ARISA Learning Material

Educational Profile and EQF level: DATA SCIENTIST – EQF 6

PLO: 1, 2, 3, 4, 5

Learning Unit (LU): MACHINE LEARNING: SUPERVISED

Topic: LINEAR MODELS AND LOGISTIC REGRESSION

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ARISA Learning Material 2024

This material is a draft version and is subject to change after review coordinated by the European Education and Culture Executive Agency (EACEA).

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Disclaimer: This learning material has been developed under the Erasmus+ project ARISA (Artificial Intelligence Skills Alliance) which aims to skill, upskill, and reskill individuals into high-demand software roles across the EU.

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- About ARISA

- The Artificial Intelligence Skills Alliance (ARISA) is a four-year transnational project funded under the EU's Erasmus+ programme. It delivers a strategic approach to sectoral cooperation on the development of Artificial Intelligence (AI) skills in Europe.
- ARISA fast-tracks the upskilling and reskilling of employees, job seekers, business leaders, and policymakers into AI-related professions to open Europe to new business opportunities.
- ARISA regroups leading ICT representative bodies, education and training providers, qualification regulatory bodies, and a broad selection of stakeholders and social partners across the industry.

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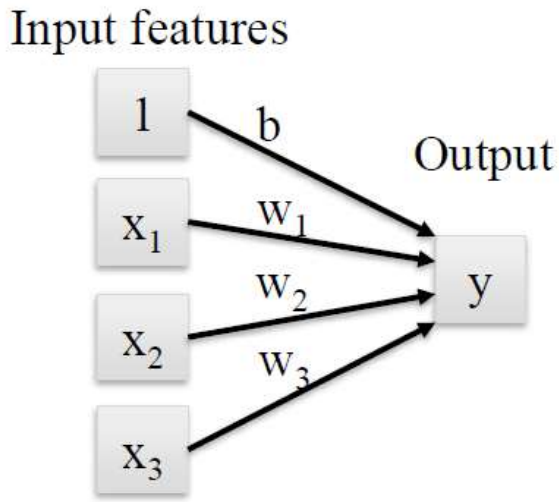
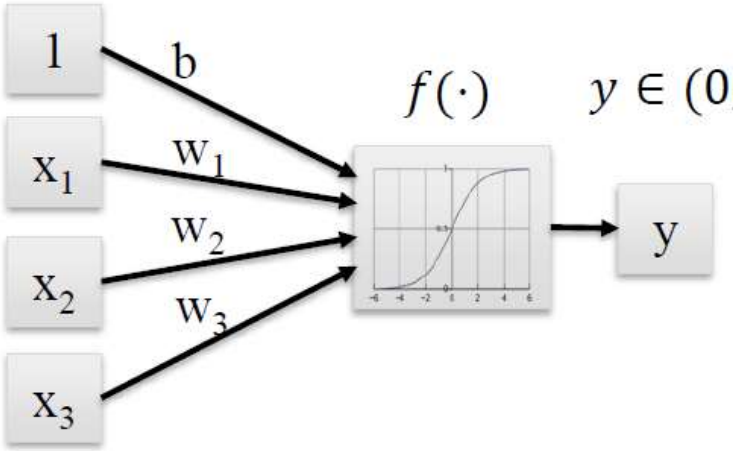
Regresión lineal

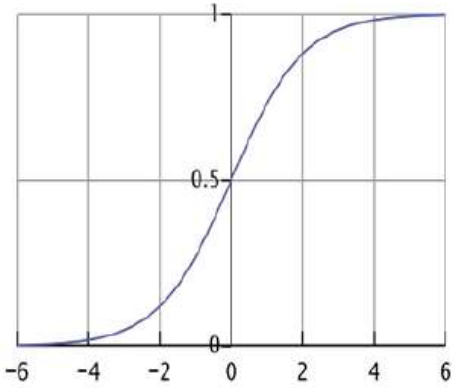


$$\hat{y} = \hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n$$

Linear models for classification: Logistic Regression

Input features





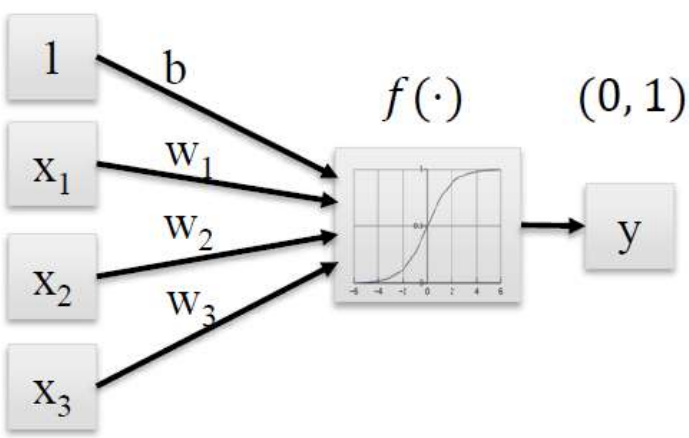
$$\hat{y} = \text{logistic}(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)$$

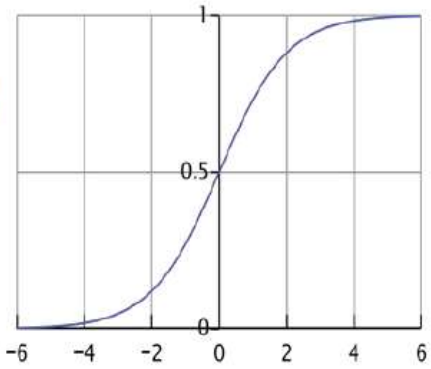
$$= \frac{1}{1 + \exp\left[-(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)\right]}$$

- Title

Linear models for classification: Logistic Regression

Input features

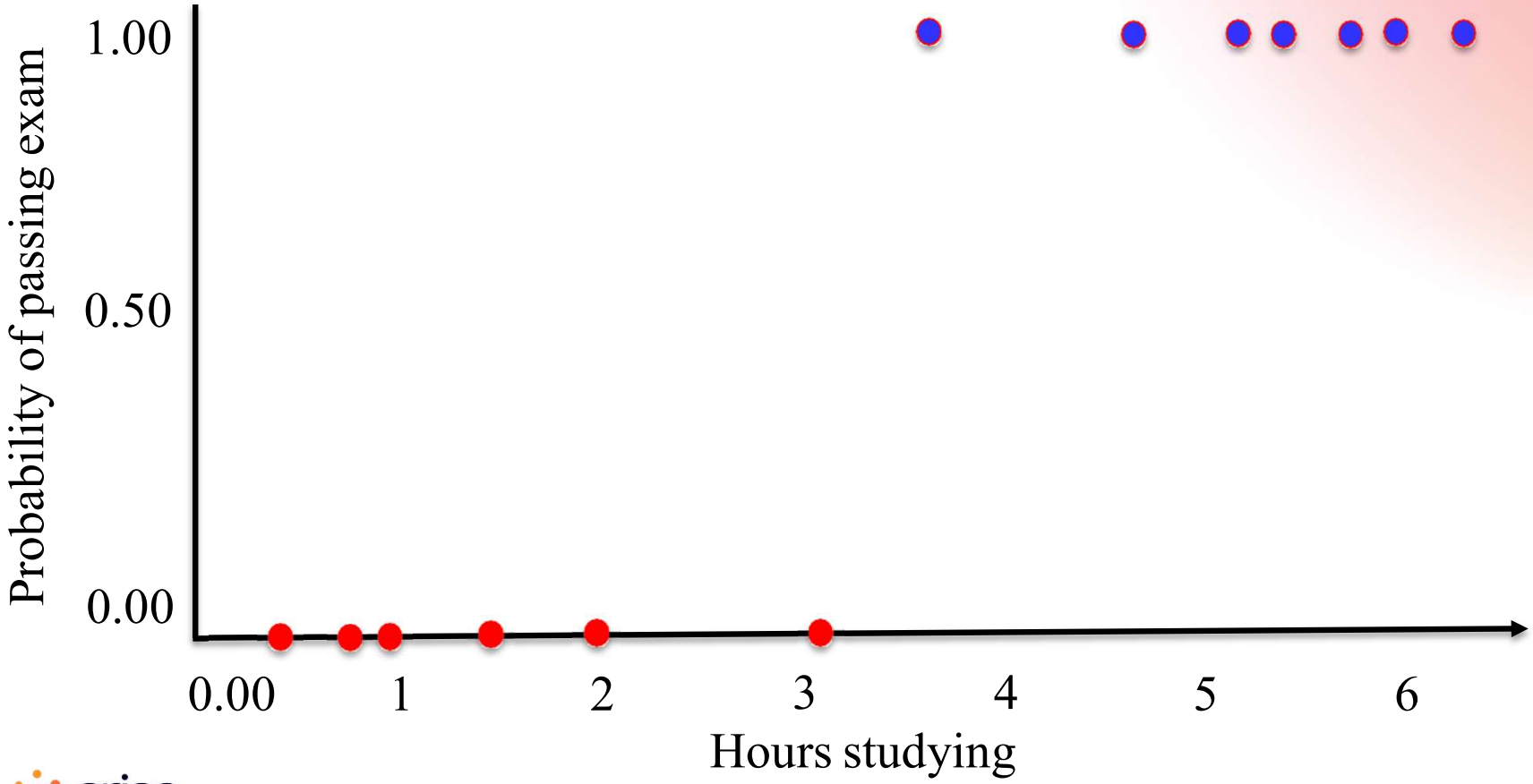




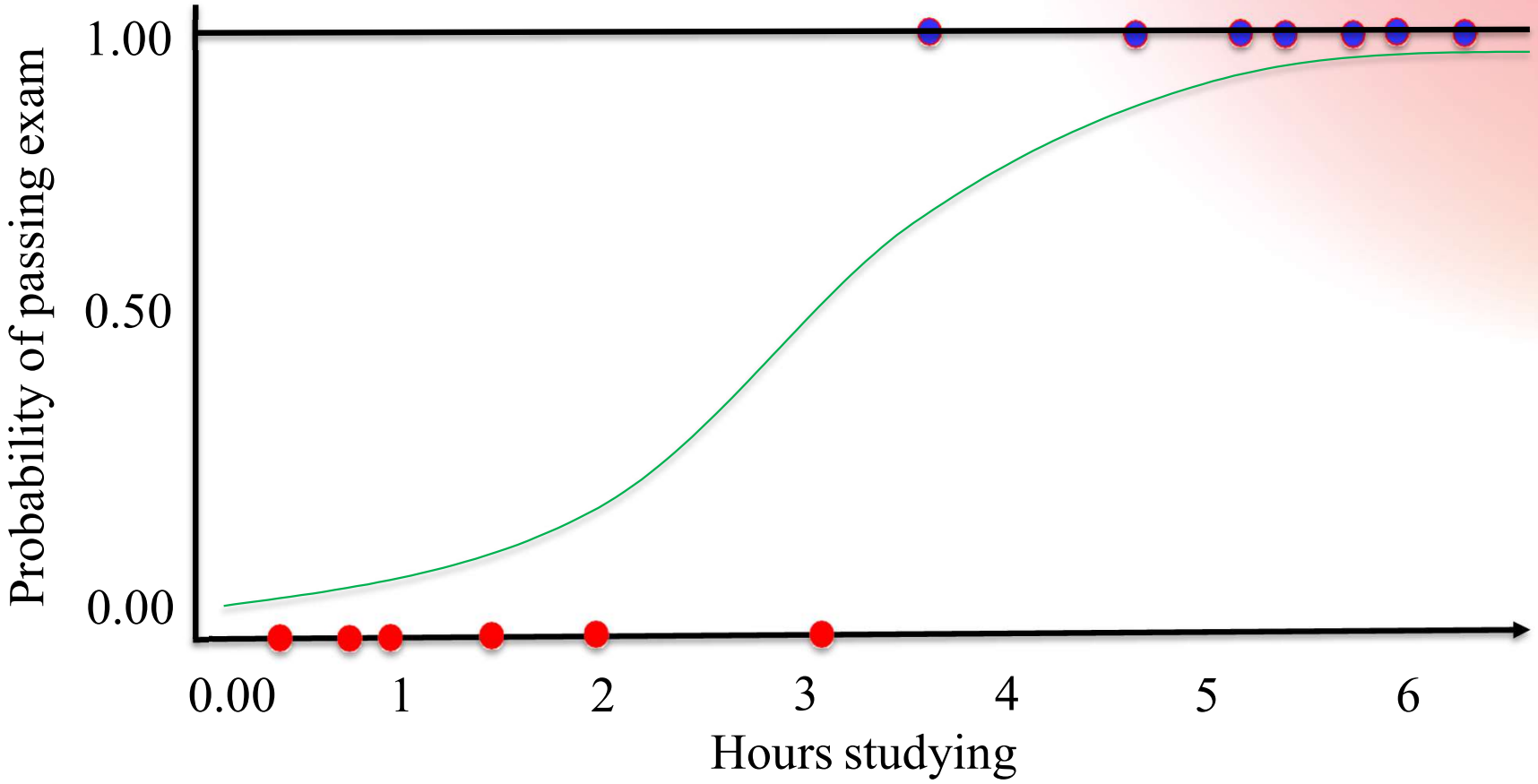
The logistic function transforms real-valued input to an output number y between 0 and 1, interpreted as the probability the input object belongs to the positive class, given its input features $(x_0, x_1, \ldots, x_n)$

$$\hat{y} = \text{logistic}(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)$$
$$= \frac{1}{1 + \exp\left[-(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)\right]}$$

Regresión logística



Regresión logística



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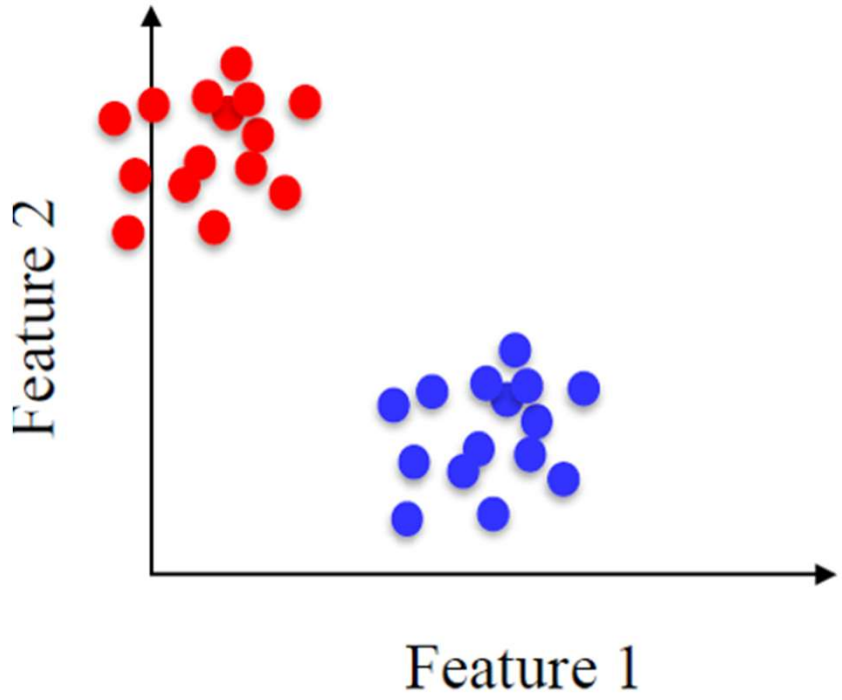
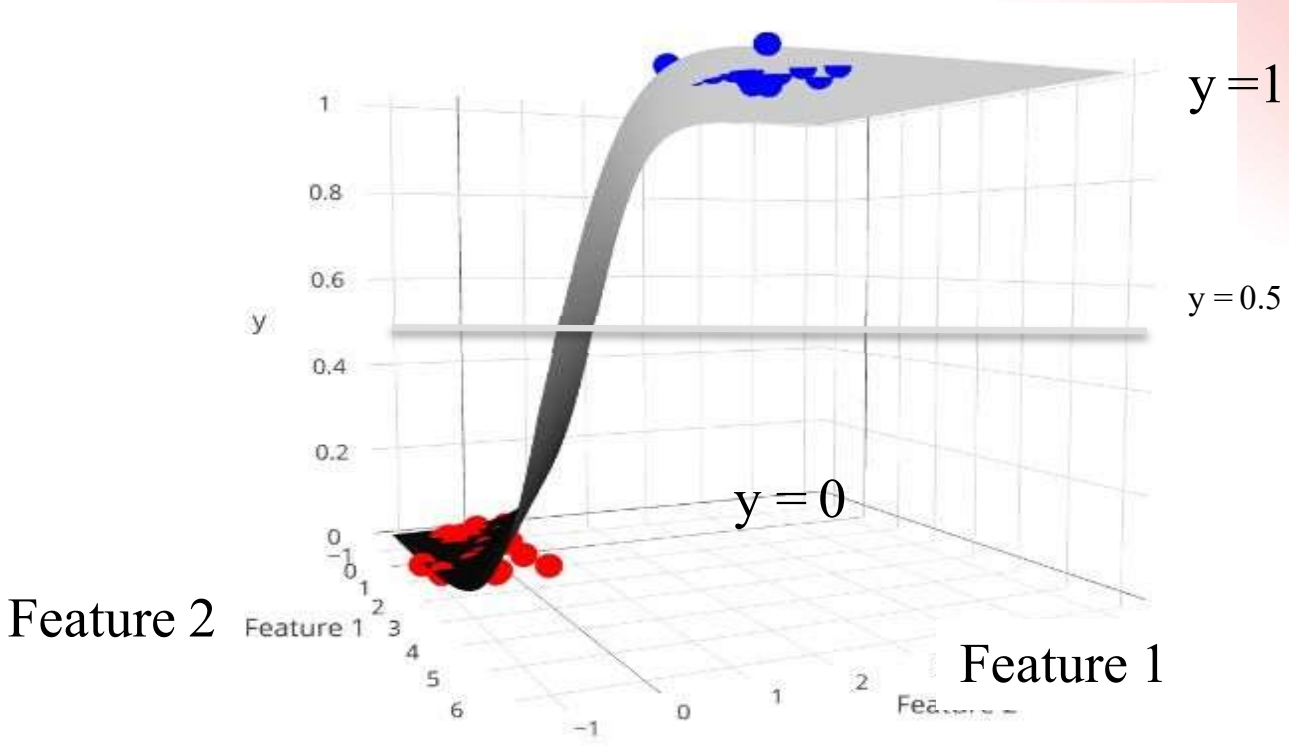
Regresión logística para la clasificación binaria

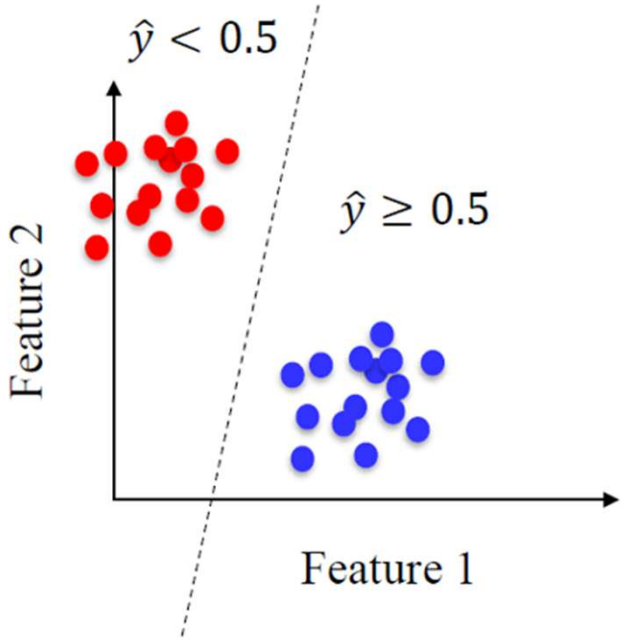


arisa

Regresión logística para la clasificación binaria

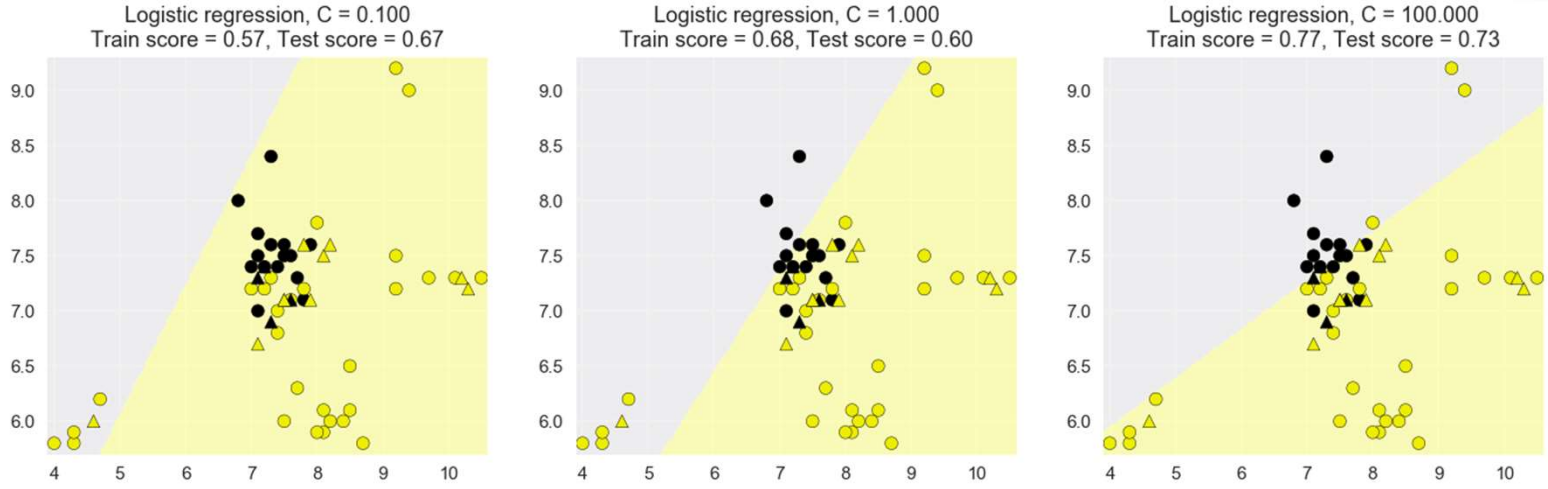


Regresión logística para la clasificación binaria



Regresión logística: Regularización

- La regularización L2 está 'activada' de forma predeterminada (como la regresión de cresta)
- El parámetro C controla la cantidad de regularización (por defecto 1.0)
- Al igual que con la regresión lineal regularizada, puede ser importante normalizar todas las entidades para que estén en la misma escala.



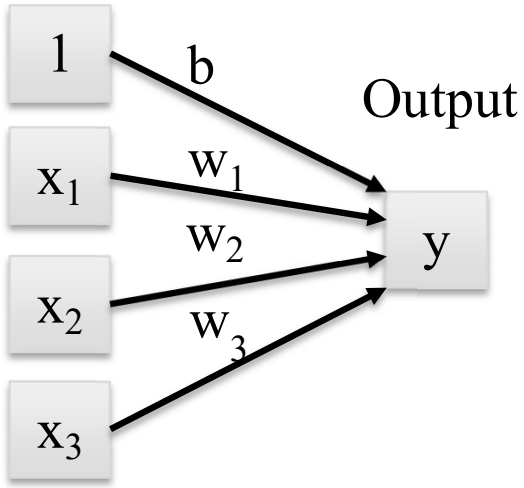
Regresión logística: Regularización

- C pequeña (regularización fuerte): más regularización - modelo más simple - mayor sesgo, menor varianza - mejor para evitar el sobreajuste
- C grande (regularización débil): - Menos regularización - Modelo más complejo - Menor sesgo, mayor varianza - Puede conducir a un sobreajuste
- Cuándo ajustar C:
  - Conjunto de datos pequeño → Considere C más pequeño
  - Conjunto de datos de gran tamaño → Puede usar C más grande

  - Consejos prácticos:
  - - Usar la búsqueda de cuadrícula o la búsqueda aleatoria para el ajuste
  - Rango común: 0,001 a 1000 -

Linear regression

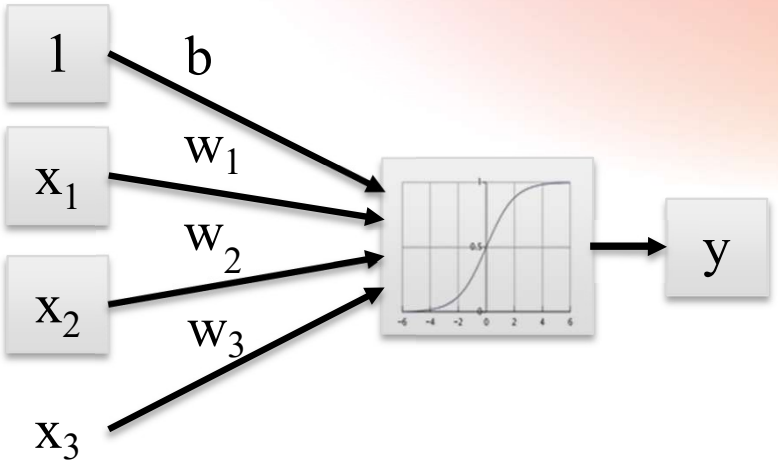
Input features



$$\hat{y} = \hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n$$

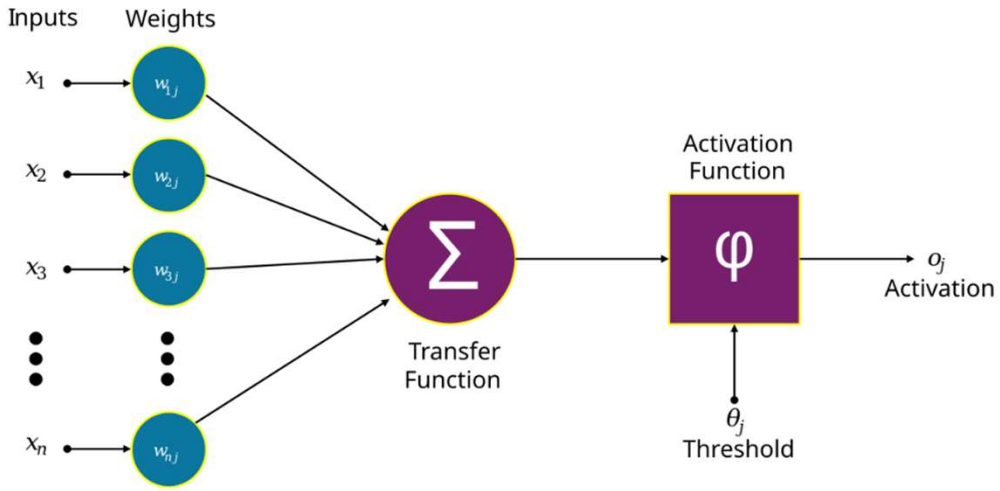
Logistic regression

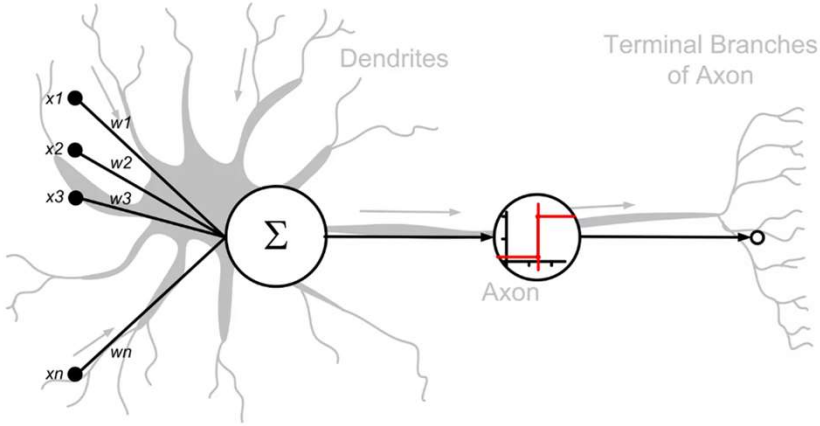
Input features



$$\hat{y} = \text{logistic}(\hat{b} + \hat{w}_1 \cdot x_1 + \cdots \hat{w}_n \cdot x_n)$$

