A

Project Report on

# Store's sales & profit

Submitted in partial fulfilment of completion of the course

## Advanced Diploma in IT, Networking and Cloud


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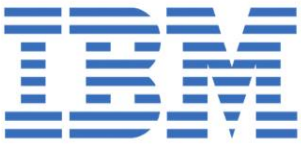



Year 2023

# Abstract

This project aims to comprehensively examine sales and profit trends within a retail superstore. Using a diverse dataset encompassing customer demographics, product categories, and geographical regions, the analysis employs exploratory data analysis, descriptive statistics, and correlation analysis to uncover insights. The study evaluates the impact of factors like promotions, seasonality, and customer segments on sales and profit, using statistical modelling and machine learning. The project seeks to provide actionable insights for Superstore management to enhance efficiency, target specific customer segments, and formulate strategies for maximising profitability. Overall, this analysis contributes to retail analytics by showcasing the importance of data-driven approaches in optimising business outcomes in the competitive retail industry.

# Acknowledgement

We would like to express our heartfelt gratitude to the Almighty for blessing us with his grace and guiding us to successfully complete our endeavour.

Our sincere thanks go to my Edunet trainers, Mrs. Mala Mishra, and Ms. Ankita Shukla. Their invaluable guidance and timely advice played a pivotal role in leading us towards the right path.

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Our heartfelt thanks also go to the other esteemed faculty members who have been instrumental in our journey.

Lastly, We would like to express our deep appreciation to our friends and family for their unwavering support and encouragement throughout our project. Their presence has been a source of our strength and motivation.

## Team Composition and Workload Division

Ishita – Analysis, Visualisation

Sadhana – Analysis, Visualisation

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## Introduction to problem

In the competitive retail landscape, this store faces challenges in optimising its operational and financial performance. Fluctuating sales figures, uncertain profit margins, and evolving customer preferences underscore the need for a strategic and data-driven approach. The absence of a comprehensive understanding of factors influencing sales, profitability, and customer behaviour hampers the company's ability to make informed decisions. Consequently, there is a pressing need for a detailed analysis of historical store sales and profit data to uncover patterns, trends, and insights that will empower the company to forecast sales accurately, enhance profit margins, understand customer behaviour, and improve overall business strategies. By addressing these data-driven challenges, this store aims to position itself for sustained growth and success in the dynamic retail market.

## Proposed Solution

The proposed solution involves leveraging advanced data analytics techniques to address the challenges faced by this store. Key components include developing accurate predictive models for sales forecasting, conducting in-depth profitability analysis to identify influential factors, understanding customer behaviour through segmentation and analysis, uncovering seasonal and temporal trends, evaluating the effectiveness of promotions, optimising inventory management, and providing intuitive visualisations and reports for effective communication. The emphasis is on continuous improvement, monitoring, and feedback incorporation to ensure the sustained relevance and effectiveness of the analytical solutions. By implementing this comprehensive data analysis strategy, this store aims to make informed decisions, optimise operations, and enhance sales and profitability in the dynamic retail market.

# Requirements

**1. Technology stack**

- Python
- Jupiter Notebook

**2. Hardware**

- Laptop/Computer

**3. Software**

- Operating system
- Version Control System
- Text editors and Integrated Development Environments (IDEs)

# Overview

This store, facing challenges in a competitive market, seeks to enhance operational efficiency and profitability through a comprehensive data analysis approach. The solution includes predictive modelling for accurate sales forecasting, profitability analysis to identify key factors, understanding customer behaviour, analysing seasonal trends, evaluating promotion effectiveness, optimising inventory management, and providing intuitive visualisations. The emphasis is on continuous improvement, monitoring, and feedback incorporation to ensure sustained relevance and effectiveness. The goal is to empower the company with data-driven decision-making capabilities, fostering strategic adjustments and sustained growth in the dynamic retail landscape.

## Source code

* Import the required libraries

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
import plotly.express as px
import plotly.graph_objects as go
import plotly.io as pio
import plotly.colors as colors
pio.templates.default = "plotly_white"
```

```
[ ] import warnings
    warnings.filterwarnings('ignore') #warning filters will get ignored
```

* Read the csv file

```
df=pd.read_csv('supp.csv')
```

```
[ ] df
```

* Print the first 5 rows

```
df.head()
```

| | Ship Mode | Segment | City | State | Region | Category | Sub-Category | Sales | Quantity | Discount | Profit |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | Second Class | Consumer | Henderson | Kentucky | South | Furniture | Bookcases | 261.9600 | 2.0 | 0.00 | 41.9136 |
| 1 | Second Class | Consumer | Henderson | Kentucky | South | Furniture | Chairs | 731.9400 | 3.0 | 0.00 | 219.5820 |
| 2 | Second Class | Corporate | Los Angeles | California | West | Office Supplies | Labels | 14.6200 | 2.0 | 0.00 | 6.8714 |
| 3 | Standard Class | Consumer | Fort Lauderdale | Florida | South | Furniture | Tables | 957.5775 | 5.0 | 0.45 | -383.0310 |
| 4 | Standard Class | Consumer | Fort Lauderdale | Florida | South | Office Supplies | Storage | 22.3680 | 2.0 | 0.20 | 2.5164 |

* Print the last 5 rows

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

| | Ship Mode | Segment | City | State | Region | Category | Sub-Category | Sales | Quantity | Discount | Profit |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 9989 | Second Class | Consumer | Miami | Florida | South | Furniture | Furnishings | 25.248 | 3.0 | NaN | NaN |
| 9990 | Standard Class | Consumer | Costa Mesa | California | West | Furniture | Furnishings | NaN | 2.0 | 0.0 | 15.6332 |
| 9991 | Standard Class | Consumer | Costa Mesa | California | West | Technology | NaN | 258.576 | 2.0 | 0.2 | 19.3932 |
| 9992 | Standard Class | Consumer | Costa Mesa | California | West | Office Supplies | Paper | 29.600 | 4.0 | 0.0 | 13.3200 |
| 9993 | Second Class | Consumer | Westminster | California | West | Office Supplies | Appliances | 243.160 | 2.0 | 0.0 | 72.9480 |

* Print the Dataset's description

```
df.describe()
```

| | Sales | Quantity | Discount | Profit |
|---|---|---|---|---|
| count | 9959.000000 | 9963.000000 | 9962.000000 | 9958.000000 |
| mean | 229.908226 | 3.790826 | 0.156363 | 28.705040 |
| std | 623.747520 | 2.225585 | 0.206682 | 234.585082 |
| min | 0.444000 | 1.000000 | 0.000000 | -6599.978000 |
| 25% | 17.230000 | 2.000000 | 0.000000 | 1.728000 |
| 50% | 54.480000 | 3.000000 | 0.200000 | 8.643600 |
| 75% | 209.940000 | 5.000000 | 0.200000 | 29.364000 |
| max | 22638.480000 | 14.000000 | 0.800000 | 8399.976000 |

* Print complete details of the dataset

```
#Displaying complete details of the dataset
print(df.to_string())
```

```
9936  Standard Class     Consumer          Cranston      Rhode Island     East  Office Supplies      Binders   102.9300     3.0  0.00   48.3771
9937    Second Class    Corporate       Los Angeles        California     West        Furniture       Tables    71.0880     2.0  0.20   -1.7772
9938  Standard Class    Corporate      New York City          New York     East        Furniture  Furnishings    60.3500     5.0  0.00   19.9155
9939  Standard Class    Corporate      New York City          New York     East  Office Supplies     Supplies    35.5200     4.0  0.00    9.9456
9940  Standard Class    Corporate      New York City          New York     East  Office Supplies          Art    11.2000     7.0  0.00    4.8160
9941  Standard Class     Consumer      San Francisco        California     West       Technology  Accessories   223.5800    14.0  0.00   87.1962
9942  Standard Class     Consumer            Anaheim        California     West  Office Supplies      Storage   998.8200     9.0  0.00   29.9646
9943  Standard Class     Consumer            Anaheim        California     West  Office Supplies     Supplies    51.1500     5.0  0.00   13.2990
9944    Second Class  Home Office            Seattle        Washington     West  Office Supplies      Storage    40.7400     3.0  0.00    0.4074
9945  Standard Class    Corporate       Philadelphia      Pennsylvania     East  Office Supplies        Paper     3.4240     1.0  0.20    1.0700
9946  Standard Class    Corporate       Philadelphia      Pennsylvania     East       Technology  Accessories   151.2000     3.0  0.20   32.1300
9947    Second Class    Corporate       Indianapolis           Indiana  Central        Furniture       Chairs  1925.8800     6.0  0.00  539.2464
9948    Second Class    Corporate       Indianapolis           Indiana  Central  Office Supplies   Appliances  2405.2000     8.0  0.00  793.7160
9949    Second Class    Corporate       Indianapolis           Indiana  Central       Technology  Accessories    83.9700     3.0  0.00   15.9543
9950    Second Class    Corporate       Indianapolis           Indiana  Central       Technology  Accessories    39.8900     1.0  0.00   14.7593
9951    Second Class    Corporate       Indianapolis           Indiana  Central  Office Supplies      Binders    17.3800     2.0  0.00    8.6900
9952    Second Class    Corporate        Los Angeles        California     West  Office Supplies      Binders    55.2640     2.0  0.20   20.7240
9953    Second Class    Corporate        Los Angeles        California     West  Office Supplies        Paper     6.4800     1.0  0.00    3.1104
9954    Second Class    Corporate        Los Angeles        California     West  Office Supplies      Binders    34.2480     3.0  0.20   11.5587
9955    Second Class    Corporate        Los Angeles        California     West        Furniture       Tables   273.5680     2.0  0.20   10.2588
9956  Standard Class  Home Office       New Rochelle          New York     East  Office Supplies        Paper    46.3500     5.0  0.00   21.7845
9957  Standard Class  Home Office       New Rochelle          New York     East  Office Supplies        Paper   223.9200     4.0  0.00  109.7208
9958  Standard Class  Home Office       New Rochelle          New York     East  Office Supplies     Supplies     7.3000     2.0  0.00    2.1900
9959  Standard Class     Consumer           Chandler           Arizona     West  Office Supplies          Art     9.3440     2.0  0.20    1.8688
9960    Second Class  Home Office           Florence          Kentucky    South       Technology  Accessories    18.0000     1.0  0.00    3.2400
9961     First Class  Home Office            Houston             Texas  Central  Office Supplies        Paper    65.5840     2.0  0.20   23.7742
9962     First Class  Home Office            Houston             Texas  Central        Furniture    Bookcases   383.4656     4.0  0.32  -67.6704
9963        Same Day     Consumer       Philadelphia      Pennsylvania     East  Office Supplies        Paper    10.3680     2.0  0.20    3.6288
9964    Second Class    Corporate            Newark          Delaware     East        Furniture  Furnishings    13.4000     1.0  0.00    6.4320
9965    Second Class    Corporate            Newark          Delaware     East  Office Supplies        Paper     4.9800     1.0  0.00    2.3406
9966    Second Class    Corporate            Newark          Delaware     East  Office Supplies    Envelopes   109.6900     7.0  0.00   51.5543
9967  Standard Class     Consumer         Plainfield        New Jersey     East  Office Supplies      Binders    40.2000     5.0  0.00   18.0900
9968  Standard Class     Consumer         Plainfield        New Jersey     East  Office Supplies      Binders   735.9800     2.0  0.00  331.1910
9969  Standard Class     Consumer         Plainfield        New Jersey     East  Office Supplies   Appliances    22.7500     7.0  0.00    6.5975
```

* Print the column's names

```
[ ] #Displaying the name of columns
    df.columns
```

```
Index(['Ship Mode', 'Segment', 'City', 'State', 'Region', 'Category',
       'Sub-Category', 'Sales', 'Quantity', 'Discount', 'Profit'],
      dtype='object')
```

* Print the no. of rows & columns of the dataset

```
#Displaying the no. of rows & columns
df.shape
```

```
(9994, 11)
```

* Print the datatypes of all the columns

```
[ ] #Displaying the datatypes of all the columns
    df.dtypes
```

```
Ship Mode        object
Segment          object
City             object
State            object
Region           object
Category         object
Sub-Category     object
Sales           float64
Quantity        float64
Discount        float64
Profit          float64
dtype: object
```

* Print basic information of the dataset

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9994 entries, 0 to 9993
Data columns (total 11 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   Ship Mode      9994 non-null   object 
 1   Segment        9989 non-null   object 
 2   City           9975 non-null   object 
 3   State          9964 non-null   object 
 4   Region         9974 non-null   object 
 5   Category       9960 non-null   object 
 6   Sub-Category   9974 non-null   object 
 7   Sales          9959 non-null   float64
 8   Quantity       9963 non-null   float64
 9   Discount       9962 non-null   float64
 10  Profit         9958 non-null   float64
dtypes: float64(4), object(7)
memory usage: 859.0+ KB
```

* Check if there's any null value in the dataset

```
[ ] #checking null values
    df.isna().sum()
```

```
Ship Mode        0
Segment          5
City            19
State           30
Region          20
Category        34
Sub-Category    20
Sales           35
Quantity        31
Discount        32
Profit          36
dtype: int64
```

* Print duplicate values of the dataset

```
[ ] df.duplicated().sum()

    47
```

* Remove the duplicate values

```
[ ] #Removing duplicated rows to avoid faults in further calculation
    df.drop_duplicates(inplace=True)
```

* Print the rows & columns after removing the duplicate values

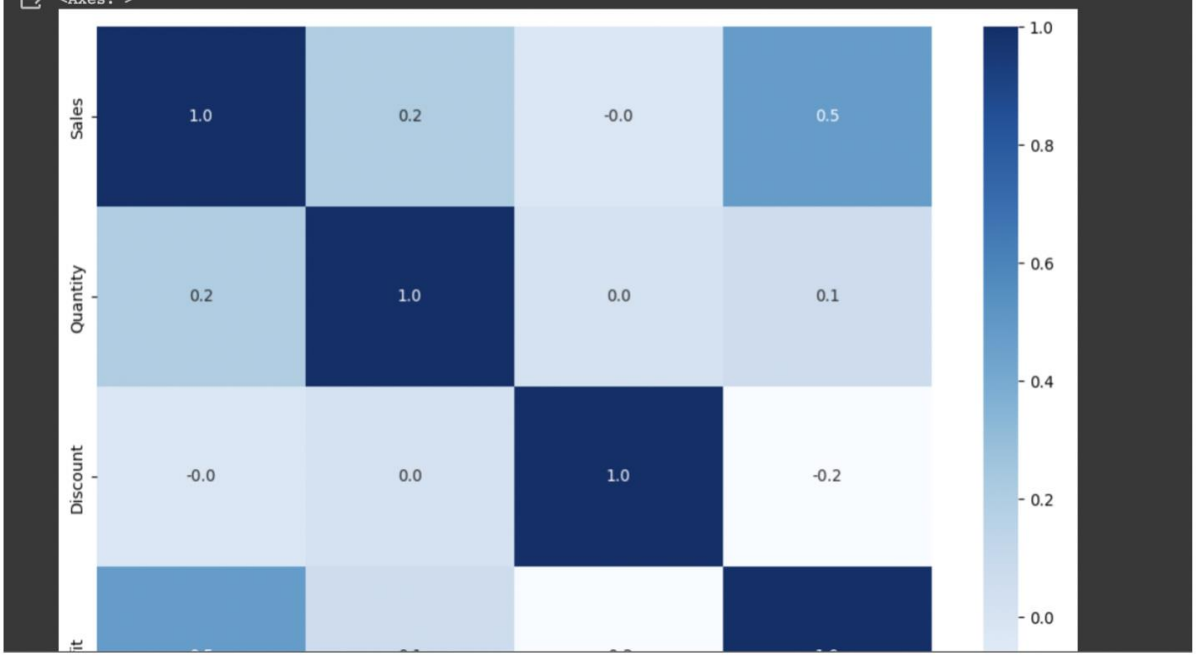
```
#After removing duplicate entries
df.shape

(9947, 11)
```

* Plot a heatmap to check the correlation between the numeric columns

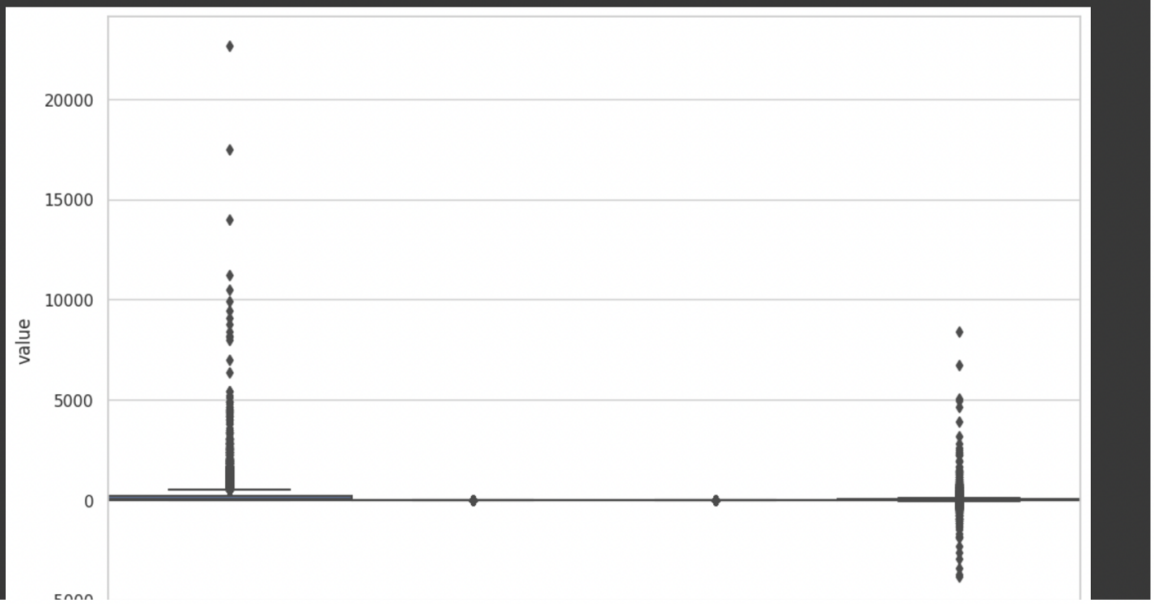
```
#Checking the corelations between numeric columns
df_con=df.select_dtypes(include=[np.number]) #getting the numerical features
f,ax = plt.subplots(figsize=(12, 8))
sns.heatmap(df_con.corr(method='pearson'), annot=True, fmt= '.1f',ax=ax, cmap="Blues") #plotting a heatmap
```

```
<Axes: >
```




* Plot a BoxPlot to see the outliers clearly

```
plt.figure(figsize=[12,8])
sns.set(style="whitegrid")
sns.boxplot(x="variable", y="value", data=pd.melt(df_con), width=1)
plt.show()
```



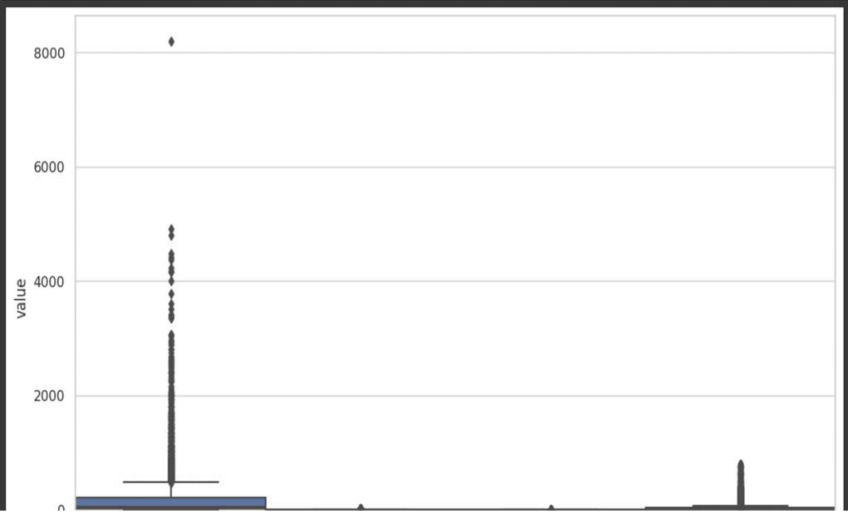
* Remove the outliers of the ‘Profit’ column

```
#Removal of Outliers (Profit)
def remove_outlier(dataset,k=3.33):
    for col in dataset.columns:
            if (dataset[col].dtype=="int64" or dataset[col].dtype=="float64"):
                mean = dataset[col].mean()
                global ds
                std = dataset[col].std()
                outlier = [i for i in dataset[col] if (i > mean - k * std)]
                outlier = [i for i in outlier if (i < mean + k * std)]
                ds = dataset.loc[dataset[col].isin(outlier)]
```

```
[ ]  remove_outlier(df,k=3.33)
```

* Check if the outliers of ‘Profit’ are removed or not

```
ds_con=ds.select_dtypes(include=[np.number])
plt.figure(figsize=[12,8])
sns.set(style="whitegrid")
sns.boxplot(x="variable", y="value", data=pd.melt(ds_con), width=1)
plt.show()
```



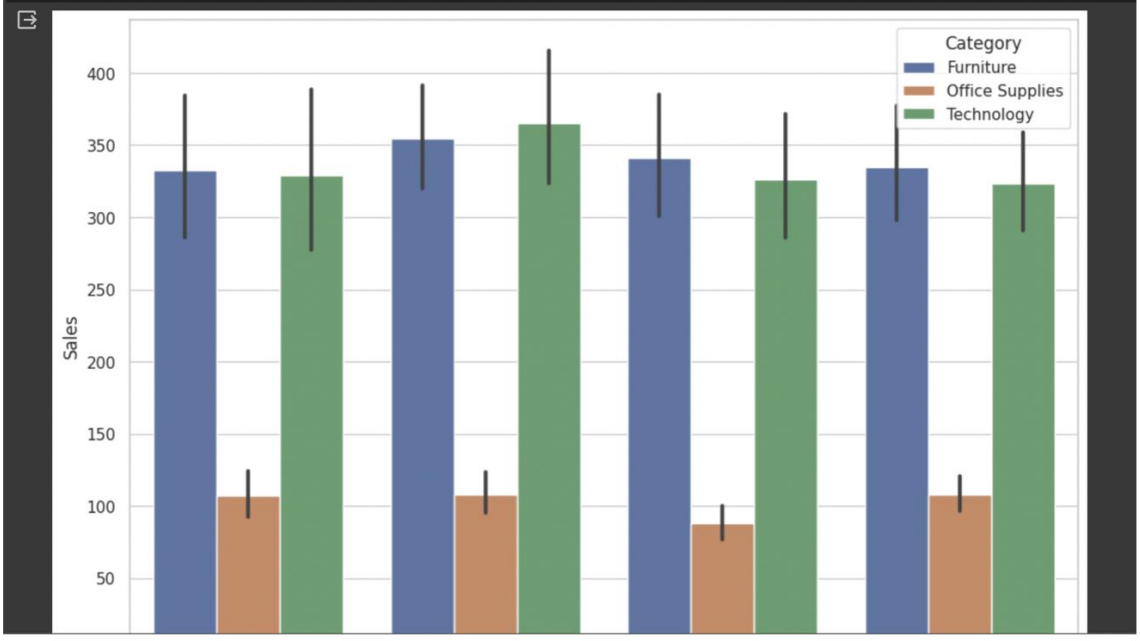
* Print the no. of unique entries in the categorical columns

```
#numbers of unique entries in the Categorical columns
for col in ds.columns:
    if ds[col].dtype=='object':
        print("Number of unique entries in",col + " are",ds[col].nunique())
        print("================================================")
```

```
Number of unique entries in Ship Mode are 4
================================================
Number of unique entries in Segment are 3
================================================
Number of unique entries in City are 530
================================================
Number of unique entries in State are 49
================================================
Number of unique entries in Region are 4
================================================
Number of unique entries in Category are 3
================================================
Number of unique entries in Sub-Category are 17
================================================
```

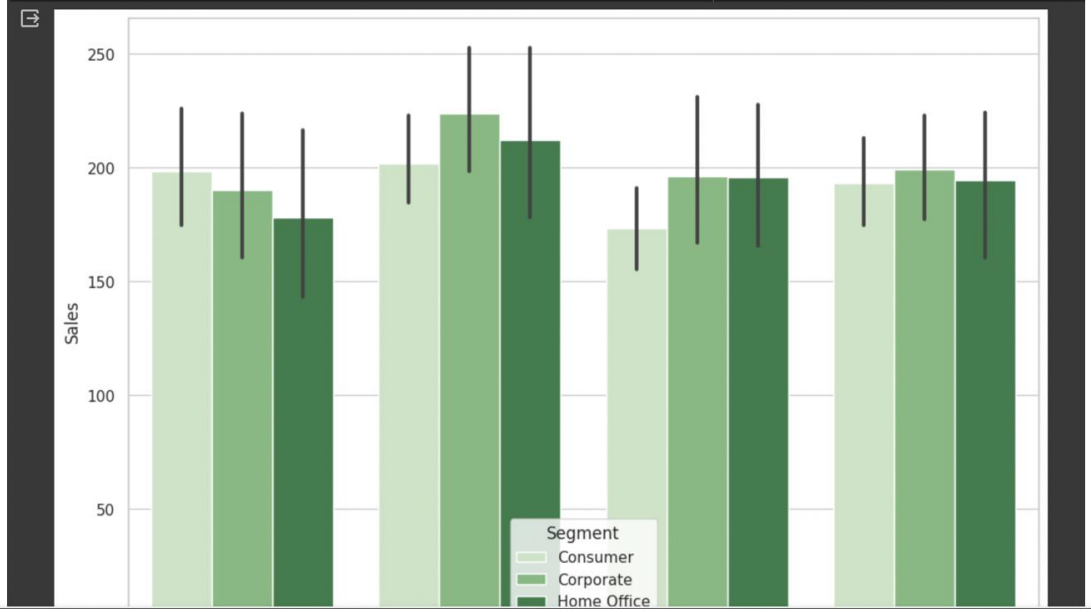
* Print Category-wise sales in each region

```
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Region", y="Sales", hue="Category", data=ds)
```



