

QUESTION 3

CS663 (DIGITAL IMAGE PROCESSING) ASSIGNMENT 5

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Question 3

Problem 1

Consider a matrix \mathbf{A} of size $m \times n, m \leq n$. Define $\mathbf{P} = \mathbf{A}^T \mathbf{A}$ and $\mathbf{Q} = \mathbf{A} \mathbf{A}^T$. (Note: all matrices, vectors and scalars involved in this question are real-valued).

1. Prove that for any vector \mathbf{y} with appropriate number of elements, we have $\mathbf{y}^T \mathbf{P} \mathbf{y} \geq 0$. Similarly show that $\mathbf{z}^T \mathbf{Q} \mathbf{z} \geq 0$ for a vector \mathbf{z} with appropriate number of elements. Why are the eigenvalues of \mathbf{P} and \mathbf{Q} non-negative?
2. If \mathbf{u} is an eigenvector of \mathbf{P} with eigenvalue λ , show that $\mathbf{A} \mathbf{u}$ is an eigenvector of \mathbf{Q} with eigenvalue λ . If \mathbf{v} is an eigenvector of \mathbf{Q} with eigenvalue μ , show that $\mathbf{A}^T \mathbf{v}$ is an eigenvector of \mathbf{P} with eigenvalue μ . What will be the number of elements in \mathbf{u} and \mathbf{v} ?
3. If \mathbf{v}_i is an eigenvector of \mathbf{Q} and we define $\mathbf{u}_i \triangleq \frac{\mathbf{A}^T \mathbf{v}_i}{\|\mathbf{A}^T \mathbf{v}_i\|_2}$. Then prove that there will exist some real, non-negative γ_i such that $\mathbf{A} \mathbf{u}_i = \gamma_i \mathbf{v}_i$.
4. It can be shown that $\mathbf{u}_i^T \mathbf{u}_j = 0$ for $i \neq j$ and likewise $\mathbf{v}_i^T \mathbf{v}_j = 0$ for $i \neq j$ for correspondingly distinct eigenvalues. (You did this in HW4 where you showed that the eigenvectors of symmetric matrices are orthonormal.) Now, define $\mathbf{U} = [\mathbf{u}_1 | \mathbf{u}_2 | \mathbf{u}_3 | \dots | \mathbf{u}_m]$ and $\mathbf{V} = [\mathbf{v}_1 | \mathbf{v}_2 | \mathbf{v}_3 | \dots | \mathbf{v}_m]$. Now show that $\mathbf{A} = \mathbf{U} \mathbf{\Gamma} \mathbf{V}^T$ where $\mathbf{\Gamma}$ is a diagonal matrix containing the non-negative values $\gamma_1, \gamma_2, \dots, \gamma_m$. With this, you have just established the existence of the singular value decomposition of any matrix \mathbf{A} . This is a key result in linear algebra and it is widely used in image processing, computer vision, computer graphics, statistics, machine learning, numerical analysis, natural language processing and data mining.
[7.5 + 7.5 + 7.5 + 7.5 = 30 points]

SECTION 1

Part 1

We are given that $\mathbf{P} = \mathbf{A}^T \mathbf{A}$ and $\mathbf{Q} = \mathbf{A} \mathbf{A}^T$.

PROOF We want to prove that $\mathbf{y}^T \mathbf{P} \mathbf{y} \geq 0$ for any vector \mathbf{y} and $\mathbf{z}^T \mathbf{Q} \mathbf{z} \geq 0$ for a vector \mathbf{z} .

Substituting \mathbf{P} with $\mathbf{A}^T \mathbf{A}$, we get

$$\mathbf{y}^T \mathbf{P} \mathbf{y} = \mathbf{y}^T \mathbf{A}^T \mathbf{A} \mathbf{y} = (\mathbf{A} \mathbf{y})^T \mathbf{A} \mathbf{y} = \|\mathbf{A} \mathbf{y}\|^2$$

Similarly, Substituting \mathbf{Q} with $\mathbf{A} \mathbf{A}^T$, we get

$$\mathbf{z}^T \mathbf{Q} \mathbf{z} = \mathbf{z}^T \mathbf{A} \mathbf{A}^T \mathbf{z} = \mathbf{z}^T \mathbf{A} (\mathbf{z}^T \mathbf{A})^T = \|\mathbf{z}^T \mathbf{A}\|^2$$

Here, $\|\cdot\|^2$ is the squared Euclidean norm of the matrices, which is always non-negative. Therefore, $\mathbf{y}^T \mathbf{P} \mathbf{y} \geq 0$ for any vector \mathbf{y} and $\mathbf{z}^T \mathbf{Q} \mathbf{z} \geq 0$ for any vector \mathbf{z} with appropriate number of elements. \square

The eigenvalues of \mathbf{P} and \mathbf{Q} are non-negative because:

- For \mathbf{P} , we have $\mathbf{P} = \mathbf{A}^T \mathbf{A}$. The eigenvalues of \mathbf{P} are the non-negative square singular values (or singular values squared) of \mathbf{A} . This is because, for any real matrix (like \mathbf{A}), the eigenvalues of a positive semidefinite (PSD) matrix (like \mathbf{P}) are square singular values of \mathbf{A} (non-negative). Therefore, all eigenvalues of \mathbf{P} are non-negative.
- For \mathbf{Q} , we have $\mathbf{Q} = \mathbf{A} \mathbf{A}^T$. The eigenvalues of \mathbf{Q} are the non-negative square singular values (or singular values squared) of \mathbf{A}^T . Therefore similarly, all eigenvalues of \mathbf{Q} are non-negative.

SECTION 2

Part 2

Part 2a :-

Given: \mathbf{u} is an eigenvector of \mathbf{P} with eigenvalue λ i.e, $\mathbf{P} \mathbf{u} = \lambda \mathbf{u}$ where $\mathbf{P} = \mathbf{A}^T \mathbf{A}$

Show: $\mathbf{Q} \mathbf{A} \mathbf{u} = \lambda \mathbf{A} \mathbf{u}$

Substituting $Q = AA^T$ in $Q\mathbf{A}u$, we get

$$Q\mathbf{A}u = AA^T\mathbf{A}u \quad (2.1)$$

$$\because P\mathbf{u} = A^T\mathbf{A}u = \lambda\mathbf{u} \quad (2.2)$$

\therefore from equation (2.1) and (2.2), we get

$$Q\mathbf{A}u = A\lambda\mathbf{u}$$

$$Q\mathbf{A}u = \lambda\mathbf{A}u$$

$\implies \mathbf{A}u$ is an eigenvector of Q with eigenvalue λ .

Part 2b :-

Given: \mathbf{v} is an eigenvector of Q with eigenvalue μ i.e, $Q\mathbf{v} = \mu\mathbf{v}$ where $Q = AA^T$

Show: $PA^T\mathbf{v} = \mu A^T\mathbf{v}$

Substituting $P = A^T A$ in $PA^T\mathbf{v}$, we get

$$PA^T\mathbf{v} = A^T AA^T\mathbf{v} \quad (2.3)$$

$$\because Q\mathbf{v} = AA^T\mathbf{v} = \mu\mathbf{v} \quad (2.4)$$

\therefore from equation (2.3) and (2.4), we get

$$PA^T\mathbf{v} = A^T\mu\mathbf{v}$$

$$PA^T\mathbf{v} = \mu A^T\mathbf{v}$$

$\implies A^T\mathbf{v}$ is an eigenvector of P with eigenvalue μ .

Part 2c :-

- Since \mathbf{u} is an eigenvector of P , it has the same number of elements as in a column of P , which is n . Therefore, \mathbf{v} is an n -dimensional vector (n elements).
- Similarly, since \mathbf{v} is an eigenvector of Q , it has the same number of elements as in a column of Q , which is m . Therefore, \mathbf{v} is an m -dimensional vector (m elements).