Neurona Artificial (ANN) y Redes Neuronales





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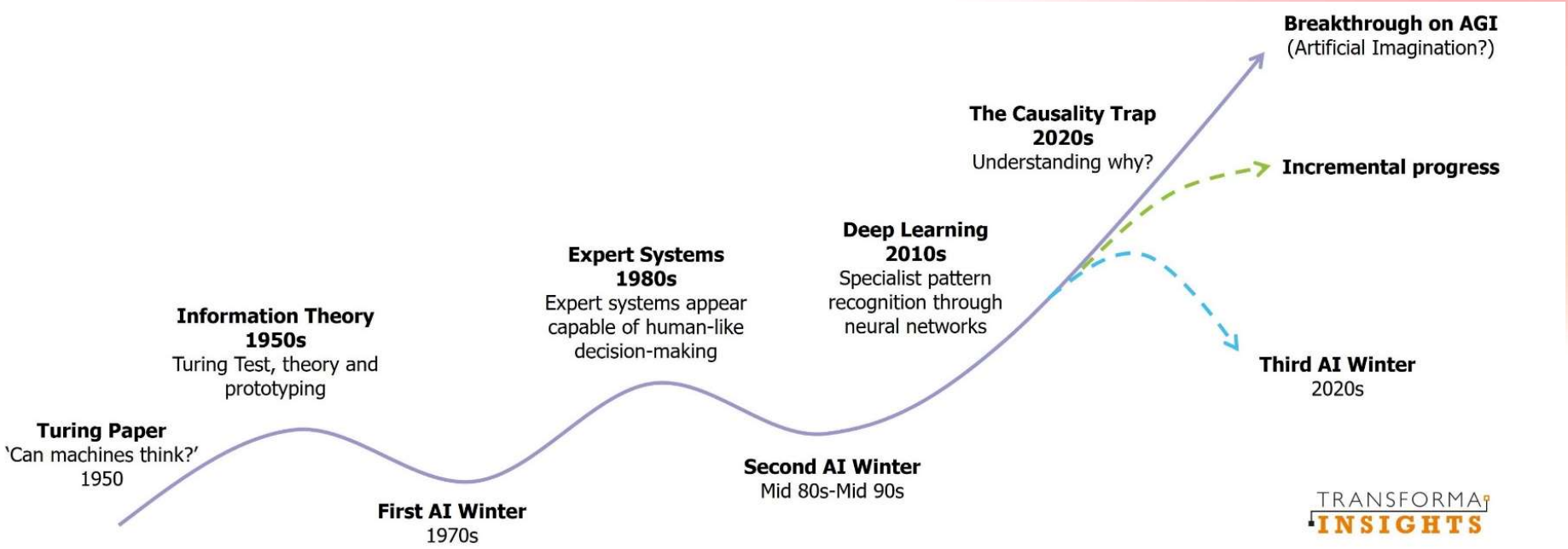
Neurona de McCullocg-Pitts

- 1943: Neurona de McCullocg-Pitts.
- Uno era neurocientífico y el otro matemático.
- "*El cerebro es un solucionador de problemas, así que copiemos al cerebro*".
- Acabó influyendo el diseño de puertas lógicas.
- 1957: Perceptron de Rosenblatt (clasificadore lineal)
- SI QUIERES SABER MÁS: https://es.wikipedia.org/wiki/Neurona_de_McCulloch-Pitts, https://en.wikipedia.org/wiki/Perceptron

Inviernos de la IA



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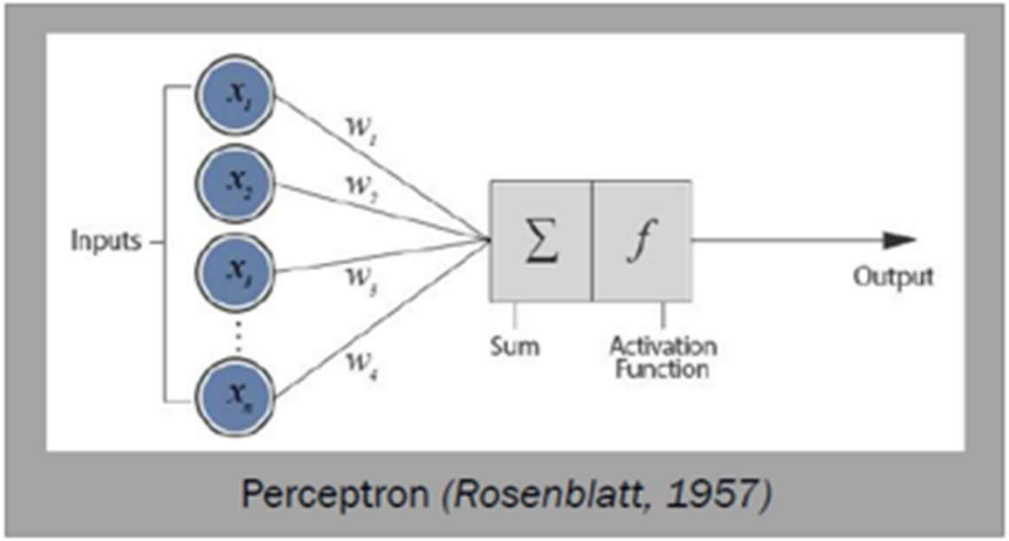
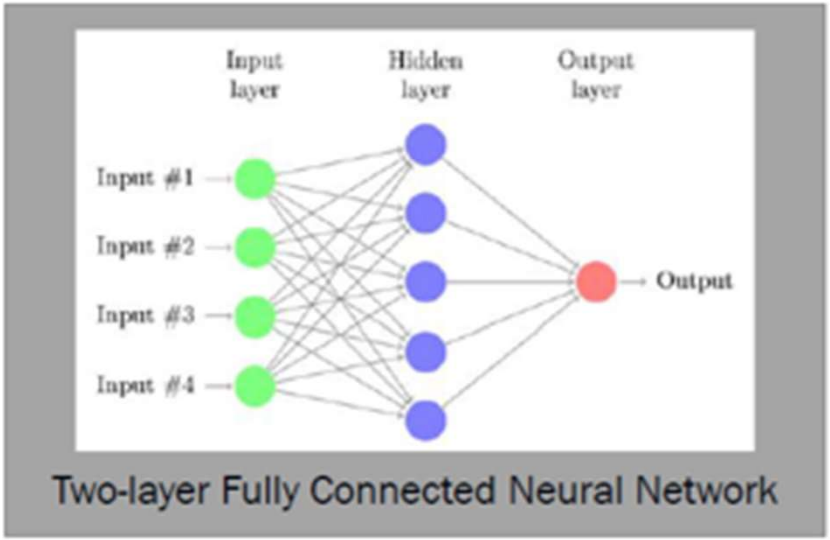
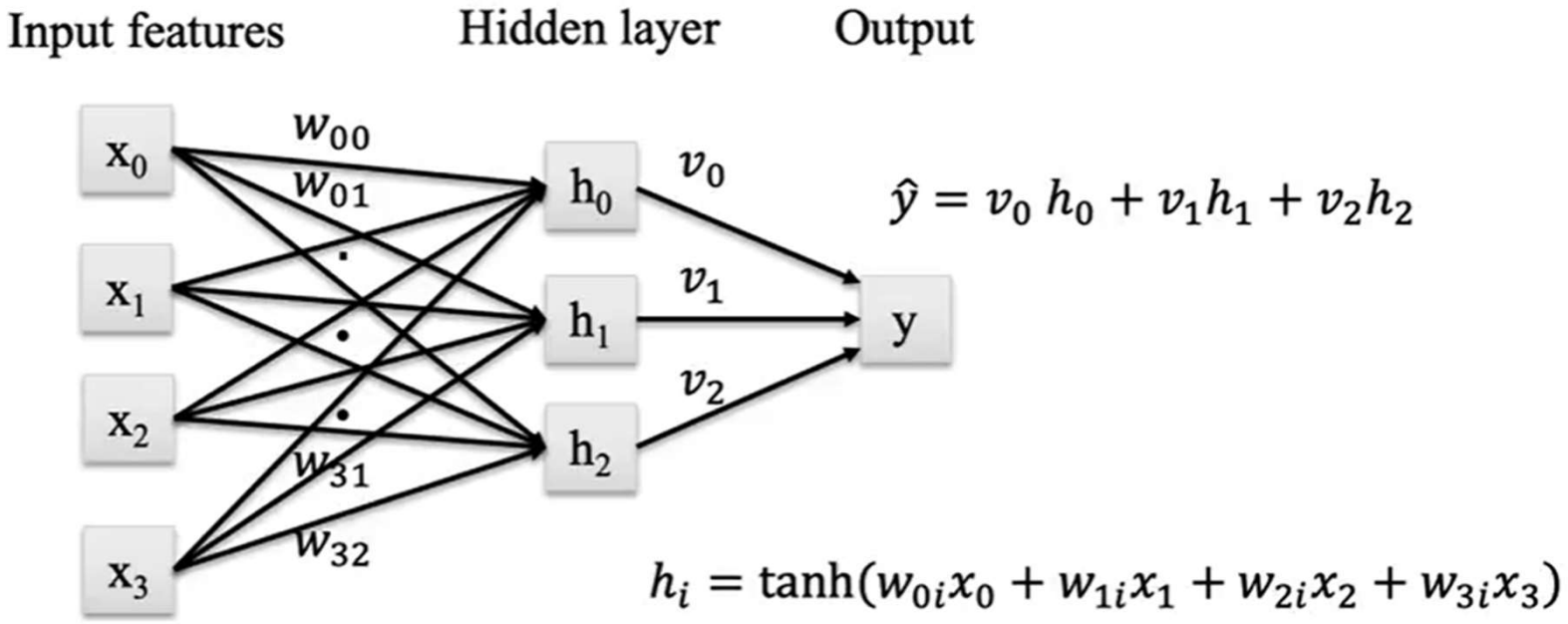


Perceptron *(Rosenblatt, 1957)*

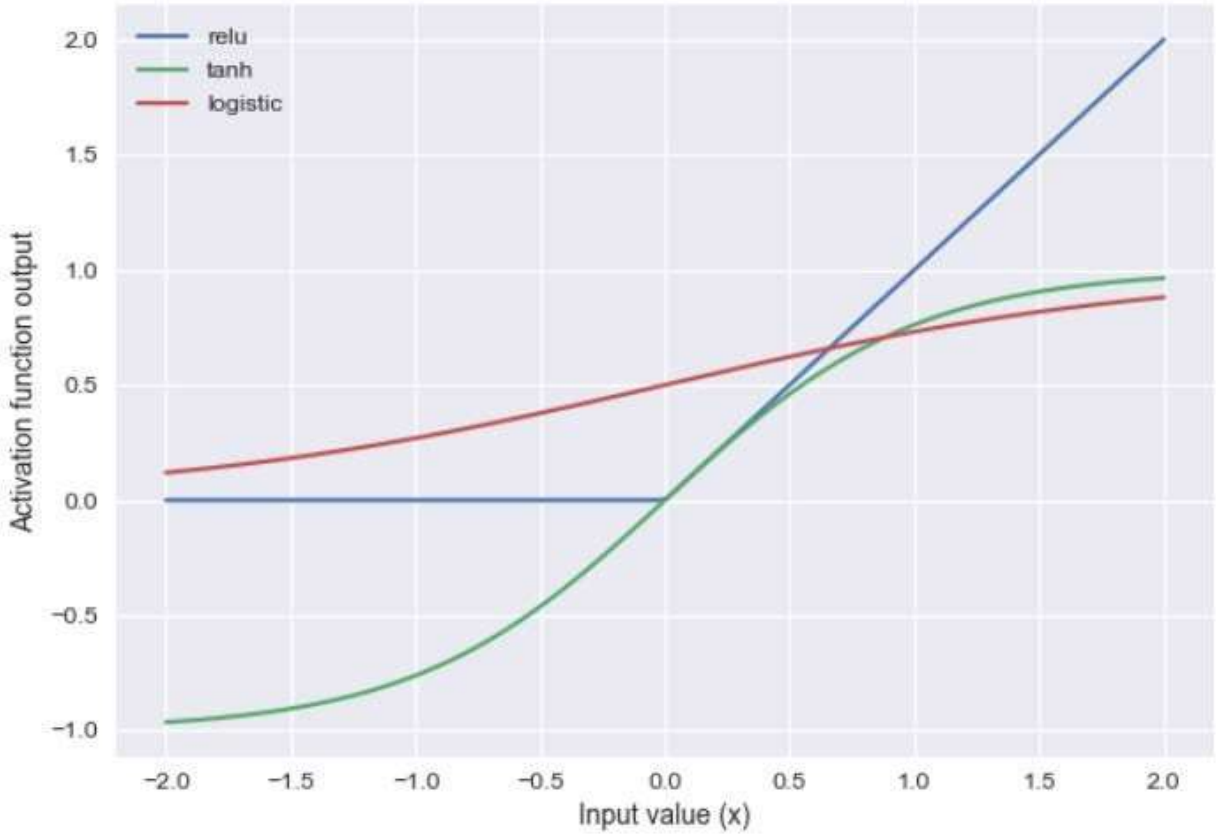


Two-layer Fully Connected Neural Network

MLP de una capa (con activación de función tanh)



Activation Functions

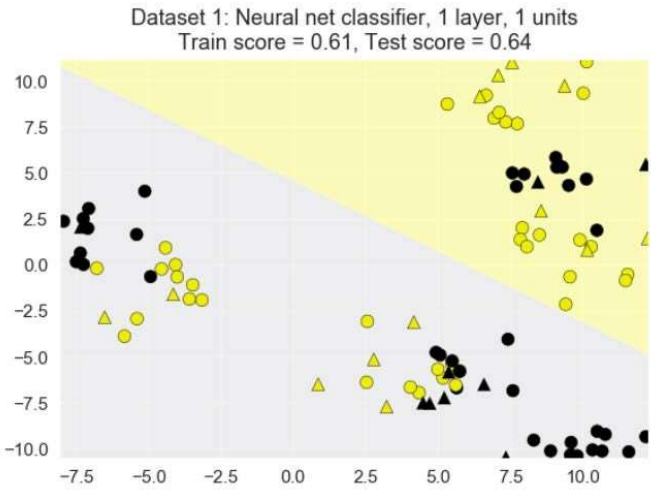


$$f(x) = \tanh(x) = \frac{2}{1 + e^{-2x}} - 1$$

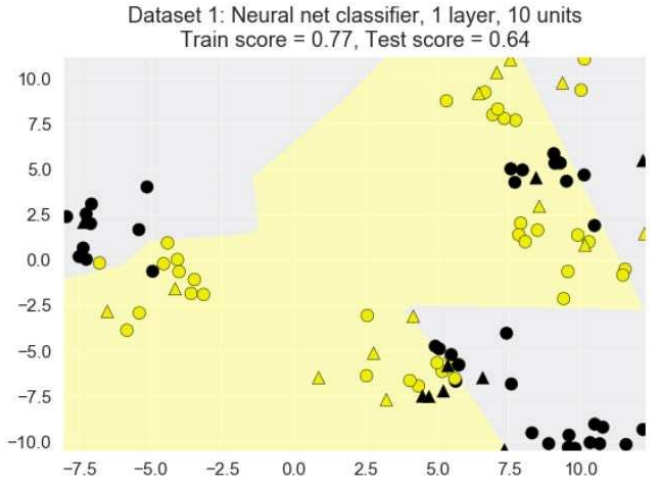
MLP

```
|: from sklearn.neural_network import MLPClassifier
   from adspy_shared_utilities import plot_class_regions_for_classifier_subplot

   X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2,
                                                       random_state=0)

   fig, subaxes = plt.subplots(3, 1, figsize=(6,18))

   for units, axis in zip([1, 10, 100], subaxes):
       nnclf = MLPClassifier(hidden_layer_sizes = [units], solver='lbfgs',
                             random_state = 0).fit(X_train, y_train)

       title = 'Dataset 1: Neural net classifier, 1 layer, {} \
   units'.format(units)

       plot_class_regions_for_classifier_subplot(nnclf, X_train, y_train,
                                                 X_test, y_test, title, axis)
       plt.tight_layout()
```

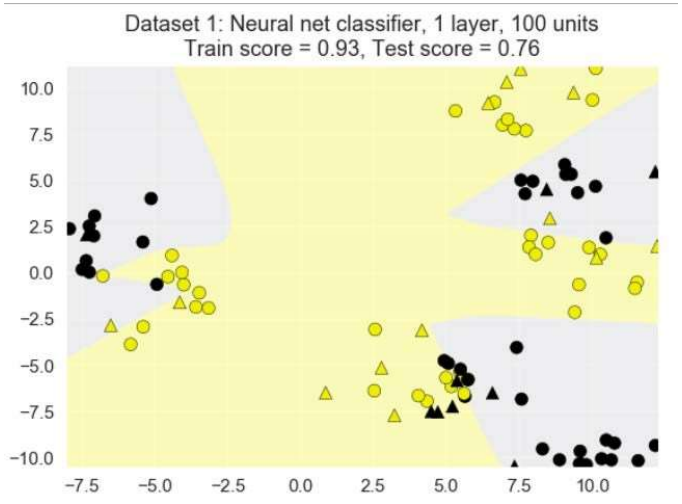
1 capa interna de 1, 10, or 100 units



1 layer, 1 unit

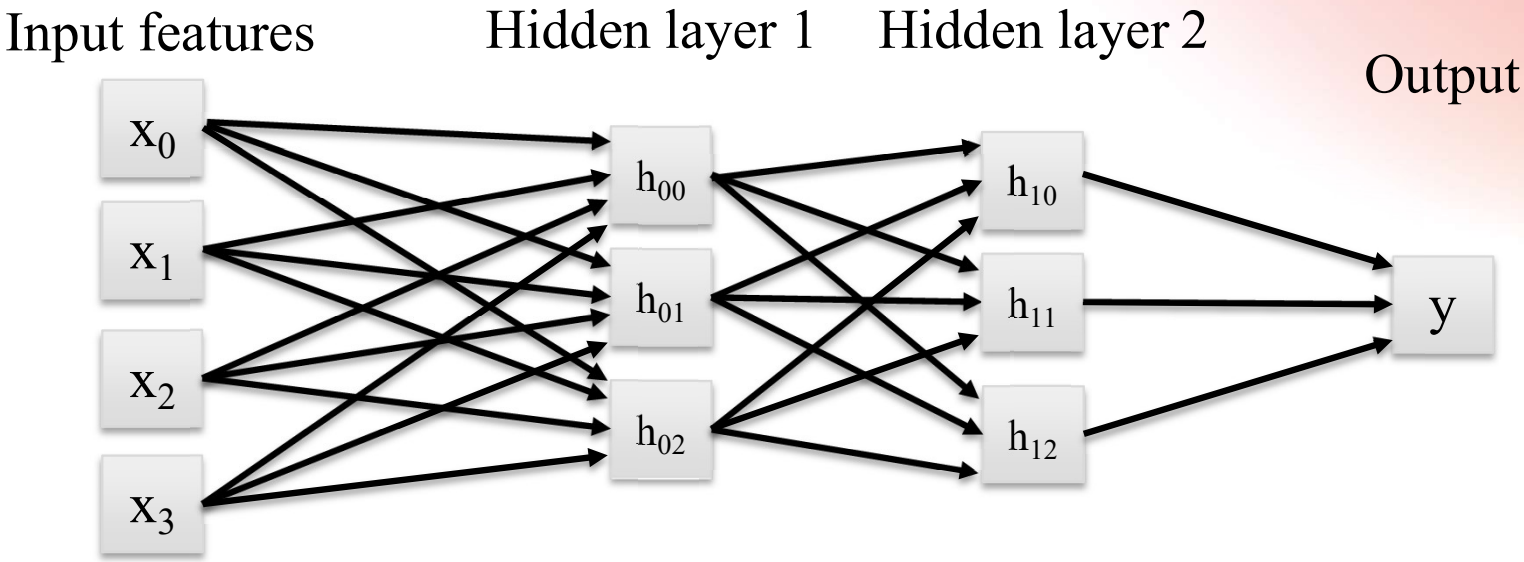


1 layer, 10 units

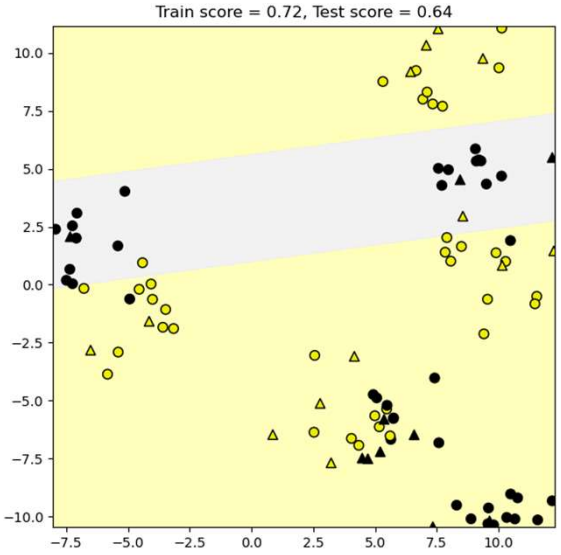


1 layer, 100 units

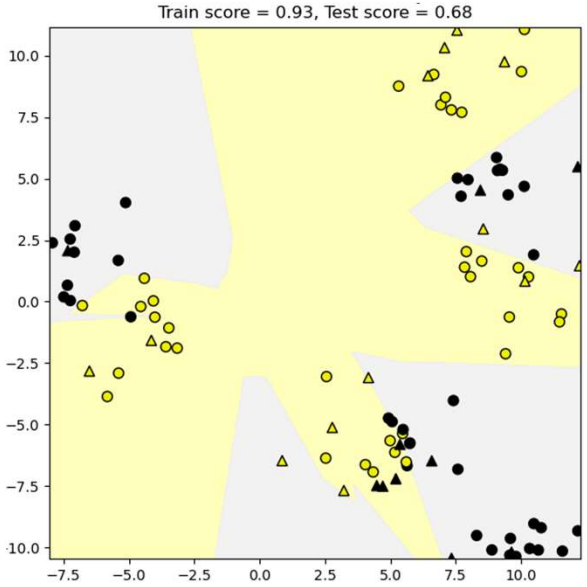
MLP 2 Capas


Input features
Hidden layer 1
Hidden layer 2
Output
x_0
x_1
x_2
x_3
h_{00}
h_{01}
h_{02}
h_{10}
h_{11}
h_{12}
y

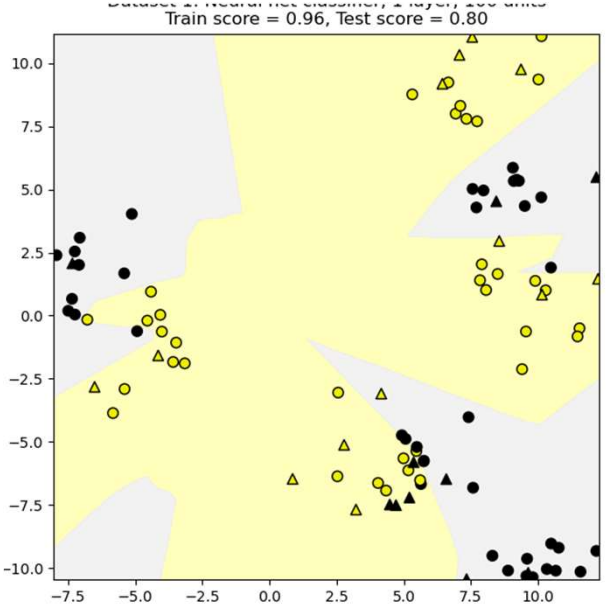
2 capa interna de 1, 10, or 100 units



2 layer, 1-10 unit

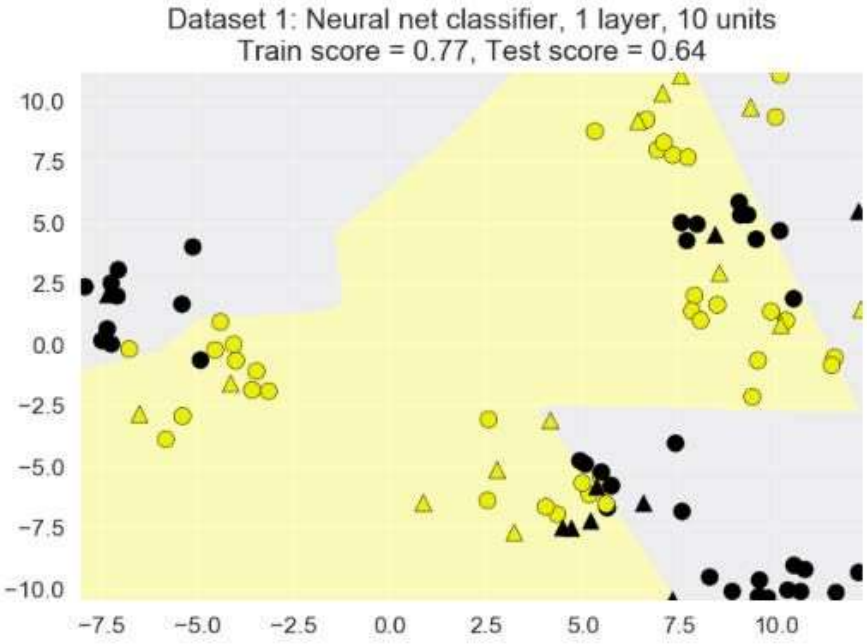


2 layer, 10-10 units

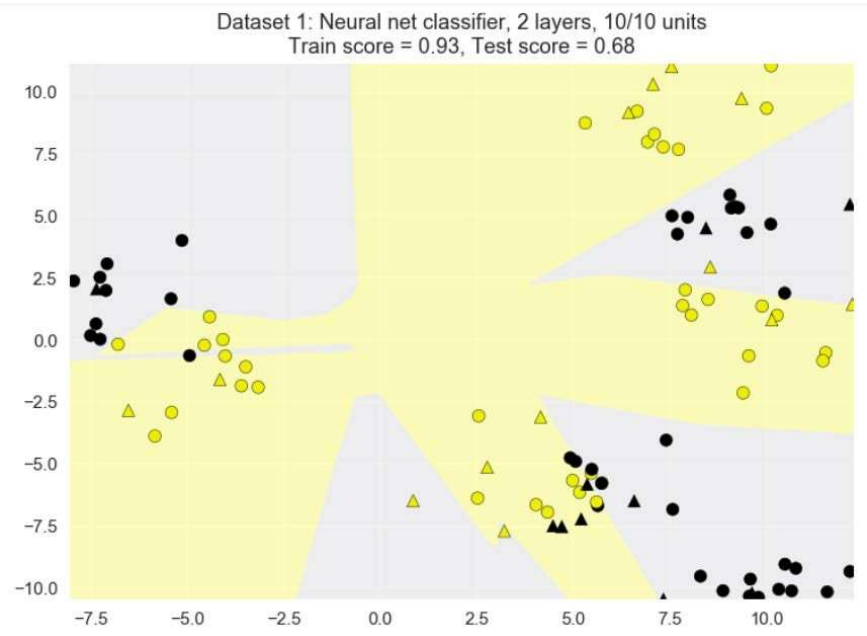


2 layer, 100-10 units

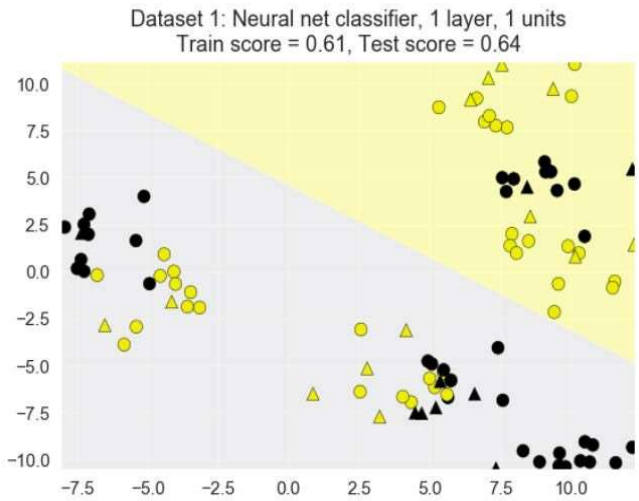
1vs 2 capas

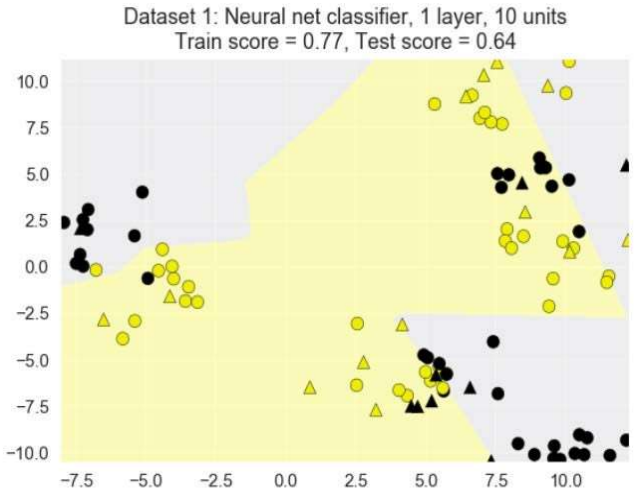


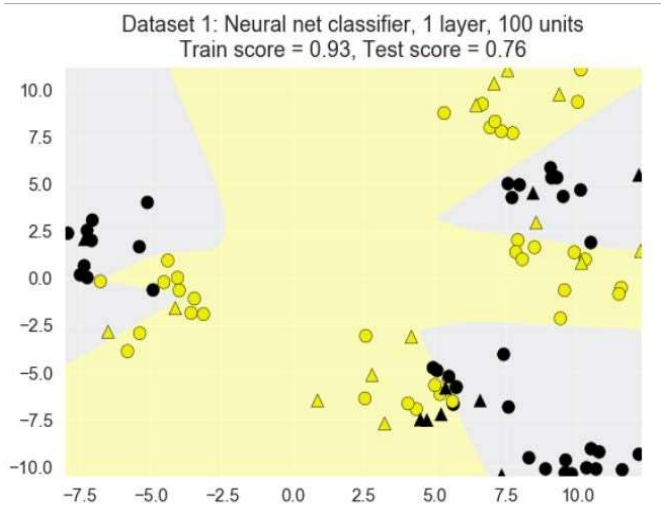
1 layer, 10 units

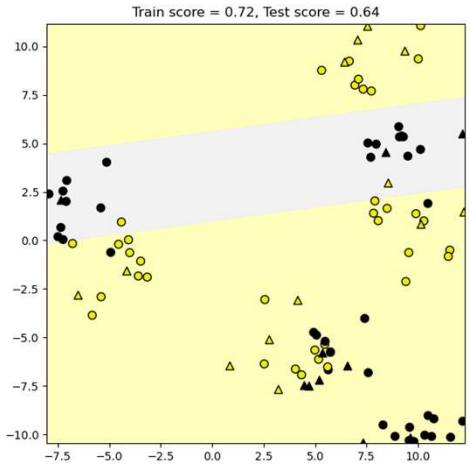


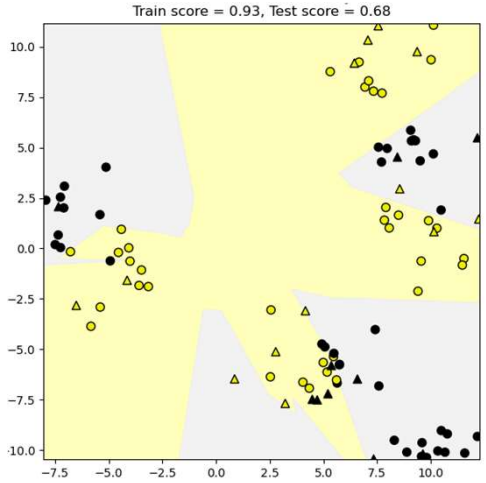
2 layers, (10, 10) units

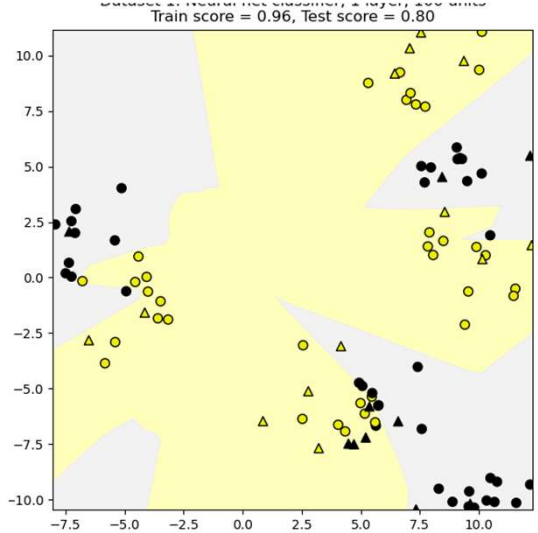












2 layer, 1-10 unit

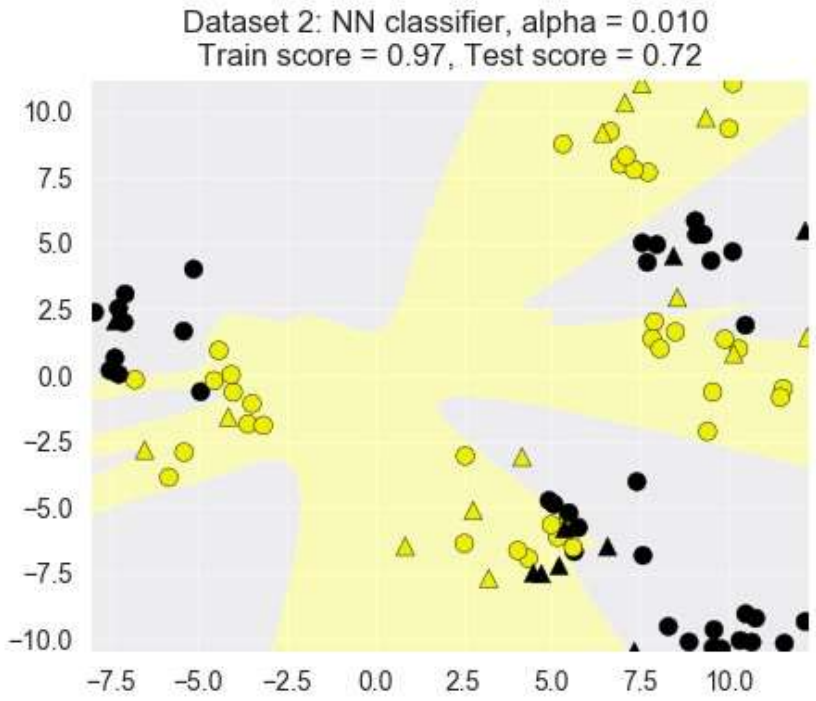
2 layer, 10-10 units

2 layer, 100-10 units

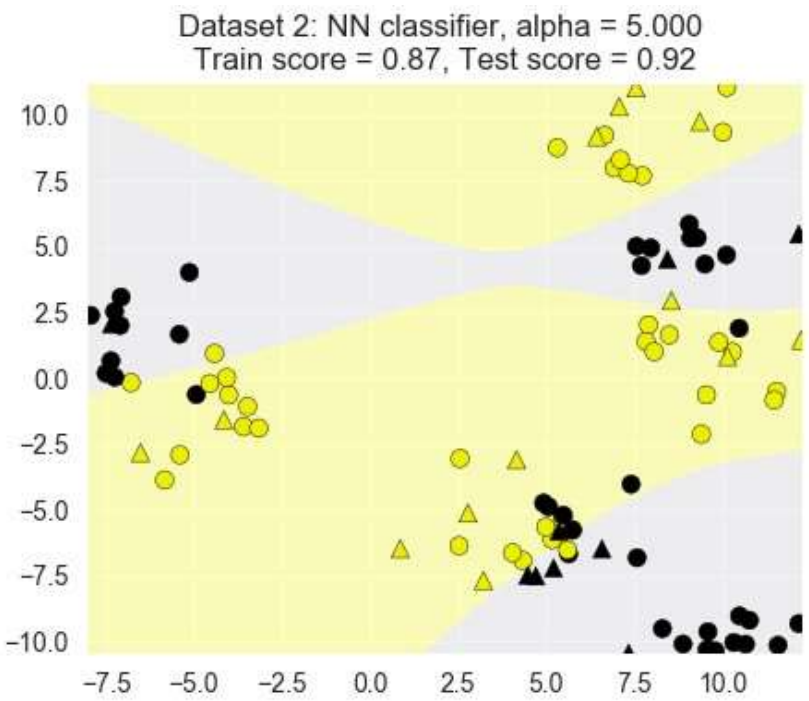
Como controlar la complejidad de NLP multicapas

- Al aumentar las capas y las neuronas aumenta la complejidad al tener que computer mas pesos
- EL modelo puede hacerse muy Complejo muy rapido por eso es muy relevante controlar la complejidad mediante regularizacion
- Al igual que en los modelos lineales la regularizacion es un peso sobre los pesos – cuando mas grande la regularizacion (alpha) mas grade es la corrección y los modelos que se generan son mas sencillos evitando por tanto el overfitting
- Normalizacion es clave para NN debido a que se basan en metricas de distancia y tiene un gran impacto para el resultado final

L2 Regularization



alpha = 0.01

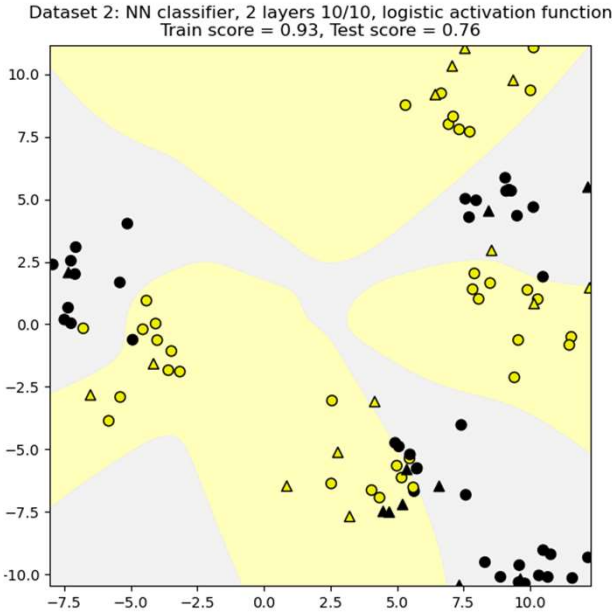


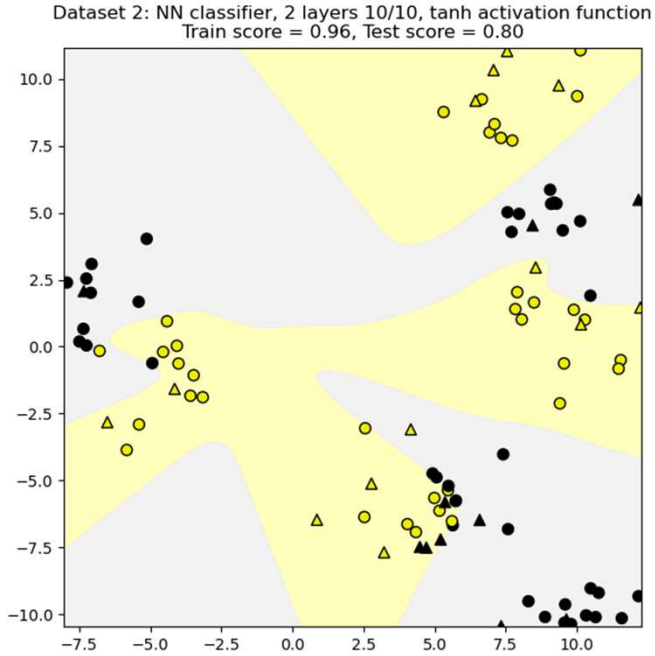
alpha = 5.0

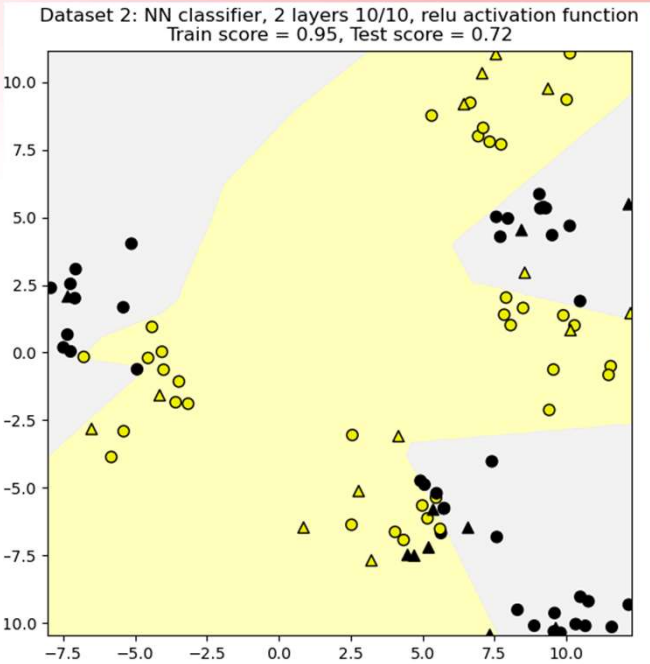
Relevancia de las funciones de activacion

```
X_train, X_test, y_train, y_test = train_test_split(X_D2, y_D2, random_state=0)

fig, subaxes = plt.subplots(3, 1, figsize=(6,18))

for this_activation, axis in zip(['logistic', 'tanh', 'relu'], subaxes):
    nnclf = MLPClassifier(solver='lbfgs', activation = this_activation,
                          alpha = 0.1, hidden_layer_sizes = [10, 10],
                          random_state = 0).fit(X_train, y_train)

    title = 'Dataset 2: NN classifier, 2 layers 10/10, {} \
activation function'.format(this_activation)

    plot_class_regions_for_classifier_subplot(nnclf, X_train, y_train,
                                              X_test, y_test, title, axis)
    plt.tight_layout()
```

Relevancia de las funciones de activacion







Importancia de la normalización para NN

```
from sklearn.neural_network import MLPClassifier
from sklearn.preprocessing import MinMaxScaler


scaler = MinMaxScaler()

X_train, X_test, y_train, y_test = train_test_split(X_cancer, y_cancer,
                                                    random_state = 0)
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)

clf = MLPClassifier(hidden_layer_sizes = [100, 100], alpha = 5.0,
                    random_state = 0, solver='lbfgs').fit(X_train_scaled,
                                                          y_train)
```

Relevancia

```
from sklearn.neural_network import MLPClassifier
from sklearn.model_selection import train_test_split

# Split dataset into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X_cancer, y_cancer, random_state=0)

# Define and train a Multi-Layer Perceptron classifier WITHOUT normalization
clf_no_scaling = MLPClassifier(hidden_layer_sizes=[100, 100], alpha=5.0,
                               random_state=0, solver='lbfgs').fit(X_train, y_train)

# Print accuracy
print('Breast cancer dataset (No Normalization)')
print('Accuracy of NN classifier on training set: {:.2f}'.format(clf_no_scaling.score(X_train, y_train)))
print('Accuracy of NN classifier on test set: {:.2f}'.format(clf_no_scaling.score(X_test, y_test)))
```

```
Breast cancer dataset (No Normalization)
Accuracy of NN classifier on training set: 0.94
Accuracy of NN classifier on test set: 0.94
```

```
Breast cancer dataset
Accuracy of NN classifier on training set: 0.98
Accuracy of NN classifier on test set: 0.97
```

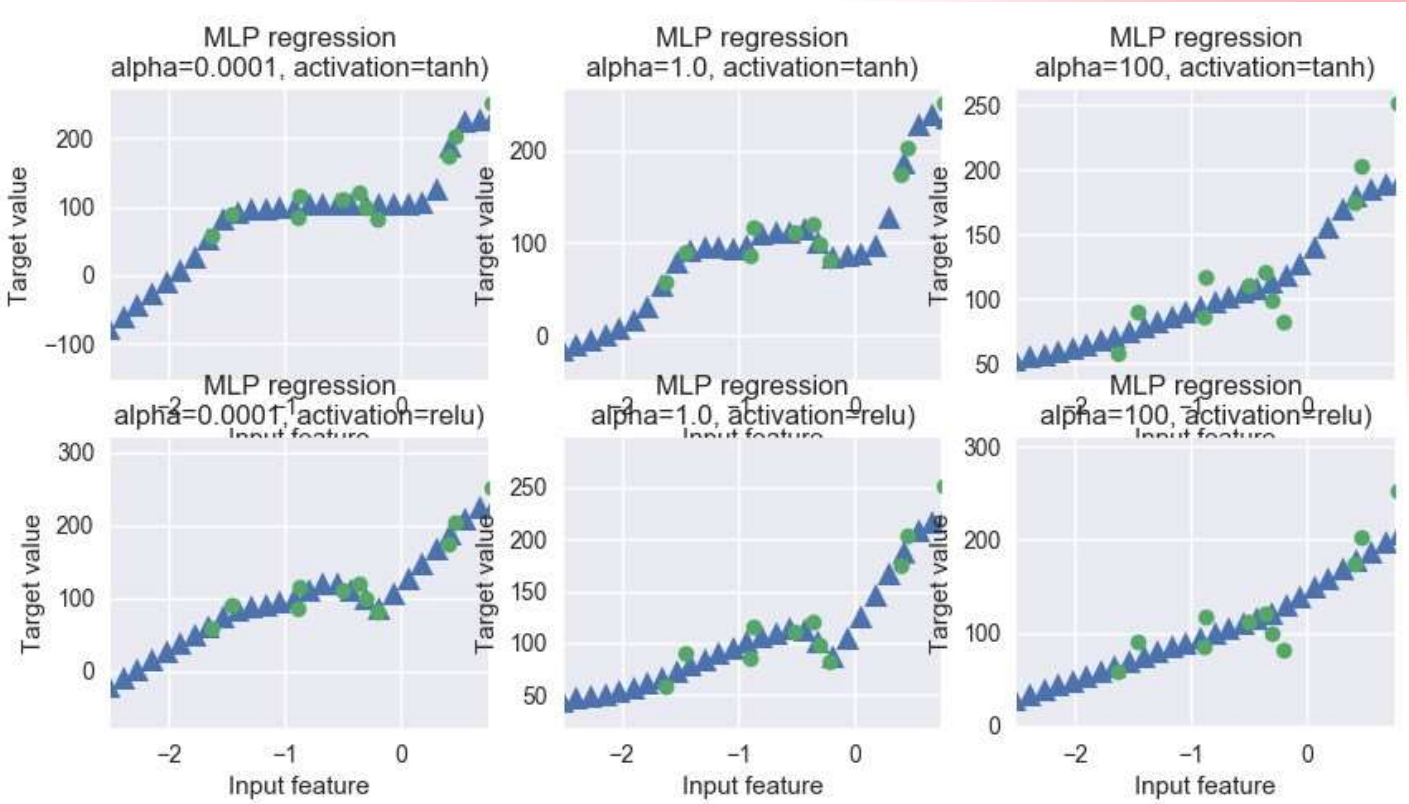
Regresión con MLP y Regularizacion (para bajar los pesos)

```
from sklearn.neural_network import MLPRegressor

fig, subaxes = plt.subplots(2, 3, figsize=(11,8), dpi=70)

X_predict_input = np.linspace(-3, 3, 50).reshape(-1,1)

X_train, X_test, y_train, y_test = train_test_split(X_R1[0::5], y_R1[0::5], random_state = 0)

for thisaxisrow, thisactivation in zip(subaxes, ['tanh', 'relu']):
    for thisalpha, thisaxis in zip([0.0001, 1.0, 100], thisaxisrow):
        mlpreg = MLPRegressor(hidden_layer_sizes = [100,100],
                              activation = thisactivation,
                              alpha = thisalpha,
                              solver = 'lbfgs').fit(X_train, y_train)
        y_predict_output = mlpreg.predict(X_predict_input)
```

Regresión con NN con MLPRegressor

activation = 'tanh'

activation = 'relu'



alpha = 0.0001 alpha = 1.0 alpha = 100.0

Increasing regularization

Parámetros

- **`hidden_layer_sizes`: sets the number of hidden layers (number of elements in list), and number of hidden units per layer (each list element).** *Default: (100).*

- **`alpha`: controls weight on the regularization penalty that shrinks weights to zero.** *Default: alpha = 0.0001.*

- **`activation`: controls the nonlinear function used for the activation function, including: `'relu'` (default), `'logistic'`, `'tanh'`.**

- https://playground.tensorflow.org/

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