Bayes Theorem

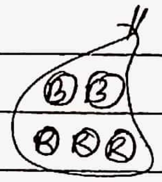
⇒ Independent Event → Toss a Coin.

$H = 0.5$

$T = 0.5$

⇒ Dependent Event:

Let's Consider a Marbel Bag.



$P(\text{1 Black}) = 2/5$ 1st Event.

$P(\text{Black}) = 1/4$ Next Event

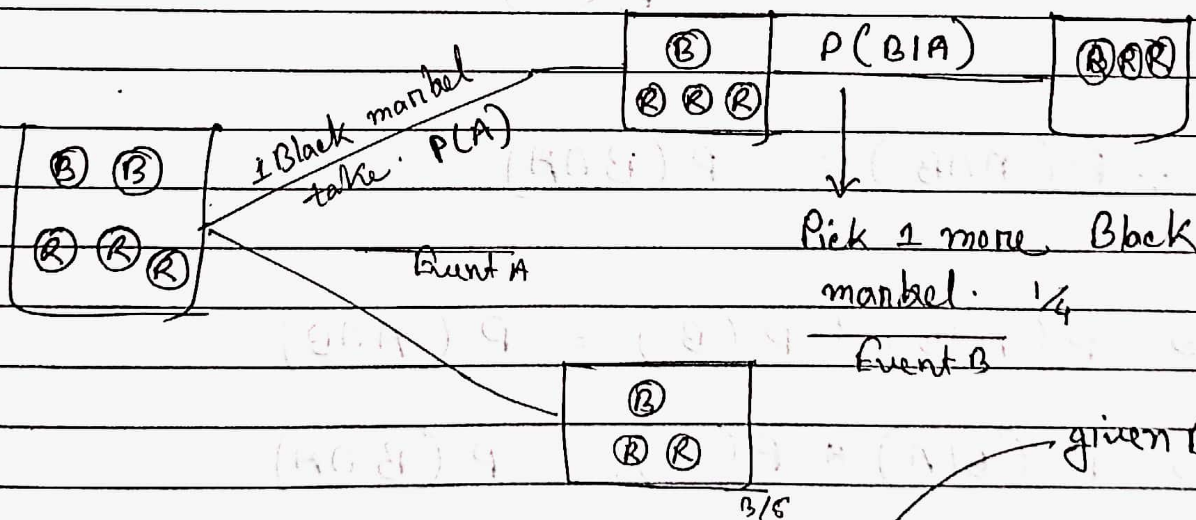
$P(B|A)$

Event-1 = A

Event 2 = B

⇒ Conditional Pro.

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



Conditional Probability → $P(A|B) = \dfrac{P(A \cap B)}{P(B)}$

given B

or Already occured.

$$P(A \cap B) = \frac{2}{5} \times \frac{1}{4} = \frac{1}{10}$$

According to the Conditional Probability

$$P(B|A) = \frac{P(B \cap A)}{P(A)} = \frac{1/10}{2/5} = \frac{1}{10} \times \frac{5}{2}$$

$$= \frac{1}{4}$$

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

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

$$\therefore P(A \cap B) = P(B \cap A)$$

$$\Rightarrow P(A|B) * P(B) = P(A \cap B)$$

$$\Rightarrow P(B|A) * P(A) = P(B \cap A)$$

$$P(A|B) * P(B) = P(B|A) * P(A)$$

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

[Bayes Theorem]

Here,

$P(A|B)$ = Posterior

$P(B)$ = Marginalization.

$P(A)$ = Prior

$P(B|A)$ = liklihood.

Naive Bayes Classifier.

Bayes theorem

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

① Dataset $\{x_1, x_2, x_3 \cdots x_n\}$ $\{y\}$

$\downarrow$ feature $\quad$ $\downarrow$ label.

$$P(\overset{A}{Y} | \overset{B}{x_1, x_2, x_3 \cdots x_n}) = \frac{P(x_1|Y) * P(x_2|Y) * \cdots P(x_n|Y) * P(Y)}{P(x_1)P(x_2)P(x_3) \cdots P(x_n)}$$

$$\Rightarrow \frac{P(Y) \cdot \prod_{i=1}^{n} P(x_i|Y)}{P(x_1) \cdot P(x_2) \cdot P(x_3) \cdots P(x_n)}$$

$$\Rightarrow \frac{P(Y) \cdot \prod_{i=1}^{n} P(x_i|Y)}{P(x_1)P(x_2)P(x_3) \cdots P(x_n)}$$

Always same, let's consider it as a constant.

$$\therefore P(Y|x_1, x_2, x_3 \cdots x_n) \cong P(Y) \cdot \prod_{i=1}^{n} P(x_i|Y)$$

Proportional

$\hat{y} = \text{argmax}_y \; P(y) \cdot \prod_{i=n}^{n} \cdot P(x_i \mid y)$

highest Probability

Yes = 0.7
No = 0.3
So Consider Yes.

Outlook

Sunny	Yes	No	P(Y)	P(N)
	2	3	2/9	3/5
Overcast	4	0	4/9	0/5
Rainy	3	2	3/9	2/5
Total	9	5	100%	100%

Temparature

	Yes	No	P(y)	P(N)
Hot	2	2	2/9	2/5
Mild	4	2	4/9	2/5
Cold	3	1	3/9	1/5
total	9	5	100%	100%

		$P(Y) \cdot P(N)$
Yes	9	$9/14$
No	5	$5/14$
Total	14	100%

Today (Sunny$_{x_1}$, Hot$_{x_2}$) ← Yes or No

$$P(\text{Yes} \mid \text{Today}) = \frac{P(\text{Sunny}\mid\text{Yes})\,P(\text{Hot}\mid\text{Yes}) * P(\text{Yes})}{P(\text{Today})}$$

← for every record this is same. so we can skip this

$$= \frac{2}{9} * \frac{\cancel{2}}{\cancel{9}} * \frac{\cancel{9}}{14}$$

$$= 0.031$$

$$P(\text{NO} \mid \text{Today}) = \frac{P(\text{Sunny}\mid\text{No})\ P(\text{Hot}\mid\text{No})\ P(\text{NO})}{P(\text{Today})}$$

$$= 3/5 * 2/9 * 5/14$$

$$= 0.08571$$

Output yes or No? How do we determine

$$0.03 / 0.031 + 0.08571$$

find P(Yes) and P(No)

Considering these values:

we have to Normalize these value.

$\rightarrow P(Yes) = \frac{0.031}{0.031 + 0.085}$

$= 0.27$

$P(No) = 1 - 0.27$

$= 0.73$

$\therefore P(NO) > P(Yes)$

→ Today (Sunny, Hot)

my output → No

⇒ Naive Bayes Classifier

With respect to Text data.

(NLP).

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

NLP → Natural language Processing.

→ Sentence → Good

Sentence → Bad

classify

Let's consider

Restaurant Review Coment.

Preprocessing.

- → Stop words
- → Bag of words
- → Steming
- → TF-IDF

Sen 1 → The food is delicious.

Sen 2 → The food is Bad.

Sen 3 → The food is Bad

⇒ unique word's as a feature frequent.

Countvector

f_1 (x_1) The	f_2 (x_2) food	f_3 (x_3) Delicious	f_4 Bad	O/P
1	1	1	0	1 → Yes
1	1	0	1	0 → No
0	1	0	1	0
0	1	1	0	1
0	0	0	1	0

is → remove by stopwords

features.

P (Yes | Sentence)

$$= P(Yes \mid x_1, x_2, x_3, \ldots x_n)$$

$$= P(Yes) * \prod_{i=1}^{n} P(x_i \mid Yes)$$

$$= \underbrace{2/5}_{P(Yes)} * \underbrace{1/2}_{P(x_1|Yes)} * \underbrace{2/4}_{P(x_2|Yes)} * \underbrace{2/2}_{P(x_3|Yes)}$$

$$= 1/10 = 0.1$$

$$P(NO \mid Sentence) = P(NO) * P(x_1 \mid NO)\ P(x_2 \mid NO)\ P(x_3 \mid NO)$$

$$= 3/5 * 1/2$$

$$= 3/10 = 0.3$$

$$P(\text{Yes} \mid \text{Sentence}) = 0.1/(0.1 + 0.3)$$

$$= 0.1/0.4$$

$$= 1/4$$

$$= \cancel{20\%}\ 25\%$$

$\therefore P(\text{NO} \mid \text{Sentence}) = 75\% >$

→ If just like. The food is delicious or tasty for tasty this not work, multiplication will be zero.

→ what happend if the dataset is imbalanced.