Module 1: Data Science Fundamentals

Video Transcript

Video 1.1: Module Introduction: Data Science Fundamentals (5:14)

Hi everyone. My name is Retsef Levi. It is my pleasure to be part of the teaching team together with my colleagues Vivek Farias, Rob Freund, and Rama Ramakrishnan. Let me start by telling you a bit about myself and my research. I've been a faculty member at the MIT Sloan School of Management since 2006. And my research is focused on the intersection between advanced analytics and complex systems that operate under uncertainty and with major consideration of risk. I've been working in a broad range of application domains including health systems, quality, safety, and optimization of manufacturing and supply chains of biologic drugs, the design and management of food and agriculture supply chains, cybersecurity, inventory, pricing and revenue management in retail environments and more. Before joining academia, I spent almost 12 years as an intelligence officer in the military in Israel where I was born.

Thus, my view on how to use data analytics includes an intelligence angle in addition to the academic view. Building on the introduction to the course that you heard from my colleague Vivek Farias, I would like to highlight a few things about the teaching approach, and how it aims to achieve the main goal that Vivek talked about, which is to equip you with the strategic capability of understanding how data can be used to inform modern business and organizational decisions. There are several principles about the teaching approach that I would like to highlight from the get go. We will use many examples and read datasets to motivate and provide context to the technical discussions about the various tools and techniques that we will cover. More importantly, we would like you to get out of the course more than just a collection of new technical tools. We want you to think differently, to think end-to-end about the process through which one can successfully leverage data to positively impact decision processes in business environments.

So, to do so, we will try to help you in developing new senses. New senses about what the important questions are, and what are the important holistic issues that you need to understand and explore to be successful in this non-trivial task of impacting complex organizations. To do so, we will constantly highlight the connection between the technical aspects of the data and analytics, and the business and organizational considerations. Finally, we will help you in developing a playbook, a concrete playbook that you will be able to apply on a daily basis in your workplace. This playbook will allow you to identify relevant problems that can be solved with data, that can be solved with analytics, formulate them appropriately, then develop relevant solutions, and most importantly, understand the key factors that are essential to successfully evaluate them and implement them in the field. Finally, I would like to discuss what I hope to accomplish in this module. At the high level, we will start talking about some principles about how to develop a system thinking that will enable you to think about analytics and data in the context of the design and implementation of intelligent processes, products, and systems that leverage data, analytics, machine learning, and artificial intelligence technologies.

Specifically, I would like to accomplish three things. The first of which is to provide a conceptual framework that rely on three major concepts: data, models, and processes. And I would emphasize the interaction of these concepts with expert operators. These are the business leaders, the technical leaders that make decisions. The second thing that I would like to accomplish is to map for you and provide context about some of the major concepts and types of models and tools that we will cover during the course. And the last thing that I would like to accomplish is to start discussing a concrete example that will present for you a dataset, and use that example to start understanding how do you effectively understand data, and how do you avoid some of the common pitfalls that could lead you to misunderstand it or misinterpret it. I look forward to the rest of the module.

Video 1.2: Systems Approaches to Analytics and ML (9:12)

It is not uncommon to view analytics, machine learning, artificial intelligence through a very technical lens that starts with data and goes to prediction. However, this lens is not sufficient to be able to leverage these technologies within business environments, and a more comprehensive system-level framework is needed. So, what I would try to do next is to introduce a framework that will allow you to think about these issues more systematically, and specifically, it will enable you to think about how you actually impact business environments with these technologies. The framework will always consider as a starting point a particular decision or workflow process that we would like to design or improve. This will be the anchor point and provide context and purpose to all the analysis and the design work that you will be doing. Remember, nothing that you do matters and you have not accomplished anything unless it enables making better decisions or improving a decision process. So, it's not merely or even primarily about the technical aspects, or about the statistical aspects. Those are important but they are just the enablers to allowing the organization to make better decisions. Another important aspect to keep in mind is that the revolution of machine learning analytics and the enhancements that they allow in many application domains are enabled primarily by the ever increasing ability of modern business systems to collect data, sense, and detect signals from business environments and organizations. This can be done today at the rate and diversity of modalities that never existed before. That said, the challenge that comes with these increasing sensing capabilities is that in most situations the sensors and the other methods or means that the system has to collect data, generate only raw data.

