Samplesuperstore Data analysis

April 25, 2024

0.0.1 importing libraries

[1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
```

0.0.2 Dataset

[2]:
```
df=pd.read_csv("SampleSuperstore.csv")
```

0.0.3 Data Exploration:

0.0.4 Dimensions of data

[3]:
```
df.shape
```

[3]:
```
(9994, 13)
```

0.0.5 peek at the data

[4]:
```
df.head(5)
```

[4]:
```
        Ship Mode    Segment        Country             City       State  \
0    Second Class   Consumer  United States        Henderson    Kentucky
1    Second Class   Consumer  United States        Henderson    Kentucky
2    Second Class  Corporate  United States      Los Angeles  California
3  Standard Class   Consumer  United States  Fort Lauderdale     Florida
4  Standard Class   Consumer  United States  Fort Lauderdale     Florida

   Postal Code Region         Category Sub-Category     Sales  Quantity  \
0        42420  South        Furniture    Bookcases  261.9600         2
1        42420  South        Furniture       Chairs  731.9400         3
2        90036   West  Office Supplies       Labels   14.6200         2
3        33311  South        Furniture       Tables  957.5775         5
4        33311  South  Office Supplies      Storage   22.3680         2

   Discount    Profit
```

```
0       0.00   41.9136
1       0.00  219.5820
2       0.00    6.8714
3       0.45 -383.0310
4       0.20    2.5164
```

[5]:
```
df.tail(5)
```

[5]:
```
           Ship Mode   Segment        Country         City       State  \
9989    Second Class  Consumer  United States        Miami     Florida
9990  Standard Class  Consumer  United States   Costa Mesa  California
9991  Standard Class  Consumer  United States   Costa Mesa  California
9992  Standard Class  Consumer  United States   Costa Mesa  California
9993    Second Class  Consumer  United States  Westminster  California

      Postal Code Region         Category Sub-Category    Sales  Quantity  \
9989        33180  South        Furniture  Furnishings   25.248         3
9990        92627   West        Furniture  Furnishings   91.960         2
9991        92627   West       Technology       Phones  258.576         2
9992        92627   West  Office Supplies        Paper   29.600         4
9993        92683   West  Office Supplies   Appliances  243.160         2

      Discount   Profit
9989       0.2   4.1028
9990       0.0  15.6332
9991       0.2  19.3932
9992       0.0  13.3200
9993       0.0  72.9480
```

[6]:
```
# general overview of data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 13 columns):
 #   Column        Non-Null Count  Dtype
---  ------        --------------  -----
 0   Ship Mode     9994 non-null   object
 1   Segment       9994 non-null   object
 2   Country       9994 non-null   object
 3   City          9994 non-null   object
 4   State         9994 non-null   object
 5   Postal Code   9994 non-null   int64
 6   Region        9994 non-null   object
 7   Category      9994 non-null   object
 8   Sub-Category  9994 non-null   object
 9   Sales         9994 non-null   float64
```

```
 10  Quantity      9994 non-null   int64
 11  Discount      9994 non-null   float64
 12  Profit        9994 non-null   float64
dtypes: float64(3), int64(2), object(8)
memory usage: 1015.1+ KB
```

[7]:
```
df.describe()
```

[7]:

	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

0.0.6 checking for missing values,

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

[8]:
```
Ship Mode       0
Segment         0
Country         0
City            0
State           0
Postal Code     0
Region          0
Category        0
Sub-Category    0
Sales           0
Quantity        0
Discount        0
Profit          0
dtype: int64
```

0.0.7 Missing values are not present in dataset

[9]:
```
df.dtypes
```

[9]:
```
Ship Mode        object
Segment          object
Country          object
City             object
State            object
Postal Code       int64
```

```
Region            object
Category          object
Sub-Category      object
Sales            float64
Quantity           int64
Discount         float64
Profit           float64
dtype: object
```

0.0.8 Data Cleaning

[10]:
```python
df.duplicated()
```

[10]:
```
0       False
1       False
2       False
3       False
4       False
        …
9989    False
9990    False
9991    False
9992    False
9993    False
Length: 9994, dtype: bool
```

0.0.9 Descriptive stastics

[11]:
```python
#Total sales
total_sales=df['Sales'].sum()
```

[12]:
```python
total_sales
```

[12]:
```
2297200.8603000003
```

[13]:
```python
# Average order value
average_order_value = df['Sales'].mean()
```

[14]:
```python
average_order_value
```

[14]:
```
229.85800083049833
```

[15]:
```python
median_sales = df['Sales'].median()
```

[16]:
```python
median_sales
```

[16]: 54.489999999999995

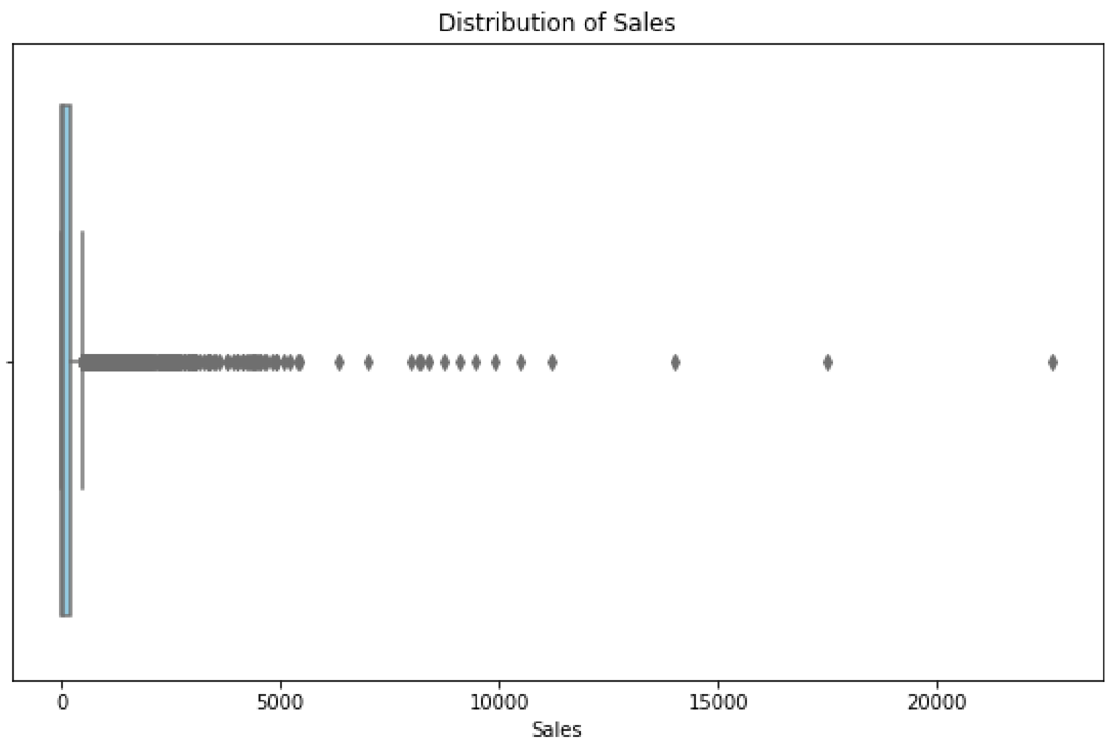
[17]:
```
std_dev_sales = df['Sales'].std()
```

[18]:
```
std_dev_sales
```

[18]: 623.2451005086807

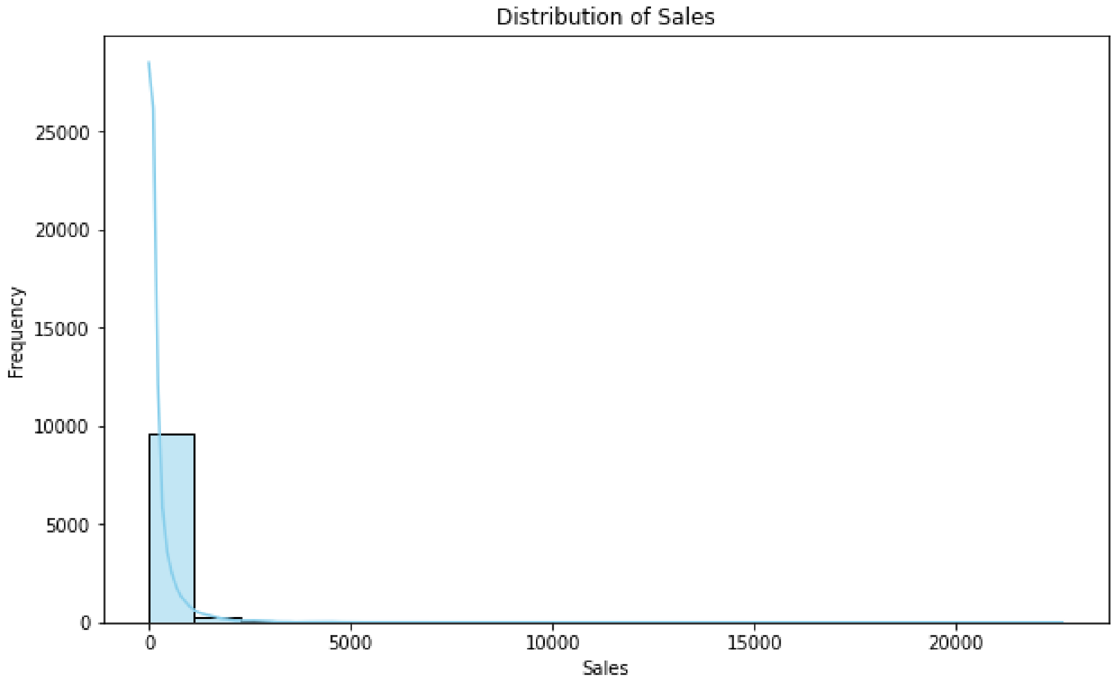
0.0.10 lets visualize distribution of sales

[19]:
```
# visualize  Distribution of sales by boxplot
plt.figure(figsize=(10, 6))
sns.boxplot(x=df['Sales'], color='skyblue')
plt.title('Distribution of Sales')
plt.xlabel('Sales')
plt.show()
```

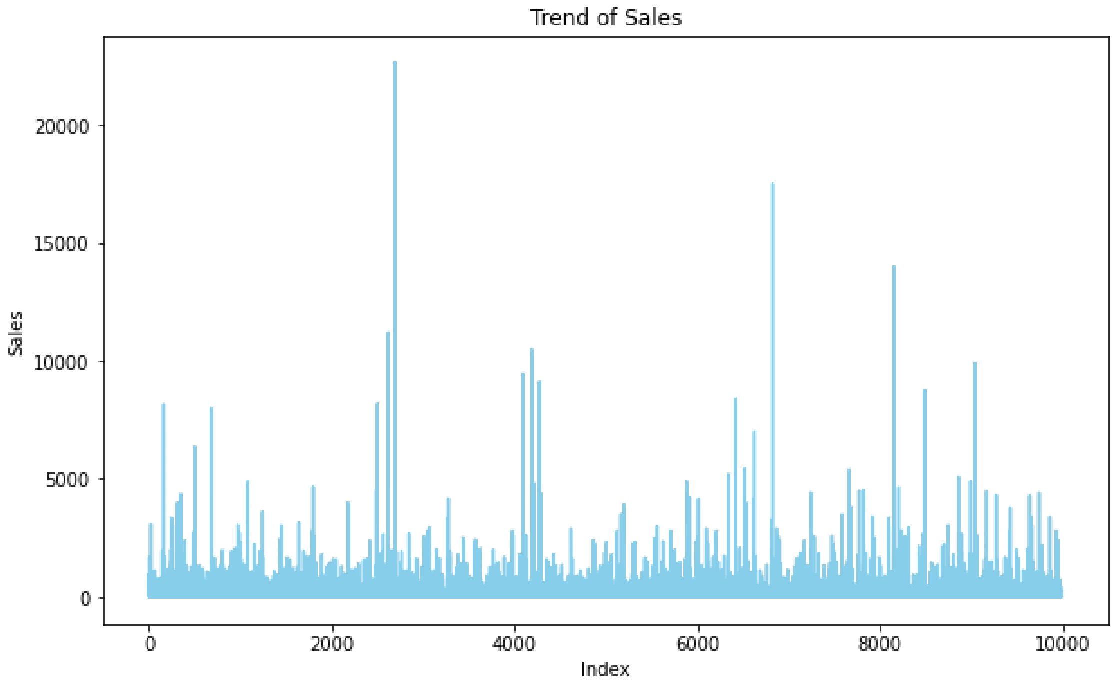


[20]:
```
# visualize  Distribution of sales by histplot
plt.figure(figsize=(10, 6))
sns.histplot(df['Sales'], bins=20, kde=True, color='skyblue')
plt.title('Distribution of Sales')
plt.xlabel('Sales')
plt.ylabel('Frequency')
```

