

Chapter 19 : orthogonality, orthogonal projections and the Gram-Schmidt Algorithm

orthogonality :

- Recall that $\vec{u}, \vec{v} \in \mathbb{R}^n$ are orthogonal $\Leftrightarrow \vec{u} \cdot \vec{v} = 0$

- The dot product satisfies :

(1) $\vec{u} \cdot \vec{u} \geq 0$ and is equal to zero iff $\vec{u} = \vec{0}$,

(2) $\vec{u} \cdot \vec{v} = \vec{v} \cdot \vec{u}$ (commutative)

(3) $(a\vec{u} + b\vec{v}) \cdot (c\vec{w}) = ac \vec{u} \cdot \vec{w} + bc \vec{v} \cdot \vec{w}$, for all $a, b, c \in \mathbb{R}$
and $\vec{u}, \vec{v}, \vec{w} \in \mathbb{R}^n$,

(4) $(a\vec{u}) \cdot (b\vec{v} + c\vec{w}) = ab \vec{u} \cdot \vec{v} + ac \vec{u} \cdot \vec{w}$ (bi-linearity)

Example : Standard basis of \mathbb{R}^3 , $(1, 0, 0)$, $(0, 1, 0)$, $(0, 0, 1)$ are all orthogonal pairwise.

Definition : A set of vectors in \mathbb{R}^n , i.e. $\{\vec{v}_1, \dots, \vec{v}_m\}$, is called "orthogonal" if

$$\vec{v}_i \cdot \vec{v}_j = 0,$$

for all $1 \leq i < j \leq m$ and $\vec{v}_i \neq \vec{0}$ for all $1 \leq i \leq m$.

(They are all non-zero vectors and pairwise orthogonal.)

Example : The standard basis of \mathbb{R}^n is an orthogonal set.

• If $\{ \vec{v}_1, \dots, \vec{v}_m \}$ is an orthogonal set, then

$$\| \vec{v}_1 + \dots + \vec{v}_m \|^2 = \| \vec{v}_1 \|^2 + \| \vec{v}_2 \|^2 + \dots + \| \vec{v}_m \|^2,$$

where $\| \vec{v}_j \|^2 = \vec{v}_j \cdot \vec{v}_j$, for $j=1, 2, \dots, m$.

Theorem (19.1):

Any orthogonal set of vectors is linearly independent,
or, any orthogonal set of vectors in \mathbb{R}^n has at most n elements,
or, any orthogonal set of n vectors in \mathbb{R}^n is a basis for \mathbb{R}^n , called
an "orthogonal basis".

Proof: please refer to the textbook VSF.

Theorem (19.2): (The Expansion Theorem)

Suppose $\{ \vec{w}_1, \dots, \vec{w}_m \}$ is an orthogonal basis for a subspace W of \mathbb{R}^n . Then any vector $\vec{w} \in W$ can be written as,

$$\vec{w} = \left(\frac{\vec{w} \cdot \vec{w}_1}{\| \vec{w}_1 \|^2} \right) \vec{w}_1 + \left(\frac{\vec{w} \cdot \vec{w}_2}{\| \vec{w}_2 \|^2} \right) \vec{w}_2 + \dots + \left(\frac{\vec{w} \cdot \vec{w}_m}{\| \vec{w}_m \|^2} \right) \vec{w}_m,$$

in which the coefficients of $\vec{w}_1, \vec{w}_2, \dots, \vec{w}_m$ are the coordinates of \vec{w} relative to the ordered basis. They are also called the "Fourier coefficients" of \vec{w} relative to the orthogonal basis. This theorem gives us a simple formula to write \vec{w} as a linear combination of basis vectors.

proof: Since $\{\vec{w}_1, \dots, \vec{w}_m\}$ form a basis of W , so

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$$\vec{w} = a_1 \vec{w}_1 + a_2 \vec{w}_2 + \dots + a_m \vec{w}_m$$
$$\Rightarrow \vec{w}_i \cdot \vec{w} = a_i \vec{w}_i \cdot \vec{w}_i \Rightarrow a_i = \frac{\vec{w}_i \cdot \vec{w}}{\vec{w}_i \cdot \vec{w}_i} = \frac{\vec{w}_i \cdot \vec{w}}{\|\vec{w}_i\|^2} \quad \square$$

Example: Let $W = \{(x, y, z, w) \in \mathbb{R}^4 \mid x - y - z + w = 0\}$. W is a subspace of \mathbb{R}^4 and $\dim(W) = 3$, since $W = \text{Null}([1, -1, -1, 1])$ and it has rank 1. So,

$$\dim(W) = \dim(\text{Null}([1, -1, -1, 1])) = 4 - \text{rank}([1, -1, -1, 1]) = 3$$

(rank-nullity theorem).

