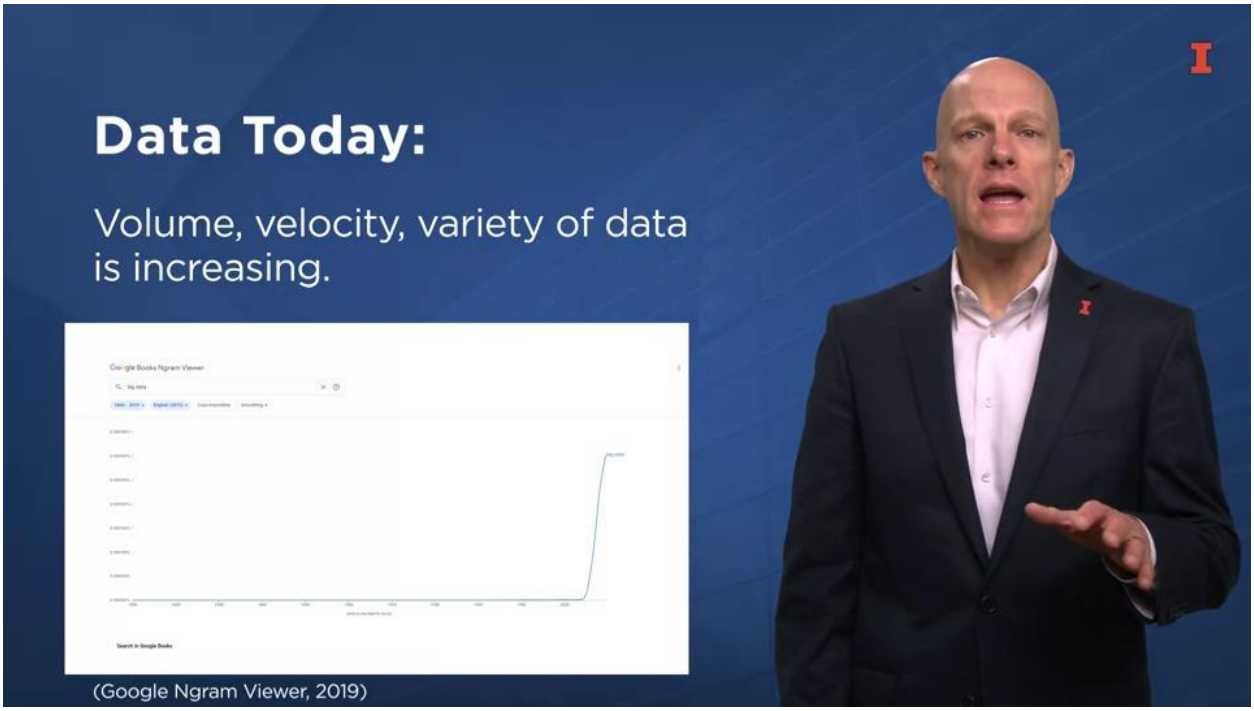
Module 2: Framework for Machine Learning and Logistic Regression

Table of Contents

Module 2 Overview

Module 2 Introduction

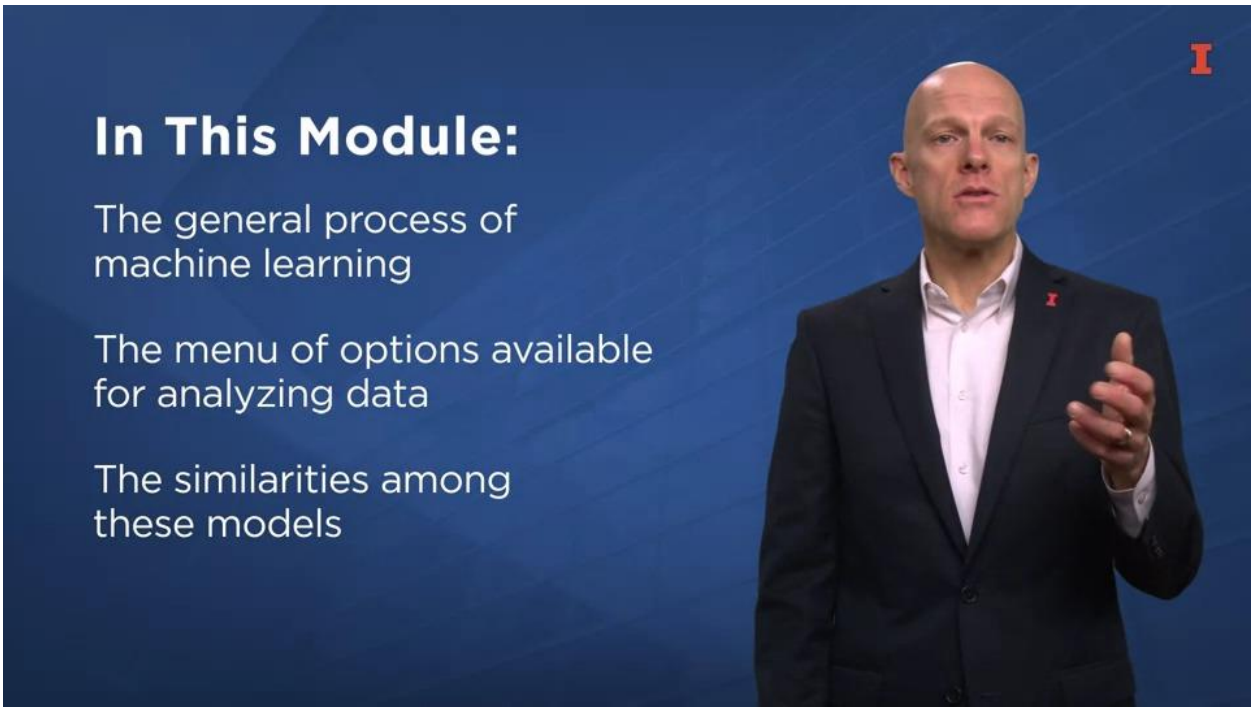


In this module, we'll do two things. First, we'll introduce you to the world of machine learning. Second, we'll examine a classic classification algorithm logistic regression. More and more managers find themselves drowning in data. It's not just the everyday transactions and sales data that stalks them. It's the shipping, the logistic data, customer loyalty data, scanners and IoT data, that's machines talking to other machines, supplier data, and employee, and HR data. The volume, velocity, variety of data is only increasing if the use of the term big data is any indication. It's not just hyperbole to say that we have more data available to analyze now than we ever have before.

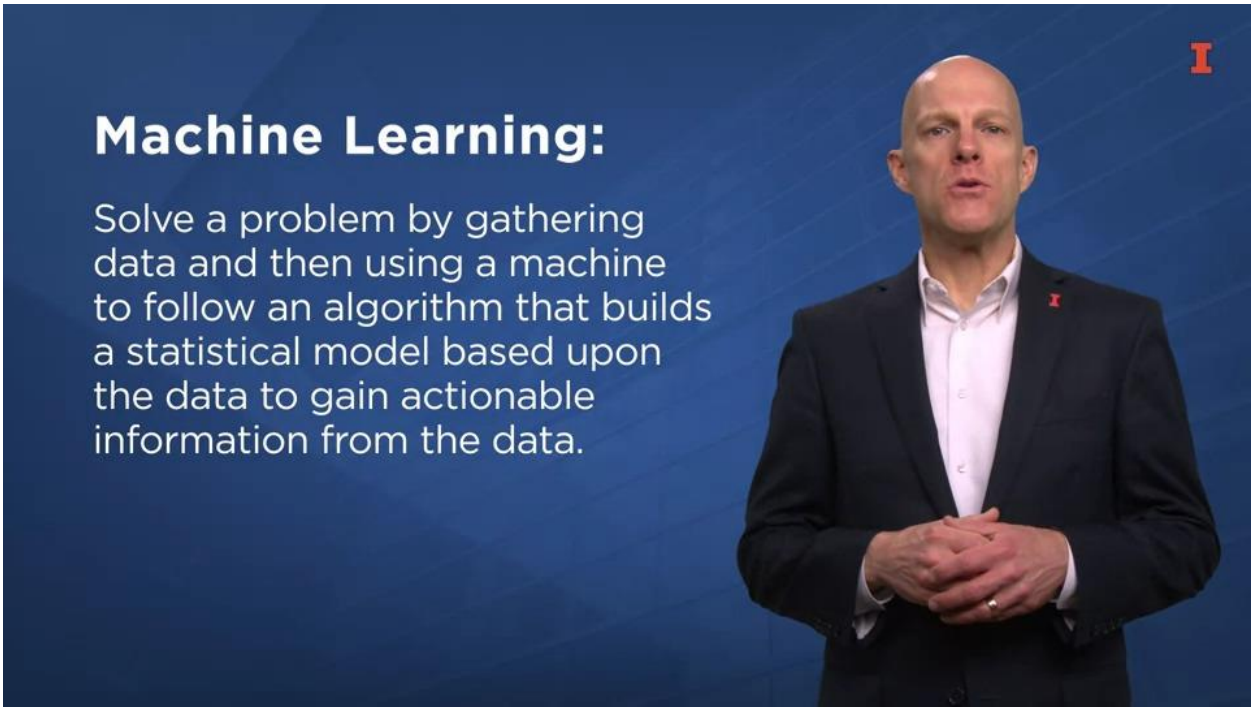
Commentators state that over 2.5 quintillion bytes of data are created every single day. That more than a megabyte of data is created every second for every person on Earth. That means that in the time you've been sitting here listening to this video so far, more data has been created just from you than most personal computers could handle in the year 2000. Now think of your own employer. How much data is available to analyze? How quickly does that data get created? Just keeping up with this data is a process in and of itself. But you are tasked with not only understanding these mountains of data, but also extracting actionable business insights from this data.

Luckily, that's what this course is about. Helping you develop the ability to use tools to extract the business insights from your data. Clearly, for most of us, there's too much data to analyze by hand. Rather we need help. That's where machines come in.

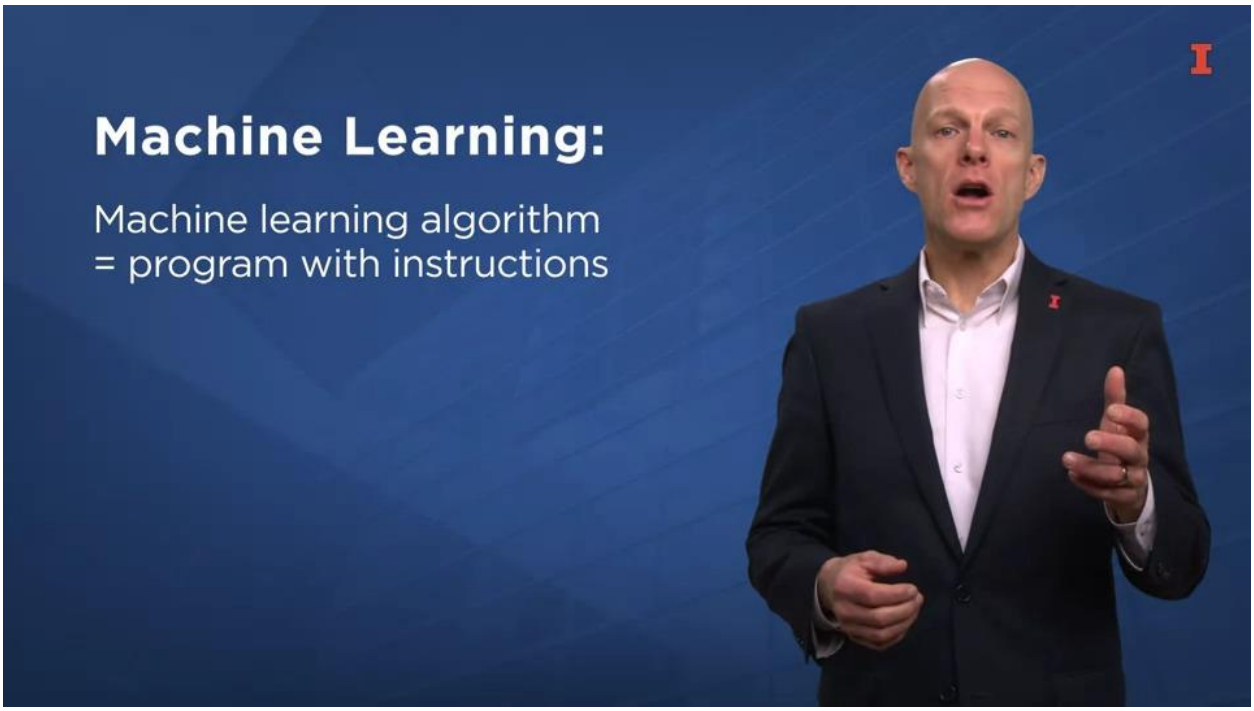
This course deals with data modeling and using machines to gather insights from data. After your data is acquired, cleansed, and ready for use, and explored, and understood it at a general level, it's time to use statistics to draw actionable insight.



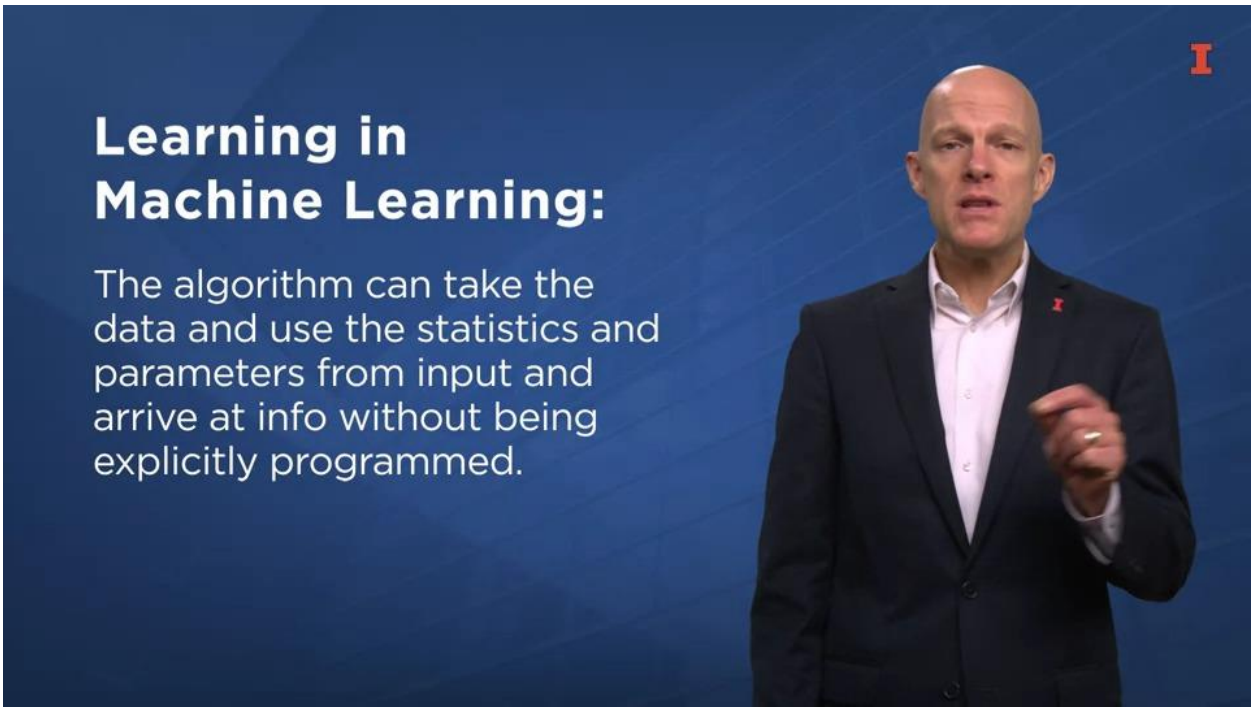
This module will discuss that general process, the menu of options available for analyzing data, and general similarities that models have.



Machine learning has many definitions. But generally refers to solving a problem by gathering data and then using a machine to follow an algorithm that builds a statistical model based upon the data to gain actionable information from the data.



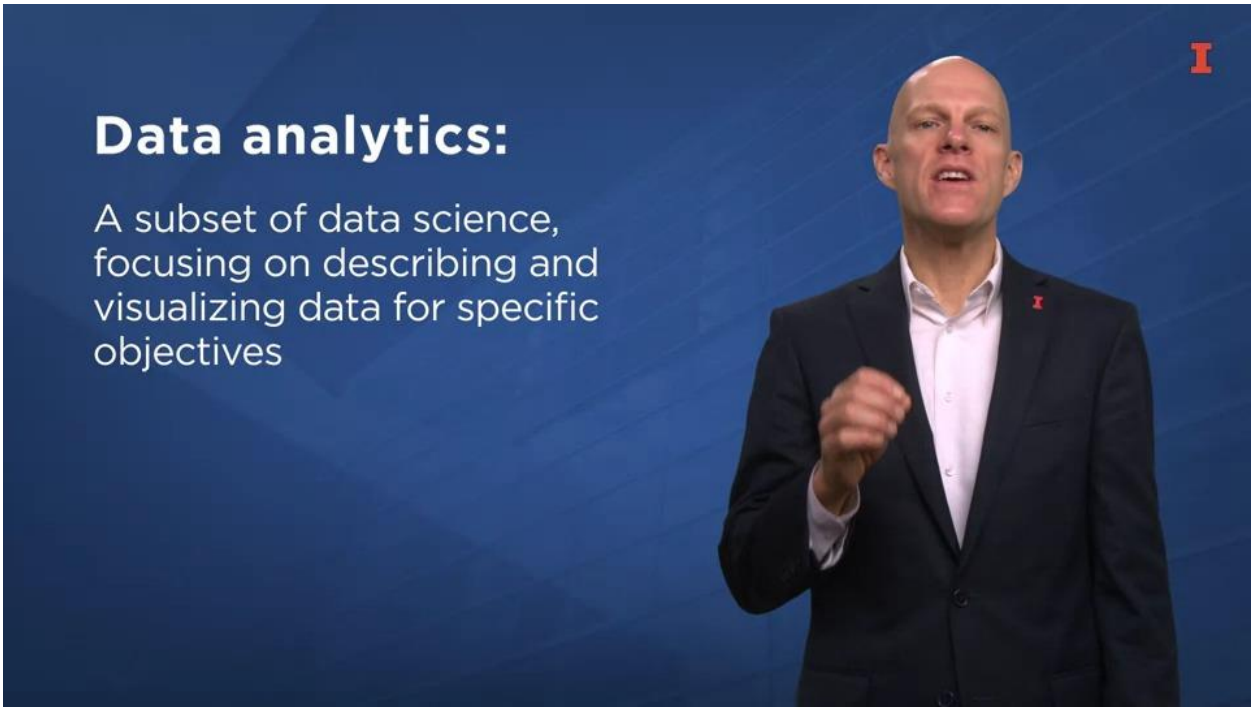
I put it in another way. A machine learning algorithm is like a program with instructions. When you apply the algorithm to data, it creates a model. The model has new data along with instructions for how to make predictions with the data.



The learning part of machine learning refers to the fact that the algorithm can take the data and use the statistics and parameters that you give it and arrive at information without being explicitly programmed to arrive at that information every step of the way. Thus, the computer takes the general directions you give it and finds information that you did not explicitly tell it to find.

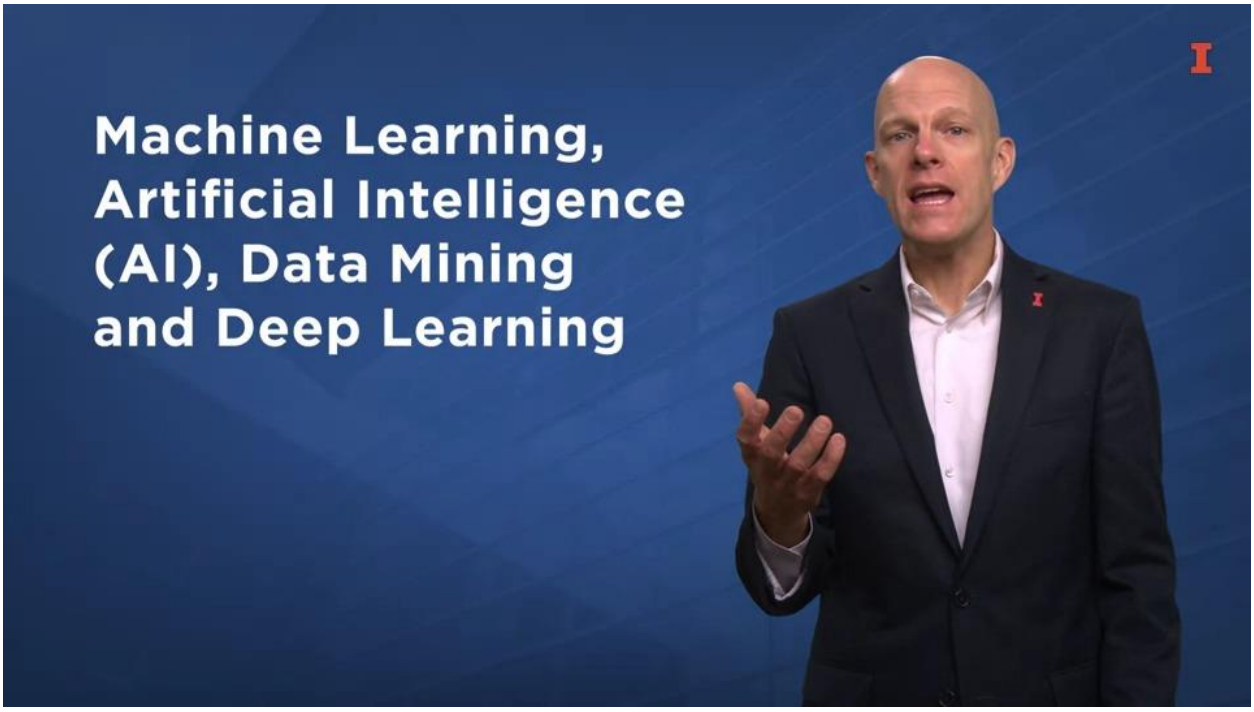
Before we move forward, it's useful to discuss some additional terminology. Let's first look at data science versus data analytics, versus business analytics. Unfortunately, for those of you who like clear definitions and distinct differentiation between terms, you'll be disappointed to learn that these terms are often used interchangeably. Most would consider data science as the broadest term and both data analytics and business analytics to be subsets of data science.

Data science comprises methods and procedures to extract knowledge and insights from data with the aid of computers.

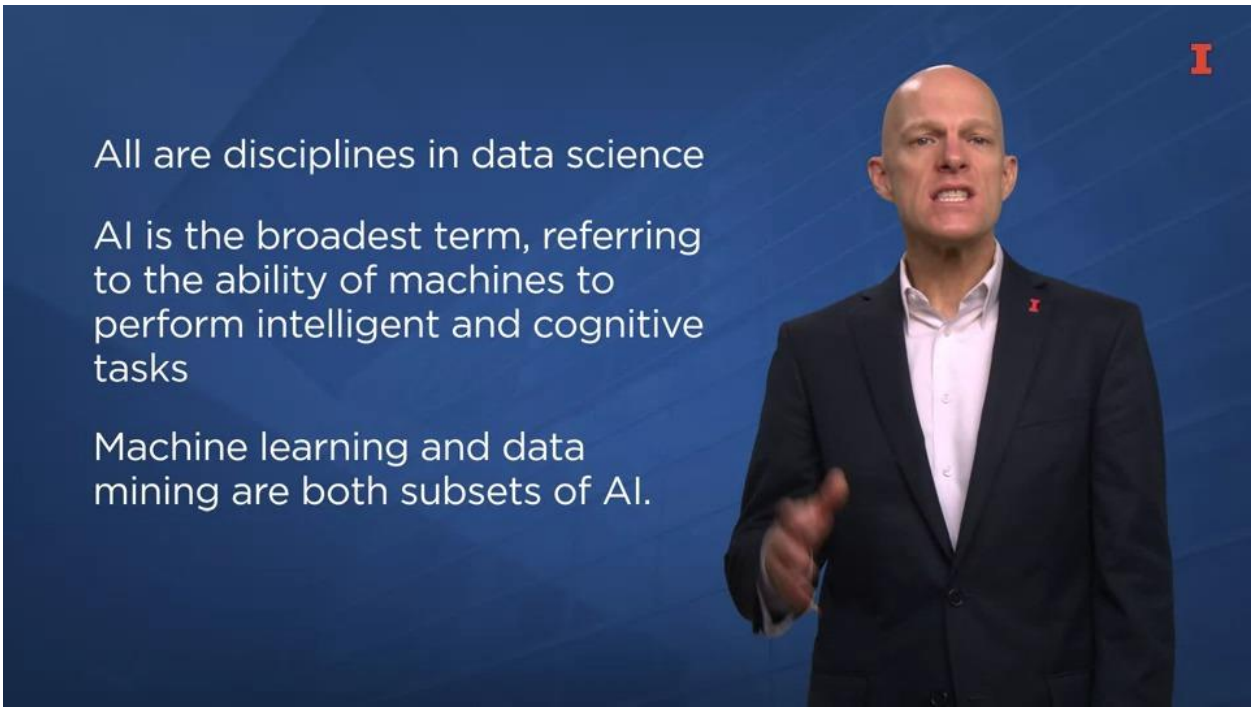


Data analytics is similar, but a subset of data science that is more focused on describing and visualizing data for specific objectives.

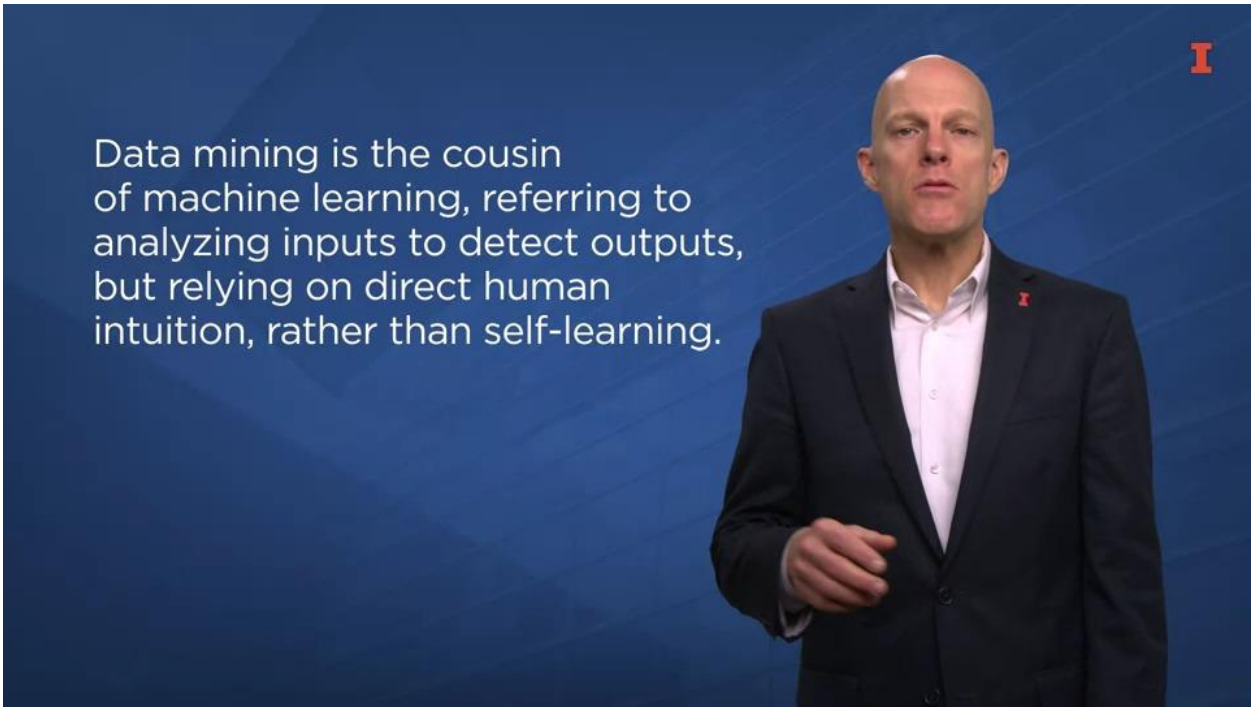
Business analytics is a subset of data analytics that focuses data and questions related to business and involves relatively few statistics.



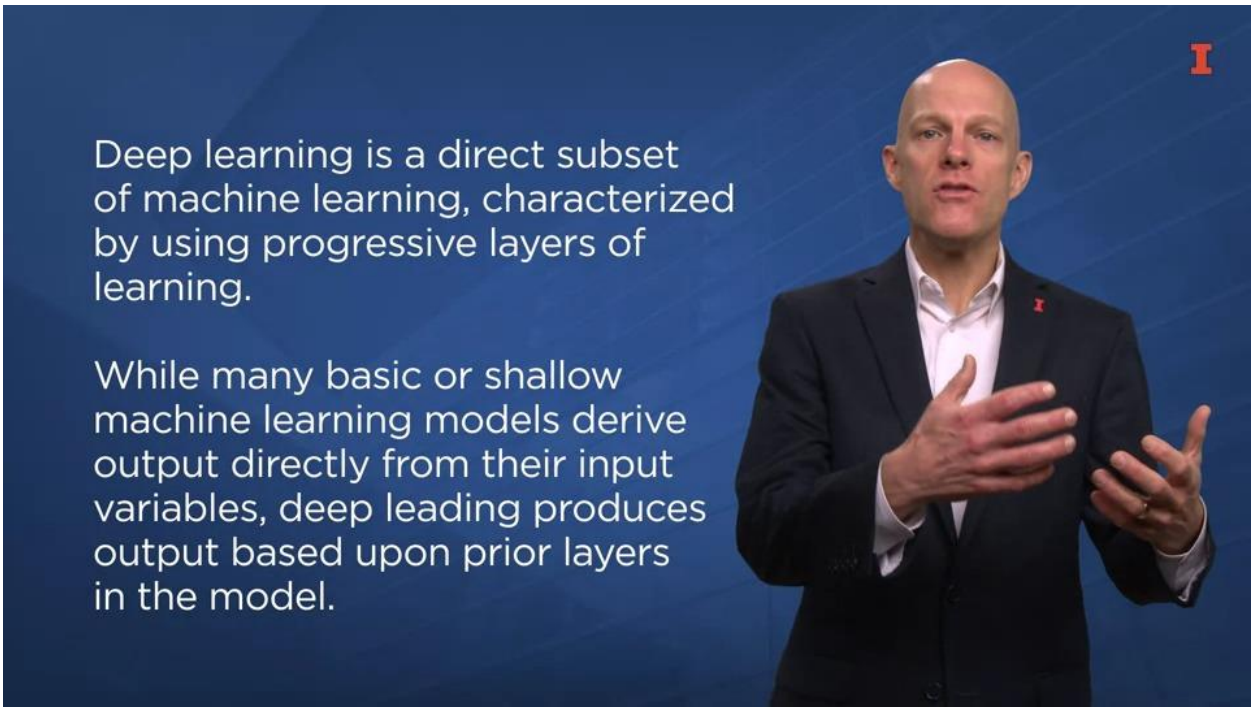
Next, let's define and distinguish machine learning, artificial intelligence or AI, data mining, and deep learning, etc. What do each of these terms mean and how are they different?



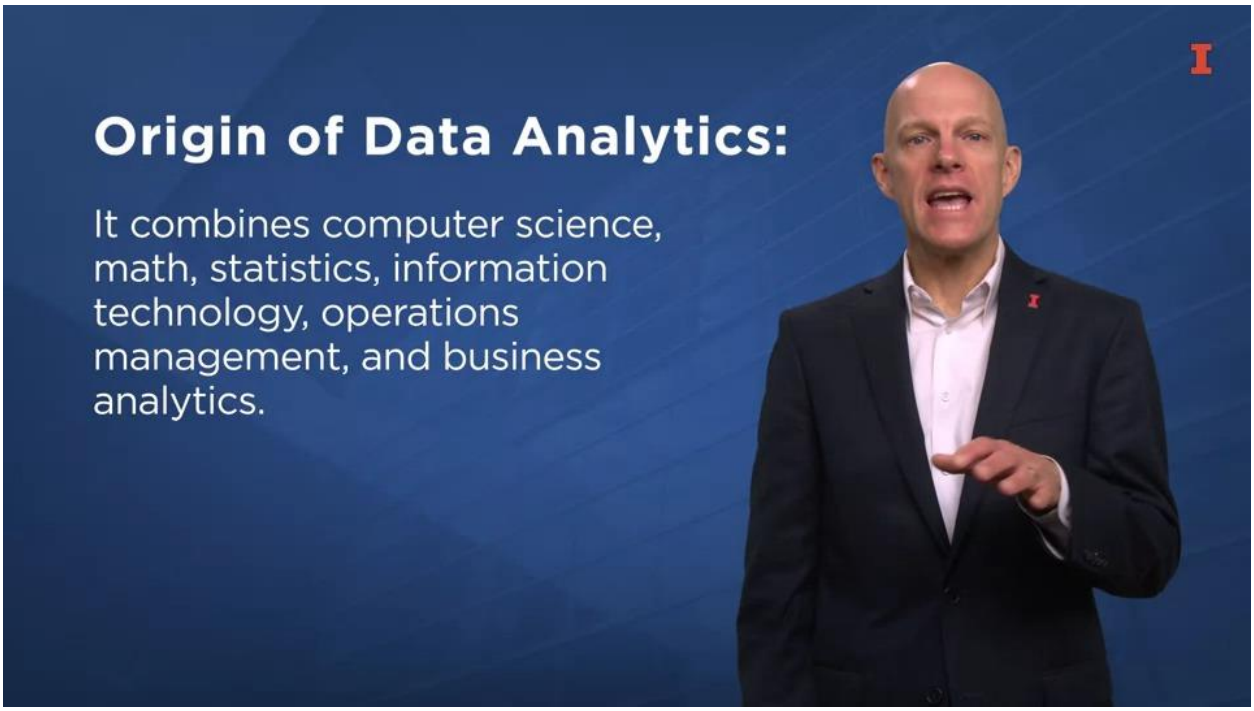
Well, all of these are disciplines in Data Science. Artificial intelligence is the broadest term. It refers to the ability of machines to perform intelligent and cognitive tasks. Thus, AI simulates thinking. Machine learning defined earlier, and data mining are both subsets of AI.



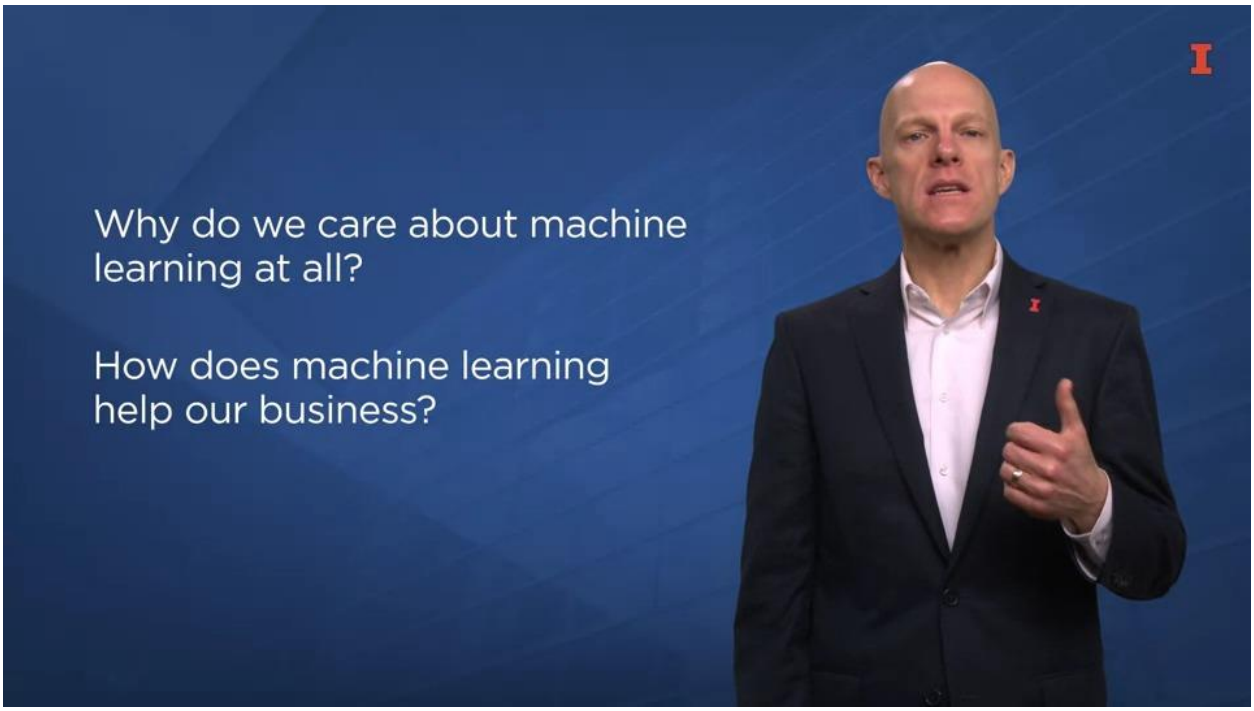
Data mining is a cousin, if you will, to machine learning. It analyzes inputs to detect outputs, but relies on direct human intuition rather than self-learning.



Finally, deep learning is a direct subset of machine learning that is characterized by using progressive layers of learning. That is, while many basic or shallow machine learning models derive output directly from their input variables, deep learning produces output based upon prior levels and prior layers of the model.



Next, it's useful to understand where this relatively new field of learning, data analytics and machine-learning came from. Data analytics is a confluence of many different disciplines, including computer science, mathematics, statistics, information technology, operations management, and business analytics. Thus, a data scientist and a data oriented business analyst is a relatively new creation.

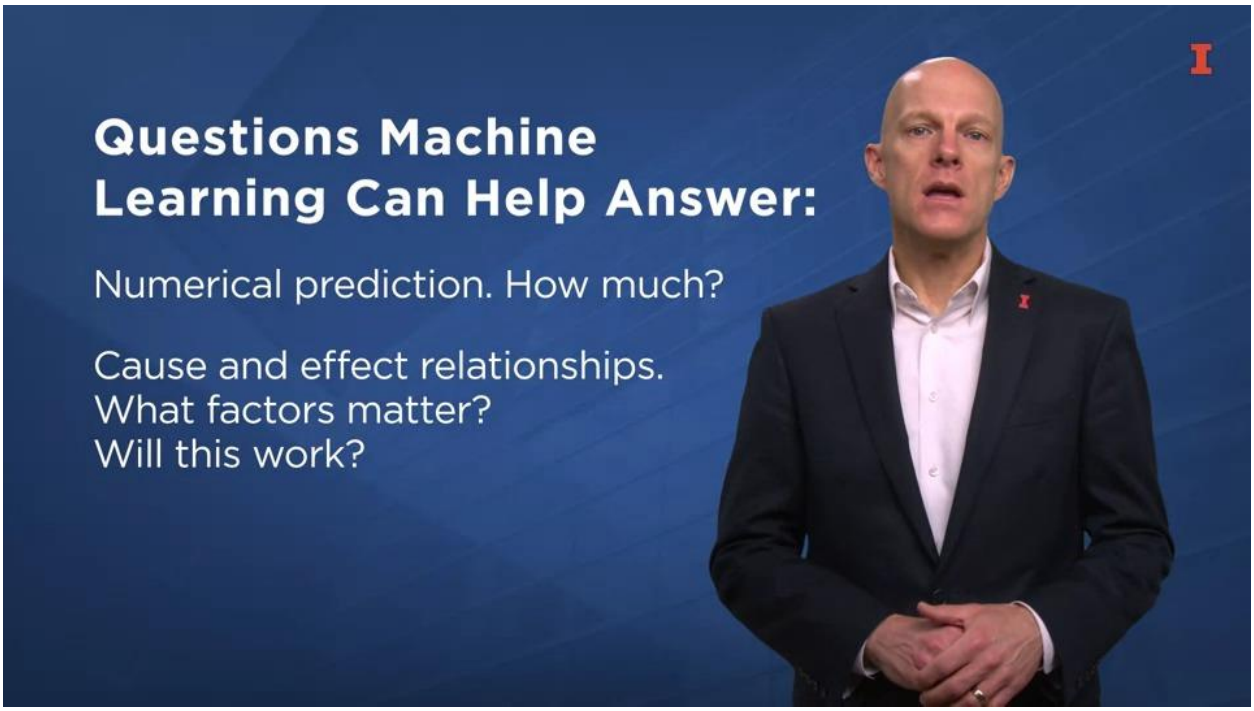


But perhaps at this point, it might be time to step back a little bit and ask, why we care about machine learning at all? How does machine learning help us in business?

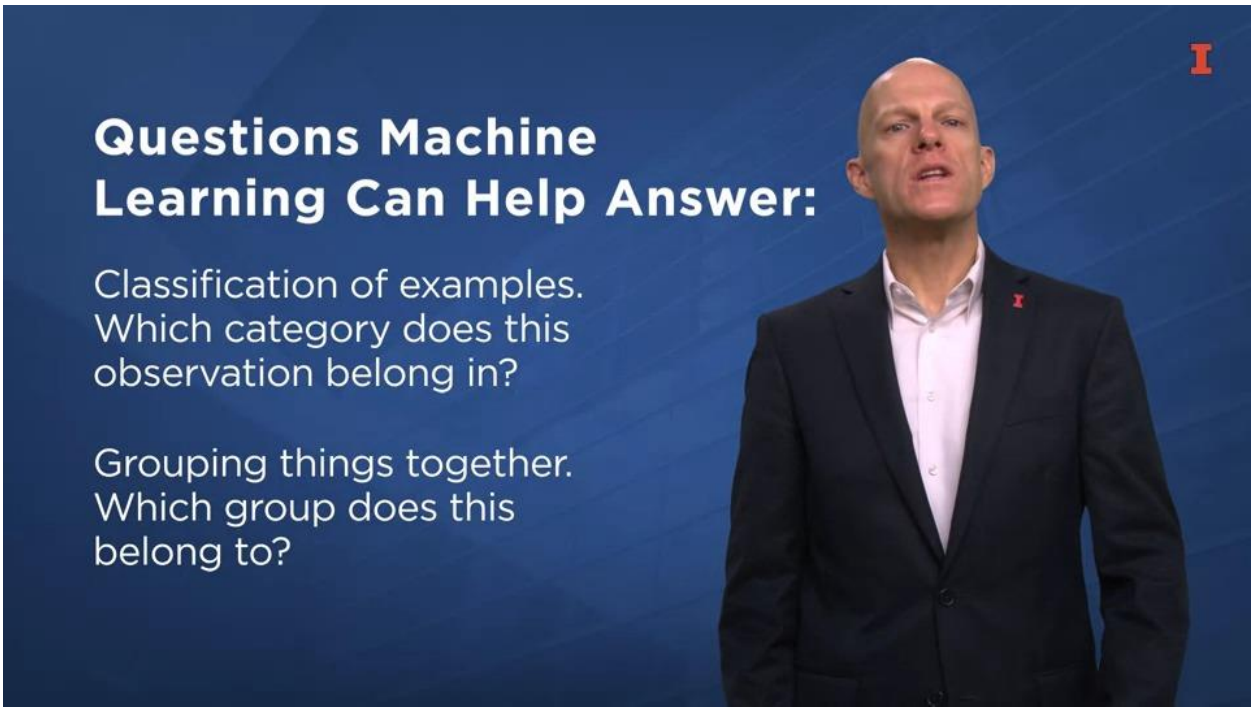
One way to think machine learning is just to relate it to the ways machines have helped businesses throughout history. Certainly, no one would doubt the usefulness to business of the steam engine or the telegraph. Like these early machines, computers and business learning process data at phenomenal rates of speed and draw connections, correlations, and insights that the analysts could get to know other way.

Of course, don't be misled by the many movies predicting machines are taking over.

Machine learning helps the analyst derive useful and actionable insights from the data.



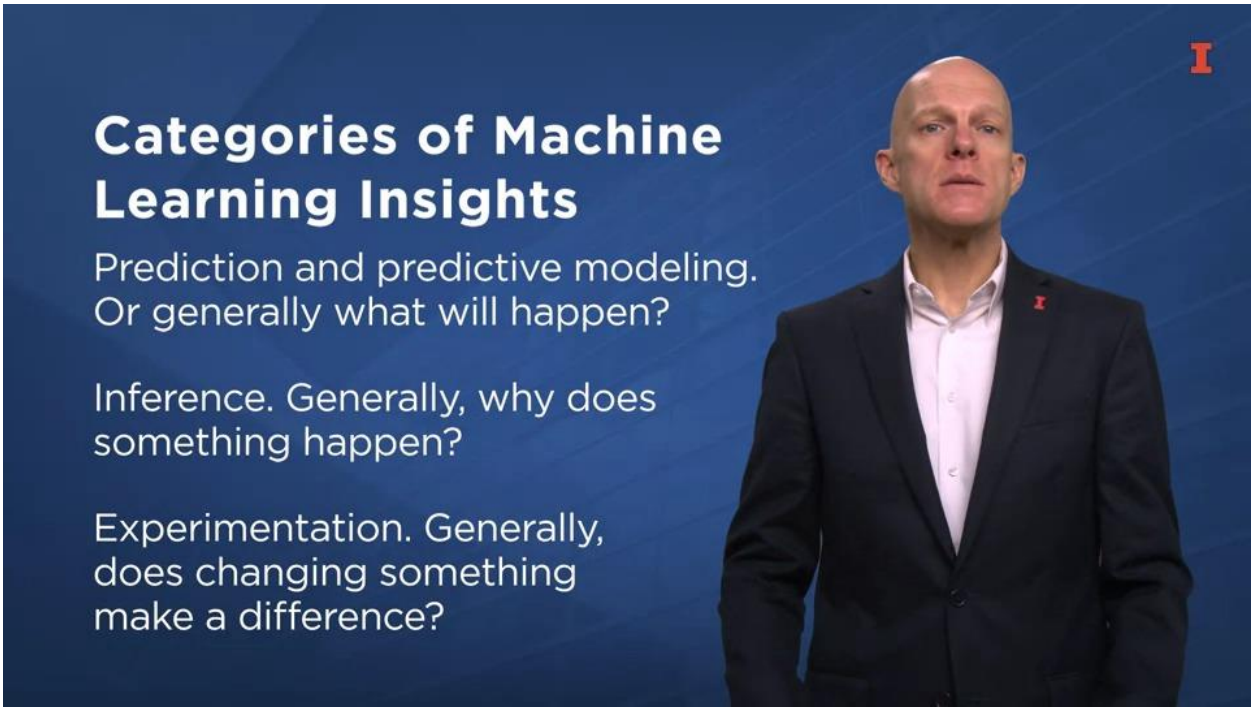
But it is still up to the analyst to act on these insights at least initially. Thus, machine learning is like a great blood hound. It helps you gain insight, but must be directed cautiously, or else it will run off chasing a squirrel. Finally, let's conclude by listing some questions that machine learning can answer. Here are some categories of problems that machine learning can help with and specific examples of problems from each category. First, numerical prediction as seen in regression. What do we expect, for example, costs to be next quarter in a segment? Next, cause and effect relationships between variables. What what factors matter? Will this work? For example, which factors have the biggest effect on shipping delay? Or does a particular change in our website improve click-through traffic? Or does this layout of our store improve sales?



