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Course: DA (Data Analytics)

Assignment No.: 1

Part: 3

Name of the Assignment: Correlation and Regression

Problem Statement:

The smartphone market in 2022 is filled with variety of phones catering to every person's needs. You can buy phones from brands like Samsung, Apple, Xiaomi, buy a phone which costs as low as Rs. 1000 or as high as Rs. 179900, buy phones with colours like Black, Blue, Rose Gold etc.

The aim of this experiment is to check if there exists a correlation and/or linear regression between a pair of variables and also to determine if the correlation/regression statistics are significant.

Implementation:

Dataset link

Colab Link

The dataset:

The chosen dataset consists of 2647 samples with 8 attributes, namely:

- Brand - Name of the Mobile Manufacturer
- Model - Model name / number of the Mobile Phone
- Colour - Colour of the model. Missing or Null values indicate no specified colour of the model offered on the ecommerce website.
- Memory - RAM of the model (4GB, 6GB, 8GB, etc.)
- Storage - ROM of the model (32GB, 64GB, 128GB, 256GB, etc.)
- Rating - Rating of the model based on reviews (out of 5). Missing or Null values indicate there are no ratings present for the model.
- Selling Price- Selling Price/Discounted Price of the model in INR when this data was scraped. Ideally price indicates the discounted price of the model
- Original Price- Actual price of the model in INR. Missing values or null values would indicate that the product is being sold at the actual price available in the 'Price' column.

Importing the required libraries:

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

Loading the data into the dataframe:

```
df_phones = pd.read_csv("/content/drive/MyDrive/Flipkart_mobile_brands_scraped_data.csv")
df_phones
```

	Brand	Model	Color	Memory	Storage	Rating	Selling Price	Original Price
0	OPPO	A53	Moonlight Black	4 GB	64 GB	4.5	11990.0	15990.0
1	OPPO	A53	Mint Cream	4 GB	64 GB	4.5	11990.0	15990.0
2	OPPO	A53	Moonlight Black	6 GB	128 GB	4.3	13990.0	17990.0
3	OPPO	A53	Mint Cream	6 GB	128 GB	4.3	13990.0	17990.0
4	OPPO	A53	Electric Black	4 GB	64 GB	4.5	11990.0	15990.0
...	...	...	...	...	...	...	...	...
2642	Xiaomi	Redmi Y3	Bold Red	4 GB	64 GB	4.3	12999.0	13999.0
2643	Xiaomi	Redmi Y3	Elegant Blue	3 GB	32 GB	4.3	9450.0	NaN
2644	Xiaomi	Redmi Y3	Elegant Blue	4 GB	64 GB	4.2	12999.0	NaN
2645	Xiaomi	Redmi Y3	Prime Black	3 GB	32 GB	4.2	9950.0	NaN
2646	Xiaomi	Redmi Y3	Prime Black	4 GB	64 GB	4.3	12499.0	13999.0

2647 rows × 8 columns

Adding the Name column:

Name of the phone = Name of Brand + Name of Model

```
df_phones["Name"] = df_phones["Brand"].astype(str) +" "+df_phones["Model"].astype(str)
df_phones
```

	Brand	Model	Color	Memory	Storage	Rating	Selling Price	Original Price	Name
0	OPPO	A53	Moonlight Black	4 GB	64 GB	4.5	11990.0	15990.0	OPPO A53
1	OPPO	A53	Mint Cream	4 GB	64 GB	4.5	11990.0	15990.0	OPPO A53
2	OPPO	A53	Moonlight Black	6 GB	128 GB	4.3	13990.0	17990.0	OPPO A53
3	OPPO	A53	Mint Cream	6 GB	128 GB	4.3	13990.0	17990.0	OPPO A53
4	OPPO	A53	Electric Black	4 GB	64 GB	4.5	11990.0	15990.0	OPPO A53
...	...	...	...	...	...	...	...	...	...
2642	Xiaomi	Redmi Y3	Bold Red	4 GB	64 GB	4.3	12999.0	13999.0	Xiaomi Redmi Y3
2643	Xiaomi	Redmi Y3	Elegant Blue	3 GB	32 GB	4.3	9450.0	NaN	Xiaomi Redmi Y3
2644	Xiaomi	Redmi Y3	Elegant Blue	4 GB	64 GB	4.2	12999.0	NaN	Xiaomi Redmi Y3
2645	Xiaomi	Redmi Y3	Prime Black	3 GB	32 GB	4.2	9950.0	NaN	Xiaomi Redmi Y3
2646	Xiaomi	Redmi Y3	Prime Black	4 GB	64 GB	4.3	12499.0	13999.0	Xiaomi Redmi Y3

