Linear Algebra 1

Industrial AI Lab.

Prof. Seungchul Lee

Linear Equations

- Set of linear equations (two equations, two unknowns)

$$4x_1 - 5x_2 = -13$$
$$-2x_1 + 3x_2 = 9$$

Linear Equations

- Solving linear equations
  - Two linear equations

$$4x_1 - 5x_2 = -13$$
$$-2x_1 + 3x_2 = 9$$

  - In a vector form, $Ax = b$, with

$$A = \begin{bmatrix} 4 & -5 \\ -2 & 3 \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad b = \begin{bmatrix} -13 \\ 9 \end{bmatrix}$$

Linear Equations

- Solving linear equations
  - Two linear equations

$$4x_1 - 5x_2 = -13$$
$$-2x_1 + 3x_2 = 9$$

  - In a vector form, $Ax = b$, with

$$A = \begin{bmatrix} 4 & -5 \\ -2 & 3 \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad b = \begin{bmatrix} -13 \\ 9 \end{bmatrix}$$

  - Solution using inverse

$$Ax = b$$
$$A^{-1}Ax = A^{-1}b$$
$$x = A^{-1}b$$

Linear Equations

- Solving linear equations
  - Two linear equations

$$4x_1 - 5x_2 = -13$$
$$-2x_1 + 3x_2 = 9$$

  - In a vector form, $Ax = b$, with

$$A = \begin{bmatrix} 4 & -5 \\ -2 & 3 \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad b = \begin{bmatrix} -13 \\ 9 \end{bmatrix}$$

  - Solution using inverse

$$Ax = b$$
$$A^{-1}Ax = A^{-1}b$$
$$x = A^{-1}b$$

  - Don't worry here about how to compute matrix inverse
  - We will use a numpy to compute

Linear Equations in Python

$$4x_1 - 5x_2 = -13$$
$$-2x_1 + 3x_2 = 9$$

$$A = \begin{bmatrix} 4 & -5 \\ -2 & 3 \end{bmatrix}, \quad x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}, \quad b = \begin{bmatrix} -13 \\ 9 \end{bmatrix}$$

```python
import numpy as np
```

```python
A = np.array([[4, -5],
              [-2, 3]])
b = np.array([[-13],
              [9]])

x = np.linalg.inv(A).dot(b)
print(x)
```

```
[[ 3.]
 [ 5.]]
```

```python
A = np.asmatrix(A)
b = np.asmatrix(b)

x = A.I*b
print(x)
```

```
[[ 3.]
 [ 5.]]
```

System of Linear Equations

- Consider a system of linear equations

$$y_1 = a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n$$
$$y_2 = a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n$$
$$\vdots$$
$$y_m = a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n$$

- Can be written in a matrix form as $y = Ax$, where

$$
y = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{bmatrix}
\qquad
A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}
\qquad
x = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}
$$

Elements of a Matrix

- Can write a matrix in terms of its columns

$$A = \begin{bmatrix} | & | & & | \\ a_1 & a_2 & \cdots & a_n \\ | & | & & | \end{bmatrix}$$

- Careful, a_i here corresponds to an entire vector $a_i \in \mathbb{R}^m$
- Similarly, can write a matrix in terms of rows

$$A = \begin{bmatrix} - & b_1^T & - \\ - & b_2^T & - \\ & \vdots & \\ - & b_m^T & - \end{bmatrix}$$

- $b_i \in \mathbb{R}^n$

Vector-Vector Products

- Inner product: $x, y \in \mathbb{R}^n$

$$x^T y = \sum_{i=1}^{n} x_i \, y_i \quad \in \mathbb{R}$$

```python
x = np.array([[1],
              [1]])
y = np.array([[2],
              [3]])

print(x.T.dot(y))
```
```
[[5]]
```

```python
x = np.asmatrix(x)
y = np.asmatrix(y)

print(x.T*y)
```
```
[[5]]
```

Matrix-Vector Products

- $A \in \mathbb{R}^{m \times n}, x \in \mathbb{R}^n \iff Ax \in \mathbb{R}^m$

- Writing A by rows, each entry of Ax is an *inner product* between x and a row of A

$$A = \begin{bmatrix} - & b_1^T & - \\ - & b_2^T & - \\ & \vdots & \\ - & b_m^T & - \end{bmatrix}, \qquad Ax \in \mathbb{R}^m = \begin{bmatrix} b_1^T x \\ b_2^T x \\ \vdots \\ b_m^T x \end{bmatrix}$$

Matrix-Vector Products

- $A \in \mathbb{R}^{m \times n}, x \in \mathbb{R}^n \iff Ax \in \mathbb{R}^m$

- Writing A by columns, Ax is a *linear combination* of the columns of A, with coefficients given by x

$$A = \begin{bmatrix} | & | & & | \\ a_1 & a_2 & \cdots & a_n \\ | & | & & | \end{bmatrix}, \qquad Ax \in \mathbb{R}^m = \sum_{i=1}^{n} a_i x_i$$

Symmetric Matrices

- Symmetric matrix:

$$A \in \mathbb{R}^{n \times n} \text{ with } A = A^T$$

- Arise naturally in many settings

- For $A \in \mathbb{R}^{m \times n}$,

$$A^T A \in \mathbb{R}^{n \times n} \text{ is symmetric}$$

Norms (Strength or Distance in Linear Space)

- A vector norm is any function $f: \mathbb{R}^n \implies \mathbb{R}$ with

  1. $f(x) \geq 0$ and $f(x) = 0 \iff x = 0$
  2. $f(ax) = |a|f(x)$ for $a \in \mathbb{R}$
  3. $f(x + y) \leq f(x) + f(y)$

- l_2 norm

$$\|x\|_2 = \sqrt{\sum_{i=1}^{n} x_i^2}$$

- l_1 norm

$$\|x\|_1 = \sum_{i=1}^{n} |x_i|$$

- $\|x\|$ measures length of vector (from origin)

Norms in Python

```python
x = np.array([[4],
              [3]])

np.linalg.norm(x, 2)
```

5.0

```python
np.linalg.norm(x, 1)
```

7.0

Orthogonality

- Two vectors $x, y \in \mathbb{R}^n$ are *orthogonal* if

$$x^T y = 0$$

- They are *orthonormal* if

$$x^T y = 0 \quad \text{and} \quad \|x\|_2 = \|y\|_2 = 1$$

Angle between Vectors

- For any $x, y \in \mathbb{R}^n$,
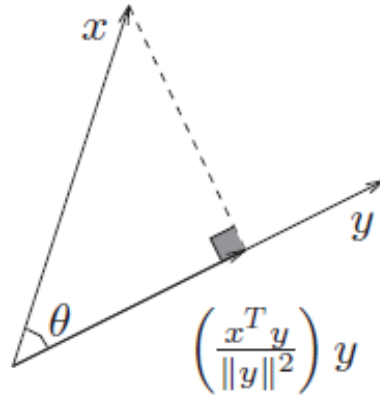
$$|x^T y| \leq \|x\| \, \|y\|$$

- (unsigned) angle between vectors in $\mathbb{R}^n$ defined as

$$\theta = \angle(x, y) = \cos^{-1} \frac{x^T y}{\|x\| \|y\|}$$

thus $x^T y = \|x\| \|y\| \cos \theta$

Angle between Vectors

$$\theta = \angle(x, y) = \cos^{-1} \frac{x^T y}{\|x\| \|y\|}$$
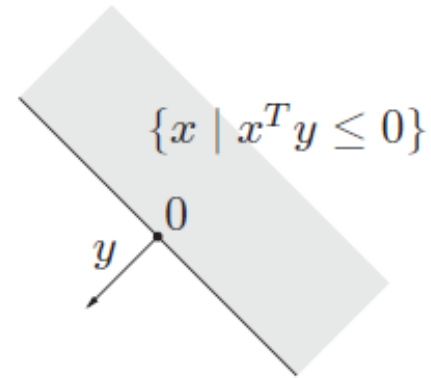
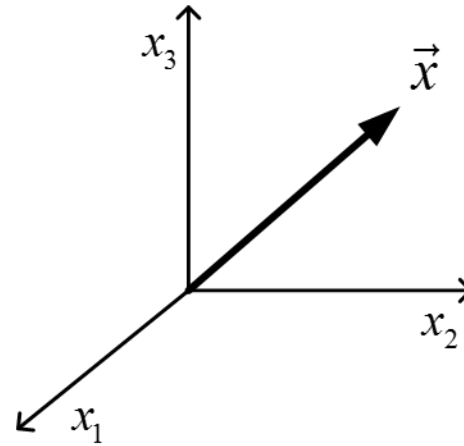- $\{x | x^T y \leq 0\}$ defines a half space with outward normal vector y, and boundary passing through 0

Linear Algebra 2

Industrial AI Lab.

Prof. Seungchul Lee

Vector

- Vector

$$\vec{x} = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

Matrix and (Linear) Transformation

$$M = \begin{bmatrix} m_{11} & m_{12} & m_{13} \\ m_{21} & m_{22} & m_{23} \\ m_{31} & m_{32} & m_{33} \end{bmatrix}$$

$$\vec{y} \quad = \quad M\vec{x}$$
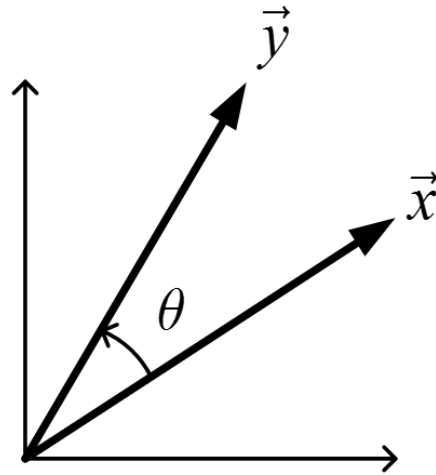
$$\begin{bmatrix} \; \\ \; \\ \; \end{bmatrix} = \begin{bmatrix} \; \\ \; \\ \; \end{bmatrix}\begin{bmatrix} \; \\ \; \\ \; \end{bmatrix}$$

Given		Interpret
linear transformation	$\longrightarrow$	matrix
matrix	$\longrightarrow$	linear transformation

$$\vec{x} \qquad \text{linear transformation} \qquad \vec{y}$$

$$\text{input} \qquad\qquad \Longrightarrow \qquad\qquad \text{output}$$
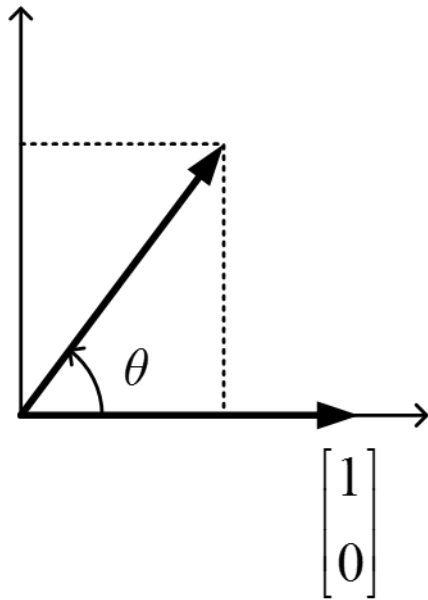
Rotation

- Is a rotation operation linear?

- Rotation matrix: $M = R(\theta)$
- Transformation: $\vec{y} = R(\theta)\vec{x}$

Rotation

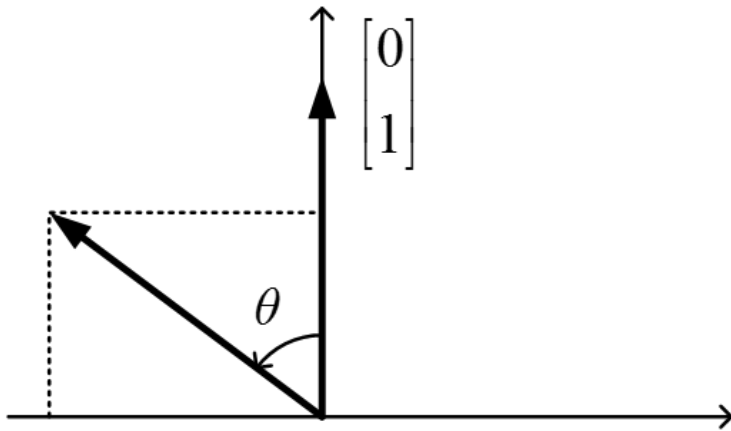- To find matrix $M = R(\theta)$

$$\vec{y} = R(\theta)\vec{x}$$

$$\begin{bmatrix} \cos(\theta) \\ \sin(\theta) \end{bmatrix} = R(\theta) \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

Rotation

- To find matrix $M = R(\theta)$

$$\vec{y} = R(\theta)\vec{x}$$

$$\begin{bmatrix} -\sin(\theta) \\ \cos(\theta) \end{bmatrix} = R(\theta) \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

Rotation

- To find matrix $M = R(\theta)$

$$M\vec{x}_1 = \vec{y}_1$$
$$M\vec{x}_2 = \vec{y}_2$$

$$\Longrightarrow \quad M \begin{bmatrix} \vec{x}_1 & \vec{x}_2 \end{bmatrix} = \begin{bmatrix} \vec{y}_1 & \vec{y}_2 \end{bmatrix}$$

$$\Longrightarrow \quad \begin{bmatrix} \cos(\theta) & -\sin(\theta) \\ \sin(\theta) & \cos(\theta) \end{bmatrix} = R(\theta) \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = R(\theta)$$