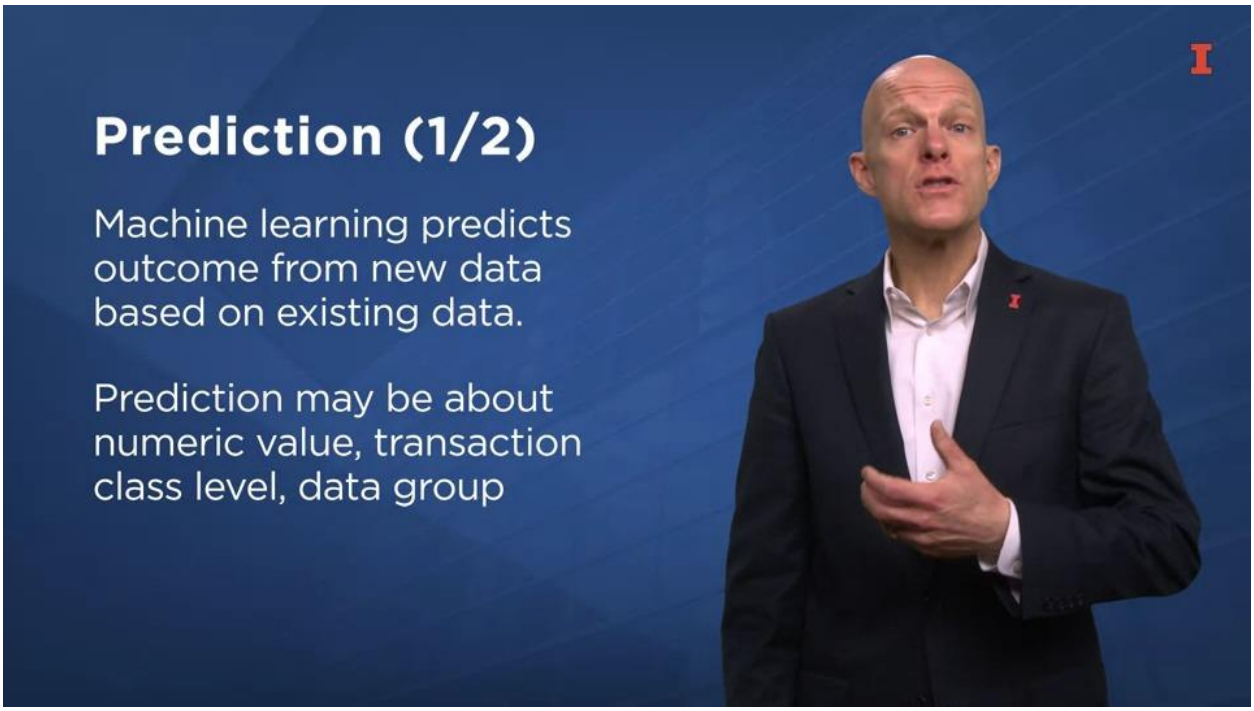
Next, would be classification examples. What category does this observation belong in? For example, is this transaction fraudulent? Or what factors increase the likelihood of a purchase? Another category would be grouping things together. For example, which group does this belong to? Which customers should receive which type of targeted promotions? There's many others.

Lesson 2-1: Machine Learning Overview

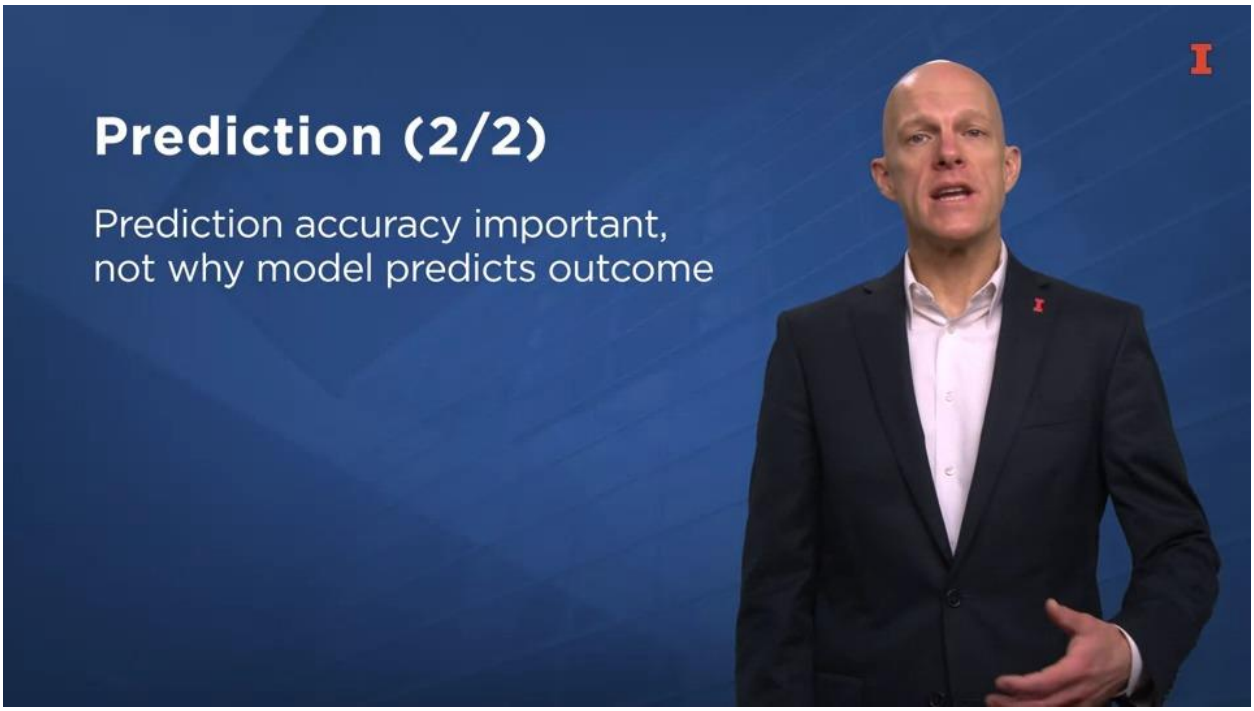
Lesson 2-1.1 Inference, Prediction, and Experimentation



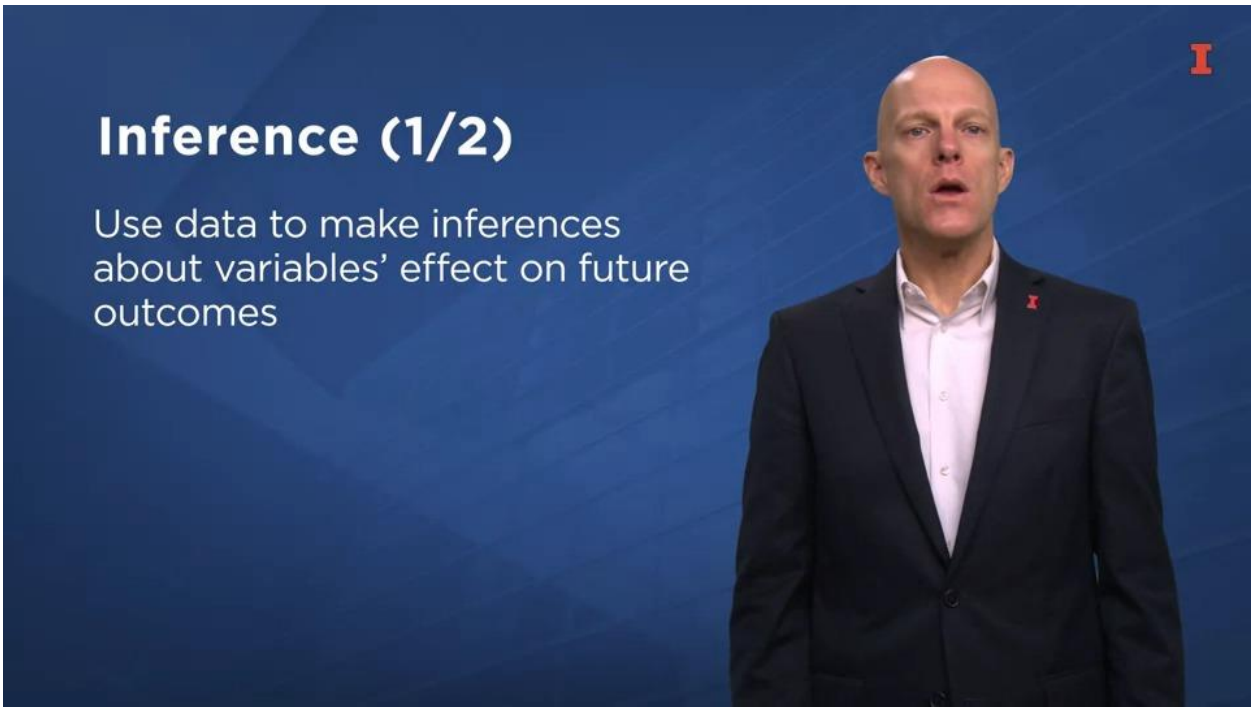
Machine learning uses statistical models to gather information from your data. The business analysts can then use that information to improve their business. There are three primary categories into which we group machine learning insights. In other words, machine learning helps us do the following three things. One, prediction and predictive modeling, generally what will happen? Two inference, generally why does something happen? Then three, experimentation. Generally, does changing something make a difference? I'll speak of each of these categories in turn and describe some examples of each.



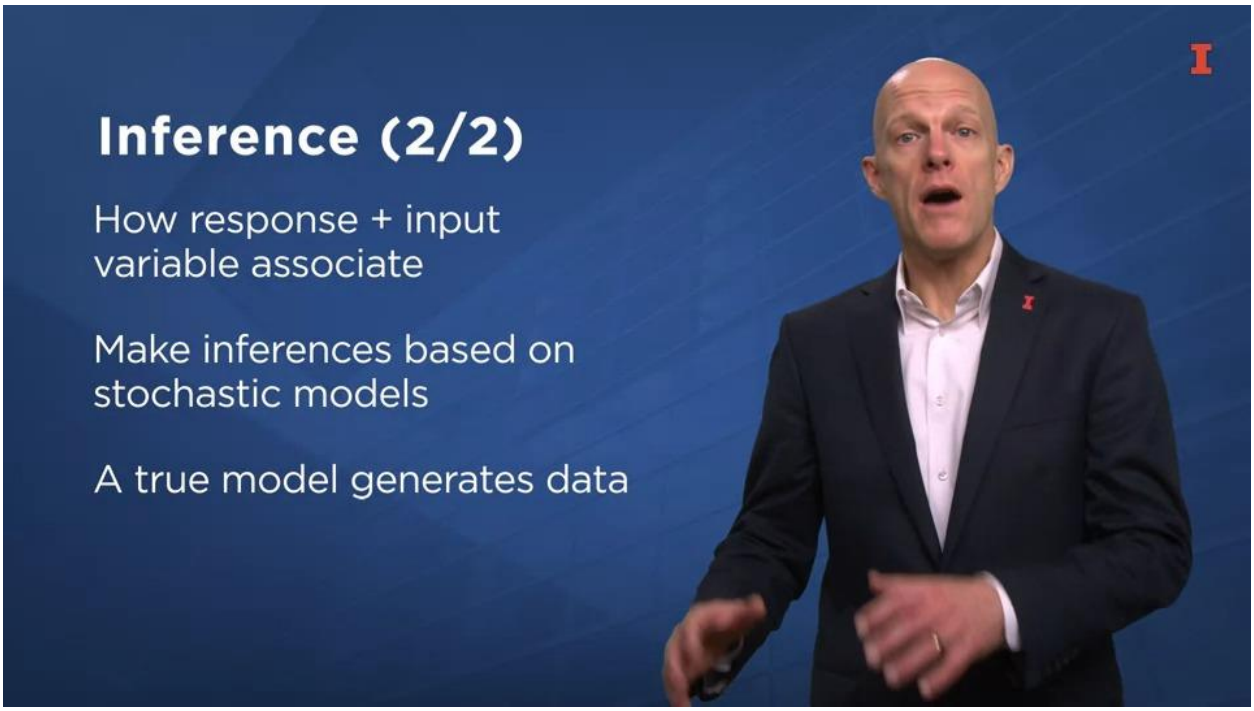
Prediction is one important use of machine learning. With prediction, you're asking machine learning to look at the existing data and then to predict an outcome from new input data. This prediction may be about a numerical value. For example, based upon past data, how much do I predict sales will be next quarter? The prediction maybe about which level of a class I expect new data to be from. For example, based on the data I have, will this new information belong to a fraudulent or a non fraudulent class or transaction? The prediction may also be about what group the data belongs to. For example, based upon the data I've analyzed, a new data example or observation might be from a customer who will likely become a loyalty customer versus one who will not.



If we are concerned only about prediction, we're not concerned about why the machine learning model predicts a certain outcome, only with how accurate the machine learning model is that prediction. Thus, we are indifferent about the underlying mechanism generating the prediction. We don't care why it predicts accurately, we just want to maximize accurate prediction. Thus, if we predict sales for the next quarter for a certain retail store, we're not concerned with why sales will be a certain number, but rather only whether the predicted number will be accurate.



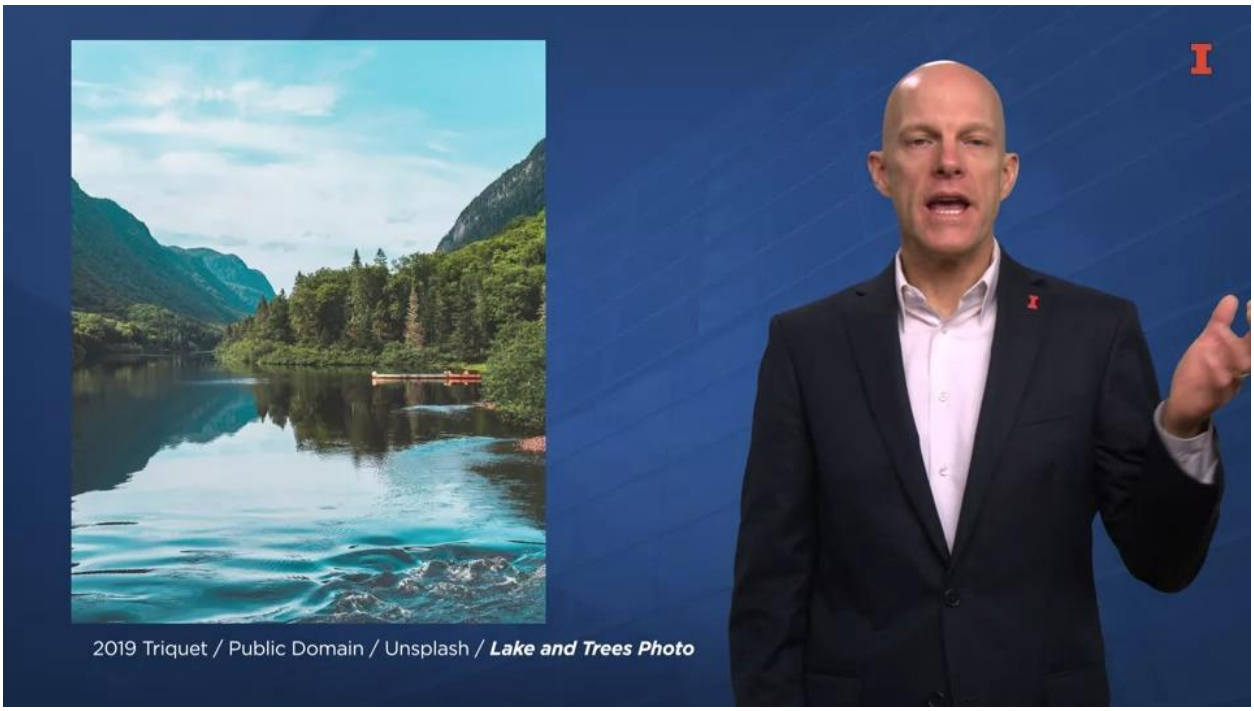
But a second goal of machine learning is to understand why something happens or why a certain outcome occurs. Under this paradigm, we're seeking to use the data we have to make inferences about whether the variables we are examining will affect future outcomes that we're interested in. Thus, we are concerned with which variables in our data affect a target value of interest. Additionally, we are concerned with how these variables affect this outcome variable.



We're seeking to develop stochastic models which fit the data and then to make inferences about the data generating mechanism based on the structure of those models. We're thus assuming that there's a true model generating the data. We're concerned about the cause of the effects we see in the data. For example, instead of predicting next quarter's sales, we might be interested in what caused that quarter's sales and how our input variables affected those sales. Perhaps a percentage of our sales that come from a certain product negatively affect sales. That is, the more of that product that we sell, the lower sales actually are. This might happen if the sale of this product reduces the sale of another more profitable product.

Of course, frequently we care about both prediction and inference. That is, we care about predicting future sales, for example, and we care about what variables affect future sales. As another example, we might use machine learning to predict the selling price of a house based upon that house's location, number of bedrooms, square footage,

color of the front door,

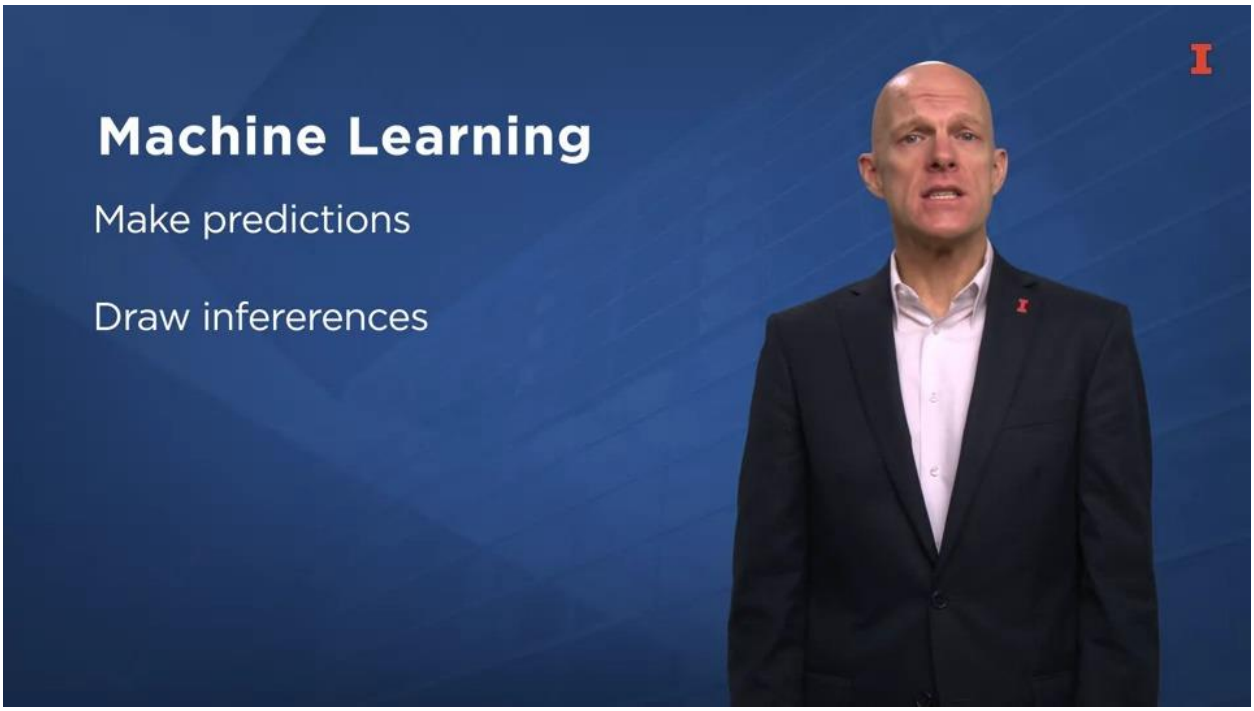


lakeside location, etcetera.

In addition, we might want to know that the location of the house next to a loud highway decreases the price of the house.

The color of the front door does not significantly affect the price of the house

and the location on a lake increases the price of the house.



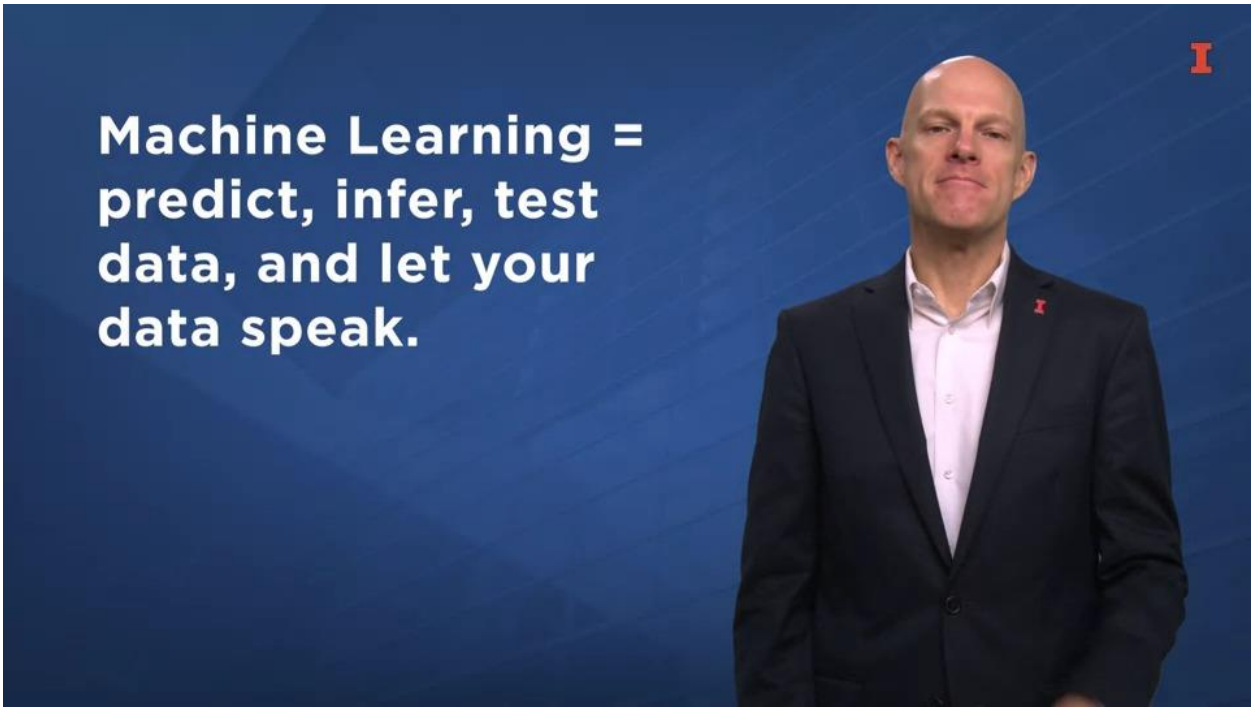
The magic of statistics allow us to address these questions and more. Understanding the ability of machine learning to make predictions and draw inferences helps us understand the usefulness of machine learning.

Finally, these two categories highlight the need to use data to capture valuable business insight. It's not enough to have data or even to understand our data. Our goal should be to use our data to build better businesses.

Thus, we should use tools like Machine Learning to experiment, be creative, and explore. Experimentation is a final, important use of machine learning.

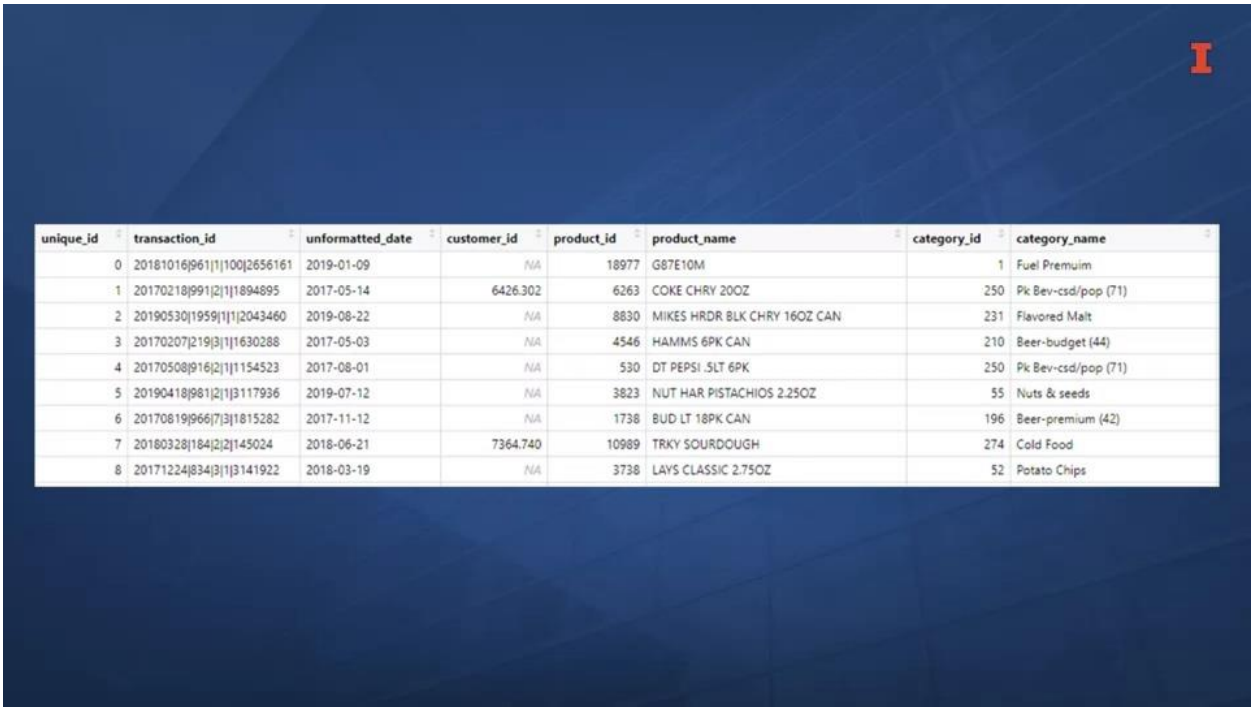
For example, a website retailer could test whether a certain change in the websites or treatments increases or decreases traffic in that part of the website. Thus, the manager leaves the website alone for some people, but then changes it for others and then uses machine learning to determine whether this changed, increased or decreased traffic on the website. This is often called A/B testing since the A group does not receive the treatment, but the B group does. A is then compared to B using machine learning to see if the treatment had a successful affect.

Stephan Tom Key and others argue that companies should be actively building a culture of experimentation. He believes that data trumps opinions and that opinions should be supported by data. Again, machine learning makes it possible to experiment and to know if those experiments succeed or fail.



In some, machine learning gives you the ability to predict, infer, and test and to let your data speak.

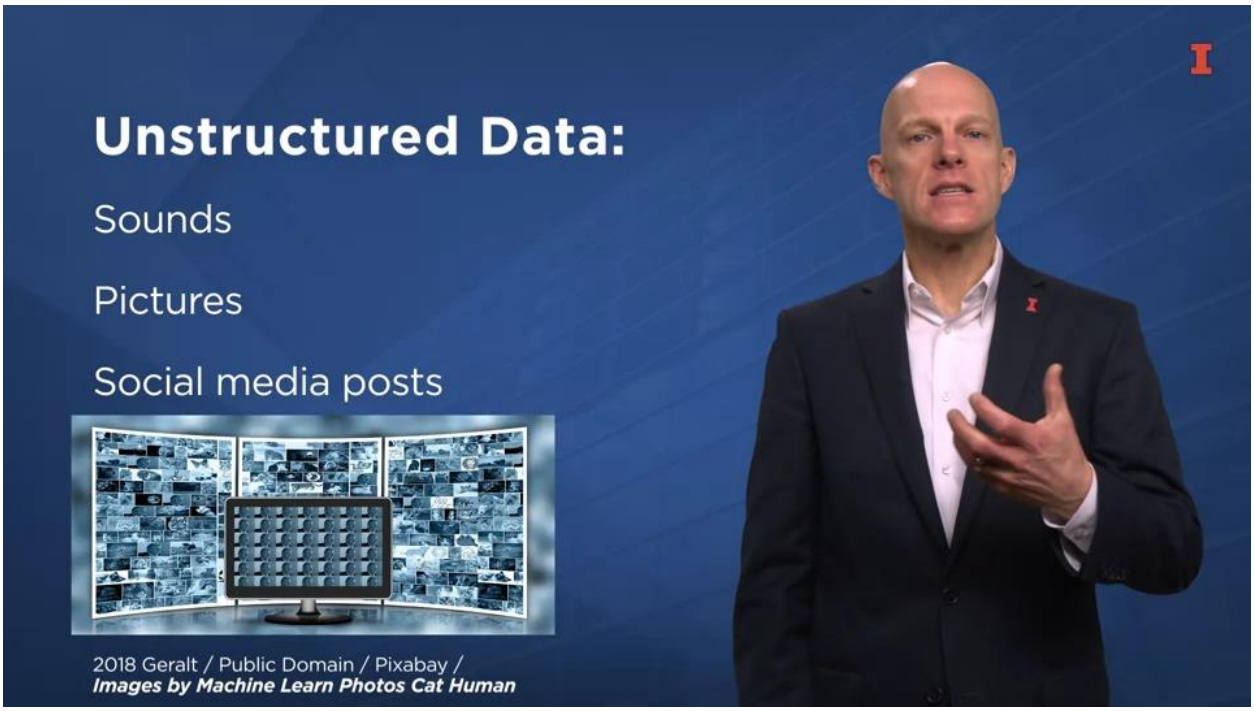
Lesson 2-1.2 Categories of ML Models, Part 1, Types of Data and Terms



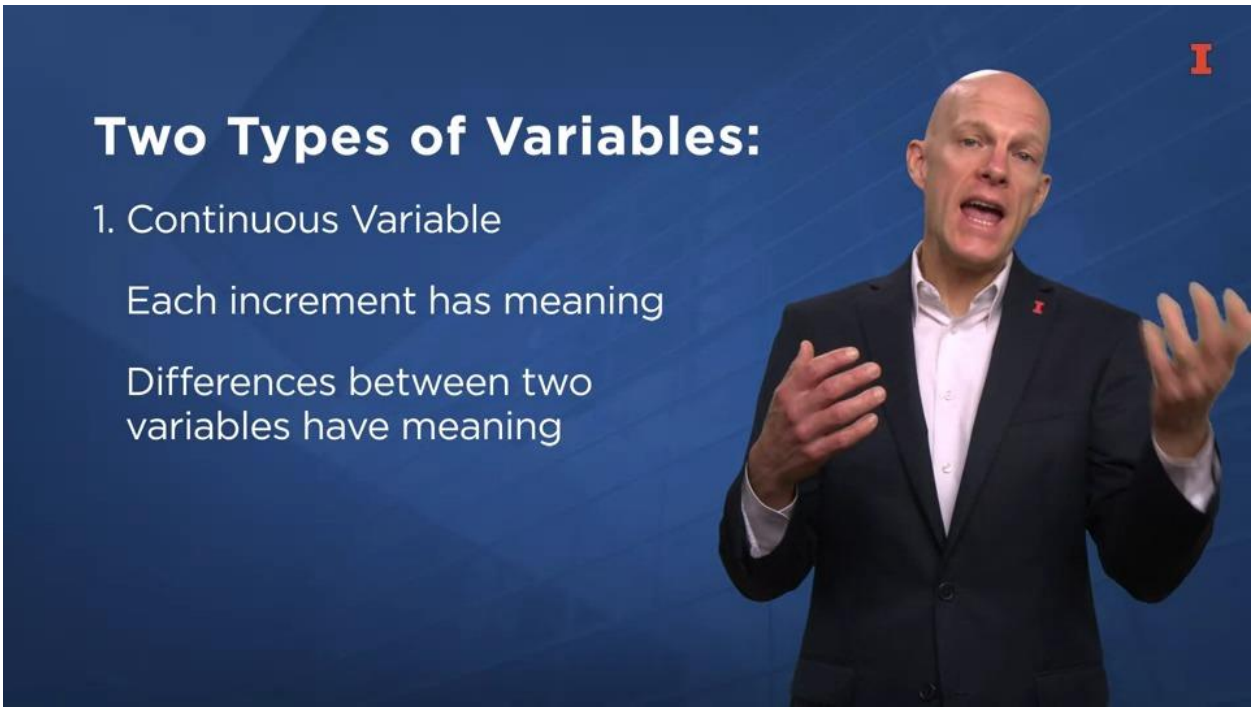
unique_id	transaction_id	unformatted_date	customer_id	product_id	product_name	category_id	category_name
0	20181016|961|1|100|2656161	2019-01-09	NA	18977	G87E10M	1	Fuel Premuim
1	20170218|991|2|1|1894895	2017-05-14	6426.302	6263	COKE CHRY 20OZ	250	Pk Bev-csd/pop (71)
2	20190530|1959|1|1|2043460	2019-08-22	NA	8830	MIKES HRDR BLK CHRY 16OZ CAN	231	Flavored Malt
3	20170207|219|3|1|1630288	2017-05-03	NA	4546	HAMMS 6PK CAN	210	Beer-budget (44)
4	20170508|916|2|1|1154523	2017-08-01	NA	530	DT PEPSI .5LT 6PK	250	Pk Bev-csd/pop (71)
5	20190418|981|2|1|3117936	2019-07-12	NA	3823	NUT HAR PISTACHIOS 2.25OZ	55	Nuts & seeds
6	20170819|966|7|3|1815282	2017-11-12	NA	1738	BUD LT 18PK CAN	196	Beer-premium (42)
7	20180328|184|2|2|145024	2018-06-21	7364.740	10989	TRKY SOURDOUGH	274	Cold Food
8	20171224|834|3|1|3141922	2018-03-19	NA	3738	LAYS CLASSIC 2.75OZ	52	Potato Chips

Our goal in this video is to look at all of machine learning, the whole landscape and build a foundation that will help you as you move forward and discuss individual algorithms in more detail. To do this, we'll need to define some terms. Our first step in building this foundation or this framework, is to understand important terms and phrases. Thus, we will discuss terms used to describe the typical dataset used for machine learning and define many aspects of it. Next, we'll introduce several different categories of machine learning algorithms. Finally, we'll introduce some of the key machine learning algorithms themselves. Let's start building our framework for machine learning. In order to extract information from data, machine learning algorithms need data, and data is why we're all here today. Broadly, there are two categories of data that we'll talk about in machine learning; a structured data and unstructured data.

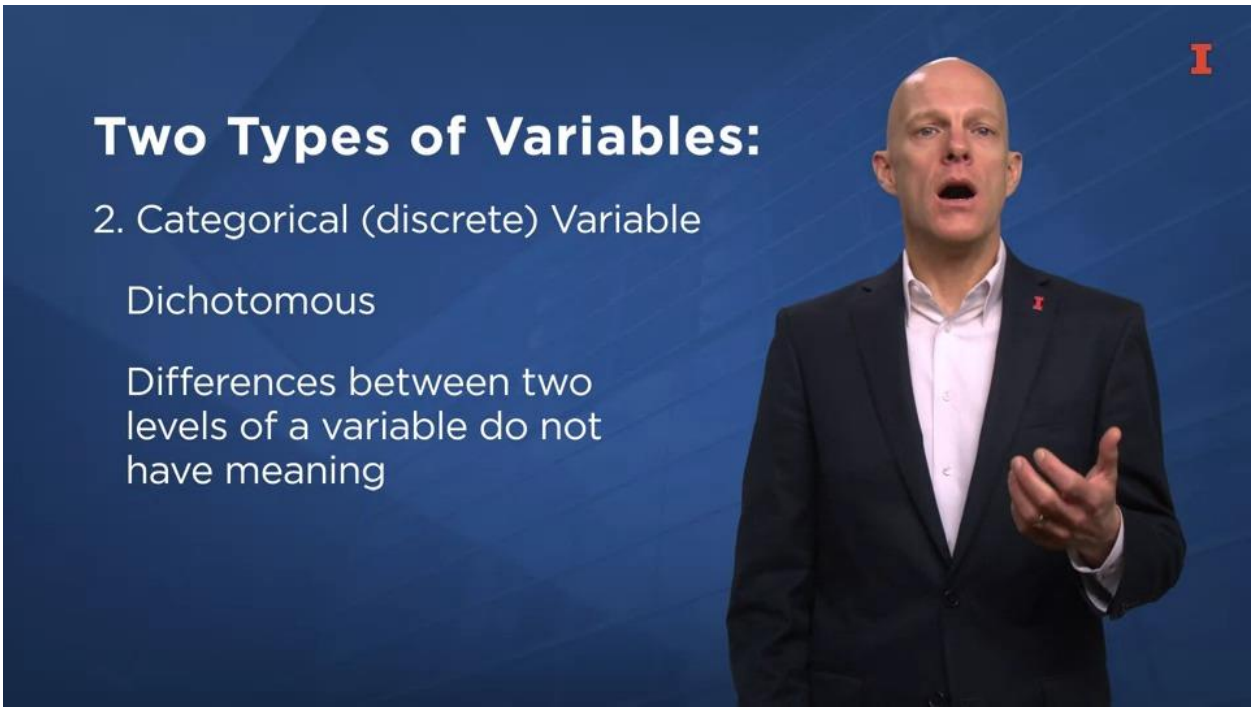
In this class, we're most concerned with structured data. Structured data is where each example has the same features. These features are organized in a form that the computer can understand easily. Thus, you can think of this as a spreadsheets or a matrix.



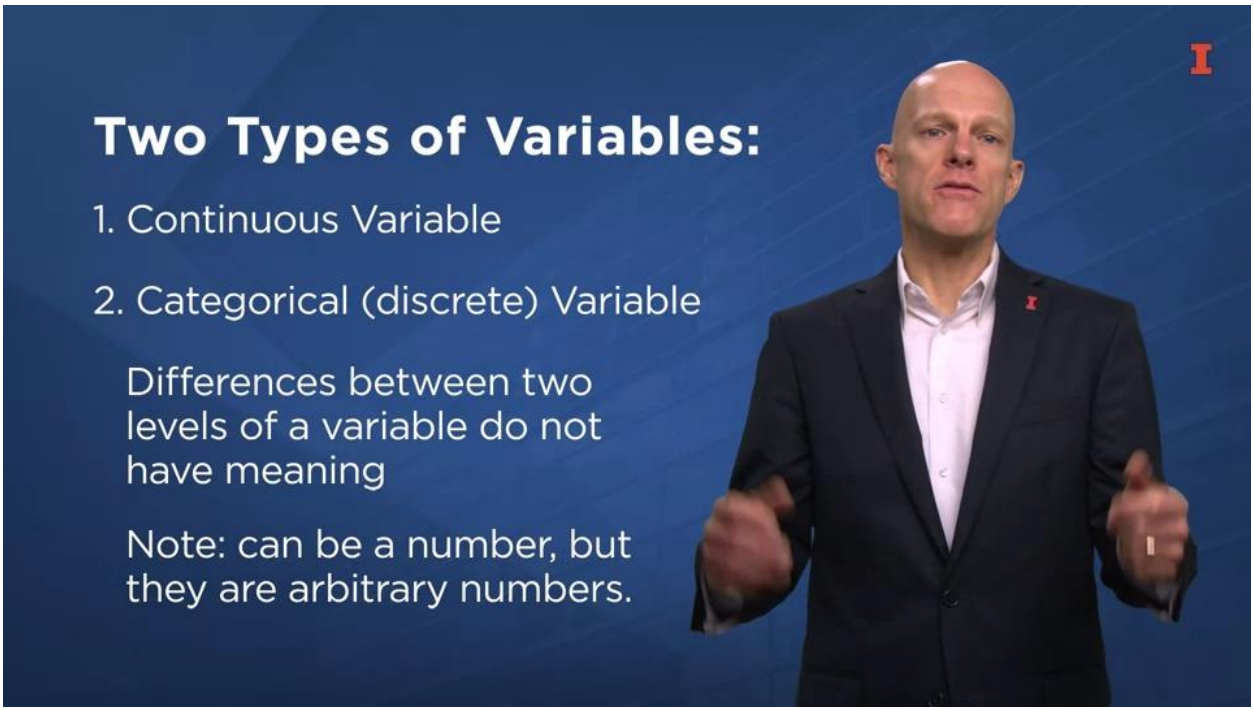
Each example is a row and each feature is a column. The second type of data is unstructured data. These data are not structured into spreadsheets. They could be sounds, pictures, and social media posts. In order to use these data will need to be structured in some way.



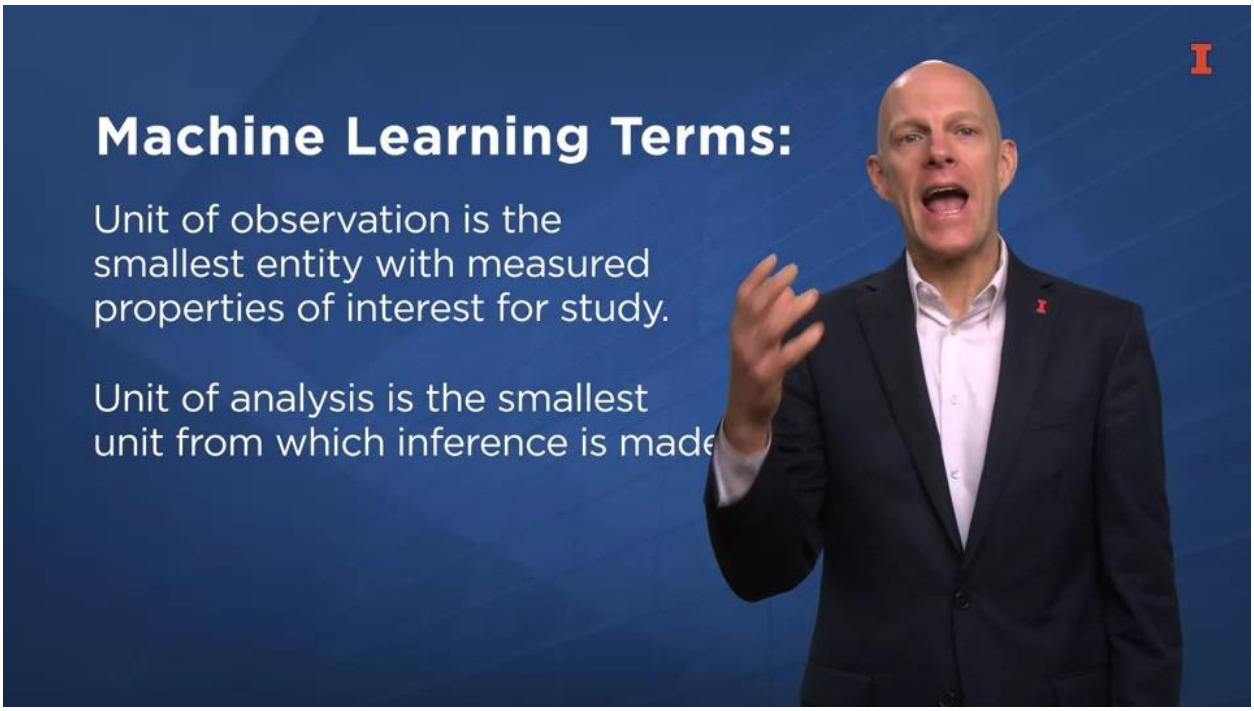
Again, in this class, we will focus on structured data in the form of a table or matrix or a spreadsheet. Within a spreadsheet, there are two broad categories of data. One, quantitative variables and two qualitative or categorical variables. Now a quantitative or continuous variable is a number where each increments and the number higher or lower has meaning. Further, the difference between two entries, for example, 10 and 12 has meaning.



