Data Science Major Projectsystem.

Online Retail Recommendation System

If you have tried online shopping, you must have noticed that when you are checking out a product on an e-Commerce site, there is a list of suggested products that you are presented with. In this project, you will develop a recommendation system.

For this, we are attaching a dataset containing information about recommendation systems for online retail data, so that we can understand what type of product can be recommended.

We are providing a dataset from Kaggle, which contains historical information about online retail data which can be usedto detect which product is highly recommended. Below are all the columns from the dataset we are using here

Invoice Number: This is the number that identifies a transaction.

Stock Code: This refers to the product ID.

Description: This describes the product that a user purchased.

Quantity: It specified the quantity of the item purchased.

Invoice Date: The date on which the transaction took place.

Unit Price: Price of one product.

Customer ID: It identifies the customer.

Country: The country where the transaction was performed.

Language Used: Python

In [1]:
```
# import libraries
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
warnings.filterwarnings('ignore')
```

In [ ]:
```
pip install mlxtend
# Mlxtend stands for Machine Learning Extensions.
# It is a third-party Python library which contains many utilities and tools for ma
# including feature selection, ensemble methods, visualization, and model evaluatio
```

In [2]:
```
from mlxtend.frequent_patterns import apriori, association_rules
```

1. Data Preprocessing

In [3]:
```
df = pd.read_excel("vnd.openxmlformats-officedocument.spreadsheetml.sheet&rendition
```

In [4]:
```
df.head()
```

Out[4]:

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

2. Exploratory Data Analysis (EDA)

In [5]:
```
df.shape
```

Out[5]:
```
(541909, 8)
```

In [6]:
```
df.columns
```

Out[6]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')
```

In [7]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 541909 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    541909 non-null  object
 1   StockCode    541909 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     541909 non-null  int64
 4   InvoiceDate  541909 non-null  datetime64[ns]
 5   UnitPrice    541909 non-null  float64
 6   CustomerID   406829 non-null  float64
 7   Country      541909 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 33.1+ MB
```

In [8]:
```
df.isnull().sum()
```

Out[8]:
```
InvoiceNo          0
StockCode          0
Description     1454
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     135080
Country            0
dtype: int64
```

In [9]:
```
df.describe().T
```

Out[9]:

	count	mean	min	25%	50%	75%	max
Quantity	541909.0	9.55225	-80995.0	1.0	3.0	10.0	80995.0
InvoiceDate	541909	2011-07-04 13:34:57.156386048	2010-12-01 08:26:00	2011-03-28 11:34:00	2011-07-19 17:17:00	2011-10-19 11:27:00	2011-12-09 12:50:00
UnitPrice	541909.0	4.611114	-11062.06	1.25	2.08	4.13	38970.0
CustomerID	406829.0	15287.69057	12346.0	13953.0	15152.0	16791.0	18287.0

Handle Null Values

In [10]:
```
# Deleting features we dont need.

df.drop(columns=['CustomerID'], axis=1, inplace=True)
```

In [11]:
```
df.head()
```

Out[11]:

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

In [12]:
```
df.isnull().sum()
```

Out[12]:
```
InvoiceNo         0
StockCode         0
Description    1454
Quantity          0
InvoiceDate       0
UnitPrice         0
Country           0
dtype: int64
```

In [13]:
```
# We have enough data so we can delete them. We could fill them with mean, mode etc

df.dropna(subset='Description',axis=0, inplace=True)
```

In [14]:
```
df.reset_index(drop=True, inplace=True)
df.head()
```

Out[14]:

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

In [15]:
```
df.isnull().sum()
```

Out[15]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
Country        0
dtype: int64
```

In [16]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 540455 entries, 0 to 540454
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    540455 non-null  object
 1   StockCode    540455 non-null  object
 2   Description  540455 non-null  object
 3   Quantity     540455 non-null  int64
 4   InvoiceDate  540455 non-null  datetime64[ns]
 5   UnitPrice    540455 non-null  float64
 6   Country      540455 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(1), object(4)
memory usage: 28.9+ MB
```

Handling Outliers

In [17]:
```
df.describe().T
```

Out[17]:

	count	mean	min	25%	50%	75%	max
Quantity	540455.0	9.603129	-80995.0	1.0	3.0	10.0	80995.0
InvoiceDate	540455	2011-07-04 16:20:42.947035392	2010-12-01 08:26:00	2011-03-28 11:49:00	2011-07-20 11:38:00	2011-10-19 11:49:00	2011-12-09 12:50:00
UnitPrice	540455.0	4.623519	-11062.06	1.25	2.08	4.13	38970.0

There is negative value when we look at the quantity and unit price, so let's examine and deal with it first

In [18]:
```
inv = df["InvoiceNo"].str.contains("C",na=False).sum()
print(f"The number of INVOICES containing 'C' : {inv}")
```

```
The number of INVOICES containing 'C' : 9288
```

In [19]:
```
def cancelledInvoice(x):
    if ('C' in str(x)):
        return np.nan
    else:
        return x
```

In [20]:
```
# Deleting datas that includes C in Invoice. Because if it includes 'C', it means t

df ['InvoiceNo'] = df['InvoiceNo'].apply(lambda x:cancelledInvoice(x))
```

In [21]:
```
df.isnull().sum()
```

Out[21]:
```
InvoiceNo      9288
StockCode         0
Description       0
Quantity          0
InvoiceDate       0
UnitPrice         0
Country           0
dtype: int64
```

In [22]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 540455 entries, 0 to 540454
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    531167 non-null  object        
 1   StockCode    540455 non-null  object        
 2   Description  540455 non-null  object        
 3   Quantity     540455 non-null  int64         
 4   InvoiceDate  540455 non-null  datetime64[ns]
 5   UnitPrice    540455 non-null  float64       
 6   Country      540455 non-null  object        
dtypes: datetime64[ns](1), float64(1), int64(1), object(4)
memory usage: 28.9+ MB
```

In [23]:
```
df.dropna(subset='InvoiceNo', axis=0, inplace=True)
```

In [24]:
```
df.isnull().sum()
```

Out[24]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
Country        0
dtype: int64
```

In [25]:
```
def cleanInvoice (x):
    if(str(x).isdigit()!=True or len(str(x)) !=6):
        return np.nan
    else:
        return x
```

In [26]:
```
# Invoice data cant be 6 digit and it must be numeric.

df['InvoiceNo']=df['InvoiceNo'].apply(lambda x: cleanInvoice(x))
```

In [27]:
```
df.isnull().sum()
```

Out[27]:
```
InvoiceNo      3
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
Country        0
dtype: int64
```

In [28]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Index: 531167 entries, 0 to 540454
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    531164 non-null  float64       
 1   StockCode    531167 non-null  object        
 2   Description  531167 non-null  object        
 3   Quantity     531167 non-null  int64         
 4   InvoiceDate  531167 non-null  datetime64[ns]
 5   UnitPrice    531167 non-null  float64       
 6   Country      531167 non-null  object        
dtypes: datetime64[ns](1), float64(2), int64(1), object(3)
memory usage: 32.4+ MB
```

In [29]:
```
df.dropna(subset='InvoiceNo',axis=0, inplace=True)
df.reset_index(drop=True, inplace=True)
df.isnull().sum()
```

Out[29]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
Country        0
dtype: int64
```

