

CS 454 Introduction to Machine Learning and Artificial Neural Networks

Homework 1 Report

Polynomial Regression and Model Selection

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Submission Date	14.03.2022

1 Introduction

In this assignment, we implement a Polynomial Regression, and we see how model selection can be done.

In this assignment, we have the one Test data set with 100 instances and 10 Training data set files each containing 25 instances. In each data set, the first column in each row is the Input - X and the second column is the desired Output - R.

1.1 Polynomial Regression

Polynomial Regression is a form of Linear regression known as a special case of Multiple linear regression which estimates the relationship as an nth degree polynomial. Polynomial Regression is sensitive to outliers so the presence of one or two outliers can also badly affect the performance.

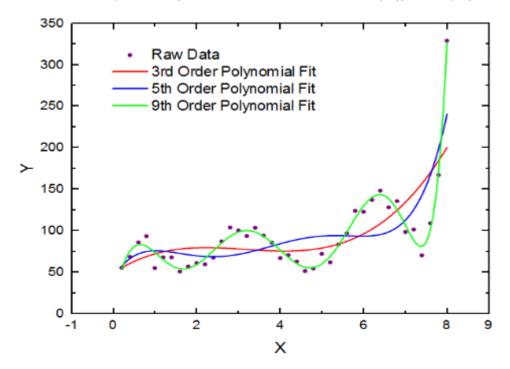


Figure 1: Example of Polynomial Regression [1]

2 Methodology

In this assignment, we apply a Polynomial Regression model methodology using Python Programming Language.

During this assignment, using only 5 different Python programming language libraries these are;

- 1. NumPy
- 2. Pandas
- 3. Scikit-Learn
- 4. Matplotlib were used.

NumPy library is used to polyfit function to find the polynomials and create the polynomial regression model. Pandas library is used to make a DataFrame. I used to Scikit-Learn library in order to use the mean_square_error function. Finally, I used the Matplotlib in order to plot and visualized the result data.

3 Implementation Details

In this assignment, firstly we import the necessary libraries which are Pandas, NumPy, Matplotlib and Scikit-Learn. After importing these libraries, we read the csv file with the help of the pandas library in Python and we have 10 sample training data .csv file & 1 testing data .csv file and after reading the 10 sample training data, I append these data to the list.

Figure 2: Libraries and Reading Training & Test Files

After reading the training & testing data, I separate the Input – X & Output – R list for each testing and training data. I separate the input and output data in order to use these values in the calculation for prediction and etc.

```
Seperate Input - X & Output - R

train_x = []
train_r = []

for index in range(10):
    train_x.append(trainDataFrame[index]['X'].values)
    train_r.append(trainDataFrame[index]['R'].values)

test_x = testDataFrame['X'].values
    test_r = testDataFrame['X'].values

Python

[5]
```

Figure 3: Separate the Data to Input & Output Data

After this process, I plot the whole training data and testing data in order to see the visualize distribution for the data.

```
Ploting the Whole Training & Testing Data

plt.title('Training Data', fontweight="bold', style="italic")
  plt.xlabel("Input - X", fontweight="bold', style="italic")
  plt.ylabel("Output - R", fontweight="bold", style="italic")
  plt.scatter(train_x, train_r, color = 'g')
  plt.show()

plt.title('Testing Data', fontweight="bold", style="italic")
  plt.xlabel("Input - X", fontweight="bold", style="italic")
  plt.ylabel("Output - R", fontweight="bold", style="italic")
  plt.scatter(test_x, test_r, color = 'b')
  plt.show()
```

Figure 4: Plotting the Existing Whole Data

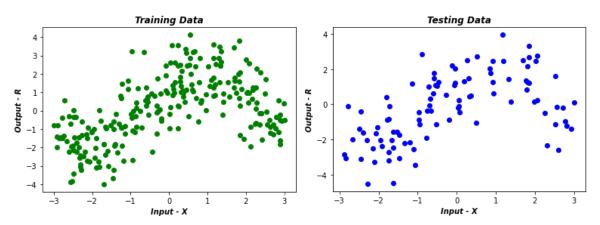


Figure 5: Visualizing Whole Training & Testing Data

3.1 Applying Polynomial Regression Model Strategy

3.1.1 Polynomials Fit of Degree 1

In this part, I fit polynomials of degree 1, 2, 3, 4, 5 and 6 to the ten data sets separately with using polyfit. For each degree, I have ten fits for the ten training sets. I plot these ten fits for each degree, and I calculate their mean square error values on the test set for each degree.

```
Polynomials Fit of Degree 1

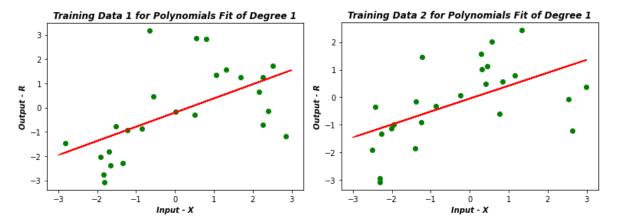
+ Code + Markdown

polyFit1 = []

for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 1)
    polyFit1.append(fit)

for index in range(10):
    plt.title('Training Data () for Polynomials Fit of Degree 1'.format(index+1), fontweight-"bold", style="italic")
    plt.xlabel('Input - X', fontweight-"bold', style="italic")
    plt.xlabel('Output - A', fontweight-"bold', style="italic")
    plt.xlater(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.polyid(polyFit1[index])(train_x), color = 'r')
    plt.show()

Python
```



