Transcript

00:00:00 Interviewer

Yeah. So I'm recording you this session after getting permission from you, yeah.

00:00:05 Interviewer

So if you have any questions you can ask.

00:00:07 Interviewee

Yes. Umm, well, read over your question here and uh, I think we have to establish a little uh.

00:00:15 Interviewee

Not rule, but like a starting point because your first question will be about describe my job role in the company.

00:00:25 Interviewee

Now is the question, should I put on my academic hat being a postdoc or should I put on my function developer hat being a function developer at " "?

00:00:34 Interviewer

So I would say whichever do you thinks can relate with the machine learning. I think Damian can also, because academia can relate because these questions are general for, for.

00:00:47 Interviewer

Person for the "", for the for the industrial, so you can see which fits for the machine learning, but obviously your working experience can count your post doc and your previous functional development.

00:01:04 Interviewee

OK. Then we will do it as follow. I'm working on as in academia. I'm working on a research project together with industry partners that is called very efficient deep learning in the Internet of Things. As you can hear deep learning, there is the machine learning part.

00:01:20 Interviewee

So I will.

00:01:21 Interviewee

Take it from the perspective of this project.

00:01:26 Interviewer

OK.

00:01:28 Interviewer

Yeah. So since how many years you are working in this company?

00:01:32 Interviewee

Yes, in January this year, so half a year.

00:01:35 Interviewer

Oh, half a year. OK, for IoT in deep learning.

00:01:42 Interviewer

So have you.

00:01:42 Interviewee

As a function developer for normal systems that are not having machine learning directly in Volvo, they have been working for three years.

00:01:51 Interviewer

OK, so before you have 30 years.

00:01:59 Interviewer

Have you any published any thesis in machine learning?

00:02:03 Interviewee

Well, my PhD thesis was applying not like deep learning but machine learning. Basically rule based machine learning.

00:02:14 Interviewee

For navigation systems of ships of autonomous ships.

00:02:21 Interviewer

OK. So can you please share your experience in the current position?

00:02:27 Interviewee

Yeah, my experience is we are, we are mostly responsible for the requirement engineering and the architecture.

00:02:36 Interviewee

Distributed systems that have some form of AI or deep learning, not AI, but yeah, deep learning specifically as AI or deep learning component in it.

00:02:50 Interviewer

Yeah. So do you have any experience in the previous company which is developing machine learning systems? I think it is now.

00:02:57 Interviewee

Well, a little bit. Uh, in talks. I've been working a lot with driver assistance systems and they're of course, uh machine learning is used for object detection in camera images.

00:03:10 Interviewer

Yeah, so is your.

00:03:13 Interviewer

Like you are? Yeah. It's service based or product based. So we can see service.

00:03:20 Interviewee

Umm yeah, but I think I mean, the research project is in cooperation with companies and these companies, they are basic, they are definitely product based companies.

00:03:29 Interviewer

OK.

00:03:32 Interviewer

Yeah. OK, fine.

00:03:34 Interviewer

So what software development model do you practise in your company? In general, like Agile or Waterfall?

00:03:41 Interviewer

Like detection or something?

00:03:43 Interviewer

Which you have shared.

00:03:46 Interviewee

Yeah, in our research project, we are definitely more project orientated water follish.

00:03:53 Interviewer

OK.

00:03:55 Interviewee

But in the company I worked before there it was agile development with waterfall.

00:04:04 Interviewee

Components. Let's put it that way, because the company that I worked before it was in the transition from a waterfall based system or project orientated software development model to an agile development model. And of course you don't change this with one day to another, so some.

00:04:24 Interviewee

Groups or teams were still working project orientated. Some teams worked agile orientated.

00:04:31 Interviewer

Hmm. OK. Yeah, thanks. So could you please share your experience with the interesting projects in machine learning that you have worked recently?

00:04:48 Interviewee

As a requirement engineer.

00:04:51 Interviewee

It is, of course, a little bit challenging to put concrete requirements on machine learning components. Mostly. The problem is that machine learning components have the tendency of being very probabilistic in nature, so you cannot put the requirement the system shall detect an object in all cases.

00:05:12 Interviewee

Because that would probabilistically, this doesn't work. You can say, OK, in 9899% of the cases, the system shall identify an object correctly and.

00:05:25 Interviewee

Yeah, this is a challenge in requirement engineering. So we are finding solutions to fix that.

00:05:32 Interviewer

Yeah. OK. So in your working experience, how many software architecture design techniques of machine learning you've worked with?

00:05:42 Interviewee

I don't know if there are typically from. If you have typical software architecture design techniques that are extremely.

00:05:50 Interviewee

Orientated towards machine learning. So what I have been working a lot with is a multilayer architectural frameworks where you have like different categories and then and different levels of abstractions and then you have different views on each of these categories.

00:06:09 Interviewer

OK.

00:06:10 Interviewer

So this is the mostly.

00:06:12 Interviewer

You work in the multi layer techniques you mean?

00:06:14 Interviewee

Multilayer architectures and multi tier architectures we use most.

00:06:18 Interviewer

OK, OK, not others. So which common software architecture design techniques of machine learning you found being used in most company through your experience?

00:06:34 Interviewee

For the research project, it's a bit difficult because we are too early there, but in my experience in in my company before the software architecture design techniques was definitely waterfall based, so it.

00:06:49 Interviewee

Was there was basically an designated team of software of Architects system Architects that designed the.

00:06:59 Interviewee

System architecture and then this architecture was kind of given to the function developers that then were developed their functions based on this architecture, which is sometimes a little problematic because the architecture is kind of very fixed and the people who designed the architecture are not necessarily the same people who designed it functions.

00:07:19 Interviewee

And and this is.

00:07:22 Interviewee

I, in my opinion, not always the most optimal.

00:07:25 Interviewee

Way to do that.

00:07:26 Interviewee

In my opinion it should be also the function developers should be much more involved in architectural decisions.

00:07:33 Interviewer

OK, so according to your experience, what are your best software architecture design techniques for machine learning and what are the benefits of using them?

00:07:49 Interviewer

We can discuss about multi Layer client, server microservices.

00:07:54 Interviewer

If you have any.

00:07:57 Interviewee

I mean.

00:07:58 Interviewee

I guess multilayer, the the multilayer architecture that I worked with came out of historical reasons even before machine learning this was used and it might not be the most suitable way of describing machine learning architectures. I think what you said set of microservices for example would maybe be better out of the following.

00:08:19 Interviewee

Reason you have when you when you do machine learning you have to get together a lot of different competences and.

00:08:29 Interviewee

People, for example, the data scientists that provide you with the training data and they often use very different tools to the people that in the end design the AI model and the people that actually integrate this AI model then into other software environment or software background that is often traditional software. So each of these groups.

00:08:50 Interviewee

Basically, they use their own set of tools, their own ways of programming like.

00:08:56 Interviewee

Data scientists they love Python And Jupyter notebooks.

00:08:59 Interviewer

Yeah, exactly.

00:09:00 Interviewee

For example, yeah, you know, people working with AI eye models, they're they often use Python too, but less do better notebooks because they're extremely not scalable. Really. Uh. So they often have some server applications that they run.

00:09:16 Interviewee

The training on.

00:09:18 Interviewee

And some huge processing capabilities and then they traditional software guys, they they hate Python basically because it's it's a very high level language and they prefer to do it on a more low level language like Java. Maybe it's a better example, but it's very popular. But for example C++ or C.

00:09:37 Interviewer

Yeah, exactly.

00:09:38 Interviewee

To integrate it and deploy the model and you see this is.

00:09:43 Interviewee

Coming up with a unified architecture for all these different people and ways of working. Basically, I think it's extremely difficult to working with microservices.

00:09:53 Interviewee

Might be much much easier, because then each group can basically define their own services and their own environments, like the data scientists, they need a special set of tools.

00:10:04 Interviewee

And then the the AI model guys need a special set of tools and then the software integration guys, they need an own set of tools and then.

00:10:15 Interviewee

It would be easier if you have these Microsoft services defined and then you have to define of course interfaces between them.

00:10:24 Interviewee

And that is where the software or the already going towards the business is basically where where the system architect has to do the work.

00:10:36 Interviewer

Hmm yeah.

00:10:40 Interviewer

So do you have any recommendations for software architecture design techniques or?

00:10:45 Interviewer

For machine learning.

00:10:47 Interviewee

Yeah, as I said, I think try not to find a unified software architecture because this will most likely fail.

00:10:55 Interviewee

Try to use the classical engineering approach of divide and conquer. So try to break it down into smaller and smaller packages that then each of the affected.

00:11:08 Interviewee

Groups can solve by themselves and.

00:11:11 Interviewee

One clearly advice is.

00:11:13 Interviewee

In my experience, do not make too many architectural decisions beforehand.

00:11:18 Interviewee

But try to involve the function developers, data scientists and so on in your architectural decisions and the architectural design process. So basically move the system architectural design closer to the function development.

00:11:36 Interviewee

I mean, those are the guys who actually will use your architecture in the end.

00:11:48 Interviewer

OK. Yeah. So what would be the best practise that would be helpful or useful in applying software architecture designing?

00:11:55 Interviewer

Of machine learning system.

00:11:57 Interviewee

Yeah, and here my Internet cut out. You have to repeat the question.

00:12:01 Interviewer

OK, So what would be the best practise like that can be helpful or useful in applying software architecture designing of machine.

00:12:12 Interviewer

So yeah.

00:12:13 Interviewee

As I said, the one practise that I really recommend is to make software or move the architectural design decisions towards the function developers.

00:12:27 Interviewee

And do not fix a software architecture before you start developing on or something on that architecture.

00:12:37 Interviewer

Thank you.

00:12:40 Interviewee

I mean, you can have a high level architecture that is absolutely required.

00:12:44 Interviewee

But like defining each and every individual detail of the architecture without the involvement of the function developers is, in my opinion a really bad idea, because then the function developers might struggle and complain and they might not be as happy. Or maybe they have really great ideas how you can simplify your architecture or have.

00:12:55 Interviewer

They have more speed.

00:13:04 Interviewee

Better interfaces, for example between function modules.

00:13:08 Interviewer

Yeah, I recently had the same kind of discussion in one of the guy. He had like 15 years of experience and he was really struggling with this one. He said that the, the, these kind of active decisions must be also.

00:13:24 Interviewer

Which percentage has been decided by the function?

00:13:28 Interviewer

He also argues something, yeah.

00:13:31 Interviewee

But you're also on the other hand, you also have to be a little bit careful because you have to have some control instances that cheques that your architecture is actually moving in the direction that you want to have it.

00:13:41 Interviewee

If you give it completely free free flow, you might end up with a nicer texture that might be extremely hard to maintain or might not be scalable in the future.

00:13:51 Interviewee

So you have to keep these.

00:13:53 Interviewee

I don't don't call them soft aspects, but like.

00:13:56 Interviewee

Let's call them quality aspects of the architecture, similar to the software, you have to keep them in mind and you have to follow them up. That they are still fulfilled. This is of course challenging, but you have to fix that somehow.

00:14:10 Interviewer

Yeah, exactly.

00:14:11 Interviewer

So what are the most common software architecture design challenges in machine learning system?

00:14:19 Interviewee

Most common software architectural design challenges.

00:14:24 Interviewee

I'm thinking.

00:14:29 Interviewer

Like quality perspective or model perspective, it can break.

00:14:39 Interviewee

Kind of a lot of certain things that I can come up with as I say, quality aspect. For example, it's hard because you cannot really.

00:14:44 Interviewee

Define well.

00:14:46 Interviewee

You can define quality aspects, but how do you test it? Like for example, if you define the quality aspect, the system shall be safe.

00:14:52 Interviewee

And you have a probabilistic system. What does this mean? Should it be safe in 99% of the cases, or should it always be safe?

00:15:02 Interviewee

But then machine learning might not be the best way to do that, because then you need some rule based system to have like some mathematically provable safety of the system.

00:15:12 Interviewer

Yeah, exactly.

00:15:12 Interviewee

So you have to be careful when you define the quality attributes of your system to keep in mind that you are dealing with a probabilistic system which many people find very challenging because they're not used to that in requirement engineering that you have to.

00:15:28 Interviewee

Rather, state hypothesis on a system that you would like to prove that they are true than stating clear rules on a system that you probably cannot.

00:15:38 Interviewee

Mathematically prove that they will be fulfilled.

00:15:41 Interviewer

Yeah. Yeah. So yeah, exactly. So I think.

00:15:46 Interviewer

The quality perspective and obviously safety.

00:15:48 Interviewee

Another another challenge that is significant and that we are working on in our research project is the data quality asset.

00:15:56 Interviewer

OK. Yeah, yeah.

00:15:59 Interviewee

UM.

00:16:00 Interviewee

The problem with machine learning is that.

00:16:03 Interviewee

In contrast, or unlike rule based systems, a AI model, they behave more like a black box. So you define an AI model, but the AI model doesn't show the behaviour that you want it. It can only do that if you provide it with the correct training.

00:16:20 Interviewee

Data and this training data must be representative for the behaviour that you want the AI model to show in the.

00:16:27 Interviewee

End so it will be 2 aspects that shows that make sure that you get the behaviour that you want.

00:16:32 Interviewee

It's on one hand the data that you give for the training and on the other hand, of course, the AI model itself. So the AI model needs to have certain capacities.

00:16:41 Interviewee

Neural capacities to be able to mimic the behaviour that you wanted to mimic if.

00:16:45 Interviewee

It's a too simple AI model. Then you might not be able to get the behaviour out of it that you want, but if it's also too complex then you might overfit the data and you still don't get the behaviour that you want.

00:16:57 Interviewee

So you have to find this sweet spot where you have the exact correct complexity of your AI model and you need to have the exact right amount of data.

00:17:07 Interviewee

And having the exact right amount of right data is really really.

00:17:12 Interviewee

If you could a common smell or mistake that I see in many companies or many development environments is that you kind of bombard your AI model with all the data that you can possibly get that would be useful. So you download these immensely huge datasets for example.

00:17:32 Interviewee

Or core Imagenet or whatever, and you train your AI model with that, and then in the end you hope that the AI model will fulfil the behaviour that you want it to do.

00:17:40 Interviewee

Uh, and this is a really bad approach in my opinion. Out of a lot of reasons. Not only is it extremely expensive to collect that much data, because you might have to label it, and then you have to pursue the data and then you have all these data privacy issues that come along with it.

00:17:56 Interviewee

But also the training process is extremely costly and takes a lot of time. It would be better if you can clearly identify.

00:18:03 Interviewee

OK, I want to have this behaviour and for this behaviour I need this kind of data and exactly this amount of data.

00:18:11 Interviewee

And then you identify.

00:18:14 Interviewee

Uhm, when you have an AI model you an AI model normally tries to mimic a probability distribution function, and for it to be able to do so, it basically needs only the tails it needs to see the tails of this probability distribution and that translated into data quality means or data attributes means it needs to see the extreme.

00:18:34 Interviewee

Behaviours of the data and then the model will be much more capable of adopting this probability distribution, so the trick is to identify the data that actually shows these extreme cases very well.

00:18:49 Interviewee

And then the eye model will be much faster, able to learn what the desired behaviour is.

00:18:56 Interviewer

Yeah, very clear. Yeah. Thanks for explaining.

00:19:00 Interviewer

Yeah. So what are the main architecture decisions and software architecture design of different machine learning systems?

00:19:09 Interviewee

The main decisions.

00:19:12 Interviewee

Regarding the software architecture.

00:19:14 Interviewer

Yeah, of differential immune systems.

00:19:19 Interviewee

Yeah, that's a difficult question. But I think that's a good question though.

00:19:25 Interviewee

I think you have to be first of all aware of what you what kind of system do you want.

00:19:30 Interviewee

Do you want to have a more? Do you want to have a static system? Meaning you train your AI model once in the beginning.

00:19:37 Interviewee

And then you deploy it into the field, but then after that you're basically not. It doesn't adapt to anything, it just.

00:19:46 Interviewee

Repeats the behaviour that it trained that it was trained for during the training process. Of course, over time you can update the AI model with a newer version that has been retrained, for example to compensate for what is called contextual drift that could occur over time. But basically the systems remain.

00:20:05 Interviewee

They take between the updates or do you want to have an adaptive system? Meaning that the system is allowed to learn while it's in operation?

00:20:16 Interviewee

So it basically collects automatically interesting data and then adopts its own behaviour or retrains itself. You'll find this often in natural language processing or voice recognition systems, like for example I think.

00:20:35 Interviewee

And Siri and Cortana from Microsoft.

00:20:40 Interviewee

You learn how to identify your voice. If you have like like me, I have a very strong German accent in my English.

00:20:48 Interviewee

So Siri, after a while will be able to identify my language much better, because it just adapts to.

00:20:54 Interviewee

It and that I see is a dynamic machine learning system, so it's not static, it adapts.

00:21:00 Interviewee

It's behaviour overtime and that requires much different and much different architectural approach. I think because one thing you have to make certain is that the adaptation still leads to the desired behaviour that you want from the system.

00:21:15 Interviewee

So that your AI model is not learning something into a direction that would compromise the desired behaviour.

00:21:23 Interviewee

And for that you will probably not get around having some form of monitoring system that cheques if the behaviour of the system is still what you kind of envisioned it when you deployed the system into the market.

00:21:36 Interviewee

In contrast to these, what I first mentioned static systems where you do not have the ability of training or adopting the behaviour where you only have this statics or these regular software updates that might come, but in between it's static, it doesn't change anything in its behaviour. There you could use some extensive.

00:21:56 Interviewee

Testing before deployment to make sure that it has still or that it fulfils all the desired behaviours in the field.

00:22:05 Interviewee

That you cannot have really with an adaptive system if you allow the AI to change its behaviour overtime.

00:22:15 Interviewer

Yeah. Yeah, I think so. This is.

00:22:20 Interviewer

Like this? Yeah. This question is really like I haven't found such papers on this question addressing to this question actually. So this is really a one of the major questions among other tools. So.

00:22:35 Interviewee

Yeah, I'm. I'm actually working on on exactly that question of when you need these kind of monitoring systems for the AI.

00:22:43 Interviewer

Yeah, exactly. So I think so.

00:22:46 Interviewer

It is.

00:22:48 Interviewer

So yeah, these are all the questions that I have for my research paper or thesis.

00:22:55 Interviewee

Yeah, I think you have a really exciting topic and it's a it's a really hot topic. So I think you will find a lot of readers of your thesis.

00:23:04 Interviewee

And I hope you will decide with your supervisor to also publish the thesis in form of a paper, because you have a really good topic.

00:23:14 Interviewer

Yeah, that Kartik plan, actually, let's see how it goes. I think I have to submit my thesis after one month.

00:23:22 Interviewer

See that how we go for the publications, maybe do more tests, adding more SLR or maybe more interviews?

00:23:31 Interviewee

Yet the nice thing is we have this project very efficient, deep learning in the Internet of Things. It's.

00:23:37 Interviewee

A new project.

00:23:38 Interviewee

Hang on, I can send.

00:23:39 Interviewee

You a link here but.

00:23:39 Interviewer

Yeah, sure. Please do it.

00:23:40 Interviewee

We have just since a couple of weeks and Nice website.

00:23:47 Interviewee

Where we have collaboration partners from the industry. So if you have a good topic for regarding software architecture for AI systems or machine learning systems here and requirement engineering challenges for example as well, then we could.

00:24:05 Interviewee

Run interviews also with participants from from our research project.

00:24:11 Interviewer

OK, so sorry, what did you set?

00:24:16 Interviewee

I said like if you if you if you have for if you need for publication further interviews and it's related to the software architectural design changes for AI systems then then we could maybe have interviews from within our video project.

00:24:37 Interviewee

Because we have.

00:24:38 Interviewee

Industry partners and we are exactly working on these kind of challenges. So it's very interesting for us.

00:24:44 Interviewer

OK. Yeah. Thank you. So if I, yeah. So.

00:24:48 Interviewee

I would like to if if possible, I would like to have a copy of your thesis because I'm really curious.

00:24:53 Interviewer

Yeah, sure, sure. I will. I will send it to you. Yeah, as soon as I have the final copy, I will. I have your e-mail address. I will.

00:25:00 Interviewer

Send it to you.

00:25:01 Interviewee

OK, great.

00:25:04 Interviewer

Yeah. Thank you so much for your time. If you have any questions you can ask.

00:25:07 Interviewee

No problem.

00:25:09 Interviewee

OK, then now I don't have any question right now, but as I said, I would be happy to get a copy of your thesis if possible.

00:25:12 Interviewer

OK.

00:25:16 Interviewer

Yeah, sure, sure, sure. I wish you a nice day and nice. And you. Bye.

00:25:20 Interviewee

Too. Enjoy your summer.