PROJECT REPORT

Project Title	Analyzing Amazon Sales data
Technologies	Data Science
Domain	E-commerce
Project Difficulties level	Advanced

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GitHub Link: Analyzing Amazon Sales Data

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 enterprise.

1) Do ETL: Extract-Transform-Load some Amazon dataset and find for me
2) Sales-trend -> month-wise, year-wise, yearly _ month-wise
3) Find key metrics and factors and show the meaningful relationships between attributes.

Do your own research and come up with your findings.

ABSTRACT

In today's highly competitive market, sales management has become pivotal for businesses striving to optimize distribution processes, reduce operational costs, and enhance profitability. The surge in data availability and complexity demands advanced analytical methods to drive strategic decisions. This study focuses on leveraging data analytics to address these challenges through a comprehensive analysis of an Amazon sales dataset.

Extract, Transform, Load (ETL) is the cornerstone of this analysis. The ETL process involves extracting relevant sales data from Amazon, transforming it into a structured format, and loading it into a data repository for further analysis. This foundational step ensures that the data is clean, consistent, and suitable for generating actionable insights.

The core of the analysis revolves around identifying sales trends on multiple dimensions—monthly, yearly, and a combination of yearly and monthly metrics. By dissecting sales data across these timeframes, we aim to uncover patterns and fluctuations that can inform strategic decisions and forecasting.

Additionally, the study will delve into key metrics and factors influencing sales performance. This includes analyzing relationships between attributes such as product categories, pricing, promotional activities, and customer demographics. Understanding these relationships will help pinpoint critical drivers of sales performance and identify opportunities for growth and optimization.

The findings from this analysis will provide valuable insights into sales trends and metrics, equipping businesses with the knowledge to enhance their sales management strategies and maintain a competitive edge in the market.

CODE SNAPSHOTS WITH EXPLANATION

Extracting data from CSV file

```
import pandas as pd
```

```
data=pd.read_csv("D:/DOWNLOADS/UNIFIED Mentor Private Limited/UM projects/selected projects/Amazon Sales data.csv")
data.head()
```

	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
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	951410.50
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	248406.36
2	Europe	Russia	Office Supplies	Offline	L	5/2/2014	341417157	5/8/2014	1779	651.21	524.96	1158502.59	933903.84	224598.75
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	19525.82
4	Sub-Saharan Africa	Rwanda	Office Supplies	Offline	L	2/1/2013	115456712	2/6/2013	5062	651.21	524.96	3296425.02	2657347.52	639077.50

```
data.shape
```

```
(100, 14)
```

The above dataset have 14 attributes(Columns) and 100 tuples(rows). The dataset provides a clear understanding of Amazon's sales operations in various countries.

Data Transformation

```
# Convert the date column to datetime format
data['Order Date'] = pd.to_datetime(data['Order Date'])
data['Ship Date'] = pd.to_datetime(data['Ship Date'])
```

```
# Extract year and month from the Order Date
data['Year'] = data['Order Date'].dt.year
data['Month'] = data['Order Date'].dt.month
```

```
# Check for missing values
data.isnull().sum()
```

```
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
Year              0
Month             0
dtype: int64
```

```
# Handle missing values if any (e.g., dropping or imputing)
data.dropna(inplace=True)
```

```
# removing duplicate rows
data.drop_duplicates(inplace=True)
```

```python
# Data after Transformation
data.head()
```

	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	Year	Month
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	2010	5
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	2012	8
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	2014	5
3	Sub-Saharan Africa	Sao Tome and Principe	Fruits	Online	C	2014-06-20	514321792	2014-07-05	8102	9.33	6.92	75591.66	56065.84	19525.82	2014	6
4	Sub-Saharan Africa	Rwanda	Office Supplies	Offline	L	2013-02-01	115456712	2013-02-06	5062	651.21	524.96	3296425.02	2657347.52	639077.50	2013	2

Data Analysis

```
After the ETL pipeline, its time for analyzing the data for identifying sales trends, key metrics and factors and finding relationship between attributes.
```

Temporal Analysis

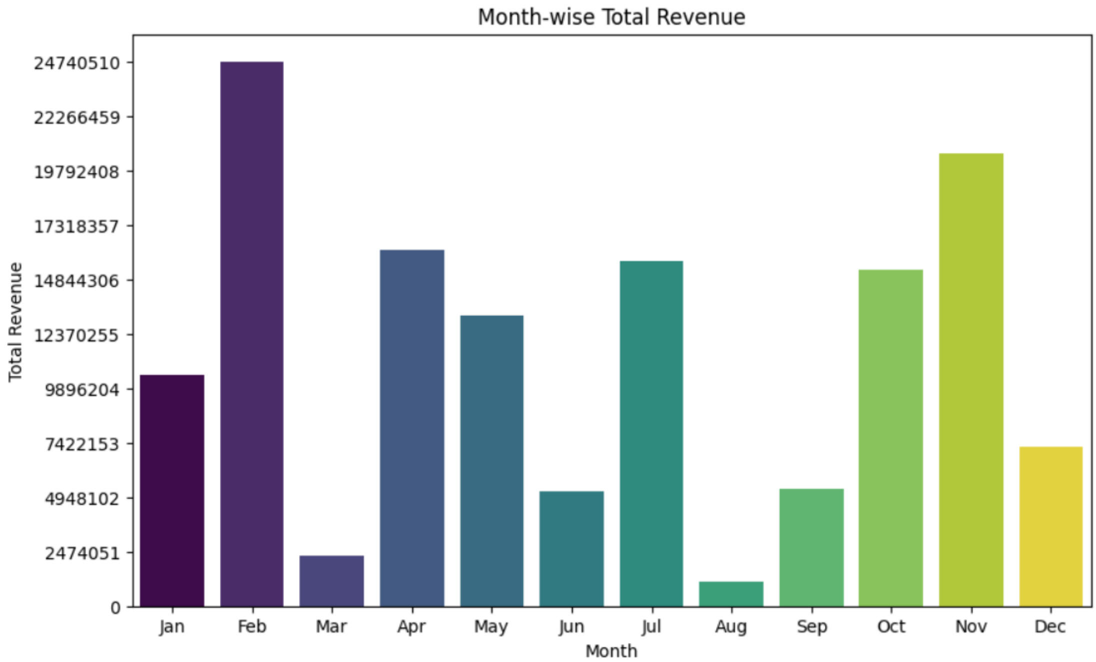
- Month-wise sales trend
- Profitability Trend over Months
- Year-wise sales trend
- Profitability Trend over years
- Yearly month-wise sales trend
- Total Sales
- Average sales

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

```python
# Month-wise sales trend
month_wise_sales = data.groupby('Month')['Total Revenue'].sum().reset_index()
month_wise_sales
```

