

# Computational Intelligence

## Lecture 3: Simple Neural Networks for Pattern Classification

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# Neural Processing

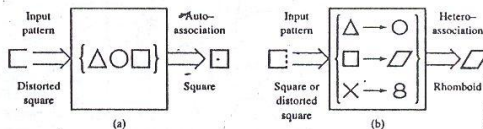
- Classification
- Discriminant Functions

# Learning

- Perceptron Learning Rule

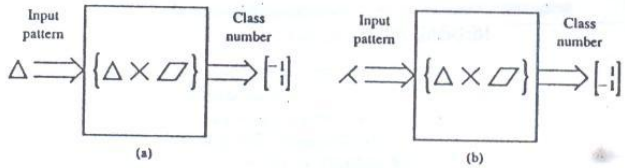
# Neural Processing

- ▶ One of the most applications of NN is in mapping inputs to the corresponding outputs  $o = f(wx)$
- ▶ The process of finding  $o$  for a given  $x$  is named **recall**.
- ▶ Assume that a set of patterns can be stored in the network.
- ▶ **Autoassociation:** The network presented with a pattern similar to a member of the stored set, it associates the input with the closest stored pattern.
  - ▶ A degraded input pattern serves as a cue for retrieval of its original
- ▶ **Hetroassociation:** The associations between pairs of patterns are stored.



Association response: (a) autoassociation and (b) heteroassociation.

- ▶ **Classification:** The set of input patterns is divided into a number of classes. The classifier recall the information regarding class membership of the input pattern. The outputs are usually binary.
  - ▶ Classification can be considered as a special class of hetroassociation.
- ▶ **Recognition:** If the desired response is numbers but input pattern does not fit any pattern.

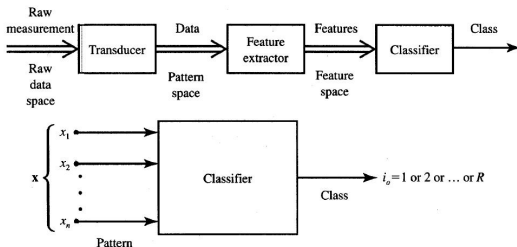


Classification response: (a) classification and (b) recognition.

- ▶ **Function Approximation:** Having I/O of a system, their corresponding function  $f$  is approximated.
  - ▶ This application is useful for control
- ▶ In all mentioned aspects of neural processing, it is assumed the data is already stored to be recalled
- ▶ Data are stored in a network in **learning process**

# Pattern Classification

- ▶ The goal of pattern classification is to assign a physical object, event, or phenomenon to one of predefined classes.
- ▶ Pattern is quantified description of the physical object or event.
- ▶ Pattern can be based on time (sensors output signals, acoustic signals) or place (pictures, fingertips):
- ▶ Example of classifiers: disease diagnosis, fingertip identification, radar and signal detection, speech recognition
- ▶ Fig. shows the block diagram of pattern recognition and classification

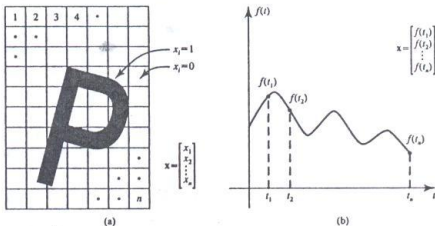


# Pattern Classification

- ▶ Input of feature extractors are sets of data vectors belonging to a certain category.
- ▶ Feature extractor compress the dimensionality as much as does not ruin the probability of correct classification
- ▶ Any pattern is represented as a point in  $n$ -dimensional Euclidean space  $E^n$ , called **pattern space**.
- ▶ The points in the space are  $n$ -tuple vectors  $X = [x_1 \dots x_n]^T$ .
- ▶ A pattern classifier maps sets of points in  $E^n$  space into one of the numbers  $i_0 = 1, \dots, R$  based on decision function  $i_0 = i_0(x)$ .
- ▶ The set containing patterns of classes  $1, \dots, R$  are denoted by  $\xi_1, \dots, \xi_n$

