Module 3: Measurement and Analysis for Process Improvements

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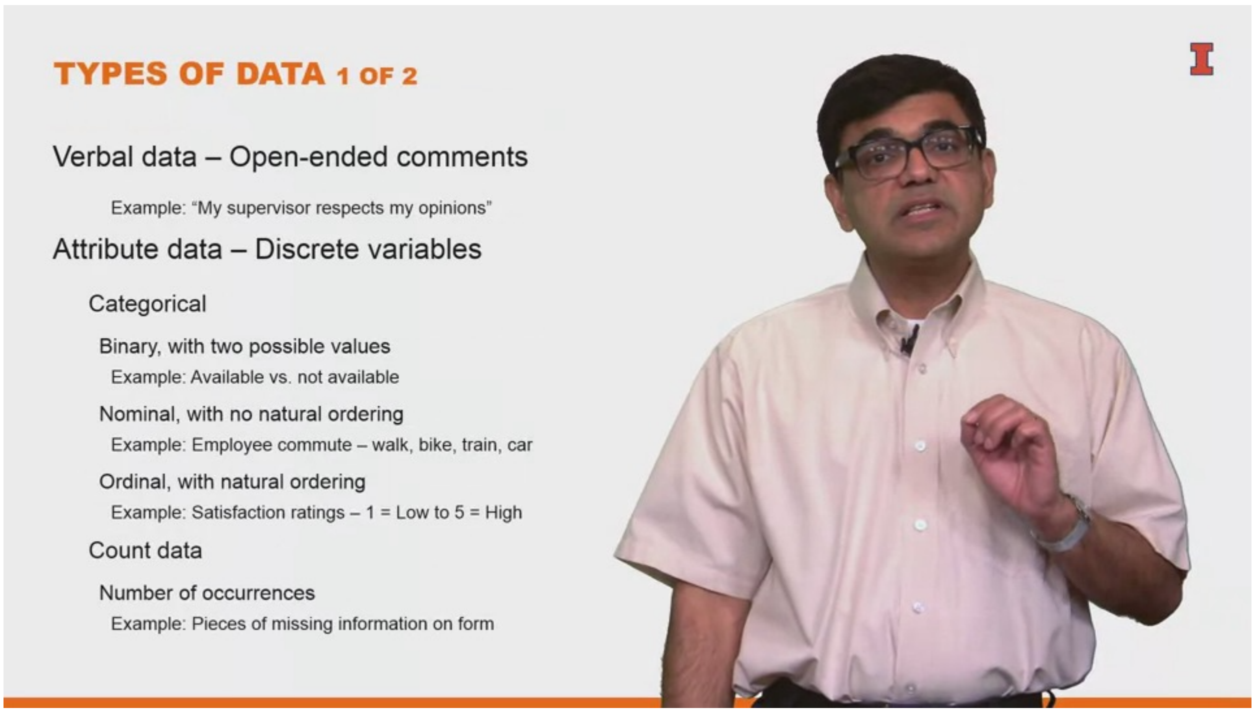
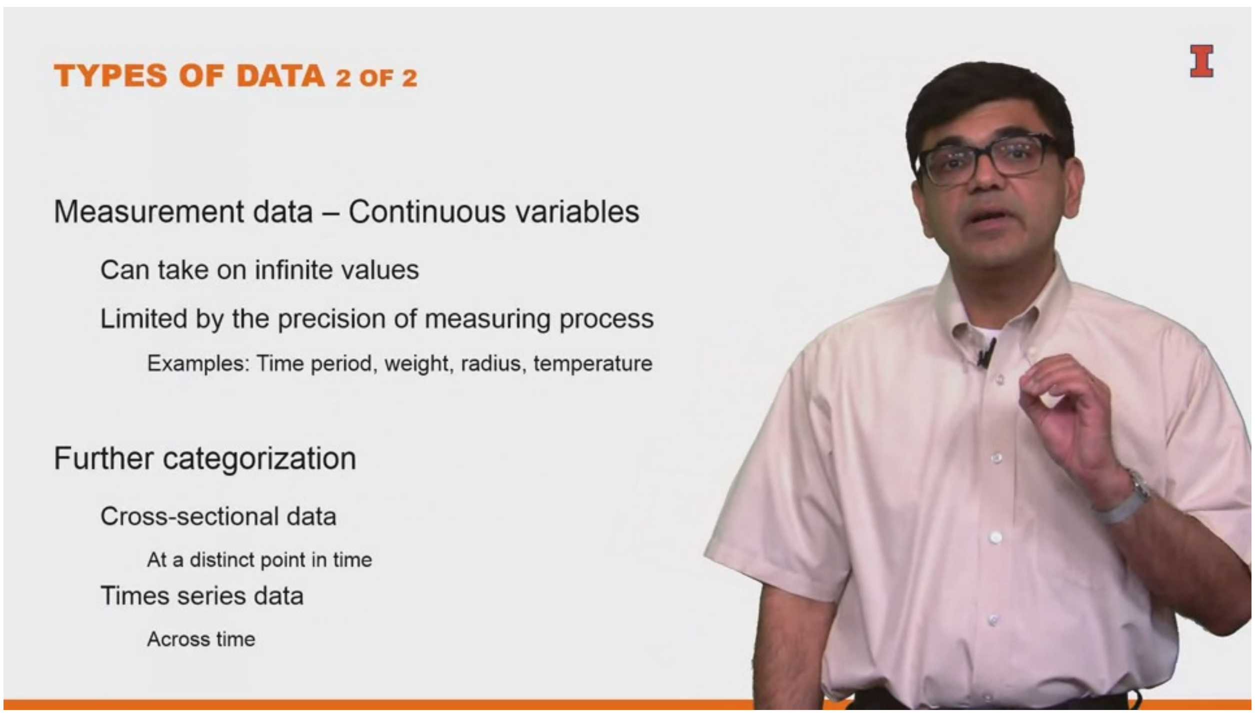
Lesson 3-1: Data, and the Normal Distribution

[Module 3.1.1 Process Measurements and Data Types]

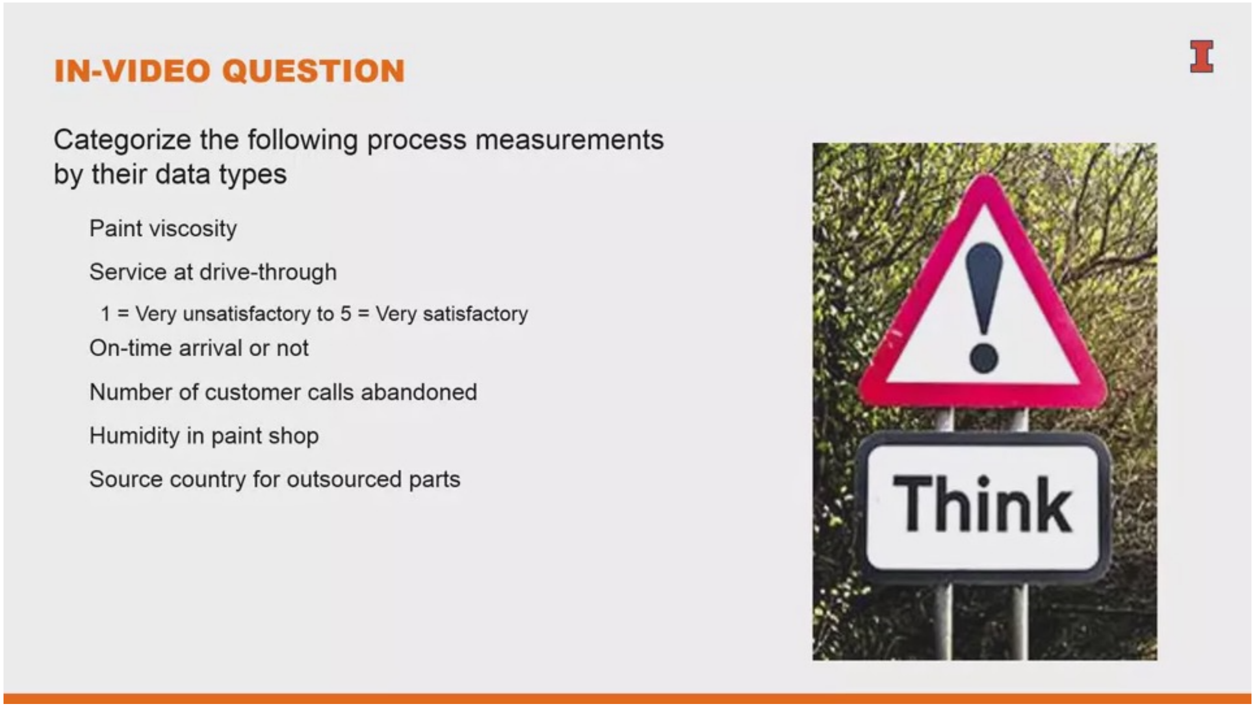
This session is about data and the normal distribution. We're going to get introduced to some concepts of the normal distribution and see how we can apply it in different phases of the Six Sigma project. But before we get there, let see what the measure phase of the Six Sigma project is all about. What happens in the measure phase? The first thing is that you identify variables. You identify the critical to quality characteristics, and you think about how you're going to measure these. Then you assess the measurement systems. The idea there is to make sure that your measurement systems are valid and they're reliable. They're valid in the sense that they're measuring what they're supposed to be measuring, they're reliable in the sense that when you use them over and over again they give you accurate results. They are sensitive to changes, that's what a measurement should be, and accessible in terms of they can be understood by people who are going to be seeing those measurements on a day-to-day basis so that they know what's going on in the process. We'll go from critical to quality characteristics to measurement systems in the measure phase. In the measure phase, we also go to establish the current performance on critical to quality characteristics. Once we've gone from figuring out what those critical to quality characteristics are and then the measurements are, then we need to establish current performance. Now, to establish current performance we use something called statistical process control. These are control charts that you can have for different types of data, for discrete data, for continuous data. There are many different types of control charts that you can use to establish the inherent capability of a process. Next, within the measure phase of the Six Sigma project, you also can establish the targets for improvement and what those targets should be. There you would be looking at things like the Sigma levels of the process, so you establish the sigma level of the process, but before that, you do a process capability analysis. A process capability analysis is to see how well the process is performing in relation to customer expectations. In relation to the voice of the customer, comparing the voice of the customer with the voice of the process, the VOC with the VOP in that sense. Those are the things that happen in the measure phase.



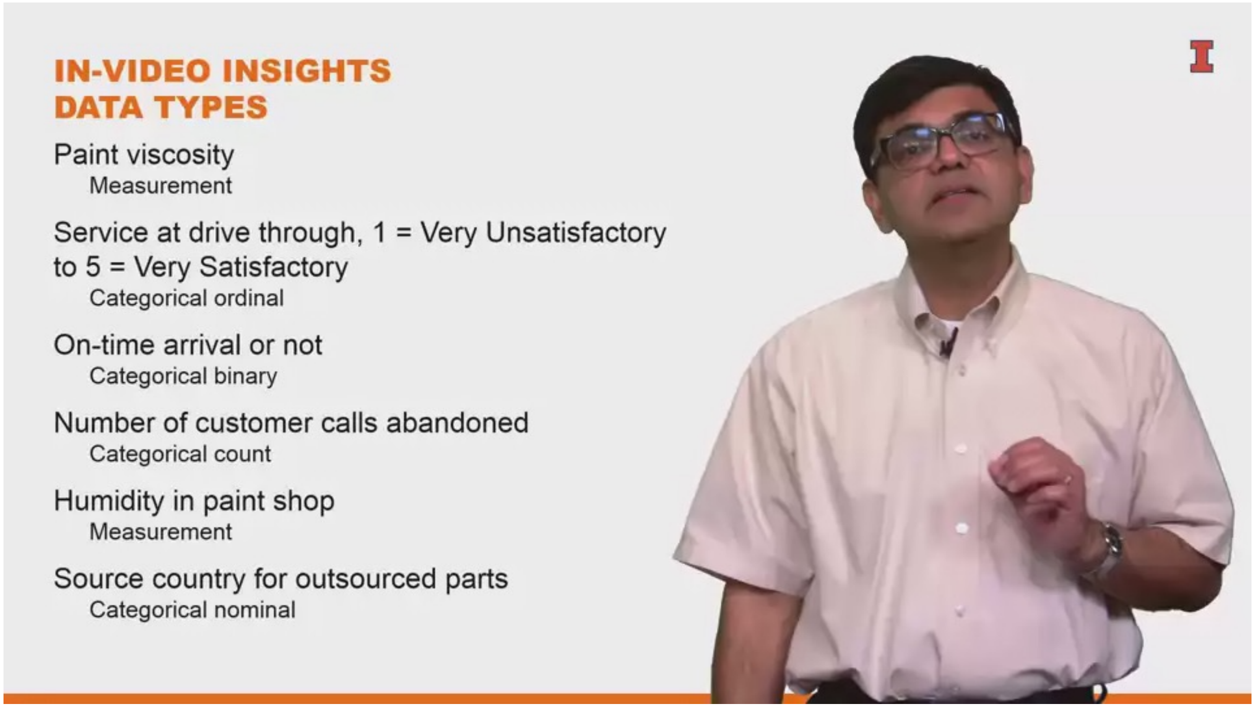
Now, let's take a look at different types of data that can be used in the measure phase and then we'll get to distributions of data next. What are the different types of data that we can use in the Six Sigma project and that we need to start thinking about in the measure phase? First is simply verbal data. This could be open-ended comments from people, if you're doing a customer survey, they're telling you something about the product or the service. If you're doing an employee survey, they're telling you something about the experience that they have with their supervisor or working in that company. Here the example that you see is a statement that says, my supervisor respects my opinions. These are open-ended comments that you would have coming out of any kind of an interview or a survey that you do of the audience that you're interested in getting data from. Next, we get into data in the sense of numeric data. First we have discrete variables, and the way you can think about discrete variables are where decimal points do not matter, do not make sense in fact, not that they don't matter, they don't make sense. When we think about things like anything that has two values, say it's available or not available, we think of it as a 0, 1 situation. Something is on time or not on time, it's a 0, 1 situation. There's no 0.5, there's no 0.75. That's the first type of a discrete variable, and the data that we're talking about there is attribute data of a binary characteristic. It is binary in the sense that there are only two possible values for it. If you think about what is the underlying distribution for that kind of data, you may be familiar with this already that it's a binary data binomial distribution; two options, yes and no, or is good or not good, those kinds of data we are talking about there. Next within the categorical data, within attribute data, we have the nominal one. Here we don't really have numbers for different types of categories, but we are considering them as four different categories. For example, here we have, how do employees commute to work? They either walk, they come by bike, or they take the train, or they drive their own car. Those are four different types of ways of commuting to work for the employees. Now you can give these numbers as 1, 2, 3, and 4, you can code them as 1, 2, 3, and 4, but they don't really have any natural ordering. We can't say that one is higher than the other. So you can code these in some way, but they're not going to mean anything in terms of their natural ordering. The next category that we go to of types of data is ordinal data. Ordinal data is going to have meaning in terms of something is higher than the other. When you think of any customer satisfaction survey that you may be familiar with, those are the things that we get in the mail, or when you go to a restaurant they put it on the table saying, could you fill this out for us, and you may also be getting these as employee satisfaction surveys. Now these surveys have scales that go from extremely dissatisfied to extremely satisfied, or extremely happy with this to extremely unhappy, whichever way its ordered. The point there is that there's going to be some meaning of that ordering, that one is either going to mean very good and five is going to mean very bad, or five is going to mean very bad and one is going to mean very good. There's going to be some natural ordering to these categories. But remember, we're still talking about discrete categories. If you think about these three types of data, the binary data, the nominal without natural ordering, and the ordinal with natural ordering, the concept here is that you are taking data that is subjective and you're converting it to objective. You're taking information and you're converting it into objective data using either a binary scale or a nominal scale, or an ordinal scale, so you can express these in terms of numbers. Within discrete variables, we also have something called count data. What is count data? It's, as the name suggests. It's counting,for example, the number of defects in a product. If I'm looking at this clicker that I'm holding and I'm saying, how many defects are there in this clicker, I can count the number of defects. If I'm looking at defects in an application form that I get, I'm counting the number of defects and again, it's going to be discrete. I cannot find 2.5 defects. It's going to be either two defects or three defects. That's why it's still a discrete distribution but I'm looking at here different type of data within a discrete distribution and it is count data. Now, what are the implications of these different types of data? The underlying statistical frequencies, the underlying frequencies of data will be different. The underlying statistical distributions that you can use for these types of data are going to be different. That is going to have implications in terms of how you're going to do the analysis. The other implications of these types of data are, some will give you more information than others. Some will be, in that sense more valuable in terms of data collected than others. Some will also be harder to collect than others. There might be some trade-offs that you're thinking about as to which type of data we should collect. Well, you might be trading off with, here this one is simple to collect. We're simply asking a yes, no question if you're talking about the binary type of data, but we're not getting much more information than simply somebody was is happy or unhappy about something. We can move to some more in-depth information if we can move to more of ordinal scale which has a survey, a battery of questions, many questions that are scaled on 1-5 or 1-7. Typically we have odd numbers in those scales. There you are capturing a little more information. It's going to take more effort. It's going to cost you more, but you're going to get more information. You can do something with that information. When you're thinking about types of data, you should be thinking about what are the cost benefits of different types of data.



Now, let's take a look at the other kind of data. When we're talking about discrete, we're talking the opposite end is the or the opposite of discrete is continuous data. Continuous data is any measurement data. There, we're basically saying that it can theoretically take infinite number of values. We can say, for example, that if you're talking about temperature, depending on the level of granularity that you want to go into, you can go up to many decimal places when you're talking about it in terms of Fahrenheit or Celsius. When you're talking about weight of something, depending on the level of granularity that you want to go into, you can be talking about 2.5 pounds, 2.68 pounds, 2.697 pounds. Then you can be thinking about it in terms of ounces if you want to get it to be more specific. That's the idea of continuous data, of measurement data. That's the data that we normally think about when you're thinking about numerical data. It's, very useful in terms of, it's a very specific measurement of something. But nevertheless it's a measurement of one characteristic. If I know that a critical to quality characteristic of a service in a restaurant is time, I can be measuring time, but it's only going to give me information about time. If I know that a critical to quality characteristic in a restaurant is temperature of food, then I can be thinking about measuring temperature of food. But then it is going to be very specific, but it's going to be only about the temperature of the food. Measurement data gives you much more information, but it's about a specific aspect of a product. Now, within measurement data, you can collect data that is cross-sectional or that is more of a time series. Simply here what we mean is that we could be looking at things as they are at a point in time or we can be looking at them over time. Is there a trend when we look at time series data? Then when we look at time series data, there are some implications in terms of, what analysis we can do? There will be specific things that we have to account for in terms of when we're doing time series data. When we're taking it from the same process over a period of time and we're trying to measure something, or if we're looking at sales over time, over different months or over different weeks, there will be some ways in fact, of adjusting to the colinearity, the obvious relationship that is going to be there when you have many weeks of sales data or many weeks of any process data. There's going to be some relationship between the previous week and the next week. You need to account for that. That's why you need to think about time series data as a little bit differently than when you're looking at cross-sectional data.

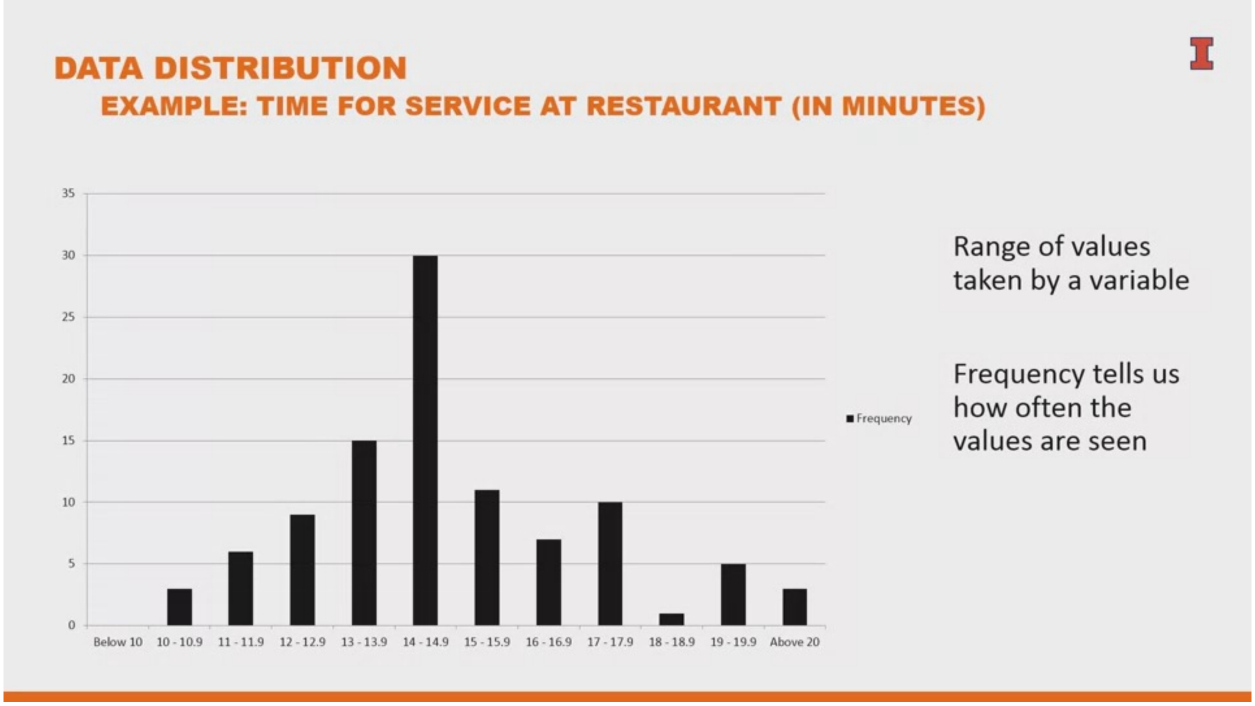


Now, let's take this categorization and apply it to some different types of data that we have over here. Here you have different measurements, different things that are being measured. What I'd like you to do is apply the categorization that we just saw in terms of, is it discrete, is it continuous and, is it within discrete the different things that we saw, the ordinal, the nominal, the binary, and the count data, and whether you can apply those? You have paint viscosity, service at drive-through, and then you have on-time arrival or not, number of customer calls abandoned, humidity in a paint shop, and source country for outsource parts. Apply those categorizations and we'll come back and see if you were able to apply them correctly.

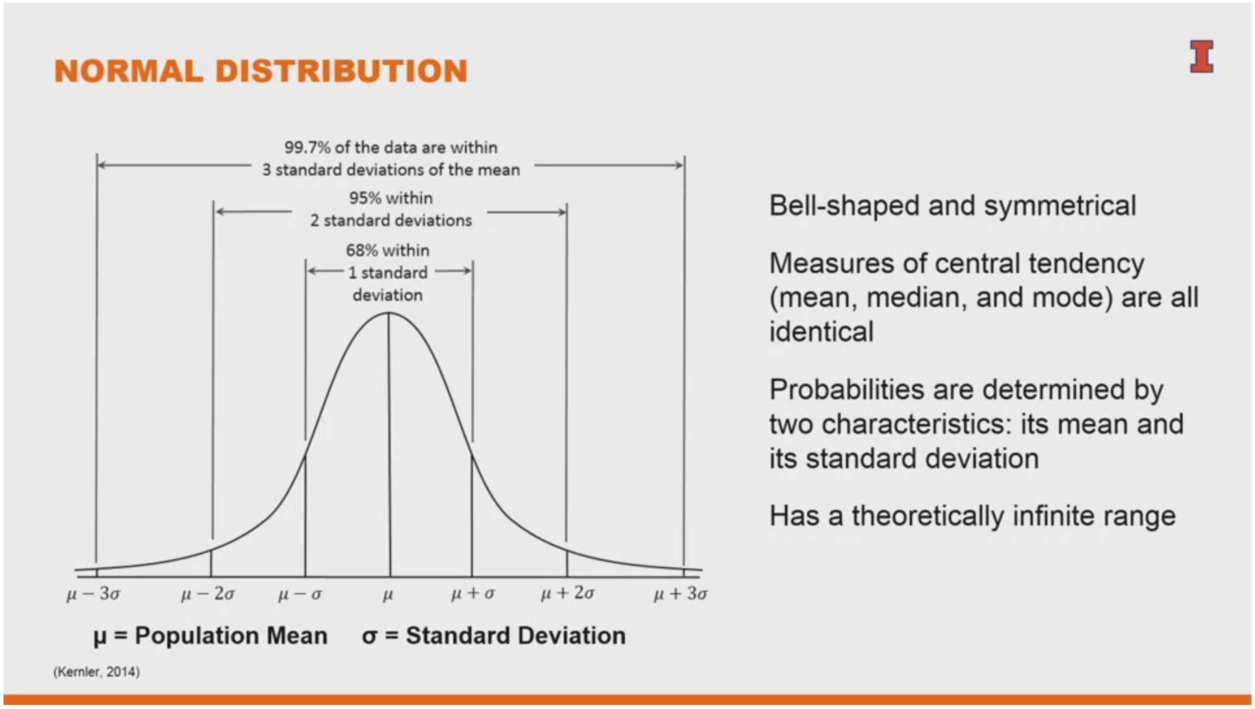


We're back to the data types that we saw before the question and paint viscosity is something that would be a continuous measurements. It would be measurement data. It's something that you might measure in units that can have decimal points. It's a continuous measurement data. Service at a drive-through going from very unsatisfactory to do very satisfactory, it's categorical data, but it's ordinal. There is meaning to one being better than five. There's an implied hierarchy in those numbers. On-time arrival or not, something was on-time or not is obviously binary. There are only two options there. Number of customer calls abandoned should give you a hint just from the point just from the fact that it's a number of calls, its count data. You're counting the number of calls that were abandoned. Humidity in a paint shop. Again, it's going to be like viscosity that you saw earlier. It's going to be measurement data. Source country for outsourced parts is going to be categorical except it's going to be nominal. You're going to put these in different countries and you're going to say that if it's a one, it indicates that it's from the US, if it's two, it indicates it's from Canada, if it's three, it indicates it's from Mexico, if it's four, it indicates that it's from China. There's going to be no implied hierarchy in terms of the numbers that you're using. In fact, you could use any numbers for any of those countries. That's what we mean by, it being categorical but nominal data. Here you've seen the application of the different data types.

Module 3.1.2 Overview of Normal Distribution



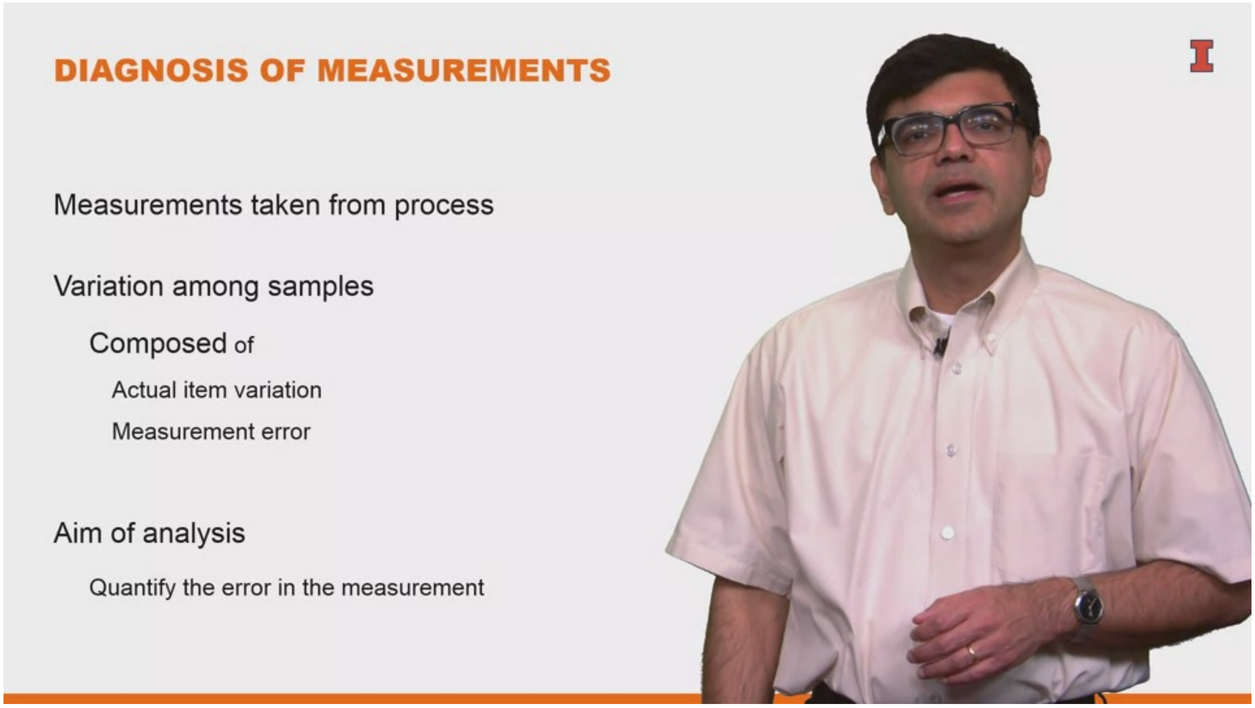
Next, let's move on to, what do we start doing with data? Here what you have in front of you is an example. This is data that I just made up. This is simply looking at time for service at a restaurant. If you think about time for service at a restaurant, if I were to collect data on this, what am I going to get? I'm going to get different times for different people. Now, without getting into reasons for why there might be different times for different people, what might happen is in this case, you can see it ranges from 10 minutes to above 20 minutes. The last category on this chart is above 20 minutes. What have I done here? I've taken the data from roughly about 105 observations that I can imagine I would have collected if I was standing at the restaurant and collecting data on times that customers took, and I've looked at the frequency. What is it saying? The first bar is telling me that on three of those 105 occasions, the time taken was within 10 and 10.9 minutes. We can keep going from there, and we can see that all the way toward the end there were three of the parties, three of the customers that took more than 20 minutes. It's giving you a range of values that were possible in this particular instance. In this context, I had a range going from 10 to above 20, and it's also giving me frequency. What do we mean by frequencies? They're simply saying, how often did this occur in my data, and you can see that it's creating what we call in statistics, a data distribution. Data distribution is nothing but simply taking data, and getting their frequencies, and then drawing a picture of it, drawing a bar chart of it and saying, how does it look. Then you start looking at the shape of this distribution, and you can say something about the shape of this distribution. You may recognize this as looking somewhat like a bell curve distribution which you may already be familiar with and which we are going to look at next.



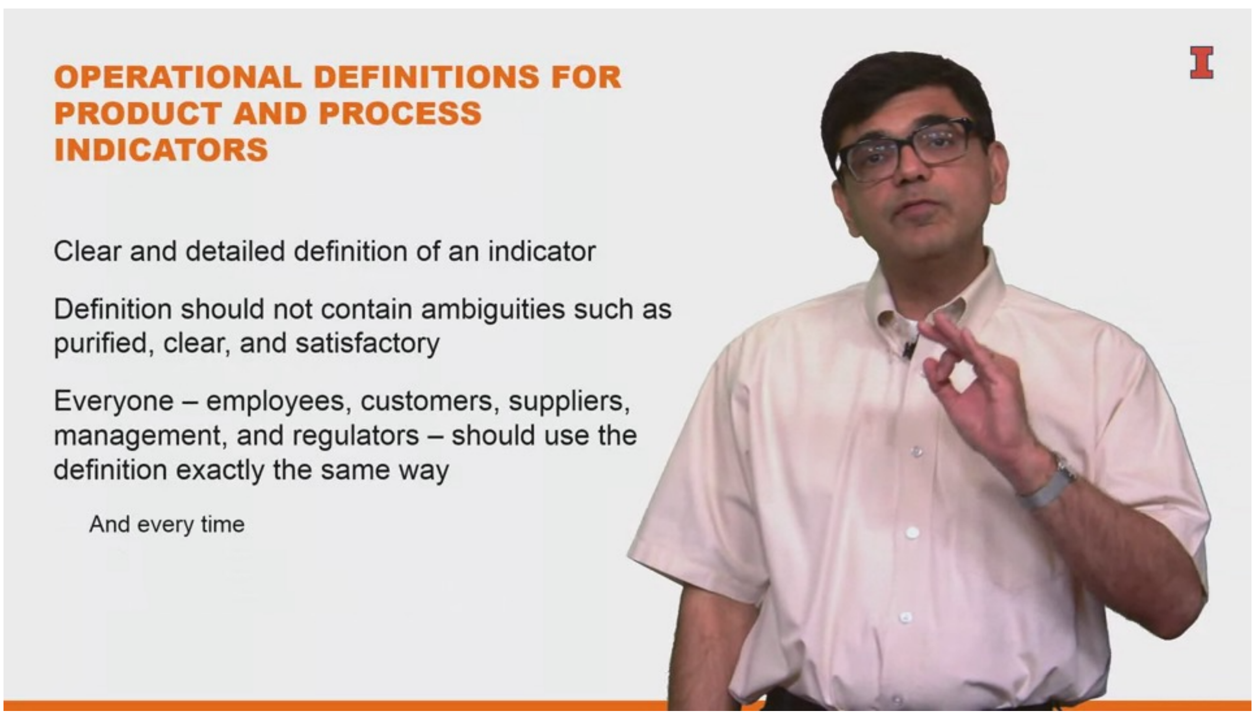
Here's the normal distribution. This is the distribution that is very common, this is the distribution that's very commonly used. We hear about it all the time, and it's because we like to convert things to the normal distribution as much as possible, it's because it gives us this power of being able to use z-scores and we'll talk about z-scores in a minute and what that means, but basically, it has properties that we can use in order to make any kind of inferences about populations based on samples that we've collected. That's why it's very popular. What is the normal distribution? It is a distribution where if you were to actually collect data, the frequencies would take this shape, it would be bell-shaped. There are two parameters to this. When we say parameters, there are two things in this distribution that matter, one is the mean, and one is the standard deviation, the mean is indicated by the Greek letter Mu, and the standard deviation is indicated by Sigma. This is where the idea of six Sigma comes from so Sigma stands for standard deviation of the population. When we have population parameters, we talk about it in Greek letters, the corresponding statistics that we get from samples are talked about as X bar and SD or S as being the standard deviation. Those are the two main things that we look at when we look at a normal distribution. Now, the cool thing about this normal distribution, or a couple of cool things about this normal distribution are that it's symmetric. One is, its 50 percent of the data is to the left of the mean, 50 percent of the data is to the right of the mean. That's what we mean by when we say that the median and the mean are exactly the same. Those two measures of central tendency are exactly the same, the mean is simply the calculated average, and then the median is where 50 percent of the values lie below that, 50 percent of the values lie above that, and then the third measure of central tendency here is the mode, which is the value that has the highest frequency. In the case of the normal distribution, all these three are identical. The center Mu value is the mean, it is also the median, it is also the mode. The probabilities of the values within this normal distribution, we know that between plus or minus 1 standard distribution, we have 68 percent, so if you go from the mean to the right, that's 34 percent. If you go from mean to the left, that's 34 percent. One standard deviation to the left, one standard deviation to the right, that encompasses 68 percent. Similarly, when you go to two standard deviations, that's 95 percent, when you go to three standard deviations, that's 99.7 percent. Theoretically speaking, although this is never true in reality, but theoretically speaking, this distribution has an infinite range. If you notice the way the normal distribution curve has been drawn in this picture, it does not touch the x-axis. It stays away from the x-axis, it becomes parallel to the x-axis, and the point is that it keeps going up to plus or minus infinity on either side, and it's infinite distribution theoretically speaking. Those are the characteristics of the normal distribution.

