Homework #5 Solution

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June 1, 2010

Excercise 5.1

33 (a)
$$A(A^T + B^T)B = AA^TB + AB^TB = (AA^T)B + A(B^TB) = B + A = A + B$$
.

(b) By (a),

$$\det(A+B) = \det(A(A^T+B^T)B) = \det A \det(A^T+B^T) \det B.$$

Since
$$(A+B)^T = A^T + B^T$$
 and by Theorem 4.10 (p.273),

$$\det\left(A^T + B^T\right) = \det\left(A + B\right).$$

Therefore,

$$\det(A+B) - \det(A(A^T+B^T)B) = \det(A+B) - \det A \det(A^T+B^T) \det B$$

$$= (1 - \det A \det B) \det(A+B)$$

$$= (1 + (\det A)^2) \det(A+B)$$
(since $\det A + \det B = 0$)
$$= 0.$$

Since $1 + (\det A)^2 \neq 0$, $\det (A + B) = 0$ and therefore A + B is not invertible.

34 Note that $Q = Q^T$ since

$$\left[\begin{array}{c|c} x_1 & \boldsymbol{y}^T \\ \hline \boldsymbol{y} & I - \left(\frac{1}{1-x_1}\right) \boldsymbol{y} \boldsymbol{y}^T \end{array} \right]^T = \left[\begin{array}{c|c} x_1 & \boldsymbol{y}^T \\ \hline (\boldsymbol{y}^T)^T & \left(I - \left(\frac{1}{1-x_1}\right) \boldsymbol{y} \boldsymbol{y}^T \right)^T \end{array} \right] = \left[\begin{array}{c|c} x_1 & \boldsymbol{y}^T \\ \hline \boldsymbol{y} & I - \left(\frac{1}{1-x_1}\right) \boldsymbol{y} \boldsymbol{y}^T \end{array} \right].$$

$$QQ^{T} = Q^{2} = \begin{bmatrix} x_{1} & \mathbf{y}^{T} \\ \mathbf{y} & I - \left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T} \end{bmatrix}^{2}$$

$$= \begin{bmatrix} x_{1}^{2} + \mathbf{y}^{T}\mathbf{y} & x_{1}\mathbf{y}^{T} + \mathbf{y}^{T}\left(I - \left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T}\right) \\ \mathbf{y}x_{1} + \left(I - \left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T}\right)\mathbf{y} & \mathbf{y}\mathbf{y}^{T} + \left(I - \left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T}\right)^{2} \end{bmatrix}^{2}$$

$$= \begin{bmatrix} x_{1}^{2} + \mathbf{y} \cdot \mathbf{y} & x_{1}\mathbf{y}^{T} + \mathbf{y}^{T} - \left(\frac{1}{1-x_{1}}\right)\mathbf{y}^{T}\mathbf{y}\mathbf{y}^{T} \\ x_{1}\mathbf{y} + \mathbf{y} - \left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T}\mathbf{y} & \mathbf{y}\mathbf{y}^{T} + I - 2\left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T} + \left(\frac{1}{1-x_{1}}\right)^{2}\mathbf{y}\mathbf{y}^{T}\mathbf{y}\mathbf{y}^{T} \end{bmatrix}$$

(a)
$$x_1^2 + \boldsymbol{y} \cdot \boldsymbol{y} = \boldsymbol{x} \cdot \boldsymbol{x} = 1.$$

(b)

$$x_1 \boldsymbol{y}^T + \boldsymbol{y}^T - \left(\frac{1}{1 - x_1}\right) \boldsymbol{y}^T \boldsymbol{y} \boldsymbol{y}^T = (x_1 + 1) \boldsymbol{y}^T - \left(\frac{1}{1 - x_1}\right) (\boldsymbol{y} \cdot \boldsymbol{y}) \boldsymbol{y}^T$$
$$= (x_1 + 1) \boldsymbol{y}^T - \left(\frac{1}{1 - x_1}\right) (1 - x_1^2) \boldsymbol{y}^T$$
$$= (x_1 + 1) \boldsymbol{y}^T - (1 + x_1^2) \boldsymbol{y}^T$$
$$= \mathbf{0}^T.$$

(c)
$$x_1 \mathbf{y} + \mathbf{y} - \left(\frac{1}{1 - x_1}\right) \mathbf{y} \mathbf{y}^T \mathbf{y} = (x_1 + 1) \mathbf{y} + -\left(\frac{1}{1 - x_1}\right) \mathbf{y} (\mathbf{y} \cdot \mathbf{y})$$

$$= (x_1 + 1) \mathbf{y} + -\left(\frac{1}{1 - x_1}\right) \mathbf{y} (1 - x_1^2)$$

$$= (x_1 + 1) \mathbf{y} + -(1 + x_1) \mathbf{y} = \mathbf{0}.$$

(d) $\mathbf{y}\mathbf{y}^{T} + I - 2\left(\frac{1}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T} + \left(\frac{1}{1-x_{1}}\right)^{2}\mathbf{y}\mathbf{y}^{T}\mathbf{y}\mathbf{y}^{T}$ $= I + \left(1 - 2\left(\frac{1}{1-x_{1}}\right)\right)\mathbf{y}\mathbf{y}^{T} + \left(\frac{1}{1-x_{1}}\right)^{2}\mathbf{y}(\mathbf{y} \cdot \mathbf{y})\mathbf{y}^{T}$ $= I - \left(\frac{1+x_{1}}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T} + \left(\frac{1-x_{1}^{2}}{(1-x_{1})^{2}}\right)\mathbf{y}\mathbf{y}^{T}$ $= I - \left(\frac{1+x_{1}}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T} + \left(\frac{1+x_{1}}{1-x_{1}}\right)\mathbf{y}\mathbf{y}^{T}$ = I.

Therefore, $QQ^T = \begin{bmatrix} 1 & \mathbf{0}^T \\ \mathbf{0} & I_{n-1} \end{bmatrix} = I_n$ and hence Q is orthogonal.

Excercise 5.2

14 Let a vector in W^{\perp} be $\boldsymbol{x} := \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix}$. Since \boldsymbol{x} should be orthogonal to \boldsymbol{w}_1 ,

 w_2 and w_3 , we get

$$\begin{bmatrix} \boldsymbol{w}_1^T \\ \boldsymbol{w}_2^T \\ \boldsymbol{w}_3^T \end{bmatrix} \boldsymbol{x} = \begin{bmatrix} 4 & 6 & -1 & 1 & -1 \\ 1 & 2 & 0 & 1 & -3 \\ 2 & 2 & 2 & -1 & 2 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \\ x_5 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$

By Gaussian elimination,

$$\begin{bmatrix} 4 & 6 & -1 & 1 & -1 \\ 1 & 2 & 0 & 1 & -3 \\ 2 & 2 & 2 & -1 & 2 \end{bmatrix} \xrightarrow{R_{1}/4} \begin{bmatrix} R_{2} - R_{1} \\ R_{3} - 2R_{1} \\ - & -1 \end{bmatrix} \xrightarrow{R_{3} - 2R_{1}} \begin{bmatrix} 1 & 3/2 & -1/4 & 1/4 & -1/4 \\ 0 & 1/2 & 1/4 & 3/4 & -11/4 \\ 0 & -1 & 5/2 & -3/2 & 5/2 \end{bmatrix}$$

$$\xrightarrow{R_{3} + R_{2}} \begin{bmatrix} R_{3} + R_{2} \\ R_{3}/3 \\ - & -1 \end{bmatrix} \xrightarrow{R_{3}/3} \begin{bmatrix} 1 & 3/2 & -1/4 & 1/4 & -1/4 \\ 0 & 1 & 1/2 & 3/2 & -11/2 \\ 0 & 0 & 1 & 0 & -1 \end{bmatrix}$$

Therefore,

$$\begin{aligned} x_3 &= x_5 \\ x_2 &= -\frac{1}{2}(x_3 + 3x_4 - 11x_5) = -\frac{1}{2}(3x_4 - 10x_5) \\ x_1 &= -\frac{1}{4}(6x_2 - x_3 + x_4 - x_5) = -\frac{1}{4}(-9x_4 + 30x_5 - x_5 + x_4 - x_5) = 2x_4 - 7x_5 \end{aligned}$$

and

$$\boldsymbol{x} = \begin{bmatrix} 2x_4 - 7x_5 \\ -\frac{1}{2}(3x_4 - 10x_5) \\ x_5 \\ x_4 \\ x_5 \end{bmatrix} = \frac{1}{2} \begin{bmatrix} 4 \\ -3 \\ 0 \\ 2 \\ 0 \end{bmatrix} x_4 + \begin{bmatrix} -7 \\ 5 \\ 1 \\ 0 \\ 1 \end{bmatrix} x_5.$$

Therefore,

$$W^{\perp} = \operatorname{span} \left(\begin{bmatrix} 4 \\ -3 \\ 0 \\ 2 \\ 0 \end{bmatrix}, \begin{bmatrix} -7 \\ 5 \\ 1 \\ 0 \\ 1 \end{bmatrix} \right).$$

25 In \mathbb{R}^3 , let

•
$$W = \operatorname{span}\left(\begin{bmatrix}1\\0\\0\end{bmatrix},\begin{bmatrix}0\\1\\0\end{bmatrix}\right),$$

•
$$\boldsymbol{w} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$
,

•
$$w' = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}$$
 and

•
$$v = w + w' = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$$
.

Clearly, \boldsymbol{w} and \boldsymbol{w}' are orthogonal but $\boldsymbol{w}' \notin W^{\perp} = \operatorname{span} \left(\begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right)$.

30 (a) Let W = span(S). Then we can orthogonally decompose $\boldsymbol{x} \in \mathbb{R}^n$ as

$$\boldsymbol{x} = \boldsymbol{w} + \boldsymbol{w}^{\perp}$$

where $\boldsymbol{w} := \operatorname{proj}_W(\boldsymbol{x})$ and $\boldsymbol{w}^{\perp} := \operatorname{perp}_W(\boldsymbol{x})$. Also, since S is an orthonormal set, by definition on p.379,

$$oldsymbol{w} = \sum_{i=1}^k (oldsymbol{v}_i \cdot oldsymbol{x}) oldsymbol{v}_i.$$

Therefore,

$$\|oldsymbol{x}\|^2 = oldsymbol{x} \cdot oldsymbol{x} = oldsymbol{(w+w^{\perp})} \cdot oldsymbol{(w+w^{\perp})} = oldsymbol{w}^{\perp} \cdot oldsymbol{w}^{\perp} + oldsymbol{w} \cdot oldsymbol{w}$$

since $\mathbf{w} \cdot \mathbf{w}^{\perp} = 0$.

Now,

$$\boldsymbol{w} \cdot \boldsymbol{w} = \left(\sum_{i=1}^k (\boldsymbol{v}_i \cdot \boldsymbol{w}) \boldsymbol{v}_i\right) \cdot \left(\sum_{i=1}^k (\boldsymbol{v}_i \cdot \boldsymbol{w}) \boldsymbol{v}_i\right) = \sum_{i=1}^k (\boldsymbol{v}_i \cdot \boldsymbol{x})^2 (\boldsymbol{v}_i \cdot \boldsymbol{v}_i) = \sum_{i=1}^k |\boldsymbol{v}_i \cdot \boldsymbol{x}|^2$$

since S is an orthonormal set. Therefore,

$$\|m{x}\|^2 = \|m{w}^\perp\|^2 + \sum_{i=1}^k |m{v}_i \cdot m{x}|^2 \geq \sum_{i=1}^k |m{v}_i \cdot m{x}|^2.$$

(b) In (a), the equality holds if and only if $\mathbf{w}^{\perp} = \mathbf{0}$, which is equivalent to satisfying $\mathbf{x} = \mathbf{w} = \operatorname{proj}_{W}(\mathbf{w})$ and hence $\mathbf{x} \in \operatorname{span}(S)$.

Excercise 5.3

10 (i)
$$v_1 = x_1 = \begin{bmatrix} 1 \\ 1 \\ -1 \\ 1 \end{bmatrix}$$

(ii)

$$v_2 = x_2 - \left(\frac{v_1 \cdot x_2}{v_1 \cdot v_1}\right) v_1$$

$$= \begin{bmatrix} 1 \\ -1 \\ 1 \\ 5 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \\ -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ -2 \\ 2 \\ 4 \end{bmatrix}$$

$$v_3 = x_3 - \left(\frac{v_1 \cdot x_3}{v_1 \cdot v_1}\right) v_1 - \left(\frac{v_2 \cdot x_3}{v_2 \cdot v_2}\right) v_2$$

$$= \begin{bmatrix} 1\\2\\0\\1 \end{bmatrix} - \begin{bmatrix} 1\\1\\-1\\1 \end{bmatrix} - 0 \begin{bmatrix} 0\\-2\\2\\4 \end{bmatrix} = \begin{bmatrix} 0\\1\\1\\0 \end{bmatrix}$$

Therefore, the orthogonal vectors are

$$\begin{bmatrix} 1\\1\\-1\\1 \end{bmatrix}, \begin{bmatrix} 0\\-2\\2\\4 \end{bmatrix}, \text{and} \begin{bmatrix} 0\\1\\1\\0 \end{bmatrix}$$

16 By normalizing the vectors, we get

$$Q = \begin{bmatrix} 1/2 & 0 & 0\\ 1/2 & -1/\sqrt{6} & 1/\sqrt{2}\\ -1/2 & 1/\sqrt{6} & 1/\sqrt{2}\\ 1/2 & 2/\sqrt{6} & 0 \end{bmatrix}$$

and since

$$R = Q^T A = \begin{bmatrix} 1/2 & 1/2 & -1/2 & 1/2 \\ 0 & -1/\sqrt{6} & 1/\sqrt{6} & 2/\sqrt{6} \\ 0 & 1/\sqrt{2} & 1/\sqrt{2} & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 2 \\ -1 & 1 & 0 \\ 1 & 5 & 1 \end{bmatrix} = \begin{bmatrix} 2 & 2 & 2 \\ 0 & 2\sqrt{6} & 0 \\ 0 & 0 & \sqrt{2} \end{bmatrix},$$

therefore

$$A = \begin{bmatrix} 1 & 1 & 1 \\ 1 & -1 & 2 \\ -1 & 1 & 0 \\ 1 & 5 & 1 \end{bmatrix} = QR = \begin{bmatrix} 1/2 & 0 & 0 \\ 1/2 & -1/\sqrt{6} & 1/\sqrt{2} \\ -1/2 & 1/\sqrt{6} & 1/\sqrt{2} \\ 1/2 & 2/\sqrt{6} & 0 \end{bmatrix} \begin{bmatrix} 2 & 2 & 2 \\ 2\sqrt{6} & 0 \\ \sqrt{2} \end{bmatrix}$$

19 We don't need to apply the Gram-Schmidt process since A is already orthogonal. Since $R = Q^T A = A^T A = I$, the QR factorization results in A = QR where Q = A and R = I.

Excercise 5.4

10 (a) Diagonalize $A (A \rightarrow PDP^{-1})$

The characteristic polynomial is, by the Laplace expansion theorem,

$$\det(A - \lambda I) = \begin{vmatrix} 2 - \lambda & 1 \\ 1 - \lambda & \\ 1 & 2 - \lambda \end{vmatrix}$$

$$= (1 - \lambda)(-1)^{1+1} \begin{vmatrix} 2 - \lambda & 1 \\ 1 & 2 - \lambda \end{vmatrix}$$

$$= (1 - \lambda)^2(-1)^{1+1} \begin{vmatrix} 2 - \lambda & 1 \\ 1 & 2 - \lambda \end{vmatrix}$$

$$= (1 - \lambda)^2((2 - \lambda)^2 - 1)$$

$$= (1 - \lambda)^2(\lambda^2 - 4\lambda + 3) = (\lambda - 1)^3(\lambda - 3)$$

(i) For $\lambda_1 = 1$,

The nullspace of
$$A - \lambda_1 I = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 \end{bmatrix}$$
 is

$$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ -x_1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ -1 \end{bmatrix} x_1 + \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix} x_3$$

and hence

$$E_1 = \operatorname{span}\left(\begin{bmatrix} 1\\0\\0\\-1 \end{bmatrix}, \begin{bmatrix} 0\\1\\0\\0 \end{bmatrix}, \begin{bmatrix} 0\\0\\1\\0 \end{bmatrix}\right).$$

(ii) For $\lambda_2 = 3$,

The nullspace of
$$A - \lambda_2 I = \begin{bmatrix} -1 & 0 & 0 & 1\\ 0 & -2 & 0 & 0\\ 0 & 0 & -2 & 0\\ 1 & 0 & 0 & -1 \end{bmatrix}$$
 is

$$\begin{bmatrix} x_1 \\ 0 \\ 0 \\ x_1 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 1 \end{bmatrix} x_1$$

and hence

$$E_3 = \operatorname{span} \left(\begin{bmatrix} 1\\0\\0\\1 \end{bmatrix} \right)$$

Here, since all the eigenvectors

$$\left\{ \begin{bmatrix} 1\\0\\0\\-1 \end{bmatrix}, \begin{bmatrix} 0\\1\\0\\0 \end{bmatrix}, \begin{bmatrix} 0\\0\\1\\0 \end{bmatrix}, \begin{bmatrix} 1\\0\\0\\1 \end{bmatrix} \right\}$$

are linearly independent, A can be diagonalizable, and

$$A = PDP^{-1}$$

where

$$P = \begin{bmatrix} 1 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -1 & 0 & 0 & 1 \end{bmatrix} \quad \text{and} \quad D = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & 3 \end{bmatrix}.$$

(b) Orthogonalize and normalize the eigenvectors by Gram-Schmidt process $(P \to Q)$

Due to Theorem 5.19, $\begin{bmatrix} 1\\0\\0\\1 \end{bmatrix}$ is orthogonal to all the vectors in E_1 .

Therefore we only need to orthogonalize the vectors in E_1 . But clearly, all the vectors

$$\begin{bmatrix} 1 \\ 0 \\ 0 \\ -1 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \text{and} \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}$$

are orthogonal. So we only need to normalize the vectors to get Q as follows:

$$Q = \begin{bmatrix} 1/\sqrt{2} & 0 & 0 & 1/\sqrt{2} \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -1\sqrt{2} & 0 & 0 & 1/\sqrt{2} \end{bmatrix}.$$

(c) Apply Q to orthogonally diagonalize A ($A \rightarrow QDQ^T$) Summing up, $A = QDQ^T$ where

$$D = \begin{bmatrix} 1 & & & \\ & 1 & & \\ & & 1 & \\ & & & 3 \end{bmatrix} . \text{ and } Q = \begin{bmatrix} 1/\sqrt{2} & 0 & 0 & 1/\sqrt{2} \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -1\sqrt{2} & 0 & 0 & 1/\sqrt{2} \end{bmatrix}.$$

15 By the Spectral theorem, A and B are real symmetric matrices. Clearly, the entries of AB are also real numbers. Now, $(AB)^T = B^TA^T = BA = AB$ therefore AB is also a real symmetric matrices and hence orthogonally diagonalizable.

7

- 25 We need to show that $\operatorname{perp}_W(\boldsymbol{v}) = \boldsymbol{v} \operatorname{proj}_W(\boldsymbol{v})$ is orthogonal to \boldsymbol{q} . Now, $\boldsymbol{q} \cdot (\boldsymbol{v} \operatorname{proj}_W(\boldsymbol{v})) = \boldsymbol{q}^T(\boldsymbol{v} \boldsymbol{q}\boldsymbol{q}^T\boldsymbol{v}) = \boldsymbol{q}^T\boldsymbol{v} (\boldsymbol{q}^T\boldsymbol{q})\boldsymbol{q}^T\boldsymbol{v} = \boldsymbol{q}^T\boldsymbol{v} \boldsymbol{q}^T\boldsymbol{v} = 0$ where $\boldsymbol{q}^T\boldsymbol{q} = \boldsymbol{q} \cdot \boldsymbol{q} = 1$ since \boldsymbol{q} is a unit vector.
- 26 (a) We need to show that for $\boldsymbol{x} \in \mathbb{R}^n$, $\operatorname{perp}_W(\boldsymbol{x}) = \boldsymbol{x} \operatorname{proj}_W(\boldsymbol{x})$ is orthogonal to all the vectors in $\{\boldsymbol{q}_1, \dots, \boldsymbol{q}_k\}$.

$$\begin{aligned} \boldsymbol{q}_i \cdot \mathrm{perp}_W(\boldsymbol{x}) &= \boldsymbol{q}_i^T (\boldsymbol{x} - \mathrm{proj}_W(\boldsymbol{x})) \\ &= \boldsymbol{q}_i^T \left(\boldsymbol{x} - \sum_{j=1}^k (\boldsymbol{q}_j \boldsymbol{q}_j^T) \boldsymbol{x} \right) \\ &= \boldsymbol{q}_i^T \boldsymbol{x} - \sum_{j=1}^k (\boldsymbol{q}_i^T \boldsymbol{q}_j \boldsymbol{q}_j^T) \boldsymbol{x} \\ &= \boldsymbol{q}_i^T \boldsymbol{x} - \sum_{j=1}^k (\boldsymbol{q}_i^T \boldsymbol{q}_j) \boldsymbol{q}_j^T \boldsymbol{x} \\ &= \boldsymbol{q}_i^T \boldsymbol{x} - (\boldsymbol{q}_i^T \boldsymbol{q}_i) \boldsymbol{q}_i^T \boldsymbol{x} \\ &= \boldsymbol{0} \end{aligned}$$

since $\{q_1, \dots, q_k\}$ is an orthonormal set.

(b) Kepping in mind that $\{q_1, \dots, q_k\}$ is an orthonormal set,

$$P^{T} = (q_{1}q_{1}^{T} + \dots + q_{k}q_{k}^{T})^{T} = (q_{1}q_{1}^{T})^{T} + \dots + (q_{k}q_{k}^{T})^{T}$$
$$= q_{1}q_{1}^{T} + \dots + q_{k}q_{k}^{T} = P$$

and

$$P^2 = (\boldsymbol{q}_1 \boldsymbol{q}_1^T + \dots + \boldsymbol{q}_k \boldsymbol{q}_k^T)^2 = \boldsymbol{q}_1 \boldsymbol{q}_1^T \boldsymbol{q}_1 \boldsymbol{q}_1^T + \dots + \boldsymbol{q}_k \boldsymbol{q}_k^T \boldsymbol{q}_k \boldsymbol{q}_k^T$$
$$= \boldsymbol{q}_1 \boldsymbol{q}_1^T + \dots + \boldsymbol{q}_k \boldsymbol{q}_k^T = P$$

since

$$\boldsymbol{q}_i \boldsymbol{q}_i^T \boldsymbol{q}_j \boldsymbol{q}_j^T = \boldsymbol{q}_i (\boldsymbol{q}_i \cdot \boldsymbol{q}_j) \boldsymbol{q}_j^T = \begin{cases} \boldsymbol{q}_i \boldsymbol{q}_j^T & i = j \\ 0 & i \neq j \end{cases}$$

(c)
$$QQ^T = \begin{bmatrix} \boldsymbol{q}_1 & \cdots & \boldsymbol{q}_k \end{bmatrix} \begin{bmatrix} \boldsymbol{q}_1^T \\ \vdots \\ \boldsymbol{q}_1^T \end{bmatrix} = \boldsymbol{q}_1 \boldsymbol{q}_1^T + \cdots + \boldsymbol{q}_k \boldsymbol{q}_k^T = P$$

By Theorem 3.25 and Theorem 3.28(a),

$$\operatorname{rank}(P) = \operatorname{rank}((QQ^T)) = \operatorname{rank}(Q^T) = \operatorname{rank}(Q) = k$$

since the columns of Q are orthogonal therefore linearly independent.