Now, let $\vec{w}_1 = (1, 1, 1, 1)$, $\vec{w}_2 = (1, -1, 1, 1)$ and $\vec{w}_3 = (1, 1, -1, -1)$.
check that $\{\vec{w}_1, \vec{w}_2, \vec{w}_3\}$ is an orthogonal set, and hence LI,
so they form an orthogonal basis for W .

Let's write $\vec{w} = (1, 2, 3, 4) \in W$ (check!) as a linear combination of $\vec{w}_1, \vec{w}_2, \vec{w}_3$, using the theorem (19.2):

$$\frac{\vec{w} \cdot \vec{w}_1}{\|\vec{w}_1\|^2} = \frac{10}{4} = 5/2, \quad \frac{\vec{w} \cdot \vec{w}_2}{\|\vec{w}_2\|^2} = \frac{-2}{4} = -1/2, \quad \frac{\vec{w} \cdot \vec{w}_3}{\|\vec{w}_3\|^2} = \frac{-4}{4} = -1,$$

Therefore,

$$\vec{w} = \frac{5}{2} \vec{w}_1 - \frac{1}{2} \vec{w}_2 - \vec{w}_3.$$

Note: Orthogonal basis are meant to simplify calculations, but without them we have to use the usual methods, such as the elementary row reductions, etc.

Definition (19.2): Orthogonal projection onto a subspace

Let W be a subspace of \mathbb{R}^n and $\{\vec{w}_1, \vec{w}_2, \dots, \vec{w}_m\}$ an orthogonal basis for W . Then for any $\vec{v} \in \mathbb{R}^n$, the orthogonal projection of \vec{v} onto W is defined by:

$$\text{proj}_W(\vec{v}) = \left(\frac{\vec{v} \cdot \vec{w}_1}{\|\vec{w}_1\|^2} \right) \vec{w}_1 + \dots + \left(\frac{\vec{v} \cdot \vec{w}_m}{\|\vec{w}_m\|^2} \right) \vec{w}_m$$

Example: $W = \{(x, y, z, w) \in \mathbb{R}^4 \mid x - y - z + w = 0\}$, $\vec{v} = (1, 2, 3, 5)$

$\vec{w}_1 = (1, 1, 1, 1)$, $\vec{w}_2 = (1, -1, 1, -1)$, $\vec{w}_3 = (1, 1, -1, -1)$: these are orthogonal basis for W :

$$\frac{\vec{v} \cdot \vec{w}_1}{\|\vec{w}_1\|^2} = \frac{11}{4}, \quad \frac{\vec{v} \cdot \vec{w}_2}{\|\vec{w}_2\|^2} = -\frac{3}{4}, \quad \frac{\vec{v} \cdot \vec{w}_3}{\|\vec{w}_3\|^2} = -\frac{5}{4}, \quad \text{therefore}$$

$$\text{proj}_W(\vec{v}) = \frac{11}{4} \vec{w}_1 - \frac{3}{4} \vec{w}_2 - \frac{5}{4} \vec{w}_3 = \frac{1}{4} (3, 9, 13, 19).$$

Also, $\vec{v} - \text{proj}_W(\vec{v}) = \frac{1}{4} (1, -1, -1, 1)$, which is orthogonal to every vector in W , since $(x, y, z, w) \in W \Leftrightarrow$

$$(x, y, z, w) \cdot (1, -1, -1, 1) = x - y - z + w = 0 \quad \checkmark$$

Theorem (19.3): "Best Approximation Theorem"

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Let W be a subspace of \mathbb{R}^n and $\vec{v} \in \mathbb{R}^n$. Then,

- (1) $\text{Proj}_W(\vec{v}) \in W$,
- (2) $\vec{v} - \text{Proj}_W(\vec{v})$ is orthogonal to every vector in W ,
- (3) $\text{Proj}_W(\vec{v})$ is the best approximation to \vec{v} by vectors in W ,
($\text{Proj}_W(\vec{v})$ is the closest vector in W to \vec{v}),
- (4) The vector $\text{Proj}_W(\vec{v})$ is the "only" vector in \mathbb{R}^n , which satisfies (1) and (2). (orthogonal projection is uniquely characterized by the two properties (1) and (2)).

proof: please refer to the textbook.

Note: Part (4) is saying that the orthogonal projection does not depend on a choice of orthogonal basis and with different bases we will obtain exactly the same projection.

⊗ The Gram-Schmidt Algorithm (Finding orthogonal basis):

Every subspace W of \mathbb{R}^n has an orthogonal basis. The Gram-Schmidt algorithm takes any basis of W as input and output an orthogonal basis of W .

Suppose $\{\vec{u}_1, \dots, \vec{u}_m\}$ is any basis for W .

