

# PCA

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## Feature Extraction

PCA

① It will reduce curse of dim<sup>n</sup>.

② It reduce higher dim<sup>n</sup> to lower dim<sup>n</sup>

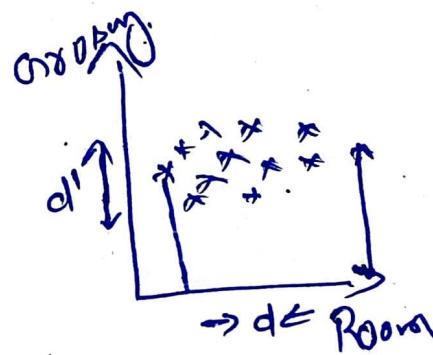
Benefit

① Faster execution of Algo

② It will help visualization

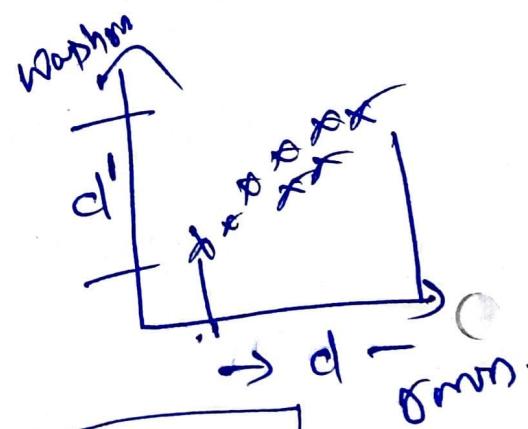
(because we can reduce higher dim<sup>n</sup> to 2D also).

No of Room	# of grocery Shelves	Price
3	2	60
4	0	130
5	6	170
2	10	90



$d > d'$   
So Room have  
higher distribution  
as compare to  $d'$

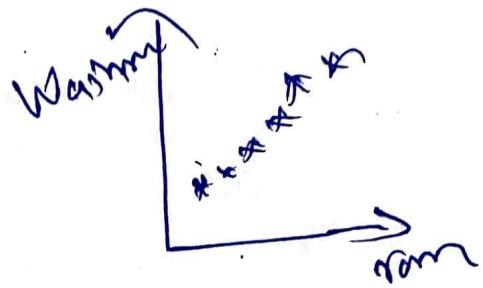
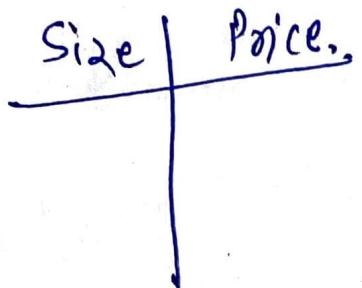
No of Room	No of Washroom	Price
3	2	20
4	3	50
5	5	100



So we can not remove Washroom from feature

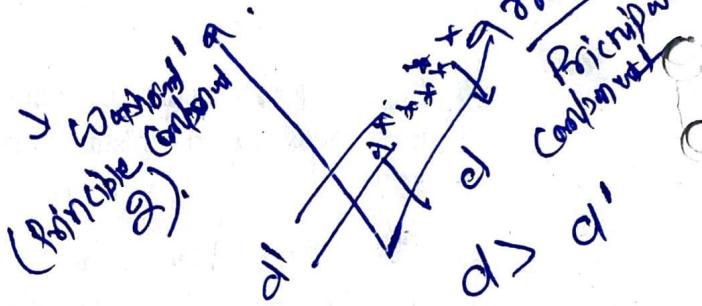
$d \approx d'$

Now we can create New feature  
that is Size



PCA  
②

With PCA will create New feature from  
all existing feature



$\#$  of PC  $\leq$  no of feature

Why Variance is important

(3) PCA

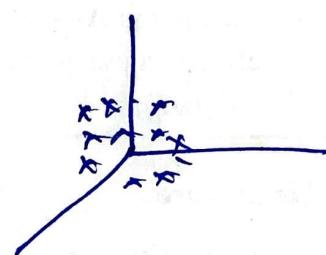
Variance

$$\frac{\sum (x_i - \bar{x})^2}{n}$$

Variance is proportional to spread of data.

