Machine Learning for Soil and Crop Management
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Lecture 03
General Overview of ML and DL Applications in Agriculture

Welcome friends to this third lecture of week 1 of this NPTEL online certification course of Machine Learning for Soil and Crop Management and in this week, we are discussing general overview of Machine Learning and Deep Learning applications in agriculture and in the first two lectures, we have discussed some important concepts.

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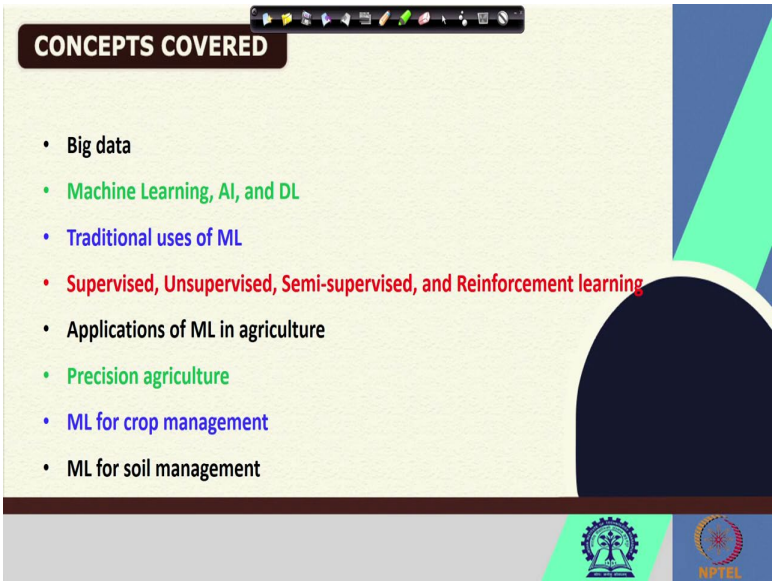

We have seen the big data as well as their storage, shift in storage concept from analog to digital. We have also covered the basic overview of machine learning and then artificial intelligence and deep learning. We have discussed the traditional uses of Machine Learning, also we have seen, the supervised. We have also discussed what is supervised? What is unsupervised? What is semi supervised learning. We have also discussed what is the difference between a classification problem as well as a regression problem? What are the common metrics for identification, common metrics for classification accuracy and what are the common metrics for regression accuracy, we have discussed in detail.

Now,, today we are going to start from the reinforced learning, which is reinforcement learning which is another very important type of machine learning. And we also use this in different sectors nowadays starting from gaming and other applications also. So,, let me go and start from the reinforcement learning.

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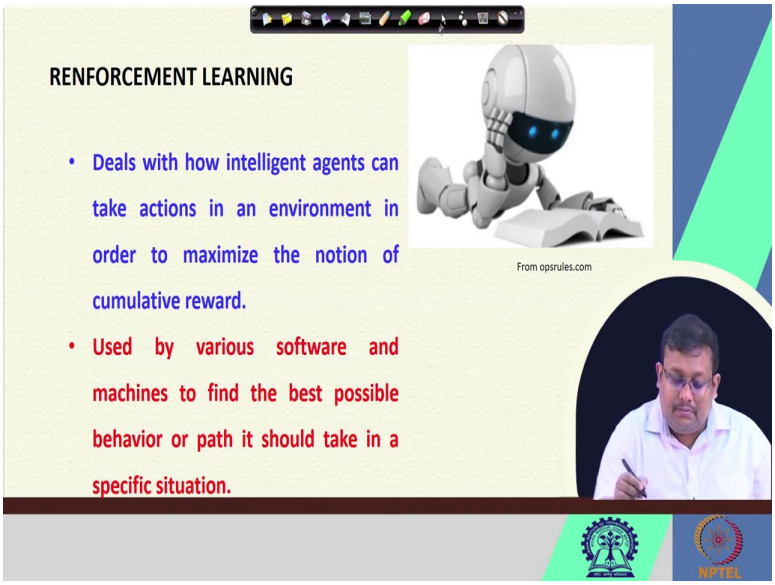

Now,, reinforcement learning if you see it deals with how intelligent agents can take actions in an environment in order to maximize the notion of cumulative reward so this is a very important concept under machine learning, again it here the agent basically deals with some actions in an environment in order to maximize the notion of cumulative reward to achieve a particular desired goal. And what are the, who uses this reinforced learning?