```
plt.show()
```

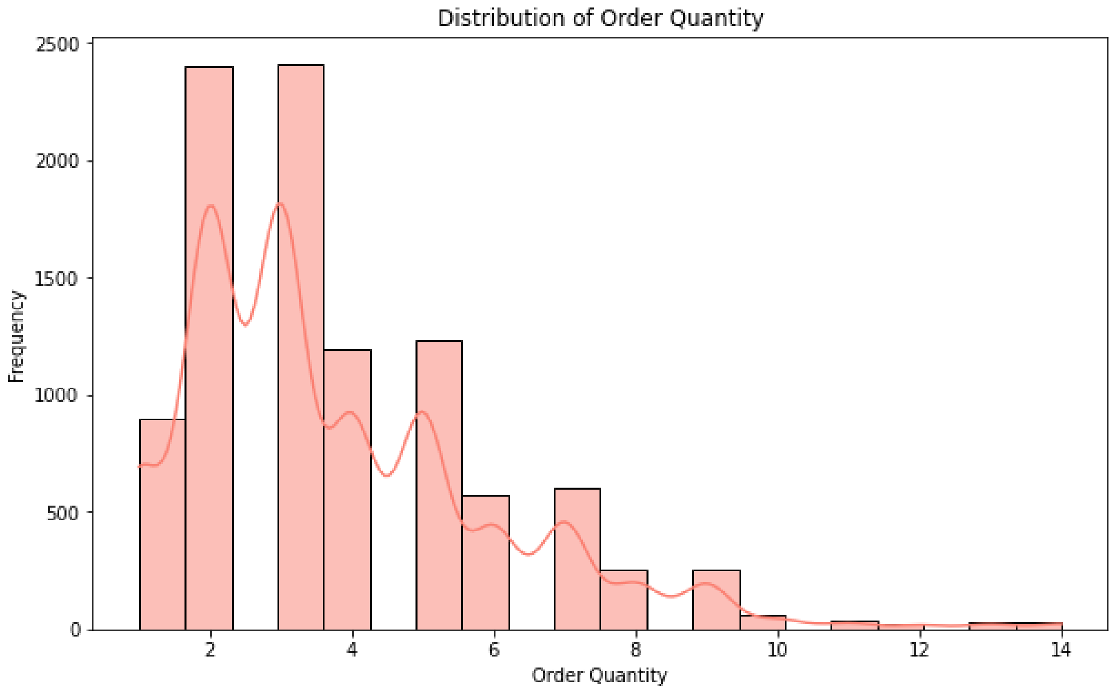


[21]:
```
# Trend of Sales
plt.figure(figsize=(10, 6))
sns.lineplot(data=df['Sales'], color='skyblue')
plt.title('Trend of Sales')
plt.xlabel('Index')
plt.ylabel('Sales')
plt.show()
```



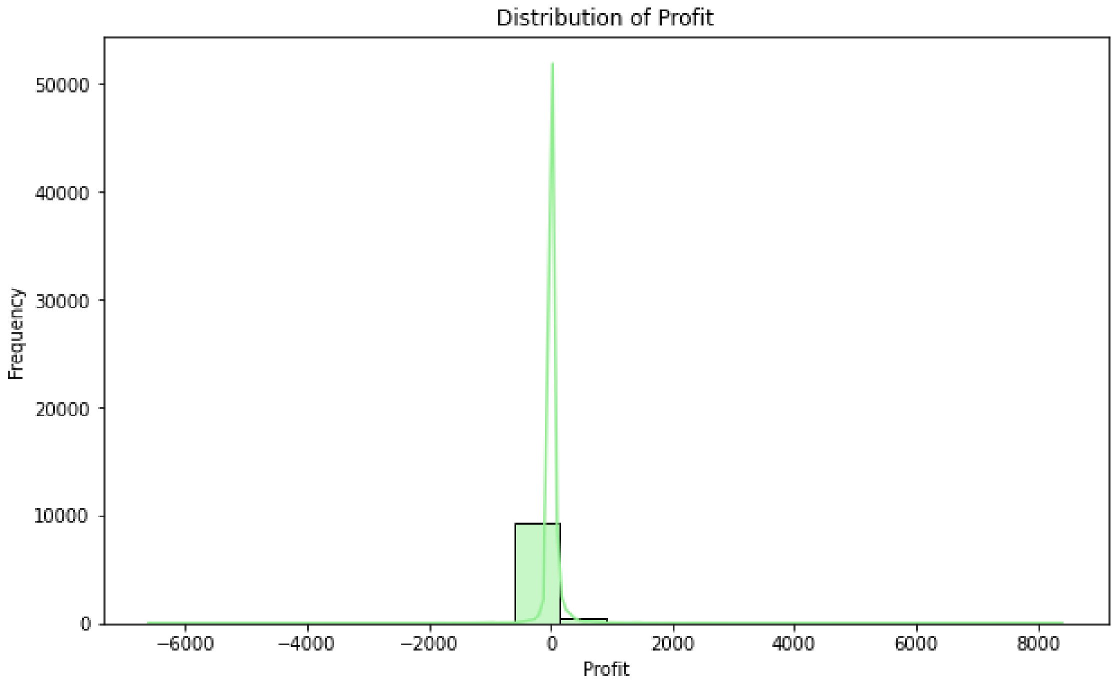
0.0.11 visualize order quantity

[22]:
```
# lets visualize the order quantity
plt.figure(figsize=(10, 6))
sns.histplot(df['Quantity'], bins=20, kde=True, color='salmon')
plt.title('Distribution of Order Quantity')
plt.xlabel('Order Quantity')
plt.ylabel('Frequency')
plt.show()
```

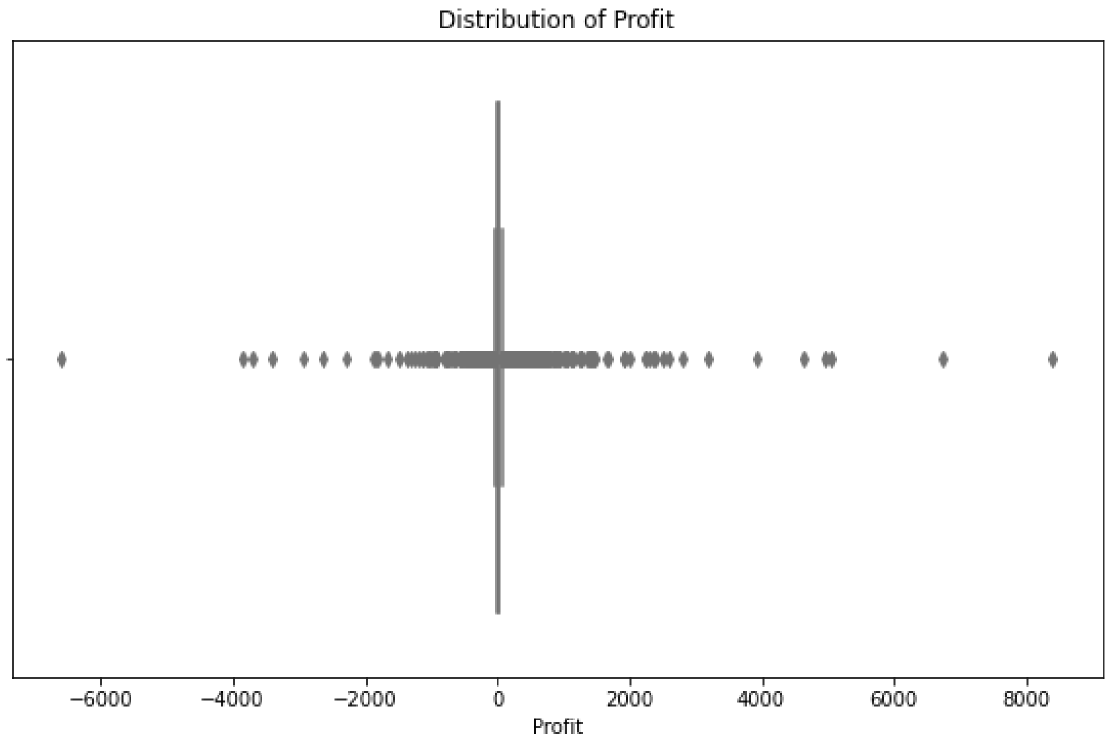


0.0.12 visualize profit

[23]:
```
# lets visualize the profit
plt.figure(figsize=(10, 6))
sns.histplot(df['Profit'], kde=True, bins=20, color='lightgreen')
plt.title('Distribution of Profit')
plt.xlabel('Profit')
plt.ylabel('Frequency')
plt.show()
```

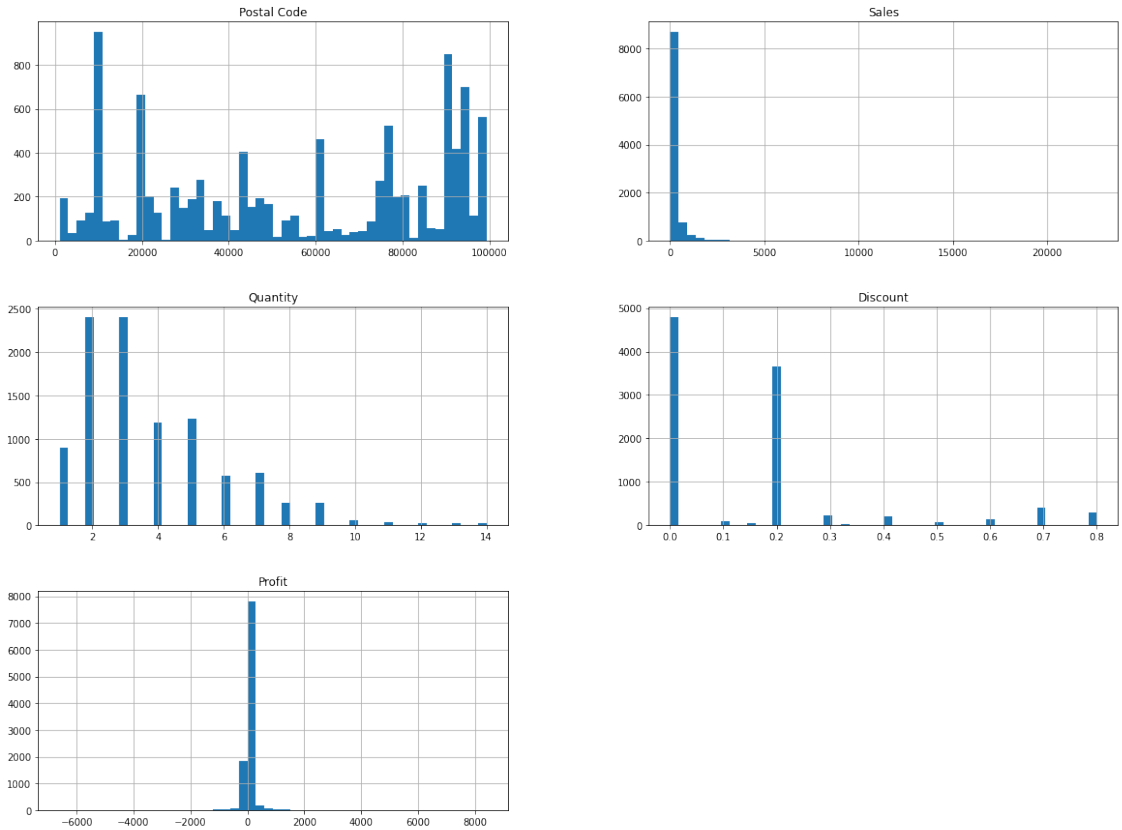


[24]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(x=df['Profit'], color='lightgreen')
plt.title('Distribution of Profit')
plt.xlabel('Profit')
plt.show()
```



0.0.13 Histogram of data

[25]:
```
df.hist(bins=50,figsize=(20,15))
plt.show()
```

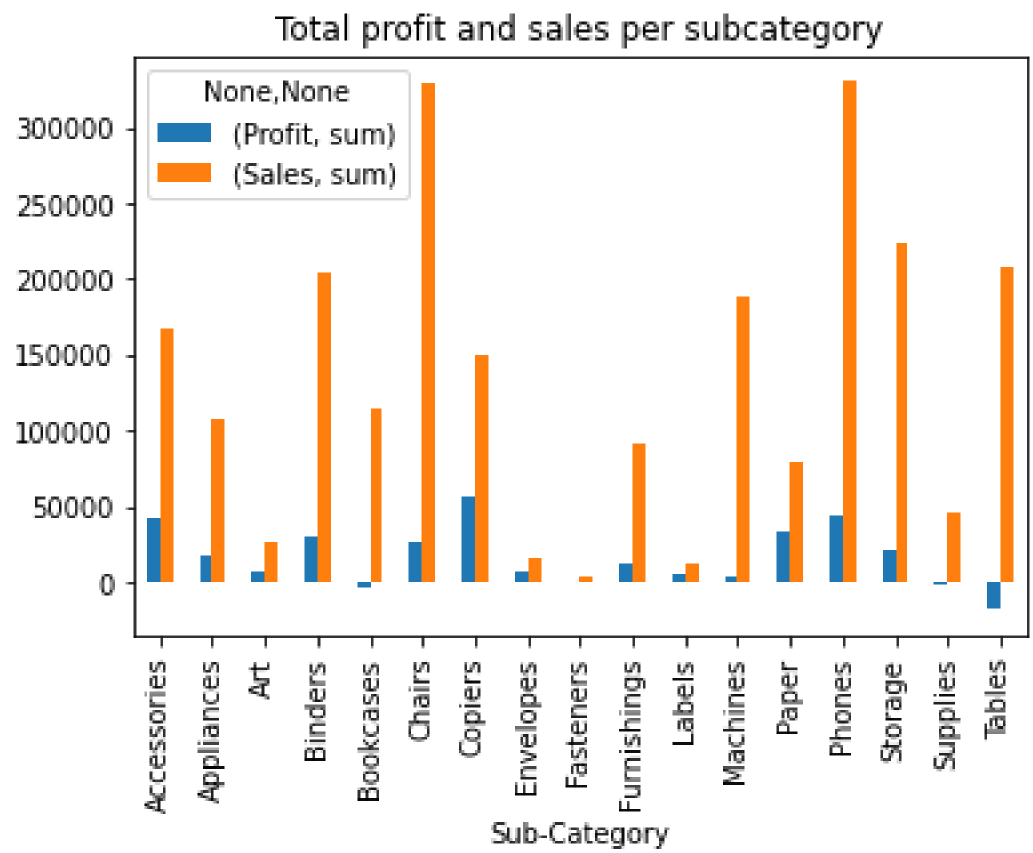


0.0.14 the sales and profit

[28]:

```
df.groupby('Sub-Category')['Profit','Sales'].agg(['sum']).plot.bar()
plt.title('Total profit and sales per subcategory')
plt.figure (figsize=[10,8])
plt.show()
```

```
/tmp/ipykernel_75/3991613971.py:1: FutureWarning: Indexing with multiple keys
(implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  df.groupby('Sub-Category')['Profit','Sales'].agg(['sum']).plot.bar()
```



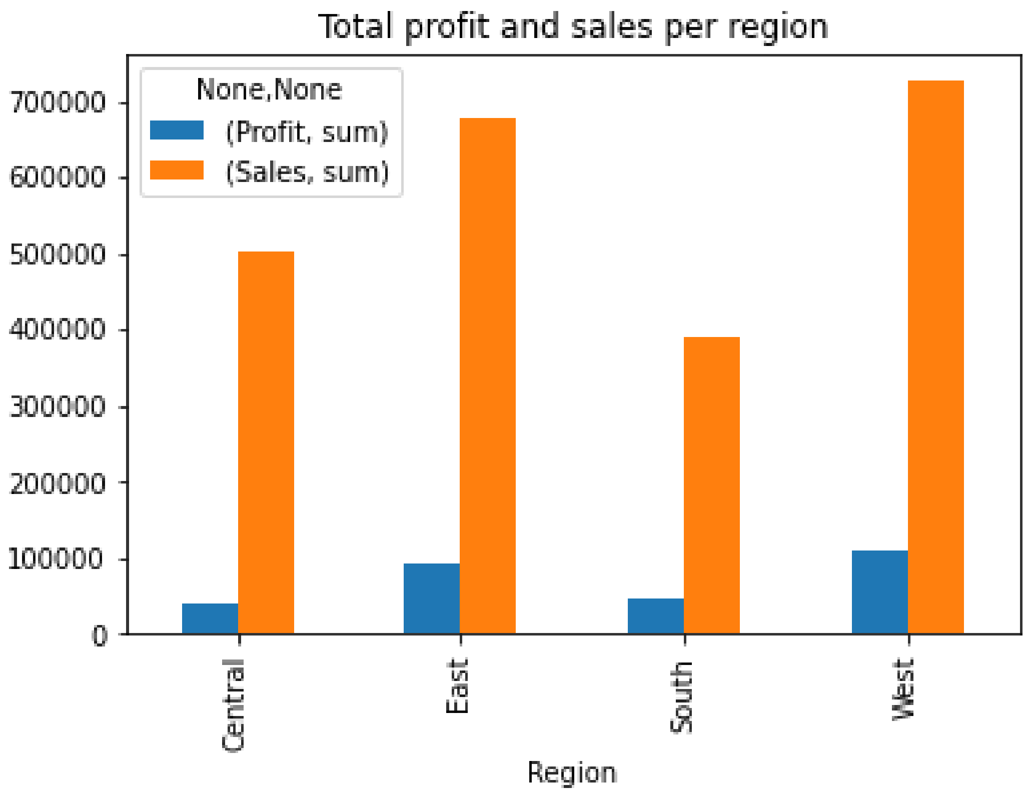

```
<Figure size 720x576 with 0 Axes>
```

0.1 highest profit is earned in copiers while selling price of chairs and phones are extremely high compared to other product.

0.2 people dont prefer to buy tables and bookcases from superstore hence these departments are in loss.

[29]:
```
df.groupby('Region')['Profit','Sales'].agg(['sum']).plot.bar()
plt.title('Total profit and sales per region')
plt.figure (figsize=[10,8])
plt.show()
```

```
/tmp/ipykernel_75/647084091.py:1: FutureWarning: Indexing with multiple keys
(implicitly converted to a tuple of keys) will be deprecated, use a list
instead.
  df.groupby('Region')['Profit','Sales'].agg(['sum']).plot.bar()
```




```
<Figure size 720x576 with 0 Axes>
```

0.2.1 Sales in west and east region is high whereas sales in south is low.

0.2.2 the profit in central region is very less and profit earned in west is highest.

0.2.3 Customer Segmentation:

[30]:
```python
# types of customers
types_of_customers = df["Segment"].unique()
print(types_of_customers)
```

```
['Consumer' 'Corporate' 'Home Office']
```

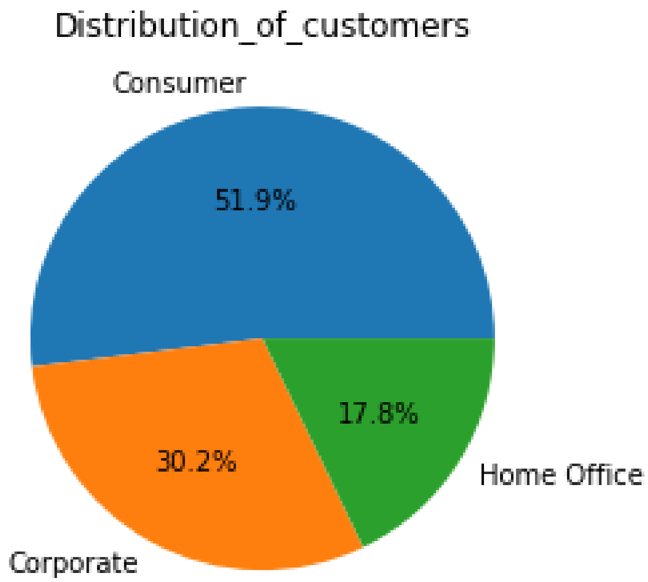
[31]:
```python
# number of customers in each segment
number_of_customers= df["Segment"].value_counts().reset_index()
number_of_customers=number_of_customers.rename(columns={'index':'Customer␣
↪Type','Segment':'Total Customers'})
print(number_of_customers)
```

```
  Customer Type  Total Customers
0      Consumer             5191
```

```
1     Corporate             3020
2   Home Office             1783
```

[32]:

```
#ploting pie chart
plt.pie(number_of_customers['Total␣
↪Customers'],labels=number_of_customers['Customer Type'],autopct='%1.1f%%')
#set pie chart labels
plt.title('Distribution_of_customers')
plt.show()
```



[33]:

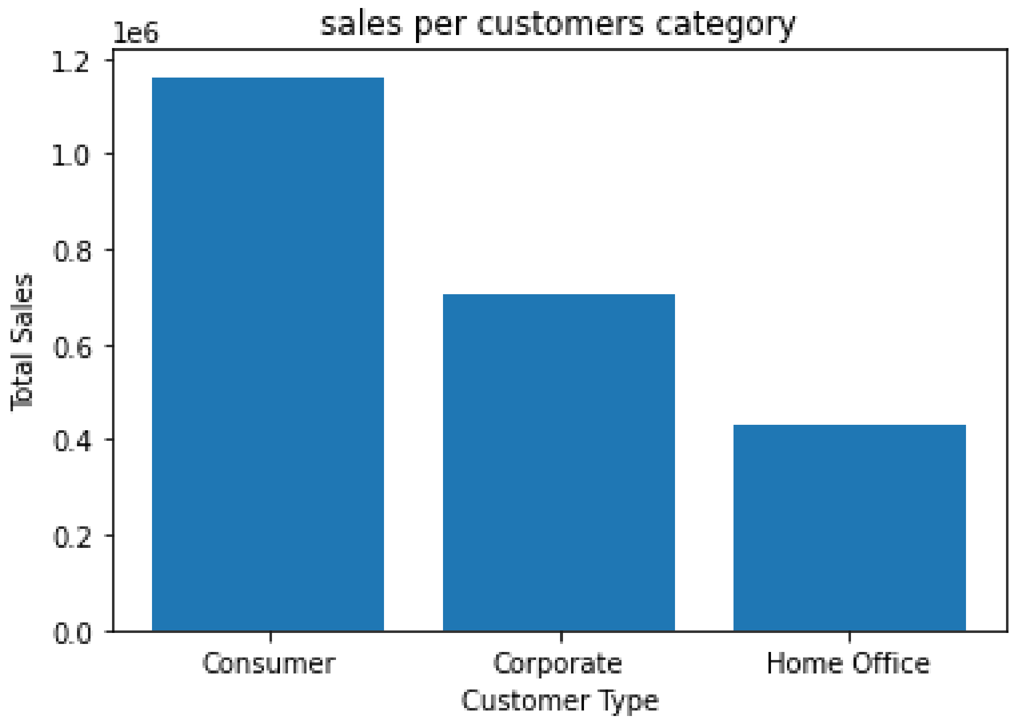
```
# sales per category
sales_per_category=df.groupby('Segment')['Sales'].sum().reset_index()
sales_per_category=sales_per_category.rename(columns={'Segment':'Customer␣
↪Type','Sales':'Total Sales'})
print(sales_per_category)
```

```
  Customer Type   Total Sales
0      Consumer  1.161401e+06
1     Corporate  7.061464e+05
2   Home Office  4.296531e+05
```

[34]:

```
# sales per customer category
plt.bar(sales_per_category['Customer Type'],sales_per_category['Total Sales'])
#label
plt.title('sales per customers category')
plt.xlabel('Customer Type')
```

```
plt.ylabel('Total Sales')
plt.show()
```



0.2.4 The segment of home office is very less and store has to focus more on home office to improve the sales

[35]:
```
# sorting unique values in the ship mode column into new series
types_of_shiping=df['Ship Mode'].unique()
print(types_of_shiping)
```

```
['Second Class' 'Standard Class' 'First Class' 'Same Day']
```

[36]:
```
# frequency use of shiping method
shiping_mode= df['Ship Mode'].value_counts().reset_index()
shiping_mode=shiping_mode.rename(columns={'index':'Mode of Shipment','Ship␣
↪Mode':'Use Frequency'})
print(shiping_mode)
```

```
  Mode of Shipment  Use Frequency
0   Standard Class           5968
1     Second Class           1945
2      First Class           1538
3         Same Day            543
```

[37]:
```
state=df['State'].value_counts().reset_index()
state=state.rename(columns={'index':'State','State':'Number of customers'})
print(state.head(7))
```

```
         State  Number of customers
0   California                 2001
1     New York                 1128
2        Texas                  985
3 Pennsylvania                  587
4   Washington                  506
5     Illinois                  492
6         Ohio                  469
```

0.3 Customer Segmentation by RFM method

[38]:
```
frequency_df = df.groupby('City').size().reset_index(name='Frequency')
```

[39]:
```
monetary_df = df.groupby('City')['Sales'].sum().reset_index()
monetary_df.rename(columns={'Sales': 'Monetary'}, inplace=True)
```

[40]:
```
rfm_df = pd.merge(frequency_df, monetary_df, on='City')
```

[41]:
```
print(rfm_df)
```

```
            City  Frequency  Monetary
0       Aberdeen          1    25.500
1        Abilene          1     1.392
2          Akron         21  2729.986
3    Albuquerque         14  2220.160
4     Alexandria         16  5519.570
..           …          …         …
526   Woonsocket          4   195.550
527      Yonkers         15  7657.666
528         York          5   817.978
529      Yucaipa          1    50.800
530         Yuma          4   840.865

[531 rows x 3 columns]
```

[42]:
```
f_score = rfm_df['Frequency'].quantile(0.75)
m_score = rfm_df['Monetary'].quantile(0.75)
```

[43]:
```
def rfm_segment(row):
    if row['Frequency'] >= f_score and row['Monetary'] >= m_score:
        return 'High Value customer'
    elif row['Frequency'] >= f_score:
        return 'Frequent customers'
```

```
    elif row['Monetary'] >= m_score:
        return 'Big Spenders'
    else:
        return 'Other'
```

[44]:
```
rfm_df['RFM_Segment'] = rfm_df.apply(rfm_segment, axis=1)
```

[46]:
```
print(rfm_df)
```

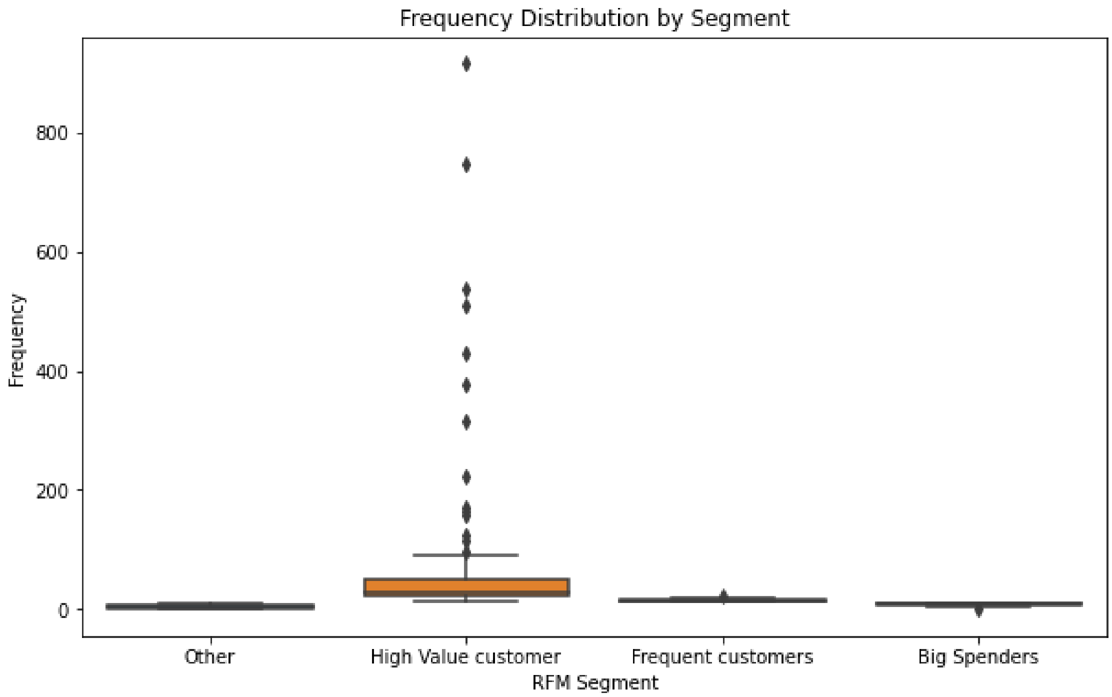
```
            City  Frequency  Monetary           RFM_Segment
0       Aberdeen          1    25.500                 Other
1        Abilene          1     1.392                 Other
2          Akron         21  2729.986   High Value customer
3    Albuquerque         14  2220.160   Frequent customers
4     Alexandria         16  5519.570   High Value customer
..           …          …        …                   …
526   Woonsocket          4   195.550                 Other
527      Yonkers         15  7657.666   High Value customer
528         York          5   817.978                 Other
529      Yucaipa          1    50.800                 Other
530         Yuma          4   840.865                 Other

[531 rows x 4 columns]
```

[47]:
```
segment_analysis = rfm_df.groupby('RFM_Segment').agg({
    'Frequency': 'mean',
    'Monetary': 'mean'
}).reset_index()
```

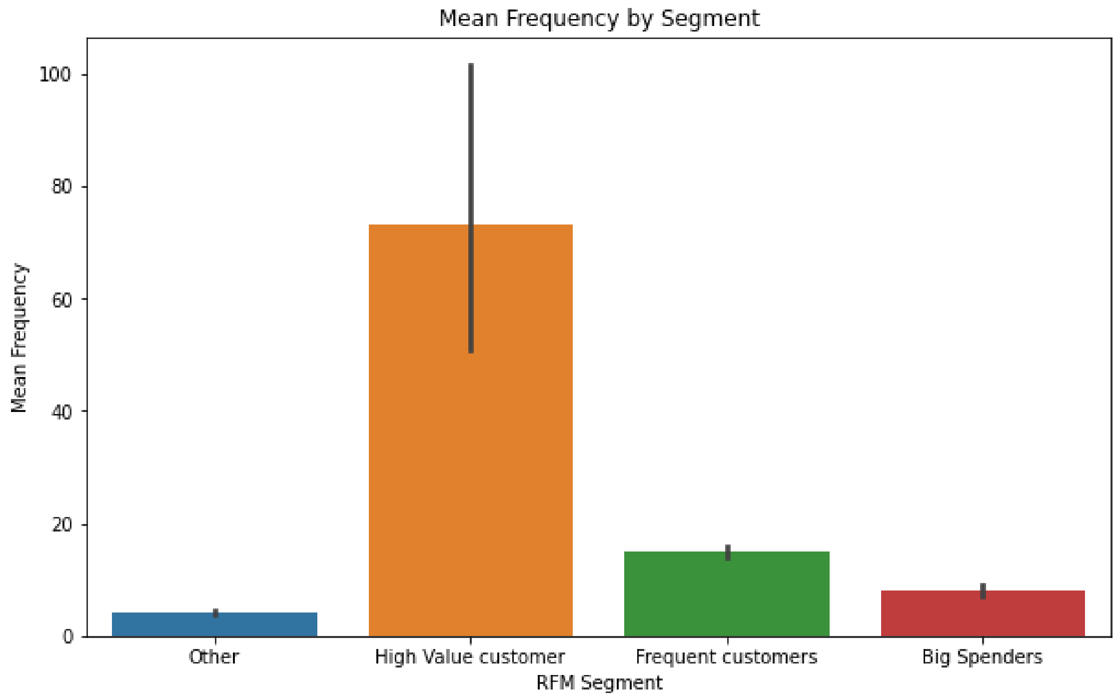
[48]:
```
print(segment_analysis)
```

```
           RFM_Segment  Frequency      Monetary
0         Big Spenders   8.153846   3990.861754
1   Frequent customers  14.928571   1719.205161
2  High Value customer  73.018692  17767.308691
3                Other   4.191892    659.996433
```

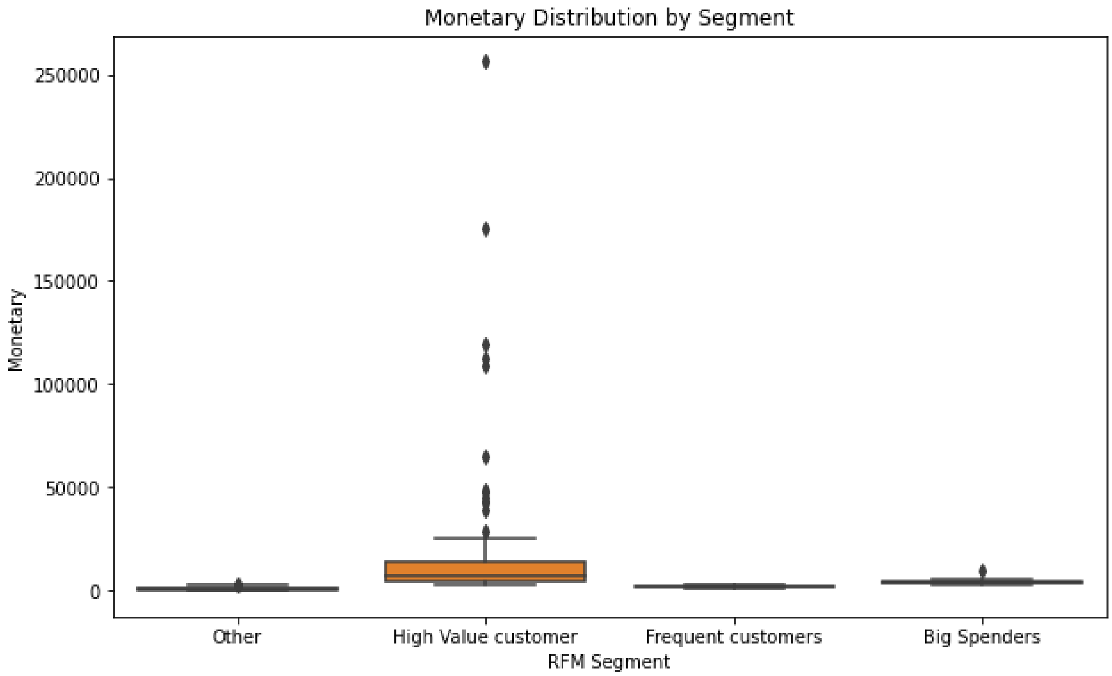
[49]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=rfm_df, x='RFM_Segment', y='Frequency')
plt.title('Frequency Distribution by Segment')
plt.xlabel('RFM Segment')
plt.ylabel('Frequency')
plt.show()
```



[50]:
```
plt.figure(figsize=(10, 6))
sns.barplot(data=rfm_df, x='RFM_Segment', y='Frequency')
plt.title('Mean Frequency by Segment')
plt.xlabel('RFM Segment')
plt.ylabel('Mean Frequency')
plt.show()
```

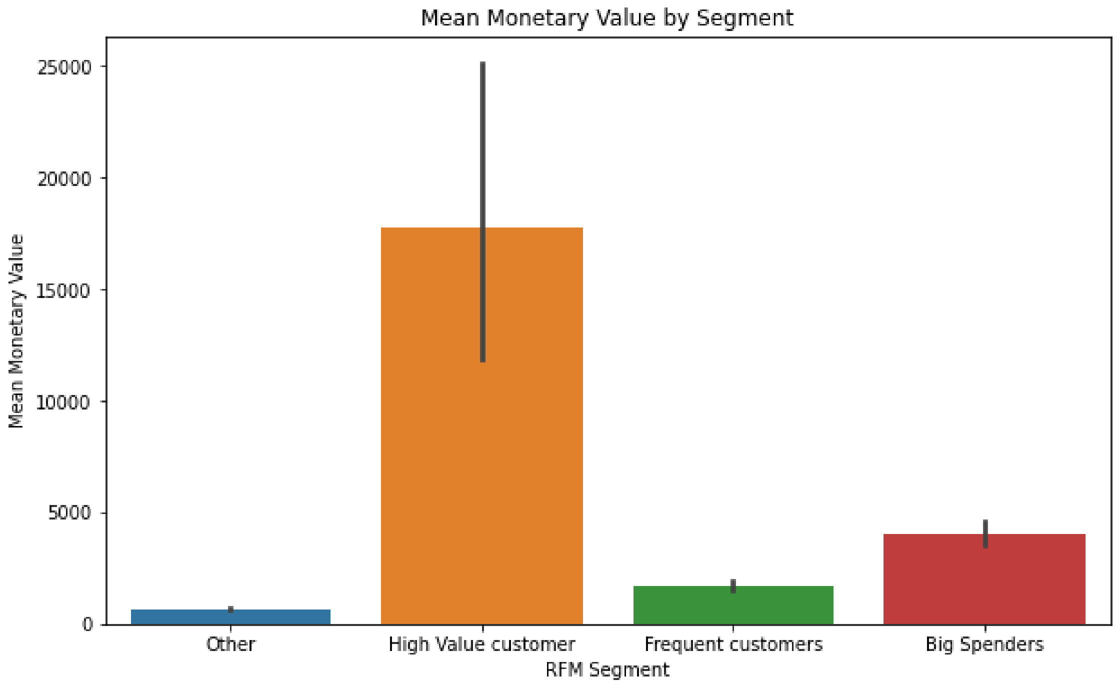


[51]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=rfm_df, x='RFM_Segment', y='Monetary')
plt.title('Monetary Distribution by Segment')
plt.xlabel('RFM Segment')
plt.ylabel('Monetary')
plt.show()
```



[53]:

```
plt.figure(figsize=(10, 6))
sns.barplot(data=rfm_df, x='RFM_Segment', y='Monetary')
plt.title('Mean Monetary Value by Segment')
plt.xlabel('RFM Segment')
plt.ylabel('Mean Monetary Value')
plt.show()
```



0.3.1 Product Analysis

[54]:
```
subcategory_count=df.groupby('Category')['Sub-Category'].nunique().reset_index()
# sort by ascending order
subcategory_count=subcategory_count.
 ↪sort_values(by='Sub-Category',ascending=False)
print(subcategory_count.reset_index(drop=True))
```

```
         Category  Sub-Category
0  Office Supplies             9
1        Furniture             4
2       Technology             4
```

[55]:
```
# sales per each category
category_sales=df.groupby(['Category'])['Sales'].sum().reset_index()
print(category_sales)
```

```
         Category        Sales
0        Furniture  741999.7953
1  Office Supplies  719047.0320
2       Technology  836154.0330
```

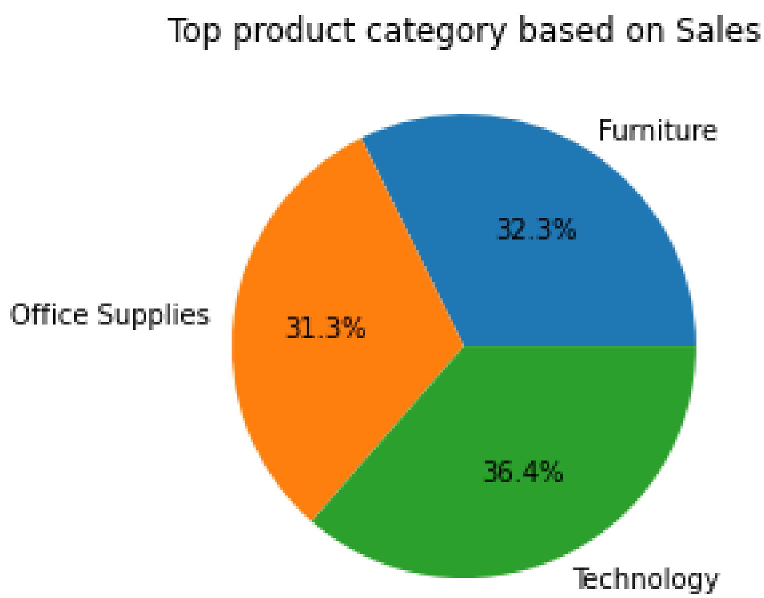
[56]:
```
top_selling_categories = df.groupby('Category').agg({'Sales': 'sum'}).
 ↪reset_index()
```

[57]:
```
top_selling_categories = top_selling_categories.sort_values(by='Sales',␣
↪ascending=False)
```

[58]:
```
print("\nTop Selling Categories:")
print(top_selling_categories.head(5))
```

```
Top Selling Categories:
          Category        Sales
2       Technology  836154.0330
0        Furniture  741999.7953
1  Office Supplies  719047.0320
```

[59]:
```
# plotting a pie chart
plt.pie(category_sales['Sales'],labels=category_sales['Category'],autopct='%1.
↪1f%%')
#set labels
plt.title('Top product category based on Sales')
plt.show()
```



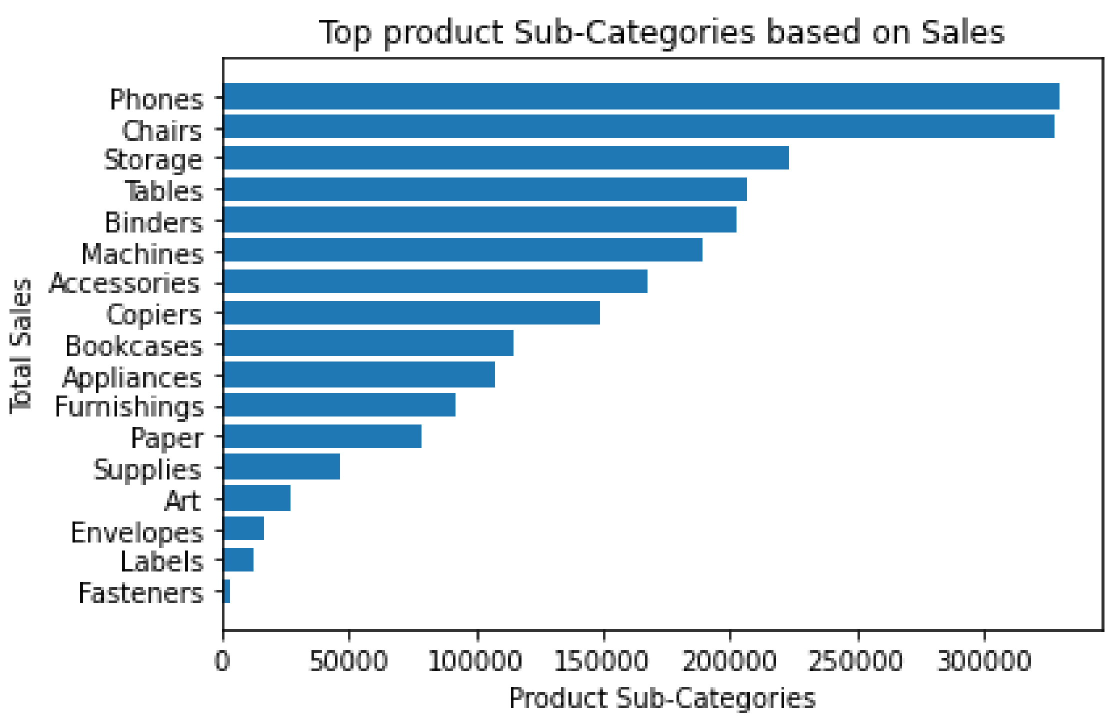
[60]:
```
top_selling_products = df.groupby('Sub-Category').agg({'Sales': 'sum'}).
↪reset_index()
```

[61]:
```
top_selling_products = top_selling_products.sort_values(by='Sales',␣
↪ascending=False)
```

[63]:
```python
print("Top Selling Products:")
print(top_selling_products.head(10))
```

```
Top Selling Products:
   Sub-Category        Sales
13        Phones  330007.0540
5         Chairs  328449.1030
14       Storage  223843.6080
16        Tables  206965.5320
3        Binders  203412.7330
11      Machines  189238.6310
0    Accessories  167380.3180
6        Copiers  149528.0300
4      Bookcases  114879.9963
1     Appliances  107532.1610
```

[64]:
```python
# plotting horizontal bar graph
top_selling_products=top_selling_products.sort_values(by='Sales',ascending=True)
plt.barh(top_selling_products['Sub-Category'],top_selling_products['Sales'])
# labels
plt.title('Top product Sub-Categories based on Sales')
plt.xlabel('Product Sub-Categories')
plt.ylabel('Total Sales')
plt.show()
```



0.3.2 Time series Analysis

0.3.3 To examin the Sales trend over different time periods the dataset does not content the data like Date,Time,Month,year.

0.3.4 to examin sales trend over different time period the data of order date or year,month is required.

[65]:
```
region_sales = df.groupby('Region')['Sales'].sum().reset_index()
```

[66]:
```
region_sales = region_sales.sort_values(by='Sales', ascending=False)
```

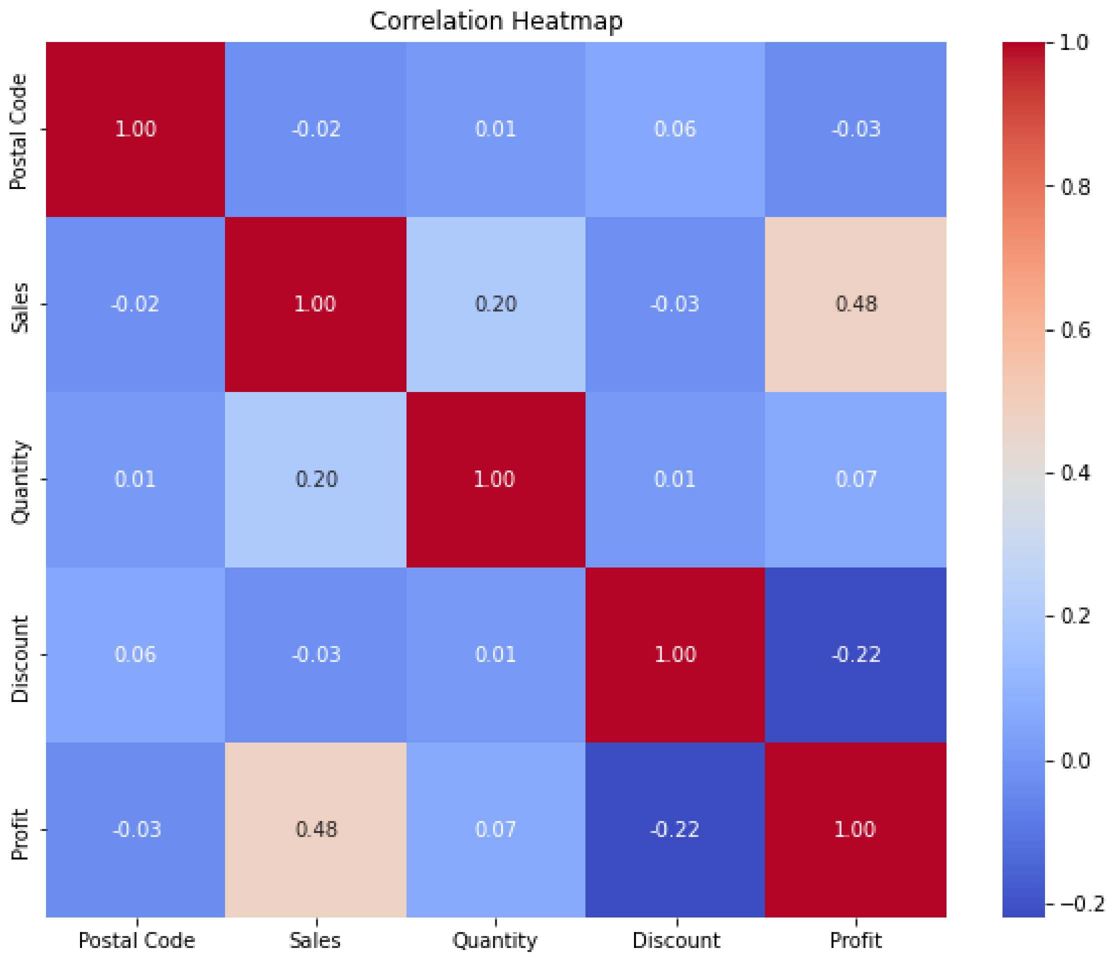
[67]:
```
print("\nSales Distribution by Region:")
print(region_sales)
```

```
Sales Distribution by Region:
    Region        Sales
3     West  725457.8245
1     East  678781.2400
0  Central  501239.8908
2    South  391721.9050
```

[68]:
```
correlation_matrix = df.corr()
```

```
/tmp/ipykernel_75/4214245630.py:1: FutureWarning: The default value of
numeric_only in DataFrame.corr is deprecated. In a future version, it will
default to False. Select only valid columns or specify the value of numeric_only
to silence this warning.
  correlation_matrix = df.corr()
```

[69]:
```
plt.figure(figsize=(10, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()
```


Correlation Heatmap
Postal Code
Sales
Quantity
Discount
Profit
1.00
-0.02
0.01
0.06
-0.03
-0.02
1.00
0.20
-0.03
0.48
0.01
0.20
1.00
0.01
0.07
0.06
-0.03
0.01
1.00
-0.22
-0.03
0.48
0.07
-0.22
1.00
Postal Code
Sales
Quantity
Discount
Profit
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

0.3.5 Correlation between profit and discount is in negative and correlation between profit and sales is postive

0.3.6 Conclusion

0.3.7 profit in south and central region is less

0.3.8 Profit in east and west region is better than south and central

0.3.9 highest profit is earned in copiers while selling price of chairs and phones are extremely high compared to other product.

0.3.10 people dont prefer to buy tables and bookcases from superstore hence these departments are in loss

0.3.11 The store has wide variety of office supplies especialy in binders and paper.

0.3.12 Negative correlation between and profit and discount

0.3.13 Total sum of profit in sale of table is negative.

0.3.14 profit is more in sale of copiers.

0.3.15 No or very less profit in supplies.

0.3.16 Technology segment is more profitable.

0.3.17 Analyzed customer segments based on purchasing behavior

0.3.18 Identified high-value customers, frequent customers, and other segments to marketing strategies and customer experiences

0.3.19 Trend Analysis (without Time Data):

0.3.20 Conducted trend analysis based on aggregated data or other available features, despite the absence of explicit date-related information.

0.3.21 Recommendations For Improving Sales

0.3.22 the correlation between profit and discount is negative Discounts can attract customers and lead to higher revenue by encouraging more purchases.

0.3.23 Offering discounts lowers the overall revenue per sale, which can decrease profit margins.

0.3.24 If not strategically planned, discounts may impact sales effectivenes

0.3.25 Product Performance: The sales of phones and chairs are highest it is frequently buyed products store has to manage there stocks to avoid shortage of quantity.

0.3.26 The sales of envlopes ,fasterners and art products are very less store has focus on this to increase sales by giving attractive discounts or schemes to the customers

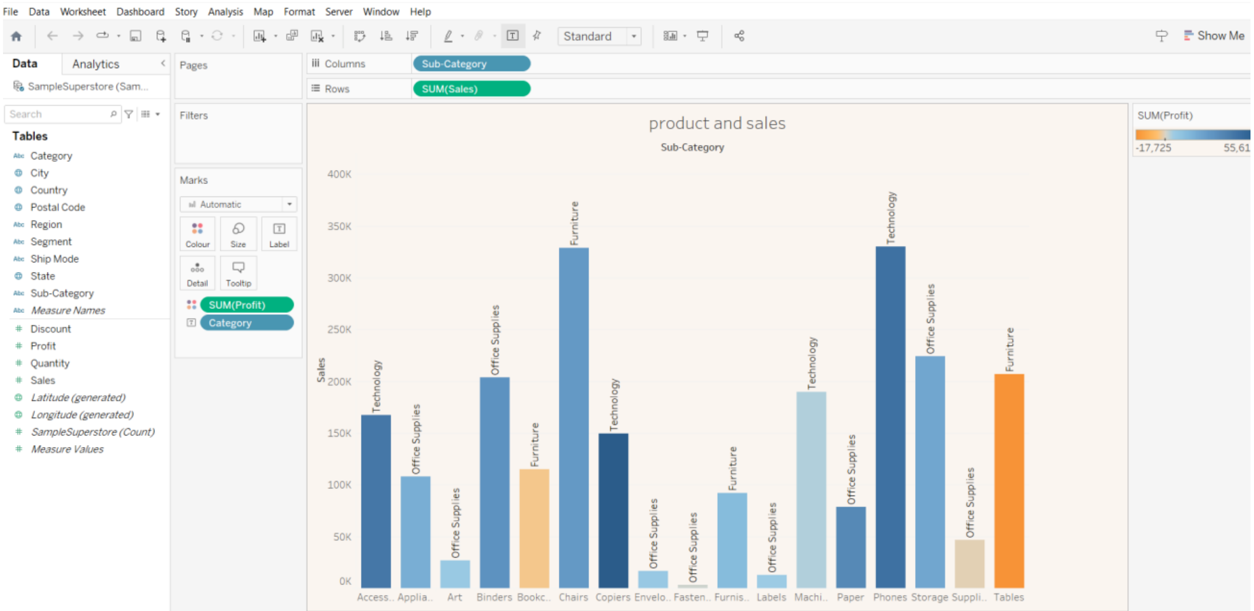
0.3.27 The sales in west and east region is very high Keep track of inventory levels to avoid stockouts or overstock situations. Use inventory management tools to ensure you have the right products available at the right time

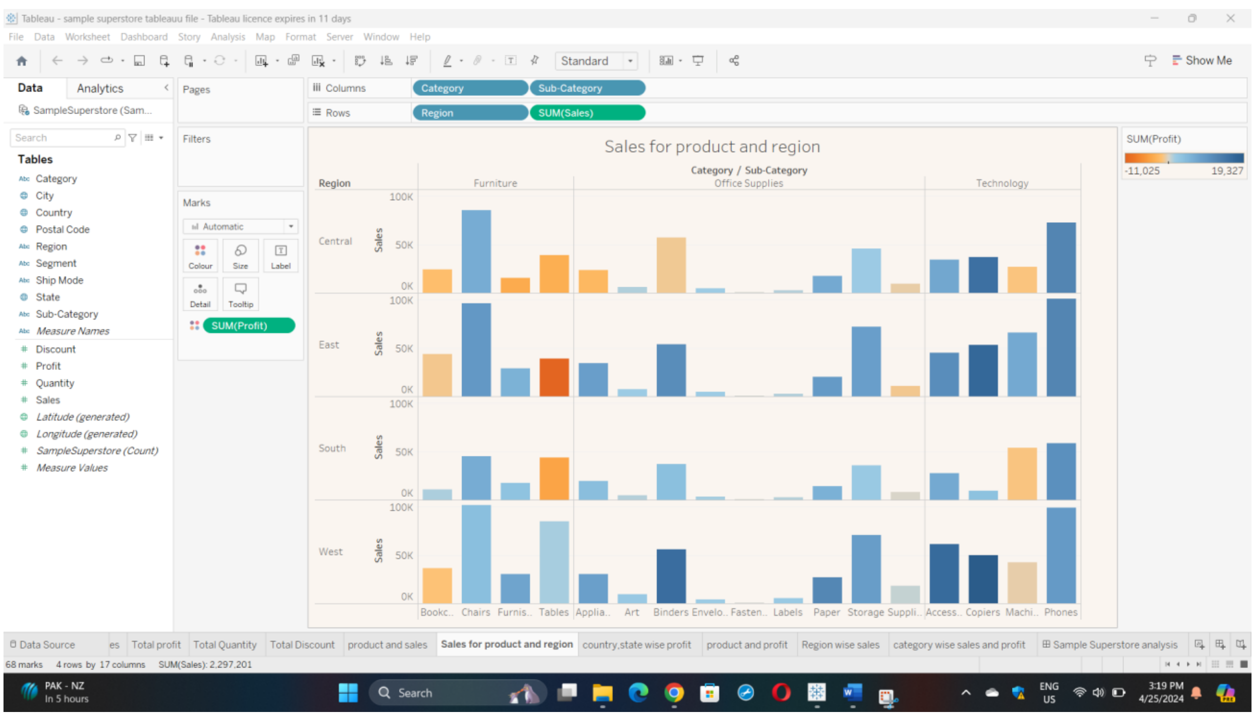
0.3.28 Repeat customers tend to spend more money with a business over time. Their loyalty translates into higher revenue for the company.

0.3.29 To increase sales into south and central region store has to conduct the Customer Loyalty Programs: These programs encourage frequent customer continue doing business by offering exclusive rewards such as discounts, seasonal

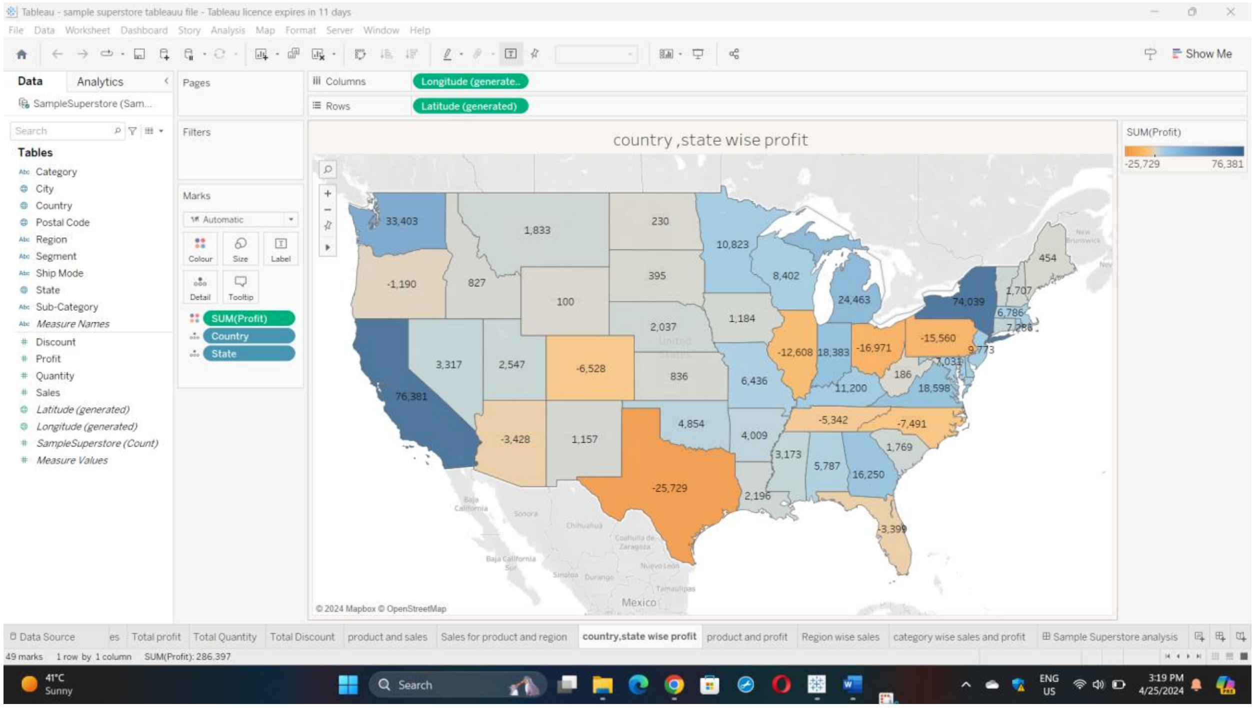
```
[ ]:
```

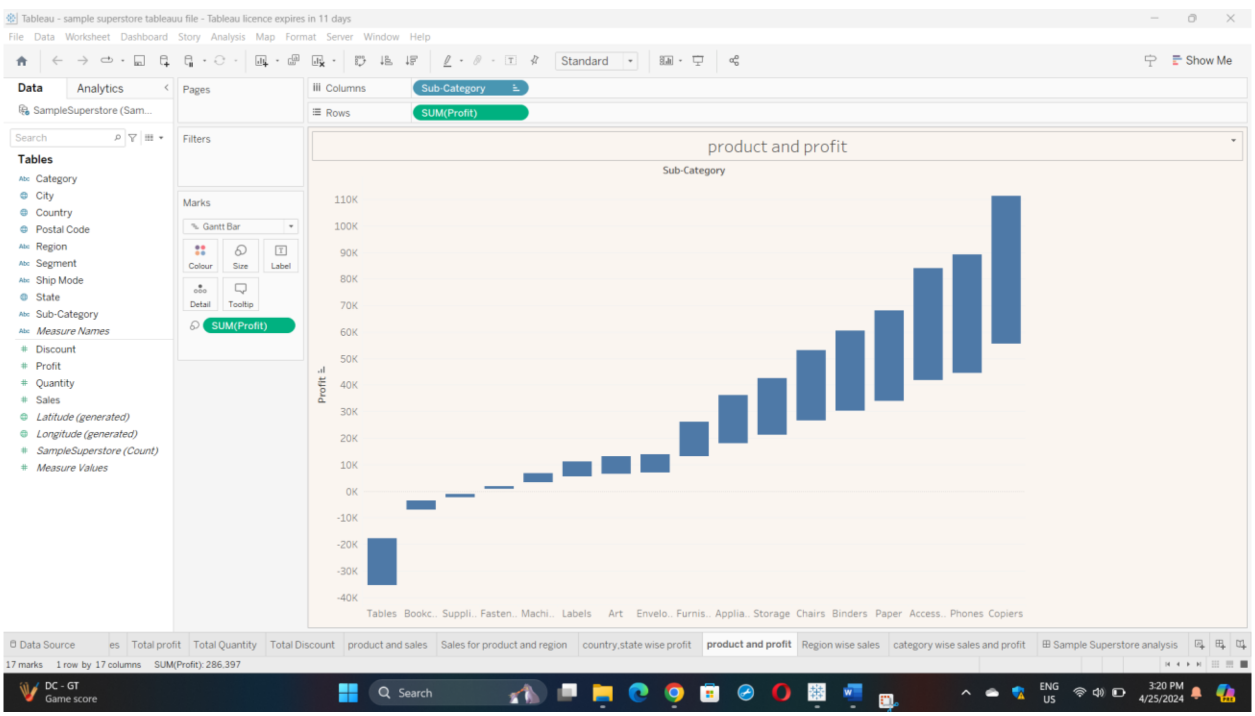
Charts,Grapghs and dashboard to visualize key findings.



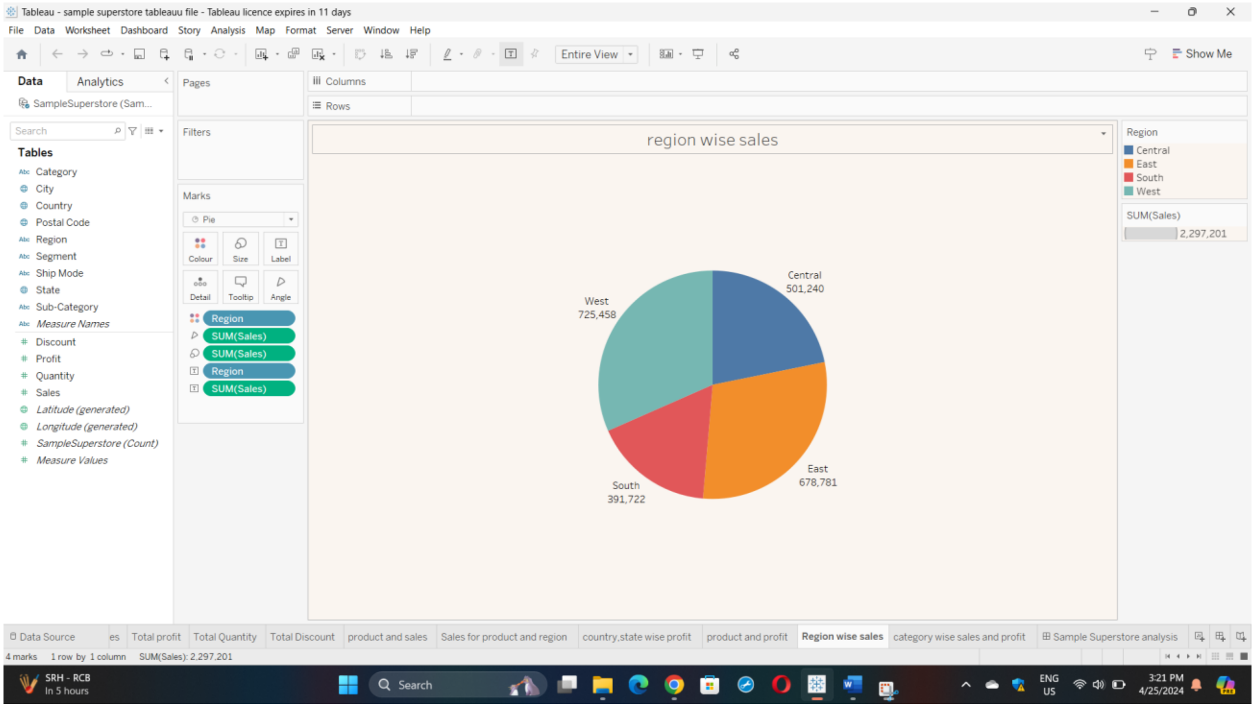


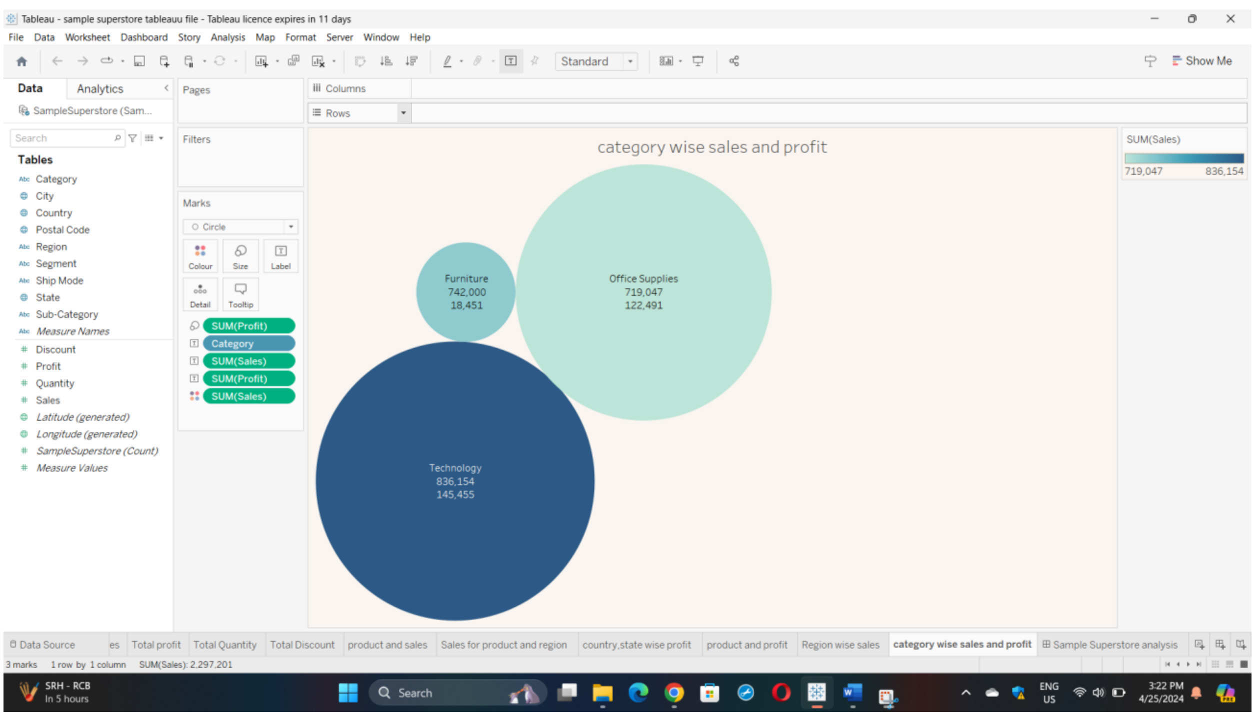
Charts,Grapghs and dashboard to visualize key findings.





Charts,Grapghs and dashboard to visualize key findings.





Charts,Grapghs and dashboard to visualize key findings.

Dashboard