

### 1. Pen-and-paper

1.

Hw 3

1. a)  $w^{[1]} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix}$   $b^{[1]} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$   $b^{[2]} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$   $b^{[3]} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$   $b^{[4]} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

Target  $- z = [-1]$

Forward Propagation:

$z^{[1]} = \begin{bmatrix} 1 & 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \\ 1 \\ 1 \\ 1 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 5 \\ 0 \\ 5 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 6 \\ 1 \\ 6 \end{bmatrix}$   $x^{[1]} = \tanh\left(\begin{bmatrix} 6 \\ 1 \\ 6 \end{bmatrix}\right) = \begin{bmatrix} 0.999988 \\ 0.761594 \\ 0.999988 \end{bmatrix}$

$z^{[2]} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0.999988 \\ 0.761594 \\ 0.999988 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 2.76157 \\ 2.76157 \end{bmatrix} + \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 3.76157 \\ 3.76157 \end{bmatrix}$   $x^{[2]} = \tanh\left(\begin{bmatrix} 3.76157 \\ 3.76157 \end{bmatrix}\right) = \begin{bmatrix} 0.99992 \\ 0.99992 \end{bmatrix}$

$z^{[3]} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} 0.99992 \\ 0.99992 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$   $x^{[3]} = \tanh\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}\right) = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

$E(t, x^{[3]}) = \frac{1}{2} \sum (x^{[3]} - t)^2 = \frac{1}{2} (1 + 1) = 1$

$\frac{\partial E}{\partial x^{[3]}}(t, x^{[3]}) = x^{[3]} - t$   $\frac{\partial z^{[3]}}{\partial b^{[3]}}(w^{[3]}, b^{[3]}, x^{[2-1]}) = 1$

$\frac{\partial x^{[3]}}{\partial z^{[3]}}(z^{[3]}) = (1 - \tanh(x)^2)$   $\frac{\partial z^{[3]}}{\partial x^{[2-1]}}(w^{[3]}, b^{[3]}, x^{[2-1]}) = w^{[3]}$

$\frac{\partial z^{[3]}}{\partial w^{[3]}} = (w^{[3]}, b^{[3]}, x^{[2-1]}) = x^{[2-1]}$

$\delta^{[3]} = \frac{\partial E}{\partial x^{[3]}} \cdot \frac{\partial x^{[3]}}{\partial z^{[3]}} = (x^{[3]} - t) \cdot (1 - \tanh(z^{[3]})^2) = \begin{bmatrix} 0 \\ 0 \end{bmatrix} - \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ -1 \end{bmatrix}$

$\delta^{[2]} = \frac{\partial z^{[3]}}{\partial x^{[2]}} \cdot \delta^{[3]} \cdot \frac{\partial x^{[3]}}{\partial z^{[2]}} = [w^{[3]}]^T \cdot \delta^{[3]} \cdot (1 - \tanh(z^{[3]})^2) = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \cdot \begin{bmatrix} -1 \\ -1 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

$\delta^{[1]} = \frac{\partial z^{[2]} \cdot \delta^{[2]} \cdot \frac{\partial x^{[2]}}{\partial z^{[1]}} = (w^{[2]})^T \cdot \delta^{[2]} \cdot (1 - \tanh(z^{[2]})^2) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \cdot \begin{bmatrix} 0 \\ 0 \end{bmatrix} \cdot \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$

$\frac{\partial E}{\partial w^{[1]}} = \delta^{[1]} \cdot \frac{\partial z^{[1]}}{\partial w^{[1]}} = \delta^{[1]} \cdot (x^{[0]})^T = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \cdot [1 \ 1 \ 1 \ 1 \ 1] = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$



$$\begin{aligned}
 w^{(1)} &= w^{(0)} - \eta \frac{\partial E}{\partial w^{(1)}} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix} - 0,1 \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0 & 0 & 0 & 0 \\ 1 & 1 & 1 & 1 \end{bmatrix} \\
 \frac{\partial E}{\partial b^{(1)}} &= \delta^{(1)} \cdot \frac{\partial z^{(1)}}{\partial b^{(1)}} = \delta^{(1)} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \quad b^{(1)} = b^{(0)} - \eta \frac{\partial E}{\partial b^{(1)}} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - 0,1 \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \\
 \frac{\partial E}{\partial w^{(2)}} &= \delta^{(2)} \cdot \frac{\partial z^{(2)}}{\partial w^{(2)}} = \delta^{(2)} \cdot [x^{(1)}]^T = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \cdot [0,999988 \quad 0,161594 \quad 0,999988] = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} \\
 w^{(2)} &= w^{(1)} - \eta \frac{\partial E}{\partial w^{(2)}} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad \delta^{(2)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad b^{(2)} = b^{(1)} - \eta \frac{\partial E}{\partial b^{(2)}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - 0,1 \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\
 \frac{\partial E}{\partial w^{(3)}} &= \delta^{(3)} \cdot \frac{\partial z^{(3)}}{\partial w^{(3)}} = \delta^{(3)} \cdot \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} -1 \\ 1 \end{bmatrix} \cdot \begin{bmatrix} 0,99892 & 0,99892 \end{bmatrix} = \begin{bmatrix} -0,99892 & -0,99892 \\ 0,99892 & 0,99892 \end{bmatrix} \\
 b^{(3)} &= b^{(2)} - \eta \frac{\partial E}{\partial b^{(3)}} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} - 0,1 \begin{bmatrix} -1 \\ 1 \end{bmatrix} = \begin{bmatrix} 0,1 \\ -0,1 \end{bmatrix} \\
 w^{(3)} &= w^{(2)} - \eta \frac{\partial E}{\partial w^{(3)}} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} - 0,1 \begin{bmatrix} -0,99892 & -0,99892 \\ 0,99892 & 0,99892 \end{bmatrix} = \begin{bmatrix} 0,0998912 & 0,0998912 \\ -0,0998912 & -0,0998912 \end{bmatrix} \\
 \text{b) } \text{learning} &= \kappa = [1 \ 1 \ 1 \ 1]^T \quad z = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \quad \eta = 0,1 \\
 \text{softmax}(z_1 \dots z_n)^T &= [u_1 \dots u_n]^T \quad u_i = \frac{\exp(z_i)}{\sum_k \exp(z_k)} \quad E(t, x^{(1)}) = -\sum_{i=1}^n t_i \log u_i^{(1)} \\
 i=j &\Rightarrow \frac{\partial u_i}{\partial z_j} = \frac{\partial}{\partial z_j} \frac{\exp(z_i)}{\sum_k \exp(z_k)} = u_i(1-u_i) \quad \frac{\partial z^{(1)}}{\partial z^{(1)}} = 1 - \tanh(z^{(1)})^2 \\
 i \neq j &\Rightarrow \frac{\partial u_i}{\partial z_j} = -u_i \cdot u_j \quad \delta^{(1)} = \begin{bmatrix} z_1^2 - t_1 \\ z_2^2 - t_2 \end{bmatrix} = \begin{bmatrix} 1^2 - 1 \\ 1^2 - 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad \frac{\partial z^{(1)}}{\partial w^{(1)}} (w^{(1)}, b^{(1)}, x^{(1)}) = x^{(1)} \\
 z^{(1)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad x^{(1)} = \text{softmax} \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} \frac{\exp(0)}{2 \exp(0)} \\ \frac{\exp(0)}{2 \exp(0)} \end{bmatrix} = \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} \quad \frac{\partial z^{(1)}}{\partial b^{(1)}} (w^{(1)}, b^{(1)}, x^{(1)}) = 1 \\
 \delta^{(1)} = \begin{bmatrix} 0,80 \\ 0,50 \end{bmatrix} - \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} -0,20 \\ 0,50 \end{bmatrix} \quad \frac{\partial z^{(1)}}{\partial x^{(1)}} (w^{(1)}, b^{(1)}, x^{(1)}) = w^{(1)} \\
 \delta^{(2)} = \begin{bmatrix} 0,999988 & 0,999988 \\ 0,999988 & 0,999988 \end{bmatrix} \begin{bmatrix} -0,5 \\ 0,5 \end{bmatrix} \cdot \begin{bmatrix} 1 - (0,999988)^2 \\ 1 - (0,999988)^2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \\
 \delta^{(3)} = \begin{bmatrix} 1 & 1 \\ 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 - (0,999988)^2 \\ 0,161594 \\ 0,999988 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix} \\
 \frac{\partial E}{\partial w^{(1)}} &= \delta^{(1)} \cdot \frac{\partial z^{(1)}}{\partial w^{(1)}} = \delta^{(1)} \cdot (x^{(1)})^T = \begin{bmatrix} -0,20 \\ 0,50 \end{bmatrix} \cdot \begin{bmatrix} 1/2 \\ 1/2 \end{bmatrix} = \begin{bmatrix} -0,10 \\ 0,25 \end{bmatrix} \quad \frac{\partial E}{\partial b^{(1)}} = \delta^{(1)} \cdot \frac{\partial z^{(1)}}{\partial b^{(1)}} = \delta^{(1)} = \begin{bmatrix} -0,20 \\ 0,50 \end{bmatrix} \\
 \frac{\partial E}{\partial w^{(2)}} &= \delta^{(2)} \cdot \frac{\partial z^{(2)}}{\partial w^{(2)}} = \delta^{(2)} \cdot (x^{(2)})^T = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \cdot (0,999988 \quad 0,161594 \quad 0,999988) = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad b^{(2)} = b^{(1)} - \eta \frac{\partial E}{\partial b^{(2)}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} - 0,1 \begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 1 \\ 1 \end{bmatrix} \\
 w^{(2)} &= w^{(1)} - \eta \frac{\partial E}{\partial w^{(2)}} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} - 0,1 \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} \quad \frac{\partial E}{\partial b^{(2)}} = \delta^{(2)} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \quad b^{(2)} = b^{(1)} - \eta \frac{\partial E}{\partial b^{(2)}} = \begin{bmatrix} 1 \\ 1 \end{bmatrix}
 \end{aligned}$$

