

# Linear Algebra from Scratch: Linear Transformations

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"It does not matter how slowly you go as long as you do not stop." - Confucius

Udemy Open Course



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  - A Linear Transformation is a Mapping that preserves Linearity
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  - Application: Computer Graphics
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# Linear Transformation

## Definition ( $L : V \rightarrow W$ is a Map)

Given Vector Spaces:  $V$  and  $W$ ,  $L : V \rightarrow W$  is a **Linear Transformation** or Linear Mapping provided:

$$\textcircled{1} : L(\alpha \mathbf{v}_1 + \beta \mathbf{v}_2) = \alpha L(\mathbf{v}_1) + \beta L(\mathbf{v}_2)$$

For each  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{v}_1, \mathbf{v}_2 \in V$ .

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$$L(\alpha \mathbf{v}_1) = \alpha L(\mathbf{v}_1)$$

For each  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{v}_1, \mathbf{v}_2 \in V$ .

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$$L(\alpha \mathbf{v}_1) = \alpha L(\mathbf{v}_1)$$

For each  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{v}_1, \mathbf{v}_2 \in V$ .

**Remark:** If  $V = W$ , then  $L$  is referred to as a **Linear Operator**.

Additionally, only  $\textcircled{1}$  or  $\textcircled{2}$  needs to hold.

## Example: Linear Operator

- ① Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = 3 * \mathbf{x}$   
Show that  $L$  is a **Linear Operator**.

## Example: Linear Operator

- ① Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = 3 * \mathbf{x}$   
Show that  $L$  is a **Linear Operator**.
- ② Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^2$ , then:

Proof.

$$L(\alpha \mathbf{x} + \beta \mathbf{y}) = \begin{bmatrix} 3(\alpha x_1 + \beta y_1) \\ 3(\alpha x_2 + \beta y_2) \end{bmatrix} = \begin{bmatrix} 3(\alpha x_1) + 3(\beta y_1) \\ 3(\alpha x_2) + 3(\beta y_2) \end{bmatrix}$$





## Example: Linear Operator

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Proof.

$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= \begin{bmatrix} 3(\alpha x_1 + \beta y_1) \\ 3(\alpha x_2 + \beta y_2) \end{bmatrix} = \begin{bmatrix} 3(\alpha x_1) + 3(\beta y_1) \\ 3(\alpha x_2) + 3(\beta y_2) \end{bmatrix} \\ &= \begin{bmatrix} 3(\alpha x_1) \\ 3(\alpha x_2) \end{bmatrix} + \begin{bmatrix} 3(\beta y_1) \\ 3(\beta y_2) \end{bmatrix} \end{aligned}$$



## Example: Linear Operator

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$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= \begin{bmatrix} 3(\alpha x_1 + \beta y_1) \\ 3(\alpha x_2 + \beta y_2) \end{bmatrix} = \begin{bmatrix} 3(\alpha x_1) + 3(\beta y_1) \\ 3(\alpha x_2) + 3(\beta y_2) \end{bmatrix} \\ &= \begin{bmatrix} 3(\alpha x_1) \\ 3(\alpha x_2) \end{bmatrix} + \begin{bmatrix} 3(\beta y_1) \\ 3(\beta y_2) \end{bmatrix} \\ &= \alpha * \begin{bmatrix} 3x_1 \\ 3x_2 \end{bmatrix} + \beta * \begin{bmatrix} 3y_1 \\ 3y_2 \end{bmatrix} = \alpha L(\mathbf{x}) + \beta L(\mathbf{y}) \end{aligned}$$



## Example: Linear Operator

- ① Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = 3 * \mathbf{x}$

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- ③ **Remark:** The Linear Operator  $L(\mathbf{x}) = 3 * \mathbf{x}$  stretches  $\mathbf{x}$  by a factor of 3. Generally, any constant of greater magnitude than 1 is a **dilation**.