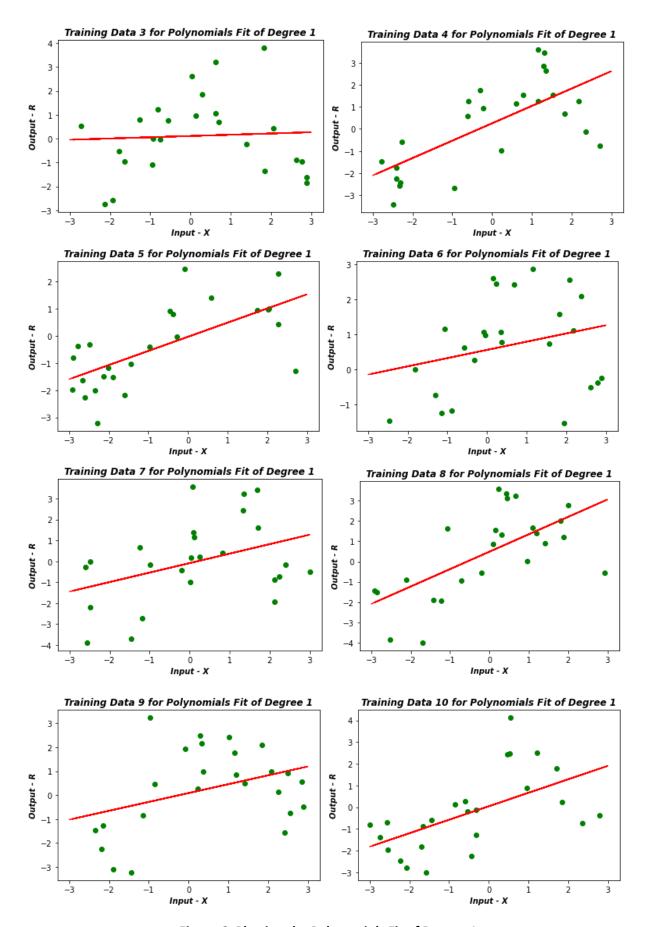


Figure 6: Plotting the Polynomials Fit of Degree 1

After plotting the ten fits for degree 1, I calculate the prediction for the degree 1 with using the formula y = mx + n which is m = polyFit1[indexx][0], $x = test_x[index]$ and n = polyFit1[indexx][1].

```
Prediction for Each Model

predictionList1 = []

for indexx in range(10):
    predictionList1.append([])
    for index in range(20):
        predictionList1.append([])
        prediction = polyFit1[indexx][0] * test_x[index] + polyFit1[indexx][1]
        predictionList1[indexx].append(prediction)

Python
```

Figure 7: Degree 1 Prediction for Each Model

After Calculated the prediction value, I use the mean_squared_error function from the Scikit-Learn and I calculate the MSE value for each 10 model for degree 1.

```
Calculating Mean Squared Error for Each Model

MeanSquaredError1 = []
for index in range(18):
    mse = mean squared error(test_r, predictionList1[index])
    MeanSquaredError1.append(mse)

Python

for index, mse in enumerate(MeanSquaredError1):
    print('MSE for Model () & Degree 1: ()'.format(index*i, mse))

***

MSE for Model 1 & Degree 1: 2.5672725281350113
MSE for Model 2 & Degree 1: 2.6695481409062464
MSE for Model 3 & Degree 1: 3.444971659701764
MSE for Model 3 & Degree 1: 3.445554764623103
MSE for Model 5 & Degree 1: 3.445554764623103
MSE for Model 6 & Degree 1: 3.45554764623103
MSE for Model 8 & Degree 1: 3.45554764624155
MSE for Model 8 & Degree 1: 3.69378178079067153
MSE for Model 9 & Degree 1: 2.751185396940917
MSE for Model 0 & Degree 1: 2.51185396940917
MSE for Model 0 & Degree 1: 2.58887038782040977
```

Figure 8: Degree 1 MSE for Each Model

After making the MSE calculation for each model, I calculate the average mean square error for degree 1's model.

```
    Calculating Avarage Mean Squared Error for Each Model

    total = 0
    length = len(MeanSquaredError1)

    for index in range(10):
        total += MeanSquaredError1[index]

    averageMSE1 = total/length
    print('Avarage MSE1:', averageMSE1)

Python

Avarage MSE1: 2.8471105575141773

Python

P
```

Figure 9: Average MSE for Degree 1

I repeat all the steps I have applied above for each degree.

