

# Review of Chapter 5, part 2, plus Chapter 6

Daniel H. Luecking

22 March 2024

## Theorem (Gram-Schmidt)

*If  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r\}$  is an independent set in an inner product space  $V$  then there exists an orthonormal set  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r\}$  such that*

$$\text{Span}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r) = \text{Span}(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r).$$

## Theorem (Gram-Schmidt)

*If  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r\}$  is an independent set in an inner product space  $V$  then there exists an orthonormal set  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r\}$  such that*  
 $\text{Span}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r) = \text{Span}(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r)$ .

The process takes  $r$  steps, and at the end of step  $j$  the vectors  $\mathbf{u}_1, \dots, \mathbf{u}_j$  have the same span as  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_j$ .

## Theorem (Gram-Schmidt)

*If  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r\}$  is an independent set in an inner product space  $V$  then there exists an orthonormal set  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r\}$  such that*  
 $\text{Span}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r) = \text{Span}(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r)$ .

The process takes  $r$  steps, and at the end of step  $j$  the vectors  $\mathbf{u}_1, \dots, \mathbf{u}_j$  have the same span as  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_j$ . If  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r\}$  is a basis for a subspace  $S$  of  $V$ , then  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r\}$  is an orthonormal basis for  $S$ .

## Theorem (Gram-Schmidt)

*If  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r\}$  is an independent set in an inner product space  $V$  then there exists an orthonormal set  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r\}$  such that  $\text{Span}(\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r) = \text{Span}(\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r)$ .*

The process takes  $r$  steps, and at the end of step  $j$  the vectors  $\mathbf{u}_1, \dots, \mathbf{u}_j$  have the same span as  $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_j$ . If  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_r\}$  is a basis for a subspace  $S$  of  $V$ , then  $\{\mathbf{u}_1, \mathbf{u}_2, \dots, \mathbf{u}_r\}$  is an orthonormal basis for  $S$ .

When computing by hand, it is quite a bit easier to first create an orthogonal (but not orthonormal) set  $\mathbf{v}_1, \dots, \mathbf{v}_r$  and then normalize them at the end by  $\mathbf{u}_j = (1/\|\mathbf{v}_j\|)\mathbf{v}_j$ .

The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .

## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .

## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .

That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .



## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .  
That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .
- Step 3: set  $\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2$  where  $\mathbf{p}_2$  is the projection of  $\mathbf{x}_3$  onto  $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ .

## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .  
That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .
- Step 3: set  $\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2$  where  $\mathbf{p}_2$  is the projection of  $\mathbf{x}_3$  onto  $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ .  
That is

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\langle \mathbf{x}_3, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_3, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2$$

## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .  
That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .

- Step 3: set  $\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2$  where  $\mathbf{p}_2$  is the projection of  $\mathbf{x}_3$  onto  $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ .  
That is

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\langle \mathbf{x}_3, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_3, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2$$

- Steps  $k > 3$ : set  $\mathbf{v}_k = \mathbf{x}_k - \mathbf{p}_{k-1}$  where  $\mathbf{p}_{k-1}$  is the projection of  $\mathbf{x}_k$  onto  $\text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_{k-1})$ .

## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .  
That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .

- Step 3: set  $\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2$  where  $\mathbf{p}_2$  is the projection of  $\mathbf{x}_3$  onto  $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ .  
That is

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\langle \mathbf{x}_3, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_3, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2$$

- Steps  $k > 3$ : set  $\mathbf{v}_k = \mathbf{x}_k - \mathbf{p}_{k-1}$  where  $\mathbf{p}_{k-1}$  is the projection of  $\mathbf{x}_k$  onto  $\text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_{k-1})$ . That is

$$\mathbf{v}_k = \mathbf{x}_k - \sum_{i=1}^{k-1} \frac{\langle \mathbf{x}_k, \mathbf{v}_i \rangle}{\langle \mathbf{v}_i, \mathbf{v}_i \rangle} \mathbf{v}_i$$

The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .  
That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .

- Step 3: set  $\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2$  where  $\mathbf{p}_2$  is the projection of  $\mathbf{x}_3$  onto  $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ .  
That is

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\langle \mathbf{x}_3, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_3, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2$$

- Steps  $k > 3$ : set  $\mathbf{v}_k = \mathbf{x}_k - \mathbf{p}_{k-1}$  where  $\mathbf{p}_{k-1}$  is the projection of  $\mathbf{x}_k$  onto  $\text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_{k-1})$ . That is

$$\mathbf{v}_k = \mathbf{x}_k - \sum_{i=1}^{k-1} \frac{\langle \mathbf{x}_k, \mathbf{v}_i \rangle}{\langle \mathbf{v}_i, \mathbf{v}_i \rangle} \mathbf{v}_i$$

Then set  $\mathbf{u}_j = (1/\|\mathbf{v}_j\|)\mathbf{v}_j$  for each  $j$ .

## The steps

- Step 1: set  $\mathbf{v}_1 = \mathbf{x}_1$ .
- Step 2: set  $\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1$ , where  $\mathbf{p}_1$  is the projection of  $\mathbf{x}_2$  onto the span of  $\mathbf{v}_1$ .  
That is  $\mathbf{v}_2 = \mathbf{x}_2 - \frac{\langle \mathbf{x}_2, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1$ .

- Step 3: set  $\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2$  where  $\mathbf{p}_2$  is the projection of  $\mathbf{x}_3$  onto  $\text{Span}(\mathbf{v}_1, \mathbf{v}_2)$ .  
That is

$$\mathbf{v}_3 = \mathbf{x}_3 - \frac{\langle \mathbf{x}_3, \mathbf{v}_1 \rangle}{\langle \mathbf{v}_1, \mathbf{v}_1 \rangle} \mathbf{v}_1 - \frac{\langle \mathbf{x}_3, \mathbf{v}_2 \rangle}{\langle \mathbf{v}_2, \mathbf{v}_2 \rangle} \mathbf{v}_2$$

- Steps  $k > 3$ : set  $\mathbf{v}_k = \mathbf{x}_k - \mathbf{p}_{k-1}$  where  $\mathbf{p}_{k-1}$  is the projection of  $\mathbf{x}_k$  onto  $\text{Span}(\mathbf{v}_1, \dots, \mathbf{v}_{k-1})$ . That is

$$\mathbf{v}_k = \mathbf{x}_k - \sum_{i=1}^{k-1} \frac{\langle \mathbf{x}_k, \mathbf{v}_i \rangle}{\langle \mathbf{v}_i, \mathbf{v}_i \rangle} \mathbf{v}_i$$

Then set  $\mathbf{u}_j = (1/\|\mathbf{v}_j\|)\mathbf{v}_j$  for each  $j$ .

It is permissible to replace any  $\mathbf{v}_k$  by any nonzero multiple of itself before going on to finding  $\mathbf{v}_{k+1}$ . That can make the later steps a bit easier.

Example: find an orthonormal basis for the span of

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

Example: find an orthonormal basis for the span of

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}.$$



Example: find an orthonormal basis for the span of

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 1/3 \\ -2/3 \\ 1 \\ 1/3 \end{pmatrix}.$$

Example: find an orthonormal basis for the span of

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 1/3 \\ -2/3 \\ 1 \\ 1/3 \end{pmatrix}.$$

Let's use  $\mathbf{v}_2 = \begin{pmatrix} 1 \\ -2 \\ 3 \\ 1 \end{pmatrix}$  instead.

Example: find an orthonormal basis for the span of

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 1/3 \\ -2/3 \\ 1 \\ 1/3 \end{pmatrix}.$$

Let's use  $\mathbf{v}_2 = \begin{pmatrix} 1 \\ -2 \\ 3 \\ 1 \end{pmatrix}$  instead.

$$\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} - \frac{2}{15} \begin{pmatrix} 1 \\ -2 \\ 3 \\ 1 \end{pmatrix} = \begin{pmatrix} -4/5 \\ 3/5 \\ 3/5 \\ 1/5 \end{pmatrix}.$$

Example: find an orthonormal basis for the span of

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix}.$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix}, \quad \mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1 = \begin{pmatrix} 1 \\ 0 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} = \begin{pmatrix} 1/3 \\ -2/3 \\ 1 \\ 1/3 \end{pmatrix}.$$

Let's use  $\mathbf{v}_2 = \begin{pmatrix} 1 \\ -2 \\ 3 \\ 1 \end{pmatrix}$  instead.