Reinforcement learning are used by various softwares and machines to find the best possible behavior or path it should take in a specific situation to achieve a specific goal. So, it is basically a trial and error kind of thing, so different types of softwares and also gaming consoles and gaming programs basically use this reinforcement learning to determine the best possible path to achieve an objective. Let us see some examples.

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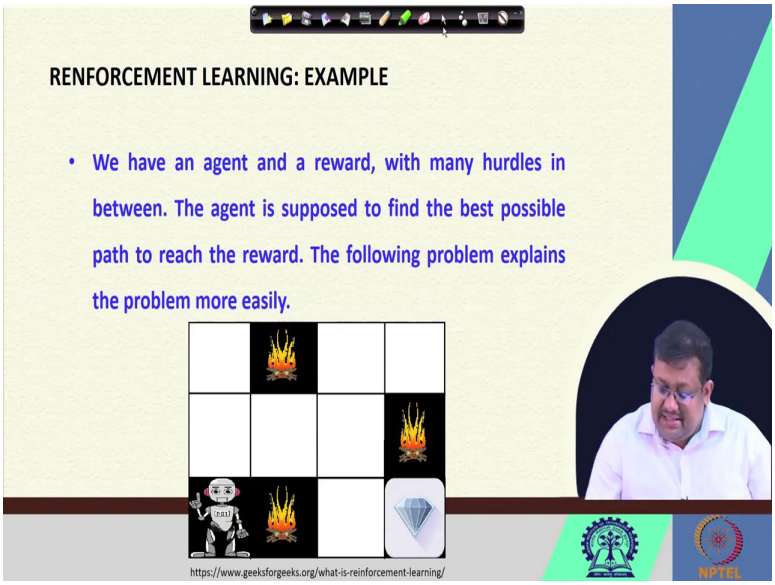

So,, we have an agent and a reward, suppose there is a game where we have an agent and a reward with many hurdles in between. So,, this agent is supposed to find the best possible path to reach the reward and the following problem you can see this following problem gives a very good example of reinforcement learning. You can see this is the agent and there are different ways through which it can reach into the final target that is this diamond.

So, these agents can take different path to reach, however there are some hurdles also and while taking a suitable path or best possible path this best possible path is determined by cumulating the rewards which is beneficial or which is conducive for achieving this final objective. So, it can take different paths to reach here, but the best possible path will be judged by a trial and error method so that it can have the maximum rewards awarded to reach this path.

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Similar example we can see in case of chess playing. So, in case of computerized chess program it learns through reinforcement learning and most of us already know this game which we played in our in our childhood this is Super Mario which is a very famous video game and in this Super Mario also Mario learns by reinforcement learning how to reach its particular objective by avoiding these hurdles, which are there in this path. So, these are some very good examples of reinforcement learning and reinforcement learning has both positive sides and negative side we are going to discuss.

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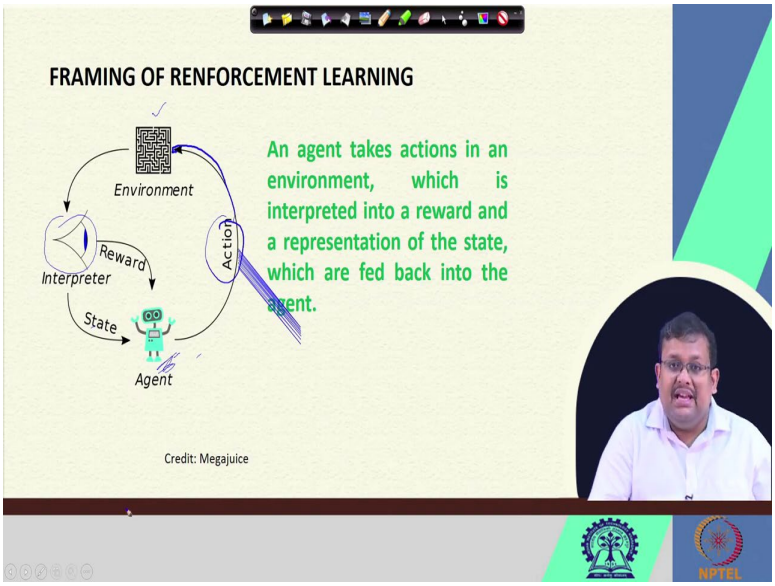

So, what are the basic frameworks of reinforcement learning? If you see the basic framework of reinforcement learning here an agent takes action in an environment, suppose this is an

environment and in this environment this agent takes an action in an environment, which is interpreted into a reward and a representation of the state. So,, here there is an interpreter who interpret whereas this agent is action should be rewarded or not and it gives an interpretation of the state and which are feedback into the agent.

