openSAP
Enterprise Machine Learning in a Nutshell

Week 1 Unit 1

00:00:11	Welcome to the openSAP course on Enterprise Machine Learning. My name is Markus Noga.
00:00:17	My Machine Learning team is part of SAP's Innovation Center Network. And we're on a mission to make all enterprise applications intelligent.
00:00:25	This first installment of the course will help you understand recent advances in machine learning. It will give you an overview of what this means for enterprise computing and for knowledge work in general.
00:00:36	And it will help you understand the module structure so you can navigate through the rest of the course more effectively. Machine learning is about computers learning from data rather than being explicitly programmed.
00:00:50	And this makes software progressively more intelligent. Examples of this surround us in our daily lives.
00:00:56	Whether it's the intelligent assistants on our smartphones, whether it's the smart thermostats in our homes,
00:01:02	or whether it's the self-driving cars all over the press, we're seeing evidence of computers becoming more intelligent.
00:01:08	And this is possible now because of advances in machine learning. Computers are dealing with unstructured information,
00:01:15	natural-language text, images, and videos rather than the neat rows and tables of structured information that were the computers' domain before.
00:01:24	And computers are learning complex functions on this unstructured data from examples rather than with explicit programming.
00:01:33	One example of this is computer vision. When I started studying computer science in the late nineties,
00:01:39	any two-year-old was better at looking at an image and saying what it's about. Today, we can toss an image into a search box or a dialog
00:01:48	and we will readily see labels and descriptions, like people or dog, coming up. And for the first time since late 2015, computers are actually better than humans at this
00:02:01	as measured on popular benchmarks. So progressively, unstructured information is becoming available for us to do interesting things with also in an enterprise context.
00:02:13	This is because we're not trying to hand-code or hard-code decision rules about what to do: If the left upper pixel of the image is red, do this. Otherwise, do that.
00:02:26	It's unfeasible to get to a good image-processing algorithm with hand-coded rules like that. Instead, what we do is throw lots of examples at the machine and have them learn fuzzy decision functions
00:02:38	from that data with an appropriate training regimen. This has huge potential.
00:02:46	Machine learning for the enterprise is projected to grow at over 50% year over year towards a $4 billion market by 2020.
00:02:56	This has the potential to transform knowledge work as we know it. Already today in blue collar work, humans and machines are working together on production
00:03:05	and assembly lines and together doing better than each could be doing individually. We will see the same in knowledge work with repetitive, high-volume,

00:03:15	high-frequency tasks increasingly becoming automated and humans focusing on value-added tasks. And together, humans and machines doing even better than before.
00:03:25	This also enables us to do what has been hitherto impossible. Think of scenarios like taking out your mobile phone, taking a picture of a part,
00:03:34	and being able to reorder immediately via the Ariba network at the click of a button. These kinds of scenarios would not be possible without machine learning.
00:03:46	Why are we at an inflection point for machine learning today? It's because of three main factors:
00:03:51	Number one, we have the data. Big Data.
00:03:54	Volumes that were unattainable even a couple of years ago allow us to train much larger networks with many more variables.
00:04:03	Big Compute. Substantial improvements in the amount of computational horsepower available to us,
00:04:09	especially on graphics cards or so-called GPUs, enable us to actually crunch and process the massive amounts of sample data and training sets.
00:04:19	Number three – improvements in machine learning algorithms, especially in deep learning and reinforcement learning. You will learn about these in the following installments of the course.
00:04:29	Taken together, this creates an inflection point also for enterprise computing as machine learning enables us to leverage the wealth of information
00:04:39	that the digital transformation provides to us and to bring together the data assets of different enterprises in clouds and on business networks
00:04:49	creating even larger pools of information to learn from. This course on Enterprise Machine Learning is organized in seven modules.
00:05:01	The next session will help you understand basic concepts behind machine learning so that deep learning and reinforcement learning are terms that have meaning to you.
00:05:10	The third section will help you understand how to take an arbitrary business challenge and to turn that into a tractable machine learning problem that machine learning engineers can actually work on
00:05:23	The fourth installment will help you understand how machine learning fits into corporate computing landscapes and how to interface with existing applications.
00:05:33	And Units 5 and 6 of this course provide end-to- end examples of taking a use case and turning that into a concrete machine learning solution.
00:05:43	Section 7 wraps up with key takeaways and next steps, as well as future learning resources.

