

# MATH 307-101 Applied Linear Algebra

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## 1 Approximating Eigenvalues with the QR Algorithm

### 1.1 Prove $A_1$ is similar to $A$

*Proof.*  $A$  is a square matrix. Let,  $A = QR$  be the QR factorization of  $A$ .  $Q$  is a square matrix, and its columns form an orthonormal basis by construction.

Therefore,  $Q^{-1} = Q^T$  and  $Q^T Q = QQ^T = I$ , i.e,  $Q$  is invertible

$A_1 = RQ$ .

A matrix  $A$  is similar to another matrix  $B$  if there exists an invertible matrix  $P$  such that:

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

For  $B = A_1$  and  $P = Q$

$$A = QA_1Q^T = Q(RQ)Q^T = QR$$

Therefore,  $A_1$  is similar to  $A$ .

Now, to prove  $A_1$  and  $A$  have the same eigenvectors.

A matrix has an eigenvalue  $\lambda$  and corresponding eigenvector  $v$  if

$$Av = \lambda v$$

Since  $A_1$  is similar to  $A$

$$Q(RQ)Q^T v = \lambda v$$

Left multiply both sides by  $Q^T$

$$(Q^T Q)(RQ)(Q^T v) = Q^T \lambda v = \lambda(Q^T v)$$

Set  $u = Q^T v$ , and since  $A_1 = RQ$ . We get,

$$A_1 u = \lambda u$$

Since  $\lambda$  and  $v$  were arbitrary, we have shown that  $A$  and  $A_1$  have the same eigenvalues.  $\square$

## 1.2 Find $A_1$ and $A$ , verify they have the same eigenvalues

$$A = \begin{bmatrix} 1 & 0 \\ 1 & 3 \end{bmatrix}$$

Finding the eigenvalues from factoring the characteristic equation, we get

$$\det(A - \lambda I) = (1 - \lambda)(3 - \lambda) = 0 \implies \lambda = 3, 1$$

The QR factorization of  $A$  results in  $A = QR$  such that

$$Q = \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}, R = \begin{bmatrix} \sqrt{2} & \frac{3}{\sqrt{2}} \\ 0 & \frac{3}{\sqrt{2}} \end{bmatrix}$$

Therefore,  $A_1 = RQ$  is

$$A_1 = RQ = \begin{bmatrix} \sqrt{2} & \frac{3}{\sqrt{2}} \\ 0 & \frac{3}{\sqrt{2}} \end{bmatrix} \begin{bmatrix} \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} \frac{5}{2} & \frac{1}{2} \\ \frac{3}{2} & \frac{3}{2} \end{bmatrix}$$

Finding the eigenvalues from factoring the characteristic equation of  $A_1$ , we get

$$\det(A_1 - \lambda I) = \left(\frac{5}{2} - \lambda\right)\left(\frac{3}{2} - \lambda\right) + \frac{3}{2 \times 2} = 0$$

$$\implies (1 - \lambda)(3 - \lambda) = 0 \implies \lambda = 3, 1$$

Therefore,  $A_1$  and  $A$  have the same eigenvalues

### 1.3 $A_k$ is similar to $A$

*Proof.* By induction.

Inductive Hypothesis:  $A_k$  is similar to  $A$  for  $k \geq 1$

Base case:  $A_1$  is similar to  $A$

For an invertible matrix  $Q$ ,

$$A = QA_1Q^T = Q(RQ)Q^T = QR$$

Assume inductive hypothesis is true, that  $A_k$  is similar to  $A$  for  $k \geq 1$

To show:  $A_{k+1}$  is similar to  $A_k$ , and therefore,  $A$

$$A_{k+1} = R_k Q_k$$

$$A_k = Q_k A_{k+1} Q_k^T = Q_k R_k Q_k Q_k^T = Q_k R_k$$

Clearly,  $A_{k+1}$  is similar to  $A_k$ . Therefore,  $A_{k+1}$  is similar to  $A_k$  (since  $A_k = Q_k R_k = R_{k-1} Q_{k-1}$  and so forth) by the inductive hypothesis.

□

### 1.4 Continuing Problem 1.2

Python code was written to calculate  $A_2, A_3, A_4, A_5$ .

See attached file Q1-4.ipynb

$$A_2 = \begin{bmatrix} 3.12 & -0.47 \\ 0.53 & 0.88 \end{bmatrix} A_3 = \begin{bmatrix} 3.06 & 0.84 \\ -0.16 & 0.94 \end{bmatrix} A_4 = \begin{bmatrix} 3.02 & -0.95 \\ 0.05 & 0.98 \end{bmatrix} A_5 = \begin{bmatrix} 3.01 & 0.98 \\ -0.02 & 0.99 \end{bmatrix}$$

As we can clearly see, the diagonals of  $A_k$  approach the eigenvalues of  $A$  as  $k$  increases.

## 1.5 An Important Theorem

### Sources:

QR-Algorithm-GoodReference.pdf,

<https://sites.math.rutgers.edu/~falk/math574/lecture9.pdf>

*Proof.*

**1.  $Q^T A Q$  is upper triangular with the eigenvalues of  $A$  on the diagonal.**

Since  $A$  is a  $n \times n$  matrix with  $n$  eigenvalues, it is diagonalizable so there exists an invertible matrix  $P$  such that:

$$A = P D P^{-1}$$

where  $D$  is a diagonal matrix with the eigenvalues of  $A$  on the diagonal and  $P$  contains the corresponding eigenvectors.

Let  $P = QR$

$$A = QRDR^{-1}Q^{-1} \implies Q^{-1}AQ = RDR^{-1}$$

Since  $RDR^{-1}$  is the product of upper triangular matrices, it is upper triangular. Therefore,  $Q^{-1}AQ = Q^T A Q$  is an upper triangular matrix whose diagonals are the eigenvalues of  $A$ .

