Neural Network and Applications
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Lecture - 05
Learning Mechanisms - Hebbian, Competitive, Boltzmann

We are going to continue with, what we were discussing in the last class. So, this lecture will be on the Learning Mechanisms in Neural Networks.

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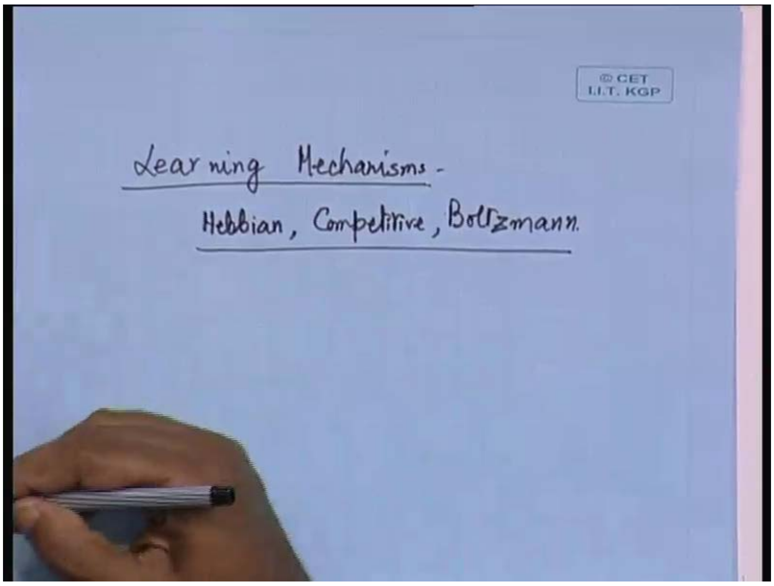

But, especially we will consider on the three types of learning mechanism, one is the Hebbian learning, which we had the left incomplete in the last class. And then, we are also going to discuss about the competitive learning. And finally, the fifth mechanism which is the Boltzmann learning, so this will be the scope of our discussion for today, in fact, as you had seen in the last class, that we can define five basic learning rules.

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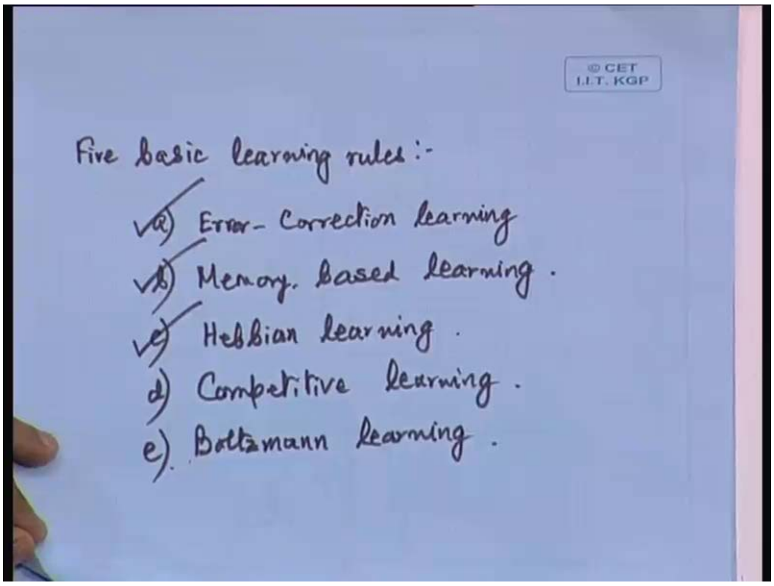

And out of that error correction learning and the memory based learning, we have already discussed and it was Hebbian learning which we were considering towards the end of the class,. In fact, for Hebbian learning as we had discussed already that, it is quite supported by the neuro physiological evidence that our brain also performs to some extent. At least some region of the brain due perform this kind of a Hebbian learning.

And the mechanism that follows for the Hebbian learning is that, when a cell fires another cell, in that case, the metabolic process should be such that the synaptic connection of such cells. They are strengthen, meaning that next time, there will be a greater strength of cell A firing the cell B. And this when translated in terms of the neural network, we had seen that, we can definite it this way.

That, if you have two neurons one defined as the presynaptic neuron and the other as the postsynaptic neuron, connected to each other by the synaptic weight. In that case, if at a given time instant, both the presynaptic as well as the post synaptic they show the similar excitation. If both of them are active together, in that case the synaptic connection of that will be strengthened.

So, that is the essentially, what we are going to have for the artificial neuron network, when we implement the Hebbian learning mechanism, so such synapses is we are referring as a Hebbian synapses. So, it is Hebbian synapses and Hebbian synapsis has got three characteristics. Firstly, is that, it is very much time dependent, so as we already emphasized that the as presynaptic and the postsynaptic neurons activation, they should be occurring at the same time, that is to say that they must occur synchronously.

So, if they are no synchronous, if they are a synchronous in nature, then we are not going to have the strengthening, then we are going to follow a weakening, so it is very much time dependent. The second thing is that it is highly local in nature; that means, to say that the synaptic weight adjustment is very much dependent upon the post synaptic and the presynaptic neuron only. So, it is absolutely local, it is not dependent upon the other neurons, so it is definitely following a kind of a spatial temporal contiguity.

And the third thing is that, it is strongly interactive and strong interactivity in this case means, that there are true interactions between the both the ends of the synapse. So, if we consider the synapse, then the presynaptic taken the postsynaptic neurons, they are surely interactive with each other. Now, as we had already shown that the positive correlation, if the presynaptic and the postsynaptic, they happen to be positively correlated.

