Linear Regression Model using Python - ML - Advertising

Importing Libraries:

In [1]:

```
# import numpy, pandas, matplotlib, seaborn, statsmodels, and sklearn

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn.metrics import r2_score
from sklearn.model_selection import train_test_split
```

Data:

In [2]:

```
media = pd.read_csv(r"C:\Users\USP\Desktop\MFE Summer Assignments\Linear Regression Model
ing ML\Data\Company_data.csv")
print(media.head())
```

```
      TV  Radio  Newspaper  Sales
0  230.1   37.8       69.2   22.1
1   44.5   39.3       45.1   10.4
2   17.2   45.9       69.3   12.0
3  151.5   41.3       58.5   16.5
4  180.8   10.8       58.4   17.9
```

Understanding the Data:

In [3]:

```
# shape, info, and description

print(media.shape)

media.info()

media.describe()
```

```
(200, 4)
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 4 columns):
TV           200 non-null float64
Radio        200 non-null float64
Newspaper    200 non-null float64
Sales        200 non-null float64
dtypes: float64(4)
memory usage: 6.3 KB
```

Out[3]:

	TV	Radio	Newspaper	Sales
count	200.000000	200.000000	200.000000	200.000000
mean	147.042500	23.264000	30.554000	15.130500
std	85.854236	14.846809	21.778621	5.283892

	TV	Radio	Newspaper	Sales
min	0.700000	0.000000	0.300000	1.600000
25%	74.375000	9.975000	12.750000	11.000000
50%	149.750000	22.900000	25.750000	16.000000
75%	218.825000	36.525000	45.100000	19.050000
max	296.400000	49.600000	114.000000	27.000000

Data Visualization:

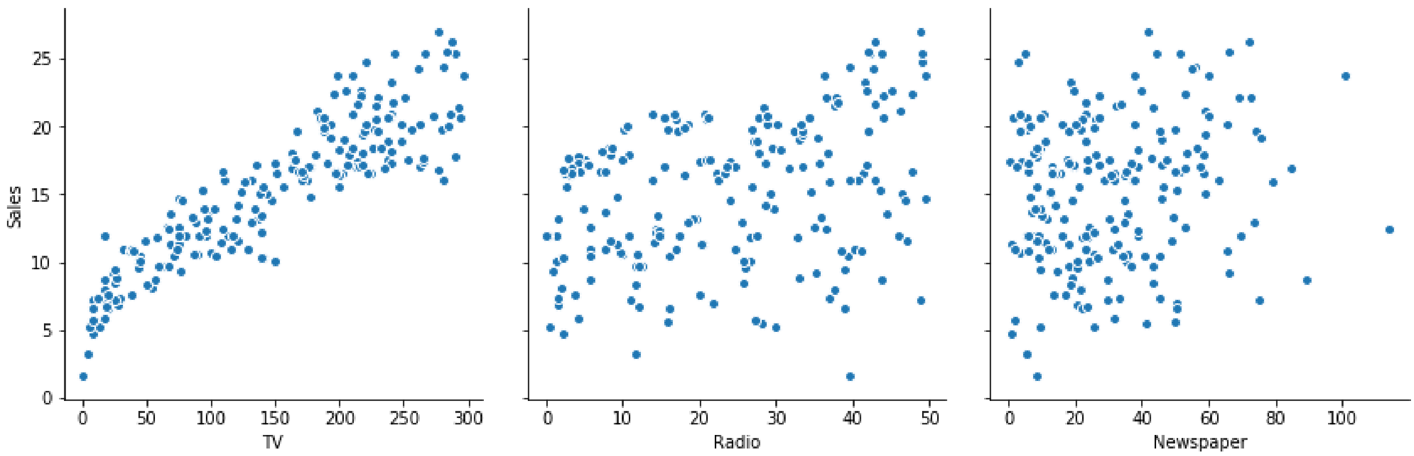
In [4]:

```
# importing as above seaborn and matplotlib for data visualisation and understanding patt
erns:

# for data correlation we will use pairplot

sns.pairplot(media, x_vars = ["TV", "Radio", "Newspaper"], y_vars = "Sales", size = 4, a
spect = 1, kind = "scatter")
print("This is the relation between different media streams with Sales: \n ")
plt.show()
```

```
This is the relation between different media streams with Sales:
```



Linear Regression:

In [5]:

```
# we will perform the linear regression using the following steps: creating X and Y, crea
ting Train and Test data, Training the data, and finally evaluating the model.


# our first independent variable will be "TV"
# dependent variable, Y

# creating X and Y:

X = media["TV"]
y = media["Sales"]
```

Splitting Data:

In [6]:

```
# Splitting data betweeen train and test data:

X_train, X_test, y_train, y_test = train_test_split(X, y, train_size = 0.7, test_size =
0.3, random_state = 100)
```

```
print(X_train)

print(y_train)
```

```
74     213.4
3      151.5
185    205.0
26     142.9
90     134.3
127     80.2
81     239.8
88      88.3
119     19.4
110    225.8
57     136.2
44      25.1
148     38.0
160    172.5
89     109.8
146    240.1
199    232.1
10      66.1
20     218.4
165    234.5
12      23.8
16      67.8
101    296.4
120    141.3
45     175.1
142    220.5
117     76.4
184    253.8
187    191.1
183    287.6
       ...
129     59.6
159    131.7
132      8.4
108     13.1
155      4.1
130      0.7
86      76.3
93     250.9
137    273.7
144     96.2
58     210.8
60      53.5
107     90.4
143    104.6
198    283.6
34      95.7
14     204.1
66      31.5
53     182.6
98     289.7
180    156.6
94     107.4
138     43.0
176    248.4
79     116.0
87     110.7
103    187.9
67     139.3
24      62.3
8        8.6
Name: TV, Length: 140, dtype: float64
74     17.0
3      16.5
185    22.6
26     15.0
90     14.0
127    11.9
```

```
81      17.3
88      12.9
119      6.6
110     18.4
57      13.2
44       8.5
148     10.9
160     16.4
89      16.7
146     18.2
199     18.4
10      12.6
20      18.0
165     16.9
12       9.2
16      12.5
101     23.8
120     15.5
45      16.1
142     20.1
117      9.4
184     17.6
187     17.3
183     26.2
        ...
129      9.7
159     12.9
132      5.7
108      5.3
155      3.2
130      1.6
86      12.0
93      22.2
137     20.8
144     12.3
58      23.8
60       8.1
107     12.0
143     10.4
198     25.5
34      11.9
14      19.0
66      11.0
53      21.2
98      25.4
180     15.5
94      11.5
138      9.6
176     20.2
79      11.0
87      16.0
103     19.7
67      13.4
24       9.7
8        4.8
Name: Sales, Length: 140, dtype: float64
```

Constructing and Training the model:

In [7]:

```
# importing statsmodels package to perform the linear regression
# we need to add constant c, as we have an intercept

X_train_sm = sm.add_constant(X_train)

X_train_sm
```

Out[7]:

	const	TV
74	1.0	213.4
3	1.0	151.5
185	1.0	205.0
26	1.0	142.9
90	1.0	134.3
127	1.0	80.2
81	1.0	239.8
88	1.0	88.3
119	1.0	19.4
110	1.0	225.8
57	1.0	136.2
44	1.0	25.1
148	1.0	38.0
160	1.0	172.5
89	1.0	109.8
146	1.0	240.1
199	1.0	232.1
10	1.0	66.1
20	1.0	218.4
165	1.0	234.5
12	1.0	23.8
16	1.0	67.8
101	1.0	296.4
120	1.0	141.3
45	1.0	175.1
142	1.0	220.5
117	1.0	76.4
184	1.0	253.8
187	1.0	191.1
183	1.0	287.6
...	...	...
129	1.0	59.6
159	1.0	131.7
132	1.0	8.4
108	1.0	13.1
155	1.0	4.1
130	1.0	0.7
86	1.0	76.3
93	1.0	250.9
137	1.0	273.7
144	1.0	96.2
58	1.0	210.8
60	1.0	53.5
107	1.0	90.4

	const	TV
143	1.0	104.6
198	1.0	283.6
34	1.0	95.7
14	1.0	204.1
66	1.0	31.5
53	1.0	182.6
98	1.0	289.7
180	1.0	156.6
94	1.0	107.4
138	1.0	43.0
176	1.0	248.4
79	1.0	116.0
87	1.0	110.7
103	1.0	187.9
67	1.0	139.3
24	1.0	62.3
8	1.0	8.6

140 rows × 2 columns

In [8]:

```
# fitting the model, regressing Sales on TV:

model = sm.OLS(y_train, X_train_sm)

results = model.fit()

print(results.params)

results.summary()
```

```
const    6.948683
TV       0.054546
dtype: float64
```

Out[8]:

OLS Regression Results

Dep. Variable:	Sales	**R-squared:**	0.816
Model:	OLS	**Adj. R-squared:**	0.814
Method:	Least Squares	**F-statistic:**	611.2
Date:	Tue, 01 Jun 2021	**Prob (F-statistic):**	1.52e-52
Time:	14:40:03	**Log-Likelihood:**	-321.12
No. Observations:	140	**AIC:**	646.2
Df Residuals:	138	**BIC:**	652.1
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	6.9487	0.385	18.068	0.000	6.188	7.709
TV	0.0545	0.002	24.722	0.000	0.050	0.059

Omnibus:	0.027	**Durbin-Watson:**	2.196
Prob(Omnibus):	0.987	**Jarque-Bera (JB):**	0.150

Prob(Omnibus):	0.987	Jarque-Bera (JB):	0.150
Skew:	-0.006	Prob(JB):	0.928
Kurtosis:	2.840	Cond. No.	328.

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

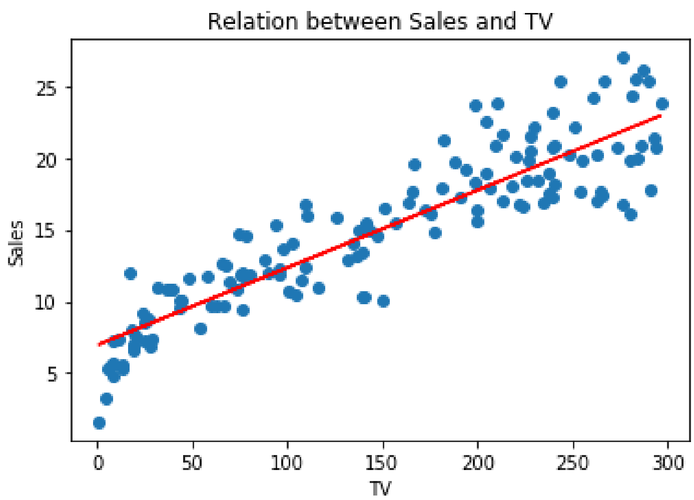
Observations: 1- The coefficient for TV is 0.054, and its corresponding p-value is very low, almost 0. That means the coefficient is statistically significant. 2- R-squared value is 0.816, which means that 81.6% of the Sales variance can be explained by the TV column using this line. 3- Prob F-statistic has a very low p-value, practically zero, which gives us that the model fit is statistically significant.

Plotting:

In [9]:

```
# Visualing the fitting line

plt.scatter(X_train, y_train)
plt.plot(X_train, 6.948 + 0.054*X_train, "r" )
plt.title("Relation between Sales and TV")
plt.xlabel("TV")
plt.ylabel("Sales")
plt.show()
```



Residual Analysis:

In [10]:

```
# Error = Actual y value - y predicated value

y_train_pred = results.predict(X_train_sm)

# residual

rs = (y_train - y_train_pred)

rs
```

Out[10]:

```
74     -1.588747
3       1.287635
185     4.469437
26      0.256729
90     -0.274178
127     0.576747
81     -2.728755
```

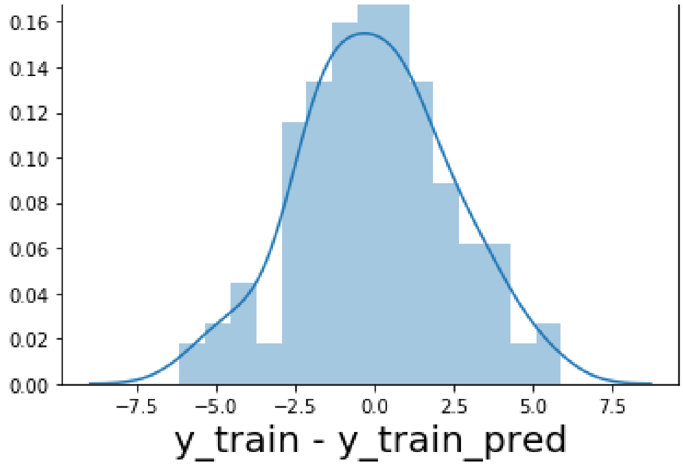
```
88      1.134927
119    -1.406871
110    -0.865114
57     -1.177815
44      0.182218
148     1.878578
160     0.042174
89      3.762193
146    -1.845118
199    -1.208752
10      2.045843
20     -0.861476
165    -2.839662
12      0.953128
16      1.853115
101     0.683956
120     0.844002
45     -0.399645
142     1.123978
117    -1.715979
184    -3.192395
187    -0.072377
183     3.563958
          ...
129    -0.499610
159    -1.232359
132    -1.706868
108    -2.363233
155    -3.972321
130    -5.386865
86      0.889476
93      1.565787
137    -1.077856
144     0.104015
58      5.353072
60     -1.766881
107     0.120381
143    -2.254169
198     3.082141
34     -0.268712
14      0.918529
66      2.333126
53      4.291262
98      2.649412
180     0.009452
94     -1.306897
138     0.305849
176    -0.297848
79     -2.275991
87      3.013102
103     2.502170
67     -1.146907
24     -0.646884
8      -2.617777
Length: 140, dtype: float64
```

In [11]:

```python
# Plotting the residuals:

fg = plt.figure()
sns.distplot(rs, bins = 15)
plt.title("Errors", fontsize = 20)
plt.xlabel("y_train - y_train_pred", fontsize = 20)
plt.show()
```

```
C:\Users\USP\Anaconda\lib\site-packages\matplotlib\axes\_axes.py:6462: UserWarning: The '
normed' kwarg is deprecated, and has been replaced by the 'density' kwarg.
  warnings.warn("The 'normed' kwarg is deprecated, and has been "
```

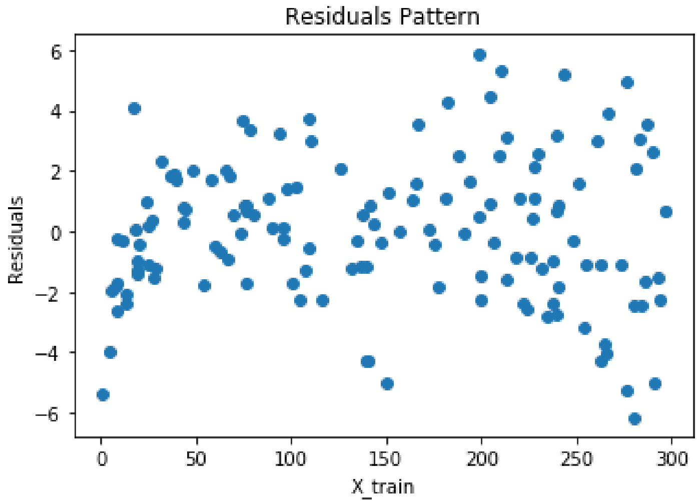


Analysis: 1- The residuals are following the normal distribution graph with a mean 0.

In [12]:

```
# plotting residuals patterns:

plt.scatter(X_train, rs)
plt.title("Residuals Pattern")
plt.xlabel("X_train")
plt.ylabel("Residuals")
plt.show()
```



Evaluating the model through Test data:

In [13]:

```
# adding a constant to the test data, as we did for the train data

X_test_sm = sm.add_constant(X_test)

# predicting the Y_test

y_test_pred = results.predict(X_test_sm)

y_test_pred
```

Out[13]:

```
126     7.374140
104    19.941482
99     14.323269
92     18.823294
111    20.132392
167    18.228745
116    14.541452
96     17.726924
52     18.752384
```

```
69      18.774202
164     13.341445
124     19.466933
182     10.014155
154     17.192376
125     11.705073
196     12.086893
194     15.114182
177     16.232370
163     15.866914
31      13.106899
11      18.659656
73      14.006904
15      17.606923
41      16.603281
97      17.034193
128     18.965113
133     18.937840
82      11.055978
139     17.034193
123     13.663265
83      10.679613
65      10.712340
151     13.548719
162     17.225103
170      9.675971
77      13.521446
32      12.250530
173     16.134188
174     19.079659
85      17.486923
168     18.697838
112     16.532372
171     15.921460
181     18.866930
7       13.505083
46      11.841437
75       7.870506
28      20.519667
29      10.799613
195      9.032331
40      17.994198
153     16.292371
115     11.045069
64      14.099631
59      18.441473
1        9.375969
192      7.886870
136      8.345054
152     17.726924
161     11.623254
dtype: float64
```

In [14]:

```python
# we imported the R2
# checking for the R2

r_square = r2_score(y_test, y_test_pred)

round(r_square, 4)
```

Out[14]:

```
0.7921
```

Analysis: If we can remember from the training data, the R^2 value = 0.815 Since the R^2 value on test data is within 5% of the R^2 value on training data, we can conclude that the model is pretty stable. Which means, what the model has learned on the training set can generalize on the unseen test set.

In [15]:

In [15]:

```
# plotting y_test and X_test

plt.scatter(X_test, y_test)
plt.plot(X_test, y_test_pred, "g")
plt.show()
```