
Marily Nika
01:53:26
So how is a model moved into production. Next.
Marily Nika
01:53:31

what the software engineers do at a high level like, do they build a pipeline to have the model keep improving with new data? And, by the way on our advanced course. I'm bringing in an Svp. Which is
Marily Nika
01:53:45
an engineer, and that's exactly what his team is doing. They're productionizing models. But yeah, Nicole, if you have any comments on productionizing. AI, that would be great.
Nikoletta B
01:53:55
Oh, that's the that's a very interesting question. There are so many things that play when productionizing models? And usually when not usually when we are working on a problem
Nikoletta B
01:54:05
where we are in hand in hand with the engineer, because usually like there is a pipeline already working, and you want to fit this model in the pipeline.
But
Nikoletta B
01:54:16
you know, it depends like on you know
Nikoletta B
01:54:20
where this model will be hosted.
Nikoletta B
01:54:24
mobile or like you know. So what are the memory requirements? What is the cost? And then
Nikoletta B
01:54:31
because you have to take into account. Like all this hallucination biases, you might have, like other tools on top to guardrail what you are generating for Llm. So there are a lot of things at play. II cover some of these in the advanced course, and that's Marilyn said. There are more dedicated talks to this, but it's a very, very interesting question.
Marily Nika
01:54:58
Alright, thank you so much. And Shawn is asking, hey, how do we collaborate? How do we set goals with Richard scientists. Well, that's exactly what we'll talk about tomorrow. We talk about Google setting so stay tuned. It's gonna be an interesting discussion.
Marily Nika
01:55:11
This chat can be saved. I will post in on this chord. There's a lot of amazing discussion like I was learning things myself. Alright. Well, thank you so much for taking the time, Nicole, I thought, thank you, everyone for joining for the questions and answers. And we're gonna see Nicole let again in the advanced course for anyone that is continuing. So we'll be there to give another talk. Alright. Thank you.
Nikoletta B
01:55:33

Hi, alright, thank you so much. Thank you for all the questions and just make sure for this call. If you have some technical question on Google Collab, because I know we went a little bit speed. Don't meet yourselves up. Don't be shy. Just post a question. Maybe it's amazing like answer. I'm I'm pretty sure like, how do I copy? Or how do I change my runtime type? So
Nikoletta B
01:55:56
of course, these are the warm up material. But don't be sigh post your question so that you have an answer, and you're not block
with the assignment.
Nikoletta B
01:56:07
Thank you so much. Thank you. Bye.

Session 3

00:00:04
Wonderful. Hello! Everyone just kicked off the recording. This is our last live session, and I'm just very excited because we have gone through so much content together, and I'm getting
Marily Nika
00:00:15
great questions. II see the conversations in the chat, and then discord, and I'm just very happy to see that. You you have been learning. So that's good. So just a request. If you're comfortable, please turn on the camera. I wanna make this as interactive as possible. And I love to talk to people and to see the reactions. Because I adjust the way I speak. Yeah, thank you. Perfect. Hi, everyone. I see you now. Okay, wonderful.
Marily Nika
00:00:40
So yesterday we discussed how Richard scientists work on their day to day, and I know it was a bit overwhelming. But.
Marily Nika
00:00:49
my primary goal was to make you feel more comfortable with the technical side of things, and, secondly, I wanted you to see what goes behind developing the core technical side of things with an experience. So it was very important to me. I'd love to hear your comments in the chat. If you would like to put them in, I want to see what people have to say.
Marily Nika
00:01:11
Now I am gonna share my screen. And I talk to you about what we're gonna discuss today.
Marily Nika
00:01:18
Alright.
Marily Nika
00:01:19

So today, we're gonna talk about metrics measuring success for AI products. And we're also gonna discuss how to set goals and setting goals as a Pm. Leader. Within this AI era is kind of a bit more complicated. I'll tell you why
Marily Nika
00:01:34
it is because when you measure the success of a product, there is this whole extra angle that you've never had until now as a Pm.
Marily Nika
00:01:42
Because you have the product health metrics. But now you have this AI side of things you're like is that gonna work cause? If the AI side of things doesn't work. Then there is no product. Right?
Marily Nika
00:01:53
So let's discuss metrics a bit. And then goal setting. Because I think that's a very, very important takeaway. I want you to leave with this course.
Marily Nika
00:02:02
The other part we're going to discuss today is interviewing. We're going to touch a bit around how you're interviewing. I told you. I had to go through this recently, because II left Mita
Marily Nika
00:02:12
and
Marily Nika
00:02:14
It's it's not fun, there is. It's a process, and I'll I'll tell you everything I know so hopefully. If you plan to either interview people or be the one interviewing, you'll be set up for success
Marily Nika
00:02:27
alright. So talking about metrics as an aipm
Marily Nika
00:02:31
as you probably know from your current roles when we measure success of a product.
Marily Nika
00:02:36
And we need to think about the bigger picture. What is our goal? Why are we creating this feature, this product, this AI product?
Marily Nika
00:02:45
Strategically, why is this Netflix recommendation engine getting
Marily Nika
00:02:50
right? We need to know this so that we can tie everything we're measuring back to the mission.
Marily Nika
00:02:58
So please only define what you need to measure. Only define the metric. Your product will actually impact

Marily Nika
00:03:05
as product managers. We have the tendency of you know, wanted to say, this is the best thing. It's going to
Marily Nika
00:03:12
bring money. It's gonna bring people. It's gonna do all these things. Please give me funding. However, that's not realistic. So the more realistic you are in your mind.
Marily Nika
00:03:22
the better it's gonna be when you advocate for your product. So please, only think about what you will actually impact now that our 2 stories. There is the story of the business, and strategically what they want to achieve. Like, Hey, I'm the business. I want to sell more headsets, or I'm Netflix, I just wanna make sure people keep me paying money. And I can increase the user base.
Marily Nika
00:03:47
So no matter what the business goal is. you need to craft narrative around your product is gonna tie in to that
Marily Nika
00:03:56
company narrative, either directly or indirectly.
Marily Nika
00:04:01
If the company says, Hey, I just I care about money. I just want more people in to pay this monthly subscription. Then you can say, Okay, well.
Marily Nika
00:04:09
what I'll create with this recommender system is going to guarantee that people will be happier with the service. They're gonna stay watch for longer. They're gonna tell their friends. So not only will you maintain the current clientele, but they're gonna bring more people in. So indirectly. I do move the needle for you. So this is kind of how you need to craft
Marily Nika
00:04:30
the story on the strategic level in your mind.
Marily Nika
00:04:34
So when it comes to product metrics, it's It's again an amazing.
Marily Nika
00:04:41
You're right. And you know what I'm gonna do. Since this is a live session. II trained my Chateau Bd to provide the perfect interview answer. So I want to tell you kind of. I want to show you what it would say, so that we can. We can start from there.
Marily Nika
00:04:59
So if you see here, I've trained this to tell me what types of questions it can answer.

Marily Nika
00:05:08
And so one of the questions that we can answer is. how do you measure success of product. Why, okay, there it is.
Marily Nika
00:05:19
So let's say, we want to measure success. We do measure success of and
Marily Nika
00:05:26
recommender veto
Marily Nika
00:05:29
on Netflix
Marily Nika
00:05:32
of an AI powered.
Marily Nika
00:05:35
Recommend
Marily Nika
00:05:38
next video to watch on Netflix.
Marily Nika
00:05:42
because you will see, I trained it to say that
Marily Nika
00:05:45
first of all, you always need to start with the mission just like I talked to you about what is the mission? Why have you created this? Why are you creating this product in the very first sense? And then with that in mind, what would be the goals of the company? What's
Marily Nika
00:06:01
why are you creating this? And if you cannot answer these 2 questions, it doesn't make sense for you to just jump in
Marily Nika
00:06:08
and saying, Here's how I will measure success for this feature. Now.
Marily Nika
00:06:12
if you're coming from more junior levels like entry levels meet career. It's totally fine to think about measuring success in terms of okay, user organization engagement retention. But I want you to always have a framing in your mind because you're a leader. You're leading this area, and you should be able to know
Marily Nika
00:06:29
why you're doing this. Okay?

Marily Nika
00:06:32
So the very first thing you need to say is, here's a mission. Here's why we're doing it. Here's high high level. The goals, for example. Hey? We want to increase the viewer engagement by providing relevant content.
Marily Nika
00:06:45
We want to improve satisfaction through personalized experiences. We wanna reduce turn rates. We wanna enhance the scale availability.
Marily Nika
00:06:52
So it doesn't matter what the goal is, as long as you know why you're building this. Okay?
Marily Nika
00:06:58
So now, in terms of metrics.
Marily Nika
00:07:00
and there are buckets of metrics.
Marily Nika
00:07:05
And this is actually there it is. This is actually one of the I did this post on sub stack about metrics and
Marily Nika
00:07:16
everyone just love kind of the parallel I wrote. So I wanna show this to you.
Marily Nika
00:07:22
There it is. So when it comes to AI products.
Marily Nika
00:07:28
I think of success as these 3 little buckets. And I added.
Marily Nika
00:07:32
Oh, ice cubes. So number one. We have our standard product, health metrics. The standard product. Health metrics are.
Marily Nika
00:07:41
Of course.
Marily Nika
00:07:43
the buckets we you already know, which is acquisition. How many users are we getting? Okay?
Marily Nika
00:07:49
Engagement?
Marily Nika
00:07:51

How much is each person on average interacting with whatever we offer. For example, how many likes per person on average, how many shares per person on average?
Marily Nika
00:08:02
How many comments per person on average, this kind of what engagement looks like.
Marily Nika
00:08:07
After that you have retention. Retention means, are people coming back?
Marily Nika
00:08:11
These are my product. Sticky? Is this feature sticky. Are people really enjoying it? And then, after that, you have referral.
Marily Nika
00:08:20
How? How many people on average, is one person bringing to me?
Marily Nika
00:08:25
And that's an interesting one, because not every product has it. But I was playing. Let's say, what was I playing?
Marily Nika
00:08:32
A great example is Farmville? I don't know if you remember Farmville, but it's this app on Facebook. Yes, it's this app of Facebook. You had a farm, you would go in. You would harvest the lemons, and whatever it is you were planting.
Marily Nika
00:08:45
But the thing is, every time you harvest it a tree.
Marily Nika
00:08:49
you it would automatically post on your wall to say, hey, Mary just harvested the tree. Click here to to get back and and claim yours.
Marily Nika
00:08:59
So people would see that. And it would create this kind of network effect of people seeing this post, and they would go in. Okay. So it was a very interesting way to bring people in.
Marily Nika
00:09:10
So some product managers wanted to measure. This so referral is another one.
Marily Nika
00:09:16
First, but not least, is money. How much money are we making, whether it is from subscriptions. Whether it is from according to our monetization strategy. If you're not familiar, monetization strategies can be subscription. Having ads
Marily Nika
00:09:32

renew model, you have something for free, and you ask to pay for like, Hey, get extra lives here. or and so on.
Marily Nika
00:09:40
So product health metrics are standard. They're not AI specific. They're there for any product. Its product. Health is very, very standard.
Marily Nika
00:09:48
You will see this in my slides as well that I will send you, so I have them right here.
Marily Nika
00:09:54
Engagement, retention, popularity, business.
Marily Nika
00:09:57
And you can think of it off
Marily Nika
00:10:01
like an acquisition funnel. So let's say I have launched an app on the app store called
Marily Nika
00:10:09
merrily.
Marily Nika
00:10:10
awareness would be out of.
Marily Nika
00:10:13
you know, who is searching for this app on the App store? Do people? Are they aware of it? Do they know of it?
Marily Nika
00:10:20
So you will measure the beginning of the final? Is the people searching for it.
Marily Nika
00:10:24
Acquisition is kind of out of these 100 people that say how many of them are actually going to click on the search result. That, says Marilyn.
Marily Nika
00:10:33
activation is, how many of these people are actually going to download the app and become a user.
Marily Nika
00:10:40
And you see, this kind of get smaller and smaller. Retention is how many people are coming back through merrily app
Marily Nika
00:10:46

revenue is, how much money are we gonna make from every person? And in total referral is, how many more people are we gonna get? So this is kind of the mental framework I want you to have in your mind.
Marily Nika
00:10:59
I am. So we talked about this.
Marily Nika
00:11:03
I added system health metrics here, because before AI, we didn't really care about system health meaning that.
Marily Nika
00:11:13
Sure, we can have 5 users. And we have a million users. This is not my job to care about.
Marily Nika
00:11:20
Hmm!
Marily Nika
00:11:20
First job, to make sure that the more users I get in
Marily Nika
00:11:25
that my my system is going to be robust. It is going to serve all these users. It is going to be reliable.
Marily Nika
00:11:32
So system health is about reliability, robustness throughput.
Marily Nika
00:11:37
I didn't care about that before I got into AI. But now, because of the AI nature, where we need to serve the results of a model
Marily Nika
00:11:46
system. Health becomes so important. You want to make sure.
Marily Nika
00:11:51
That your system is not gonna crash. I wanna make sure things are very, very important in there
Marily Nika
00:11:58
now, I'm sure you saw we talked about it before Openai.
Marily Nika
00:12:04
One day Sam Altman just tweeted and said, Hey, we just cannot have any more plus users premium users. We're just shutting this down
Marily Nika
00:12:13

mit Ctl. And so, he said, we're shutting down our main means of monetization, which is this premium kind of functionality just because they just couldn't have any more users. So you can see that they clearly
Marily Nika
00:12:27
mean, of course, they were monitoring it, but I don't think the right predictions. They couldn't predict just how much
Marily Nika
00:12:34
demand this was going to have. Alright.
Marily Nika
00:12:38
So system health metrics. It's a great problem to have. Yes, this is this, is it? This is right. Alright
Marily Nika
00:12:46
harsh. I love it. You said you weren't gonna ask me any questions today. Yet I see 1, 2, 3, 3, 3. I see. 3. Great okay.
Marily Nika
00:12:55
Do we use metrics and okrs interchangeably? No, you'll see. I have like a very good way of explaining this.
Marily Nika
00:13:04
Do we need any matrix for privacy of users? Ethical use of data? I love this.
Marily Nika
00:13:10
There is. This is not a metric. I assume that this would go before you get the go. No, go for launching your app.
Marily Nika
00:13:18
That there would be a thorough review with leads, you would make sure. As a Pm. It's yours was really to make sure things are ethical.
Marily Nika
00:13:28
There's no way to measure this. That's a very good question. I guess you can measure the amount of hallucinations.
Marily Nika
00:13:35
ratio and good answers. But that's still not ethical. It's more like, Hey, does this work, or does this not work? So it's a bit different.
Marily Nika
00:13:44
Okay.
Marily Nika
00:13:46

Harsha, bear with me. I have a lot of content, and if you're not covered, we can. Still, we can go through it. Okay.
Marily Nika
00:13:57
So now, last, but not least, we have our bucket, the AI proxy metrics. So this bucket right here is the most interesting bucket. This tells us whether our system works. This tells us what
Marily Nika
00:14:14
the key of the classification is going to be. This tells us that, hey?
Marily Nika
00:14:18
7 out of the 10 times you use me. This is gonna work. This is the accuracy, this is the core. This is the magic, and whether it works.
Marily Nika
00:14:26
Let me give you examples from my real life.
Marily Nika
00:14:30
When I was working for the speech team at Google.
Marily Nika
00:14:34
we had this Google home devices and we had a model that we embedded into these devices. And what that model did is this specific model would trigger if you said the hot word hot word meaning if I say, Okay, Google, how are you today?
Good thanks.
Marily Nika
00:14:57
I hope your day is good as well.
Marily Nika
00:15:00
So it triggered right? And I spoke in a very natural tone, and it was good.
Marily Nika
00:15:04
But when we first launch this oh, sorry I figured yours. I'm sorry. So when we first launched this. If I spoke it wouldn't understand me, or it would understand me. It would trigger
Marily Nika
00:15:18
6 out of the 10 times.
Marily Nika
00:15:19
and that was before we launched it to the world, and the Pm's sorry the scientists came to me, and they're like, is this good enough to launch? Of course it was not good enough to launch So
Marily Nika
00:15:31
they came to me, and they said this.
Marily Nika

00:15:33
Now II looked into it, and kind of to try to understand, as it turned out there were more data for male voices. So if I spoke like this, it was more likely to understand
Marily Nika
00:15:44
or there were issues with the data, not having enough diversity, because I have my Greek accent in English. II had to speak in an American accent. I cannot do this, but if I spoke in a fake American accent you would understand me right? So there are always issues that we had to to fix
Marily Nika
00:16:03
And then
Marily Nika
00:16:05
this metric is accuracy, and the way we measure it in AI is
Marily Nika
00:16:11
false, accepts false, rejects
Marily Nika
00:16:14
true, accepts through, rejects. So let me show you what this looks like I'll show this later. There you go.
Marily Nika
00:16:21
so you can have the true, positive, false, positive And actually I keep referring to my things. But this here is a great way to think about
Marily Nika
00:16:32
true positives and and true negatives. So let's say I have
Marily Nika
00:16:39
my gmail account, and my Gmail account has a feature which is classifying emails as spam or not spam. That's all. It does. Okay.
Marily Nika
00:16:48
If
Marily Nika
00:16:49
and mail is, mark this pum, and it is a spam, as you see, the very first one that I can claim 1 million euros exciting. This is a true positive. Okay?
Marily Nika
00:17:00
If something is, hey, let's catch up. Your course is amazing. Can I draw in? And it does not mark the spum. Then this is true negative, so it marked it correctly. It's not spam awesome
Marily Nika
00:17:13
if there is an email saying, Hey, mentorship request, and it's marked as spam.

