

① orthogonal vectors:

$$u \cdot v = 0$$

$$\boxed{u^T v = 0}$$

$$u \cdot v = |u||v|\cos\theta$$



② norm of a vector

$$|v|$$

$$\|v\| = \sqrt{v_1^2 + \dots + v_n^2}$$

$$\begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$$

$$\boxed{V^T V = I}$$

$$V \cdot V = I$$

$$\boxed{\|v\| = 1} = \left(\sqrt{v_1^2 + \dots + v_n^2} \right)^2 = 1$$

$$\|v\|^2 = 1 = v_1^2 + \dots + v_n^2 \leftarrow$$

$$= v^T v$$

$$[v_1 \dots v_n] \begin{bmatrix} v_1 \\ \vdots \\ v_n \end{bmatrix}$$

→ orthogonal matrix

$$V = \begin{bmatrix} | & | & & | \\ v_1 & v_2 & \dots & v_n \\ | & | & & | \end{bmatrix}$$

$$\boxed{v_i^T v_j = 0} \quad i \neq j$$

$$\boxed{v_i^T v_j = 1} \quad i = j$$

$$\boxed{V^{-1} = V^T}$$

→ eigenvectors & eigenvalues are a thing

$$Wv = \lambda v$$

→ an $n \times n$ can have at most \boxed{n} distinct eigenvalues

→ eigenvectors w/ distinct eigenvalues \Rightarrow linearly independent

→ n distinct eigenvalues \Rightarrow can have n distinct eigenvectors

→ span space of $\sqrt{\mathbb{R}^n}$

$$\begin{bmatrix} \cdot \end{bmatrix}, \begin{bmatrix} \cdot \end{bmatrix}, \begin{bmatrix} \cdot \end{bmatrix} \dots \begin{bmatrix} \cdot \end{bmatrix}$$

$$\mathbb{R}^n$$

$$\mathbb{R}^{n+1}$$



HW: $Iv = \lambda v$

$$\lambda = 1$$



$$\lambda = 1$$

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$

$$\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} v_1 \\ v_2 \end{bmatrix}$$

$$[\quad], [\quad], [\quad]$$

$$\rightarrow \sum_{i=1}^n \lambda_i = \text{Trace}(W)$$

$$\prod_{i=1}^n \lambda_i = \text{Det}(W)$$

\rightarrow n linearly indep. eigenvectors form a basis



$$V = c_1 v_1 + c_2 v_2$$

$$u = \underbrace{WV} \leftarrow$$

$$= W(c_1 v_1 + c_2 v_2)$$

$$= c_1 Wv_1 + c_2 Wv_2$$

$$= \underbrace{c_1}_{\text{scalar}} \underbrace{\lambda_1}_{\text{eigenvalue}} \underbrace{v_1}_{\text{eigenvector}} + \underbrace{c_2}_{\text{scalar}} \underbrace{\lambda_2}_{\text{eigenvalue}} \underbrace{v_2}_{\text{eigenvector}} \leftarrow$$

\rightarrow n lin. ind. eigenvectors (W)

$$W \underbrace{[v_1 \dots v_n]}_{n \times n} = [v_1 \dots v_n] \begin{bmatrix} \lambda_1 & 0 & \dots & 0 \\ \vdots & \ddots & & \vdots \\ 0 & \dots & \lambda_n \end{bmatrix}$$

$$WV = V\Lambda$$

$$\boxed{W = V\Lambda V^{-1}}$$

$$(V^{-1} = V^T)$$

$$\underline{V^{-1} W V = \Lambda} \leftarrow$$

$$\rightarrow \boxed{\lambda = 0}$$

$$\prod_{i=1}^n \lambda_i = \text{Det}$$

\uparrow
 $= 0 \Rightarrow$ NOT INVERTIBLE

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

\rightarrow symmetric matrices

→ Symmetric matrices

① eigenvectors w/ distinct eigenvalues : orthogonal

$$u^T v = 0$$

$$v_i^T v_j = 0$$

Quick proof:

$$A, \quad \lambda_1 \neq \lambda_2$$

$\downarrow \quad \quad \downarrow$
 $v_1 \quad \quad v_2$

$$v_1^T v_2 = 0$$

$$\lambda_1 v_1^T v_2$$

$$\lambda_1 v_1^T v_2 = \boxed{\lambda_1 v_1^T} \boxed{v_2} = \boxed{A v_1}^T \lambda_1 v_2$$

$$= (A v_1)^T v_2$$

$$= v_1^T A^T v_2$$

$$= v_1^T \underbrace{A v_2}_{\lambda_2 v_2}$$

$$= v_1^T \lambda_2 v_2$$

$$= \lambda_2 v_1^T v_2$$

$$(AB)^T \neq A^T B^T$$

$$= B^T A^T$$

$$A = A^T$$

$$\lambda_1 v_1^T v_2 = \lambda_2 v_1^T v_2$$

$$(\lambda_1 - \lambda_2) v_1^T v_2 = 0$$

$\lambda_1 \neq \lambda_2 \quad v_1^T v_2 = 0$

$$\rightarrow V = \begin{bmatrix} | & & | \\ v_1 & \dots & v_n \\ | & & | \end{bmatrix} \leftarrow$$