- Note on how to find a matrix from two vectors and their linearly-transformed ones
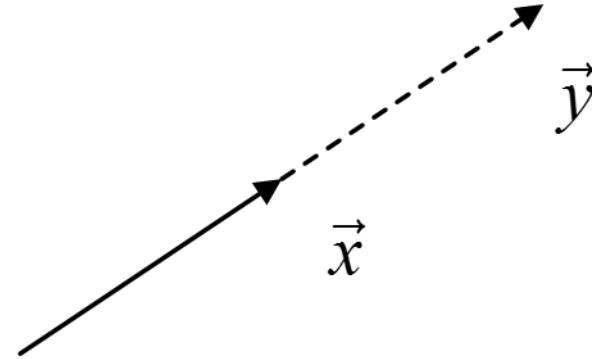
Stretch/Compress

- Stretch/Compress
  - keep the direction

$$\vec{y} = k\vec{x}$$

$$\uparrow$$

scalar (not matrix)

$$\vec{y} = kI\vec{x} \qquad \text{where } I = \text{ Identity martix}$$

$$\vec{y} = \begin{bmatrix} k & 0 \\ 0 & k \end{bmatrix} \vec{x}$$

- Still represented by a matrix

Stretch/Compress: Example

- T: stretch by a along $\hat{x}$-direction & stretch by b along $\hat{y}$-direction
- Compute the corresponding matrix A

$$\begin{bmatrix} ax_1 \\ bx_2 \end{bmatrix} = A \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \implies A = ?$$

$$= \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$A \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} a \\ 0 \end{bmatrix}$$

$$A \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ b \end{bmatrix}$$

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

- More importantly, can you think of the corresponding transformation T by looking at $A = \begin{bmatrix} a & 0 \\ 0 & b \end{bmatrix}$?

Projection

- Is a projection operation linear?

- Suppose P: Projection onto $\hat{x}$ - axis
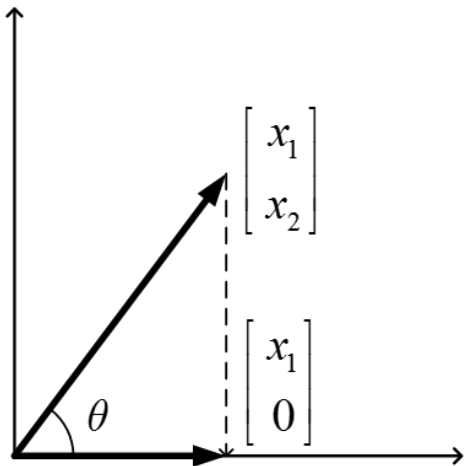
$$\begin{matrix} & P & \\ \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} & \implies & \begin{bmatrix} x_1 \\ 0 \end{bmatrix} \\ \vec{x} & & \vec{y} \end{matrix}$$

$$\vec{y} = P\vec{x} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} x_1 \\ 0 \end{bmatrix}$$

$$P \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$P \begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

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

Multiple Transformations

- T_1: transformation 1 of matrix M_1
- T_2: transformation 2 of matrix M_2
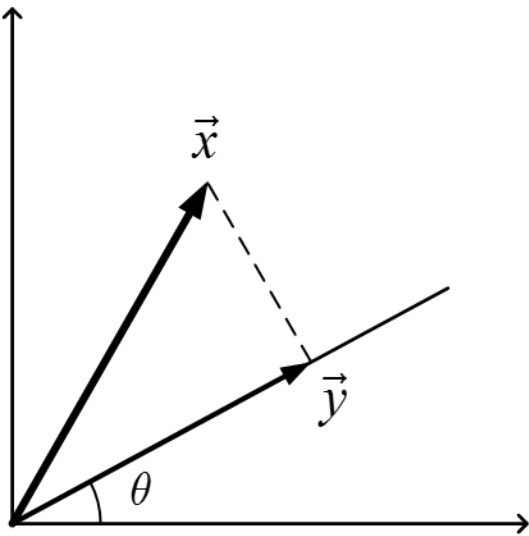- T : Do transformation 1, followed by transformation 2

$$\vec{x} \quad \overset{T_1}{\longrightarrow} \quad \vec{y} \quad \overset{T_2}{\longrightarrow} \quad \vec{z}$$

$$\vec{y} \ = M_1 \vec{x}$$
$$\vec{z} \ = M_2 \vec{y} \ = M_2 M_1 \vec{x}$$
$$= M \vec{x}$$

$$\therefore \ M = M_2 M_1$$
$$\longleftarrow$$

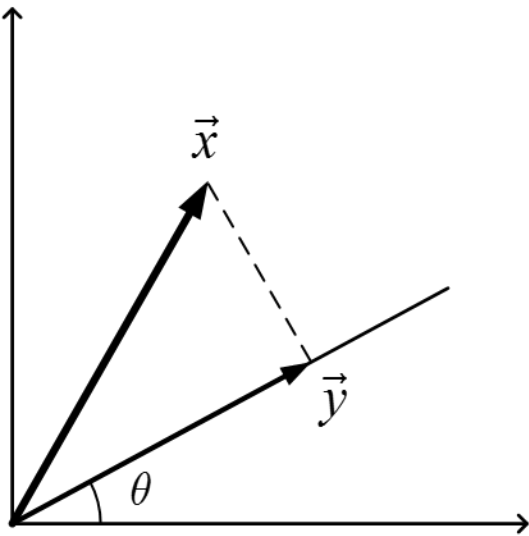# Example: Projection onto Vector = $\begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix}$

$$P\begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} \cos^2\theta \\ \cos\theta\sin\theta \end{bmatrix}$$

$$P\begin{bmatrix} 0 \\ 1 \end{bmatrix} = \begin{bmatrix} \sin\theta\cos\theta \\ \sin^2\theta \end{bmatrix}$$

$$P\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \begin{bmatrix} \cos^2\theta & \sin\theta\cos\theta \\ \cos\theta\sin\theta & \sin^2\theta \end{bmatrix}$$

Example: Projection onto Vector = $\begin{bmatrix} \cos\theta \\ \sin\theta \end{bmatrix}$

- Another way to find this projection matrix

$$
\vec{x} \implies \overset{R(-\theta)}{} \vec{x'} \implies \overset{\begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}}{} \vec{x''} \implies \overset{R(\theta)}{} \vec{y}
$$

$$
\begin{aligned}
\vec{y} &= R(\theta) \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} R(-\theta)\vec{x} \\
&= \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix} \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \\
&= \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} \cos\theta & \sin\theta \\ 0 & 0 \end{bmatrix} \\
&= \begin{bmatrix} \cos^2\theta & \cos\theta\sin\theta \\ \sin\theta\cos\theta & \sin^2\theta \end{bmatrix}
\end{aligned}
$$

Linear Transformation

- See if the given transformation is linear
  - A linear system makes our life much easier

- Superposition
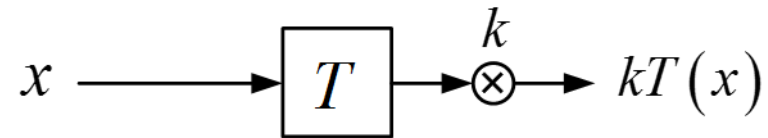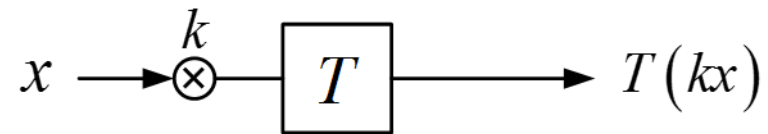- Homogeneity

