

# EE 127/227A Midterm Review Problems

EE 127/227AT: Optimization Models in Engineering

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## Problem (“Convexity”, Spring 2023 Midterm)

- (a) Let  $f : \mathbb{R} \rightarrow \mathbb{R}$  be a convex function. Fix  $a, b \in \mathbb{R}$ . Prove that for any  $x \in [a, b]$ :

$$f(x) \leq \frac{b-x}{b-a}f(a) + \frac{x-a}{b-a}f(b).$$

This problem is from [Boyd and Vandenberghe, Problem 1 a].

- (b) Let  $n$  be a positive integer. The *probability simplex* on  $\mathbb{R}^n$ , denoted  $\mathcal{P}_n$ , is the set

$$\mathcal{P}_n = \left\{ \vec{x} \in \mathbb{R}^n \mid x_i \geq 0 \ \forall i, \sum_{i=1}^n x_i = 1 \right\} \quad \text{where} \quad \vec{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix}. \quad (0.1)$$

Is  $\mathcal{P}_n$  convex? If yes, prove it. If no, justify your answer using an example.

## Problem (“Shift Matrix”, Spring 2023 Midterm)

Let  $V \in \mathbb{R}^{n \times n}$  be a square orthonormal matrix, i.e., its columns are orthogonal and have norm 1:

$$V = \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow & \uparrow \\ \vec{v}_1 & \vec{v}_2 & \dots & \vec{v}_{n-1} & \vec{v}_n \\ \downarrow & \downarrow & \dots & \downarrow & \downarrow \end{bmatrix}. \quad (0.2)$$

Now, we define the shifted matrix  $W \in \mathbb{R}^{n \times n}$ , which is composed of the columns of  $V$  shifted to the left by 1 index and padded by a zero vector:

$$W = \begin{bmatrix} \uparrow & \uparrow & \dots & \uparrow & \uparrow \\ \vec{v}_2 & \vec{v}_3 & \dots & \vec{v}_n & \vec{0} \\ \downarrow & \downarrow & \dots & \downarrow & \downarrow \end{bmatrix}. \quad (0.3)$$

- (a) What is  $\text{rank}(V)$ ? What about  $\text{rank}(W)$ ? *You do not need to justify your answers.*
- (b) Find a basis for the null space of  $V - W$  and compute  $\text{rank}(V - W)$ . *Show your work.*

## Problem (“Singular value decomposition”, Spring 2019 Midterm 1)

(13 points) The compact form of the singular value decomposition of a matrix  $A \in \mathbb{R}^{3 \times 3}$  is given as

$$A = \begin{bmatrix} \frac{2}{3} & \frac{1}{\sqrt{2}} \\ \frac{2}{3} & -\frac{1}{\sqrt{2}} \\ \frac{1}{3} & 0 \end{bmatrix} \begin{bmatrix} 3 & 0 \\ 0 & 2 \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & -\frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{6}} & \frac{1}{\sqrt{6}} & -\frac{2}{\sqrt{6}} \end{bmatrix}$$

- (a) (2 points) What is the rank of  $A$ ? Justify.
- (b) (3 points) What is the dimension of the column space (range) of  $A$ ? Write a basis for the column space (range) of  $A$ .
- (c) (4 points) What is the dimension of the null space of  $A^\top$ ? Write a basis for the null space of  $A^\top$ .
- (d) (4 points) Let  $\mathcal{B}_2$  denote the unit-norm ball in  $\ell_2$  norm:  $\mathcal{B}_2 := \{\vec{z} \in \mathbb{R}^3 : \|\vec{z}\|_2 \leq 1\}$ . Compute the minimum value of  $\vec{x}^\top A \vec{y}$ , where  $\vec{x}$  and  $\vec{y}$  are two vectors in  $\mathcal{B}_2$ ; that is, find  $\min_{\vec{x}, \vec{y} \in \mathcal{B}_2} \vec{x}^\top A \vec{y}$ .

