Lecture 19 - Linear Independence and the Gram-Schmidt Process

November 11, 2022

Goals: Use the Gram-Schmidt process to compute an orthogonal basis of V and compute dim V.

When discussing a collection of vectors throughout the course, we often used the words "redundancy" or "no redundancy." We now make this more precise:

<u>Definition:</u> For k > 1, a collection of vectors $\{\mathbf{v}_1, \dots, vv_k\}$ in \mathbb{R}^n is called **linearly dependent** if some \mathbf{v}_i belongs to the span of the others. Otherwise, the collection is called **linearly independent** (so no \mathbf{v}_i belongs to the span of the others, or there is "no redundancy").

In the case of a single vector, $\{v\}$ is linearly dependent if v = 0, otherwise it is linearly independent.

Linear independence has a nice alternative meaning:

<u>Theorem 19.1.5</u>: A collection of vectors $\mathbf{v}_1, \dots, \mathbf{v}_k \in \mathbb{R}^n$ is <u>linearly independent</u> precisely when the **only** collection of scalars a_1, \dots, a_k for which

$$a_1\mathbf{v}_1 + a_2\mathbf{v}_2 + \dots + a_k\mathbf{v}_k = 0$$

is
$$a_1 = a_2 = \dots = a_k = 0$$
.

Equivalently, the collection of \mathbf{v}_i 's is linearly dependent precisely when there is some collection of coefficients not all equal to 0 for which $\sum_{i=1}^{k} a_i \mathbf{v}_i = \mathbf{0}$ (note, we don't need **all** the a_i to be nonzero, just some a_i).

Example 1: Determine whether or not the given collection of vectors is linearly dependent or linearly independent.

•
$$\mathbf{v}_1 = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}$$
, $\mathbf{v}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$, $\mathbf{v}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(1) $\mathbf{v}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(2) $\mathbf{v}_4 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(3) $\mathbf{v}_5 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(4) $\mathbf{v}_5 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(3) $\mathbf{v}_6 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(4) $\mathbf{v}_7 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(5) $\mathbf{v}_8 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(6) $\mathbf{v}_8 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(7) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(8) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(9) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(10) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(11) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(12) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(13) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(14) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(15) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix}$
(15) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(16) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(17) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(17) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(18) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$
(19) $\mathbf{v}_9 = \begin{bmatrix} 0 \\ 0$

•
$$\mathbf{v}_1 = \begin{bmatrix} 2 \\ 1 \\ 3 \end{bmatrix}$$
, $\mathbf{v}_2 = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}$, $\mathbf{v}_3 = \begin{bmatrix} 0 \\ 2 \\ 1 \end{bmatrix}$ $\begin{pmatrix} \mathbf{v}_1 & \mathbf{v}_1 & \mathbf{v}_2 & \mathbf{v}_3 & \mathbf{v}_3 & \mathbf{v}_3 \\ \mathbf{v}_1 & \mathbf{v}_2 & \mathbf{v}_3 & \mathbf$

•
$$\mathbf{v}_1 = \begin{bmatrix} 2 \\ 0 \\ 1 \\ 0 \end{bmatrix}, \mathbf{v}_2 = \begin{bmatrix} -1 \\ 3 \\ 0 \\ 0 \end{bmatrix}, \mathbf{v}_3 = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 1 \end{bmatrix}, \mathbf{v}_4 = \begin{bmatrix} -2 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

2

Example 2: How does invertibility of an $n \times n$ matrix relate to linear dependence/independence?

$$\vec{v}_1, \dots, \vec{v}_n \in \mathbb{R}^n \longrightarrow \alpha_1 v_1 + \dots + \alpha_n v_n = 0$$

$$\begin{bmatrix} 1 \\ v_1 & \dots & 1 \\ 1 & \dots & 1 \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \vdots \\ \alpha_n \end{bmatrix} = \vec{O}$$

=> A is involved prestry when its

Orthogonal Bases and Gram-Schmidt

In Chapter 7, we learned how to find an orthogonal basis for span($\mathbf{v}_1, \mathbf{v}_2$) when \mathbf{v}_1 and \mathbf{v}_2 are not multiples of one another. We now go over the procedure for producing an orthogonal basis $\mathbf{w}_1, \mathbf{w}_2, \dots$ for the span of any number of vectors $\mathbf{v}_1 \dots, \mathbf{v}_k$.

The Gram Schmidt Process: Let v_1, \ldots, v_k be non-zero n-vectors with span V in \mathbb{R}^n . Define:

define subspaces $\longrightarrow V_1 = \operatorname{span}(\mathbf{v}_1), V_2 = \operatorname{span}(\mathbf{v}_1, \mathbf{v}_2), V_3 = \operatorname{span}(\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3), \dots$, $\mathbf{v}_{\mathbf{k}} : \mathsf{span}(\mathbf{v}_1, \mathbf{v}_2, \mathbf{v}_3), \dots$

The following algorithm gives an orthogonal basis for the span V of all the \mathbf{v}_j 's.

- Let $\mathbf{w}_1 = \mathbf{v}_1$ and define \mathcal{B}_1 to be $\{\mathbf{w}_1\}$, which is an orthogonal basis for V_1 .
- Let $\mathbf{w}_2 = \mathbf{v}_2 \mathbf{Proj}_{V_1}(\mathbf{v}_2)$.

If $\mathbf{w}_2 \neq 0$, then $\mathcal{B}_2 := \{\mathbf{w}_1, \mathbf{w}_2\}$ is an orthogonal basis for V_2 .

If $\mathbf{w}_2 = \mathbf{0}$, then $\mathbf{v}_2 \in V_1$, so $\mathcal{B}_2 := \mathcal{B}_1$ is an orthogonal basis for V_2 . $|\mathbf{v}_2| = |\mathbf{v}_2| =$

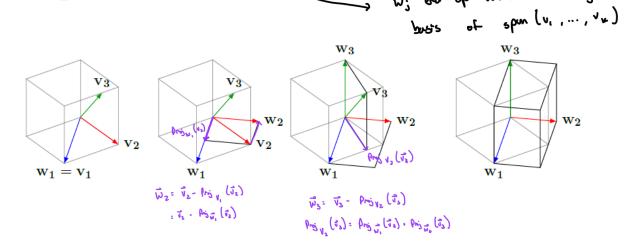
Is "defined to be" • Let $\mathbf{w}_3 = \mathbf{v}_3 - \mathbf{Proj}_{V_2}(\mathbf{v}_3)$.

If $\mathbf{w}_3 \neq \mathbf{0}$, then $\mathcal{B}_3 := \mathcal{B}_2 \cup \{\mathbf{w}_3\}$ is an orthogonal basis for V_3 .

If $\mathbf{w}_3 = \mathbf{0}$, then $\mathbf{v}_3 \in V_2$, so $\mathcal{B}_3 := \mathcal{B}_2$ is an orthogonal basis for V_3 .

• Continue this process of considering $\mathbf{w}_i := \mathbf{v}_i - \mathbf{Proj}_{V_{i-1}}(\mathbf{v}_i)$ and whether to add \mathbf{w}_i to \mathcal{B}_{i-1} or not.

After k steps, \mathcal{B}_k will be an orthogonal basis for V.



Example 3: Apply the Gram-Schmidt process to the vectors

$$\mathbf{v}_1 = \begin{bmatrix} 1 \\ 0 \\ 1 \end{bmatrix}, \quad \mathbf{v}_2 = \begin{bmatrix} 1 \\ -2 \\ 1 \end{bmatrix}, \quad \mathbf{v}_3 = \begin{bmatrix} 3 \\ 2 \\ -1 \end{bmatrix}.$$

Then, make an orthonormal basis of the span of the \mathbf{v}_i 's using your output from Gram-Schmidt.

Example 4: Compute an orthogonal basis for the span of the following three vectors:

$$\mathbf{v}_{1} = \begin{bmatrix} 2 \\ 0 \\ 1 \end{bmatrix}, \quad \mathbf{v}_{2} = \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix}, \quad \mathbf{v}_{3} = \begin{bmatrix} 2 \\ -1 \\ 0 \end{bmatrix}.$$

$$\vec{w}_{3} = \vec{v}_{3} - \rho_{1}\vec{v}_{3}\vec{v}_{1} \quad (\vec{v}_{3}) = \vec{v}_{2} - \rho_{1}\vec{v}_{3} \quad (\vec{v}_{2}) \\ \vdots \quad (\vec{v}_{1}) - \frac{\binom{o}{1} \cdot \binom{v}{2}}{\binom{v}{1} \cdot \binom{v}{2}} \quad \binom{v}{v}_{1} = \binom{-2/6}{\sqrt{1}} \\ \vdots \quad (\vec{v}_{1}) - \frac{\binom{o}{1} \cdot \binom{v}{2}}{\binom{v}{1} \cdot \binom{v}{2}} \quad (\vec{v}_{3}) = \binom{-2/6}{\sqrt{1}} \\ \vec{w}_{3} = \vec{v}_{3} - \rho_{1}\vec{v}_{3}\vec{v}_{2} \quad (\vec{v}_{3}) = \vec{v}_{3} - \left(\rho_{1}\vec{v}_{3}\vec{v}_{1} \quad (\vec{v}_{3}) + \rho_{2}\vec{v}_{3}\vec{v}_{2} \quad (\vec{v}_{3})\right)$$

$$= \begin{pmatrix} \vec{v}_{1} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{2} & \vec{v}_{1} \\ \vec{v}_{2} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v}_{1} \end{pmatrix} - \begin{pmatrix} \vec{v}_{1} & \vec{v}_{2} \\ \vec{v$$

Since the Gram-Schmidt process produces an orthogonal basis for a subspace V, we have the following theorem:

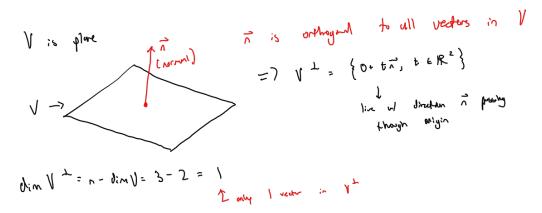
Theorem 19.2.3: If $V = \text{span}(\mathbf{v}_1, \dots, \mathbf{v}_k)$ for k nonzero vectors $\mathbf{v}_1, \dots, \mathbf{v}_k \in \mathbb{R}^n$, then $\dim(V)$ equals the number of nonzero \mathbf{w}_i 's obtained from the Gram-Schmidt process. Moreover, the following conditions are equivalent:

- $\dim(V) = k$ if $\dim(V) = k$, all \overline{w} , or reserve and $\{v_{s_1, \dots, v_k}\}$ are all w_i 's are nonzero, independent
- the collection $\{\mathbf{v}_1, \dots, \mathbf{v}_k\}$ is linearly independent.

In other words: "basis" and "linearly independent spanning set" for a nonzero subspace V of \mathbb{R}^n mean **exactly the same thing.** Moreover, we now have a way of determining the dimension of the span of more than 3 vectors.

Theorem 19.2.5: if V is a linear subspace of \mathbb{R}^n then the collection V^{\perp} of n-vectors orthogonal to everything in V. We call V^{\perp} the orthogonal complement of V. It is a linear subspace of \mathbb{R}^n and $\dim V^{\perp} = n - \dim V$.

Example 5: What is the orthogonal complement of a plane passing through $\mathbf{0}$ in \mathbb{R}^3 ? What is the orthogonal complement of \mathbb{R}^n , for any n?



Ex In
$$\mathbb{R}^{n}$$
: $\vec{v} \cdot \vec{x} = 0$ for any $\vec{x} \in \mathbb{R}^{n}$

in \mathbb{R}^{n} : $\vec{v} \cdot \vec{x} = \vec{0}$

for $(\mathbb{R}^{n})^{\frac{1}{n}} = \{\vec{v}\} = \{\vec{0}\}$

dim $\{\vec{0}\} = n - n = 0$

I \mathbb{R}^{n} so $\dim(V) = n$

E x 6:			
₩, ³ ₩,	- Proj. 32 =		
₩ ₃ = ν ₃	- ρω; η z (ŋ²)	$\frac{1}{3} = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & $	
		= (2/3 - 2/3 2/3 1	