

Analyzing Amazon Sales data

September 29, 2024

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

```
[2]: data= pd.read_csv('Amazon Sales data.csv')
data= pd.DataFrame(data= data)
data
```

```
[2]:
```

	Region	Country	Item Type \
0	Australia and Oceania	Tuvalu	Baby Food
1	Central America and the Caribbean	Grenada	Cereal
2	Europe	Russia	Office Supplies
3	Sub-Saharan Africa	Sao Tome and Principe	Fruits
4	Sub-Saharan Africa	Rwanda	Office Supplies
..
95	Sub-Saharan Africa	Mali	Clothes
96	Asia	Malaysia	Fruits
97	Sub-Saharan Africa	Sierra Leone	Vegetables
98	North America	Mexico	Personal Care
99	Sub-Saharan Africa	Mozambique	Household

	Sales Channel	Order Priority	Order Date	Order ID	Ship Date \
0	Offline	H	5/28/2010	669165933	6/27/2010
1	Online	C	8/22/2012	963881480	9/15/2012
2	Offline	L	05-02-2014	341417157	05-08-2014
3	Online	C	6/20/2014	514321792	07-05-2014
4	Offline	L	02-01-2013	115456712	02-06-2013
..
95	Online	M	7/26/2011	512878119	09-03-2011
96	Offline	L	11-11-2011	810711038	12/28/2011
97	Offline	C	06-01-2016	728815257	6/29/2016
98	Offline	M	7/30/2015	559427106	08-08-2015
99	Offline	L	02-10-2012	665095412	2/15/2012

	Units Sold	Unit Price	Unit Cost	Total Revenue	Total Cost	Total Profit
0	9925	255.28	159.42	2533654.00	1582243.50	951410.50
1	2804	205.70	117.11	576782.80	328376.44	248406.36

2	1779	651.21	524.96	1158502.59	933903.84	224598.75
3	8102	9.33	6.92	75591.66	56065.84	19525.82
4	5062	651.21	524.96	3296425.02	2657347.52	639077.50
..
95	888	109.28	35.84	97040.64	31825.92	65214.72
96	6267	9.33	6.92	58471.11	43367.64	15103.47
97	1485	154.06	90.93	228779.10	135031.05	93748.05
98	5767	81.73	56.67	471336.91	326815.89	144521.02
99	5367	668.27	502.54	3586605.09	2697132.18	889472.91

[100 rows x 14 columns]

```
[3]: data.head()
```

```
[3]:
```

	Region	Country	Item Type \
0	Australia and Oceania	Tuvalu	Baby Food
1	Central America and the Caribbean	Grenada	Cereal
2	Europe	Russia	Office Supplies
3	Sub-Saharan Africa	Sao Tome and Principe	Fruits
4	Sub-Saharan Africa	Rwanda	Office Supplies

	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold \
0	Offline	H	5/28/2010	669165933	6/27/2010	9925
1	Online	C	8/22/2012	963881480	9/15/2012	2804
2	Offline	L	05-02-2014	341417157	05-08-2014	1779
3	Online	C	6/20/2014	514321792	07-05-2014	8102
4	Offline	L	02-01-2013	115456712	02-06-2013	5062

	Unit Price	Unit Cost	Total Revenue	Total Cost	Total Profit
0	255.28	159.42	2533654.00	1582243.50	951410.50
1	205.70	117.11	576782.80	328376.44	248406.36
2	651.21	524.96	1158502.59	933903.84	224598.75
3	9.33	6.92	75591.66	56065.84	19525.82
4	651.21	524.96	3296425.02	2657347.52	639077.50

```
[4]: data.columns
```

```
[4]: 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')
```

```
[5]: data.shape
```

```
[5]: (100, 14)
```

```
[6]: data.size
```

[6]: 1400

[7]: 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
```

[8]: data.describe()

```
[8]:
```

	Order ID	Units Sold	Unit Price	Unit Cost	Total Revenue	\
count	1.000000e+02	100.000000	100.000000	100.000000	1.000000e+02	
mean	5.550204e+08	5128.710000	276.761300	191.048000	1.373488e+06	
std	2.606153e+08	2794.484562	235.592241	188.208181	1.460029e+06	
min	1.146066e+08	124.000000	9.330000	6.920000	4.870260e+03	
25%	3.389225e+08	2836.250000	81.730000	35.840000	2.687212e+05	
50%	5.577086e+08	5382.500000	179.880000	107.275000	7.523144e+05	
75%	7.907551e+08	7369.000000	437.200000	263.330000	2.212045e+06	
max	9.940222e+08	9925.000000	668.270000	524.960000	5.997055e+06	

	Total Cost	Total Profit
count	1.000000e+02	1.000000e+02
mean	9.318057e+05	4.416820e+05
std	1.083938e+06	4.385379e+05
min	3.612240e+03	1.258020e+03
25%	1.688680e+05	1.214436e+05
50%	3.635664e+05	2.907680e+05
75%	1.613870e+06	6.358288e+05
max	4.509794e+06	1.719922e+06

```
[9]: data.isna().sum()
```

```
[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
```

```
[10]: data.dtypes
```

```
[10]: Region          object
     Country         object
     Item Type       object
     Sales Channel   object
     Order Priority   object
     Order Date      object
     Order ID        int64
     Ship Date       object
     Units Sold      int64
     Unit Price      float64
     Unit Cost       float64
     Total Revenue   float64
     Total Cost      float64
     Total Profit    float64
     dtype: object
```

```
[11]: data = data.astype({'Ship Date': 'datetime64[ns]', 'Order Date':
    ↪ 'datetime64[ns]'})
```

```
[12]: data.dtypes
```

```
[12]: Region          object
     Country         object
     Item Type       object
     Sales Channel   object
     Order Priority   object
     Order Date      datetime64[ns]
```

```
Order ID                int64
Ship Date               datetime64[ns]
Units Sold              int64
Unit Price              float64
Unit Cost               float64
Total Revenue           float64
Total Cost              float64
Total Profit            float64
dtype: object
```

```
[13]: plt.figure(figsize=(10,20))
      sns.heatmap(data.isnull()) # NO ANY NULL VALUE PRESENT IN OUR DATASET.
```

```
[13]: <AxesSubplot: >
```



```
[14]: test = data.iloc[0, 12] = np.nan    # ADDING NULL VALUE JUST FOR DEMO
      test
```

```
[14]: nan
```

```
[15]: plt.figure(figsize=(10,20))
      sns.heatmap(data.isnull(),annot= True) #NULL VALUE FOUND IN 'TOTAL COST' COLUMN
```

```
[15]: <AxesSubplot: >
```



```
[16]: data = data.fillna(data.mean()) #FILL MEAN WHERE NULL VALUE PRESENT
```

C:\Users\shory\AppData\Local\Temp\ipykernel_3168\1872784004.py:1: FutureWarning: DataFrame.mean and DataFrame.median with numeric_only=None will include datetime64 and datetime64tz columns in a future version.

```
data = data.fillna(data.mean()) #FILL MEAN WHERE NULL VALUE PRESENT
```

C:\Users\shory\AppData\Local\Temp\ipykernel_3168\1872784004.py:1: FutureWarning: The default value of numeric_only in DataFrame.mean is deprecated. In a future version, it will default to False. In addition, specifying 'numeric_only=None' is deprecated. Select only valid columns or specify the value of numeric_only to silence this warning.

```
data = data.fillna(data.mean()) #FILL MEAN WHERE NULL VALUE PRESENT
```

```
[17]: data['Total Cost']= data['Total Cost'].astype('Float64')
data
```

```
[17]:
```

	Region	Country	Item Type \
0	Australia and Oceania	Tuvalu	Baby Food
1	Central America and the Caribbean	Grenada	Cereal
2	Europe	Russia	Office Supplies
3	Sub-Saharan Africa	Sao Tome and Principe	Fruits
4	Sub-Saharan Africa	Rwanda	Office Supplies
..
95	Sub-Saharan Africa	Mali	Clothes
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97	Sub-Saharan Africa	Sierra Leone	Vegetables
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	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold \
0	Offline	H	2010-05-28	669165933	2010-06-27	9925
1	Online	C	2012-08-22	963881480	2012-09-15	2804
2	Offline	L	2014-05-02	341417157	2014-05-08	1779
3	Online	C	2014-06-20	514321792	2014-07-05	8102
4	Offline	L	2013-02-01	115456712	2013-02-06	5062
..
95	Online	M	2011-07-26	512878119	2011-09-03	888
96	Offline	L	2011-11-11	810711038	2011-12-28	6267
97	Offline	C	2016-06-01	728815257	2016-06-29	1485
98	Offline	M	2015-07-30	559427106	2015-08-08	5767
99	Offline	L	2012-02-10	665095412	2012-02-15	5367

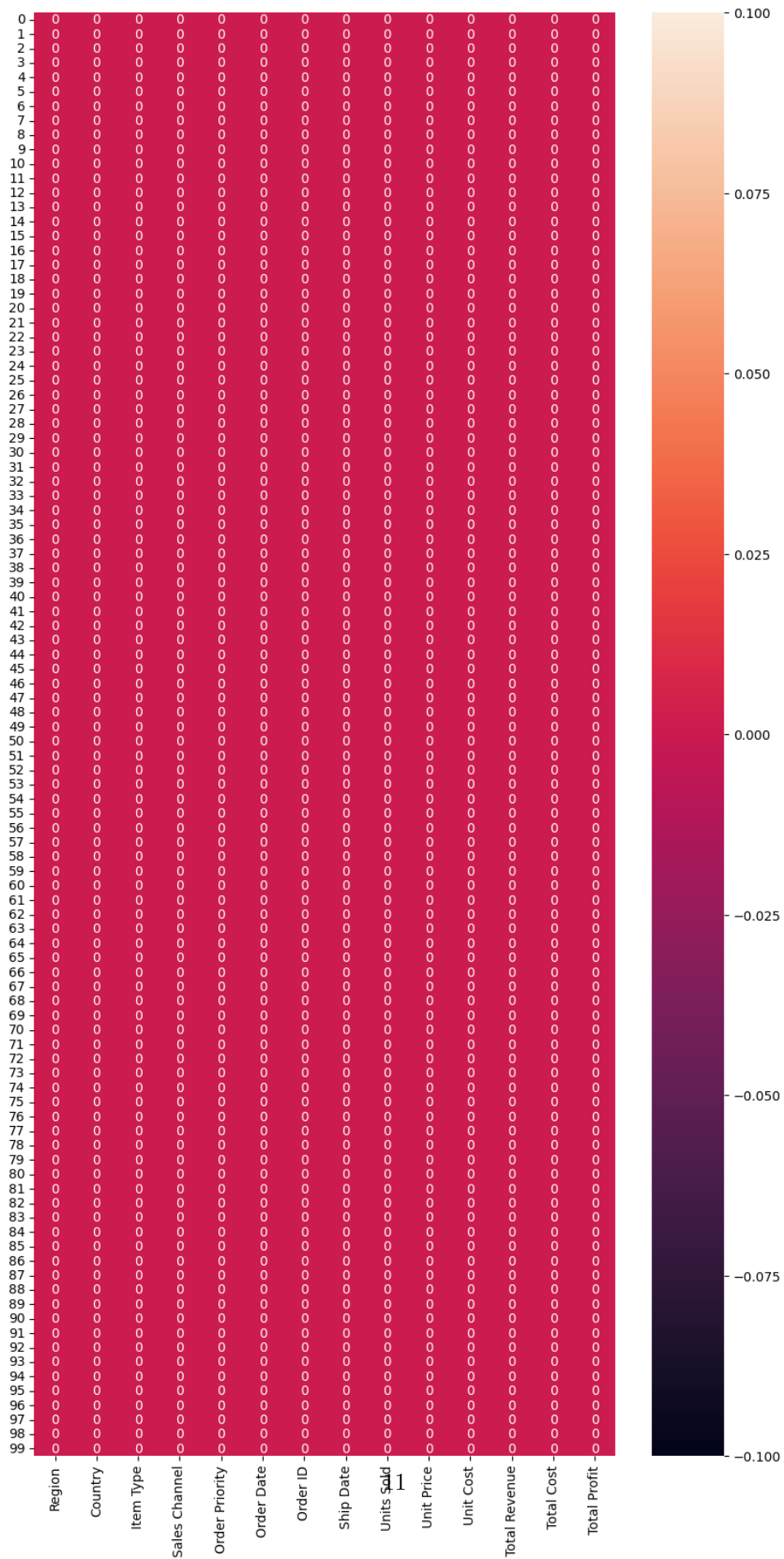
	Unit Price	Unit Cost	Total Revenue	Total Cost	Total Profit
0	255.28	159.42	2533654.00	925235.620303	951410.50
1	205.70	117.11	576782.80	328376.44	248406.36

2	651.21	524.96	1158502.59	933903.84	224598.75
3	9.33	6.92	75591.66	56065.84	19525.82
4	651.21	524.96	3296425.02	2657347.52	639077.50
..
95	109.28	35.84	97040.64	31825.92	65214.72
96	9.33	6.92	58471.11	43367.64	15103.47
97	154.06	90.93	228779.10	135031.05	93748.05
98	81.73	56.67	471336.91	326815.89	144521.02
99	668.27	502.54	3586605.09	2697132.18	889472.91

[100 rows x 14 columns]

```
[18]: plt.figure(figsize=(10,20))
      sns.heatmap(data.isnull(),annot= True)    # NO NULL VALUES
```

```
[18]: <AxesSubplot: >
```



```
[19]: data.head(3)
```

```
[19]:
```

	Region	Country	Item Type	Sales Channel	\
0	Australia and Oceania	Tuvalu	Baby Food	Offline	
1	Central America and the Caribbean	Grenada	Cereal	Online	
2	Europe	Russia	Office Supplies	Offline	

	Order Priority	Order Date	Order ID	Ship Date	Units Sold	Unit Price	\
0	H	2010-05-28	669165933	2010-06-27	9925	255.28	
1	C	2012-08-22	963881480	2012-09-15	2804	205.70	
2	L	2014-05-02	341417157	2014-05-08	1779	651.21	

	Unit Cost	Total Revenue	Total Cost	Total Profit
0	159.42	2533654.00	925235.620303	951410.50
1	117.11	576782.80	328376.44	248406.36
2	524.96	1158502.59	933903.84	224598.75

Data Analysis:

Queries:

Which regions have the highest total sales revenue?

What is the average unit price and unit cost for each item type?

Which country has the highest total profit?

How does the sales channel affect the order priority distribution?

What is the average order processing time (duration between order and ship dates) for each sales channel?

Which item types have the highest and lowest total sales?

How does the order priority vary across different regions?

What is the correlation between unit price and total profit?

Are there any seasonal trends or patterns in the sales data?

How does the number of units sold vary across different countries?

1- Which regions have the highest total sales revenue?

```
[20]: Highest_Total_Revenue= data.groupby(data['Region'])['Total Revenue'].sum()  
Highest_Total_Revenue.idxmax()
```

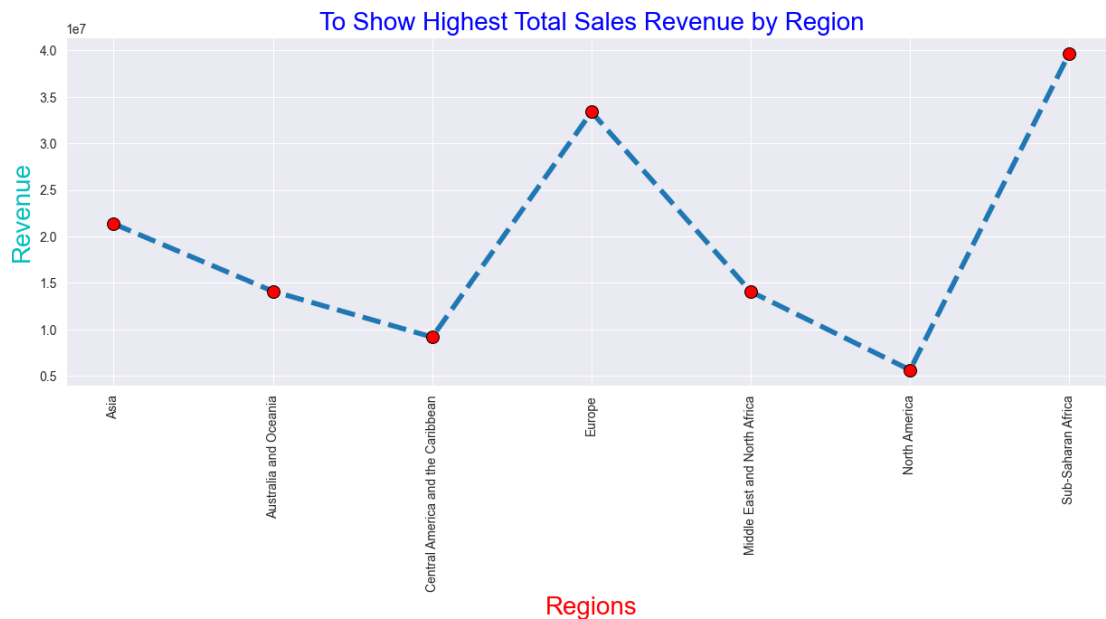
```
[20]: 'Sub-Saharan Africa'
```

```
[21]: group_data= data.groupby(data['Region'])['Total Revenue'].sum()  
sns.set_style('darkgrid')
```

```
plt.figure(figsize=(15,5))
sns.lineplot(data= group_data, linestyle= '--' ,linewidth= 4 , marker= 'o',
             ↪markersize= 10,
             markerfacecolor='red', markeredgecolor='black')

plt.xticks(rotation= 90)
plt.title('To Show Highest Total Sales Revenue by Region', fontsize= 20, color=
             ↪'Blue')
plt.xlabel('Regions', fontsize= 20, color= 'red')
plt.ylabel('Revenue', fontsize= 20, color= 'c')
plt.show()

# 1e7 is scientific form. it means 1*10**7= 10,000,000
```



2- What is the average unit price and unit cost for each item type?

