Linear Algebra

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Lecture Overview

- Elements in linear algebra
- Linear system
- Linear combination, vector equation,
  Four views of matrix multiplication
- Linear independence, span, and subspace
- Linear transformation
- <u>Least squares</u> 최소 제곱법 → why? $|b-Ax|$를 minimize 하려고.
- Eigendecomposition
- Singular value decomposition

Over-determined Linear Systems (#equations ≫ #variables)

- Recall a linear system:

Person ID	Weight	Height	Is_smoking	Life-span
1	60kg	5.5ft	Yes (=1)	66
2	65kg	5.0ft	No (=0)	74
3	55kg	6.0ft	Yes (=1)	78

$$\begin{aligned} 60x_1 + 5.5x_2 + 1 \cdot x_3 &= 66 \\ 65x_1 + 5.0x_2 + 0 \cdot x_3 &= 74 \\ 55x_1 + 6.0x_2 + 1 \cdot x_3 &= 78 \end{aligned}$$

A= (3,3)

Over-determined Linear Systems (#equations ≫ #variables)

$A(m \times n)$ 행 열 → 변수 갯수, 방정식 갯수

$m>n$: 방정식이 더 많음 = 보통 해X

$n>m$: 변수가 더 많음 = 보통 해가 무수히 많음

$m \times n$

- Recall a linear system:
- What if we have much more data examples?

Person ID	Weight	Height	Is_smoking	Life-span
1	60kg	5.5ft	Yes (=1)	66
2	65kg	5.0ft	No (=0)	74
3	55kg	6.0ft	Yes (=1)	78
⋮	⋮	⋮	⋮	⋮

$$60x_1+5.5x_2+1\cdot x_3=66$$
$$65x_1+5.0x_2+0\cdot x_3=74$$
$$55x_1+6.0x_2+1\cdot x_3=78$$
$$\vdots \quad \vdots \quad \vdots \quad \vdots$$

- Matrix equation:

$$\underbrace{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ \vdots & \vdots & \vdots \end{bmatrix}}_{A\ (n,3)} \underbrace{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}}_{\mathbf{x}\ (3,1)} = \underbrace{\begin{bmatrix} 66 \\ 74 \\ 78 \\ \vdots \end{bmatrix}}_{\mathbf{b}}$$

$m \gg n$: more equations than variables

→ Usually no solution exists

Vector Equation Perspective

- Vector equation form: $\begin{bmatrix} 60 \\ 65 \\ 55 \\ \vdots \end{bmatrix} x_1 + \begin{bmatrix} 5.5 \\ 5.0 \\ 6.0 \\ \vdots \end{bmatrix} x_2 + \begin{bmatrix} 1 \\ 0 \\ 1 \\ \vdots \end{bmatrix} x_3 = \begin{bmatrix} 66 \\ 74 \\ 78 \\ \vdots \end{bmatrix}$

$$\mathbf{a}_1 x_1 + \mathbf{a}_2 x_2 + \mathbf{a}_3 x_3 = \mathbf{b}$$

- Compared to the original space $\mathbb{R}^n$, where $\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3, \mathbf{b} \in \mathbb{R}^n$, Span $\{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\}$ will be a thin hyperplane, so it is likely that $\mathbf{b} \notin$ Span $\{\mathbf{a}_1, \mathbf{a}_2, \mathbf{a}_3\}$

  ➡ No solution exists.

Motivation for Least Squares

방정식이 해 없는 경우

"근사"

- Even if no solution exists, we want to approximately obtain the solution for an over-determined system.

- Then, how can we define the best approximate solution for our purpose?

Inner Product 내적

$u \cdot v = u_1 v_1 + \cdots + u_n v_n = \|\vec{a}\| \times \|\vec{b}\| \times \cos\theta$

$(n, 1)$

- Given $\mathbf{u}, \mathbf{v} \in \mathbb{R}^n$, we can consider $\mathbf{u}$ and $\mathbf{v}$ as $n \times 1$ matrices.
- The transpose $\mathbf{u}^T$ is a $1 \times n$ matrix, and the matrix product $\mathbf{u}^T\mathbf{v}$ is a 1×1 matrix, which we write as a scalar without brackets.
- The number $\mathbf{u}^T\mathbf{v}$ is called the **inner product** or **dot product** of $\mathbf{u}$ and $\mathbf{v}$, and it is written as $\mathbf{u} \cdot \mathbf{v}$.
- For $\mathbf{u} = \begin{bmatrix} 3 \\ 2 \\ 1 \end{bmatrix}, \mathbf{v} = \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix}, \mathbf{u} \cdot \mathbf{v} = \mathbf{u}^T\mathbf{v} = \begin{bmatrix} 3 & 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \\ 5 \end{bmatrix} = [14]$

그냥 내적의 정의 같아...

