

## Orthogonal projections

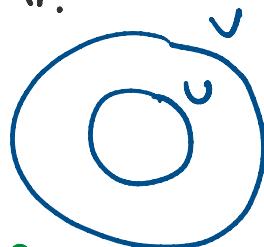
A type of linear transformation (like rotation & reflection)

high dim data  $\rightarrow$  project it to low dim space.

Defn: Let  $V$  be a V.S over  $\mathbb{R}$  and let  $U$  be a subspace of  $V$ . A linear mapping  $\pi: V \rightarrow U$  is called a projection if  $\pi^2 = \pi \circ \pi = \pi$ .

$$\pi(\vec{v}) = \vec{u}$$

$$\pi(\pi(\vec{v})) = \pi(\vec{u}) = \vec{u}$$

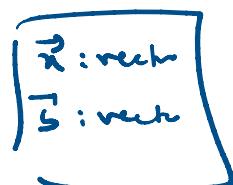


Consider the projection matrix  $P_\pi$

$$P_\pi^T = P_\pi$$

## Projection onto one-dim subspaces (lines)

Assume we are given a line through the origin with basis vector  $\vec{b} \in \mathbb{R}^n$ .



The line is a one-dim subspace  $U \subseteq \mathbb{R}^n$  spanned by  $\vec{b}$ . When we project  $\vec{v} \in \mathbb{R}^n$

spanned by  $b$ . When we project  $\vec{u} \in \mathbb{R}^n$  onto  $U$ , we seek the vector  $\Pi_U(\vec{u})$  that is closest to  $\vec{u}$ .

Two properties of a projection

(i)  $\Pi_U(\vec{u})$  is closest to  $\vec{u}$ . That is,

$\|\vec{u} - \Pi_U(\vec{u})\|$  is minimal. It follows

that the segment  $\Pi_U(\vec{u}) - \vec{u}$

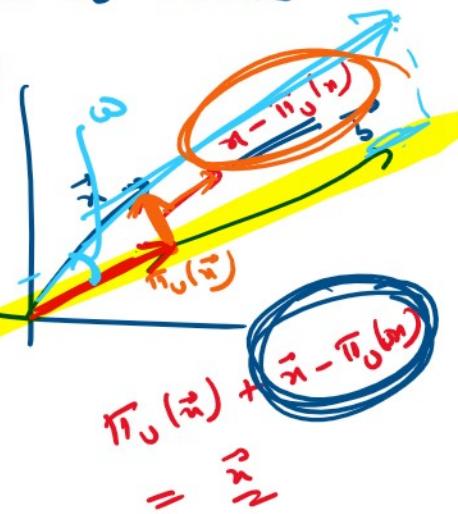
is orthogonal to  $U$  and

and therefore orthogonal to

the basis vector  $\vec{b}$  of  $U$ .

That is,

$$\langle \Pi_U(\vec{u}) - \vec{u}, \vec{b} \rangle = 0$$



(ii) the projector  $\Pi_U(\vec{u})$  must be an element of  $U$ . Therefore  $\Pi_U(\vec{u}) = \lambda \vec{b}$ ,

for some  $\lambda \in \mathbb{R}$ .

Three steps to determine  $\lambda$ , the projection  
 $\Pi_U(\vec{u}) \in U$ , and the projection matrix  
 $P_{\Pi}$  that maps  $\vec{u}$  onto  $U$ .

(i) Finding  $\lambda$ .

$$\langle \vec{u} - \Pi_U(\vec{u}), \vec{b} \rangle = 0$$

$$\langle \vec{u} - \pi_v(\vec{u}), \vec{b} \rangle = 0$$

Since  $\pi_v(\vec{u}) = \lambda \vec{b}$ ,

$$\langle \vec{u} - \lambda \vec{b}, \vec{b} \rangle = 0$$

$$\langle \vec{u}, \vec{b} \rangle - \lambda \langle \vec{b}, \vec{b} \rangle = 0$$

$$\lambda = \frac{\langle \vec{u}, \vec{b} \rangle}{\|\vec{b}\|^2} = \frac{\langle \vec{b}, \vec{u} \rangle}{\|\vec{b}\|^2}$$

