```
In [1]: import numpy as np
    import pandas as pd
    import matplotlib.pyplot as plt
    from sklearn.neural_network import MLPRegressor
    from sklearn.model_selection import train_test_split
    from sklearn.metrics import mean_squared_error
```

## Out[2]:

	<b>x</b> 1	<b>x2</b>	У
0	0.996321	2.901429	-61.310885
1	3.855952	2.197317	64.918210
2	-0.751851	1.311989	64.317646
3	-1.535331	2.732352	53.659943
4	2.808920	2.416145	120.558418

The dataset consists of continuous numbers without distinct classes/categories. Hence, the problem represents to be of Regression .

```
In [3]: X = df2.iloc[:, 0:2]
y = df2.iloc[:, 2]
```

```
pd.plotting.scatter_matrix(df2)
In [4]:
Out[4]: array([[<Axes: xlabel='x1', ylabel='x1'>,
                <Axes: xlabel='x2', ylabel='x1'>,
                <Axes: xlabel='y', ylabel='x1'>],
                [<Axes: xlabel='x1', ylabel='x2'>,
                <Axes: xlabel='x2', ylabel='x2'>,
                <Axes: xlabel='y', ylabel='x2'>],
                [<Axes: xlabel='x1', ylabel='y'>, <Axes: xlabel='x2', ylabel='y'>,
                <Axes: xlabel='y', ylabel='y'>]], dtype=object)
             5.0
             2.5
          Z
             0.0
            Q 2
            200
                                   1 2
                          x1
                                                х2
                                                                       У
```

It is observed that there exists a correlation between the dependent variable (y) and each of the independent variables (x1 & x2), while the independent variables themselves do not appear to be correlated with each other.

```
In [5]: X train, X test, y train, y test = train_test_split(X, y, test_size = 0.3, random_state = 42)
In [6]: # After working with multiple values of learning rates, this is the best list of values found.
                      learning rates = [0.3, 0.31, 0.32, 0.33, 0.34, 0.35, 0.36, 0.37, 0.38, 0.39, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49, 0.49, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49, 0.49, 0.40, 0.41, 0.42, 0.43, 0.44, 0.45, 0.46, 0.47, 0.48, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49, 0.49,
In [7]: training scores = []
                      testing scores = []
                      mse scores = []
                      for learning rate in learning rates:
                                # Selecting a Non-Linear model (Neural Network - MLPRegressor) for making predictions.
                                reg2 = MLPRegressor(learning rate='constant', learning rate init=learning rate,
                                                                                      hidden layer sizes = (100), max iter = 1000, solver = 'adam', random state=42)
                                reg2.fit(X train, y train)
                                r2 train score = reg2.score(X train, y train)
                                r2 test score = reg2.score(X test, v test)
                                y pred = reg2.predict(X test)
                                mse = mean squared error(y test, y pred)
                                mse scores.append(mse)
                                training scores.append(r2 train score)
                                testing scores.append(r2 test score)
                      # Checking for model convergence with an if-else statement; if not converged, we increase 'max iter'.
                      if reg2.n_iter_ < reg2.max_iter:</pre>
                                print("The model has converged.")
                      else:
                                print("The model has Not converged.")
```

The model has converged.

```
In [8]: print('Coefficient of Determination of Train Set:\n')
    print(training_scores)
    print()
    print('Coefficient of Determination of Test Set:\n')
    print(testing_scores)
    print()
    print('MSE:\n')
    print(mse_scores)
```

Coefficient of Determination of Train Set:

[0.7730642052912683, 0.7677638472768495, 0.7724642933581752, 0.7619249160886976, 0.8567104757916885, 0.7894969488796 887, 0.8095611119337671, 0.7592192818963264, 0.7757107478716891, 0.7539608646496643, 0.7962787455495366, 0.761504838 1993054, 0.733351543175701, 0.7490123854269676, 0.7057243373677201, 0.757411015532255, 0.799655056678284, 0.72522462 33227142, 0.6843151324488479, 0.7141793350228858, 0.7128471241402085]

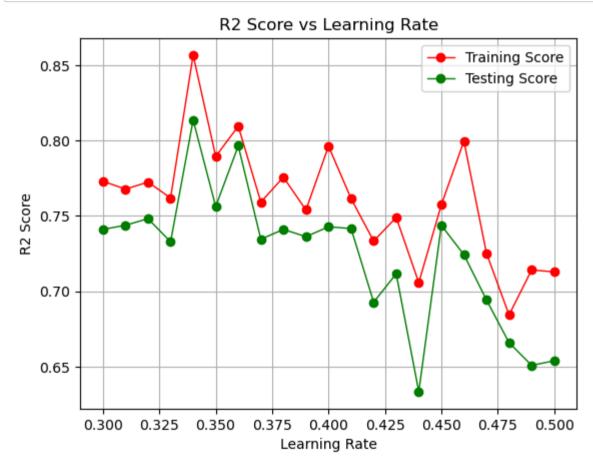
Coefficient of Determination of Test Set:

[0.7410613438333771, 0.743816620637574, 0.7481623750190556, 0.732828051830944, 0.8136403449058549, 0.756247106753374 1, 0.7964986609931246, 0.7345622010280182, 0.7410543169927741, 0.7362630226057589, 0.7427911569765824, 0.74163700327 19088, 0.6927799469013534, 0.7116160163508597, 0.6333530872398101, 0.7437452128969304, 0.7242734796369141, 0.6942357 483923105, 0.6659018910871475, 0.650859546718688, 0.6538554687518061]

## MSE:

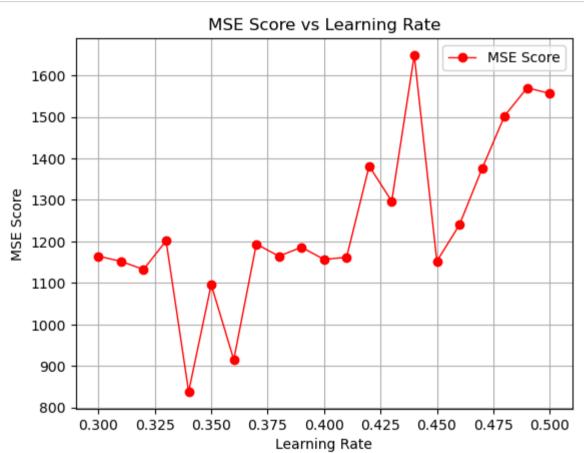
[1164.4135790452365, 1152.0234563330414, 1132.481162077307, 1201.4376261682298, 838.035217260776, 1096.125171227023 7, 915.1191483013409, 1193.6393819699429, 1164.4451778367688, 1185.9910077566306, 1156.6348335192572, 1161.824913154 035, 1381.5287639125938, 1296.825400700842, 1648.7636502533533, 1152.3445676884696, 1239.9064286758069, 1374.9822132 756196, 1502.3958975871337, 1570.039370765731, 1556.5670976460356]

```
In [9]: plt.plot(learning_rates, training_scores, label='Training Score', marker = 'o', linewidth = 1, color = 'red')
plt.plot(learning_rates, testing_scores, label='Testing Score', marker = 'o', linewidth = 1, color = 'green')
plt.xlabel('Learning Rate')
plt.ylabel('R2 Score')
plt.title('R2 Score vs Learning Rate')
plt.grid()
plt.legend()
plt.show()
```



The graph above shows us which Learning Rate gives us the highest R2-Score for both the Training Data and Testing Data.

```
In [10]: plt.plot(learning_rates, mse_scores, label='MSE Score', marker = 'o', linewidth = 1, color = 'red')
    plt.xlabel('Learning Rate')
    plt.ylabel('MSE Score')
    plt.title('MSE Score vs Learning Rate')
    plt.grid()
    plt.legend()
    plt.show()
```



The graph above shows us which learning rate gives us the Lowest MSE Score.

```
In [11]: # Selecting the best learning rate based on maximum test R2-Score achieved.
         blr = learning rates[np.argmax(testing scores)]
         print("Best Learning Rate:", blr)
         Best Learning Rate: 0.34
In [12]: # Selecting the best Learning rate based on minimum MSE score achieved.
         blr = learning rates[np.argmin(mse scores)]
         print(f"Best Learning Rate:", blr)
         Best Learning Rate: 0.34
In [13]: # Constructing a Best Regression Model using the identified Best Learning Rate.
         best reg2 = MLPRegressor(learning rate='constant', learning rate init=blr, hidden layer sizes=(100), solver = 'adam',
         best reg2.fit(X train, y train)
Out[13]:
                                           MLPRegressor
         MLPRegressor(hidden layer sizes=100, learning rate init=0.34, random state=42)
In [14]: | mse train = mean squared error(y train, best reg2.predict(X train))
         mse test = mean squared error(y test, best reg2.predict(X test))
         print("Mean Squared Error on Training Set:", mse_train)
         print("Mean Squared Error on Test Set:", mse test)
         Mean Squared Error on Training Set: 810.8100968899438
         Mean Squared Error on Test Set: 838.035217260776
```

After testing different learning rates, the rate of 0.34 gave the lowest MSE Scores: 810.810 for Training and 838.035 for Testing.

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```
In [15]: print('Generalization Error:', mse_test - mse_train)
```

Generalization Error: 27.2251203708322

A Generalization Error of 27.22 indicates that our model predicts with High Accuracy due to its low positive value.