

DATA SCIENCE

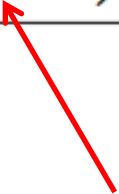
NAIVE BAYES CLASSIFICATION

*Suppose we have a dataset with features x_1, \dots, x_n and a class label C .
What can we say about classification using Bayes' theorem?*


$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

Bayes' theorem can help us to determine the probability of a record belonging to a class, given the data we observe.

*This term is the **prior probability** of C . It represents the probability of a record belonging to class C before the data is taken into account.*

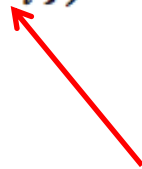
$$P(\text{class } C | \{x_i\}) = \frac{P(\{x_i\} | \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$


*This term is the **likelihood function**. It represents the joint probability of observing features $\{x_i\}$ given that that record belongs to class C .*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$


*This term is the **normalization constant**. It doesn't depend on C , and is generally ignored.*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$



*This term is the **posterior probability** of C . It represents the probability of a record belonging to class C after the data is taken into account.*

$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

*The idea of Bayesian inference, then, is to **update** our beliefs about the distribution of C using the data (“evidence”) at our disposal.*

Q: What piece of the puzzle we've seen so far looks like it could intractably difficult in practice?

A: Estimating the full likelihood function.

$$P(\{x_i\}|C) = P(\{x_1, x_2, \dots, x_n\}|C)$$

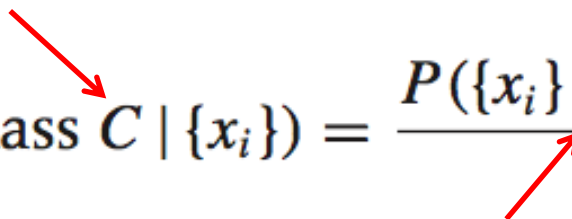
Observing this exactly would require us to have enough data for every possible combination of features to make a reasonable estimate.

Q: So what can we do about it?

A: Make a simplifying assumption. In particular, we assume that the features x_i are conditionally independent from each other:

$$P(\{x_i\}|C) = P(\{x_1, x_2, \dots, x_n\}|C) \approx P(x_1|C) * P(x_2|C) * \dots * P(x_n|C)$$

This “naïve” assumption simplifies the likelihood function to make it tractable.


$$P(\text{class } C \mid \{x_i\}) = \frac{P(\{x_i\} \mid \text{class } C) \cdot P(\text{class } C)}{P(\{x_i\})}$$

*In summary, the **training phase** of the model involves computing the **likelihood function**, which is the conditional probability of each feature given each class.*

*The **prediction phase** of the model involves computing the **posterior probability** of each class given the observed features, and choosing the class with the highest probability.*