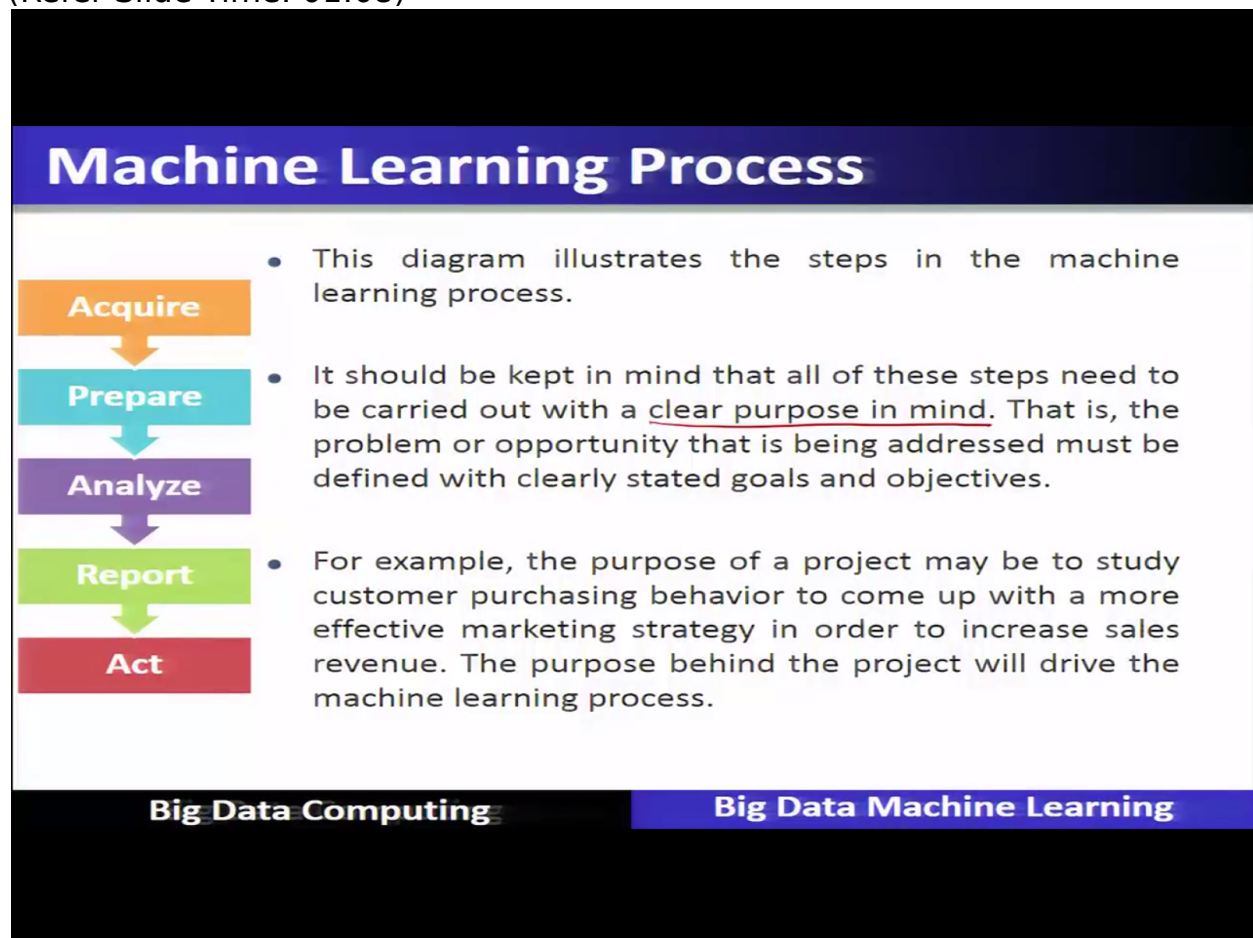


Machine learning process. Machine learning process, this diagram explains the steps in the machine learning process, which has Acquire, Prepare, Analyze, Report, and Act. So it should be kept in mind that all these steps are needed to be carried out with a clear purpose in mind that is the problem or 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.

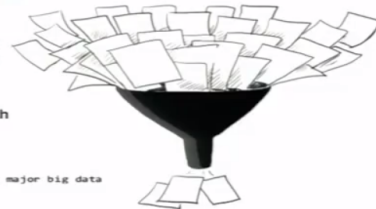
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Step 1: Acquire Data

- The first step in the machine learning process is to get all available data related to the problem at hand. Here, we need to identify all data sources, collect the data, and finally integrate data from these multiple sources.

What is Data Acquisition

It is the process of gathering, filtering and cleaning the data before it is put in a data warehouse or any other storage solution on which data analysis can be carried out.



 Data acquisition is one of the major big data challenges

Big Data Computing

Big Data Machine Learning

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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Step 2: Prepare Data

- This step is further divided into two parts, **explore data** and **pre-process data**.

Data Exploration

The first part of data preparation involves preliminary exploration of the data to understand the nature of the data that we have to work with. Things we want to understand about the data are its characteristics, format, and quality. A good understanding of the data leads to a more informed analysis and a more successful outcome.

Pre-processing

- Once we know more about the data through exploratory analysis, the next part is pre-processing of the data for analysis. This includes cleaning data, selecting the variables to use, and transforming data to make the data more suitable for analysis in the next step.



Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 05:59)

Step 3: Analyze Data ✓

- The prepared data then would be passed on to the analysis step. This step involves selecting the analytical techniques to use, building a model using the data, and assessing the results.

Selection
Fit model in data w/ selected techniques

ML techniques
- Classification
- Regression
- Clustering
- Association



Big Data Computing

Big Data Machine Learning

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 4: Communicate Results

- This includes evaluating the results with respect to the goal set for the project. Presenting the results in a easy to understand way and communicating the results to others.



Big Data Computing

Big Data Machine Learning

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.



Big Data Computing

Big Data Machine Learning

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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Iterative Process

- Note that the machine learning process is a very iterative one. Findings from one step may require a previous step to be repeated with new information.
- For example, during the prepare step, we may find some data quality issues that may require us to go back to the acquire step to address some issues with data collection or to get additional data that we didn't include in the first go around.

Big Data Computing

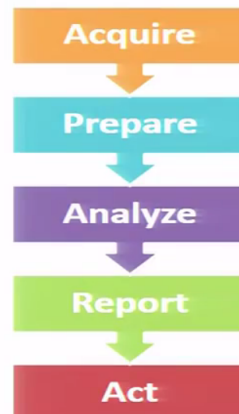
Big Data Machine Learning

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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Goals and Activities in the Machine Learning Process

- Here we will describe the goals of each step and the key activities performed in each step.



Big Data Computing

Big Data Machine Learning

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 different 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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Acquire Data

- The first step in the data science process is to acquire the data. The goal of the step is to identify and obtain all data related to the problem at hand. First, we need to identify all related data and the sources. Keep in mind, that data can come from different sources such as files, databases, the internet, mobile devices. So remember to include all data related to the problem you are addressing.