So, again, the agent makes an action, action goes to the environment and the interpreter determines whether this should be, this agent should be given and reward or there should be a punishment and then represent and gives the representation of the state which are feedback into the agent and then it learns. So, this is how this reinforcement learning basically works.

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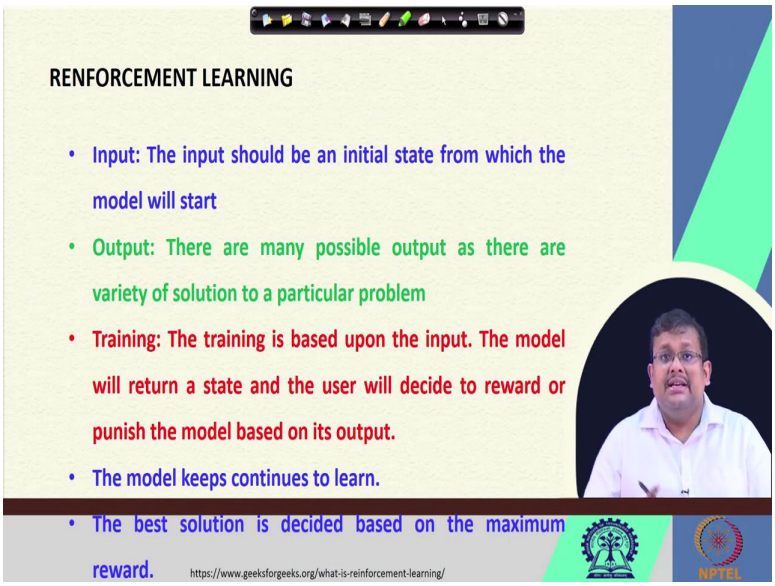

So,, in the reinforcement learning what are the inputs? Inputs are should be initial state from which the model will start, this is the input. Whereas what is output, in case of reinforcement learning there are many possible output as there are variety of solution to a particular problem. So,, just like in a chess game there are different types of solution to achieve a particular objective, different pathways through which you can move your king and queen and other pawns and other things for achieving a particular objectives there are different ways, but the output in case of reinforcement learning are various.

What is the training in this case? So,, the training is based upon the input, the model will return a state and the user will decide whether to reward or punish the model based on the output. So, here the model learns by determining whether its action should be given a reward or punish and this reward and punishment is based on how better this solution is to achieve a particular objective and remember during this reinforcement learning this model keeps

continues to learn. So, there is a continuous learning procedure in this case of learning especially reinforcement learning.

The best solution is decided based on the maximum reward, so there could be number of solutions for achieving. In case of Super Mario there could be number of ways through which we reach our final outcome but the best solution is based on the maximum reward. So, as I have told in the description of the reinforcement learning the best solution is determined by trial and error which gathers the maximum reward. So,, this is a very important point while we discuss the reinforcement learning.

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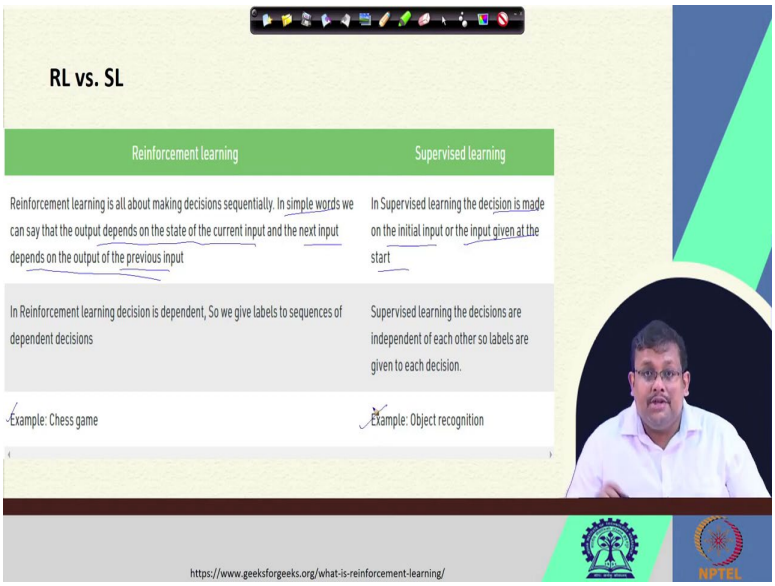