# Pattern Classification

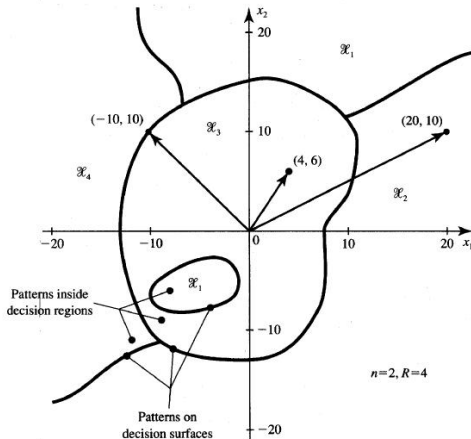
- ▶ The fig. depicts two simple method to generate the pattern vector
  - ▶ Fig. a:  $x_i$  of vector  $X = [x_1 \dots x_n]^T$  is 1 if  $i$ th cell contains a portion of a spatial object, otherwise is 0
  - ▶ Fig b: when the object is continuous function of time, the pattern vector is obtained at discrete time instance  $t_i$ , by letting  $x_i = f(t_i)$  for  $i = 1, \dots, n$



Two simple ways of coding patterns into pattern vectors: (a) spatial object and (b) temporal object (waveform).



- ▶ **Example:** for  $n = 2$  and  $R = 4$
- ▶  $X = [20 \ 10] \in \xi_2$ ,  $X = [4 \ 6] \in \xi_3$
- ▶ The regions denoted by  $\xi_i$  are called **decision regions**.
- ▶ Regions are separated by **decision surface**
  - ▶ The patterns on decision surface does not belong to any class
  - ▶ decision surface in  $E^2$  is curve, for general case,  $E^n$  is  $(n - 1)$ -dimensional hypersurface.



# Discriminant Functions

- ▶ During the classification, the membership in a category should be determined by classifier based on discriminant functions  $g_1(X), \dots, g_R(X)$
- ▶ Assume  $g_i(X)$  is scalar.
- ▶ The pattern belongs to the  $i$ th category iff  $g_i(X) > g_j(X)$  for  $i, j = 1, \dots, R, i \neq j$ .
- ▶  $\therefore$  within the region  $\xi_i$ ,  $i$ th discriminant function have the largest value.
- ▶ Decision surface contain patterns  $X$  without membership in any classes
- ▶ The decision surface is defined as:

$$g_i(X) - g_j(X) = 0$$

- **Example:** Consider six patterns, in two dimensional pattern space to be classified in two classes:

$\{[0 \ 0]', [-0.5 \ -1]', [-1 \ -2]'\}$ : class 1

$\{[2 \ 0]', [1.5 \ -1]', [1 \ -2]'\}$ : class 2

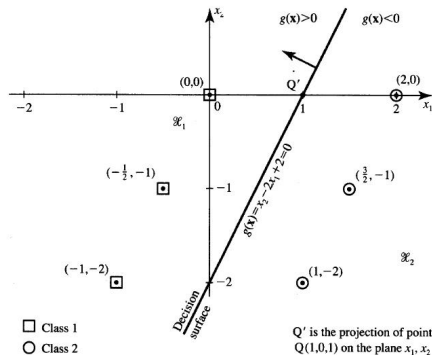
- Inspection of the patterns shows that the  $g(X)$  can be arbitrarily chosen

$$g(X) = -2x_1 + x_2 + 2$$

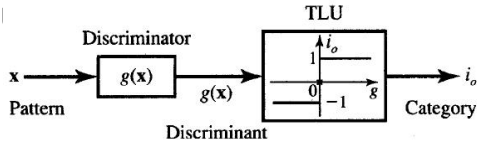
$$g(X) > 0 : \text{class 1}$$

$$g(X) < 0 : \text{class 2}$$

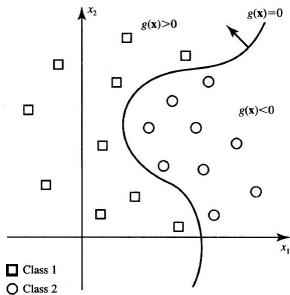
$$g(X) = 0 : \text{on the surface}$$



- ▶ The classifier can be implemented as shown in Fig. below (TLU is threshold logic)



- ▶ **Example 2:** Consider a classification problem as shown in fig. below
- ▶ the discriminant surface can not be estimated easily.
- ▶ It may result in a nonlinear function of  $x_1$  and  $x_2$ .



