MA-106 Linear Algebra

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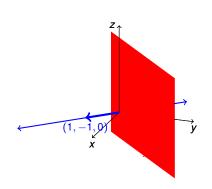


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> 20th February 2018 D1 - Lecture 21

If $\{w_1, \ldots, w_r\}$ is a orthogonal set then w_r is orthogonal to Span $\{w_1, \ldots, w_{r-1}\}$. Then every vector in Span $\{w_r\}$ is orthogonal to every vector in Span $\{w_1, \ldots, w_{r-1}\}$.

Example 1:
$$P = Span\{(1, 1, 0), (0, 0, 1)\}, L = Span(1, -1, 0).$$



Observe
$$\begin{pmatrix} t & -t & 0 \end{pmatrix} \begin{pmatrix} a \\ a \\ 0 \end{pmatrix} = 0$$
 and $\begin{pmatrix} t & -t & 0 \end{pmatrix} \begin{pmatrix} 0 \\ 0 \\ b \end{pmatrix} = 0$.

The subspace $\mathbf{L} = \{(t, -t, 0) \mid t \in \mathbb{R}\}$

is orthogonal to the subspace $P = \{(a, a, b) \mid a, b \in \mathbb{R}\}.$

Observe: $dim(\mathbf{L}) + dim(\mathbf{P}) = dim(\mathbb{R}^3)$.

Orthogonal Subspaces

Defn. (Orthogonal Subspaces) Let V and W be subspaces of \mathbb{R}^n . We say V and W are orthogonal to each other (notation: $V \perp W$) if every vector in V is orthogonal to every vector in W, i.e.,

for every
$$v \in V$$
 and $w \in W$, $v \cdot w = v^T w = 0$.

Note: Let $V = \text{Span of } \{v_1, \dots, v_r\}, \ W = \text{Span } \{w_1, \dots, w_s\}.$ If $v_i^T w_j = 0$ for all i, j, then $V \perp W$.

Proof. If
$$v = a_1v_1 + \dots + a_rv_r \in V$$
, $w = b_1w_1 + \dots + b_sw_s \in W$, then $v^Tw = (a_1v_1^T + \dots + a_rv_r^T)(b_1w_1 + \dots + b_sw_s)$

$$= a_1b_1v_1^Tw_1 + a_1b_2v_1^Tw_2 + \dots + a_1b_sv_1^Tw_s + a_2b_1v_2^Tw_1 + \dots + a_2b_sv_2^Tw_s + \dots + a_rb_sv_r^Tw_s = 0 \text{ using}$$

bilinearity.

Q. Let V be the yz-plane and W be the xz-plane. Are V and W orthogonal to each other (as subspaces of \mathbb{R}^3)? **A.** No. The vector $e_3 = (0,0,1)$ lies in V and W both and $e_3^T e_3 \neq 0$.

Remark. If V and W are orthogonal subspaces of \mathbb{R}^n , then $V \cap W = 0$. This is a necessary condition.

Q. Is it a sufficient condition? A. No.

Example. If
$$V = \operatorname{Span}\left\{\begin{pmatrix}1\\0\end{pmatrix}\right\}$$
, and $W = \operatorname{Span}\left\{\begin{pmatrix}1\\1\end{pmatrix}\right\}$.

Then $V \cap W = 0$, but V and W are not orthogonal, since

$$\begin{pmatrix} 1 & 0 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} = 1 \neq 0 \; .$$

Ex 2: Let
$$V = \operatorname{Span} \left\{ \begin{pmatrix} 1 \\ 1 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 1 \\ 0 \end{pmatrix} \right\}, W = \operatorname{Span} \left\{ \begin{pmatrix} 1 \\ -1 \\ 1 \\ 0 \end{pmatrix} \right\}.$$

Then V is orthogonal to W.

Proof. It is enough to see that both generators of V are orthogonal to the given generator of W.

Compare: In Example 1, dim (L) + dim (P) = dim (\mathbb{R}^3) . In Example 2, dim (V) + dim (W) = 3 < dim (\mathbb{R}^4) .

Q: If $W \subset \mathbb{R}^n$, can we enlarge W to W' such that $V \perp W'$ and dim $(V) + \dim(W') = \dim(\mathbb{R}^4)$?

A: Yes! We will eventually justify why this is true.

