

$$L=1, y_{in} < 0$$

Adaline Network (Adaptive linear Neuron)

Network that uses linear activation are called linear unit. A single network with single linear unit is adaline.

- * It uses bipolar activation fn.
- * Bias act like adjustable weight
- * Only one o/p unit.
- * Trained using delta rule / least mean square rule (LMS) / Widrow-Hoff rule.
- * Delta rule is used to minimise the mean square error b/w the activation and the target.
- * Delta rule is derived from ~~Back~~ Gradient descent method.
- * Delta rule updates the weight b/w the connection so as to minimise the difference.

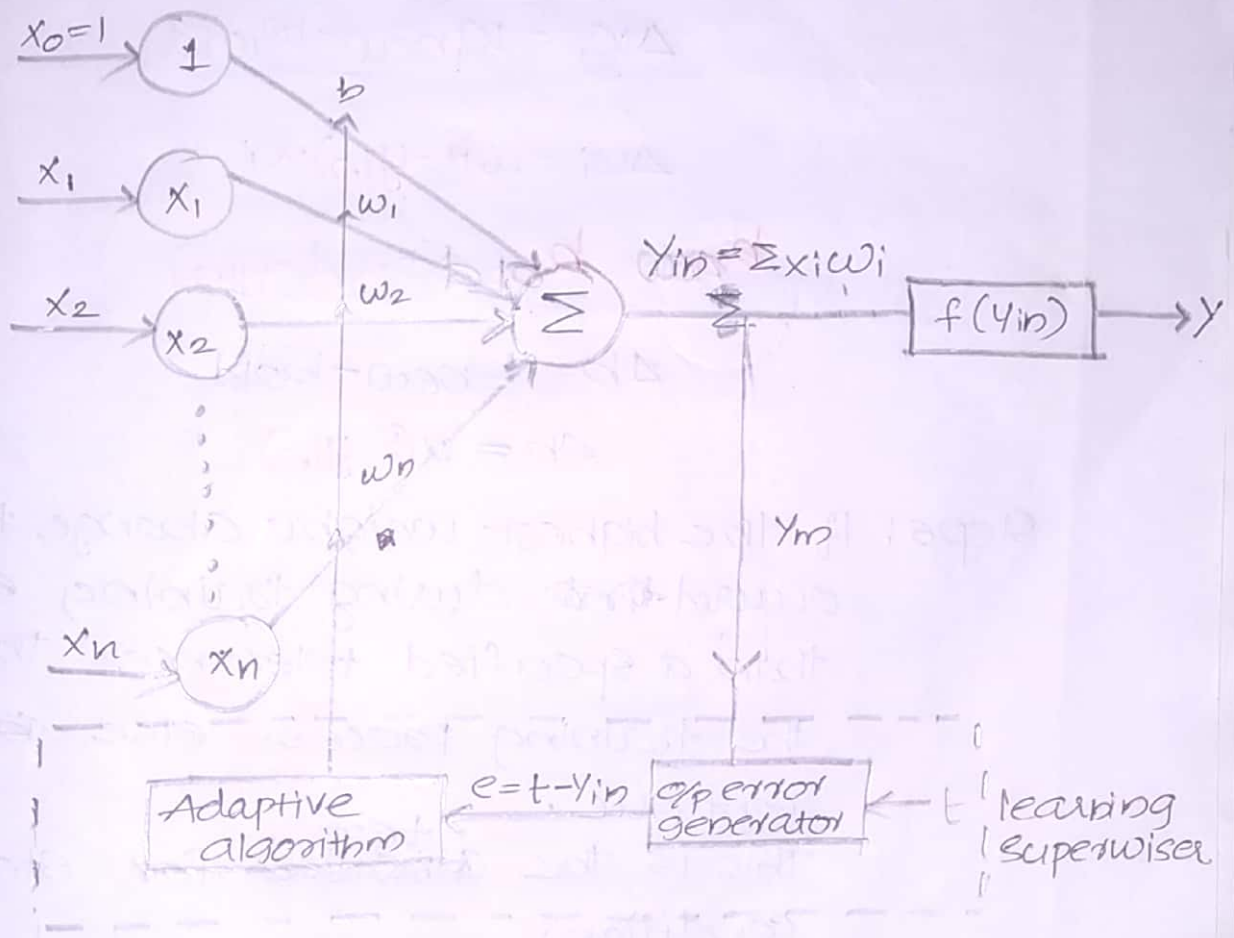
b/w net input to o/p unit and target value.

* The aim of the delta rule is to minimise the error in overall training patterns.

* Delta rule for adjusting the weight of i th pattern where $i=1$ to n is

$$\Delta w_i = \underbrace{\alpha(t - y_{in})}_{\text{Error}} x_i$$

Adaline Model



Training Algorithm

Step 0: weight & bias are set to some random values (not zero). Set the learning rate parameter, α ($0.1 < \alpha < 1.0$)

Step 1: Perform step 4-6 when stopping condition is false.

Step 2: Perform step 3-5 for each bipolar training pair (s, t)

Step 3: Set the activation for the ip unit $i=1$ to n

ie, $x_i = S_i$

Step 4: Calculate the net ip

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

Step 5: Updates the weights & bias for $i=1$ to n

$$w_{i\text{new}} = w_{i\text{old}} + \alpha(t - y_{in}) x_i$$

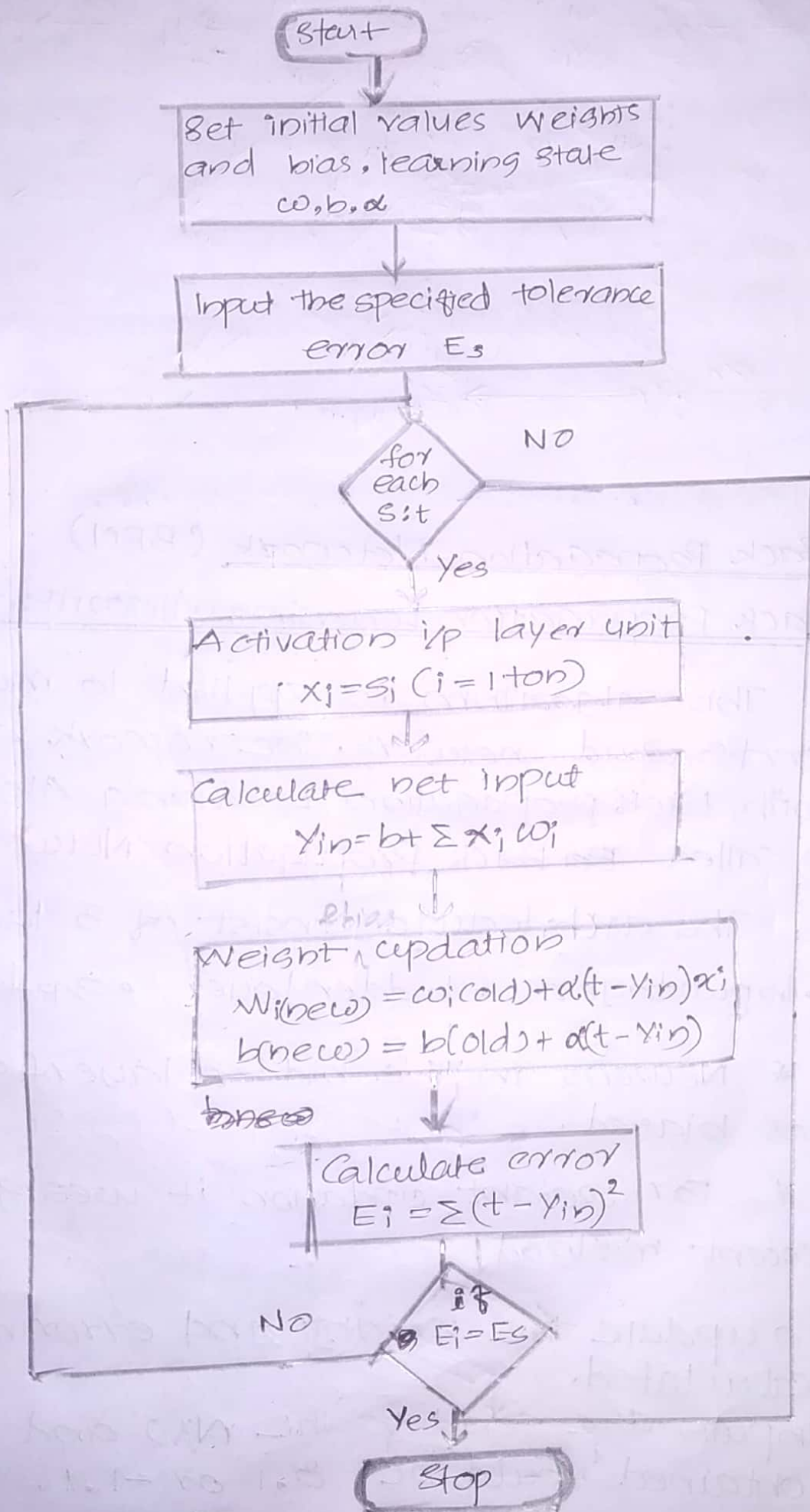
$$\Delta w_i = \alpha(t - y_{in}) x_i$$

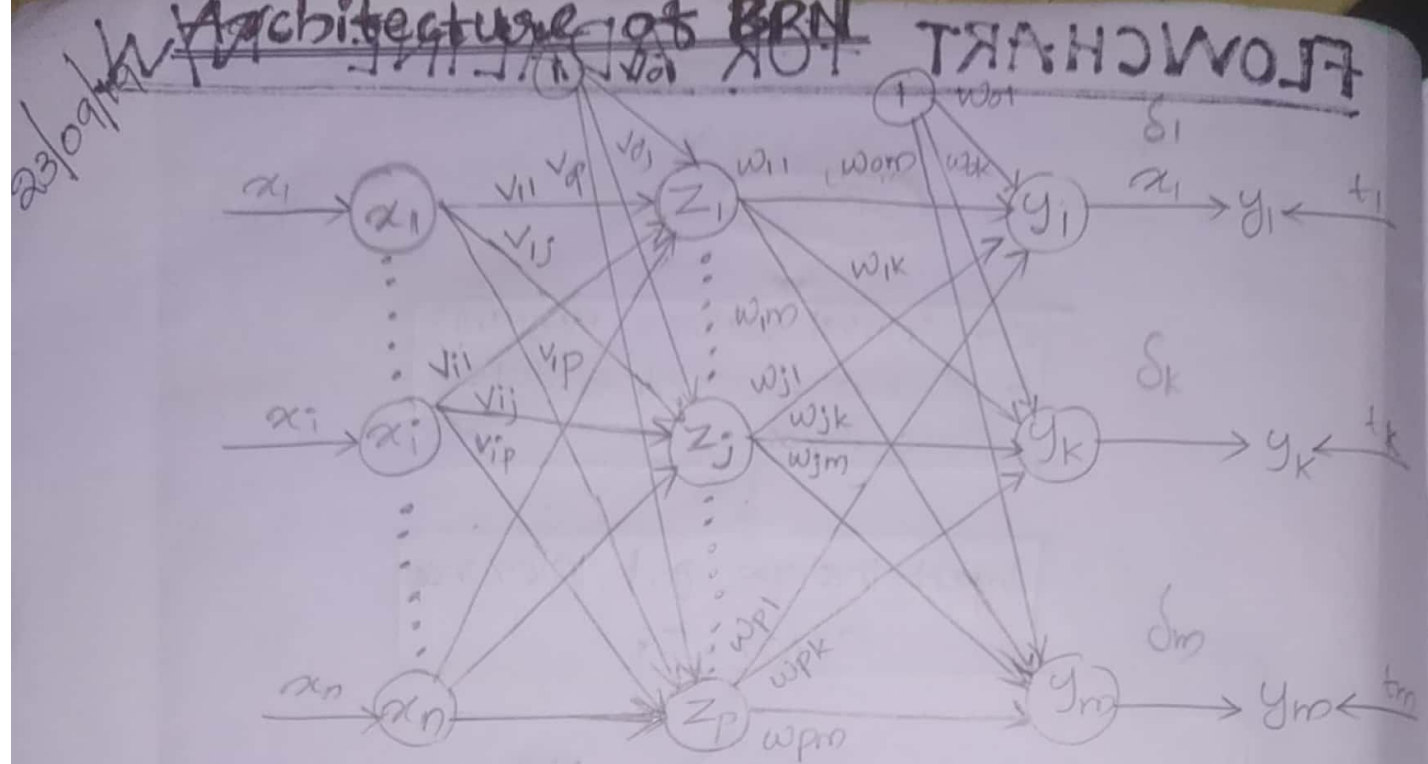
$$b_{\text{new}} = b_{\text{old}} + \alpha(t - y_{in})$$

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

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

FLOWCHART FOR ADALINE N/W





Back Propagation Network (BPN)

Back Propagation Learning Algorithm

This algorithm is applied to multi layer feedforward network. The network associated with back propagation Learning Algorithm is called **Back Propagation Network**.

The architecture consist of 3 layers.

- Input layer
- hidden layer
- op layer

* Neurons in the hidden layer & op layer has biased.

* For weight updation it uses gradient descent method.

* To update the weight and error must be calculated.

* Inputs are send to the n/w and ~~o/p~~ obtained could be 0, 1 or -1, 1.

x_i — ~~input signal~~ i^{th} neuron in the i^{p} unit/layer
 v_{oj} — Bias on the j^{th} neuron in the hidden layer
 w_{ok} — Bias on the k^{th} neuron in the ~~hidden layer~~ o^{p} layer
 z_j — j^{th} neuron in the hidden layer
 y_k — k^{th} neuron in the o^{p} layer.

δ_k : error correction weight adjustment for w_{jk} , i.e., due to the error at the o^{p} unit y_k

δ_j : error correction weight adjustment for v_{ij} due to the back propagation of the error in the hidden layer z_j .

→ There are 3 stages in the ^{training of} BPN

1. Feed forward phase
2. Back propagation of error
3. Weight and bias updation.

Training Algorithm

Step 0: Initialize weights, ~~and~~ bias and learning rate.

Step 1: Performs step 2 to a when stopping condition is false.

Step 2: Perform steps 3 to 8 for each training pair

Feed forward phase (Phase 1)

Step 3: Each i^{p} unit receives the i^{p} signals x_i and send to the hidden unit.

Step 4: Each hidden unit z_j calculate its net input

$$z_{jin} = v_{oj} + \sum_{i=1}^n x_i v_{ij}$$

~~Step~~ : Calculate the o/p of the hidden unit by applying the activation f_h, i.e.,

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

And send the o/p signal from the hidden layer to the o/p layer.

Step 5: For each neuron in the o/p layer

Calculate the net ip ~~into~~

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

Back Propagation of error (Phase: 2)

Step 6: For each o/p unit y_k where $k=1$ to m receives a target pattern corresponding to the ip training pattern and compute the error correction term.

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

where, $f'(y_{ink}) = f(y_{in})(1 - f(y_{in}))$

Step 7: On the basis of the calculated error update the change in weight and bias

$$\Delta w_{jk} = \alpha \delta_k z_j \quad \text{Change in weight}$$

$$\Delta w_{ok} = \alpha \delta_k \quad \text{Change in bias}$$

Also send δ_k to the hidden layer backwards

Step 7: For each hidden unit $z_j, j=1$ to p
Sum its delta δ_j from the op unit.

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

Now we calculate $\delta_j = \delta_{in_j} \cdot f'(z_{in_j})$

On the basis of calculated δ_j update the change in weight and bias.

~~$$\delta_{in_j} = \alpha$$~~

$$\Delta v_{ij} = \alpha \delta_j x_i$$

$$\Delta v_{oj} = \alpha \delta_j$$

Weight and bias updation (phase: 3)

Step 8: each op unit $y_k, k=1$ to m update the bias & weight.

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

$$w_{ok}(\text{new}) = w_{ok}(\text{old}) + \Delta w_{ok}$$

For each unit $z_j, j=1$ to p update the bias & weight.

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

$$v_{oj}(\text{new}) = v_{oj}(\text{old}) + \Delta v_{oj}$$

Step 9: Check for the stopping condition. The stopping condition may be certain no. of epochs reach or when the actual % equals the target %.