Now,, what are the differences between reinforcement planning and supervised learning? So, if we see in case of reinforced learning, reinforced learning is all about making decision sequentially. In simple words we can say that the output depends on the state of the current input and the next input depends on the output of the previous input. So, this is very very input, I am sorry very very important.

So, again in simple words we can say that the output depends on the state of the current input, so whether we are giving a reward or punishment is based on the state of the current input and the next input depends on the output of the previous input. However, in case of supervised learning it the decision is made on the initial input or the input given at the start.

So, in case of reinforcement learning these inputs are continuously changing and the model is continuously learning, however in case of supervised learning since both the inputs and

outputs are labeled here inputs are fixed, so decision is messed based on the initial inputs or the initial inputs given at the start of the modeling exercise.

Now,, in reinforcement learning decision is dependent, so we give labels to the sequence of dependent decisions. This is a very important point, again as I have told you that the output of the next input in a sequence depends on the output of the previous input, so that means in case of reinforcement learning the decision is always dependent, so we give labels to the sequence of dependent decision.

However, in case of supervised learning the decisions are independent of each other, so labels are given to each decision. Some examples are given in case of super reinforcement learning as you can see chess game is a very good example of reinforcement learning, however in case of object data recognition it is an example of supervised learning.

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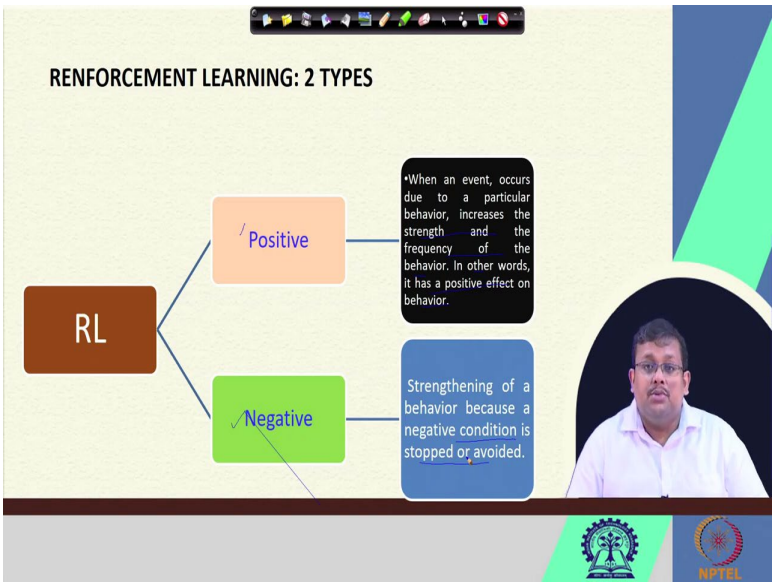

So, what are the two types of reinforcement learning? There are two types, one is called the positive reinforcement learning, another is called negative reinforcement learning. Now,, what is positive reinforcement learning? In case of positive reinforcement learning when an event occurs due to a particular behavior increases the strength and frequency of the behavior in other words it has a positive effect on the behavior or in other words when an event occurs due to a particular behavior and helpful for achieving an objective that is called positive reinforcement learning.

What is negatively reinforcement learning? Negative reinforcement learning strengthens the behavior because a negative condition is stopped or avoided. So, we know that this is not

rewarding, in case of reinforcement learning we know that which one of our step is rewarding and which one is not rewarding.

So, the one which is not rewarding we will learn it and that gives us more strength to avoid or stop that kind of situation in the next sequence. So, this is called the negative reinforcement learning. Now,, both positive reinforcement learning as well as negative reinforcement learning has some advantages and disadvantages also.

