

Linear Algebra 2

Lecture #16

The orthogonal complement of a subspace.
Orthogonal projection onto a subspace

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 - ① The orthogonal complement of a subspace

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 - ③ Orthogonal projection onto subspaces of \mathbb{R}^n

1 The orthogonal complement of a subspace

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Definition

Let V be a real or complex vector space V , equipped with a scalar product $\langle \cdot, \cdot \rangle$. For a set $A \subseteq V$,^a the *orthogonal complement* of A , denoted by A^\perp , is the set of all vectors in V that are orthogonal to A .

^aHere, A may or may not be a subspace of V .

- Thus, we have the following:

$$\begin{aligned} A^\perp &= \{ \mathbf{v} \in V \mid \mathbf{v} \perp A \} \\ &= \{ \mathbf{v} \in V \mid \mathbf{v} \perp \mathbf{a} \ \forall \mathbf{a} \in A \} \\ &= \{ \mathbf{v} \in V \mid \langle \mathbf{v}, \mathbf{a} \rangle = 0 \ \forall \mathbf{a} \in A \}. \end{aligned}$$

Proposition 6.4.1

Let V be a real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$. Let $A, B \subseteq V$. Then

- Ⓐ A^\perp is a subspace of V ;^a
- Ⓑ if $A \subseteq B$, then $A^\perp \supseteq B^\perp$.

^aNote that it is possible that $A = \emptyset$. In this case, we simply get that $A^\perp = V$. This is because every vector in V is (vacuously) orthogonal to every vector in the empty set.

Proof (outline).

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Part (b) is “obvious”: if $A \subseteq B$, then any vector that is orthogonal to every vector in B is, in particular, orthogonal to every vector in A . \square

Proposition 6.4.2

Let V be a real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$. Let $\mathbf{u}_1, \dots, \mathbf{u}_k \in V$. Then $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}^\perp = \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)^\perp$.

Proof.

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Proof. Since $\{\mathbf{u}_1, \dots, \mathbf{u}_k\} \subseteq \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)$, Prop. 6.4.1(b) guarantees that $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}^\perp \supseteq \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)^\perp$.

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Let us prove the reverse inclusion.

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Let V be a real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$. Let $\mathbf{u}_1, \dots, \mathbf{u}_k \in V$. Then $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}^\perp = \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)^\perp$.

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Let us prove the reverse inclusion. Fix $\mathbf{x} \in \{\mathbf{u}_1, \dots, \mathbf{u}_k\}^\perp$. WTS $\mathbf{x} \in \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)^\perp$.

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Let us prove the reverse inclusion. Fix $\mathbf{x} \in \{\mathbf{u}_1, \dots, \mathbf{u}_k\}^\perp$. WTS $\mathbf{x} \in \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)^\perp$. Fix $\mathbf{u} \in \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)$. Then there exist scalars $\alpha_1, \dots, \alpha_k$ s.t. $\mathbf{u} = \alpha_1 \mathbf{u}_1 + \dots + \alpha_k \mathbf{u}_k$. But now

$$\begin{aligned}\langle \mathbf{u}, \mathbf{x} \rangle &= \langle \alpha_1 \mathbf{u}_1 + \dots + \alpha_k \mathbf{u}_k, \mathbf{x} \rangle \\ &= \alpha_1 \langle \mathbf{u}_1, \mathbf{x} \rangle + \dots + \alpha_k \langle \mathbf{u}_k, \mathbf{x} \rangle \\ &\stackrel{(*)}{=} \alpha_1 0 + \dots + \alpha_k 0 = 0,\end{aligned}$$

where (*) follows from the fact that $\mathbf{x} \in \{\mathbf{u}_1, \dots, \mathbf{u}_k\}^\perp$. This proves that $\mathbf{x} \perp \mathbf{u}$, and consequently, $\mathbf{x} \in \text{Span}(\mathbf{u}_1, \dots, \mathbf{u}_k)^\perp$. \square

- Recall from subsection 3.1.3 of the Lecture Notes (last semester) that if V is a vector space over a field \mathbb{F} , and U and W are subspaces of V , then

$$U + W := \{\mathbf{u} + \mathbf{w} \mid \mathbf{u} \in U, \mathbf{w} \in W\}$$

is a subspace of V .

- Moreover, recall from subsection 3.2.6 of the Lecture Notes that if $V = U + W$ and $U \cap W = \{\mathbf{0}\}$, then we say that V is the *direct sum* of U and W , and we write $V = U \oplus W$.

Theorem 6.4.3

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V . Then U^\perp is a subspace of V , and all the following hold:

- (a) if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthogonal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp ;
- (b) if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthonormal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthonormal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthonormal basis of U^\perp ;
- (c) $(U^\perp)^\perp = U$;
- (d) $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- (e) $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof. By Proposition 6.4.1(a), U^\perp is a subspace of V . It remains to prove (a)-(e).

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Proof of (a). Assume that $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and that $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthogonal basis of V . WTS $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp .

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Proof of (a) (cont.). Reminder: WTS $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) = U^\perp$.

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We first prove that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \supseteq U^\perp$.

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We first prove that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \supseteq U^\perp$. Fix $\mathbf{x} \in U^\perp$.

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We first prove that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \supseteq U^\perp$. Fix $\mathbf{x} \in U^\perp$. Then

$$\mathbf{x} \stackrel{(*)}{=} \sum_{i=1}^n \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i \stackrel{(**)}{=} \sum_{i=k+1}^n \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i,$$

where (*) follows from Theorem 6.3.5 (since

$\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of V) and (**) follows from the fact that $\mathbf{x} \in U^\perp$ and $\mathbf{u}_1, \dots, \mathbf{u}_k \in U$, we so $\langle \mathbf{x}, \mathbf{u}_i \rangle = 0$ for all $i \in \{1, \dots, k\}$.

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- (a) if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthogonal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp ;

Proof of (a) (cont.). Reminder: WTS $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) = U^\perp$.

We first prove that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \supseteq U^\perp$. Fix $\mathbf{x} \in U^\perp$. Then

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Thus, \mathbf{x} is a linear combination of the vectors $\mathbf{u}_{k+1}, \dots, \mathbf{u}_n$, and we deduce that $\mathbf{x} \in \text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n)$.

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It remains to show that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \subseteq U^\perp$.

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It remains to show that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \subseteq U^\perp$. Fix an arbitrary $\mathbf{x} \in \text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n)$. WTS $\mathbf{x} \in U^\perp$. Fix scalars $\alpha_{k+1}, \dots, \alpha_n$ such that

$$\mathbf{x} = \alpha_{k+1}\mathbf{u}_{k+1} + \dots + \alpha_n\mathbf{u}_n.$$

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$$\mathbf{x} = \alpha_{k+1}\mathbf{u}_{k+1} + \dots + \alpha_n\mathbf{u}_n.$$

Fix any $\mathbf{u} \in U$; we must show that $\mathbf{x} \perp \mathbf{u}$. Since $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is a basis of U , we know that there exist scalars $\alpha_1, \dots, \alpha_k$ such that

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- (a) if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthogonal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp ;

Proof of (a) (cont.). Reminder: WTS $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) = U^\perp$.

