

## CS-663 Assignment 4 Q3

Soham Naha (193079003)  
Akshay Bajpai (193079002)  
Mohit Agarwala (19307R004)

November 6, 2020

3

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

- Prove that for any vector  $y$  with appropriate number of elements, we have  $y^T P y \geq 0$ . Similarly show that  $z^T Q z \geq 0$  for a vector  $z$  with appropriate number of elements. Why are the eigenvalues of  $P$  and  $Q$  non-negative?
- If  $u$  is an eigenvector of  $P$  with eigenvalue  $\lambda$ , show that  $Au$  is an eigenvector of  $Q$  with eigenvalue  $\lambda$ . If  $v$  is an eigenvector of  $Q$  with eigenvalue  $\mu$ , show that  $A^T v$  is an eigenvector of  $P$  with eigenvalue  $\mu$ . What will be the number of elements in  $u$  and  $v$ ?
- If  $v_i$  is an eigenvector of  $Q$  and we define  $u_i \triangleq \frac{A^T v_i}{\|A^T v_i\|_2}$ . Then prove that there will exist some real, non-negative  $\gamma_i$  such that  $Au_i = \gamma_i v_i$ .
- It can be shown that  $u_i^T u_j = 0$  for  $i \neq j$  and likewise  $v_i^T v_j = 0$  for  $i \neq j$  for correspondingly distinct eigenvalues.<sup>1</sup>. Now, define  $U = [u_1 | u_2 | u_3 | \dots | u_m]$  and  $V = [v_1 | v_2 | v_3 | \dots | v_m]$ . Now show that  $A = U \Gamma V^T$  where  $\Gamma$  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  $A$ . 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. [5 + 5 + 5 + 5 = 20 points]

(a) Given  $P = A^T A$   $n \times n$  and  $Q = AA^T \in \mathbb{R}^{m \times m}$ , and  $y \in \mathbb{R}^{n \times 1}$ , we have (given the correct dimension of real-valued  $y$ ):

$$\begin{aligned} y^T P y &= y^T A^T A y \\ &= (Ay)^T (Ay) \end{aligned}$$

Now let  $Ay = w \in \mathbb{R}^{m \times 1}$ . Hence, we have:

$$\begin{aligned} (Ay)^T (Ay) &= w^T w = \|w\|^2 \geq 0 \\ y^T P y &\geq 0, \forall y \end{aligned}$$

Similarly, for a real-valued  $m \times 1$  vector  $z$ , we have (given the correct dimension of real-valued  $z$ ):

$$\begin{aligned} z^T Q z &= z^T A A^T z \\ &= (A^T z)^T (A^T z) \end{aligned}$$

Now let  $A^T z = u \in \mathbb{R}^{n \times 1}$ . Hence, we have:

$$\begin{aligned} (A^T z)^T (A^T z) &= u^T u = \|u\|^2 \geq 0 \\ z^T Q z &\geq 0, \forall z \end{aligned}$$

Proof of non-negative eigenvalues of  $P$  and  $Q$ : For  $P$ , let the non-zero eigen vector be  $v$  with corresponding eigenvalue  $\lambda$ :

$$Pv = \lambda v$$

---

<sup>1</sup>This follows because  $P$  and  $Q$  are symmetric matrices. Consider  $Pu_1 = \lambda_1 u_1$  and  $Pu_2 = \lambda_2 u_2$ . Then  $u_2^T Pu_1 = \lambda_1 u_2^T u_1$ . But  $u_2^T Pu_1$  also equal to  $(P^T u_2)^T u_1 = (Pu_2)^T u_1 = (\lambda_2 u_2)^T u_1 = \lambda_2 u_2^T u_1$ . Hence  $\lambda_2 u_2^T u_1 = \lambda_1 u_2^T u_1$ . Since  $\lambda_2 \neq \lambda_1$ , we must have  $u_2^T u_1 = 0$ .

Pre-multiplying both sides by  $v^T$ , we get,

$$v^T P v = \lambda v^T v = \lambda \|v\|^2$$

$$\implies \lambda = \frac{v^T P v}{\|v\|^2}$$

Now,  $\|v\|^2$  is always positive (by-definition). Also,  $v^T P v \geq 0$  (proved earlier). Hence, value of  $\lambda$  is always non-negative. Since we made no assumptions for  $v$  or  $\lambda$ , the condition holds for all eigenvalues of  $P$ . Similarly, for  $Q$ , let:

$$Q v = \lambda v$$

Pre-multiplying both sides by  $v^T$ , we get,

$$v^T Q v = \lambda v^T v = \lambda \|v\|^2$$

$$\implies \lambda = \frac{v^T Q v}{\|v\|^2}$$

Now,  $\|v\|^2$  is always positive (by-definition). Also,  $v^T Q v \geq 0$  (proved earlier). Hence, value of  $\lambda$  is always non-negative. Since we made no assumptions for  $v$  or  $\lambda$ , the condition holds for all eigenvalues of  $Q$ .

(b)  $u$  is an eigenvector of  $P$  with eigenvalue  $\lambda$ . Now,

$$A \in \mathbb{R}^{m \times n} \implies A^T A = P \in \mathbb{R}^{n \times n} \implies u \in \mathbb{R}^n \text{ and}$$

$$P u = \lambda u$$

Pre-multiplying both sides with  $A$ , we get

$$A P u = \lambda A u$$

Using  $P = A^T A$ , we simplify this to,

$$A A^T A u = (A A^T) A u = \lambda A u$$

Simplify  $A A^T = Q$ , and  $A u = v \in \mathbb{R}^m$  to get,

$$Q(A u) = Q v = \lambda(A u) = \lambda v$$

Hence,  $A u$  is an eigenvector of  $Q$  with eigenvalue  $\lambda$ .

Similarly to prove for  $Q$ , we assume an eigenvector  $v$  with eigenvalue  $\mu$ . Now,

$$A \in \mathbb{R}^{m \times n} \implies A A^T = Q \in \mathbb{R}^{m \times m} \implies v \in \mathbb{R}^m \text{ and}$$

$$Q v = \mu v$$

Pre-multiplying both sides with  $A$ , we get

$$A^T Q v = \mu A^T v$$

Using  $Q = A A^T$ , we simplify this to,

$$A^T A A^T v = (A^T A) A^T v = \mu A^T v$$

Simplify  $A^T A = P$ , and  $A^T v = w \in \mathbb{R}^n$  to get,

Hence,  $A^T v$  is an eigenvector of  $P$  with eigenvalue  $\mu$ .

(c) We are given that  $v_i$  is an eigenvector of  $Q$  (with eigenvalue  $\alpha_i$ ). Which gives us the first equation

$$Q v_i = A A^T v_i = \alpha_i v_i$$

.

Now, given

$$u_i = \frac{A^T v_i}{\|A^T v_i\|_2}$$

We have

$$A u_i = \frac{A A^T v_i}{\|A^T v_i\|_2}$$

$$\implies Au_i = \frac{Qv_i}{\|A^T v_i\|_2} = \frac{\alpha_i v_i}{\|A^T v_i\|_2} = \left( \frac{\alpha_i}{\|A^T v_i\|_2} \right) v_i$$

Substitute  $\frac{\alpha_i}{\|A^T v_i\|_2} = \gamma_i$  to get the required equation.

$$Au_i = \gamma_i v_i$$

Now,  $\alpha_i$  is non-negative since it's an eigenvalue of  $Q$  (proved earlier), and  $\|A^T v_i\|_2$  is positive by definition, the value of  $\gamma_i$  is non-negative. There exists a non-negative  $\gamma_i$  for which the given equation holds.

(d) We know as a result that

$$u_i^T u_j = 0 \text{ for } i \neq j$$

and for

$$u_i^T u_i = \frac{(A^T v_i)^T (A^T v_i)}{\|A^T v_i\|^2} = 1$$

So, the matrix  $V = [u_1|u_2|\dots|u_n]$  is orthonormal because  $VV^T = V^T V = I_n$ . Similarly, for  $U = [v_1|v_2|\dots|v_m]$ ,  $UU^T = U^T U = I_m$  because  $v_i^T v_j = 0$  for  $i \neq j$  and  $v_i^T v_i = 1$  (because  $v_i$  and  $v_j$  are eigen-vectors of  $P$ , and which can be assumed to be of unit length for consistency). Given these results, the value of  $U^T AV$

$$= U^T AV = U^T A[u_1|u_2|\dots|u_n] = \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_m^T \end{bmatrix} A[u_1|u_2|\dots|u_n]$$

From the previous results, we have  $Au_i = \gamma_i v_i$

$$= \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_m^T \end{bmatrix} [\gamma_1 v_1 | \gamma_2 v_2 | \dots | \gamma_n v_n] \\ = [\Gamma_{ij}^T]_m * n$$

Where

$$\Gamma_{ij} = v_i^T \gamma_j v_j = \begin{cases} 0 & \text{if } i \neq j \\ \gamma_j & \text{otherwise} \end{cases}$$

Hence,  $U^T AV = \Gamma$  where  $T$  is a diagonal matrix, with  $i^{th}$  diagonal element  $= \gamma_i$

$$\implies (UU^T)A(VV^T) = U\Gamma V^T \implies A = U\Gamma V^T$$

This holds since  $U$  and  $V$  are orthonormal. Hence, proved.