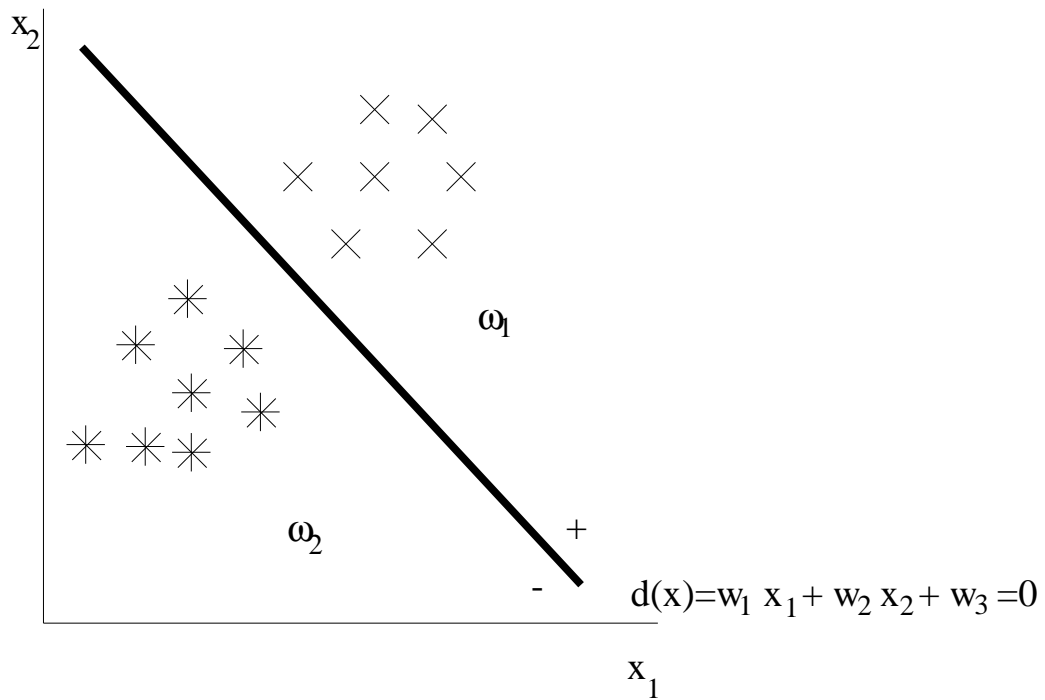


# Decision Function

Decision Functions:

- Linear Decision Functions
- Pattern Space and Weight Space
- Geometrical Properties
- Implementation of Decision Functions

Decision Function:



Success:

- (1) the form of  $d(x)$ .
- (2) determination of coefficients

## Linear Decision Functions

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$$\begin{aligned}d(x) &= w_1x_1 + \dots + w_nx_n + w_{n+1} \\ &= w'_0x + w_{n+1}\end{aligned}$$

$w_0 = (w_1, \dots, w_n)'$  – weight or parameter vector

- Introduce the augmented pattern and weight vectors:

$$\begin{aligned}x &= (x_1, \dots, x_n, 1) \\ w &= (w_1, \dots, w_n, w_{n+1})\end{aligned}$$

The decision function can be written as:

$$d(x) = w'x$$

For the two-class case, a decision function  $d(x)$  suppose to have the property

