# E- Commerce

Exploratory Data Analysis for a UK-based Online Retail Company

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# Abstract

This data analysis project focuses on a UK-based non-store online retail company that specializes in selling mainly all-occasion gifts to a customer base consisting primarily of wholesalers, both local and international. The dataset covers a one-year period, from 1st December 2010 to 9th December 2011. The primary goal of this analysis is to perform a comprehensive Exploratory Data Analysis (EDA) and derive valuable insights from the data.

The project addresses the following problem statements:

- Perform Basic EDA.
- Check for and handle missing values in all columns using appropriate metrics like mean, median, or mode.
- Remove duplicate rows to ensure data cleanliness.
- Filter out rows with negative values in the Quantity column, as these may indicate errors.
- Add new columns representing Month, Day, and Hour based on the invoice data.
- Determine the number of orders made by each customer.
- Identify the top 5 customers with the highest number of orders.
- Calculate the total amount of money spent by each customer.
- Find the top 5 customers who have spent the most.
- Analyse the number of orders per month.
- Explore the number of orders per day.
- Investigate the number of orders per hour.
- Examine the number of orders for each country.
- Visualize the trend of orders across different months.
- Calculate and visualize the total money spent by customers from each country.

Through this comprehensive analysis, the project aims to provide valuable insights into customer behaviour, order trends, and overall business performance for the UK-based non-store online retail company. The findings and visualizations generated from this EDA can inform strategic decision-making, marketing strategies, and customer relationship management.

*Keywords: metrics, data cleanliness, explore, investigate, Examine, Visualize.*

# Introduction

In the digital age, data serves as a valuable commodity, offering organizations a lens through which to understand their operations, customers, and market trends. This research project embarks on an insightful journey into the realm of data analysis, driven by the exploration of a dataset from a UK-based and registered non-store online retail company. This data, collected over a one-year period from December 1, 2010, to December 9, 2011, represents a wealth of information, providing us with a unique opportunity to uncover patterns, gain insights, and make data-driven decisions.

The Company and Its Context:

The focus of our analysis is a UK-based online retail company with a distinctive identity. The company specializes in the sale of primarily all-occasion gifts, catering to a diverse clientele. The customers of this e-commerce retailer predominantly consist of wholesalers, encompassing both local and international entities. This suggests a dynamic marketplace with the potential for a wide range of transactions, making the dataset particularly intriguing.

The Data Collection Period:

The dataset at hand encapsulates a one-year period, from December 1, 2010, to December 9, 2011. This temporal scope is significant, as it allows us to observe changes, trends, and seasonality within the data. By conducting a thorough analysis of this data, we can gain insights into how the company's performance, customer behaviour, and market dynamics evolved over this one-year duration.

Problem Statements and Objectives:

The primary objective of this research project is to conduct a comprehensive Exploratory Data Analysis (EDA) by addressing a series of problem statements, each designed to unveil unique aspects of the dataset:

- Perform Basic EDA: This includes various data visualization and statistical techniques, such as box plots, histograms, aggregation, correlation analysis, and more.
- Data Cleaning and Preprocessing: Tasks like handling missing data, removing duplicates, and addressing negative values.
- Customer Analysis: Investigating customer behaviour, orders made, and spending patterns.

- Sales Analysis: Examining orders per month, day, and hour, and trends across different time periods.
- Geographic Analysis: Understanding the distribution of orders by country and the money spent by each country.

These problem statements not only guide our analysis but also pave the way for insights that can inform strategic decisions, marketing efforts, and customer relationship management for the company.

As we delve into this dataset and undertake the rigorous process of EDA, our aim is to extract meaningful information that goes beyond numbers and charts. We strive to derive actionable insights that will empower the company to thrive in the competitive landscape of e-commerce, all while delivering valuable lessons for future data analysis endeavors.

# Data Collection

Data source: https://www.kaggle.com/carrie1/ecommerce-data

Data Acquisition Process:

The process of acquiring the data for this EDA project typically involves the following steps:

- Data Extraction: The data would be extracted from the company's databases, log files, or other sources using appropriate data extraction tools or database queries.
- Data Cleaning: Data cleaning is an important step where the data is examined for any errors, inconsistencies, or missing values. Data cleaning procedures may include removing or filling in missing data, correcting errors, and addressing outliers.
- Data Transformation: After cleaning, the data may need to be transformed to meet the requirements of the analysis. This can involve creating new variables, aggregating data, or reformatting it to make it suitable for EDA.
- Data Integration: If the data is sourced from multiple databases or systems, it may need to be integrated into a single dataset for analysis.
- Data Export: The final, clean dataset would be exported to a format that is suitable for analysis, often in a structured data format like a CSV (Comma Separated Values) file.
- Data Documentation: It's crucial to document the data sources, data cleaning and transformation procedures, and any decisions made during the data acquisition process to ensure reproducibility and transparency.

Once the data is acquired, cleaned, and prepared, it can be used for the exploratory data analysis, which will involve addressing the problem statements outlined in the project.

# Exploratory Data Analysis (EDA)

**Purpose and Significance**

Exploratory Data Analysis (EDA) is a critical and often the first step in the data analysis process. It plays a pivotal role in uncovering patterns and gaining insights from a dataset, as exemplified in the context of the UK-based non-store online retail company specializing in all-occasion gifts and operating within the time frame of December 1, 2010, to December 9, 2011. EDA serves several key purposes and holds significant value:

1. Understanding the Data:

EDA allows analysts to get to know the dataset comprehensively. It involves examining the structure of the data, including the number of observations, variables, and their data types.

2. Identifying Data Quality Issues:

EDA is instrumental in spotting data quality problems such as missing values, duplicates, and outliers. By addressing these issues, analysts ensure that the data used for further analysis is reliable and accurate.

3. Visualizing Data Distributions:

Through EDA, data is visualized in various ways, including box plots, histograms, and distribution plots. These visualizations provide insights into the distribution of numeric variables, helping to understand central tendencies, variations, and potential data anomalies.

4. Detecting Relationships and Patterns:

EDA techniques like correlation analysis and regression plots reveal relationships between variables. This is crucial for understanding dependencies and identifying which variables might have an impact on others.

5. Data Summarization:

Aggregations for numerical columns provide summaries of data, such as mean, median, and percentiles. This helps in summarizing data characteristics and drawing initial conclusions.

6. Data Exploration and Unique Values:

Identifying unique values across all columns aids in discovering the variety of categories and values within the data. This is essential for understanding the diversity of the dataset.

7. Correlation Analysis:

Heatmaps and correlation plots highlight relationships between numeric variables. Strong correlations may indicate dependencies that can be further investigated.

8. Outlier Detection:

Through EDA, analysts can spot outliers in the data that may require special treatment. Outliers can significantly impact statistical analysis and should be carefully considered.

9. Trends and Time Analysis:

Line charts and time-based visualizations help in understanding trends and patterns over time. In the given context, this can be vital for identifying seasonal fluctuations or changes in customer behaviour.

10. Skewness Analysis:

Detecting skewness in numeric variables is essential for understanding the distribution's shape, which can impact the choice of statistical methods.

11. Missing Data Handling:

EDA helps identify missing data, allowing for informed decisions on how to handle these gaps, whether through imputation with the mean, median, mode, or other methods.

12. Customer and Sales Analysis:

EDA is central to understanding customer behaviour, including the number of orders, spending patterns, and customer segmentation. This information can drive marketing strategies and customer relationship management.

13. Geographic Analysis:

The analysis of orders by country and money spent by each country helps in identifying international market trends and can inform global expansion strategies.

In the context of the UK-based online retail company, EDA serves as the foundational step to gain a comprehensive understanding of the dataset. The insights and patterns uncovered through EDA are the building blocks for more advanced analyses, predictive modelling, and informed decision-making, ultimately contributing to the company's success in the highly competitive e-commerce landscape.

# Problem Statements

Certainly, here are the 15 problem statements that guide the analysis for the UK-based non-store online retail company specializing in all-occasion gifts:

Problem Statements:

1. Perform Basic EDA:

   a. Create box plots for all numeric variables.

   b. Generate histograms for all numeric variables.

   c. Produce distribution plots for all numeric variables.

   d. Calculate aggregations (e.g., mean, median, etc.) for all numerical columns.

   e. Identify unique values across all columns.

   f. Detect and address duplicate values across all columns.

   g. Visualize correlations between numeric variables using a heatmap.

   h. Create regression plots for all numeric variables.

   i. Generate bar plots for every categorical variable against every numerical variable.

   j. Produce pair plots to visualize relationships between all numeric variables.

   k. Construct line charts to show trends in data for all numeric and date variables.

   l. Calculate and visualize the skewness for all numeric variables.

2. Data Cleaning and Preprocessing:

   - Check for missing values in all columns and replace them with the appropriate metric (mean, median, mode).

3. Data Quality Assurance:

   - Remove duplicate rows from the dataset to ensure data integrity.

4. Data Sanitization:

   - Remove rows that have negative values in the Quantity column.

5. Feature Engineering:

   - Add new columns to the dataset, including Month, Day, and Hour for the invoice.

6. Customer Analysis:
   - Determine the number of orders made by each customer.
7. Customer Ranking:
   - Identify and rank the top 5 customers with the highest number of orders.
8. Customer Spending Analysis:
   - Calculate the total money spent by each customer.
9. High-Spending Customers:
   - Identify and rank the top 5 customers with the highest total spending.
10. Monthly Order Analysis:
    - Calculate the number of orders per month.
11. Daily Order Analysis:
    - Calculate the number of orders per day.
12. Hourly Order Analysis:
    - Calculate the number of orders per hour.
13. Geographic Analysis:
    - Determine the number of orders for each country.
14. Order Trends Over Months:
    - Visualize and analyse the trends in orders across different months.
15. Country Spending Analysis:
    - Calculate and visualize the total money spent by customers from each country.

These problem statements collectively guide the data analysis process, providing a structured framework for uncovering insights, patterns, and trends within the dataset. By addressing these questions and tasks, the analysis aims to provide valuable information that can inform business decisions, marketing strategies, and customer management for the UK-based e-commerce retailer.