Week 1 Unit 2

00:00:09	Hello, and welcome to the second unit of the openSAP course "Enterprise Machine Learning in a Nutshell". My name is Daniel Dahlmeier and I am part of the machine learning team in the SAP Innovation Center Network.
00:00:22	In the first unit, we already heard about the great breakthroughs in machine learning. And in the second unit, we want to go deeper and explain to you what machine learning is.
00:00:33	So we will give a definition of what machine learning is, and we will explain some of the common tasks and the approaches in machine learning and its capabilities.
00:00:42	We will also explain how it is different to the more traditional rule-based approaches that you might be familiar with. So Tom Mitchell, who is one of the real pioneers in machine learning, gives the following definition of what machine learning is:
00:00:58	"A computer program is said to learn from experience E with respect to some class of tasks T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E."
00:01:14	Well, that's quite a mouthful. But what we can see from this definition is that the computer needs some experience to learn from,
00:01:23	and that is typically the data that we can provide to the computer program. And that learning is always with respect to some particular set of tasks,
00:01:32	and the performance measure that the computer can use to see whether it's getting better these tasks. That is different from the more general concept of learning that we use in everyday language
00:01:43	and when we think of kids learning when they grow up. So the computers really try to optimize a particular task.
00:01:51	So we have already expressed several times that computers can learn from data without being explicitly programmed through machine learning.
00:01:59	And as we have seen through the definition just now, learning here really means that the computer is trying to get better at a particular task from the data that we give to the computer to learn from.
00:02:12	So we can say that learning here really means approximating usually complex decision functions that the computer tries to approximate better and better to perform the task that it is given.
00:02:26	Let's look at a typical example. In sentiment analysis, we often want to classify consumer reviews into whether they are good, bad, or neutral.
00:02:37	So the task here is: Given a consumer review, classify it into one of the three possible labels – positive, negative, or neutral. So learning here really means that the computer is trying to approximate this function that maps reviews to the respective labels.
00:02:54	This experience that we provide to the computer to learn from is a large training set of reviews and their correct labels. The machine learning algorithm will try to approximate this mapping from reviews to labels and will give us a model.
00:03:08	This model is basically a function that we can use to classify a new review and then predict the most likely label for this review. So there's a lot of terminology around machine learning that often confuses people.
00:03:25	So how is machine learning different from AI? How is it different from analytics? How is it different from data mining? So let's try to put some of these terms into perspective.
00:03:36	Machine learning is generally seen as a subfield of artificial intelligence. But artificial intelligence includes other areas other than machine learning,
00:03:46	although machine learning is currently probably the most promising direction to achieve some of the goals of artificial intelligence. Machine learning has a lot of different subfields, for example artificial neural networks or deep learning.

00:04:02	And of course machine learning heavily uses mathematics and particular statistics. And finally, machine learning has a lot of overlap with other fields like analytics or data mining, and knowledge discovery in databases.
00:04:20	So what are some of the capabilities that we can expect from machine learning? We have seen from the definition that machine learning is fairly general and can indeed be applied to a lot of different tasks.
00:04:33	So in computer vision, for example, people use machine learning to solve problems like face recognition or object detection. In natural language processing, people use machine learning for a lot of different things,
00:04:46	including machine translation or sentiment analysis. And if you use an e-commerce recommender system, that is also used in machine learning
00:04:54	to give you the best products that you might want to buy. Recently there have been a lot of breakthroughs in the capabilities of machine learning in a particular subfield called deep learning
00:05:05	that uses very deep neural network architectures. Some of these new capabilities that were displayed was that computers were able to automatically capture images
00:05:16	with fairly accurate descriptions of what the image shows. And a computer program called AlphaGo was even able to beat the best Go player in the world
00:05:26	in the strategic board game Go, which is extremely complicated. So let's look at some of the typical tasks that we try to solve when we apply machine learning.
00:05:39	One of the most common ones is what we call classification. It's a type of supervised machine learning, which means that we give the input data and the correct answer
00:05:50	to the learning algorithm during training time. So in a training data set, we would expect some form of inputs, which we often call instances.
00:06:00	And they come with a correct answer that the computer should ultimately learn to predict. The instances are represented by features which are numerical vectors that encode some of the attributes of the data.
00:06:13	We will explain in later units in more detail how features can be derived. And what the computer now really tries to do during learning, or during the training part of the learning,
00:06:26	is that it tries to find a decision boundary that separates the one class from the other class. In our example here, it would try to learn a function that separates the pluses from the minus signs.
00:06:40	And so learning in a way means trying to approximate this function that best separates the positive and negative instances. Once we have finished the training, we can then evaluate this machine learning model, this function,
00:06:55	on a held-out test or validation set. This means we take this function, we apply it to a new set of data,
00:07:02	and we compare it with the correct results to see how well the function performed. And if it didn't go too well, we'll go back to the start and we'll try a different algorithm or we'll try a different type of feature representation.
00:07:15	If we do not try to predict a category like plus or minus, but we rather try to predict a number, then we call this a regression problem.
00:07:25	So again we would start with some form of data, some instances that are the input to the machine learning algorithm. We would represent them as features.
00:07:33	And then training would try to predict the correct output, but now the output might just be a number instead of a discrete category. There are other tasks of machine learning, like unsupervised learning or reinforcement learning,
00:07:46	but we will not go into details about these in this course. So that was the definition of what machine learning is and some of the tasks that you usually see in machine learning.