Example

$t_1$	$t_2$	$t_3$	$y$



Step I Mean Centric data convert.

II. find Co-variance Matrix

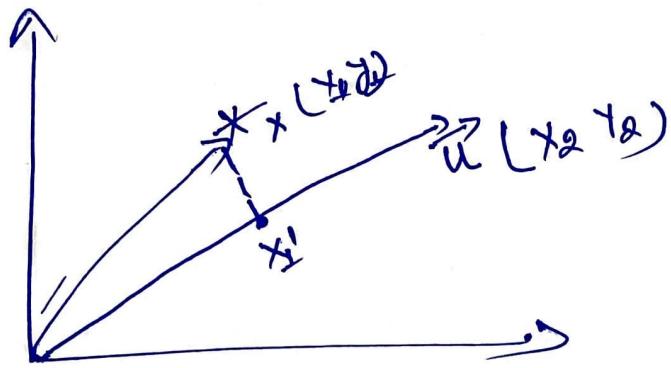
$$\begin{matrix} t_1 & \begin{bmatrix} V(t_1) & t_1 \\ t_1 & V(t_2) \\ t_1 & V(t_3) \end{bmatrix} \\ t_2 & \begin{bmatrix} C.V(t_1, t_2) & V(t_2) \\ C.V(t_2, t_3) & V(t_3) \end{bmatrix} \\ t_3 & \begin{bmatrix} C.V(t_1, t_3) & C.V(t_3, t_2) \\ V(t_3) \end{bmatrix} \end{matrix}$$

III. Find the Eigen Value & Eigen Vectors of Co-variance

in these case ( 3 - Eigen value )  
( 3 - Eigen Vector )

Find the highest ( Eigen Vector  
Eigen Value )

$\text{Sol next P.C.A.}$



$$x' = \frac{\vec{u} \cdot \vec{x}}{|\vec{u}|} = \vec{u} \cdot \vec{x} = \vec{u}^T \vec{x}$$

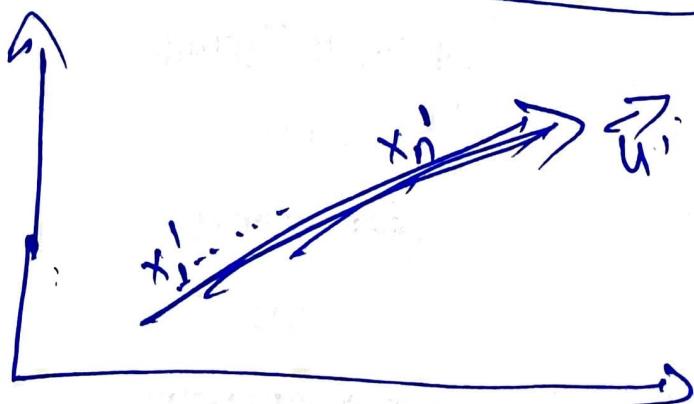
$|\vec{u}| = 1$

Unit Vector.

So, we can write that:

$$\begin{aligned} & x \quad u \\ & [x_1 \quad y_1] \quad [x_1 \quad y_2] \\ & = x \vec{u}^T \\ & = [x_1 \quad y_1] \quad [x_2 \\ & \quad \quad \quad y_2] \end{aligned}$$

