0:01

Alexey

**Hello, everyone. This week we'll talk about machine learning in healthcare, and in particular, about personalization in healthcare. We have a special guest today, Stefan [cross-talk] Okay. Stefan is from Iceland. At some point, he moved to Sweden, where he worked at King and H&M. Then he moved back to Iceland and joined Sidekick Health as a director of data science and AI. Welcome, Stefan.**

0:36

Stefan

Thank you.

# Stefan’s background

0:38

Alexey

**Before we go into our main topic of machine learning in healthcare and personalization in healthcare, let's start with your background. Can you tell us about your career journey so far?**

0:50

Stefan

Yes, absolutely. I think I better shorten it a little bit. I think I had my first job at the age of 12, in the last century. So I'll just do very short snapshots of the early career and then focus on the more relevant stuff. I started working as a developer, rather young – like 18. It was a part time job when I was in high school. That was in ‘96. In ‘99, I was given the task of building my first data pipeline for the notorious Y2K problem – that was very interesting. [laughs]

Most of my early developing work was around building programs that could control the graphics in TV programs, like live sports shows, election programs, and things like that. Today, I still think I've written most of my lines in a programming language called Delphi that nobody uses anymore.

1:58

Alexey

**Delphi - that was my first language!**

2:00

Stefan

Oh, really? [laughs] It’s a very nice language.

2:05

Alexey

**Yeah, it's a nice one. Nobody cares about it anymore. But it was a nice one.**

2:08

Stefan

I think C Sharp took over at some point. In 2006 and 2007, I had a great experience where I was building an enterprise data warehouse from scratch with a great team at the largest telecom company in Iceland. That experience has helped me a lot in my current and recent jobs. But if I fast forward over these snapshots, and start being more current, and I think I'll start in 2015 – where I made a very good decision, but a difficult one. I left a very nice and cozy job as director of analytics and modeling in one of the three major banks in Iceland and moved with my family to Stockholm, where I joined King, the makers of Candy Crush.

That was a great experience. Most of the time there, I spent building the AI team, and the AI research part of that team as well, where we did a lot of collaboration with universities and supervised quite a few Master's students. We were building some nice products – some failed, some were successful. Maybe we will discuss that a little bit later. In 2019, I decided to move over to H&M, still in Stockholm. They were in the very early phase of building up a machine learning function – machine learning team. As you can imagine, it’s one of the biggest retailers in the world with awesome data – where images, text recognition, and all of these things come together.

I learned a lot there and we were just focusing a lot on “Okay, what's the best team structure? How do we build? What are the best practices in solving all of these problems?” That was the early part of that job. When we got more people in, I moved more into a similar path as I had been doing at King before – research collaboration with universities, Master’s students, and sort of trying to be the translator between the state-of-the-art and academia. Meaning between people that were only focusing on the latest methods and then the business people that are only focusing on money and don't care about the methods. [laughs]

So you're trying to sort of merge these two and then be in-between that to create some value out of collaboration. In late 2020, I was offered this position at Sidekick Health – a startup/scale-up with a main office in Iceland. But we have offices both in Boston and Iceland and Stockholm. The job there was basically to build up the data science and AI team in the company and to contribute to making what I hope will become a fantastic data-driven company with machine learning solutions and digital therapeutics solutions. So that's something I had to basically jump on and started there in early 2021.

5:23

Alexey

**This is completely off topic, but I can't help but ask you – how are Icelandic and Swedish different? Are they very different languages or are they similar?**

5:34

Stefan

[laughs] I sometimes explain this as sort of – 1000 years ago, it was the same language and then Sweden and Denmark and Norway decided to evolve, but we did not. So we can still read the Icelandic sagas from 1200-something. Yeah, I think that's the main difference. We still have more inflections, more nuances that usually evolve out of languages. [laughs]

6:01

Alexey

**True Vikings, right?**

6:05

Stefan

[laughs] I don't know about that.

# Applications of machine learning in healthcare

6:07

Alexey

**[laughs] Okay. Coming back to our main topic of machine learning in healthcare – Usually, when I hear machine learning in healthcare (in general, in healthcare) I think about clinical trials. But when people talk about machine learning in particular then I imagine X-ray images or some images and then people would run deep learning on top of these images. So I think it’s mostly about processing medical images. Is this correct? Or are there more applications of machine learning in healthcare?**

6:41

Stefan

There are, of course. With myself, this is also what comes to mind first – a typical vision you have is that there's an X-ray of some broken arm or whatnot and then you have deep learning image recognition to tell you “Okay, this is wrong, do this.” That is a use case, of course, but there are many more. To name a few, there’s disease diagnosis where you really maybe have symptoms and measurements but it's not obvious what disease it is – so it would be trying to automatically distinguish or recognize that.

