

"Agenda"

- ① Inverse of a Matrix
- ② Trace of a Matrix
- ③ Relationship of Eigenvalues with trace and determinant
- ④ Symmetric matrix
- ⑤ Orthogonal Matrix
- ⑥ "Principal Component Analysis"

① Inverse

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = I$$

$$A \cdot B \neq B \cdot A \text{ in general}$$

$$A \cdot I = I \cdot A = A$$

$$\frac{1}{4} \cdot \left(\frac{1}{\frac{1}{4}}\right) = 1$$

If  $A \cdot B = I$ , then  $B$  is called inverse of  $A$ .

$$B \cdot A = I$$

$$A^{-1}$$

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

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

$$A = \begin{bmatrix} 4 & 3 \\ 1 & 1 \end{bmatrix}$$

$$A^{-1} = \begin{bmatrix} 1 & -3 \\ -1 & 4 \end{bmatrix}$$

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

$$A^{-1} = \frac{1}{\det(A)} \text{Adj}(A)$$

$$(I) \quad (AB)^{-1} = B^{-1} \cdot A^{-1}$$

$$(ABC)^{-1} = C^{-1} B^{-1} A^{-1}$$

(II) If the eigenvalues of  $A$  are  $\lambda_1, \lambda_2, \dots, \lambda_n$ , then the eigenvalues of  $A^{-1}$  are  $\frac{1}{\lambda_1}, \frac{1}{\lambda_2}, \dots, \frac{1}{\lambda_n}$

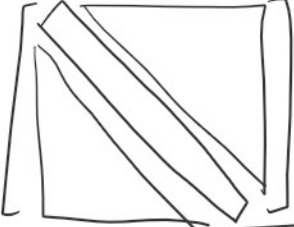
$$A = \begin{bmatrix} 0 & -3 & -2 \\ 1 & -4 & -2 \\ -3 & 4 & 1 \end{bmatrix}$$

$$A^{-1} = \begin{bmatrix} 4 & -5 & -2 \\ 5 & -6 & -2 \\ -8 & 9 & 3 \end{bmatrix}$$

$$I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

II. Trace of a matrix = Sum of diagonal elements.

III. Sum of eigenvalues = Trace of the matrix  
Product of eigenvalues = Determinant of the matrix

IV.   $a_{ij} = a_{ji}$  Symmetric

V. Orthogonal Matrix

$$AA^T = A^T A = I$$

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

$$\begin{bmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix} \begin{bmatrix} a_{11} & a_{21} & \dots & a_{n1} \\ a_{12} & a_{22} & \dots & a_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ a_{1n} & a_{2n} & \dots & a_{nn} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

VI. Positive Semi-Definite Matrix

$(A_{n \times n})$  for any non-zero vector  $x \in \mathbb{R}^n$

$$(x^T A x) \geq 0$$

then A is said to be PSD.

→ All the eigenvalues are  $\geq 0$

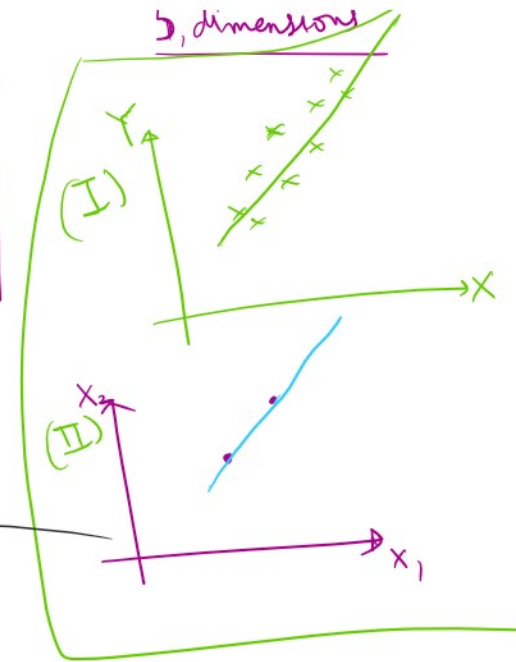
$$\begin{aligned} x &= (n \times 1) \\ [x_1, x_2] & \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ &= [x_1, x_2] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} \\ &= (x_1^2 + x_2^2) \end{aligned}$$

\* Principal Component Analysis \*

	#	#	#	#
Gender	Runs	wickets	Strike Rate	Age
Male	10321	0		

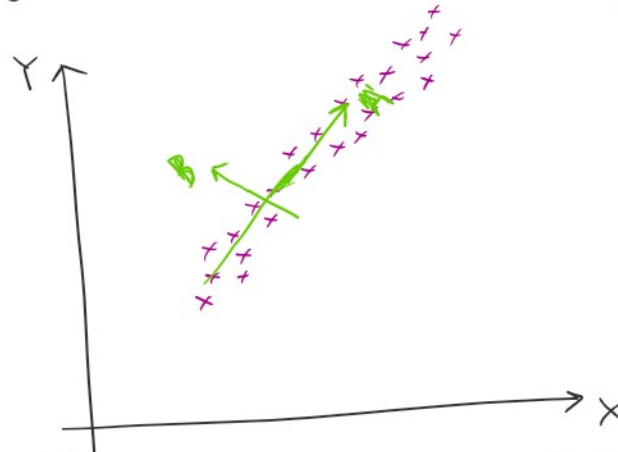
5, dimensions

	Gender	Runs	wickets	Strike Rate	Age
1	Male	10321	0		
2	Male	9231	47		
⋮	⋮	⋮	⋮	⋮	⋮
n	Male				



## ~ Curse of Dimensionality ~

- ① Feature Selection
- ② Feature Extraction



~5-dimensional~

	$f_1$	$f_2$	$f_3$	$f_4$	$f_5$
$x_1$	1				
$x_2$	1				
$x_3$	1				
⋮	⋮				
$x_{1000}$	1				

~(1000x5)~

(5x2)

=

2-dimensional

	$F_1$	$F_2$
$x_1$		
$x_2$		
$x_3$		
⋮		
$x_{1000}$		

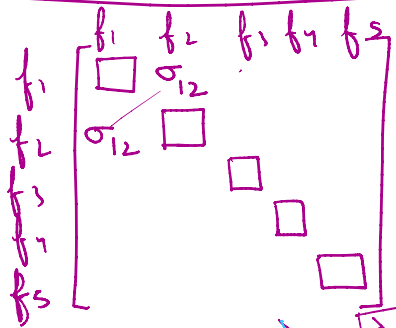
~(1000x2)~

$$F_1 = 0.8f_1 + 0.6f_3 + 0.1f_4 + 0.1f_5$$

$$F_2 = 0.1f_1 + 0.9f_5$$

$$12 - 0.917 = 0$$

## Variance-Covariance Matrix



$\sigma_i^2 =$  Variance in the  $i^{\text{th}}$  feature  
 $\sigma_{ij} =$  Covariance between  $i^{\text{th}}$  and  $j^{\text{th}}$  feature

$$\text{Cov}(X, Y) = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{n}$$

$$\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_n \geq 0$$

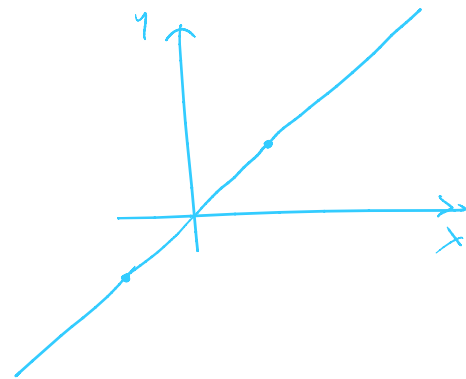
- ① Compute the eigenvalues and eigenvectors of variance-covariance matrix.
- ② Pick the  $k$  largest (if we want  $k$ -dimensions)



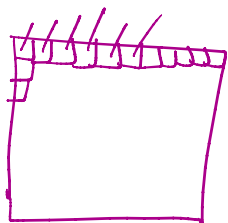
$$\frac{\lambda_1 + \lambda_2}{\lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5}$$

$$(2 \times 5)$$

$$\begin{aligned} & \sigma_1^2 + \sigma_2^2 + \sigma_3^2 + \sigma_4^2 + \sigma_5^2 \\ &= \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 \end{aligned}$$



① Pete Sampras



$$62 \times 47 = 2914$$

~~62~~

	1 <sup>st</sup>	2 <sup>nd</sup>	3 <sup>rd</sup>	...	2914 <sup>th</sup>
1					
2					
3					
⋮					
3000					

[illegible]
$$\rightarrow (62 \times 47)$$

$[3000 \times 2914]$  - original data

$[3000 \times 100]$  - Compressed Data  $\rightarrow \frac{(100 \times 2914)}{E^T}$

$$(3000 \times 2914)$$

- ① Original data <sup>(D)</sup> consists of " $N$ " records and " $n$ " features

$$[N \times n]$$

- ② Compute Variance-Covariance Matrix of size  $n \times n = \Sigma$

- ③ Compute eigenvalues and eigenvectors of  $\Sigma$ .

- ④ Sort the eigenvectors such that eigenvector corresponding to larger eigenvalue should be placed at the top in the eigenvector matrix -

$$E = \begin{bmatrix} e_1, \lambda_1 \\ e_2, \lambda_2 \\ \vdots \\ e_n, \lambda_n \end{bmatrix}$$

$$\lambda_1 \geq \lambda_2 \geq \lambda_3 \dots \geq \lambda_n \geq 0$$

- (5) If we want  $k$  dimensions, pick the first " $k$ " rows of the matrix ( $E_k$ )

⑤ If we want  $k$  dimensions, pick the first " $k$ " rows of the matrix  $(E_k)$   
 $(E_k)$  has size  $(k \times n)$

⑥ Data with new features is  $D \cdot (E_k^T) = D_k$

In order to do inverse transform,  
reconstruct as  $D_k E_k$

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