CS 321 SOFT COMPUTING

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Module - V

Introduction to Artificial Neural Networks:

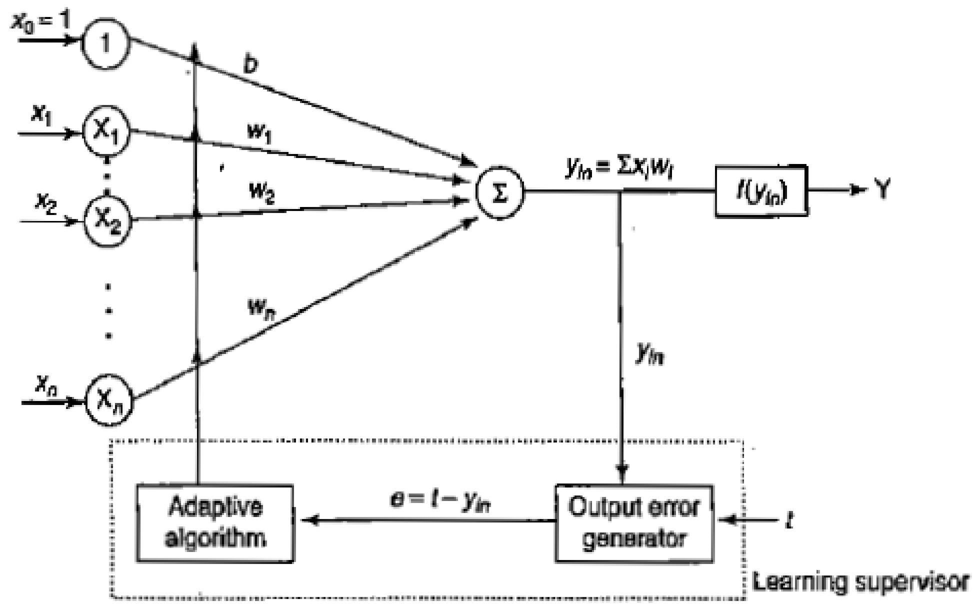
- What is a Neural Network?
- Human Brain
- Models of Neuron
- Neural Network viewed as Directed Graphs
- Feedback, Network Architecture, Knowledge Representation
- Learning processes:
  - Error correction
  - Memory-Based
  - Hebbian
  - Competitive
  - Boltzman
  - Supervised, Unsupervised
- Memory
- Adaptation

Adaptive Linear Neuron (Adaline)

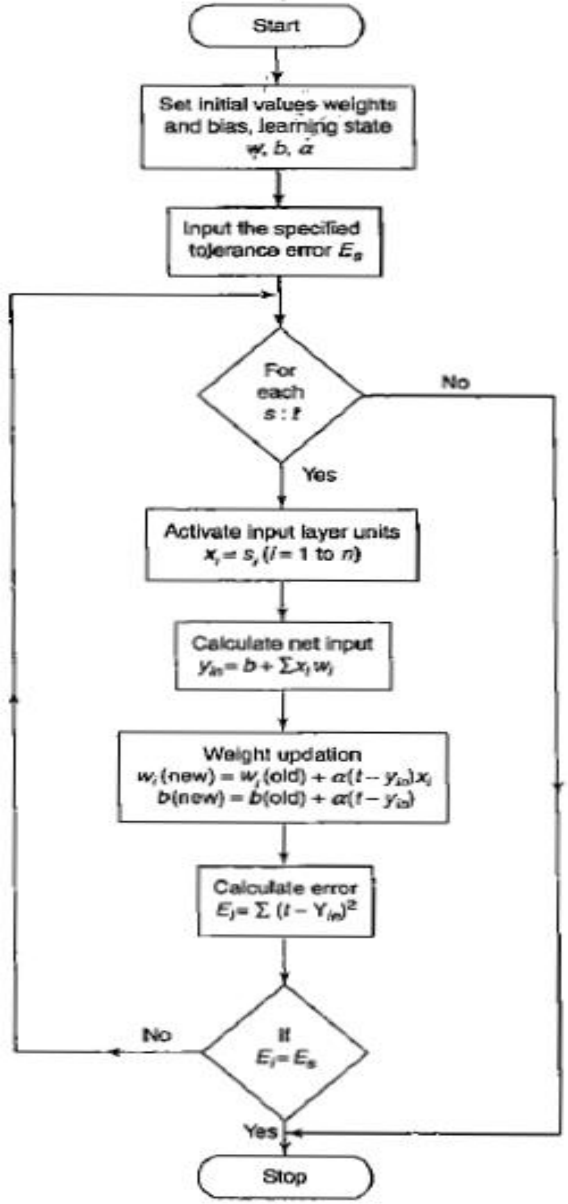
- The units with linear activation function are called linear units.
- A network with a single linear unit is called an Adaline.
- It uses bipolar activation and is trained using the Delta rule (Least Mean Square) / Widrow-Hoff rule.
- Delta rule is derived from gradient descent.
- While perceptron rule stops after finite steps, delta rule continues forever converging only to the solution.
- The delta rule for weight adjustment of i^{th} input is:

$$\Delta w_i = \alpha(t - y_{in})x_i$$

Adaptive Linear Neuron (Adaline)



Adaptive Linear Neuron (Adaline)



Adaline training algorithm

Step 0: Weights and bias are set to some random values but not zero. Set the learning rate parameter α.

Step 1: Perform Steps 2–6 when stopping condition is false.

Step 2: Perform Steps 3–5 for each bipolar training pair $s:t$.

Step 3: Set activations for input units $i = 1$ to n.

$$x_i = s_i$$

Step 4: Calculate the net input to the output unit.

$$y_{in} = b + \sum_{i=1}^{n} x_i w_i$$

Step 5: Update the weights and bias for $i = 1$ to n:

$$w_i(\text{new}) = w_i(\text{old}) + \alpha\,(t - y_{in})\,x_i$$
$$b(\text{new}) = b\,(\text{old}) + \alpha\,(t - y_{in})$$

Step 6: If the highest weight change that occurred during training is smaller than a specified tolerance then stop the training process, else continue. This is the test for stopping condition of a network.

Adaline testing algorithm

Step 0: Initialize the weights. (The weights are obtained from the training algorithm.)

Step 1: Perform Steps 2–4 for each bipolar input vector x.

Step 2: Set the activations of the input units to x.

Step 3: Calculate the net input to the output unit:

$$y_{in} = b + \sum x_i w_i$$

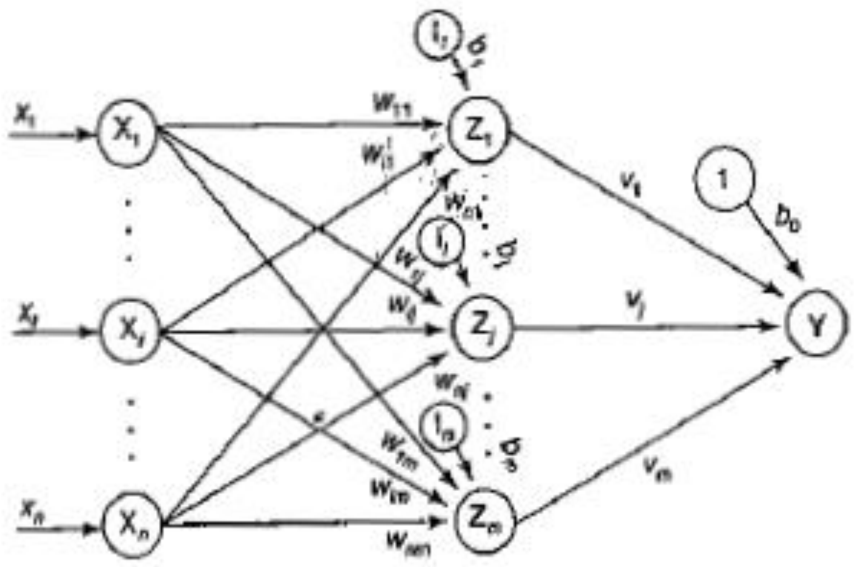
Step 4: Apply the activation function over the net input calculated:

$$y = \begin{cases} 1 & \text{if } y_{in} \geq 0 \\ -1 & \text{if } y_{in} < 0 \end{cases}$$

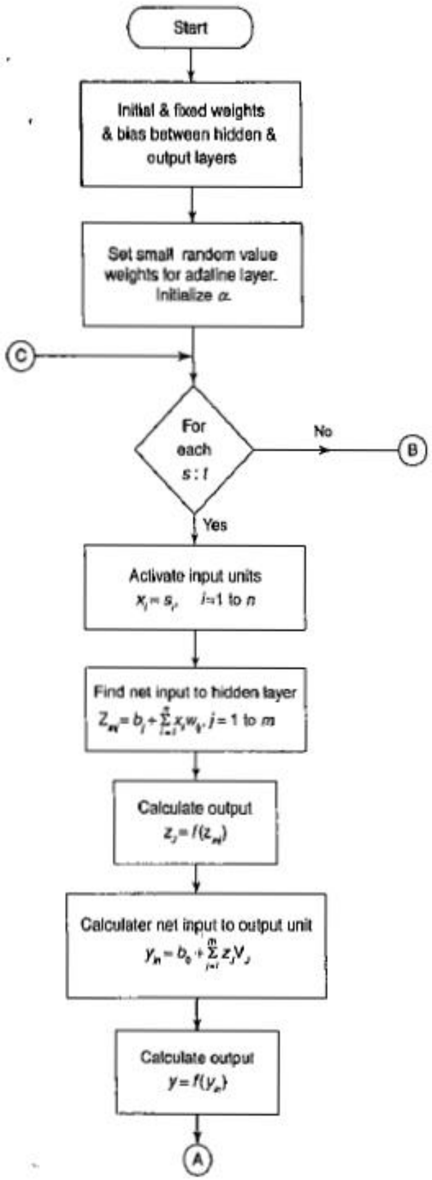
Multiple Adaptive Linear Neuron (Madaline)

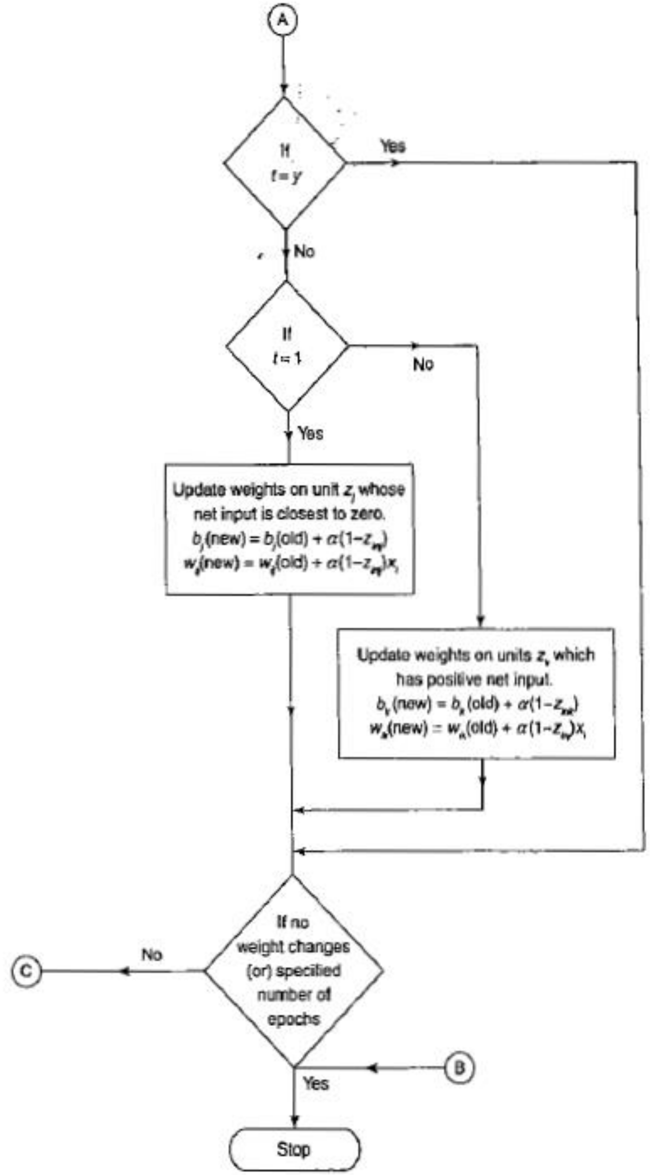
- It consists of many Adalines in parallel with a single output unit.

- It uses majority weight rule.



Multiple Adaptive Linear Neuron (Madaline)





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Madaline training algorithm

Step 0: Initialize the weights. The weights entering the output unit are set as above. Set initial small random values for Adaline weights. Also set initial learning rate α.

Step 1: When stopping condition is false, perform Steps 2–3.

Step 2: For each bipolar training pair $s:t$, perform Steps 3–7.

Step 3: Activate input layer units. For $i = 1$ to n,

$$x_i = s_i$$

Step 4: Calculate net input to each hidden Adaline unit:

$$z_{inj} = b_j + \sum_{i=1}^{n} x_i w_{ij}, \quad j = 1 \text{ to } m$$

Step 5: Calculate output of each hidden unit:

$$z_j = f(z_{inj})$$

Step 6: Find the output of the net:

$$y_{in} = b_0 + \sum_{j=1}^{m} z_j v_j$$

$$y = f(y_{in})$$

Step 7: Calculate the error and update the weights.

1. If $t = y$, no weight updation is required.
2. If $t \neq y$ and $t = +1$, update weights on z_j, where net input is closest to 0 (zero):

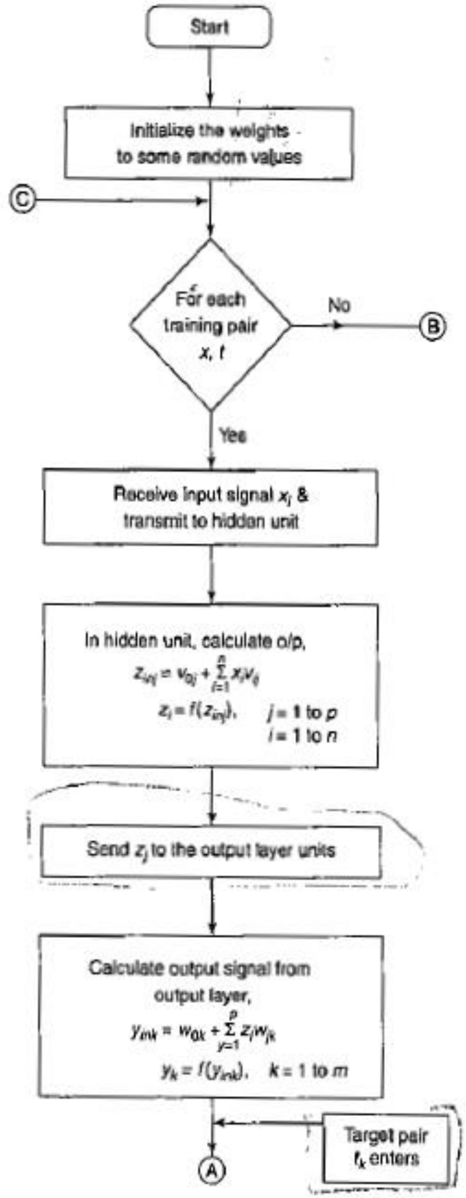
$$b_j(\text{new}) = b_j(\text{old}) + \alpha\,(1 - z_{inj})$$
$$w_{ij}(\text{new}) = w_{ij}(\text{old}) + \alpha\,(1 - z_{inj})x_i$$

3. If $t \neq y$ and $t = -1$, update weights on units z_k whose net input is positive:

$$w_{ik}(\text{new}) = w_{ik}(\text{old}) + \alpha\,(-1 - z_{ink})\,x_i$$
$$b_k(\text{new}) = b_k(\text{old}) + \alpha\,(-1 - z_{ink})$$

Step 8: Test for the stopping condition. (If there is no weight change or weight reaches a satisfactory level, or if a specified maximum number of iterations of weight updation have been performed then stop, or else continue).

Backpropagation flowchart



Backpropagation training Algorithm

Step 0: Initialize weights and learning rate (take some small random values).