$x' = x_1 x_2 + y_1 y_2$



Variance

$$\frac{1}{n} \sum (x'_i - \bar{x})^2$$

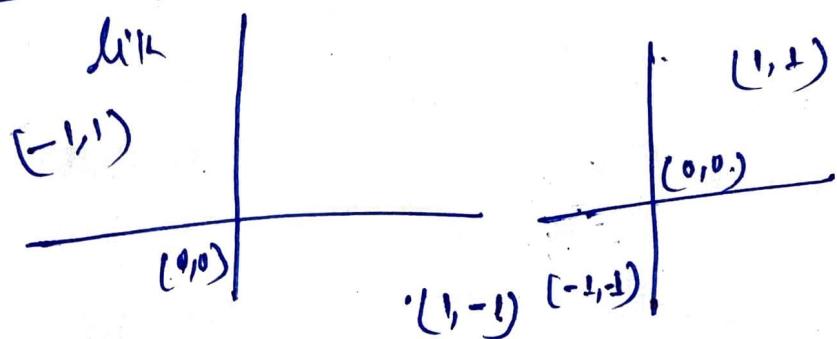
PCA 2

Variance =  $\frac{1}{n} \sum_{i=1}^n (v^T x_i - v^T \bar{x})^2$

We have to Maximize the Variance

Variance & Matrix

Variance will not provide exact answer



Variance  $\frac{1+0+1}{3}$

$\frac{1+0+1}{3}$

both the same variance

but co-variance will

$$\frac{-1 \times 1 + 0 \times 0 + 1 \times 1}{3} = \frac{1 \times 1 + 0 \times 0 + -1 \times -1}{3}$$

direction  $\vec{\begin{pmatrix} 1 \\ 0 \\ -1 \end{pmatrix}}$ , magnitude  $\sqrt{3}$   
Here value same but direction is different

Solved P(T)

## Covariance Matrix

Matrix will linear transform

$$\begin{array}{c} x_1 \quad x_2 \\ \diagdown \\ \begin{array}{cc|cc} & & x_1 & x_2 \\ x_1 & & \text{Cov}(x_1, x_1) & \text{Cov}(x_2, x_1) \\ x_2 & & \text{Cov}(x_1, x_2) & \text{Cov}(x_2, x_2) \end{array} \end{array}$$
$$\text{Cov}(x_1, x_1) = \text{Var}(x_1)$$

$$= \begin{bmatrix} \text{Var } x_1 & \text{Cov}(x_1, x_2) \\ \text{Cov}(x_2, x_1) & \text{Var } x_2 \end{bmatrix}$$



Find Eigen decomposition

that is

Eigen-Value - Eigen-Vector

Eigen-Vector (It will not change the direction) -  
only change the magnitude.)

$$Ax = \lambda x$$

Eigen Vector

Eigen Value

## Solved Example of PCA

Ex - 1

### Steps

1. Convert data Into - Centering or Standardization

$$X_i = \frac{x_i - \mu}{\sigma}$$

Where  
 $\mu$  - mean  
 $\sigma$  - S.D

2. Use Co-Variance Or Correlation Matrix

- 3 Calculate Eigen Value & Eigen Vector

4. Sort Eigenvalue (descending Order)

5. Calculate PC Proj.  $PC_1 = \frac{\lambda_1}{\sum \lambda} * X$

6. Select PC

7. Transform Data  $PC_{New} = X_{Centered} + EigenValue$

Data		C.G.PA	I.Q
1	7	110	
2	8.5	120	
3	6	105	
4	9	130	
5	7.5	115	

②

to Standardize  $X_i \leftarrow \frac{X_i - \mu}{\sigma}$

Solved  
by PC

find Mean ( $\mu$ ) C.G.PA = 7.6  
 $\bar{X} = 116.$

$$\sigma = \sqrt{\frac{\sum (X_i - \bar{X})^2}{n}}$$

$$\sigma (\text{C.G.PA}) = 1.06$$

$$\sigma (\text{I.Q}) = 8.6$$

Standardize

	C.G.A	I.Q.
1	-5.62	-0.697
2	0.843	0.465
3	-1.499	-1.279
4	-1.311	1.627
S	-0.094	-0.116

③

Find - Co-Variance Matrix

$$\text{Cov} = \frac{1}{n} Z^T \cdot Z$$

$$Z^T \cdot Z = \begin{bmatrix} 5 & 4.84 \\ 4.8 & 5 \end{bmatrix}$$

$$\text{Cov} = \frac{1}{5} \begin{bmatrix} 5 & 4.84 \\ 4.8 & 5 \end{bmatrix} = \begin{bmatrix} 1 & 0.96 \\ 0.96 & 1 \end{bmatrix}$$

