

# Math 344 Homework 4.6

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## 4.33

We know that  $A^H A$ 's eigenvalues are the squared singular values of  $A$ , and since  $(A^H A)^H = (A^H A)$ , the same thing applies for  $A^H$ . Now, we know that

$$\begin{aligned} p_A(z) &= \det(A - zI) = (\lambda_1 - z)(\lambda_2 - z) \dots (\lambda_n - z) \\ \implies p_A(0) &= \det(A) = (\lambda_1)(\lambda_2) \dots (\lambda_n) = \prod_{i=1}^n \lambda_i \end{aligned}$$

This gives us that

$$\begin{aligned} |\det(A^H A)| &= |\prod_{i=1}^n \lambda_i| \\ &= |\prod_{i=1}^n \sigma_{Ai}^2| \\ &= |\prod_{i=1}^n \sigma_{A^H i}^2| \end{aligned}$$

Since these are equal, we will denote them

$$= |\prod_{i=1}^n \sigma_i^2|$$

As for the other side of the equality, we have that

$$\det(A) = \prod_{i=1}^n \lambda_i = \det(A^H)$$

and so the left side of the equality turns into

$$\begin{aligned} |\det(A^H A)| &= |\det(A)\det(A^H)| \\ &= |\det(A)|^2 \end{aligned}$$

and we have finally that

$$\begin{aligned} |\det(A)|^2 &= |\prod_{i=1}^n \sigma_i^2| \\ \implies |\det(A)| &= |\prod_{i=1}^n \sigma_i| \\ \implies |\det(A)| &= \prod_{i=1}^n \sigma_i \end{aligned}$$

since the singular values of  $A$  are positive and real. Therefore the equality holds and we have the desired result.

#### 4.34

If we let

$$A = \begin{bmatrix} -i & 0 \\ 0 & i \end{bmatrix}$$

whose eigenvalues are  $\lambda = -i, i$  whose determinant  $\det(A) = 1$

Therefore,

$$A^H A = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

whose eigenvalue is 1. Therefore, we have that the singular value is 1.

#### 4.35

As the first  $r$  columns of  $U$  and  $V$  from the Singular Value Decomposition of  $A$  yield  $U_1$  and  $V_1$ ,  $\Sigma_1$  is the  $r \times r$  diagonal matrix with the diagonals as the non-zero eigenvalues of  $A^H A$ , we have the following

$$U_1 = \begin{bmatrix} \frac{1}{\sqrt{5}} \\ 0 \\ \frac{2}{\sqrt{5}} \end{bmatrix} \quad \Sigma_1 = [\sqrt{15}] \quad V_1 = \begin{bmatrix} \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ 0 \end{bmatrix}$$

Then we have, by the definition of the Moore-Penrose Inverse,

$$A^\dagger = \begin{bmatrix} \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ 0 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{15}} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{5}} & 0 & \frac{2}{\sqrt{5}} \end{bmatrix} = \begin{bmatrix} \frac{1}{15} & 0 & \frac{2}{15} \\ \frac{1}{15} & 0 & \frac{2}{15} \\ \frac{1}{15} & 0 & \frac{2}{15} \\ 0 & 0 & 0 \end{bmatrix}$$

Now, we have that

$$A^H A = \begin{bmatrix} 5 & 5 & 5 & 0 \\ 5 & 5 & 5 & 0 \\ 5 & 5 & 5 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} \quad A^\dagger A = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

The matrices are scalar multiples of one another.

#### 4.36

$$A = U_1 \Sigma_1 V_1^H \quad A^\dagger = V_1 \Sigma_1^{-1} U_1^H$$

So we have that

**4.36 (i)**

$$\begin{aligned}
AA^\dagger A &= U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H \\
&= U_1 \Sigma_1 I \Sigma_1^{-1} I \Sigma_1 V_1^H \\
&= U_1 I I \Sigma_1 V_1^H \\
&= U_1 \Sigma_1 V_1^H \\
&= A
\end{aligned}$$

**4.36 (ii)**

$$\begin{aligned}
A^\dagger A A^\dagger &= V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H \\
&= V_1 \Sigma_1^{-1} I \Sigma_1 I \Sigma_1^{-1} U_1^H \\
&= V_1 I \Sigma_1^{-1} U_1^H \\
&= A^\dagger
\end{aligned}$$

**4.36 (iii)**

$$\begin{aligned}
(AA^\dagger)^H &= (U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H)^H \\
&= U_1 (\Sigma_1^{-1})^H V_1^H V_1 (\Sigma_1)^H U_1^H \\
&= U_1 (\Sigma_1^{-1})^H I (\Sigma_1)^H U_1^H \\
&= U_1 (\Sigma_1 \Sigma_1^{-1})^H U_1^H \\
&= U_1 U_1^H \\
&= I
\end{aligned}$$

and we have that

$$\begin{aligned}
AA^\dagger &= U_1 \Sigma_1 V_1^H V_1 \Sigma_1^{-1} U_1^H \\
&= U_1 \Sigma_1 I \Sigma_1^{-1} U_1^H \\
&= U_1 I U_1^H \\
&= U_1 U_1^H \\
&= I
\end{aligned}$$

which is equivalent to the first expression.

#### 4.36 (iv)

$$\begin{aligned} A^\dagger A &= V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H \\ &= V_1 (\Sigma_1)^H (U_1)^H U_1 (\Sigma_1^{-1})^H V_1^H \\ &= V_1 (\Sigma_1)^H I (\Sigma_1^{-1})^H V_1^H \\ &= V_1 (\Sigma_1^{-1} \Sigma_1)^H V_1^H \\ &= V_1 (I)^H V_1^H \\ &= V_1 V_1^H \\ &= I \end{aligned}$$

and we have that

$$\begin{aligned} A^\dagger A &= V_1 \Sigma_1^{-1} U_1^H U_1 \Sigma_1 V_1^H \\ &= V_1 \Sigma_1^{-1} I \Sigma_1 V_1^H \\ &= V_1 I V_1^H \\ &= I \end{aligned}$$

which is equivalent to the first expression.

#### 4.36 (v)

$$AA^\dagger = U_1 U_1^H$$

We know, though, that the first  $r$  columns of  $U_1$  form a basis for  $\mathcal{R}(A)$ , so it follows that anything's projection onto  $\mathcal{R}(A)$  can be expressed in terms of this basis.

#### 4.36 (vi)

$$A^\dagger A = V_1 V_1^H$$

We know, though, that the first  $r$  columns of  $V_1$  form a basis for  $\mathcal{R}(A^H)$ , so it follows that anything's projection onto  $\mathcal{R}(A^H)$  can be expressed in terms of this basis.

### 4.37

Note

$$\begin{aligned} \|\Delta\|_2 &= \left\| - \sum_{i=s+1}^r \sigma_i u_i v_i^H \right\|_2 \\ &\geq \sigma_{s+1} \end{aligned}$$

by Schmidt-Eckart-Young-Mirsky

$$\begin{aligned} &= \inf_{\text{rank}(B) = s} \|A - B\|_2 \\ &= \inf_{\text{rank}(B) = s} \left\| \sum_{i=1}^r \sigma_i u_i v_i^H - \sum_{i=1}^s \sigma_i u_i v_i^H \right\|_2 \\ &= \inf_{\text{rank}(B) = s} \left\| \sum_{i=s+1}^r \sigma_i u_i v_i^H \right\|_2 \\ &= \inf_{\text{rank}(B) = s} \left\| - \sum_{i=s+1}^r \sigma_i u_i v_i^H \right\|_2 \end{aligned}$$

Which holds, so we have the inequality thanks to the infimum.

Now note

$$\begin{aligned} \left\| - \sum_{i=s+1}^r \sigma_i u_i v_i^H \right\|_F &\geq \left( \sum_{k=s+1}^r \sigma_k^2 \right)^{1/2} \\ &\text{by Schmidt-Eckart-Young-Mirsky} \end{aligned}$$

$$\begin{aligned} &= \inf \|A - B\|_F \\ &= \inf \left\| \sum_{i=s+1}^r \right\|_F \\ &= \inf \left\| - \sum_{i=s+1}^r \right\|_F \end{aligned}$$

which also holds, so we have the desired inequality thanks to the infimum.

### 4.38

Note that

$$\begin{aligned}
(I - A\Delta^\diamond)\mathbf{u}_1 &= (I - U\Sigma V^H \frac{1}{\sigma_1} \mathbf{v}_1 \mathbf{u}_1^H) \mathbf{u}_1 \\
&= \mathbf{u}_1 - U\Sigma V^H \frac{1}{\sigma_1} \mathbf{v}_1 \mathbf{u}_1^H \mathbf{u}_1 \\
&= \mathbf{u}_1 - U \frac{1}{\sigma_1} \Sigma V^H \mathbf{v}_1 \\
&= \mathbf{u}_1 - U \frac{1}{\sigma_1} \Sigma [\mathbf{v}_1 | \mathbf{v}_2 | \dots | \mathbf{v}_n]^H \mathbf{v}_1
\end{aligned}$$

Now, we know that  $\mathbf{v}_i$  are orthonormal for all  $i$ , so we have

$$\begin{aligned}
&= \mathbf{u}_1 - U \frac{1}{\sigma_1} \Sigma [\mathbf{v}_1 | \mathbf{v}_2 | \dots | \mathbf{v}_n]^H \mathbf{v}_1 \\
&= \mathbf{u}_1 - U \frac{1}{\sigma_1} \Sigma \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix}
\end{aligned}$$

We also know that because of the format of the matrix  $\Sigma$ :

$$\begin{aligned}
&= \mathbf{u}_1 - U \frac{1}{\sigma_1} \Sigma \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
&= \mathbf{u}_1 - U \frac{1}{\sigma_1} \begin{bmatrix} \sigma_1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
&= \mathbf{u}_1 - U \begin{bmatrix} 1 \\ 0 \\ \vdots \\ 0 \end{bmatrix} \\
&= \mathbf{u}_1 - \mathbf{u}_1 = \mathbf{0}
\end{aligned}$$

### 4.39

$$\|A\|_2 \|\Delta\|_2 = \sigma_1 \|\Delta\|_2 < \sigma_1 \frac{1}{\sigma_1} = 1$$

which is the desired result.

#### 4.40 (i)

Let  $\mathcal{R}(\Delta) \subset \mathcal{R}(A)$  and we have

$$\begin{aligned} A + \Delta &= (A^\dagger A + A^\dagger \Delta) \\ &= A^\dagger A(I + \Delta) \\ &= (I + A^\dagger \Delta) \end{aligned}$$

#### 4.40 (ii)

Note,  $\text{rank}(XY) < \text{rank}(X)$ . Thus,  $\exists \mathbf{v}$  s.t.  $XY\mathbf{v} = 0$ , but  $X\mathbf{v} \neq 0$ . Therefore  $\mathbf{v} \in \mathcal{N}(Y)$ , which is non-trivial, thus  $Y$  is not invertible.

#### 4.40 (iii)

Suppose  $A + \Delta$  has rank  $s < r$ . Thus, by (i) and (ii),

$$\text{rank}(A + \Delta) = \text{rank}(A(I + A^\dagger \Delta))$$

and by Thm. 4.6.7

$$\|\Delta\|_2 \geq \sigma_r$$