Machine learning process. Machine learning process, this diagram explains the steps in the machine learning process, which has Acquire, Prepare, Analyze, Report, and Act. So it should be kept in mind that all these steps are needed to be carried out with a clear purpose in mind that is the problem or the opportunity that is being addressed must be defined with a clear stated goals and objectives. For example, the purpose of a project may be to study the customer purchasing behavior. Now to come up with more effective marketing strategy in order to increase the sales, so this particular aspect must be there at all the steps. So the purpose behind the project will drive the machine learning process.
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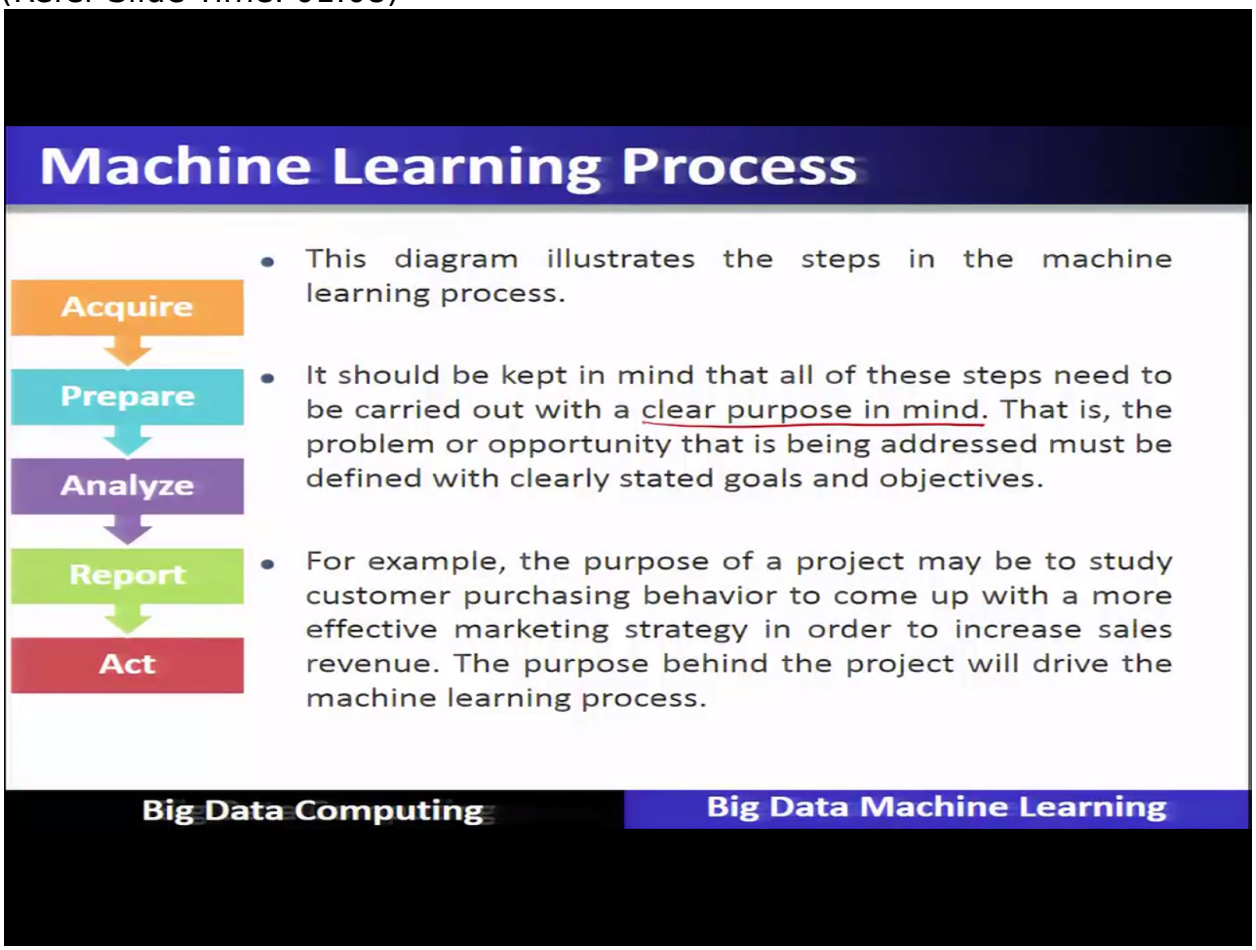

Now the first step here is called Acquire the data. So the first step in the machine learning process is to get all the available data related to the problem at hand. Hence we need to identify all data sources, collect the data and finally integrate the data from these multiple sources for that particular problem. Therefore the clear purpose or the clear objectives of a goal in a given problem must be there in the mind while in the step no. 1 to acquire the data. This step is also called data acquisition. So data acquisition is the process of gathering, filtering, and cleaning the data before it is being put in the data warehouse or any other storage solution on which

the data analysis can be carried out. So data acquisition is one of the major big data challenges.
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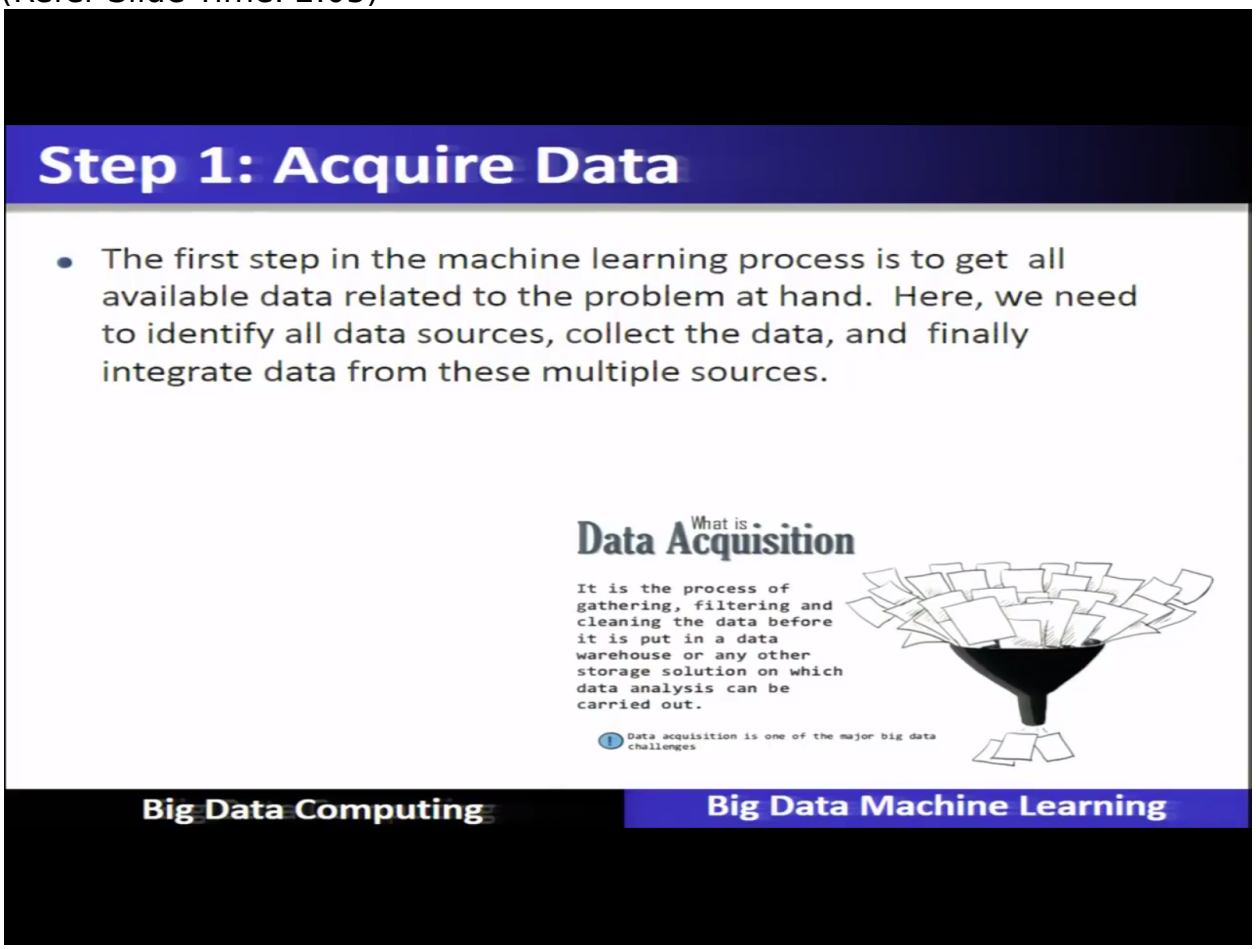

Step no. 2 in this particular machine learning process is to prepare the data. This step is further divided into two parts, to explore the data and preprocess the data. Let us understand these two aspects in more detail. Now the first part of the data preparation involves the preliminary exploration of the data to understand the nature of the data, that we have to work with. This is also called data exploration. That is the things we want to understand about the data are its characteristics, formats, quality, as per as... Now these... a good understanding of the data will lead to a more informed analysis and will become a successful outcome. So to have the better successful outcome of the machine learning result, it is necessary that very careful data exploration steps has to be performed. So once we know about data through the exploratory analysis, the next part is the preprocessing of the data for the analysis, that is called-preprocess. Now this pre processing includes the cleaning data, selecting the variables to use and transforming the data to make the data more suitable for the analysis in the next step.
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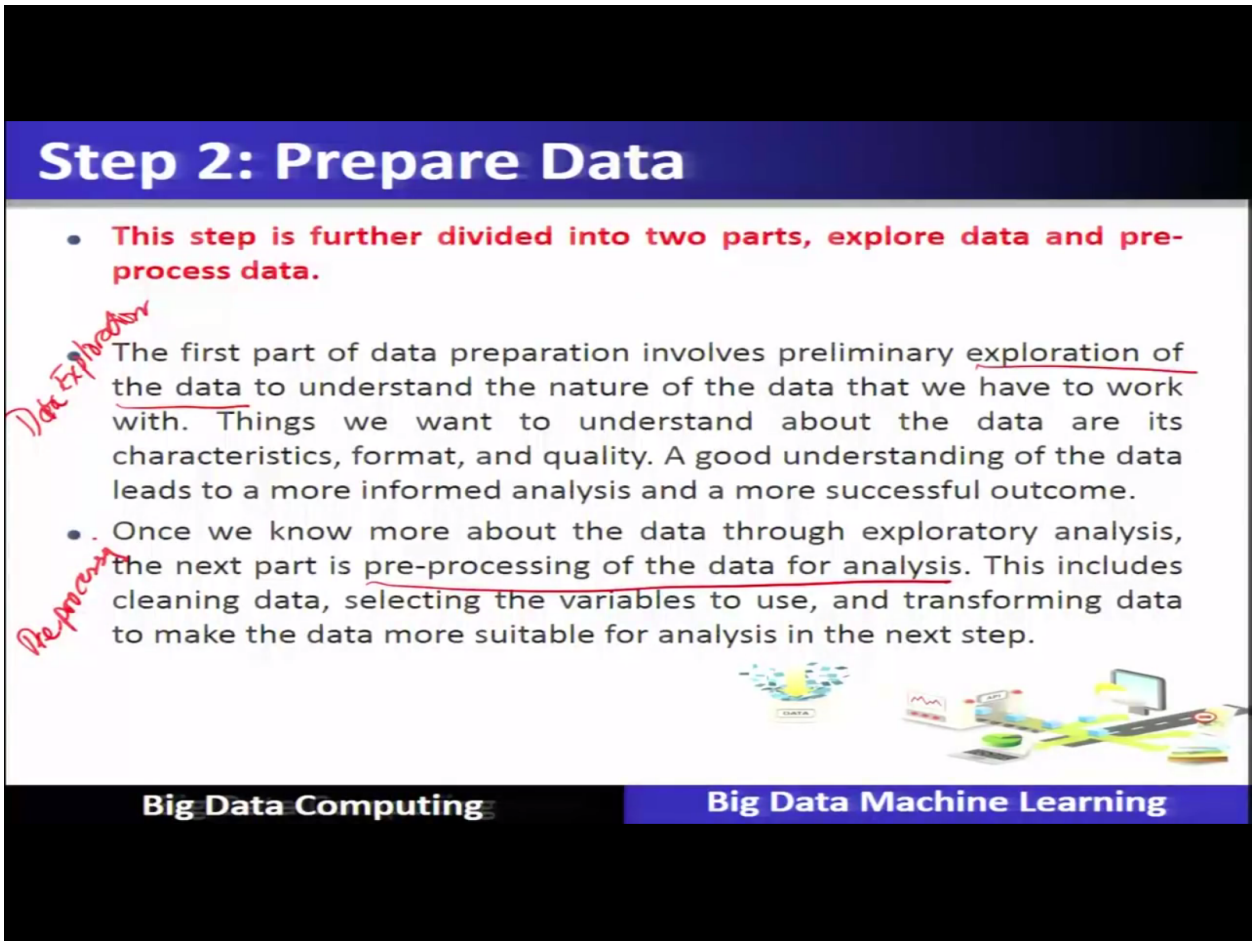

Third step is to analyze the data. Now the prepared data then would be boxed on to the analysis step. This involves selecting the analytical technique to use building a model using the data and assessing the result. Meaning to say that to analyze the data we require to select one of these techniques, analytical techniques to be used. This is one of the important decision here in this step, which is to analyze the data. So techniques involves again all the machine learning techniques which we have... which we have seen that is, we have to identify, which of these different categories or classes of machine learning is to be applied to analyze the problem, that is whether it is a classification or it is a regression or it is association or it is clustering. So all these techniques we have to identify and within each technique different algorithms are there, that is required to be selection, that required to be selected. So this becomes the selection of analytical technique to be used in building the model, that means we have to fit the model in the data using these selected techniques. So this is one of the most important step of a machine learning.

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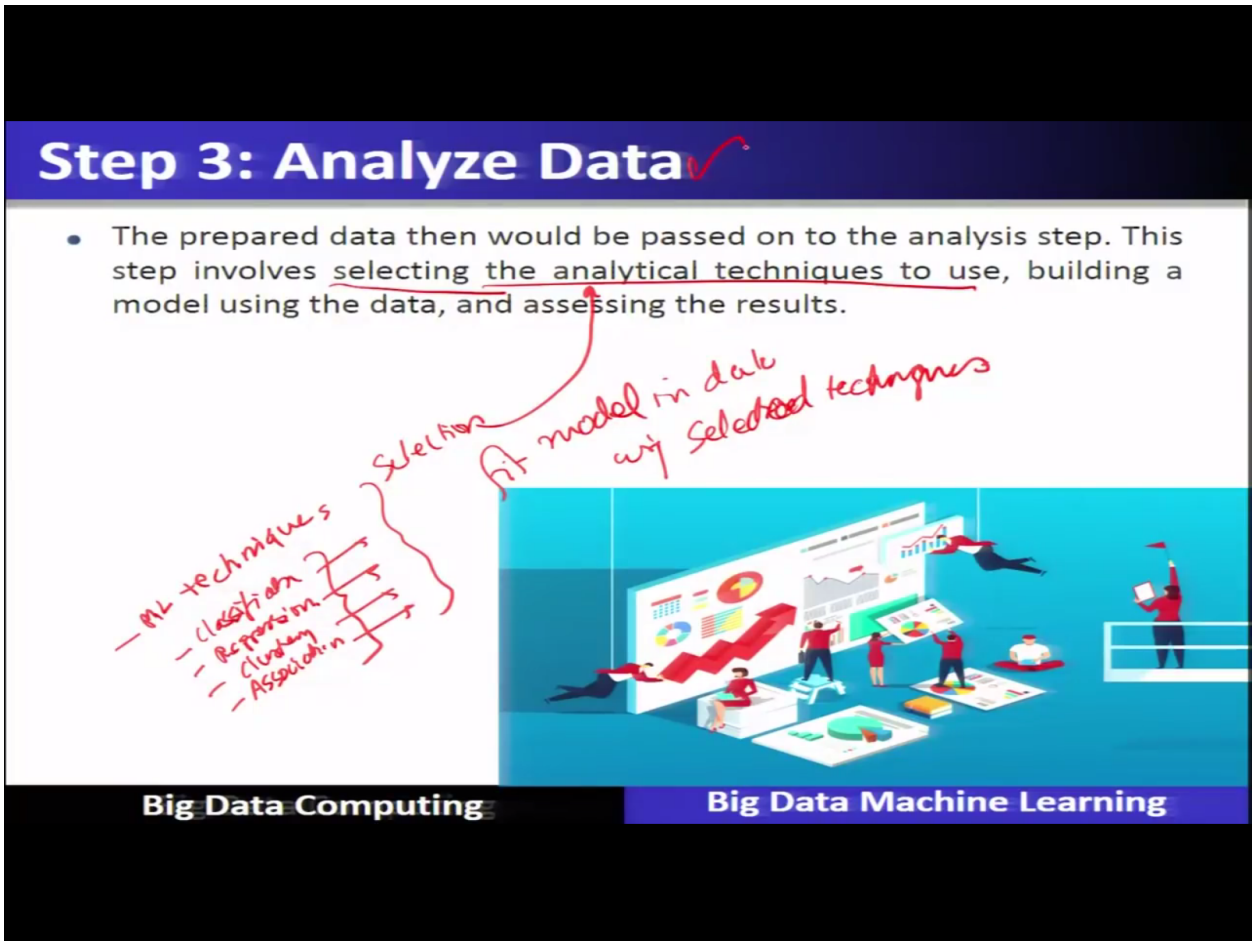

Fourth data is to Communicate Results, this include evaluation, evaluating the results with respect to the goal sets for the project. So presenting the result is… in an easy to understand way and communicating the result to others is also one of the important aspect.
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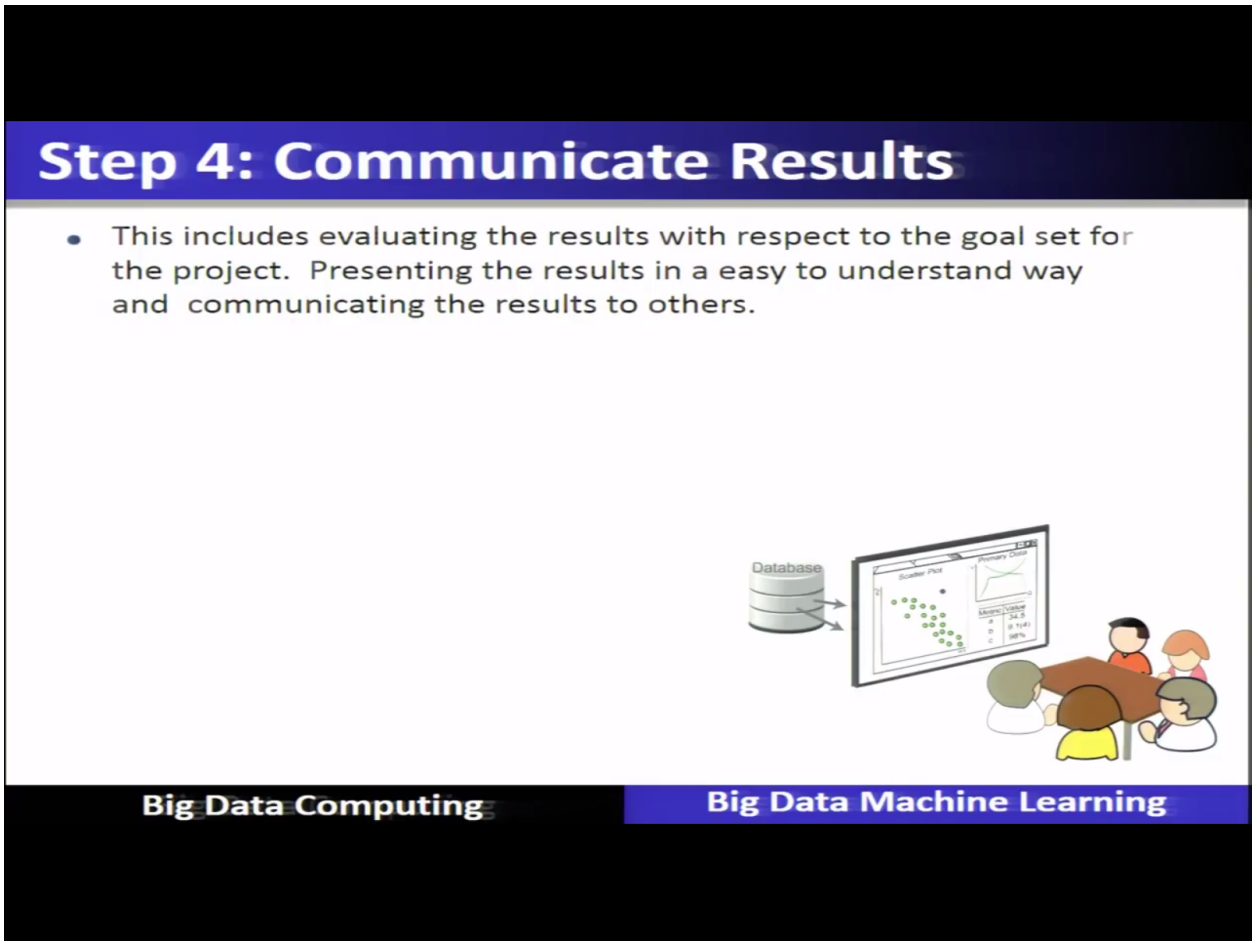

Step 5 is to apply the result. So the last step is to apply the result, this is to bring us back to the purpose of the project, how can the insight from our analysis be used to provide effective marketing to increase the sell revenue and so on. So this is also going to be very useful in using the result for different application.
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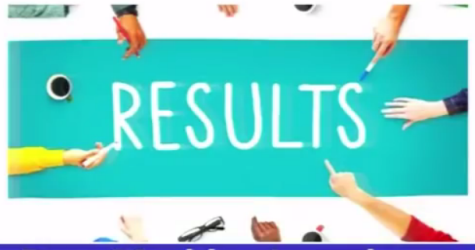
Step 5: Apply the Results

- The last step is to apply the results. This brings us back to the purpose of the project. How can the insights from our analysis be used to provide effective marketing to increase sales revenue?
- Determining actions from insights gained from analysis is the main focus of the act step.



So determining the actions for insight gain from the analysis is the main focus of this step. Now we have to see that all these steps are iterative in the nature, that means either all these steps or some of the steps, they have to be repeated. So that we will see further that… that machine learning process is very iterative and finding from… results from 1 step may require a previous step to be repeated with the new information. So for example, during the preparation step we may find some data quality issues, that may require us to move back and to acquire further information to address some issues with the data collection or to get additional data that we did not include in the first round and so on. So therefore this iteration is required in the machine learning process.

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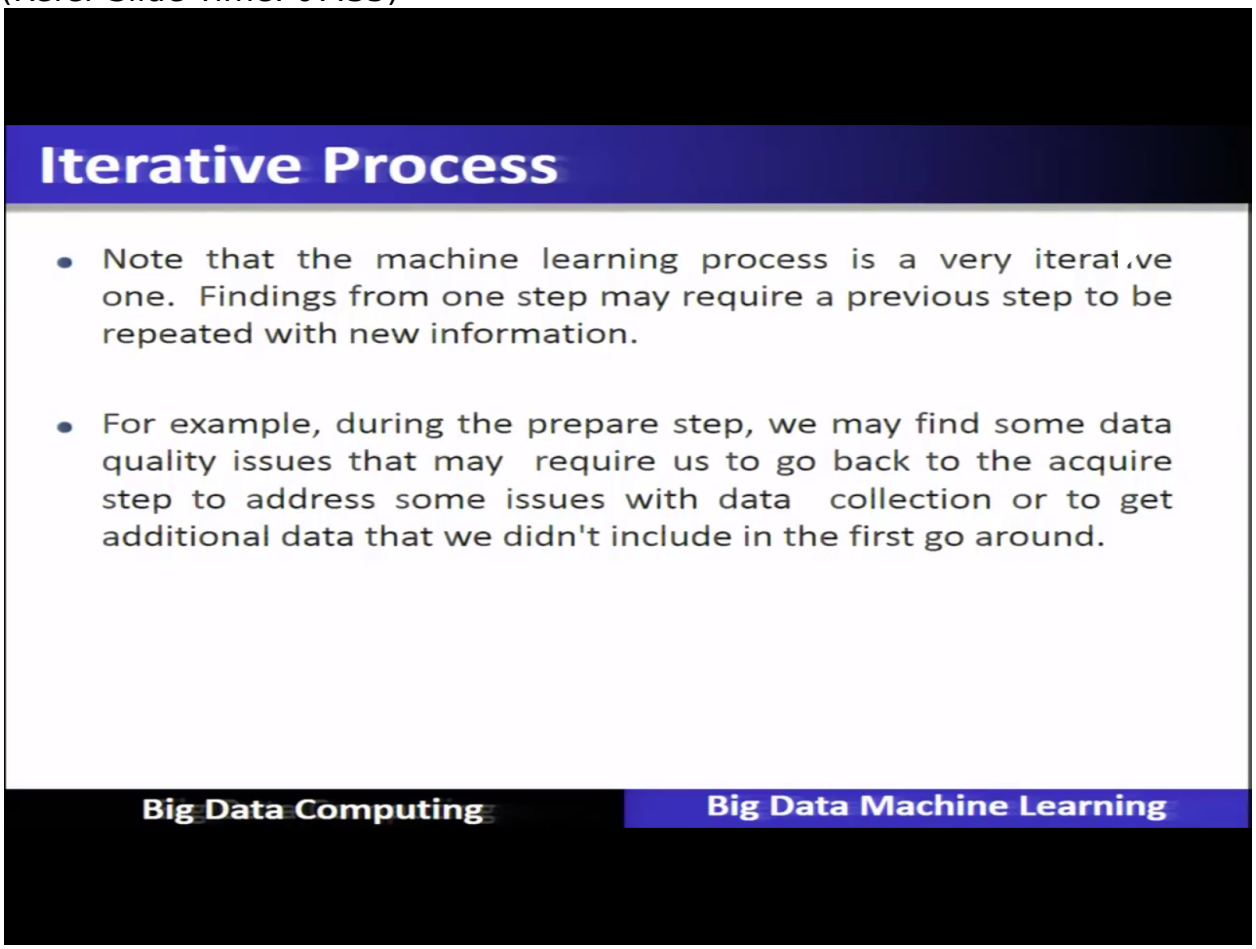

Now goals and activities in the machine learning process. So the goals and activities in the machine learning process, we will describe the goals from each step and the key activities performed in these steps.
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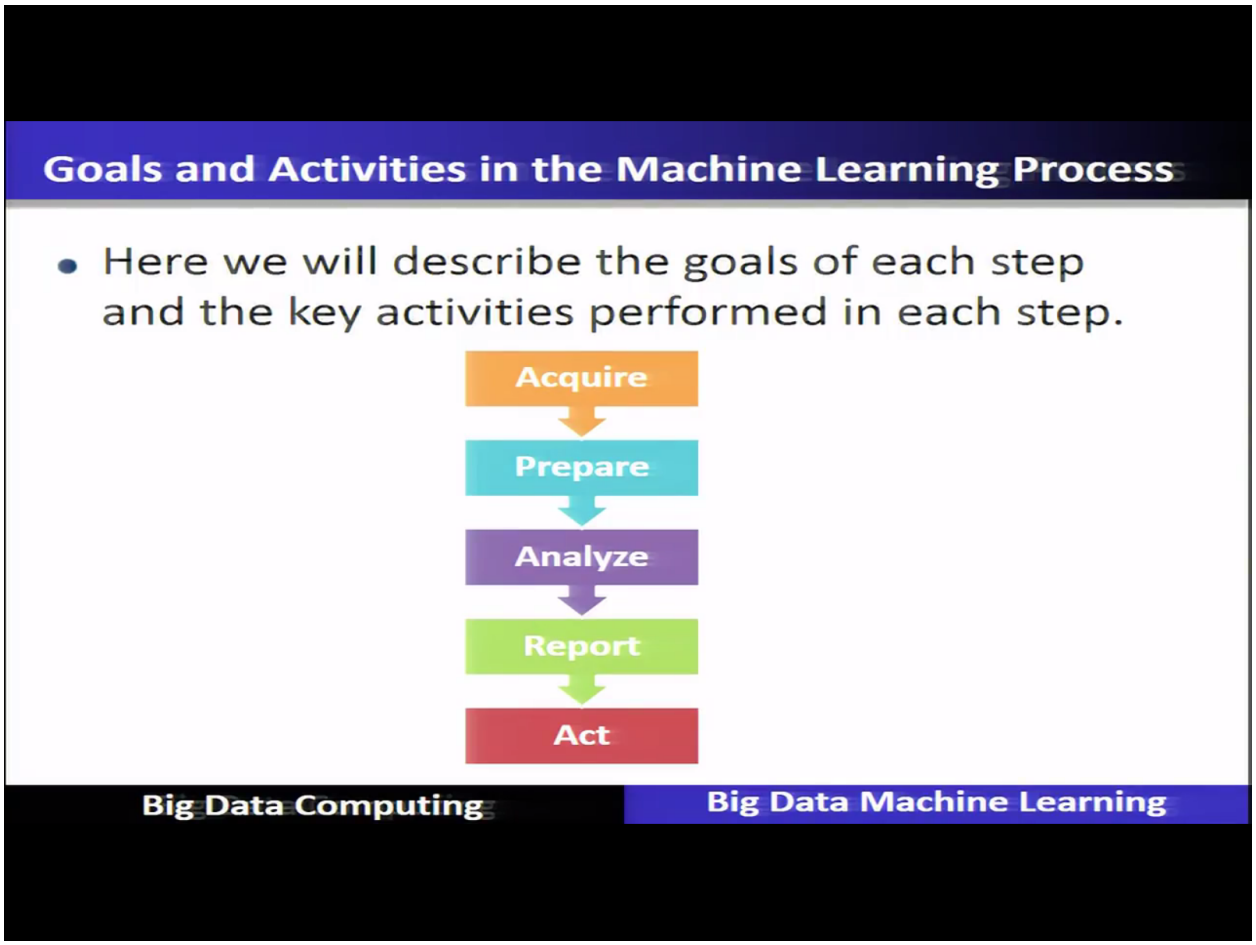

So to... in the first step, that is data acquisition or to acquire the data, the first step, this is used also in the... in the data science to acquire the data. The goal of this system is to identify and obtain all the data related to the problem at hand. First we need to identify all related data sources. Keep in mind that data can come from difference sources, such as files, databases, internet, mobile devices, and so on. So remember to include all the data related to the problem that you are addressing. So after you have identified your data and data sources, the next step is to collect the data and integrate the data from different sources. This may require conversion, as the data can come from different, with different formats, so it is required to convert the format, which is required to be use in your machine learning process. So this may require conversion as the data can come from different sources. And it may also require to align the data as the data from different sources may have different timing or special resolution. So once you have collected and integrated your data, you now have to make this data core and for your analysis.

