TASK3-EXPLORATORY DATA ANALYSIS- RETAIL

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MOUNTING GDRIVE ONTO THE COLAB NOTEBOOK

```
from google.colab import drive
drive.mount('/content/drive',force_remount=True)
print("MOUNTED SUCCESSFULLY")
```

Mounted at /content/drive MOUNTED SUCCESSFULLY

IMPORTING THE NECESSARY LIBRARIES

```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
sns.set(color_codes=True)
```

[5 rows x 13 columns]

IMPORTING AND DISPLAYING DATA HEAD AND TAIL

```
path='/content/drive/MyDrive/Colab Notebooks/SampleSuperstore.csv'
data=pd.read_csv(path)
print(data.head())
print(data.tail())
```

	Ship Mode	Segment	Country	Qu	antity Di	iscount	Profit	
0	Second Class	Consumer	United States		2	0.00	41.9136	
1	Second Class	Consumer	United States		3	0.00	219.5820	
2	Second Class	Corporate	United States		2	0.00	6.8714	
3	Standard Class	Consumer	United States		5	0.45 -	383.0310	
4	Standard Class	Consumer	United States		2	0.20	2.5164	
[5 rows x 13 columns]								
	Ship Mo	de Segmen	t Countr	y	Quantity	Discount	Profit	
998	Second Cla	ss Consume	r United State	s	3	0.2	4.1028	
999	00 Standard Cla	ss Consume	r United State	s	2	0.0	15.6332	
999	1 Standard Cla	ss Consume	r United State	s	2	0.2	19.3932	
999	2 Standard Cla	ss Consume	r United State	s	4	0.0	13.3200	
999	3 Second Cla	ss Consume	r United State	s	2	0.0	72.9480	

HERE I HAVE PRINTED THE DATA TYPE OF EACH COLUMN. A BEFORE-HAND ACCOUNT OF THIS IS A MUST FOR BETTER DATA ANALYTICS. THEN I AM PRINTING THE TOTAL NULL VALUES PRESENT IN THE ENTIRE DATASET ALONG WITH THE DATASET SHAPE

```
print(data.dtypes)
nulls=data.isnull().sum().sum()
print("Total null values=",nulls)
print("Dataset Shape=",data.shape)
```

Ship Mode object Segment object Country object object City State object Postal Code int64 object Region object Category Sub-Category object Sales float64 Quantity int64 Discount float64 Profit float64 dtype: object Total null values= 0 Dataset Shape= (9994, 13)

data.describe()

	Postal Code	Sales	Quantity	Discount	Profit
count	9994.000000	9994.000000	9994.000000	9994.000000	9994.000000
mean	55190.379428	229.858001	3.789574	0.156203	28.656896
std	32063.693350	623.245101	2.225110	0.206452	234.260108
min	1040.000000	0.444000	1.000000	0.000000	-6599.978000
25%	23223.000000	17.280000	2.000000	0.000000	1.728750
50%	56430.500000	54.490000	3.000000	0.200000	8.666500
75%	90008.000000	209.940000	5.000000	0.200000	29.364000
max	99301.000000	22638.480000	14.000000	0.800000	8399.976000

NEXT I HAVE FOUND OUT THE NUMBER OF UNIQUE VALUES PRESENT IN DIFFERENT COLUMNS OF THE DATASET

data.nunique()

Ship Mode	4
Segment	3
Country	1
City	531
State	49
Postal Code	631
Region	4
Category	3
Sub-Category	17

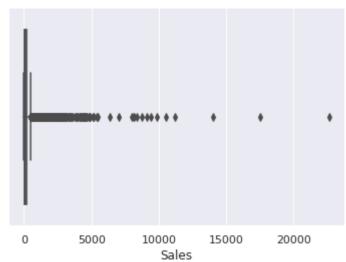
Sales 5825 Quantity 14 Discount 12 Profit 7287

dtype: int64

FOLLOWING ARE A SERIES OF BOXPLOT GRAPHS FOR A NUMBER OF FEATURES PRESENT IN THE DATASET. THIS WOULD HELP IN UNDERSTANDING WHERE ARE THE VALUES OF DIFFERENT FEATURES CONCENTRATED AND WHAT ALL VALUES ARE OUTLIERS(IF ANY)

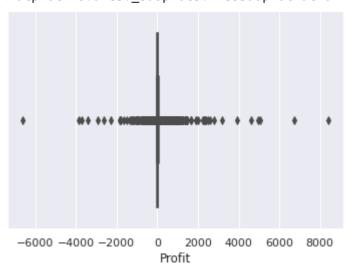
sns.boxplot(x=data['Sales'])