Observe: (0,0,0,1) is orthogonal to both V and W.

$$V = \text{Span} \{ v_1 = (1, 1, 0, 0)^T, v_2 = (0, 1, 1, 0)^T \},$$

 $W = \text{Span} \{ (1, -1, 1, 0)^T \}.$

Let
$$A = \begin{pmatrix} v_1^T \\ v_2^T \end{pmatrix} = \begin{pmatrix} 1 & 1 & 0 & 0 \\ 0 & 1 & 1 & 0 \end{pmatrix}$$
. Then $C(A^T) = V$.

Note that
$$x \in N(A) \Leftrightarrow v_1^T x = 0 = v_2^T x$$
.

$$\Rightarrow (1,-1,1,0)^T \in N(A) \Rightarrow W \subset N(A).$$

By Rank-Nullity Theorem:
$$rank(A) + dim(N(A)) = 4$$
.

Since
$$rank(A) = 2$$
, we get $dim(N(A)) = 2$. Therefore

if
$$W' = N(A)$$
, then $V \perp W'$ and dim $(V) + \dim(W') = 4$.

By inspection,
$$W' = \text{Span}\{w_1 = (1, -1, 1, 0)^T, w_2 = (0, 0, 0, 1)^T\} \perp V$$
.

The dimension of the two spaces sum up to dim (\mathbb{R}^4).

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Random Attendance

1	170070048	Bojja Sai Vamseedhar Reddy		Absent
2	17D070038	Divyansh Ahuja	Absent	
3	17D070012	Naman Rajesh Narang		
4	170070049	Modhugu Rineeth	Absent	
5	17D070015	Nikhil Arvind Bhala	adhare	Absent
6	170050074	Burudi Rajesh	Absent	
7	17D070030	Sarthak Jain	Absent	
8	17D070042	Karan Amaliya	Absent	
9	170050005	Yateesh Agrawal	Absent	
10	17D070024	Prajwal Dnyaneshw	ar Kamble	Absent

The Four Fundamental Spaces and Orthogonality

Let A be a $m \times n$ matrix.

- 1. The row space of A, $C(A^T)$ is orthogonal to N(A).
- 2. C(A) is orthogonal to the left nullspace of A, $N(A^T)$.

Example. Let
$$A = \begin{pmatrix} 1 & 2 \\ 2 & 4 \\ 3 & 6 \end{pmatrix}$$
. Then A has 1 pivot \Rightarrow rank $(A) = 1 \Rightarrow$ dim $(C(A)) = 1$ and dim $(C(A^T)) = 1$.

Observe: $C(A^T) = \text{Span}\{(1,2)^T\}, \ N(A) = \text{Span}\{(-2,1)^T\}, \ C(A) = \text{Span}\{(1,2,3)^T\}, \ N(A^T) \text{ is the plane } y_1 + 2y_2 + 3y_3 = 0.$ dim $(C(A^T)) + \text{dim}(N(A)) = 2$, dim $(C(A)) + \text{dim}(N(A^T)) = 3$.

In particular,

- N(A) = set of all vectors orthogonal to $C(A^T)$.
- $N(A^T)$ = set of all vectors orthogonal to C(A).

Fundamental Theorem of Orthogonality

Defn. Let W be a subspace of \mathbb{R}^n . Its orthogonal complement $W^{\perp} = \{ v \in \mathbb{R}^n \mid v^T w = 0 \text{ for all } w \in W \}.$

Claim. W^{\perp} is a subspace of \mathbb{R}^n .

If $v_1, v_2 \in W^{\perp}$ and $w \in W$, then $v_1^T w = 0 = v_2^T w$.

Hence for $c_1, c_2 \in \mathbb{R}$, $(c_1v_1 + c_2v_2)^T w = c_1v_1^T w + c_2v_2^T w = 0$.

 $\Rightarrow c_1 v_1 + c_2 v_2 \in W^{\perp}.$

Theorem (Fundamental Theorem of Orthogonality) Let A be an $m \times n$ matrix.

- 1. The row space of A =orthogonal complement of N(A).
- 2. The column space of A =orthogonal complement of left nullspace $N(A^T)$.
- i.e., $C(A^T) = N(A)^{\perp}$, and $C(A) = N(A^T)^{\perp}$.

Orthogonal Complements

Theorem (Orthogonal Complement)

Given a subspace $W \subseteq \mathbb{R}^n$, dim (W) + dim (W^{\perp}) = n.

Proof. Let v_1, \ldots, v_r be a basis of W. Let A be a matrix with rows v_1, \ldots, v_r . Then rank(A) = r and $W = C(A^T)$.

 $W^{\perp} = N(A)$ is of dimension n - r. This proves the theorem.

Observe: Let $V = \text{Span} \{ v_1 = (1, 1, 0, 0)^T, v_2 = (0, 1, 1, 0)^T \}$ and $W = \text{Span} \{ w_1 = (1, -1, 1, 0)^T, w_2 = (0, 0, 0, 1)^T \}.$

- $\{v_1, v_2\}$, $\{w_1, w_2\}$ are bases for V and W respectively.
- $V \perp W \Rightarrow V \subseteq W^{\perp}$ and dim (V) + dim (W) = 4 = dim (\mathbb{R}^4) $\Rightarrow V = W^{\perp}$.
- $V \cap W = 0 \Rightarrow \mathcal{B} = \{v_1, v_2, w_1, w_2\}$ is linearly independent $\Rightarrow \mathcal{B}$ is a basis of $\mathbb{R}^4 \Rightarrow V + W = \{v + w \mid v \in V, w \in W\} = \mathbb{R}^4$, and for every $x \in \mathbb{R}^4$,

 \exists unique $v \in V = W^{\perp}$ and $w \in W$ such that x = v + w.

Orthogonal Complements

To summarise: If W is a subspace of \mathbb{R}^n with basis \mathcal{B} , and \mathcal{B}' is a basis of W^{\perp} , then $\mathcal{B} \cup \mathcal{B}'$ is a basis of \mathbb{R}^n , $W \cap W^{\perp} = 0$, dim (W) + dim $(W^{\perp}) = n$, $W + W^{\perp} = \mathbb{R}^n$, and

 \exists unique $w_1 \in W$ and $w_2 \in W^{\perp}$ such that $x = w_1 + w_2$,

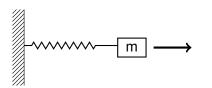
for every $x \in \mathbb{R}^n$.

Some Consequences: Let *A* be $m \times n$ of rank *r*. Then

- 1. $C(A^T) \cap N(A) = 0$ and $\mathbb{R}^n = C(A^T) + N(A)$. Similarly $C(A) \cap N(A^T) = 0$ and $\mathbb{R}^m = C(A) + N(A^T)$.
- 2. If $x \in \mathbb{R}^n$, there is a unique expression $x = x_r + x_n$, where $x_r \in C(A^T)$, $x_n \in N(A)$. Hence $Ax = Ax_r \in C(A)$. Thus

The matrix A transforms its row space into its column space.

Linear Least Squares: Motivation



Hooke's Law states that displacement x of the spring is directly proportional to the load (mass) applied, i.e., m = kx.

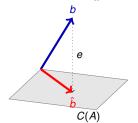
Student A performs experiments to calculate spring constant k. The data collected says for loads 4, 7, 11 kg applied, the displacement is 3, 5, 8 inches respectively. Hence we have:

$$\begin{pmatrix} 3 \\ 5 \\ 8 \end{pmatrix} k = \begin{pmatrix} 4 \\ 7 \\ 11 \end{pmatrix} \qquad (ak = b).$$

Clearly the data is inconsistent. If we allow for various errors, how do we give an estimate of the spring constant? Find a consistent system close to this one!

Linear Least Squares and Projections

Suppose system Ax = b is inconsistent, i.e. $b \notin C(A)$. The error E = ||Ax - b|| is the distance from b to $Ax \in C(A)$.



We want the least square solution \hat{x} of Ax = b, which minimizes E, i.e., we want to find \hat{b} closest to b such that $A\hat{x} = \hat{b}$ is a consistent system. Therefore, $\hat{b} = \text{proj}_{C(A)}(b)$ and $A\hat{x} = \hat{b}$.

The error vector $e = b - A\hat{x}$ must be perpendicular to C(A). So $e \in C(A)^{\perp}$ = left null space of A, $N(A^{T})$, i.e., $A^{T}(b - A\hat{x}) = 0$ or $A^{T}A\hat{x} = A^{T}b$

Therefore, to find \hat{x} , we need to solve $A^T A \hat{x} = A^T b$.

Exercise: Find the least squares solution to the Hooke's Law problem on the previous slide.