

V1

Homework 5
Q.11-54)

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Given:

$$A = \begin{bmatrix} 1 & 0 \\ 5 & 4 \\ 2 & 4 \end{bmatrix} \quad B = \begin{bmatrix} 1 & 0 & 1 \\ 5 & 4 & 9 \\ 2 & 4 & 6 \end{bmatrix}$$

Find:

Range and Nullspace

Solution

$$\text{RREF}(A) = \begin{bmatrix} 1 & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \Rightarrow R(A) = \text{span} \left(\begin{bmatrix} 1 \\ 5 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 4 \\ 4 \end{bmatrix} \right)$$

$$N(A) = \text{span}(\{0, 0, 1\}) //$$

$$\text{RREF}(B) = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} \Rightarrow R(B) = \text{span} \left(\begin{bmatrix} 1 \\ 5 \\ 2 \end{bmatrix}, \begin{bmatrix} 0 \\ 4 \\ 4 \end{bmatrix} \right)$$

$$\begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{bmatrix} x = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \Rightarrow \begin{aligned} x_1 &= -x_3 \\ x_2 &= x_1 = -x_3 \end{aligned}$$

$$N(B) = \text{span}(\{0, 0, 1\}) //$$

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Q.12 - 57)

Show that if V and W are subspaces of a vector space S , then their intersection $V \cap W$ is a subspace.

Solution:

Theorem: The nonempty subset W of vector space V is a subspace of V iff it satisfies

$$1) u, v \in W \text{ then } u+v \in W$$

$$2) u \in W, c \in \mathbb{R} \text{ then } cu \in W$$

$$\text{Let } u, v \in V \cap W \Rightarrow u, v \in V \text{ and } u, v \in W$$

$$V \text{ is a subspace } \therefore u+v \in V$$

$$W \text{ is a subspace } \therefore u+v \in W$$

Therefore $u+v$ is in both V and W , or

$$u+v \in V \cap W$$



A similar argument can be made for scalar multiplication

$$\text{Let } \alpha \in \mathbb{R}$$

$$\alpha u \in V; \alpha u \in W \Rightarrow \alpha u \in V \cap W$$



Therefore $V \cap W$ is a subspace of S



2.12 - 60)

Show that

- a) If V and W are orthogonal subspaces, then they are disjoint.
- b) If V and W are disjoint, then they are not necessarily orthogonal.

Solution

- a) Def: Let S be a vector space S and let V and W be subspaces of S . V and W are orthogonal if every vector $v \in V$ and $w \in W$ are orthogonal: $\langle v, w \rangle = 0$.

Def: Two linear subspaces are disjoint if $V \cap W = \{0\}$. That is, the only vector they have in common is the zero vector.

By the two definitions, an orthogonal set must be disjoint.

Furthermore suppose V is a subspace and $W = V^\perp$,
By theorem 2.5

If $x \in V \cap W$ then $x = 0$

//

b) By Lemma 2.3:

Let V and W be subspaces of vector space S . Then for each $x \in V+W$ there is a unique $v \in V$ and $w \in W$ such that $v+w=x$ iff V and W are disjoint.

Proof

$F = \{N \subset X : N \text{ is a linear subspace of } X \text{ and } M \cap N = \{0\}\}$

Let $(N_\alpha)_{\alpha \in \Gamma}$ be a chain of linear subspaces in F and let

$$N = \text{span} \{N_\alpha : \alpha \in \Gamma\}$$

We want to show $M \cap N = \{0\}$. Let $x \in M \cap N$, then

$$x = \sum_{k=1}^n a_k m_k$$

where $a_k \in \mathbb{Q}$ and $m_k \in N_\alpha$. $(N_\alpha)_{\alpha \in \Gamma}$ is a chain of sets in F , there must be a $\beta \in \Gamma$ that contains all the elements m_1, \dots, m_n . Thus, x is a linear combination of elements in N_β . $x \in M$ as well so $x \in M \in N_\beta = \{0\}$ and $x=0$. Therefore N is an upper bound for the chain $(N_\alpha)_{\alpha \in \Gamma}$. By Zorn's Lemma, there is a maximal element $M' \in F$. Therefore

$$M \cap M' = \{0\}$$

Clearly $X \supseteq M \cap M'$. Suppose $X \subsetneq M + M'$ \exists
 $x \in X \setminus (M + M')$ and furthermore $x \neq 0$.

