

# Basics: Orthogonal Projections

Archer Yang

McGill University

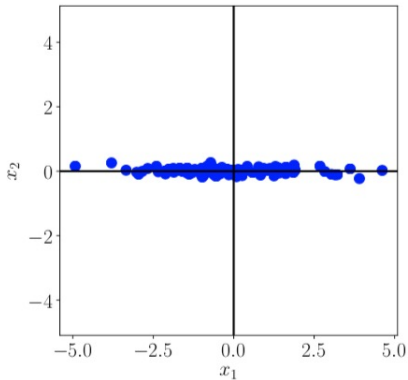
October 4, 2024

- **Reading assignment:** read chapter 3.1-3.8.2 of **Mathematics for Machine Learning** book.

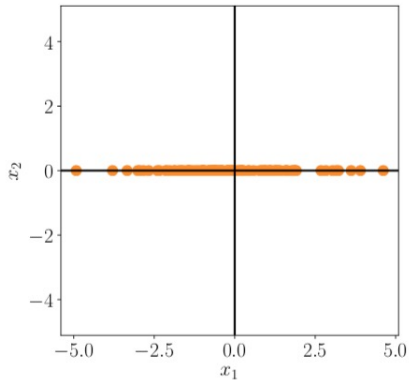
# Dimension reduction

- High-dimensional data often has only **a few** dimensions contain most information.
- When compress or visualize high-dimensional data, pick the **most informative** dimensions in the data.
- Then project the original high-dimensional data onto this lower-dimensional space.
- E.g. **principal component analysis** (PCA) by Hotelling (1933) and **deep auto-encoders** (Deng et al., 2010).
- Both techniques involves **orthogonal projection**, so let's study this concept.

# Dimension reduction



(a) Dataset with  $x_1$  and  $x_2$  coordinates.



(b) Compressed dataset where only the  $x_1$  coordinate is relevant.

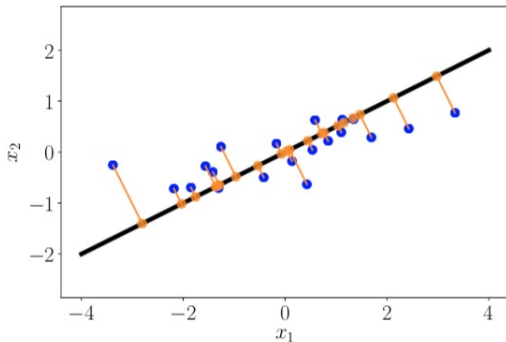
# Projection

## Definition (Projection)

Let  $V$  be a vector space and  $U \subseteq V$  a subspace of  $V$ .

A **linear** mapping  $\pi : V \rightarrow U$  is called a **projection** if

$$\pi^2 = \pi \circ \pi = \pi$$



# PROJECTION ONTO ONE-DIMENSIONAL SUBSPACES

# Projection onto one-dimensional subspaces (lines)

- Given a line through the origin with basis vector

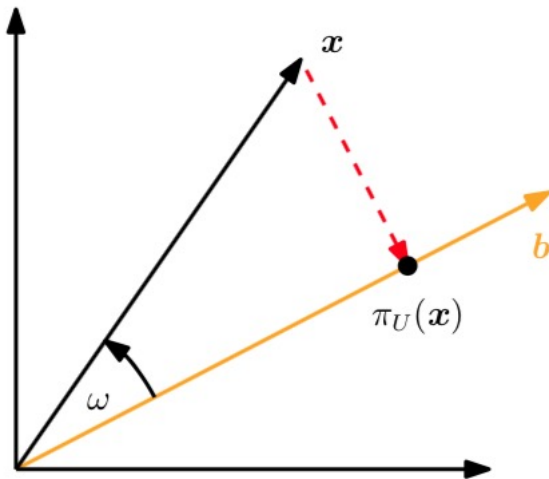
$$\mathbf{b} = (b_1, \dots, b_D)^\top \in \mathbb{R}^D.$$