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# Linear Operator: Schematic Representation

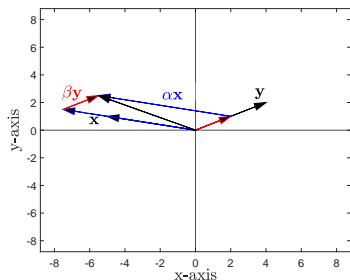
$$L : \mathbb{R}^2 \rightarrow \mathbb{R}^2.$$

①  $|\alpha| > 1 \sim \text{Stretch (Contraction)}$

②  $|\beta| < 1 \sim \text{Shrink (Dilation)}$

③ Scaling a Vector ( $\mathbf{x}$ ) in  $\mathbb{R}^2$  by a factor of  $\alpha$  is a Linear Operator because:

$$L(\alpha \mathbf{x} + \beta \mathbf{y}) = \alpha L(\mathbf{x}) + \beta L(\mathbf{y})$$





## Example: Linear Operator

- ① Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = (x_2, -x_1)$   
Show that  $L$  is a **Linear Operator**.
- ② Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^2$ , then:

Proof.

$$L(\alpha \mathbf{x} + \beta \mathbf{y}) = \begin{bmatrix} \alpha x_2 + \beta y_2 \\ -\alpha x_1 - \beta y_1 \end{bmatrix}$$



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## Example: Linear Operator

① Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = (x_2, -x_1)$

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② Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^2$ , then:

Proof.

$$\begin{aligned} L(\alpha\mathbf{x} + \beta\mathbf{y}) &= \begin{bmatrix} \alpha x_2 + \beta y_2 \\ -\alpha x_1 - \beta y_1 \end{bmatrix} \\ &= \begin{bmatrix} \alpha x_2 \\ -\alpha x_1 \end{bmatrix} + \begin{bmatrix} \beta y_2 \\ -\beta y_1 \end{bmatrix} = \alpha * \begin{bmatrix} x_2 \\ -x_1 \end{bmatrix} + \beta * \begin{bmatrix} y_2 \\ -y_1 \end{bmatrix} \\ &= \alpha L(\mathbf{x}) + \beta L(\mathbf{y}) \end{aligned}$$



③ **Remark:** The Linear Operator  $L(\mathbf{x}) = (x_2, -x_1)$  rotates  $\mathbf{x}$   $90^\circ$  Clockwise.

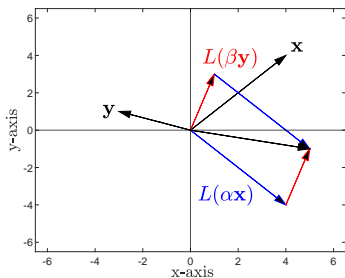
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# Linear Operator: Schematic Representation

$$L : \mathbb{R}^2 \rightarrow \mathbb{R}^2.$$

① The Linear Operator  $L(\mathbf{x}) = (x_2, -x_1)$  rotates  $\mathbf{x}$   $90^\circ$  Clockwise. ② Rotation of a Vector ( $\mathbf{x}$ ) in  $\mathbb{R}^2$  is a Linear Operator because:

$$L(\alpha\mathbf{x} + \beta\mathbf{y}) = \alpha L(\mathbf{x}) + \beta L(\mathbf{y})$$



# Example: Linear Transformation

- 1 Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = (x_1, -x_2)$   
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- ③ **Remark:** The Linear Operator  $L(\mathbf{x}) = (x_1, -x_2)$  reflects  $\mathbf{x}$  across the x-axis.

Reference: Leon, 2014 [2]

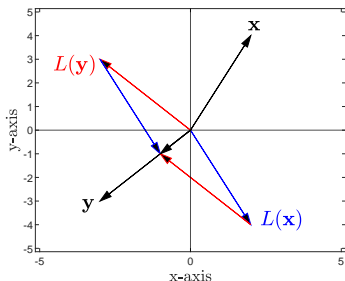
# Linear Operator: Schematic Representation

$$L : \mathbb{R}^2 \rightarrow \mathbb{R}^2.$$

① The Linear Operator

$L(\mathbf{x}) = (x_1, -x_2)$  reflects across the  $x$ -axis. ② Reflecting a Vector ( $\mathbf{x}$ ) in  $\mathbb{R}^2$  is a Linear Operator because:

$$L(\alpha \mathbf{x} + \beta \mathbf{y}) = \alpha L(\mathbf{x}) + \beta L(\mathbf{y})$$