[assume n distinct eigenvalues]
Symmetric matrices
⇒ n lin. indep. eigenvectors

$$V \Rightarrow V^T = V^{-1}$$

(b/c orthogonal)

$$W = V^{-1} V^{-1}$$

$$= V^{-1} V^{-1}$$

$$= \begin{pmatrix} 1 & 1 & \dots & 1 \\ v_1^T & v_2^T & \dots & v_n^T \\ 1 & 1 & \dots & 1 \end{pmatrix}$$

$$\begin{pmatrix} \lambda_1 & 0 & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{pmatrix}$$

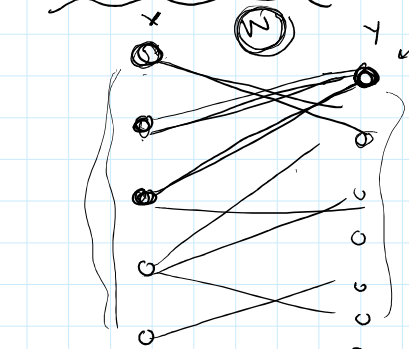
$$\begin{pmatrix} v_1^T \\ v_2^T \\ \vdots \\ v_n^T \end{pmatrix}$$

$$\begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} v_1^T \\ v_2^T \end{pmatrix}$$

$$= \begin{pmatrix} 1 & 1 & 1 \\ \vdots & \vdots & \vdots \\ v_1 & v_2 & \dots & v_n \end{pmatrix} \begin{pmatrix} \lambda_1 v_1^T \\ \vdots \\ \lambda_n v_n^T \end{pmatrix} \quad \begin{pmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{pmatrix} \begin{pmatrix} v_1 \\ v_2^T \end{pmatrix} = \begin{pmatrix} \lambda_1 v_1^T \\ \lambda_2 v_2^T \end{pmatrix}$$

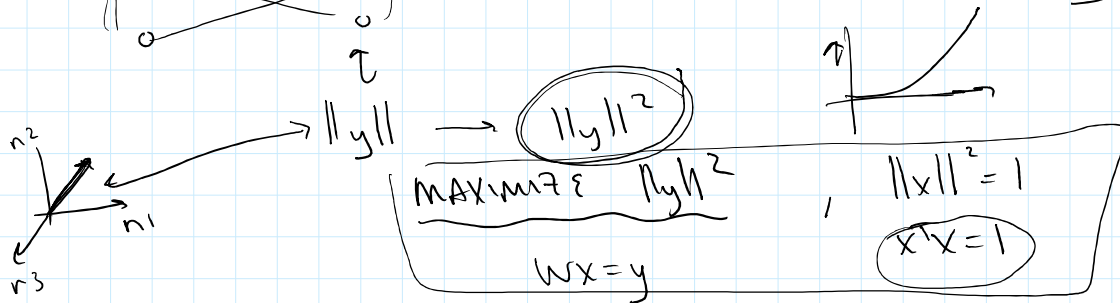
$$\Rightarrow \lambda_1 v_1 v_1^T + \dots + \lambda_n v_n v_n^T = \boxed{\sum_{i=1}^n \lambda_i v_i v_i^T}$$

Example problem



$$Wx = y$$

$$\begin{bmatrix} y_1 \\ \vdots \\ y_n \end{bmatrix} = \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ \vdots & \vdots & \vdots \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} = \begin{bmatrix} w_{11}x_1 + w_{12}x_2 + w_{13}x_3 \\ \vdots \end{bmatrix}$$



SOLVING PROBLEM

$$\|x\|^2 = x^T x$$

$$\|y\|^2 \xrightarrow{Wx=y} \|Wx\|^2 = (Wx)^T (Wx) = x^T W^T W x$$

$$(AB)^T = B^T A^T$$

general def.

