

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

```
In [2]: 1 data=pd.read_csv("Amazon Sales data.csv")
        2 data
```

Out[2]:

|     | Region                            | Country               | Item Type       | Sales Channel | Order Priority | Order Date | Order ID  | Ship Date  | Units Sold | Unit Price | Unit Cost | Revenue |
|-----|-----------------------------------|-----------------------|-----------------|---------------|----------------|------------|-----------|------------|------------|------------|-----------|---------|
| 0   | Australia and Oceania             | Tuvalu                | Baby Food       | Offline       | H              | 5/28/2010  | 669165933 | 6/27/2010  | 9925       | 255.28     | 159.42    | 25331   |
| 1   | Central America and the Caribbean | Grenada               | Cereal          | Online        | C              | 8/22/2012  | 963881480 | 9/15/2012  | 2804       | 205.70     | 117.11    | 5761    |
| 2   | Europe                            | Russia                | Office Supplies | Offline       | L              | 5/2/2014   | 341417157 | 5/8/2014   | 1779       | 651.21     | 524.96    | 11581   |
| 3   | Sub-Saharan Africa                | Sao Tome and Principe | Fruits          | Online        | C              | 6/20/2014  | 514321792 | 7/5/2014   | 8102       | 9.33       | 6.92      | 751     |
| 4   | Sub-Saharan Africa                | Rwanda                | Office Supplies | Offline       | L              | 2/1/2013   | 115456712 | 2/6/2013   | 5062       | 651.21     | 524.96    | 32961   |
| ... | ...                               | ...                   | ...             | ...           | ...            | ...        | ...       | ...        | ...        | ...        | ...       | ...     |
| 95  | Sub-Saharan Africa                | Mali                  | Clothes         | Online        | M              | 7/26/2011  | 512878119 | 9/3/2011   | 888        | 109.28     | 35.84     | 971     |
| 96  | Asia                              | Malaysia              | Fruits          | Offline       | L              | 11/11/2011 | 810711038 | 12/28/2011 | 6267       | 9.33       | 6.92      | 581     |
| 97  | Sub-Saharan Africa                | Sierra Leone          | Vegetables      | Offline       | C              | 6/1/2016   | 728815257 | 6/29/2016  | 1485       | 154.06     | 90.93     | 2281    |
| 98  | North America                     | Mexico                | Personal Care   | Offline       | M              | 7/30/2015  | 559427106 | 8/8/2015   | 5767       | 81.73      | 56.67     | 4711    |
| 99  | Sub-Saharan Africa                | Mozambique            | Household       | Offline       | L              | 2/10/2012  | 665095412 | 2/15/2012  | 5367       | 668.27     | 502.54    | 35861   |

100 rows × 14 columns

Amazon Sales data refers to sales, high performing sellers and several other data points. There are millions of Amazon sellers around the world. Amazon sales data Analysis focuses on the process of analyzing consumer behavior, sales, and several other attributes in order to make improved, data-driven decisions. It is key to successfully sustaining their businesses and earning profits and for this purpose, they analyze different metrics like sales, Sales Quantity, Discount rate, Sales over years etc. By analyzing different metrics, you will be able to increase and improve your performance in terms of sales, Items to be sold and discount rates etc. Analysis of the sales data the main factor that contributes to sellers improving their business and increasing their revenue. They can better understand the market trends and customers' buying behaviors and help them cater to what the customers really want. In the world of rising new technology and innovation, E-commerce industry is advancing with the role of Data Analytics. Data analysis can help them to understand their business in a quiet different manner and helps to improve the quality of the service by identifying the weak areas of the business. This study demonstrates the how different analysis help to make better business decisions and help analyze customer trends and satisfaction, which can lead to new and better products and services. Different analysis performed to get the key insights from this data based on which business decisions will be taken.

In [3]: 1 data.head()

Out[3]:

|   | Region                            | Country               | Item Type       | Sales Channel | Order Priority | Order Date | Order ID  | Ship Date | Units Sold | Unit Price | Unit Cost | Total Revenue |   |
|---|-----------------------------------|-----------------------|-----------------|---------------|----------------|------------|-----------|-----------|------------|------------|-----------|---------------|---|
| 0 | Australia and Oceania             | Tuvalu                | Baby Food       | Offline       | H              | 5/28/2010  | 669165933 | 6/27/2010 | 9925       | 255.28     | 159.42    | 2533654.00    | 1 |
| 1 | Central America and the Caribbean | Grenada               | Cereal          | Online        | C              | 8/22/2012  | 963881480 | 9/15/2012 | 2804       | 205.70     | 117.11    | 576782.80     |   |
| 2 | Europe                            | Russia                | Office Supplies | Offline       | L              | 5/2/2014   | 341417157 | 5/8/2014  | 1779       | 651.21     | 524.96    | 1158502.59    |   |
| 3 | Sub-Saharan Africa                | Sao Tome and Principe | Fruits          | Online        | C              | 6/20/2014  | 514321792 | 7/5/2014  | 8102       | 9.33       | 6.92      | 75591.66      |   |
| 4 | Sub-Saharan Africa                | Rwanda                | Office Supplies | Offline       | L              | 2/1/2013   | 115456712 | 2/6/2013  | 5062       | 651.21     | 524.96    | 3296425.02    | 2 |

In [4]: 1 data.shape

Out[4]: (100, 14)

In [5]: 1 data.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 100 entries, 0 to 99
Data columns (total 14 columns):
#   Column                Non-Null Count  Dtype
---  -
0   Region                100 non-null   object
1   Country               100 non-null   object
2   Item Type             100 non-null   object
3   Sales Channel         100 non-null   object
4   Order Priority        100 non-null   object
5   Order Date            100 non-null   object
6   Order ID              100 non-null   int64
7   Ship Date             100 non-null   object
8   Units Sold            100 non-null   int64
9   Unit Price            100 non-null   float64
10  Unit Cost             100 non-null   float64
11  Total Revenue         100 non-null   float64
12  Total Cost            100 non-null   float64
13  Total Profit          100 non-null   float64
dtypes: float64(5), int64(2), object(7)
memory usage: 11.1+ KB
```

In [6]: 1 data.columns

Out[6]: Index(['Region', 'Country', 'Item Type', 'Sales Channel', 'Order Priority', 'Order Date', 'Order ID', 'Ship Date', 'Units Sold', 'Unit Price', 'Unit Cost', 'Total Revenue', 'Total Cost', 'Total Profit'], dtype='object')

```
In [7]: 1 data[['Units Sold', 'Unit Price', 'Unit Cost', 'Total Revenue', 'Total Cost', 'Total Profit']].de:
```

```
Out[7]:
```

|              | Units Sold  | Unit Price | Unit Cost  | Total Revenue | Total Cost   | Total Profit |
|--------------|-------------|------------|------------|---------------|--------------|--------------|
| <b>count</b> | 100.000000  | 100.000000 | 100.000000 | 1.000000e+02  | 1.000000e+02 | 1.000000e+02 |
| <b>mean</b>  | 5128.710000 | 276.761300 | 191.048000 | 1.373488e+06  | 9.318057e+05 | 4.416820e+05 |
| <b>std</b>   | 2794.484562 | 235.592241 | 188.208181 | 1.460029e+06  | 1.083938e+06 | 4.385379e+05 |
| <b>min</b>   | 124.000000  | 9.330000   | 6.920000   | 4.870260e+03  | 3.612240e+03 | 1.258020e+03 |
| <b>25%</b>   | 2836.250000 | 81.730000  | 35.840000  | 2.687212e+05  | 1.688680e+05 | 1.214436e+05 |
| <b>50%</b>   | 5382.500000 | 179.880000 | 107.275000 | 7.523144e+05  | 3.635664e+05 | 2.907680e+05 |
| <b>75%</b>   | 7369.000000 | 437.200000 | 263.330000 | 2.212045e+06  | 1.613870e+06 | 6.358288e+05 |
| <b>max</b>   | 9925.000000 | 668.270000 | 524.960000 | 5.997055e+06  | 4.509794e+06 | 1.719922e+06 |

```
In [8]: 1 data.duplicated().sum()
```

```
Out[8]: 0
```

```
In [9]: 1 data.isnull().sum()
```

```
Out[9]: Region          0
Country          0
Item Type        0
Sales Channel     0
Order Priority    0
Order Date       0
Order ID         0
Ship Date        0
Units Sold       0
Unit Price       0
Unit Cost        0
Total Revenue    0
Total Cost       0
Total Profit     0
dtype: int64
```

Now we are changing date and time format of order date and ship date for training

```
In [10]: 1 data["Order Date"]=pd.to_datetime(data['Order Date'])
2 data["Ship Date"]=pd.to_datetime(data['Ship Date'])
3
```

Changing the data type column of different columns for training the model

```
In [11]: 1 data['Region']=data['Region'].astype(str)
2 data['Country']=data['Country'].astype(str)
3 data['Item Type']=data['Item Type'].astype(str)
4 data['Sales Channel']=data['Sales Channel'].astype(str)
5 data['Order Priority']=data['Order Priority'].astype(str)
```

```
In [12]: 1 pd.set_option('display.max_rows', None)
          2 data['Country'].value_counts()
```

```
Out[12]: The Gambia 4
         Sierra Leone 3
         Sao Tome and Principe 3
         Mexico 3
         Australia 3
         Djibouti 3
         Switzerland 2
         Myanmar 2
         Norway 2
         Turkmenistan 2
         Cameroon 2
         Bulgaria 2
         Honduras 2
         Azerbaijan 2
         Libya 2
         Rwanda 2
         Mali 2
         Gabon 1
         Belize 1
         Haiti 1
         Lithuania 1
         San Marino 1
         United Kingdom 1
         Austria 1
         Fiji 1
         Madagascar 1
         Cote d'Ivoire 1
         Tuvalu 1
         Democratic Republic of the Congo 1
         Zambia 1
         Malaysia 1
         Nicaragua 1
         Romania 1
         Slovenia 1
         Kuwait 1
         Kenya 1
         Iran 1
         Pakistan 1
         Lebanon 1
         Spain 1
         Samoa 1
         Monaco 1
         Laos 1
         Saudi Arabia 1
         Federated States of Micronesia 1
         Slovakia 1
         Lesotho 1
         Albania 1
         Russia 1
         Solomon Islands 1
         Angola 1
         Burkina Faso 1
         Republic of the Congo 1
         Senegal 1
         Kyrgyzstan 1
         Cape Verde 1
         Bangladesh 1
         Mongolia 1
         Sri Lanka 1
         East Timor 1
         Portugal 1
         New Zealand 1
         Moldova 1
         France 1
         Kiribati 1
         South Sudan 1
```

|            |   |
|------------|---|
| Costa Rica | 1 |
| Syria      | 1 |
| Brunei     | 1 |
| Niger      | 1 |
| Grenada    | 1 |
| Comoros    | 1 |
| Iceland    | 1 |
| Macedonia  | 1 |
| Mauritania | 1 |
| Mozambique | 1 |

Name: Country, dtype: int64

