

# Lecture 21

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## *Linear Transformation III*

**Instructor: Ruoyu Sun**



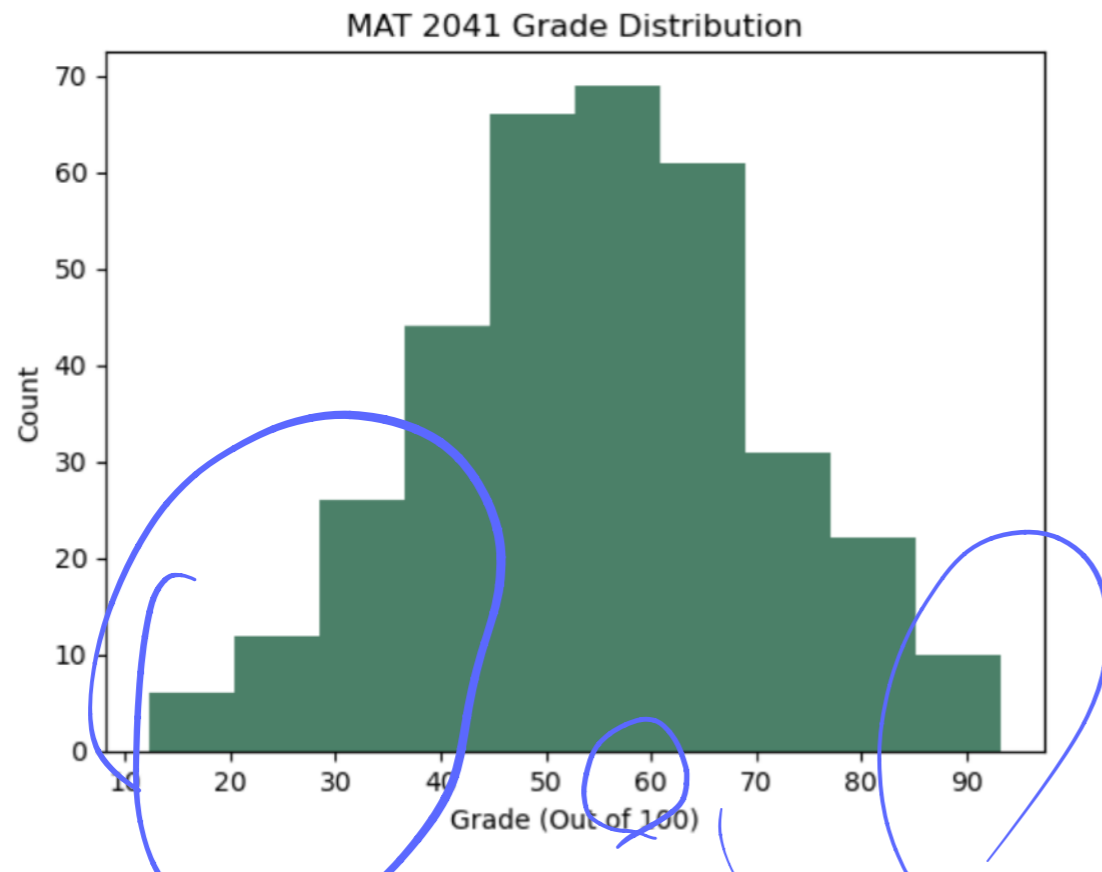
香港中文大學(深圳)

The Chinese University of Hong Kong, Shenzhen

数据科学学院

School of Data Science

# Logistics: Midterm Exam



final grade will be related to distribution

100-point system:

Average: 54.85/100

Medium: 55.56/100

Max: 93.3/100

Original (卷面):

Average: 49.3/90

Medium: 50/90

Max: 84/90

If you have difficulty, talk to me or the TA.

# Today's Lecture: Outline

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Main topic: Linear transformation II

1. View Matrix as Linear Transformation
2. Linear Transformation on General Linear Spaces
3. Matrix Representation of General Linear Transformation

Strang's book: Sec 8.1, 8.2

# Today's Lecture: Learning Goals

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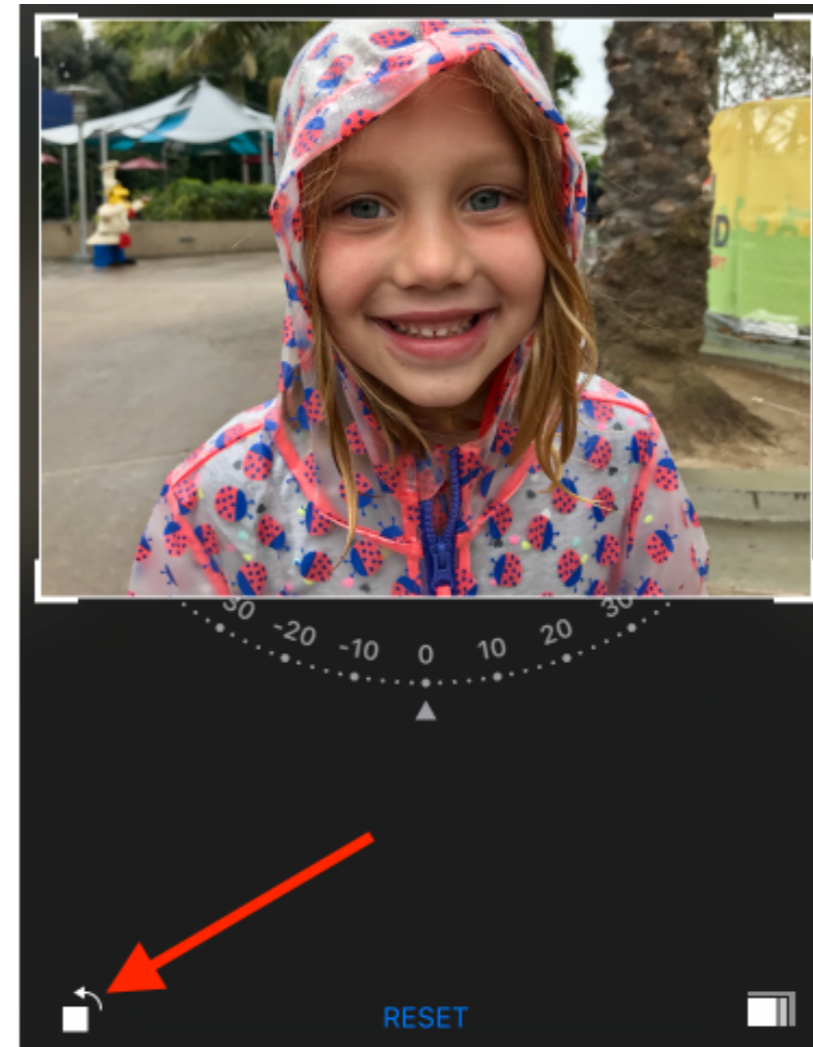
After the lecture, you should be able to

1. Tell the relation of linear transformation and matrix
2. Verify linear transformation and compute it for **general** linear spaces
3. Derive the matrix representation of general linear transformation

# Review

# Rotate Photos

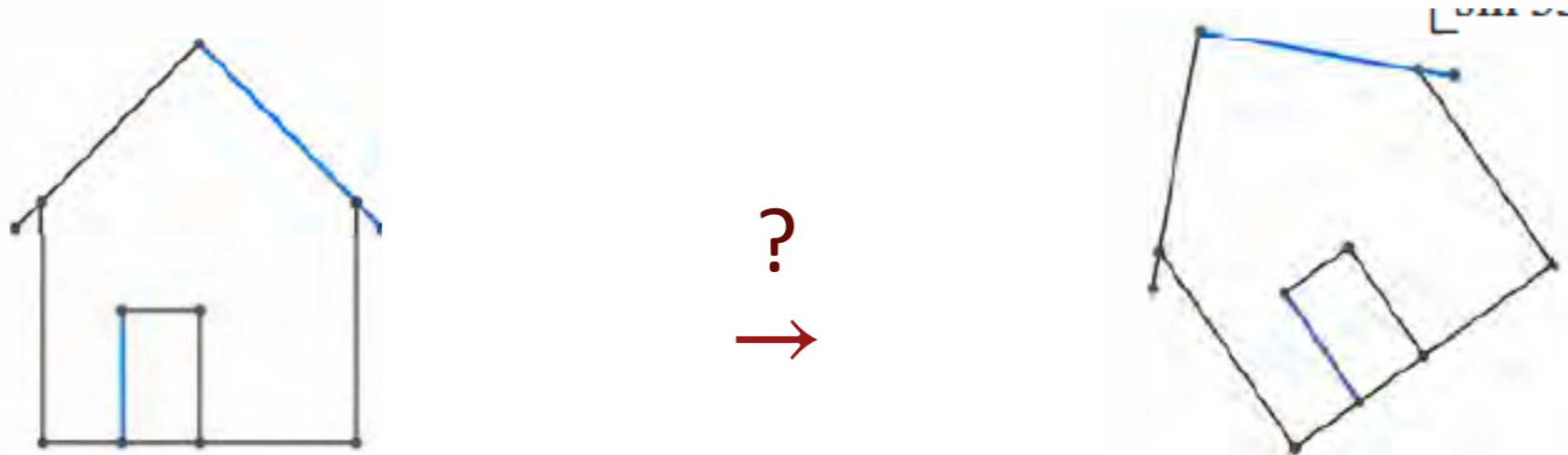
## How to rotate photos on iPhone



# Motivating Question

Yes, I know you can do it on the phones.

How do the phones accomplish the job?



**Question 1:** Is it a linear transformation?

**Question 2:** How do I derive its expression?

# Linear Transformation in Euclidean Space: Two Definitions

## Two equivalent definitions:

### Definition 19.1 (matrix form):

Suppose  $A \in \mathbb{R}^{m \times n}$  is a given real matrix.

$f(\mathbf{x}) = A\mathbf{x}$  is called a **linear transformation** from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ .

### Definition 20.1 (alternative definition of LT):

If a mapping  $f$  from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  satisfies

$$f(\alpha\mathbf{x} + \beta\mathbf{y}) = \alpha f(\mathbf{x}) + \beta f(\mathbf{y}), \quad \forall \alpha, \beta \in \mathbb{R}, \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n,$$

Then we say  $f$  is a **linear transformation** from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ .



# Why Equivalent

## Property 20.1 [Def 19.1 $\implies$ Def 20.1]

Suppose  $f: \mathbb{R}^n \rightarrow \mathbb{R}^m$  is defined as  $f(\mathbf{x}) = A\mathbf{x}$ , then

$$f(\alpha\mathbf{x} + \beta\mathbf{y}) = \alpha f(\mathbf{x}) + \beta f(\mathbf{y}), \quad \forall \alpha, \beta \in \mathbb{R}, \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n.$$

## Theorem 20.1 [Def 20.1 $\implies$ Def 19.1]

If a mapping  $f$  from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  satisfies

$$f(\alpha\mathbf{x} + \beta\mathbf{y}) = \alpha f(\mathbf{x}) + \beta f(\mathbf{y}), \quad \forall \alpha, \beta \in \mathbb{R}, \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n,$$

Then  $f(\mathbf{x}) = A\mathbf{x}$  for some matrix  $A$ .

# Computing Linear Transformation

$f$  is L.T.

## Algorithm 20.1

**Step 1:** Pick the standard basis  $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$  of  $\mathbb{R}^n$ .

**Step 2:** Compute  $f(\mathbf{e}_i) \in \mathbb{R}^m, \forall i$ .

**Step 3:** Form a matrix  $A = [f(\mathbf{e}_1), f(\mathbf{e}_2), \dots, f(\mathbf{e}_n)] \in \mathbb{R}^{m \times n}$

output of the basis of input.

**Conclusion:** For any  $\mathbf{x} \in \mathbb{R}^n$ , we have

$$f(\mathbf{x}) = \sum_i x_i f(\mathbf{e}_i) = A\mathbf{x}.$$

↓  
extend

$A$  is the matrix of the linear transformation  $f$ .

$A$

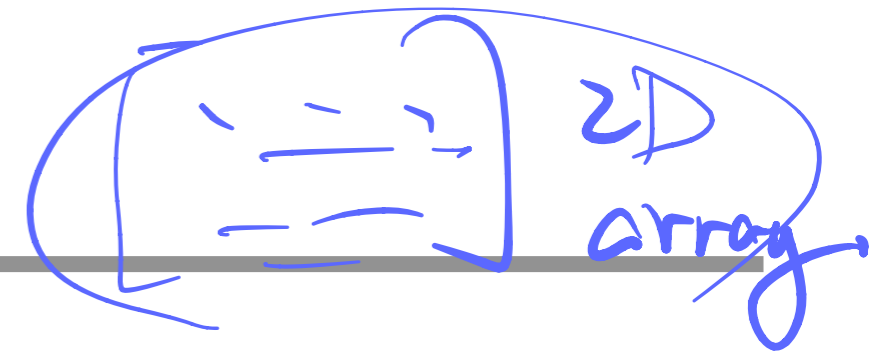
Any L.T.  $f$   $\xrightarrow{f}$   $\underline{f}$   
 $\downarrow$   
find matrix  $A$  .

Judgement: For any matrix  $A$ , can find  
linear transformation whose matrix is  $A$  .

Answer: True.  $f(x) = Ax$

# Part I View Matrix as Linear Transformation

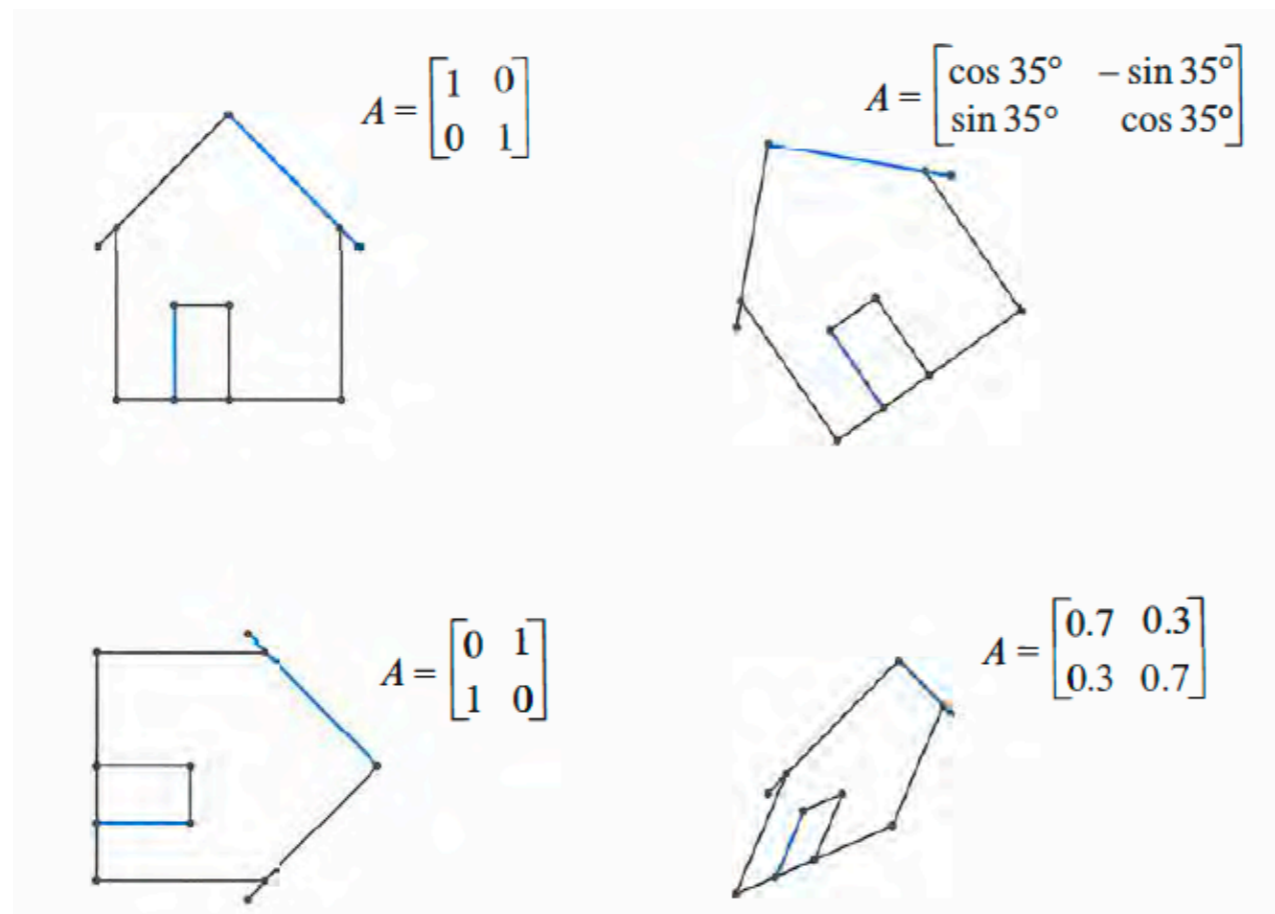
# Important New View of Matrix



**Previously:** Matrix is a representation of data. (e.g. image)

**New View:** Matrix  $\longleftrightarrow$  a linear transformation.

Columns of the matrix  $\longleftrightarrow$  transformed basis vectors.



# Transformation $\rightarrow$ Matrix

$$f(x) = Ax$$

Matrix  $A = \begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix} = [\vec{a}_1, \vec{a}_2]$

Multiplying  $A$ :  $e_1, e_2 \xrightarrow{A}$  Columns of  $A$ .

