

## Lecture 3: Analytic Geometry

Yi, Yung (이윤)

Mathematics for Machine Learning

<https://yung-web.github.io/home/courses/mathml.html>

KAIST EE

April 3, 2021

- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations

- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations

- A notion of the length of vectors
- **Definition.** A norm on a vector space  $V$  is a function  $\|\cdot\| : V \mapsto \mathbb{R}$ , such that for all  $\lambda \in \mathbb{R}$  the following hold:
  - **Absolutely homogeneous:**  $\|\lambda \mathbf{x}\| = |\lambda| \|\mathbf{x}\|$
  - **Triangle inequality:**  $\|\mathbf{x} + \mathbf{y}\| \leq \|\mathbf{x}\| + \|\mathbf{y}\|$
  - **Positive definite:**  $\|\mathbf{x}\| \geq 0$  and  $\|\mathbf{x}\| \iff \mathbf{x} = 0$

- **Manhattan Norm** (also called  $\ell_1$  norm) For  $\mathbf{x} \in \mathbb{R}^n$ ,

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

- **Euclidean Norm** (also called  $\ell_2$  norm) For  $\mathbf{x} \in \mathbb{R}^n$ ,

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

- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations

- Need to talk about the length of a vector and the angle or distance between two vectors, where vectors are defined in abstract vector spaces
- To this end, we define **inner product** in an abstract manner.
- Dot product: A kind of inner product in vector space  $\mathbb{R}^n$ .  $\mathbf{x}^T \mathbf{y} = \sum_{i=1}^n x_i y_i$
- **Question.** How can we generalize this and do a similar thing in some other vector spaces?

- An inner product is a mapping  $\langle \cdot, \cdot \rangle : V \times V \mapsto \mathbb{R}$  that satisfies the following conditions for all vectors  $\mathbf{u}, \mathbf{v}, \mathbf{w} \in V$  and all scalars  $\lambda \in \mathbb{R}$ :
  1.  $\langle \mathbf{u} + \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{u}, \mathbf{w} \rangle + \langle \mathbf{v}, \mathbf{w} \rangle$
  2.  $\langle \lambda \mathbf{v}, \mathbf{w} \rangle = \lambda \langle \mathbf{v}, \mathbf{w} \rangle$
  3.  $\langle \mathbf{v}, \mathbf{w} \rangle = \langle \mathbf{w}, \mathbf{v} \rangle$
  4.  $\langle \mathbf{v}, \mathbf{v} \rangle \geq 0$  and equal iff  $\mathbf{v} = \mathbf{0}$
- The pair  $(V, \langle \cdot, \cdot \rangle)$  is called an inner product space.



- **Example.**  $V = \mathbb{R}^n$  and the dot product  $\langle \mathbf{x}, \mathbf{y} \rangle := \mathbf{x}^T \mathbf{y}$
- **Example.**  $V = \mathbb{R}^2$  and  $\langle \mathbf{x}, \mathbf{y} \rangle := x_1 y_1 - (x_1 y_2 + x_2 y_1) + 2x_2 y_2$
- **Example.**  $V = \{\text{continuous functions in } \mathbb{R} \text{ over } [a, b]\}$ ,  $\langle u, v \rangle := \int_a^b u(x)v(x)dx$

- A square matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  that satisfies the following is called **symmetric, positive definite** (or just positive definite):

$$\forall \mathbf{x} \in V \setminus \{0\} : \mathbf{x}^T \mathbf{A} \mathbf{x} > 0.$$

If only  $\geq$  in the above holds, then  $\mathbf{A}$  is called **symmetric, positive semidefinite**.

- $\mathbf{A}_1 = \begin{pmatrix} 9 & 6 \\ 6 & 5 \end{pmatrix}$  is positive definite.
- $\mathbf{A}_2 = \begin{pmatrix} 9 & 6 \\ 6 & 3 \end{pmatrix}$  is not positive definite.