SECTION 3

Part 3

Given: $\mathbf{Q}\mathbf{v}_i = \lambda\mathbf{v}_i$ (λ is the corresponding eigenvalue of \mathbf{Q}) where

$$\mathbf{Q} = \mathbf{A}\mathbf{A}^T \text{ and } \mathbf{u}_i \triangleq \frac{\mathbf{A}^T\mathbf{v}_i}{\|\mathbf{A}^T\mathbf{v}_i\|_2}$$

To prove: $\mathbf{A}\mathbf{u}_i = \gamma_i\mathbf{v}_i$ (for some real, non-negative γ_i)

PROOF We know that

$$\mathbf{Q}\mathbf{v}_i = \mathbf{A}\mathbf{A}^T\mathbf{v}_i = \lambda\mathbf{v}_i \quad (3.1)$$

Also,

$$\mathbf{A}\mathbf{u}_i = \frac{\mathbf{A}\mathbf{A}^T\mathbf{v}_i}{\|\mathbf{A}^T\mathbf{v}_i\|_2} \quad (3.2)$$

From equation (3.1) and (3.2):

$$\mathbf{A}\mathbf{u}_i = \frac{\lambda\mathbf{v}_i}{\|\mathbf{A}^T\mathbf{v}_i\|_2}$$

$$\therefore \mathbf{A}\mathbf{u}_i = \gamma_i\mathbf{v}_i$$

where $\gamma_i = \frac{\lambda}{\|\mathbf{A}^T\mathbf{v}_i\|_2}$

γ_i is real and non-negative because

- λ is an eigenvalue of \mathbf{Q} and in Part 1 we showed that eigenvalues of \mathbf{Q} are non-negative and real.
- $\|\mathbf{A}^T\mathbf{v}_i\|_2$ (L_2 norm) is always non-negative and real.

□

SECTION 4

Part 4

Given: $\mathbf{U} = [\mathbf{v}_1|\mathbf{v}_2|\mathbf{v}_3|\dots|\mathbf{v}_m]_{m \times m}$ and $\mathbf{V} = [\mathbf{u}_1|\mathbf{u}_2|\mathbf{u}_3|\dots|\mathbf{u}_m]_{n \times m}$

Show: $\mathbf{A} = \mathbf{U}\mathbf{T}\mathbf{V}^T$

$$\mathbf{\Gamma} = \begin{bmatrix} \gamma_1 & 0 & \dots & \dots & 0 \\ 0 & \gamma_2 & \dots & & 0 \\ 0 & 0 & \ddots & & \vdots \\ \vdots & & & & \\ 0 & \dots & & \dots & \gamma_m \end{bmatrix}_{m \times m}$$

Now, we can write

$$\mathbf{A}\mathbf{V} = [\mathbf{A}\mathbf{u}_1 | \mathbf{A}\mathbf{u}_2 | \mathbf{A}\mathbf{u}_3 | \dots | \mathbf{A}\mathbf{u}_m]$$

Also, in part 3, we showed that $\mathbf{A}\mathbf{u}_i = \gamma_i \mathbf{v}_i$. Therefore,

$$\begin{aligned} [\mathbf{A}\mathbf{u}_1 | \mathbf{A}\mathbf{u}_2 | \mathbf{A}\mathbf{u}_3 | \dots | \mathbf{A}\mathbf{u}_m] &= [\gamma_1 \mathbf{v}_1 | \gamma_2 \mathbf{v}_2 | \gamma_3 \mathbf{v}_3 | \dots | \gamma_m \mathbf{v}_m] \\ \implies \mathbf{A}\mathbf{V} &= [\gamma_1 \mathbf{v}_1 | \gamma_2 \mathbf{v}_2 | \gamma_3 \mathbf{v}_3 | \dots | \gamma_m \mathbf{v}_m] \end{aligned} \quad (4.1)$$

Now expanding $\mathbf{U}\mathbf{\Gamma}$,

$$\mathbf{U}\mathbf{\Gamma} = [\gamma_1 \mathbf{v}_1 | \gamma_2 \mathbf{v}_2 | \gamma_3 \mathbf{v}_3 | \dots | \gamma_m \mathbf{v}_m] \quad (4.2)$$

From equation (4.1) and (4.2), we get

$$\mathbf{A}\mathbf{V} = \mathbf{U}\mathbf{\Gamma}$$

Postmultiplying both sides by \mathbf{V}^T

$$\mathbf{A}\mathbf{V}\mathbf{V}^T = \mathbf{U}\mathbf{\Gamma}\mathbf{V}^T$$

$\because \mathbf{V}$ is a orthonormal matrix, we can write $\mathbf{V}\mathbf{V}^T = \mathbf{I}$

$$\mathbf{A} = \mathbf{U}\mathbf{\Gamma}\mathbf{V}^T$$

Hence proved.