Data Sources related to problem at hand

- After you've identified your data and data sources, the next step is to collect the data and integrate data from the different sources. This may require conversion, as data can come in different formats. And it may also require aligning the data, as data from different sources may have different time or spatial resolutions. Once you've collected and integrated your data, you now have a coherent data set for your analysis.

Big Data Computing

Big Data Machine Learning

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. (Refer Slide Time: 09:42)

Prepare Data

- The next step after acquiring data is to prepare it to make it suitable for analysis.
- There are two parts to this step, explore data and preprocess data.

Big Data Computing

Big Data Machine Learning

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, outliers 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. Outliers 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 outliers. 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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Describe your Data

- One way to explore your data is to calculate summary statistics to numerically describe the data.
- Summary statistics are quantities that capture various characteristics of a set of values with a single number, or a small set of numbers. Some basic summary statistics that you should compute for your data set are mean, median, mode, range and standard deviation. Mean and median are measures of the location of a set of values. Mode is the value that occurs most frequently in your data set, and range and standard deviation are measures of spread in your data. Looking at these measures will give you an idea of the nature of your data. They can tell you if there's something wrong with your data.
- For example, if the range of the values for age in your data includes negative numbers, or a number much greater than a hundred, there's something suspicious in the data that needs to be examined

Big Data Computing

Big Data Machine Learning

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 set 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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Describe your Data

- One way to explore your data is to calculate summary statistics to numerically describe the data.
- Summary statistics are quantities that capture various characteristics of a set of values with a single number, or a small set of numbers. Some basic summary statistics that you should compute for your data set are mean, median, mode, range and standard deviation.
✓ Mean and median are measures of the location of a set of values. Mode is the value that occurs most frequently in your data set, and range and standard deviation are measures of spread in your data. Looking at these measures will give you an idea of the nature of your data. They can tell you if there's something wrong with your data.
- For example, if the range of the values for age in your data includes negative numbers, or a number much greater than a hundred, there's something suspicious in the data that needs to be examined

Big Data Computing

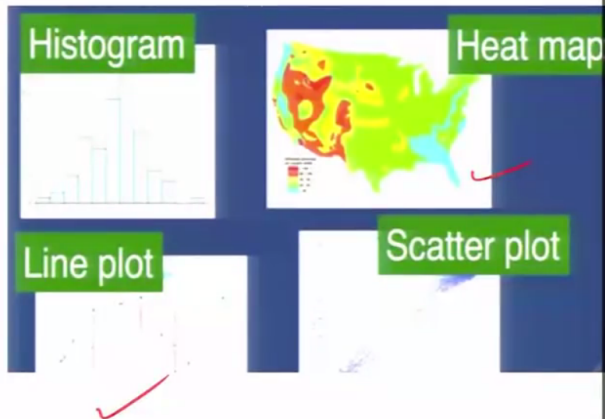
Big Data Machine Learning

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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Visualize Your Data

- Visualization techniques also provide quick and effective ways to explore your data. Some examples are, a histogram, such as the plot shown here, shows the distribution of the data and can show skewness or unusual dispersion in outliers.
- A line plot, like the one in the lower left, can be used to look at trends in the data, such as, the change in the price of a stock. A heat map can give you an idea of where the hot spots are.
- A scatter plot effectively shows correlation between two variables. Overall, there are many types of plots to visualize data. They are very useful in helping you understand the data you have.



Big Data Computing

Big Data Machine Learning

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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Step-2-B: Pre-Process

- The second part of the prepare step is preprocess. So, after we've explored the data, we need to preprocess the data to prepare it for analysis.
- The goal here is to create the data that will be used for analysis.
- The main activities on this part are to clean the data, select the appropriate variables to use and transform the data as needed.

Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 15:39)

Data Cleaning

- A very important part of data preparation is to clean the data to address quality issues. Real world data is nothing. There are many examples of quality issues with data from real applications including missing values, such as income in a survey, duplicate data, such as two different records for the same customer with different addresses.
- Inconsistent or invalid data, such as a six digit zip code. Noise in the collection of data that distorts the true values. Outliers, such as a number much larger than 100 for someone's age. It is essential to detect and address these issues that can negatively affect the quality of the data.

Big Data Computing

Big Data Machine Learning

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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Feature Transformation

- Feature transformation maps the data from one format to another. Various transformation operations exist. For example, scaling maps the data values to a specified range to prevent any one feature from dominating the analysis results.
- Filtering or aggregation can be used to reduce noise and variability in the data.
- Dimensionality reduction maps the data to a smaller subset of dimensions to simplify the subsequent analysis. We will discuss techniques to prepare data in more detail later in this course.

Big Data Computing

Big Data Machine Learning

Then feature transformation. Feature transformation maps the data from one format to another format, various transformation operations exist, for example 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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Feature Transformation

- Feature transformation maps the data from one format to another. Various transformation operations exist. For example, scaling maps the data values to a specified range to prevent any one feature from dominating the analysis results.
- Filtering or aggregation can be used to reduce noise and variability in the data.
- Dimensionality reduction maps the data to a smaller subset of dimensions to simplify the subsequent analysis. We will discuss techniques to prepare data in more detail later in this course.

Big Data Computing

Big Data Machine Learning

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-3: Analyze

- After preparing the data to address data quality issues and preprocess it to get it in the appropriate format, the next step in the machine learning process is to analyze the data. The goals of the staff are to build a machine learning model, to analyze the data and to evaluate the results that you get from the model.
- The analyze steps starts with this determining the type of problem you have. You begin by selecting appropriate machine learning techniques to analyze the data.
- Then you construct the model using the data that you've prepared. Once the model is built, you will want to apply it to new data samples to evaluate how well the model performs. Thus data analysis involves selecting the appropriate technique for your problem, building the model, then evaluating the results.

fit the ML with Data

Big Data Computing

Big Data Machine Learning

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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Step-4: Report

- The next step in the machine learning process is reporting results from your analysis. In reporting your results, it is important to communicate your insights and make a case for what actions should follow.
- In reporting your results, you will want to think about what to present, as well as how to present. In deciding what to present, you should consider what the main results are, what insights were gained from your analysis, and what added value do these insights bring to the application.
- Keep in mind that even negative results are valuable lessons learned, and suggest further avenues for additional analysis. Remember that all findings must be presented so that informs decisions can be made for next steps.
- In deciding how to present, remember that visualization is an important tool in presenting your results.
- Plots and summary statistics discussing the explore step can be used effectively here as well. You should also have tables with details from your analysis as backup, if someone wants to take a deeper dive into the results.
- In summary, you want to report your findings by presenting your results and the value added with graphs using visualization tools.

Big Data Computing

Big Data Machine Learning

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 effective 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. Assessing... 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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Step-5: Act

- The final step in the machine learning process is to determine what action should be taken based on the insights gained.
- What action should be taken based on the results of your analysis? Should you market certain products to a specific customer segment to increase sales? What inefficiency can be removed from your process? What incentives would be effective in attracting new customers?
- Once a specific action has been determined, the next step is to implement the action. Things to consider here include, how can the action be added to your application? How will end users be affected?
- Assessing the impact of the implemented action is then necessary to evaluate the benefits gained. The results of this assessment determine next steps, which could suggest additional analysis or further opportunities, which would begin another cycle of the machine learning process.