2647 rows × 9 columns

```
df_phones.shape
```

Using .shape() we can get information about the number of rows and columns of the dataset:

```
(2647, 9)
```

So, the dataset contains 2647 rows (samples) and 9 columns (features).

Removing duplicate rows:

```
duplicate_rows_df = df_phones[df_phones.duplicated()]
print("number of duplicate rows: ", duplicate_rows_df.shape)
```

This gives us the number of rows which have the same values for every column:

```
number of duplicate rows:  (107, 9)
```

So, the dataset contained 107 rows which were duplicates.

```
df_phones.count()
```

You can also check the number of rows that each column contains using the .count() method:

```
Brand             2647
Model             2645
```

```
Color              2505
Memory             2605
Storage            2568
Rating             2647
Selling Price      2644
Original Price      969
Name               2647
dtype: int64
```

You can delete the duplicate rows using just a simple method, i.e., .drop_duplicates():

```
[123] df_phones = df_phones.drop_duplicates()
      df_phones
```

	Brand	Model	Color	Memory	Storage	Rating	Selling Price	Original Price	Name
0	OPPO	A53	Moonlight Black	4 GB	64 GB	4.5	11990.0	15990.0	OPPO A53
1	OPPO	A53	Mint Cream	4 GB	64 GB	4.5	11990.0	15990.0	OPPO A53
2	OPPO	A53	Moonlight Black	6 GB	128 GB	4.3	13990.0	17990.0	OPPO A53
3	OPPO	A53	Mint Cream	6 GB	128 GB	4.3	13990.0	17990.0	OPPO A53
4	OPPO	A53	Electric Black	4 GB	64 GB	4.5	11990.0	15990.0	OPPO A53
...	...	...	...	...	...	...	...	...	...
2642	Xiaomi	Redmi Y3	Bold Red	4 GB	64 GB	4.3	12999.0	13999.0	Xiaomi Redmi Y3
2643	Xiaomi	Redmi Y3	Elegant Blue	3 GB	32 GB	4.3	9450.0	NaN	Xiaomi Redmi Y3
2644	Xiaomi	Redmi Y3	Elegant Blue	4 GB	64 GB	4.2	12999.0	NaN	Xiaomi Redmi Y3
2645	Xiaomi	Redmi Y3	Prime Black	3 GB	32 GB	4.2	9950.0	NaN	Xiaomi Redmi Y3
2646	Xiaomi	Redmi Y3	Prime Black	4 GB	64 GB	4.3	12499.0	13999.0	Xiaomi Redmi Y3

2540 rows × 9 columns

```
df_phones.count()
```

```
Brand              2540
Model              2538
Color              2407
Memory             2501
Storage            2463
Rating             2540
Selling Price      2537
Original Price      934
Name               2540
dtype: int64
```

Removing null / missing values:

```
print(df_phones.isnull().sum())
```

The .isnull().sum() command will return the number of values which are missing for every column:

```
Brand                0
Model                2
Color              133
Memory              39
Storage             77
Rating               0
Selling Price        3
Original Price    1606
Name                 0
dtype: int64
```

We will drop lines with model unknown or missing memory information or missing storage information. Put missing value of colour to "Base". Drop lines with missing both prices else fill one with the other.

```
df_phones = df_phones.dropna(subset=["Model", "Memory","Storage"])
df_phones["Selling Price"] = df_phones["Selling Price"].fillna(df_phones["Original Price"])
df_phones["Original Price"] = df_phones["Original Price"].fillna(df_phones["Selling Price"])
df_phones= df_phones.dropna(subset=["Original Price","Selling Price"])
df_phones["Color"] = df_phones["Color"].fillna("Base")
```

```
print(df_phones.isnull().sum())
```

```
Brand             0
Model             0
Color             0
Memory            0
Storage           0
Rating            0
Selling Price     0
Original Price    0
Name              0
dtype: int64
```

Now our dataset is free of null values.