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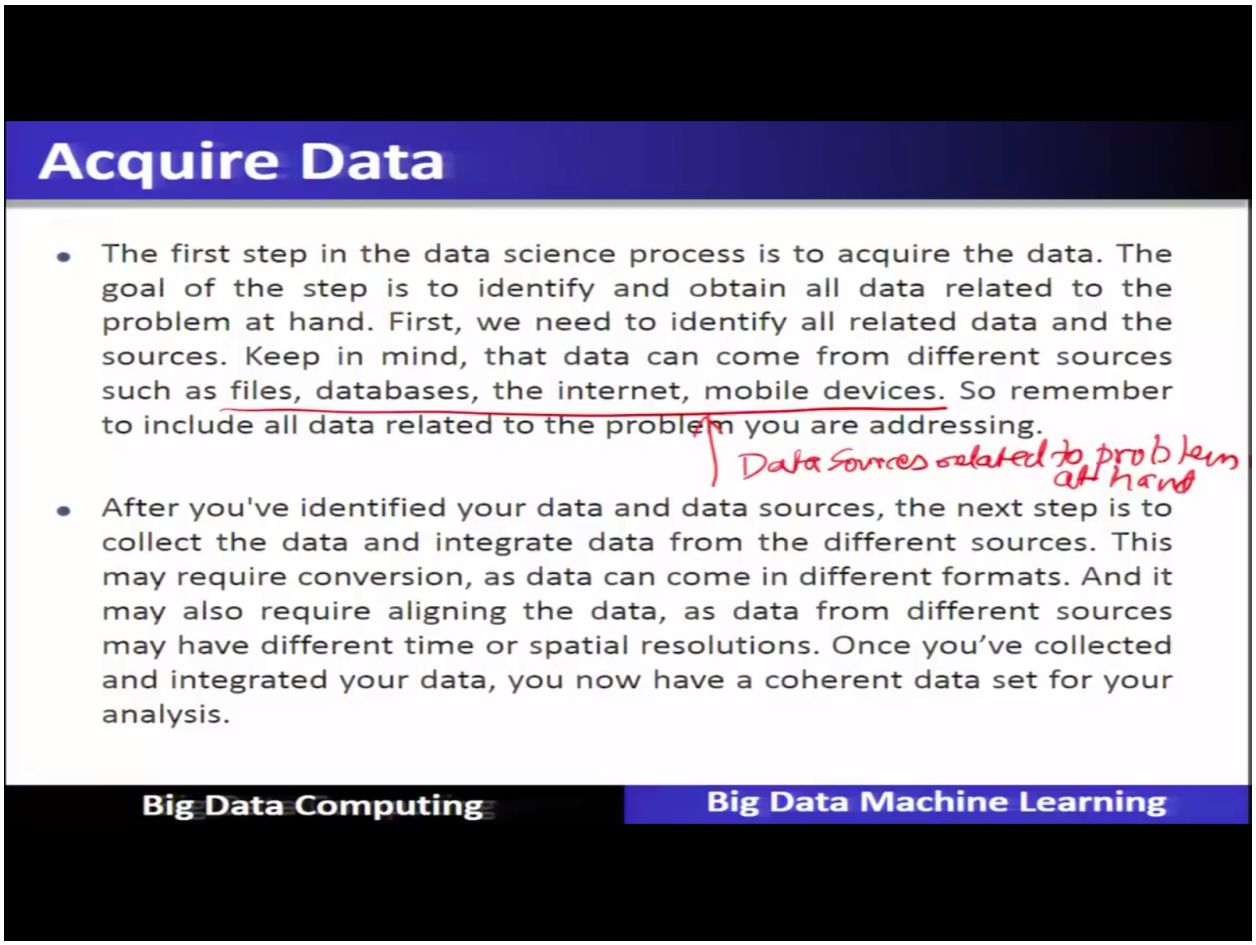

Second step is to prepare the data, the next step after acquiring the data is to prepare it to make it suitable for the analysis. There are two parts to this step, to explore the data and pre-process that we have already discussed.
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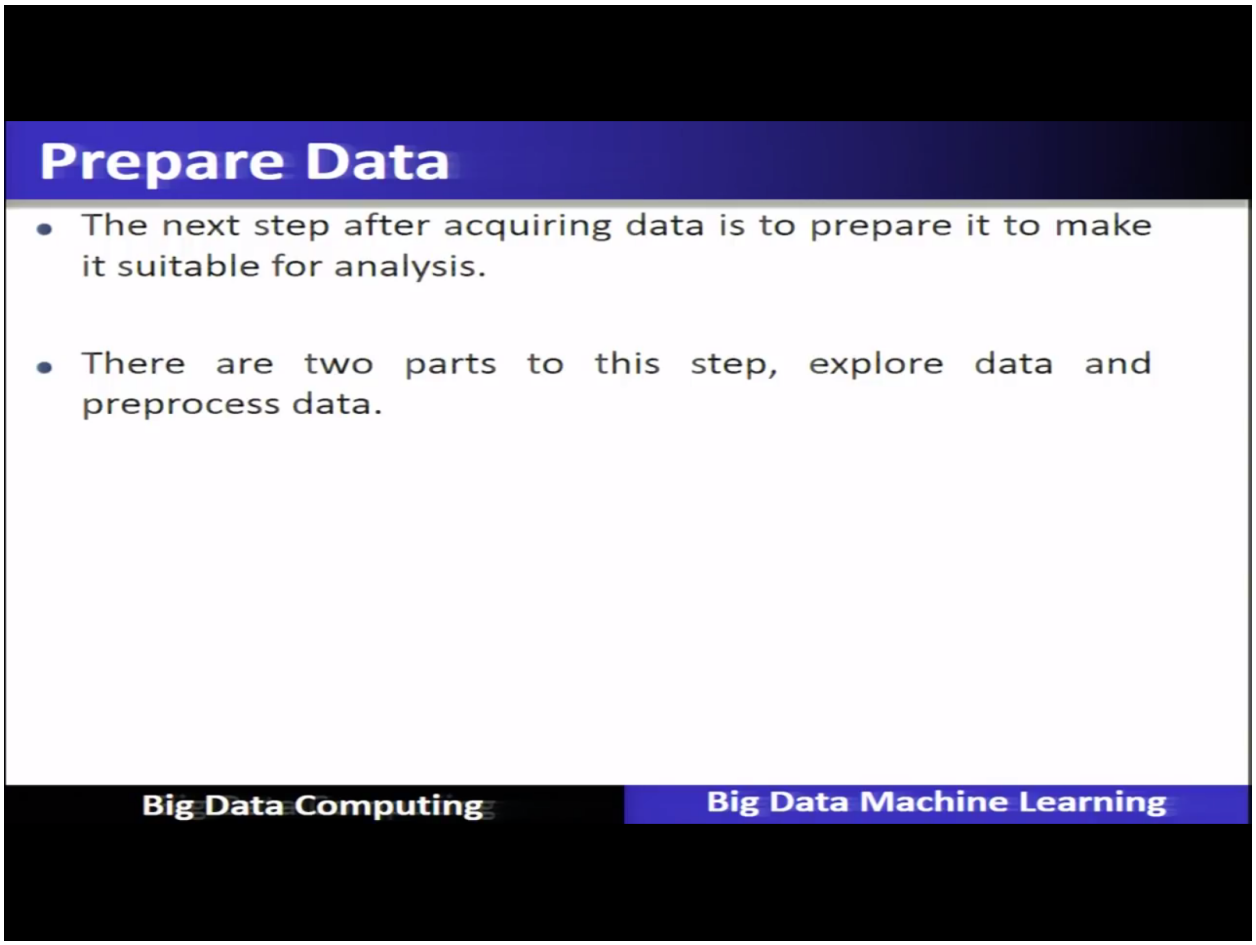

So data exploration, you want to do some preliminary investigation in order to gain the better understanding of specific characteristics of your data. This in turn will guide the rest of the process. With data exploration, you will want to look the things like correlations, general trends, outlets etc. Correlations provide the information about the relationship between the variables in your data, trends in your data will reveal if the variable is moving in a certain direction, such as transaction volume is increasing through the year. Outlets indicate the potential problems with the data or it may indicate an interesting data point that needs to be further examination. Without this exploration activity, you will not be able to use your data effectively. So the data exploration requires preliminary investigation, which needs... which involves the steps like to how to gain the better understanding of the data and by that process you will find out the correlation, general trend, and outlets. So correlations will provide the information about the relationship between different variables in your data and also it will reveal the trends if the data, if the variable is moving in certain directions such as the transaction volumes increasing throughout... throughout the year, that is it will identify the trends with the data. And third thing is very important, which will be processed in the data exploration part is called outliers. So by this

data exploration, you can identify the outliers. And this outliers have to be dealt with at this stage, that is in the data… data exploration stage.
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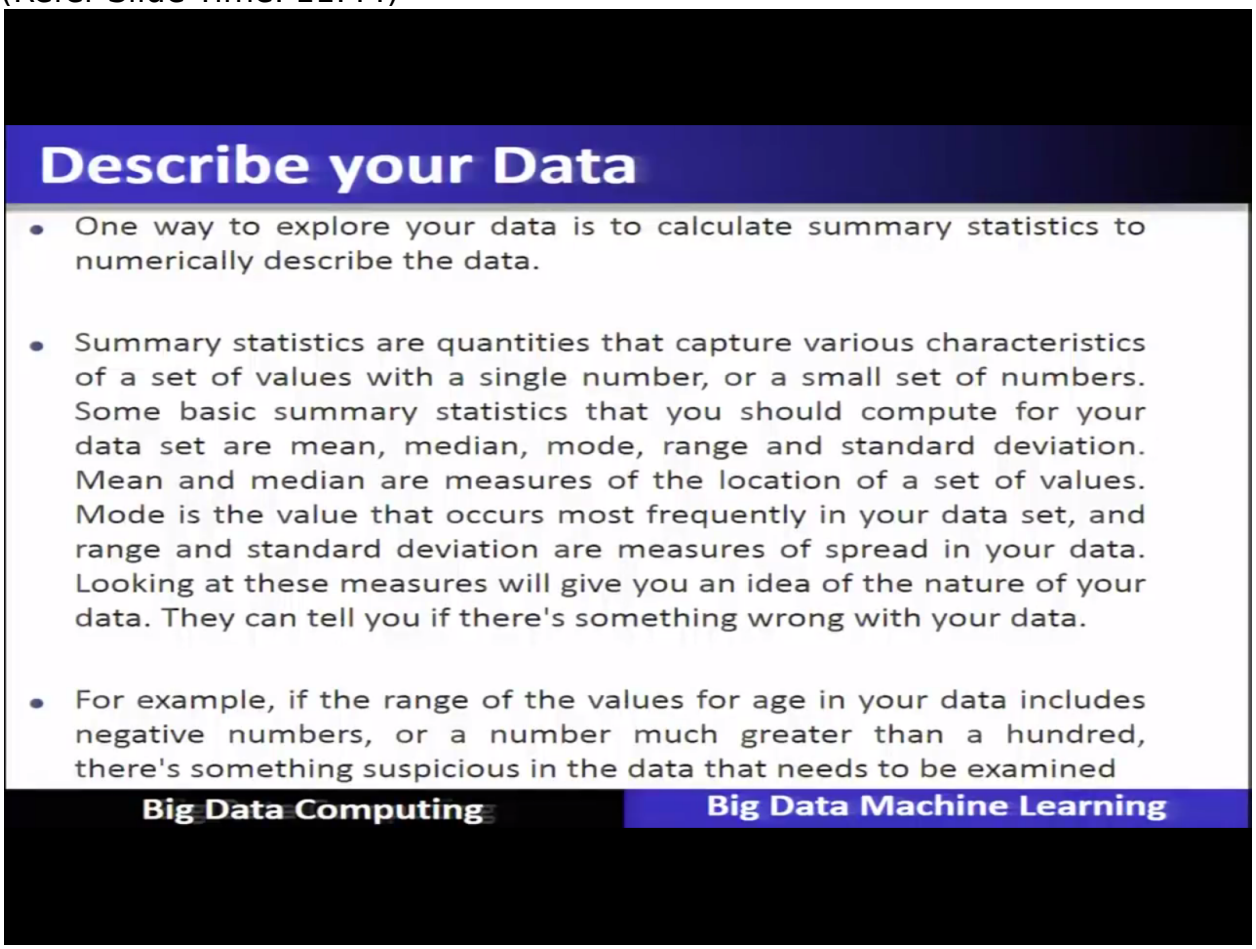

Next part is to describe your data. Once you explore your data to calculate the summary statistics to numerically describe the data, now this summary statistics are the… are the quantities that capture various characteristics of the severe of values with a single number or a set of small numbers. Some basic summary statistics that should compute your data set are mean, median, mode range, range and standard deviation. They are the summary statistics of your data. So mean and median will measure, are the measures of location of the set of values. So mean location is, for example, if this is the data, this is the mean, so it will give the central… Centrality, location of the data, location of the set of values. Similarly mode is the values that occurs most… most frequently in your data set. And the range and the standard deviation are the measures of the spread of your data. Looking at these measures you will… you will get an idea of the nature of your data and they will tell you that if your… that if there is something wrong in your data set, then you have to basically refine your data at this stage. For example if the range of values for the age in your data set includes a negative number, then obviously it is an outlier, or the number is greater than a 100 in the age,

then it's something suspicious in the data and that needs to be corrected upon.
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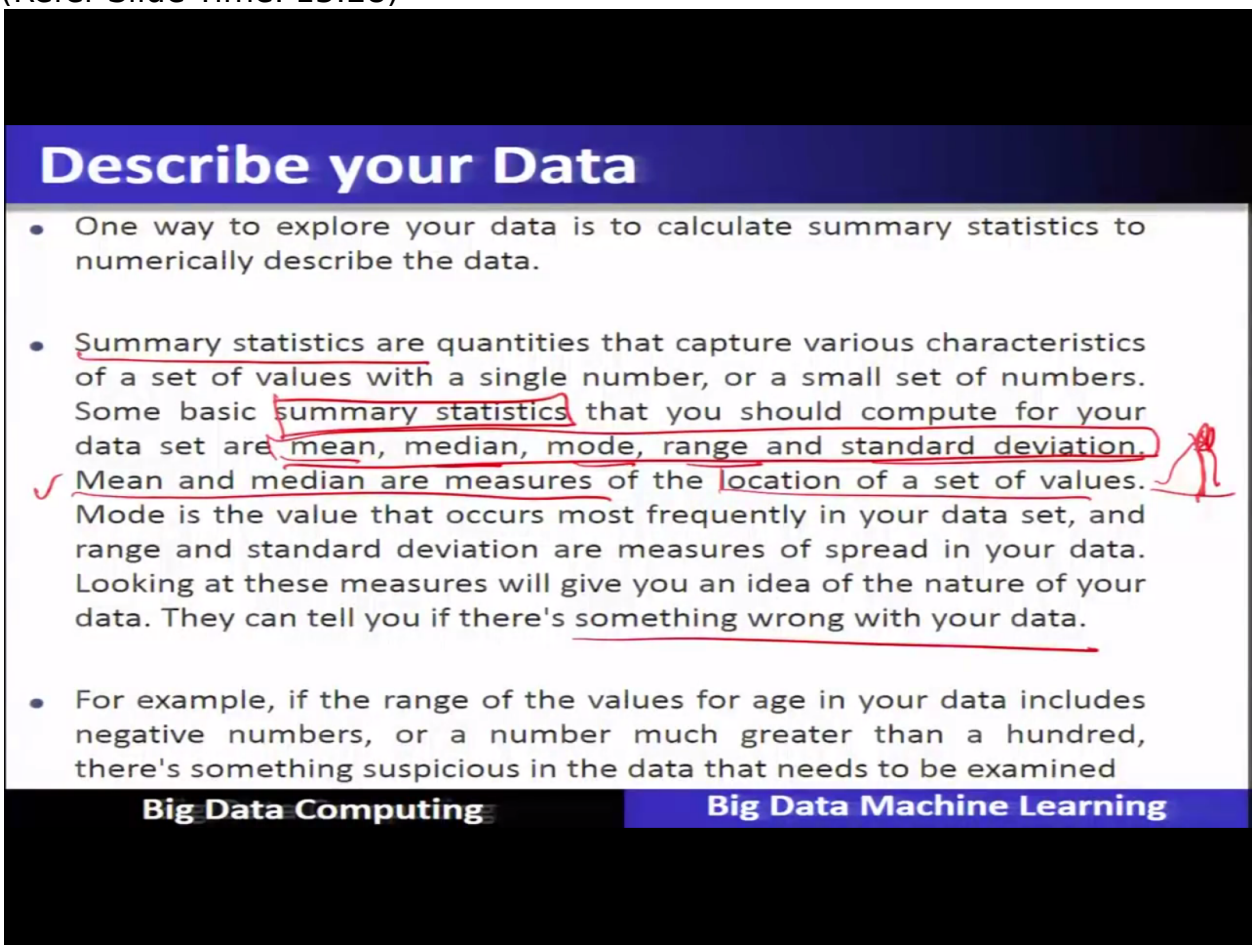

Now the next step is called the visualization, visualize your data, visualization techniques also provide the quick and effective ways to explore your data. For example the use of histogram plots will understand the distribution of data or the skewness or unusual dispersion and outliers of the data. So line plot like the one in the lower plot shown over here can be used to look the trends in the data as the change of the prize on the stock. The heat map also is one of the visualization technique of your data, give an idea about where the hot spots are. Scatter plots effectively show the correlation between the two variables and overall there are many other type of plots to visualize your data. They are very useful in helping to understand behavior of your data.
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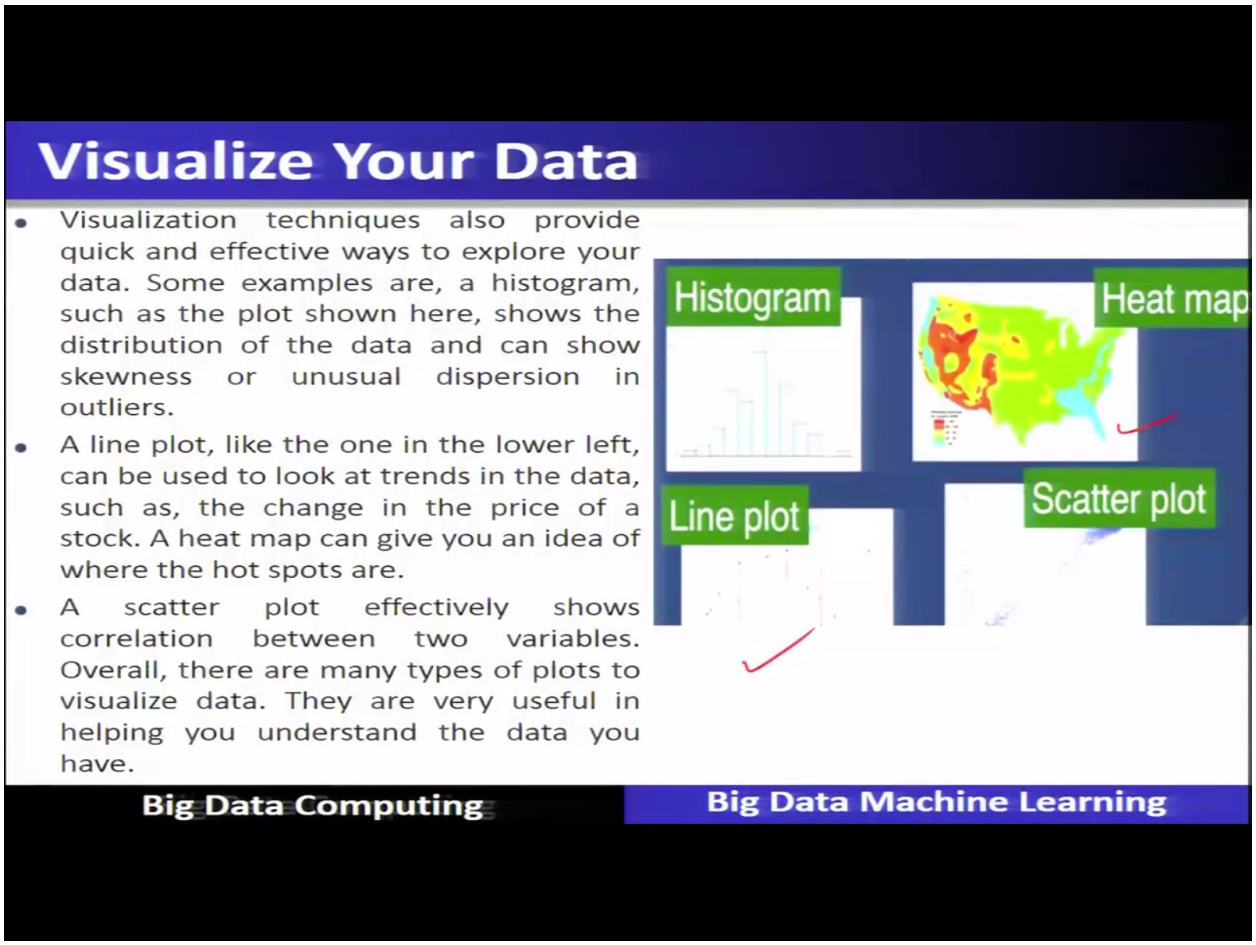

Now pre-processing step. So after you have explored the data, the next step is the pre-process the data, to prepare for the analysis. The goal here is to create the data that will be used for the analysis. The main activities of this pre-processing is to clean the data, select the appropriate variables to use and transform the data as needed.
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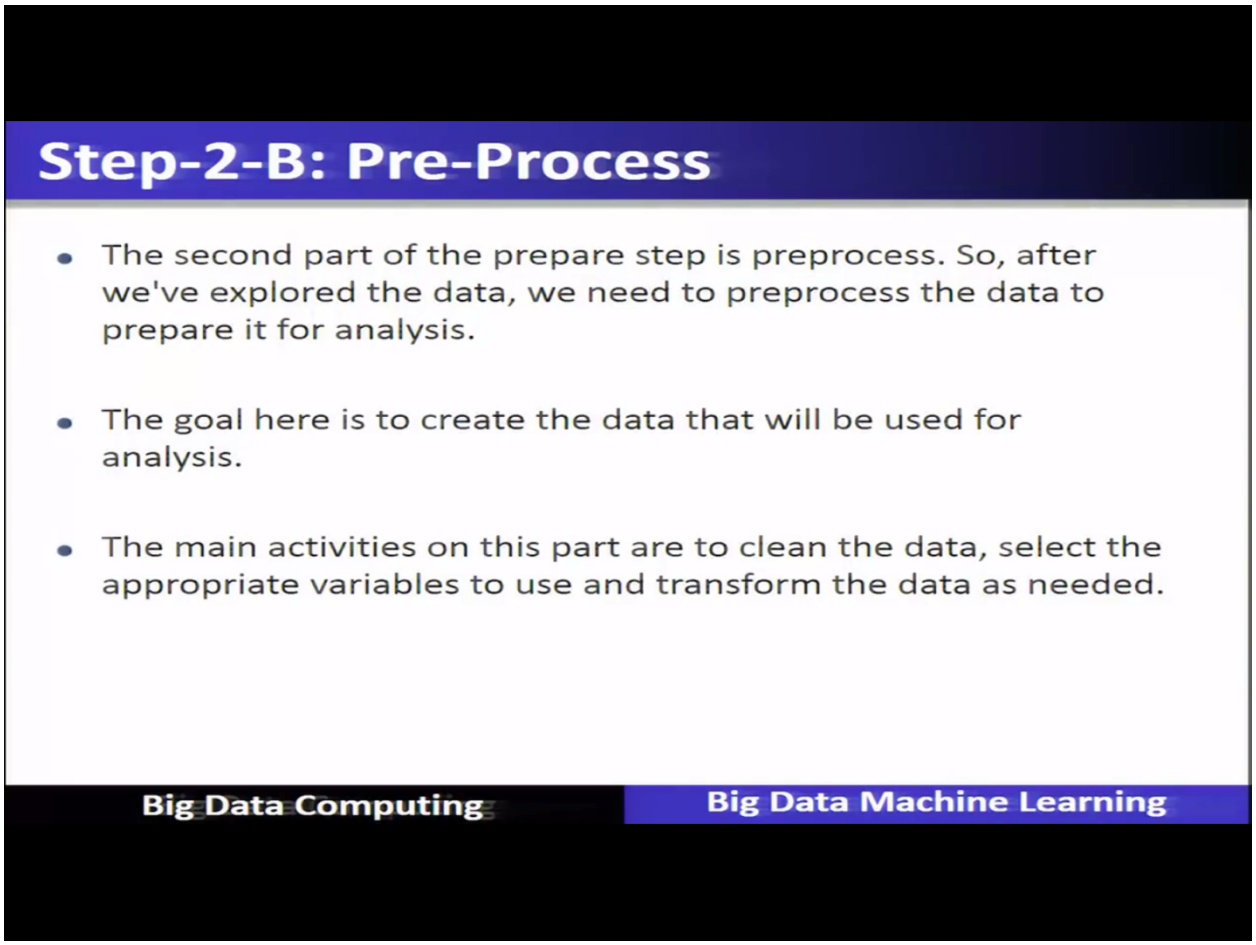

So let us see, what do you mean by cleaning the data or that data cleaning. A very important of data preparation is to clean the data to address many quality issues. Real world data is nothing and there are many examples of a quality issues with the data from the real applications including missing values, such as income in the survey duplicate data, such as two different records of the same customers with different addresses. So inconsistent or invalid data such as security zip code, noise in the collection of data that distorts the true values, outlier such as numbers larger than 100 on someone's age is also an essential to detect and address these issues that can negatively affect the quality of the data.
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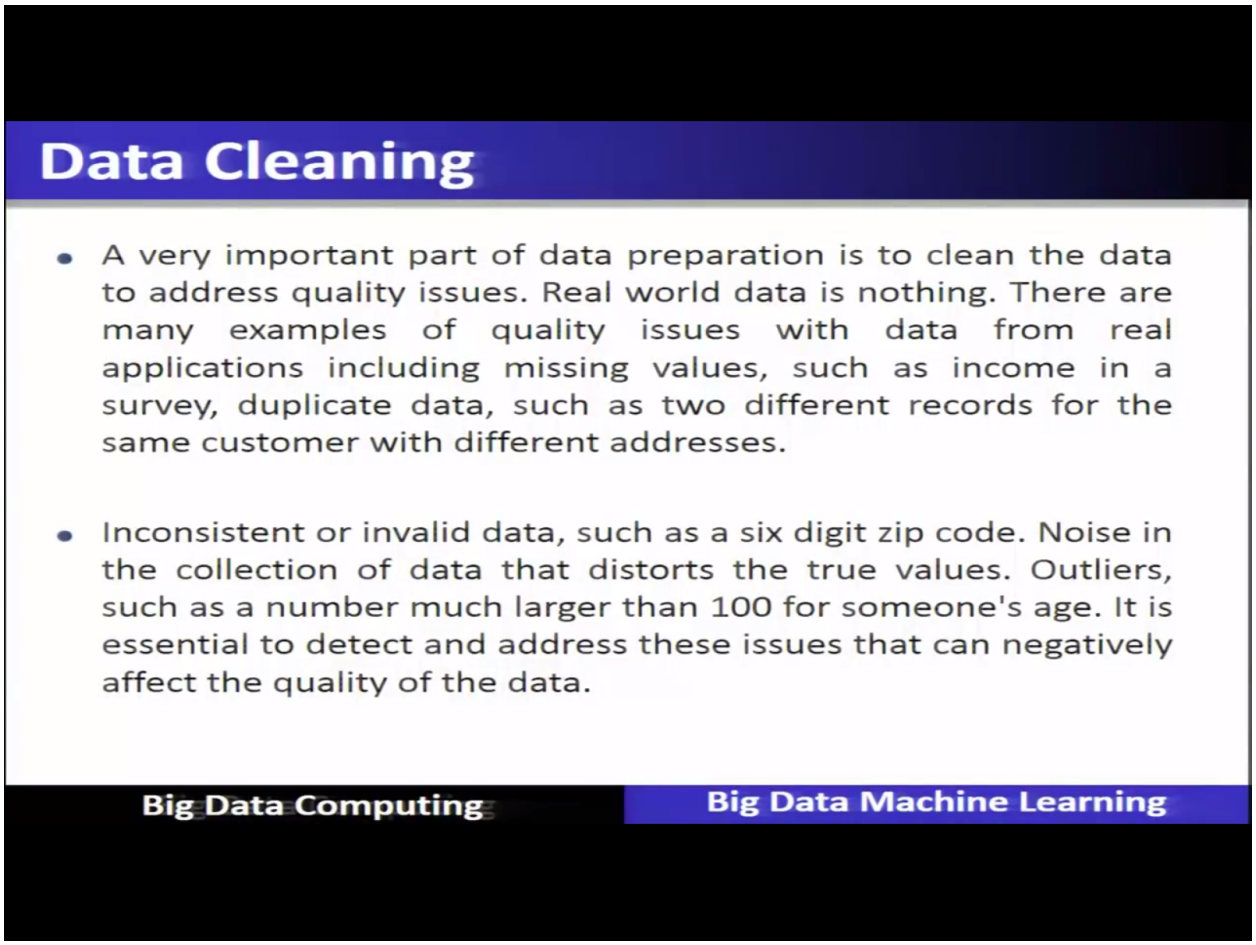

The next important part is about the feature selection, feature selection, first choosing the set of features to use, that is appropriate for the application. Feature selection can involve removing redundant or irrelevant features, combining features or creating the new features. So during the exploration data step, you may have discovered that two features are very correlated. In that case one of these features can be removed without negatively affecting the analysis result. For example the purchase price of a product and the amount of sales tax are very likely to be correlated, similarly the age and the weight of a person are highly correlated. So eliminating the sales tax would then be beneficial. So removing redundant or irrelevant features will make the subsequent analysis more simpler and more accurate. So you may also want to combine the features to create the new ones. For example adding the applicants educational level as a feature to a loan approval application would make more sense and there are also algorithm to automatically determine the most relevant feature that... based on various mathematical properties.

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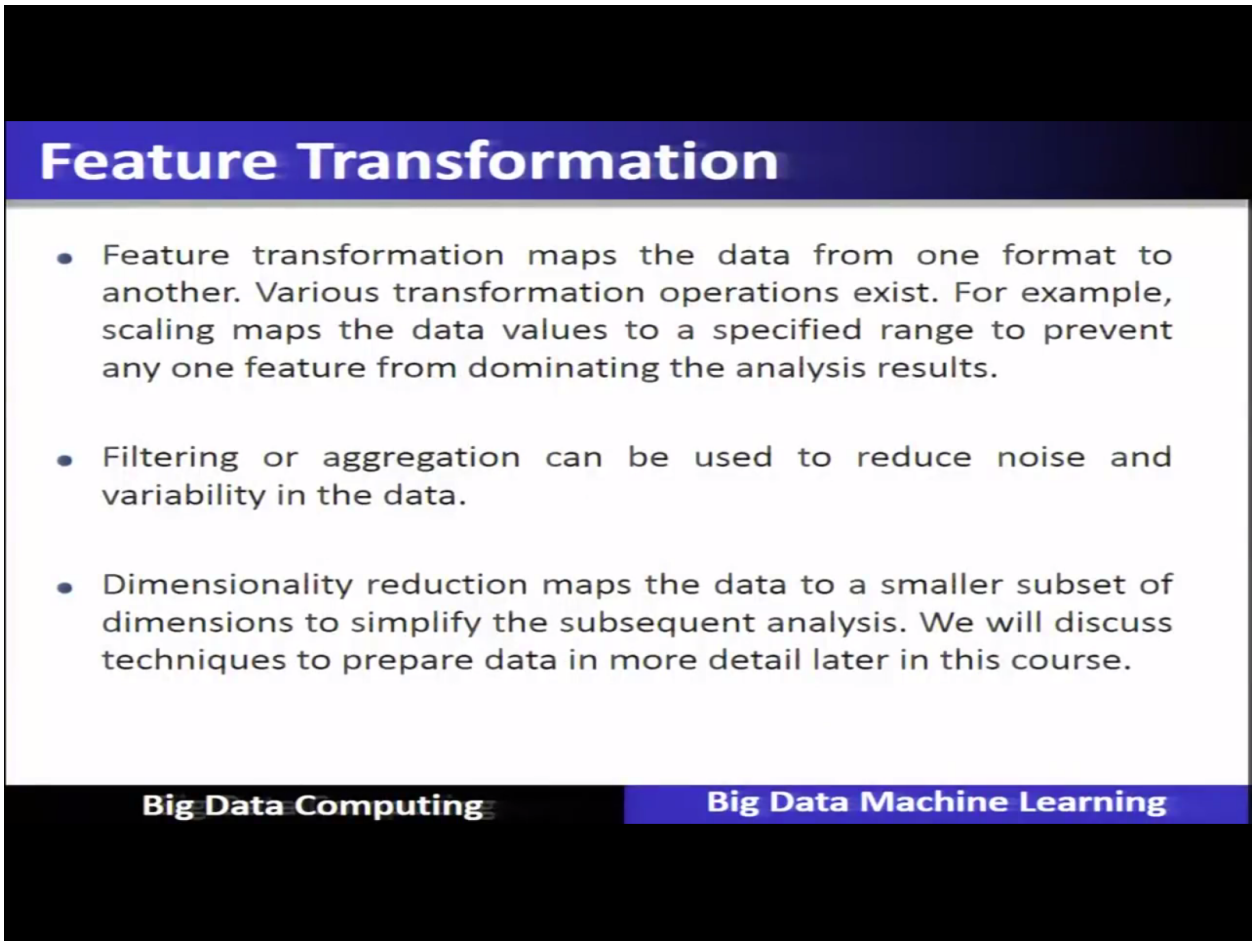

Then feature transformation. Feature transformation maps the data from one format to another format, various transformation operations exist, for exampling scaling map, the data values to a specific range to prevent any feature from dominating the analysis result. This is very important to be handled. So filtering or aggregation can be used to reduce the noise and variability in the data. Dimensionality reduction maps the data to a smaller subset of dimensions to simply file the subsequent analysis. We will discuss these techniques, how to prepare the data using future transformation in further slides.

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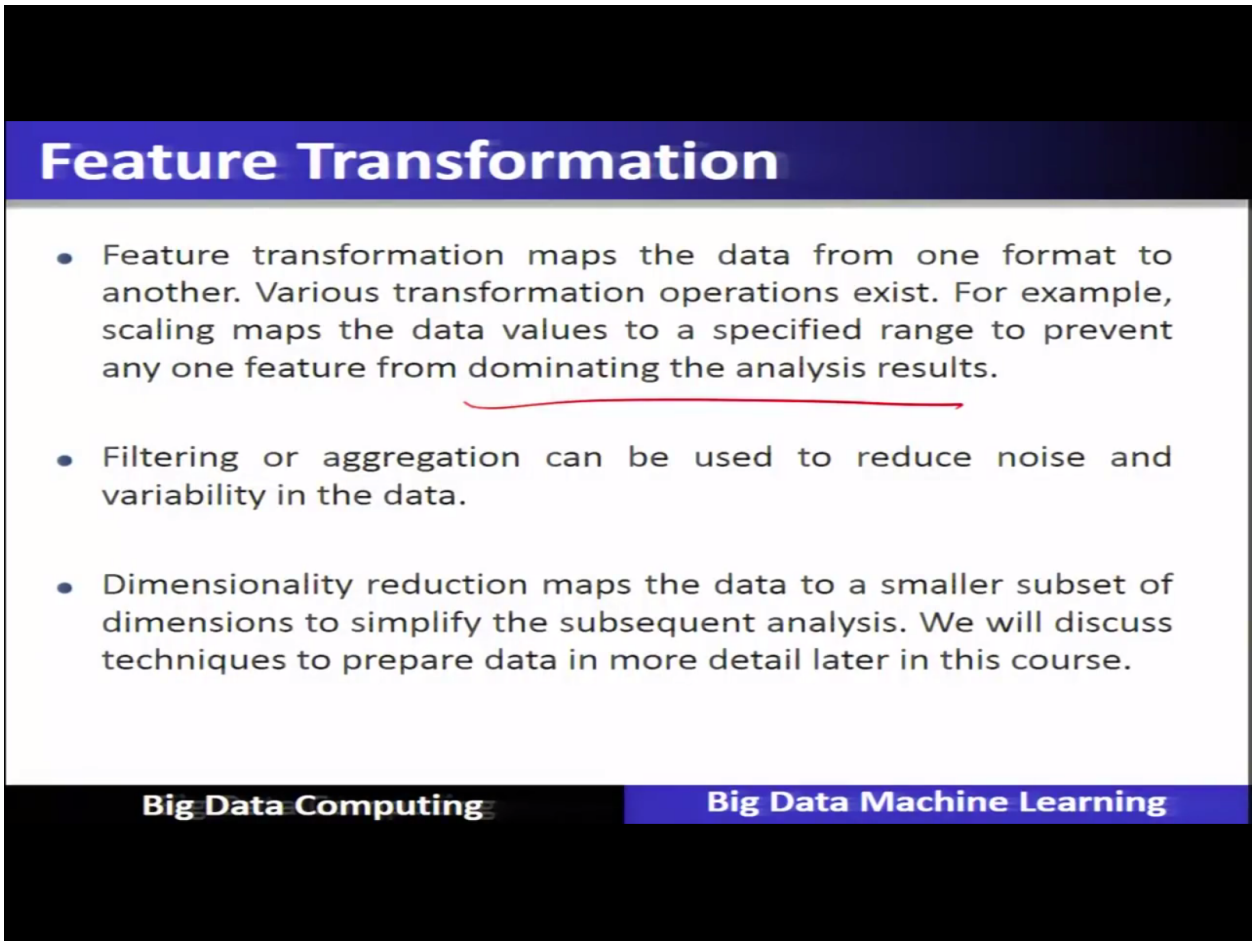

Now another step is to analyze the data. So after preparing the data to address, address the quality issues and pre-process it to get in appropriate format, the next step would be to use that particular data for the machine learning process to analyze. The goal of this... the goal of this step is to build the machine learning model to analyze the data and to evaluate the results that you get from the model. So the analysis step starts with this determining the type of problem you have, you began selecting the appropriate machine learning techniques. So the selection of machine learning techniques is the important step of analyzing the data. Then you construct the model using the data, that is also called, to fit the machine learning techniques with the data, fit the model on the data, fit the machine learning. So that is called the construction of the a modal with the data you have prepared. So once the model is build, you will want to apply this model to a new data. Sample to evaluate how well your model behaves. Thus the data analysis involves selecting the appropriate techniques for your problem, building the model and evaluating the results.
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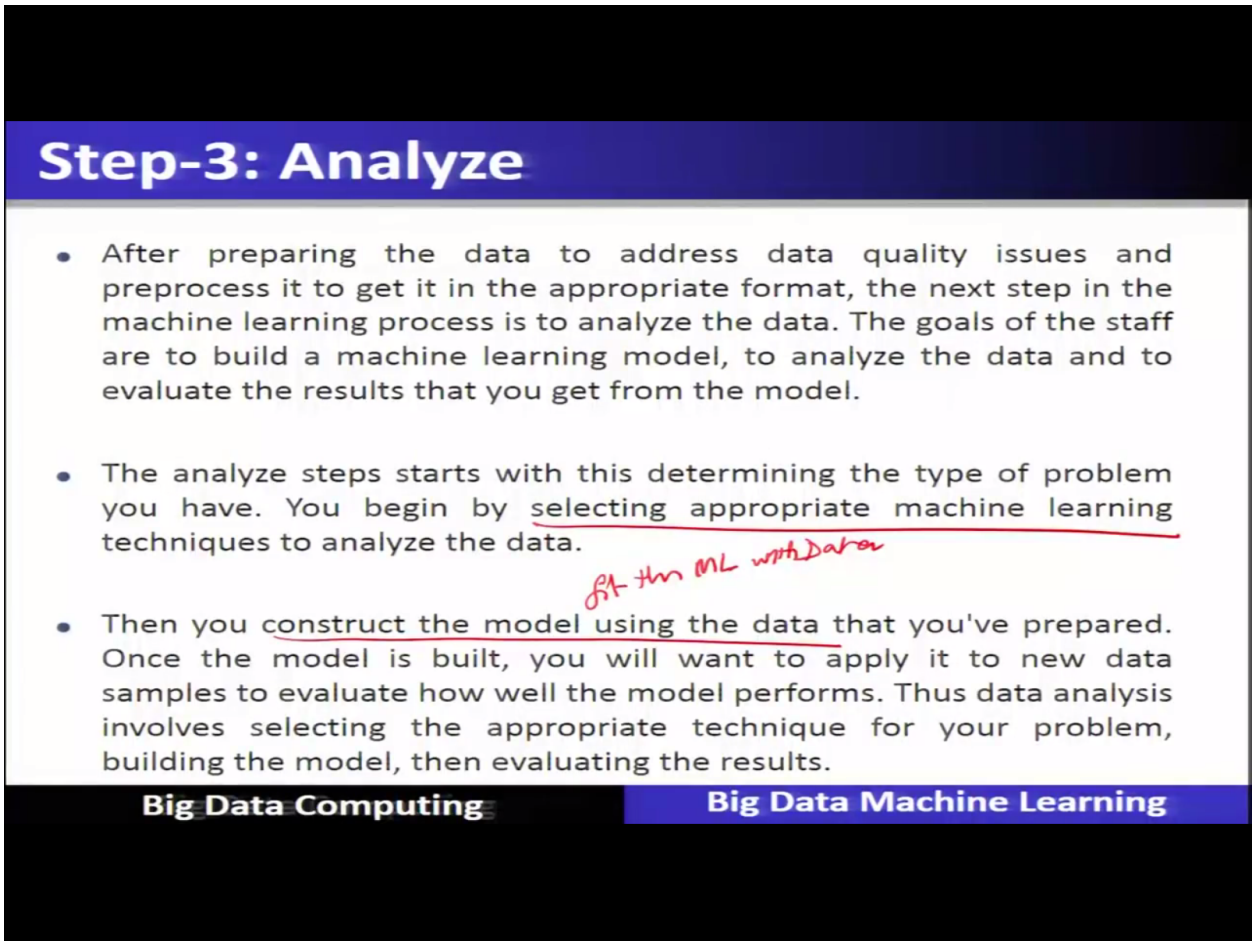

Step number four is about the report. The next step in the machine learning process is reporting the result from your analysis. In reporting your result, it is important to communicate the insight, to make a case for that action to follow. In reporting your result, you will be... think about what to present and how well to present? In deciding what to present, you consider what main results are, what insights you have gained from your analysis and what added the values to these insight to the application. Keep in mind that even the negative results are the... value will learning and suggest further avenues or additional analysis. Remember that all the findings must be presented so that it informs the decision makers for the further steps. So in deciding how to present remember that the visualization is also an important tool in presenting your results. So plots and summary statistics discussed earlier, explore... in the data exploration can be used effectively here as well. You should have the tables with the details from your analysis as backup, if someone wants to take the deeper dive into the results for that purpose. So in summary you want to report your findings by presenting your results and the value added with the graphs using the visualization tools.
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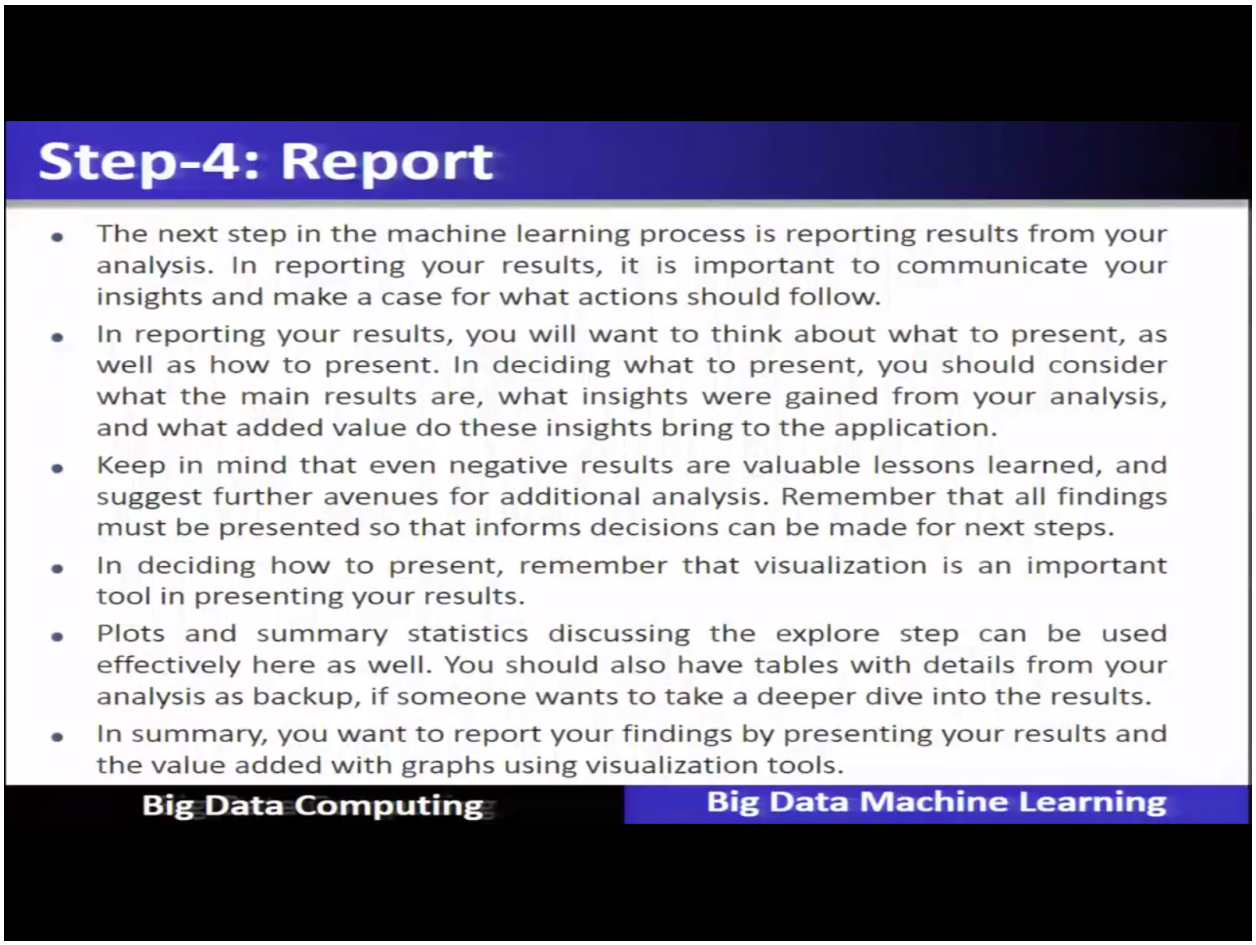

Fifth step is to act. Final step in the machine learning process is to determine what action should be taken based on the insights gained. So what action should be taken based on the results of your analysis? Should you, should you market certain products to specific customer segment to increase the sales? What inefficiency can be removed from your process? What incentive should be affective in attracting new customers. So these are some of the important actions, you can perform based on this analysis of the outcome. So once the specific action has been determined, the next step is to implement the action. And things to consider here include how can the action be added to your application. How will this... and users be affected. Accessing... assessing the impact of implementing actions is then necessary to evaluate the result benefit gained. So the result of this assessment determines the next step, which would suggest the additional analysis for further opportunities. Which can, which would begin another cycle of machine learning process.

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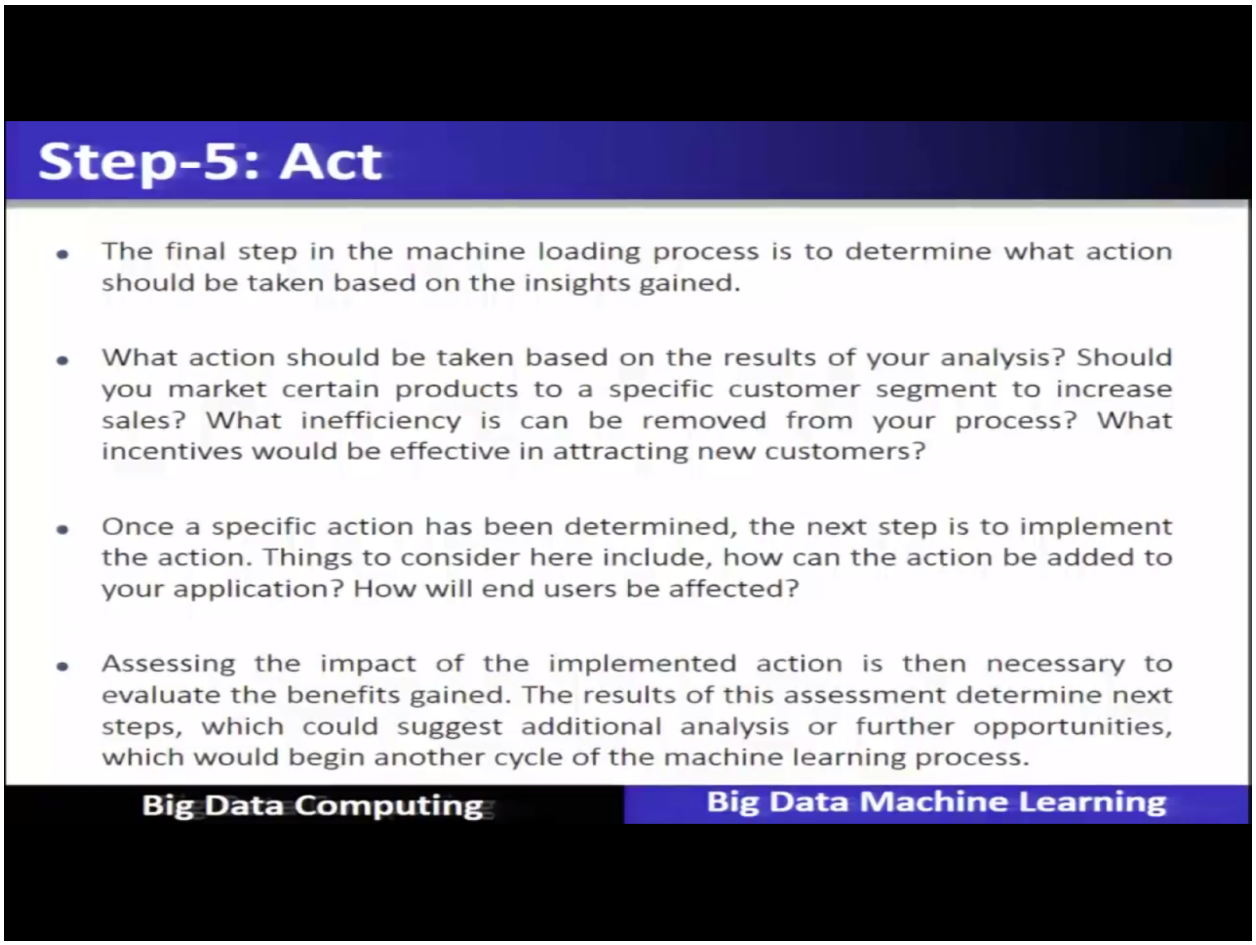

Generalization and overfitting. So the, it is about the errors in the classification of machine learning. So recall that the machine learning model maps the input, it receives to an output. So for a classification model, the model's output is predicted class labels for the input variables and the true labels is the target labels. So again in... let us see that in the classification model, the model's output is the predicted class labels for the input variables and the true labels are the target labels, meaning to say that, if this is the classification model, which is shown as the box, whereas the input is the... the data, which is basically having the input variable, input data with label, or it is also called as the label data and which is prepared in this format. So this particular classification model will give the... the predicted class label, which is also there with the... with the data. So it will give the predicted class. Now this predicted class, this is an output label. Now this label can be compared with the... with the input label. So that is what is mentioned over here. Let me summarize this. So the model's output is called the predicted label for the input variable. So the model's output is the... is called the predicted label class. So this is the output of a model. For the input variable, this is the input variable and the true label is the target. So the true label is already there. True label is known. So the predicted label and the true label, both are now compared. The true label and the predicted output level, if both

are same, so we have to now compare about these two different labels. So then if the classifier predicts the correct classes label for the sample, that is a success. And if the predicted label is different from the true class label, then there is an error. Now we have to see these two different cases. So the error rate then is the percentage of the error made over the entire data sets. That is the number of errors divided by the total number of samples in the data set. So error rate is known as the misclassification rate or simply the error. So error is the error rate by the classification model.
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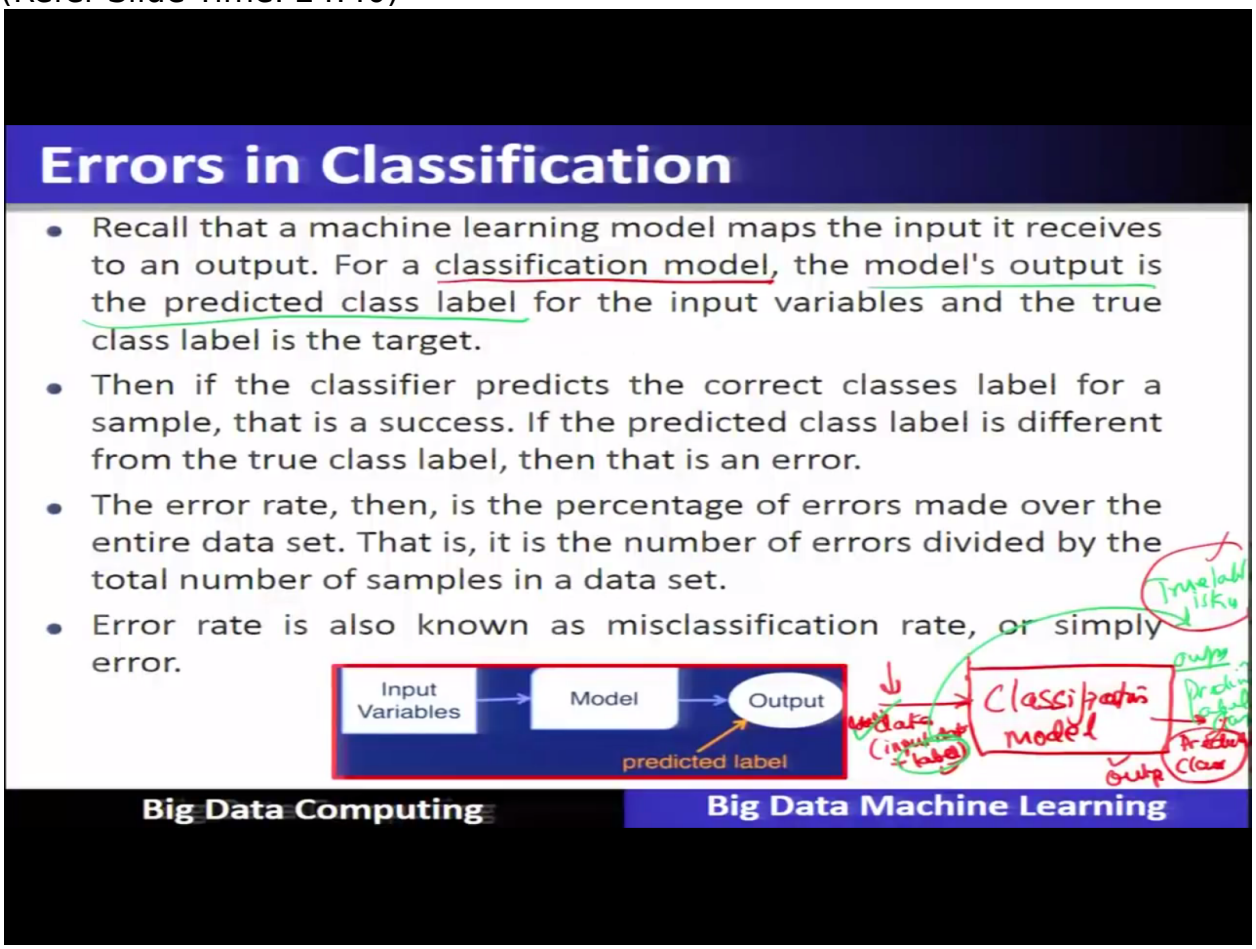

So let us discuss this machine learning stage, that is the classification. Now this classification stage is divided into the two parts, one is called the training phase and the other is called testing phase. So let us see here, this is called the training phase and the training phase includes the... the training data, which is the labeled data and also requires one machine learning algorithm. Using this particular machine learning algorithm will fit on the data and therefore it will, therefore it will build the model based on the... the machine learning technique which is applied on the training data. So once the model is build, this particular model is now available for the evaluation of the training phase. This is called training phase. Now the other phase is called the testing phase. In testing phase also we have the... the test data

and the model which is now being created. So the model is the same, which is created over the training phase. So that particular model will now be given new data and this is called as the test data... it's the new data, which is not seen by the training phase. So when a new data is given to the model, now this model will do the predictions based on this test data and it will give the result that is the output label and it will be compared with the... with the target label... output label to be compared with target label. So this particular way we are going to do the testing. So based on these particular analysis of these particular model, we are going to see the activities in the testing phase.

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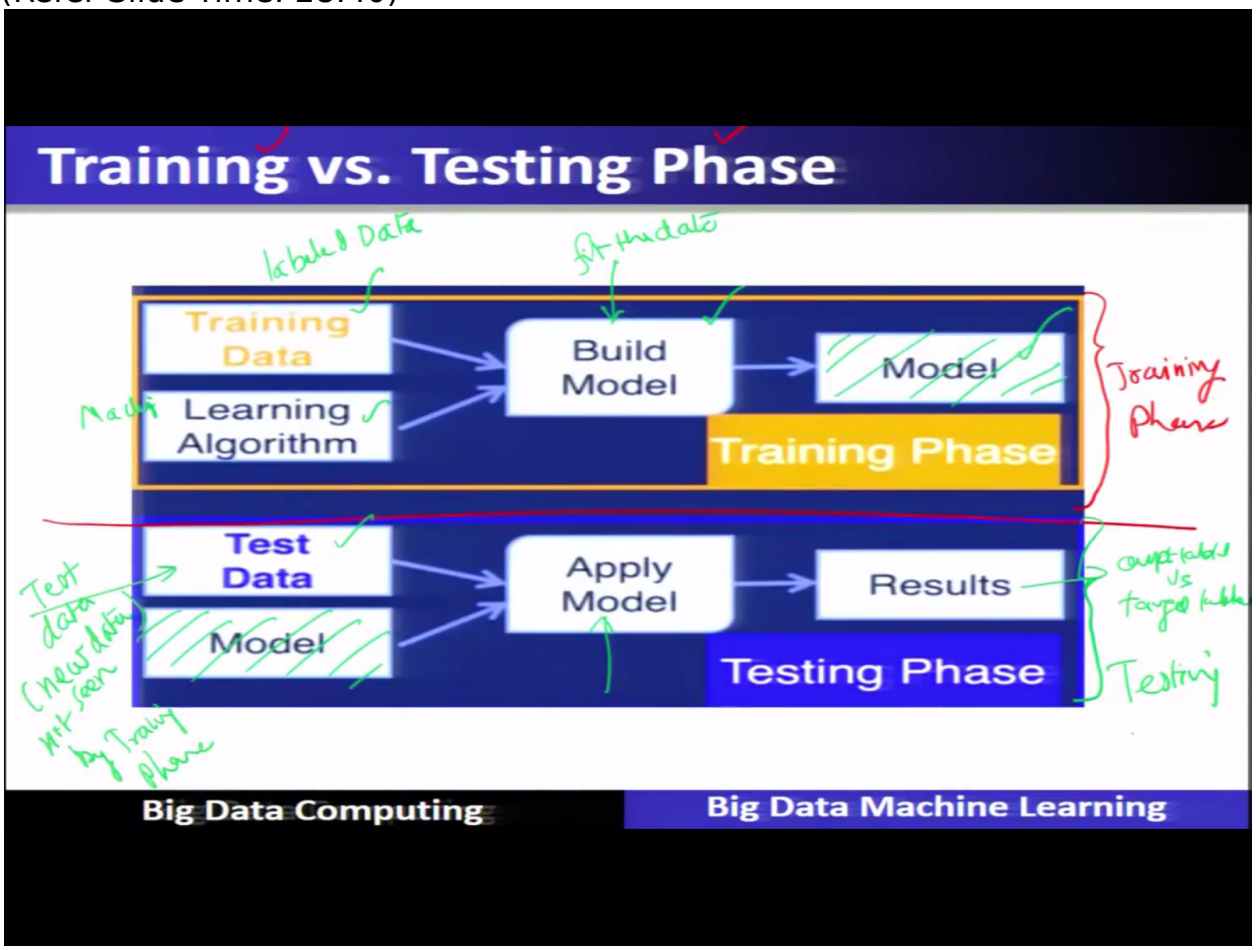

So therefore let us see more insight into the errors of... errors and the classification. The model is built using the training data and evaluated on the test data, that we have seen in the previous slides. So the training and test data are the two different data sets. The goal in building the machine learning mold is to have the model perform well on the training as well as on the test data. So the model which is... which is created, will perform well on the training as well as it will be also perform well in the test data. Now error rate are simply the error on the training is refer to as the training error, similarly the error on the test data is referred to as the test error. So there

are two types of errors. So training error or the test error. Again to understand, we have to... just you have to recall. What we have done is, there were two different phases, one was called the training phase, training phase will take the training data and the machine learning algorithm and it will build a model, this particular model will also give an error, classification errors, which are collected and it is called a training error. Now this particular model is given back again, is used again in the testing phase and we will have another data that is called test data. Test data, when it is given to the model, now it will perform and it will give an error, and this error is called testing error. So there are two different type of errors, one is called training error and the other is called testing error. So the error on the test data is an indication, how well the classifier will perform on the new data.
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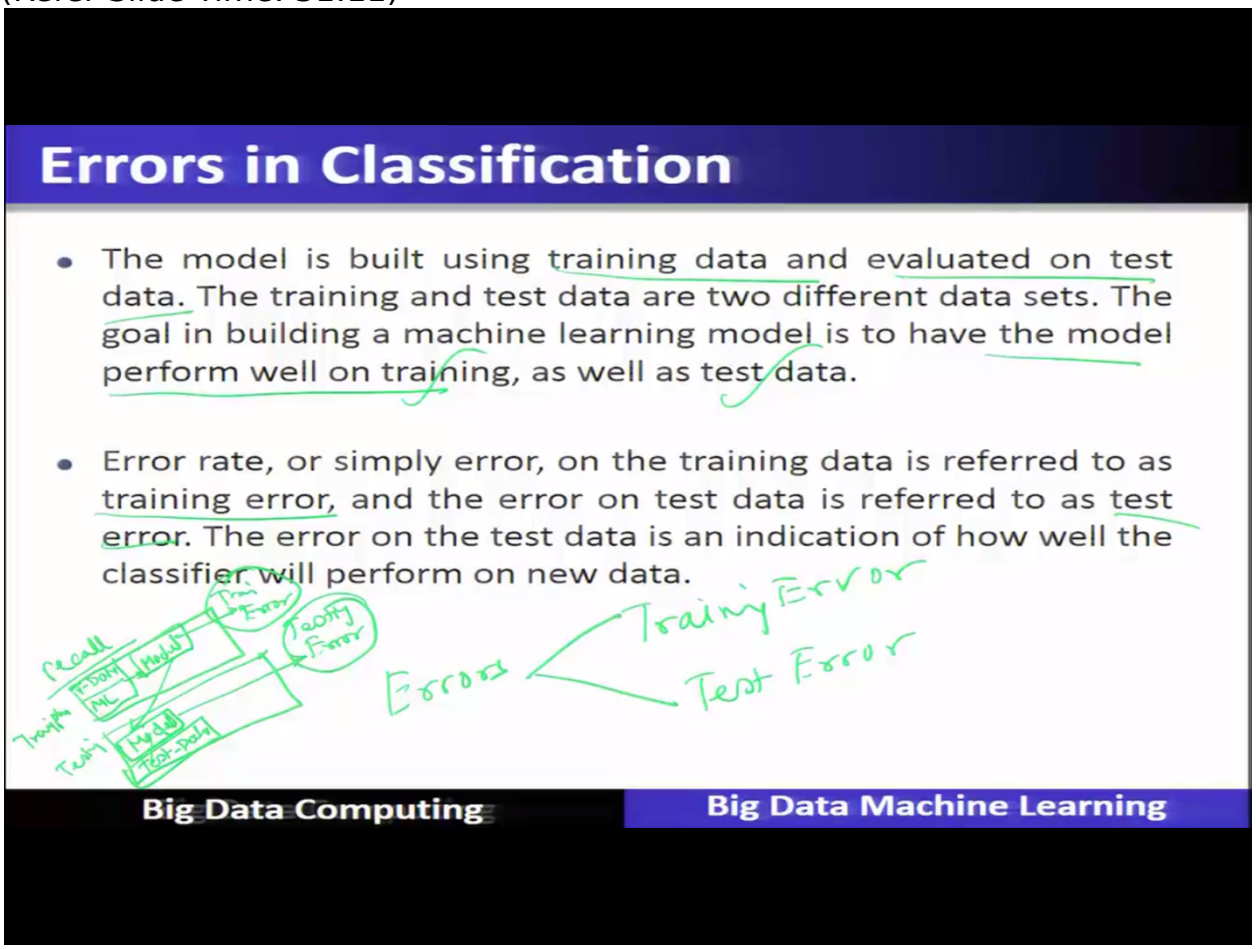

Now generalization. This is known as generalization. Generalization refers to how well your model performs on a new data, that is the data not used to train the model. Now you want your model to Generalize well to the new data. So if you model Generalizes well, then it will perform well on the data set. That I similar in the structure to the training data, but doesn't... contains exactly the same sample in the training data. Since the test error indicates

how well your model generalizes to the new data, note that the test error is also called the Generalization error.
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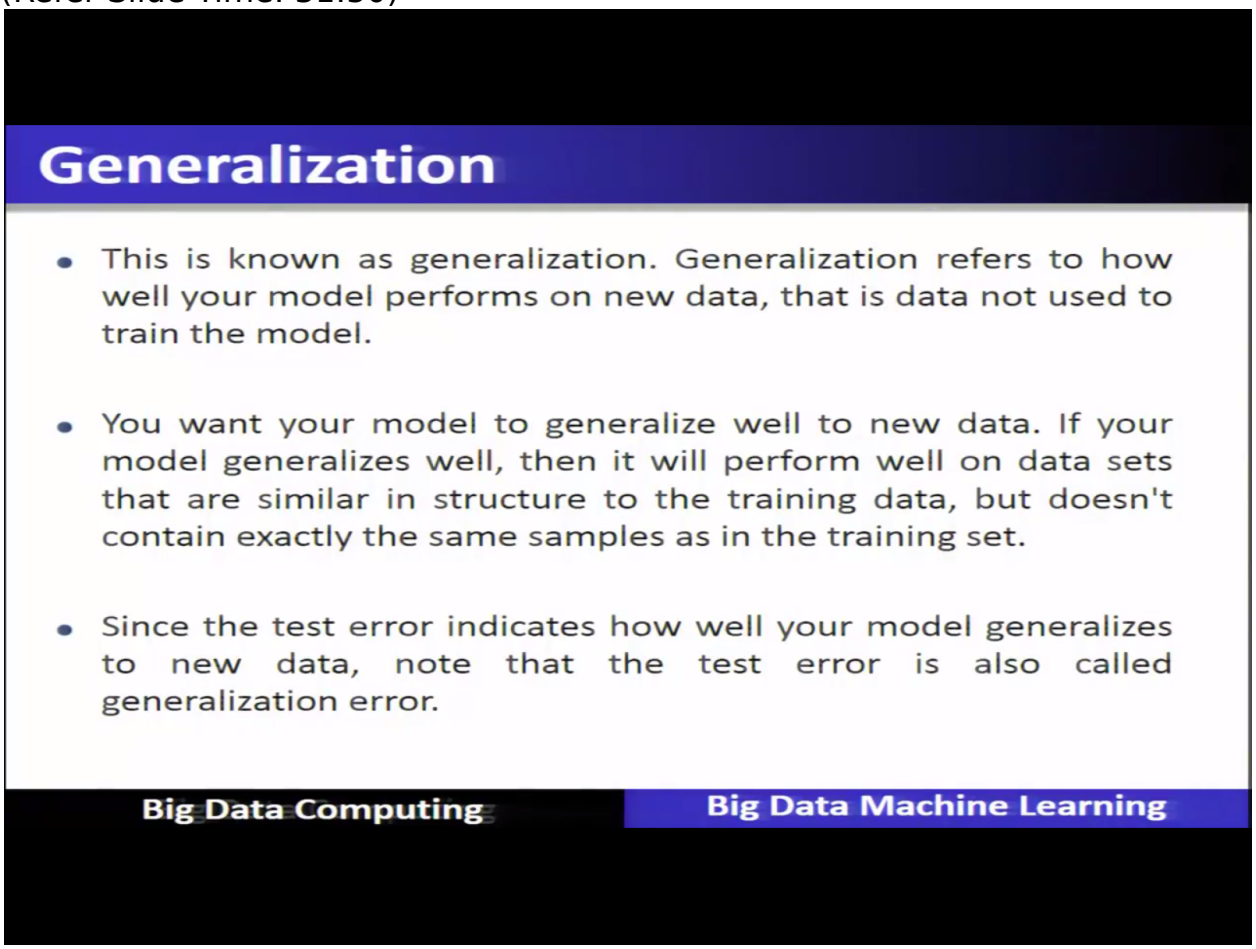

Now there is a concept which is called as overfitting. So related concept to the Generalization is called overfitting. So if your model has a very low training error, but has the high Generalization error, then it is called the overfitting. Meaning to say that during the training phase the error is less, but during the testing phase the error is more, hence it is called overfitting. This means that the model has learned to model… has learned to model the noise in the training data, instead of learning the underlying structure of the data, hence it is called overfitting. So overfitting at these plots illustrates what happens when a model overfits. So the training samples are shown as the points and the input to the… input to output mapping that the model has learned is indicated as the curve. So the plot on the left shows that the model has learned the underlying data structure as the curve follows the trend of the sample data point as well. So here you can see that this curve has learned the… the behavior of a data well. Hence it is a good fit during the training phase. Now this… there is another example, the plot on the right however, shows that the model has learned to model… the model has learned to the noise in the data set, for example this is… this curve is fitting

to the… to the noise and it has… and this is different from this particular curve, which has fit to the… to the underlying structure of the data. So this is an example of the overfitting and the left side graph, which shows this particular is a good fit. So the model which tries to capture every sample point instead of general trend of the samples together, that is the training error and that is generalization error are plotted together during the model training.