**2.  $A^{m+1} = QR(D^{m+1}LD^{-(m+1)})D^{m+1}U$ .**

$$A^{m+1} = (PDP^{-1})^{m+1} = PDP^{-1} \cdot PDP^{-1} \cdots PDP^{-1} \quad (m+1 \text{ times}).$$

When you expand this multiplication, all the intermediate  $P^{-1}P$  terms cancel out, leaving:

$$A^{m+1} = PD^{m+1}P^{-1}.$$

Assuming  $P$  does not require row interchange, as per the GoodReference Proof,  $P = LU$ . Therefore,

$$A^{m+1} = QR D^{m+1} LU = QR D^{m+1} U \tag{1}$$

**3.**  $A_m = P_m^T A P_m$

$$A_m = R_m Q_m, \quad A_{m-1} = Q_m R_m, \quad Q_m^T = Q_m^{-1}$$

So,

$$R_m = Q_m^T A_{m-1} \implies A_m = Q_m^T A_{m-1} Q_m$$

Expanding this we get,

$$A_m = Q_m^T A_{m-1} Q_m = Q_m^T Q_{m-1}^T A_{m-2} Q_{m-1} Q_m = \dots = Q_m^T \dots Q_1^T A_0 Q_1 \dots Q_m = P_m^T A P_m$$

where  $P_m = Q_1 \dots Q_m$ . Note that  $P_m$  is the product of orthogonal matrices and hence is orthogonal.

**4.**  $P_m U_m = Q R D^{m+1} U$

We know from **1.9** that  $A^{m+1} = (Q_0 Q_1 \dots Q_m)(R_m \dots R_1 R_0)$ .

Let  $U_m = R_m \dots R_0$ . Then  $A^{m+1} = P_m U_m$ . Equating this with (1):

$$P_m U_m = Q R (D^{m+1} L D^{-(m+1)}) D^{m+1} U \quad (2)$$

The matrix  $D^{m+1} L D^{-(m+1)}$  is a lower triangular matrix whose  $j, k$ -th element is given by  $l_{jk} \left( \frac{\lambda_j}{\lambda_k} \right)^{m+1}$ , when  $j > k$ . Since  $\left| \frac{\lambda_j}{\lambda_k} \right| < 1$  for  $j > k$ ,

$$\lim_{m \rightarrow \infty} D^{m+1} L D^{-(m+1)} = I.$$

Then (2) becomes  $P_m U_m = Q R D^{m+1} U$

**5.**  $A_m$  converges to  $Q^T A Q$ .

Since the QR factorization is unique,

$$\lim_{m \rightarrow \infty} P_m = Q \text{ and } \lim_{m \rightarrow \infty} U_m = \lim_{m \rightarrow \infty} R D^{m+1} U.$$

So,

$$\lim_{m \rightarrow \infty} A_m = \lim_{m \rightarrow \infty} P_m^T A P_m = Q^T A Q$$

Therefore,  $A_m$  converges to an upper triangular matrix whose diagonals are the eigenvalues of  $A$ .  $\square$

## 1.6 QR Algorithm in Python

Results from python code (QRAlgorithm(1.6-1.8).py):

Matrix	Eigenvalues
$\begin{bmatrix} 2 & 3 \\ 2 & 1 \end{bmatrix}$	4.0, -1.0
$\begin{bmatrix} 1 & 1 \\ 2 & 1 \end{bmatrix}$	2.41, -0.41
$\begin{bmatrix} 1 & 0 & -1 \\ 1 & 2 & 1 \\ -4 & 0 & 1 \end{bmatrix}$	3.01, 1.99, -1.0
$\begin{bmatrix} 1 & 1 & -1 \\ 0 & 2 & 0 \\ -2 & 4 & 2 \end{bmatrix}$	3.0, 2.0, 0.0

## 1.7 Another Example

Results from python code (QRAlgorithm(1.6-1.8).py):

Matrix	Eigenvalues
$\begin{bmatrix} 2 & 3 \\ -1 & -2 \end{bmatrix}$	2.0, -2.0

This is clearly incorrect as the eigenvalues should be 1 and -1. The basic QR algorithm has failed because the absolute values of the eigenvalues are non-distinct. The QR algorithm relies on separating eigenvalues based on their magnitudes and since the eigenvalues are the same magnitude, the algorithm fails.

## 1.8 Using a Shift

Results from python code (QRAlgorithm(1.6-1.8).py):

Matrix	Eigenvalues
$\begin{bmatrix} 2 & 3 \\ -1 & -2 \end{bmatrix}$	1.0, -1.0

$B = A + \alpha I \implies \lambda$  is an eigenvalue of A  $\iff \lambda + \alpha$  is an eigenvalue of B.

*Proof.*

( $\implies$ ) Let  $\lambda$  be an eigenvalue of A. Then there exists a non-zero vector  $x$  such that  $Ax = \lambda x$ .

Then  $Bx = (A + \alpha I)x = Ax + \alpha x = \lambda x + \alpha x = (\lambda + \alpha)x$ .

Thus,  $\lambda + \alpha$  is an eigenvalue of B.

( $\impliedby$ ) Let  $\lambda + \alpha$  be an eigenvalue of B. Then there exists a non-zero vector  $x$  such that  $Bx = (\lambda + \alpha)x$ .

Then  $Ax = (B - \alpha I)x = Bx - \alpha Ix = (\lambda + \alpha)x - \alpha x = \lambda x$ .

Thus,  $\lambda$  is an eigenvalue of  $A$ .

□

## 1.9 The $QR$ factorization of $A^{k+1}$

*Proof.*

Let  $Q_0 = Q$  and  $R_0 = R$ .

**1.**  $Q_0 Q_1 \cdots Q_{k-1} A_k = A Q_0 Q_1 \cdots Q_{k-1}$  for all  $k \geq 1$

*Base Case:*  $k = 1$  so  $A = Q_0 R_0$ ,  $A_1 = R_0 Q_0$  then,

$$Q_0 A_1 = (Q_0 R_0) Q_0 = A Q_0$$

*Inductive Step:* Assume  $Q_0 Q_1 \cdots Q_{k-1} A_k = Q_0 Q_1 \cdots Q_{k-1} R_{k-1} Q_{k-1} = A Q_0 Q_1 \cdots Q_{k-1}$ , then for  $k + 1$

$$\begin{aligned} Q_0 Q_1 \cdots Q_{k-1} Q_k A_{k+1} &= Q_0 Q_1 \cdots Q_{k-1} Q_k R_k Q_k \\ &= Q_0 Q_1 \cdots Q_{k-1} A_k Q_k \quad (\text{Since } A_k = Q_k R_k) \\ &= (Q_0 Q_1 \cdots Q_{k-1} R_{k-1} Q_{k-1}) Q_k \quad (\text{Since } A_k = R_{k-1} Q_{k-1}) \\ &= A Q_0 Q_1 \cdots Q_{k-1} Q_k \quad (\text{By Inductive Hypothesis}) \end{aligned}$$

Thus  $Q_0 Q_1 \cdots Q_{k-1} A_k = A Q_0 Q_1 \cdots Q_{k-1}$ .

