

NEURAL NETWORK LEARNING RULES CHAPTER 2

ARTIFICIAL NEURAL NETWORK LEARNING

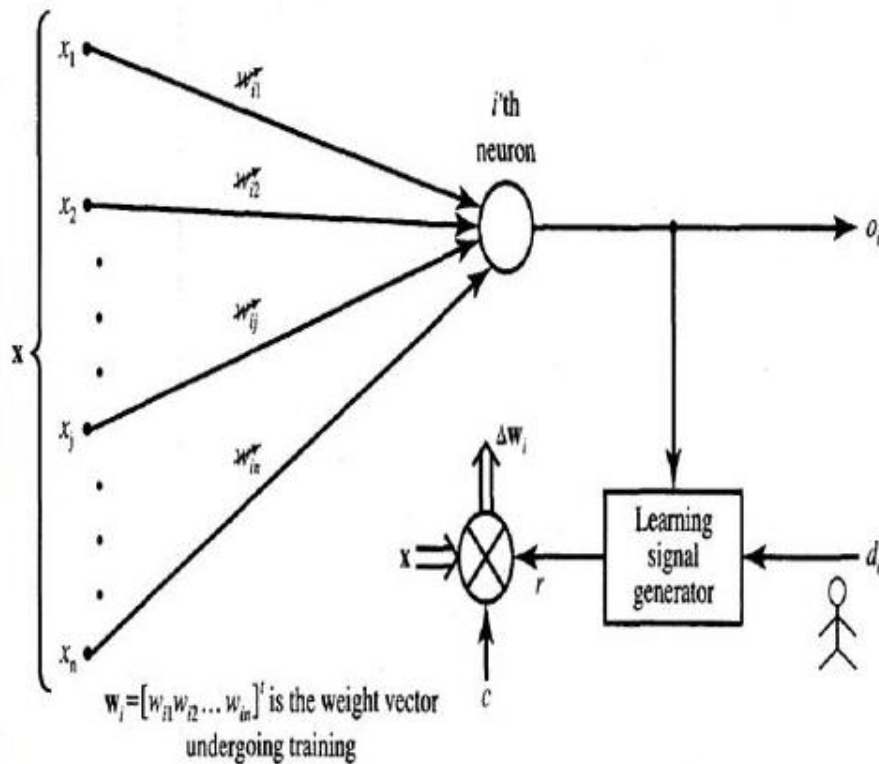


R U L E S

Neural Network Learning Rules

We know that, during ANN learning, to change the input/output behavior, we need to adjust the weights. Hence, a method is required with the help of which the weights can be modified. These methods are called Learning rules, which are simply algorithms or equations.

Neural Network Learning Rules



- The learning signal \mathbf{r} in general a function of \mathbf{w}_i , \mathbf{x} and sometimes of teacher's signal d_i .

$$r = r(\mathbf{w}_i, \mathbf{x}, d_i)$$

- Incremental weight vector \mathbf{w}_i at step t becomes:

$$\Delta \mathbf{w}_i(t) = cr [\mathbf{w}_i(t), \mathbf{x}(t), d_i(t)] \mathbf{x}(t)$$

Where c is a learning constant having +ve value.

Neural Network Learning Rules

- **Perceptron Learning Rule -- Supervised Learning**
- **Hebbian Learning Rule – Unsupervised Learning**
- **Delta Learning Rule -- Supervised Learning**
- **Widrow-Hoffs Learning Rule -- Supervised Learning**
- **Correlation Learning Rule -- Supervised Learning**
- **Winner-Take-all Learning Rule -- Unsupervised Learning**
- **Outstar Learning Rule -- Supervised Learning**

MP Neuron



$\{0, 1\}$

☹ Boolean inputs



Classification

☹ Boolean output



☹ Only one parameter, b

☹ Linear



$$loss = \sum_i (y_i - \hat{y}_i)^2$$



☹ Brute force



$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Perceptron Learning Rule -- Supervised Learning



$\{0, 1\}$

😊 Real inputs



Classification

😞 Boolean output



😊 Weights for every input

😞 Linear



~~$$loss = \sum_i (y_i - \hat{y}_i)^2$$~~

😞 $loss = \sum_i \max(0, 1 - y_i * \hat{y}_i)$



😊 Our 1st learning
algorithm





$$Accuracy = \frac{\text{Number of correct predictions}}{\text{Total number of predictions}}$$

Data and Task

									
Launch (within 6 months)	0	1	1	0	0	1	0	1	1
Weight (g)	151	180	160	205	162	182	138	185	170
Screen size (inches)	5.8	6.18	5.84	6.2	5.9	6.26	4.7	6.41	5.5
dual sim	1	1	0	0	0	1	0	1	0
Internal memory (≥ 64 GB, 4GB RAM)	1	1	1	1	1	1	1	1	1
NFC	0	1	1	0	1	0	1	1	1
Radio	1	0	0	1	1	1	0	0	0
Battery(mAh)	3060	3500	3060	5000	3000	4000	1960	3700	3260
Price (INR)	15k	32k	25k	18k	14k	12k	35k	42k	44k
Like (y)	1	0	1	0	1	1	0	1	0

Data Preparation

									
Launch (within 6 months)	0	1	1	0	0	1	0	1	1
Weight (g)	151	180	160	205	162	182	138	185	170
Screen size (inches)	5.8	6.18	5.84	6.2	5.9	6.26	4.7	6.41	5.5
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Internal memory (>= 64 GB, 4GB RAM)	1	1	1	1	1	1	1	1	1
NFC	0	1	1	0	1	0	1	1	1
Radio	1	0	0	1	1	1	0	0	0
Battery(mAh)	3060	3500	3060	5000	3000	4000	1960	3700	3260
Price (INR)	15k	32k	25k	18k	14k	12k	35k	42k	44k
Like (y)	1	0	1	0	1	1	0	1	0

screen size
5.8
6.18
5.84
6.2
5.9
6.26
4.7
6.41
5.5

Data Preparation

Standardization
formula

$$x' = \frac{x - \min}{\max - \min}$$

									
Launch (within 6 months)	0	1	1	0	0	1	0	1	1
Weight (g)	151	180	160	205	162	182	138	185	170
Screen size (inches)	5.8	6.18	5.84	6.2	5.9	6.26	4.7	6.41	5.5
dual sim	1	1	0	0	0	1	0	1	0
Internal memory (>= 64 GB, 4GB RAM)	1	1	1	1	1	1	1	1	1
NFC	0	1	1	0	1	0	1	1	1
Radio	1	0	0	1	1	1	0	0	0
Battery(mAh)	3060	3500	3060	5000	3000	4000	1960	3700	3260
Price (INR)	15k	32k	25k	18k	14k	12k	35k	42k	44k
Like (y)	1	0	1	0	1	1	0	1	0

screen size
5.8
6.18
5.84
6.2
5.9
6.26
4.7 min
6.41 max
5.5

Data Preparation

									
Launch (within 6 months)	0	1	1	0	0	1	0	1	1
Weight	0.19	0.63	0.33	1	0.36	0.66	0	0.70	0.48
Screen size	0.64	0.87	0.67	0.88	0.7	0.91	0	1	0.47
dual sim	1	1	0	0	0	1	0	1	0
Internal memory (≥ 64 GB, 4GB RAM)	1	1	1	1	1	1	1	1	1
NFC	0	1	1	0	1	0	1	1	1
Radio	1	0	0	1	1	1	0	0	0
Battery	0.36	0.51	0.36	1	0.34	0.67	0	0.57	0.43
Price	0.09	0.63	0.41	0.19	0.06	0	0.72	0.94	1
Like (y)	1	0	1	0	1	1	0	1	0

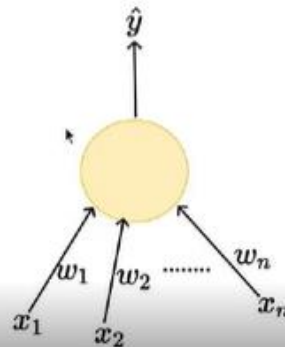
Evaluation

Training data

Launch (within 6 months)	0	1	1	0	0	1	0	1	1
Weight	0.19	0.63	0.33	1	0.36	0.66	0	0.70	0.48
Screen size	0.64	0.87	0.67	0.88	0.7	0.91	0	1	0.47
dual sim	1	1	0	0	0	1	0	1	0
Internal memory (>= 64 GB, 4GB RAM)	1	1	1	1	1	1	1	1	1
NFC	0	1	1	0	1	0	1	1	1
Radio	1	0	0	1	1	1	0	0	0
Battery	0.36	0.51	0.36	1	0.34	0.67	0	0.57	0.43
Price	0.09	0.63	0.41	0.19	0.06	0	0.72	0.94	1
Like (y)	1	0	1	0	1	1	0	1	0

$$\hat{y} = (\sum_{i=1}^n w_i x_i \geq b)$$

$$loss = \sum_i \mathbf{1}_{(y_i \neq \hat{y}_i)}$$



Evaluation

Training data

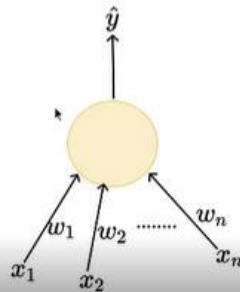
Launch (within 6 months)	0	1	1	0	0	1	0	1	1
Weight	0.19	0.63	0.33	1	0.36	0.66	0	0.70	0.48
Screen size	0.64	0.87	0.67	0.88	0.7	0.91	0	1	0.47
dual sim	1	1	0	0	0	1	0	1	0
Internal memory (>= 64 GB, 4GB RAM)	1	1	1	1	1	1	1	1	1
NFC	0	1	1	0	1	0	1	1	1
Radio	1	0	0	1	1	1	0	0	0
Battery	0.36	0.51	0.36	1	0.34	0.67	0	0.57	0.43
Price	0.09	0.63	0.41	0.19	0.06	0	0.72	0.94	1
Like (y)	1	0	1	0	1	1	0	1	0

Test data

1	0	0	1
0.23	0.34	0.44	0.54
0.74	0.93	0.34	0.42
0	1	0	0
1	0	0	0
0	0	1	0
1	1	1	0
1	1	1	0
0	0	1	0
0	1	0	0
0	1	1	0

$$\hat{y} = (\sum_{i=1}^n w_i x_i \geq b)$$

$$loss = \sum_i \mathbf{1}_{(y_i \neq \hat{y}_i)}$$



Perception Learning Rule

For the perception learning rule, signal is the difference between the desired and actual neuron's response. Thus, learning is supervised and the learning signal is equal to,

$$r = d_i - o_i$$

where $o_i = \text{sgn}(w_i^T x)$ and d_i is the desired response.

Weight adjustments in this method, Δw_i and Δw_{ij} are obtained as follows:-

$$\Delta w_i = \eta \delta_i x$$

$$\Delta w_i = c \left[\frac{d_i - \text{sgn}(w_i^T x)}{o_i} \right] x$$

$$\Delta w_{ij} = c [d_i - \text{sgn}(w_i^T x)] x_j \quad \text{for } j=1, 2, \dots$$

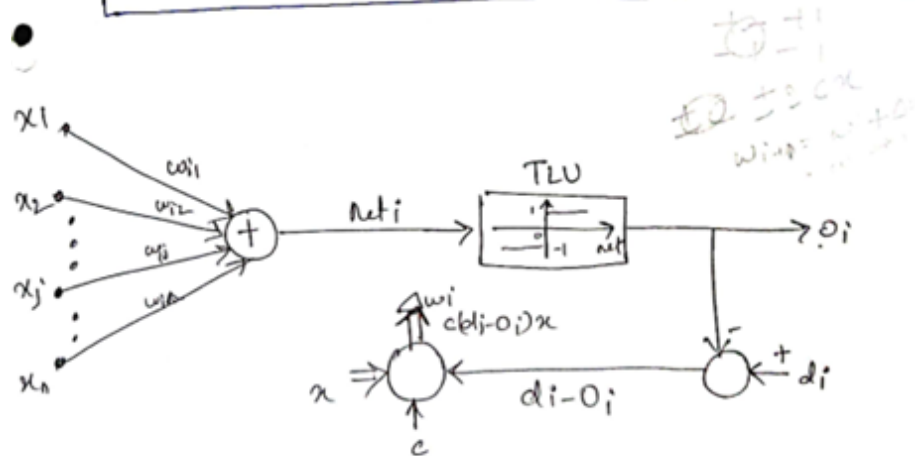
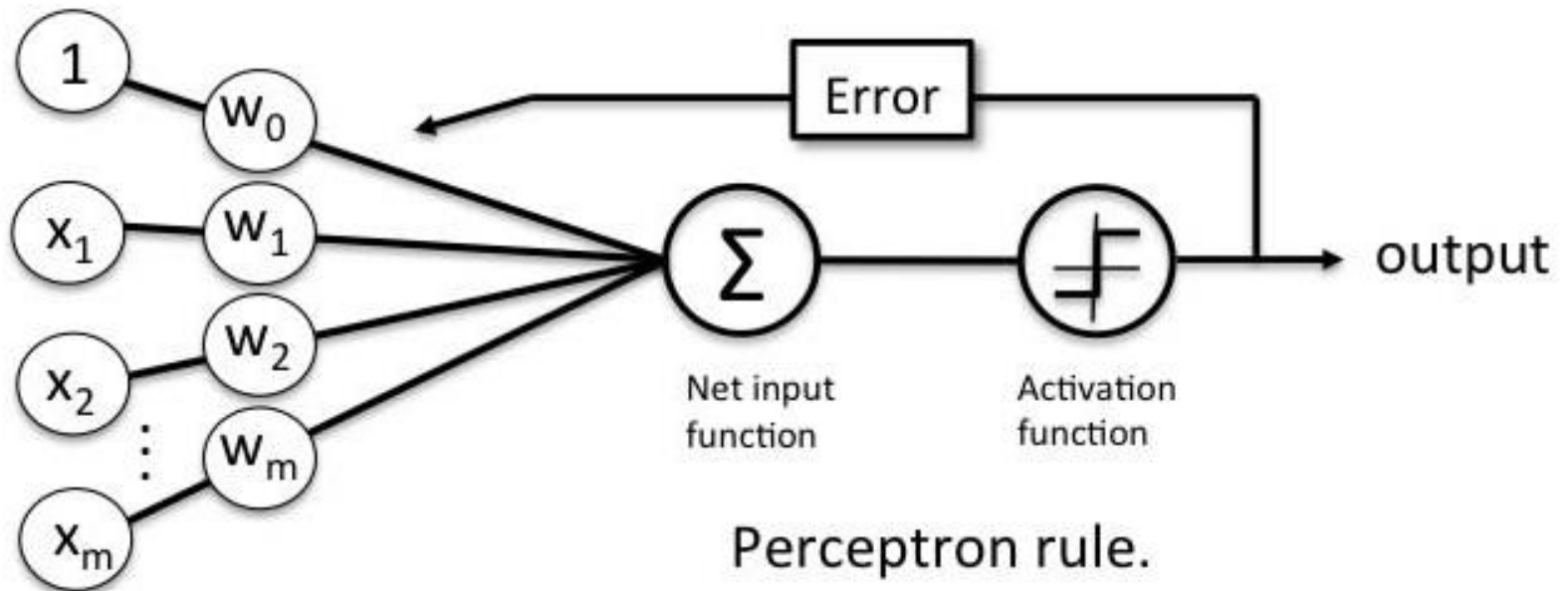


Fig: Perception Learning Rule



- ⇒ This rule is applicable for Binary neuron response. i.e. Rule for the binary bipolar
- ⇒ Under this rule weights are adjusted if and only if d_i is incorrect.
- ⇒ As the desired response is $+1$ or -1 the weight adjustment reduces to,

$\Delta w_i = \pm 2ex$

 — (2)
- ⇒ where a $+$ is applicable when $d_i = 1$ and $\text{sgn}(w^T x) = -1$
and a minus sign is applicable when $d_i = -1$ and $\text{sgn}(w^T x) = 1$.
- ⇒ The wt. adjustment formula will not be used when $d_i = \text{sgn}(w_i^T x)$
- ⇒ This is a very important rule for supervised learning Rule.
- ⇒ The weights are initialized at any value in this method.

Algorithm: Perceptron Learning Algorithm

$P \leftarrow$ inputs with label 1;

$N \leftarrow$ inputs with label 0;

Initialize \mathbf{w} randomly;

while !convergence **do**

 Pick random $\mathbf{x} \in P \cup N$;

if $\mathbf{x} \in P$ and $\sum_{i=0}^n w_i * x_i < 0$ **then**

$\mathbf{w} = \mathbf{w} + \mathbf{x}$;

end

if $\mathbf{x} \in N$ and $\sum_{i=0}^n w_i * x_i \geq 0$ **then**

$\mathbf{w} = \mathbf{w} - \mathbf{x}$;

end

end

//the algorithm converges when all the inputs are classified correctly

∴ For the given network shown in fig. we use the perceptron learning rule to adjust the weight. The set of training vectors are as -

$$x_1 = \begin{bmatrix} 1 \\ -2 \\ 0 \\ -1 \end{bmatrix}, \quad x_2 = \begin{bmatrix} 0 \\ 1.5 \\ -0.5 \\ -1 \end{bmatrix}, \quad x_3 = \begin{bmatrix} -1 \\ 1 \\ 0.5 \\ -1 \end{bmatrix}$$

Initial weight $w_1 = \begin{bmatrix} 1 \\ -1 \\ 0 \\ 0.5 \end{bmatrix}$

$C = 0.1, \quad d_1 = -1, d_2 = -1 \text{ and } d_3 = 1.$

∴ output is d_1 !