## Problem (“All I need is Q”, Spring 2020 Midterm)

(22 points) Consider a partially known matrix  $A \in \mathbb{R}^{3 \times 2}$ , given by

$$A = \begin{bmatrix} ? & 1 \\ ? & 1 \\ ? & 1 \end{bmatrix}$$

where question marks denote unknown entries of  $A$ . We can write the compact QR decomposition of  $A$  in terms of  $Q_1 \in \mathbb{R}^{3 \times 2}$  and  $R_1 \in \mathbb{R}^{2 \times 2}$  as

$$A = Q_1 R_1 = \begin{bmatrix} 1 & q_{12} \\ 0 & q_{22} \\ 0 & q_{23} \end{bmatrix} \begin{bmatrix} ? & r_{12} \\ 0 & r_{22} \end{bmatrix} \quad (0.4)$$

for some unknown entry ‘?’ and entries  $r_{12}$ ,  $r_{22}$ ,  $q_{12}$ ,  $q_{22}$ , and  $q_{23}$ , which you will calculate below. Remember that the columns of  $Q_1$  are orthonormal. Note that the ‘?’ entries of  $A$  and  $R_1$  are unknown and will remain unknown; you are NOT required to compute them.

- (a) (5 points) Suppose  $r_{22} > 0$ . **Compute**  $r_{12}$ ,  $r_{22}$ ,  $q_{12}$ ,  $q_{22}$ , **and**  $q_{23}$ . Show all your work.
- (b) (12 points) Suppose we can write the full QR decomposition of  $A$  as

$$A = QR = [Q_1 \quad Q_2] \begin{bmatrix} R_1 \\ \vec{0}_{1 \times 2} \end{bmatrix}, \quad (0.5)$$

where  $Q_1$  and  $R_1$  are as defined in Equation (0.4). Consider the least-squares problem:

$$p^* = \min_{\vec{x} \in \mathbb{R}^2} \|A\vec{x} - \vec{b}\|_2^2$$

for  $A$  given in Equation (0.4) and some  $\vec{b} \in \mathbb{R}^3$ . Consider the following two ways of rewriting this least squares problem in terms of  $Q_1$ ,  $Q_2$ , and  $R_1$ :

**Strategy 1:**

$$\begin{aligned} \|\vec{b} - A\vec{x}\|_2^2 &\stackrel{(I)}{=} \|Q^\top \vec{b} - Q^\top A\vec{x}\|_2^2 \\ &= \|Q_1^\top \vec{b} - R_1 \vec{x}\|_2^2 + \|Q_2^\top \vec{b}\|_2^2. \end{aligned}$$

**Strategy 2:**

$$\begin{aligned} \|\vec{b} - A\vec{x}\|_2^2 &= \|\vec{b} - Q_1 R_1 \vec{x}\|_2^2 \\ &\stackrel{(II)}{=} \|\vec{Q}_1^\top \vec{b} - Q_1^\top Q_1 R_1 \vec{x}\|_2^2 \\ &\stackrel{(III)}{=} \|\vec{Q}_1^\top \vec{b} - R_1 \vec{x}\|_2^2 \end{aligned}$$

**Determine whether the following labeled steps in the reformulations above are correct or incorrect and justify your answer.** When evaluating the correctness of an equality, consider only that specific equality’s correctness—i.e., ignore all earlier steps.

- (i) Equality (I):  $\|\vec{b} - A\vec{x}\|_2^2 \stackrel{(I)}{=} \|Q^\top \vec{b} - Q^\top A\vec{x}\|_2^2$ .
- (ii) Equality (II):  $\|\vec{b} - Q_1 R_1 \vec{x}\|_2^2 \stackrel{(II)}{=} \|\vec{Q}_1^\top \vec{b} - Q_1^\top Q_1 R_1 \vec{x}\|_2^2$ .
- (iii) Equality (III):  $\|\vec{Q}_1^\top \vec{b} - Q_1^\top Q_1 R_1 \vec{x}\|_2^2 \stackrel{(III)}{=} \|\vec{Q}_1^\top \vec{b} - R_1 \vec{x}\|_2^2$ .
- (c) (5 points) Now consider a different matrix  $A = QR$ , unrelated to the matrix  $A$  in previous parts. Here, let

$$Q = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 0 & 1 \\ 0 & 1 & 0 \end{bmatrix},$$

$$R = \begin{bmatrix} R_1 \\ \vec{0}_{1 \times 2} \end{bmatrix}$$

where  $R \in \mathbb{R}^{3 \times 2}$  and  $R_1 \in \mathbb{R}^{2 \times 2}$  is a completely unknown **invertible** upper triangular matrix. Let

$$\vec{b} = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}.$$

Again consider the least squares optimization problem:

$$p^* = \min_{\vec{x} \in \mathbb{R}^2} \|A\vec{x} - \vec{b}\|_2^2.$$

**Find the optimal value  $p^*$ .** Your answer should be a real number; it should NOT be an expression involving  $A, Q, R, R_1$ , or  $\vec{b}$ .