Lesson 3-2: Diagnosis of Measurements

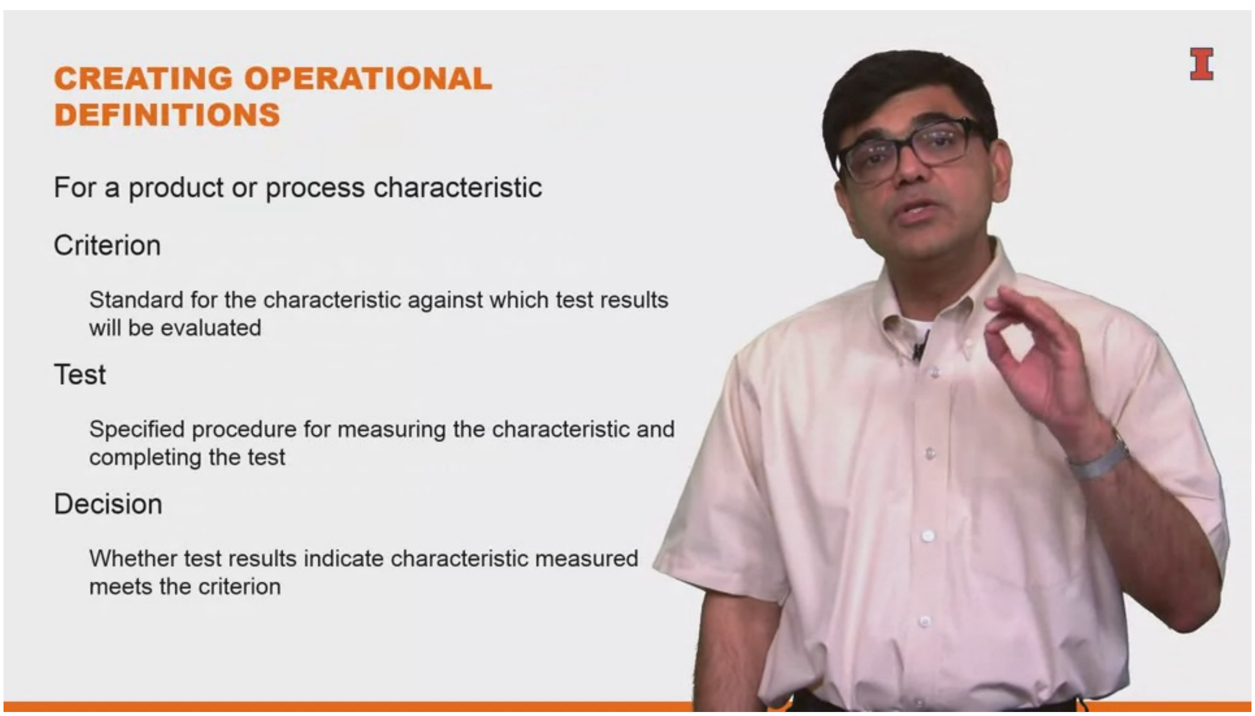
[Module 3.2.1 Measure Phase in DMAIC]



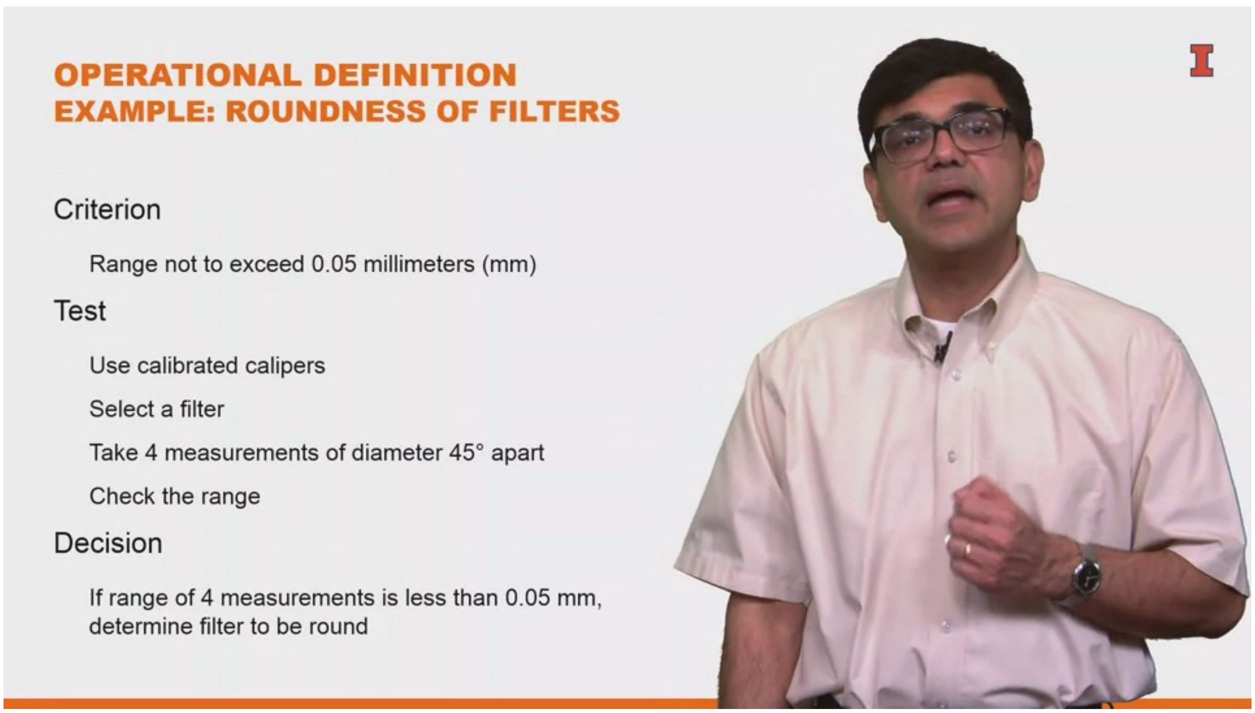
In this session, we're going to look at the Measurements. We're going to look at the measure phase of Six Sigma, and the measure phase of Six Sigma projects in the make. So we're looking at DMAIC and measure their, and we're going to look at some ways of establishing that a measurement system is good. So first we'll look at what are some of the problems that we can have with the measurement system. And then we'll we'll take a look at what are some of the things that we can do, to think about having a good measurement system. So when we take measurements from a process, what do we get? We basically get data which is over a range, we get a distribution of data. And what can happen, is there might be distribution that's coming from the actual variation in the process. But some of it might be coming from variation in the measurement. Somebody was not trained to use the instrument correctly, or the instrument was broken, was not calibrated correctly. So it's simply as talking about not doing the measurement correctly. You may remember from your high school days that when you were talking about looking at the level of liquid in a test tube, you have to think about how the liquid was shaped. And at what point of the curve, of the liquid you are going to take the measurement of how much liquid there is in a test tube. So those are the kind of things that were actually thinking about here from a Six Sigma project perspective. We're saying whatever measurement we are going to use, to establish the process performance, to be able to compare with performance for the customer. We should first be sure that the measurement is okay. So that's basically the idea of measurement analysis, when we're thinking about it from a 6-σ project perspective.



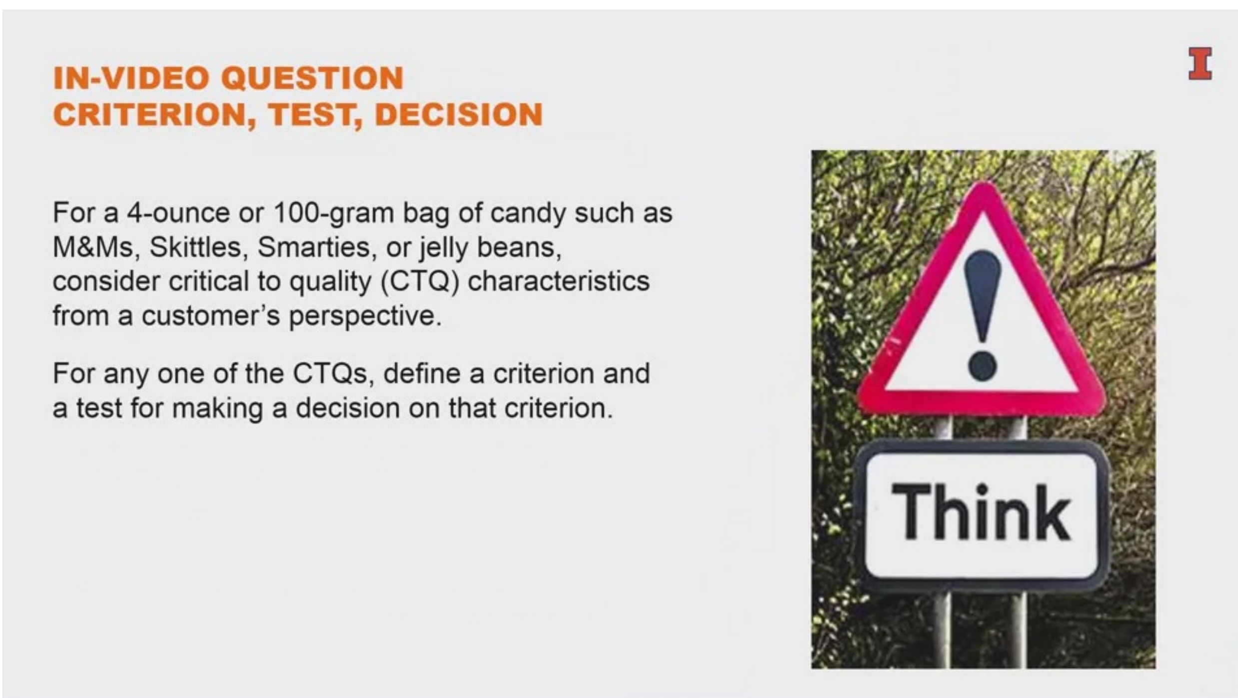
All right, so first thing before we get to measurements, it's important to think about defining things so that can be measured correctly. So the concept of operational definitions simply states that it should be a clear indicator of what we're talking about. There should be a clear indicator of a measurement. We shouldn't be saying things like, can you assess this from the point of view of, is it clear or not? What do you mean by, is it clear or not? Can you assess this on the basis of, is it satisfactory or not? Well, what is satisfactory or not? Can we get more specific? And can we get a measurement about it based on that? How are we going to take a sample? And how are we going to measure it? What kind of instrument are we going to use? And when we talk about instruments, we could be talking about physical instruments, like a vernier caliper, or a micrometer, or a simple scale, or a weighing scale. Or we could be talking about a battery of questions that we're using to get measurements of perceptions of customers, perceptions of employees. So when we talk about measurement instruments we could be talking about either, and the same concepts of worrying about whether there is a valid measurement, reliable measurements. Whether they will give you results that you can rely on in terms of their actually measuring something in the process, and not adding variations from the way it's being measured is going to be important. So the idea of operational definition, is that we should first make things clear as to what are we measuring? And not only that, it should be clear not just to the person who is writing the definition, but to everybody who reads the definition. To everybody who is going to do that measurement or deal with that measurement. Who's going to take the results of that measurement? How was this measured? And even if it was measured over time, if it was measured consistently or not? Or was there the criteria changing? Was the scale changing or what was the meaning of the scale? And was it changing over time?



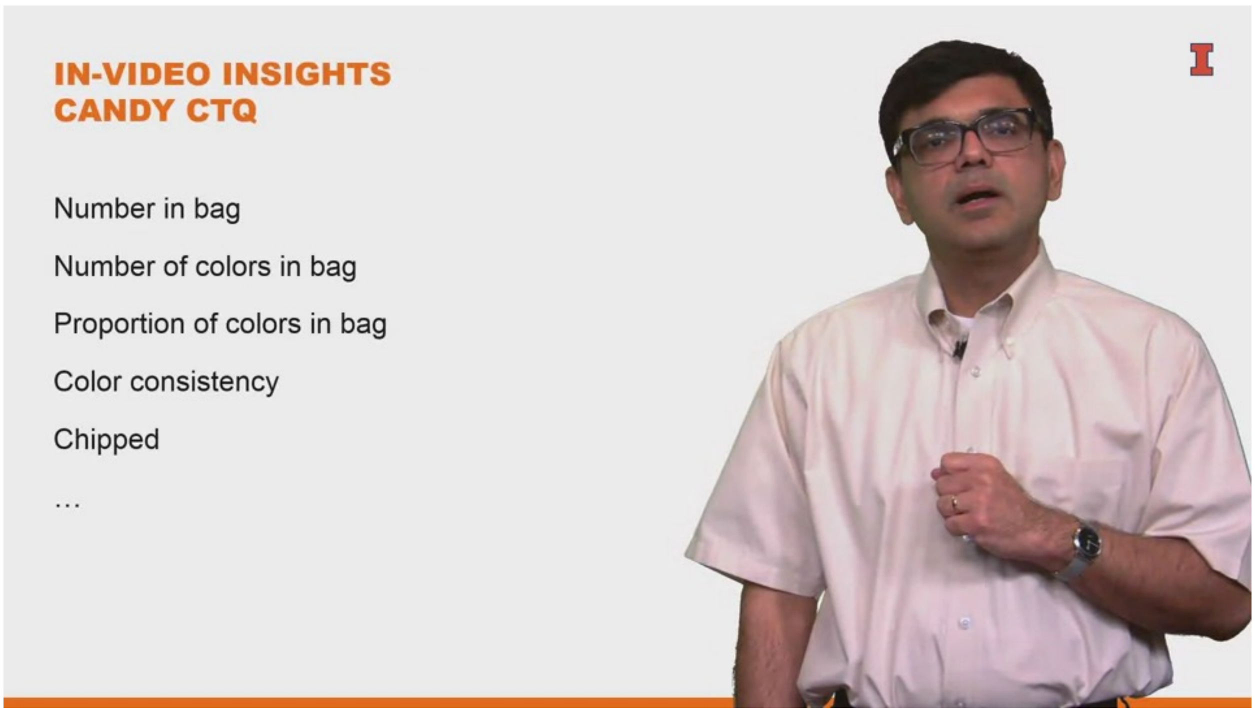
Are things that we need to be careful about, so, going further into operational definitions, and thinking about how do we create an operational definition? So for any product or process characteristic, we can think about this in terms of three things. First, is the criterion for that aspect of the product of the process. Second, is the test, how is somebody going to test and use that criteria in order to come with a decision about its measurements. So the three aspects are, what are the criteria? What kind of tests should be done? And there you can even specify how would the sampling be done, should it be a random sample that is taken from a box of material that gets delivered everyday. Or should it be every 10th house that you should be going to in order to survey, those kinds of things. You make those rules in terms of how is that test going to be done, in order to get any kind of measurement. And then the decision when the test results in something, how is the decision going to be made of, what is the measurement that you're going to call it? Are you going to call it a 01? Are you going to call it a 12345?



What is that decision you're going to make based on that? All right, so let's take a look at a specific example of using an operational definition. So here we have an example of filters. So and the criteria that we're talking about here is roundness of filters. So the specific criteria is that the range of the diameter, should not exceed more than 0.05 mm. So if you were to take measurements off the diameter multiple times off this round filter, that you should not get too much variation. If it's round, the diameter should be the same, if it's perfectly round so you should not get too much variation. So that's the criteria of 0.05, were saying there's a tolerance of 0.054 variation between the min and the max of the measurements that you would take, about the roundness of this. So how should this be tested? Well, the test is highly specified here, you use calibrated calipers now at times. These maybe calipers that are given to you by the supplier or the customer, and these may be kept at in a certain room at a certain temperature. If you are going to worry about the accuracy of it that much, if it's going to be that crucial, then those things will matter. And that's where you will say that these calipers should be stored in a situation like this, in a context like this and so on and so forth. We select a filter, now again, you can get more specific. Should you select a filter from the first box that got delivered that morning? Should you select a filter at eight o'clock every morning? Or should you select a filter at random from the production that was done yesterday? What would be your sampling that needs to be specified, but here we simply say select a filter. So it's simply saying select a filter from the box that you have, take 4 measurements of diameter 45° apart. So you're taking four measurements of that filter by going around the filter and getting four different measurements that are roughly equally apart. So you get the four different measurements, you take the max and min of those measurements. Maximum and the minimum value that you get and you check the range. If the range happens to be less than 0.05, we're going to say that the filter is round. So here you have an example of a specific criteria test and decision, of using it for a roundness of a filter. Now what we're going to do here, is we're going to take this whole aspect. Take the idea of operational definitions, and apply it to something that you may be familiar with, that you should be familiar with.



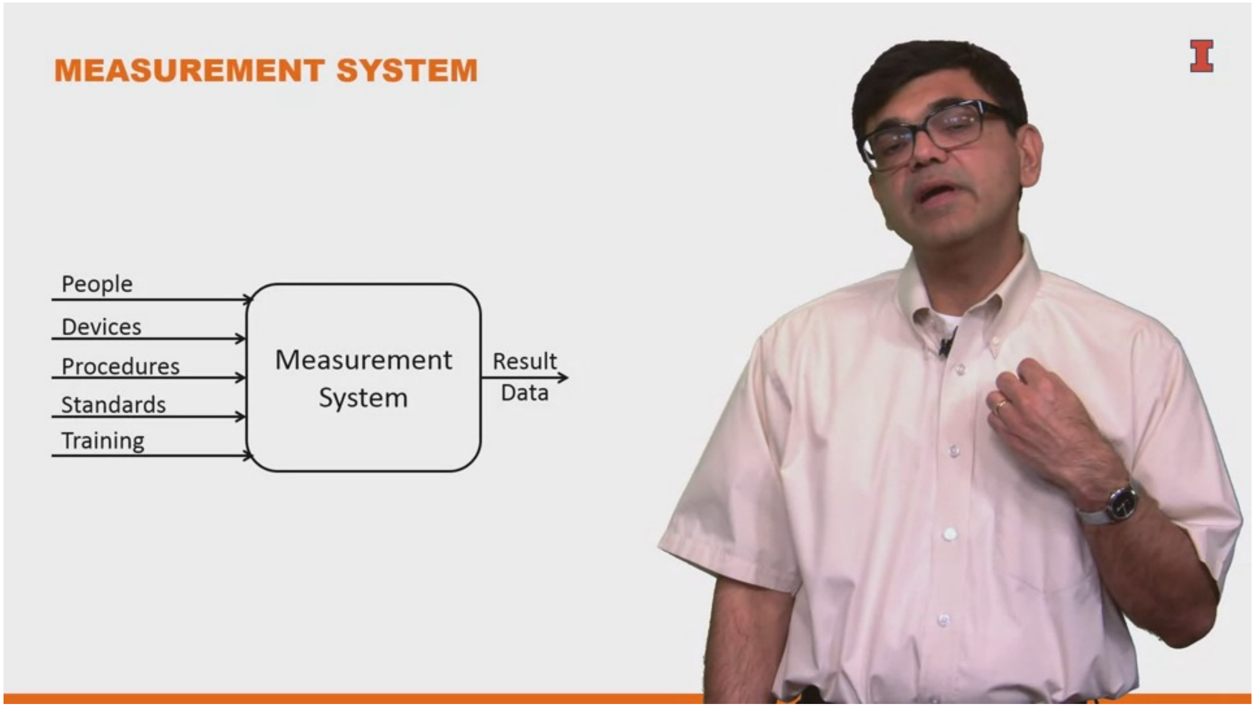
So ,take any packet of candy. So here I say for a 4-ounce or 100- gram, or 125 gram bag of candy, such as M&Ms, Skittles, anything that has many pieces in it like Smarties, or jelly beans. And if you think about any of those packets of candy, consider what the critical to quality characteristics are from a customer's perspective. So if you like candy you would be more familiar with these, but if you don't think about it from a customer perspective, what would they care about when they open a packet of this candy? What are some of the things that might be, things that they care about in terms of it's quality. And then think, once you think about a few critical to quality characteristics, what you can do is pick one of those critical to quality characteristics. And and for that particular, critical to quality characteristic, define a criterion and a test for making a decision on that criterion. So whatever criterion you pick, you pick a test for making a decision for getting a measurement of that particular criterion. And then come up with a way of testing for whatever that measurement is going to be for that criterion. So do it for any kind of candy, if you do happen to have a bag of candy that's close to you, go ahead and do it in reality. So that will give you a more real perspective of something like this. Otherwise you can just imagine that you would be doing it for a packet of candy.



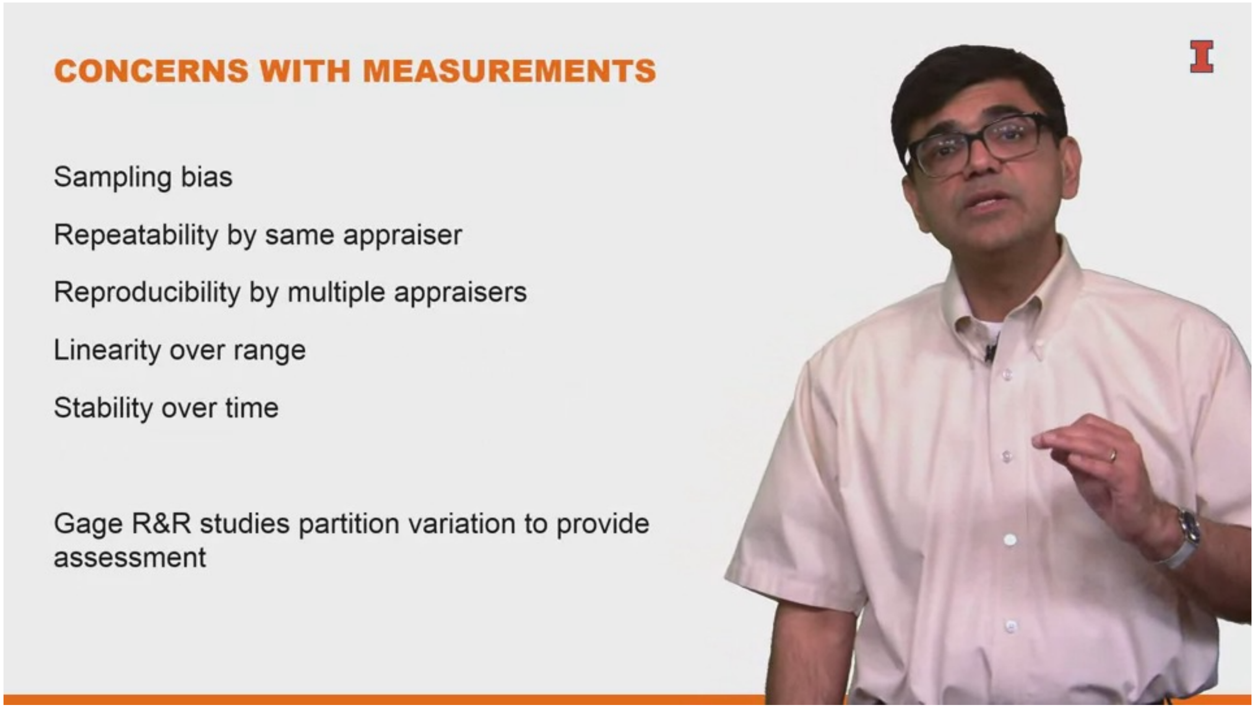
So, you may have thought of any number of things about a bag of candies. When you open a bag of candy, you critical quality characteristic of it would be, do you get a consistent number of units in the bag. You may be aware of, or you may be concerned about the number of colors that you have in the bag, and what is the distribution of the colors? What is the proportion of different colors? Color consistency, chipped or you may even go for some kind of destructive sampling by actually tasting them and seeing if you have have some sense of sweetness. It would be difficult to come up with criteria and tests for something like this. So we're going to keep that aside for a minute and I'm going to use one that is more easily amenable to to using the criteria and tests.

So I used the idea of variety of colors here because it can be used to demonstrate the notion of criteria, and tests. But hopefully you've thought of some critical to quality characteristics of candy, and you can see the perspective for some of them. It might be difficult to come up with a criteria that can be described to people, that can be written down in terms of a standard way of of them testing it. So let's take a look at at the simplistic one that I have over here, which is a variety of colors. Simply how many colors are there? And I use the criterion here of there should be at least three of each of five colors. So there should be at least three of any five colors, that may be there, but there should be five colors with three of each of them. And then they can be more with, even if they don't have three of each, that would be fine. How would I say to test this? I would say, select a bag and then open the packet and count the colors. And when you get to a point where there are three of each of five colors, you can stop the test, right? So that's your test for you reached that threshold. And now it's it's established that it does have a good variety of colors and acceptable variety of colors. So if you find three or more of five or more colors, you determine that the packet is to be deemed acceptable. So that's a demonstration for you for the idea, of the operational definition.

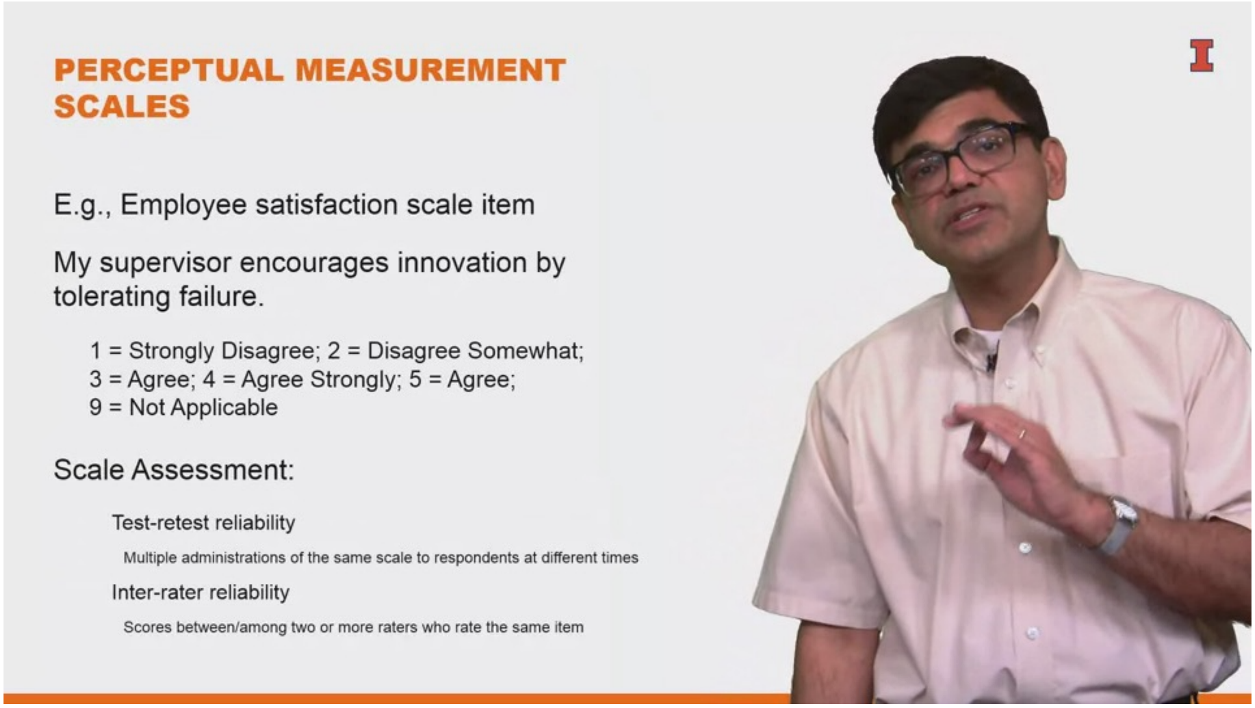
Module 3.2.2 Assessing Validity of Measurement Systems



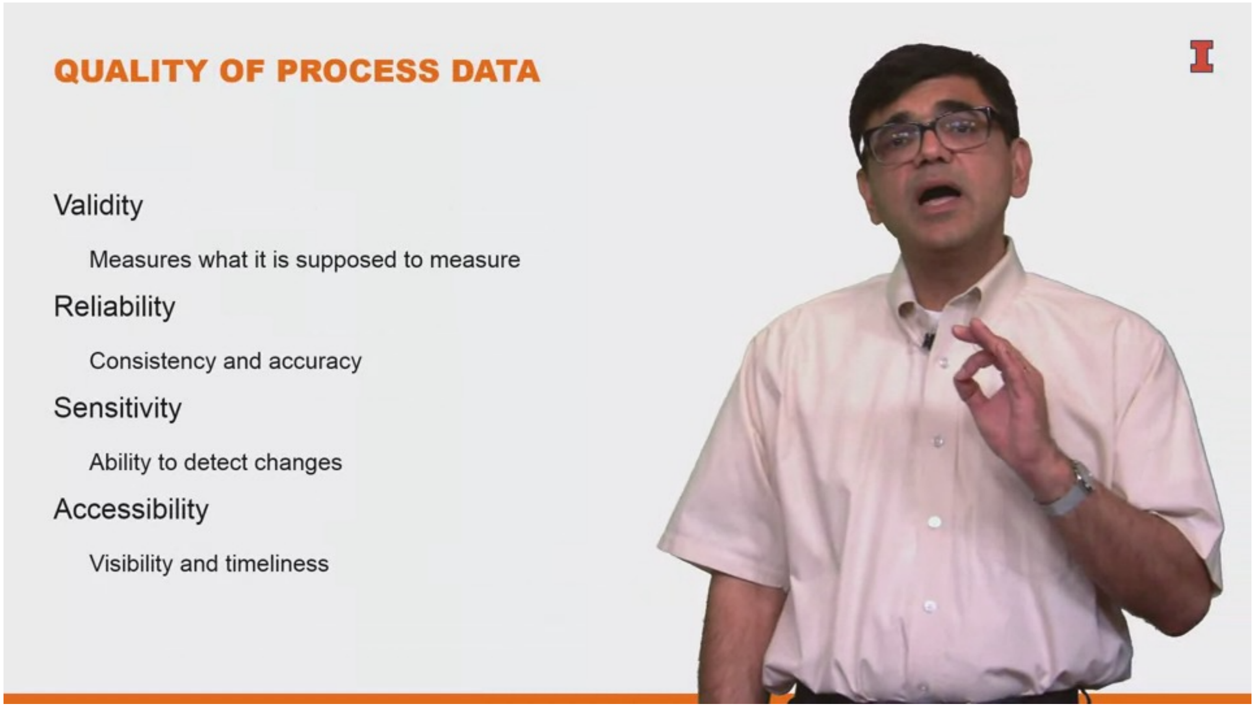
So if you think about measurement systems, what you're concerned about this, you're concerned about variation that might be coming from different places. So when you think about a measurement system, you should be thinking about are people trained to measure the same way? Are the device is going to be calibrated such that they stay consistent over time? Are the measurement instruments going to be such that they don't get affected by who's using them or by dropping them or things like that? And again, if you're thinking about perceptual measurements, you're thinking about surveys, are they going to mean the same thing to the same people? Is the wording going to be current when you're talking about using the same battery of questions over time. So you should be thinking about that as well. And then the procedures to actually do the measurements. So how are these going to be actually done? Are they going to be done taking five samples and taking the average? And then how exactly are you going to get that measurement to be done? Because you're trying to get away from getting variation from the measurement system itself, or errors from the measurement system itself? What kind of standards do you have for the measurement system? And then what kind of standards you establish for saying something is beyond a particular threshold or not? And then training people for using those measurement systems. Training people to do this correctly, getting a demonstration. So when you think about criteria and the test, you should be able to demonstrate this and somebody should be able to understand it and then be able to replicate it for you. They should have the same meeting off that critical to quality characteristic and the criteria. And the test that you do so that when anybody does this they should be able to do it the same way and get the same result. If it's the same package they should be able to get the same result. They shouldn't be variation and results from measuring the same thing over time.



So what are we concerned about when we are talking about measurements and some of this can be looked at based on data. When we collect data, we can take a look at the variation in the data and we can parts that variation out into, does it look like there is variation that's coming in because of measurement? So what are some of the things that we're concerned about with measurements? With measurements were concerned about sampling bias. So did we choose particular samples at a particular time all the time? And one way to get around it is have some sense of random sampling. And even including some kind of random sampling with some rules like saying we take a random sample from the 8 Oclock batch. Or we take a random sample for every hours batch and and so on and so forth. So depending on what is it that you're trying to look at. If it's going to be a hypothesis test, then you then random samples are better. And if it's going to be looking at process performance, then you wanted to be timed and make sure that you're getting a sample to represent each of those times. Or each of those days of the week and so on and so forth. But you have to be aware of the idea that you're sampling can bring in some bias into your measurement. And again, you could be thinking of perceptual measurements. And how did you sample the people that you talk to. The customers that you talk to are the employees that you talked to in order to get some sense of whatever you're measuring. What we're concerned about is repeatability by the same appraiser. So, if you give the same person the same object to way over time, the way it should be the same, right? If you give it to them today and you give it to them tomorrow and after the way it should be the same. That's what we mean by repeatability. Reproducibility is, if you give me that object and if you give my kids that object, if they're trained the same way they should get the same measurement. So it's multiple appraisers should get the same measurement. That's what we call the reproducibility. We're concerned about linearity over range. If you think about looking at any weighing instrument, it usually says this is accurate up to a certain weight. If you go beyond that weight, don't expect it to be accurate, right? That's what they're trying to say. So when you have a measuring scale that is meant for measuring your spices, it's going to be a small measuring scale. And if you're trying to take a pound of flower and you're trying to wait on that, it may not be calibrated to go beyond half a pound of weight. So if you're trying to measure something like a pound of flour, don't expect to get accuracy. And that's what we mean by linearity over range, that it's not going to be linear range, should be strictly linear over range. If we're talking about a continuous measurement and if it's not that, there's a problem with it. Stability over time, is that if you do the measurements over time, they should give you the stuff same kind of result. If it's you're talking about the same thing. So in order to to work with measurements, in order to get a sense of the measurements and how good they are. You can do something called a gage R&R reproducibility and repeatability analysis. And this can be based on getting data from multiple respondents for multiple objects and getting them to do the repeated kind of measurements from that same. We collect that data and you start to look at the way if there was any variation in the data and then you look at whether that could be coming from training of people. Or whether that could be coming from the instrument or whether that could be coming from instructions that you're giving people. So gage R&R is something that you can use based on data to look at these kinds of questions.



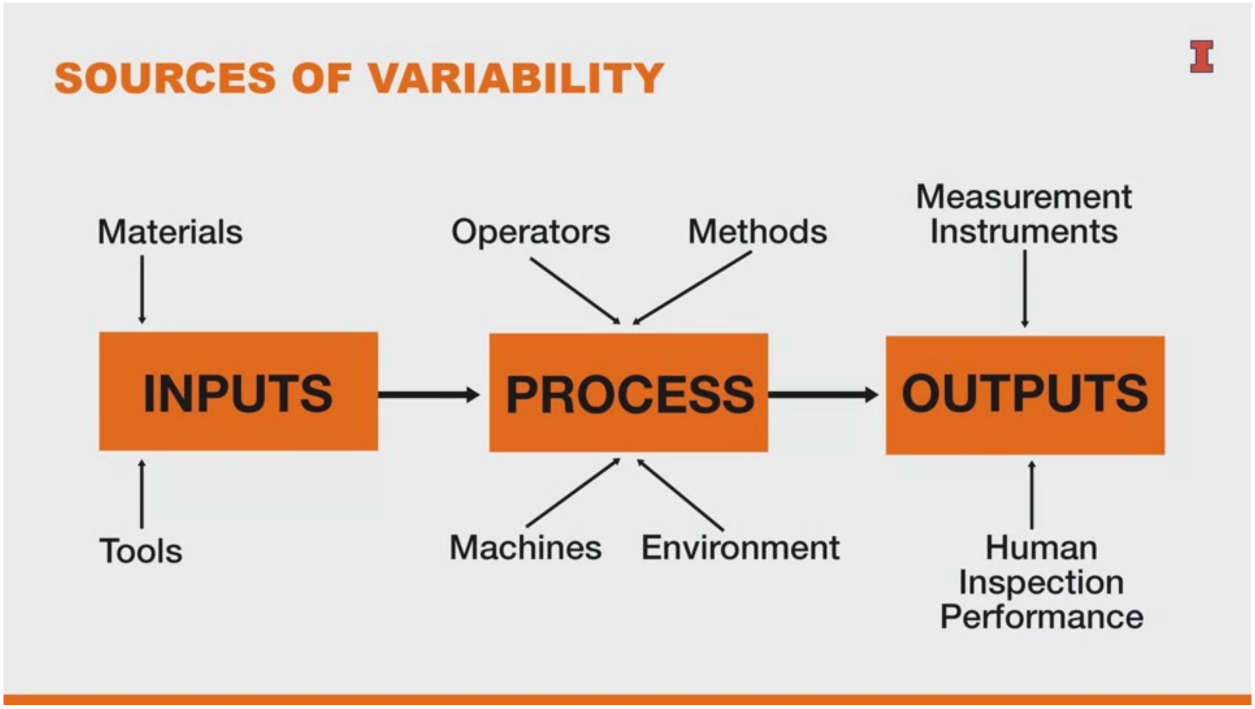
Now when we turn to perceptual scales also we can do a similar kind of analysis and here to have an example of an employee satisfaction item. So this is a single item that says, my supervisor encourages innovation by tolerating failure. Respond to this on a scale of 1-5 from strongly disagree to agree and a nine of not applicable. So here are the options that you have. How would you test this? You would test this based on test retest reliability. You're giving multiple administrations of the same scale to respondents and you're giving into them at different times. Or you could be testing people who are working in exactly the same conditions but you are trying to get into greater reliability. You're measuring whether two people would be giving the same response about the same thing when you expect it to be the same. So, that's how you could be testing this. And again you can do data analysis for this, you can collect the data and do some measurement of some assessment of the variation that you're seeing in the data to see where that variation is coming from or might be coming from.



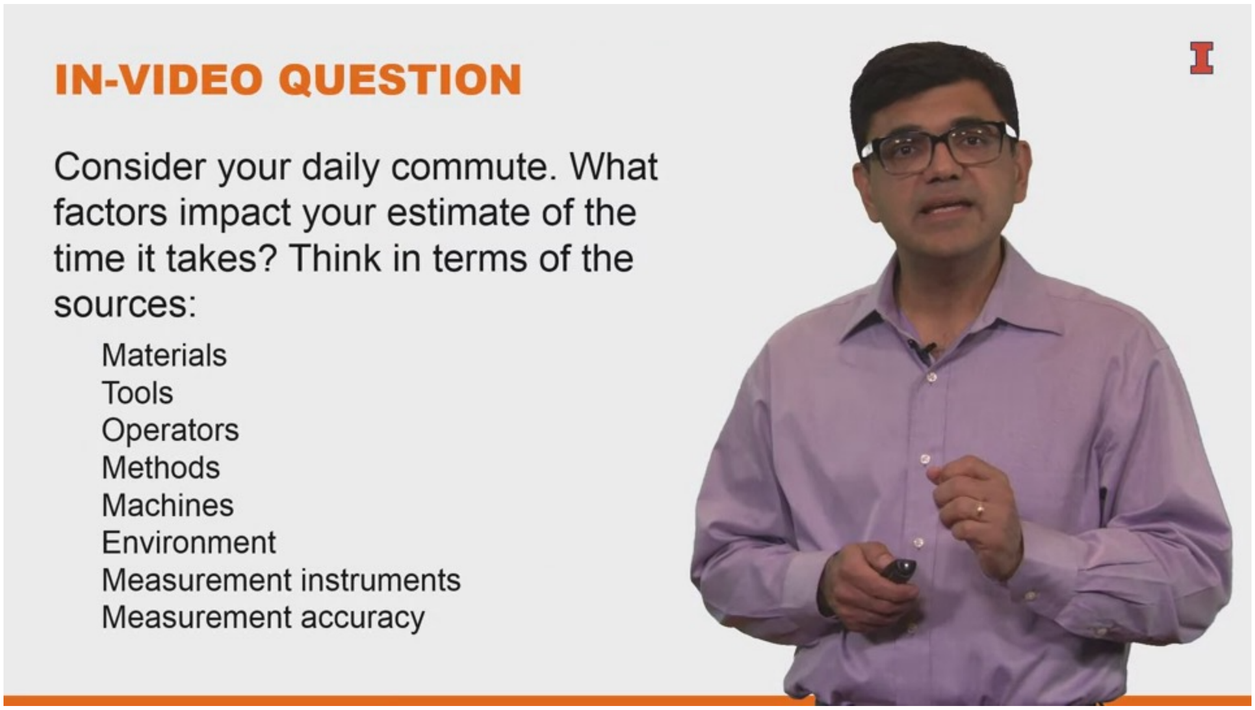
So in some about the quality of process data, what can we say? We can be looking at the validity of data. It's measuring what it's supposed to measure. It's measuring something that we expect to be measuring and it's also giving us a comprehensive measurement of something. So it's something that's useful for us to make an assessment about the product or the process. So that's what we mean by validity, it's reliable, it's consistent and accurate. It's sensitive to changes. There should be data, there should be measurement that should be sensitive to changes. It should be calibrated to a level of granularity that it's sensitive to changes. Otherwise you're not going to be able to make out the difference between two different levels when you're supposed to. And it should be accessible. It should be accessible to the people who are going to do the measurement and who are going to use it in a timely fashion. So it should be accessible and be able to use, be able to be used in a timely fashion. So the simpler it is, the more people can use it. And the simpler it is the more quickly you can get that measurement and the results from that measurement for it to be used in a timely fashion.

Lesson 3-3: Statistical Process Control

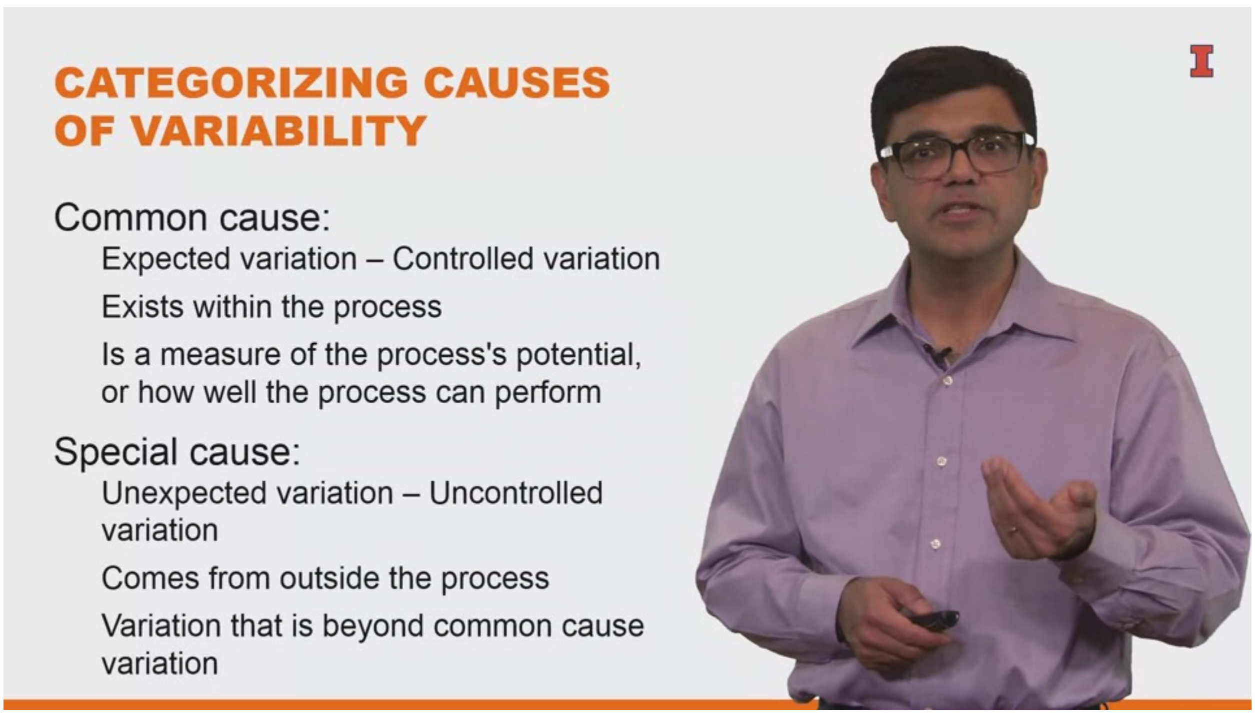
Module 3.3.1 Common and Special Cause Variation



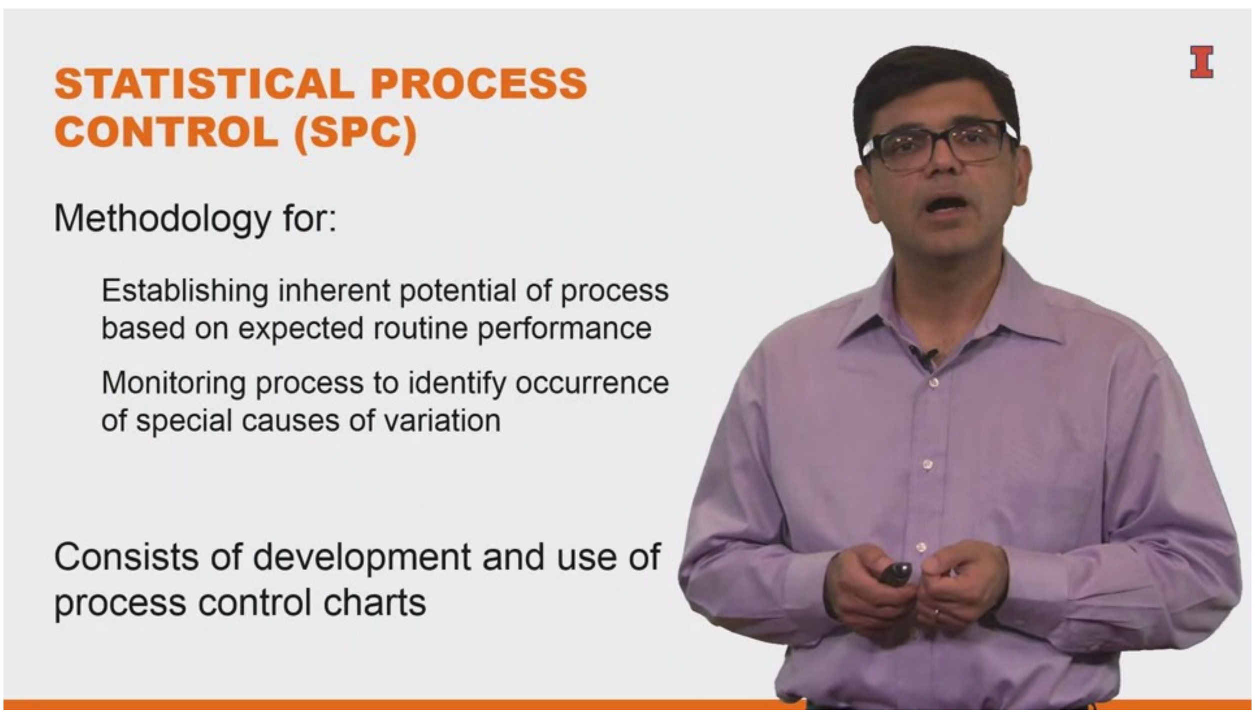
When you look at any kind of work process, there's variability that creeps into that work process as to how you get it done and you're not going to be able to get it done in exactly the same amount of time every time you're not going to get the same result exactly the many times that you do it. And the variability is going to come from different sources. So if you were to look at the input process output model, you can think of the variability coming from different sources at the input side, which is the materials that you might use. The raw materials that you might use and the tools that you might use to get started within the process. Who is doing it? The operator methods that there may be a choice of methods to do that particular process will cost some variation. There'll be machines, and the machines might perform differently based on how well they've been maintained or if there was something that went particularly wrong that day. And then there will be the environment. The environment could be factors such as the weather, if you're talking about a a process that has a lot of human involvement, the weather might have an impact on how the process is done. So there will be some variability coming into that from that as well. On the output side the fact that the output needs to be measured. There might be variation coming from the measurement instrument that's being used. So if you're talking about timing, something, maybe there's some variability that's getting into that measurement process based on how that measurement instrument is performing, how that stopwatches, performing. Whether the person who is using the stopwatch, used it correctly, started it at the right second and stopped it at the right second. And then in terms of inspecting outputs, if there's inspection, then there will be some variability based on who is inspecting and they might have different perceptions of what they're seeing in the output. So as you can see, there'll be variability coming into any process and you can apply this idea to pretty much any process, any kind of work that you see around you, any kind of work that you even do on a day to day basis.



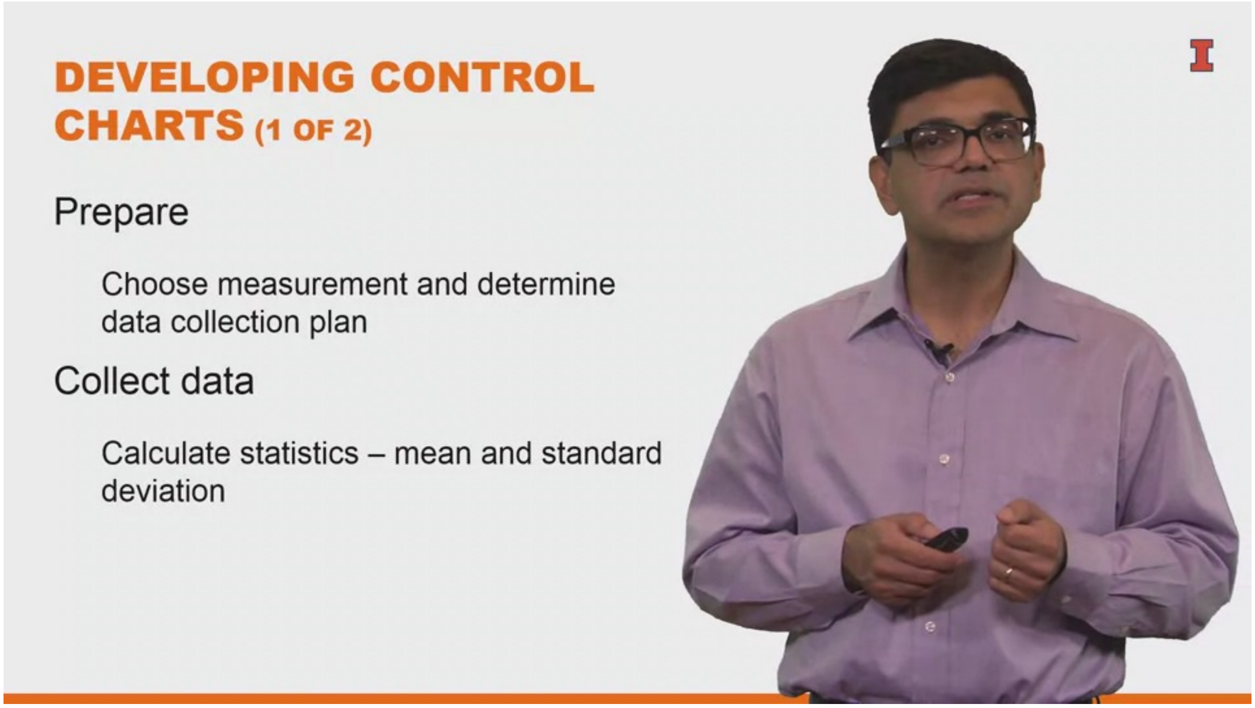
So let's take an example of a something that you can relate to, right? It's your daily commute to work wherever you go to work, it's your daily commute. And what I'd like you to do is think about the different factors that you have to keep in mind when you asked the question, how much time do you take to get to work? If you say 15-20 minutes, you've already given me a range 15-20 minutes. And what determines whether it's 15 or 17 or 20 minutes. So that's something that that you're already thinking about. So what I'd like you to do about is think through the different sources that force you to give that range of 15-20 minutes or whatever time that is. And you can have given you a few pointers from the previous slide here, in terms you can think about it in terms of the sources of that variability. So is it coming from the materials that you're using? Is it coming from the route that you take? Is it coming from something else? So, can you think of these things and see what you can come up with in terms of the sources of variability for your time to commute to work every day. All right, so depending on how you commute to work, whether you take the train, whether you take the subway, whether you use your bicycle or whether you use your car, you may have thought of different things, that cause you to give an estimate of your time, which is a range. So you usually think about it in a range and you may think about, do I have to put gas in the car? Do I have my train pass? Does it have enough money or am I having to stop at the window? If it's my bicycle, do I have to fill air in the tires before I can take off that particular morning and that's going to impact the time that I take to get to work that particular day. You can think about environmental factors and those will have a big factor, we'll have a big effect. So, for example, if it's raining that day, were snowing that day. And if it's a particularly high traffic day, for any particular reason that's going to have an impact on your estimate at the time, that it takes. And some of this is going to be, well, it will depend on whether I get all green lights or I get all reds and that might be a matter of chance for that particular day. There might be also some variability that might be coming into this based on who's driving, if you're carpooling. So that might be the factor of that is causing variability. And then what will also cause variability is depending on who's driving, how well are they at obeying the traffic rules. So that might have an impact on, on how fast you can get there. So what you can see here is that variability can come from many different sources.



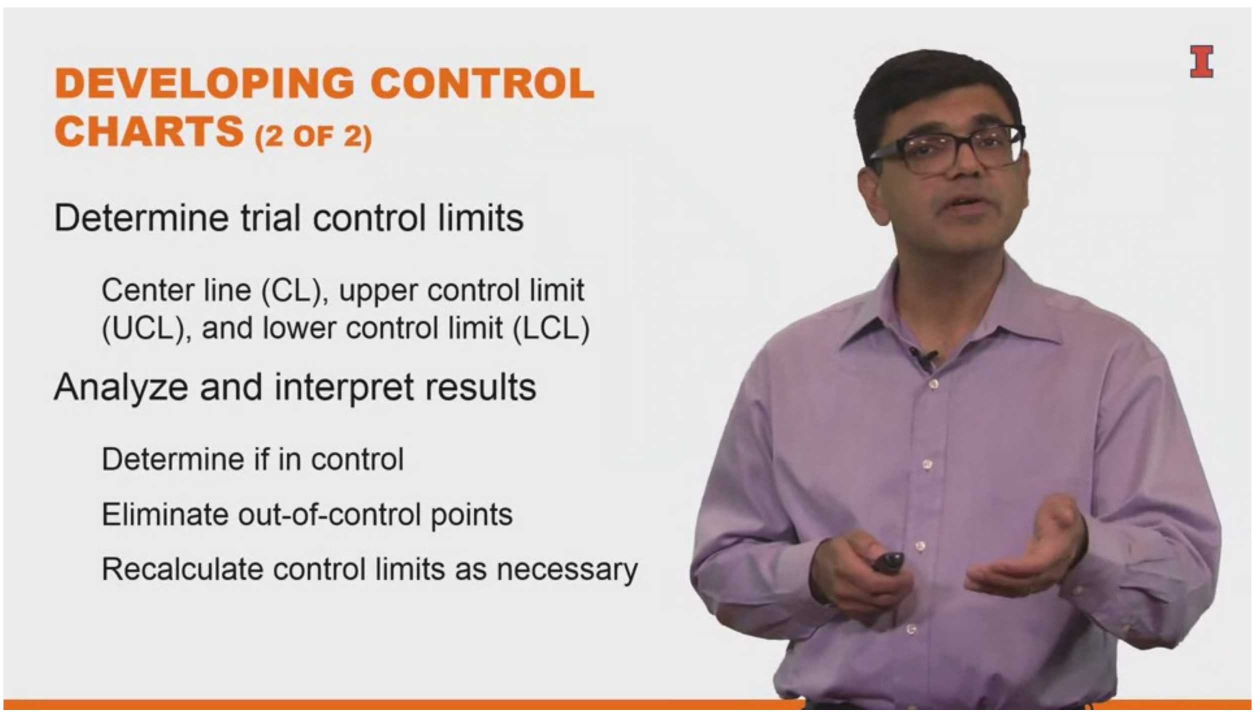
Now, when you think about variability, what you can also do is think about what is the normal course of events that can occur when you're going to work. And what is abnormal? So what we're talking about here is that there might be, you might say it takes 10 to 15 minutes depending on traffic, depending on getting the lights in the right sequence and those kinds of things. And that's something that factors into your normal course of events. Now, if you happen to have an accident on the road that day and you get stuck in the middle of two cars, and you're not able to move out there for an hour or so, you're basically talking about something that you don't factor into your daily estimate. So, if I were to ask you, how much time does it take, you're not going to take that kind of an event into account when you're talking about an estimate of your time. So that's how we distinguish between these two kinds of variability called common cause variability and special cause variability. So what is common cause variability? It is the variability that is expected in your process, based on your current way of doing that process, your current way of doing that work. It exists, it's a measure of the potential of that process, doing the process in the current way in the current steps that you're following. It is expected that you will take so much time or that the quality level is going to be something that you expect. So that's the variation that is coming from common causes, things that are expected to happen. And special causes are things that are beyond the common causes. So things that you do not expect to happen, they come from, things that are completely outside the process and that is the variation that is beyond what is the inherent capability of the process, right? So, here's the difference between these two, but I also want to caution you that you can think about any particular cause and there might be a fine line between either including it in common or special cause, right? So what do we mean by that? Do I want to include some special events in common cause? Do I want to include the fact that I did not have gas in my car that day in the common cause. And I want to include that factor in having to go and put gas in the car. If I'm thinking of the commute to work as something that occurs normally. So that's a common cause. So there's some fund ability and that you're able to make changes to common and special cause based on that. It's your definition of common and special cause in that way.



All right, so let's turn to this idea of statistical process control and this is underlying idea behind this is to use statistics to be able to distinguish between common and special cause variation, right? So it's to be able to distinguish what the inherent capability of the process is. And then once you've established the inherent capability of the process based on some statistical principles to be able to use that to monitor the process. So, you figured out that it should take you 10 to 15 minutes to get to work. You can time yourself every day and it should be between 10 to 15 minutes, right? So that gives you your established inherent capability. And then if it goes above 15, you say, well, what happened that day? And what is something that was a special cause that day, because it normally takes me 10 to 15. And on the other side, if it goes to eight minutes, you say, well, that's something that's a pleasant surprise. Why did that happen? What was the the good luck thing that happened that day? And then you might want to think about, well, can I make some changes to in order to move towards that eight minute time, so that I can actually reduce the time that it takes. So statistical process control charts serve this dual purpose of establishing the inherent capability of the process and telling you when your process has given you performance beyond the inherent capability, right? How do we do this?

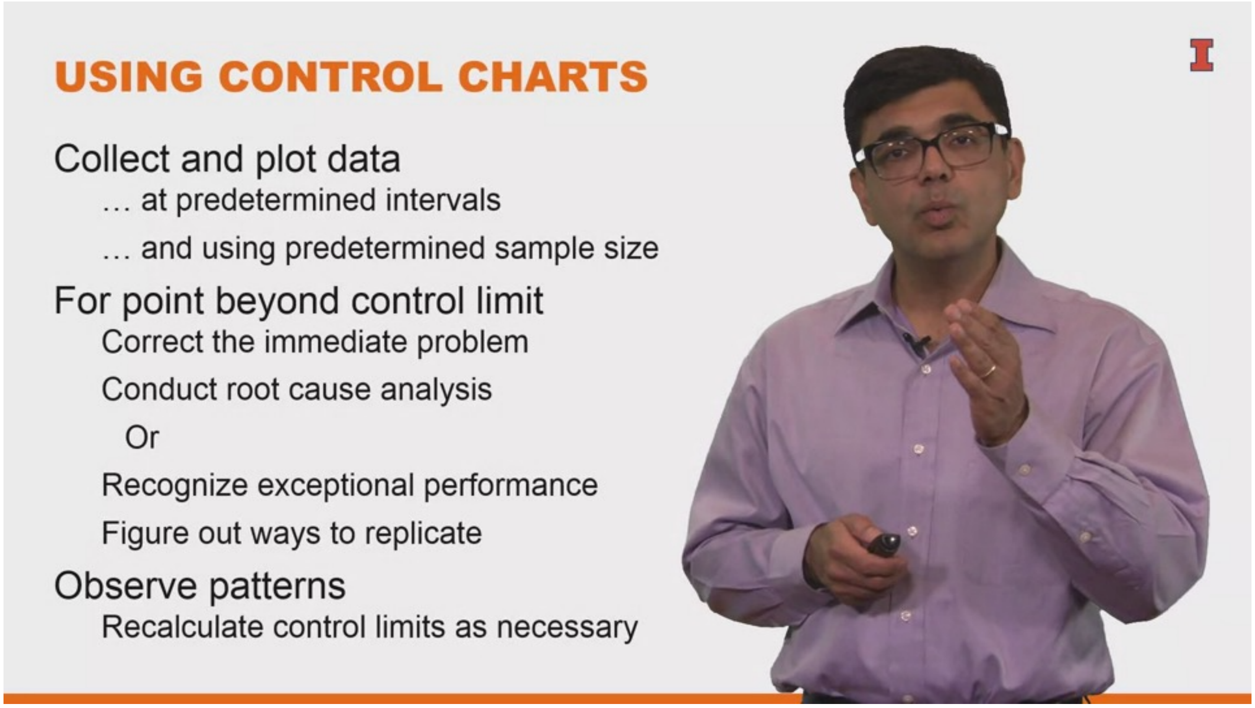


We do this based on making control charts. So when you talk about making control charts and you as a manager is going to establish the inherent capability of the process. The first step is going to be developing the control chart. So you're going to come up with that band that's going to say this is the normal capability of this process. How do you do this to get started with this? You choose what kind of measurement you're going to use, right? And we'll talk about a few types of measurement as we move along. And what do we mean by choose what type of measurement? Are you going to choose a measurement that's simply going to tell you this is a good product versus a bad product? This is a good time versus a bad time. Or is it going to be more specific. Now, why is it important to choose measurements? It's because based on what measurement you choose, you can use a different type of process control chart, right? Why is it good to have this choice of different types of process control charts. As you will see later, there are advantages and disadvantages of choosing certain types of measurements and certain types of process control charts. Nevertheless, the idea of preparing a control chart is you have to choose what kind of data you are going to use in statistical terms were saying, what kind of distributions of data are you going to use to make your statistical process control chart. You have to also choose your data collection plan, which means how often will you collect data? What is going to be the size of your sample whenever you collect data? Once you've collected your data based on that data collection plan and that sample that you've collected, you're going to calculate some statistics and the main statistics will be using here are the mean and standard deviation. Now the mean and standard deviation are going to be computed differently for different types of distribution. So this school goes back to the idea of you have to think about what kind of data you are going to use in order to come up with the statistical process control chart.

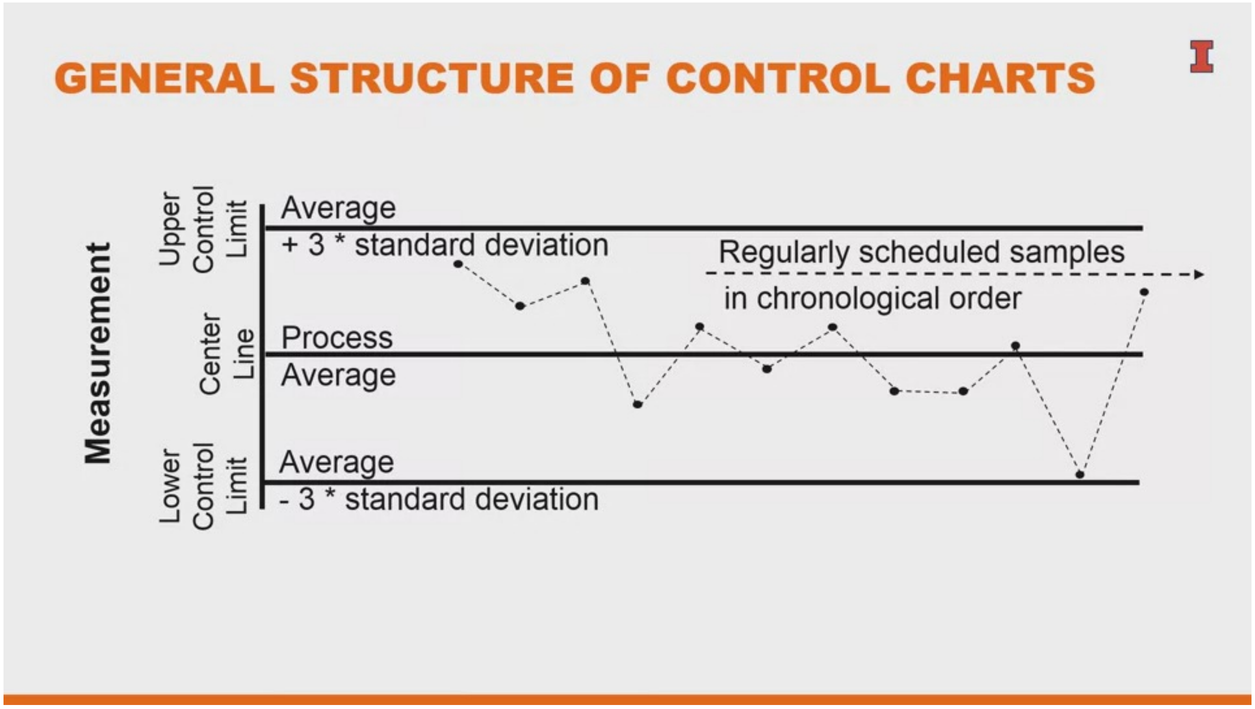


Next step you're going to do is you're going to make the actual control chart, you're going to come up with the upper and lower control limit, what we call the UCL and the LCL. And there's going to be a center line based on the average that you find that that's going to say this is the average and this is as high as you can go and call it a process in control and this is as low as you can go and call it a process in control and that gives you the wit of the inherent capability of your process. I call this trial control limits here because when you as a manager are at the point of making that control chart, you are basically calibrating an instrument, you're coming up with an instrument and you want to make sure that instrument is something that is good and reliable, right? You want a good instrument that you as a manager can use in the future and you can give to your front line people and say under normal circumstances, this is what you should get from this process right? And the reason to call the trial control limits is, if in the process of coming up with these control limits, you find that there are points outside of the control limits, right? So you make the control chart and then you go back and you plot the points that you had used to come up with these control limits and you find points outside of the control limits. It's basically telling you that you cannot really rely on these control limits, right? You have a process that's already out of statistical control and you are using the measurements from that out of control statistical process to come up with your calibration of upper and lower control limits and that's simply not going to work. It's not a reliable upper and lower control limit. So there what you have to do then is you have to go back a step and say if there is a single point that was outside of the control limits when I calibrated it. If you can figure out what happened at that point. If that was a special cause that you do not want to include, you might simply just throw off that data point, that sample and then re compute the control limits. But if you can't really figure out what the cause was and it seems to be a mystery, then you might have to simply collect new data. And the idea is that you are calibrating a control chart when the process is performing normally, quote unquote normally, which is quote unquote given the current conditions, this is how it should be performing. Because remember you're trying to get at the inherent capability of the process.

