Analyzing Amazon Sales data

This project originates from the e-commerce domain, focusing on analyzing Amazon's sales data. The goal is to uncover key metrics and insights to address our business challenges effectively.

Problem Statement:

Sales management has gained importance to meet increasing competition and the need for improved methods of distribution to reduce cost and to increase profits. **Sales management today is the most important function in a commercial and business**.

Now let us start working on a dataset in our google colab. The first step is to **import the libraries** and load data.

```
import numpy as np        #Numpy is used for large, multi-dimensional arrays and matrices, along with mathematical operators on these ar
import pandas as pd                 # Pandas is used for data manipulation and analysis.
import matplotlib.pyplot as plt     # matplotlib and seaborn are help to visulize the data
import seaborn as sns
from datetime import datetime
import warnings
warnings.filterwarnings("ignore")
```

```
Amazon_sales_data = pd.read_csv("/content/drive/MyDrive/Colab Notebooks/Amazon Sales data (1).csv")   # loading dataset
```

DATA UNDERSTANDING AND CLEANING

```
Amazon_sales_data.head()          # it gives top 5 rows of dataset
```

	Region	Country	Item Type	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold	Unit Price	Unit Cost	Total Revenue	Total Cost	T Pr
0	Australia and Oceania	Tuvalu	Baby Food	Offline	H	5/28/2010	669165933	6/27/2010	9925	255.28	159.42	2533654.00	1582243.50	95141
1	Central America and the Caribbean	Grenada	Cereal	Online	C	8/22/2012	963881480	9/15/2012	2804	205.70	117.11	576782.80	328376.44	24840
2	Europe	Russia	Office Supplies	Offline	L	5/2/2014	341417157	5/8/2014	1779	651.21	524.96	1158502.59	933903.84	22459
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	56065.84	1952

Next steps: Generate code with Amazon_sales_data View recommended plots

```
Amazon_sales_data.tail()          # it gives bottom 5 rows of dataset.
```

	Region	Country	Item Type	Sales Channel	Order Priority	Order Date	Order ID	Ship Date	Units Sold	Unit Price	Unit Cost	Total Revenue	Total Cost
95	Sub-Saharan Africa	Mali	Clothes	Online	M	7/26/2011	512878119	9/3/2011	888	109.28	35.84	97040.64	31825.9
96	Asia	Malaysia	Fruits	Offline	L	11/11/2011	810711038	12/28/2011	6267	9.33	6.92	58471.11	43367.6
97	Sub-Saharan Africa	Sierra Leone	Vegetables	Offline	C	6/1/2016	728815257	6/29/2016	1485	154.06	90.93	228779.10	135031.0
98	North America	Mexico	Personal Care	Offline	M	7/30/2015	559427106	8/8/2015	5767	81.73	56.67	471336.91	326815.8
99	Sub-Saharan Africa	Mozambique	Household	Offline	L	2/10/2012	665095412	2/15/2012	5367	668.27	502.54	3586605.09	2697132.1

```
Amazon_sales_data .shape         # it gives number of rows and columns of dataset.
```

```
(100, 14)
```

```
Amazon_sales_data.columns           # it gives columns of dataset.
```

```
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')
```

- **The dataset consists of 100 rows and 14 columns.**
- **It includes detailed sales records for various products across different regions and countries**.
- **Sales data is captured for both online and offline channels**.
- **Key financial metrics such as Total Revenue**, **Total Cost**, **and Total Profit are included**.
- **The dataset covers a range of dates, with order and ship dates specified for each sale**.

```
Amazon_sales_data.info()          # it gives non_null count and data type of each column.
```

```
<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
```

Based on the data types inferred from the dataset, some changes are necessary to ensure proper data analysis, particularly for date columns. **Order Date and Ship Date columns are currently of type object. These should be converted to datetime type.**

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

```
# Checking the data types of "Order Date" and "Ship Date" columns
print(Amazon_sales_data['Order Date'].dtype)
print(Amazon_sales_data['Ship Date'].dtype)
```

```
datetime64[ns]
datetime64[ns]
```

```
Amazon_sales_data.describe()          # it gives statistical summary of dataset.
```

	Order Date	Order ID	Ship Date	Units Sold	Unit Price	Unit Cost	Total Revenue	Total Cost	Total Profit
count	100	1.000000e+02	100	100.000000	100.000000	100.000000	1.000000e+02	1.000000e+02	1.000000e+02
mean	2013-09-16 14:09:36	5.550204e+08	2013-10-09 22:48:00	5128.710000	276.761300	191.048000	1.373488e+06	9.318057e+05	4.416820e+05
min	2010-02-02 00:00:00	1.146066e+08	2010-02-25 00:00:00	124.000000	9.330000	6.920000	4.870260e+03	3.612240e+03	1.258020e+03
25%	2012-02-14 12:00:00	3.389225e+08	2012-02-24 18:00:00	2836.250000	81.730000	35.840000	2.687212e+05	1.688680e+05	1.214436e+05
50%	2013-07-12 12:00:00	5.577086e+08	2013-08-11 12:00:00	5382.500000	179.880000	107.275000	7.523144e+05	3.635664e+05	2.907680e+05
	2015-04-07		2015-04-28						

```
Amazon_sales_data.describe(include="O")          # it gives statistical summary of categorical data.
```

	Region	Country	Item Type	Sales Channel	Order Priority
count	100	100	100	100	100
unique	7	76	12	2	4
top	Sub-Saharan Africa	The Gambia	Clothes	Offline	H
freq	36	4	13	50	30

```
Amazon_sales_data.isnull().sum()          # it gives count of null values in each column.
```

```
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
```

There are no null values in any of the columns.

```
Amazon_sales_data.duplicated().sum()          # it gives count of duplicate values.
```

```
0
```

There are no duplicate rows in this data set.

```
Amazon_sales_data["Item Type"].value_counts()
```

```
Item Type
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: count, dtype: int64
```

```
Amazon_sales_data['Sales Channel'].value_counts()
```

```
Sales Channel
Offline    50
Online     50
Name: count, dtype: int64
```

```
Amazon_sales_data["Region"].value_counts()
```

```
Region
Sub-Saharan Africa                   36
Europe                               22
Australia and Oceania                11
Asia                                 11
Middle East and North Africa         10
Central America and the Caribbean     7
North America                         3
Name: count, dtype: int64
```

```
Amazon_sales_data["Country"].value_counts()
```

```
Country
The Gambia               4
Sierra Leone             3
Sao Tome and Principe    3
Mexico                   3
Australia                3
                        ..
```

```
Comoros                 1
Iceland                 1
Macedonia               1
Mauritania              1
Mozambique              1
Name: count, Length: 76, dtype: int64
```

```
Amazon_sales_data["Order Priority"].value_counts()
```

```
Order Priority
H    30
L    27
C    22
M    21
Name: count, dtype: int64
```

```
Amazon_sales_data["Order Day"]=Amazon_sales_data["Order Date"].dt.day
Amazon_sales_data['Order Month'] = Amazon_sales_data['Order Date'].dt.month # Extract Day , Month and Year from "Order Date"
Amazon_sales_data['Order Year'] = Amazon_sales_data['Order Date'].dt.year

Amazon_sales_data["Ship day"]=Amazon_sales_data["Ship Date"].dt.day      # Extract Day , Month and Year from "Ship Date"
Amazon_sales_data["Ship Month"]=Amazon_sales_data["Ship Date"].dt.month
Amazon_sales_data["Ship Year"]=Amazon_sales_data["Ship Date"].dt.year
```

```
Amazon_sales_data.head(3)
```

	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	Or
0	Australia and Oceania	Tuvalu	Baby Food	Offline	H	2010-05-28	669165933	2010-06-27	9925	255.28	159.42	2533654.00	1582243.50	951410.50	
1	Central America and the Caribbean	Grenada	Cereal	Online	C	2012-08-22	963881480	2012-09-15	2804	205.70	117.11	576782.80	328376.44	248406.36	
2	Europe	Russia	Office Supplies	Offline	L	2014-05-02	341417157	2014-05-08	1779	651.21	524.96	1158502.59	933903.84	224598.75	

Next steps: Generate code with Amazon_sales_data View recommended plots

Average Order Value

```
Amazon_sales_data['Order value']=Amazon_sales_data['Units Sold']*Amazon_sales_data['Unit Price']
aov=Amazon_sales_data['Order value'].mean()
print("Average Order Value(AOV): ",aov)
```

```
Average Order Value(AOV):  1373487.6831
```

Average Profit Margin for the entire dataset

```
# Calculate Profit Margin for each order
Amazon_sales_data['Profit_margin'] = (Amazon_sales_data['Total Profit'] / Amazon_sales_data['Total Revenue']) * 100

# Calculate Average Profit Margin for the entire dataset
avg_profit_margin = Amazon_sales_data['Profit_margin'].mean()
print("Average Profit Margin Percentage For The Entire Dataset is:", avg_profit_margin, "%")
```

```
Average Profit Margin Percentage For The Entire Dataset is: 36.21162285657073 %
```

SQL Queries for Amazon Sales Data Analysis

```
import duckdb
conn=duckdb.connect()
conn.register('Amazon_sales_data',Amazon_sales_data)
```

```
<duckdb.duckdb.DuckDBPyConnection at 0x7c0f356c20b0>
```

```
conn.execute("""
SELECT
    SUM("Units Sold") AS Total_Sales,
    AVG("Units Sold") AS Avg_Sales,
    SUM("Total Profit") AS Total_Profit,
    AVG("Total Profit") AS Avg_Profit,
    SUM("Total Cost") AS Total_Cost,
    AVG("Total Cost") AS Avg_Cost,
    SUM("Total Revenue") AS Total_Revenue,
    AVG("Total Revenue") AS Avg_Revenue
FROM Amazon_sales_data
""").fetchdf()
```

	Total_Sales	Avg_Sales	Total_Profit	Avg_Profit	Total_Cost	Avg_Cost	Total_Revenue	Avg_Revenue
0	512871.0	5128.71	44168198.4	441681.984	93180569.91	931805.6991	1.373488e+08	1.373488e+06

Q: What are the trends in monthly sales and revenue?

```
conn.execute("""
SELECT
    EXTRACT(YEAR FROM "Order Date") AS Order_Year,
    EXTRACT(MONTH FROM "Order Date") AS Order_Month,
    SUM("Units Sold") AS Monthly_Sales,
    SUM("Total Revenue") AS Monthly_Revenue
FROM Amazon_sales_data
GROUP BY Order_Year, Order_Month
ORDER BY Order_Year, Order_Month
limit 10;
""").fetchdf()
```

	Order_Year	Order_Month	Monthly_Sales	Monthly_Revenue
0	2010	2	9503.0	3410661.12
1	2010	5	15747.0	2587973.26
2	2010	6	9905.0	1082418.40
3	2010	10	14403.0	6064933.75
4	2010	11	7910.0	3458252.00
5	2010	12	4103.0	2581786.39
6	2011	1	12914.0	1042225.35
7	2011	2	8156.0	387002.20
8	2011	4	4187.0	2798046.49
9	2011	5	5741.0	272410.45

Q:How do sales and revenue vary year-over-year ?

```
conn.execute("""
SELECT
    EXTRACT(YEAR FROM "Order Date") AS Year,
    SUM("Units Sold") AS Yearly_Sales,
    SUM("Total Revenue") AS Yearly_Revenue
FROM Amazon_sales_data
GROUP BY Year
ORDER BY Year;

""").fetchdf()
```

	Year	Yearly_Sales	Yearly_Revenue
0	2010	61571.0	19186024.92
1	2011	54768.0	11129166.07
2	2012	97967.0	31898644.52
3	2013	64663.0	20330448.66
4	2014	92040.0	16630214.43
5	2015	49480.0	12427982.86
6	2016	43156.0	12372867.22
7	2017	49226.0	13373419.63

Q:What are the key Sales ,revenue and profit drivers by region and item type?

```
conn.execute("""
SELECT
    "Region",
    "Item Type",
    SUM("Units Sold") AS Total_Sales,
    SUM("Total Revenue") AS Total_Revenue,
    SUM("Total Profit") AS Total_Profit
FROM Amazon_sales_data
GROUP BY "Region", "Item Type"
ORDER BY Total_Revenue DESC, Total_Profit DESC ,Total_Sales DESC
limit 10;
""").fetchdf()
```

	Region	Item Type	Total_Sales	Total_Revenue	Total_Profit
0	Europe	Cosmetics	30100.0	13159720.00	5233487.00
1	Sub-Saharan Africa	Office Supplies	16251.0	10582813.71	2051688.75
2	Middle East and North Africa	Cosmetics	23615.0	10324478.00	4105940.05
3	Europe	Office Supplies	14053.0	9151454.13	1774191.25
4	Asia	Household	12080.0	8072701.60	2002018.40
5	Sub-Saharan Africa	Household	11924.0	7968451.48	1976164.52
6	Asia	Office Supplies	11718.0	7630878.78	1479397.50
7	Central America and the Caribbean	Household	8974.0	5997054.98	1487261.02

Q:How is revenue distributed across different order priorities?

```
conn.execute("""
SELECT
    "Order Priority",
    SUM("Total Revenue") AS Total_Revenue
FROM Amazon_sales_data
GROUP BY "Order Priority"
ORDER BY Total_Revenue DESC;
""").fetchdf()
```

	Order Priority	Total_Revenue
0	H	48749546.05
1	L	36628127.46
2	M	33116031.75
3	C	18855063.05

Q:Which countries contribute the most to Amazon's revenue?

```
conn.execute("""
SELECT
    "Country",
    SUM("Total Revenue") AS Total_Revenue
FROM Amazon_sales_data
GROUP BY "Country"
ORDER BY Total_Revenue DESC
LIMIT 10;
""").fetch_df()
```

	Country	Total_Revenue
0	Honduras	6336545.48
1	Myanmar	6161257.90
2	Djibouti	6052890.86
3	Turkmenistan	5822036.20
4	Mexico	5643356.55
5	The Gambia	5449517.95
6	Lithuania	5396577.27
7	Rwanda	5253769.42
8	Azerbaijan	4478800.21
9	Brunei	4368316.68

Q:What is the cost structure, and how can costs be reduced to increase profitability?

```
conn.execute("""
SELECT
    "Region",
    "Item Type",
    SUM("Total Cost") AS Total_Cost,
    SUM("Total Profit") AS Total_Profit,
    SUM("Total Revenue") AS Total_Revenue
FROM Amazon_sales_data
GROUP BY "Region", "Item Type"
ORDER BY Total_Profit DESC
limit 10;
""").fetchdf()
```

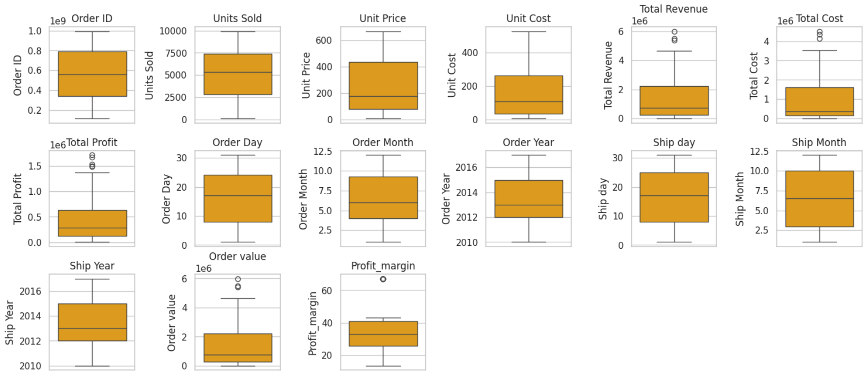
	Region	Item Type	Total_Cost	Total_Profit	Total_Revenue
0	Europe	Cosmetics	7926233.00	5233487.00	13159720.00
1	Middle East and North Africa	Cosmetics	6218537.95	4105940.05	10324478.00
2	Europe	Baby Food	3521109.54	2117259.82	5638369.36
3	Sub-Saharan Africa	Office Supplies	8531124.96	2051688.75	10582813.71
4	Sub-Saharan Africa	Cosmetics	3078854.36	2032888.04	5111742.40
5	Asia	Household	6070683.20	2002018.40	8072701.60
6	Sub-Saharan Africa	Household	5992286.96	1976164.52	7968451.48
7	Europe	Office Supplies	7377262.88	1774191.25	9151454.13
8	Australia and Oceania	Cosmetics	2542187.82	1678540.98	4220728.80
9	Sub-Saharan Africa	Cereal	2146392.08	1623677.52	3770069.60

Visualization of the Amazon dataset using Matplotlib and Seaborn

```
import matplotlib.pyplot as plt
import seaborn as sns
```

Identify Outliers Using Boxplot

```
# Select only the numerical columns
numerical_columns = Amazon_sales_data.select_dtypes(include=['float', 'int']).columns

# Set up the figure
plt.figure(figsize=(15, 15))

# Create subplots for each numerical variable
for i, var in enumerate(numerical_columns):
    plt.subplot(7, 6, i + 1)  # Adjust the grid size (7, 6) as needed
    sns.boxplot(data=Amazon_sales_data, y=var,color="orange")
    plt.title(var)

plt.tight_layout()
plt.show()
```



Observations :

Upon examining the box plots for the numerical variables in our Amazon sales dataset, it is evident that there are outliers present in the "Total Revenue," "Total Cost," and "Total Profit" columns. These outliers represent unusually high values compared to the rest of the data. While outliers often indicate data points that deviate significantly from the norm, in the context of sales data, they are not necessarily anomalies that need to be removed. Instead, these high values are crucial for a comprehensive analysis of sales performance and profitability.

```
# Create a copy of the dataset
Amazon_sales_data_copy = Amazon_sales_data.copy()

# Convert categorical columns to numerical using encoding techniques
# For simplicity, we will use label encoding for this example
from sklearn.preprocessing import LabelEncoder

# List of categorical columns
categorical_columns = ['Region', 'Country', 'Item Type', 'Sales Channel', 'Order Priority']

# Apply label encoding to each categorical column
label_encoder = LabelEncoder()
for column in categorical_columns:
    Amazon_sales_data_copy[column] = label_encoder.fit_transform(Amazon_sales_data_copy[column])
```

Calculate the correlation matrix for all columns

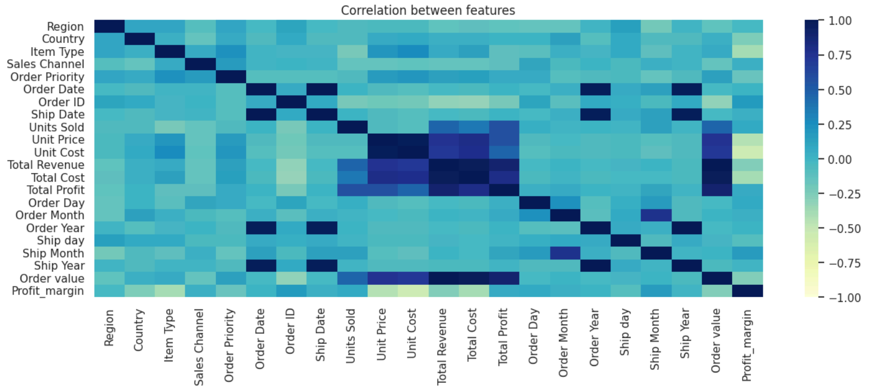
```
Amazon_sales_data_copy.corr()
```

	Region	Country	Item Type	Sales Channel	Order Priority	Order Date	Order ID	
Region	1.000000	0.090381	0.086903	-0.084149	0.088160	-0.027527	0.116983	-0
Country	0.090381	1.000000	0.016516	-0.143683	0.058582	-0.073075	0.083332	-0
Item Type	0.086903	0.016516	1.000000	0.047309	0.236258	-0.014985	-0.022389	-0
Sales Channel	-0.084149	-0.143683	0.047309	1.000000	0.161422	-0.000411	0.004590	-0
Order Priority	0.088160	0.058582	0.236258	0.161422	1.000000	-0.079675	-0.081380	-0
Order Date	-0.027527	-0.073075	-0.014985	-0.000411	-0.079675	1.000000	0.068436	0
Order ID	0.116983	0.083332	-0.022389	0.004590	-0.081380	0.068436	1.000000	0
Ship Date	-0.031119	-0.072690	-0.017681	-0.000199	-0.078790	0.999812	0.070476	1
Units Sold	-0.058390	-0.076610	-0.237976	-0.146353	-0.073288	0.011993	-0.222907	0
Unit Price	-0.054337	0.069421	0.206581	-0.144871	0.179228	-0.067132	-0.190941	-0
Unit Cost	-0.041616	0.081282	0.269253	-0.137639	0.194923	-0.078461	-0.213201	-0
Total Revenue	-0.135806	0.019152	0.058618	-0.143462	0.127140	-0.036936	-0.314688	-0
Total Cost	-0.127484	0.022350	0.131500	-0.140635	0.147566	-0.053604	-0.328944	-0
Total Profit	-0.137036	0.008522	-0.129872	-0.130019	0.058548	0.009523	-0.234638	0
Order Day	-0.147256	0.009951	-0.109738	0.104997	0.063107	-0.036196	0.110501	-0
Order Month	-0.152892	0.125203	0.033670	-0.047954	-0.091695	0.029971	-0.111219	0
Order Year	-0.005085	-0.089590	-0.018200	0.004813	-0.067682	0.990581	0.081752	0
Ship day	0.144915	0.079597	0.078800	-0.052388	-0.045670	0.061315	0.041866	0
Ship Month	-0.205356	-0.059142	-0.127728	0.037299	-0.141260	0.126219	-0.046043	0
Ship Year	-0.003980	-0.066073	-0.000787	-0.004893	-0.058957	0.990524	0.077216	0
Order value	-0.135806	0.019152	0.058618	-0.143462	0.127140	-0.036936	-0.314688	-0
Profit_margin	-0.039016	-0.247111	-0.397457	0.036780	-0.163294	0.013248	0.186907	0

22 rows × 22 columns

Correlation between features by using Heat map

```
corr = Amazon_sales_data_copy.corr()
plt.figure(figsize=(15, 5))

## plotting the heat map
sns.heatmap(corr, cmap='YlGnBu', vmax=1.0, vmin=-1.0)

# specify name of the plot
plt.title('Correlation between features')
plt.show()
```

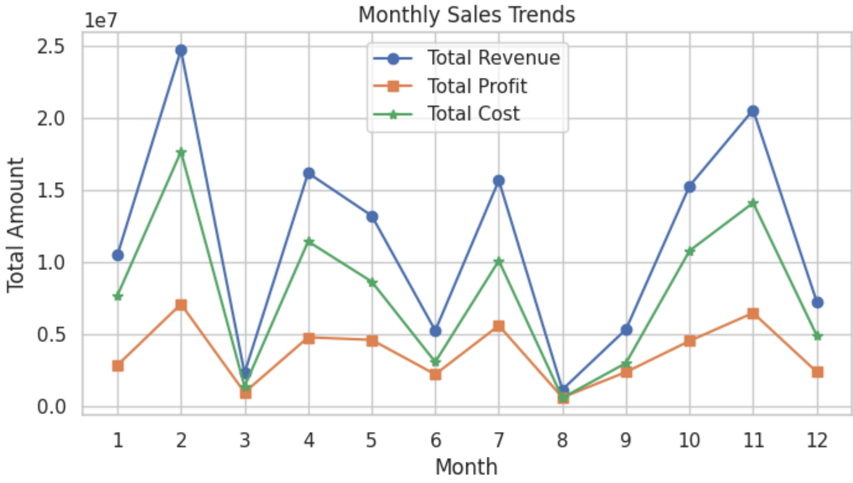


Observations :

- There is a nearly perfect positive correlation between 'Order Date' and 'Ship Date'.
- 'Total Revenue' has a very high positive correlation with 'Total Cost' and 'Total Profit'. Similarly, 'Total Cost' also shows a strong positive correlation with 'Total Profit'
- There is a strong positive correlation between 'Unit Price' and 'Unit Cost'.
- Order ID' shows a moderate positive correlation with 'Order Date' and 'Ship Date'.
- 'Units Sold' shows a moderate positive correlation with 'Total Revenue', 'Total Cost', and 'Total Profit'.
- 'Item Type' and 'Order Priority' have a moderate positive correlation.
- 'Region' shows low correlations with most other variables, indicating that it does not have a strong linear relationship with them.
- 'Country' also shows low correlations with other variables, similar to 'Region'.
- Sales Channel' has low or negligible correlations with most other variables.
- Order Year and Ship Year: 'Order Year' and 'Ship Year' show a strong positive correlation.
- 'Profit Margin' does not show strong correlations with many variables, indicating it might be influenced by a more complex set of factors rather than any single variable.
- 'Order Value' shows strong positive correlations with 'Total Revenue' and 'Total Profit'.

Monthly Sales Trends

```
# Aggregrating data for monthly sales
monthly_sales=Amazon_sales_data.groupby("Order Month").agg({"Total Cost":"sum","Total Revenue":"sum","Total Profit":"sum",}).reset_inde>

# Visualizing Monthly Sales Trends

plt.figure(figsize=(8,4))
plt.plot(monthly_sales['Order Month'],monthly_sales['Total Revenue'],marker='o',label='Total Revenue')
plt.plot(monthly_sales['Order Month'],monthly_sales['Total Profit'],marker='s',label='Total Profit')
plt.plot(monthly_sales['Order Month'],monthly_sales['Total Cost'],marker='*',label='Total Cost')
plt.xlabel("Month")
plt.ylabel("Total Amount")
plt.title("Monthly Sales Trends")
plt.legend()
plt.grid(True)
plt.xticks(monthly_sales['Order Month'])
plt.show()
```

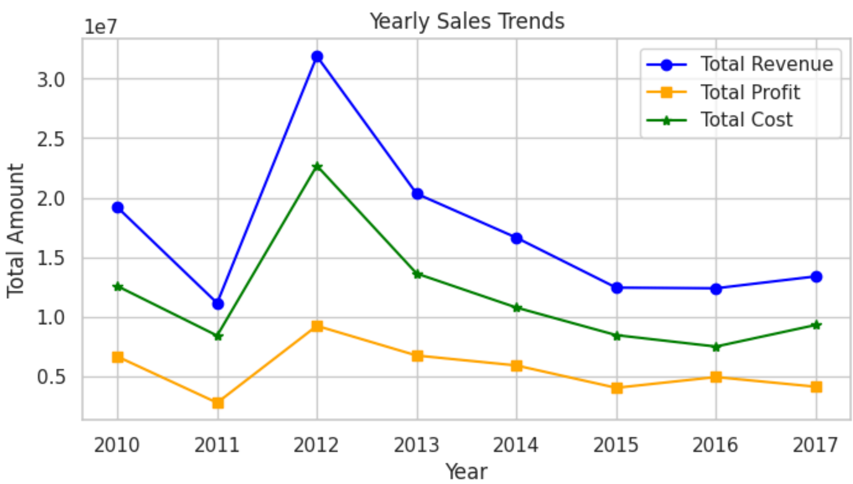


Observations :

- Sales experience significant increases in February and November. These months could represent peak sales periods, possibly due to seasonal promotions, holidays, or special events.
- Sales see marked decreases in March and August. These months might indicate a slower sales period, potentially due to seasonal factors, lower consumer spending, or fewer promotional activities.
- To maximize revenue, it may be beneficial to focus marketing and promotional efforts around the high-sales periods in February and November.
- Identifying and addressing the factors causing lower sales in March and August could help improve performance during these months.

Yearly Sales Trends

```
# Aggregrating data for yearly sales
yearly_sales=Amazon_sales_data.groupby("Order Year").agg({"Total Cost":"sum","Total Revenue":"sum","Total Profit":"sum"}).reset_index()

# Visualizing Yearly Sales Trends

plt.figure(figsize=(8,4))
plt.plot(yearly_sales['Order Year'],yearly_sales['Total Revenue'],marker='o',label='Total Revenue',color='blue')
plt.plot(yearly_sales['Order Year'],yearly_sales['Total Profit'],marker='s',label='Total Profit',color = "orange")
plt.plot(yearly_sales['Order Year'],yearly_sales['Total Cost'],marker='*',label='Total Cost',color='green')
plt.xlabel("Year")
plt.ylabel("Total Amount")
plt.title("Yearly Sales Trends")
plt.legend()
plt.grid(True)
plt.xticks(yearly_sales['Order Year'])
plt.show()
```



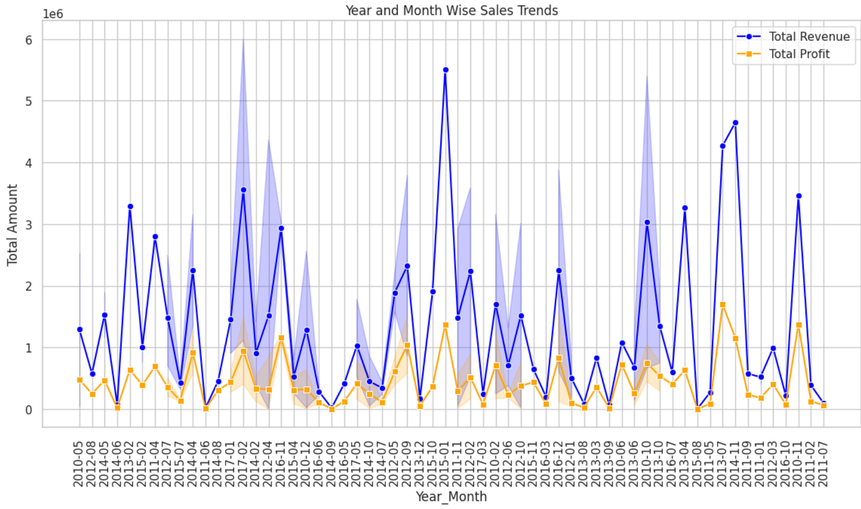
Observations :

- Sales reached their peak in 2012, indicating this was the most successful year in terms of sales performance during the analyzed period.
- The lowest sales were recorded in 2011, suggesting that this year had the weakest sales performance in the analyzed period.
- There was a significant improvement in sales from 2011 to 2012, demonstrating a strong year-over-year growth. This could be due to effective marketing strategies, introduction of popular products, or other favorable market conditions.
- Understanding the factors that contributed to the peak in 2012 can help in replicating similar success in future periods.
- Analyzing the challenges faced in 2011 can provide insights into avoiding similar pitfalls and improving sales strategies during weaker periods.

```
# Extracting Year_Month From Order Date
Amazon_sales_data['Order_Year_Month']=Amazon_sales_data['Order Date'].dt.to_period('M')
Amazon_sales_data['Order_Year_Month']=Amazon_sales_data['Order_Year_Month'].astype(str)
```

Year and Month Wise Sales Trends

```
plt.figure(figsize=(14,7))
sns.lineplot(data=Amazon_sales_data,x="Order_Year_Month",y="Total Revenue",marker='o',color='blue',label="Total Revenue")
sns.lineplot(data=Amazon_sales_data,x="Order_Year_Month",y="Total Profit",marker='s',color='orange',label="Total Profit")
plt.xticks(rotation=90)
plt.xlabel("Year_Month")
plt.ylabel("Total Amount")
plt.legend()
plt.grid(True)
plt.title("Year and Month Wise Sales Trends")
plt.show()
```



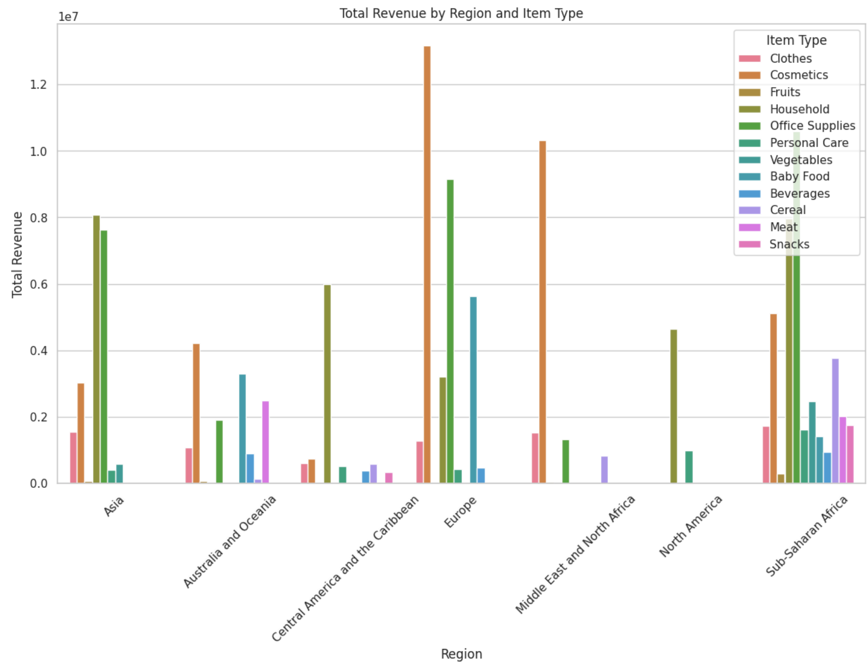
Observations:

Sales reached their peaks in November 2015, July 2013, and November 2014

```
# Aggregate data by Region and Item Type
agg_data = Amazon_sales_data.groupby(['Region', 'Item Type']).agg({
    'Units Sold': 'sum',
    'Total Revenue': 'sum',
    'Total Profit': 'sum'
}).reset_index()
```

Total Revenue by Region and Item Type

```
# Set up the seaborn theme
sns.set_theme(style="whitegrid")

# Plot Total Revenue by Region and Item Type
plt.figure(figsize=(14, 8))
revenue_plot = sns.barplot(data=agg_data, x='Region', y='Total Revenue', hue='Item Type', ci=None)
plt.title('Total Revenue by Region and Item Type')
plt.xticks(rotation=45)
plt.show()
```



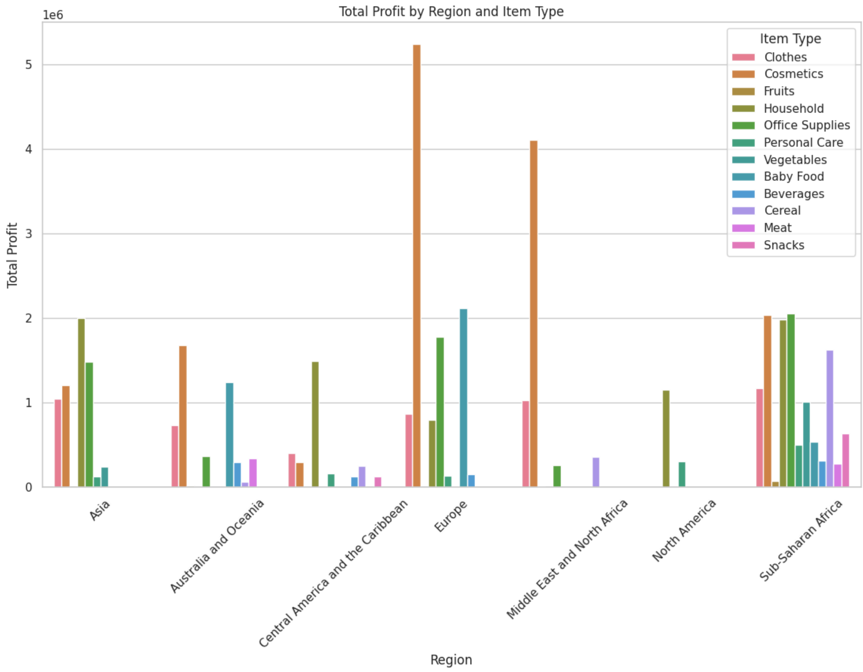
Observations :

- Asia: Household items and office supplies are major revenue contributors, indicating strong demand for these categories.
- Australia and Oceania: Cosmetics, snacks, and beverages dominate revenue, highlighting a preference for personal care and consumable products.
- Central America and the Caribbean: Fruits are the significant revenue contributor, suggesting a strong market for fresh produce.
- Europe: Cosmetics are the top revenue contributors, followed by office supplies, showing a high demand for personal care and workplace essentials.

- Middle East and North Africa: Cosmetics are the primary revenue contributors, indicating a strong market for beauty and personal care products.
- North America: Household items contribute the most to revenue, reflecting a demand for home-related products.
- Sub-Saharan Africa: Household items and office supplies are major revenue contributors, similar to Asia, indicating a market for home and workplace essentials.

Total Profit by Region and Item Type

```
# Plot Total Profit by Region and Item Type
plt.figure(figsize=(14, 8))
profit_plot = sns.barplot(data=agg_data, x='Region', y='Total Profit', hue='Item Type', ci=None)
plt.title('Total Profit by Region and Item Type')
plt.xticks(rotation=45)
plt.show()
```



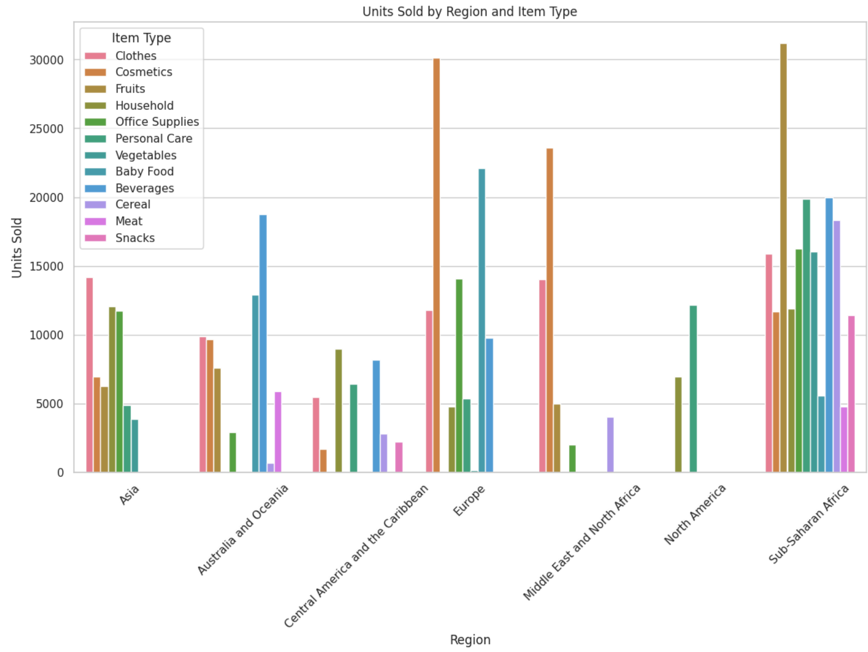
Observations :

- Asia: Household items and office supplies are major profit contributors, indicating high profitability for these categories in the region.
- Australia and Oceania: Cosmetics and beverages dominate profits, highlighting the lucrative nature of these products in the market.
- Central America and the Caribbean: Household items are the significant profit contributors, suggesting these products are essential for profitability.
- Europe: Cosmetics contribute the most to profits, showing a high demand and profitability for personal care products.
- Middle East and North Africa: Cosmetics are the primary profit contributors, indicating a strong market for beauty and personal care products.

- North America: Household items contribute the most to profits, reflecting high profitability in the home goods market.
- Sub-Saharan Africa: Cosmetics, household items, and office supplies are major profit contributors, suggesting a diverse market with high profitability in these categories.

Units Sold by Region and Item Type

```
# Plot Units Sold by Region and Item Type
plt.figure(figsize=(14, 8))
sales_plot = sns.barplot(data=agg_data, x='Region', y='Units Sold', hue='Item Type', ci=None)
plt.title('Units Sold by Region and Item Type')
plt.xticks(rotation=45)
plt.show()
```

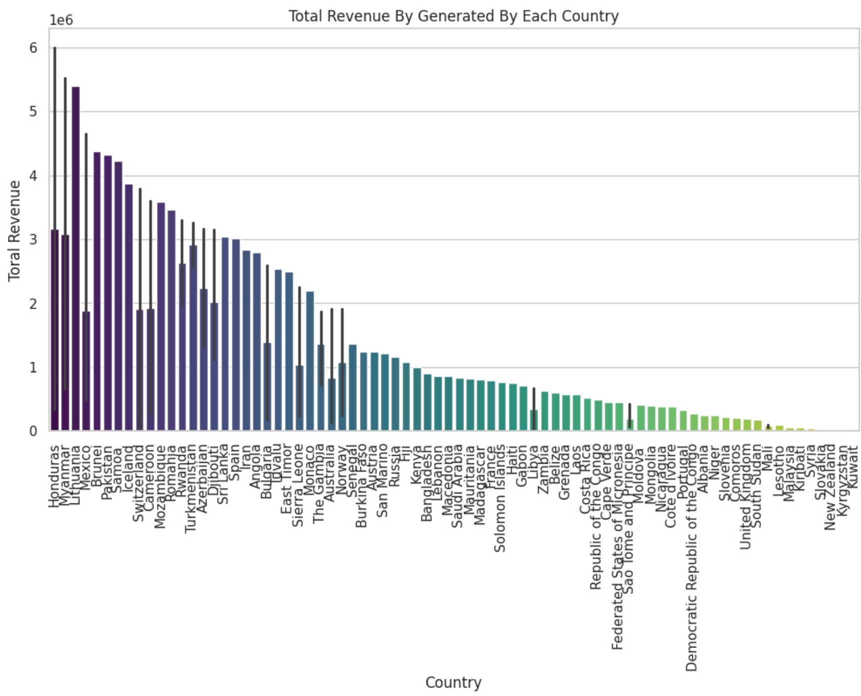


Observations :

- Asia: Snacks, household items, and office supplies have the highest units sold, indicating these categories are the most popular and in high demand.
- Australia and Oceania: Beverages dominate sales, highlighting a strong market preference for drinks.
- Central America and the Caribbean: Household items and beverages are the top sales categories, suggesting a balanced demand for both consumable and non-consumable goods.
- Europe: Cosmetics have the highest sales, followed by beverages, indicating a strong market for personal care and consumable products.
- Middle East and North Africa: Cosmetics lead in sales, followed by snacks, showing a high demand for beauty products and snacks.
- North America: Vegetables are the leading sales category, reflecting a strong market for fresh produce.
- Sub-Saharan Africa: Cosmetics have the highest sales, followed by vegetables and beverages, indicating diverse demand with a strong preference for beauty products.

Total Revenue By Generated By Each Country

```
# Sorting the country by total revenue for better visualiaztion

revenue_by_country=Amazon_sales_data.sort_values(by='Total Revenue',ascending=False)
revenue_by_country

# Plotting the total revenue by country
plt.figure(figsize=(12,6))
sns.barplot(x='Country',y='Total Revenue',data=revenue_by_country, palette='viridis')
plt.title('Total Revenue By Generated By Each Country')
plt.xlabel('Country')
plt.ylabel('Toral Revenue')
plt.xticks(rotation=90)
plt.show()
```

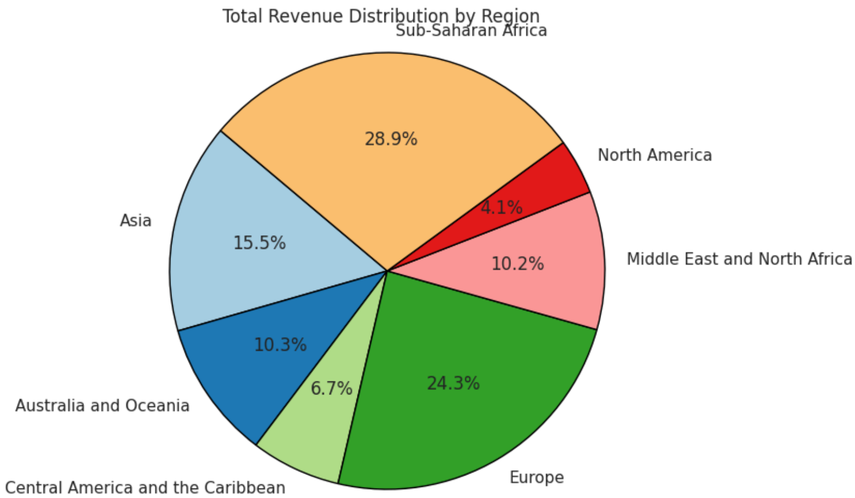


Observations :

- Honduras generates the maximum revenue, indicating it is a strong and profitable market for the business.
- Kuwait generates the minimum revenue, suggesting it is an underperforming market with lower sales and minimal contribution to overall revenue.
- Focus on maintaining and enhancing market strategies in Honduras to sustain and further increase revenue.
- Investigate and address the factors contributing to low revenue in Kuwait to identify opportunities for growth and improve sales performance in the region.

Total Revenue Distribution by Region

```
# Sum of total revenue by each region
revenue_by_region = Amazon_sales_data.groupby('Region')['Total Revenue'].sum()

# Plotting the pie chart
plt.figure(figsize=(8, 6))
plt.pie(revenue_by_region, labels=revenue_by_region.index, autopct='%1.1f%%', startangle=140, colors=plt.cm.Paired(range(len(revenue_by_
        wedgeprops={'edgecolor': 'black'})
plt.title('Total Revenue Distribution by Region  ')
plt.axis('equal')  # Equal aspect ratio ensures the pie chart is circular.
plt.show()
```



Observations :

- Sub-Saharan Africa generates the maximum revenue, contributing 29.9% of the total revenue, indicating it is the most significant and profitable market for the business.
- Sub-Saharan Africa generates the maximum revenue, contributing 29.9% of the total revenue, indicating it is the most significant and profitable market for the business.

Total Revenue Distribution by Order Priority

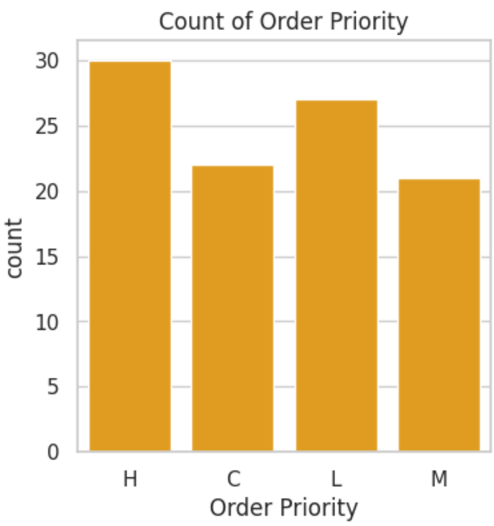
```
# Aggregate total revenue by order priority
revenue_by_priority = Amazon_sales_data.groupby('Order Priority')['Total Revenue'].sum().reset_index()

# Plotting the total revenue by order priority
plt.figure(figsize=(10, 6))
sns.barplot(data=revenue_by_priority, x='Order Priority', y='Total Revenue', palette='muted')
plt.title('Total Revenue Distribution by Order Priority')
plt.xlabel('Order Priority')
plt.ylabel('Total Revenue')
plt.show()
```

Observations :

- Orders with priority "H" (High) contribute the most to revenue, indicating that high-priority orders are the most financially significant.
- Orders with priority "C" (Critical) contribute the least to revenue, suggesting that critical-priority orders have the lowest financial impact.

Count of Order Priority

```
plt.figure(figsize=(4,4))
sns.countplot(x="Order Priority",data =Amazon_sales_data ,color="orange")
plt.title("Count of Order Priority")
plt.savefig("count of Order Priority.jpg")
plt.show()
```

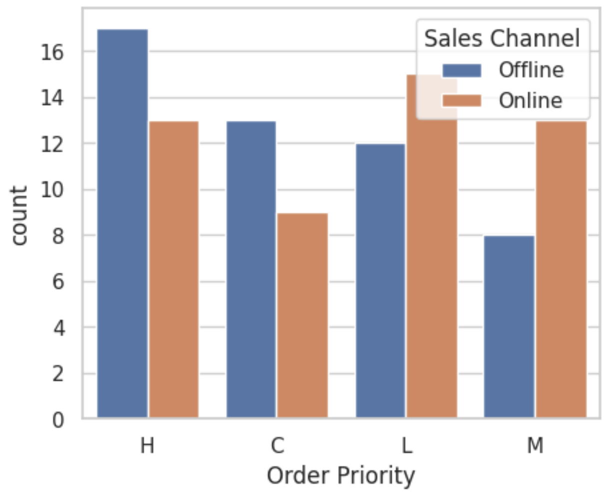


Observations:

- High priority orders have the highest count, indicating that a significant number of orders are given high priority.
- Low priority orders also have a relatively high count, slightly less than high priority orders.

Distribution of Order Priority by Sales Channel

```
plt.figure(figsize=(5,4))
sns.countplot(x='Order Priority',data= Amazon_sales_data,hue="Sales Channel")
plt.show()
```



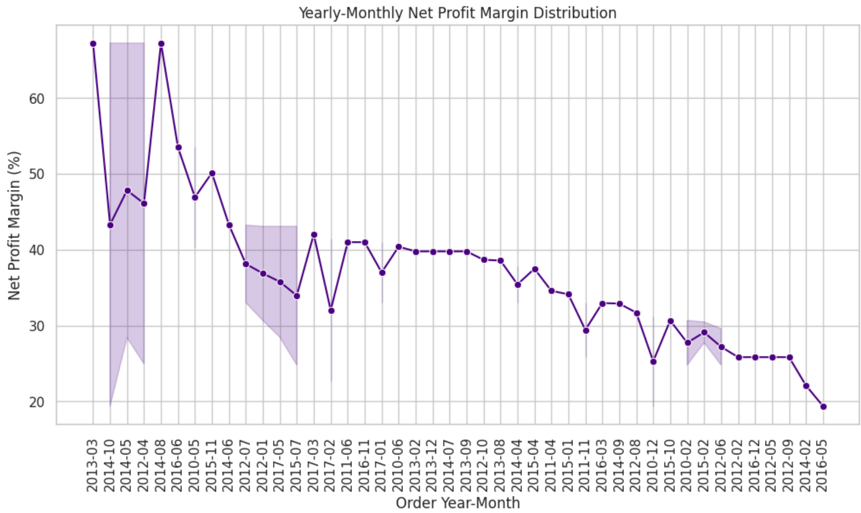
Observations:

- H has a stronger presence in offline sales.
- L shows a higher contribution in online sales.

```
#Aggregate Data For yearly_monthly profit margin
monthly_profit_margin=Amazon_sales_data.groupby("Order_Year_Month").agg({"Profit_margin":"mean"}).reset_index()
monthly_profit_margin=monthly_profit_margin.sort_values(by='Profit_margin',ascending=False)
```

Yearly-Monthly Net Profit Margin Distribution

```
# Converting Order_Year_month to string for plotting
monthly_profit_margin['Order_Year_Month']=Amazon_sales_data['Order_Year_Month'].astype(str)

#Plotting Yearly-Monthly profit margin

plt.figure(figsize=(12,6))
sns.lineplot(data=monthly_profit_margin,x="Order_Year_Month",y="Profit_margin",color='indigo',marker="o")
plt.title('Yearly-Monthly Net Profit Margin Distribution')
plt.xlabel('Order Year-Month')
plt.ylabel('Net Profit Margin (%)')
plt.grid(True)
plt.xticks(rotation=90)
plt.show()
```

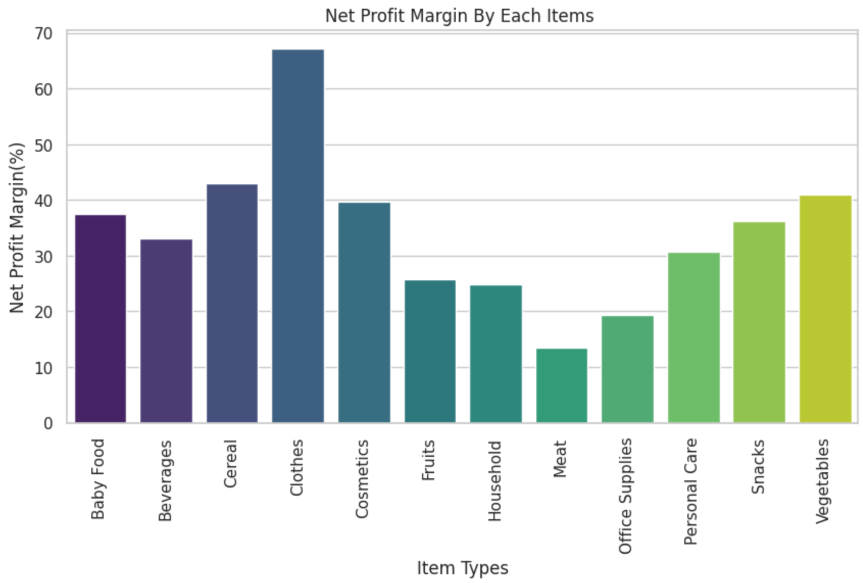


Observations:

- March 2013 and August 2014 marked the company's highest profitability, suggesting effective strategies or favorable market conditions.
- Analyzing these periods can provide valuable insights into the factors that drove success, helping to inform future business strategies.

Net Profit Margin(%)

```
item_profit_margin=Amazon_sales_data.groupby('Item Type').agg({"Profit_margin":"mean"}).reset_index()
# plotting profit margins by each items
plt.figure(figsize=(10,5))
sns.barplot(data=item_profit_margin,x="Item Type",y="Profit_margin",palette='viridis')
plt.title("Net Profit Margin By Each Items ")
plt.xlabel("Item Types")
plt.ylabel("Net Profit Margin(%)")
plt.xticks(rotation=90)
plt.show()
```

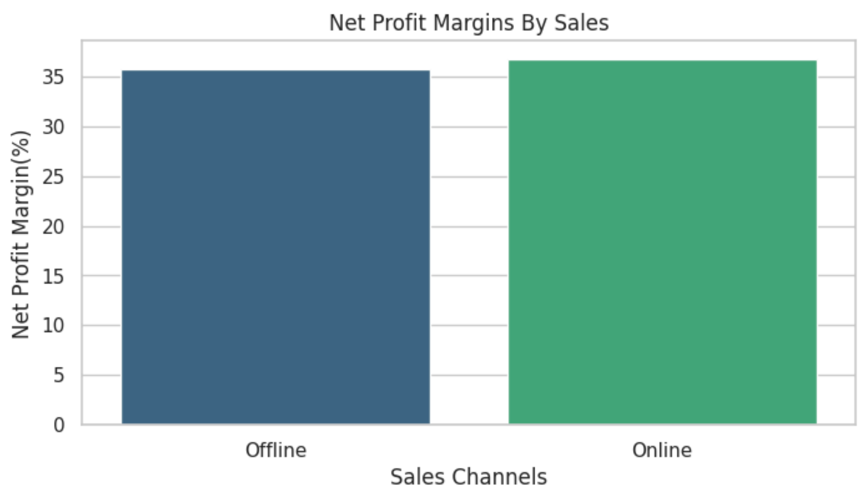


Observations :

- Between 2010 and 2017, clothes achieved the highest profit margin, indicating that this product category was the most profitable during this period.
- During the same period, meat recorded the lowest profit margin, suggesting that this product category was the least profitable and may require strategic review to improve profitability.

Net Profit Margins By Sales

```
#Aggregating data for profit margins of sales channels
channel_profit_margin=Amazon_sales_data.groupby("Sales Channel").agg({"Profit_margin":"mean"}).reset_index()
# plotting profit margins for sales channels
plt.figure(figsize=(8,4))
sns.barplot(data=channel_profit_margin,x='Sales Channel',y='Profit_margin',palette='viridis')
plt.title('Net Profit Margins By Sales')
plt.xlabel('Sales Channels')
plt.ylabel('Net Profit Margin(%)')
plt.show()
```



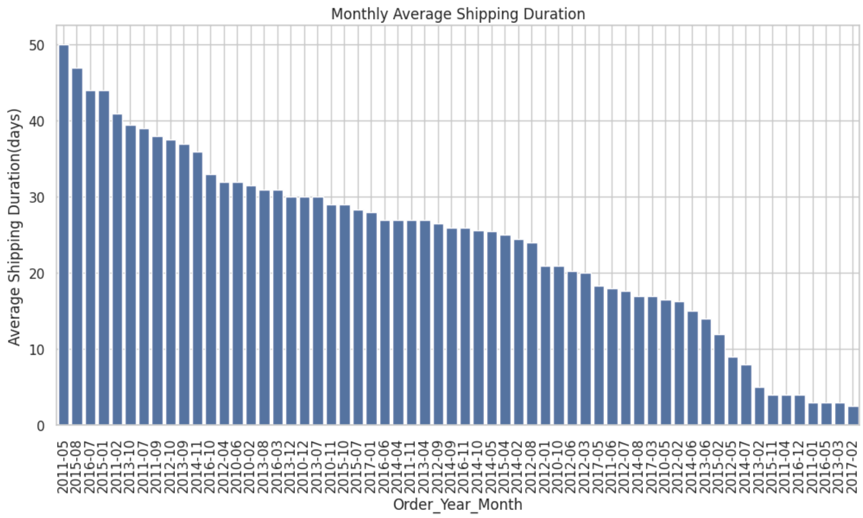
Observations:

As per observation total profit margin recursively increasing from offline sales channel to online sales channel between the year 2010 -2017

```
Amazon_sales_data['Shipping_Duration']=(Amazon_sales_data['Ship Date']-Amazon_sales_data['Order Date']).dt.days
monthly_ship_duration=Amazon_sales_data.groupby("Order_Year_Month").agg({"Shipping_Duration":"mean"}).reset_index()
monthly_ship_duration=monthly_ship_duration.sort_values(by='Shipping_Duration',ascending=False)
```

Monthly Average Shipping Duration

```
# Plotting Monthly Shipping Duration

plt.figure(figsize=(12,6))
sns.barplot(data=monthly_ship_duration,x='Order_Year_Month',y='Shipping_Duration')
plt.title('Monthly Average Shipping Duration')
plt.xlabel('Order_Year_Month')
plt.ylabel('Average Shipping Duration(days)')
plt.grid(True)
plt.xticks(rotation=90)
plt.show()
```



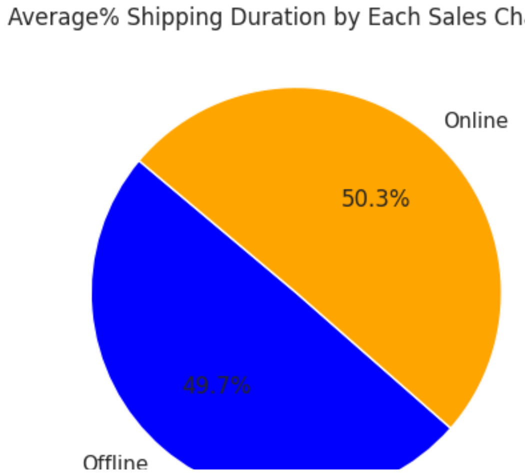
Observations:

- The average shipping duration tends to be higher during certain months, likely correlating with peak shopping periods such as May, July, and August.
- Months like January, February, and March often show shorter average shipping durations.

Average % Shipping Duration by Each Sales Channel

```
# aggregration of sales channels for average shipping
channel_ship_duration=Amazon_sales_data.groupby("Sales Channel").agg({"Shipping_Duration":"mean"}).reset_index()

# Plotting Average Shipping Duration by sales channels by pie chart
plt.figure(figsize=(10,5))
plt.pie(channel_ship_duration["Shipping_Duration"],labels=channel_ship_duration["Sales Channel"],
       autopct='%1.1f%%',startangle=140,colors=['blue','orange'])
plt.title('Average% Shipping Duration by Each Sales Channel')
```

```
Text(0.5, 1.0, 'Average% Shipping Duration by Each Sales Channel')
```



Observations:

- The average shipping duration is slightly longer for online orders compared to offline orders.
- This suggests that online orders may involve more steps or additional processing time.