<matplotlib.axes._subplots.AxesSubplot at 0x7f199c3dc790>



sns.boxplot(x=data['Profit'])

<matplotlib.axes._subplots.AxesSubplot at 0x7f199c38e890>

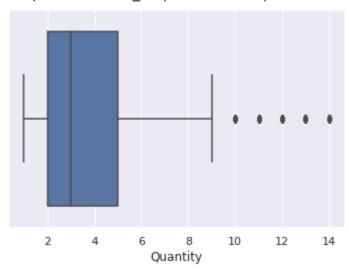


print(data['Profit'].sum(axis=0))

286397.0217

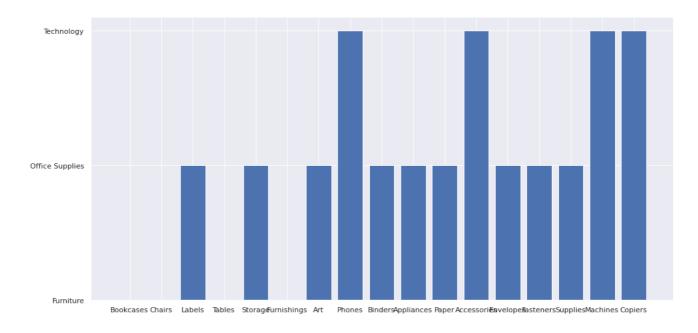
sns.boxplot(x=data['Quantity'])

<matplotlib.axes._subplots.AxesSubplot at 0x7f199bec36d0>



BAR GRAPH BETWEEN SUB-CATEGORY AND CATEGORY

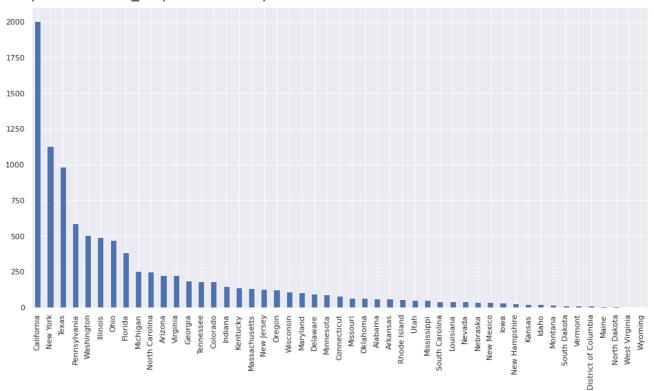
```
plt.figure(figsize=(16,8))
plt.bar('Sub-Category','Category',data=data)
plt.show()
```



NEXT ARE A SERIES OF COUNT GRAPHS THAT IS HOW MANY DATA DO WE HAVE IF THE VALUES OF A PARTICULAR COLUMN IS TO BE CONSIDERED THE DIFFERNTIATING FACTOR

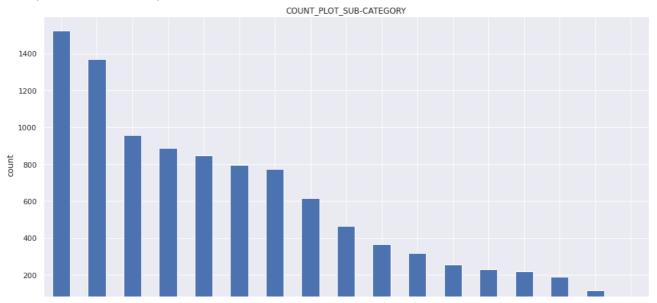
data['State'].value_counts().plot(kind='bar')

<matplotlib.axes._subplots.AxesSubplot at 0x7f199bdc76d0>



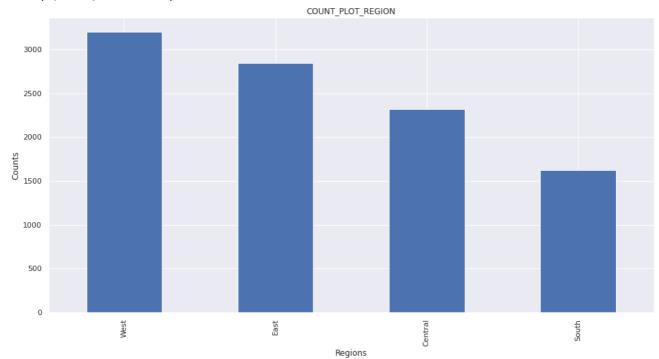
```
plt.figure(figsize=(16,8))
data['Sub-Category'].value_counts().plot(kind='bar')
plt.title("COUNT_PLOT_SUB-CATEGORY")
plt.xlabel("Sub-catrgories")
plt.ylabel("count")
```

Text(0, 0.5, 'count')



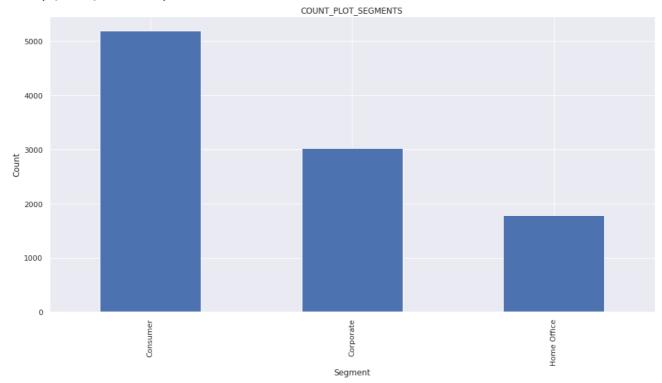
plt.figure(figsize=(16,8))
data['Region'].value_counts().plot(kind='bar')
plt.title("COUNT_PLOT_REGION")
plt.xlabel("Regions")
plt.ylabel("Counts")

Text(0, 0.5, 'Counts')

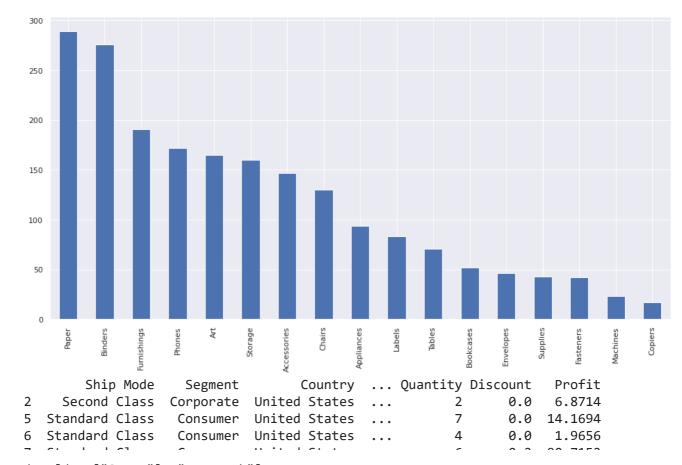


```
data['Segment'].value_counts().plot(kind='bar')
plt.title("COUNT_PLOT_SEGMENTS")
plt.xlabel("Segment")
plt.ylabel("Count")
```

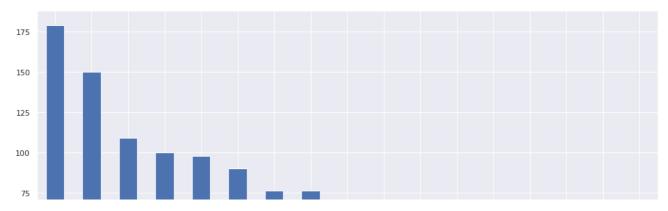
Text(0, 0.5, 'Count')



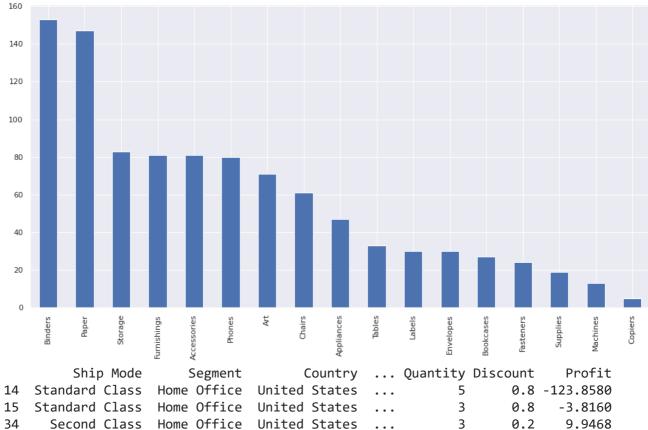
```
d_california=data[data["State"]=="California"]
plt.figure(figsize=(16,8))
d_california['Sub-Category'].value_counts().plot(kind='bar')
plt.show()
print(d_california.head())
```



```
d_ny=data[data["State"]=="New York"]
plt.figure(figsize=(16,8))
d_ny['Sub-Category'].value_counts().plot(kind='bar')
plt.show()
print(d_ny.head())
```



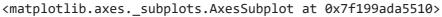
```
d_texas=data[data["State"]=="Texas"]
plt.figure(figsize=(16,8))
d_texas['Sub-Category'].value_counts().plot(kind='bar')
plt.show()
print(d_texas.head())
```



Home Office United States 0.2 7 35 First Class Corporate United States 0.2 123.4737 5 36 First Class Corporate United States 0.6 -147.9630

[5 rows x 13 columns]

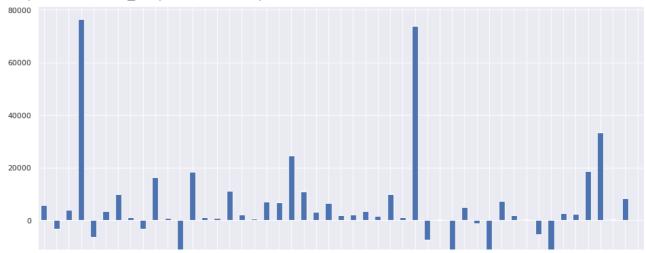
fig,axes = plt.subplots(1,1,figsize=(16,8))
sns.heatmap(data.corr(), annot= True)





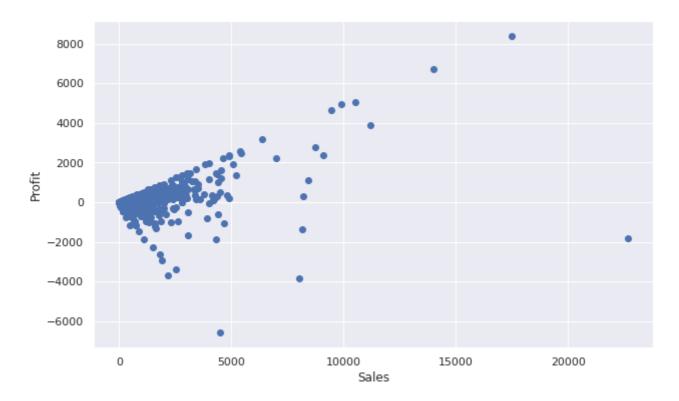
```
plt.figure(figsize=(16,8))
d_profit=data.groupby('State')['Profit']
d_profit.sum().plot(kind='bar')
```

<matplotlib.axes._subplots.AxesSubplot at 0x7f1996407ed0>



SCATTER PLOT

```
fig, ax = plt.subplots(figsize = (10 , 6))
ax.scatter(data["Sales"] , data["Profit"])
ax.set_xlabel('Sales')
ax.set_ylabel('Profit')
plt.show()
```



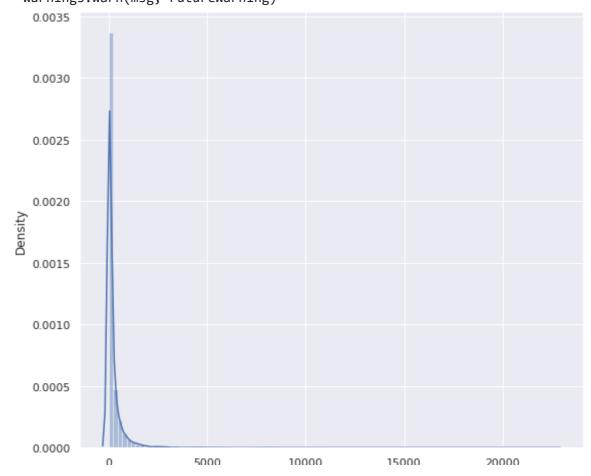
DISTRIBUTION PLOT

```
print(data['Sales'].describe())
plt.figure(figsize = (9 , 8))
sns.distplot(data['Sales'], color = 'b', bins = 100, hist_kws = {'alpha': 0.4});
```

9994.000000 count 229.858001 mean 623.245101 std min 0.444000 25% 17.280000 50% 54.490000 75% 209.940000 22638.480000 max

Name: Sales, dtype: float64

/usr/local/lib/python3.7/dist-packages/seaborn/distributions.py:2557: FutureWarning: warnings.warn(msg, FutureWarning)



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