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In order to minimize $\|AX - I_m\|_F^2$ where X is define as $\begin{bmatrix} | & & | \\ x_1 & \dots & x_m \\ | & & | \end{bmatrix}$

$$F(x) = \text{Tr}((AX - I_m)^T (AX - I_m)) = \|AX - I_m\|_F^2$$

$$= \text{Tr}(\underbrace{(AX)^T (AX)}_{\textcircled{1}}) - 2\text{Tr}(AX) + m$$

$$\textcircled{1} = \begin{bmatrix} -(AX)^T \\ \vdots \\ -(AX_m)^T \end{bmatrix} \begin{bmatrix} | & & | \\ AX_1 & \dots & AX_m \\ | & & | \end{bmatrix}$$

$$\text{Tr}((AX)^T (AX)) = \sum_{j=1}^m (AX_j)^T (AX_j)$$

$$= \sum_{j=1}^m x_j^T A^T A x_j$$

$$AX = \begin{bmatrix} -e_1^T A \\ \vdots \\ -e_m^T A \end{bmatrix} \begin{bmatrix} | & & | \\ x_1 & \dots & x_m \\ | & & | \end{bmatrix}$$

$$\text{Tr}(AX) = \sum_{j=1}^m e_j^T A x_j$$

$$\nabla F = \begin{bmatrix} 1 & \\ 2A^T A x_j & -2A^T e_j \dots \\ & 1 \end{bmatrix}$$

$$\text{if } \nabla F = 0 \Rightarrow A^T A x_j = A^T e_j$$

$$\Rightarrow A^T A X = A^T I_m = A^T \quad (3)$$

$$\text{Since } A = (U_r \Sigma_r V_r^T)_{[m \times r]}$$

$$A^T A = U_r \Sigma_r^2 V_r^T$$

$$A^T = V_r \Sigma_r U_r^T$$

$$(3) \Rightarrow V_r \Sigma_r^2 V_r^T X = V_r \Sigma_r U_r^T$$

$$\Rightarrow \Sigma_r^2 V_r^T X = \Sigma_r U_r^T$$

$$\Rightarrow V_r^T X = \Sigma_r^{-1} U_r^T$$

$$\Rightarrow \underset{(4)}{V_r V_r^T X} = \underset{(5)}{V_r \Sigma_r^{-1} U_r^T}$$

$$(5) = A^+$$

$$(4) = \begin{bmatrix} 0 & | & \\ 0 & 0 \end{bmatrix}$$

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show that

$$(1) \quad AA^+A = A$$

$$\begin{aligned} AA^+A &= A(A^+A)A \\ &= A A^+ (A^+)^+ A \\ &= A \end{aligned}$$

$$(2) \quad A^+AA^+ = A^+$$

$$\begin{aligned} A^+AA^+ &= R^{-1}Q^TQR R^{-1}Q^T \\ &= R^{-1}Q^T = A^+ \end{aligned}$$

$$(3) \quad A^+A = (A^+A)^T$$

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$$(1) \quad AA^+A = A$$

Is A full rank? We don't know

A is $m \times n$

AA^+ need to be $m \times m$ Identity matrix, which should be the pseudo invers

(2) same as (1)

I'm reading Penrose's paper, hopefully it will give me the answer.

$$(3) \quad A^+ A = (A^+ A)^T$$

Since $A^+ A$ is Hermitian?

$$(4) \quad A A^+ = (A A^+)^T$$

Since $(A A^+)^T$ is Hermitian?

All these four are Moore-Penrose conditions, which is required for Moore-Penrose inverse. I'm so confused about the logic in this question.

problem 3

Let A be $m \times n$ matrix with singular value $\sigma_1 \geq \dots \geq \sigma_n \geq 0$. show that the singular value of $\begin{bmatrix} I_n \\ A \end{bmatrix}$ are $\sqrt{1 + \sigma_i^2}$ for $i \leq n$

$$M = \begin{bmatrix} I_n \\ A \end{bmatrix}_{(n+m) \times n}$$

$$M = \begin{bmatrix} \begin{bmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{bmatrix} \\ A \end{bmatrix} \begin{matrix} n \\ m \end{matrix}$$

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

$$MM^T = \begin{bmatrix} n & n \\ m+n & n \end{bmatrix} \begin{bmatrix} n & m+n \end{bmatrix} = \begin{bmatrix} I_{n,n} & A^T \\ A & AA^T \end{bmatrix}_{m+n, m+n}$$

$$= \begin{bmatrix} I_{n \times n} & A^T_{n \times m} \\ A_{m \times n} & AA^T_{m \times m} \end{bmatrix} \text{ which is symmetric}$$

$$\det(MM^T - \lambda I) = 0$$

$$(I - \lambda)(AA^T - \lambda) - AA^T = 0 \Rightarrow \lambda_i = I - \lambda(AA^T) = 1 + \sigma_i^2$$

$$\sigma_n = \sqrt{\lambda_i} = \sqrt{1 + \sigma_i^2}$$