

MA-110 Linear Algebra and Differential Equations

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February 19, 2024
Lecture 20 D3

Orthogonal and Orthonormal Sets: Summary

Defn. A set of *non-zero* vectors $\{v_1, \dots, v_k\} \subset \mathbb{R}^n$, is said to be an **orthogonal set** if $v_i^T v_j = 0$ for all $i, j = 1, \dots, n$, $i \neq j$.

Examples: $\{(1, 3, 1), (-1, 0, 1)\} \subset \mathbb{R}^3$,
 $\{(2, 1, 0, -1), (0, 1, 0, 1), (-1, 1, 0, -1)\} \subseteq \mathbb{R}^4$,
 $\{(\frac{1}{\sqrt{2}}, 0, \frac{1}{\sqrt{2}}), (\frac{1}{\sqrt{2}}, 0, \frac{-1}{\sqrt{2}})\} \subseteq \mathbb{R}^3$, $\{e_1, \dots, e_n\} \subseteq \mathbb{R}^n$.

Of these, the last two examples have all unit vectors (vectors of length one).

Defn. An orthogonal set $\{v_1, \dots, v_k\} \subseteq \mathbb{R}^n$ with all unit vectors, i.e., $\|v_i\| = 1$ for all i , is called an **orthonormal set**.

Note: If $\{v_1, \dots, v_k\}$ is an orthogonal set, then $\{u_1, \dots, u_k\}$ is orthonormal, for $u_i = v_i / \|v_i\|$.

Exercise: If $S = \{v_1, \dots, v_k\}$ is an orthogonal set, then v_k is orthogonal to each $v \in \text{Span}\{v_1, \dots, v_{k-1}\}$.

Theorem: An orthogonal set in \mathbb{R}^n is linearly independent.

Defn. A square matrix A whose column vectors form an orthonormal set is called an **orthogonal** matrix.

Orthogonal Matrices: Examples

Examples:

1. $\begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix}.$
2. $\frac{1}{\sqrt{2}} \begin{pmatrix} 1 & 1 \\ 1 & -1 \end{pmatrix}.$
3. $\frac{1}{3} \begin{pmatrix} 2 & 1 & -2 \\ 2 & -2 & 1 \\ 1 & 2 & 2 \end{pmatrix}.$
4. $\frac{1}{2} \begin{pmatrix} 1 & -1 & -1 & 1 \\ 1 & 1 & 1 & 1 \\ -1 & -1 & 1 & 1 \\ -1 & 1 & -1 & 1 \end{pmatrix}.$

Orthogonal Basis

Defn. A basis $\mathcal{B} = \{v_1, \dots, v_k\}$ of a subspace V of \mathbb{R}^n is an **orthogonal basis** if it is an orthogonal set, i.e., $v_i^T v_j = 0$ for $i \neq j$. Furthermore, if $\|v_i\| = 1$ for each i , then \mathcal{B} is an **orthonormal basis** (or o.n.b.) of V .

Example: Consider the bases of \mathbb{R}^2 :

$$\mathcal{B}_1 = \{w_1 = (8, 0)^T, w_2 = (6, 3)^T\},$$

$$\mathcal{B}_2 = \{(8, 0)^T, (0, 3)^T\} \text{ and}$$

$$\mathcal{B}_3 = \left\{ \left(\frac{8}{\sqrt{8^2+0^2}}, 0 \right)^T, \left(0, \frac{3}{\sqrt{0^2+3^2}} \right)^T \right\}.$$

Then \mathcal{B}_1 is not orthogonal, \mathcal{B}_2 is an orthogonal basis, but not an orthonormal basis, and \mathcal{B}_3 is an orthonormal basis of \mathbb{R}^2 .

Note: If $\{u_1, \dots, u_k\} \subseteq \mathbb{R}^n$ is an orthonormal set, then it is an o.n.b. of $V = \text{Span}\{u_1, \dots, u_k\}$.

Importance of Orthogonal Basis

Example : The set $\mathcal{B} = \{v_1 = (-1, 1)^T, v_2 = (1, 1)^T\}$ is a orthogonal basis of \mathbb{R}^2 .

- Find $[v]_{\mathcal{B}} = (a, b)^T$:

$$v = av_1 + bv_2 = a(-1, 1)^T + b(1, 1)^T$$

$$v_1^T v = (-1, 1)v = a(-1, 1)(-1, 1)^T = 2a = a\|v_1\|^2$$

$$\text{Then } a = \frac{v_1^T v}{2} = \frac{v_1^T v}{\|v_1\|^2} \quad \text{and} \quad b = \frac{v_2^T v}{2} = \frac{v_2^T v}{\|v_2\|^2}$$

General Case: If $\mathcal{B} = \{v_1, \dots, v_n\}$ is an o.n.b of V , then $[v]_{\mathcal{B}} = (c_1, \dots, c_n)^T$, where $c_j = v_j^T v$.

Moreover, if $T : V \rightarrow V$ is linear, and $[T]_{\mathcal{B}}^{\mathcal{B}} = [a_{ij}]$, then $[T]_{\mathcal{B}}^{\mathcal{B}} = ([T(v_1)]_{\mathcal{B}} \quad \cdots \quad [T(v_n)]_{\mathcal{B}}) \Rightarrow a_{ij} = _ _$.

Think!

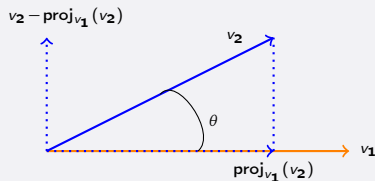
When does T map orthogonal sets to orthogonal sets?

Orthogonal Basis and Projections

Every subspace of \mathbb{R}^n has an orthogonal basis.

To construct one, we can start with any basis and modify it (Gram-Schmidt process).

First we see what happens in \mathbb{R}^2 .



To construct an orthogonal basis in \mathbb{R}^n , we need to know how to find $\text{proj}_{v_1}(v_2)$ in \mathbb{R}^n .

Orthogonal Projections in \mathbb{R}^n

If $v(\neq 0), w \in \mathbb{R}^n$, then $\text{proj}_v(w)$, is a multiple of v and $w - \text{proj}_v(w)$ is orthogonal to v . Thus

$$\begin{aligned}\text{proj}_v w &= av \text{ for some } a \in \mathbb{R} \\ v^T(w - \text{proj}_v w) &= 0 \\ v^T w - v^T av &= 0 \iff a = \frac{v^T w}{v^T v}\end{aligned}$$

Therefore $\boxed{\text{proj}_v(w) = \left(\frac{v^T w}{v^T v}\right)v.}$

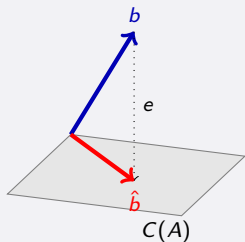
Example. If $w = (1 \ 1 \ 1)^T$ and $v = (1 \ 2 \ 3)^T$, then the orthogonal projection of w on $\text{Span}\{v\}$ is given by

$$\text{proj}_v(w) = \left(\frac{v^T w}{v^T v}\right)v = \frac{6}{14} \begin{pmatrix} 1 \\ 2 \\ 3 \end{pmatrix}.$$

Application: This can be used to “solve” an inconsistent system of equations.

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} 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 $C(A)$, which is also the row space of A^T .

So, e must be in the left null space of A , $N(A^T)$, i.e.,

$$A^T(b - A\hat{x}) = 0 \text{ or } \boxed{A^T A \hat{x} = A^T b}$$

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

Linear Least Squares and Projections

Let A be $m \times n$. Then $A^T A$ is a symmetric $n \times n$ matrix.

- $N(A^T A) = N(A)$.

Proof. $Ax = 0 \Rightarrow A^T Ax = 0$. So, $N(A) \subseteq N(A^T A)$.

For the other inclusion, take $x \in N(A^T A)$.

$$A^T Ax = 0 \Rightarrow x^T (A^T Ax) = (Ax)^T (Ax) = \|Ax\|^2 = 0 \\ \Rightarrow Ax = 0, \text{ i.e., } x \in N(A).$$

- Since $N(A) = N(A^T A)$, by rank-nullity theorem, $\text{rank}(A) = n - \dim(N(A)) = \text{rank}(A^T A)$.

- A has linearly independent columns $\Leftrightarrow \text{rank}(A) = n \Leftrightarrow \text{rank}(A^T A) = n \Leftrightarrow A^T A$ is invertible.

- If $\text{rank}(A) = n$, then the least square solution of $Ax = b$ is given by $A^T A \hat{x} = A^T b \Rightarrow \hat{x} = (A^T A)^{-1} A^T b$ and the orthogonal proj.

of b on $C(A)$ is $\hat{b} = A\hat{x} = Pb$, where $P = A(A^T A)^{-1} A^T$ is the projection matrix. **Ques:** Is $P^2 = P$?

Linear Least Squares: Example

Example: Find the least square solution to the system

$$\begin{pmatrix} -1 & 2 \\ 2 & -3 \\ -1 & 3 \end{pmatrix} x = \begin{pmatrix} 4 \\ 1 \\ 2 \end{pmatrix} \quad (Ax = b)$$

We need to solve $A^T A \hat{x} = A^T b$. Now $A^T b = \begin{pmatrix} -4 \\ 11 \end{pmatrix}$ and

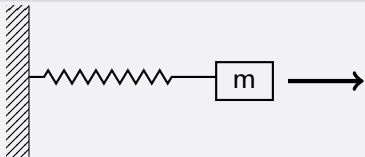
$$A^T A = \begin{pmatrix} 6 & -11 \\ -11 & 22 \end{pmatrix}.$$

$$[A^T A \mid A^T b] = \left(\begin{array}{cc|c} 6 & -11 & -4 \\ -11 & 22 & 11 \end{array} \right) \rightarrow \left(\begin{array}{cc|c} 6 & -11 & -4 \\ 0 & 11/6 & 11/3 \end{array} \right).$$

Therefore $\hat{x}_2 = 2$, and $\hat{x}_1 = 3$.

Exercise: Find the projection matrix P , and check that $Pb = A\hat{x}$.

Reading Slide: Linear Least Squares: Application



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

A student 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:

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

Clearly the data is inconsistent.

Allowing for various errors, how do we find an estimate for k ?

The method of least squares allows us to find a consistent system "close" to this one!

Exercise: Estimate k using the method of least squares.

Reading Slide: Line of Best Fit: Example

Question: We want to find the best line $y = C + Dx$ which fits the given data and gives least square error.

Data: $(x, y) = (-2, 4), (-1, 3), (0, 1),$ and $(2, 0)$.

$$\text{The system } \begin{pmatrix} 1 & -2 \\ 1 & -1 \\ 1 & 0 \\ 1 & 2 \end{pmatrix} \begin{pmatrix} C \\ D \end{pmatrix} = \begin{pmatrix} 4 \\ 3 \\ 1 \\ 0 \end{pmatrix} \quad (Ax = b)$$

is inconsistent.

Find the least square solution by solving $A^T A \hat{x} = A^T b$.

Question: Find the best quadratic curve $y = C + Dx + Ex^2$ which fits the above data and gives least square error.

Hint. The first row of the matrix A in this case will be $[1 \quad -2 \quad 4]$.

Gram-Schmidt Process

If the set of vectors v_1, \dots, v_r in \mathbb{R}^n are linearly independent, then we can find an orthonormal set of vectors q_1, \dots, q_r such that $\text{Span}\{v_1, \dots, v_r\} = \text{Span}\{q_1, \dots, q_r\}$.

First find an orthogonal set.

Let $w_1 = v_1$, $w_2 = v_2 - \text{proj}_{w_1}(v_2)$. Then $w_1 \perp w_2$ and

$\text{Span}\{v_1, v_2\} = \text{Span}\{w_1, w_2\}$.

Let $c_1 w_1 + c_2 w_2$ be the projection of v_3 on $\text{Span}\{w_1, w_2\}$. Then

$(v_3 - c_1 w_1 - c_2 w_2) \perp w_1$ and $(v_3 - c_1 w_1 - c_2 w_2) \perp w_2$.

$\Rightarrow w_1^T (v_3 - c_1 w_1 - c_2 w_2) = 0 \Rightarrow c_1 w_1 = \text{proj}_{w_1}(v_3)$ and similarly $c_2 w_2 = \text{proj}_{w_2}(v_3)$. Therefore,

$$w_3 = v_3 - \text{proj}_{\text{Span}\{w_1, w_2\}}(v_3) = v_3 - \left(\frac{w_1^T v_3}{\|w_1\|^2} \right) w_1 - \left(\frac{w_2^T v_3}{\|w_2\|^2} \right) w_2.$$

$$\text{Span}\{v_1, v_2, v_3\} = \text{Span}\{w_1, w_2, w_3\} \text{ and } w_1^T w_3 = 0, w_2^T w_3 = 0.$$

Gram-Schmidt Process (Contd.)

By induction,

$$\begin{aligned}w_r &:= v_r - \text{proj}_{\text{Span}\{w_1, \dots, w_{r-1}\}}(v_r) = \\&v_r - \text{proj}_{w_1}(v_r) - \text{proj}_{w_2}(v_r) - \dots - \text{proj}_{w_{r-1}}(v_r) \\&= v_r - \frac{w_1^T v_r}{\|w_1\|^2} w_1 - \frac{w_2^T v_r}{\|w_2\|^2} w_2 - \dots - \frac{w_{r-1}^T v_r}{\|w_{r-1}\|^2} w_{r-1}\end{aligned}$$

Now take $q_1 = \frac{w_1}{\|w_1\|}$, $q_2 = \frac{w_2}{\|w_2\|}$, ..., $q_r = \frac{w_r}{\|w_r\|}$. Then

$\{q_1, \dots, q_r\}$ is an orthonormal set and

$$W = \text{Span}\{v_1, \dots, v_r\} = \text{Span}\{w_1, \dots, w_r\} = \text{Span}\{q_1, \dots, q_r\}.$$

In particular, $\{q_1, q_2, \dots, q_r\}$ is an *orthonormal basis* for W .

Exercise: Show that if $\{w_1, \dots, w_r\}$ is an orthogonal set, then

$$\text{proj}_{\text{Span}\{w_1, \dots, w_{i-1}\}}(v_i) = \text{proj}_{w_1}(v_i) + \text{proj}_{w_2}(v_i) + \dots + \text{proj}_{w_{i-1}}(v_i).$$

Gram-Schmidt Method: Example

Q: Let $S = \left\{ v_1 = \begin{pmatrix} 3 \\ 1 \\ -1 \\ 3 \end{pmatrix}, v_2 = \begin{pmatrix} -5 \\ 1 \\ 5 \\ -7 \end{pmatrix}, v_3 = \begin{pmatrix} 1 \\ 1 \\ -2 \\ 8 \end{pmatrix} \right\}$ and $W =$

$\text{Span}(S)$. Find an orthonormal basis for W .

Exercise: First verify that $\{v_1, v_2, v_3\}$ are linearly independent. (Check that rank of $(v_1 \ v_2 \ v_3)$ is 3). Hence S is a basis of W .