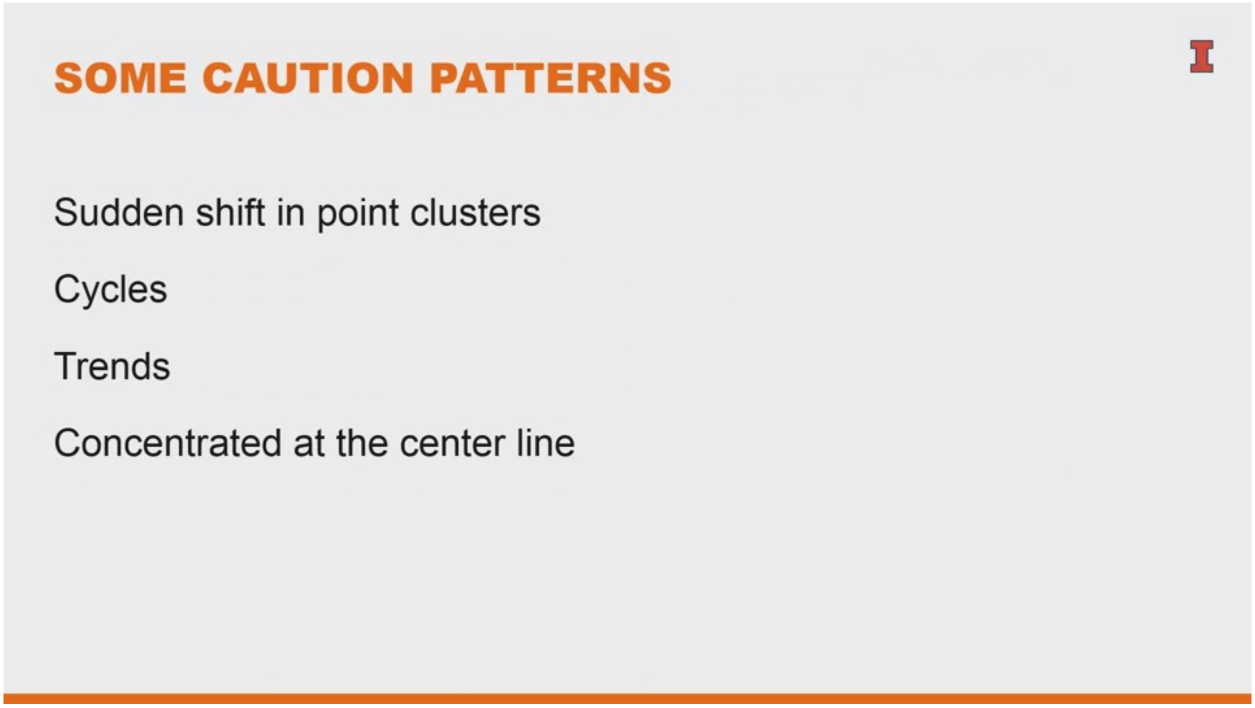
Module 3.3.2 Using Statistical Process Control (SPC)



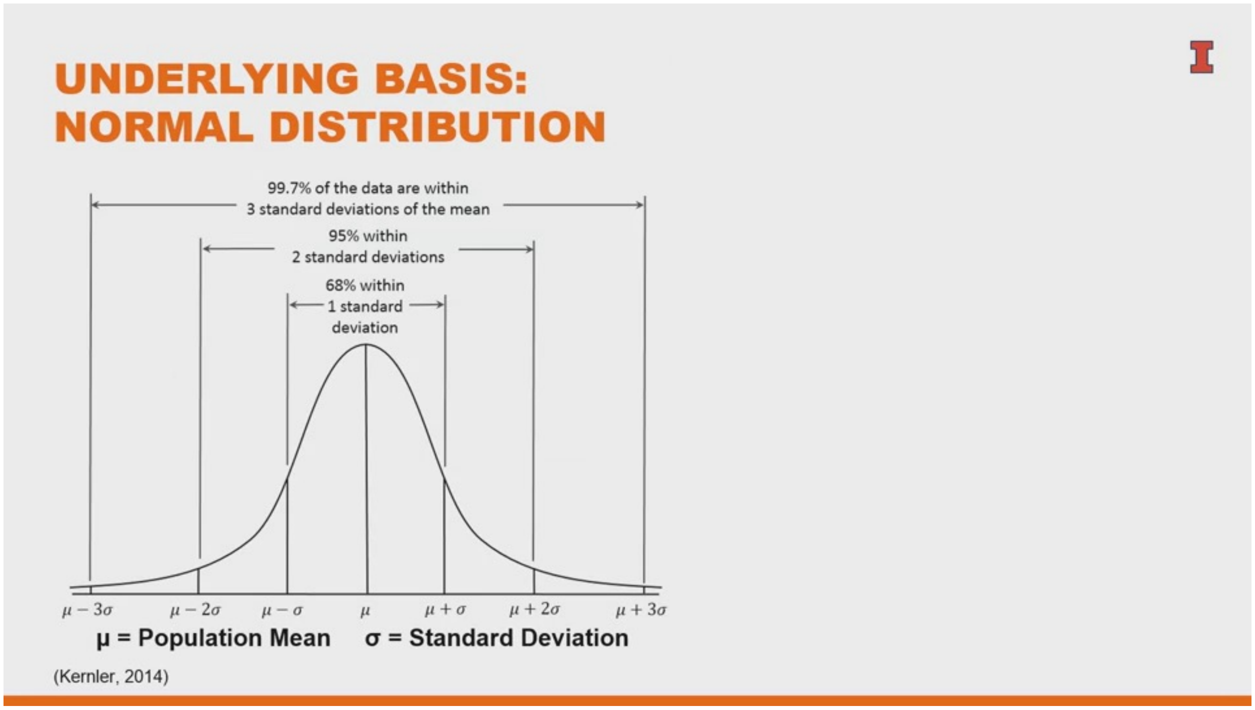
Once you've come up with the upper and lower control limits, once you've calibrated the control chart, the next step is for you as a manager to give it to somebody in the front line and then being able to use it, or for you to use this control chart to keep an eye on the future performance of your process. You've calibrated it. Now you've locked in the upper and lower control limits, and now you take daily samples from your process and you plot them. You take them at predetermined intervals. You might say, "I'm going to take five samples every day." Or you might say, "I'm going to take a sample every hour, every day and each sample is going to be of size x." It could be five, could be 10 or whatever that you've chosen. You do that, you collect the data and you plot it on the control chart and then you go and see if there is a point that's outside of the control limits. You plot the points, and as you plot the points, you look for points that are outside the control limits. If you find a point that's outside the control limits, what is that telling you? It's telling you something happened that made this process go beyond its inherent capability. Now, you would think that that's necessarily a bad thing, it's gone beyond its inherent capability. Yes, it may be a bad thing or it may be something good that happened. What do I mean by that? It's not necessary that when there's something outside of the control limits that it's a negative thing that happened, especially when you're looking at something like a proportion of defects. If you think about a control chart for proportion of defects, if there's a point outside the control limit on the lower side, that's telling you your proportion of defects was lower than you anticipate in the normal course of events, which might be a good thing. All we can say when there's a point outside of control limits is there's something that has happened that's worth going and looking at. Go see what a point outside the control limit tells us. Then finally, when you go see you may be able to take action based on what you find there. But finally, what you want to do is if you do find a lot of points going outside the control limit, you want to do something about it. You want to improve the process so that there are no points outside the control limit. But also more importantly, what that's also telling you is to recalibrate your control limits. If you're finding too many points outside, it's saying that maybe there's something that's changed in the process that you need to recalibrate your control limits and on the other extreme, we can look at patterns that will tell you something even when there is a point that's not outside the control limits, even when there's not a single point outside the control limits.



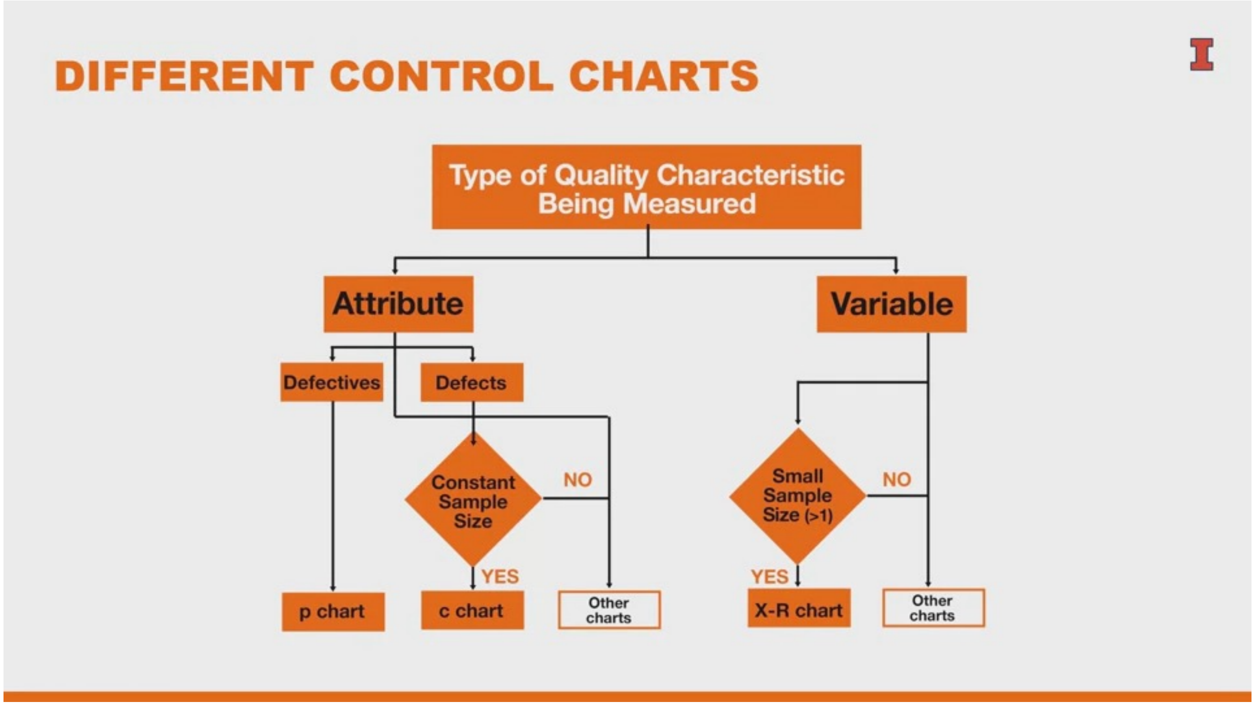
We'll look at those kind of patterns later, but before that, let's just get a sense of the general structure of control charts. Any control chart will have these three lines called the upper control limit, the center line, and the lower control limit. The center line is going to be some sort of a process average. The upper and lower control limits are going to be based on three standard deviations above, and three standard deviations below the process average. Once you've calibrated this kind of a control chart, you will plot the samples. You will take the samples from that process and you will plot them in chronological order, going left to right. The idea being that you're looking for points outside of the control limits but you're also looking for any kind of pattern that you might see in this control chart, even if there's not a single point outside of the control limit.



To put some specifics on the kinds of patterns that might be worth going and looking into. Now, this is not something that has a statistical principle behind it. It's going to be more context-specific. Based on what your context is and what that process control chart is all about, you might find something that might be worth looking into or not. The first one that you see over here is if there's a sudden shift in the point clusters. You had all the points in random fashion within the control limits all this time and there seems to be a sudden shift either upward or downward towards the upper control limit or the lower control limit and there seems to be a concentration going one side or the other. That could be a sign that's telling you something. If there's a cycling of points. If the points are all below the center line towards the lower control limit and then subsequently they are all above the center line, and then they're towards the upper control limit. Next again, they're down towards the lower control limit, lower than the center line and this cycle keeps on continuing. That may be telling you something. In this particular example, it might be telling you that there are two different distributions here. You might want to think about separating out the data for those two different distributions. The idea that there are two different operators that are working on this task at two different times and this is showing you that they're performing differently. That might be information that might be useful in terms of either coming up with two different control charts for them or saying that, well, one of them is doing a good job and one is not so let's do something about this and try to get this to be the same. Trends, similar idea to a sudden shift in point clusters. If there's a trend of points going towards one side, it's telling you that even if a process seems to be within statistical control at this point, it's heading towards going out of control. If you find all the points are concentrated at the centerline, you have an upper control limit and lower control limit and you find that the points are all very close to the centerline all the time. What it's probably telling you is that there's less variability than you expect in this process that the process has actually become much more predictable, so it's time to recalibrate the control limits and use a new process control chart with new control limits. These are some of the things that you might want to look at in addition to looking for points outside of the control limits in a control chart.



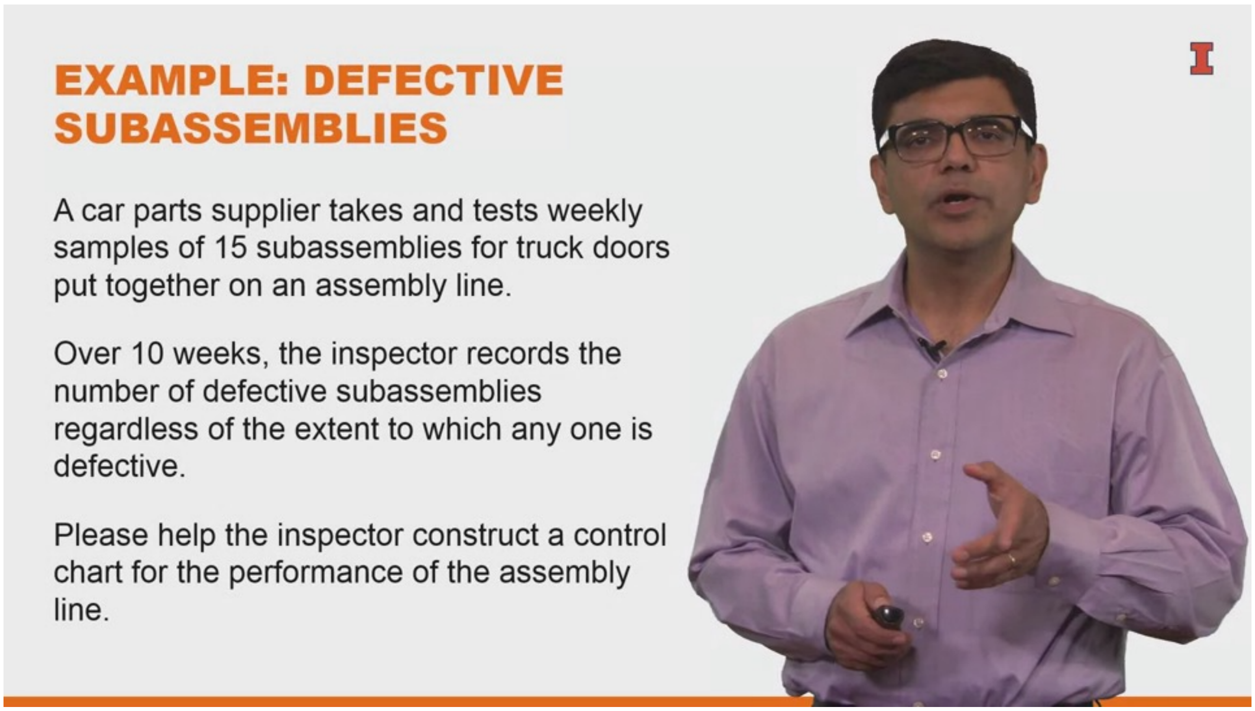
Where does this whole idea of plus or minus 3 standard deviations come from? Now, and some of you may already be familiar with this, the idea is coming from what we know as the bell curve, the standard normal distribution, and it's the idea that 99.7 percent of the observations are going to be within plus or minus 3 standard deviations. That's the idea that's being used in statistical process control. That under normal circumstances, and that's "normal circumstances," a process reflects what is seen as the normal distribution plus or minus 3 standard deviations will cover 99.7 percent of observations.



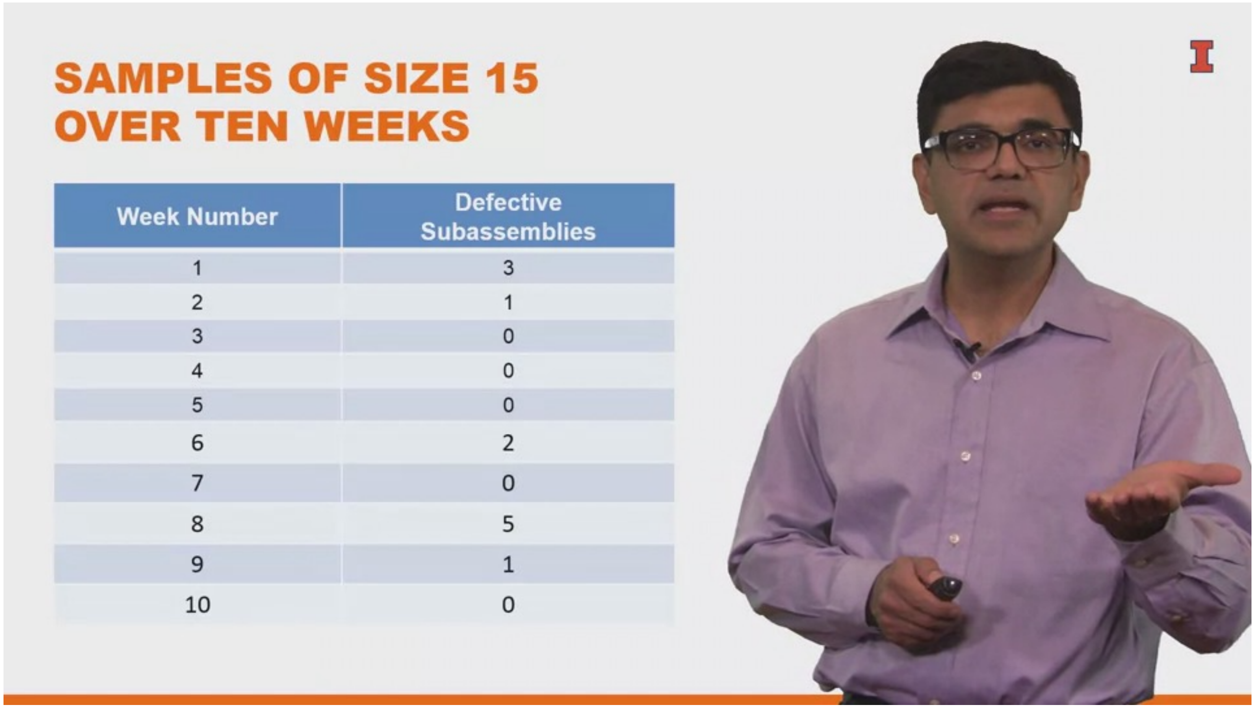
What you have here is a schematic that's showing you different types of control charts that can be used. Broadly speaking, we can take measurements based on attributes and variables. What are attributes? Attributes are things that you can count. Attributes are things that you can see in terms of something being good or bad. In statistical terms, you're talking about discrete distributions there. Attribute control charts are going to be based on discrete distribution data. Like I said, there are many types of control charts that you can use and within the attribute control charts, within the attribute type of control charts, you can have many different types of charts. What I have described over here, what you're seeing over here is that the p-chart is the one for if you're looking at proportion defective. The p stands for proportion and if you're looking at the number of defectives in a process, you're simply interested in looking at whether a product is defective or non-defective, you would use what is called a p-chart. The other attribute chart that is commonly used is called a c-chart, and a c-chart is used for defects. If you are interested in the number of defects in a particular sample of products, you would use a c-chart, and the c there stands for count. There are several other types of attribute control charts. On the other side, you have the variable type of control charts, and these are based on continuous distributions, so distributions where the decimal points have meaning. You're talking about length, weight. You're talking about viscosity of a liquid. Those are the things that you can actually measure. This is going beyond saying, I'm counting the defects or I'm looking at whether a product is defective or not. A variable control chart is actually looking at a particular aspect of that product or process and actually measuring it. Here, what we've depicted or what you're seeing is the X-R chart. The X stands for mean and the R stands for range. The X-R chart, or the X-bar R-chart, is how it is known, is one that's looking at the mean and the range and using those to come up with inherent capability of the process and then to use it further for looking at whether the process is in statistical control. In this lesson, what we'll do is we'll look at these three different types of charts, the p-chart, and the c-chart, and the X-R chart and we'll go through the mechanics of each one of these in terms of how these are constructed and used knowing that there are many other types of charts out there that you can go and select from.

Lesson 3-4: Attribute Data Control Charts - Proportion Data

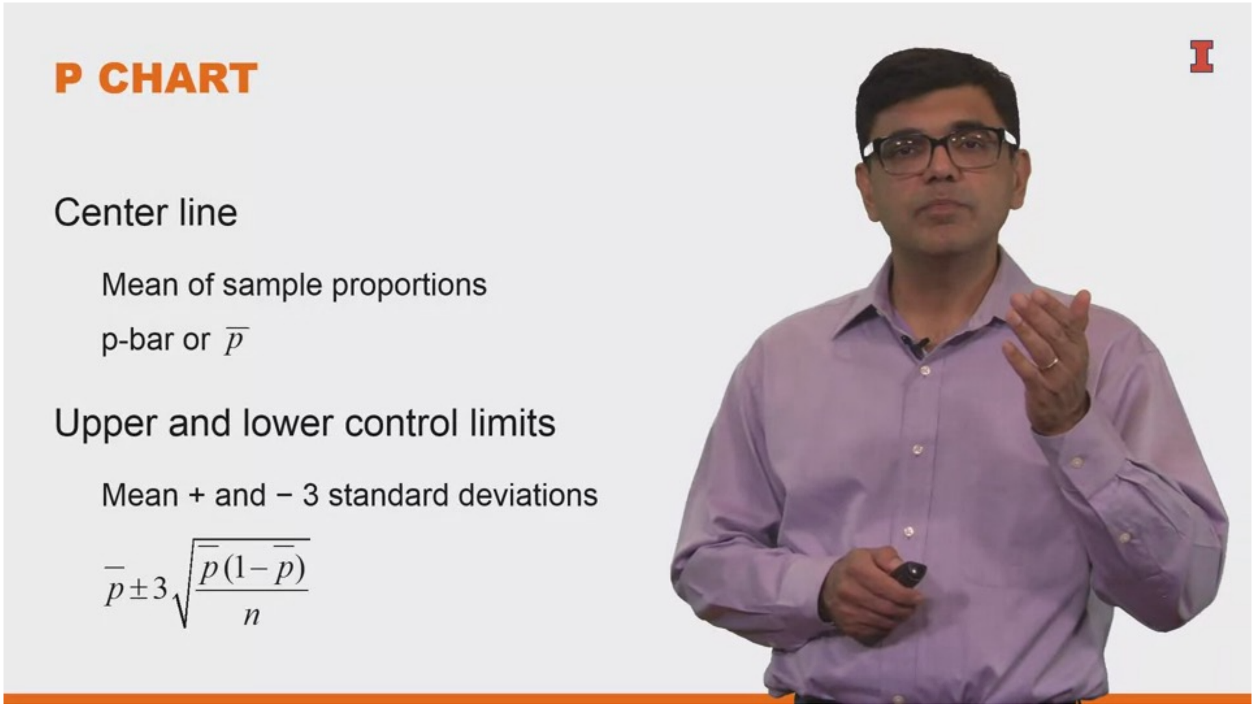
[Module 3.4.1 Attribute Data - Proportion - Control Chart]



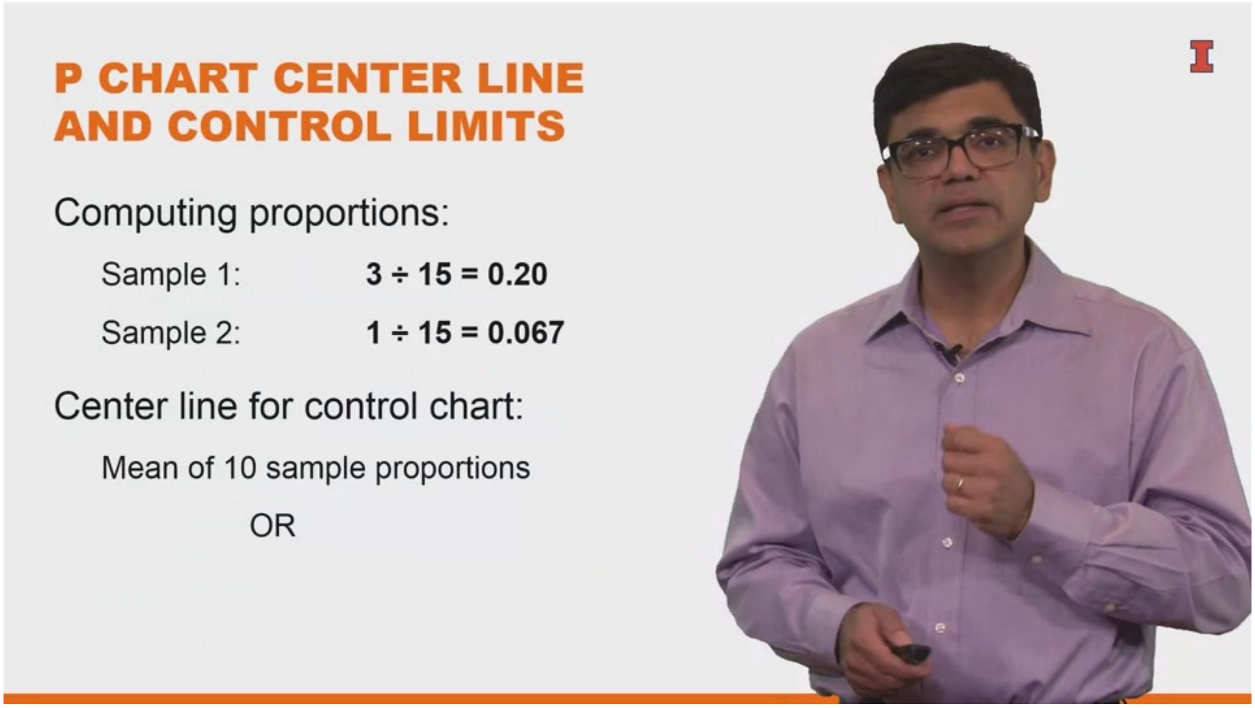
We're going to look at a particular type of control chart here and this is based on attribute data, more specifically proportion data, proportion defective. Let's take a look at it from the point of view of an example and see what we can do with it. We have a car parts supplier who is testing weekly samples of 15 subassemblies, so the sample size is 15. These subassemblies are taken from the assembly line and these are taken over ten weeks. The inspector records a number of defective subassemblies. What is the inspector doing? Looks at these 15 subassemblies every week and puts them in two different categories. Something that is defective and something that is not defective, you have a truck door that's defective, a truck door that's not defective. It can be one or the other. The inspector does not care about the extent of defects. A little scratch on a door versus a door that has a much higher degree of defect is treated the same, they're both called defective regardless of the extent of defects. If all that you care about is looking at defective versus non-defective this is the chart that would be appropriate. Coming back to the data. Over ten weeks getting samples of 15 each.



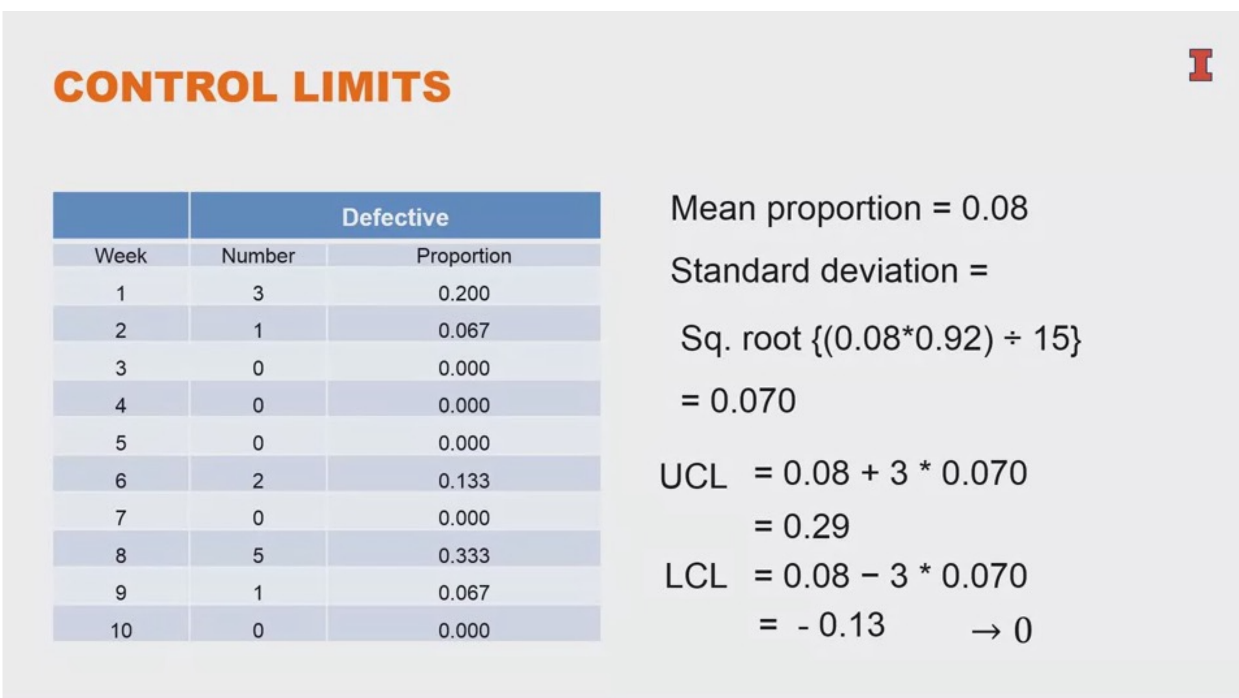
The data that we have is described over here. Week 1 through week 10, each week 15 subassemblies of doors are taken, and the number of defective ones are being recorded. You can total these up and you'll see that there are a total of 12 defective subassemblies and these are out of a total of 10 times 15, 150. That's the data that we have to start off with. We're moving towards calibrating a control chart so let's do the numbers here and see what we can find.



First thing, we want to get a average proportion of all the proportions that we saw over here. We had 10 samples each of size 15, each of the number of defects in those samples can be converted into a proportion. Each one divide by 15 is going to give us a proportion. Then we're also going to get, for purposes of constructing the control chart, the standard deviation. The reason we need to get that is because the upper and lower control limits are based on plus or minus three standard deviations. The formula that you see over here is basically telling us how do you get the upper and lower control limits. It's the mean plus or minus 3 times the standard deviation. Standard deviation is computed as whatever proportion you got as the average proportion, multiply that by 1 minus the average proportion, and divide that by the sample size, all under square root. The sample size here, this is something that you need to pay close attention to. The sample size is 15, it's 10 samples of size 15. The sample size here is a constant 15, that's what you'll be using to compute the standard deviation here.

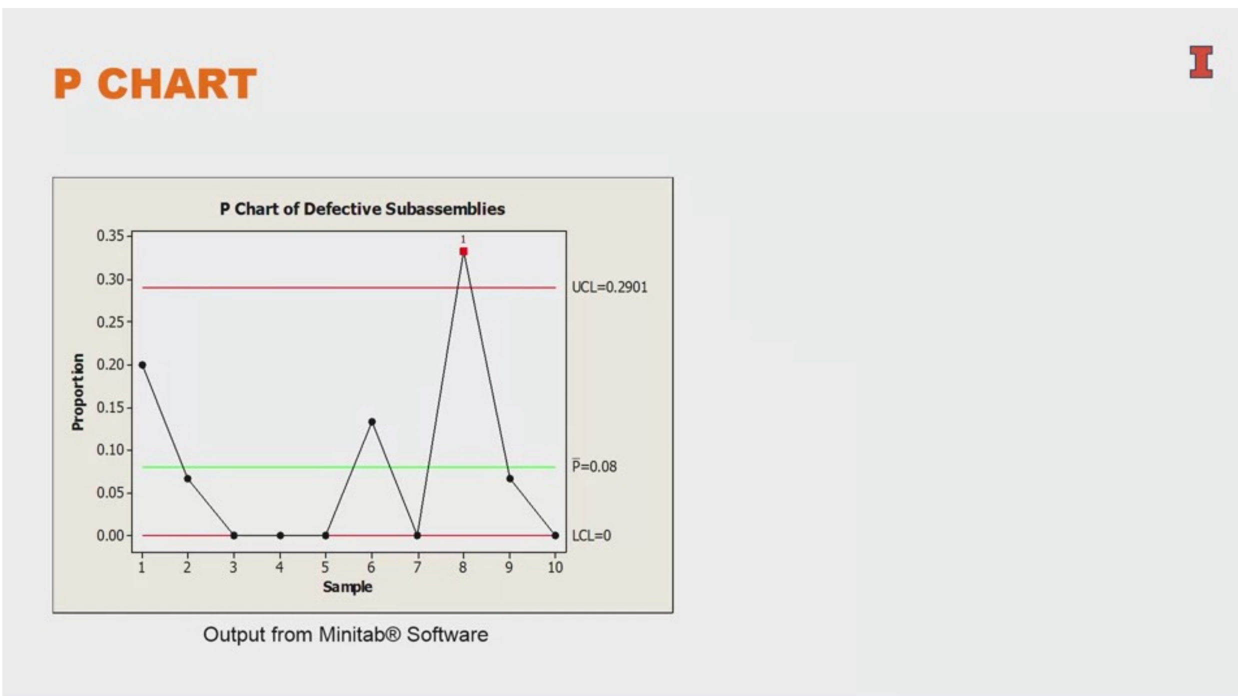


Let's go through some of these computations here. In order to get the average proportion over those ten samples, you can do it two ways. You can either take each of the proportions, so the first sample had three defective subassemblies out of 15, giving us 0.2, the second one had 1 out of 15 giving us 0.067. Or you can simply take the total 12 defective subassemblies over the 10 samples of size 15. You're going to get 12 divided by 150, and that will give you the average.

