

# NLA sheet1 solutions for problems 8,9

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Problem 8 Let  $B$  be a square  $n \times n$  matrix. Bound the  $i$ th singular values of  $AB$  using  $\sigma_i(A)$  and  $\sigma_i(B)$ : Specifically, prove that for each  $i$ ,

$$\sigma_i(A)\sigma_n(B) \leq \sigma_i(AB) \leq \sigma_i(A)\sigma_1(B).$$

(Solution:) By the Courant-Fisher theorem for singular values  $\sigma_i(AB) = \max_{Q \in \mathbb{R}^{n \times n}, Q^T Q = I_i} \min_{\|x\|=1} \|x^* Q A B\|_2$ . For any fixed vector  $y^*(= x^* Q A)$ , we have  $\|y^* B\|_2 \leq \|y^*\|_2 \|B\|_2$  (via C-F or directly via the SVD). Thus

$$\sigma_i(AB) = \max_{Q \in \mathbb{R}^{n \times n}, Q^T Q = I_i} \min_{\|x\|=1} \|x^* Q A B\|_2 \leq \max_{Q \in \mathbb{R}^{n \times n}, Q^T Q = I_i} \min_{\|x\|=1} \|x^* Q A\|_2 \|B\|_2 = \sigma_i(A)\sigma_1(B).$$

For the lower bound we use the fact  $\sigma_{\min}(B) = \min_{\|x\|_2=1} \|x^* B\|_2$  (again via C-F or directly via the SVD), hence  $\|x^* Q A B\|_2 \geq \|x^* Q A\|_2 \sigma_{\min}(B)$  for any fixed  $x$ , to obtain

$$\sigma_i(AB) = \max_{Q \in \mathbb{R}^{n \times n}, Q^T Q = I_i} \min_{\|x\|=1} \|x^* Q A B\|_2 \geq \max_{Q \in \mathbb{R}^{n \times n}, Q^T Q = I_i} \min_{\|x\|=1} \|x^* Q A\|_2 \sigma_{\min}(B) = \sigma_i(A)\sigma_n(B).$$

Problem 9 (optional; harder) Let  $A \in \mathbb{R}^{m \times n}$ ,  $m \geq n$  and  $\sigma_1(A) \geq \sigma_2(A) \geq \dots \geq \sigma_n(A) \geq 0$  be its singular values. Prove that for  $k = 1, 2, \dots, n$ ,

$$\sum_{i=1}^k \sigma_i(A) = \max_{Q^T Q = I_k, W^T W = I_k} \text{trace}(Q^T A W).$$

( $Q \in \mathbb{R}^{m \times k}$ ,  $W \in \mathbb{R}^{n \times k}$  are orthonormal. Recall for an  $k \times k$  matrix  $B$ ,  $\text{trace}(B) = \sum_{i=1}^k B_{ii}$ ; a useful property is  $\text{trace}(CD) = \text{trace}(DC)$  as long as  $CD$  is square.)

(solution:) Equality is seen to be attained when  $Q = [u_1, u_2, \dots, u_k]$ ,  $W = [v_1, \dots, v_k]$ , since then  $\text{trace}(Q^T A W) = \text{trace}(\text{diag}(\sigma_1(A), \dots, \sigma_k(A))) = \sum_{i=1}^k \sigma_i(A)$ . We need to prove this is an upper bound for  $\text{trace}(Q^T A W)$ . First note that  $\sigma_i(AB) \leq \sigma_i(A)\|B\|$  holds for any  $A, B$  s.t.  $AB$  is defined (e.g. via Courant-Fisher). Now since  $Q, W$  are orthonormal,  $\sigma_i(Q) = \sigma_i(W) = 1$  for all  $i = 1, \dots, k$ . We thus have  $\sigma_i(Q^T A W) \leq \sigma_i(A)$  for all  $i$ . We are thus done if we prove  $\text{trace}(B) \leq \sum_{i=1}^k \sigma_i(B)$  for any  $k \times k$  matrix  $B$ . Let  $B = U_B \Sigma_B V_B^T$  be the SVD. Then  $\text{trace}(B) = \text{trace}(U_B \Sigma_B V_B^T) = \text{trace}(\Sigma_B V_B^T U_B) = \sum_{i=1}^k \sigma_i(B) (V_B^T U_B)_{ii} \leq \sum_{i=1}^k \sigma_i$ , because  $V_B^T U_B$  is orthogonal and so its entries are bounded by 1 in absolute value.