```
In [13]: 1 data['Item Type'].value_counts()
```

```
Out[13]: Clothes      13
Cosmetics    13
Office Supplies 12
Fruits       10
Personal Care 10
Household     9
Beverages     8
Baby Food     7
Cereal        7
Vegetables    6
Snacks        3
Meat          2
Name: Item Type, dtype: int64
```

```
In [14]: 1 data['Sales Channel'].value_counts()
```

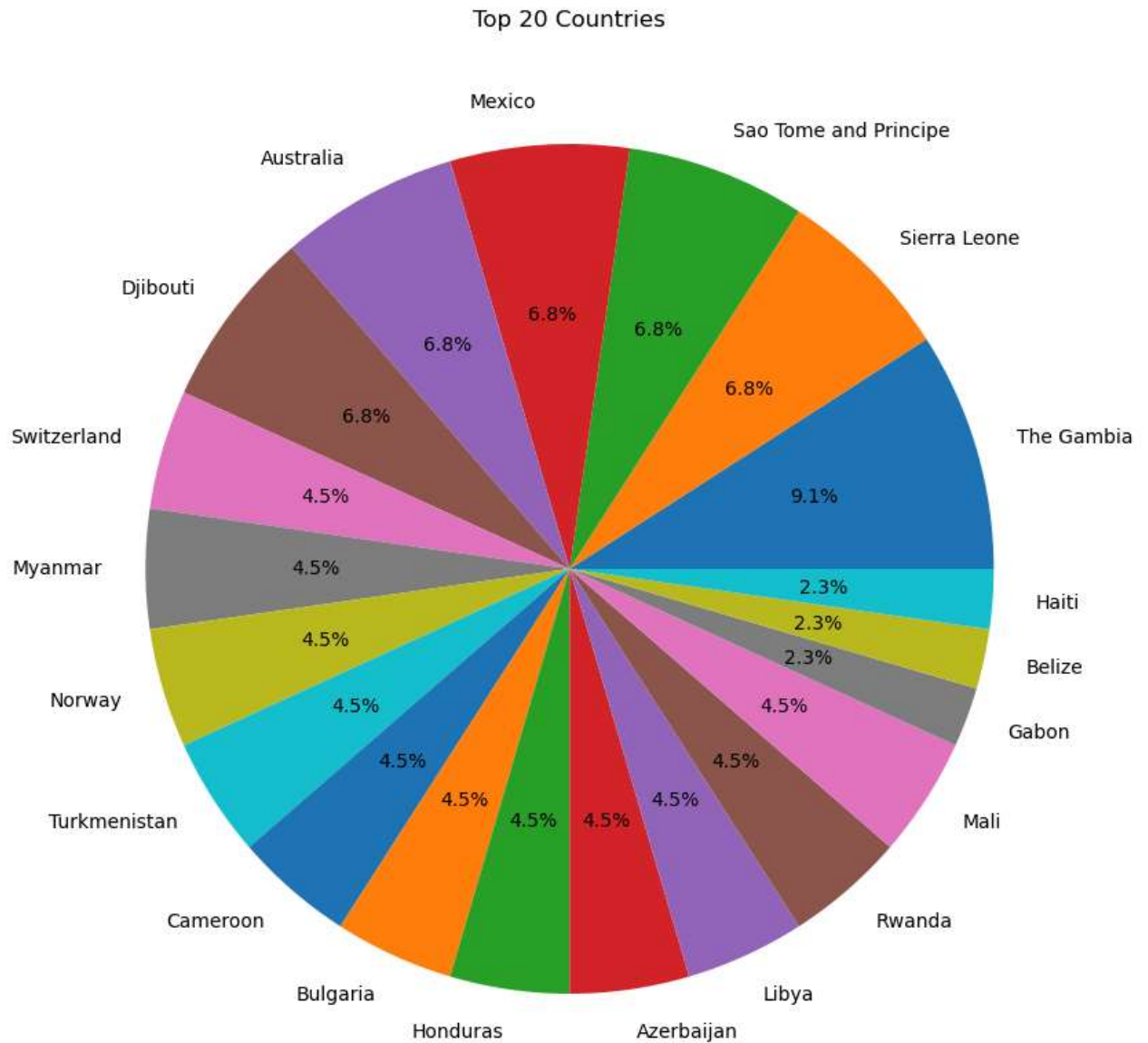
```
Out[14]: Offline    50
Online    50
Name: Sales Channel, dtype: int64
```

```
In [15]: 1 data['Order Priority'].value_counts()
2
```

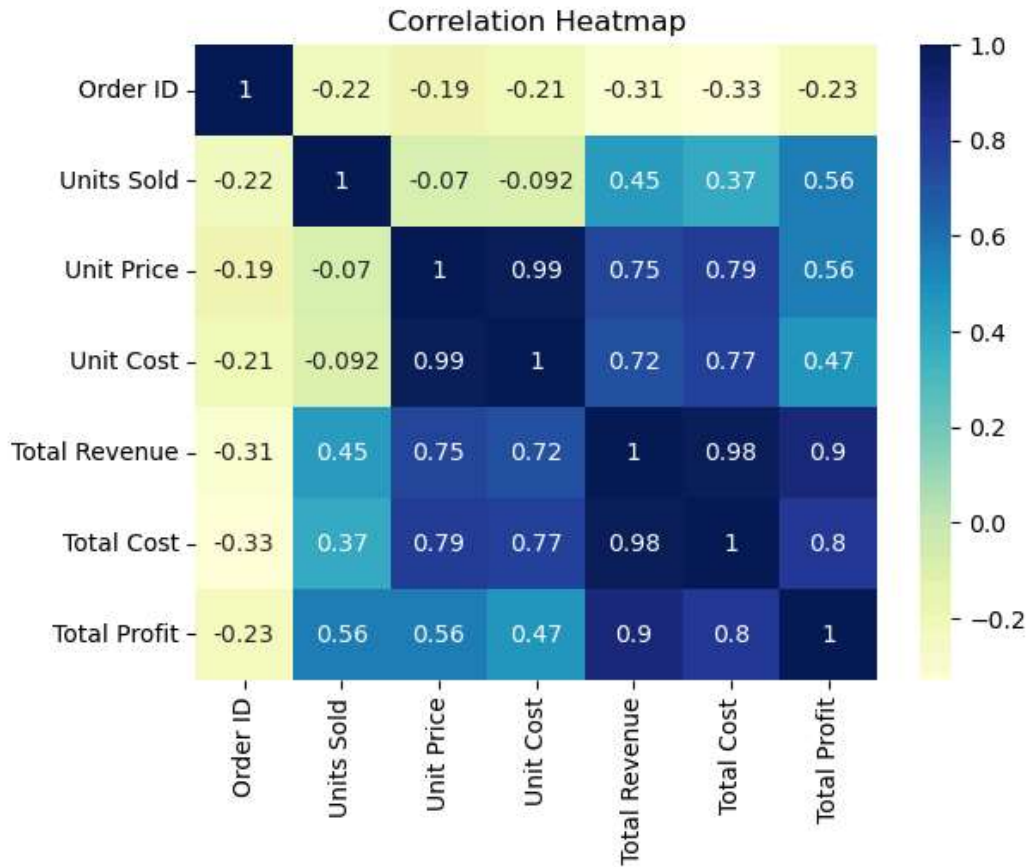
```
Out[15]: H    30
L    27
C    22
M    21
Name: Order Priority, dtype: int64
```

Let's see in pie chart for top 20 country

```
In [16]: 1 country_names = data.Country.value_counts().index
2 country_val = data.Country.value_counts().values
3 fig,ax = plt.subplots(figsize=(10,10))
4 ax.pie(country_val[:20],labels=country_names[:20],autopct='%1.1f%%')
5 plt.title("Top 20 Countries")
6 plt.show()
```



```
In [17]: 1 sns.heatmap(data.corr(),annot=True ,cmap='YlGnBu',linecolor='black')
2 plt.title('Correlation Heatmap')
3 plt.show()
```

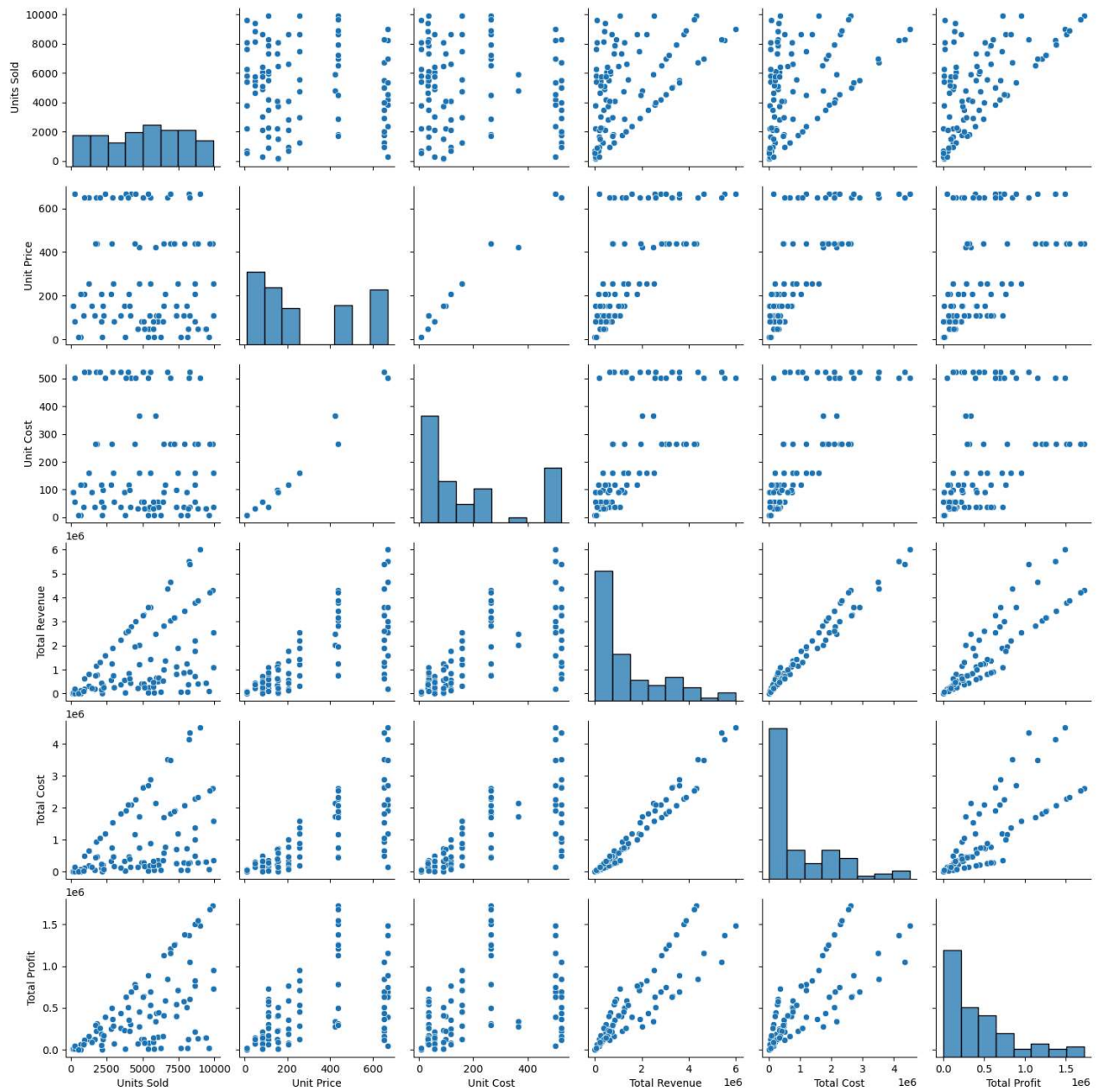


- We can see in the above heatmap Unit Price and Unit Cost are stronger correlated.
- Unit Price also related to Total Revenue and Total Cost.

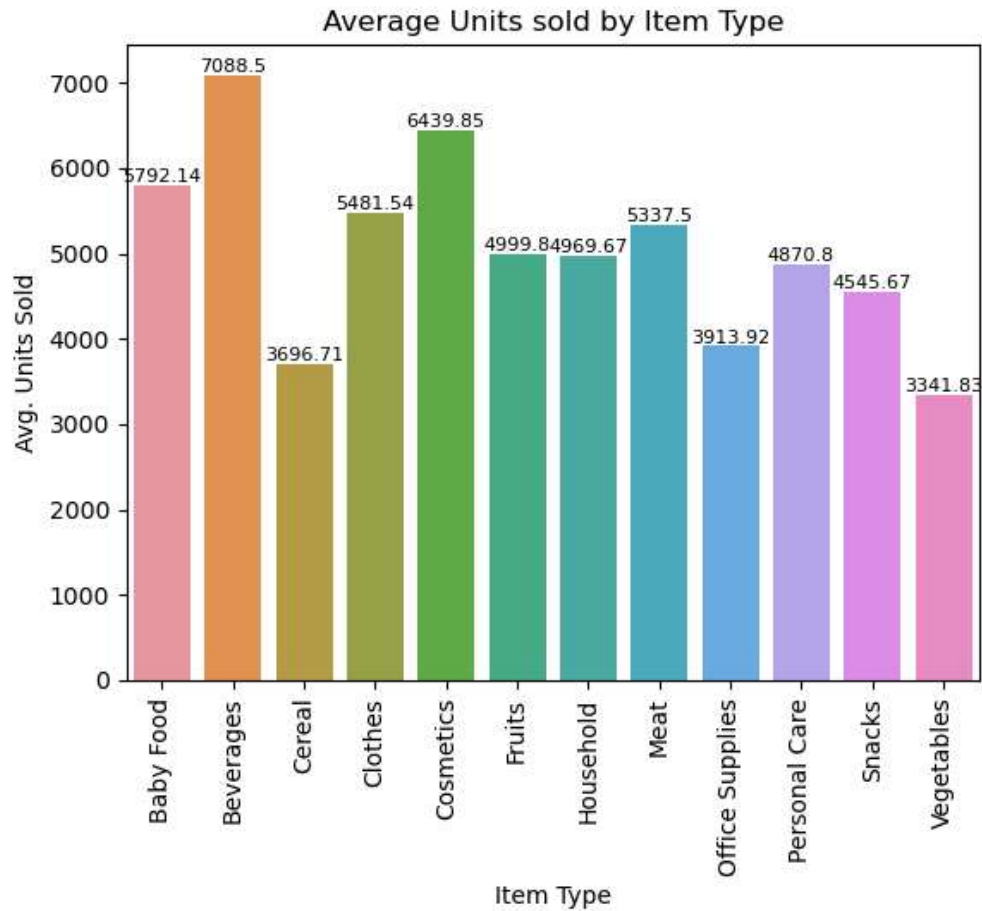
```
In [18]: 1 Variables=["Units Sold",'Unit Price',"Unit Cost","Total Revenue","Total Cost","Total Profit"]
```



```
In [19]: 1 sns.pairplot(data[Variables])
        2 plt.show()
```

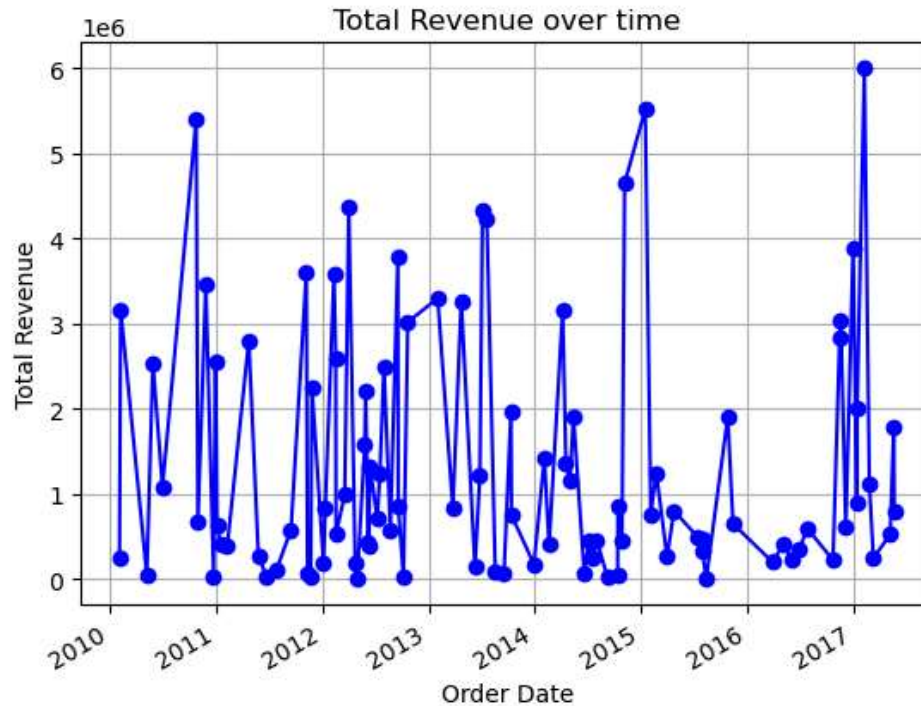


```
In [20]: 1 Avg_unitsold=data.groupby('Item Type')['Units Sold'].mean().reset_index()
2 ax=sns.barplot(x='Item Type',y='Units Sold',data=Avg_unitsold)
3 ax.bar_label(ax.containers[0],fontsize=8)
4
5 plt.xlabel('Item Type')
6 plt.ylabel('Avg. Units Sold')
7 plt.title('Average Units sold by Item Type')
8 plt.xticks(rotation=90)
9 plt.show()
```



```
In [21]: 1 data.groupby('Order Date').sum()['Total Revenue'].plot(kind = 'line',color = 'blue',marker='o')
2 plt.xlabel('Order Date')
3 plt.ylabel('Total Revenue')
4
5 plt.title('Total Revenue over time')
6 print('Total Revenue:',data['Total Revenue'].sum())
7 plt.show()
```

Total Revenue: 137348768.31

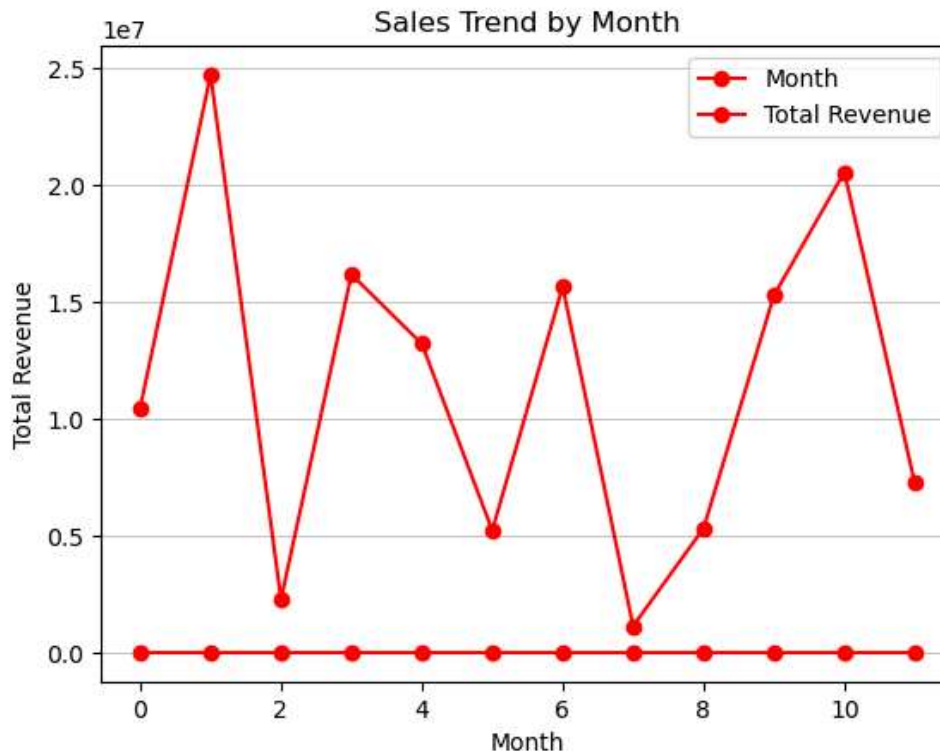


In the above line chart we can see that total revenue over all year from 2010 till 2017 is 137348768.31

```
In [22]: 1 data['Month']=data['Order Date'].dt.month
2 data['Year']=data['Order Date'].dt.year
```

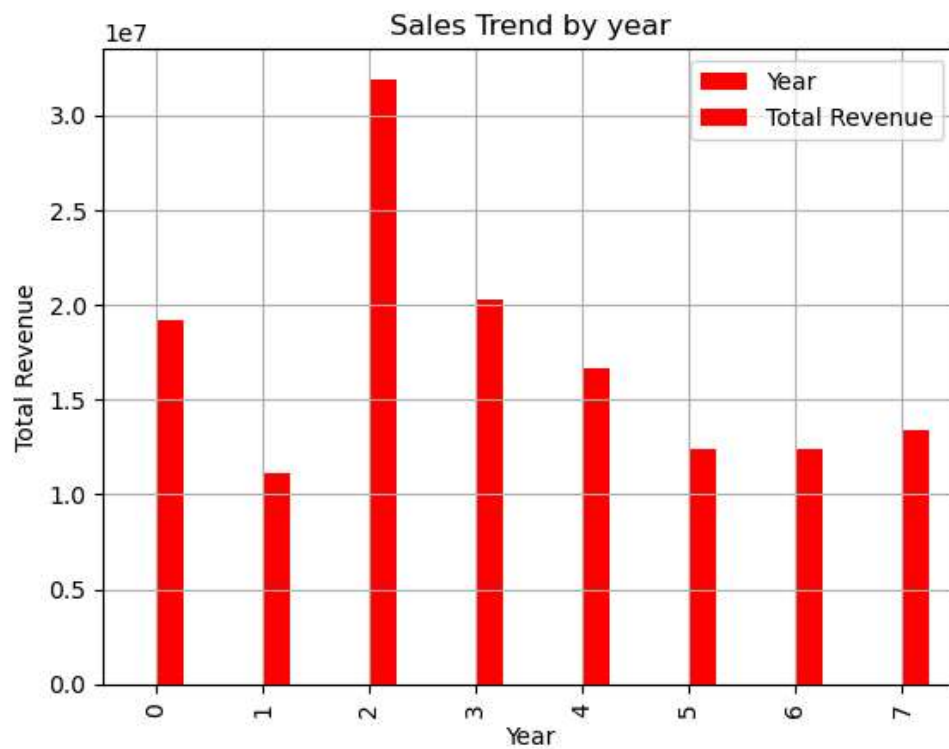
```
In [23]: 1 monthly_sales=data.groupby(data['Month'])['Total Revenue'].sum().reset_index()
```

```
In [24]: 1 ax=monthly_sales.plot(kind = 'line',marker='o',color = 'red')
2 ax.grid(axis='y', linewidth=0.5)
3 ax.set_xlabel('Month')
4 ax.set_ylabel('Total Revenue')
5 ax.set_title('Sales Trend by Month')
6 plt.show()
```

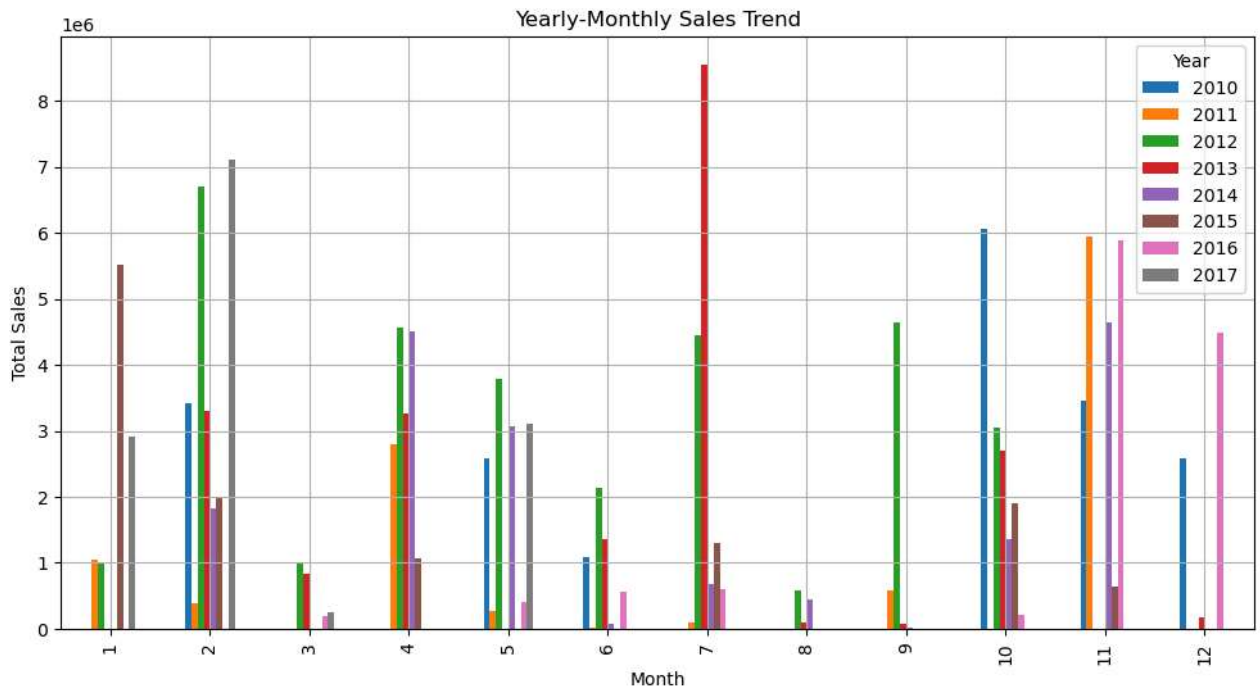


```
In [25]: 1 year_sales=data.groupby(data['Year'])['Total Revenue'].sum().reset_index()
```

```
In [26]: 1 year_sales.plot(kind = 'bar',color = 'red',grid=True)
2 plt.xlabel('Year')
3 plt.ylabel('Total Revenue')
4 plt.title('Sales Trend by year')
5 plt.show()
```



```
In [27]: 1 Yearly_Monthly_Sales = data.groupby(['Month', 'Year'])['Total Revenue'].sum().unstack()
2 Yearly_Monthly_Sales.plot(kind='bar', figsize=(12, 6))
3 plt.title('Yearly-Monthly Sales Trend')
4 plt.xlabel('Month')
5 plt.ylabel('Total Sales')
6 plt.legend(title='Year')
7 plt.grid(True)
8 plt.show()
```

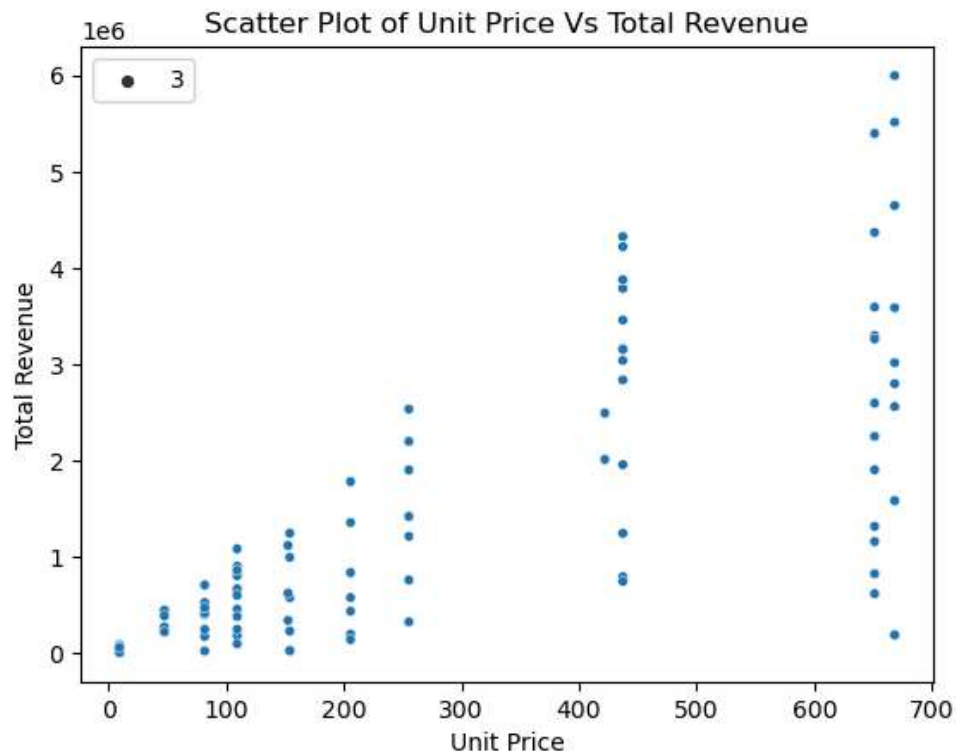


```
In [28]: 1 total_revenue = data['Total Revenue'].sum()
2 average_order_value = data['Total Revenue'].mean()
3 print(f'Total Revenue: ${total_revenue:.2f}')
4 print(f'Average Order Value: ${average_order_value:.2f}')
```

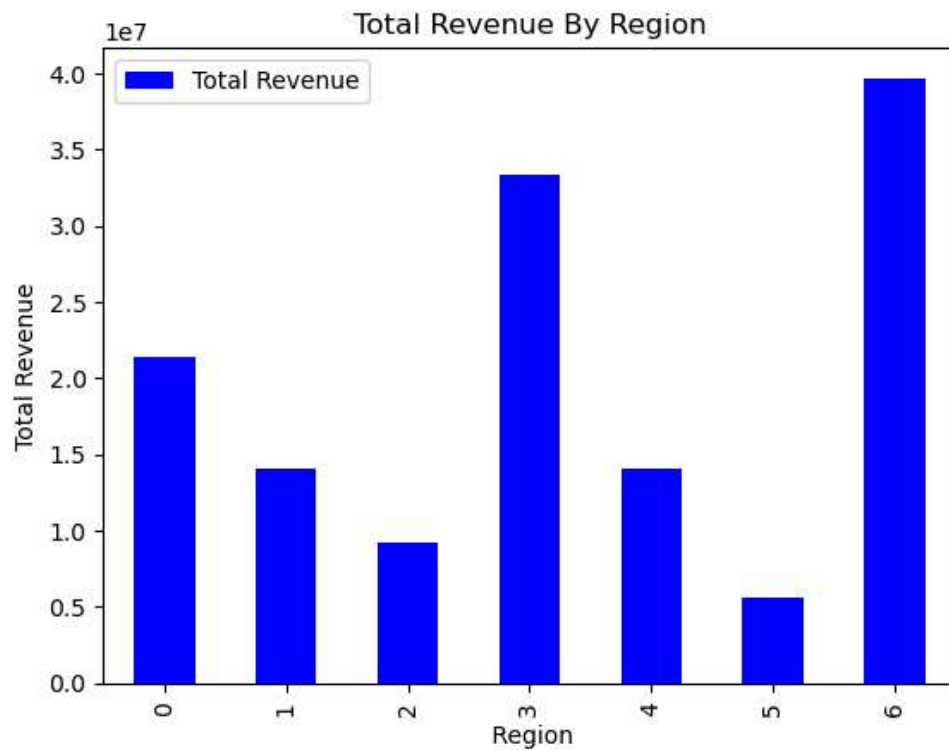
Total Revenue: \$137348768.31  
Average Order Value: \$1373487.68

```
In [29]: 1 #Relation between Unit Price and Total Revenue.
```

```
In [30]: 1 sns.scatterplot(data=data,x='Unit Price',y='Total Revenue',marker='o',size=3)
2 plt.xlabel('Unit Price')
3 plt.ylabel('Total Revenue')
4 plt.title('Scatter Plot of Unit Price Vs Total Revenue')
5 plt.show()
```



```
In [31]: 1 region=data.groupby('Region')['Total Revenue'].sum().reset_index()  
2 region.plot(kind="bar",color='blue')  
3 plt.xlabel(" Region")  
4 plt.ylabel("Total Revenue")  
5 plt.title("Total Revenue By Region")  
6 plt.show()
```





```
In [32]: 1 sns.barplot(x='Order Priority',y='Total Profit',data=data)
2 plt.xlabel(" Order Priority")
3 plt.ylabel("Total Profit")
4 plt.title("Total Revenue By Order Priority")
5 plt.show()
```



## Observation based on analysis

- Total revenue has been increasing steadily over the past few years.
- There is a positive correlation between Unit price and total revenue, indicating that higher-priced items contribute more to revenue.
- The average order value is within an acceptable range, suggesting that customers are making purchases of reasonable value.

## Recommendations:-

- Explore strategies to further increase total revenue, such as introducing premium-priced products or expanding into new markets.
- Consider optimizing pricing strategies to maximize revenue without sacrificing customer satisfaction.
- Monitor and analyze sales data regularly to identify trends and opportunities for improvement.

```
In [ ]:
```

```
1
```