Converting str variables to float

```
df_phones = df_phones[df_phones['Memory'].str.endswith('GB')]
df_phones['Memory'] = df_phones['Memory'].str.replace('GB', '').astype(float)
df_phones = df_phones[df_phones['Storage'].str.contains('^[0-9].*GB$')]
df_phones['Storage'] = df_phones['Storage'].str.replace('GB', '').astype(float)
```

```
df_phones = df_phones[df_phones['Rating'] > 0]
```

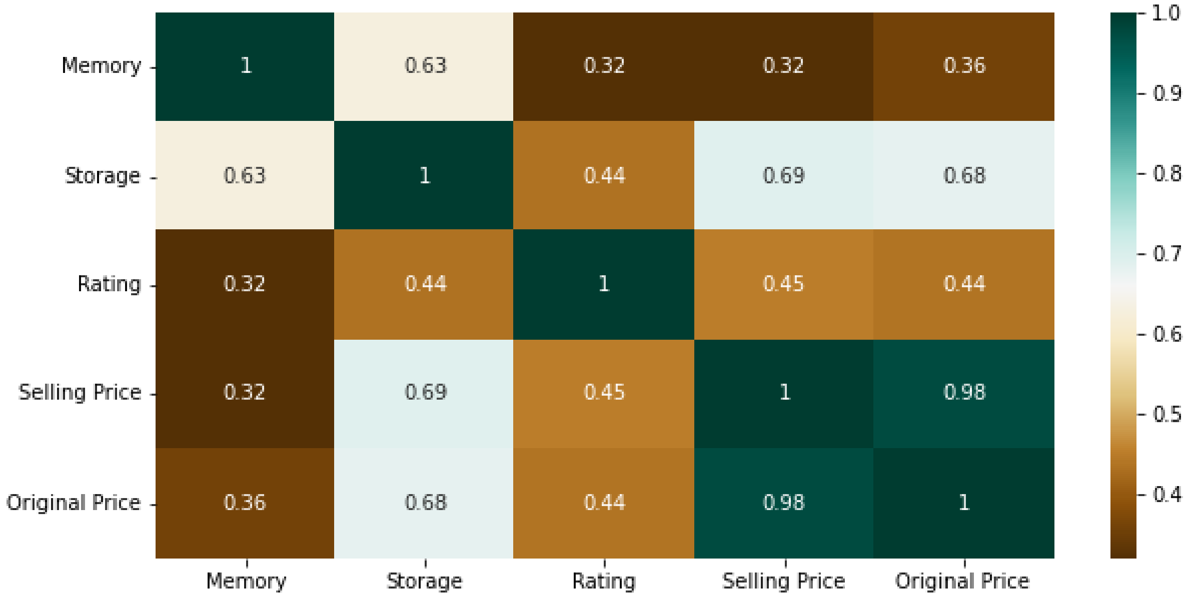
```
df_phones.describe()
```

	Memory	Storage	Rating	Selling Price	Original Price
count	2189.000000	2189.000000	2189.000000	2189.000000	2189.000000
mean	4.162403	83.641846	4.236912	24820.741434	26979.160347
std	2.261424	80.937489	0.269112	24506.682891	26858.042082
min	0.500000	4.000000	2.300000	2799.000000	2799.000000
25%	3.000000	32.000000	4.100000	9999.000000	10999.000000
50%	4.000000	64.000000	4.300000	15490.000000	16990.000000
75%	6.000000	128.000000	4.400000	27999.000000	30780.000000
max	16.000000	512.000000	5.000000	157999.000000	189999.000000

Correlation

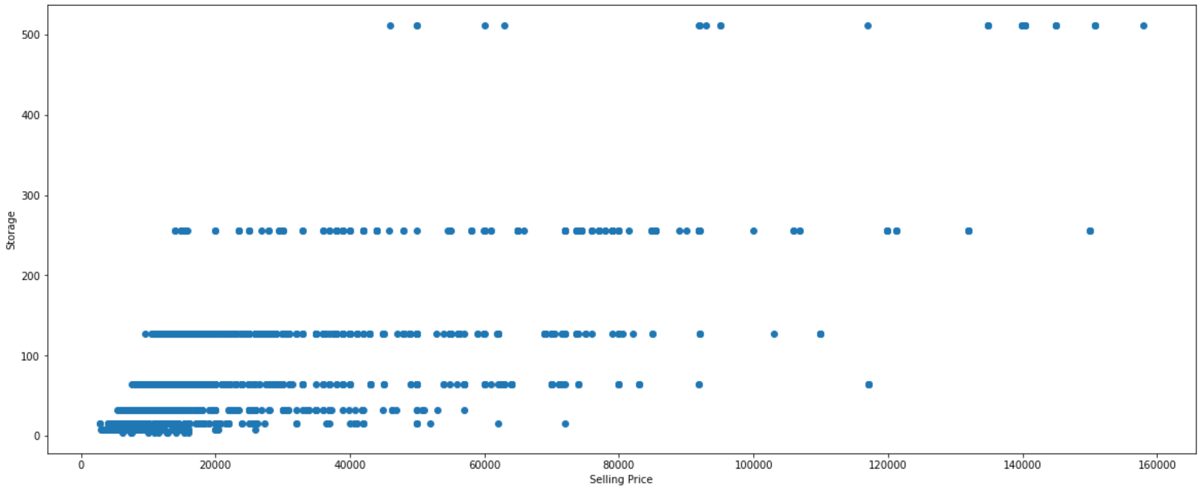
```
[209] plt.figure(figsize=(10, 5))
      c = df_phones.corr()
      sns.heatmap(c,cmap="BrBG",annot=True)
      c
```

	Memory	Storage	Rating	Selling Price	Original Price
Memory	1.000000	0.629071	0.321410	0.320008	0.358150
Storage	0.629071	1.000000	0.436402	0.691371	0.681705
Rating	0.321410	0.436402	1.000000	0.452775	0.437401
Selling Price	0.320008	0.691371	0.452775	1.000000	0.976003
Original Price	0.358150	0.681705	0.437401	0.976003	1.000000

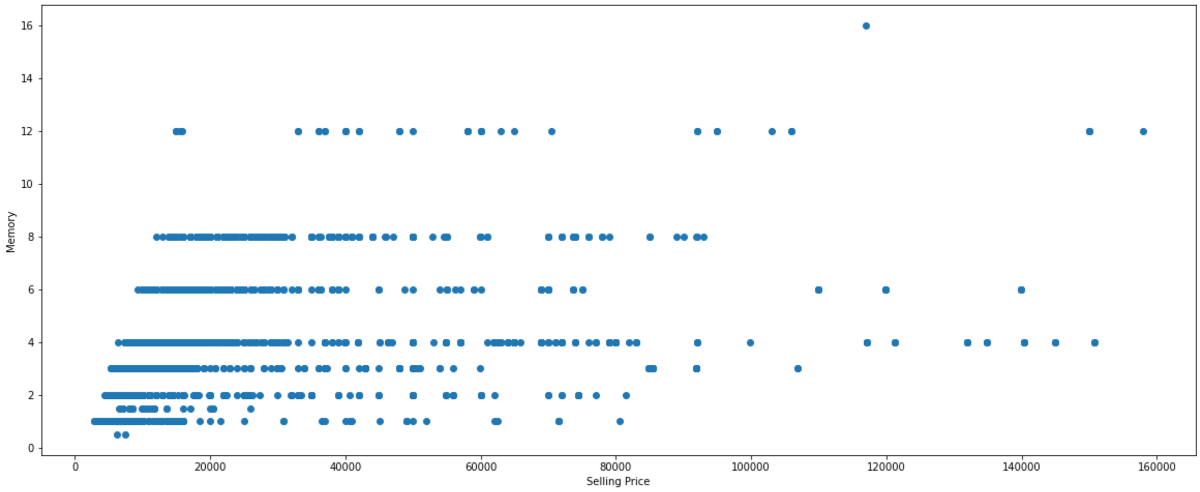


Scatter plots

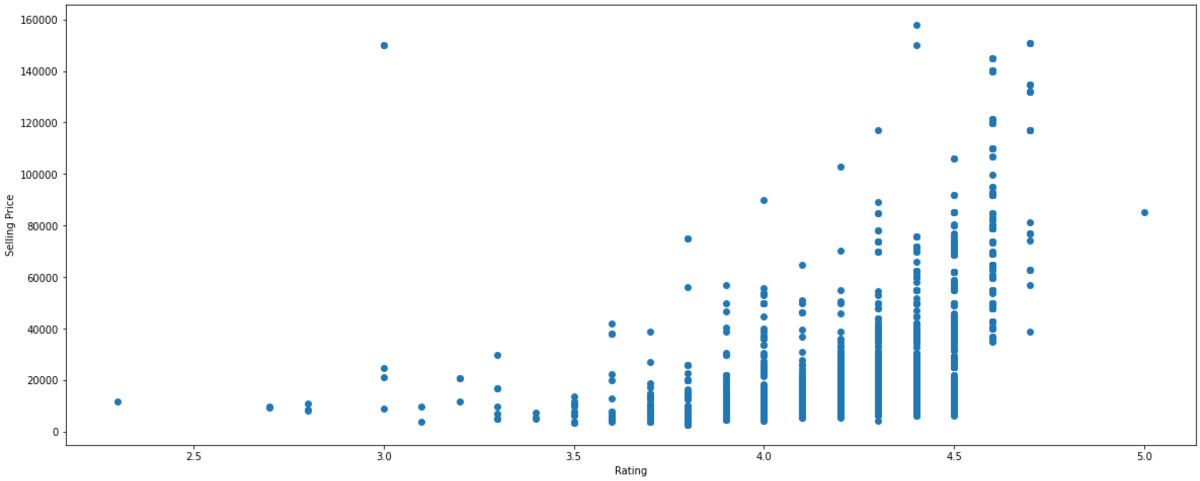
```
fig, ax = plt.subplots(figsize=(20, 8))
ax.scatter(df_phones['Selling Price'], df_phones['Storage'])
ax.set_xlabel('Selling Price')
ax.set_ylabel('Storage')
plt.show()
```



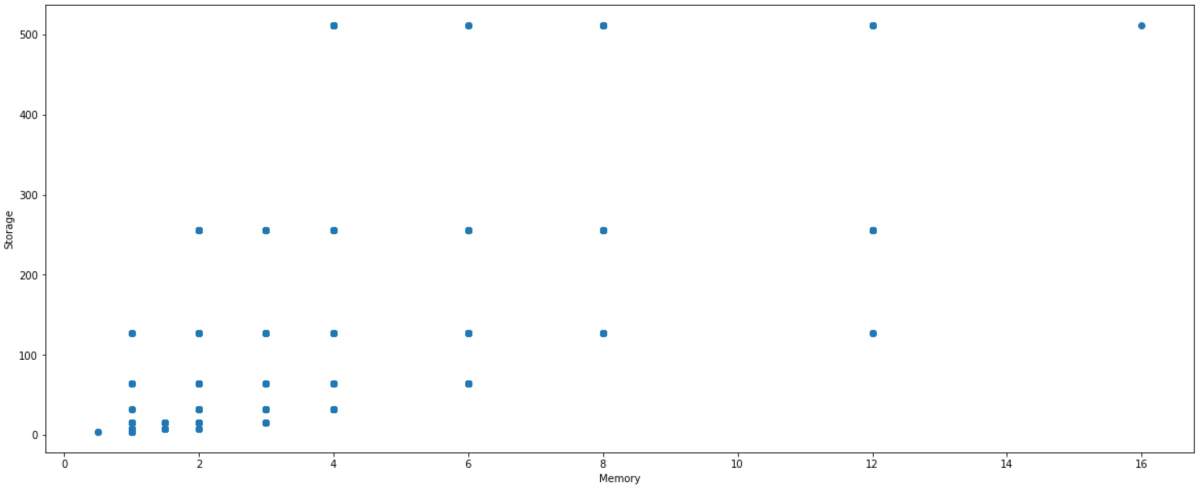

```
fig, ax = plt.subplots(figsize=(20, 8))
ax.scatter(df_phones['Selling Price'], df_phones['Memory'])
ax.set_xlabel('Selling Price')
ax.set_ylabel('Memory')
plt.show()
```




```
fig, ax = plt.subplots(figsize=(20, 8))
ax.scatter(df_phones['Rating'], df_phones['Selling Price'])
ax.set_xlabel('Rating')
ax.set_ylabel('Selling Price')
plt.show()
```




```
fig, ax = plt.subplots(figsize=(20, 8))
ax.scatter(df_phones['Memory'], df_phones['Storage'])
ax.set_xlabel('Memory')
ax.set_ylabel('Storage')
plt.show()
```



Linear Regression statistics

```
X = df_phones['Rating'].values.reshape(-1, 1)
y = df_phones['Selling Price'].values.reshape(-1, 1)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2
, random_state=0)
```

```
regressor = LinearRegression()
regressor.fit(X_train, y_train)
```

```
print(regressor.intercept_)
print(regressor.coef_)
```

```
[-140615.9860851]
[[38993.81352265]]
```

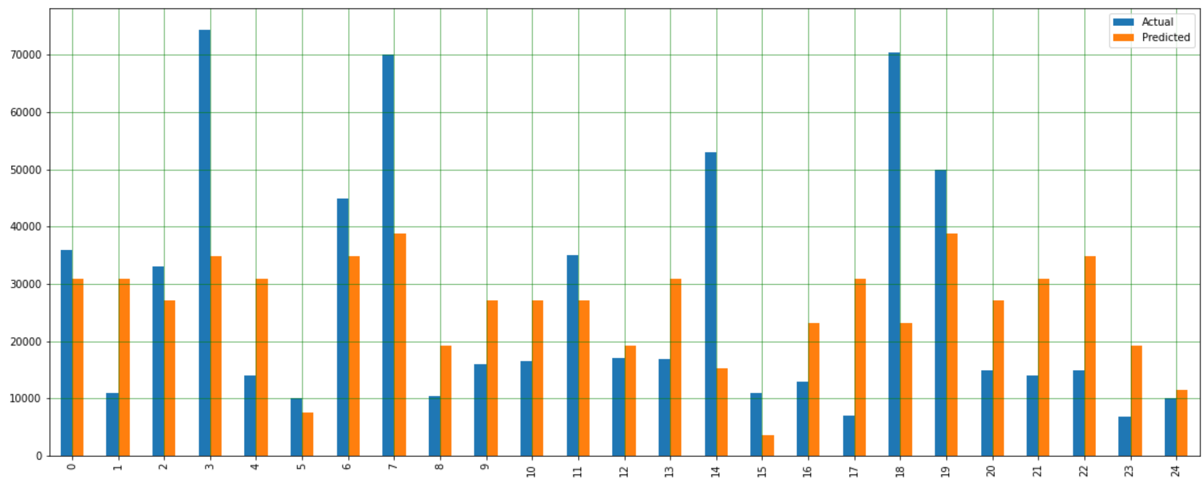
```
y_pred = regressor.predict(X_test)
```

```
df_pred = pd.DataFrame({'Actual': y_test.flatten(), 'Predicted': y_pred.flatten()})
df_pred
```

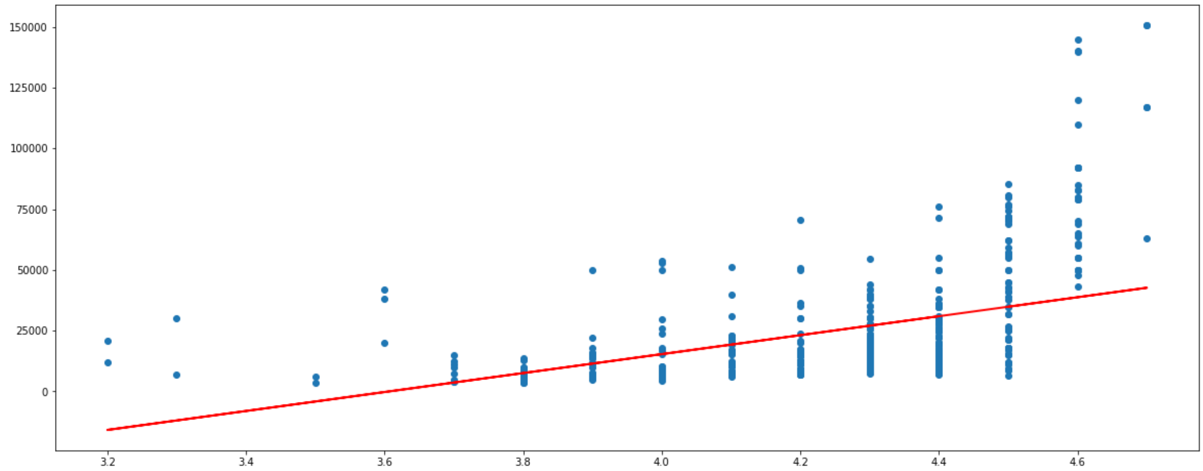
	Actual	Predicted
0	35990.0	30956.793415
1	10990.0	30956.793415
2	32990.0	27057.412062
3	74400.0	34856.174767
4	13999.0	30956.793415
...	...	...
433	7990.0	27057.412062
434	10499.0	27057.412062
435	19499.0	30956.793415
436	6999.0	7560.505301
437	17999.0	34856.174767

438 rows × 2 columns

```
df1 = df_pred.head(25)
df1.plot(kind='bar',figsize=(20, 8))
plt.grid(which='major', linestyle='-', linewidth='0.5', color='green')
plt.grid(which='minor', linestyle=':', linewidth='0.5', color='black')
plt.show()
```




```
fig, ax = plt.subplots(figsize=(20, 8))
plt.scatter(X_test, y_test)
plt.plot(X_test, y_pred, color='red', linewidth=2)
plt.show()
```




```
r_sq = regressor.score(X_test, y_test)
print('coefficient of determination:', r_sq)
```

```
coefficient of determination: 0.25218898685136426
```

```
print('intercept:', regressor.intercept_)
print('slope:', regressor.coef_)
```

```
intercept: [-140615.9860851]
slope: [[38993.81352265]]
```

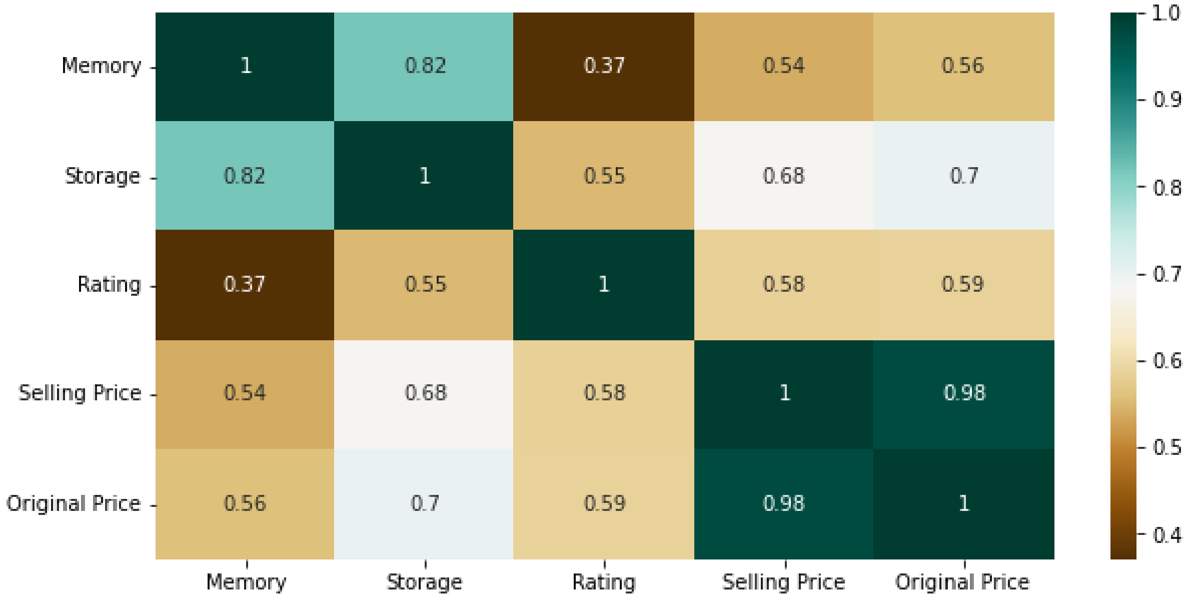
```
print('Mean Absolute Error:', metrics.mean_absolute_error(y_test, y_pre
d))
print('Mean Squared Error:', metrics.mean_squared_error(y_test, y_pred)
)
print('Root Mean Squared Error:', np.sqrt(metrics.mean_squared_error(y_
test, y_pred)))
```

```
Mean Absolute Error: 15130.299756336022
Mean Squared Error: 474562981.7514144
Root Mean Squared Error: 21784.466524370397
```

Spearman correlation coefficient

```python
plt.figure(figsize=(10, 5))
c = df_phones.corr('spearman')
sns.heatmap(c,cmap="BrBG",annot=True)
c
```

	Memory	Storage	Rating	Selling Price	Original Price
Memory	1.000000	0.820081	0.371479	0.538852	0.560446
Storage	0.820081	1.000000	0.551103	0.679909	0.700704
Rating	0.371479	0.551103	1.000000	0.584789	0.586940
Selling Price	0.538852	0.679909	0.584789	1.000000	0.976407
Original Price	0.560446	0.700704	0.586940	0.976407	1.000000




```python
X2 = sm.add_constant(X)
est = sm.OLS(y, X2)
est2 = est.fit()
print(est2.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                      y   R-squared:                       0.205
Model:                            OLS   Adj. R-squared:                  0.205
Method:                 Least Squares   F-statistic:                     564.0
Date:                Fri, 25 Mar 2022   Prob (F-statistic):          4.20e-111
Time:                        10:34:40   Log-Likelihood:                -24978.
No. Observations:                2189   AIC:                         4.996e+04
Df Residuals:                    2187   BIC:                         4.997e+04
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const      -1.499e+05   7371.108    -20.333      0.000   -1.64e+05   -1.35e+05
x1          4.123e+04   1736.239     23.748      0.000    3.78e+04    4.46e+04
==============================================================================
Omnibus:                     1148.747   Durbin-Watson:                   1.195
Prob(Omnibus):                  0.000   Jarque-Bera (JB):             8769.866
Skew:                           2.382   Prob(JB):                         0.00
Kurtosis:                      11.570   Cond. No.                         70.7
==============================================================================

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

Conclusion:

- The fitted model implies that, when comparing two phones whose Rating differ by one unit, the phone with the higher Rating will, on average, have around 39000 units higher Selling Price. This difference is statistically significant, because the p-value, shown under the column labelled *P>|t|*, is less than the significance value of 0.05. This means that there is strong evidence of a linear association between the variables Selling Price and Rating.
- The other parameter to test the efficacy of the model is the *R-squared* value, which represents the percentage variation in the dependent variable (Selling Price) that is explained by the independent variable (Rating). The higher the value, the better the explain ability of the model, with the highest value being one. In our case, the R-squared value of 0.205 means that 20% of the variation in the variable Selling Price is explained by the variable Rating. This is very low, which means that the Rating will not be accurately predicted by the Selling Price of a phone.
- The Spearman correlation coefficient is also an indicator of the extent and strength of the linear relationship between the two variables. The spearman correlation coefficient for Selling Price and Rating comes out to be 0.58. This is a slight strong positive correlation between the two variables, with the highest value being one.

References:

Dataset link

Colab link