```
[22]: Avg_Unit_Price= data.groupby(data['Item Type'])['Unit Price'].mean()
Avg_Unit_Cost= data.groupby(data['Item Type'])['Unit Cost'].mean()

Avg_Price_Cost= pd.DataFrame({'Average Unit Price': Avg_Unit_Price,
                             'Average Unit Cost': Avg_Unit_Cost})

Avg_Price_Cost
```

```
[22]:
```

	Average Unit Price	Average Unit Cost
Item Type		

Baby Food	255.28	159.42
Beverages	47.45	31.79
Cereal	205.70	117.11
Clothes	109.28	35.84
Cosmetics	437.20	263.33
Fruits	9.33	6.92
Household	668.27	502.54
Meat	421.89	364.69
Office Supplies	651.21	524.96
Personal Care	81.73	56.67
Snacks	152.58	97.44
Vegetables	154.06	90.93

3- Which country has the highest total profit?

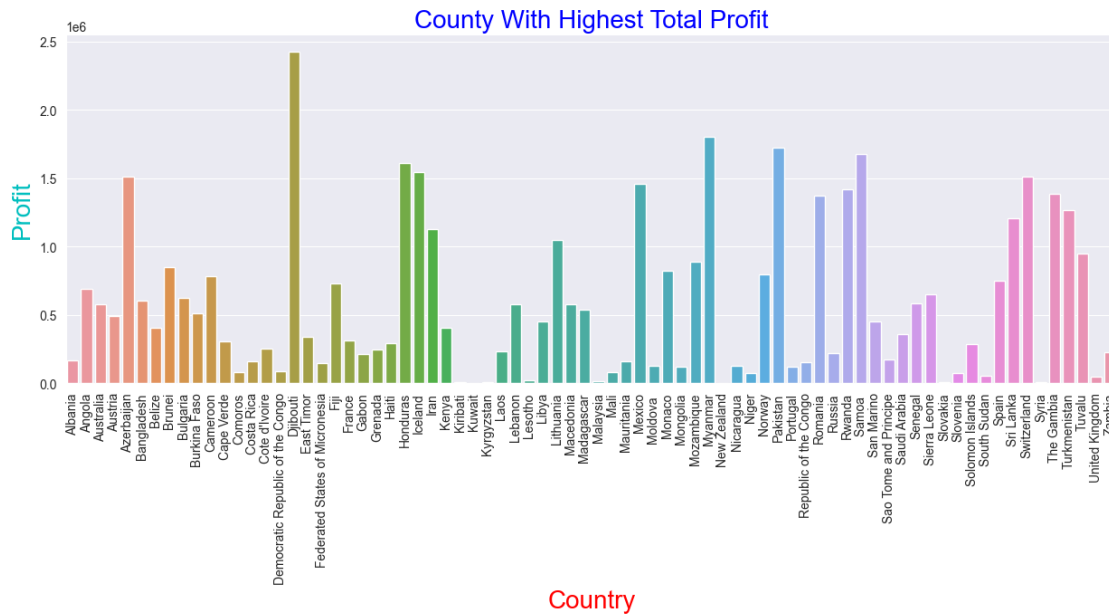
```
[23]: Total_Profit_By_Company= data.groupby(data['Country']) ['Total Profit'].sum()
Highest_Total_Profit_Country= Total_Profit_By_Company.idxmax()

print("Country with the highest total profit:",Highest_Total_Profit_Country)
```

Country with the highest total profit: Djibouti

```
[24]: group_data= data.groupby(data['Country']) ['Total Profit'].sum()
sns.set_style('darkgrid')
plt.figure(figsize=(15,5))
sns.barplot(x= group_data.index, y= group_data )

plt.xticks(rotation= 90)
plt.title('Country With Highest Total Profit', fontsize= 20, color= 'Blue')
plt.xlabel('Country', fontsize= 20, color= 'red')
plt.ylabel('Profit', fontsize= 20, color= 'c')
plt.show()
```



4- How does the sales channel affect the order priority distribution?

```
[25]: Sales_Channel_Order_Priority_Distribution= data.groupby(data['Sales Channel']).\n      ↪['Order Priority'].value_counts()\nSales_Channel_Order_Priority_Distribution
```

```
[25]: Sales Channel  Order Priority\nOffline            H            17\n                C            13\n                L            12\n                M             8\nOnline             L            15\n                H            13\n                M            13\n                C             9
```

Name: Order Priority, dtype: int64

```
[26]: Sales_Channel_Order_Priority_Distribution = data.groupby(['Sales Channel',\n      ↪'Order Priority'])['Order Priority'].count()\n\n# Reset the index to convert the grouped data into a DataFrame\nSales_Channel_Order_Priority_Distribution =\n      ↪Sales_Channel_Order_Priority_Distribution.reset_index(name='Count')\n\n# Set the style\nsns.set_style('darkgrid')
```

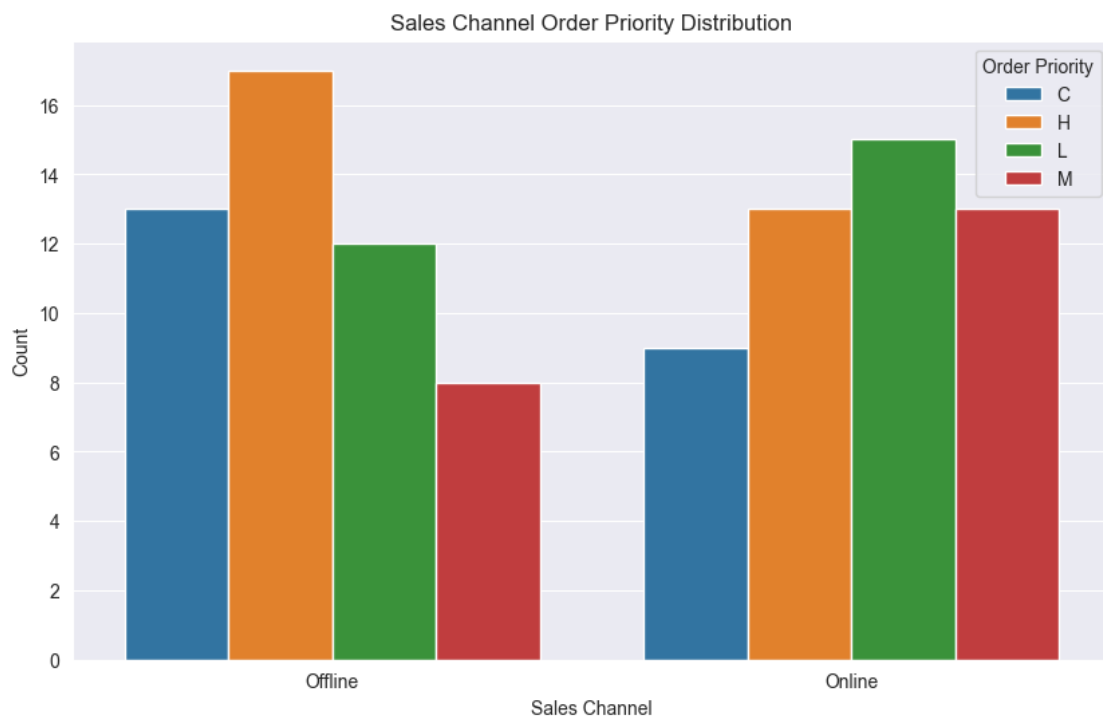
```

# Create the bar plot
plt.figure(figsize=(10, 6))
sns.barplot(x='Sales Channel', y='Count', hue='Order Priority',
            data=Sales_Channel_Order_Priority_Distribution)

# Add labels and title
plt.xlabel('Sales Channel')
plt.ylabel('Count')
plt.title('Sales Channel Order Priority Distribution')

# Display the plot
plt.show()

```



5- What is the average order processing time (duration between order and ship dates) for each sales channel?