Step 1: Perform Steps 2–9 when stopping condition is false.

Step 2: Perform Steps 3–8 for each training pair.

Feed-forward phase (Phase I)

Step 3: Each input unit receives input signal x_i and sends it to the hidden unit ($i = 1$ to n).

Step 4: Each hidden unit z_j ($j = 1$ to p) sums its weighted input signals to calculate net input:

$$z_{inj} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij}$$

Calculate output of the hidden unit by applying its activation functions over z_{inj} (binary or bipolar sigmoidal activation function):

$$z_j = f(z_{inj})$$

and send the output signal from the hidden unit to the input of output layer units.

Step 5: For each output unit y_k ($k = 1$ to m), calculate the net input:

$$y_{ink} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$$

and apply the activation function to compute output signal

$$y_k = f(y_{ink})$$

Backpropagation training Algorithm

Back-propagation of error (Phase II):

Step 6: Each output unit $y_k (k = 1$ to $m)$ receives a target pattern corresponding to the input training pattern and computes the error correction term:

$$\delta_k = (t_k - y_k) f'(y_{ink})$$

The derivative $f'(y_{ink})$ can be calculated as in Section 2.3.3. On the basis of the calculated error correction term, update the change in weights and bias:

$$\Delta w_{jk} = \alpha \delta_k z_j; \quad \Delta w_{0k} = \alpha \delta_k$$

Also, send δ_k to the hidden layer backwards.

Step 7: Each hidden unit $(z_j, j = 1$ to $p)$ sums its delta inputs from the output units:

$$\delta_{inj} = \sum_{k=1}^{m} \delta_k w_{jk}$$

The term δ_{inj} gets multiplied with the derivative of $f(z_{inj})$ to calculate the error term:

$$\boxed{\delta_j = \delta_{inj} f'(z_{inj})}$$

The derivative $f'(z_{inj})$ can be calculated as discussed in Section 2.3.3 depending on whether binary or bipolar sigmoidal function is used. On the basis of the calculated δ_j, update the change in weights and bias:

$$\Delta v_{ij} = \alpha \delta_j x_i; \quad \Delta v_{0j} = \alpha \delta_j$$

Backpropagation training Algorithm

Weight and bias updation (Phase III):

Step 8: Each output unit (y_k, $k = 1$ to m) updates the bias and weights:

$$w_{jk}(\text{new}) = w_{jk}(\text{old}) + \Delta w_{jk}$$
$$w_{0k}(\text{new}) = w_{0k}(\text{old}) + \Delta w_{0k}$$

Each hidden unit (z_j, $j = 1$ to p) updates its bias and weights:

$$v_{ij}(\text{new}) = v_{ij}(\text{old}) + \Delta v_{ij}$$
$$v_{0j}(\text{new}) = v_{0j}(\text{old}) + \Delta v_{0j}$$

Step 9: Check for the stopping condition. The stopping condition may be certain number of epochs reached or when the actual output equals the target output.

Backpropagation testing Algorithm

Step 0: Initialize the weights. The weights are taken from the training algorithm.

Step 1: Perform Steps 2–4 for each input vector.

Step 2: Set the activation of input unit for x_i ($i = 1$ to n).

Step 3: Calculate the net input to hidden unit x and its output. For $j = 1$ to p,

$$z_{inj} = v_{0j} + \sum_{i=1}^{n} x_i v_{ij}$$

$$z_j = f(z_{inj})$$

Step 4: Now compute the output of the output layer unit. For $k = 1$ to m,

$$y_{ink} = w_{0k} + \sum_{j=1}^{p} z_j w_{jk}$$

$$y_k = f(y_{ink})$$

Use sigmoidal activation functions for calculating the output.

Appropriate problems for Neural Network learning

- ANN is well suited for problems in which training data corresponds to noisy, complex sensor data.
- Instances are represented by many attribute value pairs (like pixel values)
- The target function output maybe discrete valued, real valued or a vector of several real or discrete values attributes (self driving cars).
- The training examples may contain errors.
- Long training times are acceptable.
- Fast evaluation of the learned target function may be required.
- The ability of humans to understand the learned target function is not important.