## Large Sparse Matrix Computations: Homework 01

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## Exercise 1.

*Proof.* Suppose Y is another pseudoinverse of  $A \in \mathbb{R}^{m \times n}$ , that is Y satisfies (a) AYA = A, (b) YAY = Y, (c) $(AY)^T = AY$ , (d)  $(YA)^T = YA$ .

$$X = XAX = X (AYA) X = X (AYA) Y (AYA) X$$

$$= (XA) (YA) Y (AY) (AX) = (XA)^{T} (YA)^{T} Y (AY)^{T} (AX)^{T}$$

$$= (A^{T}X^{T}A^{T}Y^{T}) Y (Y^{T}A^{T}X^{T}A^{T}) = (YAXA)^{T} Y (AXAY)^{T}$$

$$= (YA)^{T} Y (AY)^{T} = (YA) Y (AY) = Y (AYA) Y = YAY$$

$$= Y$$

Therefore, the pseudoinverse of A is unique.

## Exercise 2.

*Proof.* Claim  $1: ||A - A_k||_2 = \sigma_{k+1}$ .

$$\|A - A_k\|_2 = \|U\Sigma V^T - UDV^T\|_2 = \|U(\Sigma - D)V^T\|_2 = \|\Sigma - D\|_2,$$
where  $\Sigma = diag(\sigma_1, \dots, \sigma_r, 0, \dots, 0)$  and  $D = diag(\sigma_1, \dots, \sigma_k, 0, \dots, 0)$ . Hence
$$\Sigma - D = diag(0, \dots, \sigma_{k+1}, \dots, \sigma_r, 0, \dots, 0).$$

So  $||A - A_k||_2$  equals the greatest eigenvalue of  $\Sigma - D = \sigma_{k+1}$ .

Claim 2:  $\min_{rank(B)=k} \|A - B\|_2 = \sigma_{k+1}$ . Since  $A_k \in \{B \mid rank(B) = k\}$ ,  $\sigma_{k+1} = \|A - A_k\|_2 \ge \min_{rank(B)=k} \|A - B\|_2$  is obvious. So we need to show  $\min_{rank(B)=k} \|A - B\|_2 \ge \sigma_{k+1}$ .

For any B with rank(B) = k, implies nullity(B) = n - k. Consider the set  $S = null(B) \cap span\{v_1, v_2, \dots, v_{k+1}\}$ . Since dim(S) = (n - k) + (k + 1) = n + 1 > n, S is a nonempty set. Choose  $x \in S$  with  $||x||_2 = 1$ .

$$\begin{split} \|A - B\|_{2}^{2} &= \|A - B\|_{2}^{2} \|x\|_{2}^{2} \\ &\geq \|(A - B) x\|_{2}^{2} \\ &= \|Ax - Bx\|_{2} = \|Ax\|_{2} \text{ (Since } x \in null(B)) \\ &= \|U\Sigma V^{T} x\|_{2}^{2} = \|\Sigma V^{T} x\|_{2}^{2} \text{ (Since } U \text{ is unitary)} \\ &= \left\|\sum_{i=1}^{n} \sigma_{i} v_{i}^{T} x\right\|_{2}^{2} = \sum_{i=1}^{k+1} \sigma_{i}^{2} \left(v_{i}^{T} x\right)^{2} \text{ (Since } x \in span \{v_{1}, v_{2}, \cdots, v_{k+1}\}, v_{i}^{T} x = 0, \forall i = k+2, \cdots, n)} \\ &\geq \sigma_{k+1}^{2} \sum_{i=1}^{k+1} \left(v_{i}^{T} x\right)^{2} = \sigma_{k+1}^{2} \end{split}$$

Hence  $||A - B||_2 \ge \sigma_{k+1}$ , for any rank(B) = k, we get  $\min_{rank(B) = k} ||A - B||_2 \ge \sigma_{k+1}$ .

Therefore by claim 1 and claim 2, the proof is complete.