Simple neuron nets for pattern classification

The principle function of a decision-making system is to yield decisions concerning the class membership of the input pattern with which it is confronted, i.e., transformation of sets, or functions, from input space to the output space, which called the classification space.

- We will start with linear discriminant functions with its simple correction rule to perform network training (adaptation), which is a sequence of iterative weight adjustments.
- A pattern can be defined as the quantitive description of an object, event, or phenomenon.
- The classification may involve:

1- Spatial patterns, such as: pictures, video images, weather map.

2- Temporal patterns, such as: speech signal, signals vs time produced by sensors, ECG, …., etc.

- The goal of pattern classification is to assign a physical object, event, …, etc. to one of the prespecified class or categories.

The block diagram of recognition and classification system is as show in figure (18).

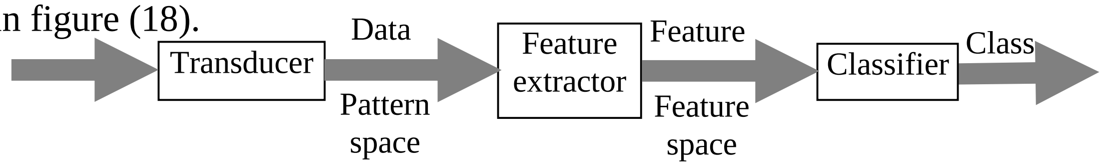


Figure (18) Block diagram of recognition and classification system

1- Transducer: is a device that converts the spatial or temporal patterns into sets of data vectors such as (camera, mic., …, etc.).

2- Feature extractor: it performs the process of data compression, i.e., dimensionally reduction of input data. Feature extractor, may be neural network architecture or any statistical methods.

3- Classifier: the n-tuple vector of the input to the classifier may be the pattern features or pattern data. In the later case the classifier will perform classification and internally extract input pattern feature.

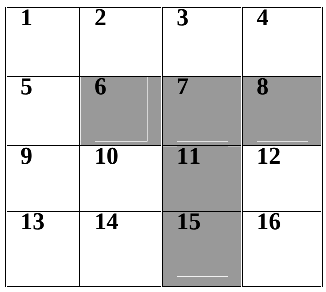
In general the classifier input components can be represented a vector

$$\mathbf{X = [\, x_1 \;\; x_2 \;\; \ldots.. \; x_n]^T}$$

The classification at the system output is obtained by the classifier implementing the decision function: $\quad$ ***i_0=1 or 2, … , or R***

Example-1: The figures shown below depicts simple method to generate the pattern vector, (a) fixed with time, (b) variable with time.

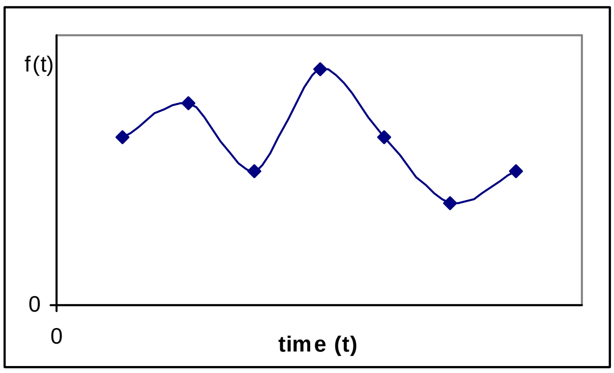
$$X = \begin{bmatrix} x_1 \\ x_2 \\ . \\ . \\ x_n \end{bmatrix}$$



(a) fixed with time

X^T =[0 0 0 0 0 1 1 1 0 0 1 0 0 0 1 0] ;

$$X = \begin{bmatrix} f(t_1) \\ f(t_2) \\ . \\ . \\ f(t_n) \end{bmatrix}$$



(b) variable with time

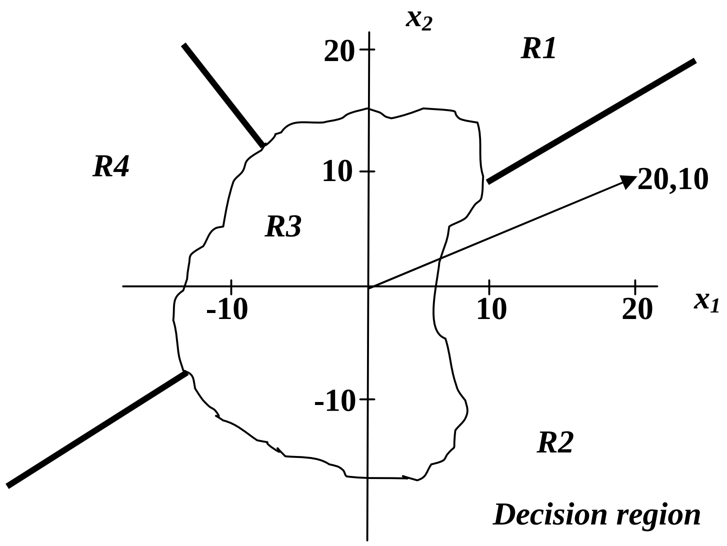
Classification can be conveniently described in geometric terms. Any pattern can be represented by a point in n-dimensional **Eucliden space E^n** called **"pattern space"**.

Thus, a pattern classifier maps sets of points in **E^n** space into one of the numbers ***i_o = 1, 2, …, R***

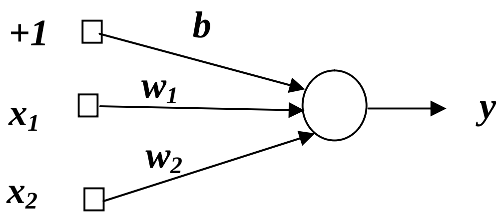
Example-2: For the case n=2 and R = 4

$i_o(x) = j$ for all xČR_j , $j = 1,2,3,4$

for the figure shown, x = [20 10] belong to R2 (class2)



In the simplest case the classifier has only two inputs and a single output as sketched in figure :



The output of the network is formed by the activation function of the output neuron, which some function of the input:

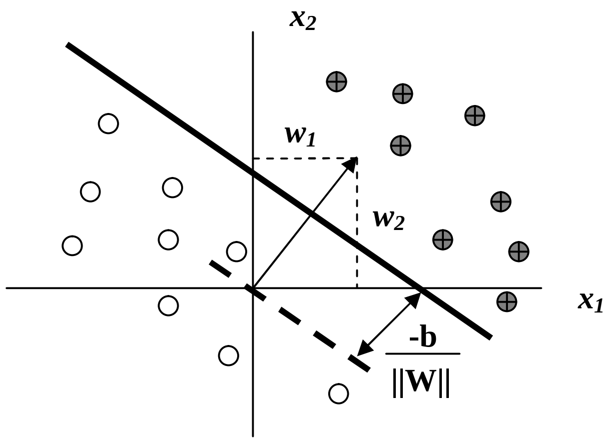
$$y = f\left(\sum_{i=1}^{2} w_i x_i + b\right)$$

Using f( ) as a bipolar threshold function, thus, the output of the network is either -1 or +1 depending on the input. The network can now be used for a classification task: it can decide whether an input pattern belongs to one of two classes. i.e., if the total input is positive, the pattern will be assigned to class +1, else it will be assigned to class -1.

The separation between the two classes in this case is a straight line given by the equation:

$$w_1x_1 + w_2x_2 + b = 0 \qquad \ldots\ldots. (*)$$

- The single layer network represents ***a linear discriminant function.***
- A geometrical representation of the linear threshold neural network is shown in figure:



Eq. (*) can be written as:

$$x_2 = -\frac{w_1}{w_2}x_1 - \frac{b}{w_2}, \qquad w_2 \neq 0$$

This equation represents the line that separates the region where the output is positive from the region where the output is negative.

- we can see that the weights determine the slop of the line and the bias determines how far the line is from the origin.
- **Note:** the weight vector is always perpendicular to the discriminant function.
- Not all simple two-input, single output mappings can be solved by a single layer net (even with a bias included) such example is the XOR .

Example-3: Response regions for the OR function

The OR function (for bipolar inputs and target) is defined as follows:

Input (x1, x2)	Output
1, 1	**+1**
1, -1	**+1**
-1, 1	**+1**
-1, -1	**-1**

The desired responses can be illustrated as shown in Figure. One possible decision boundary for this function is also shown.
An example of weights that would give the decision boundary illustrated in the figure, namely, the separating line

$$x2 = - x1 -1$$

is

$$b = 1$$
$$w_1 = 1$$
$$w_2 = 1$$

The choice of sign for b is determined by the requirement that

$$b + x_1w_1 + x_2w_2 > 0$$

where, x1 = 0 and x2 = 0.

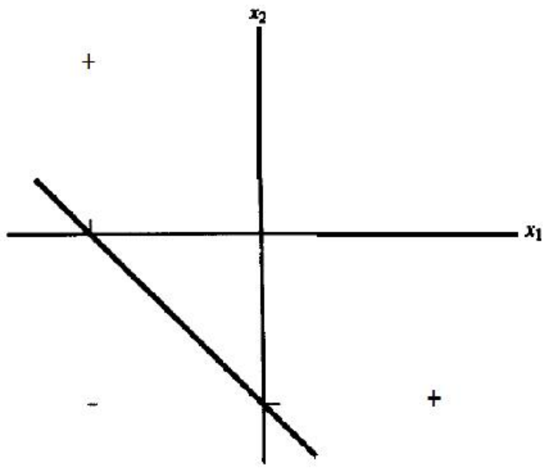


Figure Desired response for the logic function OR (for bipolar inputs), showing a possible decision boundary.