Theorem (19.4): Gram-Schmidt Algorithm

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Let $\{\vec{u}_1, \dots, \vec{u}_m\}$ be any basis of W . Define

$$(1) \vec{w}_1 = \vec{u}_1 \text{ and } V_1 = \text{span}\{\vec{w}_1\},$$

$$(2) \vec{w}_2 = \vec{u}_2 - \text{proj}_{V_1}(\vec{u}_2) \text{ and } V_2 = \text{span}\{\vec{w}_1, \vec{w}_2\},$$

$$(3) \vec{w}_3 = \vec{u}_3 - \text{proj}_{V_2}(\vec{u}_3) \text{ and } V_3 = \text{span}\{\vec{w}_1, \vec{w}_2, \vec{w}_3\},$$

\vdots

$$(m) \vec{w}_m = \vec{u}_m - \text{proj}_{V_{m-1}}(\vec{u}_m) \text{ and } V_m = \text{span}\{\vec{w}_1, \dots, \vec{w}_m\}.$$

Then, $W = V_m$ and $\{\vec{w}_1, \dots, \vec{w}_m\}$ is an orthogonal basis for W .

or,

$$(1) \vec{w}_1 = \vec{u}_1,$$

$$(2) \vec{w}_2 = \vec{u}_2 - \text{proj}_{\vec{w}_1}(\vec{u}_2),$$

$$(3) \vec{w}_3 = \vec{u}_3 - \text{proj}_{\vec{w}_1}(\vec{u}_3) - \text{proj}_{\vec{w}_2}(\vec{u}_3),$$

\vdots

$$(m) \vec{w}_m = \vec{u}_m - \sum_{i=1}^{m-1} \text{proj}_{\vec{w}_i}(\vec{u}_m).$$

Then, $\{\vec{w}_1, \dots, \vec{w}_m\}$ is an orthogonal basis for W .

* one could also scale each of the vectors \vec{w}_i by dividing by their norm to produce an "orthonormal" basis for W .

Example: $W = \{ (1, 0, 0, 1), (1, 1, 1, 0), (2, 1, -1, 1) \}$

$$\vec{w}_1 = (1, 0, 0, 1),$$

$$\begin{aligned} \vec{w}_2 &= \vec{u}_2 - \text{Proj}_{W_1}(\vec{u}_2) = \vec{u}_2 - \frac{\vec{u}_2 \cdot \vec{u}_1}{\|\vec{u}_1\|^2} \vec{u}_1 = (1, 1, 1, 0) - \frac{1}{2}(1, 0, 0, 1) \\ &= \left(\frac{1}{2}, 1, 1, -\frac{1}{2}\right), \end{aligned}$$

$$\vec{w}_3 = \vec{u}_3 - \frac{\vec{u}_3 \cdot \vec{w}_1}{\|\vec{w}_1\|^2} \vec{w}_1 - \frac{\vec{u}_3 \cdot \vec{w}_2}{\|\vec{w}_2\|^2} \vec{w}_2 = \frac{5}{2} (1, 2, -3, -1)$$

So, the resulting orthogonal basis is: (after scaling them to avoid fractions)

$$\{ \vec{w}_1, \vec{w}_2, \vec{w}_3 \} = \left\{ (1, 0, 0, 1), \frac{1}{\sqrt{10}}(1, 2, 2, -1), \frac{1}{\sqrt{15}}(1, 2, -3, -1) \right\}$$

To find the orthonormal basis, we have to divide each of these basis vectors by their norm, which would result in: (orthonormal basis)

$$\left\{ \frac{\sqrt{2}}{2} (1, 0, 0, 1), \frac{\sqrt{10}}{10} (1, 2, 2, -1), \frac{\sqrt{15}}{15} (1, 2, -3, -1) \right\}$$

Example: Find the best approximation of $\vec{v} = (1, 2, 3, 4)$ to W , where

$$W = \text{span} \{ (1, 0, 0, 1), (1, 1, 1, 0), (2, 1, -1, 1) \} = \{ (x, y, z, w) \in \mathbb{R}^4 \mid x - y - w = 0 \}.$$

orthogonal basis of $W = \{ \underbrace{(1, 0, 0, 1)}_{\vec{n}_1}, \underbrace{(1, 2, 2, -1)}_{\vec{n}_2}, \underbrace{(1, 2, -3, -1)}_{\vec{n}_3} \}$. from previous example, so

$$\text{Proj}_W(\vec{v}) = \frac{\vec{v} \cdot \vec{n}_1}{\|\vec{n}_1\|^2} \vec{n}_1 + \frac{\vec{v} \cdot \vec{n}_2}{\|\vec{n}_2\|^2} \vec{n}_2 + \frac{\vec{v} \cdot \vec{n}_3}{\|\vec{n}_3\|^2} \vec{n}_3 = \frac{1}{3} (8, 1, 9, 7).$$