00:07:59	But what really is the difference from the things that we have been using before which are often based on rules? So in a rule-based approach, the intelligence typically comes from the human who knows how to solve the problem
00:08:11	and he tries to write to this knowledge down into the computer program and specifying the rule that the computer should apply to the data.
00:08:23	And if you've ever programmed a computer, you know that you have to be very exact in the conditions that specify when the computer should execute what statement.
00:08:33	In the machine learning approach, the rules are often very complex, or we don't know how the rules really work. But we are able to provide examples, for example the positive and negative reviews.
00:08:44	And this is what we call the training data. From the training data, the machine learning algorithm then learns the rules which are part of this machine learning model that we can use
00:08:54	to predict the outcome on new data sets. Both approaches have advantages and disadvantages, so neither is strictly better here.
00:09:04	If you know the rules and they are simple enough to write down, that's probably the best way you can do it. But in a lot of cases, with fuzzy or complex decision boundaries, like the sentiment analysis as an example,
00:09:17	we really cannot write an exhaustive set of rules and therefore machine learning is often the preferred approach. This was the definition of what machine learning
00:09:31	And in the next unit, we will look at how we can apply machine learning to enterprise problems. See you there shortly.

Week 1 Unit 3

00:00:07	Hello, and welcome to Unit 3. We heard in the last unit about the definition of machine learning and typical tasks.
00:00:16	But how do we solve business problems using machine learning? This is what we want to do in this unit.
00:00:22	In particular, we want to look at a recipe, a step- by-step instruction guide on how we get from a business problem to a machine learning problem.
00:00:31	In particular, we will look at the following questions. Do you really need machine learning?
00:00:37	Can you formulate your problem clearly? Do you have sufficient examples?
00:00:42	Do you have a regular pattern in the data? And can you find meaningful representations of your data?
00:00:49	And finally, how do you define success? We will look at each of these questions in turn.
00:00:59	First, do you think you really need machine learning? We often talk to people who have heard about machine learning recently.
00:01:06	They've got excited about the new capabilities of machines, and they definitely want to use it. But not every problem in business requires machine learning.
00:01:17	In particular, you should look at the following questions. Do you want to automate the task?
00:01:23	There are a lot of things in a business context that we probably do not want to automate. Interpersonal relations, managing the employees, or meeting new clients for dinner – these are things that are best left to humans.
00:01:37	So we see great potential for high-volume tasks in a business context that you probably want to automate. And these high-volume tasks should probably include something like very complex rules or very unstructured data.
00:01:53	That might be a good candidate for machine learning. We will use the sentiment analysis task that we saw in the last unit as a running example.
00:02:03	In sentiment analysis, we are looking at consumer reviews. There are a lot of consumer reviews on the Web, so you probably don't want to read them all by yourself.
00:02:11	So we have high volume. And the consumer reviews are free text, the consumers can write anything they want.
00:02:17	There can be typos, there can be jargon, there can be things like irony. It would be very hard for us to write a comprehensive set of rules for that,
00:02:28	so we have unstructured data and we have complex and ambiguous decision rules. In particular, we find it very useful to put problems on a 2x2 matrix and so on that you can see on the slide here,
00:02:40	where we look at problems of large scale and complex decision rules. Then you probably want to use machine learning.
00:02:48	If the problem is large-scale but the rules are simple, a rule-based approach might be the way to go. And if the problem is complex but you only have a few examples,
00:02:59	maybe it's more economical to just do it manually. Second question, problem formulation: Can you formulate your problem clearly?
00:03:10	We often find people who are excited about machine learning. They want to use machine learning somehow to learn from all the data that they have.
00:03:17	But as we have seen, machine learning works on particular tasks. So a very useful pattern that you can try to apply to your problem is the following:
00:03:27	What do you want to predict given what inputs? So given X, predict Y. This is the pattern that you should ask yourself in particular for the supervised machine learning problems.
00:03:39	What is the input, and what is the output? In the sentiment analysis example, the input is the customer review and the output is the predicted sentiment label.
00:03:50	So given a customer review, predict its sentiment. The input is the customer review as represented by the text, and the output is a label – positive, neutral, or negative.

00:04:03	A clear problem formulation, and now we can start to apply machine learning. But before we can really start to implement machine learning, we need the data.
00:04:13	In a lot of cases we have seen, collecting the data is very difficult. But you need a sufficient number of examples to have the machine learn meaningful
00:04:24	approximations of the decision functions that you have. So keep in mind: Machine learning always requires data, and generally, more data is better.
00:04:34	It's hard to say at what level you have enough data – that is something you have to find out through experiments. But for any type of data, at least for supervised learning, you have to have two parts of the data you collect.
00:04:49	You must have the input, which is typically encoded at the features we have seen previously. And we need the output, what we typically call the "label".
00:04:58	In sentiment analysis, the data that we would probably collect is thousands or tens of thousands of consumer reviews and the ratings from the Web.
00:05:10	So the text of the consumer review, that is the input, that is the features that we will use, and the rating, for example a one to five stars rating,
00:05:20	that is the label that we can use to teach the computer that this review is positive or this review is negative. And that's what the computer can learn from.
00:05:31	Question number 4: Does your problem have a regular pattern? We have seen computers try to approximate some task, but in the end, they often just look at statistics.
00:05:42	So it's often very helpful to understand whether there is some kind of regular pattern in your data that the computer at least in principle could learn from.
00:05:53	So in particular, machine learning tries to find patterns and correlations in the data. And if these patterns are very rare or very irregular, the chances of machine learning succeeding are not too high.
00:06:09	In the sentiment analysis examples, we intuitively know that there are some patterns in language that correlate with positive or negative reviews.
00:06:19	So some words that have positive sentiment like "good", "awesome", or "I love it" will appear more often in highly rated reviews, while negative words like "bad", "lousy", or "disappointed" will appear more in negative reviews.
00:06:32	That's something we intuitively know, and we believe that the computers can learn these patterns and discover these patterns from the data as well.
00:06:40	If your patterns are very rare – let's say, earthquake events that only happen once in a thousand years – you might just not have enough examples to learn from that.
00:06:52	So ask yourself whether you have a regular pattern that maybe you understand intuitively and that the computer could learn from your data.
00:07:02	Question number 5: Can you find meaningful representations of the data? So here we come back to these features that we have been talking about all the time.
00:07:12	So in the end, when you really implement machine learning, the input to the machine learning learning algorithms is basically just numbers.
00:07:21	So every instance that you put into the machine learning algorithm is represented by a set of numbers, which we usually call a "feature vector".
00:07:30	And if your feature vectors give a very good representation of the data, that means the features in one class are very different from the features in another class,
00:07:41	then the chances of your machine learning algorithms performing well are very high. While if these features aren't useful, no machine learning algorithm will be successful.
00:07:53	So having good features is often the key secret ingredient to making machine learning succeed. So coming back to the sentiment analysis example,
00:08:05	how would we represent a consumer review in free text as a vector of numbers? One way of doing that is to just count how often every word appears
00:08:18	and we represent the whole document as a long vector of these word frequency counts. So the dimensionality of the vector would be the size of the vocabulary,

