

**Machine Learning**

# Naive Bayes & Bayes Classifier

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# Outline

1. Applications
2. Bayes' Theorem
3. Naive Bayes
4. Codes
5. Advantages & When to use Naive Bayes

# Applications

1. Real time prediction
2. Multi class prediction
3. Text classification, spam filtering, sentiment analysis
4. Recommendation systems

# Bayes' Theorem

$$p(Y|X) = \frac{p(X|Y)p(Y)}{p(X)}$$

- Comments:
  - Bayes' rule tells us how to 'invert' conditional probabilities, i.e. to find  $P(B|A)$  from  $P(A|B)$ .

# Example

Consider a routine screening test for a disease. Suppose the frequency of the disease in the population (base rate) is 0.5%. The test is highly accurate with a 5% **false positive** rate and a 10% **false negative** rate.

You take the test and it comes back positive. What is the probability that you have the disease?

# Bayes' Theorem

## Example

### Events:

$D+$  = 'you have the disease'

$D-$  = 'you do not have the disease'

$T+$  = 'you tested positive'

$T-$  = 'you tested negative'.

$$P(D+ | T+)$$

# Bayes' Theorem

## Example

Using :

- $P(D+) = 0.005$
- $P(D-) = \underline{\hspace{1cm}}$
- $P(T- \mid D+) = 0.1$  (false negative)
- $P(T+ \mid D+) = \underline{\hspace{1cm}}$
- $P(T+ \mid D-) = \underline{\hspace{1cm}}$  (false positive)

# Bayes' Theorem

## Example

$$P(D+ | T+) = \frac{P(T+ | D+) \cdot P(D+)}{P(T+)}$$

$$P(D+ | T+) = \frac{P(T+ | D+) \cdot P(D+)}{P(T+ | D+) \cdot P(D+) + P(T+ | D-) \cdot P(D-)}$$



# Naive Bayes

$$\hat{y} = \operatorname{argmax}_{k \in \{1, \dots, m\}} p(C_k) \prod_{i=1}^n p(x_i \mid C_k)$$

Naive Assumption

$$p(C_k \mid x_1, x_2, \dots, x_n) \propto p(C_k) \prod_{i=1}^n p(x_i \mid C_k)$$

# Naive Bayes

## Methodology

**PARTE 1:** Crear el modelo.

Para ello se necesitan **cuatro pasos**:

1. Calcular las probabilidades a priori de cada clase.
2. Para cada clase, realizar un recuento de los valores de atributos que toma cada ejemplo. Se debe distribuir cada clase por separado para mayor comodidad y eficiencia del algoritmo.
3. Aplicar la Corrección de Laplace, para que los valores "cero" no den problemas.
4. Normalizar para obtener un rango de valores  $[0,1]$ .

**PARTE 2:**

1. Aplicar la fórmula de Naïve Bayes.

# Naive Bayes

## Example

| Ejemplos | Atr. 1 | Atr. 2 | Atr. 3 | Clase    |
|----------|--------|--------|--------|----------|
| x1       | 1      | 2      | 1      | positiva |
| x2       | 2      | 2      | 2      | positiva |
| x3       | 1      | 1      | 2      | negativa |
| x4       | 2      | 1      | 2      | negativa |

For  $x_5 = \{1,1,1\}$ , what is the class ?

[ ] <http://naivebayes.blogspot.com/>

# Codes

With Scikit-Learn

## 1. Gaussian Naive Bayes

$$P(x_i | y) = \frac{1}{\sqrt{2\pi\sigma_y^2}} \exp\left(-\frac{(x_i - \mu_y)^2}{2\sigma_y^2}\right)$$

## 2. Multinomial Naive Bayes

## 3. Bernoulli Naive Bayes

$$P(x_i | y) = P(i | y)x_i + (1 - P(i | y))(1 - x_i)$$

With Scikit-Learn

# Advantages & When to Use Naive Bayes

## Advantages

- They are extremely fast for both training and prediction
- They provide straightforward probabilistic prediction
- They are often very easily interpretable
- They have very few (if any) tunable parameters

## Practice

- When the naive assumptions actually match the data (very rare in practice)
- For very well-separated categories, when model complexity is less important
- For very high-dimensional data, when model complexity is less important

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