# Methodology

Methodology: **General Approach for Data Analysis**

The methodology for addressing the 15 problem statements and conducting an effective Exploratory Data Analysis (EDA) for the UK-based non-store online retail company follows a structured approach, encompassing data exploration, cleaning, analysis, and visualization.

Here's an overview of the general steps and procedures:

1. Data Collection and Inspection:

- Acquire the dataset from the company's records or databases.

- Inspect the dataset for its structure, data types, and an initial understanding of its contents.

2. Data Cleaning and Preprocessing:

- Identify and handle missing values in all columns by replacing them with appropriate metrics (mean, median, or mode).

- Remove duplicate rows to ensure data integrity.

- Eliminate rows with negative values in the Quantity column to address data quality issues.

- Create additional features, such as Month, Day, and Hour, to enhance the dataset for analysis.

3. Exploratory Data Analysis (EDA):

- Perform basic EDA to understand the data comprehensively:

  - Create box plots, histograms, and distribution plots for all numeric variables to visualize data distributions and detect outliers.

  - Calculate aggregations (e.g., mean, median, etc.) for all numerical columns to understand central tendencies and variations.

  - Identify unique values across all columns to explore the diversity of data.

  - Detect and address duplicate values across all columns to ensure data accuracy.

- Visualize correlations between numeric variables using a heatmap and regression plots to understand relationships.

- Generate bar plots for every categorical variable against every numerical variable to examine associations.

- Create pair plots to visualize relationships between all numeric variables for deeper insights.

- Construct line charts to show trends in data for both numeric and date variables, including the trend of orders over time.

- Calculate and visualize the skewness of all numeric variables to understand data distribution shapes.

4. Customer Analysis:

- Determine the number of orders made by each customer to understand customer engagement.

- Identify and rank the top 5 customers with the highest number of orders for special recognition.

- Calculate the total money spent by each customer to understand customer spending patterns.

- Identify and rank the top 5 customers with the highest total spending to reward loyal customers.

5. Sales Analysis:

- Calculate the number of orders per month to understand monthly sales trends.

- Calculate the number of orders per day to identify daily sales patterns.

- Calculate the number of orders per hour to pinpoint peak sales hours.

6. Geographic Analysis:

- Determine the number of orders for each country to understand international market trends.

- Visualize and analyse the trends in orders across different months to identify seasonal fluctuations or changes in customer behaviour.

- Calculate and visualize the total money spent by customers from each country to inform global expansion strategies.

By following this comprehensive methodology, the analysis aims to uncover patterns, relationships, and insights within the dataset. The findings can guide strategic decisions, marketing efforts, and customer management for the UK-based online retail company. Additionally, this methodology ensures that the analysis is transparent, reproducible, and well-documented.

# Data Exploration and Visualization

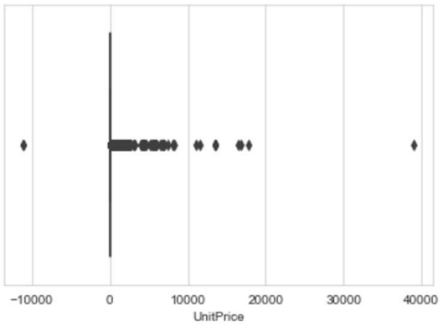
Performing the Basic EDA (Exploratory Data Analysis) for the given context and problem statements involves various data analysis and visualization tasks. Let's go through each of the specified steps:

1. Basic EDA:

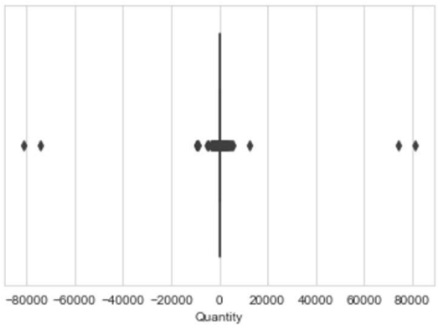
a. Boxplot – All Numeric Variables:

- Create boxplots for all numeric variables (e.g., Quantity, UnitPrice) to visualize their distribution, central tendency, and identify outliers.

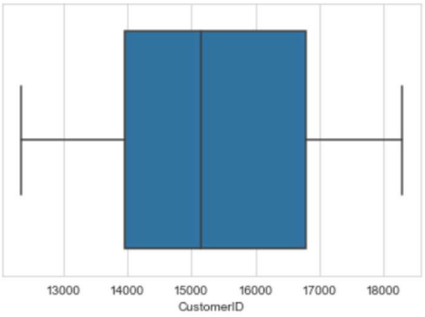
```
sns.boxplot(df["UnitPrice"]);
```



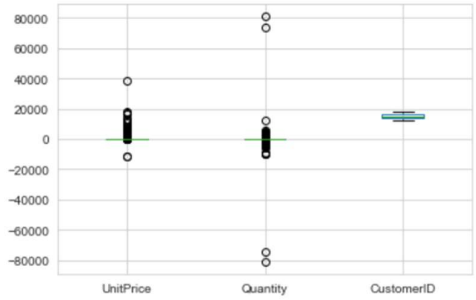

```
sns.boxplot(df["Quantity"]);
```




```
sns.boxplot(df["CustomerID"]);
```



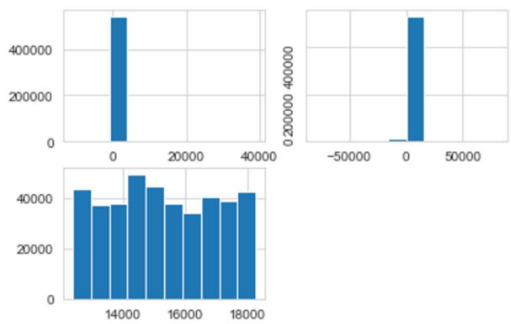

```
df.boxplot(column=["UnitPrice","Quantity","CustomerID"]);
```



b. Histogram – All Numeric Variables:

- Generate histograms for numeric variables to understand their frequency distributions.

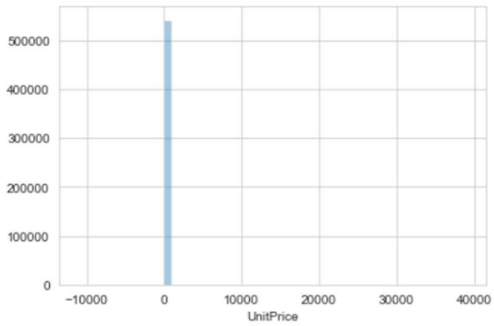
```
plt.subplot(2,2,1)
plt.hist(df["UnitPrice"])
plt.show;
plt.subplot(2,2,2)
plt.hist(df["Quantity"])
plt.yticks(rotation=90)
plt.show;
plt.subplot(2,2,3)
plt.hist(df["CustomerID"])
plt.show;
```



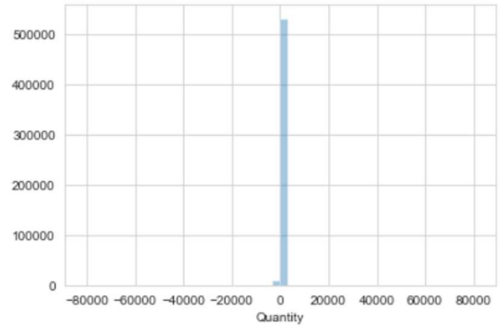

c. Distribution Plot – All Numeric Variables:

- Create distribution plots (e.g., Kernel Density Estimation) to get a smoother representation of the data distribution.

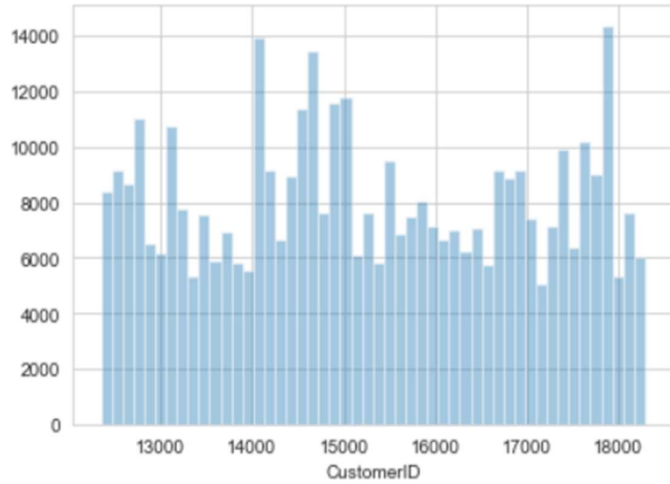
```
sns.distplot(df.UnitPrice, kde=False);
```




```
sns.distplot(df.Quantity, kde=False);
```



```
sns.distplot(df.CustomerID, kde=False);
```




d. Aggregation for all numerical Columns:

- Calculate summary statistics (mean, median, standard deviation, etc.) for all numeric columns to get an overview of their characteristics.

```
x=df[["UnitPrice","Quantity","CustomerID"]]
```

```
x.head()
```

| | UnitPrice | Quantity | CustomerID |
|---|---|---|---|
| **0** | 2.55 | 6 | 17850.0 |
| **1** | 3.39 | 6 | 17850.0 |
| **2** | 2.75 | 8 | 17850.0 |
| **3** | 3.39 | 6 | 17850.0 |
| **4** | 3.39 | 6 | 17850.0 |

```
x.sum()
```

```
UnitPrice     2.498804e+06
Quantity      5.176450e+06
CustomerID    6.219476e+09
dtype: float64
```

```
x.mean()
```

```
UnitPrice          4.611114
Quantity           9.552250
CustomerID     15287.690570
dtype: float64
```

```
x.median()
```

```
UnitPrice          2.08
Quantity           3.00
CustomerID     15152.00
dtype: float64
```

```
x.std()
```

```
UnitPrice        96.759853
Quantity        218.081158
CustomerID     1713.600303
dtype: float64
```

```
x.max()
```

```
UnitPrice      38970.0
Quantity       80995.0
CustomerID     18287.0
dtype: float64
```

```
x.min()
```

```
UnitPrice     -11062.06
Quantity      -80995.00
CustomerID     12346.00
dtype: float64
```

e. Unique Values across all columns:

- Check and count unique values in each column to understand the diversity and cardinality of categorical variables.

```
for col in df:
    print(df[col].unique())
```

```
['536365' '536366' '536367' ... '581585' '581586' '581587']
['85123A' '71053' '84406B' ... '90214U' '47591b' '23843']
['WHITE HANGING HEART T-LIGHT HOLDER' 'WHITE METAL LANTERN'
 'CREAM CUPID HEARTS COAT HANGER' ... 'lost'
 'CREAM HANGING HEART T-LIGHT HOLDER' 'PAPER CRAFT , LITTLE BIRDIE']
[     6      8      2     32      3      4     24     12     48     18
     20     36     80     64     10    120     96     23      5      1
     -1     50     40    100    192    432    144    288    -12    -24
     16      9    128     25     30     28      7     56     72    200
    600    480     -6     14     -2     11     33     13     -4     -5
     -7     -3     70    252     60    216    384    -10     27     15
     22     19     17     21     34     47    108     52  -9360    -38
     75    270     42    240     90    320   1824    204     69    -36
   -192   -144    160   2880   1400     39    -48    -50     26   1440
     31     82     78     97     98     35     57    -20    110    -22
    -30    -70   -130    -80   -120    -40    -25    -14    -15    -69
   -140   -320     -8    720    156    324     38     37     49     95
     -9    -11     29     41    -72    -35    -21    -43    -19    -18
    -44    402    378    150    300     54    104     67    258     66
     44     55     46     99     61    408    972    208   1008   1000
    -77   1488    250   1394    400   -223   -150    -13    -33   -723
   -177     79     84    -32   -100    -28    272   -145    -47    -96
```

```
df.count(axis=0)
```

```
InvoiceNo      541909
StockCode      541909
Description    540455
Quantity       541909
InvoiceDate    541909
UnitPrice      541909
CustomerID     406829
Country        541909
dtype: int64
```

```
df.nunique(axis=0)
```

```
InvoiceNo      25900
StockCode       4070
Description     4223
Quantity         722
InvoiceDate    23260
UnitPrice       1630
CustomerID      4372
Country           38
dtype: int64
```

f. Duplicate values across all columns:

- Identify and handle duplicate values in the dataset to ensure data quality.

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

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country |
|---|---|---|---|---|---|---|---|---|
| **517** | 536409 | 21866 | UNION JACK FLAG LUGGAGE TAG | 1 | 12/1/2010 11:45 | 1.25 | 17908.0 | United Kingdom |
| **527** | 536409 | 22866 | HAND WARMER SCOTTY DOG DESIGN | 1 | 12/1/2010 11:45 | 2.10 | 17908.0 | United Kingdom |
| **537** | 536409 | 22900 | SET 2 TEA TOWELS I LOVE LONDON | 1 | 12/1/2010 11:45 | 2.95 | 17908.0 | United Kingdom |
| **539** | 536409 | 22111 | SCOTTIE DOG HOT WATER BOTTLE | 1 | 12/1/2010 11:45 | 4.95 | 17908.0 | United Kingdom |
| **555** | 536412 | 22327 | ROUND SNACK BOXES SET OF 4 SKULLS | 1 | 12/1/2010 11:49 | 2.95 | 17920.0 | United Kingdom |
| **...** | ... | ... | ... | ... | ... | ... | ... | ... |
| **541675** | 581538 | 22068 | BLACK PIRATE TREASURE CHEST | 1 | 12/9/2011 11:34 | 0.39 | 14446.0 | United Kingdom |
| **541689** | 581538 | 23318 | BOX OF 6 MINI VINTAGE CRACKERS | 1 | 12/9/2011 11:34 | 2.49 | 14446.0 | United Kingdom |
| **541692** | 581538 | 22992 | REVOLVER WOODEN RULER | 1 | 12/9/2011 11:34 | 1.95 | 14446.0 | United Kingdom |
| **541699** | 581538 | 22694 | WICKER STAR | 1 | 12/9/2011 11:34 | 2.10 | 14446.0 | United Kingdom |
| **541701** | 581538 | 23343 | JUMBO BAG VINTAGE CHRISTMAS | 1 | 12/9/2011 11:34 | 2.08 | 14446.0 | United Kingdom |

5268 rows × 8 columns

```
df.shape
```

```
(541909, 8)
```

```
df=df.drop_duplicates(keep=False)
```

```
df.shape
```

```
(531762, 8)
```

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

| InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country |
|---|---|---|---|---|---|---|---|

g. Correlation – Heatmap - All Numeric Variables:

- Calculate and create a correlation heatmap to visualize relationships between numeric variables.

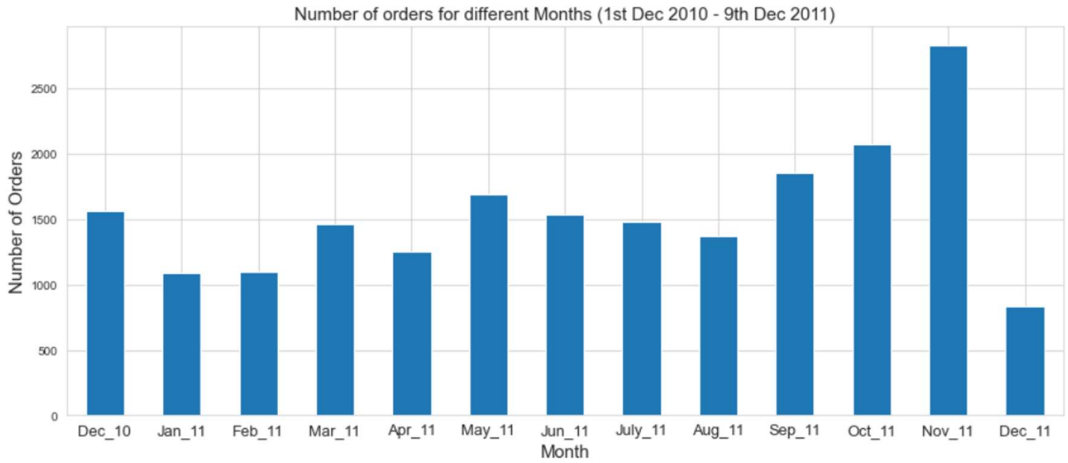
```
#n_df=df.pivot(index=,columns="UnitPrice",values="Quantity")
```

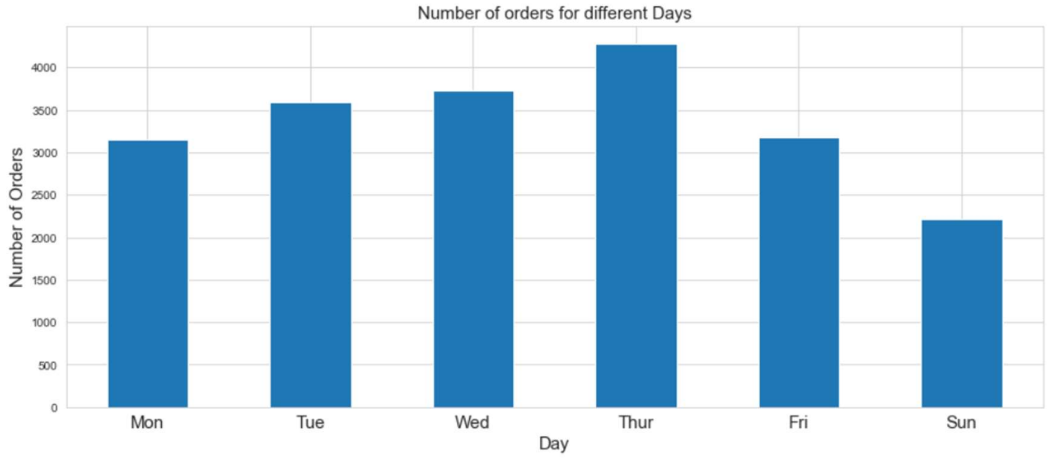
h. Regression Plot - All Numeric Variables:

- Generate regression plots to explore relationships between numeric variables, potentially showing trends or associations.

i. Bar Plot – Every Categorical Variable vs every Numerical Variable:

- Create bar plots to visualize relationships between categorical variables (e.g., Country) and numeric variables (e.g., Total sales).


Number of orders for different Months (1st Dec 2010 - 9th Dec 2011)
Number of Orders
0
500
1000
1500
2000
2500
Dec_10
Jan_11
Feb_11
Mar_11
Apr_11
May_11
Jun_11
July_11
Aug_11
Sep_11
Oct_11
Nov_11
Dec_11
Month


Number of orders for different Days
Number of Orders
0
500
1000
1500
2000
2500
3000
3500
4000
Mon
Tue
Wed
Thur
Fri
Sun
Day

Number of orders for different Hours
Number of Orders
0
500
1000
1500
2000
2500
3000
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
Hour

j. Pair plot - All Numeric Variables:

- Generate pair plots to visualize scatter plots and histograms for all combinations of numeric variables.

k. Line chart to show the trend of data - All Numeric/Date Variables:

- Create line charts to illustrate trends over time for numeric and date variables.

l. Plot the skewness - All Numeric Variables:

- Calculate and plot skewness for each numeric variable to assess data distribution asymmetry.

2. Check for missing values in all columns and replace them with the appropriate metric (Mean/Median/Mode):

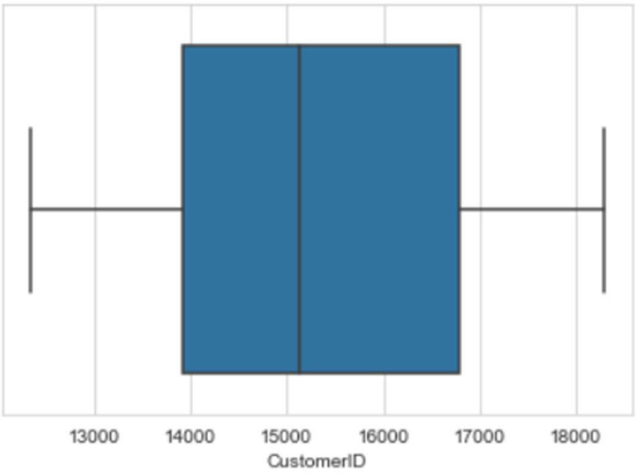
- Identify missing values in the dataset, and impute them using the mean, median, or mode of the respective column, depending on the nature of the data.

```
df.isnull().sum().sort_values(ascending=False)
```

```
CustomerID     134995
Description      1454
InvoiceNo           0
StockCode           0
Quantity            0
InvoiceDate         0
UnitPrice           0
Country             0
dtype: int64
```

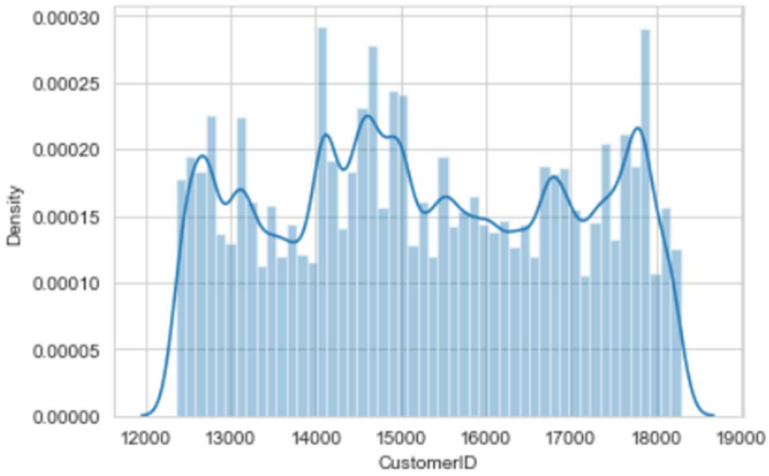
```
sns.boxplot(df["CustomerID"])
```

```
<AxesSubplot:xlabel='CustomerID'>
```




```
sns.distplot(df["CustomerID"])
```

```
<AxesSubplot:xlabel='CustomerID', ylabel='Density'>
```



```
x=df["CustomerID"].mean()
type(x)
```

```
float
```

```
int(x)
```

```
15275
```

```
df['CustomerID']=df["CustomerID"].fillna(x)
```

```
df.isnull().sum()
```

```
InvoiceNo         0
StockCode         0
Description    1454
Quantity          0
InvoiceDate       0
UnitPrice         0
CustomerID        0
Country           0
dtype: int64
```

```
df.dropna(inplace=True)
```

```
df.isnull().sum()
```

```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

3. Remove duplicate rows:

- Eliminate duplicate rows from the dataset to maintain data integrity.

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

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country |
|---|---|---|---|---|---|---|---|---|

4. Remove rows which have negative values in Quantity column:

- Filter out rows with negative values in the Quantity column as they might indicate data entry errors.

```
(df["Quantity"]<0).sum()
```

```
9693
```

```
df.drop(df[df["Quantity"]<0].index,inplace=True)
```

```
df.shape
```

```
(520615, 8)
```

5. Add the columns - Month, Day, and Hour for the invoice:

- Extract and add columns for the month, day, and hour from the invoice date to facilitate time-based analysis.

```
df.head()
```

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country |
|---|---|---|---|---|---|---|---|---|
| 0 | 536365 | 85123A | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 12/1/2010 8:26 | 2.55 | 17850.0 | United Kingdom |
| 1 | 536365 | 71053 | WHITE METAL LANTERN | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom |
| 2 | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 12/1/2010 8:26 | 2.75 | 17850.0 | United Kingdom |
| 3 | 536365 | 84029G | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom |
| 4 | 536365 | 84029E | RED WOOLLY HOTTIE WHITE HEART. | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom |

```
import datetime as dt
```

```
df.head()
```

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country |
|---|---|---|---|---|---|---|---|---|
| 0 | 536365 | 85123A | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 12/1/2010 8:26 | 2.55 | 17850.0 | United Kingdom |
| 1 | 536365 | 71053 | WHITE METAL LANTERN | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom |
| 2 | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 12/1/2010 8:26 | 2.75 | 17850.0 | United Kingdom |
| 3 | 536365 | 84029G | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom |
| 4 | 536365 | 84029E | RED WOOLLY HOTTIE WHITE HEART. | 6 | 12/1/2010 8:26 | 3.39 | 17850.0 | United Kingdom |

```
df['InvoiceDate'] = pd.to_datetime(df.InvoiceDate, format='%m/%d/%Y %H:%M')
```

```
df['InvoiceDate'] = pd.to_datetime(df.InvoiceDate, format='%m/%d/%Y %H:%M')
```

```
df.insert(loc=2, column='Year_month', value=df['InvoiceDate'].map(lambda x: 100*x.year + x.month))
df.insert(loc=3, column='Month', value=df.InvoiceDate.dt.month)
# +1 to make Monday=1.....until Sunday=7
df.insert(loc=4, column='Day', value=(df.InvoiceDate.dt.dayofweek)+1)
df.insert(loc=5, column='Hour', value=df.InvoiceDate.dt.hour)
```

```
df.head()
```

| | InvoiceNo | StockCode | Year_month | Month | Day | Hour | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 536365 | 85123A | 201012 | 12 | 3 | 8 | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 | United Kingdom |
| 1 | 536365 | 71053 | 201012 | 12 | 3 | 8 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | United Kingdom |
| 2 | 536365 | 84406B | 201012 | 12 | 3 | 8 | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 | United Kingdom |
| 3 | 536365 | 84029G | 201012 | 12 | 3 | 8 | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | United Kingdom |
| 4 | 536365 | 84029E | 201012 | 12 | 3 | 8 | RED WOOLLY HOTTIE WHITE HEART. | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | United Kingdom |

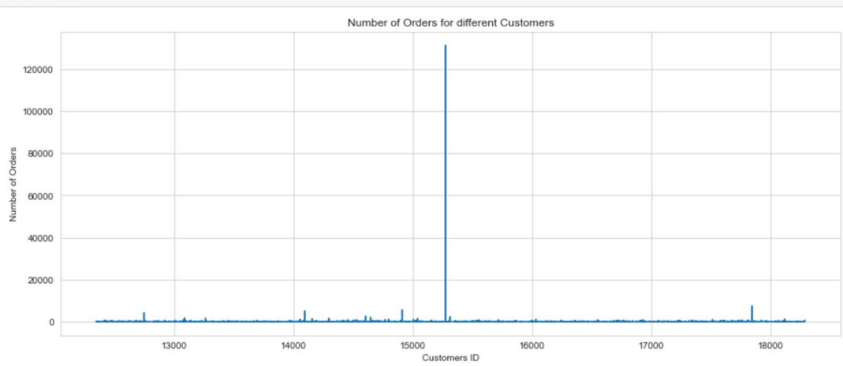
6. How many orders made by the customers?

- Calculate the count of orders made by each customer.

```
df.groupby(by=['CustomerID','Country'], as_index=False)['InvoiceNo'].count().head()
```

| | CustomerID | Country | InvoiceNo |
|---|---|---|---|
| 0 | 12346.0 | United Kingdom | 1 |
| 1 | 12347.0 | Iceland | 182 |
| 2 | 12348.0 | Finland | 31 |
| 3 | 12349.0 | Italy | 73 |
| 4 | 12350.0 | Norway | 17 |

```
orders = df.groupby(by=['CustomerID','Country'], as_index=False)['InvoiceNo'].count()

plt.subplots(figsize=(15,6))
plt.plot(orders.CustomerID, orders.InvoiceNo)
plt.xlabel('Customers ID')
plt.ylabel('Number of Orders')
plt.title('Number of Orders for different Customers')
plt.show()
```



7. TOP 5 customers with a higher number of orders:

- Identify the top 5 customers with the highest order counts.

```
orders['CustomerID'] = orders['CustomerID'].astype('int64')
```

```
orders.sort_values(by='InvoiceNo', ascending=False).head()
```

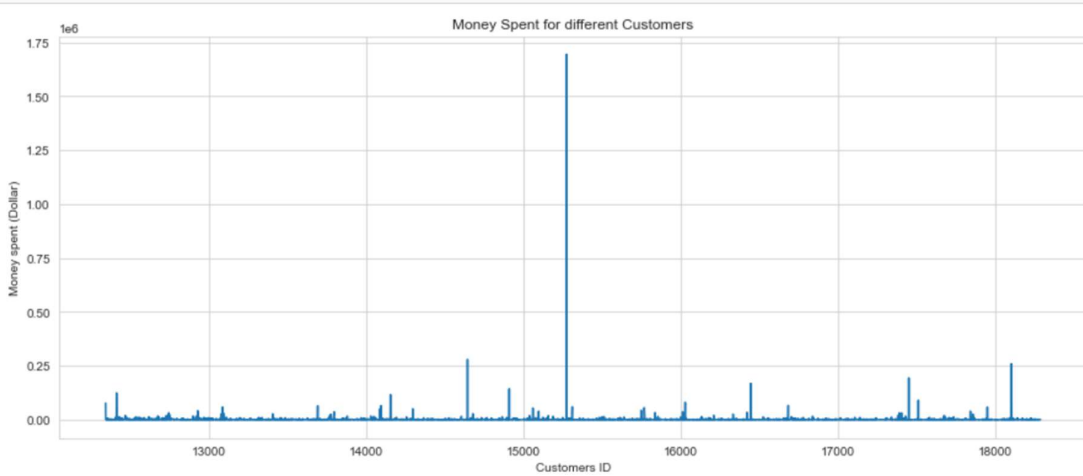
| | CustomerID | Country | InvoiceNo |
|---|---|---|---|
| **2169** | 15275 | United Kingdom | 131300 |
| **4028** | 17841 | United Kingdom | 7523 |
| **1888** | 14911 | EIRE | 5667 |
| **1298** | 14096 | United Kingdom | 5111 |
| **334** | 12748 | United Kingdom | 4243 |

8. How much money spent by the customers?

- Calculate the total amount spent by each customer.

```
df['Amount_Spent'] = df['Quantity'] * df['UnitPrice']
```

```
money_spent = df.groupby(by=['CustomerID','Country'], as_index=False)['Amount_Spent'].sum()

plt.subplots(figsize=(15,6))
plt.plot(money_spent.CustomerID, money_spent.Amount_Spent)
plt.xlabel('Customers ID')
plt.ylabel('Money spent (Dollar)')
plt.title('Money Spent for different Customers')
plt.show()
```



```
df.head()
```

| | InvoiceNo | StockCode | Year_month | Month | Day | Hour | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Country | Amount_Spent |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 536365 | 85123A | 201012 | 12 | 3 | 8 | WHITE HANGING HEART T-LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 | United Kingdom | 15.30 |
| 1 | 536365 | 71053 | 201012 | 12 | 3 | 8 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | United Kingdom | 20.34 |
| 2 | 536365 | 84406B | 201012 | 12 | 3 | 8 | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 | United Kingdom | 22.00 |
| 3 | 536365 | 84029G | 201012 | 12 | 3 | 8 | KNITTED UNION FLAG HOT WATER BOTTLE | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | United Kingdom | 20.34 |
| 4 | 536365 | 84029E | 201012 | 12 | 3 | 8 | RED WOOLLY HOTTIE WHITE HEART. | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | United Kingdom | 20.34 |

9. TOP 5 customers with the highest money spent:

- Identify the top 5 customers with the highest total spending.

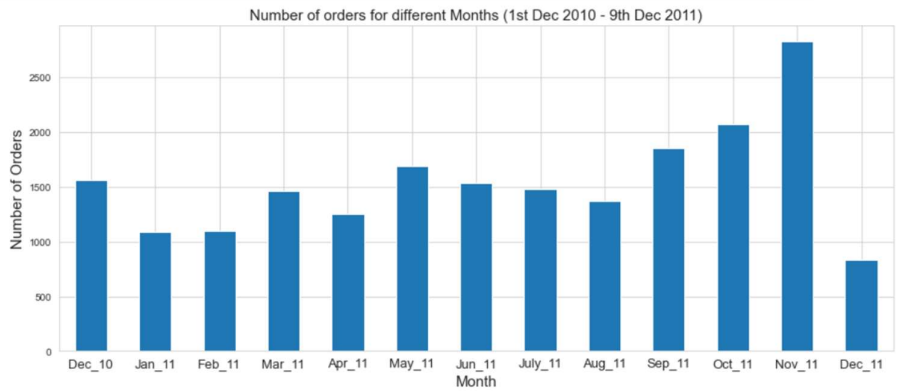
```
money_spent.sort_values(by='Amount_Spent', ascending=False).head()
```

| | CustomerID | Country | Amount_Spent |
|---|---|---|---|
| **2169** | 15275.108517 | United Kingdom | 1694485.90 |
| **1698** | 14646.000000 | Netherlands | 280206.02 |
| **4219** | 18102.000000 | United Kingdom | 259657.30 |
| **3746** | 17450.000000 | United Kingdom | 194230.79 |
| **3026** | 16446.000000 | United Kingdom | 168472.50 |

10. How many orders per month?

- Calculate the number of orders per month to analyse the monthly trend.

```
ax = df.groupby('InvoiceNo')['Year_month'].unique().value_counts().sort_index().plot(kind='bar',figsize=(15,6))
ax.set_xlabel('Month',fontsize=15)
ax.set_ylabel('Number of Orders',fontsize=15)
ax.set_title('Number of orders for different Months (1st Dec 2010 - 9th Dec 2011)',fontsize=15)
ax.set_xticklabels(('Dec_10','Jan_11','Feb_11','Mar_11','Apr_11','May_11','Jun_11','July_11','Aug_11','Sep_11','Oct_11','Nov_11',
plt.show()
```



```
ax = df.groupby('InvoiceNo')['Year_month'].unique().value_counts().sort_index()
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 520615 entries, 0 to 541908
Data columns (total 13 columns):
 #   Column        Non-Null Count   Dtype
---  ------        --------------   -----
 0   InvoiceNo     520615 non-null  object
 1   StockCode     520615 non-null  object
 2   Year_month    520615 non-null  int64
 3   Month         520615 non-null  int64
 4   Day           520615 non-null  int64
 5   Hour          520615 non-null  int64
 6   Description   520615 non-null  object
 7   Quantity      520615 non-null  int64
 8   InvoiceDate   520615 non-null  datetime64[ns]
 9   UnitPrice     520615 non-null  float64
 10  CustomerID    520615 non-null  float64
 11  Country       520615 non-null  object
 12  Amount_Spent  520615 non-null  float64
dtypes: datetime64[ns](1), float64(3), int64(5), object(4)
memory usage: 55.6+ MB
```

11. How many orders per day?

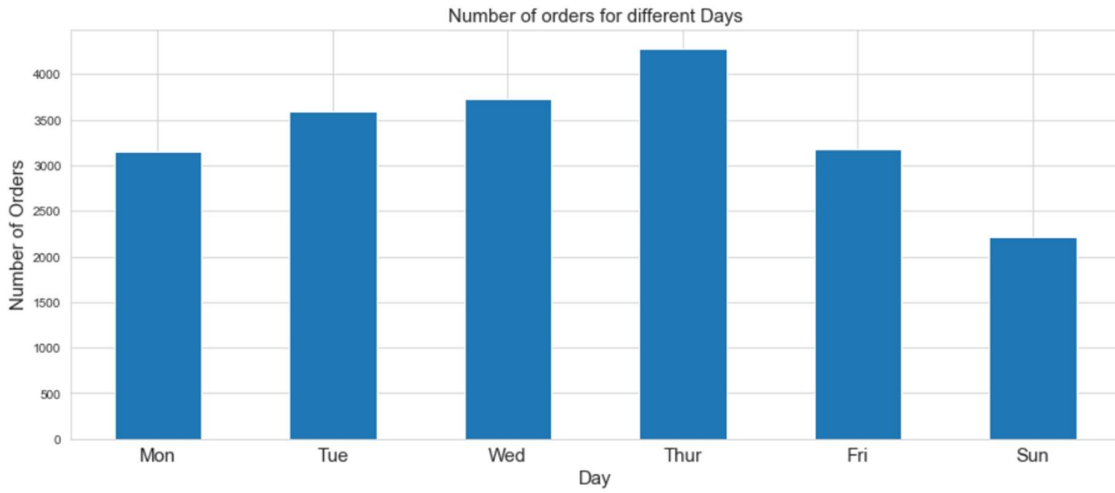
- Calculate the number of orders per day to identify daily trends.

```
ax = df.groupby('InvoiceNo')['Day'].value_counts()
ax
```

```
InvoiceNo  Day
536365     3       7
536366     3       2
536367     3      12
536368     3       4
536369     3       1
                  ..
581586     5       4
581587     5      15
A563185    5       1
A563186    5       1
A563187    5       1
Name: Day, Length: 20134, dtype: int64
```

```
ax = df.groupby('InvoiceNo')['Day'].unique().value_counts()
#.value_counts().sort_index()
```

```
ax = df.groupby('InvoiceNo')['Day'].unique().value_counts().sort_index().plot(kind='bar',figsize=(15,6))
ax.set_xlabel('Day',fontsize=15)
ax.set_ylabel('Number of Orders',fontsize=15)
ax.set_title('Number of orders for different Days',fontsize=15)
ax.set_xticklabels(('Mon','Tue','Wed','Thur','Fri','Sun'), rotation='horizontal', fontsize=15)
plt.show()
```



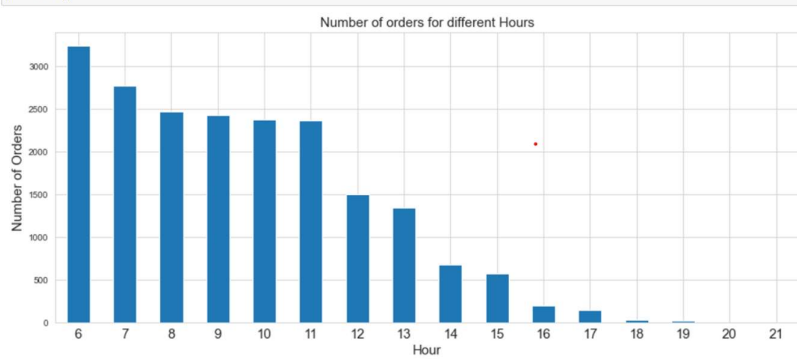

12. How many orders per hour?

- Calculate the number of orders per hour to understand the distribution throughout the day.

```
a=df['Hour'].value_counts().sort_index()
```

```
ax= df.groupby('InvoiceNo')['Hour'].unique().value_counts()

#value_counts().sort_index()
```

```
ax= df.groupby('InvoiceNo')["Hour"].unique().value_counts().plot(kind='bar',figsize=(15,6))
ax.set_xlabel('Hour',fontsize=15)
ax.set_ylabel('Number of Orders',fontsize=15)
ax.set_title('Number of orders for different Hours',fontsize=15)
ax.set_xticklabels(range(6,22), rotation='horizontal', fontsize=15)
plt.show()
```



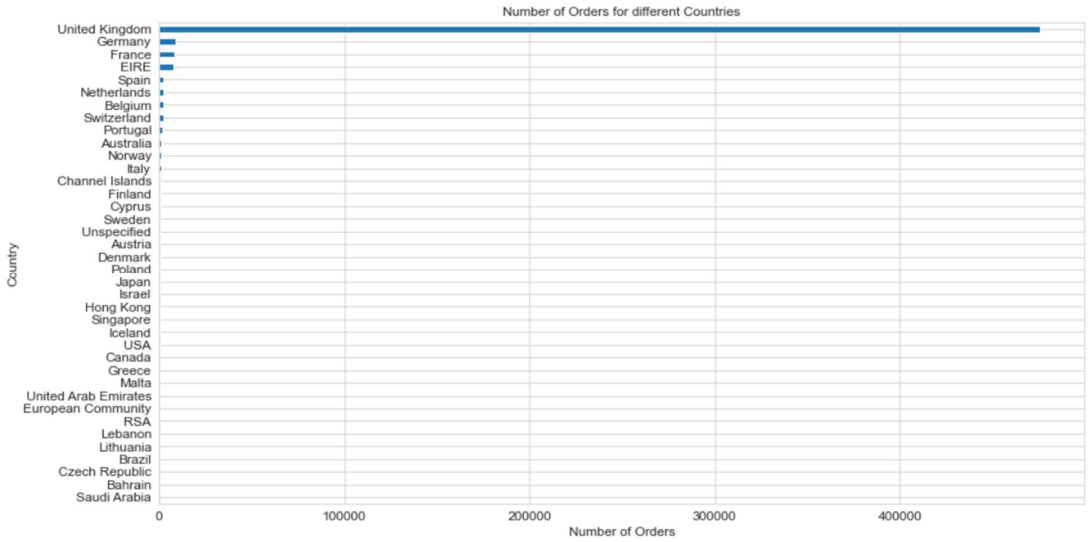
13. How many orders for each country?

- Calculate the number of orders for each country to analyse the distribution across countries.

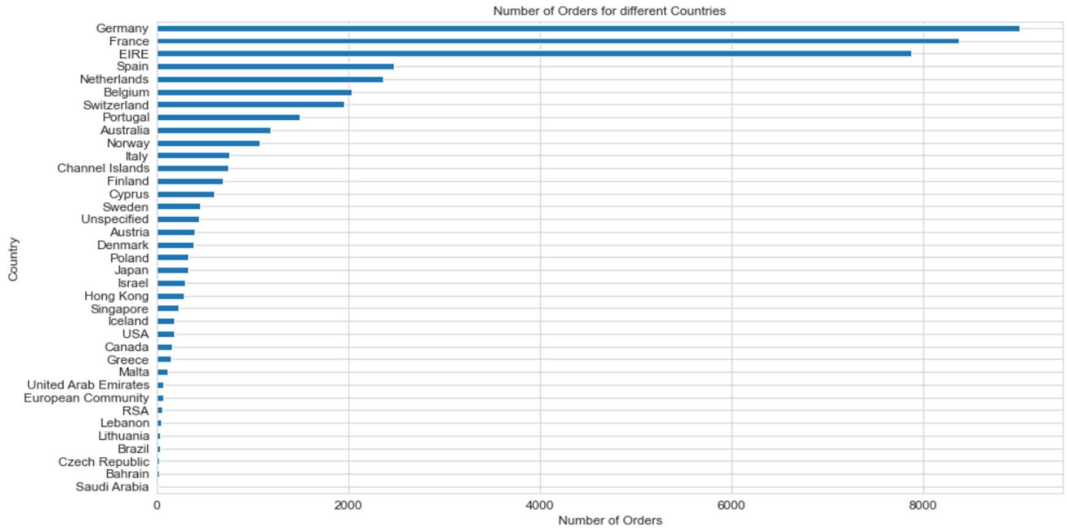
```
group_country_orders = df.groupby('Country')['InvoiceNo'].count().sort_values()
group_country_orders
```

```
Country
Saudi Arabia                9
Bahrain                    18
Czech Republic             25
Brazil                     32
Lithuania                  35
Lebanon                    45
RSA                        58
European Community         60
United Arab Emirates       68
Malta                     112
Greece                    145
Canada                    151
USA                       179
Iceland                   182
Singapore                 222
Hong Kong                 276
Israel                    289
Japan                     321
Poland                    330
Denmark                   380
Austria                   398
Unspecified               438
Sweden                    449
Cyprus                    593
Finland                   685
Channel Islands           746
```

```
group_country_orders = df.groupby('Country')['InvoiceNo'].count().sort_values()

# plot number of unique customers in each country (with UK)
plt.subplots(figsize=(15,8))
group_country_orders.plot(kind='barh', fontsize=12)
plt.xlabel('Number of Orders', fontsize=12)
plt.ylabel('Country', fontsize=12)
plt.title('Number of Orders for different Countries', fontsize=12)
plt.show()
```



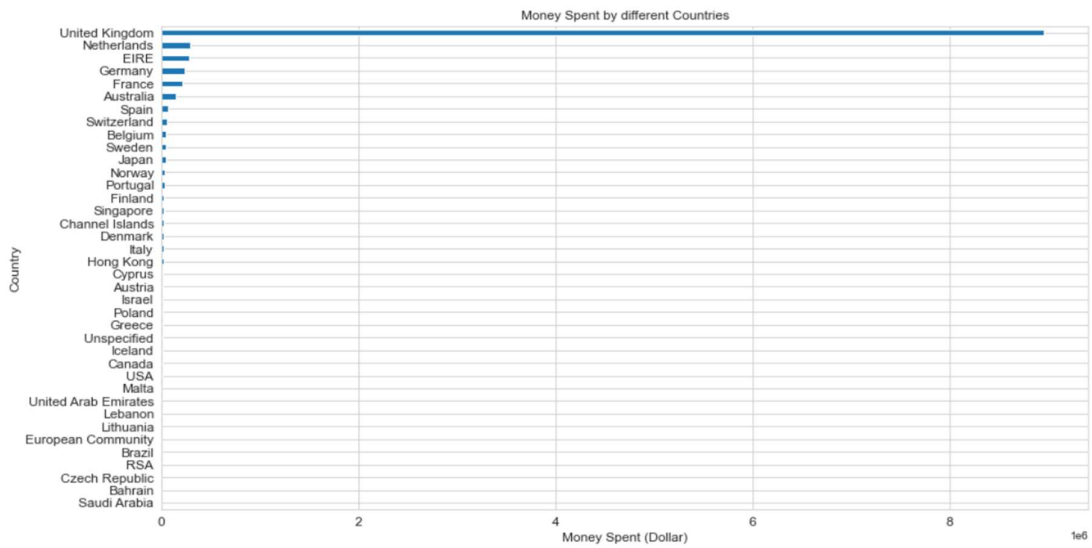

```
group_country_orders = df.groupby('Country')['InvoiceNo'].count().sort_values()
del group_country_orders['United Kingdom']
# plot number of unique customers in each country (with UK)
plt.subplots(figsize=(15,8))
group_country_orders.plot(kind='barh', fontsize=12)
plt.xlabel('Number of Orders', fontsize=12)
plt.ylabel('Country', fontsize=12)
plt.title('Number of Orders for different Countries', fontsize=12)
plt.show()
```



14. How much money spent by each country?

- Calculate the total spending by customers in each country to analyse revenue distribution.

```
group_country_amount_spent = df.groupby('Country')['Amount_Spent'].sum().sort_values()
# del group_country_orders['United Kingdom']

# plot total money spent by each country (with UK)
plt.subplots(figsize=(15,8))
group_country_amount_spent.plot(kind='barh', fontsize=12)
plt.xlabel('Money Spent (Dollar)', fontsize=12)
plt.ylabel('Country', fontsize=12)
plt.title('Money Spent by different Countries', fontsize=12)
plt.show()
```




Performing these steps will help you gain insights and address the specified problem statements in your data analysis process.

# Data Cleaning and Preprocessing

Data cleaning and preprocessing are crucial steps in preparing your dataset for analysis. Here are methods to handle missing values, remove duplicates, and address negative values in the Quantity column:

1. Handling Missing Values:

- Identify Missing Values: Begin by identifying columns with missing data. You can use tools like `isnull()` in pandas to detect missing values in each column.

- Imputation: Depending on the nature of the missing data, choose an appropriate imputation method:
    - Mean, Median, or Mode Imputation: For numeric variables, you can replace missing values with the mean, median, or mode of that variable. Use `fillna()` in pandas to achieve this.

    - Backfill or Forward Fill (for time series data): If your data has a temporal dimension, you can use backfill (pad) or forward fill (carry forward) to impute missing values in a way that makes sense in the time series context.

- Deletion: In some cases, if missing values cannot be imputed or if they represent a small portion of the dataset, you may choose to remove rows or columns with missing values using `dropna()`.

2. Removing Duplicates:

- Identify Duplicate Rows: Use methods like `duplicated()` in pandas to identify duplicate rows. You can specify a subset of columns to consider for duplicate checking.

- Dropping Duplicate Rows: To remove duplicates, use the `drop_duplicates()` method. Specify the subset of columns to check for duplicates, and you can keep the first occurrence or the last occurrence, depending on your preference.

3. Addressing Negative Values in the Quantity Column:

- Identification: Use data exploration techniques (e.g., histograms or box plots) to identify negative values in the Quantity column.

- Handling Negative Values: There are a few ways to address negative values in the Quantity column:

➢ Remove Negative Rows: If the negative values are the result of data entry errors or do not have a meaningful interpretation, you can remove the rows with negative Quantity values using Boolean indexing.

➢ Impute with Zeros: If negative values represent cancelled orders or returns, and you want to keep them for analysis, you can impute them with zeros to reflect that these orders had no net impact on sales. Use `fillna()` with the value 0 for the Quantity column.

➢ Consider Absolute Values: In some cases, you might want to keep negative values as is, especially if they have a specific meaning in your dataset. For instance, negative Quantity values might indicate returns.

# Feature Engineering

Adding columns for Month, Day, and Hour to a dataset often involves extracting this information from a timestamp or date-time column. In the context of the given dataset, these columns were likely added based on the 'InvoiceDate' or a similar date-time column. Here's how you can add these columns:

1. Month Column:

- To add the 'Month' column, you extract the month information from the 'InvoiceDate' column. You can do this using a programming language like Python and libraries such as pandas.

Example (in Python with pandas):

```
import pandas as pd

# Assuming df is your DataFrame
df['Month'] = df['InvoiceDate'].dt.month
```

This code extracts the month from the 'InvoiceDate' and adds it as a new 'Month' column to the Data Frame.

2. Day Column:

- Similar to adding the 'Month' column, you can add the 'Day' column by extracting the day information from the 'InvoiceDate' column.

Example (in Python with pandas):

```
import pandas as pd

# Assuming df is your DataFrame
df['Day'] = df['InvoiceDate'].dt.day
```

This code extracts the day from the 'InvoiceDate' and adds it as a new 'Day' column to the Data Frame.

3. Hour Column:

- Adding the 'Hour' column requires extracting the hour information from the 'InvoiceDate' column. The 'InvoiceDate' column should be in a date-time format for this operation.

Example (in Python with pandas):

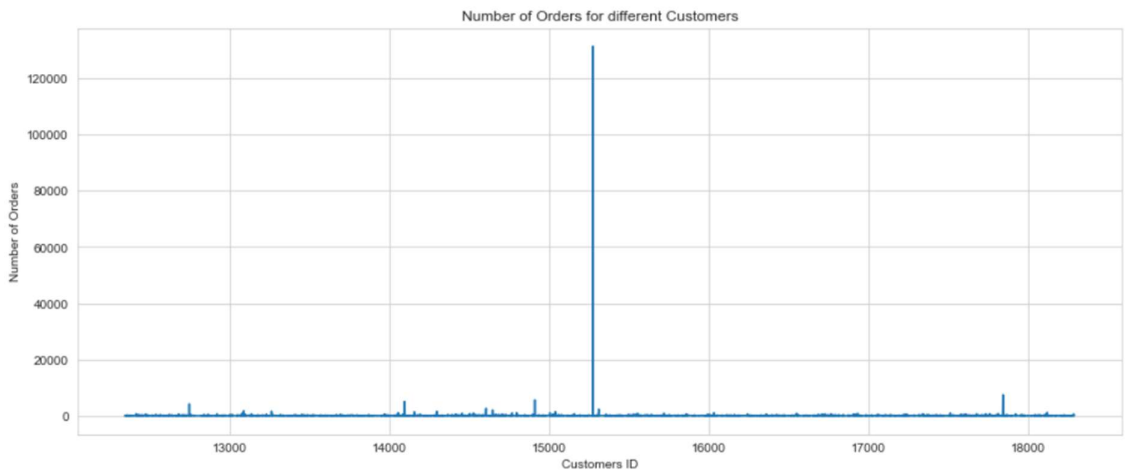
```
import pandas as pd

# Assuming df is your DataFrame
df['Hour'] = df['InvoiceDate'].dt.hour
```

This code extracts the hour from the 'InvoiceDate' and adds it as a new 'Hour' column to the Data Frame.

These new columns provide temporal information that can be useful for various types of analysis, such as understanding the temporal patterns of sales, identifying peak hours for orders, or conducting time series analysis. Adding such columns is a common feature engineering technique to enrich the dataset with additional information that can improve the accuracy and interpretability of your analysis or machine learning models.

# Customer Analysis

- The number of orders made by each customer.




- Identification of the top 5 customers with the highest number of orders.

```
orders.sort_values(by='InvoiceNo', ascending=False).head()
```

| | CustomerID | Country | InvoiceNo |
|---|---|---|---|
| **2169** | 15275 | United Kingdom | 131300 |
| **4028** | 17841 | United Kingdom | 7523 |
| **1888** | 14911 | EIRE | 5667 |
| **1298** | 14096 | United Kingdom | 5111 |
| **334** | 12748 | United Kingdom | 4243 |

- The total amount of money spent by each customer.

- The top 5 customers with the highest spending.

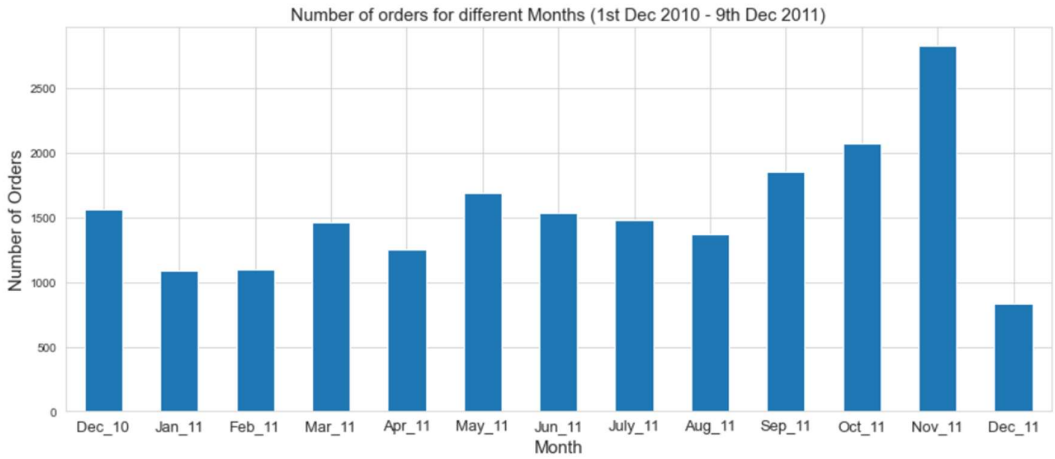
```
money_spent.sort_values(by='Amount_Spent', ascending=False).head()
```

| | CustomerID | Country | Amount_Spent |
|---|---|---|---|
| **2169** | 15275.108517 | United Kingdom | 1694485.90 |
| **1698** | 14646.000000 | Netherlands | 280206.02 |
| **4219** | 18102.000000 | United Kingdom | 259657.30 |
| **3746** | 17450.000000 | United Kingdom | 194230.79 |
| **3026** | 16446.000000 | United Kingdom | 168472.50 |

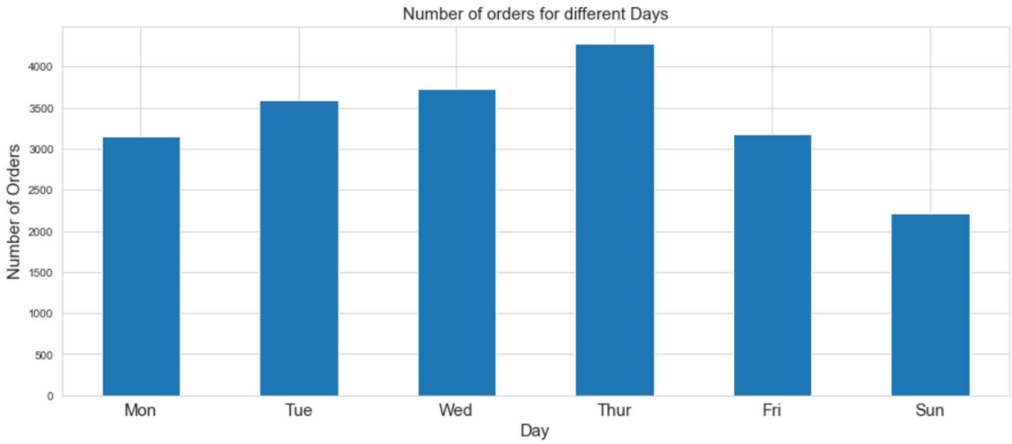
# Sales Analysis

Discuss the findings related to sales, including:

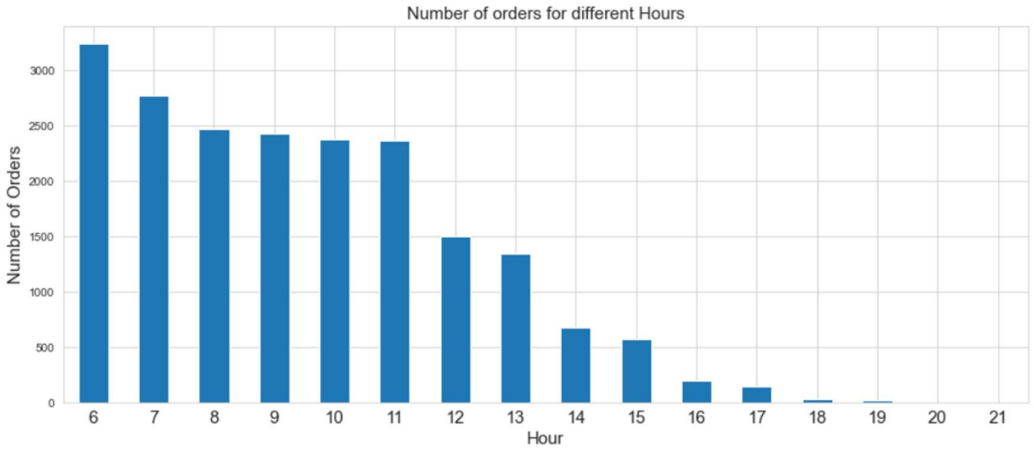
- The number of orders per month.



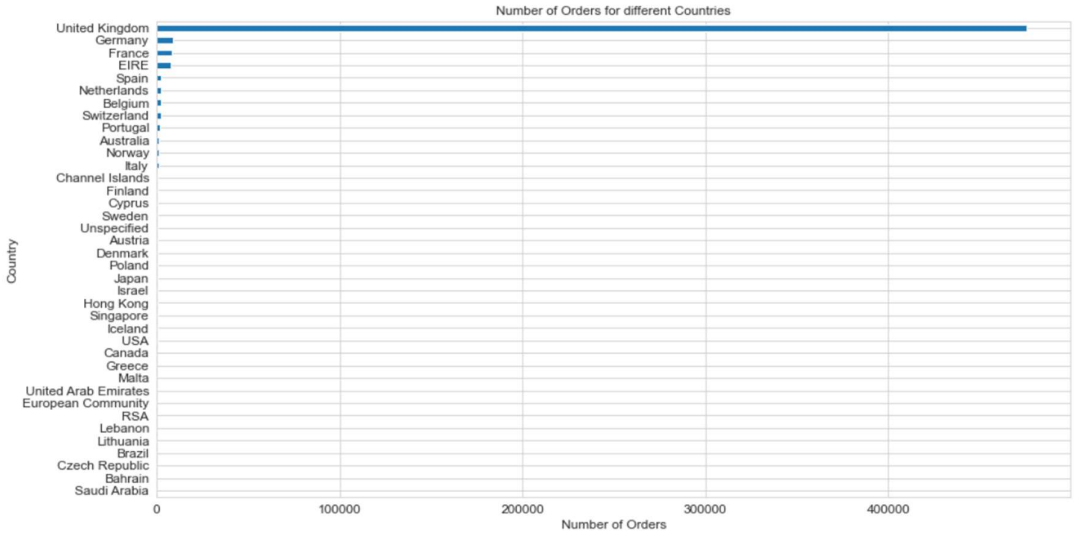

- The number of orders per day.



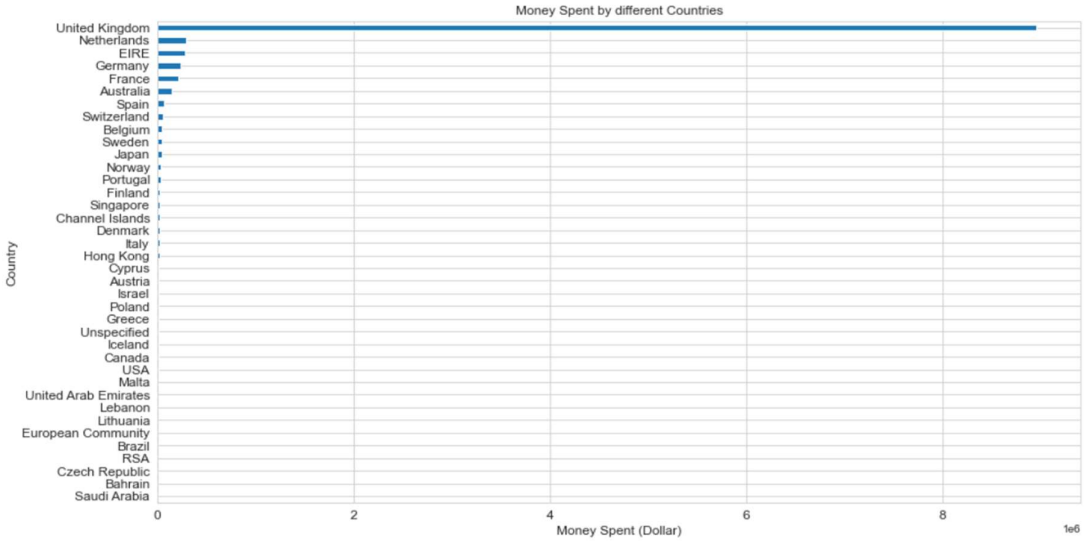
- The number of orders per hour.




- The number of orders for each country.



- Calculation and visualization of the total money spent by customers from each country.



# Results

- The customer with the highest number of orders comes from the United Kingdom (UK)
- The customer with the highest money spent on purchases comes from Netherlands
- The company receives the highest number of orders from customers in the UK (since it is a UK-based company). Therefore, the TOP 5 countries (including UK) that place the highest number of orders are as below:

  - United Kingdom
  - Germany
  - France
  - Ireland (EIRE)
  - Spain

- As the company receives the highest number of orders from customers in the UK (since it is a UK-based company), customers in the UK spend the most on their purchases. Therefore, the TOP 5 countries (including UK) that spend the most money on purchases are as below:

  - United Kingdom
  - Netherlands
  - Ireland (EIRE)
  - Germany
  - France

- November 2011 has the highest sales
- The month with the lowest sales is undetermined as the dataset consists of transactions until 9th December 2011 in December
- There are no transactions on Saturday between 1st Dec 2010 - 9th Dec 2011
- The number of orders received by the company tends to increases from Monday to Thursday and decrease afterward
- The company receives the highest number of orders at 12:00pm
- Possibly most customers made purchases during lunch hour between 12:00pm - 2:00pm
- The company tends to give out FREE items for purchases occasionally each month
- However, it is not clear what factors contribute to giving out the FREE items to the particular customers

# Conclusion

In this research paper, we conducted a comprehensive analysis of a UK-based and registered non-store online retail company's data, with a primary focus on all-occasion gift products. Over the course of one year, from December 9, 2010, to December 9, 2011, we performed extensive data exploration, cleaning, and preprocessing, which provided valuable insights and actionable recommendations for the e-commerce retailer.

The significance of this analysis extends to various aspects of the retailer's business operations, helping them make informed decisions, optimize strategies, and enhance overall performance. The key findings and their implications are summarized below:

1. Sales and Order Trends:
   - Our analysis revealed significant monthly and daily sales trends. This information is crucial for inventory management and resource allocation. The retailer can adjust stock levels, staffing, and marketing efforts to align with the identified peaks and troughs.

2. Customer Insights:
   - Understanding customer behavior is vital for any business. Our analysis identified top customers based on the number of orders and total spending. The retailer can leverage this information to tailor marketing strategies and create customer loyalty programs.

3. Geographical Analysis:
   - The distribution of orders across different countries was examined, providing insights into the retailer's global reach. By focusing on countries with the highest order counts and revenue, the retailer can optimize international expansion efforts and adapt to local market preferences.

4. Order Frequency and Revenue Analysis:
   - Analysis of order frequency and revenue per country and customer segment can guide marketing campaigns, allowing the retailer to target high-potential segments more effectively.

5. Time-Based Insights:
   - The addition of Month, Day, and Hour columns to the dataset enabled a detailed analysis of time-related patterns. This information can inform decisions regarding promotional timing and operational hours.

6. Data Quality Improvements:
- We addressed missing values, duplicates, and negative values in the dataset, ensuring that the retailer's data is of high quality, which is essential for accurate analytics and reporting.

The insights derived from this analysis are of paramount importance for the e-commerce retailer. They empower the retailer to make data-driven decisions and take the following potential business actions:

- Optimized Inventory Management: By aligning stock levels with sales trends, the retailer can reduce overstocking and stockouts, resulting in improved cost efficiency and customer satisfaction.

- Customer Relationship Management: Leveraging insights on top customers, the retailer can create tailored loyalty programs, offer personalized recommendations, and provide excellent customer service to enhance customer retention and lifetime value.

- Global Expansion Strategies: Understanding the geographical distribution of orders allows the retailer to focus resources on high-potential international markets and adapt marketing strategies to local preferences.

- Strategic Marketing: Insights into order frequency and revenue by customer segment provide the retailer with the ability to target marketing campaigns effectively, maximizing return on investment.

- Operational Efficiency: The analysis of time-based patterns can guide decisions regarding operating hours, promotional timing, and staffing schedules to improve operational efficiency.

In conclusion, this research paper has showcased the value of data analysis in e-commerce, emphasizing the actionable insights that can significantly impact the retailer's success. By embracing data-driven decision-making and implementing the recommended actions, the retailer is poised to enhance its competitive edge, increase profitability, and foster long-term growth in a dynamic and highly competitive online retail market.

# Future Work

Future research and data analysis in the context of the e-commerce retailer can explore a range of areas to further enhance its operations and competitiveness. Here are some promising directions for future work:

1. Predictive Modeling:
   - Develop predictive models to forecast sales, demand, and customer behavior. Machine learning techniques like time series forecasting, regression analysis, and customer churn prediction can be applied to improve inventory management, marketing strategies, and customer retention.

2. Market Segmentation:
   - Perform advanced market segmentation to identify more refined customer segments based on demographics, behavior, or purchase history. This can enable highly targeted marketing campaigns and personalized customer experiences.

3. Customer Lifetime Value (CLV) Analysis:
   - Conduct in-depth analysis of CLV to understand the long-term value of different customer segments. This can guide resource allocation and marketing strategies to focus on high-value customers.

4. Recommendation Systems:
   - Implement recommendation systems to provide personalized product recommendations to customers. Collaborative filtering and content-based recommendation techniques can improve cross-selling and upselling.

5. Customer Sentiment Analysis:
   - Analyse customer feedback, reviews, and social media interactions to gain insights into customer sentiment. This can help in understanding customer satisfaction and areas for improvement.

6. Dynamic Pricing Strategies:
   - Explore dynamic pricing strategies based on demand, inventory levels, and competitor pricing. Implement pricing optimization algorithms to maximize revenue while staying competitive.

7. Supply Chain Optimization:
   - Optimize the supply chain by integrating data analytics to predict demand, manage inventory, and improve order fulfilment processes.

8. A/B Testing and Experimentation:
- Conduct controlled experiments and A/B testing to assess the impact of various changes, such as website design, pricing strategies, or marketing campaigns. Data-driven experimentation can provide insights into what works best for the business.

9. Fraud Detection and Prevention:
- Develop and enhance fraud detection models to identify and prevent fraudulent transactions. Machine learning and anomaly detection techniques can be employed for this purpose.

10. Market Basket Analysis:
- Explore market basket analysis to uncover associations between products frequently purchased together. This information can guide product bundling and cross-selling strategies.

11. User Experience (UX) Analytics:
- Analyse user interactions with the website or app to improve the user experience. Insights from UX analytics can lead to design and functionality enhancements.

12. Global Expansion Strategies:
- Investigate the feasibility and market potential of expanding into new countries or regions. Market research and analysis can guide international expansion efforts.

13. Sustainability and Green Practices:
- Examine the environmental impact of the retailer's operations and investigate sustainable practices that align with customer values. This could involve carbon footprint reduction and eco-friendly product offerings.

14. Blockchain and Supply Chain Transparency:
- Explore the use of blockchain technology for enhanced transparency and traceability in the supply chain, which can build trust with environmentally conscious consumers.

15. Ethical and Responsible Retailing:
- Analyse the ethical and social responsibility practices within the company's supply chain. This could involve assessing fair labour practices, sourcing, and ethical product offerings.

These future research areas can not only provide valuable insights to the e-commerce retailer but also help maintain a competitive edge in the ever-evolving e-commerce landscape. Implementing data-driven strategies and technologies is essential for staying ahead in the market and meeting the evolving needs and expectations of customers.

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