# Example: Linear Transformation

- 1 Consider the mapping:  $L : \mathbb{R}^3 \rightarrow \mathbb{R}$  where  $L(\mathbf{x}) = x_1 + x_2 + x_3$   
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Show that  $L$  is a **Linear Transformation**.
- ② Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^3$ , then:

Proof.

$$L(\alpha \mathbf{x} + \beta \mathbf{y}) = (\alpha x_1 + \beta y_1) + (\alpha x_2 + \beta y_2) + (\alpha x_3 + \beta y_3)$$



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Proof.

$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= (\alpha x_1 + \beta y_1) + (\alpha x_2 + \beta y_2) + (\alpha x_3 + \beta y_3) \\ &= (\alpha x_1 + \alpha x_2 + \alpha x_3) + (\beta y_1 + \beta y_2 + \beta y_3) \end{aligned}$$



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$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= (\alpha x_1 + \beta y_1) + (\alpha x_2 + \beta y_2) + (\alpha x_3 + \beta y_3) \\ &= (\alpha x_1 + \alpha x_2 + \alpha x_3) + (\beta y_1 + \beta y_2 + \beta y_3) \\ &= \alpha * (x_1 + x_2 + x_3) + \beta * (y_1 + y_2 + y_3) \end{aligned}$$



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- ① Consider the mapping:  $L : \mathbb{R}^3 \rightarrow \mathbb{R}$  where  $L(\mathbf{x}) = x_1 + x_2 + x_3$   
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Proof.

$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= (\alpha x_1 + \beta y_1) + (\alpha x_2 + \beta y_2) + (\alpha x_3 + \beta y_3) \\ &= (\alpha x_1 + \alpha x_2 + \alpha x_3) + (\beta y_1 + \beta y_2 + \beta y_3) \\ &= \alpha * (x_1 + x_2 + x_3) + \beta * (y_1 + y_2 + y_3) \\ &= \alpha L(\mathbf{x}) + \beta L(\mathbf{y}) \end{aligned}$$



## Example: Not a Linear Transformation

- ① Consider the mapping:  $M : \mathbb{R}^n \rightarrow \mathbb{R}$  where  $M(\mathbf{x}) = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$   
Show that  $M$  is **not** a Linear Transformation.

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Show that  $M$  is **not** a Linear Transformation.
- ② Take  $\alpha \in \mathbb{R}$ , then:

Proof.

$$M(\alpha \mathbf{x}) = \sqrt{(\alpha x_1)^2 + (\alpha x_2)^2 + \cdots + (\alpha x_n)^2}$$



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Show that  $M$  is **not** a Linear Transformation.
- ② Take  $\alpha \in \mathbb{R}$ , then:

Proof.

$$\begin{aligned} M(\alpha \mathbf{x}) &= \sqrt{(\alpha x_1)^2 + (\alpha x_2)^2 + \cdots + (\alpha x_n)^2} \\ &= |\alpha| \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2} \end{aligned}$$



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- ① Consider the mapping:  $M : \mathbb{R}^n \rightarrow \mathbb{R}$  where  $M(\mathbf{x}) = \sqrt{x_1^2 + x_2^2 + \cdots + x_n^2}$   
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Proof.

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For  $\alpha < 0$ . Therefore,  $M$  is **not** a Linear Operator.



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## Example: Linear Transformation

- 1 Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^3$  where  $L(\mathbf{x}) = (x_2, x_1, x_1 + x_2)$   
Show that  $L$  is a **Linear Transformation**.

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Show that  $L$  is a **Linear Transformation**.
- ② Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^2$ , then:

Proof.

$$L(\alpha \mathbf{x} + \beta \mathbf{y}) = (\alpha x_2 + \beta y_2, \alpha x_1 + \beta y_1, \alpha(x_1 + x_2) + \beta(x_2 + y_2))^T$$



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Proof.

