

Linear Algebra (5th edition)

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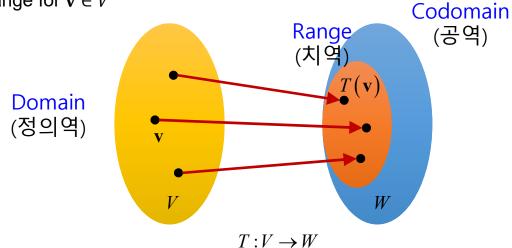
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- Linear transformations
 - Notation
 - $T: V \to W$
 - T: A function
 - V: A domain
 - W: A codomain
 - $T(\mathbf{v})$: A range for $\mathbf{v} \in V$





Linear transformations

Linear transformation:

Let V and W be vector spaces over the same field F.

We call a function $T: V \to W$ a linear transformation from V to W (or just linear) if, for all $\mathbf{x}, \mathbf{y} \in V$ and $c \in F$, we have

(a)
$$T(\mathbf{x} + \mathbf{y}) = T(\mathbf{x}) + T(\mathbf{y})$$
, and

(b)
$$T(c\mathbf{x}) = cT(\mathbf{x})$$

Properties

- 1) T is linear $\Rightarrow T(\mathbf{0}) = \mathbf{0}$
- ② T is linear \Leftrightarrow $T(c\mathbf{x} + \mathbf{y}) = cT(\mathbf{x}) + T(\mathbf{y})$ for all $\mathbf{x}, \mathbf{y} \in V$ and $c \in F$
- 3 T is linear $\Rightarrow T(\mathbf{x} \mathbf{y}) = T(\mathbf{x}) T(\mathbf{y})$ for all $\mathbf{x}, \mathbf{y} \in V$
- ④ T is linear $\Leftrightarrow T(\sum_{i=1}^n a_i \mathbf{x}_i) = \sum_{i=1}^n a_i T(\mathbf{x}_i)$ for $\mathbf{x}_1, \dots, \mathbf{x}_n \in V$ and $a_1, \dots, a_n \in F$
- Generally, property 2 often used to prove a given transformation T is linear



- Linear transformations
 - Example 2.1.1

•
$$T: \mathbb{R}^2 \to \mathbb{R}^2$$
 where $T\left(\begin{bmatrix} a_1 \\ a_2 \end{bmatrix}\right) = \begin{bmatrix} 2a_1 + a_2 \\ a_1 \end{bmatrix}$

- Q: Is function T linear?
 - Letting $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$

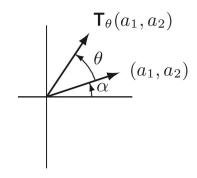
•
$$T(c\mathbf{x} + \mathbf{y}) = T\left(\begin{bmatrix} cx_1 + y_1 \\ cx_2 + y_2 \end{bmatrix}\right) = \begin{bmatrix} 2(cx_1 + y_1) + (cx_2 + y_2) \\ cx_1 + y_1 \end{bmatrix} = \begin{bmatrix} 2(cx_1 + y_1) + (cx_2 + y_2) \\ cx_1 + y_1 \end{bmatrix}$$

•
$$cT(\mathbf{x}) + T(\mathbf{y}) = c \begin{bmatrix} 2x_1 + x_2 \\ x_1 \end{bmatrix} + \begin{bmatrix} 2y_1 + y_2 \\ y_1 \end{bmatrix} = \begin{bmatrix} c(2x_1 + x_2) + 2y_1 + y_2 \\ cx_1 + y_1 \end{bmatrix} = \begin{bmatrix} 2(cx_1 + y_1) + (cx_2 + y_2) \\ cx_1 + y_1 \end{bmatrix}$$



- Linear transformations
 - Example 2.1.2 (Rotation)

•
$$T: \mathbb{R}^2 \to \mathbb{R}^2$$
 where $T\begin{pmatrix} a_1 \\ a_2 \end{pmatrix} = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} a_1 \cos \theta - a_2 \sin \theta \\ a_1 \sin \theta + a_2 \cos \theta \end{bmatrix}$



- Q: Is function T linear?
 - Letting $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$
 - $T(c\mathbf{x} + \mathbf{y}) = T(\begin{bmatrix} cx_1 + y_1 \\ cx_2 + y_2 \end{bmatrix}) = \begin{bmatrix} (cx_1 + y_1)\cos\theta (cx_2 + y_2)\sin\theta \\ (cx_1 + y_1)\sin\theta + (cx_2 + y_2)\cos\theta \end{bmatrix} = \begin{bmatrix} (cx_1 + y_1)\cos\theta (cx_2 + y_2)\sin\theta \\ (cx_1 + y_1)\sin\theta + (cx_2 + y_2)\cos\theta \end{bmatrix}$

$$\begin{aligned} & \begin{bmatrix} (cx_1 + y_1)\cos\theta & (cx_2 + y_2)\sin\theta \\ (cx_1 + y_1)\sin\theta + (cx_2 + y_2)\cos\theta \end{bmatrix} \\ & \cdot cT(\mathbf{x}) + T(\mathbf{y}) = c \begin{bmatrix} x_1\cos\theta - x_2\sin\theta \\ x_1\sin\theta + x_2\cos\theta \end{bmatrix} + \begin{bmatrix} y_1\cos\theta - y_2\sin\theta \\ y_1\sin\theta + y_2\cos\theta \end{bmatrix} = \\ & \begin{bmatrix} c(x_1\cos\theta - x_2\sin\theta) + (y_1\cos\theta - y_2\sin\theta) \\ c(x_1\sin\theta + x_2\cos\theta) + (y_1\sin\theta + y_2\cos\theta) \end{bmatrix} = \begin{bmatrix} (cx_1 + y_1)\cos\theta - (cx_2 + y_2)\sin\theta \\ (cx_1 + y_1)\sin\theta + (cx_2 + y_2)\cos\theta \end{bmatrix} \end{aligned}$$



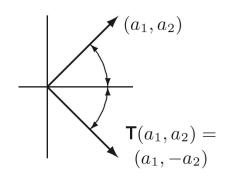
- Linear transformations
 - Example 2.1.3 (Reflection)

•
$$T: \mathbb{R}^2 \to \mathbb{R}^2$$
 where $T\left(\begin{bmatrix} a_1 \\ a_2 \end{bmatrix}\right) = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} a_1 \\ -a_2 \end{bmatrix}$

- Q: Is function T linear?
 - Letting $\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$ and $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$

•
$$T(c\mathbf{x} + \mathbf{y}) = T\left(\begin{bmatrix} cx_1 + y_1 \\ cx_2 + y_2 \end{bmatrix}\right) = \begin{bmatrix} cx_1 + y_1 \\ -cx_2 - y_2 \end{bmatrix}$$

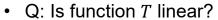
•
$$cT(\mathbf{x}) + T(\mathbf{y}) = c \begin{bmatrix} x_1 \\ -x_2 \end{bmatrix} + \begin{bmatrix} y_1 \\ -y_2 \end{bmatrix} = \begin{bmatrix} cx_1 + y_1 \\ -cx_2 - y_2 \end{bmatrix}$$





- Linear transformations
 - Example 2.1.4 (Projection on the 1st dimension)

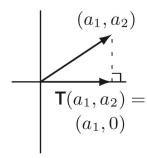
•
$$T: \mathbb{R}^2 \to \mathbb{R}^2$$
 where $T\left(\begin{bmatrix} a_1 \\ a_2 \end{bmatrix}\right) = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \end{bmatrix} = \begin{bmatrix} a_1 \\ 0 \end{bmatrix}$



• Letting
$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$
 and $\mathbf{y} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$

•
$$T(c\mathbf{x} + \mathbf{y}) = T\begin{pmatrix} cx_1 + y_1 \\ cx_2 + y_2 \end{pmatrix} = \begin{bmatrix} cx_1 + y_1 \\ 0 \end{bmatrix}$$

•
$$cT(\mathbf{x}) + T(\mathbf{y}) = c \begin{bmatrix} x_1 \\ 0 \end{bmatrix} + \begin{bmatrix} y_1 \\ 0 \end{bmatrix} = \begin{bmatrix} cx_1 + y_1 \\ 0 \end{bmatrix}$$





- Linear transformations
 - Example 2.1.5 (Transpose)
 - $T: M_{m \times n}(F) \to M_{n \times m}(F)$ where $T(A) = A^T$
 - Q: Is function T linear?

•
$$T(c\mathbf{X} + \mathbf{Y}) = (c\mathbf{X} + \mathbf{Y})^T = c\mathbf{X}^T + \mathbf{Y}^T$$

•
$$cT(\mathbf{X}) + T(\mathbf{Y}) = c\mathbf{X}^T + \mathbf{Y}^T$$



- Linear transformations
 - Example 2.1.6 (Derivatives)
 - $T: V \to V$ where $T(f) = \frac{df}{dv}$
 - Q: Is function *T* linear?
 - Letting $g \in V$ and $h \in V$

•
$$T(cg+h) = \frac{d}{dv}(cg+h) = c\frac{dg}{dv} + \frac{dh}{dv}$$

•
$$cT(g) + T(h) = c\frac{dg}{dv} + \frac{dh}{dv}$$



- Linear transformations
 - Example 2.1.7 (Integration)
 - $T: \mathbb{R} \to \mathbb{R}$ where $T(f) = \int_a^b f(t)dt$ for some $a, b \in \mathbb{R}$
 - Q: Is function T linear?
 - Letting $g \in \mathbb{R}$ and $h \in \mathbb{R}$
 - $T(cg+h) = \int_a^b cg(t) + h(t)dt = c \int_a^b g(t)dt + \int_a^b h(t)dt$
 - $cT(g) + T(h) = c \int_a^b g(t)dt + \int_a^b h(t)dt$
 - ∴ By property ②, linear!



- Linear transformations
 - Example (Identity transformation)
 - $T: V \to V$ where $T(\mathbf{x}) = \mathbf{x}$ for all $\mathbf{x} \in V$
 - Q: Is function T linear?
 - Letting $x \in V$ and $y \in V$
 - $T(c\mathbf{x} + \mathbf{y}) = c\mathbf{x} + \mathbf{y}$
 - $cT(\mathbf{x}) + T(\mathbf{y}) = c\mathbf{x} + \mathbf{y}$
 - ∴ By property ②, linear!



- Linear transformations
 - Example (Zero transformation)
 - $T: V \to W$ where $T(\mathbf{x}) = \mathbf{0}$ for all $\mathbf{x} \in V$
 - Q: Is function T linear?
 - Letting $x \in V$ and $y \in V$
 - $T(c\mathbf{x} + \mathbf{y}) = \mathbf{0}$
 - $cT(\mathbf{x}) + T(\mathbf{y}) = \mathbf{0}$
 - ∴ By property ②, linear!



Null spaces and ranges

Null space (kernel):

Let V and W be vector spaces and let function $T: V \to W$ be linear. We define null space (or kernel) N(T) of T to be the set of all vectors $\mathbf{x} \in V$ such that

$$N(T) = \{ \mathbf{x} \in V | T(\mathbf{x}) = \mathbf{0} \}$$



Null spaces and ranges

Range (image) (치역):

Let V and W be vector spaces and let function $T:V \to W$ be linear. We define range (or image) R(T) of T to be the subset of W containing all images (outputs) under T of vectors in V such that

$$R(T) = \{ T(\mathbf{x}) | \mathbf{x} \in V \}$$



- Null spaces and ranges
 - Example 2.1.8
 - $T_1: V \to V$ where $T_1(\mathbf{x}) = \mathbf{x}$ for all $\mathbf{x} \in V$ (identity transformation)
 - Null space

•
$$N(T_1) = \{0\}$$

Range

•
$$R(T_1) = V$$

- $T_2: V \to W$ where $T_2(\mathbf{x}) = \mathbf{0}$ for all $\mathbf{x} \in V$ (zero transformation)
 - Null space

•
$$N(T_2) = V$$

- Range
 - $R(T_2) = \{ \mathbf{0} \}$



- Null spaces and ranges
 - Example 2.1.9

•
$$T: \mathbb{R}^3 \to \mathbb{R}^2$$
 where $T\left(\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix}\right) = \begin{bmatrix} a_1 - a_2 \\ 2a_3 \end{bmatrix}$ for all $\begin{bmatrix} a_1 \\ a_2 \\ a_3 \end{bmatrix} \in \mathbb{R}^3$

Null space

•
$$N(T) = \left\{ \begin{bmatrix} x \\ x \\ 0 \end{bmatrix} \middle| x \in \mathbb{R} \right\}$$

- Range
 - $R(T) = \mathbb{R}^2$



Null spaces and ranges

Theorem 2.1:

Let V and W be vector spaces and let function $T: V \to W$ be linear. Then, N(T) is a subspace of V and R(T) is a subspace of W.