$$\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \\ 1 \end{pmatrix} - \frac{2}{3} \begin{pmatrix} 1 \\ 1 \\ 0 \\ 1 \end{pmatrix} - \frac{2}{15} \begin{pmatrix} 1 \\ -2 \\ 3 \\ 1 \end{pmatrix} = \begin{pmatrix} -4/5 \\ 3/5 \\ 3/5 \\ 1/5 \end{pmatrix}. \quad \text{Using } \begin{pmatrix} -4 \\ 3 \\ 3 \\ 1 \end{pmatrix}.$$

Since  $\|\mathbf{v}_1\| = \sqrt{3}$ ,  $\|\mathbf{v}_2\| = \sqrt{15}$  and  $\|\mathbf{v}_3\| = \sqrt{35}$  we get the orthonormal basis

$$\mathbf{u}_1 = \begin{pmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \\ 1/\sqrt{3} \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 1/\sqrt{15} \\ -2/\sqrt{15} \\ 3/\sqrt{15} \\ 1/\sqrt{15} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} -4/\sqrt{35} \\ 3/\sqrt{35} \\ 3/\sqrt{35} \\ 1/\sqrt{35} \end{pmatrix}.$$

Since  $\|\mathbf{v}_1\| = \sqrt{3}$ ,  $\|\mathbf{v}_2\| = \sqrt{15}$  and  $\|\mathbf{v}_3\| = \sqrt{35}$  we get the orthonormal basis

$$\mathbf{u}_1 = \begin{pmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \\ 1/\sqrt{3} \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 1/\sqrt{15} \\ -2/\sqrt{15} \\ 3/\sqrt{15} \\ 1/\sqrt{15} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} -4/\sqrt{35} \\ 3/\sqrt{35} \\ 3/\sqrt{35} \\ 1/\sqrt{35} \end{pmatrix}.$$

Example: Find an orthonormal basis for  $\mathbb{R}^3$  Using the Gram-Schmidt on the set

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

Since  $\|\mathbf{v}_1\| = \sqrt{3}$ ,  $\|\mathbf{v}_2\| = \sqrt{15}$  and  $\|\mathbf{v}_3\| = \sqrt{35}$  we get the orthonormal basis

$$\mathbf{u}_1 = \begin{pmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \\ 1/\sqrt{3} \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 1/\sqrt{15} \\ -2/\sqrt{15} \\ 3/\sqrt{15} \\ 1/\sqrt{15} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} -4/\sqrt{35} \\ 3/\sqrt{35} \\ 3/\sqrt{35} \\ 1/\sqrt{35} \end{pmatrix}.$$

Example: Find an orthonormal basis for  $\mathbb{R}^3$  Using the Gram-Schmidt on the set

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}.$$

Since  $\|\mathbf{v}_1\| = \sqrt{3}$ ,  $\|\mathbf{v}_2\| = \sqrt{15}$  and  $\|\mathbf{v}_3\| = \sqrt{35}$  we get the orthonormal basis

$$\mathbf{u}_1 = \begin{pmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \\ 1/\sqrt{3} \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 1/\sqrt{15} \\ -2/\sqrt{15} \\ 3/\sqrt{15} \\ 1/\sqrt{15} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} -4/\sqrt{35} \\ 3/\sqrt{35} \\ 3/\sqrt{35} \\ 1/\sqrt{35} \end{pmatrix}.$$

Example: Find an orthonormal basis for  $\mathbb{R}^3$  Using the Gram-Schmidt on the set

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}.$$

$$\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} - \frac{0}{1} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}.$$



Since  $\|\mathbf{v}_1\| = \sqrt{3}$ ,  $\|\mathbf{v}_2\| = \sqrt{15}$  and  $\|\mathbf{v}_3\| = \sqrt{35}$  we get the orthonormal basis

$$\mathbf{u}_1 = \begin{pmatrix} 1/\sqrt{3} \\ 1/\sqrt{3} \\ 0 \\ 1/\sqrt{3} \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 1/\sqrt{15} \\ -2/\sqrt{15} \\ 3/\sqrt{15} \\ 1/\sqrt{15} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} -4/\sqrt{35} \\ 3/\sqrt{35} \\ 3/\sqrt{35} \\ 1/\sqrt{35} \end{pmatrix}.$$