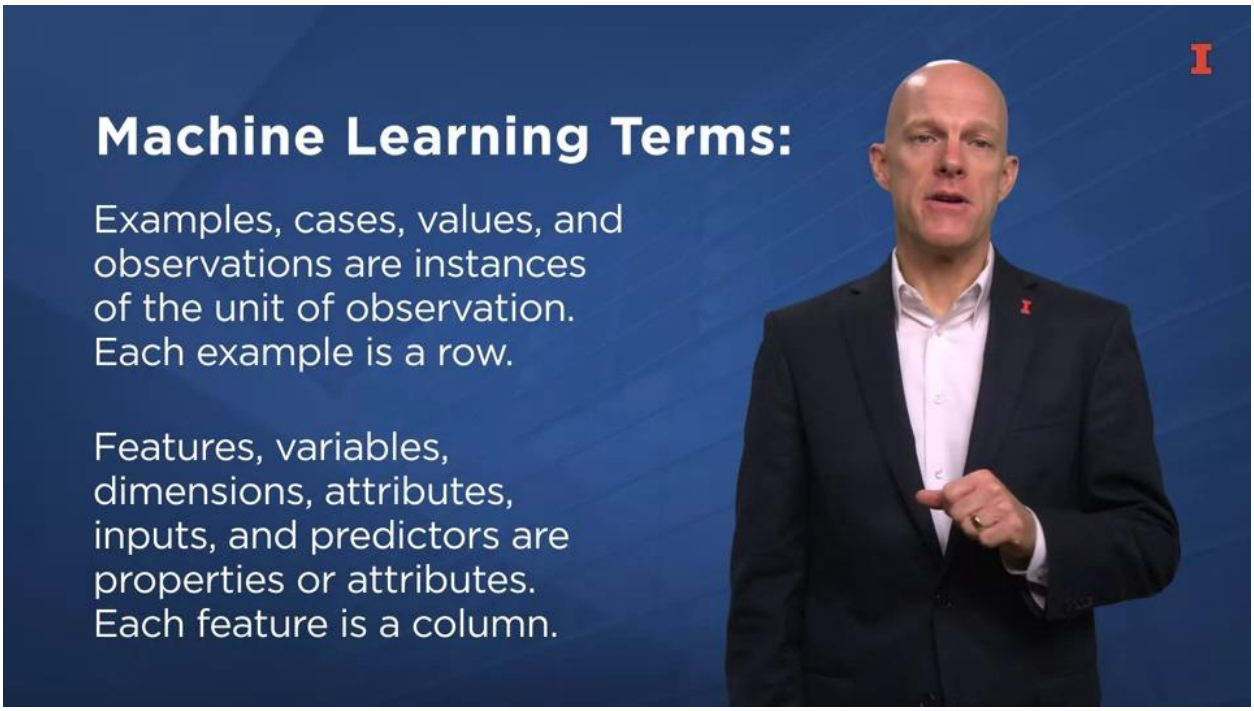
For example, you can think of revenue recorded for a product. A $10 product has meaning and that is different from a $10.50 product. Also, that 50 cents difference between those two has meaning as well. On the other hand, there's another category of variable for which in-between measurements between two categories are not meaningful. These variables are thus just categories, and we often call them categorical variables or discrete variables. If there are just two categories like yes or no, true or false, we'll call them dichotomous. A good example of this is a feature that lists cities in the United States; Burlington and Waterloo. Two different cities, for example, are categories that have no order. They're categories or classes because the difference between these two means nothing.



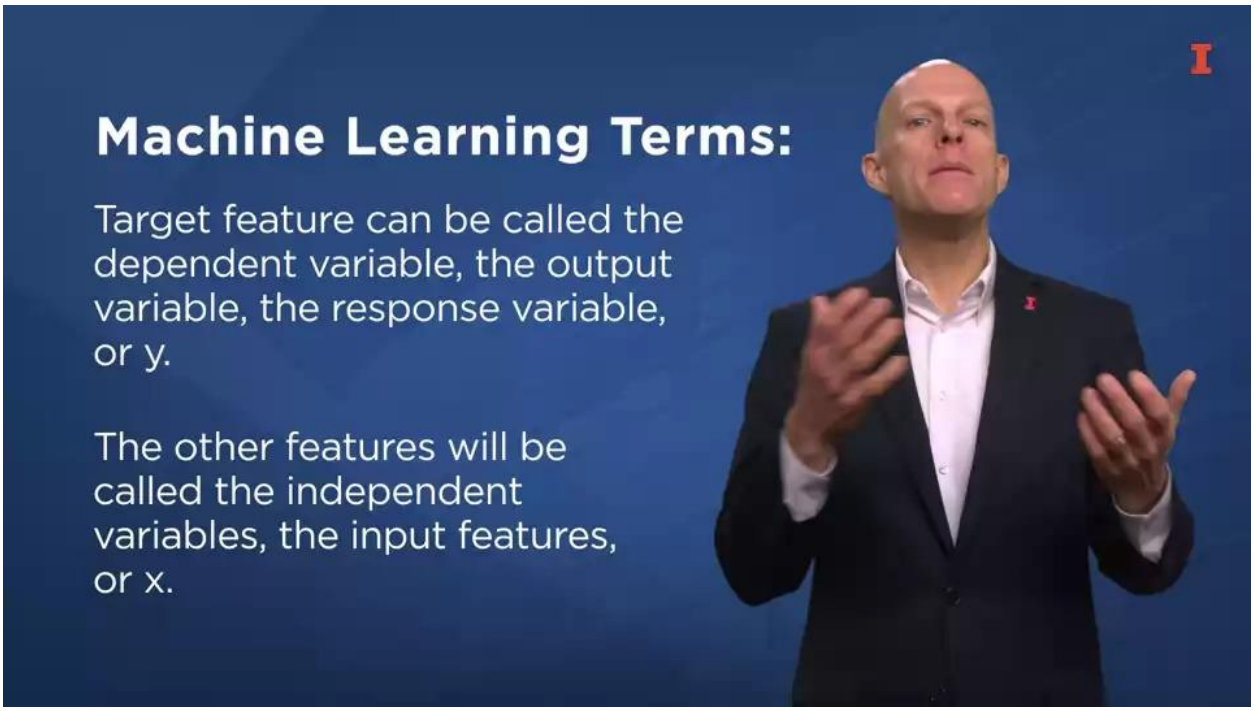
That is half of Burlington, doesn't mean anything in this context, and R would store this as a character. Now let's make one more important point. What if our column of cities did not have names in it, like Burlington and Waterloo, but instead, replace those names with a number with this column, then be categorical or continuous? This is an important question because it changes how the machine it should treat and process that variable. It's important that we get this right. It might be a bit confusing because this is clearly a number, but the correct answer here is that this is a categorical variable still. The numbers here are just arbitrary numbers that represent the cities and nothing else. Thus, even though they're numbers, the difference between two cities, in this case two numbers is still not meaningful.



Now to be successful at machine learning, we need to speak the language of machine learning. That is, we need to understand the terms that are routinely used. Thus, let's continue to explore the terms of machine learning. Please be warned that different people call these same things different names. Machine learning is not owned by any one academic discipline. It's part of statistics, part of computer science, and a bit of lots of other disciplines. Thus, the different disciplines give these things different names. I'll do my best to give you the most common names. A unit of observation is the smallest entity with measured properties of interests for study. Thus, for example, one product sold in a transaction could be a unit of observation. Next, a unit of analysis is the smallest unit from which inference is made. Thus, while one product from a transaction may be the smallest unit of observation, you may be more interested in aggregated sales over the course of a month. Thus, the unit of analysis might be the monthly sales in a product category.



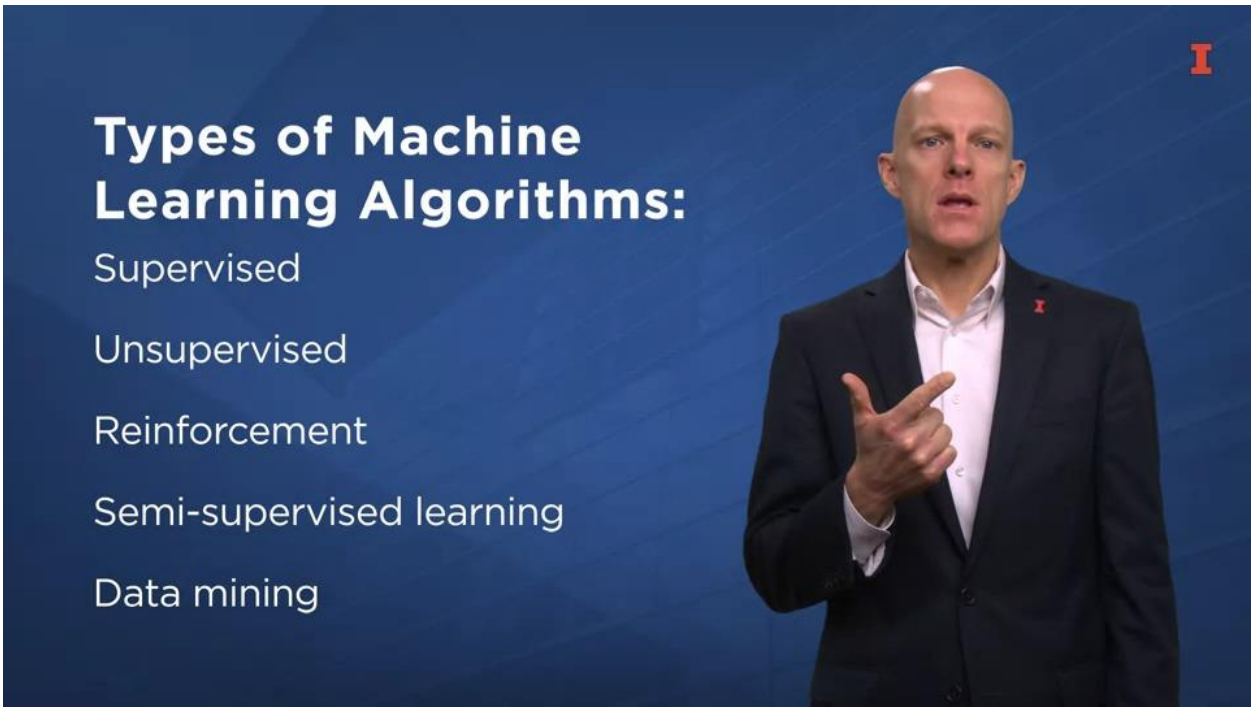
Next, examples, cases, values, and observations are instances of the unit of observation. In our case, since we're using structured data, this is a matrix or a spreadsheet, and each example is a row. Next, features, variables, dimensions, attributes, inputs, and predictors are properties or attributes of examples. Again, in our case, using matrix data, each feature would be a column. For example, if we're examining products sold in individual transactions, the feature could be the product itself, time of sale, location of sale, whether a customer had a loyalty card and etc.



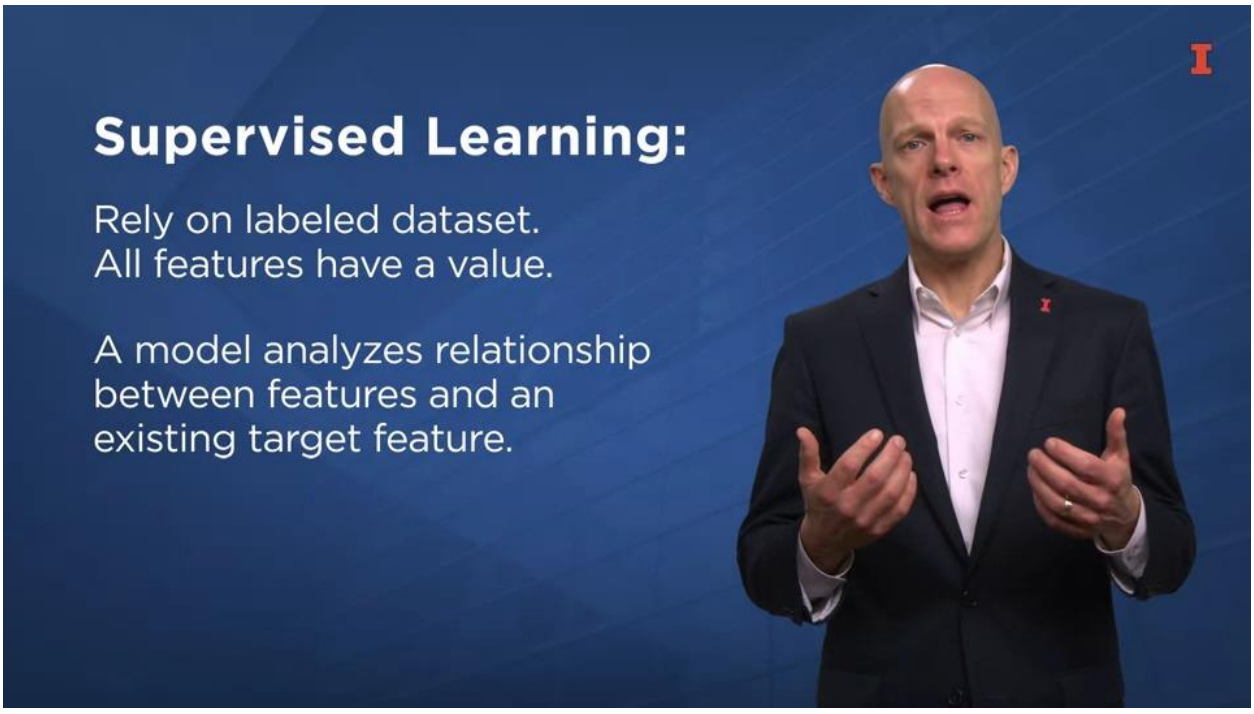
Frequently in machine learning, we're examining the effect of multiple feature of variables on one target variable. We want to predict that target variable or examine how the other features affect the target feature. When this is the case, the target feature can be called the dependent variable, the output variable, the sponsor variable or y. The other features will then be called the independent variables, the input variables or x. For example, we might want to predict next quarter's revenue for a store that we manage. Thus, the target or dependent variable is next quarter's revenue and the independent variables or the input variables, could be current revenue, direct costs, costs of goods sold, seasonal demand, etc.

Lesson 2-1.3 Categories of ML Models, Part 2, Categories of Algos

Next, in our effort to build a framework for understanding machine learning, let's explore the many different types of learning algorithms that exist. It would be really convenient and this class would be much shorter if there were one algorithm that would work in every situation. Unfortunately, every situation for which we can use machine learning is different since no two datasets are the same. Thus, as D. H. Wolpert says, there's no free lunch in machine learning. There is no one model that works best for all possible situations. There are generally three distinct categories of machine learning algorithms:



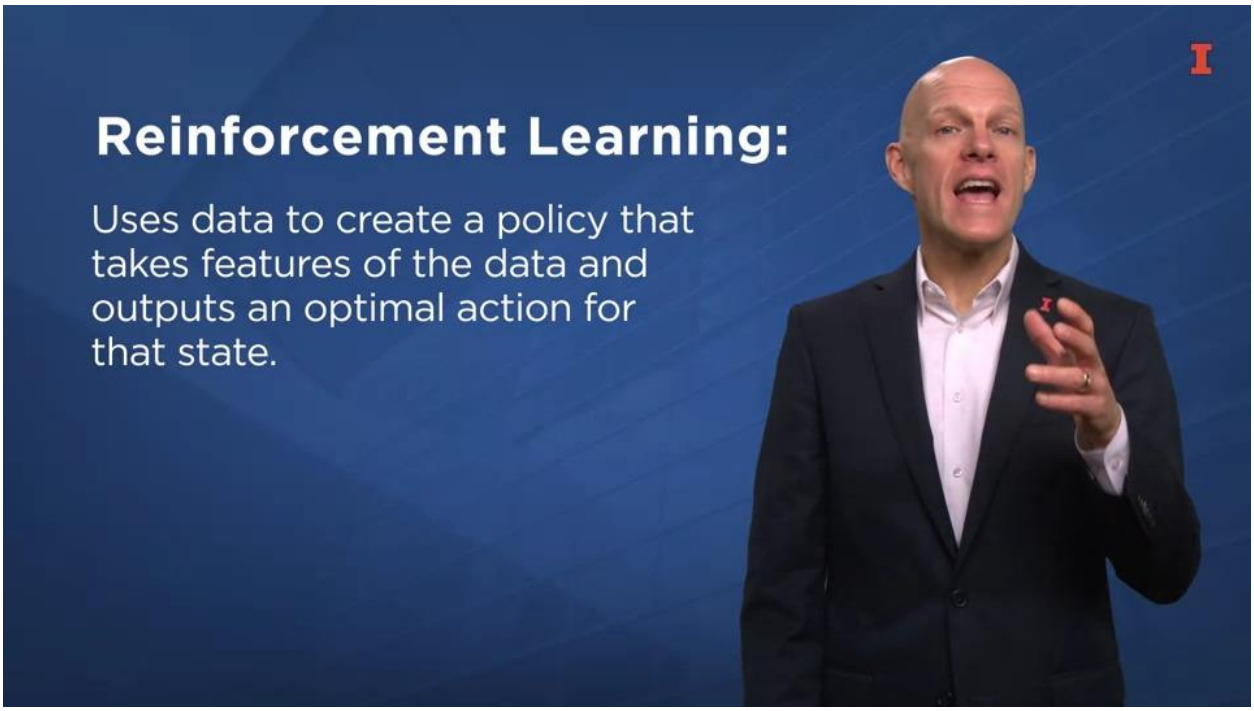
supervised, unsupervised, and reinforcement. In addition to these three main categories, we'll also talk about semi-supervised learning and also data mining.



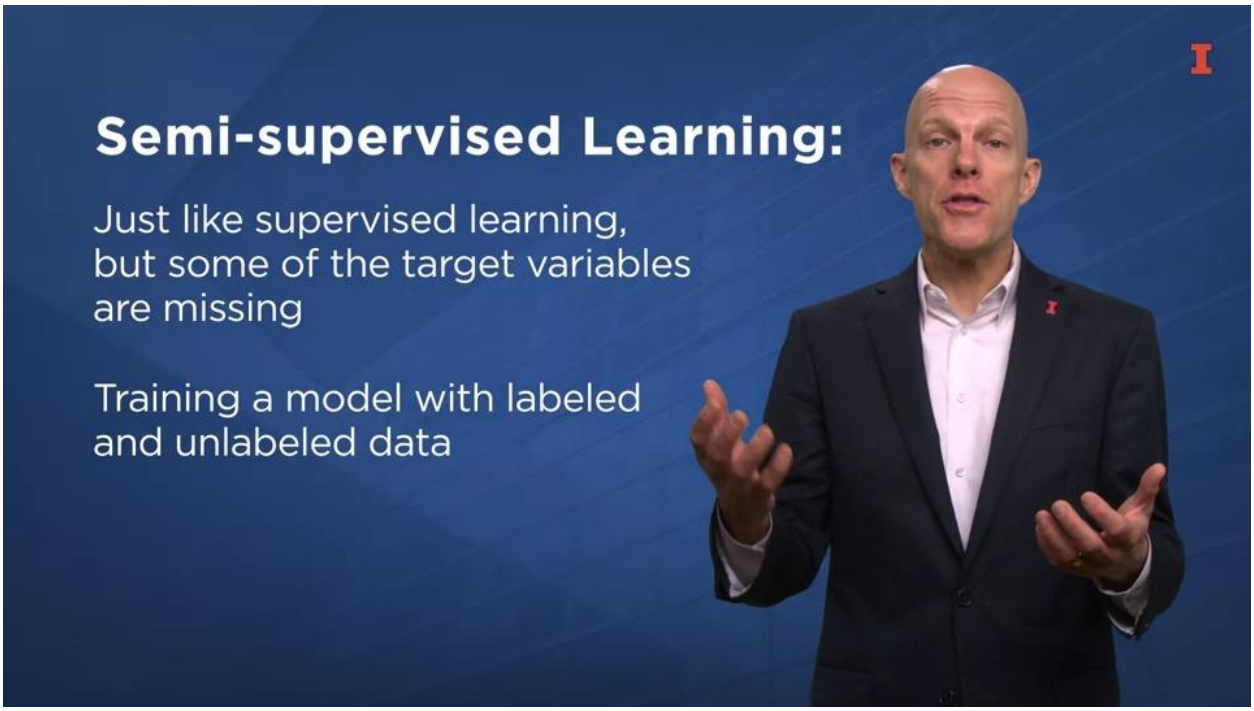
Supervised learning then is characterized as having a labeled dataset. That means that all features, including the feature of interest are labeled, and that is, they all have a value. Thus, a supervised learning algorithm uses data to create a model that finds a combination of features that results in a target feature or label, which can be a number or a category or class.

Let's state this in a slightly different and maybe more helpful way. A supervised learning algorithm uses a model to analyze and decipher the relationship between features and an existing target feature. For example, regression is a supervised learning algorithm. They could use features such as revenue last quarter, revenue last year, forecasted weather, etc, to predict the target feature of revenue for the next quarter. Next, a classification algorithm is a supervised algorithm that could use features such as time of day, amount of purchase, location of purchase, etc, to predict a label for the target variable of whether, for example, a purchase is fraudulent or not. Unsupervised learning is characterized by a dataset of unlabeled examples, that is, features without a target feature. The unsupervised algorithm transforms the features either into another vector as in dimensionality reduction, or into a value as in clustering.

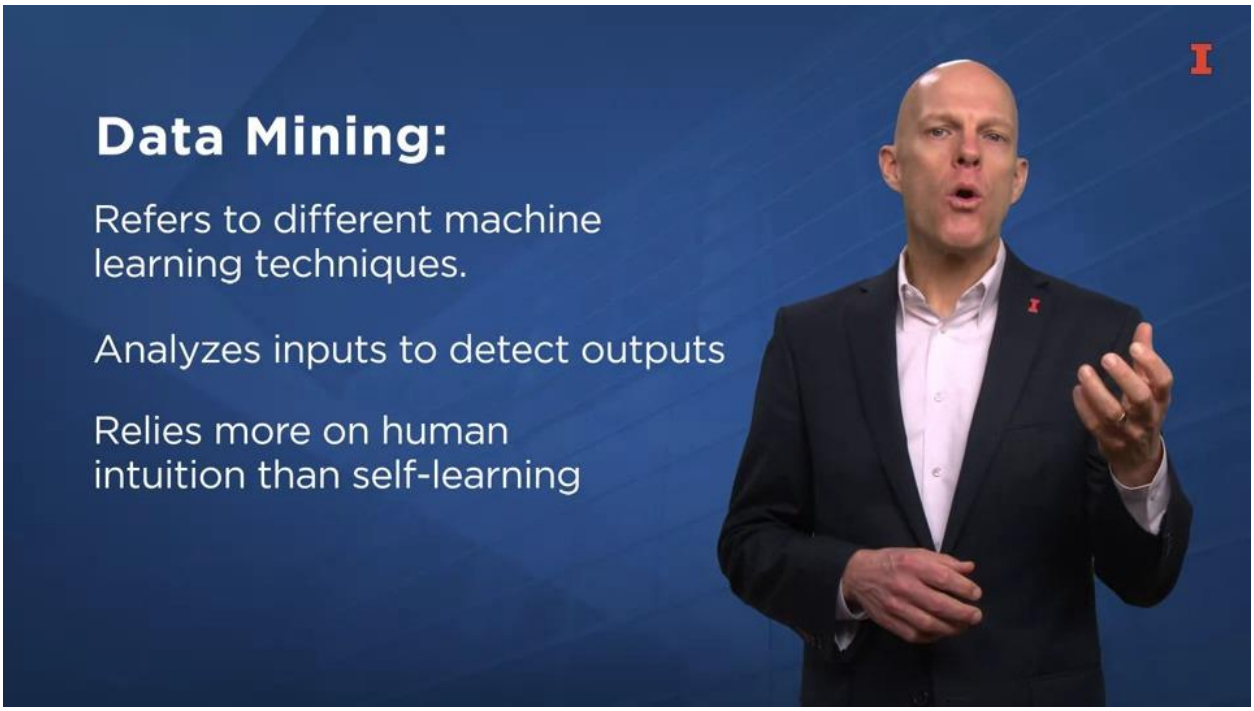
Let's put this into different, perhaps easier terms. Since only input variables are present and no targets or output variable exist, these algorithms analyzes relationships between input variables and uncover hidden patterns that can be extracted to create new labels for output variables. For example, in a clustering algorithm, you take features such as an item purchased, time of a purchase, etc, to cluster customers into groups. For example, the model might determine, based upon convenience store purchases, that a customer belongs to a fuel group, or a fountain soda group, or a weekend alcohol group, or a daily lottery group.



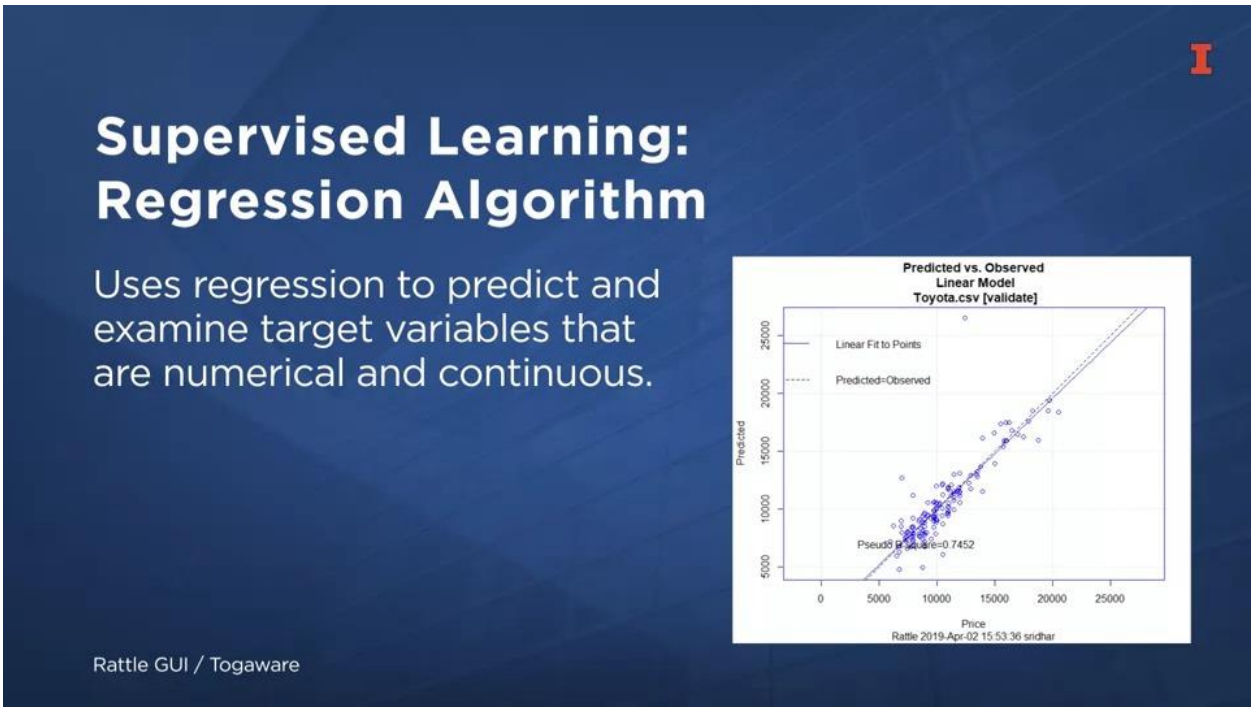
Next, reinforcement learning uses data to create a policy that takes features of the data and outputs an optimal action for that state. For example, think of learning to play a video game.



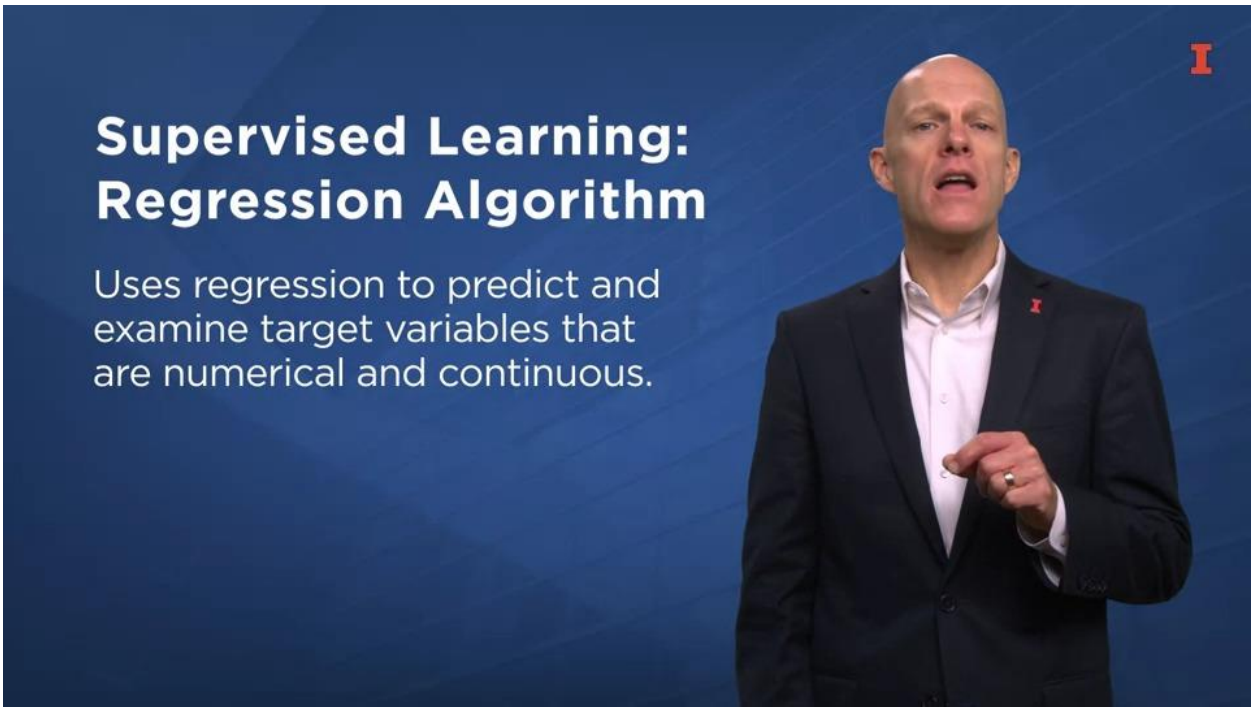
You want to maximize the outcome of success and at each stage, you learn more and use that learning to reinforce and influence subsequent gameplay. For example, reinforcement learning can help a car learn not to crash and can help a computer learning from scratch how to play chess. Next, semi-supervised is just like supervised learning, but some of the target variables are missing. Thus, you're training a model with labeled and unlabeled data. This can happen when labeling the data manually all the way through. It's too costly. Thus, you could build a model with labeled cases and then use that same model to label the remaining cases.



Finally, data mining is frequently used to refer to different machine learning techniques. Thus, many sources see data mining as the very same thing as machine learning. If we're trying to distinguish data mining from machine learning, we would say that machine learning analyzes inputs to detect outputs, but relies more on direct human intuition than on self-learning.



Finally, let's mention just a few of the key algorithms in supervised and unsupervised learning. Supervised learning uses regression to predict and examine target variables that are numerical or continuous. An example of a regression problem, that is, a business problem for which a regression algorithm could provide insight, is investigating the quarterly sales by store of a set of convenience stores.

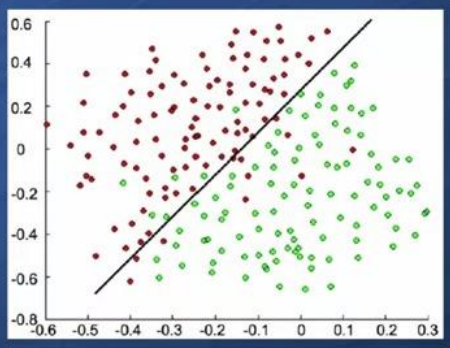


A regression model could use input variables such as store location, past sales, and current costs to predict future sales. This model would allow the analyst to examine the effect of these input variables on the output variable, quarterly sales.

Supervised Learning: Classification Algorithms

Includes logistic regression, decision trees, random forests, and k-nearest neighbors.

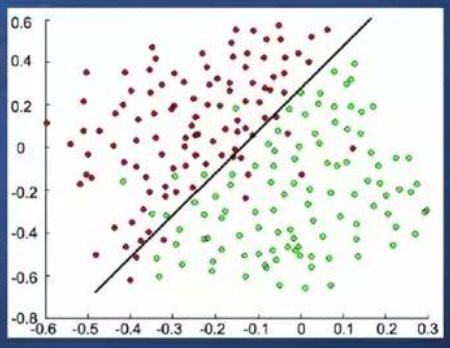
They predict and examine target variables that are categorical.



It would also be useful to predict next quarter sales, which is very valuable for forecasting and resource planning. Notice that the target feature in regression is a continuous variable. On the other hand, classification algorithms such as logistic regression, decision trees, random forests, and k-nearest neighbors, predict and examine target variables that are categorical.

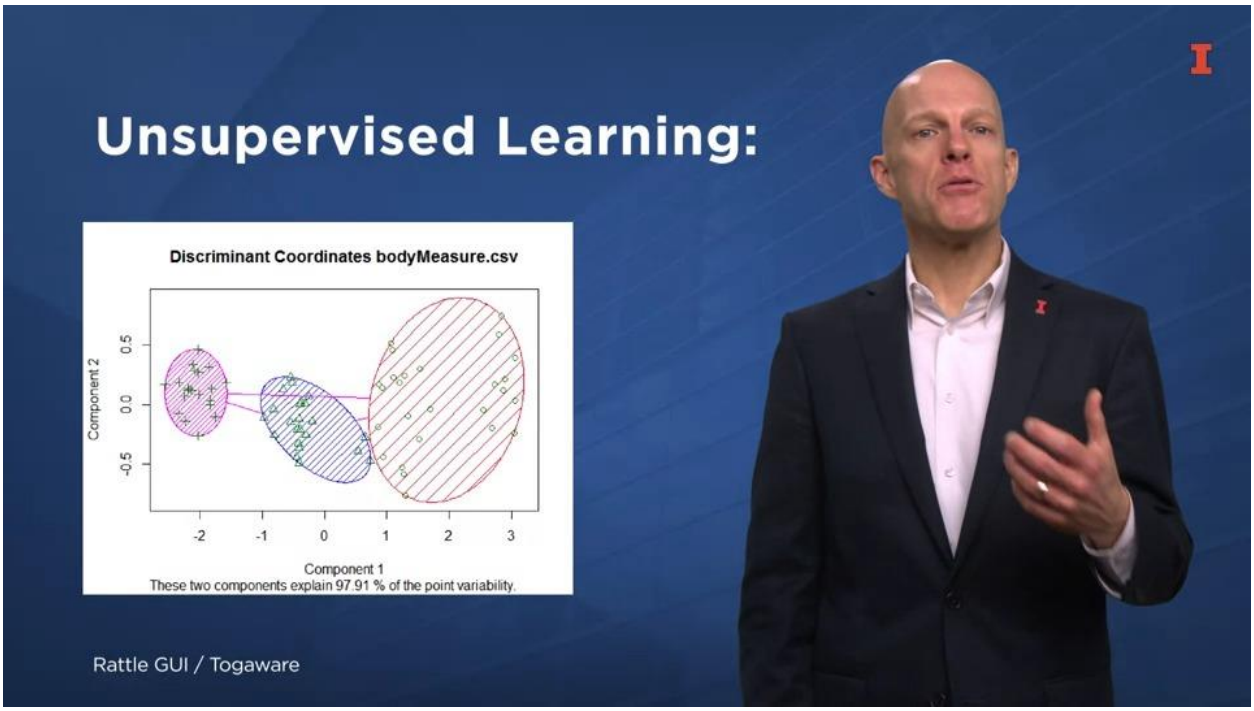
Supervised Learning: Classification Algorithms

They create decision boundaries that separate target variables into difference classes.



They create decision boundaries that separate target variables into different classes.

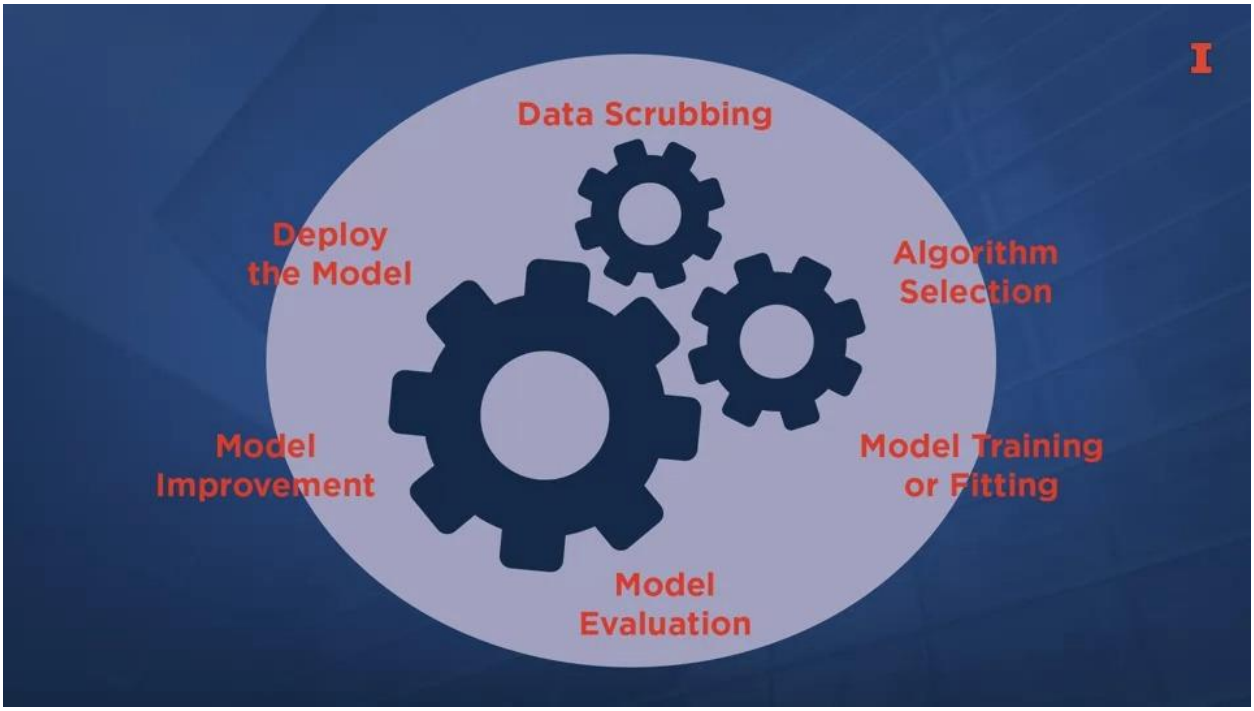
An example of a classification problem is a company that wants to predict whether a purchase will be from a loyalty customer or a non-loyalty customer. A logistic regression algorithm could use a model to take the input independent variables and predict whether the output dependent variable is a loyalty customer or not. This model would be helpful because it can be used to predict what type of product is often purchased by a loyalty customer, then that product could be used to promote the loyalty program, particularly in locations that have poor loyalty system adoption. Next, in unsupervised learning, clustering, k-means clustering, density-based clustering, group observations together based upon their features. Clustering algorithms, unlike regression and classification, work on only input variables, often called unlabeled data, to put different observations into groups based upon those variables.



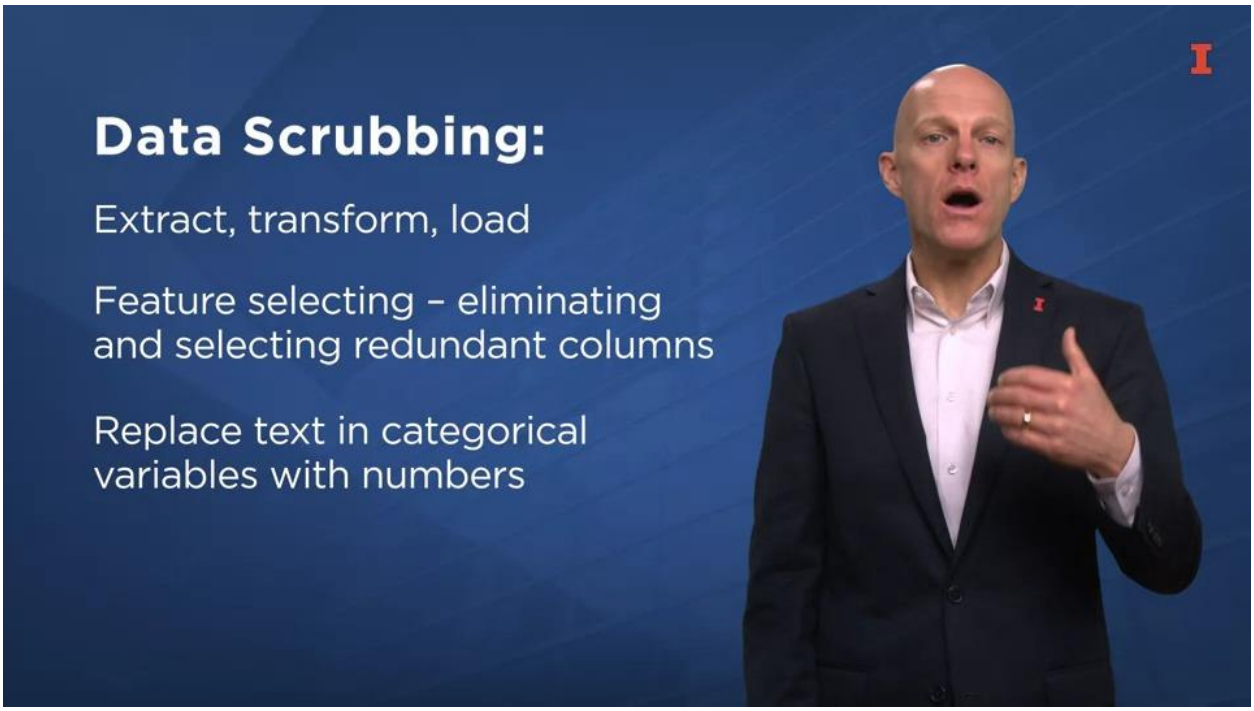
A clustering problem could be that a convenience store business wants to categorize its customers into different groups, such as a gasoline group, a morning coffee and breakfast group, and the lunch group. Being able to identify customers in this way could lead to targeted promotions and discounts to increase traffic and increase the size of purchases of each cluster.

Here's a final graphic that includes a sample of the whole landscape of machine learning.

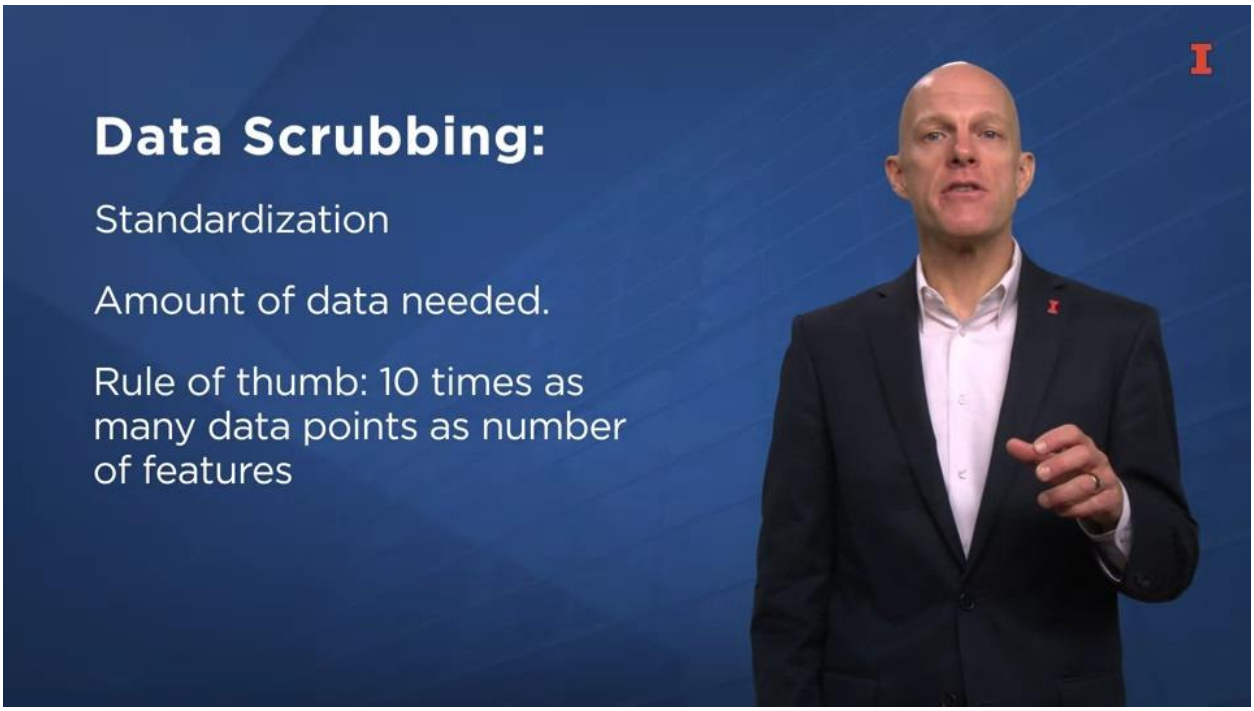
Lesson 2-1.4 How Machine Learning Works in General



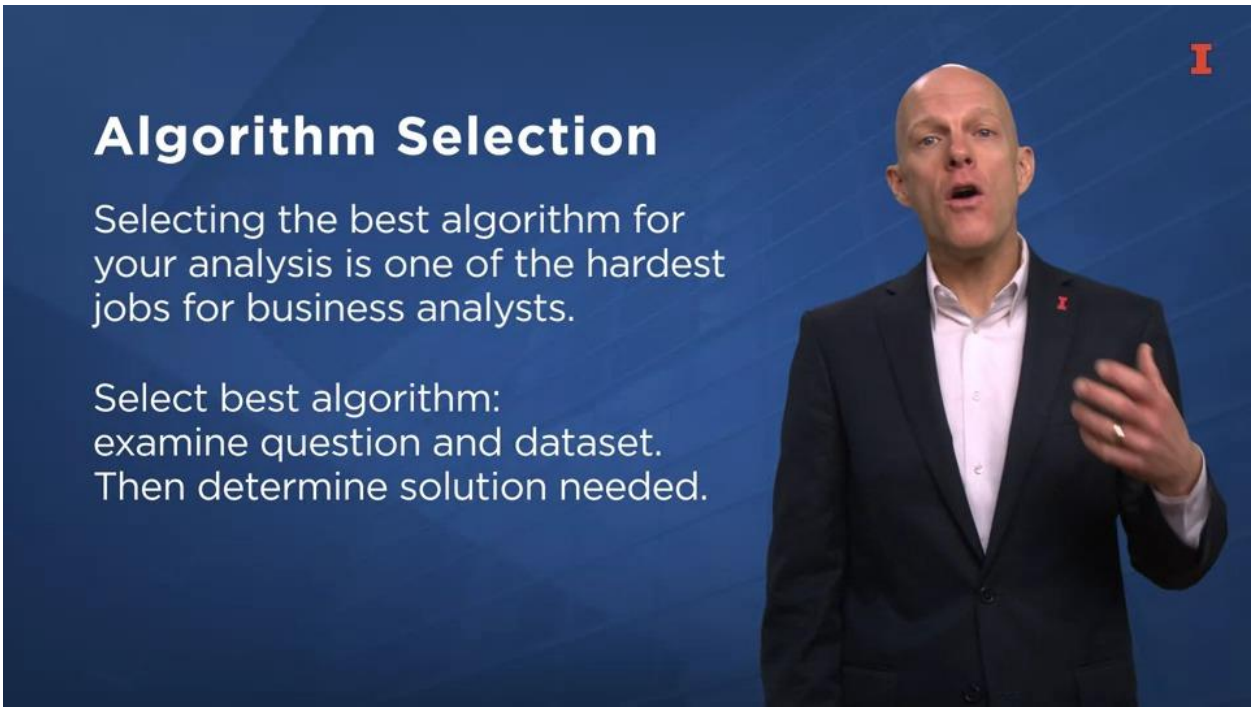
In this video, we'll discuss the basic level, how machine learning algorithms and models work. Now it's important to keep in mind that although there are many different machine learning models, options for those models called hyperparameters and questions that can be addressed with machine learning, all machine learning algorithms follow the same basic process. They take data and identify patterns that form the basis for further action. There's six general steps necessary to use machine learning. These are the following: one, data scrubbing, two, algorithm selection, three, model training or fitting, four, model evaluation, five, model improvement, and six, deploy the model. I'll talk about each of these in turn.