Marily Nika
00:17:18
then it is a false positive.
Marily Nika
00:17:21
And then, if there's a cash donation about this amount of money, and it's not marked as well as a false negative.
Marily Nika
00:17:27
So you will get this ratios, you you'll get this accuracy, and they will tell you, hey, 5 out of the 10 times. This is classified correctly, 6 out of the 10 times. This is now classified. So just like the speech example, if I speak to it 5 times and it doesn't recognize me. And then the 60 does. It's kind of a brief user experience. So you want to constantly monitor this, you wanna make sure.
Marily Nika
00:17:53
you really really want to make sure to have a solid model that will provide good experience. Now.
Marily Nika
00:18:02
as we did in the classification example, last week.
Marily Nika
00:18:06
you trained the model, and then it told you, Hey, this is this, works 67% out of the time.
Marily Nika
00:18:12
Great! Now that rating that you see there when you take it and when you productionize it out in the wild
Marily Nika
00:18:22
it there's no guarantee. It's going to perform in the same way that it performed with offline data.
Marily Nika
00:18:29
This is because they're flying data that you use. Remember the test set when we split test set and the training set the test set doesn't necessarily cause more. More likely the data is going to be good.
Marily Nika
00:18:42
But when you're out there in the wild, and anyone can ask questions to this thing. It can be a kid. It can be well, I know it can trigger for the neighbor contrib. I don't know. You can see that
Marily Nika
00:18:55
the quality is going to be much different than in the experimental version.
Marily Nika
00:19:00
So you want to track the what I call it. I call it AI proxy, which all it means is the the metric for your AI algorithm.

Marily Nika
00:19:09
So you want to make sure that this is decent. You want to make sure. Even out in the wild that they performs. Okay.
Marily Nika
00:19:16
now the beauty of data and
Marily Nika
00:19:19
proclaims one. And AI. Is that the second you launch out there in the world any interactions that happen with these devices?
Marily Nika
00:19:30
This data goes back into some database, and
Marily Nika
00:19:35
you can clean it up and you can reuse it for training. So your original model. Now it's going to be enhanced with data that are found from outer in the wild.
Marily Nika
00:19:44
So the model is gonna learn. And it's gonna perform so much better with wild data. Than
Marily Nika
00:19:51
just the experimental data.
Marily Nika
00:19:54
I hope this kind of
Marily Nika
00:19:56
makes sense. And I'm just. I'm reading the question to see if there is anything there in the chat.
Marily Nika
00:20:03
Let's see and catch, says, do the metrics depend on the nature of AI. For example, Gen. AI versus not Gen. AI
Marily Nika
00:20:11
Harsha. Thank you for answering. Yes, at a high level. It should not matter. From the product, health perspective. It does not matter. Right? Proper health is standard metrics. You always have the same
Marily Nika
00:20:23
system. Health metric. Still, it doesn't really matter, because these are standard as well, you know, like
Marily Nika
00:20:28
robustness, how throughput can you serve? The more people you get

Marily Nika
00:20:33
now the AI proxy does change a bit. There are different kind of metrics for each type type of algorithm you have. This is a great question. And I can add a little hand out to you in your portal. If you wanna read more I'd love to
Marily Nika
00:20:51
But for classification it's like the most solid example, because it has the notion of true positives, false positives. And I think that's a great way to wrap your your mind around this.
Marily Nika
00:21:02
Now I showed you this on session one, which is how AI capabilities can vary, and I think it's a great way to
Marily Nika
00:21:10
to show you for you to think about
Marily Nika
00:21:13
how sensitive you should be when it comes to the AI proxy metrics.
Marily Nika
00:21:20
So the more your product is on the top right then the more you need to pay attention to your AI proxy, the more it's on the top left bottom left.
Marily Nika
00:21:30
The least sensitive you should be to your AI proxy metrics.
Marily Nika
00:21:36
because the more you're on the top right, the more your experience depends on AI working well, whereas at the bottom left it's kind of like, okay, like, we can disguise it with some user experience, like, it's okay, if it's not perfect. So that's
Marily Nika
00:21:51
that's something to say.
Marily Nika
00:21:54
alright. So I also want to show you these growth hacking techniques. that are related to the product health metrics. But you know there are little strategies. I talked to you about Farmville at the top, right as you can see.
Marily Nika
00:22:07
So, for example, if you want to increase retention, you are going to come up with ideas like this, where? You will get into Farmville, and then Farmville will post on your wall, and to say, Hey, this tree is back.
Marily Nika
00:22:23

But what's interesting here is this, but get coins line right there.
Marily Nika
00:22:28
because if anyone from my wall clicks on this
Marily Nika
00:22:32
they will go back to their farm and they'll get coins for their farm. So this is excellent for attention.
Marily Nika
00:22:39
In fact, there was this huge Farmville craze
Marily Nika
00:22:42
where people were creating fake accounts so that they would get in there and get coins and share.
Marily Nika
00:22:50
because II think for every person that got coins they would actually give coins to the person that made the original post as well. So it's just. It was very, very.
Marily Nika
00:23:01
It was an excellent tactic when it comes to Pm. It was annoying.
Marily Nika
00:23:05
and eventually I don't know if you notice. But if you go to Facebook and you connect an app now it's gonna say, Hey, this app will never post on your wall unless you allow it to, just because never got permission to post in the wall. You just, you know, you just install that and boom, it would just
Marily Nika
00:23:20
plus people. So now this doesn't happen anymore. Thank God. I hope people learned
Marily Nika
00:23:24
alright. alright, alright
Marily Nika
00:23:30
bottom. You see, increasing engagement. Okay?
Marily Nika
00:23:34
So the bottom is the standard is Youtube, essentially, it's a Youtube channel.
Marily Nika
00:23:39
So if I go to my Youtube channel and I have a Youtube channel. I want to show you something. Let's see. Let's say, let's see.
Marily Nika
00:23:51
So I have a Youtube channel. If anyone is interested, please subscribe because I'm going to start

Marily Nika
00:23:56
to do this right. It's very difficult. I'm figuring out how it works. But what I want to show you for this is, if I go in a video
Marily Nika
00:24:06
like this one. Right?
Marily Nika
00:24:09
it asks me, hey, what do you want? Your videos end screen to be? And I'm like, Well, I want my end screen to be just to have a little preview of a video here. Okay.
Marily Nika
00:24:23
and I can choose whether that is gonna go include the playlist I create
Marily Nika
00:24:30
or whether it's gonna include the video. But check this out. It says.
Marily Nika
00:24:35
best for viewer. Allow you to to select
Marily Nika
00:24:39
the best video to suit the viewer. So
Marily Nika
00:24:42
if you go on this, you see here that you will always get a little preview. So the preview is tailored to you
Marily Nika
00:24:51
so that we can maximize the chances for what's time to go up.
Marily Nika
00:24:56
So when they're asking me, hey? Which video to serve. And I say, I want the best video from my channel, for the viewer is because they help me.
Marily Nika
00:25:07
figure out how to increase this watch time for my Youtube videos with AI.
Marily Nika
00:25:13
So it's very interesting. This is truly there to increase engagement. And
Marily Nika
00:25:18
it's kind of these little hacks you have.
Marily Nika
00:25:23
that's make truly move the the needle

Marily Nika
00:25:29
next app on the left you can see 9 gag cute.
Marily Nika
00:25:34
So this is just a Facebook page. And you can see they they literally just post the cute Corgi. That's it. Why would they do this? Well, it's because their goal is to increase activations. Because you will see this. And you will say, Oh, I want to see more of these cute corgis. I'll click there and I'll join the page.
Marily Nika
00:25:51
So this is what we call we used to call growth hacking. Now, it's what we call product led growth. So for anyone interested in growth techniques and so on. It's this is, you should be a growth. Pm.
Marily Nika
00:26:04
and back to the metrics. I wanna show you. There you go here on the right side.
Marily Nika
00:26:12
Whenever we talk about awareness, acquisition, activation. It's essentially
Marily Nika
00:26:17
product marketing. And that focuses on this. For the rest, it can be the Pm or the growth hucker.
Marily Nika
00:26:25
But it's interesting because this
Marily Nika
00:26:28
used to be a role no one cared about. But now.
Marily Nika
00:26:31
product marketing is a really nice role. In fact, if you want to be a Pm. And you're not a Pm. Yet, and you're finding it tough to become one.
Marily Nika
00:26:42
I
Marily Nika
00:26:44
I think you should definitely consider becoming a product marketing manager.
Marily Nika
00:26:48
Because if you're A. P. They're called Pmms. If you're a Pmm, you can easily more easily tell you into the Pm. Side of things. So product marketing is great is a great first step within the product world. I completely recommend it. I have so many students that
Marily Nika
00:27:03

used to be Pmms. And now our Pm's within the AI
Marily Nika
00:27:08
world. Alright.
Marily Nika
00:27:10
So
Marily Nika
00:27:13
let's talk about okrs in product management. Okay. so have created
Marily Nika
00:27:20
good. Socket is the only 9 Pm. You hear me loud and clear. Yes, yes. there are ways to become a Pm.
Marily Nika
00:27:28
That don't involve you becoming a Pm. Immediately. Okay, so it's it's totally fine to have kind of a phased approach, especially in this market, as I did right now, so I strongly recommend it
Marily Nika
00:27:39
alright. So L. Krs in AI product management.
Marily Nika
00:27:43
So in order to create an Okr.
Marily Nika
00:27:46
You see, I have this structure for you. I have at the top your high level of yeah. Remember, we talked about you need to have a mission and explain what you're doing and why. So you have your high-level objective.
Marily Nika
00:27:58
and then you will have your Q results. Q. Result one. Here's my pure product, health nor star metric. I want to generate oven 10 KB, 2 C. User signups by the android, and Ios app
Marily Nika
00:28:11
curious. All to is going to be your AI proxy metric. Okay.
Marily Nika
00:28:19
carousel, 3 is, gonna be something around your system. Health. So
Marily Nika
00:28:24
I have put together for you this resource. That I feel is very
Marily Nika
00:28:31
very, very important.
Marily Nika

00:28:35
that I had the tab open and closed it alright. Let me just pull it up for you
Marily Nika
00:28:43
I love.
Marily Nika
00:28:44
There it is. I just love the discussion. I seen the chat. This is amazing.
Marily Nika
00:28:50
So I'll share this with you.
Marily Nika
00:28:52
But essentially my, the framework. And how I see things is
Marily Nika
00:28:57
your Okr is your goal.
Marily Nika
00:29:00
Api
Marily Nika
00:29:02
is the metric you're gonna use to measure progress against that goal.
Marily Nika
00:29:08
So we talked about a lot of metrics. But these metrics don't matter.
Marily Nika
00:29:12
If they do matter for your product, then they are Kpis. Okay, so you have your goal. You have the metrics for your goal, which means the Kpis.
Marily Nika
00:29:21
and then you have your nor star metric.
Marily Nika
00:29:24
which is a kpi.
Marily Nika
00:29:26
the core metric that captures all value you're bringing in.
Marily Nika
00:29:30
Now, here's the interesting thing. You may have many. Okay. Rs. many Kpis under Hokr.
Marily Nika
00:29:37
with only one North Star metric are
Marily Nika

00:29:41
Kr, okay, and that's an interesting thing.
Marily Nika
00:29:47
I want to show you
Marily Nika
00:29:51
I have made this tweet.
Marily Nika
00:29:56
Yes, this guide is for you.
Marily Nika
00:29:58
So I had tweeted this.
Marily Nika
00:30:00
And
Marily Nika
00:30:02
it started kind of this very interesting discussion. Okay,
Marily Nika
00:30:07
And I told people, Hey, don't measure what your brother will not impact. Okay, so you have your kpi metric. And this is a very important
Marily Nika
00:30:15
discussion and distinction, before which I'm going to go making because you should know what the Kpi is what an okay R is what the North Star metric is
Marily Nika
00:30:24
so moving down this guide that I will give for you. We always. This is the framework. I believe people should be using. But this is
Marily Nika
00:30:35
objective. What is the main goal for the next quarter? Okay. this is user focused. What is it for
Marily Nika
00:30:42
and clear of the desired outcome.
Marily Nika
00:30:45
And then specific feature. What is your specific feature? I am creating this recommender for Netflix. That's gonna recommend next video to watch. What is the main metric that will showcase success increase user engagements?
Marily Nika
00:31:01
20%.

Marily Nika
00:31:03
Why does your product health metric? Okay, reduce the number of util complaints.
Marily Nika
00:31:08
What is your Garvey of metric? Another very important one. Okay, ensure that
Marily Nika
00:31:14
decrease X percent. Now, gardo metrics are very important, but you don't always need them. I think it's great practice to add them, because that's good. Pm. Craft, as I like to call it.
Marily Nika
00:31:27
and then see some health metric maintain 99% system uptime
Marily Nika
00:31:33
ensure loading times. Stay below 2 s.
Marily Nika
00:31:39
So now, if I speak to this device, oh, I found it.
Marily Nika
00:31:44
There is my extra mouse. It was hidden. She had hidden it. Okay, I have to.
Marily Nika
00:31:49
So if I speak to my Google home device, it is going. I noticed it before. I didn't respond immediately, and that is exactly one of the metrics we had added as a system, help metric. So let's see, and sorry for triggering yours as well.
Marily Nika
00:32:04
Hi, Google! What is your name?
Marily Nika
00:32:10
Oh, my God! The long time! Hey, Google, how are you today?
Marily Nika
00:32:15
I'm feeling great. Thank you for asking. I hope you're having a great day.
Marily Nika
00:32:20
So you see, it took a few seconds, and the exponential was not good like. It's not supposed to do that. You're supposed to say, Hey, how are you? And should say, I'm good. How are you? Okay? So this is a system. Health metric.
Marily Nika
00:32:29
Ai proxy metric increase the accuracy of the content recommendation algorithm by 15%.
Marily Nika
00:32:36

So this is the framework we have.
Marily Nika
00:32:40
and I have a ton of examples, for you
Marily Nika
00:32:44
have all these big tech companies like Tesla enhance the driving experience. Okay. features. Introduce 2 new features for driving style preferences. Your North Star is
Marily Nika
00:32:58
increase. The usage of autonomous mode by 15%
Prama health
Marily Nika
00:33:03
feedback related to trustworthiness. We're still driving by 20% guardrail metric. Of course, safety is clearly communicated and understood
Marily Nika
00:33:15
system. Health achieve a system, responsiveness rate of under 200 Ms. Per hazard detection.
Marily Nika
00:33:25
Maintain a vehicle integration rate under yes, this is yours. You'll find any the porter as well. But this is like a big guide.
Marily Nika
00:33:37
but obviously you would need to take us some time to kind of read and go through, because examples from zoom, from grammarly, from Amazon, from Facebook spotify all these big tech companies. And it's a very interesting way to think about it.
Marily Nika
00:33:53
Now. someone asked me, Hey, do you set these for a quarter or
Marily Nika
00:33:59
or not?
Marily Nika
00:34:02
Well.
Marily Nika
00:34:04
you can set them. You definitely need to set them for next quarter. But you, as the Pm. Especially, more leadership kind of roles. You will need to set these for the next 2. The next 4 quarters.
Marily Nika
00:34:16
You don't need to have all the information for quarters 3 and 4, but you should have a high level idea so that you can give enough of a heads up to your teams as to what to expect.