- Consider an  $n$ -dimensional vector space  $V$  with an inner product  $\langle \cdot, \cdot \rangle$  and an ordered basis  $B = (\mathbf{b}_1, \dots, \mathbf{b}_n)$  of  $V$ .
- Any  $\mathbf{x}, \mathbf{y} \in V$  can be represented as:  $\mathbf{x} = \sum_{i=1}^n \psi_i \mathbf{b}_i$  and  $\mathbf{y} = \sum_{j=1}^n \lambda_j \mathbf{b}_j$  for some  $\psi_i$  and  $\lambda_j$ ,  $i, j = 1, \dots, n$ .

$$\langle \mathbf{x}, \mathbf{y} \rangle = \left\langle \sum_{i=1}^n \psi_i \mathbf{b}_i, \sum_{j=1}^n \lambda_j \mathbf{b}_j \right\rangle = \sum_{i=1}^n \sum_{j=1}^n \psi_i \langle \mathbf{b}_i, \mathbf{b}_j \rangle \lambda_j = \hat{\mathbf{x}}^T \mathbf{A} \hat{\mathbf{y}},$$

where  $\mathbf{A}_{ij} = \langle \mathbf{b}_i, \mathbf{b}_j \rangle$  and  $\hat{\mathbf{x}}$  and  $\hat{\mathbf{y}}$  are the coordinates w.r.t.  $B$ .

- Then, if  $\forall \mathbf{x} \in V \setminus \{0\} : \mathbf{x}^T \mathbf{A} \mathbf{x} > 0$  (i.e.,  $\mathbf{A}$  is symmetric, positive definite),  $\hat{\mathbf{x}}^T \mathbf{A} \hat{\mathbf{y}}$  legitimately defines an inner product (w.r.t.  $B$ )
- Properties
  - The kernel of  $\mathbf{A}$  is only  $\{0\}$ , because  $\mathbf{x}^T \mathbf{A} \mathbf{x} > 0$  for all  $\mathbf{x} \neq 0 \implies \mathbf{A} \mathbf{x} \neq 0$  if  $\mathbf{x} \neq 0$ .
  - The diagonal elements  $a_{ii}$  of  $\mathbf{A}$  are all positive, because  $a_{ii} = \mathbf{e}_i^T \mathbf{A} \mathbf{e}_i > 0$ .

- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations

- Inner product naturally induces a norm by defining:

$$\|x\| := \sqrt{\langle x, x \rangle}$$

- Not every norm is induced by an inner product
- **Cachy-Schwarz inequality.** For the induced norm by the inner product,

$$|\langle x, y \rangle| \leq \|x\| \|y\|$$

- Now, we can introduce a notion of distance using a norm as:

**Distance.**  $d(\mathbf{x}, \mathbf{y}) := \|\mathbf{x} - \mathbf{y}\| = \sqrt{\langle \mathbf{x} - \mathbf{y}, \mathbf{x} - \mathbf{y} \rangle}$

- If the dot product is used as an inner product in  $\mathbb{R}^n$ , it is **Euclidian distance**.
- **Note.** The distance between two vectors does **NOT** necessarily require the notion of norm. Norm is just sufficient.
- Generally, if the following is satisfied, it is a suitable notion of distance (also called **metric**).
  - **Positive definite.**  $d(\mathbf{x}, \mathbf{y}) \geq 0$  for all  $\mathbf{x}, \mathbf{y}$  and  $d(\mathbf{x}, \mathbf{y}) = 0 \iff \mathbf{x} = \mathbf{y}$
  - **Symmetric.**  $d(\mathbf{x}, \mathbf{y}) = d(\mathbf{y}, \mathbf{x})$
  - **Triangle inequality.**  $d(\mathbf{x}, \mathbf{z}) \leq d(\mathbf{x}, \mathbf{y}) + d(\mathbf{y}, \mathbf{z})$

- Using C-S inequality,

$$-1 \leq \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|} \leq 1$$

- Then, there exists a unique  $\omega \in [0, \pi]$  with

$$\cos \omega = \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|}$$

- We define  $\omega$  as the angle between  $\mathbf{x}$  and  $\mathbf{y}$ .
- **Definition.** If  $\langle \mathbf{x}, \mathbf{y} \rangle = 0$ , in other words their angle is  $\pi/2$ , we say that they are **orthogonal**, denoted by  $\mathbf{x} \perp \mathbf{y}$ . Additionally, if  $\|\mathbf{x}\| = \|\mathbf{y}\| = 1$ , they are **orthonormal**.



