#### 1

# Matrix Theory(EE5609) Assignment 7

## Anshum Agrawal Roll No- AI20MTECH11006

Abstract—This document deals with QR decomposition and Singular Value Decomposition.

Download latex-tikz codes from

https://github.com/anshum0302/EE5609/blob/master/assignment7/assign7.tex

### 1 PROBLEM STATEMENT

- 1. Find the QR decomposition of  $V = \begin{pmatrix} 9 & 12 \\ 12 & 16 \end{pmatrix}$
- 2. Find the vertex  $\mathbf{c}$  of the parabola

$$9x^2 + 24xy + 16y^2 - 4y - x + 7 = 0 (1.0.1)$$

using SVD and verify the result using least squares.

#### 2 Solution

## 2.1 QR decomposition of V

Let  $v_1$  and  $v_2$  be the column vectors of matrix V. Then

$$\mathbf{v_1} = \begin{pmatrix} 9 \\ 12 \end{pmatrix} \tag{2.1.1}$$

$$\mathbf{v_2} = \begin{pmatrix} 12\\16 \end{pmatrix} \tag{2.1.2}$$

We can express column vectors of V as

$$\mathbf{v_1} = k_1 \mathbf{u_1} \tag{2.1.3}$$

$$\mathbf{v_2} = r_1 \mathbf{u_1} + k_2 \mathbf{u_2} \tag{2.1.4}$$

where

$$k_1 = ||\mathbf{v_1}|| = \sqrt{9^2 + 12^2} = 15$$
 (2.1.5)

$$\mathbf{u_1} = \frac{\mathbf{v_1}}{k_1} = \frac{1}{15} \begin{pmatrix} 9\\12 \end{pmatrix} = \frac{1}{5} \begin{pmatrix} 3\\4 \end{pmatrix} \tag{2.1.6}$$

$$r_1 = \frac{\mathbf{u_1}^T \mathbf{v_2}}{\|\mathbf{u_1}\|^2} = \frac{1}{5} \begin{pmatrix} 3 & 4 \end{pmatrix} \begin{pmatrix} 12 \\ 16 \end{pmatrix} = 20$$
 (2.1.7)

$$\mathbf{u_2} = \frac{\mathbf{v_2} - r_1 \mathbf{u_1}}{\|\mathbf{v_2} - r_1 \mathbf{u_1}\|} = \begin{pmatrix} 0 \\ 0 \end{pmatrix}$$
 (2.1.8)

$$k_2 = \mathbf{u_2}^T \mathbf{v_2} = \begin{pmatrix} 0 & 0 \end{pmatrix} \begin{pmatrix} 12 \\ 16 \end{pmatrix} = 0$$
 (2.1.9)

The equation (2.1.3) and (2.1.4) can be written as

$$\begin{pmatrix} \mathbf{v_1} & \mathbf{v_2} \end{pmatrix} = \begin{pmatrix} \mathbf{u_1} & \mathbf{u_2} \end{pmatrix} \begin{pmatrix} k_1 & r_1 \\ 0 & k_2 \end{pmatrix}$$
 (2.1.10)

$$\begin{pmatrix} \mathbf{v_1} & \mathbf{v_2} \end{pmatrix} = \mathbf{QR} \tag{2.1.11}$$

where.

$$\mathbf{Q} = \begin{pmatrix} \mathbf{u}_1 & \mathbf{u}_2 \end{pmatrix} \tag{2.1.12}$$

$$\mathbf{R} = \begin{pmatrix} k_1 & r_1 \\ 0 & k_2 \end{pmatrix} \tag{2.1.13}$$

Now Q should be an orthogonal matrix such that

$$\mathbf{O}^T \mathbf{O} = \mathbf{I} \tag{2.1.14}$$

Here, we see that the second column vector of  $\mathbf{Q}$  is zero since the column vectors of  $\mathbf{V}$  are dependent. Therefore we can write  $\mathbf{Q}$  as

$$\mathbf{Q} = \begin{pmatrix} \frac{3}{5} \\ \frac{1}{5} \end{pmatrix} \tag{2.1.15}$$

