

Inner Product and Orthogonality

CE282: Linear Algebra

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Bilinear Form



Definition

Suppose V and W are vector spaces over the same field \mathbb{F} . Then a function $f: V \times W \to \mathbb{F}$ is called a **bilinear form** if it satisfies the following properties:

- a) It is linear in its first argument:
 - i. $f(\mathbf{v_1} + \mathbf{v_2}, \mathbf{w}) = f(\mathbf{v_1}, \mathbf{w}) + f(\mathbf{v_2}, \mathbf{w})$ and
 - ii. $f(c\mathbf{v_1}, \mathbf{w}) = cf(\mathbf{v_1}, \mathbf{w})$ for all $c \in \mathbb{F}$, $\mathbf{v_1}$, $\mathbf{v_2} \in V$, and $\mathbf{w} \in W$.
- b) It is linear in its second argument:
 - i. $f(\mathbf{v}, \mathbf{w_1} + \mathbf{w_2}) = f(\mathbf{v}, \mathbf{w_1}) + f(\mathbf{v}, \mathbf{w_2})$ and
 - ii. $f(\mathbf{v}, c\mathbf{w_1}) = cf(\mathbf{v}, \mathbf{w_1})$ for all $c \in \mathbb{F}, \mathbf{v} \in V$, and $\mathbf{w_1}, \mathbf{w_2} \in W$.

Bilinear Form



Note

Let V be a vector space over a field \mathbb{F} . Then the **dual** of V, denoted by V^* , is the vector space consisting of all linear forms on V.

Example

Let V be a vector space over a field \mathbb{F} . Show that the function $g: V^* \times V \to \mathbb{F}$ defined by $g(f, \mathbf{v}) = f(\mathbf{v})$ for all $f \in V^*, \mathbf{v} \in V$ is a bilinear form.

Review: Inner products over real field



- \square An inner product on V is a function $\langle , \rangle : V \times V \rightarrow \mathbb{R}$ such that
 - 1. $\langle v, v \rangle \ge 0$ for all $v \in V$.
 - 2. $\langle v, v \rangle = 0$ if and only if v = 0.
 - 3. $\langle u + v, w \rangle = \langle u, w \rangle + \langle v, w \rangle$ for all $u, v, w \in V$.
 - 4. $\langle cw, u \rangle = c \langle w, u \rangle$ for all $u, w \in V$ and $c \in \mathbb{R}$.
 - 5. $\langle w, v \rangle = \langle v, w \rangle$.

General Inner products



Definition

Suppose that $\mathbb{F} = \mathbb{R}$ or $\mathbb{F} = \mathbb{C}$ and that V is a vector space over \mathbb{F} . Then an **inner product** on V is a function $\langle \cdot, \cdot \rangle : V \times V \to \mathbb{F}$ such that the following three properties hold for all $c \in \mathbb{F}$ and all $\mathbf{v}, \mathbf{w}, \mathbf{x} \in V$:

- a) $\langle \mathbf{v}, \mathbf{w} \rangle = \overline{\langle \mathbf{w}, \mathbf{v} \rangle}$ (conjugate symmetry)
- b) $\langle v+cx,w\rangle = \langle v,w\rangle + c\langle x,w\rangle$ (linearity)
- c) $\langle \mathbf{v}, \mathbf{v} \rangle \geq 0$, with equality if and only if $\mathbf{v} = \mathbf{0}$.

(pos. definiteness)

General Inner products



Note

- $\Box F = \mathbb{R}$ bilinear forms
- \Box $F = \mathbb{C}$ sesquilinear forms—they are linear in their first argument, but only conjugate linear in their second argument

$$\langle v, w + cx \rangle = \overline{(\langle w + cx, v \rangle)} = \overline{(\langle w, v \rangle)} + \overline{(c\langle x, v \rangle)} = \langle v, w \rangle + \overline{c}\langle v, x \rangle$$

Complex Dot Product



Example

Show that the function $\langle \cdot, \cdot \rangle : \mathbb{C}^n \times \mathbb{C}^n \to \mathbb{C}$ defined by $\langle \mathbf{v}, \mathbf{w} \rangle = \mathbf{v} \mathbf{w}^* = \sum_{i=1}^n \mathbf{v}_i \overline{w_i}$ for all $\mathbf{v}, \mathbf{w} \in \mathbb{C}^n$ is an inner product on \mathbb{C}^n .

Inner Product on Continuous Functions



Example

Let a < b be real numbers and let C[a, b] be the vector space of continuous functions on the real interval [a, b].

Show that the function $\langle \cdot, \cdot \rangle : C[a, b] \times C[a, b] \to \mathbb{R}$ defined by

$$\langle f, g \rangle = \int_a^b f(x)g(x) dx$$
 for all $f, g \in C[a, b]$

is and inner product on C[a, b].

Dot and inner product on Polynomials



Example

Find (p, q), ||p||, ||p - q|| which $p(x) = 3 - x + 2x^2$ and $q(x) = 4x + x^2$.

Inner product and norm



Theorem

Take any inner product $\langle \cdot, \cdot \rangle$ and define $f(x) = \sqrt{\langle x, x \rangle}$. Then f is a norm.

Proof

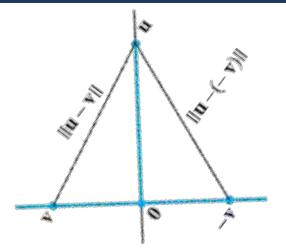
Note

Every inner product gives rise to a norm, but not every norm comes from an inner product. (Think about norm 2 and norm max)

Orthogonal vectors



Geometry



Algebra

Two vectors **u** and **v** in \mathbb{R}^n are **orthogonal** (to each other) if $\mathbf{u} \cdot \mathbf{v} = \mathbf{0}$.

Suppose *V* is an inner product space.

Two vectors $\mathbf{v}, \mathbf{w} \in V$ are called **orthogonal** if $\langle \mathbf{v}, \mathbf{w} \rangle = 0$.

The Pythagorean Theorem

Two vectors **u** and **v** are orthogonal if and only if $\|\mathbf{u} + \mathbf{v}\|^2 = \|\mathbf{u}\|^2 + \|\mathbf{v}\|^2$

Projection



- \Box Finding the distance from a point B to line l = Finding the length of line segment BP
- \square *AP*: projection of *AB* onto the line *l*



Definition

If **u** and **v** are vectors in \mathbb{R}^n and $\mathbf{u} \neq \mathbf{0}$, then the **projection of v onto u** is the vector $proj_{\mathbf{u}}(\mathbf{v})$ defined by

$$proj_{\mathbf{u}}(\mathbf{v}) = \left(\frac{\mathbf{u} \cdot \mathbf{v}}{\mathbf{u} \cdot \mathbf{u}}\right) \mathbf{u}$$

The projection of v onto u

Orthogonal Sets



• A set of vectors $\{a_1, ..., a_k\}$ in \mathbb{R}^n is orthogonal set if each pair of distinct vectors is orthogonal (mutually orthogonal vectors).

Theorem

If $S = \{a_1, ..., a_k\}$ is an orthogonal set of nonzero vectors in \mathbb{R}^n , then S is linearly independent and is a basis for the subspace spanned by S.

Proof

If k = n, then prove that S is a basis for R^n

Orthonormal vectors



Definition

A basis *B* of an inner product space *V* is called an **orthonormal basis** of *V* if

- a) $\langle \mathbf{v}, \mathbf{w} \rangle = 0$ for all $\mathbf{v} \neq \mathbf{w} \in B$, and
- b) $\|\mathbf{v}\| = 1$ for all $\mathbf{v} \in B$.

(mutual orthogonality) (normalization)

- \square set of n-vectors a_1, \dots, a_k are (mutually) orthogonal if $a_i \perp a_j$ for $i \neq j$
- \square they are *normalized* if $||a_i|| = 1$ for i = 1, ..., k
- ☐ they are *orthonormal* if both hold
- ☐ can be expressed using inner products as

$$a_i^T a_j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$

Orthonormal vectors



Independence-dimension inequality

If the n-vectors $a_1, ..., a_k$ are linearly independent, then $k \le n$.

- □ orthonormal sets of vectors are linearly independent
- \square by independence-dimension inequality, must have $k \le n$
- \square when $k=n,a_1,\ldots,a_n$ are an *orthonormal basis*

Orthonormal bases



Example

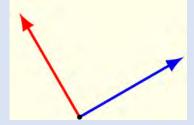
- \square Standard unit n-vectors e_1, \dots, e_n
- ☐ The 3-vectors

$$\begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix},$$

$$\frac{1}{\sqrt{2}}\begin{bmatrix}1\\1\\0\end{bmatrix}$$

$$\begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}, \qquad \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \qquad \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$$

☐ The 2-vectors shown below



 \square The standard basis in $P^p[a,b]$ (be the set of real-valued polynomials of degree at most p.)

Linear combinations of orthonormal vectors



 \square A simple way to check if an n-vector y is a linear combination of the orthonormal vectors a_1, \dots, a_k , if and only if:

$$y = (a_1^T y)a_1 + ... + (a_k^T y)a_k$$

 \square For orthogonal vectors a_1, \dots, a_k :

$$y = c_1 a_1 + \dots + c_k a_k$$

$$c_j = \frac{y \cdot a_j}{a_j \cdot a_j}$$

Linear combinations of orthonormal vectors



Example

Write x as a linear combination of a_1 , a_2 , a_3 ?

$$x = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}, \ a_1 = \begin{bmatrix} 0 \\ 0 \\ -1 \end{bmatrix}, \ a_2 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ 1 \\ 0 \end{bmatrix}, \ a_3 = \frac{1}{\sqrt{2}} \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$$

Orthogonal Complements



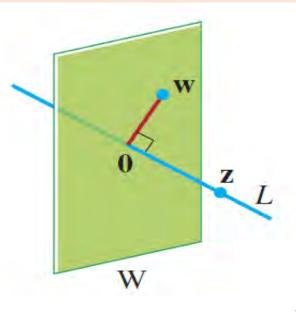
Definition

- \square If a vector z is orthogonal to every vector in a subspace W of \mathbb{R}^n , then z is said to be orthogonal to W.
- □ The set of all vectors z that are orthogonal to W is called the orthogonal complement of W and is denoted by w^{\perp}

Example

W be a plane through the origin in \mathbb{R}^3 .

$$L = W^{\perp}$$
 and $W = L^{\perp}$



Orthogonal Complements



Note

- 1) A vector x is in W^{\perp} if and only if x is orthogonal to every vector in a set that spans W.
- 2) W^{\perp} is a subspace of \mathbb{R}^n .

Important

We emphasize that W_1 and W_2 can be orthogonal without being complements.

$$W_1 = span((1,0,0))$$
 and $W_2 = span((0,1,0))$.

Orthogonal Projection of y onto W



The Orthogonal Decomposition Theorem

Let W be a subspace of \mathbb{R}^n . Then each y in \mathbb{R}^n can be written uniquely in the form:

$$\mathbf{y} = \hat{\mathbf{y}} + \mathbf{z} \qquad \text{proj}_W \mathbf{y}. \tag{1}$$

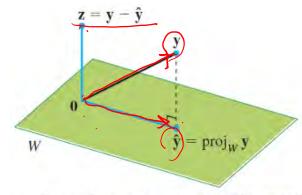
where $\hat{\mathbf{y}}$ is in W and \mathbf{z} is in W^{\perp} . In fact, if $\{\mathbf{u}_1, ..., \mathbf{u}_p\}$ is any orthogonal basis of W, then

$$\hat{\mathbf{y}} = \frac{\mathbf{y} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \dots + \frac{\mathbf{y} \cdot \mathbf{u}_p}{\mathbf{u}_p \cdot \mathbf{u}_p} \mathbf{u}_p$$
 (2)

and
$$z = \mathbf{y} - \hat{\mathbf{y}}$$

Important

The uniqueness of the decomposition (1) shows that the orthogonal projection $\hat{\mathbf{y}}$ depends only on Wand not on the particular basis used in (2).



The orthogonal projection of y onto W.

Best Approximation



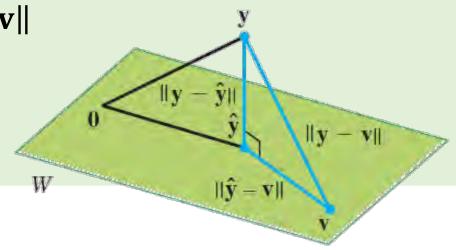
The Best Approximation Theorem

Let W be a subspace of \mathbb{R}^n . let \mathbf{y} be any vector in \mathbb{R}^n , and let $\hat{\mathbf{y}}$ be the orthogonal projection of \mathbf{y} onto W. Then $\hat{\mathbf{y}}$ is the closest point in W to \mathbf{y} , in the sense that

 $\|\mathbf{y} - \hat{\mathbf{y}}\| < \|\mathbf{y} - \mathbf{v}\|$

for all \mathbf{v} in W distinct from $\hat{\mathbf{y}}$.

Proof

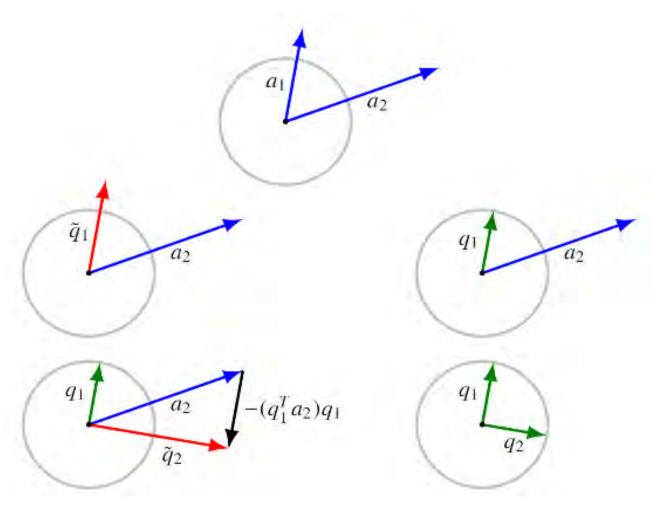


The orthogonal projection of \mathbf{y} onto W is the closest point in W to \mathbf{y} .



 \square Find orthonormal basis for span{ $a_1, a_2, ..., a_k$ }

☐ Geometry:





- \square Find orthonormal basis for span{ $a_1, a_2, ..., a_k$ }
- ☐ Algebra:

1)
$$q1 = \frac{a_1}{\|a_1\|}$$

2)
$$\widetilde{q_2} = a_2 - (q_1^T a_2) q_1 \rightarrow q_2 = \frac{\widetilde{q_2}}{\|\widetilde{q_2}\|}$$

3)
$$\widetilde{q_3} = a_3 - (q_1^T a_3) q_1 - (q_2^T a_3) q_2 \rightarrow q_3 = \frac{\widetilde{q_3}}{\|\widetilde{q_3}\|}$$

•

•

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k)
$$\widetilde{q_k} = a_k - (q_1^T a_k) q_1 - \dots - (q_{k-1}^T a_k) q_{k-1} \rightarrow q_k = \frac{\widetilde{q_k}}{\|\widetilde{q_k}\|}$$



- \square Why $\{q_1, q_2, ..., q_k\}$ is a orthonormal basis for span $\{a_1, a_2, ..., a_k\}$?
 - $\{q_1, q_2, \dots, q_k\}$ are normalized.
 - $\{q_1, q_2, \dots, q_k\}$ is a orthogonal set
 - a_i is a linear combination of $\{q_1, q_2, ..., q_i\}$

$$span\{q_1, q_2, ..., q_k\} = span\{a_1, a_2, ..., a_k\}$$

 \square q_i is a linear combination of $\{a_1, a_2, ..., a_i\}$



 \square Given n-vectors a_1, \dots, a_k

for
$$i = 1, ..., k$$

- 1. Orthogonalization: $\widetilde{q}_i = a_i (q_1^T a_i)q_1 \dots (q_{i-1}^T a_i)q_{i-1}$
- 2. Test for linear dependence: if $\tilde{q}_i = 0$, quit
- 3. Normalization: $q_i = \frac{\widetilde{q_i}}{\|\widetilde{q_i}\|}$

Note

- If G-S does not stop early (in step 2), $a_1, ..., a_k$ are linearly independent.
- If G-S stops early in iteration i = j, then a_j is a linear combination of $a_1, ..., a_{j-1}$ (so $a_1, ..., a_k$ are linearly dependent)

$$a_j = (q_1^T a_j)q_1 + \dots + (q_{j-1}^T a_j)q_{j-1}$$

Complexity of Gram–Schmidt algorithm



Gram-Schmidt algorithm gives us an explicit method for determining if a list of vectors is linearly dependent or independent.

 \square Given n-vectors $a_1, ..., a_k$

for
$$i = 1, ..., k$$

- 1. Orthogonalization: $\widetilde{q}_i = a_i (q_1^T a_i)q_1 \dots (q_{i-1}^T a_i)q_{i-1}$
- 2. Test for linear dependence: if $\tilde{q}_i = 0$, quit
- 3. Normalization: $q_i = \frac{\widetilde{q_i}}{\|\widetilde{q_i}\|}$

Class Activity



- https://docs.google.com/forms/d/e/1FAIpQLSdy5qeQrADjDvt5ca2I efi3on-oMtUABeZmxBHzIe34DipiQ/viewform?usp=sf_link
- https://forms.gle/GBTGgCwsKtN7SFiC6



for
$$i = 1, ..., k$$

- 1. Orthogonalization: $\widetilde{q}_i = a_i (q_1^T a_i)q_1 \dots (q_{i-1}^T a_i)q_{i-1}$
- 2. Test for linear dependence: if $\tilde{q}_i = 0$, quit
- 3. Normalization: $q_i = \frac{\widetilde{q_i}}{\|\widetilde{q_i}\|}$



Some Notes



- Determining if a vector is a linear combination of linearly independent vectors.
- Checking if a collection of vectors is a basis.

Gram-Schmidt



Theorem

Suppose B = $\{a_1, a_2, ..., a_n\}$ is a basis of an inner product space A. Then C = $\{q_1, q_2, ..., q_n\}$ is an orthonormal basis of $span\{a_1, a_2, ..., a_n\}$.

$$q_1 = \frac{a_1}{||a_1||} \qquad q_k = \frac{a_k - \sum_{i=1}^{k-1} \langle q_i, a_k \rangle q_i}{||a_k - \sum_{i=1}^{k-1} \langle q_i, a_k \rangle q_i||} \text{ for } 2 \le k \le n$$

Proof

We prove this result by induction on k.

TAKE HOME QUESTION



Example

Find an orthonormal basis for $P^2[-1,1]$ with respect to the inner product

$$\langle f, g \rangle = \int_{-1}^{1} f(x)g(x)dx$$

Conclusion



Existence of Orthonormal Bases

- Every finite-dimensional inner product space has an orthonormal basis.
- Since finite-dimensional inner product spaces (by definition) have a basis consisting of finitely many vectors, and the Gram-Schmidt process tells us how to convert that basis into an orthonormal basis, we now know that every finite-dimensional inner product space has an orthonormal basis.

Reference



- ☐ Chapter 1: Advanced Linear and Matrix Algebra, Nathaniel Johnston
- ☐ Chapter 6: Linear Algebra David Cherney
- ☐ Linear Algebra and Optimization for Machine Learning
- ☐ Introduction to Applied Linear Algebra Vectors, Matrices, and Least Squares