Big Data Computing

Big Data Machine Learning

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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Errors in Classification

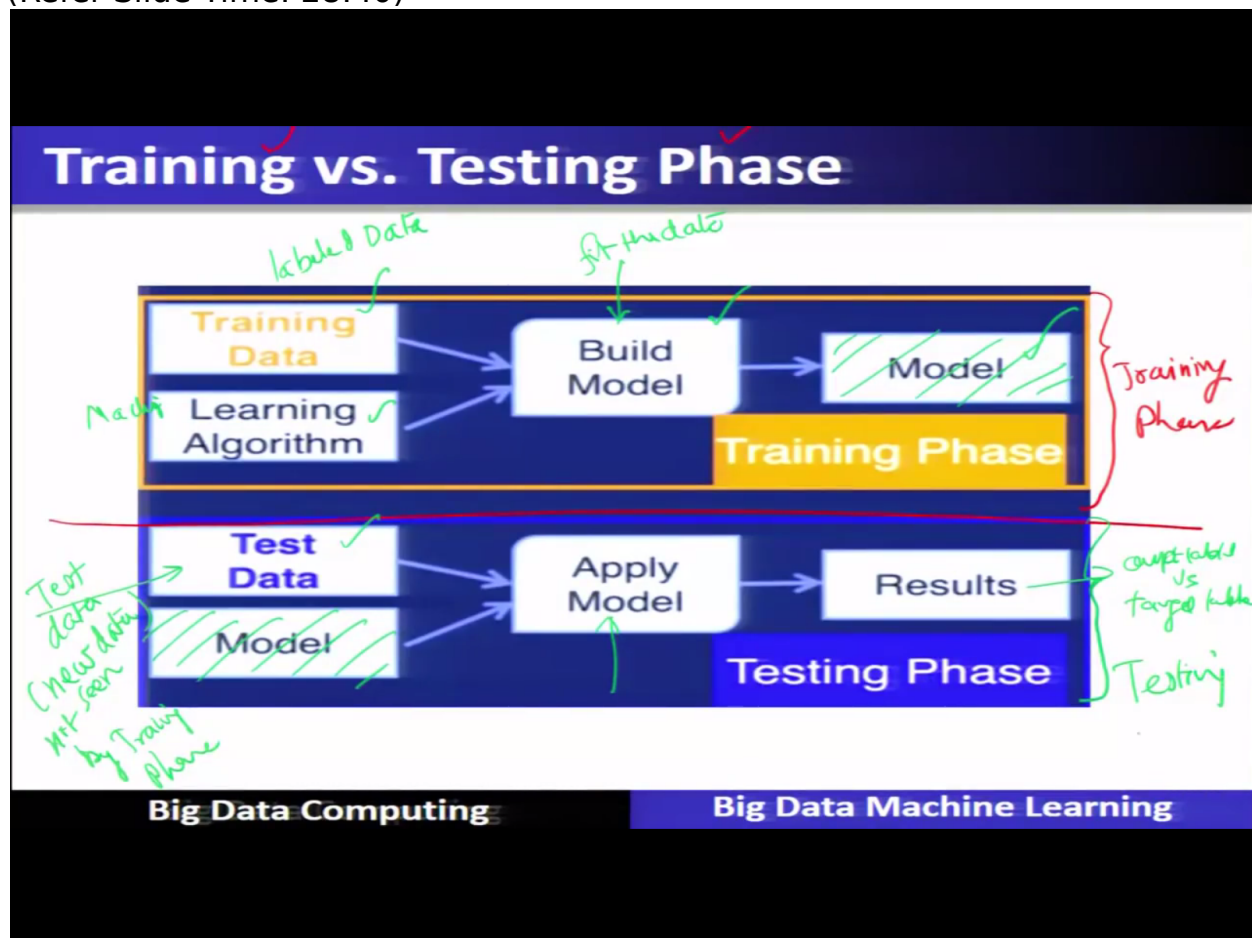
- Recall that a machine learning model maps the input it receives to an output. For a classification model, the model's output is the predicted class label for the input variables and the true class label is the target.
- Then if the classifier predicts the correct classes label for a sample, that is a success. If the predicted class label is different from the true class label, then that is an error.
- The error rate, then, is the percentage of errors made over the entire data set. That is, it is the number of errors divided by the total number of samples in a data set.
- Error rate is also known as misclassification rate, or simply error.

Big Data Computing
Big Data Machine Learning

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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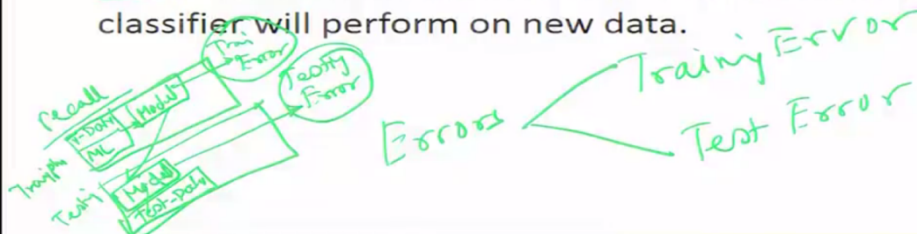


So therefore let us see more insight into the errors of... errors and the classification. The model is built using the training data and evaluated on the test data, that we have seen in the previous slides. So the training and test data are the two different data sets. The goal in building the machine 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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Errors in Classification

- The model is built using training data and evaluated on test data. The training and test data are two different data sets. The goal in building a machine learning model is to have the model perform well on training, as well as test data.
- Error rate, or simply error, on the training data is referred to as training error, and the error on test data is referred to as test error. The error on the test data is an indication of how well the classifier will perform on new data.



Big Data Computing

Big Data Machine Learning

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 is 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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Generalization

- This is known as generalization. Generalization refers to how well your model performs on new data, that is data not used to train the model.
- You want your model to generalize well to new data. If your model generalizes well, then it will perform well on data sets that are similar in structure to the training data, but doesn't contain exactly the same samples as in the training set.
- Since the test error indicates how well your model generalizes to new data, note that the test error is also called generalization error.