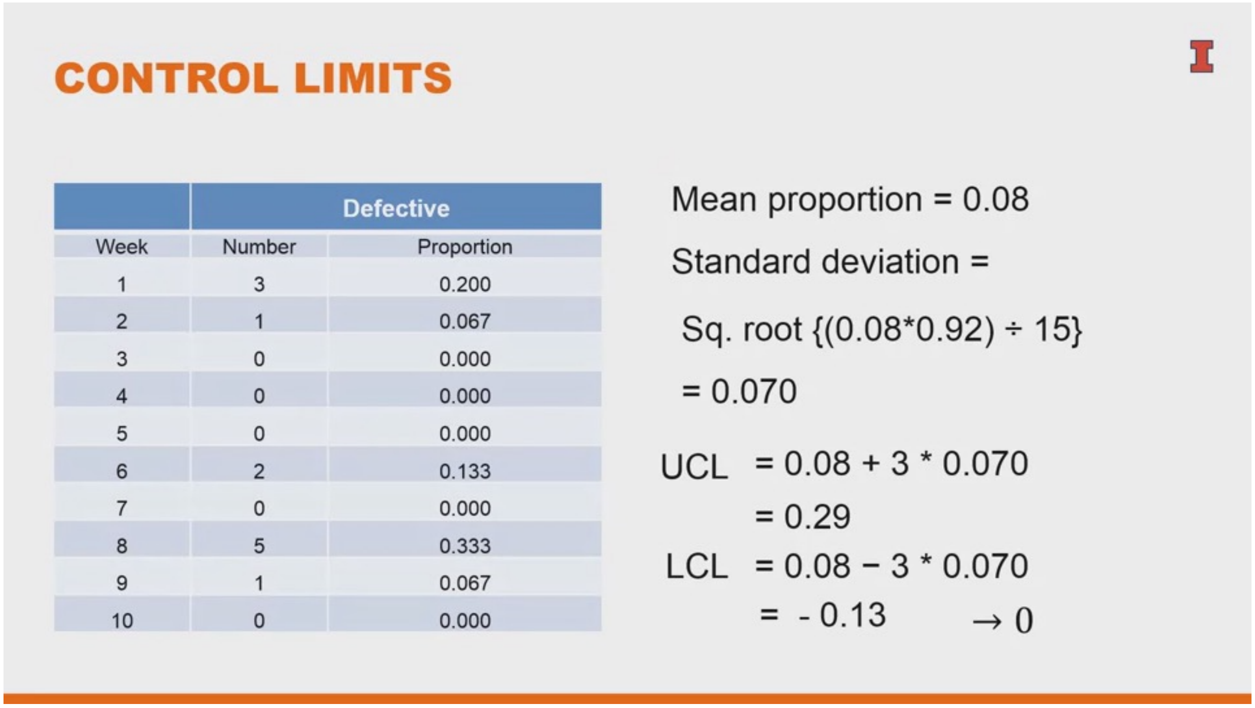


	Defective	
Week	Number	Proportion
1	3	0.200
2	1	0.067
3	0	0.000
4	0	0.000
5	0	0.000
6	2	0.133
7	0	0.000
8	5	0.333
9	1	0.067
10	0	0.000

Either way, you're going to get an average that you'll use for the centerline. If you were to take the other method, which is taking each of the proportions and averaging them out, you would get the same thing. Here you have each of the proportions shown to you for each of the samples. If you calculate the center line for this, it's based on 12 divided by 150, which is 0.08. The standard deviation is based on 0.08 times one minus 0.08 divided by 15, which is the sample size, all taken under square root, so the standard deviation works out to 0.07. The upper and lower control limits are simply computed based on plus or minus three standard deviations. Now, the point that you might want to note here is that the lower control limit actually turned out strictly based on the computation. It turned out to be negative 0.13. Now as you know, negative proportions are not going to make sense. There are no negative proportions. We're going to bump that up to a zero. The lower control limit is going to get bumped up to a zero. What this should also tell you, something that you might want to note is that this chart is not going to be symmetrical. You're keeping the mean at 0.08. The upper control limit is at 0.29 based on these calculations, and the lower control limit is now going to be zero. It's going to be an asymmetrical control chart.

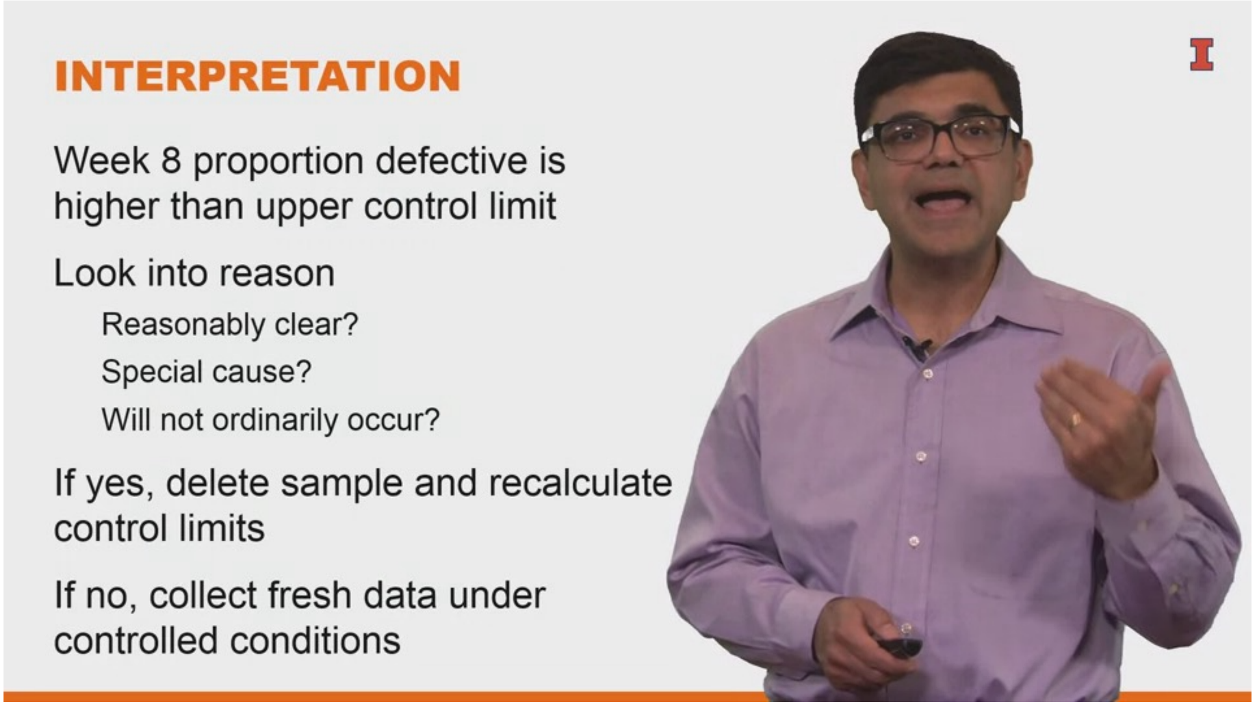


That's what we can see in terms of the chart. Here, I have the chart generated based from MiniTab software shown to you here. Now it's time to interpret this control chart. What do we see here? We see that there is a point that's marked in red that's outside of the control limit. This is the eight defective sub-assemblies out of 15 that was found in that one particular sample.



	Defective	
Week	Number	Proportion
1	3	0.200
2	1	0.067
3	0	0.000
4	0	0.000
5	0	0.000
6	2	0.133
7	0	0.000
8	5	0.333
9	1	0.067
10	0	0.000

If you go back to the data over here, you can see that sample number 8 had five defective sub-assemblies, which gave us 0.333. Staying on this slide, you can see that there's going to be a problem because 0.333 is above the upper control limit, which is also what is shown to us in this picture, that there's a point outside of the upper control limit. The question that you should be asking is, so what, what do we do next if we've found a point that's outside the control limit? Well, it's going to depend on whether you're trying to calibrate the chart at this stage or not. Here it's clear that we're trying to calibrate the control chart. We're using data from the process to come up with the upper and lower control limits. So what do you need to do?



You need to figure out what happened at that week 8. There was a proportion defective that was higher than the upper control limit. Can we figure out what the reason was for that? If it is reasonably clear, if it's clearly a special cause variation, something that should not be impacting the process on a day-to-day basis, then we can simply delete that sample and we can re-compute the control limits. We throw out that sample and we re-compute the control limits based on not having that sample in our calculations. If that's not the case, if you cannot really eliminate that particular observation, that particular sample based on a cause that's clear, then you have to go back to the drawing board and re-compute the control limits. Let's take the easy route here.

MODIFIED CONTROL LIMITS

	Defective	
Week	Number	Proportion
1	3	0.200
2	1	0.067
3	0	0.000
4	0	0.000
5	0	0.000
6	2	0.133
7	0	0.000
9	1	0.067
10	0	0.000

Mean proportion = 0.052

Standard deviation =

Sq. root {(0.052*0.948) ÷ 15}

= 0.057

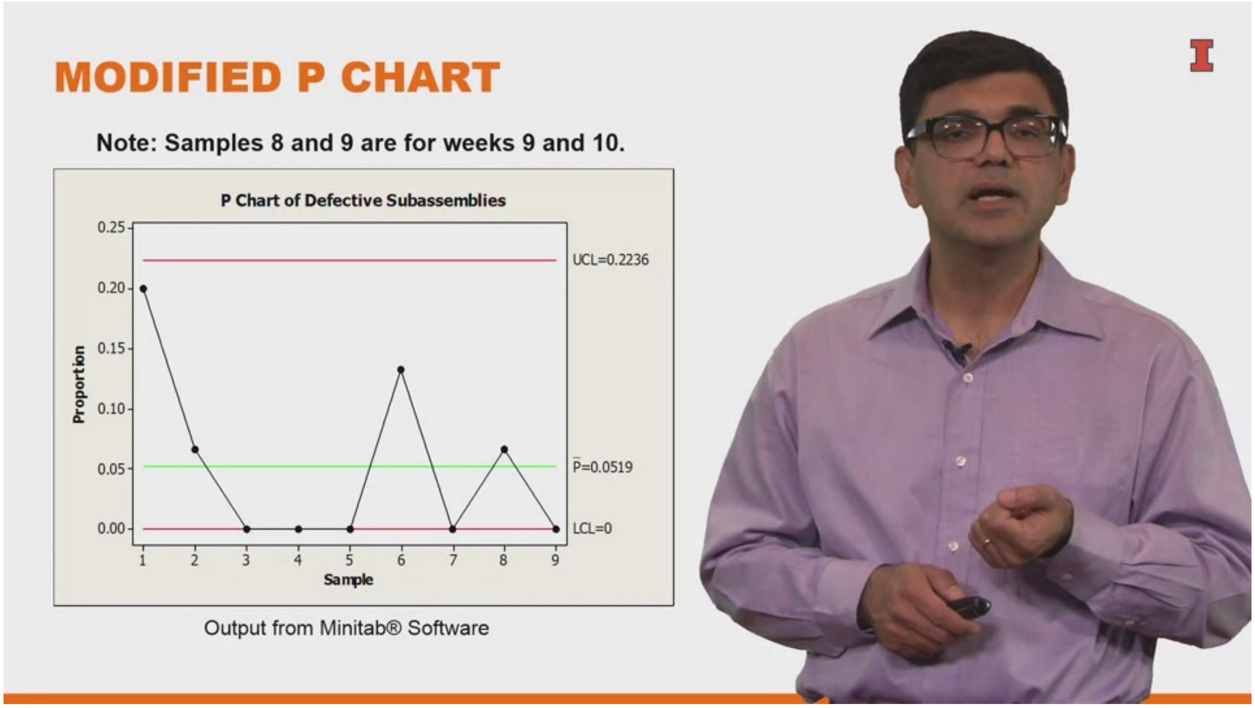
UCL = 0.052 + 3 * 0.057

= 0.224

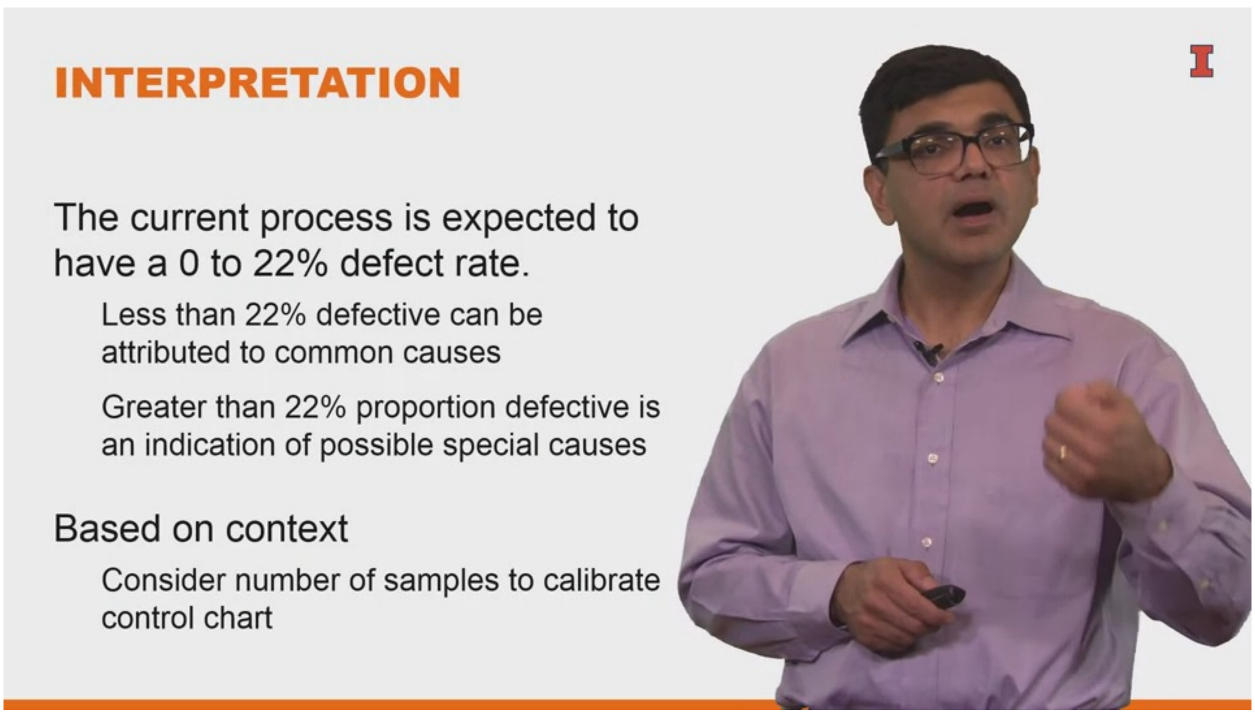
LCL = 0.052 - 3 * 0.057

= - 0.120 → 0

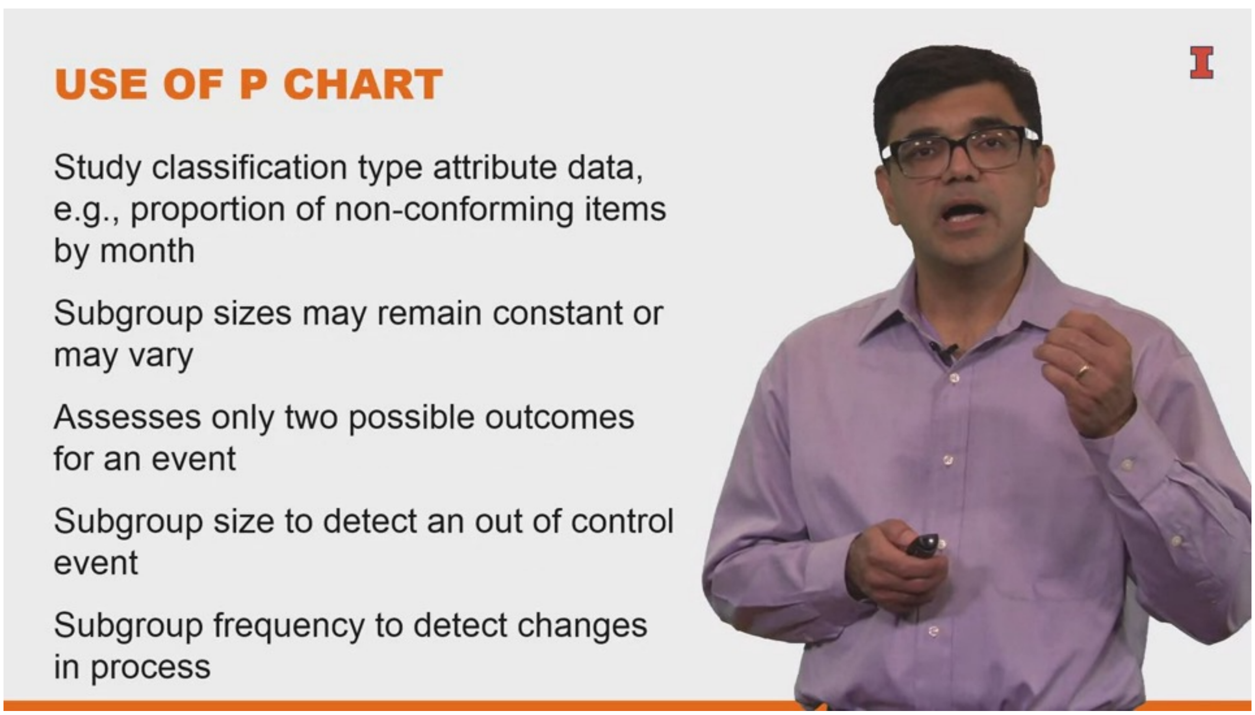
Let's say that we could figure out the reason for a weaker proportion being outside of the control limits, so eliminate that point and then you go in and you figure out the new control limits. All right. Here you see that there's no week eight being represented here. You're going from seven to nine and ten and because you've thrown out week eight, you've got the same data that you had earlier. You come up with a new mean proportion which is going to be based on now, what was it? We had 12 defects earlier. We took out the one that had five, so we have seven defects out of a total of now 135. Seven out of 135 gives us a mean proportion of 0.05. Then you get the standard deviation based on that, and then you get the upper and the lower control limits based on that. Now, what you can see from here based on the proportions that you have for each of the samples as well as the upper and lower control limits that we've already computed, you can see that there's going to be no problem in terms of points outside the control limit. All the points are going to be within the control limits based on the fact that we can see from based on this data.



Plotting it in terms of a chart, you can see the same result. You can see that all the points are within the control limits.



What you can infer from this is that the current process is expected to have between a 0-22 percent defect rate. We got the 22 percent defect rate based on the upper control limit. Given the current technology, given the way the process is designed, given the kinds of training that you have for your people, you are expecting a 0-22 percent defect rate from this particular process. Based on what your context is, it may not be appropriate for you to use just 10 samples that we used over here in order to compute the upper and lower control limits. Even moving beyond this particular problem, you might want to reflect on the fact that was 10 samples enough for you to come up with the upper and lower control limit. That's going to be context dependent in the sense that what are the different types of things you want to cover in the number of samples. If it's many shifts in the day, many samples during many shifts in the day, many days of the week, then obviously you have to have coverage for those sorts of things in your data collection, so then I would have samples that are collected over a couple of weeks to make sure that every day of the week is represented at least twice, and then if there are multiple shifts, they are being represented in the sampling that is being used to come up with the inherent capability of the process. You also want to think about whether you want to separate different days, separate different shifts, and those are the managerial decisions that you will need to make in addition to the mechanics of computing these control charts.

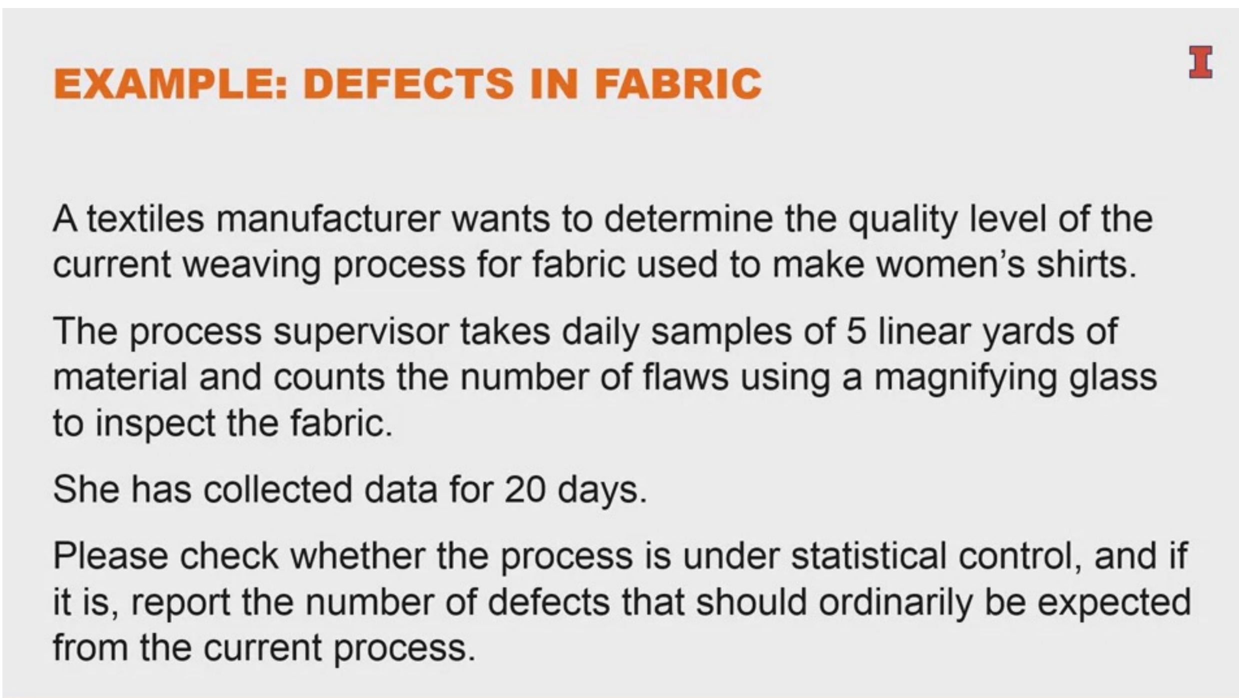


Finally, when and how do you use the control chart, the p-chart, the proportion control chart. You use it to compute control limits for attribute data. It's a discrete distribution. It's data that's dealing with conforming and nonconforming items. All it's telling you is whether there was a product that was defective or non-defective, or it was defective or as expected. You may use different subgroup sizes in order to come up with the process, with an attribute control chart, with a p-chart. What do I mean by that? Well, we used sample sizes of 15. It was a constant sample size across. It's possible for you to construct a p-chart based on having different sample sizes for each of those samples.

We simply haven't gone through those calculations. But you can find those in software. You can find those in different sources to be able to compute control charts for different sizes of samples. Recall that you're only dealing with two possible outcomes. This is based on, if you're familiar with the binomial distribution, rather, you're talking about a binary decision, a binomial distribution saying something is either good or bad, it's a zero-one decision. You want the subgroup size to be large enough to be able to capture defects. If you're finding a lot of zeros, then your subgroup size is not large enough, so you want to think about that. Then in terms of the frequency of how you collect data, whether it should be every hour or once every day, that's something that you also have to think about in terms of designing this system of assessing your process over a longer period of time.

Lesson 3-5: Attribute Data Control Charts - Count Data

[Module 3.5.1 Attribute Data - Count - Control Chart]

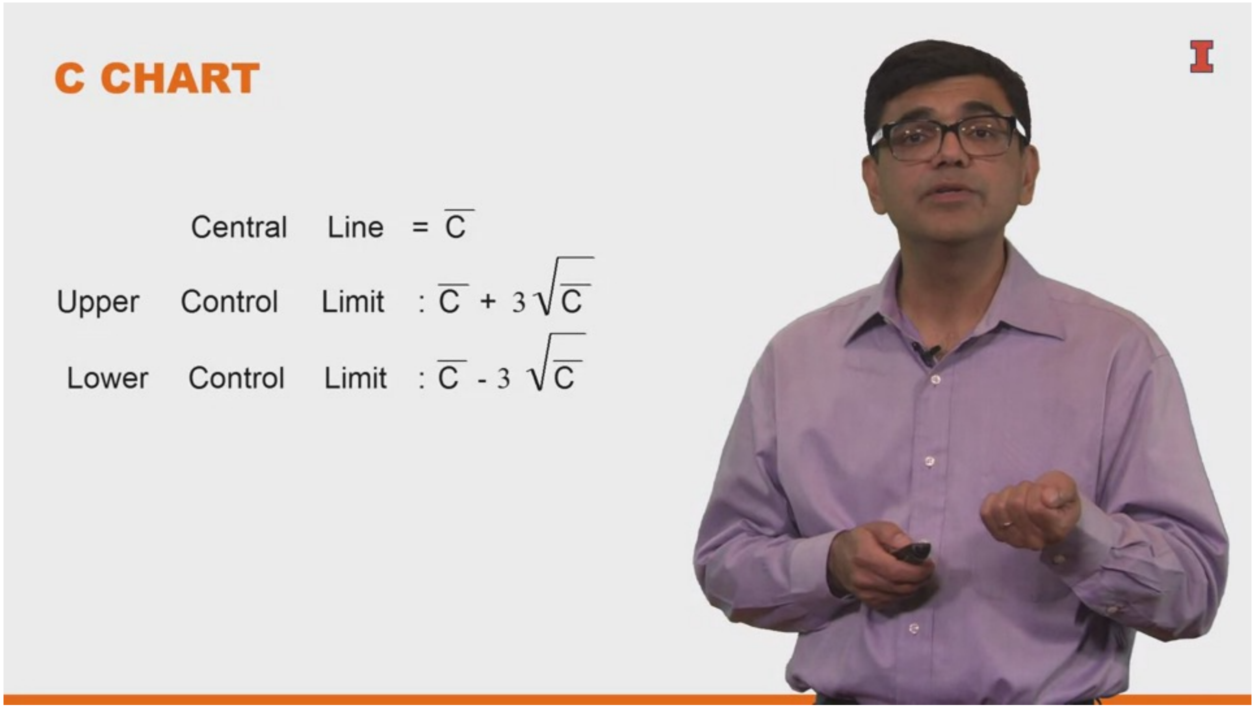


This lesson is about control charts for count kind of data. So count kind of data is different from proportion kind of data in the sense that when you're looking at proportion defective, you're only looking at whether a product is defective or non-defective, you're getting a yes/ no answer. You're getting a a binary answer and it's based on a binomial distribution. Whereas what we're doing here is we're looking at count data. So we're looking at the count of defects. We're looking at a sample and seeing how many defects did we find in that data. So, a single product or single unit of a product can have multiple defects. And that's going to have meaning in count kind of data while it did not have any meaning in proportion kind of data. So, some kind of data is still dealing with attribute kind of measurement with discrete distribution. So we're getting account, you cannot have 2.5 defects, for example. So it can be either to defects or three defects. So it's still a discrete distribution that we're dealing with. So, let's take a look at an example here to get a sense of getting the upper and lower control limits. And then using a control chart based on common data. So, we have a textile manufacturer who wants to determine the quality level of their weaving process. They take daily samples of five linear yards of material and count the number of flaws, right? So each of the samples is a sample of five linear yards. They've decided to take one sample per day and they're going to count the number of flaws. So, if you think about this for a minute, in a daily sample of five linear yards, what is the upper limit of the defects that you can find? The number of defects that you can find? And we treat we treat that as infinity. We say that the upper limit for the number of defects that you can find is going to be infinity, because we're simply not defining what a defect is. It could be many different things. And we're going to say that you can find many, many different defects in every sample of five linear yards. Why is this important? It's because we are going to use what is known as the poisson distribution as the underlying distribution for this kind of data. So, the count data is coming from a Poisson distribution and that has meaning in terms of computing the upper and lower control limits for this type of control chart. So, moving on with the problem, five linear yards of data every day, collected data for 20 days. So, what we'll have is the number of defects that you can see over a 20 day period, right?

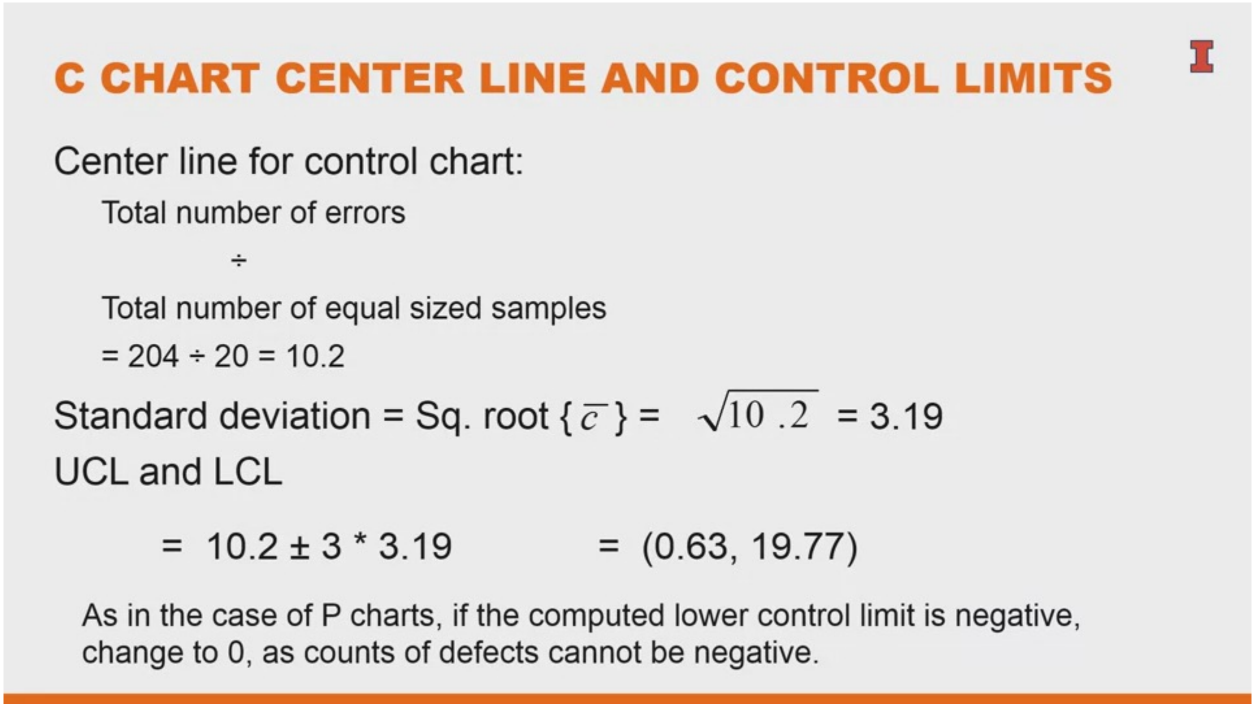
SAMPLES OF 5 LINEAR YARDS OVER 20 DAYS

Day Number	Number of Flaws	Day Number	Number of Flaws
1	9	11	13
2	6	12	8
3	18	13	11
4	11	14	4
5	10	15	7
6	8	16	9
7	12	17	5
8	11	18	12
9	17	19	9
10	14	20	10

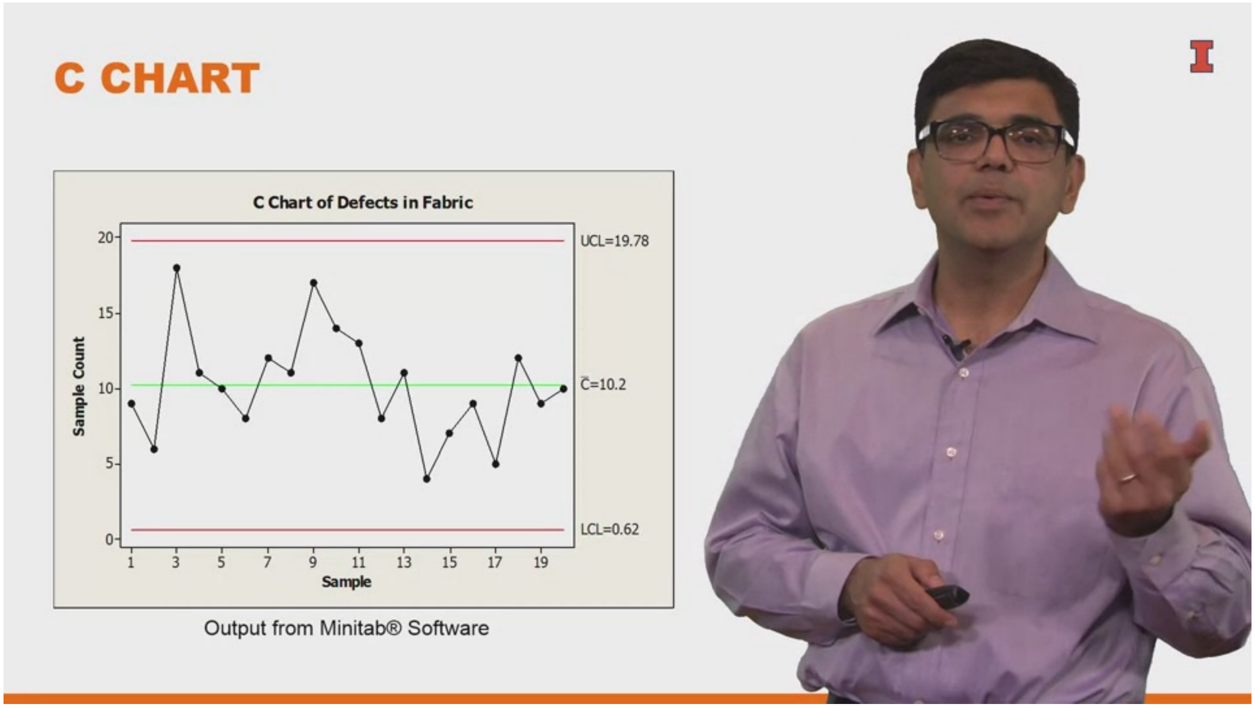
So here's the data that we have, we can see that we have 20 days worth. And how do we use this to compute control limits for a control chart? So let's take a look at the numbers and the calculations for that, right?



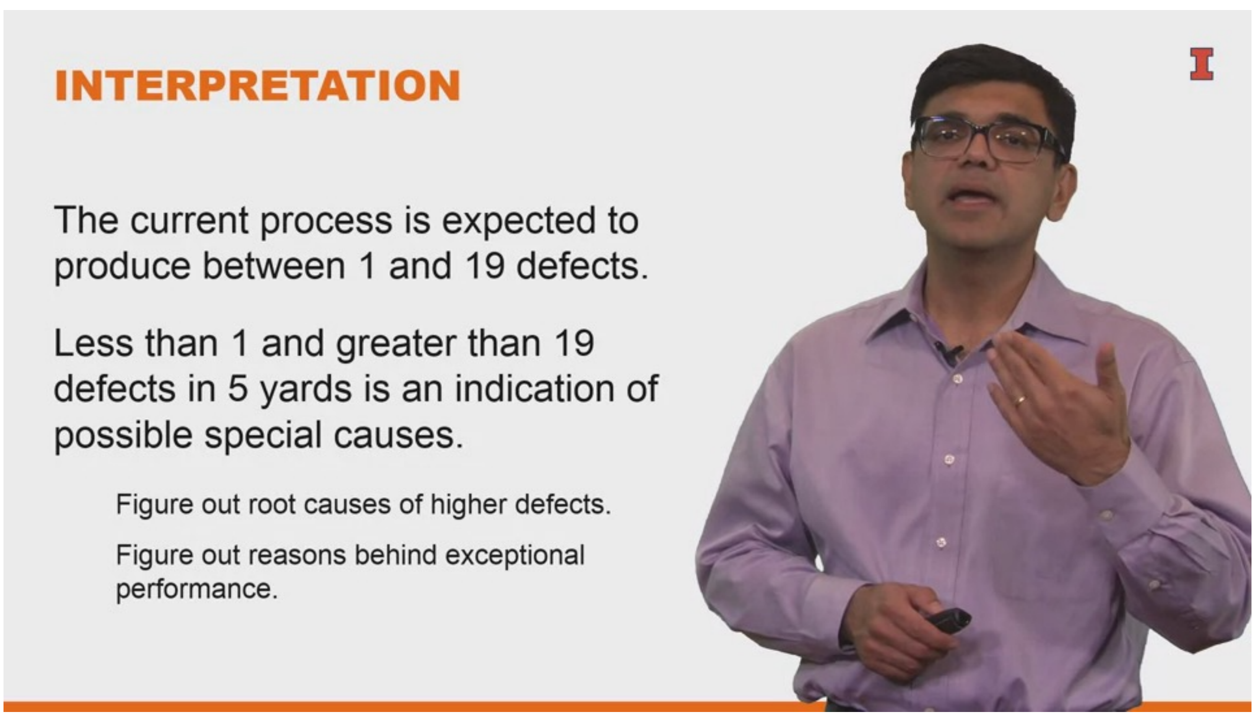
So what you have here is for the C chart, the center line is simply going to be the mean of all the defects that you found in all of the samples. So you're going to take an average and if you remember how many samples, we had we had 20 samples, so it's going to be total number of defects, divide by 20 is going to give us our center line. And the nice part about this kind of distribution is that the standard deviation is simply the square root of the mean. So you have the center line as being a C bar, that's the mean of the count of defects that you got. And the standard deviation is simply the square root of that. So the upper and lower control limits are going to be based on the mean plus or minus three times the standard deviation, which is the square root of the mean. So, so in that sense, the calculations are going to be much more easier here when we're looking at the standard deviation.



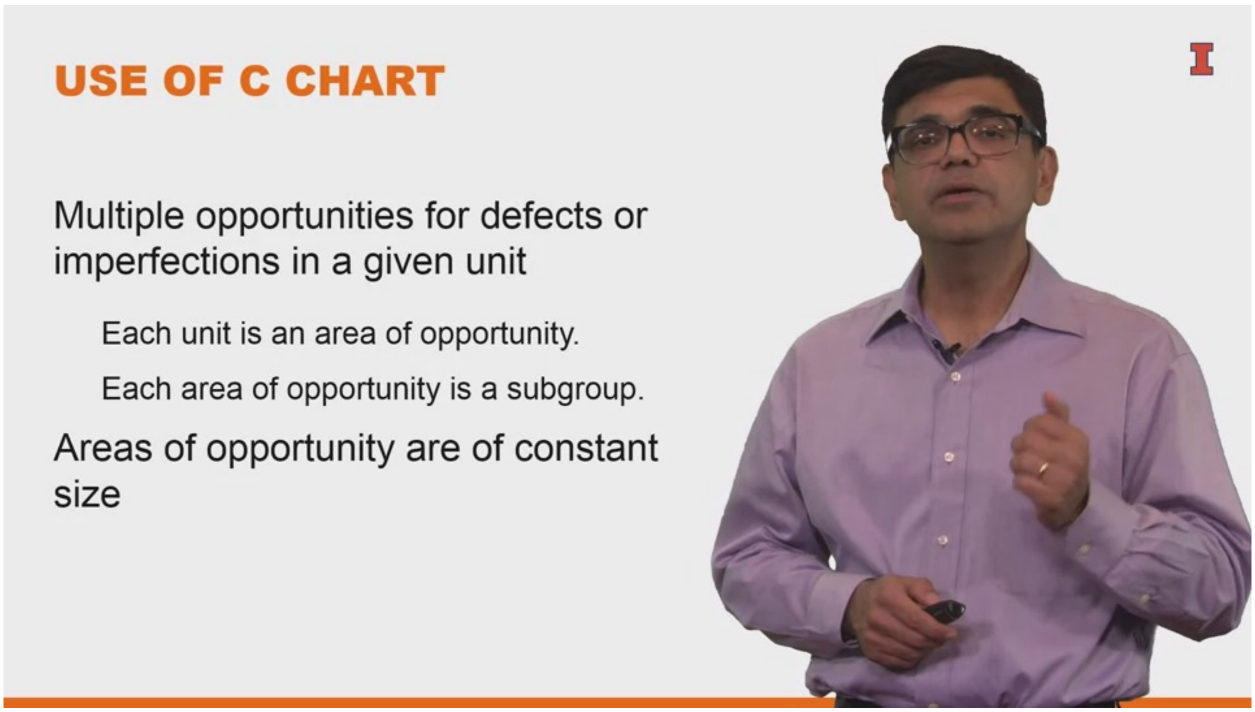
The center line for the control chart works out to be 10.2 based on 204 defects in 20 samples. And the upper control limit is going to be based on the square root off 10.2 and you take plus or minus three times the standard deviation and that gives us our upper and lower control limits. So we take this and we can compare it with the number of defects that we saw in each of the samples and if it is below one or above 20, in fact, if it's going to be above 20, we're going to call it out of control. So we can see that right from here without even plotting on the control chart. And that it needs to be between two numbers right now. One point of caution before we move on to look at the chart is that although we did not get a negative value for the lower control limit here, based on the calculations, you might get a negative value for a different problem. As we cannot have a negative count of defects, it's not going to make any sense. We'll do the same thing that we did in the case of the P chart, in the case of the proportions, will will bump it up to a 0. So we change it to 0. If we do find the lower control limit to be a negative number based on the calculations. Here that's not the case so we don't need to make any change.



We have a nice symmetrical control chart here. The upper and lower control limit are equal distance from the center line and then when we look at the plot, everything seems to be doing fine. So what can we say from this control chart based on the idea that we were calibrating the upper and lower control limits based on data that we got from the process, based on these 20 samples, we can say that the current process will produce between one and 19 defects, right?



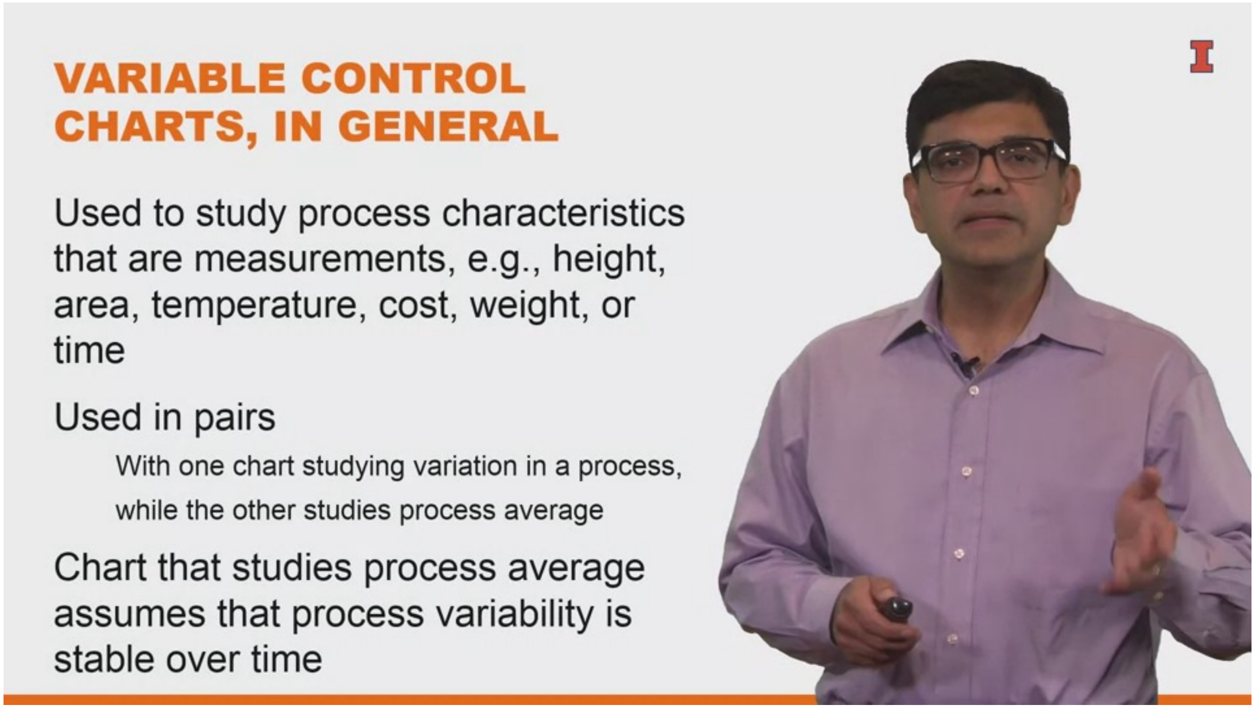
So our inherent capability of the process is to produce as many as 19 defects. The way it's running right now, right. Less than one would be something that's extraordinary and greater than 19 would be something that's extraordinary. That's what we said earlier. That's exactly what we're saying here. If we do get numbers that are above or below, we need to figure out what happened. Could be root causes of something that has gone wrong, or if it's on the lower side, it's how did we manage to get points that were lower than the lower control limit? Because we're talking about count of defects. Lower numbers are going to be better, right.



So, when do you use a C chart? To contrast this with a P chart, a P chart is used when you're talking about the number of defectives here, we're talking about the number of defects. So, this is multiple opportunities for defects. We're using a C chart when we're counting the number of defects in a sample, the condition here is that each sample has to be often equal size. So if we're talking in this particular example, we talked about five yards of cloth, five linear yards of cloth. If you're talking about a sample that you take off any kind of a product, let's say you're looking at cellphones. If you're taking a sample of 10 cell phones and you're you're counting the number of defects in the 10 cell phones, the sample size has to be constant when you're counting the number of defects. Just simply to give them the same opportunity for having defects, to be fair, in that sense, to the sample.

Lesson 3-6: Variable Data Control Charts

[Module 3.6.1 Variable Data - Mean and Range - Control Chart]



This lesson is about variable data control charts, specifically about one type of variable data control chart. Before we get to that particular kind of chart, generally speaking when we think about variable control charts, we're talking about measurement data, something that can be measured. So we're talking about characteristics of a product or a process, such as the weight of a product, the height, the length of the viscosity of of a particular liquid, the density, those kinds of things. So it's something that can be measured to put it in simpler terms, it's where decimal points have a meaning. So if we talk about 22.8° or we talk about 34.88 inches, it has meaning rather than when you're talking about discrete distributions where there are no decimal point. So we're talking about continuous distributions here, right? We're talking about measurement data. The difference, between attribute control charts and variable control charts is that variable control charts, is they are used in pairs. So you're always looking at the variability in some kind of a measurement of range or measurement of standard deviation in addition to looking at the variation in the mean. So they're always going to be in pairs. So that's why we call this the X-bar, R chart that we're going to look at next. We don't use the X-bar chart without the R chart of the R chart without the X-bar chart, they always go in pairs. They study process averages and they study the process variability and that variability can be measured, in our case will be looking at range. It can be measured as standard deviation. So there may be different types of control charge, using different aspects of variability that they're measuring.

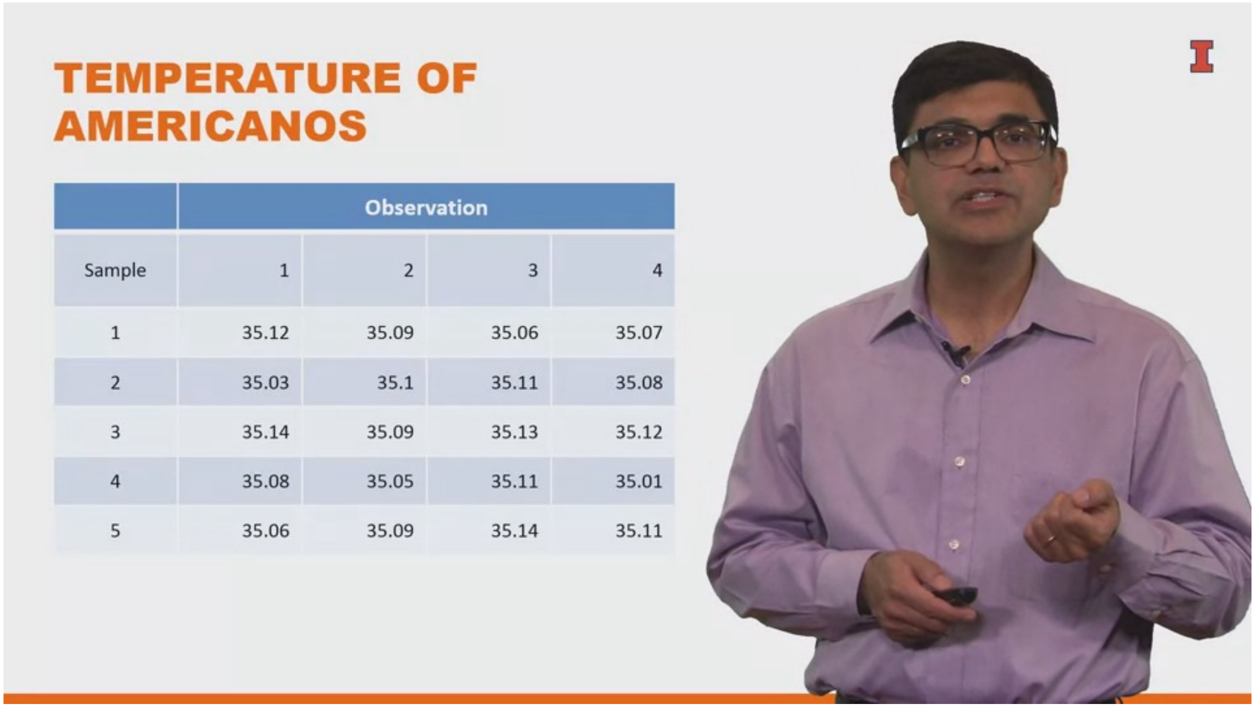
EXAMPLE: TEMPERATURE OF AMERICANOS

Holly, a barista at Mercury Coffee House, prides herself on the precision of her process for making cold milky Americanos that retains all the flavor of the coffee while cooling it down in controlled stages.

She builds each drink using an elaborate process that involves brewing espresso in cold stainless steel cups, transferring two shots into a glass cup, and adding cold milk that is maintained in a refrigerator set to 34 degrees Fahrenheit.

Holly wants to assess the consistency of the temperature of the Americanos that she serves and has collected data over the last 5 days, using samples of the first four Americanos from the 12 noon to 1 pm hour each day.

Now, let's take an example here and work through it to get a sense of the X-bar R chart. So we have Holly, who's a barista at the coffee house. And she is known for the cold Americanos that she sells. White Americanos, these are with cream and milk in them. And she prides herself on making these, right,? She builds each drink with a very elaborate process that involves making the espresso in stainless steel cups that have been pretty cold transferring them into a glass cup, adding the cold milk which is maintained in a refrigerator at a certain temperature set at 34 Fahrenhet, 0 degrees Celsius, right? Now, Holly wants to assess the consensus e of temperature that she gets from making these Americanos. So she wants to see whether this works out to be within a certain range. So she wants to see how good this is in terms of the variability that is in the process. So what she has done is she has collected data over the last five days using samples of the first four Americanos. So each of those five days, she's taken the first four Americanos that were made between the 12 noon to one PM hour each day.

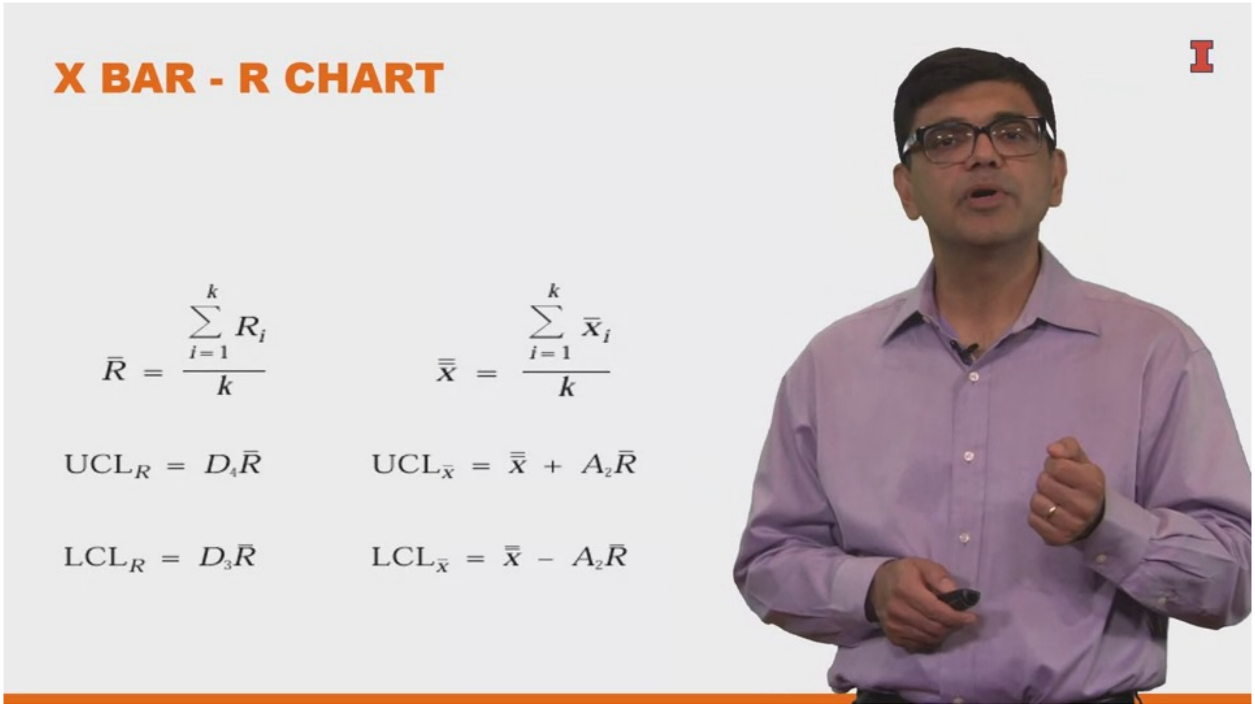


So what you have on this slide is the data that she has. So in the rows we have each of those samples. So that's day 1, day 2, day 3, day 4, day 5. And then what you have is in terms of the temperature for each Americano for Americanos that are taken on each of those five days. So what is the sample size here? The sample size is four. And the number of samples that she has taken this five, five samples of size four. This is going to have some meaning when we do some calculations. So it's worthwhile for you to make a note of that, that there are five samples of size four, right? So let's get into some basic calculations of this. So what can we see in terms of the basic averages and the range is that we can get from this.

AVERAGE OF SAMPLE AVERAGES AND RANGES

	Observation				Calculations	
Sample	1	2	3	4	Average	Range
1	35.12	35.09	35.06	35.07	35.085	0.06
2	35.08	35.05	35.11	35.01	35.063	0.1
3	35.03	35.1	35.11	35.08	35.08	0.08
4	35.06	35.09	35.14	35.11	35.1	0.08
5	35.14	35.09	35.13	35.12	35.12	0.05
				Average	35.0895	0.074

So we're moving towards a X bar R chart a mean and range chart. So the first thing that we need to do is take each sample, take each row and calculate its average. You add them up, you divide by 4, you get an average right? And then for the range for each of those rows you want to calculate take the maximum subtract from that, the minimum, and you get a range. So if you do that for all five samples, you can get the ranges and the averages for all samples. And what you have in the last row is the average of averages. So it's a mean of means. So the 35.08 is representing the mean of means for all of the samples. And then you have a range average of .074, right? So that's what we get from simply looking at the averages and the ranges. And what you're also seeing over here is these averages are going to be used as the center lines for both of those charts. So you've already got the center line for the range chart as well as the average chart.



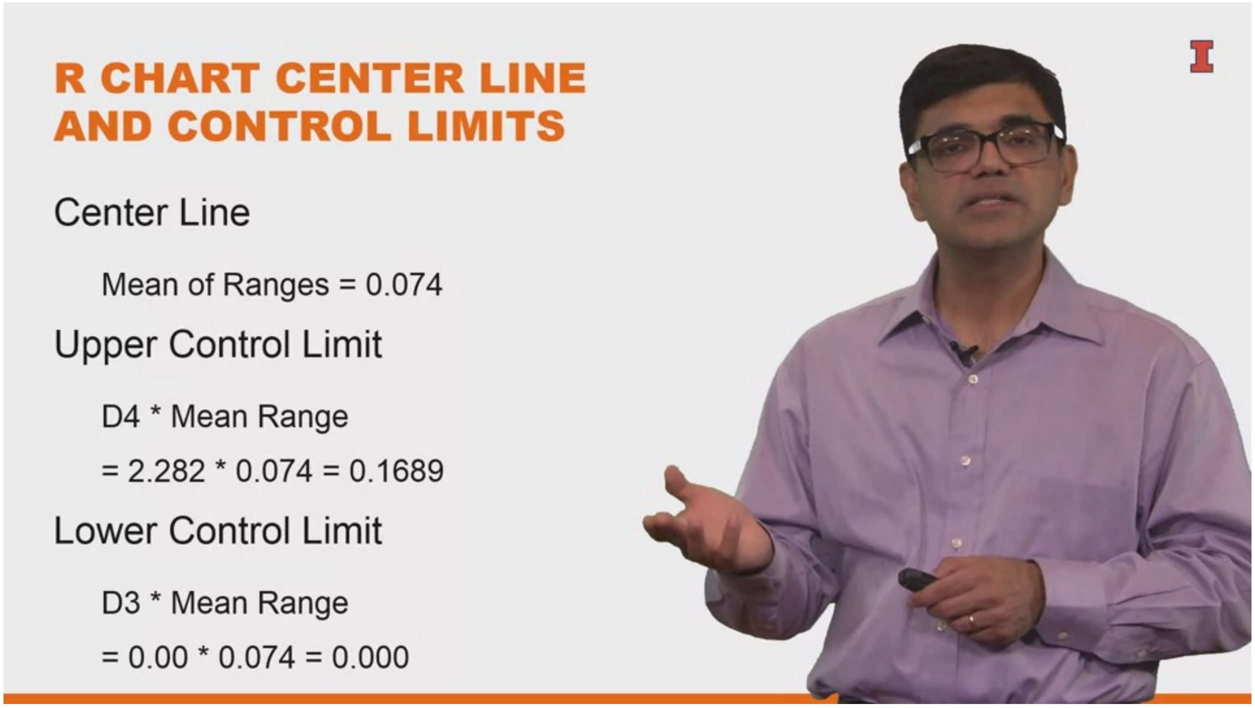
All right, now let's look at the computations for the upper and lower control limits. Now, if you're not comfortable with with symbols with Greek symbols, you might be intimidated by these. But what these are basically saying is that the upper control limit for the range control chart is going to be based on the average range that you've already got. So what you're looking at sigma R divided by k is simply the average of all the ranges. So you take the average range and you multiply with something called the D4. The lower control limit for the range chart is based on a D3 number multiply that by the average range. And then when you look at the upper and lower control limit formulas for the means chart, you're looking at the mean of means and that's why you have the double bar on top of the X. It's saying that it's the average of the five average, is that you have taken plus the A2 times R bar. Lower control limit is x double bar minus A2 times R bar. Now, the question that you should be asking, or what you should be wondering about at this point is what is this, D3, D4 and A2? What are these things and where did they come from?

CONTROL CHART CONSTANTS FOR 3 STANDARD DEVIATIONS

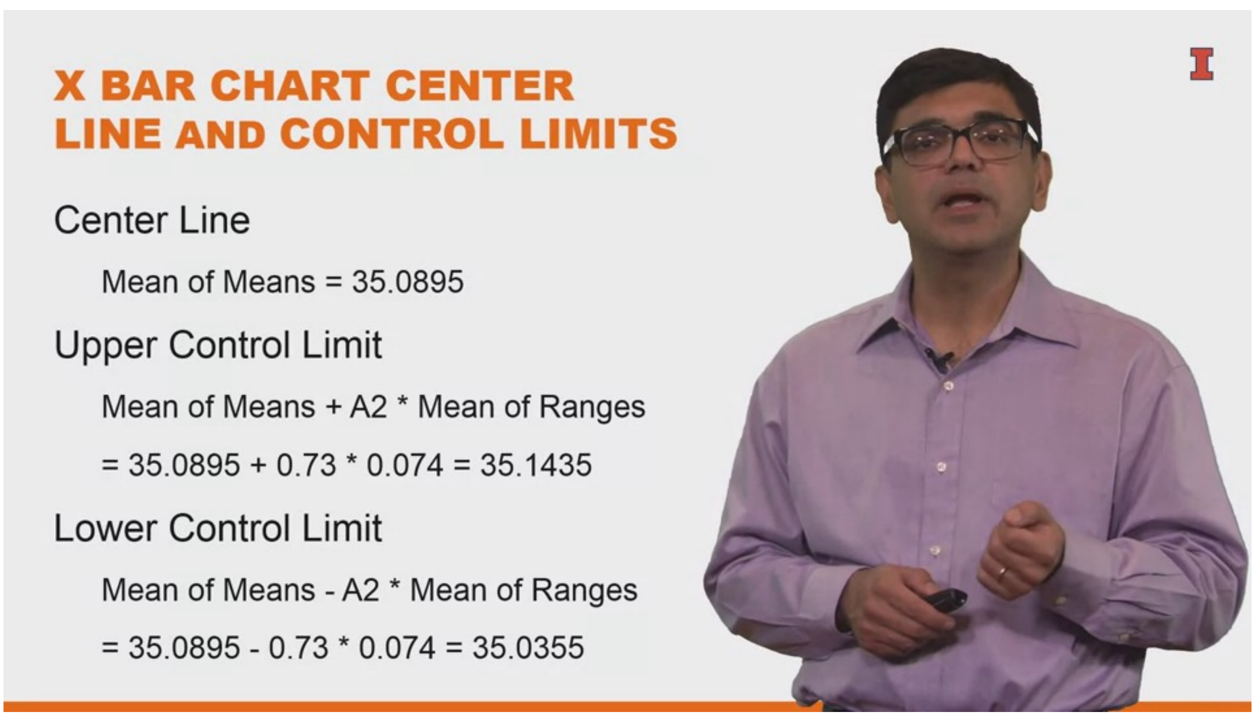
Sample Size (n)	Factor for X-bar (A_2)	Factor for LCL for R (D_3)	Factor for UCL for R (D_4)
2	1.880	0	3.267
3	1.023	0	2.574
4	0.729	0	2.282
5	0.577	0	2.114
6	0.483	0	2.004
7	0.419	0.076	1.924
8	0.373	0.136	1.864
9	0.337	0.184	1.816

Sample Size (n)	Factor for X-bar (A2)	Factor for LCL for R (D3)	Factor for UCL for R (D4)
10	0.308	0.223	1.777
12	0.266	0.284	1.716
14	0.235	0.329	1.671
16	0.212	0.364	1.636
18	0.194	0.392	1.608
20	0.180	0.414	1.586
22	0.167	0.434	1.566
24	0.157	0.452	1.548

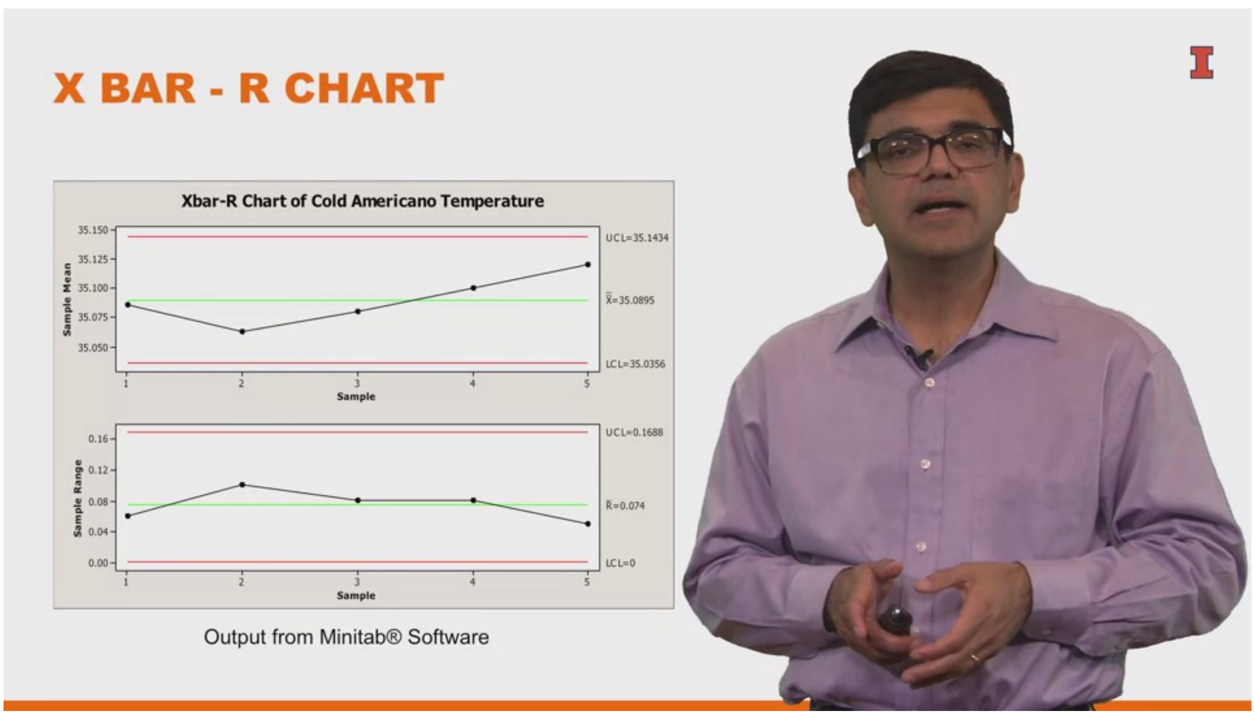
So where they come from is this chart that that we can use to to pick out these values. So what is this chart? This chart is taking the different sample sizes that you might use and giving you the different A2, D3 and D4 values that you would plug in into those formulas. Now, where are the numbers coming from? They're basically representing the idea of three standard deviations. So because we have a very small sample size, it's not appropriate for us to use standard deviations. We are using the idea of three standard deviations by substituting with these multipliers. So the A2, D3 and D4 are multipliers that help us replicate the idea of plus or minus 3 standard deviations. So the one that that is going to be the one that we are going to use here is based on our sample size off. Now, you may recall that, I said earlier, we have five samples of size four, so we go to the road that says the sample size of four and it tells us .7 minus 9 is the to value that we need to use and then zero and 2.282 are the D3 and D4 values.



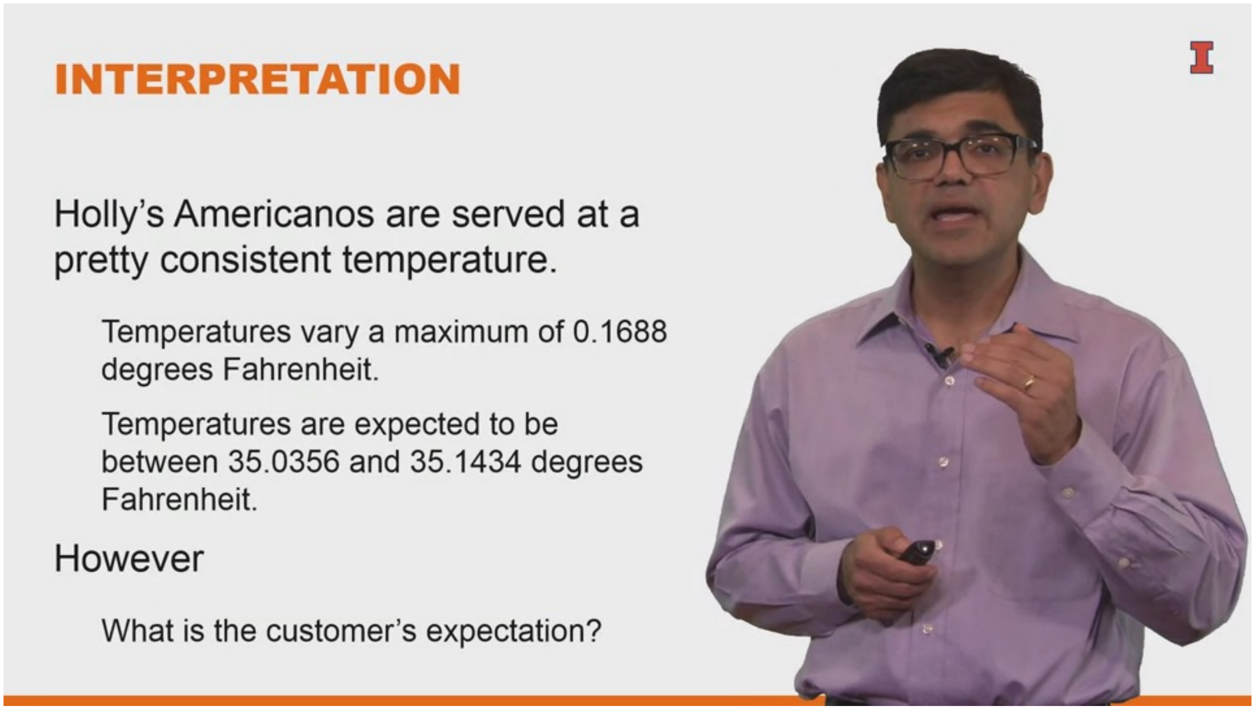
So we're simply going to take these and plug it into the formulas. The center line for the range chart is based on the mean of the ranges. We already got that earlier as 0.074 from that table that we had. The upper control limit Is going to take that 0.074, multiplied by the 2.282 multiplier that you saw on the chart on the previous slide. So upper control limit is 0.1689. Lower control limit based on a multiplier of 0 is going to be 0, right? So we get the upper and lower control limits for the R chart.



Similar calculations for the the X bar chart. Center line is based on mean of means. Upper control limit is mean of means plus the multiplier, 0.73 multiplier in this case is the A2 value. And for the lower control limit you're using the same multiplier, but you're subtracting in this case. So you have mean -0.73 times the range. Now, what you've noticed over here or what what you should have noticed over here is that between these two charts, between the R bar chart and the X bar chart, we are using the range to come up with the upper and lower control limits for the X bar chart, right? So this seems kind of strange that we're using something from a different chart to compute the upper and lower control limits. But the reason I bring this up is because it's important for the range to be in statistical control if you are going to use that range to compute the X chart. In other words, you need both of them to be in statistical control to call a process as being in statistical control or to come up with the inherent capability of the process. You need both of them to be within the statistical control limits, right? All right, so let's take a look at the interpretations of the chart by plotting the points on each of these charts.



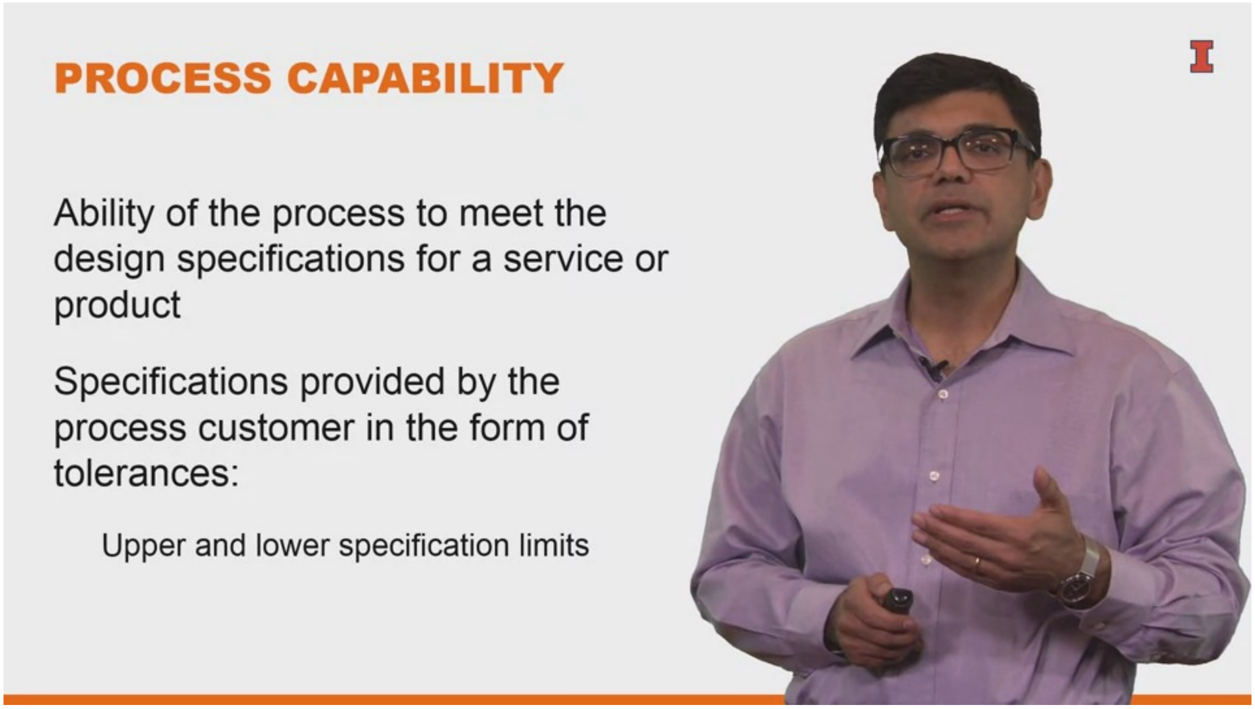
So, once again, like you had earlier for the other kinds of charts here for the export our chart, you have the points plotted on the chart of upper and lower control limits. What do you see here? You see a nice level of consistency, right? Now, once again, we've used, as we talked about in the case of the proportion chart and the count chart that we looked at earlier, we've used a very small number of samples to come up with these values. So if you were to do this problem in reality, you would want to get a larger sample and use that. What I'm talking about is the number of samples. Your sample size may remain small, but you definitely want a larger number of samples to come up with the upper and lower control limit. Five samples is not going to be enough. All right, taking these results for what they are. Let's take a look at what this implies, what this is showing us that that Holly's process is pretty consistent, right?



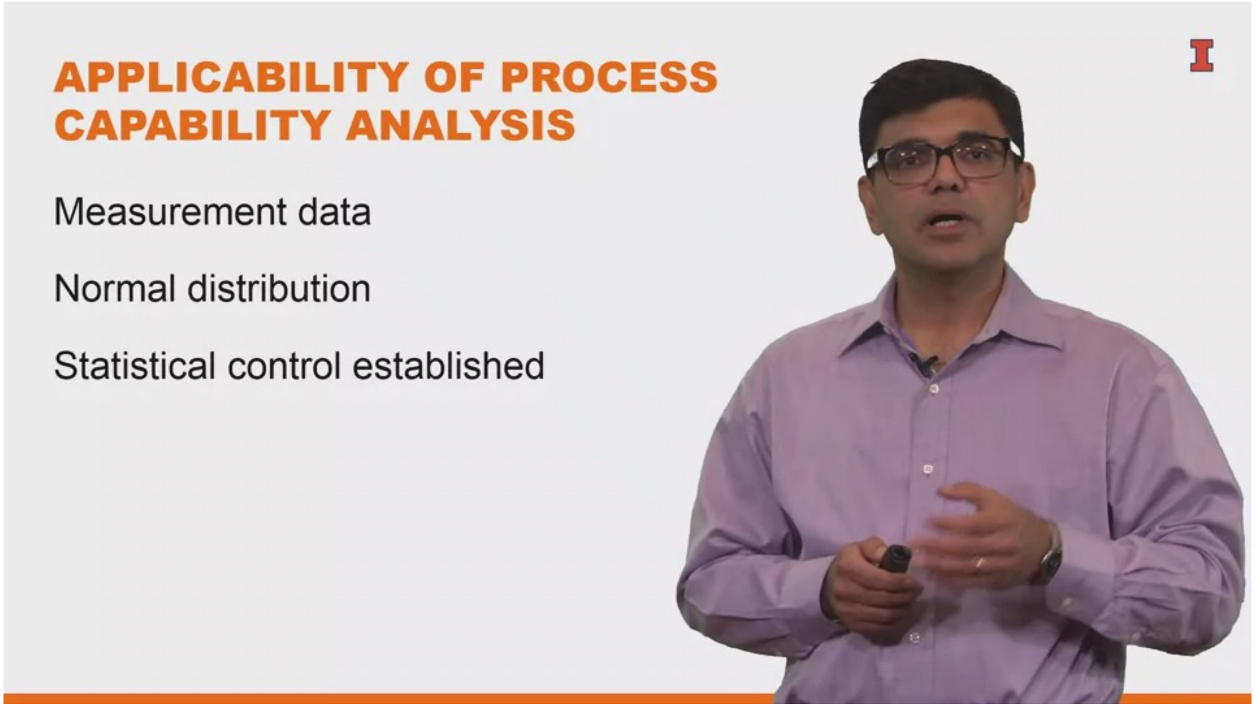
She's giving a pretty consistent temperature. The maximum that it varies is 0.1688 degrees Fahrenheit. The maximum of that range chart was a 0.1688 degrees Fahrenheit, which is pretty good. The range is pretty Small. It's between 0 and 0.1688, right? The temperatures for the actual, I see called milky Americanos is between 35.0356 and 35.1434 degrees Fahrenheit. So again, a very small range of temperatures that you're getting from this. So it seems to be a pretty tightly controlled process. She is able to achieve that consistency in the coffee that she's serving her customers. Now, the question that you have not addressed by looking at whether the process is in statistical process control and even focusing on the inherent capability of the process is what is the customer's expectation, right? We don't know how this temperature compares to what the customer expects, whether the customer is going to be happy with this particular temperature or not. That's something that you don't know from doing a statistical process control analysis. So keep a note of that.

Lesson 3-7: Process Capability

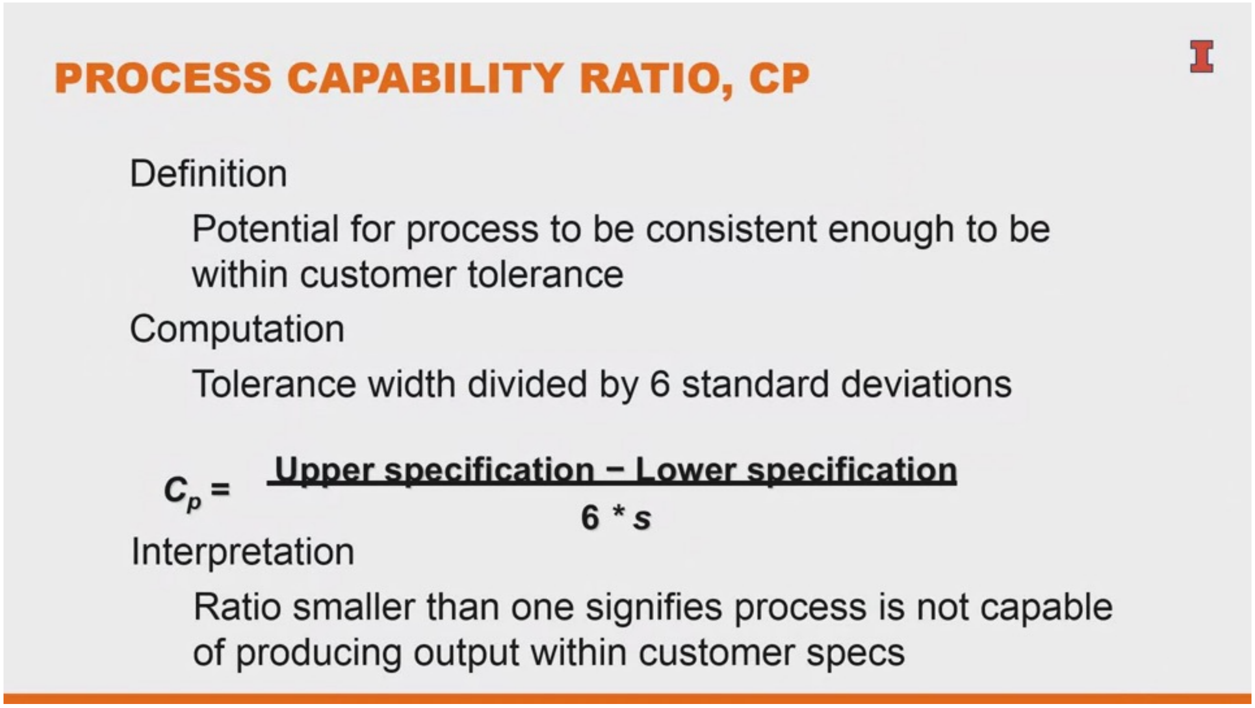
[Module 3.7.1 Customer Specification vs Process Performance Notes Discuss](#)



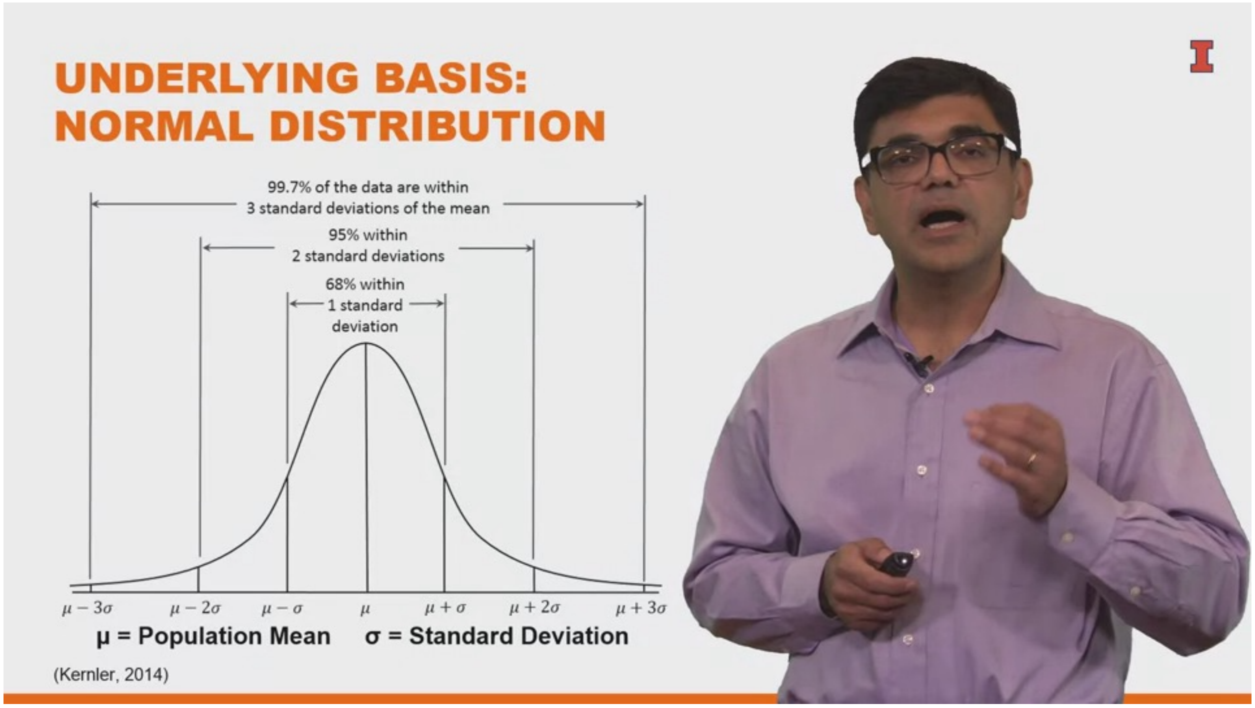
This lesson is about process capability analysis. What you're going to see is how you can compare, based on some measurements that you get from the process, how you can compare how the process is doing with what the customer is expecting. That's going to be based on some expectations of customers that you get, based on market research, based on talking to customers. We're making a comparison between customer expectations and the capability of the process. How is the process performing given the current conditions?



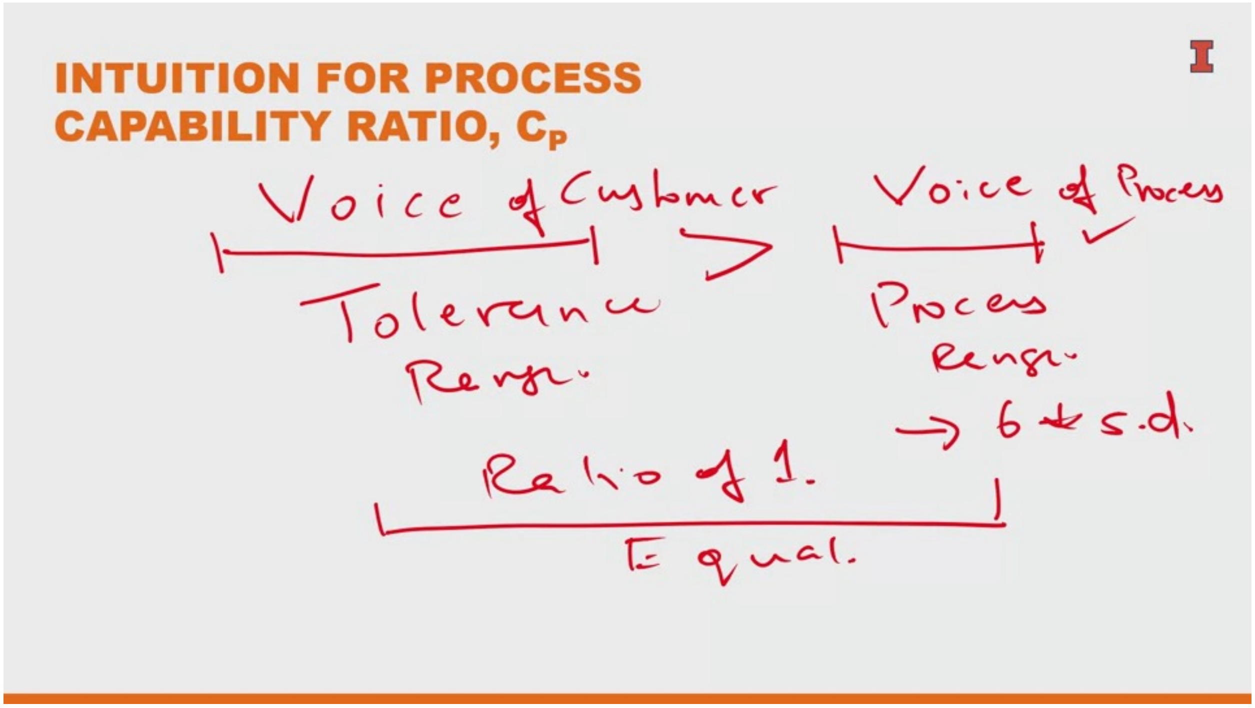
Let's see how we can do that. Process capability analysis, this type of analysis can be used, first of all, only for measurement data. We're using this for continuous data, we're talking about time to serve the, customer weight of a particular item, those data. We're assuming a normal distribution of data as we do with a lot of things in quality management. To keep things simple, we assume a normal distribution. We're assuming a normal distribution for this analysis. The most important thing here to keep in mind is that we will be doing process capability analysis with the assumption that the process is under statistical control. What this means is when you're doing this in practice, you want to make sure that statistical control has been established, that you know the inherent capability of the process based on doing some statistical process control analysis. That becomes a first step before you go into doing a process capability analysis. From an intuitive perspective that should make sense. It should make sense because what you're doing is you're going and talking to a customer and promising something. You're saying, are we going to be able to give you what you're expecting? In order to do that, you better be sure about how your process is performing. From an intuitive perspective, it should make sense that you establish the capability of your process before you check for process capability based on customer expectations.



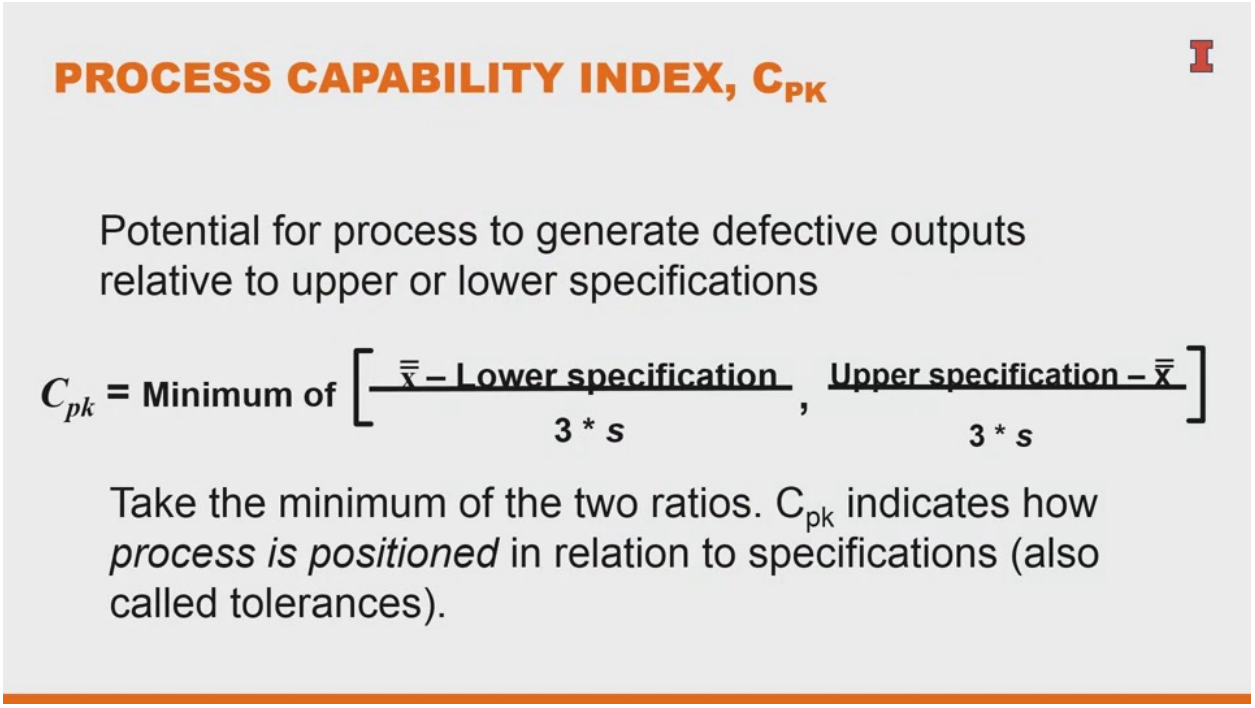
Let's take a look at some of the calculations that we'll do here. Basically, we'll look at two different ratios, the first of which is called the process capability ratio, or C_p in short. What is the C_p ratio? It's the ratio of what is the customer tolerance of whatever measurement you're talking about. How do we get the tolerance? You get it by taking the upper specification limit that the customer is giving you, subtracting the lower specification limit. You're getting the range of the tolerance for that particular measurement that the customer is giving you. For example, the customer may be telling you, I expect this to be delivered between 20 and 25 days. That gives you a range of five based on 25 minus 20. Or the customer might tell you, I expect the weight of this to be between 15.5-16.5 ounces. That gives you a one ounce range for your tolerance. That goes into the numerator of this particular ratio. What you have in the denominator of this ratio is six times the standard deviation. S stands for standard deviation and that's what you get from your process. The numerator is coming from the customer and the denominator is coming from what you measure in your process, what you find out from your process, how your process is currently doing. How do you interpret what you get from this ratio? You are looking for essentially a ratio that's greater than one. Less than one is going to indicate that it's not capable of delivering to customer specifications, one is going to say that it's just capable, and greater than one is going to say that it's better than being capable. The higher this ratio, the better it is in terms of serving customer expectations, in terms of keeping customers happy.



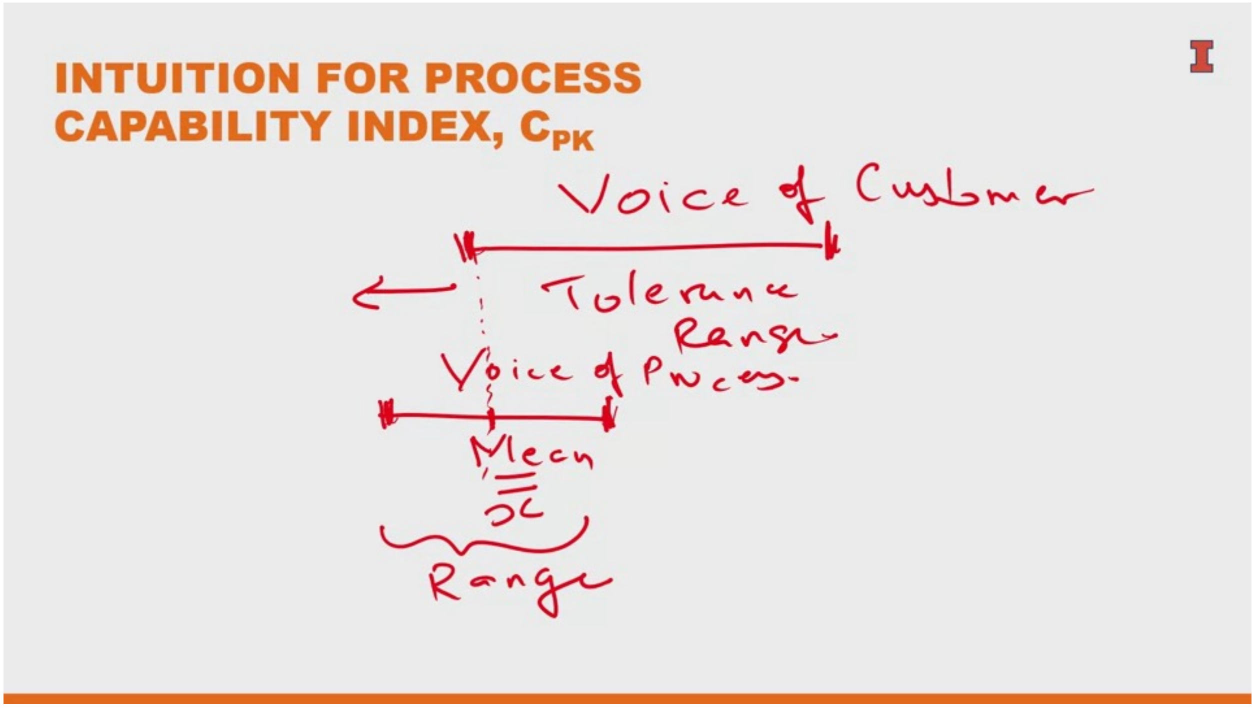
Where does this idea of six standard deviations in the denominator come from? Why do we have upper minus lower specification limit divided by six standard deviations? The idea comes from the standard normal distribution. We rely on the fact that 99.7 percent of the observations are going to be between plus and minus three standard deviations, or the other words plus and minus three standard deviations. You have plus and minus three, so you have a total of six standard deviations of range that you're getting, so that's what's going into the denominator of this particular ratio. Now, let's take a look at the intuition behind this particular ratio and see what we're getting here.



Let's take a look at the voice of the customer here first. What you have is the customer is telling you their tolerance range. We can call that the voice of the customer. It's whatever the customer is telling you. What you're saying is that this range, if you look at the width of this particular line segment, what you're saying is that, that should be greater than the voice of the process. What you're getting in terms of the variation in your process is being depicted in the denominator as six standard deviations, and that's your process range, which is being depicted by 6 times standard deviation. When we're saying that we want this ratio to be 1 or greater than 1. A ratio of 1 would mean that this voice of the process and voice of the customer are equal. If these are equal, that's saying that it's a ratio of 1. If the voice of the process is smaller and the voice of the customer has a greater range, then you're saying that the ratio is going to be greater than 1. That's the intuition behind looking for a ratio that is at least 1, and the higher it is than 1, the better it is going to be in terms of serving the customer.



Let's take a look at the next ratio that is part of this process capability analysis, and that's called the C_pk or the process capability index. The process capability index incorporates some more information than what we saw in the process capability ratio. What you have here is you have, if you look at the ratio that's given to us, the calculation, it's the minimum of the x double bar, it's called double bar because it's the mean of means. So it's the x double bar minus lower specification limit, x double bar coming to you from the process, lower specification limit coming to you from the customer, divide that by three times the standard deviation. As this next calculation, you have the upper specification minus x double bar, that should be an x double bar divided by 3 times the standard deviation. You're doing these two calculations and you're taking the minimum of these two. We'll take the minimum of these two, and we'll compare it with that same standard that we had earlier, as we want it to be 1 or greater than 1. 1 at a minimum, greater than 1 is going to be better. Lower than 1 means it's not going to fit into what the customer is expecting.



Here we have the voice of the customer, what we had earlier when we looked at the process capability ratio. The voice of the customer is given to us based on market research, there's a tolerance range that's given to us. Now here these specific numbers matter. Why do they matter? Because we're not just comparing this range with the other range, this range with the process range, we're comparing this with where the process is located. If you noticed earlier, I just looked at whether that range of the voice of the customer was greater than the range of the voice of the process, but here I'm not only looking at whether it's greater, but where it is situated in relation to each other. If this is the voice of the process, this is based on there being some kind of mean over here, which we refer typically as x double bar, and this is going to be based on your plus or minus 3 standard deviations. In this particular example, you're seeing just on the basis of this picture, that there will be output from this process that's going to go beyond the voice of the customer. What is this telling us? That this process is located, is centered too much to the left. Now if you look at the range that we had in this process, this range is smaller than the range of the tolerance of the customer. In that sense, what you're going to get if we were to put numbers on this, you're going to get a process capability ratio. That's going to be okay, that's going to be greater than 1. However, because the mean is too low, even though the range is compatible, it's falling within what the customer is expecting. It's located too far to the left and therefore, you're going to get output from this process that's going to fall outside of the customer's tolerance range. That's the intuition that you have behind the process capability index.

Module 3.7.2 Process Capability: Ratio (Cp) and Index (Cpk)

EXAMPLE: EXPEDITED ORDERS

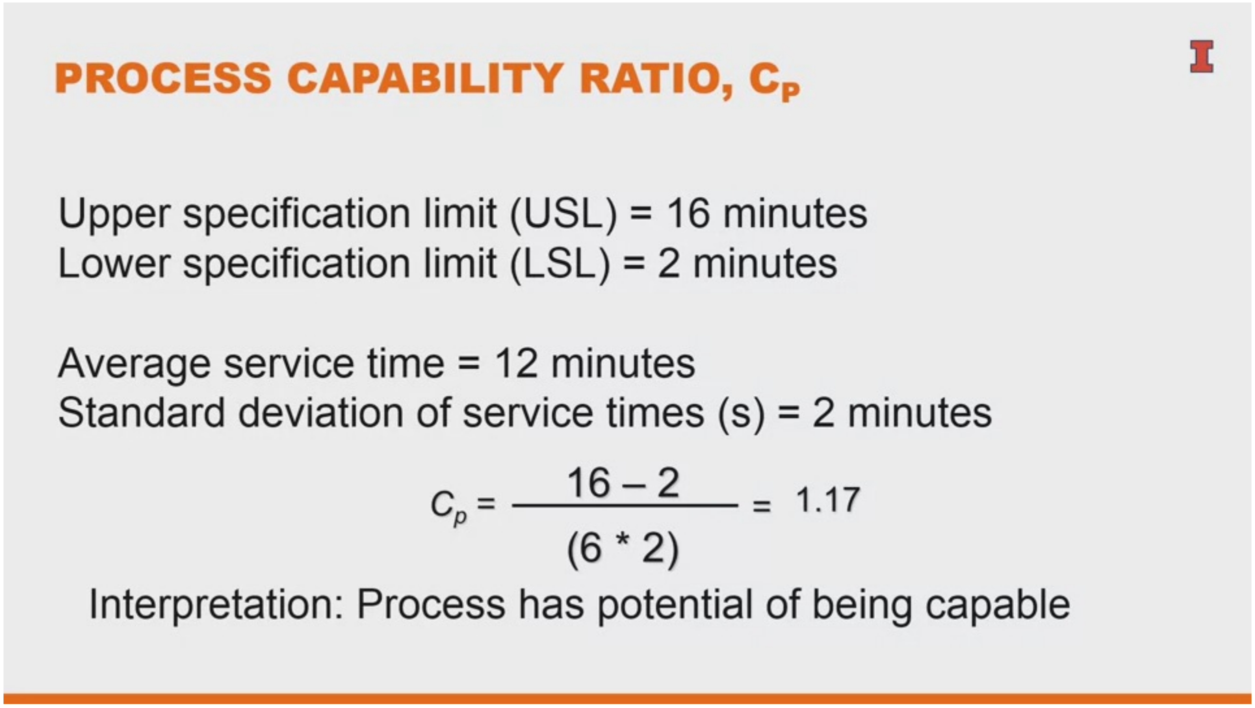
A restaurant on the "magnificent mile" in Chicago promises quick lunch meals of high quality from a limited menu and with some customization.

Market research has determined that office-going and tourist customers expect their somewhat customized orders to take between 2 and 16 minutes from order to arrival of food at the table.

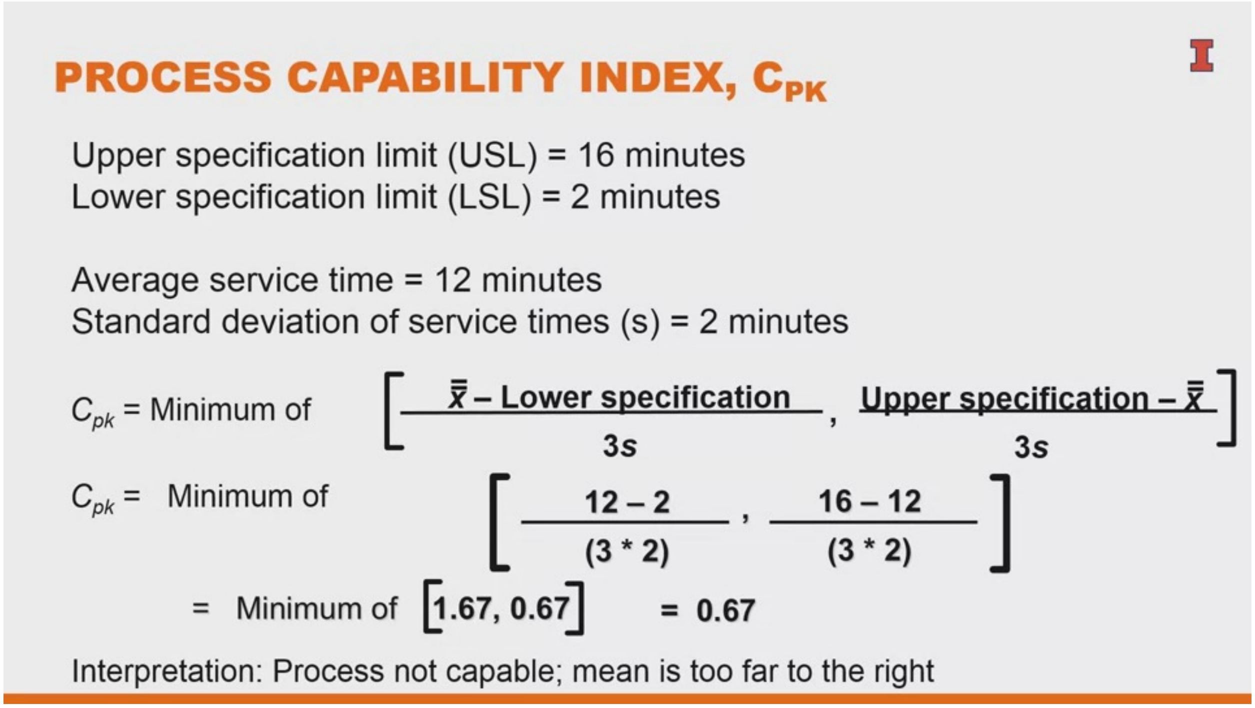
Their current process has an average turnaround time from order to arrival of food at the table of 12 minutes and a standard deviation of 2 minutes.

