Superstore Sales Data Analysis

August 22, 2023

[2]:
```python
#importing packages

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

[3]:
```python
# importing dataset

df = pd.read_csv(r"/Users/scipio/Downloads/Sales_Dataset_Project.csv")

#converting 'Order Date' column to datatiem format
df['Order Date'] = pd.to_datetime(df['Order Date'])

df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9800 entries, 0 to 9799
Data columns (total 18 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Row ID         9800 non-null   int64
 1   Order ID       9800 non-null   object
 2   Order Date     9800 non-null   datetime64[ns]
 3   Ship Date      9800 non-null   object
 4   Ship Mode      9800 non-null   object
 5   Customer ID    9800 non-null   object
 6   Customer Name  9800 non-null   object
 7   Segment        9800 non-null   object
 8   Country        9800 non-null   object
 9   City           9800 non-null   object
 10  State          9800 non-null   object
 11  Postal Code    9789 non-null   float64
 12  Region         9800 non-null   object
 13  Product ID     9800 non-null   object
 14  Category       9800 non-null   object
 15  Sub-Category   9800 non-null   object
 16  Product Name   9800 non-null   object
 17  Sales          9800 non-null   float64
```

```
dtypes: datetime64[ns](1), float64(2), int64(1), object(14)
memory usage: 1.3+ MB
```

```
/var/folders/3k/bzmghyyj1j51lkx1mc36njjw0000gn/T/ipykernel_94800/4161371504.py:6
: UserWarning: Parsing dates in DD/MM/YYYY format when dayfirst=False (the
default) was specified. This may lead to inconsistently parsed dates! Specify a
format to ensure consistent parsing.
  df['Order Date'] = pd.to_datetime(df['Order Date'])
```

1 Objective

Data Analysis of the sales data of a global superstore. The analysis will be guided by the following questions:

1. What was the most profitable region, state, and city in the dataset?
2. What was the most profitable category and sub category in the dataset?
3. What is the most profitable product in the dataset?
4. What was the most popular shipping method in the dataset?
5. What was the most profitable year in the dataset?

1.1 Analysis

1.1.1 1. What was the most profitable region, state, and city in the dataset?

[4]:
```
#Region Sales Total
region_sales_totals = round(df.groupby('Region')['Sales'].sum(),2)

#sorting results
print(region_sales_totals.sort_values(ascending = False))
```

```
Region
West       710219.68
East       669518.73
Central    492646.91
South      389151.46
Name: Sales, dtype: float64
```

[5]:
```
#Percentage Calculation
Region_Total_Sales_Pct = round(df.groupby('Region')['Sales'].sum()/df['Sales'].
 ↪sum(),2)

#Sorting Values
Region_Total_Sales_Pct.sort_values(ascending = False).head()
```

[5]:
```
Region
West       0.31
East       0.30
Central    0.22
South      0.17
```

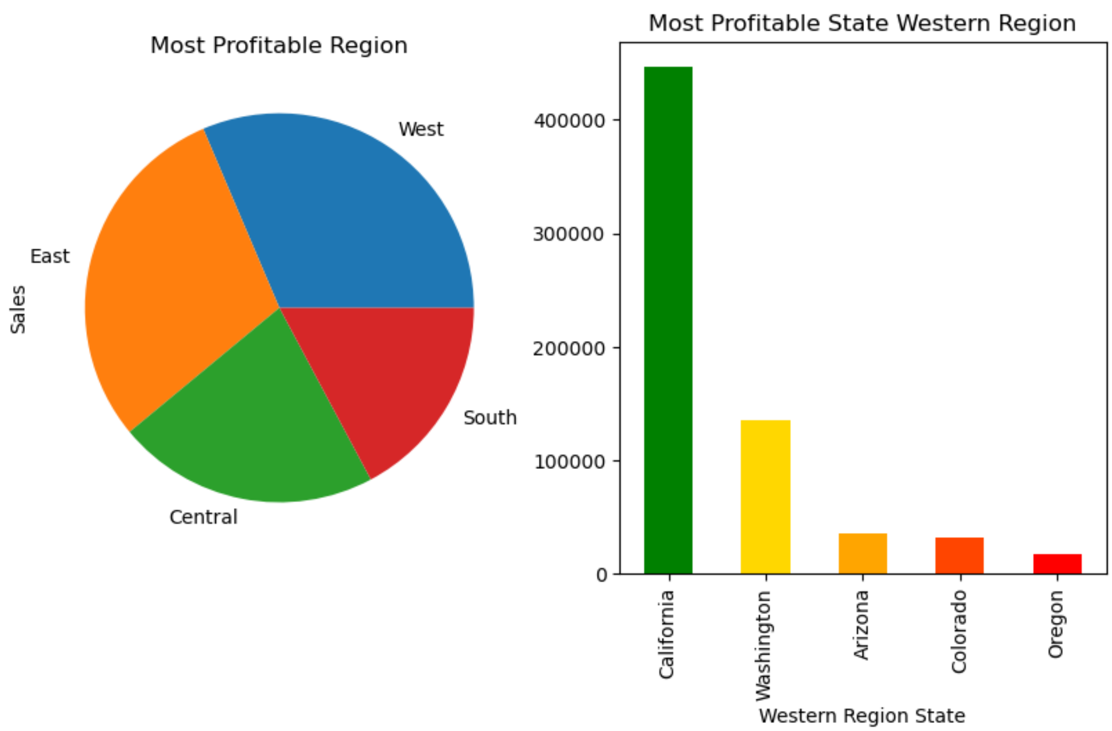
```
Name: Sales, dtype: float64
```

[6]:
```
#Most profitable state in West Region

#filtering for West region
West_State_Sales_Total = round(df[df['Region'] == 'West'].
 ↪groupby('State')['Sales'].sum(),2)

#sorting results
West_State_Sales_Total.sort_values(ascending = False).head()
```

[6]:
```
State
California    446306.46
Washington    135206.85
Arizona        35272.66
Colorado       31841.60
Oregon         17284.46
Name: Sales, dtype: float64
```

[7]:
```
# Creating Subplots
fig,axs = plt.subplots(nrows=1,ncols=2, figsize = (10,5))

#Color List
colors_5 = ['Green','Gold','Orange', 'OrangeRed', 'Red']
colors_4 = ['Green','Gold','Orange','Red']

#Subplots
region_sales_totals.sort_values(ascending = False).head(5).plot(kind = 'pie',␣
 ↪ax = axs[0], title = 'Most Profitable Region')
West_State_Sales_Total.sort_values(ascending = False).head(5).plot(kind =␣
 ↪'bar', ax = axs[1], title = 'Most Profitable State Western Region', xlabel =␣
 ↪'Western Region State', color=colors_5)
```

[7]:
```
<Axes: title={'center': 'Most Profitable State Western Region'}, xlabel='Western
Region State'>
```



The West region was the most profitable reagion in the dataset, totaling 710,219.68 USD in sales, 31% of total sales in the dataset. California was the most profitable state in the West region, totaling 446,306.46 USD in sales, accounting for 63% of the Western region's total sales.

[8]:
```python
# Most profitable state
State_Total_Sales = round(df.groupby('State')['Sales'].sum(),2)

#Sorting Results
State_Total_Sales.sort_values(ascending = False).head(5)
```

[8]:
```
State
California      446306.46
New York        306361.15
Texas           168572.53
Washington      135206.85
Pennsylvania    116276.65
Name: Sales, dtype: float64
```

[9]:
```python
#State Total Sales Percentage
State_Sales_Total_Pct = round(df.groupby('State')['Sales'].sum()/df['Sales'].
 ↪sum(),2)

#Sorting Percentages
State_Sales_Total_Pct.sort_values(ascending = False).head(5)
```

[9]:
```
State
California      0.20
New York        0.14
Texas           0.07
Washington      0.06
Pennsylvania    0.05
Name: Sales, dtype: float64
```

[10]:
```
#Most profitable city in California
Most_Profitable_City_Cali = round(df[df['State']== 'California'].
 ↪groupby('City')['Sales'].sum(),2)

# sorting values
Most_Profitable_City_Cali.sort_values(ascending = False).head()
```

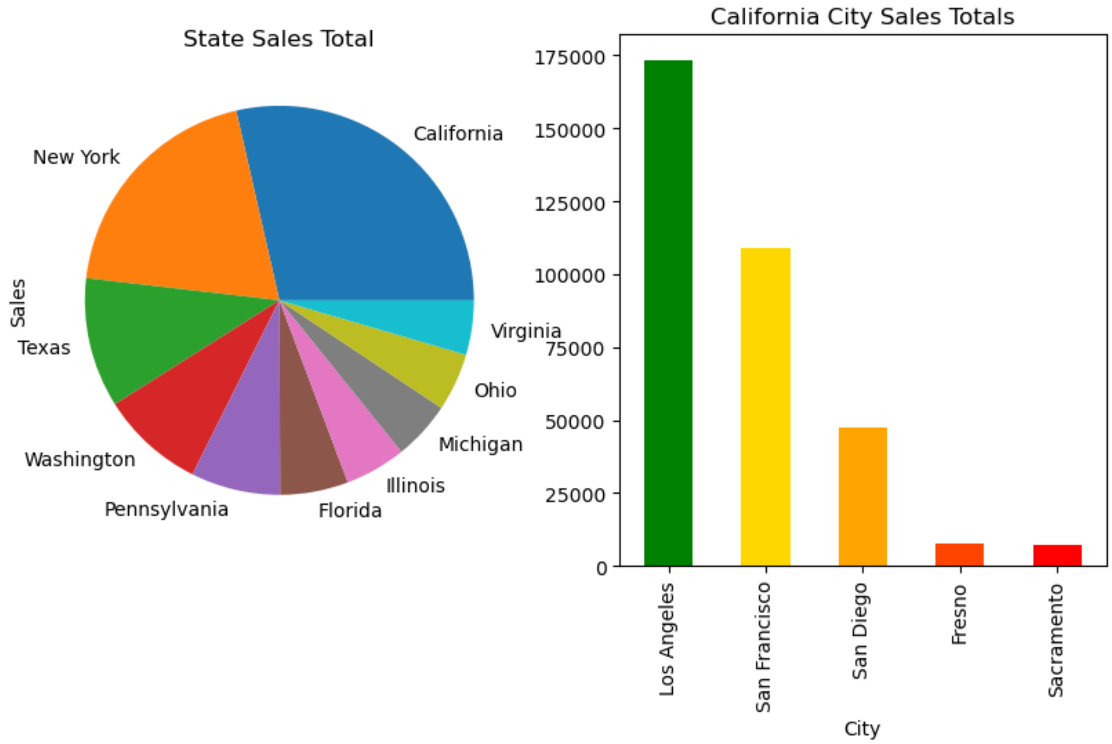
[10]:
```
City
Los Angeles      173420.18
San Francisco    109041.12
San Diego         47521.03
Fresno             7888.53
Sacramento         7311.28
Name: Sales, dtype: float64
```

[11]:
```
#California City Sales Percentage
California_City_Sales_Pct = round(df[df['State']== 'California'].
 ↪groupby('City')['Sales'].sum()/df[df['State']== 'California']['Sales'].
 ↪sum(),2)

#Sorting Values
California_City_Sales_Pct.sort_values(ascending = False).head(5)
```

[11]:
```
City
Los Angeles      0.39
San Francisco    0.24
San Diego        0.11
Fresno           0.02
Sacramento       0.02
Name: Sales, dtype: float64
```

[12]:
```
fig,axs = plt.subplots(nrows=1, ncols=2, figsize = (10,5))

colors_5 = ['Green','Gold','Orange', 'OrangeRed', 'Red']

State_Total_Sales.sort_values(ascending = False).head(10).plot(kind = 'pie',␣
 ↪title = 'State Sales Total', ax = axs[0])
Most_Profitable_City_Cali.sort_values(ascending = False).head().plot(kind =␣
 ↪'bar', color = colors_5, title = 'California City Sales Totals')
```

[12]: <Axes: title={'center': 'California City Sales Totals'}, xlabel='City'>



California was the most profitable state in the dataset, totaling 446,306.46 USD in sales, accounting for 20% of the total sales. Los Angeles was the most profitable city in California, totaling 173,420.18 USD in sales, accounting for 39% of the California sales total.

[13]:
```
# Most profitable city in the dataset
City_Sales_Totals = round(df.groupby('City')['Sales'].sum(),2)

#sorting values
City_Sales_Totals.sort_values(ascending = False).head()
```

[13]:
```
City
New York City    252462.55
Los Angeles      173420.18
Seattle          116106.32
San Francisco    109041.12
Philadelphia     108841.75
Name: Sales, dtype: float64
```

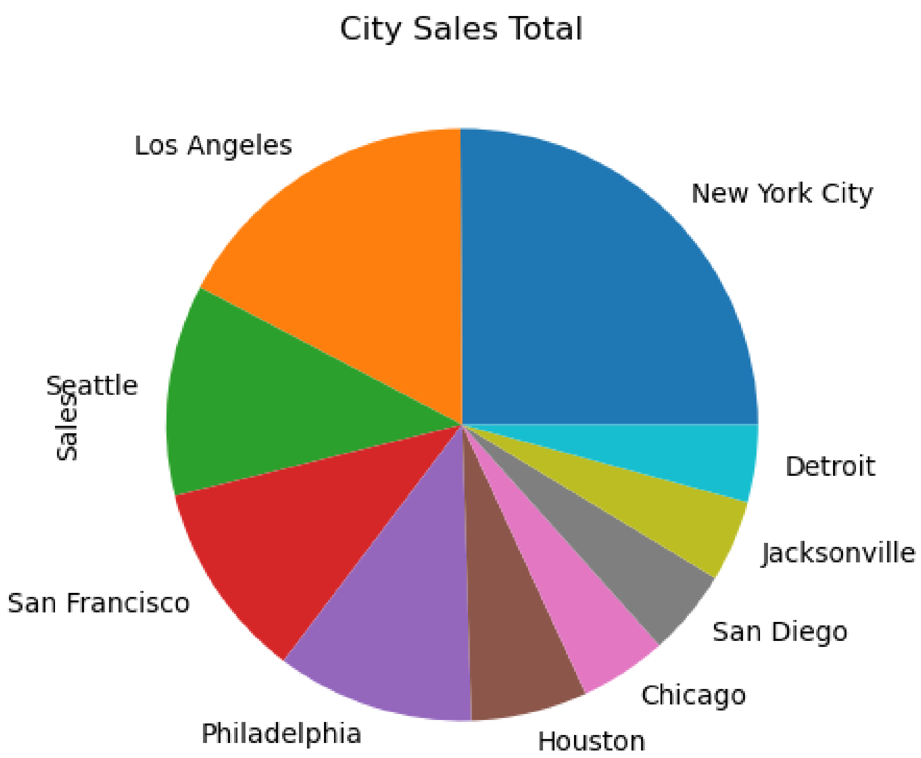
[14]:
```
#City Total Sales Percentage
City_Total_Sales_Pct = round(df.groupby('City')['Sales'].sum()/df['Sales'].
 ↪sum(),2)
```

```
#Sorting Values
City_Total_Sales_Pct.sort_values(ascending = False).head()
```

[14]:
```
City
New York City    0.11
Los Angeles      0.08
Seattle          0.05
San Francisco    0.05
Philadelphia     0.05
Name: Sales, dtype: float64
```

[15]:
```
City_Sales_Totals.sort_values(ascending = False).head(10).plot(kind = 'pie',␣
↪title = 'City Sales Total', figsize = (10,5))
```

[15]:
```
<Axes: title={'center': 'City Sales Total'}, ylabel='Sales'>
```



New York City was the most profitable city in the dataset, totaling 252,462.55 USD in sales, accounting for 11% of total sales.

1.1.2 2. What was the most profitable category and sub category in the dataset?

[16]:
```
# Category Total Sales
Category_Total_Sales = round(df.groupby('Category')['Sales'].sum(),2)

#Sorting
Category_Total_Sales.sort_values(ascending = False).head()
```

[16]:
```
Category
Technology        827455.87
Furniture         728658.58
Office Supplies   705422.33
Name: Sales, dtype: float64
```

[17]:
```
#Category Total Sales Percentage
Category_Total_Sales_Pct = round(df.groupby('Category')['Sales'].sum()/
 ↪df['Sales'].sum(),2)

#Sorting
Category_Total_Sales_Pct.sort_values(ascending = False).head()
```

[17]:
```
Category
Technology        0.37
Furniture         0.32
Office Supplies   0.31
Name: Sales, dtype: float64
```

[18]:
```
#Most Profitable Product in Technology
Tech_Category_Profitable_Product = round(df[df['Category']== 'Technology'].
 ↪groupby('Product Name')['Sales'].sum(),2)

#Sorting
Tech_Category_Profitable_Product.sort_values(ascending = False).head()
```

[18]:
```
Product Name
Canon imageCLASS 2200 Advanced Copier                        61599.82
Cisco TelePresence System EX90 Videoconferencing Unit        22638.48
Hewlett Packard LaserJet 3310 Copier                         18839.69
HP Designjet T520 Inkjet Large Format Printer - 24" Color    18374.90
Lexmark MX611dhe Monochrome Laser Printer                    16829.90
Name: Sales, dtype: float64
```

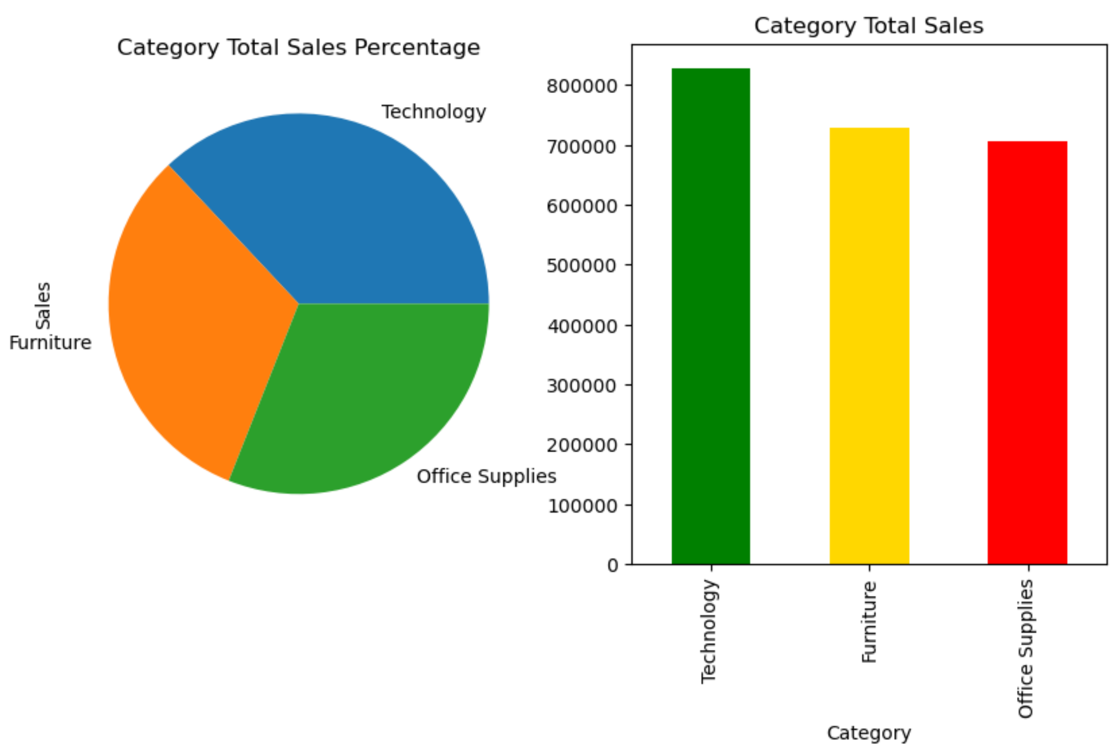
[19]:
```
#Most Profitable Product in Technology Percentage
Tech_Category_Profitable_Product_Pct = round(df[df['Category']== 'Technology'].
 ↪groupby('Product Name')['Sales'].sum()/df[df['Category']==␣
 ↪'Technology']['Sales'].sum(),2)

#Sorting
```

```
Tech_Category_Profitable_Product_Pct.sort_values(ascending = False).head()
```

[19]:
```
Product Name
Canon imageCLASS 2200 Advanced Copier                        0.07
Cisco TelePresence System EX90 Videoconferencing Unit        0.03
3D Systems Cube Printer, 2nd Generation, Magenta             0.02
Samsung Galaxy Mega 6.3                                      0.02
Lexmark MX611dhe Monochrome Laser Printer                    0.02
Name: Sales, dtype: float64
```

[20]:
```
#Subplots
fig,axs = plt.subplots(nrows = 1, ncols =2, figsize = (10,5))

colors_3= ['Green','Gold','Red']

Category_Total_Sales.sort_values(ascending = False).plot(kind = 'bar', ax =␣
 ↪axs[1], title = 'Category Total Sales', color = colors_3)
Category_Total_Sales_Pct.sort_values(ascending = False).plot(kind = 'pie', ax =␣
 ↪axs[0], title= 'Category Total Sales Percentage')
```

[20]:
```
<Axes: title={'center': 'Category Total Sales Percentage'}, ylabel='Sales'>
```



Technology was the most profitable category,totaling 827,455.87 USD in sales, accounting for 37% of total sales. The *Canon imageCLASS 2200 Advanced Copier* was the most profitable product in the Technology category totaling 61,599.82 USD in sales, accounting for 7% of the Technology category sales.

[21]:
```
#Sub Category Total Sales
Sub_Category_Sales = round(df.groupby('Sub-Category')['Sales'].sum(),2)

#Sorting
Sub_Category_Sales.sort_values(ascending = False).head()
```

[21]:
```
Sub-Category
Phones      327782.45
Chairs      322822.73
Storage     219343.39
Tables      202810.63
Binders     200028.78
Name: Sales, dtype: float64
```

[22]:
```
#Sub Category Total Sales Percentage
Sub_Category_Sales_Pct = round(df.groupby('Sub-Category')['Sales'].sum()/
 ↪df['Sales'].sum(),3)

#Sorting
Sub_Category_Sales_Pct.sort_values(ascending = False)
```

[22]:
```
Sub-Category
Phones          0.145
Chairs          0.143
Storage         0.097
Tables          0.090
Binders         0.088
Machines        0.084
Accessories     0.073
Copiers         0.065
Bookcases       0.050
Appliances      0.046
Furnishings     0.039
Paper           0.034
Supplies        0.021
Art             0.012
Envelopes       0.007
Labels          0.005
Fasteners       0.001
Name: Sales, dtype: float64
```

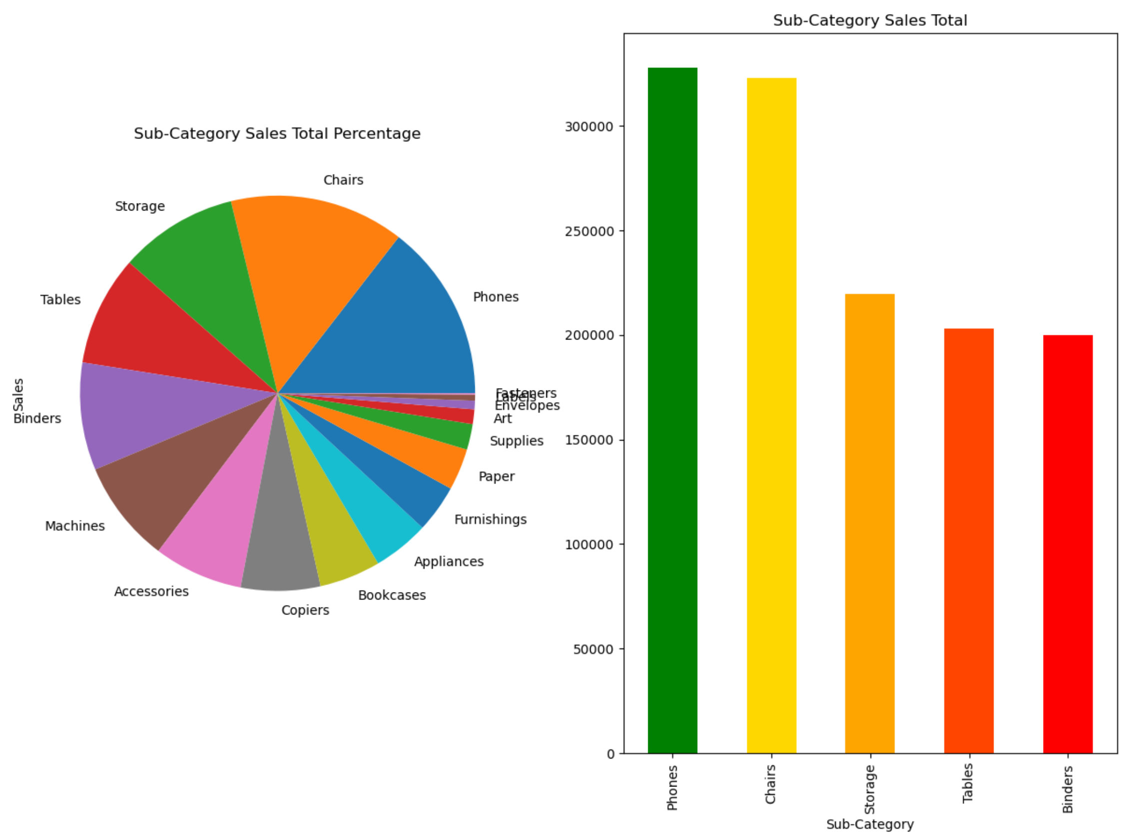
[23]:
```
# Most profitable product in sub-category phones
Sub_Cat_Phones_Sales_Total = round(df[df['Sub-Category']=='Phones'].
 ↪groupby('Product Name')['Sales'].sum(),2)
```

```
#Sorting
Sub_Cat_Phones_Sales_Total.sort_values(ascending = False).head()
```

[23]:
```
Product Name
Samsung Galaxy Mega 6.3                                 13943.67
Apple iPhone 5                                          12996.60
Wilson Electronics DB Pro Signal Booster                 8878.40
Mitel MiVoice 5330e IP Phone                             7699.72
Samsung Galaxy S III - 16GB - pebble blue (T-Mobile)     7139.80
Name: Sales, dtype: float64
```

[24]:
```
fig,axs = plt.subplots(nrows = 1, ncols =2, figsize = (15,10))
Sub_Category_Sales_Pct.sort_values(ascending = False).plot(kind = 'pie',ax =␣
↪axs[0], title = 'Sub-Category Sales Total Percentage')
Sub_Category_Sales.sort_values(ascending = False).head().plot(kind = 'bar', ax␣
↪= axs[1], color = colors_5, title = 'Sub-Category Sales Total' )
```

[24]:
```
<Axes: title={'center': 'Sub-Category Sales Total'}, xlabel='Sub-Category'>
```



Phones was the most profitable Sub-Category in the dataset, totaling 327,782.45 USD in sales, accounting for nearly 15% of the Phones Sub-Category sales totals. The Samsung Galaxy Mega

6.3 was the most popular product in the Sub-Category Phones, totaling 13,943.67 USD in sales.

1.1.3 3. What is the most profitable product in the dataset?

[25]:
```python
# Product total sales
Product_Sales_Total = round(df.groupby('Product Name')['Sales'].sum(),2)

#Sorting
Product_Sales_Total.sort_values(ascending = False).head(1)
```

[25]:
```
Product Name
Canon imageCLASS 2200 Advanced Copier    61599.82
Name: Sales, dtype: float64
```

The Canon imageCLASS 2200 Advanced Copier was the most profitable product in the dataset, totaling 61,599.82 USD in sales.

1.1.4 4. What was the most popular shipping method in the dataset?

[26]:
```python
#Ship Mode Totals
Ship_Mode_Totals = df.groupby('Ship Mode')['Ship Mode'].count()

#sorting
Ship_Mode_Totals.sort_values(ascending = False)
```

[26]:
```
Ship Mode
Standard Class    5859
Second Class      1902
First Class       1501
Same Day           538
Name: Ship Mode, dtype: int64
```

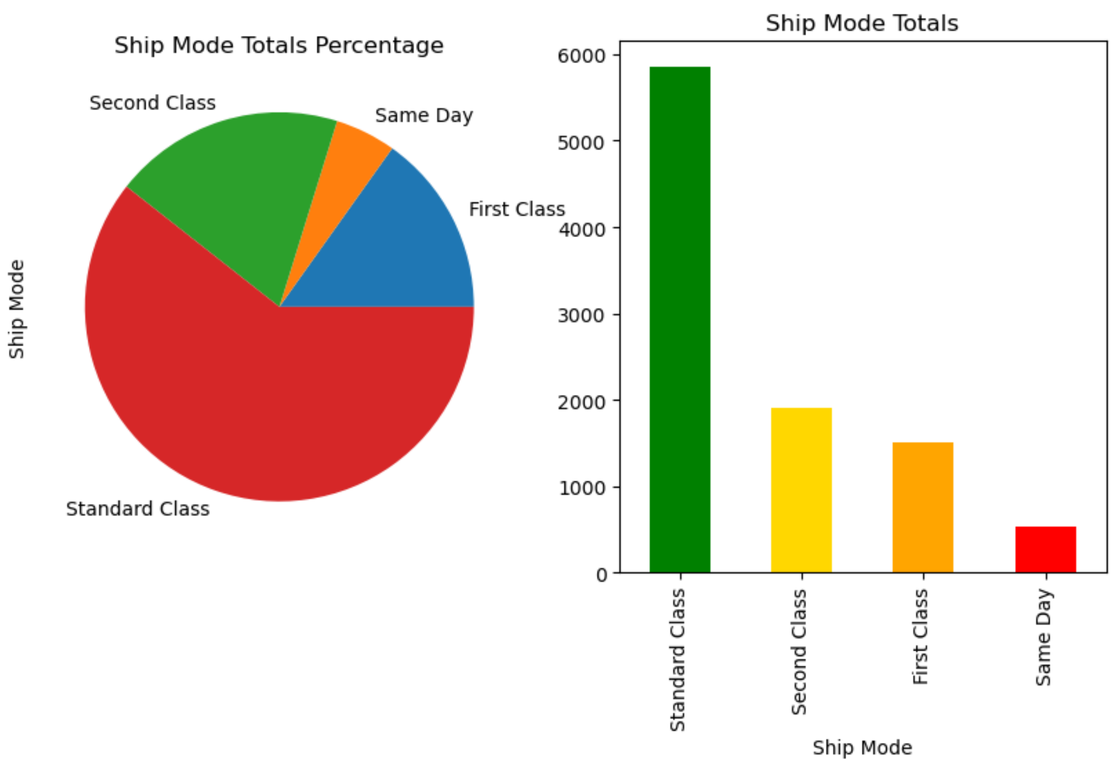
[27]:
```python
# Ship Mode Totals Percentage
Ship_Mode_Totals_Percentage = round(df.groupby('Ship Mode')['Ship Mode'].
 ↪count()/df['Ship Mode'].count(),2)

#Sorting
Ship_Mode_Totals_Percentage.sort_values(ascending = False)
```

[27]:
```
Ship Mode
Standard Class    0.60
Second Class      0.19
First Class       0.15
Same Day          0.05
Name: Ship Mode, dtype: float64
```

[28]:
```python
# subplot
fig,axs = plt.subplots(nrows = 1, ncols =2,figsize = (10,5))
```

```
Ship_Mode_Totals.sort_values(ascending = False).plot(kind = 'bar', title =␣
↪'Ship Mode Totals', ax = axs[1], color = colors_4)
Ship_Mode_Totals_Percentage.plot(kind = 'pie', title = 'Ship Mode Totals␣
↪Percentage', ax = axs[0])
```

[28]: <Axes: title={'center': 'Ship Mode Totals Percentage'}, ylabel='Ship Mode'>



The most popular shipping method was Standard Class Shipping. 5859, 60%, of orders were sent to customers via Standard Class Shipping.

[32]:
```
#importing csv with calculation of the difference of days between the order␣
↪date and ship date
df2 = pd.read_csv(r"/Users/scipio/Downloads/bquxjob_1aa3a727_18a2028d891.csv")
```

[33]:
```
df2[['Days_Difference','Sales']].plot(kind = 'scatter', x = 'Days_Difference',␣
↪y = 'Sales', title = 'Order and Ship Date Difference Sales Price␣
↪Correlation',figsize = (10,5))
```

[33]: <Axes: title={'center': 'Order and Ship Date Difference Sales Price
Correlation'}, xlabel='Days_Difference', ylabel='Sales'>

[45]:
```
#Correlation Coefficient
corr = np.corrcoef(df2['Days_Difference'],df2['Sales'])

round(corr[0,1],2)
```

[45]:
```
-0.01
```

There is no correlation between the difference between the Order Date and Ship Dates and sales price. This is indicated in scatter plot above as well as the correlation coefficient value of -0.01.

1.1.5 5. What was the most profitable year in the dataset?

[42]:
```
#Creating a Year column
df['Year'] = df['Order Date'].dt.year

# Year Total Sales
Year_Total_Sales = round(df.groupby('Year')['Sales'].sum(),2)

#Sorting
Year_Total_Sales.sort_values(ascending = False)
```

[42]:
```
Year
2018    722052.02
2017    600192.55
2015    479856.21
2016    459436.01
Name: Sales, dtype: float64
```

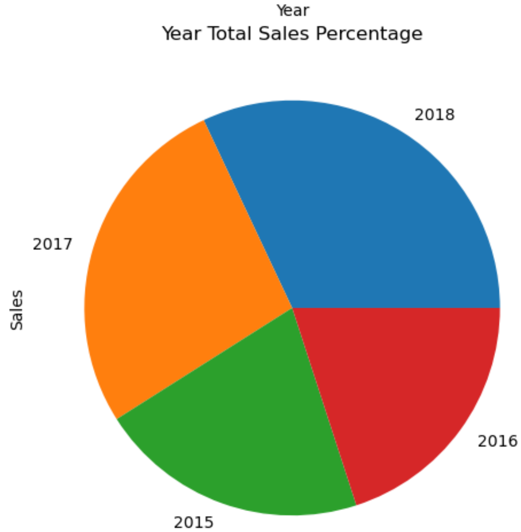
[73]:
```python
#Year Total Sale Percentages
Year_Total_Sales_Percentage = round(df.groupby('Year')['Sales'].sum()/
↪df['Sales'].sum(),2)

#Sorting
Year_Total_Sales_Percentage.sort_values(ascending = False)
```

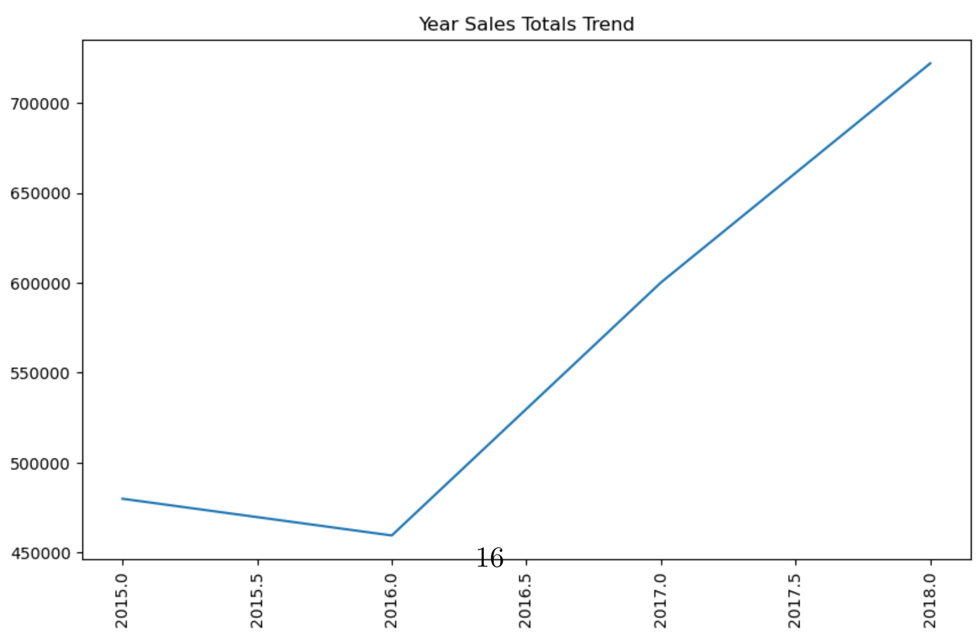
[73]:
```
Year
2018    0.32
2017    0.27
2015    0.21
2016    0.20
Name: Sales, dtype: float64
```

[75]:
```python
#Subplots
fig, axs = plt.subplots(nrows = 3, figsize = (10,20))

Year_Total_Sales.sort_values(ascending = False).plot(kind = 'bar', title =
↪'Year Total Sales', color = colors_4, ax = axs [0])
Year_Total_Sales_Percentage.sort_values(ascending = False).plot(kind = 'pie',
↪ax = axs[1], title = 'Year Total Sales Percentage')
df.groupby('Year')['Sales'].sum().plot(kind = 'line', title = 'Year Sales
↪Totals Trend', ax = axs[2], rot = 90)
```

[75]:
```
<Axes: title={'center': 'Year Sales Totals Trend'}, xlabel='Year'>
```


Year Total Sales
700000
600000
500000
400000
300000
200000
100000
0
2018
2017
2015
2016
Year


Year Total Sales Percentage
2018
2017
Sales
2016
2015


Year Sales Totals Trend
700000
650000
600000
550000
500000
450000
2015.0
2015.5
2016.0
2016.5
2017.0
2017.5
2018.0
Year

2018 was the most profitable year in the dataset, totaling 722,052.02 USD in sales, accouting for nearly a third of total sales. Additonally, there was a positive trend in total sales in the dataset. On average there was a 60,548.95 USD, 12%, year over year (YoY) increase in sales.

1.1.6 Conclusion

Overall there was a positive trend in sales YoY with an average inrease of 60,548.95 USD, 12%, YoY in total sales. 2018 was the most profitable year of sales in the dataset totaling 722,052.02 USD in sales. Additionally, the Western region was the most profitable region in the dataset, totaling 710,219.68 USD in sales, accounting for 31% of total sales. Californina was the most profitable state while New York City was the most profitable city in the dataset. The Technology category was the most profitable category in the dataset, accounting for 37% of total sales. Phones were the most profitable subcategory, totaling 327,782.45 USD in sales. The Canon imageCLASS 2200 Advanced Copier was the most profitable product in the dataset, totaling 61,599.82 USD in sales. Lastly, Standard Class Shipping was the most popular method of shipping orders, 60% of all orders were shipped using Standard Class Shipping.