

## Naive - Bayes Model.

→ Bayes Theorem :-

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

Ex : of wrenches.

→ Mach 1: 30 wrenches / hr

Mach 2: 20 wrenches / hr

→ Out of all produced parts :

We can see that 10% are defective

→ Out of all defective parts :-

We can see that 50% came from [mach 1]

(and 50% came from [mach 2])

Q. What is the probability that a part produced by mach 2 is defective = ?

→  $P(M_1) = 30/50 = 0.6$

↳ Pro. of picking wrench that was produced by M1

→  $P(M_2) = 20/50 = 0.4$

→  $P(\text{Defect}) = 10\%$

$$\hookrightarrow P(M_1 / \text{Defect}) = 50\% \quad \xrightarrow{\text{Machine 1 produces 50\% defective parts}}$$

$$\hookrightarrow P(M_2 / \text{Defect}) = 50\% \quad \xrightarrow{\text{Machine 2 produces 50\% defective parts}}$$

This machine is producing more defective parts

The question that was asked =>

$$\left[ \begin{array}{l} \text{Probability by Machine 2} \\ \text{is defective} \end{array} \right] = ?$$

||,

$$P(\text{Defect} | M_2) = ?$$

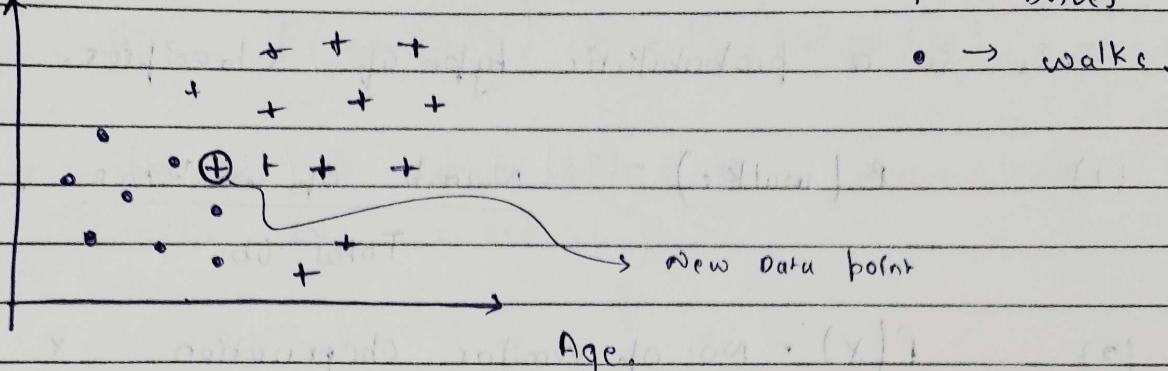
$$P(\text{Defect} | M_2) = \underline{P(M_2 / \text{Defect}) \cdot P(\text{Defect})}$$

$$\begin{aligned} &= (0.5) \cdot (0.01) \\ &= 0.0125 = 1.25\% \end{aligned}$$

# So we can say if machine produces 1000 parts 125 will be defective.

## Intuition :-

Salary.



This data represents salary and age of the people and how do they go to their office.

(Likelihood)

$$(1) P(\text{walks} | x) = \frac{P(x | \text{walks}) \cdot P(\text{walks})}{P(x)}$$

P(x) ↑  
(marginal)  
(Prior Prob.)

Posterior Prob.

$$(2) P(\text{Drives} | x) = \frac{P(x | \text{Drives}) \cdot P(\text{Drives})}{P(x)}$$

then compare Both.

$$P(\text{walks} | x) \quad v.s. \quad P(\text{Drives} | x)$$

→ then we will decide in which category we should put this data point in.

→ This is a probabilistic type of classifier.

$$(1) P(\text{walks}) = \frac{\text{Num. of walks}}{\text{Total obs.}} = \frac{10}{30}$$

$$(2) P(x) = \frac{\text{No. of similar observation}}{\text{Total Obs.}}$$

$$P(x) = \frac{4}{30}$$

$$P(x | \text{walks}) = \frac{3}{10}$$

anything that falls in that circle will be considered similar to the new point that we are adding to the circle.

$$P(\text{walks} | x) = \frac{\frac{3}{10} \cdot \frac{10}{30}}{\frac{4}{30}} = 0.75$$

Similarly

$$P(\text{Drivers} | x) = \frac{\frac{1}{20} \cdot \frac{20}{30}}{\frac{4}{30}} = 0.25$$

so the Prob. of people

who exhibits features  $x$  to work.

being the person who

Drives to work. is 0.25

so clearly.

$$P(\text{walks}/x) > P(\text{drives}/x)$$

That person is probably the person who walks to work.



Extras.

### \* Principle Component Analysis - (PCA)

→ most popular unsupervised Algorithm,  
Best Dimensionality reduction Algorithm.



Used for operations such as

- Noise Filtering
- feature Extraction
- stock market predictions
- gene data analysis.



Work of PCA is →

(1) Identify Patterns in data.

(2) detect the correlation b/w variables.



The goal is to

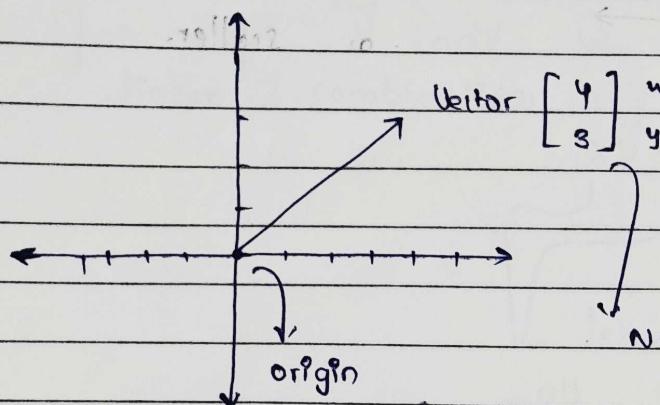
Reduce the dimensions of a d-dimensional dataset by projecting it onto a k-dimensional subspace (where  $k < d$ )

## Process if

- Standardize the data.
  - Obtain the Eigenvectors and Eigenvalues from the covariance matrix or correlation matrix or perform singular vector decomposition.
  - Sort eigenvalues in descending order and choose the  $k$  is the number of dimensions of the new features subspaces ( $k \leq d$ ).
  - Construct the projection matrix  $W$  from the selected  $k$  eigenvectors.
  - Transform the original dataset  $X$  via  $W$  to obtain a  $k$ -dimensional features subspace  $Y$ .
- PCA tries to learn abt the relationship b/w  $X$  and  $Y$  values
- find 1st of principal axes.

## linear Algebra.

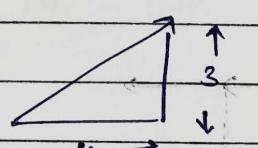
## • Vectors.



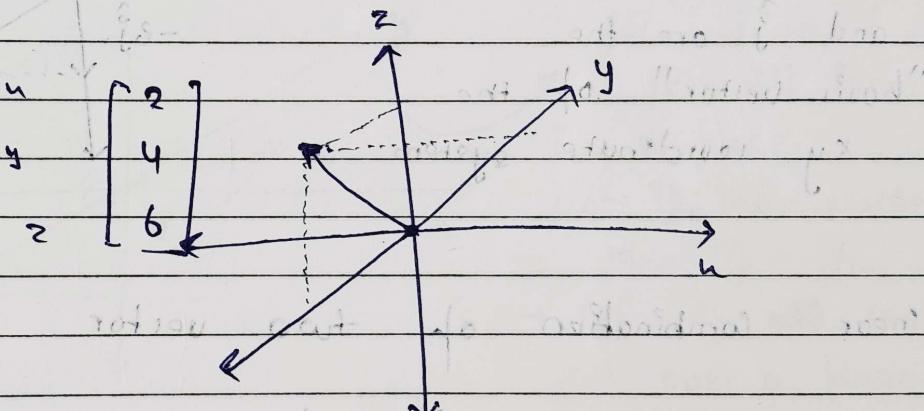
in linear algebra in  
most of the cases.

vectors will originate  
from origin.

Notation. (2 dimensional)

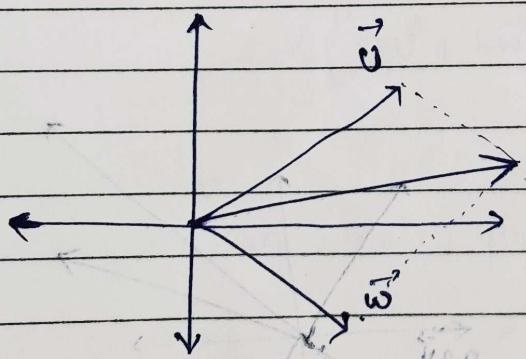


It can also be in  
3 dimensional.



## • addition of 2 vector. -

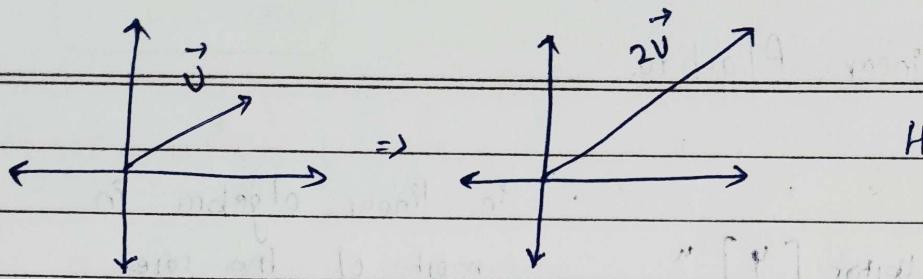
$$\text{If } \vec{v} = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix}, \quad \vec{w} = \begin{bmatrix} 3 \\ -1 \\ 1 \end{bmatrix}$$



$$\vec{v} + \vec{w} = \begin{bmatrix} 1 \\ 3 \\ 2 \end{bmatrix} + \begin{bmatrix} 3 \\ -1 \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} 4 \\ 2 \\ 3 \end{bmatrix}$$

## • multiplication of vector.



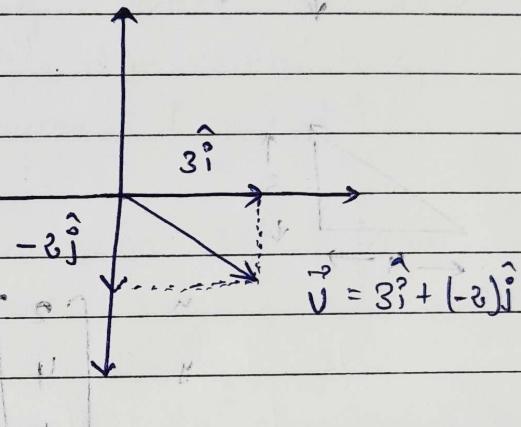
Here 'e' is called  
as scalar.

$$\rightarrow e \begin{bmatrix} u \\ y \end{bmatrix} = \begin{bmatrix} 2u \\ 2y \end{bmatrix}$$

(lengthwise & magnitude)

\*.  
let  $\vec{v} = \begin{bmatrix} 3 \\ -3 \end{bmatrix}$

$\hat{i}$  and  $\hat{j}$  are the  
"basis vector" of the  
xy coordinate system.

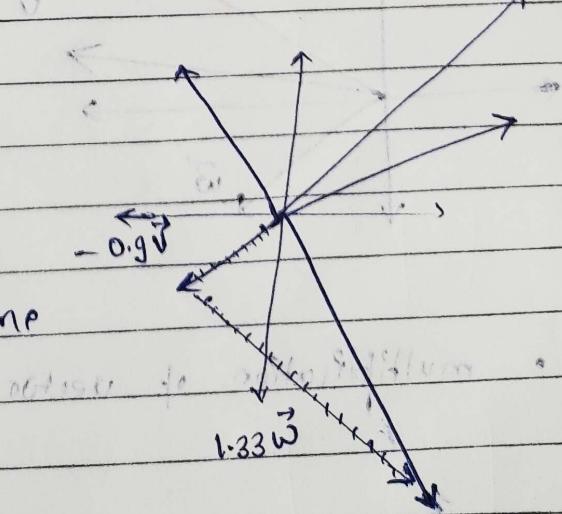


Linear combination of two vector

$$= a\vec{v} + b\vec{w}$$

$\rightarrow$  If one of the  $a$  or  $b$  is fixed then resulting vector of combination will form a "straight line"

$\rightarrow$  If non is fixed then this combination is reach every vector possible in xy plane



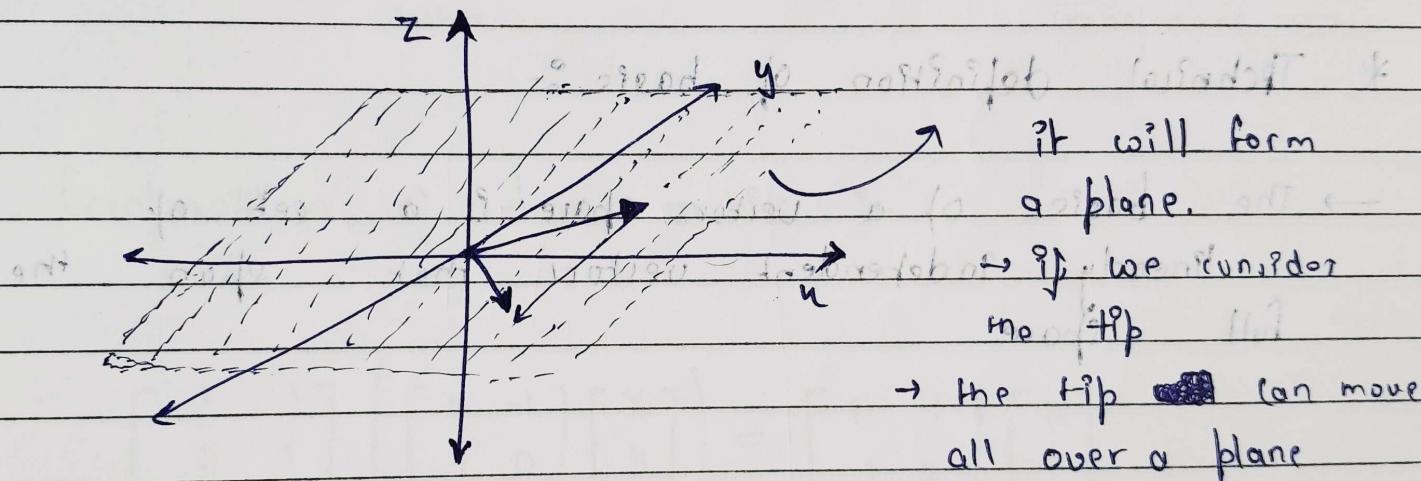
- Span of  $\vec{v}$  and  $\vec{w}$  is the set of all their linear combinations.

$$a\vec{v} + b\vec{w}$$

Let  $a$  and  $b$  vary over all real numbers.

↓↓↓↓↓

- Let's talk about span of two vectors in 3-dimensions.



- Linear combination of  $\vec{v}$ ,  $\vec{w}$ , and  $\vec{u}$ :

$$\{a\vec{v} + b\vec{w} + c\vec{u}\}$$

For span, let these constants vary.

can cover all the 3-D space.

- Linearly dependent :-

$\vec{u} = a\vec{v} + b\vec{w}$  for all values of  $a$  and  $b$

- Linearly in-dependent :-

$$\vec{u} \neq a\vec{v} + b\vec{w}$$

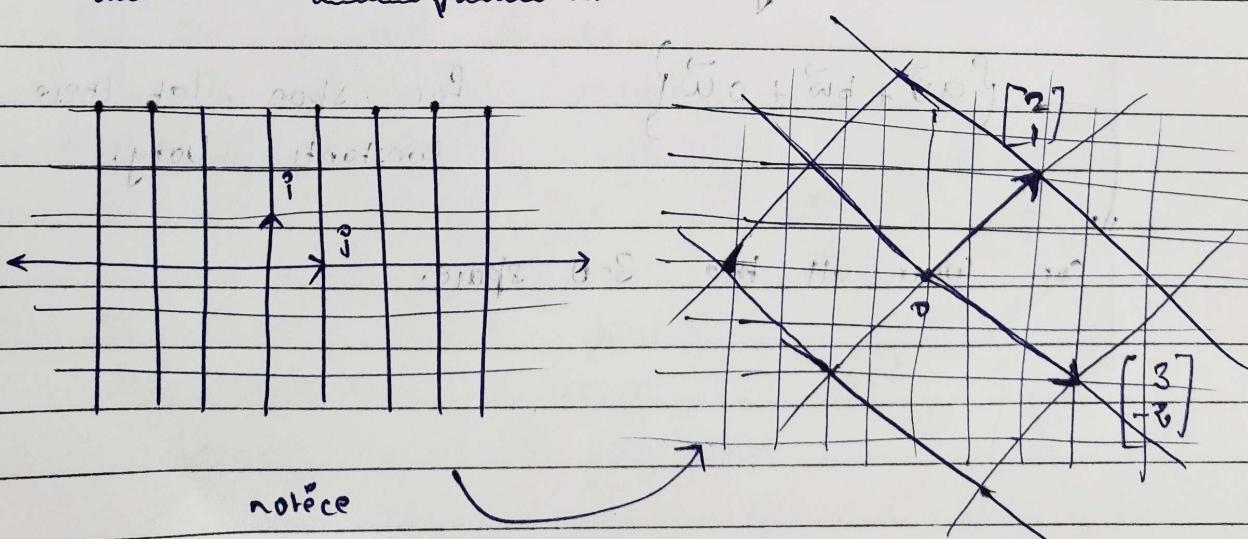
for all of  $a$  and  $b$

equivalence of saying that the two vectors are linearly independent.

### \* Technical definition of basis :-

→ The basis of a vector space is a set of linearly independent vectors that span the full space.

### \* Linear transformation :-



where does the  $i, j$  vector went after transformation

$$= \begin{bmatrix} 3 & 8 \\ -3 & 1 \end{bmatrix}$$

• ex 2 matrix

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

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where  $\hat{i}$  lands

where  $\hat{j}$  lands.

transformation

→ and vector multiplication computes what that vector does to a vector.

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix} = x \begin{bmatrix} a \\ c \end{bmatrix} + y \begin{bmatrix} b \\ d \end{bmatrix} = \begin{bmatrix} ax + by \\ cx + dy \end{bmatrix}$$

vector.

Transformed vector

\* Composition of two matrix :-

$$\underbrace{\begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}}_{\text{Shear } ②} \underbrace{\left( \underbrace{\begin{bmatrix} 0 & -1 \\ 1 & 0 \end{bmatrix}}_{\text{Rotation } ①} \begin{bmatrix} x \\ y \end{bmatrix} \right)}_{\text{Composition}} = \underbrace{\begin{bmatrix} 1 & -1 \\ 1 & 0 \end{bmatrix}}_{\text{Composition}} \begin{bmatrix} x \\ y \end{bmatrix}$$

②                    ①

Readed  
second.

②

①

Readed  
first

$$(M_1 M_2 \neq M_2 M_1) \rightarrow \text{order matter's}$$

$$A(BC) = (AB)C \quad \xrightarrow{\text{def}} \text{Associative Properties}$$

$$\begin{bmatrix} ad + bc \\ ab + cd \end{bmatrix} = \begin{bmatrix} d \\ b \end{bmatrix} E + \begin{bmatrix} c \\ a \end{bmatrix} N = \begin{bmatrix} c \\ a \end{bmatrix} \begin{bmatrix} d & e \\ b & d \end{bmatrix}$$

Figure 6: *monoprot*

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$$\begin{pmatrix} x \\ y \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} = \left( \begin{pmatrix} x \\ y \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \right) \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

*postlimyia*

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$$\left( \begin{array}{cc} 1 & 1 \\ 0 & 1 \end{array} \right) \rightarrow \left( \begin{array}{cc} 1 & 0 \\ 0 & 1 \end{array} \right) \left( \begin{array}{cc} 1 & 0 \\ 0 & 0 \end{array} \right)$$

babes

babysitter