

Aprendizagem 2022
Homework III – Group 019
Diogo Gaspar 99207, Rafael Oliveira 99311

Part I: Pen and paper

1. **Consider the basis function, $\phi_j(x) = x^j$, for performing a 3-order polynomial regression,**

$$\hat{z}(x, w) = \sum_{j=0}^3 w_j \phi_j(x) = w_0 + w_1 x + w_2 x^2 + w_3 x^3.$$

Learn the Ridge regression (l_2 regularization) on the transformed data space using the closed-form solution with $\lambda = 2$.

We have in hands a **supervised learning** problem, with a given training dataset as shown below:

	y_1	z
x_1	0.8	24
x_2	1	20
x_3	1.2	10
x_4	1.4	13
x_5	1.6	12

Table 1: Training dataset: y_1 as the input's (only) variable, z as the target variable

We can note that in the statement's estimation function, $\hat{z}(x, w)$, x is a single-element vector (with its only entry being each sample's y_1 value). Therefore, it makes sense to “expand” the table above as follows, in order to have a broader representation of the values we'll end up using in the estimation function:

	y_1	y_1^2	y_1^3	z
x_1	0.8	0.64	0.512	24
x_2	1	1	1	20
x_3	1.2	1.44	1.728	10
x_4	1.4	1.96	2.744	13
x_5	1.6	2.56	4.096	12

Table 2: Training dataset with additional information

The equation below shows the closed-form solution for the Ridge regression problem, with $\lambda = 2$:

$$w = (\Phi^T \Phi + \lambda I)^{-1} \Phi^T z = (\Phi^T \Phi + 2I)^{-1} \Phi^T z$$

Here, Φ is the result of applying the basis function to our training dataset's inputs, such that:

$$\Phi = \begin{bmatrix} 1 & \phi_1(x_1) & \phi_2(x_1) & \phi_3(x_1) \\ 1 & \phi_1(x_2) & \phi_2(x_2) & \phi_3(x_2) \\ \vdots & \vdots & \vdots & \vdots \\ 1 & \phi_1(x_5) & \phi_2(x_5) & \phi_3(x_5) \end{bmatrix} = \begin{bmatrix} 1 & 0.8 & 0.64 & 0.512 \\ 1 & 1 & 1 & 1 \\ 1 & 1.2 & 1.44 & 1.728 \\ 1 & 1.4 & 1.96 & 2.744 \\ 1 & 1.6 & 2.56 & 4.096 \end{bmatrix}$$

We are now able to learn the given polynomial regression model, with $\lambda = 2$:

$$(\Phi^T \Phi + \lambda I)^{-1} = \left(\begin{bmatrix} 1 & 0.8 & 0.64 & 0.512 \\ 1 & 1 & 1 & 1 \\ 1 & 1.2 & 1.44 & 1.728 \\ 1 & 1.4 & 1.96 & 2.744 \\ 1 & 1.6 & 2.56 & 4.096 \end{bmatrix}^T \begin{bmatrix} 1 & 0.8 & 0.64 & 0.512 \\ 1 & 1 & 1 & 1 \\ 1 & 1.2 & 1.44 & 1.728 \\ 1 & 1.4 & 1.96 & 2.744 \\ 1 & 1.6 & 2.56 & 4.096 \end{bmatrix} + \begin{bmatrix} 2 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 \\ 0 & 0 & 2 & 0 \\ 0 & 0 & 0 & 2 \end{bmatrix} \right)^{-1}$$

$$= \begin{bmatrix} 0.34168753 & -0.1214259 & -0.07490231 & -0.00932537 \\ -0.1214259 & 0.3892078 & -0.09667718 & -0.07445624 \\ -0.07490231 & -0.09667718 & 0.37257788 & -0.17135047 \\ -0.00932537 & -0.07445624 & -0.17135047 & 0.17998796 \end{bmatrix}$$

$$\Phi^T z = \begin{bmatrix} 1 & 0.8 & 0.64 & 0.512 \\ 1 & 1 & 1 & 1 \\ 1 & 1.2 & 1.44 & 1.728 \\ 1 & 1.4 & 1.96 & 2.744 \\ 1 & 1.6 & 2.56 & 4.096 \end{bmatrix}^T \begin{bmatrix} 24 \\ 20 \\ 10 \\ 13 \\ 12 \end{bmatrix} = \begin{bmatrix} 79 \\ 88.6 \\ 105.96 \\ 134.392 \end{bmatrix}$$

$$w = (\Phi^T \Phi + \lambda I)^{-1} \Phi^T z = \begin{bmatrix} 7.0450759 \\ 4.64092765 \\ 1.96734046 \\ -1.30088142 \end{bmatrix}$$

Having learned the regression model, we can now use it to predict labels z for new samples!

2. Compute the training RMSE for the learnt regression model.

We know that the Root Mean Squared Error (RMSE) for a given regression model is defined as

$$\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^N (z_i - \hat{z}_i)^2},$$

where N is the number of samples in the dataset, z_i is the true label for the i -th sample, and \hat{z}_i is the predicted label for the i -th sample. As stated in the previous question's statement, \hat{z} is given by the matrix product $\Phi \cdot w$. We can, then, compute the RMSE for the training dataset as follows:

$$\begin{aligned} \hat{z} = \Phi \cdot w &= \begin{bmatrix} 1 & 0.8 & 0.64 & 0.512 \\ 1 & 1 & 1 & 1 \\ 1 & 1.2 & 1.44 & 1.728 \\ 1 & 1.4 & 1.96 & 2.744 \\ 1 & 1.6 & 2.56 & 4.096 \end{bmatrix} \begin{bmatrix} 7.0450759 \\ 4.64092765 \\ 1.96734046 \\ -1.30088142 \end{bmatrix} = \begin{bmatrix} 11.35086463 \\ 12.35246259 \\ 13.19923625 \\ 13.8287433 \\ 14.17854143 \end{bmatrix} \\ \text{RMSE} &= \sqrt{\frac{1}{5} \sum_{i=1}^5 (z_i - \hat{z}_i)^2} \\ &= \sqrt{\frac{1}{5} ((24 - 11.35086463)^2 + \dots + (12 - 14.17854143)^2)} \\ &= 6.84329 \end{aligned}$$

3. Consider a multi-layer perceptron characterized by one hidden layer with 2 nodes. Using the activation function $f(x) = e^{0.1x}$ on all units, all weights initialized as 1 (including biases), and the half squared error loss, perform one batch gradient descent update (with learning rate $\eta = 0.1$) for the first three observations (0.8), (1) and (1.2).

Our multi-layer perceptron, considering the parameters stated above, is as follows:

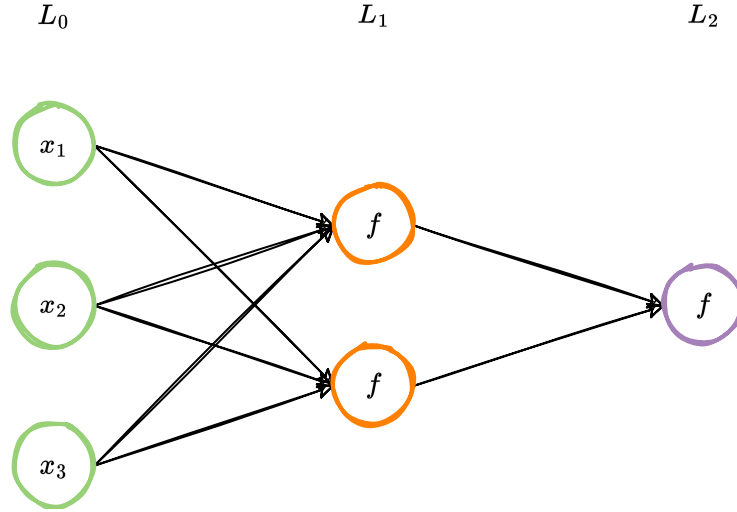


Figure 1: Multi-layer perceptron shape

Each node in the hidden layer has an activation function $f(x) = e^{0.1x}$. Moreover, we know that the learning rule for the weights of the hidden layer is given by $\Delta w = -\eta \frac{\partial E}{\partial w}$, with $\eta = 0.1$ and E being the half squared error loss.

$$E = \frac{1}{2 * 2} \sum_{i=1}^N (z_i - \hat{z}_i)^2$$

A gradient descent update will require us to go through 3 phases: forward propagation, back propagation and updates (via gradient updates, updating biases and weights).