And one of the biggest challenges that we have is how to convert that raw data to usable data. Data that we can actually use to make business decisions. This involves a range of activities, for example, digitizing data that was originally on paper, integrating data from multiple sources including for multiple modalities. However, I would like to stress out one issue that is particularly important, which is what I call data interpretation. If you think about this, most of the data and signals that are collected are the output of an existing set of processes and systems. And it is critical to deeply understand these processes and systems to be able to understand and correctly interpret the raw data and make it usable. Now, having usable data allow you to do some diagnostic analysis on your system. This includes descriptive analysis, which describes your system using what we are often calling descriptive models. But it also includes other types of analysis, such as causal inference, in which you're trying to go to the next level and understand how your system actually works and what causes what in your system. In addition, many companies today conduct a lot of experiments on a regular basis in order to understand how their system works. For example, they might test an experiment to see how the customers react to different services and products and what interventions might work better or worse and so forth. During the course, you will see several examples of diagnostic analysis. You should know that even just understanding better how your system works via diagnostic analysis could immediately provide major and highly beneficial insights that decision makers can use to improve their decision making.

But beyond that, having usable data and a better understanding of how your system works can also help you to predict how your system will behave in the future, including in situations or conditions that you haven't observed yet. And that is done using what we call predictive models and algorithms. Now, the next natural question which might occur to you is how do you know that you have a good predictive model, or a good descriptive model? Answering these questions goes right back to the starting point of what we are trying to accomplish which is to improve or enable a decision process. And therefore, a good predictive model is one that can be translated to recommendations regarding actual decisions. Predictive models by themselves are not very useful if they cannot be translated to what we call prescriptive models related to interventions and levers that you can actually influence. Now trying to evaluate the value of these models, both the predictive and prescriptive models is actually non-trivial. Because often traditional statistical metrics that a lot of academics use may not capture the actual value. And in fact, what you need to do is to understand the value of these predictions in the context of what you're trying to use them for. For example, you can have a predictive model that has an accuracy of 90%. From a statistical perspective, that's almost perfect. So, that might be great under many circumstances or context. But if you want to use this model to make a decision about whether to give a life threatening treatment to a patient, it might actually be a completely irrelevant and useless model. Now on the other hand, you can have a model with 20% accuracy, which is pretty mediocre from a statistical perspective. But if this model has to support financial investments, this could potentially make you very rich. So, context and specifically the decisions that you're trying to make based on the models matter a lot.

You should be thinking about them very deeply when you evaluate the benefits from your models. The final thing that you need to understand is the amount of work that you need to invest to disseminate the models you developed into what we call decision support and visualization tools that are integrated within a decision or workflow process. This includes things like integrating these tools into the existing IT and operational control systems, making sure that humans that interact with the models and tools can actually use them effectively and so forth. Now, if you take a typical effort to design and implement analytics tools in the field, what you are likely to experience is to spend about 6-12 months on the stage of finding the data that you need and converting it into usable data. That's often something that many companies struggle with. You then are going to spend between 3-6 months developing the models and finally you can easily spend a year, or even two years, on the last step of disseminating these tools into the decision processes. So, what I'm saying here is that while we often focus on understanding the technical tools and how you actually develop models, which is very, very important, if we don't address at the beginning, namely finding the right data, and the end very well, there is a very high likelihood that we might end up with something that is not very effective. Something that cannot be used in practice because that's where most of the difficulties arises. Finding the data and then finally disseminating these decision support tools into a working decision process.

Video 1.3: Data, Models, and Processes (3:39)

As I mentioned, the framework that I introduced rely on three major concepts: data, models, and processes. What we mean by that is that data, or more broadly speaking, signals, that are collected from business environments and business organizations can be used through models to inform the design and improvement of intelligent decision processes and systems. Now, we talked about the role of data already, I want to say something about what the role of models is, and that is to serve as a language, as a data-enabled language that allow organizations to leverage data into the design of intelligent, improved decision processes and systems. So, we talked about data and the fact that a lot of the revolution of artificial intelligence, machine learning, and analytics is enabled by the ability to collect more data and signals. What I want to do next is to provide a formal definition of what the process is. And the definition is quite simple, but this concept is quite powerful in terms of being able to model and capture many, many diverse business environments.

