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```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
[5]: data=pd.read_csv("C:\\Users\\SAMUEL_
      →K\\Desktop\\Assignment\\student_scores_dataset.csv")
     data.head()
[5]:
        Study Hours Exam Scores
                3.7
                             87.9
     1
                9.5
                            143.6
     2
                7.3
                            123.7
                6.0
                             99.9
     3
                             64.5
     4
                1.6
[9]: x=np.array(data['Study Hours']).reshape(-1,1)
     X
[9]: array([[3.7],
            [9.5],
            [7.3],
            [6.],
            [1.6],
            [1.6],
            [0.6],
            [8.7],
            [6.],
            [7.1],
            [0.2],
            [9.7],
            [8.3],
            [2.1],
            [1.8],
            [1.8],
            [3.],
            [5.2],
            [4.3],
            [2.9],
```

- [6.1],
- [1.4],
- [2.9],
- [3.7],
- [4.6],
- [7.9],
- [2.],
- [5.1],
- [5.9],
- [0.5],
- [6.1],
- [1.7],
- [0.7],
- [9.5],
- [9.7],
- [8.1],
- [3.],
- [1.],
- [6.8],
- [4.4],
- [1.2],
- [5.],
- [0.3],
- [9.1],
- [2.6],
- [6.6],
- [3.1],
- [5.2],
- [5.5],
- [1.8],
- [9.7],
- [7.8],
- [9.4],
- [8.9],
- [6.], [9.2],
- [0.9],
- [2.],
- [0.5],
- [3.3],
- [3.9],
- [2.7],[8.3],
- [3.6],
- [2.8],
- [5.4],
- [1.4],

```
[8.],
             [0.7],
             [9.9],
             [7.7],
            [2.],
             [0.1],
             [8.2],
             [7.1],
             [7.3],
             [7.7],
             [0.7],
             [3.6],
            [1.2],
             [8.6],
             [6.2],
             [3.3],
             [0.6],
             [3.1],
             [3.3],
             [7.3],
            [6.4],
            [8.9],
            [4.7],
             [1.2],
             [7.1],
             [7.6],
             [5.6],
            [7.7],
            [4.9],
            [5.2],
             [4.3],
             [0.3],
             [1.1]
[10]: y=np.array(data['Exam Scores'])
[10]: array([ 87.9, 143.6, 123.7, 99.9, 64.5,
                                                67.4, 63.2, 134., 106.1,
            118.3, 56.6, 148.6, 130.6,
                                         73.8,
                                                68.7, 73.2, 76.9, 100.8,
                                         79.2,
                                                85.5, 88.5, 126.4, 68.3,
             91.2, 71.8, 112.7, 65.3,
             97.4, 108.4, 56.7, 120.2,
                                         67.9, 57.8, 144.5, 137., 130.7,
                   72.1, 117.5, 95.5,
                                         62., 93.7, 59.2, 144.7, 79.8,
             80.8,
            111.7, 88.2, 95., 107.6,
                                         79.4, 142. , 124.7, 144.4, 137. ,
            102., 142.5, 53.5, 72., 49.9, 90.3, 85., 75.5, 136.9,
             79.5, 79.2, 110.8, 56.1, 131.1, 58.8, 152.6, 121., 63.3,
             53.2, 133., 121.9, 124.6, 123.7, 58.6, 87.3, 58., 145.6,
            114.7, 77.1, 59.6, 76.2, 86.5, 128.8, 109.7, 143.5, 99.3,
```

у

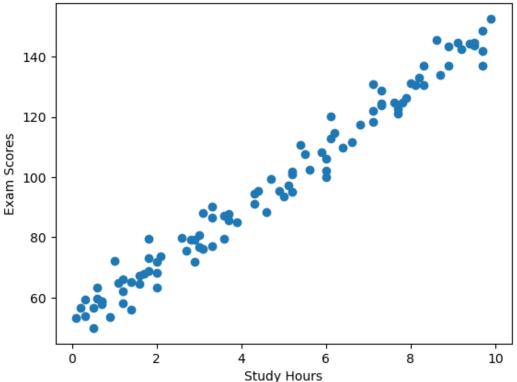
```
66.1, 130.8, 124.9, 102.4, 122.6, 95.3, 101.9, 94.5, 53.9, 64.9])
```

[12]: #checking for missing data data.isna().sum()

[12]: Study Hours 0
Exam Scores 0
dtype: int64

```
[13]: #ploting the graphs
plt.scatter(x,y)
plt.xlabel("Study Hours")
plt.ylabel("Exam Scores")
plt.title("The Relatonship between depent Variables and Indepedent Variables")
plt.show()
```

The Relatonship between depent Variables and Indepedent Variables



```
[26]: from sklearn.model_selection import train_test_split from sklearn.preprocessing import StandardScaler from sklearn.metrics import r2_score,mean_absolute_error,mean_squared_error from sklearn.linear_model import LinearRegression
```

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[33]: #splitting the data
      x_train,x_test,y_train,y_test = train_test_split(x,y,test_size =0.2,__
       →random_state=42)
[34]: #standardize the indepedent variabbles using scaling
      scaler=StandardScaler()
      x_train_scaled = scaler.fit_transform(x_train)
      x_test_scaled = scaler.transform(x_test)
[35]: #train the model using the variables of scaling
      model=LinearRegression()
      model.fit(x_train_scaled,y_train)
[35]: LinearRegression()
[43]: #making a prediction for y using scaled data
      y_pred=model.predict(x_test_scaled)
      print("y_pred", y_pred,("."))
     y pred [ 56.56910189 137.87943342 126.12372284 115.34765481 76.16195286
       93.79551874 79.10088051 134.94050578 52.6505317
                                                           86.9380209
       92.81587619 110.44944206 131.02193558 143.75728872 62.44695718
       66.36552738 126.12372284 57.54874444 132.00157813 67.34516992] .
[45]: #evaluating the performance of the model
      #finding the mean absolute error
      MAE=mean_absolute_error(y_test,y_pred)
      MAE
[45]: 2.9365732667749755
[46]: # finding mean squared error
      MSE=mean_squared_error(y_test,y_pred)
      MSE
[46]: 16.202109700645348
[47]: #finding r2 score
      r2=r2_score(y_test,y_pred)
      r2
[47]: 0.9826924926918468
[49]: # finding the coefficients and intercept
      model.intercept_
[49]: 96.5875
```

```
[52]: # getting the cefficient
      model.coef_
[52]: array([28.52556103])
[56]: #model optimization
      #implementing the necessary technniques to improve the model performance
      from sklearn.preprocessing import PolynomialFeatures
[62]: # adding a polynomial feature to improve the model
      poly_features = PolynomialFeatures(degree=2)
      x_train_pol = poly_features.fit_transform(x_train_scaled) # testing for a pol_
      \hookrightarrow featutre using the scaled x train
      x_{test_pol} = poly_{features.transform(x_{test_scaled}) # transforming our x_{test_l}
       ⇔scaled data
      #print("x_train_pol", x_train_pol)
[66]: # retrain the regression model on the updated dataset with polynomial features
      model_poly= LinearRegression()
      model_poly.fit(x_train_pol, y_train)
[66]: LinearRegression()
[69]: # making a prediction
      y_pred_poly = model_poly.predict(x_test_pol)
[70]: # evaluating the model using poly features
      MAE_poly = mean_absolute_error(y_test, y_pred_poly)
      MSE_poly = mean_squared_error(y_test, y_pred_poly)
      r2 = r2_score(y_test, y_pred_poly)
      print("mean_absolute_error",MAE)
      print("mean_squared_error",MSE)
      print("r2_score",r2)
     mean_absolute_error 2.9365732667749755
     mean_squared_error 16.202109700645348
     r2_score 0.9832890659571593
 []: According to the model the polynomial features optimized the model and
       →MAE, MSE, and r2_score had the same values
```