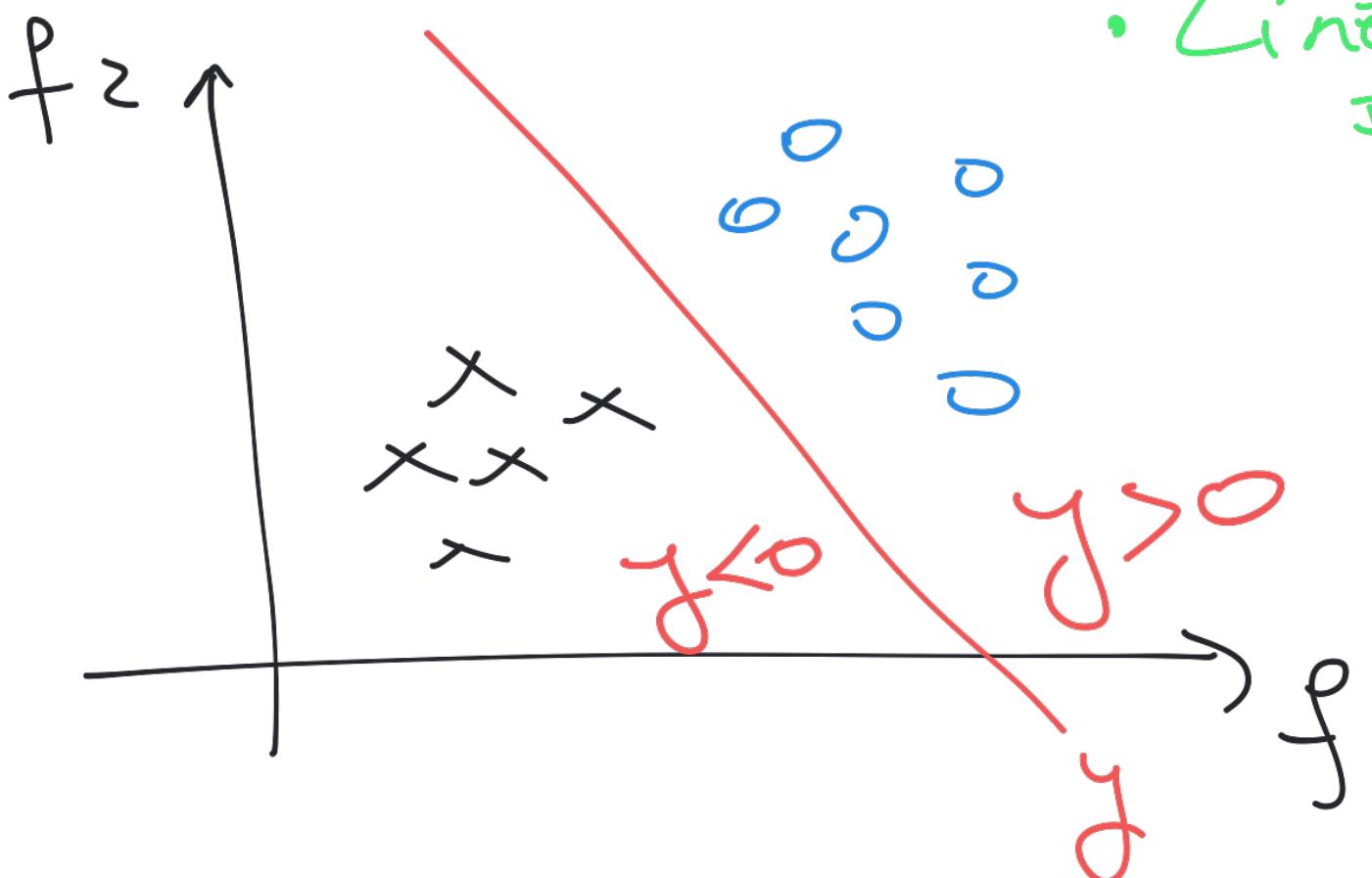


Discriminative Classifiers

↳ partition the feature into regions for each class.



- Linear Discriminant Functions

↳ finds a linear boundary

$$y = w^T x + b$$

One approach to find a linear
discriminant function / boundary
is by using

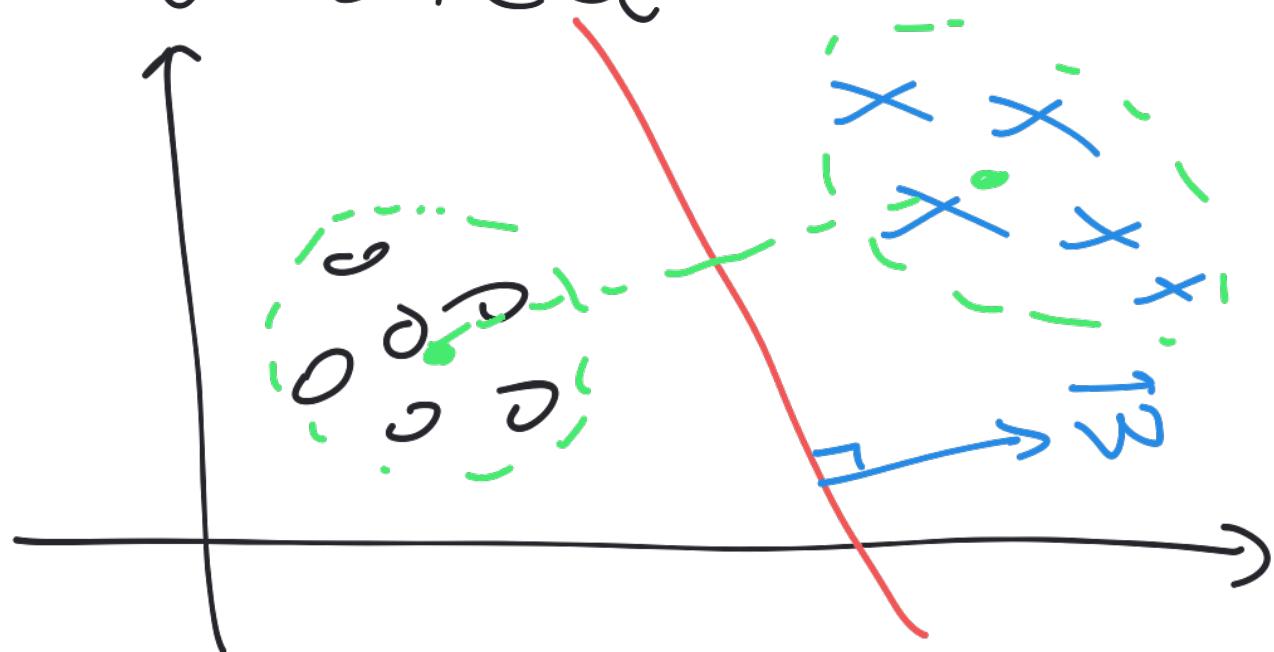
Fisher's Linear Discriminant

↳ Goal : maximize distance of
means
AND
minimize within-class
variance.

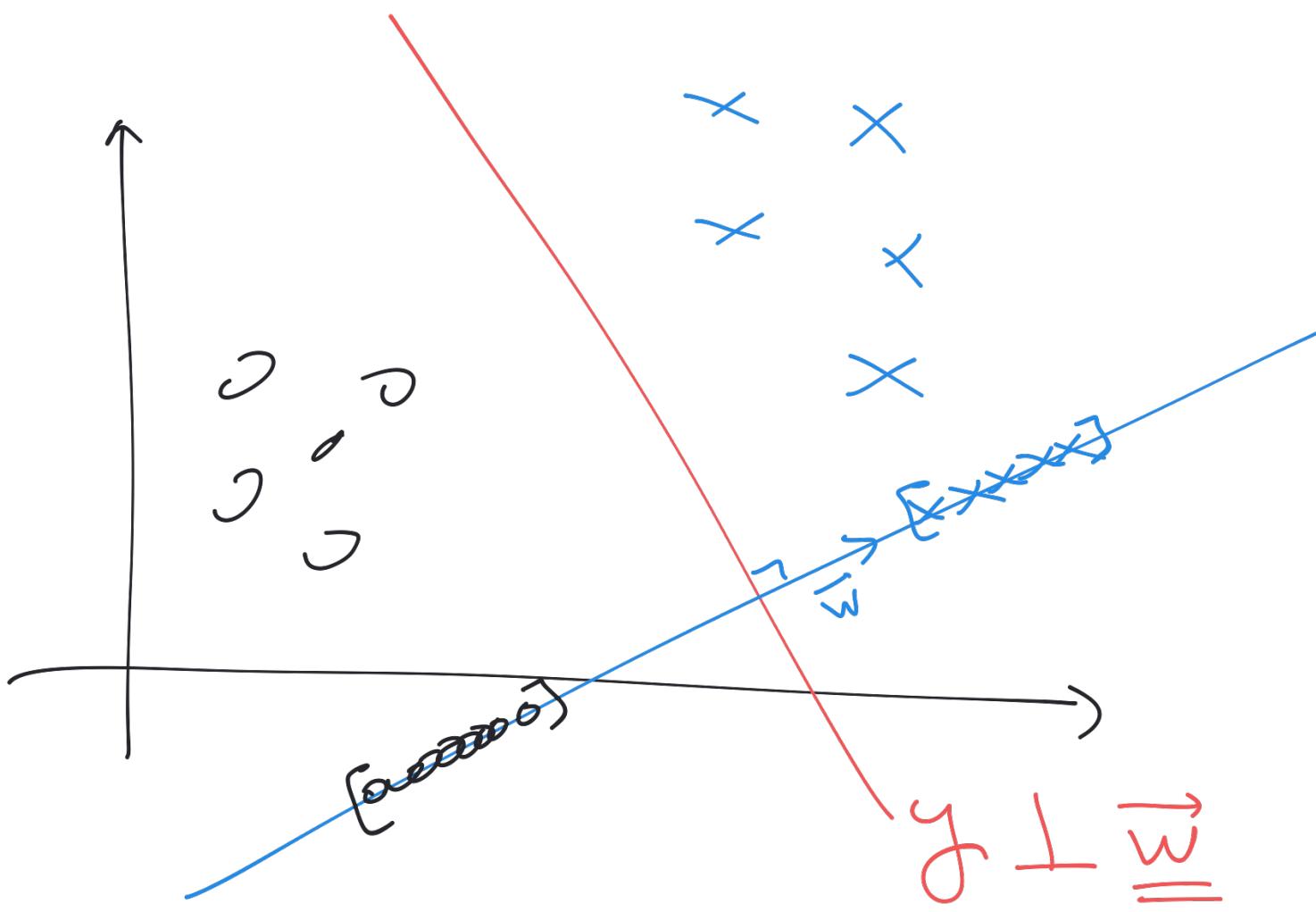
$$J(w) = \frac{w^T S_B w}{w^T S_w w}$$

$S_B = (\vec{m}_2 - \vec{m}_1)(\vec{m}_2 - \vec{m}_1)^T$ ≡ BETWEEN
class
scatter
matrix

$$S_w = \sum_{i=1}^n \left[\sum_{x_n \in C_i} (\vec{x}_n - \vec{m}_i)(\vec{x}_n - \vec{m}_i)^T \right]$$



\vec{w} : direction of
projection onto
which class
remain separable



$$y = w^T x + b$$

boundary OR
 discriminant function
 ||
 $y \perp \underline{w}$

In vector/matrix notation:

$$y = X \cdot w \quad , \text{ where } X = \begin{bmatrix} 1 & x_{1,1} & x_{1,2}, \dots, x_{1,D} \\ 1 & x_{2,1} & x_{2,2}, \dots, x_{2,D} \\ \vdots & & \\ 1 & & \end{bmatrix}_{N \times (D+1)}$$

$$\text{and } w = \begin{bmatrix} b \\ w_1 \\ w_2 \\ \vdots \\ w_D \end{bmatrix}$$

$$J(\omega) = \frac{\omega^T S_B \omega}{\omega^T S_w \omega}$$

Optimize J :

$$\arg \max_{\omega} J(\omega)$$

$$\frac{\partial J(\omega)}{\partial \omega} = 0 \Leftrightarrow \frac{2(\omega^T S_w \omega) S_B \omega - 2(\omega^T S_B \omega) S_w \cdot \omega}{(\omega^T S_w \omega)^2} = 0$$

$$\Leftrightarrow \frac{S_B \cdot \omega}{\omega^T S_w \cdot \omega} - \frac{(\omega^T S_B \cdot \omega) S_w \cdot \omega}{(\omega^T S_w \omega)^2} = 0$$

$$\Leftrightarrow S_B \cdot \omega = \boxed{\frac{\omega^T S_B \omega}{\omega^T S_w \cdot \omega}} \cdot S_w \cdot \omega \Leftrightarrow \xrightarrow{\text{next page}}$$

↑ multiply numerator by $\omega^T S_w \cdot \omega$

$$S_B w = \lambda \cdot S_w w, \quad \lambda \text{ is constant}$$

$$\lambda = \frac{w^T S_B w}{w^T S_w w}$$

$\Leftrightarrow S_w^{-1} S_B \underline{\underline{w}} = \lambda \cdot \underline{\underline{w}}$

if S_w^{-1}
Exists

matrix
Linear Transformation

constant

This is the generalized
Eigenvalue problem.

$\Rightarrow w$ is eigenvector of $S_w^{-1} S_B$.

$$S_w^{-1} = \left(\sum_1 + \sum_2 \right)^{-1}$$

$$S_B = (\vec{m}_2 - \vec{m}_1)(\vec{m}_2 - \vec{m}_1)^T$$

Plugging in the values:

$$S_w^{-1} (\vec{m}_2 - \vec{m}_1) \underbrace{(\vec{m}_2 - \vec{m}_1)^T \vec{w}}_{\alpha} = \lambda \cdot \vec{e}$$

α is constant

$$\Leftrightarrow S_w^{-1} (\vec{m}_2 - \vec{m}_1) = \frac{1}{\alpha} \cdot \vec{w}$$

Because we only care about direction of \vec{w} , not its magnitude,

$$\underline{\underline{\vec{w}}} = \underline{\underline{s_w^{-1}}} (\vec{m}_2 - \vec{m}_1)$$

but we need to make it a unit vector, i.e.

$$\vec{w}^* = \frac{\vec{w}}{\|\vec{w}\|}$$

gives us
the direction
of projection,

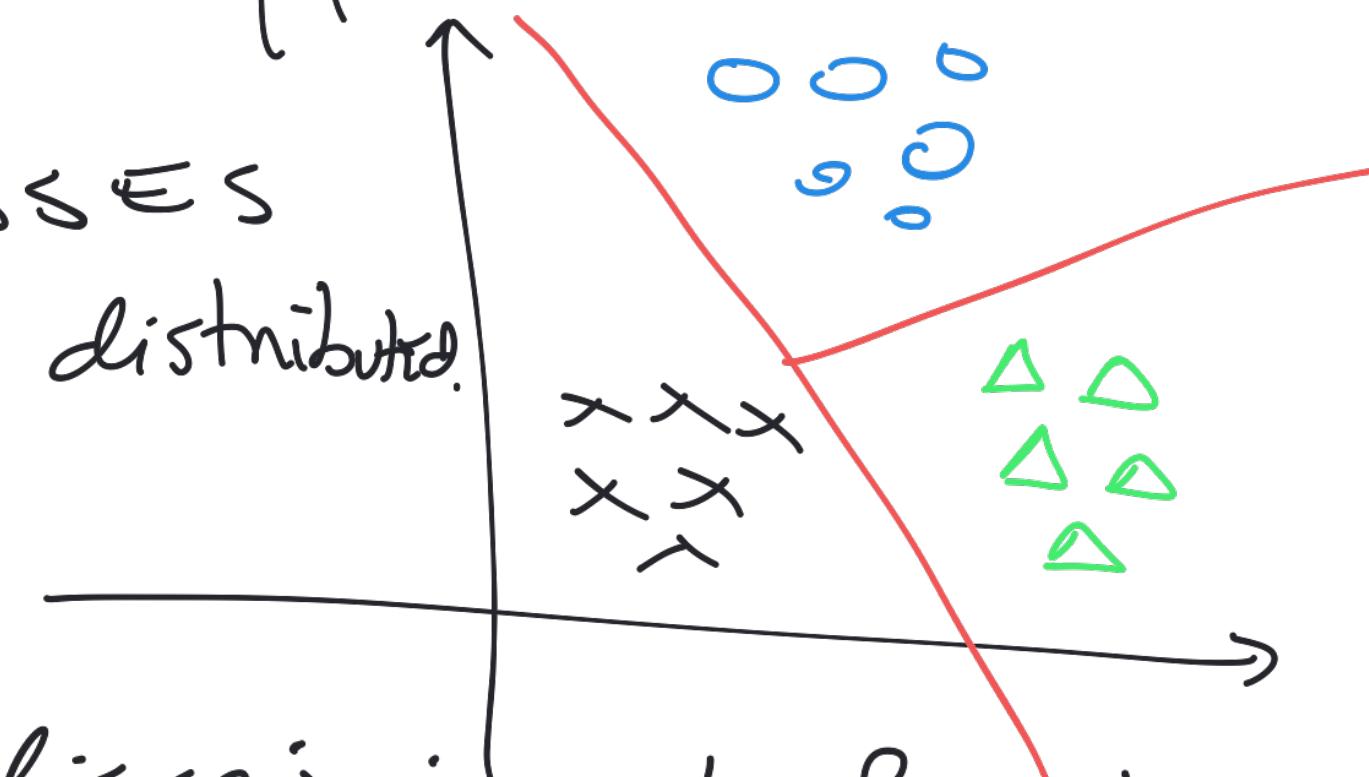
which is the 1 direction
of the discriminant
function γ .

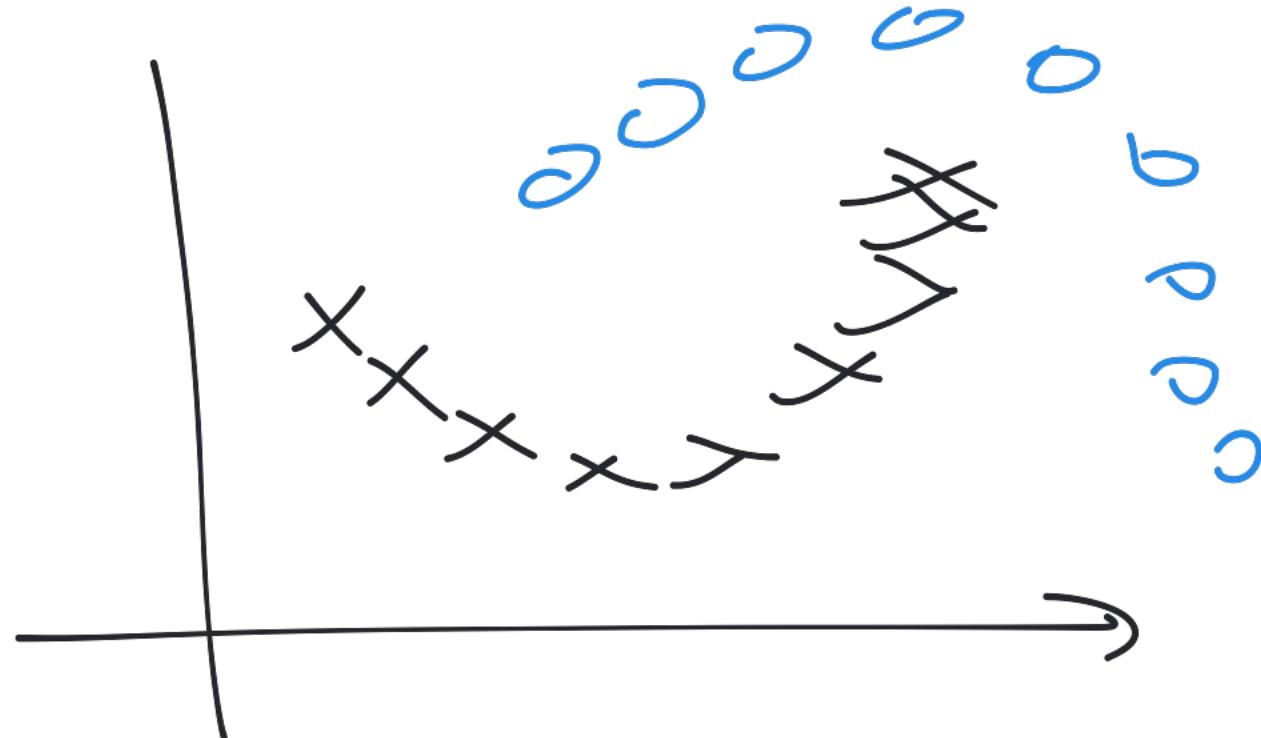
Limitations of Fisher's Discriminant Function:

① For a multi-class problem, we will find each boundary as a one-vs-all approach

② Assumes classes are Gaussian distributed.

③ It can only find linear discriminant functions.





→ when data has
a non-linear
relationship,
.

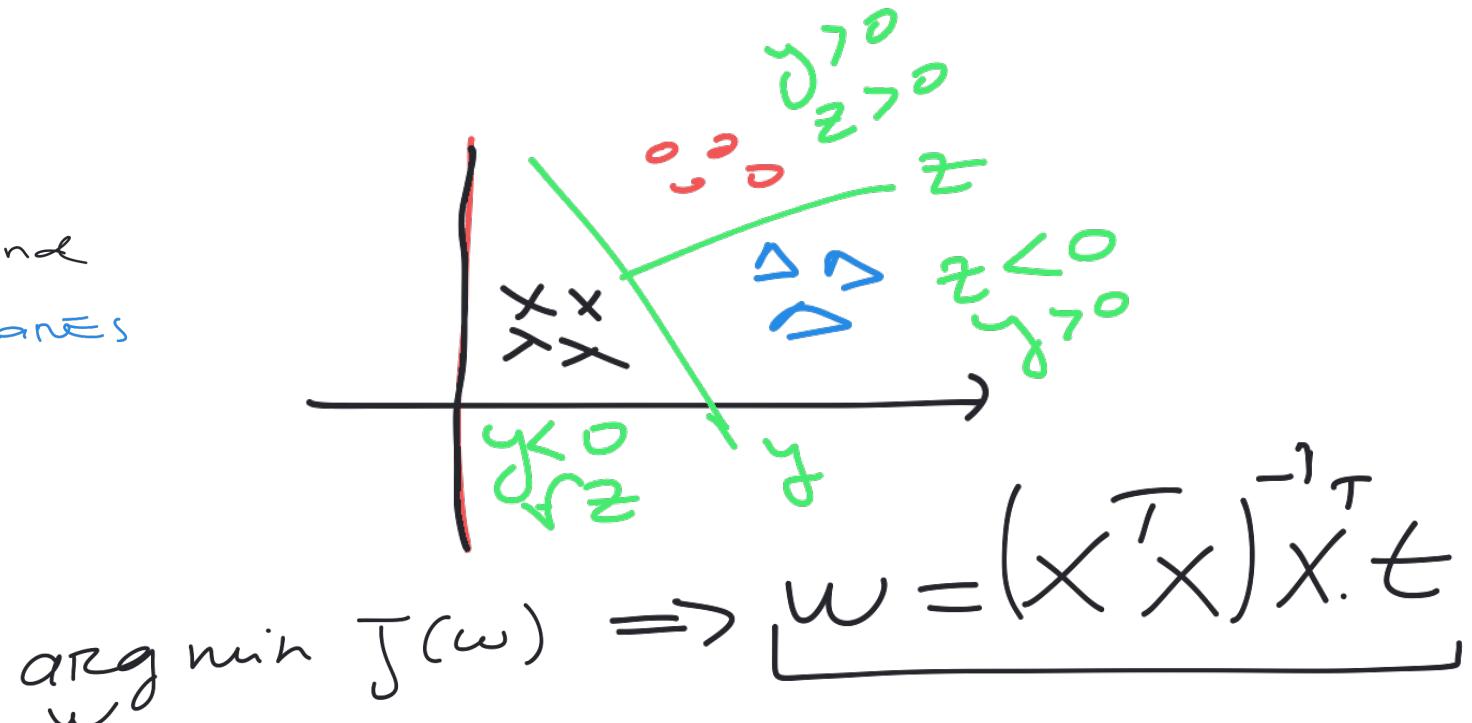
Fisher's cannot
linearly separate the two
classes.

↳ A popular variant Fisher's are
Multi-Layer Perceptron (MLP)

Another approach is to find \vec{w} as the Least Squares solution.

$$\{x, t\}, y = \vec{w}^T x + b$$

$$J(\vec{w}) = \sum_{i=1}^n (t_i - y_i)^2$$



→ If we consider y as the linear regression, then y is a continuous-valued number \neq class label

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Bishop

→ $y > 0 \Rightarrow$ assign to class 1
 $y < 0 \Rightarrow$ assign to class 2.

→ From Bayesian interpretation, we saw that the errors of Least Squares solution are Gaussian-distribution.
It does not hold when we use regression as a classification problem.

∴ **Avoid using regression for a classification problem.**

The Perceptron Algorithm

↳ search parameter space
by gradient-descent
approach