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

$A \cdot \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 3 \\ 1 \end{bmatrix}$  Column 2

$$\begin{bmatrix} 1 & 3 \\ 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 0 \end{bmatrix} \quad T(e_1)$$

$$= \begin{bmatrix} 1 \\ 2 \end{bmatrix} \cdot 1 + \begin{bmatrix} 3 \\ 1 \end{bmatrix} \cdot 0 \quad ||$$

$$= \begin{bmatrix} 1 \\ 2 \end{bmatrix} \quad \text{Column 1 of } A$$

Any vector  $\vec{x}$ :

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = x_1 \vec{e}_1 + x_2 \vec{e}_2 \xrightarrow{A} \vec{Ax}$$

$$x_1 \cdot \text{Column 1} + x_2 \cdot \text{Column 2}$$

$$x_1 \cdot T(e_1) + x_2 \cdot T(e_2)$$

Conclusion: Matrix  $A$  defines a linear transformation  $Ax$ .  
 It maps  $\vec{e}_1, \vec{e}_2$  to  $\vec{a}_1, \vec{a}_2$  (columns of  $A$ ).  $\rightarrow$  explain.


# Matrix $\rightarrow$ Transformation

Matrix  $\rightarrow$  a linear transformation.

Columns of the matrix  $\rightarrow$  transformed basis vectors.

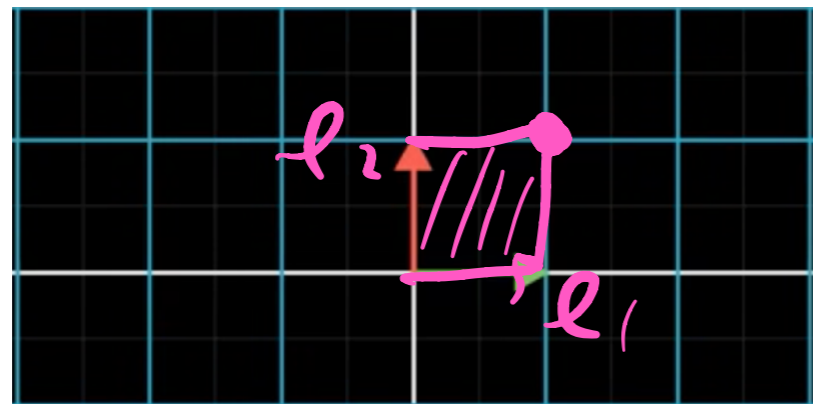
**Matrix A:**

*base*



1	3
2	1

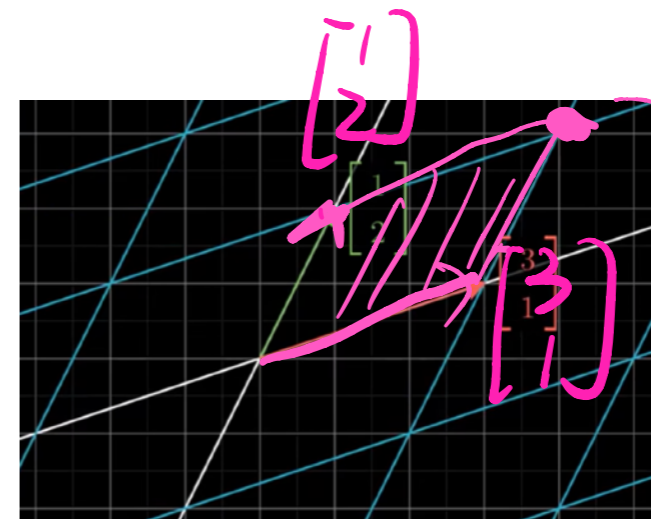
Linear transformation  $Ax$ :



Input space:

"Square tile"

*瓷磚*

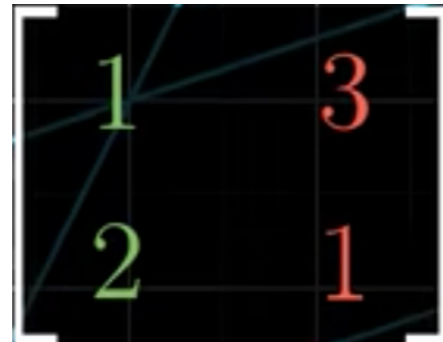


Output space:

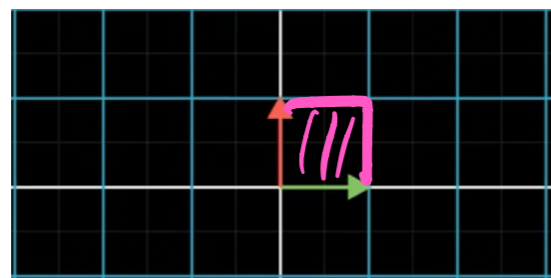
"Parallelogram tile"

# Determinant: Geometry Interpretation II

Matrix A:

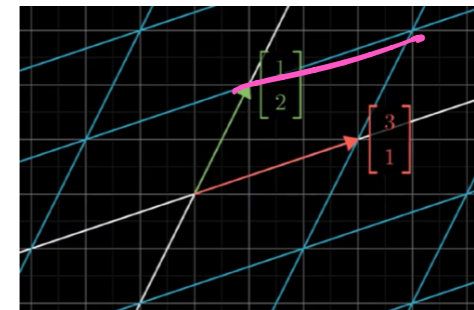


Linear transformation  $Ax$ :



Input space:  
"Square tile"

area 1



Output space:  
"Parallelogram tile"

area  $\det(A)$

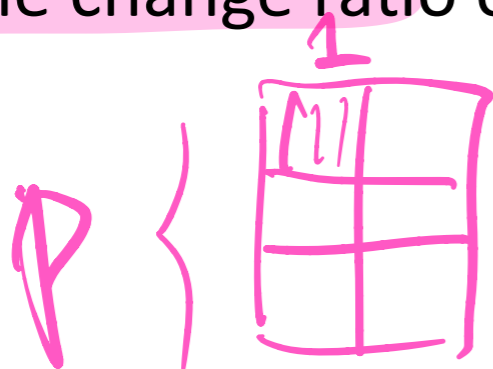
Lec 18: Area of  $\text{PARA}([a_1, a_2])$  is  $\det(A)$ .

Linear transformation perspective:

$$\det(A) = \text{area of } \text{PARA}([a_1, a_2])$$

= volume change ratio of linear transformation A

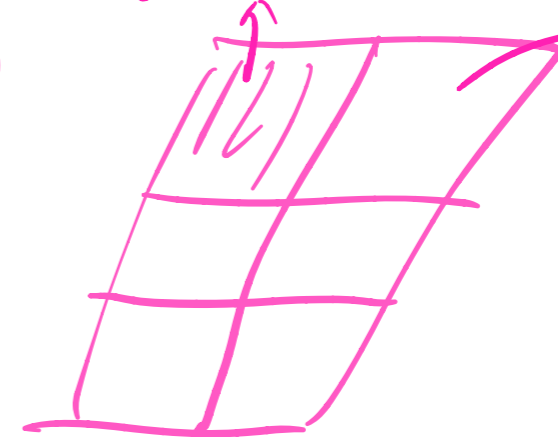
total area:



Volume change  
by  $\det(A)$  times



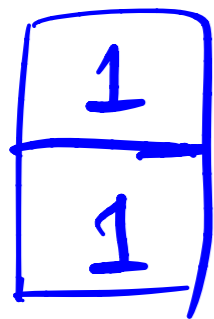
area  $\det(A)$



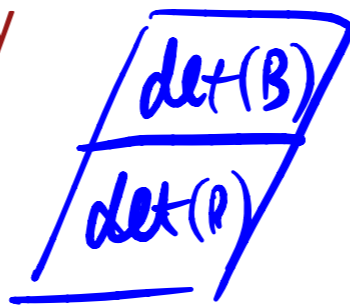
total area:  
 $p \det(A)$



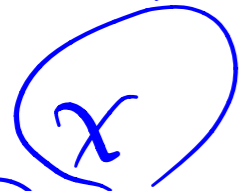
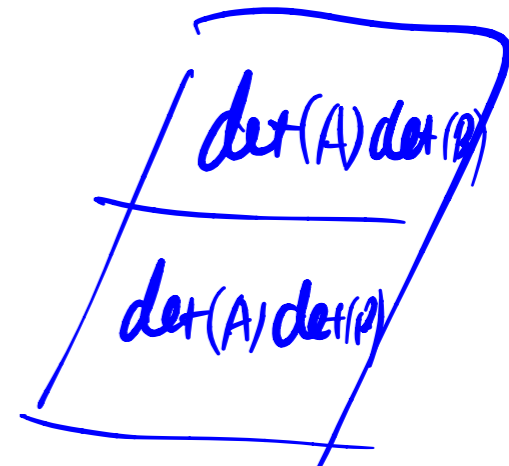
# Determinant: Geometry Interpretation II