# Pattern Classification

- ▶ In pattern classification we assume
  - ▶ The sets of classes and their members are known
- ▶ Having the patterns, We are looking to find the discriminant surface by using NN,
- ▶ The only condition is that the patterns are separable
- ▶ The patterns like first example are linearly separable and in second example are nonlinearly separable
- ▶ In first step, simple sparable systems are considered.

# Linear Machine

- ▶ Linear discernment functions are the simplest discriminant functions:

$$g(x) = w_1x_1 + w_2x_2 + \dots + w_nx_n + w_{n+1} \quad (1)$$

- ▶ Consider  $\mathbf{x} = [x_1, \dots, x_n]^T$ , and  $\mathbf{w} = [w_1, \dots, w_n]^T$ , (1) can be redefined as  $g(x) = \mathbf{w}^T \mathbf{x} + w_{n+1}$
- ▶ Now we are looking for  $\mathbf{w}$  and  $w_{n+1}$  for classification
- ▶ The classifier using the discriminant function (1) is called **Linear Machine**.
- ▶ **Minimum distance classifier (MDC)** or **nearest neighborhood** are employed to classify the patterns and find  $w$ 's:
  - ▶  $E^n$  is the  $n$ -dimensional Euclidean pattern space  $\rightsquigarrow$  Euclidean distance between two point are  $\|x_i - x_j\| = [(x_i - x_j)^T(x_i - x_j)]^{1/2}$ .
  - ▶  $P_i$  is center of gravity of cluster  $i$ .
  - ▶ A MDC computes the distance from pattern  $x$  of unknown to each prototype ( $\|x - p_i\|$ ).
  - ▶ The prototype with smallest distance is assigned to the pattern.

# Linear Machine

- ▶ Calculating the squared distance:

$$\|x - p_i\|^2 = (x - p_i)^T (x - p_i) = x^T x - 2x^T p_i + p_i^T p_i$$

- ▶  $x^T x$  is independent of  $i$

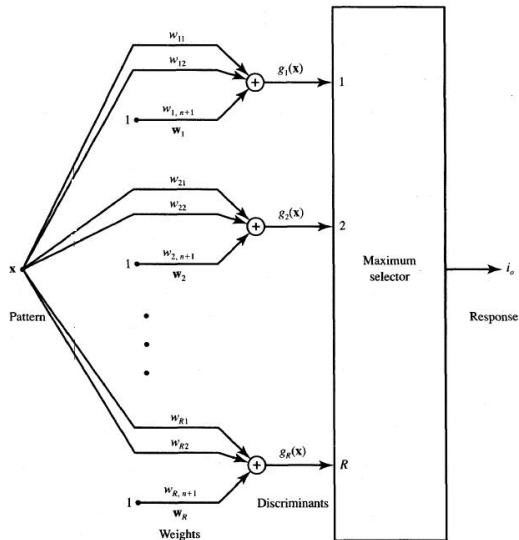
- ▶  $\therefore$  min the equation above is obtained by max the discernment function:  $g_i(x) = x^T p_i - \frac{1}{2} p_i^T p_i$

- ▶ We had  $g_i(x) = \mathbf{w}_i^T \mathbf{x} + w_{in+1}$

- ▶  $\therefore$  Considering  $p_i = (p_{i1}, p_{i2}, \dots, p_{in})^T$ ,

- ▶ The weights are defined as

$$\begin{aligned} w_{ij} &= p_{ij} \\ w_{in+1} &= -\frac{1}{2} p_i^T p_i, \\ & i = 1, \dots, R, j = 1, \dots, n \end{aligned} \quad (2)$$



A linear classifier.



## Example

- ▶ In this example a linear classifier is designed
- ▶ Center of gravity of the prototypes are known a priori

$$p_1 = \begin{bmatrix} 10 \\ 2 \end{bmatrix}, p_2 = \begin{bmatrix} 2 \\ -5 \end{bmatrix}, p_3 = \begin{bmatrix} -5 \\ 5 \end{bmatrix}$$

- ▶ Using (2) for  $R = 3$ , the weights are

$$w_1 = \begin{bmatrix} 10 \\ 2 \\ -52 \end{bmatrix}, w_2 = \begin{bmatrix} 2 \\ -5 \\ -14.5 \end{bmatrix}, w_3 = \begin{bmatrix} -5 \\ 5 \\ -25 \end{bmatrix}$$

- ▶ Discriminant functions are:

$$g_1(x) = 10x_1 + 2x_2 - 52$$

$$g_2(x) = 2x_1 - 5x_2 - 14.5$$

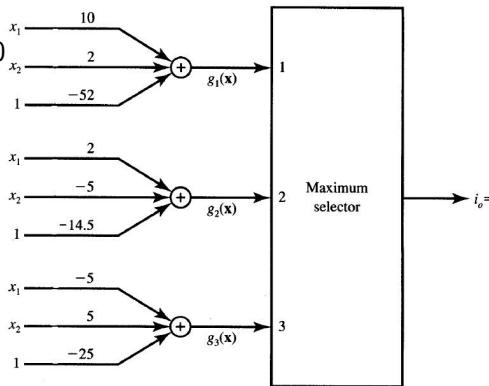
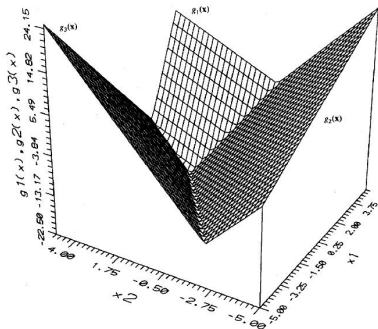
$$g_3(x) = -5x_1 + 5x_2 - 25$$

The decision lines are:

$$S_{12} : 8x_1 + 7x_2 - 37.5 = 0$$

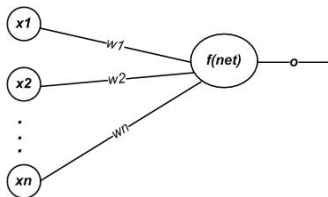
$$S_{13} : -15x_1 + 3x_2 + 27 = 0$$

$$S_{23} : -7x_1 + 10x_2 - 10.5 = 0$$



# Bias or Threshold?

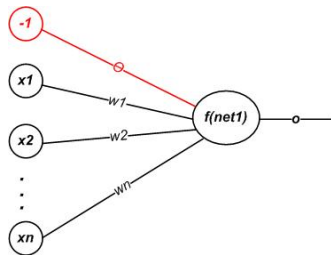
- ▶ Revisit the structure of a single layer network



- ▶ Considering the threshold ( $\theta$ ) the activation function is defined as

$$o = \begin{cases} 1 & net \geq \theta \\ -1 & net < \theta \end{cases} \quad (3)$$

- ▶ Now define  $net_1 = net - \theta$ :



► ∴ The activation function can be considered as

$$o = \begin{cases} 1 & net_1 \geq 0 \\ -1 & net_1 < 0 \end{cases} \quad (4)$$

- ∴ Bias can be play as a threshold in activation function.
- Considering neither threshold nor bias implies that discriminant function always intersects the origin which is not always correct.

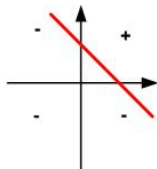
- ▶ If  $R$  linear functions

$$g_i(x) = w_1x_1 + w_2x_2 + \dots + w_nx_n + w_{n+1}, i = 1, \dots, R \text{ exists s.t}$$

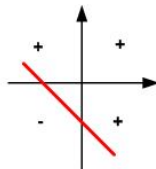
$$g_i(x) > g_j(x) \forall x \in \xi_i, i, j = 1, \dots, R, i \neq j$$

the pattern set is **linearly separable**

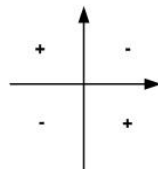
- ▶ Single layer networks can only classify linearly separable
- ▶ Nonlinearly separable patterns are classified by multiple layer networks
- ▶ **Example:** AND:  $x_2 = -x_1 + 1$  ( $b = -1, w_1 = 1, w_2 = 1$ )
- ▶ **Example:** OR:  $x_2 = -x_1 - 1$  ( $b = 1, w_1 = 1, w_2 = 1$ )



AND



OR



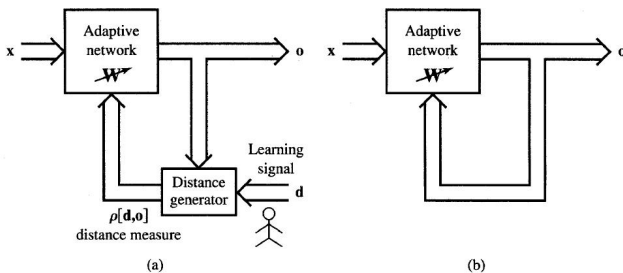
XOR

# Learning

- ▶ When there is no a priori knowledge of  $p_i$ 's, a method should be found to adjust weights ( $w_i$ ).
- ▶ We should learn the network to behave as we wish
- ▶ **Learning task** is finding  $w$  based on the set of training examples  $x$  to provide the best possible approximation of  $h(x)$ .
  - ▶ In classification problem  $h(x)$  is discriminant function  $g(x)$ .
- ▶ Two types of learning is defined
  1. **Supervised learning**: At each instant of time when the input is applied the desired response  $d$  is provided by teacher
    - ▶ The error between actual and desired response is used to correct and adjust the weights.
    - ▶ It rewards accurate classifications/ associations and punishes those yields inaccurate response.

2. **Unsupervised learning**: desired response is not known to improve the network behavior.

- ▶ A proper self-adoption mechanism has to be embedded.



Block diagram for explanation of basic learning modes: (a) supervised learning and (b) unsupervised learning.

- ▶ General learning rule is the weight vector  $w_i = [w_{i1} \ w_{i2} \ \dots \ w_{in}]^T$  increases in proportion to the product of input  $x$  and learning signal  $r$

$$\begin{aligned}w_i^{k+1} &= w_i^k + \Delta w_i^k \\ \Delta w_i^k &= cr^k(w_i^k, x^k)x^k\end{aligned}$$

$c$  is pos. const.: learning constant.

- ▶ For supervised learning  $r = r(w_i, x, d_i)$
- ▶ For continuous learning

$$\frac{dw_i}{dt} = crx$$



# Perceptron Learning Rule

- ▶ Perceptron learning rule was first time proposed by Rosenblatt in 1960.
- ▶ Learning is supervised.
- ▶ The weights are updated based the error between the system output and desired output

$$\begin{aligned}
 r^k &= d^k - o^k \\
 \Delta W_i^k &= c(d_i^k - o_i^k)x^k
 \end{aligned}
 \tag{5}$$

- ▶ Based on this rule weights are adjusted iff output  $o_i^k$  is incorrect.
- ▶ The learning is repeated until the output error is zero for every training pattern
- ▶ It is proven that by using Perceptron rule the network can learn what it can present
  - ▶ If there are desired weights to solve the problem, the network weights converge to them.

# Single Discrete Perceptron Training Algorithm

- ▶ Given  $P$  training pairs  $\{x_1, d_1, x_2, d_2, \dots, x_p, d_p\}$  where  $x_i$  is  $(n \times 1)$ ,  $d_i$  is  $(1 \times 1)$ ,  $i = 1, \dots, P$
- ▶ The augmented input vectors are  $y_i = \begin{bmatrix} x_i \\ -1 \end{bmatrix}$ , for  $i = 1, \dots, P$
- ▶ In the following,  $k$  is training step and  $p$  is step counter within training cycle.
  1. Choose  $c > 0$
  2. Initialized weights at small random values,  $w$  is  $(n + 1) \times 1$
  3. Initialize counters and error:  $k \leftarrow 1$ ,  $p \leftarrow 1$ ,  $E \leftarrow 0$
  4. Training cycle begins here. Set  $y \leftarrow y_p$ ,  $d \leftarrow d_p$ ,  $o = \text{sgn}(w^T y)$  (sgn is sign function)
  5. Update weights  $w \leftarrow w + \frac{1}{2}c(d - o)y$
  6. Find error:  $E \leftarrow \frac{1}{2}(d - o)^2 + E$
  7. If  $p < P$  then  $p \leftarrow p + 1$ ,  $k \leftarrow k + 1$ , go to step 4, otherwise, go to step 8.
  8. If  $E = 0$  the training is terminated, otherwise  $E \leftarrow 0$ ,  $p \leftarrow 1$  go to step 4 for new training cycle