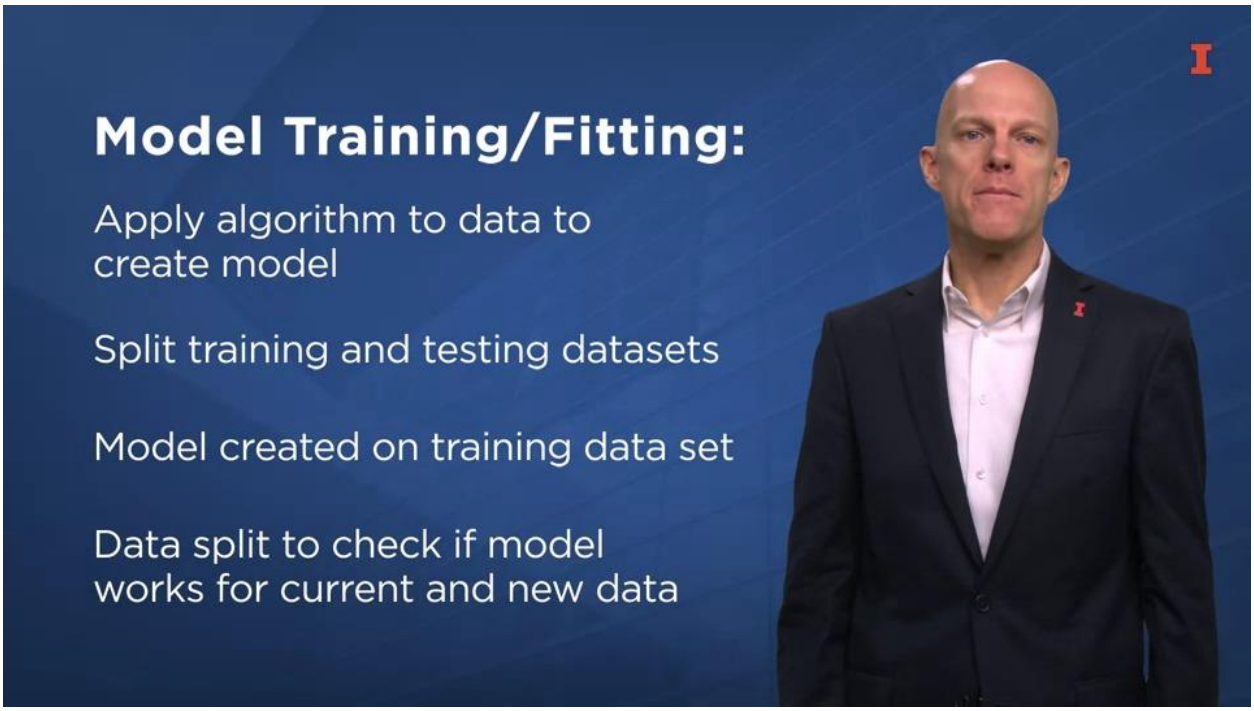
The first step in running a machine learning algorithm is getting, loading, transforming, and cleaning data. After the initial ETL or extract, transform and load process is complete, the data is in a usable form and relatively free of mistakes and problems. There are usually a few more data cleaning issues that might be necessary based upon the particular algorithm that will be used. For example, redundant columns might need to be eliminated. For example, a data set that lists products and has one column for the product name, and another column with a unique numerical identifier for each product has a redundancy. In this case, one of the columns should be removed. Eliminating and selecting columns is often called feature selection. Another data scrubbing activity would be to replace text in categorical variables with numbers. This is sometimes called one-hot encoding. For example, a column that lists cats and dogs could be changed to a column that lists zero for cats and one for dogs. This is also called dummy coding.



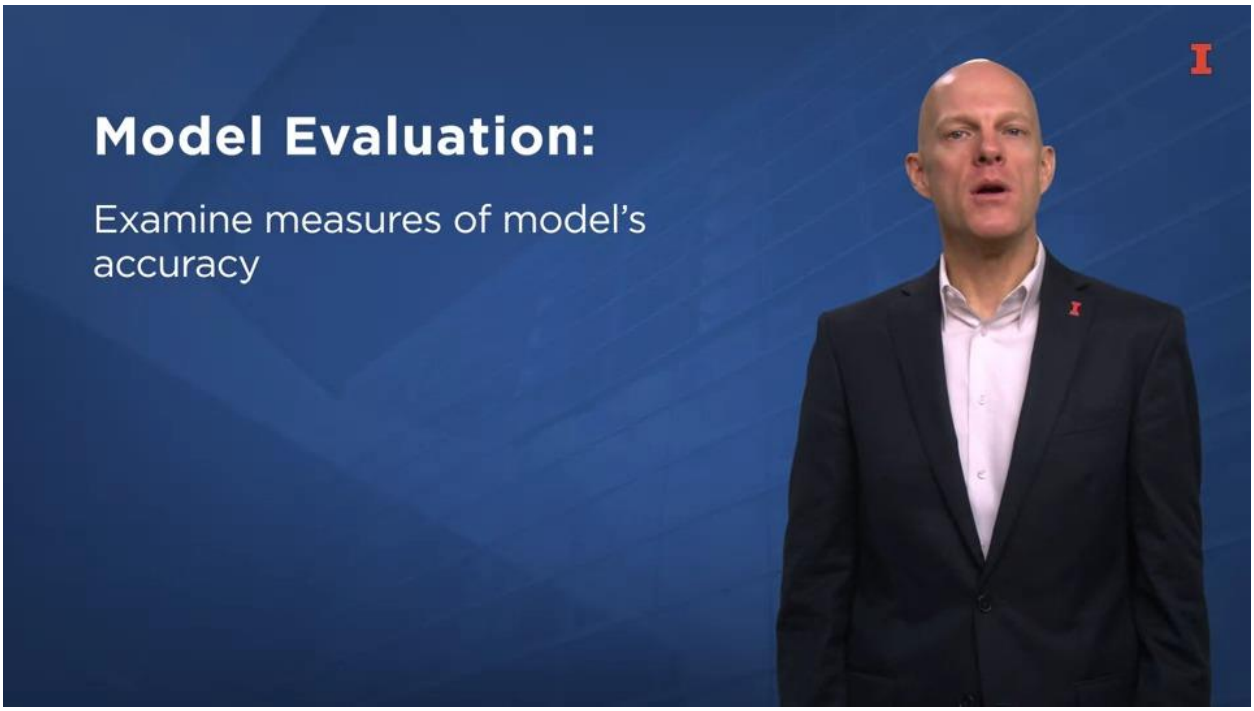
Another data preprocessing technique that may be beneficial given the machine learning algorithm that you use is standardization. Standardization, it takes variables that are on different scales and puts them on the same scale so that they have the same variance. For example, assume your data set list financial statement numbers for a company, and that's some of the numbers are in thousands while others are in millions, standardizing these figures by subtracting the mean and dividing by the standard deviation would give both measures a mean of zero and a standard deviation of one. Standardizing in this way is generally recommended for principal components, support vector machines, k-nearest neighbors, and other algorithms that use distance measures. A final topic of interest is not how the data should be scrubbed but how much data is needed in the first place. Well, there's no single definitive rule here, there are rules of thumb. Ideally, you have at least some observations for each combination of levels of the variables. For example, if a data set has two categorical variables with two levels each, for example, animal with cat and dog and age, old or young, it would be ideal to have data for old cats, young cats, old dogs, and young dogs. This way, things won't unravel at the side of unseen combinations in trying to predict the data in the future. A rule of thumb for the minimum amount of data to have to run machine learning algorithms is 10 times as many data points as the number of features. Ultimately, how much data is required depends on the algorithm that's being used. Clustering and dimensionality reduction algorithms can be effective with less than 10,000 observations. Regression and classification algorithms can get by with less than 100,000 observations while neural networks need more than 100,000 observations.



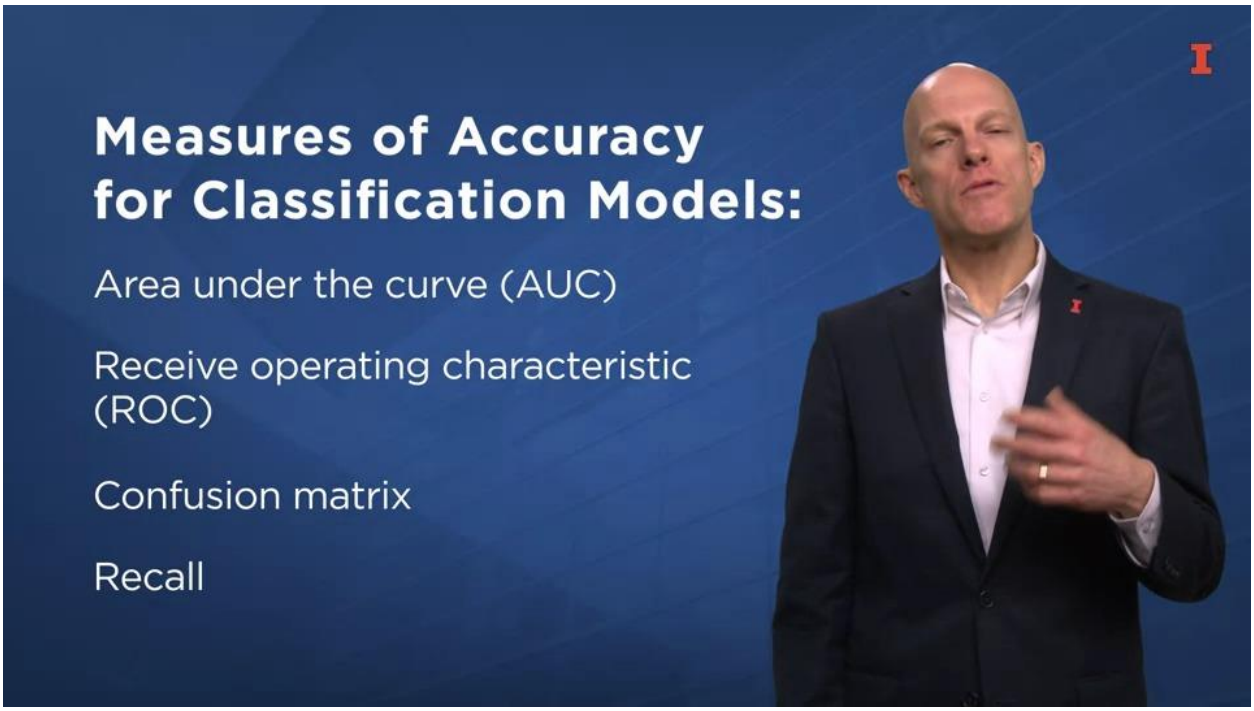
The next step is algorithm selection. Selecting an algorithm that's best for your analysis project is one of the business analysts hardest jobs. The analyst examines their question, their data set, and they need a solution and picks accordingly. Unfortunately, there's no one model that's best for every business problem and business data set. Analysts might be tempted to reuse models that they're most comfortable with, but the analyst should be aware of all the models available and also needs to be aware of recent advances in the field.



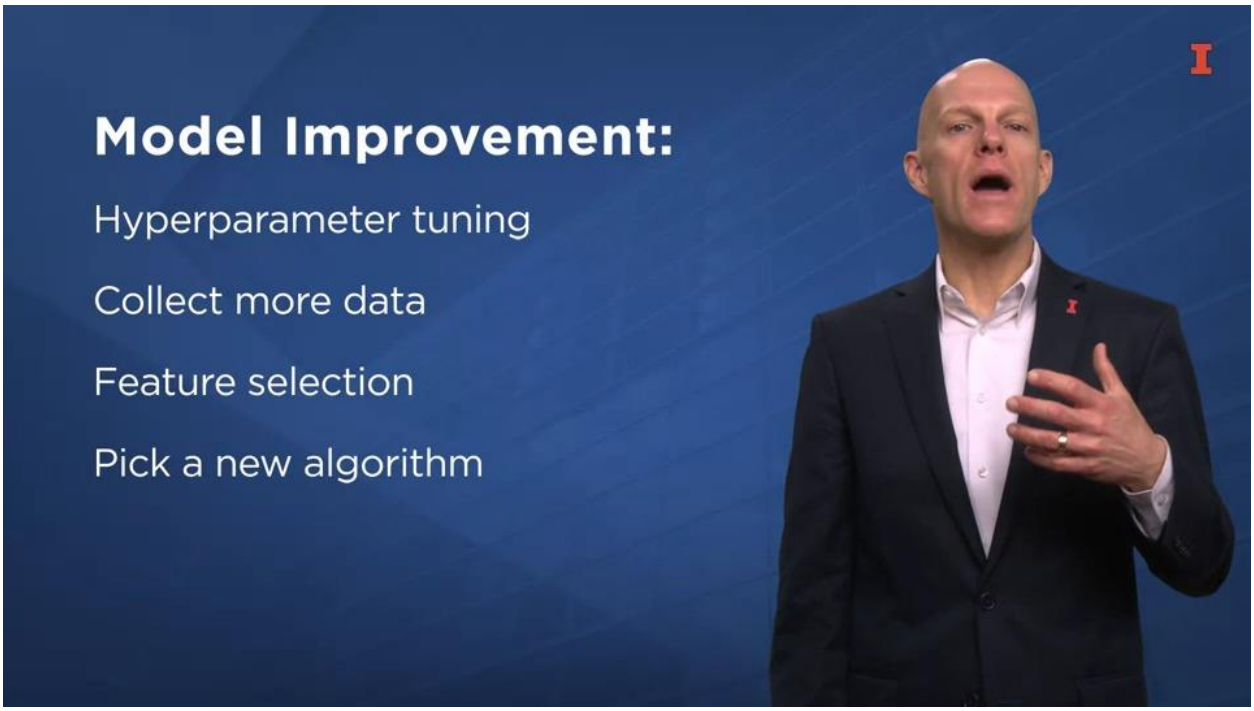
The next step then is to apply the algorithm to the data to create a model. The model takes the data set, following the rules of the algorithm, and converts it into information that can be used to solve a business problem. That is, the machine learning model includes new data generated from applying the algorithm to the data set, as well as instructions for the machine for how to use that data to create predictions on new data. Frequently, but depending on the algorithm, the model is created on a subset of the data called the training data set. Specifically, the data set is split into two separate parts, called the training data and the testing data. For example, the data set might be split 70 percent for the training and 30 percent for testing. A 60, 40 or a 80, 20 split could also be used. Now this is sometimes called split validation. Once the model is trained on the training data, the testing data can be used to check the accuracy of the model. Thus, the point of splitting the data is to check whether the model that is created works not just on the data that we have, the training data, but also on the new data, the holdout data, or the testing data as well. This avoids the situation in which our model fits the data we have perfectly, but does not generalize to the other data. That is, it does not work for new data. This is important because the goal of many machine learning solutions is to speak not only to the data we have, but also to predict future outcomes and future relationships between variables.



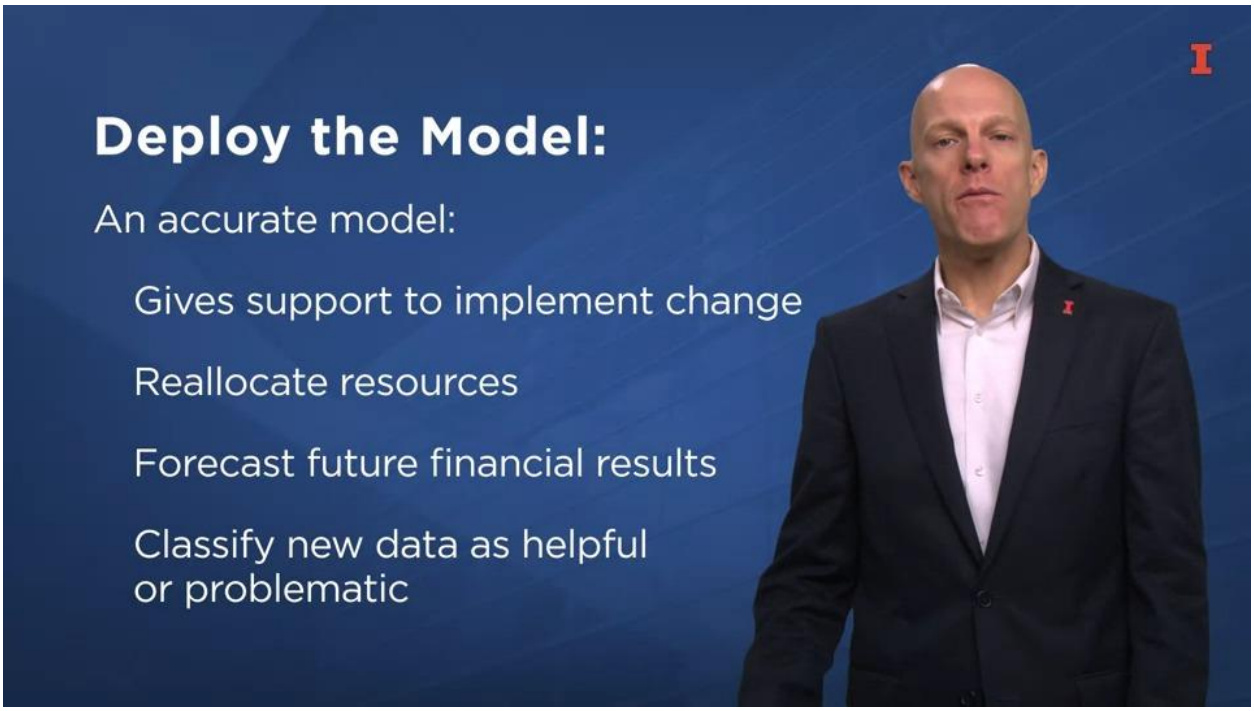
After the model is trained, the next step is to evaluate how accurate the model is. As just mentioned, the goal of creating the model is to explain or predict the data we have, but also to explain and predict new data. Since our true goal and training a model is to solve a business problem, we want our model to predict the truth as closely as possible.



To evaluate the model's ability to do that, we examine measures of accuracy for the model. For example, if our machine learning task is to accurately classify whether a purchase is fraudulent or not a classification task, we would examine how accurate the model is at predicting fraud within our training data set. Next, we would examine how accurate the model is at predicting fraud and the testing data set. If accuracy is relatively high for both the testing and the training data sets, we'll have some assurance that the model will predict fraud well for new data. Measures of accuracy for classification models, include the area under the curve, AUC, the receiving operating characteristic, the ROC, a confusion matrix, recall and etc.

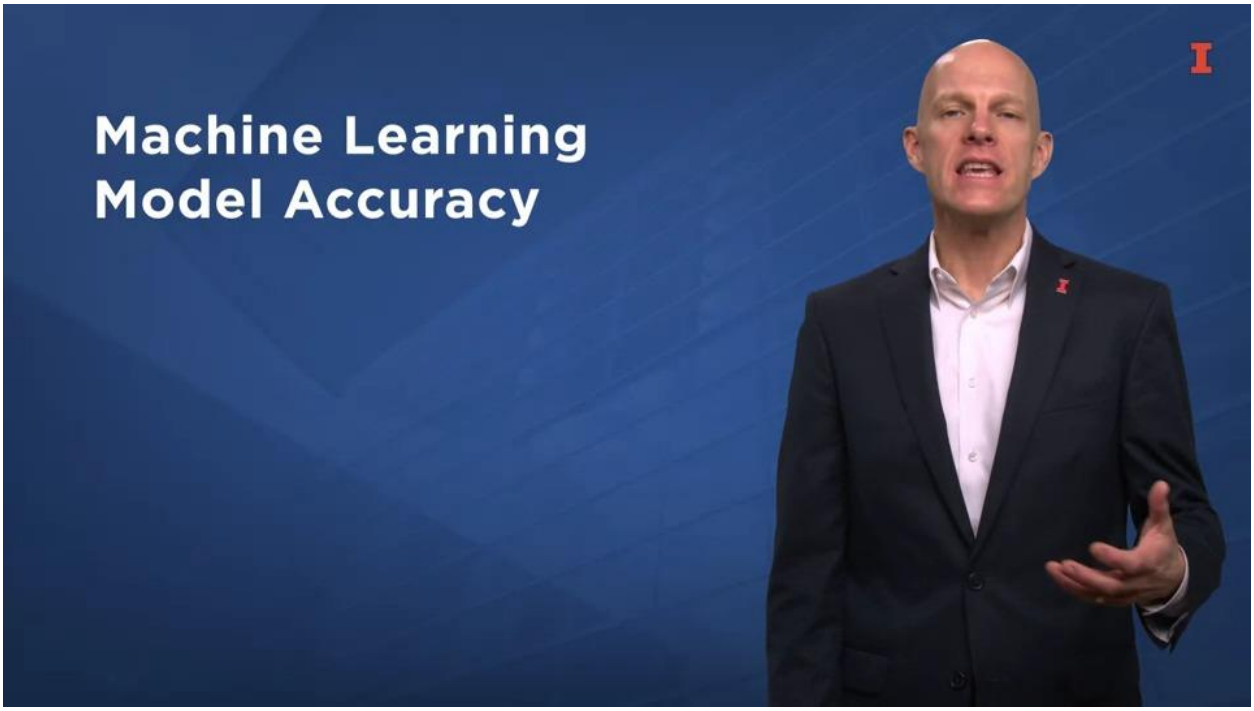


If the accuracy of the model is not good enough, the next step is to improve the model. Many methods exist to improve the quality of the model. In fact, competitions to create the most accurate and useful model are a significant part of the machine learning culture. A first step for seeking to improve the accuracy of the model is to change the instructions given to the algorithm. Algorithms have options that control and impact how the resulting model learns and which patterns to identify and analyze. These options are called hyperparameters. These options can be changed by the analysts to fine tune the model to better fit the data set. Although fitting the model too closely to the data set can cause a problem called overfitting. Next, the analysts might increase the amount of data. All data has noise or irreducible error caused by missing variables or a unique, idiosyncratic variation. Increasing the amount of data can reduce that variation. Similarly, feature selection, that is adding additional variables that strongly affect the target variable and removing less useful variables may help. Thus, it's important to understand that the data scrubbing and cleansing process can sometimes just beyond going. Finally, the analyst might need to pick an entirely new algorithm.



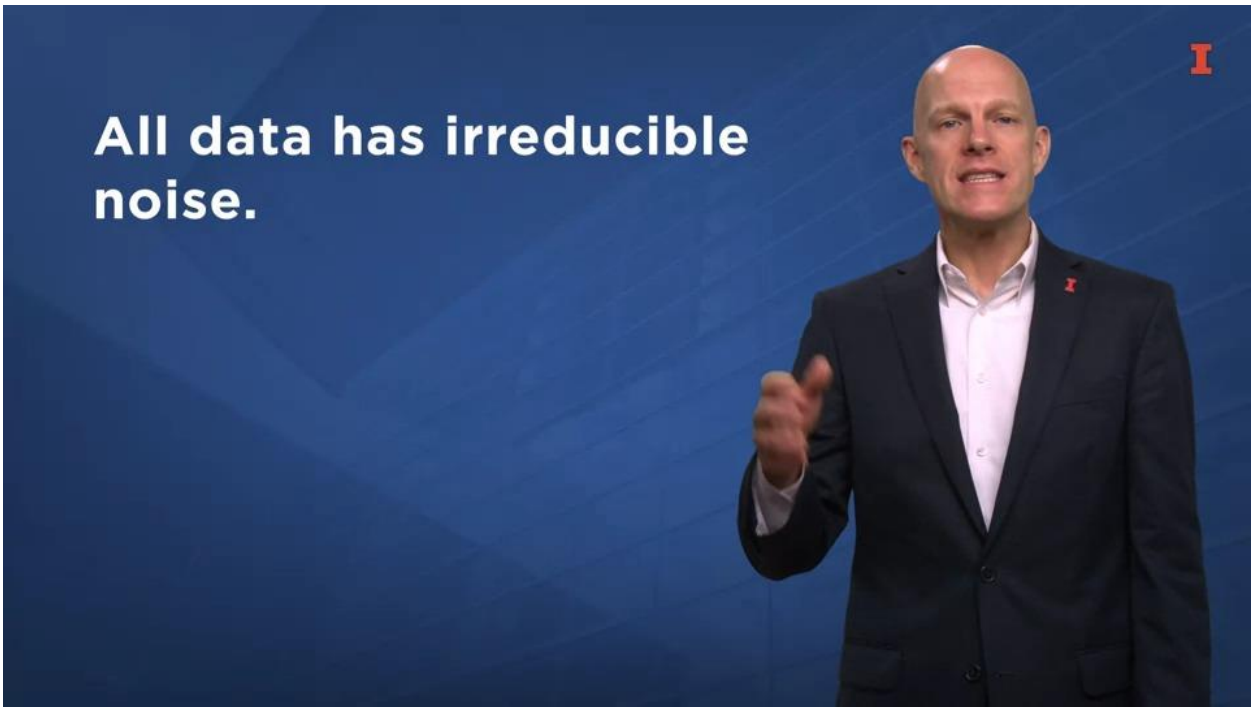
The final step in this process is to deploy the model and put it into production. The whole point of using machine learning in the first place is to create a model from your data that helps you address business problems. An accurate model can give you support to implement and test a change in your business, reallocate resources to create or emphasize different classes of products or customers, forecast future financial results for a segment of your business, and classify new data as helpful or problematic.

Lesson 2-1.5 Evaluating ML Model Quality

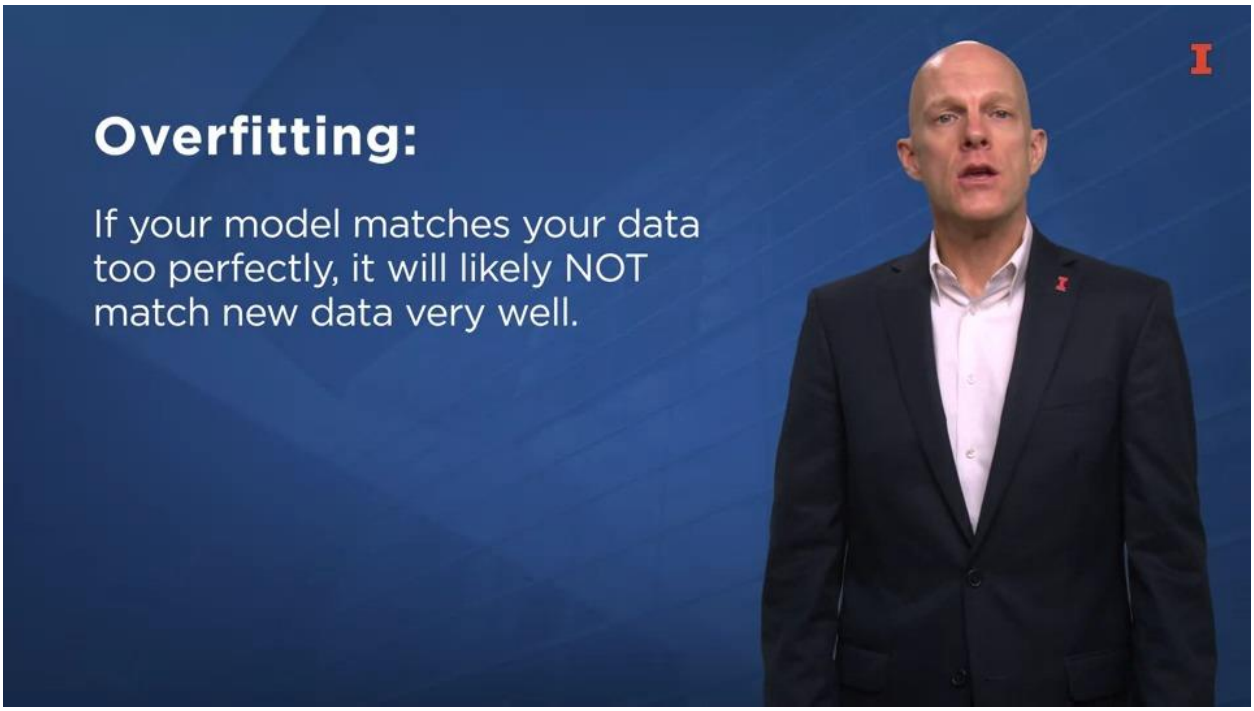


In this video, we'll discuss the important topic of machine learning model accuracy. Now, this is a nuanced topic with no simple, easy solution. The business analyst has to make trade-offs, and it's important for us to spend a little time to understand the issues at hand.

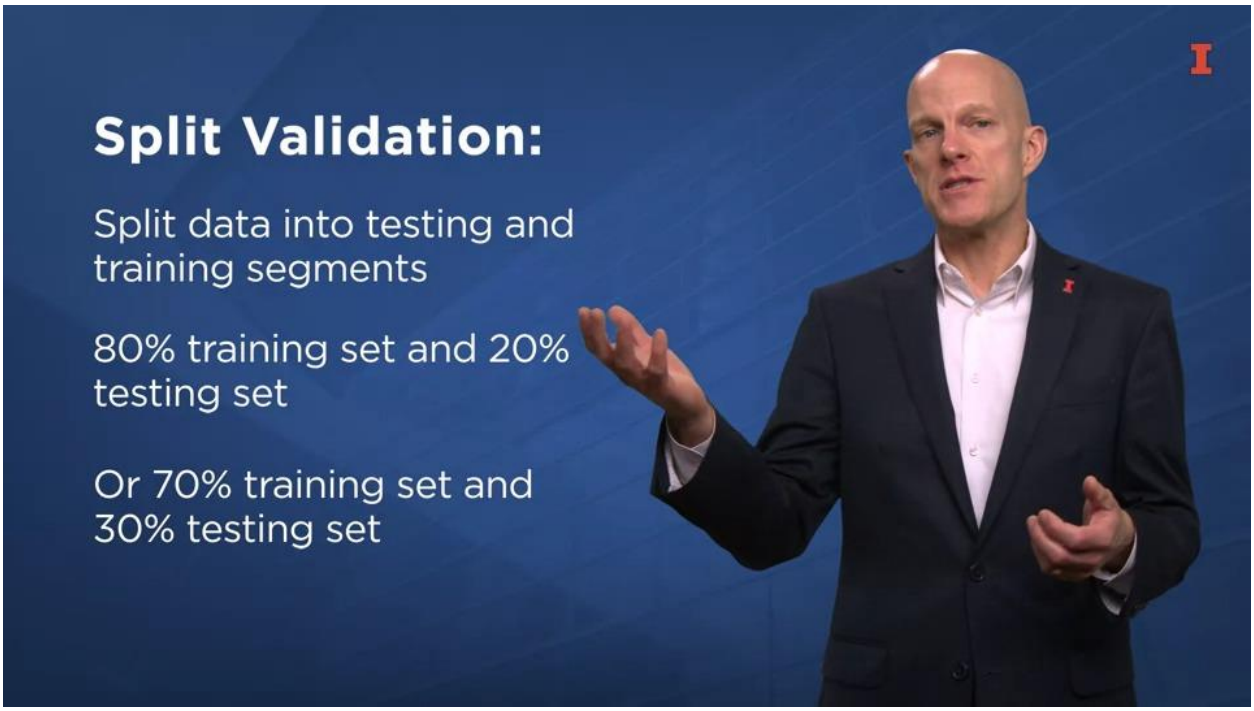
At first, it's important to remember the goal of using machine learning in the first place. Though machine learning can be used for a lot of reasons, at its core, we're interested in creating a model based upon our data that predicts or uncovers truth of some kind. Once that truth is found, we can use it to make better business decisions and solve business problems. For example, we might want to know the truth about how a certain store will perform next quarter. Alternatively, we might want to know the truth about whether a new purchase is a real purchase or a fraudulent purchase.



The problem, of course, is that it's difficult to know the truth. Now, we're not trying to get into philosophy here. We're just stating the fact that the dataset we're using to find this truth is incomplete. That is, all data has irreducible noise. Unless you're looking at every single data point that you care about, some, hopefully, a lot of your data's characteristics and relationships will translate to other similar data. But there will always be some portion that does not translate. This could be because you don't have all of the important features of the real world in your data, or just because all the data is a little bit unique. For example, say you have a dataset that lists transactions and whether those transactions are fraudulent or not. If your business problem is to predict whether a transaction is fraudulent or not, your reason for building a model is not to perfectly fit your current data, but rather to use that information to predict whether a future transaction is fraudulent. Your current data can help with that, but it does not contain every possible transaction of every variable that would explain whether a transaction is fraudulent. Further, the data you collected last Tuesday, for example, will be unique, at least in part to last Tuesday, and will not be 100 percent representative of every Tuesday ever in the future. Furthermore, there might be small errors or mistakes in that data.

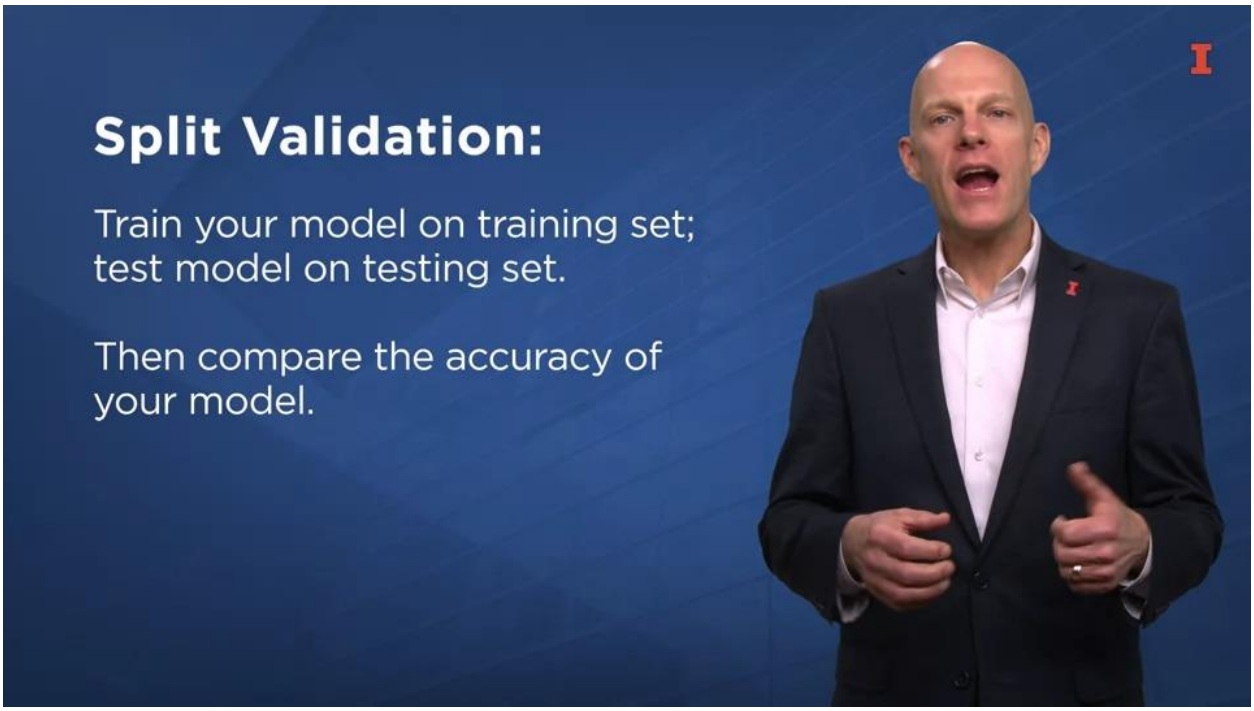


The key point is that because all data has some noise or irreducible error in it, if you want your machine learning to apply to more than just this data, you need to make an intelligent trade-off between your model being accurate, but not too accurate. Because if you're model matches your data too perfectly, it will likely not match new data very well. This is what we call overfitting. Thus, there's always a trade-off between training a model that's good, but not too perfect, not too good. You want your model to generalize, but not to memorize.

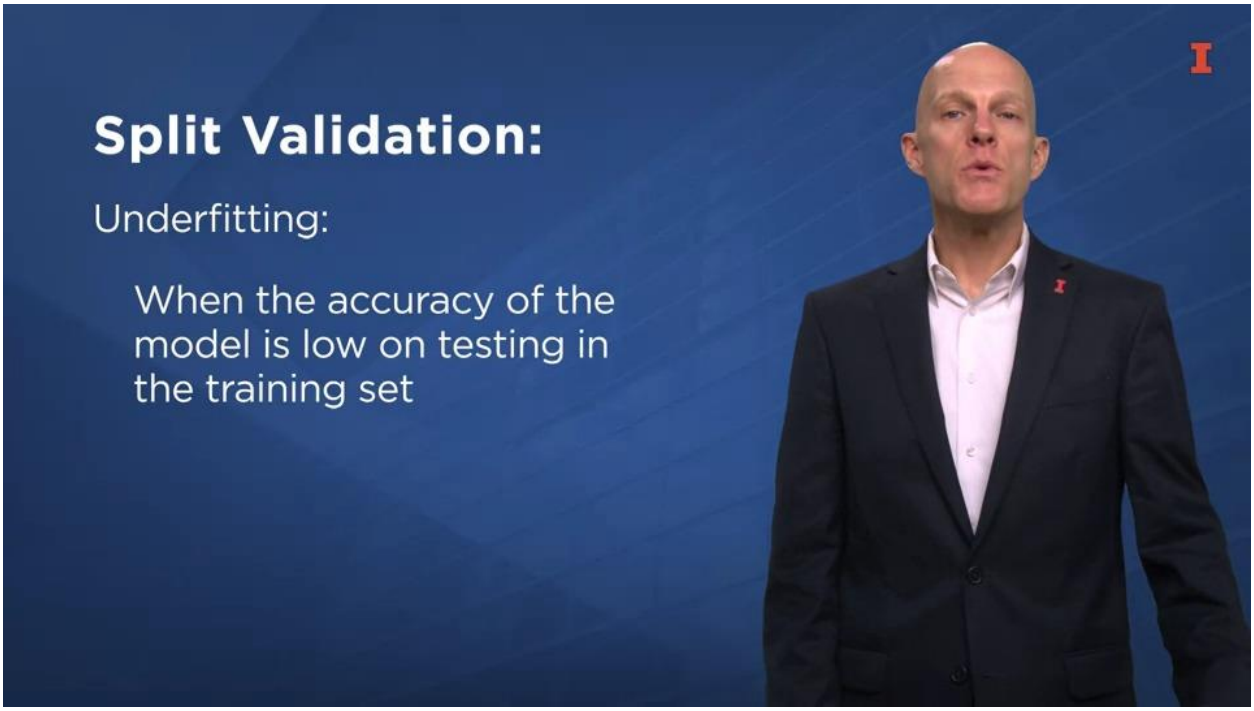


How does this work in practice? Suppose you have some data and you want to use a machine-learning algorithm to train a model that will predict a future data point. One way to avoid overfitting is to split your data into testing and training segments called split validation. Thus, you split your data into two groups of 80 percent and 20 percent, or 70 percent and 30 percent.

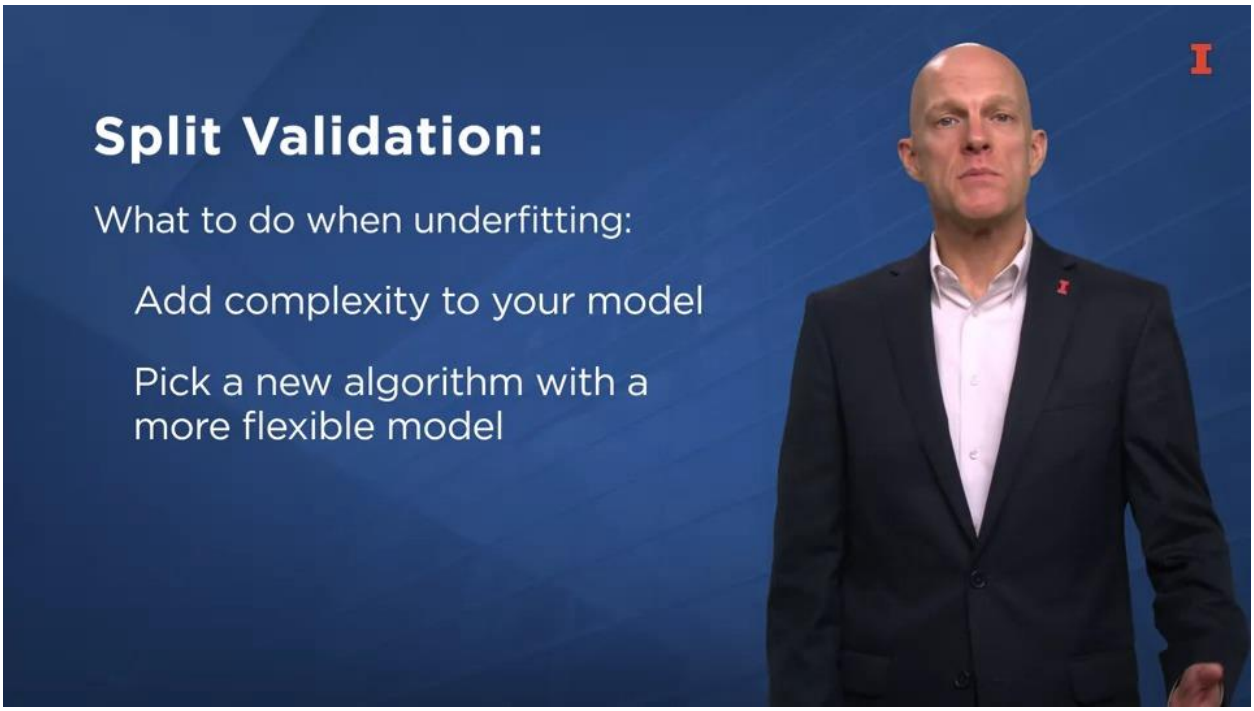
A key step to remember is certainly to randomly sort your data before splitting it into your training and testing sets. Most datasets come sorted in some logical order. If you keep the data in this order, it's likely that your training set will be systematically different from your testing set since they're on different ends of meaningfully ordered data. For example, the data might be sorted alphabetically based upon date. Thus, the testing data would be systematically newer than the training data.



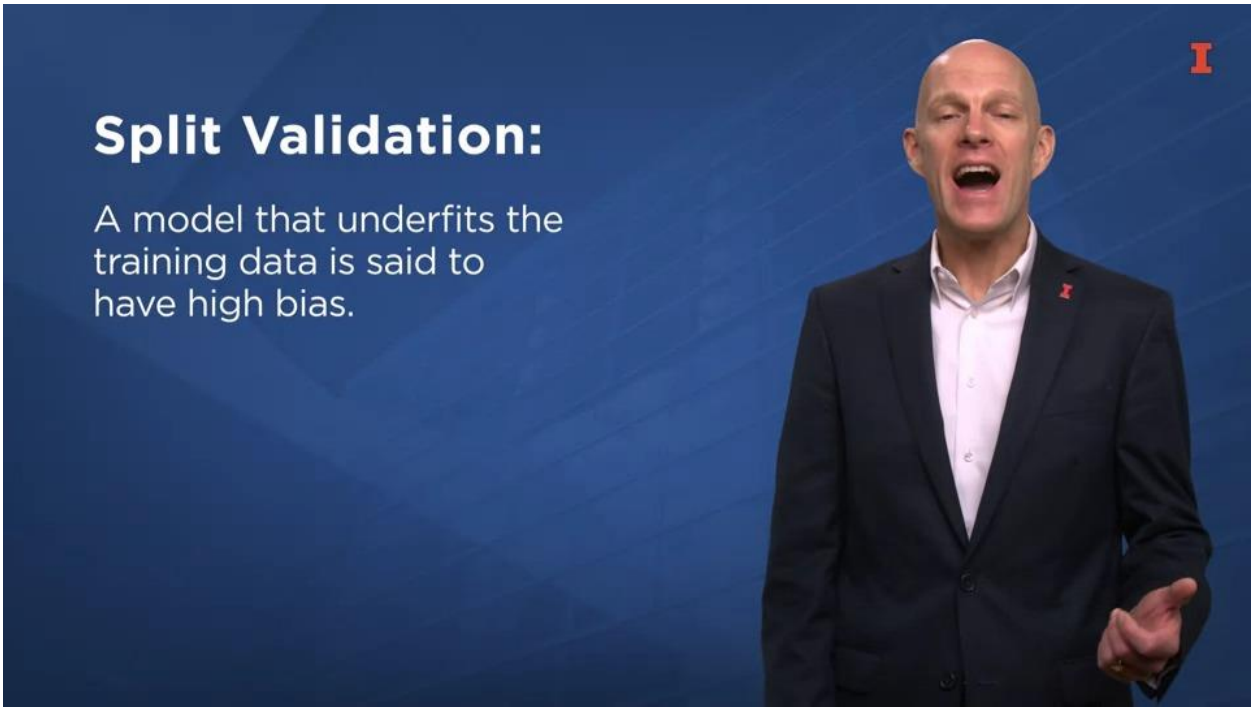
Next, to help make sure your model will generalize to new data, you train your model on the bigger portion, the training data, and then test the model on the smaller portion, the testing data. Then you compare the accuracy of your model in the training data to that in the testing data,



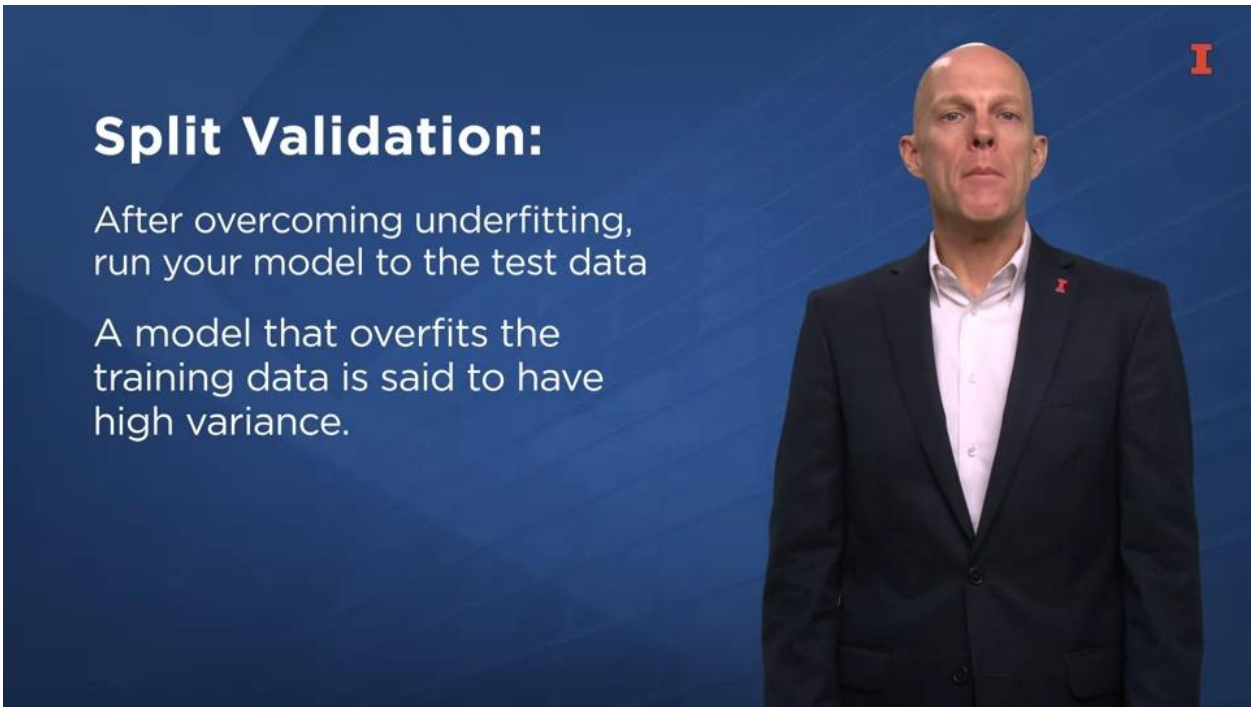
you would like the accuracy of the model to be high in the training data. If it's not, we call that underfitting. If the accuracy is low in the training data,



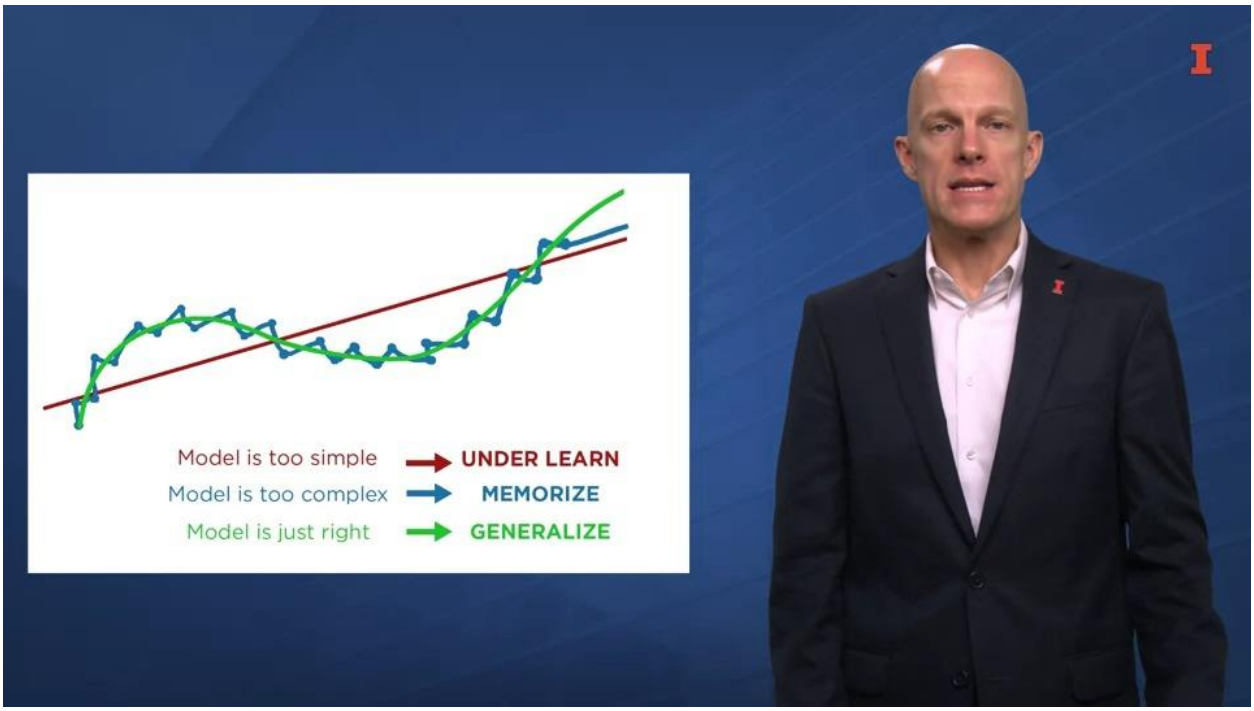
you'll need to add complexity to your model or pick a new algorithm with a more flexible model. This will help the model match the data points more specifically.



A model that underfits the training data is said to have high bias.



Next, you run the model on the test data. You want the accuracy of the model to also be high in the test data. If it's not high, you have overfit your model to the training data. The model is too specific and does not generalize. This means the model is responding too much to random chance or noise that's in the training data. If this is the case, you can add more data to the training set and/or reduce the complexity of your model, or pick a new algorithm with a less flexible model. A model that overfits the training data is said to have high variance.



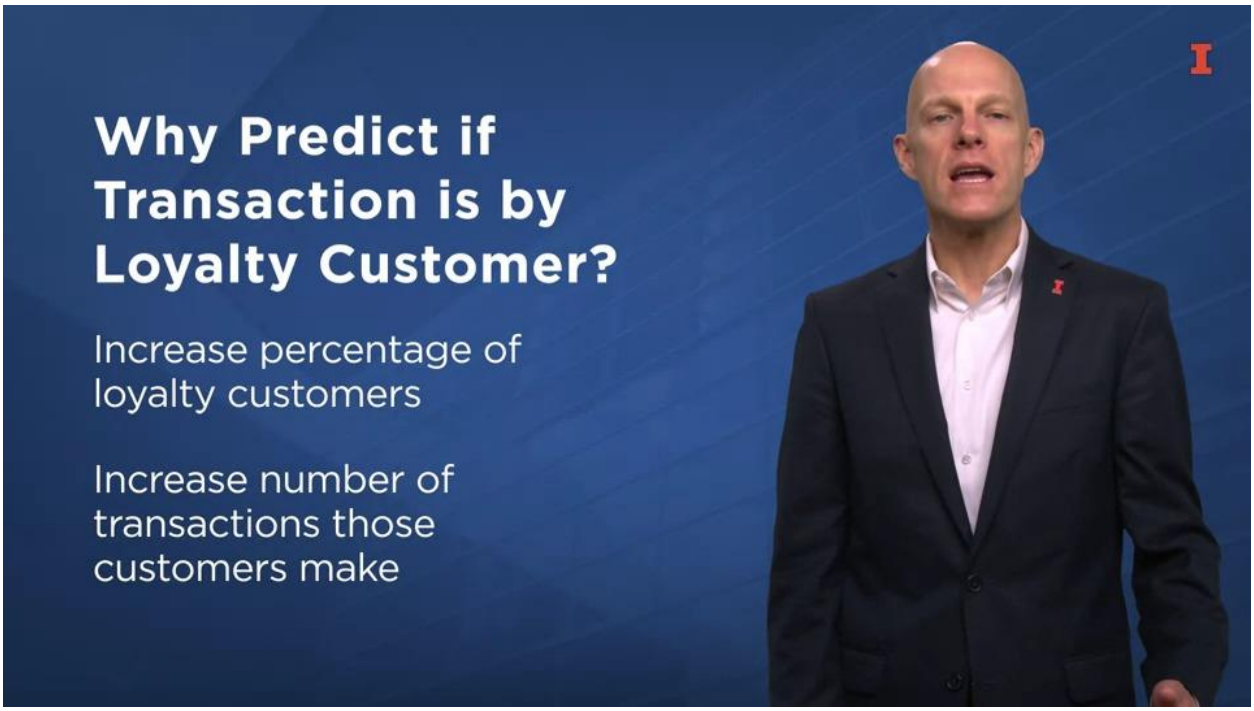
So our constant effort as analysts is to pick algorithms and tune models to avoid underfitting and overfitting, that have low bias and low variance. Let's briefly summarize this discussion by using this picture. Suppose the dots here represent your training data and suppose that the three lines are the predictions of three separate machine learning models, the red line is too simple and biased and underfits the data. However, the blue model appears to go too far. It's too complex and specific, it has too much variance and overfits the data hitting every point exactly. It's likely that when this model is run on the testing data, it will not fit the testing data well, because it so specifically matches the training data. Finally, the green model seems just right. It's more complex and specific than the red model, and thus does have some more variance, but it does match the data well, and thus reduces bias. We'll have to check with the testing data, but it appears that the green model avoids both overfitting and underfitting and will thus generalize well.

Lesson 2-2: Business Problem

Lesson 2-2.1 Introduce the Business Problem to Solve

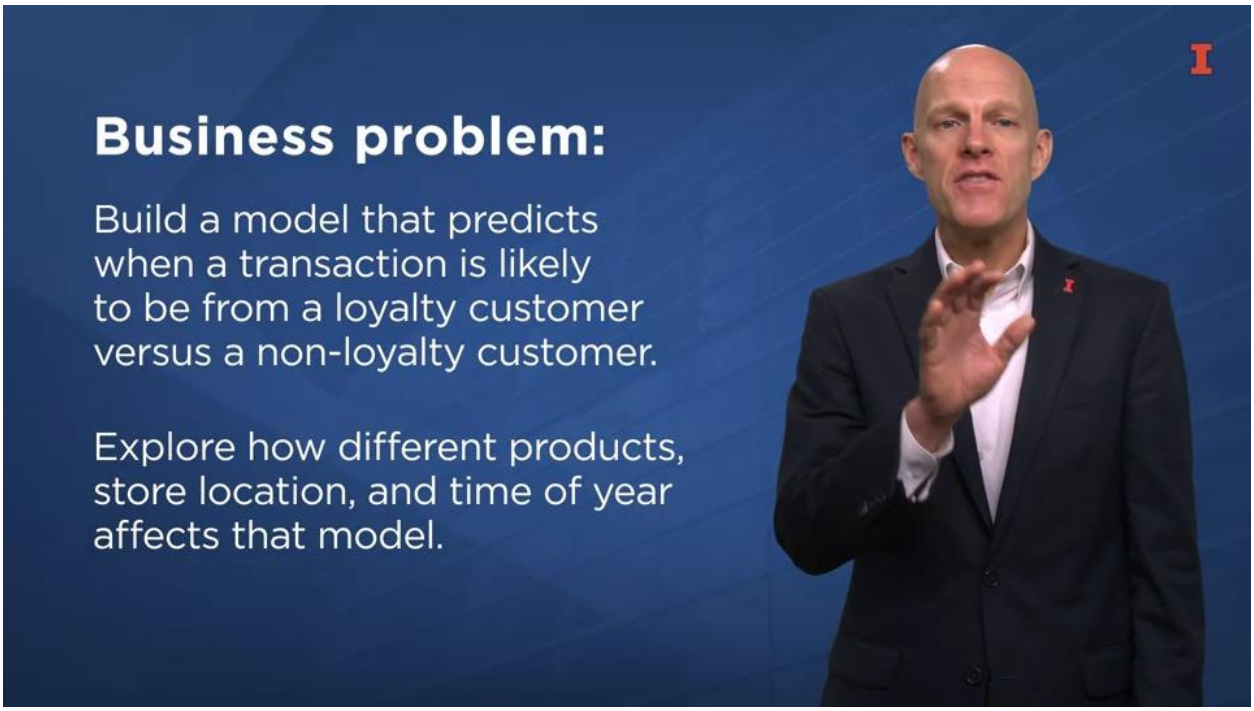
In this video, we'll set up a realistic hypothetical business problem. In subsequent videos, we'll use a new data analytics tool to gain useful insight into this problem. The hypothetical company will be helping is TECA. TECA owns over a 150 convenience stores and gas stations throughout the middle of the country. TECA knows from prior research and general industry knowledge, that a new loyalty customer is worth about $200 earn extra revenue a year. A loyalty customer is an individual who has provided certain information to TECA convenience store in order to receive a loyalty card. Loyalty cards provide discounts and benefits for those who use them frequently. You probably have a loyalty card from your favorite grocery store, convenience store, ice cream shop, or movie theater. These businesses know that the small discounts they give you on your loyalty card are more than compensated for by the increase in business you provide to them.

Not only do loyalty customers spend more money, as can be seen in this graph, loyalty customers also buy higher margin products. This graph shows the gross margin profit for non loyalty and loyalty customers. You can see that the loyalty column looks significantly higher than the non loyalty column. Thus, loyalty customers not only come into the store more often, they also buy more profitable items when they do come.



TECA would like to be able to predict when a transaction is more likely to be made by a loyalty customer for two reasons. First, they'd like to increase the percentage of their customers who are loyalty customers. Second, they would like to increase the number of transactions those customers make. Thus, TECA is embarking on a research project to examine how they can make transactions more appealing to loyalty customers.

What TECA would like to do is predict when a transaction will be from a loyalty customer. Perhaps certain products drive loyalty purchases. If that's the case, TECA can promote these products to non loyalty customers to encourage participation in the loyalty program. Perhaps there are certain times of the year when loyalty purchases are more likely to occur. If so, TECA could advertise accordingly by focusing on promotional programs on those months in which loyalty is most or least likely to occur. Finally, particular regions of the country might be better at selling to loyalty customers. If those areas and stores are identified, TECA could investigate their underlying success and replicate it elsewhere to make sure that more purchases are made by loyalty customers.



Thus, TECA would like to build a model that predicts when a transaction is likely to be from a loyalty customer versus a non loyalty customer. In addition, TECA would like to explore how different products, store location, and the time of year, affect that model.

Lesson 2-2.2 Introduce the Data

In this video, we'll take a brief look at the data we'll be analyzing throughout this module. We'll be using a neat data set created for this course called the TECA dataset.

TECA is a fictional company that owns over 150 convenience stores and gas stations throughout the middle of the country; from Wyoming to Minnesota, from Arkansas to Alabama and many states in between.

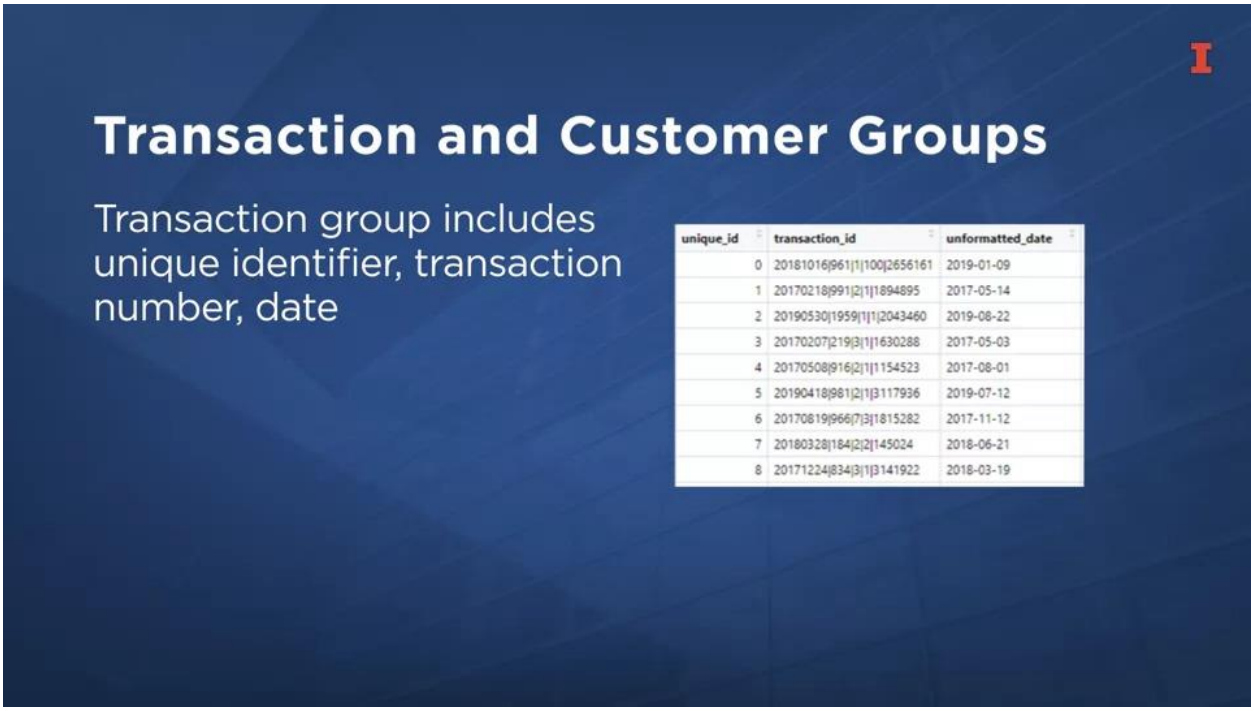
The particular dataset we'll be using is a random selection of customer transactions from these convenience stores for the years 2017-2019. These transactions include, for example, purchases of fuel, lottery tickets, soda and candy. Though our dataset is relatively large, including over a million transactions, it only includes a pretty small random sample from all of the transactions in this period. The full dataset would be over a 145 times larger than this and consist of hundreds of millions of transactions.

It's important to know the level of aggregation of the data. That is, what each row represents. In this case, each row represents a single product purchased as part of a single transaction. Thus, the data is organized at the transaction product level. Each row has an entry in the column unique ID. This number is unique to that row, meaning that no other row has that number.

Additionally, each row has an entry for transaction ID. This number is not necessarily unique since one transaction can have multiple products. For example, unique ID equals 15 could represent the purchase of an extra large fountain drink as part of transaction ID 20189999434333452532. While most transactions are for only one product, it is possible that this same transaction also included the purchase of an apple. Of course, the apple would be unique ID equals 16, since each product for each transaction has its own unique ID.

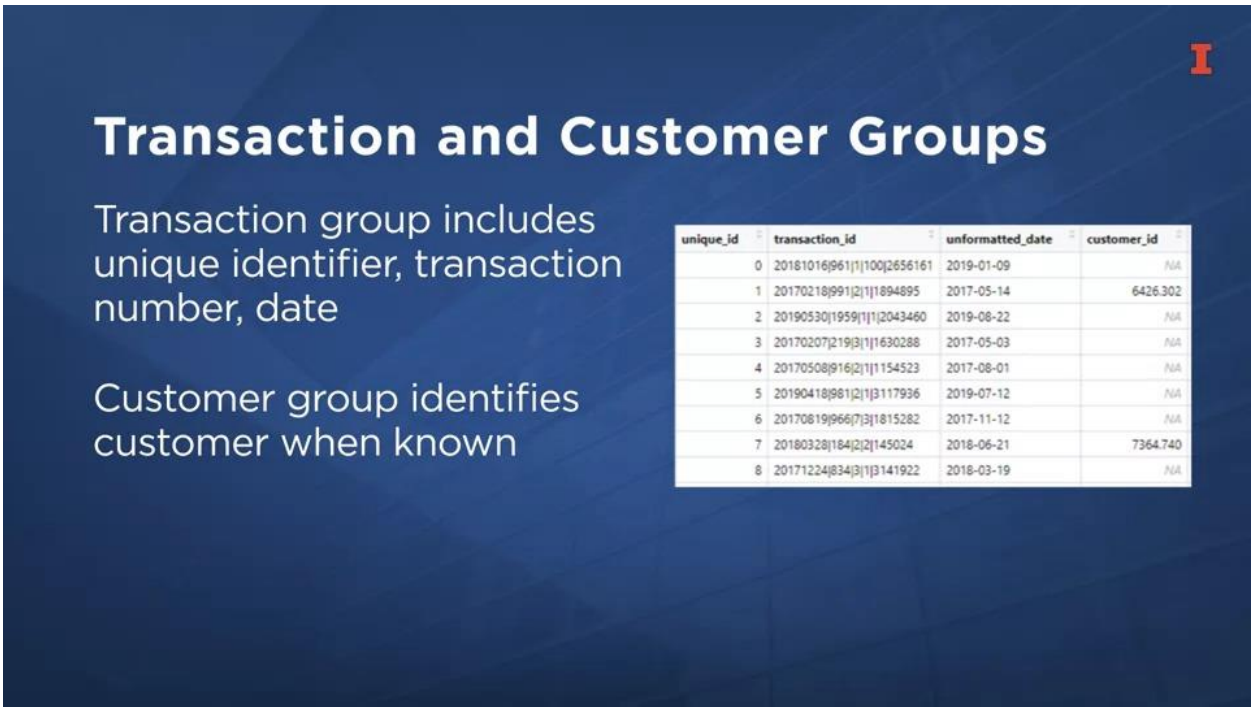
unique_id	transaction_id	unformatted_date	customer_id	product_id	product_name	category_id	category_name
0	20181016|961|1|100|2656161	2019-01-09	NA	18977	G87E10M	1	Fuel Premuim
1	20170218|991|2|1|1894895	2017-05-14	6426.302	6263	COKE CHRY 20OZ	250	Pk Bev-csd/pop (71)
2	20190530|1959|1|1|2043460	2019-08-22	NA	8830	MIKES HRDR BLK CHRY 16OZ CAN	231	Flavored Malt
3	20170207|219|3|1|1630288	2017-05-03	NA	4546	HAMMS 6PK CAN	210	Beer-budget (44)
4	20170508|916|2|1|1154523	2017-08-01	NA	530	DT PEPSI .5LT 6PK	250	Pk Bev-csd/pop (71)
5	20190418|981|2|1|3117936	2019-07-12	NA	3823	NUT HAR PISTACHIOS 2.25OZ	55	Nuts & seeds
6	20170819|966|7|3|1815282	2017-11-12	NA	1738	BUD LT 18PK CAN	196	Beer-premium (42)
7	20180328|184|2|2|145024	2018-06-21	7364.740	10989	TRKY SOURDOUGH	274	Cold Food
8	20171224|834|3|1|3141922	2018-03-19	NA	3738	LAYS CLASSIC 2.75OZ	52	Potato Chips

There's dozens of features or columns in the data. We won't describe them all here, but they can be grouped into five categories. We'll describe the five categories and the main columns or features in each category.



unique_id	transaction_id	unformatted_date
0	20181016|961|1|100|2656161	2019-01-09
1	20170218|991|2|1|1894895	2017-05-14
2	20190530|1959|1|1|2043460	2019-08-22
3	20170207|219|3|1|1630288	2017-05-03
4	20170508|916|2|1|1154523	2017-08-01
5	20190418|981|2|1|3117936	2019-07-12
6	20170819|966|7|3|1815282	2017-11-12
7	20180328|184|2|2|145024	2018-06-21
8	20171224|834|3|1|3141922	2018-03-19

First, the first group of columns is the transaction group. These columns include the unique identifier for the row, the transaction number, and the date of the transaction.



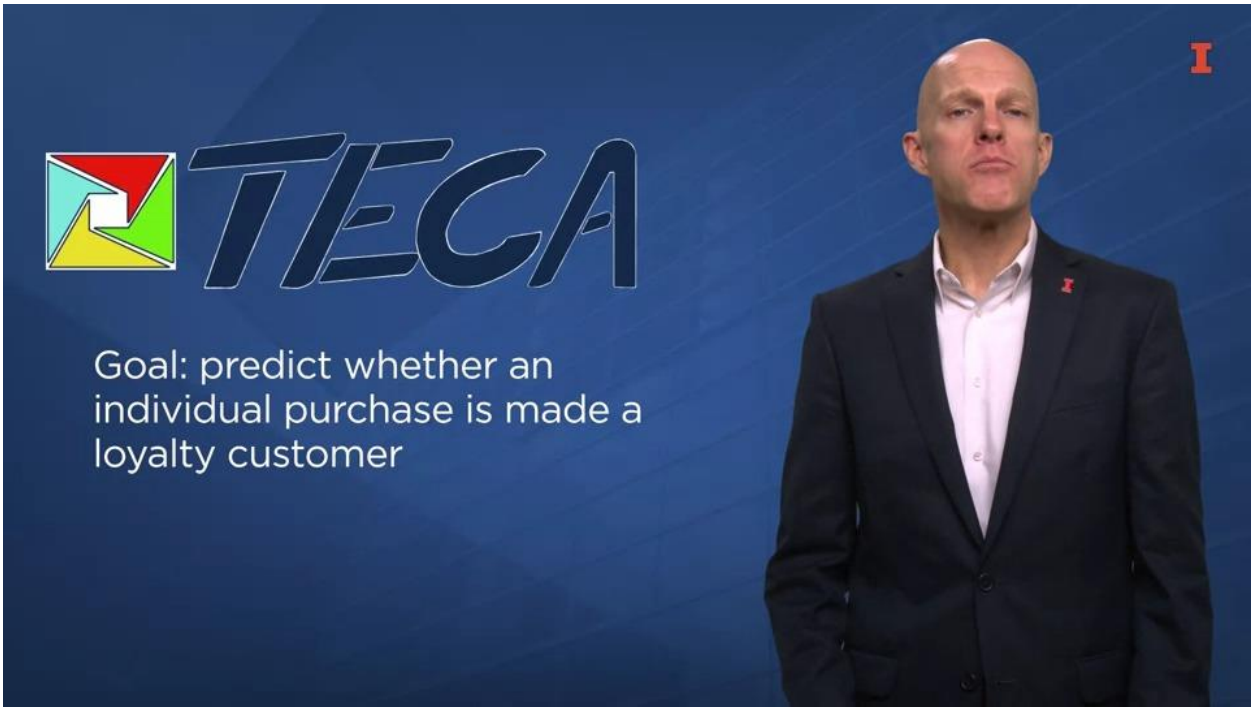
Second, the next group of columns is the customer group. Actually this is not a group of columns, but only one column called Customer ID. This column identifies the customer making the purchase when that customer is known. Customers are only known when they are loyalty reward members of the company and made their purchase with a loyalty rewards number or card.

The third group is the product and category group. This group of columns identifies the product and its name. It also identifies the type of category of product. All products are a part of a hierarchy of product categories. Thus, each product belongs to a category and that category has a parent category or a superset of that category.

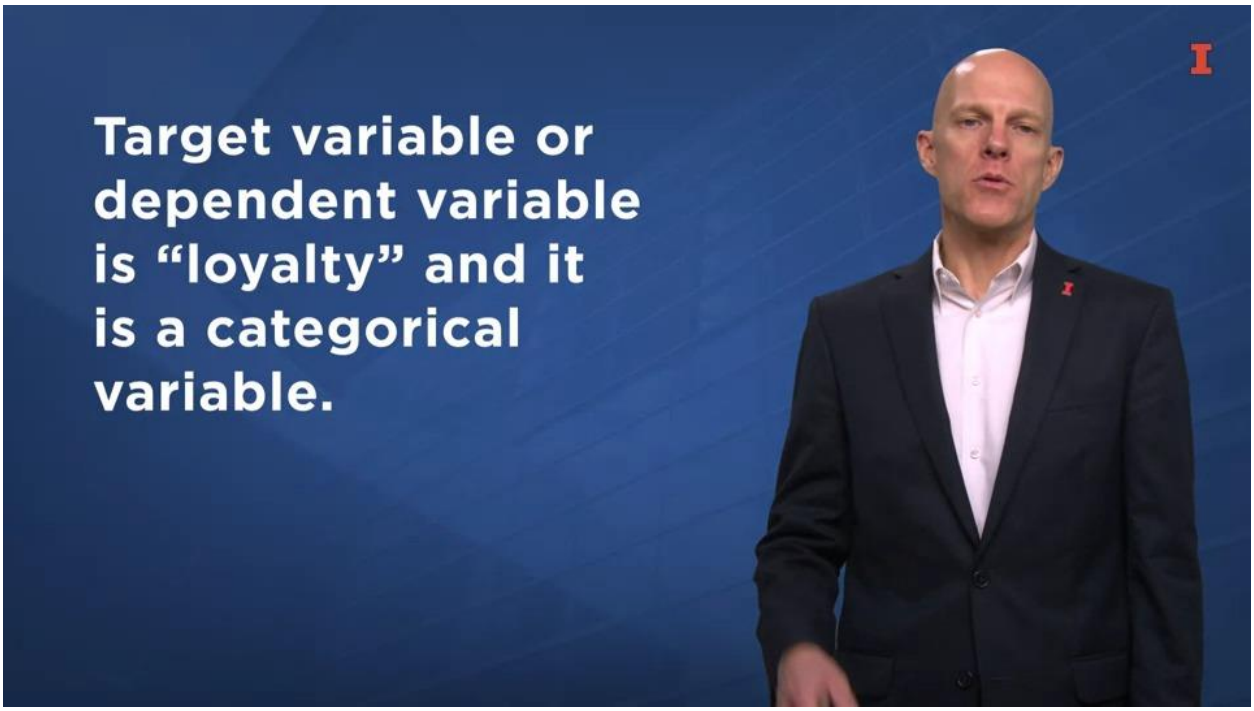
Next, the fourth group is the site group. These columns identify the convenience store where the purchase took place, including the site name, the address of the site, and the longitude and latitude. Please know, however, that to obscure the actual company using this dataset, the addresses are masked by referring to post offices instead of the actual convenience stores themselves. Nevertheless, the addresses are close to the convenience store. Finally, five, the last group of columns, present the amount of revenue and profit for the product that was sold. These columns are critical to all of our analysis going forward since TECA is a business and is interested in making money.

Lesson 2-3: Logistic Regression

Lesson 2-3.1 Introduction to Logistic Regression



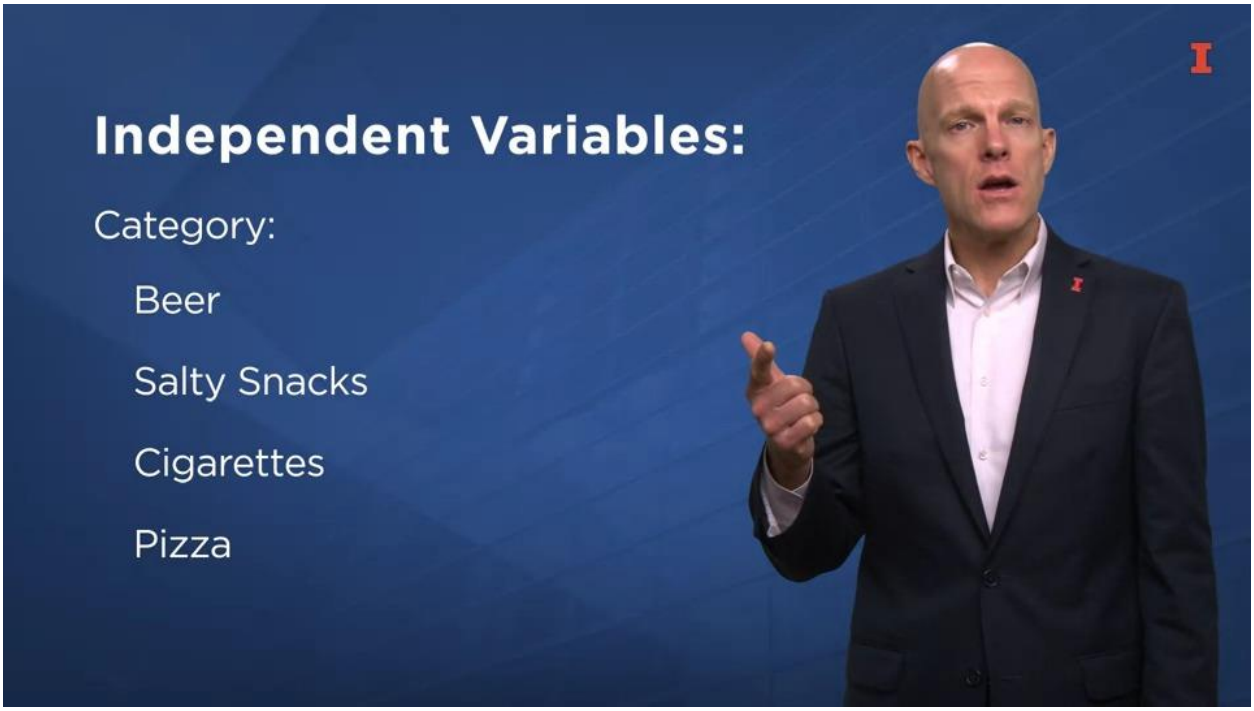
Our hypothetical company TECA wants to be able to predict whether an individual purchase is going to be made by a loyalty customer or a regular non loyalty customer. Loyalty customers are those who applied for a loyalty card with TECA in order to get discounts for purchases. TECA a has learned that they make about two $100 per new loyalty customer, and that loyalty customers buy more profitable products on average than non loyalty customers do. By predicting whether a sale is made by a loyalty or non loyalty customer take a hopes to increase the number of loyalty customers and the number of products that they buy.



While there may be many ways to investigate this issue, TECA has approached the problem by labeling each of their purchases as being made by a loyalty customer labeled as loyal or made by a non loyalty customer labeled as not loyal. Thus the targets or dependent variable here is loyalty and it's a categorical variable.

The other features, or independent variables that will be used to predict the target feature are the following category. This variable list, the top 20 most frequently purchased products and they are the following fuel, which is gasoline purchased at the gas pumps, pop, which is bottled and canned soda, cold dispensed beverage, which is fountain soda. Next juice and tonics, these are bottled juices,

lottery, these are lottery tickets, both those purchased and paid out if it's a winning ticket. Energy, these are bottled and canned energy drinks. Next candy and gum just self explanatory, hot dispense to beverage, these is coffee, tea and hot chocolate from a dispenser.



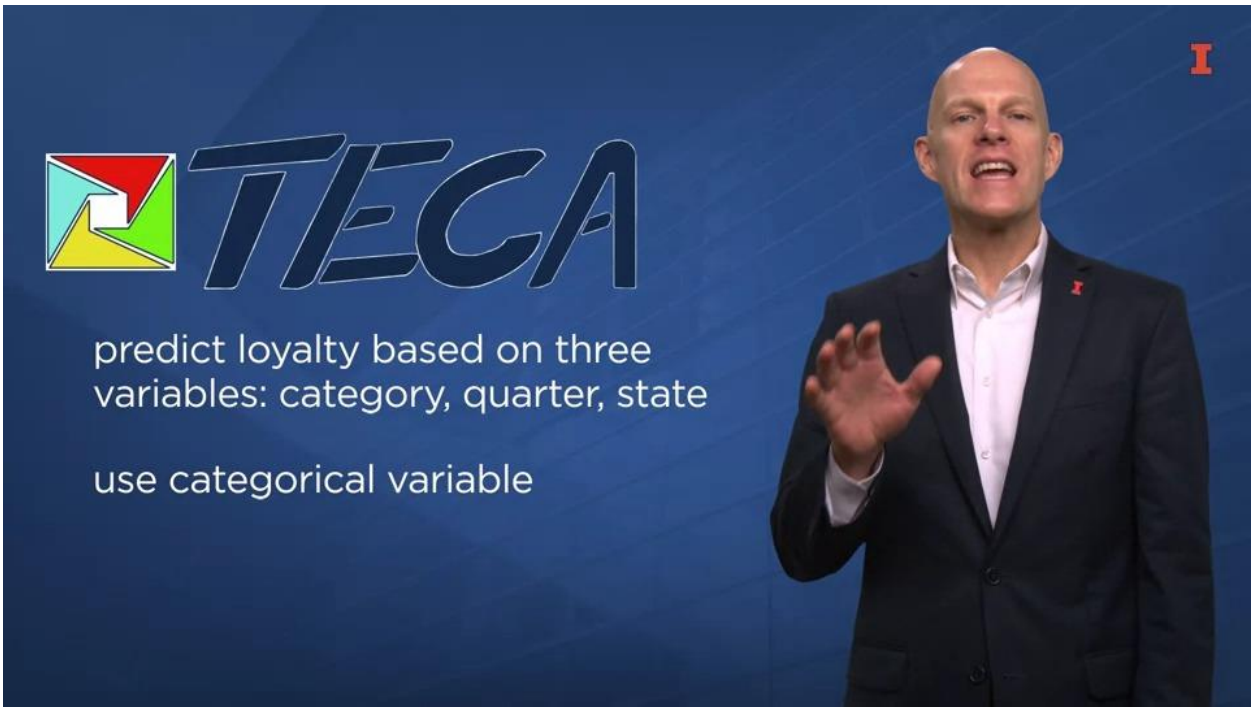
Next beer and then salty snacks, these include peanuts and sunflower seeds, for example. Cigarettes, pizza,

roller grill, these items are hot dogs and burritos that are kept warm on a roller grill. Breads and cakes, breakfast sandwiches, these refreshing take and heat breakfast sandwiches. Then bakery, these are donuts and cupcakes.

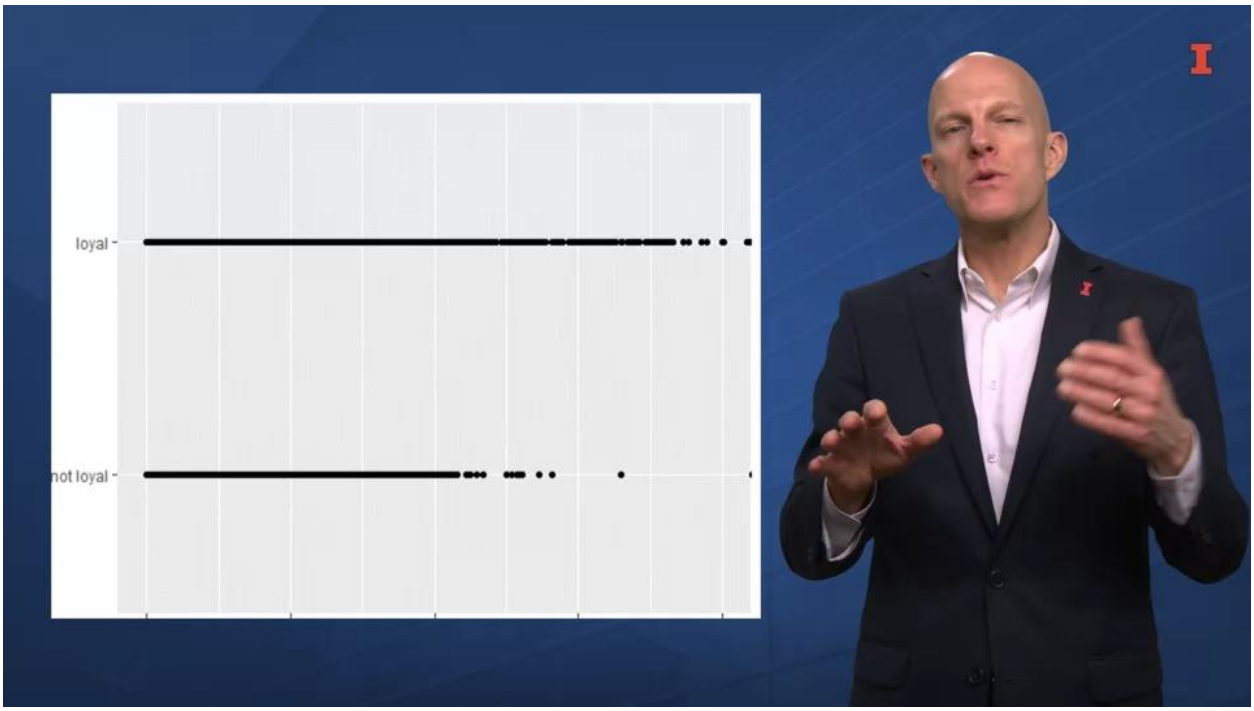
Another one is smokeless these, this is chewing tobacco and then hot sandwiches and chicken, these are ready to purchase sandwiches and chicken cigars and then chips. Here's a snapshot of the data that you can see.

	loyalty	category	quarter	state
1	loyal	Bread & Cakes	3	Colorado
2	loyal	Candy/Gum	1	Wyoming
3	loyal	Pop (587)	3	Wyoming
4	loyal	Pop (587)	4	Colorado
5	loyal	Chips	1	Oklahoma
6	loyal	Juice/tonics	2	Colorado
7	loyal	Juice/tonics	3	Wyoming
8	loyal	Bread & Cakes	2	Alabama
9	loyal	Beer	3	Alabama
10	loyal	Chips	2	Oklahoma
11	loyal	Cigarettes	1	Nebraska
12	loyal	Roller Grill	4	Arkansas
13	loyal	Pop (587)	4	Iowa
14	loyal	Salty Snacks	2	Alabama
15	loyal	Pizza	1	Nebraska
16	loyal	Salty Snacks	3	Colorado
17	loyal	Cigarettes	2	Missouri
18	loyal	Roller Grill	3	Wyoming
19	loyal	Fuel	3	Wyoming

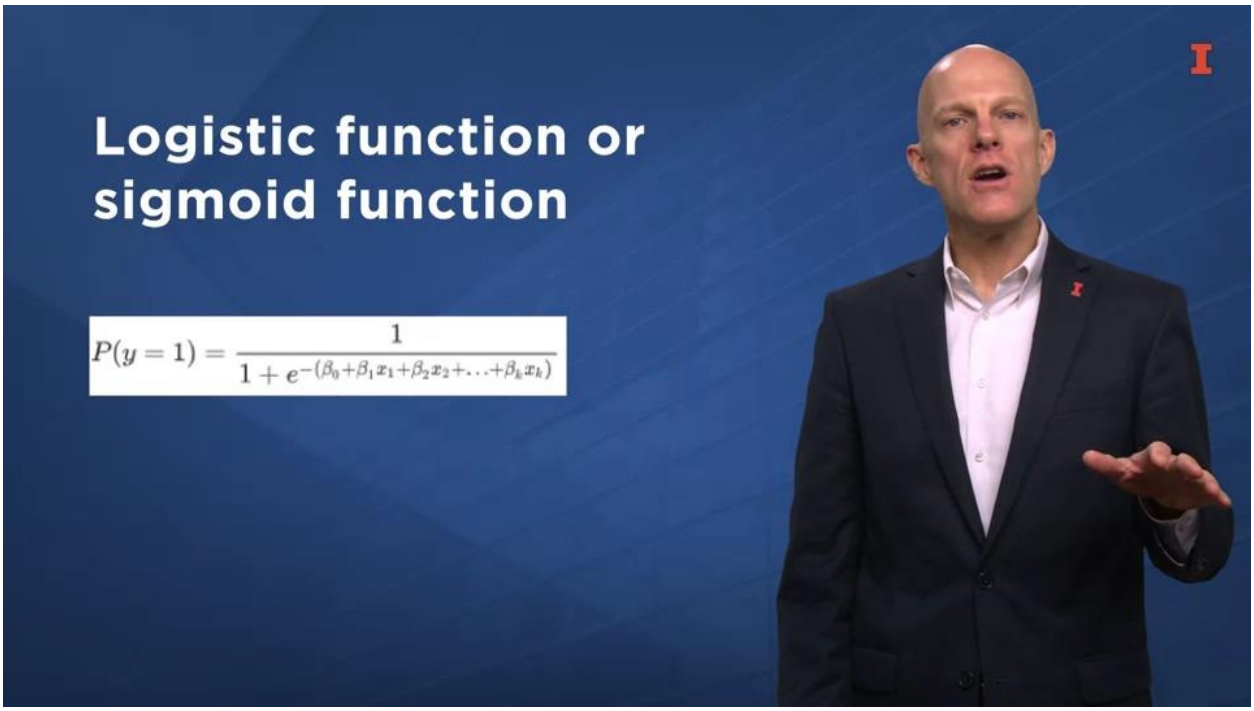
This data has been significantly cleans and manipulated for use in this module, null values and outliers have been removed and categories have been combined and eliminated. Finally, the data has been adjusted so that the number of loyalty purchase and non loyalty purchases are relatively similar.



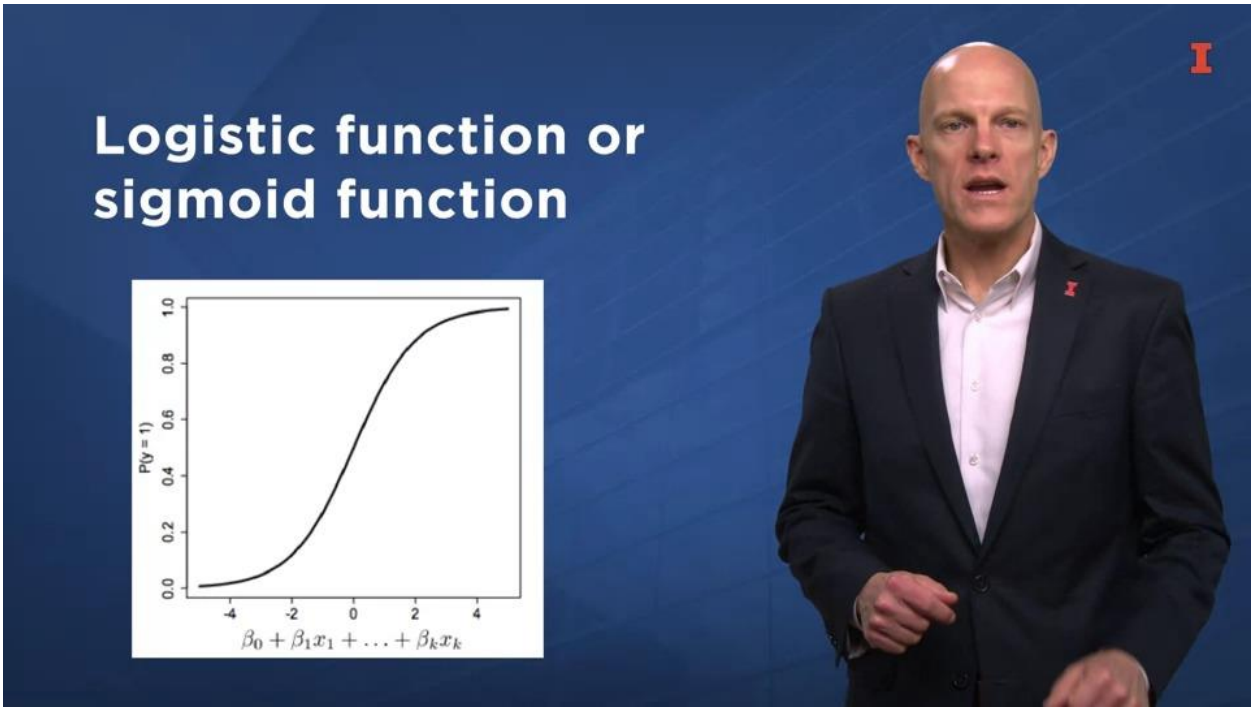
Now take a wants to predict loyalty based upon the three variables, category, Quarterl, and state. This feels like a solution that regression could handle, certainly regression examines the effect of independent variables on dependent variables and predicts an outcome. Unfortunately there is one major difference between a regression problem and our problem, that is regression predicts a continuous dependent variable. While we need to predict a categorical variable



specifically, as can be seen here, we have by variant data that is all of our data lies at two levels loyal and not loyal. Regression would pick a regression trend line that gives a continuous response and would fall outside of the range of our dependent measure. Rather than that we need a function that converts the independent variables into an expression of probability between zero and one in relation to the dependent variable which would be not loyal and loyal. That is we need a function that gives outputs between zero and one that finds coefficients to maximize the likelihood of predicting a high probability for observations that actually belong to class one, which in our case is loyalty. And predicting a low probability for observations that actually belong to class zero, which in our case is not loyal. This will then produce an S shaped curve that can convert any number and map it into a numerical value between zero and 1.



Now luckily there are many functions that can do this for logistic aggression will pick the logistic function or the sigmoid function. Here's a picture of a multi variant version of that,

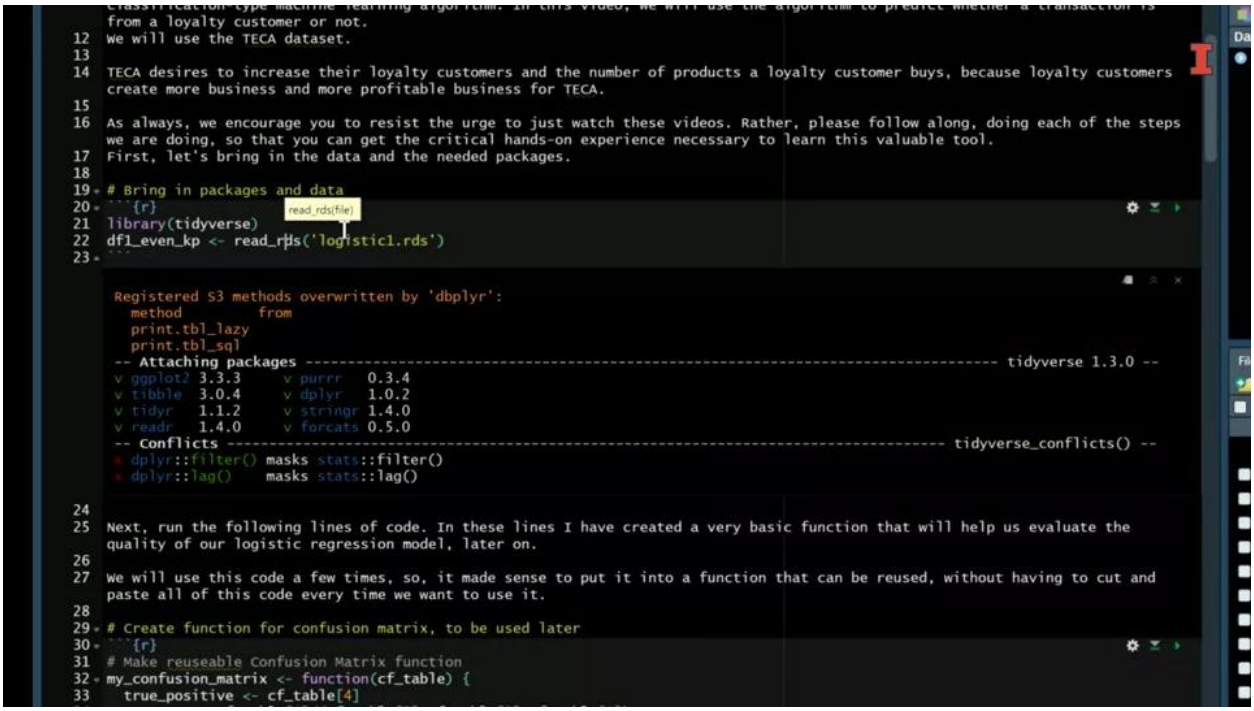


this function provides a nice S curve that gives us precisely what we're looking for. Thus this function models the probability that why the dependent variable belongs to a particular category given the x i the independent variables.

In other words, based upon the found probabilities of the independent variables, logistic regression assigns each data point to a discrete class, in our case, loyal and not loyal. Unlike the ridge regression prediction trendline, the logistic hyper plane represents a classification decision boundary that divides the data set into classes. Finally, the estimation of coefficients of this model is done via maximum likelihood. In general terms you use maximum likelihood to find the intercept and coefficient of X such that the predicted probability of Y is as close to possible to 1 for true y equals 1, and zero for true y equals zero. In summary, as it's probably clear by now, logistic regression is a classification machine learning algorithm. It's useful for prediction and exploration of categorical target variables. It's just one of many different classification algorithms.

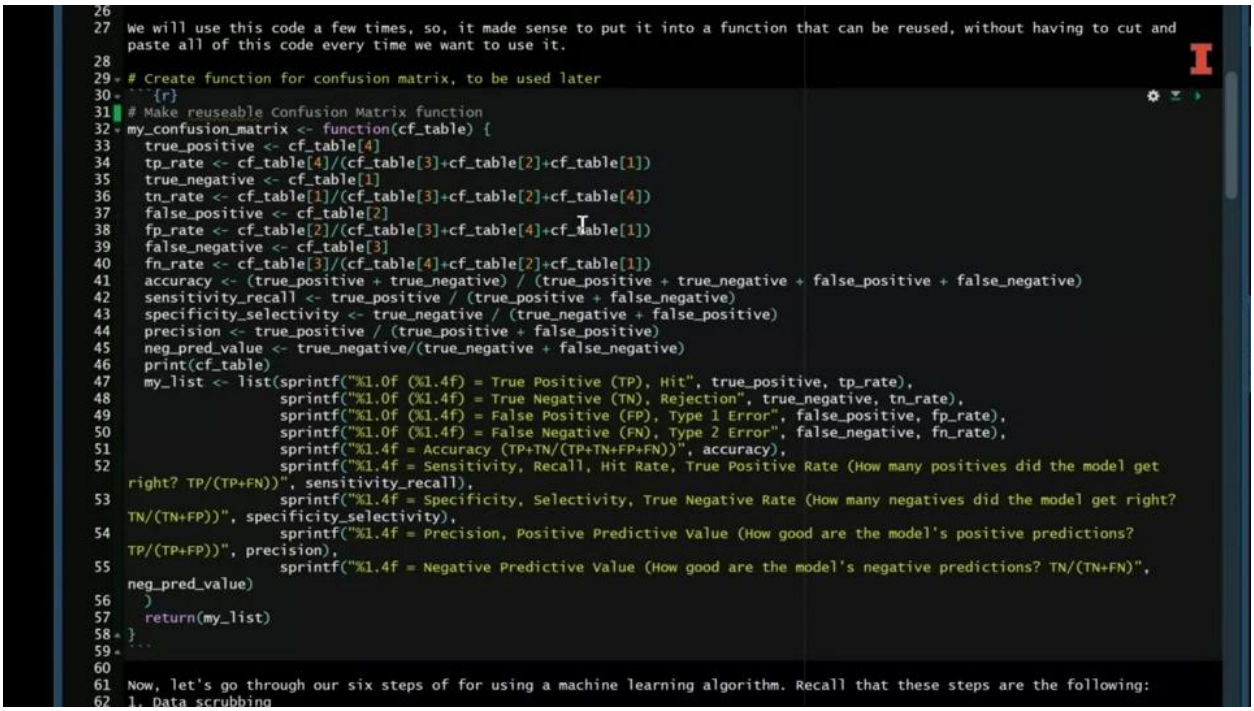
Lesson 2-3.2 Logistic Regression Hands on - One Variable (Part1)

In this video, we'll use the algorithm to predict whether a transaction is from a loyalty customer or not. We'll use the TEKA data set. TEKA desires to increase their loyalty customers and the number of products a loyalty customer buys because loyalty customers create more business, and more profitable business for TEKA. As always, we encourage you to resist the urge to just watch these videos. Rather, please follow along doing each of the steps that we're doing so that you can get the critical hands-on experience necessary to learn this valuable tool. First, let's go ahead and bring in the data-sets and the needed packages.



I'll do that here. The package we're going to use is tidy verse. We put that in the library function. If you don't have the tidy verse package, you'll need to download that yourself. Then we bring in a file that we'll call df1_even_kp. We'll use the read_rds function and the rds file that we provide for you as logistics one.

Next, let's run the following lines of code. In these lines, I've created a very basic function that will help us evaluate the quality of our logistic regression model later on. We'll use this code several times so it makes sense to put it into a function that can be re-used without having to cut and paste all the code every time that we want to use it.



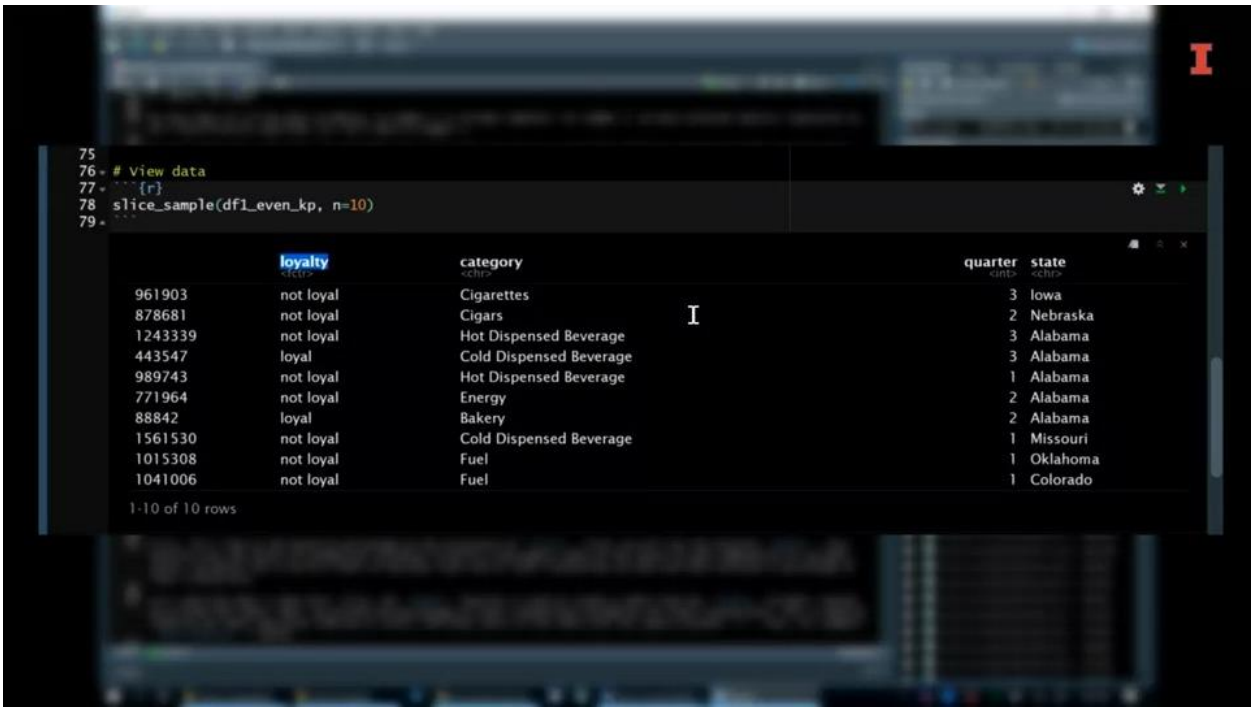
We will use this code a few times, so, it made sense to put it into a function that can be reused, without having to cut and paste all of this code every time we want to use it.

```
# Create function for confusion matrix, to be used later
```{r}
# Make reuseable Confusion Matrix function
my_confusion_matrix <- function(cf_table) {
  true_positive <- cf_table[4]
  tp_rate <- cf_table[4]/(cf_table[3]+cf_table[2]+cf_table[1])
  true_negative <- cf_table[1]
  tn_rate <- cf_table[1]/(cf_table[3]+cf_table[2]+cf_table[4])
  false_positive <- cf_table[2]
  fp_rate <- cf_table[2]/(cf_table[3]+cf_table[4]+cf_table[1])
  false_negative <- cf_table[3]
  fn_rate <- cf_table[3]/(cf_table[4]+cf_table[2]+cf_table[1])
  accuracy <- (true_positive + true_negative) / (true_positive + true_negative + false_positive + false_negative)
  sensitivity_recall <- true_positive / (true_positive + false_negative)
  specificity_selectivity <- true_negative / (true_negative + false_positive)
  precision <- true_positive / (true_positive + false_positive)
  neg_pred_value <- true_negative/(true_negative + false_negative)
  print(cf_table)
  my_list <- list(sprintf("%1.0f (%1.4f) = True Positive (TP), Hit", true_positive, tp_rate),
                  sprintf("%1.0f (%1.4f) = True Negative (TN), Rejection", true_negative, tn_rate),
                  sprintf("%1.0f (%1.4f) = False Positive (FP), Type 1 Error", false_positive, fp_rate),
                  sprintf("%1.0f (%1.4f) = False Negative (FN), Type 2 Error", false_negative, fn_rate),
                  sprintf("%1.4f = Accuracy (TP+TN/(TP+TN+FP+FN))", accuracy),
                  sprintf("%1.4f = Sensitivity, Recall, Hit Rate, True Positive Rate (How many positives did the model get right? TP/(TP+FN))", sensitivity_recall),
                  sprintf("%1.4f = Specificity, Selectivity, True Negative Rate (How many negatives did the model get right? TN/(TN+FP))", specificity_selectivity),
                  sprintf("%1.4f = Precision, Positive Predictive Value (How good are the model's positive predictions? TP/(TP+FP))", precision),
                  sprintf("%1.4f = Negative Predictive Value (How good are the model's negative predictions? TN/(TN+FN)", neg_pred_value)
  )
  return(my_list)
}
```

Now, let's go through our six steps of for using a machine learning algorithm. Recall that these steps are the following:
1. Data scrubbing

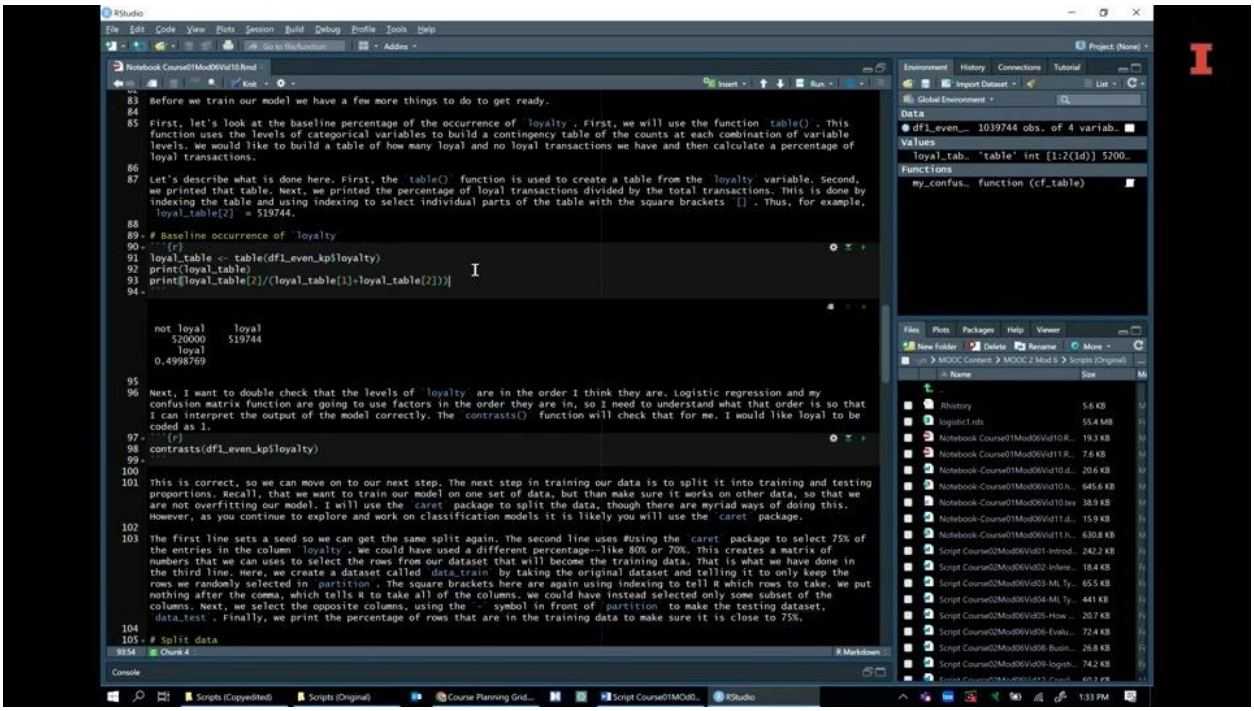
I won't describe this here, but you'll need to go ahead and run it.
```

Next, let's go through our six steps for using a machine learning algorithm. Recall that these steps are the following: one, data scrubbing; two, algorithms selection; three, model training or model fitting; four, model evaluation; and five, model improvement with; six, deploying the model. We've done all the data scrubbing already for you so number 1 is already complete. For number 2, we selected logistic regression as our classification algorithm so let's move on now to Number 3. We'll break this down into multiple parts. Our goal is to train a univariate logistic regression model using our data. That is, we'll predict whether a particular transaction is from a loyalty customer or not.



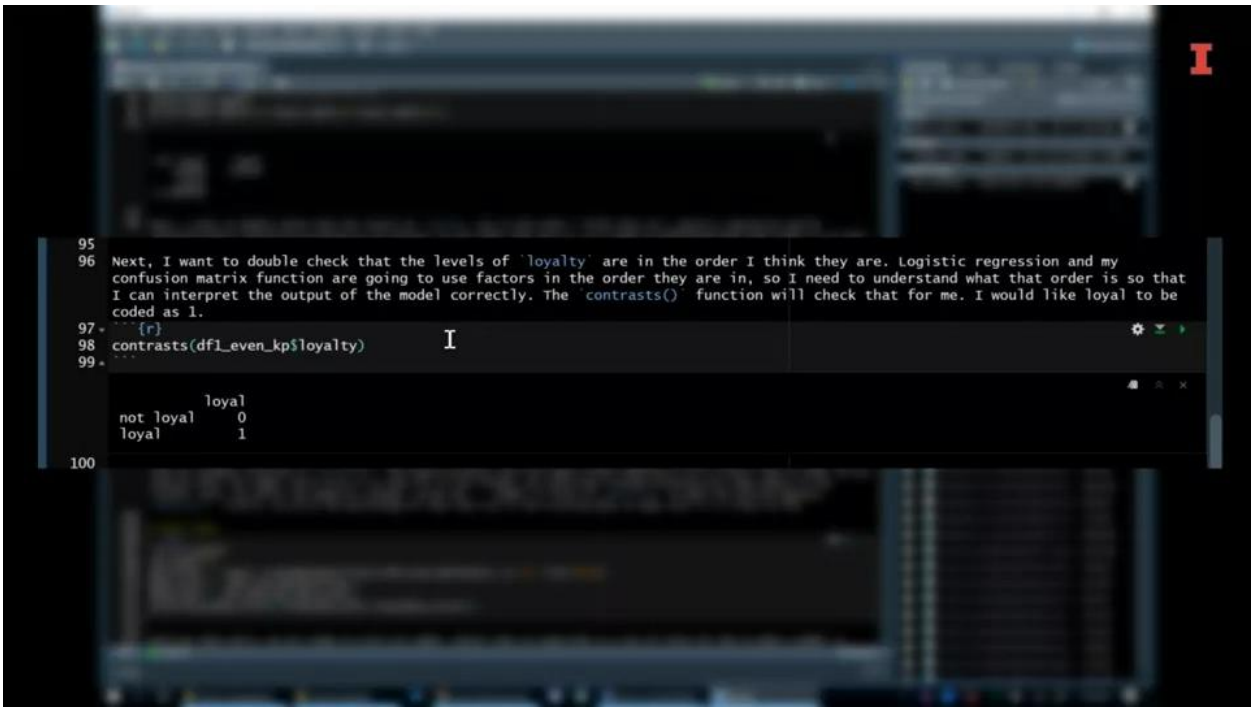
Let's look at the data to remind ourselves what it looks like. To do that, let's run this slice_sample function. Just to get a sense of what the data is, we'll pass n equals to 10 to the function so that we can view and visualize just the first 10 rows. Loyalty, this column right here, this first column, that's our dependence or output or target variable. I'll use those terms interchangeably. Then we need to pick one of the other three, category, quarter, or state, to be the independent variable.

Since TEKA is concerned with predicting what transactions will be loyalty transactions, it probably makes the most sense to use category as our independent variable. Now, before we train our model, we have a few things to do to get ready. First, let's look at the baseline percentage of the occurrence of loyalty. We'll use the function table to do that. This function uses the levels of a categorical variable to build a contingency table of the counts at each combination of variable levels. We'd like to build a table of how many loyal and non loyal transactions that we have and then calculate a percentage of loyal transactions. Let's describe what's being done here. First, the table function is used to create a table from the loyalty variable. Second, we print the table. Next, we print the percentage of loyal transactions divided by the total transactions. This is done by indexing the table and using indexing to select individual parts of the table with the square brackets. That's for example, loyalty Table 2 is 519744.



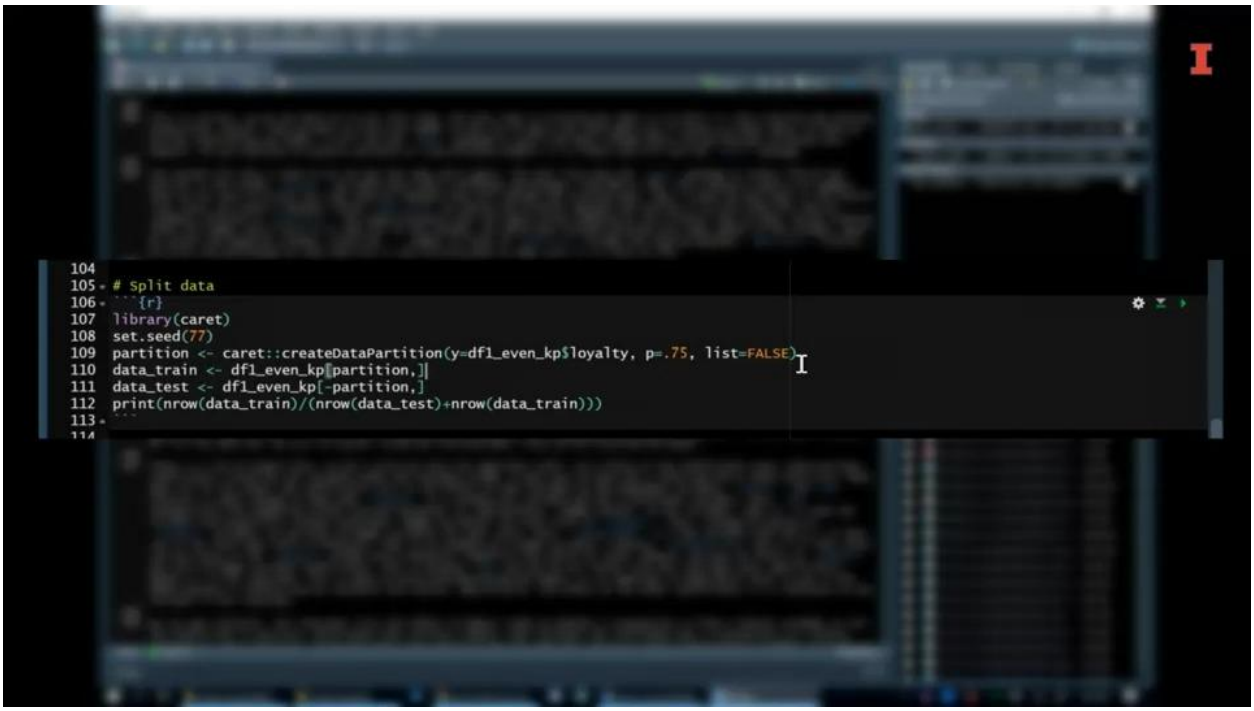
Again, we create a new table called loyal table. We take the table function and we pass the one column from df_even_kp, which is the loyalty column, then we print that table, and we simply index, by using the square brackets, the different parts of that table to create our percentages. There we go.

Overall, loyal transactions happen about 49, almost 50 percent of the time, as you can see from this number here. Next, I want to double-check that the levels of loyalty are in the order I think they are. Logistic regression and the confusion matrix that I created, that first thing we ran way before, is going to use factors in the order that they're in, in that variable. I need to understand what the correct order is so that I can interpret the output of the model correctly. The contrast function will check that for me. I'd like to have loyal be coded as one.



Let's go ahead and run that. Again, I'm simply passing the one column, loyalty column, in that contrast table. Sure enough, that's correct. I can see that zero is not loyal and one is equal to loyal. We can move on to our next step.

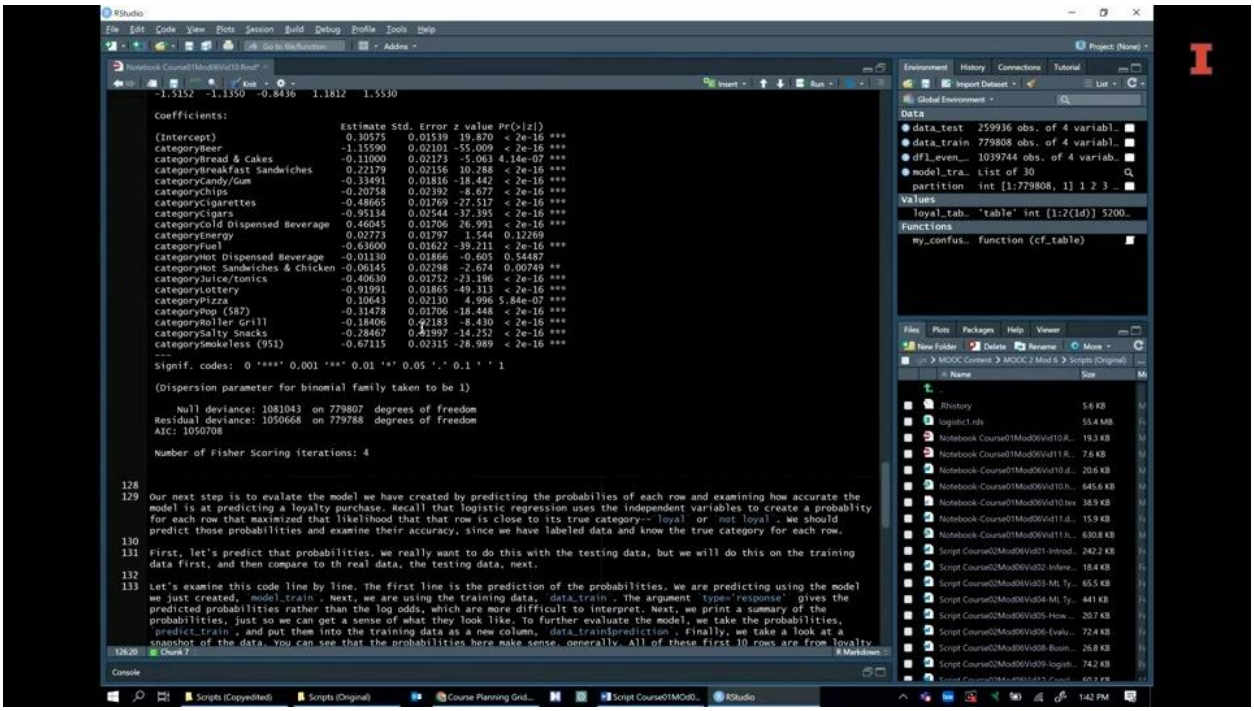
The next step in training our data is to split it into training and testing proportions. Recall that we want to train our model on one set of data but then make sure it works on the other data so that we're not over feeding our model. I'll use the caret package to split the data though there are a million of ways of doing this. However, as you continue to explore and work on classification models, it is likely that you'll probably use the caret package in the future.



This first line here just brings in the caret package using the library function. This next line uses set.seed and then just a number I put in there, 77, to create a seed so that in the third line, the create data partition is going to use the same seed or same starting point every time so we get the same split of data every time. This line then uses the caret package to select 75 percent of the entries in the column loyalty. We could have used a different percentage. We could have used 80 percent, we could have used 70 percent. Let's go ahead and go with 75. This, then creates a matrix of numbers that we can use to select the rows from our data set that will become the training data. That is what we've done in the fourth line here. Here, we create the data set called data train by selecting the original data set and telling it to only keep the rows we randomly selected in the partition that we created right above. The square brackets here are again using indexing to tell R which rows to take, which rows to use. We put nothing after the comma right here which tells R to take all of the columns. Just the rows from partition, but all of the columns. We could have instead selected only some subset of the columns. Next, we select the opposite columns in data test using this minus or dashed symbol in front of partition to make the testing data set, data_test. Finally, we print the percentage of rows that are in the training data just to make sure that it's really close to 75 percent as we intended. We run that, and sure enough we have 75 percent here.

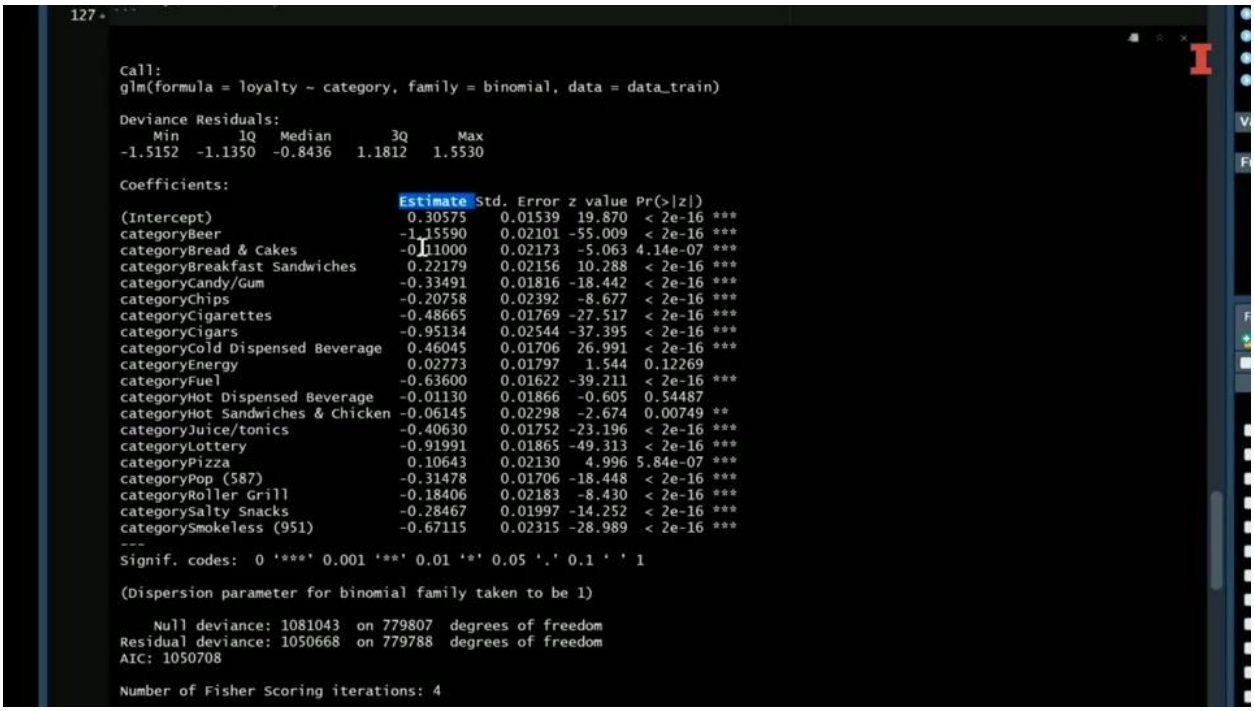
Lesson 2-3.3 Logistic Regression Hands on - One Variable (Part2)

With our Data Split, we're ready to train our model. Recall that an algorithm is a set of rules for how to make a model. A model takes our data and the options we select to create new data, new information, and additional rules for how to use that model. Below we create our model called model train. Then summarize it to view the output, we use the GLM function with the family equals binomial argument to select logistic regression model. The syntax is quite simple here, our dependent variable, loyalty goes first. Then we use the tilde sign, that squiggly line, to act like an equal sign, followed by our independent variable, category in this case. Finally, we list the data set. We are of course using the training data since we're training the model so far.



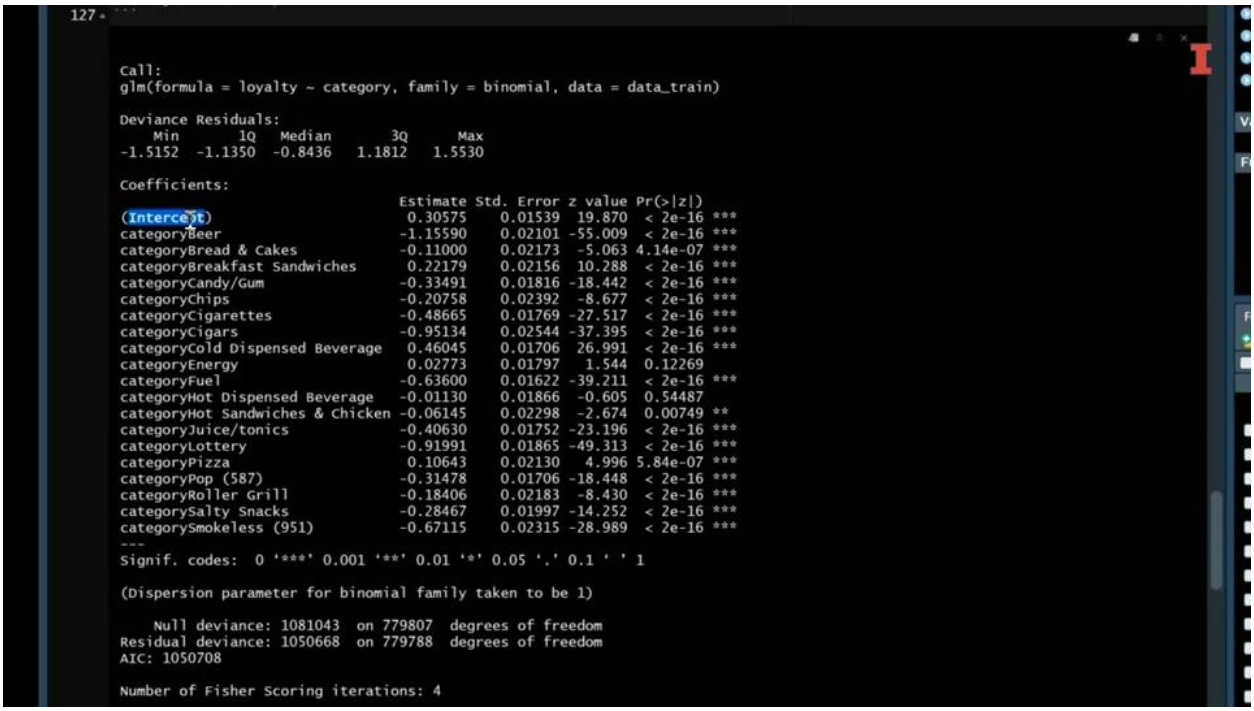
Let's go ahead and run that and we'll also summarize it with the summary function. I'll take a moment to train that and you can see we're running it and there it is.

There's a lot of data here and let's pick out only the most important things and talk about those.



We'll focus first on the coefficients area. There we have coefficients listed for our variable under the estimate column, right here. Here's the coefficients for each of those category levels.

Away over to the right here we have the z-values and the p-values, here and here. What does all this mean? The coefficients tells us the effect of that particular variable or level of variable on the dependent variable which is loyalty. The GLM function is smart enough to know that category is a categorical variable and not a continuous variable. Thus, the function automatically did something called one-hot encoding. Equivalently, we could call that dummy coding. It did that to category all on its own. That is, it took the variable and essentially created individual dummy variables for each level of category. You can see those here. Thus, instead of having one category variable, we now have 19 dummy variables for each level of category or almost each level. Thus, category beer is a new variable that has a one if that row is as a beer purchase and a zero otherwise. That's an example of a dummy variable. Likewise, category pizza, for example, has a one if that level row has pizza in the category column and a 0 otherwise.



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127

Call:
glm(formula = loyalty ~ category, family = binomial, data = data_train)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.5152  -1.1350  -0.8436   1.1812   1.5530

Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                       0.30575    0.01539  19.870  < 2e-16 ***
categoryBeer                     -1.15590    0.02101 -55.009  < 2e-16 ***
categoryBread & Cakes            -0.11000    0.02173  -5.063 4.14e-07 ***
categoryBreakfast Sandwiches      0.22179    0.02156  10.288  < 2e-16 ***
categoryCandy/Gum                -0.33491    0.01816 -18.442  < 2e-16 ***
categoryChips                    -0.20758    0.02392  -8.677  < 2e-16 ***
categoryCigarettes               -0.48665    0.01769 -27.517  < 2e-16 ***
categoryCigars                   -0.95134    0.02544 -37.395  < 2e-16 ***
categoryCold Dispensed Beverage   0.46045    0.01706  26.991  < 2e-16 ***
categoryEnergy                    0.02773    0.01797   1.544  0.12269
categoryFuel                     -0.63600    0.01622 -39.211  < 2e-16 ***
categoryHot Dispensed Beverage   -0.01130    0.01866  -0.605  0.54487
categoryHot Sandwiches & Chicken -0.06145    0.02298  -2.674  0.00749 **
categoryJuice/tonics             -0.40630    0.01752 -23.196  < 2e-16 ***
categoryLottery                  -0.91991    0.01865 -49.313  < 2e-16 ***
categoryPizza                     0.10643    0.02130   4.996 5.84e-07 ***
categoryPop (587)                -0.31478    0.01706 -18.448  < 2e-16 ***
categoryRoller Grill             -0.18406    0.02183  -8.430  < 2e-16 ***
categorySalty Snacks             -0.28467    0.01997 -14.252  < 2e-16 ***
categorySmokeless (951)          -0.67115    0.02315 -28.989  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1081043  on 779807  degrees of freedom
Residual deviance: 1050668  on 779788  degrees of freedom
AIC: 1050708

Number of Fisher Scoring iterations: 4
```
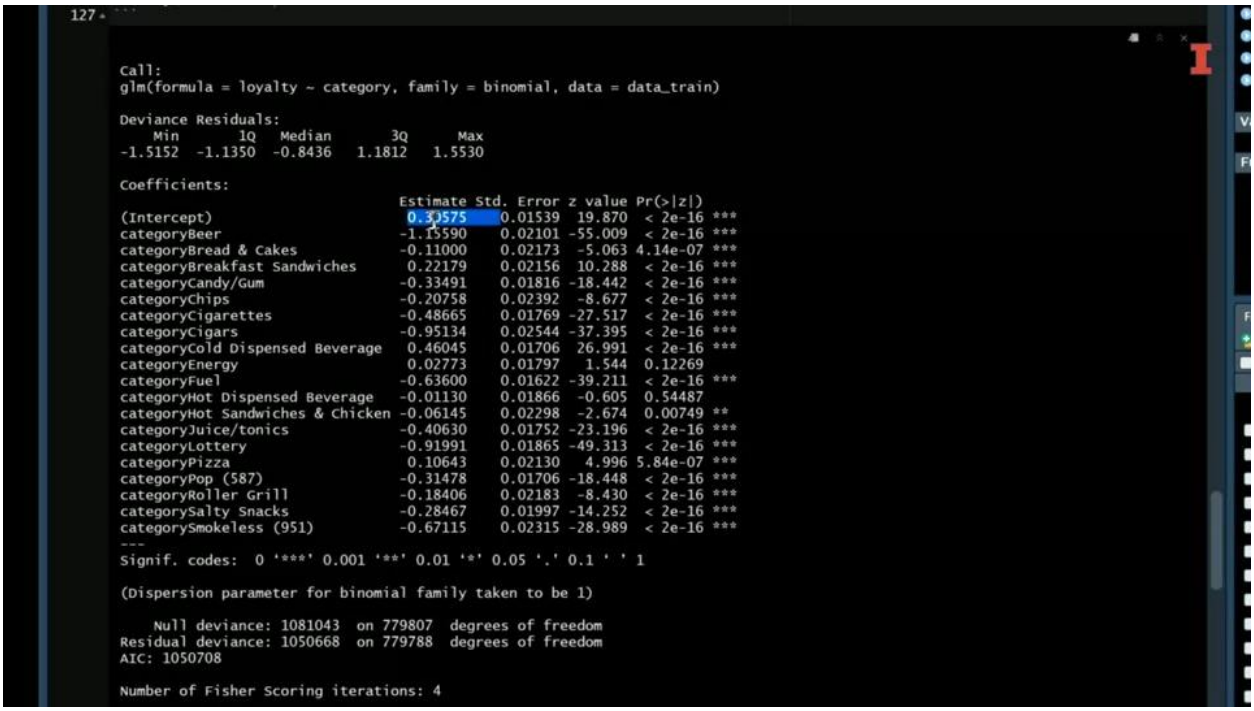
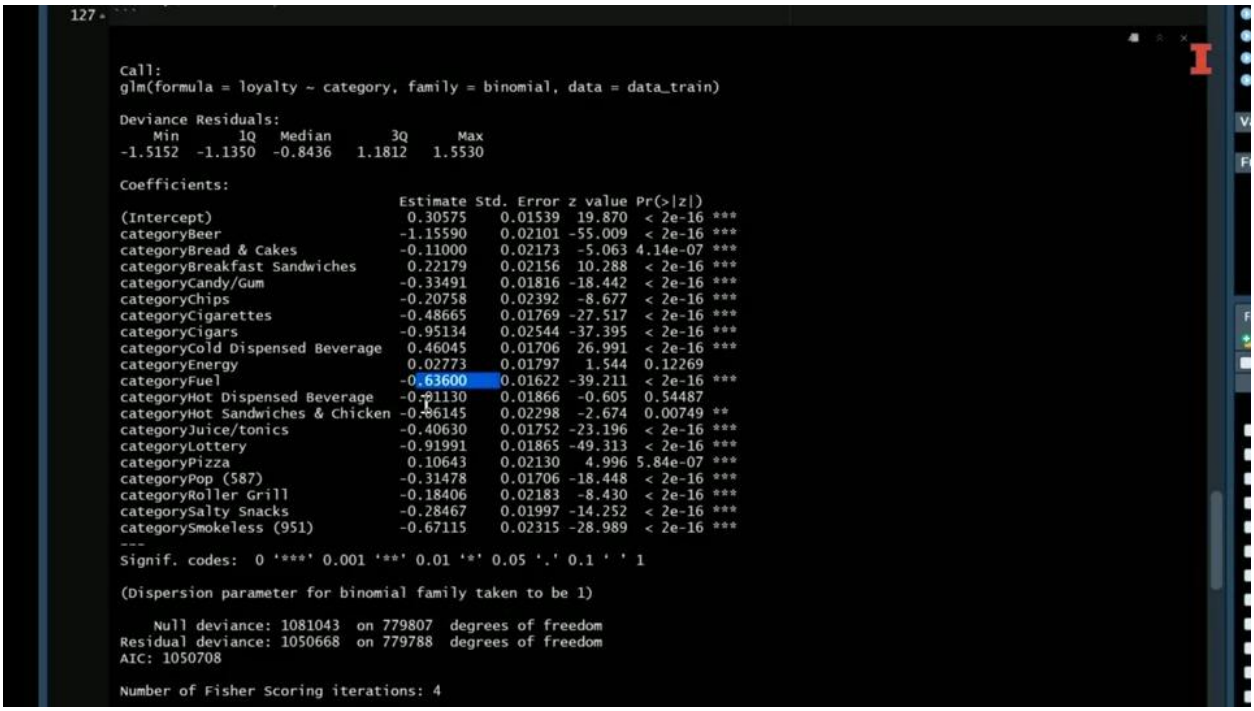

Now hopefully you noticed an issue. We have 20 levels of category, if you remember back from above, but we only have 19 dummy variables here. That's because GLM smartly puts one of the levels of our category variable in the intercept term, the intercept right here.

Specifically, bakery is in the intercept. This is done to avoid over specifying the model. It's important to know which level is not in the model and which is in the intercept because it affects how we interpret the results. Specifically, the effect of the other coefficients is in reference to the variable that's in the intercept which in this case is bakery. We can now interpret. The coefficient on intercept here lists the effect of bakery items on whether a transaction is from a loyalty customer or not.



The coefficient here is positive, which means that selling a bakery item increases the likelihood that a transaction is a loyalty transaction.

More precisely, purchasing this item increases the log odds of a loyalty purchase happening by 0.30575. Now we won't go into log odds, but it suffices to say that buying a bakery item increases the likelihood of a transaction being from a loyalty customer. Let's look at some more of our dummy variable coefficients here.



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127

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Deviance Residuals:
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Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
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categoryCandy/Gum                -0.33491    0.01816 -18.442  < 2e-16 ***
categoryChips                    -0.20758    0.02392  -8.677  < 2e-16 ***
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---
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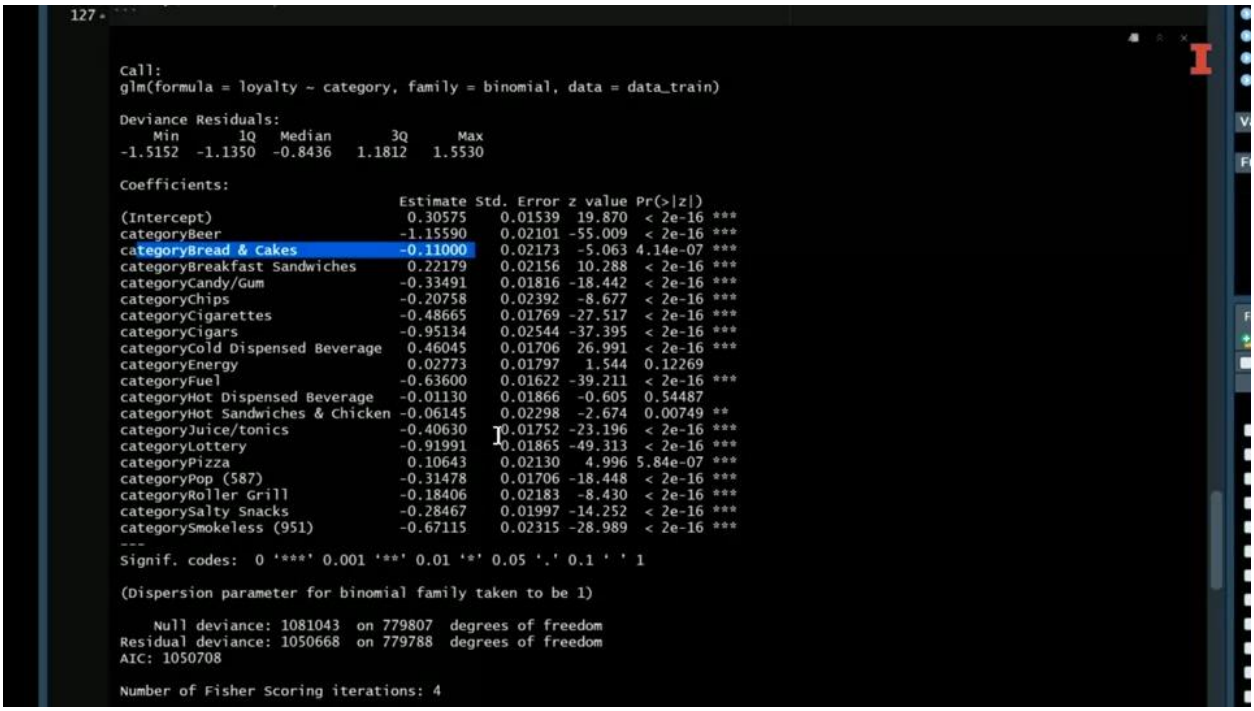
AIC: 1050708

Number of Fisher Scoring iterations: 4
```

Let's look at fuel for example. Fuel actually decreases the chance of the transaction being from a loyalty customer relative to a bakery item. Again, bakery is in the intercept,

as can be seen by this negative coefficient here. More specifically, the coefficient is still negative even relative to the intercept, which again is bakery. That is, fuels coefficient plus the intercept is still negative if we add those two together. This means that fuel decreases the chance that a loyalty customer makes a purchase. Now this does make sense since bakery item is one that you go into the store for, which is more likely to happen for a loyalty customer, whereas anyone can just drive by and purchase gas. Next, let's look at fountain soda or cold dispensed beverage. This increases the chance the purchase was from a loyalty customer, even more than purchasing a bakery item. Thus, fountain soda seems to be a big draw for our loyalty customers and it could be a way that take I could bring increased loyalty purchases. Again, we noticed that specifically by the positive coefficient,



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Number of Fisher Scoring iterations: 4
```
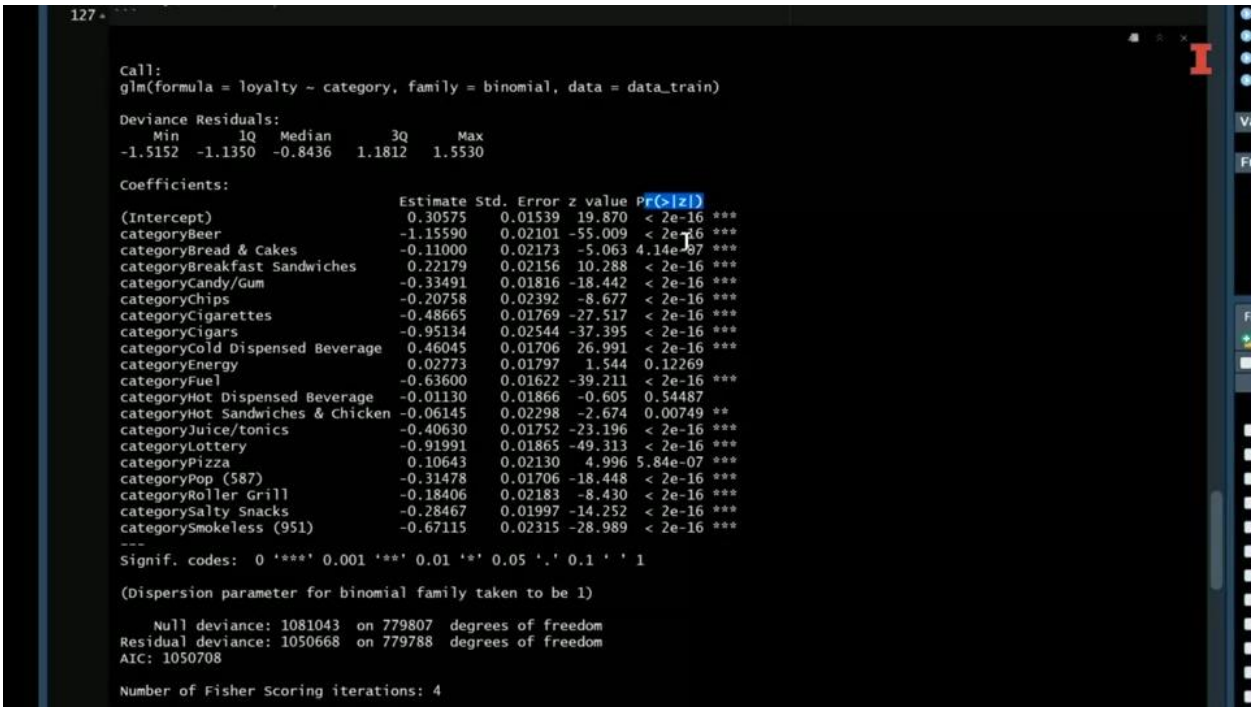
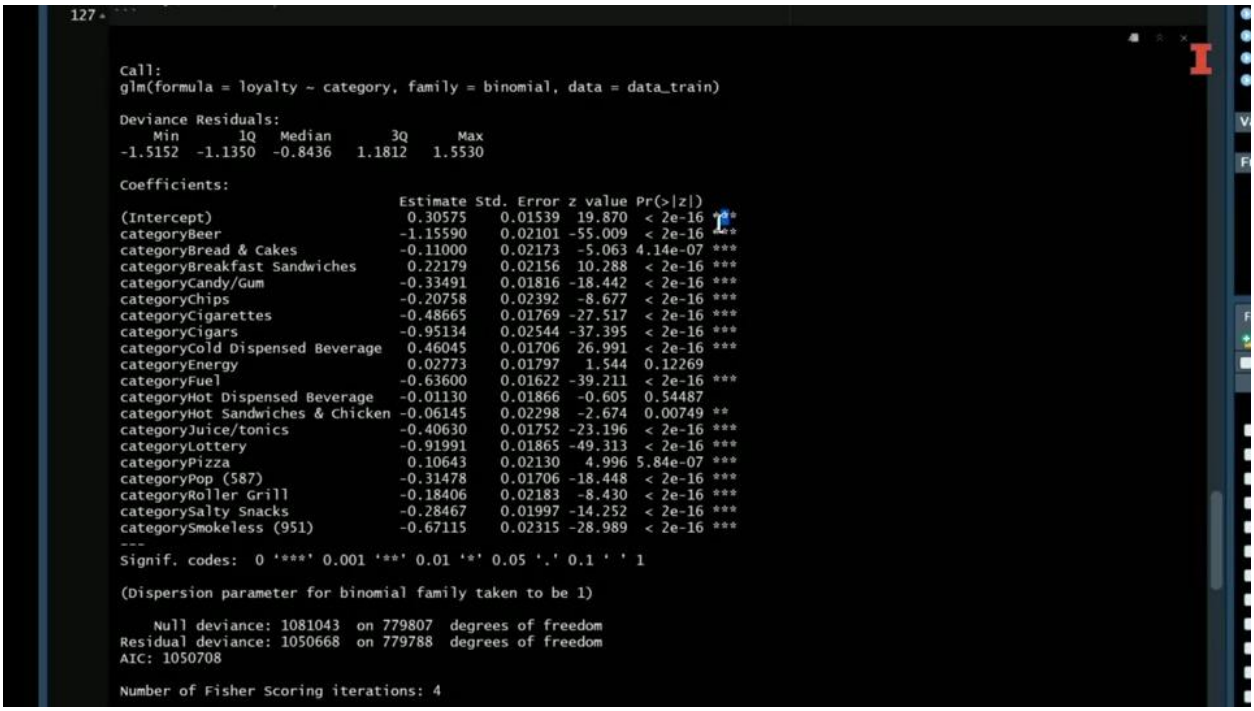

the fact that the 0.40645 is even larger than the 0.30575. Finally, let's look at the effect of bread and cakes. What effect does this have? It's a small negative coefficient,

but if we add this negative coefficient, the negative 0.11000, to the intercepts, we see that the difference is actually positive. Again, adding those two together. Thus, bread and cakes has a significant effect on the chance of purchase as a loyalty purchase. Again, we have to compare with the intercept because the bakeries in the intercept and we don't want to over specify our model. Next, it's not enough to see what the sign of the coefficients are that's what we've been doing. But we need to see whether the coefficient has a statistically significant effect on loyalty, we see this in at least two ways. First, we can look at the p level.



The p are greater than z right here, this last column or next to last column. This is the probability that the coefficient we're particularly looking at is equal to zero.

This is not the technical definition for that but it's a point to remember. The thing that you should retain is that the lower the p-value, that means that the coefficient is not equal to zero, and thus is statistically significant. Now, additionally, just to the right of that,



```
127

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categoryJuice/tonics            -0.40630    0.01752 -23.196  < 2e-16 ***
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categoryPizza                    0.10643    0.02130   4.996 5.84e-07 ***
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---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

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AIC: 1050708

Number of Fisher Scoring iterations: 4
```
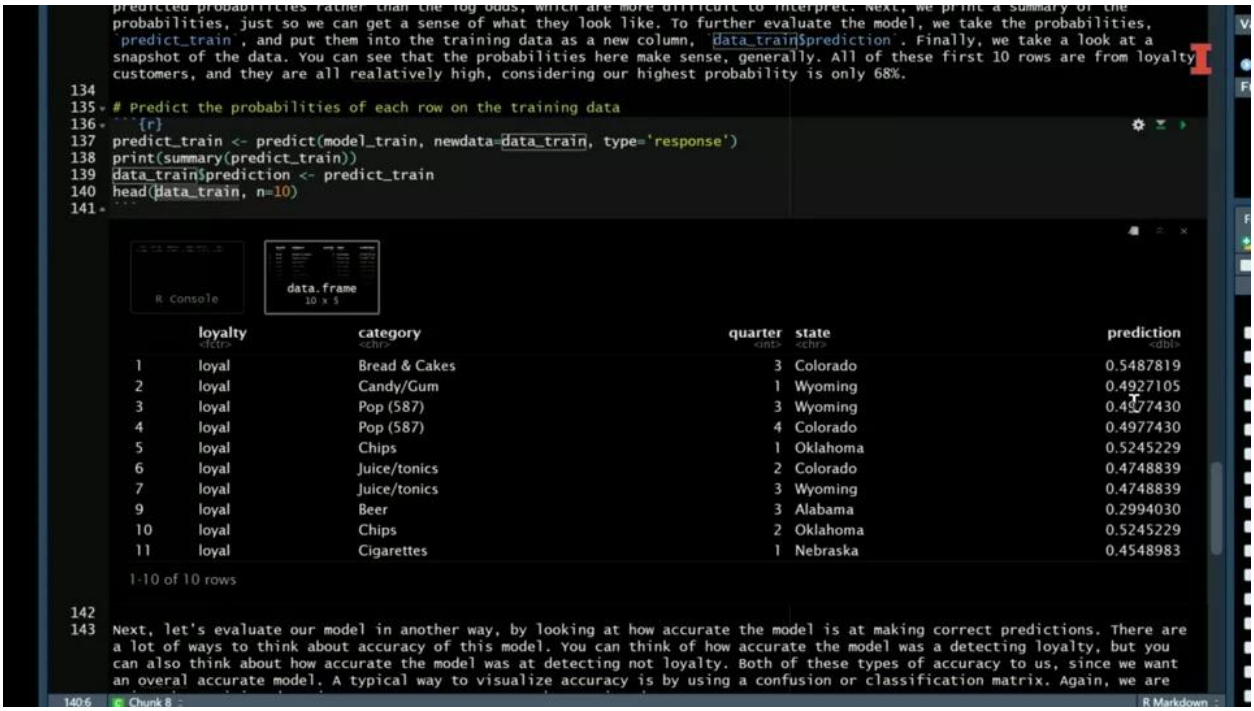

you see these asterix here, these little stars. These also indicate the significance of the coefficient.

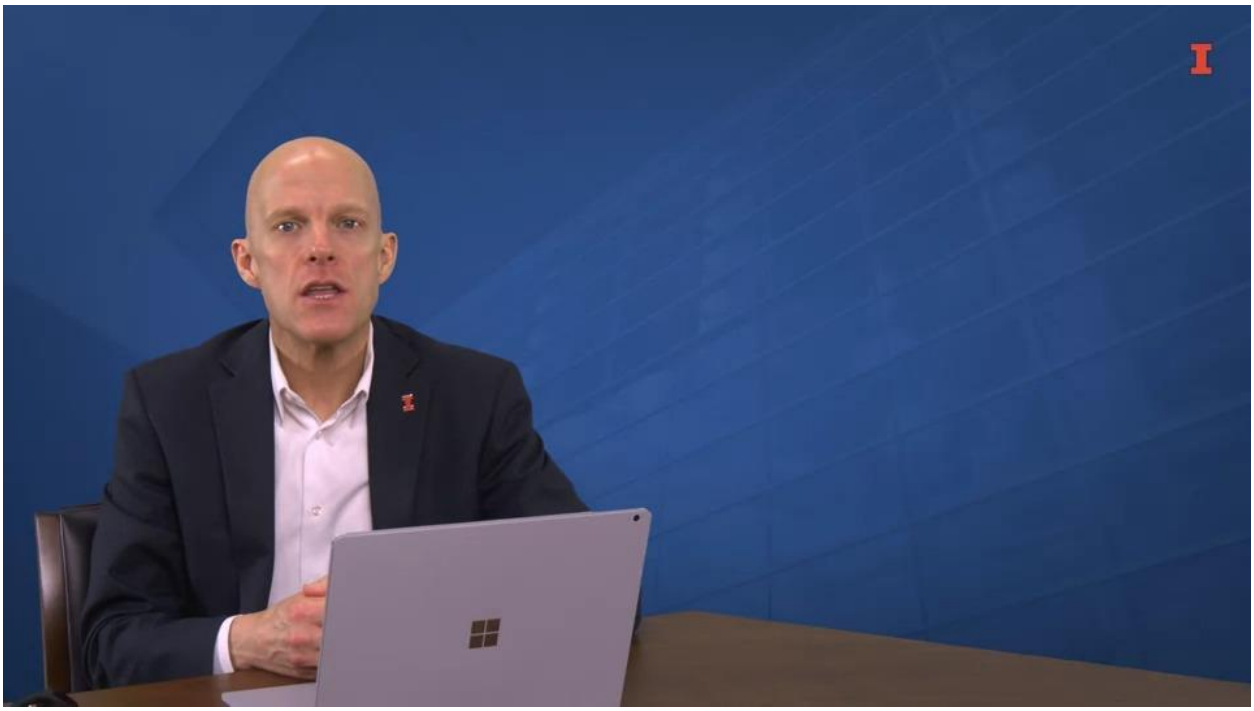
The more stars, the more significant it is, the more likely that the coefficient is not zero. We have a lot of data here and even small coefficients are likely to be significant. Sure enough, only energy drinks if we look down, and hot sandwiches and chicken are not significant relative to bakery. Overall, what do we learn from this output? We know now that several categories, such as fountain sodas, bakery items, breakfast sandwiches, help increase the chance that a customer will be a loyalty customer. Tikka could promote these products to try to draw in more loyalty customers.

Lesson 2-3.4 Logistic Regression Hands on - One Variable (Part3)

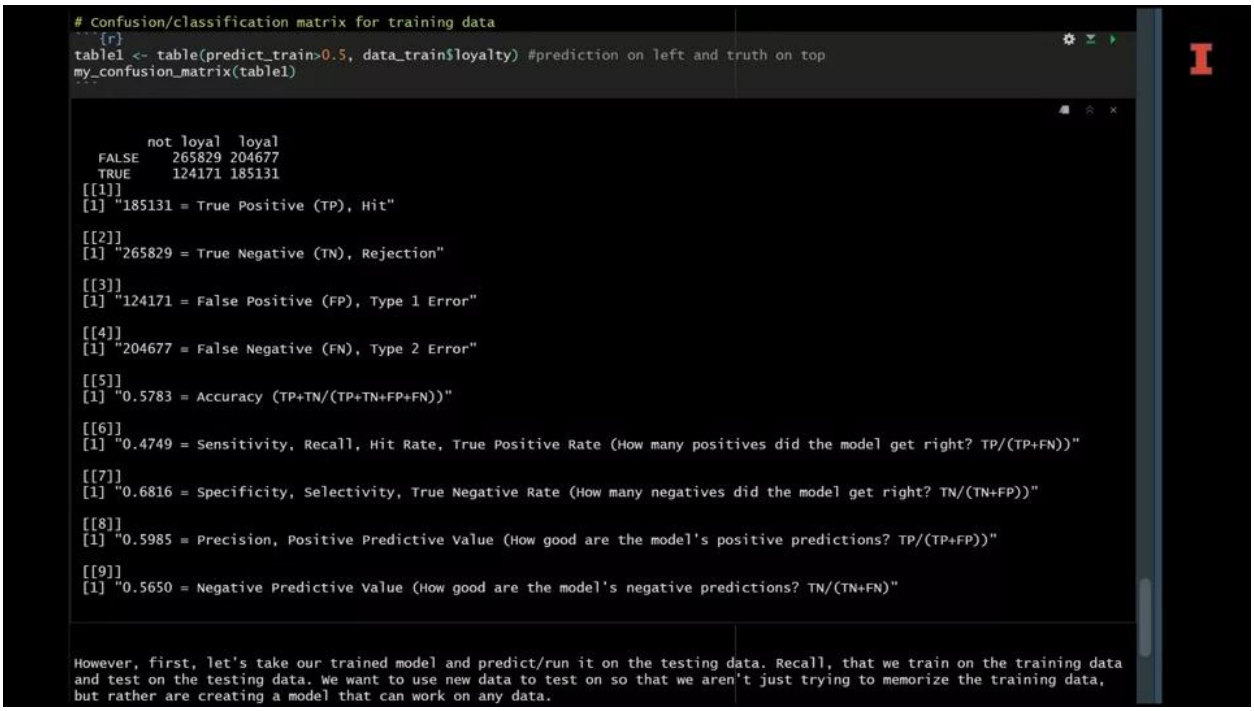
So our next step is to evaluate the model that we've created by predicting the probabilities of each row and examining how accurate the model is at predicting a loyalty purchase. Recall that logistic regression uses the independent variables to create a probability for each row that maximizes the likelihood that the row is close to the true category, loyal or not loyal. Whichever one is the true category. We should predict those probabilities and examine their accuracy since we've labeled data and we know what the true category is for each row. So first. Let's go ahead and predict the probabilities. We really want to do this with the testing data. But we'll do this with the training data first and then compare to the real data and the testing data after that.



So, let's examine this code here, line by line. The first line is the predictions of the probabilities. We're predicting using the model we just created, model train. All right. So we have the predictive function. We're going to call this new prediction object predict train. Again, we have the training data. Next, as you can see, we make sure we're using the training data by having new data equal data train. The next argument, type equals response, gives the predicted probabilities rather than the law gods, which are more difficult to interpret. So next we're going to print a summary of the probability just so that we can get a sense of what they look like. To further evaluate the model, we take the probabilities, predict underscore train and we're going to put them into the training data as a new column called prediction. Finally, we're going to take a look at a snapshot of the data. So let's run this. We train up our model, we go ahead and do head to look at the top ten rows of our training data. All of these first ten rows are from the loyalty customers as we look. They're all from loyalty and they're all relatively high under the prediction column here. Considering that all of them are are above 58% or so.

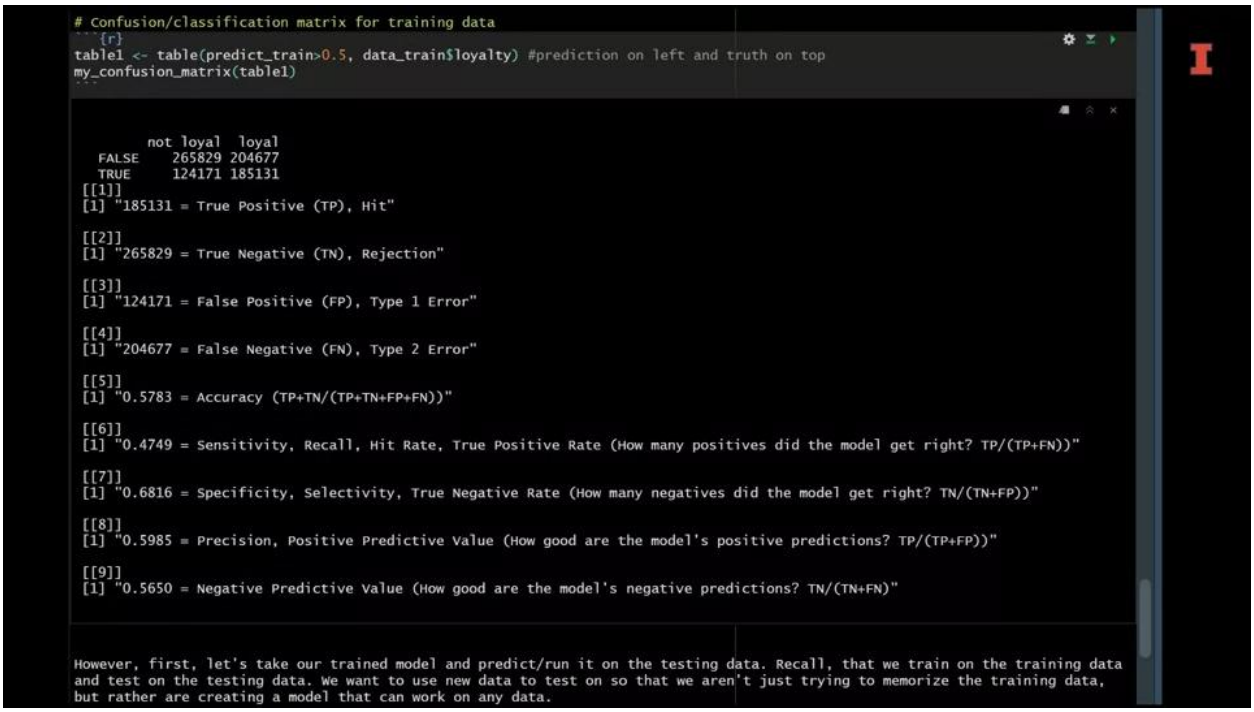


So next we want to evaluate our model in another way by looking at how accurate the model is in making correct predictions. So there's a lot of ways to think about accuracy of the model. We can think about how accurate the model is at detecting loyalty, but you can also think about how accurate the model is at detecting not loyal or a non loyalty transaction. Both of these types of accuracy makes sense since we want the overall accuracy of the model to be really good. A typical way to visualize accuracy is by using a confusion matrix or a classification matrix. Again, we're using the training data here. So just so we can compare later on to the testing data which we want to use ultimately. So let's again look at the code line by line.



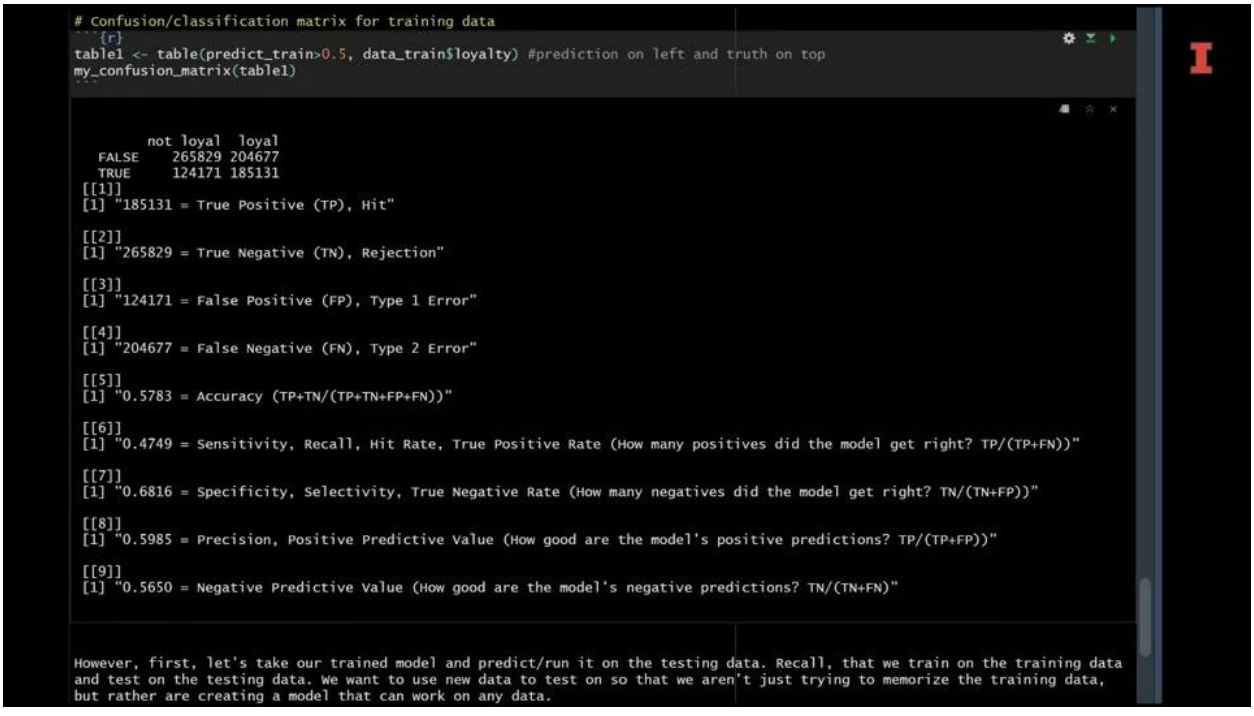
The first line creates a table using the table function that we saw before. All right. This table takes the probability predictions from above, predict underscore train and writes false if the probability is less than 0.5 and true if it's more than 0.5. These are our predictions using again the training data. So let's run that and you can see here at the top what we have. So you can see the faults and true categories here on the left of the table. So it's going to compare these with the truth, which is the loyalty column. So not loyal and loyal here on the top. So the second line then up here from the code is going to run the function from way above that we used at the beginning and ran at the beginning of the notebook.

And this function just takes the four cells of this table and labels them and manipulates them to create various types of accuracy displayed right here below. So you have that all here and let's go ahead and explore this. The table shows the following output. First, when a transaction is actually truthful, a loyalty transaction, the model correctly classifies it

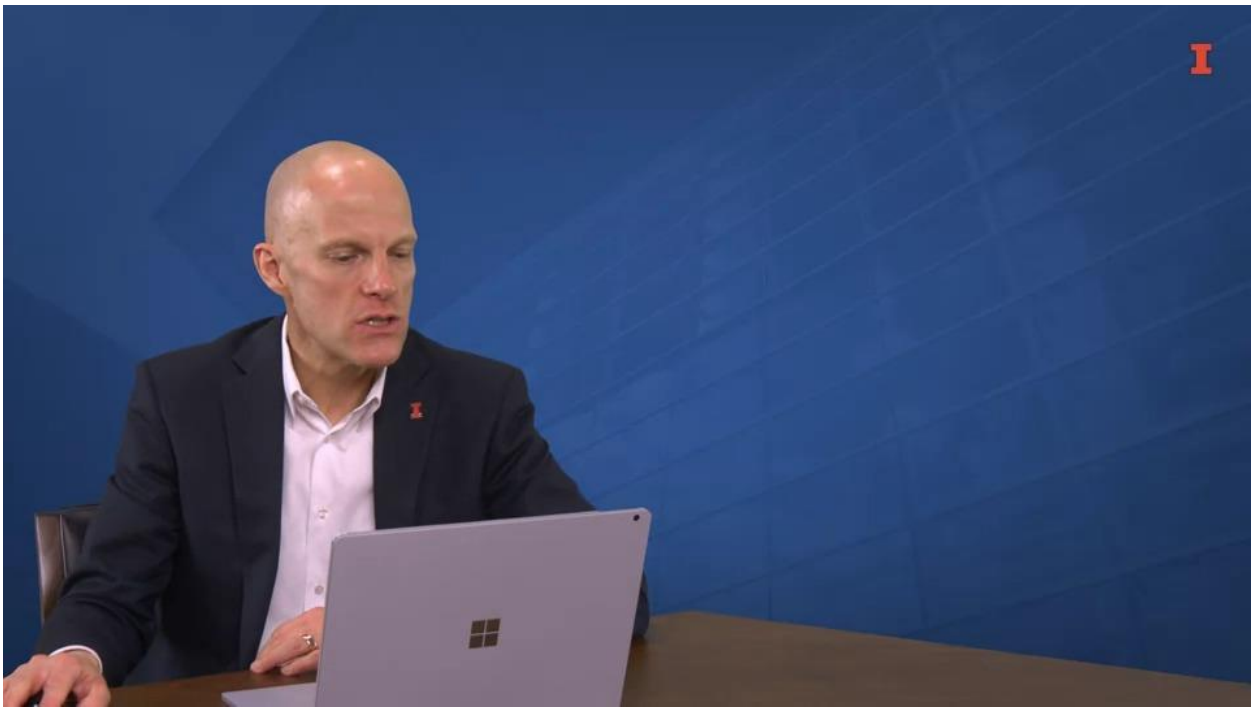


as such by saying true. So that's right. That's this right here. The 185, 185,131.

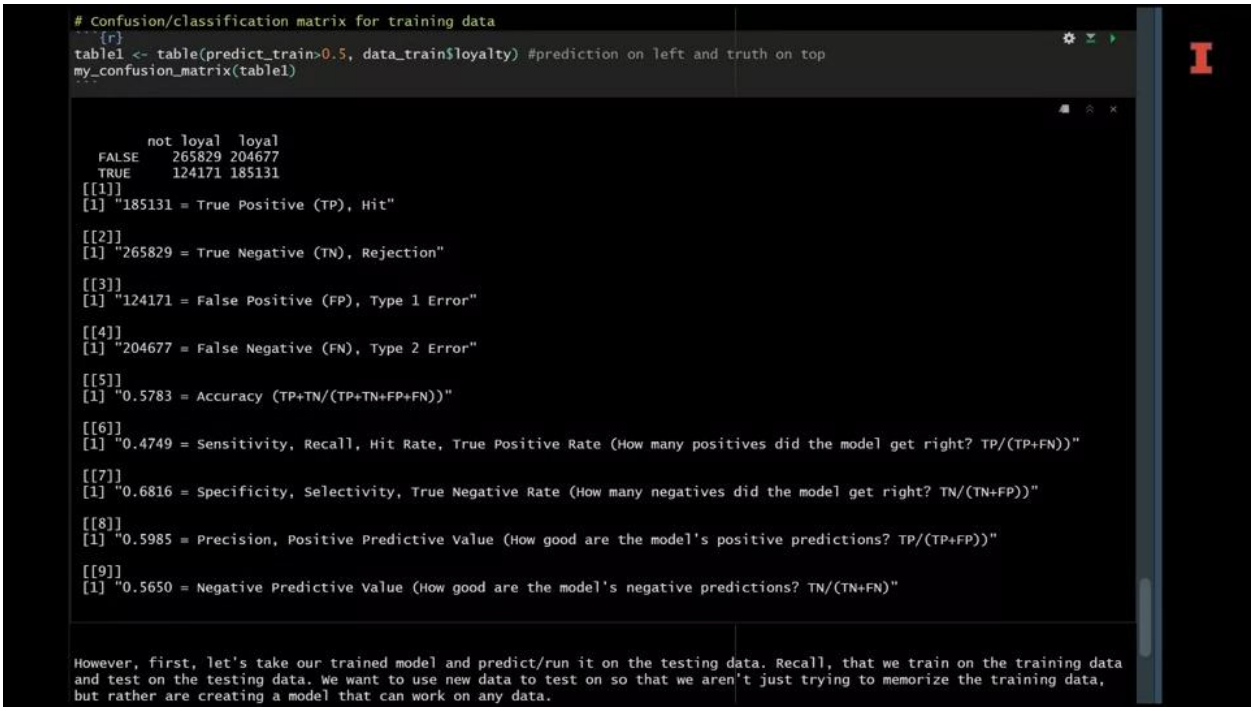
So this is called a true positive or a hit. Now, when a transaction is truthfully a non loyalty transaction, okay,



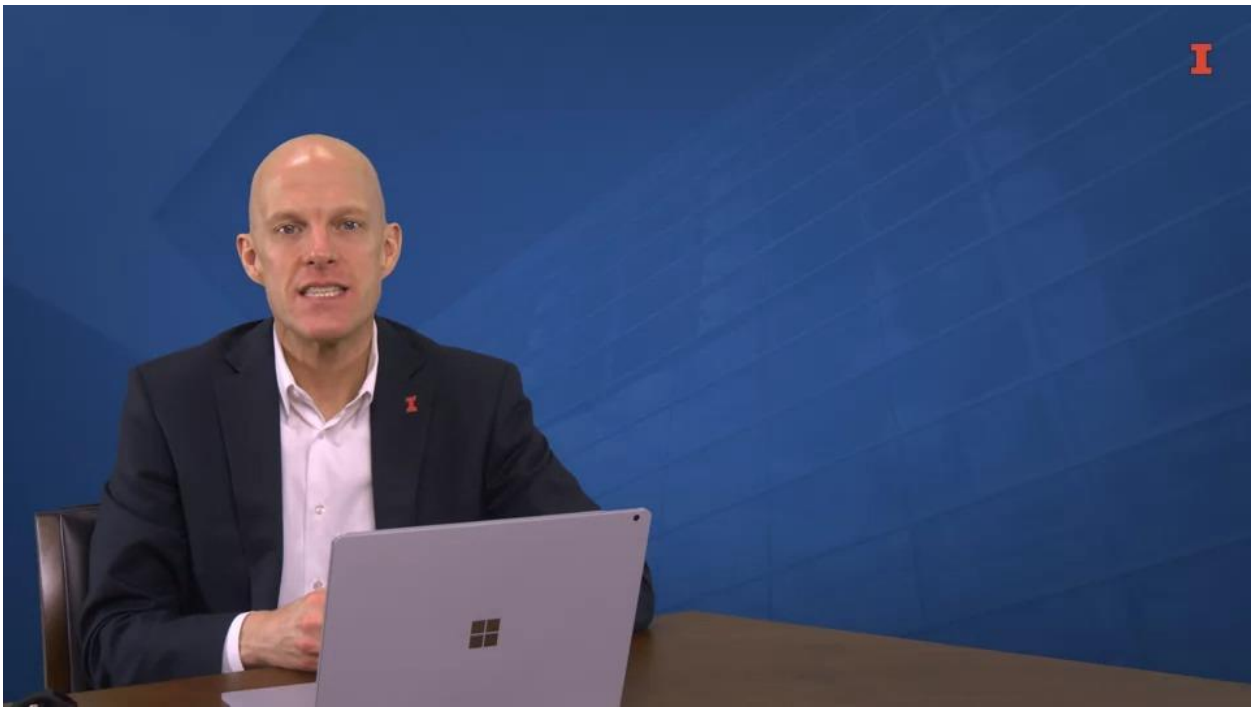
so the truth is not loyal and indeed our model says fault says It's not loyal. That happens, 265,829 times. This is called a true negative or rejection and again, that's also listed right down here.



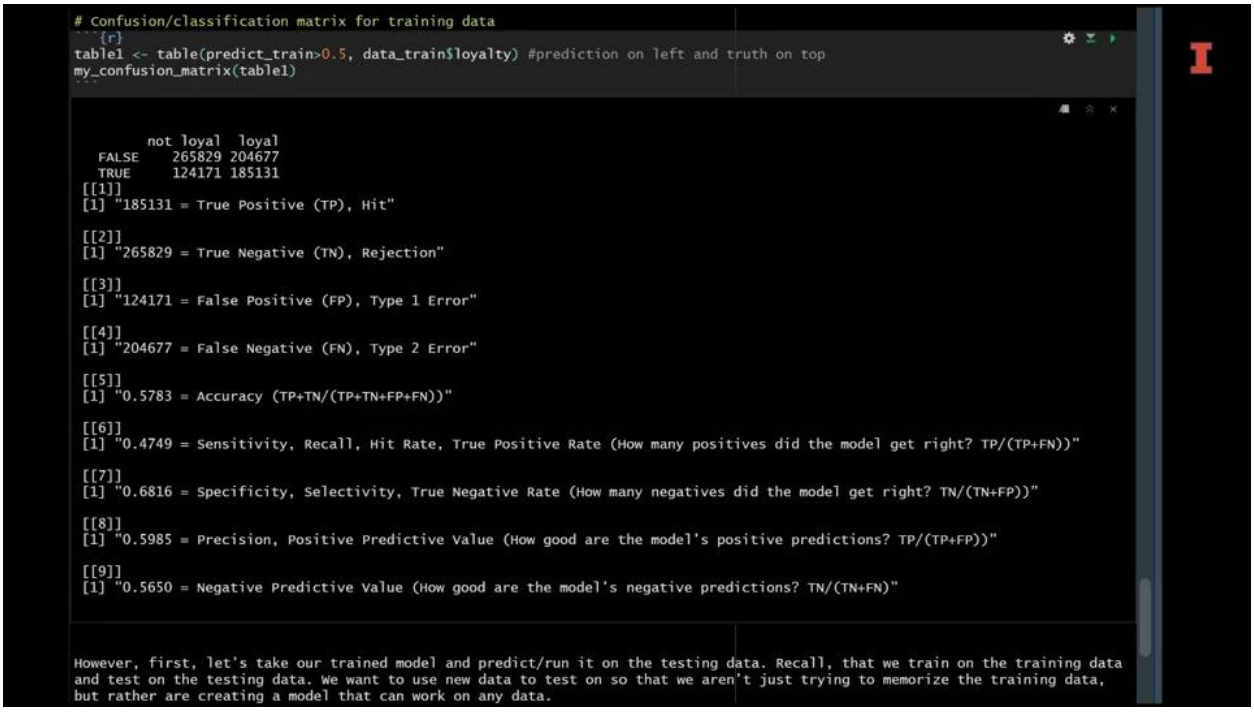
On the other hand, the model makes two kinds of errors. When the model transaction is not a loyal transaction, but the model incorrectly says that it is, this is called a fault positive or a type one error. And this happens 124,171 time. So that's here.



Again, this is not a loyalty transaction because this is truth. But the model says that it is and so that we call that a type one error.

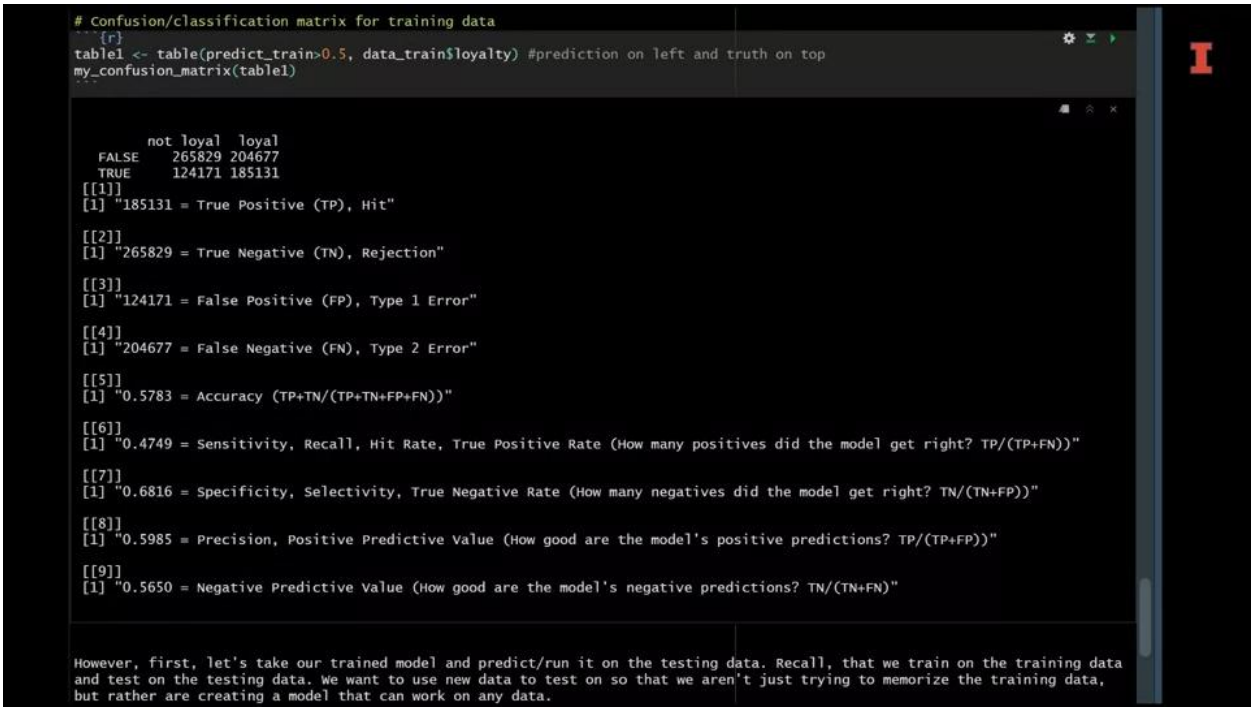


Finally, when a transaction is a loyalty transaction and the model says it is not, which here happens 204,677 times it's called a faults negative or a type one error.



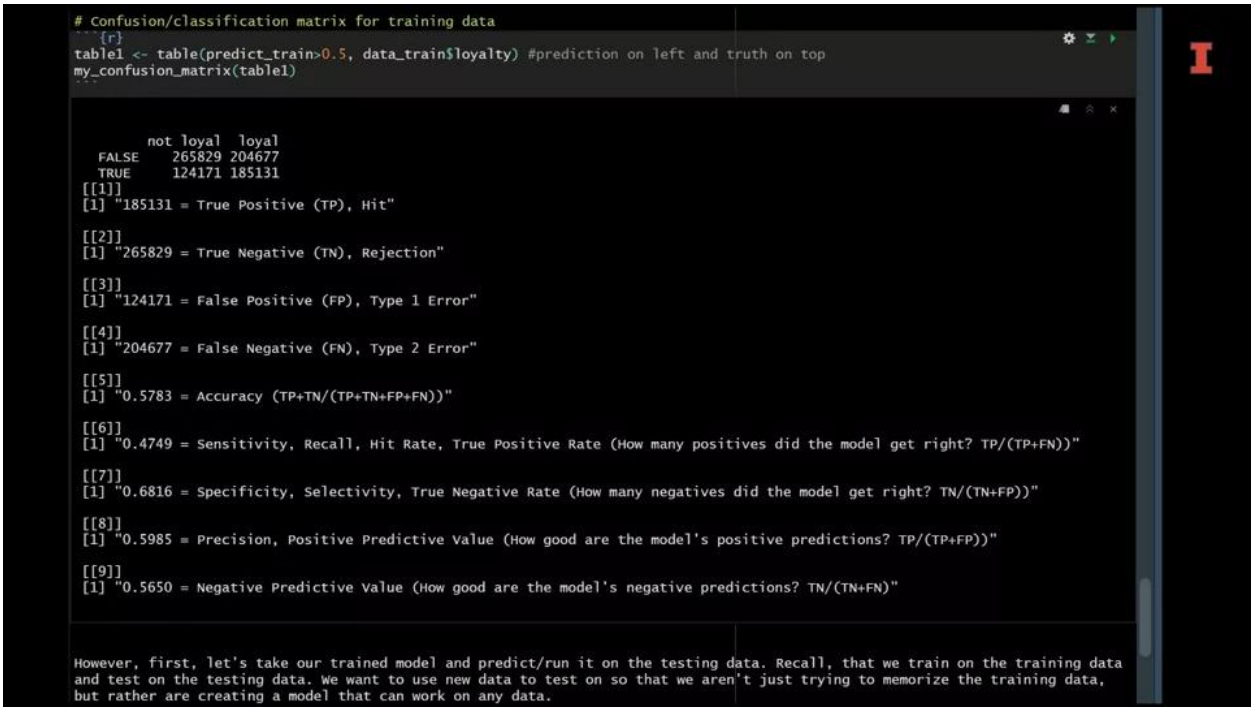
Again, we see that here where it actually is a loyalty transaction but the model says it is not.

So these numbers can then be manipulated, multiplied and divided to create different measures of accuracy that are commonly used in practice. For example,



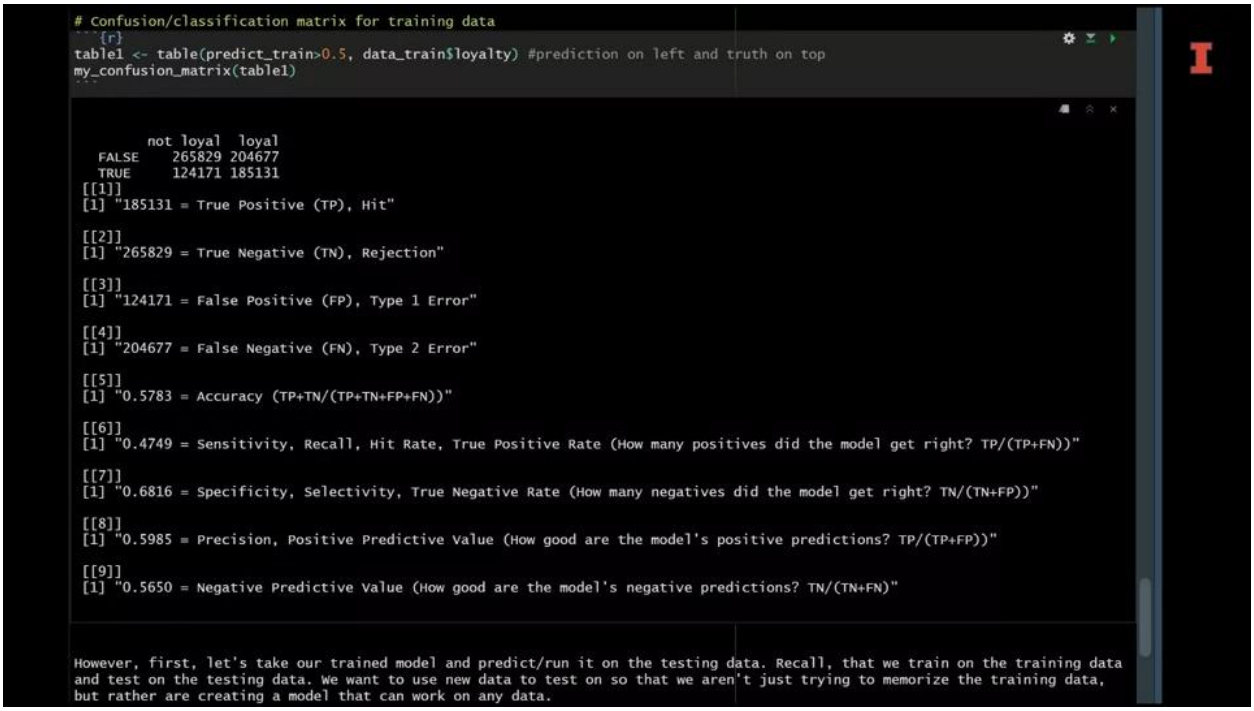
overall accuracy is probably the most important thing that we're interested in here. Overall accuracy is 57, about 58%.

Next we have sensitivity. This is also called the recall rates or the true positive rates or the hit rate. Basically, how many positives did the model get right.



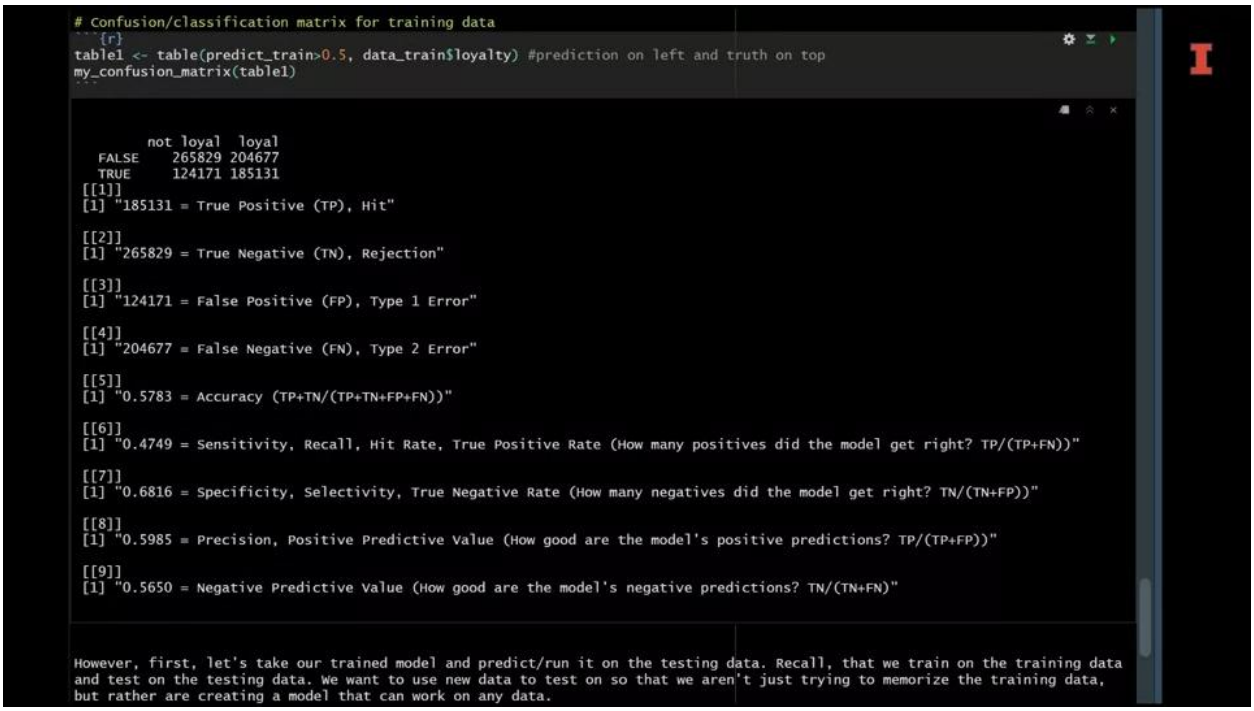
And here we're actually below 50% at 47%. Next we have specificity also called selectivity, the true negative.

This basically answers how many negatives did the model get right. And here we're at 68%.



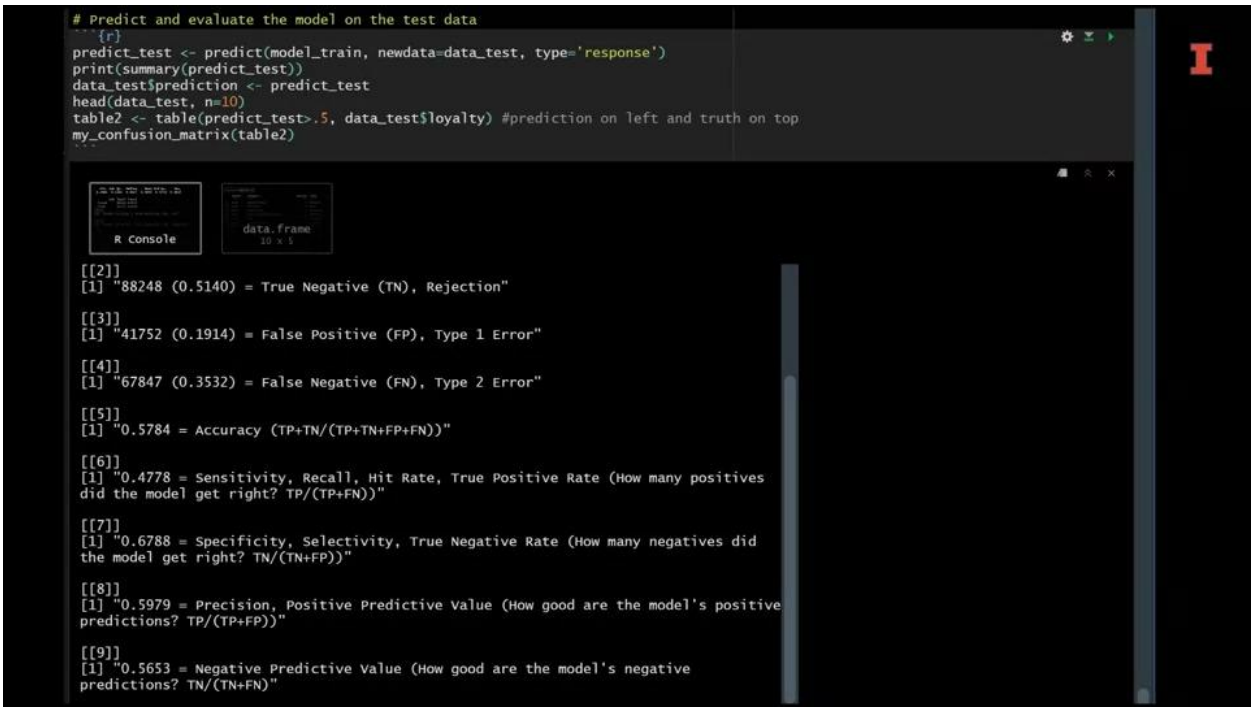
Next we have another common measure of accuracy and that's precision. Also called the positive predictive value. This basically says how good are the model's positive predictions. And again, in each case I've indicated how these are calculated, so you can refer back to that. Last, we have the negative predictive value, and this here is basically saying how good are the model's negative predictions.

Thus, overall, our model predicts better than chance, that overall accuracy level was about 57, 58%. Recall that loyalty transactions happen about 50% of the time. Thus, if we had no model at all [LAUGH] and just flipped the coin every time to guess whether a transaction was going to be a loyalty transaction or not, we'd get 50%. We'd get it right about half the time. So our model has helped us to get it right a little bit more than that. It helps us get it right 58% of the time, which is not super high, but is better than chance. Where the model really kind of falls down and is not great, is in the sensitivity area. That is, the model is pretty good at predicting not loyal,



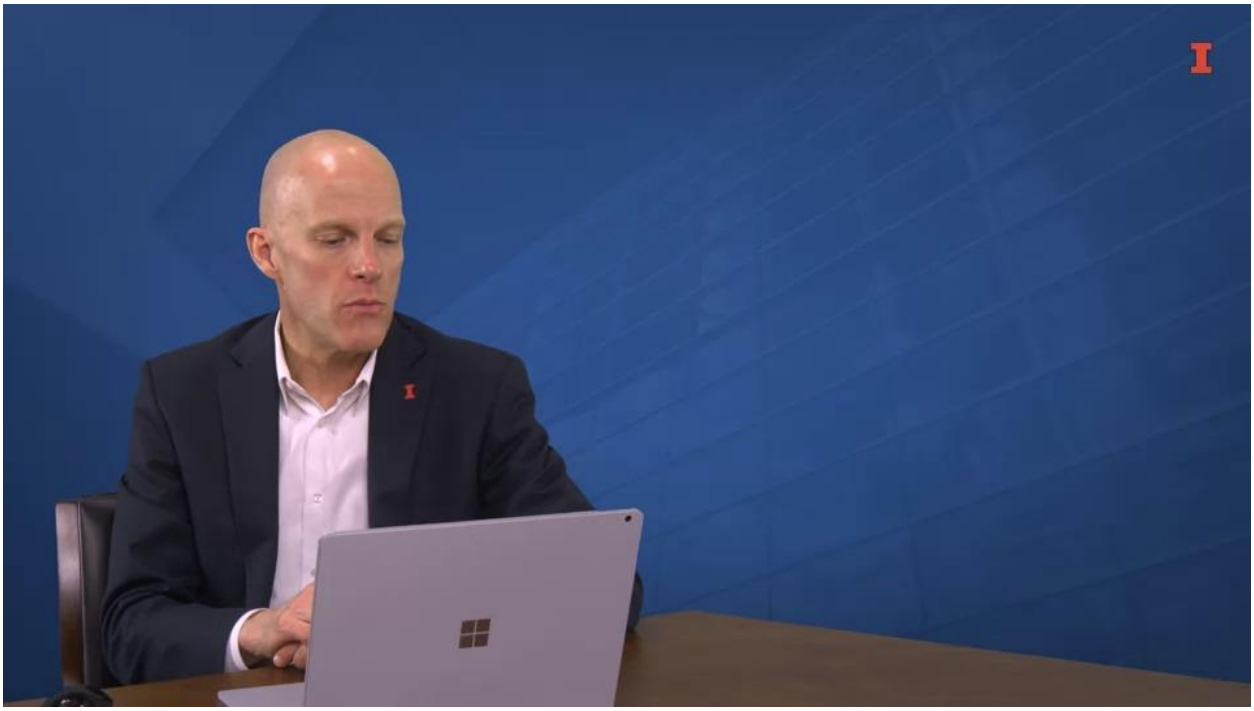
68% right here. The specificity is good but bad at predicting loyal, getting it right, only 47% of the time. That's worse than flipping a coin. So our next step is to improve this model.

However, before we do that, let's take our training model and predict or run it on the testing data. Recall that we train on the training data, we test on the testing data. So we want to use new data to test on so that we're not just trying to memorize the training data, so that we don't over fit our model. But rather we're creating a model that we can work on any data.

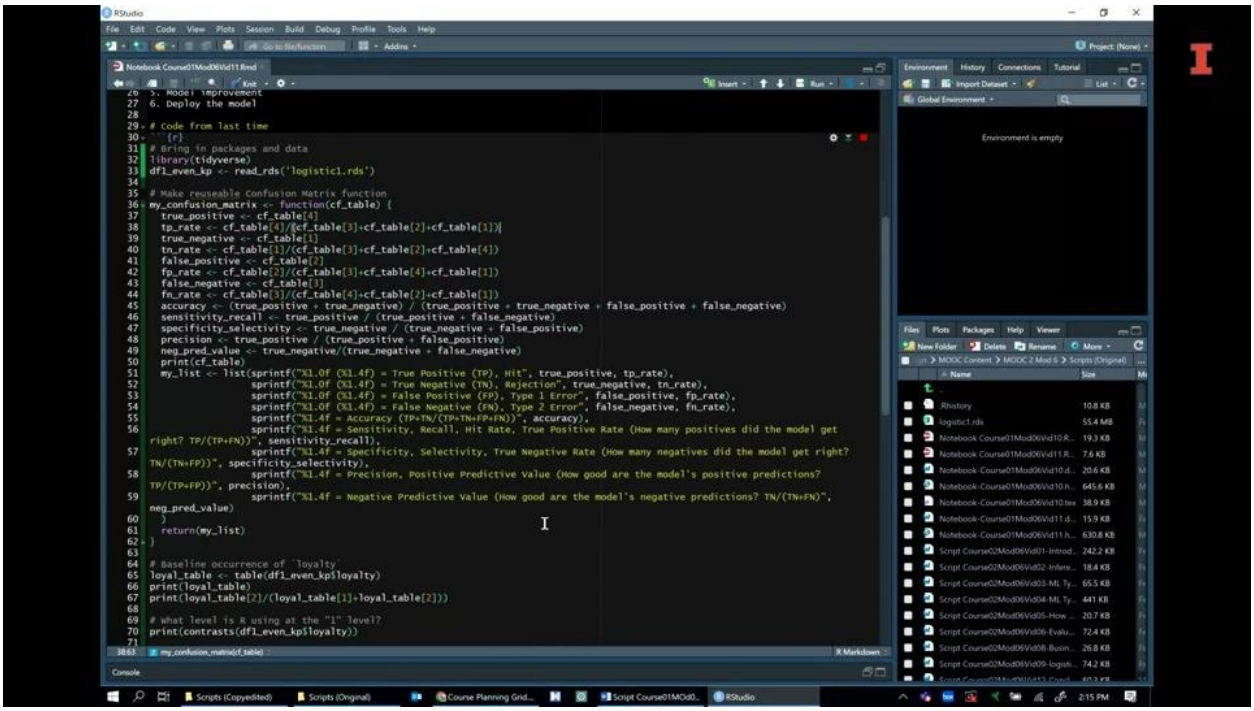


So let's do that now and run this. This code of course, looks very similar. So what we did above, the key exception here is that the data being used is now the test data. So that's the big critical key difference that you don't want to miss. So how does our model perform in the new data. Well, it actually does a little bit better than the training data. So while accuracy is is pretty similar here, you know, still about 58%. Our problem from before, the low sensitivity is slightly improved. Not much, but slightly improved.

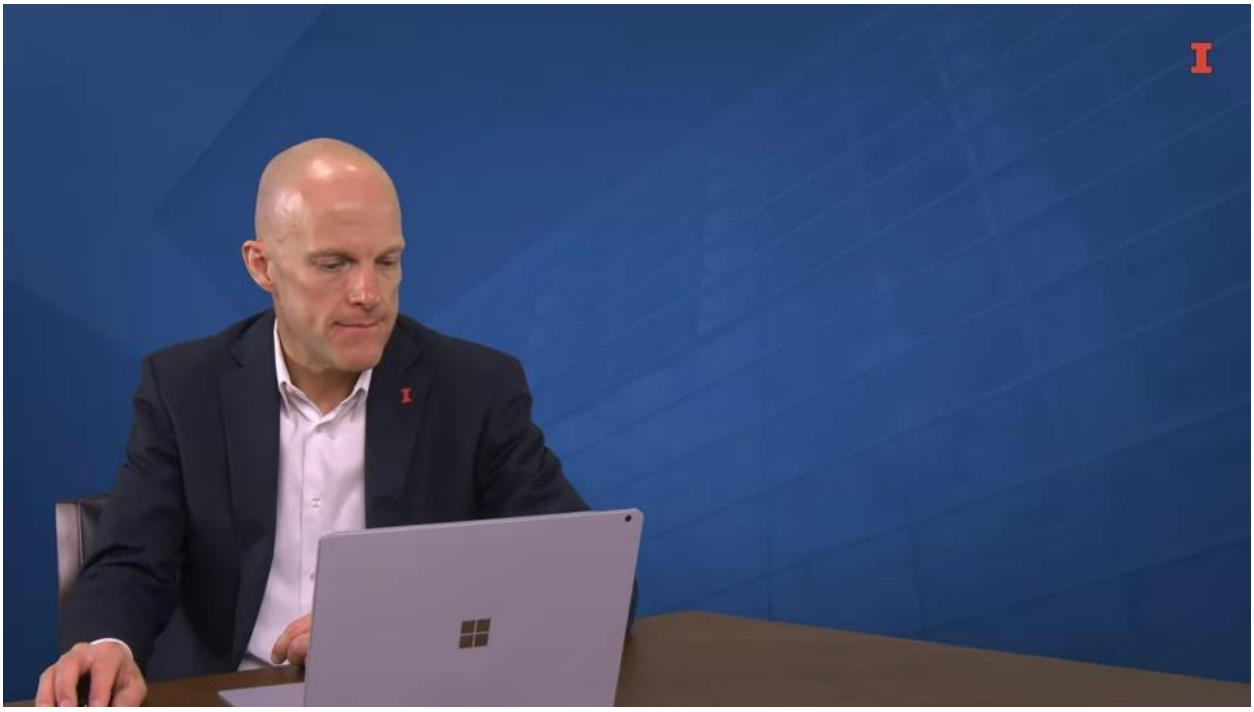
Lesson 2-3.5 Logistic Regression Hands on - Multiple Variables



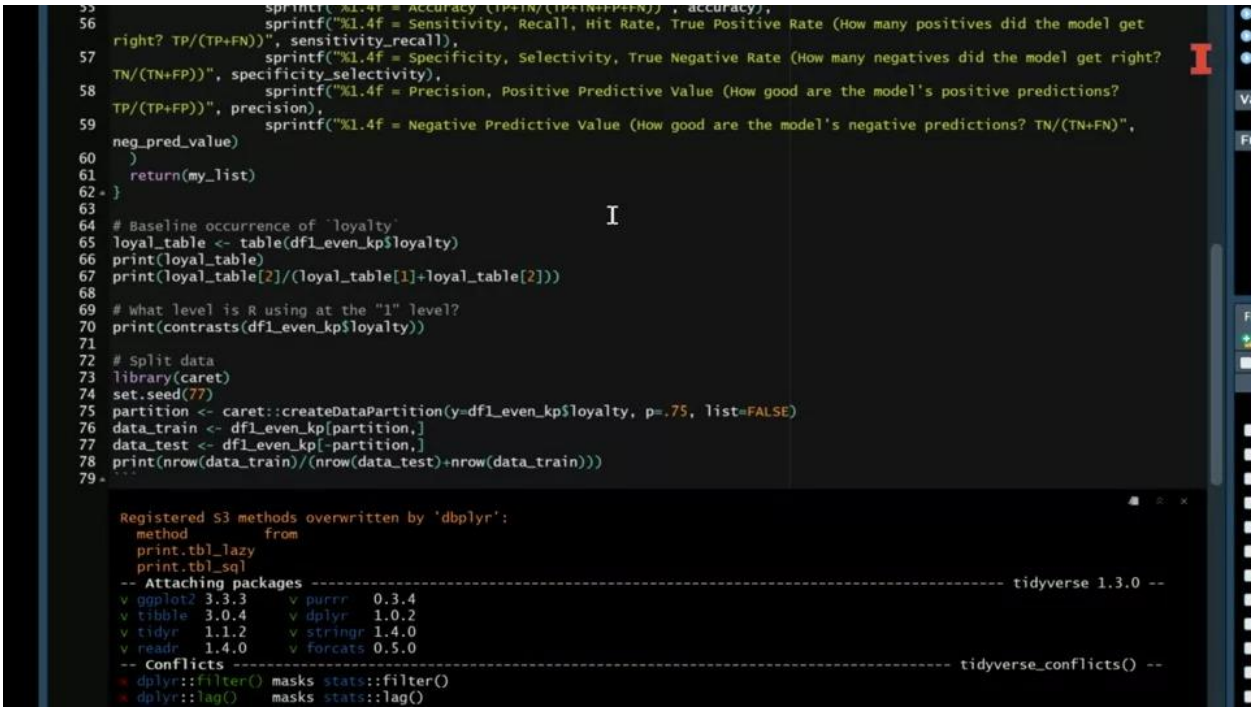
In this video, we'll continue exploring logistic regression. Logistic regression is a valuable classification type machine learning algorithm. In this video, we'll use the algorithm to predict whether a transaction is from a loyalty customer or not. We'll use the TEKA data set. Now, TEKA desires to increase the loyalty customers that they have and the number of products that their loyalty customers purchased because loyalty customers creates more business and more profitable business for them. As always, we encourage you to resist the urge to just watch the videos rather, please follow along, doing each of the steps that we're doing so that you can get the critical hands-on experience necessary to learn this valuable tool. First, let's bring in the data and the needed packages. Last time we predicted loyalty using a single variable category but this time, we'll use all of our variables. We'll see if this improves the prediction accuracy of our model. Before we get to the model statement, the code will be identical to the prior video when we used only the one variable so we'll run all of that here just right now



all the way up to the model statement. Of our six steps for using a machine learning algorithm,

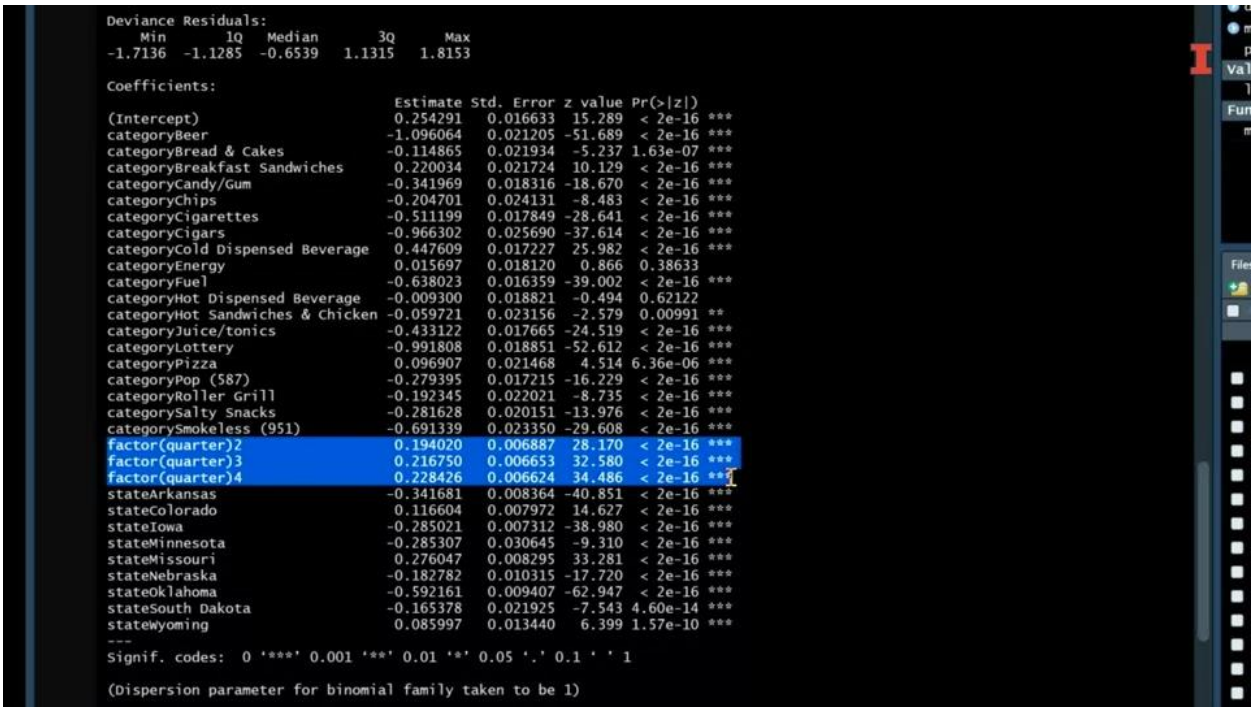


we're now focused on step 5. The first step is data scrubbing, the second was algorithms selection, third was model training or fitting, fourth was model evaluation, and five is model improvement, six is deploying the model, so we're firmly into the number five here.



All right. So as you can see as you scroll through this code again, this is just identical from last time when we had a univariate logistical regression model. Now, with a multivariate regression model with multiple independent variables, everything will be the same until we get to the model statement.

Great. So our data split. We're now ready to train our model. Recall that an algorithm is a set of rules for how to make a model. A model takes our data and options that we provide it to select and create new data and information and additional rules for how to use the model.



```
Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.7136  -1.1285  -0.6539   1.1315   1.8153

Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                      0.254291   0.016633  15.289  < 2e-16 ***
categoryBeer                    -1.096064   0.021205 -51.689  < 2e-16 ***
categoryBread & Cakes           -0.114865   0.021934  -5.237 1.63e-07 ***
categoryBreakfast Sandwiches     0.220034   0.021724  10.129  < 2e-16 ***
categoryCandy/Gum               -0.341969   0.018316 -18.670  < 2e-16 ***
categoryChips                   -0.204701   0.024131  -8.483  < 2e-16 ***
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categoryCigars                  -0.966302   0.025690 -37.614  < 2e-16 ***
categoryCold Dispensed Beverage  0.447609   0.017227  25.982  < 2e-16 ***
categoryEnergy                   0.015697   0.018120   0.866  0.38633
categoryFuel                    -0.638023   0.016359 -39.002  < 2e-16 ***
categoryHot Dispensed Beverage  -0.009300   0.018821  -0.494  0.62122
categoryHot Sandwiches & Chicken -0.059721  0.023156  -2.579  0.00991 **
categoryJuice/tonics            -0.433122   0.017665 -24.519  < 2e-16 ***
categoryLottery                 -0.991808   0.018851 -52.612  < 2e-16 ***
categoryPizza                    0.096907   0.021468   4.514 6.36e-06 ***
categoryPop (587)               -0.279395   0.017215 -16.229  < 2e-16 ***
categoryRoller Grill            -0.192345   0.022021  -8.735  < 2e-16 ***
categorySalty Snacks            -0.281628   0.020151 -13.976  < 2e-16 ***
categorySmokeless (951)         -0.691339   0.023350 -29.608  < 2e-16 ***
factor(quarter)2                 0.194020   0.006887  28.170  < 2e-16 ***
factor(quarter)3                 0.216750   0.006653  32.580  < 2e-16 ***
factor(quarter)4                 0.228426   0.006624  34.486  < 2e-16 ***
stateArkansas                   -0.341681   0.008364 -40.851  < 2e-16 ***
stateColorado                    0.116604   0.007972  14.627  < 2e-16 ***
stateIowa                       -0.285021   0.007312 -38.980  < 2e-16 ***
stateMinnesota                  -0.285307   0.030645  -9.310  < 2e-16 ***
stateMissouri                    0.276047   0.008295  33.281  < 2e-16 ***
stateNebraska                   -0.182782   0.010315 -17.720  < 2e-16 ***
stateOklahoma                   -0.592161   0.009407 -62.947  < 2e-16 ***
stateSouth Dakota               -0.165378   0.021925  -7.543 4.60e-14 ***
stateWyoming                     0.085997   0.013440   6.399 1.57e-10 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
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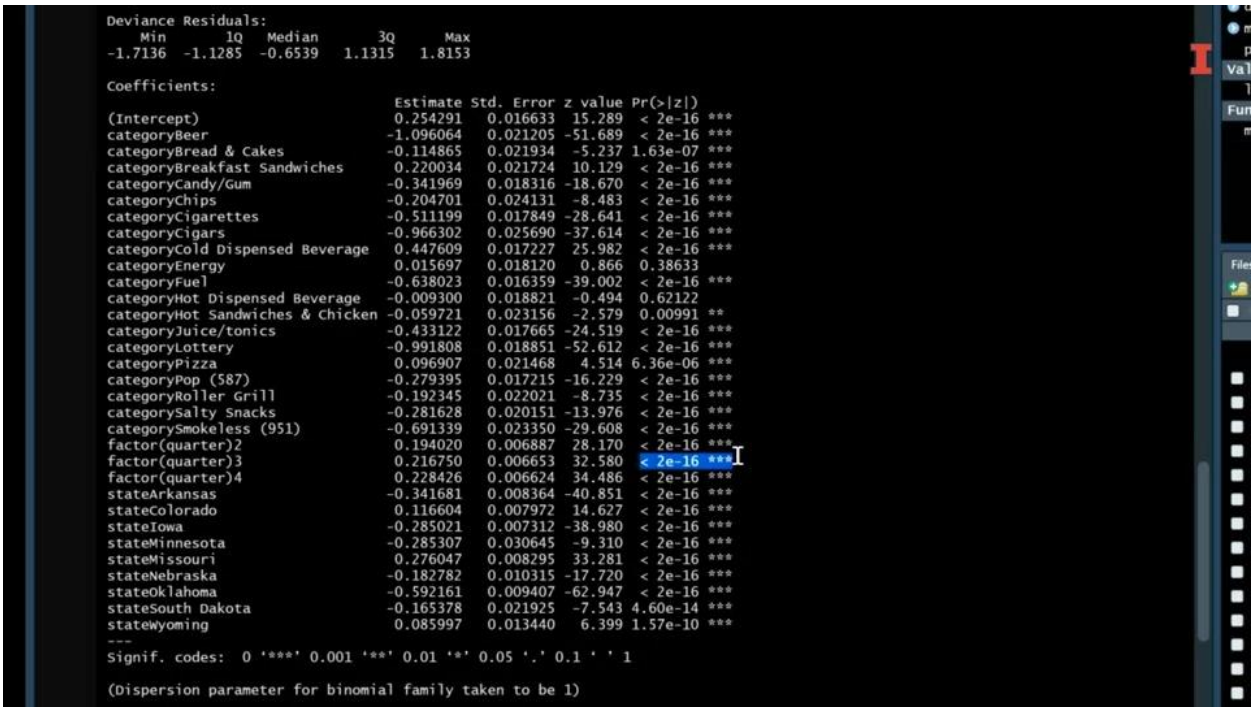
Below, we create our model called model_train and then summarize it to view the output. So we're again, using the GLM function with family equal to binomial to indicate that it's a logistic regression. Our dependent variable continues here to be loyalty, but this time will include all of our independent variables in the model, not just category. This is multivariate logistic regression so we have multiple independent variables. We are, of course, using the training data here, since we're training the model. So let's go ahead and run this and summarize as we train our model using both quarter, category and state. All right. So here's our output. Now, last time we examined the impact of category on loyalty. So let's look this time at quarter, right down here.

The quarter is just a quarter of the year. We made it into a factor here so that R knows the category. There's some debate about whether we could leave this as a continuous variable or not, since the difference between one quarter of the year and another quarter of the year does have meaning but for our purposes, we'll leave it as a factor or as a categorical variable. The first quarter of the year is the reference level of these multiple dummy variables. Thus, when we evaluate the effects of these quarters, it's in relationship to the effect of quarter 1. Looking at the signs of the coefficients and the p-values that are highlighted here, we can see that each quarter significantly increases the probability that a transaction will be a loyalty transaction. For example, the third quarter of the year has a positive coefficient



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stateSouth Dakota               -0.165378   0.021925  -7.543 4.60e-14 ***
stateWyoming                     0.085997   0.013440   6.399 1.57e-10 ***
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Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
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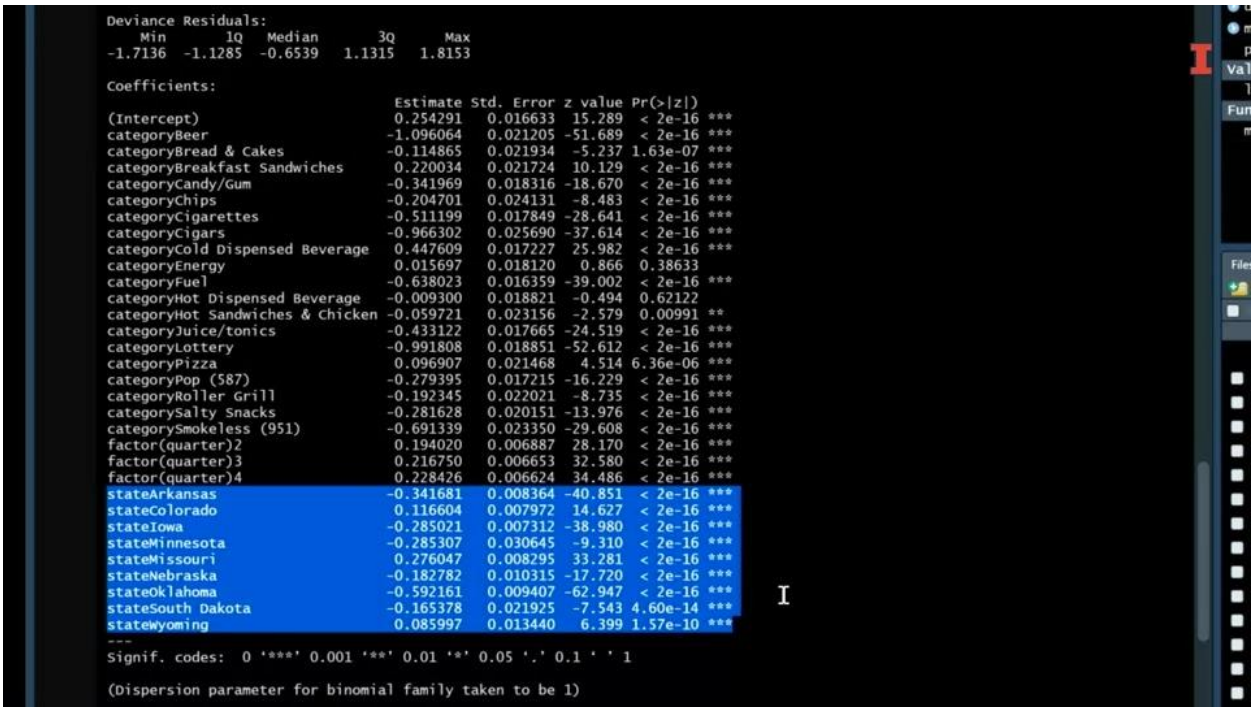
of 216750 and a very low p-value less than two with a 16 zeros in front of it.

This means that relative to, again, quarter 1, quarter 3 has more transactions that are from the loyalty customers. With this knowledge, TEKA could consider focusing on the beginning of the year in an effort to increase the number of loyalty customers that they have. Additionally, TEKA could focus on the summer and fall as key times when their loyalty customers all are already active to promote loyalty to them and help increase those loyalty customers' purchases even more. Next, let's look at how each state affects the occurrence



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categoryFuel                   -0.638023   0.016359 -39.002  < 2e-16 ***
categoryHot Dispensed Beverage -0.009300   0.018821  -0.494  0.62122
categoryHot Sandwiches & Chicken -0.059721 0.023156  -2.579  0.00991 **
categoryJuice/tonics           -0.433122   0.017665 -24.519  < 2e-16 ***
categoryLottery                -0.991808   0.018851 -52.612  < 2e-16 ***
categoryPizza                   0.096907   0.021468   4.514 6.36e-06 ***
categoryPop (587)              -0.279395   0.017215 -16.229  < 2e-16 ***
categoryRoller Grill           -0.192345   0.022021  -8.735  < 2e-16 ***
categorySalty Snacks           -0.281628   0.020151 -13.976  < 2e-16 ***
categorySmokeless (951)        -0.691339   0.023350 -29.608  < 2e-16 ***
factor(quarter)2                0.194020   0.006887  28.170  < 2e-16 ***
factor(quarter)3                0.216750   0.006653  32.580  < 2e-16 ***
factor(quarter)4                0.228426   0.006624  34.486  < 2e-16 ***
stateArkansas                  -0.341681   0.008364 -40.851  < 2e-16 ***
stateColorado                   0.116604   0.007972  14.627  < 2e-16 ***
stateIowa                      -0.285021   0.007312 -38.980  < 2e-16 ***
stateMinnesota                 -0.285307   0.030645  -9.310  < 2e-16 ***
stateMissouri                   0.276047   0.008295  33.281  < 2e-16 ***
stateNebraska                  -0.182782   0.010315 -17.720  < 2e-16 ***
stateOklahoma                  -0.592161   0.009407 -62.947  < 2e-16 ***
stateSouth Dakota              -0.165378   0.021925  -7.543 4.60e-14 ***
stateWyoming                    0.085997   0.013440   6.399 1.57e-10 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)
```
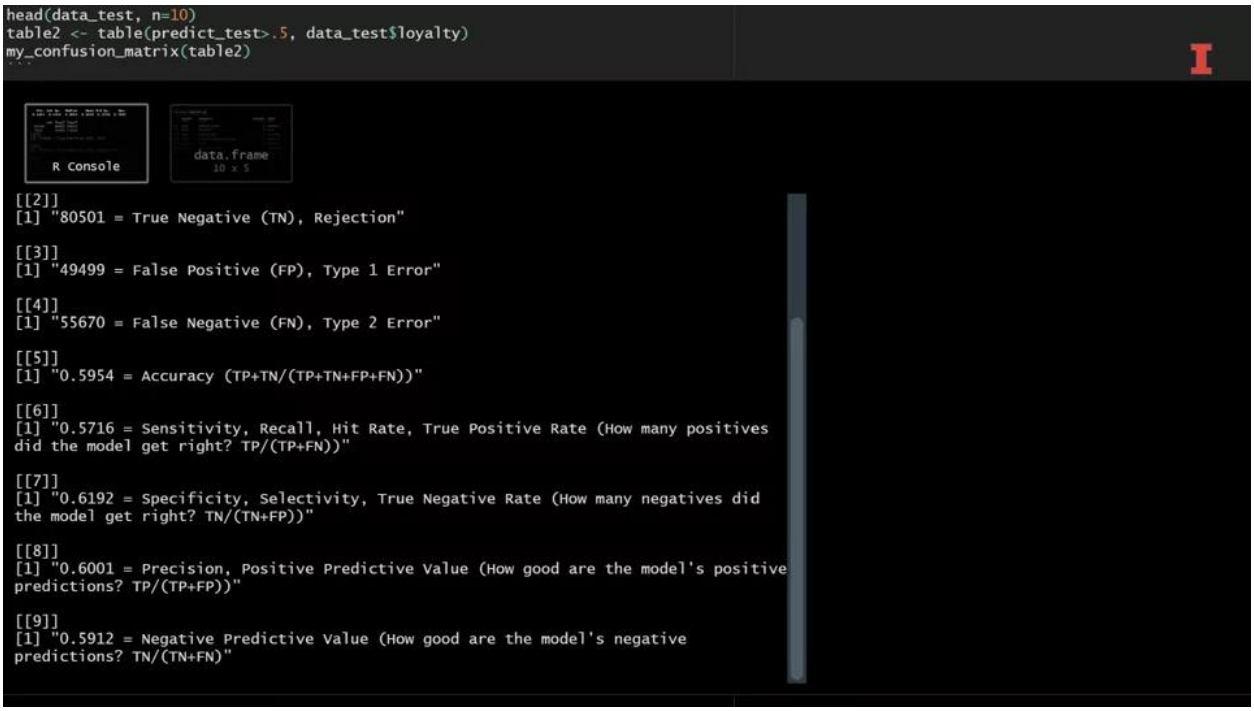

of our loyalty transactions. These are the dummy variables here. The reference state, the state up and intercept, is Alabama.

So relative to Alabama, the states that are most likely to generate loyalty transactions are Colorado, Missouri, and Wyoming. Missouri, in particular, has a strong effect. This can be seen by their relatively large coefficient. So TEKA should investigate key stores in this state to see what's going on right here. Finally, let's examine our larger, more complicated model on our test data. Recall that our single variable model had a relatively modest accuracy rate of about 57, 58 percent. The more complex model, let's look at that now.

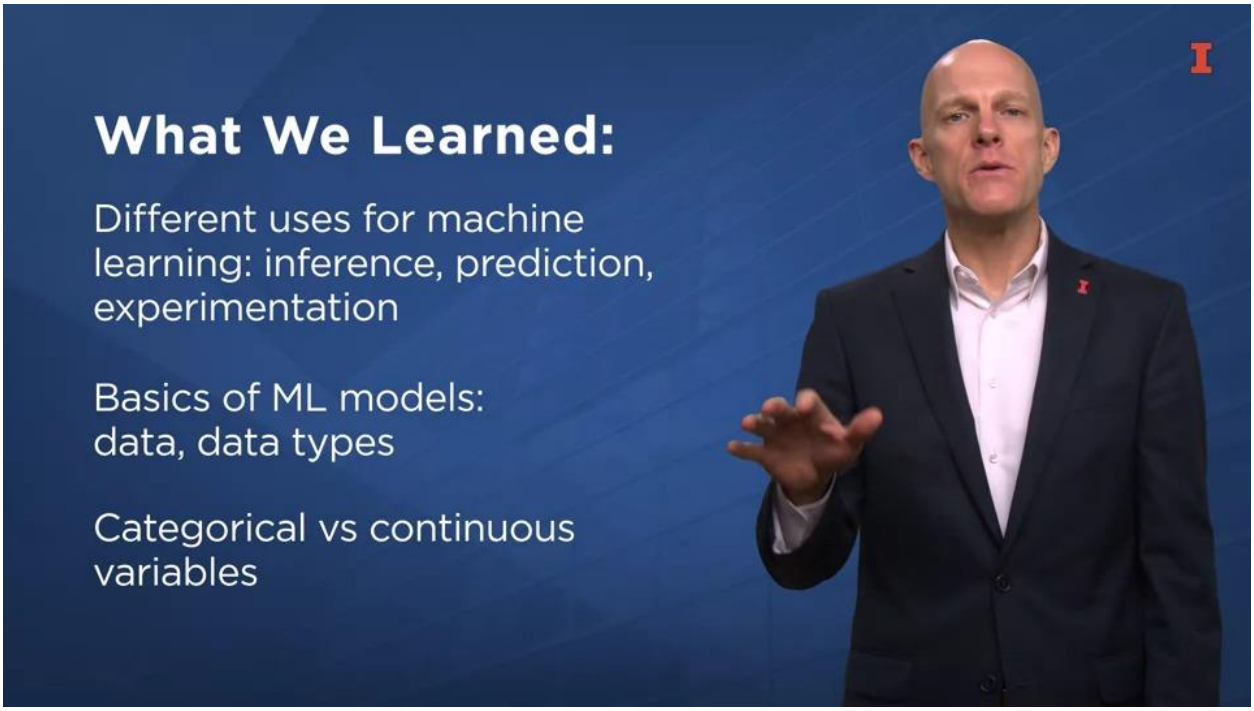


So again, here we've included our test data because we're going to run this model on the test data. We want to see how well our trained data predicts on our test data. We've run summary right here so we can view that, and then we've added our predict tests, our probabilities, back to our data set. If we wanted to, we could look at that and we see it right here. Then we've run heads so we can look at these. Finally, we are going to run this confusion matrix that we looked at last time. The more complex model has increased the accuracy slightly up to about almost 60 percent as you can see here but perhaps more importantly, the sensitivity of the model is much improved right here. Now, recall that before univariant logistic regression we had, the sensitivity or the accuracy of that mode predicting not loyal was below 50 percent,

worse than a coin flip, but this new model has increased that all the way up to 57 percent. So overall, this is not a great model. We could certainly add additional variables to make it more complex. Additionally, recall that this data is just a subset of the available data so adding data would also improve the predictability of our model.

Module 2 Review

[Module 2 Conclusion]



Congratulations. In this module we've really covered a lot of ground. First, we've done an overview of machine learning to provide you with a solid framework or foundation for how to understand machine learning. Thus in the future, in this class or your own learning efforts, when you encounter a new model, that you've never encountered before, you'll be able to slide into the framework, understand it quickly, and move more quickly through the process of understanding the new algorithm. More importantly, you'll be able to put that algorithm to work for you in solving business problems. In this module, we did the following. We discussed different uses for machine learning, inference, prediction, and experimentation. In all three of these paradigms, data is king. Data and our statistical analysis of data drives our decisions. Next, we examine the building blocks for machine learning models, data and data types. We explored the differences between categorical, and continuous variables.

Next, we talked about the different types of machine learning, and machine learning algorithms. We talked about supervised, unsupervised and reinforcement learning, their definitions and their differences. After that, we discussed regression, classification, and clustering algorithms and how they differ. We then showed a graphic to put everything in its place.

We then walked through a series of six steps for machine learning. We also discussed the difference between machine learning algorithms, and models.

Finally, we introduced a business problem from our hypothetical company TECA. We learned a classification algorithm, logistic regression and used the algorithm, and the model to gain insight into when TECA's transactions are made to loyalty versus non loyalty customers. This can help the company increase their number of loyalty customers, as well as the number of transactions their loyalty customers make.