Introducción a la Inteligencia Artificial Facultad de Ingeniería Universidad de Buenos Aires

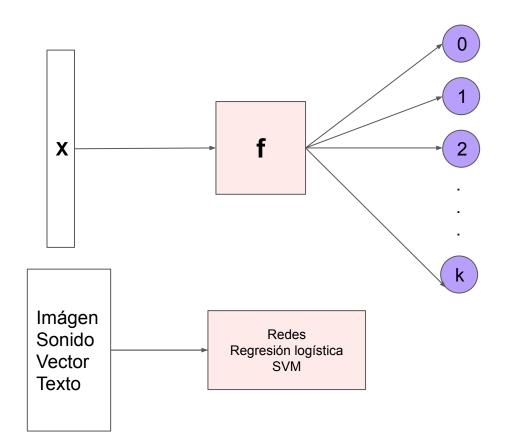


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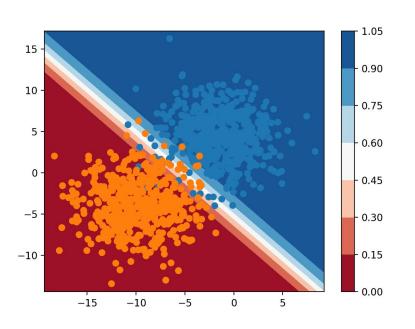


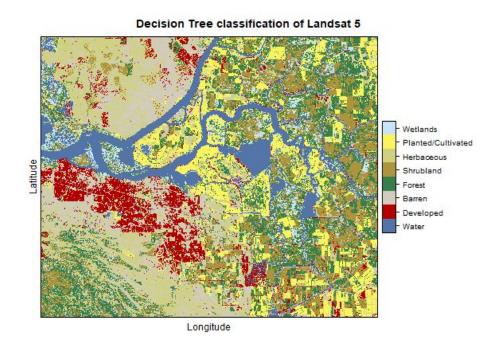


$$f: \mathbb{R}^D \to \{0, 1, 2, \cdots, k\}$$



Clasificación







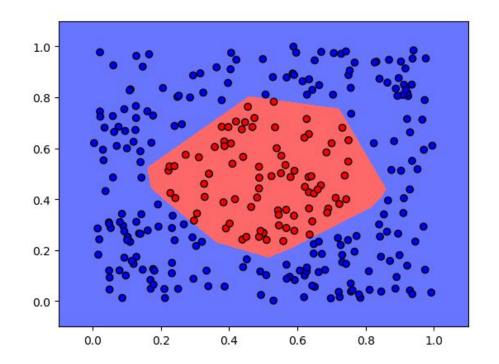
Clasificación binaria



Clasificación Binaria

Clasificación Binaria - Ejemplos

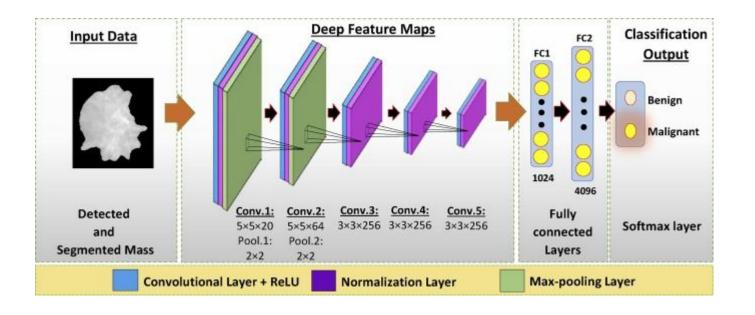
- Detección de fraudes
- Diagnóstico médico
- Detección de spam
- Sentiment Analysis
- Detección de objetos
- Outliers

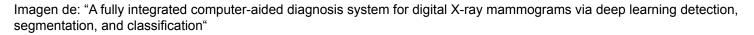




Clasificación Binaria

Clasificación Binaria - Diagnóstico médico

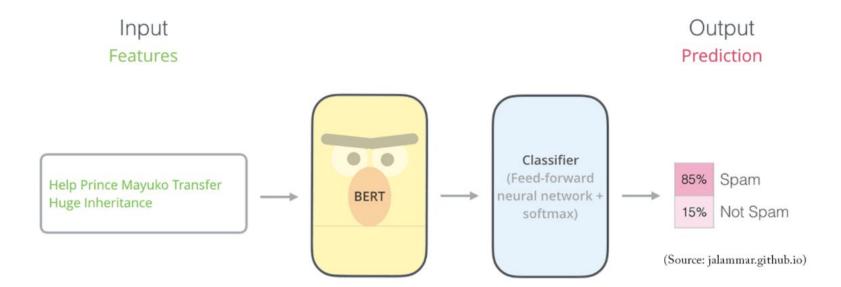






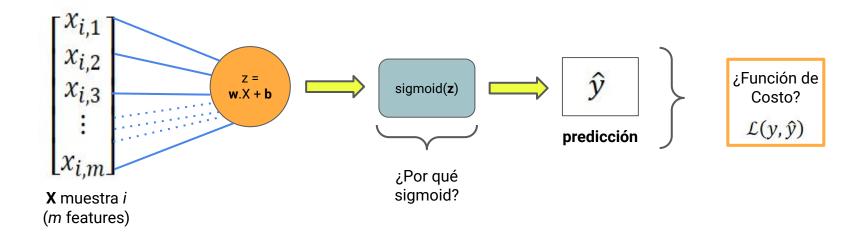
Clasificación Binaria

Clasificación Binaria - Spam detection





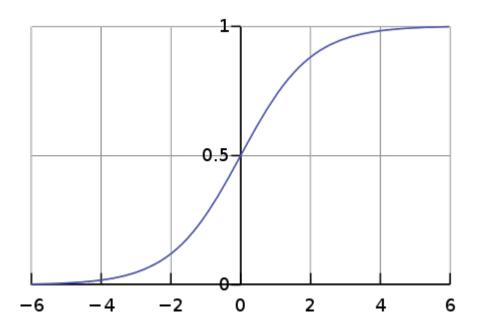
Regresión Logística





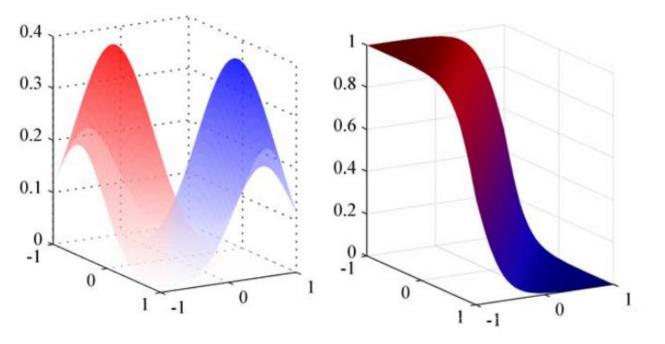
Logistic function

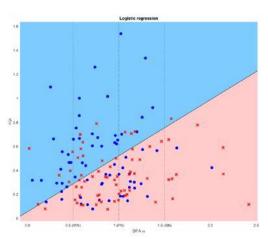
$$S(x) = rac{1}{1+e^{-x}} = rac{e^x}{e^x+1} = 1 - S(-x).$$





Regresión Logística





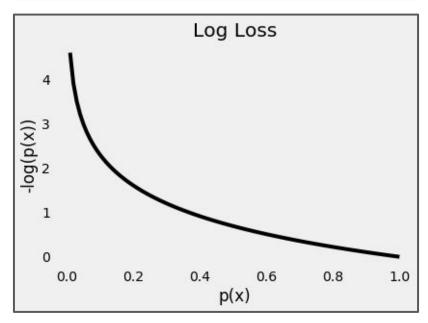
Class-conditional - P(x|Cn)

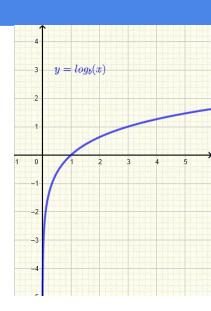
Posterior - P(Cn|x)



Función de costo - Binary cross entropy

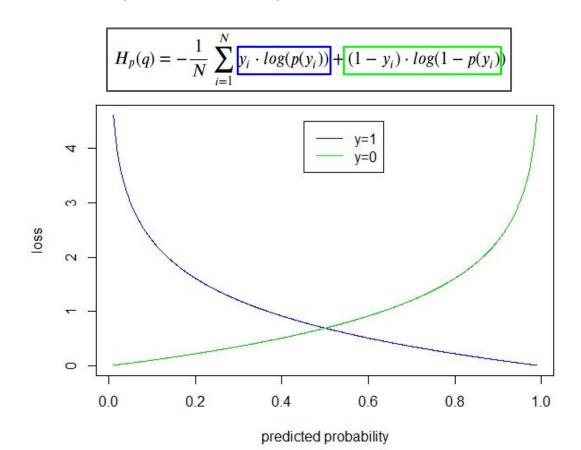
$$H_p(q) = -\frac{1}{N} \sum_{i=1}^{N} y_i \cdot log(p(y_i)) + (1 - y_i) \cdot log(1 - p(y_i))$$





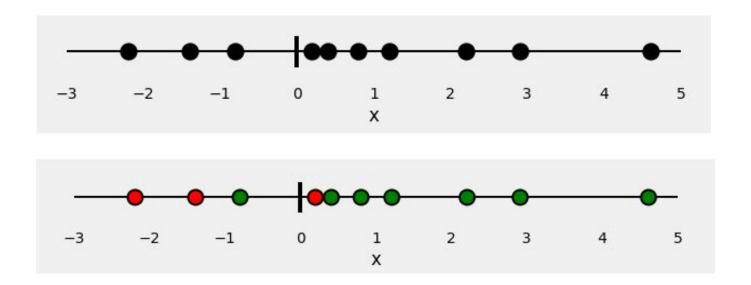


Función de costo - Binary cross entropy





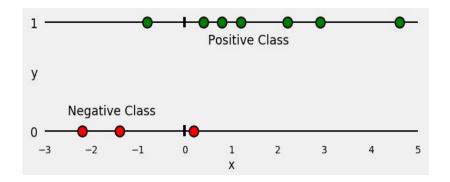
Regresión Logística

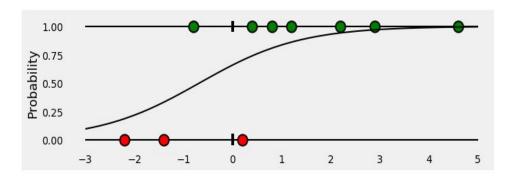


1: Verde, 0: Rojo



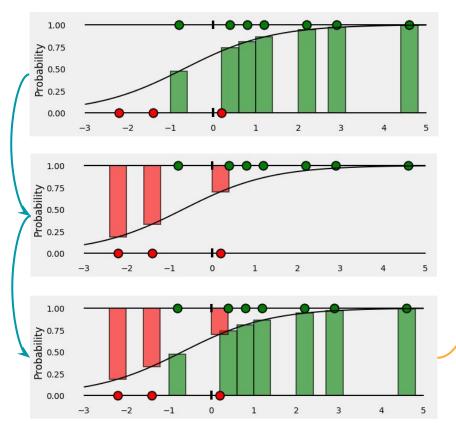
Regresión Logística

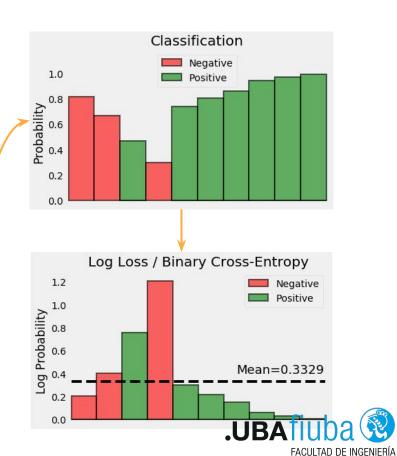






Regresión Logística



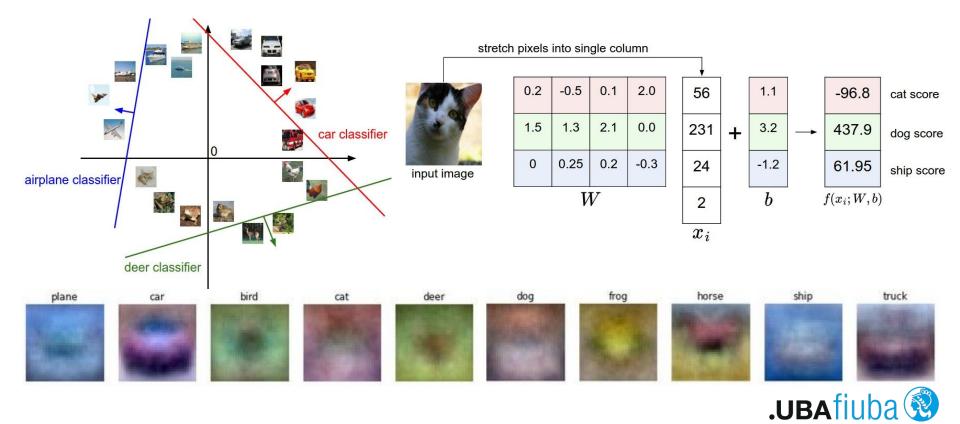


Clasificación multiclase



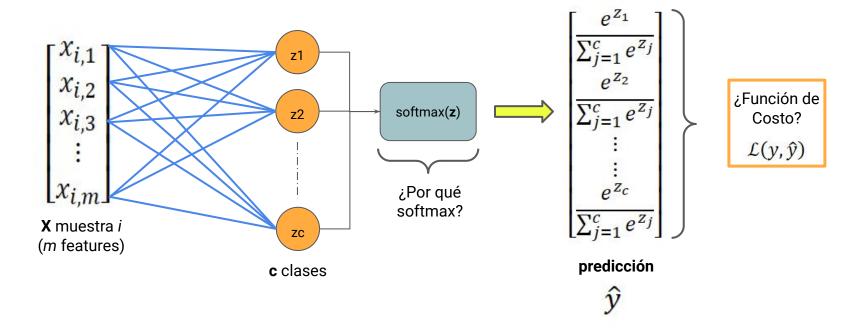
Clasificación Multiclase

Clasificación Multiclase - Motivación



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Softmax





Softmax

$$egin{aligned} P(y_i \mid x_i; W) &= rac{e^{f_{y_i}}}{\sum_j e^{f_j}} \ &rac{e^{f_{y_i}}}{\sum_j e^{f_j}} &= rac{Ce^{f_{y_i}}}{C\sum_j e^{f_j}} &= rac{e^{f_{y_i} + \log C}}{\sum_j e^{f_j + \log C}} \end{aligned}$$

$$q(\mathsf{x})$$
 $H(p,q) = -\sum_x p(x) \log q(x)$



Softmax

Cross-Entropy

Derivación Softmax

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{C} e^{z_j}}$$

$$\frac{\partial p_i}{\partial z_k} = \frac{\partial \frac{e^{z_i}}{\sum_{j=1}^C e^{z_j}}}{\partial z_k}$$

$$\frac{\partial p_i}{\partial z_k} = p_i(\delta_{ik} - p_k) \qquad \delta_{ik} = \begin{cases} 1, i = k \\ 0, i \neq k \end{cases}$$

$$\begin{split} L &= -\sum_{i} y_{i} log(p_{i}) \\ \frac{\partial L}{\partial z_{i}} &= -\sum_{j} y_{j} \frac{\partial log(p_{j})}{\partial z_{i}} \\ &= -\sum_{j} y_{j} \frac{\partial log(p_{j})}{\partial p_{j}} \times \frac{\partial p_{j}}{\partial z_{i}} / \\ &= -\sum_{j} y_{j} \frac{1}{p_{j}} \times \frac{\partial p_{j}}{\partial z_{i}} / \\ &= -\sum_{j} y_{j} \frac{1}{p_{j}} \times \frac{\partial p_{j}}{\partial z_{i}} / \\ &= \int_{j} y_{j} \frac{1}{p_{j}} \times \frac{\partial p_{j}}{\partial z_{i}} / \\ &= \frac{\partial L}{\partial z_{i}} = p_{i} - y_{i} \\ &= \frac{\partial z_{i}}{\partial W} = x_{i} \end{split}$$

Derivación

Usar gradiente descendente para actualizar W!!!



$$\frac{\partial L}{\partial W} = \sum_{i=1}^{N} (p_i - y_i) x_i$$
.UBA fiuba

Ejercicios

Ejercicio integrador

- 1. Implementar el algoritmo de regresión logística en NumPy.
- 2. Aplicar el modelo a un dataset de elección.
- 3. Comparar los resultados con Scikit-Learn.
- 4. Comparar los resultados agregando regularización.

Bibliografía

Bibliografía

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- An Introduction to Statistical Learning | Gareth James | Springer
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- Visual Information Theory | <u>Link</u>
- https://cs231n.github.io/
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