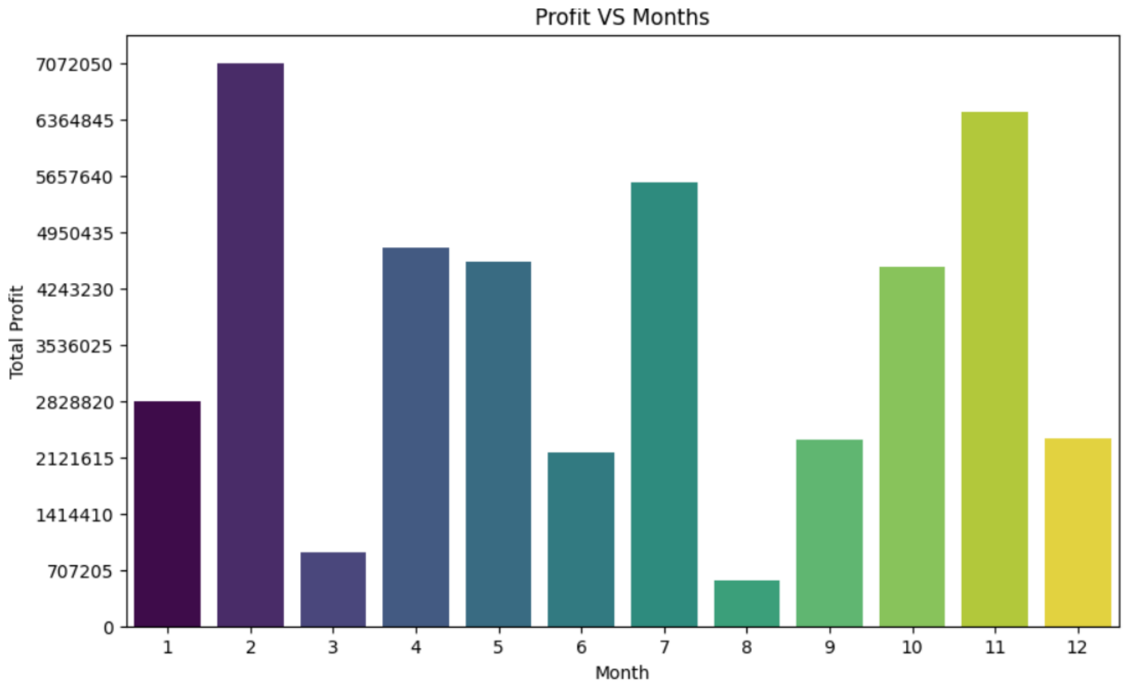
	Month	Total Revenue
0	1	10482467.12
1	2	24740517.77
2	3	2274823.87
3	4	16187186.33
4	5	13215739.99
5	6	5230325.77
6	7	15669518.50
7	8	1128164.91
8	9	5314762.56
9	10	15287576.61
10	11	20568222.76
11	12	7249462.12

```python
plt.figure(figsize=(10, 6))
sns.barplot(x='Month', y='Total Revenue', data=month_wise_sales, hue='Month', palette='viridis', dodge=False)
plt.title('Month-wise Total Revenue')
plt.xlabel('Month')
plt.ylabel('Total Revenue')
plt.xticks(range(12), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'])
plt.legend([],[], frameon=False)
max_revenue = month_wise_sales['Total Revenue'].max()
plt.yticks(range(0, int(max_revenue) + 1, int(max_revenue / 10)), range(0, int(max_revenue) + 1, int(max_revenue / 10)))
plt.show()
```




```python
# Profitability Trend over Months
total_profits_by_years=data.groupby(['Month'])['Total Profit'].sum().reset_index()
print(total_profits_by_years)

plt.figure(figsize=(10, 6))
sns.barplot(x='Month', y='Total Profit', data=total_profits_by_years, palette='viridis', legend=False, hue='Month')
plt.title('Profit VS Months')
plt.xlabel('Month')
plt.ylabel('Total Profit')
max_revenue = total_profits_by_years['Total Profit'].max()
plt.yticks(range(0, int(max_revenue) + 1, int(max_revenue / 10)), range(0, int(max_revenue) + 1, int(max_revenue / 10)))
plt.show()
```

```
    Month  Total Profit
0       1    2816857.02
1       2    7072050.51
2       3     928351.06
3       4    4760208.35
4       5    4582692.30
5       6    2185379.43
6       7    5578463.06
7       8     579276.67
8       9    2344166.03
9      10    4506923.25
10     11    6457600.65
11     12    2356230.07
```

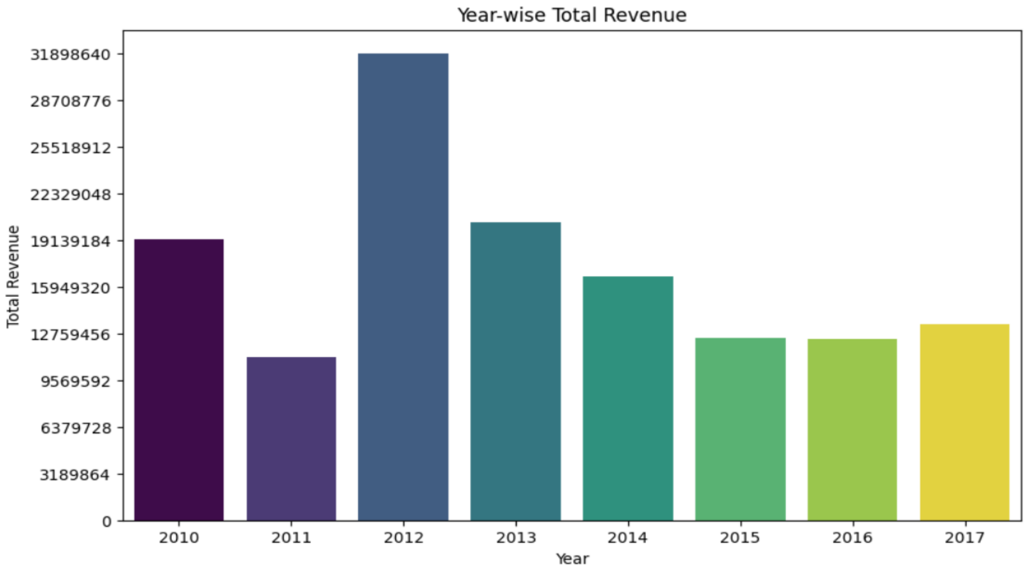



```
The graphs clearly shows the month-wise sales trends. The month of February reported most number of sales and profit.
```

```
# Year-wise sales trend
year_wise_sales = data.groupby('Year')['Total Revenue'].sum().reset_index()
year_wise_sales
```