$(1 \times 3)(3 \times 1) = 1 \times 1$

Properties of Inner Product

- **Theorem:** Let $\mathbf{u}, \mathbf{v},$ and $\mathbf{w}$ be vectors in $\mathbb{R}^n$, and let c be a scalar. Then

  a) $\mathbf{u} \cdot \mathbf{v} = \mathbf{v} \cdot \mathbf{u}$ 교환법칙

  b) $(\mathbf{u} + \mathbf{v}) \cdot \mathbf{w} = \mathbf{u} \cdot \mathbf{w} + \mathbf{v} \cdot \mathbf{w}$ 분배법칙

  c) $(c\mathbf{u}) \cdot \mathbf{v} = c(\mathbf{u} \cdot \mathbf{v}) = \mathbf{u} \cdot (c\mathbf{v})$ 결합법칙

  d) $\mathbf{u} \cdot \mathbf{u} \geq \mathbf{0}$, and $\underline{\mathbf{u} \cdot \mathbf{u} = \mathbf{0}}$ if and only if $\mathbf{u} = \mathbf{0}$

  자기자신 내적 ≥ 0

  ↳ 0벡터 여야만 $u \cdot u = 0$ 임.

+ $u \cdot v = \underbrace{u^T \times v}$

내적이 아니라 그냥 곱이야

- Properties (b) and (c) can be combined to produce the following useful rule:

$$(c_1\mathbf{u}_1 + \cdots + c_p\mathbf{u}_p) \cdot \mathbf{w} = c_1(\mathbf{u}_1 \cdot \mathbf{w}) + \cdots + c_p(\mathbf{u}_p \cdot \mathbf{w})$$

Vector Norm

- For $\mathbf{v} \in \mathbb{R}^n$, with entries $v_1, \ldots, v_n$, the square root of $\mathbf{v} \cdot \mathbf{v}$ is defined because $\mathbf{v} \cdot \mathbf{v}$ is nonnegative.

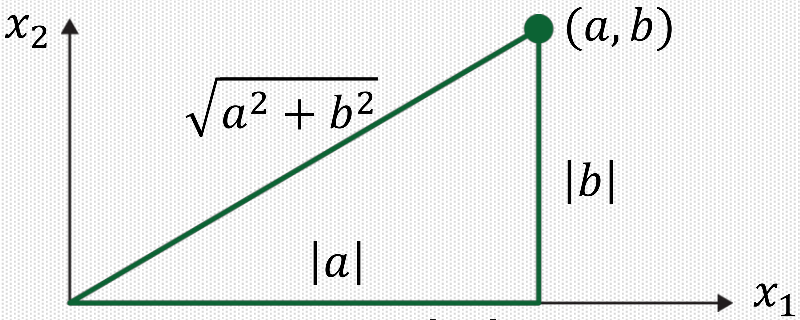
- **Definition**: The length (or norm) of $\mathbf{v}$ is the non-negative scalar $\|\mathbf{v}\|$ defined as the square root of $\mathbf{v} \cdot \mathbf{v}$:

$$\|\mathbf{v}\|_2 = \sqrt{\mathbf{v} \cdot \mathbf{v}} = \sqrt{v_1^2 + v_2^2 + \cdots + v_n^2} \text{ and } \|\mathbf{v}\|^2 = \mathbf{v} \cdot \mathbf{v}$$

cf) $\|v\|_1 = |v_1| + \cdots + |v_n|$

Geometric Meaning of Vector Norm

- Suppose $\mathbf{v} \in \mathbb{R}^2$, say, $\mathbf{v} = \begin{bmatrix} a \\ b \end{bmatrix}$.
- $\|\mathbf{v}\|$ is the length of the line segment from the origin to $\mathbf{v}$.
- This follows from Pythagorean Theorem applied to a triangle such as the one shown in the following figure:

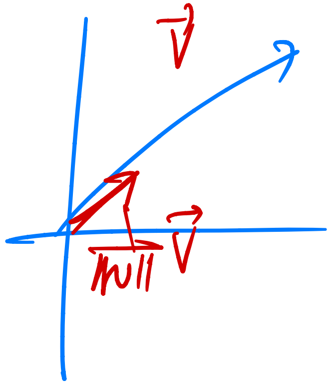


Interpretation of $\|\mathrm{v}\|$ as length

- For any scalar c, the length $c\mathbf{v}$ is $|c|$ times the length of $\mathbf{v}$ That is,

$$\|c\mathbf{v}\| = |c|\|\mathbf{v}\|$$

Unit Vector



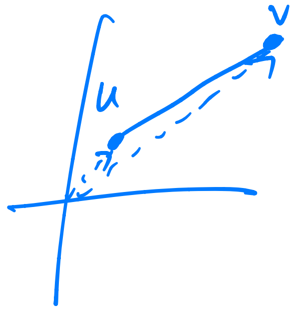
- A vector whose length is 1 is called a unit vector.

(정규화)

- Normalizing a vector: Given a nonzero vector $\mathbf{v}$, if we divide it by its length, we obtain a unit vector $\mathbf{u} = \frac{1}{\|\mathbf{v}\|}\mathbf{v}$.

- $\mathbf{u}$ is in the same direction as $\mathbf{v}$, but its length is 1.

Distance between Vectors in $\mathbb{R}^n$



- **Definition:** For $\mathbf{u}$ and $\mathbf{v}$ in $\mathbb{R}^n$, the **distance between $\mathbf{u}$ and $\mathbf{v}$**, written as dist $(\mathbf{u}, \mathbf{v})$, is the length of the vector $\mathbf{u} - \mathbf{v}$ That is,

$$\text{dist } (\mathbf{u}, \mathbf{v}) = \|\mathbf{u} - \mathbf{v}\|$$

- **Example**: Compute the distance between the vector

$$\mathbf{u} = \begin{bmatrix} 6 \\ 1 \end{bmatrix} \text{ and } \mathbf{v} = \begin{bmatrix} 3 \\ 2 \end{bmatrix}.$$

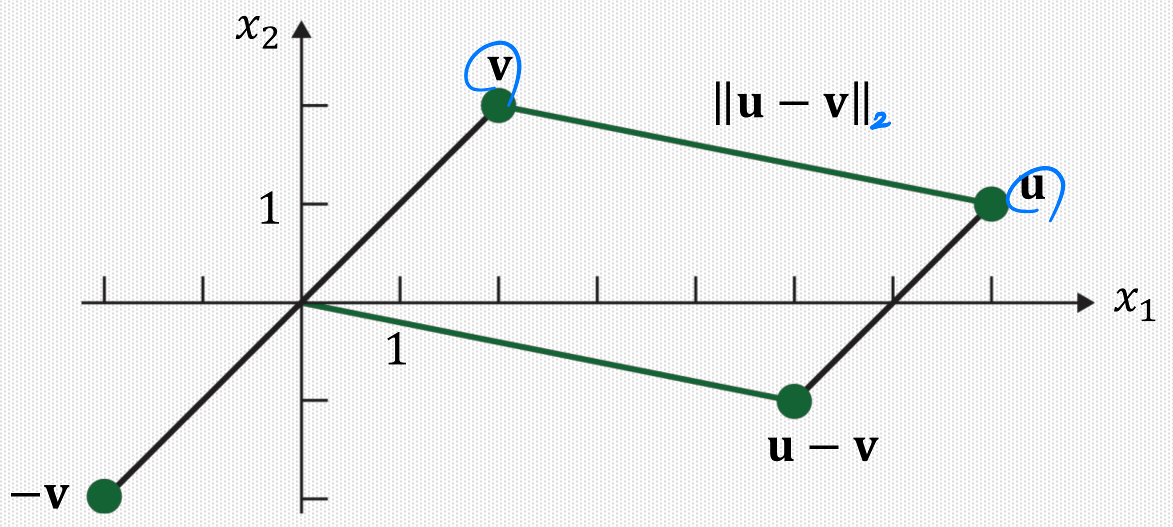
- **Solution**: Calculate

$$\mathbf{u} - \mathbf{v} = \begin{bmatrix} 6 \\ 1 \end{bmatrix} - \begin{bmatrix} 3 \\ 2 \end{bmatrix} = \begin{bmatrix} 3 \\ -1 \end{bmatrix}$$

$$\|\mathbf{u} - \mathbf{v}\| = \sqrt{3^2 + (-1)^2} = \sqrt{10}$$

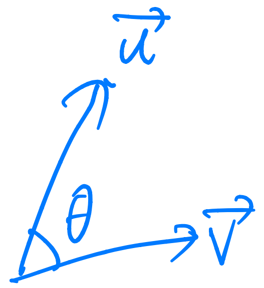
Distance between Vectors in $\mathbb{R}^n$

- The distance from $\mathbf{u}$ to $\mathbf{v}$ is the same as the distance from $\mathbf{u} - \mathbf{v}$ to 0.



The distance between $\mathbf{u}$ and $\mathbf{v}$ is the length of $\mathbf{u} - \mathbf{v}$

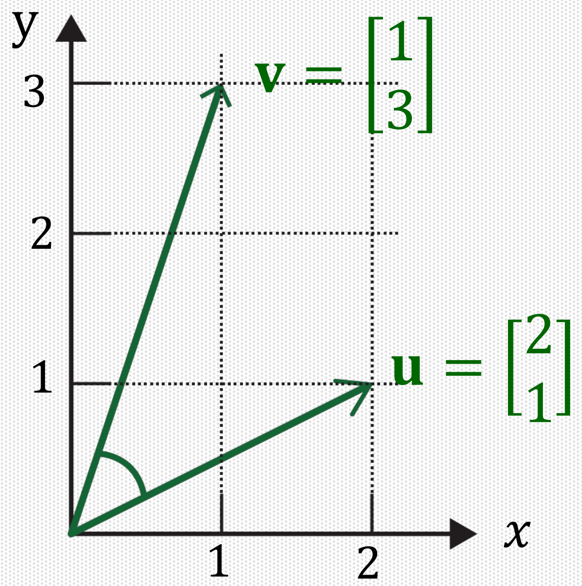
Inner Product and Angle Between Vectors



- Inner product between $\mathbf{u}$ and $\mathbf{v}$ can be rewritten using their norms and angle:

$$\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\|\|\mathbf{v}\| \cos\theta$$

- **Example**:



$$\mathbf{u} \cdot \mathbf{v} = \begin{bmatrix} 2 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 3 \end{bmatrix} = \begin{bmatrix} 2 & 1 \end{bmatrix} \begin{bmatrix} 1 \\ 3 \end{bmatrix} = 5$$

$$\|\mathbf{u}\| = \sqrt{2^2 + 1^2} = \sqrt{5} \quad \|\mathbf{v}\| = \sqrt{1^2 + 3^2} = \sqrt{10}$$

$$\mathbf{u} \cdot \mathbf{v} = 5 = \|\mathbf{u}\|\|\mathbf{v}\| \cos\theta = \sqrt{5} \cdot \sqrt{10} \cos\theta$$

$$\Rightarrow \cos\theta = \frac{5}{\sqrt{50}} = \frac{1}{\sqrt{2}}$$

$$\Rightarrow \theta = 45^\circ$$

Orthogonal Vectors

→ cos 90° = 0° → $\vec{u} \cdot \vec{v} = 0$

직교.

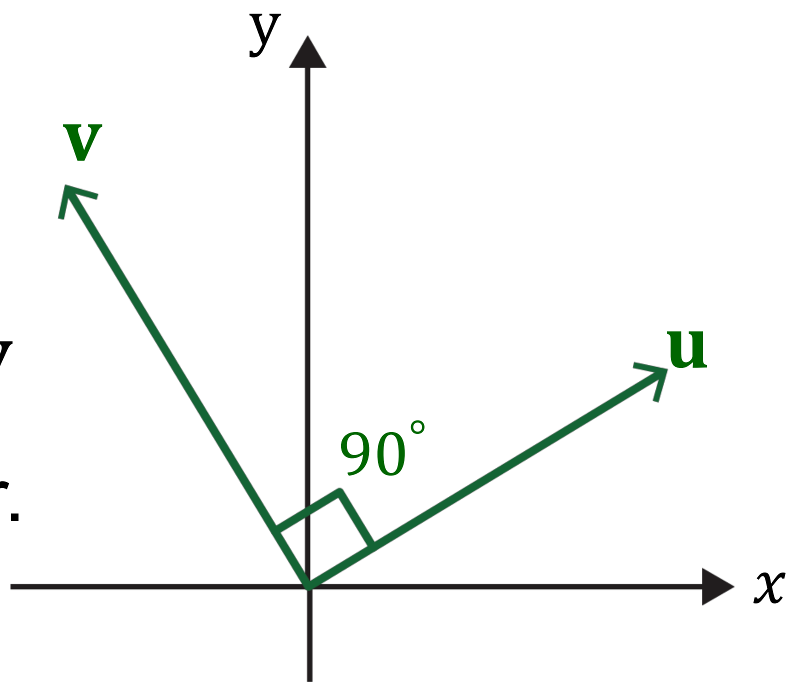
- **Definition:** $\mathbf{u} \in \mathbb{R}^n$ and $\mathbf{v} \in \mathbb{R}^n$ are **orthogonal** (to each other) if $\mathbf{u} \cdot \mathbf{v}=0$

  That is,
  $\mathbf{u} \cdot \mathbf{v} = \|\mathbf{u}\|\|\mathbf{v}\| \cos\theta = 0.$

  ⇒ $\cos\theta = 0$ for nonzero vectors $\mathbf{u}$ and $\mathbf{v}$

  ⇒ $\theta = 90°$ ($\mathbf{u} \perp \mathbf{v}$).

  ⇒ $\mathbf{u}$ and $\mathbf{v}$ are perpendicular each other.



Summary So Far

- Linear transformation
  - Properties of linear transformation
  - Standard matrix
  - One-to-one
  - Onto

- Vector norm, distance, and inner product

- Intro to least squares

Back to Over-Determined System

↳ 방정식 > 변수
$m > n$

- Let's start with the original problem:

Person ID	Weight	Height	Is_smoking	Life-span
1	60kg	5.5ft	Yes (=1)	66
2	65kg	5.0ft	No (=0)	74
3	55kg	6.0ft	Yes (=1)	78

$$\underset{A}{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \end{bmatrix}} \underset{\mathbf{x}}{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}} = \underset{\mathbf{b}}{\begin{bmatrix} 66 \\ 74 \\ 78 \end{bmatrix}}$$

- Using the inverse matrix, the solution is $\mathbf{x} = \begin{bmatrix} -0.4 \\ 20 \\ -20 \end{bmatrix}$

Back to Over-Determined System

- Let's add one more example:

Person ID	Weight (x)	Height (y)	Is_smoking (z)	Life-span
1	60kg	5.5ft	Yes (=1)	66
2	65kg	5.0ft	No (=0)	74
3	55kg	6.0ft	Yes (=1)	78
4	50kg	5.0ft	Yes (=1)	72

$$\underset{A}{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 0 \end{bmatrix}} \underset{\mathbf{x}}{\begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}} = \underset{\mathbf{b}}{\begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix}}$$

- Now, let's use the previous solution $\mathbf{x} = \begin{bmatrix} -0.4 \\ 20 \\ -20 \end{bmatrix}$

$$\underset{A}{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 1 \end{bmatrix}} \underset{\mathbf{x}}{\begin{bmatrix} -0.4 \\ 20 \\ -20 \end{bmatrix}} = \begin{bmatrix} 66 \\ 74 \\ 78 \\ 60 \end{bmatrix} \neq \underset{\mathbf{b}}{\begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix}}$$

Errors $(\mathbf{b} - A\mathbf{x})$

$$\begin{matrix} 0 \\ 0 \\ 0 \\ -12 \end{matrix}$$

Back to Over-Determined System

- How about using slightly different solution $\mathbf{x} = \begin{bmatrix} -0.12 \\ 16 \\ -9.5 \end{bmatrix}$?