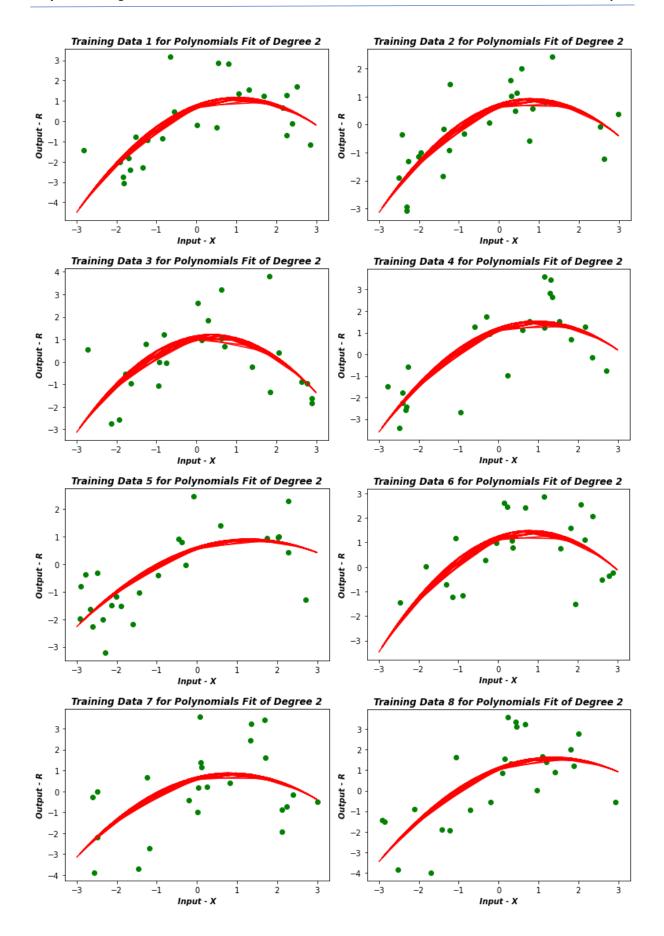
3.1.2 Polynomials Fit of Degree 2

```
Polynomials Fit of Degree 2

polyFit2 = []
    for index in range(i0):
        fit = np.polyFit(train_x[index], train_r[index], 2)
        polyFit2.append(fit)

for index in range(i0):
        plt.title('Training Data () for Polynomials Fit of Degree 2'.format(index:1), fontweight="bold", style="italic")
        plt.xlabel('Traput = X'', fontweight="bold", style="italic")
        plt.ylabel('Toutut = R'', fontweight="bold", style="italic")
        plt.state('Training Data () for Polynomials Fit of Degree 2'.format(index:1), fontweight="bold", style="italic")
        plt.ylabel('Toutut = R'', fontweight="bold", style="italic")
        plt.stater(train_x[index], train_r[index], color = 'g')
        plt.plot(train_x, np.polyid(polyFit2[index])(train_x), color = 'r')
        plt.show()
```

Figure 10: Polynomials Fit of Degree 2



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Training Data 9 for Polynomials Fit of Degree 2

Training Data 10 for Polynomials Fit of Degree 2



Figure 11: Prediction – MSE and Average MSE for Degree 2

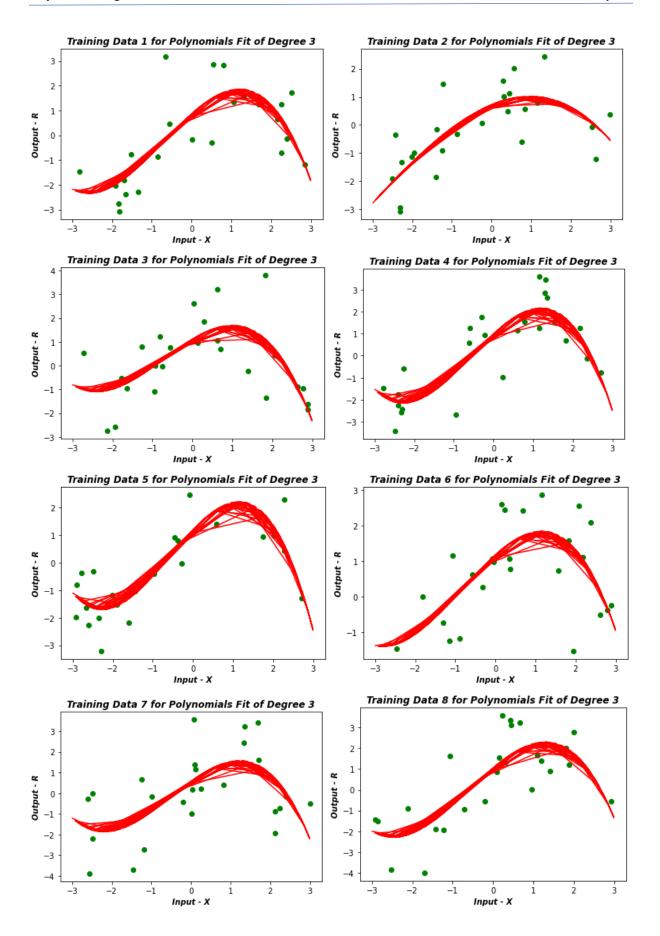
3.1.3 Polynomials Fit of Degree 3

```
polyrit3 = []

for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 3)
    polyFit3.append(fit)

for index in range(10):
    plt.title('Training Data () for Polynomials Fit of Degree 3'.format(index+1), fontweight-"bold", style="italic")
    plt.xlabel('Input - X", fontweight-"bold", style="italic")
    plt.ylabel('Output - R", fontweight-"bold", style="italic")
    plt.ylabel('Output - R", fontweight-"bold", style="italic")
    plt.scatter(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.polyid(polyFit3[index])(train_x), color = 'r')
    plt.show()
```

Figure 12: Polynomials Fit of Degree 3



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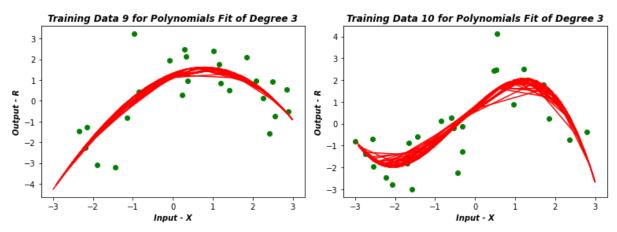


Figure 13: Plotting the Polynomials Fit of Degree 3

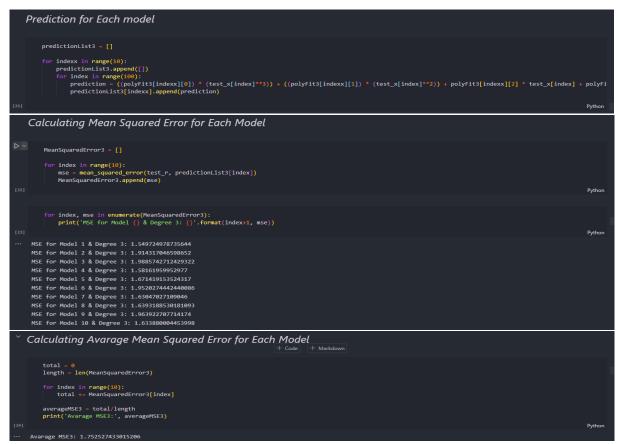


Figure 14: Prediction – MSE and Average MSE for Degree 3

3.1.4 Polynomials Fit of Degree 4

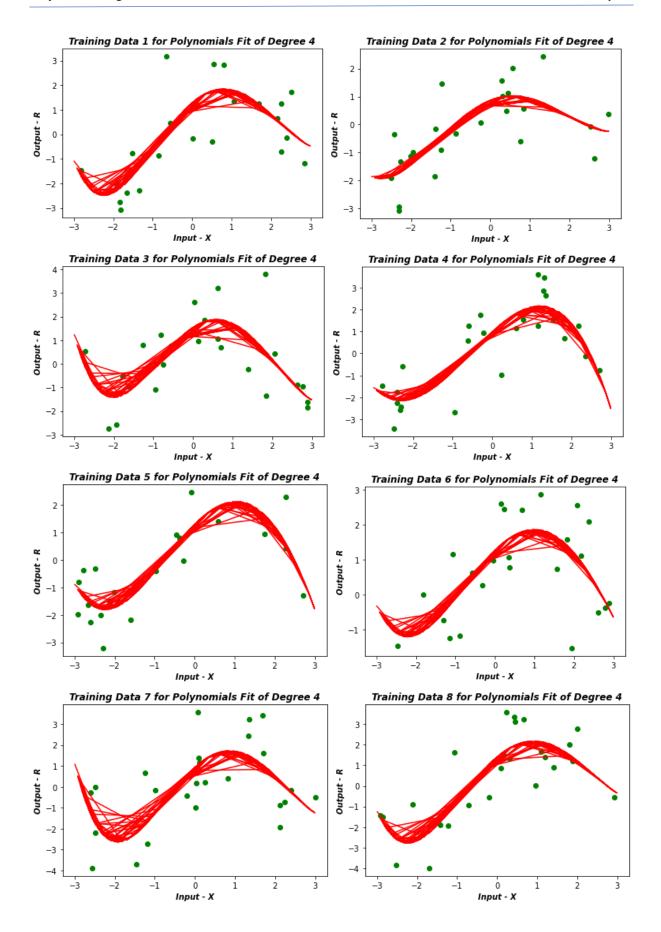
```
Polynomials Fit of Degree 4

polyfit4 = []

for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 4)
    polyfit4.append(fit)

for index in range(10):
    plt.title('Training Data () for Polynomials Fit of Degree 4'.format(index:1), fontweight="bold", style="italic")
    plt.xlabel('Output = R', fontweight="bold", style="italic")
    plt.ylabel('Output = R', fontweight="bold", style="italic")
    plt.scatter(train_x[index], rain_r[index], color = 'g')
    plt.plot(train_x, np.polyid(polyFit4[index])(train_x), color = 'r')
    plt.show()
```

Figure 15: Polynomials Fit of Degree 4



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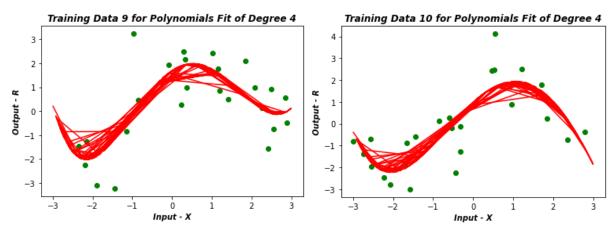


Figure 16: Plotting the Polynomials Fit of Degree 4

Figure 17: Prediction – MSE and Average MSE for Degree 4

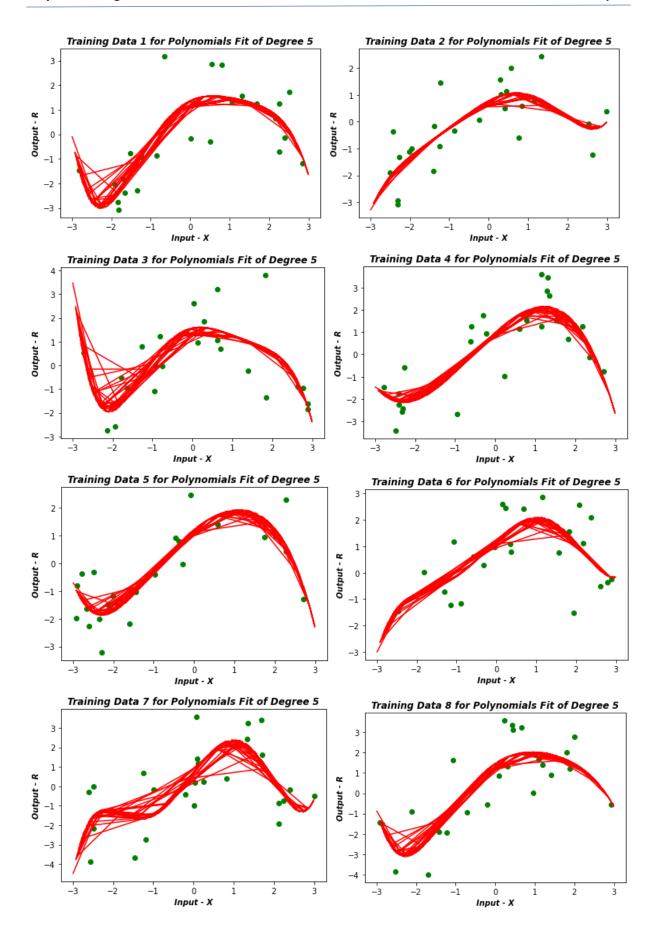
3.1.5 Polynomials Fit of Degree 5

```
Polynomials Fit of Degree 5

polyFit5 = []
    for index in range(18):
        fit = np.polyfit(train_x[index], train_r[index], 5)
        polyFit5.append(fit)

for index in range(10):
    plt.title('Training Data () for Polynomials Fit of Degree 5'.format(index+1), fontweight-"bold", style="italic")
    plt.xlabel('Input - X", fontweight-"bold", style="italic")
    plt.ylabel('Output - R", fontweight-"bold", style="italic")
    plt.ylabel('Output - R", fontweight-"bold", style="italic")
    plt.scatter(train x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit5[index])(train_x), color = 'r')
    plt.show()
```

Figure 18: Polynomials Fit of Degree 5



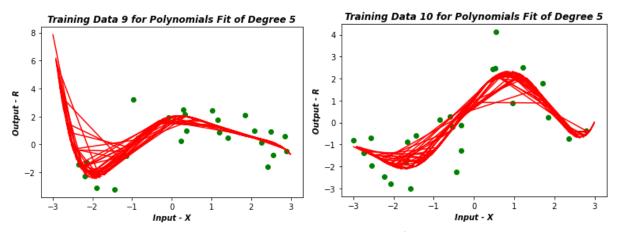


Figure 19: Plotting the Polynomials Fit of Degree 5

```
Prediction for Each model
     predictionList5 = []
     Calculating Mean Squared Error for Each Model
     MeanSquaredError5 = []
         index in range(10):
mse = mean_squared_error(test_r, predictionList5[index])
MeanSquaredError5.append(mse)
        r index, mse in enumerate(MeanSquaredError5):
    print('MSE for Model {} & Degree 5: {}'.format(index+1, mse))
                                                                                                                                                                                     Python
MSE for Model 2 & Degree 5: 1.985243595595827
MSE for Model 3 & Degree 5: 2.337159260799628
MSE for Model 4 & Degree 5: 1.5918528860579035
MSE for Model 5 & Degree 5: 1.661700393983935
 MSE for Model 6 & Degree 5: 2.0026098865789197
MSE for Model 7 & Degree 5: 1.9507208342183355
MSE for Model 8 & Degree 5: 1.7963050169128718
MSE for Model 9 & Degree 5: 3.453596649561328
Calculating Avarage Mean Squared Error for Each Model
      total = 0
length = len(MeanSquaredError5)
          index in range(10):
total += MeanSquaredError5[index]
      averageMSE5 = total/length
print('Avarage MSE5:', averageMSE5)
     arage MSE5: 2.025576128693103
```

Figure 20: Prediction – MSE and Average MSE for Degree 5

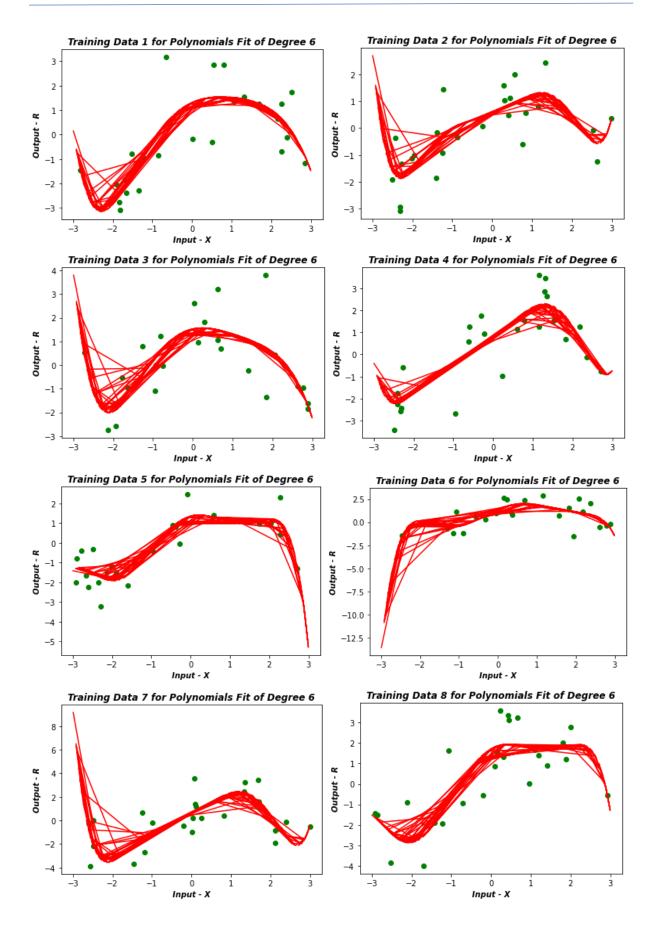
3.1.6 Polynomials Fit of Degree 6

```
Polynomials Fit of Degree 6

polyFit6 = []
    for index in range(10):
        fit = np.polyfit(train_x[index], train_r[index], 6)
        polyFit6.append(fit)

for index in range(10):
        plt.title('Training Data () for Polynomials Fit of Degree 6'.format(index:1), fontweight="bold", style="italic")
        plt.xlabel('Input - X', fontweight="bold", style="italic")
        plt.xlabel('Output - X', fontweight="bold", style="italic")
        plt.slabel('Output - X', fontweight="bold", style="italic")
        plt.slater(train_xindex], train_r[index], color = 'g')
        plt.slot('Crain_x, np.polyId(polyFit6[index])('train_x), color = 'r')
        plt.show()
```

Figure 21: Polynomials Fit of Degree 6



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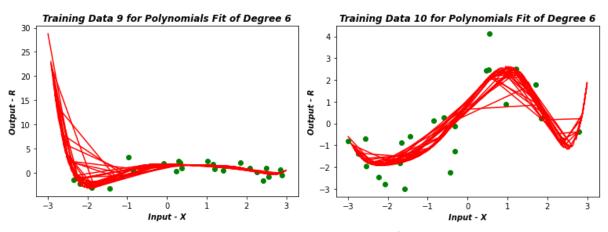


Figure 22: Plotting the Polynomials Fit of Degree 6

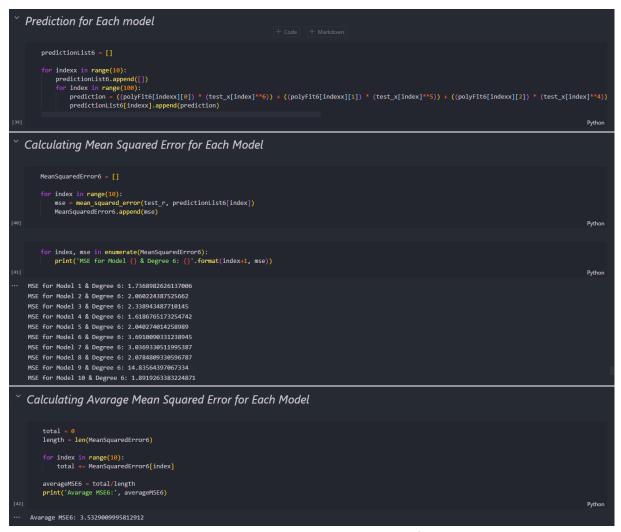


Figure 23: Prediction – MSE and Average MSE for Degree 6

4 Results

In this part, I plot the Average Mean Square Error for each degree.



Figure 24: Average Mean Square Error of Models with Different Degrees

As seen in Figure 1, the lowest error rate was found in the Degree 3 which is 1.7525. This demonstrates the importance of Degree 3 models in model selection.

5 Source Code

```
import pandas as pd
import numpy as np
from matplotlib import pyplot as plt
from sklearn.metrics import mean_squared_error
myTrainList = ['sample1.csv', 'sample2.csv', 'sample3.csv', 'sample4.csv',
'sample5.csv', 'sample6.csv', 'sample7.csv', 'sample8.csv', 'sample9.csv',
'sample10.csv']
trainDataFrame = []
for trainData in myTrainList:
    data = pd.read_csv(trainData, names=['X', 'R'], header=None)
    trainDataFrame.append(data)
testDataFrame = pd.read_csv('test.csv', names=['X', 'R'], header=None)
train_x = []
train_r = []
for index in range(10):
    train_x.append(trainDataFrame[index]['X'].values)
    train_r.append(trainDataFrame[index]['R'].values)
test_x = testDataFrame['X'].values
test_r = testDataFrame['R'].values
```

```
plt.title('Training Data', fontweight="bold", style="italic")
plt.xlabel("Input - X", fontweight="bold", style="italic")
plt.ylabel("Output - R", fontweight="bold", style="italic")
plt.scatter(train_x, train_r, color = 'g')
plt.show()
plt.title('Testing Data', fontweight="bold", style="italic")
plt.xlabel("Input - X", fontweight="bold", style="italic")
plt.ylabel("Output - R", fontweight="bold", style="italic")
plt.scatter(test_x, test_r, color = 'b')
plt.show()
polyFit1 = []
for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 1)
    polyFit1.append(fit)
for index in range(10):
    plt.title('Training Data {} for Polynomials Fit of Degree
1'.format(index+1), fontweight="bold", style="italic")
    plt.xlabel("Input - X", fontweight="bold", style="italic")
    plt.ylabel("Output - R", fontweight="bold", style="italic")
    plt.scatter(train x[index], train r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit1[index])(train_x), color = 'r')
    plt.show()
predictionList1 = []
for indexx in range(10):
    predictionList1.append([])
    for index in range(100):
        prediction = polyFit1[indexx][0] * test_x[index] + polyFit1[indexx][1]
        predictionList1[indexx].append(prediction)
MeanSquaredError1 = []
for index in range(10):
    mse = mean_squared_error(test_r, predictionList1[index])
    MeanSquaredError1.append(mse)
for index, mse in enumerate(MeanSquaredError1):
    print('MSE for Model {} & Degree 1: {}'.format(index+1, mse))
total = 0
length = len(MeanSquaredError1)
for index in range(10):
    total += MeanSquaredError1[index]
averageMSE1 = total/length
print('Avarage MSE1:', averageMSE1)
```

```
polyFit2 = []
for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 2)
    polyFit2.append(fit)
for index in range(10):
    plt.title('Training Data {} for Polynomials Fit of Degree
2'.format(index+1), fontweight="bold", style="italic")
    plt.xlabel("Input - X", fontweight="bold", style="italic")
    plt.ylabel("Output - R", fontweight="bold", style="italic")
    plt.scatter(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit2[index])(train_x), color = 'r')
    plt.show()
predictionList2 = []
for indexx in range(10):
    predictionList2.append([])
    for index in range(100):
        prediction = ((polyFit2[indexx][0]) * (test_x[index]**2)) +
polyFit2[indexx][1] * test_x[index] + polyFit2[indexx][2]
        predictionList2[indexx].append(prediction)
MeanSquaredError2 = []
for index in range(10):
    mse = mean_squared_error(test_r, predictionList2[index])
    MeanSquaredError2.append(mse)
for index, mse in enumerate(MeanSquaredError2):
    print('MSE for Model {} & Degree 2: {}'.format(index+1, mse))
total = 0
length = len(MeanSquaredError2)
for index in range(10):
    total += MeanSquaredError2[index]
averageMSE2 = total/length
print('Avarage MSE2:', averageMSE2)
polyFit3 = []
for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 3)
    polyFit3.append(fit)
for index in range(10):
    plt.title('Training Data {} for Polynomials Fit of Degree
3'.format(index+1), fontweight="bold", style="italic")
    plt.xlabel("Input - X", fontweight="bold", style="italic")
    plt.ylabel("Output - R", fontweight="bold", style="italic")
    plt.scatter(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit3[index])(train_x), color = 'r')
    plt.show()
```

```
predictionList3 = []
for indexx in range(10):
    predictionList3.append([])
    for index in range(100):
        prediction = ((polyFit3[indexx][0]) * (test_x[index]**3)) +
((polyFit3[indexx][1]) * (test_x[index]**2)) + polyFit3[indexx][2] *
test_x[index] + polyFit3[indexx][3]
        predictionList3[indexx].append(prediction)
MeanSquaredError3 = []
for index in range(10):
    mse = mean_squared_error(test_r, predictionList3[index])
    MeanSquaredError3.append(mse)
for index, mse in enumerate(MeanSquaredError3):
    print('MSE for Model {} & Degree 3: {}'.format(index+1, mse))
total = 0
length = len(MeanSquaredError3)
for index in range(10):
    total += MeanSquaredError3[index]
averageMSE3 = total/length
print('Avarage MSE3:', averageMSE3)
polyFit4 = []
for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 4)
    polyFit4.append(fit)
for index in range(10):
    plt.title('Training Data {} for Polynomials Fit of Degree
4'.format(index+1), fontweight="bold", style="italic")
    plt.xlabel("Input - X", fontweight="bold", style="italic")
    plt.ylabel("Output - R", fontweight="bold", style="italic")
    plt.scatter(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit4[index])(train_x), color = 'r')
    plt.show()
predictionList4 = []
for indexx in range(10):
    predictionList4.append([])
    for index in range(100):
        prediction = ((polyFit4[indexx][0]) * (test_x[index]**4)) +
((polyFit4[indexx][1]) * (test_x[index]**3)) + ((polyFit4[indexx][2]) *
(test_x[index]**2)) + polyFit4[indexx][3] * test_x[index] +
polyFit4[indexx][4]
        predictionList4[indexx].append(prediction)
```

```
MeanSquaredError4 = []
for index in range(10):
    mse = mean_squared_error(test_r, predictionList4[index])
    MeanSquaredError4.append(mse)
for index, mse in enumerate(MeanSquaredError4):
    print('MSE for Model {} & Degree 4: {}'.format(index+1, mse))
total = 0
length = len(MeanSquaredError4)
for index in range(10):
    total += MeanSquaredError4[index]
averageMSE4 = total/length
print('Avarage MSE4:', averageMSE4)
polyFit5 = []
for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 5)
    polyFit5.append(fit)
for index in range(10):
    plt.title('Training Data {} for Polynomials Fit of Degree
5'.format(index+1), fontweight="bold", style="italic")
    plt.xlabel("Input - X", fontweight="bold", style="italic")
    plt.ylabel("Output - R", fontweight="bold", style="italic")
    plt.scatter(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit5[index])(train_x), color = 'r')
    plt.show()
predictionList5 = []
for indexx in range(10):
    predictionList5.append([])
    for index in range(100):
        prediction = ((polyFit5[indexx][0]) * (test_x[index]**5)) +
((polyFit5[indexx][1]) * (test_x[index]**4)) + ((polyFit5[indexx][2]) *
(test_x[index]**3)) + ((polyFit5[indexx][3]) * (test_x[index]**2)) +
polyFit5[indexx][4] * test_x[index] + polyFit5[indexx][5]
        predictionList5[indexx].append(prediction)
MeanSquaredError5 = []
for index in range(10):
    mse = mean_squared_error(test_r, predictionList5[index])
    MeanSquaredError5.append(mse)
for index, mse in enumerate(MeanSquaredError5):
    print('MSE for Model {} & Degree 5: {}'.format(index+1, mse))
```

```
total = 0
length = len(MeanSquaredError5)
for index in range(10):
    total += MeanSquaredError5[index]
averageMSE5 = total/length
print('Avarage MSE5:', averageMSE5)
polyFit6 = []
for index in range(10):
    fit = np.polyfit(train_x[index], train_r[index], 6)
    polyFit6.append(fit)
for index in range(10):
    plt.title('Training Data {} for Polynomials Fit of Degree
6'.format(index+1), fontweight="bold", style="italic")
    plt.xlabel("Input - X", fontweight="bold", style="italic")
    plt.ylabel("Output - R", fontweight="bold", style="italic")
    plt.scatter(train_x[index], train_r[index], color = 'g')
    plt.plot(train_x, np.poly1d(polyFit6[index])(train_x), color = 'r')
    plt.show()
predictionList6 = []
for indexx in range(10):
    predictionList6.append([])
    for index in range(100):
        prediction = ((polyFit6[indexx][0]) * (test_x[index]**6)) +
((polyFit6[indexx][1]) * (test_x[index]**5)) + ((polyFit6[indexx][2]) *
(\text{test}_x[\text{index}]^{**4})) + ((\text{polyFit6}[\text{indexx}][3]) * (\text{test}_x[\text{index}]^{**3})) +
((polyFit6[indexx][4]) * (test_x[index]**2)) + polyFit6[indexx][5] *
test_x[index] + polyFit6[indexx][6]
        predictionList6[indexx].append(prediction)
MeanSquaredError6 = []
for index in range(10):
    mse = mean_squared_error(test_r, predictionList6[index])
    MeanSquaredError6.append(mse)
for index, mse in enumerate(MeanSquaredError6):
    print('MSE for Model {} & Degree 6: {}'.format(index+1, mse))
total = 0
length = len(MeanSquaredError6)
for index in range(10):
    total += MeanSquaredError6[index]
averageMSE6 = total/length
print('Avarage MSE6:', averageMSE6)
```

```
averageMSE = [averageMSE1, averageMSE2, averageMSE3, averageMSE4, averageMSE5,
averageMSE6]
# labels = ['Average MSE 1', 'Average MSE 2', 'Average MSE 3', 'Average MSE
4', 'Average MSE 5', 'Average MSE 6']

for index in range(6):
   plt.title('Average Mean Squared Error for Each Degree', fontweight="bold",
style="italic")
   plt.xlabel("Degree", fontweight="bold", style="italic")
   plt.ylabel("Average Mean Squared Error", fontweight="bold",
style="italic")
   plt.scatter('Degree {}'.format(index+1), averageMSE[index])
```

6 References

[1] Example of overfitting with polynomial regression ... (n.d.). Retrieved March 14, 2022, from https://www.researchgate.net/figure/Example-of-overfitting-with-polynomial-regression-lncreasing-the-order-of-the-polynomial_fig2_331733728