There's a lot of work in, of course, through the pharmacy companies and things related to that – drug discovery. What kind of drugs can you have? Are they related? Can they be tailored to your team settings or something like that? I think we've all probably heard about DeepMind and AlphaFold, where they are trying to predict the folding of proteins, which can turn out to be a very big game changer to understand the biology behind all of this.

Then you can move into more personalized medicine, where you get different drugs and slightly different treatments, for example, for your cancer treatment, based on your background and medical history and things like that. There are probably many more than I'm not mentioning, but that’s just to name a few.

8:14

Alexey

**Do you know anything about this AlphaFold? I heard that it exists, but my knowledge of biology is so non-existent, that I couldn't fully appreciate it. I heard that there was a breakthrough in biology because of deep learning, but I don't know anything about biology to really appreciate this very well.**

8:34

Stefan

I’m a little bit ashamed to say today, that when I was younger, I thought that biology was a little bit inferior – we didn't have enough numbers. [laughs] So I'm probably the same. I'm not very good with biology. But I read the paper on AlphaFold from DeepMind and it seems very interesting. But I'm on the same page as you are – I'm not an expert on this at all.

9:01

Alexey

**So did you understand a lot in that paper or your lack of knowledge in biology prevented you from this?**

9:06

Stefan

No, I think… Well, it's been some time since I read it, so I couldn't really quote it. But in my memory, I thought I understood. But that's probably also because DeepMind puts a lot of effort into making their content accessible by the public. So I've read and taken a much deeper dive on the earlier stuff they did on AlphaGo and AlphaZero. And that's very accessible or it can be.

9:45

Alexey

**I guess the target audience of this paper are machine learning researchers, not biologists, right? Or maybe both?**

9:53

Stefan

Probably both. But then, they usually get published in Nature as well. So that's where they are [cross-talk]

# Sidekick Health – gamified therapeutics

10:02

Alexey

**So basically every scientist becomes the target audience. Before this episode, I was doing a little bit of research about the company where you work right now – Sidekick Health – and I know that this is in the healthcare domain. In my mind, I thought maybe you were doing these medical images like other health care companies.**

**I went to the website, I checked the description, and it said that you're doing “gamified digital therapeutics built on science, rooted in behavioral economics, and scalable across multiple therapeutic areas”. I must admit that [laughs] most of these words do not tell me anything. So I'm not sure I really understood what you do. Maybe, can you decipher what it actually means?**

10:49

Stefan

I can try. [laughs] No, no. It should be very simple, but you know how sometimes the language in web pages are sort of put in a specific custom. [laughs] Yes. I mean, that's another field in machine learning and AI in healthcare – in the treatment itself. Can we personalize the treatment more? Can we get more out of the treatment? We take a step back and think about the fact that we have streamlined healthcare in many ways, which is great. We know that when you come in to see a doctor, you meet them for five minutes, they diagnose you, you get a treatment or a medicine and you're out. There’s nothing more to be done. This is a lot of our experience of healthcare.

Often this is just enough. But all the streamlining also means that, if you have multiple diseases, you're not really getting that communication. You just go to an expert, they treat one thing. And you're really losing the empathy, because it's been streamlined so much. And there are studies showing that empathy is a big factor and often contributes to better outcomes, or treatments, and all of that. So our goal is basically to maximize the quality life years of a person's life. That sometimes means we can try to cure a disease or help them live longer. It also means there are a lot of people that have chronic diseases, which they have to live with for decades. But just being able to educate them and help them take the right steps and develop their daily habits in a better way can actually increase their quality of life substantially. So that's what we're trying to build. We have more touch points with the users and patients than you do in normal healthcare because you have this through an app. But in the app, we’re also trying to personalize it so you feel better, you're better engaged.

We try to personalize all the contact you get. We take into account if you have more than one disease and we try to merge this together in a nice way. But that is a huge task and, of course, a work in progress. At the same time, we're trying to add this gamification level on top of it, because a big factor in changing people gradually over time is the engagement. You need to engage and you need to feel excited about what you're doing. What we do there – we have a collaboration with a charity and we create an incentive in the app. Every time you finish a task that we give you, you are handed out this altruistic reward. You collect water drops and then you can donate the water drops to people in need of fresh water. Then in the background, we are collaborating with a charity that takes care of that. So that's the setup of this – we're trying to merge this.

The three main factors of the people in the company are: medical doctors, so we have all the background and expert knowledge of the diseases, then there are behavioral psychologists that know everything that you should know about getting people to take the steps towards change and how to nudge them towards the right change. And then there are people like myself and more people in the company with a background in the gaming industry. So we're trying to merge these three together to create this encasing solution that can help you improve your life.

14:34

Alexey

**So when you mentioned gamification and creating more engagement – since you worked at King. I played some games from King – like Bubble Witch for example – King gets people on the hook really well. So I think you really mastered that at King. I guess this is one of the things that is quite useful now from your past experience that you can apply, right?**

15:04

Stefan

Yes, yes. But at the same time, there are critical differences. We don't want to keep you in the app for hours, because most of the activity you need to do is outside of the app. So that is a very interesting difference between the two use cases.