Errors

$$\underset{A}{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 1 \end{bmatrix}} \underset{\mathbf{x}}{\begin{bmatrix} -0.12 \\ 16 \\ -9.5 \end{bmatrix}} = \begin{bmatrix} 71.3 \\ 72.2 \\ 79.9 \\ 64.5 \end{bmatrix} \neq \underset{\mathbf{b}}{\begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix}} \quad \left| \quad \begin{array}{c} (\mathbf{b} - A\mathbf{x}) \\ -5.3 \\ 1.8 \\ -1.9 \\ 7.5 \end{array} \right.$$

Which One is Better Solution?

↳ error의 정도를 측정하자!

Errors

$$
\underset{A}{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 1 \end{bmatrix}}
\underset{\mathbf{x}}{\begin{bmatrix} -0.12 \\ 16 \\ -9.5 \end{bmatrix}}
=
\begin{bmatrix} 71.3 \\ 72.2 \\ 79.9 \\ 64.5 \end{bmatrix}
\overset{\neq}{\neq}
\underset{\mathbf{b}}{\begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix}}
\quad \Bigg| \quad
\underset{(\mathbf{b} - A\mathbf{x})}{\begin{matrix} -5.3 \\ 1.8 \\ -1.9 \\ 7.5 \end{matrix}}
$$

$$
\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 1 \end{bmatrix}
\begin{bmatrix} -0.4 \\ 20 \\ -20 \end{bmatrix}
=
\begin{bmatrix} 66 \\ 74 \\ 78 \\ 60 \end{bmatrix}
\neq
\begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix}
\quad \Bigg| \quad
\begin{matrix} 0 \\ 0 \\ 0 \\ -12 \end{matrix}
$$

Least Squares: Best Approximation Criterion

$\Sigma(\text{errors})^2$

Sum of Squared Error

- Let's use the squared sum of errors:

Errors | **Sum of squared errors**

$$\underset{A}{\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 1 \end{bmatrix}} \underset{\mathbf{x}}{\begin{bmatrix} -0.12 \\ 16 \\ -9.5 \end{bmatrix}} = \begin{bmatrix} 71.3 \\ 69 \\ 79.9 \\ 64.5 \end{bmatrix} \neq \underset{\mathbf{b}}{\begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix}} \quad \underset{(\mathbf{b}-A\mathbf{x})}{\begin{matrix} -5.3 \\ 1.8 \\ -1.9 \\ 7.5 \end{matrix}} \quad \left((-5.3)^2 + 1.8^2 + (-1.9)^2 + 7.5^2\right)^{0.5} = 9.55$$

Better solution

$$\begin{bmatrix} 60 & 5.5 & 1 \\ 65 & 5.0 & 0 \\ 55 & 6.0 & 1 \\ 50 & 5.0 & 1 \end{bmatrix} \begin{bmatrix} -0.4 \\ 20 \\ -20 \end{bmatrix} = \begin{bmatrix} 66 \\ 74 \\ 78 \\ 60 \end{bmatrix} \neq \begin{bmatrix} 66 \\ 74 \\ 78 \\ 72 \end{bmatrix} \quad \begin{matrix} 0 \\ 0 \\ 0 \\ -12 \end{matrix} \quad (0^2 + 0^2 + 0^2 + (-12)^2)^{0.5} = 12$$

Least Squares Problem

* m,n 미세 m>n이면 해 X
⇒ $b = Ax$일 때 $b \notin \mathrm{Col}\,A$ 이면
해 X

- Now, the $\boxed{\text{sum of squared errors}}$ can be represented as $\|\mathbf{b} - A\mathbf{x}\|_2$

- **Definition**: Given an overdetermined system $A\mathbf{x} \simeq \mathbf{b}$ where $A \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^n$, and $m \gg n$, a least squares solution $\hat{\mathbf{x}}$ is defined as

최소로 만드는 sum of squared (Norm$_2$)

x를 조정하여

$$\hat{\mathbf{x}} = \arg\min_{\mathbf{x}} \|\mathbf{b} - A\mathbf{x}\|$$

- The most important aspect of the least-squares problem is that no matter what $\mathbf{x}$ we select, the vector $A\mathbf{x}$ will necessarily be in the column space Col A.

- Thus, we seek for $\mathbf{x}$ that makes $A\mathbf{x}$ as the closest point in Col A to $\mathbf{b}$.