$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= (\alpha x_2 + \beta y_2, \alpha x_1 + \beta y_1, \alpha(x_1 + x_2) + \beta(x_2 + y_2))^T \\ &= \begin{bmatrix} \alpha x_2 \\ \alpha x_1 \\ \alpha(x_1 + x_2) \end{bmatrix} + \begin{bmatrix} \beta y_2 \\ \beta y_1 \\ \beta(y_1 + y_2) \end{bmatrix} \end{aligned}$$



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- ① Consider the mapping:  $L : \mathbb{R}^2 \rightarrow \mathbb{R}^3$  where  $L(\mathbf{x}) = (x_2, x_1, x_1 + x_2)$   
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- ② Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^2$ , then:

Proof.

$$\begin{aligned} L(\alpha \mathbf{x} + \beta \mathbf{y}) &= (\alpha x_2 + \beta y_2, \alpha x_1 + \beta y_1, \alpha(x_1 + x_2) + \beta(x_2 + y_2))^T \\ &= \begin{bmatrix} \alpha x_2 \\ \alpha x_1 \\ \alpha(x_1 + x_2) \end{bmatrix} + \begin{bmatrix} \beta y_2 \\ \beta y_1 \\ \beta(y_1 + y_2) \end{bmatrix} \\ &= \alpha * L(\mathbf{x}) + \beta * L(\mathbf{y}) \end{aligned}$$



**Remark:** If  $A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \\ 1 & 1 \end{bmatrix} \rightarrow A\mathbf{x} = L(\mathbf{x})$

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# The Matrix Representation

## Lemma (General Representation)

Consider  $\mathbf{x} \in \mathbb{R}^n$  and the Linear Mapping  $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$ , then the *Matrix Representation* given  $A \in \mathbb{R}^{m \times n}$  is:

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## Proof.

Take  $\alpha, \beta \in \mathbb{R}$  and  $\mathbf{x}, \mathbf{y} \in \mathbb{R}^n$ , then:

$$L_A(\alpha\mathbf{x} + \beta\mathbf{y}) = A(\alpha\mathbf{x} + \beta\mathbf{y}) = A(\alpha\mathbf{x}) + A(\beta\mathbf{y}) = \alpha A\mathbf{x} + \beta A\mathbf{y} = \alpha L_A(\mathbf{x}) + \beta L_A(\mathbf{y})$$



# Linear Transformation Properties

## Definition (Properties of the Linear Transformation)

Take  $V, W \sim \text{Vector Spaces}$  and  $L : V \rightarrow W$  a Linear Transformation, then the following holds:

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## Example: Linear Transformation

- 1 Consider the mapping:  $L : C[a, b] \rightarrow \mathbb{R}$  where  $L(\mathbf{f}) = \int_a^b f(x)dx$   
Show that  $L$  is a **Linear Transformation**.

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# Example: Linear Transformation

- ① Consider the mapping:  $L : C^1[a, b] \rightarrow C[a, b]$  where  $L(\mathbf{f}) = \mathbf{f}'$   
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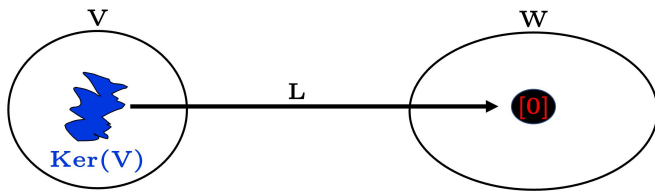


# The Kernel

## Definition (Kernel of a Linear Transformation)

Suppose  $V$  and  $W$  are Linear Spaces and  $L : V \rightarrow W$  is a Linear Transformation, then the **Kernel of  $L$**  are all the elements in  $V$  that map to the null vector in  $W$ :

$$\text{Ker}(V) = \{ \mathbf{v} \in V \mid L(\mathbf{v}) = \mathbf{0}_w \}$$



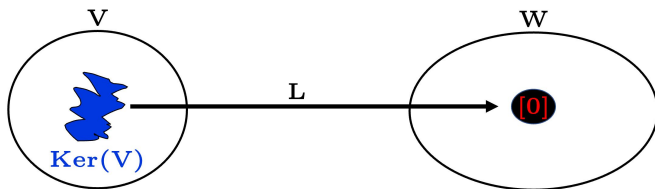
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**Remark:**  $\text{Ker}(V) \subset V$