- Note that  $\mathbf{b}$  is a **column vector**.
- The line **through the origin** creates a one-dimensional subspace  $U$  **spanned by  $\mathbf{b}$**

$$U = \{z\mathbf{b} : \forall z \in \mathbb{R}\}$$

- Now we project  $\mathbf{x} = (x_1, \dots, x_D)^\top \in \mathbb{R}^D$  onto  $U$ , denote this **projection** as  $\pi_U(\mathbf{x})$

## Projection onto one-dimensional subspaces (lines)





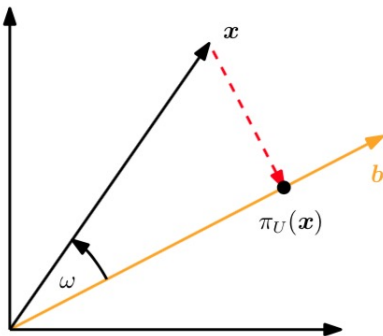
# Projection onto one-dimensional subspaces (lines)

- The projection  $\pi_U(x)$  of  $x$  onto  $U$  **must be an element** of  $U$ , i.e.

$$\pi_U(x) = zb$$

for **some**  $z \in \mathbb{R}$ .

- How to determine the coordinate  $z$ ?



## Finding the coordinate $z$

It's very easy:

- The orthogonality condition yields

$$\langle x - \pi_U(x), b \rangle = 0 \iff \pi_U(x) = zb \iff \langle x - zb, b \rangle = 0.$$

- By the bilinearity of the inner product

$$\langle x, b \rangle - z \langle b, b \rangle = 0 \iff z = \frac{\langle x, b \rangle}{\langle b, b \rangle} = \frac{\langle b, x \rangle}{\|b\|^2}$$

- In a Euclidean space,  $\langle \cdot, \cdot \rangle$  is the dot product

$$z = \frac{b^\top x}{b^\top b} = \frac{b^\top x}{\|b\|^2}$$

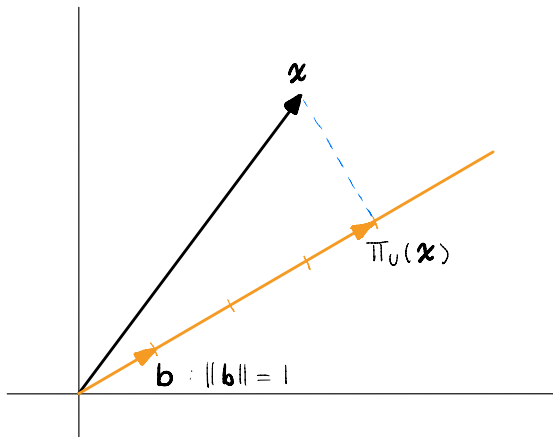
- As a special case, if  $\|b\| = 1$ , then the **coordinate**  $z$  of the projection is given by

$$z = b^\top x$$

# Key slides

- If  $\|b\| = 1$ , then the **coordinate**  $z$  of the projection is given by

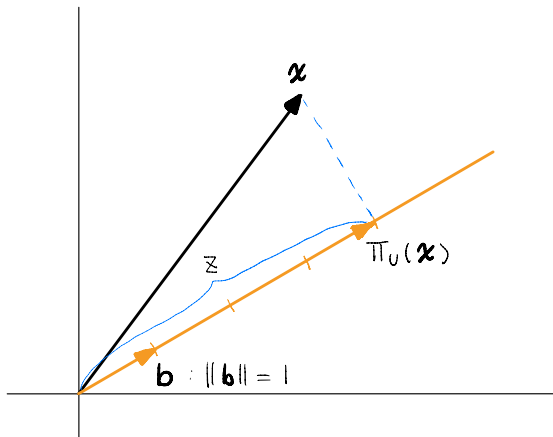
$$z = b^T x$$



## Key slides

- If  $\|b\| = 1$ , then the **coordinate**  $z$  of the projection is given by

$$z = b^T x$$



# Finding the projection point

- Since  $\pi_U(\mathbf{x}) = z\mathbf{b}$ , we get

$$\pi_U(\mathbf{x}) = z\mathbf{b} = \frac{\langle \mathbf{x}, \mathbf{b} \rangle}{\|\mathbf{b}\|^2} \mathbf{b} = \frac{\mathbf{b}^\top \mathbf{x}}{\|\mathbf{b}\|^2} \mathbf{b}$$