# Convergence of Perceptron Learning Rule

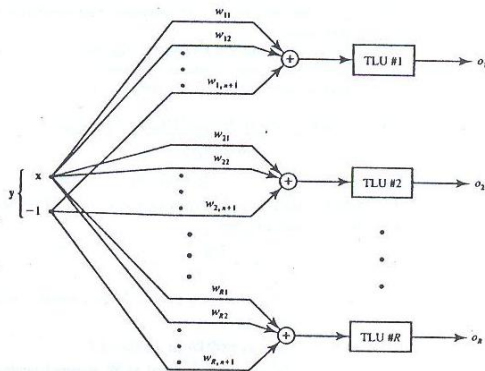
- ▶ Learning is finding optimum weights  $W^*$  s.t.

$$\begin{cases} W^{*T}y > 0 & \text{for } x \in \xi_1 \\ W^{*T}y < 0 & \text{for } x \in \xi_2 \end{cases}$$

- ▶ Training is terminated when there is no error in classification, ( $w^* = w^n = w^{n+1}$ ).
- ▶ Assume after  $n$  steps learning is terminated.
- ▶ It can be shown that  $n$  is bounded
- ▶ i.e., after limited number of updating, the weights converge to their optimum values

# Multi-category Single Layer Perceptron

- ▶ The perceptron learning rule so far was limited for two category classification
- ▶ We want to extend it for multigategory classification
- ▶ The weight of each neuron (TLU) is updated independent of other weights.
- ▶ The  $k$ 's TLU reponses  $+1$  and other TLU's  $-1$  to indicate class  $k$



*R*-category linear classifier using *R* discrete perceptrons.

## R-Category Discrete Perceptron Training Algorithm

- ▶ Given  $P$  training pairs  $\{x_1, d_1, x_2, d_2, \dots, x_p, d_p\}$  where  $x_i$  is  $(n \times 1)$ ,  $d_i$  is  $(R \times 1)$ ,  $i = 1, \dots, P$
- ▶ The augmented input vectors are  $y_i = \begin{bmatrix} x_i \\ -1 \end{bmatrix}$ , for  $i = 1, \dots, P$
- ▶ In the following,  $k$  is training step and  $p$  is step counter within training cycle.
  1. Choose  $c > 0$
  2. Initialized weights at small random values,  $W = [w_{ij}]$  is  $R \times (n + 1)$
  3. Initialize counters and error:  $k \leftarrow 1, p \leftarrow 1, E \leftarrow 0$
  4. Training cycle begins here. Set  $y \leftarrow y_p, d \leftarrow d_p, o_i = \text{sgn}(w_i^T y)$  for  $i = 1, \dots, R$  (sgn is sign function)
  5. Update weights  $w_i \leftarrow w_i + \frac{1}{2}c(d_i - o_i)y$  for  $i = 1, \dots, R$
  6. Find error:  $E \leftarrow \frac{1}{2}(d_i - o_i)^2 + E$  for  $i = 1, \dots, R$
  7. If  $p < P$  then  $p \leftarrow p + 1, k \leftarrow k + 1$ , go to step 4, otherwise, go to step 8.
  8. If  $E = 0$  the training is terminated, otherwise  $E \leftarrow 0, p \leftarrow 1$  go to step 4 for new training cycle

# Example

- ▶ Revisit the three classes example
- ▶ The discriminant values are

Discriminant	Class 1 $[10 \ 2]'$	Class 2 $[2 \ -5]'$	Class 3 $[-5 \ 5]'$
$g_1(x)$	52	-42	-92
$g_2(x)$	-4.5	14.5	-49.5
$g_3(x)$	-65	-60	25

- ▶ So the thresholds values:  $w_{13}$ ,  $w_{23}$ , and  $w_{33}$  are 52, 14.5, and 25, respectively.
- ▶ Assume additional threshold  $T_1 = T_2 = T_3 = -2$  so the threshold are changed to 50, 12.5, and 23, respectively.

- ▶ Now use perceptron learning rule:
- ▶ Consider randomly chosen initial values:  
 $w_1^1 = [1 \ -2 \ 0]'$ ,  $w_2^1 = [0 \ -1 \ 2]'$ ,  $w_3^1 = [1 \ 3 \ -1]'$
- ▶ Use the patterns in sequence to update the weights:
  - ▶  $y_1$  is input:

$$\text{sgn}([1 \ -2 \ 0] \begin{bmatrix} 10 \\ 2 \\ -1 \end{bmatrix}) = 1$$

$$\text{sgn}([0 \ -1 \ 2] \begin{bmatrix} 10 \\ 2 \\ -1 \end{bmatrix}) = -1$$

$$\text{sgn}([1 \ 3 \ -1] \begin{bmatrix} 10 \\ 2 \\ -1 \end{bmatrix}) = 1^*$$

- ▶ TLU # 3 has incorrect response. So  
 $w_1^2 = w_1^1$ ,  $w_2^2 = w_2^1$ ,  $w_3^2 = [1 \ 3 \ -1]' - [10 \ 2 \ -1]' = [-9 \ 1 \ 0]'$

- ▶  $y_2$  is input:

$$\text{sgn}([1 \ -2 \ 0] \begin{bmatrix} 2 \\ -5 \\ -1 \end{bmatrix}) = 1^*$$

$$\text{sgn}([0 \ -1 \ 2] \begin{bmatrix} 2 \\ -5 \\ -1 \end{bmatrix}) = 1$$

$$\text{sgn}([-9 \ 1 \ 0] \begin{bmatrix} 2 \\ -5 \\ -1 \end{bmatrix}) = -1$$

- ▶ TLU # 1 has incorrect response. So

$$w_1^3 = [1 \ 2 \ 0]' - [2 \ -5 \ -1]' = [-1 \ 3 \ 1]', \quad w_2^3 = w_2^2, \quad w_3^3 = w_3^2$$



- ▶  $y_3$  is input:

$$\text{sgn}([-1 \ 3 \ 1] \begin{bmatrix} -5 \\ 5 \\ -1 \end{bmatrix}) = 1^*$$

$$\text{sgn}([0 \ -1 \ 2] \begin{bmatrix} -5 \\ 5 \\ -1 \end{bmatrix}) = -1$$

$$\text{sgn}([-9 \ 1 \ 0] \begin{bmatrix} -5 \\ 5 \\ -1 \end{bmatrix}) = 1$$

- ▶ TLU # 1 has incorrect response. So  $w_1^4 = [4 \ -2 \ 2]'$ ,  $w_2^4 = w_2^3$ ,  $w_3^4 = w_3^3$
- ▶ First learning cycle is finished but the error is not zero, so the training is not terminated



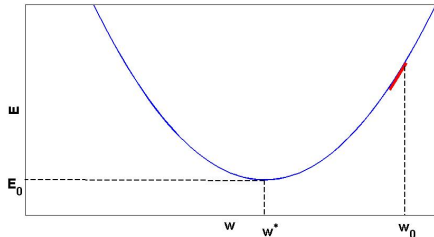
# Continuous Perceptron

- ▶ In many cases the output is not necessarily limited to two values ( $\pm 1$ )
- ▶ Therefore, the activation function of NN should be continuous
- ▶ The training is indeed defined as adjusting the optimum values of the weights, s.t. minimize a criterion function
- ▶ This criterion function can be defined based on error between the network output and desired output.
- ▶ **Sum of square root** error is a popular error function
- ▶ The optimum weights are achieved using gradient or steepest decent procedure.

- ▶ Consider the error function:  
 $E = E^0 + \lambda(w - w^*)^2 \rightsquigarrow \frac{dE}{dw} =$   
 $2\lambda(w - w^*), \frac{d^2E}{dw^2} = 2\lambda$
- ▶ The problem is finding  $w^*$  s.t min  $E$
- ▶ To achieve min error at  $w = w^*$  from initial weight  $w_0$ , the weights should move in direction of negative gradient of the curve.
- ▶  $\therefore$  The updating rule is

$$w^{k+1} = w^k - \eta \nabla E(w^k)$$

where  $\eta$  is pos. const. called learning constant.





- ▶ The TLU activation function is not useful, since its time derivative is always zero and indefinite at  $net = 0$
- ▶ Use sigmoid activation function

$$f(net) = \frac{2}{1 + \exp(-net)} - 1$$

- ▶ Time derivative of sigmoid function can be expressed based on the function itself

$$f'(net) = \frac{2\exp(-net)}{(1 + \exp(-net))^2} = \frac{1}{2}(1 - f(net))^2$$

- ▶  $o = f(net)$ , therefore,

$$\nabla E(w) = -\frac{1}{2}(d - o)(1 - o^2)y$$

- ▶ Finally the updating rule is

$$w^{k+1} = w^k + \frac{1}{2}\eta(d^k - o^k)(1 - o^{k2})y^k \quad (6)$$

- ▶ Comparing the updating rule of continuous perceptron (6) with the discrete perceptron learning ( $w^{k+1} = w^k + \frac{c}{2}(d^k - o^k)y^k$ )
  - ▶ The correction weights are in the same direction
  - ▶ Both involve adding/subtracting a fraction of the pattern vector  $y$
  - ▶ The essential difference is scaling factor  $1 - o^{k2}$  which is always positive and smaller than 1.
  - ▶ In continuous learning, a weakly committed perceptron ( *net* close to zero) the correction scaling factor is larger than the more close responses with large magnitude.

# Single Continuous Perceptron Training Algorithm

- ▶ Given  $P$  training pairs  $\{x_1, d_1, x_2, d_2, \dots, x_p, d_p\}$  where  $x_i$  is  $(n \times 1)$ ,  $d_i$  is  $(1 \times 1)$ ,  $i = 1, \dots, P$
- ▶ The augmented input vectors are  $y_i = [x_i \ -1]^T$ , for  $i = 1, \dots, P$
- ▶ In the following,  $k$  is training step and  $p$  is step counter within training cycle.
  1. Choose  $\eta > 0$ ,  $\lambda = 1$ ,  $E_{max} > 0$
  2. Initialized weights at small random values,  $w$  is  $(n + 1) \times 1$
  3. Initialize counters and error:  $k \leftarrow 1$ ,  $p \leftarrow 1$ ,  $E \leftarrow 0$
  4. Training cycle begins here. Set  $y \leftarrow y_p$ ,  $d \leftarrow d_p$ ,  $o = f(w^T y)$  ( $f(\text{net})$  is sigmoid function)
  5. Update weights  $w \leftarrow w + \frac{1}{2}\eta(d - o)(1 - o^2)y$
  6. Find error:  $E \leftarrow \frac{1}{2}(d - o)^2 + E$
  7. If  $p < P$  then  $p \leftarrow p + 1$ ,  $k \leftarrow k + 1$ , go to step 4, otherwise, go to step 8.
  8. If  $E < E_{max}$  the training is terminated, otherwise  $E \leftarrow 0$ ,  $p \leftarrow 1$  go to step 4 for new training cycle.



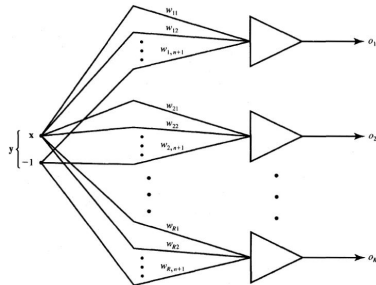
# R-Category Continuous Perceptron

- ▶ Gradient training rule derived for  $R = 2$  is also applicable for multi-category classifier
- ▶ The training rule will be changed to

$$w_i^{k+1} = w_i^k + \frac{1}{2} \eta (d_i^k - o_i^k) (1 - o_i^{k2}) y^k, \quad \text{for } i = 1, \dots, R$$

- ▶ It is equivalent to individual weight adjustment

$$w_{ij}^{k+1} = w_{ij}^k + \frac{1}{2} \eta (d_i^k - o_i^k) (1 - o_i^{k2}) y_j^k, \quad \text{for } j = 1, \dots, n + 1, \quad i = 1, \dots, R$$



R-category linear classifier using continuous perceptrons.