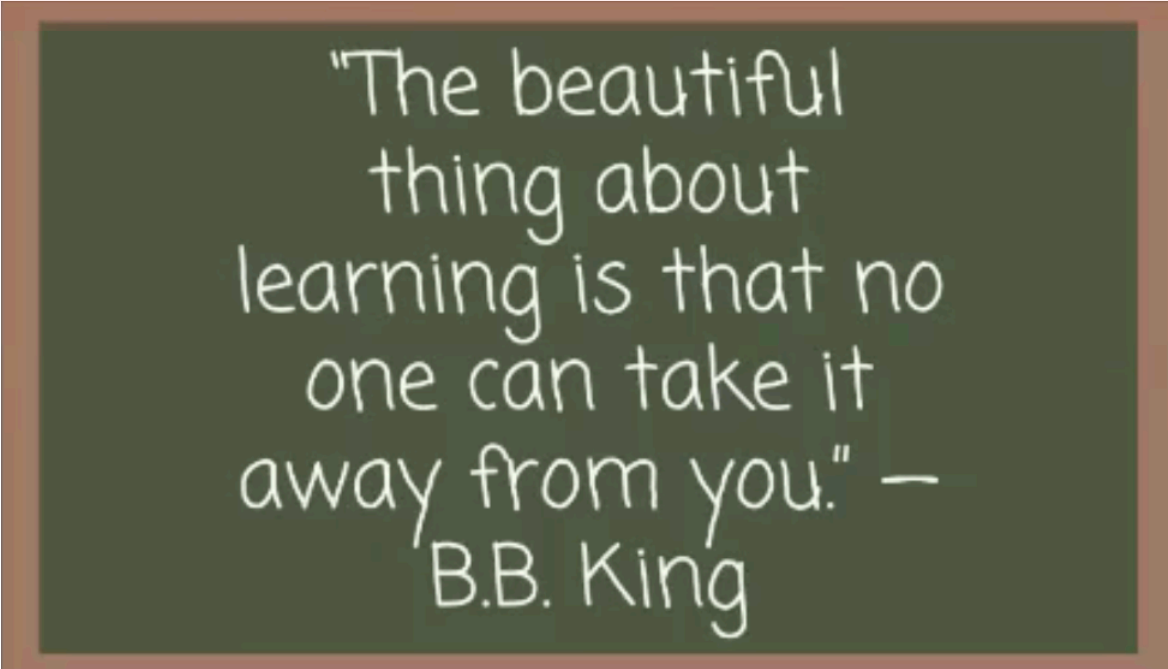


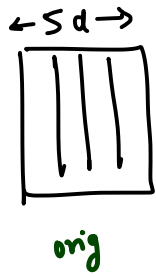
# PCA cont. t-SNE



"The beautiful  
thing about  
learning is that no  
one can take it  
away from you." —  
B.B. King

## Agenda:-

- PCA Recap
- Maths
- Limitations
- t-SNE Intuition
- t-SNE Code



PCA →

PC<sub>1</sub>    PC<sub>2</sub> - - - PC<sub>5</sub>

[ - ]

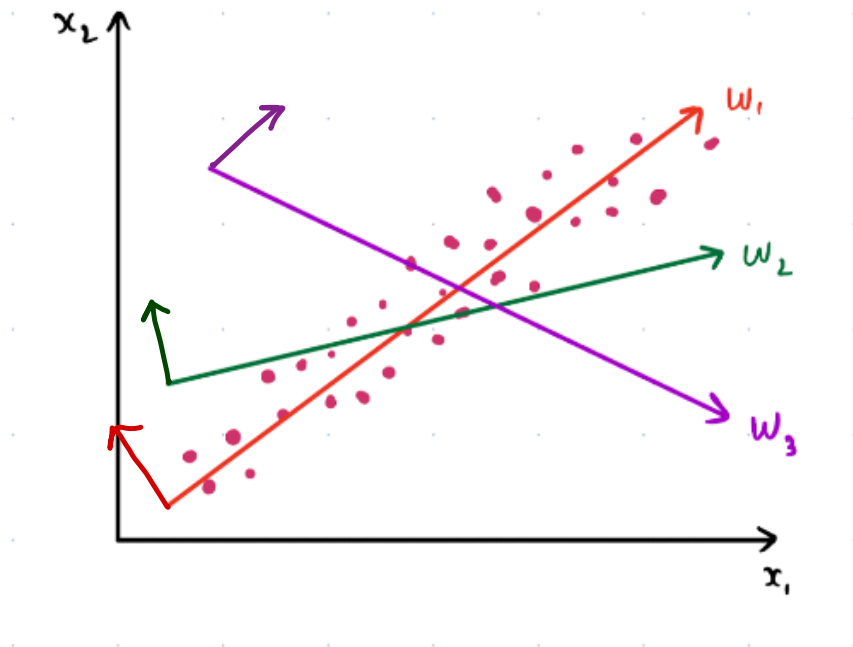
How many PCs?