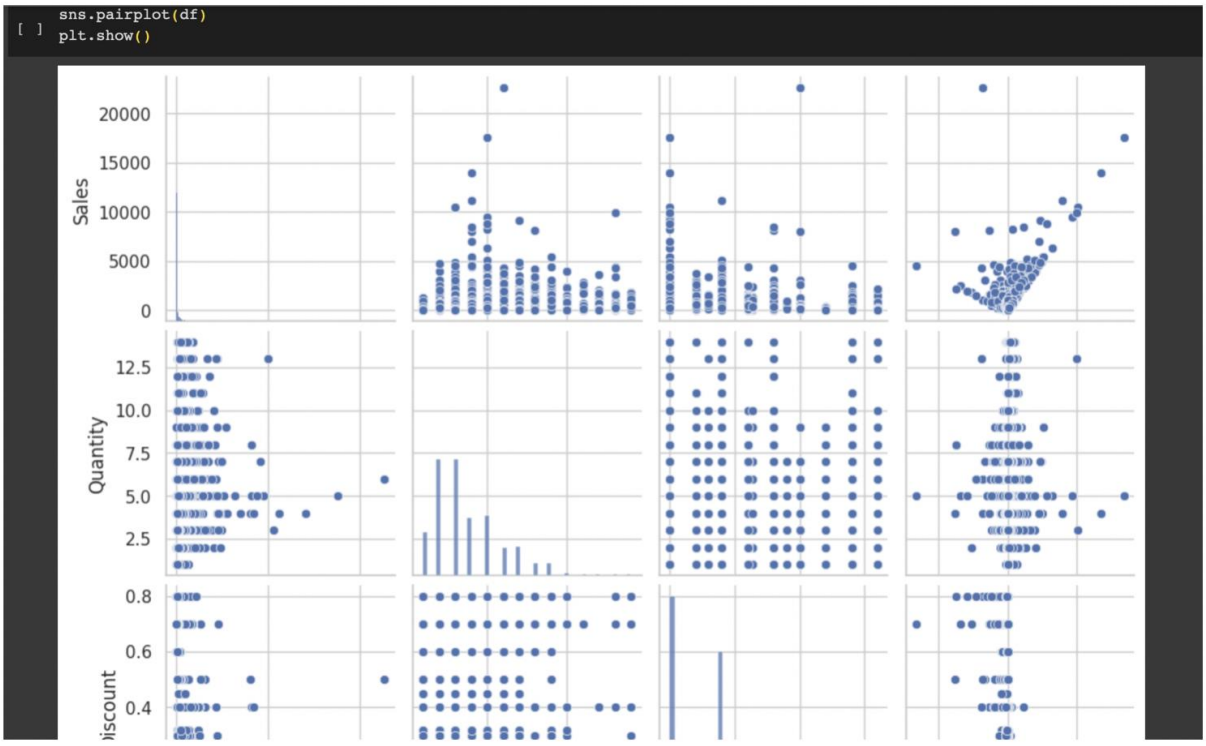
* Print Segment wise sales in each region

```
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Region", y="Sales", hue="Segment", data=ds, palette="Greens")
```




* Plot a pairplot for all the numerical columns

```
[ ]  sns.pairplot(df)
     plt.show()
```



* Grouping City & Sales to understand which city had how much sales

```
#some insights based on Cities
grouped= ds.groupby("City")
#Aggregated Sales per city
agg_sales=grouped['Sales'].agg(np.sum).sort_values(ascending=False).reset_index()
#Cities with highest total sales
agg_sales.head()
```

| | City | Sales |
|---|---|---|
| 0 | New York City | 193174.057 |
| 1 | Los Angeles | 162836.213 |
| 2 | San Francisco | 107922.747 |
| 3 | Seattle | 95640.724 |
| 4 | Philadelphia | 91635.577 |

* Print profit per city

```
#Aggregated Profit per city
agg_profit=grouped['Profit'].agg(np.sum).sort_values(ascending=False).reset_index()
#Cities with Highest total Profit
agg_profit.head()
```

| | City | Profit |
|---|---|---|
| 0 | New York City | 39931.8712 |
| 1 | Los Angeles | 26344.2100 |
| 2 | Seattle | 18905.1617 |
| 3 | San Francisco | 16375.4373 |
| 4 | Detroit | 7953.2432 |

* Print Discount per city

```
#Aggregates Discount per city
agg_dist=grouped['Discount'].agg(np.sum).sort_values(ascending=False).reset_index()

#Cities with highest aggregated Discount
agg_dist.head()
```

| | City | Discount |
|---|---|---|
| 0 | Philadelphia | 171.90 |
| 1 | Houston | 137.54 |
| 2 | Chicago | 115.30 |
| 3 | Dallas | 55.30 |
| 4 | Los Angeles | 53.50 |

* Print cities with highest average sales

```
#Average Sales per city
avg_sales=grouped['Sales'].agg(np.mean).sort_values(ascending=False).reset_index()
#Cities with highest Average sales
avg_sales.head()
```

| | City | Sales |
|---|---|---|
| 0 | Cheyenne | 1603.136000 |
| 1 | Bellingham | 1263.413333 |
| 2 | Independence | 1208.685000 |
| 3 | Burbank | 1082.386000 |
| 4 | Buffalo | 906.349600 |

* Print cities with lowest average sales

```
#Cities with lowest Average sales
avg_sales.tail()
```

| | City | Sales |
|---|---|---|
| 525 | San Luis Obispo | 3.620 |
| 526 | Ormond Beach | 2.808 |
| 527 | Jupiter | 2.064 |
| 528 | Elyria | 1.824 |
| 529 | Abilene | 1.392 |

* Print average profit per city

```
#Average Profit per city
avg_profit=grouped['Profit'].agg(np.mean).sort_values(ascending=False).reset_index()
#Cities with highest Average profit
avg_profit.head()
```

| | City | Profit |
|---|---|---|
| 0 | Independence | 487.831500 |
| 1 | Appleton | 277.383150 |
| 2 | Burbank | 254.844600 |
| 3 | Lehi | 225.831300 |
| 4 | Beverly | 218.306467 |

* Print cities with lowest average profit

```
#Cities with lowest Average profit
avg_profit.tail()
```

| | City | Profit |
|---|---|---|
| 525 | Rockford | -104.500709 |
| 526 | Normal | -110.023200 |
| 527 | Yuma | -116.497725 |
| 528 | Oswego | -178.709200 |
| 529 | Champaign | -182.352000 |

* Print cities with highest average discount

```
#Average Discount per city
avg_dist=grouped['Discount'].agg(np.mean).sort_values(ascending=False).reset_index()
#Cities with highest Average discount
avg_dist.head()
```

| | City | Discount |
|---|---|---|
| 0 | Deer Park | 0.8 |
| 1 | Romeoville | 0.8 |
| 2 | Missouri City | 0.8 |
| 3 | Abilene | 0.8 |
| 4 | Littleton | 0.7 |

* Print cities with lowest average discount

```
#Cities with lowest Average Discount
avg_dist.tail()
```

| | City | Discount |
|---|---|---|
| 525 | Cedar Rapids | 0.0 |
| 526 | Paterson | 0.0 |
| 527 | Belleville | 0.0 |
| 528 | Perth Amboy | 0.0 |
| 529 | Aberdeen | 0.0 |

* Print cities with high average discounts

```
#Cities having High Average Discounts
high_dist=avg_dist[avg_dist['Discount'] >=0.7]
high_dist
```

| | City | Discount |
|---|---|---|
| 0 | Deer Park | 0.8 |
| 1 | Romeoville | 0.8 |
| 2 | Missouri City | 0.8 |
| 3 | Abilene | 0.8 |
| 4 | Littleton | 0.7 |
| 5 | Elyria | 0.7 |
| 6 | Ormond Beach | 0.7 |

* Print cities with low/no average discounts

```
#Cities having low/no Average Discounts
low_dist=avg_dist[avg_dist['Discount']==0]
low_dist
```

| | City | Discount |
|---|---|---|
| 345 | Waynesboro | 0.0 |
| 346 | Wichita | 0.0 |
| 347 | Fargo | 0.0 |
| 348 | Elkhart | 0.0 |
| 349 | Cottage Grove | 0.0 |
| ... | ... | ... |
| 525 | Cedar Rapids | 0.0 |
| 526 | Paterson | 0.0 |
| 527 | Belleville | 0.0 |
| 528 | Perth Amboy | 0.0 |
| 529 | Aberdeen | 0.0 |

185 rows × 2 columns

* Print cities with high average sales

```
#Cities having High Average Sales
high_sales=avg_sales[avg_sales['Sales']>500]
high_sales
```

| | City | Sales |
|---|---|---|
| 0 | Cheyenne | 1603.136000 |
| 1 | Bellingham | 1263.413333 |
| 2 | Independence | 1208.685000 |
| 3 | Burbank | 1082.386000 |
| 4 | Buffalo | 906.349600 |
| 5 | Beverly | 861.063333 |
| 6 | Sparks | 853.986667 |
| 7 | Appleton | 835.655000 |
| 8 | Torrance | 783.067000 |
| 9 | Noblesville | 772.795000 |
| 10 | Lehi | 758.363000 |
| 11 | Kissimmee | 751.984000 |
| 12 | Saint Peters | 697.160000 |
| 13 | San Gabriel | 687.003333 |
| 14 | Norman | 675.665000 |
| 15 | Richardson | 644.232000 |
| 16 | Harrisonburg | 626.958571 |
| 17 | Twin Falls | 574.403000 |

* Print cities with low average sales

```
#Cities having low Average Sales
low_sales=avg_sales[avg_sales['Sales']<50]
low_sales
```

| | City | Sales |
|---|---|---|
| 435 | Urbandale | 49.706667 |
| 436 | Woonsocket | 48.887500 |
| 437 | Frankfort | 48.816000 |
| 438 | Thousand Oaks | 47.760800 |
| 439 | The Colony | 47.386667 |
| ... | ... | ... |
| 525 | San Luis Obispo | 3.620000 |
| 526 | Ormond Beach | 2.808000 |
| 527 | Jupiter | 2.064000 |
| 528 | Elyria | 1.824000 |
| 529 | Abilene | 1.392000 |

95 rows × 2 columns

* Print cities with high average profit

```
#Cities having High Average Profit
high_profit=avg_profit[avg_profit['Profit']>100]
high_profit
```

| | City | Profit |
|---|---|---|
| 0 | Independence | 487.831500 |
| 1 | Appleton | 277.383150 |
| 2 | Burbank | 254.844600 |
| 3 | Lehi | 225.831300 |
| 4 | Beverly | 218.306467 |
| 5 | Bellingham | 203.530267 |
| 6 | Morristown | 165.842750 |
| 7 | Dubuque | 159.224800 |
| 8 | Saint Cloud | 156.538000 |
| 9 | Missoula | 152.495000 |
| 10 | Saint Peters | 146.403600 |
| 11 | Torrance | 136.287750 |
| 12 | Norman | 134.764350 |
| 13 | Twin Falls | 133.082450 |
| 14 | Harrisonburg | 127.074843 |
| 15 | Edmond | 121.551950 |
| 16 | Indianapolis | 119.202339 |
| 17 | Greenwood | 117.933050 |

* Print cities with low average profit

```
#Cities having low Average profit
low_profit=avg_profit[avg_profit['Profit']<0]
low_profit
```

| | City | Profit |
|---|---|---|
| 421 | Austin | -0.522918 |
| 422 | Hickory | -0.547800 |
| 423 | Altoona | -0.591750 |
| 424 | Bolingbrook | -0.776833 |
| 425 | Elyria | -1.398400 |
| ... | ... | ... |
| 525 | Rockford | -104.500709 |
| 526 | Normal | -110.023200 |
| 527 | Yuma | -116.497725 |
| 528 | Oswego | -178.709200 |
| 529 | Champaign | -182.352000 |

109 rows × 2 columns

* Print cities with high-average discounts but low-average sales

```
#Cities with High-Average-Discounts but Low-Average-Sales
merged= pd.merge(high_dist,low_sales, on=['City'],how='inner')
merged
```

| | City | Discount | Sales |
|---|---|---|---|
| 0 | Deer Park | 0.8 | 6.924 |
| 1 | Romeoville | 0.8 | 8.952 |
| 2 | Missouri City | 0.8 | 6.370 |
| 3 | Abilene | 0.8 | 1.392 |
| 4 | Elyria | 0.7 | 1.824 |
| 5 | Ormond Beach | 0.7 | 2.808 |

* Print cities with high average sales & high average profit

```
#Cities with high Average Sales as well as Average Profit
merged2= pd.merge(high_sales,high_profit, on=['City'], how='inner')
merged2
```

| | City | Sales | Profit |
|---|---|---|---|
| 0 | Cheyenne | 1603.136000 | 100.196000 |
| 1 | Bellingham | 1263.413333 | 203.530267 |
| 2 | Independence | 1208.685000 | 487.831500 |
| 3 | Burbank | 1082.386000 | 254.844600 |
| 4 | Beverly | 861.063333 | 218.306467 |
| 5 | Appleton | 835.655000 | 277.383150 |
| 6 | Torrance | 783.067000 | 136.287750 |
| 7 | Lehi | 758.363000 | 225.831300 |
| 8 | Saint Peters | 697.160000 | 146.403600 |
| 9 | Norman | 675.665000 | 134.764350 |
| 10 | Harrisonburg | 626.958571 | 127.074843 |
| 11 | Twin Falls | 574.403000 | 133.082450 |
| 12 | Dubuque | 562.433333 | 159.224800 |
| 13 | Morristown | 539.853333 | 165.842750 |
| 14 | Madison | 534.679000 | 112.365520 |

* Print cities with low average discount but high average sales

```
[ ] #Cities where Average Discount is less but Average Sales is High
merged3= pd.merge(low_dist,high_sales, on='City', how='inner')
merged3
```

| | City | Discount | Sales |
|---|---|---|---|
| 0 | Saint Peters | 0.0 | 697.160000 |
| 1 | Dubuque | 0.0 | 562.433333 |
| 2 | Appleton | 0.0 | 835.655000 |
| 3 | Morristown | 0.0 | 539.853333 |
| 4 | Madison | 0.0 | 534.679000 |
| 5 | Harrisonburg | 0.0 | 626.958571 |
| 6 | Independence | 0.0 | 1208.685000 |
| 7 | Noblesville | 0.0 | 772.795000 |
| 8 | Norman | 0.0 | 675.665000 |
| 9 | Beverly | 0.0 | 861.063333 |

* Print cities with high average sales and low average profit

```
[ ] #Cities with high Average sales but low Average profit
    merged4= pd.merge(high_sales,low_profit, on='City', how='inner')
    merged4
```

| | City | Sales | Profit |
|---|---|---|---|
| 0 | Richardson | 644.232 | -12.24465 |

* Print cities with high average discount and low average profit

```
#Cities with high Average discount but low Average profit
merged5= pd.merge(high_dist,low_profit, on='City', how='inner')
merged5
```

| | City | Discount | Profit |
|---|---|---|---|
| 0 | Deer Park | 0.8 | -10.3860 |
| 1 | Romeoville | 0.8 | -14.7708 |
| 2 | Missouri City | 0.8 | -9.5550 |
| 3 | Abilene | 0.8 | -3.7584 |
| 4 | Littleton | 0.7 | -98.8018 |
| 5 | Elyria | 0.7 | -1.3984 |
| 6 | Ormond Beach | 0.7 | -1.9656 |

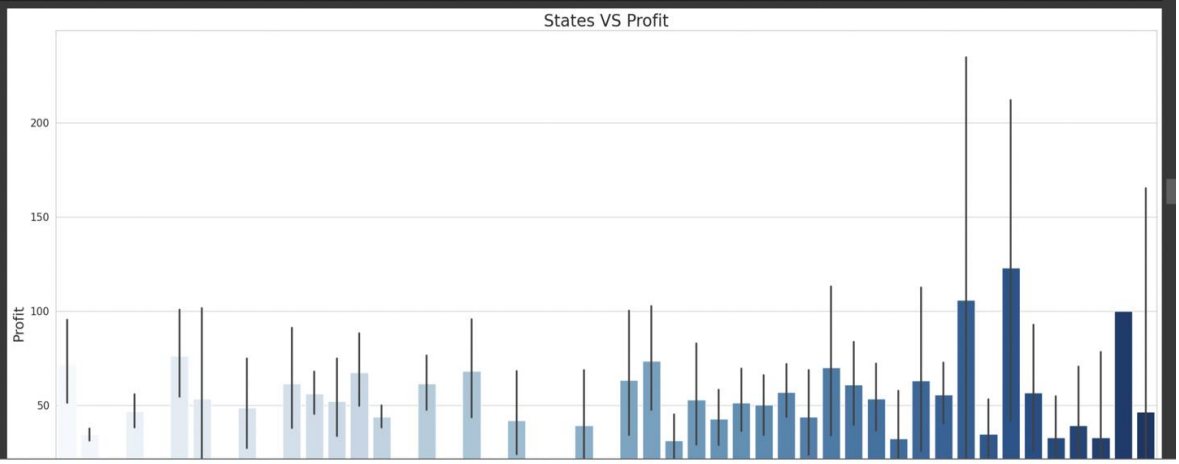
* Print cities with low average discount and high average profit

```
#Cities with low Average discount but High Average profit
merged6= pd.merge(low_dist, high_profit, on='City', how='inner')
merged6
```

| | City | Discount | Profit |
|---|---|---|---|
| 0 | Saint Cloud | 0.0 | 156.538000 |
| 1 | Saint Peters | 0.0 | 146.403600 |
| 2 | Dubuque | 0.0 | 159.224800 |
| 3 | Washington | 0.0 | 105.958930 |
| 4 | Vacaville | 0.0 | 110.052800 |
| 5 | Edmond | 0.0 | 121.551950 |
| 6 | Appleton | 0.0 | 277.383150 |
| 7 | Kenosha | 0.0 | 114.230311 |
| 8 | Morristown | 0.0 | 165.842750 |
| 9 | Muskogee | 0.0 | 110.649150 |
| 10 | Madison | 0.0 | 112.365520 |
| 11 | Broken Arrow | 0.0 | 115.104520 |
| 12 | Harrisonburg | 0.0 | 127.074843 |
| 13 | Greenwood | 0.0 | 117.933050 |
| 14 | Independence | 0.0 | 487.831500 |
| 15 | Norman | 0.0 | 134.764350 |
| 16 | Indianapolis | 0.0 | 119.202339 |
| 17 | Beverly | 0.0 | 218.306467 |

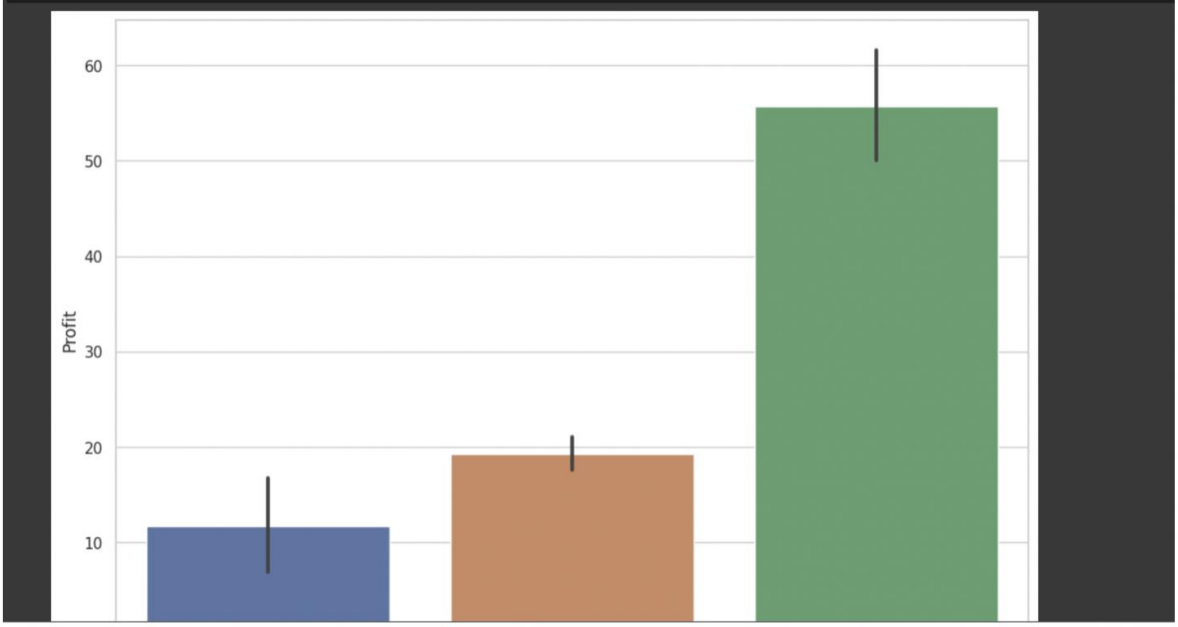
* Plot profit of each state

```
plt.figure(figsize=[24,15])
ax = sns.barplot(x="State", y="Profit", data=ds, palette="Blues")
plt.xticks(rotation=90, fontsize=16)
plt.yticks(fontsize=15)
plt.title("States VS Profit",fontsize=24)
plt.xlabel("States",fontsize=20)
plt.ylabel("Profit",fontsize=20)
plt.tight_layout()
```



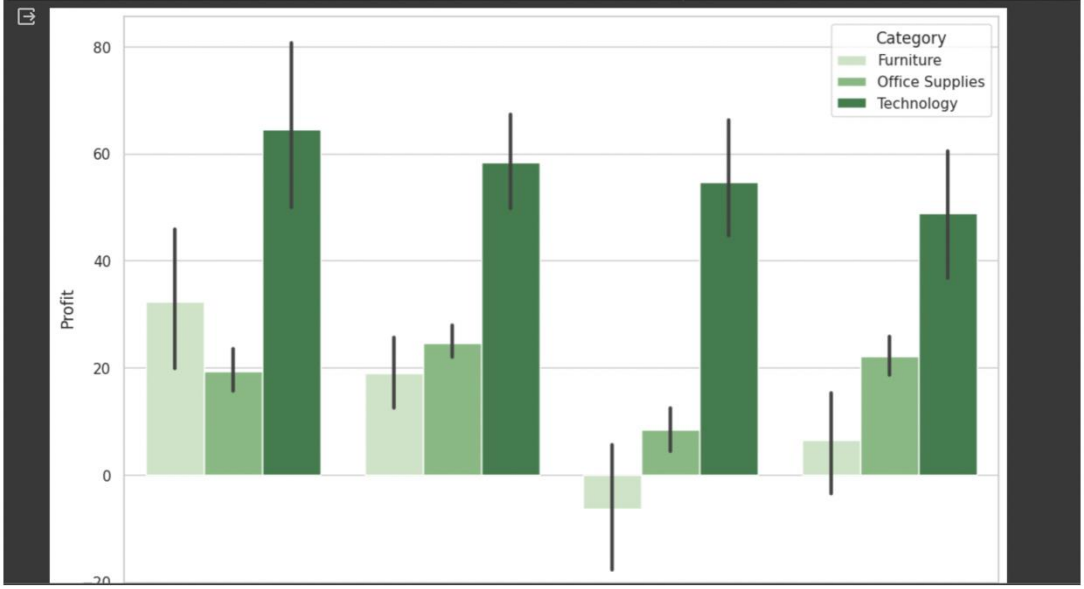

* Print category-wise profit in the whole country

```
[ ]
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Category", y="Profit", data=ds)
```



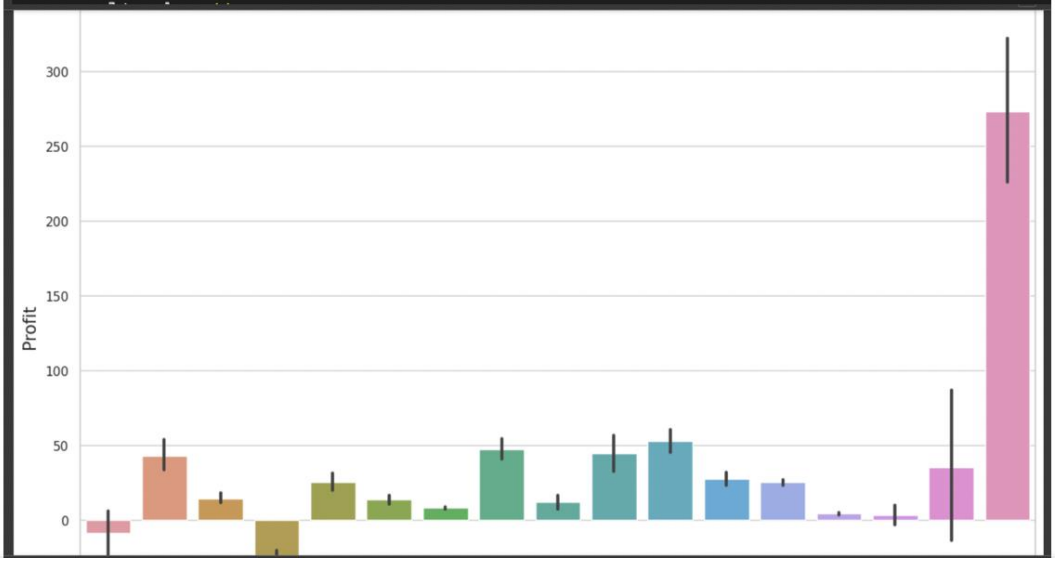
* Print category wise Profit in Each Region

```
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Region", y="Profit", hue="Category", data=ds, palette="Greens")
```




* Print sub-category wise profit

```
#Subcategory wise profit
plt.figure(figsize=[15,10])
ax = sns.barplot(x="Sub-Category", y="Profit", data=ds)
plt.xlabel("Subcategory", fontsize=15)
plt.ylabel("Profit",fontsize=15)
plt.xticks(rotation=90)
```



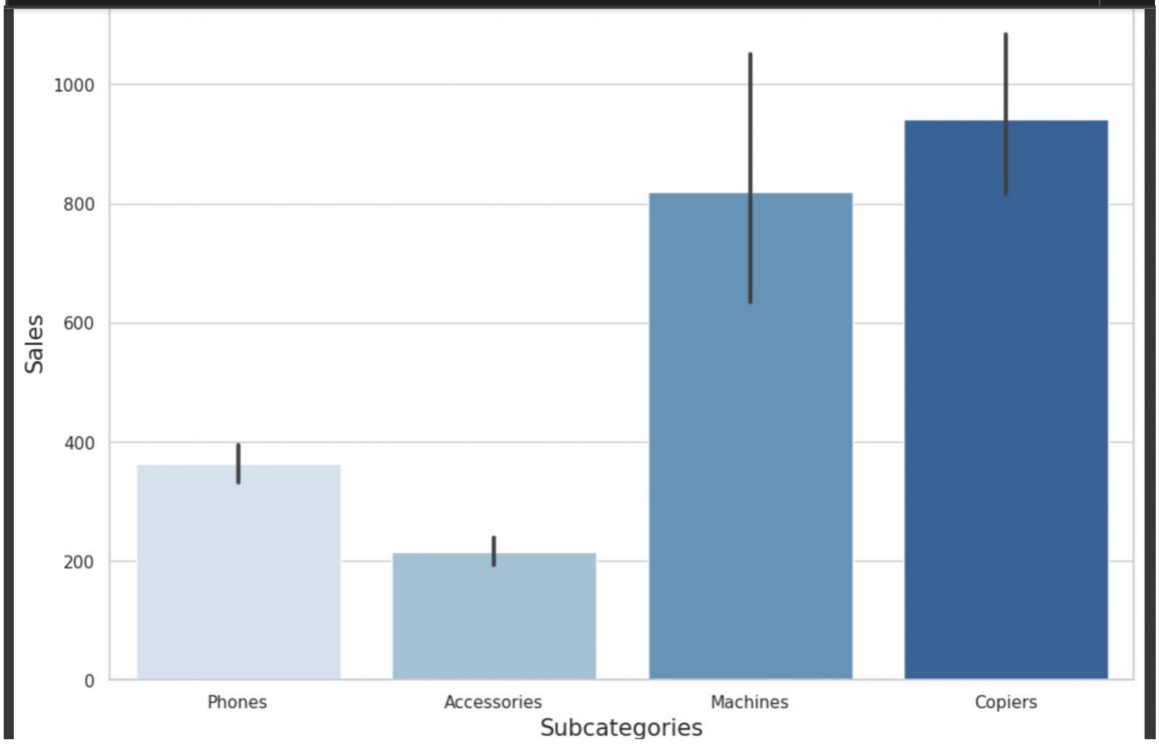
* Print those rows where technology = category

```
[ ] #Entries with Category=Technology
    ds_tech=ds[(ds['Category']=="Technology")]
    ds_tech.head()
```

| | Ship Mode | Segment | City | State | Region | Category | Sub-Category | Sales | Quantity | Discount | Profit |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 7 | Standard Class | Consumer | Los Angeles | California | West | Technology | Phones | 907.152 | 6.0 | 0.2 | 90.7152 |
| 11 | Standard Class | Consumer | NaN | California | West | Technology | Phones | NaN | 4.0 | 0.2 | 68.3568 |
| 19 | Second Class | Consumer | San Francisco | California | West | Technology | Phones | NaN | 3.0 | 0.2 | 16.0110 |
| 26 | Second Class | Consumer | Los Angeles | California | West | Technology | Accessories | 90.570 | 3.0 | 0.0 | 11.7741 |
| 35 | First Class | Corporate | Richardson | Texas | Central | Technology | Phones | 1097.544 | 7.0 | 0.2 | 123.4737 |

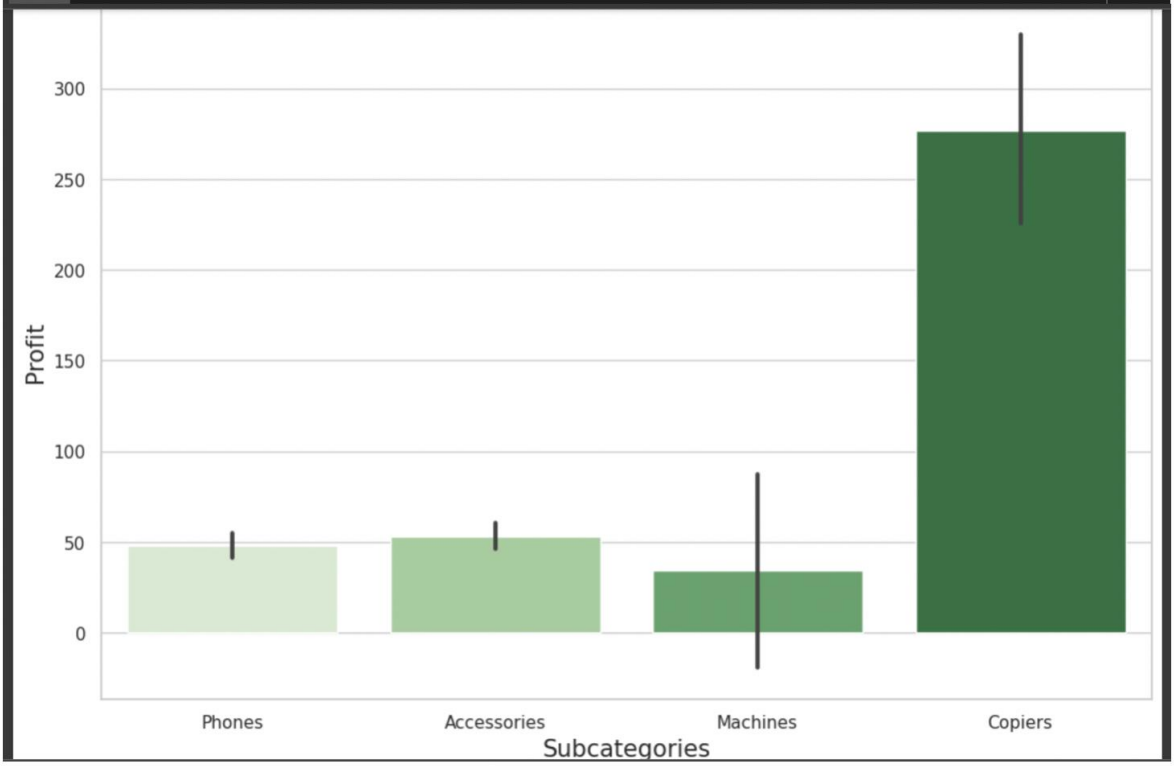
* Print sales of each Sub-category which comes under the Technology category

```
#Sales of each Subcategory under Technology
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Sub-Category", y="Sales", data=ds_tech, palette="Blues")
plt.xlabel("Subcategories",fontsize=15)
plt.ylabel("Sales",fontsize=15)
```



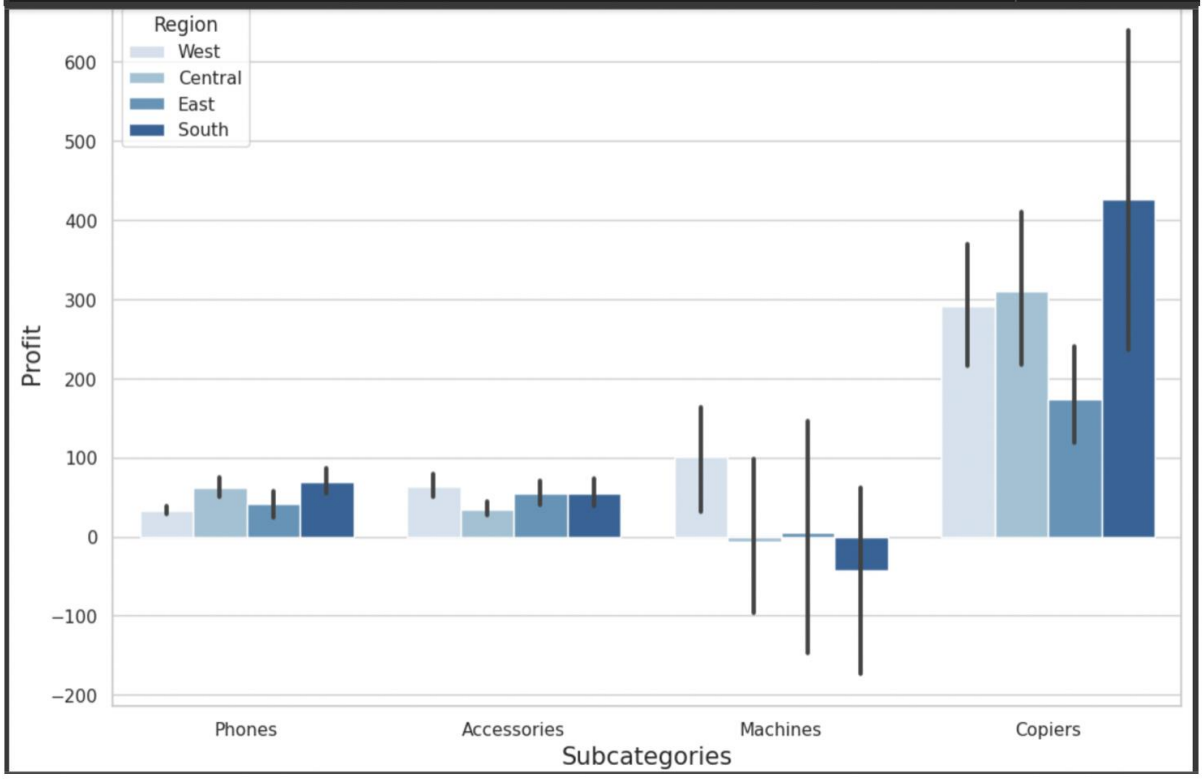
* Print profit of each Sub-category which comes under the Technology category

```
#Profit of each Subcategory under Technology
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Sub-Category", y="Profit", data=ds_tech, palette="Greens")
plt.xlabel("Subcategories",fontsize=15)
plt.ylabel("Profit",fontsize=15)
```



* Print Region-wise profit of each sub-category under Technology category

```
#Profit of each Subcategory under Technology for each Region
plt.figure(figsize=[12,8])
ax = sns.barplot(x="Sub-Category", y="Profit",hue="Region", data=ds_tech, palette="Blues")
plt.xlabel("Subcategories",fontsize=15)
plt.ylabel("Profit",fontsize=15)
```




* Check skewness of profit

```
[ ]  #checking skewness of Profit
     df['Profit'].skew()
```

```
7.538715203527991
```

* Check skewness of all the numerical columns

```
# Checking Skewness from 'Ship Mode' to 'Profit'

df_filtered_univar=df.loc[:,'Ship Mode':'Profit']
df_filtered_univar=df_filtered_univar.select_dtypes([np.int, np.float])
for i, col in enumerate(df_filtered_univar.columns):
    print("\nSkewness of "+col +" is", df_filtered_univar[col].skew()) #measures skewness
```

```
Skewness of Sales is 12.956466331241966

Skewness of Quantity is 1.2752018630542497

Skewness of Discount is 1.679624000034756

Skewness of Profit is 7.538715203527991
```

* Replace the null values with median

```
# Replace the null values with median

df['Sales'].fillna(df['Sales'].median(),inplace=True)
df['Quantity'].fillna(df['Quantity'].median(),inplace=True)
df['Discount'].fillna(df['Discount'].median(),inplace=True)
df['Profit'].fillna(df['Profit'].median(),inplace=True)
```

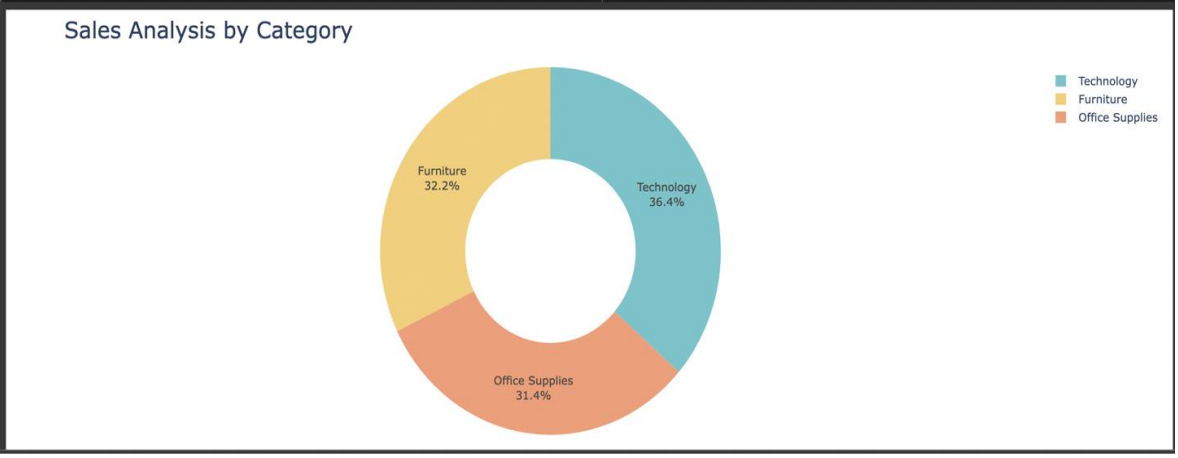
* Print unique values of the ‘subcategory' column

```
[ ] # Check unique values
    df["Sub-Category"].unique()
```

```
array(['Bookcases', 'Chairs', 'Labels', 'Tables', 'Storage',
       'Furnishings', 'Art', 'Phones', 'Binders', 'Appliances', 'Paper',
       'Accessories', 'Envelopes', 'Fasteners', 'Supplies', 'Machines',
       nan, 'Copiers'], dtype=object)
```

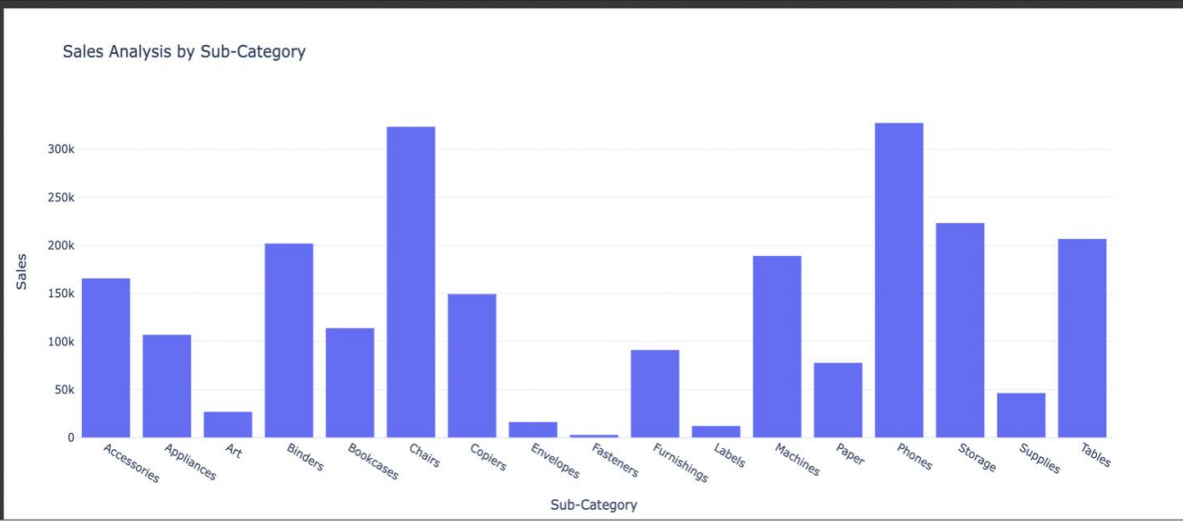
* Plot a piechart to graph sales analysis of each category

```
sales_by_category = df.groupby('Category')['Sales'].sum().reset_index()
fig = px.pie(sales_by_category,
             values='Sales',
             names='Category',
             hole=0.5,
             color_discrete_sequence=px.colors.qualitative.Pastel)
fig.update_traces(textposition='inside', textinfo='percent+label')
fig.update_layout(title_text='Sales Analysis by Category', title_font=dict(size=24))
fig.show()
```



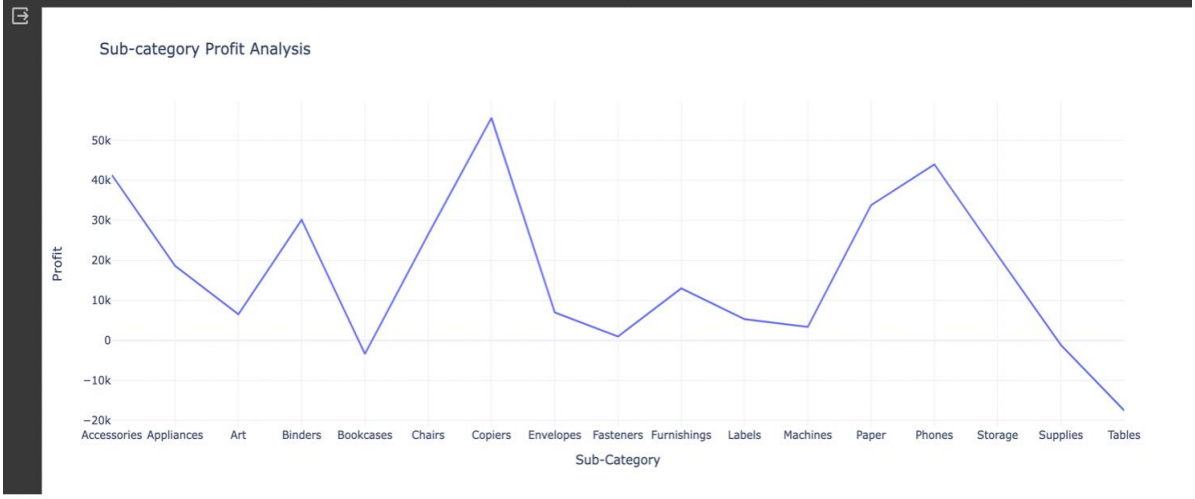

* Plot a barplot to graph subcategory-wise sales analysis

```
sales_by_subcategory = df.groupby('Sub-Category')['Sales'].sum().reset_index()
fig = px.bar(sales_by_subcategory,
             x='Sub-Category',
             y='Sales',
             title='Sales Analysis by Sub-Category')
fig.show()
```



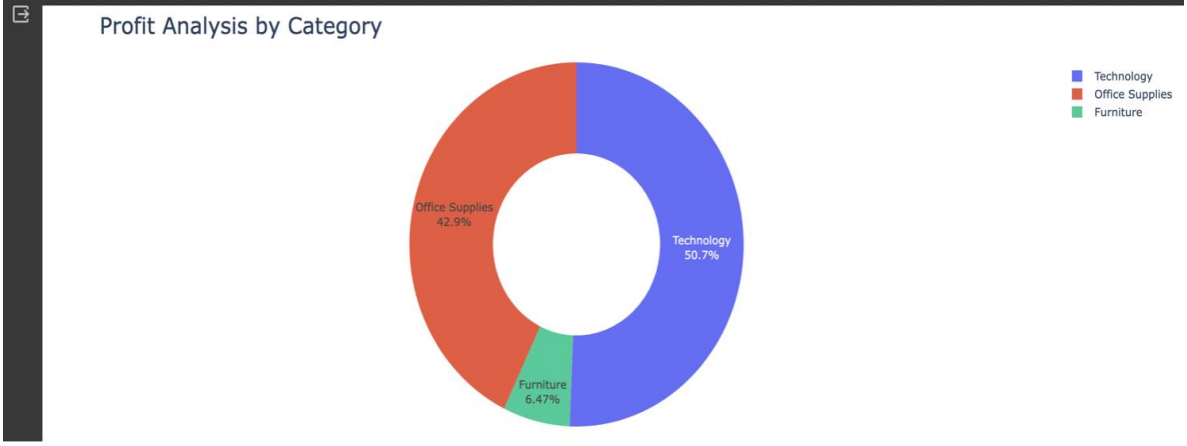
* Plot a lineplot to graph sub-category profit analysis

```
profit_by_subcategory = df.groupby('Sub-Category')['Profit'].sum().reset_index()
fig = px.line(profit_by_subcategory,
              x='Sub-Category',
              y='Profit',
              title='Sub-category Profit Analysis')
fig.show()
```




* Plot a piechart to graph profit analysis by category

```
profit_by_category = df.groupby('Category')['Profit'].sum().reset_index()
fig = px.pie(profit_by_category,
             values='Profit',
             names='Category',
             hole=0.5,
            )
fig.update_traces(textposition='inside', textinfo='percent+label')
fig.update_layout(title_text='Profit Analysis by Category', title_font=dict(size=24))
fig.show()
```



* Plot a barplot to graph sales & profit analysis by customer segment

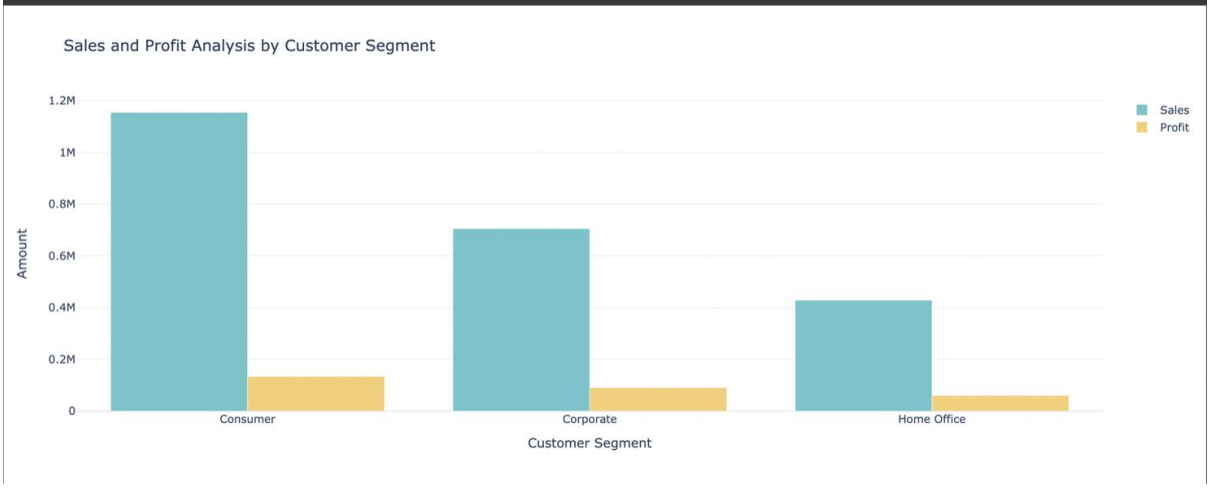
```
sales_profit_by_segment = df.groupby('Segment').agg({'Sales': 'sum', 'Profit': 'sum'}).reset_index()

color_palette = colors.qualitative.Pastel

fig = go.Figure()
fig.add_trace(go.Bar(x=sales_profit_by_segment['Segment'],
                     y=sales_profit_by_segment['Sales'],
                     name='Sales',
                     marker_color=color_palette[0]))
fig.add_trace(go.Bar(x=sales_profit_by_segment['Segment'],
                     y=sales_profit_by_segment['Profit'],
                     name='Profit',
                     marker_color=color_palette[1]))

fig.update_layout(title='Sales and Profit Analysis by Customer Segment',
                  xaxis_title='Customer Segment', yaxis_title='Amount')

fig.show()
```




* Print Sales to profit ratio of each segment

```
[ ] sales_profit_by_segment = df.groupby('Segment').agg({'Sales': 'sum', 'Profit': 'sum'}).reset_index()
    sales_profit_by_segment['Sales_to_Profit_Ratio'] = sales_profit_by_segment['Sales'] / sales_profit_by_segment['Profit']
    print(sales_profit_by_segment[['Segment', 'Sales_to_Profit_Ratio']])
```

```
        Segment  Sales_to_Profit_Ratio
0      Consumer              8.596148
1     Corporate              7.731070
2  Home Office               7.117491
```

* Replace null values of the categorical columns

```
[ ] # Replace the null values in "segment","region","city"
    df["Segment"].fillna("unknown", inplace = True)
    df["Region"].fillna("can't say", inplace = True)
    df["City"].fillna("no idea", inplace = True)
    df["State"].fillna("didn't mention", inplace = True)
    df["Category"].fillna("NA", inplace = True)
    df["Sub-Category"].fillna("doesn't exist", inplace = True)
```

* Check if all the null values are removed or not

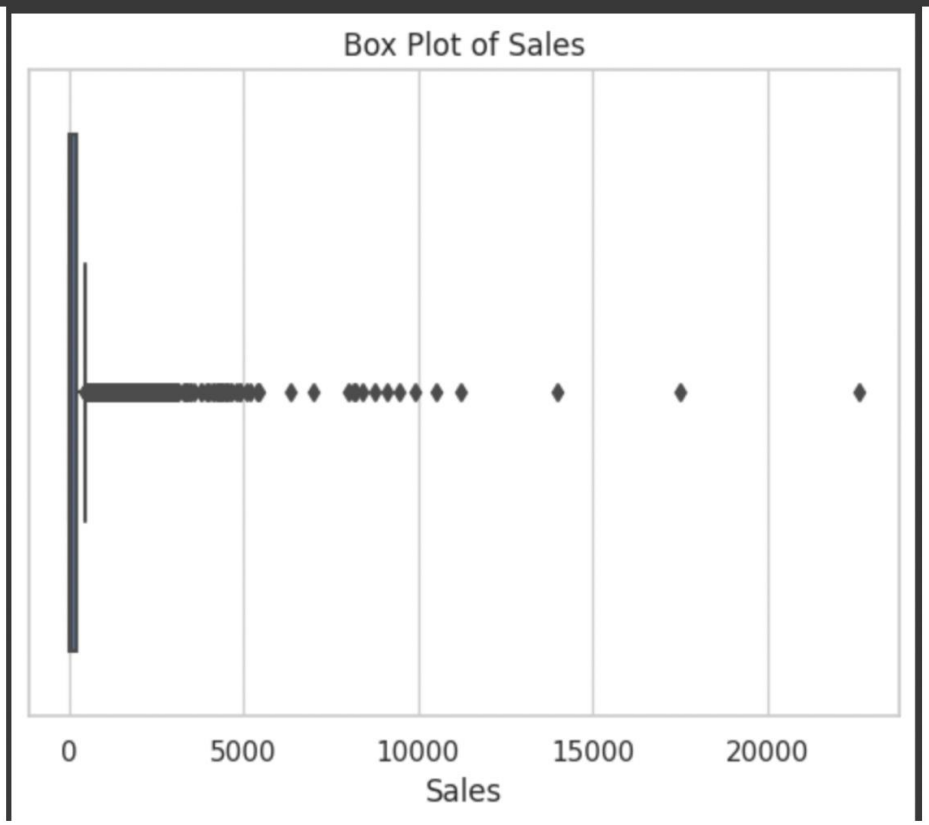
```
#All null values are removed
df.isna().sum()
```

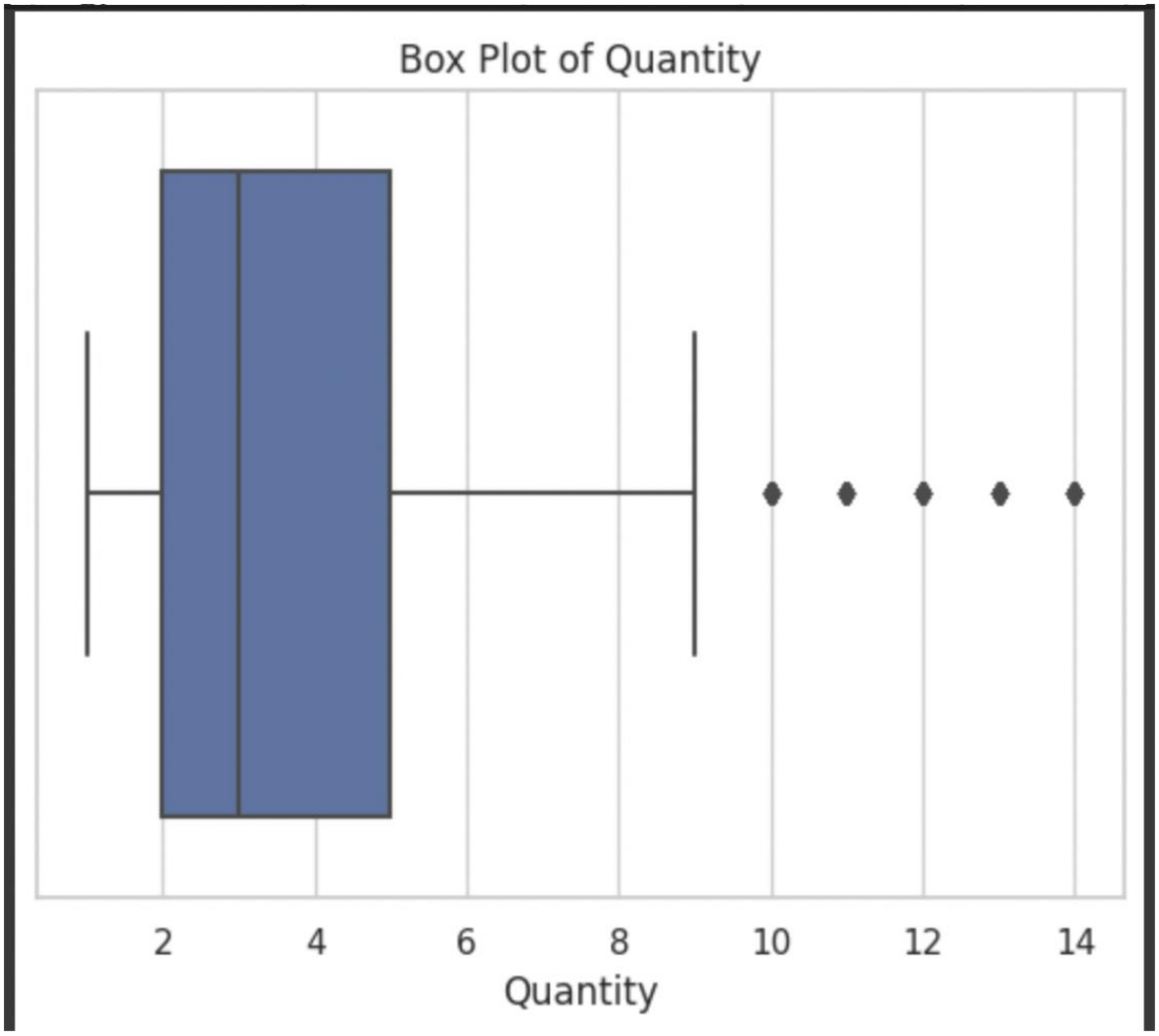
```
Ship Mode       0
Segment         0
City            0
State           0
Region          0
Category        0
Sub-Category    0
Sales           0
Quantity        0
Discount        0
Profit          0
dtype: int64
```

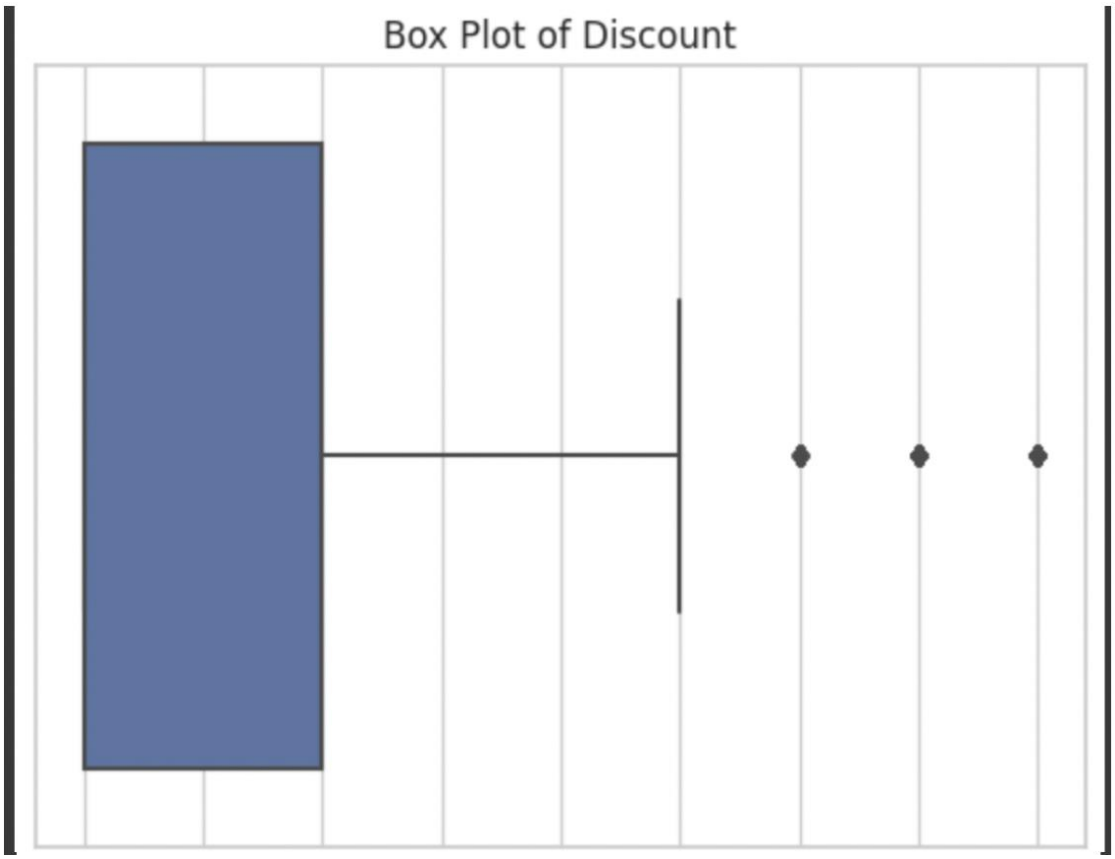
* Graph BoxPlot to summarise all the numerical columns (Sales, Quantity, Discount, Profit)

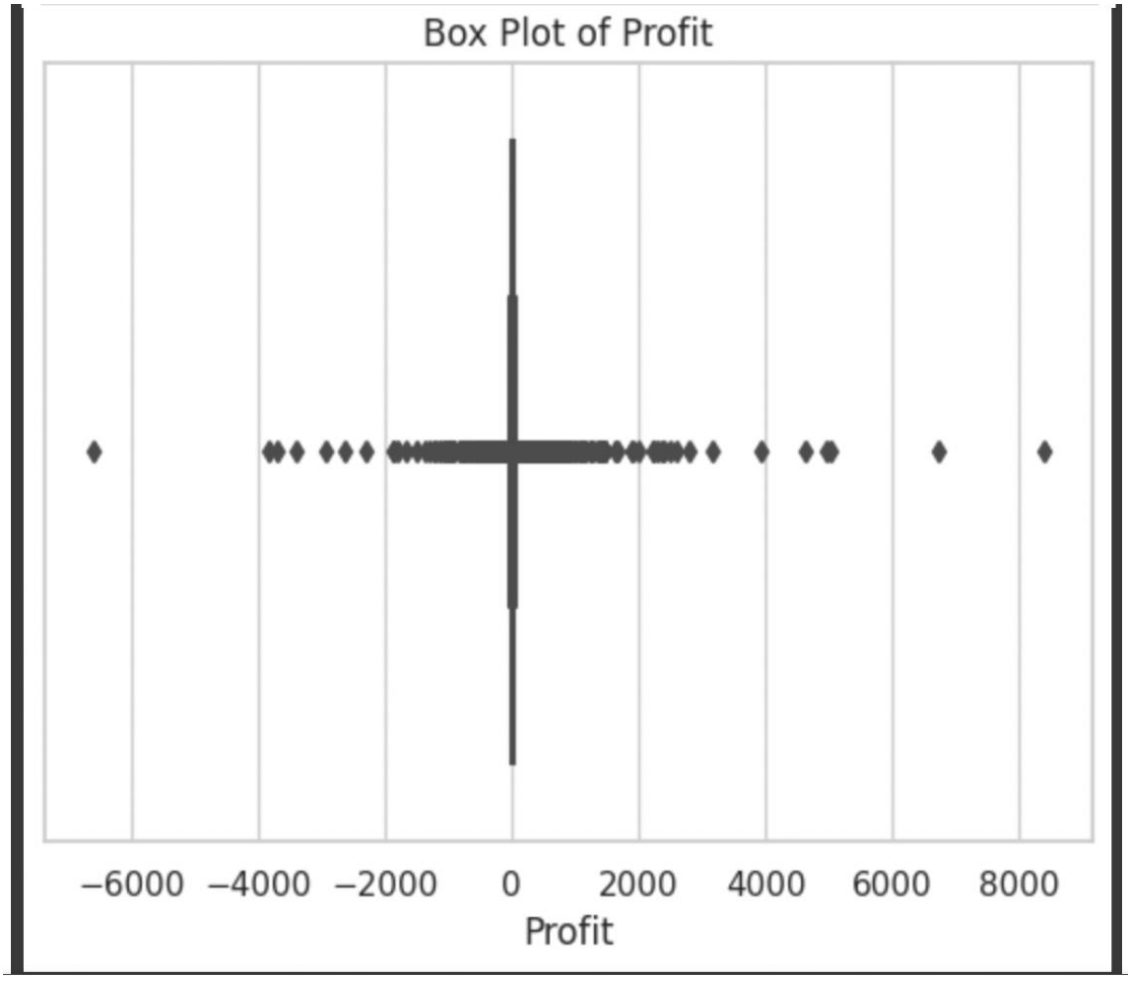
```
df_filtered_univar_1=df.loc[:,'Ship Mode':'Profit']
df_filtered_univar_1=df_filtered_univar_1.select_dtypes([np.int, np.float])

for i, col in enumerate(df_filtered_univar_1.columns):
  plt.figure(i)
  sns.boxplot(x=col, data=df_filtered_univar_1).set_title("Box Plot of "+col)
```




Box Plot of Quantity
2
4
6
8
10
12
14
Quantity

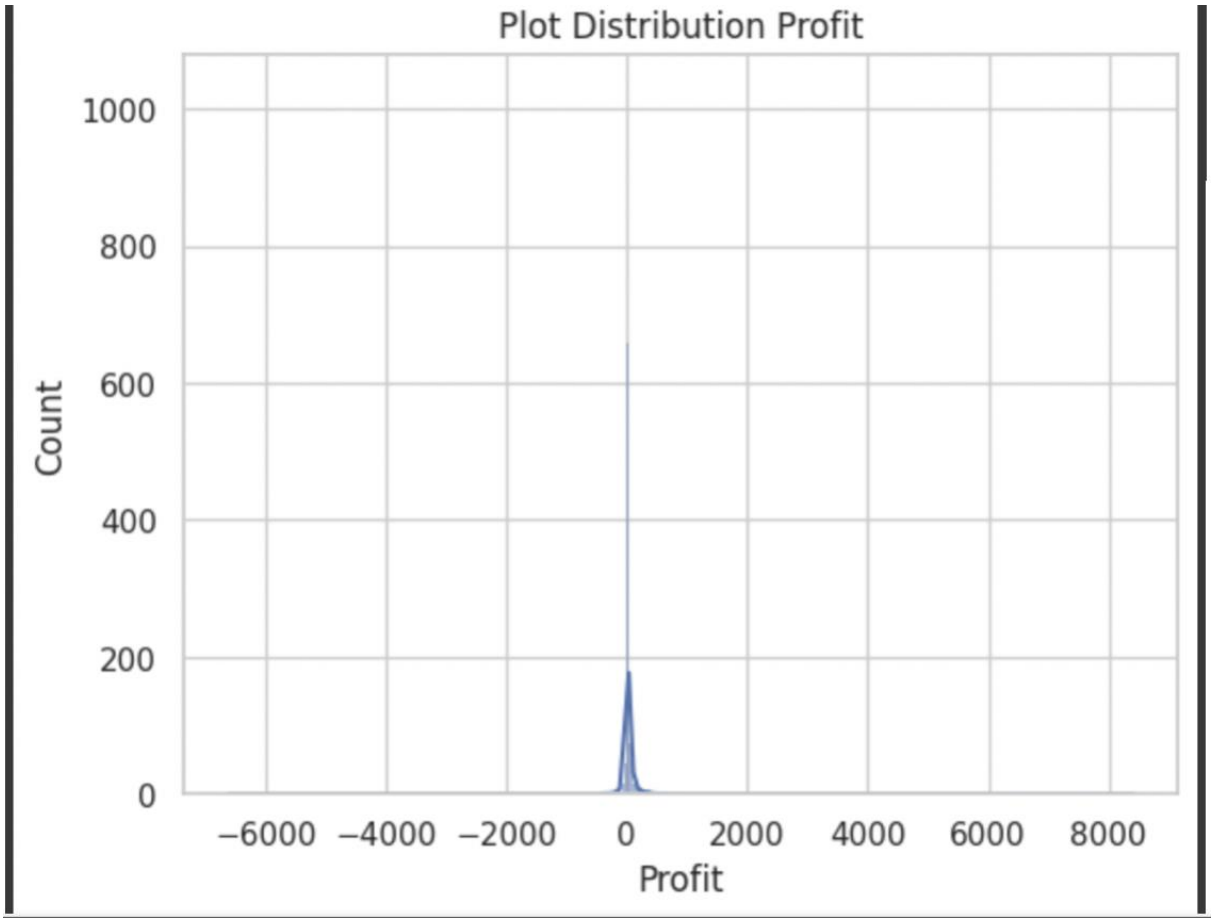

Box Plot of Discount

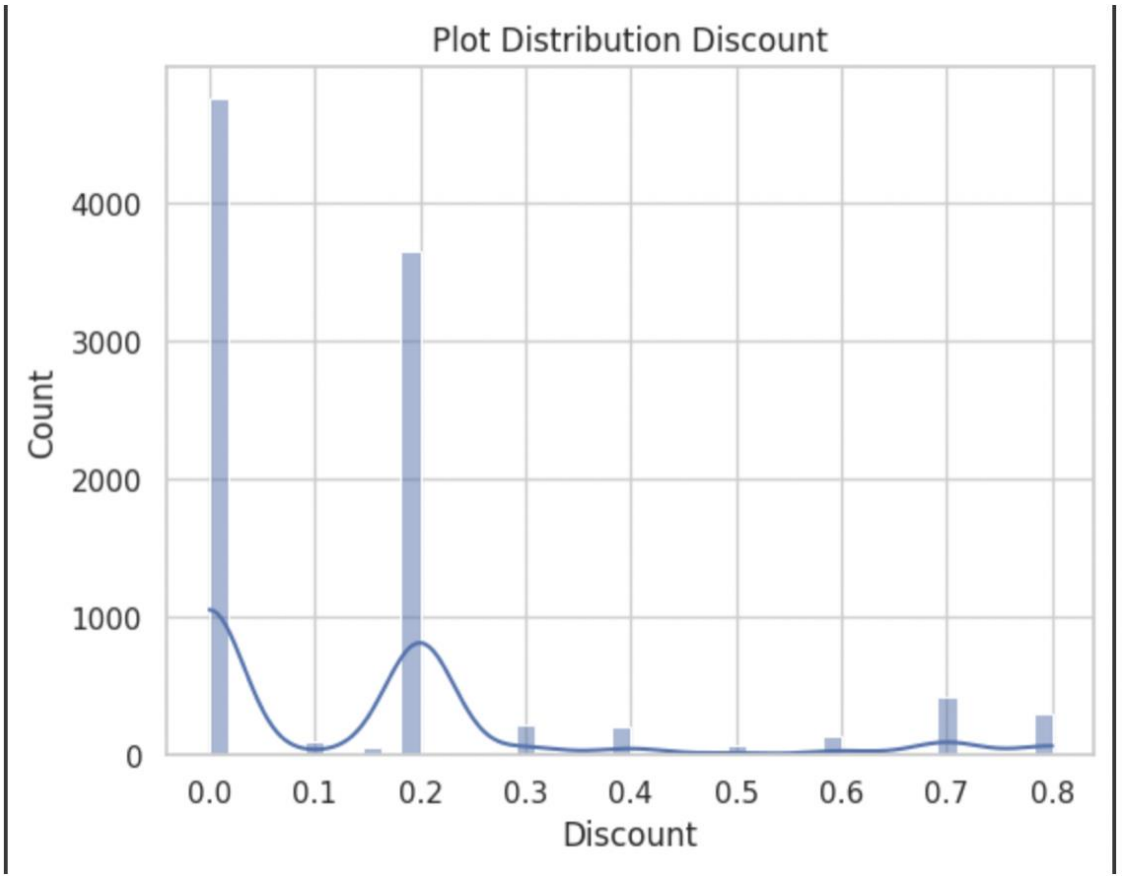

Box Plot of Profit
−6000
−4000
−2000
0
2000
4000
6000
8000
Profit

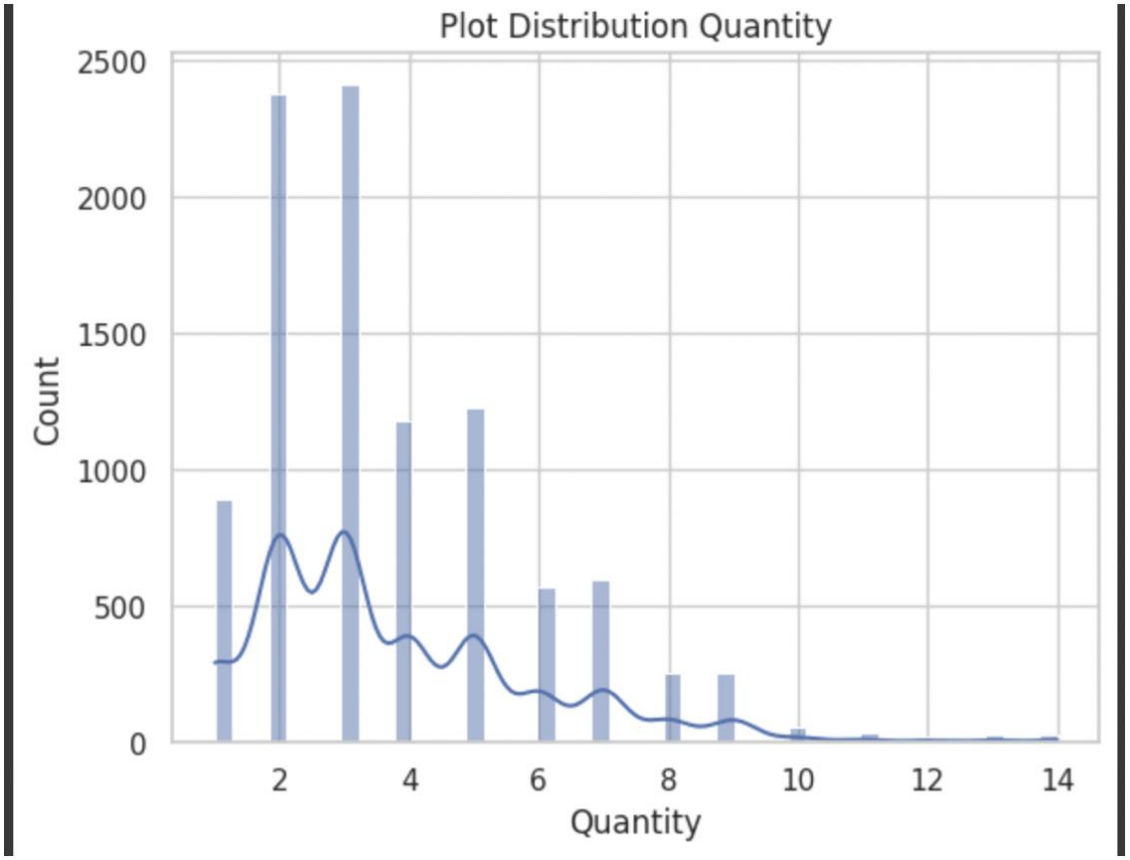
* Plot histplot for all the numerical columns

```
df_filtered_univar_1=df.loc[:,'Ship Mode':'Profit']
df_filtered_univar_1=df_filtered_univar_1.select_dtypes([np.int, np.float])

for i, col in enumerate(df_filtered_univar_1.columns):
  plt.figure(i)
  sns.histplot(x=col, data=df_filtered_univar_1, kde=True).set_title("Plot Distribution "+col)
```


Plot Distribution Discount
Count
4000
3000
2000
1000
0
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
Discount


Plot Distribution Quantity
Count
2500
2000
1500
1000
500
0
2
4
6
8
10
12
14
Quantity

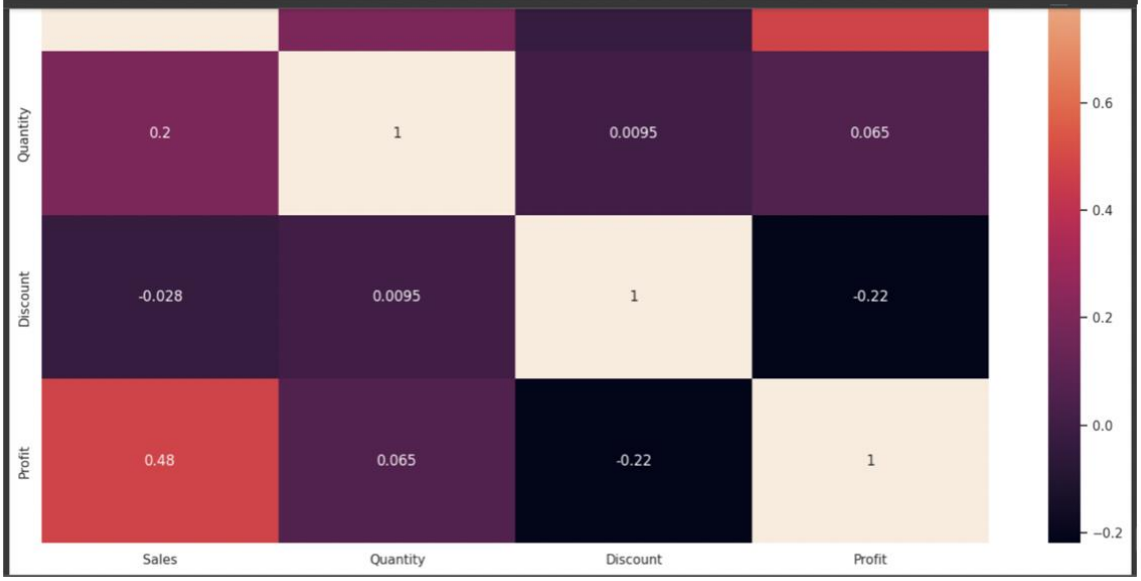
* Print correlation between all the numerical columns

```
#Correlation
df.corr()
```

| | Sales | Quantity | Discount | Profit |
|---|---|---|---|---|
| **Sales** | 1.000000 | 0.199429 | -0.028421 | 0.478635 |
| **Quantity** | 0.199429 | 1.000000 | 0.009518 | 0.064951 |
| **Discount** | -0.028421 | 0.009518 | 1.000000 | -0.218722 |
| **Profit** | 0.478635 | 0.064951 | -0.218722 | 1.000000 |

* Plot a heat map for correlation

```
#plotting the heatmap for correlation
plt.figure(figsize=(18,10))
Corr=df.corr()
correlation_heatMap = sns.heatmap(Corr, annot=True)
```



* Using Machine learning model - KNN(Regressor)

```
[ ]  from sklearn.model_selection import train_test_split
     from sklearn.neighbors import KNeighborsRegressor
```

* Assign values to X & Y to split independent and dependent variables

```
X = df[['Sales', 'Quantity', 'Discount']]
y = df['Profit']
```

* Splitting the dataset - 20% (testing) and 80% (training)

```
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=11)
```

* Create a model using Knn

```
[ ]  #creating a model
     model = KNeighborsRegressor()
```

* Fit the training data in the model

```
#fitting the training data in the model
model.fit(X_train, y_train)
```

```
▾ KNeighborsRegressor
KNeighborsRegressor()
```

* Use the model to print your predicted values

```
[ ] y_pred = model.predict(X_test)
    y_pred
```

```
array([ 21.0128 ,   9.53092,  12.80922, ..., -41.81418,  15.9884 ,
         0.98454])
```

* Print the accuracy by comparing the actual value with the predicted value

```
model.score(X_test, y_test)
```

```
0.7116594330180604
```

* Import Mean squared error and mean absolute error

```
[ ] from sklearn.metrics import mean_absolute_error, mean_squared_error
```

* Print Mean absolute error and Root mean squared error of your predicted values

```
mae = mean_absolute_error(y_test, y_pred)
rmse = np.sqrt(mean_squared_error(y_test, y_pred))

print(f'Mean Absolute Error: {mae}')
print(f'Root Mean Squared Error: {rmse}')
```

```
Mean Absolute Error: 51.85685897487438
Root Mean Squared Error: 189.4931559784699
```

## Future scope

The future scope for store sales and profit data analysis entails leveraging advanced techniques and technologies to enhance accuracy, efficiency, and strategic decision-making. Key areas of development include exploring advanced predictive modelling, incorporating external data for a holistic view, implementing dynamic pricing strategies, personalising marketing campaigns, optimising the entire supply chain, integrating emerging technologies, enhancing visualisation and business intelligence, adopting an adaptive analytics framework, ensuring ethical data use, promoting collaboration, exploring global expansion opportunities, and prioritising continuous training and skill development. Embracing these future possibilities will position XYZ Retail Company for sustained innovation, adaptability to market changes, and continued success in the dynamic retail landscape.

## Conclusion

In conclusion, the data analysis initiative for store sales and profit at XYZ Retail Company is poised to bring transformative benefits. The proposed solution, incorporating predictive modelling, customer behaviour analysis, and optimisation strategies, sets the stage for informed decision-making and strategic adjustments. The future scope emphasises the adoption of advanced technologies, personalised strategies, and ethical data practices to stay ahead in the dynamic retail market. By committing to continuous training, collaboration, and innovation, XYZ Retail Company anticipates not only addressing current challenges but also fostering a culture of data-driven excellence. The integration of data-derived insights is positioned as a guiding force for the company's future, promising sustained growth, operational efficiency, and customer satisfaction. This data-centric approach represents an investment in the company's resilience and success in the evolving retail landscape.