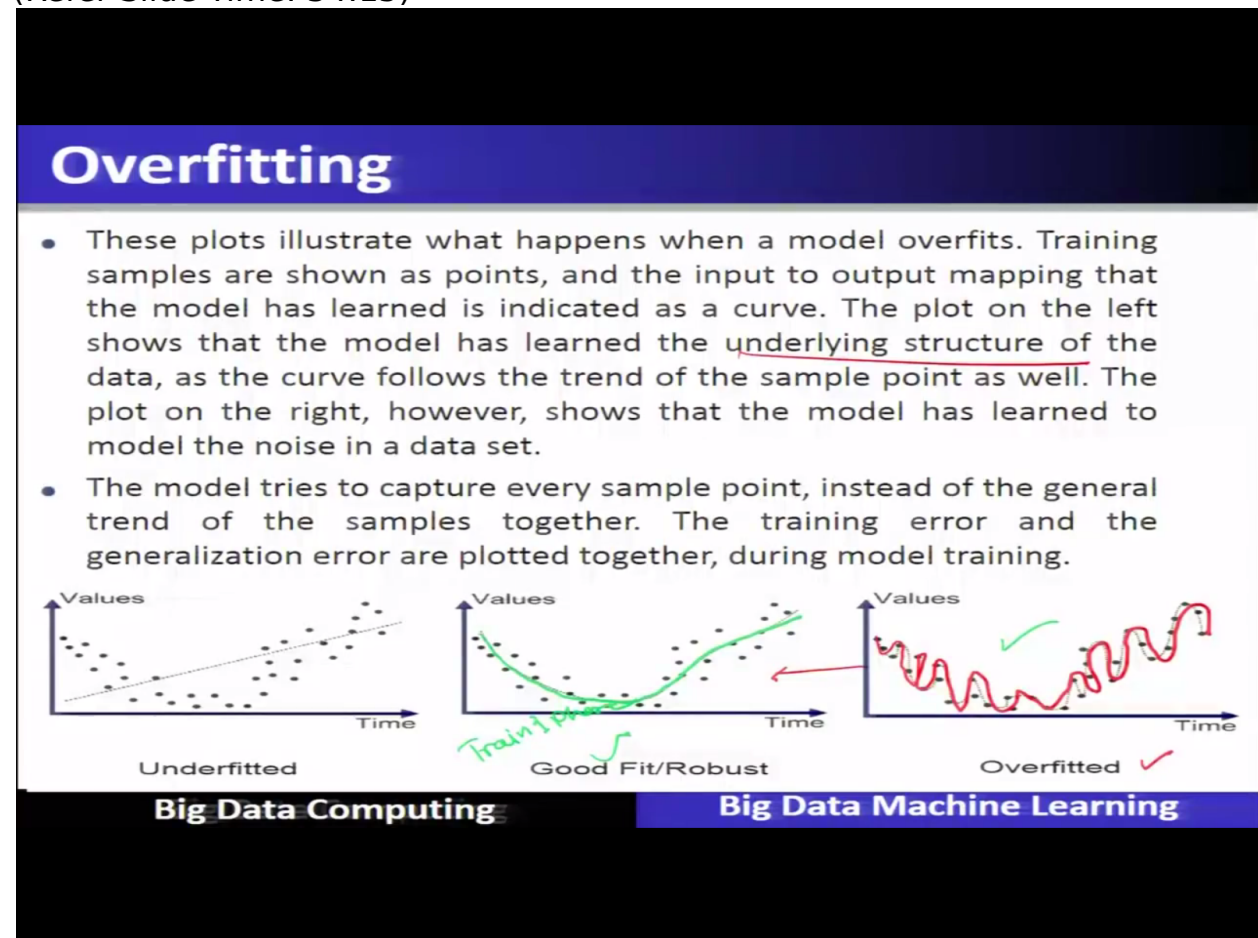
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Now there is a concept which is called as overfitting. So related concept to the Generalization is called overfitting. So if your model has a very low training error, but has the high Generalization error, then it is called the overfitting. Meaning 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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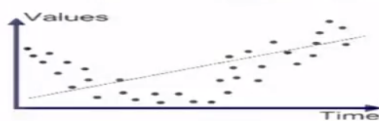
A model that overfits will not generalize well to the new data. So the model will do well on just the training data, but not perform well on the new data set, or rather it will perform poorly. So a classifier that performs well on just the training data set will not be only useful. So it is essential 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.

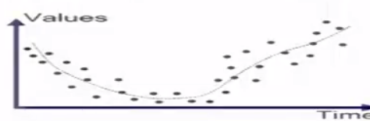
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Overfitting and Underfitting

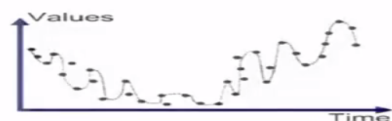
- Overfitting occurs when the model is fitting to the noise in the training data. This results in low training error and high test error.
- Underfitting on the other hand, occurs when the model has not learned the structure of the data. This results in high training error and high test error. ✓
- Both are undesirable, since both mean that the model will not generalize well to new data. Overfitting generally occurs when a model is too complex, that is, it has too many parameters relative to the number of training samples. So to avoid overfitting, the model needs to be kept as simple as possible, and yet still solve the input/output mapping for the given data set.



Underfitted



Good Fit/Robust



Overfitted

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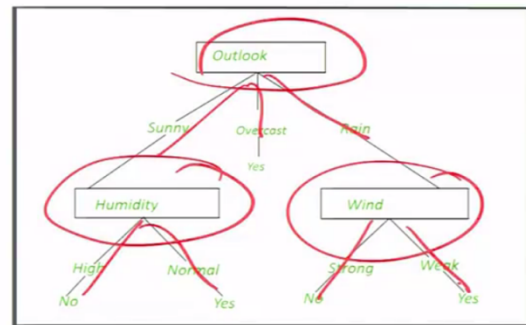
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Now let us see, what causes overfitting? In summary overfitting is when your model has learned the noise in the training data instead of underlying structure of the data, so you want to avoid overfitting, so your model will generalize well to the new 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 node gets split into three cases. Here this node splits into two. So this particular process of splitting the node and growing the tree is called tree induction.

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Decision Tree Induction

- A decision tree, also referred to as tree induction, the tree repeatedly splits the data in a node in order to get successively paired subsets of data.



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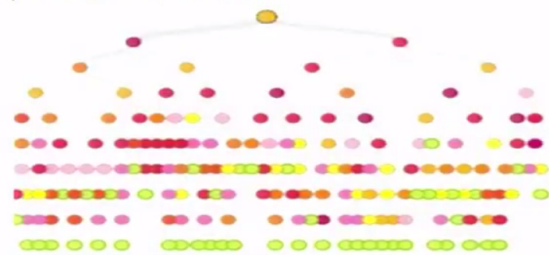
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Now let us see, the concept of overfitting in this decision trees. Note that the decision tree classifier can potentially expand its nodes until it can perfectly classify the samples in the training data. But if the tree grows, the nodes to fit the 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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Overfitting in Decision Trees

- Note that a decision tree classifier can potentially expand its nodes until it can perfectly classify samples in the training data.
- But if the tree grows nodes to fit the noise in the training data, then it will not classify a new sample well.
- This is because the tree has partitioned the input space according to the noise in the data instead of to the true structure of a data. In other words, it has overfit.



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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 nodes 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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Avoiding Overfitting in Decision Trees

Two methods:-
①

Pre-Pruning

Stop growing tree before fully grown

② Post-Pruning

Grow tree to max size, then prune

Control number of nodes to limit complexity of tree

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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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Pre-pruning

- With pre-pruning, the idea is to stop tree induction before a fully grown tree is built that perfectly fits the training data.
-
- To do this, restrictive stopping conditions for growing nodes must be used. For example, a node stops expanding if the number of samples in the node is less than some minimum threshold.
- Another example is to stop expanding a node if the improvement in the impurity measure falls below a certain threshold.

Post-pruning, in the post-pruning the tree is grown to a maximum size and then the tree is pruned 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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Post-pruning

- In post-pruning, the tree is grown to its maximum size, then the tree is pruned by removing nodes using a bottom up approach.
- That is, the tree is trimmed starting with the leaf nodes. The pruning is done by replacing a subtree with a leaf node if this improves the generalization error, or if there is no change to the generalization error with this replacement.