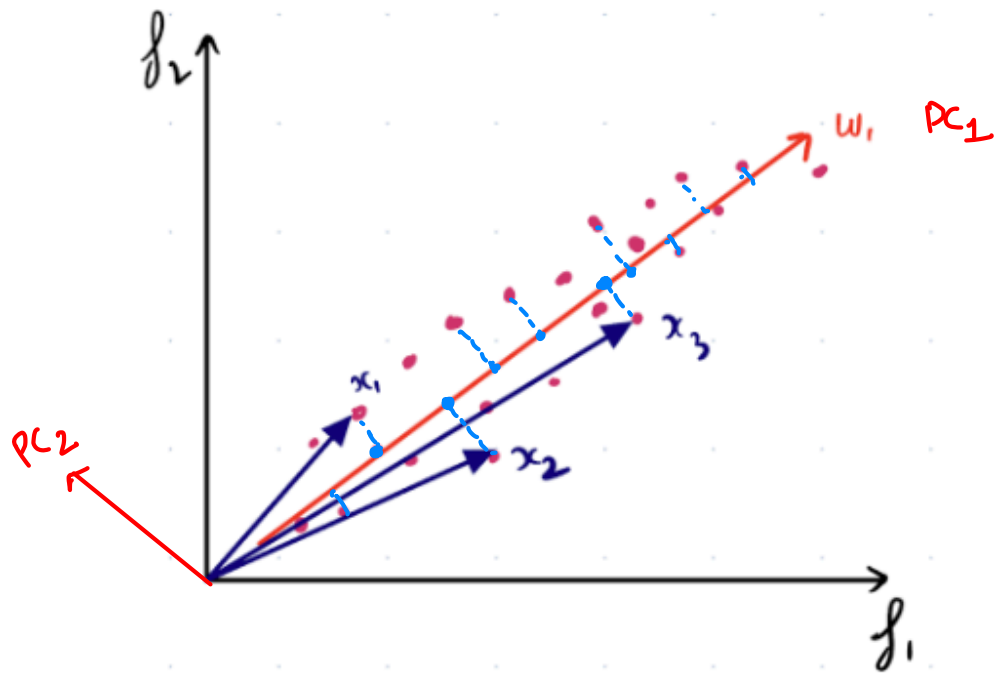
Q → angle b/w PC<sub>3</sub>, PC<sub>5</sub> ?

A → 90° orthogonal.

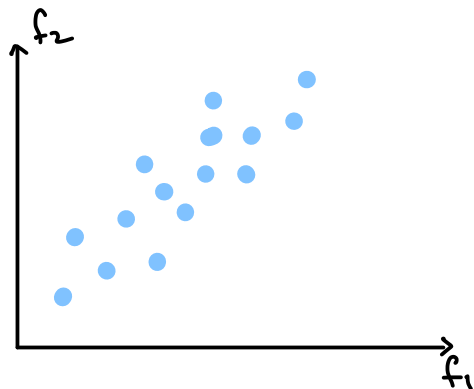
Q → M.C exists after PCA?

A → yes.