- Orthogonality is defined by a given inner product. Thus, different inner products may lead to different results about orthogonality.
- **Example.** Consider two vectors  $\mathbf{x} = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$  and  $\mathbf{y} = \begin{pmatrix} -1 \\ 1 \end{pmatrix}$
- Using the dot product as the inner product, they are orthogonal.
- However, using  $\langle \mathbf{x}, \mathbf{y} \rangle = \mathbf{x}^T \begin{pmatrix} 2 & 0 \\ 0 & 1 \end{pmatrix} \mathbf{y}$ , they are not orthogonal.

$$\cos \omega = \frac{\langle \mathbf{x}, \mathbf{y} \rangle}{\|\mathbf{x}\| \|\mathbf{y}\|} = -\frac{1}{3} \implies \omega \approx 1.91 \text{ rad} \approx 109.5^\circ$$

- **Definition.** A square matrix  $\mathbf{A} \in \mathbb{R}^{n \times n}$  is an **orthogonal matrix**, iff its columns (or rows) are **orthonormal** so that

$$\mathbf{A}\mathbf{A}^T = \mathbf{I} = \mathbf{A}^T\mathbf{A}, \text{ implying } \mathbf{A}^{-1} = \mathbf{A}^T.$$

- We can use  $\mathbf{A}^{-1} = \mathbf{A}^T$  for the definition of orthogonal matrices.
- Fact 1.  $\mathbf{A}, \mathbf{B}$ : orthogonal  $\implies \mathbf{AB}$ : orthogonal
- Fact 2.  $\mathbf{A}$ : orthogonal  $\implies \det(\mathbf{A}) = \pm 1$
- The linear mapping  $\Phi$  by orthogonal matrices preserve **length** and **angle** (for the dot product)

$$\|\Phi(\mathbf{x})\| = \|\mathbf{Ax}\|^2 = (\mathbf{Ax})^T(\mathbf{Ax}) = \mathbf{x}^T\mathbf{A}^T\mathbf{Ax} = \mathbf{x}^T\mathbf{x} = \|\mathbf{x}\|^2$$

$$\cos \omega = \frac{(\mathbf{Ax})^T(\mathbf{Ay})}{\|\mathbf{Ax}\| \|\mathbf{Ay}\|} = \frac{\mathbf{x}^T\mathbf{A}^T\mathbf{Ay}}{\sqrt{\mathbf{x}^T\mathbf{A}^T\mathbf{Ax} \mathbf{y}^T\mathbf{A}^T\mathbf{Ay}}} = \frac{\mathbf{x}^T\mathbf{y}}{\|\mathbf{x}\| \|\mathbf{y}\|}$$

- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations

- Basis that is orthonormal, i.e., they are all orthogonal to each other and their lengths are 1.
- Standard basis in  $\mathbb{R}^n$ ,  $\{\mathbf{e}_1, \dots, \mathbf{e}_n\}$ , is orthonormal.
- **Question.** How to obtain an orthonormal basis?

