

\* PCA

Q3. Consider a matrix  $A$  of size  $m \times n$ ,  $m \leq n$  and  $P = A^T A$  (size  $n \times n$ ) and  $Q = A A^T$  (size  $m \times m$ )

(a) Let  $y$  be any  $n \times 1$  size vector.

We have

$$\begin{aligned} y^T P y &= y^T A^T A y \\ &= (A y)^T A y \\ &= \|A y\|_2^2 \geq 0 \end{aligned}$$

$A y$  is a vector of size  $m \times 1$  and  $L_2$  norm square of it contains sum of square terms which will always be non-negative

$$\therefore y^T P y \geq 0 \rightarrow \textcircled{1}$$

\* Similarly, we can prove  $z^T Q z \geq 0$  where  $z$  is any  $m \times 1$  vector

$$\begin{aligned} z^T Q z &= z^T A A^T z \\ &= (A^T z)^T A^T z \\ &= \|A^T z\|_2^2 \geq 0 \end{aligned}$$

$$\therefore z^T Q z \geq 0 \rightarrow \textcircled{2}$$

Eg<sup>n</sup>  $\textcircled{1}$  and  $\textcircled{2}$  ~~are~~ ~~test~~ both resembles the test to check if a matrix is <sup>positive</sup> semi definite i.e. a symmetric matrix with all non-negative eigen values.



Lets see how equ<sup>n</sup> ① is able to say that all the eigen values of  $P$  are non-negative

consider a eigen value of  $P$  as  $\lambda$  with  $x$  as corresponding eigen vector.

$$\therefore Px = \lambda x$$

$$x^T Px = \lambda x^T x \quad \dots \text{premultiply by } x^T$$

$$\text{but } x^T Px \geq 0 \quad \dots \text{from equ<sup>n</sup> ①}$$

$$\therefore \lambda x^T x \geq 0$$

$$\therefore \lambda \|x\|_2^2 \geq 0$$

$$\therefore \lambda \geq 0 \quad \text{as 2<sup>nd</sup> term is always positive due to } x \neq 0$$

As ' $\lambda$ ' was any arbitrary eigen value, above is true for all eigen values of  $P$ .

If a <sup>symmetric</sup> matrix  $X$  satisfies  $y^T X y \geq 0$  for any real vector  $y$  then its eigen values are non-negative  $\lambda$  is thus positive semi-definite.  $\rightarrow$  ③

$\therefore$  From equ<sup>n</sup> ①, ② & ③ eigen values of  $P$  &  $Q$  are non-negative.



Q3. b.

Let 'u' be eigen vector of P with eigen value  $\lambda$ .

$$Pu = \lambda u$$

$$\therefore A^T A u = \lambda u \quad \dots \quad P = A^T A$$

$$\therefore A A^T (A u) = \lambda (A u) \quad \dots \quad \text{premultiply by } A$$

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

So we get Au as eigen vector of Q with eigen value  $\lambda$ .

Similarly, let 'v' be eigen vector of Q with eigen value  $\mu$ .

$$Q v = \mu v$$

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

$$\therefore A^T A (A^T v) = \mu (A^T v) \quad \dots \quad \text{premultiply by } A^T$$

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

So, here also, we get  $A^T v$  as eigen vector of P with eigen value  $\mu$ .

$$u \in \mathbb{R}^n \quad \& \quad v \in \mathbb{R}^m$$

Q3.c

Given:  $v_i$  is eigen vector of  $Q$

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

Consider

$$A u_i = A \frac{A^T v_i}{\|A^T v_i\|_2} \quad \dots \text{substitute } u_i$$

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

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

$$= \frac{\mu_i v_i}{\|A^T v_i\|_2} \quad \dots \mu_i \text{ is the eigen value having eigen vector } v_i$$

$$A u_i = \gamma_i v_i \quad \dots \gamma_i = \frac{\mu_i}{\|A^T v_i\|_2}$$

$\mu_i$  is real and non-negative as it's a eigen value of positive semi-definite matrix  $Q$  (proved this in Q3.a) & denominator is positive

$$\therefore A u_i = \gamma_i v_i \quad \dots \gamma_i \text{ is real \& non-negative}$$



Q3-d

As we have been following;  $u_i \dots 1 \leq i \leq n$  are the eigen vectors of matrix  $P = A^T A$  and  $v_i \dots 1 \leq i \leq m$  are that of matrix  $Q = A A^T$

For symmetric matrices the eigen vectors are orthonormal.

$$\therefore u_i^T u_j = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases} \rightarrow (1)$$

and

$$v_i^T v_j = \begin{cases} 1 & i=j \\ 0 & i \neq j \end{cases} \rightarrow (2)$$

Consider,

$$U^T A V = \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_m^T \end{bmatrix}_{m \times m} A_{m \times n} \begin{bmatrix} u_1 & u_2 & \dots & u_n \end{bmatrix}_{n \times n}$$

$$= \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_m^T \end{bmatrix} \begin{bmatrix} A u_1 & A u_2 & \dots & A u_n \end{bmatrix}$$

$$= \begin{bmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_m^T \end{bmatrix} \begin{bmatrix} \sigma_1 v_1 & \sigma_2 v_2 & \dots & \sigma_n v_n \end{bmatrix}$$

$$\dots \dots A u_i = \sigma_i v_i$$

proved in Q3-c

$$= \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \sigma_n \end{bmatrix}$$

using (2)  $\Sigma_{ij} = v_i^T \sigma_j v_j = \begin{cases} \sigma_j & i=j \\ 0 & i \neq j \end{cases}$

$$\therefore U^T A V = \Sigma$$

$$\therefore U U^T A V = U \Sigma$$

$$A V V^T = U \Sigma V^T$$

$$\boxed{A = U \Sigma V^T}$$

$U$  and  $V$  are orthonormal

proved.