Marily Nika
00:34:34
Alright. So
Marily Nika
00:34:37
tender matching is another very interesting one. Okay. here, product, health increase, 20% improvement in user feedback scores.
Marily Nika
00:34:47
The AI specific one is
Marily Nika
00:34:52
15% improvement in match relevance scores. Okay.
Marily Nika
00:34:56
so you can see here all the different use cases and how we come up with them.
Marily Nika
00:35:00
Now the question, How do we come up with? The sentence.
Marily Nika
00:35:07
We are placing numbers from there. But here's what you're doing.
Marily Nika
00:35:11
At the end of a quarter
Marily Nika
00:35:14
you will grade your Okrs, and you will see whether you achieved your goals or not
Marily Nika
00:35:20
grading happens from 0 to one. If it's one.
Marily Nika
00:35:24
you completed everything in your care. if it's 0, you did nothing.
Marily Nika
00:35:28
Now, here's the weird thing. If you grade your Okr at one.
Marily Nika
00:35:35
It means your team did not do well.
Marily Nika
00:35:38
It means you did not do.
Marily Nika
00:35:40
because you didn't challenge yourself enough.

Marily Nika
00:35:44
You want to aim to reach 0 point 7
Marily Nika
00:35:50
0 point 7 means that you did 70% of what you should have.
Marily Nika
00:35:55
So when you set goals.
Marily Nika
00:35:57
you need to say that
Marily Nika
00:36:01
you know 70 s. Arrived when a while ago?
Marily Nika
00:36:04
So I'll add 30% extra to these percentages so that I can make sure people will meet the 70% mark. It's a very weird
Marily Nika
00:36:13
way of seeing this. Okay.
Marily Nika
00:36:17
this is how Meta work this, how Google works. We never wanted to reach 100%. We want to reach 70%.
Marily Nika
00:36:24
It's because you want to challenge teams. This is because you want to add a little buffer. So whenever you see this 20% improvement, if you get like a 13%, you should still be very, very happy.
Marily Nika
00:36:34
When people come to see you and say, Hey, 15 is too high. You will say, Okay, well, let's have this as a goal whole. Steve. 70%.
Marily Nika
00:36:44
Okay. I hope this. Helps. It's a very interesting way of of seeing this. Alright.
Marily Nika
00:36:55
It's okrs can be financial can be. Customer facing can be AI focused can be product can be tech.
Marily Nika
00:37:03
I have more examples for the AI team that I will show you like. I will share everything with you. Please read it at your own time. But
Marily Nika

00:37:10
what I want to do now, as you may be able to guess, is
Marily Nika
00:37:16
Send you to breakout rooms because I want you to create your own. Okay, ours
Marily Nika
00:37:22
for a product of your choice.
Marily Nika
00:37:26
So here's how this exercise came out will work.
Marily Nika
00:37:30
aye. want you all to make a copy
Marily Nika
00:37:37
of this link right here
Marily Nika
00:37:41
and then
Marily Nika
00:37:44
perfect.
Marily Nika
00:37:45
I just love when people keep in mind, and then I want you to go into rooms, and I will give you
Marily Nika
00:37:53
the exact
Marily Nika
00:37:55
prompt that I want you. So I'll give you the product that I want you to work on
Marily Nika
00:38:00
with your team, and I want you to literally do the
Marily Nika
00:38:05
out what your cars are based on this guide as kind of a proxy. Okay, so
Marily Nika
00:38:13
let me find if I had rooms. And I'll explain a bit more. Let me just open them. Just give me a second, and we can do
Marily Nika
00:38:21
there we are there. We are. Okay.
Marily Nika

00:38:25
Excellent.
Marily Nika
00:38:27
So we have 1015 rooms. Okay?
Marily Nika
00:38:32
So
Marily Nika
00:38:34
rooms from one to 5, and I will write them. Here are going to work on some matching algorithm.
Marily Nika
00:38:41
Let me write it here. So you have it. Rooms one to 5, matching. Algorithm theme there, or bamboo
Marily Nika
00:38:51
6 to 10 are, gonna have
Marily Nika
00:38:59
fix it in are going to be recommendation engine, like Netflix or spotify.
Marily Nika
00:39:03
And then
Marily Nika
00:39:09
so according to which room you're in, you will
Marily Nika
00:39:14
algorithm recommendation engine or chatboard Google home, Alexa.
Marily Nika
00:39:18
and you will all work on one
Marily Nika
00:39:21
spreadsheet on one deck. So you did make a copy for your for yourselves. But please share the one file that you will walk with your team so that you all work in one.
Marily Nika
00:39:31
and then we'll come back to discuss. So I want you to write
Marily Nika
00:39:34
2 2 sets of 4 krs for your team
Marily Nika
00:39:38
and please include

Marily Nika
00:39:41
on the high level. These kind of structure. You don't have to choose all of them right. This is kind of
Marily Nika
00:39:46
too many, but it's up to you if you want to have, you know.
Marily Nika
00:39:50
guard rail, if you all want to have a system health. But please definitely have an AI one and definitely have a problem.
Marily Nika
00:39:57
So with that, said, We'll go, and I'll be coming from room to room. To discuss.
Marily Nika
00:40:03
Yes, you have it. It's here, and it's also in your report
Marily Nika
00:40:10
alright. So let's do this, and I'll be coming from room to room. And we can pick it from there.
Sean Peters
00:40:15
Share my screen while other people don't want to share it
Marily Nika
00:40:18
alright. Go for it, share your screen and tell us. What room were you? In? Which product did you do?
Sean Peters
00:40:24
Yeah. So I was me and my lowering group. And we we picked Netflix
Sean Peters
00:40:30
And looking at your 15 different examples, there, you had one for Netflix. So we wanted to kind of straight away from that. Just not do that. So we look back at Netflix Mission, and it is to entertain the world. And so with that we then deviated from there to see if we could come up with a different objective that was different than yours, and so that was enhanced exposure for what Netflix subscribers can be entertained with by delivering recommendations for new media types.
Sean Peters
00:40:55
So we know that Netflix is going down the path of for shorter form, content, games, so on and so forth. And we want to ensure that we were continuing to expand what people could be entertained with with Netflix. So we looked at 3 different key results, first, one being a north star, and that was to transform Netflix into a multimedia company by improving click the rates of new content by 20.
Sean Peters

00:41:20
And then we looked at Pritel and that was to boost user feedback scores related to the usability of the new content by 20. So the example that we kept linked to, or games something like Grant that thought it was kind of like their big pilot, I think. And could you actually find the game as usable?
Sean Peters
00:41:37
And however you were consuming whether that was desktop, whether that was like your smart TV remote. Whatever the case is, did you get same experience? And so we want to ensure that
Sean Peters
00:41:48
that user building still there and then the AI proxy that we went with for keepers. All 3 was ensure that users self returned to the recommended content. Targeting 15% improvement. So it wasn't necessarily a oh, yeah, I try to winds. It's kind of cool, but I'll never really do that again. And that you continue to come back and prove that the model was actually working.
Marily Nika
00:42:13
Very interesting. I love it transforming into a multimedia company by improving Ctr. Of Ugandan. This is a very, very interesting. I, yeah, this is super super good. And the AI proxy self return to recommend a content targeting 15% improvement. Okay?
Marily Nika
00:42:28
You know, I don't know if this is an AI proxy.
Marily Nika
00:42:32
It would be an AI proxy if you said something like make sure the recommended content is accurate.
Marily Nika
00:42:39
relevant. It's the right for this cohort of people.
Marily Nika
00:42:43
but it's not about any user behavior. You know, it's about the raw technology itself. So that's the only thing. Okay, I'll point out.
Sean Peters
00:42:53
okay, interesting. And then I guess.
Sean Peters
00:42:56
with the way that we were thinking about is you would self return to that content because it was relevant because it was accurate. But we could probably be a little bit more specific.
Marily Nika
00:43:04
Yeah, okay, yep, increase relevancy by 15% which would result in users self returning. But yeah.
Sean Peters
00:43:14

gotcha I know that we're short on time. I had a quick question, though, because an interesting conversation came up about this. So Netflix massive Company, they're gonna have other Pms that are very focused on their recommendation. Models specifically for their other videos. So they want to continue people using other videos.
Sean Peters
00:43:32
our product team can more concerned concerned with new content. How should we reconcile that? The company itself is going to care about just what's going to increase time. That's going to keep people more esteem. That's going to get people to up their subscriptions for Netflix. How do we think about that as 2 separate product teams wait. So are we talking about? Is it one company, 2 different teams, or 2 different companies.
Marily Nika
00:43:57
one copy, 2 different teams and tell me what the other team is doing. Again, recommendations for just videos on Netflix
Marily Nika
00:44:05
recommendation for videos on Netflix. Okay? Well, you need to work with the Pm, so that do, you can make sure you don't cannibalize them and they don't cannibalize you. So product and feature. Com. Nebilization is a huge thing. Where what you wanna achieve goes completely opposite to what other people want to achieve. And it goes back to the discussion we had yesterday about the short form, comments and long form content on Youtube.
Marily Nika
00:44:31
so the way to think about it is just you need to be aligned with both rollouts. Now, from a pro perspective,
Marily Nika
00:44:39
you can trigger this specific feature on specific journeys, part of the journey of the user. So you can say, Okay, you recommend here. I recommend here. And it's kind of they both sounds like they have different use cases, anyway.
Sean Peters
00:44:54
Awesome. Thank you awesome. Thank you. Thank you so much.
Marily Nika
00:44:57
Alright cool. So I am gonna switch gears because what I wanna do now is
Marily Nika
00:45:07
discuss interviewing a bit. We're not going to have time to get through interviews much, but I want to walk you through my framework as to how I feel. You should think about interviewing
Marily Nika
00:45:21
So I've created this checklist for breaking into AI products.
Marily Nika
00:45:27

and it has different phases before applying, which is where you're at. Right now
Marily Nika
00:45:31
I want you to understand what aipm is all about so perfect. You take that box.
Marily Nika
00:45:36
gain some experience in creating and launching.
Marily Nika
00:45:40
so
Marily Nika
00:45:42
lot like, I swear to you, 70% of the students, 70% of the students
Marily Nika
00:45:48
have already worked in some AI feature without knowing it.
Marily Nika
00:45:53
So if you've learned something that's smart.
Marily Nika
00:45:56
Just go to your engineers and say, Hey, did we use any AI for this, and truly understand what they did?
Marily Nika
00:46:02
They dated behind the scenes.
Marily Nika
00:46:04
and when I say AI, I mean literally just calling in some Api or something that can do something around. I don't know. Speech, something smart. Translate something. So you've done. AI. Very, very likely without knowing
Marily Nika
00:46:18
I'm here to figure this out.
Marily Nika
00:46:21
number 2.
Marily Nika
00:46:22
If you do not have that experience, there are amazing ways to get it, and I think I mentioned devpost. It's an amazing place for hackathons
Marily Nika
00:46:32
you can join in for free. They last like 1, 2, or 3 days. They have prizes.
Marily Nika
00:46:38

There are so many about AI, and you can get in there
Marily Nika
00:46:43
form teams. There you go. Yeah, to heal whatever about one month left. You will form teams, and you can be the Pm. Of your team. So at the end of it you will have something to show, for you can have a little portfolio. You can have
Marily Nika
00:46:57
3, 4, 5 of them.
Marily Nika
00:46:59
so that you can showcase that, hey? I am a product marketing manager. But look, I ha hands on participating in this Jain AI Hackathon, I won or I have this product to show you. Okay, like this, 19 to 21. Right?
Marily Nika
00:47:14
Gen. AI,
Marily Nika
00:47:16
and you can form teams within this platform. It's a super super good platform. Okay? So make sure to get some experience.
Marily Nika
00:47:26
get your storytelling right? That's a Pm. Trade. But I want you to be comfortable with telling your storytelling for AI as well. So everything we've been talking about from like what? The what features does AI entail recommendations automation, scaling, generating everything we discussed on day one. Just make sure to be comfortable with the features and understanding what it can add to the users.
Marily Nika
00:47:53
Application time. we revamp our online presence. It really matters.
Marily Nika
00:47:59
especially nowadays. You need solid online presence
Marily Nika
00:48:02
offline revamp. You want to have a regime that looks good. Tell your friends, your colleagues, Linkedin, with your available
Marily Nika
00:48:12
apply everywhere, even if you are, or you aren't crazy about the jobs.
Marily Nika
00:48:18
But but
Marily Nika
00:48:21

the best way to do it is to reach out to people that work in these companies that can refer you. and the even better way is to find who the hiding manager of a role is and reach out to them.
Marily Nika
00:48:35
And I know this sounds like very uncomfortable, but
Marily Nika
00:48:38
if I'm a hiring manager and I get a message from someone saying, Hey, I saw you have this opening. I'm perfect for it. Here's my regimen. Here's why I'll appreciate that pass Link so much.
Marily Nika
00:48:49
and like that you have a direct touch with the heading manager
Marily Nika
00:49:07
merrily froze for me. Is she frozen for others? There's no license.
Marily Nika
00:49:13
Yeah, it's really really bad. Unfortunately. So make sure online. Be right offline. Be right. I have a template arrangement template. I want to share with people here
Marily Nika
00:49:23
that I have created. Let me just open it up there it is
Marily Nika
00:49:29
my templates right here.
Marily Nika
00:49:34
Oh, did I froze on my back? Yeah, yes.
Marily Nika
00:49:38
okay, cool, cool.
Marily Nika
00:49:42
So yes, I don't know if you heard me. But please reach out to the hiding manager. Specifically on Linkedin. I know it's sunk over and scary, but they will appreciate it.
Marily Nika
00:49:53
do I? And you get rejected? It's probably some automated system that rejects you. So please just go ahead, and apply reach out to the people.
Marily Nika
00:50:07
you know, you are, gonna apply like to 20 or 30 roles. You're gonna get one interview, and that's fine. You just care about one
Marily Nika
00:50:13

when you get an interview. Take it seriously. Okay, it's it can change your life, so do the work that's needed. This is the moment that matters. I'm
Marily Nika
00:50:24
so my level. I'm a group product manager, right? And I got into Meta as an All 7, which is kind of it's it's difficult to get in all 7. Okay, and
Marily Nika
00:50:36
and the interview questions I got were
Marily Nika
00:50:41
so I got
Marily Nika
00:50:42
the first question was, Hey, how do you build? A dog walking app? And it's just really interesting to get this type of question when you expect something around AI and leadership and people building and people are like, Hey, how'd you build an app for dog walking? And it's kind of like, okay.
Marily Nika
00:50:59
you have to play the game. You have to take it seriously. Okay, so do the work. This is the moment that matters.
Marily Nika
00:51:07
No question is low enough for you. No question is too complicated like you can figure it out. Okay. ask for time. When the reporter decides to you. The recorder wants you to interview yesterday. But you.
Marily Nika
00:51:23
I think if you ask anywhere from 2 to 3 weeks, it's perfectly fine, and I think it's a great practice to do it so that you can prepare
Marily Nika
00:51:29
do mocks with your friends, prepare, prepare, prepare.
Marily Nika
00:51:34
It's an amazing trap.
Marily Nika
00:51:36
To you. You read something like, okay, I got this. I know this. I know how to do this.
Marily Nika
00:51:41
but it's different to say it out loud. Okay, use my, the Gbts I created. They're they're just for you. To help you.
Marily Nika
00:51:52

since this one specifically is tailored for AI
Marily Nika
00:51:55
and of course I the estimation one that I gave you before. This is also there
Marily Nika
00:52:03
to help you practice
Marily Nika
00:52:04
and then, at the end of the day expect to fail. I will not
Marily Nika
00:52:10
okay. But it just matters that you'll get in once.
Marily Nika
00:52:13
Now.
Marily Nika
00:52:16
yeah, failing like is a part of it. And failing nowadays doesn't mean you didn't do well, it means they got someone internal, right? So it's just unfortunately, the market is really tough.
Marily Nika
00:52:26
the whole thing is going to take from 4 to 6 weeks. Okay. so I want you to know this. I want you to be prepared.
Marily Nika
00:52:35
Now the interview themes.
Marily Nika
00:52:38
They're not gonna tell you, hey? This is AI specific.
Marily Nika
00:52:41
but they are. Gonna ask you a question that they expect you to come up with a smart feature answer. So they want you to embed AI in there so that they can see you think and breathe of it. So they're not gonna say, Hey.
Marily Nika
00:52:54
tell me about an AI way of solving this pain point? No, you need to have it in the back of your head. Okay. number one. It's gonna be product sense. How will you design
Marily Nika
00:53:07
an alarm clock for someone that's blind.
Marily Nika
00:53:10
How would you design a fridge?
Marily Nika

00:53:12
Analytical one will be
Marily Nika
00:53:14
how do you measure success of an AI feature? Everything we just talked about.
Marily Nika
00:53:21
It's gonna be estimate the amount of
Marily Nika
00:53:25
dog food required in the Us course. Functional course. Functional is.
Marily Nika
00:53:31
some comments call it transactional. Have some comments call it craft and execution.
Marily Nika
00:53:36
Essentially, number 3 is about
Marily Nika
00:53:40
How do you get buy in from your team? How? Just like the question we answered before, like, there's someone in the company building the exact same thing like, what do you do?
Marily Nika
00:53:50
It's about stakeholder management getting buy in resolving situations like, hey, what areas does your
Marily Nika
00:54:00
company-wide update
Marily Nika
00:54:02
tag contain for you? Strategy is going to be
Marily Nika
00:54:07
Should we get into self-driving cars? Strategy is very straightforward, cross, functional is very straightforward.
Marily Nika
00:54:15
So for strategy, if they ask you this, we also talked about that right where we said, Hey,
Marily Nika
00:54:20
Should we get into self-driving cars, and what you need to say is, Well, my mission is this, as a company?
Marily Nika
00:54:26
This sounds like that lines. Well, with my mission. Here's how it affect that you would affect us internally like, does it fit in the portfolio that we have internally

Marily Nika
00:54:36
here's the barriers of entry like it's expensive. We can just build an in-house.
Marily Nika
00:54:42
It's
Marily Nika
00:54:44
you know, there's a war. There's
Marily Nika
00:54:46
something happening outside. So I don't know if it's the right time for investment. So this is the external factors. And then you make a recommendation like.
Marily Nika
00:54:53
I don't focus too much on this, because I just think it's very people. People will be okay. But the difficult ones are one and 2. And that's why I created this Gbts
Marily Nika
00:55:06
leadership. You only get this if you're interviewing for level 6 and above in big tech.
Marily Nika
00:55:12
6. And above means like
Marily Nika
00:55:15
6 years of experience and more. This gonna be like,
Marily Nika
00:55:21
Well, if you're monitoring a team, it's gonna
Marily Nika
00:55:24
do you set the right scope for your team? How do you define the roles? Your team should have?
Marily Nika
00:55:31
It would be. Hey? How do you deliver difficult news to someone? So things like that
Marily Nika
00:55:37
number 6 take a home exercise you should wish for a take-a-home exercise and presentation. People hate them usually, but it's a blessing because you get to do really well on one
Marily Nika
00:55:48
aspect of the interview, cause you will have time to prepare technical interview. some companies use to ask for something technical.
Marily Nika
00:55:59

People asks for a more technical interview for AI folks. They will ask you about architecture, which is very.
Marily Nika
00:56:07
I was coaching someone through it, and
Marily Nika
00:56:10
was kind of interesting to see the level of depth they wanted to get in.
Marily Nika
00:56:14
That person did go in, but they were an ex engineer, so they knew, like very technical things. So these people were not looking for an aipm. They were looking for an engineer that is, gonna be called a Pm. It was very tough.
Marily Nika
00:56:26
Google had a technical interview. They now removed it. So you don't have to worry about this.
Marily Nika
00:56:33
I'll give this to you. It's kind of secrets on how to prepare.
Marily Nika
00:56:38
I feel. If you want the starter company for Big tech. Amazon is the best way to go.
Marily Nika
00:56:44
Amazon is the most straightforward company. because the questions are are like.
Marily Nika
00:56:50
Tell me about a time when you solve the problem. Tell me by the time where you got by in.
Marily Nika
00:56:56
tell me about the time where you came up with how to improve your product.
Marily Nika
00:57:02
So Amazon is wonderful, like the interview process is just way more straightforward than Hey, build a
Marily Nika
00:57:09
a dog walking up. Okay. Sahil says that Pmt. At Amazon requires 2 tech interview.
Marily Nika
00:57:17
Well, that's the thing. There. There is a standard product manager. And then there is the technical product manager, Amazon. It's a bit different. What is the bar razor interviewer? Vanisha? Can you let us know? I don't know what that is.
Venetia Tay
00:57:33

Oh, I mean that books written about this. But when I was thinking of going to Amazon well, my first was telling me that there is a bar raiser, basically someone who's actually not in the interview loop. You actually have to get training to be a bar razor interview. And their job is to make sure that you're the best of the best. So it's almost the hardest interview that you ever face, and if that person says no, your chances are like out like even everyone says yes, but the bar raiser says, No, you're not. You're not in
Venetia Tay
00:58:02
so as to keep the standards
Sahil Sachdeva
00:58:04
some friendly at Amazon. So it's basically not anybody can interview you. You have to apply to be a bar raiser.
Sahil Sachdeva
00:58:12
Then they test. They interview you so you could interview somebody else.
Sahil Sachdeva
00:58:16
So you have to go through some hurdles just to be a person who, wanting to be external candidates or even internal.
Marily Nika
00:58:25
Oh, my God, okay, very interesting. Well, I personally think.
Marily Nika
00:58:30
that's interesting where you're in. Yeah. Any interview trainings I've had internally where you know standard calibrations, but nothing like that. I don't think I would pass this very interesting. But yeah, I love honestly interview. I went through it. I think it's just super great.
Marily Nika
00:58:45
Meta and Google are.
Marily Nika
00:58:49
It's interesting, because if you want to interview for these companies, they will likely give you
Marily Nika
00:58:54
either the option or depending on the team. You will either go through the generic track where you know you interview with someone random.
Marily Nika
00:59:04
and it's gonna be generic. Pm, questions. And then if you pass. You do kind of an internal team matching process. Let's be dating, they will say. Hey, we shared your profile with this hiring managers. Here are the people that were interested have calls with each one of them so that you can decide which one you want and see if it's a mutual fit.
Marily Nika
00:59:24

So they could either say, this, go through the generic one, or they will say, you can go through the specialized
Marily Nika
00:59:30
interview for a specific role directly.
Marily Nika
00:59:33
They offer you a choice.
Marily Nika
00:59:36
You do not want to do that generic one. You want to go through the specific one, because
Marily Nika
00:59:40
I feel that's my personal opinion. I feel that the generic one the bar, is kind of higher in the sense that
Marily Nika
00:59:48
you're competing with the perfect storyteller, with the perfect communicator, with the perfect Pm. Versus the specialized one.
Marily Nika
00:59:57
You have something that others don't. You have a niche skill in your background that you're chosen for, and you are. Gonna talk to the hiring manager as part of the interview, and the hiding manager will have a say as to Hey, Mary should go in or not. Okay, so go for the specialized interviews. Always
Marily Nika
01:00:18
the specialized interview is the one that will have AI focused questions. So they will ask you something. And you will need to make sure. You answer.
Marily Nika
01:00:27
you know, with an AI enhanced and an AI powered feature in mind.
Marily Nika
01:00:32
So every time I've gone through the generic track. I failed every time I've gone through specialized tracks I've passed so very important. If you given the choice, ask
Marily Nika
01:00:41
people to first find a team for you, if possible, or do what I say, which is, reach out to on Linkedin to hiding managers. Don't be shy also, don't be creepy. Your message like you don't wanna be like it's talking like, Hey? I've been monitoring you for a while, though it should be like, Hey.
Marily Nika
01:00:58
I found your name. I know you're hiring for this.
Marily Nika

01:01:01
I'm so excited. Here's why I'm perfect. Here's my regiment, if interested, let me know. That's it. No, follow ups. No, hey? I wanna make sure you show this? No, no, no, just once
Marily Nika
01:01:12
throw plant the seed, and that's it.
Marily Nika
01:01:14
Because there's this perception that if you apply and get rejected automatically. You're like, Oh, I'm not good enough. It's not worth it.
Marily Nika
01:01:24
It's
Marily Nika
01:01:27
Yes.
Marily Nika
01:01:28
it's it's very, very important to to know this.
Marily Nika
01:01:32
Nvidia. I did that, too. It's
Marily Nika
01:01:35
great! I'm it was interesting, was, it? Felt, more corporate than Mira and Google. But it was.
Marily Nika
01:01:43
you can tell. That's that's a rocket ship. You can tell that this is where the future is, with the hardware and everything that's happening. They're like
Marily Nika
01:01:52
perfectly position, like, if you can get in and be there right now. I think it's it's an amazing place to be.
Marily Nika
01:01:57
So I know we're running out of time. I have so much to tell you. So here's a couple of things, I wanna tell you.
Marily Nika
01:02:05
I have
Marily Nika
01:02:08
as part of the boot camp. We will be running a an interview
Marily Nika
01:02:14
the 4 h interview workshop

Marily Nika
01:02:16
and because of popular demand. I'm allowing other people to join in just for these 4 h. If you're interested, you can do this. I'll be here for you in case you have any questions, any support, any help. Me and me hire amazing course. Manager is here to answer. Any questions that you have?
Marily Nika
01:02:37
Please go through the material and maven submit the homework. The homework is optional. It's for you. It keeps you accountable. You you learn while going through this homework
Marily Nika
01:02:51
fully up to you. I think it's great, and it also kind of makes you feel more comfortable that you know you've done AI specific work.
Marily Nika
01:02:58
So with that, said I know that 3 weeks are not enough to to get you. you know, to to finish this huge domain that AI Pm is. But hopefully.
Marily Nika
01:03:12
just give you a good head start and an understanding as to what to expect, and of course, if anyone is interested in continuing with the advanced course, we'd love to have you, or upgrading to the Bootcamp. We will also love to have you.
Marily Nika
01:03:25
Last thing I'm gonna say before, for questions is
Marily Nika
01:03:30
maven recommends my course to people
Marily Nika
01:03:35
depending on their reviews. So if I have tens, you will recommended to people. If I don't have tens, it doesn't recommend it to people.
Marily Nika
01:03:43
So if you're willing to add to 10. Please click here and just add a 10. I would appreciate it if you don't feel this course was worth attend. Do not
Marily Nika
01:03:51
do it reach out to me offline. I'll talk to you one on one. I wanna make sure everyone is happy and satisfied. So just had to say this.
Marily Nika
01:03:59
thank you. Harsh, alright, so
Marily Nika
01:04:03

I want everyone to. Just raise your hands. If you're having questions, reach your hand. I'm happy to answer anything you need, and thank you so much. You will always have access to the course. It will never get out there. Always you have the recordings. You'll have it all. Alright, Charles, go for it.
Charles Wilson (DTO DXT)
01:04:20
I struggled a little bit with the Okrs and the AI proxy, the example that was shared earlier with you know, Netflix? And the AI proxy.
Charles Wilson (DTO DXT)
01:04:31
My understanding is you said, what AI specific metric are you aiming to improve?
Charles Wilson (DTO DXT)
01:04:37
What's some examples of like AI specific metrics? Is it like, reduce false positives, reduce, increase true positives? Or is it more so like increase efficiency of algorithm I, I'm a little grey on that.
Thank you. Very good question.
Marily Nika
01:04:53
For years, not months, years, I had recurring, okay, which were reduce
Marily Nika
01:05:00
false rejects by 2%, 3%,
Marily Nika
01:05:06
5% improve the accuracy of the algorithm by 2%.
Marily Nika
01:05:11
Or it was literally something like train a model to detect which language is getting spoken with an input
Marily Nika
01:05:21
train, a model. Not even accuracy, not even data like train 5 models that can do this or run
Marily Nika
01:05:29
3 experiments of
Marily Nika
01:05:33
that using.
Marily Nika
01:05:35
you know, use 3 new models in production, see which one performs better and choose which new model to deploy.
Marily Nika
01:05:41
So in such big companies.

Marily Nika
01:05:44
success from a Pm perspective can be, hey? We created and deployed a new model that's serving millions of people every day.
Marily Nika
01:05:53
So there's a ton of little nuances, and how you can name it, but it can be, as I said, like accuracy. It can be just training a model. It can be testing out 2 models.
Marily Nika
01:06:04
and to answer, kind of this adjacent question I saw before, which was like, Hey, how do we know how much data we need?
Marily Nika
01:06:10
The answer is.
Marily Nika
01:06:12
you run experiments. And you're like, Okay, is this model good enough? If it doesn't seem like it's good enough. It means I need more data. So it's all about experiment experiment. It's it's just the nature of what an aipm does.
Marily Nika
01:06:30
Awesome. Let's see, Harsha.
Harsha Srivatsa
01:06:33
yes, Marilyn, I asked this question before, but I love to get your thoughts. So I've been working on that spreadsheet you gave in the workshop. You know that spreadsheet. It says AI features, and put some really hard thought into it. Right? So how do we know this pain point should be addressed by AI Jen AI. So I'm working on a table which says, Where does Jnai work? Where doesn't it work? So I'm going very systematically, saying, for this particular feature, pain point is AI, the right answer, or if Jenny is the right answer?
Harsha Srivatsa
01:07:03
If so, you know W. You know, if what is the case, and then I come up with a framework for the trade-off. So it's pretty split it up into business trade-offs and technical trade-offs, and and see how to use the trade-offs towards rice. You know the selecting, the feature, the right prioritization. So what I'm asking is I'll post my work on the discord channel on the spreadsheet. So please take a look and see if that makes sense. And you know
Harsha Srivatsa
01:07:28
I can use that, I feel there's so much value, because when I do the Prd. Or any of this thing, so if I can talk through some of the how I go about the feature prioritization, how do I go about so, you know, have a great viewpoint, and whether AI is the right answer or not, and then I'll have that leadership point. So I love to post that thing, and you know, please, you know, look at the discount, and and you know, give your feedback. So basically, I'm enhancing your thing. So I would love to get your, you know.

Harsha Srivatsa
01:07:55
Oh, that sounds that sounds good. And I'm happy. You found Vio in it. So yeah, absolutely absolutely.
Marily Nika
01:08:01
yeah, perfect, perfect. I would love to.
Marily Nika
01:08:08
Excellent
Marily Nika
01:08:11
Well, alright either. No more like oh, there's one more question like it. Let's see.
Marily Nika
01:08:18
At what point do you compare to? I open AI model, and it's expect the users and their sources, including staffing.
Marily Nika
01:08:29
So
Marily Nika
01:08:30
you don't compare the value of the model itself. You integrate the model in an experience, and then you test out the experience.
Marily Nika
01:08:40
and then you test out the metrics and matter in this experience in an experimental server. With dogfooding, let's say.
Marily Nika
01:08:47
and then, once you feel you reached the Mvq. Which is the minimum viable quality for this experience you launch.
Marily Nika
01:08:54
If there's already a model out. Remember, I was telling about 80 tests. Yesterday you launched to a part of a population.
Marily Nika
01:09:02
and then you compare your key metrics
Marily Nika
01:09:05
just to see how it's performing. So you kind of decide whether to launch.
Marily Nika
01:09:11
That's kind of what I
Marily Nika

01:09:13
I was thinking.
Marily Nika
01:09:16
Alright
Marily Nika
01:09:17
excellent. Thank you all so much. Let's keep the conversation going. So this chord, primarily, is for you to connect with each other. But I will go in this chord as well to make sure we answer any questions at the same time.
Marily Nika
01:09:33
Alright, thank you all so much for the DM's. And the conversation is just a lot. It's it's very good. Thank you. Thank you. Thank you. Enjoy. Please go through the exercises and keep in touch, and we can take it from there.
Marily Nika
01:09:44
Thank you all. Thank you all.
Tatyana Emelyanova - Acclimate
01:09:47
Thank you. Bye.