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 nodes should 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. (Refer Slide Time: 40:05)

Overfitting in Decision Trees

- In other words, if removing a subtree does not have a negative effect on the generalization error, then the nodes in that subtree only add to the complexity of the tree, and not to its overall performance.
- So those nodes should be removed. In practice, post-pruning tends to give better results. This is because pruning decisions are based on 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 to 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.
(Refer Slide Time: 40:44)

Avoiding Overfitting

- Recall that a model that overfits does not generalize well to new data.
- Recall also that overfitting generally occurs when a model is too complex.
- So to have a model with good generalization performance, model training has to stop before the model gets too complex.
- How do you determine when this should occur?

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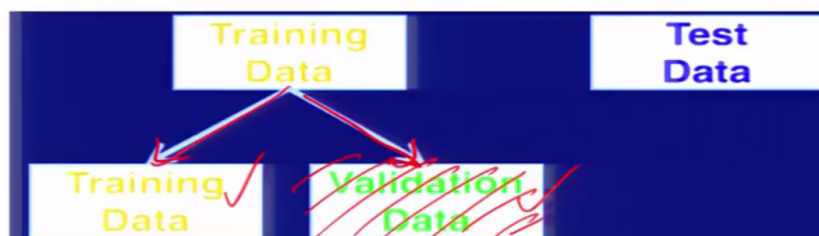
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So there is a technique which is called using the validation set. A validation set can be used to guide the training process to avoid the overfitting and deliver the good generalization performance. Now we have discussed having the training set and 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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Validation Set

- A validation set can be used to guide the training process to avoid overfitting and deliver good generalization performance.
- We have discussed having a training set and a separate test set. The training set is used to build a model and the test set is used to see how the model performs a new data.



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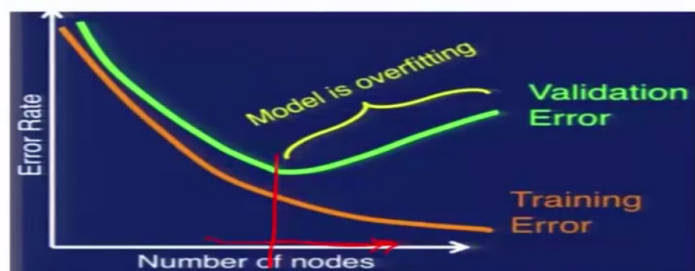
So training and validation error. Now we want to further divide up the training into the training and the validation set. So the training set is used to train the model as before and the validation is used to determine when to stop the training model to avoid the overfitting in order to get the best 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 diverges. 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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Training and Validation Error

- The idea is to look at the errors on both training set and validation set during model training as shown here. The orange solid line on the plot is the training error and the green line is the validation error. We see that as model building progresses along the x-axis, the number of nodes increases. That is the complexity of the model increases. We can see that as the model complexity increases, the training error decreases. On the other hand, the validation error initially decreases but then starts to increase.
- When the validation error increases, this indicates that the model is overfitting, resulting in decreased generalization performance.



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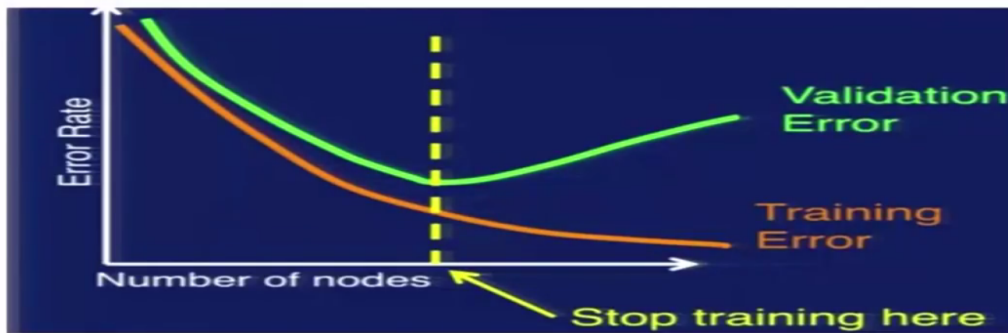
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So when to stop this particular training or tree induction. So this can be used to determine when to stop the tree induction, where the validation error starts to increase, is when you get the best generalization performance. So the training... so 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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When to Stop Training ?

This can be used to determine when to stop training. Where validation error starts to increase is when you get the best generalization performance, so training should stop there. This method of using a validation set to determine when to stop training is referred to as model selection since you're selecting one from many of varying complexities. Note that this was illustrated for a decision tree classifier, but the same method can be applied to any type of machine learning model.



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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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Ways to create and use the validation set

- There are several ways to create and use the validation set to avoid overfitting. The different methods are:
- Holdout method
- Random subsampling
- K-fold cross-validation, and
- Leave-one-out cross-validation

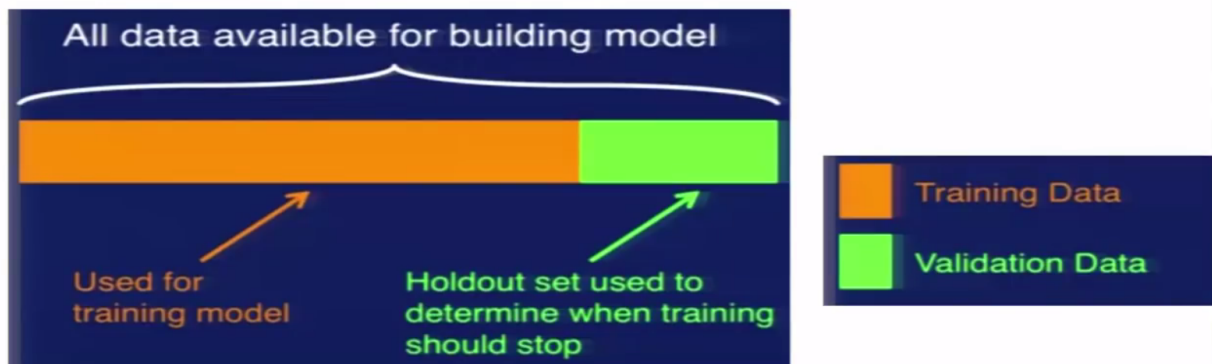
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So hold out method, the first way to use the validation set is a hold down method, this describes the scenario that we are... that we have discussed, where the part of the training is reserved as the validation set, the validation is then... is then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

- The first way to use a validation set is the holdout method. This describes the scenario that we have been discussing, where part of the training data is reserved as a validation set. The validation set is then the holdout set.



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This method we have already seen.
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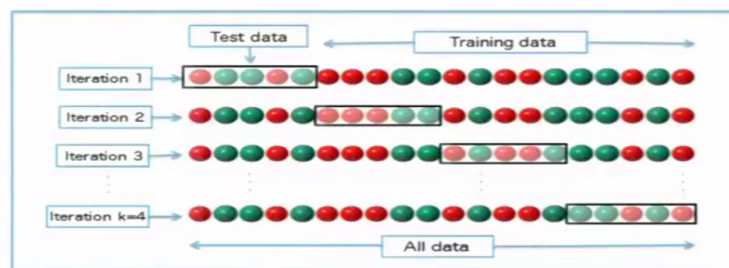
Repeated Holdout Method

- Repeating holdout method several times
- Randomly select different hold out set each iteration
- Average validation errors over all repetitions.