If we use dot product as the inner product,

then

$$\boxed{\lambda = \frac{\vec{b}^T \vec{u}}{\|\vec{b}\|^2}}$$

$$\vec{b} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix} \quad \vec{u} = \begin{bmatrix} 1 \\ 2 \\ 3 \\ 4 \end{bmatrix}$$

$$\text{If } \|\vec{b}\|=1, \text{ then } \lambda = \underline{\vec{b}^T \vec{u}} \quad \vec{b}^T = \underline{\begin{bmatrix} 1 & 2 & 3 & 4 \end{bmatrix}}$$

(ii) Finding the projection point  $\pi_v(\vec{u})$

$$\pi_v(\vec{u}) = \lambda \vec{b} = \frac{\langle \vec{u}, \vec{b} \rangle}{\|\vec{b}\|^2} \vec{b} = \frac{\vec{b}^T \vec{u}}{\|\vec{b}\|^2} \vec{b}$$

$$\|\alpha \vec{v}\| = |\alpha| \|\vec{v}\|$$

(for dot products)

From the definition of norm/length,

$$\|\pi_v(\vec{u})\| = \|\lambda \vec{b}\| = |\lambda| \|\vec{b}\|$$

When dot product is the inner product under

When dot product is the inner product under consideration,

$$\begin{aligned}\|\Pi_{\mathcal{S}}(\vec{u})\| &= \frac{|\vec{b}^T \vec{u}|}{\|\vec{b}\|^2} \|\vec{b}\| = \frac{|\cos \omega| \|\vec{u}\| \|\vec{b}\| \|\vec{b}\|}{\|\vec{b}\|^2} \\ &= \|\vec{u}\| |\cos \omega|\end{aligned}$$

(iii) Finding the projection matrix  $P_{\mathcal{S}}$

$$\Pi_{\mathcal{S}}(\vec{u}) = \lambda \vec{b} = \vec{b} \lambda = \vec{b} \frac{\vec{b}^T \vec{u}}{\|\vec{b}\|^2} = \frac{\vec{b} \vec{b}^T}{\|\vec{b}\|^2} \vec{u}$$

Thus,

$$P_{\mathcal{S}} = \frac{\vec{b} \vec{b}^T}{\|\vec{b}\|^2}$$

If  $\vec{b}$  is a symmetric matrix.

*(assuming dot product as the inner product)*

$$\vec{b} = \begin{bmatrix} & \\ & \end{bmatrix}_{n \times n}, \quad \vec{b}^T = \begin{bmatrix} & \\ & \end{bmatrix}_{1 \times n}$$

Projection onto general subspace

Projection of  $\vec{u} \in \mathbb{R}^n$  onto a lower dimensional subspace  $V \subseteq \mathbb{R}^n$  with  $\dim(V) = m \geq 1$ .

$$1 \leq m \leq n.$$

Let  $\{\vec{b}_1, \vec{b}_2, \dots, \vec{b}_m\}$  be a basis of  $U$ .

Let  $\Pi_U(\vec{v})$  denote the projection of  $\vec{v}$  onto  $U$ . We know  $\Pi_U(\vec{v}) \in U$ . Let

$$\Pi_U(\vec{v}) = \sum_{i=1}^m \lambda_i \vec{b}_i$$

Like we did in the 1-dim case, we follow a 3-step procedure to find  $\lambda_1, \dots, \lambda_m$ ,  $\Pi_U(\vec{v})$  and the projection matrix  $P_U$ .

1. Finding  $\lambda_1, \lambda_2, \dots, \lambda_m$

$$\Pi_U(\vec{v}) = \sum_{i=1}^m \lambda_i \vec{b}_i = \mathbf{B}\boldsymbol{\lambda}, \text{ where}$$

$$\mathbf{B} = [\vec{b}_1, \vec{b}_2, \dots, \vec{b}_m] \in \mathbb{R}^{n \times m}$$

$$\boldsymbol{\lambda} = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_m \end{bmatrix} = \begin{bmatrix} \vec{b}_1 & \vec{b}_2 & \cdots & \vec{b}_m \end{bmatrix}^{-1} \begin{bmatrix} \vec{v} \end{bmatrix}$$

$$\begin{bmatrix} \vdots \\ \lambda_m \end{bmatrix}_{m \times 1} = \begin{bmatrix} \text{U}_1 \\ \text{U}_2 \\ \vdots \\ \text{U}_m \end{bmatrix}$$

