

This homework is due at 11 PM on February 2, 2024.

Submission Format: Your homework submission should consist of a single PDF file that contains all of your answers (any handwritten answers should be scanned).

1. Miscellaneous

- (a) Let m, n be positive integers where $m \geq n$, and let $U \in \mathbb{R}^{m \times n}$ be an orthonormal matrix (i.e., having orthonormal columns). Show that for any $\vec{x} \in \mathbb{R}^n$ we have

$$\|U\vec{x}\|_2 = \|\vec{x}\|_2. \quad (1)$$

- (b) Using the Gram-Schmidt process, find an orthonormal basis $\{\vec{v}_1, \vec{v}_2, \vec{v}_3\}$ of \mathbb{R}^3 , where

$$\vec{v}_1 = \begin{bmatrix} 1/\sqrt{2} \\ 1/\sqrt{2} \\ 0 \end{bmatrix}. \quad (2)$$

2. Diagonalization and Singular Value Decomposition

Let matrix $A = \begin{bmatrix} 0 & 1 \\ \frac{1}{2} & \frac{1}{2} \end{bmatrix}$.

- (a) Compute the eigenvalues and associated eigenvectors of A .
- (b) Express A as $P\Lambda P^{-1}$, where Λ is a diagonal matrix and $PP^{-1} = I$. State P , Λ , and P^{-1} explicitly.
- (c) Compute $\lim_{k \rightarrow \infty} A^k$.
- (d) Give the singular values σ_1 and σ_2 of A .

3. Distinct Eigenvalues, Orthogonal Eigenspaces

Let $A \in \mathbb{S}^n$ (i.e., the set of $n \times n$ symmetric matrices) and $(\lambda_1, \vec{u}_1), (\lambda_2, \vec{u}_2), \lambda_1 \neq \lambda_2$ be distinct eigen-pairs of A . Show that $\vec{u}_1^\top \vec{u}_2 = 0$, i.e., eigenspaces corresponding to distinct eigenvalues are mutually orthogonal.

HINT: First try to prove that $\lambda_1 \vec{u}_1^\top \vec{u}_2 = \lambda_2 \vec{u}_1^\top \vec{u}_2$, then show that this implies $\vec{u}_1^\top \vec{u}_2 = 0$.

NOTE: This exercise is part of the proof of the spectral theorem.

4. Gram Schmidt

Any set of n linearly independent vectors in \mathbb{R}^n could be used as a basis for \mathbb{R}^n . However, certain bases could be more suitable for certain operations than others. For example, an orthonormal basis could facilitate solving linear equations.

- (a) Given a matrix $A \in \mathbb{R}^{n \times n}$, it could be represented as a multiplication of two matrices

$$A = QR, \quad (3)$$

where $Q \in \mathbb{R}^{n \times n}$ is an orthonormal matrix and $R \in \mathbb{R}^{n \times n}$ is an upper-triangular matrix. For the matrix A , describe how Gram-Schmidt process could be used to find the Q and R matrices, and apply this to

$$A = \begin{bmatrix} 3 & -3 & 1 \\ 4 & -4 & -7 \\ 0 & 3 & 3 \end{bmatrix} \quad (4)$$

to find an orthonormal matrix Q and an upper-triangular matrix R .

- (b) Given an invertible matrix $A \in \mathbb{R}^{n \times n}$ and an observation vector $\vec{b} \in \mathbb{R}^n$, the solution to the equality

$$A\vec{x} = \vec{b} \quad (5)$$

is given as $\vec{x} = A^{-1}\vec{b}$. For the matrix $A = QR$ from part (a), assume that we want to solve

$$A\vec{x} = \begin{bmatrix} 8 \\ -6 \\ 3 \end{bmatrix}. \quad (6)$$

By using the fact that Q is an orthonormal matrix, find \vec{v} such that

$$R\vec{x} = \vec{v}. \quad (7)$$

Then, given the upper-triangular matrix R in part (a) and \vec{v} , find the elements of \vec{x} sequentially.

- (c) Given an invertible matrix $B \in \mathbb{R}^{n \times n}$ and an observation vector $\vec{c} \in \mathbb{R}^n$, find the computational cost of finding the solution \vec{z} to the equation $B\vec{z} = \vec{c}$ by using the QR decomposition of B . Assume that Q and R matrices are available, and adding, multiplying, and dividing scalars take one unit of “computation”.

As an example, computing the inner product $\vec{a}^T \vec{b}$ is said to be $\mathcal{O}(n)$, since we have n scalar multiplication for each $a_i b_i$. Similarly, matrix vector multiplication is $\mathcal{O}(n^2)$, since matrix vector multiplication can be viewed as computing n inner products. The computational cost for inverting a matrix in \mathbb{R}^n is $\mathcal{O}(n^3)$, and consequently, the cost grows rapidly as the set of equations grows in size. This is why the expression $A^{-1}\vec{b}$ is usually not computed by directly inverting the matrix A . Instead, the QR decomposition of A is exploited to decrease the computational cost.

5. Eigenvectors of a Symmetric Matrix

Let $\vec{p}, \vec{q} \in \mathbb{R}^n$ be two linearly independent vectors, with unit norm ($\|\vec{p}\|_2 = \|\vec{q}\|_2 = 1$). Define the symmetric matrix $A := \vec{p}\vec{q}^\top + \vec{q}\vec{p}^\top$. In your derivations, it may be useful to use the notation $c := \vec{p}^\top \vec{q}$.

- (a) Show that A is symmetric.
- (b) Show that $\vec{p} + \vec{q}$ and $\vec{p} - \vec{q}$ are eigenvectors of A , and determine the corresponding eigenvalues.
- (c) Determine the nullspace and rank of A .
- (d) Find an eigenvalue decomposition of A , in terms of \vec{p}, \vec{q} . *HINT: Use the previous two parts.*

6. PSD Matrices

In this problem, we will analyze properties of positive semidefinite (PSD) matrices. A *symmetric* matrix $M \in \mathbb{R}^{n \times n}$ is a PSD matrix if $\vec{x}^\top M \vec{x} \geq 0$ for all $\vec{x} \in \mathbb{R}^n$, and we denote that as $M \succeq 0$ or $M \in \mathbb{S}_+^n$.

Assume $A \in \mathbb{R}^{n \times n}$ is a symmetric matrix.

- (a) Show that $A \succeq 0$ if and only if all eigenvalues of A are non-negative.
- (b) Show that if $A \succeq 0$ then all diagonal entries of A are non-negative, $A_{ii} \geq 0$.

Now we will show that $A \in \mathbb{S}_+^n$ (i.e., $A \in \mathbb{R}^{n \times n}$ and $A \succeq 0$) if and only if there exists $P \in \mathbb{S}_+^n$ such that $A = P^\top P = P^2$. Such a matrix P is known as a *PSD square root* of A .

- (c) First, show that if $A \in \mathbb{S}_+^n$, then there exists $P \in \mathbb{S}_+^n$ such that $A = P^2$.
- (d) Now, show that for any matrix $Q \in \mathbb{R}^{m \times n}$, if $A = Q^\top Q$ then $A \in \mathbb{S}_+^n$.

NOTE: If we take $Q = P \in \mathbb{S}_+^n$, we have $A = P^2 \in \mathbb{S}_+^n$; this proves the other direction of the above “if-and-only-if.”

We will use positive semidefinite matrices to construct the singular value decomposition (SVD). One can construct the SVD of a matrix $B \in \mathbb{R}^{m \times n}$ in two ways, using either the matrices $BB^\top \in \mathbb{R}^{m \times m}$ or $B^\top B \in \mathbb{R}^{n \times n}$, and usually one chooses the method depending on which matrix is smaller. The following result shows that the singular values will be the same no matter what construction you use.

- (e) Let $B \in \mathbb{R}^{m \times n}$ be an arbitrary matrix (not necessarily PSD or even square). From the previous parts of this problem, BB^\top and $B^\top B$ are PSD, thus having real non-negative eigenvalues. Prove that the non-zero eigenvalues of BB^\top are the same as the non-zero eigenvalues of $B^\top B$.

7. Homework Process

With whom did you work on this homework? List the names and SIDs of your group members.

NOTE: If you didn't work with anyone, you can put "none" as your answer.