E-commerce Sales – Data Analysis Overview 📊

This project explores an E-commerce Sales dataset to uncover patterns in sales. The dataset includes detailed records of order details, shipping details, product details and other affecting factors.

In this project, we analyze this dataset using Python libraries such as Pandas, NumPy, and Matplotlib/Seaborn.

Objectives:

- Explore dataset structure
- Perform cleaning and preprocessing
- Generate insights from data
- Visualize important trends

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import skew, kurtosis
import warnings
warnings.filterwarnings("ignore")
```

In [2]:

```
file = pd.read_csv("E-commerce Sales.csv")
file.head()
```

Out[2]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Segment	City	State	Country	Market	Region	Product ID	Category	Sub-Category	Sales	Quant
0	32298	CA-2012-124891	7/31/2012	7/31/2012	Same Day	RH-19495	Consumer	New York City	New York	United States	US	East	TEC-AC-10003033	Technology	Accessories	2309.65	
1	26341	IN-2013-77878	02-05-2013	02-07-2013	Second Class	JR-16210	Corporate	Wollongong	New South Wales	Australia	APAC	Oceania	FUR-CH-10003950	Furniture	Chairs	3709.40	
2	25330	IN-2013-71249	10/17/2013	10/18/2013	First Class	CR-12730	Consumer	Brisbane	Queensland	Australia	APAC	Oceania	TEC-PH-10004664	Technology	Phones	5175.17	
3	13524	ES-2013-1579342	1/28/2013	1/30/2013	First Class	KM-16375	Home Office	Berlin	Berlin	Germany	EU	Central	TEC-PH-10004583	Technology	Phones	2892.51	
4	47221	SG-2013-4320	11-05-2013	11-06-2013	Same Day	RH-9495	Consumer	Dakar	Dakar	Senegal	Africa	Africa	TEC-SHA-10000501	Technology	Copiers	2832.96	

2. Explore the dataset

We have to check dataset dimensions, columns, data types, and summary statistics.

- Using `file.info()` to know the
  - dimensions of the dataset,
  - column names,
  - data types of the columns,
  - count of non null values

In [3]:
```
file.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 51290 entries, 0 to 51289
Data columns (total 19 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Row ID          51290 non-null  int64  
 1   Order ID        51290 non-null  object 
 2   Order Date      51290 non-null  object 
 3   Ship Date       51290 non-null  object 
 4   Ship Mode       51290 non-null  object 
 5   Customer ID     51290 non-null  object 
 6   Segment         51290 non-null  object 
 7   City            51290 non-null  object 
 8   State           51290 non-null  object 
 9   Country         51290 non-null  object 
 10  Market          51290 non-null  object 
 11  Region          51290 non-null  object 
 12  Product ID      51290 non-null  object 
 13  Category        51290 non-null  object 
 14  Sub-Category    51290 non-null  object 
 15  Sales           51290 non-null  float64
 16  Quantity        51290 non-null  int64  
 17  Shipping Cost   51290 non-null  float64
 18  Order Priority  51290 non-null  object 
dtypes: float64(2), int64(2), object(15)
memory usage: 7.4+ MB
```

Observation in Exploring the Data

- The above dataset have 51290 rows with 19 availble columns.
- It has 13 categorical columns, 2 date columns and 4 numerical columns.
- All the 19 columns were non-null columns.
- All the columns datatypes are correct.

3. Data Cleaning

For data cleaning purposes, we used different techniques based on our scenario which are explained in-depth as follows:

1. Checking the Null values
2. Check for duplicates
3. Standardize the Data
4. Checking Outliers

1. Checking the Null Values

In [4]:
```
file.isnull().sum()
```

Out[4]:
```
Row ID            0
Order ID          0
Order Date        0
Ship Date         0
Ship Mode         0
Customer ID       0
Segment           0
City              0
State             0
Country           0
Market            0
Region            0
Product ID        0
Category          0
Sub-Category      0
Sales             0
Quantity          0
Shipping Cost     0
Order Priority    0
dtype: int64
```

Observation in Checking the Null Values

- Here we can confirm that there is no null values in this dataset.

2. Check for duplicates

In [5]:
```
print(file.duplicated().sum())
print(file.duplicated('Row ID').sum())
```

```
0
0
```

Observation in Check for Duplicates

- By using duplicated function in pandas, we can see that there is duplicates found in this dataset.

3. Feature Engineering

- As we seen earlier, we have Order Date and Ship Date columns in this dataset.
- Create columns for month and day from Order Date for deeper analysis.

In [6]:
```
#converting into datetime dtype
file['Order Date'] = pd.to_datetime(file['Order Date'], format='mixed', dayfirst=False)
file['Ship Date'] = pd.to_datetime(file['Ship Date'], format='mixed', dayfirst=False)
```

In [7]:
```
#creating month and day column
file['Order_Month'] = file['Order Date'].dt.month_name()
month_order = ['January', 'February', 'March', 'April', 'May', 'June',
               'July', 'August', 'September', 'October', 'November', 'December']
file['Order_Month'] = pd.Categorical(file['Order_Month'], categories=month_order, ordered=True)

file['Order_Day'] = file['Order Date'].dt.day_name()
day_order = ['Sunday', 'Monday', 'Tuesday', 'Wednesday', 'Thursday', 'Friday',
             'Saturday']
file['Order_Day'] = pd.Categorical(file['Order_Day'], categories=day_order, ordered=True)

file['Order_Year'] = file['Order Date'].dt.year

file.head()
```

Out[7]:

	Row ID	Order ID	Order Date	Ship Date	Ship Mode	Customer ID	Segment	City	State	Country	...	Product ID	Category	Sub-Category	Sales	Quantity	Shipping Cost	Order Priority
0	32298	CA-2012-124891	2012-07-31	2012-07-31	Same Day	RH-19495	Consumer	New York City	New York	United States	...	TEC-AC-10003033	Technology	Accessories	2309.65	7	933.57	Critical
1	26341	IN-2013-77878	2013-02-05	2013-02-07	Second Class	JR-16210	Corporate	Wollongong	New South Wales	Australia	...	FUR-CH-10003950	Furniture	Chairs	3709.40	9	923.63	Critical
2	25330	IN-2013-71249	2013-10-17	2013-10-18	First Class	CR-12730	Consumer	Brisbane	Queensland	Australia	...	TEC-PH-10004664	Technology	Phones	5175.17	9	915.49	Medium
3	13524	ES-2013-1579342	2013-01-28	2013-01-30	First Class	KM-16375	Home Office	Berlin	Berlin	Germany	...	TEC-PH-10004583	Technology	Phones	2892.51	5	910.16	Medium
4	47221	SG-2013-4320	2013-11-05	2013-11-06	Same Day	RH-9495	Consumer	Dakar	Dakar	Senegal	...	TEC-SHA-10000501	Technology	Copiers	2832.96	8	903.04	Critical

5 rows × 22 columns

4. Checking Outlier

- Using describe function, we can get some statistical distribution of the data of each numerical column.

In [8]:
```
file.describe()
```

Out[8]:

	Row ID	Order Date	Ship Date	Sales	Quantity	Shipping Cost	Order_Year
count	51290.00000	51290	51290	51290.000000	51290.000000	51290.000000	51290.000000
mean	25645.50000	2013-05-11 21:26:49.155781120	2013-05-15 20:42:42.745174528	246.490685	3.476545	26.375915	2012.777208
min	1.00000	2011-01-01 00:00:00	2011-01-03 00:00:00	0.440000	1.000000	0.000000	2011.000000
25%	12823.25000	2012-06-19 00:00:00	2012-06-23 00:00:00	30.762500	2.000000	2.610000	2012.000000
50%	25645.50000	2013-07-08 00:00:00	2013-07-12 00:00:00	85.055000	3.000000	7.790000	2013.000000
75%	38467.75000	2014-05-22 00:00:00	2014-05-26 00:00:00	251.055000	5.000000	24.450000	2014.000000
max	51290.00000	2014-12-31 00:00:00	2015-01-07 00:00:00	22638.480000	14.000000	933.570000	2014.000000
std	14806.29199	NaN	NaN	487.565388	2.278766	57.296804	1.098931

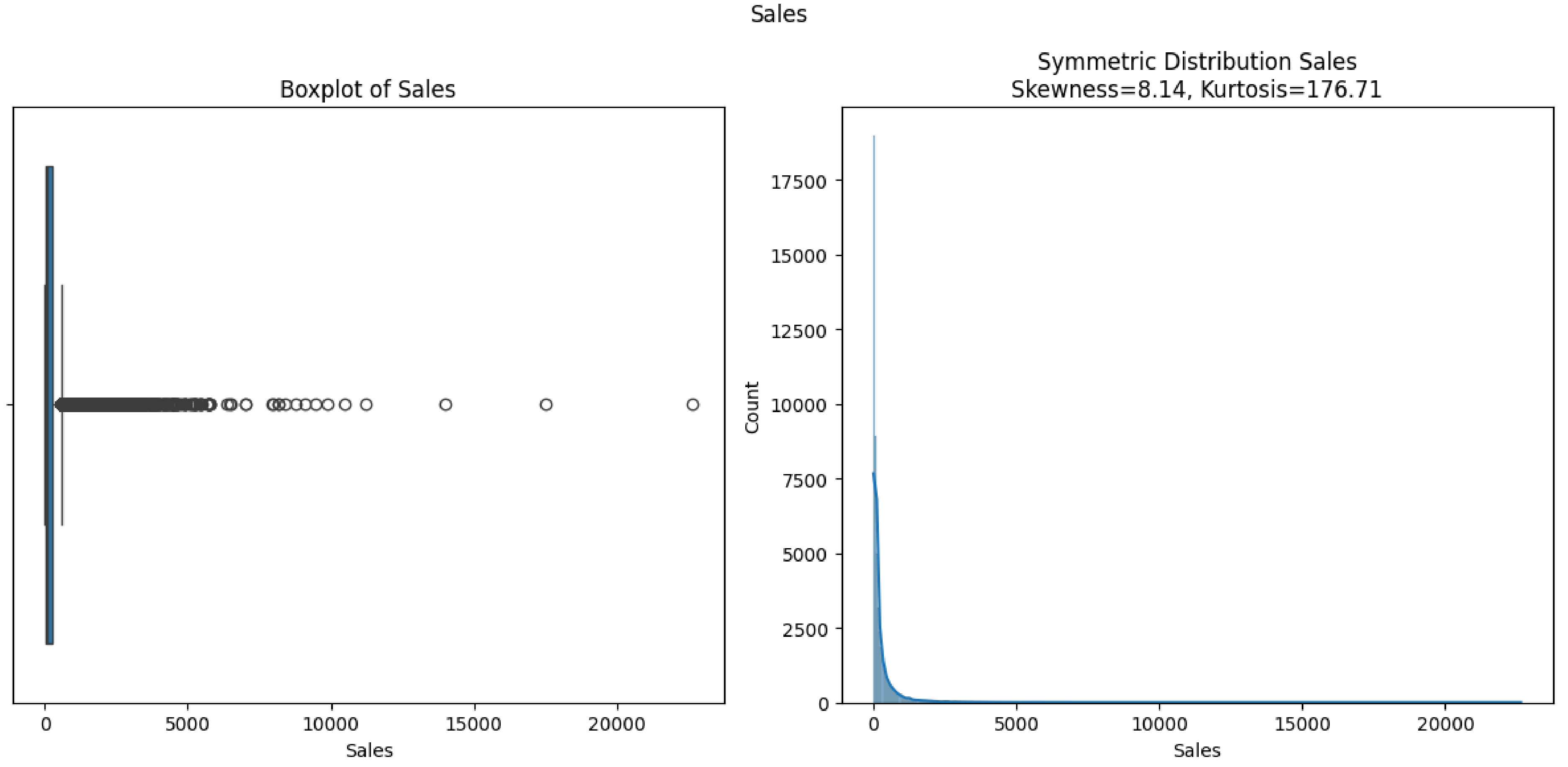
- When seeing the statistical measures, we can see irrelevant range of distribution in sales and shipping cost columns.
- Difference between the Min value & 25th qantile and Max & 75th quantile is varied so much.

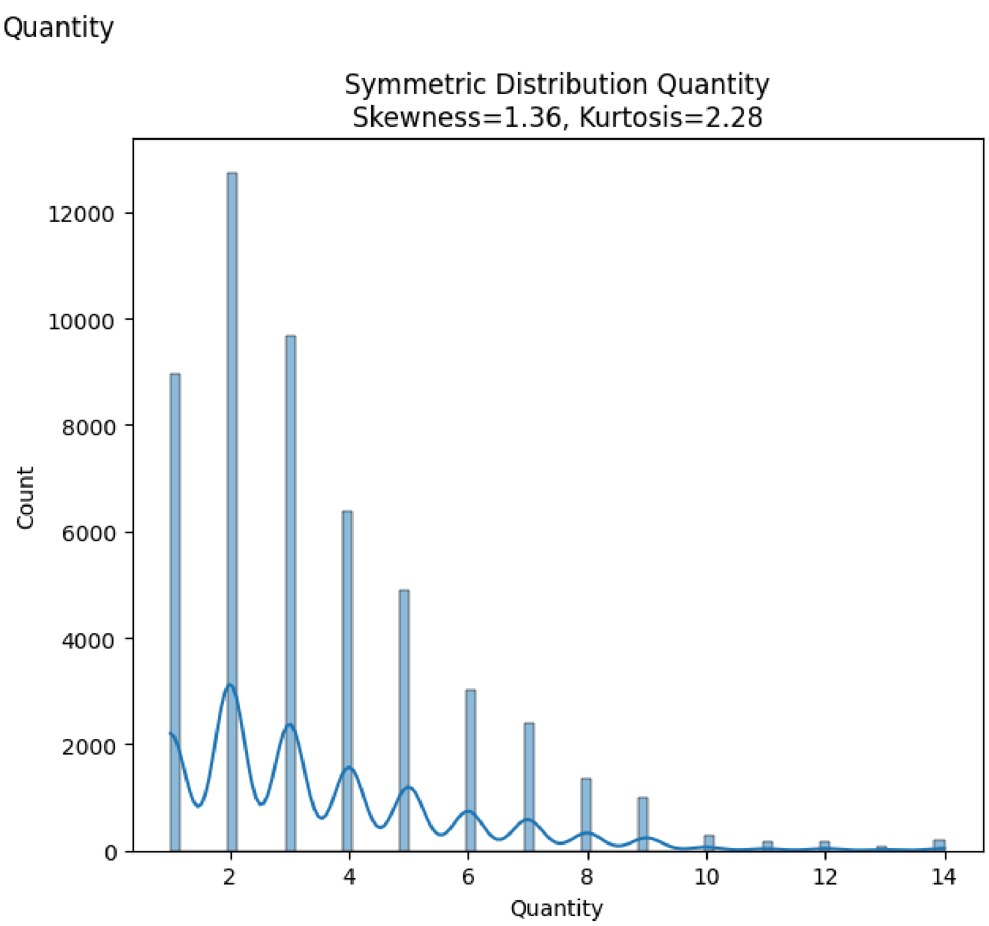
In [9]:
```
#checking outliers through graph
def outlier_graph(cols):

    for i in range(1,len(cols)+1):
        col = cols[i-1]
        sk = skew(file[col])
        ku = kurtosis(file[col])

        plt.figure(figsize=(12,6))
        plt.suptitle(f'{col}')

        plt.subplot(1,2,1)
        plt.title(f'Boxplot of {col}')
        sns.boxplot(file[col], orient='h')

        plt.subplot(1,2,2)
        plt.title(f"Symmetric Distribution {col}\nSkewness={sk:.2f}, Kurtosis={ku:.2f}")
        sns.histplot(file[col], kde=True)
        plt.tight_layout()
        plt.show()

#By using the User Defined Function below, we can find and drop the outliers easily
outlier_df_dict = {}
```

```python
def outlier_handle(i):
    global outlier_df_dict

    #finding the first quartile
    Q1 = file[i].quantile(0.25)
    #finding the thirt quartile
    Q3 = file[i].quantile(0.75)
    print(f"Q1 = {Q1} ,Q3 = {Q3}")

    #finding inter quartile range(IQR)
    IQR = Q3 - Q1
    print("IQR = ",IQR)

    #finding the lower bound
    LB = Q1 - (1.5 * IQR)
    #finding the lower bound
    UB = Q3 + (1.5 * IQR)
    print(f"LB = {LB} ,UB = {UB}")

    #checking for outliers in df
    outliers_df = file[(file[i] < LB) | (file[i] > UB)]



    #getting teh index for outliers
    outliers_index = outliers_df.index

    print(f"""
    No. of. Outliers: {len(outliers_index)}
    Availabe no. of. records: {len(file.index)}
    After removing, Availabe no. of. records: {(len(file[i].index) - len(outliers_index))}
    """)

    #asking to remove outlier
    YorN = input("Continue to Remove Outliers?(Y/N): ")
    if YorN.upper() == 'Y':
        #saving the outlier df in a dictionary
        outlier_df_dict[f"df_{i}"] = outliers_df

        #removing teh outliers
        file.drop(outliers_index, inplace=True)

        print(f"""
        No. of. Outliers Removed: {len(outliers_index)}
        Availabe no. of. records: {len(file.index)}
        Removed Outliers stored in: outlier_df_dict["df_{i}"]
        """)


        plt.title(f'{i}')
```

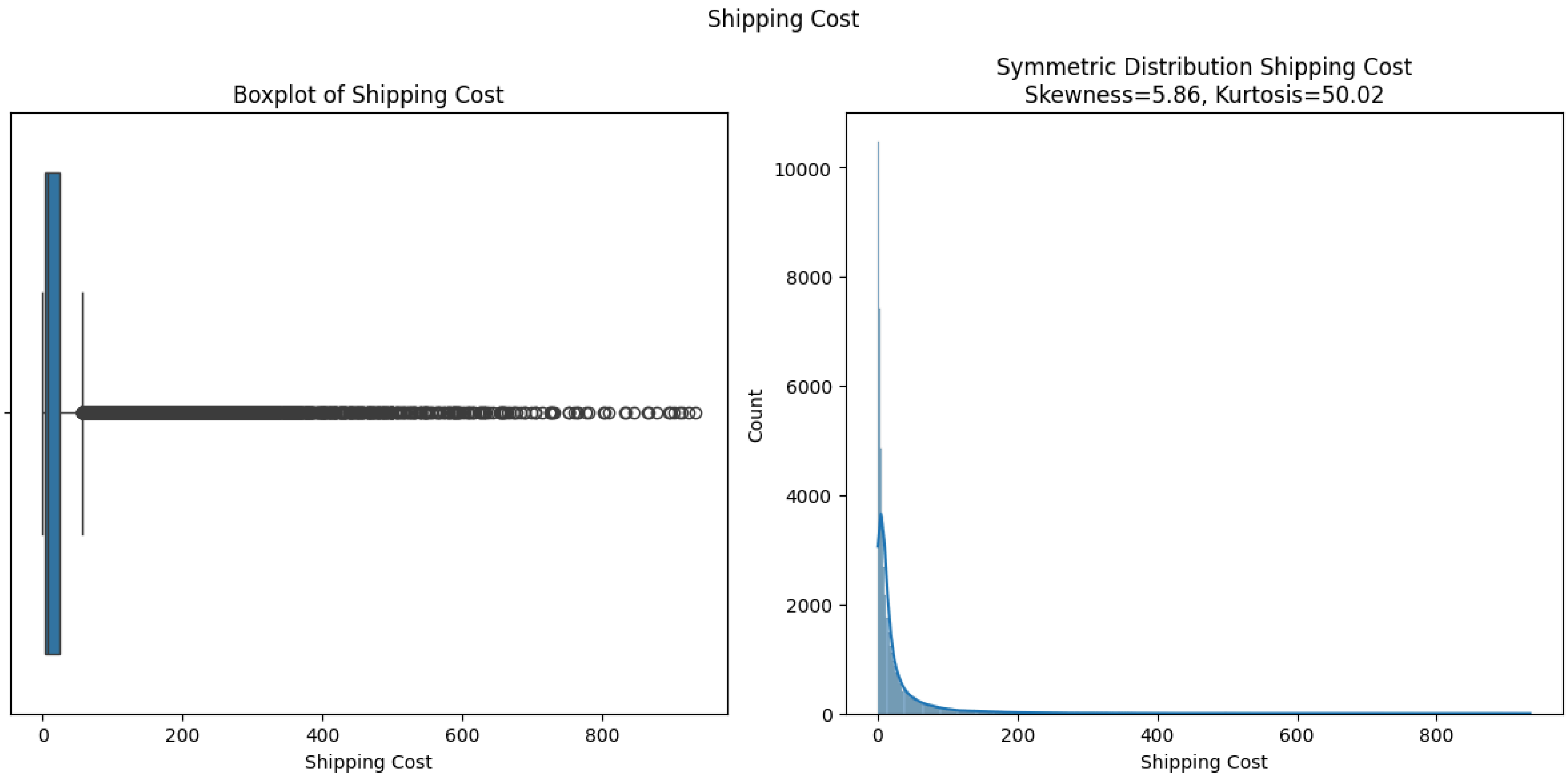
```
        sns.boxplot(file[i],orient='h')
        plt.tight_layout()
        plt.show()

    elif YorN.upper() == 'N':
        print("No outliers removed")
        print(f"""
        Availabe no. of. records: {len(file.index)}
        """)
    else:
        print("Invalid input")
```

In [10]:
```
outlier_graph(['Sales','Quantity','Shipping Cost'])
```





Quantity
Boxplot of Quantity
Symmetric Distribution Quantity
Skewness=1.36, Kurtosis=2.28
Count
Quantity
2
4
6
8
10
12
14
0
2000
4000
6000
8000
10000
12000

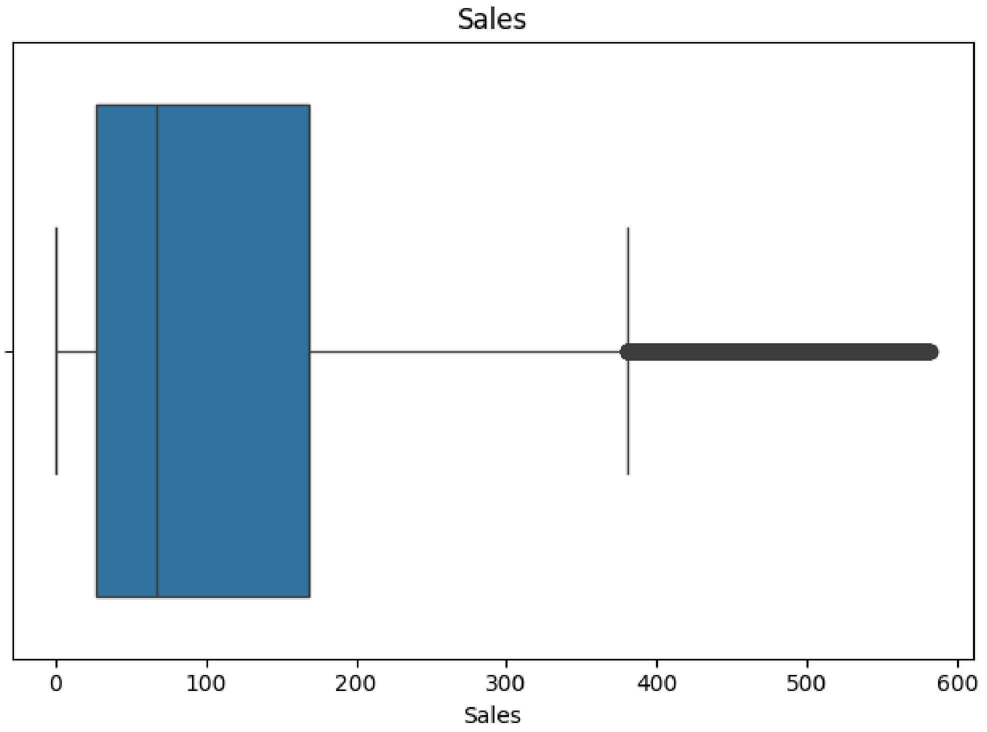


- Here we can see that there is a huge amount of outliers.
- Comparitively Sales column has the most outliers, so lets drop the outliers on the Sales column.

In [11]:
```
outlier_handle("Sales")
```

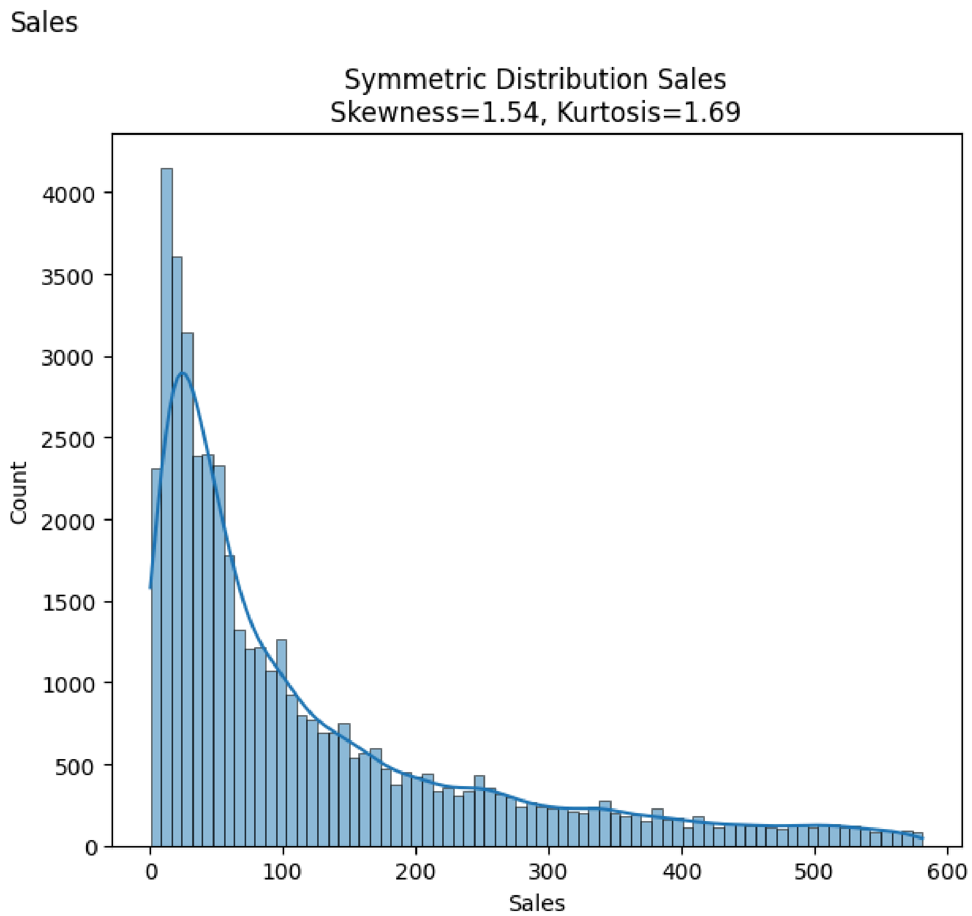
```
Q1 = 30.762500000000003 ,Q3 = 251.055
IQR =  220.29250000000002
LB = -299.67625000000004 ,UB = 581.4937500000001

    No. of. Outliers: 5655
    Availabe no. of. records: 51290
    After removing, Availabe no. of. records: 45635
```

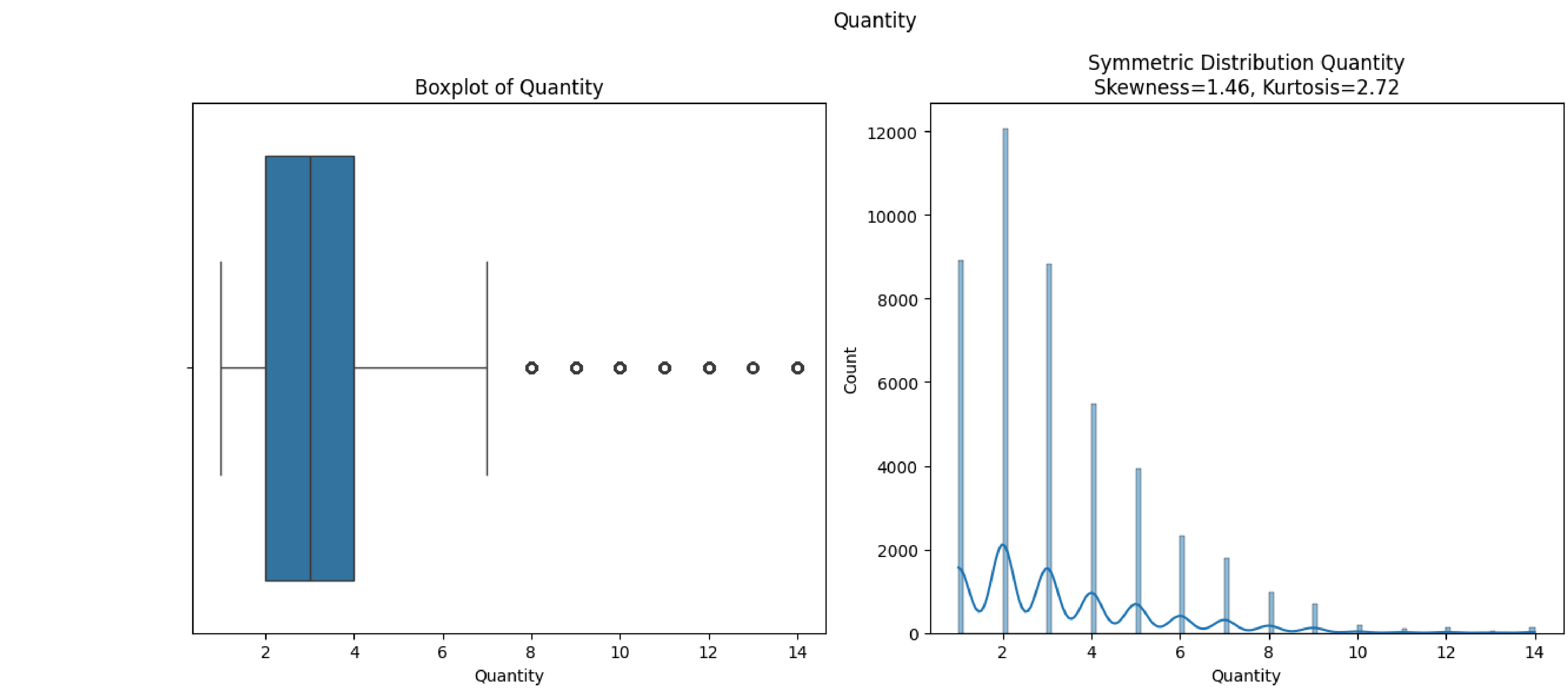
```
No. of. Outliers Removed: 5655
Availabe no. of. records: 45635
Removed Outliers stored in: outlier_df_dict["df_Sales"]
```



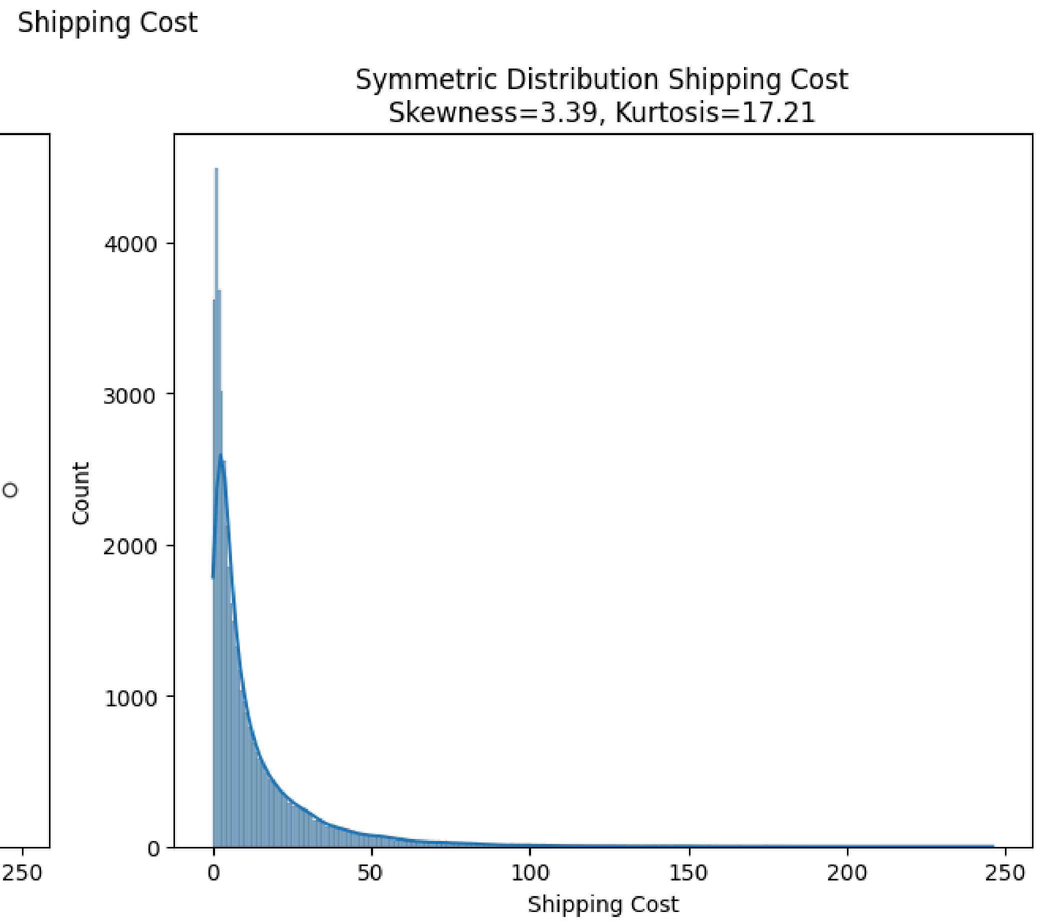
- Removed outliers in the basis of Sales column, lets check the outliers in other columns.

In [12]:
```
outlier_graph(['Sales','Quantity','Shipping Cost'])
```


Sales
Boxplot of Sales
Symmetric Distribution Sales
Skewness=1.54, Kurtosis=1.69
Count
0
500
1000
1500
2000
2500
3000
3500
4000
0
100
200
300
400
500
600
Sales
0
100
200
300
400
500
600
Sales



Quantity
Boxplot of Quantity
2
4
6
8
10
12
14
Quantity
Symmetric Distribution Quantity
Skewness=1.46, Kurtosis=2.72
Count
0
2000
4000
6000
8000
10000
12000
2
4
6
8
10
12
14
Quantity

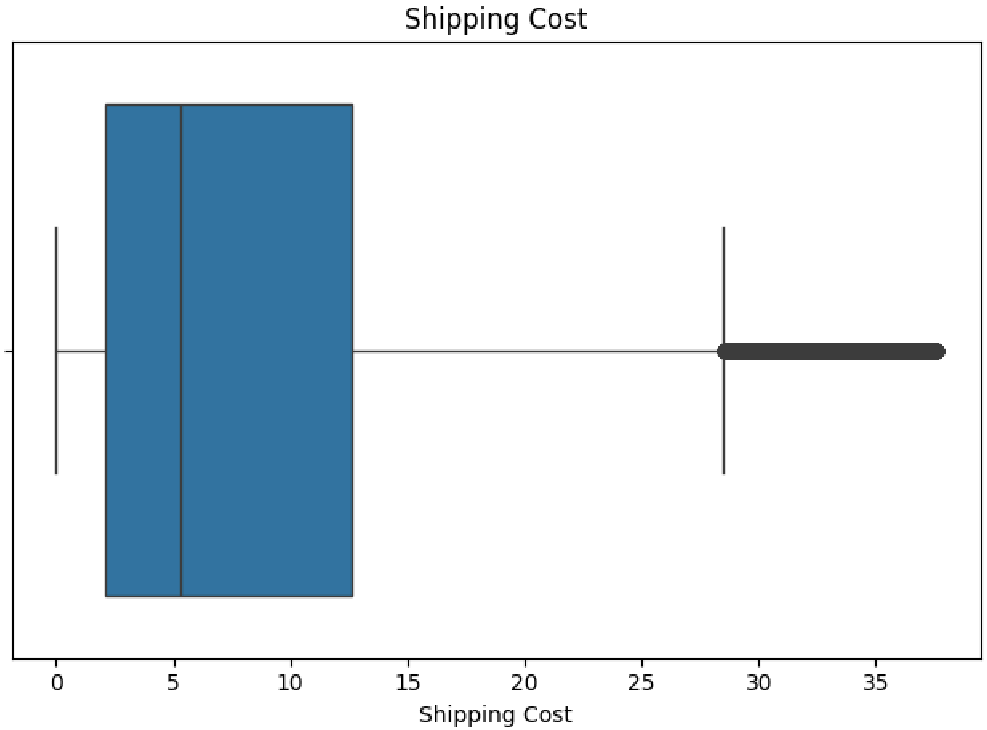


- Still we can see the outliers in Shipping cost column which will affect the quality of the analysis.

In [13]:
```
outlier_handle("Shipping Cost")
```

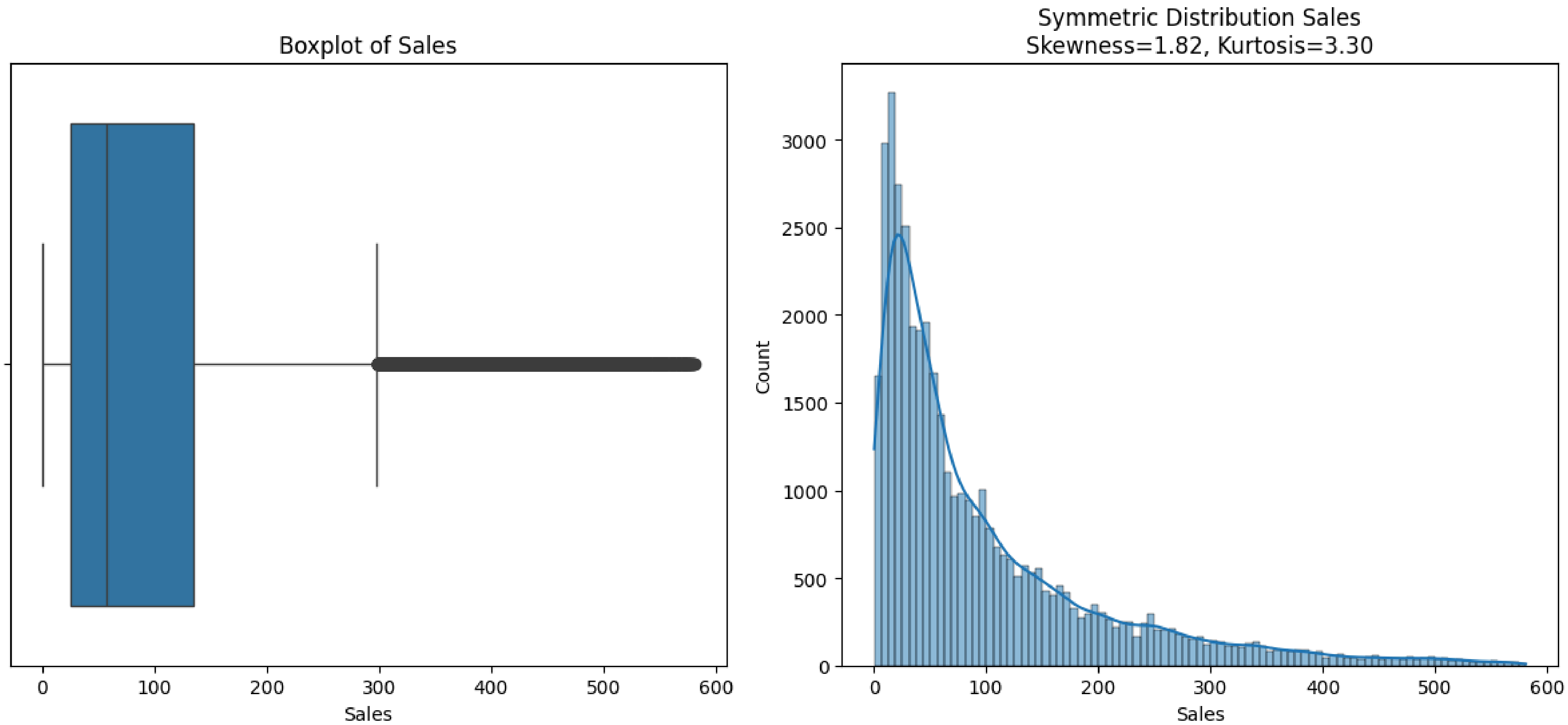
```
Q1 = 2.28 ,Q3 = 16.41
IQR =  14.13
LB = -18.915 ,UB = 37.605000000000004

    No. of. Outliers: 3827
    Availabe no. of. records: 45635
    After removing, Availabe no. of. records: 41808
```

```
No. of. Outliers Removed: 3827
Availabe no. of. records: 41808
Removed Outliers stored in: outlier_df_dict["df_Shipping Cost"]
```

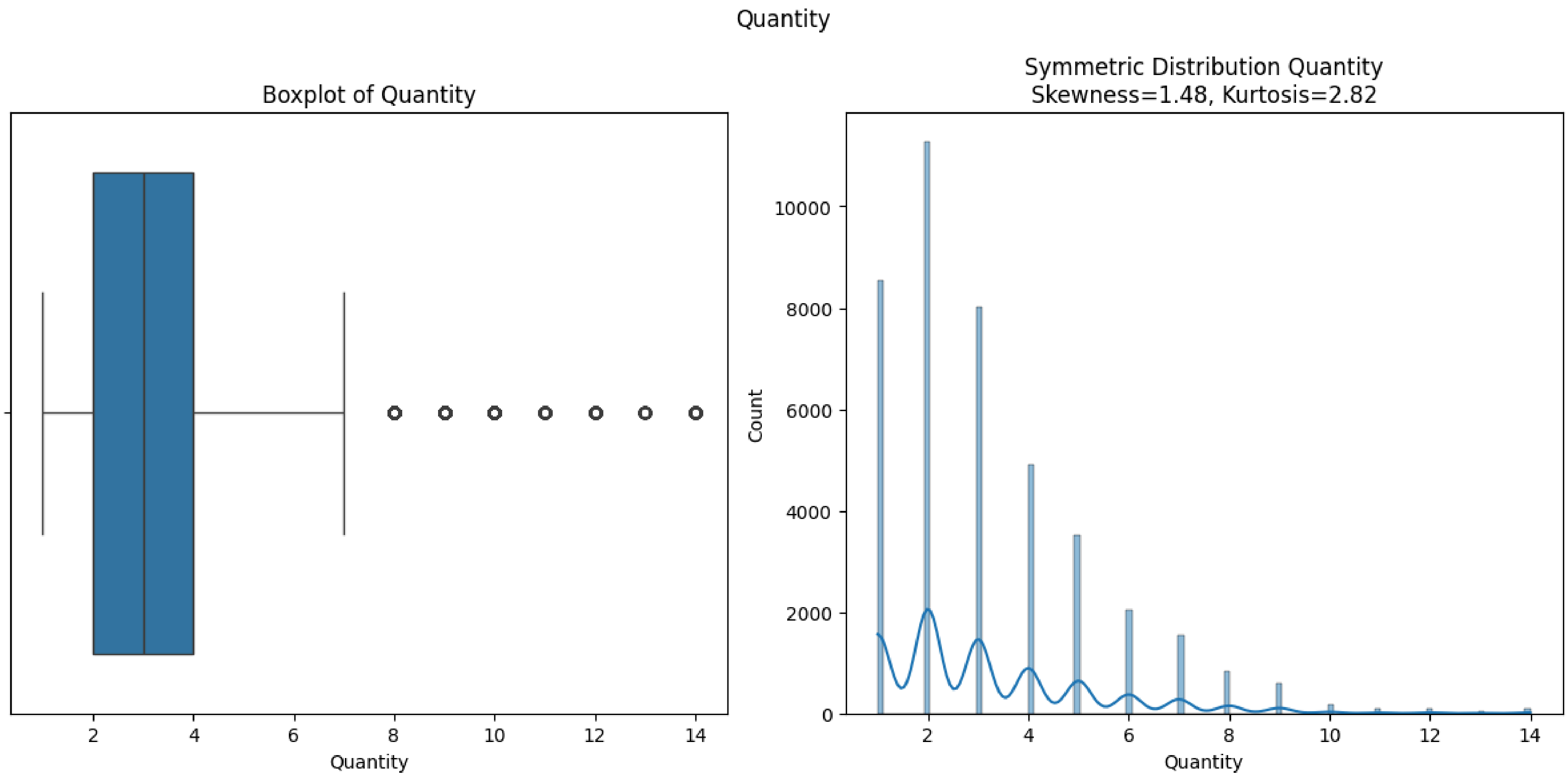


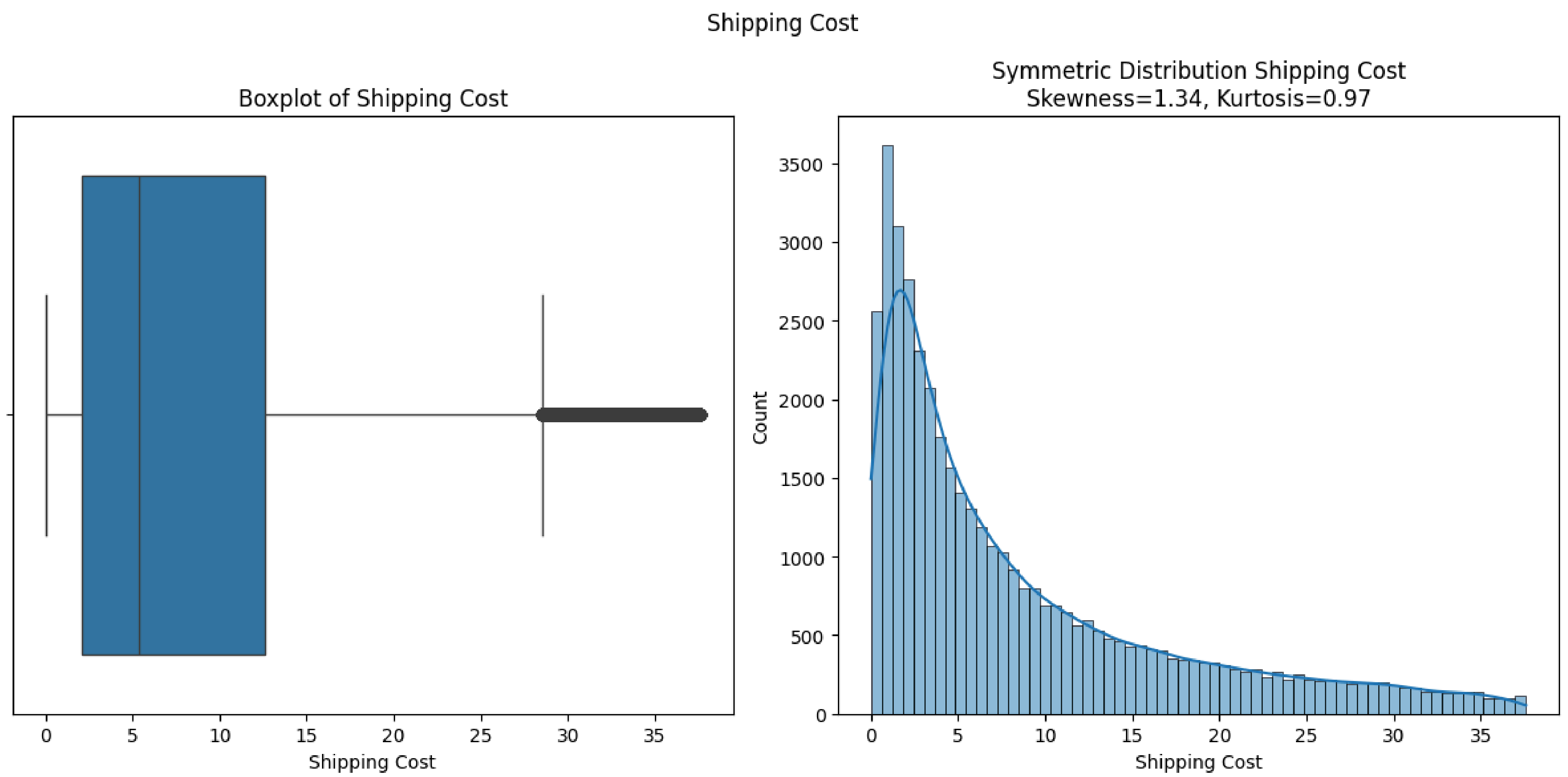
In [14]:
```
outlier_graph(['Sales','Quantity','Shipping Cost'])
```

Sales



Boxplot of Sales
0
100
200
300
400
500
600
Sales
Symmetric Distribution Sales
Skewness=1.82, Kurtosis=3.30
3000
2500
2000
1500
1000
500
0
Count
0
100
200
300
400
500
600
Sales


Quantity
Boxplot of Quantity
Symmetric Distribution Quantity
Skewness=1.48, Kurtosis=2.82
Count
Quantity
Quantity
2
4
6
8
10
12
14
0
2000
4000
6000
8000
10000



Observation in Data Cleaning

- There is no duplicates and null values in this dataset.
- Converted date column data type from object to datetime for better analysis.
- Additionally, 2(Order_Month, Order_Day) columns were created from Order date columns.
- Using describe function and statistics, we found wide range of outliers, so we removed from original dataset and stored in another dictionery.

3. Exploratory Data Analysis

1. Summary Statistics
2. Analysis Visualizations

3. Providing Insights

1. Statistical Description

In [15]:
```
file[['Sales','Quantity','Shipping Cost']].describe()
```

Out[15]:

	Sales	Quantity	Shipping Cost
count	41808.000000	41808.000000	41808.000000
mean	98.750540	3.188839	8.735613
std	105.961474	2.110392	8.843581
min	0.440000	1.000000	0.000000
25%	25.057500	2.000000	2.060000
50%	57.900000	3.000000	5.340000
75%	134.385000	4.000000	12.640000
max	581.040000	14.000000	37.600000

- After handling the outlier, we can see a good distribution of data compared to before handling the outlier.

In [16]:
```
file.describe(include='object')
```

Out[16]:

	Order ID	Ship Mode	Customer ID	Segment	City	State	Country	Market	Region	Product ID	Category	Sub-Category	Order Priority
count	41808	41808	41808	41808	41808	41808	41808	41808	41808	41808	41808	41808	41808
unique	22484	4	1589	3	3503	1076	147	7	13	9303	3	17	4
top	NI-2014-8880	Standard Class	BE-11335	Consumer	New York City	California	United States	LATAM	Central	OFF-AR-10003651	Office Supplies	Binders	Medium
freq	13	26119	76	21647	746	1661	8358	8575	8976	35	29066	5978	25291

2. Analysis

📦 Product Category Analysis

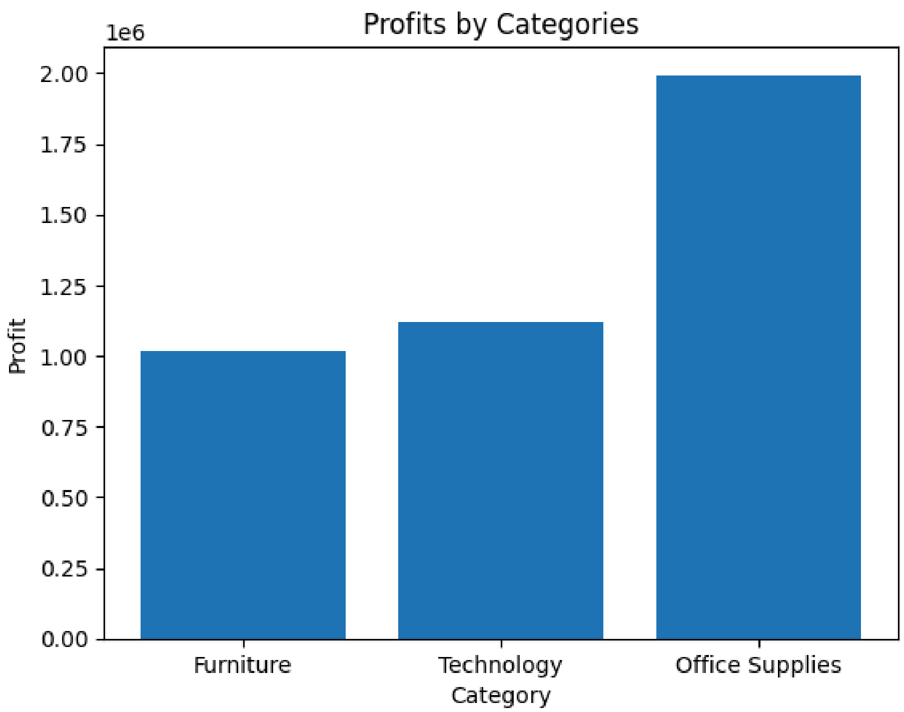
Features used: `Category` , `Sub-Category` , `Sales` , `Quantity` , `Profit`

1. Which product category generates the highest total profit?
2. Which sub-category contributes most to overall profit?
3. Which sub-category has the highest total quantity sold?
4. What is the average quantity purchased per sub-category?
5. Is there any sub-category with high sales but low profit?

In [17]:
```
#1. Which product category generates the highest total profit?
profit_cat = file.groupby(['Category'])['Sales'].sum().sort_values()
profit_cat
```

Out[17]:
```
Category
Furniture          1017719.42
Technology         1118453.37
Office Supplies    1992389.80
Name: Sales, dtype: float64
```

In [18]:
```
plt.bar(profit_cat.index,profit_cat.values)
plt.title("Profits by Categories")
plt.xlabel("Category")
plt.ylabel("Profit")
plt.show()
```

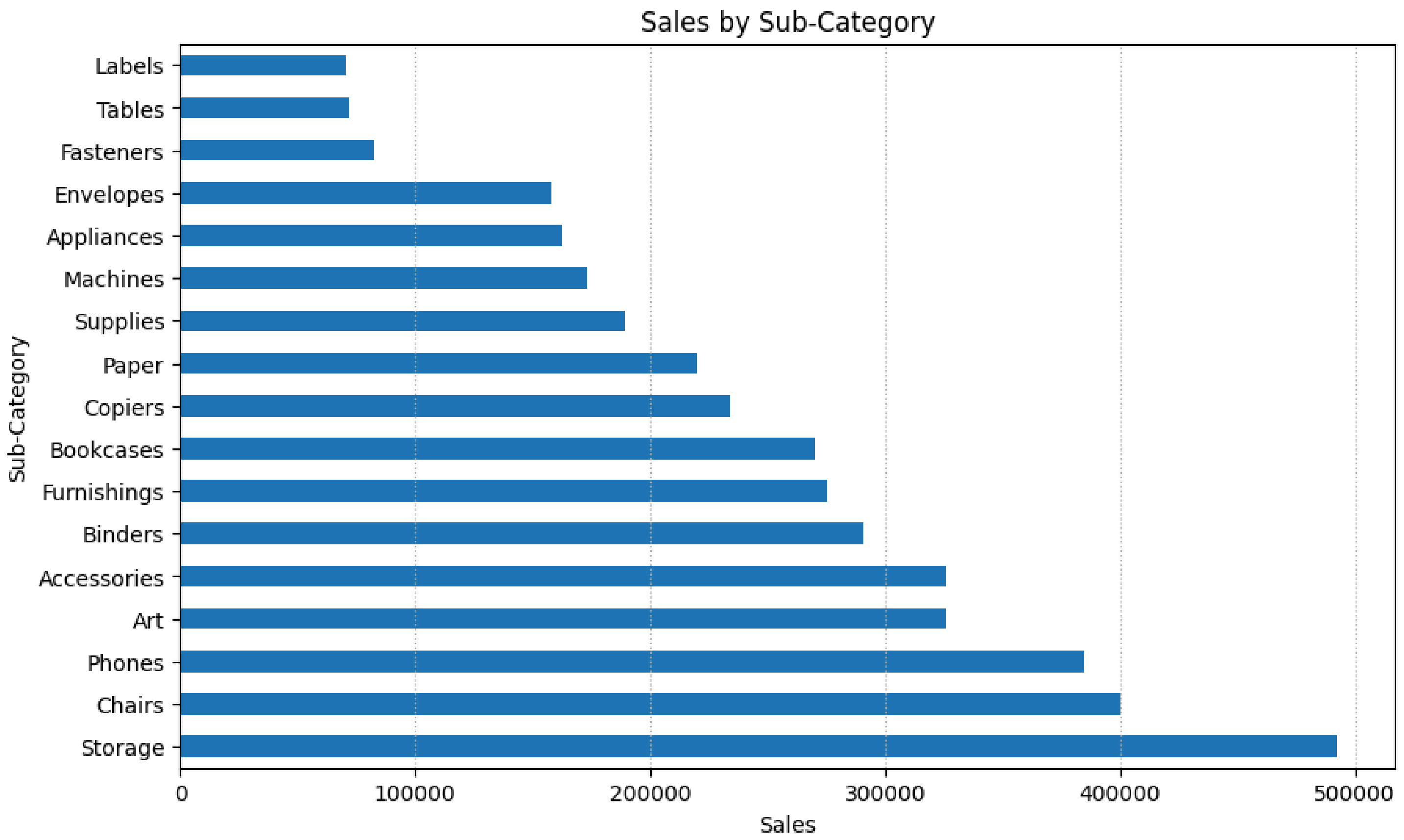


- This dataset have 3 Category of products.
- Among these, Office supply products are the top sales made products with sales of 19,92,389.80
- Other categories like Technology and Furniture category products have generated a revenue above 10,00,000 each.
- The total sales amount is 41,28,562.59

In [19]:
```
#2. Which sub-category contributes most to overall profit?
sub_cat_profit = file.groupby('Sub-Category')['Sales'].sum().sort_values(ascending=False)
sub_cat_profit
```

Out[19]:
```
Sub-Category
Storage        492509.26
Chairs         400110.19
Phones         384896.05
Art            326355.36
Accessories    326100.03
Binders        290746.89
Furnishings    275237.79
Bookcases      270191.10
Copiers        234342.78
Paper          219867.01
Supplies       188997.54
Machines       173114.51
Appliances     162740.87
Envelopes      157901.20
Fasteners       82682.67
Tables          72180.34
Labels          70589.00
Name: Sales, dtype: float64
```

In [20]:
```
plt.figure(figsize=(10,6))
sub_cat_profit.plot(kind='barh',title='Sales by Sub-Category',xlabel='Sales',ylabel='Sub-Category')
plt.grid(axis='x',linestyle=':')
plt.show()
```

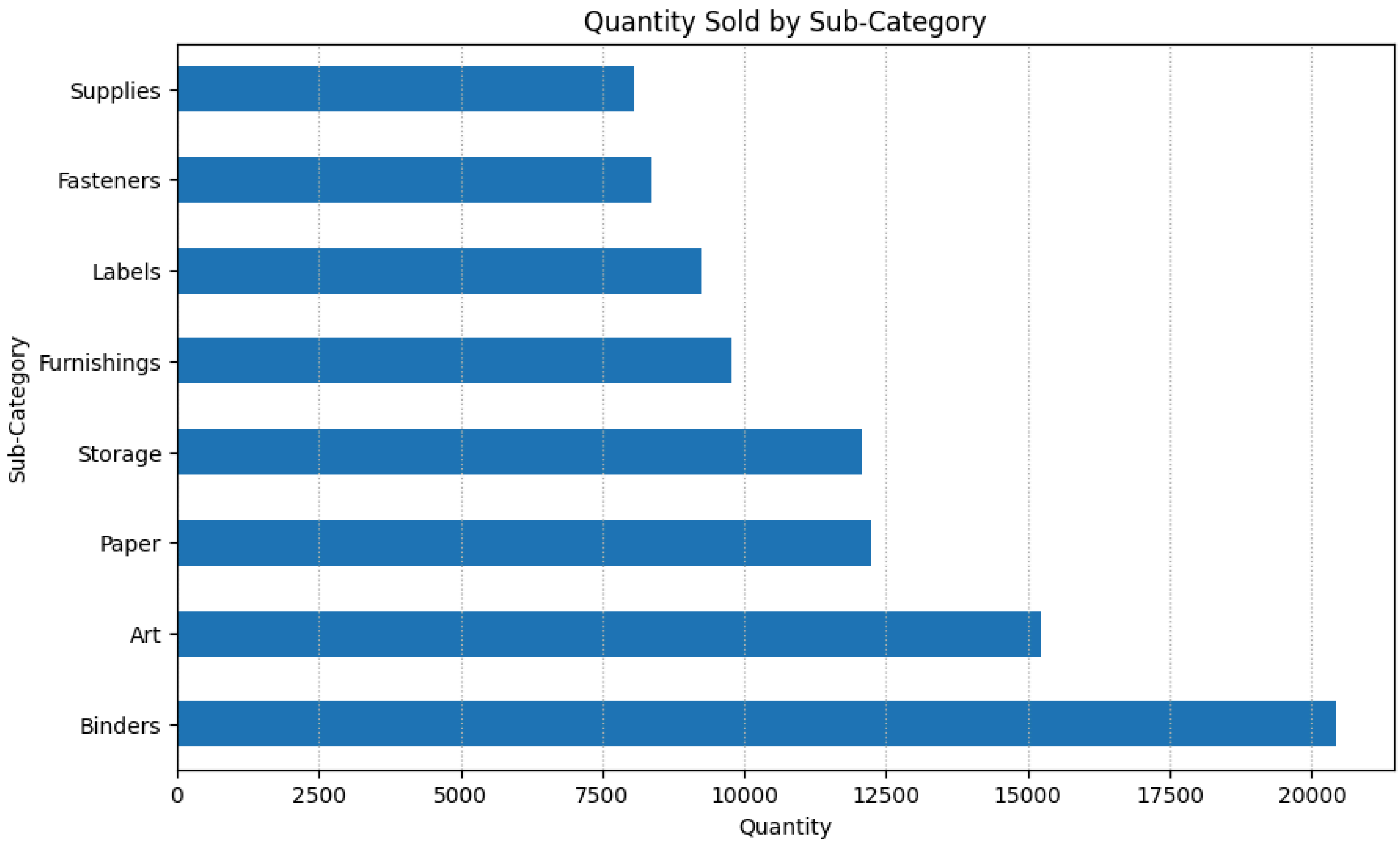


- Storage products contributes most to the overall profit(492509.26).
- Other top sales sub categories are chairs, phones, art, accessories with sales above 300000.
- Labels, tables, fasteners, were the least sold sub category products with sales below 100000.
- Other products were achieved a sales in the range between 150000 to 300000.

In [21]:
```
#3. Which sub-category has the highest total quantity sold?
quan_sub_cat = file.groupby("Sub-Category")['Quantity'].sum().sort_values(ascending=False).head(8)
quan_sub_cat
```

```
Out[21]: Sub-Category
Binders        20431
Art            15225
Paper          12227
Storage        12071
Furnishings     9776
Labels          9261
Fasteners       8352
Supplies        8071
Name: Quantity, dtype: int64
```

```
In [22]: plt.figure(figsize=(10,6))
quan_sub_cat.plot(kind='barh',title='Quantity Sold by Sub-Category',xlabel='Quantity',ylabel='Sub-Category')
plt.grid(axis='x',linestyle=':')
plt.show()
```



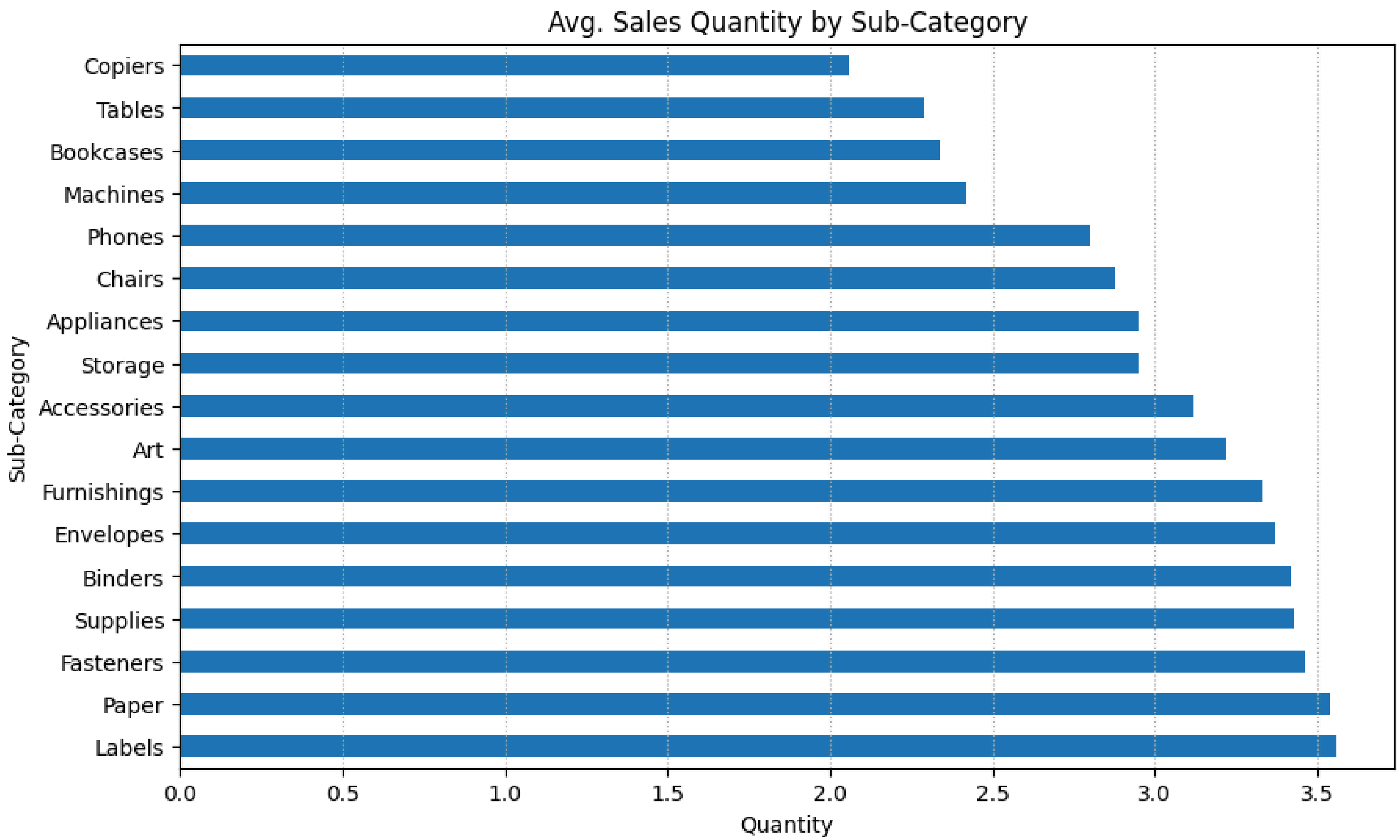
- Binders are thetop sub category products with highest sales quantity of 20431.

- Other top sales sub category were Art, Paper, Storage products with sales quantity above 10000.
- Supplies and Fasteners were standing in last with low sales quantity.

In [23]:
```
#4. What is the average quantity purchased per sub-category?
avg_quan_sub_cat = file.groupby("Sub-Category")['Quantity'].mean().round(2).sort_values(ascending=False)
avg_quan_sub_cat
```

Out[23]:
```
Sub-Category
Labels         3.56
Paper          3.54
Fasteners      3.46
Supplies       3.43
Binders        3.42
Envelopes      3.37
Furnishings    3.33
Art            3.22
Accessories    3.12
Storage        2.95
Appliances     2.95
Chairs         2.88
Phones         2.80
Machines       2.42
Bookcases      2.34
Tables         2.29
Copiers        2.06
Name: Quantity, dtype: float64
```

In [24]:
```
plt.figure(figsize=(10,6))
avg_quan_sub_cat.plot(kind='barh',title='Avg. Sales Quantity by Sub-Category',xlabel='Quantity',ylabel='Sub-Category')
plt.grid(axis='x',linestyle=':')
plt.show()
```



- Here we can clearly see that all the category products have an average purchase quantity above 2.
- Labels and Paper were the top categories with high avg quantity(above 3).
- Copiers and tables were the least categories with low avg sales quantity(2.5)
- The most sold products by sales like storage, phone, chair, art and accessories products were sold with 2.8 to 3.2 of avg. quantity.

In [25]:

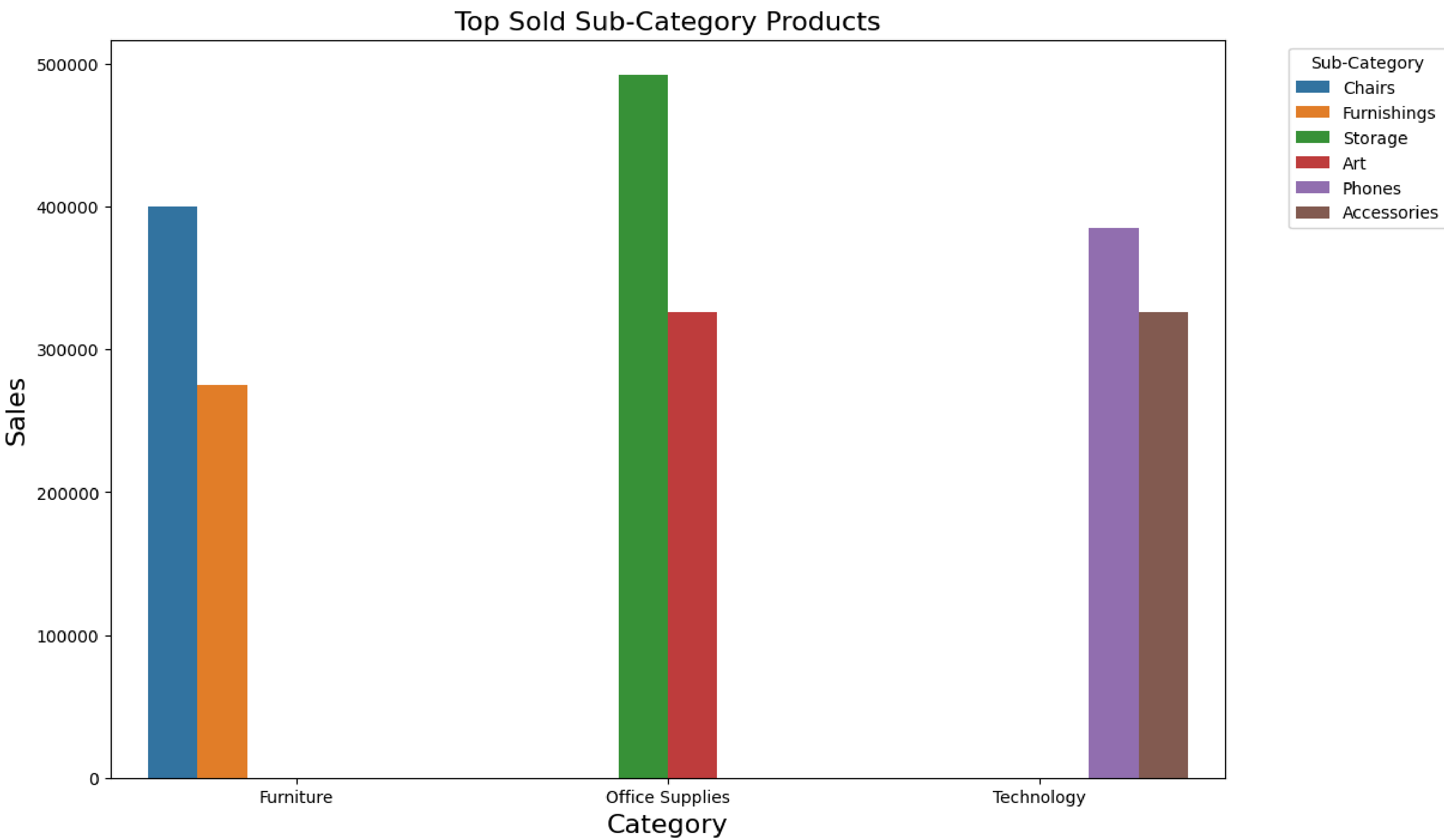
```
#5. What are the top sold sub-category products for each Main Category?

sub_cat = file.groupby(['Category', 'Sub-Category'])['Sales'].sum().reset_index(name='Sum_Sales')

sub_cat_sorted = sub_cat.sort_values(['Category', 'Sum_Sales'], ascending=[True, False])

top_sold = sub_cat_sorted.groupby('Category').nth((0,1))

top_sold
```

Out[25]:

	Category	Sub-Category	Sum_Sales
1	Furniture	Chairs	400110.19
2	Furniture	Furnishings	275237.79
11	Office Supplies	Storage	492509.26
5	Office Supplies	Art	326355.36
16	Technology	Phones	384896.05
13	Technology	Accessories	326100.03

In [26]:

```
plt.figure(figsize=(12, 8))
sns.barplot(x='Category', y='Sum_Sales', hue='Sub-Category', data=top_sold)
plt.title('Top Sold Sub-Category Products',fontsize = 16)
plt.xlabel('Category',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
plt.legend(title='Sub-Category', bbox_to_anchor=(1.05, 1), loc=2)
plt.show()
```

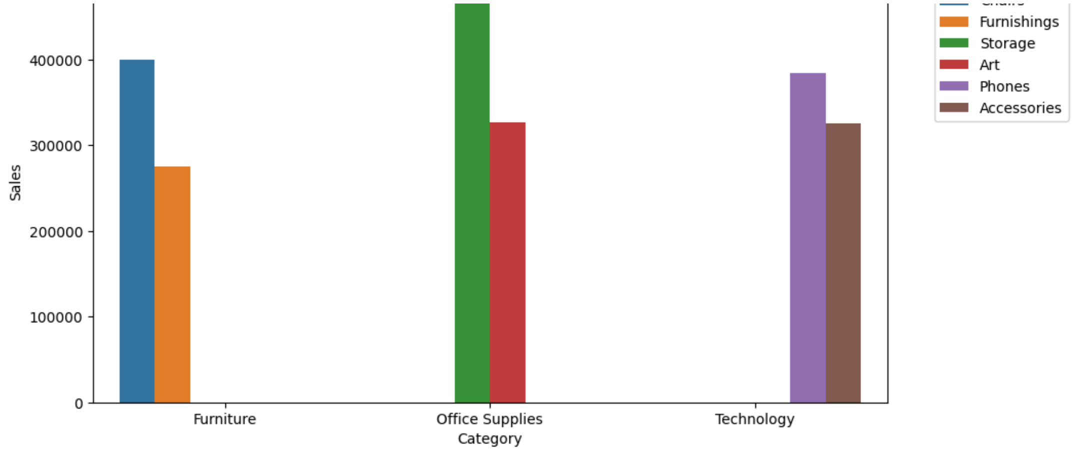


- Here we can see the top 2 sold sub category products on each main category.
- In furniture category, Chairs and Furnishings were the top sales sub category products.
- In office supplies category, Storage and Arts were the top sales sub category products.
- In furniture category, Phones and Accessories were the top sales sub category products.

In [82]:
```
plt.figure(figsize=(22,20))
plt.suptitle("Product Analysis",fontsize = 24)
```

```
plt.tight_layout()



plt.subplot(3,2,1)

plt.bar(profit_cat.index,profit_cat.values)
plt.title("Profits by Categories")
plt.xlabel("Category")
plt.ylabel("Profit")
plt.grid(axis='y',linestyle=':')



plt.subplot(3,2,2)

sub_cat_profit.plot(kind='barh',title='Sales by Sub-Category',xlabel='Sales',ylabel='Sub-Category')
plt.grid(axis='x',linestyle=':')



plt.subplot(3,2,3)

quan_sub_cat.plot(kind='barh',title='Quantity Sold by Sub-Category',xlabel='Quantity',ylabel='Sub-Category')
plt.grid(axis='x',linestyle=':')



plt.subplot(3,2,4)

avg_quan_sub_cat.plot(kind='barh',title='Avg. Sales Quantity by Sub-Category',xlabel='Quantity',ylabel='Sub-Category')
plt.grid(axis='x',linestyle=':')



plt.subplot(3,2,5)

sns.barplot(x='Category', y='Sum_Sales', hue='Sub-Category', data=top_sold)
plt.title('Top Sold Sub-Category Products',fontsize = 16)
plt.xlabel('Category')
plt.ylabel('Sales')
plt.legend(title='Sub-Category', bbox_to_anchor=(1.05, 1), loc=2)






plt.subplots_adjust(hspace=0.4,top=0.93)
plt.show()
```


Product Analysis
Profits by Categories
1e6
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Profit
Furniture
Technology
Office Supplies
Category
Sales by Sub-Category
Labels
Tables
Fasteners
Envelopes
Appliances
Machines
Supplies
Paper
Copiers
Bookcases
Furnishings
Binders
Accessories
Art
Phones
Chairs
Storage
Sub-Category
0
100000
200000
300000
400000
500000
Sales
Quantity Sold by Sub-Category
Supplies
Fasteners
Labels
Furnishings
Storage
Paper
Art
Binders
Sub-Category
0
2500
5000
7500
10000
12500
15000
17500
20000
Quantity
Avg. Sales Quantity by Sub-Category
Copiers
Tables
Bookcases
Machines
Phones
Chairs
Appliances
Storage
Accessories
Art
Furnishings
Envelopes
Binders
Supplies
Fasteners
Paper
Labels
Sub-Category
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Quantity
Top Sold Sub-Category Products
500000
Sub-Category
Chairs



💰 Monetary Analysis

Features used: `Sales`, `Profit`, `Discount`, `Sub-Category`, `Order_Month`

1. Which months stands top and low in total sales?
2. Which category sold most and least in top sales month?
3. What is the total sales amount by each sub-category?
4. Which sub-categories have high discounts but low profit?
5. Which sub-categories have high sales but low quantity sold?

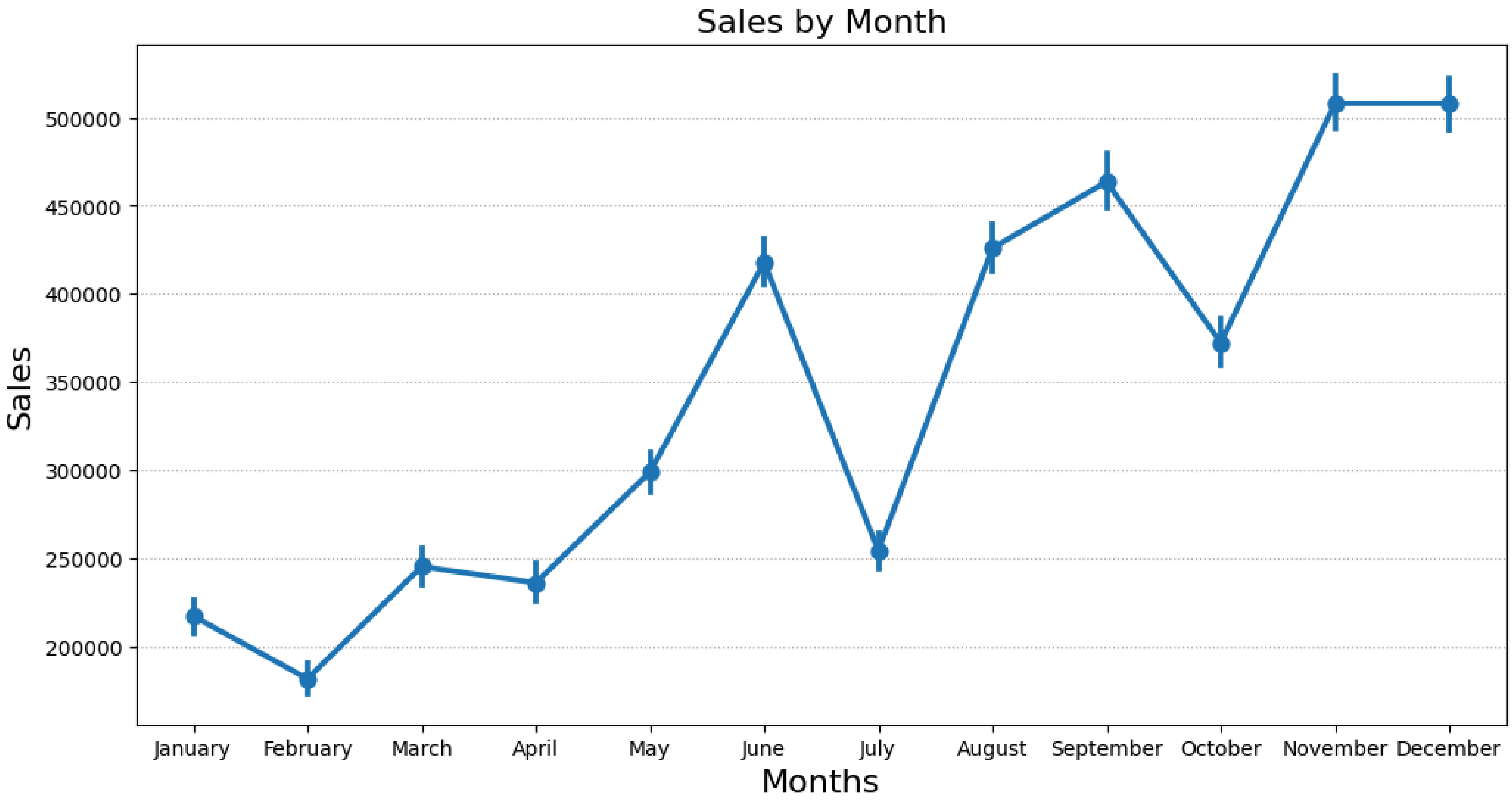
In [27]:

```
#1. Which months show top and low in total sales?
month_sales = file.groupby('Order_Month')['Sales'].sum().sort_values(ascending=False)

print(f"""
Top sales month :
{month_sales.head(1)}

Low sales month :
{month_sales.tail(1)}
""")
```

```
Top sales month :
Order_Month
December    508172.66
Name: Sales, dtype: float64

Low sales month :
Order_Month
February    181454.58
Name: Sales, dtype: float64
```

In [28]:

```
plt.figure(figsize=(12, 6))
sns.pointplot(x='Order_Month', y='Sales',  data=file,estimator='sum')
plt.title('Sales by Month',fontsize = 16)
plt.xlabel('Months',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
plt.grid(axis='y',linestyle=':')
plt.show()
```



- Top sales month : December Sales : 508172.66
- Low sales month : February Sales : 181454.58

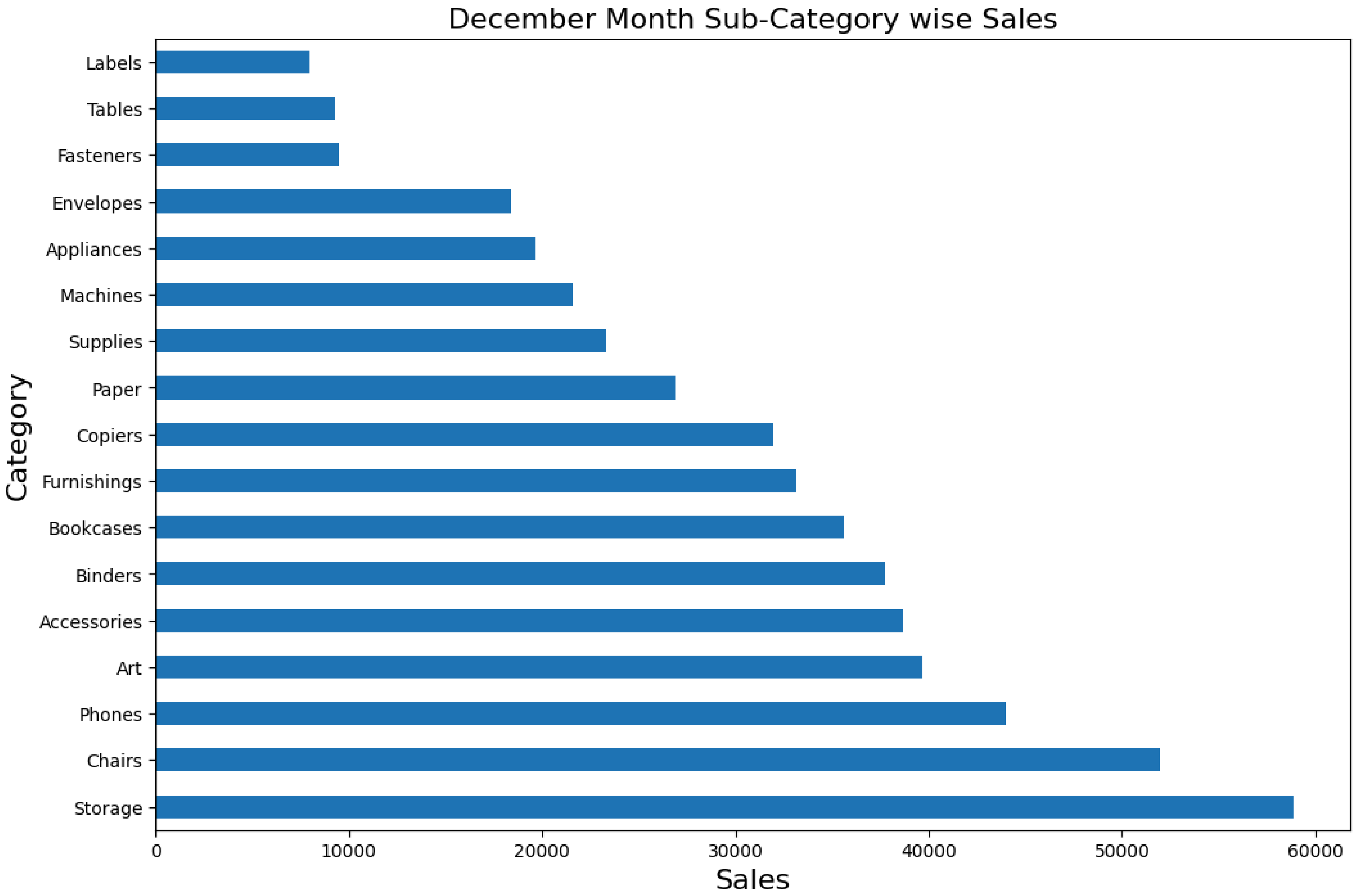
In [29]:

```
#2. Which category sold most and least in top sales month?
top_cat = file[file['Order_Month'] == 'December'].groupby('Sub-Category')['Sales'].sum().sort_values(ascending=False)
print(f"""
High Sales Sub-Category in Top sales month :
{top_cat.head(1)}

Low Sales Sub-Category in Top sales month :
{top_cat.tail(1)}
""")
```

```
High Sales Sub-Category in Top sales month :
Sub-Category
Storage    58873.91
Name: Sales, dtype: float64

Low Sales Sub-Category in Top sales month :
Sub-Category
Labels    7976.38
Name: Sales, dtype: float64
```

In [30]:

```
plt.figure(figsize=(12, 8))
top_cat.plot(kind='barh')
plt.title('December Month Sub-Category wise Sales',fontsize = 16)
plt.ylabel('Category',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)
plt.show()
```

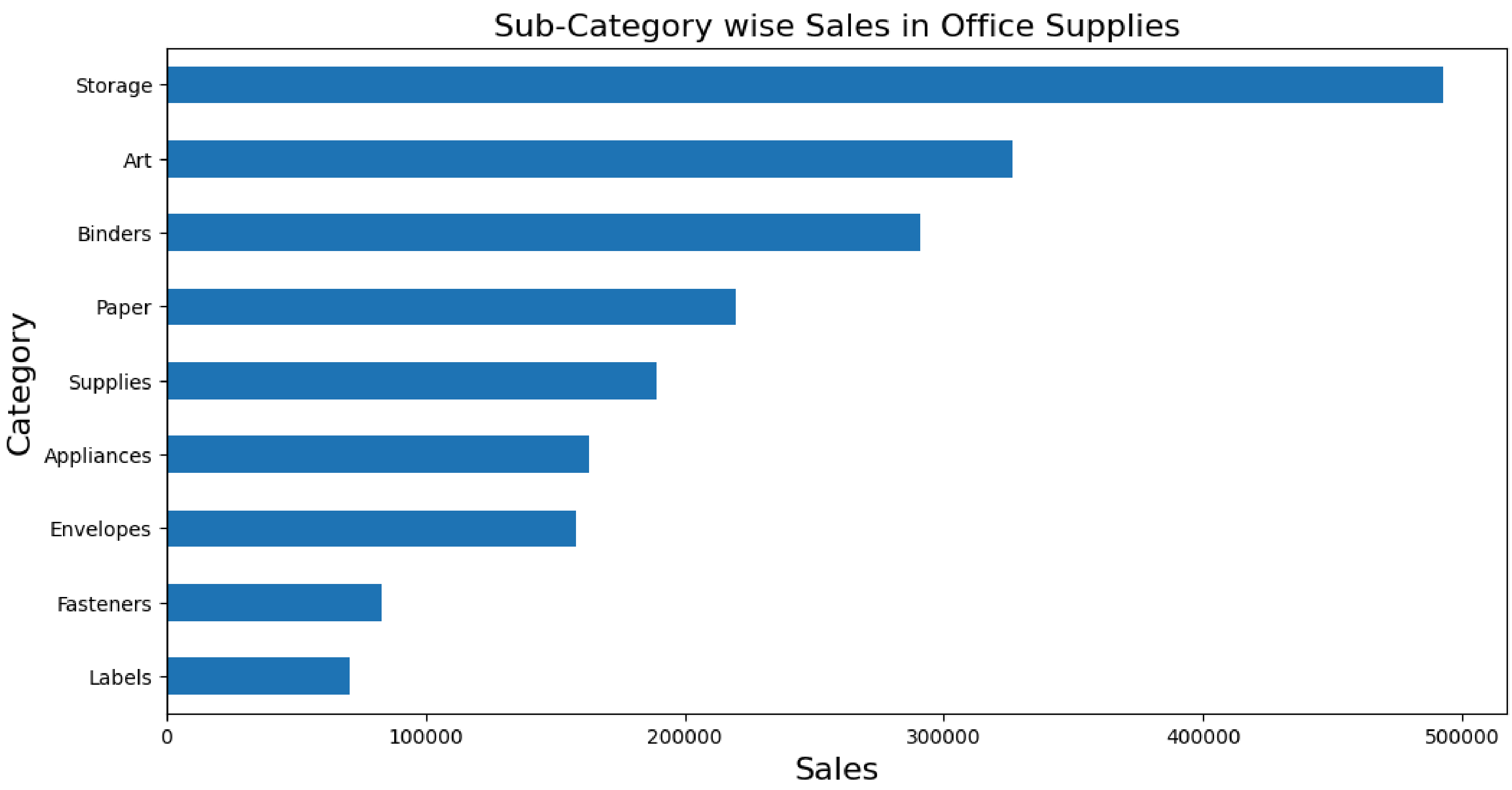


- High Sales Sub-Category in Top sales month :
  - Sub-Category Storage 58873.91
- Low Sales Sub-Category in Top sales month :
  - Sub-Category Labels 7976.38

In [31]:
```
#3. What is the total sales amount by each sub-category in most sold category?
# We already know that 'Office Supplies' is the top category
t_sales_sub_cat = file[file['Category'] == 'Office Supplies'].groupby('Sub-Category')['Sales'].sum().sort_values()
t_sales_sub_cat
```

Out[31]:
```
Sub-Category
Labels          70589.00
Fasteners       82682.67
Envelopes      157901.20
Appliances     162740.87
Supplies       188997.54
Paper          219867.01
Binders        290746.89
Art            326355.36
Storage        492509.26
Name: Sales, dtype: float64
```

In [56]:
```
plt.figure(figsize=(12, 6))
t_sales_sub_cat.plot(kind='barh')
plt.title('Sub-Category wise Sales in Office Supplies',fontsize = 16)
plt.ylabel('Category',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)
plt.show()
```



- Storage products were the high sales products in December Month.
- Art products were the 2nd high sales products in December Month followed by Binders.
- Labels and Fasteners were the low sales made products in December.

In [33]:
```
#4. Which sub-categories have high shipping cost but low sales?

sub_cat_ship_sale = (file.groupby('Sub-Category')
                     .agg({'Shipping Cost':'mean','Sales':'sum'})
                     .sort_values(by='Shipping Cost', ascending = False)
                     )
avg_ship = sub_cat_ship_sale['Shipping Cost'].mean()
avg_sales = sub_cat_ship_sale['Sales'].mean()
sub_cat_Hship_Lsale = sub_cat_ship_sale[(sub_cat_ship_sale['Shipping Cost'] > avg_ship) & (sub_cat_ship_sale['Sales'] < avg_sales)]
print(f"""
Avg. Shipping Cost = {avg_ship}
```

```
Avg. Sales = {avg_sales}
Lets consider more than average is high and less than average is low
""")
sub_cat_Hship_Lsale
```

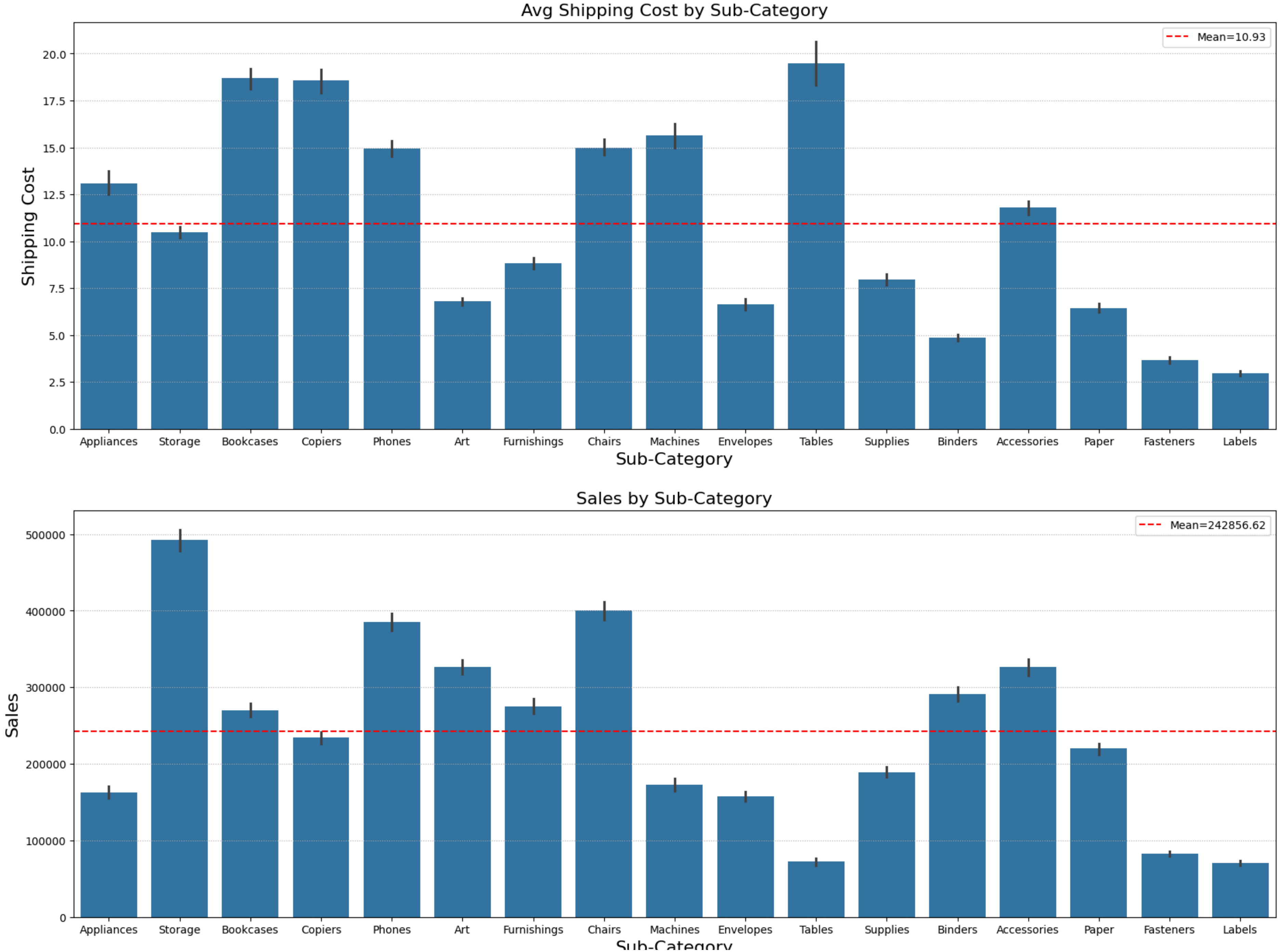
```
Avg. Shipping Cost = 10.929013091099733
Avg. Sales = 242856.62294117647
Lets consider more than average is high and less than average is low
```

Out[33]:

	Shipping Cost	Sales
Sub-Category		
Tables	19.474060	72180.34
Copiers	18.557261	234342.78
Machines	15.642059	173114.51
Appliances	13.096546	162740.87

In [34]:

```
plt.figure(figsize=(20,15))
plt.subplot(2,1,1)
sns.barplot(x='Sub-Category', y='Shipping Cost',  data=file,estimator='mean')
plt.axhline(avg_ship, color='red', linestyle='--',label=f"Mean={np.round((avg_ship),2)}")
plt.title('Avg Shipping Cost by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.ylabel('Shipping Cost',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')

plt.subplot(2,1,2)
sns.barplot(x='Sub-Category', y='Sales',  data=file,estimator='sum')
plt.axhline(avg_sales, color='red', linestyle='--',label=f"Mean={np.round((avg_sales),2)}")
plt.title('Sales by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')

plt.show()
```


Avg Shipping Cost by Sub-Category
Mean=10.93
Shipping Cost
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
Appliances
Storage
Bookcases
Copiers
Phones
Art
Furnishings
Chairs
Machines
Envelopes
Tables
Supplies
Binders
Accessories
Paper
Fasteners
Labels
Sub-Category
Sales by Sub-Category
Mean=242856.62
Sales
0
100000
200000
300000
400000
500000
Appliances
Storage
Bookcases
Copiers
Phones
Art
Furnishings
Chairs
Machines
Envelopes
Tables
Supplies
Binders
Accessories
Paper
Fasteners
Labels
Sub-Category

Sub-Category

- These were the produts having high shipping cost but low sales

Sub-Category	Shipping Cost	Sales
Tables	19.474060	72180.34
Copiers	18.557261	234342.78
Machines	15.642059	173114.51
Appliances	13.096546	162740.87

In [35]:
```
#5. Which sub-categories have low quantity sold but high revenue genrated?
sub_cat_sale_quantity = file.groupby('Sub-Category').agg({'Sales':'sum','Quantity':'mean'}).sort_values(by='Sales')

avg_Sales = sub_cat_sale_quantity['Sales'].mean().round(2)
avg_Quantity = sub_cat_sale_quantity['Quantity'].mean().round(2)

sub_cat_Hsale_Lquantity = (sub_cat_sale_quantity[(sub_cat_sale_quantity['Sales'] > avg_Sales)
    & (sub_cat_sale_quantity['Quantity'] < avg_Quantity)])

print(f"""
Avg. Quantity = {avg_Quantity}
Avg. Sales = {avg_Sales}
Lets consider more than average is high and less than average is low
""")
sub_cat_Hsale_Lquantity
```

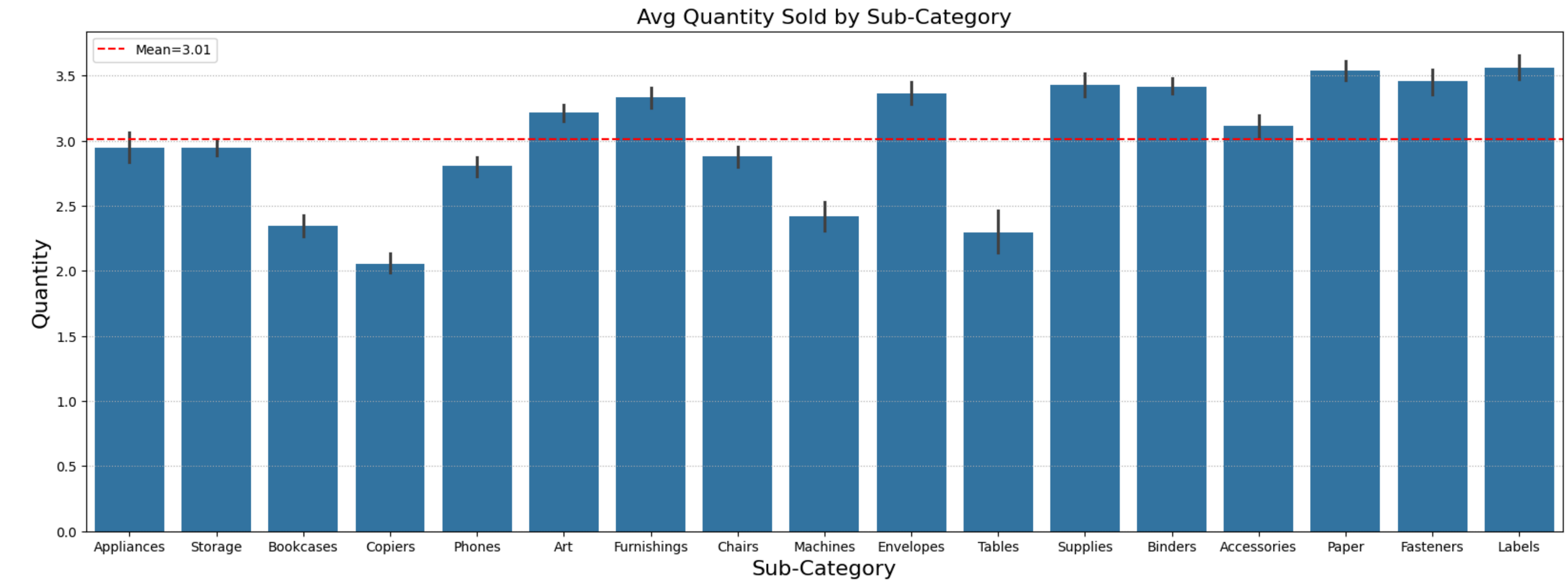
```
Avg. Quantity = 3.01
Avg. Sales = 242856.62
Lets consider more than average is high and less than average is low
```

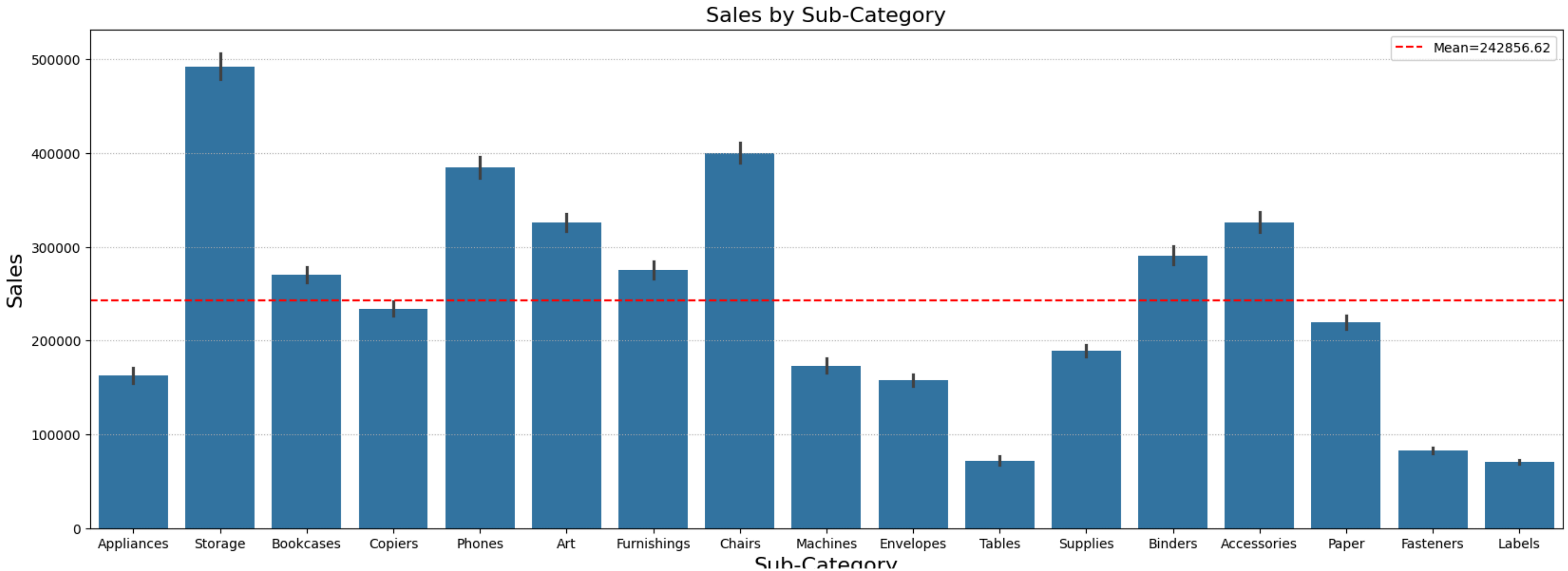
Out[35]:

Sub-Category	Sales	Quantity
Bookcases	270191.10	2.343863
Phones	384896.05	2.803519
Chairs	400110.19	2.880000
Storage	492509.26	2.947741

In [36]:
```
plt.figure(figsize=(20,15))
plt.subplot(2,1,1)
sns.barplot(x='Sub-Category', y='Quantity',  data=file,estimator='mean')
plt.axhline(avg_Quantity, color='red', linestyle='--',label=f"Mean={np.round((avg_Quantity),2)}")
```

```
plt.title('Avg Quantity Sold by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.ylabel('Quantity',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')

plt.subplot(2,1,2)
sns.barplot(x='Sub-Category', y='Sales',  data=file,estimator='sum')
plt.axhline(avg_Sales, color='red', linestyle='--',label=f"Mean={np.round((avg_Sales),2)}")
plt.title('Sales by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')

plt.show()
```


Avg Quantity Sold by Sub-Category
Mean=3.01
Quantity
0.0
0.5
1.0
1.5
2.0
2.5
3.0
3.5
Appliances
Storage
Bookcases
Copiers
Phones
Art
Furnishings
Chairs
Machines
Envelopes
Tables
Supplies
Binders
Accessories
Paper
Fasteners
Labels
Sub-Category


Sales by Sub-Category
Mean=242856.62
Sales
0
100000
200000
300000
400000
500000
Appliances
Storage
Bookcases
Copiers
Phones
Art
Furnishings
Chairs
Machines
Envelopes
Tables
Supplies
Binders
Accessories
Paper
Fasteners
Labels

Sub-Category

- These were the produts having low quantity sold but high revenue genrated

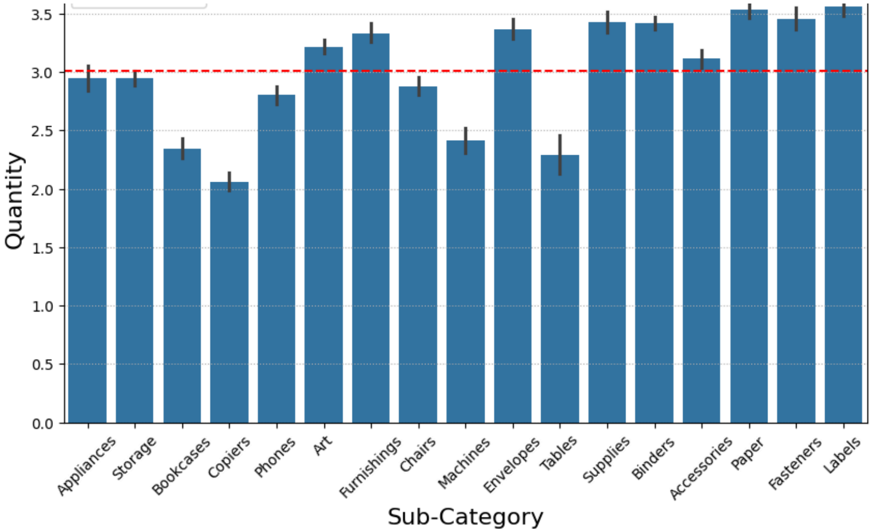
Sub-Category	Sales	Quantity
Bookcases	270191.10	2.34
Phones	384896.05	2.80
Chairs	400110.19	2.88
Storage	492509.26	2.94

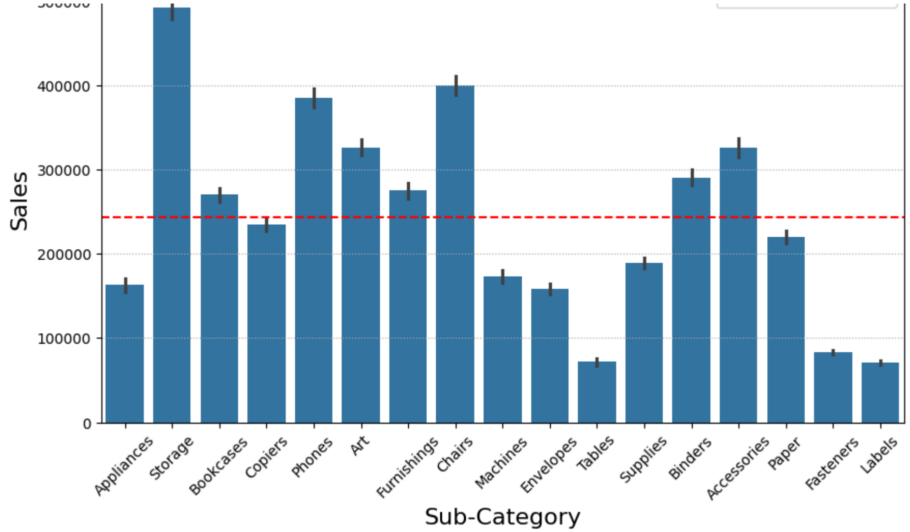
In [78]:

```
plt.figure(figsize=(22,20))
plt.suptitle("Monetery Analysis",fontsize = 24)
plt.tight_layout()



plt.subplot(3,2,1)

sns.pointplot(x='Order_Month', y='Sales',  data=file,estimator='sum')
plt.title('Sales by Month',fontsize = 16)
plt.xlabel('Months',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Sales',fontsize = 16)
plt.grid(axis='y',linestyle=':')



plt.subplot(3,2,2)

t_sales_sub_cat.plot(kind='barh')
plt.title('Sub-Category wise Sales in Office Supplies',fontsize = 16)
plt.ylabel('Category',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)



plt.subplot(3,2,3)

sns.barplot(x='Sub-Category', y='Shipping Cost',  data=file,estimator='mean')
plt.axhline(avg_ship, color='red', linestyle='--',label=f"Mean={np.round((avg_ship),2)}")
plt.title('Avg Shipping Cost by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Shipping Cost',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')
```

```
plt.subplot(3,2,4)

sns.barplot(x='Sub-Category', y='Sales',  data=file,estimator='sum')
plt.axhline(avg_sales, color='red', linestyle='--',label=f"Mean={np.round((avg_sales),2)}")
plt.title('Sales by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Sales',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')



plt.subplot(3,2,5)

sns.barplot(x='Sub-Category', y='Quantity',  data=file,estimator='mean')
plt.axhline(avg_Quantity, color='red', linestyle='--',label=f"Mean={np.round((avg_Quantity),2)}")
plt.title('Avg Quantity Sold by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Quantity',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')



plt.subplot(3,2,6)

sns.barplot(x='Sub-Category', y='Sales',  data=file,estimator='sum')
plt.axhline(avg_Sales, color='red', linestyle='--',label=f"Mean={np.round((avg_Sales),2)}")
plt.title('Sales by Sub-Category',fontsize = 16)
plt.xlabel('Sub-Category',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Sales',fontsize = 16)
plt.legend()
plt.grid(axis='y',linestyle=':')


plt.subplots_adjust(hspace=0.4,top=0.93)
plt.show()
```

Monetery Analysis





🌍 Market Analysis

Features used: `Market`, `Segment`, `Sales`, `Profit`, `Order Priority`

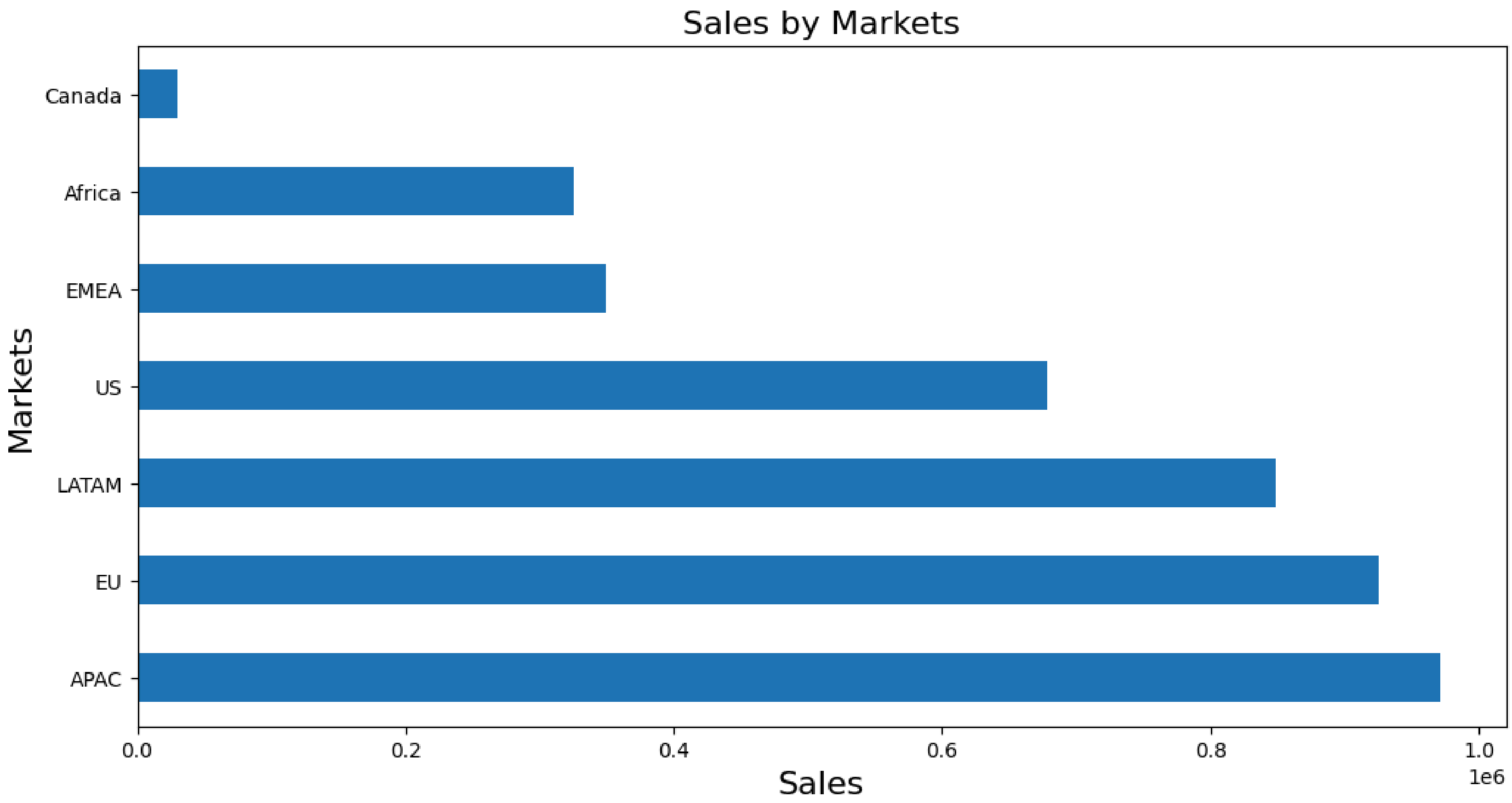
1. Which market has the highest total sales?
2. Which sub-category was standing high in highest total sales market?
3. Which customer segment dominates each market?
4. How does order priority vary across different markets?
5. Which months have the highest number of orders?

In [37]:
```
#1. Which market has the highest total sales?
high_market = file.groupby("Market")['Sales'].sum().sort_values(ascending=False)
high_market
```

Out[37]:
```
Market
APAC      971662.39
EU        924911.76
LATAM     848998.17
US        678280.96
EMEA      349721.80
Africa    325225.17
Canada     29762.34
Name: Sales, dtype: float64
```

In [38]:
```
plt.figure(figsize=(12, 6))
high_market.plot(kind='barh')
plt.title('Sales by Markets',fontsize = 16)
```

```
plt.ylabel('Markets',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)
plt.show()
```



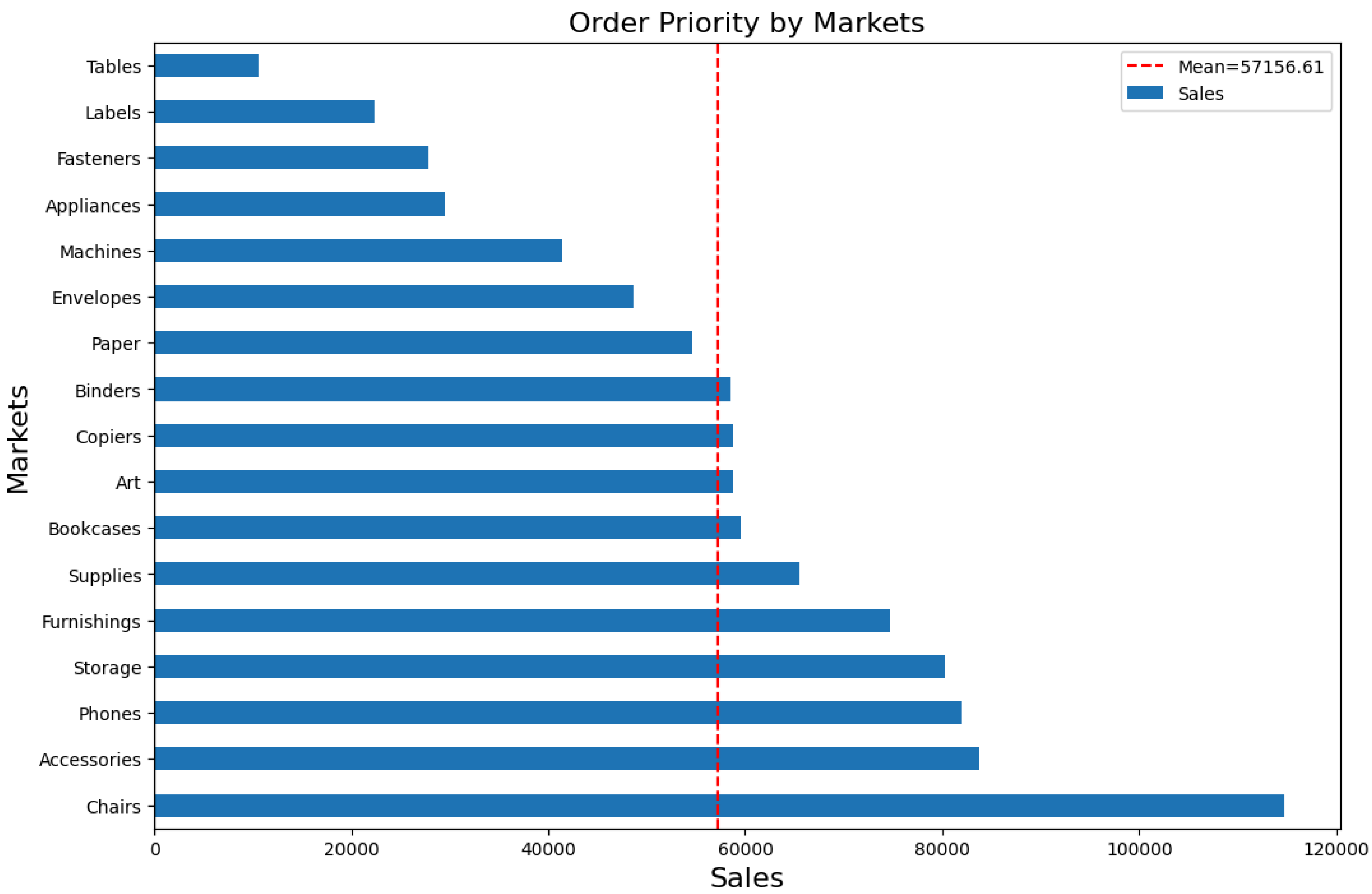
Rank	Market	Sales
1	APAC(Asia PACific)	971662.39
2	EU(Europe Union)	924911.76
3	LATAM(LATin AMerica)	848998.17
4	US(United States)	678280.96
5	EMEA(Europe, Middle East, Africa)	349721.80
6	Africa	325225.17
7	Canada	29762.34

- APAC market is in the top in Sales.
- Canada and Africa markets were last in the sales table with comparitively low sales.
- EU, LATAM, US were stands in the middle position in the ranking table.

In [39]:
```
#2. Which sub-category was standing high in top market?
#We already knew that 'APAC' is the top mraket on Sales
sub_cat_top_mar = file[file['Market'] == 'APAC'].groupby('Sub-Category')['Sales'].sum().sort_values(ascending = False)
sub_cat_top_mar
```

Out[39]:
```
Sub-Category
Chairs         114727.08
Accessories     83772.31
Phones          82017.41
Storage         80238.21
Furnishings     74730.89
Supplies        65505.56
Bookcases       59545.91
Art             58826.36
Copiers         58792.76
Binders         58532.37
Paper           54628.99
Envelopes       48672.24
Machines        41427.20
Appliances      29515.12
Fasteners       27851.17
Labels          22323.21
Tables          10555.60
Name: Sales, dtype: float64
```

In [40]:
```
plt.figure(figsize=(12, 8))
sub_cat_top_mar.plot(kind='barh')
plt.title('Order Priority by Markets',fontsize = 16)
plt.ylabel('Markets',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)
plt.axvline(sub_cat_top_mar.values.mean(),color='red', linestyle='--',label=f"Mean={np.round((sub_cat_top_mar.values.mean()),2)}")
plt.legend()
plt.show()
```



- Chairs were made the high sales in the APAC market than others.
- Labels weer sold least in this list.
- Chairs made 11 times more slaes than the lables.

In [41]:
```
#3. Which customer segment dominates each market?
seg_mar = file.groupby(['Market','Segment'])['Sales'].sum().reset_index()
```

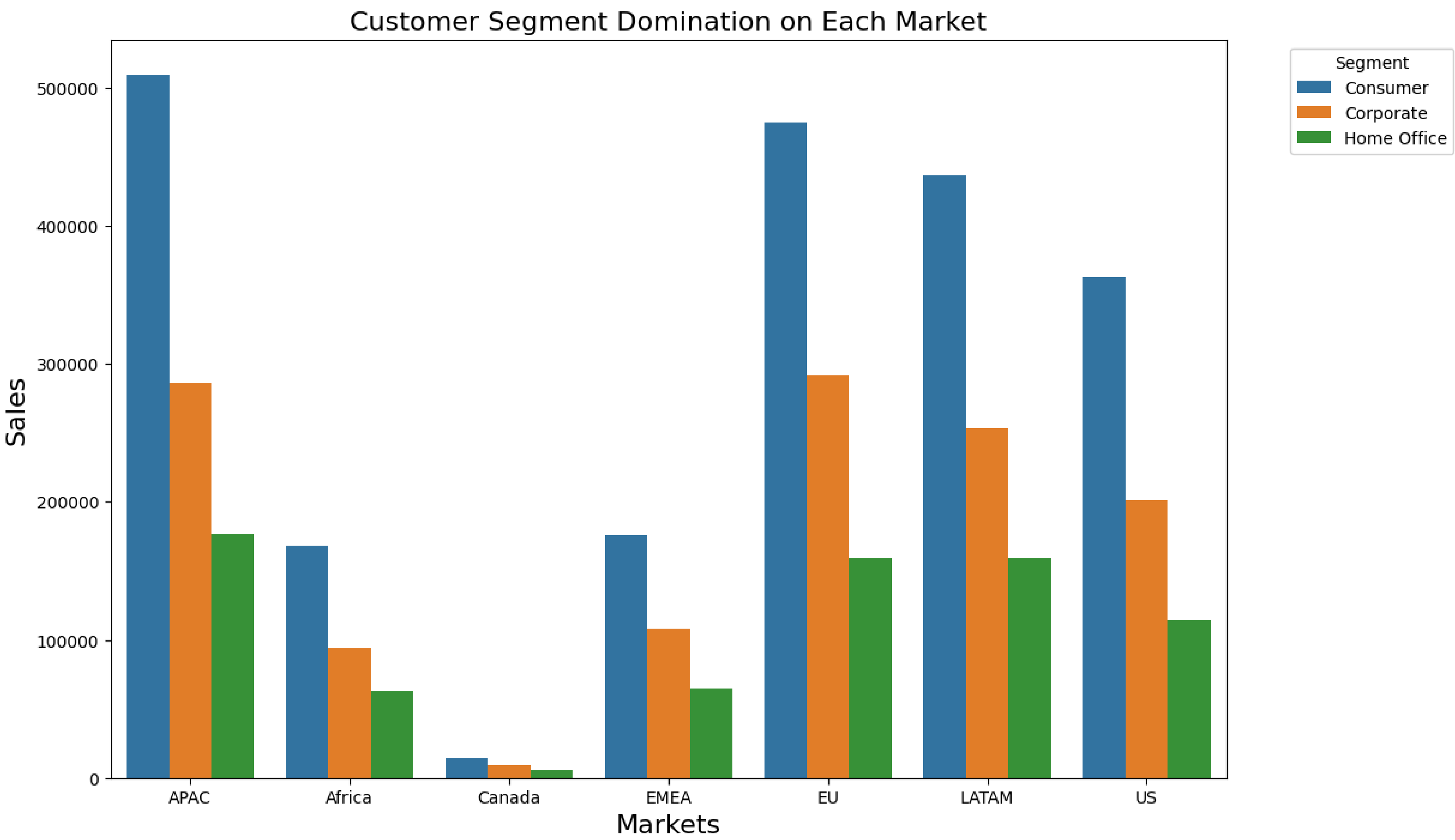
```
sort_seg_mar = seg_mar.sort_values(by=['Market','Sales'],ascending=[True,False])
top_sort_seg_mar = sort_seg_mar.groupby("Market").nth(0)
top_sort_seg_mar
```

Out[41]:

	Market	Segment	Sales
0	APAC	Consumer	509295.40
3	Africa	Consumer	168016.65
6	Canada	Consumer	14636.76
9	EMEA	Consumer	175956.59
12	EU	Consumer	474243.47
15	LATAM	Consumer	436110.36
18	US	Consumer	362421.65

In [42]:

```
plt.figure(figsize=(12, 8))
sns.barplot(x='Market', y='Sales', hue='Segment', data=sort_seg_mar)
plt.title('Customer Segment Domination on Each Market',fontsize = 16)
plt.xlabel('Markets',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
plt.legend(title='Segment', bbox_to_anchor=(1.05, 1), loc=2)
plt.show()
```



- Here we can clearly see that 'Comsumer' segment is the most dominated segment in all the markets.
- Especially in the Asia Pacific(APAC) market, Consumer segment goods made a sales for 509295.
- Corporate segment goods got the second place in domination all the markets followed by Home Office Segment.

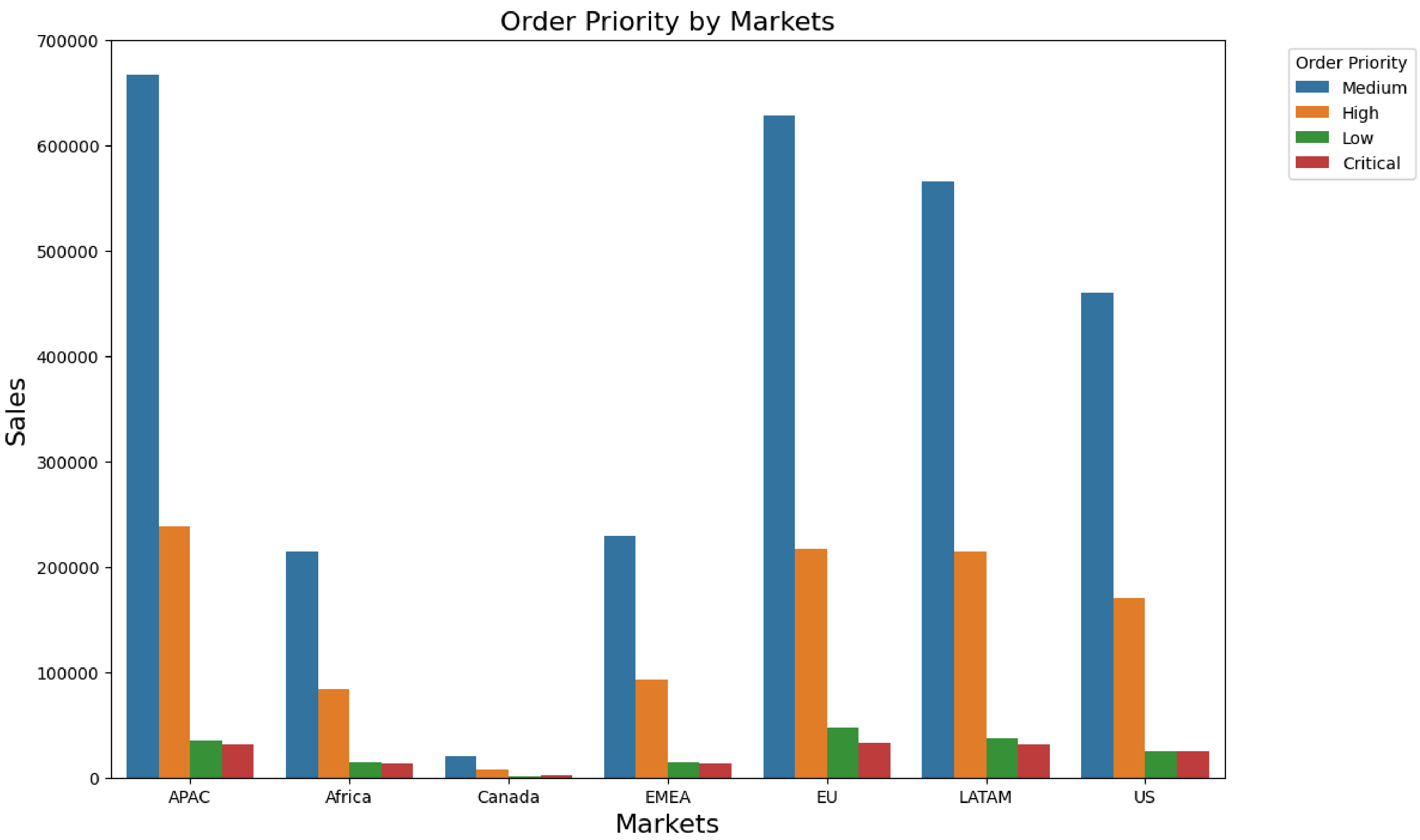
In [43]:
```
#4. How does order priority vary across different markets?
order_priority_market = file.groupby(['Market','Order Priority'])['Sales'].sum().reset_index()
sort_order_priority_market = order_priority_market.sort_values(by=['Market','Sales'],ascending = [True,False])
```