Then, the positive correlation leads to a synaptic strengthening. Whereas, if they happen to be uncorrelated, uncorrelated in the sense that, one does not affect the other. Then, we can say that, it is uncorrelated or it could be negatively correlated. Like, if it is such that, supposing we define a binary state of the neurons. It could be in the plus 1 state or minus 1 state.

And for such kind of binary activations, if it is such that when cell A, which is to be regarded as the presynaptic that goes to a state of plus 1 and the post synaptic, that is at a state of minus 1 at the same time synchronously. Then, we can define that to be a negative correlation and a Hebbian mechanism, simply means that in case of such negative correlation, we are going to have a synaptic weakening.

Now, this is surely, what we can expect that positive correlation should lead to strengthening and negative correlation should lead to weakening. But, whether uncorrelated should lead to a strengthening or a weakening or it remains the same. That is one issue on which one can debate upon. So, although I said here, that uncorrelated any kind of uncorrelation between the presynaptic and the postsynaptic neurons, they lead to weakening.

One can also define the Hebbian learning mechanism in such a way that, there is neither strengthening nor weakening, in fact, based on these, we can develop three different classifications for synaptic modifications.

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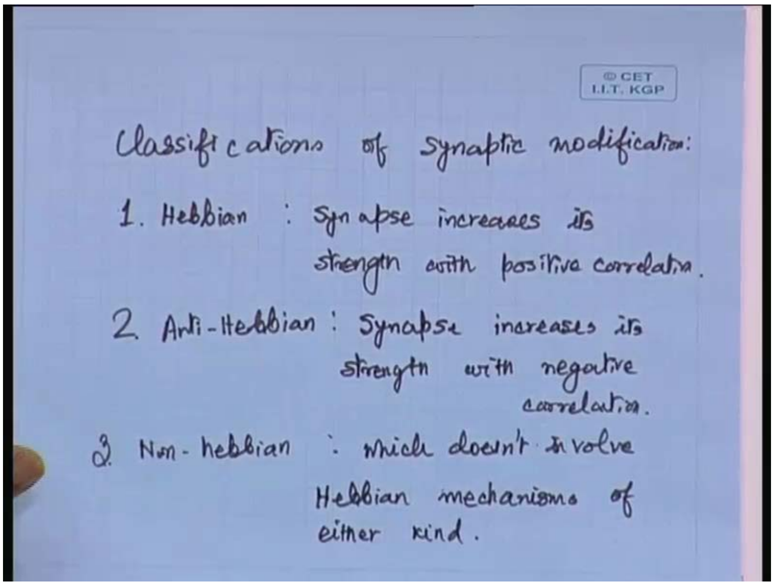

So, the classifications of synaptic modification could be stated us follows. One mechanism is the Hebbian synaptic modification as we have already seen, that the synapse, that increases it is strength with positive correlation. A second category of synaptic modification one can think over, that is called as the Anti-Hebbian and what is Anti-Hebbian.

Anti-Hebbian means something that behaves exactly opposite to how the Hebbian learning mechanism behaves. That means to say that, if you have negative correlation, if one end of the synapses minus 1 and the other end of the synapse is plus 1, in that case you should strengthen that. So, that means to say that the synapse in the case of Anti-Hebbian, it increases it is strength, but not with positive correlation, but with negative correlation.

And the third classification that we are going to define is a Non-Hebbian and what is a Non-Hebbian, Non-Hebbian means that, which does not involve Hebbian mechanism of either kind. I think, it is fairly simple to understand that strengthening, Hebbian means with positive correlation, there is a strengthening. Anti-Hebbian means with negative correlation, there is a strengthening and vice versa.

That means to say that when you have Anti-Hebbian and there is a positive correlation it leads to weakening, obviously and Non-Hebbian means, which does not follow either Hebbian or anti Hebbian. Now, we are going to see the mathematical model for Hebbian modifications.

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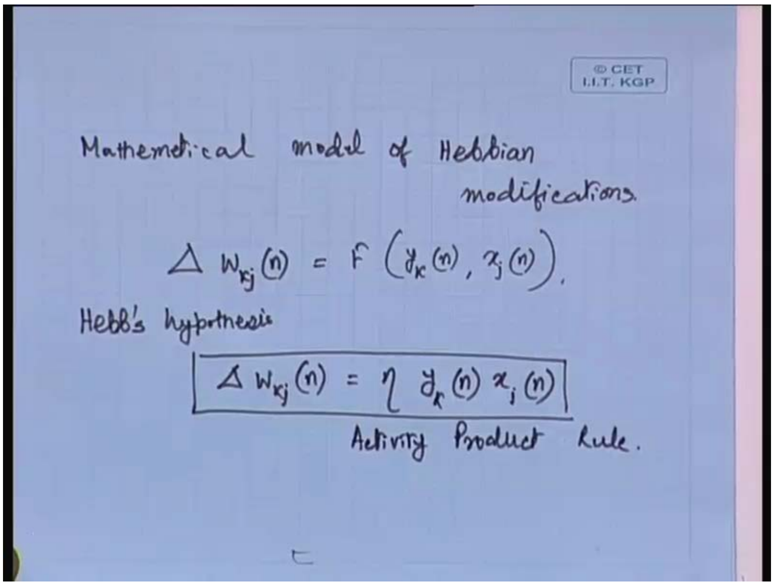

Now, when stated in a very simple way. So, this is the Mathematical model of Hebbian modifications and this can be stated as follows, that delta W k j at the time step n. That is surely a function of y k n and x j n and I think we have already defined the nomenclature for this. It necessarily means that w k j happens to be the synaptic strength between the neuron j and the neuron k.

From neuron, j to neuron k that means to say and x j is the input neuron and y k is the output and what you are seeing within the parenthesis n is the definition that we have at the time step n. Now, surely the change of weight that has to take place has to be a function of the presynaptic, that is x j of n is the presynaptic signal and y k of n, which happens to be the postsynaptic signal. So, it is definitely a function of that and if we are going to have a positive correlation as is the case with the Hebbian synapse.

In that case, one has to show the positive correlation in a form of some mathematical expression, because just telling function F, does mean that whether it is showing a positive correlation or a negative correlation, it can show either.

Now, it is according to hebb's hypothesis, that we can define the delta W k j at the time step n as the product of the postsynaptic and the presynaptic signals, which means to say y k of n times x j of n not exactly a product. But, the product multiplied by the learning rate, so eta as usual is our learning rate. So, it is eta y k n x j n, in fact this expression the one which I had just now written, this is defined as the activity product rule, this is also called the activity product rule.

Now, if we plot these, in fact by keeping x j constant, let us say that we keep the x j constant, we vary y k, eta is of course, a constant, because eta is a learning parameter. So, keeping eta constant, keeping the x j also constant, we plot delta W k j verses y k. So, what s it going to be, it is going to be a straight line. A straight line that passes through the origin simply, so it is curve is going to be is simply this.

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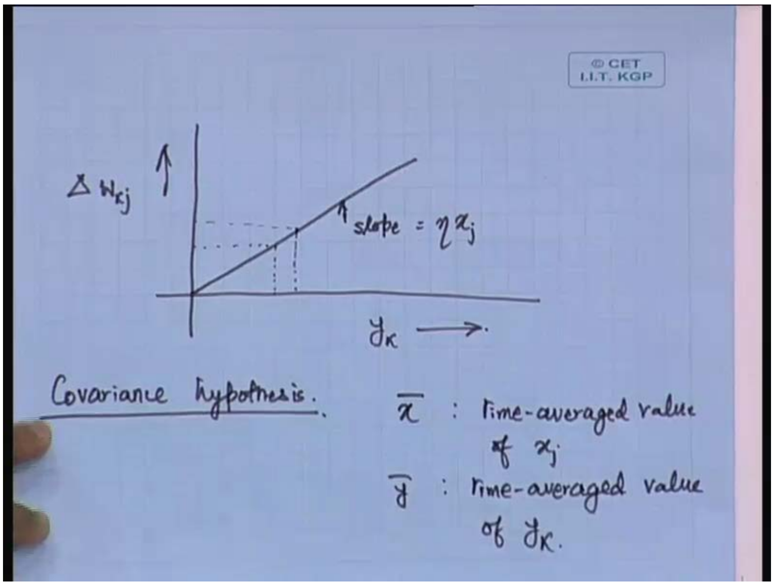

That, we will be having y k on this axis and delta W k j on the y axis and according to hebb's hypothesis, we are going to have a straight line of slope is equal to eta x j and this straight line is going to obviously, pass through the origin, that is very clear shown here. So, now if we analyze the behavior of this network, what is it, going to be, supposing we keep the x j's strength the same, let us say that, we keep the s, x j to be the same that means to say, that according to this curve.

We will be getting some y k and that necessarily means that, there is a delta W k j, some positive delta W k j will be there. Supposing, already the W k j is positive, so whenever we have got a constant x j, then we will be having a positive y k necessarily. And positive y k will mean that, there is a positive delta W k j which means to say that the W k j further gone increases. So, if we begin with say this value of y k, let us say. We are going to have this much of delta W k j added to our W k j.

So, in the next time step, the W k j that we are going to have is W k j plus delta W k j and that will necessarily mean that, with the same x j with a constant x j. We are going to have an increased y k and increased y k necessarily means that we are going to have an increased W k j. And increased W k j will mean that, weight will be further more increased. So, y k will be further more increased and this keeps building up.

So, in the end what happens where is the limit, so it is going to have an exponential growth, we are going to show the delta W k j verse y k. but, if we are seeing W k j verses y k, in that case it is going to follow an exponential growth surely and where is the limit, where does it end. Does it continue forever, will it continuously takes place, no. Certainly, there has to be somewhere, some saturation.

So, there will be a stage, where the synaptic weight or the synaptic strength, reaches it is saturation value and beyond that point there will not be any further leaning. So; obviously, this poses some kind of a limitation. Now, the original hebb’s hypotheses has been somewhat modified by proposing, what is called as the covariance hypotheses. In the case of covariance hypothesis, we are going to take a very similar kind of a mechanism that is delta W k j will still be treated as a function of y k and x j.

But, only thing is that, in the case of the covariance hypothesis, we are not going to take the product as it is, not eta y k x j, but instead of taking it to be y k and x j, we are going to consider, it is strength above some average value. So, if we define some time averaged value of x j and some time averaged value of y k. Let us say that, x bar is the time averaged value of x j and let us take y bar to be the time averaged value of y k.

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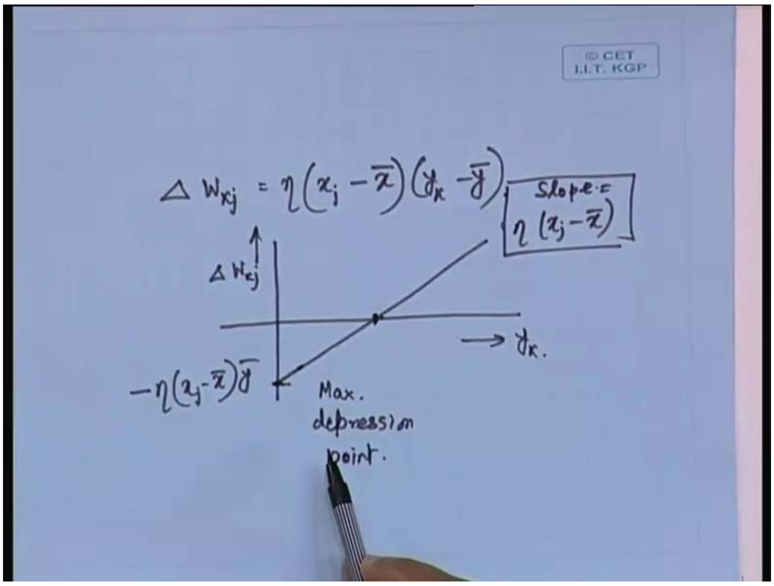

So, this we can then write the covariance hypothesis as delta W k j equal to eta x j minus x bar y k minus y bar. And in this case, if we keep the synaptic strength to be, if we take the input to be the same, let us say that we keep the input at x j only. And it is average; average you do not means that, it is average for the x j only. And average over the entire system, if you are having several inputs, which you are going to have surely.

So, considering it is average effect, which is going to be x bar. So, x bar also will be some constant, at a given time, x bar is going to be a constant and x j is also going to be a constant and then, let us see that what the learning means in this case. So, in this case, if we are going to plot the same thing that is delta W k j, we plot as a function of y k. In this case, what happens is that, we are also going to get the same straight line in this case, but in this case the slope of that straight is going to be not eta x j, but eta x j minus x bar.

So, we are going to have the slope of the line as eta x j minus x bar. So, this is going to be the slope of the straight line that we are going to draw over here. And this straight line, when you draw it fully that should intersect with the y axis at which point, it is going to intersect it as minus eta x j minus x bar, y bar. So, it is going to intersect over here and this is going to be our maximum depression point.

So, in this case, you can see that, it is not that, all the time delta W k j has to increase only. Delta W k j, when y k is equal to y bar, in that case, delta W k j is going to be equal to 0. And above that, it is going to be positive; above below that, it is going to be negative. So, covariance hypothesis has got a stability effect, yes any questions on this.

Student: ((Refer Time: 22:14))

Time average value of x j means, you take all the x j's, all the inputs and it is times averaged behavior, it is time averaged as strength, that is all. See, this is only the learning equation, that means, to say that for a given x j. We are going to find out, that how much of delta W k j we are having, so once that is adjusted. So, during the time on which you are updating this W k j, you are assuming that the signal strength is not changing.

In fact, this is true for a stationary environment, one thing which I think you must try to think of that neural network. When, we are putting neural network into any practical system, that time one inherent assumption, that we have to make it is that the neural network is working in a stationary environment. Stationary environment in the sense that, it is environment is not dynamically changing. It is not that within the time, which you take in order to adjust this weight delta W k, by an amount delta W k j the input also changes.

Although, strictly speaking it is not always very practical, you may be having some kind of non stationarity also. In which case, the neural network has to be more adaptive, more adaptive to non stationary behavior. But, even non stationary behavior also means that for a very short time, we can model it as a stationary. So, there is nothing wrong in assuming that the input is going to remain at the same strength, by the time this delta W k j is arranged, any other question.

Student: If you have series of input, x bar is an average of all those inputs

X bar is an average of all those inputs, very correct

Student: Why should all the input affect my ((Refer Time: 24:29)) from the x j to y j, why should all the other input affect this way

This is just an average behavior, from an average behavior point of view, that if you are assuming that all the inputs are equally likely in a system. It is not that always you have taken it to be the average over the system; you can consider that even x j also may be slowly changing. So, you could take an averaged effect of that, depends what type of time averaging you are doing.

Doing average over the set of neurons that you are having or doing average over only the neuron, that you are considering. It is only over and above some average, that we are considering in the case of covariance hypothesis. Now, one thing that, yes please

Student: ((Refer Time: 25:36))

Exactly, so in fact, we can summarize it as follows.

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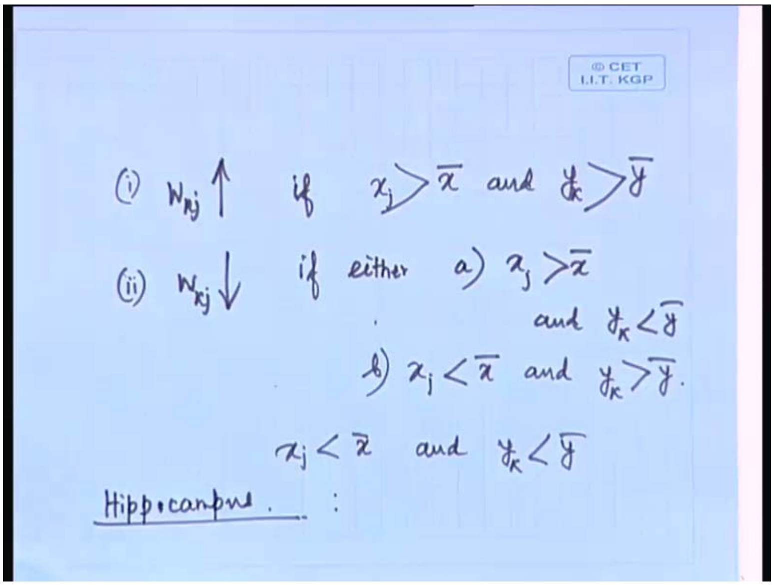

That the W k j is going to increase the increase, I am just denoting by this symbol. If x j happens to be x bar; that means, to say that suddenly if it is in fact, let me answer to the earlier question in a better way that instead of taking it to be. If you are having any problems in imagining that how is it going to be over a system. Let us consider only one presynaptic and one postsynaptic neuron. Even, then also there is no harm in conceptualizing that x bar is the time averaged strength of x j.

So, that means to say that, if it is such that x j is greater than x bar and y k is greater than y bar, in that case W k j is going to be increasing, that is very clear from here. Because, x j minus x bar is positive y k minus y bar is positive eta is positive delta W k j is positive; that means, to save W k j increases in it is strength. So, that is one of the behavior and we are also going to have a decrease of W k j means W k j decreasing. If what, either we have that x j is greater than x bar and y k less than y bar.

If that is the case, then W k j decreases in strength or also the other way; that means to say, if we have x j less than x bar and y k greater y bar. So, this is what the covariance hypothesis is giving us.

Student: ((Refer Time: 27:55))

Exactly, if x j is less than x bar and y k is less than y bar, then also you are going to have an increase, which is obviously Hebbian. That means to say that, if both x j and y k, they are decreasing from their average strength, then you are going to strengthen it up. So, again x j less than x bar and y k less y bar necessarily means that the presynaptic and the postsynaptic neurons are again positively correlated.

So, in fact, there is a strong physiological evidence of Hebbian learning, going on in our brain, in fact the area of the brain, which is called as the hippocampus. This is one region of the brain, where there is strong physiological evidence, that we are adopting a Hebbian learning mechanism. So, it is physiologically very much supported and in fact, it is the

Student: ((Refer Time: 29:18))

Covariance is indeed supporting the Hebbian, only thing is that, here the behavior is defined with respect to the average value. So, it is there, that it is going to stabilize, you see that when is it stabilized. that means to say that the point, where there is no further delta W k j taking place, that is at it is average value, that is at this point, where is it going to be stabilized.

Any other questions, any other observations that you would like to add at this point. So, we can go over to the next mechanism of learning, which we can call as the competitive learning.

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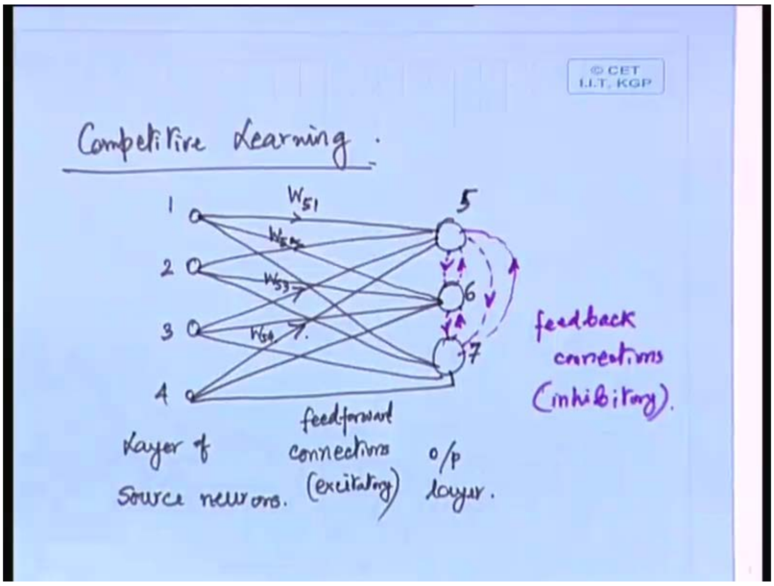

Competitive learning, yes please feels free to ask questions

Student: Delta W k j as 0

Delta W k j as 0, yes, delta W k j, yes, if delta W k j is equal to 0, in that case there is no further updating of weight that is taking place. In fact, that means, to say that it is within it is average behavior. We do not have to modify it is strength supported, that is what the covariance mechanism is telling us that. If it is during it is average mechanism, if it is following it is average behavior, you need not have to alter it.

What you have to do is that, if both are going in the same ways strengthen it. If one is going this way, other is going other way, weaken it, that simply what it is saying that is the translated form of the Hebbian rule, your observations are absolutely very correct. So, I think with this in mind, we can proceed to the next variant of the learning mechanism, which we are calling as the competitive learning.

Now, again competitive learning is something which is white interesting. So, for what we have seen for the Hebbian is that, we have considered existence of two neurons, presynaptic postsynaptic. In fact, that is not the only two neurons in the system, there will be many other such neurons existing in the system. And so that means to say the typically, there will be several inputs, several outputs, they will be connected to each other by synaptic weights.

Now, a Hebbian mechanism means that, there could be that more than one number of output neurons active, remaining active, that is quite possible. That more than one output neurons could remain active, because it is not restricting anything, that only one of the output neurons will be active and at the cost of others. Now, what happens in the case of competitive learning is that, something like a rat race.

You see in a competition, what happens. In a competition, there are several competitors in any competition, take a competition in a real life. What you have, you have several persons, you are competing, let us say that the first position in the class, being the topper of the class, it is competitive. Now, what you are having is that, you are receiving the same set of inputs; all of you are listening to the same lectures from the teachers.

All of you are reading from the same books more or less. Unless, one suddenly finds outs some text material, which he does not want to disclose to the others. That also happens; in fact I am coming to that, but otherwise given a situation that everybody is listening to the lecture to the same set of lectures. Everybody is also having the same text; the prescribed texts are also the same.

And there is a competition, what happens is that out of let say 40 students in the class. One is going to be the topper and other 39 are not going to be the topper, right, simple mechanism. Now, here what happens is that, the set of inputs will be all you are learning materials, lecture notes, etcetera, etcetera and outputs will be your final performance. And I am not referring to the marks, that the students are getting only a classification that somebody is a topper and somebody is not a topper, something like a binary classification that we are getting.

Now, here what happens is that the topper and the other competitors, there are several competitors; there are 40 competitors, who are existing in the class. Now, we not only get and strengthen our, those who are competing, they not only try to strengthen themselves with the kind of inputs that they receive, not only that, they also try to weaken others, I mean it happens.

So, do not tell me, that it does not happen in real life, it can happen. In fact, if you find a very good material for study. Then, you may disclose it to friend who is not going to be your close competitor, but if you are contemplating to be the toper of the class. Certainly, you are not going to tell all this information to the person, who is closely following you in the rank, who also is equally competing in order to become the topper. So; that means, to say that, there is some kind of a relative inhibition between the competitors.

So, the competitors they are inhibiting amongst themselves, but they are trying to strengthening, they are trying to strengthen, all the connections which are they are in the feed forward mechanism. Feed forward mechanism means, from the learning material to the output performance, there whatever is the flow. There it is being strengthened and within the competitors it is getting weakened. And finally, it is one who is the winner, the others are looser.

Now, in real life, it is such that, if one person becomes the winner, if he is the topper of the class, this time it does not mean that in the next semester. He is going to repeat the same performance or there is any special preference for that person, who has become the topper. In fact, it should not be done that way, that we support the person, who has already become a topper; we try to help him more. So, that he becomes the topper in next time. We do not do that, we try to have equal opportunities for all once again.

So, if somebody has become topper in this semester, well and fine he is the topper of this semester. But, next semester again it will be based on equal opportunity of learning and next somebody else could be topper. But, in the case of neural network, what happens is that, if somebody is a topper, then he will be favored, he will be favored in the sense that the synaptic connections will be. So, modified that next time, it will be easy for him to become a topper.

Something like an examiner, who will follow the policy of partiality, you know that if I know that a student is already good, he is the topper of the class, then I will try to give him more marks and I will help him in becoming the topper. Something of that mechanism, but it happens in the case of competitive learning. That means to say that, in the case of competitive learning, what happens is that, the winner will be favored next time.

So, winner will have preference in terms of the synaptic connections, so this is the spirit of the competitive learning.

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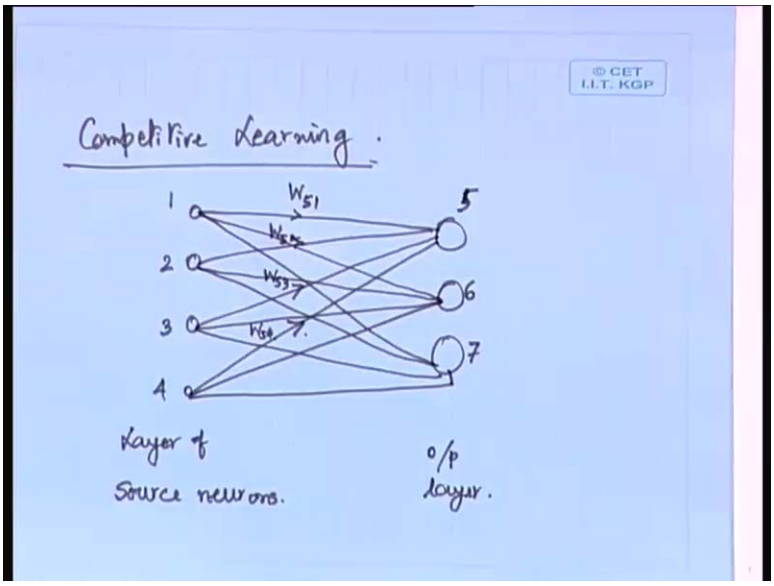

So, in the case of competitive learning, what we are going to have is of course, some input layer, that is say that this is a layer of source neurons. And then, we are going to have an output layer. Supposing, we just show three neurons, which are there in the output layer and now in the case of competitive learning, they will be fully interconnected. Fully interconnected means, that all these four inputs will be connected to all the output neurons followed, so this will be connected to these 4.

Let say that, this is output neuron 1, let us number the neuron 1, 2, 3, 4 and supposing this is the output layer wise, we are going to call it as let us say 5, 6, 7. So, I can say that this is W 51, W 52, W 53 and W 54 and likewise, we will be having W 61, W 62, W 63 and W 64 and likewise we are going to have W 71, W 72, W 73 and W 74. So, all these three neurons, so are supposed to be competing amongst themselves, they are connected to the same set of inputs.

Why, that reason you think over later on, everything I should not tell you, but here you see another. So, all these things, all these connections that I have shown so for; that means to say these connections, that I have already indicating by the arrows, they are the feed forward connection. In fact, the feed forward connections they are excitatory in nature, they are all excitatory connections.

And over and above the excitatory connection in the feed forward, we are also going to have some feedback connections or interconnections between the outputs themselves.

So, like what 5 connected to 6, 6 connected to 5, 6 connected to 7, 7 connected to 6, 5 connected to 7, 7 connected to 5. Now, all these connections, I have deliberately drawn with dotted path, meaning that all the feedback connections, which I have drawn with a different color obtained.

All this feedback connections, they are going to be inhibitory in nature; that means to say that the competitors, never support themselves, they only try to weaken the other competitors. Now, what happens is that the competitive leaning network follows a mathematical model like this; it is going to follow a very simple mathematical model.

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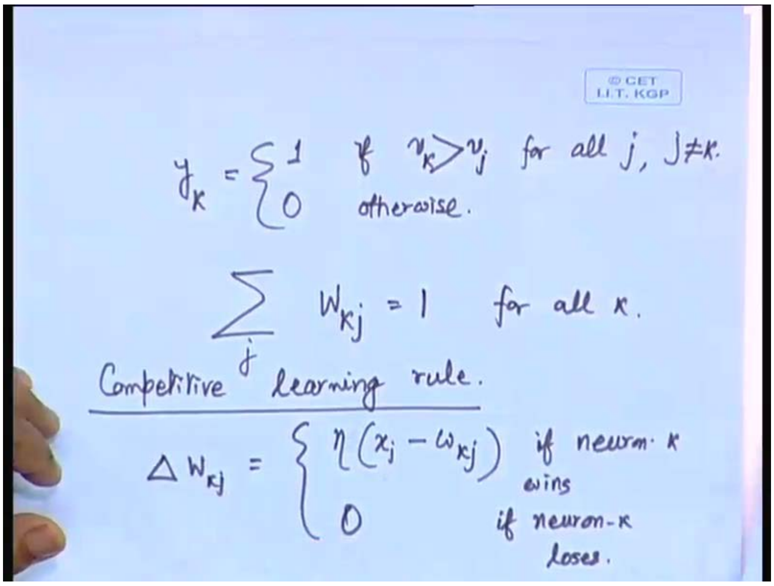


It says that y k, that is the output of the kth unit, the output kth unit will be equal to 1, if v k, what is v k, again the combined response. If v k is greater than v j, for all j, where j is not equal to k and y k is equal to 0, otherwise. This mathematical definition is not at all difficult to follow, it just follows from the definition of the competition itself; that means to say that, if v k happens to be the highest amongst all the neurons, then that is going to be the winner.

And if it is the winner, it is output y k is going to be 1 and otherwise if v k is not greater than v j at least for some j's, v k is not greater than v j, then it is surely a looser. Then, we have got more output strength available with some other neurons and that is going to be the winner, but certainly not this 1. So, this is the very basic definition and another thing which a competitive leaning network always constraints is that the sum total of the weights to a particular neuron.

That is to say that, if we consider the neuron k, then the summation of W k j, meaning what, that for the kth neuron all the inputs that it is receiving, if you sum them up, that means, to say that, if you sum them up over j. In this particular example, if you summit up for j is equal to 1 to 4 and then the summation of W k j will be equal to 1 for all k. This is another constraint, that we define on the weight; that means to say that the sum total of the weights.

Some total of the synaptic weights to any output neurons is going to be 1. Meaning that summation of W 51, 52, 53 and 54 is going to be 1. Likewise, summation of W 61, 62, 63 and 64, they are going to be 1 and now we are going to define the competitive learning rule. So, every learning mechanism has got learning rule, which we have understood by now.

So, competitive learning rule states that delta W k j, again delta W k j means how much of change of weight, you are going to do in that case the rule is pretty simple, it says that W k j is equal to x j minus W k j, if neuron k wins the competition. If neuron k wins the competition and delta W k j is equal to 0, if neuron k loses, again think of it is significance. This means to say what, that we are clearly favoring the winning neuron in what sense, that if the neuron is looser, we do not bothered to readjust it is weight.

If supposing, 5 is the loser, if neuron 5 is the loser, in that case, we are going to keep W 51, W 53, W 53 and W 54 as it is, without doing any modification and supposing out of these three neurons, W 5, 6 and 7, it so happens. So, happens how, that the set of inputs that you feed, the set of inputs that you feed is such, that and the existing connections are such that neurons 6 becomes the winner.

In that case, what we are going to do is that, we are going to adjust the weights of W 61, 63, 63 and 64. So, we are only going to adjust the weights of the winning neuron, but again are we going to increase the strengths of all the connections, which are there to a winning neuron. Yes or no, no we are not going to increase everything, because again we are constrained by this expression.

So, if 6 is the winner, that necessarily means that summation of W 61, 62, 63 and 64 that is going to be equal to 1; that means, to say, that if we decide to increase, let us say 1 or 2 out of them. Supposing, we decide to increase W 61 and W 64 may be to maintain this equation that is summation of W k j equal to 1, we will have to reduce sum. So, that in total W is, summation of W k j is going to be equal to 1, that adjustment we need to do.

So, here what do you conclude out of this, this means to say that, if x j is very close to W k j, then you are not adjusting the weight. But, if x j is much deviated from W k j, then you are going to adjust it heavily, heavily in what direction then you are going to have delta W k j as a large quantity. So, you are going to increase W k j, please follow my point.

If you have x j much greater than W k j, then x j minus W k j is going to be a large quantity, delta W k j is going to be large, that means to say, that you are increasing W k j. That means to say, that next time you are going to have even more delta W k j value or lesser W delta W k j value. That means to say that, now that W k j has already increased next time delta W k j is going to be small, but even then there will be some positive delta W k j.

So, in the next titration W k j will again increase not by the earlier amount, but somewhat it is going to increase and likewise W k j is going to follow what, x j. So, ultimately W k j is going to be what x j is. So; that means to say that the connection weights that we have to follow. Those connection weights will necessarily be of that of the input pattern to which it has become a winner.