It remains to show that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \subseteq U^\perp$. Fix an arbitrary $\mathbf{x} \in \text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n)$. WTS $\mathbf{x} \in U^\perp$. Fix scalars $\alpha_{k+1}, \dots, \alpha_n$ such that

$$\mathbf{x} = \alpha_{k+1}\mathbf{u}_{k+1} + \dots + \alpha_n\mathbf{u}_n.$$

Fix any $\mathbf{u} \in U$; we must show that $\mathbf{x} \perp \mathbf{u}$. Since $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is a basis of U , we know that there exist scalars $\alpha_1, \dots, \alpha_k$ such that

$$\mathbf{u} = \alpha_1\mathbf{u}_1 + \dots + \alpha_k\mathbf{u}_k.$$

Since $\{\mathbf{u}_1, \dots, \mathbf{u}_k\} \perp \{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$, it readily follows that $\mathbf{x} \perp \mathbf{u}$ (details: Lecture Notes), and we deduce that $\text{Span}(\mathbf{u}_{k+1}, \dots, \mathbf{u}_n) \subseteq U^\perp$. This proves (a).

Theorem 6.4.3

- Ⓐ if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthogonal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp ;
- Ⓑ if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthonormal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthonormal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthonormal basis of U^\perp ;

Proof of (b). Part (b) follows immediately from part (a).

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U .

Theorem 6.4.3

- ⓐ $(U^\perp)^\perp = U$;
- ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U . So, by Corollary 6.3.11(a), U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
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Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U . So, by Corollary 6.3.11(a), U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$. By Corollary 6.3.11(b), the orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V .

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U . So, by Corollary 6.3.11(a), U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$. By Corollary 6.3.11(b), the orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By (a), $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp .

Theorem 6.4.3

- (c) $(U^\perp)^\perp = U$;
- (d) $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- (e) $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U . So, by Corollary 6.3.11(a), U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$. By Corollary 6.3.11(b), the orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By (a), $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp . But then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n, \mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of V that extends $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$,

Theorem 6.4.3

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- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U . So, by Corollary 6.3.11(a), U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$. By Corollary 6.3.11(b), the orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By (a), $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp . But then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n, \mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of V that extends $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$, and so by (a) applied to the vector space U^\perp , we have that $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of $(U^\perp)^\perp$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to prove (c), (d), and (e).

First, since V is finite-dimensional, so is U . So, by Corollary 6.3.11(a), U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$. By Corollary 6.3.11(b), the orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By (a), $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp . But then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n, \mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of V that extends $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$, and so by (a) applied to the vector space U^\perp , we have that $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of $(U^\perp)^\perp$. But now $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is a basis of both U and $(U^\perp)^\perp$, and it follows that $U = (U^\perp)^\perp$, i.e. (c) holds.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Further, we have the following:

- $\dim(U) = k$, since $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is a basis of U ;
- $\dim(U^\perp) = n - k$, since $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is a basis of U^\perp ;
- $\dim(V) = n$, since $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is a basis of V .

It now immediately follows that $\dim(V) = \dim(U) + \dim(U^\perp)$, i.e. (e) holds.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Let us first show that $U \cap U^\perp = \{\mathbf{0}\}$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Let us first show that $U \cap U^\perp = \{\mathbf{0}\}$. Since U and U^\perp are both subspaces of V , they both contain $\mathbf{0}$, and consequently, $\mathbf{0} \in U \cap U^\perp$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Let us first show that $U \cap U^\perp = \{\mathbf{0}\}$. Since U and U^\perp are both subspaces of V , they both contain $\mathbf{0}$, and consequently, $\mathbf{0} \in U \cap U^\perp$.

Now, fix any $\mathbf{u} \in U \cap U^\perp$; we must show that $\mathbf{u} = \mathbf{0}$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Let us first show that $U \cap U^\perp = \{\mathbf{0}\}$. Since U and U^\perp are both subspaces of V , they both contain $\mathbf{0}$, and consequently, $\mathbf{0} \in U \cap U^\perp$.

Now, fix any $\mathbf{u} \in U \cap U^\perp$; we must show that $\mathbf{u} = \mathbf{0}$. Since $\mathbf{u} \in U$ and $\mathbf{u} \in U^\perp$, we have that $\mathbf{u} \perp \mathbf{u}$, i.e. $\langle \mathbf{u}, \mathbf{u} \rangle = 0$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Let us first show that $U \cap U^\perp = \{\mathbf{0}\}$. Since U and U^\perp are both subspaces of V , they both contain $\mathbf{0}$, and consequently, $\mathbf{0} \in U \cap U^\perp$.

Now, fix any $\mathbf{u} \in U \cap U^\perp$; we must show that $\mathbf{u} = \mathbf{0}$. Since $\mathbf{u} \in U$ and $\mathbf{u} \in U^\perp$, we have that $\mathbf{u} \perp \mathbf{u}$, i.e. $\langle \mathbf{u}, \mathbf{u} \rangle = 0$. But then by the definition of a scalar product, we have that $\mathbf{u} = \mathbf{0}$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). Finally, we prove (d).

Let us first show that $U \cap U^\perp = \{\mathbf{0}\}$. Since U and U^\perp are both subspaces of V , they both contain $\mathbf{0}$, and consequently, $\mathbf{0} \in U \cap U^\perp$.

Now, fix any $\mathbf{u} \in U \cap U^\perp$; we must show that $\mathbf{u} = \mathbf{0}$. Since $\mathbf{u} \in U$ and $\mathbf{u} \in U^\perp$, we have that $\mathbf{u} \perp \mathbf{u}$, i.e. $\langle \mathbf{u}, \mathbf{u} \rangle = 0$. But then by the definition of a scalar product, we have that $\mathbf{u} = \mathbf{0}$. This proves that $U \cap U^\perp = \{\mathbf{0}\}$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to show that $V = U + U^\perp$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to show that $V = U + U^\perp$.

It is clear that $U + U^\perp \subseteq V$, and so we need only show that $V \subseteq U + U^\perp$.

Theorem 6.4.3

- Ⓒ $(U^\perp)^\perp = U$;
- Ⓓ $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- Ⓔ $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to show that $V = U + U^\perp$.

It is clear that $U + U^\perp \subseteq V$, and so we need only show that $V \subseteq U + U^\perp$.

Fix any $\mathbf{v} \in V$.

Theorem 6.4.3

- (c) $(U^\perp)^\perp = U$;
- (d) $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- (e) $\dim(V) = \dim(U) + \dim(U^\perp)$.

Proof (continued). It remains to show that $V = U + U^\perp$.

It is clear that $U + U^\perp \subseteq V$, and so we need only show that $V \subseteq U + U^\perp$.