Volume change by  $\det(B)$  times  
 →  
 Multiply B



Volume change by  $\det(A)$  times  
 →  
 Multiply A



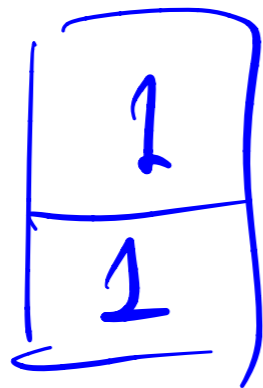
$Bx$



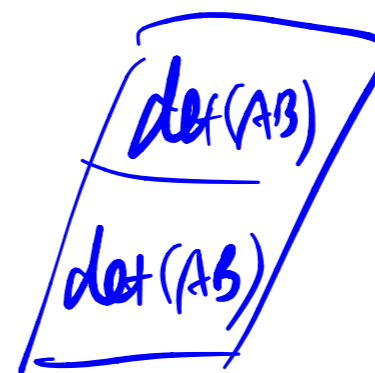
$A(Bx)$

Volume: ↑

Volume change by  $\det(AB)$  times  
 →  
 Multiply AB



$x$



$ABx$

Volume:  $\det(B) \det(A) \cdot P$

Volume:  $\det(AB) \cdot P$

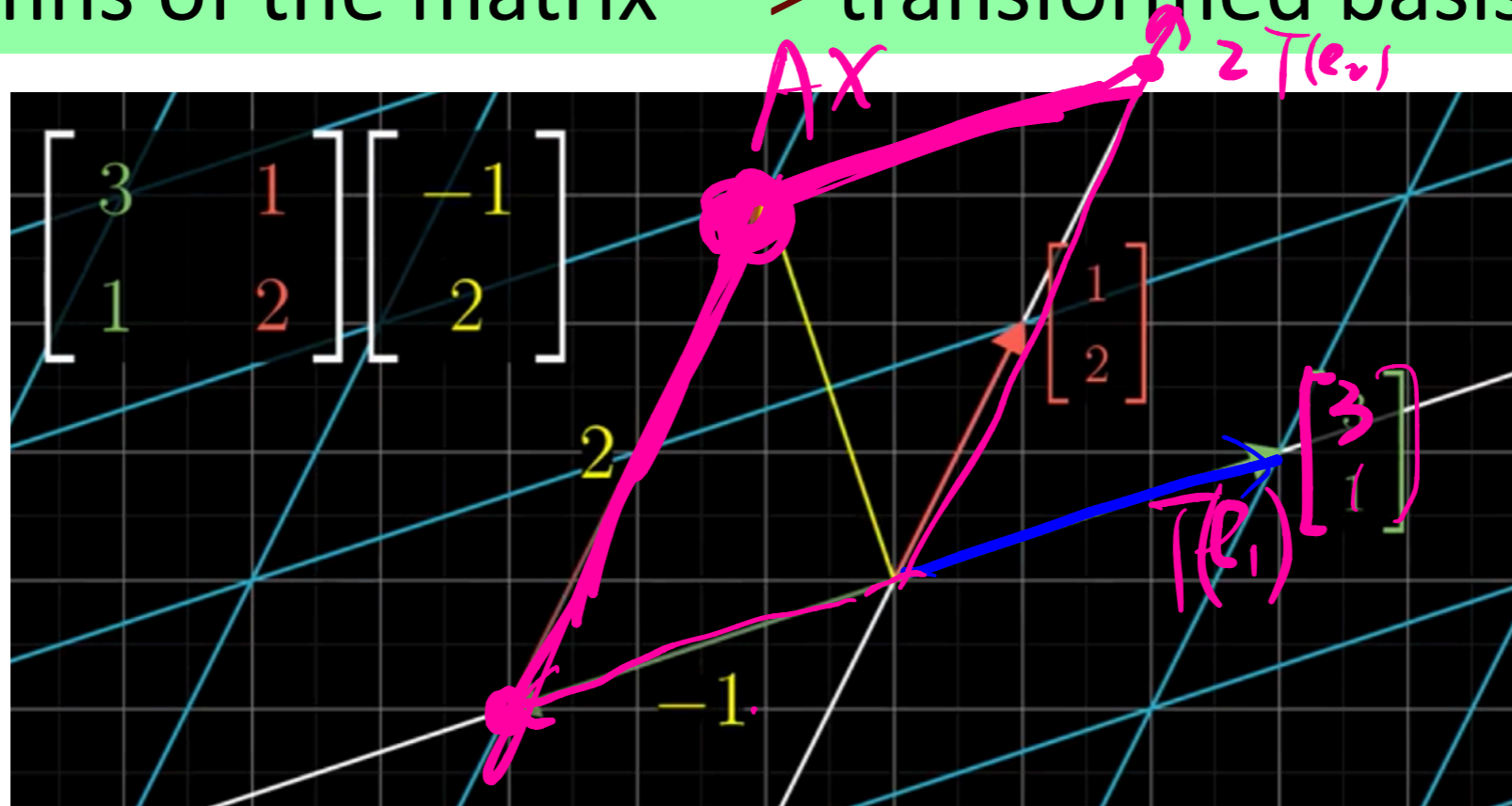
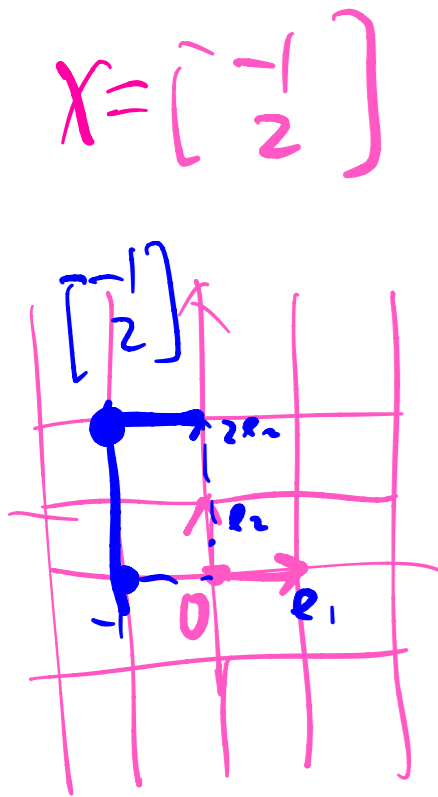
Volume: ↓

Geometrical proof of  $\det(AB) = \det(A) \det(B)$

# Matrix $\rightarrow$ Transformation: coordinate (坐标)

Matrix  $\rightarrow$  a linear transformation.

Columns of the matrix  $\rightarrow$  transformed basis vectors.



matrix A times vector (-1,2) gives a point with coordinate (-1,2) in the new system where basis is columns of A

# Matrix $\rightarrow$ Transformation: Dependent Columns

Matrix  $\rightarrow$  a linear transformation.

Dependent columns of the matrix

$\rightarrow$  transformed "basis vectors" are degenerate

$$T(e_1) \parallel T(e_2)$$

Matrix A:

$$\begin{bmatrix} 2 & -2 \\ 1 & -1 \end{bmatrix}$$

$$A: \mathbb{R}^2 \rightarrow \mathbb{R}^2$$

$$x \mapsto Ax$$

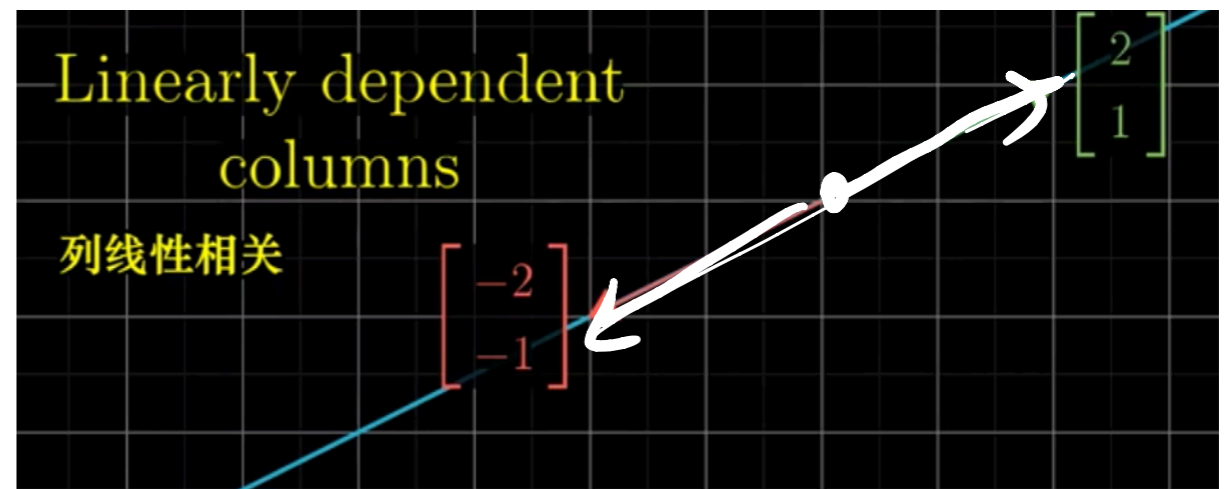
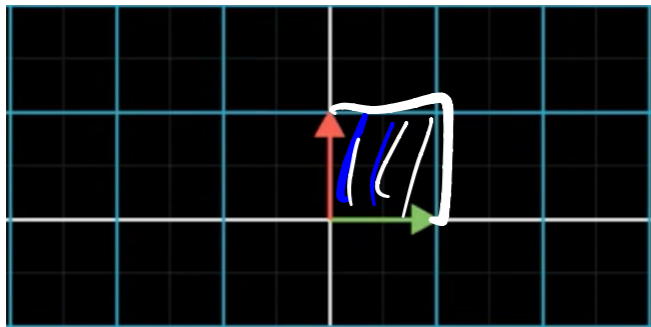
The set  $\{Ax: x \in \mathbb{R}^2\}$

