EE908 Assignment-2 Solution

eMasters in Communication Systems, IITK

EE908: Optimization in SPCOM **Instructor:** Prof. Ketan Rajawat

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- 1. Let $\lambda_i(A)$ denote an eigenvalue of a symmetric matrix A. Find the following in terms of $\lambda_i(A)$
 - a. $Tr(A^3)$

Solution:

According to EVD/spectral theorem, a symmetric real matrix can be decomposed or diagonalized such that:

$$A = Q\Lambda Q^T$$

Where:

- Λ is a diagonal matrix of eigenvalues of A
- Q is matrix of corresponding eigenvectors of A which is orthogonal matrix $QQ^T = Q^TQ = I$
- From matrix relationships:

$$\circ \quad Tr(ABC) = Tr(CAB) = Tr(BCA)$$

$$\therefore Tr(A^3) = Tr(Q\Lambda^3 Q^T) = Tr(QQ^T\Lambda^3) = Tr(I\Lambda^3) = Tr(\Lambda^3)$$

 Λ is a diagonal matrix with eigenvalues λ_i on the diagonal. So Λ^3 is also a diagonal matrix with eigenvalues cubed on the diagonal.

$$Tr(A^3) = Tr(\Lambda^3) = \sum_{i=1}^n \lambda_i^3 - n$$
 is the size of the symmetric matrix

b. $\lambda_i(A^{-2})$

Solution:

Given:

-
$$Av = \lambda_i v \Rightarrow A^{-1}Av = A^{-1}\lambda_i v \Rightarrow v = A^{-1}\lambda_i v \Rightarrow \frac{1}{\lambda_i} v = A^{-1}v$$

 $\Rightarrow A^{-1}v = \frac{1}{\lambda_i} v$

Therefore, $\frac{1}{\lambda_i}$ is the eigenvalue(s) of A^{-1} with the same eigenvector(s) v $A^{-2} = (A^{-1})^2$

A is symmetric, hence its inverse is also symmetric and per EVD,

So, if $\lambda_i(A)$ denotes the eigenvalues of A, then $\frac{1}{\lambda_i(A)}$ are the eigenvalues of A^{-1} as derived above

Based on the proof from (a) above, if $\frac{1}{\lambda_i(A)}$ are eigenvalues of A^{-1} , then $(A^{-1})^2$ eigenvalues are $\left(\frac{1}{\lambda_i(A)}\right)^2$

$$\therefore \lambda_i(A^{-2}) = \left(\frac{1}{\lambda_i(A)}\right)^2$$

c.
$$\lambda_i(A-I)$$



Solution:

Given: $Av = \lambda_i(A)v$

So, let's consider (A - I) matrix and its action on same eigenvector v:

$$(A - I)v = Av - Iv = \lambda_i(A)v - Iv = (\lambda_i(A) - 1)v$$

$$\therefore (A - I)v = (\lambda_i(A) - 1)v$$

This satisfies the eigenvalue and eigen vector relationship for A and v.

Therefore, the eigenvalues of matrix (A-I) of eigen vector v are $(\lambda_i(A)-1)$

In general, $(A - kI)v = Av - kIv = \lambda_i(A)v - kv = (\lambda_i(A) - k)v$

Therefore, the eigenvalues of matrix (A - kI) of eigen vector v are $(\lambda_i(A) - k)$

d.
$$\lambda_i(I+2A)$$

Solution:

Given: $Av = \lambda_i(A)v$

So, let's consider (I + 2A) matrix and its action on same eigenvector v:

$$(I + 2A)v = Iv + 2Av = v + 2\lambda_i(A)v = (1 + 2\lambda_i(A))v$$

 $\therefore (I + 2A)v = (1 + 2\lambda_i(A))v$

This satisfies the eigen value and eigenvector relationship for A and v.

Therefore, the eigenvalues of matrix (I+2A) of eigen vector v are $(1+2\lambda_i(A))$

In general, $(I + kA)v = Iv + kAv = v + k\lambda_i(A)v = (1 + k\lambda_i(A))v$

Therefore, the eigenvalues of matrix (I + kA) of eigen vector v are $(1 + k\lambda_i(A))$

2. Prove the following results for A > 0:

a.
$$A^{-1} > 0$$

Solution:

Let's prove the inverse of matrix A is also positive definite if A is positive definite leveraging properties of matrix positive definiteness and eigenvalues.

Given $A_{n\times n}$ is positive definite \Rightarrow All its eigenvalues are positive, $\lambda_i > 0$

As proved in question (1) above, the eigenvalues of A^{-1} will be reciprocals of eigenvalues of A $\Rightarrow \frac{1}{\lambda}$.

Since all
$$\lambda_i > 0 \Rightarrow \frac{1}{\lambda_i} > 0$$

 \therefore All eigenvalues of A^{-1} are positive which implies that A^{-1} is also positive definite Hence if A>0, then $A^{-1}>0$

QED

b. $[A]_{ii} > 0$ for all i, where $[A]_{ii}$ denotes the i-th diagonal entry of A

Solution:

If a symmetric $n \times n$ matrix $A = [a_{ij}]$ is positive definite, then for any non-zero column vector v, the quadratic form $v^T P v$ is strictly positive and its eigenvalues are greater than zero

$$i.e.v^T Av > 0, \forall v \neq 0$$

Let's consider a vector (standard basis vector) $e_i = [1,0,...0,...0] \in \mathbb{R}^n$ – all elements are 0 except the one at position i which is 1.

For a standard basis vector $e_i \Rightarrow e^T A e = a_{ii}$

From the positive definiteness of A, $e^T Ae > 0$

 $\Rightarrow e^T A e = A_{ii} = [a_{ii}] > 0$ for all i. $A_{ii} = [a_{ii}]$ of this matrix are all diagonal elements.

Hence, if A > 0, then $A_{ii} = [a_{ii}] > 0$

QED





3. A matrix A is idempotent if $A^2=A$. Show that the only possible eigenvalues of an idempotent matrix are $\lambda=0$ and $\lambda=1$

Solution:

Given: $A^2 = A$

EVD for an idempotent matrix:

$$Av = \lambda v$$
 and $A^2v = \lambda v$

$$\Rightarrow A^2v = A(Av) = A(\lambda v) = \lambda(Av) = \lambda(\lambda v) = \lambda^2v$$

However, from the property of idempotent $\Rightarrow A^2v = Av = \lambda v$

Since v is an eigenvector and $\neq 0$, hence $(\lambda^2 - \lambda) = 0$

Therefore,
$$\lambda(\lambda-1)=0\Rightarrow\lambda=0$$
 or 1

QED

4. Given an $m \times n$ matrix A with SVD $A = A = \sum_{i=1}^r \sigma_i v_i u_i^T$, show that $||A||_F^2 \coloneqq tr(A^T A) = \sum_{i=1}^r \sigma_i^2$ Solution:

SVD of A:
$$A = \sum_{i=1}^{r} \sigma_i v_i u_i^T$$

We need to show that $||A||_F^2 = Tr(A^T A)$

Substituting A:

$$A^TA = (\sum_{i=1}^r \sigma_i v_i u_i^T)^T (\sum_{i=1}^r \sigma_i v_i u_i^T) = (\sum_{i=1}^r \sigma_i v_i^T u_i) (\sum_{i=1}^r \sigma_i v_i u_i^T) = \sum_{i=1}^r \sum_{j=1}^r \sigma_i \sigma_j u u_i^T v_j v_j^T u_i^T u_j \text{ and } v_i^T v_j \text{ terms are 1 if } i = j \text{ else 0 as these singular vectors are orthonormal} \\ \therefore Tr(A^TA) = Tr(\sum_{i=1}^r \sigma_i^2)$$

QED

5. The ℓ_2 norm of a matrix A is defined as $||A||_2 = \max_{\|x\|_2 = 1} ||Ax||_2$. Derive an expression for $||A||_2$ in terms of $\{\sigma_i\}_{i=1}^r$

Solution:

$$||A||_2 = \max_{\|x\|_2=1} ||Ax||_2$$

 $||x||_2$ is the Euclidean norm of vector x. To derive an expression for $||A||_2$ in terms of the singular values σ_i , we need to find the maximum value of $||Ax||_2$ over all unit vectors x. ||Ax|| is the Euclidean norm of vector Ax.

$$||Ax||_2 = \left\| \left(\sum_{i=1}^r \sigma_i v_i u_i^T \right) x \right\|_2 = \left\| \sum_{i=1}^r \sigma_i v_i (u_i^T x) \right\|_2$$

$$u_i^T x$$
 is a scalar $\Rightarrow \left\| \sum_{i=1}^r \sigma_i(u_i^T x) v_i \right\|_2$

Note above is a linear combination of the singular vectors v_i with coefficients $u_i^T x$. To maximize the norm of this linear combination, choose x such that it aligns with singular vector corresponding to the maximum singular value $\Rightarrow x = u_1$ Assuming σ_1 is maximum singular value.

$$||Ax||_2 = ||\sigma_1 v_1||_2 = \sigma_1 ||v_1||_2$$

Corresponding to the maximum singular value $\Rightarrow x = u_1$ Assuming σ_1 is maximum singular value.

Since
$$||v_1||_2 = 1 \Rightarrow ||Ax||_2 = \sigma 1$$

$$\therefore \|A\|_2 = \max\{\sigma_i\}_{i=1}^r$$

QED

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