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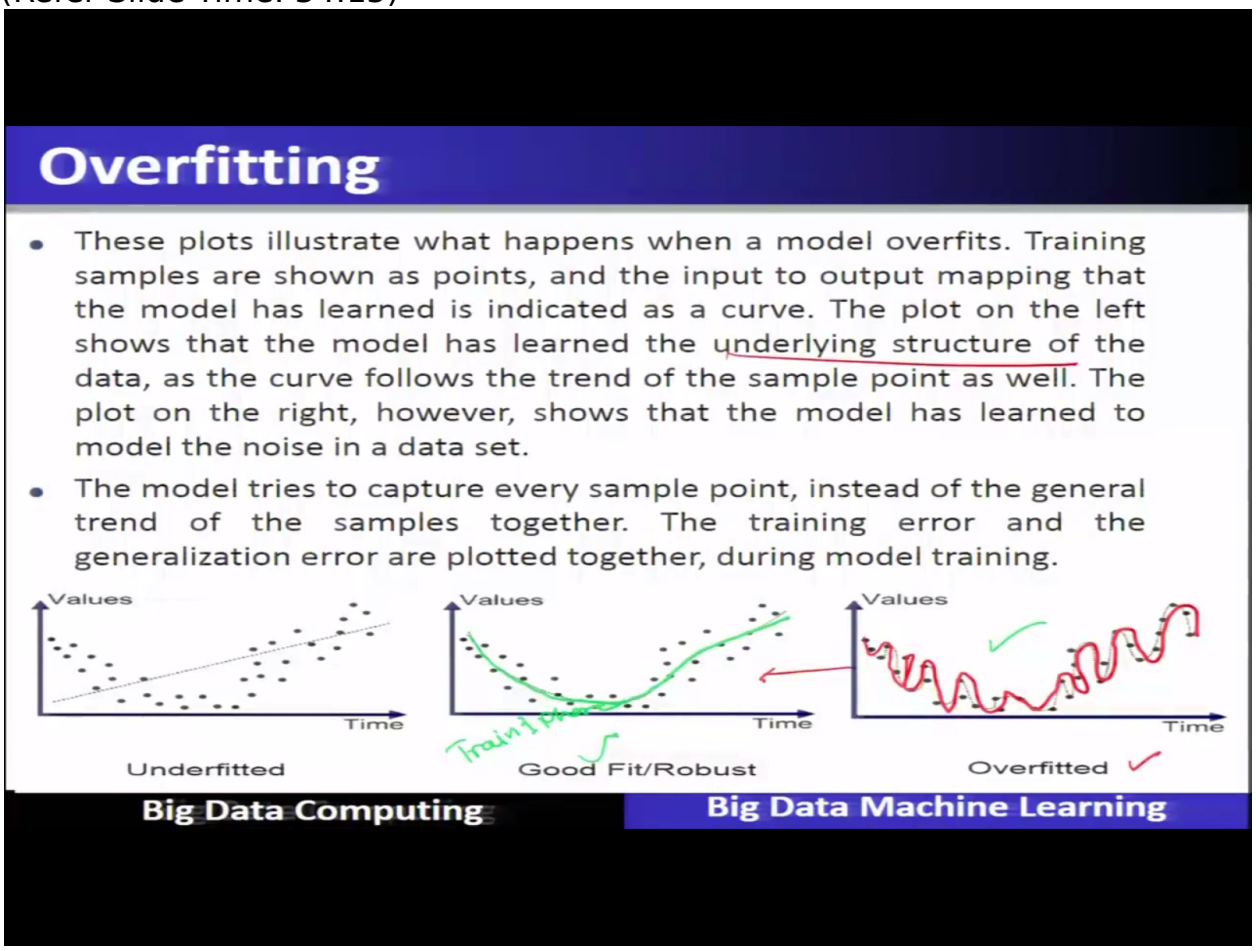

A model that overfits will not generalize well to the new data. So the model will do well on just the training data, but not perform well on the new data set, or rather it will perform poorly. So a classifier that performs well on just the training data set will not be only useful. So it is essential that the goal of the good generalization performance should be kept in mind before building the model. So overfitting and underfitting. So underfitting occurs when the model is fitted to the noise in the training data, this result is… this results in a low training error and high test error, so that is called overfitting. Now there is another thing which is called underfitting. Underfitting on the other hand occurs when the model has not learned the structure of the data. This results in high training error and high test error. When both the errors are very high, that is the training error is also very high and test error is very

high, then it is called underfitting. Now both are un-decidable, overfitting and underfitting are un-decidable. Since both mean that the model will not generalize well to the new data. So overfitting generally occurs when the model is too complex, that is it has too many parameter relative to the number of training samples. So to avoid overfitting the model needs to be kept as simple as possible and yet will solve the input output mapping for a given data set.
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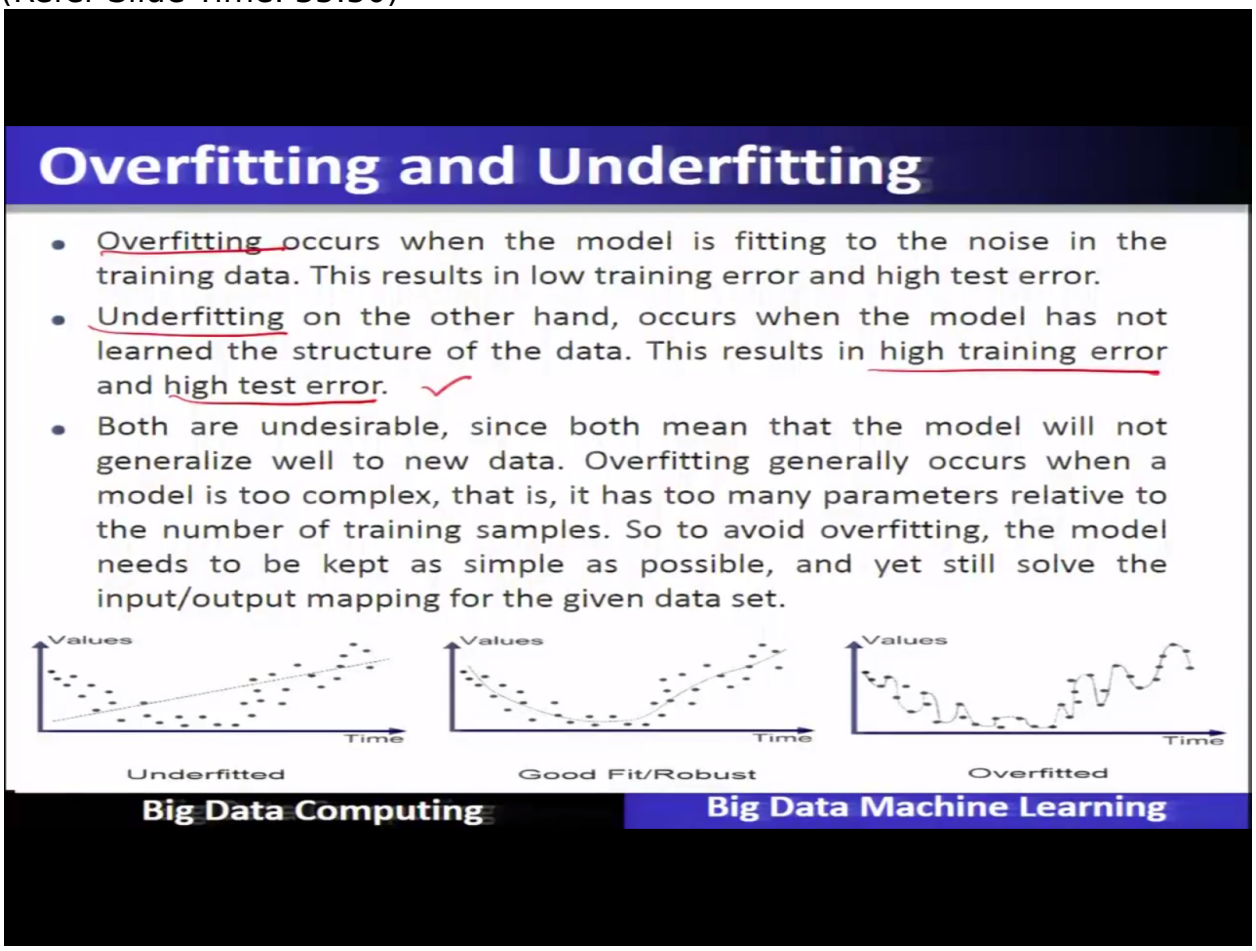

Now let us see, what causes overfitting? In summary overfitting is when your model has learned the noise in the training data instead of underlying structure of the data, so you want to avoid overfitting, so your model will generalize well to the new data. Now let us discuss the overfitting in the decision trees. Now decision tree induction, that is the decision tree also referred as the tree induction, the tree repeatedly splits the data in a node in order to get successfully paired subsets of data. So this is, here the... the note gets split into three cases. Here this note splits into two. So this particular process of splitting the note and growing the tree is called tree induction.
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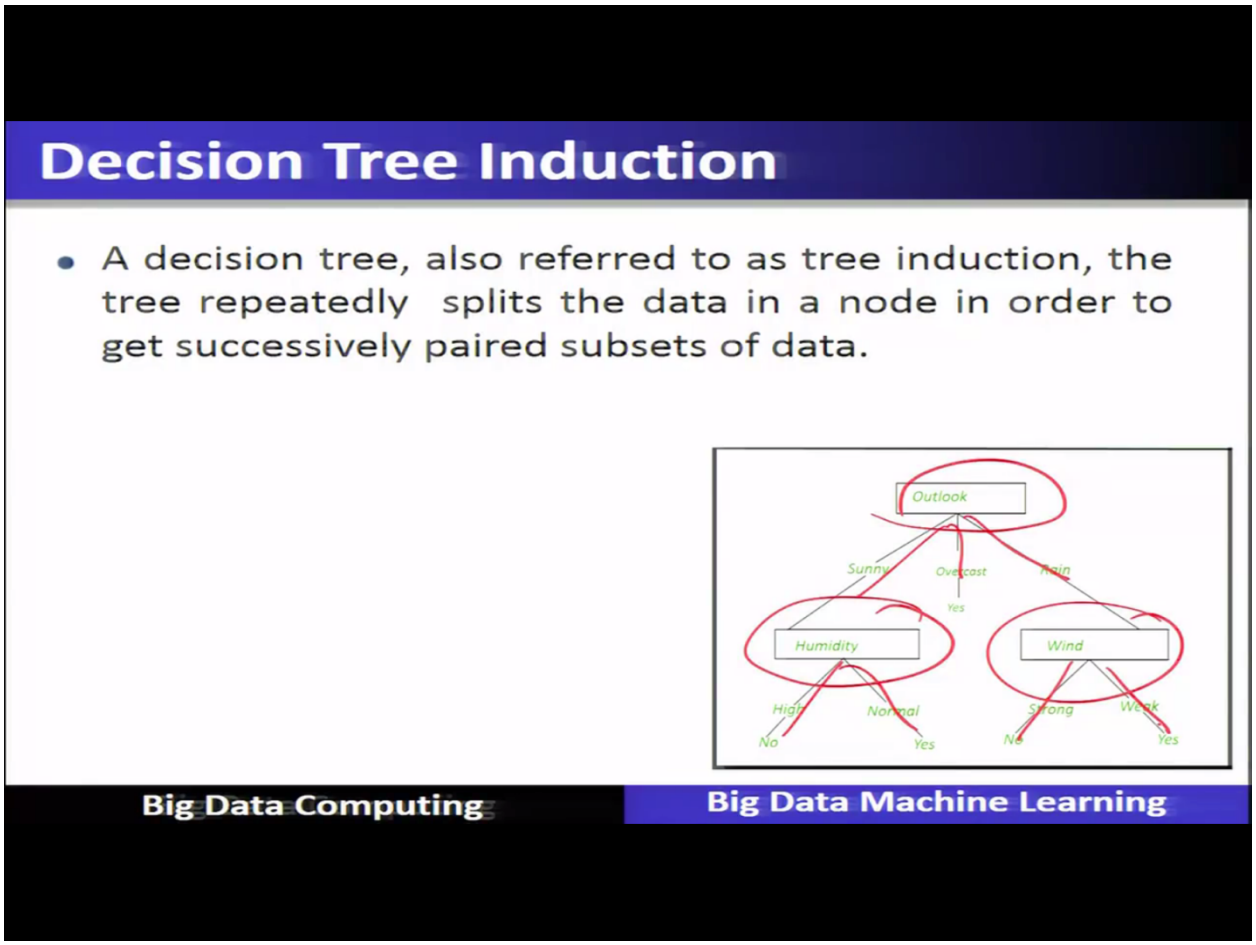

Now let us see, the concept of overfitting in this decision trees. Note that the decision tree classifier can potentially expand its notes until it can perfectly classify the samples in the training data. But if the tree grows, the notes to fit the noise in the training data, then it will not classify the model for a new sample. This is because the tree has partitioned the input space according to the noise in the... in the data instead of the true structure of the data, in other words it overfits.
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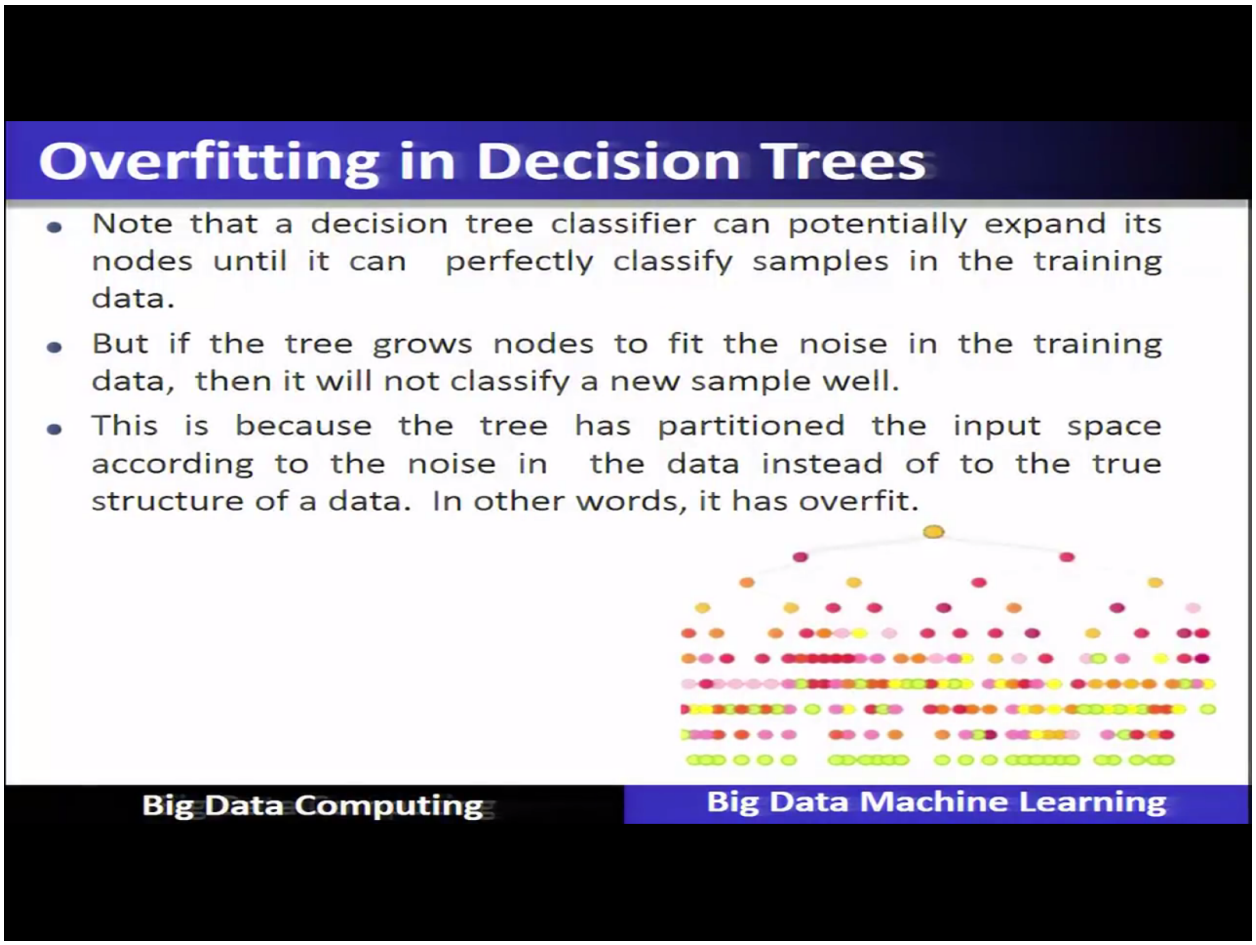

So how to avoid overfitting in the decision tree. So there are two methods, one is called pre-pruning, the other method is called post-pruning. There are two methods to avoid the overfitting in decision trees. The first one is called pre-pruning, the other one is called post-pruning. So pre-pruning says that to stop growing the tree before it is fully grown, why because in this particular case, it is... the data is, so the tree is fully grown, that means it is growing according to the noise in the data, hence it has to be stopped before it is fully grown and so it will control the number of notes to limit the complexity of the tree. The second method of avoiding the overfitting in the decision tree is called post-pruning. Post-pruning means let the tree grow to its maximum size and then prune the tree so that it can reduce or it can overcome from the overfitting.

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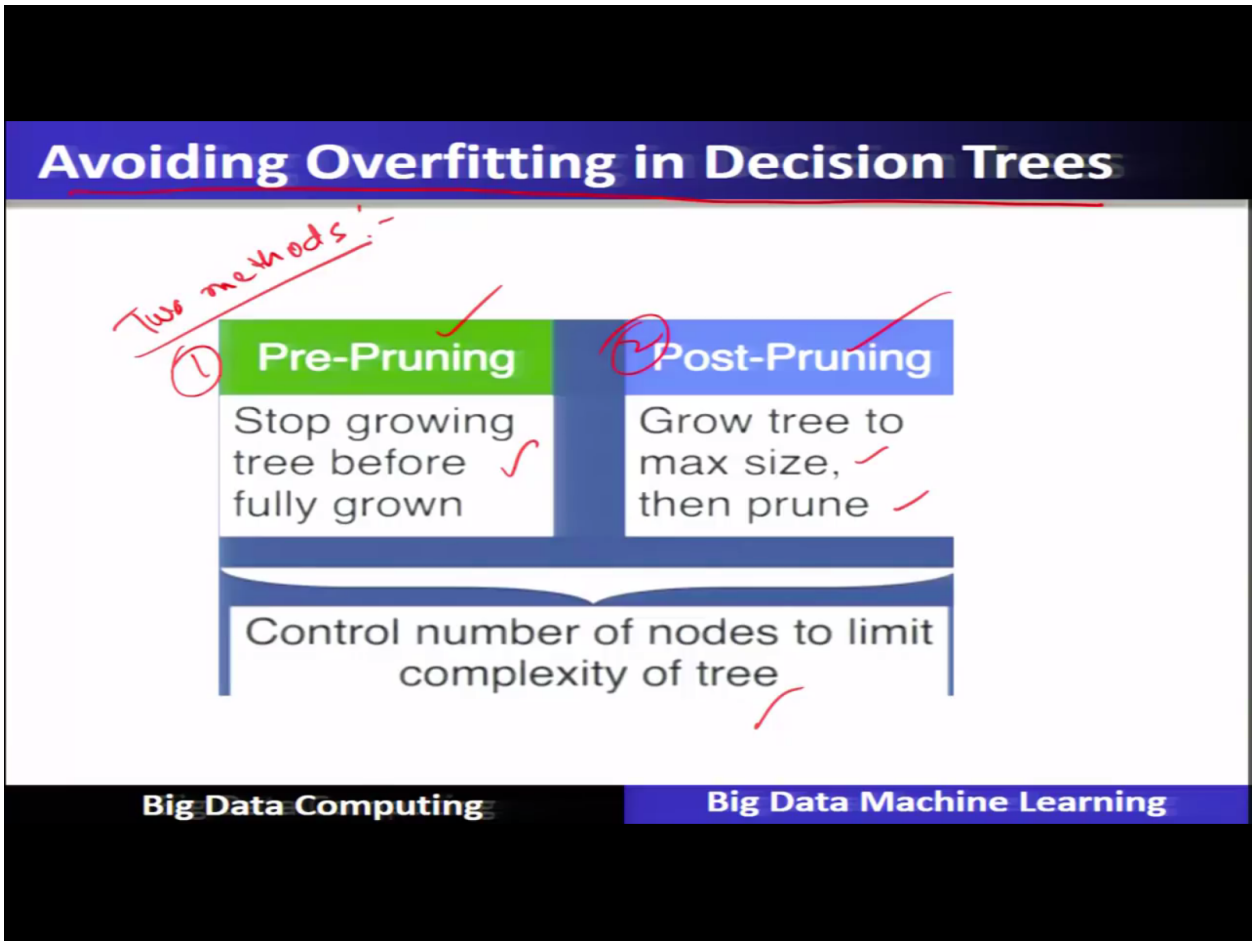

Now let us see the pre-pruning step. So with the pre-pruning, the idea is to stop the tree induction before fully grown tree is build, that perfectly fits the training data. To do this, restrictive stopping conditions for growing tree must be used. For example noise stops expanding if the number of samples in the node is less than some minimal threshold. Another example is to stop expanding the node, if the... if the improvement in the impurity measures also below a certain threshold.
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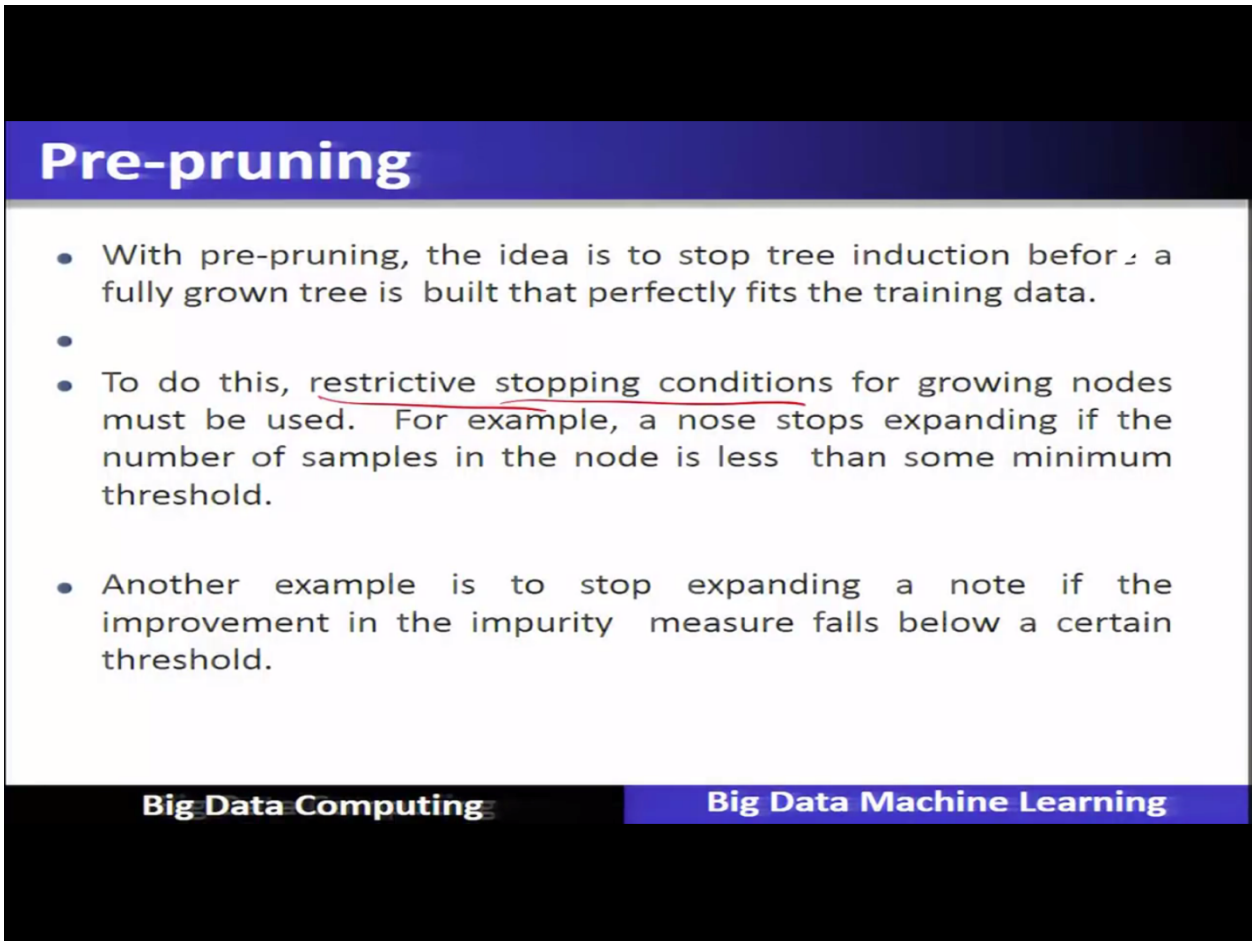

Post-pruning, in the post-pruning the tree is grown to a maximum size and then the tree is prune to removing by removing the nodes using the bottom up approach, that is the tree is trimmed starting with the leaf nodes. The pruning is done by replacing the sub-tree with a leaf node. If this improves the generalization error or if there is no change to the generalization error with this replacement.

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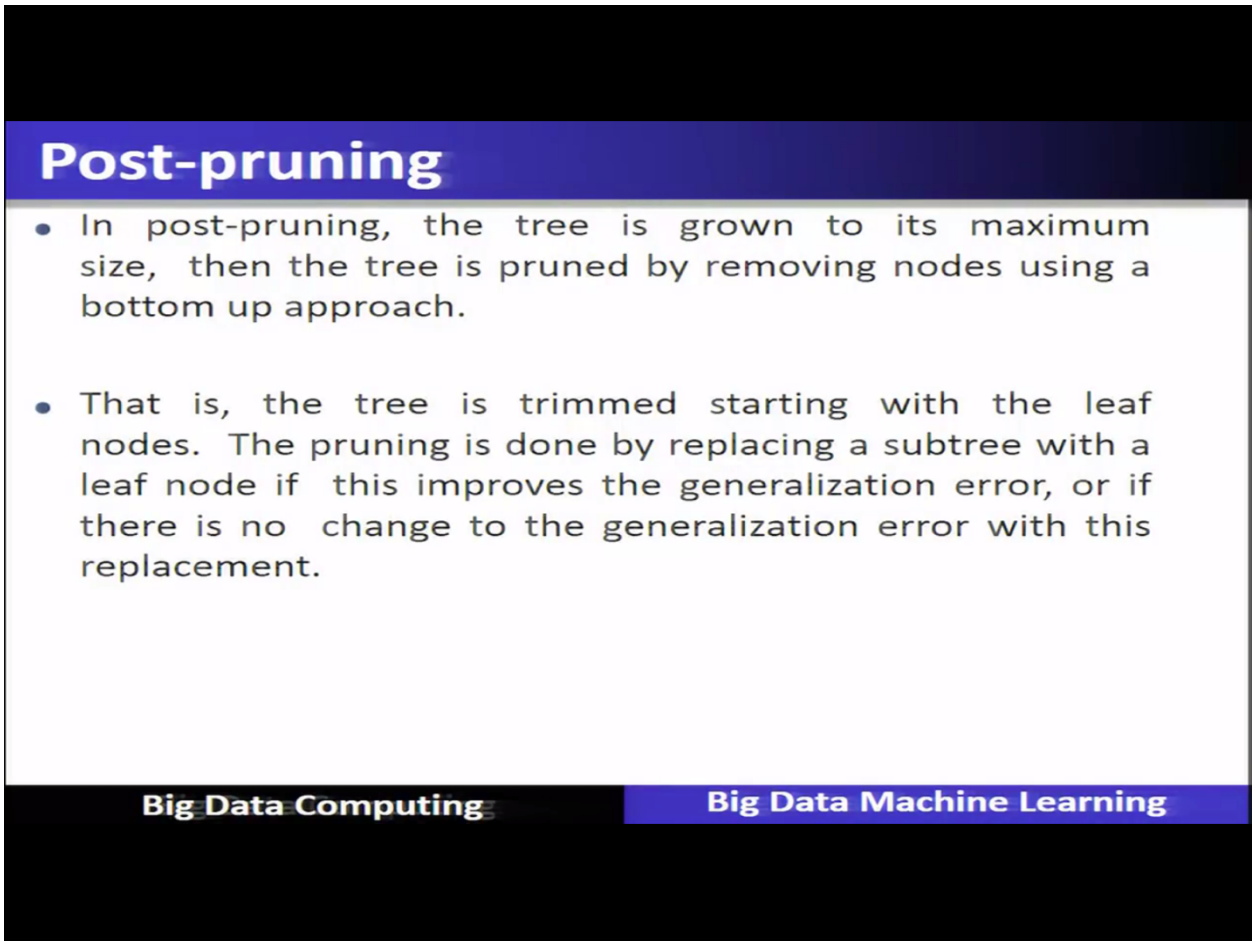

Now overfitting in the decision tree, in other words if removing the sub trees does not have the negative effect on generalization error then the nodes in that sub tree only add to the complexity of the tree and not to its overall performance. So those notes showed be removed, in practice post-pruning tends to give better results. This is because pruning decisions are based on the information from the full tree. Pre-pruning on the other hand may stop the tree growing process prematurely, however, post-pruning is more computationally expensive, since the tree has to be expanded on its full size.
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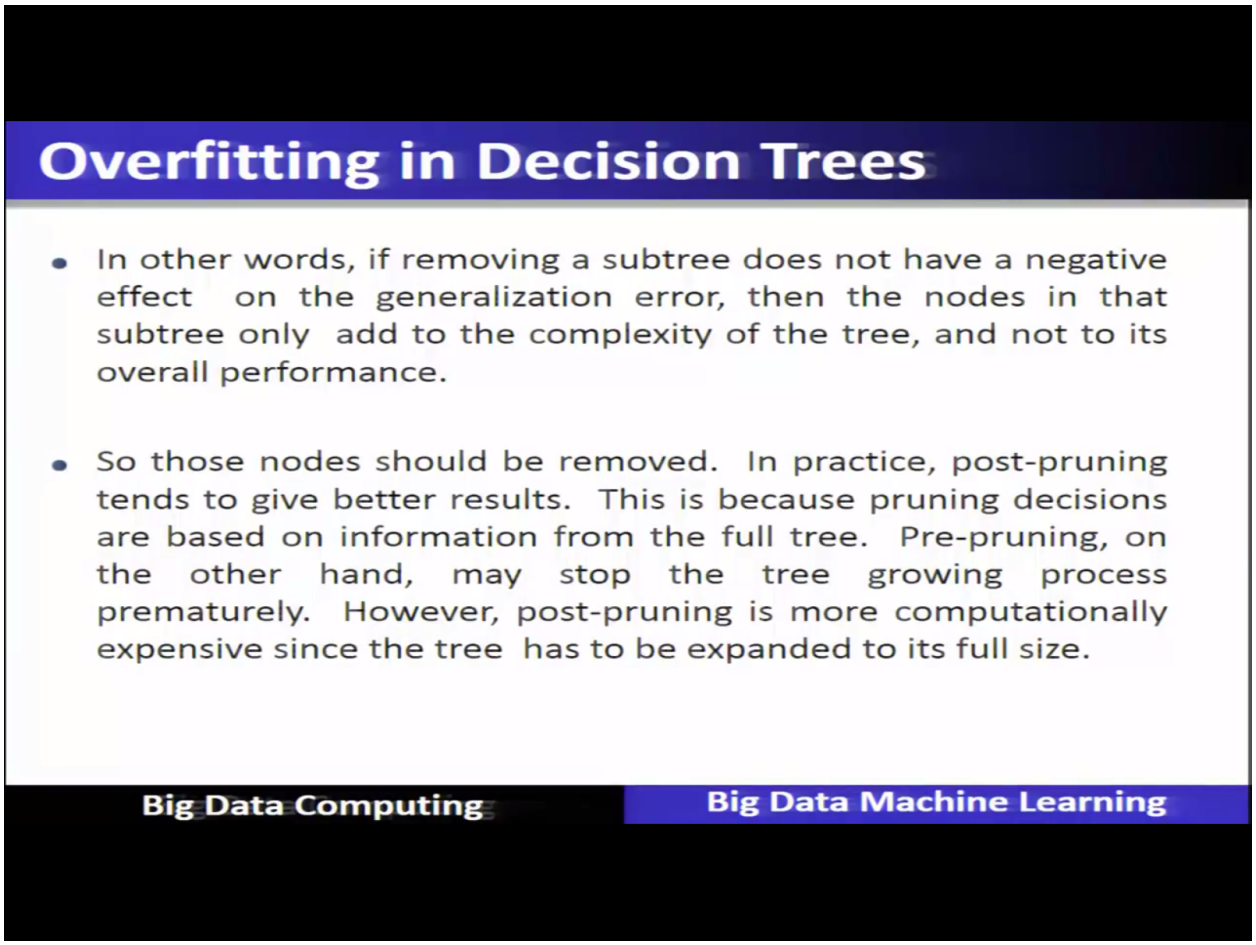

Let us see how the validation set is used for these purposes. So now we have again looking back to the same diagram, that is the training phase and the testing phase, and this particular process. So how to avoid the overfitting and recall that the model that over fit does not generalize well to the new data, recall also that overfitting generalizes, generally occurs when the data is too complex. And how to determine when it should occur.
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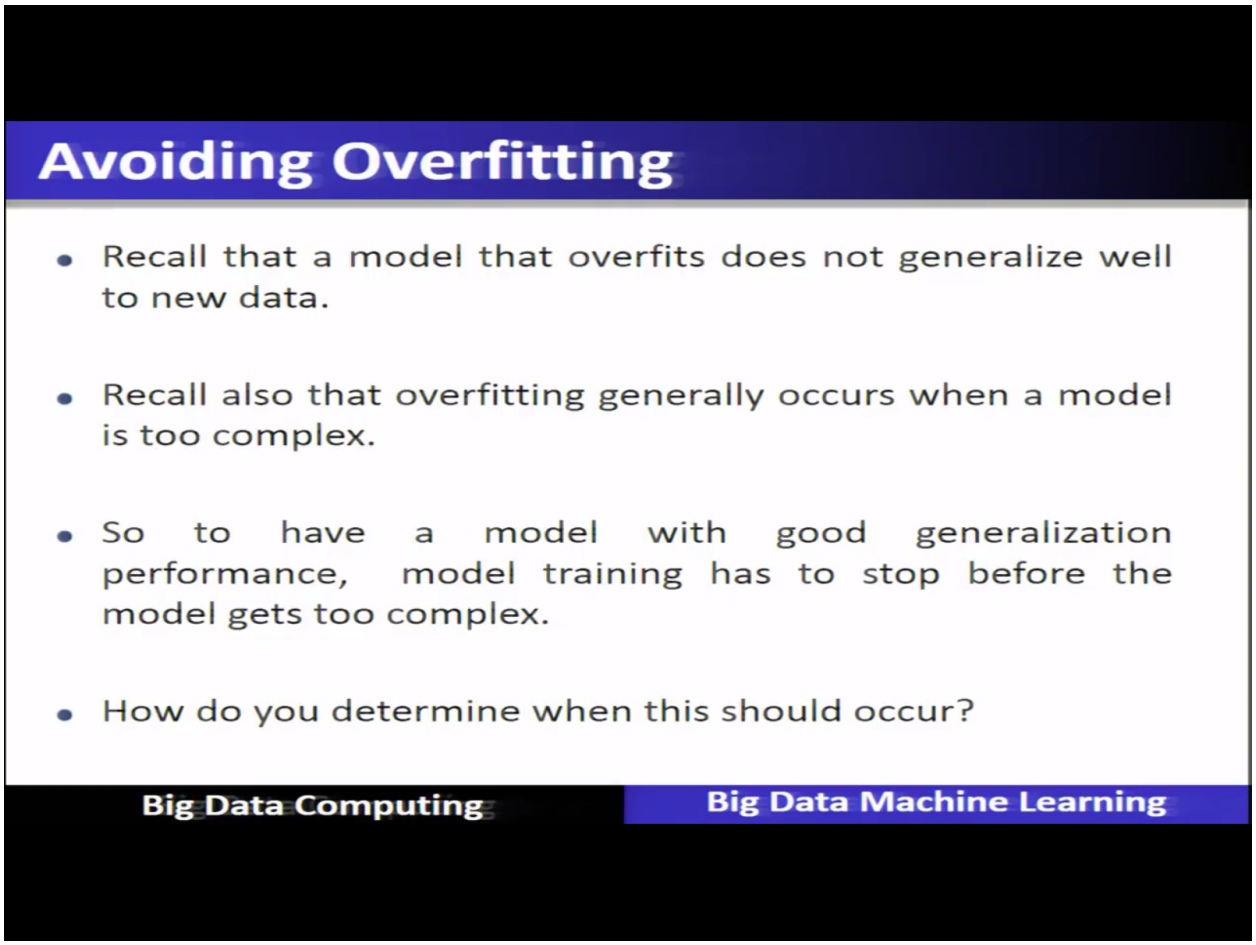

So there is a technique which is called using the validation set. A validation set can be used to guide the training process to avoid the overfitting and deliver the good generalization performance. Now we have discussed having the training set and a separate. So the training set is used to build the model and a test set is used to see how the model performs in a new data. So the training data is now further divided into two different sets, one is called the training data and the other is called validation data So training data is not fully used for the training purpose, but it is divided into the validation data. Let us see what do you mean by the validation data, which is taken out from the training data. So this particular validation set is used to guide the training process to avoid the overfitting and deliver the good generalization, how that is all done, we will see.

