

## Eigen Vectors.

$$A x_i = \lambda_i x_i$$

$$\Rightarrow A \underbrace{[x_1 \dots x_n]}_P = [\lambda_1 x_1 \dots \lambda_n x_n] = \underbrace{[x_1 \dots x_n]}_P \begin{bmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{bmatrix}$$

$$\Rightarrow A = P \underbrace{\Sigma}_{\text{diagonal}} P^{-1}$$

## A Symmetric

$$A = P \Sigma P^{-1}$$

$$A^T = P^{-T} \Sigma P^T \Rightarrow P = P^{-T}$$

$$P^{-T} = (P^{-1})^T = (P^T)^{-1}$$

$$\Leftrightarrow P^T P = P P^T = I$$

↑  
orthogonal matrix

$$\Downarrow$$

$$A = P \Sigma P^T \text{ if } A \text{ symmetric } P \text{ orthogonal.}$$

## SVD

$$A = Q \Sigma P^T \quad \begin{array}{l} Q, P \text{ orthog.} \\ \Sigma \text{ diag} \end{array}$$

eigen of  $AA^T$       eigen of  $A^T A$

-  $A^T A$  is symmetric

$$A^T A = (Q \Sigma P^T)^T Q \Sigma P = P^T \underbrace{\Sigma^T}_{I} Q^T Q \Sigma P$$

$$= P^T \underbrace{\Sigma \Sigma}_{\text{diagonal}} P$$

-  $A A^T$  is symmetric.  $A A^T = Q \Sigma \Sigma Q.$

## Orthogonal Matrix

$$P^T P = I$$

write down  $P$  using column representation.

$$P = [v_1 \dots v_n]$$

$$P^T = \begin{bmatrix} v_1^T \\ \vdots \\ v_n^T \end{bmatrix}$$

then  $P^T P =$

$$\begin{bmatrix} v_1^T v_1 & v_1^T v_2 & \dots & v_1^T v_n \\ v_2^T v_1 & v_2^T v_2 & \dots & v_2^T v_n \\ \vdots & \vdots & \ddots & \vdots \\ v_n^T v_1 & v_n^T v_2 & \dots & v_n^T v_n \end{bmatrix}$$

$P^T P = I_n$  means.

$$v_i^T v_1 = v_3^T v_2 = \dots = v_n^T v_n = 1$$

$$v_i^T v_j = 0 \text{ (if } i \neq j)$$

means  $v_i$  have no correlation with  $v_j$

Projection using Orthogonal Basis.

$$A = [v_1 \dots v_n]$$

Projection:  $(A^T A)^{-1} A^T b = \begin{bmatrix} v_1^T b \\ \vdots \\ v_n^T b \end{bmatrix}$   
*I<sub>n</sub> by orthogonal*

So  $A(A^T A)^{-1} A^T b = \underbrace{[v_1 \dots v_n]}_{\text{coef}} \underbrace{\begin{bmatrix} v_1^T b \\ \vdots \\ v_n^T b \end{bmatrix}}_{\text{basis}} = (v_1^T b) v_1 + \dots + (v_n^T b) v_n$

PCA

$X \leftarrow \text{data}$

$$X = \begin{bmatrix} | & \dots & | \end{bmatrix} \begin{matrix} n \text{ #delete} \\ p \text{ # feature} \end{matrix}$$

SVD  $X = Q \Sigma P$   
*#feature*  $\rightarrow$   $Q$   $\rightarrow$   $\Sigma$   $\rightarrow$   $P$   
*λ # feature*  $\rightarrow$   $\Sigma$   $\rightarrow$   $P$   
*#data × #data*  $\rightarrow$   $P$

$Q, P$  are orthogonal.

$\Sigma$  is covariance matrix  $\Rightarrow$  eigen of  $X X^T$  are orthogonal basis  
*principle component*  $\Rightarrow$  eigen of  $X X^T$   
*are orthogonal basis*

- correlation between principle component are 0
- $\Sigma$ : feature importance  $\Rightarrow$  eigen value of  $X X^T$

$v_1 \dots v_k$  are first  $k$ -principle component.

$X_i \approx (X_i^T v_1) v_1 + (X_i^T v_2) v_2 + \dots + (X_i^T v_k) v_k$   
*i-th data*  $\rightarrow$   $X_i$

The best  $k$  features to reconstruct the data. !