If $(m' + \lambda x) \in M$ for some $m' \in M'$ then $\lambda x \in M \cap M'$.
 But $\lambda = 0$ since $x \neq 0$ so $m' \in M$ but $m' \in M \cap M' = \{0\}$, so
 $m' = 0$. Therefore $(M' + \text{span}(x)) \in F$, but that contradicts
 the maximality of M . Thus

$$X = M + M'$$

Hence, M has an algebraic complement //



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2.13-64)

If V is a vector, show that the matrix which projects onto $\text{span}(V)$ is.

$$P_V = \frac{VV^H}{V^H V}$$

Solution:

Let v be a vector in $V \in \mathbb{C}^n$. Suppose

$x = vc$ s.t. c is an operator $\Phi: S \rightarrow \mathbb{C}$

We wish to minimize

$$\min \|\hat{x} - x\| \quad \text{s.t. } \hat{x} \in V$$

This is minimized when

$$\langle \hat{x} - vc, v \rangle = 0$$

$$\langle \hat{x}, v \rangle - \langle vc, v \rangle = 0$$

$$\langle \hat{x}, v \rangle = \langle vc, v \rangle$$

$$\hat{x}^H v = c v^H v$$

$$c = \frac{v^H \hat{x}}{v^H v}$$

Plug
back
in

$$x = vc = V \frac{V^H \hat{x}}{V^H V}$$

$$= \frac{V V^H}{V^H V} \hat{x}$$

Y

Q. 13 - 65)

Show the matrix

$$P_A = A(A^H A)^{-1} A^H$$

is a projection matrix

Solution

Def: A linear transformation P of a linear space into itself is a projection if $P^2 = P$.

$$\begin{aligned} P_A^2 &= (A(A^H A)^{-1} A^H)^2 = (A(A^H A)^{-1} A^H)(A(A^H A)^{-1} A^H) \\ &= A(A^H A)^{-1} \cancel{A^H A} (A^H A)^{-1} A^H \\ &= A(A^H A^{-1})^T (A^H A)^{-1} A^H \\ &= A(A^H A)^{-1} A^H \end{aligned}$$



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Q.13 - (6)

Given:

$$P_{A^H W} = A(A^H W A)^{-1} A^H W$$

Find:

a) Show $P_{A^H W}^2 = P_{A^H W}$

b) Show $P_{A^H W} = I - P_{A^H W}$ is orthogonal to $P_{A^H W}$ using the weighted inner product.

Solution:

a)

$$\begin{aligned} P_{A^H W}^2 &= A(A^H W A)^{-1} \xrightarrow{\quad} A^H W \xrightarrow{\quad} A(A^H W A)^{-1} A^H W \\ &= A(A^H W A)^{-1} A^H W \quad // \end{aligned}$$

b) $\langle P_{A^H W}, I - P_{A^H W} \rangle = \langle P_{A^H W}, I \rangle - \langle P_{A^H W}, P_{A^H W} \rangle$

$$= P_{A^H W} - P_{A^H W}^2 = P_{A^H W} - P_{A^H W} = 0 \quad //$$

Y

(2.13-67)

Given

$$P_1 = [1 \ 2 \ 3 \ 4]^T, P_2 = [4 \ -2 \ -6 \ -7]^T$$

$$P_3 = [3 \ 4 \ -2 \ 1]^T$$

$$x = [1 \ -2 \ 3 \ 7]^T$$

Find:

The nearest vector \hat{x} in $\text{span}[P_1, P_2, P_3]$. Also determine the orthogonal complement of x in $\text{span}[P_1, P_2, P_3]$.

Solution:

$$\text{Let } A = [P_1 \ P_2 \ P_3]$$

$$\text{we know } P_A = A(A^H A)^{-1} A^H$$

$$\hat{x} = P_A x = A(A^H A)^{-1} A^H x$$

$$\hat{x} = [0.8946 \ 2.9665 \ 4.1247 \ 5.6996]^T$$

$$\text{REF}(A) = \left[\begin{array}{ccc|c} 1 & 0 & 0 & \\ 0 & 1 & 0 & \\ 0 & 0 & 1 & \\ 0 & 0 & 0 & \end{array} \right] \Rightarrow \text{NCA} = \text{span}([0 \ 0 \ 0 \ 1])$$

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Q.B-69)

Given:

The orthogonal projections are said to be orthogonal
if $P_A P_B = 0 \cdot (P_A \perp P_B)$.

