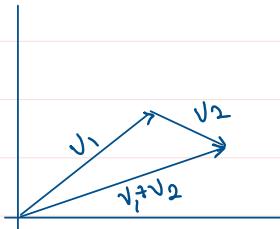
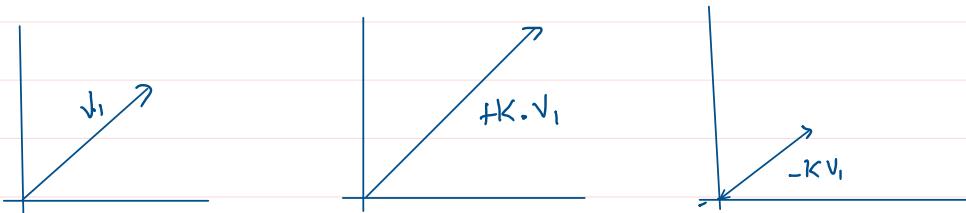


- Vectors

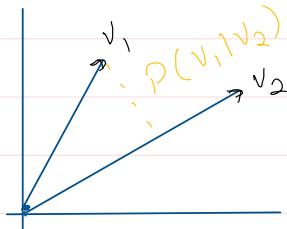
→ Vector Addition (Dot Product)



→ Scalar Multiplication



→ Projection



If we are able to project v_1 on v_2 then we are able to find unknown features of v_1 .

- Matrices

Suppose we have 2 equations:

$$\begin{aligned} 2x + 2y &= 10 \\ 4x + y &= 18 \end{aligned}$$

This in Matrix Form is:

$$\begin{bmatrix} 2 & 2 \\ 4 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} 10 \\ 18 \end{bmatrix}$$

→ Matrix Addition

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} + \begin{bmatrix} A & B \\ C & D \end{bmatrix} = \begin{bmatrix} a+A & b+B \\ c+C & d+D \end{bmatrix}$$

Same order \Rightarrow must

→ Matrix Multiplication

$$\begin{bmatrix} 2 & 2 \\ 4 & 1 \end{bmatrix} \times \begin{bmatrix} 2 & 3 \\ 1 & 4 \end{bmatrix} = \begin{bmatrix} 2*2+2*1 & 2*3+2*4 \\ 4*2+1*1 & 4*3+1*4 \end{bmatrix} \rightarrow \begin{bmatrix} 4+2 & 6+8 \\ 8+1 & 12+4 \end{bmatrix}$$

\downarrow

$$\begin{bmatrix} 6 & 14 \\ 9 & 16 \end{bmatrix}$$

→ Transpose ($\text{Row} \rightleftharpoons \text{Col}$)

$$n = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \quad n^T = \begin{bmatrix} A & C \\ B & D \end{bmatrix}$$

→ Determinant of Matrix

$$n = \begin{bmatrix} a & b & c \\ d & e & f \\ \cdot & \cdot & \cdot \end{bmatrix}$$

it gives the scalar value of the Matrix

$$n = \begin{bmatrix} a & b \\ d & e \\ g & h \end{bmatrix}$$

matrix

$$\text{Det}(n) = a * \begin{vmatrix} e & b \\ h & i \end{vmatrix} - b * \begin{vmatrix} d & f \\ g & i \end{vmatrix} + c * \begin{vmatrix} d & e \\ g & h \end{vmatrix}$$

→ Inverse of Matrix

- matrix when multiplied with inverse gives identity Matrix.

- it helps to apply transformations easily.
- Some matrix do not have an inverse that mean they contain very noisy & un-reliable data.

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$

For order 3 and above

$$A = \begin{bmatrix} a & b & c \\ d & e & f \\ g & h & i \end{bmatrix}$$

$$\text{Inv}(A) = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

$$\text{Inv}(A) = \frac{1}{\det(A)} \begin{bmatrix} \begin{vmatrix} e & f \\ h & i \end{vmatrix} & \begin{vmatrix} d & f \\ g & i \end{vmatrix} & \begin{vmatrix} d & e \\ g & h \end{vmatrix} \\ \begin{vmatrix} b & c \\ h & i \end{vmatrix} & \begin{vmatrix} a & c \\ g & i \end{vmatrix} & \begin{vmatrix} a & b \\ g & h \end{vmatrix} \\ \begin{vmatrix} b & c \\ e & f \end{vmatrix} & \begin{vmatrix} a & c \\ d & f \end{vmatrix} & \begin{vmatrix} a & b \\ d & e \end{vmatrix} \end{bmatrix}$$

→ Scaling

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \begin{bmatrix} s_x & 0 \\ 0 & s_y \end{bmatrix}$$

→ Shearing

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ m & 1 \end{bmatrix}$$

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \begin{bmatrix} 1 & 0 \\ m & 1 \end{bmatrix}$$

→ Rotation

$$\begin{bmatrix} x' \\ y' \end{bmatrix} = \begin{bmatrix} x \\ y \end{bmatrix} \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix}$$

→ Row Echelon method

$$\begin{aligned} 2x + y - z &= 2 \\ x + 3y + 2z &= 1 \\ x + y + z &= 2 \end{aligned}$$

matrix
 $\begin{bmatrix} 2 & 1 & -1 & 2 \\ 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 1 \end{bmatrix}$

ans

$$x = 2$$

$$y = -1$$

$$z = 1$$

Step 1 $R_1 = R_1 / 2$

$$A = \begin{bmatrix} 2 & 1 & -1 & 2 \\ 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 2 \end{bmatrix}$$

Step 2 $R_2 = R_2 - R_1$

$$\begin{bmatrix} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 1 & 3 & 2 & 1 \\ 1 & 1 & 1 & 2 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 0 & \frac{5}{2} & \frac{5}{2} & 0 \\ 1 & 1 & 1 & 2 \end{bmatrix}$$

Step 3 $R_3 = R_3 - R_1$

$$\left[\begin{array}{cccc} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 0 & \frac{5}{2} & \frac{5}{2} & 0 \\ 0 & 1 & 1 & 2 \end{array} \right] \rightarrow \left[\begin{array}{cccc} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 0 & \frac{5}{2} & \frac{5}{2} & 0 \\ 0 & \frac{1}{2} & \frac{3}{2} & 1 \end{array} \right]$$

Step 4 $R_2 = \frac{2}{5}(R_2)$

$$\left[\begin{array}{cccc} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 0 & \frac{5}{2} & \frac{5}{2} & 0 \\ 0 & \frac{1}{2} & \frac{3}{2} & 1 \end{array} \right] \rightarrow \left[\begin{array}{cccc} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 0 & 1 & 1 & 0 \\ 0 & \frac{1}{2} & \frac{3}{2} & 1 \end{array} \right]$$

Step 5 $R_1 = R_1 - \frac{1}{2}(R_2)$

$$\left[\begin{array}{cccc} 1 & \frac{1}{2} & -\frac{1}{2} & 1 \\ 0 & 1 & 1 & 0 \\ 0 & \frac{1}{2} & \frac{3}{2} & 1 \end{array} \right] \rightarrow \left[\begin{array}{cccc} 1 & 0 & -1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & \frac{1}{2} & \frac{3}{2} & 1 \end{array} \right]$$

Step 6 $R_3 = R_3 - \frac{1}{2}(R_2)$

$$\left[\begin{array}{cccc} 1 & 0 & -1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & \frac{1}{2} & \frac{3}{2} & 1 \end{array} \right] \rightarrow \left[\begin{array}{cccc} 1 & 0 & -1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{array} \right]$$

Step 7 $R_1 = R_1 + R_3$

$$\left[\begin{array}{cccc} 1 & 0 & -1 & 1 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{array} \right] \rightarrow \left[\begin{array}{cccc} 1 & 0 & 0 & 2 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{array} \right]$$

Step 8 $R_2 = R_2 - R_3$

$$\begin{bmatrix} 1 & 0 & 0 & 2 \\ 0 & 1 & 1 & 0 \\ 0 & 0 & 1 & 1 \end{bmatrix} \rightarrow \begin{bmatrix} 1 & 0 & 0 & 2 \\ 0 & 1 & 0 & -1 \\ 0 & 0 & 1 & 1 \end{bmatrix}$$

↓

$$\begin{aligned} x &= 2 \\ y &= -1 \\ z &= 1 \end{aligned}$$

only they should have values (1)
rest all should be zero.

∴ Transform matrix such that only diagonals have 1's rest all other should contain 0's.

→ Inverse

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

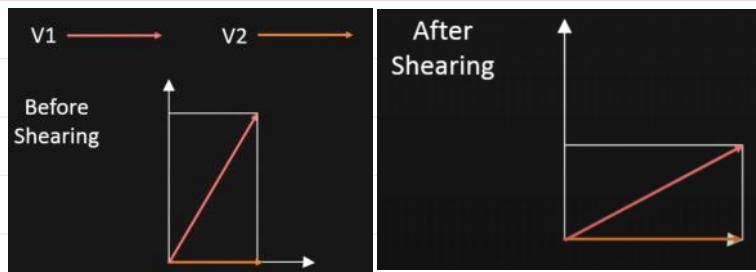
Let's suppose $AB = C$

$$A^{-1} = \frac{1}{ab-bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

$$\begin{aligned} &\Rightarrow AA^{-1}B = CA^{-1} \\ &\Rightarrow \underline{\underline{B = CA^{-1}}} \end{aligned}$$

→ Eigen Vector

- doesn't change direction even after transformation is applied.



this is the reason even after applying shearing operation vector remains the same

→ Uses of Linear algebra

a) PCA

- a) PCA
- b) Pictures
- c) Dataset Encoding
- d) Singular Value decomposing
- e) Latent Semantic Analysis for NLP

→ Differentiation :-

Constant Rule	$\frac{d}{dx} [C] = 0$
Power Rule	$\frac{d}{dx} x^n = nx^{n-1}$
Product Rule	$\frac{d}{dx} [f(x)g(x)] = f'(x)g(x) + f(x)g'(x)$
Quotient Rule	$\frac{d}{dx} \left[\frac{f(x)}{g(x)} \right] = \frac{g(x)f'(x) - f(x)g'(x)}{[g(x)]^2}$
Chain Rule	$\frac{d}{dx} [f(g(x))] = f'(g(x)) g'(x)$

$$x^n = nx^{n-1}$$

$$x^a + x^b = ax^{a-1} + bx^{b-1}$$

$$x^a \cdot x^b = ax^{a-1}x^b + bx^{b-1}x^a$$

→ Partial Differentiation :-

$$\begin{aligned} & \text{With respect to } x \\ & (y, z).f^1(x) \\ \text{Partial Differentiations} \quad f^1(x, y, z) &= \begin{array}{l} \text{With respect to } y \\ (x, z).f^1(y) \end{array} \quad \text{Complete Differentiation} \\ & f^1(x, y, z) = (y, z).f^1(x) + (x, z).f^1(y) + (x, y).f^1(z) \\ & \text{With respect to } z \\ & (x, y).f^1(z) \end{aligned}$$

Eg: $f = x^2 + 3y + hz^2$

$$x \rightarrow 2x + 4z^2$$

$$y \rightarrow 3$$

$$z \rightarrow 8xz$$

$$f(x, y, z) = 2x + hz^2 + 3 + 8xz$$

→ Applications -

- Jacobian helps find global maxima of dataset.
Also helps linearizing a non-linear function to linear at a point.
- Hessian helps minimize error.

- c) Deep learning
- d) Gradient Descent method for optimizing weights.

→ it is the measure of how likely an event will occur.

$$P = \text{desired} / \text{total}$$

Events → Joint (Common Outcome)

→ Dis-Joint (un-common Outcome)

Distribution → Probability Density Function

⇒ it describes a continuous distribution

→ Normal Distribution

⇒ it depends on mean & std deviation,

→ Central Limit Theorem

⇒ Sampling distribution of mean of any independent random variable will be normal, if Sample Size is big enough

Probability → Marginal

⇒ probability of occurrence of single event.

→ Joint Probability

⇒ prob. of two events happening at same time

→ Conditional Probability

⇒ Prob. of event B is that the event will occur given that event A has already occurred.

$$P(B|A) = \frac{P(A \cap B)}{P(A)}$$

$$- P(A)$$

→ Bayes Theorem

Shows relation b/w one conditional probability & its inverse.

$$\leftarrow P(B|A) = \frac{P(A|B) P(B)}{P(B)} \rightarrow \{ \text{Prior} \}$$

Prob of occurrence of B
given A
 $\{ \text{Posterior} \}$

→ Application

- a) optimize Model
- b) classification by algo requires Probability
- c) Loss can be calculated by Probability

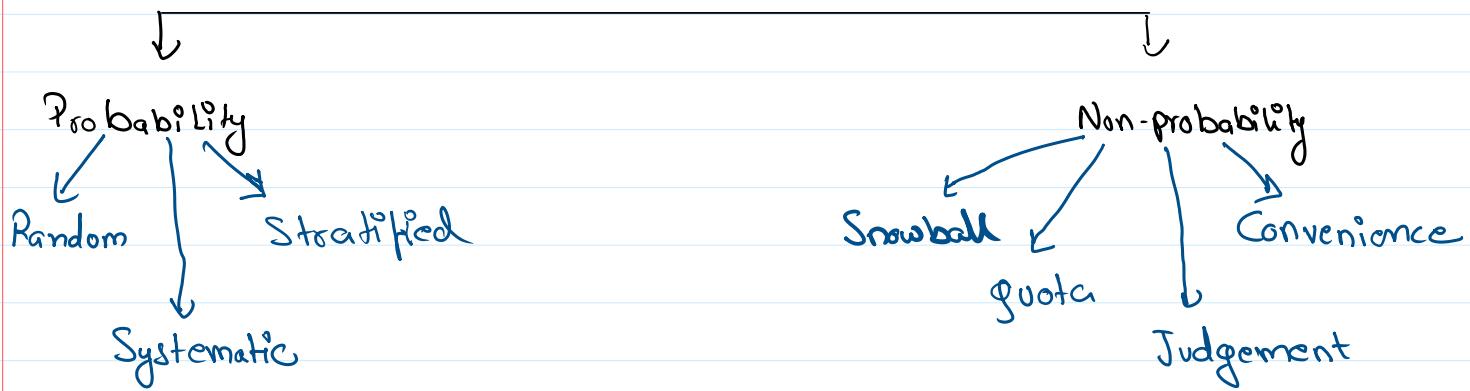
Population

Collection or set of individual or object or events whose properties are to be analyzed.

Sample

Subset of population

Sampling



Statistics

Descriptive

use to provide description of population

{ it focuses mainly on the main characteristics of data. To provide graphical summary of data. }

Types :-

Inferential

makes inference and predictions about a population based on sample of data taken from population

{ generalize large data set and apply probability to draw conclusions }

Types :-

① Measures of Centre

mean, median & mode

② Measures of Spread

① Range ② Inter-Quartile Range ③ Variance

④ Standard Deviation