00:00:04
Wonderful. Hello! Everyone just kicked off the recording. This is our last live session, and I'm just very excited because we have gone through so much content together, and I'm getting
Marily Nika
00:00:15
great questions. II see the conversations in the chat, and then discord, and I'm just very happy to see that. You you have been learning. So that's good. So just a request. If you're comfortable, please turn on the camera. I wanna make this as interactive as possible. And I love to talk to people and to see the reactions. Because I adjust the way I speak. Yeah, thank you. Perfect. Hi, everyone. I see you now. Okay, wonderful.
Marily Nika
00:00:40
So yesterday we discussed how Richard scientists work on their day to day, and I know it was a bit overwhelming. But.
Marily Nika
00:00:49
my primary goal was to make you feel more comfortable with the technical side of things, and, secondly, I wanted you to see what goes behind developing the core technical side of things with an experience. So it was very important to me. I'd love to hear your comments in the chat. If you would like to put them in, I want to see what people have to say.
Marily Nika
00:01:11
Now I am gonna share my screen. And I talk to you about what we're gonna discuss today.
Marily Nika

00:01:18
Alright.
Marily Nika
00:01:19
So today, we're gonna talk about metrics measuring success for AI products. And we're also gonna discuss how to set goals and setting goals as a Pm. Leader. Within this AI era is kind of a bit more complicated. I'll tell you why
Marily Nika
00:01:34
it is because when you measure the success of a product, there is this whole extra angle that you've never had until now as a Pm.
Marily Nika
00:01:42
Because you have the product health metrics. But now you have this AI side of things you're like is that gonna work cause? If the AI side of things doesn't work. Then there is no product. Right?
Marily Nika
00:01:53
So let's discuss metrics a bit. And then goal setting. Because I think that's a very, very important takeaway. I want you to leave with this course.
Marily Nika
00:02:02
The other part we're going to discuss today is interviewing. We're going to touch a bit around how you're interviewing. I told you. I had to go through this recently, because II left Mita
Marily Nika
00:02:12
and
Marily Nika
00:02:14
It's it's not fun, there is. It's a process, and I'll I'll tell you everything I know so hopefully. If you plan to either interview people or be the one interviewing, you'll be set up for success
Marily Nika
00:02:27
alright. So talking about metrics as an aipm
Marily Nika
00:02:31
as you probably know from your current roles when we measure success of a product.
Marily Nika
00:02:36
And we need to think about the bigger picture. What is our goal? Why are we creating this feature, this product, this AI product?
Marily Nika
00:02:45
Strategically, why is this Netflix recommendation engine getting
Marily Nika
00:02:50
right? We need to know this so that we can tie everything we're measuring back to the mission.

Marily Nika
00:02:58
So please only define what you need to measure. Only define the metric. Your product will actually impact
Marily Nika
00:03:05
as product managers. We have the tendency of you know, wanted to say, this is the best thing. It's going to
Marily Nika
00:03:12
bring money. It's gonna bring people. It's gonna do all these things. Please give me funding. However, that's not realistic. So the more realistic you are in your mind.
Marily Nika
00:03:22
the better it's gonna be when you advocate for your product. So please, only think about what you will actually impact now that our 2 stories. There is the story of the business, and strategically what they want to achieve. Like, Hey, I'm the business. I want to sell more headsets, or I'm Netflix, I just wanna make sure people keep me paying money. And I can increase the user base.
Marily Nika
00:03:47
So no matter what the business goal is. you need to craft narrative around your product is gonna tie in to that
Marily Nika
00:03:56
company narrative, either directly or indirectly.
Marily Nika
00:04:01
If the company says, Hey, I just I care about money. I just want more people in to pay this monthly subscription. Then you can say, Okay, well.
Marily Nika
00:04:09
what I'll create with this recommender system is going to guarantee that people will be happier with the service. They're gonna stay watch for longer. They're gonna tell their friends. So not only will you maintain the current clientele, but they're gonna bring more people in. So indirectly. I do move the needle for you. So this is kind of how you need to craft
Marily Nika
00:04:30
the story on the strategic level in your mind.
Marily Nika
00:04:34
So when it comes to product metrics, it's It's again an amazing.
Marily Nika
00:04:41

You're right. And you know what I'm gonna do. Since this is a live session. II trained my Chateau Bd to provide the perfect interview answer. So I want to tell you kind of. I want to show you what it would say, so that we can. We can start from there.
Marily Nika
00:04:59
So if you see here, I've trained this to tell me what types of questions it can answer.
Marily Nika
00:05:08
And so one of the questions that we can answer is. how do you measure success of product. Why, okay, there it is.
Marily Nika
00:05:19
So let's say, we want to measure success. We do measure success of and
Marily Nika
00:05:26
recommender veto
Marily Nika
00:05:29
on Netflix
Marily Nika
00:05:32
of an AI powered.
Marily Nika
00:05:35
Recommend
Marily Nika
00:05:38
next video to watch on Netflix.
Marily Nika
00:05:42
because you will see, I trained it to say that
Marily Nika
00:05:45
first of all, you always need to start with the mission just like I talked to you about what is the mission? Why have you created this? Why are you creating this product in the very first sense? And then with that in mind, what would be the goals of the company? What's
Marily Nika
00:06:01
why are you creating this? And if you cannot answer these 2 questions, it doesn't make sense for you to just jump in
Marily Nika
00:06:08
and saying, Here's how I will measure success for this feature. Now.
Marily Nika
00:06:12

if you're coming from more junior levels like entry levels meet career. It's totally fine to think about measuring success in terms of okay, user organization engagement retention. But I want you to always have a framing in your mind because you're a leader. You're leading this area, and you should be able to know
Marily Nika
00:06:29
why you're doing this. Okay?
Marily Nika
00:06:32
So the very first thing you need to say is, here's a mission. Here's why we're doing it. Here's high high level. The goals, for example. Hey? We want to increase the viewer engagement by providing relevant content.
Marily Nika
00:06:45
We want to improve satisfaction through personalized experiences. We wanna reduce turn rates. We wanna enhance the scale availability.
Marily Nika
00:06:52
So it doesn't matter what the goal is, as long as you know why you're building this. Okay?
Marily Nika
00:06:58
So now, in terms of metrics.
Marily Nika
00:07:00
and there are buckets of metrics.
Marily Nika
00:07:05
And this is actually there it is. This is actually one of the I did this post on sub stack about metrics and
Marily Nika
00:07:16
everyone just love kind of the parallel I wrote. So I wanna show this to you.
Marily Nika
00:07:22
There it is. So when it comes to AI products.
Marily Nika
00:07:28
I think of success as these 3 little buckets. And I added.
Marily Nika
00:07:32
Oh, ice cubes. So number one. We have our standard product, health metrics. The standard product. Health metrics are.
Marily Nika
00:07:41
Of course.
Marily Nika

00:07:43
the buckets we you already know, which is acquisition. How many users are we getting? Okay?
Marily Nika
00:07:49
Engagement?
Marily Nika
00:07:51
How much is each person on average interacting with whatever we offer. For example, how many likes per person on average, how many shares per person on average?
Marily Nika
00:08:02
How many comments per person on average, this kind of what engagement looks like.
Marily Nika
00:08:07
After that you have retention. Retention means, are people coming back?
Marily Nika
00:08:11
These are my product. Sticky? Is this feature sticky. Are people really enjoying it? And then, after that, you have referral.
Marily Nika
00:08:20
How? How many people on average, is one person bringing to me?
Marily Nika
00:08:25
And that's an interesting one, because not every product has it. But I was playing. Let's say, what was I playing?
Marily Nika
00:08:32
A great example is Farmville? I don't know if you remember Farmville, but it's this app on Facebook. Yes, it's this app of Facebook. You had a farm, you would go in. You would harvest the lemons, and whatever it is you were planting.
Marily Nika
00:08:45
But the thing is, every time you harvest it a tree.
Marily Nika
00:08:49
you it would automatically post on your wall to say, hey, Mary just harvested the tree. Click here to to get back and and claim yours.
Marily Nika
00:08:59
So people would see that. And it would create this kind of network effect of people seeing this post, and they would go in. Okay. So it was a very interesting way to bring people in.
Marily Nika
00:09:10
So some product managers wanted to measure. This so referral is another one.
Marily Nika

00:09:16
First, but not least, is money. How much money are we making, whether it is from subscriptions. Whether it is from according to our monetization strategy. If you're not familiar, monetization strategies can be subscription. Having ads
Marily Nika
00:09:32
renew model, you have something for free, and you ask to pay for like, Hey, get extra lives here. or and so on.
Marily Nika
00:09:40
So product health metrics are standard. They're not AI specific. They're there for any product. Its product. Health is very, very standard.
Marily Nika
00:09:48
You will see this in my slides as well that I will send you, so I have them right here.
Marily Nika
00:09:54
Engagement, retention, popularity, business.
Marily Nika
00:09:57
And you can think of it off
Marily Nika
00:10:01
like an acquisition funnel. So let's say I have launched an app on the app store called
Marily Nika
00:10:09
merrily.
Marily Nika
00:10:10
awareness would be out of.
Marily Nika
00:10:13
you know, who is searching for this app on the App store? Do people? Are they aware of it? Do they know of it?
Marily Nika
00:10:20
So you will measure the beginning of the final? Is the people searching for it.
Marily Nika
00:10:24
Acquisition is kind of out of these 100 people that say how many of them are actually going to click on the search result. That, says Marilyn.
Marily Nika
00:10:33
activation is, how many of these people are actually going to download the app and become a user.
Marily Nika

00:10:40
And you see, this kind of get smaller and smaller. Retention is how many people are coming back through merrily app
Marily Nika
00:10:46
revenue is, how much money are we gonna make from every person? And in total referral is, how many more people are we gonna get? So this is kind of the mental framework I want you to have in your mind.
Marily Nika
00:10:59
I am. So we talked about this.
Marily Nika
00:11:03
I added system health metrics here, because before AI, we didn't really care about system health meaning that.
Marily Nika
00:11:13
Sure, we can have 5 users. And we have a million users. This is not my job to care about.
Marily Nika
00:11:20
Hmm!
Marily Nika
00:11:20
First job, to make sure that the more users I get in
Marily Nika
00:11:25
that my my system is going to be robust. It is going to serve all these users. It is going to be reliable.
Marily Nika
00:11:32
So system health is about reliability, robustness throughput.
Marily Nika
00:11:37
I didn't care about that before I got into AI. But now, because of the AI nature, where we need to serve the results of a model
Marily Nika
00:11:46
system. Health becomes so important. You want to make sure.
Marily Nika
00:11:51
That your system is not gonna crash. I wanna make sure things are very, very important in there
Marily Nika
00:11:58
now, I'm sure you saw we talked about it before Openai.
Marily Nika
00:12:04

One day Sam Altman just tweeted and said, Hey, we just cannot have any more plus users premium users. We're just shutting this down
Marily Nika
00:12:13
mit Ctl. And so, he said, we're shutting down our main means of monetization, which is this premium kind of functionality just because they just couldn't have any more users. So you can see that they clearly
Marily Nika
00:12:27
mean, of course, they were monitoring it, but I don't think the right predictions. They couldn't predict just how much
Marily Nika
00:12:34
demand this was going to have. Alright.
Marily Nika
00:12:38
So system health metrics. It's a great problem to have. Yes, this is this, is it? This is right. Alright
Marily Nika
00:12:46
harsh. I love it. You said you weren't gonna ask me any questions today. Yet I see 1, 2, 3, 3, 3. I see. 3. Great okay.
Marily Nika
00:12:55
Do we use metrics and okrs interchangeably? No, you'll see. I have like a very good way of explaining this.
Marily Nika
00:13:04
Do we need any matrix for privacy of users? Ethical use of data? I love this.
Marily Nika
00:13:10
There is. This is not a metric. I assume that this would go before you get the go. No, go for launching your app.
Marily Nika
00:13:18
That there would be a thorough review with leads, you would make sure. As a Pm. It's yours was really to make sure things are ethical.
Marily Nika
00:13:28
There's no way to measure this. That's a very good question. I guess you can measure the amount of hallucinations.
Marily Nika
00:13:35
ratio and good answers. But that's still not ethical. It's more like, Hey, does this work, or does this not work? So it's a bit different.
Marily Nika
00:13:44

Okay.
Marily Nika
00:13:46
Harsha, bear with me. I have a lot of content, and if you're not covered, we can. Still, we can go through it. Okay.
Marily Nika
00:13:57
So now, last, but not least, we have our bucket, the AI proxy metrics. So this bucket right here is the most interesting bucket. This tells us whether our system works. This tells us what
Marily Nika
00:14:14
the key of the classification is going to be. This tells us that, hey?
Marily Nika
00:14:18
7 out of the 10 times you use me. This is gonna work. This is the accuracy, this is the core. This is the magic, and whether it works.
Marily Nika
00:14:26
Let me give you examples from my real life.
Marily Nika
00:14:30
When I was working for the speech team at Google.
Marily Nika
00:14:34
we had this Google home devices and we had a model that we embedded into these devices. And what that model did is this specific model would trigger if you said the hot word hot word meaning if I say, Okay, Google, how are you today?
Good thanks.
Marily Nika
00:14:57
I hope your day is good as well.
Marily Nika
00:15:00
So it triggered right? And I spoke in a very natural tone, and it was good.
Marily Nika
00:15:04
But when we first launch this oh, sorry I figured yours. I'm sorry. So when we first launched this. If I spoke it wouldn't understand me, or it would understand me. It would trigger
Marily Nika
00:15:18
6 out of the 10 times.
Marily Nika
00:15:19
and that was before we launched it to the world, and the Pm's sorry the scientists came to me, and they're like, is this good enough to launch? Of course it was not good enough to launch So
Marily Nika

00:15:31
they came to me, and they said this.
Marily Nika
00:15:33
Now II looked into it, and kind of to try to understand, as it turned out there were more data for male voices. So if I spoke like this, it was more likely to understand
Marily Nika
00:15:44
or there were issues with the data, not having enough diversity, because I have my Greek accent in English. II had to speak in an American accent. I cannot do this, but if I spoke in a fake American accent you would understand me right? So there are always issues that we had to to fix
Marily Nika
00:16:03
And then
Marily Nika
00:16:05
this metric is accuracy, and the way we measure it in AI is
Marily Nika
00:16:11
false, accepts false, rejects
Marily Nika
00:16:14
true, accepts through, rejects. So let me show you what this looks like I'll show this later. There you go.
Marily Nika
00:16:21
so you can have the true, positive, false, positive And actually I keep referring to my things. But this here is a great way to think about
Marily Nika
00:16:32
true positives and and true negatives. So let's say I have
Marily Nika
00:16:39
my gmail account, and my Gmail account has a feature which is classifying emails as spam or not spam. That's all. It does. Okay.
Marily Nika
00:16:48
If
Marily Nika
00:16:49
and mail is, mark this pum, and it is a spam, as you see, the very first one that I can claim 1 million euros exciting. This is a true positive. Okay?
Marily Nika
00:17:00
If something is, hey, let's catch up. Your course is amazing. Can I draw in? And it does not mark the spum. Then this is true negative, so it marked it correctly. It's not spam awesome

Marily Nika
00:17:13
if there is an email saying, Hey, mentorship request, and it's marked as spam.
Marily Nika
00:17:18
then it is a false positive.
Marily Nika
00:17:21
And then, if there's a cash donation about this amount of money, and it's not marked as well as a false negative.
Marily Nika
00:17:27
So you will get this ratios, you you'll get this accuracy, and they will tell you, hey, 5 out of the 10 times. This is classified correctly, 6 out of the 10 times. This is now classified. So just like the speech example, if I speak to it 5 times and it doesn't recognize me. And then the 60 does. It's kind of a brief user experience. So you want to constantly monitor this, you wanna make sure.
Marily Nika
00:17:53
you really really want to make sure to have a solid model that will provide good experience. Now.
Marily Nika
00:18:02
as we did in the classification example, last week.
Marily Nika
00:18:06
you trained the model, and then it told you, Hey, this is this, works 67% out of the time.
Marily Nika
00:18:12
Great! Now that rating that you see there when you take it and when you productionize it out in the wild
Marily Nika
00:18:22
it there's no guarantee. It's going to perform in the same way that it performed with offline data.
Marily Nika
00:18:29
This is because they're flying data that you use. Remember the test set when we split test set and the training set the test set doesn't necessarily cause more. More likely the data is going to be good.
Marily Nika
00:18:42
But when you're out there in the wild, and anyone can ask questions to this thing. It can be a kid. It can be well, I know it can trigger for the neighbor contrib. I don't know. You can see that
Marily Nika
00:18:55
the quality is going to be much different than in the experimental version.
Marily Nika

00:19:00
So you want to track the what I call it. I call it AI proxy, which all it means is the the metric for your AI algorithm.
Marily Nika
00:19:09
So you want to make sure that this is decent. You want to make sure. Even out in the wild that they performs. Okay.
Marily Nika
00:19:16
now the beauty of data and
Marily Nika
00:19:19
proclaims one. And AI. Is that the second you launch out there in the world any interactions that happen with these devices?
Marily Nika
00:19:30
This data goes back into some database, and
Marily Nika
00:19:35
you can clean it up and you can reuse it for training. So your original model. Now it's going to be enhanced with data that are found from outer in the wild.
Marily Nika
00:19:44
So the model is gonna learn. And it's gonna perform so much better with wild data. Than
Marily Nika
00:19:51
just the experimental data.
Marily Nika
00:19:54
I hope this kind of
Marily Nika
00:19:56
makes sense. And I'm just. I'm reading the question to see if there is anything there in the chat.
Marily Nika
00:20:03
Let's see and catch, says, do the metrics depend on the nature of AI. For example, Gen. AI versus not Gen. AI
Marily Nika
00:20:11
Harsha. Thank you for answering. Yes, at a high level. It should not matter. From the product, health perspective. It does not matter. Right? Proper health is standard metrics. You always have the same
Marily Nika
00:20:23
system. Health metric. Still, it doesn't really matter, because these are standard as well, you know, like

Marily Nika
00:20:28
robustness, how throughput can you serve? The more people you get
Marily Nika
00:20:33
now the AI proxy does change a bit. There are different kind of metrics for each type type of algorithm you have. This is a great question. And I can add a little hand out to you in your portal. If you wanna read more I'd love to
Marily Nika
00:20:51
But for classification it's like the most solid example, because it has the notion of true positives, false positives. And I think that's a great way to wrap your your mind around this.
Marily Nika
00:21:02
Now I showed you this on session one, which is how AI capabilities can vary, and I think it's a great way to
Marily Nika
00:21:10
to show you for you to think about
Marily Nika
00:21:13
how sensitive you should be when it comes to the AI proxy metrics.
Marily Nika
00:21:20
So the more your product is on the top right then the more you need to pay attention to your AI proxy, the more it's on the top left bottom left.
Marily Nika
00:21:30
The least sensitive you should be to your AI proxy metrics.
Marily Nika
00:21:36
because the more you're on the top right, the more your experience depends on AI working well, whereas at the bottom left it's kind of like, okay, like, we can disguise it with some user experience, like, it's okay, if it's not perfect. So that's
Marily Nika
00:21:51
that's something to say.
Marily Nika
00:21:54
alright. So I also want to show you these growth hacking techniques. that are related to the product health metrics. But you know there are little strategies. I talked to you about Farmville at the top, right as you can see.
Marily Nika
00:22:07

So, for example, if you want to increase retention, you are going to come up with ideas like this, where? You will get into Farmville, and then Farmville will post on your wall, and to say, Hey, this tree is back.
Marily Nika
00:22:23
But what's interesting here is this, but get coins line right there.
Marily Nika
00:22:28
because if anyone from my wall clicks on this
Marily Nika
00:22:32
they will go back to their farm and they'll get coins for their farm. So this is excellent for attention.
Marily Nika
00:22:39
In fact, there was this huge Farmville craze
Marily Nika
00:22:42
where people were creating fake accounts so that they would get in there and get coins and share.
Marily Nika
00:22:50
because II think for every person that got coins they would actually give coins to the person that made the original post as well. So it's just. It was very, very.
Marily Nika
00:23:01
It was an excellent tactic when it comes to Pm. It was annoying.
Marily Nika
00:23:05
and eventually I don't know if you notice. But if you go to Facebook and you connect an app now it's gonna say, Hey, this app will never post on your wall unless you allow it to, just because never got permission to post in the wall. You just, you know, you just install that and boom, it would just
Marily Nika
00:23:20
plus people. So now this doesn't happen anymore. Thank God. I hope people learned
Marily Nika
00:23:24
alright. alright, alright
Marily Nika
00:23:30
bottom. You see, increasing engagement. Okay?
Marily Nika
00:23:34
So the bottom is the standard is Youtube, essentially, it's a Youtube channel.
Marily Nika
00:23:39

So if I go to my Youtube channel and I have a Youtube channel. I want to show you something. Let's see. Let's say, let's see.
Marily Nika
00:23:51
So I have a Youtube channel. If anyone is interested, please subscribe because I'm going to start
Marily Nika
00:23:56
to do this right. It's very difficult. I'm figuring out how it works. But what I want to show you for this is, if I go in a video
Marily Nika
00:24:06
like this one. Right?
Marily Nika
00:24:09
it asks me, hey, what do you want? Your videos end screen to be? And I'm like, Well, I want my end screen to be just to have a little preview of a video here. Okay.
Marily Nika
00:24:23
and I can choose whether that is gonna go include the playlist I create
Marily Nika
00:24:30
or whether it's gonna include the video. But check this out. It says.
Marily Nika
00:24:35
best for viewer. Allow you to to select
Marily Nika
00:24:39
the best video to suit the viewer. So
Marily Nika
00:24:42
if you go on this, you see here that you will always get a little preview. So the preview is tailored to you
Marily Nika
00:24:51
so that we can maximize the chances for what's time to go up.
Marily Nika
00:24:56
So when they're asking me, hey? Which video to serve. And I say, I want the best video from my channel, for the viewer is because they help me.
Marily Nika
00:25:07
figure out how to increase this watch time for my Youtube videos with AI.
Marily Nika
00:25:13
So it's very interesting. This is truly there to increase engagement. And
Marily Nika

00:25:18
it's kind of these little hacks you have.
Marily Nika
00:25:23
that's make truly move the the needle
Marily Nika
00:25:29
next app on the left you can see 9 gag cute.
Marily Nika
00:25:34
So this is just a Facebook page. And you can see they they literally just post the cute Corgi. That's it. Why would they do this? Well, it's because their goal is to increase activations. Because you will see this. And you will say, Oh, I want to see more of these cute corgis. I'll click there and I'll join the page.
Marily Nika
00:25:51
So this is what we call we used to call growth hacking. Now, it's what we call product led growth. So for anyone interested in growth techniques and so on. It's this is, you should be a growth. Pm.
Marily Nika
00:26:04
and back to the metrics. I wanna show you. There you go here on the right side.
Marily Nika
00:26:12
Whenever we talk about awareness, acquisition, activation. It's essentially
Marily Nika
00:26:17
product marketing. And that focuses on this. For the rest, it can be the Pm or the growth hucker.
Marily Nika
00:26:25
But it's interesting because this
Marily Nika
00:26:28
used to be a role no one cared about. But now.
Marily Nika
00:26:31
product marketing is a really nice role. In fact, if you want to be a Pm. And you're not a Pm. Yet, and you're finding it tough to become one.
Marily Nika
00:26:42
I
Marily Nika
00:26:44
I think you should definitely consider becoming a product marketing manager.
Marily Nika
00:26:48

Because if you're A. P. They're called Pmms. If you're a Pmm, you can easily more easily tell you into the Pm. Side of things. So product marketing is great is a great first step within the product world. I completely recommend it. I have so many students that
Marily Nika
00:27:03
used to be Pmms. And now our Pm's within the AI
Marily Nika
00:27:08
world. Alright.
Marily Nika
00:27:10
So
Marily Nika
00:27:13
let's talk about okrs in product management. Okay. so have created
Marily Nika
00:27:20
good. Socket is the only 9 Pm. You hear me loud and clear. Yes, yes. there are ways to become a Pm.
Marily Nika
00:27:28
That don't involve you becoming a Pm. Immediately. Okay, so it's it's totally fine to have kind of a phased approach, especially in this market, as I did right now, so I strongly recommend it
Marily Nika
00:27:39
alright. So L. Krs in AI product management.
Marily Nika
00:27:43
So in order to create an Okr.
Marily Nika
00:27:46
You see, I have this structure for you. I have at the top your high level of yeah. Remember, we talked about you need to have a mission and explain what you're doing and why. So you have your high-level objective.
Marily Nika
00:27:58
and then you will have your Q results. Q. Result one. Here's my pure product, health nor star metric. I want to generate oven 10 KB, 2 C. User signups by the android, and Ios app
Marily Nika
00:28:11
curious. All to is going to be your AI proxy metric. Okay.
Marily Nika
00:28:19
carousel, 3 is, gonna be something around your system. Health. So
Marily Nika
00:28:24

I have put together for you this resource. That I feel is very
Marily Nika
00:28:31
very, very important.
Marily Nika
00:28:35
that I had the tab open and closed it alright. Let me just pull it up for you
Marily Nika
00:28:43
I love.
Marily Nika
00:28:44
There it is. I just love the discussion. I seen the chat. This is amazing.
Marily Nika
00:28:50
So I'll share this with you.
Marily Nika
00:28:52
But essentially my, the framework. And how I see things is
Marily Nika
00:28:57
your Okr is your goal.
Marily Nika
00:29:00
Api
Marily Nika
00:29:02
is the metric you're gonna use to measure progress against that goal.
Marily Nika
00:29:08
So we talked about a lot of metrics. But these metrics don't matter.
Marily Nika
00:29:12
If they do matter for your product, then they are Kpis. Okay, so you have your goal. You have the metrics for your goal, which means the Kpis.
Marily Nika
00:29:21
and then you have your nor star metric.
Marily Nika
00:29:24
which is a kpi.
Marily Nika
00:29:26
the core metric that captures all value you're bringing in.
Marily Nika
00:29:30

Now, here's the interesting thing. You may have many. Okay. Rs. many Kpis under Hokr.
Marily Nika
00:29:37
with only one North Star metric are
Marily Nika
00:29:41
Kr, okay, and that's an interesting thing.
Marily Nika
00:29:47
I want to show you
Marily Nika
00:29:51
I have made this tweet.
Marily Nika
00:29:56
Yes, this guide is for you.
Marily Nika
00:29:58
So I had tweeted this.
Marily Nika
00:30:00
And
Marily Nika
00:30:02
it started kind of this very interesting discussion. Okay,
Marily Nika
00:30:07
And I told people, Hey, don't measure what your brother will not impact. Okay, so you have your kpi metric. And this is a very important
Marily Nika
00:30:15
discussion and distinction, before which I'm going to go making because you should know what the Kpi is what an okay R is what the North Star metric is
Marily Nika
00:30:24
so moving down this guide that I will give for you. We always. This is the framework. I believe people should be using. But this is
Marily Nika
00:30:35
objective. What is the main goal for the next quarter? Okay. this is user focused. What is it for
Marily Nika
00:30:42
and clear of the desired outcome.
Marily Nika
00:30:45

And then specific feature. What is your specific feature? I am creating this recommender for Netflix. That's gonna recommend next video to watch. What is the main metric that will showcase success increase user engagements?
Marily Nika
00:31:01
20%.
Marily Nika
00:31:03
Why does your product health metric? Okay, reduce the number of util complaints.
Marily Nika
00:31:08
What is your Garvey of metric? Another very important one. Okay, ensure that
Marily Nika
00:31:14
decrease X percent. Now, gardo metrics are very important, but you don't always need them. I think it's great practice to add them, because that's good. Pm. Craft, as I like to call it.
Marily Nika
00:31:27
and then see some health metric maintain 99% system uptime
Marily Nika
00:31:33
ensure loading times. Stay below 2 s.
Marily Nika
00:31:39
So now, if I speak to this device, oh, I found it.
Marily Nika
00:31:44
There is my extra mouse. It was hidden. She had hidden it. Okay, I have to.
Marily Nika
00:31:49
So if I speak to my Google home device, it is going. I noticed it before. I didn't respond immediately, and that is exactly one of the metrics we had added as a system, help metric. So let's see, and sorry for triggering yours as well.
Marily Nika
00:32:04
Hi, Google! What is your name?
Marily Nika
00:32:10
Oh, my God! The long time! Hey, Google, how are you today?
Marily Nika
00:32:15
I'm feeling great. Thank you for asking. I hope you're having a great day.
Marily Nika
00:32:20

So you see, it took a few seconds, and the exponential was not good like. It's not supposed to do that. You're supposed to say, Hey, how are you? And should say, I'm good. How are you? Okay? So this is a system. Health metric.
Marily Nika
00:32:29
Ai proxy metric increase the accuracy of the content recommendation algorithm by 15%.
Marily Nika
00:32:36
So this is the framework we have.
Marily Nika
00:32:40
and I have a ton of examples, for you
Marily Nika
00:32:44
have all these big tech companies like Tesla enhance the driving experience. Okay. features. Introduce 2 new features for driving style preferences. Your North Star is
Marily Nika
00:32:58
increase. The usage of autonomous mode by 15%
Prama health
Marily Nika
00:33:03
feedback related to trustworthiness. We're still driving by 20% guardrail metric. Of course, safety is clearly communicated and understood
Marily Nika
00:33:15
system. Health achieve a system, responsiveness rate of under 200 Ms. Per hazard detection.
Marily Nika
00:33:25
Maintain a vehicle integration rate under yes, this is yours. You'll find any the porter as well. But this is like a big guide.
Marily Nika
00:33:37
but obviously you would need to take us some time to kind of read and go through, because examples from zoom, from grammarly, from Amazon, from Facebook spotify all these big tech companies. And it's a very interesting way to think about it.
Marily Nika
00:33:53
Now. someone asked me, Hey, do you set these for a quarter or
Marily Nika
00:33:59
or not?
Marily Nika
00:34:02
Well.
Marily Nika

00:34:04
you can set them. You definitely need to set them for next quarter. But you, as the Pm. Especially, more leadership kind of roles. You will need to set these for the next 2. The next 4 quarters.
Marily Nika
00:34:16
You don't need to have all the information for quarters 3 and 4, but you should have a high level idea so that you can give enough of a heads up to your teams as to what to expect.
Marily Nika
00:34:34
Alright. So
Marily Nika
00:34:37
tender matching is another very interesting one. Okay. here, product, health increase, 20% improvement in user feedback scores.
Marily Nika
00:34:47
The AI specific one is
Marily Nika
00:34:52
15% improvement in match relevance scores. Okay.
Marily Nika
00:34:56
so you can see here all the different use cases and how we come up with them.
Marily Nika
00:35:00
Now the question, How do we come up with? The sentence.
Marily Nika
00:35:07
We are placing numbers from there. But here's what you're doing.
Marily Nika
00:35:11
At the end of a quarter
Marily Nika
00:35:14
you will grade your Okrs, and you will see whether you achieved your goals or not
Marily Nika
00:35:20
grading happens from 0 to one. If it's one.
Marily Nika
00:35:24
you completed everything in your care. if it's 0, you did nothing.
Marily Nika
00:35:28
Now, here's the weird thing. If you grade your Okr at one.
Marily Nika

00:35:35
It means your team did not do well.
Marily Nika
00:35:38
It means you did not do.
Marily Nika
00:35:40
because you didn't challenge yourself enough.
Marily Nika
00:35:44
You want to aim to reach 0 point 7
Marily Nika
00:35:50
0 point 7 means that you did 70% of what you should have.
Marily Nika
00:35:55
So when you set goals.
Marily Nika
00:35:57
you need to say that
Marily Nika
00:36:01
you know 70 s. Arrived when a while ago?
Marily Nika
00:36:04
So I'll add 30% extra to these percentages so that I can make sure people will meet the 70% mark. It's a very weird
Marily Nika
00:36:13
way of seeing this. Okay.
Marily Nika
00:36:17
this is how Meta work this, how Google works. We never wanted to reach 100%. We want to reach 70%.
Marily Nika
00:36:24
It's because you want to challenge teams. This is because you want to add a little buffer. So whenever you see this 20% improvement, if you get like a 13%, you should still be very, very happy.
Marily Nika
00:36:34
When people come to see you and say, Hey, 15 is too high. You will say, Okay, well, let's have this as a goal whole. Steve. 70%.
Marily Nika
00:36:44
Okay. I hope this. Helps. It's a very interesting way of of seeing this. Alright.

Marily Nika
00:36:55
It's okrs can be financial can be. Customer facing can be AI focused can be product can be tech.
Marily Nika
00:37:03
I have more examples for the AI team that I will show you like. I will share everything with you. Please read it at your own time. But
Marily Nika
00:37:10
what I want to do now, as you may be able to guess, is
Marily Nika
00:37:16
Send you to breakout rooms because I want you to create your own. Okay, ours
Marily Nika
00:37:22
for a product of your choice.
Marily Nika
00:37:26
So here's how this exercise came out will work.
Marily Nika
00:37:30
aye. want you all to make a copy
Marily Nika
00:37:37
of this link right here
Marily Nika
00:37:41
and then
Marily Nika
00:37:44
perfect.
Marily Nika
00:37:45
I just love when people keep in mind, and then I want you to go into rooms, and I will give you
Marily Nika
00:37:53
the exact
Marily Nika
00:37:55
prompt that I want you. So I'll give you the product that I want you to work on
Marily Nika
00:38:00
with your team, and I want you to literally do the
Marily Nika
00:38:05
out what your cars are based on this guide as kind of a proxy. Okay, so

Marily Nika
00:38:13
let me find if I had rooms. And I'll explain a bit more. Let me just open them. Just give me a second, and we can do
Marily Nika
00:38:21
there we are there. We are. Okay.
Marily Nika
00:38:25
Excellent.
Marily Nika
00:38:27
So we have 1015 rooms. Okay?
Marily Nika
00:38:32
So
Marily Nika
00:38:34
rooms from one to 5, and I will write them. Here are going to work on some matching algorithm.
Marily Nika
00:38:41
Let me write it here. So you have it. Rooms one to 5, matching. Algorithm theme there, or bamboo
Marily Nika
00:38:51
6 to 10 are, gonna have
Marily Nika
00:38:59
fix it in are going to be recommendation engine, like Netflix or spotify.
Marily Nika
00:39:03
And then
Marily Nika
00:39:09
so according to which room you're in, you will
Marily Nika
00:39:14
algorithm recommendation engine or chatboard Google home, Alexa.
Marily Nika
00:39:18
and you will all work on one
Marily Nika
00:39:21
spreadsheet on one deck. So you did make a copy for your for yourselves. But please share the one file that you will walk with your team so that you all work in one.
Marily Nika

00:39:31
and then we'll come back to discuss. So I want you to write
Marily Nika
00:39:34
2 2 sets of 4 krs for your team
Marily Nika
00:39:38
and please include
Marily Nika
00:39:41
on the high level. These kind of structure. You don't have to choose all of them right. This is kind of
Marily Nika
00:39:46
too many, but it's up to you if you want to have, you know.
Marily Nika
00:39:50
guard rail, if you all want to have a system health. But please definitely have an AI one and definitely have a problem.
Marily Nika
00:39:57
So with that, said, We'll go, and I'll be coming from room to room. To discuss.
Marily Nika
00:40:03
Yes, you have it. It's here, and it's also in your report
Marily Nika
00:40:10
alright. So let's do this, and I'll be coming from room to room. And we can pick it from there.
Sean Peters
00:40:15
Share my screen while other people don't want to share it
Marily Nika
00:40:18
alright. Go for it, share your screen and tell us. What room were you? In? Which product did you do?
Sean Peters
00:40:24
Yeah. So I was me and my lowering group. And we we picked Netflix
Sean Peters
00:40:30
And looking at your 15 different examples, there, you had one for Netflix. So we wanted to kind of straight away from that. Just not do that. So we look back at Netflix Mission, and it is to entertain the world. And so with that we then deviated from there to see if we could come up with a different objective that was different than yours, and so that was enhanced exposure for what Netflix subscribers can be entertained with by delivering recommendations for new media types.

Sean Peters
00:40:55
So we know that Netflix is going down the path of for shorter form, content, games, so on and so forth. And we want to ensure that we were continuing to expand what people could be entertained with with Netflix. So we looked at 3 different key results, first, one being a north star, and that was to transform Netflix into a multimedia company by improving click the rates of new content by 20.
Sean Peters
00:41:20
And then we looked at Pritel and that was to boost user feedback scores related to the usability of the new content by 20. So the example that we kept linked to, or games something like Grant that thought it was kind of like their big pilot, I think. And could you actually find the game as usable?
Sean Peters
00:41:37
And however you were consuming whether that was desktop, whether that was like your smart TV remote. Whatever the case is, did you get same experience? And so we want to ensure that
Sean Peters
00:41:48
that user building still there and then the AI proxy that we went with for keepers. All 3 was ensure that users self returned to the recommended content. Targeting 15% improvement. So it wasn't necessarily a oh, yeah, I try to winds. It's kind of cool, but I'll never really do that again. And that you continue to come back and prove that the model was actually working.
Marily Nika
00:42:13
Very interesting. I love it transforming into a multimedia company by improving Ctr. Of Ugandan. This is a very, very interesting. I, yeah, this is super super good. And the AI proxy self return to recommend a content targeting 15% improvement. Okay?
Marily Nika
00:42:28
You know, I don't know if this is an AI proxy.
Marily Nika
00:42:32
It would be an AI proxy if you said something like make sure the recommended content is accurate.
Marily Nika
00:42:39
relevant. It's the right for this cohort of people.
Marily Nika
00:42:43
but it's not about any user behavior. You know, it's about the raw technology itself. So that's the only thing. Okay, I'll point out.
Sean Peters
00:42:53
okay, interesting. And then I guess.
Sean Peters

00:42:56
with the way that we were thinking about is you would self return to that content because it was relevant because it was accurate. But we could probably be a little bit more specific.
Marily Nika
00:43:04
Yeah, okay, yep, increase relevancy by 15% which would result in users self returning. But yeah.
Sean Peters
00:43:14
gotcha I know that we're short on time. I had a quick question, though, because an interesting conversation came up about this. So Netflix massive Company, they're gonna have other Pms that are very focused on their recommendation. Models specifically for their other videos. So they want to continue people using other videos.
Sean Peters
00:43:32
our product team can more concerned concerned with new content. How should we reconcile that? The company itself is going to care about just what's going to increase time. That's going to keep people more esteem. That's going to get people to up their subscriptions for Netflix. How do we think about that as 2 separate product teams wait. So are we talking about? Is it one company, 2 different teams, or 2 different companies.
Marily Nika
00:43:57
one copy, 2 different teams and tell me what the other team is doing. Again, recommendations for just videos on Netflix
Marily Nika
00:44:05
recommendation for videos on Netflix. Okay? Well, you need to work with the Pm, so that do, you can make sure you don't cannibalize them and they don't cannibalize you. So product and feature. Com. Nebilization is a huge thing. Where what you wanna achieve goes completely opposite to what other people want to achieve. And it goes back to the discussion we had yesterday about the short form, comments and long form content on Youtube.
Marily Nika
00:44:31
so the way to think about it is just you need to be aligned with both rollouts. Now, from a pro perspective,
Marily Nika
00:44:39
you can trigger this specific feature on specific journeys, part of the journey of the user. So you can say, Okay, you recommend here. I recommend here. And it's kind of they both sounds like they have different use cases, anyway.
Sean Peters
00:44:54
Awesome. Thank you awesome. Thank you. Thank you so much.
Marily Nika
00:44:57
Alright cool. So I am gonna switch gears because what I wanna do now is
Marily Nika

00:45:07
discuss interviewing a bit. We're not going to have time to get through interviews much, but I want to walk you through my framework as to how I feel. You should think about interviewing
Marily Nika
00:45:21
So I've created this checklist for breaking into AI products.
Marily Nika
00:45:27
and it has different phases before applying, which is where you're at. Right now
Marily Nika
00:45:31
I want you to understand what aipm is all about so perfect. You take that box.
Marily Nika
00:45:36
gain some experience in creating and launching.
Marily Nika
00:45:40
so
Marily Nika
00:45:42
lot like, I swear to you, 70% of the students, 70% of the students
Marily Nika
00:45:48
have already worked in some AI feature without knowing it.
Marily Nika
00:45:53
So if you've learned something that's smart.
Marily Nika
00:45:56
Just go to your engineers and say, Hey, did we use any AI for this, and truly understand what they did?
Marily Nika
00:46:02
They dated behind the scenes.
Marily Nika
00:46:04
and when I say AI, I mean literally just calling in some Api or something that can do something around. I don't know. Speech, something smart. Translate something. So you've done. AI. Very, very likely without knowing
Marily Nika
00:46:18
I'm here to figure this out.
Marily Nika
00:46:21
number 2.
Marily Nika

00:46:22
If you do not have that experience, there are amazing ways to get it, and I think I mentioned devpost. It's an amazing place for hackathons
Marily Nika
00:46:32
you can join in for free. They last like 1, 2, or 3 days. They have prizes.
Marily Nika
00:46:38
There are so many about AI, and you can get in there
Marily Nika
00:46:43
form teams. There you go. Yeah, to heal whatever about one month left. You will form teams, and you can be the Pm. Of your team. So at the end of it you will have something to show, for you can have a little portfolio. You can have
Marily Nika
00:46:57
3, 4, 5 of them.
Marily Nika
00:46:59
so that you can showcase that, hey? I am a product marketing manager. But look, I ha hands on participating in this Jain AI Hackathon, I won or I have this product to show you. Okay, like this, 19 to 21. Right?
Marily Nika
00:47:14
Gen. AI,
Marily Nika
00:47:16
and you can form teams within this platform. It's a super super good platform. Okay? So make sure to get some experience.
Marily Nika
00:47:26
get your storytelling right? That's a Pm. Trade. But I want you to be comfortable with telling your storytelling for AI as well. So everything we've been talking about from like what? The what features does AI entail recommendations automation, scaling, generating everything we discussed on day one. Just make sure to be comfortable with the features and understanding what it can add to the users.
Marily Nika
00:47:53
Application time. we revamp our online presence. It really matters.
Marily Nika
00:47:59
especially nowadays. You need solid online presence
Marily Nika
00:48:02
offline revamp. You want to have a regime that looks good. Tell your friends, your colleagues, Linkedin, with your available

Marily Nika
00:48:12
apply everywhere, even if you are, or you aren't crazy about the jobs.
Marily Nika
00:48:18
But but
Marily Nika
00:48:21
the best way to do it is to reach out to people that work in these companies that can refer you. and the even better way is to find who the hiding manager of a role is and reach out to them.
Marily Nika
00:48:35
And I know this sounds like very uncomfortable, but
Marily Nika
00:48:38
if I'm a hiring manager and I get a message from someone saying, Hey, I saw you have this opening. I'm perfect for it. Here's my regimen. Here's why I'll appreciate that pass Link so much.
Marily Nika
00:48:49
and like that you have a direct touch with the heading manager
Marily Nika
00:49:07
merrily froze for me. Is she frozen for others? There's no license.
Marily Nika
00:49:13
Yeah, it's really really bad. Unfortunately. So make sure online. Be right offline. Be right. I have a template arrangement template. I want to share with people here
Marily Nika
00:49:23
that I have created. Let me just open it up there it is
Marily Nika
00:49:29
my templates right here.
Marily Nika
00:49:34
Oh, did I froze on my back? Yeah, yes.
Marily Nika
00:49:38
okay, cool, cool.
Marily Nika
00:49:42
So yes, I don't know if you heard me. But please reach out to the hiding manager. Specifically on Linkedin. I know it's sunk over and scary, but they will appreciate it.
Marily Nika
00:49:53

do I? And you get rejected? It's probably some automated system that rejects you. So please just go ahead, and apply reach out to the people.
Marily Nika
00:50:07
you know, you are, gonna apply like to 20 or 30 roles. You're gonna get one interview, and that's fine. You just care about one
Marily Nika
00:50:13
when you get an interview. Take it seriously. Okay, it's it can change your life, so do the work that's needed. This is the moment that matters. I'm
Marily Nika
00:50:24
so my level. I'm a group product manager, right? And I got into Meta as an All 7, which is kind of it's it's difficult to get in all 7. Okay, and
Marily Nika
00:50:36
and the interview questions I got were
Marily Nika
00:50:41
so I got
Marily Nika
00:50:42
the first question was, Hey, how do you build? A dog walking app? And it's just really interesting to get this type of question when you expect something around AI and leadership and people building and people are like, Hey, how'd you build an app for dog walking? And it's kind of like, okay.
Marily Nika
00:50:59
you have to play the game. You have to take it seriously. Okay, so do the work. This is the moment that matters.
Marily Nika
00:51:07
No question is low enough for you. No question is too complicated like you can figure it out. Okay. ask for time. When the reporter decides to you. The recorder wants you to interview yesterday. But you.
Marily Nika
00:51:23
I think if you ask anywhere from 2 to 3 weeks, it's perfectly fine, and I think it's a great practice to do it so that you can prepare
Marily Nika
00:51:29
do mocks with your friends, prepare, prepare, prepare.
Marily Nika
00:51:34
It's an amazing trap.
Marily Nika

00:51:36
To you. You read something like, okay, I got this. I know this. I know how to do this.
Marily Nika
00:51:41
but it's different to say it out loud. Okay, use my, the Gbts I created. They're they're just for you. To help you.
Marily Nika
00:51:52
since this one specifically is tailored for AI
Marily Nika
00:51:55
and of course I the estimation one that I gave you before. This is also there
Marily Nika
00:52:03
to help you practice
Marily Nika
00:52:04
and then, at the end of the day expect to fail. I will not
Marily Nika
00:52:10
okay. But it just matters that you'll get in once.
Marily Nika
00:52:13
Now.
Marily Nika
00:52:16
yeah, failing like is a part of it. And failing nowadays doesn't mean you didn't do well, it means they got someone internal, right? So it's just unfortunately, the market is really tough.
Marily Nika
00:52:26
the whole thing is going to take from 4 to 6 weeks. Okay. so I want you to know this. I want you to be prepared.
Marily Nika
00:52:35
Now the interview themes.
Marily Nika
00:52:38
They're not gonna tell you, hey? This is AI specific.
Marily Nika
00:52:41
but they are. Gonna ask you a question that they expect you to come up with a smart feature answer. So they want you to embed AI in there so that they can see you think and breathe of it. So they're not gonna say, Hey.
Marily Nika
00:52:54

tell me about an AI way of solving this pain point? No, you need to have it in the back of your head. Okay. number one. It's gonna be product sense. How will you design
Marily Nika
00:53:07
an alarm clock for someone that's blind.
Marily Nika
00:53:10
How would you design a fridge?
Marily Nika
00:53:12
Analytical one will be
Marily Nika
00:53:14
how do you measure success of an AI feature? Everything we just talked about.
Marily Nika
00:53:21
It's gonna be estimate the amount of
Marily Nika
00:53:25
dog food required in the Us course. Functional course. Functional is.
Marily Nika
00:53:31
some comments call it transactional. Have some comments call it craft and execution.
Marily Nika
00:53:36
Essentially, number 3 is about
Marily Nika
00:53:40
How do you get buy in from your team? How? Just like the question we answered before, like, there's someone in the company building the exact same thing like, what do you do?
Marily Nika
00:53:50
It's about stakeholder management getting buy in resolving situations like, hey, what areas does your
Marily Nika
00:54:00
company-wide update
Marily Nika
00:54:02
tag contain for you? Strategy is going to be
Marily Nika
00:54:07
Should we get into self-driving cars? Strategy is very straightforward, cross, functional is very straightforward.
Marily Nika
00:54:15

So for strategy, if they ask you this, we also talked about that right where we said, Hey,
Marily Nika
00:54:20
Should we get into self-driving cars, and what you need to say is, Well, my mission is this, as a company?
Marily Nika
00:54:26
This sounds like that lines. Well, with my mission. Here's how it affect that you would affect us internally like, does it fit in the portfolio that we have internally
Marily Nika
00:54:36
here's the barriers of entry like it's expensive. We can just build an in-house.
Marily Nika
00:54:42
It's
Marily Nika
00:54:44
you know, there's a war. There's
Marily Nika
00:54:46
something happening outside. So I don't know if it's the right time for investment. So this is the external factors. And then you make a recommendation like.
Marily Nika
00:54:53
I don't focus too much on this, because I just think it's very people. People will be okay. But the difficult ones are one and 2. And that's why I created this Gbts
Marily Nika
00:55:06
leadership. You only get this if you're interviewing for level 6 and above in big tech.
Marily Nika
00:55:12
6. And above means like
Marily Nika
00:55:15
6 years of experience and more. This gonna be like,
Marily Nika
00:55:21
Well, if you're monitoring a team, it's gonna
Marily Nika
00:55:24
do you set the right scope for your team? How do you define the roles? Your team should have?
Marily Nika
00:55:31
It would be. Hey? How do you deliver difficult news to someone? So things like that
Marily Nika
00:55:37

number 6 take a home exercise you should wish for a take-a-home exercise and presentation. People hate them usually, but it's a blessing because you get to do really well on one
Marily Nika
00:55:48
aspect of the interview, cause you will have time to prepare technical interview. some companies use to ask for something technical.
Marily Nika
00:55:59
People asks for a more technical interview for AI folks. They will ask you about architecture, which is very.
Marily Nika
00:56:07
I was coaching someone through it, and
Marily Nika
00:56:10
was kind of interesting to see the level of depth they wanted to get in.
Marily Nika
00:56:14
That person did go in, but they were an ex engineer, so they knew, like very technical things. So these people were not looking for an aipm. They were looking for an engineer that is, gonna be called a Pm. It was very tough.
Marily Nika
00:56:26
Google had a technical interview. They now removed it. So you don't have to worry about this.
Marily Nika
00:56:33
I'll give this to you. It's kind of secrets on how to prepare.
Marily Nika
00:56:38
I feel. If you want the starter company for Big tech. Amazon is the best way to go.
Marily Nika
00:56:44
Amazon is the most straightforward company. because the questions are are like.
Marily Nika
00:56:50
Tell me about a time when you solve the problem. Tell me by the time where you got by in.
Marily Nika
00:56:56
tell me about the time where you came up with how to improve your product.
Marily Nika
00:57:02
So Amazon is wonderful, like the interview process is just way more straightforward than Hey, build a
Marily Nika
00:57:09
a dog walking up. Okay. Sahil says that Pmt. At Amazon requires 2 tech interview.