So, what is a process? A process is a concept in which we take an input and through a set of activities and resources, convert it to an output. Now, the most natural example is to think about the manufacturing settings, right? The input is going to be raw material. The activities will be assembling, doing different manufacturing activities, using resources like machines and humans, and then the output is going to be a final product. That said, this concept can apply to a much broader set of settings. For example, let's just think about education, right? What will be the input in this setting? It's going to be students. What's going to be the output of this activity? It's going to be hopefully more educated and knowledgeable students. And what will be the activities? The activities will be lectures, assignments, discussions, and so forth. And the resources might be classrooms, slide decks, and so forth and so forth. So, I hope that this example illustrates to you that while this concept of a process is very, very simple, it's very, very generalizable to many, if not every business environment. And in fact, you can describe almost any business environment as a collection of processes that interact with each other.

Now, let me say a few words about what a decision process is and how we specialize these concepts into what we call a decision process. A decision process is a process in which the inputs are going to be data, predictions, decisions, and so forth. The output will be actions or levers. The resources could be databases, tools, human experts, and so forth. And finally, the activities can be meetings, discussions, analysis, and algorithms. So, that's kind of a specializing the definition of our process to what we call a decision process. And the reason why it's important to talk about this, that a lot of what we're going to do will be focusing on how to improve decision processes.

Video 1.4: Defining Models (11:08)

So, we talked about the three major concepts of data, models, and processes. And again, what are models? Models are a language, a data-enabled language that allow us to use data and inform decision processes and workflow processes. And what I would like to do next is to formally define what the model is because that's going to be, as I said, a major concept throughout the course. So, a model is, at a high level, a concept that captures relationships between different quantities in the real world. Specifically, it captures the relationship between the model's input that is usually observed and that input can be decisions, measurements, observations, and so forth. And the model's output or outcome that can be either observed or unobserved. Now, most of the course will focus on models in which the relationship between the input and the output will be described through mathematical laws or rules, or mathematical equations or formulas. However, there are models for which the relationship is described through more qualitative rules in words. And while, as I mentioned, we are going to focus mostly on quantitative mathematical models in this program, I would like to point out that often quantitative models emerge after you've developed some intuitive qualitative models that do not describe the relationship through precise formula necessarily. The third important elements in models beyond the input and the output, and the relationship and the rules that describe the relationship are the model's parameters that are often being estimated from data and capture essentially a parameterized family of models, one for each value of the parameters. Now, more complex models have more parameters and more complex rules that capture more complex relationship between the input and the output and vice versa. And the choice of the model's parameter is often done with the goal of finding the model that explains the data we have best. And we're going to formalize what best means throughout the course. So, let me give an example that will illustrate these concepts. In one of the future modules, you will be discussing the concept and the model of linear regression. In that case, the inputs are what we would call independent variables and the output is what we would call a dependent variable that we would like to predict. And the parameters of the model are estimated from data and are the coefficients of the independent variables in the linear equations that is assumed by the model to capture the relationship between the independent input variables and the output dependent variable. Now, in more complex predictive models that you're going to learn about, for example, a neural network, the parameters will be more complex than linear regression. And that is why these models are far more complex than linear regression, which is maybe the simplest predictive models that you can have. Now, what I would like to highlight next is very, very critical. And that is that you have to understand and acknowledge that every model is merely an approximation of the real world. It's never 100% precise. And in fact, in many cases, it could be highly imprecise. So, a major consideration when using models and data is the choice what model to select and what model to use. This is really a choice. And we're going to learn in this course how to make these choices more smartly and more effectively.

Now, this choice is typically informed by a multi-facet trade-off that includes the accuracy of the different models, their computational complexity, how much data do you need to use each one of them, and how interpretable each model is. All of these issues will be discussed during the course. So, hopefully, by the end of the course, you will have a much better sense of what are the major considerations when you select the best model to be used in every specific situation. What I would like to do next is to discuss with you a specific model just to illustrate some of the concepts that we already discussed. And this model will be focused on how to describe epidemics or pandemics. Specifically, if you want to think about specific example, COVID-19 pandemic. Now, as you know, during the COVID-19 pandemics, individuals, state governments, health systems, business and companies had to face many decisions they've never faced before. So, let's just think what do they need in order to inform those decisions and improve them. Well, they definitely needed to be able to understand what has happened. So, they needed diagnostic and descriptive models and tools. They need to be able to predict what will happen, what-if scenarios. And for that they needed to be able to predict and use predictive models. And then finally, they needed decision support tools that will be able to leverage what has happened, and what might happen, and what we predict will happen into better decisions and better recommended decisions on various aspects of the pandemic management.

