

# Problem Set #1:

1. Let  $A$  be square invertible matrix,  $\alpha$  scalar,  $u$  vector. Simplify  $(A + \alpha uu^H)^{-1}$ .

Lemma:  $(B^{-1} + CD^{-1}C^H)^{-1} = B - BC(D + C^HB C)^{-1}C^HB$

Let  $B^{-1} = A$  or  $B = A^{-1}$ ,  $D^{-1} = \alpha$  or  $D = \frac{1}{\alpha}$ ,  $C = u$ ,  $C^H = u^H$

$(B^{-1} + CD^{-1}C^H)^{-1} = (A + \alpha uu^H)^{-1} \rightarrow$  apply lemma

$$(A + \alpha uu^H)^{-1} = A^{-1} - A^{-1}u \left( \frac{1}{\alpha} + u^H A^{-1}u \right)^{-1} u^H A^{-1}$$

$$= A^{-1} - \left( \frac{1}{\alpha} + u^H A^{-1}u \right)^{-1} A^{-1}uu^H A^{-1}$$

Take special case  $A = \delta I$ . Simplify the expression and determine the condition  $\alpha$  for this to be invertible.

$$(\delta I + \alpha uu^H)^{-1} = \frac{1}{\delta} I - \left( \frac{1}{\alpha} + \frac{1}{\delta} u^H u \right)^{-1} \left( \frac{1}{\delta} \right) I uu^H \left( \frac{1}{\delta} \right) I$$

$$= \left( \frac{1}{\delta} \right) I - \frac{1}{\delta^2} \left( \frac{\delta + \alpha u^H u}{\alpha \delta} \right)^{-1} uu^H$$

$$= \left( \frac{1}{\delta} \right) I - \frac{\alpha}{\delta (\delta + \alpha u^H u)} uu^H$$

$$\delta + \alpha u^H u \neq 0 \Leftrightarrow \alpha u^H u \neq -\delta \Leftrightarrow \alpha \neq -\delta (u^H u)^{-1}$$

2. Let  $\{u_i\}_{i=1}^r$  lin. indep.  $M \times 1$  vects,  $\{v_i\}_{i=1}^r$  lin. indep.  $N \times 1$

Show that  $M \times N$  matrix  $A = \sum_{i=1}^r u_i v_i^H$  has rank  $r$  exactly.

$$\left[ \sum_{i=1}^r (u_i v_i^H) \right] x = 0 \Leftrightarrow v_i^H x = 0 \forall i \Leftrightarrow x \in (\text{span}\{v_i\}_{i=1}^r)^\perp$$

So  $N_A = (\text{span}\{v_i\}_{i=1}^r)^\perp$ ,  $N_A^\perp = \text{span}\{v_i\}_{i=1}^r$ ,  $r$ -dimensional

$\therefore N_A^\perp, R_A$  are  $r$ -dim,  $A$  is rank  $r$

3. Let  $x, u$  be  $M \times 1$  col. vects. Find optimal  $\alpha$  s.t.  $x \approx \alpha u$ .

(a) Find  $u^H$ , show that  $\alpha = \frac{\langle x, u \rangle}{|u|^2}$

$$x = u\alpha \rightarrow u^H x = u^H u \alpha \rightarrow \alpha = \frac{u^H x}{u^H u} = \frac{\langle x, u \rangle}{|u|^2}$$

( $M \times 1$ ) ( $M \times 1$ ) ( $1 \times 1$ )

(b) Let  $D = \text{diag}\{d_i\}$

$$[DA]_{ij} = \sum_{k=1}^N d_{ik} a_{kj} = d_{ii} a_{ij} \leftarrow \text{scales rows}$$

$$[AD]_{ij} = \sum_{k=1}^N a_{ik} d_{kj} = a_{ij} d_{jj} \leftarrow \text{scales cols}$$

$DA$  scales the rows,  $AD$  scales the columns

switched  $u$  to  $A$  b/c notation was easier

(c) Let  $A \in \mathbb{C}^{M \times N}$  with orthogonal columns  $\{a_i\}$ . Find the SVD of  $A$ , use that to find  $A^H$ , use this to find  $\{x_i\}$  s.t.  $x \approx \sum \alpha_i a_i$

$$A^H A = V \Sigma U^H U \Sigma V^H = V \Sigma^2 V^H$$

$$\begin{bmatrix} a_1^H \\ \vdots \\ a_N^H \end{bmatrix} \begin{bmatrix} a_1 & \dots & a_N \end{bmatrix} = \begin{bmatrix} |a_1|^2 & & \\ & |a_2|^2 & \\ & & \ddots & |a_N|^2 \end{bmatrix}$$

$M \times 1$  col. vect

$$V = I_{(N \times N)}, \quad \Sigma = \begin{bmatrix} |a_1| & |a_2| & \dots & |a_N| \end{bmatrix} \quad \leftarrow \text{by inspection}$$

$$A = U \Sigma V^H \rightarrow AV = U \Sigma \rightarrow A v_i = \sigma_i u_i \rightarrow u_i = \frac{A v_i}{\sigma_i}$$

$$u_i = \frac{A e_i}{|a_i|} = \frac{a_i}{|a_i|} \rightarrow U = \begin{bmatrix} \frac{a_1}{|a_1|} & \dots & \frac{a_N}{|a_N|} \end{bmatrix}$$

$\uparrow_{M \times 1}$

$$A^H = (A^H A)^{-1} A^H = \begin{bmatrix} \frac{1}{|a_1|^2} & \dots & \frac{1}{|a_N|^2} \end{bmatrix} \begin{bmatrix} a_1^H \\ \vdots \\ a_N^H \end{bmatrix}$$

$$= \begin{bmatrix} \frac{a_1^H / |a_1|^2}{a_N^H / |a_N|^2} \end{bmatrix}$$

$$x \approx \sum \alpha_i a_i = A \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix} \rightarrow \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix} \approx A^H x$$

$$\begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_N \end{bmatrix} = \begin{bmatrix} \frac{a_1^H x / |a_1|^2}{a_N^H x / |a_N|^2} \end{bmatrix} x = \begin{bmatrix} \frac{a_1^H x / |a_1|^2}{a_N^H x / |a_N|^2} \end{bmatrix}$$

\*  $P$  is an orthogonal projection?  
 $\alpha_i = \frac{a_i^H x}{|a_i|^2} = \frac{\langle x, a_i \rangle}{|a_i|^2}$  (consistent with part b)

4. Let  $U$  be a linear subspace of  $\mathbb{C}^M$ ,  $P$  be the  $M \times M$  projection onto  $U$ .  $P = P^H$  and  $P = P^2$ .

(a) Prove the converse: If  $P$  is  $M \times M$  Hermitian with  $P = P^2$ , then it is the projection matrix onto a subspace.

$$\forall x, y, \quad \langle (I-P)y, (I-P)x \rangle = y^H (I-P^H) P x = (y^H y^H P) (P x)$$

$$= y^H P x - y^H P^2 x = 0 \rightarrow R_P \text{ and } R_{I-P} \text{ are orthogonal}$$

$$\forall v \in \mathbb{C}^M, \quad v = v_1 + v_2, \quad v_1 \in R_P, \quad v_2 \in R_{I-P} \text{ or } v_1 = P x_1$$

$$v_2 = (I-P)x_2 \text{ for some } x_1, x_2$$

$$P v = P(v_1 + v_2) = P v_1 + P v_2 = P(P x_1) + P(I-P)x_2$$

$$= P^2 x_1 + P x_2 - P^2 x_2 = P x_1 + P x_2 - P x_2 = P x_1 = v_1$$

So  $P$  is an orthogonal projection onto  $U$

(b) Let  $P =$  orth. projection onto  $U$ .  $H = I - 2P$ . Consider  $x = x_1 + x_2$ ,  $x_1 \in U$ ,  $x_2 \in U^\perp$ . Express  $Hx$  in terms of  $x_1$  and  $x_2$ .

$$Hx = (I - 2P)x = x - 2Px = (x_1 + x_2) - 2x_1 = x_2 - x_1$$