Is the process capable of conforming to customer expectations about lunch order turnaround time?

Let's take a look at an example to see how this plays out. So here we have a restaurant on the magnificent mile in Chicago that promises quick lunch meals of high quality from a limited menu with some customization. Market research has determined that the customers that come in there, they're mainly people who are working in the offices on Michigan avenue and and nearby offices or they are tourists who are walking in there together quick meal. They expect to their orders to take between two and 16 minutes. So what is our customer expectation? The lower specification limit or the LSL for customer expectation is two minutes. The upper specification limit to 16 minutes. Right, they're expecting that because of the customization, it can't be zero. So it's going to take at least two minutes for for it to get done. And but they're expecting it to be done in a maximum of 16 minutes. That's their expectation. When you go and look at the the actual process, when this restaurant assessed their actual process, they found the average turnaround time from order to arrival to be 12 minutes. So this is coming from the process. This is coming from data collected about the process and they find an average of 12 minutes. And the standard Deviation of two minutes. So the question is, is this process going to be capable of conforming to customer expectations? Now, remember that we are assuming that this process is in statistical Control that the 2 and 12 represent the inherent capability of the process. So in that sense, we are quite confident of the 2 and 12 when we're comparing it With the two and 16. Right, so the standard deviation of 2 and the mean of 12, we're quite confident about that when we are comparing it with the specification limits given to us by the customer. All right, so let's do some of the calculations and and see what we can find. So, what we're going to calculate is the CP and CPK process capability ratio and the process capability index. Both of these have to be calculated at all times. You can't do one without the other.



All right, so, let's take a look at the process capability ratio first. Upper specification limit of 16, lower specification limited to we subtract 16 -2. And we divide that by six times the standard deviation. Where did the six come from? That's part of the formula that came from having plus or minus 3 standard deviations. So, we used that property of the normal distribution and the two is the standard deviation in the denominator in the numerator. You have the upper and lower specification limits coming from the customer ratio works out to greater than one. You can see that the numerator is greater than the denominator. So it fits into the range of the process fits into the range of the customer in this case. Right, let's look at the next thing. And that's going to be your process capability index. Now, if you notice here, before we get to the process capability index, I said the process has the potential of being capable. Because remember what we saw in the picture earlier that you can have a range that falls within the customer specifications. You can have a process range that falls within the customer range, however it might be located in terms of centering of that process, it might be too much to the left or the right.



All right, so let's take a look at the process capability index. Calculations are going to be based on we need to do to calculations based on incorporating the mean of the process. So here we're actually going to use that average service time of 12 minutes in our calculations. If you noticed in the CPI calculation, we had nothing to do with the 12 minutes, we simply relied under 2 minutes of standard deviation. So we're going to take the minimum of these two ratios. And when you calculate these through, you get 1.67 and 0.67. So what is this telling us? It's telling us that there's going to be a problem. Right? We find a ratio that's less than one. It's telling us that this process is not capable of serving this customer. In fact, it's telling us that the mean is too far to the right now, how do we know that? Two ways, you can look at which of those two ratios gave us a 0.67. And you'll see that it was on the upper Side when you take 16-12. That's where you got the number, that was less than one. So that's telling us that it is on going to be on the upper side. You can also simply take a look at the upper and lower specification limits. And compare with the the the center of the process that that you have from the process average. Right, so if you look at the center of the upper and lower specification limits of the customer, it's it's between 16 and to so that's going to be at nine. Right, so you have 2 plus 79, 7 plus 916. So 9 is the center. And then you can See the average service time of 12 minutes is higher than 9. So it's too much to the right. Too far to the right. And that's why you have times that are going to be higher than the upper specification limit coming out of this process. Right, so this gives us a quick indication that this process is not going to be capable of serving these types of customers. They're going to be unhappy customers. So overall interpretation.

OVERALL INTERPRETATION AND POSSIBLE ACTION

Variability in the process is low enough for possibly fulfilling customer expectations

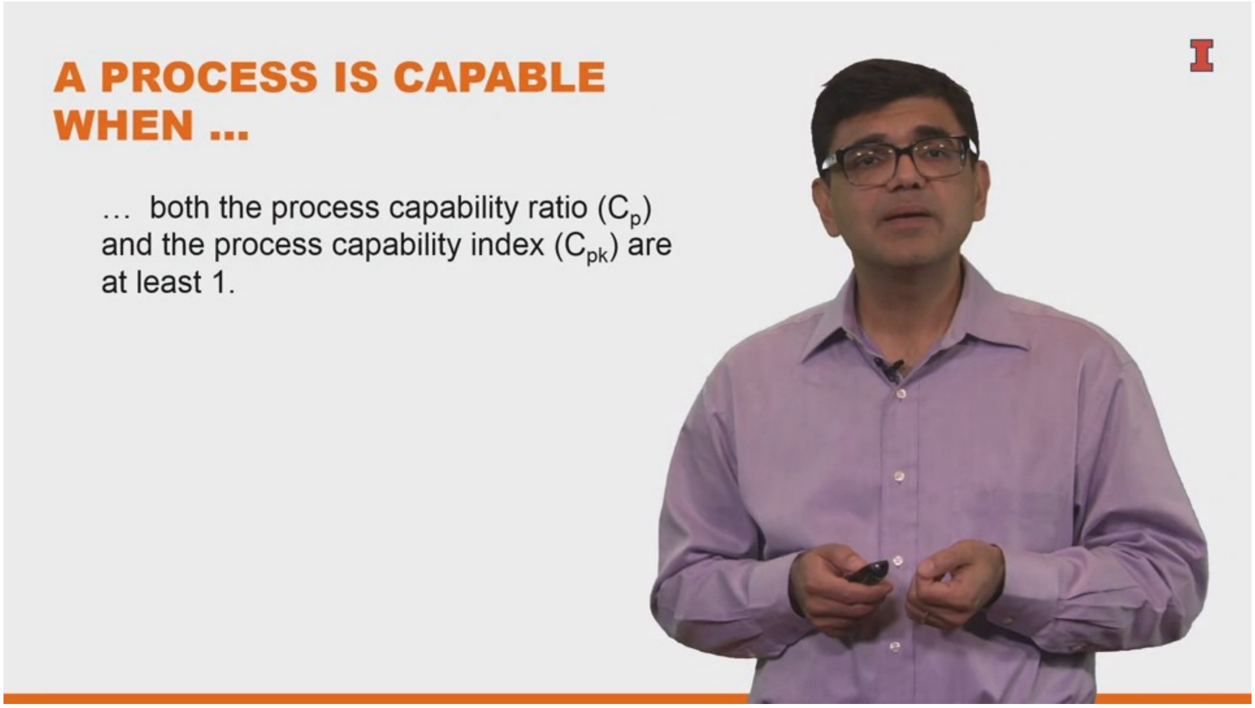
Average time of 12 minutes is too high

- Compare to the center of the customer tolerance range
  - Center point between 2 and 16 is 9 minutes

Reducing the standard deviation (e.g., to 1) would also make process capable

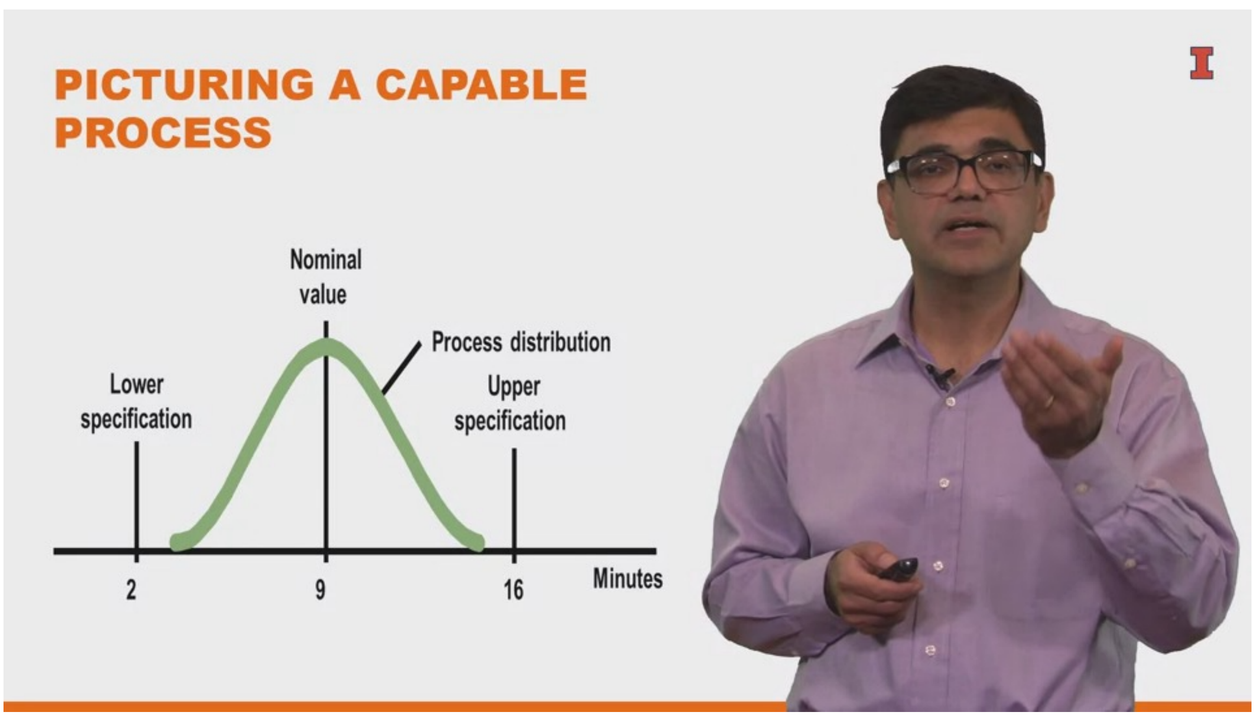
Combination of reducing mean and standard deviation

The variability seems to be okay, it's low enough for us to fulfill customer expectations for the restaurant to fulfill customer expectations, but the average is too high. What can this restaurant do? I can do two things. It can reduce the average, get it to 9, by getting it to 9, it's going to have a process that will look capable of serving the customer expectation. Or you can reduce the standard deviation. So the restaurant were to make their process more predictable. Have the standard deviation of the process reduce, let's say from 2 to 1. Right, now, the standard deviation is 2, if they can have that standard deviation to 1, that would also make the process capable. Now which one this restaurant is able to do? That's going to need more information. Right, I mean, whether they can actually reduce the time that it takes. It may not be able to reduce the average time based on the kinds of orders that it gets and the kinds of things it needs to do to produce those orders. Can it reduce the standard deviation? May be based on different training of different people who are working in the kitchen and and different training of different people who are serving and taking orders outside. There might be some things that can be done to reduce the variation, to reduce the standard deviation of the process. And if that can be reduced then the process will become capable of serving these kinds of customers. You'll get a ratio that is going to be greater than one, both in the case of CP and CPK.

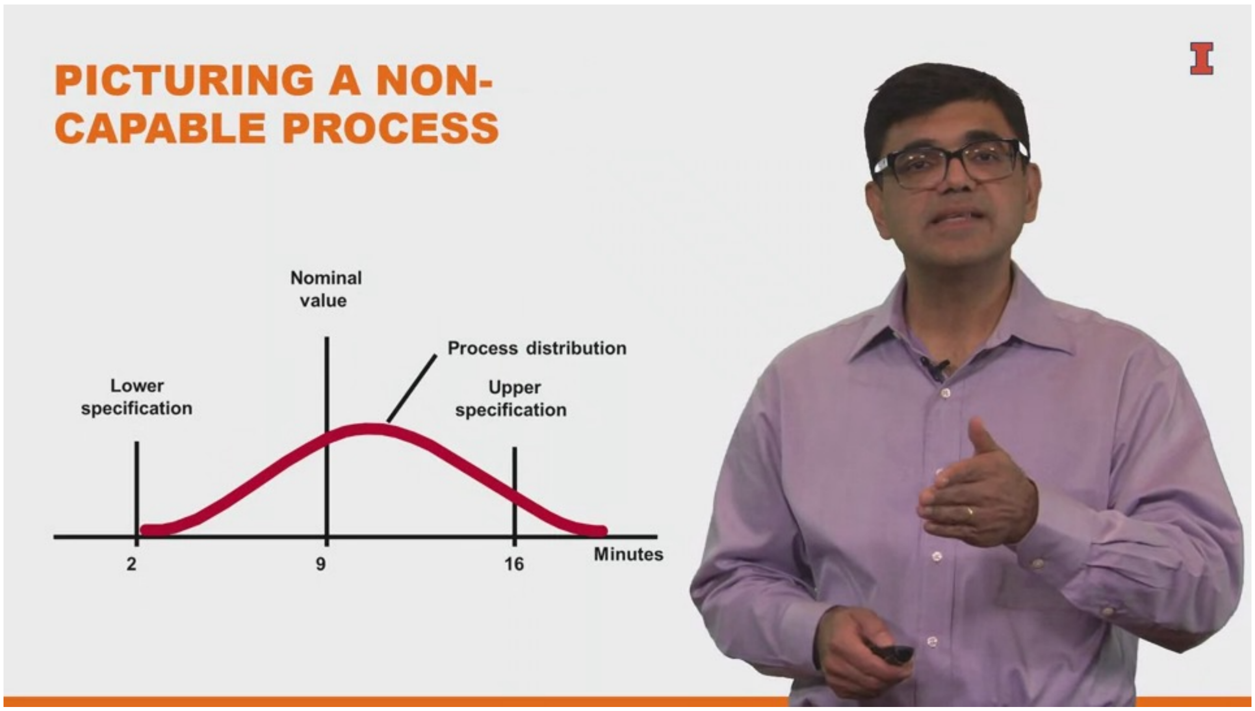


Right, so, in summary, what we're saying is that the process is capable when you have a process capability ratio, as well as the process capability index, both being one or greater. One is a minimum greater than one better. The higher the better.

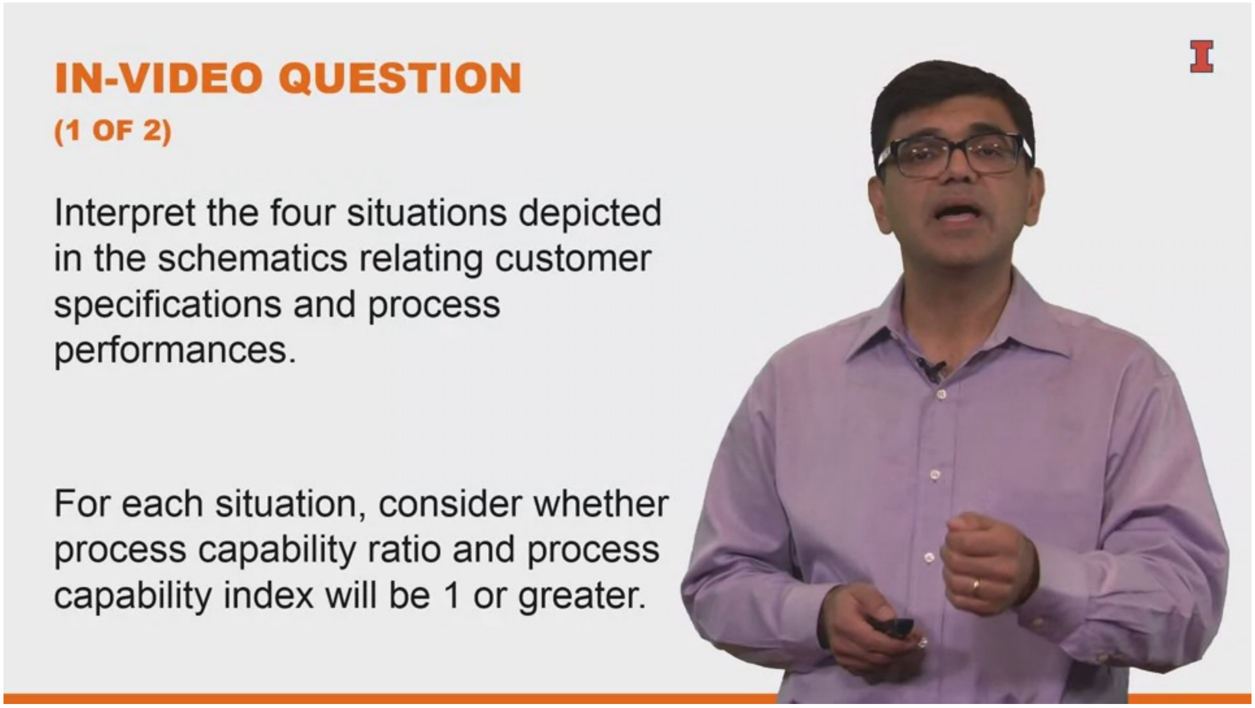
[Module 3.7.3 Implications of Cp and Cpk Results]



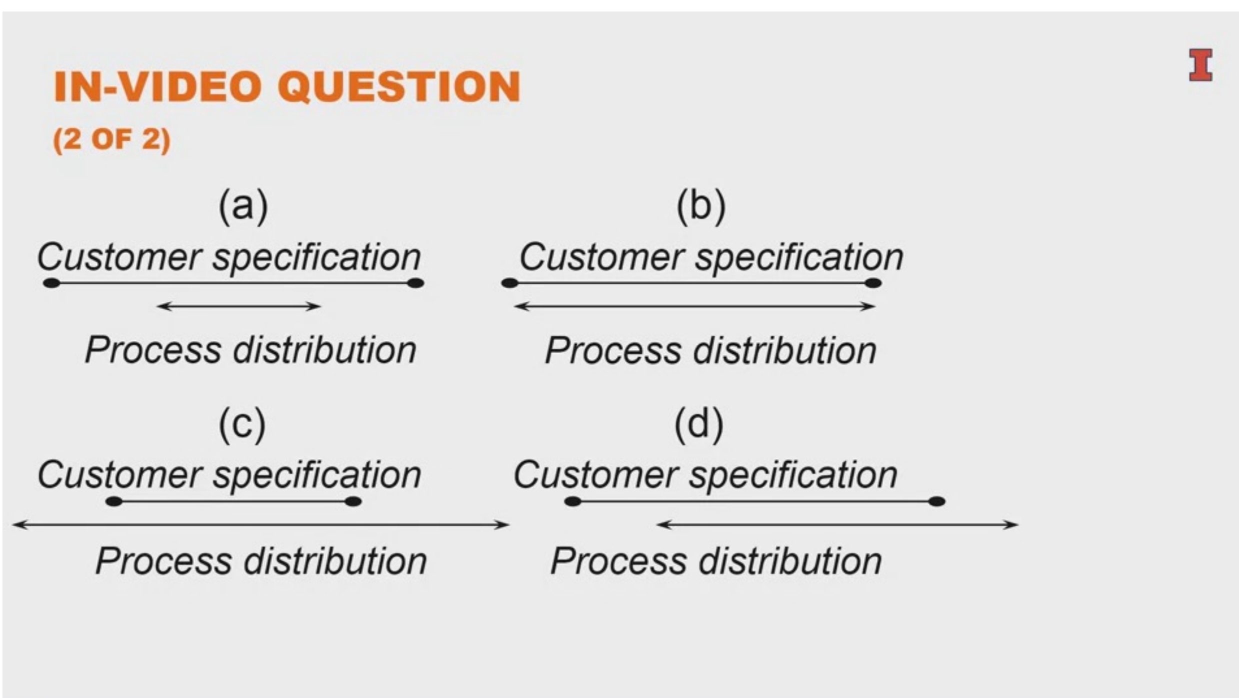
Let's take a look at this whole idea in terms of pictures. What are we saying here? If a process is capable, this is how it will look. You have the center value of nine, we can call that the nominal value that the customer has given us. We have a lower specification limit of two minutes, upper specification limit of 16 minutes, the nine minutes is a nominal value. That's the center value, that's the ideal value that the customer is expecting. What we're saying with a process that is capable, is we are saying that the process distribution falls within the lower and upper specification limits.



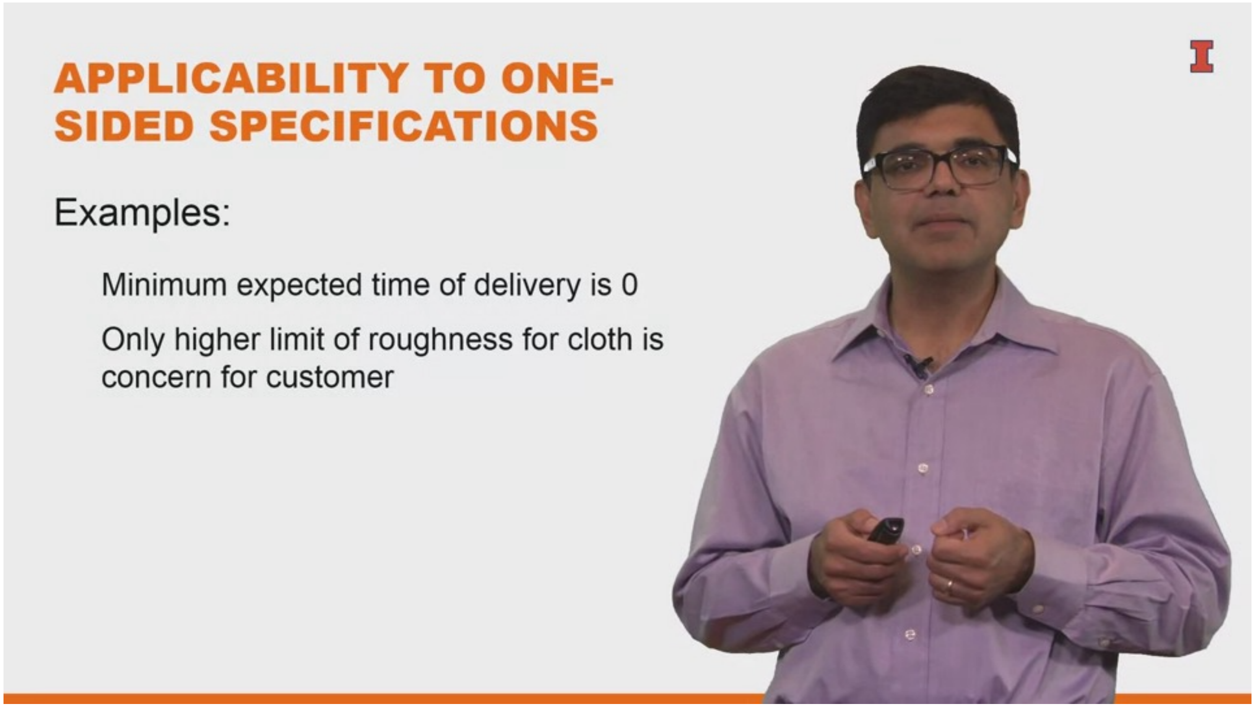
Picture this with a process that is not capable of serving these kinds of customers, so we're saying that we found the process to be centered too far to the right. The mean was 12 minutes, so if you look at 12 minutes and the standard deviation going from 12 minutes towards the higher side, it was falling too much to outside of the upper specification limits. You needed to either shift the mean or reduce the standard deviation, get this distribution to be tighter for that red graph that you have to fall within two and 16, more importantly, at less than 16. That's an interpretation that you can see in terms of pictures.



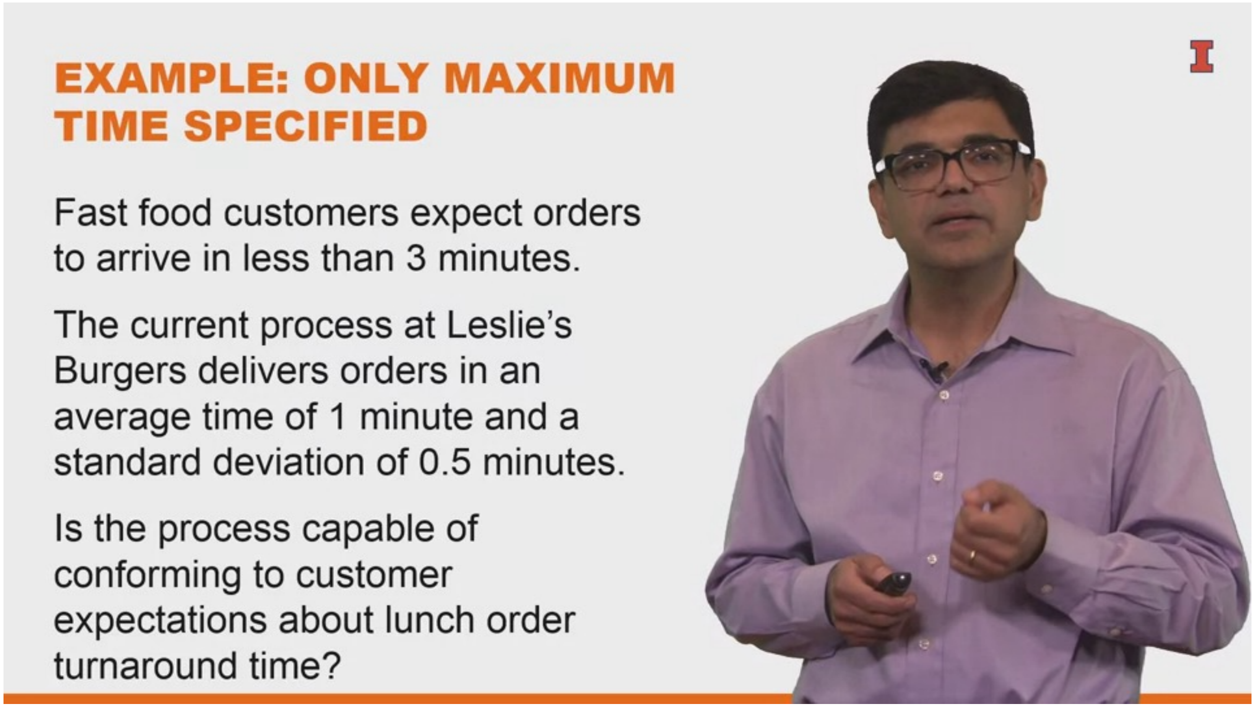
Let's take this and try to apply it in terms of different scenarios. What you'll see in the next slide, is you will see four different situations based on customer specifications and process distribution being depicted. What I would like you to do is for each situation, just think about what it's telling you in terms of whether this process is going to be capable, or whether the process capability ratio and the process capability index will be one or greater in each of these cases, simply based on looking at these pictures, no numbers here, simply looking at pictures and being able to say whether the ratio and the index are going to be one or greater in each of these cases.



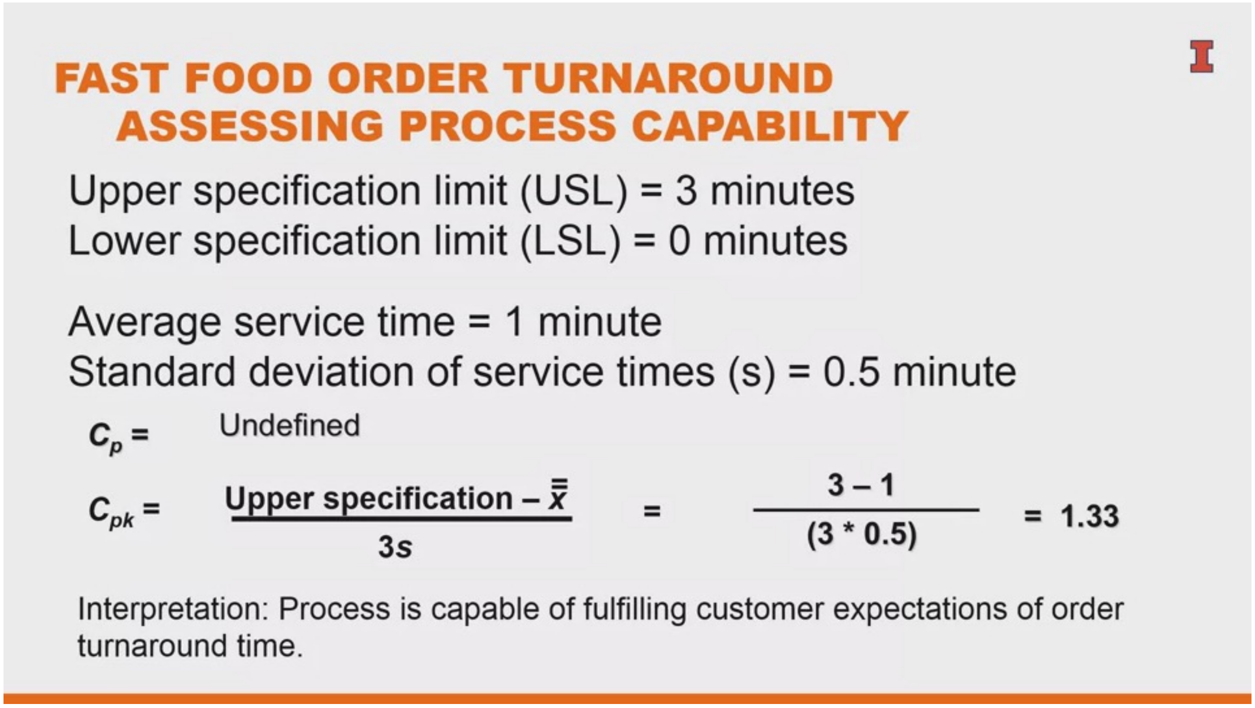
Take a look at these pictures now. What can we see from here? We can see that when you look at the scenario a, the customer specification is much wider than the process distribution. The process capability ratio is definitely going to be greater than one. It's going to be quite larger than one, simply because the denominator of that ratio is going to be much smaller than the numerator. The customer specification is what goes into the numerator. The process capability index is also going to be greater than one, simply because the process is centered exactly at where the customer specification is. That's scenario a for you. For scenario b, what can you say? You can say that each of those, the ratio and the index, both of them are going to be exactly one. The variability in the process, if you look at plus or minus three standard deviations, makes up exactly the customer specification range. If you look at upper minus lower specifications and you compare that to six times the standard deviation, this is telling you that it's going to be exactly equal, so the ratio will be one and the index will also be one in this case, because it's centered exactly at the nominal value of the customer. Let's take a look at c. What can you expect there? C is clearly going to be a case where your process capability ratio is going to be less than one. Process distribution is much wider than customer specification, so right off the bat, you can say that you're going to have a lot of output from the process that's falling above and below customer specification. The Cp or the process capability ratio is going to be less than one. The process capability index is also going to be less than one simply because you have points that are outside of the upper and lower specification limit of the customer. What you can actually infer from c is that if you have a process capability ratio, if you have a Cp value, so a process capability ratio that is less than one, there's no point of even calculating the index, the Cpk, because then the Cpk is also going to be less than one. In other words, what you can generally say is that the Cpk value is always going to be either equal to or less than the Cp value. If you've already calculated a Cp value that's less than one, the Cpk value is either going to be equal to that or less than that, so there's no point of even looking at the Cpk value. In terms of scenario D, what do you see there? You see that the customer specification, the range that you get from that and the process distribution are equal, so the process capability ratio will be exactly one. However, the process is centered too much to the right, the average of the process is too much on the higher side, so you're going to get a lot of output or you're going to get output that's going to be beyond customer specifications on the right side. That's going to be a case of Cp being one, and Cpk being less than one.



Let's take an example now of a situation where you don't really care about both sides of the ratio. We looked at the time that it took at a restaurant in the previous example. There may be situations where you say, look, I expect the time to be 0, it should be instantaneous. If I'm talking about a fast food restaurant, then it's curtailed at 0 on the left side, your expectation of the customer is 0. Another example that you can think of is when you're looking at something like a roughness of cloth. Well, customer expectation is going to be that the roughness of cloth is not there, that it's perfect, that it's smooth, and therefore you don't have anything towards the lower specification limit. All you have is an upper specification limit that you can tolerate.



Let's take a look at an example of that and see the difference in calculations there and how you would go about looking at the process capability there. Here's a fast food restaurant now, and the customers expect orders to arrive in less than three minutes. In other words, we're saying 0-3 minutes, so it's lower specification of 0. Current process is at a burger joint. Leslie's Burgers delivers orders in an average of one minute. X double bar is one minute and a standard deviation or s of 0.5 minutes. Is the process capable of conforming to customer expectations? Since we don't have a lower specification limit here, the calculations are going to be slightly different.



Let's take a look at these calculations. When you don't have a lower specification limit or the lower specification limit is 0, you basically do not even need to look at the process capability ratio, it's going to be meaningless because it's bounded on the left side. You don't really have a meaning of comparing the range of what the customer is expecting to the range of what your process is doing. In calculating the C_pk, you're only going to care about one side. You're not going to look at the minimum of both of them, like you did in the previous example, but you're only going to care on the upper side in this case. That calculation in this case works out to 1.33. It's telling us that the process is capable of fulfilling customer expectations. When you're dealing with a one-sided specification limit, you would go about it in terms of simply calculating the C_pk and a one-sided C_pk, you're not even going to calculate both sides for the particular index.

IN GENERAL, USES OF PROCESS CAPABILITY ASSESSMENT

Quick indicators of the chances of fulfilling and failing process customer requirements

Comparison across different processes and suppliers

Supplier cost calculations

Effective tracking and communication tool for buyer-supplier communications

(Linn, Tsung, & Ellis 2006)

In general, what are the uses of the process capability? It gives a quick indicator of the chance that this process or what you're getting from the process is going to fulfill customer requirements. If you scrutinize the idea of process capability analysis and if you're familiar with statistics in general, it's not giving you any new information other than simply comparing the mean of the process and looking at when you go plus or minus three standard deviations from the mean of the process, whether that falls within the range of upper and lower specification limits. You're not getting any new information more than that, but it's giving you a quick indicator. Thinking about it in terms of process capability, ratio and index of one, a minimum of one tells you that it's going to fall within specification limits or not. It gives you the ability to compare this particular metric across different processes. If you have different suppliers, who you're considering or you're comparing, you want the C_p and C_pk to be higher for the suppliers that you choose. You can do that. It helps you think about the cost calculations for supplies that you're getting from particular suppliers. The higher the C_p and the C_pk numbers of suppliers, the lower the chances of you getting a defective raw material, the lower the chances of you having to work with defective raw material and get defective product at your end. That gives you a sense of calculating costs from different suppliers. It becomes an effective tool in terms of giving specifications to suppliers. You can use this ratio and index to tell suppliers what you expect in terms of the process capability ratio or the process capability overall for particular items that you're dealing with.