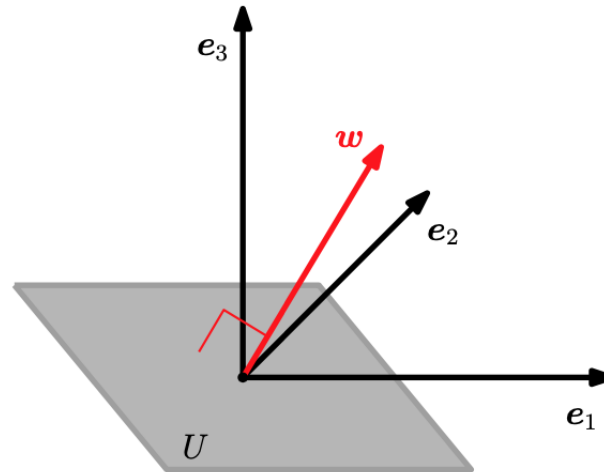
1. Use Gaussian elimination to find a basis for a vector space spanned by a set of vectors.
  - Given a set  $\{\mathbf{b}_1, \dots, \mathbf{b}_n\}$  of unorthogonal and unnormalized basis vectors. Apply Gaussian elimination to the augmented matrix  $(\mathbf{B}\mathbf{B}^T | \mathbf{B})$
2. Constructive way: Gram-Schmidt process (we will cover this later)

- Consider  $D$ -dimensional vector space  $V$  and  $M$ -dimensional subspace  $W \subset V$ . The **orthogonal complement**  $U^\perp$  is a  $(D - M)$ -dimensional subspace of  $V$  and contains all vectors in  $V$  that are orthogonal to every vector in  $U$ .
- $U \cap U^\perp = 0$
- Any vector  $x \in V$  can be uniquely decomposed into:

$$\mathbf{x} = \sum_{m=1}^M \lambda_m \mathbf{b}_m + \sum_{j=1}^{D-M} \psi_j \mathbf{b}_j^\perp, \quad \lambda_m, \psi_j \in \mathbb{R},$$

where  $(\mathbf{b}_1, \dots, \mathbf{b}_M)$  and  $(\mathbf{b}_1^\perp, \dots, \mathbf{b}_{D-M}^\perp)$  are the **bases** of  $U$  and  $U^\perp$ , respectively.

## Orthogonal Complement (2)



- The vector  $w$  with  $\|w\| = 1$ , which is orthogonal to  $U$ , is the basis of  $U^\perp$ .
- Such  $w$  is called **normal vector** to  $U$ .
- For a linear mapping represented by a matrix  $\mathbf{A} \in \mathbb{R}^{m \times n}$ , the solution space of  $\mathbf{A}\mathbf{x} = 0$  is  $\text{row}(\mathbf{A})^\perp$ , where  $\text{row}(\mathbf{A})$  is the row space of  $\mathbf{A}$  (i.e., span of row vectors). In other words,  $\text{row}(\mathbf{A})^\perp = \ker(\mathbf{A})$

- Earlier,  $V = \{\text{continuous functions in } \mathbb{R} \text{ over } [a, b]\}$ , the following is a proper inner product.

$$\langle u, v \rangle := \int_a^b u(x)v(x)dx$$

- **Example.** Choose  $u(x) = \sin(x)$  and  $v(x) = \cos(x)$ , where we select  $a = -\pi$  and  $b = \pi$ . Then, since  $f(x) = u(x)v(x)$  is odd (i.e.,  $f(-x) = -f(x)$ ),

$$\int_{-\pi}^{\pi} u(x)v(x)dx = 0.$$

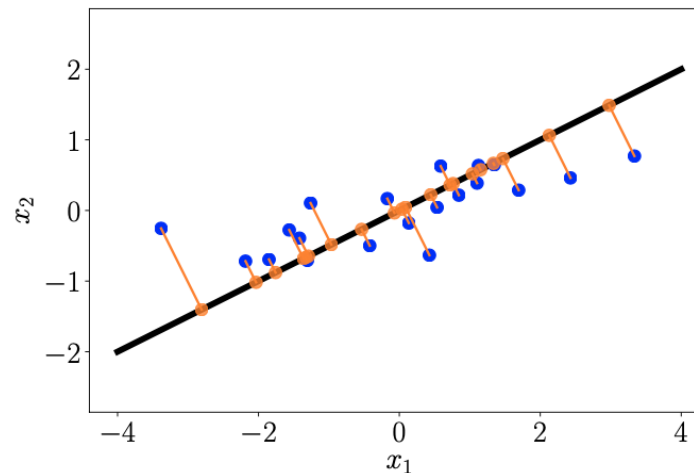
- Thus,  $u$  and  $v$  are orthogonal.
- Similarly,  $\{1, \cos(x), \cos(2x), \cos(3x), \dots, \}$  is orthogonal over  $[-\pi, \pi]$ .

- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations



# Projection: Motivation

- Big data: high dimensional
- However, most information is contained in a few dimensions
- **Projection**: A process of reducing the dimensions (hopefully) without loss of much information
- **Example**. Projection of 2D dataset onto 1D subspace



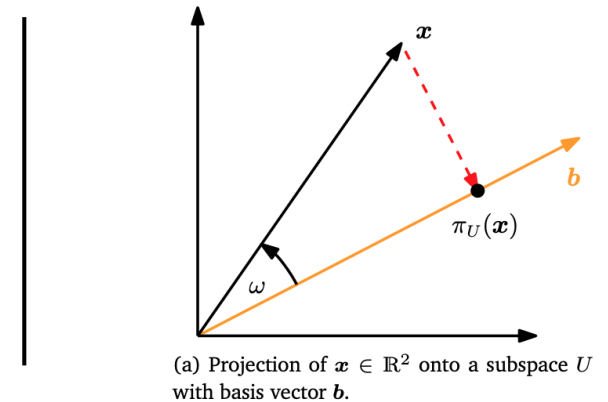
# Projection onto Lines (1D Subspaces)

- Consider a 1D subspace  $U \subset \mathbb{R}^n$  spanned by the basis  $\mathbf{b}$ .
- For  $\mathbf{x} \in \mathbb{R}^n$ , what is its projection  $\pi_U(\mathbf{x})$  onto  $U$  (assume the dot product)?

$$\langle \mathbf{x} - \pi_U(\mathbf{x}), \mathbf{b} \rangle = 0 \xleftrightarrow{\pi_U(\mathbf{x}) = \lambda \mathbf{b}} \langle \mathbf{x} - \lambda \mathbf{b}, \mathbf{b} \rangle = 0$$
$$\Rightarrow \lambda = \frac{\langle \mathbf{b}^\top, \mathbf{x} \rangle}{\|\mathbf{b}\|^2} = \frac{\mathbf{b}^\top \mathbf{x}}{\|\mathbf{b}\|^2}, \text{ and } \pi_U(\mathbf{x}) = \lambda \mathbf{b} = \frac{\mathbf{b}^\top \mathbf{x}}{\|\mathbf{b}\|^2} \mathbf{b}$$

- Projection matrix  $\mathbf{P}_\pi \in \mathbb{R}^{n \times n}$  in  $\pi_U(\mathbf{x}) = \mathbf{P}_\pi \mathbf{x}$

$$\pi_U(\mathbf{x}) = \lambda \mathbf{b} = \mathbf{b} \lambda = \frac{\mathbf{b} \mathbf{b}^\top}{\|\mathbf{b}\|^2} \mathbf{x}, \quad \mathbf{P}_\pi = \frac{\mathbf{b} \mathbf{b}^\top}{\|\mathbf{b}\|^2}$$

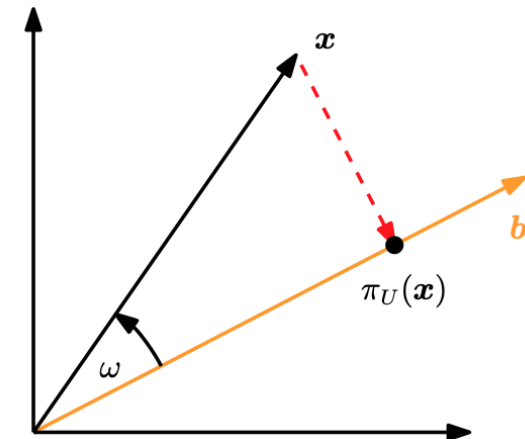


# Inner Product and Projection

- We project  $\mathbf{x}$  onto  $\mathbf{b}$ , and let  $\pi_{\mathbf{b}}(\mathbf{x})$  be the projected vector.
- **Question.** Understanding the inner product  $\langle \mathbf{x}, \mathbf{b} \rangle$  from the projection perspective?

$$\langle \mathbf{x}, \mathbf{b} \rangle = \|\pi_{\mathbf{b}}(\mathbf{x})\| \times \|\mathbf{b}\|$$

- In other words, the inner product of  $\mathbf{x}$  and  $\mathbf{b}$  is the product of (length of the projection of  $\mathbf{x}$  onto  $\mathbf{b}$ )  $\times$  (length of  $\mathbf{b}$ )



(a) Projection of  $\mathbf{x} \in \mathbb{R}^2$  onto a subspace  $U$  with basis vector  $\mathbf{b}$ .

## Example

- $\mathbf{b} = \begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix}$

$$\mathbf{P}_\pi = \frac{\mathbf{b}\mathbf{b}^\top}{\|\mathbf{b}\|^2} = \frac{1}{9} \begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix} (1 \ 2 \ 2) = \frac{1}{9} \begin{pmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{pmatrix}$$

For  $\mathbf{x} = \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}$ ,

$$\pi_U(\mathbf{x}) = \mathbf{P}_\pi \mathbf{x} = \frac{1}{9} \begin{pmatrix} 1 & 2 & 2 \\ 2 & 4 & 4 \\ 2 & 4 & 4 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix} = \frac{1}{9} \begin{pmatrix} 5 \\ 10 \\ 10 \end{pmatrix} \in \text{span}\left[\begin{pmatrix} 1 \\ 2 \\ 2 \end{pmatrix}\right]$$

- $\mathbb{R}^n \rightarrow 1\text{-Dim}$
- A basis vector  $\mathbf{b}$  in 1D subspace

$$\pi_U(\mathbf{x}) = \frac{\mathbf{b}\mathbf{b}^\top \mathbf{x}}{\mathbf{b}^\top \mathbf{b}}, \quad \lambda = \frac{\mathbf{b}^\top \mathbf{x}}{\mathbf{b}^\top \mathbf{b}}$$

$$\mathbf{P}_\pi = \frac{\mathbf{b}\mathbf{b}^\top}{\mathbf{b}^\top \mathbf{b}}$$

- $\mathbb{R}^n \rightarrow m\text{-Dim}, (m < n)$

- A basis matrix  
 $\mathbf{B} = (\mathbf{b}_1, \dots, \mathbf{b}_m) \in \mathbb{R}^{n \times m}$

$$\pi_U(\mathbf{x}) = \mathbf{B}(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{x}, \quad \boldsymbol{\lambda} = (\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{x}$$

$$\mathbf{P}_\pi = \mathbf{B}(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top$$

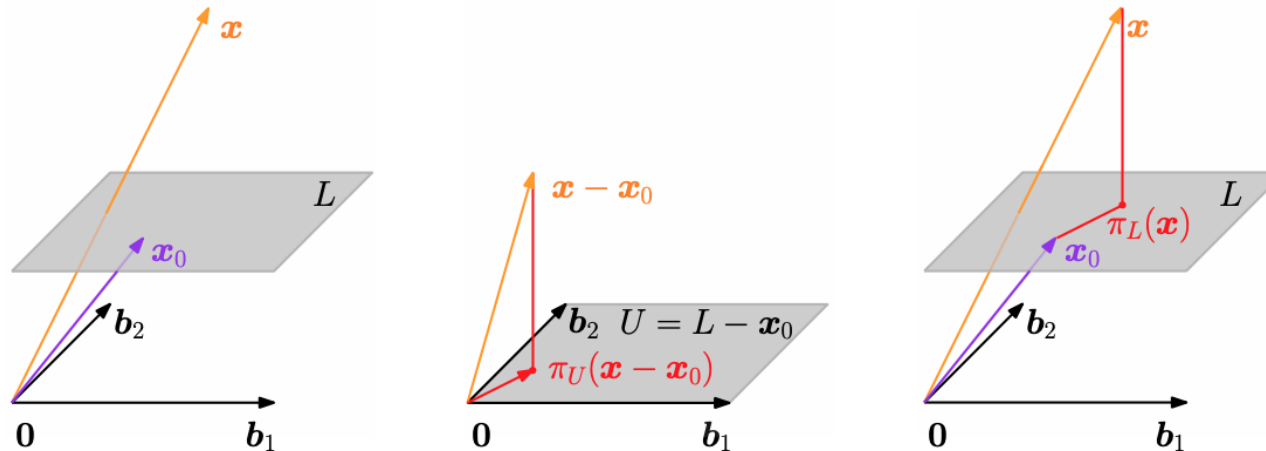
- $\lambda \in \mathbb{R}^1$  and  $\boldsymbol{\lambda} \in \mathbb{R}^m$  are the coordinates in the projected spaces, respectively.
- $(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top$  is called **pseudo-inverse**.
- How to derive is analogous to that of lines (see pp. 71).

