Sales Analysis using Python

About Dataset

The Dataset is called *'Superstore Dataset'*. This Dataset contains the sales of superstore in United States of America. This Dataset contains the summary of almost 10000 orders in the superstore. This dataset contains Order dates, ID's, region, city, etc.

Kaggle link for the Dataset - [https://www.kaggle.com/datasets/vivek468/superstore-dataset-final (https://www.kaggle.com/datasets/vivek468/superstore-dataset-final)](https://www.kaggle.com/datasets/vivek468/superstore-dataset-final)

Importing the libraries

In [99]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

Checking the data

In [3]:

```
#Reading the CSV and checking the data
ss = pd.read_csv("Superstore.csv", encoding='windows-1252')
ss.head()
```

Out[3]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Customer Name	Segment	Country	
0	1	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	H
1	2	CA-2016-152156	11/8/2016	11/11/2016	Second Class	CG-12520	Claire Gute	Consumer	United States	H
2	3	CA-2016-138688	6/12/2016	6/16/2016	Second Class	DV-13045	Darrin Van Huff	Corporate	United States	
3	4	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	La
4	5	US-2015-108966	10/11/2015	10/18/2015	Standard Class	SO-20335	Sean O'Donnell	Consumer	United States	La

5 rows × 21 columns

In [4]:

```
ss.shape
```

Out[4]:

```
(9994, 21)
```

In [5]:

```
ss.columns
```

Out[5]:

```
Index(['Row ID', 'Order ID', 'Order Date', 'Ship Date', 'Ship Mode',
       'Customer ID', 'Customer Name', 'Segment', 'Country', 'City', 'Stat
e',
       'Postal Code', 'Region', 'Product ID', 'Category', 'Sub-Category',
       'Product Name', 'Sales', 'Quantity', 'Discount', 'Profit'],
      dtype='object')
```

Checking the null values

In [7]:

```
ss.isnull().sum()
```

Out[7]:

```
Row ID           0
Order ID         0
Order Date       0
Ship Date        0
Ship Mode        0
Customer ID      0
Customer Name    0
Segment          0
Country          0
City             0
State            0
Postal Code      0
Region           0
Product ID       0
Category         0
Sub-Category     0
Product Name     0
Sales            0
Quantity         0
Discount         0
Profit           0
dtype: int64
```

There is no null values in the dataset, so we begin to analyize the data

Analyzing and Visualizing the dataset

In [8]:

```
ss.describe()
```

Out[8]:

	Row ID	Postal Code	Sales	Quantity	Discount	Profit
count	9994.000000	9994.000000	9994.000000	9994.000000	9994.000000	9994.000000
mean	4997.500000	55190.379428	229.858001	3.789574	0.156203	28.656896
std	2885.163629	32063.693350	623.245101	2.225110	0.206452	234.260108
min	1.000000	1040.000000	0.444000	1.000000	0.000000	-6599.978000
25%	2499.250000	23223.000000	17.280000	2.000000	0.000000	1.728750
50%	4997.500000	56430.500000	54.490000	3.000000	0.200000	8.666500
75%	7495.750000	90008.000000	209.940000	5.000000	0.200000	29.364000
max	9994.000000	99301.000000	22638.480000	14.000000	0.800000	8399.976000

In [6]:

```
ss.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 21 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Row ID         9994 non-null   int64  
 1   Order ID       9994 non-null   object 
 2   Order Date     9994 non-null   object 
 3   Ship Date      9994 non-null   object 
 4   Ship Mode      9994 non-null   object 
 5   Customer ID    9994 non-null   object 
 6   Customer Name  9994 non-null   object 
 7   Segment        9994 non-null   object 
 8   Country        9994 non-null   object 
 9   City           9994 non-null   object 
 10  State          9994 non-null   object 
 11  Postal Code    9994 non-null   int64  
 12  Region         9994 non-null   object 
 13  Product ID     9994 non-null   object 
 14  Category       9994 non-null   object 
 15  Sub-Category   9994 non-null   object 
 16  Product Name   9994 non-null   object 
 17  Sales          9994 non-null   float64
 18  Quantity       9994 non-null   int64  
 19  Discount       9994 non-null   float64
 20  Profit         9994 non-null   float64
dtypes: float64(3), int64(3), object(15)
memory usage: 1.6+ MB
```

In [55]:

```
ss['Order Date'] = pd.to_datetime(ss['Order Date'])
ss['Ship Date'] = pd.to_datetime(ss['Ship Date'])
```

In [56]:

```
ss.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 22 columns):
 #   Column         Non-Null Count  Dtype
---  ------         --------------  -----
 0   Row ID         9994 non-null   int64
 1   Order ID       9994 non-null   object
 2   Order Date     9994 non-null   datetime64[ns]
 3   Ship Date      9994 non-null   datetime64[ns]
 4   Ship Mode      9994 non-null   object
 5   Customer ID    9994 non-null   object
 6   Customer Name  9994 non-null   object
 7   Segment        9994 non-null   object
 8   Country        9994 non-null   object
 9   City           9994 non-null   object
 10  State          9994 non-null   object
 11  Postal Code    9994 non-null   int64
 12  Region         9994 non-null   object
 13  Product ID     9994 non-null   object
 14  Category       9994 non-null   object
 15  Sub-Category   9994 non-null   object
 16  Product Name   9994 non-null   object
 17  Sales          9994 non-null   float64
 18  Quantity       9994 non-null   int64
 19  Discount       9994 non-null   float64
 20  Profit         9994 non-null   float64
 21  Month Year     9994 non-null   object
dtypes: datetime64[ns](2), float64(3), int64(3), object(14)
memory usage: 1.7+ MB
```

In [35]:

```
ss['Order Date'].min()
```

Out[35]:

```
Timestamp('2014-01-03 00:00:00')
```

In [36]:

```
ss['Order Date'].max()
```

Out[36]:

```
Timestamp('2017-12-30 00:00:00')
```

In [57]:

```
ss.sort_values(['Order Date'], inplace = True)
```

In [58]:

```
ss['Month Year'] = ss['Order Date'].apply(lambda x: x.strftime('%y-%m'))
```

In [59]:

```
ss['Month Year']
```

Out[59]:

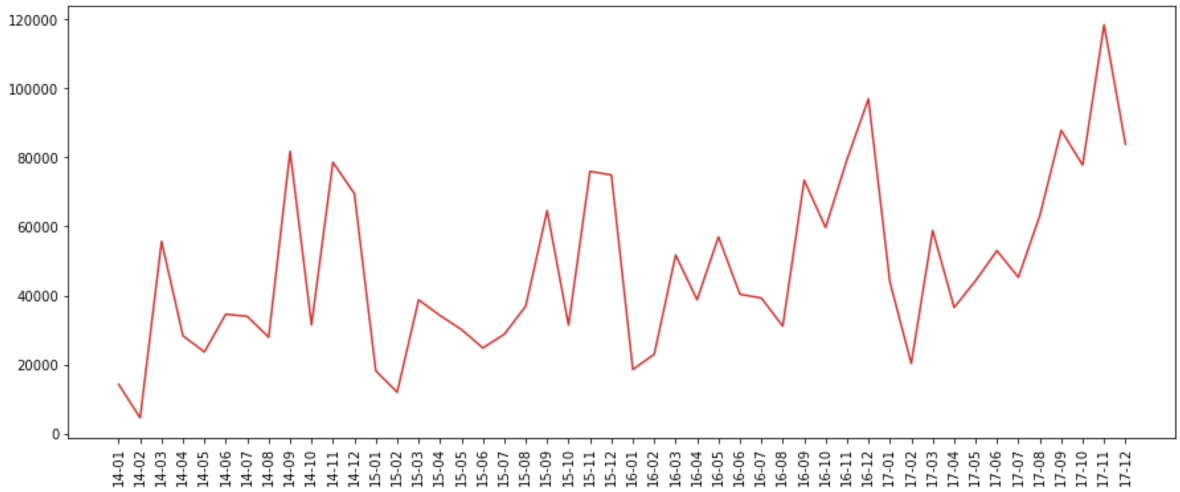
```
7980    14-01
739     14-01
740     14-01
741     14-01
1759    14-01
        ...
5091    17-12
908     17-12
907     17-12
1296    17-12
906     17-12
Name: Month Year, Length: 9994, dtype: object
```

In [62]:

```
Monthly_trend = ss.groupby('Month Year').sum()['Sales'].reset_index()
```

In [66]:

```
plt.figure(figsize = (15,6))
plt.plot(Monthly_trend['Month Year'], Monthly_trend['Sales'], color = '#D0362F')
plt.xticks(rotation = 'vertical')
plt.show()
```



We can see that the sales in first two months of the year 2014 were very low but in 3rd month the sales went upto 60,000. Further the sales went to 80,000 in 8th month of 2014. The sales saw a downfall in the 2nd month of 2015, 1st month of 2016 and 2nd month of 2017. We can also observe that sales saw a downfall in first quater of every four year. The sales topped the chart in 11th Month of 2017 with total sales around 120,000

In [86]:

```
df = pd.DataFrame(ss.groupby('Sub-Category').sum()['Sales'])
Sub_Sales = df.sort_values('Sales', ascending = False)
```

In [88]:

```
Sub_Sales[:10]
```

Out[88]:

	Sales
Sub-Category	
Phones	330007.0540
Chairs	328449.1030
Storage	223843.6080
Tables	206965.5320
Binders	203412.7330
Machines	189238.6310
Accessories	167380.3180
Copiers	149528.0300
Bookcases	114879.9963
Appliances	107532.1610

In [89]:

```
df = pd.DataFrame(ss.groupby('Sub-Category').sum()['Quantity'])
Sub_quan = df.sort_values('Quantity', ascending = False)
```

In [95]:

```
Sub_quan[:10]
```

Out[95]:

	Quantity
Sub-Category	
Binders	5974
Paper	5178
Furnishings	3563
Phones	3289
Storage	3158
Art	3000
Accessories	2976
Chairs	2356
Appliances	1729
Labels	1400

In [91]:

```
df = pd.DataFrame(ss.groupby('Sub-Category').sum()['Profit'])
Sub_pro = df.sort_values('Profit', ascending = False)
```

In [93]:

```
Sub_pro.head(10)
```

Out[93]:

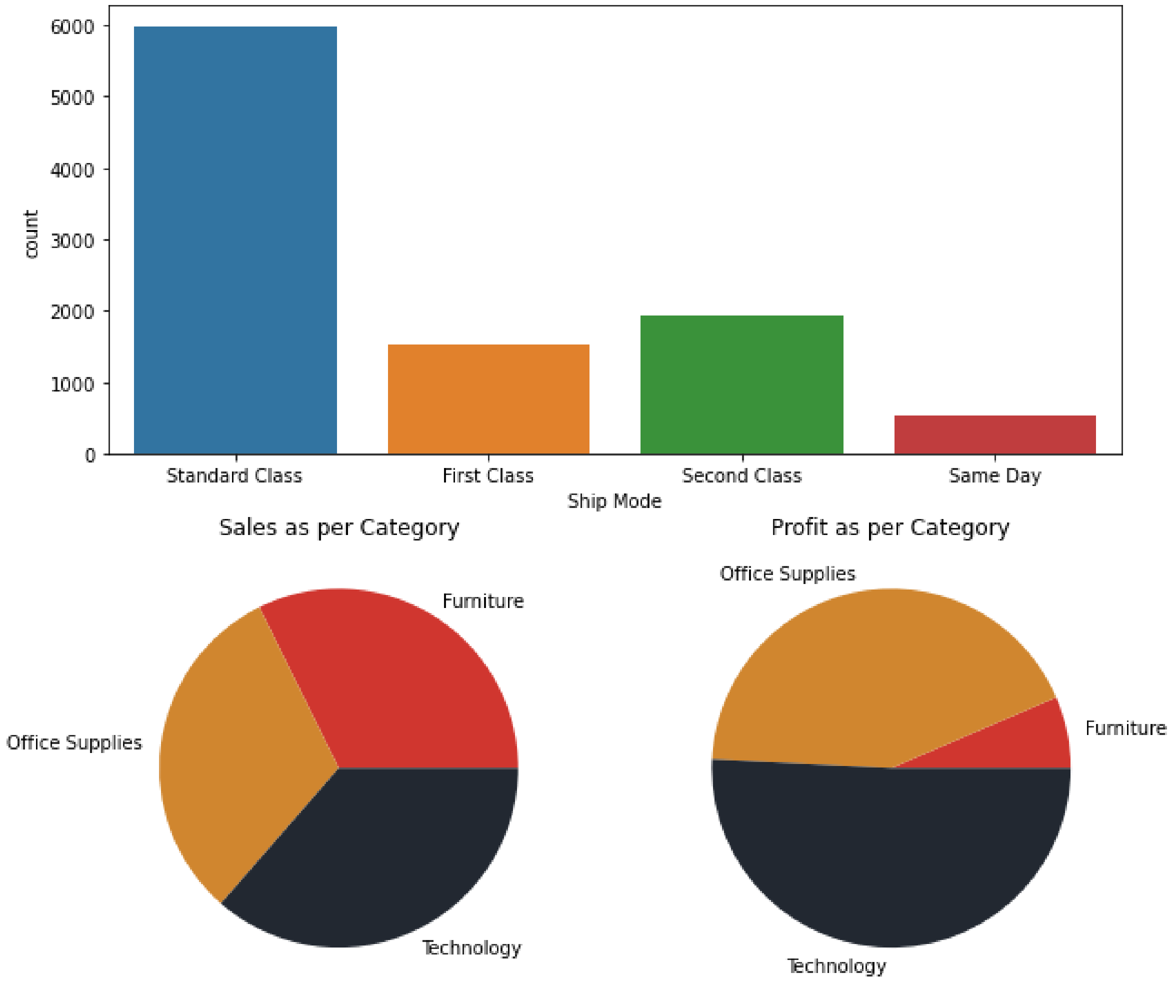
	Profit
Sub-Category	
Copiers	55617.8249
Phones	44515.7306
Accessories	41936.6357
Paper	34053.5693
Binders	30221.7633
Chairs	26590.1663
Storage	21278.8264
Appliances	18138.0054
Furnishings	13059.1436
Envelopes	6964.1767

We can see the Phone topped the chart in Sales Category and is in top 5 Sales in Quantity and 2nd in making Profit. Though chair sales is on 2nd rank in Sales but the profit on chair is comparatively low as compared to its sales. Copiers are 8th in Sales and not even in top 10 in Sales as per quantity but is still on the top in Profit.

Envelopes has made their place in top 10 profitable items too.

In [108]:

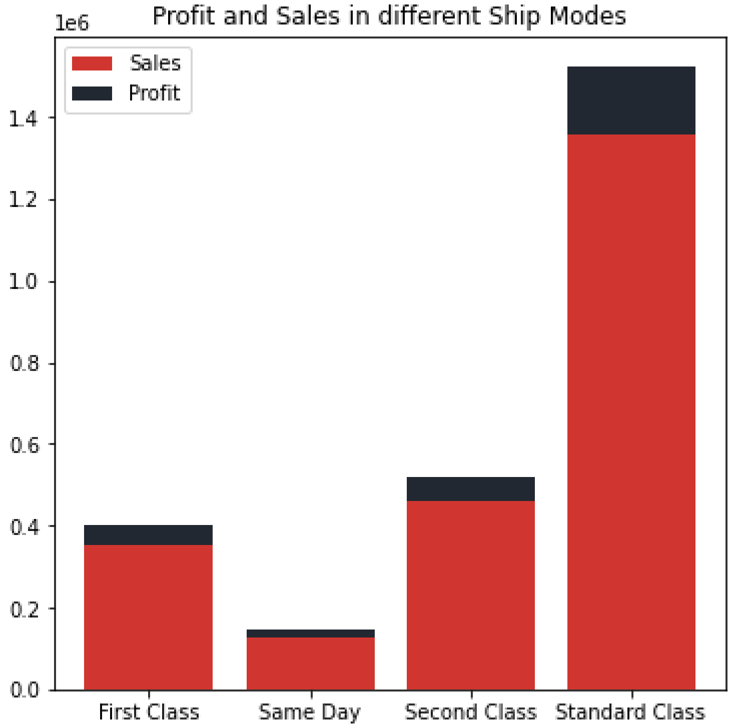
```
plt.figure(figsize=[10,10])

#Making Stack Bar Chart
ss_stack = ss[['Profit', 'Sales', 'Ship Mode']]
ss_stackbar = ss_stack.groupby(['Ship Mode']).sum().reset_index()

plt.subplot(2,1,1)
sns.countplot(ss_stack['Ship Mode'])

#Making Pie Diagran
ss_data = ss[['Category','Sales','Profit']]
ss_dia = ss_data.groupby(['Category']).sum().reset_index()

plt.subplot(2,2,3)
plt.pie(ss_dia['Sales'], labels=ss_dia['Category'], colors=['#D0362F','#D0862F','#222831'])
plt.title("Sales as per Category")

plt.subplot(2,2,4)
plt.pie(ss_dia['Profit'], labels=ss_dia['Category'], colors=['#D0362F','#D0862F','#222831']
plt.title("Profit as per Category")

plt.show()
```



From the first figure, we can assume that consumers mostly prefer Standard Class delivery mode. Also from next two figure we can identify that the sales is almost same for every category i.e for Office supplies, Furniture and Technology but thry vary in their profits. Technology is the most profitable category followed by office supplies.

In [115]:

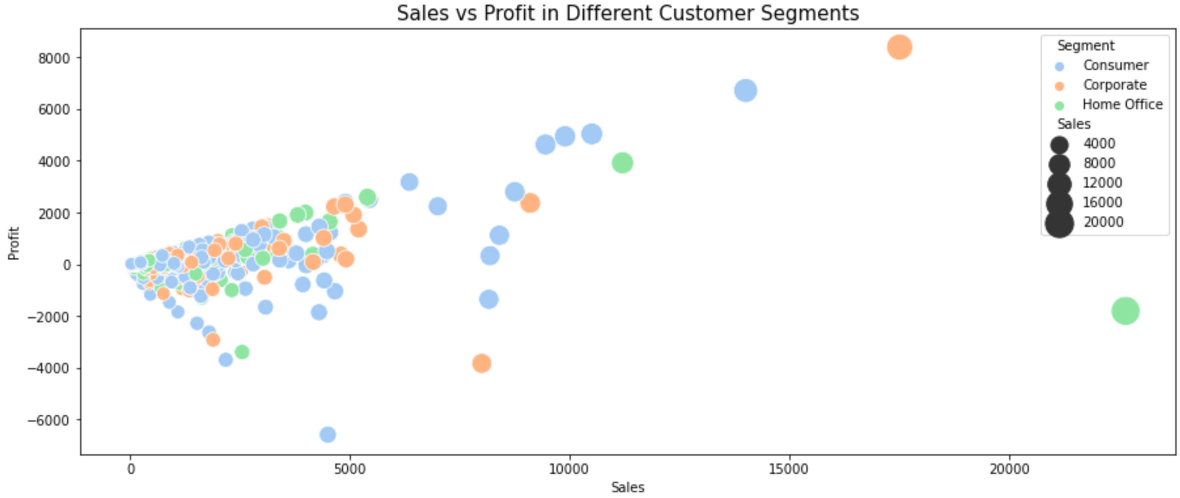
```
plt.figure(figsize=(6,6))
plt.bar(x = ss_stackbar['Ship Mode'], height = ss_stackbar['Sales'], color = '#D0362F')
plt.bar(x = ss_stackbar['Ship Mode'], height = ss_stackbar['Profit'], bottom = ss_stackbar[
plt.title("Profit and Sales in different Ship Modes")
plt.legend(['Sales','Profit'])
plt.show()
```



As we know the most preffered shipmode was Standard Class and now we can see that this is the most profitable mode. The least preffered mode is the Same day Shipment and also this shipment is the least profitable mode.

In [10]:

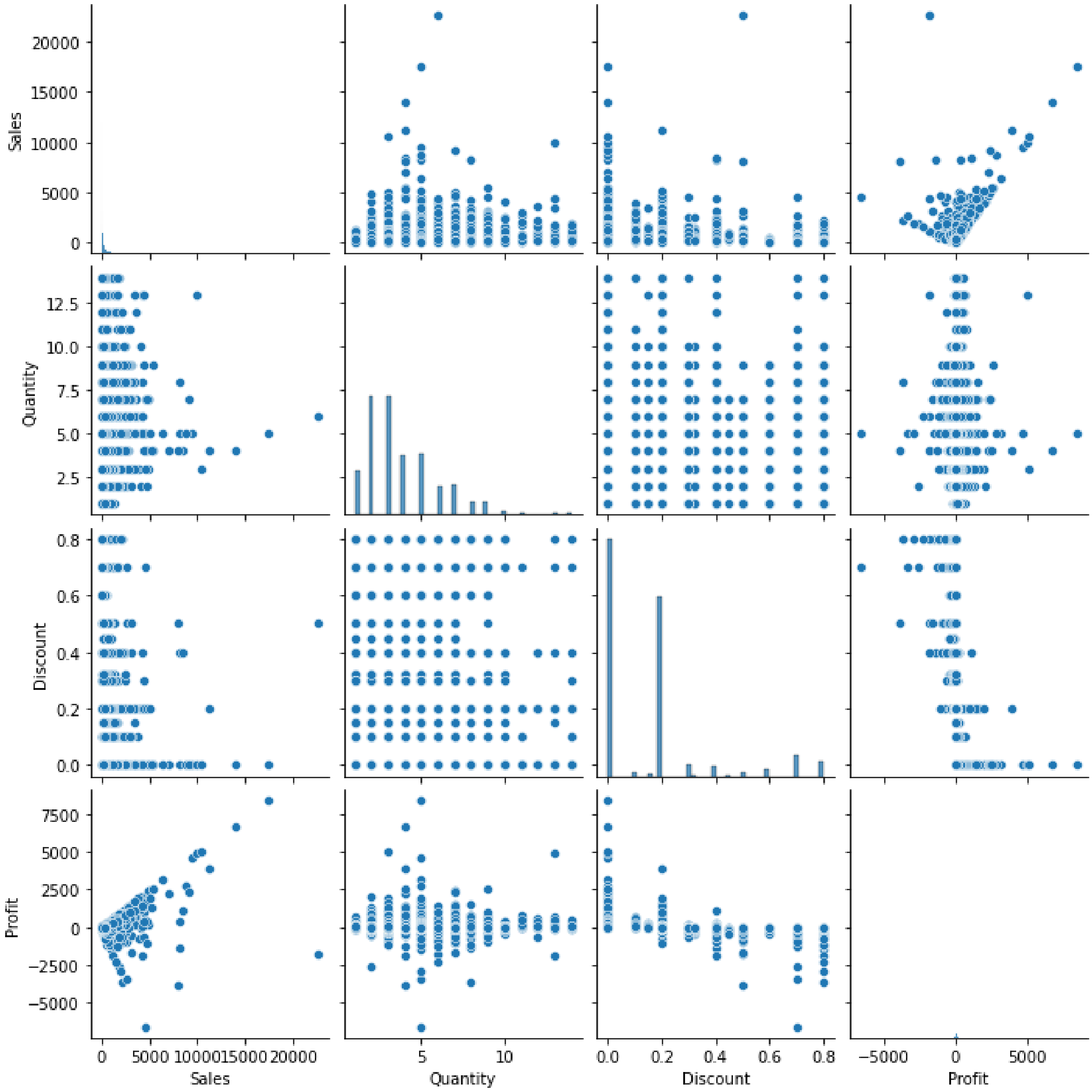
```
plt.figure(figsize=[15,6])
sns.scatterplot(x=ss['Sales'], y=ss['Profit'], hue=ss['Segment'], palette='pastel', size=ss
plt.title("Sales vs Profit in Different Customer Segments", size=15)
plt.show()
```



This diagram shows the scatterplot of Sales vs Profit in Different Customer Segments. We can clearly see that the Consumer segment is clearly dominating the Sales as well as the Profit section followed by Corporate and Home Offices respectively.

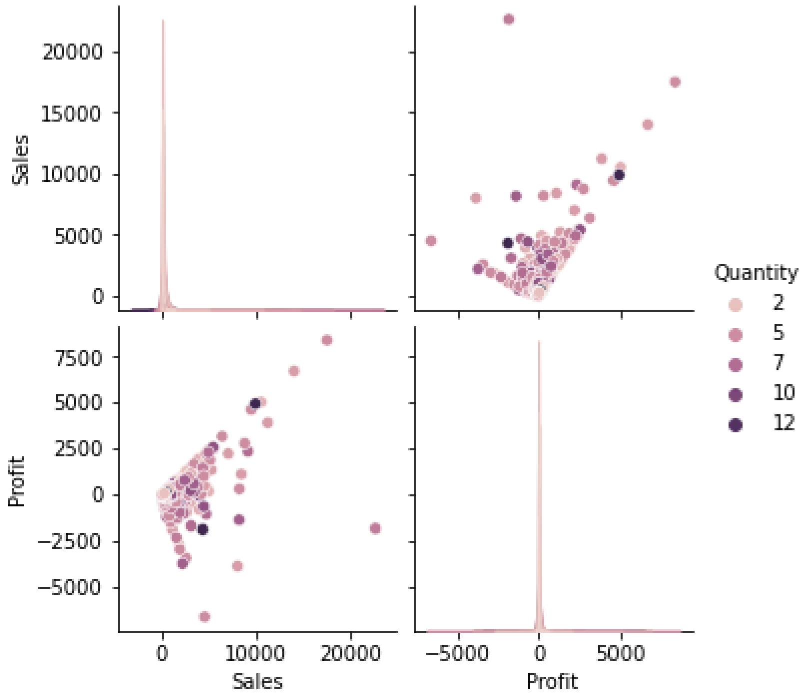
In [131]:

```
drop_ss = ss.drop(['Row ID', 'Postal Code'], axis = 1)
sns.pairplot(drop_ss)
plt.show()
```



In [11]:

```
sns.pairplot(ss[['Sales', 'Profit', 'Quantity']], hue ="Quantity", diag_kind="kde")
plt.show()
```



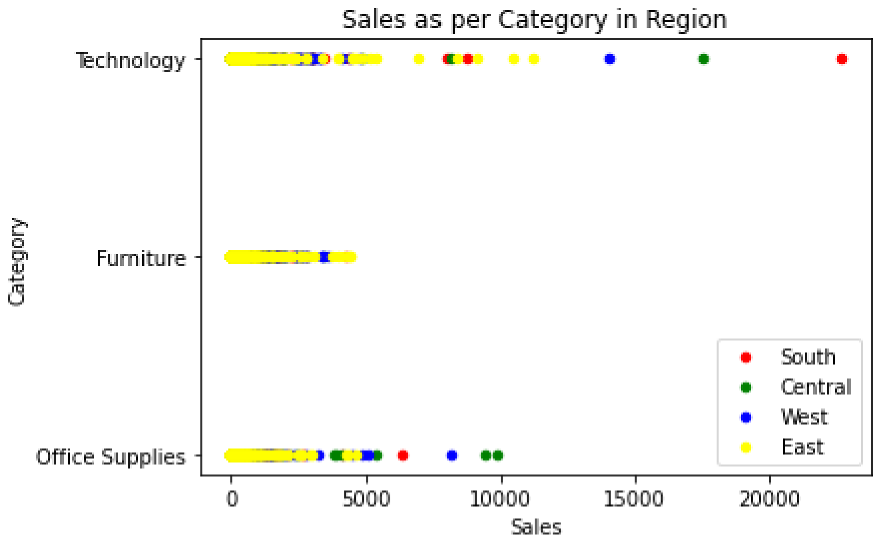
This pairplot explains us the relation between Sales and Profi with respect to Quantity.

In [68]:

```
ax = ss[ss.Region == 'South'].plot.scatter(x = 'Sales', y = 'Category', color = 'red', labe
ss[ss.Region == 'Central'].plot.scatter(x = 'Sales', y = 'Category', color = 'green', label
ss[ss.Region == 'West'].plot.scatter(x = 'Sales', y = 'Category', color = 'blue', label = '
ss[ss.Region == 'East'].plot.scatter(x = 'Sales', y = 'Category', color = 'Yellow', label =
ax.set_title('Sales as per Category in Region')
```

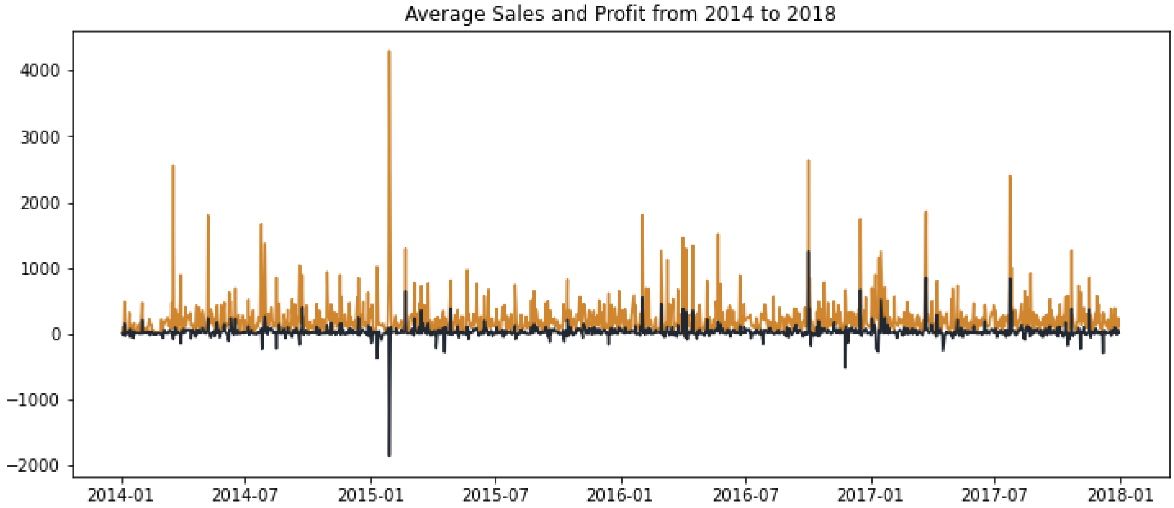
Out[68]:

```
Text(0.5, 1.0, 'Sales as per Category in Region')
```



In [129]:

```
plt.figure(figsize=[12,5])
ss_line = ss[['Order Date','Sales','Profit']].sort_values('Order Date')
ss_line = ss_line.groupby('Order Date').mean()

plt.plot(ss_line.index, 'Sales', data=ss_line, color='#D0862F')
plt.plot(ss_line.index, 'Profit', data=ss_line, color='#222831')
plt.title("Average Sales and Profit from 2014 to 2018")

plt.show()
```



In [ ]: