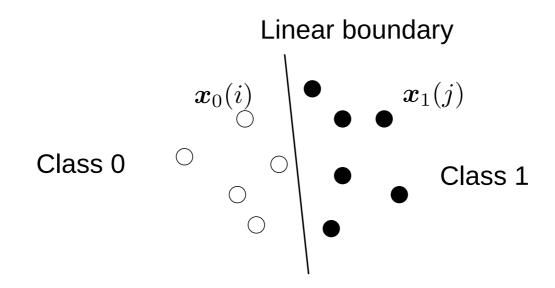
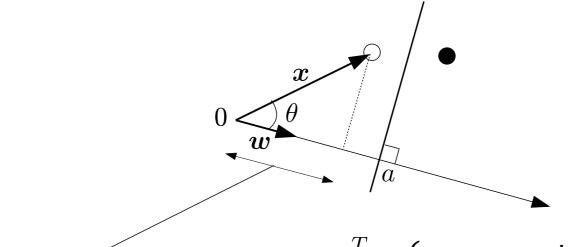
- Discriminant function analysis(判別分析) classifies data into classes
  - Suppose that we have two classes, class 0 and class 1.
    - For example, class 0 may correspond to a normal class while class 1 may correspond to an abnormal (failure, disease, etc) class
  - The problem is to find the best boundary between the two classes
  - Data
    - Data vectors  $x_0(1), \ldots, x_0(n_0)$  belong to class 0
    - Data vectors  $x_1(1), \ldots, x_1(n_1)$  belong to class 1

- Linear discriminant function(線形判別関数)
  - The linear function that determines the boundary between the classes. The boundary is linear (a line, a plane or a hyper-plane)



Linear discriminant function

Linear boundary



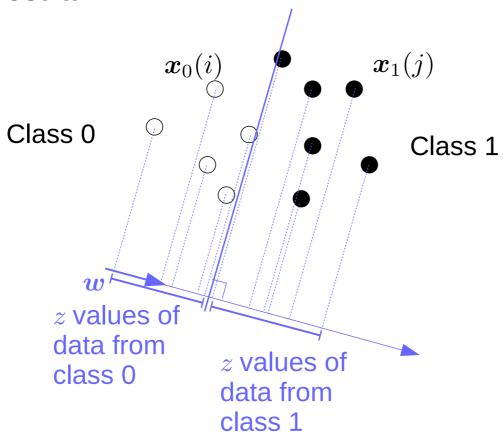
The length = 
$$\|\boldsymbol{x}\|\cos\theta = \frac{\boldsymbol{x}^T\boldsymbol{w}}{\|\boldsymbol{w}\|} \begin{cases} < a & \dots \, \boldsymbol{x} \text{ belongs to class 0} \\ > a & \dots \, \boldsymbol{x} \text{ belongs to class 1} \end{cases}$$

Here  $b = a\|\boldsymbol{w}\|$  .

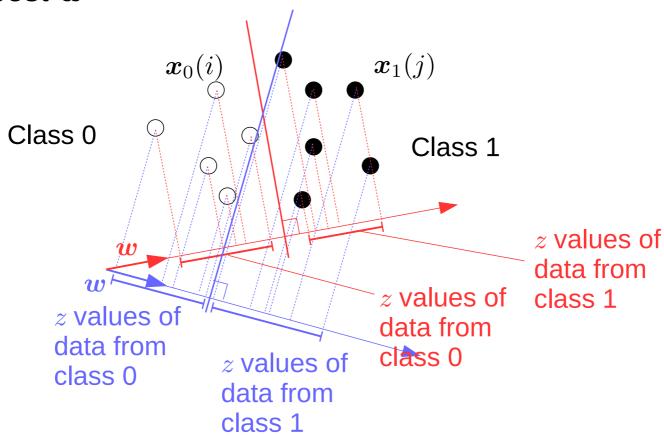
Note that the inequality signs can be the other way round depending on the direction of  $\boldsymbol{w}$  relative to the positions of the classes

We want to find the best w.

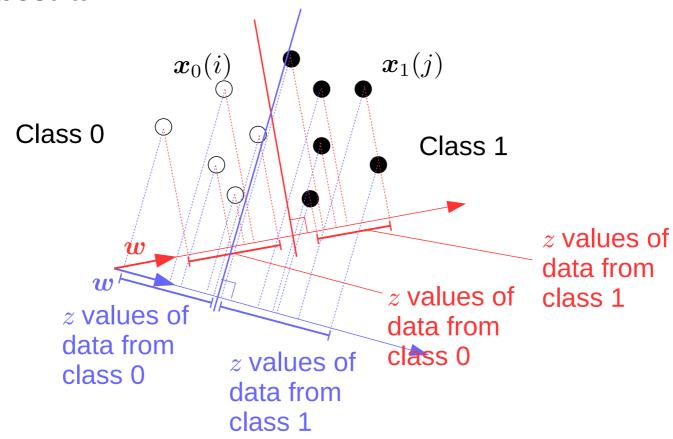
• The best w



• The best w



• The best w



Good  $w \Longrightarrow$ 

The values of z from different classes are well separated, while the z values within the same class are close to each other.

- Evaluation of closeness (or dispersity) of z values
  - Averages of x
    - $\bar{x}_0 = \frac{1}{n_0} \sum_{i=1}^{n_0} x_0(i)$  : the average of x from class 0.
    - $\bar{x}_1=rac{1}{n_1}\sum_{j=1}^{n_1} x_1(j)$  : the average of  $m{x}$  from class 1.

- Averages of z
  - Let us define  $z_0(i) = \boldsymbol{w}^T \boldsymbol{x}_0(i)$  and  $z_1(j) = \boldsymbol{w}^T \boldsymbol{x}_1(j)$ .
  - The average of z from class 0

$$ar{z}_0 = rac{1}{n_0} \sum_{i=1}^{n_0} z_0(i) = rac{1}{n_0} \sum_{i=1}^{n_0} oldsymbol{w}^T oldsymbol{x}_0(i) = oldsymbol{w}^T rac{1}{n_0} \sum_{i=1}^{n_0} oldsymbol{x}_0(i) = oldsymbol{w}^T ar{oldsymbol{x}}_0.$$

• The average of z from class 1

$$ar{z}_1 = rac{1}{n_1} \sum_{j=1}^{n_1} z_1(j) = m{w}^T ar{m{x}}_1.$$

Average of all z from either class

$$\bar{z} = \frac{1}{n_0 + n_1} \left( \sum_{i=1}^{n_0} z_0(i) + \sum_{j=1}^{n_1} z_1(j) \right) = \frac{n_o \bar{z}_0 + n_1 \bar{z}_1}{n_0 + n_1}.$$

 Sum of squares of deviations (sum of squares of differences from the average)

$$V = \sum_{i=1}^{n_0} (z_0(i) - \bar{z})^2 + \sum_{j=1}^{n_1} (z_1(j) - \bar{z})^2$$

$$= \sum_{i=1}^{n_0} (z_0(i) - \bar{z}_0 + \bar{z}_0 - \bar{z})^2$$

$$= \sum_{i=1}^{n_0} \left[ (z_0(i) - \bar{z}_0)^2 + 2(z_0(i) - \bar{z}_0)(\bar{z}_0 - \bar{z}) + (\bar{z}_0 - \bar{z})^2 \right]$$

$$= \sum_{i=1}^{n_0} (z_0(i) - \bar{z}_0)^2 + 2(\bar{z}_0 - \bar{z}) \sum_{i=1}^{n_0} (z_0(i) - \bar{z}_0) + n_0(\bar{z}_0 - \bar{z})^2$$

$$= \sum_{i=1}^{n_0} (z_0(i) - \bar{z}_0)^2 + n_0(\bar{z}_0 - \bar{z})^2$$

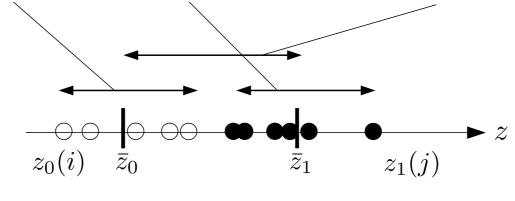
$$V = \sum_{i=1}^{n_0} (z_0(i) - \bar{z}_0)^2 + n_0(\bar{z}_0 - \bar{z})^2 + \sum_{j=1}^{n_1} (z_1(j) - \bar{z}_1)^2 + n_1(\bar{z}_1 - \bar{z})^2$$

$$= \sum_{i=1}^{n_0} (z_0(i) - \bar{z}_0)^2 + \sum_{j=1}^{n_1} (z_1(j) - \bar{z}_1)^2 + n_0(\bar{z}_0 - \bar{z})^2 + n_1(\bar{z}_1 - \bar{z})^2$$

Dispersion or variation 変動)within class 0

Dispersion or variation (ばらつき, (ばらつき, 変動)within class 1

Spread(広がり) of averages of class 0 and class 1 around the average of all the data



Class 0

Class 1

Intra-class dispersity

$$\begin{split} V_W &= \sum_{i=1}^{n_0} \left(z_0(i) - \bar{z}_0\right)^2 + \sum_{j=1}^{n_1} \left(z_1(j) - \bar{z}_1\right)^2 \\ &= \sum_{i=1}^{n_0} (\boldsymbol{w}^T \boldsymbol{x}_0(i) - \boldsymbol{w}^T \bar{\boldsymbol{x}}_0)^2 + \sum_{j=1}^{n_1} (\boldsymbol{w}^T \boldsymbol{x}_1(j) - \boldsymbol{w}^T \bar{\boldsymbol{x}}_1)^2 \\ &= \sum_{i=1}^{n_0} \boldsymbol{w}^T (\boldsymbol{x}_0(i) - \bar{\boldsymbol{x}}_0) (\boldsymbol{x}_0(i) - \bar{\boldsymbol{x}}_0)^T \boldsymbol{w} \\ &+ \sum_{j=1}^{n_1} \boldsymbol{w}^T (\boldsymbol{x}_1(j) - \bar{\boldsymbol{x}}_1) (\boldsymbol{x}_1(j) - \bar{\boldsymbol{x}}_1)^T \boldsymbol{w} \\ &= \boldsymbol{w}^T W \boldsymbol{w}, \end{split}$$

where

$$W = \sum_{i=1}^{n_0} (\boldsymbol{x}_0(i) - \bar{\boldsymbol{x}}_0)(\boldsymbol{x}_0(i) - \bar{\boldsymbol{x}}_0)^T + \sum_{j=1}^{n_1} (\boldsymbol{x}_1(j) - \bar{\boldsymbol{x}}_1)(\boldsymbol{x}_1(j) - \bar{\boldsymbol{x}}_1)^T$$

#### Inter-class dispersity

$$V_{B} = n_{0}(\bar{z}_{0} - \bar{z})^{2} + n_{1}(\bar{z}_{1} - \bar{z})^{2}$$

$$= n_{0} \left(\bar{z}_{0} - \frac{n_{0}\bar{z}_{0} + n_{1}\bar{z}_{1}}{n_{0} + n_{1}}\right)^{2} + n_{1} \left(\bar{z}_{1} - \frac{n_{0}\bar{z}_{0} + n_{1}\bar{z}_{1}}{n_{0} + n_{1}}\right)^{2}$$

$$= n_{0} \left(\frac{n_{1}\bar{z}_{0} - n_{1}\bar{z}_{1}}{n_{0} + n_{1}}\right)^{2} + n_{1} \left(\frac{n_{0}\bar{z}_{1} - n_{0}\bar{z}_{0}}{n_{0} + n_{1}}\right)^{2}$$

$$= \frac{n_{0}n_{1}^{2} + n_{1}n_{0}^{2}}{(n_{0} + n_{1})^{2}}(\bar{z}_{0} - \bar{z}_{1})^{2} = \frac{n_{0}n_{1}}{n_{0} + n_{1}}(\bar{z}_{0} - \bar{z}_{1})^{2}$$

$$= \frac{n_{0}n_{1}}{n_{0} + n_{1}}(\boldsymbol{w}^{T}\bar{\boldsymbol{x}}_{0} - \boldsymbol{w}^{T}\bar{\boldsymbol{x}}_{1})^{2}$$

$$= \frac{n_{0}n_{1}}{n_{0} + n_{1}}\boldsymbol{w}^{T}(\bar{\boldsymbol{x}}_{0} - \bar{\boldsymbol{x}}_{1})(\bar{\boldsymbol{x}}_{0} - \bar{\boldsymbol{x}}_{1})^{T}\boldsymbol{w}$$

$$= \boldsymbol{w}^{T}B\boldsymbol{w},$$

where

$$B = \frac{n_0 n_1}{n_0 + n_1} (\bar{x}_0 - \bar{x}_1) (\bar{x}_0 - \bar{x}_1)^T$$

#### • Good w

- Small  $V_W$ , i.e., z values from each class gather closely, and large  $V_B$ , i.e., z values from the two classes are well separated.
- The best  ${m w}$  is derived by maximizing  $V_B$  while keeping  $V_W$  constant, say 1, which is formulated as

maximize 
$$\mathbf{w}^T B \mathbf{w}$$
 subject to  $\mathbf{w}^T W \mathbf{w} - 1 = 0$ .

- By using a Lagrange multiplier (page 186), the condition for the best  $m{w}$  is derived as

$$\frac{\partial}{\partial \boldsymbol{w}}(\boldsymbol{w}^T B \boldsymbol{w}) - v \cdot \frac{\partial}{\partial \boldsymbol{w}}(\boldsymbol{w}^T W \boldsymbol{w} - 1) = \mathbf{0}.$$

$$\Big( ext{ Recall the condition } 
abla f(m{x}_0) + \sum_{i=1}^m v_i 
abla h_i(m{x}_0) = 0 ext{ derived on page 186.} \Big)$$

$$\frac{\partial}{\partial \boldsymbol{w}} (\boldsymbol{w}^T B \boldsymbol{w}) - v \cdot \frac{\partial}{\partial \boldsymbol{w}} (\boldsymbol{w}^T W \boldsymbol{w} - 1) = \mathbf{0}$$
$$B \boldsymbol{w} + B^T \boldsymbol{w} - v \cdot (W \boldsymbol{w} + W^T \boldsymbol{w}) = \mathbf{0}$$

Here

$$B^{T} = \left\{ \frac{n_0 n_1}{n_0 + n_1} (\bar{\boldsymbol{x}}_0 - \bar{\boldsymbol{x}}_1) (\bar{\boldsymbol{x}}_0 - \bar{\boldsymbol{x}}_1)^T \right\}^T = \frac{n_0 n_1}{n_0 + n_1} (\bar{\boldsymbol{x}}_0 - \bar{\boldsymbol{x}}_1) (\bar{\boldsymbol{x}}_0 - \bar{\boldsymbol{x}}_1)^T = B,$$

$$W^T = \left\{ \sum_{i=1}^{n_0} (m{x}_0(i) - ar{m{x}}_0) (m{x}_0(i) - ar{m{x}}_0)^T + \sum_{j=1}^{n_1} (m{x}_1(j) - ar{m{x}}_1) (m{x}_1(j) - ar{m{x}}_1)^T 
ight\}^T = W,$$

and therefore

$$2B\mathbf{w} - 2vW\mathbf{w} = \mathbf{0}$$
$$B\mathbf{w} = vW\mathbf{w}$$

Notice that if  $n_0$  and  $n_1$  are sufficiently large, the matrix W has its inverse matrix  $W^{-1}$ .

Substituting  $B=\frac{n_0n_1}{n_0+n_1}(\bar{\boldsymbol x}_0-\bar{\boldsymbol x}_1)(\bar{\boldsymbol x}_0-\bar{\boldsymbol x}_1)^T$  into  $B\boldsymbol w=vW\boldsymbol w$  , we derive

$$\frac{\frac{n_0n_1}{n_0+n_1}(\bar{\boldsymbol{x}}_0-\bar{\boldsymbol{x}}_1)(\bar{\boldsymbol{x}}_0-\bar{\boldsymbol{x}}_1)^T\boldsymbol{w}=\underline{v}W\boldsymbol{w}.}{\text{A scalar}} = \underline{v}W\boldsymbol{w}.$$

Therefore the vector  $\bar{x}_0 - \bar{x}_1$  and the vector Ww have the same direction.

In other words, the vector w and the vector  $W^{-1}(\bar{x}_0 - \bar{x}_1)$  have the same direction.

Since only the direction of  $oldsymbol{w}$  matters (its length does not matter), we set

$$w = W^{-1}(\bar{x}_0 - \bar{x}_1).$$

Then we define

$$z = w^T x = (\bar{x}_0 - \bar{x}_1)^T W^{-1} x.$$

- The value of *b* 
  - The class is determined depending on whether  $z = \boldsymbol{w}^T \boldsymbol{x} > b$  or not.

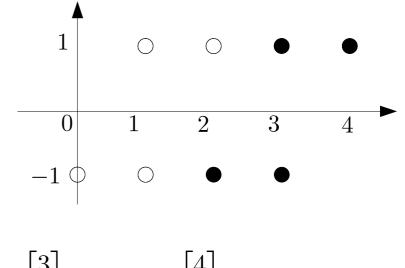
The value of b is set to the value corresponding to the midpoint between  $\bar{x}_0$  and  $\bar{x}_1$ .

$$b = \mathbf{w}^{T} \frac{\bar{\mathbf{x}}_{0} + \bar{\mathbf{x}}_{1}}{2} = \{W^{-1}(\bar{\mathbf{x}}_{0} - \bar{\mathbf{x}}_{1})\}^{T} \frac{\bar{\mathbf{x}}_{0} + \bar{\mathbf{x}}_{1}}{2}$$
$$= \frac{1}{2}(\bar{\mathbf{x}}_{0} - \bar{\mathbf{x}}_{1})^{T} W^{-1}(\bar{\mathbf{x}}_{0} + \bar{\mathbf{x}}_{1})$$

### Example

- Data

$$m{x}_0(1) = egin{bmatrix} 0 \ -1 \end{bmatrix}, m{x}_0(2) = egin{bmatrix} 1 \ -1 \end{bmatrix}, \ m{x}_0(3) = egin{bmatrix} 1 \ 1 \end{bmatrix}, m{x}_0(4) = egin{bmatrix} 2 \ 1 \end{bmatrix}$$



$$m{x}_1(1) = egin{bmatrix} 2 \ -1 \end{bmatrix}, m{x}_1(2) = egin{bmatrix} 3 \ -1 \end{bmatrix}, m{x}_1(3) = egin{bmatrix} 3 \ 1 \end{bmatrix}, m{x}_1(4) = egin{bmatrix} 4 \ 1 \end{bmatrix}$$

- Solution

$$ar{m{x}}_0 = egin{bmatrix} 1 \ 0 \end{bmatrix}, ar{m{x}}_1 = egin{bmatrix} 3 \ 0 \end{bmatrix}$$

$$\mathbf{b} = \frac{1}{2} (\bar{\mathbf{x}}_0 - \bar{\mathbf{x}}_1)^T W^{-1} (\bar{\mathbf{x}}_0 + \bar{\mathbf{x}}_1) = \frac{1}{2} \begin{bmatrix} -2 & 0 \end{bmatrix} \begin{bmatrix} 0.5 & -0.25 \\ -0.25 & 0.25 \end{bmatrix} \begin{bmatrix} 4 \\ 0 \end{bmatrix}$$
$$= \begin{bmatrix} -1 & 0 \end{bmatrix} \begin{bmatrix} 2 \\ -1 \end{bmatrix} = -2$$

