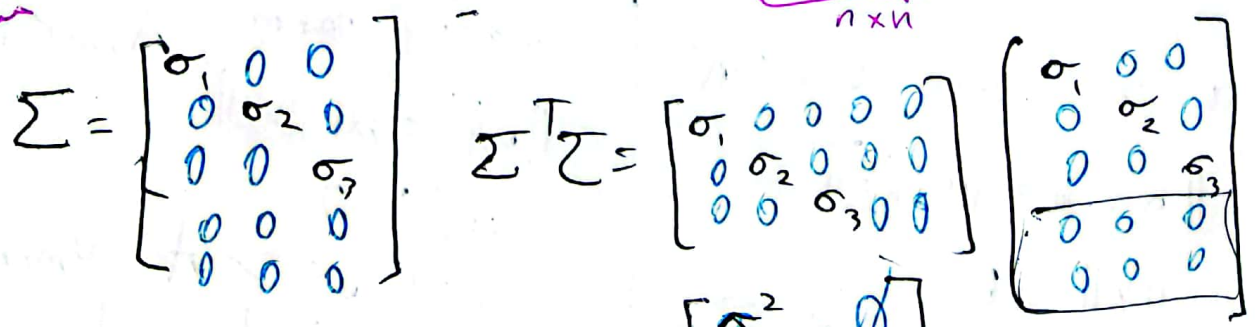


$A = U \Sigma V^T$ (m x n)

$A^T A = (U \Sigma V^T)^T (U \Sigma V^T) = V \Sigma^T \underbrace{U^T U}_I \Sigma V^T$
 $= V \Sigma^T \Sigma V^T$

$n \times n$ (مربع متماثل)



$A^T A = \underline{V} \underline{\Lambda} \underline{V}^T$ $\Lambda = \Sigma^T \Sigma$

$\Lambda = \begin{bmatrix} \sigma_1^2 & & \\ & \sigma_2^2 & \\ & & \sigma_3^2 \end{bmatrix}$

$$X = \begin{bmatrix} | & | & \dots & | \\ x_1 & x_2 & \dots & x_n \\ | & | & \dots & | \end{bmatrix} \quad \bar{X} = [x_{1-\mu}, x_{2-\mu}, \dots, x_{n-\mu}]$$

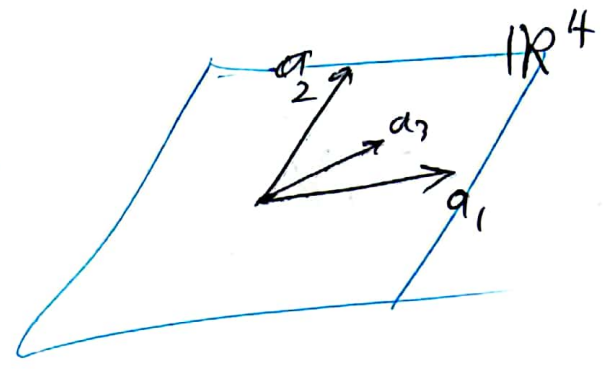
$$\text{Cov} = \frac{1}{n} \sum_{i=1}^n (x_i - \mu)(x_i - \mu)^T = \frac{1}{n} \bar{X} \bar{X}^T$$

$$A = \begin{bmatrix} \vec{a}_1 & \vec{a}_2 & \vec{a}_3 \end{bmatrix}$$

4x3

rank(A) = 2

$\vec{a}_1, \vec{a}_2, \vec{a}_3 \in \mathbb{R}^4$



$$\text{rank}(A + \text{noise}(4,3)) = 3$$

$$A = U \Sigma V^T = U \begin{bmatrix} 10.2 & 0 & 0 \\ 0 & 7.1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} V^T$$

$$A + \underset{\substack{\downarrow \\ \text{noise}}}{\Sigma} = U' \Sigma' V'^T = U' \begin{bmatrix} 10.2001 & 0 & 0 \\ 0 & 7.09998 & 0 \\ 0 & 0 & 0.00001 \\ 0 & 0 & 0 \end{bmatrix}$$

$$A = \sigma_1 \vec{u}_1 \vec{v}_1^T + \sigma_2 \vec{u}_2 \vec{v}_2^T + \sigma_3 \vec{u}_3 \vec{v}_3^T$$

vector norm $u, v \in \mathbb{R}^n$

$$\|\alpha \vec{v}\| = |\alpha| \|\vec{v}\|$$

$$\|\vec{v}\| \geq 0$$

$$\|\vec{v}\| = 0 \iff \vec{v} = \vec{0}$$

$$\|\vec{u} + \vec{v}\| \leq \|\vec{u}\| + \|\vec{v}\|$$

matrix norm $A, B \in \mathbb{R}^{m \times n}$

$$\|\alpha A\| = |\alpha| \|A\|$$

$$\|A\| \geq 0$$

$$\|A\| = 0 \iff A = 0_{m \times n}$$

$$\|A+B\| \leq \|A\| + \|B\|$$

$$\|AB\| \leq \|A\| \|B\|$$

submultiplicative norm

Operator Norm

$$Y = \begin{matrix} \downarrow \\ \mathbb{R}^m \end{matrix} \left[\begin{matrix} \downarrow \\ m \times n \end{matrix} A \right] \begin{matrix} \downarrow \\ \mathbb{R}^n \end{matrix} X$$

$$\max_X \left\{ \|Ax\|_{\text{norm1}} \mid \|x\|_{\text{norm2}} = 1 \right\}$$

$$\max_X \frac{\|Ax\|_{\text{norm1}}}{\|x\|_{\text{norm2}}}$$

spectral norm

$$\rho = \max_X \frac{\|Ax\|_2}{\|x\|_2} = \sigma_1 = \sigma_{\max}$$

A (symmetric) positive definite

$$A = V \Lambda V^T = V \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \ddots \\ & & & \lambda_n \end{bmatrix} V^T$$

$$\lambda_1, \lambda_2, \dots, \lambda_n > 0$$

$$A^{1/2} = V \begin{bmatrix} \lambda_1^{1/2} & & \\ & \lambda_2^{1/2} & \\ & & \ddots \\ & & & \lambda_n^{1/2} \end{bmatrix} V^T$$

$$A^{1/2} A^{1/2} = V \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \ddots \\ & & & \lambda_n \end{bmatrix} V^T V \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \ddots \\ & & & \lambda_n \end{bmatrix} V^T = V \begin{bmatrix} \lambda_1 & & \\ & \lambda_2 & \\ & & \ddots \\ & & & \lambda_n \end{bmatrix} V^T$$

$$\|A\|_F = \text{trace}((A^T A)^{1/2}) =$$

$$A = V \Sigma V^T \in \mathbb{R}^{m \times n}$$

$$A^T A = V \Sigma^T \Sigma V^T = V \begin{bmatrix} \sigma_1^2 & & \\ & \sigma_2^2 & \\ & & \ddots \\ & & & \sigma_n^2 \end{bmatrix} V^T$$

$$(A^T A)^{1/2} = V \begin{bmatrix} \sigma_1 & & \\ & \sigma_2 & \\ & & \ddots \\ & & & \sigma_n \end{bmatrix} V^T$$

$A \in \mathbb{R}^{n \times n}$ Symmetric

$x \in \mathbb{R}^n$ $x^T A x \in \mathbb{R}$

$$\begin{bmatrix} x^T \\ | \times n \end{bmatrix} \begin{bmatrix} A \\ | \times n \end{bmatrix} \begin{bmatrix} x \\ | \times 1 \end{bmatrix} \in \mathbb{R}$$

argmax $x \in \mathbb{R}^n$ $x^T A x$ s.t. $\|x\|_2 = 1$



max x $x^T A x$ s.t. $\|x\| = 1$
 $\|x\|^2 = 1$
 $x^T x = 1$

max x $\frac{x^T A x}{x^T x}$ A symmetric
min x $\frac{x^T A x}{x^T x}$

A symmetric $\Rightarrow A = V \Lambda V^{-1} = V \Lambda V^T$

$$A = \begin{bmatrix} v_1 & \dots & v_n \end{bmatrix} \begin{bmatrix} \lambda_1 & & 0 \\ & \ddots & \\ 0 & & \lambda_n \end{bmatrix} \begin{bmatrix} v_1^T \\ \vdots \\ v_n^T \end{bmatrix} = \text{matrix} \quad \|v_i\| = 1$$

$$A = \lambda_1 v_1 v_1^T + \lambda_2 v_2 v_2^T + \dots + \lambda_n v_n v_n^T$$

$$Ax = \lambda_1 v_1 (v_1^T x) + \lambda_2 v_2 (v_2^T x) + \dots + \lambda_n v_n (v_n^T x) \quad \|x\| = 1$$

~~$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n$~~

$$x^T A x = \lambda_1 \|x^T v_1\|^2 + \lambda_2 \|x^T v_2\|^2 + \dots + \lambda_n \|x^T v_n\|^2$$

max $\|Ax\|_2$

$$A \in \mathbb{R}^{m \times n}$$

$$\max_x \|A\vec{x}\|_2 \quad \text{s.t.} \quad \|\vec{x}\|_2 = 1$$

~~$$\max_x$$~~

$$\min_x \|A\vec{x}\|_2 \quad \text{subject to} \quad \|\vec{x}\|_2 = 1$$

$$\|A\vec{x}\|^2 = \langle A\vec{x}, A\vec{x} \rangle = (A\vec{x})^T (A\vec{x})$$

$$= \vec{x}^T A^T A \vec{x}$$

$$A = \begin{bmatrix} | & | & & | \\ u_1 & u_2 & \dots & u_m \\ | & | & & | \end{bmatrix} \begin{bmatrix} \sigma_1 & & & & & & \\ & \sigma_2 & & & & & \\ & & \ddots & & & & \\ & & & \sigma_n & & & \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} | & | & & | \\ v_1^T & v_2^T & \dots & v_n^T \\ | & | & & | \end{bmatrix}$$

$m \geq n$
 $m \times n$

$$\max_x \frac{\|A\vec{x}\|}{\|\vec{x}\|} = \sigma_1 = \sigma_{\max} / \text{argmax} = \vec{v}_1$$

$$\min_x \frac{\|A\vec{x}\|}{\|\vec{x}\|} = \sigma_n = \sigma_{\min} / \text{argmin} = \vec{v}_n^T$$

$$\begin{bmatrix} | & | & & | \\ A & & & \\ | & | & & | \end{bmatrix} \vec{x} = \vec{0}$$

$m \times n$ $m \geq n$

جواباً علينا $\text{rank}(A) = n-1$
 $\Rightarrow \dim(N(A)) = n - \text{rank}(A) = 1$

In practice $\text{rank}(A) = n$ but A is near-low-rank $\dim(N(A)) = 0$
 $N(A) = \{\vec{0}\}$

$$\underline{\underline{\|A\vec{x}\| > 0 \quad \vec{x} \neq \vec{0}}}$$

$$\frac{Ax \approx 0}{\|Ax\| \geq 0}$$

$$x = \operatorname{argmin}_x \|Ax\| \quad \text{s.t. } \|x\|=1$$

~~$$U, \Sigma, V^T$$~~

$$A = U \Sigma V^T$$

$$= U \Sigma \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{bmatrix}$$

$$x^* = \operatorname{argmin} \|Ax\| \quad \text{s.t. } \|x\|=1 = \underline{\underline{v_n^T}}$$