

BAYES' THEOREM

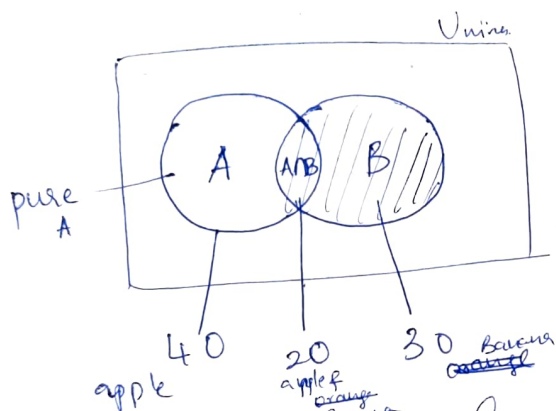
①

Pre-requisite - Conditional Probability.

→ Finding out probability of event A given that event B has already occurred. →
$$P(A|B) = \frac{P(A \cap B)}{P(B)}$$

(Probability of A and B by probability of B)

→ Event B is serving as a condition here.



when no condition applied whole Universe is my sample space.

Once I apply condition, i.e., sample space reduces. that B has occurred.

(Our Sample Space comprises of events occurred i.e. B & A ∩ B.)

Let find out the values of occurred events.

Let says there are 100 kids, out of which 40 like apples, 30 like Bananas & 20 like Both.

$A \rightarrow 40, B \rightarrow 30, A \cap B = 20$

$$\therefore P(B) = \frac{30}{100} = 0.3, \quad P(A \cap B) = \frac{20}{100} = 0.2$$

$$\therefore P(A|B) = \frac{0.2}{0.3} = 0.67 //$$

Lets Consider two Events A & B.

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

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

① We can write these as \Rightarrow

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

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

Observe in Equation ② R.H.S is Same.

\therefore We can Equate their L.H.S as follows:

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

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

Posterior Probability \leftarrow $P(A|B)$ \leftarrow Prior $P(A)$
Likelihood $P(B)$ \rightarrow Marginal

which is your Baye's Theorem.

\rightarrow where A is your hypothesis, B is your data or evidence. Hence we read, ~~prob~~ find probability of the hypothesis, given that B is some data or we have observed some evidence. So we compute the probability of hypothesis given the evidence or data.

* Cannot find out posteriors which knowing, likelihood and prior probabilities.

Likelihood \rightarrow Probability of Evidence, given the hypothesis⁽²⁾ is true.

Prior \rightarrow Probability of hypothesis, before considering Evidence.

Marginal \rightarrow Pure Probability of data or Evidence.

Ex: $P(\text{King} | \text{Face})$ find probability that Card is King,
[given that it was face.

$$P(\text{King} | \text{Face}) = \frac{P(\text{Face} | \text{King}) \cdot P(\text{King})}{P(\text{Face})}$$

$$= \frac{1 \cdot 4/52}{12/52} = \frac{1 \cdot 1/13}{3/13} = \frac{1}{3} //$$

2. Does patient have Cancer or not.

\rightarrow Two Outcomes +ve and -ve.

\rightarrow Test results correct +ve result in only 98% of cases in which disease is actually present.

\rightarrow Test results correct -ve result in only 97% of cases in which disease is not present.

\rightarrow Furthermore 0.008 of the entire population have Cancer.

$$P(\text{Cancer}) = 0.008, \quad P(\neg \text{Cancer}) = 0.992 \rightarrow (1 - 0.008) = 0.992$$

$$P(+ | \text{Cancer}) = 0.98$$

$$P(- | \text{Cancer}) = 0.02 \rightarrow (1 - 0.98)$$

$$P(+ | \neg \text{Cancer}) = 0.03$$

$$P(- | \neg \text{Cancer}) = 0.97 \rightarrow (1 - 0.03)$$

- * Suppose we now observe a new patient for whom the lab test returns a positive result.
- * Should we diagnose the patient as having Cancer or not?

$$P(A|B) = \frac{P(B|A) P(A)}{P(B)} \rightarrow \text{(Probability of Entire data set)}$$

$$P(\text{cancer} | +) = \frac{P(+ | \text{cancer}) P(\text{cancer})}{P(+)}$$

maximized here ignore.

$$= 0.98 * 0.008 = 0.0078 \quad \downarrow \downarrow$$

$$P(\neg \text{cancer} | +) = P(+ | \neg \text{cancer}) * P(\neg \text{cancer}) = 0.03 * 0.992 = 0.0298$$

- * Suppose we now observe a new patient for whom the lab test returns a negative result.
- * Should we diagnose the patient as having Cancer or not?

$$P(\text{cancer} | -) = P(- | \text{cancer}) * P(\text{cancer})$$

$$= 0.02 * 0.008 = 0.00016$$

$$P(\neg \text{cancer} | -) = P(- | \neg \text{cancer}) * P(\neg \text{cancer})$$

$$= 0.97 * 0.992 = 0.96224 \quad \checkmark \text{ greater.}$$

* Naive Bayes Classifier - Ex:

①

| Ex. No | Color | Type | Origin | Stolen? |
|--------|--------|--------|----------|---------|
| 1 | Red | Sports | Domestic | Yes |
| 2 | Red | Sports | " | No |
| 3 | Red | Sports | " | Yes |
| 4 | Yellow | Sports | " | No |
| 5 | Yellow | Sports | Imported | Yes |
| 6 | Yellow | SUV | " | No |
| 7 | Yellow | SUV | " | Yes |
| 8 | Yellow | SUV | Domestic | No |
| 9 | Red | SUV | Imported | No |
| 10 | Red | Sports | Imported | Yes |

New Instance = (Red, SUV, Domestic). — No ✓

$$P(\text{Yes}) = \frac{5}{10} = 0.5, \quad P(\text{No}) = \frac{5}{10} = 0.5.$$

| Color | Yes | No |
|--------|-----|-----|
| Red | 3/5 | 2/5 |
| Yellow | 2/5 | 3/5 |

| Type | Yes | No |
|--------|-----|-----|
| Sports | 4/5 | 2/5 |
| SUV | 1/5 | 3/5 |

| Origin | Yes | No |
|----------|-----|-----|
| Domestic | 2/5 | 3/5 |
| Imported | 3/5 | 2/5 |

$$\begin{aligned}
 P(\text{Yes}) &= P(\text{Yes}) * P(\text{Red}|\text{Yes}) * P(\text{SUV}|\text{Yes}) * P(\text{Domestic}|\text{Yes}) \\
 \text{New instance} &= 0.5 * \frac{3}{5} * \frac{1}{5} * \frac{2}{5} = 0.5 * 0.6 * 0.2 * 0.4 \\
 &= 0.024.
 \end{aligned}$$

$$\begin{aligned}
 P(\text{No}) &= P(\text{No}) * P(\text{Red}|\text{No}) * P(\text{SUV}|\text{No}) * P(\text{Domestic}|\text{No}) \\
 \text{New instance} &= 0.5 * \frac{2}{5} * \frac{3}{5} * \frac{3}{5} = 0.5 * 0.4 * 0.6 * 0.6 \\
 &= 0.072.
 \end{aligned}$$

$$\therefore P(\text{No}|\text{New instance}) > P(\text{Yes}|\text{New instance}),$$