Find:

- P_A and P_B are orthogonal iff their ranges are orthogonal.
- $(P_A + P_B)$ is a projection operator iff P_A and P_B are orthogonal.

Solution:

Let $L : X \rightarrow Y$ be an operator. The range space $R(L)$ is

$$R(L) = \{y = Lx : x \in X\}$$

The null space is

$$N(L) = \{x : Lx = 0 : x \in X\}$$

Let $R(P_A)$ and $R(P_B)$ be the ranges of P_A and P_B , respectively. Let $R(P_A) \perp R(P_B)$. Now suppose

$$P_A P_B x = \hat{x} \in R(P_A) \cap R(P_B)$$

If $R(P_A) \perp R(P_B)$ then $\hat{x} \in \{0\}$
 $\therefore P_A P_B = 0$.

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$$b) (P_A + P_B)^2 = P_A + P_B$$

$$(P_A + P_B)(P_A + P_B) = P_A^2 + 2P_A P_B + P_B^2$$

If $P_A P_B = 0$ then

$$P_A^2 + P_B^2 = P_A + P_B //$$



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2.13-71)

Given:

 P_1, P_2, \dots, P_m are a set of orthogonal projectors.

$$P_i P_j = 0 \quad \forall i, j = 1, 2, \dots, m \text{ and } i \neq j$$

Find:

Show $Q = P_1 + P_2 + \dots + P_m$ is an orthogonal projection

Solution:

Need to show $Q^2 = Q$

$$Q^2 = (P_1 + P_2 + \dots + P_m)(P_1 + P_2 + \dots + P_m)$$

We know that $P_{ij} = 0$ for $i \neq j$. Therefore, all cross terms go to zero and we are left with

$$P_1^2 + P_2^2 + \dots + P_m^2 = P_1 + P_2 + \dots + P_m$$



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2.13 - 73)

Given:

S is a vector space and let V_1, V_2, \dots, V_n be linear subspaces such that V_i is orthogonal to $\sum_{j \neq i} V_j$ for each i and where

$$S = V_1 + V_2 + \dots + V_n$$

Let P_i be the projection on S for which $R(P_i) = V_i$ and $N(P_i) = \sum_{j \neq i} V_j$. Define an operator

$$P = \lambda_1 P_1 + \lambda_2 P_2 + \dots + \lambda_n P_n$$

Find:

a) Show that if $x \in V_j$ then $Px = \lambda_j x$

b) Show that P is a projection iff λ_j is 0 or 1.

Solution:

$$V_i \perp \sum_{j \neq i} V_j \quad ; \quad N(P_i) = \sum_{j \neq i} V_j$$

$$R(P_i) = V_i$$

a) If $x \in V_j$ and we know $N(P_i) = \sum_{j \neq i} V_j$ then

$$\begin{aligned} Px &= (\lambda_1 P_1 + \lambda_2 P_2 + \dots + \lambda_i P_i + \dots + \lambda_n P_n)x \\ &= \lambda_i P_i x \end{aligned}$$

We know $R(P_i) = V_i$ and $x \in V_j$

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so P_j is redundant

$$P_x = \lambda_j X //$$

b) $P = P^2 = (\lambda_1 P_1 + \lambda_2 P_2 + \dots + \lambda_n P_n)(\lambda_1 P_1 + \lambda_2 P_2 + \dots + \lambda_n P_n)$
We know that $V_i \perp \sum_{j \neq i} V_j$, so the cross terms go to 0

$$\lambda_1^2 P_1^2 + \lambda_2^2 P_2^2 + \lambda_3^2 P_3^2 + \dots + \lambda_n^2 P_n^2 = P^2$$

if $x \in V_i$ then

$$P^2 = \lambda_i^2 P_i^2$$

if $\lambda_i = 0$ then $x \notin V_i$ and $P = P^2 = \{0\}$

if $\lambda_i = 1$ then $x \in V_i$ and $P = P^2 = P_i //$



(2.15 - 80)

Given:

Let

$$A = [P_1 \ P_2 \ \dots \ P_n] \in \mathbb{R}^{m \times n}$$

at the k^{th} step of the Gram-Schmidt algorithm

$$e_k = p_k - \sum_{i=1}^{k-1} \langle p_k, q_i \rangle q_i$$

with $q_k = e_k / \|e_k\|$. We can stack the results of the computations as

$$A = [q_1 \ \dots \ q_n] \left[\begin{array}{cccc} \|p_1\| & \langle p_2, q_1 \rangle & \langle p_3, q_1 \rangle & \dots & \langle p_n, q_1 \rangle \\ 0 & \|e_2\| & \langle p_3, q_2 \rangle & \langle p_4, q_2 \rangle & \dots & \langle p_n, q_2 \rangle \\ \vdots & 0 & \|e_3\| & \langle p_4, q_3 \rangle & \dots & \langle p_n, q_3 \rangle \\ \ddots & \ddots & \ddots & \ddots & \ddots & \|e_n\| \end{array} \right]$$

$$= QR$$

where $Q^T Q = I$ (orthogonal), and R is the upper triangular matrix. The Gram-Schmidt process works but is poor numerically. We will reformulate the problem to have better numerical properties. In this new formulation at each step a new column and row are obtained.

Let the i^{th} row of the R matrix be denoted by r_i^T

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find:

a) Show $A = \sum_{i=1}^n q_i r_i^T$

b) Let $A^{(k)}$ be an $m \times (n-k+1)$ matrix defined by

$$A - \sum_{i=1}^{n-k} q_i r_i^T = [0_{m \times k-1} \ A^{(k)}]$$

Show that

$$[0_{m \times k-1} \ A^{(k)}] = \sum_{i=k}^n q_i r_i^T$$

c) Write

$$A^{(k)} = [e_k \ B^{(k)}]$$

where $B^{(k)}$ is an $m \times n-k$ matrix. Then $e_k = e_k / \|e_k\|$,
recall that when $k=1$, $e_k = p_1$ and observe that $A^{(1)} = A$.

Show that

$$q_k^T B^{(k)} = [r_{k,k+1} \ r_{k,k+2} \ r_{k,k+3} \dots \ r_{k,n}]$$

d). Explain why we can move to the next step by computing

$$A^{(k+1)} = B^{(k)} - q_k [r_{k,k+1} \ r_{k,k+2} \ \dots \ r_{k,n}]$$

(Then we set $k \leftarrow k+1$ and return to (c))

e) Code the Gram-Schmidt Algorithm

Solution:

a)

$$A = QR \text{ where}$$

$$Q = [q_1 \ q_2 \ \dots \ q_n] \quad R = \begin{bmatrix} r_1^T \\ r_2^T \\ \vdots \\ r_n^T \end{bmatrix}_{m \times n}$$

$$A = [q_1 \ q_2 \ \dots \ q_n] \begin{bmatrix} r_1^T \\ r_2^T \\ \vdots \\ r_n^T \end{bmatrix} = \sum_{i=1}^n q_i r_i^T //$$

b) We know R is an upper triangular matrix, so the first $k-1$ elements are 0 . If we want to produce a row/column matrix starting at the k^{th} element then the matrix must be padded with $(m \times k-1)$ zeros. The $A^{(k)}$ matrix is defined as (a), but starting at $i=k$. Thus,

$$\begin{bmatrix} 0_{m \times k-1} & A^{(k)} \end{bmatrix} = \sum_{i=k}^n q_i r_i^T$$

Furthermore let us write out

$$\sum_{i=1}^n q_i r_i^T - \sum_{i=1}^{k-1} q_i r_i^T$$

Then we know the first $k-1$ elements are 0 leaving us with

the summation $\sum_{i=k}^n q_i r_i^T$. The first ($m \times k-1$) values are 0

So we (again) find that

$$[0_{m \times k-1} \ A^{(k)}] = \sum_{i=k}^n q_i r_i^T \quad //$$

c) $q_k = \frac{e_k}{\|e_k\|}$ which means that it is normalized.

$$\overset{(4)}{B} = [p_{k+1} \ p_{k+2} \ \dots \ p_n]$$

$$q_k^T [p_{k+1} \ p_{k+2} \ \dots \ p_n] = \langle p_{k+1}, q_k \rangle \ \langle p_{k+2}, q_k \rangle \ \dots \ \langle p_n, q_k \rangle$$

$$= [r_{k,k+1} \ r_{k,k+2} \ \dots \ r_{k,n}] \quad //$$

d) Going to $[0_{m \times k-1} \ A^{(k)}] = \sum_{i=k+1}^n q_i r_i^T$

If we increment k by 1 it is equivalent to

$$A^{(k)} = \sum_{i=k+1}^n q_i r_i^T + q_k r_k^T = B^{(k)}$$

$$\sum_{i=k+1}^n q_i r_i^T = B^{(k)} - q_k r_k^T = A^{(k+1)} \quad //$$

e) See gram-schmidt.m