Probability

- independent
- Dependent → Conditional Prob
- mutually exclusive event

Bayes theorem

Prob

Naive Bayes classifier → Classification → Categorical

Prob → stats → Prob dist →

1) Normal Dis
2) Binomial
3) multinomial Dis

Naive → Simply classify or nonsophisticated

→ text data (My name is Sunny. I am working in iNeuron. My designation is Data Science.)

→ entire Pipeline

ML

Supervised
- ~~Regression~~
- classification
  - Binary → 2 classes
  - multiclass → more than 2 class

Unsupervised

Bayes | Naive bayes → simple

Conditional Prob :-

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

$A \cap B$

$P(B\cap A)$

find out Prob. of target

target

$B \cap A$

$$P(A\cap B) = P(B|A)\,P(A) \quad \text{— 1}$$

$$P(B\cap A) = P(A|B)\,P(B) \quad \text{— 2}$$

x y

yes	Prob(y) →	0.7
No	Prob(no) →	0.3

?

$$P(B|A)\,P(A) = P(A|B)\,P(B) \ ?$$

feature target

$$\boxed{P(A|B) = \frac{P(B|A)\,P(A)}{P(B)}} \rightarrow \text{Bayes theoram.}$$

y target, feature

Prob. → Bayes.

Dependent :-

$= \frac{2}{5} \times \frac{1}{4}$

$P(A \cap B) = P(A) \; P(B|A)$

↓ Cond

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

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

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

→ Data

outlook	temp	humid.	wind	(play) - Y/N target
Sunny	hot	High	strong	Y
Rainy	low	Normal	weak	N
overcast	mild			

$$\boxed{P(\text{class} \mid \text{feature}) = \frac{P(\text{feat} \mid \text{class})\; P(\text{class})}{P(\text{feat})}}$$

P(Y | Sunny, hot, high, strong)

P(N | Sunny, hot, high, strong)

Naive Bayes for text data.

voice

text

Naive bayes

how?

word

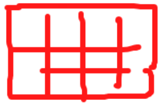
senten

paragraph

(wikipedia)

Data.

Structure data



Unstructure data.

Image data/ videos

(Computer vision)

mimic human vision

text voice

(Natural language Processing)

mimic human language

Deep learning

text data:-

I am Sunny.
Sunny working in ineuron.
Sunny is data scientist.

→ **Naive bayes**
→ text **classification**

Naive bayes

NLP:-
(1) text genration
(2) text classification → Sentiment analysis → (sentences 1) → +ve
(3) filling the blank
(4) spot keyword

text clarify

Naive bayes

sentence 2 → -ve
sentence → +ve

Naive Bayes

text classification :-

Sunny is DS
Sunny live in Banglore

1) data → text → Structure
2) EDA
3) PP
4) model — Naive bayes
5) evaluation

(Analysis) → visulization (case study)

Restaurant

USA Rest

x_1	x_2	x_3	x_4	Predict
—	—	—	—	Risk
—	—	—	—	Risk

Data → Machine learning

structure Data

1) Data
2) EDA
3) PP
4) model
5) evaluation

PreProcessing

text (clean)

- stemming
- lemmitization
- grammer
- textpreprocessing

→ encode (vector)

docmat tfidf word2vec glove elmo

Naive bayes algo

Data →

Sunny is DS

Sunny live in Bang

Sunny Like Southindian food

food	Sunny	DS	Love in	Banglor	southindian
1	0	0	0	0	0
0	1	0	0	0	0
0	0	1	0	0	0
0	0	0	1	0	0
0	0	0	0	1	0
0	0	0	0	0	

Naive bayes

Machine lear NLP :- Python

Model

BTT

Prob

Naive bayes

Text classification + huge Prob - NLP - Sentiment analysis (twitter)

- Email ham | spam

- News classification

- NLTK

- Text BlOB

- SPACY

→ text Processing

ANN → RNN

LSTM | GRU

encoder | decoder

Attention

self attention

transformers

SOTA

Prob Approch
Naive bayes

DL Approch

I am Sunny | Sunny is a Boy | Sunny like SI food

(Num)

Sent :-

NLP model

Simple ML Approach Naive bayes class

→ classification