online_retail

October 7, 2024

1 Portfolio Project: Online Retail Exploratory Data Analysis with Python

1.1 Case Study

In this project, you will be working with transactional data from an online retail store. The dataset contains information about customer purchases, including product details, quantities, prices, and timestamps.

By conducting exploratory data analysis, you will identify patterns, outliers, and correlations in the data, allowing you to make data-driven decisions and recommendations to optimize the store's operations and improve customer satisfaction. Through visualizations and statistical analysis, you will uncover key trends, such as the busiest sales months, best-selling products, popular products and the store's most valuable customers.

Ultimately, this project aims to provide actionable insights that can drive strategic business decisions and enhance the store's overall performance in the competitive online retail market.

1.2 Project Objectives

1. Describe data to answer key questions to uncover insights
2. Gain valuable insights that will help improve online retail performance
3. Provide analytic insights and data-driven recommendations

1.3 Dataset

It contains transactional data of an online retail store from 2010 to 2011. The dataset is available as a .xlsx file named `Online Retail.xlsx`.

The dataset contains the following columns:

- InvoiceNo: Invoice number of the transaction
- StockCode: Unique code of the product
- Description: Description of the product
- Quantity: Quantity of the product in the transaction
- InvoiceDate: Date and time of the transaction
- UnitPrice: Unit price of the product
- CustomerID: Unique identifier of the customer

- Country: Country where the transaction occurred

1.4 Task 1: Load the Data

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

[2]:
```
#Load data
path = "Online_Retail.xlsx"
df = pd.read_excel(path)
```

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

[3]:

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

[4]:
```
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
```

[5]:
```
#Some Statistics
df.describe()
```

[5]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

1.5 Task 2. Perform data cleaning

1.5.1 Primeras observaciones

1. Hay 541909 registros y 8 columnas.
2.
   - 4 columnas categóricas
   - 2 de tipo float
   - 1 Datetime
   - 1 integer
3. Faltan datos en `Description`, `CustomerID`
4. Quantity y UnitPrice tienen valores negativos

[6]:
```
#Count the null values
df.isna().sum()
```

[6]:
```
InvoiceNo          0
StockCode          0
Description     1454
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     135080
Country            0
dtype: int64
```

1.5.2 Valores negativos o 0 en UnitPrice

Son valores inesperados para esta variable, con lo cual los observaremos más en detalle para encontrar la razón.

[19]:
```
mask = (df['UnitPrice']<0)
df[mask].head()
```

[19]:
```
       InvoiceNo StockCode      Description  Quantity         InvoiceDate  \
299983   A563186         B  Adjust bad debt         1 2011-08-12 14:51:00
299984   A563187         B  Adjust bad debt         1 2011-08-12 14:52:00

         UnitPrice  CustomerID         Country
299983  -11062.06         NaN  United Kingdom
299984  -11062.06         NaN  United Kingdom
```

[20]:
```
df[df['Description']=='Adjust bad debt']
```

[20]:
```
       InvoiceNo StockCode      Description  Quantity         InvoiceDate  \
299982   A563185         B  Adjust bad debt         1 2011-08-12 14:50:00
299983   A563186         B  Adjust bad debt         1 2011-08-12 14:51:00
299984   A563187         B  Adjust bad debt         1 2011-08-12 14:52:00

         UnitPrice  CustomerID         Country
299982   11062.06         NaN  United Kingdom
299983  -11062.06         NaN  United Kingdom
299984  -11062.06         NaN  United Kingdom
```

[21]:
```
#Drop Adjust bad debt
df = df[df['Description'] != 'Adjust bad debt']
```

[22]:
```
df[df['UnitPrice']==0].info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 0 entries
Data columns (total 8 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   InvoiceNo    0 non-null      object
 1   StockCode    0 non-null      object
 2   Description  0 non-null      object
 3   Quantity     0 non-null      int64
 4   InvoiceDate  0 non-null      datetime64[ns]
 5   UnitPrice    0 non-null      float64
 6   CustomerID   0 non-null      float64
 7   Country      0 non-null      object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 0.0+ bytes
```

[23]:
```
#Drop UnitPrice = 0
df = df[df['UnitPrice']!=0]
```

1.5.3 Evaluar registros que no son productos en STOCK CODE

[24]:
```
mask = (df['UnitPrice']>500)
df[mask]['Description'].unique()
```

[24]:
```
array(['DOTCOM POSTAGE', 'Manual', 'AMAZON FEE', 'Bank Charges',
       'Discount', 'POSTAGE', 'PICNIC BASKET WICKER 60 PIECES', 'SAMPLES',
       'CRUK Commission'], dtype=object)
```

[12]:
```
df[df['UnitPrice']>500]['StockCode'].unique()
```

[12]:
```
array(['DOT', 'M', 'AMAZONFEE', 'BANK CHARGES', 'D', 'POST', 22502, 'S',
       'B', 'CRUK'], dtype=object)
```

Dentro de los `UnitPrice` con valores más altos, encontramos descripciones que no corresponden a productos y su `StockCode` también lo confirma. Los analizaremos brevemente para proceder o no a su eliminación.