Fix any $\mathbf{v} \in V$. Since $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is a basis of V , we know that there exist scalars $\alpha_1, \dots, \alpha_n$ such that $\mathbf{v} = \alpha_1 \mathbf{u}_1 + \dots + \alpha_n \mathbf{u}_n$. Set $\mathbf{v}_1 := \alpha_1 \mathbf{u}_1 + \dots + \alpha_k \mathbf{u}_k$ and $\mathbf{v}_2 := \alpha_{k+1} \mathbf{u}_{k+1} + \dots + \alpha_n \mathbf{u}_n$. Then $\mathbf{v} = \mathbf{v}_1 + \mathbf{v}_2$. Since $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is a basis of U , we see that $\mathbf{v}_1 \in U$, and since $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is a basis of U^\perp , we see that $\mathbf{v}_2 \in U^\perp$. So, $\mathbf{v} = \mathbf{v}_1 + \mathbf{v}_2$ belongs to $U + U^\perp$, and it follows that $V \subseteq U + U^\perp$. This proves (d), and we are done. \square

Theorem 6.4.3

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V . Then U^\perp is a subspace of V , and all the following hold:

- (a) if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthogonal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp ;
- (b) if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthonormal basis of U , and $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an extension of that basis to an orthonormal basis of V , then $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthonormal basis of U^\perp ;
- (c) $(U^\perp)^\perp = U$;
- (d) $V = U \oplus U^\perp$, that is, $V = U + U^\perp$ and $U \cap U^\perp = \{\mathbf{0}\}$;
- (e) $\dim(V) = \dim(U) + \dim(U^\perp)$.

- As a corollary of Theorem 6.4.3(a-b), we obtain the following computationally useful proposition.
 - The proposition is long, and we need to slides to state it.

Proposition 6.4.4

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ be any linearly independent set of vectors V , and let $\{\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n\}$ be an extension of that linearly independent set to a basis of V . Set $U := \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_k)$.

- If the Gram-Schmidt orthogonalization process (version 1) is applied to input vectors $\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n$ to produce output vectors $\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n$, then both the following hold:
 - $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , and $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp ;
 - $\left\{ \frac{\mathbf{u}_1}{\|\mathbf{u}_1\|}, \dots, \frac{\mathbf{u}_k}{\|\mathbf{u}_k\|} \right\}$ is an orthonormal basis of U , and $\left\{ \frac{\mathbf{u}_{k+1}}{\|\mathbf{u}_{k+1}\|}, \dots, \frac{\mathbf{u}_n}{\|\mathbf{u}_n\|} \right\}$ is an orthonormal basis of U^\perp .

Proposition 6.4.4

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ be any linearly independent set of vectors V , and let $\{\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n\}$ be an extension of that linearly independent set to a basis of V . Set $U := \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_k)$.

- ⓑ If the Gram-Schmidt orthogonalization process (version 2) is applied to input vectors $\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n$ to produce output vectors $\mathbf{z}_1, \dots, \mathbf{z}_k, \mathbf{z}_{k+1}, \dots, \mathbf{z}_n$, then $\{\mathbf{z}_1, \dots, \mathbf{z}_k\}$ is an orthonormal basis of U , and $\{\mathbf{z}_{k+1}, \dots, \mathbf{z}_n\}$ is an orthonormal basis of U^\perp .

Proposition 6.4.4

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ be any linearly independent set of vectors V , and let $\{\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n\}$ be an extension of that linearly independent set to a basis of V . Set $U := \text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_k)$.

- ⓑ If the Gram-Schmidt orthogonalization process (version 2) is applied to input vectors $\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n$ to produce output vectors $\mathbf{z}_1, \dots, \mathbf{z}_k, \mathbf{z}_{k+1}, \dots, \mathbf{z}_n$, then $\{\mathbf{z}_1, \dots, \mathbf{z}_k\}$ is an orthonormal basis of U , and $\{\mathbf{z}_{k+1}, \dots, \mathbf{z}_n\}$ is an orthonormal basis of U^\perp .
- This is an easy corollary of Theorem 6.4.3 (details: Lecture Notes).

Example 6.4.5

Consider the following vectors in \mathbb{R}^4 :

$$\mathbf{a}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \quad \mathbf{a}_2 = \begin{bmatrix} 2 \\ 2 \\ 2 \\ 0 \end{bmatrix}, \quad \mathbf{a}_3 = \begin{bmatrix} 0 \\ 3 \\ 3 \\ 3 \end{bmatrix}, \quad \mathbf{a}_4 = \begin{bmatrix} 2 \\ 4 \\ 4 \\ 2 \end{bmatrix}.$$

Compute an orthonormal basis of $U := \text{Span}(\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \mathbf{a}_4)$ and an orthonormal basis of U^\perp .

Solution.

Example 6.4.5

Consider the following vectors in \mathbb{R}^4 :

$$\mathbf{a}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \quad \mathbf{a}_2 = \begin{bmatrix} 2 \\ 2 \\ 2 \\ 0 \end{bmatrix}, \quad \mathbf{a}_3 = \begin{bmatrix} 0 \\ 3 \\ 3 \\ 3 \end{bmatrix}, \quad \mathbf{a}_4 = \begin{bmatrix} 2 \\ 4 \\ 4 \\ 2 \end{bmatrix}.$$

Compute an orthonormal basis of $U := \text{Span}(\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \mathbf{a}_4)$ and an orthonormal basis of U^\perp .

Solution. First, we need to find a basis of U and extend it to a basis of \mathbb{R}^4 . For this, we use Proposition 3.3.21. We consider the standard basis $\mathcal{E}_4 = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \mathbf{e}_4\}$ of \mathbb{R}^4 , and we form the matrix

$$\begin{aligned} C &:= \left[\begin{array}{cccc|cccc} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \mathbf{a}_4 & \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 & \mathbf{e}_4 \end{array} \right] \\ &= \left[\begin{array}{cccc|cccc} 1 & 2 & 0 & 2 & 1 & 0 & 0 & 0 \\ 1 & 2 & 3 & 4 & 0 & 1 & 0 & 0 \\ 1 & 2 & 3 & 4 & 0 & 0 & 1 & 0 \\ 0 & 0 & 3 & 2 & 0 & 0 & 0 & 1 \end{array} \right]. \end{aligned}$$

Solution (continued). Reminder:

$$C := \left[\mathbf{a}_1 \quad \mathbf{a}_2 \quad \mathbf{a}_3 \quad \mathbf{a}_4 \mid \mathbf{e}_1 \quad \mathbf{e}_2 \quad \mathbf{e}_3 \quad \mathbf{e}_4 \right].$$

Solution (continued). Reminder:

$$C := \left[\mathbf{a}_1 \quad \mathbf{a}_2 \quad \mathbf{a}_3 \quad \mathbf{a}_4 \mid \mathbf{e}_1 \quad \mathbf{e}_2 \quad \mathbf{e}_3 \quad \mathbf{e}_4 \right].$$

By row reducing, we obtain

$$\text{RREF}(C) = \left[\begin{array}{cccc|cccc} 1 & 2 & 0 & 2 & 0 & 0 & 1 & -1 \\ 0 & 0 & 1 & 2/3 & 0 & 0 & 0 & 1/3 \\ 0 & 0 & 0 & 0 & 1 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right].$$

Solution (continued). Reminder:

$$C := \left[\mathbf{a}_1 \quad \mathbf{a}_2 \quad \mathbf{a}_3 \quad \mathbf{a}_4 \mid \mathbf{e}_1 \quad \mathbf{e}_2 \quad \mathbf{e}_3 \quad \mathbf{e}_4 \right].$$

By row reducing, we obtain

$$\text{RREF}(C) = \left[\begin{array}{cccc|cccc} 1 & 2 & 0 & 2 & 0 & 0 & 1 & -1 \\ 0 & 0 & 1 & 2/3 & 0 & 0 & 0 & 1/3 \\ 0 & 0 & 0 & 0 & 1 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right].$$

As we can see, the pivot columns of C are its **first**, **third**, **fifth**, and **sixth** column.

Solution (continued). Reminder:

$$C := \left[\begin{array}{cccc|cccc} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \mathbf{a}_4 & \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 & \mathbf{e}_4 \end{array} \right].$$

By row reducing, we obtain

$$\text{RREF}(C) = \left[\begin{array}{cccc|cccc} 1 & 2 & 0 & 2 & 0 & 0 & 1 & -1 \\ 0 & 0 & 1 & 2/3 & 0 & 0 & 0 & 1/3 \\ 0 & 0 & 0 & 0 & 1 & 0 & -1 & 1 \\ 0 & 0 & 0 & 0 & 0 & 1 & -1 & 0 \end{array} \right].$$

As we can see, the pivot columns of C are its **first**, **third**, **fifth**, and **sixth** column. So, by Proposition 3.3.21, $\{\mathbf{a}_1, \mathbf{a}_3\}$ is a basis of U , and $\{\mathbf{a}_1, \mathbf{a}_3, \mathbf{e}_1, \mathbf{e}_2\}$ is a basis of \mathbb{R}^4 that extends $\{\mathbf{a}_1, \mathbf{a}_3\}$.

Solution (continued). Reminder:

$$C := \left[\begin{array}{cccc|cccc} \mathbf{a}_1 & \mathbf{a}_2 & \mathbf{a}_3 & \mathbf{a}_4 & \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 & \mathbf{e}_4 \end{array} \right].$$

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As we can see, the pivot columns of C are its **first**, **third**, **fifth**, and **sixth** column. So, by Proposition 3.3.21, $\{\mathbf{a}_1, \mathbf{a}_3\}$ is a basis of U , and $\{\mathbf{a}_1, \mathbf{a}_3, \mathbf{e}_1, \mathbf{e}_2\}$ is a basis of \mathbb{R}^4 that extends $\{\mathbf{a}_1, \mathbf{a}_3\}$. By applying the Gram-Schmidt orthogonalization process (version 2) to the vectors $\mathbf{a}_1, \mathbf{a}_3, \mathbf{e}_1, \mathbf{e}_2$, we obtain the following vectors (next slide):

Solution (continued).

$$\mathbf{z}_1 = \begin{bmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \end{bmatrix}, \quad \mathbf{z}_2 = \begin{bmatrix} -2/\sqrt{15} \\ 1/\sqrt{15} \\ 1/\sqrt{15} \\ 3/\sqrt{15} \end{bmatrix},$$

$$\mathbf{z}_3 = \begin{bmatrix} 2/\sqrt{10} \\ -1/\sqrt{10} \\ -1/\sqrt{10} \\ 2/\sqrt{10} \end{bmatrix}, \quad \mathbf{z}_4 = \begin{bmatrix} 0 \\ 1/\sqrt{2} \\ -1/\sqrt{2} \\ 0 \end{bmatrix}.$$

Solution (continued).

$$\mathbf{z}_1 = \begin{bmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \end{bmatrix}, \quad \mathbf{z}_2 = \begin{bmatrix} -2/\sqrt{15} \\ 1/\sqrt{15} \\ 1/\sqrt{15} \\ 3/\sqrt{15} \end{bmatrix},$$

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By Proposition 6.4.4(b), $\{\mathbf{z}_1, \mathbf{z}_2\}$ is an orthonormal basis of U , whereas $\{\mathbf{z}_3, \mathbf{z}_4\}$ is an orthonormal basis of U^\perp . \square

Example 6.4.5

Consider the following vectors in \mathbb{R}^4 :

$$\mathbf{a}_1 = \begin{bmatrix} 1 \\ 1 \\ 1 \\ 0 \end{bmatrix}, \quad \mathbf{a}_2 = \begin{bmatrix} 2 \\ 2 \\ 2 \\ 0 \end{bmatrix}, \quad \mathbf{a}_3 = \begin{bmatrix} 0 \\ 3 \\ 3 \\ 3 \end{bmatrix}, \quad \mathbf{a}_4 = \begin{bmatrix} 2 \\ 4 \\ 4 \\ 2 \end{bmatrix}.$$

Compute an orthonormal basis of $U := \text{Span}(\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \mathbf{a}_4)$ and an orthonormal basis of U^\perp .

- **Remark:** We could also have applied the Gram-Schmidt orthogonalization process (version 1) to the vectors $\mathbf{a}_1, \mathbf{a}_3, \mathbf{e}_1, \mathbf{e}_2$, and then normalized the output vectors. We would have gotten the same vectors $\mathbf{z}_1, \mathbf{z}_2, \mathbf{z}_3, \mathbf{z}_4$ as above. Proposition 6.4.4(a) would then imply that $\{\mathbf{z}_1, \mathbf{z}_2\}$ is an orthonormal basis of U , whereas $\{\mathbf{z}_3, \mathbf{z}_4\}$ is an orthonormal basis of U^\perp .

2 Orthogonal projection onto a subspace

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Theorem 6.5.1

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V , and let $\mathbf{x} \in V$. Then there exists a unique vector $\mathbf{x}_U \in U$ that has the property that

$$\| \mathbf{x} - \mathbf{x}_U \| = \min_{\mathbf{u} \in U} \| \mathbf{x} - \mathbf{u} \|.$$

Moreover, if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , then this vector \mathbf{x}_U is given by the formula

$$\mathbf{x}_U = \sum_{i=1}^k \text{proj}_{\mathbf{u}_i}(\mathbf{x}) = \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i.$$

- **Terminology/Notation:** The vector \mathbf{x}_U from Theorem 6.5.1 is called the *orthogonal projection* of \mathbf{x} onto U .

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Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V , and let $\mathbf{x} \in V$. Then there exists a unique vector $\mathbf{x}_U \in U$ that has the property that

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- **Remarks:**

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- **Remarks:**

- If $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an **orthonormal** basis of U , then

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- If $\{ \mathbf{u}_1, \dots, \mathbf{u}_k \}$ is an **orthonormal** basis of U , then

$$\mathbf{x}_U = \sum_{i=1}^k \text{proj}_{\mathbf{u}_i}(\mathbf{x}) = \sum_{i=1}^k \langle \mathbf{x}, \mathbf{u}_i \rangle \mathbf{u}_i.$$

- If $\mathbf{x} \in U$, then $\mathbf{x}_U = \mathbf{x}$, since in this case, the expression $\| \mathbf{x} - \mathbf{u} \|$ (for $\mathbf{u} \in U$) is minimized for $\mathbf{u} = \mathbf{x}$.

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- Now let's prove the theorem!

Proof.

Proof. Using Corollary 6.3.11, we fix an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U , and we extend it to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V .

Proof. Using Corollary 6.3.11, we fix an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ of U , and we extend it to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By Theorem 6.4.3(a), $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp .

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$$\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i.$$

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Since \mathbf{u}^* is a linear combination of the vectors $\mathbf{u}_1, \dots, \mathbf{u}_k$, which form a basis of U , we see that $\mathbf{u}^* \in U$.

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Since \mathbf{u}^* is a linear combination of the vectors $\mathbf{u}_1, \dots, \mathbf{u}_k$, which form a basis of U , we see that $\mathbf{u}^* \in U$.

Now, fix any $\mathbf{u} \in U$. We must show that $\|\mathbf{x} - \mathbf{u}^*\| \leq \|\mathbf{x} - \mathbf{u}\|$, and that equality holds iff $\mathbf{u}^* = \mathbf{u}$. Clearly, this is sufficient to prove the theorem.

Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS
 $\|\mathbf{x} - \mathbf{u}^*\| \leq \|\mathbf{x} - \mathbf{u}\|$ and that equality holds iff $\mathbf{u}^* = \mathbf{u}$.

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$\|\mathbf{x} - \mathbf{u}^*\| \leq \|\mathbf{x} - \mathbf{u}\|$ and that equality holds iff $\mathbf{u}^* = \mathbf{u}$.

Let us first prove that $(\mathbf{u}^* - \mathbf{u}) \perp (\mathbf{x} - \mathbf{u}^*)$.

Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

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Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

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By Theorem 6.3.5, we have that

$$\mathbf{x} = \sum_{i=1}^n \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i,$$

Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

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Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

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So, $\mathbf{x} - \mathbf{u}^*$ is a linear combination of the vectors $\mathbf{u}_{k+1}, \dots, \mathbf{u}_n$; since those $n - k$ vectors form a basis of U^\perp , it follows that $\mathbf{x} - \mathbf{u}^* \in U^\perp$.

Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

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By Theorem 6.3.5, we have that

$$\mathbf{x} = \sum_{i=1}^n \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i,$$

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So, $\mathbf{x} - \mathbf{u}^*$ is a linear combination of the vectors $\mathbf{u}_{k+1}, \dots, \mathbf{u}_n$; since those $n - k$ vectors form a basis of U^\perp , it follows that $\mathbf{x} - \mathbf{u}^* \in U^\perp$. This proves that $(\mathbf{u}^* - \mathbf{u}) \perp (\mathbf{x} - \mathbf{u}^*)$.

Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

$\|\mathbf{x} - \mathbf{u}^*\| \leq \|\mathbf{x} - \mathbf{u}\|$ and that equality holds iff $\mathbf{u}^* = \mathbf{u}$.

Now that we have shown that vectors $\mathbf{u}^* - \mathbf{u}$ and $\mathbf{x} - \mathbf{u}^*$ are orthogonal to each other, we can apply the Pythagorean theorem to them, as follows:

$$\begin{aligned} \|\mathbf{x} - \mathbf{u}\|^2 &= \|(\mathbf{x} - \mathbf{u}^*) + (\mathbf{u}^* - \mathbf{u})\|^2 \\ &\stackrel{(*)}{=} \|\mathbf{x} - \mathbf{u}^*\|^2 + \|\mathbf{u}^* - \mathbf{u}\|^2 \\ &\geq \|\mathbf{x} - \mathbf{u}^*\|^2, \end{aligned}$$

where (*) follows from the Pythagorean theorem.

Proof (continued). Reminder: $\mathbf{u}^* := \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$; $\mathbf{u} \in U$; WTS

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where (*) follows from the Pythagorean theorem. Consequently, we have that $\|\mathbf{x} - \mathbf{u}^*\| \leq \|\mathbf{x} - \mathbf{u}\|$. Moreover, the inequality above is an equality iff $\|\mathbf{u}^* - \mathbf{u}\| = 0$, i.e. iff $\mathbf{u}^* = \mathbf{u}$. This completes the argument. \square

Theorem 6.5.1

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V , and let $\mathbf{x} \in V$. Then there exists a unique vector $\mathbf{x}_U \in U$ that has the property that

$$\| \mathbf{x} - \mathbf{x}_U \| = \min_{\mathbf{u} \in U} \| \mathbf{x} - \mathbf{u} \|.$$

Moreover, if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is an orthogonal basis of U , then this vector \mathbf{x}_U is given by the formula

$$\mathbf{x}_U = \sum_{i=1}^k \text{proj}_{\mathbf{u}_i}(\mathbf{x}) = \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i.$$

- **Terminology/Notation:** The vector \mathbf{x}_U from Theorem 6.5.1 is called the *orthogonal projection* of \mathbf{x} onto U .

Corollary 6.5.2

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let \mathbf{u} be any non-zero vector in V , and set $U := \text{Span}(\mathbf{u})$.^a Then for every $\mathbf{x} \in V$, we have that

$$\mathbf{x}_U = \text{proj}_{\mathbf{u}}(\mathbf{x}) = \frac{\langle \mathbf{x}, \mathbf{u} \rangle}{\langle \mathbf{u}, \mathbf{u} \rangle} \mathbf{u}.$$

^aSo, U is a one-dimensional subspace of V .

Proof.

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Proof. Clearly, $\{\mathbf{u}\}$ is an orthogonal basis of U . So, the result follows immediately from Theorem 6.5.1. \square

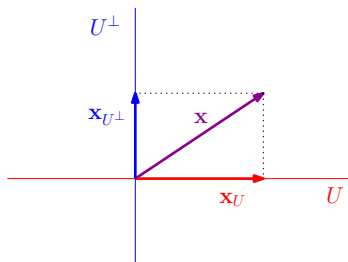
Corollary 6.5.3

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V , and let $\mathbf{x} \in V$. Then

$$\mathbf{x} = \mathbf{x}_U + \mathbf{x}_{U^\perp}.$$

Moreover, this is the unique way of expressing \mathbf{x} as a sum of a vector in U and a vector in U^\perp .^a

^aThis means that for all $\mathbf{y} \in U$ and $\mathbf{z} \in U^\perp$, if $\mathbf{x} = \mathbf{y} + \mathbf{z}$, then $\mathbf{y} = \mathbf{x}_U$ and $\mathbf{z} = \mathbf{x}_{U^\perp}$.



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Proof. By Corollary 6.3.11, U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$, and moreover, this basis can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By Theorem 6.4.3(a), we have that $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp .

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Proof. By Corollary 6.3.11, U has an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$, and moreover, this basis can be extended to an orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_k, \mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ of V . By Theorem 6.4.3(a), we have that $\{\mathbf{u}_{k+1}, \dots, \mathbf{u}_n\}$ is an orthogonal basis of U^\perp . Now, by Theorem 6.3.5, we have that

$$\mathbf{x}_U = \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i \quad \text{and} \quad \mathbf{x}_{U^\perp} = \sum_{i=k+1}^n \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i.$$

Solution (continued). On the other hand, by Theorem 6.3.5, we have that

$$\mathbf{x} = \sum_{i=1}^n \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i.$$

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It remains to prove the uniqueness part of the corollary.

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$$\mathbf{x}_U + \mathbf{x}_{U^\perp} = \mathbf{x} = \mathbf{y} + \mathbf{z},$$

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But $\mathbf{x}_U - \mathbf{y} \in U$ and $\mathbf{z} - \mathbf{x}_{U^\perp} \in U^\perp$. Since $U \cap U^\perp = \{\mathbf{0}\}$ (by Theorem 6.4.3(d)), it follows that $\mathbf{x}_U - \mathbf{y} = \mathbf{z} - \mathbf{x}_{U^\perp} = \mathbf{0}$,

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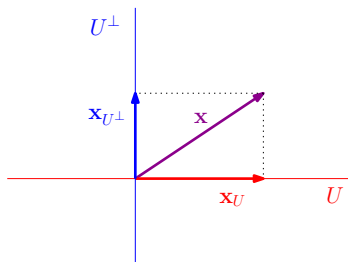
Corollary 6.5.3

Let V be a finite-dimensional real or complex vector space, equipped with a scalar product $\langle \cdot, \cdot \rangle$ and the induced norm $\| \cdot \|$. Let U be a subspace of V , and let $\mathbf{x} \in V$. Then

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- We can then define the function $\text{proj}_U : V \rightarrow V$ by setting $\text{proj}_U(\mathbf{x}) = \mathbf{x}_U$ for all $\mathbf{x} \in V$ (where \mathbf{x}_U is the orthogonal projection of \mathbf{x} onto U , as in Theorem 6.5.1).

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- Using the formula from Theorem 6.5.1, we can easily see that the function proj_U is linear.
- Indeed, if $\{\mathbf{u}_1, \dots, \mathbf{u}_k\}$ is any orthogonal basis of U (such a basis exists by Corollary 6.3.11), then the following hold (next two slides):

- for all $\mathbf{x}, \mathbf{y} \in V$, we have that

$$\begin{aligned}\text{proj}_U(\mathbf{x} + \mathbf{y}) &\stackrel{(*)}{=} \sum_{i=1}^k \frac{\langle \mathbf{x} + \mathbf{y}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i \\ &\stackrel{(**)}{=} \sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle + \langle \mathbf{y}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i \\ &= \left(\sum_{i=1}^k \frac{\langle \mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i \right) + \left(\sum_{i=1}^k \frac{\langle \mathbf{y}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i \right) \\ &\stackrel{(*)}{=} \text{proj}_U(\mathbf{x}) + \text{proj}_U(\mathbf{y}),\end{aligned}$$

where both instances of (*) follow from Theorem 6.5.1, and (**) follows from r.2 or c.2;

- for all $\mathbf{x} \in V$ and scalars α , we have that

$$\text{proj}_U(\alpha\mathbf{x}) \stackrel{(*)}{=} \sum_{i=1}^k \frac{\langle \alpha\mathbf{x}, \mathbf{u}_i \rangle}{\langle \mathbf{u}_i, \mathbf{u}_i \rangle} \mathbf{u}_i$$

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 - Since proj_U is linear, it has a standard matrix.
 - Note that this matrix belongs to $\mathbb{R}^{n \times n}$.
 - Our goal is to we give formulas for the standard matrices of orthogonal projections onto various subspaces of \mathbb{R}^n .

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- So, we (re)defined the row space of a matrix to be the span of the transposes of its rows.

- For example, for the matrix

$$A = \begin{bmatrix} 1 & 2 & 1 & 2 \\ 2 & 3 & 2 & 3 \\ 3 & 4 & 3 & 4 \end{bmatrix},$$

we have that

$$A^T = \begin{bmatrix} 1 & 2 & 3 \\ 2 & 3 & 4 \\ 1 & 2 & 3 \\ 2 & 3 & 4 \end{bmatrix},$$

and consequently,

$$\text{Row}(A) = \text{Span}\left(\begin{bmatrix} 1 \\ 2 \\ 1 \\ 2 \end{bmatrix}, \begin{bmatrix} 2 \\ 3 \\ 2 \\ 3 \end{bmatrix}, \begin{bmatrix} 3 \\ 4 \\ 3 \\ 4 \end{bmatrix} \right).$$

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- If this change of definition bothers you, then every time you see $\text{Row}(\square)$, mentally replace it with $\text{Col}(\square^T)$.

Theorem 6.6.1

Let $A \in \mathbb{R}^{n \times m}$. Then $\text{Row}(A)^\perp = \text{Nul}(A)$ and $\text{Row}(A) = \text{Nul}(A)^\perp$.

Proof.

Theorem 6.6.1

Let $A \in \mathbb{R}^{n \times m}$. Then $\text{Row}(A)^\perp = \text{Nul}(A)$ and $\text{Row}(A) = \text{Nul}(A)^\perp$.

Proof. In view of Theorem 6.4.3(c), it suffices to show that $\text{Row}(A)^\perp = \text{Nul}(A)$.

- Indeed, by Theorem 6.4.3(c), we have that

$$(\text{Row}(A)^\perp)^\perp = \text{Row}(A).$$

- So, if $\text{Row}(A)^\perp = \text{Nul}(A)$, then

$$\text{Nul}(A)^\perp = (\text{Row}(A)^\perp)^\perp = \text{Row}(A).$$

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- Indeed, by Theorem 6.4.3(c), we have that

$$(\text{Row}(A)^\perp)^\perp = \text{Row}(A).$$

- So, if $\text{Row}(A)^\perp = \text{Nul}(A)$, then

$$\text{Nul}(A)^\perp = (\text{Row}(A)^\perp)^\perp = \text{Row}(A).$$

Set

$$A = \begin{bmatrix} \mathbf{a}_1^T \\ \vdots \\ \mathbf{a}_n^T \end{bmatrix},$$

so that $\text{Row}(A) = \text{Span}(\mathbf{a}_1, \dots, \mathbf{a}_n)$.

Proof (continued). Now, for all vectors $\mathbf{x} \in \mathbb{R}^m$:

$$\begin{aligned} \mathbf{x} \in \text{Nul}(A) &\iff A\mathbf{x} = \mathbf{0} \\ &\iff \begin{bmatrix} \mathbf{a}_1^T \\ \vdots \\ \mathbf{a}_n^T \end{bmatrix} \mathbf{x} = \mathbf{0} \\ &\iff \begin{bmatrix} \mathbf{a}_1 \cdot \mathbf{x} \\ \vdots \\ \mathbf{a}_n \cdot \mathbf{x} \end{bmatrix} = \mathbf{0} \\ &\iff \mathbf{a}_i \cdot \mathbf{x} = 0 \quad \forall i \in \{1, \dots, n\} \\ &\iff \mathbf{a}_i \perp \mathbf{x} \quad \forall i \in \{1, \dots, n\} \\ &\iff \mathbf{x} \in \{\mathbf{a}_1, \dots, \mathbf{a}_n\}^\perp \\ &\stackrel{(*)}{\iff} \mathbf{x} \in \text{Span}(\mathbf{a}_1, \dots, \mathbf{a}_n)^\perp \\ &\iff \mathbf{x} \in \text{Row}(A)^\perp, \end{aligned}$$

where (*) follows from the fact that

$\{\mathbf{a}_1, \dots, \mathbf{a}_m\}^\perp = \text{Span}(\mathbf{a}_1, \dots, \mathbf{a}_m)^\perp$ (by Proposition 6.4.2). This proves that $\text{Nul}(A) = \text{Row}(A)^\perp$, and we are done. \square

Theorem 6.6.1

Let $A \in \mathbb{R}^{n \times m}$. Then $\text{Row}(A)^\perp = \text{Nul}(A)$ and $\text{Row}(A) = \text{Nul}(A)^\perp$.