```python
top_sort_order_priority_market = sort_order_priority_market.groupby('Market').nth(0)
top_sort_order_priority_market
```

Out[43]:

	Market	Order Priority	Sales
3	APAC	Medium	666820.26
7	Africa	Medium	214304.28
11	Canada	Medium	20234.07
15	EMEA	Medium	229389.49
19	EU	Medium	628489.00
23	LATAM	Medium	566173.18
27	US	Medium	459566.86

In [44]:
```python
plt.figure(figsize=(12, 8))
sns.barplot(x='Market', y='Sales', hue='Order Priority', data=sort_order_priority_market)
plt.title('Order Priority by Markets',fontsize = 16)
plt.xlabel('Markets',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
plt.legend(title='Order Priority', bbox_to_anchor=(1.05, 1), loc=2)
plt.show()
```



- Here we can clearly see that Order Priority level of 'Medium' is the most prefered level in all the markets.

In [45]:
```
#5. Which months have the highest number of orders?
#all years
month_high_orders = file.groupby("Order_Month")['Order ID'].count()
month_high_orders.sort_values(ascending=False)

#2011
```

```
month_high_orders2011 = file[file["Order_Year"] == 2011].groupby("Order_Month")['Order ID'].count()
month_high_orders2011.sort_values(ascending=False)

#2012
month_high_orders2012 = file[file["Order_Year"] == 2012].groupby("Order_Month")['Order ID'].count()
month_high_orders2012.sort_values(ascending=False)

#2013
month_high_orders2013 = file[file["Order_Year"] == 2013].groupby("Order_Month")['Order ID'].count()
month_high_orders2013.sort_values(ascending=False)

#2014
month_high_orders2014 = file[file["Order_Year"] == 2014].groupby("Order_Month")['Order ID'].count()
month_high_orders2014.sort_values(ascending=False)
```

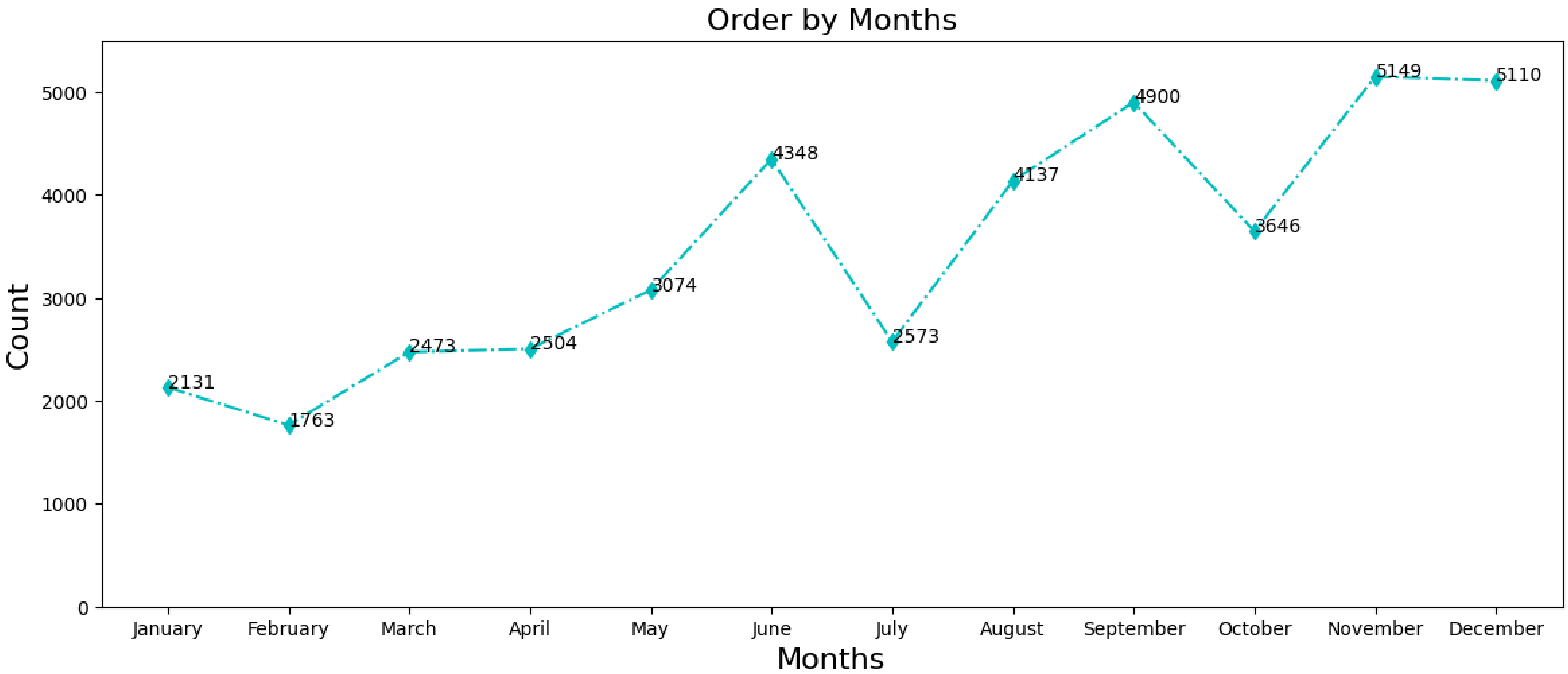
Out[45]:

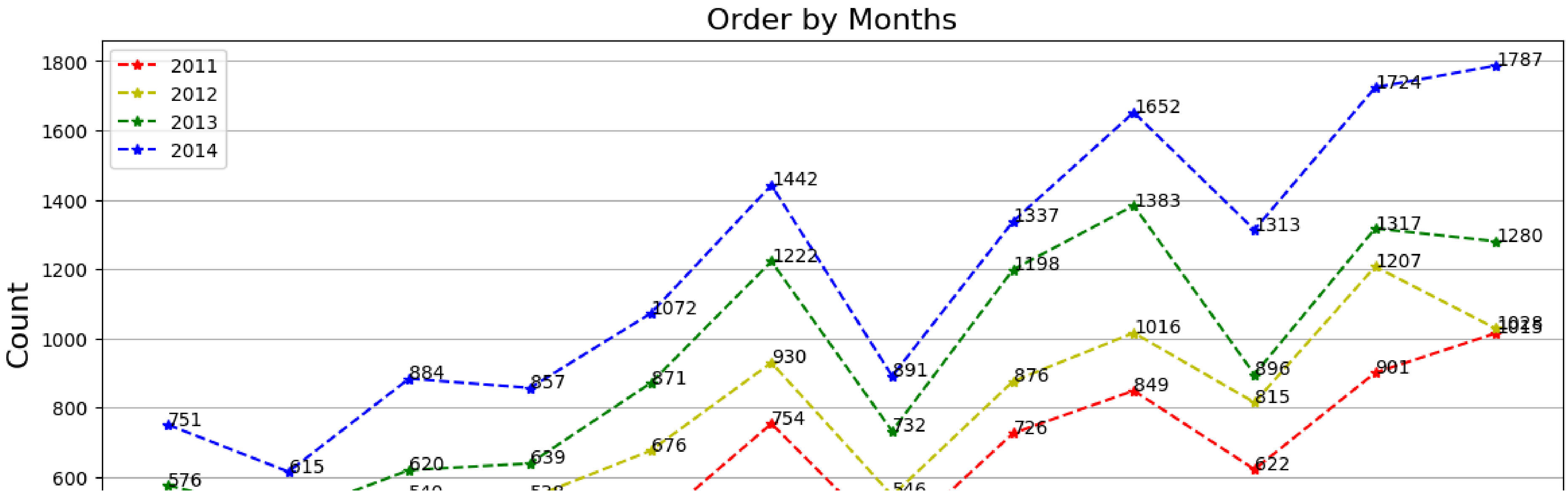
```
Order_Month
December     1787
November     1724
September    1652
June         1442
August       1337
October      1313
May          1072
July          891
March        884
April        857
January      751
February     615
Name: Order ID, dtype: int64
```

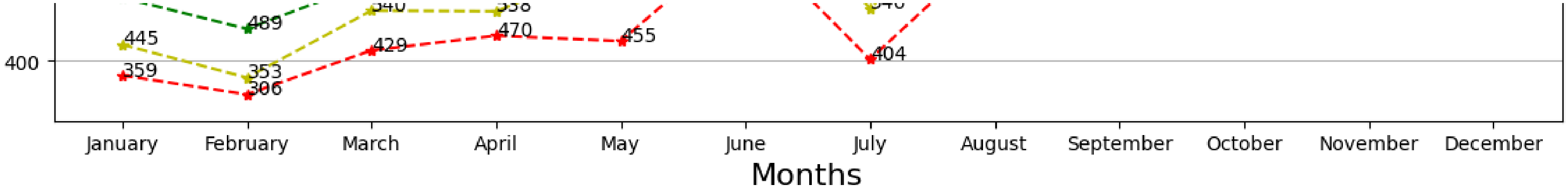
In [46]:

```
plt.figure(figsize=(14,12))
plt.subplot(2,1,1)
plt.plot(month_high_orders.index,month_high_orders.values,'dc-.')
plt.title("Order by Months",fontsize = 16)
plt.xlabel('Months',fontsize = 16)
plt.ylabel('Count',fontsize = 16)
plt.ylim(0,5500)
for x,y in zip(month_high_orders.index,month_high_orders.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))


plt.subplot(2,1,2)
plt.plot(month_high_orders2011.index,month_high_orders2011.values,'*r--',label='2011')
plt.plot(month_high_orders2012.index,month_high_orders2012.values,'*y--',label='2012')
plt.plot(month_high_orders2013.index,month_high_orders2013.values,'*g--',label='2013')
plt.plot(month_high_orders2014.index,month_high_orders2014.values,'*b--',label='2014')
plt.title("Order by Months",fontsize = 16)
plt.xlabel('Months',fontsize = 16)
plt.ylabel('Count',fontsize = 16)
plt.grid(axis='y')
for x,y in zip(month_high_orders2011.index,month_high_orders2011.values):
```

```
    plt.annotate(y,xy=(x,y),xytext=(x,y))
for x,y in zip(month_high_orders2012.index,month_high_orders2012.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
for x,y in zip(month_high_orders2013.index,month_high_orders2013.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
for x,y in zip(month_high_orders2014.index,month_high_orders2014.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
plt.legend()
plt.show()
```


Order by Months
Count
Months
January
February
March
April
May
June
July
August
September
October
November
December
0
1000
2000
3000
4000
5000
2131
1763
2473
2504
3074
4348
2573
4137
4900
3646
5149
5110


Order by Months
Count
2011
2012
2013
2014
600
800
1000
1200
1400
1600
1800
751
615
884
857
1072
1442
891
1337
1652
1313
1724
1787
576
620
639
871
1222
732
1198
1383
896
1317
1280
676
930
876
1016
815
1207
754
726
849
622
901

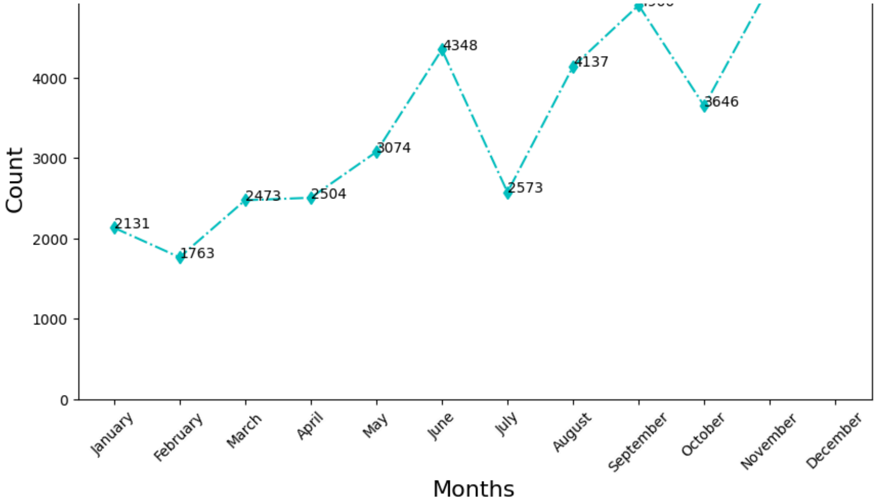


- November month received the highest sales over years.
- In 2011, December with most sales.
- In 2012, November with most sales.
- In 2013, September with most sales.
- In 2014, December with most sales.

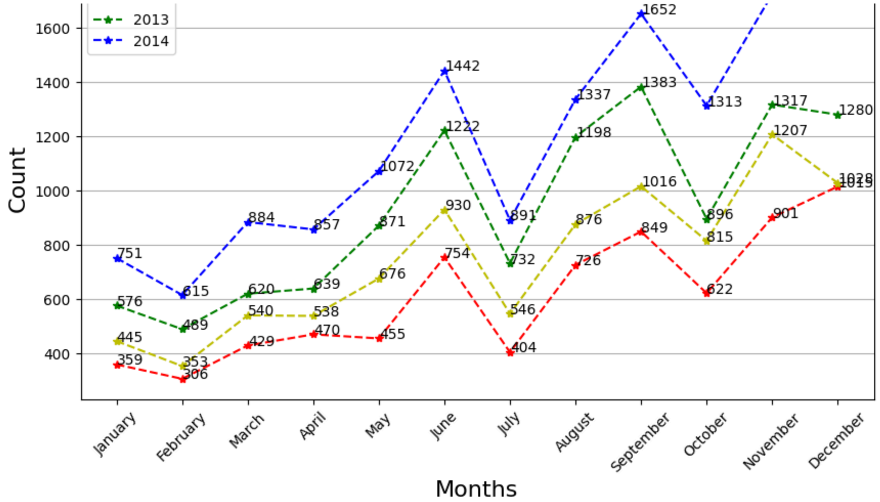
In [80]:
```
plt.figure(figsize=(22,20))
plt.tight_layout(rect=[0, 0.03, 1, 0.95])
plt.suptitle("Market Analysis",fontsize = 24)


plt.subplot(3,2,1)

high_market.plot(kind='barh')
plt.title('Sales by Markets',fontsize = 16)
plt.ylabel('Markets',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)



plt.subplot(3,2,2)

sub_cat_top_mar.plot(kind='barh')
plt.title('Order Priority by Markets',fontsize = 16)
plt.ylabel('Markets',fontsize = 16)
plt.xlabel('Sales',fontsize = 16)
plt.axvline(sub_cat_top_mar.values.mean(),color='red', linestyle='--',label=f"Mean={np.round((sub_cat_top_mar.values.mean()),2)}")
plt.legend()



plt.subplot(3,2,3)

sns.barplot(x='Market', y='Sales', hue='Order Priority', data=sort_order_priority_market)
plt.title('Order Priority by Markets',fontsize = 16)
plt.xlabel('Markets',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)
```

```
plt.subplot(3,2,4)

sns.barplot(x='Market', y='Sales', hue='Segment', data=sort_seg_mar)
plt.title('Customer Segment Domination on Each Market',fontsize = 16)
plt.xlabel('Markets',fontsize = 16)
plt.ylabel('Sales',fontsize = 16)



plt.subplot(3,2,5)

plt.plot(month_high_orders.index,month_high_orders.values,'dc-.')
plt.title("Order by Months",fontsize = 16)
plt.xlabel('Months',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Count',fontsize = 16)
plt.ylim(0,5500)
for x,y in zip(month_high_orders.index,month_high_orders.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))



plt.subplot(3,2,6)

plt.plot(month_high_orders2011.index,month_high_orders2011.values,'*r--',label='2011')
plt.plot(month_high_orders2012.index,month_high_orders2012.values,'*y--',label='2012')
plt.plot(month_high_orders2013.index,month_high_orders2013.values,'*g--',label='2013')
plt.plot(month_high_orders2014.index,month_high_orders2014.values,'*b--',label='2014')
plt.title("Order by Months",fontsize = 16)
plt.xlabel('Months',fontsize = 16)
plt.xticks(rotation=45)
plt.ylabel('Count',fontsize = 16)
plt.grid(axis='y')
for x,y in zip(month_high_orders2011.index,month_high_orders2011.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
for x,y in zip(month_high_orders2012.index,month_high_orders2012.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
for x,y in zip(month_high_orders2013.index,month_high_orders2013.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
for x,y in zip(month_high_orders2014.index,month_high_orders2014.values):
    plt.annotate(y,xy=(x,y),xytext=(x,y))
plt.legend()


plt.subplots_adjust(hspace=0.4,top=0.93)
plt.show()
```


Market Analysis
Sales by Markets
Canada
Africa
EMEA
US
LATAM
EU
APAC
Markets
0.0
0.2
0.4
0.6
0.8
1.0
1e6
Sales
Order Priority by Markets
Mean=57156.61
Sales
Tables
Labels
Fasteners
Appliances
Machines
Envelopes
Paper
Binders
Copiers
Art
Bookcases
Supplies
Furnishings
Storage
Phones
Accessories
Chairs
Markets
0
20000
40000
60000
80000
100000
120000
Sales
Order Priority by Markets
Order Priority
Medium
High
Low
Critical
700000
600000
500000
400000
300000
200000
100000
0
Sales
APAC
Africa
Canada
EMEA
EU
LATAM
US
Markets
Customer Segment Domination on Each Market
Segment
Consumer
Corporate
Home Office
500000
400000
300000
200000
100000
0
Sales
APAC
Africa
Canada
EMEA
EU
LATAM
US
Markets
Order by Months
5000
4900
5149
5110
Order by Months
1800
2011
2012
1724
1787



Count
Months
0
1000
2000
3000
4000
January
February
March
April
May
June
July
August
September
October
November
December
2131
1763
2473
2504
3074
4348
2573
4137
3646



2013
2014
Count
Months
400
600
800
1000
1200
1400
1600
January
February
March
April
May
June
July
August
September
October
November
December
751
615
884
857
1072
1442
891
1337
1652
1313
576
489
620
639
871
1222
732
1198
1383
896
1317
1280
445
353
540
538
676
930
546
876
1016
815
1207
359
306
429
470
455
754
404
726
849
622
901