Starting by the forward propagation, and considering l as a given layer, we have that:

$$z^{(l)} = w^{(l)} x^{(l-1)} + b^{(l)}, \quad x^{(l)} = f(z^{(l)})$$

From the question's statement, we're able to gather the following:

$$x^{(0)} = \begin{bmatrix} 0.8 \\ 1 \\ 1.2 \end{bmatrix}, \quad w^{(1)} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix}, \quad b^{(1)} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}, \quad w^{(2)} = [1 \quad 1 \quad 1], \quad b^{(2)} = [1]$$

Applying the algorithm will lead us to the following results:

$$\begin{aligned} z^{(1)} &= \begin{bmatrix} 4.00000000 \\ 4.00000000 \\ 4.00000000 \end{bmatrix}, & x^{(1)} &= \begin{bmatrix} 1.4918247 \\ 1.4918247 \\ 1.4918247 \end{bmatrix}, \\ z^{(2)} &= [5.47547409], & x^{(2)} &= [1.7290072] \end{aligned}$$

We're now ready for the back propagation phase. Applying batch gradient descent, and looking at the half squared error loss, we have that:

$$\Delta w^{[l]} = -\eta \frac{\partial E}{\partial w^{[l]}}, \quad \Delta b^{[l]} = -\eta \frac{\partial E}{\partial b^{[l]}}$$

We'll want to propagate information backwards; for that, we'll need to use the chain rule, multiplying successive derivatives as we go backwards. With L being the **last layer** - will be useful for reusing previously calculated δ 's - we have the following:

$$\begin{aligned} \frac{\partial E}{\partial w^{[L]}} &= \frac{\partial E}{\partial x^{[L]}} \circ \frac{\partial x^{[L]}}{\partial z^{[L]}} \frac{\partial z^{[L]}}{\partial w^{[L]}} \\ \frac{\partial E}{\partial b^{[L]}} &= \frac{\partial E}{\partial x^{[L]}} \circ \frac{\partial x^{[L]}}{\partial z^{[L]}} \frac{\partial z^{[L]}}{\partial b^{[L]}} \\ \delta^{[L]} &= \frac{\partial E}{\partial x^{[L]}} \circ \frac{\partial x^{[L]}}{\partial z^{[L]}} \\ \delta^{[l]} &= \frac{\partial z^{[l+1]}}{\partial x^{[l]}} \cdot \delta^{[l+1]} \circ \frac{\partial x^{[l]}}{\partial z^{[l]}} \end{aligned}$$

We'll now be able to start propagating (considering the following equalities, derived both in class and in the curricular unit's book):

$$\begin{aligned} \frac{\partial E}{\partial x^{[2]}} &= \frac{\partial \frac{1}{4} \sum_{i=1}^N (z_i - x_i^{[2]})^2}{\partial x^{[2]}} = \frac{x^{[2]} - z_i}{2}, & \frac{\partial x^{[l]}}{\partial z^{[l]}} &= \frac{\partial e^{0.1z^{[l]}}}{\partial z^{[l]}} = 0.1e^{0.1z^{[l]}} \\ \frac{\partial z^{[l]}}{\partial x^{[l-1]}} &= w^{[l]}, & \frac{\partial z^{[l]}}{\partial b^{[l]}} &= 1, & \frac{\partial z^{[l]}}{\partial w^{[l]}} &= x^{[l-1]} \end{aligned}$$

$$\begin{aligned}
\delta^{[2]} &= \frac{\partial E}{\partial x^{[2]}} \circ \frac{\partial x^{[2]}}{\partial z^{[2]}} = (x^{[2]} - z_i) \circ 0.1e^{0.1z^{[2]}} \\
&= \left(\left[1.72900727/2 \right] - [1] \right) \circ 0.1e^{0.1[5.47547409]} \\
&= [-0.135496365] \circ [0.1e^{0.547547409}] \\
&= [-0.02342741996]
\end{aligned}$$

