# 0.1 Naive Bayes

### 0.1.1 Probability Laws

Bayes' Theorem

$$P(Y|X) = \frac{P(Y \cap X)}{P(X)} = \frac{P(X|Y) \times P(Y)}{P(X)}$$

Law of total probability

$$P(A) = P(A \cap B) + P(A \cap \neg B)$$

# 0.1.2 Naive Bayes

Suppose the categorical outcome variable Y takes on values in the set  $\{y_1, y_2, \dots, y_k\}$  and there are m feature variables  $X_1, X_2, \dots, X_m$ . By Bayes Theorem, for  $j = 1, 2, \dots, k$ ,

$$P(Y = y_j | X_1 = x_1, X_2 = x_2, \dots, X_m = x_m)$$

$$= \frac{P(X_1 = x_1, X_2 = x_2, \dots, X_m = x_m | Y = y_j) \times P(Y = y_j)}{P(X_1 = x_1, X_2 = x_2, \dots, X_m = x_m)}$$

# **Assume Conditional Independence**

$$P(X_1 = x_1, X_2 = x_2, \dots, X_m = x_m | Y = y_j)$$

$$= P(X_1 = x_1 | Y = y_j) P(X_2 = x_2 | Y = y_j) \dots P(X_m = x_m | Y = y_j)$$

$$= \prod_{i=1}^m P(X_i = x_i | Y = y_j)$$

#### Ignore Denominator

$$P(X_1 = x_1, X_2 = x_2, \dots, X_m = x_m)$$

#### Finally

For 
$$j = 1, 2, ..., k$$
,

$$P(Y = y_j | X_1 = x_1, X_2 = x_2, ..., X_m = x_m)$$
  
 $\propto P(Y = y_j) \times \prod_{i=1}^{m} P(X_i = x_i | Y = y_j)$ 

# 0.1.3 Numerical Underflow

To prevent probability scores from becoming too small to be accurately stored in a computer, we can take logarithm on both sides,

$$\log P(Y = y_i | X_1 = x_1, X_2 = x_2, \dots, X_m = x_m)$$

$$\propto \log P(Y = y_j) + \sum_{i=1}^{m} \log P(X_i = x_i | Y = y_j)$$

# 0.1.4 R Implementation

# 0.1.5 Calculation Intensive Exam Questions & Solutions

```
table_to_naiveBayes <- function(features, feature_categories, )

## Error: <text>:1:63: unexpected ')'
## 1: table_to_naiveBayes <- function(features, feature_categories, )
##</pre>
```

Prediction from Table of Data