

A3 Eryk Hlaticki

$$1.a) \quad v_1 = a_1, \quad w_1 = \text{span}(a_1)$$

$$v_2 = a_2 - \text{proj}_{v_1}(a_2)$$

$$= a_2 - \left[\frac{(a_2 \cdot v_1)}{\|v_1\|^2} v_1 \right]$$

$$= \begin{bmatrix} 4 \\ -2 \\ 0 \end{bmatrix} - \frac{(4 \cdot 3 + (-1) \cdot (-2) + 2 \cdot 0)}{3^2 + (-1)^2 + 2^2} v_1$$

$$= \begin{bmatrix} 4 \\ -2 \\ 0 \end{bmatrix} - \frac{14}{14} v_1$$

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

$$W = \text{span} \left\{ \begin{bmatrix} 3 \\ -1 \\ 2 \end{bmatrix}, \begin{bmatrix} 1 \\ -1 \\ -2 \end{bmatrix} \right\}$$

$$\begin{matrix} 1 & 2 & 3 \\ 2 & & \\ 3 & & \end{matrix}$$

$$b) \quad y = c_1 v_1 + c_2 v_2$$

$$c_1 = \frac{y \cdot v_1}{\|v_1\|^2} = \frac{(7 \cdot 3 + (-1) \cdot (-1) + 2 \cdot 18)}{14} = \frac{56}{14} = 4$$

$$c_2 = \frac{y \cdot v_2}{\|v_2\|^2} = \frac{7 \cdot 1 + 1 \cdot -1 + 18 \cdot -2}{6} = -5$$

$$y = 4v_1 - 5v_2$$

$$c) i) P = \frac{1}{\|v_1\|^2} v_1 v_1^T + \frac{1}{\|v_2\|^2} v_2 v_2^T$$

$$= \frac{1}{14} \begin{bmatrix} 9 & -3 & 6 \\ -3 & 1 & -2 \\ 6 & -2 & 4 \end{bmatrix} + \frac{1}{6} \begin{bmatrix} 1 & -1 & -2 \\ -1 & 1 & 2 \\ -2 & 2 & 4 \end{bmatrix}$$

$$= \begin{bmatrix} 0.81 & -0.38 & 0.10 \\ -0.38 & 0.23 & 0.14 \\ 0.10 & 0.19 & 0.45 \end{bmatrix}$$

$$ii) P x = x$$

$$= \begin{bmatrix} -8.24 \\ 3.52 \\ -2.38 \end{bmatrix}$$

$$iii) u = u_1 + u_2$$

$$\leftarrow u_1 = x$$

$$u_2 = u - u_1$$

$$= \begin{bmatrix} 1.24 \\ 2.48 \\ -0.62 \end{bmatrix}$$

$$2. a) Pu = u_1, \quad u = u_1 + u_2$$

$$(I - P)u = x$$

$$u - Pu = x$$

$$u - x = Pu$$

$$Pu - x = u_1$$

$$u - x = u - u_2$$

$$x = u_2$$

$$\text{so, } (I - P)u = u_2$$

and u_2 is orthogonal to

u_1 , so $(I - P)$ is the

projection matrix onto K^\perp

$\nwarrow u_1$ is projection
of u onto K

u_2 is projection of
 u onto K^\perp

$$b) i) A = uu^T + vv^T$$

$$Ax = (uu^T + vv^T)x$$

$$= uu^Tx + vv^Tx$$

$$= u(u \cdot x) + v(v \cdot x)$$

so, Ax produces vectors that are

linear combinations of u and v , meaning

Ax is in the subspace spanned

by $\{u, v\}$. $\therefore \dim(\text{Col}(A)) = 2$

$$\dim(\text{Col}(A)) = \dim(\text{Row}(A))$$

$$\dim(\text{Row}(A)) + \dim(\text{Null}(A)) = n$$

$$\dim(\text{Null}(A)) = n - 2$$

ii) Q contains a set of orthonormal basis vectors spanning $\text{Col}(A)$

using these, we can create a projection matrix P , which projects a vector x onto $\text{Col}(A)$.

$$P = Q_1 Q_1^T + Q_2 Q_2^T + Q_3 Q_3^T$$

$$= Q Q^T \quad (\text{no need to normalize since } Q \text{ is already normalized})$$

$$= \begin{bmatrix} 0.67 & -0.33 & 0 & 0.33 \\ -0.33 & 0.67 & 0 & 0.33 \\ 0 & 0 & 1 & 0 \\ 0.33 & 0.33 & 0 & 0.67 \end{bmatrix} = P$$

now using Pb we can find $\text{proj}_{\text{Col}(A)}(b)$.