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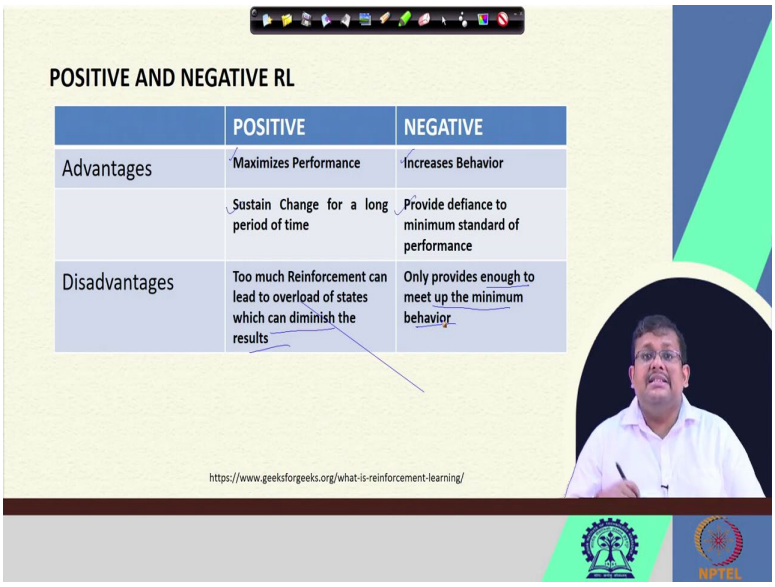

So, if we talk about the positive points, the advantages of the positive reinforcement learning is, first of all in case of positive reinforcement learning it maximizes the performance however in case of negative reinforcement learning it increases the behavior. And in case of positive learning, it sustains change for a long period of time; however, in case of negative reinforcement learning provide defiance to minimum standard of the performance. So, these are the different types of advantages of positive reinforcement learning and negative reinforcement.

However, there are some disadvantages also, now too much reinforcement in case of positive learning can lead to overloaded state which can diminish the result. So, this is one disadvantage, another disadvantage in case of negative learning is only provides enough to meet up the minimum behavior. So, we only know how to avoid the minimum standard of performance and we get only the minimum, enough to meet up the, we get only the required information enough to meet up our minimum behavior. So, these are the different advantages and disadvantages of reinforcement learning.

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Now, what are the different reinforcement learning application students? So, there are numerous reinforcement learning applications I already told you in the gaming, in the chess game as well as in robotics for industrial automation as you can see in this picture, there are application of robotics in the industrial application so that learns by reinforcement learning. Machine learning and data processing and also training system that provides the custom instruction and materials according to the requirement of the students are also, they also learn through reinforcement learning.

So, reinforcement learning is a very powerful tool of machine learning and which is sensitive to the outcome of the interaction with its surrounding environment and it continuously learns to get the maximum possible output through the maximum rewarding pathway. So, this is how this reinforcement learning has got tremendous importance in the contemporary machine learning applications.

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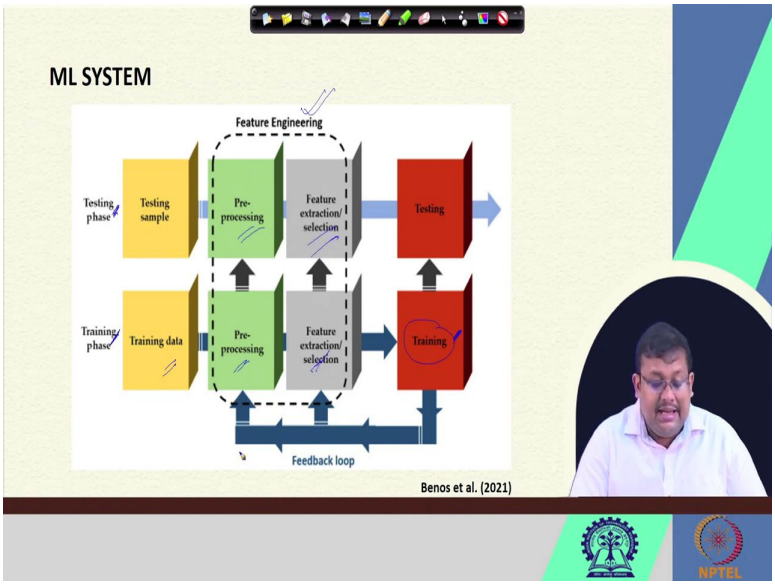

Now, if we see the basic framework of a machine learning as a whole, the basic overview of machine learning system these gives you a very good understanding. So, in any machine learning framework there are two phases. One is called the testing phase or calibration phase another one is called, I am sorry, one is called the training phase or calibration phase, another one is called the testing phase or validation phase.

So, first we starts with the training data and we do some preprocessing and feature extraction and selection and both this combined preprocessing and feature selections are known as the feature engineering and finally we develop a training model based on the selected features or extracted features. Now, how to test this training model? To test this training model again we take some testing samples?

Testing samples can be drawn from a number of ways through either randomly or totally independent samples or by randomly dividing the samples or by clustering the samples based on some kind of similarity. So, once we decide the testing sample these testing samples are required to to judge the robustness of the training models. Sometime trading models are very optimistic however, testing fails miserably. So, that is why we do already always we do the testing for judging the model robustness.

So, you can see that just like in case of trading phase also, we also do the feature engineering in the testing phase also. Just like the training data we also do you know preprocessing as well as feature extraction or selection in case of testing phase. So, this is the basic overview of the machine learning system.

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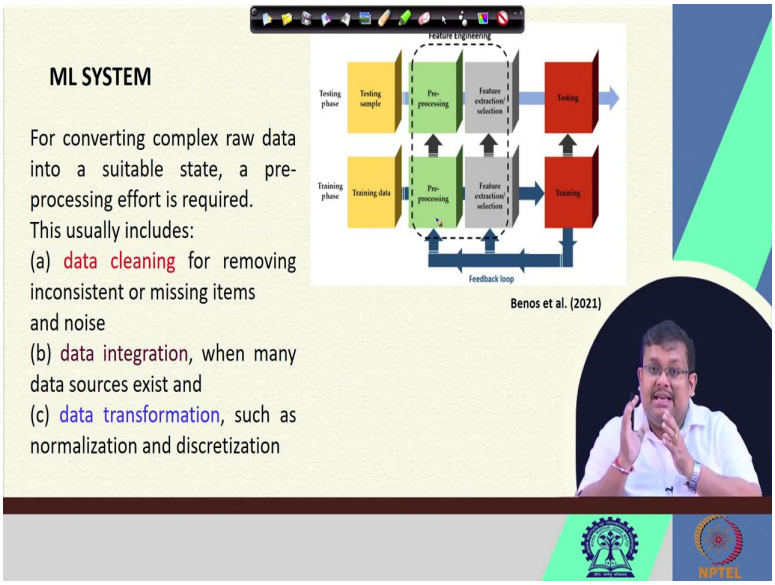

So, for converting the raw complex data into a suitable state a preprocessing effort is required. So, I told you that there are some pre-processing of data is required, preprocessing could be of hundred types, either you can clean the data or you can remove the inconsistent or missing items or you can do some data integration when many data sources are there, you can do data transformations such as normalization and discretization, you can do box cox transformation, you can do centering and scaling of the data, there are lots of ways through which you can do transformation of the data.

Either you can take logarithmic for log normal data you take logarithm of the data and then log of data and then you use that data and also you can also do some box cox transformation, also you can do centering and scaling to prepare your data before executing the model, also you can do some data integration data integration means if there are multiple sources we in the later phase of this course you will know about sensor fusion.

Now, in the sensor fusion what we do we basically concatenate or we can combine the data from two or three different sources together and we make a large data set and this large input data set is further used to as an input in subsequent machine learning applications. So, data integration is another preprocessing also in case of spectral methods which we are going to discuss in the later phase of this course you will see that we are doing different types of spectral preprocessing for increasing the signal to noise ratio.

So, there are different ways and also, we can clean the data when there are some inconsistencies, if there are some outlets we sometime remove the data which will affect the results, so there are different types of methods which we use to treat our data before we go

for feature extraction and model development. So, these are called the pre-processing step, sometime we call also data pre-treatment step, so this pretreatment step is very very important and it is a subset of the whole feature engineering step.

