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- ## Naive Bayes

It is a probabilistic supervised ML algo based on Bayes Theorem, used mainly for classification problem.

* ### Bayes Formula

$$P(C|X) = \frac{P(X|C) \cdot P(C)}{P(X)}$$

C = class label
X = Input data (Feature)
$P(C|X)$ = Posterior Probability (what we want)
$P(X|C)$ = likelihood
$P(C)$ = Prior Probability
$P(X)$ = Evidence (constant).

If input features → $X = (x_1, x_2, x_3, \dots x_n)$.
Naive Bayes assumes.
$P(X|C) = P(x_1|C) \cdot P(x_2|C) \dots P(x_n|C)$
Each feature is independent.

* ### Working

1- Calculate Prior Probability $P(C)$.
2- Calculate Likelihood $P(x_i|C)$
↳ Probability of each feature given in class.
3- Apply Naive Bayes Assumption
↳ $P(X|C) = P(x_i|C)$.
4- Calculate Posterior Score
$P(C|X) \propto P(C) \times \prod P(x_i|C)$.
5- Predict class
↳ with maximum Probability.

Date: __.__.__

→ Three types of Naive Bayes.

↳ Multinomial
↳ Gaussian
↳ Bernoulli

① Multinomial

Used when feature / data is text.
When features show how many times something appears.

ex →

| Day | Outlook | temp | Decision |
|---|---|---|---|
| 1 | Sunny | Hot | No |
| 2 | Sunny | Hot | No |
| 3 | Overcast | Hot | Yes |
| 4 | Rain | Mild | Yes |
| 5 | Rain | Cool | Yes |
| 6 | Rain | Cool | No |
| 7 | Overcast | Cool | Yes |
| 8 | Sunny | Mild | No |
| 9 | Sunny | Cool | Yes |
| 10 | Rain | Mild | Yes |
| 11 | Sunny | Mild | Yes |
| 12 | Overcast | Mild | Yes |
| 13 | Overcast | Hot | Yes |
| 14 | Rain | Mild | No |
| | | | |
| 15 | Sunny | Cool | ? |

$P(Yes) = \frac{9}{14}$ $\quad P(No) = \frac{5}{14}$. $\left\{ \text{Prior Probability} \right\}$

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Date: __.__.____

Likelihood Probability of feature (X) given class C

(Yes)

$P(\text{Sunny} \mid \text{Yes}) = \frac{2}{9}$ $P(\text{Cool} \mid \text{Yes}) = \frac{3}{9}$

(No)

$P(\text{Sunny} \mid \text{No}) = \frac{3}{5}$ $P(\text{Cool} \mid \text{No}) = \frac{1}{5}$

Posterior Probabity

$P(\text{Yes} \mid \text{Sunny, Cool}) = P(\text{Sunny} \mid \text{Yes}) \times P(\text{Cool} \mid \text{Yes}) \times P(\text{Yes})$.

$= \frac{2}{9} \times \frac{3}{9} \times \frac{9}{14} \approx 0.0476$

$P(\text{No} \mid \text{Sunny, Cool}) = \frac{3}{5} \times \frac{1}{5} \times \frac{5}{14} \approx 0.0425$

Normalizing them

$0.0476 + 0.0425 = 0.0905$

$P(\text{Yes} \mid \text{Sunny, Cool}) = \frac{0.0476}{0.0905} \approx 0.526$

$P(\text{No} \mid \text{Sunny, Cool}) = \frac{0.0425}{0.0905} \approx 0.474$

High Posterior Probability Score : 0.526,

So Prediction is (Yes

Like in this way this naive Bayes works.

② Gaussian Naive Bayes

↳ Used when features are continuous.

Formula → $P(x|C) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$

$\mu \rightarrow$ mean, $\sigma^2 \rightarrow$ variance.

In this Likehihood Probability is using this formula rest remains same.

③ Bernoulli Naive Bayes

↳ Used when features are binary (0 or 1). Feature indicates presence or absence.

$$P(x|C) = p^x (1-p)^{1-x}.$$

ex → dataset

| mail | Free | Win | Hello | Spam / Not |
|---|---|---|---|---|
| Free win | 1 | 1 | 0 | 1 |
| win Hello | 0 | 1 | 1 | 1 |
| Hello | 0 | 0 | 1 | 0 |
| Free Hello | 1 | 0 | 1 | 0 |

For these type Bernoulli used.