Linear Transformation

- Superposition
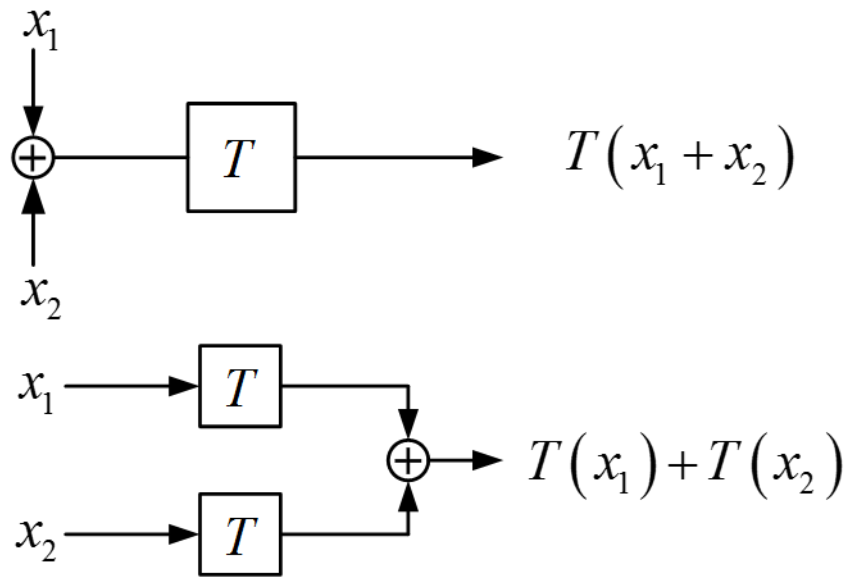
$$T(x_1 + x_2) = T(x_1) + T(x_2)$$

Linear Transformation

- Homogeneity

$$T(kx) = kT(x)$$

Linear Transformation

- Linear vs. Non-linear

<table>
<tr><th>linear</th><th>non-linear</th></tr>
<tr><td>$f(x) = 0$</td><td>$f(x) = x + c$</td></tr>
<tr><td>$f(x) = kx$</td><td>$f(x) = x^2$</td></tr>
<tr><td>$f(x(t)) = \dfrac{dx(t)}{dt}$</td><td>$f(x) = \sin x$</td></tr>
<tr><td>$f(x(t)) = \int_a^b x(t)dt$</td><td></td></tr>
</table>

Linear Transformation

- If $\vec{v}_1$ and $\vec{v}_2$ are basis, and we know $T(\vec{v}_1) = \vec{\omega}_1$ and $T(\vec{v}_2) = \vec{\omega}_2$

- Then, for any $\vec{x}$

$$\vec{x} \qquad = a_1\vec{v}_1 + a_2\vec{v}_2 \qquad\qquad (a_1 \text{ and } a_2 \text{ unique})$$

$$
\begin{aligned}
T(\vec{x}) \quad &= T(a_1\vec{v}_1 + a_2\vec{v}_2) \\
&= a_1 T(\vec{v}_1) + a_2 T(\vec{v}_2) \\
&= a_1\vec{\omega}_1 + a_2\vec{\omega}_2
\end{aligned}
$$

- This is why a linear system makes our life much easier
- Only thing that we need is to observe how basis are linearly-transformed

Eigenvalue and Eigenvector

$$A\vec{v} = \lambda\vec{v}$$

$A\vec{v}$ parallel to $\vec{v}$

$$\lambda \quad = \quad \begin{cases} \text{positive} \\ 0 \\ \text{negative} \end{cases}$$

$\lambda\vec{v}$: stretched vector
(same direction with $\vec{v}$)

$A\vec{v}$: linearly transformed vector
(generally rotate + stretch)

Linear Transformation

- If $\vec{v}_1$ and $\vec{v}_2$ are basis and eigenvectors, and we know $T(\vec{v}_1) = \vec{\omega}_1 = \lambda_1 \vec{v}_1$ and $T(\vec{v}_2) = \vec{\omega}_2 = \lambda_2 \vec{v}_2$

- Then, for any $\vec{x}$

$$\vec{x} = a_1 \vec{v}_1 + a_2 \vec{v}_2 \qquad (a_1 \text{ and } a_2 \text{ unique})$$

$$
\begin{aligned}
T(\vec{x}) &= T(a_1 \vec{v}_1 + a_2 \vec{v}_2) \\
&= a_1 T(\vec{v}_1) + a_2 T(\vec{v}_2) \\
&= a_1 \lambda_1 \vec{v}_1 + a_2 \lambda_2 \vec{v}_2 \\
&= \lambda_1 a_1 \vec{v}_1 + \lambda_2 a_2 \vec{v}_2
\end{aligned}
$$

- This is why a linear system makes our life much easier
- Only thing that we need is to observe how each basis is independently scaled

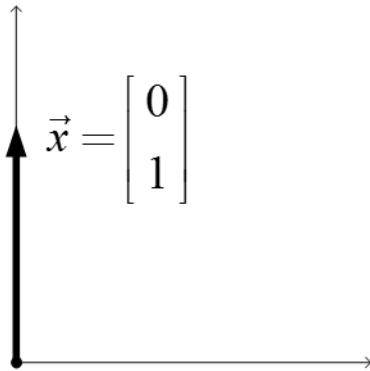# How to Compute Eigenvalue and Eigenvector

$$A\vec{v} = \lambda\vec{v} = \lambda I\vec{v}$$
$$A\vec{v} - \lambda I\vec{v} = (A - \lambda I)\vec{v} = 0$$

$\implies$ $A - \lambda I = 0$ or

$\vec{v} = 0$ or

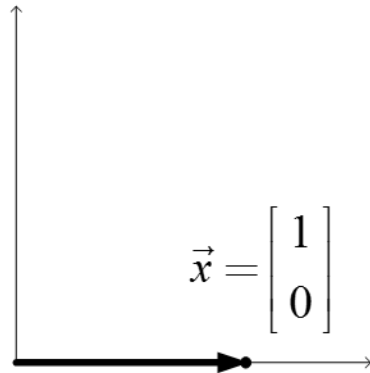$(A - \lambda I)^{-1}$ does not exist

$\implies$ $\det(A - \lambda I) = 0$

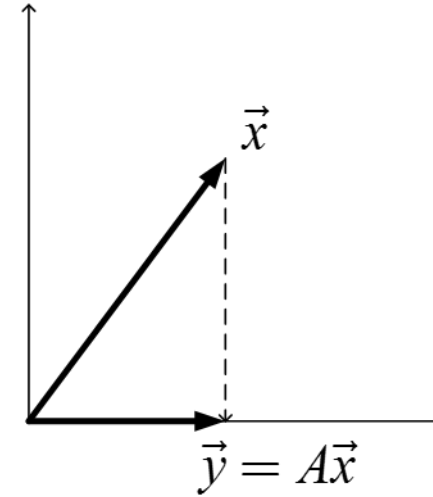# Example: Eigen Analysis of $A = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$

