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NO PHOTOCOPY

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NEWYORK UNIVERSITY  
Linear Algebra Final Review

Subject: MATH-UA 140 Linear Algebra  
Name of Examiners: . \_\_\_\_\_

Year: 2024(Sem 2)  
Time allow: 1001

Instruction to Candidate : (only on page 1)

- (1) This paper contains \_\_\_\_\_ questions.
- (2) Candidates must answer \_\_\_\_\_ questions.

Question No   1  

Diagonalize  $A$  and compute  $V\Lambda^kV^{-1}$  to prove this formula for  $A^k$ :

$$A = \begin{pmatrix} 2 & -1 \\ -1 & 2 \end{pmatrix} \text{ has } A^k = \frac{1}{2} \begin{pmatrix} 1 + 3^k & 1 - 3^k \\ 1 - 3^k & 1 + 3^k \end{pmatrix}.$$

and what is the meaning of  $\lim_{k \rightarrow \infty} \frac{1}{3^k} A^k$ .  $= \left( \frac{A}{3} \right)^k$ .

**Solution:**

The eigenvalues of  $A$  are 3 and 1, and the corresponding eigenvectors are  $v_1 = (-1, 1)$ ,  $v_2 = (1, 1)$ . Therefore,  $A$  can be diagonalized as  $A = V\Lambda V^{-1}$ , where  $V = [v_1, v_2]$ ,

$$\Lambda = \begin{pmatrix} 3 & 0 \\ 0 & 1 \end{pmatrix} \text{ and } V^{-1} = \begin{pmatrix} -1/2 & 1/2 \\ 1/2 & 1/2 \end{pmatrix}. \quad A^k = V\Lambda^kV^{-1} = \frac{1}{2} \begin{pmatrix} 1 + 3^k & 1 - 3^k \\ 1 - 3^k & 1 + 3^k \end{pmatrix}.$$

$$\lim_{k \rightarrow \infty} \frac{1}{3^k} A^k = \lim_{k \rightarrow \infty} \frac{1}{2} \begin{pmatrix} \frac{1}{3^k} + 1 & \frac{1}{3^k} - 1 \\ \frac{1}{3^k} - 1 & \frac{1}{3^k} + 1 \end{pmatrix} = \begin{pmatrix} \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & \frac{1}{2} \end{pmatrix} \text{ (the largest eigen vector)}$$

Examination Requirements: NIL

$$\begin{aligned} \rightarrow \lambda_1 &= 1 & v_1 &= (-1, 1) \\ \rightarrow \lambda_2 &= 3 & v_2 &= (1, 1) \end{aligned}$$

$\frac{1}{2}v_1 - \frac{1}{2}v_2 \rightarrow$  eigenvector of  
largest eigenvalue

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Householder Matrix

Question No 2

For  $u$  is a unit vector prove that  $Q = I - 2uu^T$  is an symmetric orthogonal matrix. Prove  $\|Qx\| = \|x\|$ .

$P = uu^T$  is a projection

$$Q^T Q = Q Q^T = I$$

**Solution:**

$Q$  is symmetric because  $uu^T$  is symmetric.

$$\text{Then } QQ^T = QQ = Q^2 = (I - 2uu^T)^2 = I - 2uu^T - 2uu^T + 4u \underbrace{u^T u}_{u^T u = \|u\|^2 = 1} u^T = I -$$

$$4uu^T + 4uu^T = I$$

For all orthogonal matrix  $Q$ , we have

$$\|Qx\|^2 = (Qx)^T (Qx) = x^T Q^T Q x = x^T x = \|x\|^2$$

for  $Q^T Q = I$

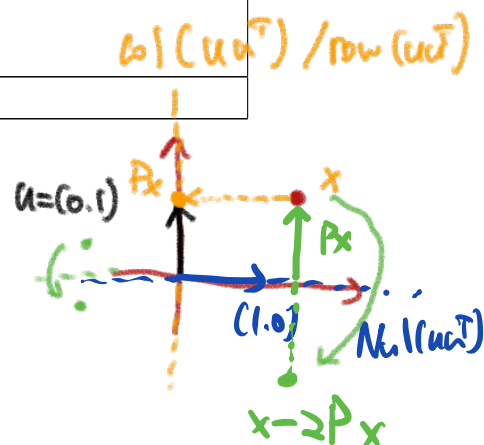
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Example.  $\vec{u} = (0, 1)$

$$\vec{u} u^T = \begin{pmatrix} 0 \\ 1 \end{pmatrix} (0, 1) = \begin{pmatrix} 0 & 0 \\ 0 & 1 \end{pmatrix}$$

$$I - 2\vec{u} \vec{u}^T = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix}$$

$$(I - 2uu^T) \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} x \\ -y \end{pmatrix}$$



$$(I - 2P)x = x - 2P_x$$

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Question No   3  

What are the four fundamental subspaces of  $M = I - P$  in terms of the column space of  $P$ .

**Solution**

For a projection matrix  $P$ : (projection matrix is always symmetric)

- $x \in \text{col}(P) = \text{row}(P)$ :  $Px=x$
- $x \in \text{Nul}(P) = \text{LeftNul}(P)$ :  $Px=0$

For matrix  $I - P$

- $x \in \text{col}(P) = \text{row}(P)$ :  $(I-P)x=x-Px=x-x=0$
- $x \in \text{Nul}(P) = \text{LeftNul}(P)$ :  $(I-P)x=x-Px=x-0=x$

is also a projection matrix.

Left Null space = Right Null space = Column space of  $P$ .

Column space = Row space = orthogonal complement of the column space of  $P$ .

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Question No 4

$P$  is a Projection Matrix, prove  $P$  is symmetric and  $P^2 = P$ . What is the eigenvalue of Projection matrix  $P$ . Prove that  $I - 2P$  is an orthogonal matrix

**Solution**

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

- $P^2 = A \underbrace{(A^T A)^{-1} A^T A}_{=I} (A^T A)^{-1} A^T = A(A^T A)^{-1} A^T = P$
- $P^T = (A(A^T A)^{-1} A^T)^T = A^T (A^T A)^{-T} A = A(A^T A)^{-1} A^T$  (For  $A^T A$  symmetric)

Eigenvalue is 1, 0 (for  $P^2 = P$  so eigenvalues should satisfies  $\lambda^2 = \lambda$ )

Since  $P$  is a projection matrix, we have  $P = P^T$ . To show that  $Q$  is an orthogonal matrix, we need to check that  $QQ^T = I$ . We have

$$\begin{aligned} QQ^T &= (I - 2P)(I - 2P)^T \\ &= (I - 2P)(I^T - 2P^T) \\ &= (I - 2P)(I - 2P) \quad (\text{since } I \text{ and } P \text{ are symmetric}) \\ &= I - 4P + 4P^2 \end{aligned}$$

Since for a projection matrix we have  $P^2 = P$ , this product is equal to  $QQ^T = I$ , as required.

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Question No 5

If  $A^2 = -A$ , what is the possible value of  $\det(A)$ .

**Solution**

$A^2 = -A$  means  $\det(A^2) = \det(-A)$  however

- $\det(A^2) = \det(A)^2$   $\det(AB) = \det(A)\det(B)$   $\det(c \cdot A) = c^n \det(A)$   $A \in \mathbb{R}^{n \times n}$
- $\det(-A) = (-1)^n \det(A) = \begin{cases} -\det(A) & \text{if } n \text{ is odd} \\ \det(A) & \text{if } n \text{ is even} \end{cases}$

Thus

$$\det(A)^2 = \begin{cases} -\det(A) & \text{if } n \text{ is odd} \\ \det(A) & \text{if } n \text{ is even} \end{cases}$$

which means

$$\det(A) = \begin{cases} 0, -1 & \text{if } n \text{ is odd} \\ 0, 1 & \text{if } n \text{ is even} \end{cases}$$

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Question No   5  

Suppose an  $m \times n$  matrix  $A$  has rank  $r$ . What are the ranks of

- (a)  $A^T$ ?
- (b)  $AA^T$ ?
- (c)  $AA^T + \lambda I$  ( $\lambda > 0$ )?
- (d)  $A^T AA^T$ ?

**Solution**

**Answer 1**

- (A)  $r$
- (B) we showed in class it's  $r$  (page 17 in <https://2prime.github.io/files/linear/linearslide14filled.pdf>)
- (C) it's a positive definite matrix with all eigenvalues larger than  $\lambda$ , think why.
- (D)  $r$  (similar page 17 in <https://2prime.github.io/files/linear/linearslide14filled.pdf>)

**Answer 2 Using SVD**

- (A)  $\text{rank}(A^T) = \dim(\text{row}(A^T)) = \dim(\text{col}(A)) = \text{rank}(A) = r$ .
- (B) Let  $A = U\Sigma V^T$  be a full SVD. Then,

$$AA^T = (U\Sigma V^T)(U\Sigma V^T)^T = U\Sigma V^T V \Sigma^T U^T = U\Sigma^2 U^T.$$

Thus,  $U\Sigma^2 U^T$  is a SVD of  $AA^T$ . If  $\Sigma$  has  $r$  positive singular values then so will  $\Sigma^2$ . Therefore, the rank of  $AA^T$  is  $r$ .

- (C) Since  $I_m = UU^T$ , the equation above yields  $AA^T + \lambda I = U\Sigma^2 U^T + \lambda I = U(\Sigma^2 + \lambda I_m)U^T$ . Since  $\Sigma^2 + \lambda I = \text{diag}(\sigma_1^2 + \lambda, \dots, \sigma_r^2 + \lambda, \dots, \lambda)$ , the rank is  $m$ .
- (D)  $A^T AA^T = (U\Sigma V^T)^T (U\Sigma V^T) (U\Sigma V^T)^T = V\Sigma^T U^T U \Sigma V^T U^T U \Sigma V^T = V\Sigma^T \Sigma \Sigma^T V^T = V\Sigma^3 V^T$ .  $\Sigma^3$  has  $r$  positive singular values as like  $\Sigma$ . Therefore, the rank is  $r$ .

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Question No   6  

The following matrices have only one eigenvalue: 1. What are the dimensions of the eigenspaces in each case?

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}, \quad \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 0 & 1 & 1 \end{pmatrix}, \quad \begin{pmatrix} 1 & 0 & 0 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}, \quad \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 1 & 0 & 1 \end{pmatrix}$$

For a matrix  $A$ , the eigenspace with eigenvalue  $\lambda$  is the kernel of the matrix  $A - \lambda I$ . Here we have  $\lambda = 1$ , so we subtract  $I$  from each of the matrices above:

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}, \quad \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}, \quad \begin{pmatrix} 0 & 0 & 0 \\ 1 & 0 & 0 \\ 1 & 1 & 0 \end{pmatrix}, \quad \begin{pmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 1 & 0 & 0 \end{pmatrix}$$

and find the dimensions of the kernels.

The ranks of these matrices are 0, 2, 2, 1 respectively, so by the rank-nullity theorem the dimensions of the kernels are 3, 1, 1, 2.

**Answer:** 3, 1, 1, 2.

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Question No 7

For  $A \in \mathbb{R}^{n \times n}$  has singular value  $\sigma_1, \dots, \sigma_n$  prove

- $\text{tr}(A^T A) = \sigma_1^2 + \dots + \sigma_n^2$
- $\text{tr}((A^T A + \lambda I)^{-1} A^T A) = \frac{\sigma_1^2}{\sigma_1^2 + \lambda} + \dots + \frac{\sigma_n^2}{\sigma_n^2 + \lambda}$

**Solution**

Using SVD  $A = U \Sigma V^T$  Then we have

- $A^T A = V \Sigma^T \Sigma V^T$  so  $\text{tr}(A^T A) = \text{tr}(\Sigma^T \Sigma) = \sigma_1^2 + \dots + \sigma_n^2$
- $(A^T A + \lambda I) = V(\Sigma^T \Sigma + \lambda I)V^T$ ,  $(A^T A + \lambda I)^{-1} = V(\Sigma^T \Sigma + \lambda I)^{-1}V^T$

diag

- $(A^T A + \lambda I)^{-1} A^T A = V(\Sigma^T \Sigma + \lambda I)^{-1} \Sigma^T \Sigma V^T = V \begin{bmatrix} \frac{\sigma_1^2}{\sigma_1^2 + \lambda} & 0 & \dots & 0 \\ 0 & \frac{\sigma_2^2}{\sigma_2^2 + \lambda} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \frac{\sigma_n^2}{\sigma_n^2 + \lambda} \end{bmatrix} V^T$

•

$$\text{trace}((A^T A + \lambda I)^{-1} A^T A) = \text{trace} \left( \begin{bmatrix} \frac{\sigma_1^2}{\sigma_1^2 + \lambda} & 0 & \dots & 0 \\ 0 & \frac{\sigma_2^2}{\sigma_2^2 + \lambda} & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & \frac{\sigma_n^2}{\sigma_n^2 + \lambda} \end{bmatrix} \right) = \frac{\sigma_1^2}{\sigma_1^2 + \lambda} + \dots + \frac{\sigma_n^2}{\sigma_n^2 + \lambda}$$

Examination Requirements: NIL



Projection -

$$\underline{A\vec{x} = \vec{b}}$$

$$A\vec{x} \in \text{Col}(A)$$

Question What is the nearest point of  $\vec{b}$  in  $\text{Col}(A)$

answer projection Matrix

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

behind

$$\underline{A\vec{x} = \vec{b}} \Rightarrow A^T A \vec{x} = A^T \vec{b} \Rightarrow \vec{x} = \underline{(A^T A)^{-1} A^T \vec{b}}$$

least square.

$$A\vec{x} = \underline{A(A^T A)^{-1} A^T \vec{b}}$$

projection matrix

- Hints (Exercise 2-4)

①  $\underline{\|u\|=1}$ .  $P = u(u^T u)^{-1} u^T = \underline{uu^T}$   $\|u\|=1$   $u^T u = \|u\|^2 = 1$

$\underline{u^T u = 1}$  rank 1 matrix projection

②  $P$  is a Projection Matrix.

$$\underline{P^2 = P} \quad \underline{P = P^T}$$

$$P^2 = A(A^T A)^{-1} \underline{A^T A} (A^T A)^{-1} A^T = A(A^T A)^{-1} A^T = P$$

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

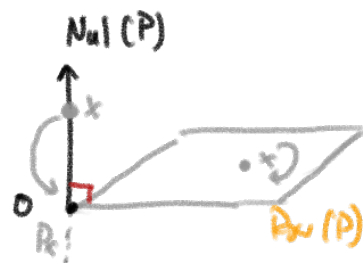
③  $P^2 = P$

means

$$P(Px) = Px$$

projection  
2 times

Projection  
1 time



row(P)  
-  $x \in \text{Col}(P)$

$Px = x$ .  $x$  is eigenvector with eigenvalue 1

-  $x \in \text{Nul}(P)$

$Px = 0$

$\text{Nul}(P) \perp \text{Row}(P)$

$x$  is eigenvector with eigenvalue 0

④  $P$  only have eigenvalue 1 or 0

$$P^2 = P \Rightarrow P^2 - P = 0 \Rightarrow \lambda^2 - \lambda = 0 \Rightarrow \lambda = 1, 0$$

△ If  $\lambda$  is the eigenvalue of  $P$ , Then  $\lambda^2 - \lambda$  is the eigen  $P^2 - P$

$$Px = \lambda x \Rightarrow (P^2 - P)x = P^2 x - Px = (\lambda^2 x - \lambda x) = (\lambda^2 - \lambda)x$$

⑤

$$P = \underline{u_1 u_1^T + u_2 u_2^T + \dots + u_r u_r^T} + 0 \cdot \underline{u_{r+1} u_{r+1}^T + \dots + u_n u_n^T}$$

$u_1, \dots, u_r$  is the orthonormal basis of  $\text{row}(P)/\text{Col}(P)$

$u_{r+1}, \dots, u_n$  is the orthonormal basis of  $\text{Nul}(P)/\text{left Nul}$  (P)

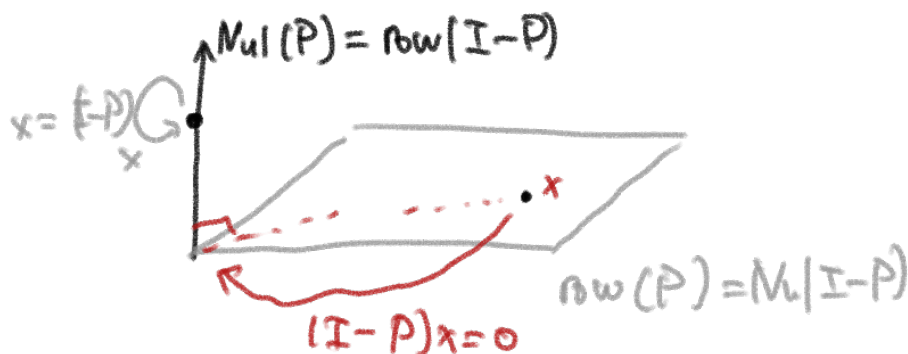
$$\textcircled{b} \quad I = u_1 u_1^T + u_2 u_2^T + \dots + u_r u_r^T + u_{r+1} u_{r+1}^T + \dots + u_n u_n^T$$

$u_1 \dots u_n$  are  $I$ 's eigenvector with eigenvalue 1

$$I - P = \underbrace{0 \cdot u_1 u_1^T + 0 \cdot u_2 u_2^T + \dots + 0 \cdot u_r u_r^T}_{u_1, u_2, \dots, u_r \text{ is the orthonormal basis of } \text{Nul}(I-P) / \text{left Nul}(I-P)} + \underbrace{u_{r+1} u_{r+1}^T + \dots + u_n u_n^T}_{u_{r+1}, \dots, u_n \text{ is the orthonormal basis of } \text{Col}(I-P) / \text{Row}(I-P)}$$

$u_1, u_2, \dots, u_r$  is the orthonormal basis of  $\text{Nul}(I-P) / \text{left Nul}(I-P)$

$u_{r+1}, \dots, u_n$  is the orthonormal basis of  $\text{Col}(I-P) / \text{Row}(I-P)$



Gram-Schmidt Process.

-  $\{x_1, \dots, x_n\}$  basis  $\rightarrow \{u_1, \dots, u_n\}$  orthogonal.

Hint. Orthogonal matrix  $\rightarrow$  Column is orthonormal.

If you want orthogonal, you need to normalize your vector to unit vector!

- QR Decomposition.  $R = Q^T A$

$$A = QR, \quad A^T A = R^T \underbrace{Q^T Q}_I R = \underbrace{(R^T)}_{\text{lower}} \underbrace{(R)}_{\text{upper}}$$

But it's not LU Decomposition!

$\downarrow$

LU need diag of  $L$  to be 1.

# Diagonalization & Eigenvectors,

$$A = X \Lambda X^{-1}$$

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

$$X = [x_1 \cdots x_n]$$

$x_1 \cdots x_n$  are linear independent Eigen vectors

This is not always true.

- In the case,  $\lambda_1, \lambda_2, \dots, \lambda_n$  are all different numbers, this is true.

(Exercise 6)

- Example .  $A = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$   $p(\lambda) = (\lambda - 1)^2$   
 $\lambda_1 = 1 \quad \lambda_2 = 1$

$$\Rightarrow A - I = \begin{bmatrix} 0 & 1 \\ 0 & 0 \end{bmatrix} \rightarrow 1 \text{ dimension eigen space}$$

-  $A^k = X \Lambda^k X^{-1}$  Exercise 1

-  $A = X B X^{-1}$  similar matrix

same eigenvalue .  $\rightarrow$  different eigenvectors .

same trace

same det .

$$Ax = \lambda x$$

$$X B X^{-1} x = \lambda x$$

$$\Rightarrow B X^{-1} x = \lambda X^{-1} x$$

$$\Rightarrow X^{-1} x \text{ is the eigen}$$



hint us the way  
to compute the  
matrix  $X$ , (If we know  
 $A$  and  $B$ )

# Symmetric Matrix

- Eigenvalue is real, can always be diagonalized

Eigenvectors are orthogonal to each other.

$$Q^T = Q^{-1}$$

-  $A = \underbrace{Q}_{\substack{\uparrow \\ \text{eigenvector}}} \Lambda \underbrace{Q^T}_{\substack{\uparrow \\ \text{eigenvalue}}} \Rightarrow A \text{ is similar to } \Lambda$

$Q$  is an orthogonal matrix

eigenvalue eigenvector

-  $A = \overset{\uparrow}{\lambda_1} \underbrace{u_1 u_1^T}_{\substack{\text{rank 1} \\ \text{symmetric} \\ \text{projection matrix}}} + \lambda_2 \underbrace{u_2 u_2^T}_{\substack{\text{rank 1} \\ \text{symmetric} \\ \text{projection matrix}}} + \dots + \lambda_n \underbrace{u_n u_n^T}_{\substack{\text{rank 1} \\ \text{symmetric} \\ \text{projection matrix}}}$

## SVD

Any Matrix

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

-  $A = \underbrace{U}_{\substack{m \times m \\ \text{orth}}} \underbrace{\Sigma}_{\substack{m \times n \\ \text{diag}}} \underbrace{V^T}_{\substack{n \times n \\ \text{orth}}}$

symmetric  $AA^T = U \Sigma \Sigma^T U^T$ ,  $U$ : eigenvectors of  $AA^T$

symmetric  $A^T A = V \Sigma^T \Sigma V^T$ ,  $V$ : eigenvectors of  $A^T A$

-  $A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T$

$\Rightarrow U, V$  can provide orthonormal basis of the four fundamental subspaces of  $A$ .

- How to compute SVD

- Use  $U$  : eigenvector of  $AA^T$  **or**  
 $V$  : eigenvector of  $A^T A$

- Use

$$u_i = \frac{1}{\sigma_i} A v_i \quad \text{or} \quad v_i = \frac{1}{\sigma_i} A^T u_i$$

- Properties of Det

- Cofactor.

- Check if a Transform is linear Transform **(HW6)**

Orthogonal Matrix  $Q \in \mathbb{R}^{n \times n}$  square matrix

$$Q^T Q = I \Leftrightarrow Q Q^T = I$$

both mean  $Q^T = Q^{-1}$

Orthogonal Matrix  $Q \in \mathbb{R}^{n \times m}$

$Q^T Q$   $m \times m$  matrix  $= I$  eigen  $\underbrace{1 \dots 1}_m$

$Q Q^T$   $n \times n$  matrix

$\Downarrow$   
eigen  $\underbrace{1 \dots 1}_n$   $\underbrace{0 \dots 0}_{m-n}$