00:08:29	and we just put a count for how often the word appears in the reviews. Most of the counts will be zero, but that's not a problem, we just need to know the counts.
00:08:40	This representation would not really care about the ordering of the words in the document, but as it turns out, that is often not really necessary to differentiate good and bad reviews.
00:08:54	And then we need the label. So how would we get from, let's say, a 5-star consumer rating to a label?
00:09:03	If we're just interested in positive, negative, and neutral, we could, for example, say four and five stars are considered positive, one to two stars are considered negative, and if the review has three stars, I would call that neutral.
00:09:16	Now we would have a representation of the input and the output in a numerical form that the computer can work with. If we apply deep learning, which has been very popular recently, the computer can actually also try to learn better representations from the data,
00:09:31	and maybe it finds a better representation than a simple count. But again, that is something that you'll have to try out experimentally.
00:09:41	The final question: How do you define success? We have seen in the definition of machine learning that machine learning is always
00:09:50	evaluated with a certain performance measure on the task. So you have to be clear about the performance measure, or what we call the "evaluation criteria",
00:10:00	that you provide to the machine learning algorithm. So typically the computer will just try to optimize this evaluation measure,
00:10:08	and whether this evaluation measure is really helpful for your business problem, that is something you need to define. In the sentiment analysis example, we could probably evaluate in terms of accuracy.
00:10:20	We would just look at the percentage of correctly predicted labels. So all the correct predictions divided by the total in our test set,
00:10:30	and that gives us a number between 0 and 100 percent, where 100 would be perfect and 0 would be completely wrong. And that would probably be it for sentiment analysis.
00:10:41	But in some problems, the data might be very skewed, so just accuracy might not be a good idea. And so there you have to be clear about how you measure success.
00:10:53	For example, in a Web search accuracy might not be so useful because you just care about the first few search results, not really about all the 10,000 possible Web pages that Google might recommend to you.
00:11:08	So how do we put all these criteria together? Here's a little cheat sheet that you can use to find out whether a problem that you're trying to solve is a good candidate for machine learning.
00:11:24	So starting with your problem, ask yourself: Do I actually need to automate a task? If you do, could you do it by writing a few rules down and putting them into a computer program?
00:11:37	If you can't, ask yourself: Can I formulate my problem clearly as, for example, in the form "given X, predict Y"? If you can, consider whether you have the right data to execute this.
00:11:52	And if you do, do you think the data that you have has some patterns that the computer could pick up? And then: How could you represent this data in a meaningful feature representation?
00:12:04	And then think about how you measure success. If you say "yes" to all of these – except for the rule-writing question –
00:12:13	then machine learning might be a good approach to solve your business problem. We really hope that this unit was helpful for you to try to bridge this gap between
00:12:27	the business world, where people try to solve a particular business-focused problem, and the machine learning guys, who think in terms of machine learning algorithms but they often can't really talk to each other.
00:12:41	See you in the next unit.