- Proof) (N(T) is a subspace of V)
 - Theorem 1.3(a)
 - $\mathbf{0} \in N(T)$ since property ① of linear transformation indicates that $T(\mathbf{0}) = \mathbf{0}$
 - Theorem 1.3(b)
 - $\mathbf{x} + \mathbf{y} \in N(T)$ since $T(\mathbf{x} + \mathbf{y}) = T(\mathbf{x}) + T(\mathbf{y}) = \mathbf{0}$ for $\mathbf{x}, \mathbf{y} \in N(T)$
 - Theorem 1.3(c)
 - $c\mathbf{x} \in N(T)$ since $T(c\mathbf{x}) = cT(\mathbf{x}) = \mathbf{0}$ for $\mathbf{x} \in N(T)$
 - ∴ Subspace!



Null spaces and ranges

Theorem 2.1:

Let V and W be vector spaces and let function $T: V \to W$ be linear. Then, N(T) is a subspace of V and R(T) is a subspace of W.

- Proof) (R(T) is a subspace of W)
 - Theorem 1.3(a)
 - $\mathbf{0} \in R(T)$ since $\mathbf{0} \in V$ and property ① of linear transformation indicates that $T(\mathbf{0}) = \mathbf{0}$
 - Theorem 1.3(b)
 - $\mathbf{x} + \mathbf{y} \in R(T)$ since $\mathbf{x} + \mathbf{y} = T(\mathbf{v}_1) + T(\mathbf{v}_2) = T(\mathbf{v}_1 + \mathbf{v}_2) \in R(T)$ for $\mathbf{x} = T(\mathbf{v}_1), \mathbf{y} = T(\mathbf{v}_2) \in R(T)$ and $\mathbf{v}_1, \mathbf{v}_2 \in V$
 - Theorem 1.3(c)
 - $c\mathbf{x} \in R(T)$ since $c\mathbf{x} = cT(\mathbf{v}_1) = T(c\mathbf{v}_1) \in R(T)$ for $\mathbf{x} = T(\mathbf{v}_1) \in R(T)$ and $\mathbf{v}_1 \in V$
 - ∴ Subspace!



Null spaces and ranges

Theorem 2.2:

Let V and W be vector spaces and let function $T: V \to W$ be linear. $\beta = \{\mathbf{v}_1, ..., \mathbf{v}_n\}$ is a basis of $V \Rightarrow R(T) = \operatorname{span}(T(\beta)) = \operatorname{span}(T(\mathbf{v}_1), ..., T(\mathbf{v}_n))$

- Proof)
 - $(\operatorname{span}(T(\beta)) \subseteq R(T))$
 - Note that $T(\mathbf{v}_i) \in R(T), \forall i$
 - From Theorem 2.1, R(T) is a subspace
 - \Rightarrow span $(T(\mathbf{v}_i)) = \text{span}(T(\beta)) \in R(T)$ by Theorem 1.5
 - $(\operatorname{span}(T(\beta)) \supseteq R(T))$
 - $\mathbf{v} = \sum_{i=1}^{n} a_i \mathbf{v}_i$ for any $\mathbf{v} \in V$
 - $\Rightarrow T(\mathbf{v}) \in R(T)$
 - $T(\mathbf{v}) = T(\sum_{i=1}^{n} a_i \mathbf{v}_i) = \sum_{i=1}^{n} a_i T(\mathbf{v}_i) \in \text{span}(\{T(\mathbf{v}_i)\}) = \text{span}(T(\beta)) \text{ for any } T(\mathbf{v}) \in R(T)$
 - $\Rightarrow R(T) \in \operatorname{span}(T(\beta))$



- Null spaces and ranges
 - Example 2.1.10
 - $T: V = \mathbb{R}^3 \to M_{2 \times 2}(\mathbb{R})$ where

•
$$T(\mathbf{v}) = \begin{bmatrix} v_2 - v_3 & 0 \\ 0 & v_1 \end{bmatrix}$$
 for $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}$

- Linear
- For a standard basis $\beta = \left\{ \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix}, \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \right\}$

•
$$R(T) = \operatorname{span}(T(\beta)) = \operatorname{span}\left(\left\{T\begin{pmatrix}\begin{bmatrix}1\\0\\0\end{bmatrix}\right\}, T\begin{pmatrix}\begin{bmatrix}0\\1\\0\end{bmatrix}\right\}, T\begin{pmatrix}\begin{bmatrix}0\\1\\0\end{bmatrix}\right)\right) = \operatorname{span}\left(\left\{\begin{bmatrix}0&0\\0&1\end{bmatrix}, \begin{bmatrix}1&0\\0&0\end{bmatrix}, \begin{bmatrix}-1&0\\0&0\end{bmatrix}\right\}\right) = \operatorname{span}\left(\left\{\begin{bmatrix}0&0\\0&1\end{bmatrix}, \begin{bmatrix}1&0\\0&0\end{bmatrix}\right\}\right)$$

•
$$\Rightarrow \dim(R(T)) = 2$$



- Null spaces and ranges
 - Example 2.1.10
 - $T: V = \mathbb{R}^3 \to M_{2 \times 2}(\mathbb{R})$ where

•
$$T(\mathbf{v}) = \begin{bmatrix} v_2 - v_3 & 0 \\ 0 & v_1 \end{bmatrix}$$
 for $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \\ v_3 \end{bmatrix}$

- Linear
- To find a basis for N(T), by letting $T(\mathbf{v}) = \mathbf{0}$,

•
$$N(T) = \operatorname{span} \begin{pmatrix} \begin{bmatrix} 0 \\ 1 \\ 1 \end{bmatrix} \end{pmatrix}$$

- $\Rightarrow \dim(N(T)) = 1$
- Note that $\dim(V) = \dim(N(T)) + \dim(R(T))$
 - (Theorem 2.3 coming soon!)



Null spaces and ranges

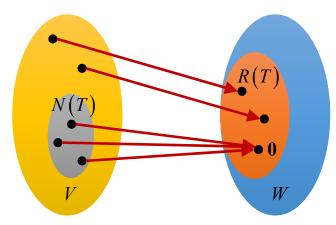
Nullity and rank:

Let V and W be vector spaces and let function $T: V \to W$ be linear. If N(T) and R(T) are finite-dimensional,

$$\operatorname{nullity}(T) \triangleq \dim(N(T))$$

 $\operatorname{rank}(T) \triangleq \dim(R(T))$

- Intuition
 - The larger the nullity, the smaller the rank
 - The more vectors carried into **0**, the smaller the range



 $T:V\to W$



Null spaces and ranges

Theorem 2.3 (Dimension Theorem):

Let V and W be vector spaces and let function $T: V \to W$ be linear. If V is finite-dimensional,

$$\operatorname{nullity}(T) + \operatorname{rank}(T) = \dim(V)$$

- Proof)
 - Let $n = \dim(V)$ and $k = \dim(N(T))$ where $n \ge k$.
 - Let $\{\mathbf{v}_1, ..., \mathbf{v}_k\}$ be a basis for N(T).
 - Note that N(T) is a subspace of vector space V.
 - \Rightarrow From Corollary 1.11.1, we may extend $\{\mathbf{v}_1, ..., \mathbf{v}_k\}$ to a basis $\beta = \{\mathbf{v}_1, ..., \mathbf{v}_k, \mathbf{v}_{k+1}, ..., \mathbf{v}_n\}$ for V.



Null spaces and ranges

Theorem 2.3 (Dimension Theorem):

Let V and W be vector spaces and let function $T: V \to W$ be linear. If V is finite-dimensional,

$$\operatorname{nullity}(T) + \operatorname{rank}(T) = \dim(V)$$

- Proof)
 - From Theorem 2.2,
 - $R(T) = \operatorname{span}(T(\beta)) = \operatorname{span}(T(\mathbf{v}_1), \dots, T(\mathbf{v}_k), T(\mathbf{v}_{k+1}), \dots, T(\mathbf{v}_n))$
 - Noting that $T(\mathbf{v}_1) = \cdots = T(\mathbf{v}_k) = \mathbf{0}$
 - $R(T) = \operatorname{span}(\{T(\mathbf{v}_{k+1}), \dots, T(\mathbf{v}_n)\})$
 - $\Rightarrow \{T(\mathbf{v}_{k+1}), ..., T(\mathbf{v}_n)\}$ spans R(T)



Null spaces and ranges

Theorem 2.3 (Dimension Theorem):

Let V and W be vector spaces and let function $T: V \to W$ be linear. If V is finite-dimensional,

$$\operatorname{nullity}(T) + \operatorname{rank}(T) = \dim(V)$$

- Proof)
 - If $\{T(\mathbf{v}_{k+1}), \dots, T(\mathbf{v}_n)\}$ is a linearly independent set,
 - $\sum_{i=k+1}^{n} b_i T(\mathbf{v}_i) = \mathbf{0}$ only when $b_i = 0, i = k+1, ..., n$
 - From the linear property of T,
 - $\sum_{i=k+1}^{n} b_i T(\mathbf{v}_i) = T(\sum_{i=k+1}^{n} b_i \mathbf{v}_i)$
 - If $T(\sum_{i=k+1}^n b_i \mathbf{v}_i) = \mathbf{0}$, then
 - $\sum_{i=k+1}^{n} b_i \mathbf{v}_i \in N(T)$
 - Hence, $\sum_{i=k+1}^{n} b_i \mathbf{v}_i$ may be expressed as a linear combination of the basis of N(T)
 - $\sum_{i=k+1}^{n} b_i \mathbf{v}_i = \sum_{i=1}^{k} c_i \mathbf{v}_i$ for some c_i 's
 - Since $\mathbf{v}_1, \dots, \mathbf{v}_k, \mathbf{v}_{k+1}, \dots, \mathbf{v}_n$ are a basis for V,
 - $\sum_{i=k+1}^{n} b_i \mathbf{v}_i \sum_{i=1}^{k} c_i \mathbf{v}_i = 0$ only when $b_i = 0, i = k+1, ..., n$



Null spaces and ranges

Theorem 2.3 (Dimension Theorem):

Let V and W be vector spaces and let function $T:V\to W$ be linear. If V is finite-dimensional,

$$\operatorname{nullity}(T) + \operatorname{rank}(T) = \dim(V)$$

- Proof)
 - Hence $\{T(\mathbf{v}_{k+1}), ..., T(\mathbf{v}_n)\}$ is a basis for R(T)
 - $\Rightarrow \dim(R(T)) = \operatorname{rank}(T) = n k$
 - ∴ Q.E.D.



Null spaces and ranges

Theorem 2.4:

Let V and W be vector spaces and let function $T: V \to W$ be linear.

Then, T is one-to-one
$$\Leftrightarrow$$
 $N(T) = \{0\}$

- Proof)
 - (*T* is one-to-one \Rightarrow $N(T) = \{0\}$)
 - From the one-to-one property, there exists only one x to satisfy T(x) = 0.
 - In the meantime, by the linear property, $T(\mathbf{0}) = \mathbf{0}$.