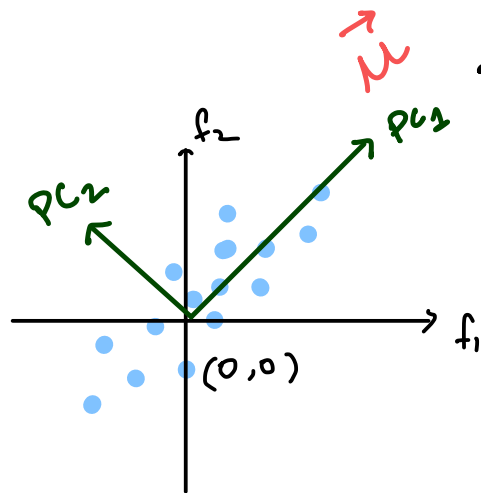
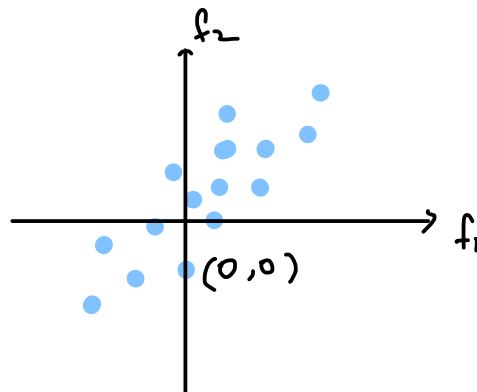




# # Maths [Heavy Maths Ahead]



feature scaling  
[ mean centering  
unit var. ]

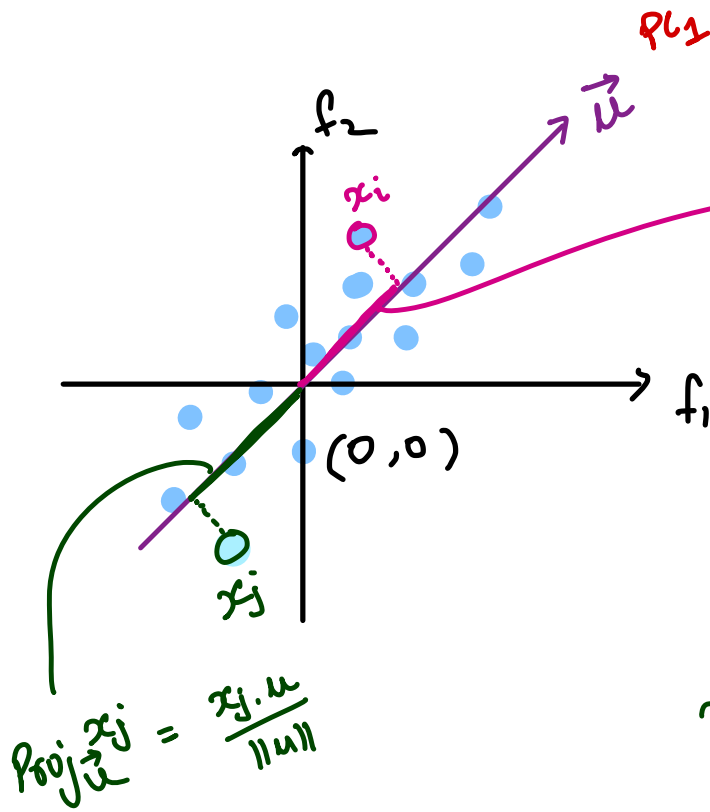


$$w^T x + w_0 = 0$$
$$[w_0 = 0]$$

$$w^T x = 0$$

$$\mu^T x = 0$$

$$\mu = \begin{bmatrix} 2.5 \\ 3.1 \end{bmatrix}$$



$$\text{Proj}_{\vec{u}} x_i = \frac{x_i \cdot u}{\|u\|}$$

Calculate Proj of All data points onto  $\vec{u}$

$$\max \left[ \frac{1}{n} \sum_{i=1}^n \right]$$

$$\frac{x_i \cdot u}{\|u\|}$$

→ avg length  
of Proj.  
of all  
data pts

$$\max_{\vec{u}} \left[ \frac{1}{n} \sum_{i=1}^n \left( \frac{x_i \cdot u}{\|u\|} \right)^2 \right]$$

Constraint:  $\|u\| = 1$

→ -ve & +ve  
Proj length  
→ diff

Constraint optimization



Unconstraint optimization





$$\max_{u, \lambda} \quad \frac{1}{n} \sum_{i=1}^n (x_i \cdot u)^2 + \lambda (\|u\|^2 - 1)$$

$$A^2 = A^T A = \|A\|^2$$

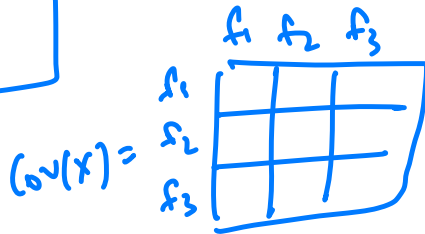
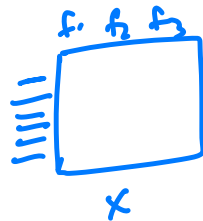
$$\max_{u, \lambda} \quad \frac{(X \cdot \vec{u})^2}{n} + \lambda (\|u\|^2 - 1)$$

$$\frac{(X \cdot u)^T \cdot (X \cdot u)}{n} + \lambda (u^T u - 1)$$

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

$$\max_{\lambda, u} \frac{u^T \underbrace{X^T \cdot X}_n u}{n} + \lambda (u^T u - 1)$$

$\downarrow$   
 Cover matrix (X)  
 $= \checkmark$



$L =$

$$\max_{u, \lambda} \left[ u^T V \cdot u + \lambda u^T u - \lambda \right]$$

$$L = \max_{\mu, \lambda} [\mu^T V \cdot u + \lambda u^T u - \lambda]$$

$$a = a^T a = a^2$$

$$\frac{da^T a}{da} = 2a$$

$$\frac{da^2}{da} = 2a$$

$$\frac{\partial L}{\partial \mu} = 2V\mu + 2\mu\lambda = 0$$

Scalar derivative		Vector derivative	
$f(x)$	$\rightarrow \frac{df}{dx}$	$f(\mathbf{x})$	$\rightarrow \frac{df}{d\mathbf{x}}$
$bx$	$\rightarrow b$	$\mathbf{x}^T \mathbf{B}$	$\rightarrow \mathbf{B}$
$bx$	$\rightarrow b$	$\mathbf{x}^T \mathbf{b}$	$\rightarrow \mathbf{b}$
$x^2$	$\rightarrow 2x$	$\mathbf{x}^T \mathbf{x}$	$\rightarrow 2\mathbf{x}$
$bx^2$	$\rightarrow 2bx$	$\mathbf{x}^T \mathbf{B} \mathbf{x}$	$\rightarrow 2\mathbf{B} \mathbf{x}$

$$\frac{\partial L}{\partial \lambda} = 0 + \mu^T \mu - 1 = 0$$

Set = 0

$$[\mu^T \mu = 1]$$

$$2V\mu + 2\mu\lambda = 0$$

$$2V\mu = -2\mu\lambda$$

$$V\mu = \lambda' \mu$$

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

$$[1, 2, 3] \begin{bmatrix} 1 \\ 2 \\ 3 \end{bmatrix} =$$

$$\lambda' = -\lambda$$

$$V \cdot \vec{u} = \lambda \vec{u}$$

Diagram illustrating the eigenvalue equation  $V \cdot \vec{u} = \lambda \vec{u}$  with annotations:

- $V$ : Matrix ( $d \times d$ )
- $\vec{u}$ : vector ( $d \times 1$ )
- $\lambda$ : scalar
- $\vec{u}$ : vector ( $d \times 1$ )

just find  $\vec{u}$  using 'eig'

# # Conclusion / Summary

$$X_{(n,5)} \xrightarrow{\text{PCA}} X_{\text{new}}_{(n,2)}$$



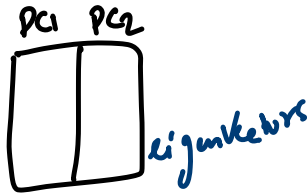
① Scaling  $\xrightarrow{\text{PCA}} (d \times d)$

② Covar matrix  $V = \frac{X^T X}{n}$

③ find  $\vec{u}$  &  $\lambda$  for  $V'$   $\text{evec, eval} = \text{np.linalg.eig}(V)$

$PC_1$  &  $\lambda_1$

$PC_2$  &  $\lambda_2$



all  $PC$ 's (eigen vectors)  
all  $\lambda$ 's (eigen values)

④ Projection of all points ( $x$ )  
on 2  $PC$ 's

$$X \cdot \text{eVector} \Rightarrow (n,2)$$

$\downarrow \quad \downarrow$   
 $(n,d) \quad (d,2) \Rightarrow (n,2)$

# Calculate Importance of PC's

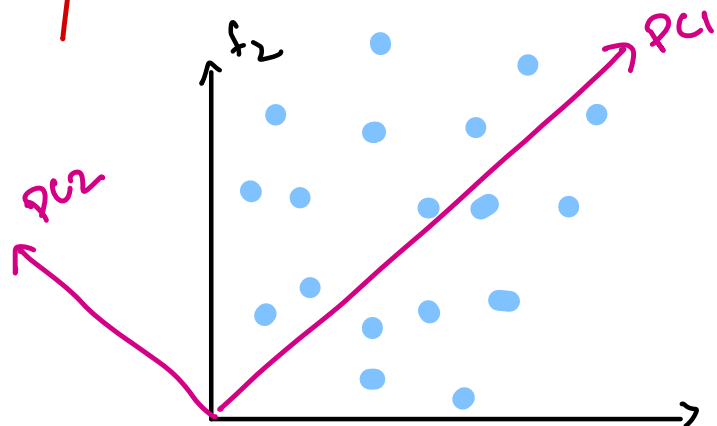
d features

$\mu_1$	$\mu_2$	$\mu_3$	$\dots$	$\mu_d$
$\lambda_1$	$\lambda_2$	$\lambda_3$		$\lambda_d$
$3.8$	$2.9$	$1.4$		$0.07$

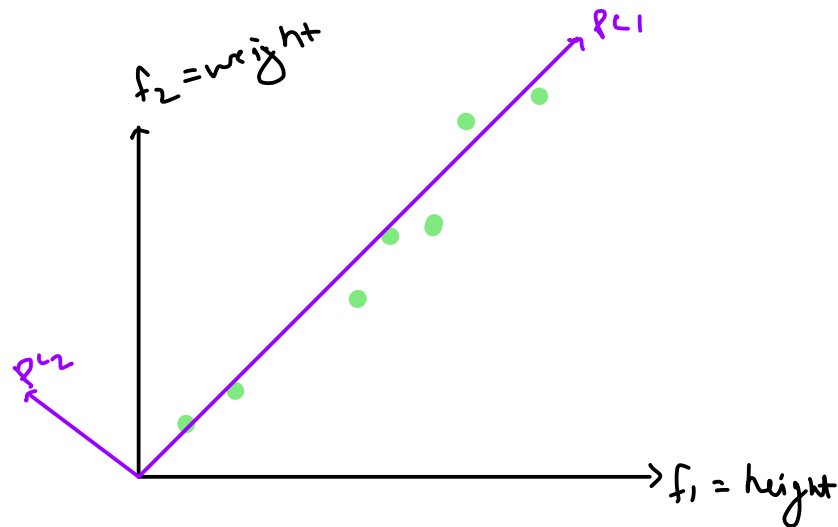
$$\text{Imp}(\mu_1) = \frac{3.8}{\text{sum all } \lambda\text{'s}} = \frac{\lambda_1}{\lambda_1 + \lambda_2 + \dots + \lambda_d}$$

$$\text{Info Preserved}(\mu_1, \mu_2) = \frac{\lambda_1 + \lambda_2}{\sum \lambda_i\text{'s}}$$

# Assumptions



PCAX



# Limitations

① Low Interpretability of PC's

$$f_1' PC_1 = 0.8 \text{ mileage} + 1.4 \text{ odo} + \dots$$

$$PC_2 = 4.9 \text{ age} + \dots$$

② Trade off b/w info lost & dim<sup>n</sup> reduction

③ PCA is not robust to outliers!



# t-SNE

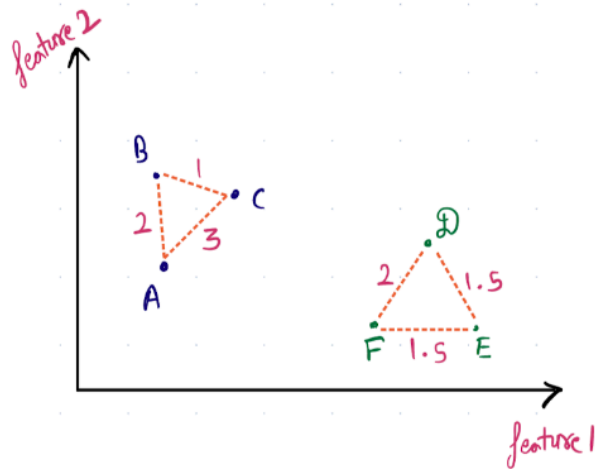
→ 2008

Geoff Hinton

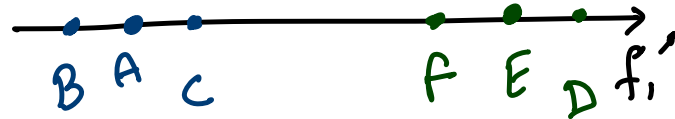
[only viz]

2D, 3D

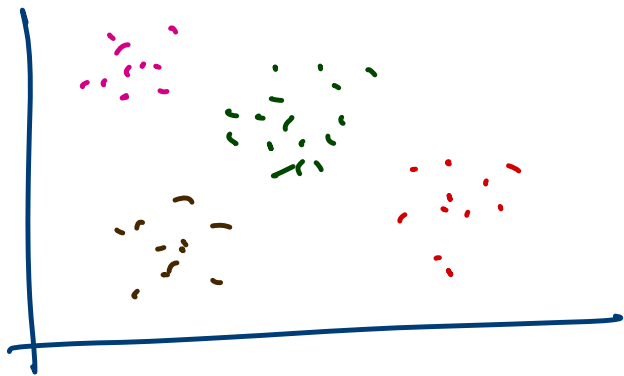
[t-distributed Stochastic Neighbourhood Embedding]



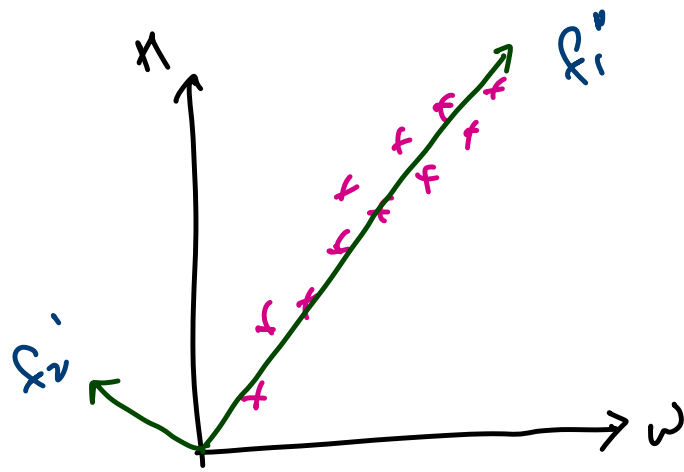
1D →



→ local neighbourhood  
→ relative distances



$$\left[ \begin{array}{l} \text{Probability}_N(i,j) \\ \text{High Dim}^n \end{array} \right] \approx \left[ \begin{array}{l} \text{Probability}_N(i,j) \\ \text{Low Dim}^n \end{array} \right]$$



$$f_1' = 1.8H + 0.3\omega$$