15:21

Alexey

**Yeah. If I understood correctly, your main target audience of the app consists of patients, not doctors. Or is it both?**

15:30

Stefan

No, the main target is the patients. But we are collaborating with pharmacy companies or insurance providers as well. Not doctors.

15:37

Alexey

**Okay. Not doctors who take in patients every day,**

15:42

Stefan

Not at the moment.

15:45

Alexey

**Okay. Because I imagine that they don't really care much about gamification. They just have so many patients to deal with, so they probably just don't have time. So if I understood correctly, what you do is – let's say a person has some chronic disease and they need to enter these details in the app, and then the app will tell them, “Okay, you need to drink more water, drink less coffee, exercise more,” this is what my doctor tells me. [laughs]**

16:17

Stefan

[laughs] Yes, but there's a little bit more than that. Today, you are given a specific PIN code that lets you go in and so that you enter the right program right away. But a big, big part of that is – take a typical diabetes patient, for example. A big proportion of people dealing with diabetes are dealing with problems that come from lack of health literacy. So just having very accessible content on, “Okay, you have this disease because of this. You can control it with this.” Just having that in a very clear way. Because speaking to a doctor can be difficult. As I said, they have five minutes. There is big doctor language and they are often very proud of that language – so you don't understand half of what they say. That's the first step – just to get closer to the people, so they feel “Okay, there is empathy here. You really care about me. You can speak to me.”

This involves educating people about “Okay, maybe your diet isn't the best. This is your disease. You need to think about the diet and how you rest and how you exercise.” But that's just the starting part. Then you need to create a program where you go step-by-step with behavioral psychology to nudge people towards creating habits. That's a non-trivial task to do. How often do you start something, have great hopes, and then you maybe fail? [chuckles]

17:56

Alexey

**Every January. [laughs]**

17:58

Stefan

[laughs] Every January, exactly.

18:01

Alexey

**[laughs] And then like, maybe in the first week, I'm so adamant about doing exercises. Then it's winter, I don't really want to run, maybe I'll wait for summer. But then in the summer...**

18:13

Stefan

A big part of that is behavioral psychology, and the goal setting is maybe not the best. You aim too high, or you don't have small steps to gradually push you towards something – you don't have someone constantly reminding you, like a friendly app. Or it's just, “It's okay, don't worry. Continue.” We all forget one day to continue. “Let's try to do 3000 steps today,” something like that.

# How is working for King different from Sidekick Health?

18:39

Alexey

**Interesting. I really want to try it now. [laughs] So we already talked a bit about how your previous background was useful, at King for example, where you knew how to attract or keep people engaged. But it also seems like it's quite different from your previous jobs. Right? Although now, when I think about this, actually, this is an app and what you were doing before it was also an app, so to some extent, there are some similarities. Can you maybe tell us about the differences between what you do now and what you were doing before as a data scientist at King?**

19:27

Stefan

Exactly. I think it's much more similar than you would think in the beginning. You basically have a program – some kind of solution – and you're in a company where you really want to create this data-driven culture from the data science perspective. You want decisions to be data-driven. If you're going to change features in the app, you want them to be backed by data. And you want some kind of machine learning part of it as well. So on a very high level, it's actually very similar. You need to create this culture, you need to build up the infrastructure, and have the buy-in from the business people that, “Okay, don't just shoot from the hip – we need to be data driven.” That's exactly the same in both places.

But as I sort of hinted earlier, there is a big, big and very interesting difference. Because with King, we have social media, we have gaming apps that are optimized for just keeping you in the app forever or whatever platform they're working on. They give you content, they play on your feelings. That's currently all the debate about Facebook that is dividing people into because it's always optimized to give you more and more things that you get more emotional about. We're not trying this. We don't care if you spend just 10 minutes a day in the app just reading the educational content and seeing “Okay, these are my tasks. I'll do them.” Then you come in again, “Okay, I'll finish this.” Something like that – that's fine. If you just follow the path and get better. That's the main difference there.

21:16

Alexey

**There is a main metric for you. Let's say games like Candy Crush, Bubble Witch – they aim at maximizing the time you spent in the app, right? Time you spend playing.**

21:31

Stefan

Or the money you spend. [laughs]

21:32

Alexey

**Or the money, yes. It depends on how exactly you monetize this particular app. But then when we talk about your application – the one you’re working on right now – something that comes to my mind is how often people return, like how many days they open the app let's say? So probably what you want to have is “people open the app every day,” it doesn't matter if it's five minutes or more than that. Is this the metric that you want to optimize? Or is there something else?**

22:02

Stefan

No, exactly. Creating an app is exactly this. You need to just think “Okay, if we can make you open the app for 10 minutes every day at three o'clock in the afternoon – that would be awesome for us. Then you're probably following the directions.” It's only a proxy, but it's probably highly correlated with you following the therapy or the program we give you. Plus you are gradually building up a habit. The building of a habit takes weeks or months, so just being able to have this happening repeatedly is more important than you staying in the app for hours. That’s much more important.

We absolutely don't want to spend time in the app when you should be out working. [laughs] But there is another difference also with an environment like Candy Crush – you are with patients in treatment. Therefore you have to be much more careful. If you're chasing a feature in Candy Crush, “okay, should this level be slightly more difficult or slightly easier than it is today?” You just do it and see what happens. [chuckles]

23:09

Alexey

**You do an A/B test, right?**

23:10

Stefan

Yes. But in healthcare, you really need to be careful about “Okay, let's make sure that this is okay and that we're not jeopardizing anyone's health.”

23:21

Alexey

**The experiment in this scenario could be “Let's ask people to, instead of walking 3000 steps per day, let's ask them to walk 4000 steps and then we see if it changes the habit.” Right?**

23:35

Stefan

Exactly. That's why companies like King and games like Candy Crush and social media are so good at retaining you – they are constantly experimenting and doing A/B tests, giving the audience two or three different versions and then you pick a winner to that. Then you could actually build up to a better, more engaging solution. We are definitely doing A/B testing a lot, but the metric that we're optimizing for is not necessarily the click through rate or time spent.

24:12

Alexey

**Have you ever used Duolingo?**

24:14

Stefan

Yes.

# The rewards systems in gamified apps

24:15

Alexey

**Yeah. For those who haven't, this is a tool (an app) for learning languages that has gamification inside to keep you motivated to learn. My wife is actually using it to learn French right now. I can see that they did quite a good job of keeping people engaged and making sure that they come back.**

**The question we have from Gregoire is, “I’m wondering how difficult it is to enforce such behavior that you can push using approaches like Duolingo by adding gamification. Do you get help?”**

25:05

Stefan

Yes. We do a lot of user research, of course, where we interview people afterwards and ask them “What is working? What is not working? What needs improvement?” And people are generally very happy with the reward system. Probably the strongest part is the empathy and the companionship you feel with it. [cross-talk]

25:33

Alexey

**We talked about the reward system, right? Maybe you can also say a few words about what kind of reward people get for something like walking 4000 steps?**

25:43

Stefan

Yes. We give them a task every day according to a program. Every time they finish a task, they collect water drops, at the moment.

25:51

Alexey

**Ah, right. We did talk about that.**

25:55

Stefan

That can be extended if you're looking into something like – maybe we want to offer them, through different kinds of charity collaboration, different kinds of rewards – so it's closer to your heart. I mean, planting trees in the Amazon or something else, so it's more engaging, and you're more enthusiastic about, “Okay, I really want to do this donation.”

26:21

Alexey

**In Duolingo, the reward system that they have is just made out of thin air, right?**

26:27

Stefan

Yes.

26:28

Alexey

**It's basically a leaderboard where you compete against people you don't know. And somehow it works, right?**

26:35

Stefan

It works. You see in many games, where you have these vanity items that people really respond to. We just thought that for this kind of app that we're building, you need a little bit more.

# The importance of building a strong foundation for a data science team

26:53

Alexey

**Can you maybe tell us about what kind of problems your team solves? Maybe you can also mention a few of the last projects that you worked on.**

27:02

Stefan

Yes. We have been putting a lot of effort into just building the foundation. I started a little over a year ago and then we were a much smaller company with just two data scientists. Nothing was in place, basically. We needed to build up all the foundation and infrastructure. We built data pipelines, dashboards, just as the first steps to make everyone data driven. I have a very (probably personally) strong opinion about, “Okay, we want to go into machine learning and personalization, but every machine learning project you start without proper analytics and proper data is bound to fail.”

That's why we have been putting a lot of effort into the foundation and building up A/B testing capabilities and things like that. That said, we have done a lot of that, so we are able to start and have started working on what we think are pretty exciting projects. Personalization is going to be a key part of this. We have some simple logic today, but we want to make that so much, much more advanced – the treatment personalization, the task we give and the modules you get at each given point in time is the correct one (the one you need at the moment). People are very different. With a chronic disease, you might want to be quite depressed, then we need to slow down and say “Okay, let's not put tasks that are too demanding on you. Let's give you content where you can do more mindfulness and things like that.” So we need to be very adapted to this and then just all the tasks you are given, “Okay, we know that people that are similar to you, who like these kinds of tasks.”

29:06

Alexey

**May I interrupt you? Sorry. I'm really curious about this slowing down approach. Do you have a model that says, “Okay, this user seems like he's not in a good mood.” You have a model that detects that?**

29:20

Stefan

At the moment, we have rather frequent questionnaires where you can emphasize how you are feeling.

29:27

Alexey

**Yeah. If you can solve something without machine learning, it’s better. Right? [laughs] Just ask the user.**

29:33

Stefan

Yeah, [reluctantly] I mean – you should start there. I think that should always be the approach – start with something simple. Then you have data and then you have everything in place to automate it. Don't try to automate out of thin air. But we also have just received a report that the activity in the app is dropping, and we have started and want to go much more into that direction – where you have your wearable, where you can measure your heart rate variability, your number of steps. We already have that, of course – but more and more of this.

# The challenges of building an app in the healthcare industry

30:08

Alexey

**Okay. Usually when I think of the healthcare industry, (I might be wrong. Don't judge me. I never worked in healthcare.) But usually when I think about this, it's regulated – it's quite slow. There is a lot of legacy software, a lot of outdated software. But what you described to me is pretty much different from that. Right? You realize the importance of having proper analytics data pipelines, having A/B tests, etc. Is it because, like you said, it’s a scale-up? It's a rather fresh company, right? You now realize the importance of being data driven and all that, right?**

30:52

Stefan

Usually innovation is at its best when you have experts from different fields coming together. Somehow the space between them – that makes it automatic. And I think that's what we have. We have the medical doctors and the behavioral psychologists that come with all of the theory and everything around the [inaudible] and psychology. But then you have a lot of people coming from the gaming industry, not only myself, but the CTO and many of the developers that developed the whole solution from the beginning – they all come from the gaming industry. So you have this dynamic there that I think is very important. The gaming industry is very data-driven in general. People are always testing out their hypotheses.

31:41

Alexey

**We have a question. I mentioned that healthcare is quite a regulated area. And usually in healthcare, people take questions about data privacy and this kind of stuff very seriously. Does it change the way you work? You have to keep these things in mind, like data privacy and all that? How difficult does it become that you need to deal with all these kinds of things?**

32:10

Stefan

I absolutely love that question. I think it's the other way around. I think all the other industries need to pick up with data privacy, and they are – gradually. But we have seen so many instances of data abuse. So I don't see this as a problem, I see this as something that’s great – I'm starting at the right end. [chuckles] I'm not starting with everything messed up and then gradually trying to clean it up. I started with just “Okay, this has to be good.” I think that's just where we are moving with every solution. Apple has, for example, completely changed their policies – your default settings were usually opt-in instead of opt-out and there's a huge change happening in this.

33:00

Alexey

**You basically need to do a lot of prior work to prepare for that. Then once you have a framework in place, that can take care of all these data privacy issues and you can move as fast as in, let's say, a traditional IT company, right?**

33:17

Stefan

Yes. We just make sure that we are using the best possible solutions. We also make sure that “Okay, there is personally identifiable data and that's very locked away.” But then we just de-personalize all the data and the data scientists and data analysts come in and they can do all of the same work as before – they just never see the personalized data.

33:44

Alexey

**There is a question from Nelson, “How do we, in general, deal with issues of ethics in healthcare when it comes to machine learning?”**

33:54

Stefan

Sorry, can you repeat that? I didn't follow.

# Dealing with ethics issues

33:56

Alexey

**Yeah. The question is, “How do we deal with issues of ethics in machine learning and health care?” I guess you mentioned that one of these things is making sure that (following Apple’s lead of opt-in instead of opt-out) we keep track of all personalized data and unless we really need it, we don't use it. Things like this. How else can we deal with all these ethical issues that come together with medical data?**

34:26

Stefan

Well, first of all, ethics means that you need people to think independently, because ethics is different from just “rules”. Right? I think that's an important fact. You need to have people that really care about this. They care about the patient – they’re trying to do the best for them. We can hurt them if we don’t do this in the best way we can.

34:56

Alexey

**This is the empathy you mentioned, right? You need to be empathetic.**

35:00

Stefan

Yes, exactly. We have, of course, rules like GDPR and HIPAA in the US – they are quite strict and very useful and should be used everywhere. [laughs] Of course. But I think you will also always need this kind of independent thinking. You're always going to end up on a crossroad of “Okay, am I crossing a gray line here or not?” Where the rules are not catching up with you. I mean, they always come afterwards. So I think that's needed as well.

# Sidekick Health’s personalized recommendations and content

35:39

Alexey

**Okay. I wanted to go back to what we were talking about. You said that the app is based on the customer profile – patient profile – it makes different recommendations, or personalized recommendations, based on that. Can you maybe tell us a bit more about that? How does this personalization work?**

36:01

Stefan

Yes. Again, this is, of course, a work in progress. But I think it's quite interesting. Think about Spotify and Netflix – there you have recommender systems that are always giving you more and more content similar to what you liked before. You have this collaborative filtering, where you are, through some nice technique –matrix factorization or something more advanced – you know how people similar to you watch content that you haven't seen before.

But I think what we are trying to do – I sometimes explain this internally as – imagine Spotify, where you come in and you have a heavy metal profile. You listen to rock music. But Spotify has an agenda – they want you to listen to country music. So they're trying to nudge you towards that. First they give you occasional Johnny Cash songs. But after two months, you're just listening to Dolly Parton. [laughs] So that's kind of the recommender system that we are trying to build. We're trying to move you gradually towards better behavior and maybe it's not *as* difficult as making someone listen to Dolly Parton, but [chuckles] it's still an interesting task. It's sort of a recommender system with an agenda.

37:24

Alexey

**Does Spotify actually do that?**

37:27

Stefan

[laughs] Do they make you listen to Dolly Parton? I don’t know. [laughs]

37:34

Alexey

**[laughs] When it comes to podcasts, I think they're trying to make me listen to Joe Rogan.**

37:40

Stefan

Maybe, maybe. But that's probably just coming from marketing. I don't think they’re doing that [cross-talk]. Or I don't know.

37:49

Alexey

**Maybe they have a hidden agenda there [chuckles] But this is Spotify’s podcast, so that's why they advertise it everywhere. Interesting. And in this case – in your case – country music would be better habits?**

38:09

Stefan

Yes, kind of. Of course, it's an analogy. So it's not a perfect analogy. I just thought it was funny to bring in country music. I'm not a big fan though. [laughs]

38:20

Alexey

**[laughs] So country music is good for your health, right?**

38:25

Stefan

Yeah. Okay. Now I see where the analogy is breaking. [laughs]

38:32

Alexey

**I'm wondering. You say you have this collaborative filtering – and in this case, we have the rows that are users or columns, whatever. So users are users, but what are the items that you're recommending? Are they articles? Are they particular tasks or things people need to do? Or both?**

38:53

Stefan

We are building up a library of content, sort of. I mean, from educational contents – videos explaining something – some content cards that can be read, and then exercises and all of these things. So we are building up this catalog. We will eventually have a large list of products, basically, to offer you. You end up with a typical recommender system from that. But then there is added flavor in the end.

39:32

Alexey

**Because I imagine if you start with recommendations of I don't know, “You need to do 10 push-ups per day” or something like this, then for an average person like me, “Okay, I know it's good for my health, but I'm not going to do that.” [laughs] You probably want to start slowly, and push me gradually towards listening to country music, rather than “Okay, like here's the country music. Listen to it.”**

39:57

Stefan

Yes, exactly. But this touches a little bit on the fact of how you approach machine learning. I think just jumping into complicated collaborative filtering is not the right way. The first step is maybe just setting an A/B test and seeing how two different versions of a content work. Then ask the developers to develop the program in such a way that you can actually show two different contents. And that's a key thing you need to have (can't speak English anymore, sorry) for building up more advanced features – just having the variant availability. So you need to start very simple. Then even if you have a variant that beats, on average, everything else, you can start there – okay, offer that to everyone. But gradually, you're building up knowledge and datasets that you can actually train on later. Instead of jumping ahead of myself and thinking that I know I have the vision of this awesome model, but I have to hold my horses. It’s not time for it yet.

# The importance of having the right approach in A/B tests (strong analytics and good data)

41:13

Alexey

**When it comes to A/B tests, it feels to me (maybe I'm wrong) but they're less personalized, right? You're trying to test the same piece of content – or two pieces of content in this case, if we're talking about an A/B test on the entire population or maybe on one segment of your users. But this is not the same as a personalized recommendation.**

41:32

Stefan

But it is very linked. Because if you offer everyone an A/B test to begin with, there are so many low hanging fruits, but you're just improving your program easily if you just take the winner of two in every test. But then you gradually reach a point where you see, “Okay, now I'm increasing *this* but decreasing *this*,” or “*This* is good for *this* part of the population, but not *this* one.” *Now* you're starting to think, “What's the difference between these groups?” And then for a mobile game, for example, you see, “Okay, *these* are the payers. *These are not* the payers.” Now, we can start to personalize.

You offer this to the payers and not to the non-payers. And then “Okay, this is smart. How about more segments?” And you add a few more segments. Now you have four or five segments. That makes sense. But it's starting to get complicated to maintain all of these different versions. So that's where you move into, “Okay. Now, I actually have a lot of training data from all of this testing. Can I just optimize the collaborative filtering or just clustering to begin with? Okay, and I'll just look at the 100 nearest neighbors of you.” That's the first approach. There, you will be similar to them. So I think this is important. The people gradually take the baby steps.

43:00

Alexey

**Here, the fundamentally important thing is having this platform for experimenting, right? If you don't have this and if you directly jump into collaborative filtering or something like the latest deep learning model for recommender systems without having that – you're moving in the dark. Right?**

43:21

Stefan

Yeah, exactly. In my mind, the two most important inputs into starting machine learning is to have strong analytics. You need to be able to analyze what is happening. You need to break down the A/B test and understand the data that you have. Then, of course, you need good data. If either of these is missing, in my experience, this is usually the deciding factor. If you have all of them, the machine learning project will go well. If you are ignoring either of them, you will probably fail.

43:53

Alexey

**And you fail quite late after spending many months. Right?**

43:58

Stefan

Exactly. [cross-talk]

44:01

Alexey

**That's even worse than just failing, right? Just training a model and finding out that it's not working on your refined data is one thing, but spending many, many months trying to build a model only to find out that users actually don't like it, that’s even worse.**

44:16

Stefan

Exactly. That's what you gain with taking the baby steps. You're always creating value. You know where you stand today – you're going from A to B – and you know where you want to be (approximately) and if you just jump to building that B part, you're doing exactly what you explained. But if you try to form a path from A to B that gives you the most value along the way, you will learn much faster and you will create value along the way too. Then you will get a much better buy-in from everyone around you. Because often, when you're starting a machine learning project, there isn't just one person doing something. You really need buy-in to have more resources, more computing power, and all of these things that you actually need.

45:00

Alexey

**I think companies – like gaming companies, IT, tech companies, e-commerce companies – have learned that it's important to have analytics, to have an experimentation platform and all that. But what do you think is the state in the healthcare industry? Do companies, or vendors, that operate in this industry also realize the importance of these things? Or is it a bit behind?**

45:29

Stefan

It depends on where you are in the industry. The old pharmacy world has been doing this for decades. [cross-talk] There is definitely a question for this. People are aware of this. I mean, all the kinds of biases that you create when you don't really have an A/B test, or RCT, which is some clinical trial lingo for it. So there's a question for all that, and they know that “Okay, if you're not doing perfect splits in A and B and even C, you will create biases.” There is a survival bias, when you're only measuring the people that actually do something and all the people that didn't do something, they just left your platform. I mean, there are so many pitfalls there. So there's definitely knowledge about this. I'm not knowledgeable enough, but there might be a difference between “Okay, how do you transform that to feature improvement?” So that's slightly different, because typical clinical trials are huge, they cost a terrible amount of money and they take years versus when you're developing an app – that's no good.

46:51

Alexey

**I think the general population learned about clinical trials now when COVID vaccinations were tested, right? Everyone was asking “Why does it take so long to develop a vaccine?” Because of these clinical trials. They need to test that this thing actually works.**

47:07

Stefan

“Why does it take so long?” [chuckles] It was done, of course, in record time – one year – when it should have taken ten.

47:16

Alexey

**It usually takes a lot more to actually run all these tests, right? Hopefully, they worked. [laughs] We'll find out soon, right?**

47:27

Stefan

[laughs] We’ll find out, yes. [cross-talk]

# The importance of having domain knowledge to work as a data professional in the healthcare industry

47:33

Alexey

**So if I want to work in the healthcare industry as a machine learning engineer or a data scientist or a data engineer, how much do I need to know about healthcare in general? Do I need to have MD status to work there?**

47:48

Stefan

I think it differs a lot between what exactly you're doing. Probably, in some parts of it, you really need to have domain expert knowledge. But from my experience in just data science, it's more important just to have the right approach. You come to a problem and then you know, “Okay, this is the kind of approach I need to have. I need to take this (as we talked about earlier) take these baby steps, build up the knowledge, be humble about ‘maybe my solution is wrong – maybe there's something wrong here and there.’” And just this way of working is probably more important than domain knowledge in many cases. But there are definitely some cases where that's probably not enough.

# Making a data-driven company

48:41

Alexey

**You mentioned that you have medical doctors who are domain experts, in your case, then behavioral scientists who are also domain experts, and then the engineers, the data scientists, who take care of the way of working, as you mentioned. Then what you do is basically get everyone in the same room – virtual room, I guess, because you're in different countries – and you figure out, “Okay, how do we use this knowledge from these people and put this knowledge into their way of working when it comes to data, building these analytical platforms, data pipelines and so on?” Was it difficult for you to actually learn this?**

49:25

Stefan

No, not at all. All of these people are very data-driven just by nature. The biggest challenges may be to tell a medical doctor, “Okay, now we're testing a feature in the app. Let's just test it.” “What?! No, no. Wait!” [laughs] When we do medical things, we are much more careful, but it's all about the risk involved. If you're testing a feature that doesn't have any risk involved, then I think you should take the gaming industry approach – just test it. Your gut feeling may be correct half of the time at best. Just test and ask the users. They will tell you much faster and much more accurately about what they like and what they don't like. So but that was a little bit of a challenge.

Also, when you're building up a question in a company, one of our main objectives is to build a data-driven company. And that means that you have to be quick enough with the answers – the business is making a decision *now*. But many data scientists sort of, – they've studied through university, “Okay, I need to be perfect in what I do.” And if you are, you're basically killing the objective of being data-driven. You need to be able to act fast, give somewhat accurate numbers, but they're not perfect – there's a little bit of a contradiction in that and that's also something that needs a lot of communication.

If we want to be data driven, we need to act fast, we need to iterate. We start with data pipelines that are just spaghetti code – just to get something out. Then you gradually make a proper pipeline out of it and everything you need. But if you start with “No, I want to build this in AirFlow.” There's just radio silence for months for the business. [laughs]

# Risks for Sidekick Health

51:28

Alexey

**Right. You mentioned risk. As I understand, for your case, the risk is not that high, because you're not recommending medicine. Right? You're not saying “You have to take these pills.”**

51:42

Stefan

It depends. Some parts of the problem can be very sensitive.

51:48

Alexey

**Okay. So there are some risks?**

51:50

Stefan

Yes.

51:52

Alexey

**You cannot recommend eating sweets to people with diabetes, right?**

51:55

Stefan

No, no. An example we often use to remind ourselves of this is – if you have heart failure problems, it's not good to drink too much water, because your lungs cannot process all of that, so you end up with liquid in your lungs. But in most other programs, it's good to drink more water. We could not just create an A/B test “Let's suggest 10 glasses of water.” We always need to have this discussion with the medical doctors to see, “Okay, we want to test this. Does it make sense? Is it safe?” And when it's safe, we can be very agile about it. When it's not safe, we need to be much more careful.

52:39

Alexey

**Yeah, makes sense. Makes total sense. But you *don't* recommend medicine, right? It's more about lifestyle rather than taking a certain kind of pills?**

52:50

Stefan

Well, we *are* collaborating with pharmacy companies, but then there is a specific medicine that they have been prescribed from a doctor before.

52:59

Alexey

**So you still need to go to a doctor and then say, “Okay, this app recommended me to take a pill.”**

53:03

Stefan

Yes, we can [cross-talk]

53:08

Alexey

**Sometimes it's annoying. I know I need to have this medicine – I just need to go to the doctor and all the doctor does is give me a prescription.**

53:18

Stefan

[laughs] Yes, a lot of legal processes also.

# Sidekick Health growth strategy

53:21

Alexey

**Yeah, but it’s better this way rather than just going to the pharmacy by doing self-diagnosis and buying something that can cause more harm than good. I've heard you're hiring. Can you tell us more about that?**

53:39

Stefan

Yes, we've been growing very rapidly. When I started, we were maybe 13-something. I think we're 130-40 today and we'll probably be 250 by the end of the year. And we are rapidly growing the data science and AI team. We are about 10 at the moment – I think we will double in size at the end of the year. That's counting everyone – all the data engineers, all the machine learning engineers, data analysts, data scientists – everyone included there. So yes, we are looking for good people. We know that this is a domain where there’s fierce competition. We are fully aware that we need to build a world-class solution. There is no middle ground. Either you're a top-class app or you’re dead. There's nothing in between. So we need to hire great people for that.

54:39

Alexey

**You're hiring in Germany, in Sweden and in Iceland. Right?**

54:43

Stefan

Yes, that's the focus now. So as I said, we have offices in these countries but also in Boston, but we're focusing our efforts in and mostly Berlin and Stockholm and also in Reykjavík. As you might know, there are fewer people in Iceland than most other countries.

# Using AI to help people live better lives

55:03

Alexey

**You're the first guest we had from Iceland. Not that many people – I don't think I know anyone apart from you. [laughs] I noticed that we have a question from Slido. The question is (I don't know if you know about this) “What are your thoughts on brain/computer interfaces like Neuralink?” Do you know anything about this?**

55:31

Stefan

I don't know enough to say anything intelligent about that, I'm afraid. [laughs] Sorry about that.

55:42

Alexey

**Do you think AI could be used to treat or cure psychiatric disorders like bipolar disorders?**

55:53

Stefan

That's a very interesting question. Of course, I'm not sure. But it could probably help, at least. A disease like bipolar disease, you're affected a lot by just “Okay, now there's more brightness. Now there's more darkness.” You get more swings. So if you can predict that and know about that in advance, for example, if you could monitor the heart rate variability or something like that. This is an indication that you're going too high – it's been rising or increasing over the past week. Yeah, it could definitely help. But cure is a different thing, probably.

56:44

Alexey

**More like learning how to live better? Like you said, with chronic diseases it's all about learning – educating people how to lead a better life with these diseases. And this is what you do, right? You educate people how to form habits such that they can lead a better life? Okay, I think on that note, we can wrap up, maybe? Is there anything that you want to mention before we finish?**

57:18

Stefan

No, I can't really think of anything. Just thanks a lot for the talk. It was very nice to talk to you. And it's always nice to talk about this kind of subject.

57:29

Alexey

**If somebody has questions, what's the best way to reach out? LinkedIn?**

57:35

Stefan

Yes.

57:36

Alexey

**Okay, then that's all for me. Thanks again for joining us today, for sharing your expertise with us. And thanks, everyone, for joining us as well. Thanks for asking questions. And have a great weekend!**

57:49

Stefan

Yep. Bye guys. Thanks. Bye-bye.