Week 1 Unit 4

00:00:09	Hello, you're half way there – this is Unit 4 of the course. In the last unit, we saw how you get from a business problem to a machine learning problem.
00:00:20	And in this unit, we now want to touch on how we get machine learning deployed in an enterprise application context. So we want to give you an idea of how machine learning fits into an enterprise application landscape,
00:00:35	and we visit some of the common tasks and the architecture principles that come with machine learning. It's important to understand that when you talk to enterprises, they are not always interested in machine learning per se.
00:00:51	Rather they want to solve their business problems using machine learning. So their goal is not necessarily to use deep learning or to use machine learning.
00:01:01	Their goal is to transform the enterprise data that they have into a new business value, and that can mean a lot of things depending on the business problem they're trying to solve.
00:01:11	For example, they might try to get higher revenue by optimizing the data they have in CRM to optimize their sales process. Or they could lower costs by automating knowledge work.
00:01:23	Maybe they want to increase customer satisfaction through better service. Or they want to improve the quality time at work for their employees by making their whole operations run better.
00:01:35	So the goal for enterprises is not typically: "Hey, we want to use machine learning." The goal is typically a business problem, and therefore it is very important that machine learning
00:01:44	can play together with the existing enterprise application landscape that they already have. And that is what we want to explain at a high level in this unit.
00:01:55	So let's revisit for a moment the traditional rule- based approaches and how they differ from machine learning. In a traditional business intelligence (BI) context, you also try to get insight from the data that you have in the enterprise.
00:02:10	But typically the data is structured and it resides in a database. You then form a query, or a set of rules, that you run against this database or the business warehouse that you have.
00:02:23	And the query and the rules are defined by a human analyst or by a business user. And after you run this query over your database, you get a result that you can then read
00:02:35	or you can visualize it in a dashboard or another graphical explorer. And typically the business intelligence kind of reports are focused on the current state of the business and the historical data that you have.
00:02:50	If we compare that with a machine learning approach, we first have to recognize that in machine learning we don't start with a human-defined query,
00:02:59	we start with the historical training data, and maybe with an idea of what kind of problem we want to solve. So first we have to use the historical data we have in the enterprise to train a machine learning model.
00:03:12	So it has to go through a machine learning training process, which we will explain in more detail in a moment. And then after that, we have a model, which is basically a function that we can use to predict outcomes on your data points.
00:03:27	So we can feed new data into the model, and we get a prediction and a result. And we often find that the data might change over time or we get more and more data which we want to use to make the model better,
00:03:39	so we need to be able to regularly retrain the model with new data points. So machine learning is more focused on making predictions on new data, looking into the future,
00:03:51	rather than just analyzing the data that you have. And as we have seen, machine learning is often very useful when you deal with unstructured data,
00:04:00	or a combination of unstructured and structured data, which is another difference from the traditional BI approaches. Okay, let's look in a little bit more detail at what the training process looks like.

00:04:13	So creating a machine learning model is typically a non-trivial task. So you always start with the data – we have learned that you need some form of inputs and outputs.
00:04:24	So the inputs of the instances that you want to classify, and the labels, which are the correct answers. We then typically split this data into two parts.
00:04:34	On the one hand, we have the training data – that is the one that we will use to learn the algorithm. And then we have another set which is called the "validation set" or the "test set",
00:04:43	and that is used to measure how well the algorithm does on new data points. Training involves a couple of steps.
00:04:52	For example, data cleaning is very important in a lot of enterprise contexts. You have defined these right feature representations that we have seen.
00:05:00	Often you want to try a few different models to see which one is the best. And models often come with their own set of parameters, which you probably want to optimize.
00:05:09	All of these are non-trivial and you often need a machine learning expert already assigned this to do that, unless the model is already provided and trained for you by somebody else.
00:05:20	We will not go into all the details of this, but there are very good data science courses, including many on openSAP,
00:05:26	that will explain to a data science audience what this process looks like and what tools you can At the end of the training, you get the model,
00:05:37	and the model is basically a function that you can use to make predictions on your data points. The model is often a black box.
00:05:47	It's often hard to explain to business users what it does and why it does it. But you can evaluate it by making predictions on the test set,
00:05:57	and then you compare these predictions from the model with the true answers from the held-out test set. And then you can measure how good your model is, how well it performs
00:06:07	according to your measure of accuracy or the evaluation criteria that you use. So if we have done this successfully and we have a model that is accurate and does what we want it to do,
00:06:22	how do we now get that out into an enterprise application landscape? So the question is often: Well, now we have a machine learning model,
00:06:32	how do we deploy that in our enterprise application landscape in a way that works with our existing applications? So there are a couple of emerging machine learning architecture principles.
00:06:43	that we want to just sketch here for you to have an idea of how machine learning can be useful for your business. So one of the things we have seen is that machine learning needs to process a lot of data, Big Data.
00:06:56	And often we have different data that we want to bring together to train the model. So cloud platforms are a natural way to address both of these problems.
00:07:06	So we see machine learning is often built on cloud platforms. When we have the model, basically we have a function, and the function should be made available to other applications.
00:07:17	And we want to be able to retrain this function, update it, without disrupting the whole enterprise system. So one natural way of addressing that is the architecture principle of microservices,
00:07:31	which is increasingly becoming popular for enterprise computing in general. So in a lot of cases, we see machine learning models are deployed through microservices in an enterprise landscape.
00:07:45	And these microservices have to be used or consumed by the rest of the enterprise applications. And that is typically done through API portals,
00:07:54	and the APIs' management can take care of things like authorization, metering, or for example billing. So we have a microservice that exposes the model, and we put an API on top that allows other enterprise applications to use that model.
00:08:14	And we differentiate between two types of machine learning services that we make available. We often call them "business services" and "technical services" – so what's the difference?