Assuming dot product as the inner product,  
since  $\pi_U(\vec{v})$  is closest to  $\vec{v}$ , we have

$$\langle \vec{b}_1, (\vec{v} - \pi_U(\vec{v})) \rangle = \vec{b}_1^T (\vec{v} - \pi_U(\vec{v})) = 0$$

$$\langle \vec{b}_2, (\vec{v} - \pi_U(\vec{v})) \rangle = \vec{b}_2^T (\vec{v} - \pi_U(\vec{v})) = 0$$

$$\vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots \quad \vdots$$

$$\langle \vec{b}_m, (\vec{v} - \pi_U(\vec{v})) \rangle = \vec{b}_m^T (\vec{v} - \pi_U(\vec{v})) = 0$$

Using ① to replace  $\pi_U(\vec{v})$  with  $B\lambda$ ,

$$\vec{b}_1^T (\vec{v} - B\lambda) = 0$$

$$\vec{b}_2^T (\vec{v} - B\lambda) = 0$$

$$\vdots \quad \vdots \quad \vdots$$

$$\vec{b}_m^T (\vec{v} - B\lambda) = 0$$

From here, we obtain the following homogeneous system of linear equations

$$\begin{bmatrix} \vec{b}_1^T \\ \vec{b}_2^T \\ \vdots \\ \vdots \\ \vec{b}_m^T \end{bmatrix}_{m \times n} \begin{bmatrix} \vec{x} - B\lambda \end{bmatrix}_{n \times 1} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{bmatrix}_{m \times 1}$$

That is,

$$B^T (\vec{x} - B\lambda) = \vec{0}_{m \times 1}$$

or

$$\begin{bmatrix} B^T B \lambda \end{bmatrix}_{m \times 1} = B^T \vec{x}_{n \times 1}$$

$$\vec{x}^T A \vec{x} \geq 0 \text{ always}$$

and  $= 0$  only when  $\vec{x} = \vec{0}$

it is symmetric,  
it is positive definite  
and therefore it is  
invertible

Thus

$$\lambda = (B^T B)^{-1} B^T \vec{x}$$

$$2. \quad \pi_U(\vec{x}) = B \underbrace{\lambda}_{n \times 1} \quad (\text{from Eqn ①})$$

$$= B \underbrace{(B^T B)}_{m \times m}^{-1} B^T \vec{x}$$

3. Projection matrix

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

Remark:

$\underbrace{m=1}_{\text{is a scalar.}}$

$$\dim(v) = 1$$

Therefore,  $P_\pi = \frac{B B^T}{B^T B} = \frac{\vec{b} \vec{b}^T}{\|\vec{b}\|^2}$

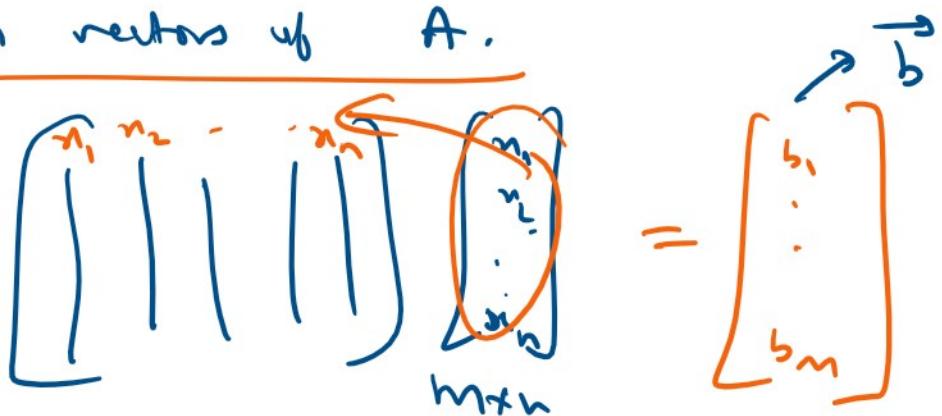
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Remark:

$$A \underbrace{\vec{u}}_{m \times n} = \underbrace{\vec{b}}_{m \times 1} \quad \text{sys of lin eqns.}$$

Suppose it does not have a solution. This means

Suppose it does not have a solution. This means  
 $\vec{b}$  does not lie in the space spanned by  
the column vectors of  $A$ .



Let  $U_A$  denote the space spanned by the column vectors of  $A$ . Project  $\vec{b}$  onto  $U_A$  to get an approximate solution.