Aprendizagem 2021/22  
**Homework III – Group 114**

$$\frac{\partial E}{\partial w^3} = \delta^{[3]} \cdot \frac{\partial z^{[3]} T}{\partial w^3} = \delta^{[3]} \cdot (x^{[2]})^T = \begin{bmatrix} -0,5 \\ 0,5 \end{bmatrix} \cdot \begin{bmatrix} 0,999892 & 0,499892 \end{bmatrix} = \begin{bmatrix} -0,499946 & -0,499946 \\ 0,499946 & 0,499946 \end{bmatrix}$$

$$w^3 = w^3 - \eta \frac{\partial E}{\partial w^3} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix} - 0,1 \begin{bmatrix} -0,499946 & -0,499946 \\ 0,499946 & 0,499946 \end{bmatrix} = \begin{bmatrix} 0,0499946 & 0,0499946 \\ -0,0499946 & -0,0499946 \end{bmatrix}$$

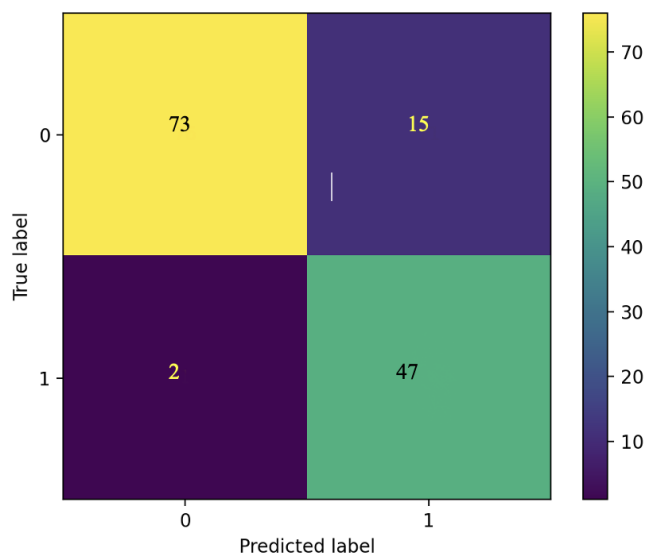
$$\frac{\partial E}{\partial b^3} = \delta^{[3]} \cdot \frac{\partial z^{[3]} T}{\partial b^3} = \delta^{[3]} = \begin{bmatrix} -0,5 \\ 0,5 \end{bmatrix}$$

$$b^3 = b^3 - \eta \frac{\partial E}{\partial b^3} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} - 0,1 \begin{bmatrix} -0,5 \\ 0,5 \end{bmatrix} = \begin{bmatrix} 0,05 \\ 0,05 \end{bmatrix}$$

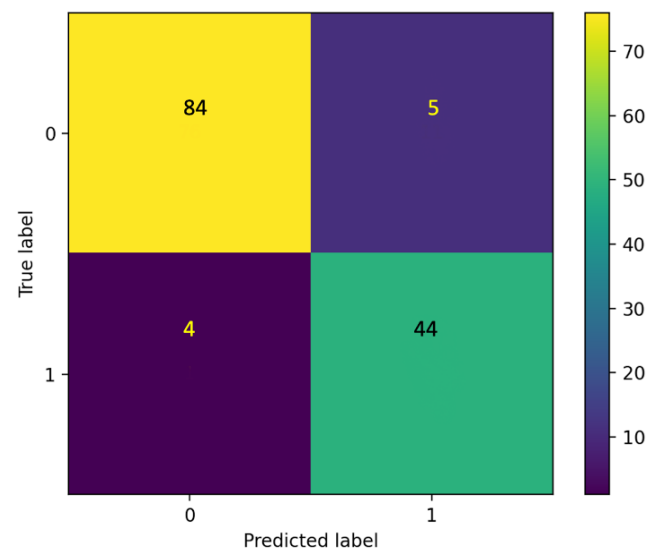
Os passos intermédios, nomeadamente cálculo de derivadas, foram baseados no documento pdf disponibilizado pelo Prof. Andrzej Wichert em [practical lectures](#).

## II. Programming and critical analysis

### 2. Answer 2



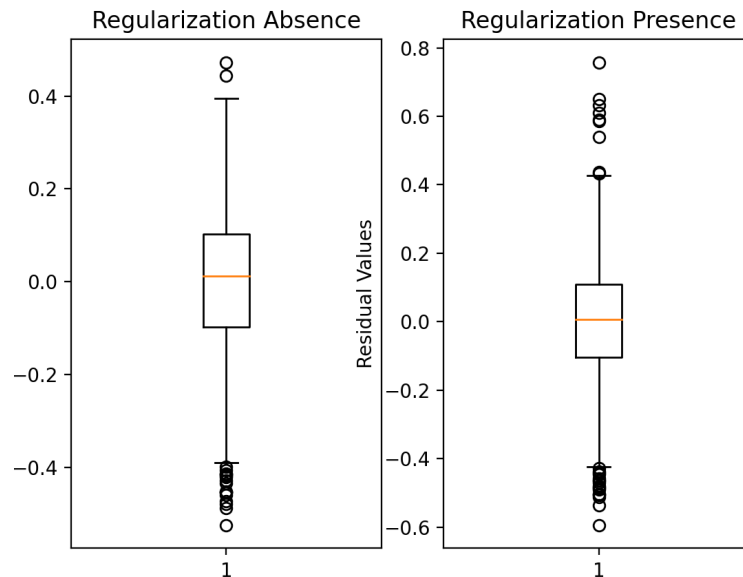
(early stopping = false)



(early stopping = true)

É possível reduzir o overfitting através da redução do espaço de amostra de dados, dividindo a amostra em menos quantidades, e também fixando o tamanho de cada dimensão do espaço permitindo que o erro fique reduzido ao máximo. Assim que o erro começa a aumentar, o early stopping termina a classificação, o que é positivamente verificável nesta experiência.

3. Answer 3



Para reduzir o erro é necessário:

- ☐ fixar a regularização, entre 0 e 1, aumentando o fator de aprendizagem;
- ☐ fixar o random\_state diferente de 0 (por exemplo 114) (shuffle);
- ☐ Aumentar o número de iterações (epochs), quanto mais iterações mais pequeno vai ser o erro.
- ☐ Alterar a função de ativação :  $\tanh(x)$

### III. APPENDIX

#### Exercise 2

```
import pandas as pd
import numpy as np
from scipy.io.arff.arffread import print_attribute
from scipy.io.arff import loadarff
from sklearn.model_selection import cross_val_score
from sklearn.model_selection import KFold
from sklearn.neural_network import MLPClassifier
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split
from sklearn.metrics import plot_confusion_matrix
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
from sklearn.neural_network import MLPRegressor
from sklearn.model_selection import cross_val_predict

if __name__ == '__main__':
    raw_data = loadarff('breast.w.arff')
    df_data = pd.DataFrame(raw_data[0])
    classe = df_data.pop('Class')
    df_data = df_data.values
    df_data = df_data.astype(int)

    Y = np.array(classe)
    Y = Y.astype(int)
    kf = KFold(n_splits=5, random_state=0, shuffle=True)

    clf = MLPClassifier(hidden_layer_sizes=(3,2), early_stopping=False, random_state=120)
    #clf = MLPClassifier(hidden_layer_sizes=(3,2), early_stopping=True, random_state=120)
    for train_ind, test_ind in kf.split(df_data):
        X_train, X_test = df_data[train_ind], df_data[test_ind]
        y_train, y_test = Y[train_ind], Y[test_ind]
        clf.fit(X_train, y_train)
        plot_confusion_matrix(clf, X_test, y_test)
        plt.show()
```

#### Exercise 3

```
if __name__ == '__main__':
    raw_data = loadarff('kin8nm.arff')
    df_data = pd.DataFrame(raw_data[0])
    Y = df_data.pop('y')
    df_data = df_data.values
    df_data = df_data.astype(float)
    alphas = np.logspace(-1, 1, 5)
    kf = KFold(n_splits=5, random_state=0, shuffle=True)
    vec = []
    fig, axs = plt.subplots(1,2)
    for train_ind, test_ind in kf.split(df_data):
        X_train, X_test = df_data[train_ind], df_data[test_ind]
        y_train, y_test = Y[train_ind], Y[test_ind]
        regr = MLPRegressor(hidden_layer_sizes=(3,2), activation='relu', random_state=
0, alpha=0).fit(X_train, y_train)
        y_test_data_pred = regr.predict(X_test)
        fold_testing_error = y_test - y_test_data_pred
        vec.append(fold_testing_error)
    axs[0].boxplot(vec)
    axs[0].set_title("Regularization Absence")
    kf = KFold(n_splits=5, random_state=0, shuffle=True)
```

Aprendizagem 2021/22  
**Homework III – Group 114**

```
vet=[]
for train_ind, test_ind in kf.split(df_data):
    X_train, X_test = df_data[train_ind], df_data[test_ind]
    y_train, y_test = Y[train_ind], Y[test_ind]
    regr = MLPRegressor(hidden_layer_sizes=(3,2),activation='relu',random_state=
0,alpha=1).fit(X_train, y_train)
    y_test_data_pred = regr.predict(X_test)
    fold_testing_errors = y_test-y_test_data_pred
vet.append(fold_testing_errors)
axs[1].boxplot(vet)
axs[1].set_title("Regularization Presence")
plt.ylabel("Residual Values")
plt.show()
```

**END**