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.
(Refer Slide Time: 46:29)

K-Fold Cross-Validation

- A way to improve on the repeated holdout method is use cross-validation. Cross-validation works as follows. Segment the data into k number of disjoint partitions. During each iteration, one partition is used as the validation set. Repeat the process k times. Each time using a different partition for validation. So each partition is used for validation exactly once. This is illustrated in this figure. In the first iteration, the first partition, is used for validation. In the second iteration, the second partition is used for 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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K-Fold Cross-Validation

- The overall validation error is calculated by averaging the validation errors for all k iterations.
- The model with the smallest average validation error then is selected. The process we just described is referred to as k -fold cross-validation. This is a very commonly used approach to model selection in practice.
- This approach gives you a more structured way to divide available data up between training and validation datasets and provides a way to overcome the variability in performance that you can get when using a single partitioning 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.
(Refer Slide Time: 47:45)

Leave-One-Out Cross-Validation

- Leave-one-out cross-validation is a special case of k-fold cross-validation where k equals N , where N is the size of your dataset.
- Here, for each iteration the validation set has exactly one sample. So the model is trained to using N minus one samples and is validated on the remaining sample.
- The rest of the process works the same way as regular k-fold cross-validation.
- Note that cross-validation is often abbreviated CV and leave-one-out cross-validation is in abbreviated L-O-O-C-V 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.
(Refer Slide Time: 48:04)

Uses of Datasets

- With the addition of the validation set, you really need three distinct datasets when you build a model. Let's review these datasets.
- The training dataset is used to train the model, that is to adjust the parameters of the model to learn the input to output mapping.
- The validation dataset is used to determine when training should stop in order to avoid overfitting.
- The test data set is used to evaluate the performance of the model on new data.

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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.
(Refer Slide Time: 51:03)

Uses of Datasets

- With the addition of the validation set, you really need three distinct datasets when you build a model. Let's review these datasets.
- 1 The training dataset is used to train the model, that is to adjust the parameters of the model to learn the input to output mapping.
- 2 The validation dataset is used to determine when training should stop in order to avoid overfitting.
- 3 The test data set is used to evaluate the performance of the model on new data.

```
graph TD
    DS[DataSet] --> TDS[Training Data Set]
    DS --> TDS
    TDS --> BM[builds model]
    BM --> IM[Improved model]
    IM --> EV[Evaluation]
    EV --> TDS
    EV --> TDS
```

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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 class, 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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Uses of Datasets

- Note that the test data set should never, ever be used in any way to create or tune the model. It should not be used, for example, in a cross-validation process to determine when to stop training.
- The test dataset must always remain independent from model training and remain untouched until the very end when all training has been completed. Note that in sampling the original dataset to create the training, validation, and test sets, all datasets must contain the same distribution of the target classes.
- For example, if in the original dataset, 70% of the samples belong to one class and 30% to the other class, then this same distribution should approximately be present in each of the training, validation, and test sets. Otherwise, analysis results 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.

(Refer Slide Time: 52:48)

Validation Set Summary

- We have discuss the need for three different datasets in building model. A training set to train the model, a validation set to determine when to stop training, and a test to evaluate performance on new data.
- We learned how a validation set can be used to avoid overfitting and in the process, provide an estimate of generalization performance.
- And we covered different ways to create and use a validation set such as k-fold cross-validation.

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Now metrics to evaluate the model performance.

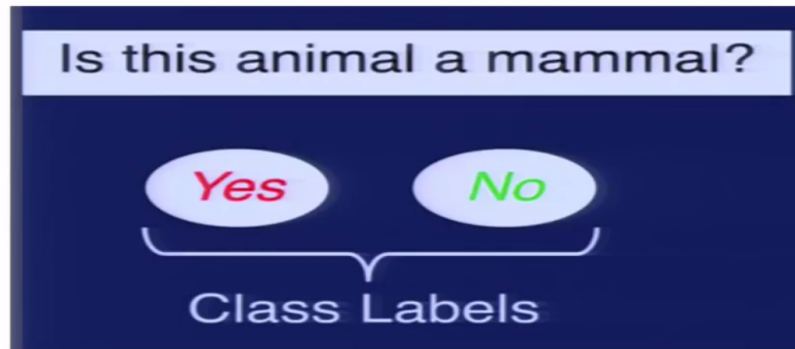
Metrics to Evaluate Model Performance

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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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Class Labels

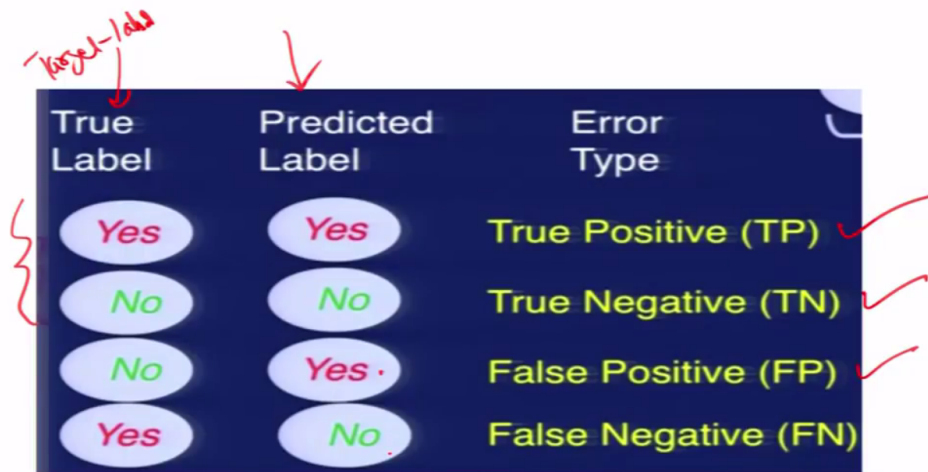


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Now using this particular target label we now can see the difference between the true target label, this is called target label, this is the true label and this is the label, which is the predicted label out of the classification algorithm, this is 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.
(Refer Slide Time: 54:43)

Types of Classification Errors



True Label	Predicted Label	Error Type
Yes	Yes	True Positive (TP)
No	No	True Negative (TN)
No	Yes	False Positive (FP)
Yes	No	False Negative (FN)

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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.
(Refer Slide Time: 55:48)

Error Rate

Error Rate		True	Predicted
		Yes	Yes
		No	No
		No	Yes
		Yes	No

Error Rate	=	$\frac{\# \text{ incorrect predictions}}{\# \text{ total predictions}}$
	=	$1 - \text{Accuracy Rate}$
	=	$1 - 0.7 = 0.3$

Error
True Positive (TP)
True Negative (TN)
False Positive (FP)
False Negative (FN)

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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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Precision and Recall

Precision & Recall

True	Predicted	True
Yes	Yes	True
No	No	True
No	Yes	False
Yes	No	False

Precision = $\frac{TP}{TP + FP}$ ← All samples with Predicted = Yes

Recall = $\frac{TP}{TP + FN}$ ← All samples with True = Yes

Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 56:45)

Precision and Recall

- Precision is considered a measure of exactness because it calculates the percentage of samples predicted as positive, which are actually in a positive class.
- Recall is considered a measure of completeness, because it calculates the percentage of positive samples that the model correctly identified.