**2.**  $(Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0) = A(Q_0 Q_1 \cdots Q_{k-1})(R_{k-1} \cdots R_1 R_0)$

*Base Case:*  $k = 1$  so  $A = Q_0 R_0$ ,  $A_1 = R_0 Q_0$  then,

$$\begin{aligned} (Q_0 Q_1)(R_1 R_0) &= Q_0 Q_1 R_1 R_0 = Q_0 A_1 R_0 \quad (\text{Since } A_1 = Q_1 R_1) \\ &= Q_0 R_0 Q_0 R_0 \quad (\text{Since } A_1 = R_0 Q_0) \\ &= A Q_0 R_0 \quad (\text{Since } A = Q_0 R_0) \end{aligned}$$

*Inductive Step:* Assume  $(Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0) = A(Q_0 Q_1 \cdots Q_{k-1})(R_{k-1} \cdots R_1 R_0)$ , then for  $k + 1$

$$\begin{aligned} (Q_0 Q_1 \cdots Q_k Q_{k+1})(R_{k+1} R_k \cdots R_1 R_0) &= Q_0 Q_1 \cdots Q_k Q_{k+1} R_{k+1} R_k \cdots R_1 R_0 \\ &= Q_0 Q_1 \cdots Q_k A_{k+1} R_k \cdots R_1 R_0 \quad (\text{Since } A_{k+1} = Q_{k+1} R_{k+1}) \\ &= Q_0 Q_1 \cdots Q_k R_k Q_k R_k \cdots R_1 R_0 \quad (\text{Since } A_{k+1} = R_k Q_k) \\ &= (Q_0 Q_1 \cdots Q_{k-1} A_k) Q_k R_k R_{k-1} \cdots R_1 R_0 \quad (\text{Since } A_k = Q_k R_k) \\ &= (A Q_0 Q_1 \cdots Q_{k-1}) Q_k R_k R_{k-1} \cdots R_1 R_0 \quad (\text{By 1.}) \\ &= A(Q_0 Q_1 \cdots Q_{k-1} Q_k)(R_k R_{k-1} \cdots R_1 R_0) \end{aligned}$$

Thus  $(Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0) = A(Q_0 Q_1 \cdots Q_{k-1})(R_{k-1} \cdots R_1 R_0)$ .

**3.**  $A^{k+1} = (Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0)$



*Base Case:*  $k = 0$  so  $A^1 = Q_0 R_0 = Q R = A$

*Inductive Step:* Assume  $A^{k+1} = (Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0)$ , then for  $k + 2$

$A^{k+2} = A A^{k+1} = A(Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0)$  (By Inductive Hypothesis)

$$= (Q_0 Q_1 \cdots Q_k Q_{k+1})(R_{k+1} R_k \cdots R_1 R_0) \text{ (By 2.)}$$

Thus  $A^{k+1} = (Q_0 Q_1 \cdots Q_k)(R_k \cdots R_1 R_0)$  for all  $k \geq 0$ .  $\square$

## 1.10 Reduction to Upper Hessenberg Form

### 1.10.1 The $2 \times 2$ matrix $Q$

*Proof.* Given:

$$u = \frac{x - y}{\|x - y\|} = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}, \quad \|x\| = \|Qx\| = \|y\|, \quad y = \pm \|x\| u, \quad u^\perp = \begin{bmatrix} -d_2 \\ d_1 \end{bmatrix}$$

We define:

$$Q = I - 2uu^T$$

where  $I$  is the identity matrix of size  $2 \times 2$ .

Now,

$$u = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix}, \quad uu^T = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} \begin{bmatrix} d_1 & d_2 \end{bmatrix} = \begin{bmatrix} d_1^2 & d_1 d_2 \\ d_1 d_2 & d_2^2 \end{bmatrix}$$

Thus:

$$Q = I - 2 \begin{bmatrix} d_1^2 & d_1 d_2 \\ d_1 d_2 & d_2^2 \end{bmatrix}$$

Expanding  $I$  and subtracting:

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} - \begin{bmatrix} 2d_1^2 & 2d_1 d_2 \\ 2d_1 d_2 & 2d_2^2 \end{bmatrix}$$

$$Q = \begin{bmatrix} 1 - 2d_1^2 & -2d_1 d_2 \\ -2d_1 d_2 & 1 - 2d_2^2 \end{bmatrix}$$

This matrix represents the standard matrix  $Q$  of the reflection in the line through the origin in direction  $u$ , i.e.:

$$Q = I - 2uu^T$$

□

### 1.10.2 An example of $Q$

$$(a) \quad u = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} \frac{3}{5} \\ \frac{4}{5} \end{bmatrix} \implies d_1 = \frac{3}{5}, d_2 = \frac{4}{5}$$

$$Q = \begin{bmatrix} 1 - 2d_1^2 & -2d_1d_2 \\ -2d_1d_2 & 1 - 2d_2^2 \end{bmatrix} = \begin{bmatrix} 1 - 2(\frac{3}{5})^2 & -2(\frac{3}{5})(\frac{4}{5}) \\ -2(\frac{3}{5})(\frac{4}{5}) & 1 - 2(\frac{4}{5})^2 \end{bmatrix} = \begin{bmatrix} \frac{7}{25} & -\frac{24}{25} \\ -\frac{24}{25} & -\frac{7}{25} \end{bmatrix}$$

$$(b) \quad x = \begin{bmatrix} d_1 \\ d_2 \end{bmatrix} = \begin{bmatrix} 5 \\ 5 \end{bmatrix}, \quad y = \begin{bmatrix} 1 \\ 7 \end{bmatrix}$$

$$u = \frac{x-y}{\|x-y\|} = \frac{\begin{bmatrix} 5 \\ 5 \end{bmatrix} - \begin{bmatrix} 1 \\ 7 \end{bmatrix}}{\left\| \begin{bmatrix} 5 \\ 5 \end{bmatrix} - \begin{bmatrix} 1 \\ 7 \end{bmatrix} \right\|} = \frac{\begin{bmatrix} 4 \\ -2 \end{bmatrix}}{\left\| \begin{bmatrix} 4 \\ -2 \end{bmatrix} \right\|} = 2\sqrt{5} \begin{bmatrix} 4 \\ -2 \end{bmatrix} = \begin{bmatrix} \frac{2}{\sqrt{5}} \\ -\frac{1}{\sqrt{5}} \end{bmatrix}$$

$$\implies d_1 = \frac{2}{\sqrt{5}}, d_2 = -\frac{1}{\sqrt{5}}$$

$$Q = \begin{bmatrix} 1 - 2d_1^2 & -2d_1d_2 \\ -2d_1d_2 & 1 - 2d_2^2 \end{bmatrix} = \begin{bmatrix} 1 - 2(\frac{2}{\sqrt{5}})^2 & -2(\frac{2}{\sqrt{5}})(-\frac{1}{\sqrt{5}}) \\ -2(\frac{2}{\sqrt{5}})(-\frac{1}{\sqrt{5}}) & 1 - 2(-\frac{1}{\sqrt{5}})^2 \end{bmatrix} = \begin{bmatrix} -\frac{3}{5} & \frac{4}{5} \\ \frac{4}{5} & \frac{3}{5} \end{bmatrix}$$

### 1.10.3 Properties of Householder Matrices

*Proof.*

Let  $Q$  be a Householder matrix where  $Q = I - 2uu^T$  where  $u$  is a unit vector

in the direction of  $x - y$ .

(a)  $Q$  is symmetric

$$\begin{aligned} Q &= I - 2uu^T \\ Q^T &= (I - 2uu^T)^T = I^T - (2uu^T)^T = I - 2(u^T)^T u^T = I - 2uu^T = Q \\ \text{Thus, } Q &\text{ is symmetric.} \end{aligned}$$

(b)  $Q$  is orthogonal

$$\begin{aligned} Q^T Q &= QQ = I \\ Q^T Q &= (I - 2uu^T)(I - 2uu^T) = I - 2uu^T - 2uu^T + 4uu^T uu^T = \\ &= I - 4uu^T + 4uu^T = I \\ \text{Thus, } Q &\text{ is orthogonal.} \end{aligned}$$

(c)  $Q^2 = I$

$$\begin{aligned} Q^2 &= QQ = I \text{ (from (a) \& (b))} \\ \text{Thus, } Q^2 &= I. \end{aligned}$$

□

#### 1.10.4 Computing $Q\mathbf{v}$ for some vectors $\mathbf{v}$

*Proof.* If  $Q$  is a Householder matrix corresponding to the unit vector  $\mathbf{u}$ , then

$$Q\mathbf{v} = \begin{cases} -\mathbf{v}, & \text{if } \mathbf{v} \in \text{span}\{\mathbf{u}\}, \\ \mathbf{v}, & \text{if } \mathbf{v} \cdot \mathbf{u} = 0. \end{cases}$$

**Case 1:**  $Qv = -v$  if  $v \in \text{span}\{u\}$

$$\text{span}\{u\} = \{cu | c \in \mathbb{R}\}$$

$$v = cu \text{ for some } c \in \mathbb{R}$$

$$\begin{aligned} Qv &= Q(cu) = cQu = c(I - 2uu^T)u = c(u - 2uu^T u) \\ &= c(u - 2u\|u\|^2) = c(u - 2u) \text{ (Since } \|u\| = 1) \\ &= c(-u) = -cu = -v \end{aligned}$$

**Case 2:**  $Qv = v$  if  $v \cdot u = 0$

$$Qv = (I - 2uu^T)v = v - 2uu^Tv = v - 2u(v \cdot u) = v - 2u(0) = v$$

Thus,

$$Q\mathbf{v} = \begin{cases} -\mathbf{v}, & \text{if } \mathbf{v} \in \text{span}\{\mathbf{u}\}, \\ \mathbf{v}, & \text{if } \mathbf{v} \cdot \mathbf{u} = 0. \end{cases}$$

□

### 1.10.5 Proving that $Qx = y$

Let  $x \neq y$  with  $\|x\| = \|y\|$  and  $u = \frac{x-y}{\|x-y\|}$ . Let  $Q$  be the corresponding Householder matrix.

*Proof.*

$$Qx = (I - 2uu^T)x = x - 2uu^Tx.$$

Recall that  $u = \frac{x-y}{\|x-y\|}$ . So:

$$Qx = x - 2 \left( \frac{x-y}{\|x-y\|} \right) \left( \frac{x-y}{\|x-y\|} \right)^T x = x - 2 \left( \frac{x-y}{\|x-y\|} \right) \frac{(x-y)^Tx}{\|x-y\|}$$

Since  $(x-y)^Tx$  is a scalar, we can move it to the left and combine the denominators:

$$\begin{aligned} &= x - 2 \frac{(x-y)^Tx}{\|x-y\|^2} (x-y) = x - 2 \frac{x^Tx - y^Tx}{(x-y)^T(x-y)} (x-y) \\ &= x - 2 \left( \frac{x^Tx - y^Tx}{x^Tx - x^Ty - y^Tx + y^Ty} \right) (x-y) \\ &= x - 2 \left( \frac{x^Tx - y^Tx}{2x^Tx - x^Ty - y^Tx} \right) (x-y) \quad (\text{Since } x^Tx = y^Ty) \\ &= x - 2 \left( \frac{x^Tx - y^Tx}{2x^Tx - 2y^Tx} \right) (x-y) \quad (\text{Since } x^Ty = y^Tx) \\ &= x - \left( \frac{x^Tx - y^Tx}{x^Tx - y^Tx} \right) (x-y) \end{aligned}$$

The fraction consists of all scalars with the denominator = numerator so:

$$= x - (x-y) = y$$

□

**Verifying with:**  $x = \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix}, y = \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix}$

$$\begin{aligned}
u &= \frac{x-y}{\|x-y\|} = \frac{\begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix}}{\left\| \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} - \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix} \right\|} = \frac{\begin{bmatrix} -2 \\ 2 \\ 2 \end{bmatrix}}{\left\| \begin{bmatrix} -2 \\ 2 \\ 2 \end{bmatrix} \right\|} = \frac{1}{2\sqrt{3}} \begin{bmatrix} -2 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} -\frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{bmatrix} \\
Q &= I - 2uu^T = I - 2 \begin{bmatrix} -\frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \\ \frac{1}{\sqrt{3}} \end{bmatrix} \begin{bmatrix} -\frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} & \frac{1}{\sqrt{3}} \end{bmatrix} = I - 2 \begin{bmatrix} \frac{1}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -\frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\frac{1}{3} & \frac{1}{3} & \frac{1}{3} \end{bmatrix} \\
&= \begin{bmatrix} 1 - \frac{2}{3} & \frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & 1 - \frac{2}{3} & -\frac{2}{3} \\ \frac{2}{3} & -\frac{2}{3} & 1 - \frac{2}{3} \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & \frac{1}{3} & -\frac{2}{3} \\ \frac{2}{3} & -\frac{2}{3} & \frac{1}{3} \end{bmatrix} \\
Qx &= \begin{bmatrix} \frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & \frac{1}{3} & -\frac{2}{3} \\ \frac{2}{3} & -\frac{2}{3} & \frac{1}{3} \end{bmatrix} \begin{bmatrix} 1 \\ 2 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ 0 \\ 0 \end{bmatrix} = y
\end{aligned}$$

### 1.10.6 Reduction to Upper Hessenberg Form

(a) Orthogonality and symmetry of  $H_1$ :

*Proof.*  $H_1$  matrix is orthogonal if  $H_1^T H_1 = I$ , where  $I$  is the identity matrix.

$$H_1 = \begin{bmatrix} 1 & 0 \\ 0 & Q_1 \end{bmatrix} \implies H_1^T = \begin{bmatrix} 1 & 0 \\ 0 & Q_1^T \end{bmatrix}$$

Since  $Q_1$  is a Householder matrix,  $Q_1$  is orthogonal so  $Q_1^T Q_1 = I$ . Therefore,

$$H_1^T H_1 = \begin{bmatrix} 1 & 0 \\ 0 & Q_1^T \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & Q_1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & Q_1^T Q_1 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & I \end{bmatrix} = I$$

Thus,  $H_1$  is orthogonal.

$H_1$  is symmetric if  $H_1 = H_1^T$ .

$$H_1 = \begin{bmatrix} 1 & 0 \\ 0 & Q_1 \end{bmatrix} \implies H_1^T = \begin{bmatrix} 1 & 0 \\ 0 & Q_1^T \end{bmatrix}$$

Since  $Q_1$  is a Householder matrix,  $Q_1$  is symmetric so  $Q_1 = Q_1^T$ . Therefore,

$H_1 = H_1^T$  so  $H_1$  is symmetric.

□

(b) Let  $A_1 = H_1 A H_1$ . Then the eigenvalues of  $A$  are the eigenvalues of  $A_1$ :

*Proof.* Let  $A_1 = H_1 A H_1$ . Since  $H_1$  is orthogonal and symmetric  $H_1 = H_1^{-1}$  so  $A_1 = H_1 A H_1 = H_1 A H_1^{-1}$  meaning that  $A$  is similar to  $A_1$ . By **1.1**,  $A_1$  has the same eigenvalues as  $A$ . □

(c) Show that  $A_1 = H_1 A H_1^T$  is a matrix of the form:

$$A_1 = \begin{bmatrix} a_{11} & b_{12} & b_{13} & b_{14} \\ \pm \|x\| & b_{22} & b_{23} & b_{24} \\ 0 & b_{32} & b_{33} & b_{34} \\ 0 & b_{42} & b_{43} & b_{44} \end{bmatrix}$$

$$\text{Let } A = \begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \\ a_{31} & a_{32} & a_{33} & a_{34} \\ a_{41} & a_{42} & a_{43} & a_{44} \end{bmatrix}, \quad H_1 = \begin{bmatrix} 1 & 0 \\ 0 & Q_1 \end{bmatrix}, \quad x = \begin{bmatrix} a_{21} \\ a_{31} \\ a_{41} \end{bmatrix},$$

$$y = \begin{bmatrix} \pm\|x\| \\ 0 \\ 0 \end{bmatrix}$$

Applying  $H_1$  to the left of  $A$ , the first entry of the resulting matrix

$$\text{becomes } a_{11} \text{ because } \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \\ a_{41} \end{bmatrix} = a_{11}.$$

$$\text{Then } \begin{bmatrix} a_{21} \\ a_{31} \\ a_{41} \end{bmatrix} = x \text{ are the remaining entries of the first column of } A.$$

To calculate the resulting corresponding entries we can use the for-

$$\text{mula } Qx = y \text{ where } x \text{ is the remaining column of } A \text{ and } y = \begin{bmatrix} \pm\|x\| \\ 0 \\ 0 \end{bmatrix}.$$

$$\text{So the first column of } H_1 A \text{ is: } \begin{bmatrix} a_{11} \\ \pm\|x\| \\ 0 \\ 0 \end{bmatrix}.$$

Multiplying that column by  $H_1^T = H_1$  will result in the first column

$$\text{of } H_1 A H_1^T \text{ being } \begin{bmatrix} a_{11} \\ \pm\|x\| \\ 0 \\ 0 \end{bmatrix} \text{ because } a_{11} \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = a_{11}, \pm\|x\| \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = \pm\|x\|,$$

and  $0 \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix} = 0$ . The remaining columns of  $A$  are affected but the shape remains the same as  $A$  and  $H_1$  are both 4x4 matrices.

$$\text{So } A_1 = H_1 A H_1^T = \begin{bmatrix} a_{11} & b_{12} & b_{13} & b_{14} \\ \pm\|x\| & b_{22} & b_{23} & b_{24} \\ 0 & b_{32} & b_{33} & b_{34} \\ 0 & b_{42} & b_{43} & b_{44} \end{bmatrix}.$$

(d) Upper Hessenberg form of

$$A = \begin{bmatrix} 1 & 1 & -1 & 4 \\ -2 & -1 & -5 & -1 \\ 4 & -3 & 0 & 2 \\ 4 & 2 & 3 & 1 \end{bmatrix}$$

**Find  $Q_1$  and  $H_1$ :**

$$(i) \ x = \begin{bmatrix} -2 \\ 4 \\ 4 \end{bmatrix}, \quad y = \begin{bmatrix} \pm\|x\| \\ 0 \\ 0 \end{bmatrix}, \quad \|x\| = \sqrt{(-2)^2 + 4^2 + 4^2} = \pm 6.$$

$$\text{Choose } y = \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix} \text{ since } +6 \text{ is opposite sign to } -2.$$



$$v = y - x = \begin{bmatrix} 6 \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} -2 \\ 4 \\ 4 \end{bmatrix} = \begin{bmatrix} 8 \\ -4 \\ -4 \end{bmatrix}$$

$$\begin{aligned} \text{(ii)} \quad P &= \frac{vv^T}{v^T v} \\ &= \frac{\begin{bmatrix} 8 \\ -4 \\ -4 \end{bmatrix} \begin{bmatrix} 8 & -4 & -4 \end{bmatrix}}{\begin{bmatrix} 8 & -4 & -4 \end{bmatrix} \begin{bmatrix} 8 \\ -4 \\ -4 \end{bmatrix}} = \frac{1}{64+16+16} \begin{bmatrix} 64 & -32 & -32 \\ -32 & 16 & 16 \\ -32 & 16 & 16 \end{bmatrix} = \frac{1}{96} \begin{bmatrix} 64 & -32 & -32 \\ -32 & 16 & 16 \\ -32 & 16 & 16 \end{bmatrix} \end{aligned}$$

$$P = \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -\frac{1}{3} & \frac{1}{6} & \frac{1}{6} \\ -\frac{1}{3} & \frac{1}{6} & \frac{1}{6} \end{bmatrix}$$

$$\begin{aligned} \text{(iii)} \quad Q_1 &= I - 2P = I - 2 \begin{bmatrix} \frac{2}{3} & -\frac{1}{3} & -\frac{1}{3} \\ -\frac{1}{3} & \frac{1}{6} & \frac{1}{6} \\ -\frac{1}{3} & \frac{1}{6} & \frac{1}{6} \end{bmatrix} = \begin{bmatrix} 1 - \frac{4}{3} & \frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & 1 - \frac{1}{3} & -\frac{1}{3} \\ \frac{2}{3} & -\frac{1}{3} & 1 - \frac{1}{3} \end{bmatrix} = \\ & \begin{bmatrix} -\frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ \frac{2}{3} & \frac{2}{3} & -\frac{1}{3} \\ \frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \end{bmatrix} \end{aligned}$$

$$\text{(iv)} \quad H_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -\frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ 0 & \frac{2}{3} & \frac{2}{3} & -\frac{1}{3} \\ 0 & \frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \end{bmatrix}$$

**Find**  $A_1 = H_1 A H_1^T = H_1 A H_1$ :

$$A_1 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -\frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ 0 & \frac{2}{3} & \frac{2}{3} & -\frac{1}{3} \\ 0 & \frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \end{bmatrix} \begin{bmatrix} 1 & 1 & -1 & 4 \\ -2 & -1 & -5 & -1 \\ 4 & -3 & 0 & 2 \\ 4 & 2 & 3 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & -\frac{1}{3} & \frac{2}{3} & \frac{2}{3} \\ 0 & \frac{2}{3} & \frac{2}{3} & -\frac{1}{3} \\ 0 & \frac{2}{3} & -\frac{1}{3} & \frac{2}{3} \end{bmatrix}$$

$$A_1 = \begin{bmatrix} 1 & \frac{5}{3} & -\frac{4}{3} & \frac{11}{3} \\ 6 & \frac{37}{9} & \frac{13}{9} & \frac{1}{9} \\ 0 & -\frac{14}{9} & -\frac{47}{9} & -\frac{5}{9} \\ 0 & -\frac{17}{9} & \frac{4}{9} & \frac{10}{9} \end{bmatrix}$$

**Find**  $Q_2$  and  $H_2$ :

$$(i) \quad x = \begin{bmatrix} -\frac{14}{9} \\ -\frac{17}{9} \end{bmatrix}, \quad y = \begin{bmatrix} \pm \|x\| \\ 0 \end{bmatrix}.$$

$$\|x\| = \sqrt{\left(-\frac{14}{9}\right)^2 + \left(-\frac{17}{9}\right)^2} = \pm \frac{\sqrt{485}}{9}.$$

$$\text{Choose } y = \begin{bmatrix} \frac{\sqrt{485}}{9} \\ 0 \\ 0 \end{bmatrix} \text{ since } +\frac{\sqrt{485}}{9} \text{ is opposite sign to } -\frac{14}{9}.$$

$$v = y - x = \begin{bmatrix} \frac{\sqrt{485}}{9} \\ 0 \\ 0 \end{bmatrix} - \begin{bmatrix} -\frac{14}{9} \\ -\frac{17}{9} \end{bmatrix} = \begin{bmatrix} \frac{14+\sqrt{485}}{9} \\ \frac{17}{9} \end{bmatrix}$$

$$(ii) \quad P = \frac{vv^T}{v^T v}$$

$$\begin{aligned}
&= \frac{\begin{bmatrix} \frac{14+\sqrt{485}}{9} \\ \frac{17}{9} \end{bmatrix}}{\begin{bmatrix} \frac{14+\sqrt{485}}{9} & \frac{17}{9} \end{bmatrix} \begin{bmatrix} \frac{14+\sqrt{485}}{9} \\ \frac{17}{9} \end{bmatrix}} = \frac{81}{970+28\sqrt{485}} \begin{bmatrix} \frac{681+28\sqrt{485}}{81} & \frac{17(14+\sqrt{485})}{81} \\ \frac{17(14+\sqrt{485})}{81} & \frac{289}{81} \end{bmatrix} \\
P &= \begin{bmatrix} \frac{681+28\sqrt{485}}{970+28\sqrt{485}} & \frac{17(14+\sqrt{485})}{970+28\sqrt{485}} \\ \frac{17(14+\sqrt{485})}{970+28\sqrt{485}} & \frac{289}{970+28\sqrt{485}} \end{bmatrix} = \begin{bmatrix} \frac{485+14\sqrt{485}}{970} & \frac{17}{2\sqrt{485}} \\ \frac{17}{2\sqrt{485}} & \frac{485-14\sqrt{485}}{970} \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
\text{(iii) } Q_2 &= I - 2P = I - 2 \begin{bmatrix} \frac{485+14\sqrt{485}}{970} & \frac{17}{2\sqrt{485}} \\ \frac{17}{2\sqrt{485}} & \frac{485-14\sqrt{485}}{970} \end{bmatrix} \\
Q_2 &= \begin{bmatrix} 1 - \frac{485+14\sqrt{485}}{485} & -\frac{17}{\sqrt{485}} \\ -\frac{17}{\sqrt{485}} & 1 - \frac{485-14\sqrt{485}}{485} \end{bmatrix} = \begin{bmatrix} -\frac{14}{\sqrt{485}} & -\frac{17}{\sqrt{485}} \\ -\frac{17}{\sqrt{485}} & \frac{14}{\sqrt{485}} \end{bmatrix}
\end{aligned}$$

