

# Exercises: Linear Algebra Recall (for Optimization)

## 1. Diagonalization and spectrum

**Exercise 1** (Spectrum and invertibility). Let  $A \in \mathbb{R}^{n \times n}$ .

- (a) Show that  $A$  is invertible if and only if  $0 \notin \sigma(A)$ .
- (b) Show that if  $A$  is invertible then every eigenvalue of  $A^{-1}$  is of the form  $1/\lambda$  where  $\lambda \in \sigma(A)$ .

**Exercise 2** (Distinct eigenvalues  $\Rightarrow$  diagonalizable). Assume  $A \in \mathbb{R}^{n \times n}$  has  $n$  distinct real eigenvalues. Show that  $A$  is diagonalizable over  $\mathbb{R}$ .

**Exercise 3** (Orthogonal diagonalization is special). Give an example of a diagonalizable (real) matrix  $A$  that is not orthogonally diagonalizable (i.e., there is no orthogonal  $Q$  with  $A = Q\Lambda Q^\top$ ).

## 2. PSD order and spectral theorem

**Exercise 4** (Loewner order is a partial order). On  $S_n$  (real symmetric matrices), define  $A \preceq B$  iff  $B - A \succeq 0$ . Show that  $\preceq$  is a partial order on  $S_n$  (reflexive, antisymmetric, transitive).

**Exercise 5** (PSD/PD and eigenvalues). Let  $A \in S_n$  with spectral decomposition  $A = Q\Lambda Q^\top$ .

- (a) Prove  $A \succeq 0$  if and only if all eigenvalues satisfy  $\lambda_i \geq 0$ .
- (b) Prove  $A \succ 0$  if and only if all eigenvalues satisfy  $\lambda_i > 0$ .
- (c) Assume  $A \succeq 0$ . Define  $A^{1/2} = Q\Lambda^{1/2}Q^\top$  with  $\Lambda^{1/2} = \text{diag}(\sqrt{\lambda_i})$ . Show that  $A^{1/2}A^{1/2} = A$ .

**Exercise 6** (Rayleigh quotient extrema). Let  $A \in S_n$  and define  $R_A(x) = \frac{x^\top Ax}{x^\top x}$  for  $x \neq 0$ . Show that

$$\lambda_{\min}(A) = \min_{\|x\|_2=1} x^\top Ax, \quad \lambda_{\max}(A) = \max_{\|x\|_2=1} x^\top Ax$$

**Exercise 7** (Eigenvalue bounds from PSD order). Let  $A, B \in S_n$  and assume  $A \preceq B$ . Prove that  $\lambda_{\min}(A) \leq \lambda_{\min}(B)$  and  $\lambda_{\max}(A) \leq \lambda_{\max}(B)$ .

## 3. Orthogonal projectors

**Exercise 8** (Projector onto a subspace given an orthonormal basis). Let  $Q \in \mathbb{R}^{n \times k}$  have orthonormal columns ( $Q^\top Q = I_k$ ). Define  $P = QQ^\top$ .

- (a) Prove that  $P$  is an orthogonal projector.
- (b) Prove that  $\text{Im}(P) = \text{Im}(Q)$ .
- (c) Show that for all  $x$ ,  $Px$  is the unique minimizer of  $\min_{y \in \text{Im}(Q)} \|x - y\|_2$ .

**Exercise 9** (Projection onto a hyperplane). Let  $a \in \mathbb{R}^n$  with  $a \neq 0$  and consider the hyperplane  $H = \{x \in \mathbb{R}^n : a^\top x = b\}$ .

- (a) Show that the Euclidean projection of  $x_0$  onto  $H$  is

$$\Pi_H(x_0) = x_0 - \frac{a^\top x_0 - b}{\|a\|_2^2} a.$$

- (b) Deduce the projector onto the subspace  $\{x : a^\top x = 0\}$ .

## 4. Norms and inner products

**Exercise 10** (Norm inequalities). Let  $x \in \mathbb{R}^n$ . Prove

$$\|x\|_\infty \leq \|x\|_2 \leq \|x\|_1 \leq \sqrt{n} \|x\|_2 \leq n \|x\|_\infty.$$

**Exercise 11** (Cauchy–Schwarz equality case). Let  $\langle \cdot, \cdot \rangle$  be an inner product and  $\|x\| = \sqrt{\langle x, x \rangle}$ . Prove that for  $x \neq 0$  and  $y \neq 0$ , equality in  $|\langle x, y \rangle| \leq \|x\| \|y\|$  holds if and only if  $y = \alpha x$  for some  $\alpha \in \mathbb{R}$ .

