

Linear Algebra 2020.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{|A|} \cdot \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

Vector Space: ① add
② Multiply C, (C ∈ ℝ)

Column space C(A)	r
Null Space N(A)	n-r
C(A ^T)	r
N(A ^T)	m-r

Linear Transformations

$$T(C_1x_1 + C_2x_2) = C_1T(x_1) + C_2T(x_2)$$

$$C(A^T) \perp N(A)$$

Projection of b on a

$$\hat{b} = \frac{a \cdot a^T}{\|a\|^2} \cdot b = P \cdot b$$

(projection Matrix) $P = P^2$

$$\min \|Ax - b\|^2$$

$$x^* = (A^T A)^{-1} A^T b$$

GRAM-SCHMIDT

$$q_1 = \frac{a}{\|a\|}$$

$$q_2 = \frac{b - (q_1^T b) q_1}{\|b - (q_1^T b) q_1\|}$$

$$q_3 = \frac{c - (q_1^T c) q_1 - (q_2^T c) q_2}{\|c - (q_1^T c) q_1 - (q_2^T c) q_2\|}$$

⋮

$$q_{k+1} = \frac{a_{k+1} - (q_1^T a_{k+1}) q_1 - \dots - (q_k^T a_{k+1}) q_k}{\|a_{k+1} - \sum_{i=1}^k (q_i^T a_{k+1}) q_i\|}$$

$$A = Q \cdot R \quad (Q^{-1} = Q^T, R \text{ is upper diagonal})$$

$$A \cdot \begin{bmatrix} b_1 & b_2 & b_3 & \dots \end{bmatrix} = \begin{bmatrix} Ab_1 & Ab_2 & Ab_3 & \dots \end{bmatrix}$$

$$\begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ \vdots \end{bmatrix} \cdot B = \begin{bmatrix} a_1 B \\ a_2 B \\ a_3 B \\ \vdots \end{bmatrix}$$

$$A \cdot \underbrace{x_p + A \cdot x_h}_0 = b$$

x_p - particular solution.

x_h - all the x such that $Ax=0$.

$$\text{Area of triangle} = \frac{1}{2} \left| \begin{vmatrix} a & b \\ c & d \end{vmatrix} \right|$$

$$\text{Volumen} = \det(a_1, a_2, a_3)$$

$$AS = SA \quad \Lambda = \begin{pmatrix} \lambda_1 & & \\ & \ddots & \\ & & \lambda_n \end{pmatrix}$$

$$\Lambda = S^{-1} A S \quad A^k x = \Lambda^k x$$

$$\det(A) = \lambda_1 \cdot \lambda_2 \cdot \dots \cdot \lambda_n$$

$$\text{tr}(A) = \lambda_1 + \lambda_2 + \dots + \lambda_n$$

If A has n distinct eigen values then it is diagonalizable.

$$(e^{\lambda t} \cdot y)' = \lambda e^{\lambda t} y$$

Cayley-Hamilton Theorem

$$\text{if } |A - \lambda I| = P(\lambda), P(A) = 0.$$

$$e^{At} = I + \frac{At}{1!} + \dots + \frac{A^n t^n}{n!} + \dots$$

$$\Delta(\lambda) = \lambda^2 - \text{tr}(A) \cdot \lambda + \det(A)$$

Similarity of Matrices:

$$B = M^{-1} A M$$

$$\begin{bmatrix} r(t) \\ w(t) \end{bmatrix} = e^{At} \cdot \begin{bmatrix} r_0 \\ w_0 \end{bmatrix}, e^{At} = S \cdot \begin{bmatrix} e^{\lambda_1 t} \\ e^{\lambda_2 t} \end{bmatrix} \cdot S^{-1}$$

$$A = LU$$

L - Lower tri with 1 on diagonal

U - Upper tri

$$n \geq m = r$$

$$(AA^T)^{\dagger} (AA^T)^{-1} = I_{m \times m}$$

right inverse

$$m \geq n$$

$$(B^T B)^{-1} B^T B = I_{n \times n}$$

left inverse

Positive Definite (semi >0)

sym, $A=A^T$, A is P.D. iff

$$(i) \lambda(A) > 0$$

$$(ii) x^T A x > 0, \text{ every } x \in \mathbb{R}^n (x \neq 0)$$

sym, $A=A^T$, A is P.D. iff

$$(i) x^T A x > 0 \quad \forall x \in \mathbb{R}^n (x \neq 0)$$

$$\Leftrightarrow (ii) \lambda(A) > 0$$

$$\Leftrightarrow (iii) \begin{bmatrix} a_{11} & a_{12} & a_{13} & \dots & a_{1n} \\ a_{21} & a_{22} & a_{23} & \dots & a_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ a_{n1} & \dots & \dots & \dots & a_{nn} \end{bmatrix}$$

$$\Delta_1 = \det(a_{11}) > 0$$

$$\Delta_2 = \det \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} > 0$$

⋮

Singular value decomposition SVD

$$A_{m \times n} = U_{m \times m} \Sigma_{m \times n} V_{n \times n}^T$$

$$U \cdot U^T = I \quad V \cdot V^T = I$$

$$\Sigma = \left[\begin{array}{c|c} \begin{matrix} \sigma_1 & \dots & 0 \\ 0 & \dots & \sigma_r \end{matrix} & \begin{matrix} 0 \\ \vdots \\ 0 \end{matrix} \\ \hline \begin{matrix} 0 \\ \vdots \\ 0 \end{matrix} & \begin{matrix} 0 \\ \vdots \\ 0 \end{matrix} \end{array} \right] \begin{matrix} r \\ m-r \end{matrix}$$

U: eigen vectors of AA^T

V: eigen vectors of $A^T A$

$\sigma_1^2, \dots, \sigma_r^2$: eigen values of $AA^T, A^T A$

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

Pseudo Inverse:

$$A^{\dagger} = V \cdot \begin{bmatrix} \Sigma^{-1} & 0 \\ 0 & 0 \end{bmatrix} U^T$$

Norms of vectors & Matrices.

$x \in \mathbb{R}^n \rightarrow \mathbb{R}$ Vector.

1. $\|x\| \geq 0$
2. $\|a \cdot x\| = |a| \cdot \|x\|$, any $a \in \mathbb{R}$, $x \in \mathbb{R}^n$
3. $\|x+y\| \leq \|x\| + \|y\|$ (Triangle)

$A_{m \times n} \rightarrow \mathbb{R}$ Matrix

1. $\|A\| \geq 0$
2. $\|aA\| = |a| \cdot \|A\|$, any $a \in \mathbb{R}$
3. $\|A+B\| \leq \|A\| + \|B\|$ (Triangle)

Spectral Norm.

$$\|A\| \stackrel{\text{def}}{=} \max_x \frac{\|Ax\|_2}{\|x\|_2}$$

Fact 1. $\|Ax\| \leq \|A\| \cdot \|x\|$
vec Mat vec

Fact 2. $\|AB\| \leq \|A\| \cdot \|B\|$

$$A(x+dx) = b+db$$

$$\frac{\|dx\|}{\|x\|} \leq \|A^{-1}\| \cdot \|A\| \cdot \frac{\|db\|}{\|b\|}$$

Condition number of $A = \|A^{-1}\| \cdot \|A\|$

$$\|A^{-1}\| \cdot \|A\| = \frac{|\lambda_{\max}(A)|}{|\lambda_{\min}(A)|}$$

$$\|A\|^2 = \lambda_{\max}(A^T A)$$

$$A = \underset{\text{Lower diagonal}}{L} + \underset{\text{diagonal}}{D} + \underset{\text{upper diagonal}}{U}$$

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ c & 0 \end{bmatrix} + \begin{bmatrix} a & 0 \\ 0 & d \end{bmatrix} + \begin{bmatrix} 0 & b \\ 0 & 0 \end{bmatrix}$$

* Jacobi $D^{-1}(-L-U)$

* Gauss-Seidel $(D+L)^{-1}(-U)$

* SOR $\lambda_{\max} = \max \lambda_{\text{Jacobi}}$

$$W_{\text{opt}} = \frac{2(1 - \sqrt{1 - \mu^2_{\max}})}{\mu^2_{\max}}$$

Gershgorin Circle.

The eigen values of A are in the union of the circles: $|\lambda - a_{ii}| \leq \sum_{j \neq i} |a_{ij}|$
(radius)

Frobenius norm

$$\|A\|_F = \sqrt{\sum_{i,j} a_{ij}^2}$$

$$\|A^T\| = \|A\|$$

$$\|A\|_F = \sqrt{\text{tr}(A^T A)} = \sqrt{\sum \sigma_i^2}$$

$$x_{k+1} = (I + \epsilon A)x_k - \epsilon b \quad \text{Iteration}$$

Converges iff $|\lambda(I + \epsilon A)| < 1$

CHOLESKY FACTORIZATION

$$A = LU \text{ (Lower diag, upper diag)}$$

KRONECKER PRODUCTS \otimes

$$I_{m \times m} \otimes I_{n \times n} = I_{(m \cdot n) \times (m \cdot n)}$$

$$(A \otimes B) \cdot (C \otimes D) = (A \cdot C) \otimes (B \cdot D)$$

$$(A \otimes B)^T = A^T \otimes B^T$$

$$A, B \text{ symmetric} \Rightarrow A \otimes B \text{ symmetric}$$

$$A, B \text{ non-singular} \Rightarrow (A \otimes B)^{-1} = A^{-1} \otimes B^{-1}$$

$$A, B \text{ orthogonal } (A^T = I) \Rightarrow A \otimes B \text{ orthogonal}$$

$$A \text{ SVD: } U_A \Sigma_A V_A^T$$

$$B \text{ SVD: } U_B \Sigma_B V_B^T$$

$$A \otimes B \text{ SVD: } (U_A \otimes U_B)(\Sigma_A \otimes \Sigma_B)(V_A^T \otimes V_B^T)$$

$$\text{rank}(A \otimes B) = (\text{rank } A) \cdot (\text{rank } B)$$

$$A \sim \lambda_i \quad B \sim \mu_j$$

$$A \otimes B \sim \lambda_i \mu_j \text{ e-vec } (x_i \otimes z_j)$$

$$\text{tr}(A \otimes B) = (\text{tr } A) \cdot (\text{tr } B)$$

$$A_{n \times n} \quad B_{m \times m}$$

$$\det(A \otimes B) = (\det A)^m (\det B)^n$$

Markov

$$\text{has } \lambda=1 \text{ and } |\lambda_i| < 1$$

$$\exists \pi_e: \pi_e P = \pi_e$$

$$J = \mu^{-1} A \mu$$