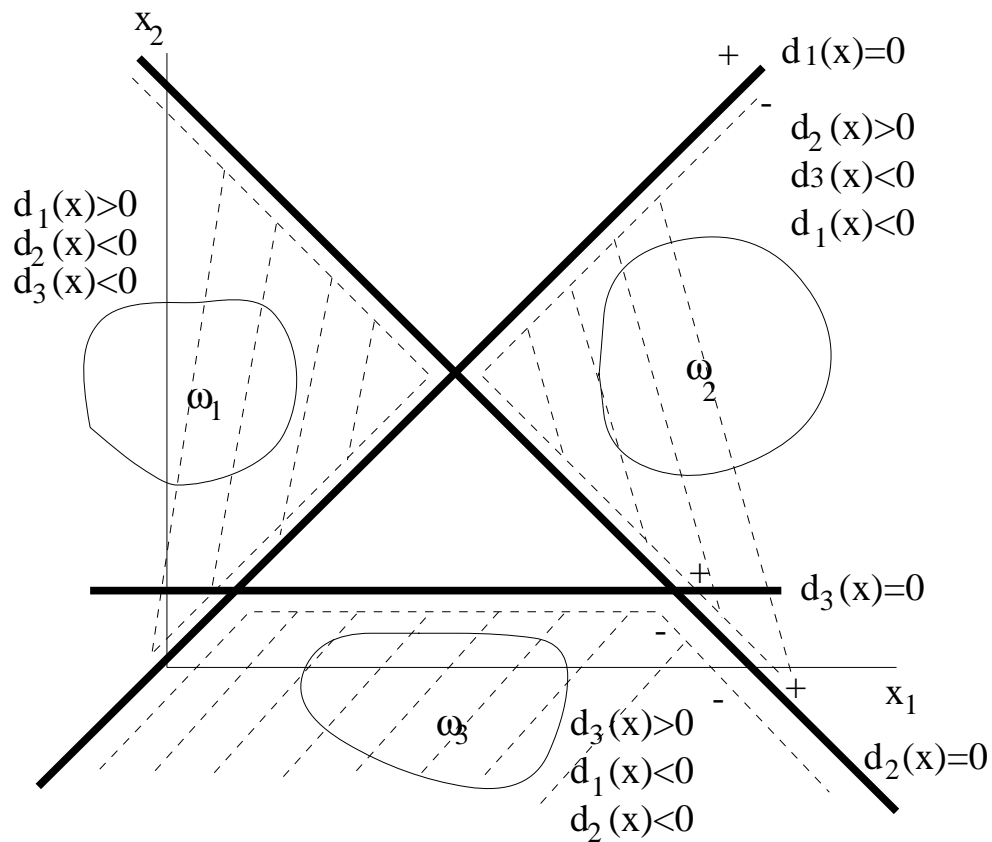
$$d(x) = w'x \begin{cases} > 0 & \text{if } x \in \omega_1 \\ < 0 & \text{if } x \in \omega_2 \end{cases}$$

For the multi-class case, denoted as  $\omega_1, \dots, \omega_M$ , there are three cases to occur:

Case 1. Each pattern class separable from others by a single surface

$$d_i(x) = w'_i x \begin{cases} > 0 & \text{if } x \in \omega_i \\ < 0 & \text{otherwise} \end{cases}$$

$$i = 1, \dots, M$$



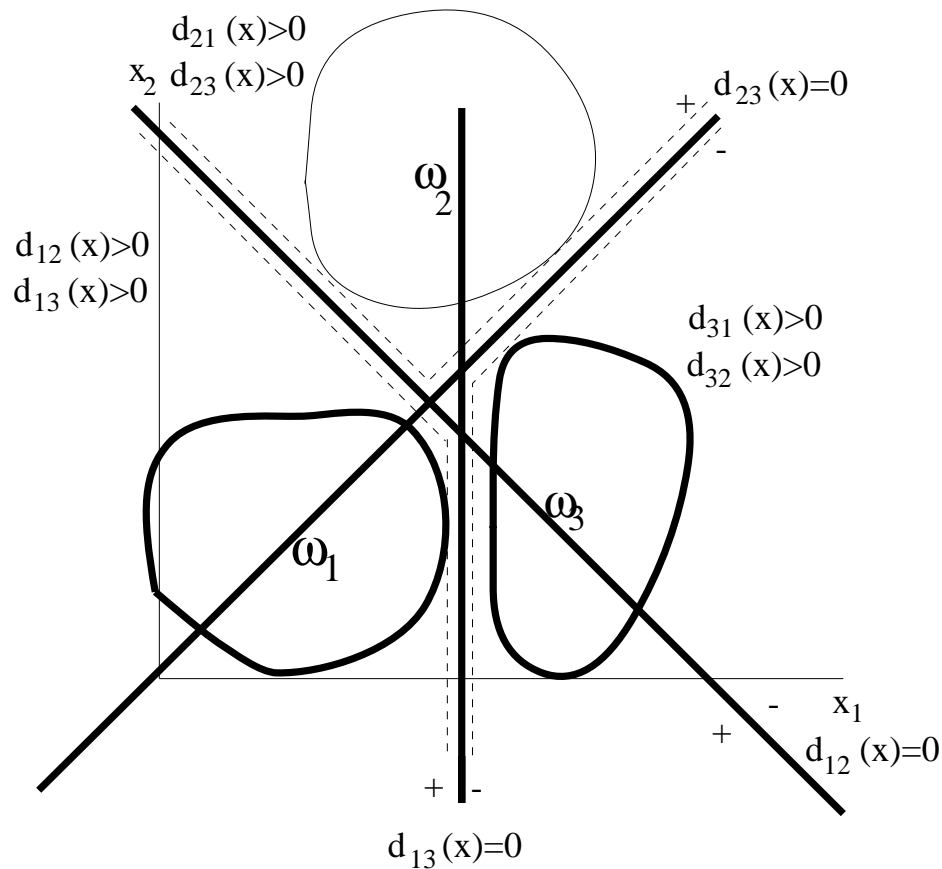
Case 2. Each pattern class separable from every other individual class by a distinct decision surface

$$d_{ij}(x) = w'_{ij}x > 0 \text{ if } x \in \omega_i$$

for all  $j \neq i$

where  $d_{ij}(x) = -d_{ji}(x)$  totally  $\frac{M(M-1)}{2}$  decision surfaces

- No class separable from others by a single decision surface



Case 3. There exist  $M$  decision functions,

$$d_k(x) = w'_k x, \quad k = 1, \dots, M$$

so that

$$\begin{aligned} d_i(x) &> d_j(x) \text{ if } x \in \omega_i \\ &\text{for all } j \neq i \end{aligned}$$

This is a special instance of Case 2 since we may define

$$\begin{aligned} d_{ij}(x) &= d_i(x) - d_j(x) \\ &= (w_i - w_j)'x \\ &= w'_{ij}x \end{aligned}$$

Case 2 is more general than Case 3!

## General Decision Functions

- The pattern classes are linearly separable, if classifiable by any of linear decision function cases discussed above.
- One useful way to generalize the linear decision function concept is to consider the quadratic decision function

$$d(x) = x'Ax + x'b + c$$

## Pattern Space and Weight Space

- Suppose we observe  $k = k_1 + k_2$ , pattern vectors from the pattern space  $E^n$  so that  $k_1$  pattern vectors among them belong to  $\omega_1$  and  $k_2$  pattern vectors among them belong to  $\omega_2$ :

$$\left. \begin{array}{l} x_1^{(1)}, \dots, x_{k_1}^{(1)} : \omega_1 \\ x_1^{(2)}, \dots, x_{k_2}^{(2)} : \omega_2 \end{array} \right\} x_j^{(i)} \in E^n$$

- Find  $w = (w_1, \dots, w_{n+1})' \in E^{n+1}$  :

$$\left\{ \begin{array}{l} (x_j^{(1)'}, 1)w > 0, \\ j \leq k_1, \end{array} \right. \quad \left\{ \begin{array}{l} (x_l^{(2)'}, 1)w < 0, \\ l \leq k_2, \end{array} \right.$$

or

$$\left\{ \begin{array}{l} (x_j^{(1)'}, 1)w > 0, \quad j \leq k_1 \\ (-x_l^{(1)'}, -1)w > 0, \quad l \leq k_2 \end{array} \right.$$

- The desired weights  $w$  are the solution to  $k$  linear inequalities:

$$x_1'w > 0, \dots, x_k'w > 0$$

Composes a convex polyhedral cone in  $E^{n+1}$   
where  $x_1, \dots, x_k, w \in E^{n+1}$ .

- Convex:  $w_1, w_2$  are solutions  $\Rightarrow$   
 $\alpha w_1 + (1 - \alpha)w_2$  is a solution for  $0 \leq \alpha \leq 1$ .

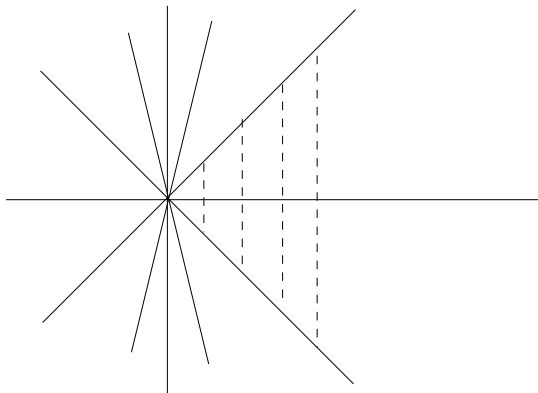
- cone:

$w$  is a solution  $\Rightarrow$

$\lambda w$  is a solution for  $\lambda > 0$ .

- polyhedral:

The solution to each individual linear inequality  $x'_j w > 0$  composes a half space in  $E^{n+1}$ . The intersection of those  $k$  half spaces in  $E^{n+1}$  forms a polyhedral shape.



## Geometric Properties

- For multiclass cases,

the boundary between  $\omega_i$  and all  $\omega_{j \neq i}$  in case 1 is given by

$$d_i(x) = \sum_{j=1}^n w_{ij} x_j + w_{i, n+1} = 0.$$

The boundary between  $\omega_i$  and  $\omega_j$  in case 2 is given by

$$d_{ij}(x) = \sum_{k=1}^n w_{ijk} x_k + w_{ij, n+1} = 0,$$

The boundary between  $\omega_i$  and  $\omega_j$  in case 3 is given by

$$\begin{aligned} d_{ij}(x) &= d_i(x) - d_j(x) \\ &= \sum_{k=1}^n (w_{ik} - w_{jk}) x_k + (w_{i, n+1} - w_{j, n+1}) \\ &= 0 \end{aligned}$$

- Geometric interpretation of

$$\begin{aligned} d(x) &= w_1x_1 + \dots + w_nx_n + w_{n+1} \\ &= w_0'x + w_{n+1} = 0 \end{aligned}$$

where

$$\begin{aligned} w_0 &= (w_1, \dots, w_n)', \\ x &= (x_1, \dots, x_n)'. \end{aligned}$$

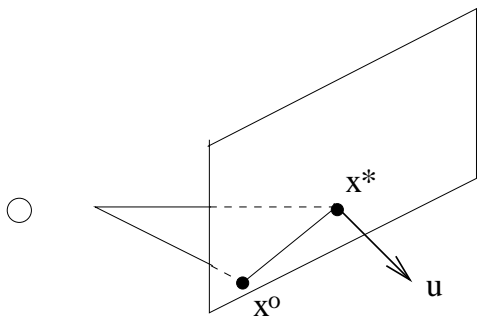
Hyperplane:  $w_0'x + w_{n+1} = 0 \Rightarrow$

$$\left(\frac{w_0}{\|w_0\|}\right)'x = -\frac{w_{n+1}}{\|w_0\|}$$

where  $\|w_0\| = \sqrt{w_1^2 + \dots + w_n^2}$ .

Let  $u$  denote the unit vector  $\frac{w_0}{\|w_0\|}$ . Then  $u$  is the normal to the hyperplane.

Proof: If  $x^*$ ,  $x^o$  belong to the hyperplane,  $u$  is orthogonal to  $x^* - x^o$ .



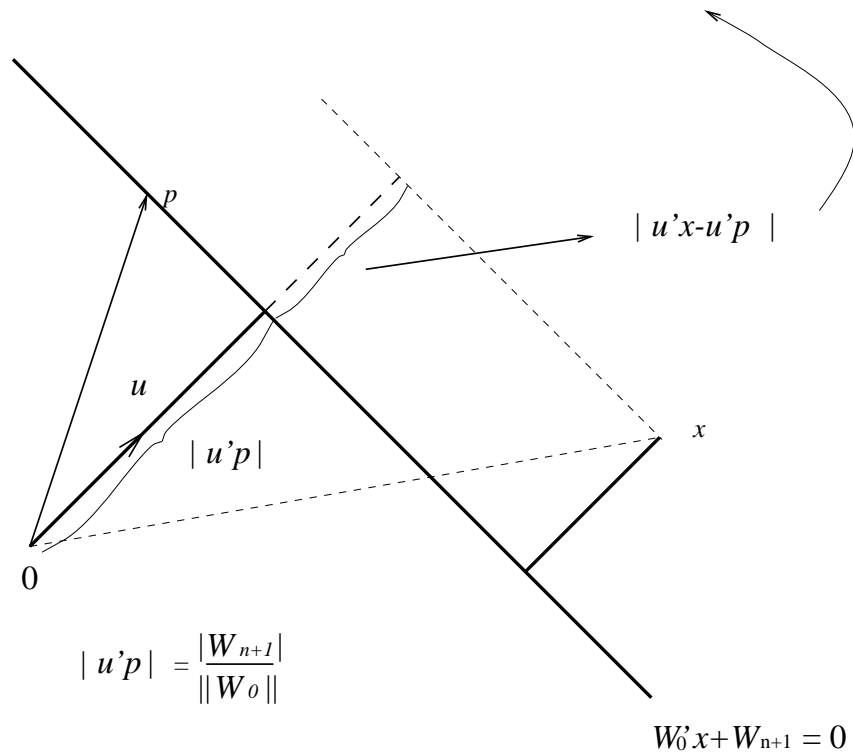
$$\left. \begin{aligned} u'x^* &= -\frac{w_{n+1}}{\|w_0\|} \\ u'x^o &= -\frac{w_{n+1}}{\|w_0\|} \end{aligned} \right\} u'(x^* - x^o) = 0$$

The distance from the origin to the hyperplane is given by

$$D_u = \frac{|w_{n+1}|}{\|w_0\|}.$$

The distance from an arbitrary point  $x$  to a hyperplane is given by

$$D_x = \left| \frac{w'_0 x + w_{n+1}}{\|w_0\|} \right|$$



## Implementation of Decision Functions

- In most of applications, the entire pattern recognition system is implemented in a computer.
- A multiclass linear pattern classifier (Case 3).