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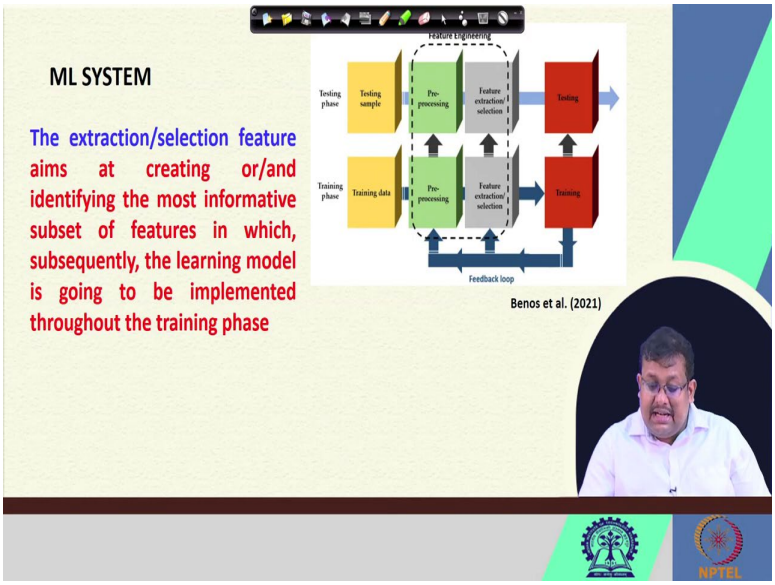

Now, let us see what is the extraction and selection feature step? So, in the extraction and selection feature step it aims at creating or identifying the most informative subset of features in which subsequently the learning model is going to be implemented throughout the training phase. Sometime you will see that after doing the pre-processing of the data, sometime there are multi collinearity.

What is multi collinearity we will discuss in our subs in our coming lectures, multicollinearity means when in the inputs or the features are highly correlated that creates problem, so overfitting that means over optimistic performance of your training model is sometime depends on incorporating huge number of correlated variables or unnecessary redundant variables. So, do we need all the thousand variables or inputs or features while running a specific model, the answer is no.

We want our model to be as simple as possible so for this we do some kind of extraction or feature selection. In extraction and feature selection process it extracts or select only those important features, which are generally non-correlated and which gives the information or required information or distinct information for our target analyte and then we use those extracted features in our subsequent machine learning model or deep learning model.

So, this is how we do the feature selection or extraction and it creates an identify most informative subset of features, it does not necessarily will take the whole input features it will only select a subset of the features, which are enough informative to generate a meaningful and robust machine learning or deep learning training model specifically in the training phase. So, this is called the feature extraction and selection, remember both these preprocessing as well as the feature extraction selection are known as the feature engineering step, which is the intermediate step between the inputs as well as the training model.

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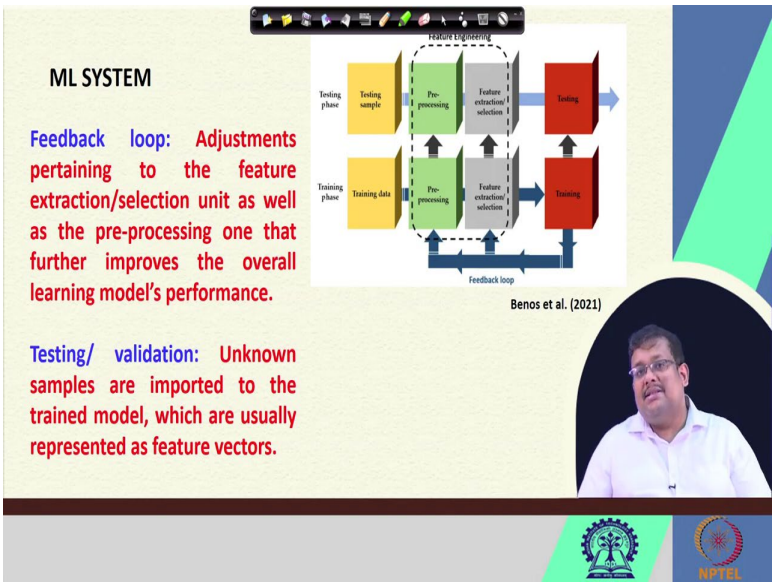

Now, what is feedback loop you can see here there is a feedback loop? Feedback loop gives the adjustment pertaining to the feature extraction or selection unit as well as the preprocessing one that further improves the overall learning model performance. So, once we do once we incorporate the training model and then we do the preprocessing feature extraction and then we go for the training model development and we see the model performance by using some of the matrices, which we have already covered in our last lecture. So, using those matrices we can see whether our model is robust or our model is good or bad.