$$\begin{aligned}
\delta^{[1]} &= \frac{\partial z^{[2]T}}{\partial x^{[1]}} \cdot \delta^{[2]} \circ \frac{\partial x^{[1]}}{\partial z^{[1]}} \\
&= \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} \cdot [-0.02342741996] \circ [0.1e^{0.1z^{[1]}}] \\
&= \begin{bmatrix} -0.02342741996 \\ -0.02342741996 \\ -0.02342741996 \end{bmatrix} \circ \begin{bmatrix} 0.1e^{0.4} \\ 0.1e^{0.4} \\ 0.1e^{0.4} \end{bmatrix} \\
&= \begin{bmatrix} -0.003494960370 \\ -0.003494960370 \\ -0.003494960370 \end{bmatrix}
\end{aligned}$$

In the last phase, we'll be updating our model: after computing the gradients, we'll be able to update weights and biases!

Starting with weight matrices:

$$\frac{\partial E}{\partial w^{[1]}} = \delta^{[1]} \cdot \frac{\partial z^{[1]T}}{\partial w^{[1]}} = \delta^{[1]} \cdot x^{[0]T} = \begin{bmatrix} -0.00279597 & -0.00349496 & -0.00419395 \\ -0.00279597 & -0.00349496 & -0.00419395 \\ -0.00279597 & -0.00349496 & -0.00419395 \end{bmatrix}$$

$$\frac{\partial E}{\partial w^{[2]}} = \delta^{[2]} \cdot \frac{\partial z^{[2]T}}{\partial w^{[2]}} = \delta^{[2]} \cdot x^{[1]T} = [-0.0349496 \quad -0.0349496 \quad -0.0349496]$$

$$\begin{aligned}
w^{[1]} &= w^{[1]} - \eta \cdot \frac{\partial E}{\partial w^{[1]}} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & 1 & 1 \\ 1 & 1 & 1 \end{bmatrix} - 0.1 \cdot \begin{bmatrix} -0.00279597 & -0.00349496 & -0.00419395 \\ -0.00279597 & -0.00349496 & -0.00419395 \\ -0.00279597 & -0.00349496 & -0.00419395 \end{bmatrix} \\
&= \begin{bmatrix} 1.000279597 & 1.000349496 & 1.000419395 \\ 1.000279597 & 1.000349496 & 1.000419395 \\ 1.000279597 & 1.000349496 & 1.000419395 \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
w^{[2]} &= w^{[2]} - \eta \cdot \frac{\partial E}{\partial w^{[2]}} = \begin{bmatrix} 1 & 1 & 1 \end{bmatrix} - 0.1 \cdot \begin{bmatrix} -0.0349496 & -0.0349496 & -0.0349496 \end{bmatrix} \\
&= \begin{bmatrix} 1.00349496 & 1.00349496 & 1.00349496 \end{bmatrix}
\end{aligned}$$

After updating weights, we'll update biases:

$$\frac{\partial E}{\partial b^{[1]}} = \delta^{[1]} \cdot \frac{\partial z^{[1]T}}{\partial b^{[1]}} = \delta^{[1]} \cdot 1 = \delta^{[1]} = \begin{bmatrix} -0.003494960370 \\ -0.003494960370 \\ -0.003494960370 \end{bmatrix}$$

$$\frac{\partial E}{\partial b^{[2]}} = \delta^{[2]} \cdot \frac{\partial z^{[2]T}}{\partial b^{[2]}} = \delta^{[2]} \cdot 1 = \delta^{[2]} = \begin{bmatrix} -0.02342741996 \end{bmatrix}$$

$$\begin{aligned}
b^{[1]} &= b^{[1]} - \eta \cdot \frac{\partial E}{\partial b^{[1]}} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix} - 0.1 \cdot \begin{bmatrix} -0.003494960370 \\ -0.003494960370 \\ -0.003494960370 \end{bmatrix} \\
&= \begin{bmatrix} 1.000349496037 \\ 1.000349496037 \\ 1.000349496037 \end{bmatrix}
\end{aligned}$$

$$\begin{aligned}
b^{[2]} &= b^{[2]} - \eta \cdot \frac{\partial E}{\partial b^{[2]}} = \begin{bmatrix} 1 \end{bmatrix} - 0.1 \cdot \begin{bmatrix} -0.02342741996 \end{bmatrix} \\
&= \begin{bmatrix} 1.002342741996 \end{bmatrix}
\end{aligned}$$

Part II: Programming and critical analysis

The code utilized to answer the following questions is available in this report's appendix.

4. Compute the MAE of the three regressors: linear regression, MLP_1 and MLP_2 .

We opted to utilize sklearn's `mean_absolute_error` function to compute the MAE of the three regressors. The regressors were created as shown in the appendix (using Ridge and MLPRegressor with the respective parameters).

We gathered the following results:

Regressor	MAE
Linear Regression (Ridge)	0.16283
MLP_1	0.06804
MLP_2	0.09781

Table 3: Gathered Mean Absolute Errors for each specified regressor

5. Plot the residues (in absolute value) using two visualizations: boxplots and histograms.

Each regressor's residues, calculated as the absolute difference between the predicted and actual values, were plotted using both boxplots and histograms (using, respectively, seaborn's `boxplot` and `histplot` functions), as shown in this report's appendix (figures after the code).

6. How many iterations were required for MLP_1 and MLP_2 to converge?

Calling the `print_regressor` method for each regressor shows us not only the MAE, but also the number of iterations required for each of the MLP regressors to converge. In this case, the number of iterations required for MLP_1 (MLP with early stopping) to converge was 452, while MLP_2 (MLP without early stopping) required only 77.

7. What can be motivating the unexpected differences on the number of iterations? Hypothesize one reason underlying the observed performance differences between the MLPs.

As has been noted in the previous question's answer, MLP_1 takes many more iterations to converge than MLP_2 - almost six times as many. It's probably worth emphasizing that the number of iterations in a batch gradient descent algorithm matches the number of epochs ran - the amount of times the algorithm goes through the entire dataset. Early stopping, however, is a technique which allows us to **stop an epoch** at a given point, not the entire algorithm.

Regarding performance, we were able to assert in the first question's answer that MLP_1 performed better than MLP_2 - it had a lower MAE, which effectively tells us that it was able to better approximate the function we were trying to learn to the data. With MLP_1 utilizing early stopping, it's likely that the regressor was able to avoid overfitting the data a bit better than MLP_2 - stopping at the "right point" of an epoch, instead of running the algorithm for all samples, could allow it to generalize better to unseen data.

Appendix

```
1 import numpy as np
2 import pandas as pd
3 import matplotlib.pyplot as plt
4 import seaborn as sns
5 from scipy.io.arff import loadarff
6 from sklearn.linear_model import Ridge
7 from sklearn.model_selection import train_test_split
8 from sklearn.metrics import mean_absolute_error
9 from sklearn.neural_network import MLPRegressor
10 sns.set_style('darkgrid')
11
12 # Load data
13 data = loadarff('data/kin8nm.arff')
14 df = pd.DataFrame(data[0])
15
16 X = df.drop('y', axis=1).values
17 y = df['y'].values
18
19 X_train, X_test, y_train, y_test = train_test_split(
20     X, y,
21     test_size=0.3,
22     random_state=0
23 )
24
25 def predict(regressor):
26     regressor.fit(X_train, y_train)
27     return regressor.predict(X_test)
28
29 def plot_regressor_residues(regressor, description, y_pred):
30     """Utilized for answering question 2."""
31     residues = np.abs(y_test - y_pred)
32
33     fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
34     sns.histplot(data=residues, ax=ax1)
35     ax1.set_title('Residues histogram')
36     ax1.set_xlabel('Residues')
37     sns.boxplot(data=residues, ax=ax2, orient='h')
38     ax2.set_title('Residues boxplot')
39     ax2.set_xlabel('Residues')
40     plt.suptitle(description)
41     plt.show()
42
43 def print_regressor(regressor, description, y_pred):
44     """Utilized for answering questions 1. and 3."""
45     print(description)
46     print('MAE: {:.5f}'.format(mean_absolute_error(y_test, y_pred)))
47     if "MLP" in description:
48         print('Iterations: {}'.format(regressor.n_iter_))
49
50 regressors = {
51     "Ridge Regression": Ridge(alpha=0.1),
52     "MLP 1": MLPRegressor(
53         hidden_layer_sizes=(10, 10),
54         activation='tanh',
```

```

55     max_iter=500,
56     random_state=0,
57     early_stopping=True
58 ),
59 "MLP 2": MLPRegressor(
60     hidden_layer_sizes=(10, 10),
61     activation='tanh',
62     max_iter=500,
63     random_state=0
64 )
65 }
66
67 for description, regressor in regressors.items():
68     y_pred = predict(regressor)
69     print_regressor(regressor, description, y_pred)
70     plot_regressor_residues(regressor, description, y_pred)

```

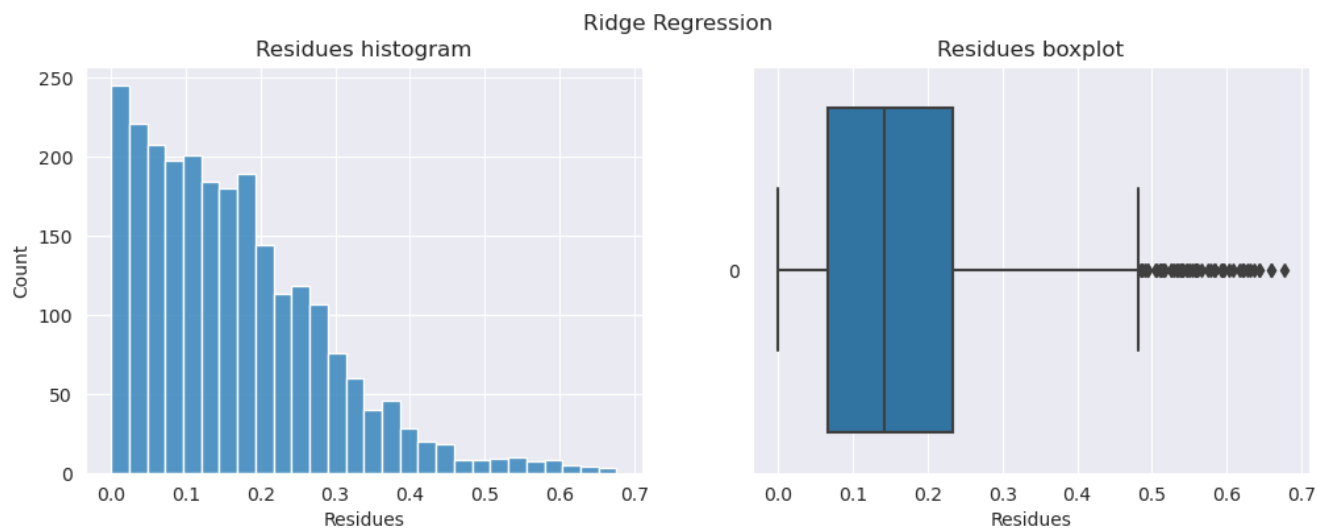


Figure 2: Ridge regression's residue plotting

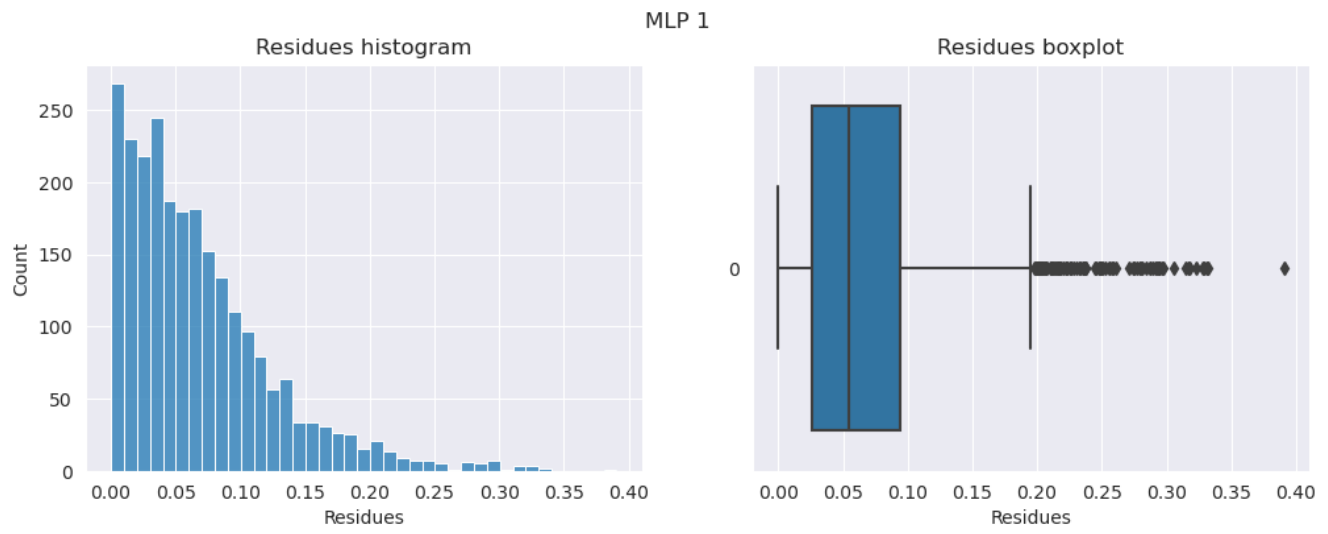


Figure 3: MLP_1 regression's residue plotting

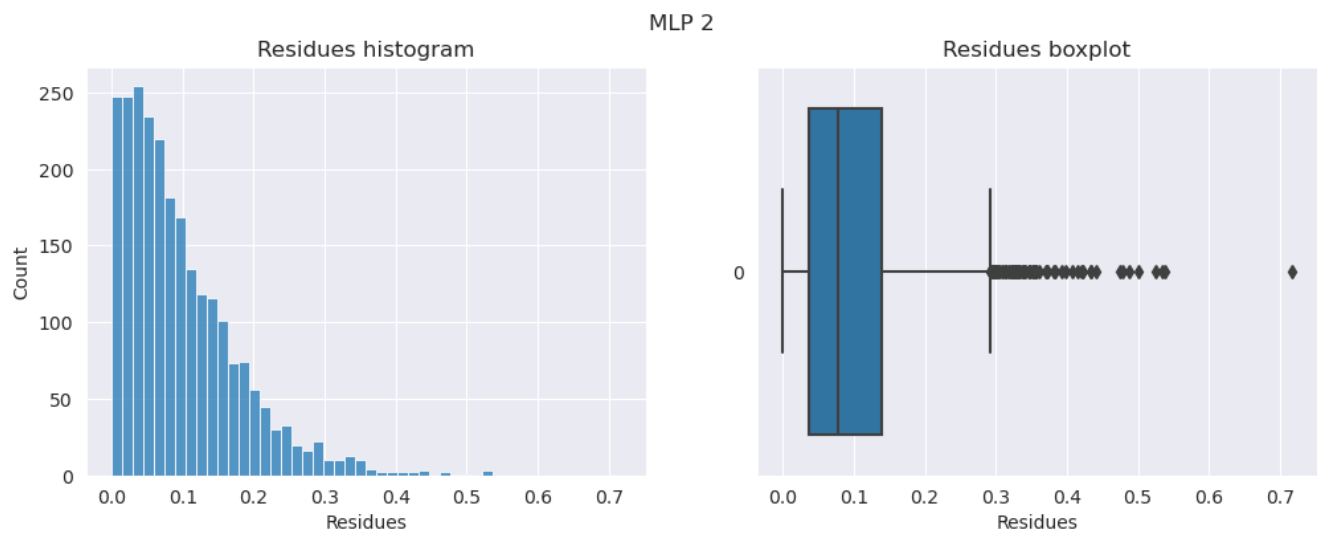


Figure 4: MLP_2 regression's residue plotting