$$A^T = A$$

$$W^T W = (V \Lambda V^T)$$

$$x^T (V \Lambda V^T) x$$

$$x^T \left(\sum \lambda_i v_i v_i^T \right) x$$

$$(W^T W)^T = W^T W$$

$W W^T$
 $W^T (W^T)^T$
 $W^T W$

$$\begin{aligned}
 & \vec{x}^T (\lambda_1 \vec{v}_1 \vec{v}_1^T + \lambda_2 \vec{v}_2 \vec{v}_2^T + \dots + \lambda_n \vec{v}_n \vec{v}_n^T) \vec{x} \quad \lambda_1 \geq \dots \geq \lambda_n \\
 & \Rightarrow \vec{x}^T (\lambda_1 \vec{v}_1 \vec{v}_1^T + \lambda_2 \vec{v}_2 \vec{v}_2^T + \dots + \lambda_n \vec{v}_n \vec{v}_n^T) \vec{x} \\
 & \lambda_1 \vec{x}^T (\underbrace{\vec{v}_1 \vec{v}_1^T + \dots + \vec{v}_n \vec{v}_n^T}_{\substack{[\vec{v}_1 \dots \vec{v}_n] [\vec{v}_1^T \dots \vec{v}_n^T]^T \\ \vec{V} \vec{V}^T}}) \vec{x} \rightarrow \lambda_1 \vec{x}^T \underbrace{\vec{V} \vec{V}^T}_{\vec{I}} \vec{x} \quad \vec{V} \vec{V}^T = \vec{V} \vec{V}^{-1} = \vec{I} \\
 & \quad \quad \quad \lambda_1 \vec{x}^T \vec{x} = \lambda_1 \quad \vec{x}^T \vec{x} = 1 \quad \vec{x} = \vec{v}_1 \\
 & \quad \quad \quad \lambda_1 \vec{x}^T \vec{x} = 1 \quad \lambda_1
 \end{aligned}$$

$$\begin{aligned}
 & \rightarrow \vec{x}^T (\lambda_1 \vec{v}_1 \vec{v}_1^T + \dots + \lambda_n \vec{v}_n \vec{v}_n^T) \vec{x} = \lambda_1 \\
 & \rightarrow \vec{x}^T \lambda_1 \vec{v}_1 \vec{v}_1^T \vec{x} + \dots + \vec{x}^T \lambda_n \vec{v}_n \vec{v}_n^T \vec{x} \quad \vec{x} = \vec{v}_1 \\
 & \quad \quad \quad \lambda_1 \underbrace{(\vec{v}_1^T \vec{v}_1)}_{=1} \underbrace{(\vec{v}_1^T \vec{v}_1)}_{=1} = \lambda_1
 \end{aligned}$$

$$\begin{aligned}
 & \rightarrow \text{to max } \frac{\|\vec{y}\|^2}{\|\vec{W}\vec{x}\|^2} \\
 & \quad \quad \quad \vec{x}^T \vec{W}^T \vec{W} \vec{x} \\
 & \quad \quad \quad \vec{x}^T (\vec{V} \vec{\Lambda} \vec{V}^T) \vec{x} \\
 & \quad \quad \quad \vec{x}^T (\sum \lambda_i \vec{v}_i \vec{v}_i^T) \vec{x} \leq \lambda_1 \vec{x}^T (\sum \vec{v}_i \vec{v}_i^T) \vec{x} \\
 & \quad \quad \quad \leq \lambda_1 \underbrace{\vec{x}^T \vec{x}}_1 = \lambda_1
 \end{aligned}$$

$$\vec{x}^T (\sum \lambda_i \vec{v}_i \vec{v}_i^T) \vec{x} = \lambda_1$$

when $\vec{x} = \vec{v}_1$.

\Rightarrow to max $\|\vec{y}\|^2$, choose eigenvector of $\vec{W}^T \vec{W}$ w/ largest eigenvalue.

$$\begin{aligned}
 & \|\vec{y}\| \\
 & \|\vec{y}\|^2 = \vec{y}^T \vec{y}
 \end{aligned}$$

$$\vec{A} \vec{B} \neq \vec{B} \vec{A}$$

$$\vec{v}_i^T \vec{v}_j = \vec{v}_j^T \vec{v}_i \quad \vec{a}^T \vec{b} = \vec{b}^T \vec{a}$$

$$\vec{v}_i^T \vec{a} \vec{v}_j = \vec{a} \vec{v}_i^T \vec{v}_j$$

$$\vec{A} \vec{V} \neq \vec{V} \vec{A}$$

$$\lambda_1 \geq \dots \geq \lambda_n$$

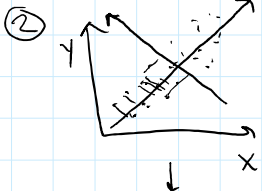
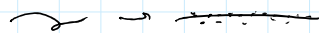
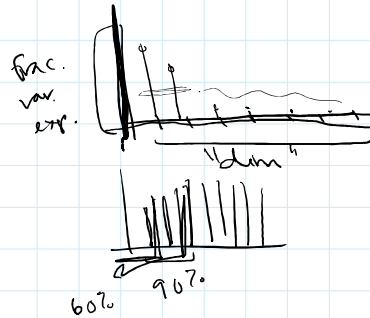
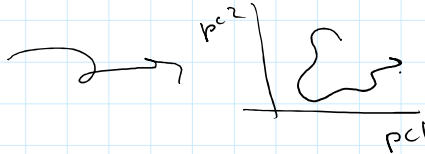
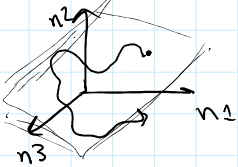
$$\|y\|$$

$$\|y\|^2 = y^T y$$

π

PCA

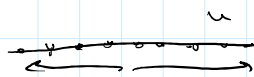
① dim red. method



Data matrix:

$$\begin{bmatrix} x_1 & \dots & x_n \\ y_1 & \dots & y_n \end{bmatrix}$$

Goal: find line that captures greatest variance in your data



$$[u_1 \dots u_n]$$

← max variance of these

$$\begin{bmatrix} u_1 & \dots & u_n \end{bmatrix} = \begin{bmatrix} p_1 & p_2 \end{bmatrix} \begin{bmatrix} x_1 & \dots & x_n \\ y_1 & \dots & y_n \end{bmatrix}$$

$$u_1 = p_1 x_1 + p_2 y_1$$

$$u_2 = p_1 x_2 + p_2 y_2$$

⋮

→ what variance again? $[u_1 \dots u_n]$

$$\text{var}(u) = \frac{1}{n} u u^T$$

$$\text{var} = \frac{1}{n} \sum_{i=1}^n x_i^2$$

← zero-mean data

$u u^T$ ← max this!

$$\begin{bmatrix} s_1 & \dots & s_n \end{bmatrix} = \begin{bmatrix} u_1 & u_2 \end{bmatrix} \begin{bmatrix} x_1 & \dots & x_n \\ y_1 & \dots & y_n \end{bmatrix}$$

$s = u^T X$

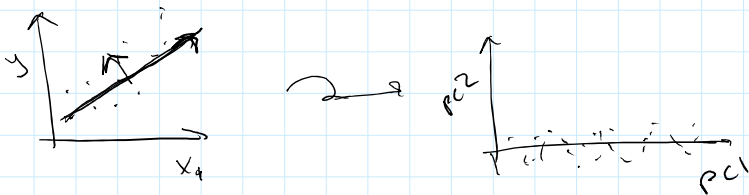
$S = [p_1 p_2] X$

$s \rightarrow \text{max variance!}$
 $S = \frac{1}{N} \sum_{n=1}^N x_n x_n^T$
 $U^T \rightarrow \begin{matrix} 1 & 2 & \dots & n \end{matrix}$
 $\text{var}(u^T x) = \frac{1}{N} (u^T x) (u^T x)^T$
 $= \frac{1}{N} (u^T \underbrace{X X^T}_{\text{covariance matrix}} u)$
 $\frac{1}{N} X X^T \leftarrow \text{covariance matrix}$
 $X X^T \rightarrow \text{var}$

$\lambda_1 \leftarrow \text{max this!}$
 $(X X^T)^T = X X^T$

$\lambda_1 \leftarrow \text{largest eigenval of } W = X X^T$
 $\text{covariance matrix of your data}$
 $u \rightarrow \text{eigenvector assoc w/ eigenvalue}$

$u^T (X X^T) u \leftarrow \text{variance of } u^T x$
 $\leftarrow \text{variance of projected data } s$
 $\text{max at } \boxed{\lambda_1}$



$$\begin{bmatrix} u_1 & \dots & u_n \\ v_1 & \dots & v_n \end{bmatrix} = \begin{bmatrix} p_1 & p_2 \\ r_1 & r_2 \end{bmatrix} \begin{bmatrix} x_1 & \dots & x_n \\ y_1 & \dots & y_n \end{bmatrix}$$

$$\begin{bmatrix} u_1 & \dots & u_T \\ v_1 & \dots & v_T \end{bmatrix} = \begin{bmatrix} p_1 & p_2 & \dots & p_T \\ r_1 & r_2 & \dots & r_T \end{bmatrix} \begin{bmatrix} x_{11} & \dots & x_{1T} \\ \vdots & & \vdots \\ x_{N1} & \dots & x_{NT} \end{bmatrix}$$

time \rightarrow
 cell \rightarrow