**Exercise 12** ( $\|\cdot\|_Q$  norm and eigenvalue bounds).

Let  $Q \in S_n^+$  and define  $\|x\|_Q := \sqrt{x^\top Q x}$ .

- (a) Show that  $\|\cdot\|_Q$  is a norm if and only if  $Q \succ 0$ .  
 (b) Assume  $Q \succ 0$ . Show that

$$\|x\|_Q \leq \sqrt{\lambda_{\max}(Q)} \|x\|_2, \quad \|x\|_2 \leq \frac{1}{\sqrt{\lambda_{\min}(Q)}} \|x\|_Q.$$

**5. Dual norms and operator norms**

**Exercise 13** (Dual norm basics). Let  $\|\cdot\|$  be a norm and define its dual norm by  $\|y\|_\star := \sup_{\|x\| \leq 1} y^\top x$ .

- (a) Prove the generalized Cauchy–Schwarz inequality:  $|y^\top x| \leq \|y\|_\star \|x\|$ .  
 (b) Compute the duals of  $\|\cdot\|_2$ ,  $\|\cdot\|_1$ , and  $\|\cdot\|_\infty$ .

**Exercise 14** (Induced operator norm). Given a vector norm  $\|\cdot\|$ , define

$$\|A\|_{op} := \sup_{x \neq 0} \frac{\|Ax\|}{\|x\|}.$$

- (a) Show that  $\|A\|_{op} = \sup_{\|x\| \leq 1} \|Ax\|$ .  
 (b) Prove submultiplicativity:  $\|AB\|_{op} \leq \|A\|_{op} \|B\|_{op}$ .  
 (c) For the Euclidean norm, show that  $\|A\|_2^2 = \lambda_{\max}(A^\top A)$ .

**6. Linear systems and factorizations**

**Exercise 15** (LU and triangular solves). Assume  $A = LU$  with  $L$  lower triangular and  $U$  upper triangular, both invertible. Show that solving  $Ax = b$  reduces to two triangular solves.

**Exercise 16** (Cholesky and SPD). (a) Let  $A \in S_n$  and assume  $A = LL^\top$  for some invertible lower triangular  $L$ . Prove that  $A \succ 0$ .

- (b) Compute the Cholesky factorization of  $A = \begin{pmatrix} 4 & 2 \\ 2 & 3 \end{pmatrix}$ .

(c) Reuse your factorization to solve  $Ax = b$  for  $b = (2, 1)^\top$  and for  $b = (0, 1)^\top$ .

**7. Least squares problems**

**Exercise 17** (Solve least squares via thin QR).

Let  $A \in \mathbb{R}^{m \times n}$  with  $m \geq n$  and assume  $A$  has full column rank. Let  $A = QR$  be a thin QR factorization with  $Q \in \mathbb{R}^{m \times n}$ ,  $Q^\top Q = I_n$ , and  $R \in \mathbb{R}^{n \times n}$  upper triangular (hence invertible).

Let  $P := QQ^\top$ . Prove the identity

$$\|Ax - b\|_2^2 = \|Rx - Q^\top b\|_2^2 + \|(I - P)b\|_2^2 \quad \forall x \in \mathbb{R}^n.$$

- (b) Deduce that the unique minimizer of  $\min_x \|Ax - b\|_2^2$  satisfies

$$Rx^\star = Q^\top b,$$

and explain why this can be solved by backward substitution.

**Exercise 18** (Normal equations square the conditioning). Assume  $A \in \mathbb{R}^{m \times n}$  has full column rank. Recall  $\kappa_2(A) = \|A\|_2 \|A^\dagger\|_2$  (where  $A^\dagger = (A^\top A)^{-1} A^\top$ ) and  $\kappa_2(A^\top A) = \|A^\top A\|_2 \|(A^\top A)^{-1}\|_2$ .

- (a) Show that  $\|A^\top A\|_2 = \|A\|_2^2$ .  
 (b) Show that  $\|(A^\top A)^{-1}\|_2 = \|A^\dagger\|_2^2$  and deduce  $\kappa_2(A^\top A) = \kappa_2(A)^2$ .

(c) Interpret why this suggests avoiding normal equations in finite precision.

**8. SVD, conditioning, and numerical stability**

**Exercise 19** (SVD on a simple matrix). Let  $A =$

$$\begin{pmatrix} 1 & 0 \\ 0 & \varepsilon \end{pmatrix} \text{ with } \varepsilon > 0.$$

- (a) Compute the singular values of  $A$ .  
 (b) Compute  $\kappa_2(A)$ .