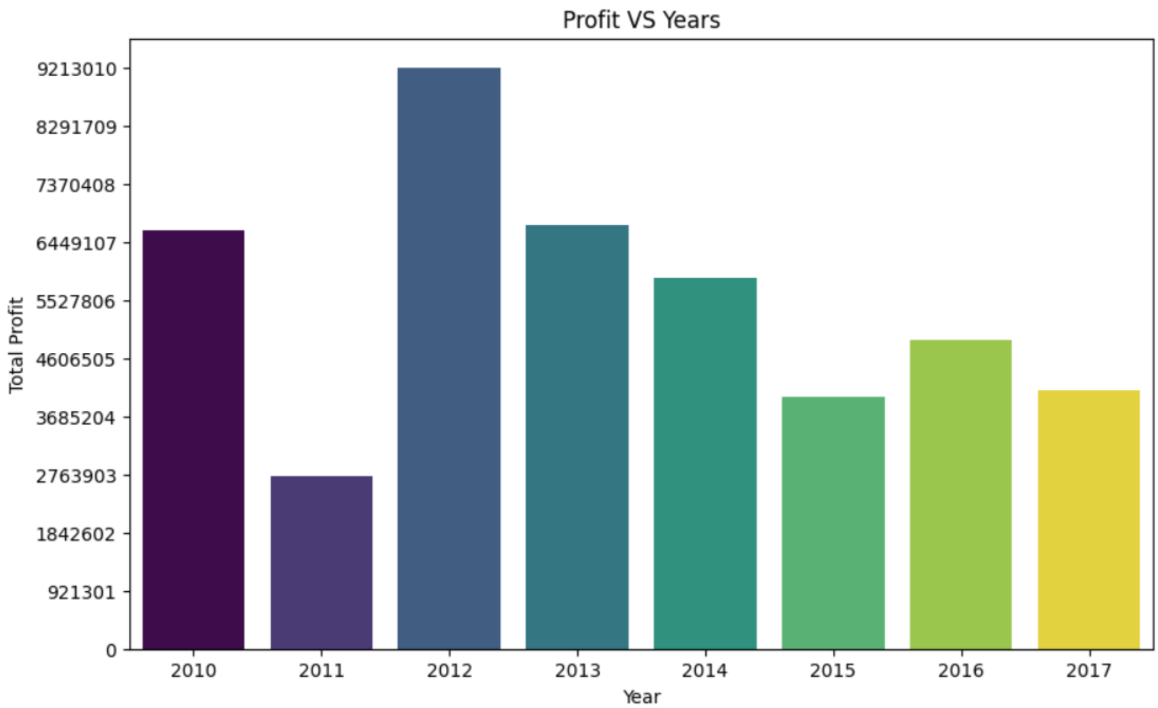
	Year	Total Revenue
0	2010	19186024.92
1	2011	11129166.07
2	2012	31898644.52
3	2013	20330448.66
4	2014	16630214.43
5	2015	12427982.86
6	2016	12372867.22
7	2017	13373419.63

```
plt.figure(figsize=(10, 6))
sns.barplot(x='Year', y='Total Revenue', data=year_wise_sales, palette='viridis', legend=False, hue='Year')
plt.title('Year-wise Total Revenue')
plt.xlabel('Year')
plt.ylabel('Total Revenue')
max_revenue = year_wise_sales['Total Revenue'].max()
plt.yticks(range(0, int(max_revenue) + 1, int(max_revenue / 10)), range(0, int(max_revenue) + 1, int(max_revenue / 10)))
plt.show()
```




```
# Profitability Trend over years
total_profits_by_years=data.groupby(['Year'])['Total Profit'].sum().reset_index()
print(total_profits_by_years)

plt.figure(figsize=(10, 6))
sns.barplot(x='Year', y='Total Profit', data=total_profits_by_years, palette='viridis', legend=False, hue='Year')
plt.title('Profit VS Years')
plt.xlabel('Year')
plt.ylabel('Total Profit')
max_revenue = total_profits_by_years['Total Profit'].max()
plt.yticks(range(0, int(max_revenue) + 1, int(max_revenue / 10)), range(0, int(max_revenue) + 1, int(max_revenue / 10)))
plt.show()
```

```
   Year  Total Profit
0  2010    6629567.43
1  2011    2741008.23
2  2012    9213010.12
3  2013    6715420.04
4  2014    5879461.68
5  2015    3996539.44
6  2016    4903838.01
7  2017    4089353.45
```

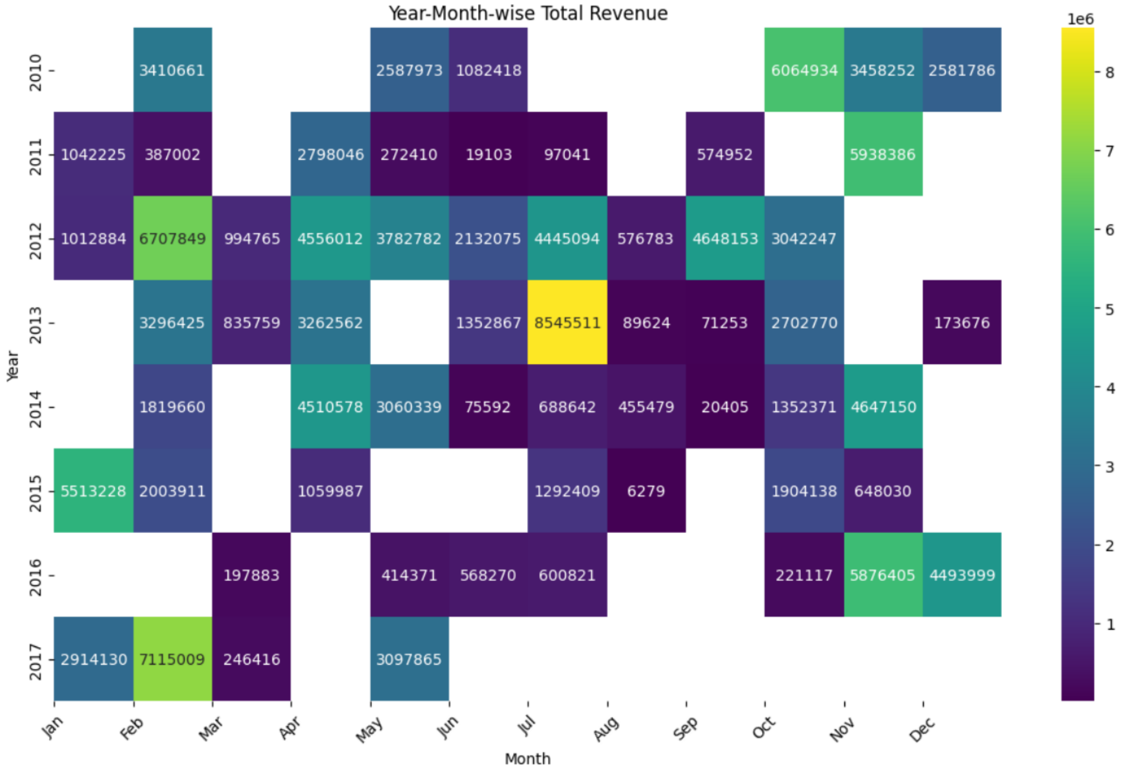


```
The year of 2012 was financially most profitable.
```

```python
# Yearly month-wise sales trend
year_month_wise_sales = data.groupby(['Year', 'Month'])['Total Revenue'].sum().unstack()
year_month_wise_sales
```

Month	1	2	3	4	5	6	7	8	9	10	11	12
Year												
2010	NaN	3410661.12	NaN	NaN	2587973.26	1082418.40	NaN	NaN	NaN	6064933.75	3458252.00	2581786.39
2011	1042225.35	387002.20	NaN	2798046.49	272410.45	19103.44	97040.64	NaN	574951.92	NaN	5938385.58	NaN
2012	1012884.00	6707849.42	994765.42	4556012.38	3782781.82	2132075.27	4445093.92	576782.80	4648152.72	3042246.77	NaN	NaN
2013	NaN	3296425.02	835759.10	3262562.10	NaN	1352867.40	8545511.20	89623.98	71253.21	2702770.40	NaN	173676.25
2014	NaN	1819660.25	NaN	4510578.10	3060338.59	75591.66	688641.85	455479.04	20404.71	1352370.65	4647149.58	NaN
2015	5513227.50	2003911.12	NaN	1059987.26	NaN	NaN	1292409.45	6279.09	NaN	1904138.04	648030.40	NaN
2016	NaN	NaN	197883.40	NaN	414371.10	568269.60	600821.44	NaN	NaN	221117.00	5876405.20	4493999.48
2017	2914130.27	7115009.64	246415.95	NaN	3097864.77	NaN	NaN	NaN	NaN	NaN	NaN	NaN

```python
plt.figure(figsize=(14, 8))
sns.heatmap(year_month_wise_sales, cmap='viridis', annot=True, fmt='.0f')
plt.title('Year-Month-wise Total Revenue')
plt.xlabel('Month')
plt.ylabel('Year')
plt.xticks(range(12), ['Jan', 'Feb', 'Mar', 'Apr', 'May', 'Jun', 'Jul', 'Aug', 'Sep', 'Oct', 'Nov', 'Dec'], rotation=45)
plt.show()
```



This graph shows that July, 2013 reported highest gross revenue.

```
# Total sales
total_sales = data['Total Revenue'].sum()
print(total_sales)
```

```
137348768.31
```

```
# Average sales
average_sales = data['Total Revenue'].mean()
print(average_sales)
```

```
1373487.6831
```

```
# Number of transactions
num_transactions = data.shape[0]
print(num_transactions)
```

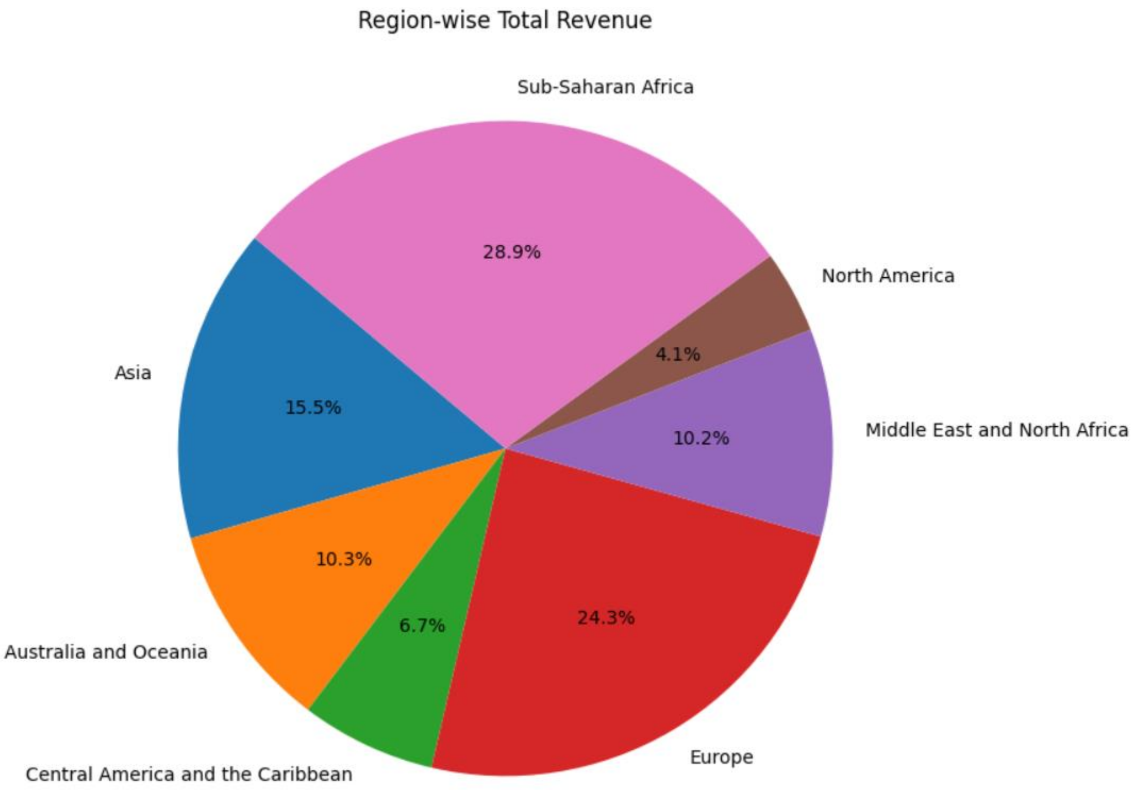
```
100
```

Geographical Analysis

- Region-wise Sales Analysis
- Country-wise Sales Analysis

```
# Total Revenue by region
region_sales = data.groupby('Region')['Total Revenue'].sum()
print(region_sales)

plt.figure(figsize=(10, 8))
plt.pie(region_sales, labels=region_sales.index, autopct='%1.1f%%', startangle=140)
plt.title('Region-wise Total Revenue')
plt.show()
```

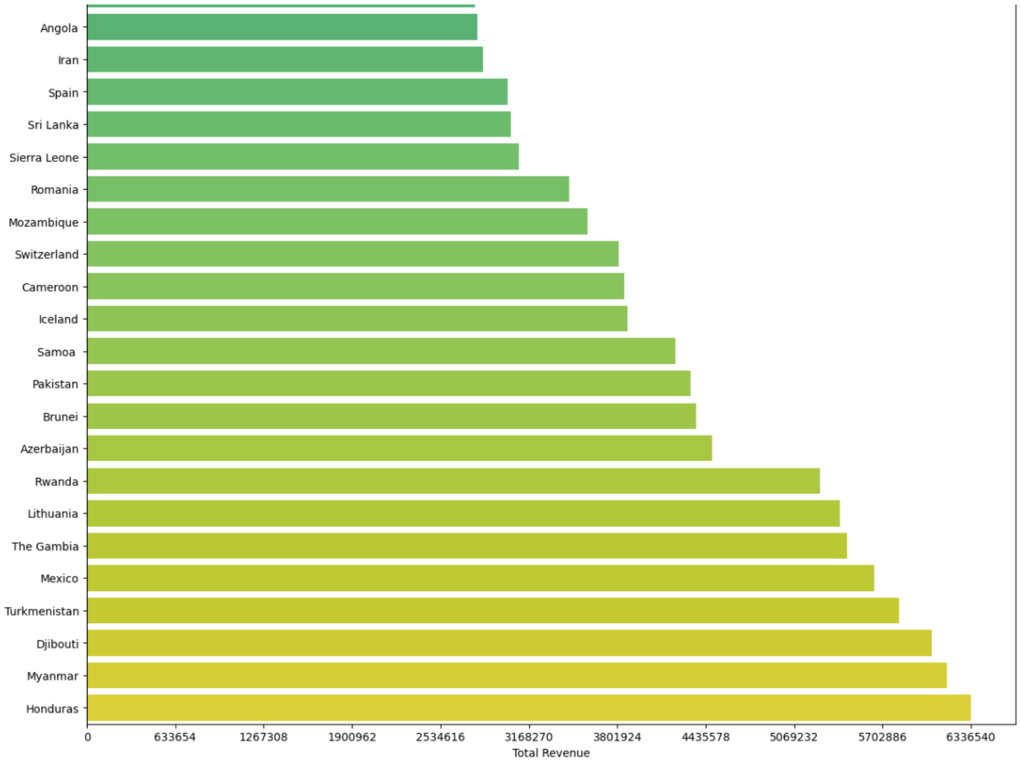
```
Region
Asia                                 21347091.02
Australia and Oceania                14094265.13
Central America and the Caribbean     9170385.49
Europe                               33368932.11
Middle East and North Africa         14052706.58
North America                         5643356.55
Sub-Saharan Africa                   39672031.43
Name: Total Revenue, dtype: float64
```



From this Pie Chart, we can infer that Sub-Sahara Africa region is the most profitable region for Amazon, followed by Europe. Also, North America is the region where they need to focus more as it contributes least among all regions.

```
# Total Revenue by Countries
country_sales = data.groupby('Country')['Total Revenue'].sum().reset_index()
print(country_sales)

# Sorting countries in descending order
country_sales = country_sales.sort_values(by='Total Revenue')

plt.figure(figsize=(15, 40))
sns.barplot(x='Total Revenue', y='Country', data = country_sales , palette='viridis', legend=False, hue='Country')
plt.title('Country-wise Total Revenue')
plt.ylabel('Countries')
plt.xlabel('Total Revenue')
max_revenue = country_sales['Total Revenue'].max()
plt.xticks(range(0, int(max_revenue) + 1, int(max_revenue / 10)), range(0, int(max_revenue) + 1, int(max_revenue / 10)))
plt.show()
```

```
           Country  Total Revenue
0          Albania      247956.32
1           Angola     2798046.49
2        Australia     2489933.49
3          Austria     1244708.40
4       Azerbaijan     4478800.21
..             ...            ...
71      The Gambia     5449517.95
72    Turkmenistan     5822036.20
73          Tuvalu     2533654.00
74  United Kingdom      188452.14
75          Zambia      623289.30
```

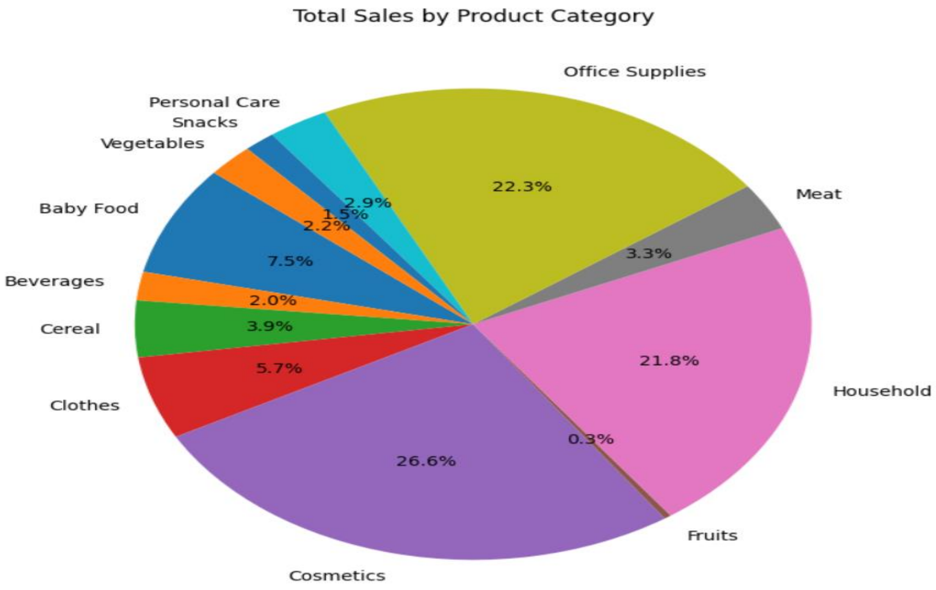



```
The Bar Graph shows revenue generated in each country in increasing order of revenue. Kuwait is the Country which generates almost 0 revenue and
Honduras registered highest revenue in the past 8 years.
```

Product Analysis

- Item Type Sales Analysis
- Sales Channel Analysis
- comparing the number of items sold online versus offline

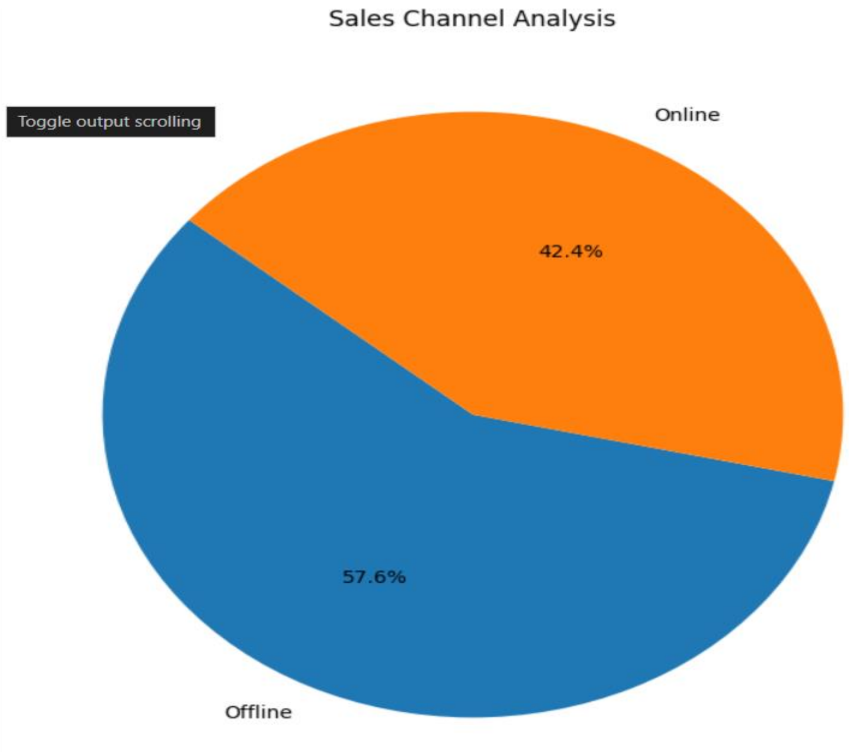
```
# Total sales by product category
category_sales = data.groupby('Item Type')['Total Revenue'].sum()
print(category_sales)

plt.figure(figsize=(10, 8))
plt.pie(category_sales, labels=category_sales.index, autopct='%1.1f%%', startangle=140)
plt.title('Total Sales by Product Category')
plt.show()
```




```
This Pie Chart shows the sales distribution of all item types. Clearly, Cosmetics items have highest number of sales. Similarly, fruits hold the label of least sold item category. Amazon can either identify the cause and improve the sales of fruits, or they can stop selling fruits.
```

```python
# Sales channel Analysis
sales_channel = data.groupby('Sales Channel')['Total Revenue'].sum()
print(sales_channel)

plt.figure(figsize=(10, 8))
plt.pie(sales_channel, labels=sales_channel.index, autopct='%1.1f%%', startangle=140)
plt.title('Sales Channel Analysis')
plt.show()
```

```
Sales Channel
Offline    79094809.20
Online     58253959.11
Name: Total Revenue, dtype: float64
```

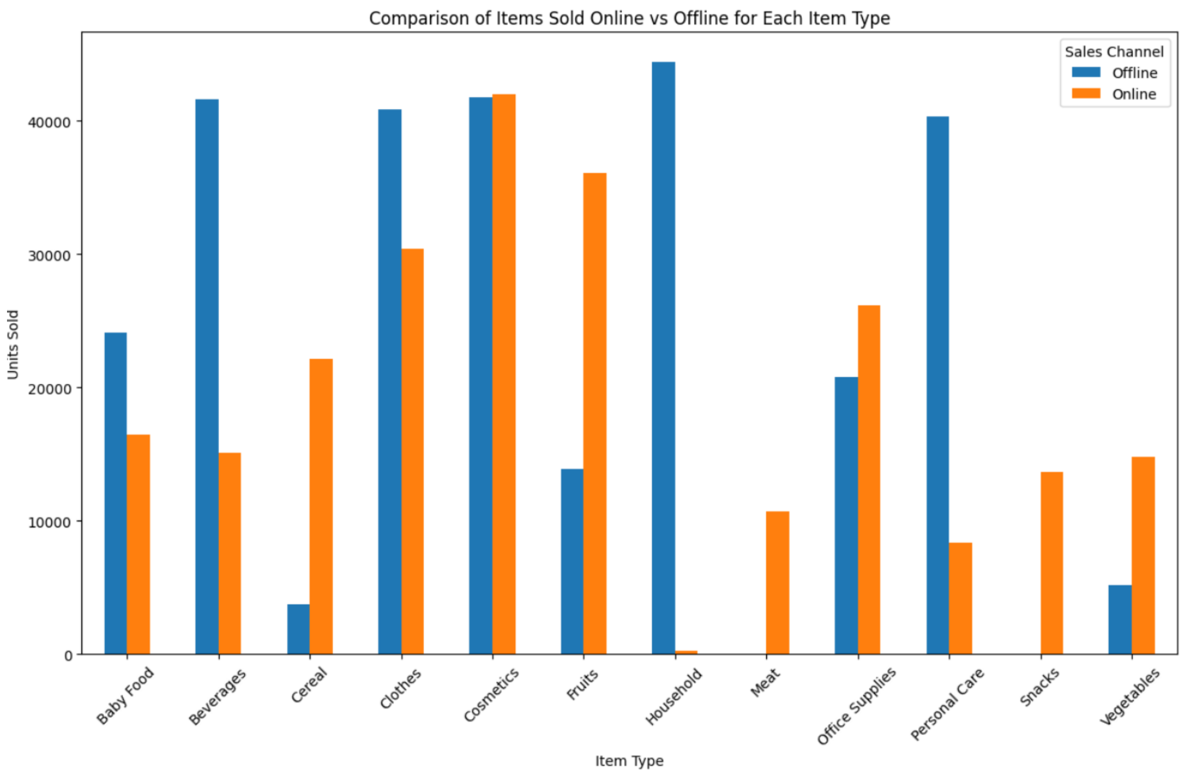



```
More than half of the Amazons sales are using offline channel.
```

```python
# comparing the number of items sold online versus offline
sales_channel_group = data.groupby(['Item Type', 'Sales Channel'])['Units Sold'].sum().unstack().fillna(0)
sales_channel_group
```

Sales Channel	Offline	Online
Item Type		
Baby Food	24098.0	16447.0
Beverages	41588.0	15120.0
Cereal	3761.0	22116.0
Clothes	40871.0	30389.0
Cosmetics	41749.0	41969.0
Fruits	13904.0	36094.0
Household	44445.0	282.0
Meat	0.0	10675.0
Office Supplies	20799.0	26168.0
Personal Care	40350.0	8358.0
Snacks	0.0	13637.0
Vegetables	5217.0	14834.0

```python
sales_channel_group.plot(kind='bar', figsize=(14, 8))
plt.title('Comparison of Items Sold Online vs Offline for Each Item Type')
plt.xlabel('Item Type')
plt.ylabel('Units Sold')
plt.legend(title='Sales Channel')
plt.xticks(rotation=45)
plt.show()
```

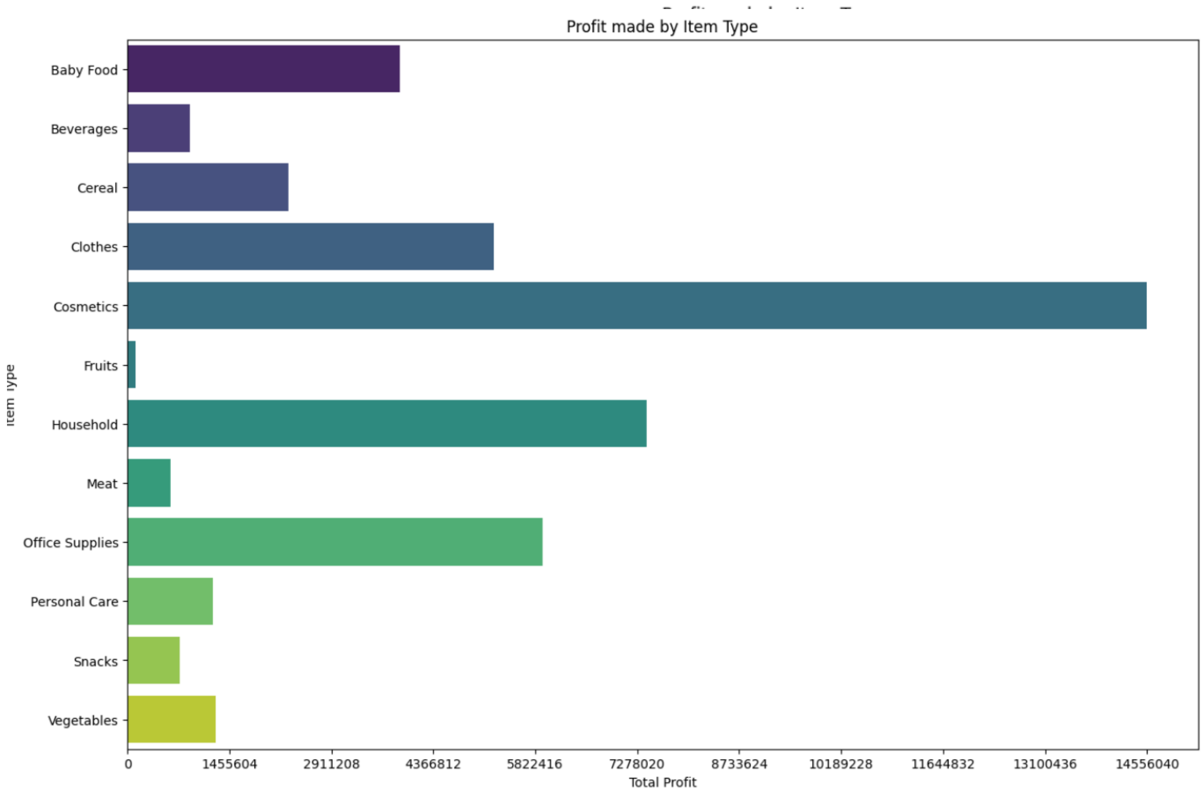


Financial Analysis

- Profitability Trend of Item Types

```
# Profitability Trend of Item Types
total_profits_by_years=data.groupby(['Item Type'])['Total Profit'].sum().reset_index()
print(total_profits_by_years)

plt.figure(figsize=(15, 10))
sns.barplot(x='Total Profit', y='Item Type', data=total_profits_by_years, palette='viridis', legend=False, hue='Item Type')
plt.title('Profit made by Item Type')
plt.ylabel('Item Type')
plt.xlabel('Total Profit')
max_revenue = total_profits_by_years['Total Profit'].max()
plt.xticks(range(0, int(max_revenue) + 1, int(max_revenue / 10)), range(0, int(max_revenue) + 1, int(max_revenue / 10)))
plt.show()
```

```
          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
```



Cosmetics make the highest profits, which is clearly due to its high sales. Similarly Fruits make least profit due to there low sale. This clearly depicts a direct relationship between sales and profits. Sales and Profits are directly proportional, i.e. Higher sales means higher profits. Focusing on increasing sales will indeed increase profits.

```
# # most profitable item:
# profit=data['Unit Price']-data['Unit Cost']
# group=data.groupby(['Item Type'])
```

```
# max(profit)
```

```
# Calculating most profitable item and how much profit is made by selling one unit of the item.

data['Profit per Unit'] = data['Unit Price'] - data['Unit Cost']
max_profit_item = data.loc[data['Profit per Unit'].idxmax()]

item_name = max_profit_item['Item Type']
max_profit = max_profit_item['Profit per Unit']

print("The item with the highest profit per unit is: \n", item_name)
print("The profit per unit for this item is: \n", max_profit)
```

```
The item with the highest profit per unit is:
 Cosmetics
The profit per unit for this item is:
 173.87
```

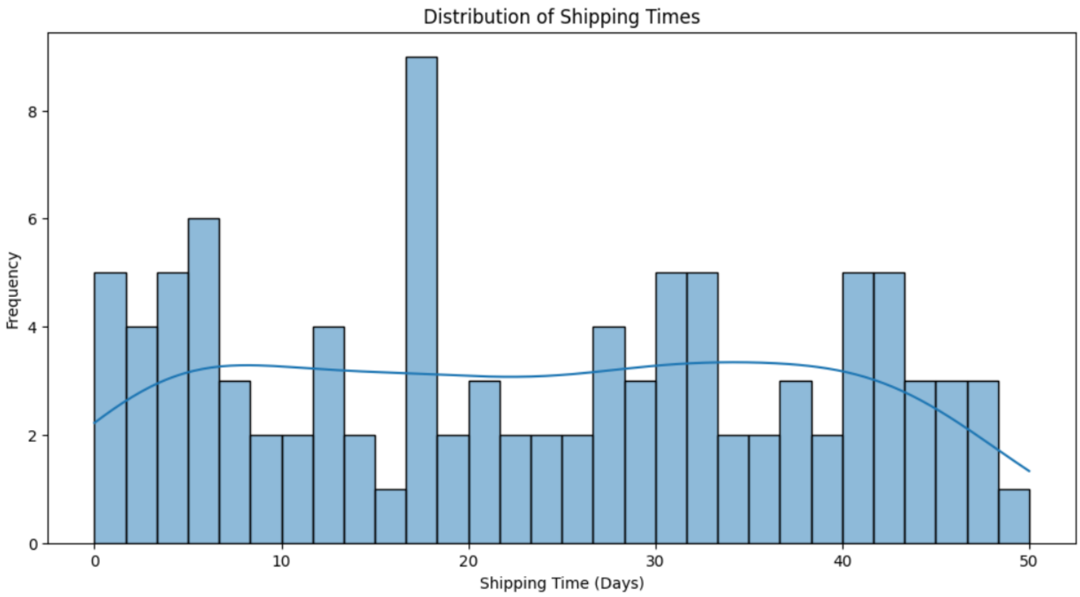
Operational Analysis

- Shipping Analysis

```
# Calculate the difference between Ship Date and Order Date
data['Shipping Time (Days)'] = (data['Ship Date'] - data['Order Date']).dt.days
```

```
shipping_stats = data['Shipping Time (Days)'].describe()
print(shipping_stats)

plt.figure(figsize=(12, 6))
sns.histplot(data['Shipping Time (Days)'], bins=30, kde=True)
plt.title('Distribution of Shipping Times')
plt.xlabel('Shipping Time (Days)')
plt.ylabel('Frequency')
plt.show()
```

```
count    100.000000
mean      23.360000
std       14.742586
min        0.000000
25%        9.750000
50%       23.500000
75%       36.250000
max       50.000000
Name: Shipping Time (Days), dtype: float64
```




```
# Define a threshold for delays. I choose 7 as it is a generally considered late after one week.
delay_threshold = 7
data['Delayed'] = data['Shipping Time (Days)'] > delay_threshold
```

```
num_delayed_shipments = data['Delayed'].sum()
print(f"Number of delayed shipments: {num_delayed_shipments}")
```

```
Number of delayed shipments: 79
```

```
percent_delayed_shipments = (num_delayed_shipments / len(data)) * 100
print(f"Percentage of delayed shipments: {percent_delayed_shipments:.2f}%")
```

```
Percentage of delayed shipments: 79.00%
```

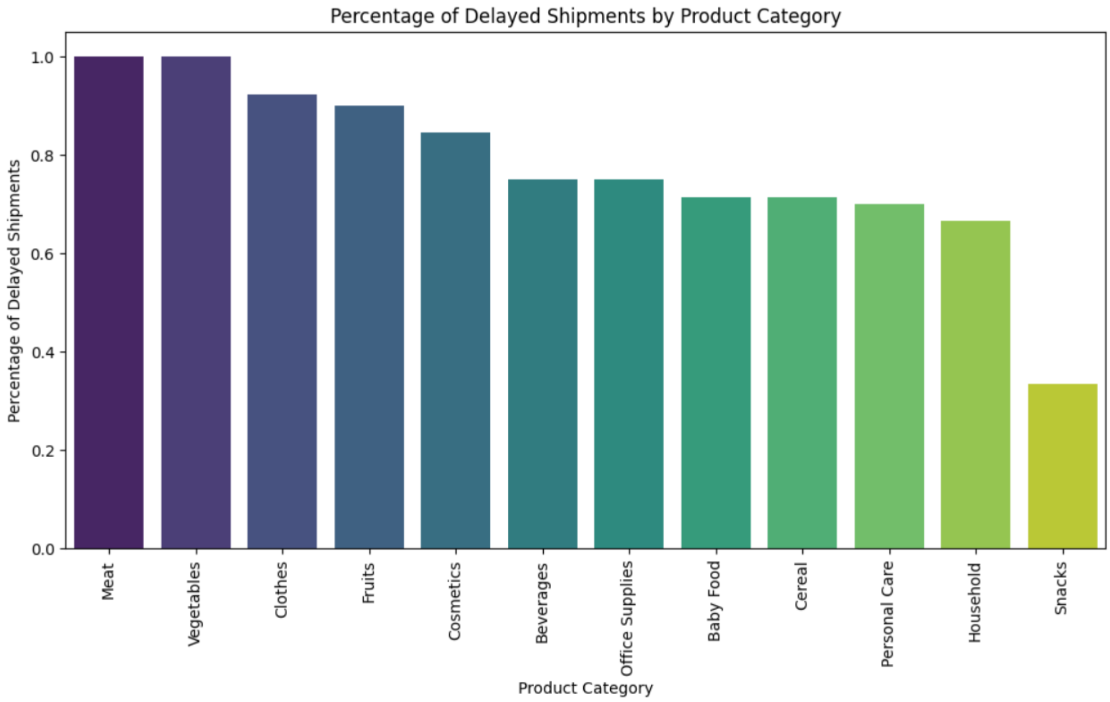
```
Amazon clearly need to upgrade it delivery system. 79% of its orders take more than 7 days to get delivered.
```

```
# Analyze delays by product category
delays_by_category = data.groupby('Item Type')['Delayed'].mean().sort_values(ascending=False)
print(delays_by_category)
```


```
# Analyze delays by product category
delays_by_category = data.groupby('Item Type')['Delayed'].mean().sort_values(ascending=False)
print(delays_by_category)
```


```
Item Type
Meat               1.000000
Vegetables         1.000000
Clothes            0.923077
Fruits             0.900000
Cosmetics          0.846154
Beverages          0.750000
Office Supplies    0.750000
Baby Food          0.714286
Cereal             0.714286
Personal Care      0.700000
Household          0.666667
Snacks             0.333333
Name: Delayed, dtype: float64
```

```
# Plot delays by product category
plt.figure(figsize=(12, 6))
sns.barplot(x=delays_by_category.index, y=delays_by_category.values, palette='viridis', hue=delays_by_category.index)
plt.title('Percentage of Delayed Shipments by Product Category')
plt.xlabel('Product Category')
plt.ylabel('Percentage of Delayed Shipments')
plt.xticks(rotation=90)
plt.show()
```



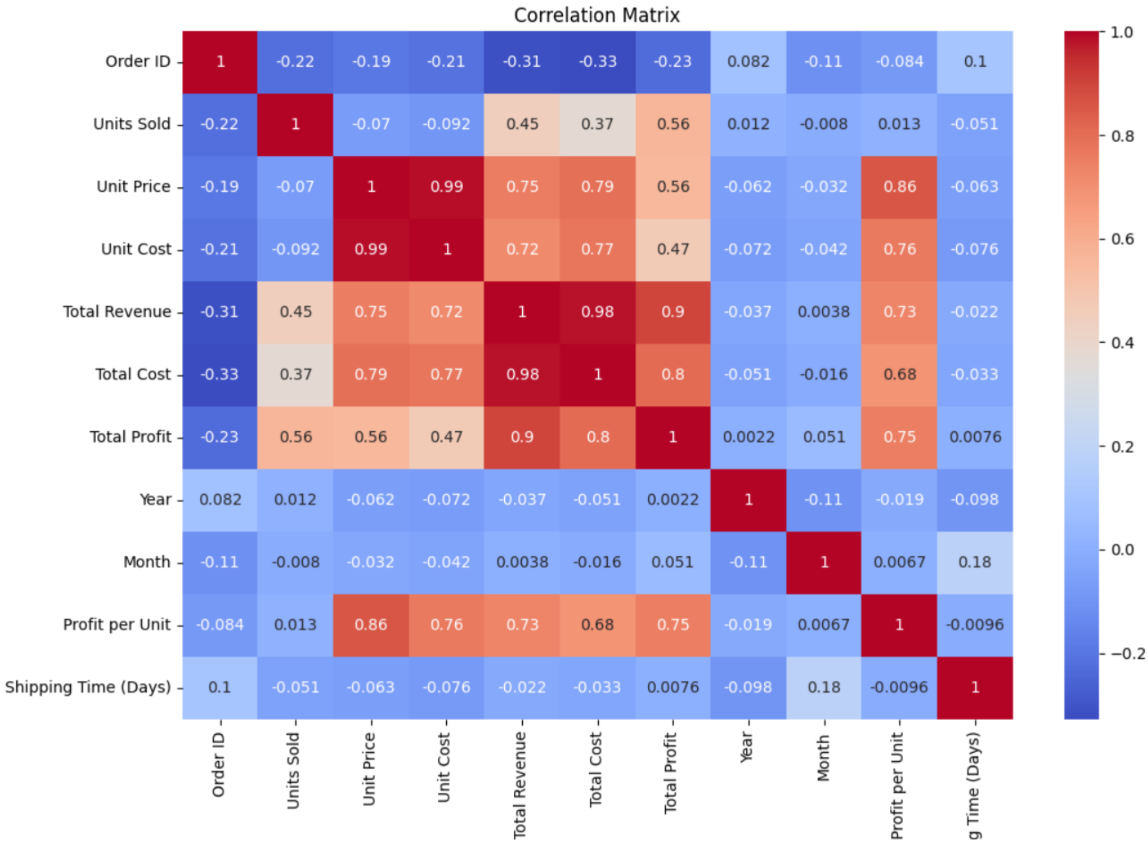

```
Delay on vegetables and meat is highest. Snacks are delivered fastest as compared to any other item.
```

Correlation Analysis

```python
import statsmodels.api as sm

X = data['Unit Price']
y = data['Total Profit']
X = sm.add_constant(X)  # Adds a constant term to the predictor

model = sm.OLS(y, X).fit()
predictions = model.predict(X)

# Print out the statistics
print(model.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:           Total Profit   R-squared:                       0.311
Model:                            OLS   Adj. R-squared:                  0.304
Method:                 Least Squares   F-statistic:                     44.16
Date:                Sat, 20 Jul 2024   Prob (F-statistic):           1.71e-09
Time:                        19:11:44   Log-Likelihood:                -1421.9
No. Observations:                 100   AIC:                             2848.
Df Residuals:                      98   BIC:                             2853.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const       1.545e+05   5.66e+04      2.729      0.008    4.22e+04    2.67e+05
Unit Price  1037.4951    156.117      6.646      0.000     727.685    1347.305
==============================================================================
Omnibus:                       15.537   Durbin-Watson:                   2.151
Prob(Omnibus):                  0.000   Jarque-Bera (JB):               17.735
Skew:                           0.890   Prob(JB):                     0.000141
Kurtosis:                       4.043   Cond. No.                         561.
==============================================================================
```

```python
# Selecting numerical columns for making Correlation matrix
numerical_data = data.select_dtypes(include=[float, int])

# Correlation matrix
correlation_matrix = numerical_data.corr()

# Plot the correlation matrix
plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



CONCLUSION

Key Insights from the correlation matrix:

1. High Correlations (close to 1 or -1):

- Unit Price and Unit Cost (0.99): There is a very strong positive correlation between Unit Price and Unit Cost, indicating that higher-priced items also tend to have higher costs.

- Total Revenue and Total Profit (0.90): Total Revenue and Total Profit are highly correlated. As revenue increases, profit also increases significantly.

- Unit Price and Total Revenue (0.75): Unit Price is strongly correlated with Total Revenue. Higher unit prices contribute significantly to higher total revenue.

2. Weak Correlations (between 0.2 and 0.5):

- Units Sold and Total Profit (0.37): There is a weak positive correlation between Units Sold and Total Profit. This indicates that simply selling more units doesn't strongly influence profit, as other factors like cost and price are also crucial.

- Unit Price and Total Profit (0.56): Unit Price has a moderate correlation with Total Profit. Higher unit prices are somewhat associated with higher profits.

3. Negative Correlations (close to -1):

- Order ID and Total Profit (-0.23): There is a weak negative correlation between Order ID and Total Profit. This might suggest that there is no strong relationship between the order ID and profit, as order IDs are usually arbitrary and not related to sales metrics.

Summary:

- Profitability Drivers: Higher Unit Prices and higher Total Costs are major drivers of higher Total Revenues and Total Profits.

- Cost-Price Relationship: There is a very strong relationship between Unit Price and Unit Cost, suggesting that more expensive items tend to have higher costs.

- Sales Volume: The number of units sold has a moderate impact on revenue but a weaker impact on profit, indicating that volume alone isn't sufficient to drive profitability.

- Revenue-Expense Link: There is a very strong relationship between Total Cost and Total Revenue, indicating that as businesses spend more, they also tend to earn more.

These insights can guide decision-making processes, such as focusing on pricing strategies and managing costs effectively to maximize profitability.

MAJOR CONCLUSIONS FROM DATA ANALYSIS:

1. Monthly and Yearly Sales Trends:

- Monthly Trends: Certain months consistently show higher total revenue, indicating peak sales periods. This trend can be leveraged for inventory planning and promotional activities.

- Yearly Trends: The yearly analysis shows an upward or downward trend in sales, reflecting the overall growth or decline in the business. This helps in long-term strategic planning.

2. Key Metrics and Factors:

- Unit Price and Unit Cost: Both are strongly correlated with Total Revenue and Total Profit. Higher unit prices and unit costs generally lead to higher total revenues and profits.

- Units Sold: This metric is crucial as it directly impacts the total revenue and total profit. It is moderately correlated with Total Revenue and Total Profit.

3. Correlation Insights:

- Strong Correlations:

  - Unit Price and Unit Cost have a near-perfect correlation (0.99), indicating that as the unit price increases, the unit cost also increases proportionally.

  - Total Revenue and Total Profit have a high positive correlation (0.9), indicating that higher revenues generally lead to higher profits.

- Moderate Correlations:

  - Units Sold has a moderate positive correlation with Total Revenue (0.56) and Total Profit (0.56), indicating that higher sales volumes contribute to increased revenue and profit.

4. Profitability Analysis:

- The item with the highest profit per unit can be identified by calculating the difference between unit price and unit cost. This item can be a focal point for marketing and sales strategies to maximize profitability.

5. Shipping Analysis:

- By comparing order dates with ship dates, it is possible to analyze shipping times and identify any delays. Efficient shipping is critical for customer satisfaction and retention.

6. Online vs. Offline Sales Comparison:

- Grouped Bar Chart: The grouped bar chart comparing units sold online versus offline for each item type shows distinct differences in sales channels for various products. This insight can guide marketing strategies and resource allocation for each sales channel.

Visual Insights:

1. Correlation Matrix:

- Highlights the relationships between key metrics, showing which factors are closely related and which are not, guiding focus areas for improving business performance.

2. Bar Charts (Month-wise, Year-wise, Year-Month-wise):

- Clearly depict sales trends over different time periods, helping in identifying peak periods and making data-driven decisions for sales and marketing campaigns.

3. Grouped Bar Chart (Online vs. Offline Sales):

- Provides a clear comparison of sales channels, helping to understand customer preferences and optimize sales strategies for different item types.

RECOMMENDATIONS

1. Focus on High-Profit Items:

- Prioritize marketing and sales efforts on items with the highest profit margins to maximize profitability.

2. Inventory and Promotional Planning:

- Use monthly and yearly sales trends to plan inventory and promotions effectively, ensuring stock availability during peak periods and avoiding overstocking during low demand periods.

3. Optimize Sales Channels:

- Analyze the online and offline sales data to optimize resource allocation and marketing efforts for each channel, ensuring a balanced approach that maximizes overall sales.

4. Improve Shipping Efficiency:

- Address any identified shipping delays to enhance customer satisfaction and improve repeat business.

By leveraging these insights and recommendations, the business can improve its sales management, enhance profitability, and better meet customer demands.