= Column space of A

$$= \{\alpha \begin{bmatrix} 2 \\ 1 \end{bmatrix} + \beta \begin{bmatrix} -2 \\ -1 \end{bmatrix} : \alpha, \beta \in \mathbb{R}\} = \text{span} \left( \begin{bmatrix} 2 \\ 1 \end{bmatrix} \right)$$

$$T(e_1) = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \quad T(e_2) = \begin{bmatrix} -2 \\ -1 \end{bmatrix}$$

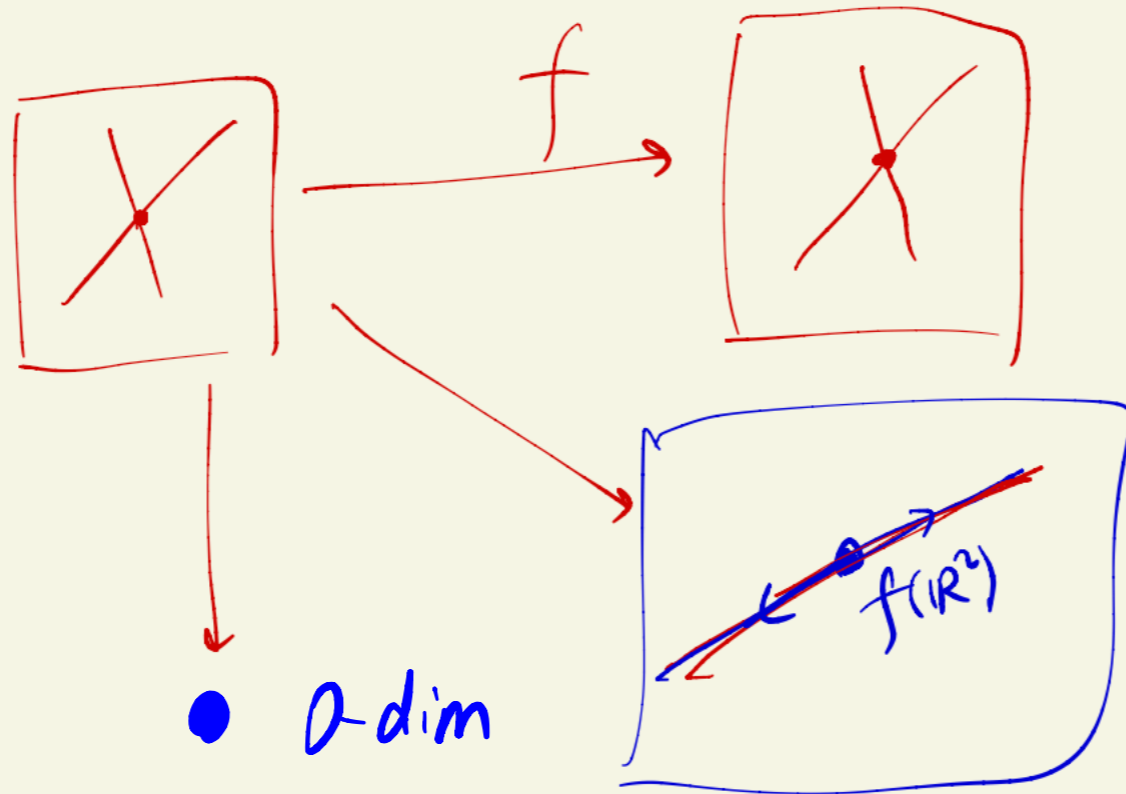
Linear transformation Ax:



# Three Cases of $f(\mathbb{R}^2) \stackrel{\circ}{=} \{f(x); x \in \mathbb{R}^2\} = C(A)$ .

Suppose  $f(x) = Ax$ .

$\{f(x); x \in \mathbb{R}^2\} \stackrel{\circ}{=} f(\mathbb{R}^2)$  can be  $\mathbb{R}^2$ , a line or  $\{0\}$ .  
column space of  $A$   
||



2D subspace in  $\mathbb{R}^2$   
( $= \mathbb{R}^2$ )

1D subspace in  $\mathbb{R}^2$   
(a line)

eg.  $A = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$ ,  $Ax = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \forall x$ .

Remark.  $\{0\}$  is 0-dimensional space.

## Exercise

**Judgement:** Suppose  $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$  is a standard basis of  $\mathbb{R}^n$ .

Suppose  $f(\mathbf{x}) = A\mathbf{x}$ , where  $A \in \mathbb{R}^{m \times n}$ .

Then  $f(\mathbf{e}_1), f(\mathbf{e}_2), \dots, f(\mathbf{e}_n) \in \mathbb{R}^{m \times 1}$  form a basis of  $\mathbb{R}^{m \times 1}$ .

False.

Counter-example:  $f(x) = \begin{bmatrix} 1 & z \\ 1 & 2 \end{bmatrix} x$ ,  $x \in \mathbb{R}^{2 \times 1}$ .

Then  $\{f(\mathbf{e}_1), f(\mathbf{e}_2)\} = \left\{ \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \begin{bmatrix} z \\ 2 \end{bmatrix} \right\}$

is not a basis of  $\mathbb{R}^{2 \times 1}$ .

# Example: Mapping to Higher-Dim Space

Lesson from this page;

The codomain of a linear transformation can have higher dimension than the dim of the domain

Note:

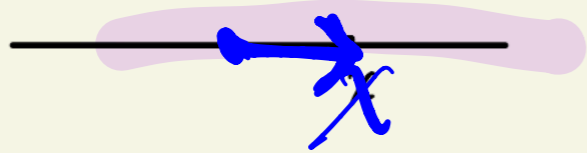
$$f: \mathbb{R}^n \rightarrow \mathbb{R}^m,$$

If  $n < m$ ,

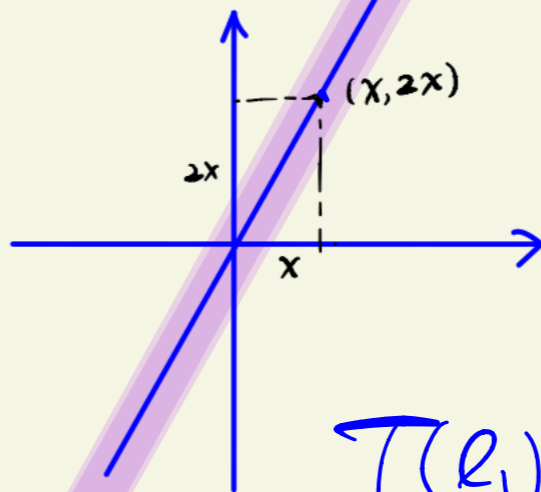
$f(\mathbb{R}^n)$  is a subspace of  $\mathbb{R}^m$ , NOT  $\mathbb{R}^m$ .

$$A = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \in \mathbb{R}^{2 \times 1}: \mathbb{R}^1 \rightarrow \mathbb{R}^2$$

$$A: \underset{\mathbb{R}^1}{x} \mapsto x \cdot \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} x \\ 2x \end{bmatrix}$$



$$e_1 = 1,$$



$$T(e_1) = \begin{bmatrix} 1 \\ 2 \end{bmatrix}$$

$$A: e_1 = 1 \mapsto \begin{bmatrix} 1 \\ 2 \end{bmatrix} = T(e_1)$$

$$A(\mathbb{R}^1) = \text{span}(Ae_1) = \text{subspace of } \mathbb{R}^2,$$

$$\underline{f(\mathbb{R}^1) \neq \mathbb{R}^2}$$

$$e_1 \rightarrow T(e_1)$$

# Wrap-Up: What We Learned So Far?

How to understand linear transformation?

Def.  $\Rightarrow T(\underbrace{x_1 e_1 + x_2 e_2}_x) = x_1 T(e_1) + x_2 T(e_2)$  (\*)

This definition (\*) has a few implications.

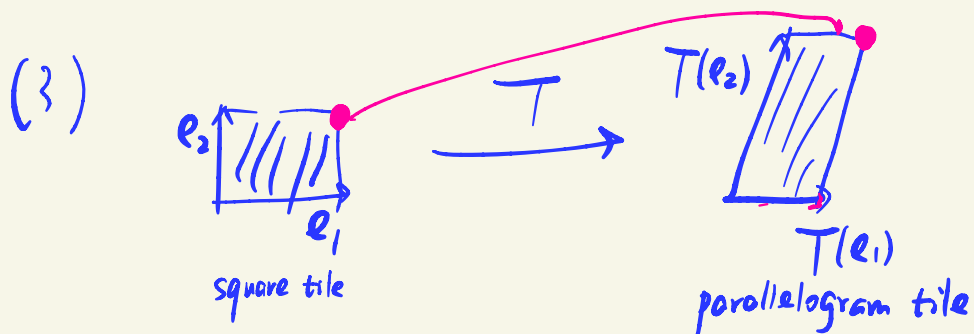
(1) Interpretation: If you know  $T(e_1), T(e_2)$  then you should know  $T(x), \forall x$ .

(2) coordinate  $(x_1, x_2) \longrightarrow$  coordinate  $(x_1, x_2)$

"basis"  $(e_1, e_2) \longrightarrow (T(e_1), T(e_2))$  [Remark:  $T(e_1), T(e_2)$  may be dependent, thus they are just spanning set of  $\{Tx : x \in \mathbb{R}^2\}$ .

This : coordinates stay, "basis" change  $\longrightarrow$  "tile change"

Today (Geometrical interpretation)



(4) One more corollary:  
When  $T(x) = Ax$ ,  
we have:  $T(e_1), T(e_2)$   
are columns of  $A$ .

# Part II Linear Transformation between Two Linear Spaces



# Linear Transformation for Any Linear Space

## Definition 21.1 (Linear Transformation)

Let  $V$  and  $W$  be two **linear spaces**.

A mapping  $L : V \rightarrow W$  is called a **linear transformation** if

$$L(\alpha v + \beta u) = \alpha L(v) + \beta L(u), \text{ for all } \alpha, \beta \in \mathbb{R}, \text{ and } v, u \in V.$$

$V$  is the **domain** of the linear transformation

$W$  is the **codomain** of the linear transformation

**Remark:** This is an extension of Def 20.1 from Euclidean spaces to any spaces.

# Linear Transformation for Any Linear Space

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**Remark:**

$$L(\alpha v + \beta w) = \alpha L(v) + \beta L(w)$$

for all  $\alpha, \beta \in \mathbb{R}, v, w \in V$

$\iff$

$$L(v + w) = L(v) + L(w)$$

$$L(\alpha v) = \alpha L(v)$$

for all  $\alpha \in \mathbb{R}, v, w \in V$ .

# Simple Examples on Matrix Space

Eg: Suppose  $X \in \mathbb{R}^{m \times n}$  is a matrix variable.

Then  $f(X) = 2X$  is a linear transformation from  $\mathbb{R}^{m \times n}$  to  $\mathbb{R}^{m \times n}$ .

$$\begin{array}{l} f(\alpha X) \stackrel{?}{=} \alpha f(X) \\ \parallel \\ 2(\alpha X) \stackrel{\checkmark}{=} \alpha \cdot 2X \end{array}$$

$$\begin{array}{l} f(X+Y) \stackrel{?}{=} f(X) + f(Y) \\ \parallel \\ 2(X+Y) \stackrel{\checkmark}{=} 2X + 2Y \\ \downarrow \\ \text{Scalar distrib} \end{array}$$

Eg: Suppose  $A \in \mathbb{R}^{k \times m}$  is fixed.  $X \in \mathbb{R}^{m \times n}$  is a matrix variable.

Then  $f(X) = AX$  is a linear transformation from  $\mathbb{R}^{m \times n}$  to  $\mathbb{R}^{k \times n}$ .

$$\begin{array}{l} f(\alpha X) \stackrel{?}{=} \alpha f(X) \\ \parallel \\ A(\alpha X) = \alpha \cdot (AX) \\ \downarrow \quad \downarrow \\ \text{scalar} \quad \text{scalar} \end{array}$$

$$\begin{array}{l} f(X+Y) \stackrel{?}{=} f(X) + f(Y) \\ \parallel \\ A(X+Y) = AX + AY \\ \downarrow \\ \text{matrix distributive rule} \end{array}$$

# Examples or Non-Examples on Matrix Space

Exercise: Is "inverse" a linear transformation?

$$X: \mathbb{R}^{n \times n} \quad X^{-1}: \mathbb{R}^{n \times n}$$

Suppose  $X \in \mathbb{R}^{n \times n}$  is a matrix variable.

Then  $f(X) = X^{-1}$  is NOT a linear transformation.

Reason 1.  $X^{-1}$  NOT defined for every matrix  $X$ .

Reason 2.  $(X+Y)^{-1} \neq X^{-1} + Y^{-1}$       $\frac{1}{x+y} \neq \frac{1}{x} + \frac{1}{y}$

Exercise: Is "transpose" a linear transformation?

Suppose  $X \in \mathbb{R}^{m \times n}$  is a matrix variable.

$$\mathbb{R}^{m \times n} \rightarrow \mathbb{R}^{n \times m}$$

Then  $f(X) = X^T$  is a linear transformation.

$$f(X+Y) = (X+Y)^T = X^T + Y^T = f(X) + f(Y)$$

$$f(\alpha X) = (\alpha \cdot X)^T = X^T \cdot \alpha^T = \underset{\substack{\downarrow \\ \text{scalar}}}{\alpha} \cdot X^T = \alpha f(X)$$

# Examples on Polynomial Space

## Example

Let  $T : P_3 \rightarrow \mathbb{R}^{2 \times 2}$  be a mapping defined as:

$$T(ax^3 + bx^2 + cx + d) = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

Is this  $L$  a linear transformation?

For any  $\alpha \in \mathbb{R}$ ,  $f, g \in P_3$ ,

Suppose  $f(x) = \sum_{i=0}^3 a_i x^i$ ,  $g(x) = \sum_{i=0}^3 b_i x^i$ ,

Then  $(f+g)(x) = \sum_{i=0}^3 (a_i + b_i) x^i \rightarrow$  poly-addition

$$L(f+g) = \begin{bmatrix} a_3 + b_3 & a_2 + b_2 \\ a_1 + b_1 & a_0 + b_0 \end{bmatrix} \Rightarrow \begin{bmatrix} a_3 & a_2 \\ a_1 & a_0 \end{bmatrix} + \begin{bmatrix} b_3 & b_2 \\ b_1 & b_0 \end{bmatrix} = L(f) + L(g)$$

$\downarrow$  matrix addition

$$L(\alpha f) = \begin{bmatrix} \alpha \cdot a_3 & \alpha \cdot a_2 \\ \alpha \cdot a_1 & \alpha \cdot a_0 \end{bmatrix} = \alpha \cdot \begin{bmatrix} a_3 & a_2 \\ a_1 & a_0 \end{bmatrix} = \alpha L(f)$$

scalar times poly

scalar times matrix

求导.

# Is Differentiation a Linear Transformation?

Eg: Is  $T(u) = \frac{du}{dx}$  is a linear transformation?

$$T(f) = f'$$

Reminder of notation: e.g. If  $u(x) = x^2$ , then  $\frac{du}{dx} = 2x$ .

Check:

$$T(\alpha u) \stackrel{?}{=} \alpha T(u)$$

$$(\alpha \cdot u)' = \alpha \cdot u'$$

$$T(u+v) \stackrel{?}{=} T(u) + T(v) ?$$

$$(u+v)' = u' + v'$$

e.g.  $(\sin x + e^x)'$

$$= (\sin x)' + (e^x)'$$

$$= \cos x + e^x$$

$$T(f) = f'$$

$$T(x^2) = 2x$$

$$x^2 \mapsto 2x$$

$$\sin x \mapsto \cos x$$

$$e^x \mapsto e^x$$

$$T(\sin(x)) = \cos(x)$$

$$T(e^x) = e^x$$

# Domain Shall be Linear Space

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Eg: Is  $T(u) = \frac{du}{dx}$  is a linear transformation?

**Definition 20.1** (Linear Transformation)

□ Let  $V$  and  $W$  be two **linear spaces**. □

A mapping  $L : V \rightarrow W$  is called a **linear transformation** if

**Notice:**  $T$  is not defined for all functions.

Need to specify a **linear space** s.t.  **$T$  is defined!**

# Function Space

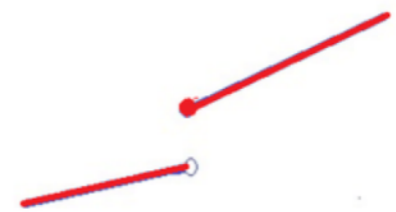
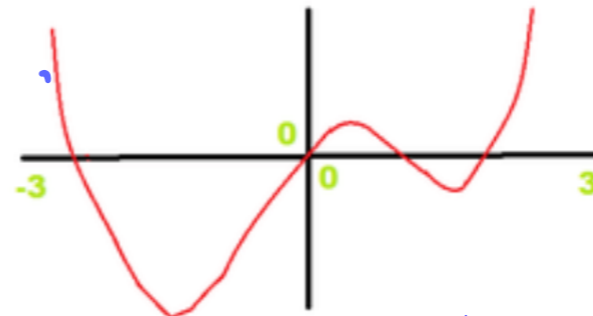
Continuous function space  $C(\mathbb{R})$ : The set of continuous functions form a linear space. (equipped with "function addition" and "scalar-function product")

Recall: Definition of two operations:

$$(f+g)(x) = \text{value at } x = f(x)+g(x)$$

$$(\alpha f)(x) = \text{value at } x = \alpha \cdot f(x)$$

Need to show: These operations satisfy 8 axioms of Definition of linear space. [skipped here]

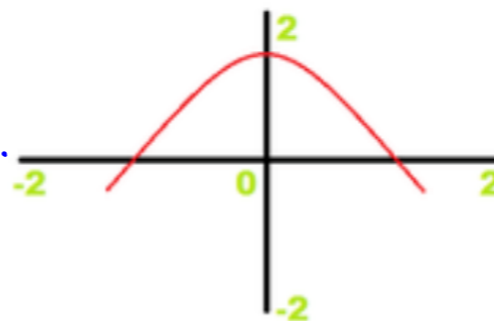


Continuously differentiable function space  $C^1(\mathbb{R})$ : a linear space.

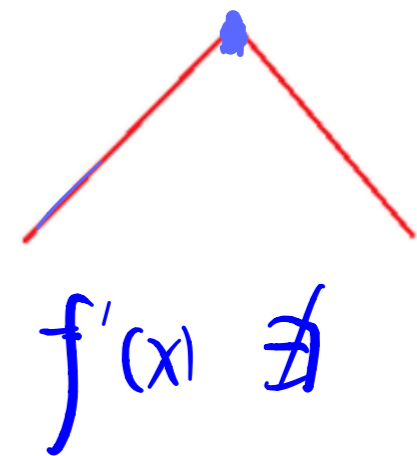
set of functions whose derivative exists and is continuous function.

$$\stackrel{\Delta}{=} \{f: \mathbb{R} \rightarrow \mathbb{R} \mid f'(x) \exists \text{ and } f'(x) \text{ is a continuous function}\}$$

Doesn't have a sharp corner



Having the sharp curve



Need to verify the axioms.

Skip details here.



# Differentiation is Linear Transformation

**Claim:**  $T(u) = \frac{du}{dx}$  defined on  $C^1(\mathbb{R})$  is a mapping from  $C^1(\mathbb{R})$  to  $C(\mathbb{R})$ .

It is a linear transformation.

$$T: C^1(\mathbb{R}) \rightarrow C(\mathbb{R})$$
$$f(x) \mapsto \frac{df}{dx}$$

Proof Sketch: ① Input space  $C^1(\mathbb{R})$ , output space are both linear spaces.

②  $T$  is well-defined on  $C^1(\mathbb{R})$ , ③  $T(\alpha f + \beta g) = \alpha T(f) + \beta T(g)$ ,  
 $\forall \alpha, \beta \in \mathbb{R}, f, g \in C^1(\mathbb{R})$ .

**Claim:**  $T(u) = \frac{du}{dx}$  defined on  $P_3$  is a mapping from  $P_3$  to  $P_2$ .

It is a linear transformation. [skip proof]

$$ax^3 + bx^2 + cx + d$$

$\downarrow T$

$$3ax^2 + 2bx + c$$

$$T: P_3 \rightarrow P_2$$

$$ax^3 + bx^2 + cx + d \xrightarrow{\text{differentiate}} 3ax^2 + 2bx + c$$

# Part III Matrix Representation of Linear Transformation for Any Linear Spaces

# Recall: Two Definitions

## Euclidean Space

### Definition 19.1 (matrix form):

Suppose  $A \in \mathbb{R}^{m \times n}$  is a given real matrix.

$f(\mathbf{x}) = A\mathbf{x}$  is called a **linear transformation** from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ .

Matrix

### Definition 20.1 (alternative definition of LT):

If a mapping  $f$  from  $\mathbb{R}^n$  to  $\mathbb{R}^m$  satisfies

$$f(\alpha\mathbf{x} + \beta\mathbf{y}) = \alpha f(\mathbf{x}) + \beta f(\mathbf{y}), \quad \forall \alpha, \beta \in \mathbb{R}, \forall \mathbf{x}, \mathbf{y} \in \mathbb{R}^n,$$

Then we say  $f$  is a **linear transformation** from  $\mathbb{R}^n$  to  $\mathbb{R}^m$ .

S.P.

## General Space

Matrix

### Definition 21.2 (Linear Transformation)

Let  $V$  and  $W$  be two **linear spaces**.

A mapping  $L : V \rightarrow W$  is called a **linear transformation** if

$$L(\alpha v + \beta u) = \alpha L(v) + \beta L(u), \text{ for all } \alpha, \beta \in \mathbb{R}, \text{ and } v, u \in V..$$

extend

# Matrix Representation of Differentiation

$T(u) = \frac{du}{dx}$  defined on  $P_3$  is a linear transformation from  $P_3$  to  $P_2$ .

Is  $T$  related to a matrix?

Try to apply Algorithm 20.1?

**FUNCTIONS**

## Algorithm 20.1

**Step 1:** Pick the standard basis  $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$  of  $\mathbb{R}^n$ .

**Step 2:** Compute  $f(\mathbf{e}_i) \in \mathbb{R}^m, \forall i$ .

**Step 3:** Form  $A = [f(\mathbf{e}_1), f(\mathbf{e}_2), \dots, f(\mathbf{e}_n)] \in \mathbb{R}^{m \times n}$

**Conclusion:** For any  $\mathbf{x} \in \mathbb{R}^n$ , we have

$$f(\mathbf{x}) = \sum_i x_i f(\mathbf{e}_i) = A\mathbf{x}.$$

But how to form a matrix, if no vectors?

$P_3$      $1, x, x^2, x^3$   
            $\parallel \parallel \parallel \parallel$   
            $\mathbf{e}_1, \mathbf{e}_2, \mathbf{e}_3, \mathbf{e}_4$

$[T(\mathbf{e}_1), T(\mathbf{e}_2), T(\mathbf{e}_3), T(\mathbf{e}_4)]$   
 $[1, 0, 2x, 3x^2]$

# Recall: Vector Representation of Linear Space

**Proposition** (Unique Representation via Basis)

$$\omega(f+g) = \omega(f) + \omega(g)$$

Let  $\mathcal{U} = \{v_1, \dots, v_n\}$  be a basis of a linear space  $X$ .

Any element  $x \in X$  can be **uniquely** represented as a linear combination of  $\{v_1, \dots, v_n\}$ .  
[discussed in a lecture before]

$\mathcal{P}_3$ : basis  $\{1, x, x^2, x^3\}$

$$f(x) = \underbrace{a_0 + a_1 x + a_2 x^2 + a_3 x^3}_{\text{functions}} = [1, x, x^2, x^3] \begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix}$$

coordinate

$$\begin{pmatrix} a_0 \\ a_1 \\ a_2 \\ a_3 \end{pmatrix} \begin{matrix} b_0 \\ b_1 \\ b_2 \\ b_3 \end{matrix}$$

# Matrix Representation

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$$X \longrightarrow Y$$

$$\underline{v_1} \mapsto \underline{T(v_1)}$$

$$\underline{v_2} \mapsto \underline{T(v_2)}$$

$$\underline{x = [v_1, v_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}} \mapsto y = \underline{T(x)} =$$

# Matrix Representation

$X \longrightarrow Y$     new basis of  $Y$ :  $\underline{u_1, u_2, u_3}$

$v_1 \mapsto T(v_1) = \underline{[u_1, u_2, u_3]} \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \end{bmatrix} = [u_1, u_2, u_3] \vec{a}_1$

$v_2 \mapsto T(v_2) = \underline{[u_1, u_2, u_3]} \begin{bmatrix} a_{12} \\ a_{22} \\ a_{32} \end{bmatrix} = [u_1, u_2, u_3] \cdot \vec{a}_2$

previous view: spanning set  $\{v_1, v_2\} \rightarrow \{T(v_1), T(v_2)\}$ .

but  $[T(v_1), T(v_2)]$  is NOT a matrix.

$x = \underline{[v_1, v_2]} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \mapsto y = T(x) = \underline{[T(v_1), T(v_2)]} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

old basis

express  $T(v_i)$  by basis  $\{u_1, u_2, u_3\}$ .

$\uparrow$   
 $\equiv [ (u_1, u_2, u_3) \vec{a}_1, (u_1, u_2, u_3) \vec{a}_2 ] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

split to get "matrix"

$\uparrow$   
 $\equiv \underline{(u_1, u_2, u_3)} [ \vec{a}_1, \vec{a}_2 ] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$

new basis.

# Relation to Part I

Last Page:

Any linear spaces:

$$\begin{array}{ccc} X & \xrightarrow{T} & Y \\ \downarrow & & \downarrow \\ \dim(X)=2 & & \dim(Y)=3. \end{array}$$

$$\begin{array}{ccc} \text{Basis:} & \{v_1, v_2\} & \{u_1, u_2, u_3\} \\ & x \mapsto & y \end{array}$$

$$x = [v_1, v_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\mapsto y = [u_1, u_2, u_3] [\vec{\alpha}_1, \vec{\alpha}_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

Part I.

Euclidean Spaces:

$$\begin{array}{ccc} \mathbb{R}^2 & \rightarrow & \mathbb{R}^3 \\ X = \mathbb{R}^2 & & Y = \mathbb{R}^3 \end{array}$$

$$\begin{array}{ccc} \text{Basis:} & \{e_1, e_2\} & \{\eta_1, \eta_2, \eta_3\} \\ & x \mapsto & y \end{array}$$

$$x = \underbrace{[e_1, e_2]}_{I_2} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\begin{aligned} \mapsto y &= \underbrace{[\eta_1, \eta_2, \eta_3]}_{I_3} [T(e_1), T(e_2)] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ &= [T(e_1), T(e_2)] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \end{aligned}$$

Lesson about relation of last page & Part I:

If we pick  $\{v_1, v_2\}, \{u_1, u_2, u_3\}$  as standard basis of  $\mathbb{R}^2$  &  $\mathbb{R}^3$ , then we get the derivation of Part I.

For general linear spaces, we have extra  $[v_1, v_2], [u_1, u_2, u_3]$ , to relate  $X, Y$  to Euclidean spaces.



# Expression for General Linear Space

## Computing $T(u)$ :

$u = c_1v_1 + c_2v_2 + \dots + c_nv_n$  must transform to

$$T(u) = c_1T(v_1) + c_2T(v_2) + \dots + c_nT(v_n)$$

Suppose you know  $T(v)$  for all vectors  $v_1, \dots, v_n$  in a basis  
Then you know  $T(u)$  for every vector  $u$  in the space.

## Matrix representation of $T$ :

$T(v_j)$  is a combination  $a_{j1}w_1 + \dots + a_{jn}w_n$  of the output basis for  $W$ .

The matrix  $(a_{ij})_{m \times n}$  is the matrix representation of  $T$ .

**Key rule:** The  $j$ th column of  $A$  is found by applying  $T$  to the  $j$ th basis vector  $v_j$

# Matrix Representation of T: Algorithm

Algorithm 21.1 (for general linear space)

**Step 1:** Pick a basis  $\{\mathbf{v}_1, \dots, \mathbf{v}_n\}$  of input space  $V$ .

**Step 2:** Compute  $f(\mathbf{v}_i) \in W, \forall i$ .

**Step 3:** Find vectors.

**Step 3.1:** Pick a basis  $\{\mathbf{u}_1, \dots, \mathbf{u}_m\}$  of output space  $W$ .

**Step 3.2:** Express  $f(\mathbf{v}_i) = \sum_{j=1}^m a_{ij} \mathbf{u}_j = [\mathbf{u}_1, \dots, \mathbf{u}_m] \begin{bmatrix} a_{i1} \\ \dots \\ a_{im} \end{bmatrix}$

**Step 4:** Form  $A = [\mathbf{a}_1, \dots, \mathbf{a}_n] \in \mathbb{R}^{m \times n}$

Remark: Once  $A$  is computed, it can be used to compute  $f(x)$  for any  $x$ .

**Step 5:** Compute  $y = f(x)$ , for any  $x \in V$ .

Step 5.1 Express  $x$  as  $x = \sum_{i=1}^n x_i \mathbf{v}_i$ .

Step 5.2 Compute  $\begin{pmatrix} y_1 \\ \vdots \\ y_m \end{pmatrix} = A \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$

Step 5.3 Compute  $y = \sum_{j=1}^m y_j \mathbf{u}_j$ .

[ Explain Step 5 ] .

# Diagram: View L.T. as Operating on Coordinates

If we know 'matrix A', how to compute  $f(x)$ ?

Basis:  $\{v_1, \dots, v_n\}$   $X \longrightarrow Y$  Basis:  $\{u_1, u_2, \dots, u_m\}$ .

Original Space

$$x = \sum_{i=1}^n x_i v_i$$

$$y = \sum_{j=1}^m y_j u_j$$

omit basis, coordinate

expression of y based on "coordinate"

Coordinate of x

Coordinate of  $y = T(x)$

$$(x_1, \dots, x_n) \xrightarrow{\text{multiply } A} (y_1, \dots, y_m) = A x$$

Euclidean space.

# Matrix Representation of Differentiation

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Problem 1. Consider  $T(u) = \frac{du}{dx} : P_2 \rightarrow P_1$ .

Find the matrix of  $T$  under the basis of input space  $\{1, x, x^2\}$   
and the basis of the output space  $\{1, x\}$ .

Method 1. (intuitive way).

$$T: ax^2 + bx + c \mapsto 2ax + b$$

Under the two bases, the coordinates are:

$$\vec{w} = [c, b, a]^T \mapsto \vec{z} = [b, 2a]^T \stackrel{\text{want}}{=} A\vec{w}.$$

$$\text{Since } \begin{bmatrix} b \\ 2a \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} c \\ b \\ a \end{bmatrix}.$$

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

## Method 2 (Use Algorithm 2.1.1)

We compute the representation of  $T(v_1), T(v_2)$   
under the basis of  $P_1: \{1, x\}$

$$v_1 = 1, T(v_1) = 0 = [1, x] \begin{bmatrix} 0 \\ 0 \end{bmatrix}, \text{ under basis of } P_1, \text{ coordinate } \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$v_2 = x, T(v_2) = 1 = [1, x] \begin{bmatrix} 1 \\ 0 \end{bmatrix}, \text{ under basis of } P_1, \text{ coordinate } \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$v_3 = x^2, T(v_3) = 2x = [1, x] \begin{bmatrix} 0 \\ 2 \end{bmatrix}, \text{ under basis of } P_1, \text{ coordinate } \begin{bmatrix} 0 \\ 2 \end{bmatrix}$$

Combine three vectors, get matrix

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

## How to Use "Matrix" Form?

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Problem 2. Compute  $T(u) = \frac{du}{dx}$  for any  $u \in P_2$ .

Method 1 (classical way)

For any  $ax^2 + bx + c \in P_2$ ,

from calculus rule,  $T(ax^2 + bx + c) = 2ax + b$ .

Method 2. (matrix form)

For any  $f(x) = a + bx + cx^2 \in P_2$ ,

under basis  $\{1, x, x^2\}$ , its coordinate is  $[a, b, c]^T$ .

Compute  $A \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} b \\ 2c \end{bmatrix}$ .

Thus output  $T(f) = [1, x] \begin{bmatrix} b \\ 2c \end{bmatrix} = b + 2cx$ .  $\square$

Remark: Method 2 is more complicated than Method 1,  
thus not necessary for this specific example.

It serves as an illustration of Algorithm 21.1, and help you understand better what "differentiation" is from a different angle.

# Matrix Representation of Differentiation

$T(u) = \frac{du}{dx}$  defined on  $P_2$  is a linear transformation from  $P_2$  to  $P_1$ .

Is  $T$  related to a matrix?

Answer.

Under the basis of input space  $\{1, x, x^2\}$   
and the basis of the output space  $\{1, x\}$ ,

$$A = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} = \text{matrix form of the derivative } T = \frac{d}{dx}.$$

**Input  $u$**   
 $a + bx + cx^2$

**Multiplication**  $Au = \begin{bmatrix} 0 & 1 & 0 \\ 0 & 0 & 2 \end{bmatrix} \begin{bmatrix} a \\ b \\ c \end{bmatrix} = \begin{bmatrix} b \\ 2c \end{bmatrix}$

**Output**  $\frac{du}{dx} = b + 2cx.$


## Exercise,

Problem.  $A = \begin{pmatrix} a & b \\ c & d \end{pmatrix} \in \mathbb{R}^{2 \times 2}$  is fixed.

Consider  $f(X) = AX - XA$ , where  $X \in \mathbb{R}^{2 \times 2}$ .

Prove  $f$  is a linear transformation,  
and find the matrix form of  $f$ .





# Summary Today (Write Your Own)

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**One sentence summary:**

**Detailed summary:**

# Summary Today (Write Your Own)

## One sentence summary:

We learned general linear transformation and how to “express” it.

## Detailed summary:

order

### Linear transformation view of matrix.

- Columns of a matrix are  $T(e_i)$ 's
- $\det(A) =$  volume change ratio of the transformation

### Linear transformation between two linear spaces.

- Define by superposition property.
- Differentiation is a linear transformation.
- **Matrix representation of general linear transformation:**
  - Step 1: Find the transformed input basis elements;
  - Step 2: Find their vector representations under output basis;
  - Step 3: Combine these vectors to get a matrix.