LR_MLR_PR_Mano

July 25, 2022

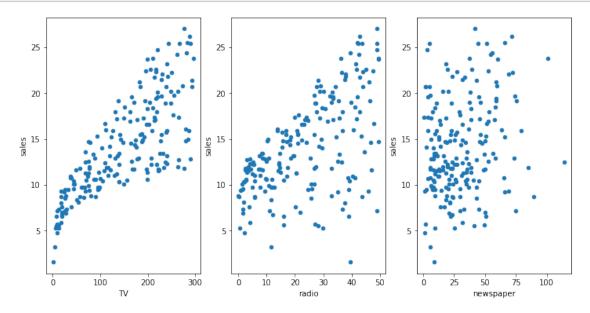
```
[1]: # importing the necessary Libraries
[2]: import numpy as np
     import pandas as pd
     import seaborn as sns
     import matplotlib.pyplot as plt
     np.random.seed(11)
[3]: # Importing the dataset
[4]: adv_data = pd.read_csv("Advertising.csv")
     adv_data.head()
[4]:
        Unnamed: 0
                       TV radio newspaper
                                             sales
                                       69.2
                 1
                   230.1
                            37.8
                                               22.1
                                       45.1
     1
                 2
                     44.5
                            39.3
                                               10.4
                            45.9
                                       69.3
     2
                 3
                     17.2
                                               9.3
                 4 151.5
                            41.3
                                       58.5
                                               18.5
                    180.8
                            10.8
                                       58.4
     4
                                               12.9
[5]: adv_data = pd.read_csv("Advertising.csv",index_col=0) ## Removing the first_
     → column
     adv_data.head()
[5]:
              radio
                      newspaper
                                 sales
           TV
     1 230.1
                37.8
                           69.2
                                  22.1
     2
       44.5
                39.3
                           45.1
                                  10.4
       17.2
               45.9
                           69.3
                                  9.3
     3
     4 151.5
                41.3
                           58.5
                                  18.5
     5 180.8
                10.8
                           58.4
                                  12.9
[6]: adv_data.shape
[6]: (200, 4)
[7]: adv_data.columns
```

```
[7]: Index(['TV', 'radio', 'newspaper', 'sales'], dtype='object')
```

```
[8]: # Scatter plot to view the relation between the features(Tv/radio/newspaper)

→ and Targert(Sales)
```

```
[9]: fig, axs = plt.subplots(1, 3)
adv_data.plot(kind='scatter', x='TV', y='sales', ax=axs[0], figsize=(12,6))
adv_data.plot(kind='scatter', x='radio', y='sales', ax=axs[1])
adv_data.plot(kind='scatter', x='newspaper', y='sales', ax=axs[2]);
```



```
[10]: # Checking the co-relation between the features and target
```

[11]: sns.heatmap(adv_data.corr(), annot = True);

```
- 1.0
           1
                        0.055
                                        0.057
≥
                                                                         - 0.8
         0.055
                                                        0.58
                           1
                                        0.35
                                                                         - 0.6
newspaper
         0.057
                         0.35
                                          1
                                                        0.23
                                                                         - 0.4
sales
                                                                         - 0.2
                         0.58
                                        0.23
                                                          1
          TV
                         radio
                                     newspaper
                                                        sales
```

```
[12]: ## Individually doing the linear regression for all the feature
[13]: adv_data.columns
[13]: Index(['TV', 'radio', 'newspaper', 'sales'], dtype='object')
[14]: # For only TV
      features_TV = adv_data[['TV']].values
      target_sales = adv_data[['sales']].values
[15]: # For only radio
      features_radio = adv_data[['radio']].values
      target_sales = adv_data[['sales']]
[16]: # For only newspaper
      features_newspaper = adv_data[['newspaper']].values
      target_sales = adv_data[['sales']]
[17]: ## Splitting the data as train and test data
      from sklearn.model_selection import train_test_split
[18]: X_train_TV, X_test_TV, y_train_TV, y_test_TV =
       →train_test_split(features_TV, target_sales, random_state=6)
```

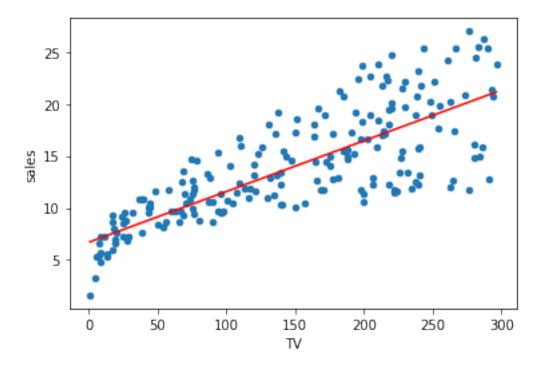
```
[19]: print(X_train_TV.shape)
      print(X_test_TV.shape)
      print(y_train_TV.shape)
      print(y_test_TV.shape)
     (150, 1)
     (50, 1)
     (150, 1)
     (50, 1)
[20]: X_train_radio,X_test_radio,y_train_radio,y_test_radio =_
       →train test split(features radio, target sales, random state=6)
[21]: print(X_train_radio.shape)
      print(X_test_radio.shape)
      print(y_train_radio.shape)
      print(y_test_radio.shape)
     (150, 1)
     (50, 1)
     (150, 1)
     (50, 1)
[22]: X_train_newspaper,X_test_newspaper,y_train_newspaper,y_test_newspaper =__
      -train_test_split(features_newspaper,target_sales,random_state=6)
[23]: print(X_train_newspaper.shape)
      print(X_test_newspaper.shape)
      print(y_train_newspaper.shape)
      print(y_test_newspaper.shape)
     (150, 1)
     (50, 1)
     (150, 1)
     (50, 1)
[24]: # importing the library
      from sklearn.linear_model import LinearRegression
[25]: my_tv_model = LinearRegression()
      my_radio_model = LinearRegression()
      my_newspaper_model = LinearRegression()
```

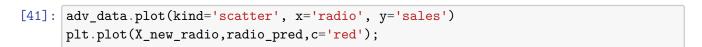
0.1 TV - Model Fit

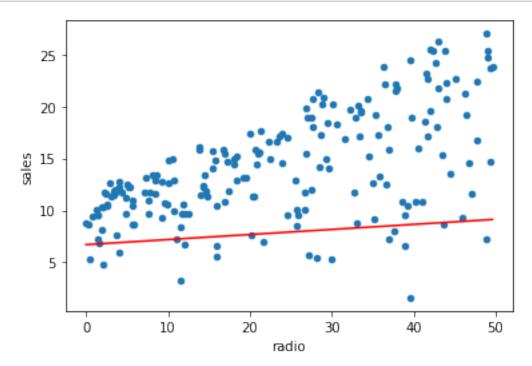
```
[26]: my_tv_model.fit(X_train_TV,y_train_TV)
[26]: LinearRegression()
[27]: my_tv_model.coef_
[27]: array([[0.04873499]])
[28]: my_tv_model.intercept_
[28]: array([6.70910349])
         Radio - Model Fit
     0.2
[29]: my_radio_model.fit(X_train_radio,y_train_radio)
[29]: LinearRegression()
[30]: my_radio_model.coef_
[30]: array([[0.21590796]])
[31]: my_radio_model.intercept_
[31]: array([9.17863927])
     0.3 Newspaper - Model Fit
[32]: my_newspaper_model.fit(X_train_newspaper,y_train_newspaper)
[32]: LinearRegression()
[33]: my_newspaper_model.coef_
[33]: array([[0.07750161]])
[34]: my_newspaper_model.intercept_
[34]: array([11.88037471])
```

0.4 Plot the best fit Line - TV/Radio/Newspaper

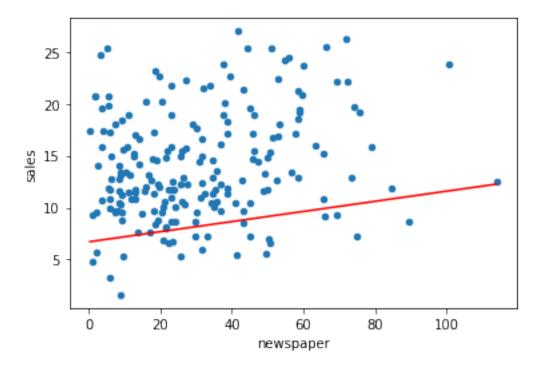
```
[35]: X_new_TV = pd.DataFrame({'TV':[adv_data.TV.min(),adv_data.TV.max()]})
      X_new_radio = pd.DataFrame({'radio':[adv_data.radio.min(),adv_data.radio.
       \rightarrowmax()]})
      X new_newspaper = pd.DataFrame({'newspaper':[adv_data.newspaper.min(),adv_data.
      →newspaper.max()]})
      X_new_TV.head()
[35]:
            TV
      0
           0.7
      1 296.4
[36]: X new radio.head()
[36]:
         radio
      0
           0.0
      1
          49.6
[37]: X_new_newspaper.head()
[37]:
         newspaper
      0
               0.3
             114.0
      1
[38]: TV_pred = my_tv_model.predict(X_new_TV)
      radio_pred = my_tv_model.predict(X_new_radio)
      newspaper_pred = my_tv_model.predict(X_new_newspaper)
     /usr/local/lib/python3.7/site-packages/sklearn/base.py:444: UserWarning: X has
     feature names, but LinearRegression was fitted without feature names
       f"X has feature names, but {self.__class__.__name__} was fitted without"
     /usr/local/lib/python3.7/site-packages/sklearn/base.py:444: UserWarning: X has
     feature names, but LinearRegression was fitted without feature names
       f"X has feature names, but {self. class . name } was fitted without"
     /usr/local/lib/python3.7/site-packages/sklearn/base.py:444: UserWarning: X has
     feature names, but LinearRegression was fitted without feature names
       f"X has feature names, but {self.__class__.__name__} was fitted without"
[39]: \#data.plot(kind='scatter', x='TV', y='sales')
      #plt.plot(X new,preds,c='red');
[40]: adv_data.plot(kind='scatter', x='TV', y='sales')
      plt.plot(X_new_TV,TV_pred,c='red');
```







```
[42]: adv_data.plot(kind='scatter', x='newspaper', y='sales')
plt.plot(X_new_newspaper,newspaper_pred,c='red');
```



0.5 STAT - Calculation

```
[43]: import statsmodels.formula.api as smf
[44]: adv_data.columns
[44]: Index(['TV', 'radio', 'newspaper', 'sales'], dtype='object')
[45]: my_stat_model_TV = smf.ols(formula='sales ~ TV', data=adv_data).fit()
      my_stat_model_TV.pvalues
[45]: Intercept
                   1.406300e-35
      TV
                   1.467390e-42
      dtype: float64
[46]: my_stat_model_radio = smf.ols(formula='sales ~ radio', data=adv_data).fit()
      my_stat_model_radio.pvalues
[46]: Intercept
                   3.561071e-39
      radio
                   4.354966e-19
```

1 Model Predication - for Train data - TV/Radio/Newspaper

[52]: model_TV_pred_train = my_tv_model.predict(X_train_TV)

model radio pred train = my radio model.predict(X train radio)

[50]: 0.05212044544430516

:2.56
Mean Absolute Error_Train_data - Radio - 'Predicted' and 'Actual_Test' value is :3.297

Mean Absolute Error_Train_data - TV - 'Predicted' and 'Actual_Test' value is

```
Mean Absolute Error_Train_data - Newspaper - 'Predicted' and 'Actual_Test' value is :4.171
```

```
[55]: #MSE
      TV_MSE_train = mean_squared_error(model_TV_pred_train,y_train_TV)
      Radio_MSE_train = mean_squared_error(model_radio_pred_train,y_train_TV)
      Newspaper_MSE_train = mean_squared_error(model_newspaper_pred_train,y_train_TV)
      print(" Mean Squared Error_Train_data - TV - 'Predicted' and 'Actual_Test'_
       →value is :{}".format(round(TV_MSE_train,3)))
      print(" Mean Squared Error Train data - Radio - 'Predicted' and 'Actual Test'
       →value is :{}".format(round(Radio_MSE_train,3)))
      print(" Mean Squared Error_Train_Data - Newspaper - 'Predicted' and
        → 'Actual_Test' value is :{}".format(round(Newspaper_MSE_train,3)))
       Mean Squared Error_Train_data - TV - 'Predicted' and 'Actual_Test' value is
      :10.892
       Mean Squared Error_Train_data - Radio - 'Predicted' and 'Actual_Test' value is
       Mean Squared Error_Train_Data - Newspaper - 'Predicted' and 'Actual_Test' value
      is:26.4
[134]: #RMSE
      TV_RMSE_train = np.sqrt(mean_squared_error(model_TV_pred_train,y_train_TV))
      Radio_RMSE_train = np.
       →sqrt(mean_squared_error(model_radio_pred_train,y_train_TV))
      Newspaper RMSE train = np.

¬sqrt(mean_squared_error(model_newspaper_pred_train,y_train_TV))
      print(" Root Mean Squared Error_Train_data - TV - 'Predicted' and 'Actual_Test'
       →value is :{}".format(round(TV_RMSE_train,3)))
      print(" Root Mean Squared Error_Train_data - Radio - 'Predicted' and⊔
       → 'Actual Test' value is :{}".format(round(Radio RMSE train,3)))
      print(" Root Mean Squared Error_Train_data - Newspaper - 'Predicted' and∟
        → 'Actual Test' value is :{}".format(round(Newspaper RMSE_train,3)))
       Root Mean Squared Error_Train_data - TV - 'Predicted' and 'Actual_Test' value
      is:3.3
       Root Mean Squared Error Train data - Radio - 'Predicted' and 'Actual Test'
      value is :4.298
       Root Mean Squared Error Train data - Newspaper - 'Predicted' and 'Actual Test'
      value is :5.138
[57]: # R- Squared on test data
      TV_R2_train = my_tv_model.score(X_train_TV,y_train_TV)
      Radio_R2_train = my_radio_model.score(X_train_radio,y_train_radio)
      Newspaper_R2_train = my_newspaper_model.
       →score(X_train_newspaper,y_train_newspaper)
      print(" R-squared value on Train Data - TV :{}".format(round(TV_R2_train,3)))
```

```
R-squared value on Train Data - TV :0.623
R-squared value on Train Data - Radio :0.361
R-squared value on Train Data - Newspaper :0.087
```



```
[58]: model_TV_pred = my_tv_model.predict(X_test_TV)
model_radio_pred = my_radio_model.predict(X_test_radio)
model_newspaper_pred = my_newspaper_model.predict(X_test_newspaper)
```

```
[59]: from sklearn.metrics import mean_squared_error,mean_absolute_error
```

3 Error - Predicted and Actual - Test data

```
Mean Absolute Error - TV - 'Predicted' and 'Actual_Test' value is :2.469

Mean Absolute Error - Radio - 'Predicted' and 'Actual_Test' value is :3.294

Mean Absolute Error - Newspaper - 'Predicted' and 'Actual_Test' value is :4.156
```

```
print(" Mean Squared Error - Newspaper - 'Predicted' and 'Actual_Test' value is⊔
       →:{}".format(round(Newspaper_MSE,3)))
      Mean Squared Error - TV - 'Predicted' and 'Actual_Test' value is :9.503
      Mean Squared Error - Radio - 'Predicted' and 'Actual_Test' value is :17.228
      Mean Squared Error - Newspaper - 'Predicted' and 'Actual Test' value is :24.681
[62]: #RMSE
      TV_RMSE = np.sqrt(mean_squared_error(model_TV_pred,y_test_newspaper))
      Radio_RMSE = np.sqrt(mean_squared_error(model_radio_pred,y_test_newspaper))
      Newspaper_RMSE = np.
      →sqrt(mean_squared_error(model_newspaper_pred,y_test_newspaper))
      print(" Root Mean Squared Error - TV - 'Predicted' and 'Actual_Test' value is :
       →{}".format(round(TV_RMSE,3)))
      print(" Root Mean Squared Error - Radio - 'Predicted' and 'Actual_Test' value∟
       →is :{}".format(round(Radio_RMSE,3)))
      print(" Root Mean Squared Error - Newspaper - 'Predicted' and 'Actual Test'
       →value is :{}".format(round(Newspaper_RMSE,3)))
      Root Mean Squared Error - TV - 'Predicted' and 'Actual_Test' value is :3.083
      Root Mean Squared Error - Radio - 'Predicted' and 'Actual_Test' value is :4.151
      Root Mean Squared Error - Newspaper - 'Predicted' and 'Actual_Test' value is
     :4.968
[63]: |\#print('R-squared\ on\ Train\ Data\ :',\ my_mlr_model.score(X_train,\ y_train)) -->_{\sqcup}
      \rightarrowReference line
      # R- Squared on test data
      TV_R2 = my_tv_model.score(X_test_TV,y_test_TV)
      Radio_R2 = my_radio_model.score(X_test_radio,y_test_radio)
      Newspaper_R2 = my_newspaper_model.score(X_test_newspaper,y_test_newspaper)
      print(" R-squared value on Test Data - TV :{}".format(round(TV_R2,3)))
      print(" R-squared value on Test Data - Radio :{}".format(round(Radio_R2,3)))
      print(" R-squared value on Test Data - Newspaper :{}".
       →format(round(Newspaper_R2,3)))
      R-squared value on Test Data - TV: 0.56
      R-squared value on Test Data - Radio :0.202
      R-squared value on Test Data - Newspaper :-0.143
          *********Multiple Linear Regression**********
[64]: adv_data
[64]:
              TV radio newspaper sales
      1
          230.1
                   37.8
                              69.2
                                     22.1
```

```
2
      3
            17.2
                   45.9
                               69.3
                                       9.3
      4
           151.5
                   41.3
                               58.5
                                      18.5
           180.8
                               58.4
                                      12.9
                   10.8
             •••
            38.2
                    3.7
                                       7.6
      196
                               13.8
      197
            94.2
                    4.9
                                8.1
                                       9.7
      198 177.0
                                      12.8
                    9.3
                                6.4
                   42.0
      199
           283.6
                               66.2
                                      25.5
      200
          232.1
                    8.6
                                8.7
                                      13.4
      [200 rows x 4 columns]
[65]: adv_data.columns
[65]: Index(['TV', 'radio', 'newspaper', 'sales'], dtype='object')
[66]: features_all = adv_data[['TV', 'radio', 'newspaper']]
      target_all = adv_data[['sales']]
[67]: features_all.head()
[67]:
            TV radio newspaper
      1 230.1
                 37.8
                             69.2
      2
          44.5
                 39.3
                             45.1
      3
          17.2
                 45.9
                             69.3
      4 151.5
                 41.3
                             58.5
      5 180.8
                 10.8
                             58.4
[68]: target_all.head()
[68]:
         sales
          22.1
      1
      2
          10.4
      3
           9.3
      4
          18.5
          12.9
```

10.4

45.1

1- Splitting the data as Train and test

44.5

39.3

```
[69]: from sklearn.linear_model import LinearRegression
      from sklearn.model_selection import train_test_split
[70]: X_train_all, X_test_all, y_train_all, y_test_all =__
       →train_test_split(features_all,target_all,random_state=10,test_size=.20)
```

```
[71]: # Getting the shape of the train and split data
      print(X_train_all.shape)
      print(X_test_all.shape)
      print(y_train_all.shape)
      print(y_test_all.shape)
     (160, 3)
     (40, 3)
     (160, 1)
     (40, 1)
[72]: # call the model
[73]: my_mlr_model = LinearRegression()
      my_mlr_model
[73]: LinearRegression()
[74]: my_mlr_model.fit(X_train_all,y_train_all)
[74]: LinearRegression()
[75]: my_mlr_model.coef_
[75]: array([[ 0.0437726 , 0.19343299, -0.00222879]])
[76]: my_mlr_model.intercept_
[76]: array([3.25409711])
```

5 Multiple linear regression - Model predict for new data (X_test)

```
[82]: MLR_predict = my_mlr_model.predict(X_test_all)
```

5.0.1 Evaluation on Train data

MAE on Train Data : 1.0661435033472693 MSE on Train Data : 1.8585966709492499 RMSE on Train Data : 1.3633035872281896 R-squared on Train Data : 0.9209087553499528

5.1 Evaluatio on test data

```
[84]: MLR_predict_test = my_mlr_model.predict(X_test_all)
#MLR_predict_test
```

MAE on Test Data : 1.8850130310423148 MSE on Test Data : 6.700486756528875 RMSE on Test Data : 2.58852984462781

R-squared on Test Data : 0.8353672324670594

5.2 OLS Model

```
[86]: my_ols_model = smf.ols(formula='sales ~ TV + radio + newspaper', data = →adv_data).fit()
```

[87]: my_ols_model.summary()

[87]: <class 'statsmodels.iolib.summary.Summary'>

OLS Regression Results

Dep. Variable:	sales	R-squared:	0.897					
Model:	OLS	Adj. R-squared:	0.896					
Method:	Least Squares	F-statistic:	570.3					
Date:	Mon, 25 Jul 2022	Prob (F-statistic):	1.58e-96					
Time:	22:43:31	Log-Likelihood:	-386.18					
No. Observations:	200	AIC:	780.4					
Df Residuals:	196	BIC:	793.6					
Df Model:	3							

Df Model: 3 Covariance Type: nonrobust

	coef	std err	t	P> t	[0.025	0.975]	
Intercept	2.9389	0.312	9.422	0.000	2.324	3.554	

TV	0.0458	0.001	32.809	0.000	0.043	0.049
radio	0.1885	0.009	21.893	0.000	0.172	0.206
newspaper	-0.0010	0.006	-0.177	0.860	-0.013	0.011
=========		========		========	========	========
Omnibus:		60	.414 Durb	in-Watson:		2.084
Prob(Omnibus	s):	0	.000 Jarq	ue-Bera (JB)	:	151.241
Skew:		-1	.327 Prob	(JB):		1.44e-33
Kurtosis:		6	.332 Cond	. No.		454.

Warnings:

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

11 11 11

 Polynominal

Regression

[88]: adv_data

```
[88]:
             TV radio newspaper
                                  sales
          230.1
                  37.8
                            69.2
                                   22.1
     1
     2
          44.5
                  39.3
                            45.1
                                   10.4
          17.2 45.9
     3
                            69.3
                                   9.3
     4
          151.5
                 41.3
                            58.5
                                  18.5
     5
          180.8 10.8
                            58.4
                                   12.9
     196
         38.2
                   3.7
                            13.8
                                   7.6
     197
          94.2
                   4.9
                             8.1
                                   9.7
     198 177.0 9.3
                                   12.8
                             6.4
     199 283.6
                                   25.5
                  42.0
                            66.2
     200 232.1
                  8.6
                             8.7
                                   13.4
```

[200 rows x 4 columns]

```
[89]: # Importing the necessary library for polynominal Regression from sklearn.preprocessing import PolynomialFeatures
```

[90]: adv_data.columns

[90]: Index(['TV', 'radio', 'newspaper', 'sales'], dtype='object')

5.4 converting the Features to Polynominal features - Degree 2

```
[92]: features_poly = PolynomialFeatures(degree=2)
      TV_poly2 = features_poly.fit_transform(features_all[['TV']])
      radio_poly2 = features_poly.fit_transform(features_all[['radio']])
      newspaper_poly2 = features_poly.fit_transform(features_all[['newspaper']])
[93]: # Checking the data - How will it looks in polynominal degree 2
      pd.DataFrame(TV_poly2, columns = ['constant', 'TV', 'TV-squared'])
[93]:
                            TV-squared
           constant
                        TV
                              52946.01
      0
                1.0 230.1
      1
                1.0
                      44.5
                               1980.25
      2
                1.0
                      17.2
                                295.84
      3
                1.0
                     151.5
                              22952.25
      4
                1.0
                     180.8
                              32688.64
      195
                1.0
                      38.2
                               1459.24
      196
                1.0
                      94.2
                               8873.64
                1.0 177.0
      197
                              31329.00
      198
                1.0
                     283.6
                              80428.96
      199
                1.0
                     232.1
                              53870.41
      [200 rows x 3 columns]
[94]: features_poly2 = pd.concat([pd.DataFrame(TV_poly2),pd.DataFrame(radio_poly2),pd.
       →DataFrame(newspaper_poly2)],axis=1)
      features_poly2
[94]:
             0
                    1
                                    0
                                          1
                                                        0
                                                              1
                                 1.0
                                       37.8
                                             1428.84
                                                      1.0
                                                           69.2
      0
           1.0
                230.1 52946.01
                                                                 4788.64
      1
           1.0
                 44.5
                        1980.25
                                 1.0
                                       39.3
                                             1544.49
                                                      1.0
                                                           45.1
                                                                 2034.01
      2
           1.0
                 17.2
                         295.84
                                 1.0
                                       45.9
                                             2106.81
                                                      1.0
                                                           69.3
                                                                 4802.49
      3
               151.5 22952.25
                                       41.3
                                             1705.69
                                                           58.5
                                                                 3422.25
           1.0
                                 1.0
                                                      1.0
      4
           1.0
               180.8 32688.64 1.0
                                       10.8
                                              116.64
                                                     1.0
                                                           58.4
                                                                 3410.56
                                       ... ...
      195
          1.0
                 38.2
                        1459.24 1.0
                                        3.7
                                               13.69
                                                     1.0
                                                           13.8
                                                                   190.44
                 94.2
                        8873.64 1.0
                                               24.01
      196
          1.0
                                        4.9
                                                      1.0
                                                            8.1
                                                                   65.61
      197
          1.0 177.0 31329.00
                                 1.0
                                        9.3
                                               86.49
                                                      1.0
                                                            6.4
                                                                   40.96
      198
          1.0
                283.6 80428.96
                                 1.0
                                      42.0
                                             1764.00
                                                      1.0
                                                           66.2
                                                                 4382.44
      199
          1.0 232.1 53870.41
                                 1.0
                                        8.6
                                               73.96
                                                      1.0
                                                            8.7
                                                                   75.69
      [200 rows x 9 columns]
[95]: target_all
```

```
[95]:
            sales
             22.1
       1
       2
             10.4
       3
              9.3
       4
             18.5
       5
             12.9
              •••
              7.6
       196
       197
             9.7
            12.8
       198
       199
             25.5
       200
             13.4
       [200 rows x 1 columns]
 [96]: # Splitting the data - test and train
 [97]: X_train_poly2, X_test_poly2, y_train_poly2, y_test_poly2 =__
        →train_test_split(features_poly2,target_all,random_state=6)
 [98]: print(X_train_poly2.shape)
       print(X_test_poly2.shape)
       print(y_train_poly2.shape)
       print(y_test_poly2.shape)
      (150, 9)
      (50, 9)
      (150, 1)
      (50, 1)
 [99]: from sklearn.linear_model import LinearRegression
[100]: my_model_ploy2 = LinearRegression()
       my_model_ploy2
[100]: LinearRegression()
[101]: my_model_ploy2.fit(X_train_poly2,y_train_poly2)
[101]: LinearRegression()
[102]: my_model_ploy2.coef_
[102]: array([[ 0.00000000e+00, 7.76366570e-02, -1.12220872e-04,
                6.95624114e-16, 1.46025928e-01, 9.36830450e-04,
               -2.77555756e-17, 2.13781336e-02, -2.07802344e-04]])
```

```
[103]: my_model_ploy2.intercept_
[103]: array([1.41776908])
```

6 Prediction and Evaluation on Train data - Degree 2

7 Predication and Evaluation on Test data - Degree 2

```
[106]: ## Orginal source data adv_data
```

```
[106]:
              TV radio newspaper sales
      1
           230.1
                   37.8
                             69.2
                                    22.1
                                   10.4
      2
           44.5 39.3
                             45.1
      3
           17.2 45.9
                             69.3 9.3
      4
          151.5 41.3
                             58.5 18.5
           180.8 10.8
                             58.4 12.9
      . .
            •••
                             •••
      196
            38.2
                  3.7
                             13.8
                                   7.6
      197 94.2 4.9
                             8.1
                                    9.7
      198 177.0 9.3
                              6.4
                                   12.8
      199 283.6 42.0
                             66.2
                                    25.5
      200 232.1 8.6
                              8.7
                                    13.4
      [200 rows x 4 columns]
[107]: # Columns of the dataset
      adv_data.columns
[107]: Index(['TV', 'radio', 'newspaper', 'sales'], dtype='object')
[109]: # Importing the necessary library for polynominal Regression
      from sklearn.preprocessing import PolynomialFeatures
      ## Converting the features to polynominal feature
      ## Degree--> 3
      features_poly3 = PolynomialFeatures(degree=3)
      TV_poly3 = features_poly3.fit_transform(features_all[['TV']])
      radio poly3 = features poly3.fit transform(features all[['radio']])
      newspaper_poly3 = features_poly3.fit_transform(features_all[['newspaper']])
      ## Degree--> 5
      features_poly5 = PolynomialFeatures(degree=5)
      TV_poly5 = features_poly5.fit_transform(features_all[['TV']])
      radio_poly5 = features_poly5.fit_transform(features_all[['radio']])
      newspaper poly5 = features poly5.fit transform(features all[['newspaper']])
      ## Degree--> 10
      features_poly10 = PolynomialFeatures(degree=10)
      TV poly10 = features poly10.fit transform(features all[['TV']])
      radio_poly10 = features_poly10.fit_transform(features_all[['radio']])
```

```
newspaper poly10 = features poly10.fit_transform(features_all[['newspaper']])
       ## Degree--> 100
       features_poly100 = PolynomialFeatures(degree=100)
       TV poly100 = features poly100.fit transform(features all[['TV']])
       radio_poly100 = features_poly100.fit_transform(features_all[['radio']])
       newspaper_poly100 = features_poly100.fit_transform(features_all[['newspaper']])
       ## Degree--> 150
       features_poly150 = PolynomialFeatures(degree=150)
       TV_poly150 = features_poly150.fit_transform(features_all[['TV']])
       radio_poly150 = features_poly150.fit_transform(features_all[['radio']])
       newspaper poly150 = features poly150.fit_transform(features_all[['newspaper']])
      /usr/local/lib/python3.7/site-packages/sklearn/preprocessing/_polynomial.py:469:
      RuntimeWarning: overflow encountered in multiply
        casting="no",
      /usr/local/lib/python3.7/site-packages/sklearn/preprocessing/_polynomial.py:469:
      RuntimeWarning: overflow encountered in multiply
        casting="no",
 []:
[110]: ## Concatenate the data
       #features_poly2 = pd.concat([pd.DataFrame(TV_poly2),pd.
       → DataFrame(radio_poly2), pd. DataFrame(newspaper_poly2)], axis=1)
       #features poly2
       features_poly3 = pd.concat([pd.DataFrame(TV_poly3),pd.DataFrame(radio_poly3),pd.
       →DataFrame(newspaper_poly3)],axis=1)
       features_poly5 = pd.concat([pd.DataFrame(TV_poly5),pd.DataFrame(radio_poly5),pd.
       →DataFrame(newspaper_poly5)],axis=1)
       features_poly10 = pd.concat([pd.DataFrame(TV_poly10),pd.
       →DataFrame(radio_poly10),pd.DataFrame(newspaper_poly10)],axis=1)
       features_poly100 = pd.concat([pd.DataFrame(TV_poly100),pd.
       →DataFrame(radio_poly100),pd.DataFrame(newspaper_poly100)],axis=1)
       features poly150 = pd.concat([pd.DataFrame(TV poly150),pd.
        →DataFrame(radio_poly150), pd. DataFrame(newspaper_poly150)], axis=1)
[111]: # Shape of the polynominal feature
       print(features_poly3.shape)
       print(features_poly5.shape)
       print(features_poly10.shape)
       print(features_poly100.shape)
```

```
print(features_poly150.shape)
      (200, 12)
      (200, 18)
      (200, 33)
      (200, 303)
      (200, 453)
[113]: target_all
[113]:
            sales
       1
             22.1
       2
             10.4
       3
              9.3
       4
             18.5
       5
             12.9
              •••
              7.6
       196
       197
              9.7
       198
             12.8
       199
             25.5
       200
             13.4
       [200 rows x 1 columns]
[114]: # Splitting the data - test and train
[116]: X_train_poly3, X_test_poly3, y_train_poly3, y_test_poly3 = ___
        →train_test_split(features_poly3,target_all,random_state=6)
                                                                                 ##_
        →Degree -->3 (Data split - Train and Test)
       X_train_poly5, X_test_poly5, y_train_poly5, y_test_poly5 =
        →train_test_split(features_poly5,target_all,random_state=6)
                                                                                 ##
        → Degree -->5 (Data split - Train and Test)
       X_train_poly10, X_test_poly10, y_train_poly10, y_test_poly10 =_
        →train_test_split(features_poly10, target_all, random_state=6)
                                                                             ## Degree
       \rightarrow -->10 (Data split - Train and Test)
       X train_poly100, X_test_poly100, y_train_poly100, y_test_poly100 =__
        →train_test_split(features_poly100,target_all,random_state=6) ## Degree_
        →-->100 (Data split - Train and Test)
       X_train_poly150, X_test_poly150, y_train_poly150, y_test_poly150 =_
        →train_test_split(features_poly150,target_all,random_state=6) ## Degree_
        \rightarrow -->150 (Data split - Train and Test)
[117]: print(X_train_poly3.shape)
       print(X_test_poly3.shape)
       print(y_train_poly3.shape)
       print(y_test_poly3.shape)
```

```
(150, 12)
      (50, 12)
      (150, 1)
      (50, 1)
[118]: from sklearn.linear_model import LinearRegression
[119]: my_model_ploy3 = LinearRegression()
       my_model_ploy5 = LinearRegression()
       my_model_ploy10 = LinearRegression()
       my_model_ploy100 = LinearRegression()
       my_model_ploy150 = LinearRegression()
[120]: my_model_ploy3.fit(X_train_poly3,y_train_poly3)
       my_model_ploy5.fit(X_train_poly5,y_train_poly5)
       my_model_ploy10.fit(X_train_poly10,y_train_poly10)
       my_model_ploy100.fit(X_train_poly100,y_train_poly100)
       \#my\_model\_ploy150.fit(X\_train\_poly150,y\_train\_poly150)
[120]: LinearRegression()
[135]: my_model_ploy150.fit(X_train_poly150,y_train_poly150)
      /usr/local/lib/python3.7/site-packages/numpy/core/fromnumeric.py:86:
      RuntimeWarning: overflow encountered in reduce
        return ufunc.reduce(obj, axis, dtype, out, **passkwargs)
              ValueError
                                                         Traceback (most recent call_
       →last)
              <ipython-input-135-08ed31da5842> in <module>
          ---> 1 my_model_ploy150.fit(X_train_poly150,y_train_poly150)
              /usr/local/lib/python3.7/site-packages/sklearn/linear_model/_base.py in_
       →fit(self, X, y, sample_weight)
              661
              662
                          X, y = self._validate_data(
          --> 663
                              X, y, accept_sparse=accept_sparse, y_numeric=True,_
       →multi_output=True
              664
              665
```

```
/usr/local/lib/python3.7/site-packages/sklearn/base.py in_
→_validate_data(self, X, y, reset, validate_separately, **check_params)
       579
                           y = check array(y, **check y params)
       580
                           X, y = check_X_y(X, y, **check_params)
  --> 581
       582
                       out = X, y
       583
       /usr/local/lib/python3.7/site-packages/sklearn/utils/validation.py in_
→check X_y(X, y, accept_sparse, accept_large sparse, dtype, order, copy, __
→force_all_finite, ensure_2d, allow_nd, multi_output, ensure_min_samples, u
→ensure_min_features, y_numeric, estimator)
       974
                   ensure_min_samples=ensure_min_samples,
       975
                   ensure min features=ensure min features,
   --> 976
                   estimator=estimator,
       977
               )
       978
       /usr/local/lib/python3.7/site-packages/sklearn/utils/validation.py in_
→check array(array, accept_sparse, accept_large_sparse, dtype, order, copy, ___
oforce_all_finite, ensure_2d, allow_nd, ensure_min_samples, □
→ensure_min_features, estimator)
       798
       799
                   if force_all_finite:
   --> 800
                       _assert_all_finite(array, allow_nan=force_all_finite ==_
→"allow-nan")
       801
       802
               if ensure_min_samples > 0:
       /usr/local/lib/python3.7/site-packages/sklearn/utils/validation.py inu
→_assert_all_finite(X, allow_nan, msg_dtype)
       114
                       raise ValueError(
       115
                           msg_err.format(
  --> 116
                               type_err, msg_dtype if msg_dtype is not None⊔
→else X.dtype
       117
                           )
       118
                       )
       ValueError: Input contains NaN, infinity or a value too large for⊔
→dtype('float64').
```

```
[121]: #print("Poly Degree 3 Coefficent : ", my_model_ploy3.coef_)
```

8 Prediction and Evaluation on Train data - Degree 3/5/10/100/150

8.1 Polynominal Degree 3 - Train data

Mean Squared Error for Deg-3: 2.120643703536337 RMSE for Deg-100: 1.456243009781107 R2 Score for Deg-3: 0.926647207589578

8.2 Polynominal Degree 5 - Train data

```
[124]: pred_poly5_train = my_model_ploy5.predict(X_train_poly5)

print("Mean Absolute Error for Deg-3 :__

→",mean_absolute_error(pred_poly5_train,y_train_poly5))

print("Mean Squared Error for Deg-3 :__

→",mean_squared_error(pred_poly5_train,y_train_poly5))

print("RMSE for Deg-100 : ", np.

→sqrt(mean_squared_error(pred_poly5_train,y_train_poly5)))
```

```
print("R2 Score for Deg-3 : ",my_model_ploy5.score(X_train_poly5,y_train_poly5))

Mean Absolute Error for Deg-3 : 1.0595851105502019

Mean Squared Error for Deg-3 : 1.8922826954150969

RMSE for Deg-100 : 1.3756026662576286

R2 Score for Deg-3 : 0.9345461854307959
```

8.3 Polynominal Degree 10 - Train data

Mean Absolute Error for Deg-3 : 1.6513966080825802 Mean Squared Error for Deg-3 : 4.710914902602763 RMSE for Deg-100 : 2.170464213619465 R2 Score for Deg-3 : 0.8370500606313366

8.4 Polynominal Degree 100 - Train data

Mean Absolute Error for Deg-3 : 4.1761220444034 Mean Squared Error for Deg-3 : 25.407476171600422 RMSE for Deg-100 : 5.040582919821915 R2 Score for Deg-3 : 0.12115867357620169

9 Prediction and Evaluation on Test data - Degree 3/5/10/100/150

```
[127]: #pred_poly2_test = my_model_ploy2.predict(X_test_poly2)
       #print("Mean Absolute Error for Deg-2 :□
       \rightarrow", mean_absolute_error(pred_poly2_test,y_test_poly2))
       #print("Mean Squared Error for Deg-2 :__
       → ", mean_squared_error(pred_poly2_test,y_test_poly2))
       \#print("R2\ Score\ for\ Deg-2: ",my_model_ploy2.score(X_test_poly2,y_test_poly2))
[128]: pred_poly3_test = my_model_ploy3.predict(X_test_poly3)
       print("Mean Absolute Error for Deg-3: LL
       →",mean_absolute_error(pred_poly3_test,y_test_poly3))
       print("Mean Squared Error for Deg-3 :...
       →",mean_squared_error(pred_poly3_test,y_test_poly3))
       print("RMSE for Deg-3 : ", np.
       →sqrt(mean_squared_error(pred_poly3_test,y_test_poly3)))
       print("R2 Score for Deg-3 : ",my_model_ploy3.score(X_test_poly3,y_test_poly3))
      Mean Absolute Error for Deg-3 : 1.011890531356669
      Mean Squared Error for Deg-3: 1.656634448047036
      RMSE for Deg-3 : 1.287103122537987
      R2 Score for Deg-3 : 0.9233001115404571
[129]: pred_poly5_test = my_model_ploy5.predict(X_test_poly5)
       print("Mean Absolute Error for Deg-5: __
       →",mean_absolute_error(pred_poly5_test,y_test_poly5))
       print("Mean Squared Error for Deg-5:
       →",mean_squared_error(pred_poly5_test,y_test_poly5))
       print("RMSE for Deg-5 : ", np.
       →sqrt(mean_squared_error(pred_poly5_test,y_test_poly5)))
       print("R2 Score for Deg-5 : ",my model_ploy5.score(X_test_poly5,y_test_poly5))
      Mean Absolute Error for Deg-5 : 1.042980523465403
      Mean Squared Error for Deg-5: 2.535458724171236
      RMSE for Deg-5 : 1.5923123827224468
      R2 Score for Deg-5 : 0.8826117605082016
[130]: pred_poly10_test = my_model_ploy10.predict(X_test_poly10)
       print("Mean Absolute Error for Deg-10: ...
       →",mean_absolute_error(pred_poly10_test,y_test_poly10))
       print("Mean Squared Error for Deg-10 :...
       →",mean_squared_error(pred_poly10_test,y_test_poly10))
       print("RMSE for Deg-10 : ", np.
        →sqrt(mean_squared_error(pred_poly10_test,y_test_poly10)))
```

```
print("R2 Score for Deg-10 : ",my_model_ploy10.
       ⇒score(X_test_poly10,y_test_poly10))
      Mean Absolute Error for Deg-10 : 1.9393912179254782
      Mean Squared Error for Deg-10: 5.43395305572854
      RMSE for Deg-10 : 2.3310840945209463
      R2 Score for Deg-10 : 0.7484154734557724
[131]: | pred_poly100_test = my_model_ploy100.predict(X_test_poly100)
       print("Mean Absolute Error for Deg-100 :...
       →",mean_absolute_error(pred_poly100_test,y_test_poly100))
       print("Mean Squared Error for Deg-100 :⊔
       →",mean_squared_error(pred_poly100_test,y_test_poly100))
       print("RMSE for Deg-100 : ", np.
       →sqrt(mean_squared_error(pred_poly100_test,y_test_poly100)))
       print("R2 Score for Deg-100 : ",my_model_ploy100.
        ⇒score(X test poly100,y test poly100))
      Mean Absolute Error for Deg-100 : 3.6754222244411863
      Mean Squared Error for Deg-100: 20.174031770485307
      RMSE for Deg-100 : 4.491551154165486
      R2 Score for Deg-100 : 0.06597017320289067
[132]: #print('RMSE on Train Data:', np.
       \rightarrow sqrt(mean_squared_error(MLR_predict_test,y_test)))
[133]: ##print("RMSE for Deg-100 : ", np.
        →sqrt(mean_squared_error(pred_poly100_test,y_test_poly100)))
 []:
```