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In §2.2, we defined dot product, norm(length), orthogonal(perpendicular) and angle.

Definition. [Distance Between Vectors]

The **distance** dist (\vec{u}, \vec{v}) between vectors $\vec{u}, \vec{v} \in \mathbb{R}^n$ is defined as

$$dist(\vec{u}, \vec{v}) = ||\vec{u} - \vec{v}|| = \sqrt{(u_1 - v_1)^2 + \dots + (u_n - v_n)^2}$$

Note that $\operatorname{dist}(\vec{u}, \vec{v}) \geq 0$ for any pair of vectors $\vec{u}, \vec{v} \in \mathbb{R}^n$.

 $dist(\vec{u}, \vec{v}) = 0$ if and only if $\vec{u} = \vec{v}$.

 $\operatorname{dist}(\vec{u}, \vec{v}) = \operatorname{dist}(\vec{v}, \vec{u}).$

Theorem. [Pythagorean Theorem]

Two vectors $\vec{u}, \vec{v} \in \mathbb{R}^n$ are orthogonal if and only if they satisfy the **Pythagorean** Relation

$$||\vec{u} + \vec{v}||^2 = ||\vec{u}||^2 + ||\vec{v}||^2.$$

Proof: Two vectors $\vec{u}, \vec{v} \in \mathbb{R}^n$ are orthogonal if and only if $\vec{u} \cdot \vec{v} = 0$. $||\vec{u} + \vec{v}||^2 = (\vec{u} + \vec{v}) \cdot (\vec{u} + \vec{v}) = \vec{u} \cdot \vec{u} + \vec{u} \cdot \vec{v} + \vec{v} \cdot \vec{u} + \vec{v} \cdot \vec{v} = ||\vec{u}||^2 + ||\vec{v}||^2 + 2\vec{u} \cdot \vec{v}$

Theorem. [Cauchy-Schwarz inequality]

$$|\vec{x} \cdot \vec{y}| \le ||\vec{x}|| \cdot ||\vec{y}||$$

Proof: First, we have $\vec{y} = \text{proj}_{\vec{x}}(\vec{y}) + \vec{y}^{\perp}$.

$$\begin{aligned} ||\vec{y}||^2 &= \vec{y} \cdot \vec{y} = ||\operatorname{proj}_{\vec{x}}(\vec{y})||^2 + ||\vec{y}^{\perp}||^2 = \frac{(\vec{y} \cdot \vec{x})^2}{\vec{x} \cdot \vec{x}} + ||\vec{y}^{\perp}||^2 \ge \frac{(\vec{y} \cdot \vec{x})^2}{\vec{x} \cdot \vec{x}} \\ \text{Hence } ||\vec{y}||^2 ||\vec{x}||^2 \ge (\vec{x} \cdot \vec{y})^2. \text{ That is } |\vec{x} \cdot \vec{y}| \le ||\vec{x}|| \cdot ||\vec{y}||. \end{aligned}$$

The equality holds if and only if $\vec{y}^{\perp} = \vec{0}. \end{aligned}$

Recall that

$$\cos \theta = \frac{\vec{x} \cdot \vec{y}}{||\vec{x}|| \cdot ||\vec{y}||}$$

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 $|\vec{x} \cdot \vec{y}| = ||\vec{x}|| \cdot ||\vec{y}||$ if and only \vec{x} and \vec{y} in the same or opposite direction.

Example 1. Find the norm, angle, and distance between vectors $\vec{v}_1 = \begin{bmatrix} 3 \\ 1 \\ 1 \end{bmatrix}$ and $\vec{v}_2 = \begin{bmatrix} -1 \\ 2 \\ 1 \end{bmatrix}$

$$\theta = \arccos \frac{\overrightarrow{V} \cdot \overrightarrow{V}}{\|\overrightarrow{V}\| \|\overrightarrow{W}\|} = \arccos \frac{0}{117 \sqrt{5}} = \frac{75}{2}$$

$$\overrightarrow{V} - \overrightarrow{V} = \begin{bmatrix} 4\\ -1\\ 0 \end{bmatrix}$$

$$\operatorname{dotone}(\overrightarrow{V}, \overrightarrow{K}) = \|\overrightarrow{V} - \overrightarrow{K}\| = \sqrt{16+1} = \sqrt{17}$$

Definition. [Orthogonal Set]

A set $\{\vec{u}_1, \ldots, \vec{u}_p\}$ of vectors in \mathbb{R}^n is called **orthogonal** if $\vec{u}_i \cdot \vec{u}_j = 0$ for any choice of indices $i \neq j$.

Theorem.

