

Exploratory Data Analysis

Overview of the dataset:

- In this project, 50 pages from Flipkart – smart phones data has been scrapped
- Population dataset contains 996 rows/observations and 16 columns/fields

Field Name	Data Type	Blanks	Unique Values
Product_Name	String	0	382
Rating	float64	0	22
Display	float64	0	43
Battery	int32	0	57
Price	int32	0	219
RAM	String	0	8
ROM	String	0	15
Expandable_Memory	String	258	10
Rear_Camera	String	0	72
Front_Camera	String	92	22
Processor	String	0	163
Brand_Name	category	0	13
Processor_Category	category	0	5
Price_Category	category	0	9
Battery_Category	category	0	6
Rating_Category	category	0	6

- Input and data cleansing files:
 - Input - Flipkart scrapped file
 - Data cleansing:
 - Processor category – to tag all processors from specific brand into one group
 - Brand Name – Based on product name bunch of phones from same brand are grouped into one

Below is the sample dataset:

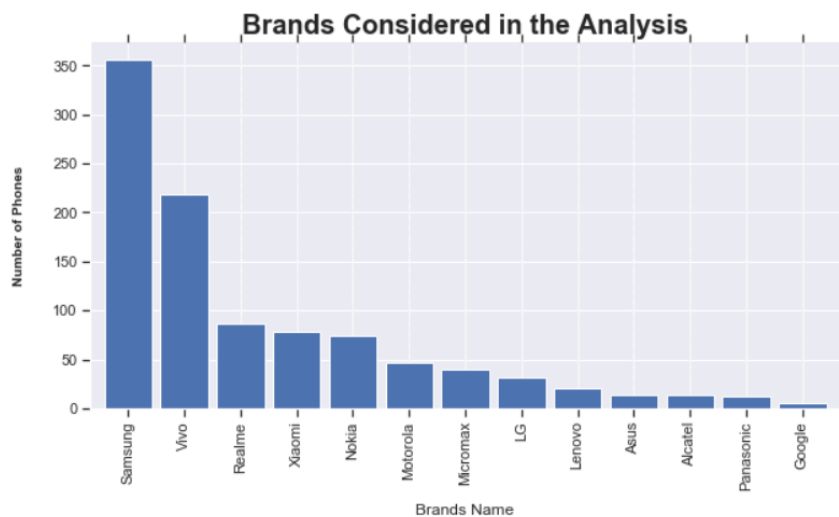
Product_Name	Rating	Display	Price	RAM	ROM	Expandable_Memory	Rear_Camera	Front_Camera	Battery	Processor	Brand_Name	Processor_Category
Realme Narzo 10 (That White, 128 GB)	4.5	6.5	11999	4 GB RAM	128 GB ROM	Expandable Upto 256 GB	48MP + 8MP + 2MP + 2MP	16MP	5000	MediaTek Helio G80 (12 nm)	Realme	MediaTek
Realme Narzo 10 (That White, 128 GB)	4.5	6.5	11999	4 GB RAM	128 GB ROM	Expandable Upto 256 GB	48MP + 8MP + 2MP + 2MP	16MP	5000	MediaTek Helio G80 (12 nm)	Realme	MediaTek
Realme Narzo 10 (That Green, 128 GB)	4.5	6.5	11999	4 GB RAM	128 GB ROM	Expandable Upto 256 GB	48MP + 8MP + 2MP + 2MP	16MP	5000	MediaTek Helio G80 (12 nm)	Realme	MediaTek
Realme Narzo 10 (That Green, 128 GB)	4.5	6.5	11999	4 GB RAM	128 GB ROM	Expandable Upto 256 GB	48MP + 8MP + 2MP + 2MP	16MP	5000	MediaTek Helio G80 (12 nm)	Realme	MediaTek
Motorola G8 Power Lite (Arctic Blue, 64 GB)	4.5	6.5	8999	4 GB RAM	64 GB ROM	Expandable Upto 256 GB	16MP + 2MP + 2MP	8MP	5000	MediaTek Helio P35	Motorola	MediaTek

Exploratory Data Analysis:

Which brand phone do you use?

```
x = data1.groupby('Brand_Name')['Product_Name'].count().sort_values(ascending=False)
ax = x.plot(kind='bar', figsize=(10, 5), zorder=2, width=0.85)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
#ax.spines['left'].set_visible(False)
#ax.spines['bottom'].set_visible(False)
ax.set_title('Brands Considered in the Analysis', weight='bold', size=20)
ax.tick_params(axis="both", which="both", bottom="off", top="off", labelbottom="on", left="off", right="off", labelleft="on")
vals = ax.get_xticks()
for tick in vals:
    ax.axvline(x=tick, linestyle='dashed', alpha=0.4, color='#eeeeee', zorder=1)
# Set x-axis label
ax.set_xlabel("Brands Name", labelpad=10, size=12)
# Set y-axis label
ax.set_ylabel("Number of Phones", labelpad=20, weight='bold', size=10)

#for p in ax.patches:
#    width, height = p.get_width(), p.get_height()
#    x,y = p.get_xy()
#    ax.annotate('{:.0%}'.format(height), (x,y + height + 0.1 ))
```



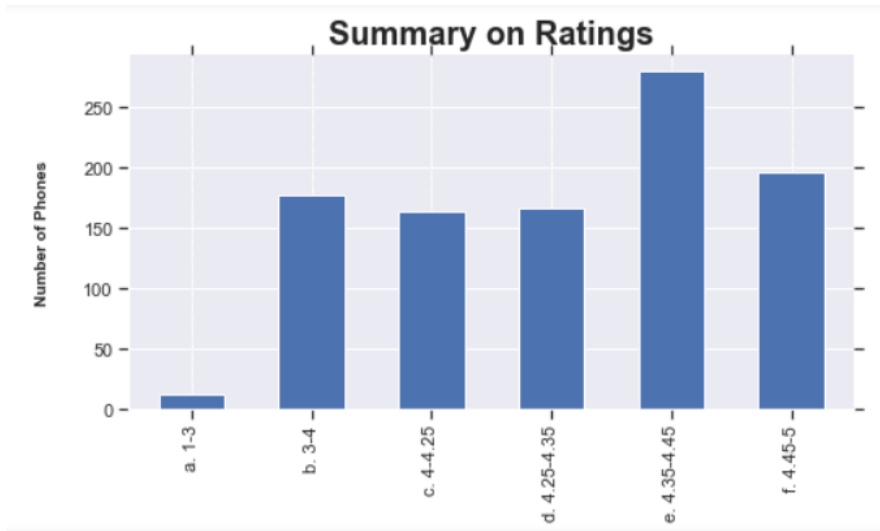
data1['Brand_Name'].value_counts(sort=False)		(data1['Brand_Name'].value_counts(sort=False)/data1['Brand_Name'].count()*100)	
Google	6	Google	0.602410
Micromax	40	Micromax	4.016064
Nokia	74	Nokia	7.429719
Xiaomi	78	Xiaomi	7.831325
Panasonic	12	Panasonic	1.204819
LG	32	LG	3.212851
Motorola	46	Motorola	4.618474
Alcatel	14	Alcatel	1.405622
Realme	86	Realme	8.634538
Samsung	356	Samsung	35.742972
Lenovo	20	Lenovo	2.008032
Vivo	218	Vivo	21.887550
Asus	14	Asus	1.405622

Insights:

- There are 13 companies considered in this analysis
- Maximum number of records scrapped are from Samsung followed by Vivo, Realme and Xiaomi, top 4 brands constitute to 74% of the total data scrapped
- Google has least number of phones with 0.6% of the data

How much do you rate your phone?

```
x = data1.groupby('Rating_Category')['Product_Name'].count()
ax = x.plot(kind='bar', figsize=(8, 4), zorder=2, width=0.55)
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
#ax.spines['left'].set_visible(False)
#ax.spines['bottom'].set_visible(False)
ax.set_title('Summary on Ratings', weight='bold', size=20)
ax.tick_params(axis="both", which="both", bottom="off", top="off", labelbottom="on", left="off", right="off", labelleft="on")
vals = ax.get_xticks()
for tick in vals:
    ax.axvline(x=tick, linestyle='dashed', alpha=0.4, color='#eeeeee', zorder=1)
# Set x-axis label
ax.set_xlabel("Rating Category", labelpad=20, weight='bold', size=10)
# Set y-axis label
ax.set_ylabel("Number of Phones", labelpad=20, weight='bold', size=10)
```

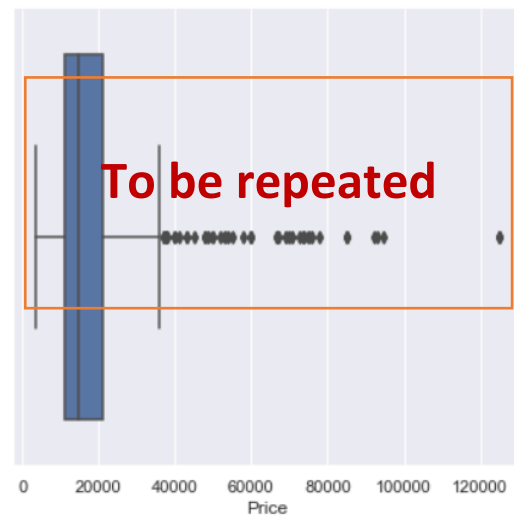
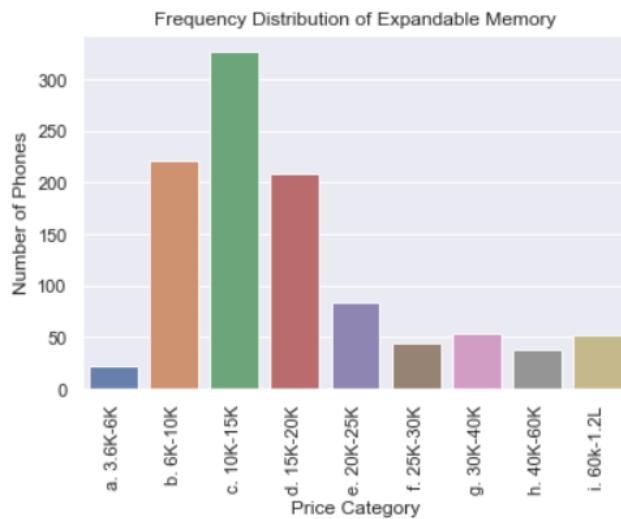


<code>data1['Rating_Category'].value_counts(sort=False)</code>	<code>(data1['Rating_Category'].value_counts(sort=False)/data1['Rating_Category'].count())*100</code>
a. 1-3 12	a. 1-3 1.204819
b. 3-4 178	b. 3-4 17.871486
c. 4-4.25 164	c. 4-4.25 16.465863
d. 4.25-4.35 166	d. 4.25-4.35 16.666667
e. 4.35-4.45 280	e. 4.35-4.45 28.112450
f. 4.45-5 196	f. 4.45-5 19.678715

Insights:

- There are 190 records with rating <3, 19% of the population
- Between rating 4-5 we have 18% of the data i.e. 806 records. Rating 4-5 is further split to better understand the data.
- 61 % data is present within the range 4-4.45

What is the cost range of your phone?



```
data1['Price_Category'].value_counts(sort=False)
```

```
a. 3.6K-6K      24
b. 6K-10K      206
c. 10K-15K     264
d. 15K-20K     234
e. 20K-25K      68
f. 25K-30K      52
g. 30K-40K      46
h. 40K-60K      50
i. 60K-1.2L     52
Name: Price_Category, dtype: int64
```

```
(data1['Price_Category'].value_counts(sort=False)/
 data1['Price_Category'].count()*100)
```

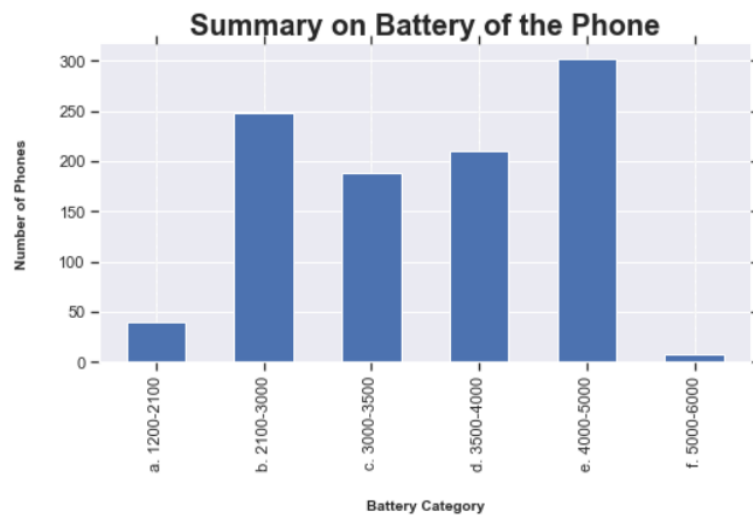
```
a. 3.6K-6K      2.409639
b. 6K-10K      20.682731
c. 10K-15K     26.506024
d. 15K-20K     23.493976
e. 20K-25K      6.827309
f. 25K-30K      5.220884
g. 30K-40K      4.618474
h. 40K-60K      5.020080
i. 60K-1.2L     5.220884
Name: Price_Category, dtype: float64
```

In sights:

- In our analysis 71% of the data has price range 6,000 to 20,000
- Using box plot we observe below Q1 and above Q3 line is near 40,000; after which we can consider it as outliers
- From the summary, records below 6K is 24 records and above 40K is 102 records. Together after excluding outliers we will be losing 126 records which is 13% of the population
- Out of curiosity want to know which brands these 126 records belongs to:

Price_Category	Brand_Name	Product_Name
a. 3.6K-6K	Alcatel	2
	Micromax	12
	Nokia	4
	Panasonic	2
	Samsung	4
h. 40K-60K	LG	6
	Realme	6
	Samsung	36
	Xiaomi	2
i. 60K-1.2L	Google	2
	Motorola	4
	Samsung	46

Is your display and battery dependent on each other?



```
data1['Battery_Category'].value_counts(sort=False)
```

a. 1200-2100	40
b. 2100-3000	248
c. 3000-3500	188
d. 3500-4000	210
e. 4000-5000	302
f. 5000-6000	8

```
(data1['Battery_Category'].value_counts(sort=False)/  
data1['Battery_Category'].count())*100
```

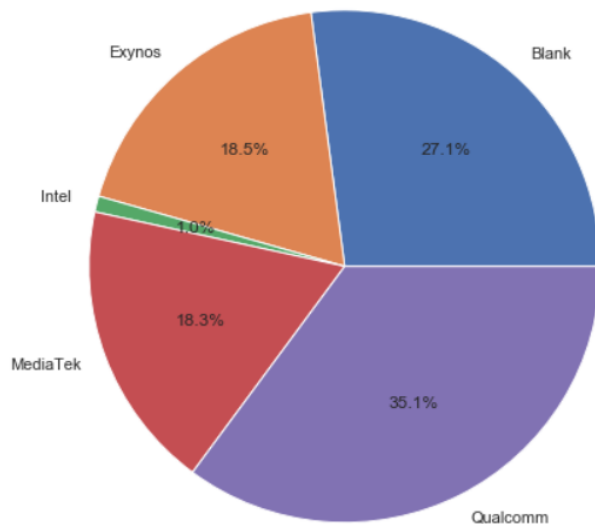
a. 1200-2100	4.016064
b. 2100-3000	24.899598
c. 3000-3500	18.875502
d. 3500-4000	21.084337
e. 4000-5000	30.321285
f. 5000-6000	0.803213

Insights:

- 95% has battery ranging from 2100 – 5000 mAh
- Looking at the summary table we can observe the categories with battery range 1200-2100 and 5000-6000 together constitutes to 4.8% of the population which is 48 records
- Is battery dependent on other features of the phone?
We will look into it in bivariate analysis!

Processor Category:

```
labels = data1['Processor_Category'].astype('category').cat.categories.tolist()
counts = data1['Processor_Category'].value_counts()
sizes = [counts[var_cat] for var_cat in labels]
fig1, ax1 = plt.subplots()
ax1.pie(sizes, labels=labels, autopct='%1.1f%%', radius=2) #autopct is show the % on plot
#ax1.axis('equal')
plt.show()
```



```
data1['Processor_Category'].value_counts(sort=False)
```

Blank	270
MediaTek	182
Exynos	184
Qualcomm	350
Intel	10

```
(data1['Processor_Category'].value_counts(sort=False)/  
data1['Processor_Category'].count())*100
```

Blank	27.108434
MediaTek	18.273092
Exynos	18.473896
Qualcomm	35.140562
Intel	1.004016

Insights:

- Multiple versions from Processor are grouped into each of the above values
- Qualcomm takes a major share of 35% in the entire population; however, 27% is blank.
- If we consider in the data available; then Qualcomm share increases to 48%
- There is only 1% of data available with Intel processor, which is 10 record and can be removed as outlier

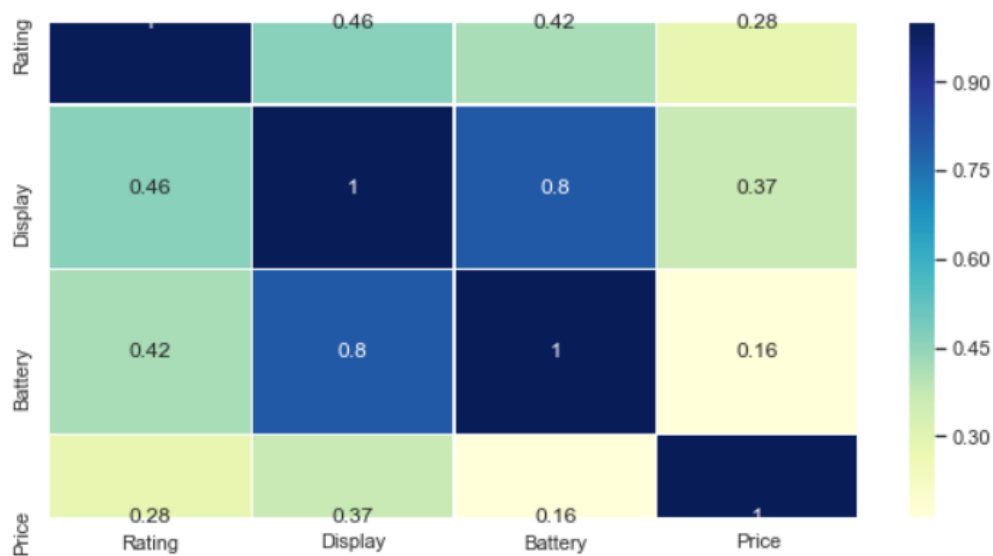
Bi-Variate Analysis

Correlation

```
corelation = data2.corr()
```

```
plt.figure(figsize=(10,5))
sns.heatmap(corelation,xticklabels=corelation.columns,
            yticklabels=corelation.columns,cmap="YlGnBu", annot=True, linewidth=0.5)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x1b8db360088>
```

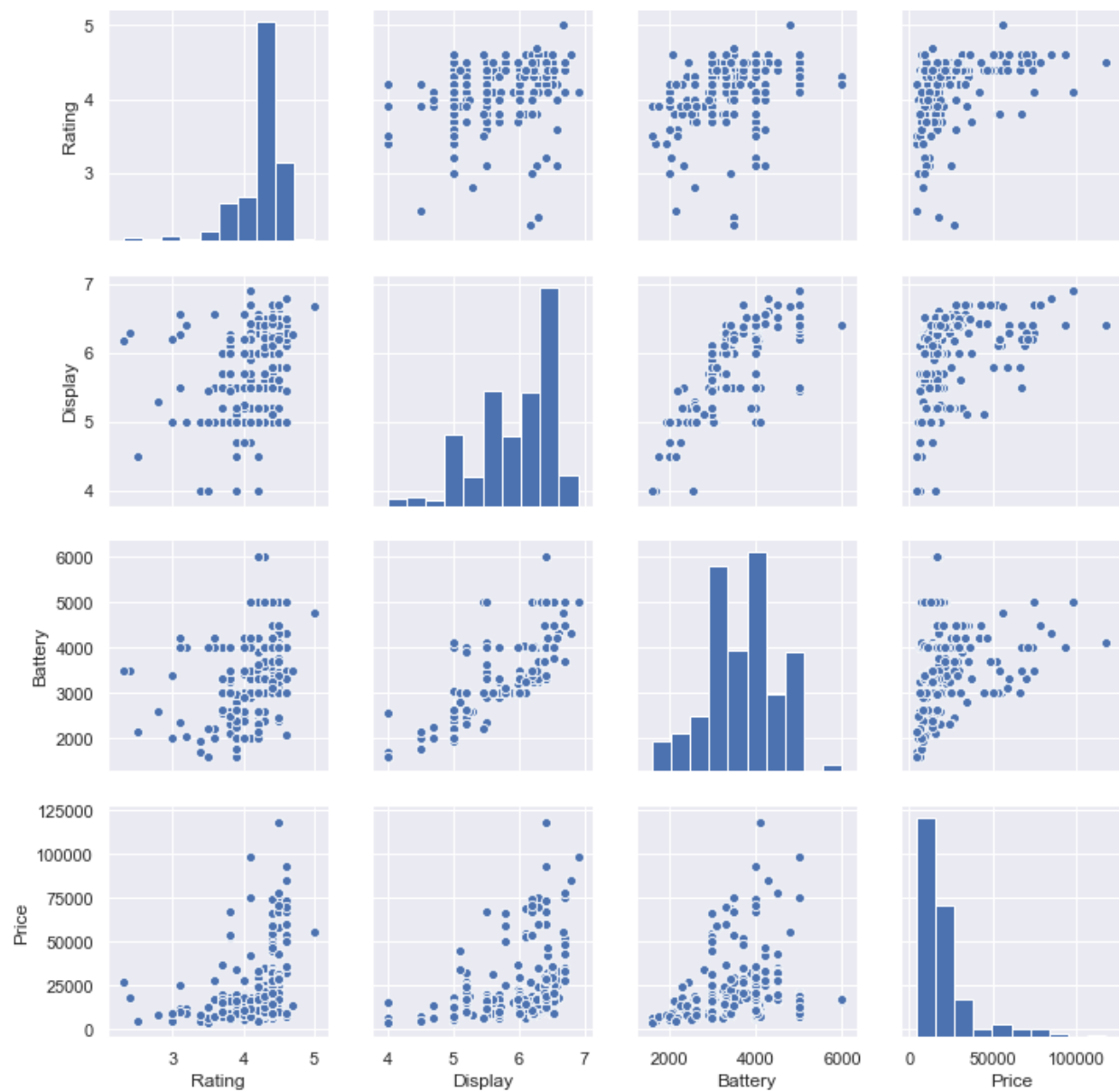


Insights:

Display and battery are strongly dependent on each other

In the next category we have Rating dependent on Display and Battery

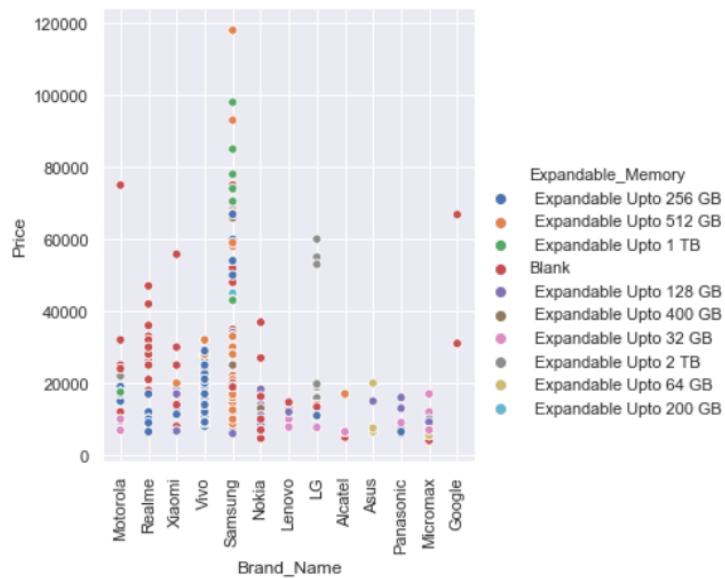
Pairplot:



Relation between Brand Name Price and Rating:

```
sns.relplot(x='Brand_Name', y='Price', hue='Expandable_Memory', data=data1)
plt.xticks(rotation='vertical')
#sns.barplot(carrier_count.index, carrier_count.values, alpha=0.9)
```

([0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12],
<a list of 13 Text xticklabel objects>)



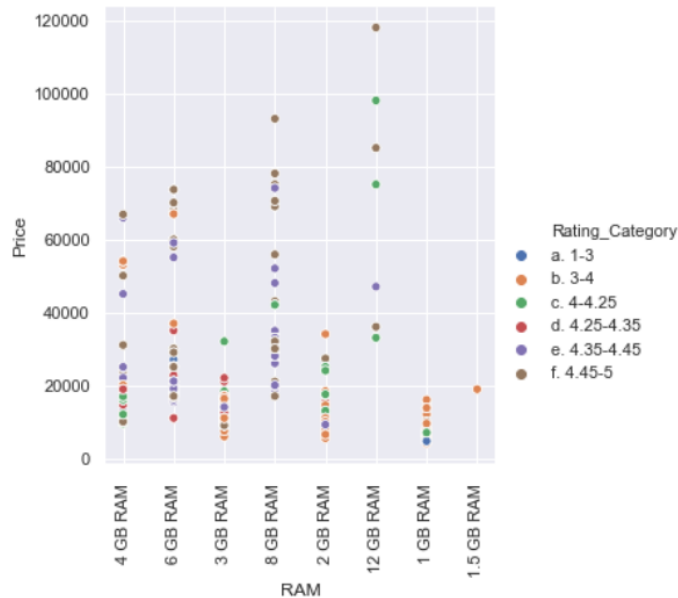
Insights:

- Very strong positive correlation would be between Display and Battery
- Very weak positive correlation would be between Battery and Price
- The Price range of Samsung phones have higher bandwidth
- Expandable memory is directly proportional to Price i.e., As the Expandable memory increases the price of the smartphones are increasing E.g., Samsung

Relation between RAM, Price and Rating:

```
sns.relplot(x='RAM', y='Price', hue='Rating_Category', data=data1)
plt.xticks(rotation='vertical')
#sns.barplot(carrier_count.index, carrier_count.values, alpha=0.9)
```

([0, 1, 2, 3, 4, 5, 6, 7], <a list of 8 Text xticklabel objects>)



Insights:

- RAM is directly proportional to Price i.e., When RAM is higher the price of the smartphones are high and similarly when RAM is high it tends to have good rating. E.g., 8GB RAM has an average rating of 4.5
- Conclusion: Good/high RAM with higher Price Range will have good Rating
- E.g., 12GB RAM with Price range from 70,000 to 1,20,000 has an average rating of 4.4