## EE278 Statistical Signal Processing Stanford, Autumn 2023

## Homework 4

Due: Thursday, October 26, 2023, 1:30pm on Gradescope

Please upload your answers timely to Gradescope. Start a new page for every problem. For the programming/simulation questions you can use any reasonable programming language. Comment your source code and include the code and a brief overall explanation with your answers.

1. $\mathbf{1 0} \mathbf{~ p t s}$ As we discussed in class, all symmetric square real matrices have real eigenvalues and $n$ orthogonal eigenvectors.
a) ( $\mathbf{5} \mathbf{~ p t s}$ ) Give an example of a square real matrix which has no real eigenvalues.
b) ( 5 pts ) Give an example of a square real matrix whose eigenvectors cannot be chosen to be orthogonal.
2. ( $\mathbf{1 0} \mathbf{~ p t s}$ ) Exercise 3.8 in text.

Exercise 3.8 (a) Let $[K]=\left[\begin{array}{cc}0.75 & 0.25 \\ 0.25 & 0.75\end{array}\right]$. Show that 1 and $1 / 2$ are eigenvalues of $[K]$ and find the normalized eigenvectors. Express $[K]$ as $\left[Q \Lambda Q^{-1}\right.$ ], where $[\Lambda]$ is diagonal and [ $Q$ ] is orthonormal.
(b) Let $\left[K^{\prime}\right]=\alpha[K]$ for real $\alpha \neq 0$. Find the eigenvalues and eigenvectors of $\left[K^{\prime}\right]$. Do not use brute force - think!
(c) Find the eigenvalues and eigenvectors of $\left[K^{m}\right]$, where $\left[K^{m}\right]$ is the $m$ th power of $[K]$.
3. ( $\mathbf{1 5} \mathbf{~ p t s}$ ) Missing Proofs from the KL Expansion Discussion

We will first prove the following preliminary results:
(i) (1 pts) Prove that for two matrices $A \in \mathbb{R}^{n \times m}$ and $B \in \mathbb{R}^{m \times n}$, $\operatorname{Trace}(A B)=$ Trace (BA).
(ii) (2 pts) Suppose $V \in \mathbb{R}^{n \times k}, k \leq n$, and $V^{T} V=I_{k}$, that is the columns of $V$ are orthonormal in $\mathbb{R}^{n}$. (Note that $V$ is not $n \times n$ so $V V^{T}$ is not equal to the identity matrix.) Show that

$$
\left\|V^{T} \mathbf{a}\right\|^{2} \leq\|\mathbf{a}\|^{2} \quad \text { for all } \quad \mathbf{a} \in \mathbb{R}^{n} .
$$

By choosing the vector $\mathbf{a}=\mathbf{e}_{i}$, where $\mathbf{e}_{i}$ is the $i$ th column of the identity matrix, show that $0 \leq\left(V V^{T}\right)_{i i} \leq 1$ for all $1 \leq i \leq n$.
(iii) (1 pts) Given a non-negative integer $k$, and a positive integer $n \geq k$, let $P=\{\mathbf{x}=$ $\left.\left(x_{1}, \ldots, x_{n}\right): 0 \leq x_{i} \leq 1, \sum_{i} x_{i}=k\right\}$ ( $P$ is the subset of the $n$-dimensional unit cube on which the coordinates sum to $k$.) Suppose $c_{1} \geq \cdots \geq c_{n}$ are real numbers. Show that

$$
\max _{\mathbf{x} \in P} \sum_{i=1}^{n} c_{i} x_{i}=\sum_{i=1}^{k} c_{i} .
$$

We will next turn to proving one of the claims we stated in the lecture. Suppose $K \in$ $\mathbb{R}^{n \times n}$ is a real and symmetric matrix. We know that such a matrix can be written as $K=U \Lambda U^{T}$ where $U$ is orthonormal and $\Lambda=\operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right)$, with $\lambda_{i} \in \mathbb{R}$. Without loss of generality, assume that we have permuted the rows and columns of $K$ so that $K_{11} \geq K_{22} \geq \cdots \geq K_{n n}$, and we have indexed the eigenvalues so that $\lambda_{1} \geq \lambda_{2} \geq \cdots \geq \lambda_{n}$.
(a) (2 pts) Show that $\max _{\mathbf{v} \in \mathbb{R}^{n}: \mathbf{v}^{T} \mathbf{v}=1} \mathbf{v}^{T} K \mathbf{v}=\lambda_{1}$.
(b) ( 2 pts) Show that $K_{11} \leq \lambda_{1}$.
(c) ( $\mathbf{3} \mathbf{p t s})$ Show that for any $k=1, \ldots, n$,

$$
\max _{V \in \mathbb{R}^{n \times k}: V^{T} V=I_{k}} \operatorname{Trace}\left(V^{T} K V\right)=\max _{V \in \mathbb{R}^{n \times k}: V^{T} V=I_{k}} \operatorname{Trace}\left(V^{T} \Lambda V\right)=\sum_{i=1}^{k} \lambda_{i} .
$$

