online-retail

March 30, 2025

1 Portfolio Project: Online Retail Exploratory Data Analysis with Python

1.1 Overview

In this project, you will step into the shoes of an entry-level data analyst at an online retail company, helping interpret real-world data to help make a key business decision.

1.2 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. Your task is to explore and analyze this dataset to gain insights into the store's sales trends, customer behavior, and popular products.

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, 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.

1.3 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

1.4 Dataset

The dataset you will be working with is the "Online Retail" 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`. This data file is already included in the Coursera Jupyter Notebook environment, however if you are working off-platform it can also be downloaded here.

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

1.5 Tasks

You may explore this dataset in any way you would like - however if you'd like some help getting started, here are a few ideas:

1. Load the dataset into a Pandas DataFrame and display the first few rows to get an overview of the data.
2. Perform data cleaning by handling missing values, if any, and removing any redundant or unnecessary columns.
3. Explore the basic statistics of the dataset, including measures of central tendency and dispersion.
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.
5. Analyze the sales trends over time. Identify the busiest months and days of the week in terms of sales.
6. Explore the top-selling products and countries based on the quantity sold.
7. Identify any outliers or anomalies in the dataset and discuss their potential impact on the analysis.
8. Draw conclusions and summarize your findings from the exploratory data analysis.

1.6 Task 0: Load Important Python Modules

[1]:
```
# your code here
import unidecode

# Standard operational package imports.
import pandas as pd
import numpy as np

# Visualization package imports.
import matplotlib
import seaborn as sns

# Others
import calendar as cal
import re
import random

# Important imports for preprocessing, modeling, and evaluation.
from statsmodels.stats.outliers_influence \
    import variance_inflation_factor as smvif
import statsmodels.formula.api as smfapi
```

```
import statsmodels.api as smapi
import statsmodels.tools.tools as smtools
import statsmodels.stats.multicomp as smmulti
import sklearn.model_selection as sklmodslct
import sklearn.linear_model as skllinmod
import sklearn.metrics as sklmtrcs
```

[2]:
```
# importing all my important data analysis functions
import data_analysis_functions
```

1.7 Task 1: Load the Data

[3]:
```
# load the online-retail dataset xlsx
data = pd.read_excel("online-retail_dataset.xlsx")
data_analysis_functions.df_head(data,10)
```

	InvoiceNo	StockCode	Description	Quantity	\
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	
1	536365	71053	WHITE METAL LANTERN	6	
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	
5	536365	22752	SET 7 BABUSHKA NESTING BOXES	2	
6	536365	21730	GLASS STAR FROSTED T-LIGHT HOLDER	6	
7	536366	22633	HAND WARMER UNION JACK	6	
8	536366	22632	HAND WARMER RED POLKA DOT	6	
9	536367	84879	ASSORTED COLOUR BIRD ORNAMENT	32	

	InvoiceDate	UnitPrice	CustomerID	Country
0	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
5	2010-12-01 08:26:00	7.65	17850.0	United Kingdom
6	2010-12-01 08:26:00	4.25	17850.0	United Kingdom
7	2010-12-01 08:28:00	1.85	17850.0	United Kingdom
8	2010-12-01 08:28:00	1.85	17850.0	United Kingdom
9	2010-12-01 08:34:00	1.69	13047.0	United Kingdom

1.8 Task 2: Data Cleaning

Perform data cleaning by handling missing values, if any, and removing any redundant or unnecessary columns.

Also, to makesure datetime columns are actually in datetime and numeric columns are actually numeric and not strings.

[4]:
```
# get all data types of the columns
print("number rows and columns before dropna(axis=0)")
data_analysis_functions.df_print_row_and_columns(data)
old_row_numbers = data.shape[0]
print("")

print("data types:")
data_analysis_functions.df_info_dtypes(data)
print("")
#data_analysis_functions.df_info_dtypes(data)

# get summary statistics
print("summary statistics:")
print(data.describe())
print("")

# removing empty rows
data = data.dropna(axis=0).reset_index(drop=True)
print("number rows and columns after dropna(axis=0)")
data_analysis_functions.df_print_row_and_columns(data)
new_row_numbers = data.shape[0]

# % missing data
percentage_nadata = format(1-(new_row_numbers/old_row_numbers),"0.2%")
print("{} missing (null) data".format(percentage_nadata))

# need to further mask using InvoiceNo
returns = data[(data['Quantity'] < 0.0)]
returns_customer_id = returns['CustomerID'].values.tolist()
returns_unit_price = returns['StockCode'].values.tolist()
mask_list = []
columns = data.columns.tolist()
data_returns_calculated = pd.DataFrame(columns=columns)
for i in range(len(returns_customer_id)):
    cust_id = returns_customer_id[i]
    unit_p = returns_unit_price[i]
    mask = (data['CustomerID'] == cust_id) & (data['StockCode'] == unit_p)
    masked = data[mask]
    mask_list += masked.index.tolist()
    sum_quantity = masked['Quantity'].sum()
    average_unit_p = masked['UnitPrice'].mean()
    invoice_code = masked.iloc[0:1,0:1].values[0][0]
    invoice_date = masked.iloc[0:1,4:5].values[0][0]
    country = masked.iloc[0:1,7:8].values[0][0]
    description = masked.iloc[0:1,2:3].values[0][0]
    new_df_list = [invoice_code, unit_p, description, sum_quantity,␣
 ↪invoice_date, average_unit_p, cust_id, country]
```

```
    data_returns_calculated.loc[i] = new_df_list
mask_list = list(set(mask_list))
data_returns_filter = data.index.isin(mask_list)
data_purchases_constructor = data[~data_returns_filter]
data_purchases = pd.concat([data_purchases_constructor,␣
 ↪data_returns_calculated], ignore_index=True)
data_purchases = data_purchases[data_purchases['Quantity'] >= 0]
print(data_purchases)

# discount only
discounts = data[data['Description'] == 'Discount']
```

```
number rows and columns before dropna(axis=0)
rows = 541909
columns = 8

data types:
<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
None

summary statistics:
            Quantity                    InvoiceDate      UnitPrice  \
count  541909.000000                         541909  541909.000000
mean        9.552250  2011-07-04 13:34:57.156386048       4.611114
min    -80995.000000            2010-12-01 08:26:00  -11062.060000
25%         1.000000            2011-03-28 11:34:00       1.250000
50%         3.000000            2011-07-19 17:17:00       2.080000
75%        10.000000            2011-10-19 11:27:00       4.130000
max     80995.000000            2011-12-09 12:50:00   38970.000000
std       218.081158                            NaN      96.759853

          CustomerID
count  406829.000000
mean    15287.690570
```

```
min      12346.000000
25%      13953.000000
50%      15152.000000
75%      16791.000000
max      18287.000000
std       1713.600303

number rows and columns after dropna(axis=0)
rows = 406829
columns = 8
24.93% missing (null) data
       InvoiceNo StockCode                          Description  Quantity  \
0         536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1         536365     71053                  WHITE METAL LANTERN         6
2         536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3         536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4         536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6
…            …       …                                     …       …
388830    552575     22178      VICTORIAN GLASS HANGING T-LIGHT       573
388831    552575     23144      ZINC T-LIGHT HOLDER STARS SMALL       349
388833    537195     21258           VICTORIAN SEWING BOX LARGE        46
388834    539404     84978     HANGING HEART JAR T-LIGHT HOLDER       167
388835    573911     20979        36 PENCILS TUBE RED RETROSPOT         1

                InvoiceDate  UnitPrice  CustomerID         Country
0       2010-12-01 08:26:00   2.550000     17850.0  United Kingdom
1       2010-12-01 08:26:00   3.390000     17850.0  United Kingdom
2       2010-12-01 08:26:00   2.750000     17850.0  United Kingdom
3       2010-12-01 08:26:00   3.390000     17850.0  United Kingdom
4       2010-12-01 08:26:00   3.390000     17850.0  United Kingdom
…                       …         …        …              …
388830 2011-05-10 12:25:00   1.677778     14397.0  United Kingdom
388831 2011-05-10 12:25:00   0.821538     14397.0  United Kingdom
388833 2010-12-05 13:55:00  11.113636     15311.0  United Kingdom
388834 2010-12-17 12:24:00   1.168571     17315.0  United Kingdom
388835 2011-11-01 15:40:00   1.250000     17315.0  United Kingdom

[387758 rows x 8 columns]
```

COMMENT: All columns are of the expected data type. However there is negative quantity

[5]:
```
# get all data only positive quantity and unitprice columns
print("number rows and columns after dropping negatives")
neg_row_numbers = old_row_numbers - data_purchases.shape[0]
percentage_negdata = format((neg_row_numbers/old_row_numbers),"0.2%")
print("{} irrelevant (negative) data".format(percentage_negdata))
print(data_purchases.describe())
```

```
number rows and columns after dropping negatives
```

```
28.45% irrelevant (negative) data
            Quantity                    InvoiceDate      UnitPrice  \
count  387758.000000                         387758  387758.000000
mean       13.201938  2011-07-10 10:12:12.433631744       3.035461
min         0.000000            2010-12-01 08:26:00       0.000000
25%         2.000000            2011-04-05 15:00:00       1.250000
50%         5.000000            2011-07-31 12:16:00       1.850000
75%        12.000000            2011-10-20 14:52:00       3.750000
max     12540.000000            2011-12-09 12:50:00    8142.750000
std        62.216133                            NaN      18.052927

          CustomerID
count  387758.000000
mean    15294.693752
min     12346.000000
25%     13969.000000
50%     15159.000000
75%     16795.000000
max     18287.000000
std      1712.365073
```

1.9 Task 3: Exploratory Data Analysis

View the descriptive statistics such as mean, mode and median as well as standard deviation, range etc.

[6]:
```
# get all exploratory stats about CENTRAL TENDENCY
data_mode = data_purchases[['Quantity','UnitPrice','Country']].agg([pd.Series.
  ↪mode])
print(data_mode)
data_mean = data_purchases[['Quantity','UnitPrice']].agg([pd.Series.mean])
print(data_mean)
data_median = data_purchases[['Quantity','UnitPrice']].agg([pd.Series.median])
print(data_median)
```

```
  Quantity UnitPrice         Country
      mode      mode            mode
0        1      1.25  United Kingdom
       Quantity  UnitPrice
mean  13.201938   3.035461
        Quantity  UnitPrice
median       5.0       1.85
```

[7]:
```
# get all exploratory stats about SPREAD
data_std = data_purchases[['Quantity','UnitPrice']].agg([pd.Series.std])
print(data_std)
data_skew = data_purchases[['Quantity','UnitPrice']].agg([pd.Series.skew])
print(data_skew)
```

```
print("")
# data_iqr = data[['Quantity','UnitPrice']].agg([pd.Series.quantile(q=0.25)])\
#            - data[['Quantity','UnitPrice']].agg([pd.Series.quantile(q=0.75)])
# print(data_iqr)
```

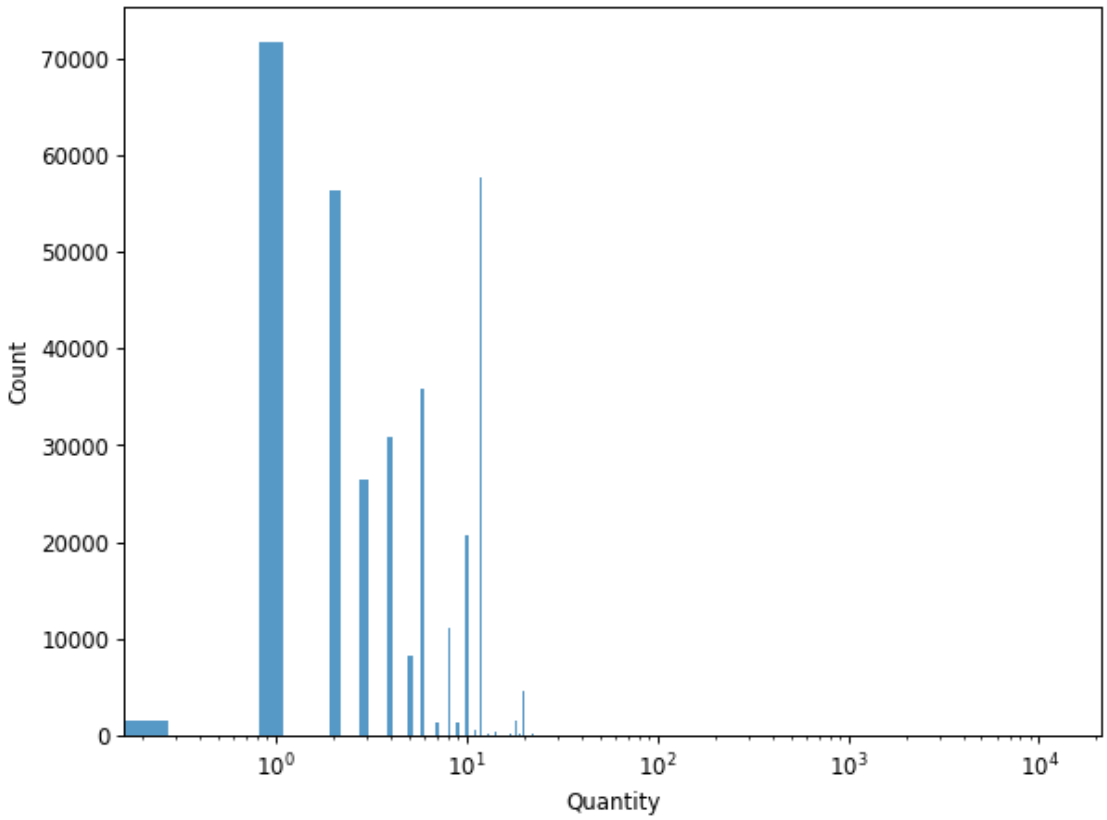
```
      Quantity  UnitPrice
std  62.216133  18.052927
      Quantity   UnitPrice
skew  73.14429  270.587024
```

Quite high skew in unit price which can be seen by th

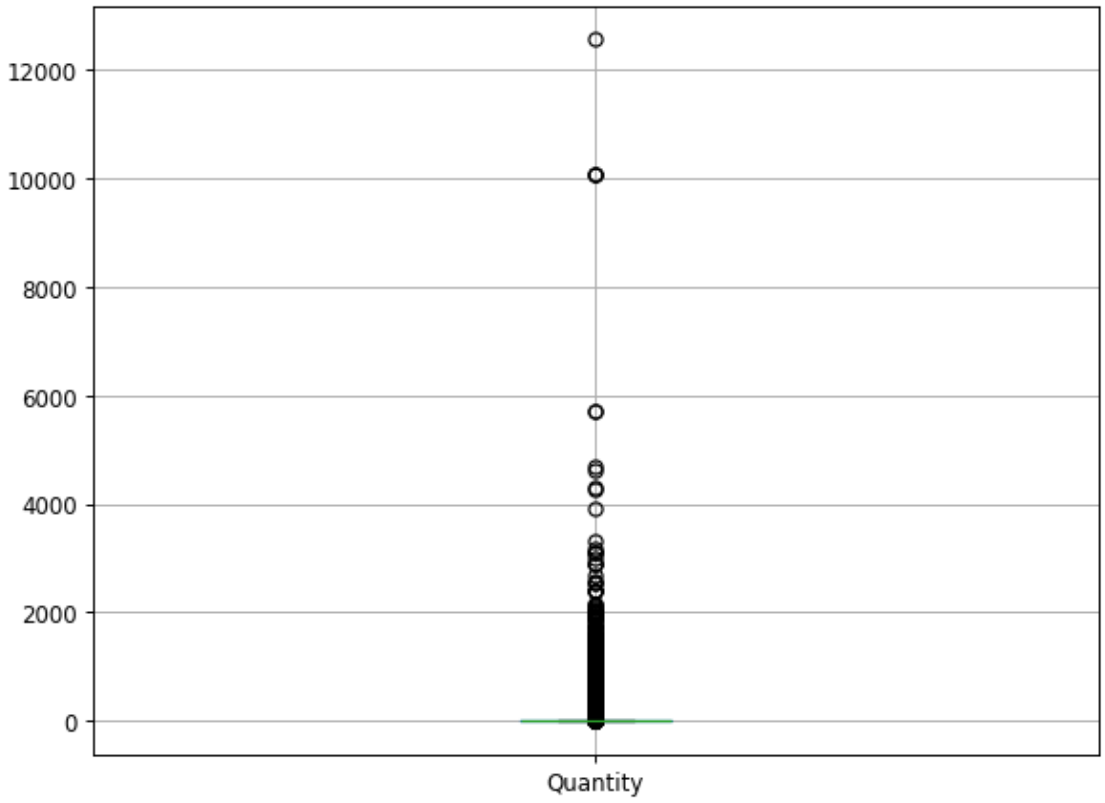
1.10 Task 4: Data Visualisation

To gain insights and to visualise outliers

[8]:
```
# use histogram
fig = matplotlib.pyplot.subplots(figsize=(8, 6), dpi=85)
sns.histplot(data=data_purchases, x="Quantity")
matplotlib.pyplot.xscale('log')
matplotlib.pyplot.show()
```

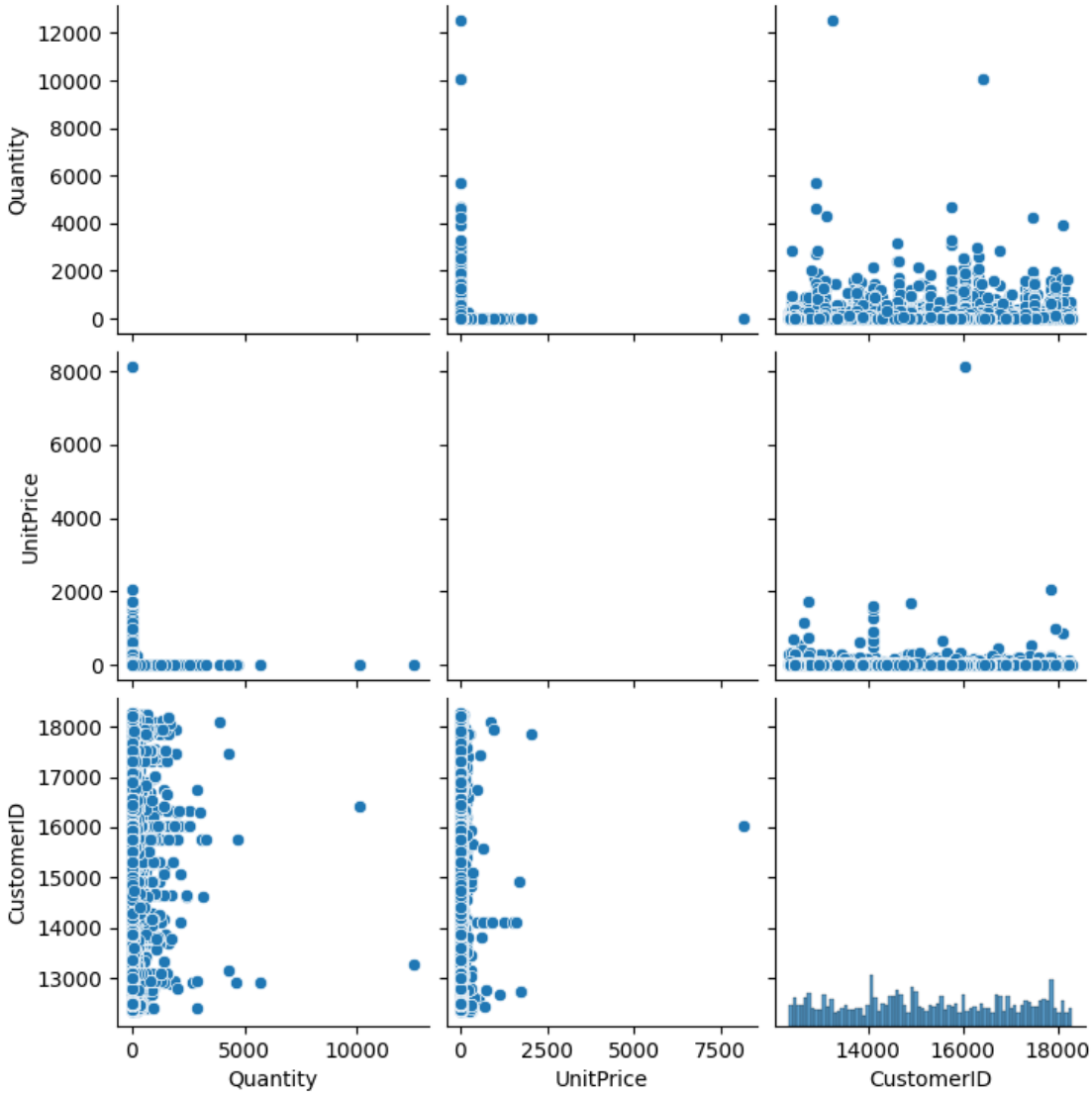


[9]:
```
# use boxplot to visualize extreme outliers
fig2 = matplotlib.pyplot.subplots(figsize=(8, 6), dpi=85)
data_purchases.boxplot(column=['Quantity'], return_type='axes')
matplotlib.pyplot.show()
```



[10]:
```
# use matrix scatter plot to visualise data relationships
data_analysis_functions.df_pairplot(data_purchases)
```

```
<Figure size 510x510 with 0 Axes>
```



1.11 Task 5: Analyse Trends over Time and also Analyse Busiest Months

We will make another column called "Total Price", then divide the data into years by making a new "Year" column, and then strftime by month (New "Month" column) to visualise what the trends were like over the months 1. Average Sale Quantity per month 2. Average Price per Purchase 3. Price per Invoice 4. Total Sales per month 5. Total Sales of particular product per month

[11]:
```
# creating total price column
data_purchases.loc[:,"TotalRevenue"] = data_purchases["Quantity"].
  ↪multiply(data_purchases["UnitPrice"])
print(data_analysis_functions.df_head(data_purchases, 10))
```

```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
```

```
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6
5    536365     22752         SET 7 BABUSHKA NESTING BOXES         2
6    536366     22633               HAND WARMER UNION JACK         6
7    536367     84879        ASSORTED COLOUR BIRD ORNAMENT        32
8    536367     22745           POPPY'S PLAYHOUSE BEDROOM         6
9    536367     22748            POPPY'S PLAYHOUSE KITCHEN         6

          InvoiceDate  UnitPrice  CustomerID         Country  TotalRevenue
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom         15.30
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom         20.34
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom         22.00
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom         20.34
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom         20.34
5 2010-12-01 08:26:00       7.65     17850.0  United Kingdom         15.30
6 2010-12-01 08:28:00       1.85     17850.0  United Kingdom         11.10
7 2010-12-01 08:34:00       1.69     13047.0  United Kingdom         54.08
8 2010-12-01 08:34:00       2.10     13047.0  United Kingdom         12.60
9 2010-12-01 08:34:00       2.10     13047.0  United Kingdom         12.60
None
```

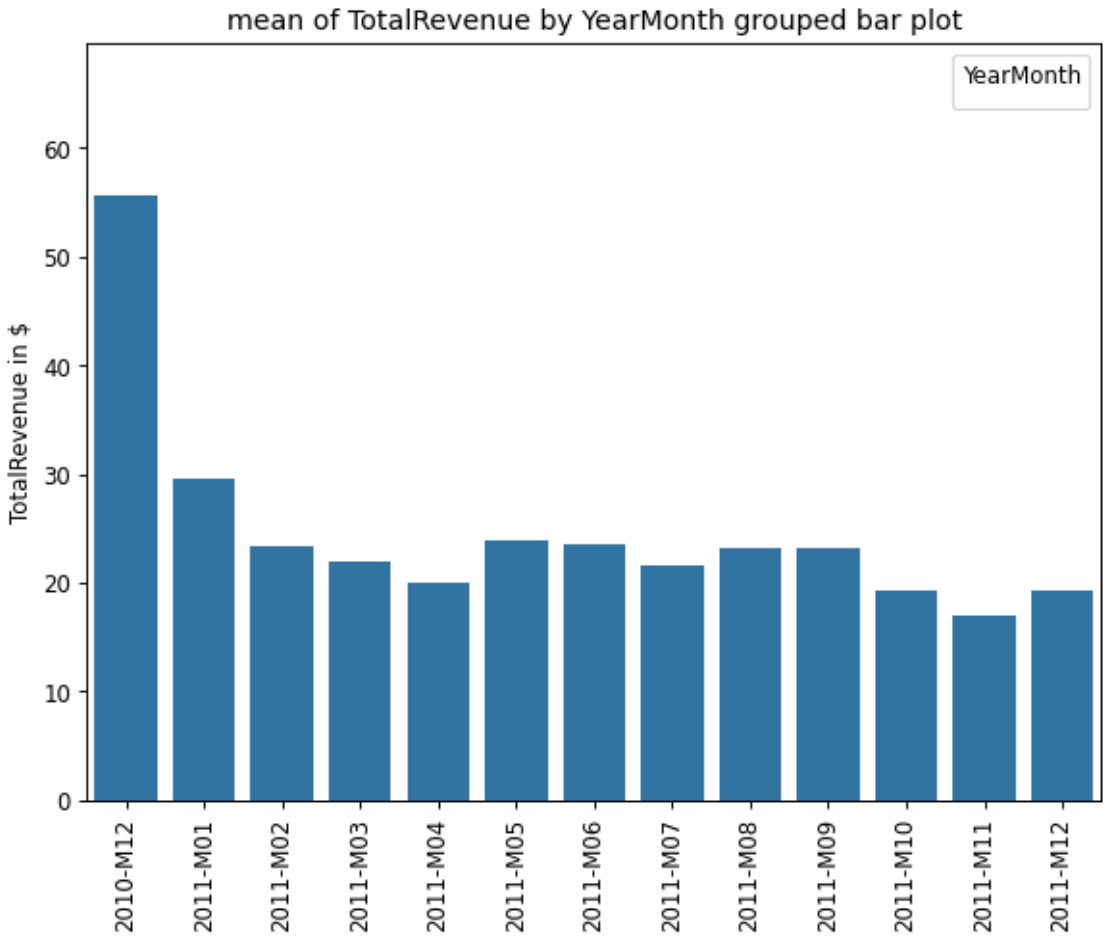
[12]:
```
# strfint year and month
data_purchases.loc[:,"YearMonth"] = data_purchases.loc[:,"InvoiceDate"].dt.
  ↪strftime("%Y-M%m")
print(data_analysis_functions.df_head(data_purchases, 10))
```

```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6
5    536365     22752         SET 7 BABUSHKA NESTING BOXES         2
6    536366     22633               HAND WARMER UNION JACK         6
7    536367     84879        ASSORTED COLOUR BIRD ORNAMENT        32
8    536367     22745           POPPY'S PLAYHOUSE BEDROOM         6
9    536367     22748            POPPY'S PLAYHOUSE KITCHEN         6

          InvoiceDate  UnitPrice  CustomerID         Country  TotalRevenue  \
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom         15.30
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom         20.34
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom         22.00
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom         20.34
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom         20.34
5 2010-12-01 08:26:00       7.65     17850.0  United Kingdom         15.30
6 2010-12-01 08:28:00       1.85     17850.0  United Kingdom         11.10
```

```
7 2010-12-01 08:34:00       1.69     13047.0  United Kingdom         54.08
8 2010-12-01 08:34:00       2.10     13047.0  United Kingdom         12.60
9 2010-12-01 08:34:00       2.10     13047.0  United Kingdom         12.60

  YearMonth
0  2010-M12
1  2010-M12
2  2010-M12
3  2010-M12
4  2010-M12
5  2010-M12
6  2010-M12
7  2010-M12
8  2010-M12
9  2010-M12
None
```

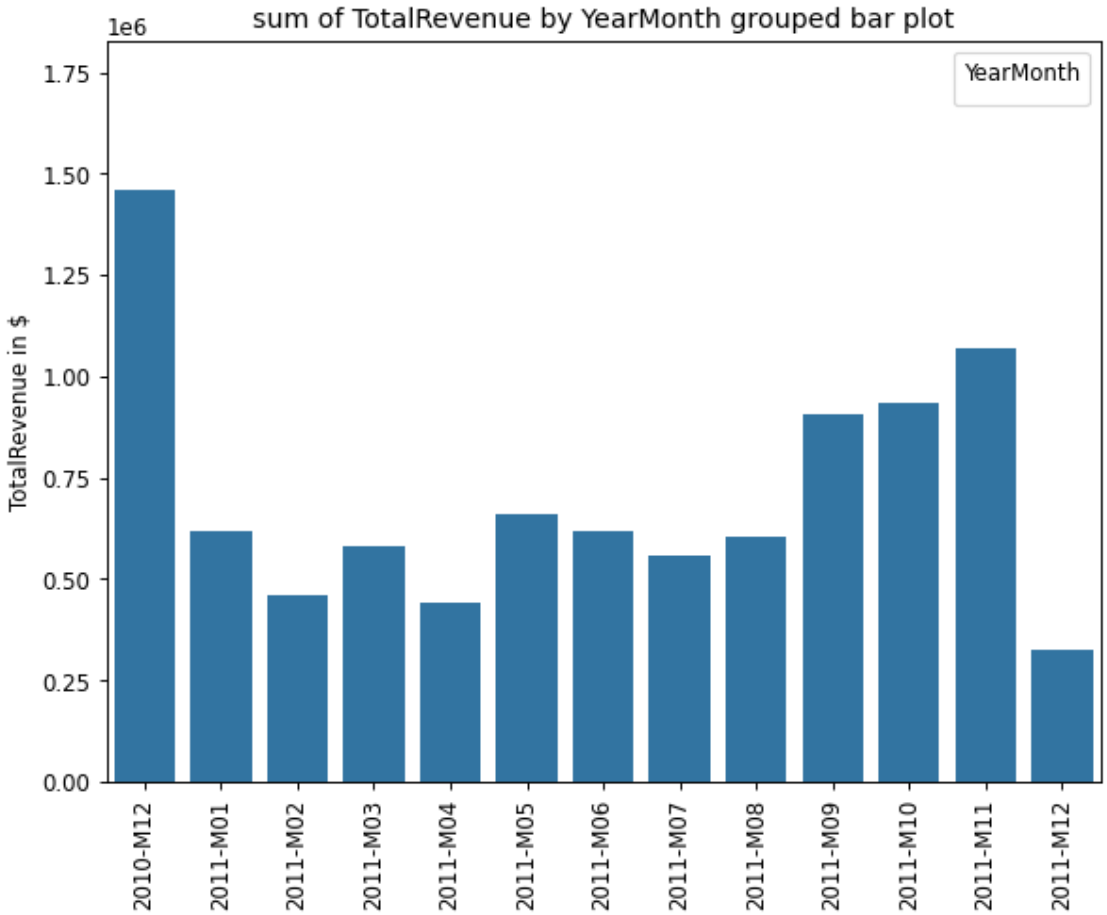
[13]:
```
# monthly_revenue = data_analysis_functions.
  ↪df_groupby_mask_operate(data_purchases, "YearMonth", "TotalRevenue", False,␣
  ↪'0', 'mean')
data_analysis_functions.df_grouped_barplotter(data_purchases, "YearMonth",␣
  ↪"TotalRevenue", 1, 'mean')
```

```
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:156: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer keys will
always be treated as labels (consistent with DataFrame behavior). To access a
value by position, use `ser.iloc[pos]`
  y_plot = [index[0] for row, index in df_grouped.iterrows()]
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:164: UserWarning: No artists with
labels found to put in legend.  Note that artists whose label start with an
underscore are ignored when legend() is called with no argument.
  matplotlib.pyplot.legend(title=col_groupby)
```



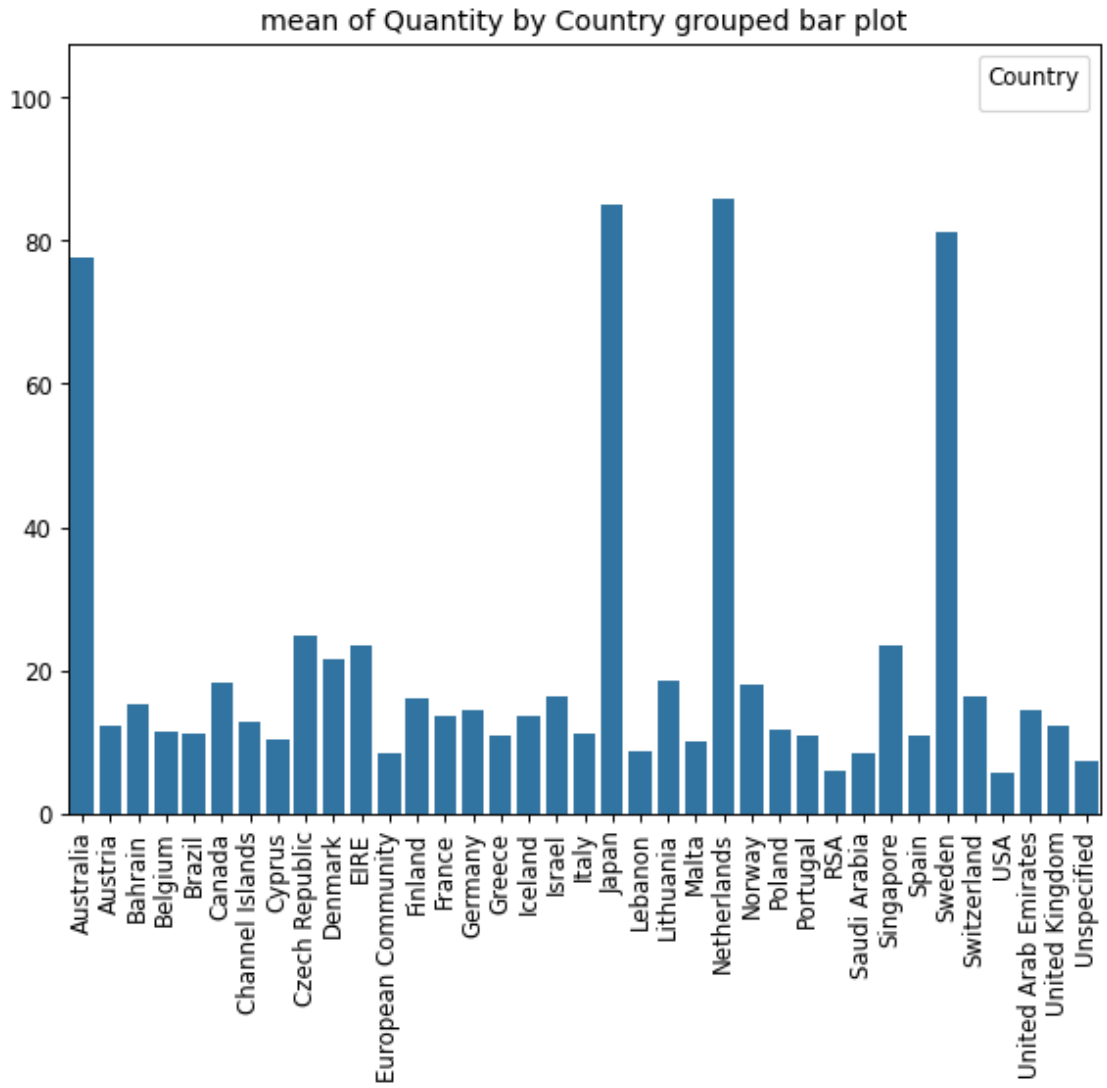
[14]:
```
data_analysis_functions.df_grouped_barplotter(data_purchases, "YearMonth",␣
↪"TotalRevenue", 1, 'sum')
```

```
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:156: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer keys will
always be treated as labels (consistent with DataFrame behavior). To access a
value by position, use `ser.iloc[pos]`
  y_plot = [index[0] for row, index in df_grouped.iterrows()]
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:164: UserWarning: No artists with
labels found to put in legend.  Note that artists whose label start with an
underscore are ignored when legend() is called with no argument.
  matplotlib.pyplot.legend(title=col_groupby)
```



[15]:
```
# mean quantity purchased per purchase in countries
data_analysis_functions.df_grouped_barplotter(data_purchases, "Country",␣
 ↪"Quantity", 2, 'mean')
```

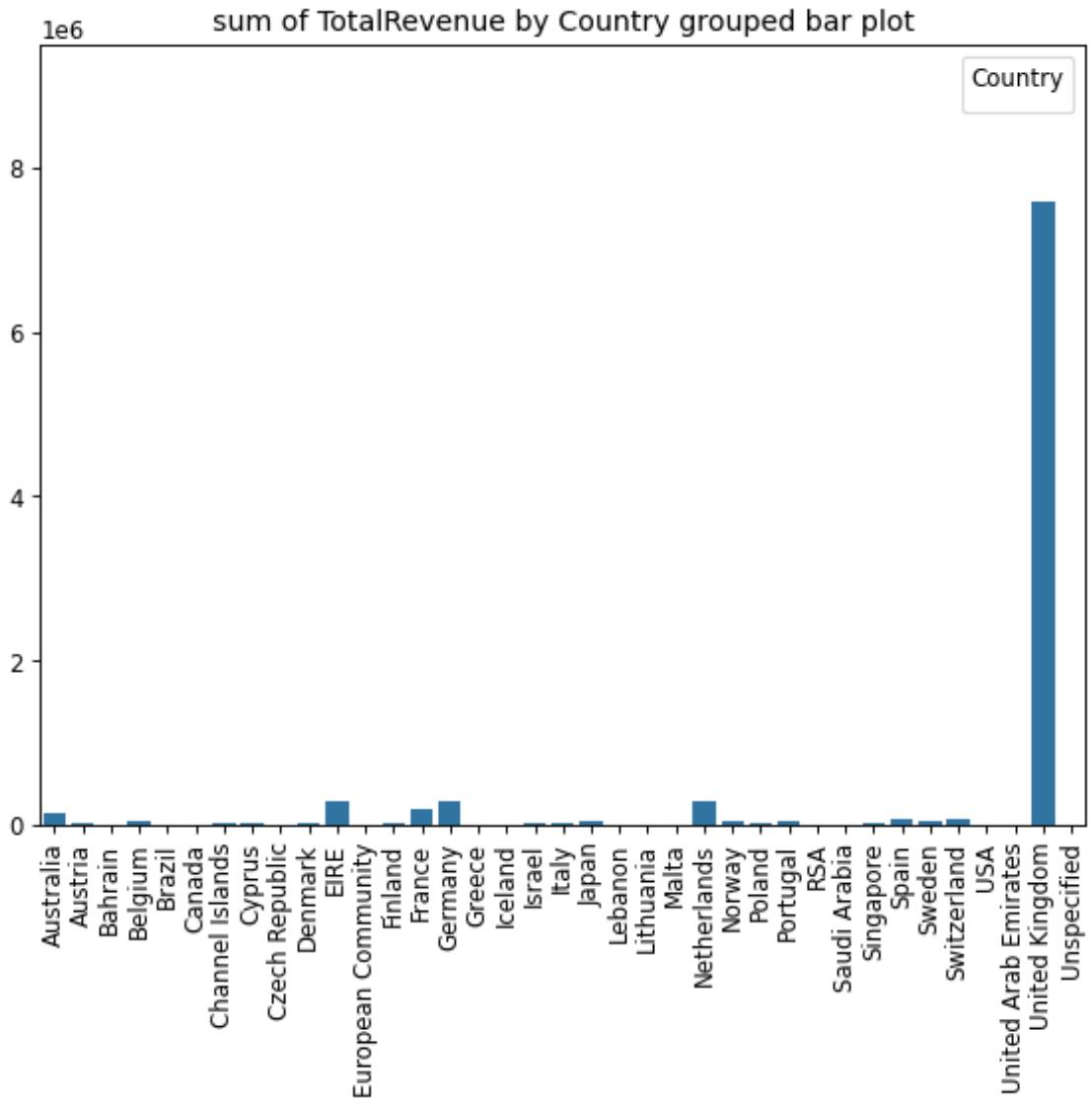
```
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:156: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer keys will
always be treated as labels (consistent with DataFrame behavior). To access a
value by position, use `ser.iloc[pos]`
  y_plot = [index[0] for row, index in df_grouped.iterrows()]
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:164: UserWarning: No artists with
labels found to put in legend.  Note that artists whose label start with an
underscore are ignored when legend() is called with no argument.
  matplotlib.pyplot.legend(title=col_groupby)
```



[16]:
```
# total quantity purchased per countries
data_analysis_functions.df_grouped_barplotter(data_purchases, "Country",␣
 ↪"TotalRevenue", 2, 'sum')
```

```
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:156: FutureWarning: Series.__getitem__
treating keys as positions is deprecated. In a future version, integer keys will
always be treated as labels (consistent with DataFrame behavior). To access a
value by position, use `ser.iloc[pos]`
  y_plot = [index[0] for row, index in df_grouped.iterrows()]
/home/kb/python-data-engineering/data-analysis-projects/project02_perform-eda-
on-retail-data/data_analysis_functions.py:164: UserWarning: No artists with
labels found to put in legend.  Note that artists whose label start with an
underscore are ignored when legend() is called with no argument.
```

```
matplotlib.pyplot.legend(title=col_groupby)
```



The UK had the most purchases by far, and also was the largest source of revenue even the the average sale price was lower.

1.12 TASK 6: Explore the top-selling products and countries based on the quantity sold.

Here we shall simply groupby and aggreagate and show the products in terms of total revenue

[17]:

```
# total quantity purchased per product
quantity_per_product = data_analysis_functions.
 ↪df_groupby_mask_operate(data_purchases, "Description", "Quantity", False,␣
 ↪"0", "sum")
col = quantity_per_product.columns.tolist()
quantity_per_product.sort_values(by=col, inplace=True, ascending=0)
print("Ten higher selling products are:")
print(data_analysis_functions.df_head(quantity_per_product, 10))
```

```
Ten higher selling products are:
                                  Quantity
                                       sum
Description
JUMBO BAG RED RETROSPOT                58967
WORLD WAR 2 GLIDERS ASSTD DESIGNS      58927
BROCADE RING PURSE                     43114
SMALL POPCORN HOLDER                   38035
WHITE HANGING HEART T-LIGHT HOLDER     36483
ASSORTED COLOUR BIRD ORNAMENT          35315
PACK OF 72 RETROSPOT CAKE CASES        33555
POPCORN HOLDER                         28312
RABBIT NIGHT LIGHT                     27314
MINI PAINT SET VINTAGE                 26057
None
```

[18]:
```
# total revenue purchased per product
revenue_per_product = data_analysis_functions.
 ↪df_groupby_mask_operate(data_purchases, "Description", "TotalRevenue",␣
 ↪False, "0", "sum")
col = revenue_per_product.columns.tolist()
revenue_per_product.sort_values(by=col, inplace=True, ascending=0)
print("Ten higher grossing products are:")
print(data_analysis_functions.df_head(revenue_per_product, 10))
```

```
Ten higher grossing products are:
                                  TotalRevenue
                                           sum
Description
BROCADE RING PURSE                316740.478235
REGENCY CAKESTAND 3 TIER          236902.001134
Manual                            126966.653475
JUMBO BAG RED RETROSPOT           108066.113841
WHITE HANGING HEART T-LIGHT HOLDER 100117.311176
POSTAGE                            71844.391746
PARTY BUNTING                      69990.342727
ASSORTED COLOUR BIRD ORNAMENT      56530.150000
RABBIT NIGHT LIGHT                 51625.241000
CHILLI LIGHTS                      46241.385952
```

```
None
```

1.13 Task 7: Identify any outliers or anomalies in the dataset and discuss their potential impact on the analysis.

[19]:
```
# identification of outliers
# method 1, percentile, we we set the outliers at the 90th percentile.
percentile_ninenty = np.percentile(data_purchases['Quantity'], 90)
data_outliers = data_purchases[data_purchases['Quantity'] > percentile_ninenty]
print(data_outliers['Quantity'])
data_purchases.loc[:,'Quantity'] = data_purchases.loc[:,'Quantity'].
 ↪apply(lambda x: (percentile_ninenty if x > percentile_ninenty else x))
print(data_purchases['Quantity'])

# use boxplot to visualize extreme outliers
#fig3 = matplotlib.pyplot.subplots(figsize=(8, 6), dpi=85)
#data_purchases.boxplot(column=['Quantity'], return_type='axes')
#matplotlib.pyplot.show()
```

```
7          32
28         48
41         36
42         80
66         48
          ...
388828    111
388830    573
388831    349
388833     46
388834    167
Name: Quantity, Length: 30107, dtype: int64
0          6
1          6
2          8
3          6
4          6
          ..
388830    24
388831    24
388833    24
388834    24
388835     1
Name: Quantity, Length: 387758, dtype: int64
```

Now we see the outliers are removed,

1.14 Task 8: Draw conclusions and summarize your findings from the exploratory data analysis.

1. We clearly see that the United Kingdom has the highest sales volume
2. We can also see that there are outliers in quantities, but these are mitigated for and removed, the negative quantities and negative unit prices, we see that some of these are discounts and some of them were returns of a product.
3. We also see that there is little correlation amongst any of the data fields here.
4. We also see that the month with the highest sales volume was November 2011.