Therefore, for the given matrix V, we can write QR decomposition as the product of respective row and column vectors as

$$\mathbf{V} = \mathbf{Q}\mathbf{R} \tag{2.1.16}$$

$$\implies \begin{pmatrix} 9 & 12 \\ 12 & 16 \end{pmatrix} = \begin{pmatrix} \frac{3}{5} \\ \frac{4}{5} \end{pmatrix} \begin{pmatrix} 15 & 20 \end{pmatrix} \tag{2.1.17}$$

2.2 Finding vertex c using SVD

$$\mathbf{V} = \begin{pmatrix} 9 & 12 \\ 12 & 16 \end{pmatrix} \tag{2.2.1}$$

$$\mathbf{u} = \begin{pmatrix} -\frac{1}{2} \\ -2 \end{pmatrix} \tag{2.2.2}$$

$$f = 7 \tag{2.2.3}$$

$$\mathbf{P} = \begin{pmatrix} \mathbf{p_1} & \mathbf{p_2} \end{pmatrix} = \frac{1}{5} \begin{pmatrix} -4 & 3\\ 3 & 4 \end{pmatrix} \tag{2.2.4}$$

$$\eta = 2\mathbf{p_1}^T \mathbf{u} = -\frac{8}{5} \tag{2.2.5}$$

And the expression for vertex  $\mathbf{c}$  is given by

$$\begin{pmatrix} \mathbf{u}^T + \eta \mathbf{p_1}^T \\ \mathbf{V} \end{pmatrix} \mathbf{c} = \begin{pmatrix} -f \\ \eta \mathbf{p_1} - \mathbf{u} \end{pmatrix}$$
 (2.2.6)

Substituting values from (2.2.1) to (2.2.5) in equation (2.2.6) we get

$$\begin{pmatrix} \frac{39}{50} & -\frac{74}{25} \\ 9 & 12 \\ 12 & 16 \end{pmatrix} \mathbf{c} = \begin{pmatrix} -7 \\ \frac{89}{50} \\ \frac{26}{25} \end{pmatrix}$$
 (2.2.7)

This is of the form

$$\mathbf{Ac} = \mathbf{b} \tag{2.2.8}$$

where

$$\mathbf{A} = \begin{pmatrix} \frac{39}{50} & -\frac{74}{25} \\ 9 & 12 \\ 12 & 16 \end{pmatrix} \tag{2.2.9}$$

$$\mathbf{b} = \begin{pmatrix} -7\\ \frac{89}{50}\\ \frac{26}{26} \end{pmatrix} \tag{2.2.10}$$

To solve (2.2.8) we perform Singular value decomposition of **A** as follows:

$$\mathbf{A} = \mathbf{U}\mathbf{S}\mathbf{V}^T \tag{2.2.11}$$

where columns of V are eigenvectors of  $A^TA$ , columns of  $\mathbf{U}$  are eigenvectors of  $\mathbf{A}\mathbf{A}^T$  and  $\mathbf{S}$  is diagonal matrix of the square roots of eigen values of  $A^TA$ . Substituting (2.2.11) in (2.2.8) we get

$$\mathbf{USV}^T\mathbf{c} = \mathbf{b} \tag{2.2.12}$$

$$\implies \mathbf{c} = \mathbf{V}\mathbf{S}_{+}\mathbf{U}^{T}\mathbf{b} \tag{2.2.13}$$

Where  $S_+$  is the Moore-Penrose pseudo-Inverse of S.Now using (2.2.9) we get

$$\mathbf{A}\mathbf{A}^{T} = \begin{pmatrix} \frac{937}{100} & -\frac{57}{2} & -38\\ -\frac{57}{2} & 225 & 300\\ -38 & 300 & 400 \end{pmatrix}$$
 (2.2.14)

$$\mathbf{A}^T \mathbf{A} = \begin{pmatrix} \frac{564021}{2500} & \frac{186057}{625} \\ \frac{186057}{625} & \frac{255476}{625} \end{pmatrix}$$
 (2.2.15)

Eigen values of  $AA^T$  can be found as

$$|\mathbf{A}\mathbf{A}^T - \lambda \mathbf{I}| = 0 \quad (2.2.16)$$

$$\Rightarrow \begin{vmatrix} \frac{937}{100} - \lambda & -\frac{57}{2} & -38 \\ -\frac{57}{2} & 225 - \lambda & 300 \\ -38 & 300 & 400 - \lambda \end{vmatrix} = 0 \quad (2.2.17)$$

$$\implies -\lambda^3 + \frac{63437}{100}\lambda^2 - 3600\lambda = 0 \quad (2.2.18)$$

Solving (2.2.18) we get

$$\lambda_1 = \frac{63437 + \sqrt{3880252969}}{200} \tag{2.2.19}$$

$$\implies \lambda_1 = 628.6434$$
 (2.2.20)

$$\lambda_2 = \frac{63437 - \sqrt{3880252969}}{200} \tag{2.2.21}$$

$$\implies \lambda_2 = 5.7266 \tag{2.2.22}$$

$$\lambda_3 = 0 \tag{2.2.23}$$

The normalized eigenvectors corresponding to these eigenvalues are

$$\mathbf{u}_1 = \begin{pmatrix} -0.07648\\ 0.59823\\ 0.79764 \end{pmatrix} \tag{2.2.24}$$

$$\mathbf{u}_2 = \begin{pmatrix} 0.99707 \\ 0.04589 \\ 0.06118 \end{pmatrix} \tag{2.2.25}$$

$$\mathbf{u}_3 = \begin{pmatrix} 0 \\ -0.8 \\ 0.6 \end{pmatrix} \tag{2.2.26}$$

Hence we obtain U of (2.2.11) as

$$\mathbf{U} = \begin{pmatrix} -0.07648 & 0.99707 & 0\\ 0.59823 & 0.04589 & -0.8\\ 0.79764 & 0.06118 & 0.6 \end{pmatrix}$$
 (2.2.27)

Similarly eigen values of  $A^TA$  can be found as

$$\left|\mathbf{A}^T \mathbf{A} - \lambda \mathbf{I}\right| = 0 \tag{2.2.28}$$

$$\begin{vmatrix} \mathbf{A}^{T} \mathbf{A} - \lambda \mathbf{I} | = 0 & (2.2.28) \\ \implies \begin{vmatrix} \frac{564021}{2500} - \lambda & \frac{186057}{625} \\ \frac{186057}{625} & \frac{255476}{625} - \lambda \end{vmatrix} = 0 & (2.2.29)$$

$$\implies \lambda^2 - \frac{63437}{100}\lambda + 3600 = 0 \qquad (2.2.30)$$

Solving (2.2.30) we get

$$\lambda_4 = \frac{63437 + \sqrt{3880252969}}{200} \tag{2.2.31}$$

$$\implies \lambda_4 = 628.6434 \tag{2.2.32}$$

$$\lambda_5 = \frac{63437 - \sqrt{3880252969}}{200} \tag{2.2.33}$$

$$\implies \lambda_5 = 5.7266 \tag{2.2.34}$$

The normalized eigenvectors corresponding to these Solving the augmented matrix eigenvalues are

$$\mathbf{v}_1 = \begin{pmatrix} 0.59412 \\ 0.80437 \end{pmatrix} \tag{2.2.35}$$

$$\mathbf{v}_2 = \begin{pmatrix} 0.80438 \\ -0.59412 \end{pmatrix} \tag{2.2.36}$$

Hence we obtain V of (2.2.11) as

$$\mathbf{V} = \begin{pmatrix} 0.59412 & 0.80437 \\ 0.80437 & -0.59412 \end{pmatrix} \tag{2.2.37}$$

**S** of equation (2.2.11) corresponding to  $\lambda_4, \lambda_5$  is

$$\mathbf{S} = \begin{pmatrix} \sqrt{628.6434} & 0\\ 0 & \sqrt{5.7266}\\ 0 & 0 \end{pmatrix} \tag{2.2.38}$$

$$\implies \mathbf{S} = \begin{pmatrix} 25.07276 & 0\\ 0 & 2.39303\\ 0 & 0 \end{pmatrix} \tag{2.2.39}$$

Moore-Penrose Pseudo-Inverse of S is given by

$$\mathbf{S}_{+} = \begin{pmatrix} \frac{1}{25.07276} & 0 & 0\\ 0 & \frac{1}{2.39303} & 0 \end{pmatrix}$$
 (2.2.40)  
$$\mathbf{S}_{+} = \begin{pmatrix} 0.03988 & 0 & 0\\ 0 & 0.41788 & 0 \end{pmatrix}$$
 (2.2.41)

$$\mathbf{S}_{+} = \begin{pmatrix} 0.03988 & 0 & 0\\ 0 & 0.41788 & 0 \end{pmatrix} \tag{2.2.41}$$

Now using values from (2.2.27), (2.2.37), (2.2.41), (2.2.10) in (2.2.13) we get

$$\mathbf{U}^{T}\mathbf{b} = \begin{pmatrix} 2.429755 \\ -6.834179 \\ -0.8 \end{pmatrix}$$
 (2.2.42)  
$$\mathbf{S}_{+}\mathbf{U}^{T}\mathbf{b} = \begin{pmatrix} 0.096899 \\ -2.855867 \end{pmatrix}$$
 (2.2.43)

$$\mathbf{S}_{+}\mathbf{U}^{T}\mathbf{b} = \begin{pmatrix} 0.096899 \\ -2.855867 \end{pmatrix}$$
 (2.2.43)

$$\mathbf{c} = \mathbf{V}\mathbf{S}_{+}\mathbf{U}^{T}\mathbf{b} = \begin{pmatrix} -2.2396 \\ 1.7747 \end{pmatrix}$$
 (2.2.44)

Verifying this solution using least squares,

$$\mathbf{A}^T \mathbf{A} \mathbf{c} = \mathbf{A}^T \mathbf{b} \tag{2.2.45}$$

Substituting the values from equations (2.2.9) and (2.2.10) here, we get

$$\begin{pmatrix} \frac{564021}{2500} & \frac{186057}{625} \\ \frac{186057}{625} & \frac{255476}{625} \end{pmatrix} \mathbf{c} = \begin{pmatrix} \frac{576}{25} \\ \frac{1468}{25} \end{pmatrix}$$
 (2.2.46)

$$\begin{pmatrix} \frac{564021}{2500} & \frac{186057}{625} & \frac{576}{25} \\ \frac{186057}{625} & \frac{255476}{625} & \frac{1468}{25} \end{pmatrix} \stackrel{R_1 \leftarrow \frac{2500}{564021}}{\underbrace{R_1 \leftarrow \frac{2500}{564021}}} R_1 \begin{pmatrix} 1 & \frac{744228}{564021} & \frac{57600}{564021} \\ \frac{255476}{625} & \frac{1468}{25} \end{pmatrix} \\ & (2.2.47) \\ & \stackrel{R_2 \leftarrow R_2 - \frac{186057}{625}}{\underbrace{R_1 \leftarrow \frac{744228}{564021}}} \begin{pmatrix} 1 & \frac{744228}{564021} & \frac{57600}{564021} \\ 0 & \frac{9000000}{564021} & \frac{15972300}{564021} \end{pmatrix} \\ & (2.2.48) \\ & \stackrel{R_2 \leftarrow \frac{564021}{9000000}}{\underbrace{R_2 \leftarrow \frac{564021}{9000000}}} R_2 \begin{pmatrix} 1 & \frac{744228}{564021} & \frac{57600}{564021} \\ 0 & 1 & \frac{17747}{10000} \\ (2.2.49) \\ & \stackrel{R_1 \leftarrow R_1 - \frac{744228}{564021}}{\underbrace{R_2 \leftarrow \frac{564021}{564021}}} R_2 \\ & & \begin{pmatrix} 1 & 0 & -\frac{22396}{100000} \\ 0 & 1 & \frac{17747}{10000} \\ 0 & 1 &$$

Therefore

$$\mathbf{c} = \begin{pmatrix} -\frac{22396}{10000} \\ \frac{17747}{10000} \end{pmatrix} = \begin{pmatrix} -2.2396 \\ 1.7747 \end{pmatrix}$$
 (2.2.51)

Hence, verified