[Hint: You may find the preliminary results (i), (ii) and (iii) useful.]
(d) $(\mathbf{2} \mathbf{p t s})$ Show that for any $k=1, \ldots, n$,

$$
\sum_{i=1}^{k} K_{i i} \leq \sum_{i=1}^{k} \lambda_{i}
$$

and that equality holds when $k=n$.
(e) ( $\mathbf{2} \mathbf{~ p t s})$ Finally, we will connect the result we proved above to the notation we used in class. Let $V \in \mathbb{R}^{n \times k}$ be such that $V^{T} V=I_{k}$ as above. Let $\mathbf{Z}=\left[Z_{1} \ldots Z_{k}\right]^{T}=V^{T} \mathbf{X}$ where $\mathbf{X} \in \mathbb{R}^{n}$ is a random vector with covariance matrix $K_{\mathbf{X}}$. Show that

$$
\sum_{i=1}^{k} \operatorname{Var}\left(Z_{i}\right)=\operatorname{Trace}\left(V^{T} K_{\mathbf{X}} V\right)
$$

4. ( $\mathbf{1 5}$ pts) You are interested in estimating the $m$ by $m$ covariance matrix $K$ of a $m$ dimensional random vector $\mathbf{X}$. Your data is $\mathbf{X}_{1}, \mathbf{X}_{2}, \ldots, \mathbf{X}_{n}$, drawn independently from the same distribution as $\mathbf{X}$. For simplicity, assume that all entries of $\mathbf{X}$ take values in the interval $[a, b]$.
For simplicity we will first assume that $\mathbf{X}$ has zero mean.
a) ( $\mathbf{5} \mathbf{~ p t s}$ ) Suppose $m=1$, i.e. the data are scalars $X_{1}, \ldots, X_{n}$.
i. ( 2 pts ) What does $K$ become in this case?
ii. ( $\mathbf{3} \mathbf{p t s}$ ) Propose an estimator $\hat{K}_{n}$ of $K$, computed from the data, and show that it satisfies two properties:

- It is unbiased, i.e. $E\left[\hat{K}_{n}\right]=K$.
- $\hat{K}_{n}$ converges in probability to $K$ as $n \rightarrow \infty$, i.e. for any $\epsilon>0$

$$
\mathbb{P}\left(\left|\hat{K}_{n}-K\right| \geq \epsilon\right) \rightarrow 0 \quad \text { as } \quad n \rightarrow \infty
$$

b) ( $\mathbf{5} \mathbf{~ p t s}$ ) Now let us consider the general case for $m>1$ while still assuming that $\mathbf{X}$ has zero mean. Propose an estimator $\hat{K}_{n}$ of $K$ and show that it satisfies two properties:
i. It is unbiased, i.e. $E\left[\hat{K}_{n}\right]=K$. (Recall that the expectation of a random matrix is just taking the expectation of each entry of the matrix.)
ii. Each entry of $\hat{K}_{n}$ converges in probability to the corresponding entry of $K$ as $n \rightarrow \infty$.
iii. $\hat{K}_{n}$ converges in probability to $K$ as $n \rightarrow \infty$. This means that all the entries of $\hat{K}_{n}$ uniformly converge to the corresponding entries of $K$, i.e.

$$
\mathbb{P}\left(\exists(i, j) \quad \text { s.t. } \quad\left|\left(\hat{K}_{n}\right)_{i, j}-K_{i, j}\right| \geq \epsilon\right) \rightarrow 0 \quad \text { as } \quad n \rightarrow \infty
$$

c) ( $\mathbf{5} \mathbf{~ p t s}$ ) Now suppose $\mathbf{X}$ has non-zero mean and you do not know the mean.
i. ( $\mathbf{1} \mathbf{~ p t s}$ ) Propose an unbiased estimator for the mean from the data. Show that your estimator is unbiased.
ii. ( 4 pts ) Propose an unbiased estimator $\hat{K}_{n}$ for $K$ and show that it is unbiased. Hint: Assume that you first use the data to estimate the mean of $\mathbf{X}$ and then use your estimate for the mean to modify the estimator you suggested in part (b). Check whether it is unbiased for $m=1$ before looking at the $m>1$ case. If it turns out to be biased, can you scale it by a small factor and make it unbiased?