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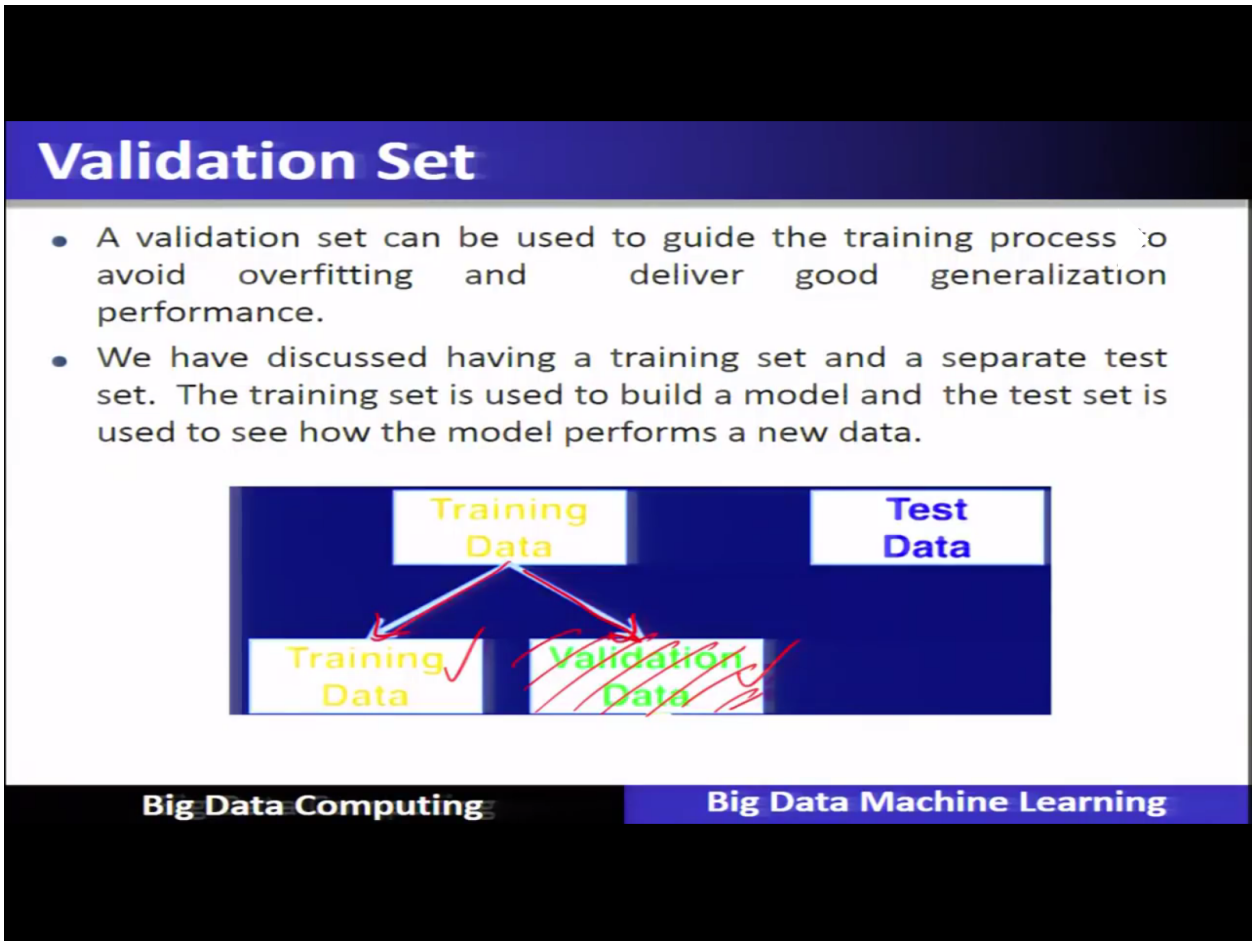

So training and validation error. Now we want to further divide up the training into the training and the validation set. So the training set is used to train the model as before and the validation is used to determine when to stop the training model to avoid the overfitting in order to get the best result performance. So let us see that there are two different data sets, one is the training data set, which is shown over here that it is giving the errors, which is called the training error. Now with the validation data set, we are also getting the errors and we can now compare these to graphs. What we see here at this stage, this validation is not consistent with the training error, here it divert. So this is the position, where this particular… this is the position when the… the model is not behaving consistently with the validation set and the training set, and there validation and the training error are differs at this point where validation error rate is more compared to the… to the training set error. One is growing, the other is decreasing. So therefore this particular, at this point the model overfits. So we have to identify, when to, at what stage the growing of the tree has to be used using this particular method. So now let us understand this. The… So the training set is used to train the model as before and the validation is used to determine when to stop the training model to avoid the overfitting in order to get the best generalization. So the… so the data is to… the idea is to look at the errors of

both the training and the validation set during the model training and the orange line here on the plot is shown as the training error and the green line is validation. We see that the model building progress is along X axis, so the number of node increases, that is the complexity of the node of the model increases here, as the number of node, the complexity. So we can see that the model complexity increases at this... after... beyond this particular stage. The training error decreases, whereas the validation error increases, start increasing. So when the validation error increases, this indicates that the model is overfitting and resulting into the decreased generalization performance.
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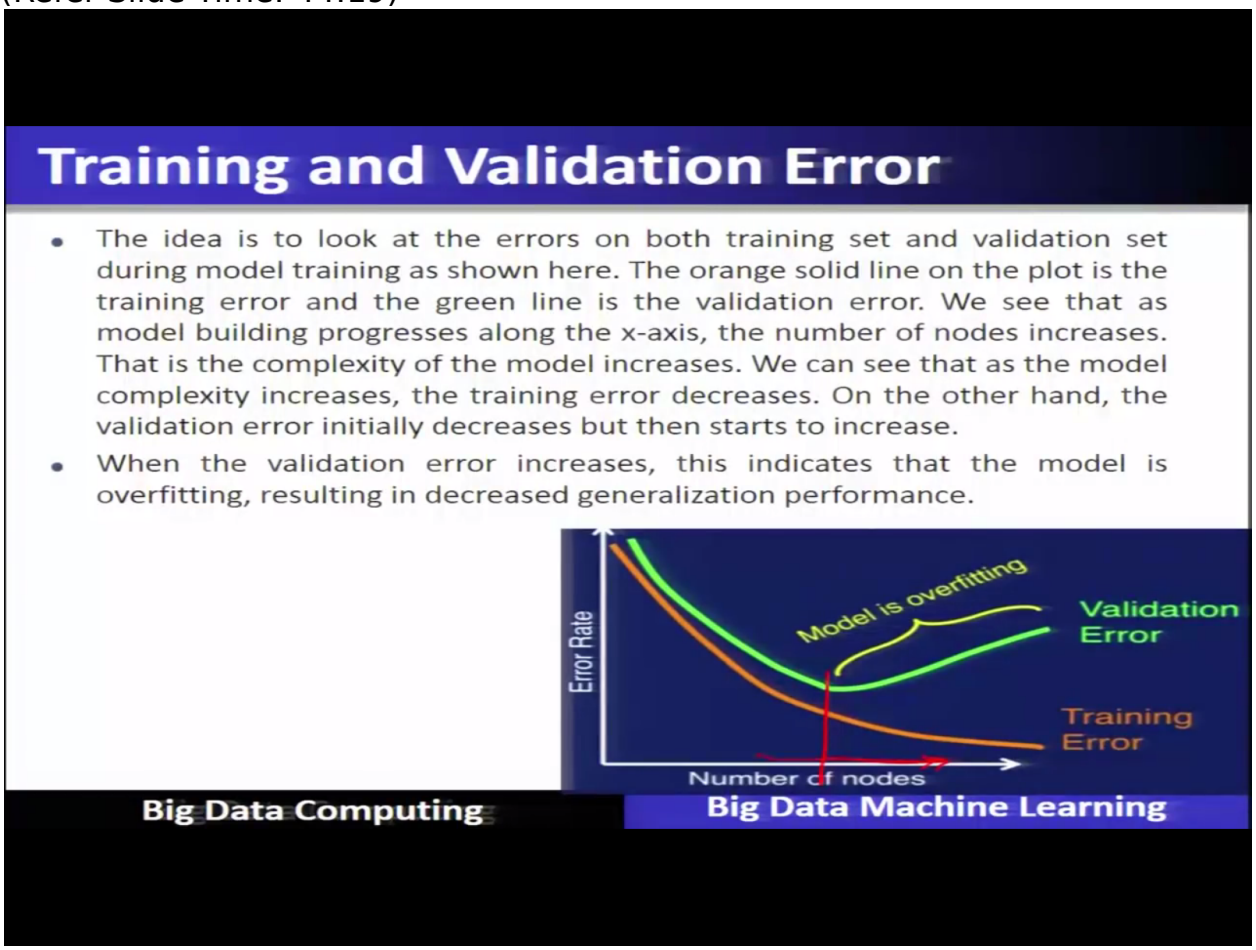

So when to stop this particular training or tree induction. So this can be used to determine when to stop the tree induction, where the validation error starts to increase, is when you get the best generalization performance. So the training... so the tree induction should be stopped here. This method is using the validation set to determine when to stop the training, is referred to as model selection, since you are selecting, one from many varying complexities. Note that this was illustrated for the decision tree classifier and the same method can be applied to other machine learning models.
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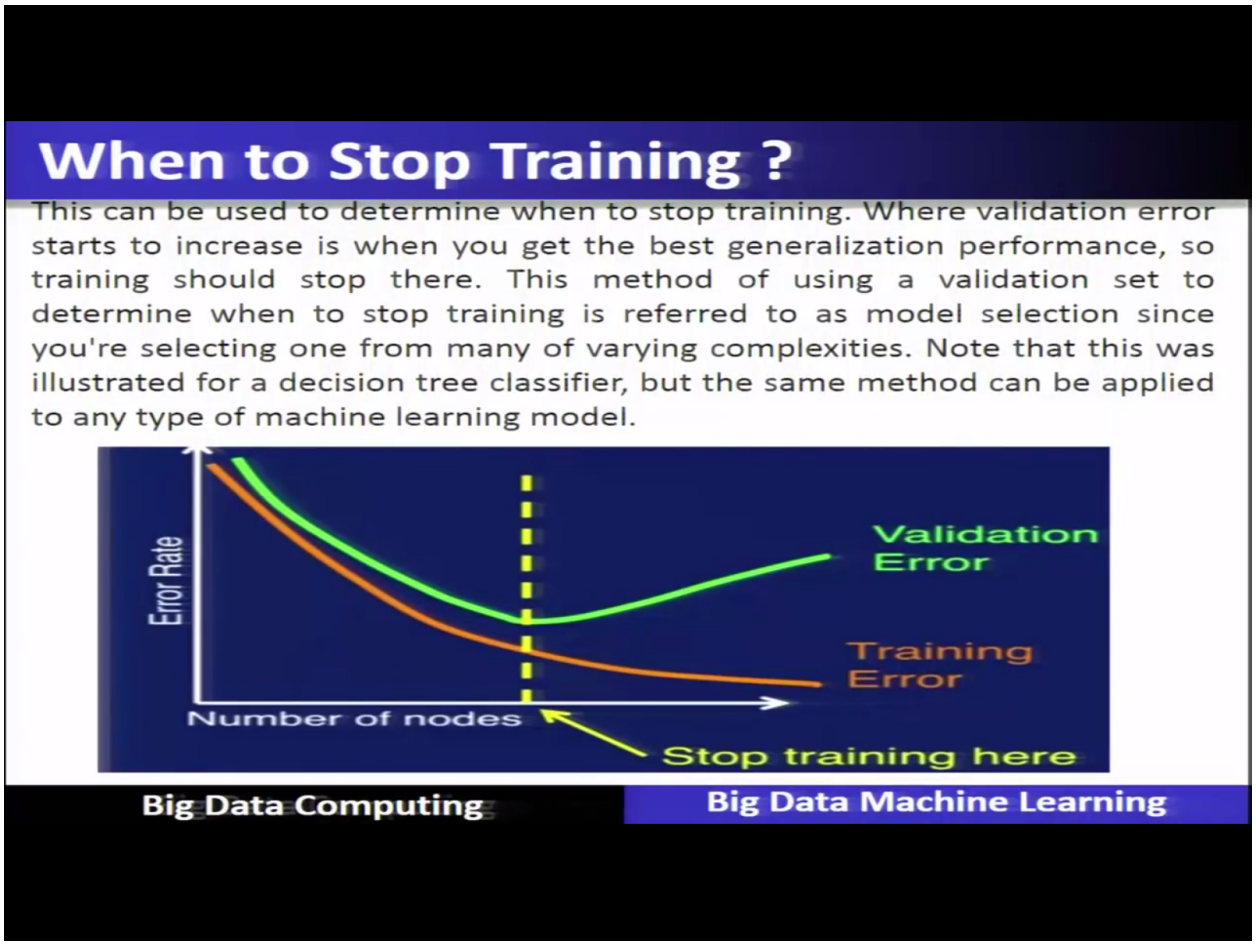

What are the ways to create and use the validation sets? There are several ways to create and use the validation sets to avoid the overfitting. The different models are cooled out method, random subsampling, K-fold, cross-validation, and leave-out cross-validation, leave-one-out cross-validation LOOC.

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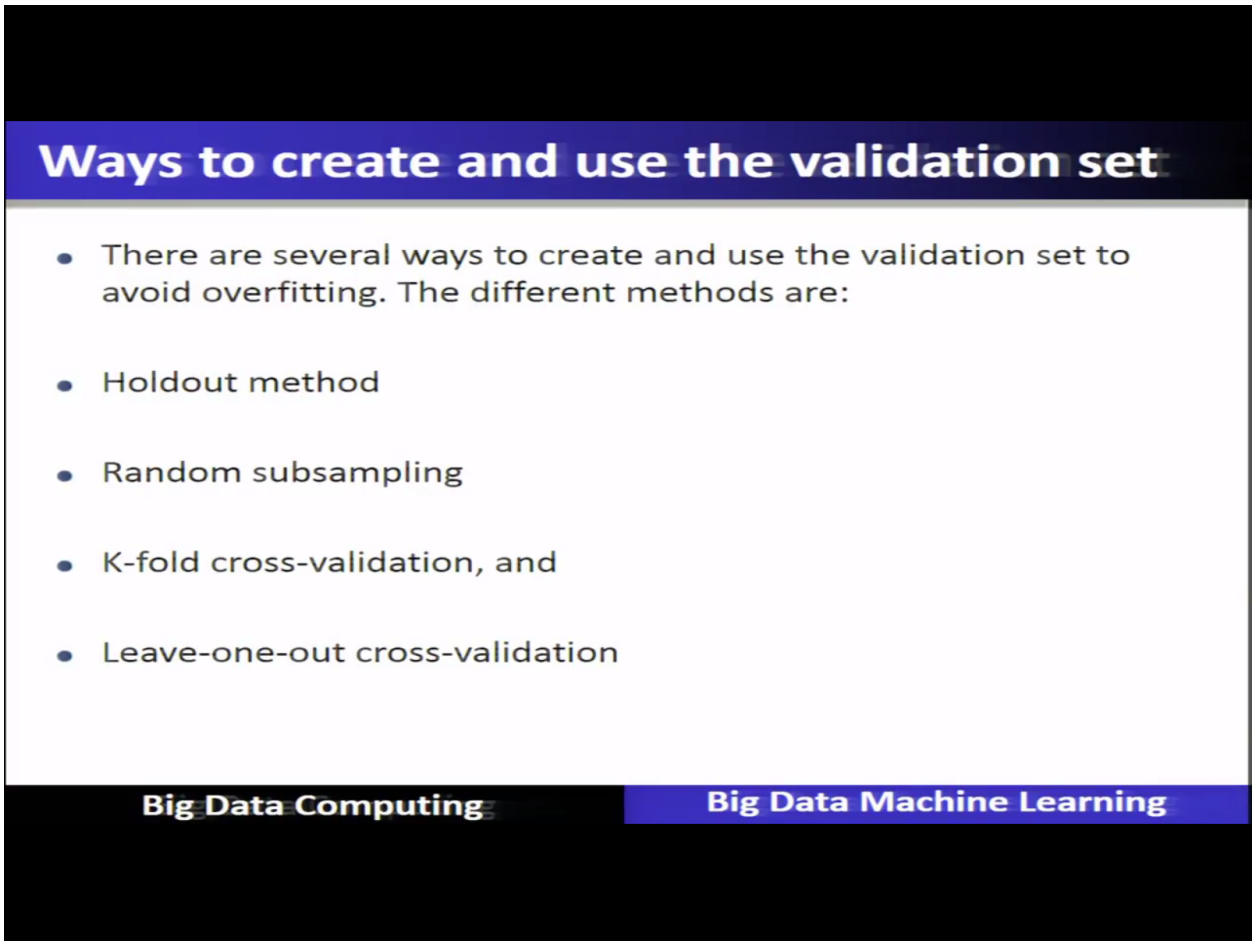

So hold out method, the first way to use the validation set is a hold down method, this describes the scenario that we are… that we have discussed, where the part of the training is reserved as the validation set, the validation is then… is then the hold out set.
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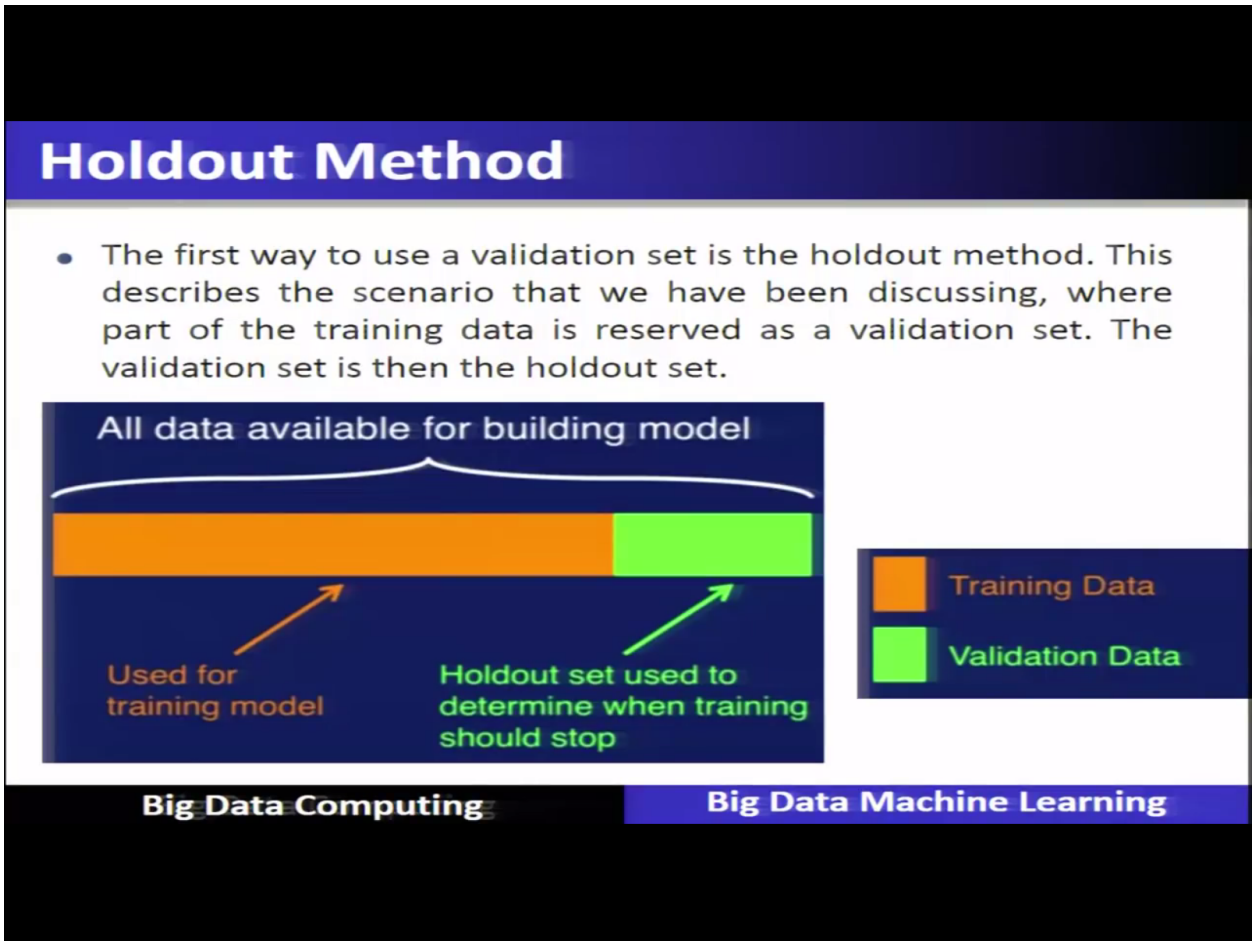

This method we have already seen.
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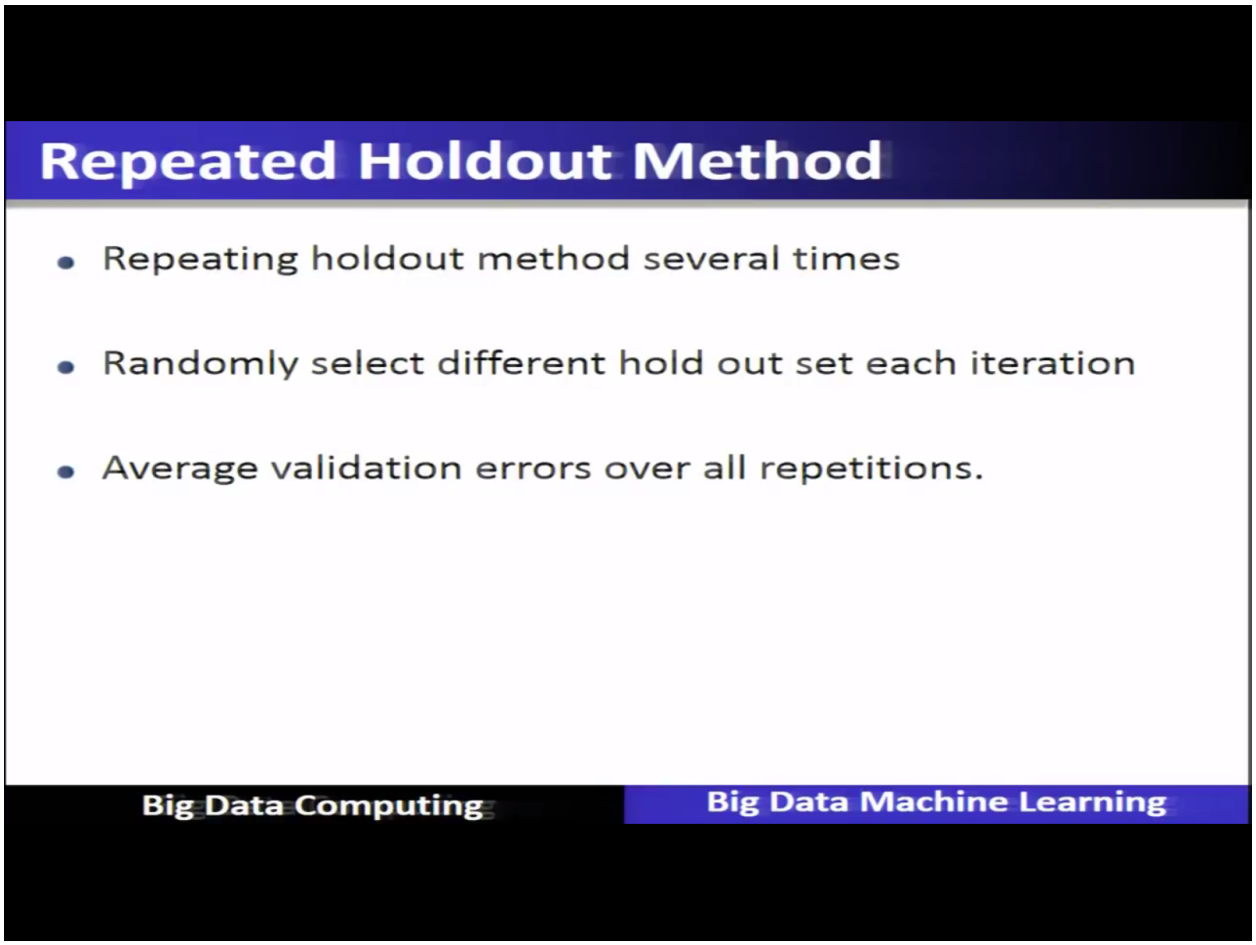

Now K-fold cross-validation, the way to improve the repeated hand out, hold-out method is to use cross-validation. Cross-validation works as follows. Segment the data into K number of joint partitions. During each partition, during each iteration, one partition is used as the validation set. Repeat the process K times, each time a different partition for the validation, so echocardiogram partition is used for validation exactly once, this is illustrated in the figure. In the first iteration, the first partition is used for the validation. In the second iteration, the second partition is used for the validation and so on.
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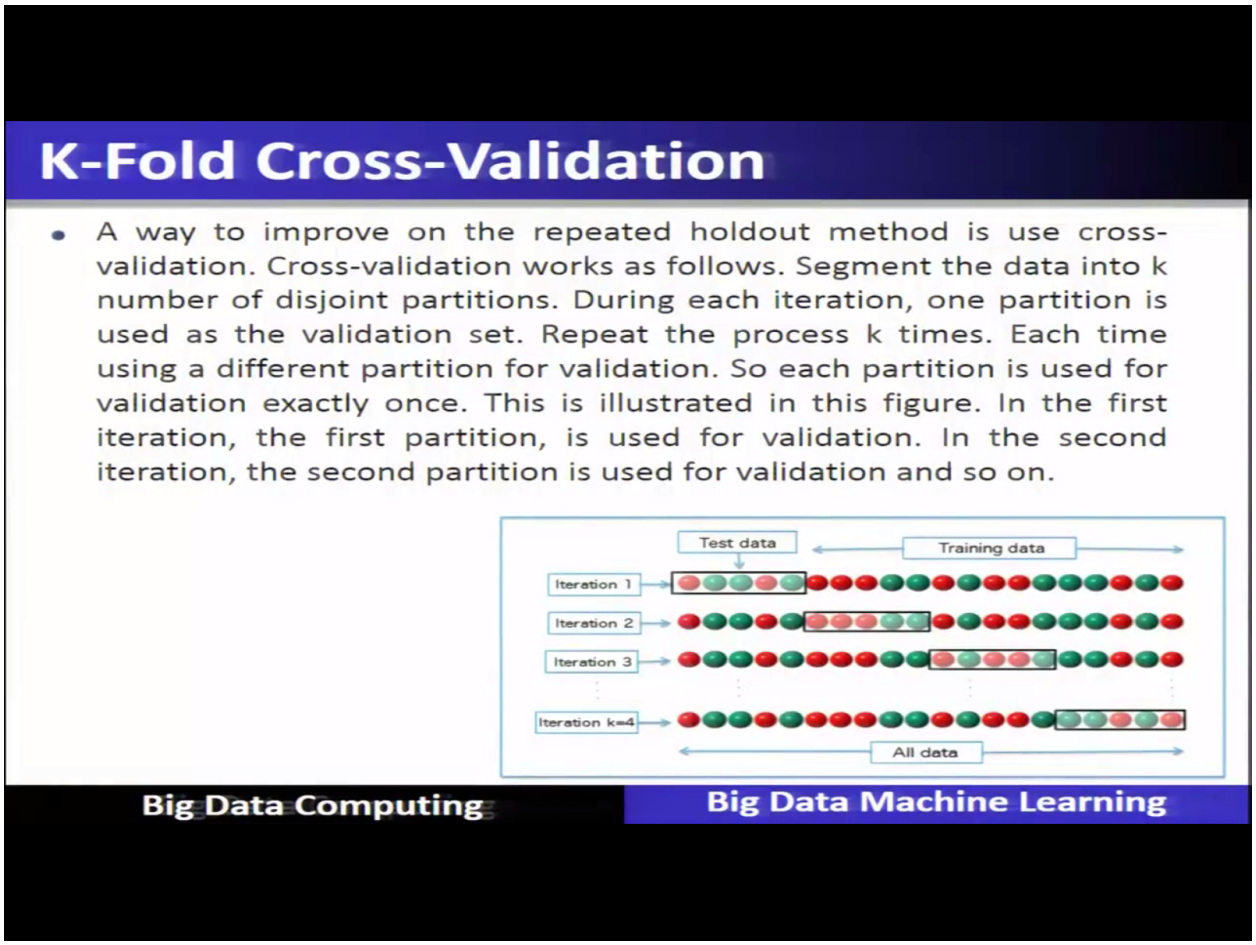

Now K-fold cross-validation. The overall validation error is calculated by averaging the validation for K different iteration. The model with the smallest average validation error is then selected. The process is just described, referred the as K-fold cross-validation. This is very commonly used approach to model selection in practice. This particular approach gives you the more structured way to divide available data up between the training and the validation data set provide a way to overcome the variability in the performance, that you can get when using a… using a single partition of the data.

