```python
import pandas as pd

train = pd.read_csv("./dataset/ressonanciaMLP.csv")
test = pd.read_csv("./dataset/ressonanciaMLPTest.csv")

base = pd.concat([train, test])

base
```

```
        x1      x2      x3       d
0   0.8799  0.7998  0.3972  0.8399
1   0.5700  0.5111  0.2418  0.6258
2   0.6796  0.4117  0.3370  0.6622
3   0.3567  0.2967  0.6037  0.5969
4   0.3866  0.8390  0.0232  0.5316
..     ...     ...     ...     ...
15  0.8882  0.3077  0.8931  0.8093
16  0.2225  0.9182  0.7820  0.7581
17  0.1957  0.8423  0.3085  0.5826
18  0.9991  0.5914  0.3933  0.7938
19  0.2299  0.1524  0.7353  0.5012

[220 rows x 4 columns]
```

```python
import pandas as pd
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.neural_network import MLPRegressor
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import mean_squared_error

# Carregar e pré-processar os dados
class DataLoader:
    @staticmethod
    def load_data(path):
        data = pd.read_csv(path)
        return data

class DataPreprocessor:
    def __init__(self, df):
        self.df = df

    def split_features_and_target(self, target_column='d'):
        X = self.df[['x1', 'x2', 'x3']]
        y = self.df[target_column]
        return X, y

    def normalize_features(self, X):
        scaler = StandardScaler().fit(X)
        X = scaler.transform(X)
        return X, scaler
```

```python
class MLPTrainer:
    def __init__(self, activation, hidden_layer_sizes,
learning_rate_init=0.01, max_iter=1000, random_state=42):
        self.model = MLPRegressor(
            activation=activation,
            hidden_layer_sizes=hidden_layer_sizes,
            learning_rate_init=learning_rate_init,
            max_iter=max_iter,
            random_state=random_state
        )

    def train(self, X_train, y_train):
        self.model.fit(X_train, y_train)
        return self.model

    def evaluate(self, X_test, y_test):
        y_pred = self.model.predict(X_test)
        loss = mean_squared_error(y_test, y_pred)
        return loss, self.model.n_iter_




# Carregar os dados
data = base.copy()


data
```

	x1	x2	x3	d
0	0.8799	0.7998	0.3972	0.8399
1	0.5700	0.5111	0.2418	0.6258
2	0.6796	0.4117	0.3370	0.6622
3	0.3567	0.2967	0.6037	0.5969
4	0.3866	0.8390	0.0232	0.5316
..	...	...	...	...
15	0.8882	0.3077	0.8931	0.8093
16	0.2225	0.9182	0.7820	0.7581
17	0.1957	0.8423	0.3085	0.5826
18	0.9991	0.5914	0.3933	0.7938
19	0.2299	0.1524	0.7353	0.5012

[220 rows x 4 columns]

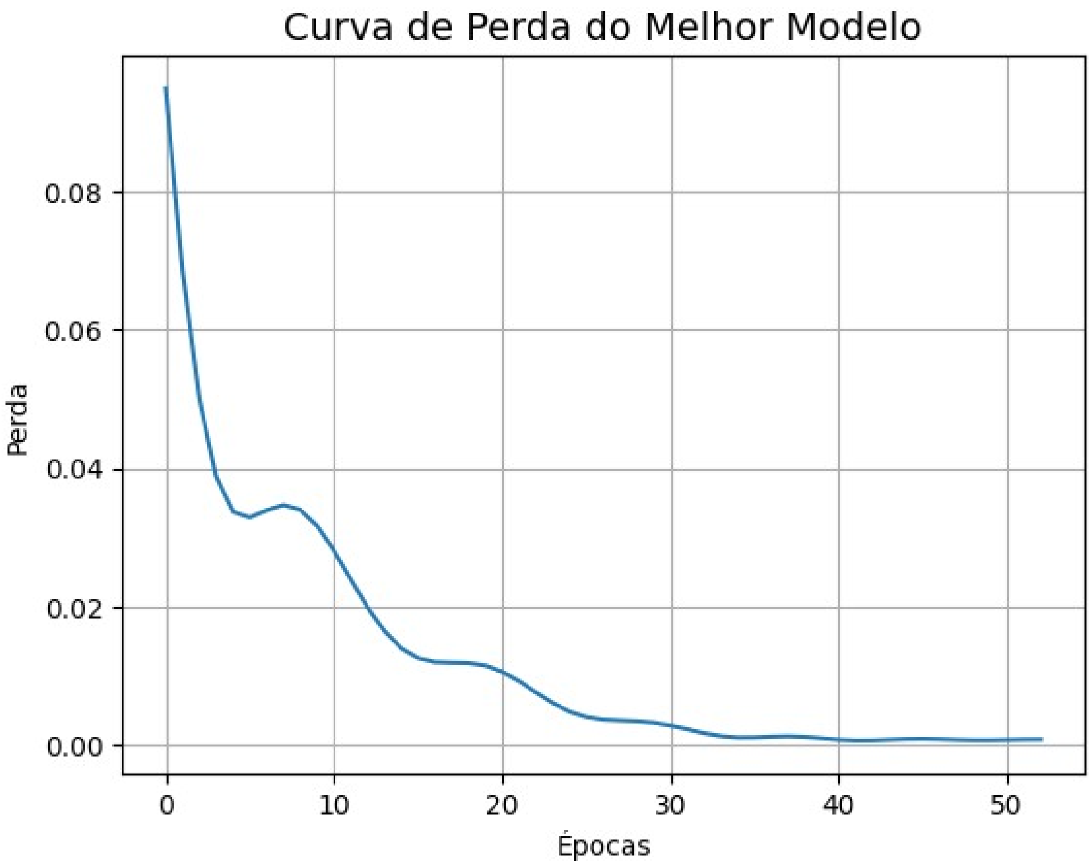
```python
# Pré-processar os dados
preprocessor = DataPreprocessor(data)
X, y = preprocessor.split_features_and_target()
#X, scaler = preprocessor.normalize_features(X)

from prettytable import PrettyTable
```

```python
# Dividir os dados em conjunto de treinamento e teste
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3, random_state=42)
# Configurações para os treinamentos
activations = ['tanh', 'relu', 'logistic']
neurons = [5, 10, 15]
results = []
# Executar os treinamentos
for activation in activations:
    for neuron in neurons:
        trainer = MLPTrainer(activation=activation,
hidden_layer_sizes=(neuron,))
        model = trainer.train(X_train, y_train)
        loss, epochs = trainer.evaluate(X_test, y_test)
        results.append((activation, neuron, loss, epochs, model))

    # Classificar os resultados
results.sort(key=lambda x: x[2])

table = PrettyTable()
table.field_names = ["Treinamento", "Neurônios", "Ativação", "Perda
Final", "Número de Épocas", "Model"]

for i, (activation, neuron, loss, epochs, model) in enumerate(results,
start=1):
        table.add_row([f"{i}º (T{i})", neuron, activation,
f"{loss:.4f}", epochs, model])

print(table)
```

```
+-------------+-----------+----------+-------------+------------------
+-----------------------------------------------------------------------
-----------+
| Treinamento | Neurônios | Ativação | Perda Final | Número de Épocas
|                                       Model
|
+-------------+-----------+----------+-------------+------------------
+-----------------------------------------------------------------------
-----------+
|   1º (T1)   |     15    |   relu   |    0.0015   |        53
| MLPRegressor(hidden_layer_sizes=(15,), learning_rate_init=0.01,
max_iter=1000, |
|             |           |          |             |
|                                       random_state=42)
|
|   2º (T2)   |     10    |   relu   |    0.0015   |        65
| MLPRegressor(hidden_layer_sizes=(10,), learning_rate_init=0.01,
max_iter=1000, |
|             |           |          |             |
```

```
|                                       random_state=42)
|
|   3º (T3)   |     5     |   tanh   |    0.0017   |       127
|            MLPRegressor(activation='tanh', hidden_layer_sizes=(5,),
|
|             |           |          |             |
|                  learning_rate_init=0.01, max_iter=1000,
random_state=42)      |
|   4º (T4)   |     15    |   tanh   |    0.0031   |        28
|           MLPRegressor(activation='tanh', hidden_layer_sizes=(15,),
|
|             |           |          |             |
|                  learning_rate_init=0.01, max_iter=1000,
random_state=42)      |
|   5º (T5)   |     15    | logistic |    0.0168   |        18
|         MLPRegressor(activation='logistic',
hidden_layer_sizes=(15,),          |
|             |           |          |             |
|                  learning_rate_init=0.01, max_iter=1000,
random_state=42)      |
|   6º (T6)   |     10    | logistic |    0.0218   |        20
|         MLPRegressor(activation='logistic',
hidden_layer_sizes=(10,),          |
|             |           |          |             |
|                  learning_rate_init=0.01, max_iter=1000,
random_state=42)      |
|   7º (T7)   |     5     | logistic |    0.0251   |        35
|          MLPRegressor(activation='logistic',
hidden_layer_sizes=(5,),          |
|             |           |          |             |
|                  learning_rate_init=0.01, max_iter=1000,
random_state=42)      |
|   8º (T8)   |     5     |   relu   |    0.0301   |        79
| MLPRegressor(hidden_layer_sizes=(5,), learning_rate_init=0.01,
max_iter=1000,  |
|             |           |          |             |
|                                       random_state=42)
|
|   9º (T9)   |     10    |   tanh   |    0.0591   |        23
|           MLPRegressor(activation='tanh', hidden_layer_sizes=(10,),
|
|             |           |          |             |
|                  learning_rate_init=0.01, max_iter=1000,
random_state=42)      |
+-------------+-----------+----------+-------------+-----------------
+-------------------------------------------------------------------
-----------+

import matplotlib.pyplot as plt
```

```
best_model = results[0][4]
plt.plot(best_model.loss_curve_)
plt.title("Curva de Perda do Melhor Modelo", fontsize=14)
plt.xlabel('Épocas')
plt.ylabel('Perda')
plt.grid(True)
plt.show()
```



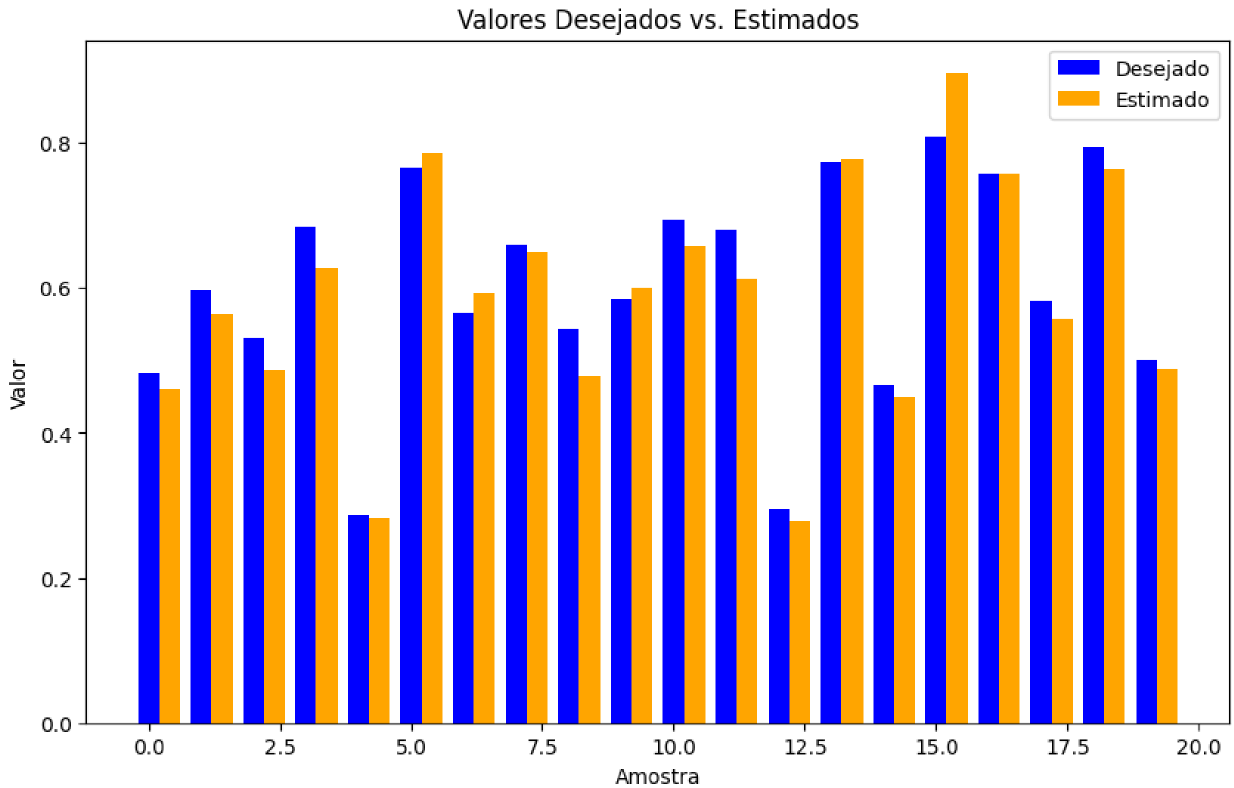

```
results
```

```
[('relu', 15, 0.0015170114658609683, 53),
 ('relu', 10, 0.0015295566920569925, 65),
 ('tanh', 5, 0.001735316666974427, 127),
 ('tanh', 15, 0.003109737315709396, 28),
 ('logistic', 15, 0.01680438358616946, 18),
 ('logistic', 10, 0.021775989215754365, 20),
 ('logistic', 5, 0.025114968531775538, 35),
 ('relu', 5, 0.03007950069396447, 79),
 ('tanh', 10, 0.05913046287692675, 23)]
```

```
import pandas as pd
import numpy as np
```

```python
from sklearn.metrics import mean_absolute_error, mean_squared_error
import matplotlib.pyplot as plt

# Dados de teste fornecidos
test_data = {
    'x1': [0.0611, 0.5102, 0.0004, 0.9430, 0.1399, 0.6423, 0.6492,
0.1818, 0.7382, 0.3879,
           0.1903, 0.8401, 0.0029, 0.7088, 0.1283, 0.8882, 0.2225,
0.1957, 0.9991, 0.2299],
    'x2': [0.2860, 0.7464, 0.6916, 0.4476, 0.1610, 0.3229, 0.0007,
0.5078, 0.2647, 0.1307,
           0.6523, 0.4490, 0.3264, 0.9342, 0.1882, 0.3077, 0.9182,
0.8423, 0.5914, 0.1524],
    'x3': [0.7464, 0.0860, 0.5006, 0.2648, 0.2477, 0.8567, 0.6422,
0.9046, 0.1916, 0.8656,
           0.7820, 0.2719, 0.2476, 0.2763, 0.7253, 0.8931, 0.7820,
0.3085, 0.3933, 0.7353],
    'd': [0.4831, 0.5965, 0.5318, 0.6843, 0.2872, 0.7663, 0.5666,
0.6601, 0.5427, 0.5836,
          0.6950, 0.6790, 0.2956, 0.7742, 0.4662, 0.8093, 0.7581,
0.5826, 0.7938, 0.5012]
}

test = pd.DataFrame(test_data)
# Realizar a predição com o modelo treinado
y_pred = best_model.predict(test[['x1', 'x2', 'x3']])

# Calcular as métricas de avaliação
mae = mean_absolute_error(test_data['d'], y_pred)
mse = mean_squared_error(test_data['d'], y_pred)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((test_data['d'] - y_pred) / test_data['d'])) *
100

# Plotar um gráfico de barras comparando os valores estimados e
desejados
plt.figure(figsize=(10, 6))
plt.bar(np.arange(len(test_data['d'])), test_data['d'], width=0.4,
label='Desejado', color='blue', align='center')
plt.bar(np.arange(len(y_pred)) + 0.4, y_pred, width=0.4,
label='Estimado', color='orange', align='center')
plt.xlabel('Amostra')
plt.ylabel('Valor')
plt.title('Valores Desejados vs. Estimados')
plt.legend()
plt.show()

# Exibir as métricas de avaliação
print('Mean Absolute Error (MAE):', mae)
print('Mean Squared Error (MSE):', mse)
```

```python
print('Root Mean Squared Error (RMSE):', rmse)
print('Mean Absolute Percentage Error (MAPE):', mape)
```




```
Mean Absolute Error (MAE): 0.02990738521857437
Mean Squared Error (MSE): 0.001412530598836247
Root Mean Squared Error (RMSE): 0.03758364802458972
Mean Absolute Percentage Error (MAPE): 4.948898357013116
```