Now, I'm going to talk today about a specific model but more broadly, you have to understand that during this pandemic, there were many data-enabled models that were brought to bear and helped different decision-makers make better decisions. The specific model that I'm going to talk about is called the SIR model, is one of the most fundamental models that is being used for many, many decades to describe the dynamics of a pandemic. And SIR stands for susceptible, infectious, and recovered. What I'm going to do next, I'm going to describe to you very quickly the input, the output, and the relationship between the input and the output of the model as well as the different parameters of the model. And then, there will be more reading that you will have to go through in preparation for the following module in which we're going to get back to this model and discuss it further. So, what is the input of this model? This model describes a population of N individuals that are partitioned into three sets. The set S of susceptible individuals. These are ones that were not infected yet but can be infected. The set I that stands for infectious. These are the individuals that are currently infected and can infect others. And the set R, recovered, these are the individuals that already recovered. They were infected and recovered. So, that's the input of the model and think about the input as a daily input or a period input. It can be a daily or weekly input. And what the model describes is the relationship between the state of these three sets today and how they will evolve and change tomorrow. So, the relationship that is being captured is how individuals move from the susceptible set to the infectious set and from the infectious set to the recovered set. And it's capturing this relationship using two parameters: beta and gamma. Beta is going to capture the high-level, how infectious the virus is, and gamma will capture the high-level, how quickly people recover after they are being infected. And essentially, if I start with S, I and R, today what you're going to see on the slide is how S, I, and R evolved. Effectively speaking or specifically, S is going to be subtracted by the quantity beta times S over N times I. That's going to be the number of people that are going to be moving from S to I in the next period. And I is going to be subtracted with gamma times I, individuals that will move from I to R and on the other hand, would receive the people that will moved from S to I. So, you will see here, what you see here is the flow from S to I, and from I to R is being captured by the formulas that you see in front of you.

Now, you're going to have a lot more time to read about this model offline and as you do that, I would like you to think about specifically the following questions. What is the intuition of the model's parameters beta and gamma? Try to understand yourself using the reading materials, how you should be thinking about beta and gamma, and specifically, how the pandemic evolves when beta is greater than gamma. Also think about what are some of the assumptions and simplifications that the model has. Remember, every model is only an approximation of the real world and this model is by no means different. So, it's very important for you to ask yourself what are the simplifications that this model is making? And then, think about how it could be useful to support related decisions. And what we're going to do in module two, we're going to come back to this model and we'll try to see how you can use it in different use cases to actually support decisions. And hopefully, that will close the loop for you and we'll be able to have a end-to-end example of how to use a model to support decisions.

Video 1.5: Hospital Discharge Prediction Tool Case Study: Part One (7:04)

What I would like to do next is to discuss with you a use case that is based on work that I've been doing with a major hospital system in the Boston area. And my hope is that this use case will illustrate how some of the concepts that I have been talking about so far, namely data, processes, and models play a role together in a specific real work setting. So, first let me give you some background and context about the hospital environment and the specific decision process this effort aimed to improve. Specifically, this use case concerns with the management of perhaps the most scarce resource in the hospital or in any hospital, the patient's bed. So, what you see here is a scaled down example of four surgical floors here in the blue in the middle. And one way to view the system is through inputs and outputs, where the inputs that are typically called admissions consists of admitted patients to the hospital who can come through multiple different channels. Some patients arrive through scheduled or planned admissions. These are typically coming from the surgeon's offices. The surgeon decides that the patient needs to have a surgery and the surgery is scheduled weeks or even months in advance and then the patient comes to the hospital on the day of the surgery or a day before, hopefully to have the surgery as planned and recover.

At the same time, there are patients that arrive to the hospital through the emergency department or from one of the hospital floors in the hospital. And they arrive because they need an unexpected, urgent, or even emergent surgery. These admissions are unplanned. And finally, patients can be transferred from other hospitals or just be sent by their doctors directly to the hospital, not through the emergency department. Now, one of the things that is true about admissions is that relatively speaking, there is a good centralized situational awareness of what these admissions are. The reason for that is that many of them are planned in advance and even those who are not, require to first fill a bed request. And all the bed requests are being managed by a centralized unit in the hospital and therefore, the information is quite centralized and there is a good awareness of the number of admissions. Now, one way to view these admissions is the demand for beds, the daily demand for beds. Now, where does the supply to satisfy this demand for beds come from? The supply of beds is created by discharges of patients that currently occupy hospital beds. As a patient is discharged, they free up a bed which can be reused for other patients and typically, patients are discharged from the hospital either home if they are healthy enough, or to another facility, in case they need some more support in their recovery. Unlike the admissions, there is very little centralized awareness about which patients are ready to go home or be discharged to a facility and what kind of barriers they might have for discharge to happen. And that blindness to the discharges creates a lot of disruptions in the hospital. A lot of disruptions to the operations of the hospital, including crowding of patients staying in the hospitals longer than needed and more disruptions. Now to provide a sense of the real scale of the problem, it's not about four floors we are talking about, there are many more than four floors, as you can see from this picture, and there are over 1000 hospital beds to manage. So, this is, I hope you appreciate a very complex system.

Now, the specific projects that I'm going to talk about is focused on trying to use machine learning and data to predict each day which patients are likely to go home in the next 24 hours. And the goal is to facilitate a better and more effective discharge process as well as more effective bed management in the hospital. Now, in contrast, an alternative task, one could imagine an attempt to predict upon patient's admission, how long the patient would stay in the hospital? This is often called the length of stay. So, now, what is the problem with this? Imagine that you have a fairly accurate model that can predict how long the patient will stay. Let's say the model predicts that the patient will stay three days, say with 80% chance and then four days with 10% chance and then maybe five days or longer with 10% chance. The problem is that this would not be something that lends itself to any actionable activity or decision that the clinical teams or the administrative personnel in the hospitals could be making in order to make timely decisions. So, while statistically, you might have a fairly good model, practically speaking, this model does not support any real decisions.

On the other hand, if I can accurately predict that the patient will likely to go home or be ready for discharge in the next 24 hours, and what are the barriers related to that, this is something very actionable. So, at the high level, this is what our model is doing. It leverages a lot of data streams that you can see here on the left; clinical notes, tests that were conducted on the patient, details about the patients and so forth, and so forth. And its taking all of this and is predicting every day, for every patient in the hospital, it predicts the score and the highest score is, the more likely the patient is to be discharged in the next 24 hours. And additionally, for every patient, the model predicts what are the barriers that need to be resolved, that the patient will be able to go home. Now, before or instead of diving into the details of this model, what I would like to do is to step back and walk you through the modeling work that we had to do in order to arrive and be able to implement a model like that.

Video 1.6: Hospital Discharge Prediction Tool Case Study: Part Two (6:33)

So, I'm going to step back and look at the very high level about the process or the processes that take place from the moment the patient is admitted until the moment the patient is discharged. These are very complex set of processes. They involve a lot of diagnostic work, a lot of therapeutic work and so forth. Now, when we started this project, there was no consistent language in the hospital to describe and speak about this project, let alone a data driven language. So, the first thing that we had to do was to develop a common language. And the first concept that we developed was called clinical and logistical readiness. What do we mean by that?

This stems from the fact that when you think about when a patient is ready to leave the hospital and be discharged, it has to do with two dimensions of readiness. One is obvious. The clinical readiness is quite obvious. The patient has to be stable and recovered enough to be able to go home or to another facility, but that's not sufficient. So, for example, imagine a patient that just had gone through a hip replacement surgery. It's a relatively straightforward surgery and usually after a day or two, the patient is likely to be clinically ready to leave the hospital. But, say this patient lives alone and has a bedroom in the second floor. That implies that while the patient is clinically ready, there is a logistical challenge and there is no logistical readiness for the patient to go home, and that patient needs some more support, perhaps to be discharged to a facility to, perhaps to be able to get support at home in order to make his discharge possible. So, to summarize, what it takes to be able to discharge a patient is not only clinical readiness but also logistical readiness.

And these were the two major concepts that we coined in starting to develop a common organizational language to talk about this process. Now, this is an example of what we call a qualitative model. The concept of clinical and logistical readiness constitute a qualitative model. This model does not have any exact equation that describes some precise connection or relationship, like for example, physical laws. But nevertheless, it uses instead more high-level qualitative terms and objects to describe in words the system and the processes that are involved from the moment the patient is admitted throughout the moment it's ready to be discharged. Therefore, it's called a descriptive model. It describes this process. Now, this is an important first step. But as you can imagine, a qualitative model does not lend itself to use large scale data and that's a missing step here.

And what I'm going to do next is to show you how we use this initial qualitative model and leverage that to a far more precise and data enabled quantitative model. And that relied on two major concepts: clinical milestones and barriers for discharge. So, let me first talk about the concept of clinical milestones. One way to think about this, that if you think about the patient that was just admitted, you think about a sequence of event, a list of events that signify progress of the patient towards discharge. Think about intuitively as a checklist of events that every event that is checked signifies progress towards discharge. And let's just talk about the specific example. So, what you see here is a specific surgery with a specific milestones that are relevant for that surgery. So, the first milestone is that the patient has to have stable vital signs,

like you cannot go home unless you have that, and if you have a stable vital signs, that signifies that you are making progress. Additionally, if you think about this patient, there were a few tubes that were inserted into the patient as part of the treatment and these tubes have to be taken out before the patient is ready to be discharged. So, if you already know that were taken out, that signifies progress towards discharge. Finally, the patient currently is on IV narcotics, and before the patient can go home, these narcotics has to be stopped. So again, if the patient narcotics were stopped already, that signifies progress towards discharge. So, that's the concept of clinical milestones, for example. Next, I would like to talk about the second concept which is barriers for discharge. And barriers for discharge can constitute many things or multiple things. The first example of a barrier is delays in milestones.

For example, think about, again the same example, and let's say that this patient has to see a physiotherapist to be assessed that they can swallow and can walk appropriately before they can leave the hospital. And let's say that basically, we know already that the order for a physiotherapy consult was placed but the consult didn't take place. So, now we have a delay, a barrier that doesn't allow us to accomplish the milestone that is necessary for the patient to go home. I mean, another type of barriers could be that there is some remission or some worsening of the patient's vital. So, now there is a new abnormal clinical indicator that could signify a barrier that needs to be resolved before the patient can go home. And maybe the third example could be, we have a situation in the patient's home that does not allow the patient to go home before it's being resolved. So, hopefully you've got a sense of what clinical milestones are and what barriers for discharges are. And these are already concepts that you can use data to enable them and we're going to see that next.

Video 1.7: Quantitative Model to Describe the Patient Progression Toward Discharge (4:21)

So, now we're going to go back to the process from the moment the patient is admitted until the patient is ready to be discharged. But we are going to use now the concept of clinical milestones and barriers to represent this process or describe this process in a completely different, more detailed manner. So, let's just look at this example. The patient just had surgery and here are all the details and characteristics of the patient that you can see here. And now, on day zero, the patient just had the surgery, we already identified three barriers that are relevant for this patients. The patient is on a special diet. So, it needs to go back to regular diet. The patient needs to see and be assessed by a physiotherapist. And the patient is currently having an IV narcotics, so they need to be off for the patient to be ready to be discharged. So, let's see what happens on day one. On day one, the first two barriers are resolved.

The patient has got back to regular diet, physiotherapy has been assessed. But we have now, still the third barrier from yesterday still on. But now we have another barrier, and we need to do some drainage to the surgery site. So, we have another barrier. And then in the second day, there are now multiple more barriers that were added.

There are some abnormal clinical indicators that were discovered, and now we need also cardiology consult. And now we're moving to the third day. And now, what we see is that most of the barriers are resolved. So, that might be a moment in time where we're going to say that this patient is approaching a situation when they might be ready to be discharged relatively soon. Now, hopefully you can appreciate that it's a completely different way to talk about the process or the processes that the patient goes through from the moment they are admitted until the moment they are already discharged.

What you just saw is a way to convert the qualitative model that we had about clinical and logistical readiness to what we call a data-enabled quantitative model that takes the concept of readiness, both clinical and logistical readiness, and translate them to a model that is data-enabled. This is a data-enabled quantitative model that describe the process of discharge. And it also represents the patient. So, we often call this a representation model in a very, very different and data-driven manner. Now, remember this is very impressive maybe, but even this model is not entirely precise. Patients are more complex than that. But hopefully, this model provides a good approximations that allow common data-driven language among professionals. But nevertheless, always remember that every model and this model as well has their own boundaries, and you have to appreciate that.

So, you need to understand the benefits of the model. It really takes to another level the ability to communicate about patient using data, but at the same time, it doesn't capture everything about the patient and it's still an approximation. And what we've been doing, one of the most critical element of our work was basically to take all the raw data, all the data that was collected in the electronic medical record of the hospital, and be able in an automated way to detect what barriers and what milestones are in play or not everyday using the data on the left. And that took us months to figure out. That took us a lot of effort to understand how the data is generated and how to interpret the data correctly so we can convert and represent the data into the concept and the language, the modeling language of barriers and clinical milestones.

Video 1.8: Model Results (9:25)

So, one of the things that we talked about is how to evaluate, how to know that you have a good predictive model. And let me discuss the performance of the algorithm that we developed in the context of the work in the hospital. So, what we've done here is what we call a classification model. What is a classification model? Again, you're going to learn about logistic regression as one example of classification model later in the course and a few other models. But in a classification model, you're trying to predict one or zero, one of two classes. So, one way to view our algorithm is that for every patient, every day we're trying to predict whether they belong to the class of patients that will be discharged in the next 24 hours, that's one, and zero otherwise. And one of the most common statistical metrics to evaluate the quality and the performance of a classification algorithm like ours is what is called the area under the curve.

Again, you're going to talk more about this metric later in the course. But at the high level, this metric can get a value between half, in which case, your algorithm is a completely random guess, it's completely useless to one in which case your algorithm is essentially perfect. And what you can see here is that the AUC that our model can accomplish is 0.9. So, it's almost perfect statistically. So, if I'm a data scientist, if I'm an academic, I'm feel very proud of myself, but I have to tell you when we started to use this model in the field and show it to clinicians, surgeons and so forth, we actually did get some reactions that the model is not performing very well. So, why was that? Let's just try and understand why was that. So, at the end of the day, you cannot communicate to a surgeon a score. You have to communicate to the surgeon, is the patient going to be discharged or not? And one way to do that is to take the score that the patient received from the model and decide how to round it up or down. So, for example, one natural way would be, hey, if the score is above half, we're going to predict that the patient is going to be discharged, and otherwise we're going to predict that the patient is not going to be discharged. For example, when you do that, you find out that only 68% of the time when you say that the patient is going to be discharged, they actually go home, and vice versa, you only capture 68% of the patients that actually go home. Now, from a statistical perspective, that's actually very expected. Like these models are not perfect. There is some uncertainty, and no model is going to be perfect. But when you actually communicate with professionals, with humans that might not be data scientists that might not work very well for them.

So, again there is a gap between the statistical performance of the model and the actual performance of the model and how it's being perceived by the people that are using it at the end, which are not statisticians in most cases. Now, here's another metric that is actually not a statistical metric that we developed in evaluating this model. And that's leave within 48 hours. What do we mean by that? What we observed is that many of the patients that we predicted to be discharged in the next 24 hours did not leave in 24 hours and that was an error of the model, to say the least. But nevertheless, they actually were able to leave the hospital in 48 hours. And essentially, what you can see here that more than 87% of the patients that we predicted to be discharged in the next 24 hours left at the latest, after 48 hours. Now, we started to investigate what is happening with these patients. And what we found out that for the vast majority of them, we couldn't see any apparent reason why they could not leave the hospital in 24 hours. Now, there are multiple lessons to take from this observation. The first of which goes back to one of the comments that we made earlier about the fact that the data that we usually use is generated by an existing system.

Now, if you think about what the data that we have here is this data does not represent any absolute truth on whether the patient is ready to be discharged or not. This data represent the current decision-making of the teams of the hospital about whether to discharge the patient or not and this decision making by itself is not perfect. So, that was not an error for the model. That was actually an opportunity to improve the system because that led us to identify system level reasons why patients might not be able to leave on time in spite of the fact that they could. Now, that brings about a more generic and more high level issue and a very important issue, which is about how data and models interact. Because that's a very important tension that you have to appreciate which exists from the moment you start thinking about the models throughout the time or the process in which you use models.

You have to, all the time, contrast the models with data and you're going to learn a lot from that. So, for example, when we actually analyzed these errors, we learned a few things. One thing that we learned about is that some of our interpretation of the data was wrong and we had to go back to the model and correct it. Another thing that we learned about the model is that we might not be using all the relevant data sources. For example, we found out that some of the data that is important to understand the state of the patient is not captured through structured data but instead through the unstructured clinical notes of the nurses. So, what we did next was to build additional modeling and algorithmic layers to be able to bring these nurse notes into the model. But as I mentioned, we also learned that the model is not wrong in some cases but rather than, we need to go and improve the system that the model is trying to capture.

So, these are all the benefits that you get when you contrast models with data. Now, just to summarize what we've seen in this example, we've seen layers of models that we had to develop in order to be able to go from data and signals at the bottom up to the ability to use this to inform decisions at the top, and the layers were, we went from data and signals to representation models. This is the concept of clinical barriers and clinical milestones. This was a representation model that was fed by the data. On top of that, we build a descriptive model that describes the process that the patient goes through from the moment they're admitted until the moment they are discharged as a dynamic change in the state of different barriers and clinical milestones. And then, we use that to build a predictive models that can predict whether the patient is likely to be discharged in the next 24 hours and what are their respective barriers.

And that allowed now physicians and administrators to make decisions based on these predictions and hopefully improve their decision process. Now, this is a modeling concept and the model layers that you see here are going to be something that we're going to revisit again and again, and it's going to be something very, very practical for you to understand because these are the layers that you need to build in order to move from data and signals to actually informing decisions. The other thing that I want to highlight again is the interaction between data and models, and I want to summarize that because that's a very, very important topic. So, as you can see on the left hand side, we start using data even when we think about qualitative models. Again, there is a lot of approximation there. There are a lot of errors that are being introduced because no model is perfect. What we did then, based on the data, we developed a qualitative concepts of clinical and logistical readiness. And then we used more data to convert that qualitative model into a quantitative data enabled model and again we introduced some more errors. That allowed us to take the concept of clinical milestones and barriers and enable a predictive model. We contrasted the predictions of the predictive models with the actual observations of what happened to the patients to improve the model, to bring about more data into the model as well as to improve the system that we were trying to model. And finally, all of these hopefully enabled better decision making in the hospital with respect to their bed management.

Video 1.9: Module Wrap-Up (5:00)

I would like to conclude this module and highlight some of the main takeaways from what we discussed. The first takeaway is that you always have to understand the business processes that generated the data in order to properly interpret the data. And there are a few examples that we discussed. The first one, remember my example, my experience at the emergency department boarding time. But we also looked at it, we also had this aspect when we looked on the airline data,

when we had to understand that some of the flights were canceled. So, the flights delayed percentage and the flights on time percentage did not sum up necessarily to 100%. That's another example where how the data is generated can make a big difference in how you interpreted some of the numbers that you're looking at. The second takeaway is models. And we discussed multiple examples of representation models, descriptive models, predictive, and prescriptive models, and we're going to discuss many more during the course, are key to enable the use of data within decision processes. This is going to be a central concept that we continue to hone on throughout the course.

So, the other takeaway is that you should always worry when you look on data regarding hidden important confounding factors. Again, go back to the comparison between Optima and Quanta. If we didn't consider or account for the specific legs and understand that each one of the legs may have completely different inherent-based risk for delay, we would not be able to understand the data appropriately. And that's called again, risk adjustment and risk stratification, that's a very common pitfall. And in order to get over that, you have to use expert-based intuition to ask the right questions, to ask yourself, "Am I missing confounding factors? Am I doing the right risk stratification or not?" And this is not just about science. This is also about having a sense to ask the right questions. Another takeaway is that you have to try and validate your conclusions with data from different sources. If something is really true in the underlying system, many different data analyses will lead to the same conclusion. And that's again, this is again they going back to the example of Quanta and Optima, where if you just did the initial analyses and stay with that, you would get to the wrong conclusion.

So, you needed to do multiple analyses, cut and slice the data in different ways in order to actually understand what's going on. Similarly, in the project that we described to develop the discharge prediction tools, we had to really dive into the data and validate different aspects of the data to see that we interpreted the data correctly. So, this is something very, very important. Never do one-dimensional data analysis. Always try to cut and slice it from different directions and see if you get agreement. And that connects to another takeaway, which is you have to develop a sixth sense for data, both for the potential opportunities that the data provide as well as what are the pitfalls are. And there are very subtle nuances here that even for seemingly simple data, like the Quanta Optima data that we considered, you can actually make mistakes. And so imagine the challenge when you have very complicated data.

And again, I'm going to go back to the discharge prediction tool that involved very messy data. This is something you have to develop to yourself. And again, there are no rules here, but it's about looking at many examples and develop your own takeaways and your own approach to how to approach data with patience and curiosity. And again, very important to be aware of the common interpretation pitfalls that people are making. Now, just as a very high-level summary of the takeaway, hopefully you get out of this module energized, that data softwares are readily available, but at the same time remember that they are not a substitute for your own thinking. And they are no substitute for solid domain knowledge. So, as you think about data, you have to be able to leverage technical tools and you're going to learn about many of them, but it's never going to be a substitute of your common sense and your expertise in the domain you're dealing with.