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 weights recall more in this case and F0.5 measure gives the weights precision more in this case. (Refer Slide Time: 57:25)

F-Measure

Precision



Recall

$$F_1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}}$$

- F_1 : evenly weighted
- F_2 : weights Recall more
- $F_{0.5}$: weights Precision more

Let us see the confusion matrix.

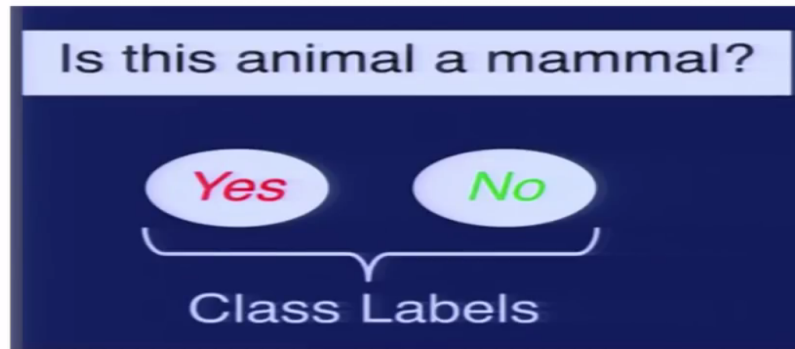
Confusion Matrix

Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 57:38)

Classification



Big Data Computing

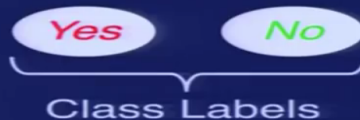
Big Data Machine Learning

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.

(Refer Slide Time: 58:36)

Confusion Matrix

Is this animal a mammal?



True Class Label	Predicted Class Label	
	Yes	No
Yes	True Positive (TP)	False Negative (FN)
No	False Positive (FP)	True Negative (TN)

Big Data Computing

Big Data Machine Learning

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. (Refer Slide Time: 60:51)

True Label	Predicted Label
Yes	No ✓
No	No ✓
No	No ✓
Yes	Yes ✓
Yes	Yes ✓
No	No ✓
Yes	No ✓
Yes	Yes ✓
No	No ✓
No	Yes ✓

True Class Label	Predicted Class Label	
	Yes	No
Yes	True Positive (TP) $\cdot 3$	False Negative (FN) $\cdot 2$
No	False Positive (FP) $\cdot 1$	True Negative (TN) $\cdot 4$

Confusion matrix

10%

70%

Big Data Computing

Big Data Machine Learning

So let us see the machine learning tools.

Machine Learning Tool

Big Data Computing

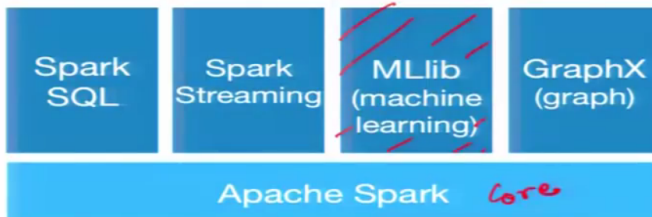
Big Data Machine Learning

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.

(Refer Slide Time: 62:45)

Spark MLlib

- **Spark MLlib** is a distributed machine-learning framework on top of Spark Core. *→ Big Data*
- MLlib is Spark's scalable machine learning library consisting of common learning algorithms and utilities, including classification, regression, clustering, collaborative filtering, dimensionality reduction.



Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 64:11)

Spark MLlib Component

Algorithms

- Classification
- Regression
- Clustering
- Collaborative Filtering

Pipeline

- Constructing
- Evaluating
- Tuning
- Persistence

Featurization

- Extraction
- Transformation

Utilities

- Linear algebra
- Statistics

Big Data Computing

Big Data Machine Learning

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 (Refer Slide Time: 65:55).

Steps for Classification in Spark

1. Load weather data into DataFrame (Read Data)
2. Drop unused and missing data. (Data preparation)
3. Create a categorical variable for low humidity days (Transformation)
4. Aggregate features used to make predictions. (Feature Selection)
5. Split the data into training and test sets. (Split Data-sets into Train & Test)
6. Create and train the decision tree.
7. Save the predictions to a CSV file

Big Data Computing

Big Data Machine Learning

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 read 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.

(Refer Slide Time: 67:47)

1. Load weather data into DataFrame

The first cell contains the classes we need to load to run this exercise. Next we create SQL context and load the weather data CSV into a data frame.

The second cell also prints all the columns in this data frame.

The third cell defines the columns in the weather data we will use for the decision tree classifier.

```
In [ ]: from pyspark.sql import SQLContext
from pyspark.sql import DataFrameNaFunctions
from pyspark.ml import Pipeline
from pyspark.ml.classification import DecisionTreeClassifier
from pyspark.ml.feature import Binarizer
from pyspark.ml.feature import VectorAssembler, StringIndexer, VectorIndexer

In [ ]: sqlContext = SQLContext(sc)
df = sqlContext.read.load('file:///home/cloudera/Downloads/big_data-4/daily_weather.csv',
                          format='com.databricks.spark.csv',
                          header='true', inferSchema='true')
df.columns

In [ ]: featureColumns = ['air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am', 'avg_wind_speed_9am',
                        'max_wind_direction_9am', 'max_wind_speed_9am', 'rain_accumulation_9am',
                        'rain_duration_9am']
```

Big Data Computing

Big Data Machine Learning

So the data frame columns are again summarized here in a nice manner.
(Refer Slide Time: 67:57)

```
header='true',inferSchema='true')

df.columns

Out[2]: ['number',
'air_pressure_9am',
'air_temp_9am',
'avg_wind_direction_9am',
'avg_wind_speed_9am',
'max_wind_direction_9am',
'max_wind_speed_9am',
'rain_accumulation_9am',
'rain_duration_9am',
'relative_humidity_9am',
'relative_humidity_3pm']

In [ ]: featureColumns = ['air_pressure_9am','air_temp_9am','avg_wind_direction_9am','avg_wind_speed_9am',
'max_wind_direction_9am','max_wind_speed_9am','rain_accumulation_9am',
'rain_duration_9am']
```

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.
(Refer Slide Time: 69:45)