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Corollary 6.6.2

Let $A \in \mathbb{R}^{n \times m}$. Then all the following hold:

- a) $\text{Nul}(A^T A) = \text{Nul}(A)$;
- b) $\text{Row}(A^T A) = \text{Row}(A)$;
- c) $\text{rank}(A^T A) = \text{rank}(A)$.

Proof.

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Proof. We first prove (a).

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Proof. We first prove (a). Note that $A^T A \in \mathbb{R}^{m \times m}$, and that both $\text{Nul}(A)$ and $\text{Nul}(A^T A)$ are subspaces of \mathbb{R}^m .

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Suppose first that $\mathbf{x} \in \text{Nul}(A)$. Then $A\mathbf{x} = \mathbf{0}$, and consequently, $A^T A\mathbf{x} = \mathbf{0}$. So, $\mathbf{x} \in \text{Nul}(A^T A)$.

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Let $A \in \mathbb{R}^{n \times m}$. Then $\text{Row}(A)^\perp = \text{Nul}(A)$ and $\text{Row}(A) = \text{Nul}(A)^\perp$.

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Proof (continued). Suppose, conversely, that $\mathbf{x} \in \text{Nul}(A^T A)$.

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Proof (continued). Suppose, conversely, that $\mathbf{x} \in \text{Nul}(A^T A)$. Then $A^T A \mathbf{x} = \mathbf{0}$, and it follows that $\mathbf{x}^T A^T A \mathbf{x} = \mathbf{0}$.

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$$\mathbf{x}^T A^T A \mathbf{x} = (A\mathbf{x})^T (A\mathbf{x}) = (A\mathbf{x}) \cdot (A\mathbf{x}) = \|A\mathbf{x}\|^2;$$

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$$\mathbf{x}^T A^T A \mathbf{x} = (\mathbf{Ax})^T (\mathbf{Ax}) = (\mathbf{Ax}) \cdot (\mathbf{Ax}) = \|\mathbf{Ax}\|^2;$$

consequently, $\|\mathbf{Ax}\|^2 = 0$. It follows that $\|\mathbf{Ax}\| = 0$, and therefore, $\mathbf{Ax} = \mathbf{0}$, i.e. $\mathbf{x} \in \text{Nul}(A)$. This proves (a).

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Let $A \in \mathbb{R}^{n \times m}$. Then $\text{Row}(A)^\perp = \text{Nul}(A)$ and $\text{Row}(A) = \text{Nul}(A)^\perp$.

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- (c) $\text{rank}(A^T A) = \text{rank}(A)$.

Proof (continued). For (b), we observe that

$$\begin{aligned}\text{Row}(A^T A) &= \text{Nul}(A^T A)^\perp && \text{by Theorem 6.6.1} \\ &= \text{Nul}(A)^\perp && \text{by (a)} \\ &= \text{Row}(A) && \text{by Theorem 6.6.1.}\end{aligned}$$

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Proof (continued). Finally, for (c), we have the following:

$$\begin{aligned} \text{rank}(A^T A) &= \dim(\text{Row}(A^T A)) && \text{by Theorem 3.3.9} \\ &= \dim(\text{Row}(A)) && \text{by (b)} \\ &= \text{rank}(A) && \text{by Theorem 3.3.9.} \end{aligned}$$

This completes the argument. \square

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof.

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Proof. Fix $\mathbf{x} \in \mathbb{R}^n$. We must first check that the expression $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to $C = \text{Col}(A)$.

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$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof. Fix $\mathbf{x} \in \mathbb{R}^n$. We must first check that the expression $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to $C = \text{Col}(A)$.

First, note that $A^T A \in \mathbb{R}^{m \times m}$, and that by Corollary 6.6.2(a), we have that $\text{rank}(A^T A) = \text{rank}(A) = m$.

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

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Proof. Fix $\mathbf{x} \in \mathbb{R}^n$. We must first check that the expression $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to $C = \text{Col}(A)$.

First, note that $A^T A \in \mathbb{R}^{m \times m}$, and that by Corollary 6.6.2(a), we have that $\text{rank}(A^T A) = \text{rank}(A) = m$. So, by the Invertible Matrix Theorem, $A^T A$ is invertible, and we see that $(A^T A)^{-1}$ is defined and belongs to $\mathbb{R}^{m \times m}$.

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Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

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First, note that $A^T A \in \mathbb{R}^{m \times m}$, and that by Corollary 6.6.2(a), we have that $\text{rank}(A^T A) = \text{rank}(A) = m$. So, by the Invertible Matrix Theorem, $A^T A$ is invertible, and we see that $(A^T A)^{-1}$ is defined and belongs to $\mathbb{R}^{m \times m}$. Since $A \in \mathbb{R}^{n \times m}$, $(A^T A)^{-1} \in \mathbb{R}^{m \times m}$, and $A^T \in \mathbb{R}^{m \times n}$, we see that $A(A^T A)^{-1}A^T \in \mathbb{R}^{n \times n}$;

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof. Fix $\mathbf{x} \in \mathbb{R}^n$. We must first check that the expression $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to $C = \text{Col}(A)$.

First, note that $A^T A \in \mathbb{R}^{m \times m}$, and that by Corollary 6.6.2(a), we have that $\text{rank}(A^T A) = \text{rank}(A) = m$. So, by the Invertible Matrix Theorem, $A^T A$ is invertible, and we see that $(A^T A)^{-1}$ is defined and belongs to $\mathbb{R}^{m \times m}$. Since $A \in \mathbb{R}^{n \times m}$, $(A^T A)^{-1} \in \mathbb{R}^{m \times m}$, and $A^T \in \mathbb{R}^{m \times n}$, we see that $A(A^T A)^{-1}A^T \in \mathbb{R}^{n \times n}$; since $\mathbf{x} \in \mathbb{R}^n$, we see that $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to \mathbb{R}^n .

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof. Fix $\mathbf{x} \in \mathbb{R}^n$. We must first check that the expression $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to $C = \text{Col}(A)$.

First, note that $A^T A \in \mathbb{R}^{m \times m}$, and that by Corollary 6.6.2(a), we have that $\text{rank}(A^T A) = \text{rank}(A) = m$. So, by the Invertible Matrix Theorem, $A^T A$ is invertible, and we see that $(A^T A)^{-1}$ is defined and belongs to $\mathbb{R}^{m \times m}$. Since $A \in \mathbb{R}^{n \times m}$, $(A^T A)^{-1} \in \mathbb{R}^{m \times m}$, and $A^T \in \mathbb{R}^{m \times n}$, we see that $A(A^T A)^{-1}A^T \in \mathbb{R}^{n \times n}$; since $\mathbf{x} \in \mathbb{R}^n$, we see that $A(A^T A)^{-1}A^T \mathbf{x}$ is defined and belongs to \mathbb{R}^n . Meanwhile, $(A^T A)^{-1}A^T \mathbf{x}$ is a vector in \mathbb{R}^m , and so (next slide):

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof (continued).

$$A(A^T A)^{-1}A^T \mathbf{x} = \underbrace{A}_{\in \mathbb{R}^{n \times m}} \left(\underbrace{(A^T A)^{-1}A^T \mathbf{x}}_{\in \mathbb{R}^m} \right)$$

is a linear combination of the columns of A . By definition, this means that $A(A^T A)^{-1}A^T \mathbf{x} \in \text{Col}(A) = C$.

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof (continued). In view of Corollary 6.5.3, it is now enough to prove that $(\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x}) \in C^\perp$, for it will then follow that $\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}$, which is what we need to show.

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

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Proof (continued). In view of Corollary 6.5.3, it is now enough to prove that $(\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x}) \in C^\perp$, for it will then follow that $\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}$, which is what we need to show.

- Indeed, if we can show that $(\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x}) \in C^\perp$, then we get that

$$\mathbf{x} = \underbrace{A(A^T A)^{-1}A^T \mathbf{x}}_{\in C} + \underbrace{(\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x})}_{\in C^\perp},$$

which (by Corollary 6.5.3) implies that $\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}$ and $\mathbf{x}_{C^\perp} = \mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x}$.

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof (continued). But note that

$$C^\perp = \text{Col}(A)^\perp = \text{Row}(A^T)^\perp \stackrel{(*)}{=} \text{Nul}(A^T),$$

where (*) follows from Theorem 6.6.1.

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1} A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1} A^T \mathbf{x}.$$

Proof (continued). But note that

$$C^\perp = \text{Col}(A)^\perp = \text{Row}(A^T)^\perp \stackrel{(*)}{=} \text{Nul}(A^T),$$

where (*) follows from Theorem 6.6.1. So, it in fact suffices to show that the vector $\mathbf{x} - A(A^T A)^{-1} A^T \mathbf{x}$ belongs to $\text{Nul}(A^T)$.

Theorem 6.6.3

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

$$\mathbf{x}_C = A(A^T A)^{-1}A^T \mathbf{x}.$$

Proof (continued). But note that

$$C^\perp = \text{Col}(A)^\perp = \text{Row}(A^T)^\perp \stackrel{(*)}{=} \text{Nul}(A^T),$$

where (*) follows from Theorem 6.6.1. So, it in fact suffices to show that the vector $\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x}$ belongs to $\text{Nul}(A^T)$. For this, we compute:

$$A^T (\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x}) = A^T \mathbf{x} - \underbrace{A^T A(A^T A)^{-1}A^T}_{=I_m} \mathbf{x} = \mathbf{0}.$$

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$$A^T \left(\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x} \right) = A^T \mathbf{x} - \underbrace{A^T A(A^T A)^{-1}A^T}_{=I_m} \mathbf{x} = \mathbf{0}.$$

This proves that $\mathbf{x} - A(A^T A)^{-1}A^T \mathbf{x} \in \text{Nul}(A^T)$, and we are done. \square

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Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank m (i.e. A is a matrix of full column rank). Then the matrix $A(A^T A)^{-1}A^T$ is the standard matrix of orthogonal projection onto $\text{Col}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto $C := \text{Col}(A)$ is given by

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Corollary 6.6.4

Let \mathbf{a} be a non-zero vector in \mathbb{R}^n . Then the standard matrix of projection onto the line $L := \text{Span}(\mathbf{a})$ is the matrix

$$\mathbf{a}(\mathbf{a}^T \mathbf{a})^{-1} \mathbf{a}^T = \mathbf{a}(\mathbf{a} \cdot \mathbf{a})^{-1} \mathbf{a}^T = \frac{1}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T.$$

Consequently, for every vector $\mathbf{x} \in \mathbb{R}^n$, we have that

$$\mathbf{x}_L = \text{proj}_L(\mathbf{x}) = \frac{1}{\mathbf{a} \cdot \mathbf{a}} \mathbf{a} \mathbf{a}^T \mathbf{x}.$$

Proof. This is a special case of Theorem 6.6.3 for $A = \begin{bmatrix} \mathbf{a} \end{bmatrix}$. \square

Theorem 6.6.5

Let U be a subspace of \mathbb{R}^n , and let $P \in \mathbb{R}^{n \times n}$ be the standard matrix of proj_U . Then $I_n - P$ is the standard matrix of proj_{U^\perp} , that is, for all $\mathbf{x} \in \mathbb{R}^n$, the orthogonal projection of \mathbf{x} onto U^\perp is given by $\mathbf{x}_{U^\perp} = (I_n - P)\mathbf{x}$.

Proof.

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Proof. We observe that for all $\mathbf{x} \in \mathbb{R}^n$, we have that

$$(I_n - P)\mathbf{x} = I_n\mathbf{x} - P\mathbf{x} \stackrel{(*)}{=} \mathbf{x} - \mathbf{x}_U \stackrel{(**)}{=} \mathbf{x}_{U^\perp},$$

where $(*)$ follows from the fact that P is the standard matrix of proj_U , and $(**)$ follows from Corollary 6.5.3. So, $I_n - P$ is indeed the standard matrix of proj_{U^\perp} . \square

- Theorem 6.6.5: if $P \in \mathbb{R}^{n \times n}$ is the standard matrix of proj_U , then $I_n - P$ is the standard matrix of proj_{U^\perp} .

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Corollary 6.6.6

Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank n (i.e. A is a matrix of full row rank). Then the matrix $I_m - A^T(AA^T)^{-1}A$ is the standard matrix of orthogonal projection onto $N := \text{Nul}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^m$, the orthogonal projection of \mathbf{x} onto N is given by $\mathbf{x}_N = (I_m - A^T(AA^T)^{-1}A)\mathbf{x}$.

Proof.

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Proof. First, note that

$$\text{Nul}(A) \stackrel{(*)}{=} \text{Row}(A)^\perp = \text{Col}(A^T)^\perp.$$

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where (*) follows from Theorem 6.6.1. Note further that $A^T \in \mathbb{R}^{m \times n}$ and that $\text{rank}(A^T) = \text{rank}(A) = n$, i.e. A^T has full column rank.

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Let $A \in \mathbb{R}^{n \times m}$ be a matrix of rank n (i.e. A is a matrix of full row rank). Then the matrix $I_m - A^T(AA^T)^{-1}A$ is the standard matrix of orthogonal projection onto $N := \text{Nul}(A)$, that is, for all $\mathbf{x} \in \mathbb{R}^m$, the orthogonal projection of \mathbf{x} onto N is given by $\mathbf{x}_N = (I_m - A^T(AA^T)^{-1}A)\mathbf{x}$.

Proof. First, note that

$$\text{Nul}(A) \stackrel{(*)}{=} \text{Row}(A)^\perp = \text{Col}(A^T)^\perp.$$

where (*) follows from Theorem 6.6.1. Note further that $A^T \in \mathbb{R}^{m \times n}$ and that $\text{rank}(A^T) = \text{rank}(A) = n$, i.e. A^T has full column rank. So, by Theorem 6.6.3, the standard matrix of orthogonal projection onto $\text{Col}(A^T)$ is $A^T(AA^T)^{-1}A$. Finally, by Theorem 6.6.5, the standard matrix of orthogonal projection onto $\text{Col}(A^T)^\perp = \text{Nul}(A)$ is $I_m - A^T(AA^T)^{-1}A$. \square