Based on that we can further loop around and we can further see whether we can do some other type of feature engineering so that more informative knowledge or more informative subset of the total features can be further extracted for improving or augmenting the model performance. This is a very important step of that is called feedback loop and testing and validation are, as I have already told you that unknown samples are imported to the training model.

And all those unknown samples a subset of samples under go through the same process of feature engineering as the training samples did and then it determine whether your training model is perfect or not whether your training model is good or bad, so which are usually represent as a feature vector, so generally in case of testing and validation we generally use them as a feature vector and then put in to incorporate into the model to see their performance and then finally validate whether our model, machine learning model is robust or not.

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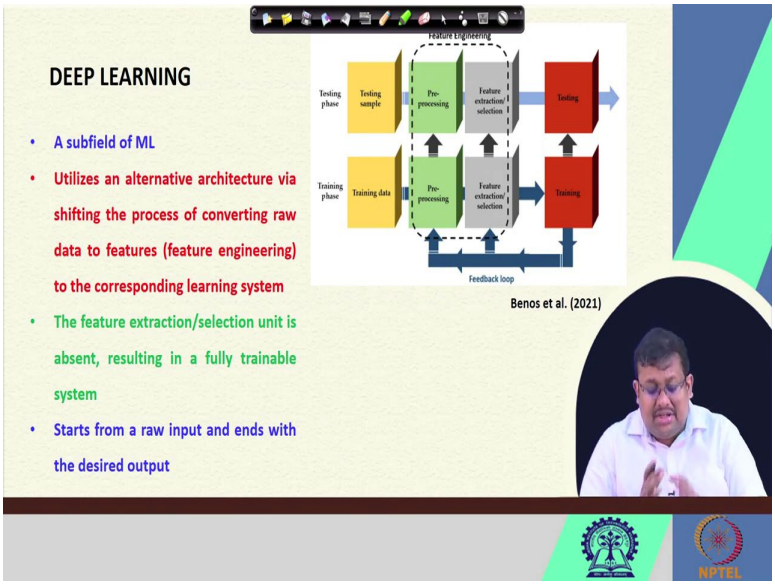

So, deep learning, so we have completed the machine learning now we are going to see some definition and some description of the deep learning. We will be very very brief in this because in the subsequent weeks we will be discussing them in details. So, deep learning it is a sub field of machine learning as I have already told in our previous lectures. It utilizes an alternative architecture via shifting the process of converting raw data to features that is feature engineering.

So, in case of deep learning this feature engineering step is shifted to the corresponding learning system and so the feature extraction and selection unit is absent in case of deep learning resulting in a fully trainable system and it starts from the raw input and ends with the desired output. So, this is also same in case of deep learning however this feature engineering step is not present in case of deep learning model, and ultimately results in fully trainable system.

So, guys I hope that you have learnt something new in this lecture, you have learned what is reinforcement learning and then what are the features of the reinforcement learning, you have seen the applications of the reinforcement learning, what are the positive and negative

reinforcement, what are the differences between reinforcement learning and supervised learning and also we have seen the basic machine learning system, what training phase, testing phase then feature engineering which is composed of both feature selection as well as data preprocessing and also different types of data preprocessing in broadly.

Also, we have seen what is the calibration and how we can calibrate, how we can validate the model using the testing data set and we also have a basic overview of deep learning where this feature engineering step is absent. It has been, it is shifted and resulting in a fully trainable system, some examples of deep learning methods are artificial neural network, convolutional neural network, and recurrent neural network.

We will see them in details in our subsequent, in our in our upcoming lectures, but I hope that you have some basic understanding of these techniques and let us meet in our next lecture to discuss them, to start from here and then we will discuss some more about the deep learning and then we will enter into the application of machine learning in the agriculture sector and how and what are the different types of application focusing on crop and soil we will learn in details. Thank you very much.