## Problem (“Vector Calculus”, Spring 2023)

1. Let  $A \in \mathbf{R}^{n \times n}$  be an  $n \times n$  symmetric matrix. Compute the gradient with respect to  $\vec{x}$  of the function  $f: \mathbb{R}^n \setminus \{\vec{0}\} \rightarrow \mathbb{R}$  given by:

$$f(\vec{x}) \doteq \frac{\vec{x}^\top A \vec{x}}{\vec{x}^\top \vec{x}}. \quad (0.6)$$

*Hint:* Recall the quotient rule for finding the gradient of  $h(\vec{x}) = \frac{n(\vec{x})}{d(\vec{x})}$  where  $n$  and  $d$  are scalar-valued functions:

$$\nabla h(\vec{x}) = \frac{d(\vec{x})\nabla n(\vec{x}) - n(\vec{x})\nabla d(\vec{x})}{(d(\vec{x}))^2}. \quad (0.7)$$

2. Let  $\vec{u} \in \mathbb{R}^n$ . Compute the Jacobian with respect to  $\vec{x}$  of the function  $\vec{g}: \mathbb{R}^n \rightarrow \mathbb{R}^n$  given by

$$\vec{g}(\vec{x}) \doteq \vec{x}(\vec{x}^\top \vec{u}). \quad (0.8)$$

## Problem (“Low-rank Matrix Completion”, Spring 2023)

Consider a matrix  $A \in \mathbb{R}^{m \times n}$ . If some entries are corrupted, one principled way to identify  $A$  is to find the matrix  $B \in \mathbb{R}^{m \times n}$  of minimal rank that agrees with  $A$  on all known entries. This can be formulated as an optimization problem whose objective function is  $\text{rank}(B)$ . Because the  $\text{rank}(\cdot)$  function is not continuous, we use the intuition that a low-rank matrix will only have a few nonzero singular values, and instead use the sum-of-singular-values function as the objective:

$$f(B) \doteq \sum_{i=1}^{\text{rank}(B)} \sigma_i\{B\} \quad (0.9)$$

where  $\sigma_i\{B\}$  is the  $i^{\text{th}}$  largest singular value of  $B$ . In this problem we will explore some properties of  $f$ .

(a) **Prove that**

$$f(B) \leq \max_{\substack{C \in \mathbb{R}^{m \times n} \\ \|C\|_2 \leq 1}} \text{Tr}(C^\top B). \quad (0.10)$$

*Hint.* Expand  $B$  into its SVD. Try to find a  $D \in \mathbb{R}^{m \times n}$  such that  $\|D\|_2 = 1$  and  $\text{Tr}(D^\top B) = f(B)$ .

*Hint.* You may use the cyclic property of traces *without proof*. If  $XYZ$  and  $ZXY$  are valid matrix products then  $\text{Tr}(XYZ) = \text{Tr}(ZXY)$ .

(b) **Prove that**

$$f(B) \geq \max_{\substack{C \in \mathbb{R}^{m \times n} \\ \|C\|_2 \leq 1}} \text{Tr}(C^\top B). \quad (0.11)$$

*Hint.* Let  $r \doteq \text{rank}(B)$  and expand  $B$  into its *outer product* SVD, i.e.,  $B = \sum_{i=1}^r \sigma_i\{B\} \vec{u}_i \vec{v}_i^\top$ .

*Hint.* You may use the cyclic and linearity properties of traces *without proof*. If  $XYZ$  and  $ZXY$  are valid matrix products then  $\text{Tr}(XYZ) = \text{Tr}(ZXY)$ . Also,  $\text{Tr}(\alpha X + \beta Y) = \alpha \text{Tr}(X) + \beta \text{Tr}(Y)$  for  $\alpha, \beta \in \mathbb{R}$ .

## Optional Problem (“Symmetric Matrices”, Spring 2023)

1. Let  $A \in \mathbf{R}^{n \times n}$  be a square matrix. Prove that if  $A$  is symmetric then  $A^{2k}$  is symmetric positive semidefinite for all integers  $k > 1$ .
2. Prove that if  $A \in \mathbf{R}^{n \times n}$  is symmetric then its *matrix exponential*, defined as  $e^A \in \mathbf{R}^{n \times n}$  given by

$$e^A = I + A + \frac{1}{2}A^2 + \cdots = \sum_{k=0}^{\infty} \frac{1}{k!}A^k \quad (0.12)$$

is symmetric positive definite.