In [30]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 531164 entries, 0 to 531163
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    531164 non-null  float64       
 1   StockCode    531164 non-null  object        
 2   Description  531164 non-null  object        
 3   Quantity     531164 non-null  int64         
 4   InvoiceDate  531164 non-null  datetime64[ns]
 5   UnitPrice    531164 non-null  float64       
 6   Country      531164 non-null  object        
dtypes: datetime64[ns](1), float64(2), int64(1), object(3)
memory usage: 28.4+ MB
```

In [31]:
```
df["InvoiceNo"] = df["InvoiceNo"].astype('int64').astype(str)
```

In [32]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 531164 entries, 0 to 531163
Data columns (total 7 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    531164 non-null  object
 1   StockCode    531164 non-null  object
 2   Description  531164 non-null  object
 3   Quantity     531164 non-null  int64
 4   InvoiceDate  531164 non-null  datetime64[ns]
 5   UnitPrice    531164 non-null  float64
 6   Country      531164 non-null  object
dtypes: datetime64[ns](1), float64(1), int64(1), object(4)
memory usage: 28.4+ MB
```

In [33]:
```
df.describe().T
```

Out[33]:

	count	mean	min	25%	50%	75%	max
Quantity	531164.0	10.293676	-9600.0	1.0	3.0	10.0	80995.0
InvoiceDate	531164	2011-07-04 19:55:06.271509248	2010-12-01 08:26:00	2011-03-28 12:13:00	2011-07-20 12:41:30	2011-10-19 12:54:00	2011-12-09 12:50:00
UnitPrice	531164.0	3.879001	0.0	1.25	2.08	4.13	13541.33

In [34]:
```
df.head()
```

Out[34]:

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

In [35]:
```
qtt = df.loc[df["Quantity"]<0,"Quantity"].count()
print(f"The number of negative QUANTITY values: {qtt}")
```

```
The number of negative QUANTITY values: 474
```

In [36]:
```
up=df.loc[df["UnitPrice"]<0,"UnitPrice"].count()
up
```

Out[36]:
```
0
```

In [37]:
```
# Eliminate Quantity data that are less then 0

df=df[(df['Quantity'] > 0)]
```

In [38]:
```
df.reset_index(drop=True, inplace=True)
```

In [39]:
```
df.head()
```

Out[39]:

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

In [40]:
```
df
```

Out[40]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	United Kingdom
...	...	...	...	...	...	...	...
530685	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	France
530686	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	France
530687	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	France
530688	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	France
530689	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	France

530690 rows × 7 columns

In [41]:
```
qtt = df.loc[df["Quantity"]<0,"Quantity"].count()
print(f"The number of negative QUANTITY values: {qtt}")
```

```
The number of negative QUANTITY values: 0
```

In [42]:
```
df.describe().T
```

Out[42]:

	count	mean	min	25%	50%	75%	max
Quantity	530690.0	10.605873	1.0	1.0	3.0	10.0	80995.0
InvoiceDate	530690	2011-07-04 19:01:04.928526848	2010-12-01 08:26:00	2011-03-28 11:59:00	2011-07-20 12:14:00	2011-10-19 12:35:00	2011-12-09 12:50:00
UnitPrice	530690.0	3.882466	0.0	1.25	2.08	4.13	13541.33

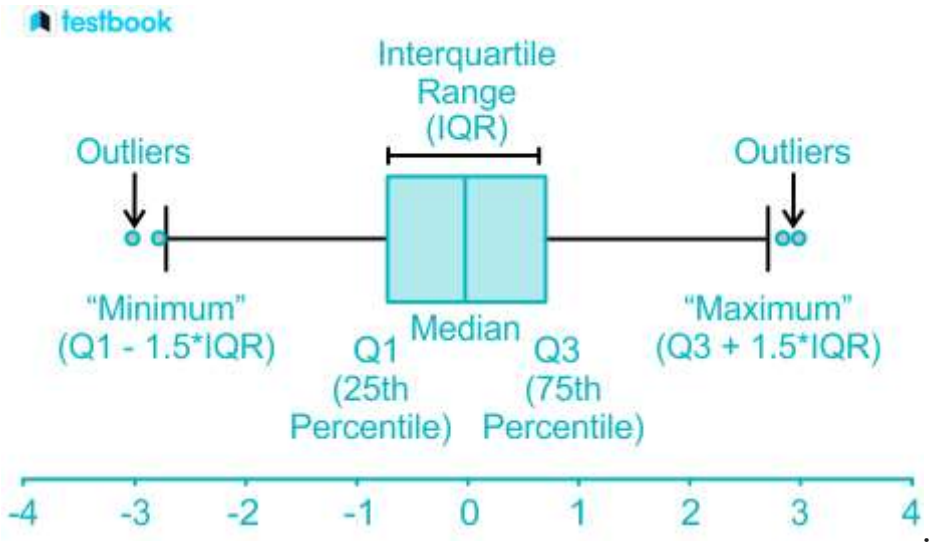
Negative price values also improved

Second, lets deal with outlier values using interquantile range

INTERQUARTILE RANGE

What is interquantile range?

In descriptive statistics, the interquartile range (IQR) is a measure of statistical dispersion, which is the spread of the data. The IQR may also be called the midspread, middle 50%, fourth spread, or H-spread. It is defined as the difference between the 75th and 25th percentiles of the data



In [43]:
```
df['Country'].unique()
```

Out[43]:
```
array(['United Kingdom', 'France', 'Australia', 'Netherlands', 'Germany',
       'Norway', 'EIRE', 'Switzerland', 'Spain', 'Poland', 'Portugal',
       'Italy', 'Belgium', 'Lithuania', 'Japan', 'Iceland',
       'Channel Islands', 'Denmark', 'Cyprus', 'Sweden', 'Finland',
       'Austria', 'Bahrain', 'Israel', 'Greece', 'Hong Kong', 'Singapore',
       'Lebanon', 'United Arab Emirates', 'Saudi Arabia',
       'Czech Republic', 'Canada', 'Unspecified', 'Brazil', 'USA',
       'European Community', 'Malta', 'RSA'], dtype=object)
```

In [44]:
```
df.columns
```

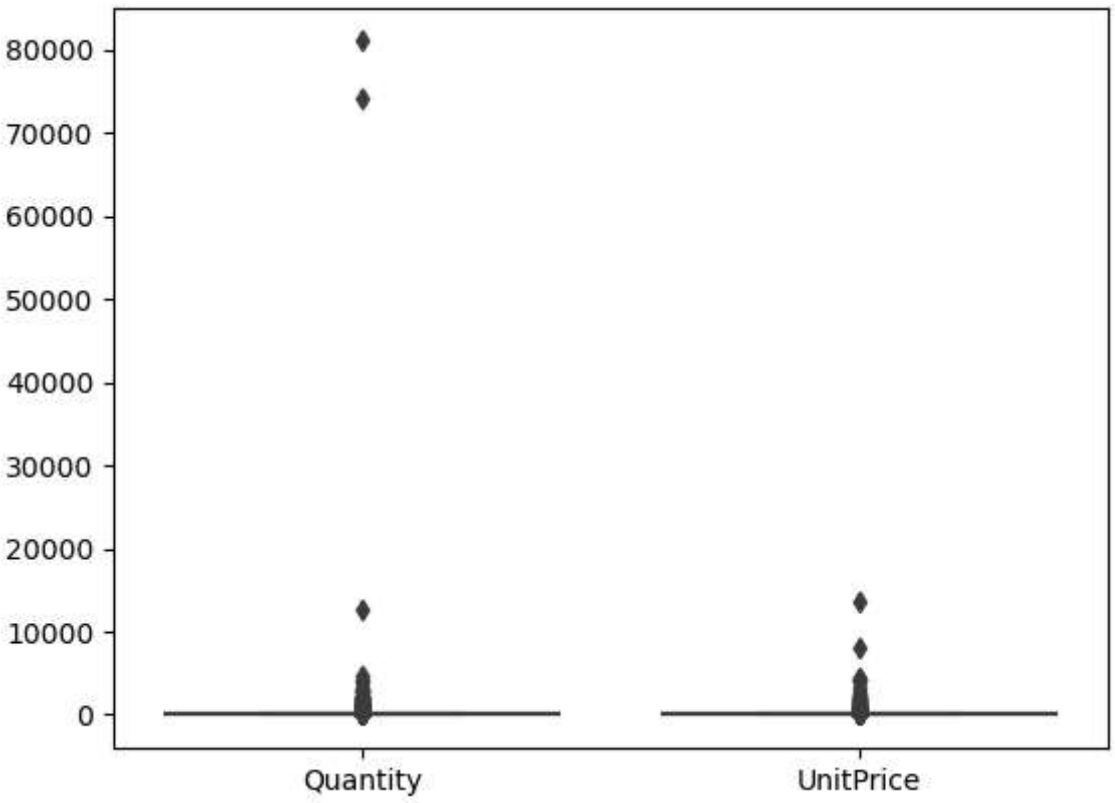
Out[44]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'Country'],
      dtype='object')
```

In [45]:
```
# We can see is there outliers in our dataset by using boxplot.

sns.boxplot(df[['Quantity','UnitPrice']])
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
```

Out[45]:
```
<Axes: >
```



In [46]:
```
def handling_outlier(df,variable):
    quartile1 = df[variable].quantile(0.01)
```

```
    quartile3 = df[variable].quantile(0.99)
    interquantile_range = quartile3 - quartile1
    up_limit = quartile3 + 1.5 * interquantile_range
    low_limit = quartile1 - 1.5 * interquantile_range
    df.loc[df[variable] < low_limit, variable] = low_limit
    df.loc[df[variable] > up_limit, variable] = up_limit
```

In [47]:
```
handling_outlier(df,"Quantity")
handling_outlier(df,"UnitPrice")
```

In [48]:
```
df.reset_index(drop=True, inplace=True)
df
```

Out[48]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6.0	2010-12-01 08:26:00	2.55	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6.0	2010-12-01 08:26:00	3.39	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8.0	2010-12-01 08:26:00	2.75	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6.0	2010-12-01 08:26:00	3.39	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6.0	2010-12-01 08:26:00	3.39	United Kingdom
...	...	...	...	...	...	...	...
530685	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12.0	2011-12-09 12:50:00	0.85	France
530686	581587	22899	CHILDREN'S APRON DOLLY GIRL	6.0	2011-12-09 12:50:00	2.10	France
530687	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4.0	2011-12-09 12:50:00	4.15	France
530688	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4.0	2011-12-09 12:50:00	4.15	France
530689	581587	22138	BAKING SET 9 PIECE RETROSPOT	3.0	2011-12-09 12:50:00	4.95	France

530690 rows × 7 columns

In [54]:
```
df.describe().T
```

Out[54]:

	count	mean	min	25%	50%	75%	max	
Quantity	13870.0	24.662581	1.0	6.0	12.0	24.0	248.5	40.9
InvoiceDate	13870	2011-07-08 00:36:02.080749824	2010-12-01 08:45:00	2011-03-31 10:27:00	2011-07-29 13:28:00	2011-10-12 11:22:00	2011-12-09 12:50:00	
UnitPrice	13870.0	3.210857	0.0	1.06	1.65	3.75	42.015	4.4

they look good

In [50]:
```
# Selecting some countries from the data set
list_cntry = ["Greece","Singapore","Netherlands","Switzerland","Cyprus","France","K
for number,country in enumerate(list_cntry):
    list_cntry[number] = df[df['Country'] == country]
```

In [51]:
```
del df
df = pd.concat(list_cntry,axis=0)
df = df.sort_index()
```

In [52]:
```
df = df.reset_index(drop=True)
df.shape
```

Out[52]: (13870, 7)

In [53]:
```
df
```

Out[53]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country
0	536370	22728	ALARM CLOCK BAKELIKE PINK	24.0	2010-12-01 08:45:00	3.75	France
1	536370	22727	ALARM CLOCK BAKELIKE RED	24.0	2010-12-01 08:45:00	3.75	France
2	536370	22726	ALARM CLOCK BAKELIKE GREEN	12.0	2010-12-01 08:45:00	3.75	France
3	536370	21724	PANDA AND BUNNIES STICKER SHEET	12.0	2010-12-01 08:45:00	0.85	France
4	536370	21883	STARS GIFT TAPE	24.0	2010-12-01 08:45:00	0.65	France
...	...	...	...	...	...	...	...
13865	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12.0	2011-12-09 12:50:00	0.85	France
13866	581587	22899	CHILDREN'S APRON DOLLY GIRL	6.0	2011-12-09 12:50:00	2.10	France
13867	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4.0	2011-12-09 12:50:00	4.15	France
13868	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4.0	2011-12-09 12:50:00	4.15	France
13869	581587	22138	BAKING SET 9 PIECE RETROSPOT	3.0	2011-12-09 12:50:00	4.95	France

13870 rows × 7 columns

2.1 Data Analysis & Visualization

In [55]:
```python
# Top 10 best selling products

product_count = df.groupby("Description")["Quantity"].sum().nlargest(10)
product_count=product_count.reset_index()
```

In [56]:
```python
plt.figure(figsize=(12, 8))

ax = sns.barplot(data=product_count,y="Description",x="Quantity",palette="icefire")

for i in ax.containers:
    ax.bar_label(i,)