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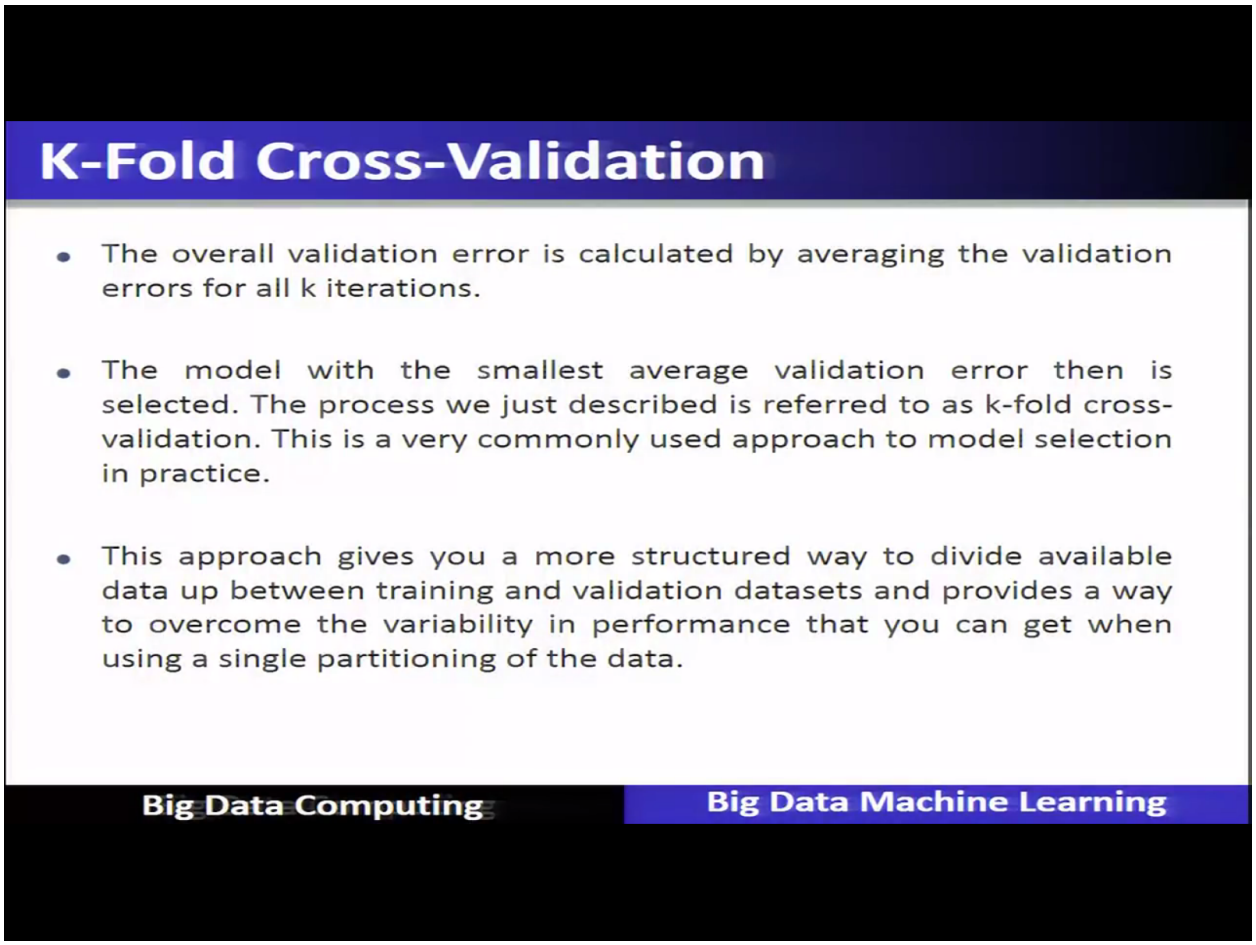

Leave out, leave one out cross-validation, Leave one out cross-validation is a special case of K-fold cross-validation, where K=N, where N is the size of data set. Here for each interaction, the validation set has exactly one sample. So the model is trained to use N-1 sample is validated on the remaining. So the rest of the process works the same as K-fold cross mode, that the cross-validation is often abbreviated as CV and leave out... leave one out cross-validation is referred as LOOCV and pronounced LOOCV.
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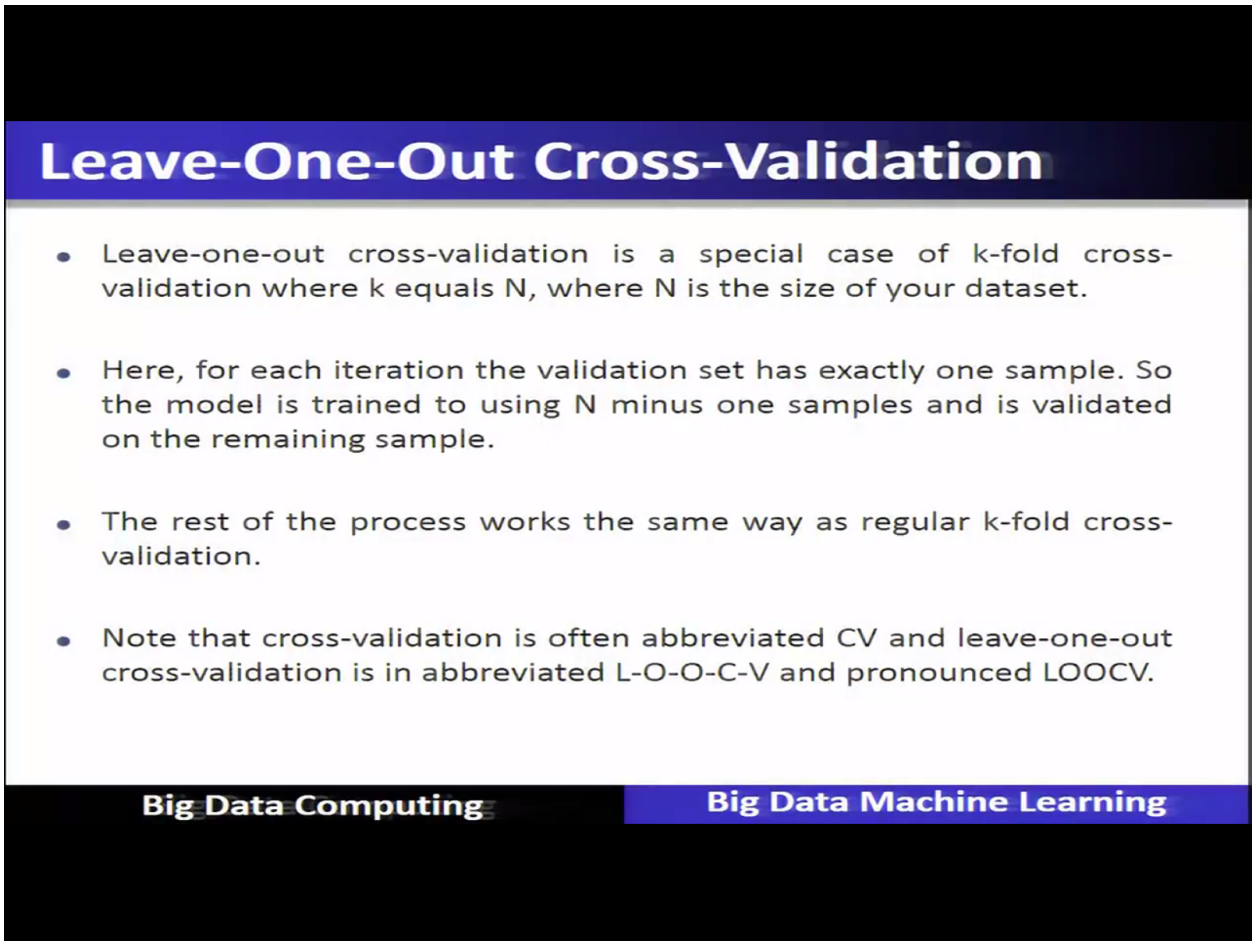

Uses of validation set. Note that the validation error that comes out of this process can also be used to estimate the generalization performance of the model. In other words the error on the validation set provides an estimate of the error on the test set.
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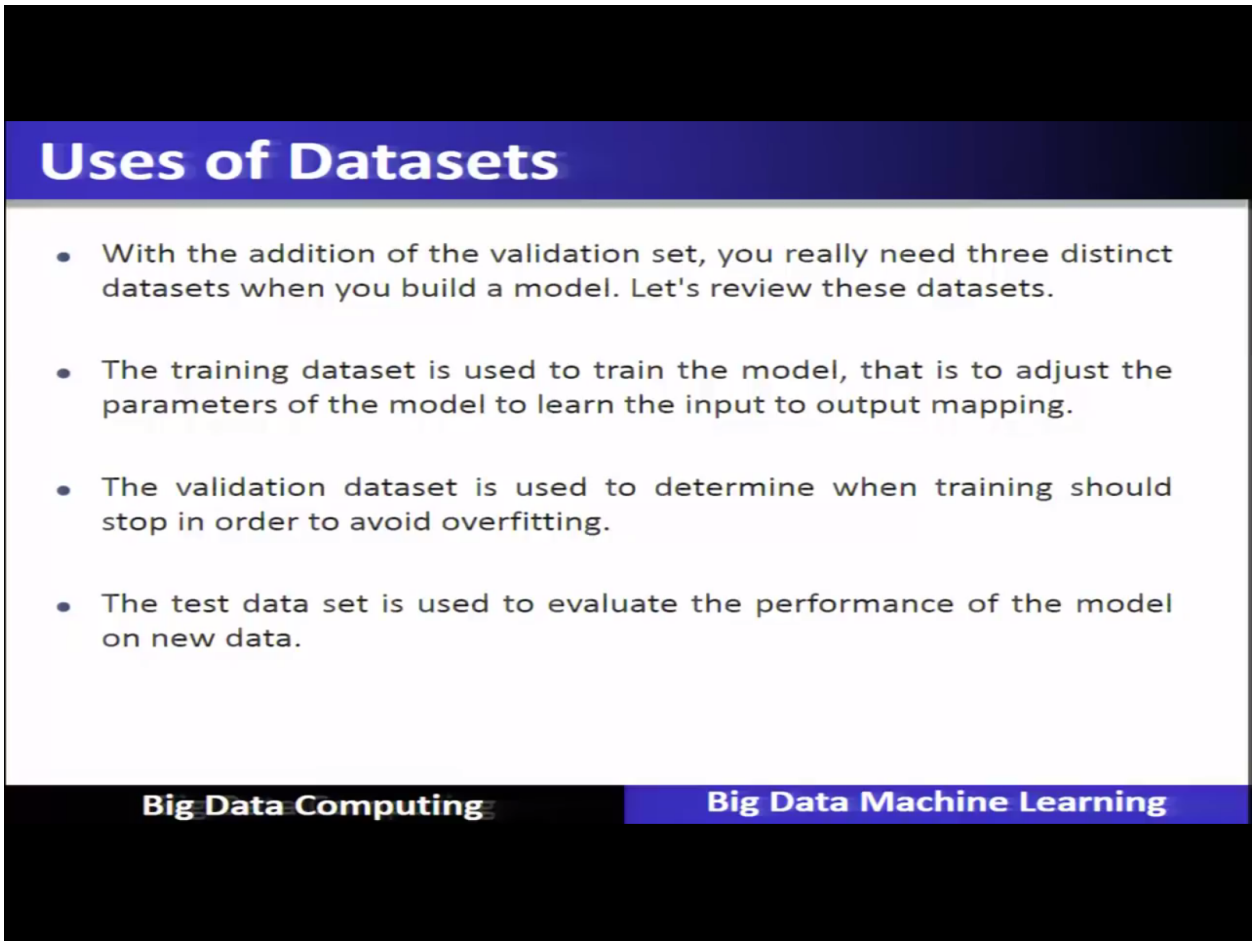

Uses of data sets, with the addition of validation set, you really need three distinct data sets, when you build a model. Let us review these data sets. So we have seen, the first type of data set is called the training data set, which is used to train the model, that is to adjust the parameters of the model to learn the input to the output mapping, that is called the training data set. The validation data set is used to determine when the training should stop in order to avoid overfitting, so this is called the validation data set. Third is called the test data set, is used to evaluate the performance of the model on the new data set. So that means the data set is divided into three different type of data sets, one is called the testing or training data set, then it is the validation data set, third is called test data set. Let us see that the training data set is used to train the model, that is to adjust the parameter of the model to learn the mapping from input to the output. So that means training data set will build the model and the validation data set is used to determine when the training should stop in order to avoid the overfitting. So while building the model it will refine this particular model so that it will be improved model, which will not have the overfitting. Finally the test data set is used to evaluate the performance of the model. So this evaluation of this improved model will be done using the test data set. Now let us see that how

this data set or given data set is divided into three different parts, which are called training data set, validation data set, and test data set.
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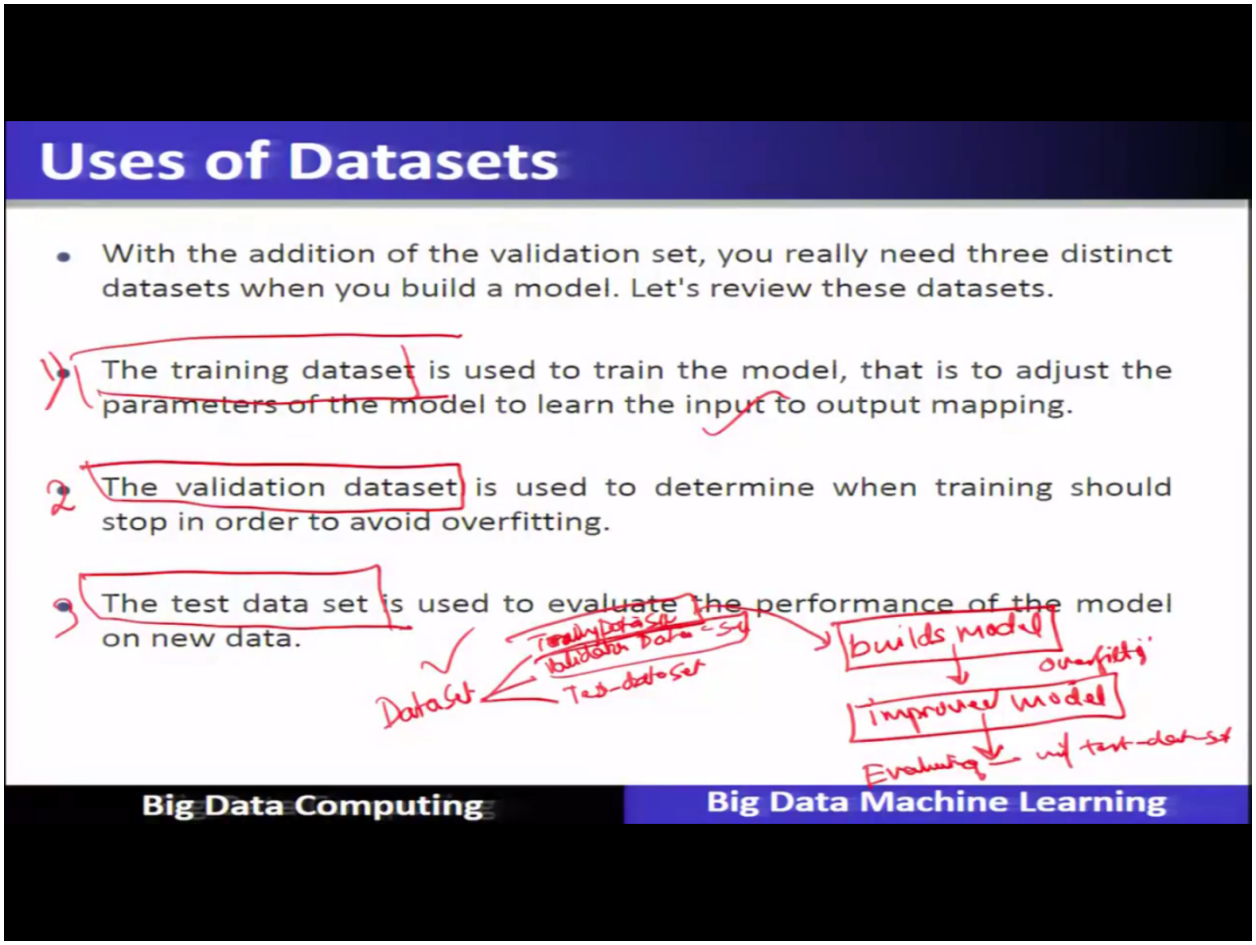

So note that the test data set should never be used in any way to create or tune the model. So it should be a new data set which is shown. For example in a cross-validation process to determine when to stop the training, it should not be used there. So the test data set must always remain independent from the model training and remain untouched until the very end, when all the training has been completed. Note that the sampling, the original data set to created training validation test, all the data set must contain the same distribution of the target class. For example if the original data set, if in the original data 75% samples belong to one clase, 30% samples to the other class, then this same distribution should approximately be present in each of the training validation and test set, otherwise, the analysis will be misleading.
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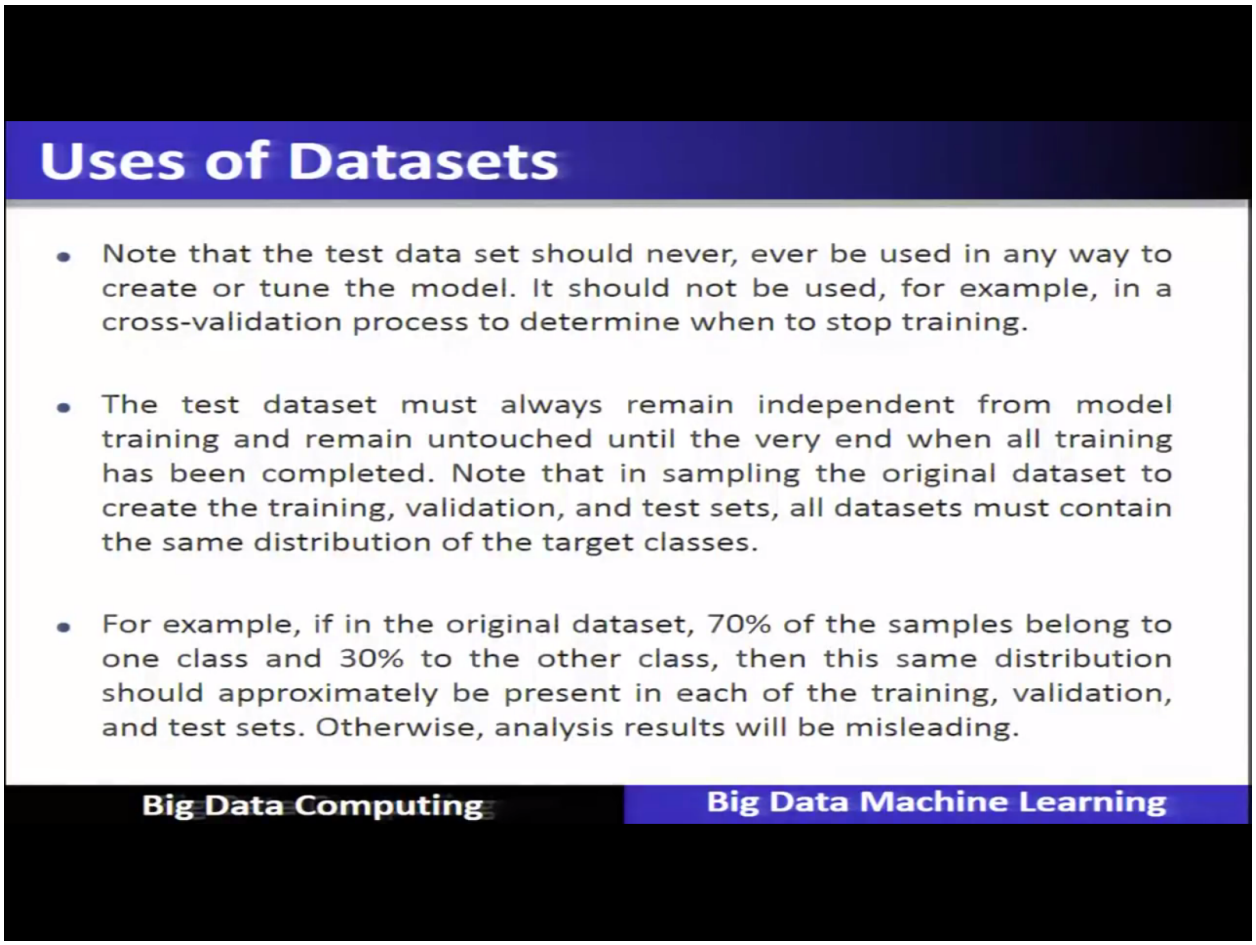

So validation set summary. So we have discussed the need for three different data sets in the model building. So the training set is to train the model, the validation set is to determine, when to stop the training process and test to evaluate the performance on the new data. We have learned how a validation set can be used to avoid overfitting, and in the process to provide an estimate general performance, estimate of generalized performance, and the generalization performance. And we cover different types to create and use validation set such as K-fold cross-validation.

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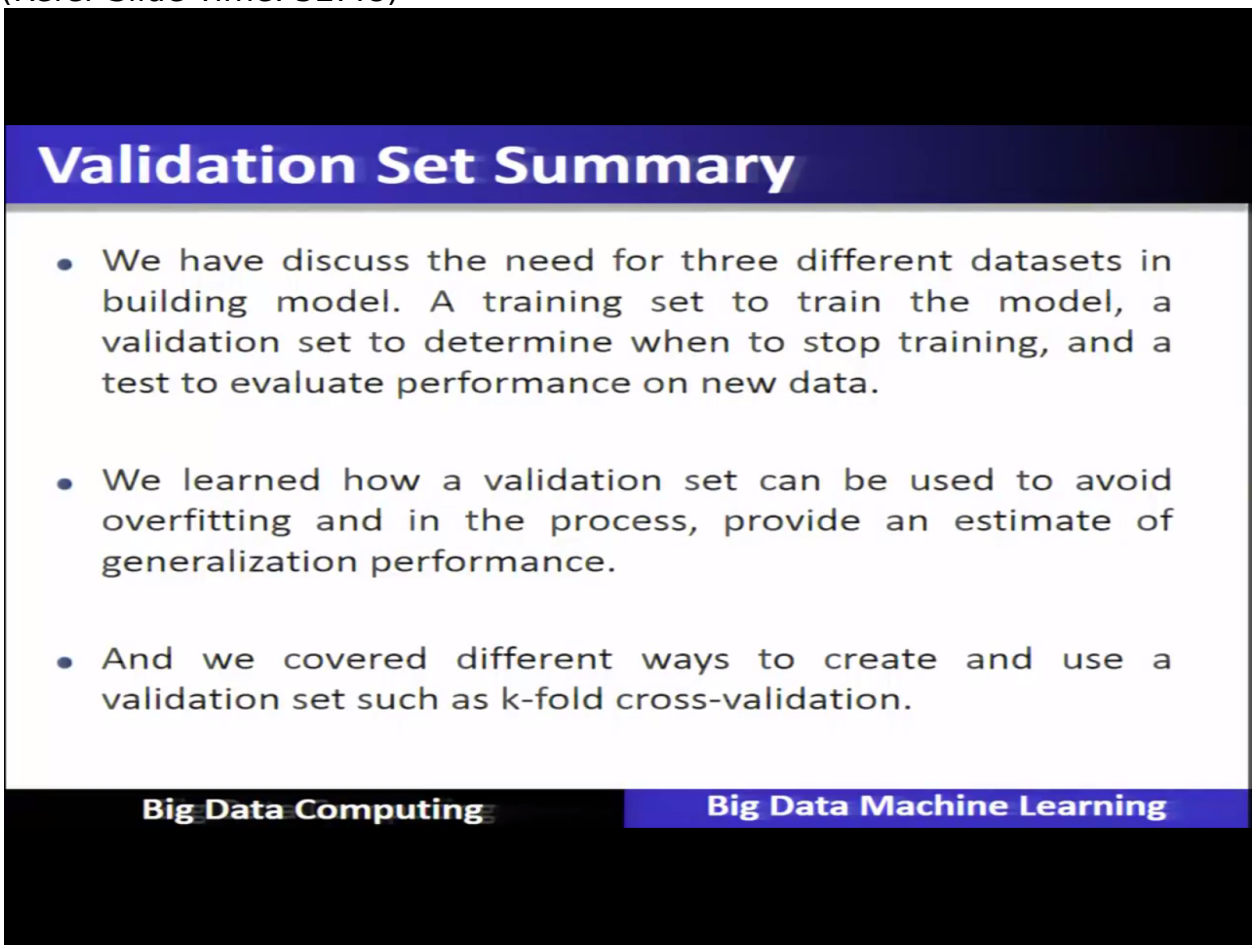
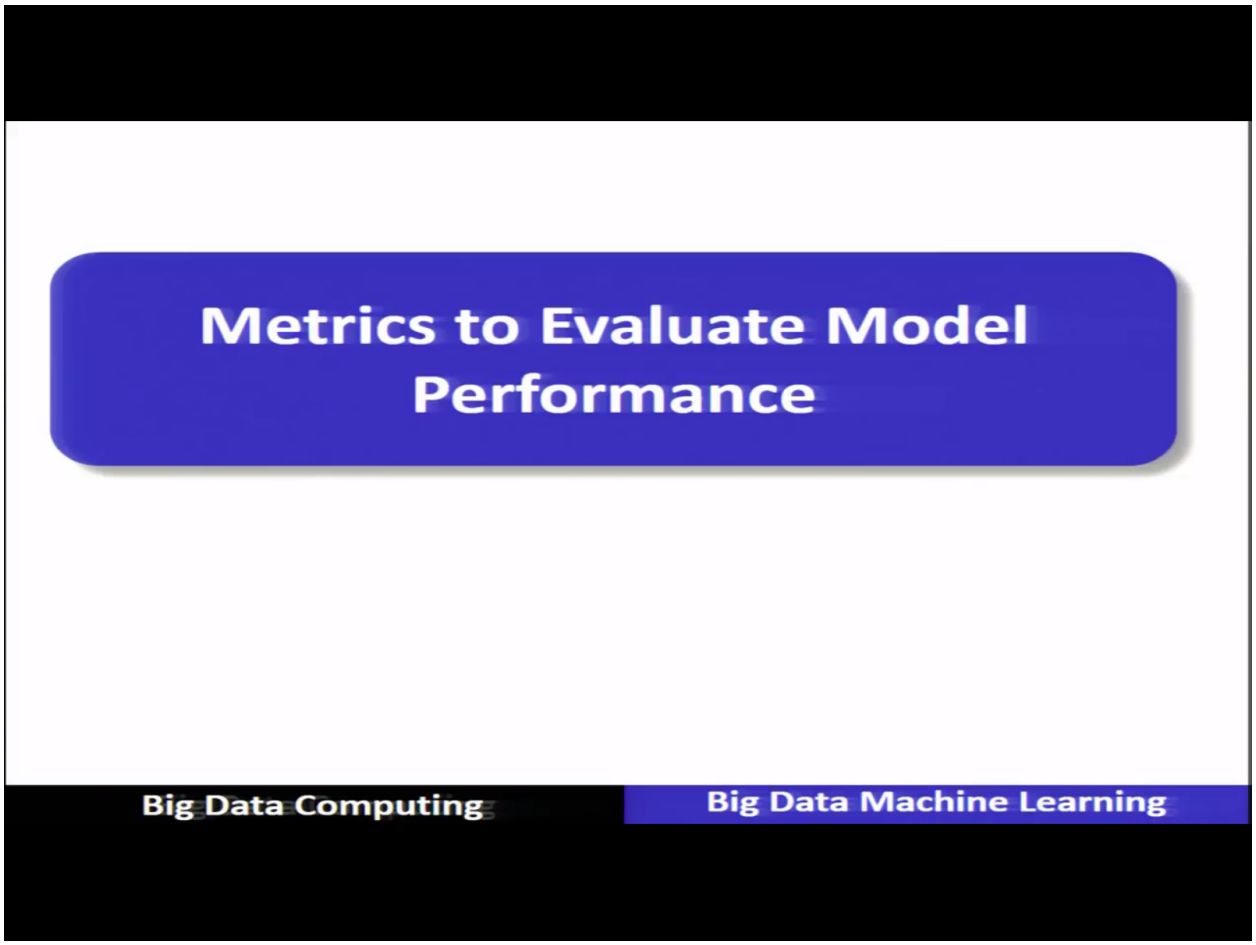


Now metrics to evaluate the model performance.



So here we give the class labels to the data set in supervised learning that is done, is the animal mammal, yes or no is the class label.
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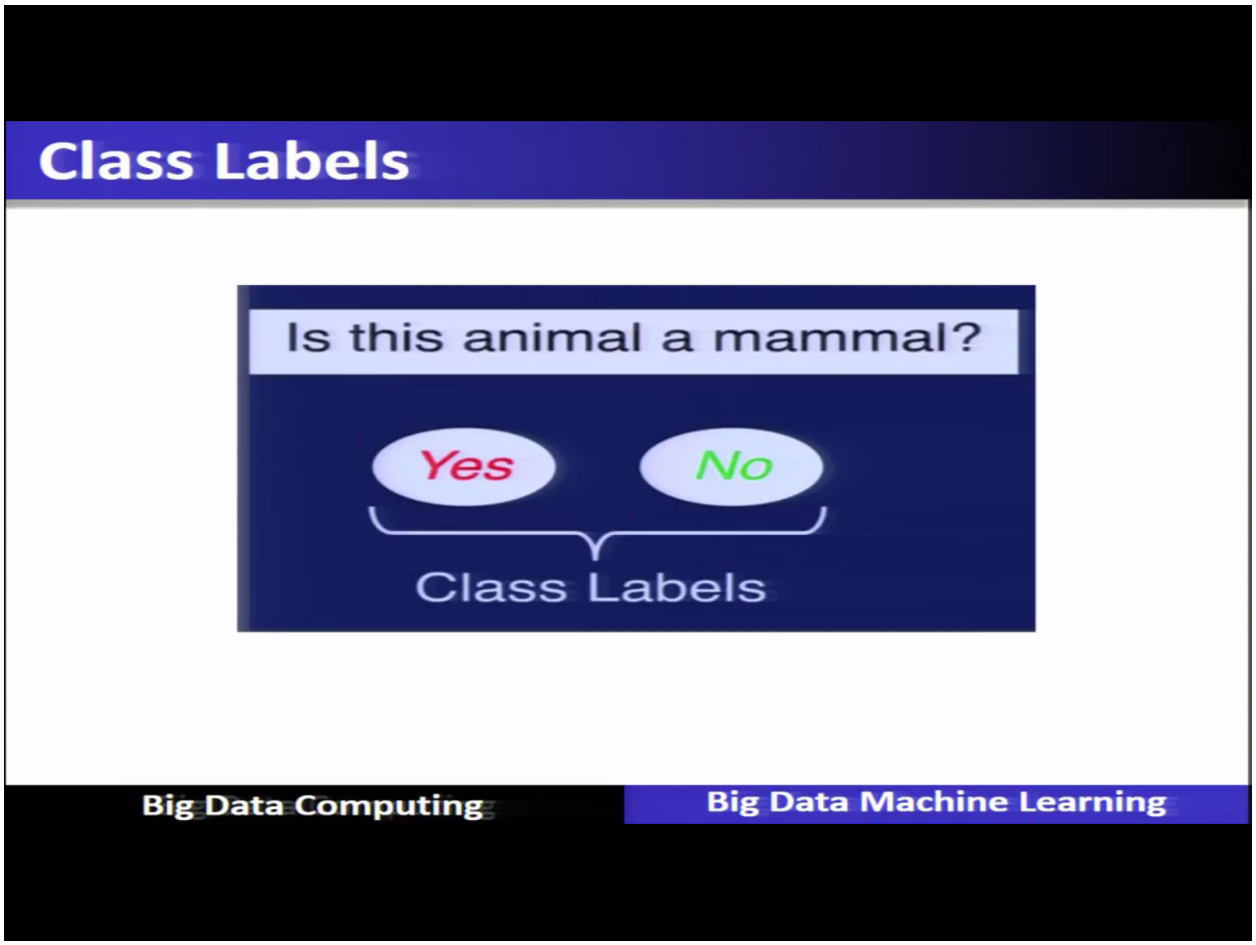

Now using this particular target label we now can see the difference between the true target label, this is called target label, this is the true label and this is the label, which is the predicted label out of the classification algorithm, this is called predicted label. Now if you compare them, if both the labels are same then the error type is called, there is no error, and it is called true positive. When the true label is no and the predicted is also no, then also it is called the true negative. So both are not having any errors. Now when the true label is no, but the predicted label is yes, then it is called the false positive. So this positive is falsely given, hence it is called a false positive. Now if the true label is yes and the predicted label is no, so it is false negative. So these different classes, we are now going to see, this is called the types of classification error. So there are four different types of classification error true positive, true negative is there... there is no error, and the predicted label is wrongly saying yes, then it is called false positive and if the predicted label is saying wrongly no... yeah it is saying wrongly no, then it is called false negative.

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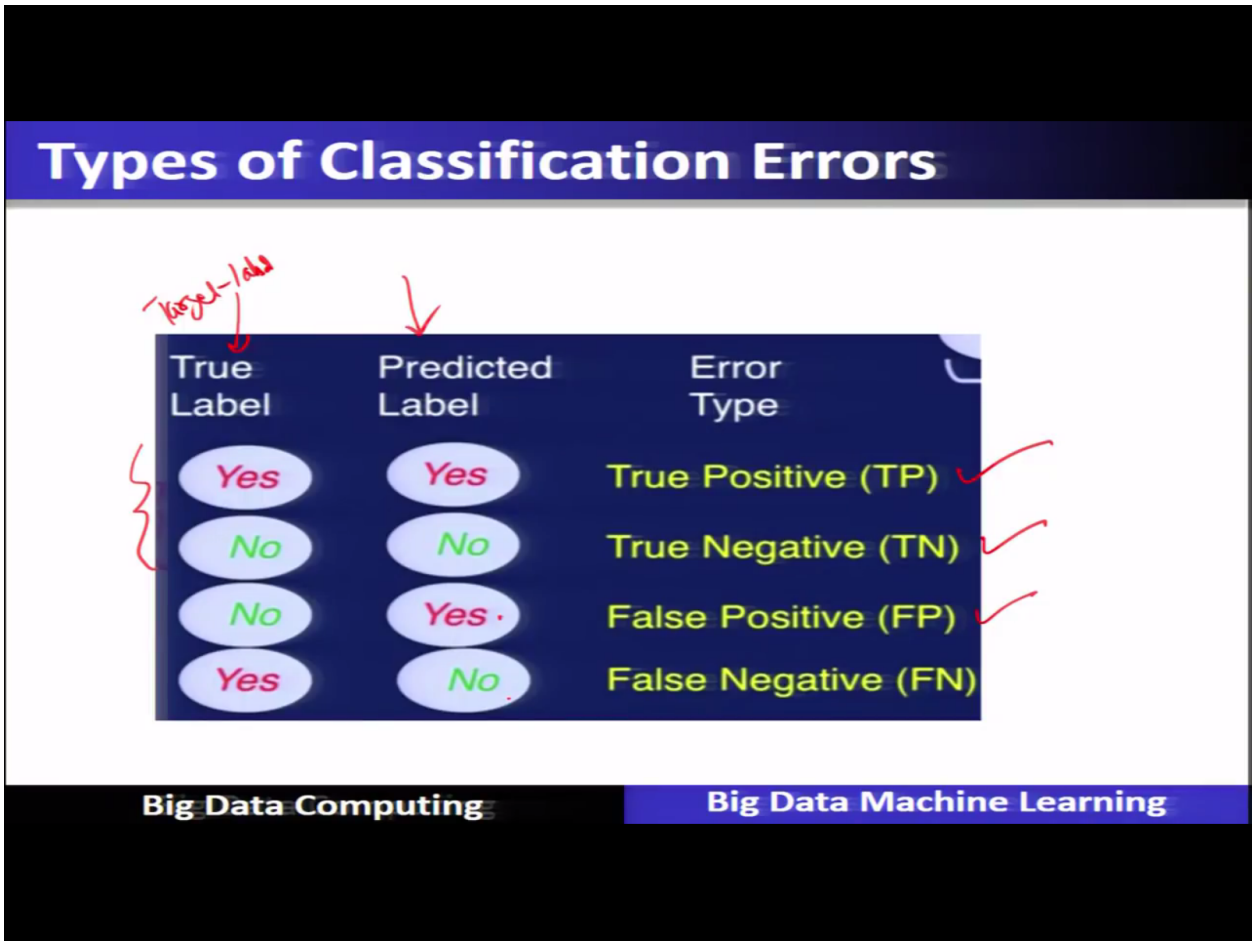

So let us see… calculate the accuracy rate out of this error types. So accuracy rate is nothing, but the number of correct predictions divided by total predictions. So number of correct predictions here you can see that the true value is yes, so it is also predicting yes, true is no, it is also saying no, and number of correct predictions, and here in all other 2 cases it is wrongly predicted. So the number of correct predictions is 2 divided by how, there are 4 different. So in that particular sample, we have to find out how many such false positions, false negatives, true positive, and true negatives are there and based on that we can find out the accuracy rate and error rate is 1-the accuracy rate, that is 0.3 here in this case.

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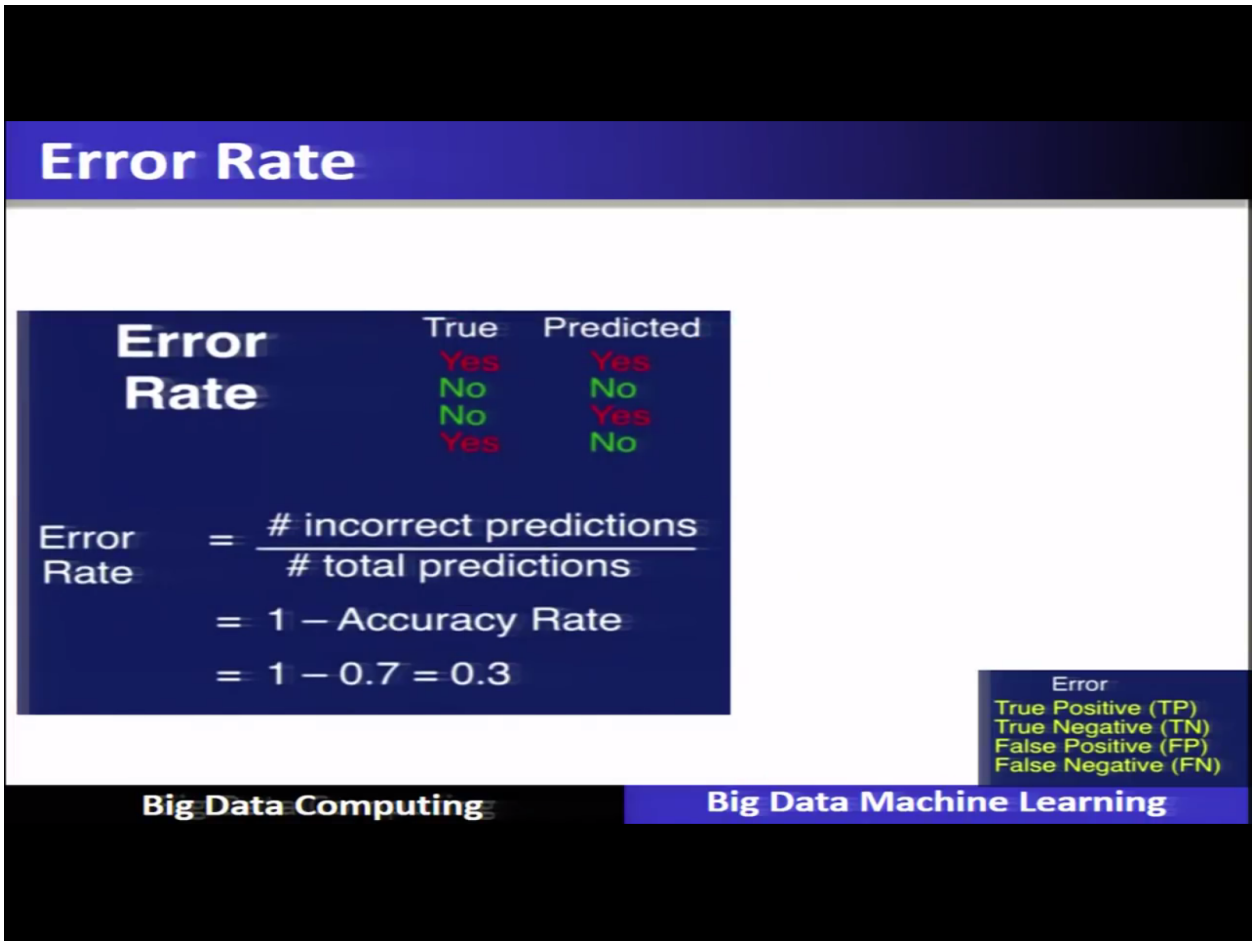

So let us see, another thing is called, recall precision says that true positives divided by true positive and false positives, so all positives. True positives divided by all positives, which is predicted by the... the prediction is called precision. And recall is true positives divided by that is true positions and false negatives, that is all samples with... So this is called recall.
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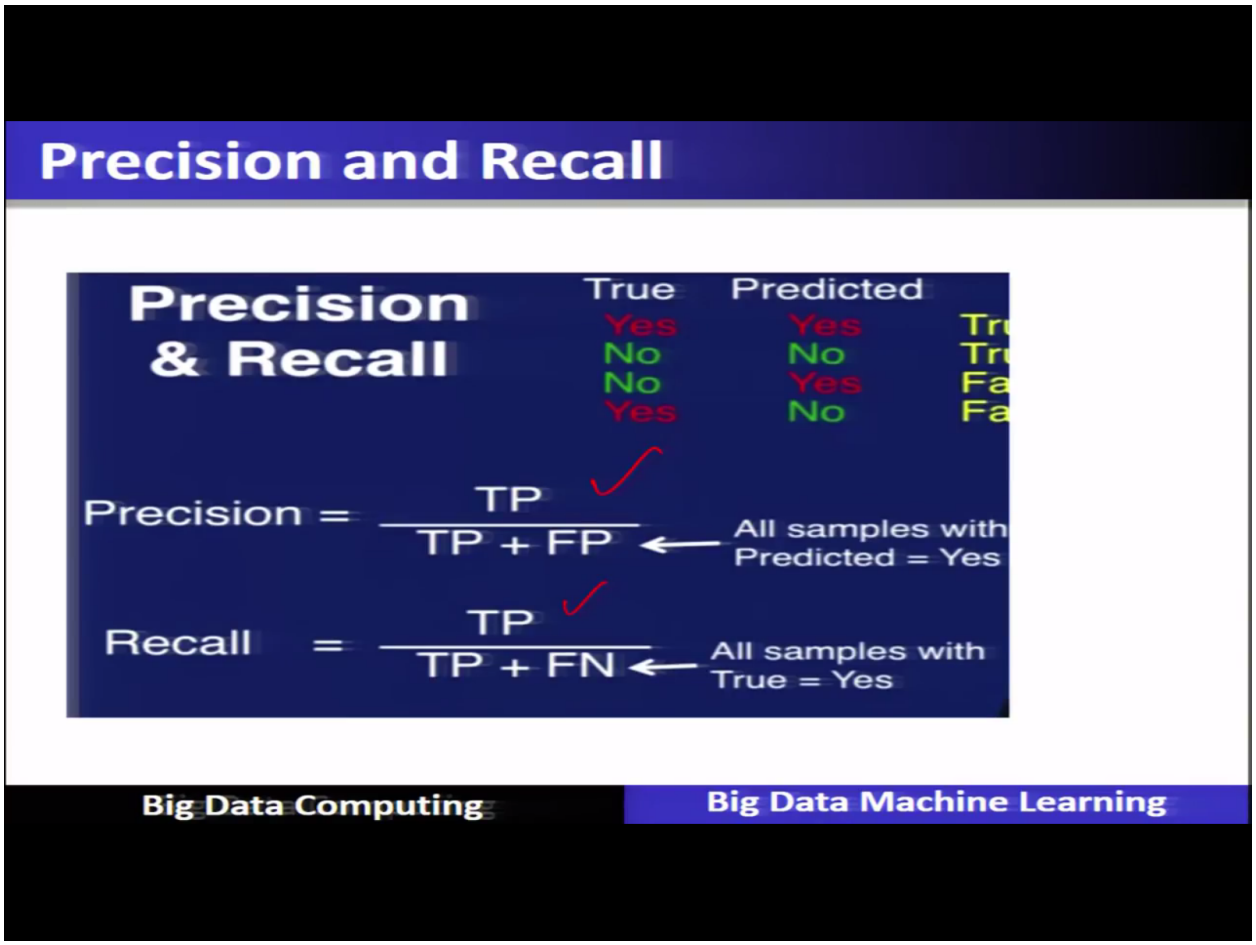

So precision and recall, precision is considered as the major of exactness, because it calculates the percentage of samples predicted as positive, which are actually positive in the class. Recall is considered as the major of completeness because it calculates the percentage of positive samples that... that the model correctly identifies.
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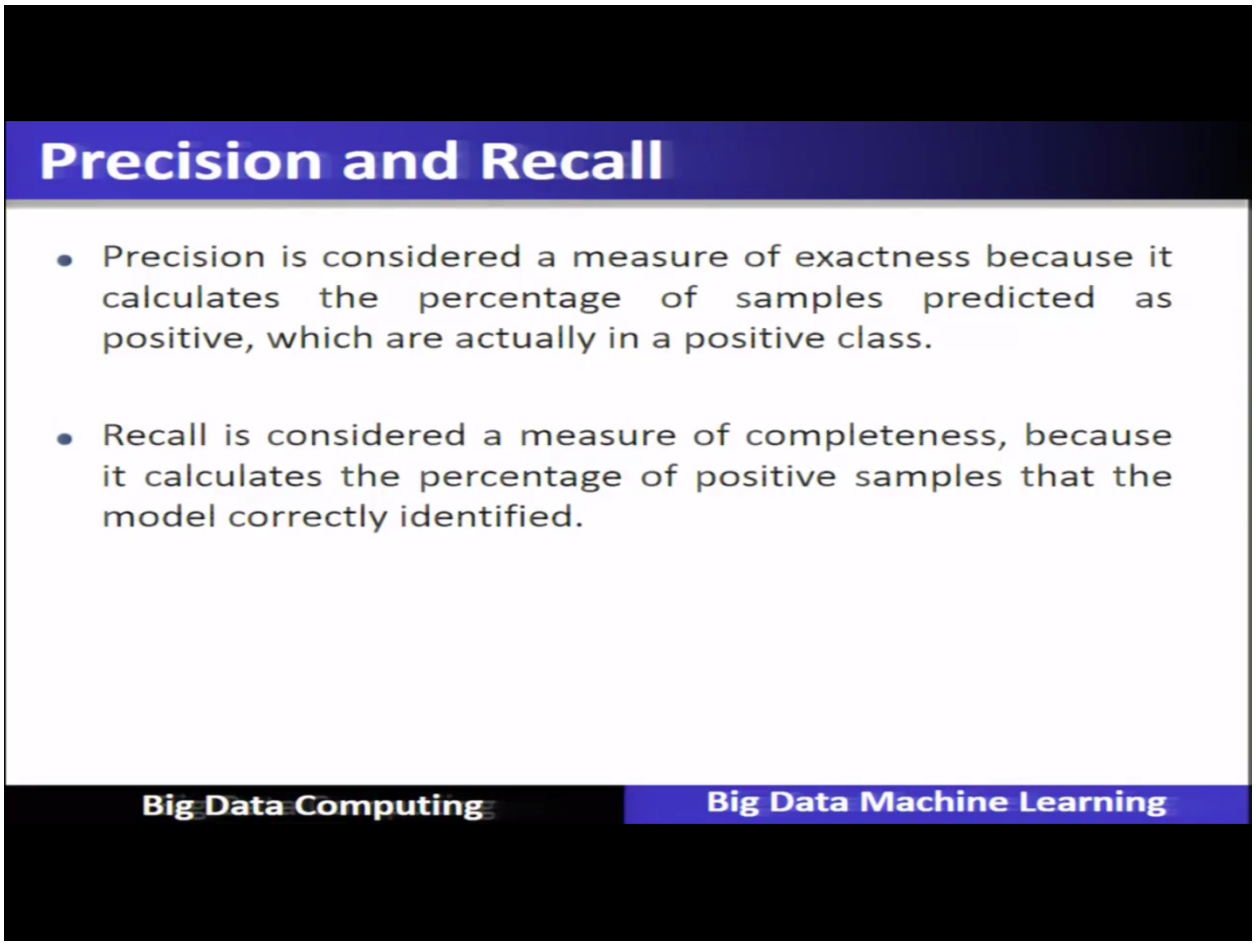

So besides precision and recall, there is something, which is called the F-Measure, which combines both of them. So F1 measure is nothing but two times precision * recall divided by precision + recall. Where F1 is evenly weighted, that means the precision and recall are given equal weights, then it is called F1 measure. And F2 measure, here the weighs recall more in this case and F0.5 measure gives the weights precision more in this case.
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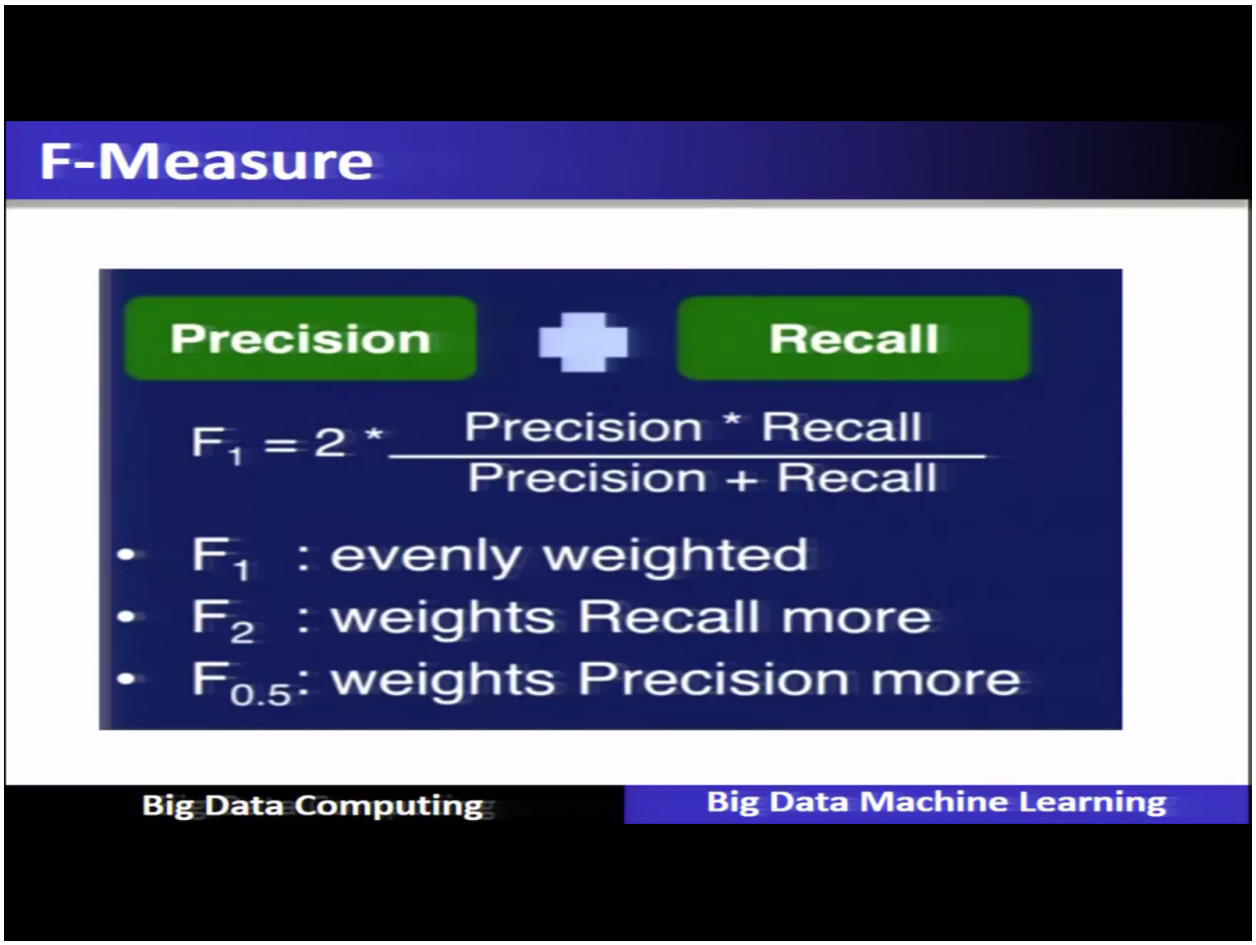
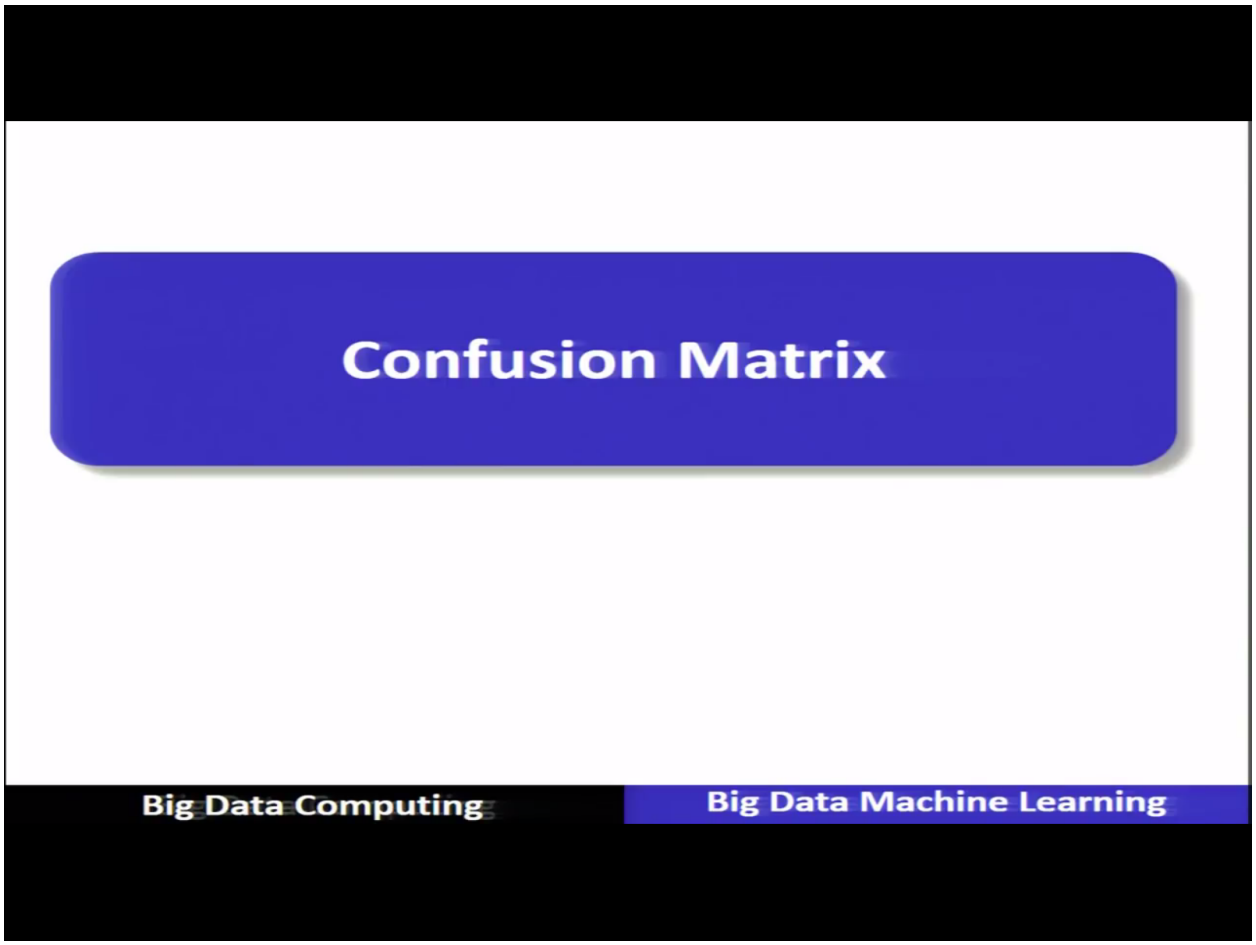


Let us see the confusion matrix.



So again we will see that if the animal is the animal mammal, so this data set of animal we are going to label that yes or no.
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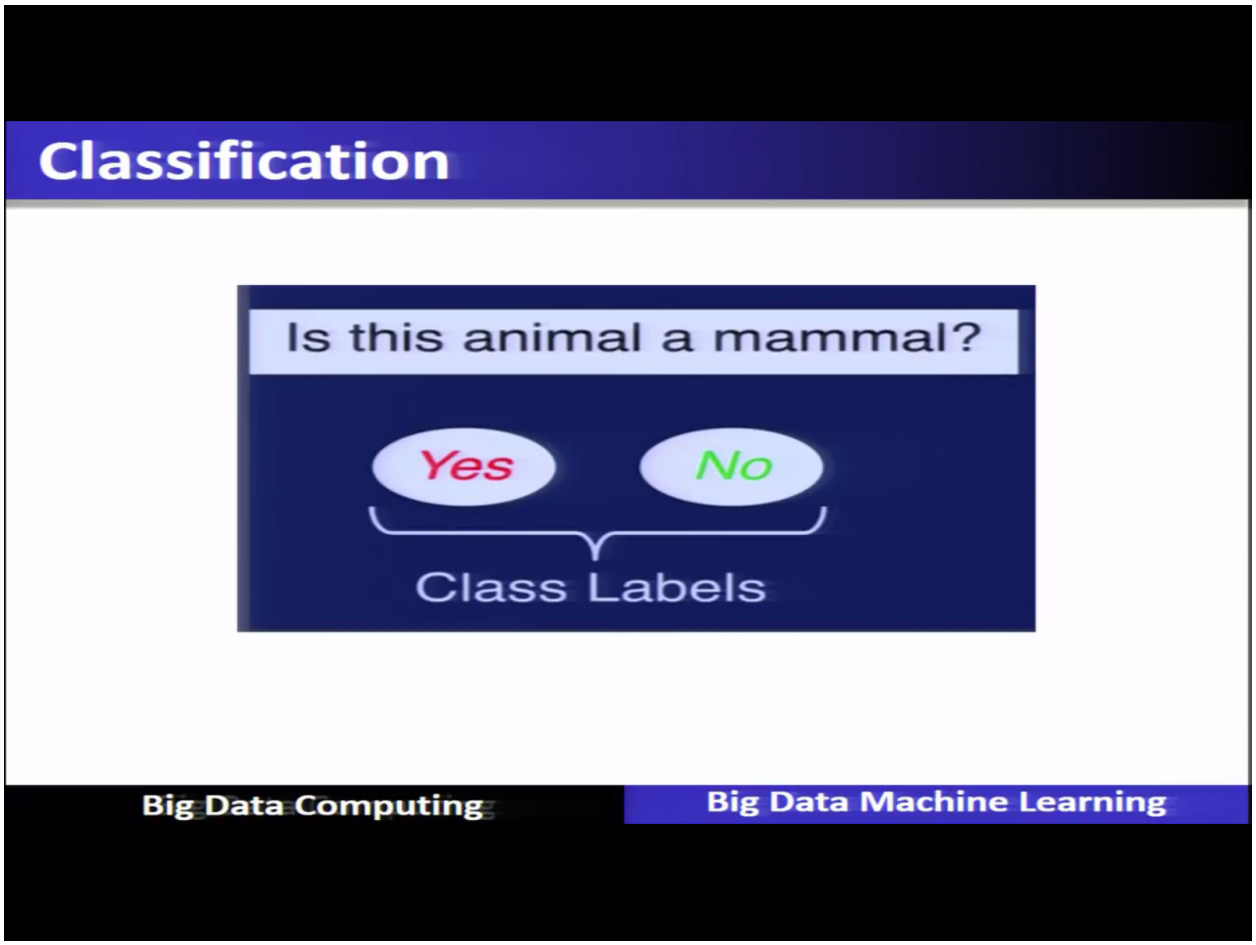

So again there are four different classification errors. Based on these classification errors, we can draw a confusion matrix. So confusion matrix on the X axis gives the true class label and whereas the Y is called predicted class label. So if the true class label is yes and the predicted class label is also yes, then it is called true positive and if the true class label is yes and the predicted is no, then it is called the... the false negative. Similarly if the true class label is no and the predicted class label is yes, then it is called false positive. And if the true label is no and the predicted is also no, then it is called true negative. So this particular matrix is called the confusion matrix.

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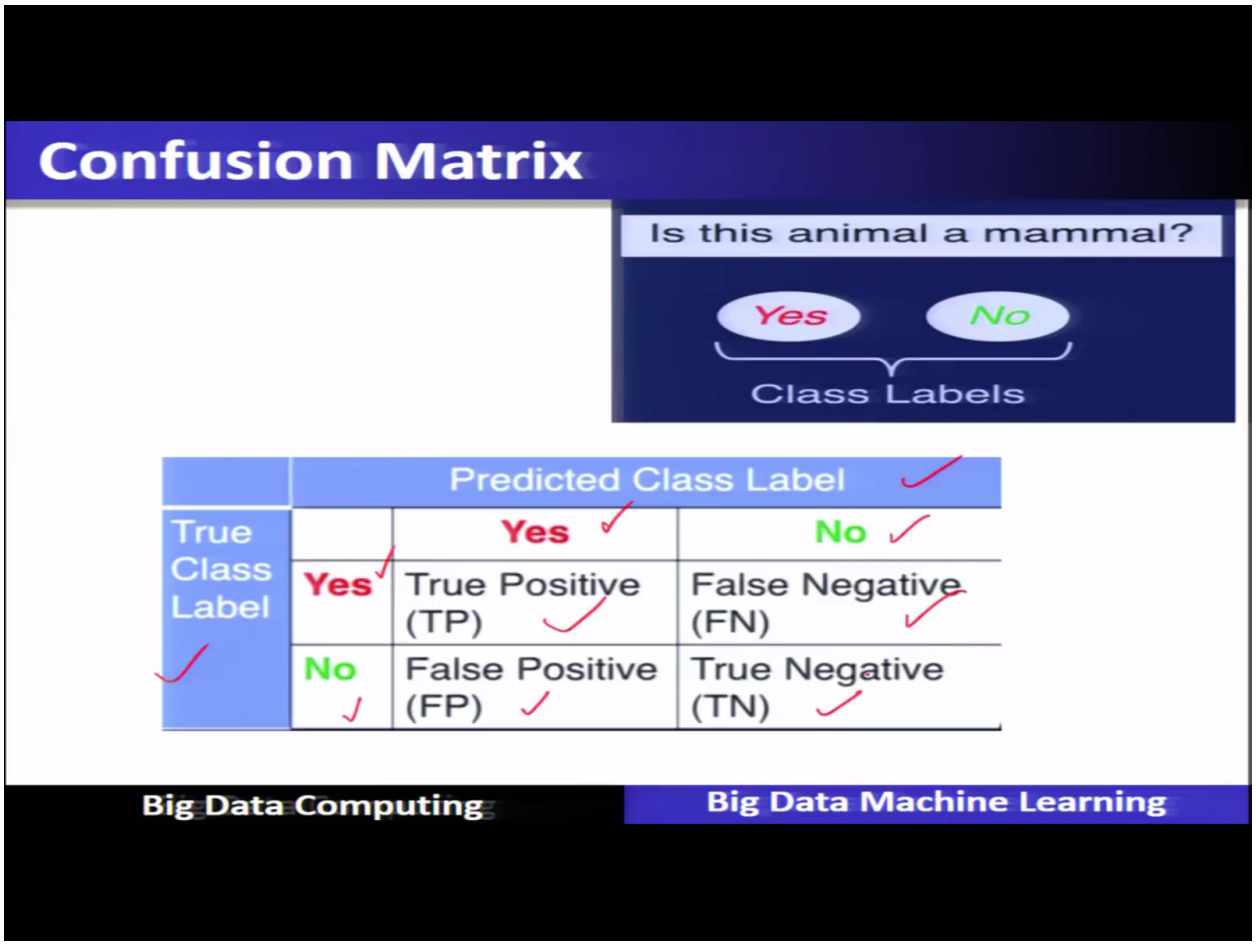

So let us see the confusion matrix for this particular example and here in this particular example, we can see that this is the true label and this true times, so… so this is the correct… this is correctly predicted and this is also correctly saying. So yes, if it is yes, then it is correctly predicted how many times 1 2 3, so it is 3 times it is appearing and when it is… when it is no, it is also correctly predicting negative, how many times? 1 2 3 and 4, 4 times it is correctly predicting. And it is… when it is no and yes, so there it is no and it is… there it is no and yes it is one times, it is false positive and the remaining is yes or no 1 and 2 times. So this we have calculated the confusion matrix. So total number of samples is 1 2 3 4 5 6 7 8 9 10, so it is 0.3 0.2 0.4 0.1, so that means number of false positive is 10% and number of true negative, so true positive is 30% and so this is the correct outcomes, so that means 70% is the accuracy of this particular case, whereas 30% is the inaccuracy.
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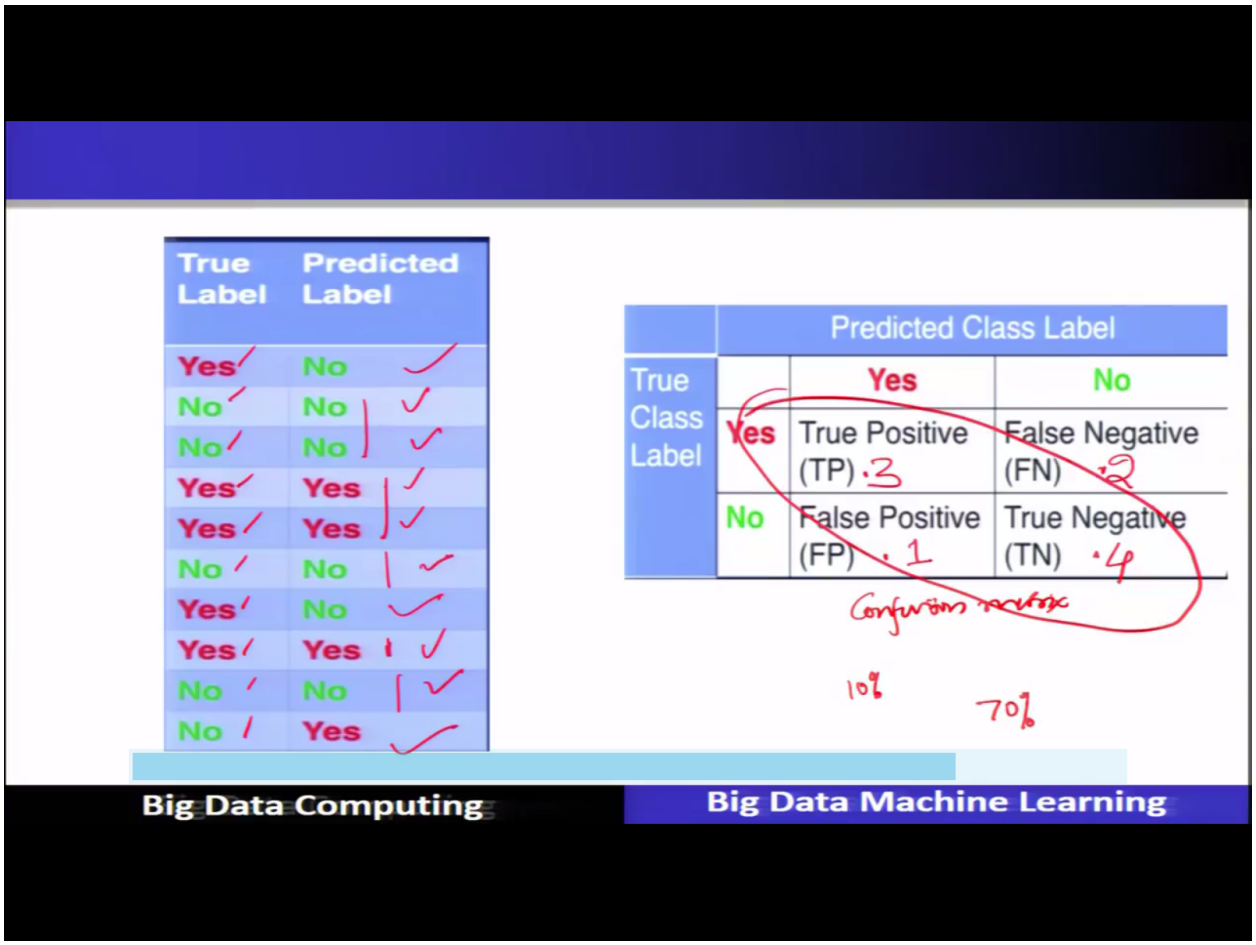

So let us see the machine learning tools.

Spark MLlib. Spark MLlib is the distributed machine learning framework on top of the spark core. So this is the spark core and on top of it is the machine learning MLlib library is positioned. So machine learning spark MLlib is a distributed machine learning framework. So what do you mean by distributed machine learning. We will see that this machine learning, that means the data is big, that the machine learning requires the data, so that it will build the model, it will learn the model and it will solve the problem. So the data is a big data, which cannot be stored on a single system, therefore the data is to be stored on a distributed platform and the machine learning algorithm also to be applied on that distributed way, hence it is called the distributed machine learning. So spark MLlib is the... the distributed machine learning framework build on top of the spark core. MLlib is a spark scalable machine learning library, consistent of common machine learning algorithms and utilities including classification, regression, clustering, collaborative filtering, and dimensionality reduction. So what do you mean by scalable machine learning library is that the cluster machines can follow the property of scale out, hence the particular algorithm that is machine learning algorithm, follows that... that particular property, hence it is called as scalable machine learning libraries, which is the sparks MLlib.
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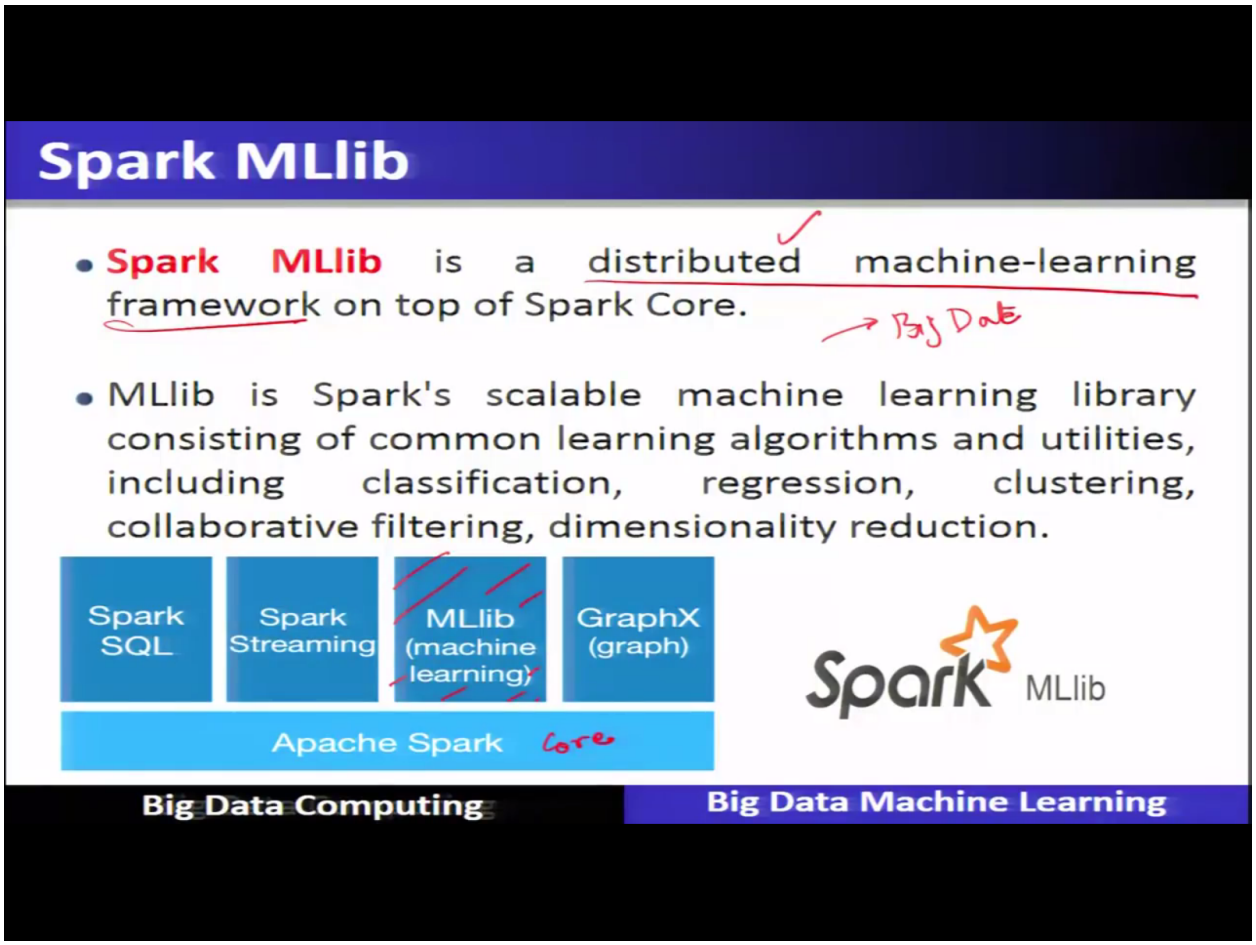

Now spark MLlib has library, has four different components. So first component is called different analysis algorithms for machine learning purpose. So the... all the algorithms which is machine learning algorithms are available as a part of spark MLlib, that is the classification, regression, clustering, and collaborative filtering. Now besides these algorithm, it is also having a feature, which is called a pipeline. So the... so the data scientist working in the big data scenario, they can write their own pipeline and do the... and apply the machine learning approach on the big data using pipeline. We will see in this particular part of the discussion that Spark MLlib provides much pipeline and how pipeline can be used for big data analytics. Then another component of MLlib is called featurization, which has two parts, very important parts, which are called extraction and transformation. So we will see, what do you mean by these extraction and transformation in this building up the pipeline. And it has also the utilities such as linear algebra and forming different statistics.

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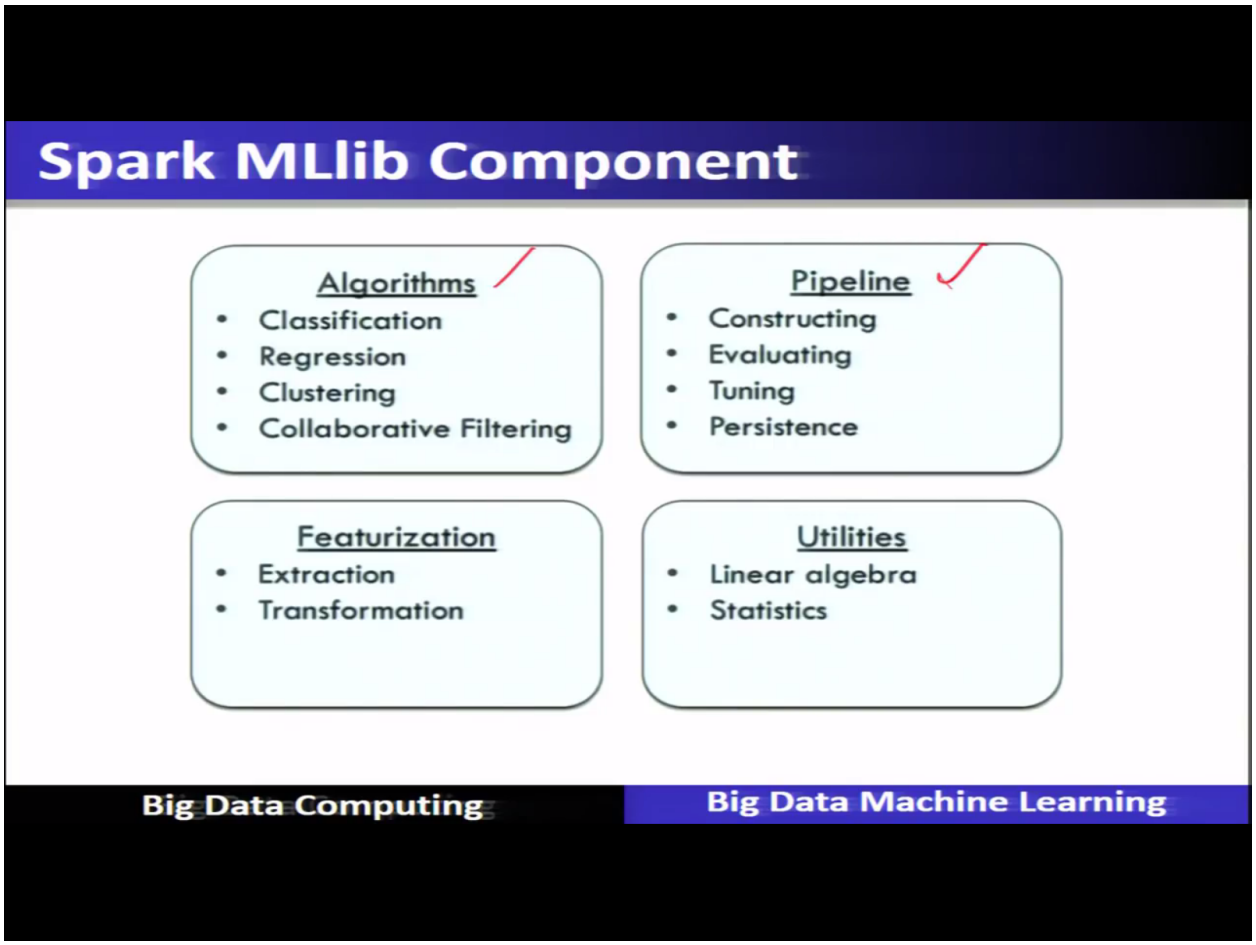

Now let us see the classification algorithm, which are available in the spark. First let us see, what are the steps of our doing the classification in spark. So these are the steps we will follow and we will see an example, how the classification is performed in the spark. Classification is to... first step is to load the data into the data frame, second is to drop unused and missing data item. So this is the data preparation. Here is to read the data, then we have to create a categorical variable for the low humidity days, so that means we will transform the data to be required in our format. Then we have to perform the aggregate features used to make predictions and that means you have to do a feature engineering or feature selection. And then split the data into the training and test data sets. Then we will create and train the decision tree and then we will save the predictions to the file
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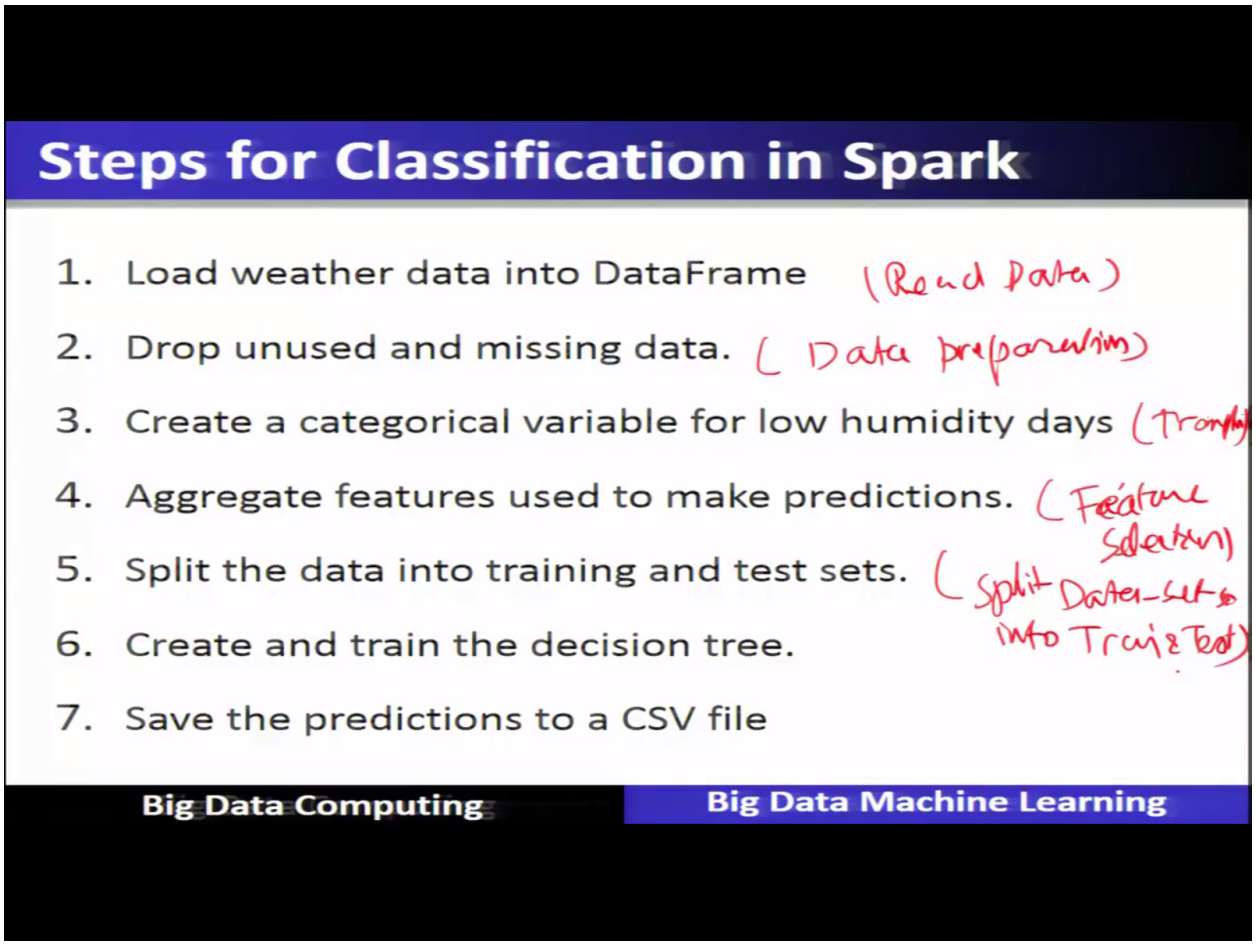

Let us see how to read the weather data into the data in spark MLlib or in spark format. So here we can see that this is the data file and we have to load using… the load data file using SQL context. So we are using SQL spark SQL… using SQL context we will read the data file, which is shown over here using these commands of spark. So using SQL context we will read this particular file and the format is given as .CSV and other information, let us say header is also there and infer schema is also available as far as spark SQL. So we will now read in the form of a data frames. So the weather data will be loaded into data frames and now if you want to see what are the different columns, after performing this red operation, what are the columns read, then these are the different columns of the data set, which is being read into the data frames. That is air pressure at 9 am, air pressure… air temperature at 9 am, average wind direction at 9 am, average wind speed at 9 am, average wind direction at 9 am, maximum wind speed 9 am, rain accumulation 9 am, rain duration 9 am. So these are different columns of your data set and this column will be used to construct the decision trees later on.

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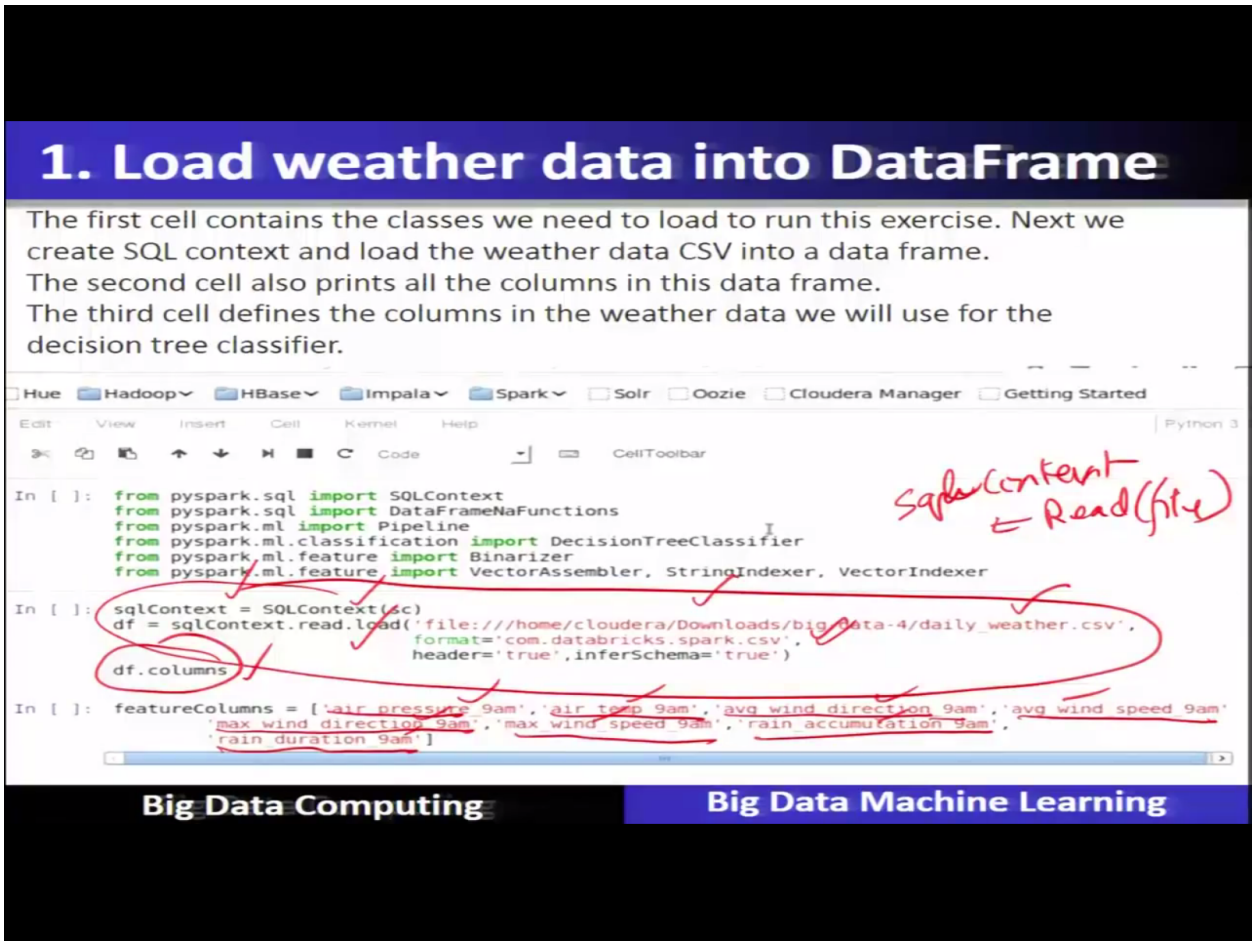

So the data frame columns are again summarized here in a nice manner.
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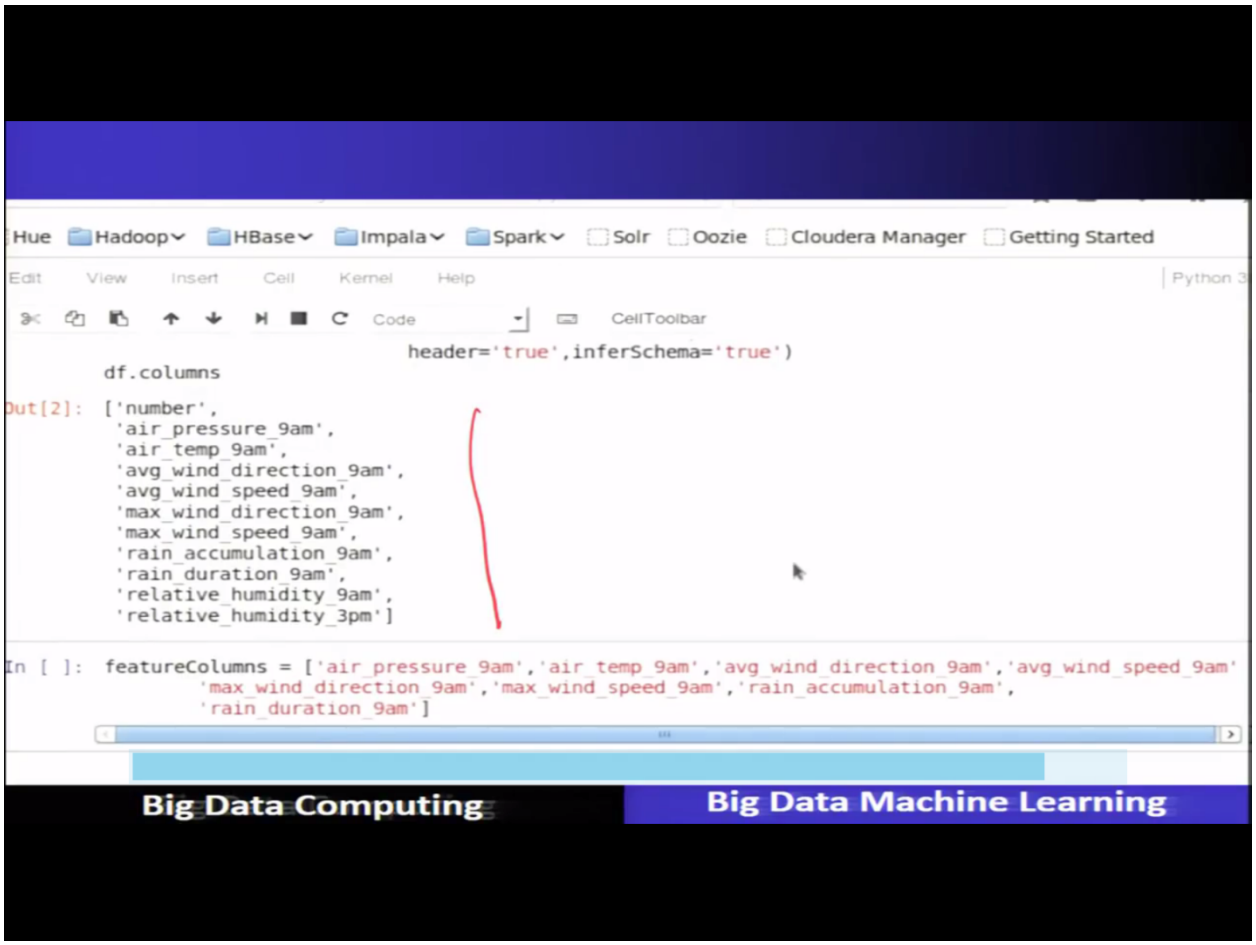

And after that then we will prepare the data, so that all the unused or the missing data can be removed. So use the column name and drop... use the column name... number and drop from... drop that from the data frame and if... when... whenever there is a row, which is missing, and then we will print the number of rows and columns in the... let us see how we can do this to drop this one data, which is having missing data. So let us see, we will find out this one, the total count. So total count of this one... data value is 1064 and we will also see that. So using DF count and the length of that data frame, of the columns, we will find out the total number of data set and we will find out how many columns or data is available and if there is a difference, so we will find out, those the missing data item and remove it. So therefore we will calculate the total number of... and we will drop all those... we will drop the... the missing data item from that particular column. And then after that we will see that it comes out to be the data set, which does not have any missed data.

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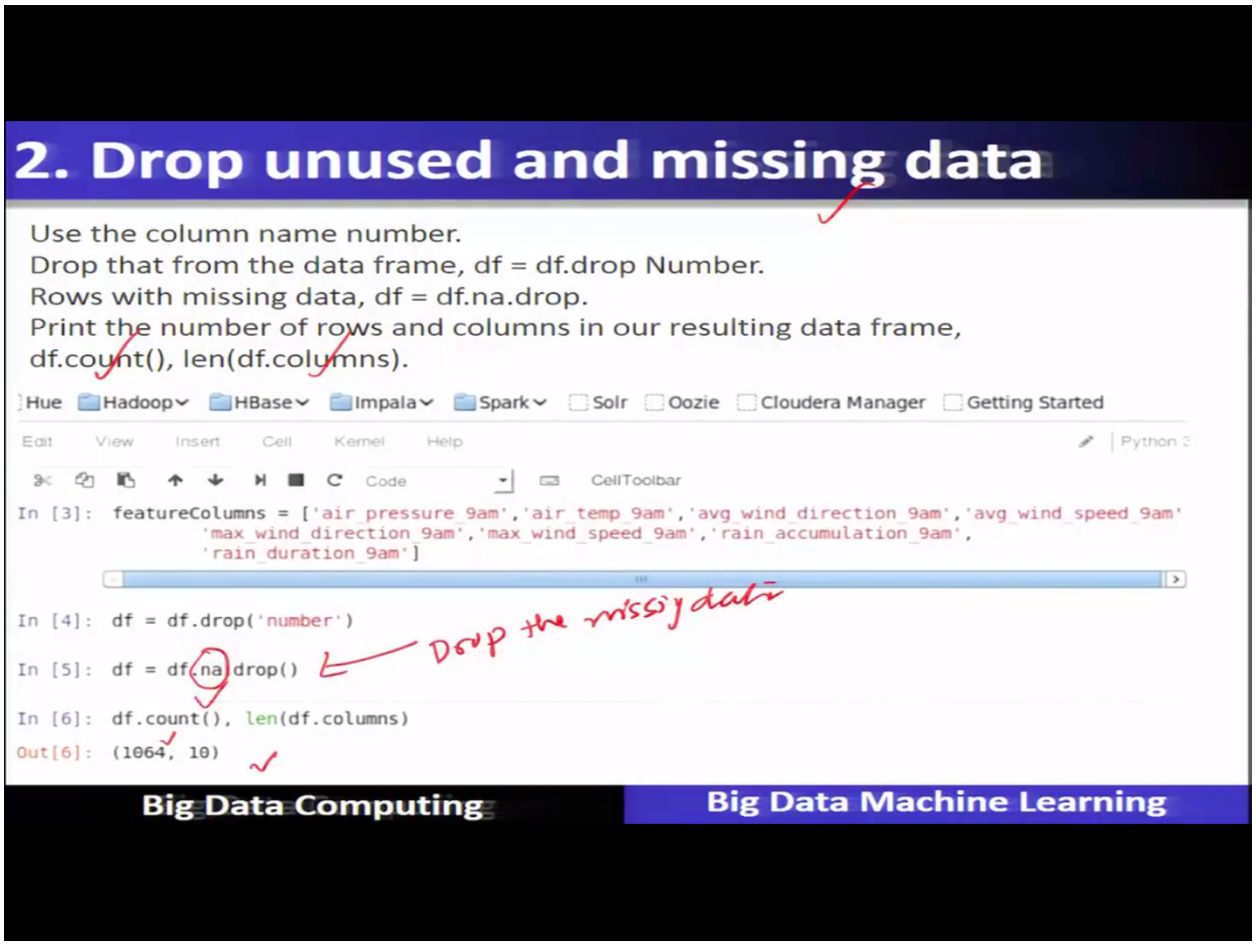

Now third step is to create the categorical variable for the low humidity days. So meaning to say that, what we will do here is that, wherever the numbers are… wherever the values… categorical values are there, these variables are to be converted into the number and this conversion can be performed from categorical data to the numerical data. And here we can see that these labels are bannerized. So these values are bannerized and the values are shown as the categorical data.

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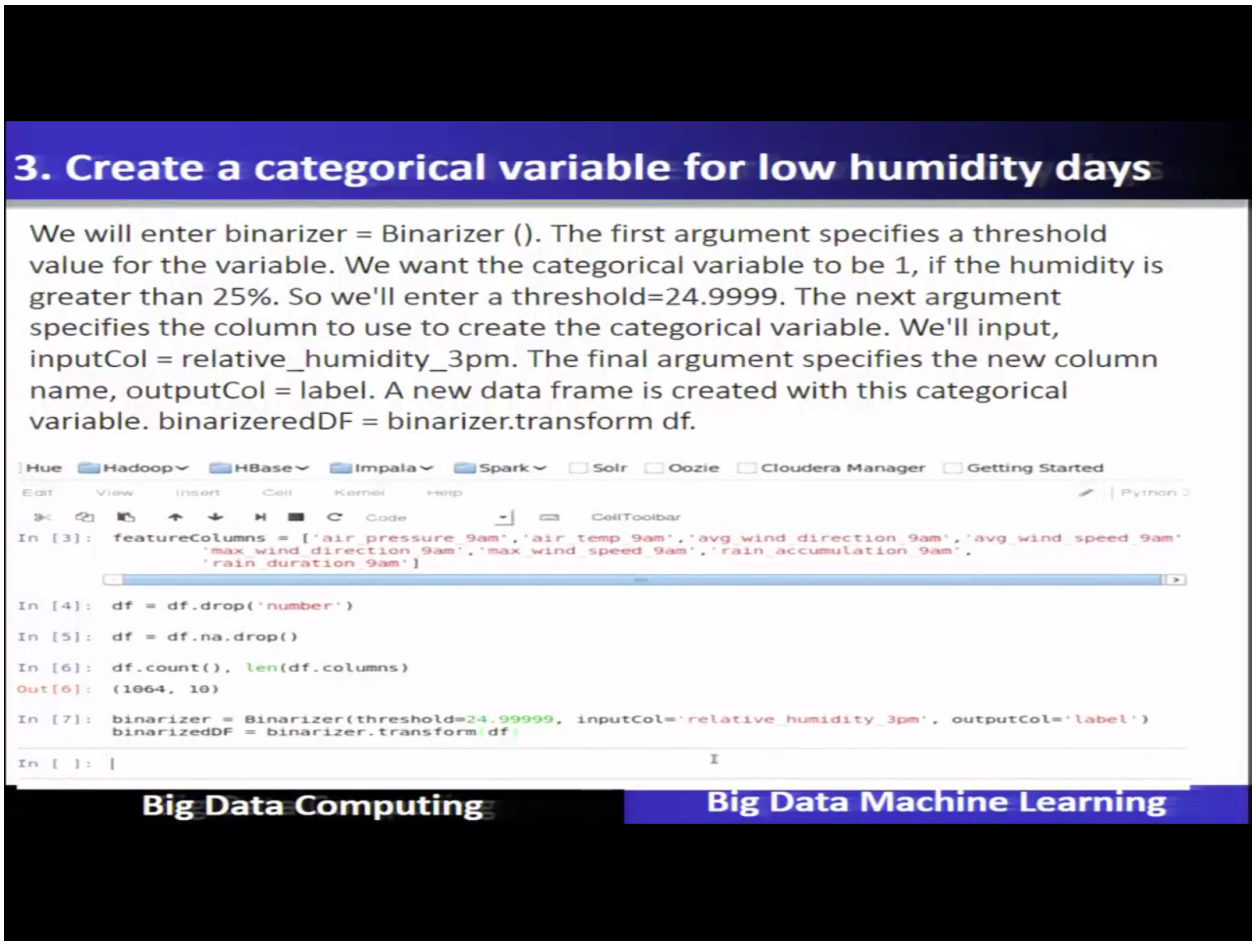

Now aggregate features will be used to make the predictions and now this particular data set will be split into, once the data is prepared, then it will be split into the training and the test data. So this will be having 80% and 20%. 80% will be training and 20% will be test data, and then we will randomly split that and using the training data we will now fit... we will process it to build the decision trees. Let us see how we will do this. So after doing this here we can see that we are building the... we are setting up the decision tree and in the decision tree pipeline we have to build and now we will perform the... the this one... to fit the model. So model is when it is fit... that training... on a training data, the model will be the decision tree and once the model is fit, then we will perform the predictions on that particular data.
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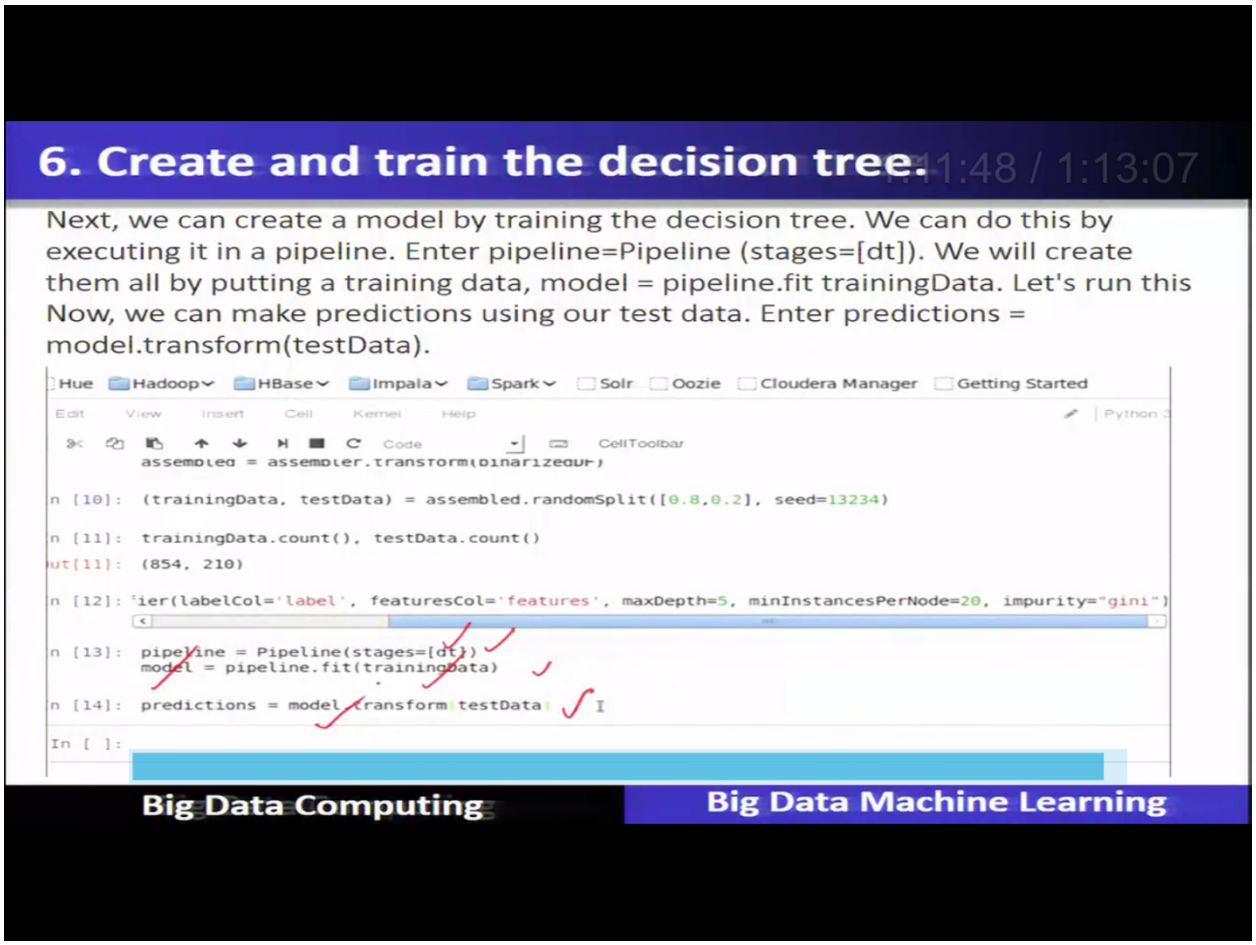

So once the… the predictions are made, we will see the… the labels and the prediction values. So here you see that all are having same and now we will see prediction accuracy using. So these predictions values are now stored on the… on the file, CSV file.
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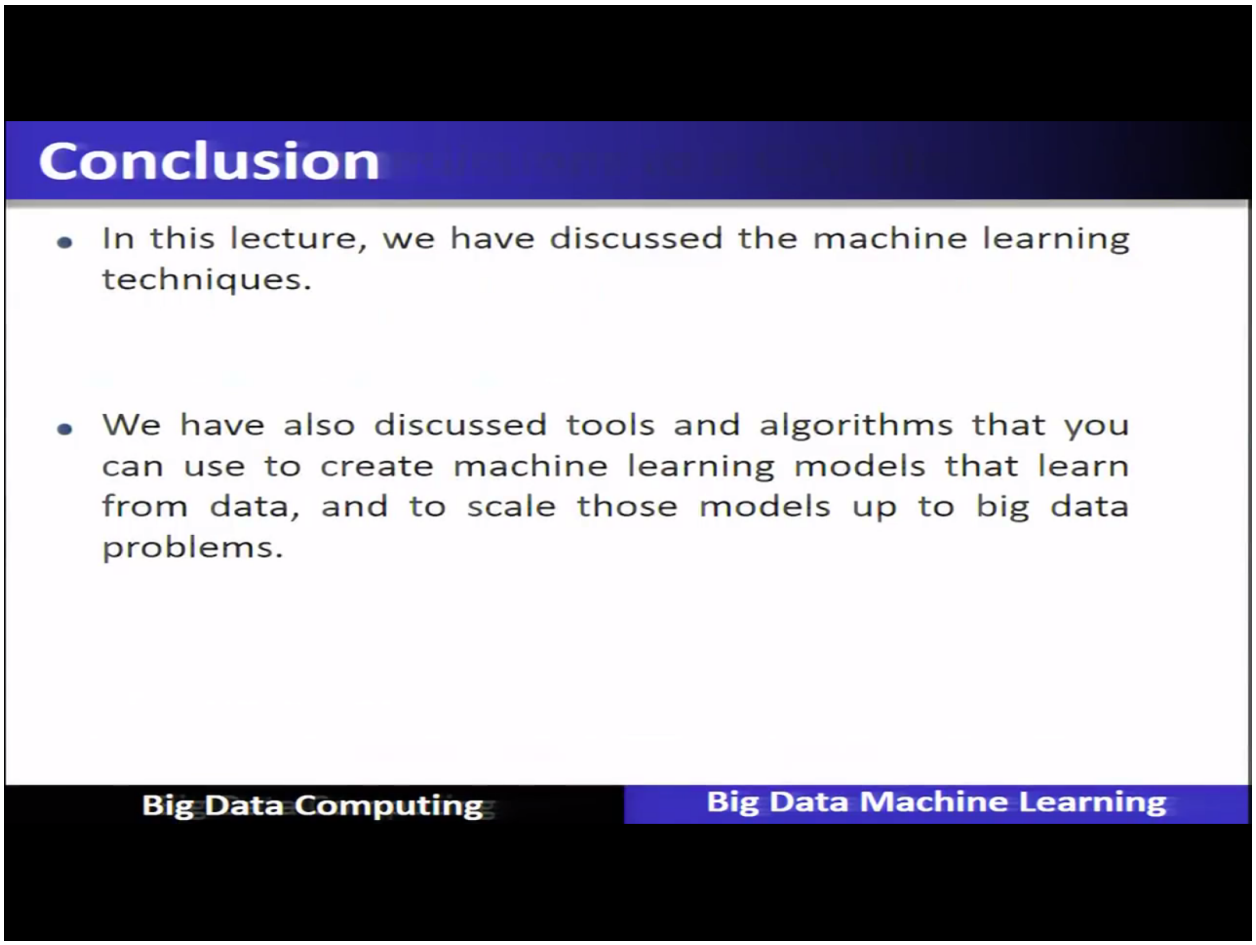

So conclusion, in this lecture we have discussed the machine learning techniques. We have also discussed the tools and algorithms that you can use to create the machine learning models that learned from the data and to scale those models up to the big data problem. Thank you.
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Conclusion

- In this lecture, we have discussed the machine learning techniques.

- We have also discussed tools and algorithms that you can use to create machine learning models that learn from data, and to scale those models up to big data problems.