Flipkart Mobile Analysis

Flipkart Mobiles Dataset

This dataset containing specs of various Mobile brands in India has been scraped from an ecommerce website 'Flipkart'. This dataset has 3114 samples with 8 attributes. There are some missing values as well.

Attributes-

Brand- Name of the Mobile Manufacturer

Model- Model number of the Mobile Phone

Color- Color of the model.

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.

In [2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [3]:
```
import warnings
warnings.simplefilter(action="ignore")
```

In [4]:
```
df = pd.read_csv("Flipkart_Mobiles.csv") # Reading csv file
```

In [5]:
```
df.head()
```

Out[5]:

	Brand	Model	Color	Memory	Storage	Rating	Selling Price	Original Price
0	OPPO	A53	Moonlight Black	4 GB	64 GB	4.5	11990	15990
1	OPPO	A53	Mint Cream	4 GB	64 GB	4.5	11990	15990
2	OPPO	A53	Moonlight Black	6 GB	128 GB	4.3	13990	17990
3	OPPO	A53	Mint Cream	6 GB	128 GB	4.3	13990	17990
4	OPPO	A53	Electric Black	4 GB	64 GB	4.5	11990	15990

In [6]:
```
df.isnull().sum()
```

Out[6]:
```
Brand               0
Model               0
Color               0
Memory             43
Storage            39
Rating            144
Selling Price       0
Original Price      0
dtype: int64
```

Replacing NULL Ratings with Average Rating

In [7]:
```
df["Rating"].replace(np.nan,df["Rating"].mean(),inplace=True)
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
Brand              0
Model              0
Color              0
Memory            43
Storage           39
Rating             0
Selling Price      0
Original Price     0
dtype: int64
```

In [9]:
```
df.shape
```

Out[9]:
```
(3114, 8)
```

Dropping Rows with NULL Memory and Storage

In [10]:
```
df.dropna(subset=["Memory","Storage"],inplace=True)
```

In [11]:
```
df.shape # After dropping NULL values
```

Out[11]:
```
(3032, 8)
```

In [12]:
```
df.isnull().sum() # Checking for NULL Values
```

Out[12]:
```
Brand             0
Model             0
Color             0
Memory            0
Storage           0
Rating            0
Selling Price     0
Original Price    0
dtype: int64
```

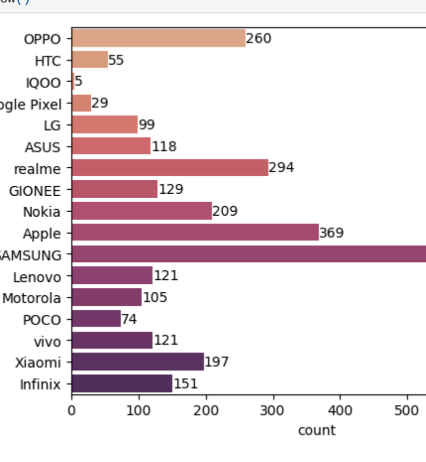
In [13]:
```
df.describe()
```

Out[13]:

	Rating	Selling Price	Original Price
count	3032.000000	3032.000000	3032.000000
mean	4.241398	26186.404354	28113.184697
std	0.266696	29291.841572	30843.861948
min	2.300000	1000.000000	1000.000000
25%	4.100000	9996.000000	10490.000000
50%	4.300000	15299.500000	16990.000000
75%	4.400000	28999.000000	31489.250000
max	5.000000	179900.000000	189999.000000

Analysing brands

In [14]:
```
ax = sns.countplot(y="Brand",data=df,palette="flare")
for bars in ax.containers:
    ax.bar_label(bars)
plt.show()
```

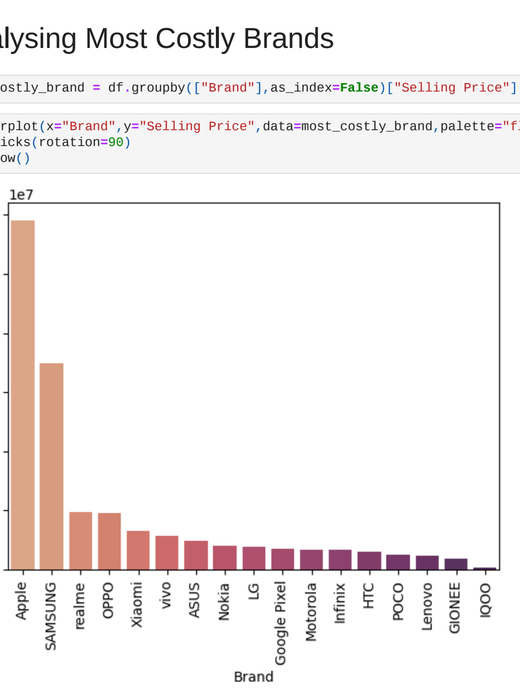


Samsung has the most number of mobile phones followed by Apple and realme

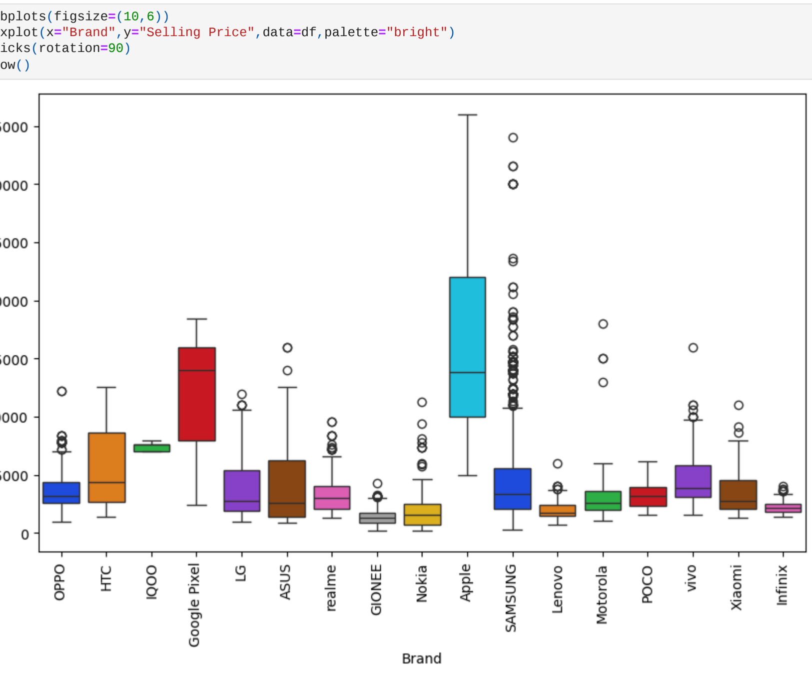
Analysing Most Costly Brands

In [15]:
```
most_costly_brand = df.groupby(["Brand"],as_index=False)["Selling Price"].sum().sort_values(by="Selling Price",ascending=False)
```

In [16]:
```
sns.barplot(x="Brand",y="Selling Price",data=most_costly_brand,palette="flare")
plt.xticks(rotation=90)
plt.show()
```



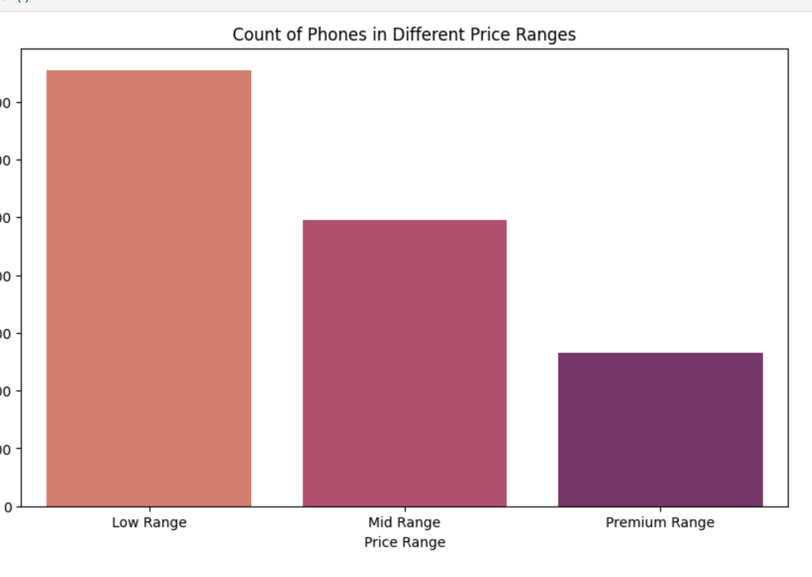
In [17]:
```
plt.subplots(figsize=(10,6))
sns.boxplot(x="Brand",y="Selling Price",data=df,palette="bright")
plt.xticks(rotation=90)
plt.show()
```



Apple is the most costly selling brand followed by Samsung

Range Wise Analysis (Low Range(0-15000) , Mid Range(16000-40000) ,Premium Range(above 40000) Smartphones)

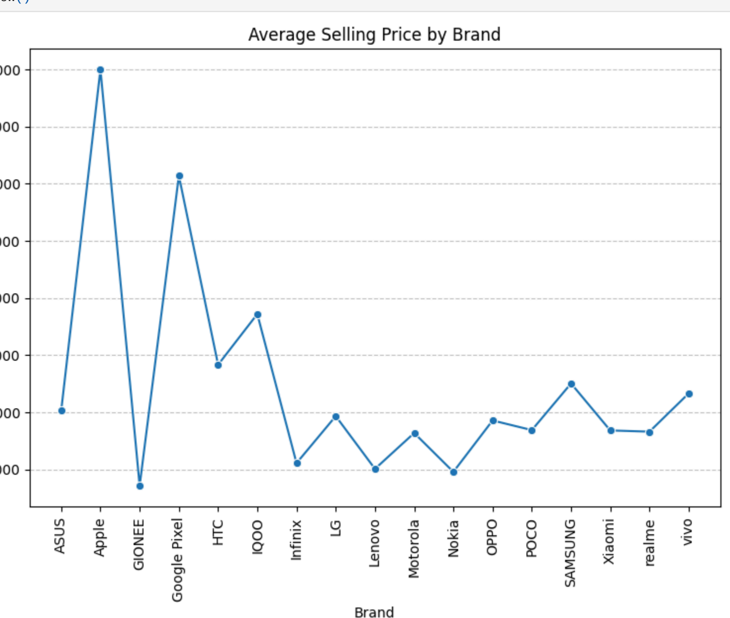
In [18]:
```
df["Price Range"] = pd.cut(df["Selling Price"], bins=[0, 15000, 40000, float("inf")], labels=["Low Range", "Mid Range", "Premium Range"])

plt.figure(figsize=(10, 6))
sns.countplot(x="Price Range",data=df,palette="flare")
plt.title("Count of Phones in Different Price Ranges")
plt.xlabel("Price Range")
plt.ylabel("Count")
plt.show()
```



Most Smartphones Belong to Low Range Category (0-15000 Rs)

Average Selling Price of Each Brand

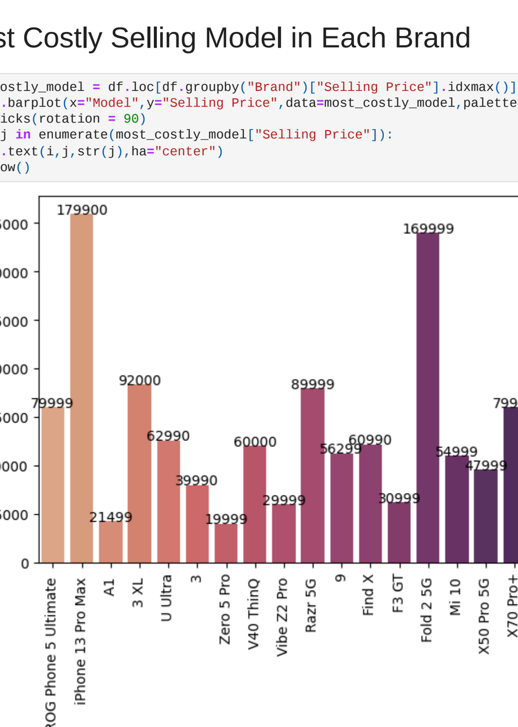
In [19]:
```
avg_sp_bybrand = df.groupby(["Brand"], as_index=False)["Selling Price"].mean()

plt.figure(figsize=(9, 6))
sns.lineplot(x="Brand", y="Selling Price", data=avg_sp_bybrand, marker="o")
plt.xticks(rotation=90)
plt.xlabel("Brand")
plt.ylabel("Average Selling Price")
plt.title("Average Selling Price by Brand")
plt.grid(axis='y', linestyle='--', alpha=0.7)
plt.show()
```



Apple Brand has the highest average selling price among all followed by Google Pixel then followed by IQOO

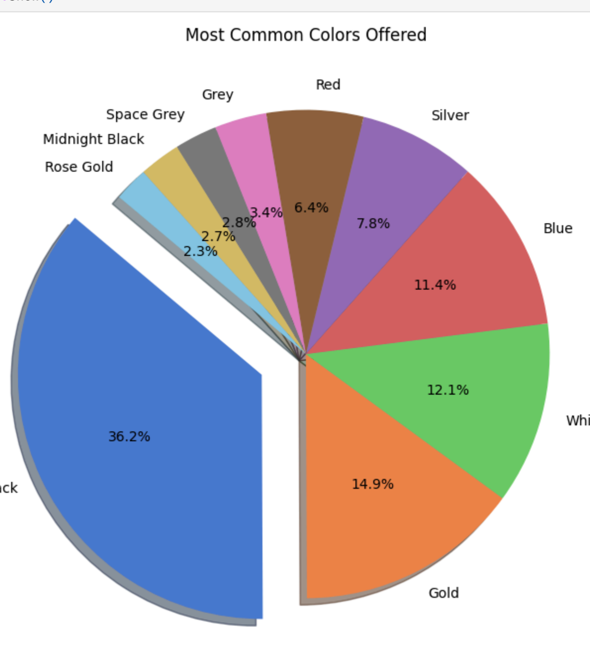
Most Costly Selling Model in Each Brand

In [20]:
```
most_costly_model = df.loc[df.groupby("Brand")["Selling Price"].idxmax()]
ax=sns.barplot(x="Model",y="Selling Price",data=most_costly_model,palette="flare")
plt.xticks(rotation = 90)
for i,j in enumerate(most_costly_model["Selling Price"]):
    ax.text(i,j,str(j),ha="center")
plt.show()
```



Most Common colors offered

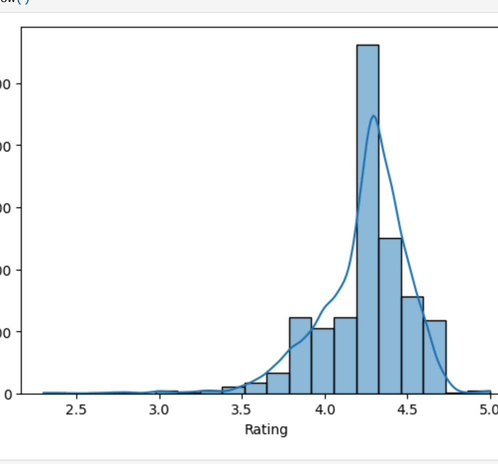
In [21]:
```
common_colors = df["Color"].value_counts().head(10)
plt.figure(figsize=(8, 8))
plt.pie(common_colors,labels=common_colors.index,autopct='%1.1f%%',startangle=140,colors=sns.color_palette("muted"),explode=[0.2,0,0,0,0,0,0,0,0,0],shadow=True)
plt.title("Most Common Colors Offered")
plt.show()
```



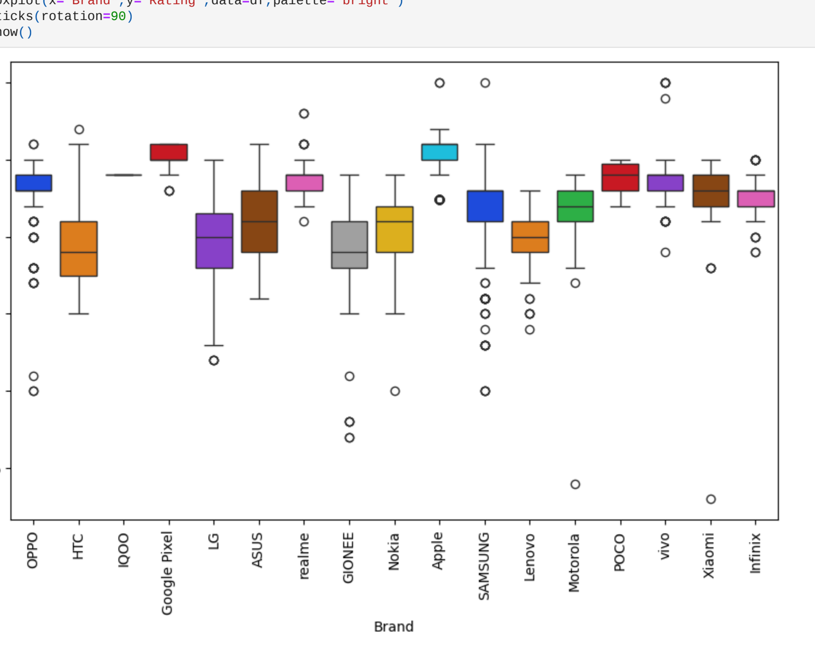
Most Common Color offered is black followed by gold then followed by white and then followed by blue.

Rating wise analysis of brands

In [22]:
```
sns.histplot(df['Rating'], bins=20, kde=True)
plt.show()
```



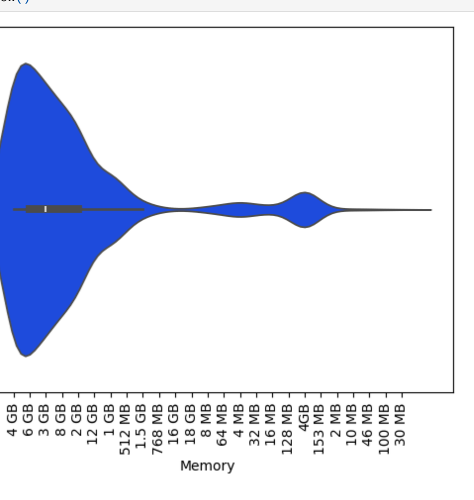
In [23]:
```
plt.subplots(figsize=(10,6))
sns.boxplot(x="Brand",y="Rating",data=df,palette="bright")
plt.xticks(rotation=90)
plt.show()
```



Apple is the most rated brand followed by Google Pixel

Analysis by RAM offered

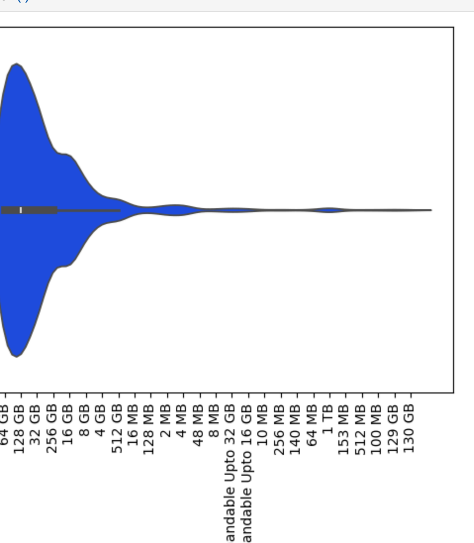
In [24]:
```
sns.violinplot(x="Memory",data=df,palette="bright")
plt.xticks(rotation=90)
plt.show()
```



Most phones which are available have 4GB RAM

Analysis by Storage Offered

In [25]:
```
sns.violinplot(x="Storage",data=df,palette="bright")
plt.xticks(rotation=90)
plt.show()
```



Most phones which are available have 64GB Storage

Top 10 rated models

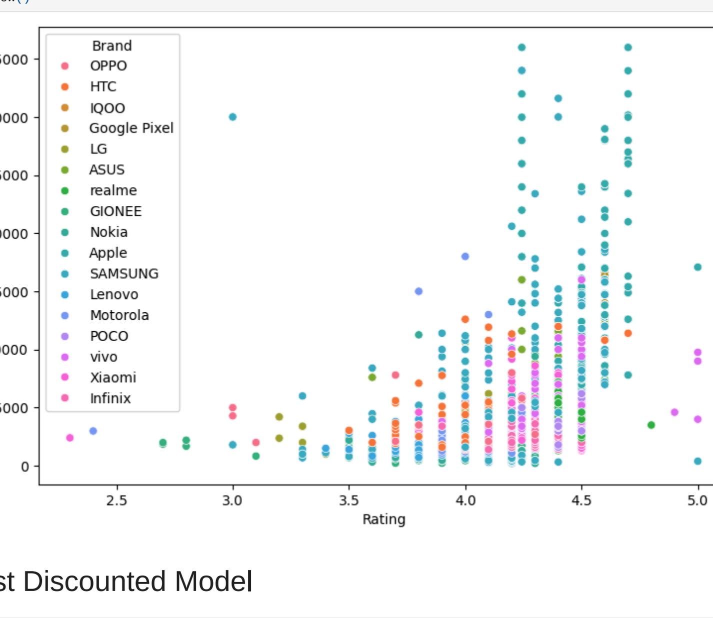
In [26]:
```
top10_models = df.nlargest(10,"Rating")
top10_models
```

Out[26]:

	Brand	Model	Color	Memory	Storage	Rating	Selling Price	Original Price	Price Range
1252	Apple	iPhone 7 Plus	Red	3 GB	256 GB	5.0	85400	85400	Premium Range
1348	Apple	iPhone 7 Plus	Red	3 GB	256 GB	5.0	85400	85400	Premium Range
2021	SAMSUNG	SM-B310EZDDINS	Black	100 MB	100 MB	5.0	1949	1949	Low Range
2789	vivo	X60 Pro	Shimmer Blue	12 GB	256 GB	5.0	48780	48780	Premium Range
2791	vivo	X50	Frost Blue	8 GB	256 GB	5.0	44990	44990	Premium Range
2797	vivo	Z1x	Phantom Purple	6 GB	64 GB	5.0	19990	19990	Mid Range
2799	vivo	S2	Diamond Black	4 GB	128 GB	5.0	19990	19990	Mid Range
2771	vivo	Y33T	Mirror Black	8 GB	128 GB	4.9	22990	22990	Mid Range
3061	realme	9 5G	Meteor Black	6 GB	128 GB	4.8	17499	20999	Mid Range
3062	realme	9 5G	Stargaze White	6 GB	128 GB	4.8	17499	20999	Mid Range

Rating V/S Selling Price

In [34]:
```
plt.figure(figsize=(9,6))
sns.scatterplot(x='Rating', y='Selling Price', data=df,hue="Brand")
plt.show()
```



Most Discounted Model

In [28]:
```
df['Discount Percentage'] = ((df['Original Price'] - df['Selling Price']) / df['Original Price']) * 100
df[df['Discount Percentage']==df['Discount Percentage'].max()]
```

Out[28]:

	Brand	Model	Color	Memory	Storage	Rating	Selling Price	Original Price	Price Range	Discount Percentage
803	GIONEE	Pioneer P3	White	512 MB	4 GB	3.6	2350	7996	Low Range	70.610305

GIONEE Brand is offering a 70.61 percent discount on Model Pioneer P3 which is the highest discount percentage among all models

Correlation Matrix

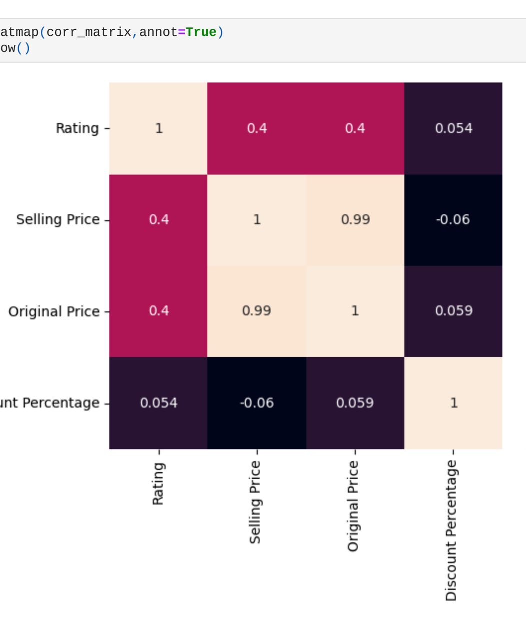
In [29]:
```
corr_matrix = df.corr(numeric_only=True)
corr_matrix
```

Out[29]:

	Rating	Selling Price	Original Price	Discount Percentage
Rating	1.000000	0.404179	0.403896	0.053857
Selling Price	0.404179	1.000000	0.985189	-0.060141
Original Price	0.403896	0.985189	1.000000	0.059051
Discount Percentage	0.053857	-0.060141	0.059051	1.000000

HeatMap

In [30]:
```
sns.heatmap(corr_matrix,annot=True)
plt.show()
```



Conclusion :-

The availability of Low Range Phones Should be Increased as most buyers buy phones in 15000 range

Vivo is providing more rated products and are value for money.

It is not true that only higher selling price products have a higher rating maximum mobiles lying between 0 to 25000 also have a good rating