- The length of  $\pi_U(\mathbf{x})$  is

$$\|\pi_U(\mathbf{x})\| = \|z\mathbf{b}\| = |z| \|\mathbf{b}\|$$

- As a special case, when  $\|\mathbf{b}\| = 1$ ,

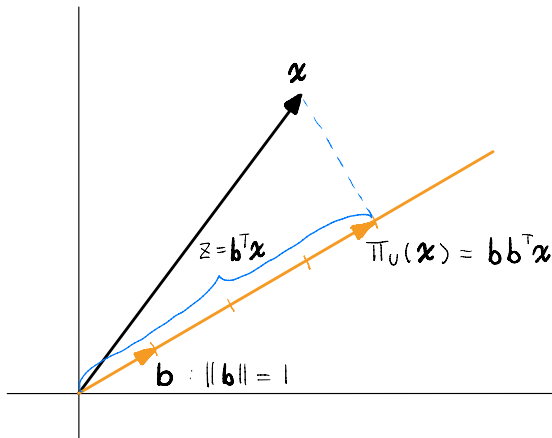
$$\pi_U(\mathbf{x}) = z\mathbf{b} = \mathbf{b}\mathbf{b}^\top \mathbf{x}$$

and  $\|\pi_U(\mathbf{x})\| = |z|$ .

## Key slides

- If  $\|b\| = 1$ , then the **projection**  $\pi_U(x)$  is

$$\pi_U(x) = zb = bz = bb^T x$$



# A practice

- (Homework) Given that

$$\mathbf{x}^\top \mathbf{y} = \|\mathbf{x}\| \|\mathbf{y}\| \cos \omega$$

show that

$$\|\pi_U(\mathbf{x})\| = |\cos \omega| \|\mathbf{x}\|$$

- (Homework) If  $\|\mathbf{x}\| = 1$  (lies on the unit circle), then

$$\|\pi_U(\mathbf{x})\| = |\cos \omega|$$

## Finding the projection matrix $P_\pi$

- The operation of the linear projection  $\pi_U$  can be represented by a projection matrix  $P_\pi$ , s.t.

$$\pi_U(x) = P_\pi x$$

- Since

$$\pi_U(x) = \frac{b^\top x}{\|b\|^2} b = \frac{bb^\top x}{\|b\|^2} = \frac{bb^\top}{\|b\|^2} x$$

we see that

$$P_\pi = \frac{bb^\top}{\|b\|^2} \tag{1}$$

- Note that  $bb^\top$  is a symmetric matrix (of rank 1), and  $\|b\|^2$  is a scalar.
- As a special case, if  $\|b\| = 1$ , then  $P_\pi = bb^\top$ .



## A practice

- (Homework) Show that a projection matrix satisfies

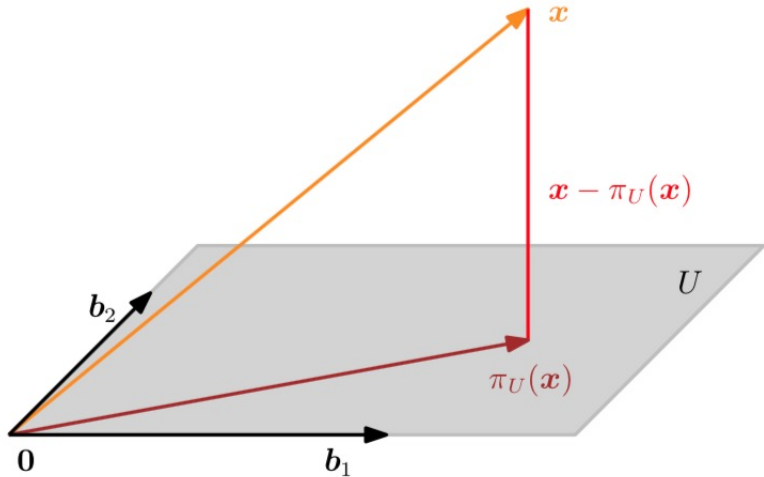
$$P_{\pi}^2 x = P_{\pi} x$$

this verifies that mapping  $P_{\pi}$  indeed satisfies the definition of projection

# PROJECTION ONTO GENERAL SUBSPACES

## Projection onto general subspaces

Now consider orthogonal projections of  $\mathbf{x} \in \mathbb{R}^D$  onto lower-dimensional subspaces  $U \subseteq \mathbb{R}^D$  with  $\dim(U) = M \geq 1$ .



# Projection onto general subspaces

- Assume  $\mathbf{b}_1, \dots, \mathbf{b}_M$  is an ordered basis of  $U$ .
- The projection  $\pi_U(\mathbf{x})$  of  $\mathbf{x}$  onto  $U$  **must be an element** of  $U$ , i.e.  
 $\pi_U(\mathbf{x})$  can be represented as linear combinations of the basis vectors

$$\mathbf{b}_1, \dots, \mathbf{b}_M$$

of  $U$ ,

$$\pi_U(\mathbf{x}) = \sum_{i=1}^M z_i \mathbf{b}_i$$

- How to determine  $z_1, \dots, z_M$ ?

## Finding the coordinates $z_1, \dots, z_M$

- First we use the matrix notation

$$\pi_U(\mathbf{x}) = \sum_{i=1}^M z_i \mathbf{b}_i = \mathbf{B}\mathbf{z}$$

where

$$\mathbf{B} = \begin{pmatrix} | & | & & | \\ \mathbf{b}_1 & \mathbf{b}_2 & \cdots & \mathbf{b}_M \\ | & | & & | \end{pmatrix} \in \mathbb{R}^{D \times M}, \quad \mathbf{z} = (z_1, \dots, z_M)^\top \in \mathbb{R}^M$$

## Finding the coordinates $z_1, \dots, z_M$

- Need to find  $\pi_U(\mathbf{x})$  in  $U$  that is closest to  $\mathbf{x} \in \mathbb{R}^D$ .
- This implies that  $\mathbf{x} - \pi_U(\mathbf{x})$  must be orthogonal to all basis vectors of  $U$ :

$$\langle \mathbf{b}_1, \mathbf{x} - \pi_U(\mathbf{x}) \rangle = \mathbf{b}_1^\top (\mathbf{x} - \pi_U(\mathbf{x})) = 0$$

$$\vdots$$

$$\langle \mathbf{b}_M, \mathbf{x} - \pi_U(\mathbf{x}) \rangle = \mathbf{b}_M^\top (\mathbf{x} - \pi_U(\mathbf{x})) = 0$$

## Finding the coordinates $z_1, \dots, z_M$

- With  $\pi_U(x) = Bz$

$$b_1^\top (x - Bz) = 0$$

$$\vdots$$

$$b_M^\top (x - Bz) = 0$$

- In a matrix format

$$\begin{bmatrix} b_1^\top \\ \vdots \\ b_M^\top \end{bmatrix} [x - Bz] = 0 \iff B^\top (x - Bz) = 0$$

$$\iff B^\top Bz = B^\top x.$$

- Since  $\mathbf{b}_1, \dots, \mathbf{b}_M$  are a basis of  $U$  and therefore linearly independent, therefore

$$\text{rank}(\mathbf{B}) = M \quad \text{where } M \leq D$$

- Meanwhile  $\mathbf{B}^\top \mathbf{B} \in \mathbb{R}^{M \times M}$  is invertible since

$$\text{rank}(\mathbf{B}^\top \mathbf{B}) = \text{rank}(\mathbf{B}) = M \quad (2)$$

we get

$$\mathbf{z} = (\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{x}$$

- The matrix  $(\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top$  is also called the **pseudo-inverse** of non-square matrix  $\mathbf{B}$ .



## Proof of Eq. (2)

- First we see that  $\text{nullity}(B^\top B) = \text{nullity}(B)$ , this is because for any  $x$  that satisfies

$$B^\top Bx = 0$$

we also have

$$\|Bx\|^2 = xB^\top Bx = 0$$

hence  $Bx = 0$ . Therefore  $\text{nullity}(B^\top B) = \text{nullity}(B)$

- By rank–nullity theorem, we have  $\text{nullity}(B) = M - \text{rank}(B) = 0$ , then

$$\text{rank}(B^\top B) = M - \text{nullity}(B^\top B) = M - \text{nullity}(B) = M$$

# Finding the projection point

- We already know that

$$\pi_U(x) = Bz$$

Therefore

$$\pi_U(x) = B(B^\top B)^{-1}B^\top x$$

## Finding the projection matrix $P_\pi$

- We see that the projection matrix that solves

$$\pi_U(x) = P_\pi x$$

must be

$$P_\pi = B(B^\top B)^{-1}B^\top$$

- **Remark 1:** this result includes the 1D case as a special case: if  $\dim(U) = 1$ , then  $M = 1$  and  $B^\top B \in \mathbb{R}$  is a scalar, we can then write

$$P_\pi = B(B^\top B)^{-1}B^\top = \frac{BB^\top}{B^\top B}$$

which coincides with Eq. (1).

## Finding the projection matrix $P_\pi$

- **Remark 2:** The projections  $\pi_U(x)$  are still vectors in  $\mathbb{R}^D$  although they lie in an  $M$ -dimensional subspace  $U \subseteq \mathbb{R}^D$ . However, to represent a projected vector we only need the  $M$  coordinates  $z_1, \dots, z_M$  with respect to the basis vectors  $b_1, \dots, b_M$ . i.e.  $\pi_U(x) \in \mathbb{R}^D$  however  $z = (z_1, \dots, z_M)^\top \in \mathbb{R}^M$ .

- If the basis  $\{\mathbf{b}_1, \dots, \mathbf{b}_M\}$  for the subspace  $U$  is an orthonormal basis, i.e for all  $i, j = 1, \dots, M$

$$\langle \mathbf{b}_i, \mathbf{b}_j \rangle = \mathbf{b}_i^\top \mathbf{b}_j = 0 \quad \text{for } i \neq j$$

$$\langle \mathbf{b}_i, \mathbf{b}_i \rangle = \mathbf{b}_i^\top \mathbf{b}_i = 1$$

Then

$$\mathbf{B}^\top \mathbf{B} = (\mathbf{b}_1, \dots, \mathbf{b}_M)^\top (\mathbf{b}_1, \dots, \mathbf{b}_M) = \mathbf{I}_{M \times M}$$

- In this case, the coordinate of the orthogonal projection reduces to

$$\mathbf{z} = (\mathbf{B}^\top \mathbf{B})^{-1} \mathbf{B}^\top \mathbf{x} = \mathbf{I}_{M \times M}^{-1} \mathbf{B}^\top \mathbf{x} = \mathbf{B}^\top \mathbf{x}$$

and the **projection**  $\pi_U(\mathbf{x})$  reduces to

$$\pi_U(\mathbf{x}) = \mathbf{B}\mathbf{z} = \mathbf{B}\mathbf{B}^\top \mathbf{x}$$

with the projection matrix  $\mathbf{P}_\pi = \mathbf{B}\mathbf{B}^\top$