## Example: Projection onto 2D Subspace

- $U = \text{span}\left[\begin{pmatrix} 1 \\ 1 \\ 1 \end{pmatrix}, \begin{pmatrix} 0 \\ 1 \\ 2 \end{pmatrix}\right] \subset \mathbb{R}^3$  and  $\mathbf{x} = \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix}$ . Check that  $\{(1 \ 1 \ 1)^T, (0 \ 1 \ 2)^T\}$  is a basis.
- Let  $\mathbf{B} = \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{pmatrix}$ . Then,  $\mathbf{B}^T \mathbf{B} = \begin{pmatrix} 1 & 1 & 2 \\ 0 & 1 & 2 \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 1 & 1 \\ 1 & 2 \end{pmatrix} = \begin{pmatrix} 3 & 3 \\ 3 & 5 \end{pmatrix}$
- Can see that  $\mathbf{P}_\pi = \mathbf{B}(\mathbf{B}^T \mathbf{B})^{-1} \mathbf{B}^T = \frac{1}{6} \begin{pmatrix} 5 & 2 & -1 \\ 2 & 2 & 2 \\ -1 & 2 & 5 \end{pmatrix}$ , and
$$\pi_U(\mathbf{x}) = \frac{1}{6} \begin{pmatrix} 5 & 2 & -1 \\ 2 & 2 & 2 \\ -1 & 2 & 5 \end{pmatrix} \begin{pmatrix} 6 \\ 0 \\ 0 \end{pmatrix} = \begin{pmatrix} 5 \\ 2 \\ -1 \end{pmatrix}$$

-

# Projection onto Affine Subspaces



- Affine space:  $L = \mathbf{x}_0 + U$
- Affine subspaces are not vector spaces
- Idea: (i) move  $\mathbf{x}$  to a point in  $U$ , (ii) do the projection, (iii) move back to  $L$

$$\pi_L(\mathbf{x}) = \mathbf{x}_0 + \pi_U(\mathbf{x} - \mathbf{x}_0)$$



- (1) Norms
- (2) Inner Products
- (3) Lengths and Distances
- (4) Angles and Orthogonality
- (5) Orthonormal Basis
- (6) Orthogonal Complement
- (7) Inner Product of Functions
- (8) Orthogonal Projections
- (9) Rotations

- A linear mapping that rotates the given coordinate system by an angle  $\theta$ .
- Basis change
- $\mathbf{e}_1 = \begin{pmatrix} 1 \\ 0 \end{pmatrix} \rightarrow \begin{pmatrix} \cos \theta \\ \sin \theta \end{pmatrix}$  and  $\mathbf{e}_2 = \begin{pmatrix} 0 \\ 1 \end{pmatrix} \rightarrow \begin{pmatrix} -\sin \theta \\ \cos \theta \end{pmatrix}$
- Rotation matrix  $\mathbf{R}(\theta) = \begin{pmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{pmatrix}$
- Properties
  - Preserves distance:  $\|\mathbf{x} - \mathbf{y}\| = \|\mathbf{R}_\theta(\mathbf{x}) - \mathbf{R}_\theta(\mathbf{y})\|$
  - Preserves angle

Questions?

1)