[25]:
```
#Create a list with extras that seems no products
extras = ['AMAZON FEE', 'Bank Charges','DOTCOM POSTAGE', 'Manual', 'Discount', \
          'POSTAGE', 'SAMPLES','CRUK Commission']
```

[27]:
```
print("Amazon FEE: ", df[df['StockCode'] == 'AMAZONFEE']['Country'].
 ↪value_counts())

print("Bank Charges: ", df[df['StockCode'] == 'BANK CHARGES']['Country'].
 ↪value_counts())

print("Bank Charges: ", df[df['StockCode'] == 'CRUK']['Country'].value_counts())
```

```
Amazon FEE:  United Kingdom    34
Name: Country, dtype: int64
Bank Charges:  United Kingdom    37
Name: Country, dtype: int64
Bank Charges:  United Kingdom    16
Name: Country, dtype: int64
```

[17]:
```
df[df['StockCode'] == 'AMAZONFEE'].head()
```

[17]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
14514	C537600	AMAZONFEE	AMAZON FEE	-1	2010-12-07 12:41:00			
15016	C537630	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:04:00			
15017	537632	AMAZONFEE	AMAZON FEE	1	2010-12-07 15:08:00			
16232	C537644	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:34:00			
16313	C537647	AMAZONFEE	AMAZON FEE	-1	2010-12-07 15:41:00			

```
14514       1.00         NaN  United Kingdom
15016   13541.33         NaN  United Kingdom
15017   13541.33         NaN  United Kingdom
16232   13474.79         NaN  United Kingdom
16313    5519.25         NaN  United Kingdom
```

[18]:
```
df[df['StockCode'] == 'BANK CHARGES'].head()
```

[18]:
```
      InvoiceNo     StockCode   Description  Quantity         InvoiceDate  \
4406     536779  BANK CHARGES  Bank Charges         1 2010-12-02 15:08:00
14435   C537572  BANK CHARGES  Bank Charges        -1 2010-12-07 12:00:00
28992   C538680  BANK CHARGES  Bank Charges        -1 2010-12-13 17:10:00
62508    541505  BANK CHARGES  Bank Charges         1 2011-01-18 15:58:00
64573   C541653  BANK CHARGES  Bank Charges        -1 2011-01-20 11:50:00

       UnitPrice  CustomerID         Country
4406       15.00     15823.0  United Kingdom
14435      95.38         NaN  United Kingdom
28992     966.92         NaN  United Kingdom
62508      15.00     15939.0  United Kingdom
64573    1050.15         NaN  United Kingdom
```

[29]:
```
df[df['StockCode'] == 'CRUK'].head()
```

[29]:
```
       InvoiceNo StockCode      Description  Quantity         InvoiceDate  \
317508   C564763      CRUK  CRUK Commission        -1 2011-08-30 10:49:00
324023   C565382      CRUK  CRUK Commission        -1 2011-09-02 15:45:00
333779   C566216      CRUK  CRUK Commission        -1 2011-09-09 15:17:00
338848   C566565      CRUK  CRUK Commission        -1 2011-09-13 12:32:00
351003   C567655      CRUK  CRUK Commission        -1 2011-09-21 14:40:00

        UnitPrice  CustomerID         Country
317508       1.60     14096.0  United Kingdom
324023      13.01     14096.0  United Kingdom
333779      15.96     14096.0  United Kingdom
338848      52.24     14096.0  United Kingdom
351003     608.66     14096.0  United Kingdom
```

Ambos datos sólo figuran para `United Kingdom`, son 34 en el caso de AMAZON FEE y 37 de BANK CHARGES, no corresponden a ventas ni devoluciones y los mantendremos al margen del análisis.

[49]:
```
#About SAMPLES
df[df['Description']=='SAMPLES']['CustomerID'].unique()
```

[49]:
```
array([nan])
```

[48]:
```
#About Description
df[df['Description']=='Discount'].sort_values('UnitPrice').head()
```

[48]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
108088	C545478	D	Discount	-720	2011-03-03 11:08:00	0.01	16422.0	United Kingdom
182729	C552569	D	Discount	-240	2011-05-10 12:06:00	0.03	12901.0	United Kingdom
196362	C553841	D	Discount	-48	2011-05-19 12:19:00	0.20	16029.0	United Kingdom
226396	C556796	D	Discount	-96	2011-06-14 14:40:00	0.70	16013.0	United Kingdom
183138	C552650	D	Discount	-18	2011-05-10 14:03:00	1.45	16672.0	United Kingdom

[30]:
```
df[df['Description'].isin(extras)].groupby('Description')['Country'].
↪value_counts()
```

[30]:

Description	Country	
AMAZON FEE	United Kingdom	34
Bank Charges	United Kingdom	37
CRUK Commission	United Kingdom	16
DOTCOM POSTAGE	United Kingdom	707
Discount	United Kingdom	74
	EIRE	1
	Italy	1
	Netherlands	1
Manual	United Kingdom	476
	Germany	15
	Portugal	14
	Singapore	14
	EIRE	12
	France	9
	Hong Kong	6
	Norway	6
	Japan	3
	Spain	3
	Channel Islands	2
	Cyprus	2
	Finland	1
	Italy	1
	Netherlands	1
	Sweden	1
POSTAGE	Germany	383
	France	311

```
                    United Kingdom          140
                    Belgium                  98
                    Spain                    62
                    Finland                  41
                    Netherlands              39
                    Switzerland              33
                    Portugal                 30
                    Sweden                   24
                    Norway                   20
                    Italy                    18
                    Austria                  14
                    Denmark                  14
                    Poland                    5
                    Greece                    4
                    Malta                     4
                    European Community        3
                    Australia                 2
                    Czech Republic            2
                    Hong Kong                 2
                    Canada                    1
                    Cyprus                    1
                    United Arab Emirates      1
SAMPLES             United Kingdom           63
Name: Country, dtype: int64
```

1.5.4 Eliminación de datos que no corresponden a productos

[31]:
```
#Drop extras from df
df = df[~(df['Description'].isin(extras))]
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 536639 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    536639 non-null  object
 1   StockCode    536639 non-null  object
 2   Description  536639 non-null  object
 3   Quantity     536639 non-null  int64
 4   InvoiceDate  536639 non-null  datetime64[ns]
 5   UnitPrice    536639 non-null  float64
 6   CustomerID   405013 non-null  float64
 7   Country      536639 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 36.8+ MB
```

1.5.5 Valores negativos en Quantity

Estos valores podrían corresponder a descuentos o devoluciones. Sería una pregunta para hacer a los responsables de los datos aunque, al no poder proceder con este intercambio de información, intentaré hacer hablar a los datos.

[32]:
```
df3 = pd.concat([df[df['Quantity']==df['Quantity'].max()],␣
↪df[df['Quantity']==df['Quantity'].min()]])
df3
```

[32]:
```
       InvoiceNo StockCode                      Description  Quantity  \
540421    581483     23843  PAPER CRAFT , LITTLE BIRDIE     80995
540422   C581484     23843  PAPER CRAFT , LITTLE BIRDIE    -80995

               InvoiceDate  UnitPrice  CustomerID         Country
540421 2011-12-09 09:15:00       2.08     16446.0  United Kingdom
540422 2011-12-09 09:27:00       2.08     16446.0  United Kingdom
```

Con esto comprobamos que los valores negativos corresponden a devoluciones o descuentos, las `Invoice` llevan un prefijo 'C' cuando se trata una devolución mientras que las compras no llevan prefijo.

[33]:
```
#Count return and discounts
df[df['InvoiceNo'].str[0]=='C'].describe()
```

[33]:
```
           Quantity    UnitPrice    CustomerID
count   8706.000000  8706.000000   8540.000000
mean     -31.246497     4.420997  14996.510656
std     1183.307228     9.128259   1704.268454
min   -80995.000000     0.030000  12346.000000
25%       -6.000000     1.450000  13534.000000
50%       -2.000000     2.550000  14903.000000
75%       -1.000000     4.950000  16393.000000
max       -1.000000   295.000000  18282.000000
```

1.5.6 Columnas: Month, Year, WeekDay, SubTotal

[34]:
```
#Create column Month
df['Month'] = df['InvoiceDate'].dt.month

#Create column Year
df['Year'] = df['InvoiceDate'].dt.year

#Create column quarter of year
df['Quarter'] = df['InvoiceDate'].dt.quarter

#Create column for Week Day by number Monday=0, Sunday=6
```

```
df['WeekDay'] = df['InvoiceDate'].dt.weekday
```

[35]:
```
#Create column SubTotal
df['SubTotal'] = df['Quantity'] * df['UnitPrice']
```

1.6 Task 3. Explore the basic statistics of the dataset

including measures of central tendency and dispersion.

[36]:
```
df.describe(include='all')
```

[36]:

	InvoiceNo	StockCode	Description
count	536639.0	536639	536639
unique	23198.0	3928	4033
top	573585.0	85123A	WHITE HANGING HEART T-LIGHT HOLDER
freq	1113.0	2307	2365
first	NaN	NaN	NaN
last	NaN	NaN	NaN
mean	NaN	NaN	NaN
std	NaN	NaN	NaN
min	NaN	NaN	NaN
25%	NaN	NaN	NaN
50%	NaN	NaN	NaN
75%	NaN	NaN	NaN
max	NaN	NaN	NaN

	Quantity	InvoiceDate	UnitPrice	CustomerID
count	536639.000000	536639	536639.000000	405013.000000
unique	NaN	21311	NaN	NaN
top	NaN	2011-10-31 14:41:00	NaN	NaN
freq	NaN	1113	NaN	NaN
first	NaN	2010-12-01 08:26:00	NaN	NaN
last	NaN	2011-12-09 12:50:00	NaN	NaN
mean	9.886061	NaN	3.297442	15295.017755
std	215.925492	NaN	4.565467	1710.211905
min	-80995.000000	NaN	0.001000	12346.000000
25%	1.000000	NaN	1.250000	13969.000000
50%	3.000000	NaN	2.080000	15159.000000
75%	10.000000	NaN	4.130000	16794.000000
max	80995.000000	NaN	649.500000	18287.000000

	Country	Month	Year	Quarter
count	536639	536639.000000	536639.000000	536639.000000
unique	38	NaN	NaN	NaN
top	United Kingdom	NaN	NaN	NaN
freq	491431	NaN	NaN	NaN

```
first              NaN            NaN            NaN            NaN
last               NaN            NaN            NaN            NaN
mean               NaN       7.558558    2010.921689       2.836499
std                NaN       3.508899       0.268661       1.137102
min                NaN       1.000000    2010.000000       1.000000
25%                NaN       5.000000    2011.000000       2.000000
50%                NaN       8.000000    2011.000000       3.000000
75%                NaN      11.000000    2011.000000       4.000000
max                NaN      12.000000    2011.000000       4.000000

              WeekDay       SubTotal
count   536639.000000  536639.000000
unique            NaN            NaN
top               NaN            NaN
freq              NaN            NaN
first             NaN            NaN
last              NaN            NaN
mean         2.434471      18.262520
std          1.847292     367.889413
min          0.000000 -168469.600000
25%          1.000000       3.750000
50%          2.000000       9.840000
75%          4.000000      17.400000
max          6.000000  168469.600000
```

[177]:
```
Q1 = df.quantile(0.25)
Q3 = df.quantile(0.75)
IQR = Q3 - Q1

print("IQR")
print(IQR)
```

```
IQR
Quantity         9.00
UnitPrice        2.88
CustomerID    2825.00
Month            6.00
Year             0.00
Quarter          2.00
WeekDay          3.00
SubTotal        13.65
dtype: float64
```

1.6.1 Observaciones

- Hay datos de 38 paises y el más frecuente es United Kingdom
- Se observan outliers en UnitPrice y Quantity

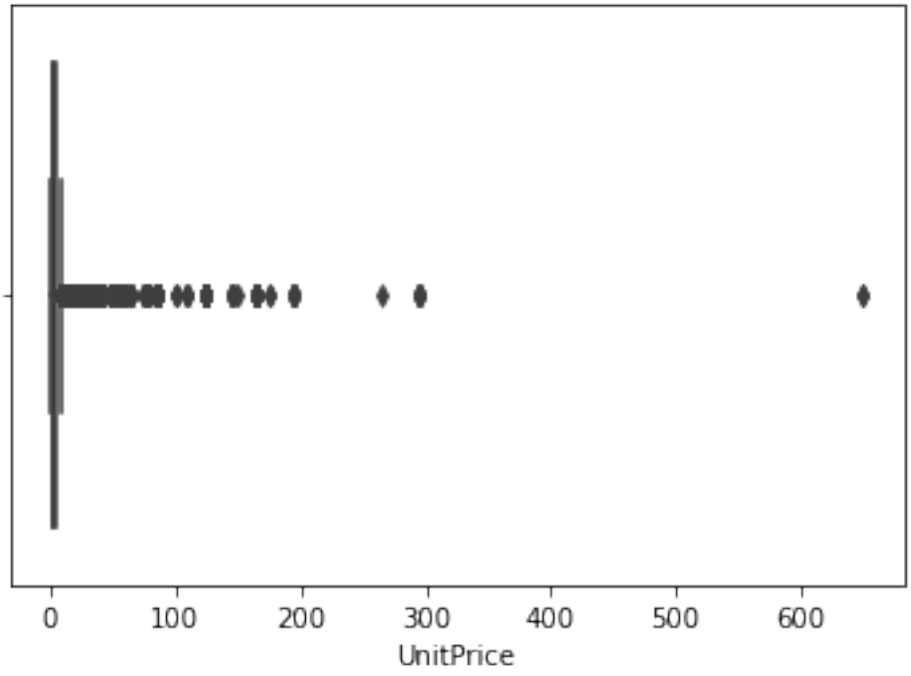
- Sólo se tienen registros de 6 días de la semana

1.7 Task 4. Perform data visualization to gain insights into the dataset.

Generate appropriate plots, such as histograms, scatter plots, or bar plots, to visualize different aspects of the data.

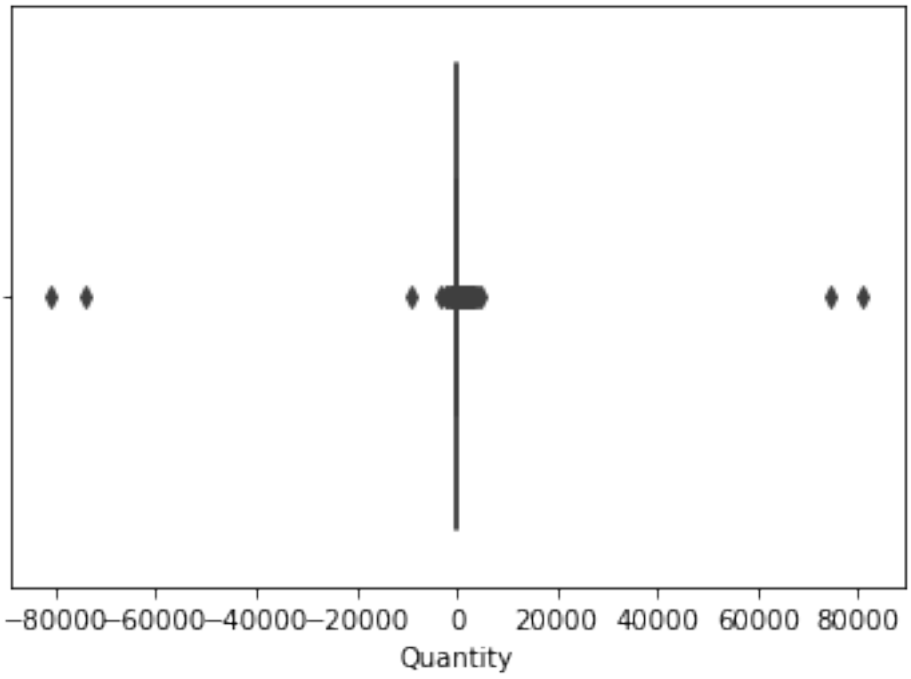
[37]:
```
sns.boxplot(df['UnitPrice'])
```

[37]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f985b3a9cd0>
```

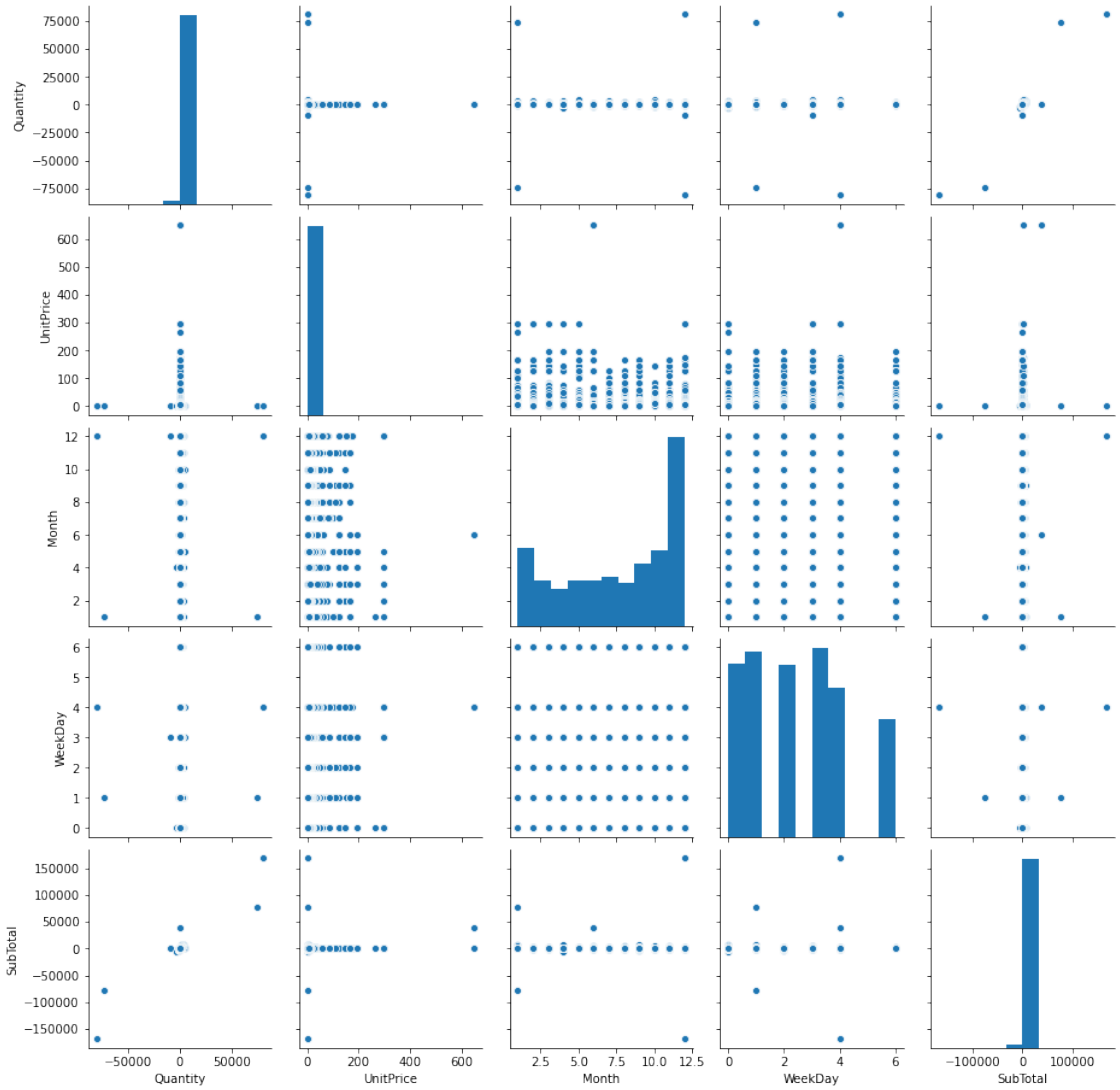


[38]:
```
sns.boxplot(df['Quantity'])
```

[38]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f986499d310>
```



[183]:
```
# Create a pairplot of the data.

# 1. Select the columns
# 2. Create a pairplot for this columns only
cols = ['Quantity', 'UnitPrice', 'Month', 'WeekDay', 'Country', 'SubTotal']
sns.pairplot(df[cols]);
```

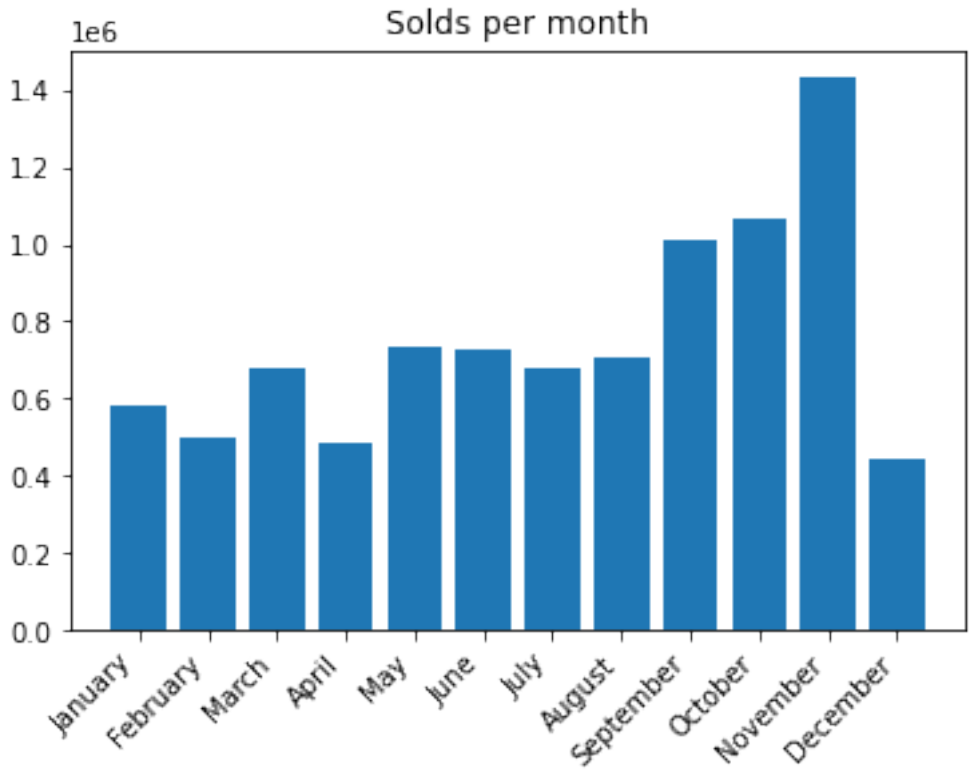


1.7.1 Visualización de ventas de 2011

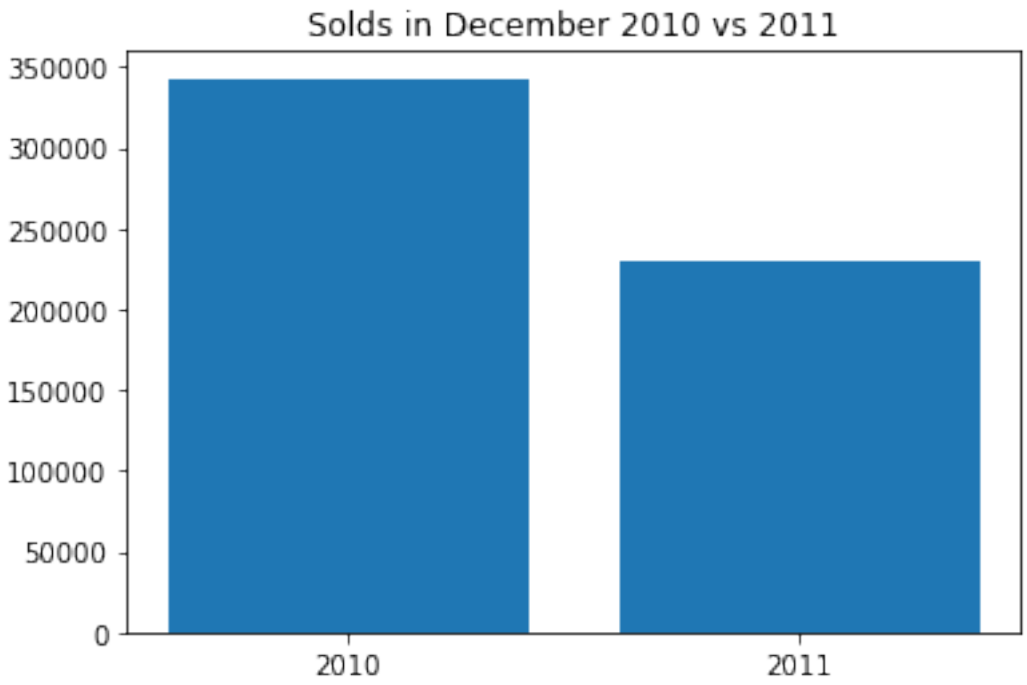
Los registros sólo poseen datos de Diciembre de 2010 no se podrían compara ambos años, representaremos sólo los datos de 2011 que están completos. Luego podríamos comprar Diciembre de 2010 y Diciembre de 2011.

[39]:
```
month_order = ["January", "February", "March", "April", "May", "June",
               "July", "August", "September", "October", "November",
               "December"]

results = df[df['Year']==2011].groupby('Month').sum()
plt.bar(month_order, results['SubTotal'])
```

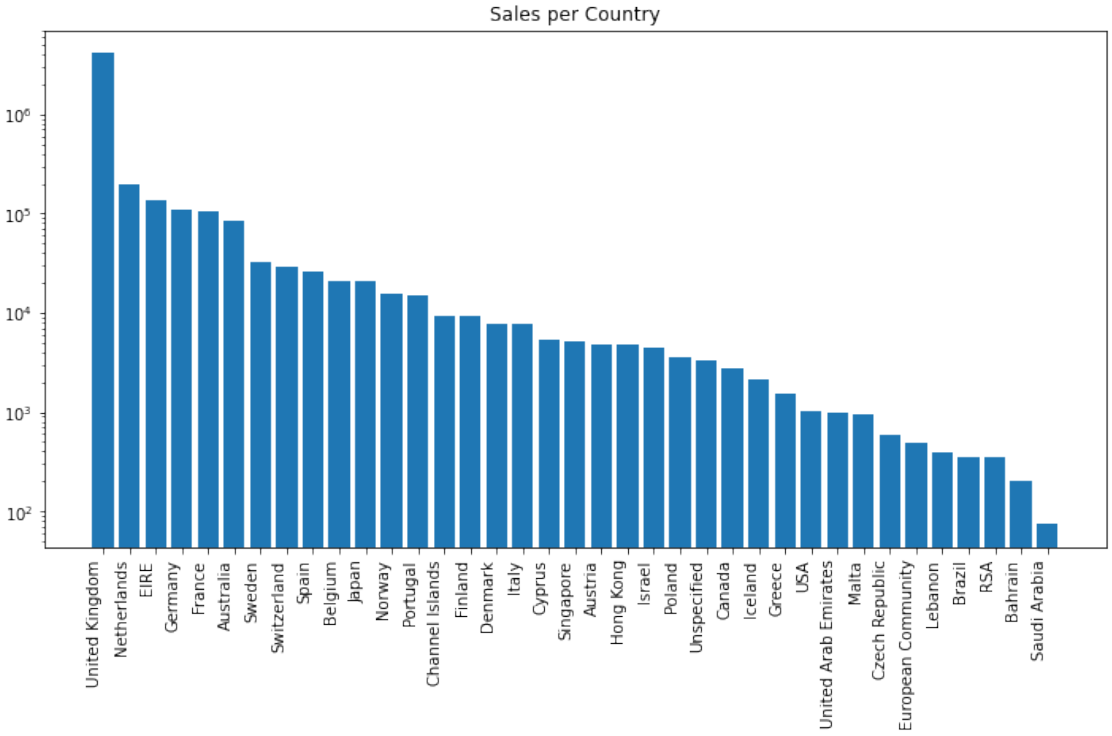
```
plt.title('Solds per month')

plt.xticks(rotation=45, horizontalalignment='right')

plt.show()
```



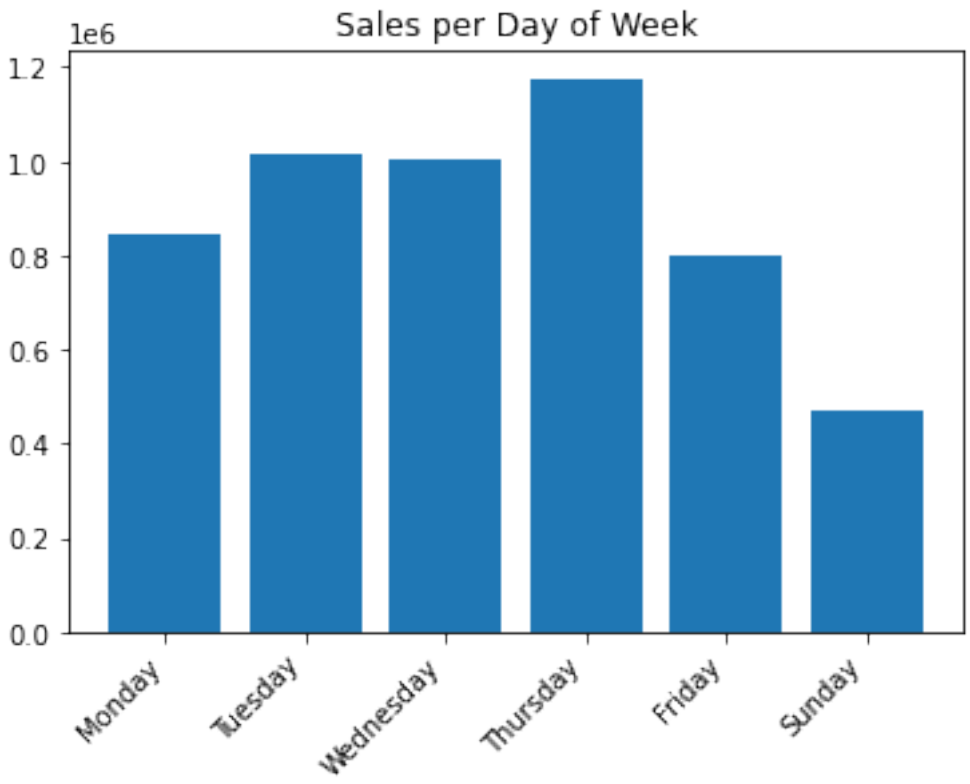
[41]:
```
bins = [2010, 2011]

results = df[df['Month']==12].groupby('Year').sum()
plt.bar(bins, results['Quantity'])

plt.xticks(bins)
plt.title('Solds in December 2010 vs 2011')

plt.show()
```



[47]:
```
#Sales per Country 2011
results = df[df['Year']==2011].groupby('Country').sum().sort_values('Quantity',␣
 ↪ascending=False)

#Exclude United Kingdom
#results = results.iloc[1:30,]

countries = [i for i in results.index]

plt.figure(figsize=(12,6))
plt.bar(countries, results['Quantity'])

plt.title('Sales per Country')

plt.xticks(rotation='vertical', horizontalalignment='right')

plt.yscale('log')

plt.show()
```



[49]:
```
results = df.groupby('WeekDay')['Quantity'].sum().sort_index()
days = ['Monday', 'Tuesday', 'Wednesday','Thursday','Friday','Sunday']


plt.bar(days, results.values)

plt.title('Sales per Day of Week')

plt.xticks(rotation=45, horizontalalignment='right')

plt.show()
```



1.8 Task 5. Analyze the sales trends over time.

Identify the busiest months and days of the week in terms of sales.

1.8.1 Combining Invoice in one column

[51]:
```
# 1. Select only duplicated invoices
df_dup = df[df['InvoiceNo'].duplicated(keep=False)]

# 2. Group Invoice Products in one column Grouped
df_dup['Grouped'] = df_dup.groupby('InvoiceNo')['StockCode'].transform(lambda x:
 ↪ ','.join(x.astype(str)))

# 3. Calculate Total of Invoice
df_dup['Total'] = df_dup.groupby('InvoiceNo')['SubTotal'].transform(lambda x: x.
 ↪sum())

# 4. Calculate Total of Invoice
df_dup['TotalQuantity'] = df_dup.groupby('InvoiceNo')['Quantity'].
 ↪transform(lambda x: x.sum())
```

```
# 5. Delete duplicated and keep only one
df_temp = df_dup.drop_duplicates(['InvoiceNo'])
```

[52]:
```
# Delete columns Quantity and UnitPrice
df_temp.drop(columns=['Quantity', 'UnitPrice'], axis=1, inplace=True)

# Rename column for future merge
df_temp.rename(columns={'TotalQuantity':'Quantity'}, inplace=True)
```

[53]:
```
# Get no duplicated invoices
df_nodup = df.drop_duplicates(['InvoiceNo'], keep=False)

#Group Invoice Products in one column Grouped
df_nodup['Grouped'] = df_nodup['StockCode']

#Calculate Total of Invoice
df_nodup['Total'] = df_nodup['SubTotal']
```

[55]:
```
#Join both dataFrames
df_invoices = pd.merge(df_nodup, df_temp, how='outer')

#Drop the unnecessary columns
df_invoices.drop(['UnitPrice', 'SubTotal'], axis=1, inplace=True)
```

[48]:
```
#Save invoices and cleaned data
df_invoices.to_csv("online_invoice.csv")

df.to_csv("online_retail_clean.csv")
```

[83]:
```
#Delete DataFrames

del df_nodup
del df_dup
del df_temp
```

1.8.2 Busiest Month of 2011

[56]:
```
#Exclude returns from this
mask_2011 = (df_invoices['Year']==2011)
```

[157]:
```
# Get the Busiest Month of 2011

# 1. Filter the dataset by year 2011
# 2. Group the dataframe by 'Month'.
# 3. Calculate the sum of 'Quantity' and 'Total' for each group.
```

```
df_invoices[mask_2011].groupby(['Month'])[['Quantity','Total']].sum().
 ↪sort_values('Quantity', ascending=False)
```

[157]:

Month	Quantity	Total
11	737773	1433884.990
10	597897	1063394.330
9	562883	1014355.681
8	409797	703075.640
7	395423	678538.531
5	391347	732763.510
6	381627	725651.040
3	372787	681340.640
1	307646	580616.110
4	294926	483392.881
2	280650	500792.000
12	229738	441574.840

[156]:
```
# Get the Busiest Days of the week

# 1. Group the dataframe by 'WeekDay'.
# 2. Calculate the sum of 'Quantity' for each group.

df.groupby(['WeekDay'])[['Quantity']].sum().
 ↪sort_values('Quantity',ascending=False)
```

[156]:

WeekDay	Quantity
3	1175922
1	1016504
2	1004294
0	843639
4	797458
6	467429

1.9 Task 7. Identify any outliers or anomalies in the dataset

1.9.1 Otuliers en 'UnitPrice'

[81]:
```
df.sort_values('UnitPrice', ascending=False).head()
```

[81]:

	InvoiceNo	StockCode	Description	Quantity	\
222682	556446	22502	PICNIC BASKET WICKER 60 PIECES	1	
222680	556444	22502	PICNIC BASKET WICKER 60 PIECES	60	
118769	546480	22656	VINTAGE BLUE KITCHEN CABINET	1	

```
205759    554836     22655     VINTAGE RED KITCHEN CABINET         1
82768     543253     22655     VINTAGE RED KITCHEN CABINET         1

                InvoiceDate  UnitPrice  CustomerID         Country  Month  \
222682 2011-06-10 15:33:00      649.5     15098.0  United Kingdom      6
222680 2011-06-10 15:28:00      649.5     15098.0  United Kingdom      6
118769 2011-03-14 11:38:00      295.0     13452.0  United Kingdom      3
205759 2011-05-26 16:25:00      295.0     13015.0  United Kingdom      5
82768  2011-02-04 15:32:00      295.0     14842.0  United Kingdom      2

        Year  Quarter  WeekDay  SubTotal
222682  2011        2        4     649.5
222680  2011        2        4   38970.0
118769  2011        1        0     295.0
205759  2011        2        3     295.0
82768   2011        1        4     295.0
```

[82]:
```
df.sort_values('Quantity', ascending=False).head()
```

[82]:
```
       InvoiceNo StockCode                          Description  Quantity  \
540421    581483     23843        PAPER CRAFT , LITTLE BIRDIE     80995
61619     541431     23166     MEDIUM CERAMIC TOP STORAGE JAR     74215
421632    573008     84077  WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
206121    554868     22197                SMALL POPCORN HOLDER      4300
97432     544612     22053              EMPIRE DESIGN ROSETTE      3906

                InvoiceDate  UnitPrice  CustomerID         Country  Month  \
540421 2011-12-09 09:15:00       2.08     16446.0  United Kingdom     12
61619  2011-01-18 10:01:00       1.04     12346.0  United Kingdom      1
421632 2011-10-27 12:26:00       0.21     12901.0  United Kingdom     10
206121 2011-05-27 10:52:00       0.72     13135.0  United Kingdom      5
97432  2011-02-22 10:43:00       0.82     18087.0  United Kingdom      2

        Year  Quarter  WeekDay   SubTotal
540421  2011        4        4  168469.60
61619   2011        1        1   77183.60
421632  2011        4        3    1008.00
206121  2011        2        4    3096.00
97432   2011        1        1    3202.92
```

Los Outliers parecen estar relacionados con franqueos, ajustes manuales. Investigaremos estos conceptos que habría que considerar de manera diferente a los productos en sí mismos.

1.10 Task 6. Explore the top-selling products and countries based on the quantity sold.

1.10.1 Producto con más unidades vendidas

[167]:
```
# 1. Group the dataframe by 'StockCode'.
# 2. Calculate the sum of 'Quantity' for each group.
# 3. Reset the index to make 'StockCode' columns again.

best_products = df.groupby(['StockCode'])[['Quantity']] \
        .sum().sort_values('Quantity', ascending=False) \
        .reset_index().head()

# 4. Use the 'index' attribute of 'best_products' to get the indices.
# 5. Use the 'map' method to apply a lookup on 'df['Description']' using these␣
 ↪indices.
# 6. Assign the resulting descriptions to the 'Description' column in␣
 ↪'best_products'.
best_products['Description'] = best_products.index.map(df['Description'])
best_products
```

[167]:

	StockCode	Quantity	Description
0	22197	56450	WHITE HANGING HEART T-LIGHT HOLDER
1	84077	53847	WHITE METAL LANTERN
2	85099B	47359	CREAM CUPID HEARTS COAT HANGER
3	84879	36381	KNITTED UNION FLAG HOT WATER BOTTLE
4	21212	36039	RED WOOLLY HOTTIE WHITE HEART.

1.10.2 Top 5 países con más ventas

[150]:
```
# Get the best country by quantity of purchases
# 1. Group the dataframe by 'Country'.
# 2. Calculate the sum of 'Quantity' for each group.
# 3. Get idxmax to print the first Country on the list

print("Best Country: ", df_invoices.groupby(['Country'])['Quantity'].sum().
 ↪idxmax())

df_invoices.groupby(['Country'])['Quantity'].sum().sort_values(ascending=False).
 ↪head(5)
```

```
Best Country:  United Kingdom
```

[150]:
```
Country
United Kingdom    4396322
Netherlands        199934
```

```
EIRE                142366
Germany             116341
France              109693
Name: Quantity, dtype: int64
```

1.10.3 Cliente con más compras

[154]:
```
# Get the best buyer by quantity of purchases
# 1. Group the dataframe by 'CustomerID' and 'Country'.
# 2. Calculate the sum of 'Quantity' for each group.
# 3. Get idxmax to print the first Country on the list

print("Best buyer: ", df_invoices.groupby(['CustomerID',␣
 ↪'Country'])['Quantity'].sum().idxmax())

df_invoices.groupby(['CustomerID', 'Country'])[['Quantity']].sum() \
            .sort_values('Quantity', ascending=False) \
            .reset_index().head(5)
```

```
Best buyer:  (14646.0, 'Netherlands')
```

[154]:

	CustomerID	Country	Quantity
0	14646.0	Netherlands	196556
1	12415.0	Australia	76946
2	14911.0	EIRE	76931
3	17450.0	United Kingdom	69041
4	18102.0	United Kingdom	64124

1.11 Task 8. Draw conclusions and summarize your findings from the EDA.

- Los meses con más ventas (basado en Quantity) son Noviembre, Octubre y Septiembre
- Los días de la semana con más ventas son Jueves, Martes y Miércoles
- No se observan datos los sábados, lo cual es muy llamativo y evidencia falta de datos importantes.
- Hay un notable decenso en las ventas de Diciembre comparado con el año anterior.
- Los países que registran más ventas son: United Kingdom, Netherlands, EIRE (Ireland), Germany and France.
- Hay una notable diferencia entre UK y los siguientes en la lista aunque el cliente con más compras pertenece a Netherlands, el cuarto en la lista procede de UK.
- La mayor correlación entre las variables que encontramos es entre Quantity y Total, lo cual es esperable.
- Sugerimos recolectar datos sobre satisfacción de usuarios.

1.11.1 Autoría: María Anastasia Livio, October 2024