Example: Find an orthonormal basis for  $\mathbb{R}^3$  Using the Gram-Schmidt on the set

$$\mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{x}_2 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}, \quad \mathbf{x}_3 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix}$$

$$\mathbf{v}_1 = \mathbf{x}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}.$$

$$\mathbf{v}_2 = \mathbf{x}_2 - \mathbf{p}_1 = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} - \frac{0}{1} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix}.$$

$$\mathbf{v}_3 = \mathbf{x}_3 - \mathbf{p}_2 = \begin{pmatrix} 1 \\ 0 \\ 1 \end{pmatrix} - \frac{1}{1} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} - \frac{1}{2} \begin{pmatrix} 0 \\ 1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ -1/2 \\ 1/2 \end{pmatrix}$$

$$\text{So, } \mathbf{u}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 0 \\ 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

$$\text{So, } \mathbf{u}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 0 \\ 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

## Eigenstuff

### Definition (Eigenvalue/eigenvector)

If  $A$  is an  $n \times n$  matrix and  $\mathbf{x} \in \mathbb{R}^n$  is a **nonzero** vector such that  $A\mathbf{x} = \lambda\mathbf{x}$  for some scalar  $\lambda$  then  $\mathbf{x}$  is called an *eigenvector* for  $A$  and  $\lambda$  is an *eigenvalue*. For a given eigenvalue  $\lambda$ , the set of solutions of  $A\mathbf{x} = \lambda\mathbf{x}$  is called the *eigenspace associated to  $\lambda$* .

$$\text{So, } \mathbf{u}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 0 \\ 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

## Eigenstuff

### Definition (Eigenvalue/eigenvector)

If  $A$  is an  $n \times n$  matrix and  $\mathbf{x} \in \mathbb{R}^n$  is a **nonzero** vector such that  $A\mathbf{x} = \lambda\mathbf{x}$  for some scalar  $\lambda$  then  $\mathbf{x}$  is called an *eigenvector* for  $A$  and  $\lambda$  is an *eigenvalue*. For a given eigenvalue  $\lambda$ , the set of solutions of  $A\mathbf{x} = \lambda\mathbf{x}$  is called the *eigenspace associated to  $\lambda$* .

Every eigenvector has an associated eigenvalue.

$$\text{So, } \mathbf{u}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 0 \\ 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

## Eigenstuff

### Definition (Eigenvalue/eigenvector)

If  $A$  is an  $n \times n$  matrix and  $\mathbf{x} \in \mathbb{R}^n$  is a **nonzero** vector such that  $A\mathbf{x} = \lambda\mathbf{x}$  for some scalar  $\lambda$  then  $\mathbf{x}$  is called an *eigenvector* for  $A$  and  $\lambda$  is an *eigenvalue*. For a given eigenvalue  $\lambda$ , the set of solutions of  $A\mathbf{x} = \lambda\mathbf{x}$  is called the *eigenspace associated to  $\lambda$* .

Every eigenvector has an associated eigenvalue.

If  $\lambda$  is an eigenvalue for  $A$  then  $(A - \lambda I)\mathbf{x} = \mathbf{0}$  has a nontrivial solution, so  $\det(A - \lambda I) = 0$ . This is how we find eigenvalues.

$$\text{So, } \mathbf{u}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}, \quad \mathbf{u}_2 = \begin{pmatrix} 0 \\ 1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}, \quad \mathbf{u}_3 = \begin{pmatrix} 0 \\ -1/\sqrt{2} \\ 1/\sqrt{2} \end{pmatrix}.$$

## Eigenstuff

### Definition (Eigenvalue/eigenvector)

If  $A$  is an  $n \times n$  matrix and  $\mathbf{x} \in \mathbb{R}^n$  is a **nonzero** vector such that  $A\mathbf{x} = \lambda\mathbf{x}$  for some scalar  $\lambda$  then  $\mathbf{x}$  is called an *eigenvector* for  $A$  and  $\lambda$  is an *eigenvalue*. For a given eigenvalue  $\lambda$ , the set of solutions of  $A\mathbf{x} = \lambda\mathbf{x}$  is called the *eigenspace associated to  $\lambda$* .

Every eigenvector has an associated eigenvalue.

If  $\lambda$  is an eigenvalue for  $A$  then  $(A - \lambda I)\mathbf{x} = \mathbf{0}$  has a nontrivial solution, so  $\det(A - \lambda I) = 0$ . This is how we find eigenvalues.

We find eigenvectors by finding the nontrivial solutions of  $(A - \lambda I)\mathbf{x} = \mathbf{0}$  once we know the eigenvalues

Ideally, for applications, we want a basis of eigenvectors. If we have that, say  $\mathcal{B} = [\mathbf{v}_1, \mathbf{v}_1, \dots, \mathbf{v}_n]$  is a basis and  $A\mathbf{v}_j = \lambda_j\mathbf{v}_j$  for every  $j$ , then we have the following:

Suppose  $[\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}$ . This means that  $\mathbf{x} = c_1\mathbf{v}_1 + \dots + c_n\mathbf{v}_n$

Ideally, for applications, we want a basis of eigenvectors. If we have that, say  $\mathcal{B} = [\mathbf{v}_1, \mathbf{v}_1, \dots, \mathbf{v}_n]$  is a basis and  $A\mathbf{v}_j = \lambda_j\mathbf{v}_j$  for every  $j$ , then we have the following:

Suppose  $[\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}$ . This means that  $\mathbf{x} = c_1\mathbf{v}_1 + \dots + c_n\mathbf{v}_n$  and therefore

$$A\mathbf{x} = \lambda_1c_1\mathbf{v}_1 + \dots + \lambda_nc_n\mathbf{v}_n.$$



Ideally, for applications, we want a basis of eigenvectors. If we have that, say  $\mathcal{B} = [\mathbf{v}_1, \mathbf{v}_1, \dots, \mathbf{v}_n]$  is a basis and  $A\mathbf{v}_j = \lambda_j\mathbf{v}_j$  for every  $j$ , then we have the following:

Suppose  $[\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}$ . This means that  $\mathbf{x} = c_1\mathbf{v}_1 + \dots + c_n\mathbf{v}_n$  and therefore

$A\mathbf{x} = \lambda_1c_1\mathbf{v}_1 + \dots + \lambda_nc_n\mathbf{v}_n$ . So,

$$[A\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} \lambda_1c_1 \\ \vdots \\ \lambda_nc_n \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{pmatrix} [\mathbf{x}]_{\mathcal{B}}.$$

Ideally, for applications, we want a basis of eigenvectors. If we have that, say  $\mathcal{B} = [\mathbf{v}_1, \mathbf{v}_1, \dots, \mathbf{v}_n]$  is a basis and  $A\mathbf{v}_j = \lambda_j\mathbf{v}_j$  for every  $j$ , then we have the following:

Suppose  $[\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}$ . This means that  $\mathbf{x} = c_1\mathbf{v}_1 + \dots + c_n\mathbf{v}_n$  and therefore

$A\mathbf{x} = \lambda_1c_1\mathbf{v}_1 + \dots + \lambda_nc_n\mathbf{v}_n$ . So,

$$[A\mathbf{x}]_{\mathcal{B}} = \begin{pmatrix} \lambda_1c_1 \\ \vdots \\ \lambda_nc_n \end{pmatrix} = \begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{pmatrix} [\mathbf{x}]_{\mathcal{B}}. \text{ Moreover, if}$$

$S = \begin{pmatrix} \mathbf{v}_1 & \dots & \mathbf{v}_n \end{pmatrix}$  (the transition matrix from  $\mathcal{B}$  to  $\mathcal{E}$ ), then  $S^{-1}AS$  is a diagonal matrix, with eigenvalues of  $A$  on the diagonal.

All this is only possible when there is a basis of eigenvectors.

All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together.

All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together. This will be independent, but will be a basis of  $\mathbb{R}^n$  only if the sum of the dimensions of the eigenspaces is  $n$ .

**Finding eigenvalues and eigenvectors.**

All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together. This will be independent, but will be a basis of  $\mathbb{R}^n$  only if the sum of the dimensions of the eigenspaces is  $n$ .

### **Finding eigenvalues and eigenvectors.**

Example.

All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together. This will be independent, but will be a basis of  $\mathbb{R}^n$  only if the sum of the dimensions of the eigenspaces is  $n$ .

### **Finding eigenvalues and eigenvectors.**

Example.

Find the eigenvalues of  $A = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 2 \end{pmatrix}$ .

All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together. This will be independent, but will be a basis of  $\mathbb{R}^n$  only if the sum of the dimensions of the eigenspaces is  $n$ .

### **Finding eigenvalues and eigenvectors.**

Example.

Find the eigenvalues of  $A = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 2 \end{pmatrix}$ . Find the determinant

$$\det(A - \lambda I) = \begin{vmatrix} 2 - \lambda & 0 & 0 \\ 0 & 1 - \lambda & 0 \\ 0 & 1 & 2 - \lambda \end{vmatrix} = (2 - \lambda)(1 - \lambda)(2 - \lambda)$$



All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together. This will be independent, but will be a basis of  $\mathbb{R}^n$  only if the sum of the dimensions of the eigenspaces is  $n$ .

### **Finding eigenvalues and eigenvectors.**

Example.

Find the eigenvalues of  $A = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 2 \end{pmatrix}$ . Find the determinant

$$\det(A - \lambda I) = \begin{vmatrix} 2 - \lambda & 0 & 0 \\ 0 & 1 - \lambda & 0 \\ 0 & 1 & 2 - \lambda \end{vmatrix} = (2 - \lambda)(1 - \lambda)(2 - \lambda)$$

So  $\lambda = 2$  and  $\lambda = 1$  are eigenvalues of  $A$ .

All this is only possible when there is a basis of eigenvectors. To get this, we take a basis of each eigenspace and put them together. This will be independent, but will be a basis of  $\mathbb{R}^n$  only if the sum of the dimensions of the eigenspaces is  $n$ .

### **Finding eigenvalues and eigenvectors.**

Example.

Find the eigenvalues of  $A = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 2 \end{pmatrix}$ . Find the determinant

$$\det(A - \lambda I) = \begin{vmatrix} 2 - \lambda & 0 & 0 \\ 0 & 1 - \lambda & 0 \\ 0 & 1 & 2 - \lambda \end{vmatrix} = (2 - \lambda)(1 - \lambda)(2 - \lambda)$$

So  $\lambda = 2$  and  $\lambda = 1$  are eigenvalues of  $A$ .

Find the eigenspaces for these eigenvalues.

The nullspace of  $A - 2I$ :

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \xrightarrow{2 \text{ EROs}} \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

The nullspace of  $A - 2I$ :

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \xrightarrow{2 \text{ EROs}} \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_2$  is the only leading variable,  $x_1$  and  $x_3$  are free and the equation is  $x_2 = 0$ .

The nullspace of  $A - 2I$ :

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \xrightarrow{2 \text{ EROs}} \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_2$  is the only leading variable,  $x_1$  and  $x_3$  are free and the equation is  $x_2 = 0$ . This gives the eigenspace

$$\left\{ \begin{pmatrix} \alpha \\ 0 \\ \beta \end{pmatrix} \mid \alpha, \beta \in \mathbb{R} \right\}$$

The nullspace of  $A - 2I$ :

$$\begin{pmatrix} 0 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 1 & 0 \end{pmatrix} \xrightarrow{2 \text{ EROs}} \begin{pmatrix} 0 & 1 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_2$  is the only leading variable,  $x_1$  and  $x_3$  are free and the equation is  $x_2 = 0$ . This gives the eigenspace

$$\left\{ \left\{ \begin{pmatrix} \alpha \\ 0 \\ \beta \end{pmatrix} \mid \alpha, \beta \in \mathbb{R} \right\} \right\}$$

So we get a basis for this eigenspace:  $\mathbf{v}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$  and  $\mathbf{v}_2 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$

The nullspace of  $A - I$ :

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \xrightarrow{R_2 \leftrightarrow R_3} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

The nullspace of  $A - I$ :

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \xrightarrow{R_2 \leftrightarrow R_3} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_1$  and  $x_2$  are the leading variables and  $x_3$  is free. The equations are  $x_1 = 0$  and  $x_2 = -x_3$ . This gives the eigenspace

$$\left\{ \begin{pmatrix} 0 \\ -\alpha \\ \alpha \end{pmatrix} \mid \alpha \in \mathbb{R} \right\}$$



The nullspace of  $A - I$ :

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \xrightarrow{R_2 \leftrightarrow R_3} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_1$  and  $x_2$  are the leading variables and  $x_3$  is free. The equations are  $x_1 = 0$  and  $x_2 = -x_3$ . This gives the eigenspace

$$\left\{ \left( \begin{array}{c} 0 \\ -\alpha \\ \alpha \end{array} \right) \mid \alpha \in \mathbb{R} \right\}$$

So we get a basis for this eigenspace:  $\mathbf{v}_3 = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix}$ .

The nullspace of  $A - I$ :

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \xrightarrow{R_2 \leftrightarrow R_3} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_1$  and  $x_2$  are the leading variables and  $x_3$  is free. The equations are  $x_1 = 0$  and  $x_2 = -x_3$ . This gives the eigenspace

$$\left\{ \left( \begin{array}{c} 0 \\ -\alpha \\ \alpha \end{array} \right) \mid \alpha \in \mathbb{R} \right\}$$

So we get a basis for this eigenspace:  $\mathbf{v}_3 = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix}$ .

Because we have altogether 3 independent vectors, we have a basis for  $\mathbb{R}^3$  consisting of eigenvectors.

The nullspace of  $A - I$ :

$$\begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 1 & 1 \end{pmatrix} \xrightarrow{R_2 \leftrightarrow R_3} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & 0 & 0 \end{pmatrix}$$

Then  $x_1$  and  $x_2$  are the leading variables and  $x_3$  is free. The equations are  $x_1 = 0$  and  $x_2 = -x_3$ . This gives the eigenspace

$$\left\{ \left( \begin{array}{c} 0 \\ -\alpha \\ \alpha \end{array} \right) \mid \alpha \in \mathbb{R} \right\}$$

So we get a basis for this eigenspace:  $\mathbf{v}_3 = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix}$ .

Because we have altogether 3 independent vectors, we have a basis for  $\mathbb{R}^3$  consisting of eigenvectors. If we put the basis vectors in a matrix  $S$  and find its inverse  $S^{-1}$ , then the product  $S^{-1}AS$  will be a diagonal matrix  $D$  with 2, 2, 1 on the diagonal:

That is,  $S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 1 \end{pmatrix}$ ,  $S^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & -1 & 0 \end{pmatrix}$

That is,  $S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 1 \end{pmatrix}$ ,  $S^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & -1 & 0 \end{pmatrix}$  and

$$D = S^{-1}AS = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

That is,  $S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 1 \end{pmatrix}$ ,  $S^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & -1 & 0 \end{pmatrix}$  and

$$D = S^{-1}AS = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Note that  $A = SDS^{-1}$ . This allows us to compute successive powers of  $A$  easily:

$$A^2 = SDS^{-1}SDS^{-1} = SDIDS^{-1} = SD^2S^{-1}$$

$$A^3 = SD^2S^{-1}SDS^{-1} = SD^2IDS^{-1} = SD^3S^{-1}$$

and so on for  $A^n = SD^nS^{-1}$ .

That is,  $S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 1 \end{pmatrix}$ ,  $S^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & -1 & 0 \end{pmatrix}$  and

$$D = S^{-1}AS = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Note that  $A = SDS^{-1}$ . This allows us to compute successive powers of  $A$  easily:

$$A^2 = SDS^{-1}SDS^{-1} = SDIDS^{-1} = SD^2S^{-1}$$

$$A^3 = SD^2S^{-1}SDS^{-1} = SD^2IDS^{-1} = SD^3S^{-1}$$

and so on for  $A^n = SD^nS^{-1}$ . This is an advantage because  $D^n = \begin{pmatrix} 2^n & 0 & 0 \\ 0 & 2^n & 0 \\ 0 & 0 & 1^n \end{pmatrix}$

is essentially trivial to calculate.

That is,  $S = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 1 \end{pmatrix}$ ,  $S^{-1} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 1 \\ 0 & -1 & 0 \end{pmatrix}$  and

$$D = S^{-1}AS = \begin{pmatrix} 2 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 1 \end{pmatrix}$$

Note that  $A = SDS^{-1}$ . This allows us to compute successive powers of  $A$  easily:

$$A^2 = SDS^{-1}SDS^{-1} = SDIDS^{-1} = SD^2S^{-1}$$

$$A^3 = SD^2S^{-1}SDS^{-1} = SD^2IDS^{-1} = SD^3S^{-1}$$

and so on for  $A^n = SD^nS^{-1}$ . This is an advantage because  $D^n = \begin{pmatrix} 2^n & 0 & 0 \\ 0 & 2^n & 0 \\ 0 & 0 & 1^n \end{pmatrix}$

is essentially trivial to calculate. This works for negative powers as well.