
Linear Algebra

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Orthogonal Projection Perspective

숙직인 그랑자

- Back to the case of invertible $C = A^T A$, consider the orthogonal projection of \mathbf{b} onto $\text{Col } A$ as

$$\hat{\mathbf{b}} = f(\mathbf{b}) = A\hat{\mathbf{x}} = \underline{A(A^T A)^{-1} A^T \mathbf{b}}$$

수행의 방향 $\hat{\mathbf{x}} = (A^T A)^{-1} A^T \mathbf{b}$

Orthogonal and Orthonormal Sets

→ 모든 벡터 수직일 때

- **Definition:** A set of vectors $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ in \mathbb{R}^n is an **orthogonal set** if each pair of distinct vectors from the set is orthogonal. That is, if $\mathbf{u}_i \cdot \mathbf{u}_j = 0$ whenever $i \neq j$.

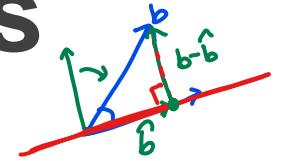
→ orthogonal set의 벡터
길이만 1

- **Definition:** A set of vectors $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ in \mathbb{R}^n is an **orthonormal set** if it is an orthogonal set of **unit vectors**.

- Is an orthogonal (or orthonormal) set also a **linearly independent set**? What about its converse?

자동적으로 선형 독립

Orthogonal and Orthonormal Basis



- Consider basis $\{\mathbf{v}_1, \dots, \mathbf{v}_p\}$ of a p -dimensional subspace W in \mathbb{R}^n .
- Can we make it as an orthogonal (or orthonormal) basis?
 - Yes, it can be done by Gram–Schmidt process. \rightarrow QR factorization.
- Given the orthogonal basis $\{\mathbf{u}_1, \dots, \mathbf{u}_p\}$ of W ,
let's compute the orthogonal projection of $\mathbf{y} \in \mathbb{R}^n$ onto W .

Orthogonal Projection \hat{y} of y onto Line

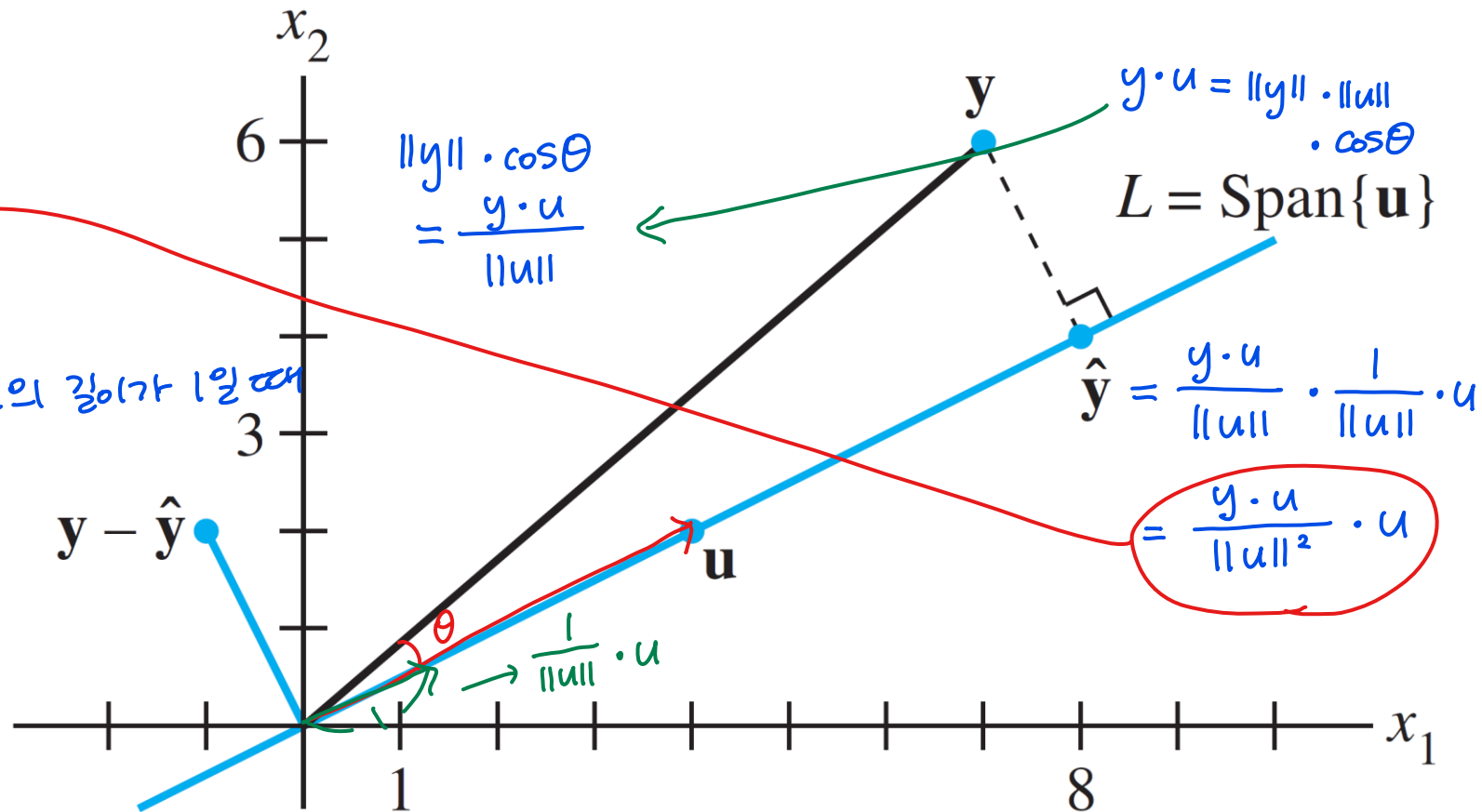
- Consider the orthogonal projection \hat{y} of y onto one-dimensional subspace L .

- $\hat{y} = \text{proj}_L y = \frac{y \cdot u}{u \cdot u} u$

- If u is a unit vector, $\rightarrow u$ 의 길이가 1일 때

$$\hat{y} = \text{proj}_L y = (y \cdot u)u$$

$$\left(\begin{bmatrix} \end{bmatrix} \begin{bmatrix} \end{bmatrix} \right) u$$



Orthogonal Projection \hat{y} of y onto Plane

- Consider the orthogonal projection \hat{y} of y onto two-dimensional subspace W

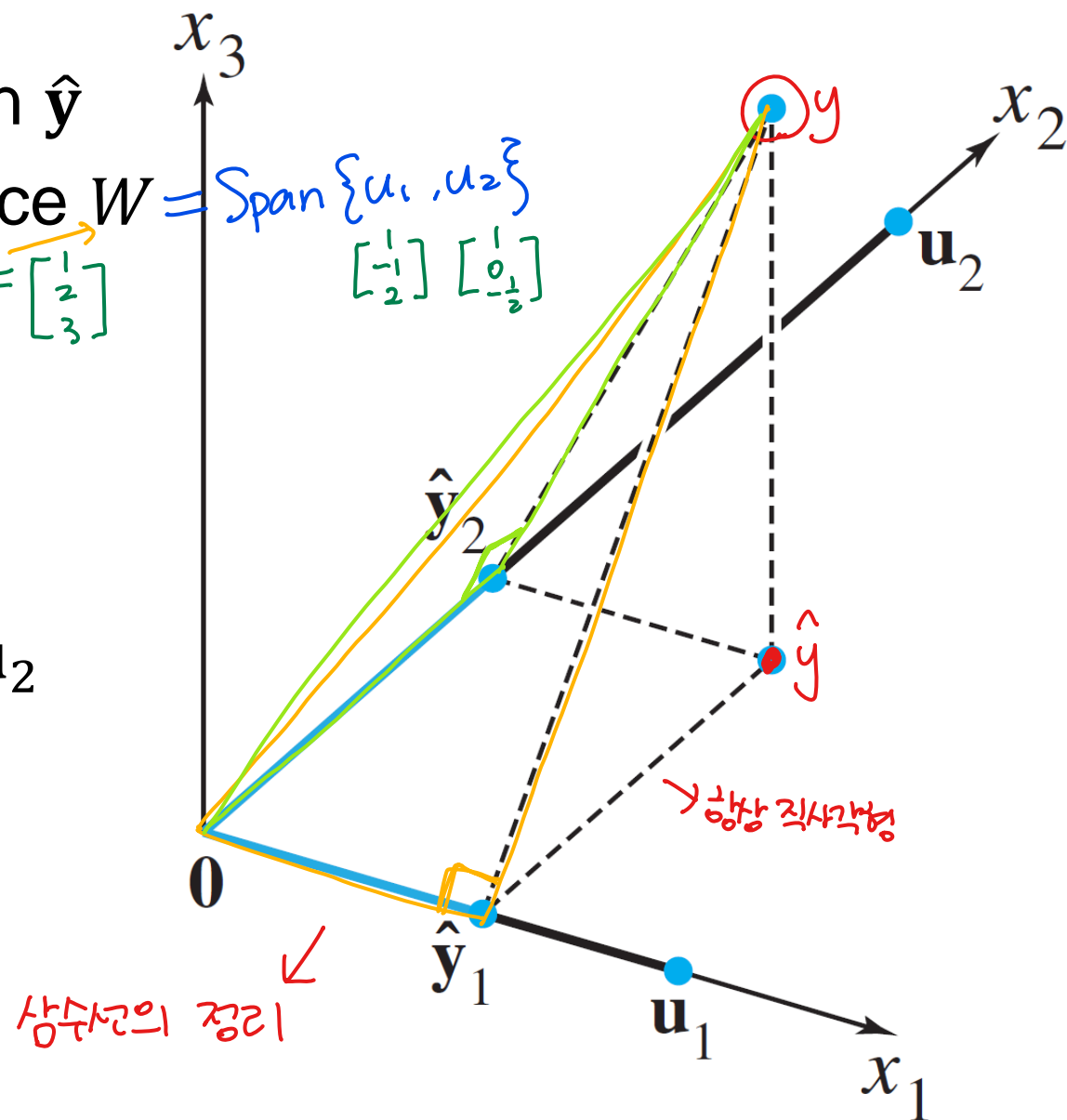
$$y = \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix}$$

$$W = \text{Span}\{u_1, u_2\}$$
$$\begin{bmatrix} 1 \\ -1 \\ 2 \end{bmatrix} \quad \begin{bmatrix} 1 \\ 0 \\ -1 \end{bmatrix}$$

- $\hat{y} = \text{proj}_L y = \frac{y \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{y \cdot u_2}{u_2 \cdot u_2} u_2$

- If u_1 and u_2 are unit vectors,
 $\hat{y} = \text{proj}_L y = (y \cdot u_1)u_1 + (y \cdot u_2)u_2$

- Projection is done independently on each orthogonal basis vector.

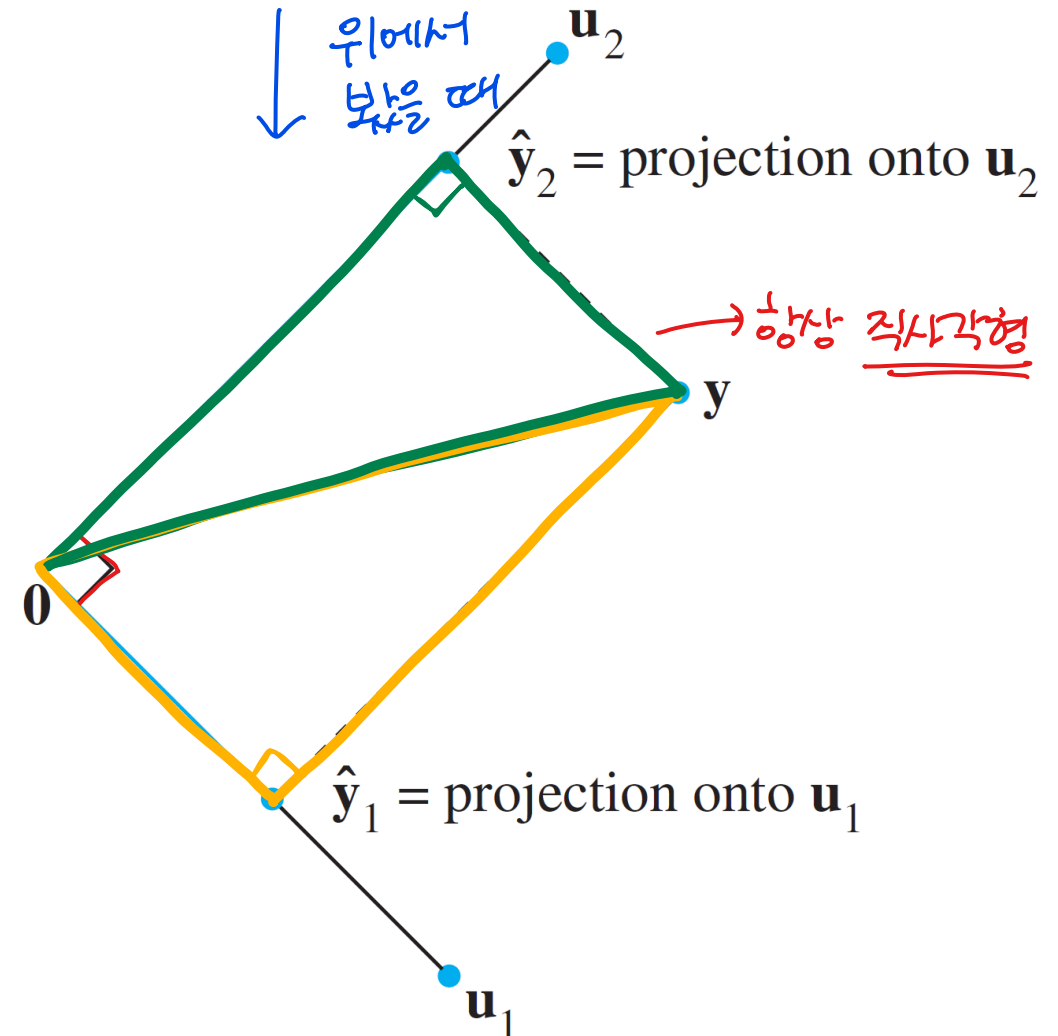


Orthogonal Projection when $y \in W$

- Consider the orthogonal projection \hat{y} of y onto two-dimensional subspace W , where $y \in W$

- $\hat{y} = \text{proj}_L y = y = \frac{y \cdot u_1}{u_1 \cdot u_1} u_1 + \frac{y \cdot u_2}{u_2 \cdot u_2} u_2$

- If u_1 and u_2 are unit vectors,
 $\hat{y} = y = (y \cdot u_1)u_1 + (y \cdot u_2)u_2$
- The solution is the same as before.
Why?



Transformation: Orthogonal Projection

- Consider a transformation of orthogonal projection $\hat{\mathbf{b}}$ of \mathbf{b} , given **orthonormal** basis $\{\mathbf{u}_1, \mathbf{u}_2\}$ of a subspace W :

$$\hat{\mathbf{b}} = f(\mathbf{b}) = (\mathbf{b} \cdot \mathbf{u}_1)\mathbf{u}_1 + (\mathbf{b} \cdot \mathbf{u}_2)\mathbf{u}_2 \rightarrow \frac{\mathbf{b} \cdot \mathbf{u}_1}{\mathbf{u}_1 \cdot \mathbf{u}_1} \mathbf{u}_1 + \frac{\mathbf{b} \cdot \mathbf{u}_2}{\mathbf{u}_2 \cdot \mathbf{u}_2} \mathbf{u}_2$$

$$= (\mathbf{u}_1^T \mathbf{b})\mathbf{u}_1 + (\mathbf{u}_2^T \mathbf{b})\mathbf{u}_2$$

$$= \mathbf{u}_1(\mathbf{u}_1^T \mathbf{b}) + \mathbf{u}_2(\mathbf{u}_2^T \mathbf{b})$$

$$= (\mathbf{u}_1 \mathbf{u}_1^T) \mathbf{b} + (\mathbf{u}_2 \mathbf{u}_2^T) \mathbf{b}$$

$$= (\mathbf{u}_1 \mathbf{u}_1^T + \mathbf{u}_2 \mathbf{u}_2^T) \mathbf{b}$$

$$= \underbrace{[\mathbf{u}_1 \quad \mathbf{u}_2]}_U \underbrace{\begin{bmatrix} \mathbf{u}_1^T \\ \mathbf{u}_2^T \end{bmatrix}}_{U^T} \mathbf{b} = \underline{UU^T} \mathbf{b} \Rightarrow \text{linear transformation!}$$

Diagram illustrating the projection process:

Top: $(\mathbf{u}_1^T \mathbf{b}) \mathbf{u}_1$ is shown as a scalar $\mathbf{u}_1^T \mathbf{b}$ (in a box) multiplied by a vector \mathbf{u}_1 (in a box). A red arrow points to the scalar with the text "스칼라 곱하기" (scalar multiplication). An example is given: $\text{ex) } 4 \cdot \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} 4 \\ 8 \end{bmatrix} = \begin{bmatrix} 1 \\ 2 \end{bmatrix} \cdot 4$.

Bottom: $(\mathbf{u}_1 \mathbf{u}_1^T) \mathbf{b}$ is shown as a matrix $\mathbf{u}_1 \mathbf{u}_1^T$ (in a box) multiplied by a vector \mathbf{b} (in a box). A red arrow points to the matrix with the text " \mathbf{u}_1 or \mathbf{u}_1^T 의 outer product" (outer product of \mathbf{u}_1 or \mathbf{u}_1^T).

Orthogonal Projection Perspective

- Let's verify the following, when $A = U = [\mathbf{u}_1 \quad \mathbf{u}_2]$ has orthonormal columns:

→ u_1 과 u_2 가 수직 관계

Back to the case of invertible $C = A^T A$, consider the orthogonal projection of \mathbf{b} onto $\text{Col } A$ as

$$\hat{\mathbf{b}} = A\hat{\mathbf{x}} = A(A^T A)^{-1}A^T \mathbf{b} = f(\mathbf{b})$$

- $C = A^T A = \begin{bmatrix} \mathbf{u}_1^T \\ \mathbf{u}_2^T \end{bmatrix} [\mathbf{u}_1 \quad \mathbf{u}_2] = I$. Thus,

$$\begin{bmatrix} u_1^T u_1 & u_1^T u_2 \\ u_2^T u_1 & u_2^T u_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \rightarrow \text{값이 1인 orthonormal 이므로}$$

$$\hat{\mathbf{b}} = A\hat{\mathbf{x}} = A \underbrace{(A^T A)^{-1}}_{=I} A^T \mathbf{b} = A(I)A^T \mathbf{b} = AA^T \mathbf{b} = UU^T \mathbf{b}$$