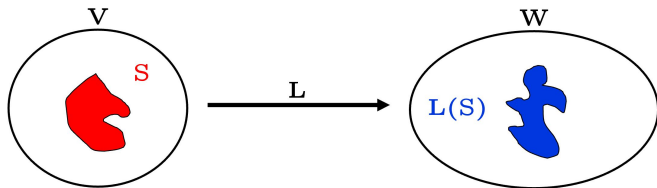
# The Image

## Definition (The Image of a Linear Transformation)

Suppose  $V$  and  $W$  are Linear Spaces and  $S \subset V$ . Consider  $L : V \rightarrow W$  as a Linear Transformation, then the **Image of  $S$  under  $L$**  are all the elements mapped to  $W$  from an element in  $S$ :

$$L(S) = \{\mathbf{w} \in W \mid \mathbf{w} = L(\mathbf{v}) \text{ for some } \mathbf{v} \in S\}$$

**Remark:** The **Range** of  $L$  is the Image of  $V$  under  $L$  denoted:  $L(V)$ .



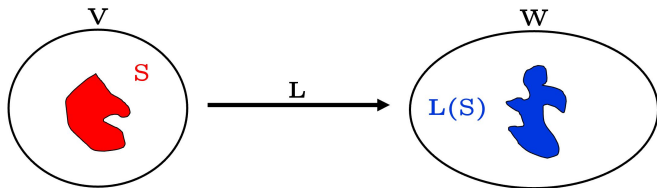
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**Remark:** The **Range** of  $L$  is the Image of  $V$  under  $L$  denoted:  $L(V)$ .  
Lastly,  $L(S) \subset W$



## Example: Kernel and Image

- 1 Consider the mapping:  $D : P_3 \rightarrow P_2$  where  $D(\mathbf{p}(x)) = p'(x)$   
Calculate the **Kernel** and **Image** of the Linear Transformation.

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Calculate the **Kernel** and **Image** of the Linear Transformation.
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Proof.

$$\mathbf{p}(x) = \alpha_0 + \alpha_1 x + \alpha_2 x^2$$

$$D(\mathbf{p}) = \alpha_1 + 2\alpha_2 x = 0 \iff \mathbf{p}(x) = \alpha_0$$

$$\text{Ker}(D) = \{\mathbf{p} \in P_3 \mid \mathbf{p} = \alpha_0\}$$

$$D(P_3) = P_2$$



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  - Image and Kernel of a Linear Transformation
- 2 4.2: Matrix Representation of a Linear Transformation
  - Application: Computer Graphics
- 3 4.3: Similarity

# The Matrix Representation of $L$

## Theorem (Matrix Representation)

Suppose  $L : \mathbb{R}^n \rightarrow \mathbb{R}^m$  is a Linear Transformation, then the *Matrix Representation of a Linear Transformation* is  $A \in \mathbb{R}^{m \times n}$  such that:

$$Ax = L(x)$$

For each  $x \in \mathbb{R}^n$ , where  $a_j = L(e_j)$ .

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$$L(\mathbf{x}) = L(x_1 e_1 + x_2 e_2 + \cdots + x_n e_n)$$





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# Example: Matrix Representation

Consider the mapping:  $L : \mathbb{R}^3 \rightarrow \mathbb{R}^2$  where  $L(\mathbf{x}) = (x_1 + x_2, x_2 + x_3)$

Find the **Matrix Representation of the Linear Transformation**.

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$$A = [a_1, a_2, a_3] = \begin{bmatrix} 1 & 1 & 0 \\ 0 & 1 & 1 \end{bmatrix}$$



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## Example: Matrix Representation

Consider the Linear Operator  $L(\mathbf{x}) = (-x_2, x_1)$  that rotates a vector  $\mathbf{x} \in \mathbb{R}^2$  by  $90^\circ$  Counter-Clockwise.

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Suppose that the first column of  $A$  is:

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Where  $\theta = \tan^{-1}(x_2/x_1) \in \mathbb{R}$  is the angle rotated Counter-Clockwise.



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# Matrix Representation Theorem

## Theorem (Matrix Representation of a $L : V \rightarrow W$ )

*Suppose:  $E = \{v_1, v_2, \dots, v_n\}$  and  $F = \{w_1, w_2, \dots, w_n\}$  are ordered basis on Vector Space  $V$  and  $W$  respectively. Consider  $L : V \rightarrow W$  as a Linear Transformation and take  $[v]_E$  as the coordinate vector with respect to the ordered basis  $E$ , then there is  $A \in \mathbb{R}^{m \times n}$  such that:*

$$[L(v)]_F = A[v]_E \text{ For each } v \in V$$

*We will refer to  $A$  as the **Matrix Representing  $L$  relative to the ordered basis:  $E$  and  $F$ .***

# Ordered Basis of $P_n$

## Lemma (An Ordered Basis of $P_n$ )

*Suppose that  $P_n$  is the vector space consisting of all polynomials with degree  $n - 1$ , then  $E = \{1, x, x^2, \dots, x^j, \dots, x^{n-1}\}$  is an **Ordered Basis** on  $P_n$ .*

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## Proof.

For any  $\mathbf{p}(x) \in P_n$ , one has:

$$\mathbf{p}(x) = \sum_{j=0}^{n-1} \alpha_j x^j$$

One can take  $\alpha = (\alpha_0, \alpha_1, \dots, \alpha_{n-1})' \triangleq [\mathbf{p}]_E$  as the **coordinate vector** of  $\mathbf{p}(x)$  with respect to  $P_n$ . □

## Example: Matrix Representation

- ① Consider the mapping:  $D : P_3 \rightarrow P_2$  where  $D(\mathbf{p}) = \mathbf{p}'$ . Suppose that  $E = \{1, x, x^2\}$  and  $F = \{1, x\}$  are ordered basis on  $P_3$  and  $P_2$  respectively.
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- ② For each  $\mathbf{p}(x) \in P_3$ , one has:  $D(\mathbf{p}) = \alpha_1 + 2\alpha_2 x$ . Since  $\alpha_1, \alpha_2 \in \mathbb{R}$  are arbitrary, then the Image of  $D$  is  $P_2$ . Likewise,  $\text{Ker}(D) = P_1$ .

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One obtains the Matrix Representation of the Linear Transformation by applying  $D$  to each basis element of  $E$  and expressing in terms of elements of the ordered basis on  $F$ :

$$D(1) = 0 * 1 + 0 * x \text{ \& } D(x) = 1 * 1 + 0 * x \text{ \& } D(x^2) = 0 * 1 + 2 * x$$



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$$a_1 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad a_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad a_3 = \begin{bmatrix} 0 \\ 2 \end{bmatrix} \rightarrow A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix}$$





# Representation of Geometric Operations in $2D$

- ① We can create a **Triangle**, by expressing the **ordered tuples** of the vertices as columns of  $T \in \mathbb{R}^{2 \times 4}$ :  $T = \begin{bmatrix} x_1 & y_1 & z_1 & x_1 \\ x_2 & y_2 & z_2 & x_2 \end{bmatrix}$  The 4<sup>th</sup> column is the same as the 1<sup>st</sup> column to guarantee formation of a closed polygon.

## Geometric Transformations in $\mathbb{R}^2$ .

# Representation of Geometric Operations in 2D

- ① We can create a **Triangle**, by expressing the **ordered tuples** of the vertices as columns of  $T \in \mathbb{R}^{2 \times 4}$ :  $T = \begin{bmatrix} x_1 & y_1 & z_1 & x_1 \\ x_2 & y_2 & z_2 & x_2 \end{bmatrix}$  The 4<sup>th</sup> column is the same as the 1<sup>st</sup> column to guarantee formation of a closed polygon.