•
$$\Rightarrow x = 0$$

•
$$\Rightarrow N(T) = \{\mathbf{0}\}$$

- (T is one-to-one $\leftarrow N(T) = \{0\}$)
 - By contradiction, assume *T* is not one-to-one.

•
$$\Rightarrow T(\mathbf{x}) = T(\mathbf{y})$$
 for some distinct $\mathbf{x}, \mathbf{y} \in V$

• By the linear property, $\mathbf{0} = T(\mathbf{x}) - T(\mathbf{y}) = T(\mathbf{x} - \mathbf{y})$

•
$$\Rightarrow$$
 $\mathbf{x} - \mathbf{y} \in N(T)$ where $\mathbf{x} - \mathbf{y} \neq \mathbf{0}$

- ∴ Contradiction
- ∴ Q.E.D.



Null spaces and ranges

Theorem 2.5:

Let V and W be finite-dimensional vector spaces of equal dimension, and let function $T: V \to W$ be linear.

Then, T is one-to-one \Leftrightarrow T is onto \Leftrightarrow rank $(T) = \dim(V)$

- "One-to-one" (Appendix B)
 - $T(\mathbf{v}_1) = T(\mathbf{v}_2) \Rightarrow \mathbf{v}_1 = \mathbf{v}_2$, for some $\mathbf{v}_1, \mathbf{v}_2 \in V$
 - Equivalently, $\mathbf{v}_1 \neq \mathbf{v}_2 \Rightarrow T(\mathbf{v}_1) \neq T(\mathbf{v}_2)$, for some $\mathbf{v}_1, \mathbf{v}_2 \in V$
- "Onto" (Appendix B)
 - $T(\mathbf{v}) = W$, for all $\mathbf{v} \in V$



Null spaces and ranges

Theorem 2.5:

Let V and W be finite-dimensional vector spaces of equal dimension, and let function $T: V \to W$ be linear.

```
Then, T is one-to-one \Leftrightarrow T is onto \Leftrightarrow rank(T) = \dim(V)
```

- Proof)
 - From Theorem 2.4, T is one-to-one $\Leftrightarrow N(T) = \{0\}$ or nullity(T) = 0
 - Also, from Theorem 2.3 (Dimension theorem), nullity(T) + rank(T) = dim(V)
 - $\Rightarrow T$ is one-to-one \Leftrightarrow rank $(T) = \dim(V)$
 - From the equal dimension condition,
 - $\Rightarrow \operatorname{rank}(T) = \dim(V) \Leftrightarrow \operatorname{rank}(T) = \dim(W)$
 - From Theorem 1.11,
 - \Rightarrow rank $(T) = \dim(W) \Leftrightarrow R(T) = W$
 - ∴ Q.E.D.



- Null spaces and ranges
 - Example 2.1.12
 - $T: \mathbb{R}^2 \to \mathbb{R}^2$ where

•
$$T(\mathbf{v}) = \begin{bmatrix} v_1 + v_2 \\ v_1 \end{bmatrix}$$
 for $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$

- Linear
- To find a vector for N(T), by letting $T(\mathbf{v}) = \mathbf{0}$,
 - $N(T) = \{ \mathbf{0} \}$
- By Theorem 2.4
 - One-to-one
- By Theorem 2.5
 - Onto



Null spaces and ranges

Theorem 2.6:

Let V and W be vector spaces of equal dimension, and suppose that $\{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_n\}$ is a basis for V.

For $\mathbf{w}_1, ..., \mathbf{w}_n \in W$, there exists exactly one linear transformation $T: V \to W$ such that $T(\mathbf{v}_i) = \mathbf{w}_i$.

- Proof)
 - From the linear property, for $\mathbf{v} = \sum_{i=1}^{n} a_i \mathbf{v}_i$ with unique scalars a_1, \dots, a_n

•
$$T(\mathbf{v}) = T(\sum_{i=1}^n a_i \mathbf{v}_i) = \sum_{i=1}^n a_i T(\mathbf{v}_i) = \sum_{i=1}^n a_i \mathbf{w}_i$$

• If there exists another linear function $U: V \to W$ such that $U(\mathbf{v}_i) = \mathbf{w}_i$

•
$$U(\mathbf{v}) = U(\sum_{i=1}^n a_i \mathbf{v}_i) = \sum_{i=1}^n a_i U(\mathbf{v}_i) = \sum_{i=1}^n a_i \mathbf{w}_i$$

- Then, we must have $T(\mathbf{v}_i) = U(\mathbf{v}_i), \forall i$.
- Hence, U = T



- Null spaces and ranges
 - An implication of Theorem 2.6
 - A linear transformation completely determined by its action on a basis



2.2 The matrix representation of a linear transformation



2.2 The matrix representation of a linear transformation

- Section 2.1
 - Studying linear transformations by examining their null spaces and ranges
- Section 2.2
 - Representing linear transformations by a matrix
 - Developing a one-to-one correspondence between matrices and linear transformations



Ordered basis

Ordered basis:

Let V be a finite-dimensional vector space.

An ordered basis for V is a basis for V endowed with a specific order.

That is, an ordered basis is a finite sequence of linearly independent vectors in *V* that spans *V*.

• Example 2.2.1

- $\beta = \{\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3\}$
 - A standard ordered basis in \mathbb{F}^3 where \mathbf{e}_i , $\forall i$ is a standard basis
- $\gamma = \{\mathbf{e}_2, \mathbf{e}_1, \mathbf{e}_3\}$
 - Another ordered basis
- From the perspective of orders, $\beta \neq \gamma$



Ordered basis

Coordinate vector:

Let $\beta = \{\mathbf{v}_1, ..., \mathbf{v}_n\}$ be an ordered basis for a finite-dimensional vector space V. For $\mathbf{v} = \sum_{i=1}^n a_i \mathbf{v}_i \in V$, we define the coordinate vector of \mathbf{v} relative to β by

$$[\mathbf{v}]_{\beta} \triangleq \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}$$

With unique scalars $a_1, ..., a_n$

- Example 2.2.2
 - $V = \mathbb{R}^3$ with $\beta = \{\mathbf{e}_2, \mathbf{e}_1, \mathbf{e}_3\}$
 - The coordinate vector of $\mathbf{v} = \begin{bmatrix} 1 \\ 3 \\ 6 \end{bmatrix} = 1 \cdot \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} + 3 \cdot \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} + 6 \cdot \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = 1\mathbf{e}_1 + 3\mathbf{e}_2 + 6\mathbf{e}_3$
 - \Rightarrow $[\mathbf{v}]_{\beta} = \begin{bmatrix} 3\\1\\6 \end{bmatrix}$



- The matrix representation of a linear transformation
 - Letting
 - *V* be a vector space with an ordered basis $\beta = \{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_n\}$
 - W be a vector space with an ordered basis $\gamma = \{\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_m\}$
 - $T: V \to W$ be a linear function
 - Then, using the ordered basis γ
 - $T(\mathbf{v}_j) = \sum_{i=1}^m a_{ij} \mathbf{w}_i$ with unique scalars $a_{ij} \in F$ for i = 1, ..., m for each j = 1, ..., n



The matrix representation of a linear transformation

Matrix representation:

We call the $m \times n$ matrix \mathbf{A} defined by $[\mathbf{A}]_{ij} = a_{ij}$ the matrix representation of T in the ordered bases β and γ and write $\mathbf{A} = [T]_{\beta}^{\gamma}$. If V = W and $\beta = \gamma$, then we write $\mathbf{A} = [T]_{\beta}$.

• For instance, with n=2 and m=3 such that $T: \mathbb{R}^2 \to \mathbb{R}^3$,

•
$$[T(\mathbf{v}_1) \ T(\mathbf{v}_2)] = [\mathbf{w}_1 \ \mathbf{w}_2 \ \mathbf{w}_3] \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \mathbf{A} = [T]_{\beta}^{\gamma}$$

$$[T(\mathbf{v}_1)]_{\gamma} [T(\mathbf{v}_2)]_{\gamma}$$



- The matrix representation of a linear transformation
 - Example 2.2.3

• If
$$T(\begin{bmatrix} v_1 \\ v_2 \end{bmatrix}) = \begin{bmatrix} v_1 + 3v_2 \\ 0 \\ 2v_1 - 4v_2 \end{bmatrix}$$
, $\beta = \{\mathbf{v}_1 = \mathbf{e}_1, \mathbf{v}_2 = \mathbf{e}_2\}$, $\gamma = \{\mathbf{w}_1 = \mathbf{e}_1, \mathbf{w}_2 = \mathbf{e}_2, \mathbf{w}_3 = \mathbf{e}_3\}$
• $T(\mathbf{v}_1) = \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} = \underbrace{1 \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + 2 \cdot \mathbf{w}_3}_{a_{21}} \text{ and } T(\mathbf{v}_2) = \begin{bmatrix} 3 \\ 0 \\ -4 \end{bmatrix} = \underbrace{3 \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + (-4) \cdot \mathbf{w}_3}_{a_{22}} + \underbrace{(-4) \cdot \mathbf{w}_3}_{a_{32}} + \underbrace{(-$

• For
$$\gamma_2 = \{\mathbf{w}_1 = \mathbf{e}_3, \mathbf{w}_2 = \mathbf{e}_2, \mathbf{w}_3 = \mathbf{e}_1\}$$
• $T(\mathbf{v}_1) = \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} = \underbrace{2 \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + 1 \cdot \mathbf{w}_3}_{a_{21}} \text{ and } T(\mathbf{v}_2) = \begin{bmatrix} 3 \\ 0 \\ -4 \end{bmatrix} = \underbrace{(-4) \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + 3 \cdot \mathbf{w}_3}_{a_{32}}$
• $\Rightarrow [T]_{\beta}^{\gamma_2} = \begin{bmatrix} 2 & -4 \\ 0 & 0 \\ 1 & 3 \end{bmatrix}$



- The matrix representation of a linear transformation
 - Letting
 - *V* be a vector space with an ordered basis $\beta = \{\mathbf{v}_1, \mathbf{v}_2, ..., \mathbf{v}_n\}$
 - W be a vector space with an ordered basis $\gamma = \{\mathbf{w}_1, \mathbf{w}_2, ..., \mathbf{w}_m\}$
 - $T: V \to W$ be a linear function
 - (Zero transformation) Then, using the ordered basis γ

•
$$T(\mathbf{v}_j) = \mathbf{0} = 0 \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + \dots + 0 \cdot \mathbf{w}_m$$
 for $j = 1, \dots, n$

•
$$\Rightarrow [T]^{\gamma}_{\beta} = \begin{bmatrix} 0 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & 0 \end{bmatrix} = [\mathbf{0}]$$

• (Identity transformation) For n = m and $\beta = \gamma$,

•
$$T(\mathbf{v}_j) = \mathbf{v}_j = 0 \cdot \mathbf{v}_1 + \dots + 1 \cdot \mathbf{v}_j + \dots + 0 \cdot \mathbf{v}_n$$
 for $j = 1, \dots, n$

•
$$\Rightarrow [T]^{\gamma}_{\beta} = \begin{bmatrix} 1 & & \\ & \ddots & \\ & & 1 \end{bmatrix} = \mathbf{I_n}$$



The matrix representation of a linear transformation

Kronecker delta:

$$\delta_{ij} \triangleq \begin{cases} 1, & i = j \\ 0, & i \neq j \end{cases}$$

- For instance,
 - $[\mathbf{I}_n]_{ij} = \delta_{ij}, \forall i, j$



The matrix representation of a linear transformation

Addition and scalar multiplication of functions:

Let V and W be vector spaces over F. Let $T, U: V \to W$ be arbitrary functions. Then, for all $\mathbf{x} \in V$ and $a \in F$,

```
T + U: V \to W \triangleq (T + U)(\mathbf{x}) = T(\mathbf{x}) + U(\mathbf{x})
aT: V \to W \triangleq (aT)(\mathbf{x}) = aT(\mathbf{x})
```



The matrix representation of a linear transformation

Theorem 2.7:

Let V and W be vector spaces over F.

Let $T, U: V \to W$ be linear functions.

Then, for all $\mathbf{x} \in V$ and $a \in F$,

- (a) aT + U is linear, i.e., $(aT + U)(c\mathbf{x} + \mathbf{y}) = c(aT + U)(\mathbf{x}) + (aT + U)(\mathbf{y})$
- (b) The collection of all linear transformations from V to W is a vector space over F.
- Proof)
 - (a)
 - Let $\mathbf{x}, \mathbf{y} \in V$ and $c \in F$.
 - $(aT + U)(c\mathbf{x} + \mathbf{y}) = (aT)(c\mathbf{x} + \mathbf{y}) + U(c\mathbf{x} + \mathbf{y}) = c(aT)(\mathbf{x}) + (aT)(\mathbf{y}) + cU(\mathbf{x}) + U(\mathbf{y}) = c(aT)(\mathbf{x}) + U(\mathbf{x}) + (aT)(\mathbf{y}) + U(\mathbf{y}) = c(aT + U)(\mathbf{x}) + (aT + U)(\mathbf{y})$
 - (b)
 - (Left as an exercise)



The matrix representation of a linear transformation

The vector space of all linear transformations:

Let V and W be vector spaces over F.

We denote the vector space of all linear transformations from V into W by $\mathcal{L}(V,W)$.

If V = W, we write $\mathcal{L}(V)$.



The matrix representation of a linear transformation

Theorem 2.8:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively.

Let $T, U: V \to W$ be linear transformations.

(a)
$$[T + U]^{\gamma}_{\beta} = [T]^{\gamma}_{\beta} + [U]^{\gamma}_{\beta}$$

- (b) $[cT]^{\gamma}_{\beta} = c[T]^{\gamma}_{\beta}$ for all scalars c
- Proof)
 - (a)
 - Let $\beta = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ and $\gamma = \{\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_m\}$.
 - $T(\mathbf{v}_j) = \sum_{i=1}^m a_{ij} \mathbf{w}_i$ for unique scalars a_{ij} , $\forall i, j$
 - $U(\mathbf{v}_j) = \sum_{i=1}^m b_{ij} \mathbf{w}_i$ for unique scalars b_{ij} , $\forall i, j$



The matrix representation of a linear transformation

Theorem 2.8:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively.

Let $T, U: V \to W$ be linear transformations.

(a)
$$[T + U]^{\gamma}_{\beta} = [T]^{\gamma}_{\beta} + [U]^{\gamma}_{\beta}$$

(b)
$$[cT]^{\gamma}_{\beta} = c[T]^{\gamma}_{\beta}$$
 for all scalars c

- Proof)
 - (a)
 - Then, $(T+U)(\mathbf{v}_j) = T(\mathbf{v}_j) + U(\mathbf{v}_j) = \sum_{i=1}^m (a_{ij} + b_{ij}) \mathbf{w}_i$
 - Thus, $\left[\left[T+U\right]_{\beta}^{\gamma}\right]_{ij}=a_{ij}+b_{ij}=\left[\left[T\right]_{\beta}^{\gamma}\right]_{ij}+\left[\left[U\right]_{\beta}^{\gamma}\right]_{ij}$



The matrix representation of a linear transformation

Theorem 2.8:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively.

Let $T, U: V \to W$ be linear transformations.

(a)
$$[T + U]^{\gamma}_{\beta} = [T]^{\gamma}_{\beta} + [U]^{\gamma}_{\beta}$$

(b)
$$[cT]^{\gamma}_{\beta} = c[T]^{\gamma}_{\beta}$$
 for all scalars c

- Proof)
 - (b)

•
$$(cT)(\mathbf{v}_j) = cT(\mathbf{v}_j) = c\sum_{i=1}^m a_{ij}\mathbf{w}_i$$

• Thus,
$$\left[\left[cT\right]_{\beta}^{\gamma}\right]_{ij}=ca_{ij}=c\left[\left[T\right]_{\beta}^{\gamma}\right]_{ij}$$



- The matrix representation of a linear transformation
 - Example 2.2.5
 - Let $T, U: \mathbb{R}^2 \to \mathbb{R}^3$ be linear and $\beta = \{\mathbf{v}_1 = \mathbf{e}_1, \mathbf{v}_2 = \mathbf{e}_2\}$ for V and $\gamma = \{\mathbf{w}_1 = \mathbf{e}_1, \mathbf{w}_2 = \mathbf{e}_2, \mathbf{w}_3 = \mathbf{e}_3\}$ for W

• If
$$T\left(\begin{bmatrix} v_1 \\ v_2 \end{bmatrix}\right) = \begin{bmatrix} v_1 + 3v_2 \\ 0 \\ 2v_1 - 4v_2 \end{bmatrix}$$

•
$$T(\mathbf{v}_1) = \begin{bmatrix} 1 \\ 0 \\ 2 \end{bmatrix} = \mathbf{1} \cdot \mathbf{w}_1 + \mathbf{0} \cdot \mathbf{w}_2 + \mathbf{2} \cdot \mathbf{w}_3 \text{ and } T(\mathbf{v}_2) = \begin{bmatrix} 3 \\ 0 \\ -4 \end{bmatrix} = 3 \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + (-4) \cdot \mathbf{w}_3$$

•
$$\Rightarrow [T]^{\gamma}_{\beta} = \begin{bmatrix} 1 & 3 \\ 0 & 0 \\ 2 & -4 \end{bmatrix}$$

•
$$U(\mathbf{v}_1) = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} = \mathbf{1} \cdot \mathbf{w}_1 + \mathbf{2} \cdot \mathbf{w}_2 + \mathbf{3} \cdot \mathbf{w}_3 \text{ and } U(\mathbf{v}_2) = \begin{bmatrix} -1 \\ 0 \\ 2 \end{bmatrix} = (-1) \cdot \mathbf{w}_1 + \mathbf{0} \cdot \mathbf{w}_2 + \mathbf{2} \cdot \mathbf{w}_3$$

•
$$\Rightarrow [U]^{\gamma}_{\beta} = \begin{bmatrix} 1 & -1 \\ 2 & 0 \\ 3 & 2 \end{bmatrix}$$



- The matrix representation of a linear transformation
 - Example 2.2.5

• Since
$$(T + U) \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = T \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} + U \begin{pmatrix} v_1 \\ v_2 \end{pmatrix} = \begin{bmatrix} v_1 + 3v_2 \\ 0 \\ 2v_1 - 4v_2 \end{bmatrix} + \begin{bmatrix} v_1 - v_2 \\ 2v_1 \\ 3v_1 + 2v_2 \end{bmatrix} = \begin{bmatrix} 2v_1 + 2v_2 \\ 2v_1 \\ 5v_1 - 2v_2 \end{bmatrix}$$
• $(T + U)(\mathbf{v}_1) = \begin{bmatrix} 2 \\ 2 \\ 5 \end{bmatrix} = \mathbf{2} \cdot \mathbf{w}_1 + \mathbf{2} \cdot \mathbf{w}_2 + \mathbf{5} \cdot \mathbf{w}_3 \text{ and } (T + U)(\mathbf{v}_2) = \begin{bmatrix} 2 \\ 0 \\ -2 \end{bmatrix} = \mathbf{2} \cdot \mathbf{w}_1 + \mathbf{0} \cdot \mathbf{w}_2 + (-2) \cdot \mathbf{w}_3$
• $\Rightarrow [T + U]_{\beta}^{\gamma} = \begin{bmatrix} 2 & 2 \\ 2 & 0 \\ 5 & -2 \end{bmatrix}$

Note that

•
$$[T]_{\beta}^{\gamma} + [U]_{\beta}^{\gamma} = \begin{bmatrix} 1 & 3 \\ 0 & 0 \\ 2 & -4 \end{bmatrix} + \begin{bmatrix} 1 & -1 \\ 2 & 0 \\ 3 & 2 \end{bmatrix} = \begin{bmatrix} 2 & 2 \\ 2 & 0 \\ 5 & -2 \end{bmatrix} = [T + U]_{\beta}^{\gamma}$$





- Section 2.1
 - Studying linear transformations by examining their null spaces and ranges
- Section 2.2
 - Representing linear transformations by a matrix
 - Developing a one-to-one correspondence between matrices and linear transformations
- Section 2.3
 - How the matrix representation of a composite of linear transformations is related to the matrix representation of each of the associated linear transformations



Composition

Theorem 2.9:

Let V, W and Z be vector spaces over the same field F.

Let $T: V \to W$ and $U: W \to Z$ be linear.

Then, $UT: V \rightarrow Z$ is linear.

- Proof)
 - Let $\mathbf{x}, \mathbf{y} \in V$ and $a \in F$
 - $(UT)(a\mathbf{x} + \mathbf{y}) = U(T(a\mathbf{x} + \mathbf{y})) = U(aT(\mathbf{x}) + T(\mathbf{y})) = aU(T(\mathbf{x})) + U(T(\mathbf{y})) = a(UT)(\mathbf{x}) + (UT)(\mathbf{y})$
 - ∴ Q.E.D.



Composition

Theorem 2.10:

Let V be a vector space. Let $T, U_1, U_2 \in \mathcal{L}(V)$ (linear) Then,

- (a) $T(U_1 + U_2) = TU_1 + TU_2$ and $(U_1 + U_2)T = U_1T + U_2T$
- (b) $T(U_1U_2) = (TU_1)U_2$
- (c) TI = IT = T
- (d) $a(U_1U_2) = (aU_1)U_2 = U_1(aU_2)$ for all scalars a
- Proof)
 - (Exercise)



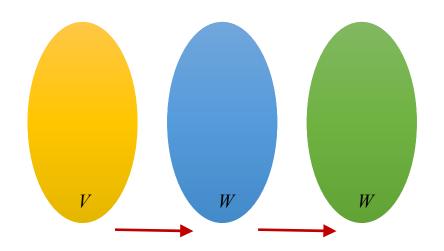
- Composition
 - If $T \in \mathcal{L}(V)$
 - $T^0 \triangleq I$
 - $T^k \triangleq T^{k-1}T$



Multiplication of matrices

- Let
 - *V*, *W* and *Z*: Finite-dimensional vector spaces
 - $T: V \to W$ linear
 - $U:W\to Z$ linear
 - $\alpha = \{\mathbf{v}_1, \dots, \mathbf{v}_n\}$ ordered basis for V
 - $\beta = \{\mathbf{w}_1, ..., \mathbf{w}_m\}$ ordered basis for W
 - $\gamma = \{\mathbf{z}_1, \dots, \mathbf{z}_p\}$ ordered basis for Z
 - $\mathbf{A} = [U]^{\gamma}_{\beta}$
 - $\mathbf{B} = [T]^{\beta}_{\alpha}$
- Then,

•
$$(UT)(\mathbf{v}_j) = U(T(\mathbf{v}_j)) = U(\sum_{k=1}^m [\mathbf{B}]_{kj} \mathbf{w}_k) = \sum_{k=1}^m [\mathbf{B}]_{kj} U(\mathbf{w}_k) = \sum_{k=1}^m [\mathbf{B}]_{kj} \left(\sum_{i=1}^p [\mathbf{A}]_{ik} \mathbf{z}_i\right) = \sum_{i=1}^p \left(\sum_{k=1}^m [\mathbf{A}]_{ik} [\mathbf{B}]_{kj}\right) \mathbf{z}_i = \sum_{i=1}^p [\mathbf{C}]_{ij} \mathbf{z}_i$$





Multiplication of matrices

Matrix product:

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

Let **B** be an $n \times p$ matrix.

We define the product of **A** and **B**, denoted **AB**, to be the $m \times p$ matrix such that

$$[\mathbf{AB}]_{ij} = \sum_{k=1}^{n} [\mathbf{A}]_{ik} [\mathbf{B}]_{kj}$$

for i = 1, ..., m and j = 1, ..., p.

That is, $[AB]_{ij}$ is the sum of products of corresponding entries from the *i*-th row of **A** and the *j*-th column of **B**.

Caution on the dimension

$$\underbrace{\mathbf{A}}_{(m\times n)}\underbrace{\mathbf{B}}_{(n\times p)} = \underbrace{\mathbf{AB}}_{(m\times p)}$$



- Multiplication of matrices
 - Example 2.3.1

•
$$\begin{bmatrix} 1 & 2 & 1 \\ 0 & 4 & -1 \end{bmatrix} \begin{bmatrix} 4 \\ 2 \\ 5 \end{bmatrix} = \begin{bmatrix} 1 \cdot 4 + 2 \cdot 2 + 1 \cdot 5 \\ 0 \cdot 4 + 4 \cdot 2 + (-1) \cdot 5 \end{bmatrix} = \begin{bmatrix} 13 \\ 3 \end{bmatrix}$$

- Dimension being $(2 \times 3)(3 \times 1) \rightarrow (2 \times 1)$
- Not commutative
 - $AB \neq BA$
 - e.g.,

•
$$\begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix}$$
•
$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix}$$

•
$$\begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 1 & 1 \end{bmatrix}$$



- Multiplication of matrices
 - Transpose of matrix multiplication
 - For some $\mathbf{A} \in M_{m \times n}(F)$ and $\mathbf{B} \in M_{n \times p}(F)$,
 - $[AB]_{ij}^T = [AB]_{ji} = \sum_{k=1}^n [A]_{jk} [B]_{ki}$
 - $[\mathbf{B}^T \mathbf{A}^T]_{ij} = \sum_{k=1}^n [\mathbf{B}^T]_{ik} [\mathbf{A}^T]_{kj} = \sum_{k=1}^n [\mathbf{B}]_{ki} [\mathbf{A}]_{jk}$
 - $\therefore (\mathbf{A}\mathbf{B})^T = \mathbf{B}^T \mathbf{A}^T$



Multiplication of matrices

Theorem 2.11:

Let V, W and Z be finite-dimensional vector spaces with ordered bases α, β and γ , respectively. For linear $T: V \to W$ and $U: W \to Z$,

$$[UT]_{\alpha}^{\gamma} = [U]_{\beta}^{\gamma} [T]_{\alpha}^{\beta}$$

- Example 2.3.2
 - Let $T: V = \mathbb{R}^2 \to W = \mathbb{R}^3$ and $U: W = \mathbb{R}^3 \to V = \mathbb{R}^2$
 - Ordered bases
 - $\alpha = \{ \mathbf{v}_1 = \mathbf{e}_1, \mathbf{v}_2 = \mathbf{e}_2 \}$ for V
 - $\beta = \{ \mathbf{w}_1 = \mathbf{e}_1, \mathbf{w}_2 = \mathbf{e}_2, \mathbf{w}_3 = \mathbf{e}_3 \}$ for W



Multiplication of matrices

Theorem 2.11:

Let V, W and Z be finite-dimensional vector spaces with ordered bases α, β and γ , respectively. For linear $T: V \to W$ and $U: W \to Z$,

$$[UT]_{\alpha}^{\gamma} = [U]_{\beta}^{\gamma} [T]_{\alpha}^{\beta}$$

• Example 2.3.2

• For
$$T(\mathbf{v}) = \begin{bmatrix} \frac{1}{2}v_1 \\ v_2 \\ 0 \end{bmatrix}$$
 for $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \in \mathbb{R}^2$
• $T(\mathbf{v}_1) = \begin{bmatrix} \frac{1}{2} \\ 0 \\ 0 \end{bmatrix} = \frac{1}{2} \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + 0 \cdot \mathbf{w}_3$ and $T(\mathbf{v}_2) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = 0 \cdot \mathbf{w}_1 + 1 \cdot \mathbf{w}_2 + 0 \cdot \mathbf{w}_3$
• $\Rightarrow [T]_{\alpha}^{\beta} = \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$



Multiplication of matrices

Theorem 2.11:

Let V, W and Z be finite-dimensional vector spaces with ordered bases α, β and γ , respectively. For linear $T: V \to W$ and $U: W \to Z$,

$$[UT]_{\alpha}^{\gamma} = [U]_{\beta}^{\gamma} [T]_{\alpha}^{\beta}$$

• Example 2.3.2

• For
$$U(\mathbf{w}) = \begin{bmatrix} 2w_1 \\ w_2 \end{bmatrix}$$
 for $\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \in \mathbb{R}^3$

•
$$U(\mathbf{w}_1) = \begin{bmatrix} 2 \\ 0 \end{bmatrix} = 2 \cdot \mathbf{v}_1 + 0 \cdot \mathbf{v}_2$$
, $U(\mathbf{w}_2) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 0 \cdot \mathbf{v}_1 + 1 \cdot \mathbf{v}_2$ and $U(\mathbf{w}_3) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = 0 \cdot \mathbf{v}_1 + 0 \cdot \mathbf{v}_2$

•
$$\Rightarrow [U]^{\alpha}_{\beta} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$



Multiplication of matrices

Theorem 2.11:

Let V, W and Z be finite-dimensional vector spaces with ordered bases α, β and γ , respectively. For linear $T: V \to W$ and $U: W \to Z$,

$$[UT]_{\alpha}^{\gamma} = [U]_{\beta}^{\gamma} [T]_{\alpha}^{\beta}$$

Example 2.3.2

• For
$$(UT)(\mathbf{v}) = U\begin{pmatrix} \begin{bmatrix} \frac{1}{2}v_1 \\ v_2 \\ 0 \end{bmatrix} \end{pmatrix} = \begin{bmatrix} 2\begin{pmatrix} \frac{1}{2}v_1 \\ v_2 \end{bmatrix} \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$
 for $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \in \mathbb{R}^3$

•
$$(UT)(\mathbf{v}_1) = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \mathbf{1} \cdot \mathbf{v}_1 + \mathbf{0} \cdot \mathbf{v}_2 \text{ and } (UT)(\mathbf{v}_2) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \mathbf{0} \cdot \mathbf{v}_1 + \mathbf{1} \cdot \mathbf{v}_2$$

•
$$\Rightarrow [UT]^{\alpha}_{\alpha} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

• Note that
$$[U]^{\alpha}_{\beta}[T]^{\beta}_{\alpha} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = [UT]^{\alpha}_{\alpha}$$



Multiplication of matrices

Corollary 2.11.1:

Let V be a finite-dimensional vector space with an ordered basis β .

Let $T, U \in \mathcal{L}(V)$

$$[UT]_{\beta} = [U]_{\beta}[T]_{\beta}$$



Multiplication of matrices

Theorem 2.12:

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

Let **B** and **C** be $n \times p$ matrices.

Let **D** and **E** be $q \times m$ matrices.

(a)
$$A(B+C) = AB + AC$$
 and $(D+E)A = DA + EA$

(b)
$$a(AB) = (aA)B = A(aB)$$
 for any scalar a

(c)
$$\mathbf{I}_m \mathbf{A} = \mathbf{A} = \mathbf{A} \mathbf{I}_n$$

- Proof)
 - (Exercise)



Multiplication of matrices

Corollary 2.12.1:

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

Let $\mathbf{B}_1, \mathbf{B}_2, \dots, \mathbf{B}_k$ be $n \times p$ matrices.

Let $C_1, C_2, ..., C_k$ be $q \times m$ matrices.

Let $a_1, a_2, ..., a_k$ be scalars.

Then.

(a)
$$\mathbf{A}(\sum_{i=1}^k a_i \mathbf{B}_i) = \sum_{i=1}^k a_i \mathbf{A} \mathbf{B}_i$$

(b) $(\sum_{i=1}^k a_i \mathbf{C}_i) \mathbf{A} = \sum_{i=1}^k a_i \mathbf{C}_i \mathbf{A}$

(b)
$$\left(\sum_{i=1}^k a_i \mathbf{C}_i\right) \mathbf{A} = \sum_{i=1}^k a_i \mathbf{C}_i \mathbf{A}$$

- Proof)
 - (Exercise)



- Multiplication of matrices
 - For an $n \times n$ matrix A,
 - $\mathbf{A}^0 \triangleq \mathbf{I}_n$
 - $\mathbf{A}^k \triangleq \mathbf{A}^{k-1}\mathbf{A}$



Multiplication of matrices

Theorem 2.13:

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

Let **B** be $n \times p$ matrices.

Let \mathbf{u}_i be the *j*-th column of \mathbf{AB} .

Let \mathbf{v}_i be the *j*-th column of \mathbf{B} .

(a)
$$\mathbf{u}_i = \mathbf{A}\mathbf{v}_i$$

(b)
$$\mathbf{v}_j = \mathbf{B}\mathbf{e}_j$$



- Multiplication of matrices
 - Proof) (a) $\mathbf{u}_j = \mathbf{A}\mathbf{v}_j$

$$\mathbf{u}_{j} = \begin{bmatrix} \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{1j} \\ \vdots \\ \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{ij} \\ \vdots \\ \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{ij} \\ \vdots \\ \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{nj} \end{bmatrix} = \begin{bmatrix} \sum_{k=1}^{m} \begin{bmatrix} \mathbf{A} \end{bmatrix}_{1k} \begin{bmatrix} \mathbf{B} \end{bmatrix}_{kj} \\ \vdots \\ \sum_{k=1}^{m} \begin{bmatrix} \mathbf{A} \end{bmatrix}_{ik} \begin{bmatrix} \mathbf{B} \end{bmatrix}_{kj} \end{bmatrix} = \begin{bmatrix} \mathbf{A}_{\text{row},1} \mathbf{v}_{j} \\ \vdots \\ \mathbf{A}_{\text{row},n} \mathbf{v}_{j} \end{bmatrix} = \mathbf{A}\mathbf{v}_{j}$$

$$\vdots$$

$$\sum_{k=1}^{m} \begin{bmatrix} \mathbf{A} \end{bmatrix}_{nk} \begin{bmatrix} \mathbf{B} \end{bmatrix}_{kj} \end{bmatrix}$$

$$\mathbf{A} = \begin{bmatrix} \begin{bmatrix} \mathbf{A} \end{bmatrix}_{11} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{12} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{1m} \\ \vdots & \vdots & \ddots & \mathbf{A}_{\text{row},i} \\ \vdots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A} \end{bmatrix}_{n1} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{i2} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{nm} \end{bmatrix}$$

$$\mathbf{B} = \begin{bmatrix} \begin{bmatrix} \mathbf{B} \end{bmatrix}_{11} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{1j} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{1j} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{1p} \\ \begin{bmatrix} \mathbf{B} \end{bmatrix}_{21} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{2p} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{2p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{B} \end{bmatrix}_{m1} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{mp} \end{bmatrix}$$



- Multiplication of matrices
 - Proof) (b) $\mathbf{v}_j = \mathbf{B}\mathbf{e}_j$

$$\mathbf{Be}_{j} = \begin{bmatrix} \mathbf{[B]}_{11} & \cdots & \mathbf{[B]}_{1j} & \cdots & \mathbf{[B]}_{1p} \\ \mathbf{[B]}_{21} & \cdots & \mathbf{[B]}_{2j} & \cdots & \mathbf{[B]}_{2p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \mathbf{[B]}_{m1} & \cdots & \mathbf{[B]}_{mj} & \cdots & \mathbf{[B]}_{mp} \end{bmatrix} \begin{bmatrix} 0 \\ \vdots \\ 1 \\ 0 \end{bmatrix} = \begin{bmatrix} \mathbf{[B]}_{1j} \\ \mathbf{[B]}_{2j} \\ \vdots \\ \mathbf{[B]}_{mj} \end{bmatrix} = \mathbf{v}_{j}$$



- Multiplication of matrices
 - Theorem 2.13
 - Column j of AB = A linear combination of the columns of A with column j of B

$$\mathbf{A}\mathbf{B} = \begin{bmatrix} \begin{bmatrix} \mathbf{A} \end{bmatrix}_{11} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{12} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A} \end{bmatrix}_{i1} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{i2} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{1m} \\ \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{B} \end{bmatrix}_{21} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{2p} \\ \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{B} \end{bmatrix}_{m1} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{mp} \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{11} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{1p} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{1p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{i1} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{ip} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{ip} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{n1} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{np} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{np} \end{bmatrix}$$



- Multiplication of matrices
 - Analogous
 - Row i of AB = A linear combination of the row i of A with columns of B

$$\mathbf{A}\mathbf{B} = \begin{bmatrix} \begin{bmatrix} \mathbf{A} \end{bmatrix}_{11} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{12} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A} \end{bmatrix}_{i1} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{i2} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{im} \\ \begin{bmatrix} \mathbf{B} \end{bmatrix}_{21} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{2j} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{2p} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A} \end{bmatrix}_{n1} & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{n2} & \cdots & \begin{bmatrix} \mathbf{A} \end{bmatrix}_{nm} \end{bmatrix} \begin{bmatrix} \begin{bmatrix} \mathbf{B} \end{bmatrix}_{n1} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{nj} & \cdots & \begin{bmatrix} \mathbf{B} \end{bmatrix}_{np} \end{bmatrix} = \begin{bmatrix} \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{i1} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{ij} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{ip} \\ \vdots & \ddots & \vdots & \ddots & \vdots \\ \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{n1} & \cdots & \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{np} \end{bmatrix} = \begin{bmatrix} \mathbf{A}\mathbf{B} \end{bmatrix}_{n1} & \cdots & \mathbf{A}\mathbf{B} \end{bmatrix}_{np} \begin{bmatrix} \mathbf{A}\mathbf{B}$$



Multiplication of matrices

Theorem 2.14:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively. For linear $T: V \to W$,

$$[T(\mathbf{u})]_{\gamma} = [T]_{\beta}^{\gamma} [\mathbf{u}]_{\beta}, \forall \mathbf{u} \in V$$

- Proof)
 - Let $f: F \to V$ by $f(a) = a\mathbf{u}$ for $a \in F$.
 - An ordered basis

•
$$\alpha = \{f_1 = 1\} \text{ for } F$$

• $[T(\mathbf{u})]_{\gamma} = [Tf]_{\gamma} = [T]_{\beta}^{\gamma} [f]_{\alpha}^{\beta} = [T]_{\beta}^{\gamma} [f]_{\alpha}^{\beta} = [T]_{\beta}^{\gamma} [\mathbf{u}]_{\beta}$



Multiplication of matrices

Theorem 2.14:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively. For linear $T: V \to W$,

$$[T(\mathbf{u})]_{\gamma} = [T]_{\beta}^{\gamma} [\mathbf{u}]_{\beta}, \forall \mathbf{u} \in V$$

- Example 2.3.3
 - Let $T: V = \mathbb{R}^2 \to W = \mathbb{R}^3$ and $U: W = \mathbb{R}^3 \to V = \mathbb{R}^2$
 - Ordered bases
 - $\beta = \{ \mathbf{v}_1 = \mathbf{e}_1, \mathbf{v}_2 = \mathbf{e}_2 \}$ for V
 - $\gamma = \{\mathbf{w}_1 = \mathbf{e}_1, \mathbf{w}_2 = \mathbf{e}_2, \mathbf{w}_3 = \mathbf{e}_3\}$ for W



Multiplication of matrices

Theorem 2.14:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively. For linear $T: V \to W$,

$$[T(\mathbf{u})]_{\gamma} = [T]_{\beta}^{\gamma} [\mathbf{u}]_{\beta}, \forall \mathbf{u} \in V$$

Example 2.3.3

• For
$$T(\mathbf{v}) = \begin{bmatrix} \frac{1}{2}v_1 \\ v_2 \\ 0 \end{bmatrix}$$
 for $\mathbf{v} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \in \mathbb{R}^3$
• $T(\mathbf{v}_1) = \begin{bmatrix} \frac{1}{2} \\ 0 \\ 0 \end{bmatrix} = \frac{1}{2} \cdot \mathbf{w}_1 + 0 \cdot \mathbf{w}_2 + 0 \cdot \mathbf{w}_3$ and $T(\mathbf{v}_2) = \begin{bmatrix} 0 \\ 1 \\ 0 \end{bmatrix} = 0 \cdot \mathbf{w}_1 + 1 \cdot \mathbf{w}_2 + 0 \cdot \mathbf{w}_3$
• $\Rightarrow [T]_{\beta}^{\gamma} = \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix}$



Multiplication of matrices

Theorem 2.14:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively. For linear $T: V \to W$,

$$[T(\mathbf{u})]_{\gamma} = [T]_{\beta}^{\gamma} [\mathbf{u}]_{\beta}, \forall \mathbf{u} \in V$$

• Example 2.3.3

• Note that
$$[T]_{\beta}^{\gamma}[\mathbf{v}]_{\beta} = \begin{bmatrix} \frac{1}{2} & 0 \\ 0 & 1 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{2}v_1 \\ v_2 \\ 0 \end{bmatrix} = [T(\mathbf{v})]_{\gamma}$$



Multiplication of matrices

Theorem 2.14:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively. For linear $T: V \to W$,

$$[T(\mathbf{u})]_{\gamma} = [T]_{\beta}^{\gamma} [\mathbf{u}]_{\beta}, \forall \mathbf{u} \in V$$

• Example 2.3.3

• For
$$U(\mathbf{w}) = \begin{bmatrix} 2w_1 \\ w_2 \end{bmatrix}$$
 for $\mathbf{w} = \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} \in \mathbb{R}^3$

•
$$U(\mathbf{w}_1) = \begin{bmatrix} 2 \\ 0 \end{bmatrix} = 2 \cdot \mathbf{v}_1 + 0 \cdot \mathbf{v}_2, \ U(\mathbf{w}_2) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 0 \cdot \mathbf{v}_1 + 1 \cdot \mathbf{v}_2 \text{ and } U(\mathbf{w}_3) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = 0 \cdot \mathbf{v}_1 + 0 \cdot \mathbf{v}_2$$

•
$$\Rightarrow [U]_{\gamma}^{\beta} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

• Note that
$$[U]_{\gamma}^{\beta}[\mathbf{w}]_{\gamma} = \begin{bmatrix} 2 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \\ w_3 \end{bmatrix} = \begin{bmatrix} 2w_1 \\ w_2 \end{bmatrix} = [U(\mathbf{w})]_{\beta}$$



Left multiplication

Left multiplication:

Let **A** be an $m \times n$ matrix with entries from a field F.

We denote by $L_{\mathbf{A}}$ the mapping $L_{\mathbf{A}}: F^n \to F^m$ defined by $L_{\mathbf{A}}(\mathbf{x}) = \mathbf{A}\mathbf{x}$ (the matrix product of \mathbf{A} and \mathbf{x}) for each column vector $\mathbf{x} \in F^n$.

We call $L_{\mathbf{A}}$ a left-multiplication transformation.

• Example 2.3.4

• Let
$$\mathbf{A} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix} \in M_{2 \times 3}(\mathbb{R})$$

• Then,
$$L_{\mathbf{A}}(\mathbf{x}) = \mathbf{A}\mathbf{x} \in F^2$$
 for some $\mathbf{x} \in F^3$.

• For example, with
$$\mathbf{x} = \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix}$$
,

•
$$L_{\mathbf{A}}(\mathbf{x}) = \mathbf{A}\mathbf{x} = \begin{bmatrix} 1 & 2 & 1 \\ 0 & 1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ -1 \end{bmatrix} = \begin{bmatrix} 6 \\ 1 \end{bmatrix}$$



Left multiplication

Theorem 2.15:

Let **A** be an $m \times n$ matrix with entries from F.

Then, the left-multiplication transformation $L_A: F^n \to F^m$ is linear.

Furthermore, if **B** is any other $m \times n$ matrix and β and γ are the standard ordered bases for F^n and F^m , respectively,

(a)
$$[L_{\mathbf{A}}]^{\gamma}_{\beta} = \mathbf{A}$$

(b)
$$L_{\mathbf{A}} = L_{\mathbf{B}} \Leftrightarrow \mathbf{A} = \mathbf{B}$$

- (c) $L_{A+B} = L_A + L_B$ and $L_{aA} = aL_A$ for all $a \in F$
- (d) If $T: F^n \to F^m$ is linear, then there exists a unique $m \times n$ matrix \mathbf{C} such that $T = L_{\mathbf{C}}$ or $\mathbf{C} = [T]_{\beta}^{\gamma}$.
- (e) If **E** is an $n \times p$ matrix, then $L_{AE} = L_A L_E$
- (f) If m = n, then $L_{\mathbf{I}_n} = \mathbf{I}_{F^n}$



- Left multiplication
 - Proof) (a) $[L_{\mathbf{A}}]^{\gamma}_{\beta} = \mathbf{A}$
 - The *j*-th column of $[L_{\mathbf{A}}]_{\beta}^{\gamma}$
 - $L_{\mathbf{A}}(\mathbf{e}_j) = \mathbf{A}\mathbf{e}_j$
 - \Rightarrow The j-th column of A
 - ∴ Q.E.D.
 - Proof) (b) $L_{\mathbf{A}} = L_{\mathbf{B}} \Leftrightarrow \mathbf{A} = \mathbf{B}$
 - (⇒)
 - By (a), $\mathbf{A} = [L_{\mathbf{A}}]^{\gamma}_{\beta} = [L_{\mathbf{B}}]^{\gamma}_{\beta} = \mathbf{B}$
 - (⇐)
 - Trivial
 - ∴ Q.E.D.



- Left multiplication
 - Proof) (c) $L_{A+B} = L_A + L_B$ and $L_{aA} = aL_A$ for all $a \in F$
 - (Exercise)
 - Proof) (d) If $T: F^n \to F^m$ is linear, then there exists a unique $m \times n$ matrix \mathbf{C} such that $T = L_{\mathbf{C}}$ or $\mathbf{C} = [T]_{\mathcal{B}}^{\gamma}$.
 - By Theorem 2.14 and (a)
 - $[T(\mathbf{x})]_{\gamma} = [T]_{\beta}^{\gamma}[\mathbf{x}]_{\beta} = \mathbf{C}[\mathbf{x}]_{\beta} = [L_{\mathbf{C}}]_{\beta}^{\gamma}[\mathbf{x}]_{\beta}$
 - By (b), C is unique.
 - ∴ Q.E.D.



- Left multiplication
 - Proof) (e) If **E** is an $n \times p$ matrix, then $L_{AE} = L_A L_E$.
 - By Theorem 2.13,
 - $(\mathbf{AE})\mathbf{e}_{j} = \mathbf{A}(\mathbf{Ee}_{j})$
 - Then, $L_{AE}(\mathbf{e}_j) = (AE)\mathbf{e}_j = A(E\mathbf{e}_j) = L_A(E\mathbf{e}_j) = L_A(L_E(\mathbf{e}_j)) = (L_AL_B)(\mathbf{e}_j)$
 - ∴ Q.E.D.
 - Proof) (f) If m = n, then $L_{\mathbf{I}_n} = \mathbf{I}_{F^n}$
 - (Exercise)



Left multiplication

Theorem 2.16:

Let A, B and C be matrices such that A(BC) is defined. Then, (AB)C is also defined and A(BC) = (AB)C (associative)

- Proof)
 - By Theorem 2.15 (e),
 - $L_{A(BC)} = L_A L_{BC} = L_A L_B L_C = (L_A L_B) L_C = L_{AB} L_C = L_{(AB)C}$
 - By Theorem 2.15 (b),
 - A(BC) = (AB)C
 - ∴ Q.E.D.





Invertibility

Invertibility:

Let V and W be vector spaces.

Let $T: V \to W$ be linear.

A function $U: W \to V$ is said to be an inverse of T if $TU = I_W$ and $UT = I_V$.

If T has an inverse, then T is said to be invertible.

If T is invertible, then the inverse of T is unique and denoted by T^{-1} .

- Facts for invertible functions T and U
 - $(TU)^{-1} = U^{-1}T^{-1}$
 - $(T^{-1})^{-1} = T$
 - T^{-1} being invertible
 - $T: V \to W$ invertible \Leftrightarrow one-to-one and onto \Leftrightarrow rank $(T) = \dim(V)$
 - (Theorem 2.5)



Invertibility

- Example 2.4.1
 - Let $T: \mathbb{R}^2 \to \mathbb{R}^2$ be $T \left(\begin{bmatrix} a \\ b \end{bmatrix} \right) = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = \begin{bmatrix} a \\ a+b \end{bmatrix}$
 - Let $U: \mathbb{R}^2 \to \mathbb{R}^2$ be $U\left(\begin{bmatrix} c \\ d \end{bmatrix}\right) = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix} \begin{bmatrix} c \\ d \end{bmatrix} = \begin{bmatrix} c \\ -c + d \end{bmatrix}$
 - Then, $(TU) {c \brack d} = T \left(U {c \brack d} \right) = T \left(\begin{bmatrix} c \\ -c + d \end{bmatrix} \right) = \begin{bmatrix} c \\ d \end{bmatrix}$
 - $\Rightarrow TU = I_{\mathbb{R}^2}$
 - Then, $(UT) \left(\begin{bmatrix} a \\ b \end{bmatrix} \right) = U \left(T \left(\begin{bmatrix} a \\ b \end{bmatrix} \right) \right) = U \left(\begin{bmatrix} a \\ a+b \end{bmatrix} \right) = \begin{bmatrix} a \\ b \end{bmatrix}$
 - $\Rightarrow UT = I_{\mathbb{R}^2}$
 - $T^{-1} = U$ and $T^{-1} = T$



Invertibility

Theorem 2.17:

Let V and W be vector spaces. Let $T: V \to W$ be linear and invertible Then, $T^{-1}: W \to V$ is linear.

- Proof)
 - Let $y_1, y_2 \in W$ and $c \in F$.
 - T is invertible \Leftrightarrow T is onto and one-to-one
 - \Rightarrow There exist unique vectors \mathbf{x}_1 and \mathbf{x}_2 such that $T(\mathbf{x}_1) = \mathbf{y}_1$ and $T(\mathbf{x}_2) = \mathbf{y}_2$
 - $\Rightarrow T^{-1}(y_1) = x_1 \text{ and } T^{-1}(y_2) = x_2$
 - Then,

•
$$T^{-1}(c\mathbf{y}_1 + \mathbf{y}_2) = T^{-1}(cT(\mathbf{x}_1) + T(\mathbf{x}_2)) = T^{-1}(T(c\mathbf{x}_1 + \mathbf{x}_2)) = c\mathbf{x}_1 + \mathbf{x}_2 = cT^{-1}(\mathbf{y}_1) + T^{-1}(\mathbf{y}_2)$$

• ∴ Q.E.D.



Invertibility

Corollary 2.17.1:

Let V and W be vector spaces.

Let $T: V \to W$ be linear and invertible

Then, V is finite-dimensional \Leftrightarrow W is finite-dimensional.

In this case, $\dim(V) = \dim(W)$

- Proof) (V is finite-dimensional $\Rightarrow W$ is finite-dimensional)
 - Let $\beta = \{\mathbf{x}_1, \mathbf{x}_2, ..., \mathbf{x}_n\}$ be a basis for V.
 - By Theorem 2.2,
 - $\Rightarrow T(\beta)$ spans R(T).
 - Since T is onto, R(T) = W
 - $\Rightarrow T(\beta)$ spans W.
 - By Theorem 1.9,
 - $\Rightarrow W$ is finite-dimensional.



Invertibility

Corollary 2.17.1:

Let V and W be vector spaces.

Let $T: V \to W$ be linear and invertible

Then, V is finite-dimensional \Leftrightarrow W is finite-dimensional.

In this case, $\dim(V) = \dim(W)$

- Proof) (V is finite-dimensional $\leftarrow W$ is finite-dimensional)
 - Let $\gamma = \{\mathbf{y}_1, \mathbf{y}_2, ..., \mathbf{y}_m\}$ be a basis for W.
 - By Theorem 2.2,
 - $\Rightarrow T^{-1}(\gamma)$ spans $R(T^{-1})$.
 - Since T^{-1} is onto, $R(T^{-1}) = V$
 - $\Rightarrow T^{-1}(\gamma)$ spans V.
 - By Theorem 1.9,
 - ⇒ V is finite-dimensional.
 - ∴ Q.E.D.



Invertibility

Corollary 2.17.1:

Let *V* and *W* be vector spaces.

Let $T: V \to W$ be linear and invertible

Then, V is finite-dimensional \Leftrightarrow W is finite-dimensional.

In this case, $\dim(V) = \dim(W)$

- Proof) $(\dim(V) = \dim(W))$
 - Since T is one-to-one
 - \Rightarrow nullity(T) = 0
 - \Rightarrow rank $(T) = \dim(V)$
 - Since T is onto
 - \Rightarrow rank $(T) = \dim(W)$
 - $\therefore \dim(V) = \dim(W)$



- Invertibility
 - By Theorem 2.5, for a linear transformation *T* between vector spaces of equal finite dimension,
 - Invertible ⇔ one-to-one ⇔ onto



Invertibility

Invertible matrix:

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

Then, **A** is invertible if there exists an $n \times n$ matrix **B** such that $AB = BA = I_n$.

- Example 2.4.2
 - $\mathbf{A} = \begin{bmatrix} 5 & 7 \\ 2 & 3 \end{bmatrix}$
 - $\bullet \quad \mathbf{A}^{-1} = \begin{bmatrix} 3 & -7 \\ -2 & 5 \end{bmatrix}$
 - (Section 3.2 for more detail)



Invertibility

Theorem 2.18:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively.

For linear $T: V \to W$, T is invertible. $\Leftrightarrow [T]^{\gamma}_{\beta}$ is invertible.

Furthermore,

$$[T^{-1}]^{\beta}_{\gamma} = \left([T]^{\gamma}_{\beta} \right)^{-1}$$

- Proof) (T is invertible. \Rightarrow $[T]^{\gamma}_{\beta}$ is invertible.)
 - For invertible *T*, by Corollary 2.17.1,
 - $\dim(V) = \dim(W)$
 - Letting $n = \dim(V) = \dim(W)$, by Theorem 2.11,

•
$$\mathbf{I}_n = [I_V]_{\beta} = [T^{-1}T]_{\beta} = [T^{-1}]_{\gamma}^{\beta} [T]_{\beta}^{\gamma}$$

•
$$\mathbf{I}_n = [I_W]_{\gamma} = [TT^{-1}]_{\gamma} = [T]_{\beta}^{\gamma} [T^{-1}]_{\gamma}^{\beta}$$

•
$$\therefore \left([T]_{\beta}^{\gamma} \right)^{-1} = [T^{-1}]_{\gamma}^{\beta}$$



Invertibility

Theorem 2.18:

Let V and W be finite-dimensional vector spaces with ordered bases β and γ , respectively.

For linear $T: V \to W$, T is invertible. \Leftrightarrow $[T]^{\gamma}_{\beta}$ is invertible.

Furthermore,

$$[T^{-1}]_{\gamma}^{\beta} = \left([T]_{\beta}^{\gamma} \right)^{-1}$$

- Proof) (T is invertible. $\Leftarrow [T]^{\gamma}_{\beta}$ is invertible.)
 - Letting the inverse matrix $[U]_{\gamma}^{\beta} = [T]_{\beta}^{\gamma}$,
 - $[U]_{\gamma}^{\beta}[T]_{\beta}^{\gamma} = \mathbf{I}_n$ and $[T]_{\beta}^{\gamma}[U]_{\gamma}^{\beta} = \mathbf{I}_n$
 - By Theorem 2.11,
 - $[U]_{\gamma}^{\beta}[T]_{\beta}^{\gamma} = [UT]_{\beta} = \mathbf{I}_{n} = [I_{V}]_{\beta} \text{ and } [T]_{\beta}^{\gamma}[U]_{\gamma}^{\beta} = [TU]_{\gamma} = \mathbf{I}_{n} = [I_{W}]_{\gamma}$



Invertibility

- Example 2.4.3
 - Let $T, U: \mathbb{R}^2 \to \mathbb{R}^2$ be linear and $\beta = \{\mathbf{v}_1 = \mathbf{e}_1, \mathbf{v}_2 = \mathbf{e}_2\}$ for $V = \mathbb{R}^2$ and $\gamma = \{\mathbf{w}_1 = \mathbf{e}_1, \mathbf{w}_2 = \mathbf{e}_2\}$ for $W = \mathbb{R}^2$

• If
$$T\left(\begin{bmatrix} v_1 \\ v_2 \end{bmatrix}\right) = \begin{bmatrix} v_1 \\ v_1 + v_2 \end{bmatrix}$$

•
$$T(\mathbf{v}_1) = \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \mathbf{1} \cdot \mathbf{w}_1 + \mathbf{1} \cdot \mathbf{w}_2$$
 and $T(\mathbf{v}_2) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \mathbf{0} \cdot \mathbf{w}_1 + \mathbf{1} \cdot \mathbf{w}_2$

•
$$\Rightarrow [T]^{\gamma}_{\beta} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}$$

• If
$$U\left(\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}\right) = \begin{bmatrix} w_1 \\ -w_1 + w_2 \end{bmatrix}$$

•
$$U(\mathbf{w}_1) = \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \mathbf{1} \cdot \mathbf{w}_1 + (-1) \cdot \mathbf{w}_2$$
 and $U(\mathbf{w}_2) = \begin{bmatrix} 0 \\ 1 \end{bmatrix} = 0 \cdot \mathbf{w}_1 + 1 \cdot \mathbf{w}_2$

•
$$\Rightarrow [U]_{\gamma}^{\beta} = \begin{bmatrix} 1 & 0 \\ -1 & 1 \end{bmatrix}$$



Invertibility

- Example 2.4.3
 - Note that (Example 2.4.1)

•
$$(TU)\left(\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}\right) = T\left(U\left(\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}\right)\right) = T\left(\begin{bmatrix} w_1 \\ -w_1 + w_2 \end{bmatrix}\right) = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

•
$$\Rightarrow TU = I_{\mathbb{R}^2}$$

•
$$(UT)\left(\begin{bmatrix}v_1\\v_2\end{bmatrix}\right) = U\left(T\left(\begin{bmatrix}v_1\\v_2\end{bmatrix}\right)\right) = U\left(\begin{bmatrix}v_1\\v_1+v_2\end{bmatrix}\right) = \begin{bmatrix}v_1\\v_2\end{bmatrix}$$

•
$$\Rightarrow UT = I_{\mathbb{R}^2}$$

•
$$[T]^{\gamma}_{\beta}[U]^{\beta}_{\gamma} = \mathbf{I}_2$$

•
$$[U]_{\gamma}^{\beta}[T]_{\beta}^{\gamma} = \mathbf{I}_2$$

•
$$T^{-1} = U$$
 and $T^{-1} = T$

•
$$\therefore ([T]_{\beta}^{\gamma})^{-1} = [U]_{\gamma}^{\beta} = [T^{-1}]_{\gamma}^{\beta} \text{ and } ([U]_{\gamma}^{\beta})^{-1} = [T]_{\beta}^{\gamma} = [U^{-1}]_{\beta}^{\gamma}$$



Invertibility

Corollary 2.18.1:

Let V be a finite-dimensional vector space with an ordered bases β .

Let $T: V \to W$ be linear.

Then, T is invertible. \Leftrightarrow $[T]_{\beta}$ is invertible.

Furthermore,

$$[T^{-1}]_{\beta} = \left([T]_{\beta} \right)^{-1}$$



Invertibility

Corollary 2.18.2:

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

Then, T is invertible. \Leftrightarrow $L_{\mathbf{A}}$ is invertible.

Furthermore,

$$(L_{\mathbf{A}})^{-1} = L_{\mathbf{A}^{-1}}$$



Isomorphisms

Isomorphism:

Let V and W be vector spaces.

Then, V is isomorphic to W if there exists a linear transformation $T:V\to W$ that is invertible.

Such a linear transformation is called an isomorphism from V onto W.

- Example 2.4.4
 - $T: F^2 \to M_{2\times 1}(F)$

•
$$T\left(\begin{bmatrix}v_1\\v_2\end{bmatrix}\right) = \begin{bmatrix}v_1\\v_2\end{bmatrix}$$

• .: Invertible, isomorphism



Isomorphisms

Isomorphism:

Let V and W be vector spaces.

Then, V is isomorphic to W if there exists a linear transformation $T:V \to W$ that is invertible.

Such a linear transformation is called an isomorphism from V onto W.

Example 2.4.5

•
$$T: F^4 \to M_{2\times 2}(F)$$

• $T\begin{pmatrix} v_1 \\ v_2 \\ v_3 \\ v_4 \end{pmatrix} = \begin{bmatrix} v_1 & v_3 \\ v_2 & v_4 \end{bmatrix}$

• :: Invertible, isomorphism





Examples

• 1 Calculus

$$\int 2xe^{x^2}dx$$

• By a change of variable $u = x^2$, du = 2xdx

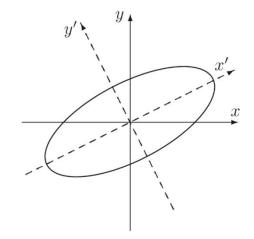
$$\int 2xe^{x^2} dx = \int e^u du = e^u + c = e^{x^2} + c$$

• ② Geometry

$$2x^2 - 4xy + 5y^2 = 1$$

• By change of variables,
$$\begin{cases} x = \frac{2}{\sqrt{5}}x' - \frac{1}{\sqrt{5}}y' \\ y = \frac{1}{\sqrt{5}}x' + \frac{2}{\sqrt{5}}y' \end{cases}$$

$$(x')^2 + 6(y')^2 = 1$$



- An x'y'-coordinate system with coordinate axes rotated from the original xy-coordinate axes
- $\beta = \{\mathbf{e}_1, \mathbf{e}_2\} \Rightarrow \beta' = \left\{\frac{1}{\sqrt{5}}\begin{bmatrix}2\\1\end{bmatrix}, \frac{1}{\sqrt{5}}\begin{bmatrix}-1\\2\end{bmatrix}\right\}$



Change of coordinates

Theorem 2.22:

Let β and β' be two ordered bases for a finite-dimensional vector space V. Let $\mathbf{Q} = [I_V]_{\beta'}^{\beta}$

- (a) **Q** is invertible.
- (b) For any $\mathbf{v} \in V$, $[\mathbf{v}]_{\beta} = \mathbf{Q}[\mathbf{v}]_{\beta'}$
- Proof)
 - (a) (Theorem 2.18)
 - (b)
 - For any $v \in V$, by Theorem 2.14,
 - $[\mathbf{v}]_{\beta} = [I_V]_{\beta} = [I_V]_{\beta'}^{\beta} [\mathbf{v}]_{\beta'} = \mathbf{Q}[\mathbf{v}]_{\beta'}$



Change of coordinates

• Example 2.5.1

• Let
$$\beta = \{ \mathbf{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \}$$
 and $\beta' = \{ \mathbf{w}_1 = \begin{bmatrix} 2 \\ 4 \end{bmatrix}, \mathbf{w}_2 = \begin{bmatrix} 3 \\ 1 \end{bmatrix} \}$

• If
$$I_V\left(\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}\right) = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

•
$$I_V(\mathbf{w}_1) = \begin{bmatrix} 2 \\ 4 \end{bmatrix} = 3 \cdot \mathbf{v}_1 + (-1) \cdot \mathbf{v}_2$$
 and $I_V(\mathbf{w}_2) = \begin{bmatrix} 3 \\ 1 \end{bmatrix} = 2 \cdot \mathbf{v}_1 + 1 \cdot \mathbf{v}_2$

•
$$\Rightarrow [I_V]_{\beta'}^{\beta} = \begin{bmatrix} 3 & 2 \\ -1 & 1 \end{bmatrix}$$

•
$$\therefore \mathbf{Q} = \begin{bmatrix} I_V \end{bmatrix}_{\beta'}^{\beta} = \begin{bmatrix} 3 & 2 \\ -1 & 1 \end{bmatrix}$$



- Linear operator
 - Mapping a vector space *V* into itself.



Linear operator

Theorem 2.23:

Let T be a linear operator on a finite-dimensional vector space V Let β and β' be ordered bases for V.

Suppose that \mathbf{Q} is the change of coordinate matrix that changes β' -coordinates into β -coordinates.

Then,

$$[T]_{\beta'} = \mathbf{Q}^{-1}[T]_{\beta}\mathbf{Q}$$

- Proof)
 - By Theorem 2.11,
 - $\mathbf{Q}[T]_{\beta'} = [I_V]_{\beta'}^{\beta}[T]_{\beta'}^{\beta'} = [I_V T]_{\beta'}^{\beta} = [TI_V]_{\beta'}^{\beta} = [T]_{\beta}^{\beta}[I_V]_{\beta'}^{\beta} = [T]_{\beta}\mathbf{Q}$
 - $\Rightarrow [T]_{\beta}$, $= \mathbf{Q}^{-1}[T]_{\beta}\mathbf{Q}$
 - ∴ Q.E.D.



Linear operator

• Example 2.5.2

• Let
$$\beta = \left\{ \mathbf{v}_1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{v}_2 = \begin{bmatrix} 1 \\ -1 \end{bmatrix} \right\}$$
 and $\beta' = \left\{ \mathbf{w}_1 = \begin{bmatrix} 2 \\ 4 \end{bmatrix}, \mathbf{w}_2 = \begin{bmatrix} 3 \\ 1 \end{bmatrix} \right\}$

• From Example 2.5.1,
$$\mathbf{Q} = \begin{bmatrix} 3 & 2 \\ -1 & 1 \end{bmatrix}$$
 and $\mathbf{Q}^{-1} = \frac{1}{5} \begin{bmatrix} 1 & -2 \\ 1 & 3 \end{bmatrix}$

• If
$$T\left(\begin{bmatrix} v_1 \\ v_2 \end{bmatrix}\right) = \begin{bmatrix} 3v_1 - v_2 \\ v_1 + 3v_2 \end{bmatrix}$$

•
$$T(\mathbf{v}_1) = \begin{bmatrix} 2 \\ 4 \end{bmatrix} = 3 \cdot \mathbf{v}_1 + (-1) \cdot \mathbf{v}_2$$
 and $T(\mathbf{v}_2) = \begin{bmatrix} 4 \\ -2 \end{bmatrix} = 1 \cdot \mathbf{v}_1 + 3 \cdot \mathbf{v}_2$

•
$$\Rightarrow [T]^{\beta}_{\beta} = [T]_{\beta} = \begin{bmatrix} 3 & 1 \\ -1 & 3 \end{bmatrix}$$

Also.

•
$$T(\mathbf{w}_1) = \begin{bmatrix} 2 \\ 14 \end{bmatrix} = 4 \cdot \mathbf{w}_1 + (-2) \cdot \mathbf{w}_2$$
 and $T(\mathbf{w}_2) = \begin{bmatrix} 8 \\ 6 \end{bmatrix} = 1 \cdot \mathbf{w}_1 + 2 \cdot \mathbf{w}_2$

•
$$\Rightarrow [T]_{\beta'}^{\beta'} = [T]_{\beta'} = \begin{bmatrix} 4 & 1 \\ -2 & 2 \end{bmatrix}$$

Then,

•
$$\mathbf{Q}^{-1}[T]_{\beta}\mathbf{Q} = \frac{1}{5}\begin{bmatrix} 1 & -2 \\ 1 & 3 \end{bmatrix}\begin{bmatrix} 3 & 1 \\ -1 & 3 \end{bmatrix}\begin{bmatrix} 3 & 2 \\ -1 & 1 \end{bmatrix} = \begin{bmatrix} 4 & 1 \\ -2 & 2 \end{bmatrix} = [T]_{\beta'}$$



Linear operator

• Example 2.5.3 (The reflection T about y = 2x)

•
$$T\left(\begin{bmatrix}1\\2\end{bmatrix}\right) = \begin{bmatrix}1\\2\end{bmatrix}$$
 and $T\left(\begin{bmatrix}-2\\1\end{bmatrix}\right) = \begin{bmatrix}2\\-1\end{bmatrix}$

• Let
$$\beta = \{ \mathbf{v}_1 = \mathbf{e}_1, \mathbf{v}_2 = \mathbf{e}_2 \}$$
 and $\beta' = \{ \mathbf{w}_1 = \begin{bmatrix} 1 \\ 2 \end{bmatrix}, \mathbf{w}_2 = \begin{bmatrix} -2 \\ 1 \end{bmatrix} \}$

•
$$T(\mathbf{w}_1) = \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \mathbf{1} \cdot \mathbf{w}_1 + \mathbf{0} \cdot \mathbf{w}_2$$
 and $T(\mathbf{w}_2) = \begin{bmatrix} 2 \\ -1 \end{bmatrix} = \mathbf{0} \cdot \mathbf{w}_1 + (-1) \cdot \mathbf{w}_2$

•
$$\Rightarrow [T]_{\beta'}^{\beta'} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

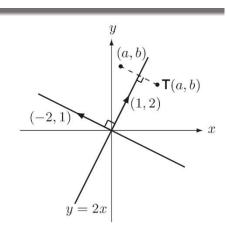
•
$$\Rightarrow [T]_{\beta'} = \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

• If
$$I_V\left(\begin{bmatrix} w_1 \\ w_2 \end{bmatrix}\right) = \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}$$

•
$$I_V(\mathbf{w}_1) = \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \mathbf{1} \cdot \mathbf{v}_1 + \mathbf{2} \cdot \mathbf{v}_2$$
 and $I_V(\mathbf{w}_2) = \begin{bmatrix} -2 \\ 1 \end{bmatrix} = (-2) \cdot \mathbf{v}_1 + 1 \cdot \mathbf{v}_2$

•
$$\Rightarrow [I_V]_{\beta'}^{\beta} = \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix}$$

•
$$\Rightarrow \mathbf{Q} = \begin{bmatrix} I_V \end{bmatrix}_{\beta'}^{\beta} = \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix}$$
 and $\mathbf{Q}^{-1} = \frac{1}{5} \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix}$



•
$$\mathbf{Q}[T]_{\beta'}\mathbf{Q}^{-1} = \begin{bmatrix} 1 & -2 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix} \frac{1}{5} \begin{bmatrix} 1 & 2 \\ -2 & 1 \end{bmatrix} = \frac{1}{5} \begin{bmatrix} -3 & 4 \\ 4 & 3 \end{bmatrix} = [T]_{\beta}$$



Linear operator

Similar matrices:

Let **A** and **B** be matrices in $M_{n\times n}(F)$.

We say that **B** is similar to **A** if there exists an invertible matrix **Q** such that $\mathbf{B} = \mathbf{Q}^{-1}\mathbf{A}\mathbf{Q}$

• $[T]_{\beta'}$ similar to $[T]_{\beta}$