Marily Nika
00:57:17
Well, that's the thing. There. There is a standard product manager. And then there is the technical product manager, Amazon. It's a bit different. What is the bar razor interviewer? Vanisha? Can you let us know? I don't know what that is.
Venetia Tay
00:57:33
Oh, I mean that books written about this. But when I was thinking of going to Amazon well, my first was telling me that there is a bar raiser, basically someone who's actually not in the interview loop. You actually have to get training to be a bar razor interview. And their job is to make sure that you're the best of the best. So it's almost the hardest interview that you ever face, and if that person says no, your chances are like out like even everyone says yes, but the bar raiser says, No, you're not. You're not in
Venetia Tay
00:58:02
so as to keep the standards
Sahil Sachdeva
00:58:04
some friendly at Amazon. So it's basically not anybody can interview you. You have to apply to be a bar raiser.
Sahil Sachdeva
00:58:12
Then they test. They interview you so you could interview somebody else.
Sahil Sachdeva
00:58:16
So you have to go through some hurdles just to be a person who, wanting to be external candidates or even internal.
Marily Nika
00:58:25
Oh, my God, okay, very interesting. Well, I personally think.
Marily Nika
00:58:30
that's interesting where you're in. Yeah. Any interview trainings I've had internally where you know standard calibrations, but nothing like that. I don't think I would pass this very interesting. But yeah, I love honestly interview. I went through it. I think it's just super great.
Marily Nika
00:58:45
Meta and Google are.
Marily Nika
00:58:49
It's interesting, because if you want to interview for these companies, they will likely give you
Marily Nika
00:58:54
either the option or depending on the team. You will either go through the generic track where you know you interview with someone random.
Marily Nika

00:59:04
and it's gonna be generic. Pm, questions. And then if you pass. You do kind of an internal team matching process. Let's be dating, they will say. Hey, we shared your profile with this hiring managers. Here are the people that were interested have calls with each one of them so that you can decide which one you want and see if it's a mutual fit.
Marily Nika
00:59:24
So they could either say, this, go through the generic one, or they will say, you can go through the specialized
Marily Nika
00:59:30
interview for a specific role directly.
Marily Nika
00:59:33
They offer you a choice.
Marily Nika
00:59:36
You do not want to do that generic one. You want to go through the specific one, because
Marily Nika
00:59:40
I feel that's my personal opinion. I feel that the generic one the bar, is kind of higher in the sense that
Marily Nika
00:59:48
you're competing with the perfect storyteller, with the perfect communicator, with the perfect Pm. Versus the specialized one.
Marily Nika
00:59:57
You have something that others don't. You have a niche skill in your background that you're chosen for, and you are. Gonna talk to the hiring manager as part of the interview, and the hiding manager will have a say as to Hey, Mary should go in or not. Okay, so go for the specialized interviews. Always
Marily Nika
01:00:18
the specialized interview is the one that will have AI focused questions. So they will ask you something. And you will need to make sure. You answer.
Marily Nika
01:00:27
you know, with an AI enhanced and an AI powered feature in mind.
Marily Nika
01:00:32
So every time I've gone through the generic track. I failed every time I've gone through specialized tracks I've passed so very important. If you given the choice, ask
Marily Nika
01:00:41

people to first find a team for you, if possible, or do what I say, which is, reach out to on Linkedin to hiding managers. Don't be shy also, don't be creepy. Your message like you don't wanna be like it's talking like, Hey? I've been monitoring you for a while, though it should be like, Hey.
Marily Nika
01:00:58
I found your name. I know you're hiring for this.
Marily Nika
01:01:01
I'm so excited. Here's why I'm perfect. Here's my regiment, if interested, let me know. That's it. No, follow ups. No, hey? I wanna make sure you show this? No, no, no, just once
Marily Nika
01:01:12
throw plant the seed, and that's it.
Marily Nika
01:01:14
Because there's this perception that if you apply and get rejected automatically. You're like, Oh, I'm not good enough. It's not worth it.
Marily Nika
01:01:24
It's
Marily Nika
01:01:27
Yes.
Marily Nika
01:01:28
it's it's very, very important to to know this.
Marily Nika
01:01:32
Nvidia. I did that, too. It's
Marily Nika
01:01:35
great! I'm it was interesting, was, it? Felt, more corporate than Mira and Google. But it was.
Marily Nika
01:01:43
you can tell. That's that's a rocket ship. You can tell that this is where the future is, with the hardware and everything that's happening. They're like
Marily Nika
01:01:52
perfectly position, like, if you can get in and be there right now. I think it's it's an amazing place to be.
Marily Nika
01:01:57
So I know we're running out of time. I have so much to tell you. So here's a couple of things, I wanna tell you.
Marily Nika

01:02:05
I have
Marily Nika
01:02:08
as part of the boot camp. We will be running a an interview
Marily Nika
01:02:14
the 4 h interview workshop
Marily Nika
01:02:16
and because of popular demand. I'm allowing other people to join in just for these 4 h. If you're interested, you can do this. I'll be here for you in case you have any questions, any support, any help. Me and me hire amazing course. Manager is here to answer. Any questions that you have?
Marily Nika
01:02:37
Please go through the material and maven submit the homework. The homework is optional. It's for you. It keeps you accountable. You you learn while going through this homework
Marily Nika
01:02:51
fully up to you. I think it's great, and it also kind of makes you feel more comfortable that you know you've done AI specific work.
Marily Nika
01:02:58
So with that, said I know that 3 weeks are not enough to to get you. you know, to to finish this huge domain that AI Pm is. But hopefully.
Marily Nika
01:03:12
just give you a good head start and an understanding as to what to expect, and of course, if anyone is interested in continuing with the advanced course, we'd love to have you, or upgrading to the Bootcamp. We will also love to have you.
Marily Nika
01:03:25
Last thing I'm gonna say before, for questions is
Marily Nika
01:03:30
maven recommends my course to people
Marily Nika
01:03:35
depending on their reviews. So if I have tens, you will recommended to people. If I don't have tens, it doesn't recommend it to people.
Marily Nika
01:03:43
So if you're willing to add to 10. Please click here and just add a 10. I would appreciate it if you don't feel this course was worth attend. Do not
Marily Nika
01:03:51

do it reach out to me offline. I'll talk to you one on one. I wanna make sure everyone is happy and satisfied. So just had to say this.
Marily Nika
01:03:59
thank you. Harsh, alright, so
Marily Nika
01:04:03
I want everyone to. Just raise your hands. If you're having questions, reach your hand. I'm happy to answer anything you need, and thank you so much. You will always have access to the course. It will never get out there. Always you have the recordings. You'll have it all. Alright, Charles, go for it.
Charles Wilson (DTO DXT)
01:04:20
I struggled a little bit with the Okrs and the AI proxy, the example that was shared earlier with you know, Netflix? And the AI proxy.
Charles Wilson (DTO DXT)
01:04:31
My understanding is you said, what AI specific metric are you aiming to improve?
Charles Wilson (DTO DXT)
01:04:37
What's some examples of like AI specific metrics? Is it like, reduce false positives, reduce, increase true positives? Or is it more so like increase efficiency of algorithm I, I'm a little grey on that.
Thank you. Very good question.
Marily Nika
01:04:53
For years, not months, years, I had recurring, okay, which were reduce
Marily Nika
01:05:00
false rejects by 2%, 3%,
Marily Nika
01:05:06
5% improve the accuracy of the algorithm by 2%.
Marily Nika
01:05:11
Or it was literally something like train a model to detect which language is getting spoken with an input
Marily Nika
01:05:21
train, a model. Not even accuracy, not even data like train 5 models that can do this or run
Marily Nika
01:05:29
3 experiments of
Marily Nika
01:05:33
that using.

Marily Nika
01:05:35
you know, use 3 new models in production, see which one performs better and choose which new model to deploy.
Marily Nika
01:05:41
So in such big companies.
Marily Nika
01:05:44
success from a Pm perspective can be, hey? We created and deployed a new model that's serving millions of people every day.
Marily Nika
01:05:53
So there's a ton of little nuances, and how you can name it, but it can be, as I said, like accuracy. It can be just training a model. It can be testing out 2 models.
Marily Nika
01:06:04
and to answer, kind of this adjacent question I saw before, which was like, Hey, how do we know how much data we need?
Marily Nika
01:06:10
The answer is.
Marily Nika
01:06:12
you run experiments. And you're like, Okay, is this model good enough? If it doesn't seem like it's good enough. It means I need more data. So it's all about experiment experiment. It's it's just the nature of what an aipm does.
Marily Nika
01:06:30
Awesome. Let's see, Harsha.
Harsha Srivatsa
01:06:33
yes, Marilyn, I asked this question before, but I love to get your thoughts. So I've been working on that spreadsheet you gave in the workshop. You know that spreadsheet. It says AI features, and put some really hard thought into it. Right? So how do we know this pain point should be addressed by AI Jen AI. So I'm working on a table which says, Where does Jnai work? Where doesn't it work? So I'm going very systematically, saying, for this particular feature, pain point is AI, the right answer, or if Jenny is the right answer?
Harsha Srivatsa
01:07:03
If so, you know W. You know, if what is the case, and then I come up with a framework for the trade-off. So it's pretty split it up into business trade-offs and technical trade-offs, and and see how to use the trade-offs towards rice. You know the selecting, the feature, the right prioritization. So what I'm asking is I'll post my work on the discord channel on the spreadsheet. So please take a look and see if that makes sense. And you know
Harsha Srivatsa

01:07:28
I can use that, I feel there's so much value, because when I do the Prd. Or any of this thing, so if I can talk through some of the how I go about the feature prioritization, how do I go about so, you know, have a great viewpoint, and whether AI is the right answer or not, and then I'll have that leadership point. So I love to post that thing, and you know, please, you know, look at the discount, and and you know, give your feedback. So basically, I'm enhancing your thing. So I would love to get your, you know.
Harsha Srivatsa
01:07:55
Oh, that sounds that sounds good. And I'm happy. You found Vio in it. So yeah, absolutely absolutely.
Marily Nika
01:08:01
yeah, perfect, perfect. I would love to.
Marily Nika
01:08:08
Excellent
Marily Nika
01:08:11
Well, alright either. No more like oh, there's one more question like it. Let's see.
Marily Nika
01:08:18
At what point do you compare to? I open AI model, and it's expect the users and their sources, including staffing.
Marily Nika
01:08:29
So
Marily Nika
01:08:30
you don't compare the value of the model itself. You integrate the model in an experience, and then you test out the experience.
Marily Nika
01:08:40
and then you test out the metrics and matter in this experience in an experimental server. With dogfooding, let's say.
Marily Nika
01:08:47
and then, once you feel you reached the Mvq. Which is the minimum viable quality for this experience you launch.
Marily Nika
01:08:54
If there's already a model out. Remember, I was telling about 80 tests. Yesterday you launched to a part of a population.
Marily Nika
01:09:02
and then you compare your key metrics

Marily Nika
01:09:05
just to see how it's performing. So you kind of decide whether to launch.
Marily Nika
01:09:11
That's kind of what I
Marily Nika
01:09:13
I was thinking.
Marily Nika
01:09:16
Alright
Marily Nika
01:09:17
excellent. Thank you all so much. Let's keep the conversation going. So this chord, primarily, is for you to connect with each other. But I will go in this chord as well to make sure we answer any questions at the same time.
Marily Nika
01:09:33
Alright, thank you all so much for the DM's. And the conversation is just a lot. It's it's very good. Thank you. Thank you. Thank you. Enjoy. Please go through the exercises and keep in touch, and we can take it from there.
Marily Nika
01:09:44
Thank you all. Thank you all.
Tatyana Emelyanova - Acclimate
01:09:47
Thank you. Bye.

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## AI Product Strategy and Vision

1. Establishing a Comprehensive and Aligned AI Strategy

A holistic AI strategy is foundational, extending beyond isolated technological advancements to encompass the entire enterprise's vision and mission. Effective AI adoption requires the initiative to stem from a clear understanding of the organization's goals, ensuring that AI solutions are not merely innovative but also intrinsically linked to the core business objectives. It's not enough to have a forward-thinking AI strategy; it must resonate and integrate seamlessly with the company's overarching ambitions, driving growth, and fostering competitive advantage. This alignment necessitates an ongoing dialogue between technology experts and business strategists, ensuring that AI initiatives are grounded in real business needs and opportunities.

Moreover, the AI strategy should be dynamic, capable of evolving in response to new market trends, emerging technologies, and shifts in consumer behavior. Leaders should foster a culture of continuous learning and adaptability, encouraging teams to stay informed about the latest AI developments and think critically about how these innovations can be harnessed to solve existing business challenges or create new opportunities. In addition, it's crucial to establish clear metrics and KPIs to measure the success of AI initiatives, ensuring that the strategy delivers tangible results and aligns with the company's strategic objectives.

2. Tailoring AI Strategy to Business Context and Data Availability

The applicability and impact of AI significantly depend on the specific context of a business, including its industry, the nature of its data, and the decision-making velocity. Companies with a rich reservoir of structured, high-quality data can deploy AI to uncover deep, actionable insights, propelling them ahead of competitors who may lack such a data foundation. Leaders must conduct a thorough assessment of their data landscape, identifying gaps and investing in robust data management practices to ensure that AI systems have the fuel they need to generate value. In industries where decisions are made infrequently based on limited data, the role of AI might initially seem less pronounced. However, even in these settings, AI can play a crucial role by enhancing decision-making processes, providing predictive insights, and helping to navigate uncertainties with greater precision. It's essential for leaders to understand not only the quantity and quality of their data but also the decision-making cadence of their industry, tailoring their AI strategy to maximize impact where it's most needed.

**3. Focusing on Both Efficiency and Value Creation in AI Initiatives**

LESSON 3

While efficiency gains are often the most immediate and measurable benefits of AI, focusing solely on these aspects can lead to missed opportunities for value creation. A well-rounded AI strategy should encompass both operational efficiency and the exploration of new business models, revenue streams, and customer engagement strategies. By striking a balance between these two dimensions, organizations can ensure that their AI initiatives contribute to both short-term performance improvements and long-term strategic transformation【16†source】.

Value creation through AI goes beyond automating existing processes; it involves reimagining how business is done. This might include leveraging AI to personalize customer experiences, develop new products or services, or enter new markets. To achieve this, organizations need to foster a culture of innovation, where teams are encouraged to think creatively and experiment with new AI-driven solutions. Leaders should also ensure that there are mechanisms in place to capture the learnings from these initiatives, whether successful or not, to continuously refine and enhance the AI strategy.

4. **The Role of Visionary Leadership in AI Transformation**

AI transformation isn't solely a technological challenge; it's fundamentally a leadership endeavor. It demands a clear vision from the top, coupled with the ability to inspire and mobilize the entire organization towards this vision. Leaders must articulate a **compelling narrative** about the role of AI in the company's future, setting clear and ambitious goals that galvanize teams across functions. This vision serves as a north star, guiding the development and implementation of AI initiatives and ensuring they remain aligned with the organization's strategic objectives.

**How to create a compelling narrative:**

However, visionary leadership is not just about setting a direction; it's also about creating an environment where this vision can be realized. This involves fostering a culture of collaboration, where cross-functional teams work together towards common goals, leveraging their diverse expertise to solve complex problems. Leaders need to ensure that teams have the resources, support, and autonomy they need to experiment, learn, and iterate on their AI initiatives. They also need to build a robust governance framework that ensures AI is used responsibly and ethically, aligning with the organization's values and societal norms.

In conclusion, advancing AI product strategy and vision for senior leaders involves a comprehensive approach that integrates strategic alignment, data-driven insights, balanced objectives, and visionary leadership. By focusing on these areas, senior leaders can navigate the complexities of AI integration effectively and leverage its potential to driveCreating an impactful AI product strategy for senior leaders involves a nuanced understanding of the intersections between technology, business objectives, and organizational dynamics. This extended guide delves deeper into the facets of AI Product Strategy and Vision, providing insights and actionable strategies for senior leaders aiming to drive meaningful change and capitalize on AI's transformative potential.