- Orthogonal vectors are linear independent.
- Orthonormal vectors $\{\vec{u}_1, \ldots, \vec{u}_n\}$ in \mathbb{R}^n form a basis of \mathbb{R}^n .

Definition.

- An orthogonal basis for a subspace W of \mathbb{R}^n is any basis for W which is also an orthogonal set.
- If each vector is a **unit** vector in an orthogonal basis, then it is an **orthonormal basis**.

Example 2. Is the set $\mathscr{B} = \left\{ \vec{v}_1 = \begin{bmatrix} 3\\1\\1 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} -1\\2\\1 \end{bmatrix}, \vec{v}_3 = \begin{bmatrix} -1\\-4\\7 \end{bmatrix} \right\}$ is an orthogonal basis for \mathbb{R}^3 ? If it is, normalize this basis.

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Theorem. [Coordinates with respect to an orthogonal basis]

Let $\mathscr{B} = {\vec{u}_1, \ldots, \vec{u}_p}$ be an **orthogonal** basis for a subspace W of \mathbb{R}^n , and let \vec{y} be any vector in W. Then

$$\vec{y} = \left(\frac{\vec{y} \cdot \vec{u}_1}{\vec{u}_1 \cdot \vec{u}_1}\right) \vec{u}_1 + \dots + \left(\frac{\vec{y} \cdot \vec{u}_p}{\vec{u}_p \cdot \vec{u}_p}\right) \vec{u}_p$$

If $W = \mathbb{R}^n$, then the \mathscr{B} -coordinates of \vec{y} are given by:

$$[\vec{y}]_{\mathscr{B}} = \begin{bmatrix} c_1 \\ \vdots \\ c_n \end{bmatrix} \quad \text{with} \quad c_i = \frac{\vec{y} \cdot \vec{u}_i}{\vec{u}_i \cdot \vec{u}_i} = \frac{\vec{y} \cdot \vec{u}_i}{||\vec{u}_i||^2}$$

Let $\mathscr{B} = \{\vec{u}_1, \ldots, \vec{u}_p\}$ be an **orthonormal** basis for a subspace W of \mathbb{R}^n , and let \vec{y} be any vector in W. Then

$$\vec{y} = (\vec{y} \cdot \vec{u}_1) \, \vec{u}_1 + \dots + (\vec{y} \cdot \vec{u}_p) \, \vec{u}_p$$

Example 3. Find the coordinate of $\vec{y} = \begin{bmatrix} 6\\1\\-8 \end{bmatrix}$ relative basis of \mathbb{R}^3 in Example 1.

$$C_{1} = \frac{\vec{y} \cdot \vec{v}}{\vec{p} \cdot \vec{v}} = \frac{1}{11} = 1$$

$$S_{0} \quad \left[\vec{y}\right]_{\mathcal{B}} = \left[\begin{array}{c} 6\\ -\frac{1}{8} \end{array} \right]$$

$$C_{2} = \frac{\vec{y} \cdot \vec{v}}{\vec{p} \cdot \vec{v}} = \frac{-12}{6} = -2$$

$$C_{3} = \frac{\vec{y} \cdot \vec{v}}{\vec{p} \cdot \vec{v}} = \frac{-66}{-6} = -1$$
Example 4. Is the set $\mathscr{B} = \left\{ \vec{v}_{1} = \begin{bmatrix} 1\\ 1\\ 2\\ 0 \end{bmatrix}, \vec{v}_{2} = \begin{bmatrix} 1\\ -1\\ 0\\ 0 \end{bmatrix}, \vec{v}_{3} = \begin{bmatrix} -1\\ -1\\ 1\\ 0\\ 0 \end{bmatrix} \right\}$ is an orthogonal basis for \mathbb{R}^{3} ? If it is, normalize this basis. Find the coordinate of $\vec{y} = \begin{bmatrix} 0\\ -4\\ 5\\ 0 \end{bmatrix}$ relative to \mathscr{B} .

$$\vec{X} \cdot \vec{V}_{n} = 0$$

$$\vec{X} \cdot \vec{V}_{n} = 0$$

$$\vec{Y} \cdot \vec{V}_{n} = 0$$

$$\vec{V} \cdot \vec{V} = 0$$

$$\vec{V} \cdot \vec{V} = 0$$

$$\vec{V} \cdot \vec{V} = 0$$

$$\vec{V} \cdot \vec{V$$

We defined the Orthogonal Projection Onto A Line in §2.2:

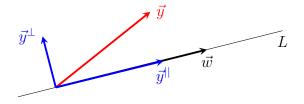
Let $L = \text{Span}\{\vec{w}\}$ be the line in \mathbb{R}^n spanned by $\vec{w} \in \mathbb{R}^n$. For a given vector $\vec{y} \in \mathbb{R}^n$, the vector

$$y^{\parallel} = \operatorname{proj}_{L}(\vec{y}) := \left(\frac{\vec{y} \cdot \vec{w}}{\vec{w} \cdot \vec{w}}\right) \vec{w}$$

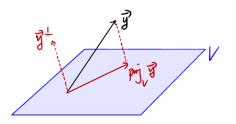
is called the **orthogonal projection of** \vec{y} **onto** L (or onto \vec{w}) and

 $\vec{y}^{\perp} := \vec{y} - \operatorname{proj}_L(\vec{y})$

the component of \vec{y} orthogonal to L (or \vec{w}).



We can define the orthogonal projection on to an plane.



More generally, given a subspace W of \mathbb{R}^n and a vector $\vec{y} \in \mathbb{R}^n$, we can ask if/how one can find a decomposition of \vec{y} as

$$\vec{y} = \operatorname{proj}_W(\vec{y}) + \vec{y}^{\perp}$$

with $\operatorname{proj}_W(\vec{y}) \in W$ (the orthogonal projection of \vec{y} on to W) and \vec{y}^{\perp} is the component of \vec{y} perpendicular to W.

Theorem. Orthogonal Decomposition

Let W be any subspace of \mathbb{R}^n and let $\vec{y}\in\mathbb{R}^n$ be any vector. Then there exists a unique decomposition

$$\vec{y} = \operatorname{proj}_W(\vec{y}) + \vec{y}^{\perp}$$

with $\operatorname{proj}_W(\vec{y}) \in W$ and \vec{y}^{\perp} is perpendicular to W.

Theorem. Orthogonal Decomposition

If $\{\vec{u}_1, \ldots, \vec{u}_p\}$ is an *orthogonal basis* for W, then

$$\operatorname{proj}_{W}(\vec{y}) = \left(\frac{\vec{y} \cdot \vec{u}_{1}}{\vec{u}_{1} \cdot \vec{u}_{1}}\right) \vec{u}_{1} + \dots + \left(\frac{\vec{y} \cdot \vec{u}_{p}}{\vec{u}_{p} \cdot \vec{u}_{p}}\right) \vec{u}_{p}$$

and $\vec{y}^{\perp} = \vec{y} - \text{proj}_W(\vec{y})$.

Example 5. Let V be a subspace of \mathbb{R}^3 spanned by $\vec{v}_1 = \begin{bmatrix} 1 \\ 1 \\ 2 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 1 \\ -1 \\ 0 \end{bmatrix}$. Find the

orthogonal projection of $\vec{y} = \begin{bmatrix} 1\\ 2\\ 6 \end{bmatrix}$ on to V and find the orthogonal component of \vec{y} .

 $\vec{\nabla} \cdot \vec{V}_{2} = 0 \quad \text{so} \quad ordingmul.$ $P \vec{p}_{1} \cdot \vec{y} = \frac{\vec{y} \cdot \vec{u}}{\vec{u}_{1} \cdot \vec{u}_{1}} \cdot \vec{u}_{1} + \frac{\vec{y} \cdot \vec{u}_{2}}{\vec{u}_{2} \cdot \vec{u}_{2}} \cdot \vec{u}_{2} = \frac{5}{2} \begin{bmatrix} 1 \\ 2 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix} = \begin{bmatrix} 2 \\ 3 \\ 5 \end{bmatrix}$ $\vec{y}^{\perp} = \vec{y} - p \vec{n} \vec{q}_{1} \cdot \vec{u}_{1} + \frac{1}{2} \cdot \vec{u}_{2} \cdot \vec{u}_{2} = \begin{bmatrix} 1 \\ -1 \\ -1 \end{bmatrix}$

Definition. [Orthogonal Complements]

Given a nonempty subset (finite or infinite) W of \mathbb{R}^n , we define its orthogonal complement W^{\perp} (pronounced "W perp") as the set of all vectors $\vec{v} \in \mathbb{R}^n$ such that

$$\vec{v} \cdot \vec{w} = 0$$
, for all $\vec{w} \in W$.

Expressed in set notation:

$$W^{\perp} = \{ \vec{v} \in \mathbb{R}^n \mid \vec{v} \cdot \vec{w} = 0 \text{ for all } \vec{w} \in W \}$$

Example 6. Find a basis for
$$V^{\perp}$$
, where $V = \text{Span} \left\{ \begin{bmatrix} 0\\0\\2\\8 \end{bmatrix}, \begin{bmatrix} 1\\5\\2\\-5 \end{bmatrix}, \begin{bmatrix} 2\\10\\6\\-2 \end{bmatrix} \right\}$

$$V^{\perp} = \left(\vec{x} \in R^{4} \middle| \begin{array}{c} \vec{x} : \vec{y}_{1} = 0 \\ \vec{x}^{2} \vec{y}_{2}^{2} = 0 \end{array} \right)$$

$$= \left\{ \vec{x} \in R^{4} \middle| \begin{array}{c} 2x_{3} + 8x_{4} = 0 \\ x_{1} + 5x_{2} + 2x_{3} - 5x_{4} = 0 \\ x_{1} + 5x_{2} + 2x_{3} - 5x_{4} = 0 \end{array} \right\}$$

$$A = \begin{bmatrix} 0 & 0 & 2 & 8 \\ 1 & 5 & 2 & -5 \\ 2 & 10 & 6 & -2 \end{bmatrix} \text{ So, } V^{\perp} = \ker(A) \text{ which has a basis} \left\{ \begin{bmatrix} -5 \\ 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 13 \\ 0 \\ -4 \\ 1 \end{bmatrix} \right\}$$

Theorem.

Let W be a subset of \mathbb{R}^n . Let V = Span(W), then

- 1. $V^{\perp} = W^{\perp}$
- 2. If $V = \operatorname{Span}(\mathscr{B})$, then $V^{\perp} = \mathscr{B}^{\perp}$
- 3. W^{\perp} is a subspace of \mathbb{R}^n (even when W is not).
- 4. $(V^{\perp})^{\perp} = V$.
- 5. dim $V + \dim V^{\perp} = n$.

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

The row space of A is Row(A), spanned by the row vectors of A.

The column space of A is Col(A), so Col(A) = im(A).

The kernel of A is also called the **null space** of A, denoted Nul(A).

Theorem.

Let A be an $m \times n$ matrix, then

 $(\operatorname{Row} A)^{\perp} = \ker(A)$

Theorem.

Let A be an $m\times n$ matrix, then

$$(\operatorname{im} A)^{\perp} = \ker A^T.$$

Example 7. In Example 6,
$$A = \begin{bmatrix} 0 & 0 & 2 & 8 \\ 1 & 5 & 2 & -5 \\ 2 & 10 & 6 & -2 \end{bmatrix}$$
 then

$$V = \operatorname{Row} A = \operatorname{Span} \left\{ \begin{bmatrix} 0 \\ 0 \\ 2 \\ 8 \end{bmatrix}, \begin{bmatrix} 1 \\ 5 \\ 2 \\ -5 \end{bmatrix}, \begin{bmatrix} 2 \\ 10 \\ 6 \\ -2 \end{bmatrix} \right\}$$
Example 8. Let V be a subspace of \mathbb{R}^3 spanned by $\vec{v}_1 = \begin{bmatrix} 2 \\ -2 \\ 1 \\ 0 \end{bmatrix}, \vec{v}_2 = \begin{bmatrix} 1 \\ 2 \\ 2 \\ 0 \end{bmatrix}$.

(1) Is $\{\vec{v}_1, \vec{v}_2\}$ an orthogonal basis for V?

Yes, since $\vec{v}_1 \cdot \vec{v}_2 = 0$.

(2). Find the decomposition of
$$\vec{y} = \begin{bmatrix} 1\\2\\3\\0 \end{bmatrix}$$
 as $\vec{y} = \vec{y_1} + \vec{y_2}$ such that $\vec{y_1} \in V$ and $\vec{y_2} \in V^{\perp}$.

(3). Find a basis for V^{\perp}

$V^{\perp} = \ker \left(\begin{bmatrix} 2 - 2 & i & 0 \\ i & 2 & 2 & 0 \end{bmatrix} \right)$	
$\begin{bmatrix} 2 & -2 & 1 & 0 \\ 1 & 2 & 2 & 0 \end{bmatrix} \xrightarrow{\longrightarrow} \xrightarrow{\longrightarrow} \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & \pm & 0 \end{bmatrix} \begin{bmatrix} X_1 + X_3 = 0 \\ X_2 + \frac{1}{2} X_3 = 0 \end{bmatrix}$	
$\begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} = \begin{bmatrix} -x_3 \\ -\frac{1}{2}x_3 \\ x_5 \\ x_4 \end{bmatrix} = x_3 \begin{bmatrix} -1 \\ -\frac{1}{2} \\ 0 \end{bmatrix} + x_4 \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} S_0 \begin{cases} \begin{bmatrix} -1 \\ -\frac{1}{2} \\ 0 \\ 0 \end{bmatrix} \end{bmatrix} \text{ is a basis for } 1$	