- $A = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$: projection onto $\hat{x}$ - axis

- Find eigenvalues and eigenvectors of A.

$$\vec{x} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\vec{y} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} = A\vec{x} = 0 \cdot \vec{x}$$

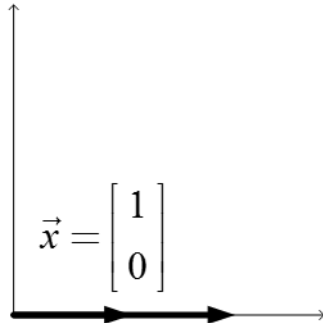$$\lambda_1 = 0 \ \text{ and } \ \vec{v}_1 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\vec{y} = \begin{bmatrix} 1 \\ 0 \end{bmatrix} = A\vec{x} = 1 \cdot \vec{x}$$

$$\lambda_2 = 1 \ \text{ and } \ \vec{v}_2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\vec{x} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

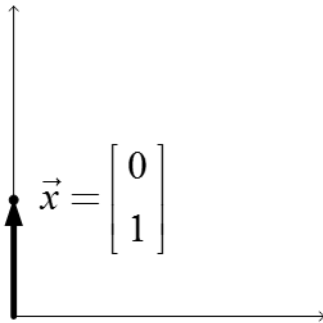$$\vec{x}$$

$$\vec{y} = A\vec{x}$$

Example: Eigen Analysis of $A = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$
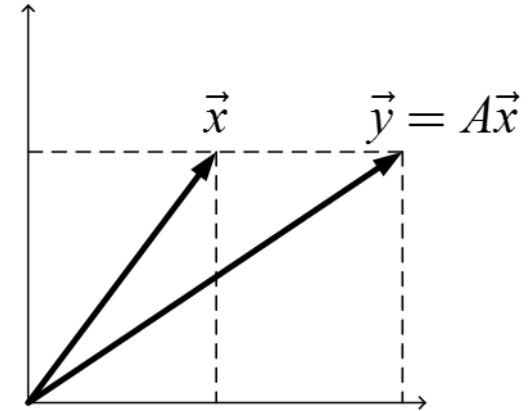
- $A = \begin{bmatrix} 2 & 0 \\ 0 & 1 \end{bmatrix}$:   stretch by 2 along $\vec{x}$- axis

  stretch by 1 along $\vec{y}$- axis

- Find eigenvalues and eigenvectors.

$$\lambda_1 = 2 \text{ and } \vec{v}_1 = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\vec{x} = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$$

$$\lambda_2 = 1 \text{ and } \vec{v}_2 = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$$\vec{x} = \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

POSTECH

Eigen Analysis in Python

```python
A = np.array([[2, 0],
              [0, 1]])
D, V = np.linalg.eig(A)

idx = np.argsort(-D)
D = D[idx]
V = V[idx]

print('D :', D)
print('V :', V)
```
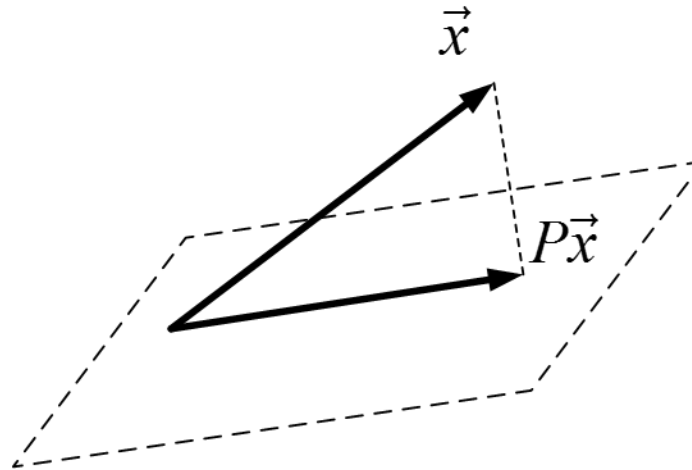
```
D : [ 2.  1.]
V : [[ 1.  0.]
 [ 0.  1.]]
```

Example: Eigen Analysis of Projection

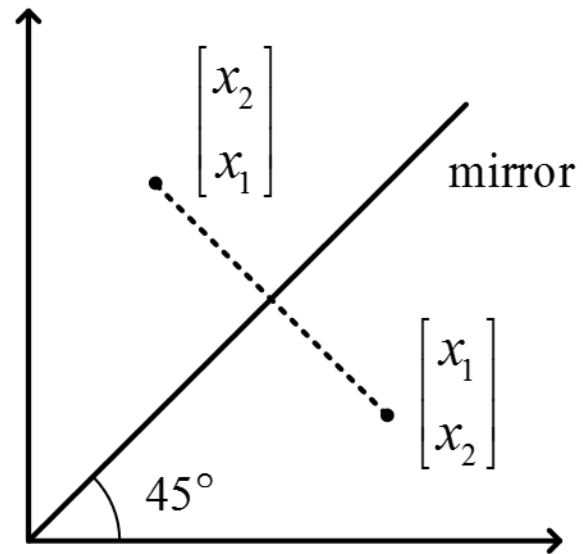- Projection onto the plane

- Find eigenvalues and eigenvectors

- For any $\vec{x}$ in the plane, $P\vec{x} = \vec{x} \rightarrow \lambda = 1$

- For any $\vec{x}$ perpendicular to the plane, $P\vec{x} = \vec{0} \rightarrow \lambda = 0$

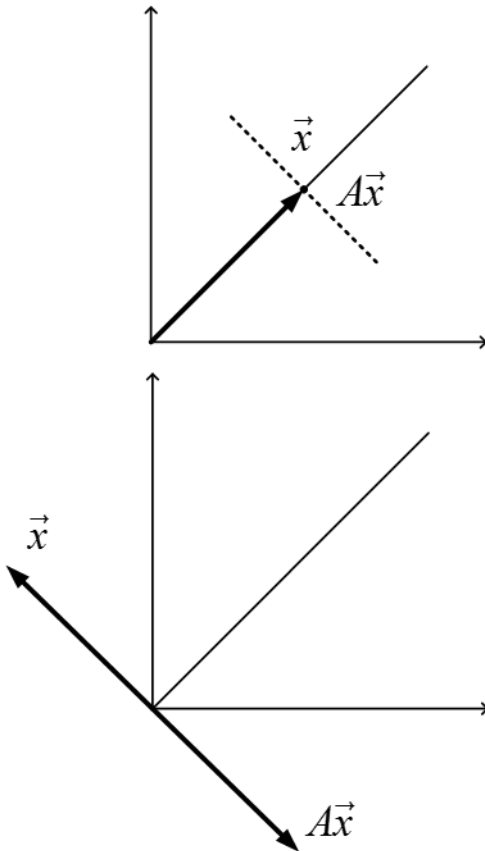$$A = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}$$

- What kind of a linear transformation?

$$\begin{bmatrix} x_2 \\ x_1 \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$
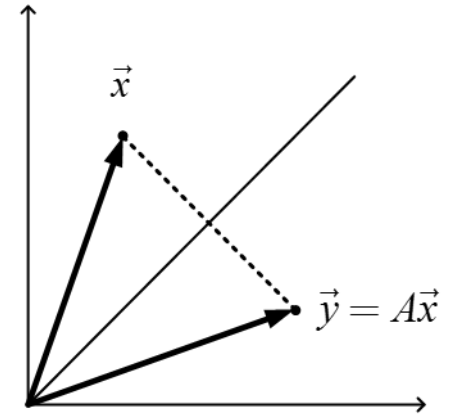
Example: Eigen Analysis of Mirror

- Eigenvalues and eigenvectors?
  - can $\vec{x}$ be an eigenvector?

$$A\vec{x} = \vec{x}, \quad \lambda = 1$$

$$A\vec{x} = -\vec{x}, \quad \lambda = -1$$
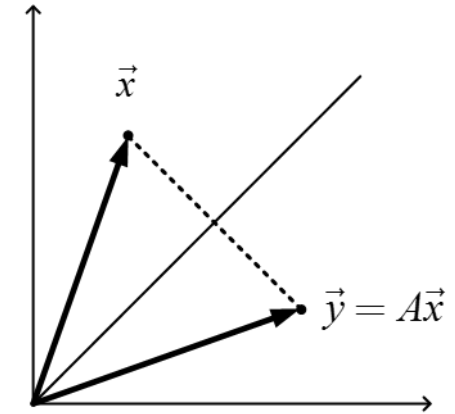
Example: Eigen Analysis of Mirror

- Side note: Matrix A can be seen as a multiple transformations

$$A = R(45)MR(-45)$$

$$R(45) = \begin{bmatrix} \cos\frac{\pi}{4} & -\sin\frac{\pi}{4} \\ \sin\frac{\pi}{4} & \cos\frac{\pi}{4} \end{bmatrix} = \frac{1}{\sqrt{2}}\begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$$

$$M \quad : \text{ mirror along } \hat{x}\text{- axis, } \begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}$$

$$A \quad = \left(\frac{1}{\sqrt{2}}\right)^2 \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}\begin{bmatrix} 1 & 0 \\ 0 & -1 \end{bmatrix}\begin{bmatrix} 1 & 1 \\ -1 & 1 \end{bmatrix}$$

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

- What kind of a linear transformation?

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

$$A = R\left(\frac{\pi}{2}\right) = R(90°) = \begin{bmatrix} \cos\frac{\pi}{2} & -\sin\frac{\pi}{2} \\ \sin\frac{\pi}{2} & \cos\frac{\pi}{2} \end{bmatrix}$$
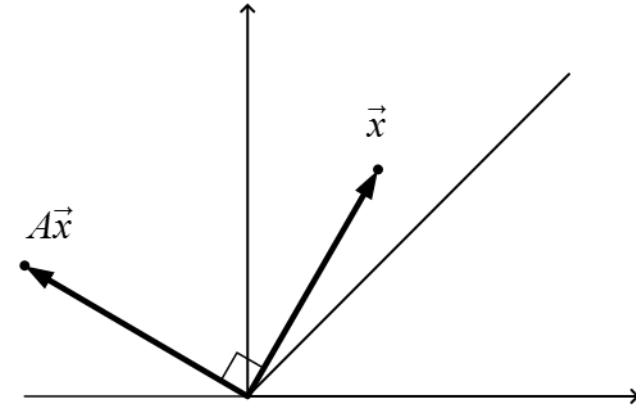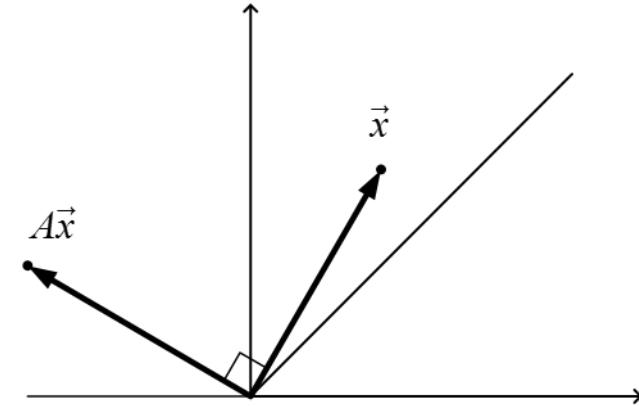
$$A = \begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}$$

- What kind of a linear transformation?

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

$$A = R\left(\frac{\pi}{2}\right) = R(90°) = \begin{bmatrix} \cos\frac{\pi}{2} & -\sin\frac{\pi}{2} \\ \sin\frac{\pi}{2} & \cos\frac{\pi}{2} \end{bmatrix}$$

- Multiple transformations

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

Example: Eigen Analysis of Rotation

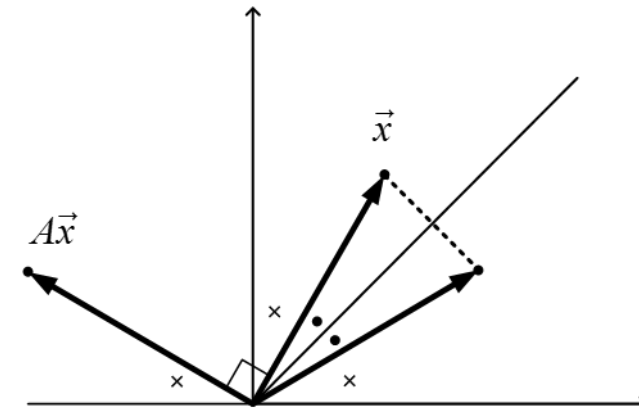- What kind of a linear transformation?

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

$$A = R\left(\tfrac{\pi}{2}\right) = R(90^\circ) = \begin{bmatrix} \cos\tfrac{\pi}{2} & -\sin\tfrac{\pi}{2} \\ \sin\tfrac{\pi}{2} & \cos\tfrac{\pi}{2} \end{bmatrix}$$

- Eigenvalues: complex numbers

$$\Rightarrow \quad \det(A - \lambda I) = 0$$

$$\begin{vmatrix} -\lambda & -1 \\ 1 & -\lambda \end{vmatrix} = \lambda^2 + 1 = 0$$

$$\therefore \ \lambda = \pm i$$

- What is the physical meaning?

Linear Transformation and Eigenvectors

- If $\vec{v}_1$ and $\vec{v}_2$ are basis and eigenvectors, and we know $T(\vec{v}_1) = \vec{\omega}_1 = \lambda_1 \vec{v}_1$ and $T(\vec{v}_2) = \vec{\omega}_2 = \lambda_2 \vec{v}_2$

- Then, for any $\vec{x}$

$$\vec{x} \qquad = a_1 \vec{v}_1 + a_2 \vec{v}_2 \qquad\qquad (a_1 \text{ and } a_2 \text{ unique})$$

$$
\begin{aligned}
T(\vec{x}) &= T(a_1 \vec{v}_1 + a_2 \vec{v}_2) \\
&= a_1 T(\vec{v}_1) + a_2 T(\vec{v}_2) \\
&= a_1 \lambda_1 \vec{v}_1 + a_2 \lambda_2 \vec{v}_2 \\
&= \lambda_1 a_1 \vec{v}_1 + \lambda_2 a_2 \vec{v}_2
\end{aligned}
$$

- This is why a linear system makes our life much easier
- Only thing that we need is to observe how each basis is independently scaled
- (optional) Fourier transform
    - Sinusoids are orthonormal basis and eigenvectors for functions (or signals)

Linear Algebra 3

Industrial AI Lab.
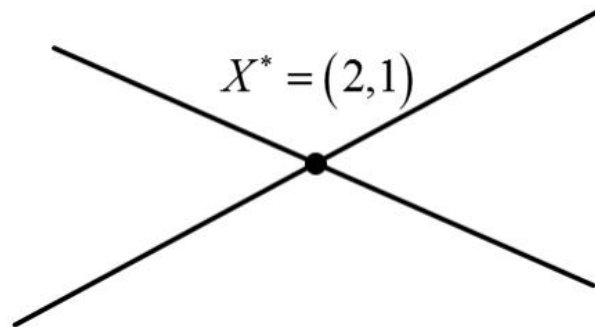
Prof. Seungchul Lee

System of Linear Equations

- Well-determined linear systems
- Under-determined linear systems
- Over-determined linear systems

Well-Determined Linear Systems

- System of linear equations

$$
\begin{aligned}
2x_1 + 3x_2 &= 7 \\
x_1 + 4x_2 &= 6
\end{aligned}
\quad \Longrightarrow \quad
\begin{aligned}
x_1^* &= 2 \\
x_2^* &= 1
\end{aligned}
$$

- Geometric point of view

$X^* = (2,1)$

Well-Determined Linear Systems

- System of linear equations

$$
\begin{aligned}
2x_1 + 3x_2 &= 7 \\
x_1 + 4x_2 &= 6
\end{aligned}
\quad \Longrightarrow \quad
\begin{aligned}
x_1^* &= 2 \\
x_2^* &= 1
\end{aligned}
$$

- Matrix form

$$
\begin{aligned}
a_{11}x_1 + a_{12}x_2 &= b_1 \\
a_{21}x_1 + a_{22}x_2 &= b_2
\end{aligned}
\quad
\begin{array}{c}
\text{Matrix form} \\
\Longrightarrow
\end{array}
\quad
\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}
\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}
=
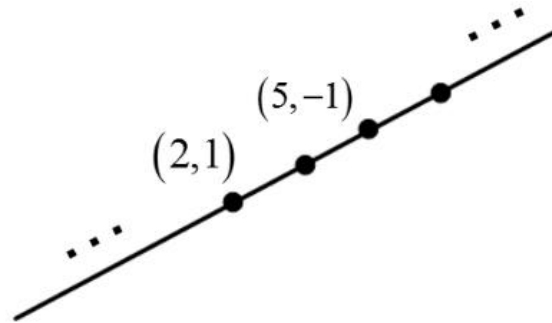\begin{bmatrix} b_1 \\ b_2 \end{bmatrix}
$$

$$
AX = B
$$

$$
\therefore \quad X^* = A^{-1}B \quad \text{if } A^{-1} \text{ exists}
$$

Under-Determined Linear Systems

- System of linear equations

$$2x_1 + 3x_2 = 7 \implies \quad \text{Many solutions}$$

- Geometric point of view

Under-Determined Linear Systems

- System of linear equations

$$2x_1 + 3x_2 = 7 \implies \text{Many solutions}$$

- Matrix form

$$a_{11}x_1 + a_{12}x_2 = b_1 \quad \overset{\text{Matrix form}}{\implies} \quad \begin{bmatrix} a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = b_1$$
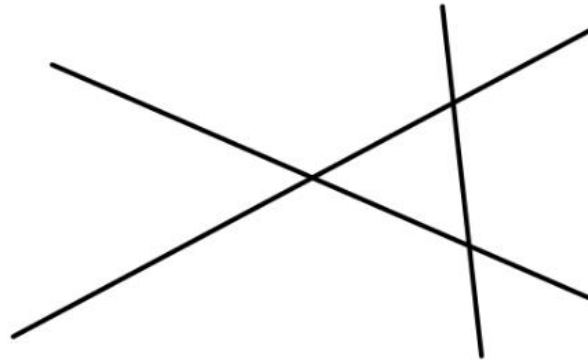
$$AX = B$$

$\therefore$ Many Solutions when A is fat

Over-Determined Linear Systems

- System of linear equations

$$
\begin{aligned}
2x_1 + 3x_2 &= 7 \\
x_1 + 4x_2 &= 6 \quad \Longrightarrow \quad \text{No solutions} \\
x_1 + x_2 &= 4
\end{aligned}
$$

- Geometric point of view

Over-Determined Linear Systems

- System of linear equations

$$
\begin{aligned}
2x_1 + 3x_2 &= 7 \\
x_1 + 4x_2 &= 6 \quad \Longrightarrow \quad \text{No solutions} \\
x_1 + x_2 &= 4
\end{aligned}
$$

- Matrix form

$$
\begin{aligned}
a_{11}x_1 + a_{12}x_2 &= b_1 \\
a_{21}x_1 + a_{22}x_2 &= b_2 \\
a_{31}x_1 + a_{32}x_2 &= b_3
\end{aligned}
\quad
\begin{aligned}
\text{Matrix form} \\
\Longrightarrow
\end{aligned}
\quad
\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix}
\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}
=
\begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}
$$

$$AX = B$$

$\therefore$ No Solutions when A is skinny

Summary of Linear Systems

$$AX = B$$

- Square: Well-determined

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$

- Fat: Under-determined

$$\begin{bmatrix} a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = b_1$$

- Skinny: Over-determined

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

Least-Norm Solution

- For under-determined linear system

$$\begin{bmatrix} a_{11} & a_{12} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = b_1 \quad \text{or} \quad AX = B$$

- Find the solution of $AX = B$ that minimize $\|X\|$ or $\|X\|^2$
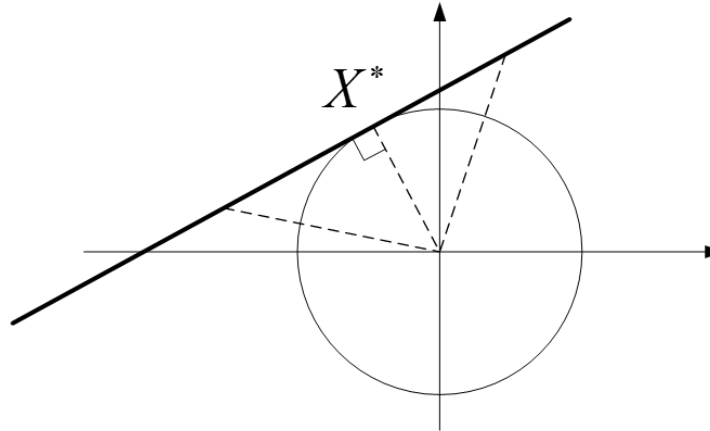
- *i.e.,* optimization problem

$$\begin{aligned} \min \quad & \|X\|^2 \\ \text{s. t.} \quad & AX = B \end{aligned}$$

Least-Norm Solution

- Optimization problem

$$\min \quad \|X\|^2$$
$$\text{s. t. } AX = B$$

- Geometric interpretation

- Select one solution among many solutions
- Often control problem

$$X^* = A^T \left(AA^T\right)^{-1} B \quad \text{Least norm solution}$$

Least-Square Solution

- For over-determined linear system

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \\ a_{31} & a_{32} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \neq \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix} \quad \text{or} \quad AX \neq B$$

$$x_1 \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \end{bmatrix} + x_2 \begin{bmatrix} a_{12} \\ a_{22} \\ a_{32} \end{bmatrix} \neq \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

- Find X that minimizes $\|E\|$ or $\|E\|^2$ (error)

- *i.e.* optimization problem

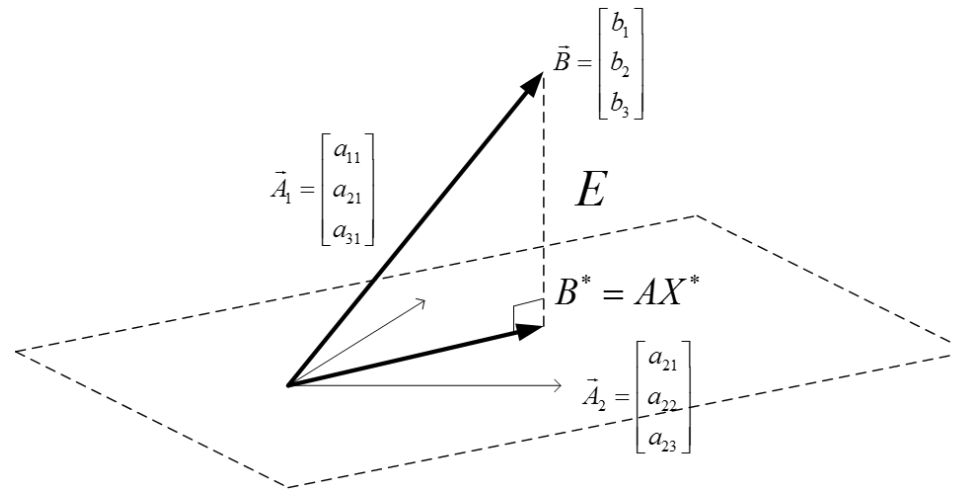$$\min_X \|E\|^2 = \min_X \|AX - B\|^2$$

Least-Square Solution

- *i.e.* optimization problem

$$\min_{X} \|E\|^2 = \min_{X} \|AX - B\|^2$$

$$X^* = \left(A^T A\right)^{-1} A^T B$$

$$B^* = AX^* = A\left(A^T A\right)^{-1} A^T B$$

- Geometric interpretation
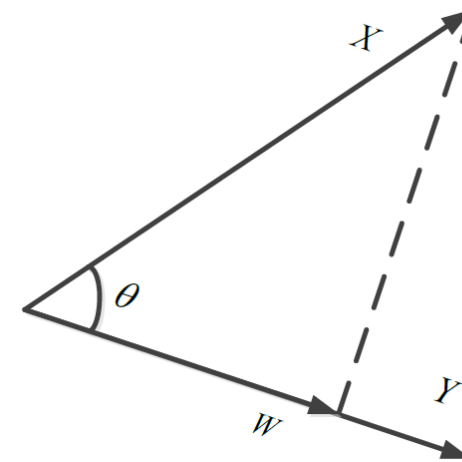

- Often estimation problem

Vector Projection onto Y

- The vector projection of a vector X on (or onto) a nonzero vector Y is the orthogonal projection of X onto a straight line parallel to Y

$$W = \omega \hat{Y} = \omega \frac{Y}{\|Y\|}, \text{ where } \omega = \|W\|$$

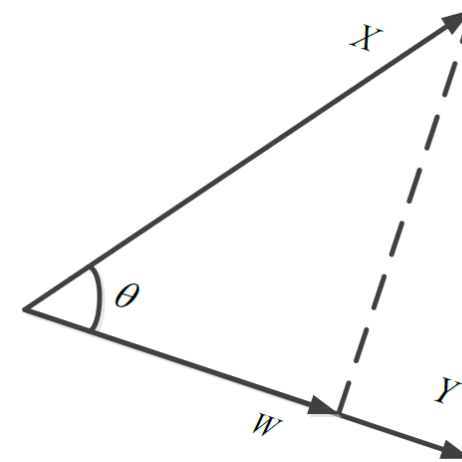$$\omega = \|X\| \cos\theta = \|X\| \frac{X \cdot Y}{\|X\|\|Y\|} = \frac{X \cdot Y}{\|Y\|}$$

$$W = \omega \hat{Y} = \frac{X \cdot Y}{\|Y\|} \frac{Y}{\|Y\|} = \frac{X \cdot Y}{\|Y\|\|Y\|} Y = \frac{X^T Y}{Y^T Y} Y = \frac{\langle X, Y \rangle}{\langle Y, Y \rangle} Y$$

$$= Y \frac{X^T Y}{Y^T Y} = Y \frac{Y^T X}{Y^T Y} = \frac{Y Y^T}{Y^T Y} X = PX$$

Vector Projection onto Y

- Another way of computing ω and W

$$Y \perp (X - W)$$

$$\implies Y^T (X - W) = Y^T \left(X - \omega \frac{Y}{\|Y\|} \right) = 0$$

$$\implies \omega = \frac{Y^T X}{Y^T Y} \|Y\|$$

$$W = \omega \frac{Y}{\|Y\|} = \frac{Y^T X}{Y^T Y} Y = \frac{\langle X, Y \rangle}{\langle Y, Y \rangle} Y$$

Orthogonal Projection onto a Subspace

- Projection of B onto a subspace U of span of A_1 and A_2
- Orthogonality

$$\min_X \|E\|^2 = \min_X \|AX - B\|^2$$

$$X^* = \left(A^T A\right)^{-1} A^T B$$

$$B^* = AX^* = A\left(A^T A\right)^{-1} A^T B$$

$$A \perp (AX^* - B)$$
$$A^T (AX^* - B) = 0$$
$$A^T A X^* = A^T B$$
$$X^* = \left(A^T A\right)^{-1} A^T B$$
$$B^* = AX^* = A\left(A^T A\right)^{-1} A^T B$$

$$\vec{B} = \begin{bmatrix} b_1 \\ b_2 \\ b_3 \end{bmatrix}$$

$$\vec{A}_1 = \begin{bmatrix} a_{11} \\ a_{21} \\ a_{31} \end{bmatrix}$$

$$E$$

$$B^* = AX^*$$

$$\vec{A}_2 = \begin{bmatrix} a_{21} \\ a_{22} \\ a_{23} \end{bmatrix}$$