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- ③ **Dilation** and **Contraction**:  $L(\mathbf{x}) = \alpha \mathbf{x}$  where

$$|\alpha| < 1 \sim \text{Contraction} \ \& \ |\alpha| > 1 \sim \text{Dilation} \rightarrow A = \begin{bmatrix} \alpha & 0 \\ 0 & \alpha \end{bmatrix}$$



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- ⑤ Rotation:  $L \sim$  Linear Transformation that rotates  $\mathbf{x} \in \mathbb{R}^2$  by an angle of  $\theta$

$$\text{Counter-Clockwise. } L(\mathbf{x}) = A\mathbf{x} \text{ where: } A = \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix}$$



# Linear Operator: Schematic Representation

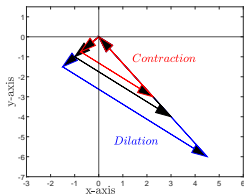


Figure: Scaling

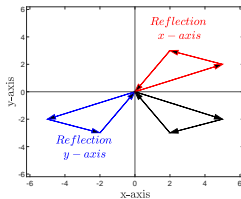


Figure: Reflection

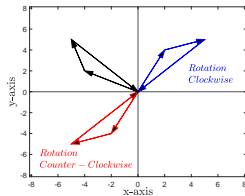


Figure: Rotation

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## Example.

② Let  $L(\mathbf{x}) = (2x_1, x_1 + x_2)^T$ . We will first find the matrix representation according to the Standard Basis:  $E = \{\mathbf{e}_1, \mathbf{e}_2\}$ .

$$L(\mathbf{e}_1) = \mathbf{a}_1 = \begin{bmatrix} 2 \\ 1 \end{bmatrix}$$

$$L(\mathbf{e}_2) = \mathbf{a}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$A = \begin{bmatrix} 2 & 0 \\ 1 & 1 \end{bmatrix}$$



## Example Cont'd

- ① Consider the ordered basis:  $F = \{\mathbf{u}_1, \mathbf{u}_2\}$  where:  $U = [\mathbf{u}_1, \mathbf{u}_2] = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$

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② The Transition Matrix from ordered basis  $F$  to  $E$  is:  $S_1 = I_2^{-1}U = U$ .  
Likewise, The Transition Matrix from ordered basis  $E$  to  $F$  is:  $S_2 = U^{-1}I_2 = U^{-1}$ .

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③ It follows that  $U^{-1} = \begin{bmatrix} 1/2 & 1/2 \\ -1/2 & 1/2 \end{bmatrix}$ .

To obtain the matrix representation of  $L$  wrt to Basis  $F$  we will pre-multiply by  $S_2$  on  $Au_j$  for  $j = 1, 2$ .

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### Computation.

$$U^{-1}Au_1 = \begin{bmatrix} 2 \\ 0 \end{bmatrix} \quad U^{-1}Au_2 = \begin{bmatrix} -1 \\ 1 \end{bmatrix}$$

$$B = U^{-1}AU = \begin{bmatrix} 2 & -1 \\ 0 & 1 \end{bmatrix}$$



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We obtained a **Similar** Matrix  $B = U^{-1}AU$  provided:

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- ②  $A$  is The Matrix Representation of  $L$  with respect to the Ordered Basis:  $E = \{\mathbf{e}_1, \mathbf{e}_2\}$ .
- ③  $U$  is the Transition Matrix corresponding to the change of basis from  $F$  to  $E$ .



# Similarity Matrices in General

## Theorem (Similar Matrices)

Consider  $E = \{\mathbf{v}_1, \mathbf{v}_2, \dots, \mathbf{v}_n\}$  and  $F = \{\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_n\}$  as two Ordered Bases on Vector Space  $V$ . Consider a Linear Operator:  $L : V \rightarrow V$ .

Take  $A$  as the Matrix Representation of  $L$  wrt  $E$ .

Take  $B$  as the Matrix Representation of  $L$  wrt  $F$ , then there is nonsingular  $S$  such that:

$$B = S^{-1}AS$$

We say that  $B$  is **Similar** to  $A$ .

**Remark:** In fact,  $A$  is **Similar** to  $B$  since:  $A = SBS^{-1}$ .

We refer to  $A$  and  $B$  as **Similar Matrices**.

# References I

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