$$\text{(iv) } H_2 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & -\frac{14}{\sqrt{485}} & -\frac{17}{\sqrt{485}} \\ 0 & 0 & -\frac{17}{\sqrt{485}} & \frac{14}{\sqrt{485}} \end{bmatrix}$$

**Find**  $A_2 = H_2(A_1)H_2$ :

$$A_2 = \begin{bmatrix} 1 & \frac{5}{3} & -\frac{131}{3\sqrt{485}} & \frac{74}{\sqrt{485}} \\ 6 & \frac{37}{9} & -\frac{199}{9\sqrt{485}} & -\frac{23}{\sqrt{485}} \\ 0 & \frac{\sqrt{485}}{9} & -\frac{1312}{873} & -\frac{254}{97} \\ 0 & 0 & -\frac{351}{97} & -\frac{253}{97} \end{bmatrix} \quad \text{This is the upper Hessenberg form}$$

of  $A$ .

- (e) Why the upper Hessenberg form of a symmetric matrix is always a tridiagonal matrix:

*Proof.*

- (i) **Upper Hessenberg Form Definition:**
  - A matrix is in upper Hessenberg form if all entries below the first subdiagonal are zero. For an  $n \times n$  matrix, this means  $a_{ij} = 0$  for  $i > j + 1$ .
- (ii) **Symmetric Matrix Property:**
  - A symmetric matrix satisfies  $a_{ij} = a_{ji}$  for all  $i, j$ .
- (iii) **Preservation of matrix structure under similarity transformations:**
  - Similarity transformations preserve the structure of a matrix, meaning that the upper Hessenberg form of a symmetric matrix must also be symmetric.
- (iv) **Combining the Two Properties:**
  - In the upper Hessenberg form,  $a_{ij} = 0$  for  $i > j + 1$ . Due to symmetry,  $a_{ji} = 0$  whenever  $a_{ij} = 0$ .
  - This means  $a_{ij} = 0$  for both  $i > j + 1$  and  $j > i + 1$ , effectively enforcing  $a_{ij} = 0$  for all  $|i - j| > 1$ .
- (v) **Resulting Matrix Structure:**
  - The only nonzero entries of the symmetric matrix are along the main diagonal ( $|i - j| = 0$ ) and the first subdiagonals ( $|i - j| = 1$ ), making it a **tridiagonal matrix**.

Thus, the upper Hessenberg form of a symmetric matrix naturally becomes tridiagonal because the symmetry constraint forces zeros to appear below and above the second subdiagonals.  $\square$

## 1.11 QR Algorithm with Shifts

$A_{k-1}$  and  $A_k$  from the Practical QR Algorithm have the same eigenvalues.

*Proof.*

The matrix  $A_{k-1}$  can be written as:

$$A_{k-1} = Q_k R_k + \mu_k I \implies A_{k-1} - \mu_k I = Q_k R_k.$$

where  $Q_k$  is orthogonal. Multiplying both sides on the left by  $Q_k^\top$ , we get:

$$Q_k^\top (A_{k-1} - \mu_k I) = R_k.$$

The next matrix  $A_k$  is defined as:

$$A_k = R_k Q_k + \mu_k I.$$

Substituting  $R_k = Q_k^\top (A_{k-1} - \mu_k I)$ , we can rewrite  $A_k$  as:

$$A_k = Q_k^\top (A_{k-1} - \mu_k I) Q_k + \mu_k I.$$

Simplifying this expression:

$$A_k = Q_k^\top A_{k-1} Q_k - Q_k^\top (\mu_k I) Q_k + \mu_k I.$$

Since  $Q_k^\top Q_k = I$ , this simplifies further to:

$$A_k = Q_k^\top A_{k-1} Q_k.$$

Since  $Q$  is orthogonal,  $Q^{-1} = Q^\top$ . Therefore,  $A_k$  and  $A_{k-1}$  are similar matrices and thus share eigenvalues as proven in **1.1**.

Thus, for every  $k \geq 1$ , the matrices  $A_{k-1}$  and  $A_k$  share the same eigenvalues.  $\square$

## 2 Image Compression

### 2.1 The Outer Product Form of the SVD

(a) Prove theorem 2.1

*Proof.*

We have  $A = U \Sigma V^T$ , the SVD Decomposition of  $A$

Let  $U = \begin{bmatrix} u_1 & u_2 & \dots & u_r & u_{r+1} & \dots & u_m \end{bmatrix}$  and,

Let  $V = \begin{bmatrix} v_1 & v_2 & \dots & v_r & v_{r+1} & \dots & v_n \end{bmatrix}$

$$\text{Therefore, } V^T = \begin{bmatrix} v_1^T \\ v_2^T \\ \dots \\ v_r^T \\ v_{r+1}^T \\ \dots \\ v_n^T \end{bmatrix}$$

We want to show that

$$A = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T$$

$$U \Sigma V^T = \begin{bmatrix} u_1 & u_2 & \dots & u_r & u_{r+1} & \dots & u_m \end{bmatrix} \begin{bmatrix} \begin{bmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & \dots & \sigma_r \\ & & 0 & \end{bmatrix} & \begin{bmatrix} 0 \\ 0 \end{bmatrix} \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \dots \\ v_r^T \\ v_{r+1}^T \\ \dots \\ v_n^T \end{bmatrix}$$

$$\implies U \Sigma V^T = \begin{bmatrix} \sigma_1 u_1 & \sigma_2 u_2 & \dots & \sigma_r u_r & (0)u_{r+1} & \dots & (0)u_n \end{bmatrix} \begin{bmatrix} v_1^T \\ v_2^T \\ \dots \\ v_r^T \\ v_{r+1}^T \\ \dots \\ v_n^T \end{bmatrix}$$

$$\implies U\Sigma V^T = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T + (0)u_{r+1}v_{r+1}^T + \dots + (0)u_n v_n^T$$

$$\implies A = U\Sigma V^T = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \dots + \sigma_r u_r v_r^T$$

□

$$(b) \quad A = \begin{bmatrix} -2 & 2 \\ -1 & 1 \\ 2 & -2 \end{bmatrix}$$

$$A^T A = \begin{bmatrix} -2 & -1 & 2 \\ 2 & 1 & -2 \end{bmatrix} \begin{bmatrix} -2 & 2 \\ -1 & 1 \\ 2 & -2 \end{bmatrix} = \begin{bmatrix} 9 & -9 \\ -9 & 9 \end{bmatrix}$$

Solving the characteristic equation,  $\det(A^T A - \lambda I) = 0$

$$(9 - \lambda)^2 - (-9)^2 = 0 \iff 81 + \lambda^2 - 18\lambda - 81 = 0 \iff \lambda^2 - 18\lambda = 0$$

$$\lambda = 18, 0$$

Finding the respective eigenvectors,

Solving  $A^T A - \lambda I = 0$  For  $\lambda = 18$

$$A^T A - 18I = \begin{bmatrix} -9 & -9 \\ -9 & -9 \end{bmatrix}$$

$$\implies -9x_1 = 9x_2 \implies x_1 = -x_2 \implies v_1' = x_2 \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$\implies v_1 = \begin{bmatrix} \frac{-1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

For  $\lambda = 0$

$$A^T A - 0I = \begin{bmatrix} 9 & -9 \\ -9 & 9 \end{bmatrix}$$

$$\implies 9x_1 = 9x_2 \implies x_1 = x_2 \implies v'_2 = x_2 \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\implies v_2 = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$\text{Therefore, } V = [v_1 v_2] = \begin{bmatrix} \frac{-1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} \implies V^T = \begin{bmatrix} \frac{-1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$\text{And, } \Sigma = \begin{bmatrix} \sqrt{18} & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Finally, we need to calculate  $U$

Since  $r = 1$ , we can only calculate one left singular value

$$u_1 = \frac{1}{\sigma_1} A v_1 = \frac{1}{\sqrt{18}} \begin{bmatrix} -2 & 2 \\ -1 & 1 \\ 2 & -2 \end{bmatrix} \begin{bmatrix} \frac{-1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} \end{bmatrix} = \frac{1}{\sqrt{18}} \begin{bmatrix} \frac{4}{\sqrt{2}} \\ \frac{2}{\sqrt{2}} \\ \frac{-4}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} \frac{4}{6} \\ \frac{2}{6} \\ \frac{-4}{6} \end{bmatrix} = \begin{bmatrix} 2/3 \\ 1/3 \\ -2/3 \end{bmatrix}$$

Need  $x$  such that  $x \cdot u_1 = 0$

$$\frac{2}{3}x_1 + \frac{1}{3}x_2 - \frac{2}{3}x_3 = 0 \implies 2x_1 + x_2 = 2x_3 \implies x_3 = \frac{1}{2}x_2 + x_1$$

$$\implies x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = x_1 \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} + x_2 \begin{bmatrix} 0 \\ 1 \\ 1/2 \end{bmatrix}$$

$$\text{Therefore we have, } w_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, w_2 = \begin{bmatrix} 0 \\ 1 \\ 1/2 \end{bmatrix}$$

Applying Gram-Schmidt,

$$u'_2 = w_1$$



$$u_2 = \frac{u_2'}{\|u_2'\|} = \begin{bmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

$$u_3' = w_2 - (w_2 \cdot u_2)u_2 = \begin{bmatrix} 0 \\ 1 \\ 1/2 \end{bmatrix} - (0 + 0 + \frac{1}{2\sqrt{2}}) \begin{bmatrix} \frac{1}{\sqrt{2}} \\ 0 \\ \frac{1}{\sqrt{2}} \end{bmatrix}$$

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

$$u_3 = \frac{u_3'}{\|u_3'\|} = \begin{bmatrix} \frac{-1}{3\sqrt{2}} \\ \frac{2\sqrt{2}}{3} \\ \frac{1}{3\sqrt{2}} \end{bmatrix}$$

$$\text{Then, we have } U = [u_1 u_2 u_3] = \begin{bmatrix} \frac{2}{3} & \frac{1}{\sqrt{2}} & \frac{-1}{3\sqrt{2}} \\ \frac{1}{3} & 0 & \frac{2\sqrt{2}}{3} \\ -\frac{2}{3} & \frac{1}{\sqrt{2}} & \frac{1}{3\sqrt{2}} \end{bmatrix}$$

Finally, we have

$$A = \begin{bmatrix} -2 & 2 \\ -1 & 1 \\ 2 & -2 \end{bmatrix} = U \Sigma V^T = \begin{bmatrix} \frac{2}{3} & \frac{1}{\sqrt{2}} & \frac{-1}{3\sqrt{2}} \\ \frac{1}{3} & 0 & \frac{2\sqrt{2}}{3} \\ -\frac{2}{3} & \frac{1}{\sqrt{2}} & \frac{1}{3\sqrt{2}} \end{bmatrix} \begin{bmatrix} \sqrt{18} & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \frac{-1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \\ \frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix}$$

And the **Reduced Singular Value Decomposition** is:

$$A = \sigma_1 u_1 v_1^T = \sqrt{18} \begin{bmatrix} \frac{2}{3} \\ \frac{1}{3} \\ -\frac{2}{3} \end{bmatrix} \begin{bmatrix} -\frac{1}{\sqrt{2}} & \frac{1}{\sqrt{2}} \end{bmatrix} = \begin{bmatrix} -2 & 2 \\ -1 & 1 \\ 2 & -2 \end{bmatrix} = A$$

As expected.

## **2.2 Digital Image Compression**

See attached file Q2-2.ipynb