ax.set_title("Top 10 Best Selling Products")
plt.xlabel("Total Quantity")
plt.ylabel("Products")
plt.tight_layout()
plt.show()
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
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C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
```
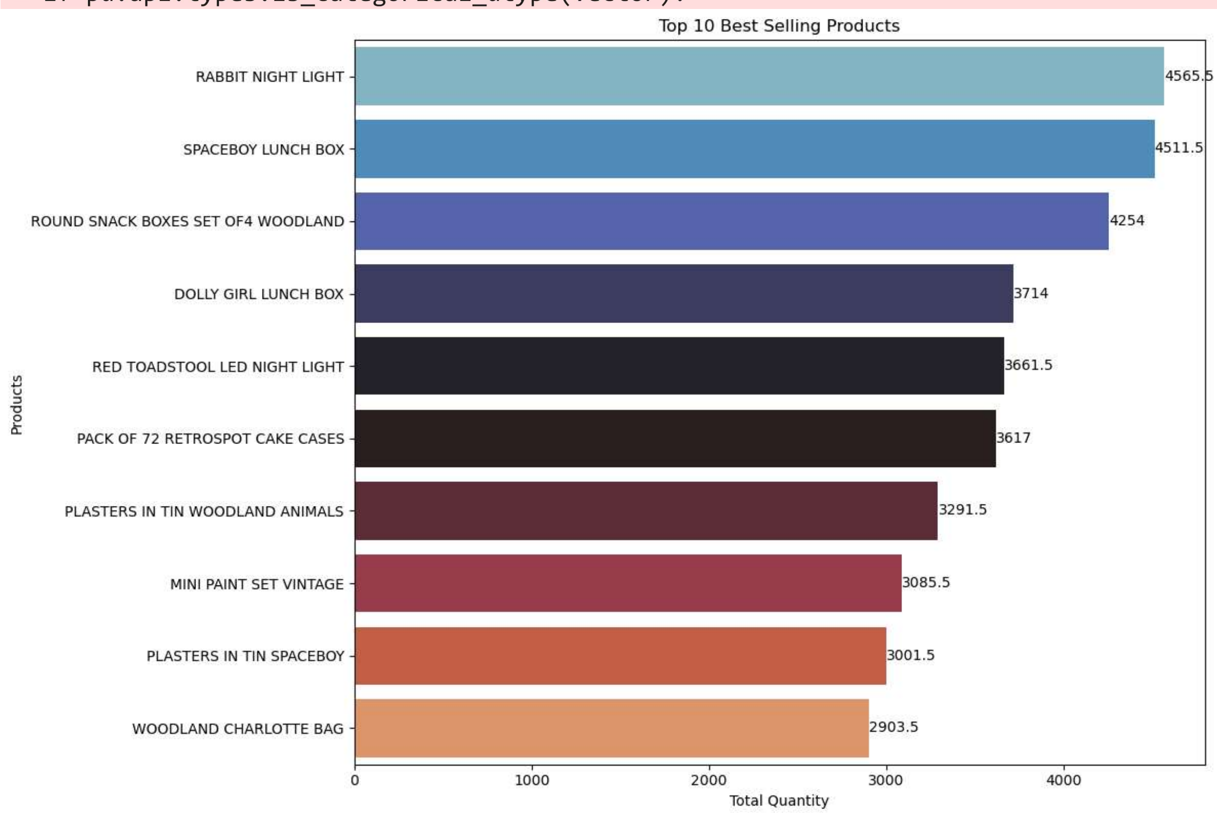
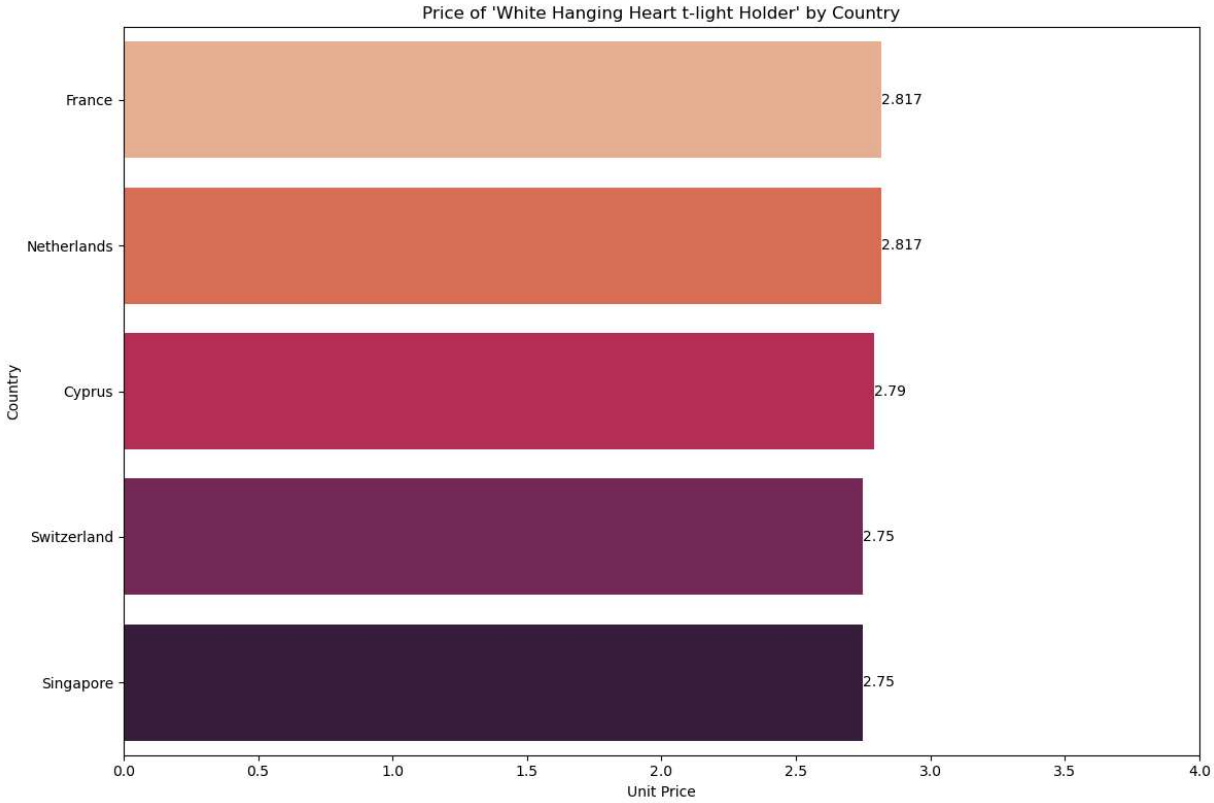



In [57]:
```
# Price of any product by country

list_country, list_price = [], []
for col in df["Country"].unique():
    price = df.loc[(df["Country"] == col) & (df["Description"] == "WHITE HANGING HE

    list_country.append(col)
    list_price.append(round(price,3))

df_price = pd.DataFrame(columns=["Country"],data=list_price,index=list_country)
df_price.dropna(inplace=True)
df_price = df_price.sort_values(by="Country",ascending=False)
```

In [58]:
```
plt.figure(figsize=(12, 8))

ax = sns.barplot(data=df_price,y=df_price.index,x="Country",palette="rocket_r")

for i in ax.containers:
    ax.bar_label(i,)

ax.set_title("Price of 'White Hanging Heart t-light Holder' by Country")
plt.xlim(0, 4)
plt.xlabel("Unit Price")
plt.ylabel("Country")
plt.tight_layout()
plt.show()
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
```



In [59]:
```
# Total amount of the first 10 products

