

# Machine Learning Reference for R

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# Data Preparation

## Normalization

Features sometimes need to be scaled so they fit into a standard range. This involves transforming variables into a narrower or wider range than they are found in the observed data.

Two common methods for scaling features are **min-max normalization** and **z-score normalization**:

$$X_{new} = \frac{X - \min(X)}{\max(X) - \min(X)}$$

$$X_{new} = \frac{X - \mu}{\sigma} = \frac{X - \text{mean}(X)}{\text{StdDev}(X)}$$

## Algorithms

### Classification Algorithms

#### Naive Bayes

The **Naive Bayes classifier** is a probabilistic machine learning algorithm that predicts class labels for a factor by using a probability found from the training data. The classifier assumes that all features contribute equally and are independent of each other. This classifier relies on **conditional probability**, or the probability of an event  $A$  occurring, given that an event  $B$  has occurred:

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

In the Naive Bayes setting, the probability of level  $L$  for class  $C$  (denoted  $C_L$ ), given feature  $F$ , is:

$$P(C_L|F) = \frac{P(F|C_L)P(C_L)}{P(F)}$$

This is generalizable to:

$$P(C_L|F_1, F_2, \dots, F_n) = \frac{P(F_1, F_2, \dots, F_n|C_L)P(C_L)}{P(F_1, F_2, \dots, F_n)} = P(C_L) \prod_{i=1}^n P(F_i|C_L)$$