Solved  
EP PCA-3

④ Find EigenValue

$$\det(\text{cov} - \lambda I) = 0$$

$$\det \begin{bmatrix} 1-\lambda & 0.96 \\ 0.96 & 1-\lambda \end{bmatrix} = 0$$

$$\cancel{\lambda^2 - 2\lambda + 0.06 = 0}$$

$$\lambda = \frac{2 \pm \sqrt{3.7552}}{2}$$

$$\lambda = \frac{2 \pm 1.93}{2}$$

$$\lambda_1 = 1.96 \quad \lambda_2 = 0.03$$

⑤ find top P.C

$$PCL = \left( \frac{1.96}{1.96+0.03} \right) = 98.45\%$$

$$PC2 = \left( \frac{0.03}{1.96+0.03} \right) = 1.58\%$$

⑥ find EigenVector:

$$\lambda_1 = 1.96$$

$$\begin{bmatrix} 1-1.96 & 0.96 \\ 0.96 & 1-1.96 \end{bmatrix} \begin{bmatrix} V_{1x} \\ V_{1y} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$-0.96 V_{1x} + 0.96 V_{1y} = 0$$

so take  $\boxed{V_{1x}=1}$

$$V_{1x} = V_{1y}$$

Solved

PCA-4

$$\|V_1\| = \sqrt{1^2 + 1^2} = \sqrt{2} = 1.41$$

Normalize PC1

$$e_1 = \begin{bmatrix} 1/1.41 \\ 1/1.41 \end{bmatrix} = \begin{bmatrix} 0.70 \\ 0.70 \end{bmatrix}$$

$$\text{for } \lambda_2 = \frac{0.03}{0.03}$$

$$(Cov - 0.03I) V_2 = 0$$

$$\begin{bmatrix} 0.96 & 0.96 \\ 0.96 & 0.96 \end{bmatrix} \begin{bmatrix} V_{2x} \\ V_{2y} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$0.96 V_{2x} + 0.96 V_{2y} = 0$$

$$V_{2x} = -V_{2y}$$

It

$$\begin{cases} V_{2x} = 1 \\ V_{2y} = -1 \end{cases}$$

$$V_2 = \begin{bmatrix} 1/1.41 \\ -1/1.41 \end{bmatrix} = \begin{bmatrix} 0.70 \\ -0.70 \end{bmatrix}$$

Normal value =  $\sqrt{1^2 + 1^2} = 1.41$

PCA-S

Solved  
ex

⑦ Transform data.

for  $PC_1$

$$PC_1 = \text{Stand} \times e_1$$

$$PC_2 = \text{Stand} \times e_2$$

$$e_1 = [0.7, 0.7]$$

$$e_2 = [0.7, -0.7]$$

$$PC_1 = (-5.62) * \underline{0.70} + (-6.97 * \underline{0.70}) = -0.89$$

$$PC_2 = (-5.62) * \underline{0.70} + (-6.97 * \underline{-0.70}) = 0.096$$

<u>Stand-Data-1</u>	$\{ PC_1$
(8.43, 0.96)	$\downarrow PC_2$
(-1.49, -1.27)	$\{ PC_1$
Stand-Data-3	$\{ PC_2$
(1.3, 1.62)	$\{ PC_1$
Stand-Data-4	$\{ PC_2$
Stand-Data-5	$\{ PC_1$
(-0.09, -0.11)	$\{ PC_2$

Final Value

$PC_1$	$PC_2$
-0.89	0.096
0.92	0.26
-1.96	-0.15
0.07	-0.224
-0.140	0.016