```

[27]: data['Processing Time']= data['Ship Date']-data['Order Date']

Avg_Processing_Time= data.groupby(data['Sales Channel'])['Processing Time'].
    mean()
Avg_Processing_Time

```

```

[27]: Sales Channel
Offline    23 days 04:48:00

```

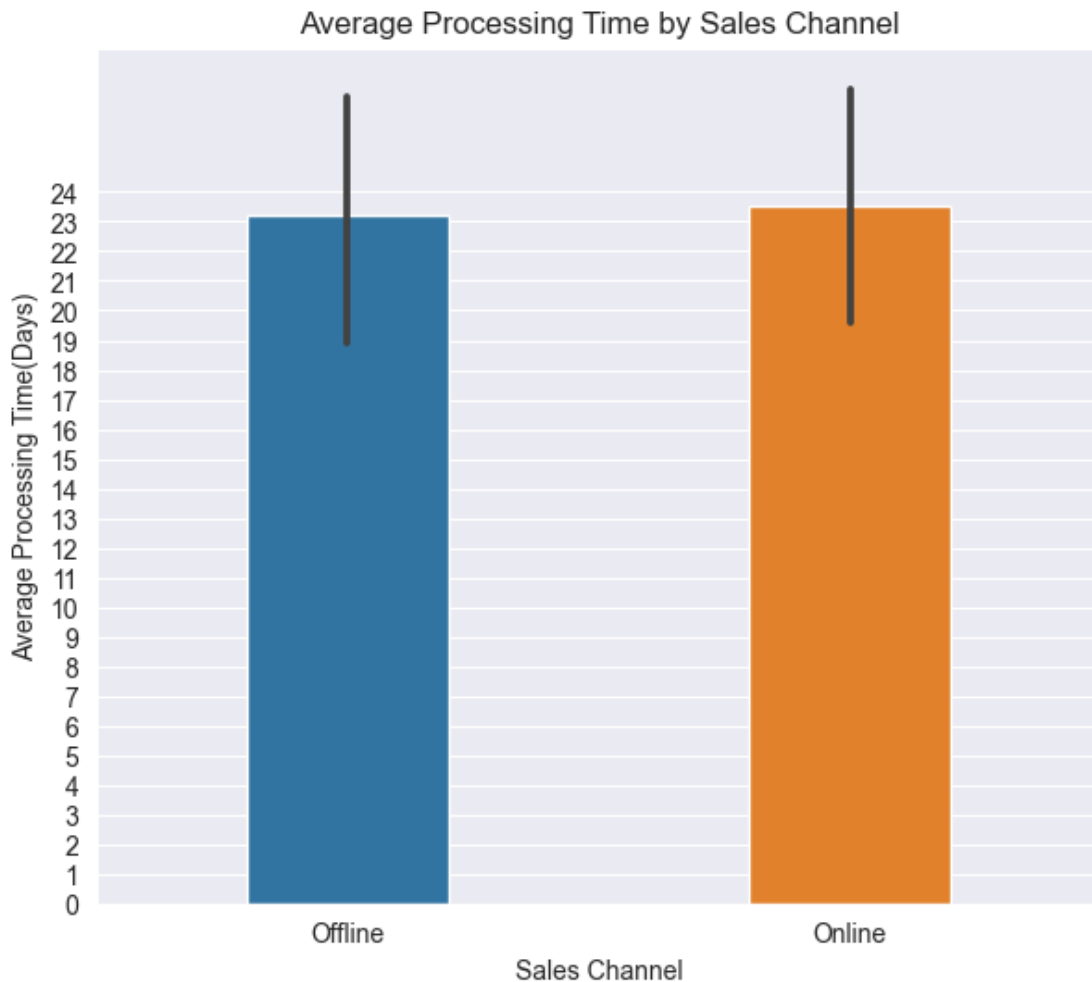

Online 23 days 12:28:48
Name: Processing Time, dtype: timedelta64[ns]

```
[28]: plt.figure(figsize=(7, 6))

sns.barplot(data= data, x= data['Sales Channel'], y=data['Processing Time'].dt.
    ↪days, width= 0.4 )

plt.title('Average Processing Time by Sales Channel')
plt.xlabel('Sales Channel')
plt.yticks(np.arange(0,25,1))
plt.ylabel('Average Processing Time(Days)')

plt.show()
```



6- Which item types have the highest and lowest total sales?

```
[29]: group_item_type= data.groupby(data['Item Type'])['Total Revenue'].sum()

highest_sales_revenue_item_type= group_item_type.idxmax()
lowest_sales_revenue_item_type= group_item_type.idxmin()

print("{ 'Highest Sales Revenue By Item Type':",
      ↪highest_sales_revenue_item_type, "\n'Lowest Sales Revenue By Item Type':",
      ↪lowest_sales_revenue_item_type, "}")
```

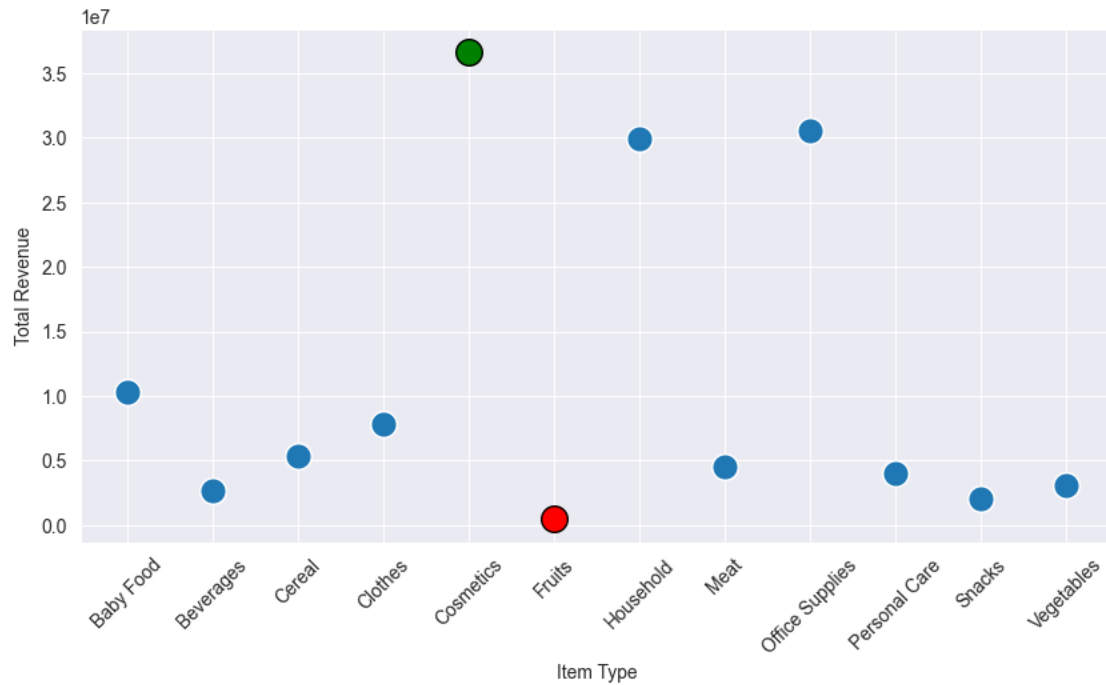
```
{ 'Highest Sales Revenue By Item Type': Cosmetics
  'Lowest Sales Revenue By Item Type': Fruits }
```

```
[30]: plt.figure(figsize=(10,5))

# Highlight Max Value
sns.scatterplot(x=group_item_type.index, y=group_item_type, s=200)
max_index = group_item_type.idxmax()
plt.scatter(x=max_index, y=group_item_type[max_index], s=200, color='Green',
            ↪edgecolor='black')

# Highlight the minimum value
min_index = group_item_type.idxmin()
plt.scatter(x=min_index, y=group_item_type[min_index], s=200, color='RED',
            ↪edgecolor='black')

plt.yticks(rotation= 0)
plt.xticks(rotation= 45)
plt.show()
```



7- How does the order priority vary across different regions?