Remark 2:

If  $\{\vec{b}_1, \vec{b}_2, \dots, \vec{b}_m\}$  is an orthonormal basis, then

$$\Pi_{U_A}(\vec{u}) = \vec{B} \vec{B}^T \vec{u} \quad (\text{since } \vec{B}^T \vec{B} = I)$$

$$\text{and } \vec{x} = \vec{B}^T \vec{u}$$

column vectors orthogonal

Gram-Schmidt Orthogonalization

Transform an... basis  $\{ \vec{v}_1, \vec{v}_2, \dots, \vec{v}_n \}$

Transform any basis  $\{\vec{b}_1, \vec{b}_2, \dots, \vec{b}_n\}$  of an  $n$ -dim V.S.  $V$  into an orthogonal/orthonormal basis  $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$  of  $V$ .

$$\vec{u}_1 = \vec{b}_1$$

$$\vec{u}_2 = \vec{b}_2 - \pi_{\text{span}(\vec{u}_1)}(\vec{b}_2)$$

$$\vec{u}_3 = \vec{b}_3 - \pi_{\text{span}(\vec{u}_1, \vec{u}_2)}(\vec{b}_3)$$

$$\vec{u}_4 = \vec{b}_4 - \pi_{\text{span}(\vec{u}_1, \vec{u}_2, \vec{u}_3)}(\vec{b}_4)$$

. . . .

' / | / | . . . .

$$\vec{u}_k = \vec{b}_k - \pi_{\text{span}(\vec{u}_1, \vec{u}_2, \dots, \vec{u}_{k-1})}(\vec{b}_k)$$

What we have got,  $\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$ , is an orthogonal basis of  $V$ . To make it orthonormal divide each vector by its norm.

$$\{\vec{u}_1, \vec{u}_2, \dots, \vec{u}_n\}$$

$$\left\{ \frac{\vec{u}_1}{\|\vec{u}_1\|}, \frac{\vec{u}_2}{\|\vec{u}_2\|}, \dots, \frac{\vec{u}_n}{\|\vec{u}_n\|} \right\}$$

orthonormal basis of  $V$ .

Projection onto affine spaces

Let  $V$  be a  $n$ -dim V-S over reals.

$L = \vec{x}_0 + U$ , where  $U$  is a subspace of  $V$ . and  $\vec{x}_0$  is any vector in  $V$ .

affine subspace.

To project a vector  $\vec{x}$  onto  $L$ :

$$\Pi_L(\vec{x}) = \vec{x}_0 + \Pi_U(\vec{x} - \vec{x}_0)$$

Rotations

Recall

columns are orthonormal  
orthogonal matrices

$$A^{-1} = A^T$$

Transformation using such matrices preserves length and angles between vectors.

Defn. A rotation is a linear mapping

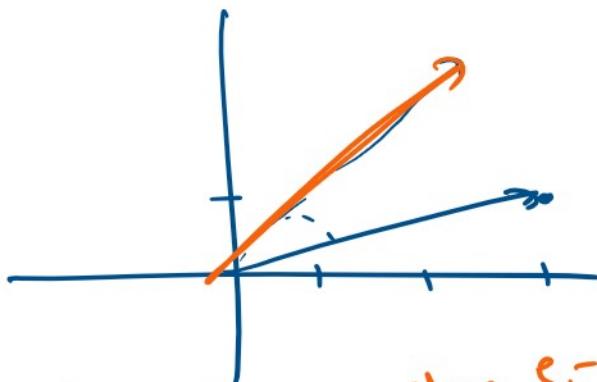
III. rotation is a linear mapping that rotates a plane by an angle  $\theta$  about the origin.

Convention: rotate in counterclockwise direction for any true angle  $\theta$ .

$$\cos \theta = \frac{\text{adj}}{\text{hyp}} \quad \text{or} \quad \text{adj} = \text{hyp.} \cos \theta$$

$$R(\theta) = \begin{bmatrix} \cos \theta & -\sin \theta \\ \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} 3 \\ 1 \end{bmatrix} = \begin{bmatrix} ? \\ ? \end{bmatrix}$$

$$\begin{bmatrix} 3 \\ 1 \end{bmatrix}$$



rotation about  $e_1$ -axis (rotation along  $e_1 - e_2$  plane)

$$\begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos \theta & -\sin \theta \\ 0 & \sin \theta & \cos \theta \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \cos \theta$$

