* Naive Bayes

→ It is a Probabilistic

Naive → Simplicity

Statistic (Bayesian Statistics)

Machine learning (Bayesian ML)

Probability → Conditional Probability → Bayes theorem

simple classify

- Naive Bayes —This is→ Probabilistic based approach

Naive → Simple

Bayes → theorem

Probabilistic :- Independent
Dependent | Conditional
Mutual Exclusive

Formula

- Probability = $\frac{\text{Sample}}{\text{Total}}$ (or) $P = \frac{\text{No. of event}}{\text{Total event}}$

- Compliment = 1 − Probability

eg: Coin Based

$P(H) = \frac{1}{2} = 0.5$ $P(T) = \frac{1}{2} = 0.5$

toss, 3 times consecutive Head in sequence = $\frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} = \frac{1}{8} \Rightarrow 0.125$

Dice

Single dice = 6 (Total outcome)

2 Dice = 36 (Total outcome)

- Pro for comming (5) = $\frac{1}{6}$

- Sum (4) = $\frac{3}{36}$

- Pro for comming (3) = $\frac{1}{6}$

Cards

→ Pro of getting (King) = $\frac{4}{52}$

* INDEPENDENT Pro

Coin

↳ $P(H) = \frac{1}{2}$

Next time toss $P(H) = \frac{1}{2}$

Next time toss $P(H) = \frac{1}{2}$

Dice

↳ $P(1) = \frac{1}{6}$

$P(1) = \frac{1}{6}$

$P(5) = \frac{1}{6}$

Imp

* present Event does not having effect from previous Event

Imp ⇒ Current Event (Present event) is totally independent from the previous Event

* Dependent Event → Conditional Prob

→ Card

↳ $P(\text{King}) = \frac{4}{52}$ | Took one card (King) $= \frac{3}{51}$ (or) $\frac{4}{51}$

eg:- 2 King Consecutive

$\boxed{P(A \text{ and } B) = P(A) \times P(B|A)}$

$= \frac{4}{52} \times \frac{3}{51}$

* Mutually Exclusive

→ Card = 52

FACE card = 16

P(K), P(A)

{King and face we cannot get same time}

Coin

P(H), P(T)

{Cannot get H or T at the Same time}

eg : Student pass or Fail at the same time Not possible

Bayes Theorem

↳ This is Naive Bayes classifier → we can use on any categorical or text data

∘ Conditional Pro ⇒ $P(A \text{ and } B) = P(A) \times \underbrace{P(B|A)}_{P \text{ of } B \text{ given } A}$

$$\boxed{\therefore P(B|A) = \frac{P(A \text{ and } B)}{P(A)}}$$

$P(A \cap B) = P(B|A)\, P(A)$ — ①

$P(B \cap A) = P(A|B)\, P(B)$ — ②

Derive

$P(A \text{ and } B) = P(B \text{ and } A)$

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

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

∘ Bayes Theorem

$$\boxed{\underset{\text{target}}{P(A}|\underset{\text{feature}}{B)} = \frac{\underset{\text{target}}{P(A)}\ \underset{\text{feature}}{P(B}|\underset{\text{target}}{A)}}{\underset{\text{feature}}{P(B)}}}$$

Wikipedia {Naive Bayes Classifier}

∘ Shatterline.com (blog)

Bayes Theorem ⇒ $\underset{\text{Target}}{P(C_k} | \underset{\text{feature}}{x)} = \frac{P(C_k)\, P(x | C_k)}{P(x)}$ — nom / denom

Note:- we have to find out the Pro of Target colum w.r.t these featurs

Text Data

Data:- Chandu is DS, Live in Mumbai

{for converting text to Numeric (NLP) # concept

Techniqus (TFID, word2vec)

Apply one Hot encoding ← After preprocessing

Chandu	DS	Live	Mumbai
1	0	0	0
0	1	0	0
0	0	1	0
0	0	0	1

Applications ⇒ ① Diagnostic Test Scenario, ② Spam ham Email, ③ Cancer or Not Cancer