df["TOTAL_AMOUNT"] = df["Quantity"] * df["UnitPrice"]
df.head()
```

Out[59]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	Country	TOTAL_A
0	536370	22728	ALARM CLOCK BAKELIKE PINK	24.0	2010-12-01 08:45:00	3.75	France	
1	536370	22727	ALARM CLOCK BAKELIKE RED	24.0	2010-12-01 08:45:00	3.75	France	
2	536370	22726	ALARM CLOCK BAKELIKE GREEN	12.0	2010-12-01 08:45:00	3.75	France	
3	536370	21724	PANDA AND BUNNIES STICKER SHEET	12.0	2010-12-01 08:45:00	0.85	France	
4	536370	21883	STARS GIFT TAPE	24.0	2010-12-01 08:45:00	0.65	France	

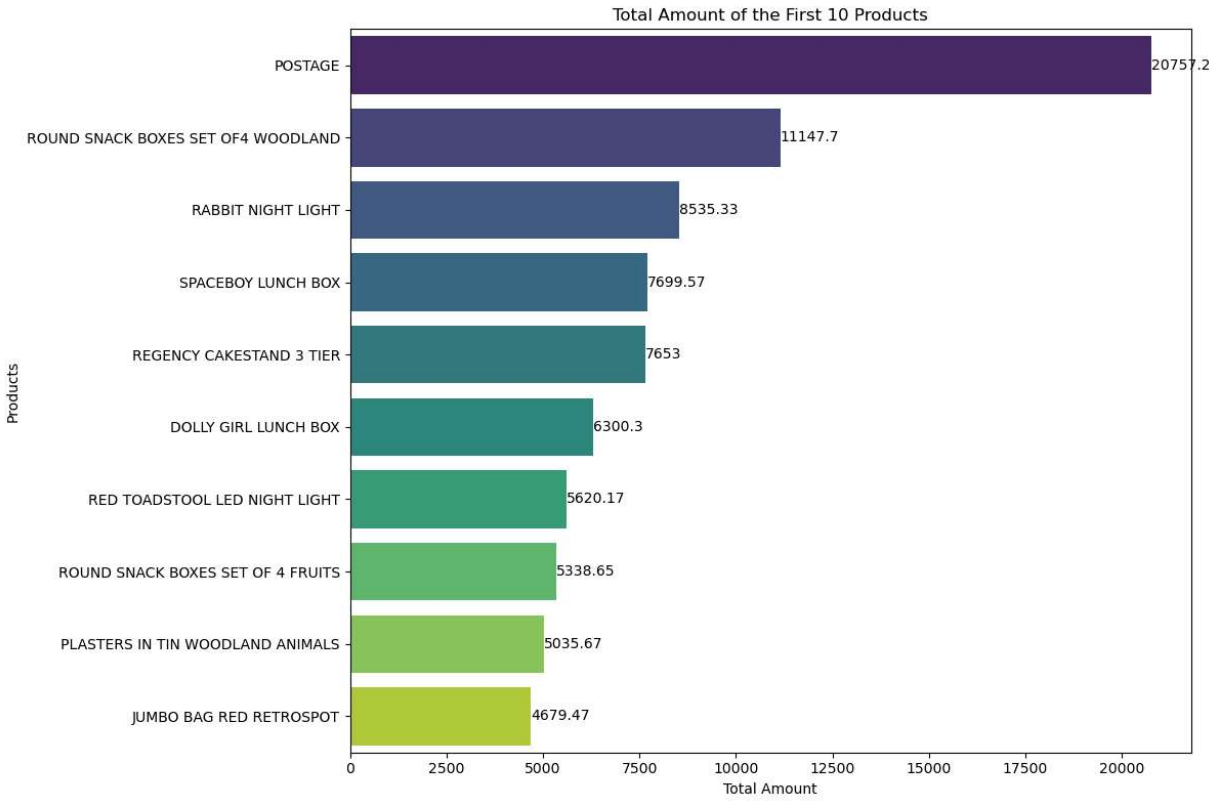
In [60]:

```
total_amount = df.groupby("Description")["TOTAL_AMOUNT"].sum().nlargest(10)
total_amount=total_amount.reset_index()
```

In [61]:

```
plt.figure(figsize=(12, 8))

ax = sns.barplot(data=total_amount,y="Description",x="TOTAL_AMOUNT",palette="viridi

for i in ax.containers:
    ax.bar_label(i,)

ax.set_title("Total Amount of the First 10 Products")
plt.xlabel("Total Amount")
plt.ylabel("Products")
plt.tight_layout()
plt.show()
```

```
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
C:\ProgramData\anaconda3\Lib\site-packages\seaborn\_oldcore.py:1498: DeprecationWarn
ing: is_categorical_dtype is deprecated and will be removed in a future version. Use
isinstance(dtype, pd.CategoricalDtype) instead
  if pd.api.types.is_categorical_dtype(vector):
```



3. Preparing the ARL Data Structure0.

Invoice-Product Matrix

Setting it so that there are invoices in the rows and products in the columns. If there are products, 1, otherwise 0.

In [62]:
```
# Reaching the product quantities in each invoice.
df.groupby(["InvoiceNo","Description"])["Quantity"].sum().head(20)

# if you want you can use this code, it gives same result
# df.groupby(["INVOICE","DESCRIPTION"]).agg({"QUANTITY":"sum"}).head(20)
```

Out[62]:
```
InvoiceNo  Description
536370     ALARM CLOCK BAKELIKE GREEN            12.0
           ALARM CLOCK BAKELIKE PINK             24.0
           ALARM CLOCK BAKELIKE RED              24.0
           CHARLOTTE BAG DOLLY GIRL DESIGN       20.0
           CIRCUS PARADE LUNCH BOX               24.0
           INFLATABLE POLITICAL GLOBE            48.0
           LUNCH BOX I LOVE LONDON               24.0
           MINI JIGSAW CIRCUS PARADE             24.0
           MINI JIGSAW SPACEBOY                  24.0
           MINI PAINT SET VINTAGE                36.0
           PANDA AND BUNNIES STICKER SHEET       12.0
           POSTAGE                                3.0
           RED TOADSTOOL LED NIGHT LIGHT         24.0
           ROUND SNACK BOXES SET OF4 WOODLAND    24.0
           SET 2 TEA TOWELS I LOVE LONDON        24.0
           SET/2 RED RETROSPOT TEA TOWELS        18.0
           SPACEBOY LUNCH BOX                    24.0
           STARS GIFT TAPE                       24.0
           VINTAGE HEADS AND TAILS CARD GAME     24.0
           VINTAGE SEASIDE JIGSAW PUZZLES        12.0
Name: Quantity, dtype: float64
```

In [63]:
```
# Sorting descriptions by columns
df.groupby(["InvoiceNo", "Description"]).agg({"Quantity": "sum"}).unstack().iloc[0:
```

Out[63]:

	Quantity				
Description	**10 COLOUR SPACEBOY PEN**	**12 COLOURED PARTY BALLOONS**	**12 EGG HOUSE PAINTED WOOD**	**12 MESSAGE CARDS WITH ENVELOPES**	**12 PENCIL SMALL TUBE WOODLAND**
InvoiceNo					
536370	NaN	NaN	NaN	NaN	NaN
536403	NaN	NaN	NaN	NaN	NaN
536852	NaN	NaN	NaN	NaN	NaN
536858	NaN	NaN	NaN	NaN	NaN
536974	NaN	NaN	NaN	NaN	NaN

In [64]:
```
# Filling nan values with zero
df.groupby(['InvoiceNo', 'Description']).agg({"Quantity": "sum"}).unstack().fillna(
```

Out[64]:

	Quantity				
Description	10 COLOUR SPACEBOY PEN	12 COLOURED PARTY BALLOONS	12 EGG HOUSE PAINTED WOOD	12 MESSAGE CARDS WITH ENVELOPES	12 PENCIL SMALL TUBE WOODLAND
InvoiceNo					
536370	0.0	0.0	0.0	0.0	0.0
536403	0.0	0.0	0.0	0.0	0.0
536852	0.0	0.0	0.0	0.0	0.0
536858	0.0	0.0	0.0	0.0	0.0
536974	0.0	0.0	0.0	0.0	0.0

In [65]:
```
# 0,0 is converted to 0, if there is a value then it is 1
df.groupby(['InvoiceNo', 'Description']).agg({"Quantity": "sum"}).unstack().fillna(
```

Out[65]:

	Quantity				
Description	10 COLOUR SPACEBOY PEN	12 COLOURED PARTY BALLOONS	12 EGG HOUSE PAINTED WOOD	12 MESSAGE CARDS WITH ENVELOPES	12 PENCIL SMALL TUBE WOODLAND
InvoiceNo					
536370	0	0	0	0	0
536403	0	0	0	0	0
536852	0	0	0	0	0
536858	0	0	0	0	0
536974	0	0	0	0	0

In [66]:
```
# Changing product names with stock code
df.groupby(['InvoiceNo', 'StockCode']).agg({"Quantity": "sum"}).unstack().fillna(0)
```

Out[66]:

	Quantity				
StockCode	**10002**	**10120**	**10125**	**10133**	**10135**
InvoiceNo					
536370	1	0	0	0	0
536403	0	0	0	0	0
536852	0	0	0	0	0
536858	0	0	0	0	0
536974	0	0	0	0	0

In [67]:
```
# It ready !!
df_arl = df.groupby(['InvoiceNo', 'StockCode']).agg({"Quantity": "sum"}).unstack().
```

In [68]:
```
# Finding product name from stock code
def prdct_name_finder(data,stckcde):
    product_name = data[data["StockCode"] == stckcde][["Description"]].values[0].to
    print(product_name)
prdct_name_finder(df,"85014A")
```

```
['BLACK/BLUE POLKADOT UMBRELLA']
```

it works

4. Association Rule Analysis

What is Association Rule?

Association rule mining finds interesting associations and relationships among large sets of data items. This rule shows how frequently a itemset occurs in a transaction. A typical example is a Market Based Analysis.

In [69]:
```
frequent_itemsets = apriori(df_arl,min_support=0.01,use_colnames=True)
```

```
C:\Users\dshem\AppData\Roaming\Python\Python311\site-packages\mlxtend\frequent_patte
rns\fpcommon.py:109: DeprecationWarning: DataFrames with non-bool types result in wo
rse computationalperformance and their support might be discontinued in the future.P
lease use a DataFrame with bool type
  warnings.warn(
```

In [70]:
```
frequent_itemsets.sort_values("support", ascending=False)
```

Out[70]:

	support	itemsets
625	0.648696	((Quantity, POST))
206	0.182609	((Quantity, 22326))
274	0.165217	((Quantity, 22554))
118	0.161739	((Quantity, 21731))
276	0.154783	((Quantity, 22556))
...	...	...
11317	0.010435	((Quantity, 23173), (Quantity, 22423), (Quanti...
11319	0.010435	((Quantity, 23204), (Quantity, 22423), (Quanti...
11320	0.010435	((Quantity, 23209), (Quantity, 22423), (Quanti...
11322	0.010435	((Quantity, 23254), (Quantity, 22423), (Quanti...
21382	0.010435	((Quantity, 22661), (Quantity, 22712), (Quanti...

21383 rows × 2 columns

In [71]:
```
rules = association_rules(frequent_itemsets,metric="support",min_threshold=0.01)
```

In [72]:
```
# Filtering
rules[(rules["support"]>0.05) & (rules["confidence"]>0.1) & (rules["lift"]>5)]
```

Out[72]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
1722	((Quantity, 21086))	((Quantity, 21080))	0.104348	0.109565	0.074783	0.716667	6.541005
1723	((Quantity, 21080))	((Quantity, 21086))	0.109565	0.104348	0.074783	0.682540	6.541005
1724	((Quantity, 21094))	((Quantity, 21080))	0.100870	0.109565	0.078261	0.775862	7.08128
1725	((Quantity, 21080))	((Quantity, 21094))	0.109565	0.100870	0.078261	0.714286	7.08128
1888	((Quantity, 21094))	((Quantity, 21086))	0.100870	0.104348	0.092174	0.913793	8.75718
1889	((Quantity, 21086))	((Quantity, 21094))	0.104348	0.100870	0.092174	0.883333	8.75718
7018	((Quantity, 22629))	((Quantity, 22630))	0.144348	0.113043	0.086957	0.602410	5.32900
7019	((Quantity, 22630))	((Quantity, 22629))	0.113043	0.144348	0.086957	0.769231	5.32900
7644	((Quantity, 22726))	((Quantity, 22727))	0.076522	0.074783	0.060870	0.795455	10.63689
7645	((Quantity, 22727))	((Quantity, 22726))	0.074783	0.076522	0.060870	0.813953	10.63689
7646	((Quantity, 22726))	((Quantity, 22728))	0.076522	0.078261	0.059130	0.772727	9.87373
7647	((Quantity, 22728))	((Quantity, 22726))	0.078261	0.076522	0.059130	0.755556	9.87373
7680	((Quantity, 22727))	((Quantity, 22728))	0.074783	0.078261	0.057391	0.767442	9.80620
7681	((Quantity, 22728))	((Quantity, 22727))	0.078261	0.074783	0.057391	0.733333	9.80620
8596	((Quantity, 23254))	((Quantity, 23256))	0.074783	0.083478	0.066087	0.883721	10.58624
8597	((Quantity, 23256))	((Quantity, 23254))	0.083478	0.074783	0.066087	0.791667	10.58624
23572	((Quantity, 21094), (Quantity, 21086))	((Quantity, 21080))	0.092174	0.109565	0.073043	0.792453	7.23270
23573	((Quantity, 21094),	((Quantity, 21086))	0.078261	0.104348	0.073043	0.933333	8.94444

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
	(Quantity, 21080))						
23574	((Quantity, 21080), (Quantity, 21086))	((Quantity, 21094))	0.074783	0.100870	0.073043	0.976744	9.68324(
23575	((Quantity, 21094))	((Quantity, 21080), (Quantity, 21086))	0.100870	0.074783	0.073043	0.724138	9.68324(
23576	((Quantity, 21086))	((Quantity, 21094), (Quantity, 21080))	0.104348	0.078261	0.073043	0.700000	8.94444
23577	((Quantity, 21080))	((Quantity, 21094), (Quantity, 21086))	0.109565	0.092174	0.073043	0.666667	7.23270
23800	((Quantity, POST), (Quantity, 21086))	((Quantity, 21080))	0.081739	0.109565	0.057391	0.702128	6.40830
23802	((Quantity, POST), (Quantity, 21080))	((Quantity, 21086))	0.076522	0.104348	0.057391	0.750000	7.18750(
23803	((Quantity, 21086))	((Quantity, POST), (Quantity, 21080))	0.104348	0.076522	0.057391	0.550000	7.18750(
23805	((Quantity, 21080))	((Quantity, POST), (Quantity, 21086))	0.109565	0.081739	0.057391	0.523810	6.40830
24034	((Quantity, 21094), (Quantity, POST))	((Quantity, 21080))	0.074783	0.109565	0.059130	0.790698	7.21668
24036	((Quantity, POST), (Quantity, 21080))	((Quantity, 21094))	0.076522	0.100870	0.059130	0.772727	7.66065
24037	((Quantity, 21094))	((Quantity, POST),	0.100870	0.076522	0.059130	0.586207	7.66065

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
		(Quantity, 21080))					
24039	((Quantity, 21080))	((Quantity, 21094), (Quantity, POST))	0.109565	0.074783	0.059130	0.539683	7.21668
25288	((Quantity, 21094), (Quantity, POST))	((Quantity, 21086))	0.074783	0.104348	0.069565	0.930233	8.91472
25290	((Quantity, POST), (Quantity, 21086))	((Quantity, 21094))	0.081739	0.100870	0.069565	0.851064	8.43727
25291	((Quantity, 21094))	((Quantity, POST), (Quantity, 21086))	0.100870	0.081739	0.069565	0.689655	8.43727
25293	((Quantity, 21086))	((Quantity, 21094), (Quantity, POST))	0.104348	0.074783	0.069565	0.666667	8.91472
38088	((Quantity, 22326), (Quantity, 22554))	((Quantity, 22551))	0.066087	0.149565	0.052174	0.789474	5.27845
38089	((Quantity, 22551))	((Quantity, 22326), (Quantity, 22554))	0.149565	0.066087	0.052174	0.348837	5.27845
52714	((Quantity, 22726), (Quantity, 22727))	((Quantity, 22728))	0.060870	0.078261	0.050435	0.828571	10.58730
52715	((Quantity, 22726), (Quantity, 22728))	((Quantity, 22727))	0.059130	0.074783	0.050435	0.852941	11.40560
52716	((Quantity, 22727), (Quantity, 22728))	((Quantity, 22726))	0.057391	0.076522	0.050435	0.878788	11.48416
52717	((Quantity, 22726))	((Quantity, 22727),	0.076522	0.057391	0.050435	0.659091	11.48416

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
		(Quantity, 22728))					
52718	((Quantity, 22727))	((Quantity, 22726), (Quantity, 22728))	0.074783	0.059130	0.050435	0.674419	11.40560
52719	((Quantity, 22728))	((Quantity, 22726), (Quantity, 22727))	0.078261	0.060870	0.050435	0.644444	10.58730
87888	((Quantity, 21094), (Quantity, POST), (Quantit...	((Quantity, 21080))	0.069565	0.109565	0.055652	0.800000	7.30158
87890	((Quantity, 21094), (Quantity, POST), (Quantit...	((Quantity, 21086))	0.059130	0.104348	0.055652	0.941176	9.01960
87891	((Quantity, 21080), (Quantity, POST), (Quantit...	((Quantity, 21094))	0.057391	0.100870	0.055652	0.969697	9.61337
87892	((Quantity, 21094), (Quantity, 21086))	((Quantity, POST), (Quantity, 21080))	0.092174	0.076522	0.055652	0.603774	7.89022
87893	((Quantity, 21094), (Quantity, POST))	((Quantity, 21080), (Quantity, 21086))	0.074783	0.074783	0.055652	0.744186	9.95132
87894	((Quantity, 21094), (Quantity, 21080))	((Quantity, POST), (Quantity, 21086))	0.078261	0.081739	0.055652	0.711111	8.69976
87895	((Quantity, POST), (Quantity, 21086))	((Quantity, 21094), (Quantity, 21080))	0.081739	0.078261	0.055652	0.680851	8.69976
87896	((Quantity, 21080), (Quantity, 21086))	((Quantity, 21094), (Quantity, POST))	0.074783	0.074783	0.055652	0.744186	9.95132

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
87897	((Quantity, POST), (Quantity, 21080))	((Quantity, 21094), (Quantity, 21086))	0.076522	0.092174	0.055652	0.727273	7.890223
87898	((Quantity, 21094))	((Quantity, 21080), (Quantity, POST), (Quantit...	0.100870	0.057391	0.055652	0.551724	9.613375
87899	((Quantity, 21086))	((Quantity, 21094), (Quantity, POST), (Quantit...	0.104348	0.059130	0.055652	0.533333	9.019608
87901	((Quantity, 21080))	((Quantity, 21094), (Quantity, POST), (Quantit...	0.109565	0.069565	0.055652	0.507937	7.301587

In [73]:
```
# Filtering by confidence
rules[(rules["support"]>0.05) & (rules["confidence"]>0.1) & (rules["lift"]>5)].sort
```

Out[73]:

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
23574	((Quantity, 21080), (Quantity, 21086))	((Quantity, 21094))	0.074783	0.100870	0.073043	0.976744	9.68324(
87891	((Quantity, 21080), (Quantity, POST), (Quantit...	((Quantity, 21094))	0.057391	0.100870	0.055652	0.969697	9.613375
87890	((Quantity, 21094), (Quantity, POST), (Quantit...	((Quantity, 21086))	0.059130	0.104348	0.055652	0.941176	9.019608
23573	((Quantity, 21094), (Quantity, 21080))	((Quantity, 21086))	0.078261	0.104348	0.073043	0.933333	8.944444
25288	((Quantity, 21094), (Quantity, POST))	((Quantity, 21086))	0.074783	0.104348	0.069565	0.930233	8.914729
1888	((Quantity, 21094))	((Quantity, 21086))	0.100870	0.104348	0.092174	0.913793	8.757184
8596	((Quantity, 23254))	((Quantity, 23256))	0.074783	0.083478	0.066087	0.883721	10.586240
1889	((Quantity, 21086))	((Quantity, 21094))	0.104348	0.100870	0.092174	0.883333	8.757184
52716	((Quantity, 22727), (Quantity, 22728))	((Quantity, 22726))	0.057391	0.076522	0.050435	0.878788	11.484160
52715	((Quantity, 22726), (Quantity, 22728))	((Quantity, 22727))	0.059130	0.074783	0.050435	0.852941	11.405609
25290	((Quantity, POST), (Quantity, 21086))	((Quantity, 21094))	0.081739	0.100870	0.069565	0.851064	8.437271
52714	((Quantity, 22726), (Quantity, 22727))	((Quantity, 22728))	0.060870	0.078261	0.050435	0.828571	10.587302

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
7645	((Quantity, 22727))	((Quantity, 22726))	0.074783	0.076522	0.060870	0.813953	10.636892
87888	((Quantity, 21094), (Quantity, POST), (Quantit...	((Quantity, 21080))	0.069565	0.109565	0.055652	0.800000	7.301587
7644	((Quantity, 22726))	((Quantity, 22727))	0.076522	0.074783	0.060870	0.795455	10.636892
23572	((Quantity, 21094), (Quantity, 21086))	((Quantity, 21080))	0.092174	0.109565	0.073043	0.792453	7.232704
8597	((Quantity, 23256))	((Quantity, 23254))	0.083478	0.074783	0.066087	0.791667	10.586240
24034	((Quantity, 21094), (Quantity, POST))	((Quantity, 21080))	0.074783	0.109565	0.059130	0.790698	7.216685
38088	((Quantity, 22326), (Quantity, 22554))	((Quantity, 22551))	0.066087	0.149565	0.052174	0.789474	5.278458
1724	((Quantity, 21094))	((Quantity, 21080))	0.100870	0.109565	0.078261	0.775862	7.081281
7646	((Quantity, 22726))	((Quantity, 22728))	0.076522	0.078261	0.059130	0.772727	9.873737
24036	((Quantity, POST), (Quantity, 21080))	((Quantity, 21094))	0.076522	0.100870	0.059130	0.772727	7.660658
7019	((Quantity, 22630))	((Quantity, 22629))	0.113043	0.144348	0.086957	0.769231	5.329008
7680	((Quantity, 22727))	((Quantity, 22728))	0.074783	0.078261	0.057391	0.767442	9.806202
7647	((Quantity, 22728))	((Quantity, 22726))	0.078261	0.076522	0.059130	0.755556	9.873737
23802	((Quantity, POST), (Quantity, 21080))	((Quantity, 21086))	0.076522	0.104348	0.057391	0.750000	7.187500

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
87893	((Quantity, 21094), (Quantity, POST))	((Quantity, 21080), (Quantity, 21086))	0.074783	0.074783	0.055652	0.744186	9.951325
87896	((Quantity, 21080), (Quantity, 21086))	((Quantity, 21094), (Quantity, POST))	0.074783	0.074783	0.055652	0.744186	9.951325
7681	((Quantity, 22728))	((Quantity, 22727))	0.078261	0.074783	0.057391	0.733333	9.806202
87897	((Quantity, POST), (Quantity, 21080))	((Quantity, 21094), (Quantity, 21086))	0.076522	0.092174	0.055652	0.727273	7.890223
23575	((Quantity, 21094))	((Quantity, 21080), (Quantity, 21086))	0.100870	0.074783	0.073043	0.724138	9.683240
1722	((Quantity, 21086))	((Quantity, 21080))	0.104348	0.109565	0.074783	0.716667	6.541005
1725	((Quantity, 21080))	((Quantity, 21094))	0.109565	0.100870	0.078261	0.714286	7.081281
87894	((Quantity, 21094), (Quantity, 21080))	((Quantity, POST), (Quantity, 21086))	0.078261	0.081739	0.055652	0.711111	8.699764
23800	((Quantity, POST), (Quantity, 21086))	((Quantity, 21080))	0.081739	0.109565	0.057391	0.702128	6.408308
23576	((Quantity, 21086))	((Quantity, 21094), (Quantity, 21080))	0.104348	0.078261	0.073043	0.700000	8.944444
25291	((Quantity, 21094))	((Quantity, POST), (Quantity, 21086))	0.100870	0.081739	0.069565	0.689655	8.437271
1723	((Quantity, 21080))	((Quantity, 21086))	0.109565	0.104348	0.074783	0.682540	6.541005
87895	((Quantity, POST),	((Quantity, 21094),	0.081739	0.078261	0.055652	0.680851	8.699764

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
	(Quantity, 21086))	(Quantity, 21080))					
52718	((Quantity, 22727))	((Quantity, 22726), (Quantity, 22728))	0.074783	0.059130	0.050435	0.674419	11.40560
23577	((Quantity, 21080))	((Quantity, 21094), (Quantity, 21086))	0.109565	0.092174	0.073043	0.666667	7.23270
25293	((Quantity, 21086))	((Quantity, 21094), (Quantity, POST))	0.104348	0.074783	0.069565	0.666667	8.91472
52717	((Quantity, 22726))	((Quantity, 22727), (Quantity, 22728))	0.076522	0.057391	0.050435	0.659091	11.48416
52719	((Quantity, 22728))	((Quantity, 22726), (Quantity, 22727))	0.078261	0.060870	0.050435	0.644444	10.58730
87892	((Quantity, 21094), (Quantity, 21086))	((Quantity, POST), (Quantity, 21080))	0.092174	0.076522	0.055652	0.603774	7.89022
7018	((Quantity, 22629))	((Quantity, 22630))	0.144348	0.113043	0.086957	0.602410	5.32900
24037	((Quantity, 21094))	((Quantity, POST), (Quantity, 21080))	0.100870	0.076522	0.059130	0.586207	7.66065
87898	((Quantity, 21094))	((Quantity, 21080), (Quantity, POST), (Quantit...	0.100870	0.057391	0.055652	0.551724	9.61337
23803	((Quantity, 21086))	((Quantity, POST), (Quantity, 21080))	0.104348	0.076522	0.057391	0.550000	7.18750
24039	((Quantity, 21080))	((Quantity, 21094),	0.109565	0.074783	0.059130	0.539683	7.21668

	antecedents	consequents	antecedent support	consequent support	support	confidence	lif
		(Quantity, POST))					
87899	((Quantity, 21086))	((Quantity, 21094), (Quantity, POST), (Quantit...	0.104348	0.059130	0.055652	0.533333	9.019608
23805	((Quantity, 21080))	((Quantity, POST), (Quantity, 21086))	0.109565	0.081739	0.057391	0.523810	6.408308
87901	((Quantity, 21080))	((Quantity, 21094), (Quantity, POST), (Quantit...	0.109565	0.069565	0.055652	0.507937	7.301587
38089	((Quantity, 22551))	((Quantity, 22326), (Quantity, 22554))	0.149565	0.066087	0.052174	0.348837	5.278458

5. Application

For example, a member purchased a product with stock code 85123A ...

In [74]:
```
def prdct_name_finder(data,stckcde):
    product_name = data[data["StockCode"] == stckcde][["Description"]].values[0].to
    return product_name
```

In [75]:
```
def arl_recommender(rules_df, product_id, rec_count):