00:08:26	When we say technical services, we typically mean core machine learning building blocks. Pretrained components that other developers or machine learning developers or data scientists can use in the applications.
00:08:39	For example, we might build a sentiment analysis service, and instead of training your own, you can just use it as part of your application.
00:08:48	Or maybe we build a face detection algorithm and just make that available, and you can just use it on your images without building your own model for face detection.
00:08:58	And that is what we see being made available on a lot of cloud machine learning platforms. And when we say business services, we think more about machine learning services that directly target a business scenario
00:09:11	and directly integrate into business applications to solve a particular business problem. For example, matching invoices and payments in a financial scenario, or matching job applications and résumés in an HR scenario.
00:09:25	So these are things that directly support a business use case rather than just technical components for developers for when they build their own applications.
00:09:35	So on the right you see a small picture of how we see enterprise computing using machine learning. At the top you see the enterprise applications, whether it's financials, HR, customer service, or marketing.
00:09:52	And these applications can then consume the underlying business services and technical services on a machine learning cloud platform through APIs.
00:10:03	Plus you have a component for training new models if you have a particular model you want to build yourself and you have your own data science team or your own developers who want to build new or extended cloud applications.
00:10:19	So we hope this was useful for you to understand how machine learning fits into your enterprise application landscape, and how it can be orchestrated with the other enterprise applications you already have or the ones that you want to build.
00:10:33	In the next two units, we will look at end-to-end examples of machine learning enterprise applications. See you there shortly.

Week 1 Unit 5

00:00:09	Hello, and welcome to Unit 5. In the past sessions, we have seen what machine learning is,
00:00:16	we have learned how to get from a business problem to a machine learning problem, and we have seen how machine learning can be deployed in an enterprise application landscape.
00:00:25	In this unit, we now want to look at two end-to- end examples of how this can be done, and we will take natural language processing as an example.
00:00:35	So we will look at two enterprise application problems that involve natural language text, and we will explain step by step how to get from the business problem to a machine learning problem.
00:00:49	So we will have one example from the support background, and one from an HR/recruiting background. So let's look at the first example: support ticket classification.
00:01:01	So the task here is to classify support tickets that we receive from our customers and put them into categories so that we are then able to route them to the respective agents, who can solve the problem for our customer.
00:01:15	Let's look at some of the criteria we have previously established for getting from a business problem to a machine learning problem.
00:01:23	First question: Do we need machine learning? Well, typically support tickets are high-volume, especially for large customers,
00:01:32	and we'll definitely have a lot of them coming through various channels, like e-mails or social media. And the language in the text of the ticket is complex and it might be ambiguous,
00:01:45	so simple rules might not always work for figuring out what a ticket is about and in which category it should belong. The second question: Can we formulate the problem clearly?
00:01:58	Well, a customer support ticket is the input that we receive and we want to put it into one of the categories, so we can formulate the problem as: Given a customer support ticket, predict its correct service category.
00:02:15	The third question is: Do we have sufficient examples? Well, we already said there's a high volume of tickets coming in,
00:02:21	which can be hundreds or even thousands of tickets per day for large customers, and we definitely have a lot of input data, so where would we get the labels from?
00:02:33	Well, one way of doing that is to look into the customer support ticket system that a company is using and dig out historical tickets that have already been classified and categorized by the support agents manually.
00:02:47	And so here we would have a large number of labels that we can use for the training. Question 4: Do we have a regular pattern in the data?
00:03:01	Well, the issue is that tickets are categorized to typically represent common questions or problems customers have. So the customers will express their issues or concerns using repetitive keywords.
00:03:23	So in a scenario where a customer is having problems with a payment, they will probably use words like "bill", "payment", "credit card", and so on.
00:03:33	So we have a fairly good intuition that there should be a regular pattern that the machine could learn between the words in the incoming support ticket message and the category that eventually the ticket should be routed to.
00:03:50	Can we find meaningful representations? Well, we have already seen in the sentiment analysis example that we can represent
00:03:58	the text in the tickets as a vector of word counts, and there are other possibilities. The label that we want to predict is a service category.
00:04:08	And so we would have a feature representation of the inputs, for example, word count frequencies, and we would have a label, which is a service category.
00:04:18	And finally, how would we define success? Well, there are different ways of doing that, but a reasonable start would be to measure the percentage of correctly classified tickets.

00:04:30	So count the number of correct predictions by a model, divide it by the total size of the tickets, and that would give us a fairly good way of estimating how good the model is.
00:04:42	And we could also compare that with how good humans actually are at figuring out what the support ticket should be about, because even humans might not be perfect in this task.
00:04:54	And then finally this ticket classification model could be made available in an enterprise context by deploying it through a microservice and an
00:05:04	and the support agents could use their applications, which are then again used as the underlying API to automatically categorize the ticket and give him a first suggestion of what the algorithm thinks the ticket is about.
00:05:19	If it's accurate enough, we could even think about the machine learning algorithm directly routing the ticket based on the predicted category to the next service agent.
00:05:33	Let's look at another example, this time from an HR/recruiting background. Recruiters often get hundreds or even thousands of applications for a single job.
00:05:45	So especially for a junior position, they put up one job profile, one open job that a company wants to hire for, and they get hundreds or literally thousands of applications pouring in.
00:05:56	So that sounds like a high-volume job that we want to automate, or rather give the recruiter better tools to find the good candidates. Because the manual effort of reading through every application, every CV or résumé that a recruiter gets is very laborious and tedious,
00:06:15	and is something that recruiters would like to automate. So can we formulate the problem clearly?
00:06:24	Well, given a candidate's CV and a job description, we could try to predict a score between, let's say, 0 and 1 that measures the candidate's suitability for that particular job.
00:06:39	So a candidate with a score of 1 would be the perfect candidate, and a candidate with a score of 0 would be a complete non-match. So as input we would have the pairing of a candidate's CV and the job description that the company has posted,
00:06:55	and the output might just be a binary label that says "yes, it's a good match" or "it's not a match". That would be a reasonable first definition of putting CV matching in recruiting into a machine learning application.
00:07:16	Third question: Do you have the data? Well, I just said companies receive hundreds or thousands of applications for a single job,
00:07:25	so if they store all these and also remember which candidate they actually hired in the past, or at least invited for an interview, you would have both the job description with the CVs of historical, previous candidates,
00:07:42	and you would have a label which is the recruiter's decision of whether to invite the candidate or not. So we would have a binary label, and we would have the CV and the job description as data to learn from.
00:08:01	Does your problem have a regular pattern? Well, probably.
00:08:05	When recruiters read through a CV, they look for particular keywords, and in particular they look for keywords in the CV that also match the job description that they have posted.
00:08:15	So a first good pattern that a computer could look for is whether the keywords in the job description overlap with the keywords that the candidate has in his CV.
00:08:32	And there are other features or patterns that a computer could learn from. For example, good CVs typically don't have typos, they are not too long or too short,
00:08:42	and all that could be represented through features that the computer can learn from. So we could represent a pairing of a CV and a job description as a feature vector
00:08:54	that would measure some form of matching or similarity between these two unstructured documents, and the label would just be whether the candidate was invited for an interview based on the human recruiter's choice.
00:09:12	Now we would be ready to apply machine learning to that. Final question: How would we define success?

00:09:18	Well, again there are different ways of doing that, but a reasonable first choice would be to look at the precision. So how accurate is the model when it says we should invite someone?
00:09:28	And the recall – so how many of the candidates that the recruiter said we should invite did the computer pick out? And if that matches the recruiter's choice, then we could probably take the machine learning algorithm,
00:09:46	put it into an HR application through a microservice, and then help the recruiter to screen his hundreds or even thousands of résumés in a much faster manner.
00:10:01	So we hope this was useful for you to see an end-to-end example and to understand how natural language text can be used in a more intelligent way in enterprise computing using machine learning.
00:10:15	In the next unit, we will look at computer vision as a final example of machine learning in enterprise computing.

Week 1 Unit 6

00:00:08	Hello. Welcome to Unit 6. In the last unit, we saw two end-to-end examples of machine learning in enterprise computing that involved natural language.
00:00:19	In this unit, we want to look into a different domain, and that is computer vision. So we will explain two end-to-end examples of machine learning used in enterprise computing.
00:00:30	One is from retail and the other one is from the fashion industry. So, the first use case is retail shelf analytics.
00:00:40	Consumer product companies want to ensure that their products are placed in the correct way in all the retail outlets that their products are sold in.
00:00:51	So we can formulate it as a problem and say: "Given a picture of a retail shelf, detect all the products in the picture and then compare them to the planned layout
00:01:03	and tell me whether my products are properly placed on the shelf." Well, is that something where we need machine learning?
00:01:11	Well, if you want to do that every day for every retail shop that my products are sold in, that is a very laborious and high-volume task and automation might be something worth considering.
00:01:22	And detecting products in an image is not something we can do with simple rules. So machine learning might be a reasonable thing to explore.
00:01:33	How would we formulate this as a machine learning problem? Well, we could formulate it in the following way:
00:01:40	"Given an image of a shelf, first detect the products that are in the picture, and then compare the position of the bounding box with the planned shelf layout that we agreed with the retailer."
00:01:53	So the input would be a photo and the output would be a set of bounding boxes of the products that are seen in the picture.
00:02:03	Where would we get the data from? Do we have sufficient examples?
00:02:08	Well in this case, it is not so straightforward as taking historical data out of an existing system. We might actually have to invest upfront and pay people to take these pictures and label them with the bounding boxes of the products.
00:02:23	Crowd sourcing platforms could be one way of collecting this data. Would we have a regular pattern that the machine learning algorithm could pick up?
00:02:34	Well, products are typically packaged in a way that they have a regular shape. They will have distinct colors, they will have distinct company logos on them.
00:02:45	So there will be regularities in the pixels of the image that a computer algorithm could potentially learn from. And what would be the representations for the data?
00:02:57	Well a photo is typically represented as an array of pixel values. And so the bounding boxes, the patches of pixels that contain products that we're interested
00:03:12	would be positive examples for a machine learning classifier. And we could just take some random patches from the image to have negative examples that are not products in the image.
00:03:24	How would we define success? Again, we could look at how precise the algorithm is in detecting patches that are products
00:03:33	and how many of the true products it actually identified as such. And then we can use the bounding boxes detected by the computer vision algorithm
00:03:44	and compare them with a true layout, or rather with the human-labeled boxes that we have as a ground truth. And that would give us a meaningful way of evaluating the algorithm.
00:03:59	This machine learning service for detecting the product could then be deployed as a microservice in the cloud environment. And it could be linked up to various retail store analytic systems that we have in the enterprise.

00:04:18	The second example would be from the fashion industry. A lot of people take pictures of their apparel and their new fashion items that they've bought
00:04:27	and they post it on social media or on the Web. So fashion retailers are very interested in discovering these trends
00:04:36	and putting that back into their production, planning, or their marketing campaigns. So the example here is that for the fashion apparel industry, players would like to analyze the color trends
00:04:50	from the pictures that people take with their products and put them on social media. So what are the trending colors for the next season?
00:04:58	Is that a machine learning problem? Well, if we look at the high volume of photos that people put on social media, on the Web,
00:05:06	we can be sure enough that we do not want to do that manually ourselves. And again, detecting objects in an image is something we cannot do with simple rules.
00:05:17	Can we formulate the problem? Well, very similar to the retail shelf analytics use case, we would be given an image
00:05:25	and the task would be to detect objects, in this case fashion apparel, in the picture. And once we have detected the region of the image that contains the fashion apparel object,
00:05:42	then it's relatively easy to compute a color histogram over all these pixels in the bounding So again the input would be a photo.
00:05:49	But in this case the output would not just be a bounding box. In this case, we probably want to compute a color histogram based on the object that we have detected.
00:06:01	Where would we get the examples from? Well, we could get social media messages that contain fashion objects,
00:06:11	basically photos of our fashion products and apparel that we're interested in. And again, we might have to invest some effort or money to get people to label the bounding boxes that contain the fashion apparel.
00:06:27	And then based on these bounding boxes, we could compute the color histograms of the fashion apparel, and that could be used later for training and for evaluation.
00:06:40	Do you have a regular pattern? Well, fashion apparel has regular shapes, regular color patterns.
00:06:47	It's similar to the retail shelf analytics use case. We can assume that machine learning could pick up these color and shape patterns from the image.
00:06:58	And again, the representation here would be that the image input is an array of pixel values. And again, we could take positive examples of image patches that contain fashion apparel
00:07:10	and maybe just a few random patches that are the negative examples, that are not fashion examples. And again, we could look at matrices like precision and recall
00:07:23	to train the algorithm to be more specific in finding the patches in the image that contains fashion apparel, and also making sure that it contains as many of them as possible.
00:07:36	And once we have these bounding boxes where fashion apparel is shown in the picture, then calculating a histogram over the pixel values and the colors is relatively straightforward.
00:07:47	And then this can be used to inform our marketing what the trending colors for the upcoming season are. Well, we're almost at the end.
00:08:00	We hope this has been instructive and useful for you to see how we can get from this grand and promising idea of machine learning to real, concrete business outcomes and applications.
00:08:12	And how do we get from a business problem that I really need to solve to a qualified machine learning statement that tells me how I get machine learning to solve my business problem?
00:08:24	We're almost at the end – one more session to go to wrap it up. Goodbye.

Week 1 Unit 7

00:00:10	You're almost there! This is the last unit of the Enterprise Machine Learning course on openSAP. Let's recap quickly what we've learned in the course
00:00:20	and point you towards additional learning resources to dive deeper into specific machine learning or related topics.
00:00:28	Machine learning is about computers learning from data without being explicitly programmed. This requires large amounts of historical data
00:00:37	but it does not require us to hand-code substantial amounts of rules. Machine learning can have a substantial impact on enterprise applications and knowledge work in general.
00:00:48	The future of humans and intelligent applications working together will transform the way office work is done. To figure out whether your business problem is indeed a machine learning problem,
00:01:00	consider the following questions: Is it a high-volume problem? Is it a repetitive, recurring problem?
00:01:07	And do I have large amounts of unstructured data that are involved in the challenge? If yes, this may be a machine learning problem.
00:01:16	On the other hand, if you lack the data or if the decision rules required for dealing with the data can be written down relatively easily, it may be a challenge that's more suited to traditional programming approaches.
00:01:30	Should machine learning be the thing for your business problem, then consider a few architectural principles.
00:01:37	Machine learning does come with a separate training and inference phase, and the training phase is particularly data and compute intensive.
00:01:45	Big Data platforms are a common architectural pattern for dealing with this. The inference phase is about integration into existing transactional applications
00:01:54	and microservices and API abstractions are another common architectural pattern for dealing with that. Here's where to learn more.
00:02:04	openSAP offers a number of related courses. "Driving Business Results with Big Data" helps you understand how Big Data works in an enterprise context.
00:02:14	"Big Data with SAP HANA Vora" and "Text Analytics with the SAP HANA Platform" help double-click on specific technologies and products of SAP.
00:02:23	And the forthcoming "Data Science" course from openSAP will point you towards the universe of data science. Additional learning resources on the Web include our SAP machine learning microsite at http://sap.com/ml
00:02:39	which provides an overview of all intelligent applications and forthcoming solutions. And last but not least, learning resources on the Web also include
00:02:49	Massive Open Online Courses by Coursera, Udacity, and many others that help you dive deeper into the technical aspects of specific machine learning algorithms.
00:03:00	With that, thank you for joining and I wish you luck for your course assignments.

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