

**Machine Learning**

# Naive Bayes & Bayes Classifier

**Marchelo Bragagnini**

[cesarbrma91@gmail.com](mailto:cesarbrma91@gmail.com)

[@MarchBragagnini](#)



Universidad Católica  
**San Pablo**



**Centro de Investigación  
e Innovación en  
Ciencia Computación**

# Applications

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

# Independent Events

Two events are independent if the result of the second event is not affected by the result of the first event. If A and B are independent events, the probability of both events occurring is the product of the probabilities of the individual events.

$$P(A \text{ and } B) = P(A) \cdot P(B)$$

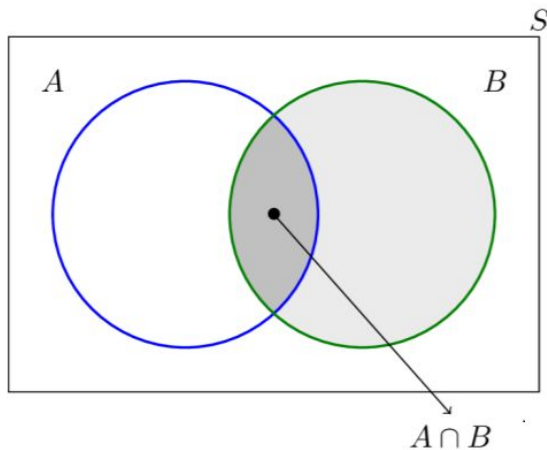
# Dependent Events

Two events are dependent if the result of the first event affects the outcome of the second event so that the probability is changed. The probability of both events occurring is the product of the probabilities of the individual events:

$$P(A \text{ and } B) = P(A) \cdot P(B/A)$$

# Conditional Probability

The conditional probability of an event A is the probability that the event will occur given the knowledge that an event B has already occurred. This probability is written  $P(A|B)$ , notation for the probability of A given B.



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

# Conditional Probability

**Ejercicio:** Hallar la probabilidad de que un sólo lanzamiento de un dado resulte en un número menor que 4, (a) no se da ninguna otra información, (b) se da que el lanzamiento resultó en número impar.

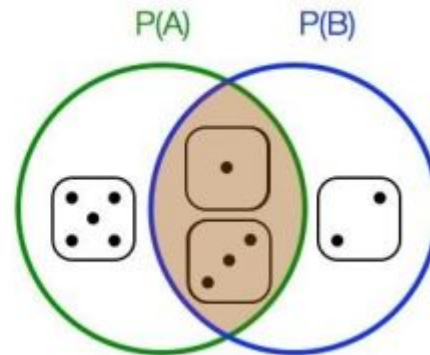
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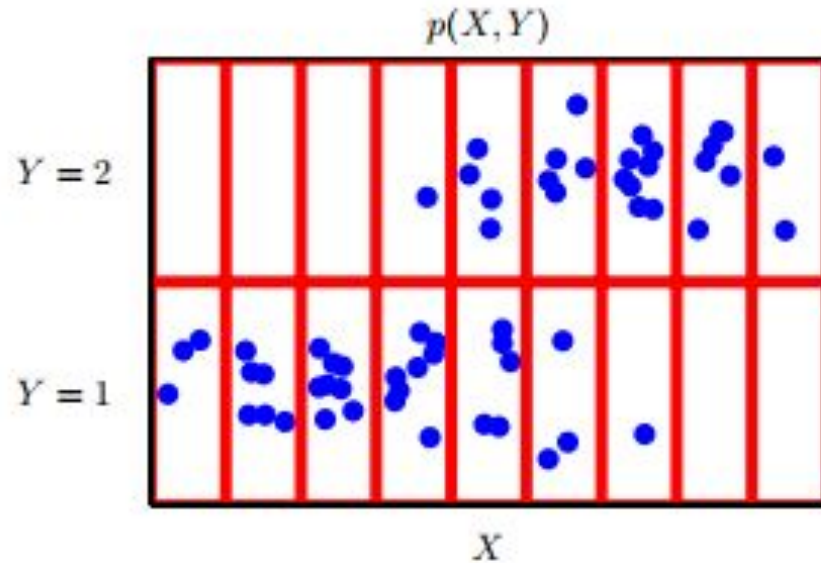
What is the Probability of  
rolling a dice and it's  
value is less than 4

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

knowing that the value is  
an odd number



# Marginal Probability





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**Exercise:** An urn contains 5 red balls and 2 green balls. Two balls are drawn one after the other. What is the probability that the second ball is red?

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Solution:

The sample space is  $\Omega = \{rr, rg, gr, gg\}$ . Let  $R1$  be the event 'the first ball is red',  $G1$  = 'first ball is green',  $R2$  = 'second ball is red',  $G2$  = 'second ball is green'. We are asked to find  $P(R2)$ .

$$P(R2) = P(R2|R1)P(R1) + P(R2|G1)P(G1)$$

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$$\begin{aligned} &= \frac{4}{6} \cdot \frac{5}{7} + \frac{5}{6} \cdot \frac{2}{7} \\ &= \frac{30}{42} = \frac{5}{7}. \end{aligned}$$

# 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 :

- $P(D+) = 0.005$
- $P(D-) = \underline{\hspace{2cm}}$
- $P(T- \mid D+) = 0.1$  (false negative)
- $P(T+ \mid D+) = \underline{\hspace{2cm}}$
- $P(T+ \mid D-) = \underline{\hspace{2cm}}$  (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

The diagram shows the Naive Bayes formula with arrows pointing from descriptive labels to the corresponding terms in the equation:

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

Labels and their corresponding terms:

- Likelihood** points to  $P(x | c)$
- Class Prior Probability** points to  $P(c)$
- Posterior Probability** points to  $P(c | x)$
- Predictor Prior Probability** points to  $P(x)$

# 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

# Code

- Naive Bayes with Scikit Learn

<https://github.com/marbramen/100DaysOfMLCode/blob/master/Day%2056%20-%20Naive%20Bayes%20with%20Scikit%20Learn.ipynb>

- Naive Bayes with Gaussian Density Function

<https://github.com/marbramen/100DaysOfMLCode/blob/master/Day%2051%20-%20Naive%20Bayes%20with%20Gaussian%20Density%20Function.ipynb>

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