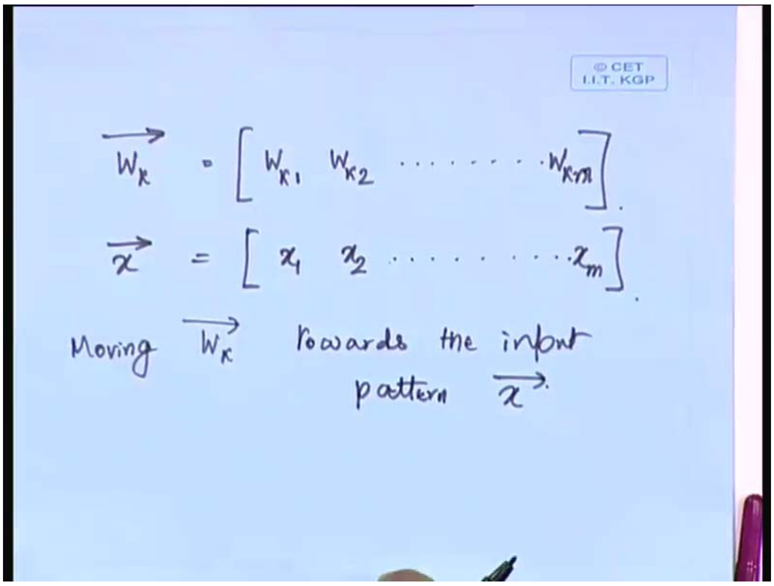
Mind you, the very fact that the neuron k has become a winner, for a particular pattern does not mean that the neuron k is going to be a winner for all the patterns. Topper of one subject or the person say, having securing the highest marks in one subject does not mean that he is going to get highest marks in all the subjects. For a different subject, someone else may be the topper.

So, likewise for a different pattern, may be that for a particular set of patterns, 6 is the winner and we are going to favor 6, for that. Favor 6 in one sense, that whatever connections strengths we are going to have, those connection strengths will be as per this inputs, 1, 2, 3, 4 and what is going to be the and next time, another pattern we feed for a different pattern, may be the 5 will be the winner.

May be for a different pattern 7 may be the winner, may be for another pattern for which 6 is already a winner, it does not mean that 6 will be winner for only one particular pattern. Any pattern, that is close to the pattern which has caused it is winning, there also 6 could continue to be a winner, will possible. We could be feeding a large number of patterns and in a typical situation, let say that here we have only three neurons in the competition.

So, basically it is an open competition only, but the thing is that, what we observe out of this competitive learning rule is that, this rule has the overall effect of moving, the synaptic weight vector W k.

(Refer Slide Time: 51:55)



So, what is this W k vector, W k vector means the vector that we will be having as W k 1, W k 2, etcetera, etcetera up to W k m, thus say, where m is the number of inputs. So, this W k vector and if x is another vector, whereby we define the inputs, so if these are the set of the inputs x 1 to x m. Then, the competitive learning rule has got the effect of moving W k vector towards the input pattern vector, x vector.

Now, I can explain this thing in a little more lucid way and I will do that in the next class, taking a kind of a geometrical analogy, for the competitive learning. And although, I promised that I will be doing the Boltzmann learning in this class, but we are running short of time. So, in the next class, we will consider the geometrical interpretation, then the Boltzmann learning and also go over to the next topic. Is there any question, yes please

Student: ((Refer Time: 53:41))

Yes, all the neurons, so I have said the summation W k j equal to 1, for all k

Student: ((Refer Time: 53:51))

No, if one of the connection, see this you have to maintain; that means to say that the connection will be such that, one will be boosted, one will weakened. You see, again another constraint will follow on the input pattern itself, that you cannot arbitrarily select any input pattern, the input pattern also follow a constraint. Let us say for example, input pattern of constant Euclidean length. In that case, if you are having some inputs high, there will be some inputs which has to be low

Student: ((Refer Time: 54:31))

Y k j becoming greater than x j, yes we are not ruling all that possibility

Student: ((Refer Time: 54:40))

No, but y k j in this case is a binary, either winning the competition or losing, the competition simply

Student: ((Refer Time: 54:49))

W k j, yes, in this case there will be some W k j's, which are greater than x j and there are some W k j's which are less than x j's, so

Student: ((Refer Time: 55:03))

Well, yes you are very correct, but there this eta has to play a role, that if the eta is small, then the oscillation will be less, but if the eta is large, then the possibility of oscillation could be more, yes

Student: ((Refer Time: 55:18))

Yes,

Student: ((Refer Time: 55:26))

Yes, actually speaking the inhibitory connections is not mandatory, but in inhibitory connections may exist over and above the feed forward connection. But, the learning mechanism that we have shown is for the excitatory connection, for the feed forward connection, not for the inhibitories, any other questions

Student: ((Refer Time: 55:54))

Yes

Student: ((Refer Time: 55:57))

Yes, the thing is that, all the inputs, the sum total of that, has to be less than 1, the x j is also has to follow that constraint, whatever constraint is there with W k j, the same constraint x j also has to follow, you are very correct, function of feedback connection. We did not use it over here, but feedback connections are inhibitory means that this will further strengthen the winner and this will weaken the losers.

Student: ((Refer Time: 56:55))

We did not talk about the weights of the inhibitory connections, whatever learning rule we have shown, that is only for the feed forward connections. It is it is only for these that we have shown the learning rule.

Thank you very much.