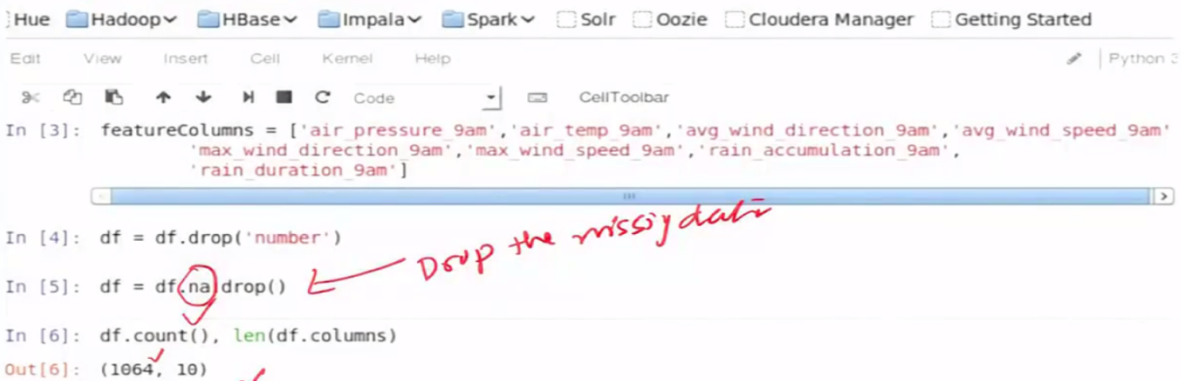
2. Drop unused and missing data

Use the column name number.

Drop that from the data frame, `df = df.drop Number`.

Rows with missing data, `df = df.na.drop`.

Print the number of rows and columns in our resulting data frame, `df.count()`, `len(df.columns)`.



```
Hue Hadoop HBase Impala Spark Solr Oozie Cloudera Manager Getting Started
Edit View Insert Cell Kernel Help Python 3
Code CellToolbar
In [3]: featureColumns = ['air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am', 'avg_wind_speed_9am',
    'max_wind_direction_9am', 'max_wind_speed_9am', 'rain_accumulation_9am',
    'rain_duration_9am']

In [4]: df = df.drop('number')

In [5]: df = df.na.drop()

In [6]: df.count(), len(df.columns)
Out[6]: (1064, 10)
```

Drop the missing data (handwritten note pointing to `df.na.drop()`)

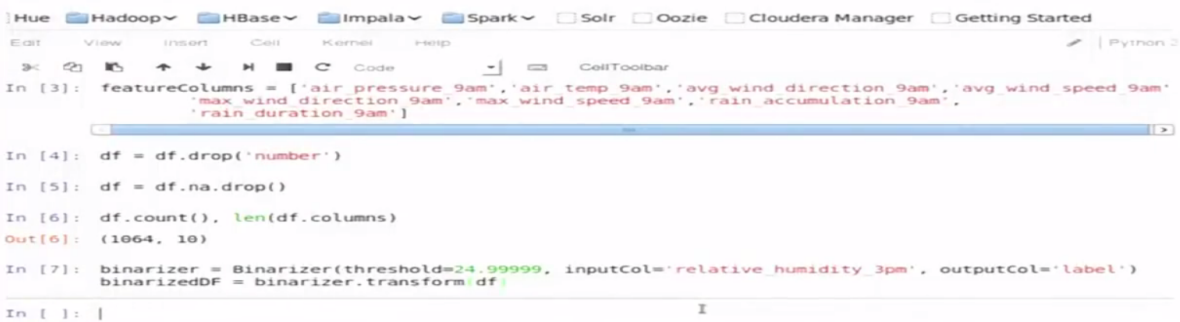
Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 70:15)

3. Create a categorical variable for low humidity days

We will enter `binarizer = Binarizer()`. The first argument specifies a threshold value for the variable. We want the categorical variable to be 1, if the humidity is greater than 25%. So we'll enter a `threshold=24.9999`. The next argument specifies the column to use to create the categorical variable. We'll input, `inputCol = relative_humidity_3pm`. The final argument specifies the new column name, `outputCol = label`. A new data frame is created with this categorical variable. `binarizedDF = binarizer.transform df`.



The screenshot shows the Hue interface with a Python script being executed. The script defines feature columns, drops unnecessary columns, and creates a binary label for low humidity days.

```
In [3]: featureColumns = ['air_pressure_9am', 'air_temp_9am', 'avg_wind_direction_9am', 'avg_wind_speed_9am',  
    'max_wind_direction_9am', 'max_wind_speed_9am', 'rain_accumulation_9am',  
    'rain_duration_9am']  
  
In [4]: df = df.drop('number')  
  
In [5]: df = df.na.drop()  
  
In [6]: df.count(), len(df.columns)  
Out[6]: (1064, 10)  
  
In [7]: binarizer = Binarizer(threshold=24.9999, inputCol='relative_humidity_3pm', outputCol='label')  
    binarizedDF = binarizer.transform(df)  
  
In [ ]: |
```

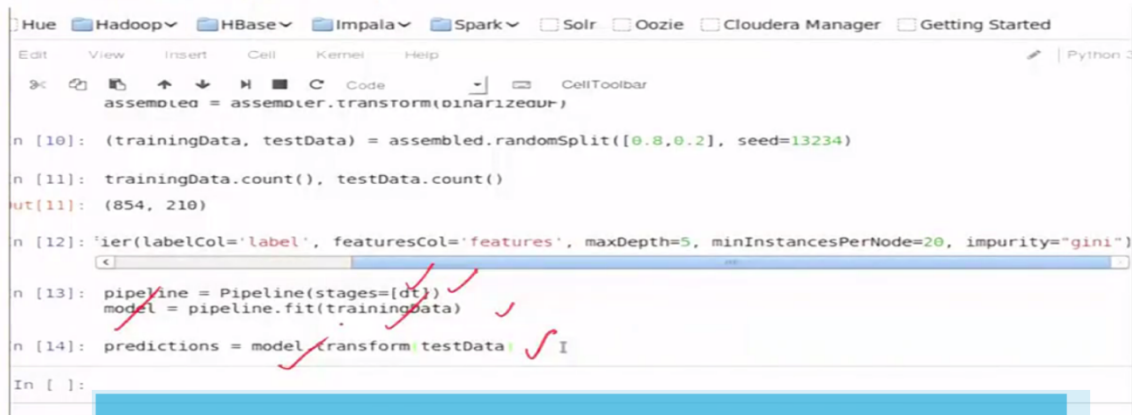
Big Data Computing

Big Data Machine Learning

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. (Refer Slide Time: 71:52)

6. Create and train the decision tree. 1:48 / 1:13:07

Next, we can create a model by training the decision tree. We can do this by executing it in a pipeline. Enter `pipeline=Pipeline (stages=[dt])`. We will create them all by putting a training data, `model = pipeline.fit trainingData`. Let's run this Now, we can make predictions using our test data. Enter `predictions = model.transform(testData)`.



```
assembled = assembler.transform(binarizedour)

n [10]: (trainingData, testData) = assembled.randomSplit([0.8,0.2], seed=13234)
n [11]: trainingData.count(), testData.count()
out[11]: (854, 210)

n [12]: 'ier(labelCol='label', featuresCol='features', maxDepth=5, minInstancesPerNode=20, impurity="gini")
n [13]: pipeline = Pipeline(stages=[dt])
        model = pipeline.fit(trainingData)
n [14]: predictions = model.transform(testData)
```

Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 72:15)

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.

Big Data Computing

Big Data Machine Learning

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.
(Refer Slide Time: 72:32)

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.