```
[31]: Diff_regions_by_order_priority= data.groupby(data['Region'])['Order Priority'].
      ↪value_counts()
      Diff_regions_by_order_priority
```

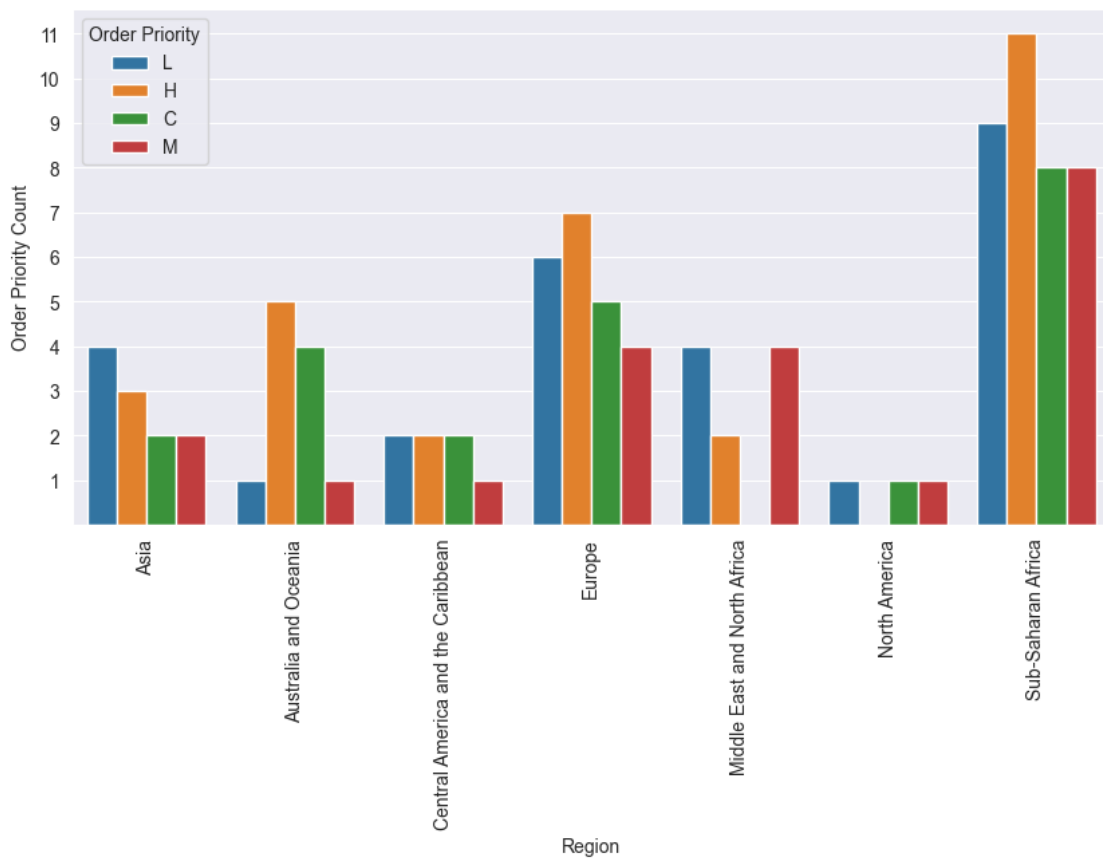
```
[31]: Region          Order Priority
Asia                L              4
                H              3
                C              2
                M              2
Australia and Oceania  H              5
                C              4
                L              1
                M              1
Central America and the Caribbean  C              2
                H              2
                L              2
                M              1
Europe              H              7
                L              6
                C              5
                M              4
Middle East and North Africa  L              4
                M              4
```

	H	2
North America	C	1
	L	1
	M	1
Sub-Saharan Africa	H	11
	L	9
	C	8
	M	8

Name: Order Priority, dtype: int64

```
[32]: Diff_regions_by_order_priority= data.groupby(data['Region'])['Order Priority'].
      ↪value_counts().reset_index(name='Order Priority Count')
plt.figure(figsize= (10,5))
sns.barplot(data= Diff_regions_by_order_priority, x= 'Region', y= 'Order_
      ↪Priority Count', hue= 'Order Priority')
plt.xticks(rotation= 90)
plt.yticks(np.arange(1,12,1))

plt.show()
```



8- What is the correlation between unit price and total profit?

```
[33]: Correlation_Unit_Price_Total_Profit= data['Unit Price'].corr(data['Total_
      ↪Profit'])

      print("Correlation between Unit Price and Total Profit:",
      ↪Correlation_Unit_Price_Total_Profit)
```

Correlation between Unit Price and Total Profit: 0.5573652488121267

```
[34]: plt.figure(figsize=(4,2))
      plt.scatter(x= Correlation_Unit_Price_Total_Profit, y=
      ↪Correlation_Unit_Price_Total_Profit, s= 200, color= 'RED' )
      plt.xticks(np.arange(-1,2,0.5))
      plt.yticks(np.arange(-1,2,0.5))
      plt.title('Correlation_Unit_Price_Total_Profit')

      plt.show
```

```
[34]: <function matplotlib.pyplot.show(close=None, block=None)>
```



9- Are there any seasonal trends or patterns in the sales data?

```
[35]: month_names= {1: 'JAN',
                    2: 'FEB',
                    3: 'MAR',
                    4: 'APR',
                    5: 'MAY',
                    6: 'JUN',
                    7: 'JUL',
                    8: 'AUG',
                    9: 'SEPT',
                    10: 'OCT',
```

```

        11: 'NOV',
        12: 'DEC'}
monthly_sales = data.groupby(data['Order Date'].dt.month)['Total Revenue'].sum()
monthly_sales.index= monthly_sales.index.map(month_names)

monthly_sales

```

```

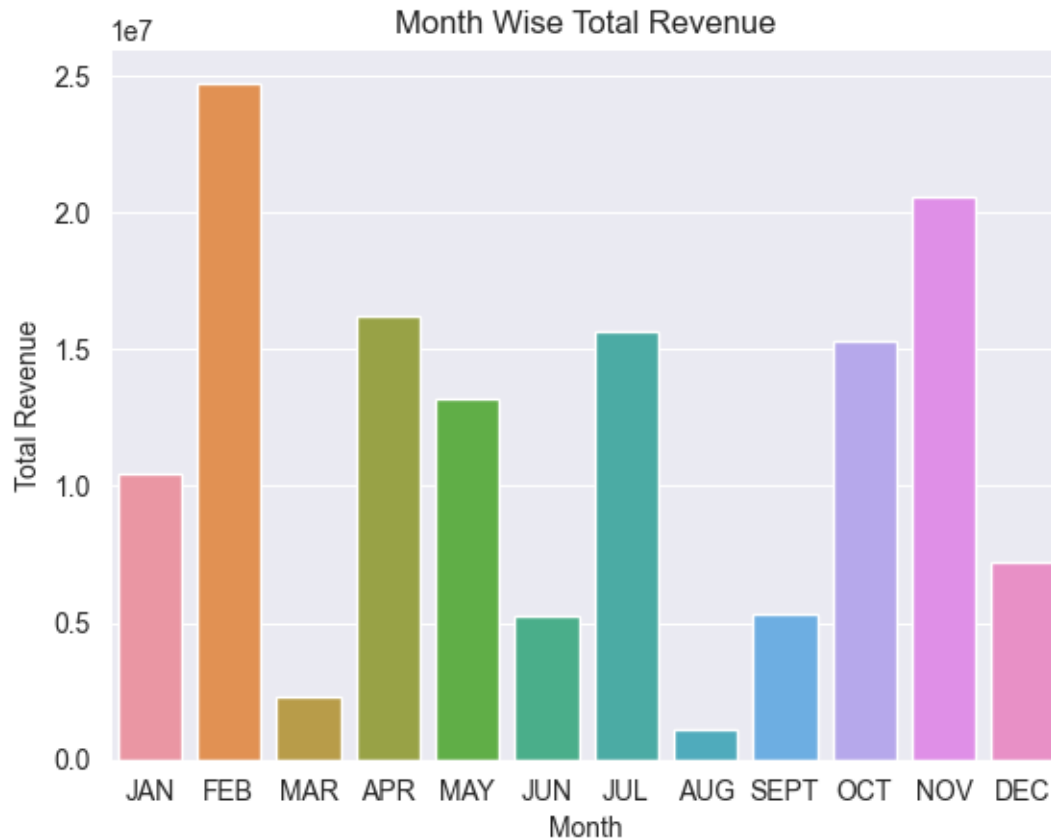
[35]: Order Date
      JAN      10482467.12
      FEB      24740517.77
      MAR       2274823.87
      APR      16187186.33
      MAY      13215739.99
      JUN       5230325.77
      JUL      15669518.50
      AUG       1128164.91
      SEPT      5314762.56
      OCT      15287576.61
      NOV      20568222.76
      DEC       7249462.12
      Name: Total Revenue, dtype: float64

```

```

[36]: sns.barplot(x= monthly_sales.index, y= monthly_sales)
      plt.title('Month Wise Total Revenue')
      plt.xlabel('Month')
      plt.ylabel('Total Revenue')
      plt.show()

```



10- How does the number of units sold vary across different countries?

```
[37]: Diff_countries_by_unit_sold= data.groupby(data['Country'])['Units Sold'].sum().
      ↪reset_index(name= 'Unit Sold')
      pd.set_option('display.max_rows',None)
      Diff_countries_by_unit_sold
```

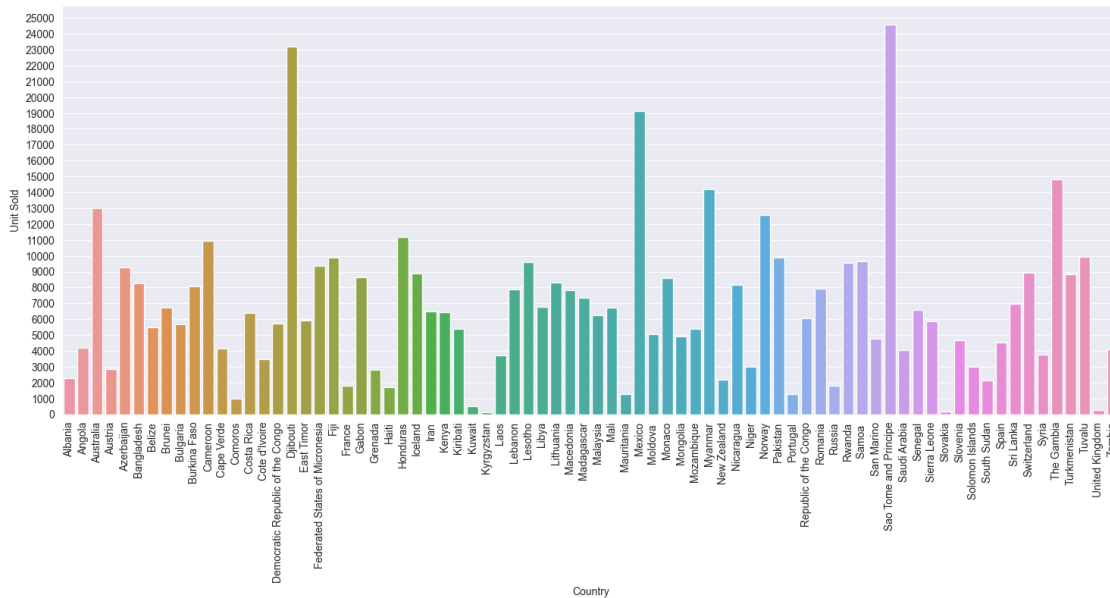
```
[37]:
```

	Country	Unit Sold
0	Albania	2269
1	Angola	4187
2	Australia	12995
3	Austria	2847
4	Azerbaijan	9255
5	Bangladesh	8263
6	Belize	5498
7	Brunei	6708
8	Bulgaria	5660
9	Burkina Faso	8082
10	Cameroon	10948
11	Cape Verde	4168

12	Comoros	962
13	Costa Rica	6409
14	Cote d'Ivoire	3482
15	Democratic Republic of the Congo	5741
16	Djibouti	23198
17	East Timor	5908
18	Federated States of Micronesia	9379
19	Fiji	9905
20	France	1815
21	Gabon	8656
22	Grenada	2804
23	Haiti	1705
24	Honduras	11199
25	Iceland	8867
26	Iran	6489
27	Kenya	6457
28	Kiribati	5398
29	Kuwait	522
30	Kyrgyzstan	124
31	Laos	3732
32	Lebanon	7884
33	Lesotho	9606
34	Libya	6789
35	Lithuania	8287
36	Macedonia	7842
37	Madagascar	7342
38	Malaysia	6267
39	Mali	6710
40	Mauritania	1266
41	Mexico	19143
42	Moldova	5070
43	Monaco	8614
44	Mongolia	4901
45	Mozambique	5367
46	Myanmar	14180
47	New Zealand	2187
48	Nicaragua	8156
49	Niger	3015
50	Norway	12574
51	Pakistan	9892
52	Portugal	1273
53	Republic of the Congo	6070
54	Romania	7910
55	Russia	1779
56	Rwanda	9539
57	Samoa	9654
58	San Marino	4750

59	Sao Tome and Principe	24568
60	Saudi Arabia	4063
61	Senegal	6593
62	Sierra Leone	5890
63	Slovakia	171
64	Slovenia	4660
65	Solomon Islands	2974
66	South Sudan	2125
67	Spain	4513
68	Sri Lanka	6952
69	Switzerland	8934
70	Syria	3784
71	The Gambia	14813
72	Turkmenistan	8840
73	Tuvalu	9925
74	United Kingdom	282
75	Zambia	4085

```
[38]: plt.figure(figsize= (18,7))
sns.barplot( data= Diff_countries_by_unit_sold, x= 'Country', y= 'Unit Sold')
plt.xticks(rotation= 90)
plt.yticks(np.arange(0,26000,1000))
plt.show()
```



Other Queries:

How does the total sales revenue vary across different countries?

What is the distribution of unit prices for each item type?

Which sales channel has the highest average unit price?

Are there any outliers in the total cost distribution?

How does the total profit vary across different item types?

What is the average order processing time for each country?

Which region has the highest average total revenue per order?

Is there a relationship between the number of units sold and the total profit?

How does the order priority vary based on the item type?

Are there any trends or patterns in the order dates?

11- How does the total sales revenue vary across different countries?

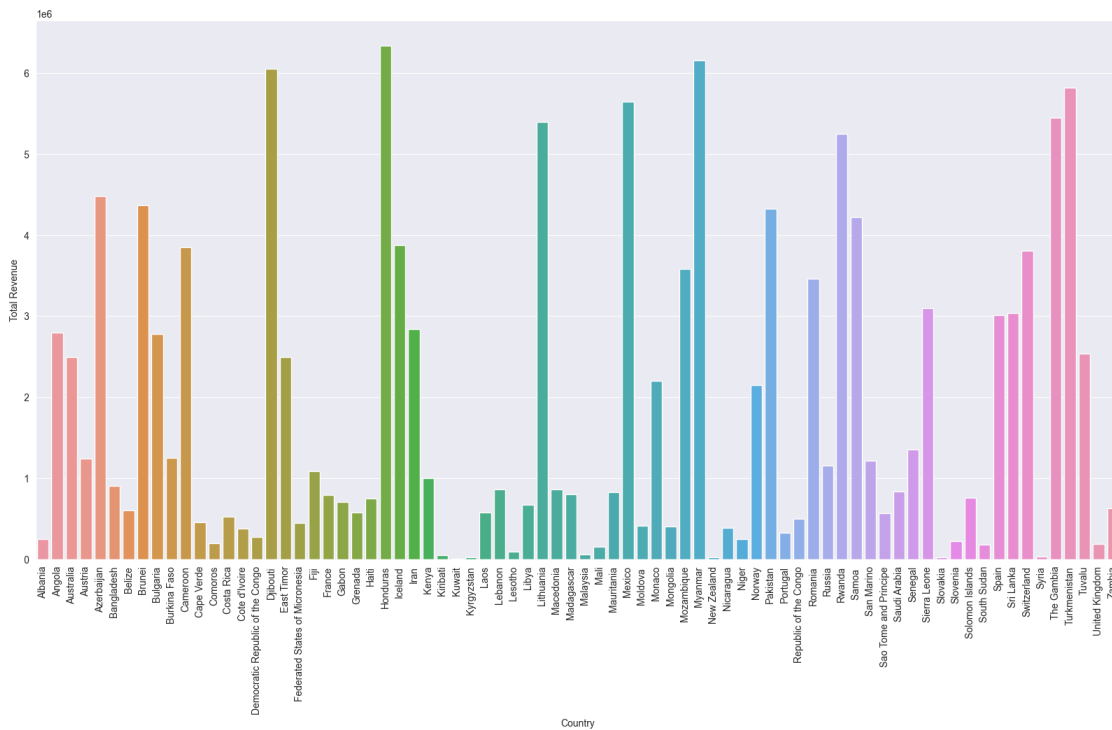
```
[49]: sales_revenue_by_countries= data.groupby(data['Country']) ['Total Revenue'].
      ↪sum().reset_index(name= 'Total Revenue')
sales_revenue_by_countries
```

```
[49]:
```

	Country	Total Revenue
0	Albania	247956.32
1	Angola	2798046.49
2	Australia	2489933.49
3	Austria	1244708.40
4	Azerbaijan	4478800.21
5	Bangladesh	902980.64
6	Belize	600821.44
7	Brunei	4368316.68
8	Bulgaria	2779199.71
9	Burkina Faso	1245112.92
10	Cameroon	3851030.28
11	Cape Verde	455479.04
12	Comoros	197883.40
13	Costa Rica	523807.57
14	Cote d'Ivoire	380512.96
15	Democratic Republic of the Congo	272410.45
16	Djibouti	6052890.86
17	East Timor	2492526.12
18	Federated States of Micronesia	445033.55
19	Fiji	1082418.40
20	France	793518.00
21	Gabon	707454.88
22	Grenada	576782.80
23	Haiti	745426.00
24	Honduras	6336545.48
25	Iceland	3876652.40
26	Iran	2836990.80
27	Kenya	994765.42

28	Kiribati	50363.34
29	Kuwait	4870.26
30	Kyrgyzstan	19103.44
31	Laos	574951.92
32	Lebanon	861563.52
33	Lesotho	89623.98
34	Libya	674635.57
35	Lithuania	5396577.27
36	Macedonia	856973.76
37	Madagascar	802333.76
38	Malaysia	58471.11
39	Mali	151359.90
40	Mauritania	824431.86
41	Mexico	5643356.55
42	Moldova	414371.10
43	Monaco	2198981.92
44	Mongolia	400558.73
45	Mozambique	3586605.09
46	Myanmar	6161257.90
47	New Zealand	20404.71
48	Nicaragua	387002.20
49	Niger	246415.95
50	Norway	2144969.80
51	Pakistan	4324782.40
52	Portugal	324971.44
53	Republic of the Congo	496101.10
54	Romania	3458252.00
55	Russia	1158502.59
56	Rwanda	5253769.42
57	Samoa	4220728.80
58	San Marino	1212580.00
59	Sao Tome and Principe	565780.92
60	Saudi Arabia	835759.10
61	Senegal	1356180.10
62	Sierra Leone	3097359.15
63	Slovakia	26344.26
64	Slovenia	221117.00
65	Solomon Islands	759202.72
66	South Sudan	173676.25
67	Spain	3015902.51
68	Sri Lanka	3039414.40
69	Switzerland	3808901.49
70	Syria	35304.72
71	The Gambia	5449517.95
72	Turkmenistan	5822036.20
73	Tuvalu	2533654.00
74	United Kingdom	188452.14

```
[58]: plt.figure(figsize=(20,10))
sns.barplot(x= sales_revenue_by_countries['Country'], y=
↳sales_revenue_by_countries['Total Revenue'])
plt.xticks(rotation= 90)
plt.show()
```



12- What is the distribution of unit prices for each item type?

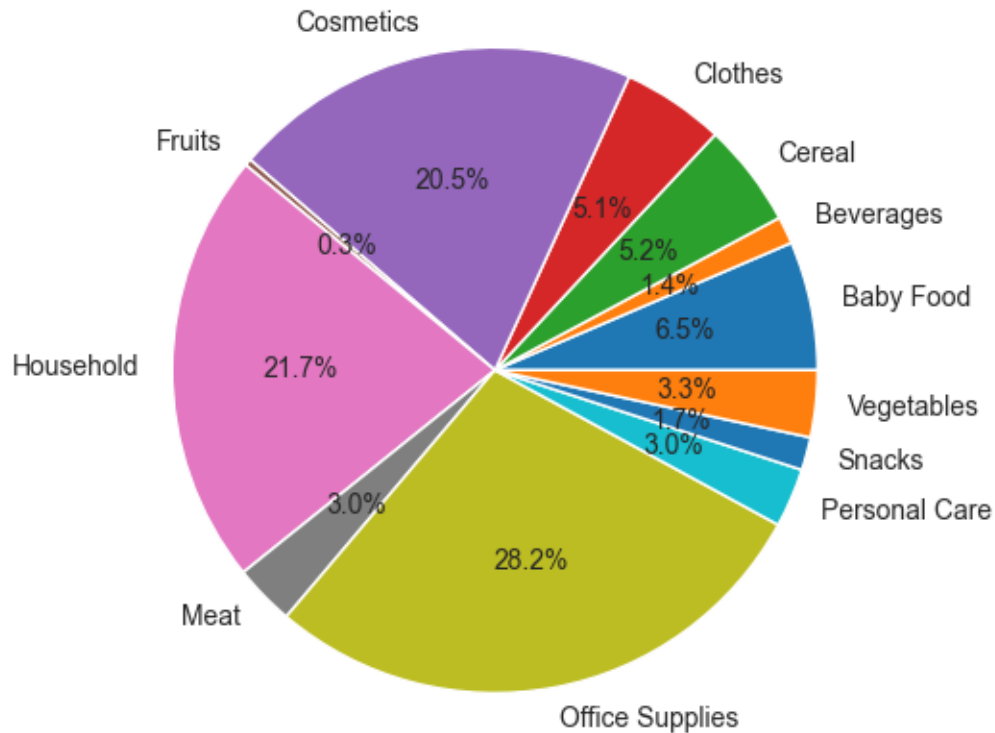
```
[81]: unit_price_and_item_type_distribution= data.groupby(data['Item Type'])['Unit_
↳Price'].sum().reset_index(name= 'Unit Price')
unit_price_and_item_type_distribution
```

```
[81]:
```

	Item Type	Unit Price
0	Baby Food	1786.96
1	Beverages	379.60
2	Cereal	1439.90
3	Clothes	1420.64
4	Cosmetics	5683.60
5	Fruits	93.30
6	Household	6014.43
7	Meat	843.78
8	Office Supplies	7814.52

9	Personal Care	817.30
10	Snacks	457.74
11	Vegetables	924.36

```
[114]: plt.pie(x= unit_price_and_item_type_distribution['Unit Price'], labels=
        ↪unit_price_and_item_type_distribution['Item Type'],autopct='%1.1f%%')
plt.axis('equal')
plt.show()
```



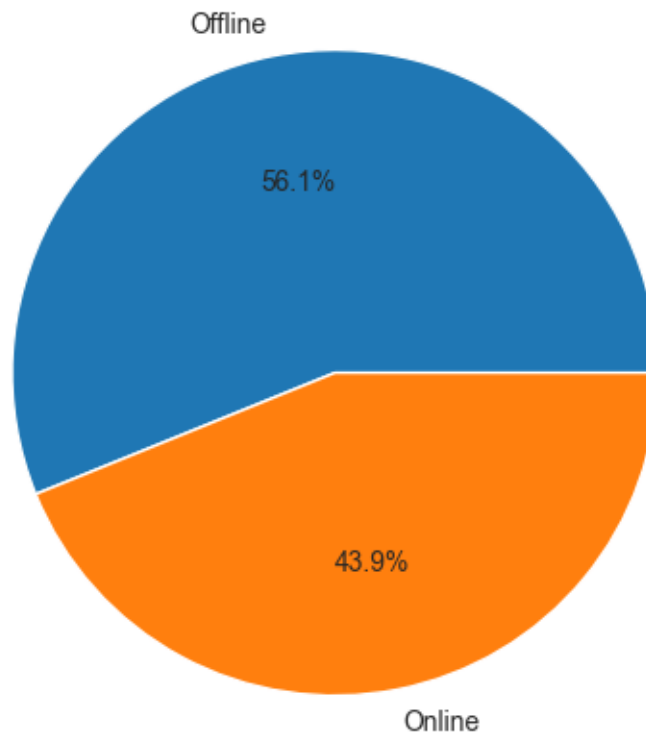
13- Which sales channel has the highest average unit price?

```
[122]: Highest_avg_unit_price_for_sales_channel= data.groupby(data['Sales Channel'])
        ↪['Unit Price'].mean().reset_index(name= 'new')
Highest_avg_unit_price_for_sales_channel
```

```
[122]: Sales Channel    new
0      Offline  310.7206
1      Online   242.8020
```

```
[130]: plt.pie(x=
        ↪Highest_avg_unit_price_for_sales_channel['new'],labels=Highest_avg_unit_price_for_sales_cha
        ↪Channel', autopct= '%1.1f%%')
plt.axis('equal')
```

```
plt.show()
```



14- Are there any outliers in the total cost distribution?

```
[42]: q1= data['Total Cost'].quantile(0.25)
      q3= data['Total Cost'].quantile(0.75)

      iqr= q3-q1

      lower_fence= q1-1.5*iqr
      upper_fence= q3+1.5*iqr

      outliers= data[(data['Total Cost']<lower_fence)| (data['Total_C
↵Cost']>upper_fence)].reset_index(drop= True)
      outliers
```

```
[42]:
```

	Region	Country	Item Type	\
0	Central America and the Caribbean	Honduras	Household	
1	Asia	Myanmar	Household	
2	Europe	Lithuania	Office Supplies	

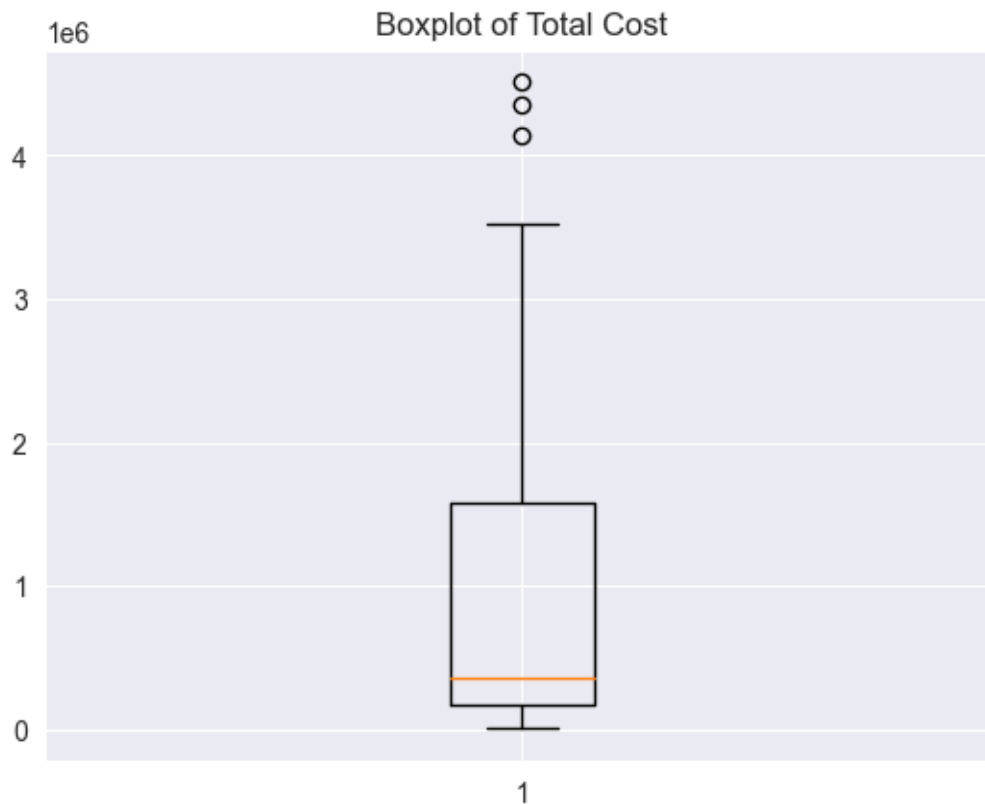
	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold	\
0	Offline	H	2017-02-08	522840487	2017-02-13	8974	

1	Offline	H	2015-01-16	177713572	2015-03-01	8250
2	Offline	H	2010-10-24	166460740	2010-11-17	8287

	Unit Price	Unit Cost	Total Revenue	Total Cost	Total Profit \
0	668.27	502.54	5997054.98	4509793.96	1487261.02
1	668.27	502.54	5513227.50	4145955.0	1367272.50
2	651.21	524.96	5396577.27	4350343.52	1046233.75

	Processing Time
0	5 days
1	44 days
2	24 days

```
[134]: plt.boxplot(data['Total Cost'])
plt.title('Boxplot of Total Cost')
plt.show()
```



15- How does the total profit vary across different item types?

```
[43]: total_profit_and_diff_item_types= data.groupby(data['Item Type'])['Total_
Profit'].sum().reset_index(name='Total Profit')
```

```
total_profit_and_diff_item_types
```

```
[43]:
```

	Item Type	Total Profit
0	Baby Food	3886643.70
1	Beverages	888047.28
2	Cereal	2292443.43
3	Clothes	5233334.40
4	Cosmetics	14556048.66
5	Fruits	120495.18
6	Household	7412605.71
7	Meat	610610.00
8	Office Supplies	5929583.75
9	Personal Care	1220622.48
10	Snacks	751944.18
11	Vegetables	1265819.63

16- What is the average order processing time for each country?

```
[44]: Avg_Processing_Time_by_country= data.groupby(data['Country'])['Processing_
      ↪Time'].mean()
      Avg_Processing_Time_by_country
```

```
[44]: Country
      Albania                44 days 00:00:00
      Angola                  4 days 00:00:00
      Australia              18 days 16:00:00
      Austria                 7 days 00:00:00
      Azerbaijan             30 days 00:00:00
      Bangladesh             47 days 00:00:00
      Belize                 44 days 00:00:00
      Brunei                  37 days 00:00:00
      Bulgaria               26 days 12:00:00
      Burkina Faso           10 days 00:00:00
      Cameroon               12 days 12:00:00
      Cape Verde             17 days 00:00:00
      Comoros                31 days 00:00:00
      Costa Rica             13 days 00:00:00
      Cote d'Ivoire          19 days 00:00:00
      Democratic Republic of the Congo 50 days 00:00:00
      Djibouti               13 days 08:00:00
      East Timor             42 days 00:00:00
      Federated States of Micronesia 18 days 00:00:00
      Fiji                   32 days 00:00:00
      France                 14 days 00:00:00
      Gabon                   1 days 00:00:00
      Grenada                24 days 00:00:00
      Haiti                  34 days 00:00:00
      Honduras               15 days 12:00:00
```


Iceland	0 days 00:00:00
Iran	23 days 00:00:00
Kenya	20 days 00:00:00
Kiribati	28 days 00:00:00
Kuwait	18 days 00:00:00
Kyrgyzstan	18 days 00:00:00
Laos	38 days 00:00:00
Lebanon	20 days 00:00:00
Lesotho	31 days 00:00:00
Libya	32 days 12:00:00
Lithuania	24 days 00:00:00
Macedonia	31 days 00:00:00
Madagascar	33 days 00:00:00
Malaysia	47 days 00:00:00
Mali	21 days 00:00:00
Mauritania	2 days 00:00:00
Mexico	25 days 16:00:00
Moldova	3 days 00:00:00
Monaco	4 days 00:00:00
Mongolia	4 days 00:00:00
Mozambique	5 days 00:00:00
Myanmar	24 days 00:00:00
New Zealand	26 days 00:00:00
Nicaragua	41 days 00:00:00
Niger	17 days 00:00:00
Norway	28 days 12:00:00
Pakistan	42 days 00:00:00
Portugal	34 days 00:00:00
Republic of the Congo	42 days 00:00:00
Romania	29 days 00:00:00
Russia	6 days 00:00:00
Rwanda	25 days 00:00:00
Samoa	18 days 00:00:00
San Marino	5 days 00:00:00
Sao Tome and Principe	19 days 00:00:00
Saudi Arabia	3 days 00:00:00
Senegal	42 days 00:00:00
Sierra Leone	26 days 00:00:00
Slovakia	35 days 00:00:00
Slovenia	33 days 00:00:00
Solomon Islands	17 days 00:00:00
South Sudan	30 days 00:00:00
Spain	40 days 00:00:00
Sri Lanka	29 days 00:00:00
Switzerland	36 days 00:00:00
Syria	11 days 00:00:00
The Gambia	17 days 06:00:00

```
Turkmenistan      24 days 00:00:00
Tuvalu            30 days 00:00:00
United Kingdom    40 days 00:00:00
Zambia            1 days 00:00:00
Name: Processing Time, dtype: timedelta64[ns]
```

17- Which region has the highest average total revenue per order?

```
[137]: data['avg total revenue']= data['Total Revenue']/data['Units Sold']
highest_avg_total_revenue_per_order= data.groupby(data['Region']) ['avg total_
↪revenue'].mean()
highest_avg_total_revenue_per_order.sort_values(ascending=True)
highest_avg_total_revenue_per_order.head(1)
```

```
[137]: Region
Asia      335.809091
Name: avg total revenue, dtype: float64
```

19- Is there a relationship between the number of units sold and the total profit?

```
[46]: Correlation_unit_sold_and_total_profit= data['Units Sold'].corr(data['Total_
↪Profit'])
print(f"Correlation coefficient: {Correlation_unit_sold_and_total_profit}")
```

Correlation coefficient: 0.5645504620845976

20- How does the order priority vary based on the item type?

```
[47]: Order_priority_vary_on_item_type= data.groupby(data['Order Priority'])['Item_
↪Type'].value_counts().reset_index(name= 'No. Of Items')
Order_priority_vary_on_item_type
```

```
[47]:
```

	Order Priority	Item Type	No. Of Items
0	C	Beverages	7
1	C	Clothes	4
2	C	Office Supplies	2
3	C	Personal Care	2
4	C	Vegetables	2
5	C	Baby Food	1
6	C	Cereal	1
7	C	Cosmetics	1
8	C	Fruits	1
9	C	Household	1
10	H	Cosmetics	8
11	H	Cereal	5
12	H	Baby Food	3
13	H	Clothes	3
14	H	Vegetables	3
15	H	Fruits	2

16	H	Household	2
17	H	Office Supplies	2
18	H	Beverages	1
19	H	Personal Care	1
20	L	Fruits	5
21	L	Household	5
22	L	Personal Care	4
23	L	Clothes	3
24	L	Office Supplies	3
25	L	Baby Food	2
26	L	Snacks	2
27	L	Cosmetics	1
28	L	Meat	1
29	L	Vegetables	1
30	M	Office Supplies	5
31	M	Clothes	3
32	M	Cosmetics	3
33	M	Personal Care	3
34	M	Fruits	2
35	M	Baby Food	1
36	M	Cereal	1
37	M	Household	1
38	M	Meat	1
39	M	Snacks	1

[]: