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# Lecture 5

$$\text{eign}(A) \rightarrow [\vec{v}_1 : \vec{v}_2] \quad A\vec{v}_1 = \lambda_1 \vec{v}_1, \quad A\vec{v}_2 = \lambda_2 \vec{v}_2$$

$$\rightarrow \{\lambda_1, \lambda_2\}$$

$$A[\vec{v}_1 : \vec{v}_2] = [\vec{v}_1 : \vec{v}_2] \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \quad AV = VD \rightarrow A = VDV^{-1}$$

$$Y = \{0, 1\}$$

$x_1, \dots, x_p$  features

need  $\hat{y}^* = g(\vec{x}^*)$

$$D = \left\{ \begin{bmatrix} \leftarrow x_1 \rightarrow \\ \leftarrow x_2 \rightarrow \\ \vdots \\ \leftarrow x_n \rightarrow \end{bmatrix}, \begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} \right\}$$

$$g = A(\mathcal{H}, D)$$

$$\mathcal{H} = \{ \vec{w} \cdot \vec{x} > 0, \vec{w} \in \mathbb{R}^{p+1} \}$$

$$SAE(g) = \sum_{i=1}^n \mathbb{1}_{\hat{y}_i \neq y_i}$$

objective function, cost function, fitness function  
(# of errors in  $D$ )

## Perceptron Learning Algorithm

① Initialize  $\vec{w} = \vec{0} = \vec{w}^{t=0}$  or random

② Calculate  $\hat{y}_i = \mathbb{1}_{\vec{w}^{t=0} \cdot \vec{x}_i}$

③ Update all weights  $j=1 \dots p+1$

$$w_1^{t+1} = w_1^{t=0} + (y_i - \hat{y}_i) x_{i1}$$

$$w_2^{t+1} = w_2^{t=0} + (y_i - \hat{y}_i) x_{i2}$$

$\vdots$

$$w_{p+1}^{t+1} = w_{p+1}^{t=0} + (y_i - \hat{y}_i) x_{ip+1}$$

④ Repeat for  $i=1 \dots n$

⑤ Repeat steps 2-4 until a threshold error is reached or max. # of iterations.

If  $D$  is "linearly separable" i.e.  $\exists \vec{w}$  s.t.  $\mathbb{1}_{\vec{w} \cdot \vec{x} > 0}$  <sup>yields no errors in</sup>  ~~$D$~~   $D$ , then it has no errors

(But in practice its rare because few things are separable)