However, we need $\text{proj}_{\text{Null}(A^T)}(b)$. Q2.a)

$\text{Null}(A^T) = \text{Col}(A)^\perp$, meaning $(I-P)$ will be the projection matrix onto $\text{Null}(A^T)$.

$$(I-P)b = \begin{bmatrix} 0.33 \\ 0.33 \\ 0.00 \\ -0.33 \end{bmatrix}$$

3. step: find orthonormal basis for

$$q_1 = \frac{a_1}{\|a_1\|} = \frac{\text{Col}(A)}{\|a_1\|} = \begin{bmatrix} 1/\sqrt{3} \\ 0 \\ 1/\sqrt{3} \\ 1/\sqrt{3} \end{bmatrix}$$

$$v_2 = a_2 - \text{proj}_{q_1}(a_2)$$

$$= a_2 - (a_2 \cdot q_1)q_1$$

$$= a_2 - \begin{bmatrix} 1 \\ 0 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 2 \\ -1 \\ 2 \end{bmatrix}$$

$$q_2 = \frac{v_2}{\|v_2\|} = \begin{bmatrix} -1/\sqrt{10} \\ 2/\sqrt{10} \\ -1/\sqrt{10} \\ 2/\sqrt{10} \end{bmatrix}$$

$$v_3 = a_3 - \text{proj}_{W_2}(a_3)$$

$$= a_3 - (a_3 \cdot q_1)q_1 - (a_3 \cdot q_2)q_2$$

$$= a_3 - \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix} - \begin{bmatrix} -1 \\ 2 \\ -1 \\ 2 \end{bmatrix} = \begin{bmatrix} -3 \\ -3 \\ 1 \\ 2 \end{bmatrix}$$

$$q_3 = \frac{v_3}{\|v_3\|}$$

$$= \begin{bmatrix} -3/\sqrt{23} \\ -3/\sqrt{23} \\ 1/\sqrt{23} \\ 2/\sqrt{23} \end{bmatrix}$$

$$Q = \begin{bmatrix} 1/\sqrt{3} & -1/\sqrt{10} & -3/\sqrt{23} \\ 0 & 2/\sqrt{10} & -3/\sqrt{23} \\ 1/\sqrt{3} & -1/\sqrt{10} & 1/\sqrt{23} \\ 1/\sqrt{3} & 2/\sqrt{10} & 2/\sqrt{23} \end{bmatrix}$$

$$Q^T Q = I, \text{ since } Q_i^T Q_j = 1 \text{ if } i = j$$

$$Q_i^T Q_j = 0 \text{ if } i \neq j$$

$$Q_i \cdot Q_i = 1$$

Since they
are the
same unit vector.

$$Q_i \cdot Q_j = 0$$

since all
basis vectors
are orthogonal
in Q

$$\text{so, } A = QR$$

$$Q^T A = Q^T Q R$$

$$Q^T A = R$$

$$Q^T A = \begin{bmatrix} 0.58 & 0 & 0.58 & 0.58 \\ -0.32 & 0.63 & -0.32 & 0.63 \\ -0.63 & -0.63 & 0.21 & 0.42 \end{bmatrix} \begin{bmatrix} 1 & 0 & 3 \\ 0 & 2 & -1 \\ 1 & 0 & 1 \\ 1 & 3 & 5 \end{bmatrix}$$

$$R = \begin{bmatrix} 1.73 & 1.73 & 1.73 \\ 0 & 3.16 & 3.16 \\ 0 & 0 & 4.8 \end{bmatrix}$$

4. a) $A^{-1} = A^T$

$$\therefore A^T A = I \quad 1.$$

$$A A^T = I \quad 2.$$

1. $A^T A = \begin{bmatrix} a_1 \cdot a_1 & a_1 \cdot a_2 & \dots \\ a_2 \cdot a_1 & a_2 \cdot a_2 & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$

if $A^T A \neq I$, then $a_i \cdot a_i \neq 1$ or $a_i \cdot a_j \neq 0$

Neither of which are possible $(j \neq i)$

if a matrix is orthogonal, since $a_i \cdot a_i = 1$ for any unit vector, and $a_i \cdot a_j = 0$ for all

orthogonal vectors. So $A^T A$ must $= I$ if A is orthogonal.

2. $A A^T = I$

Since A 's columns are an orthonormal set, we know the columns of A are linearly independent. Additionally, A is square. (I columns + Square = invertible). So, we know A is invertible, and that $A^T A = I$.

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

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

~~$$A^{-1} A^{-1} = A^T A A^T$$~~

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

b) False.

$A = QR$ implies Q 's columns are an orthonormal set, but A may not be square, resulting in Q not being square, which disqualifies Q from being orthogonal.

c) True.

if A^2 is orthogonal $A^2(A^2)^T = I$.

$$A^2(A^2)^T = I$$

$$A(AA^T)A^T = I$$

$$A I A^T$$

$$A A^T = I \checkmark \therefore A^2 \text{ is also orthogonal}$$

d) True.

if A is $n \times n$, but an orthonormal set

then $A^T A = I$, since $A^T = n \times n$ $A = n \times n$

$$A^T A = n \times n \times n \times n$$

$$= n \times n.$$

and the diagonal entries will be the dot products of

each column with themselves, which $= 1$. All remaining entries will be 0, since $a_i \cdot a_j = 0$ for $i \neq j$ and a_i that are orthogonal.

So, A can be a non-square matrix with orthonormal columns, ~~and~~ with $A^T A = I$, but not be orthogonal since it isn't square.

S. a. True.

$$\text{proj}_u(\text{proj}_u(y)) = \text{proj}_u\left(\left(\frac{y \cdot u}{u \cdot u}\right)u\right)$$

so $\text{proj}_u(y)$ is a scalar multiple of vector u , let's call this cu .

$$\begin{aligned}\text{proj}_v(cu) &= c \text{proj}_v(u) \\ &= c \cdot 0 \\ &= 0\end{aligned}$$

since v and u are orthogonal,
 $\text{proj}_v(u) = 0$

b) False

~~We~~ we can still find a Q with orthonormal vectors by doing QR factorization, and choosing an arbitrary orthogonal vector for the a_i 's in A that are dependant (since $a_i - \text{proj}_{W_{i-1}}(a_i)$ will $= 0$, since a_i will already be in W_{i-1}).

However, unlike with a set of linearly independent vectors, there will be diagonal entries in R that are 0 , since

linearly dependant columns will just produce

$$r_i = \begin{bmatrix} cr_{i1} \\ cr_{i2} \\ \vdots \\ cr_{ij} \\ 0 \\ \vdots \\ 0 \end{bmatrix} \text{ for some dependant } a_j$$

regardless, A will be upper triangular, just not satisfying $r_{ii} \neq 0$

c) True.

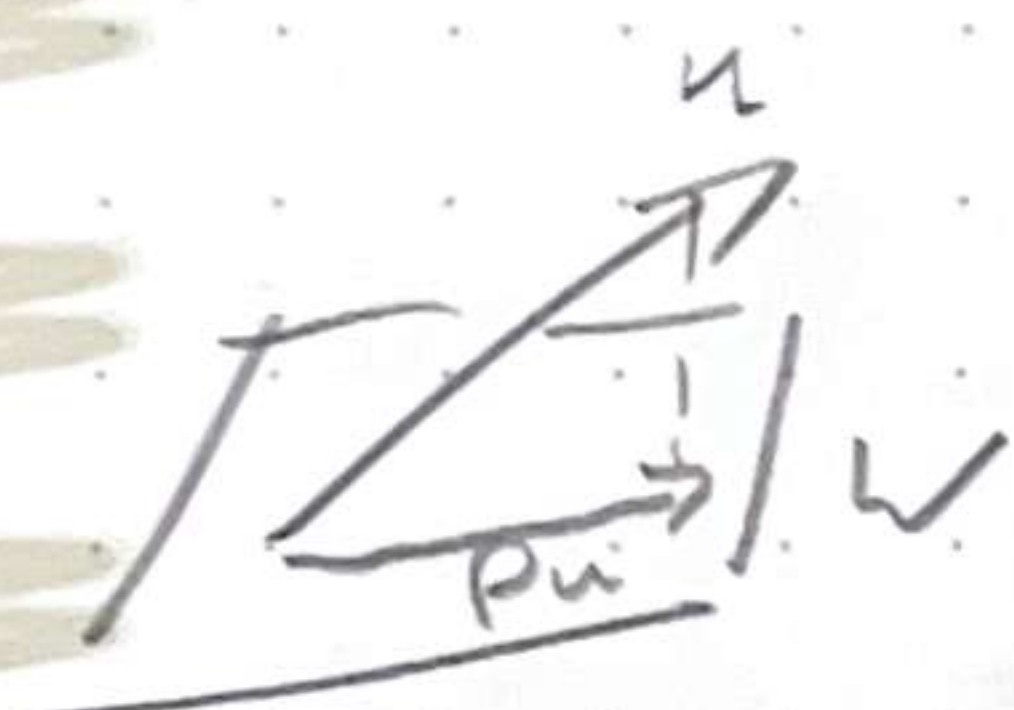
if A has linearly independent columns,
 $r_{ii} > 0$, in Matrix R .

Since R is upper triangular, the determinant
of R is the product of diagonal entries.

Furthermore, $r_{ii} > 0$, so $\det(R) > 0$,

so R is invertible.

d) True.



Let u be a vector in \mathbb{R}^n .

Pu will be in subspace

W . If we apply P

again, PPu , the resulting
vector doesn't change, since

it's already in W .

$\therefore P^2 = P$, and even $P^n = P$

for $n \geq 1$.

6. $A = PBP^{-1}$ (similar)

a) $A_1 = RQ$ $A = QR$

~~A~~ $A = QA_1Q^{-1}$

$= \cancel{QR} \cancel{QR} Q^{-1}$

$= QR \checkmark$

Q is invertible since
 A is square

$\therefore A$ and A_1 are similar,

Since A can be represented as

QA_1Q^{-1}

$Ax = \lambda x$

$(QA_1Q^{-1})x = \lambda x$

~~$Q^{-1}QA_1Q^{-1}x = \lambda Q^{-1}x$~~

$A_1(Q^{-1}x) = \lambda(Q^{-1}x)$

$\therefore A_1$ has same eigenvalues as

A , with corresponding eigenvectors

of form $x \rightarrow Q^{-1}x$

$$b) A_0 = Q_0 R_0 = Q_0 \overbrace{R_0}^{A_1} Q_0^{-1}$$

$$A_1 = R_0 Q_0 = Q_1 \overbrace{R_1}^{A_2} Q_1^{-1}$$

$$A_2 = R_1 Q_1 = Q_2 \overbrace{R_2}^{A_3} Q_2^{-1}$$

for any k , we can represent

$$A \text{ as } A = Q_0 Q_1 \dots \underbrace{(R_{k-1} Q_{k-1})}_{A_k} Q_{k-2}^{-1} \dots Q_0^{-1}$$

so A is similar to A_k via the similarity matrix

$$Q_0 Q_1 Q_2 \dots Q_{k-2}$$

which is invertible

$$\text{by } (Q_0 Q_1 Q_2 \dots Q_{k-2})^T$$

$$= Q_{k-2}^T Q_{k-3}^T \dots Q_0^T$$

$$= Q_{k-2}^{-1} Q_{k-3}^{-1} \dots Q_0^{-1}$$

Since Q is orthogonal $Q^T = Q^{-1}$


```
1 import numpy as np
2
3 arr_a = np.array([[2,3],[2,1]], dtype=float)
4 arr_b = np.array([[1,0,-1],[1,2,1],[-4,0,1]], dtype=float)
5
6 def qr_algorithm(A, iterations):
7     Ak = A
8     for i in range(iterations):
9         Q,R = np.linalg.qr(Ak)
10        Ak = R@Q
11    return Ak
12
13 print(f"Eigenvalues of \n{arr_a}\nare\n {np.diagonal(qr_algorithm(arr_a, 100).round(2))}")
14 print(f"Eigenvalues of \n{arr_b}\nare\n {np.diagonal(qr_algorithm(arr_b, 100).round(2))}")
15 □
```



```
2 erykhalicki@mac A3 % python3 Q6.py
3 Eigenvalues of
4 [[2. 3.]
5  [2. 1.]]
6 are
7  [ 4. -1.]
8 Eigenvalues of
9 [[ 1.  0. -1.]
10 [ 1.  2.  1.]
11 [-4.  0.  1.]]
12 are
13 [ 3.  2. -1.]
```

rm: // - /Documents/School/UPC/year3/MATH207/A2//18251 - /b