    sorted_rules = rules_df.sort_values("lift", ascending=False)
    recommendation_list = []
    recommendation_list_name = []

    for i, product in enumerate(sorted_rules["antecedents"]):
        for j in list(product):
            if j[1] == product_id:
                for k in list(sorted_rules.iloc[i]["consequents"]):
                    if k[1] not in recommendation_list:
                        recommendation_list.append(k[1])
    added_product = prdct_name_finder(df,product_id)
    print(f"Added to Cart:           {added_product[0]}\n\n")
    print(f"Members Who Bought This Also Bought:\n\n")
    for i in range(0,rec_count):
```

```
        recommendation_list_name.append(prdct_name_finder(df,recommendation_list[i]
        print(f"                          {recommendation_list_name[i][0]}\n")
```

In [81]:
```
arl_recommender(rules, "84997C", 3)
```

```
Added to Cart:          BLUE 3 PIECE POLKADOT CUTLERY SET

Members Who Bought This Also Bought:

                        RED 3 PIECE RETROSPOT CUTLERY SET

                        GREEN 3 PIECE POLKADOT CUTLERY SET

                        POSTAGE
```

In [83]:
```
arl_recommender(rules, "15056BL", 3)
```

```
Added to Cart:          EDWARDIAN PARASOL BLACK

Members Who Bought This Also Bought:

                        EDWARDIAN PARASOL RED

                        POSTAGE

                        RED RETROSPOT UMBRELLA
```

In [ ]: