0:44

Alexey

**This week, we'll talk about data science in healthcare. We have a special guest today, Elena. Elena is a machine learning researcher and educator. She's passionate about using data science to improve health care and save human lives. Her expertise includes signal processing, deep learning, and data-driven design. Welcome!**

1:05

Elena

Thank you. Also, thank you for the invitation to the podcast. I have been following some previous podcasts that you did – some other talks. But I'm also glad to meet you like that in life. But I'm familiar with this setting, and also seeing you, but not in an interview. [chuckles]

1:26

Alexey

**Thanks. [chuckles] And big thanks to Antonis, who recommended Elena. It's also not the first guest that he recommended, so thanks, Antonis, a lot. Also, the questions for today's interview were prepared by Johanna Bayer. Thanks a lot, Johanna, for your help. Yeah, let's start.**

# Elena’s background

1:45

Alexey

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

1:55

Elena

So, as I said, I am Greek – I was born and raised there. I went to university there at the University of Patras. I did electrical and computer engineering, which is a five-year Bachelor's and Master's – a joint degree. During those studies, I did Erasmus and I did part of my thesis in Brussels – I stayed there for one year. It was my first international experience. And then I got excited…

2:28

Alexey

**At which University?**

2:30

Elena

It was VUB (Vrije Universiteit Brussel)

2:33

Alexey

**So it was a Dutch-speaking university. I studied in the French one.**

2:41

Elena

ULB

2:43

Alexey

**Yeah, ULB exactly.**

2:45

Elena

I also did some courses there because I needed to pick up some courses. So I also did a bit of ULB. But mainly it was VUB. Then after that, I was excited about going abroad, and I applied for an internship at Philips Healthcare in the Netherlands. So I moved to the Netherlands. Actually, now, I’ve spent the last seven years here and I have been doing different things. The main focus is always healthcare. I also worked there at Philips Healthcare after some point.

Then I did the two-year engineering doctorate diploma in data science. That's the only thing that was not related to healthcare because we were involved in multiple projects and we worked with different companies and organizations. But then after that degree, I got back into healthcare again, and I worked for a startup – working on developing monitoring systems for vital signs for pediatric patients in Africa. In short, that's my journey, but if you have questions, you can ask them and we can go into more detail.

4:03

Alexey

**How's your Dutch?**

4:05

Elena

It's good [chuckles]. [speaks Dutch] Around B1 level, let's say.

4:14

Alexey

**Because in the Netherlands, everyone speaks English, so I guess it's very difficult to actually learn and practice Dutch, right?**

4:22

Elena

It's true. But I find it interesting and also sometimes useful because some things are just written in Dutch or sometimes, I need to search for something in Dutch and I can find better results. So that's why I stuck with it a bit. I also have a personal interest in learning it.

# Some of Elena’s past projects

4:43

Alexey

**Nice. Well, I have never heard about Philips Healthcare. What I know about Philips is that they produce lamps. I have a few smart lamps – Philips Hue. I also know that they produce trimmers (for shaving) but that's pretty much the extent of what I know about Philips. [chuckles] I know it's a gigantic company and I know that their headquarters is in Eindhoven, right? What does Philips Healthcare actually do?**

5:20

Elena

They don't make lamps anymore – they sold the company. Any lamps with smart lighting and all those things, it's called Signify. Now Philips is focusing on home care – shaving machines, toothbrushes, and things like that – and also health care, but broad care of health: at home, in the hospitals, they have MRI scans, they have big machines as well. I did my internship in the C-arm, which is like a machine used in the operation room. When I was working at Philips Healthcare, I also worked in the pregnancy department. There were two different projects focusing on different areas of healthcare. It's a huge company.

6:20

Alexey

**From what I understood, it's mostly about different devices that doctors use for different things like MRI scans or support integration rooms or things like that. [Elena agrees] At your current company, what do you do? You mentioned helping people in Africa – maybe you can tell us more about that.**

6:48

Elena

I actually left my current company in July. I'm actually now on sabbatical. I worked for them for almost two years, focusing more on designing things like, “What is the future of data science in the company and how can we develop data science into the vital sign monitoring system that we were working on?” That was actually a system that recorded vital signs, like heart rate, respiration rate, etc of pediatric patients… [cross-talk]

7:29

Alexey

**Devices like this? [Alexey points at a wearable health tracker] Wearables? Or something more precise?**

7:34

Elena

It was actually a system for the intensive care unit. But then the difference was that we were working on a design for low-resource settings and also a more simplified design because sometimes, healthcare professionals there might find it more convenient if the device is simpler for them. Actually, a lot of hospitals… We were working with Malawi, and a lot of hospitals there don't have monitoring systems. I was mainly working on the design because we were involved in a data collection process – we were collecting data and there was this big question, “What are we going to do with this data and how can we use it to predict vital signs for patients and to associate lab tests we were getting to identify specific clinical outcomes?” Things like that. But one of my learnings there was that it's a very long process, starting from the research part that I was mainly focusing on, into really integrating those algorithms into the real setting and making it usable for people.

9:05

Alexey

**As I understood, the devices are already there – all the things that collect data from patients (all these vitals) are already there and what you were doing was thinking, “Okay, we have all this data – how can we use it?”**

9:20

Elena

The devices were also there because we were part of a bigger research project. They were installed there for the purpose of the research.

# Why Elena chose to go into healthcare

9:34

Alexey

**Okay. That's quite interesting. You spent a couple of years there, right? [Elena agrees] So you started in Philips Healthcare and then you worked in this company. Why did you decide to go into healthcare? Why did you decide to choose this field?**

9:58

Elena

Before choosing and going into engineering, I had this big question whether to go into studying to be a doctor or to go into engineering. I went with engineering because I was into math. When the time came to decide on what kind of thesis I wanted to do, the only topics that I found most interesting were topics related to healthcare because I found that there is a greater direct impact on people. I still remember, for example, that there were some projects on developing games, and I found that, for me, personally, it was not impactful. So I choose to do that. Indeed, it was true that I felt that my work went into something that could impact people's lives.

10:59

Alexey

**What was your thesis topic?**

11:03

Elena

I worked together with IMEC, which is a Belgian Research Institute. There, we were working on… I had images from white blood cells and I was analyzing those images with basic, conventional image processing methods. The main goal was to classify those images into subcategories of white blood cells. That was part of a bigger project because they were working on the development of a cell sorter machine. With this machine, they wanted to filter people’s blood and classify the blood cells into “good cells” and cancerous cells. They wanted to filter out the cancerous cells. I was just working on a small part of this project – on the white blood cells.

12:12

Alexey

**I was going to ask, “Why exactly do you need to categorize cells?” But you answered that – if the cell is cancerous, you don’t want to have it there.**

12:24

Elena

Yes. They wanted to prevent the metastasis of cancer into other tissues.

12:33

Alexey

**Yeah, that does sound very impactful. For you, as a student working on I think like that… I can see why it was very interesting. You worked on this Master’s thesis and then the company… You did some models, and then the company integrated this into their sorting mechanism, right? [Elena agrees] That's pretty cool. So you really liked this topic and then you started researching, “Okay, where can I go next?” And then you found Philips Healthcare. Is that right?**

13:13

Elena

Yeah. And there, I worked on a topic that was not really related to data science. They have this C-arm, which is in the shape of a C, like that [Elena shows the shape of the letter C with her hand] and on the top of this arm, there are four cameras. Here [points to thumb] it's the bed of the patient. Those four cameras take [photos of the patient from] different perspectives and different angles. My task there was to take those four images, calculate the geometry, and create the 3D object representation of the patient.

13:57

Alexey

**Well, it still sounds very mathematically heavy, right?**

14:01

Elena

Yes! [chuckles] It was very mathematically heavy. Not like machine learning and those things, but it was, yes.

14:08

Alexey

**Do you know if this problem is being solved these days with machine learning (with neural nets)?**

14:17

Elena

I'm not aware of this.

# 3D imaging and healthcare metric tracking

14:19

Alexey

**Because I saw… It's not related to health care at all, but I saw some demos where people were going around Berlin (or other different cities) taking pictures. Then there is a model or something that just takes all these images and creates a 3D model of these things. It looked really impressive – what they could do with just a few images.**

14:46

Elena

I'm sure that machine learning can probably help with the challenges of these computational methods. For example, sometimes we had occlusions, which means that… When there was no object between the cameras, it was easy to reconstruct a 3D object, but when we had a surgical object, it was harder to create the shape of the 3D model. This computational method was not really tackling this challenge. But machine learning can probably create a better graphical model. [Alexey agrees]

15:28

Alexey

**Okay. But it was still quite mathematically heavy and then, eventually, after working on this 3D reconstruction, you probably continued work in these data science areas, right? Also in Philips?**

15:43

Elena

Yeah, I worked as a data analyst afterward, on a project that was a research project. Again, because I mainly worked in research all those years. We were actually collecting data from pregnant women. That project was directed… The users were midwives. They wanted to see how pregnant women are doing at home. So it was homecare – and the pregnant women were weighing themselves every day, they were wearing a smartwatch that calculated their heart rate. This was important information for the midwives because it's also very important during the pregnancy – to see how much weight the pregnant woman is gaining because it needs to be within certain limits. I was working as a data analyst there on developing a dashboard, visualizing this information for the midwives in a user-friendly way. We were calculating this because we were getting a lot of feedback from them on what is useful for them to see and what is not. It was quite interesting. I really liked that I was getting feedback from them, and we were creating it together.

17:15

Alexey

**I'm trying to look at what we discussed so far. First, your thesis was about cell classification for a cell sorter. Then you worked with this 3D reconstruction. Then [there was] the thing you just described – it was more not for the operation room (not for a hospital) but something you wear at home, for pregnant women. I’m wondering… These areas appear quite different from one another. They're different. I'm wondering if there is any area of healthcare that you're more interested in or if they're all equally interesting to you.**

18:05

Elena

As you said, they're quite different from one another. Also, if you consider the projects I work on later, they're also quite different. But they have a common theme in that the things that you're looking at when you're working are healthcare data. But personally, what I find interesting is to work on the research side of healthcare, because I like the novelty of creating new ideas. Another common thing that I find interesting is to work on projects that also have the potential for clinical application, or that they're already tested in a real-world setting.

# Making an impact and signal processing

19:00

Alexey

**So, there is no specific area – you focused more on “Can I make an impact now? Can I publish a paper?” Or “Will they think I work on go and affect lives after I finish?” It must be really cool to see things that you work on in action, right?**

19:17

Elena

Yes. It's quite rewarding.

19:22

Alexey

**You published a few research papers, right? What were these papers about?**

19:28

Elena

During the period when I was working for this company where we were working on vital sign monitoring systems in Africa, I was working on… It is called ballistography signal data. It's a novel signal… I'm thinking of how to explain it to make it easier for people. This signal is meant to replace the electrocardiography signal. In simple terms, if a patient is in the intensive care unit, they just put the electrodes on the patient, and they need to have the electrodes there for many hours, which could be tiring for the patient since the patient cannot move around. Meanwhile, this sensor is actually a mat that goes below the patient's bed, which records the signal of the movement, including the movement that comes from the respiration rate and the heart rate. I was working on that – I was using the ballistography signal and the electrocardiography signal as a reference, and I was trying to remove the noise from the ballistography signal and extract the vitals from there. So that was a novel application.

21:16

Alexey

**So if I understood correctly, there is a method that is more… not intrusive, but annoying – and inconvenient method – when the patient is covered with all these electrodes. It's not convenient. Then there is a less annoying method, which is just placing a mat under the patient. What you were doing was trying to use machine learning to go from the signal noisier signal to a more accurate signal. Right? [Elena agrees] That’s awesome.**

21:49

Elena

Yes. You have the estimation of the heart rate and respiration rate. For the respiration rate, I used more conventional signal processing approaches, because it's simpler to estimate the respiration rate since you get a much stronger signal. But then for the heart rate, it was much more challenging and that's why we went into deep learning. Also, I have the approach that if we can solve a problem with basic signal processing, then it's much better to do it like that. And if we need to use something more advanced, then we can go into deep learning machine learning techniques.

22:29

Alexey

**What is basic signal processing? Is this like the Fourier method? Something like that?**

22:35

Elena

Yes. Filters, Fourier methods – yes. I focused on the frequencies of the respiration rate that we were interested in. Of course, there were some challenges because we had to deal with pediatric patients, which meant weaker signals and more movement. We also had the challenge that sometimes the frequencies of the respiration rate and the heart rate can overlap and then it's hard to make out what is what. But yeah, it's very interesting research, I think.

23:15

Alexey

**I see that you shared a link to one of your publications, which is “A U - Net Deep Learning Model for Infant Heart Rate Estimation from Ballistography”. That's the paper you're talking about?**

23:31

Elena

Yeah. This is the paper where we were estimating the heart rate. We used this U net, which is actually used for object segmentation in images, but in this case, we used it for the signal because, in the ballistography signal, there is a very distinct pattern for the heart rate. Our focus was to identify this distinct pattern in the signal.

24:06

Alexey

**Quite interesting. I'm looking at the paper – well, not at the actual paper but more at the Research Gate website. we will definitely put the link in the description so people can check it out. There are a lot of words I don't understand, like “BSG waveform”. It's quite an interesting read. Okay, thanks. You probably wanted to talk about some other papers or some other research before we move on, right?**

24:43

Elena

This is my first publication. But then I also published a poster that is not available online. It was about calculating a patient’s score based on the vitals of the patient. The main idea behind this was to have an overall assessment of the health status of the patient so that healthcare professionals can have an idea of how critical the patient is.

# The challenges of working in healthcare

25:23

Alexey

**I already see quite a few questions, and this is actually one of the questions we also have for this interview. It is about the challenges of working in healthcare. It's quite a regulated field, right? I guess there are a lot of privacy concerns and things like that. So what are the typical challenges of working there?**

25:53

Elena

Yes, one is getting regulatory approval, including algorithms, and machine learning algorithms in the devices. The reason behind that is that it's like a black box. Of course, it's sometimes hard to understand why a machine learning model predicts a specific outcome. There, a lot of work needs to be done in the Explainable AI part, how we can give an explanation of why the algorithm predicts a specific outcome. This field of AI is still in a very early stage. I think the more this field is developed, the more trust there will be from the side of the healthcare professionals, and also from the people who approve the devices to be used in hospitals.

Another challenge is a lack of data sometimes or a lack of consistent data. In real datasets, a lot of the time, we see that there are many data gaps. This makes it hard for algorithms to take the inputs properly. Sometimes we need to make assumptions on what kind of data we would expect for that patient. But then, still, this is also not always the way to go. So that's a problem. Another big problem is that oftentimes the data is being collected without having in mind what kind of a use this organization wants to perform with this. For example, one common problem is a lack of annotations – they say we want to do a predictive algorithm for a specific clinical outcome, but then the proper data annotations for this outcome are not there.

28:07

Alexey

**What kind of outcomes? Is it like whether a patient is going to have a stroke – things like that?**

28:12

Elena

Yeah. In my previous research, I was working on estimating sepsis, let’s say, based on the vital signs of the patient, and also the clinical data.

28:26

Alexey

**I don't know if I want to Google what sepsis is. Ah, “Sepsis is the body's extreme response to an infection. It is a life-threatening medical emergency.” So I guess you want to predict that this thing is about to happen – you want to act as fast as possible, right?**

28:48

Elena

Yes, because the faster you act on that, the more chances you have to treat it.

28:56

Alexey

**I guess that's why Explainable AI is very important, because if the algorithm predicts, “Hey, this patient is going to have sepsis.” And the doctor looks at the patient and thinks, “Okay, they look normal.” They need to understand why exactly the algorithm (this model) thinks that there is a problem. Maybe if the doctor understands that, they can think, “Okay, yeah. Now it makes sense. Let's perform a few checks.” Right?**

29:25

Elena

What I think about this topic is the approach that should be taken for the algorithms – it needs to be used as a tool for decision-making. The algorithms are now not on a level to do the decision-making. That's why we need to be careful with that. It's just a tool to help the doctors assess a situation. What I've seen is that people tend to really go far ahead and say, “We want to predict what the patients have. We want to give advice on what the doctor should do.” However, I think a more data-driven approach needs to be integrated slowly into the hospital setting by just, in the beginning, giving some recommendations or even saying, “There's a 60% chance that this patient might have this kind of disease.” To make the doctors aware that this is not a certainty – they just need to look more at that.

30:25

Alexey

**So it's more to gain trust from the doctors (from the medical personnel) that they see, “Okay, this model is actually making our lives simpler. Now we trust it.” Then it could be integrated into their workflow more and more. Right?**

30:43

Elena

Also, what I think is that sometimes even just data visualizations of historical data – what happened to similar patients in the past – can already be helpful, without any predictions. Then this is more data science and not machine learning – just making doctors more aware of what happened in the past.

# Jumping over hurdles, gaining trust, and collecting feedback

31:10

Alexey

**You spoke about these regulatory approvals, and I imagine that these things make it very difficult to… Let's say you’re working on a thesis or you're working on a model and the time comes to actually “ship this model to production” – this process of actually bringing this model and algorithm from research to production could be quite challenging, right? There is also a question from David about this, “How difficult is it to come up with a solution that is actually used in the field?” There are some political barriers that might appear along the way. How difficult is it and how do you usually solve these problems?**

32:02

Elena

What we were doing was getting a lot of feedback from the healthcare professionals on what they needed – from the doctors, from the nurses – because they were also using the vital sign monitoring system. But indeed, the regulatory approval part is a very big challenge. There are also other people involved that are experts on that. Asking those people what the way to go is can be helpful for bringing those things into production. Oftentimes we have the application, but it gets stuck – it might take five years to be used in a hospital. [cross-talk]

32:56

Alexey

**I guess, in this case, what you want is doctors to also actively advocate on your behalf, saying, “Look, this thing is really useful. We want to have it.” Like you said, you want to get feedback from these healthcare professionals. Because if the feedback is positive, and they clearly see the value in this thing, they help you – right?**

33:20

Elena

Then they also trust it more. There is also a lack of trust sometimes. There is also this approach that people have, where they don't want to try something new. They say, “Oh, no. We already work with this.” And they don't want to change to something else.

33:38

Alexey

**So you need to find doctors (or healthcare professionals) who are a little more open-minded than others, right? [Elena agrees] That can be difficult. [Elena agrees]**

# Convincing professionals to try new things

33:54

Alexey

**I see that there is a comment from Sylvia. “Thanks, Eleni, for sharing your experience. How advanced and trusted is data science in healthcare compared to other sectors?” For example, I worked in e-commerce, and I think in e-commerce, people already know that they have to have a recommender system. That’s the default, so it is automatically trusted. “We know that machine learning and data science will help e-commerce, so let's use it.” There are usually no questions asked. But in healthcare, as you said, people are not willing to try new things, it's not always clear what exactly it brings, and there are also the regulatory approvals, which might be difficult. I imagine that maybe the data science there is less advanced than in other fields. Is it the correct assumption?**

34:48

Elena

It’s true. There's also something. Like you said, you worked in e-commerce, and everything is digital there. You can have a lot of data – you can track what customers are doing. In the hospitals, it's not like this. Sometimes you have data, but you don't have the timestamp of when this happened, or you have a timestamp that might be wrong, so then you need to assume that “This happened around this time.” There are a lot of things that happen offline, which makes the data less accurate. From the beginning, that's already a difficulty. Of course, the second thing is that the impact of a prediction can be much bigger – if an e-commerce client gets a wrong recommendation, what's the worst thing that can happen?

# How data science will evolve in the healthcare field

35:45

Alexey

**Exactly. They just would not buy the things and continue living their life. Meanwhile, in healthcare, it can sometimes actually be a matter of life and death. How do you think this will evolve? Do you think it will get more trust in the future? Are there successful use cases, studies?**

36:12

Elena

There is a lot of research and investment in that. I think that already means that they are going to become better. There is also a reason why there is no trust – it's not that this field is not really evolved and the predictions are not always to be trusted. There is a lot of research. Also, that means that we have data from different populations – because that's also a problem. What also I noticed during my previous work experience is that we were collecting data from Africa, but there is not a lot of data for Africa. We cannot use an algorithm that we developed in Europe (with European patients) for African patients. I think, with time, we will have data from different populations and then the algorithms will become better in that. So I see there is a lot of potential, that's why I'm also motivated to contribute to that. But I think, even if AI or generative AI is really advanced – AI is not really advanced in all the fields in society. There are still fields that need a lot of work to be done.

37:40

Alexey

**One of the points you mentioned is that you can’t just easily take data collected in Europe and use it for Africa, which makes sense, but also not exactly intuitive when I first think about this. On one hand, people are people – everywhere – but then there are probably things like the living conditions that are different, the climate is different, etc. So why can't we just take data from Europe and use it for Africa? What are the reasons?**

38:08

Elena

One thing is that in Africa, there are more malaria patients, for example, than in Europe. What I want to say is that there are also sometimes different diseases in people based on the location where they live. That's why it's important to take those things into account. Also, in different settings – maybe in Europe, it's easier to collect data for every single metric of the patient, but in Africa, this is not possible. You have limited data collected, and you need to make a decision based on that as well.

38:47

Alexey

**I imagine that an average person who lives in Norway is probably very different from an average person living in Nigeria.**

39:05

Elena

Yeah, they have different lifestyles, different [inaudible].

39:09

Alexey

**Interesting. But still, is this European data not useful at all?**

39:18

Elena

Mmm… We need to be careful when we do these kinds of things. But it can also be useful maybe for drawing some conclusions for us – but not really for developing an algorithm to apply in low-resource settings.

# The issue of automating away human jobs

39:37

Alexey

**Okay. So you need to think “Okay, for this specific feature or dataset, are there any problems that might occur? Is there something that makes the way the data was collected in Europe different from the data that was collected in Africa? Can we actually use it?” For each specific case, you need to think about that, right? [Elena agrees] While we were talking about integrating the solutions (the algorithms) – bringing them from research to production – there is some pushback from people who don't want to try new things. I remember, even in e-commerce settings, as I was working with moderation teams in the past, there were some moderators that were thinking, “Now these data scientists come, create machine learning models, this AI will automate our jobs and will become redundant. So, let's not help them.” I'm not saying that people were explicitly saying that there, but I sensed this sentiment.**

**My job as a data scientist was also to educate them and say, “Hey, we are not going to make you redundant. We are not going to fire you. We actually want to help you be more effective.” I wonder, is there something similar that you see in healthcare? Maybe there is this lack of trust that comes from these healthcare professionals because they think, “Okay, now my job will be automated. There will be these sensors that monitor the patient's condition. So why am I needed there? I won’t be needed anymore, so I will not try to help you. Why would I help you make myself redundant?”**

41:28

Elena

I have not seen it because they still have a lot of impact in decision-making. Those algorithms are not too far ahead. For now, I think they probably don't feel that their job is at risk. Maybe in the further, further future, but for now, I have not seen anything like that. What I personally believe is that, by the time that AI will become more developed, this is an actual risk. It already happens with some jobs.

For example, in the Netherlands, there are many supermarkets that have automatic cashier machines. Before, people were working there, and now just one person observes if everything is going right. This is simple automation, but in the future, more complex decision-making processes can replace humans. Okay, I know the viewpoints on this topic are controversial sometimes. [chuckles]

42:42

Alexey

**I mean, maybe the cashiers who worked and were replaced by machines can now do something else in the same store. They don't need to do this monotonous work every day. Maybe it's actually a good thing. But we don't know what happened with the cashiers, right? [chuckles]**

43:01

Elena

Yeah. But let's see. I'm also curious how this thing is going to be developed.

# The challenge of data collection and storage in healthcare

43:10

Alexey

**I see that there is a comment about India, “In smaller cities, data is not created properly, especially in healthcare.” Even in Germany – it's such a mess, to be honest. [chuckles] Germany is a pretty advanced country, but when it comes to healthcare, it's so decentralized – all the different doctors’ offices have their own methods of collecting data. It's quite messy.**

43:46

Elena

Yes, this is true. [chuckles] But I think there is a lot of work that is being done on organizing the systems. Also, I think the healthcare system in the Netherlands… When I came to the Netherlands, it was much less organized. Now, they have patient files, and they can just send your electronic file to another hospital. When I initially came, those things were less automatic and less connected. So, yes, there are people that are working on standardizing the systems that the data is going through and saved on. That's also another thing – sometimes data is not properly saved in secured places.

44:39

Alexey

**I think, in general, the Netherlands is a pretty advanced country in many aspects, not just healthcare, and the way data is collected. In Germany, people still send faxes. I recently did an MRI examination, and all I got was a compact disc. I don't know… I don't even have places where I can put a compact disc anymore. [laughs] Well, at least it wasn't a diskette or whatever. [chuckles] It could have been a diskette, too. Right?**

45:15

Elena

Maybe I also see big differences because I see that healthcare in Greece, for example, is also different from the Netherlands. They don't have the digitalization that they have here. They also give compact discs sometimes. [chuckles]

45:32

Alexey

**Yeah, okay. [chuckles] Well, from what I heard about the Netherlands, it is doing a really amazing job when it comes to all this digitalization of things. Coming back to this trust topic, I imagine that most of these healthcare problems, like cell classification and, I don't know… The thing you were talking about – quick signal predicting, what the patient’s vitals are – since we know that machine learning is not always accurate, I imagine that in many cases, it's not a 100% accurate prediction. It can be 80%, 70%. Does it make it more difficult? Do we have to have really accurate systems to use them? Or if it's 60% accurate, that's already good enough?**

# The importance of gradual and cyclical change

46:32

Elena

I think in the case where it's not very accurate, we need to give more information to the people so that they can make decisions. As I said before, it can say, “We have 60% accuracy.” Then the person knows that this is just an estimation and it's not really what the reality is. They need to check by themselves, or they need to see that and say, “Okay, we will do this extra lab test because of that.” In the end, it's not a tool that says what happens in reality, but it's more like a notification, “Maybe this patient has this.” Or even if we want to make systems that don't say, “This patient has this critical outcome,” it can be that you say, “This patient has a high risk factor,” which is more generic. There are different things and different ways you can phrase things and you can give estimations about the situation of the patient.

What I think is that we need to build this thing gradually. Maybe at first, we just give a description of the data of the patient in a better visualization – data visualization is also a part of this – so that the healthcare professional can understand the current status. Then, if you develop a mathematical model, you can say, “This patient has a big higher risk. Just look at this place.” Maybe, with time, those algorithms, as I said, will be developed more and they will be more accurate. Plus, I think, for the algorithm to be developed and to be more accurate, we need feedback from the healthcare professionals. If there is a prediction, then they can say, “This was a good prediction. This was a bad prediction.” And give the reasons. Then the algorithm can take this feedback and improve.

48:39

Alexey

**So it all comes back to two things that we already talked about: getting feedback from healthcare professionals and investing in better data collection processes.**

48:50

Elena

More feedback on the prediction. You have the prediction and then they respond to that. But what I see, this is kind of a cyclical process. So it's not that, “I have the algorithms and they will be ready and they will be used in a linear way.” It's more about cyclically making more and more accurate predictions. I think, for me, it's important to be as transparent as possible and to give information to the people – and not make big claims about things.

49:29

Alexey

**[chuckles] Okay. It’s not like, “This patient definitely has sepsis.” Instead, it’s, “This is a high-risk patient, please check them.” Then the doctor makes an examination and says, “Okay, indeed. This was a high-risk case.” Then you get this feedback and you try to incorporate this feedback – collect this and add this to your data. Right?**

49:55

Elena

Yeah.

# Data engineering in healthcare

49:56

Alexey

**There is a question from Avinash about data engineering and data science, which made me think, “Okay, we talked about the data science part.” But there is also… For example, (I'm, again, thinking about the e-commerce setting). Say there is a data scientist who develops a machine learning algorithm (a model) and then there is typically a machine learning engineer who takes this model and takes care of all the engineering around the model. Is there something like that? How exactly do you go about deploying this thing, provided that all these bureaucratic things are solved? I imagine that it's not like you just take this pickle file and put it on the device – there is a process and there is a lot of engineering involved there as well, right?**

50:50

Elena

This is indeed, for the data engineer to just take the model that the data scientists create, and then deploy that on the machine so that it also works and aligns with the rest of the software there. Also, they take into account the restrictions of that. For example, in the low-resource setting, for example, you sometimes cannot have the model on the cloud – it's not a good idea, because there is no internet and there is not a lot of constant connectivity. Then you need to deploy the model on the device itself. So you need to take into account the specific use case where you deploy the model.

51:43

Alexey

**For this U Net that we talked about, was it on the device or in the cloud?**

51:50

Elena

U Net was more in the research phase. We wanted to validate it further. It was in that phase. [chuckles] Things don’t go very fast. We need to keep at it.

52:07

Alexey

**It was more about, “Okay, we have this data. We're applying the model. The research looks promising. Let's continue.” Rather than, “Okay, we already deployed it and it’s working everywhere.”**

52:17

Elena

And the continuation is also the validation of this. Before deploying it, we validate it with new data, check whether it works or not, and what the accuracy of it is. There are many steps to it. And regulatory approval – it's also a big one. It takes more time to deploy.

52:45

Alexey

**You mentioned that you're having a sabbatical at the moment. Are you working on some personal projects that are related to healthcare as well?**

52:57

Elena

I'm working on some personal projects and I'm also doing some traveling. I also have some plans for the next [several] months. I'm actually reflecting on what I'm going to do next. I’m taking a break to rejuvenate.

53:17

Alexey

**Is there something you can already tell us or will we need to wait till the next interview?**

53:23

Elena

You will need to wait. [chuckles]

53:25

Alexey

**Okay, okay. [chuckles] We will keep an eye on your LinkedIn profile.**

# Getting into healthcare as a data scientist

53:31

Alexey

**If somebody wants to get into healthcare (somebody as a data scientist) how would you recommend they do that? Let's say I'm a data scientist, I have this typical e-commerce experience, but I got so motivated after listening to you right now that I think I want to do something [in healthcare]. How can I get started? How can I start using my skills for that?**

54:01

Elena

First, I think it's more about getting a general idea on, “Do you want to focus on research? Do you want to apply for a company where they already have people working on regulatory approval, so that you can quickly work on deploying those models in actual devices that are being sold?” It depends. It starts with you and what you want. But from my experience, because I had a technical background and I was working on different healthcare projects, when I started the project, I learned a lot of clinical information. In the beginning, because the healthcare field is different, I had a lot of unknown conditions and unknown words (like sepsis was new for me, as it was for you). It was unknown, but then after a while, it became just another word in my vocabulary. If you have the technical knowledge, then you also get the context by spending two months in the setting.

55:10

Alexey

**What you said is – it's about you and what you want. But is it enough for me to just want to work in healthcare? Or do I also need to get some prior knowledge to be able to do that? For a typical data scientist who has experience working at an internet company, they have no idea what sepsis means (just as I don’t). Can they just start applying because the skills they have are already enough? Or should there be some preparation before that?**

55:46

Elena

I think the skills are already enough. Maybe they will get a more technical job in the beginning in a healthcare company, and then they can receive more [medical-related work] if they want. That's what I saw, for example, in Philips Healthcare – people entered the company, and they found their way.

56:09

Alexey

**Okay, so the important thing is, as you said, what you want. If you already have the skills, then you can just apply and learn along the way. [Elena agrees] In general… I imagine that there are many… It's not the easiest job to have because of all the problems or the difficulties we discussed. What I’m trying to ask is – is there a lack of people who want to work in health care? Or is there usually a lot of interest from candidates (from data scientists)?**

56:50

Elena

I think there is a lot of interest, but they also ask for a lot of people in general, in the field of data science. So that's what I have seen. It also depends on the country, but still. For example, in the Netherlands, there are plenty of options. But indeed, there are plenty of data scientists as well. What I have noticed with many people is that they shift to that domain – there is a trend.

57:26

Alexey

**Well, it's great that there is funding. There are companies who can pay money and there are data scientists who are interested in working on this so they can find each other and actually make something – work on something meaningful while not starving (while making enough money to live). That's really good.**

57:49

Elena

Especially in the healthcare domain, there are still a lot of fields that haven't included a lot of data science yet. They use statistics, they use linear regression models. Yes, there is already funding, so they need a lot of people to work on that.

58:09

Alexey

**Why I mention starving – I remember talking to somebody a few years ago and they said that sometimes these projects are not really well-funded. So there are people who want to make a change but they have to be very enthusiastic about this, compared to working in an internet company that sometimes pays less. People need to be really willing to do this work. I hope this has changed.**

58:51

Elena

I have not seen this. [chuckles] But maybe it also depends on the country. In different countries, there are different funds as well.

58:59

Alexey

**So the Netherlands is pretty advanced, as we discussed. So hopefully, it's not an issue there. Okay, this is all we have time for today. Thanks a lot, Elana, for joining us today – for sharing your experience with us. It was really interesting to listen to your stories and everything you said. And thanks, everyone else, for joining us today, and listening in, and asking questions.**

59:24

Elena

Thanks, as well, for inviting me. It was nice to talk to you.

59:29

Alexey

**Likewise, and thanks again, Antonis, for introducing Elena and me. Looking forward to seeing what happens after your sabbatical. I’ll keep an eye out. Good luck with everything.**

59:44

Elena

Thank you.

59:45

Alexey

**Okay. Bye and have a great week!**