

Data Science

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Outline

1 Naive Bayes

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Conditional probability and Bayes

- Notations:

- ▶ $P(A)$ the probability of an event $\setminus(A)$
- ▶ $P(A \cap B)$ or $P(A, B)$ the probability of having both events A and B .
- ▶ $P(A | B)$ the probability of having the event $\setminus(A)$ knowing $\setminus(B)$.

Definition of Conditional probabilities

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

So

Donc

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

Bayes Theorem

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

A little abuse of notations

- $P(X = x)$ is written $P(x)$. ($P(x)$ means that the random variable X has value x hence this is the probability of the event $X = x$)
- *Example* : In the case where we have several attributes $P(X = (0, 0))$, $P(X = (0, 1))$, are written $P(0, 0)$, $P(0, 1)$, etc... also written by $P(x)$ or $P(x_1, x_2)$

Back to learning

Reminders

- The data are generated by a fixed but unknown joint probability of having a data description x and a class y , written $P(x, y)$.
- We want to solve the problem of finding the best y when we observe a x .

Bayes' rule

- The best rule is

$$\operatorname{argmax}_y P(y \mid x)$$

- **Bayes error:** Error of this rule
- is the smallest error that can be made for this learning if the examples are described by x .

Difficult to calculate

- $P(y | x)$ can't be calculated because P is unknown.
- If we apply the ERM principle, by Bayes' rule we have

$$P(y | x) = \frac{P(y)P(x | y)}{P(x)}$$

- We're looking for the value of y that maximizes this quantity. But $P(x)$ does not depend on y . Simply solve

$$\operatorname{argmax}_y P(y)P(x | y)$$

- Problem: the calculation can't be done efficiently x and of the values it can take. Example: In the binary case with 5 attributes, we have 2^5 possibilities and therefore 2 times 2^5 quantities to be estimated for all cases of $P(x | y)$.

The chain rule

$$\begin{aligned} P(x_1, x_2, \dots, x_n) &= P(x_1 | x_2, \dots, x_n)P(x_2, \dots, x_n) \\ &= P(x_1 | x_2, \dots, x_n)P(x_2, | x_3, \dots, x_n)P(x_3, \dots, x_n)\dots \end{aligned}$$

- Obtained by applying $P(A, B) = P(A|B)P(B)$ repeatedly when B is an event that can be a conjunction of events.
- By recursion

$$P(\mathbf{x} | \mathbf{y}) = \prod_{k=1}^n P(x_k | x_{k-1}, \dots, x_1, y)$$

Conditional Independence and Naive Bayes

- If A and B are independent, then $P(A | B) = P(A)$.
- If we assume that all attributes are independent, i.e. if x_i and x_j are independent for every

$i \neq j$, then the product is written :

$$P(\mathbf{x} | y) = \prod_{k=1}^n P(x_k | y)$$

- To calculate each of these $P(x_k | y)$ just count!
- It's a **strong approximation**!
- But the calculation is **low complexity**.

$$\operatorname{argmax}_y P(y) \prod_{k=1}^n P(x_k | y)$$