Capstone Project 3 - Retail

September 30, 2021

CapStone Project 3 - Retail

Problem Statement

• It is a critical requirement for business to understand the value derived from a customer. RFM is a method used for analyzing customer value. • Customer segmentation is the practice of segregating the customer base into groups of individuals based on some common characteristics such as age, gender, interests, and spending habits • Perform customer segmentation using RFM analysis. The resulting segments can be ordered from most valuable (highest recency, frequency, and value) to least valuable (lowest recency, frequency, and value). Dataset Description This is a transnational data set which contains all the transactions that occurred between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique and all-occasion gifts.

[212]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from operator import attrgetter
import matplotlib.colors as mcolors
import matplotlib.pyplot as plt
import datetime as dt
from scipy.stats import skewnorm
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder
import pylab as p
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans


from sklearn.model_selection import learning_curve
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import cross_val_score
from sklearn.metrics import classification_report, confusion_matrix
```

[213]:

```
df=pd.read_excel(r'D:\OneDrive\Studies\AI - ML\Capstone Project\OnlineRetail.
 ↪xlsx',sheet_name='Online Retail')
df.head()
```

[213]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0   C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1   C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
2    556690     23005         printing smudges/thrown away     -9600
3    556691     23005         printing smudges/thrown away     -9600
4   C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360

          InvoiceDate  UnitPrice  CustomerID         Country
0 2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1 2011-01-18 10:17:00       1.04     12346.0  United Kingdom
2 2011-06-14 10:37:00       0.00         NaN  United Kingdom
3 2011-06-14 10:37:00       0.00         NaN  United Kingdom
4 2010-12-02 14:23:00       0.03     15838.0  United Kingdom
```

Project Task: Week 1 Data Cleaning: 1. Perform a preliminary data inspection and data cleaning.

8 columns are available. The item related are - Stock Code (Quantifible), & Description Sale Realted are - Invoice number and Invoice Date & Quantity & Unit Price Customer Realted are - Customer Id & Country

The main or basic inferred data are - Spending pattern, Spending categories, Customer Spending Behaviour

a. Check for missing data and formulate an apt strategy to treat them.

[4]:
```
df
```

[4]:
```
       InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
2         556690     23005         printing smudges/thrown away     -9600
3         556691     23005         printing smudges/thrown away     -9600
4        C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
…            …        …                                  …        …
541904    573008     84077    WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
541905    542504     37413                                  NaN      5568
541906    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
541907    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
541908    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
2      2011-06-14 10:37:00       0.00         NaN  United Kingdom
3      2011-06-14 10:37:00       0.00         NaN  United Kingdom
4      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
…                        …        …           …              …
541904 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
541905 2011-01-28 12:03:00       0.00         NaN  United Kingdom
```

```
541906 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
541907 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
541908 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

[541909 rows x 8 columns]
```

[5]:
```
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
```

Column - Description, & CustomerID, have some Null Values in them

Description Column is No Value add so there is no problem in dropping it. Since Customer Id is the main identifying element, Unique Identifying Entity, it's absence would be difficult to fill through Unlike cost or Sale Unit, where we could use average, we cannot use any other means to treat this except deletion.

Identifying & Removing Null Values. Starting from the column that has max null values. If it clears the null values in other columns, we would not need to repeat the activity with other columns

[6]:
```
df.isnull().sum()
```

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

[7]:
```
df.dropna(subset=['CustomerID'], inplace=True)
```

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

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

b. Identify & Remove duplicate data records.

[9]:
```
# occurrence based on all columns
duplicate = df[df.duplicated(subset=None, keep='first')]
duplicate
```

[9]:
```
       InvoiceNo StockCode                          Description  Quantity  \
44       C570556     20971      PINK BLUE FELT CRAFT TRINKET BOX     -1296
349      C570556     22568               FELTCRAFT CUSHION OWL      -144
350      C570556     20969     RED FLORAL FELTCRAFT SHOULDER BAG      -144
543      C568419    51014C                FEATHER PEN,COAL BLACK       -96
1555     C575940     23309   SET OF 60 I LOVE LONDON CAKE CASES        -24
…            …         …                                   …        …
534720    570242     21810      CHRISTMAS HANGING STAR WITH BELL        96
536335    564327    85099B               JUMBO BAG RED RETROSPOT       100
536373    565475     20725               LUNCH BAG RED RETROSPOT       100
541294    548910     21982             PACK OF 12 SUKI TISSUES        432
541855    561873     84568        GIRLS ALPHABET IRON ON PATCHES      1440

               InvoiceDate  UnitPrice  CustomerID         Country
44     2011-10-11 11:10:00       1.06     16029.0  United Kingdom
349    2011-10-11 11:10:00       3.39     16029.0  United Kingdom
350    2011-10-11 11:10:00       3.39     16029.0  United Kingdom
543    2011-09-27 11:16:00       0.39     13694.0  United Kingdom
1555   2011-11-13 11:38:00       0.55     17838.0  United Kingdom
…                        …         …          …               …
534720 2011-10-09 15:40:00       0.39     16380.0  United Kingdom
536335 2011-08-24 13:33:00       1.74     16029.0  United Kingdom
536373 2011-09-05 10:47:00       1.45     14156.0            EIRE
541294 2011-04-05 08:51:00       0.20     17940.0  United Kingdom
541855 2011-07-31 11:48:00       0.17     13316.0  United Kingdom

[5225 rows x 8 columns]
```

[10]:
```
df=df.drop_duplicates()
df.duplicated().sum()
```

[10]: 0

[11]:
```
df.describe()
```

[11]:

	Quantity	UnitPrice	CustomerID
count	401604.000000	401604.000000	401604.000000
mean	12.183273	3.474064	15281.160818
std	250.283037	69.764035	1714.006089
min	-80995.000000	0.000000	12346.000000
25%	2.000000	1.250000	13939.000000
50%	5.000000	1.950000	15145.000000
75%	12.000000	3.750000	16784.000000
max	80995.000000	38970.000000	18287.000000

Get names of indexes for which Column Unit Price which has value negative value. Assuming that the shop keeper does not pay customer to purchase. There is one such instance, removing this data set as incorrect

c. Perform descriptive analytics on the given data.

However, not doing the same with Quantity. The assumption here is that these might be billed in previous cycle which is not included in this database and were returned to seller in this cycle. Approx ~2% was returned

[12]:
```
indexNames = df[df['UnitPrice'] < 0 ].index
indexNames
df.drop(indexNames , inplace=True)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\pandas\core\frame.py:4308:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  return super().drop(
```

[13]:
```
#Counting % of Returns

indexNames = df[df['Quantity'] < 0 ].index
PercentageReturn = (indexNames.size / df['Quantity'].size)*100
PercentageReturn
```

[13]: 2.209141343213713

[14]:
```
df.describe()
```

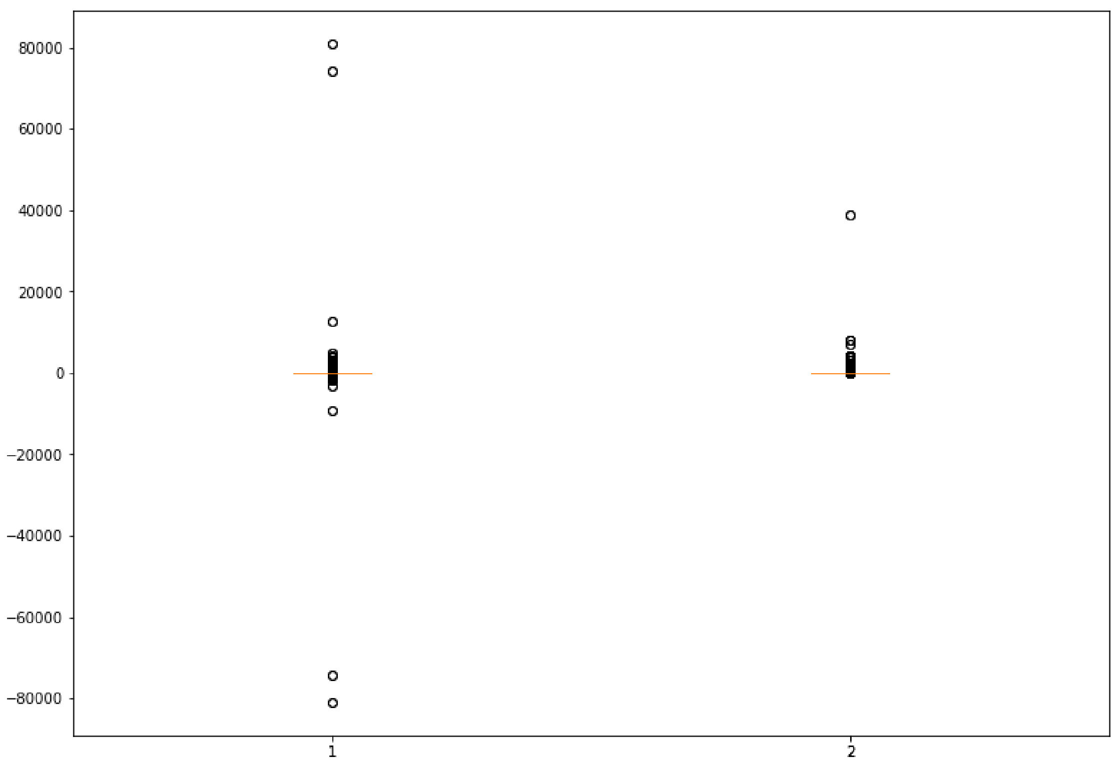
[14]:

	Quantity	UnitPrice	CustomerID
count	401604.000000	401604.000000	401604.000000
mean	12.183273	3.474064	15281.160818
std	250.283037	69.764035	1714.006089
min	-80995.000000	0.000000	12346.000000

25%	2.000000	1.250000	13939.000000
50%	5.000000	1.950000	15145.000000
75%	12.000000	3.750000	16784.000000
max	80995.000000	38970.000000	18287.000000

[15]:
```
fig = plt.figure(figsize =(10, 7))
data = [df['Quantity'], df['UnitPrice']]
fig = plt.figure(figsize =(10, 7))

# Creating axes instance
ax = fig.add_axes([0, 0, 1, 1])

# Creating plot
bp = ax.boxplot(data)


# Creating plot
plt.boxplot(data)

# show plot
plt.show()
```

<Figure size 720x504 with 0 Axes>

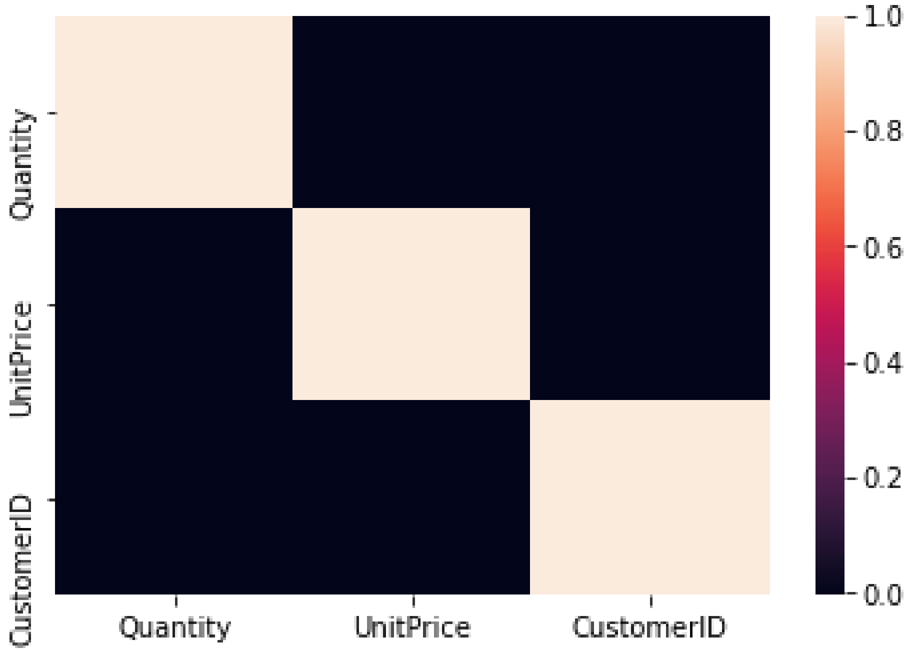


AS we see from Standard Deviation and also the boxplot that there are lot of outliers in Quantity ordered and in Unit Price Now for Desriptive Analysis.

[16]:
```
corr = df.corr()
print(corr)
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

```
            Quantity  UnitPrice  CustomerID
Quantity    1.000000  -0.001243   -0.003457
UnitPrice  -0.001243   1.000000   -0.004524
CustomerID -0.003457  -0.004524    1.000000
```

[16]: <AxesSubplot:>



[17]:
```
#Unique Countries
pd.DataFrame(df['Country'].unique())
```

[17]:

	0
0	United Kingdom
1	Japan
2	Netherlands
3	EIRE
4	Spain
5	Germany

```
6                   France
7                   Sweden
8              Switzerland
9                Australia
10                 Austria
11                     USA
12                  Cyprus
13                  Israel
14                 Finland
15                 Denmark
16          Czech Republic
17                Portugal
18                  Norway
19                   Italy
20                 Belgium
21                  Poland
22            Saudi Arabia
23                   Malta
24         Channel Islands
25     European Community
26               Singapore
27                  Greece
28                  Canada
29             Unspecified
30    United Arab Emirates
31                     RSA
32                 Lebanon
33                  Brazil
34                 Bahrain
35                 Iceland
36               Lithuania
```

[18]:
```
#Unique Customers
UniqueCustomer = pd.DataFrame(df['CustomerID'].unique())
#Unique Customers are 4372 out
UniqueCustomer
```

[18]:

	0
0	16446.0
1	12346.0
2	15838.0
3	15749.0
4	16938.0
…	…
4367	16754.0
4368	15195.0
4369	15118.0

```
4370  13135.0
4371  13256.0

[4372 rows x 1 columns]
```

[19]:
```python
count = pd.DataFrame(df['CustomerID'])
x= pd.DataFrame(df['CustomerID'].value_counts())
x.rename({'CustomerID': 'Freq'}, axis='columns', inplace = True)
x
```

[19]:
```
         Freq
17841.0  7812
14911.0  5898
14096.0  5128
12748.0  4459
14606.0  2759
…         …
17948.0     1
15590.0     1
16061.0     1
18174.0     1
18068.0     1

[4372 rows x 1 columns]
```

[20]:
```python
# column Freq has value = 1
SBuyer = x[x.Freq == 1]
SBuyer
#Only 79 buyer purchased once
```

[20]:
```
         Freq
16093.0     1
15524.0     1
13154.0     1
15562.0     1
16995.0     1
…         …
17948.0     1
15590.0     1
16061.0     1
18174.0     1
18068.0     1

[79 rows x 1 columns]
```

[21]:
```python
SBuyer['CustomerID']= SBuyer.index
SBuyer
```

```
<ipython-input-21-3f9936befc2d>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  SBuyer['CustomerID']= SBuyer.index
```

[21]:

	Freq	CustomerID
16093.0	1	16093.0
15524.0	1	15524.0
13154.0	1	13154.0
15562.0	1	15562.0
16995.0	1	16995.0
…	…	…
17948.0	1	17948.0
15590.0	1	15590.0
16061.0	1	16061.0
18174.0	1	18174.0
18068.0	1	18068.0

[79 rows x 2 columns]

[22]:
```
#Percentage of single purchaser is,
len(SBuyer)/len(UniqueCustomer)*100
```

[22]: 1.8069533394327537

[23]:
```
x['CustomerID']= x.index
# get names of indexes for which
# column Freq has value = 1
index_names = x[ x['Freq'] <= 1 ].index

# drop these row indexes
# from dataFrame
x.drop(index_names, inplace = True)
```

[24]:
```
#Repeat Customers are 4293
x
```

[24]:

	Freq	CustomerID
17841.0	7812	17841.0
14911.0	5898	14911.0
14096.0	5128	14096.0
12748.0	4459	12748.0
14606.0	2759	14606.0
…	…	…
15423.0	2	15423.0

```
14642.0     2     14642.0
13130.0     2     13130.0
13298.0     2     13298.0
14821.0     2     14821.0

[4293 rows x 2 columns]
```

[25]:
```
df
```

[25]:
```
       InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
4        C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
10       C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
20       C550456     21175           GIN + TONIC DIET METAL SIGN     -2000
…            …       …                                    …       …
541903    554868     22197                 SMALL POPCORN HOLDER      4300
541904    573008     84077    WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
541906    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
541907    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
541908    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
4      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
10     2011-04-18 13:08:00       2.10     15749.0  United Kingdom
20     2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                      …        …          …              …
541903 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
541904 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
541906 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
541907 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
541908 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

[401604 rows x 8 columns]
```

[26]:
```
#Corelation between One Time Sale and Returned Goods
#Now we are using .merge() with one unique key combination

# using .merge() function
df1 = pd.merge(df, SBuyer, how='inner', on=['CustomerID'])
df1
```

[26]:
```
   InvoiceNo StockCode                          Description  Quantity  \
0    C538110     21232        STRAWBERRY CERAMIC TRINKET BOX      -144
1    C538100    84798A      PINK FOXGLOVE ARTIIFCIAL FLOWER       -12
```

```
2    C538717     22457     NATURAL SLATE HEART CHALKBOARD        -12
3    C539055     22890  NOVELTY BISCUITS CAKE STAND 3 TIER       -12
4    C539601     22768          FAMILY PHOTO FRAME CORNICE        -2
..       …          …                                   …       …
74     569420     15036           ASSORTED COLOURS SILK FAN       600
75     581115     22413     METAL SIGN TAKE IT OR LEAVE IT      1404
76     561638     84568     GIRLS ALPHABET IRON ON PATCHES      1440
77     554868     22197                 SMALL POPCORN HOLDER      4300
78     578841     84826      ASSTD DESIGN 3D PAPER STICKERS     12540

           InvoiceDate  UnitPrice  CustomerID         Country  Freq
0  2010-12-09 15:24:00       1.06     17307.0  United Kingdom     1
1  2010-12-09 15:00:00       2.55     16579.0  United Kingdom     1
2  2010-12-14 11:09:00       2.95     18141.0  United Kingdom     1
3  2010-12-15 16:36:00       8.50     13829.0  United Kingdom     1
4  2010-12-20 13:58:00       9.95     14119.0  United Kingdom     1
..                 …        …         …             …   …
74 2011-10-04 10:33:00       0.72     16881.0  United Kingdom     1
75 2011-12-07 12:20:00       2.75     15195.0  United Kingdom     1
76 2011-07-28 14:54:00       0.17     15118.0  United Kingdom     1
77 2011-05-27 10:52:00       0.72     13135.0  United Kingdom     1
78 2011-11-25 15:57:00       0.00     13256.0  United Kingdom     1

[79 rows x 9 columns]
```

[27]:
```python
corr = df1.corr()
print(corr)
sns.heatmap(corr,
        xticklabels=corr.columns,
        yticklabels=corr.columns)
```

```
            Quantity  UnitPrice  CustomerID  Freq
Quantity    1.000000  -0.048550   -0.201286   NaN
UnitPrice  -0.048550   1.000000    0.082662   NaN
CustomerID -0.201286   0.082662    1.000000   NaN
Freq             NaN        NaN         NaN   NaN
```

[27]: <AxesSubplot:>

[28]:
```
#Countries from where Buyers are from
pd.DataFrame(df['Country'].unique())
```

[28]:

	0
0	United Kingdom
1	Japan
2	Netherlands
3	EIRE
4	Spain
5	Germany
6	France
7	Sweden
8	Switzerland
9	Australia
10	Austria
11	USA
12	Cyprus
13	Israel
14	Finland
15	Denmark
16	Czech Republic
17	Portugal
18	Norway
19	Italy
20	Belgium

```
21                  Poland
22            Saudi Arabia
23                   Malta
24         Channel Islands
25      European Community
26               Singapore
27                  Greece
28                  Canada
29             Unspecified
30    United Arab Emirates
31                     RSA
32                 Lebanon
33                  Brazil
34                 Bahrain
35                 Iceland
36               Lithuania
```

[29]:

```python
#Buyer And country
c=pd.DataFrame(df.groupby('Country')['CustomerID'].nunique())
customercoutrywise=pd.DataFrame(c).sort_values(by='CustomerID', ascending=False)
customercoutrywise
```

[29]:

	CustomerID
Country	
United Kingdom	3950
Germany	95
France	87
Spain	31
Belgium	25
Switzerland	21
Portugal	19
Italy	15
Finland	12
Austria	11
Norway	10
Netherlands	9
Australia	9
Denmark	9
Channel Islands	9
Cyprus	8
Sweden	8
Japan	8
Poland	6
USA	4
Canada	4
Unspecified	4
Israel	4

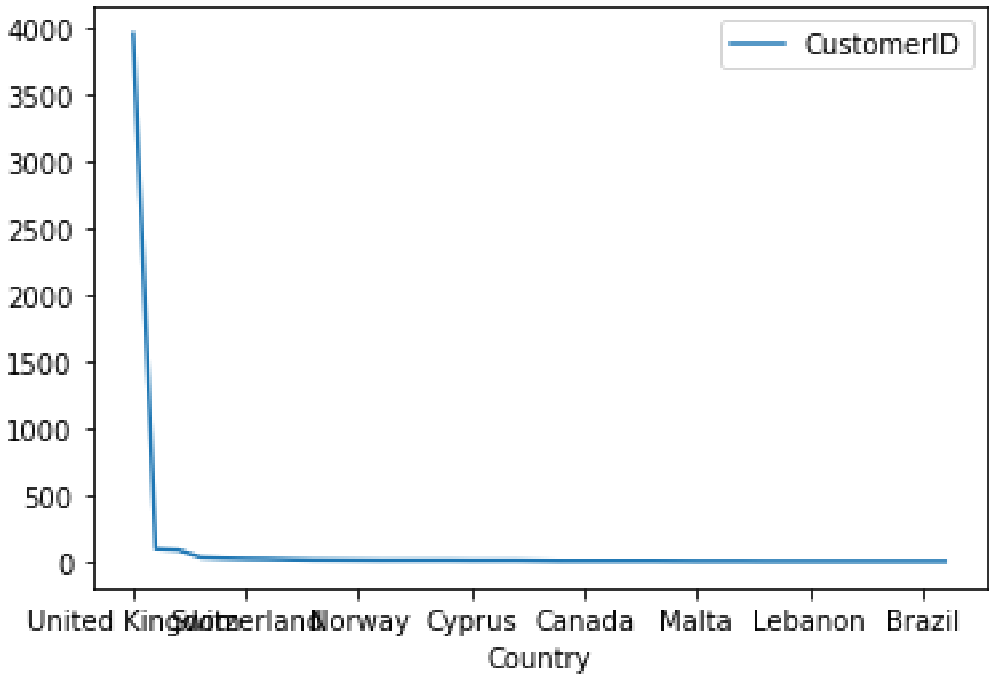
```
Greece                         4
EIRE                           3
Malta                          2
United Arab Emirates           2
Bahrain                        2
Czech Republic                 1
Lithuania                      1
Lebanon                        1
RSA                            1
Saudi Arabia                   1
Singapore                      1
Iceland                        1
Brazil                         1
European Community             1
```

[30]:
```
df.Country.value_counts(normalize=True).head(10).mul(100).round(1).astype(str)␣
↪+ '%'
```

[30]:
```
United Kingdom    88.8%
Germany            2.4%
France             2.1%
EIRE               1.9%
Spain              0.6%
Netherlands        0.6%
Belgium            0.5%
Switzerland        0.5%
Portugal           0.4%
Australia          0.3%
Name: Country, dtype: object
```

[31]:
```
customercoutrywise.plot()
#UK is the major player from where Buyers are from, which is 89%
```

[31]:
```
<AxesSubplot:xlabel='Country'>
```



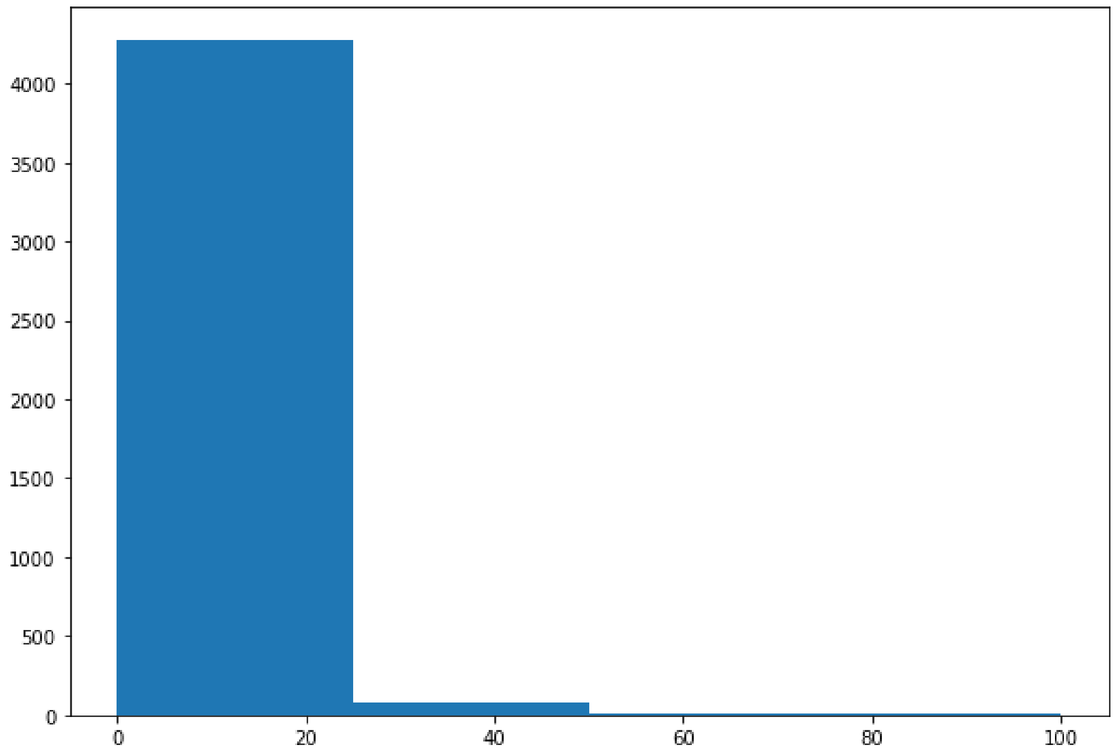
[32]:

```
#Customer who pircahsed more than 1 items
n_orders = df.groupby(['CustomerID'])['InvoiceNo'].nunique()
mult_orders_perc = np.sum(n_orders > 1) / df['CustomerID'].nunique()
print(f'{100 * mult_orders_perc:.2f}% of customers ordered more than one item.')
```

```
69.97% of customers ordered more than one item.
```

[33]:

```
# Creating histogram
fig, ax = plt.subplots(figsize =(10, 7))
ax.hist(n_orders, bins = [0, 25, 50, 75, 100])

# Show plot
plt.show()
ax.set(title='Distribution of number of orders per customer',
       xlabel='# of orders',
       ylabel='# of customers');
```



[34]:
```
# Check the oldest and latest date in the dataset.
print(f'Oldest date is - {df.InvoiceDate.min()}\n')
print(f'Latest date is - {df.InvoiceDate.max()}')
```

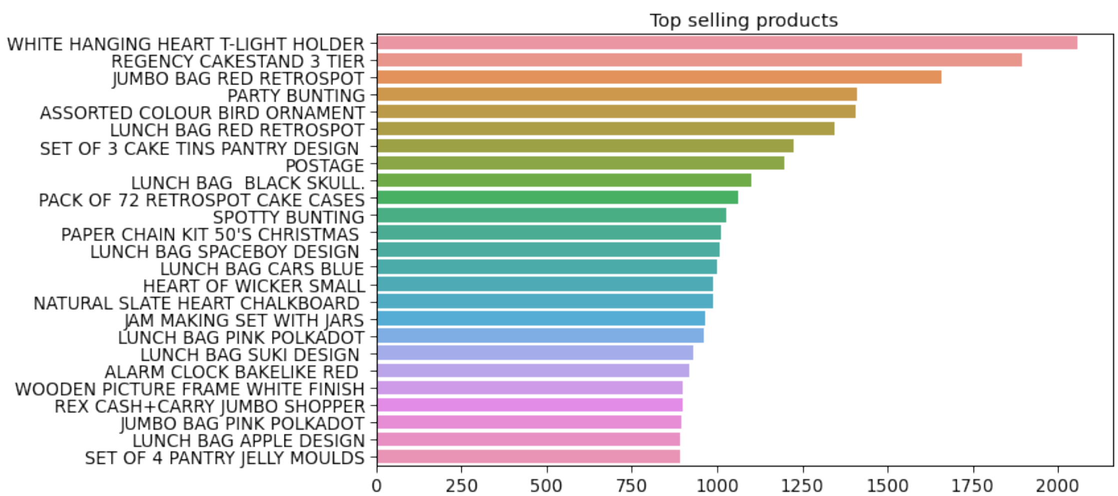
```
Oldest date is - 2010-12-01 08:26:00

Latest date is - 2011-12-09 12:50:00
```

[35]:
```
#Monthly Sales
# importing DateTime module to convert extracted dates
def get_month(x):
    return dt.datetime(x.year, x.month, 1)
df['InvoiceMonth'] = df['InvoiceDate'].apply(get_month)
df.head()
```

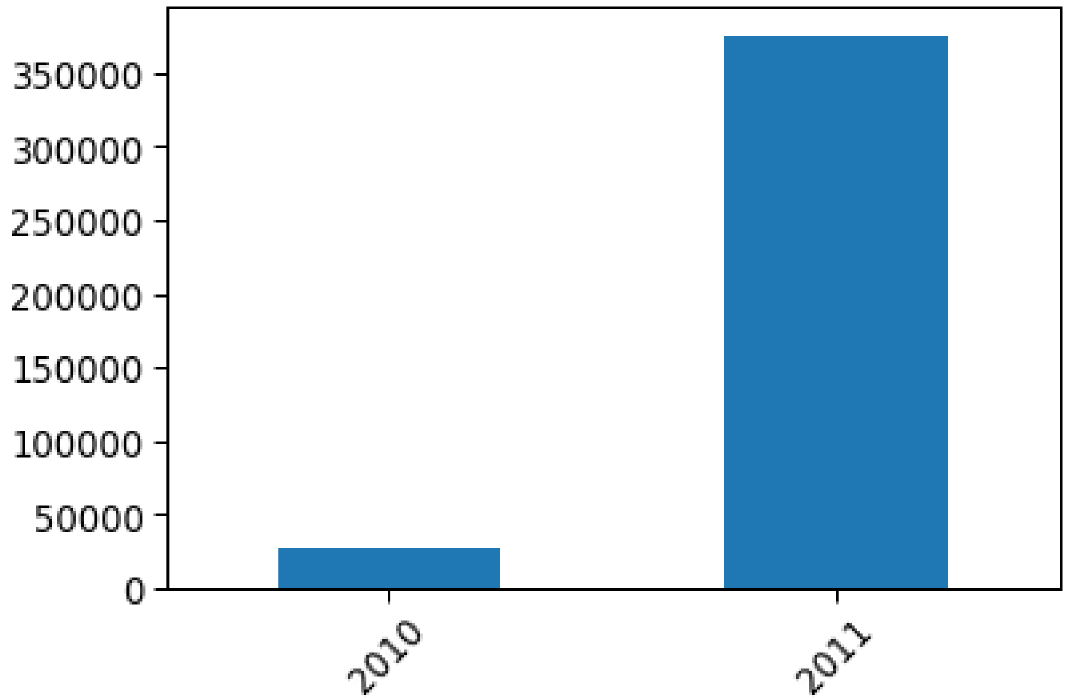
```
<ipython-input-35-8d7c6a548b34>:5: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['InvoiceMonth'] = df['InvoiceDate'].apply(get_month)
```

[35]:
```
   InvoiceNo StockCode                          Description  Quantity  \
0    C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1    C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
4    C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
10   C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
20   C550456     21175          GIN + TONIC DIET METAL SIGN     -2000

           InvoiceDate  UnitPrice  CustomerID         Country InvoiceMonth
0  2011-12-09 09:27:00       2.08     16446.0  United Kingdom   2011-12-01
1  2011-01-18 10:17:00       1.04     12346.0  United Kingdom   2011-01-01
4  2010-12-02 14:23:00       0.03     15838.0  United Kingdom   2010-12-01
10 2011-04-18 13:08:00       2.10     15749.0  United Kingdom   2011-04-01
20 2011-04-18 13:08:00       1.85     15749.0  United Kingdom   2011-04-01
```

[36]:
```python
# Top selling products
top_products = df['Description'].value_counts()[:25]
plt.figure(figsize=(10,6))
sns.set_context("paper", font_scale=1.5)
sns.barplot(y = top_products.index,
            x = top_products.values)
plt.title("Top selling products")
plt.show();
```



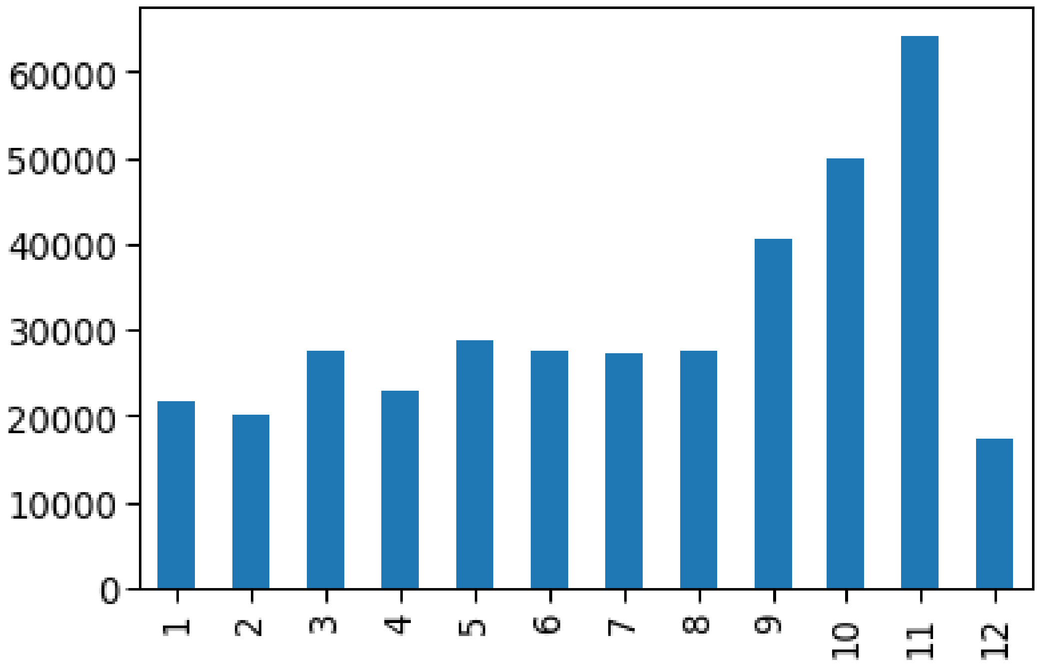
[37]:
```python
# Count of transactions in different years
df.InvoiceDate.dt.year.value_counts(sort=False).plot(kind='bar', rot=45);
```



Most of the records belong to 2011. Now doing monthly break up. And we see that max transaction is in Nov & Oct. Could be Black Friday or Halloween. Dec is lesser does not indicating advance buying, because in this data, sales till 09th is condidered.

[38]:
```
df[df.InvoiceDate.dt.year==2011].InvoiceDate.dt.month.value_counts(sort=False).
 ↪plot(kind='bar')
```

[38]:
```
<AxesSubplot:>
```



[39]:
```
df['Total_cost'] = df['UnitPrice']*df['Quantity']
df
```

```
<ipython-input-39-630b9a1d7480>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Total_cost'] = df['UnitPrice']*df['Quantity']
```

[39]:

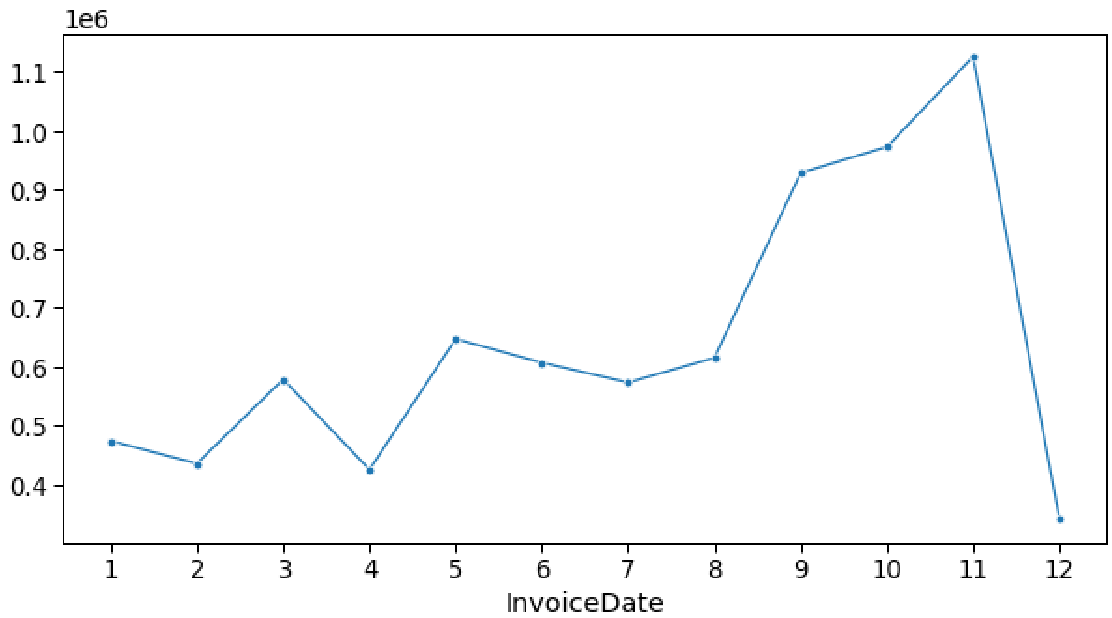
	InvoiceNo	StockCode	Description	Quantity	\
0	C581484	23843	PAPER CRAFT , LITTLE BIRDIE	-80995	
1	C541433	23166	MEDIUM CERAMIC TOP STORAGE JAR	-74215	
4	C536757	84347	ROTATING SILVER ANGELS T-LIGHT HLDR	-9360	
10	C550456	21108	FAIRY CAKE FLANNEL ASSORTED COLOUR	-3114	
20	C550456	21175	GIN + TONIC DIET METAL SIGN	-2000	
…	…	…	…	…	
541903	554868	22197	SMALL POPCORN HOLDER	4300	
541904	573008	84077	WORLD WAR 2 GLIDERS ASSTD DESIGNS	4800	
541906	578841	84826	ASSTD DESIGN 3D PAPER STICKERS	12540	
541907	541431	23166	MEDIUM CERAMIC TOP STORAGE JAR	74215	
541908	581483	23843	PAPER CRAFT , LITTLE BIRDIE	80995	

InvoiceDate	UnitPrice	CustomerID	Country	\

```
0       2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1       2011-01-18 10:17:00       1.04     12346.0  United Kingdom
4       2010-12-02 14:23:00       0.03     15838.0  United Kingdom
10      2011-04-18 13:08:00       2.10     15749.0  United Kingdom
20      2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                     …        …         …              …
541903 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
541904 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
541906 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
541907 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
541908 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost
0        2011-12-01   -168469.6
1        2011-01-01    -77183.6
4        2010-12-01      -280.8
10       2011-04-01     -6539.4
20       2011-04-01     -3700.0
…             …          …
541903   2011-05-01      3096.0
541904   2011-10-01      1008.0
541906   2011-11-01         0.0
541907   2011-01-01     77183.6
541908   2011-12-01    168469.6

[401604 rows x 10 columns]
```

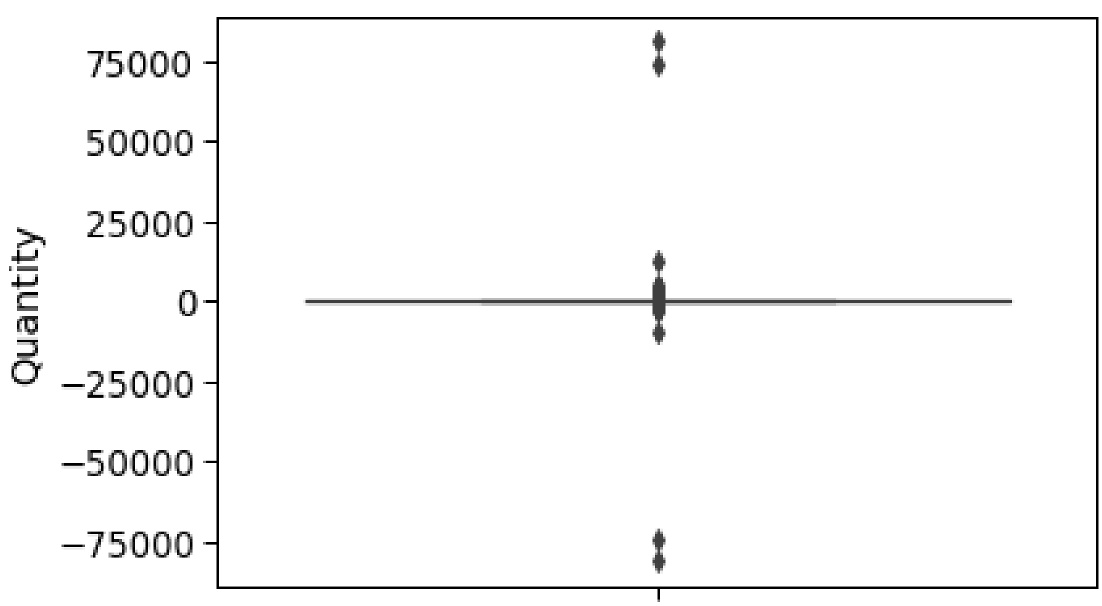
[40]:

```
monthly_gross = df[df.InvoiceDate.dt.year==2011].groupby(df.InvoiceDate.dt.
 ↪month).Total_cost.sum()
plt.figure(figsize=(10,5))
sns.lineplot(y=monthly_gross.values,x=monthly_gross.index, marker='o');
plt.xticks(range(1,13))
plt.show();
```

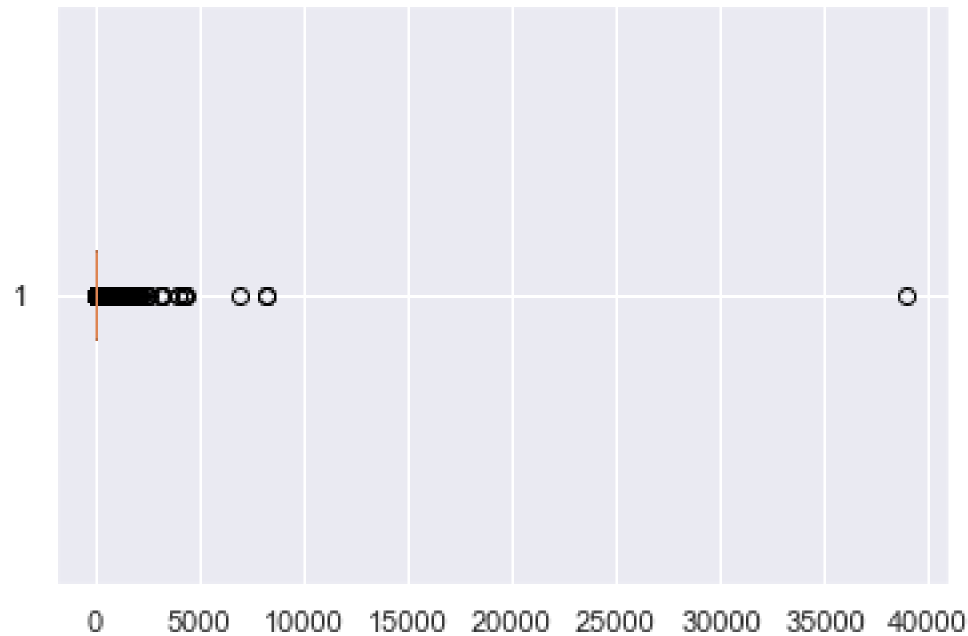


[41]:
```
# Boxplot to for Quantity distribution
sns.boxplot(y='Quantity', data=df, orient='h');
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_core.py:1312: UserWarning:
Horizontal orientation ignored with only `y` specified.
  warnings.warn(single_var_warning.format("Horizontal", "y"))
```



[42]:
```
#Unit price distribution
sns.set(style="darkgrid")
plt.boxplot(df['UnitPrice'], vert = 0)

#plt.tight_layout()
plt.show()

#sns.boxplot(y='UnitPrice', data=df)
```



Perform cohort analysis (a cohort is a group of subjects that share a defining characteristic). Observe how a cohort behaves across time and compare it to other cohorts. a. Create month cohorts and analyze active customers for each cohort. b. Analyze the retention rate of customers.

Time cohorts Time cohorts are customers who signed up for a product or service during a particular time frame. Analysing these cohorts shows the customers' behaviour depending on the time they started using the company's products or services. The time may be monthly or quarterly, even daily.

[43]:
```
#Assigning Cohor to each group
group = df.groupby('CustomerID')['InvoiceMonth']
group.head()
```

[43]:
```
0          2011-12-01
1          2011-01-01
4          2010-12-01
10         2011-04-01
```

```
20        2011-04-01
             …
541900    2011-07-01
541903    2011-05-01
541906    2011-11-01
541907    2011-01-01
541908    2011-12-01
Name: InvoiceMonth, Length: 21206, dtype: datetime64[ns]
```

[44]:
```
df['Month'] = df.groupby('CustomerID')['InvoiceMonth'].transform('min')
df
```

```
<ipython-input-44-7bf596724d9d>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Month'] = df.groupby('CustomerID')['InvoiceMonth'].transform('min')
```

[44]:
```
       InvoiceNo StockCode                      Description  Quantity  \
0        C581484     23843       PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166      MEDIUM CERAMIC TOP STORAGE JAR    -74215
4        C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
10       C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
20       C550456     21175          GIN + TONIC DIET METAL SIGN     -2000
…          …       …                                  …       …
541903    554868     22197                SMALL POPCORN HOLDER      4300
541904    573008     84077    WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
541906    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
541907    541431     23166      MEDIUM CERAMIC TOP STORAGE JAR     74215
541908    581483     23843         PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
4      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
10     2011-04-18 13:08:00       2.10     15749.0  United Kingdom
20     2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                      …         …          …               …
541903 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
541904 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
541906 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
541907 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
541908 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost      Month
0        2011-12-01   -168469.6 2011-05-01
```

```
1        2011-01-01    -77183.6 2011-01-01
4        2010-12-01      -280.8 2010-12-01
10       2011-04-01     -6539.4 2011-01-01
20       2011-04-01     -3700.0 2011-01-01
…             …           …          …
541903   2011-05-01      3096.0 2011-05-01
541904   2011-10-01      1008.0 2011-03-01
541906   2011-11-01         0.0 2011-11-01
541907   2011-01-01     77183.6 2011-01-01
541908   2011-12-01    168469.6 2011-05-01

[401604 rows x 11 columns]
```

[45]:
```python
#monthly cohorts based on the month each customer has made their first␣
↪transaction.
def get_month(x):
    return dt.datetime(x.year,x.month,1)

# Create InvoiceMonth column
df['InvoiceMonth'] = df['InvoiceDate'].apply(get_month)

# Group by CustomerID and select the InvoiceMonth value
grouping = df.groupby('CustomerID')['InvoiceMonth']

# Assign a minimum InvoiceMonth value to the dataset
df['Month'] = grouping.transform('min')
```

```
<ipython-input-45-535ac4d3f548>:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['InvoiceMonth'] = df['InvoiceDate'].apply(get_month)
<ipython-input-45-535ac4d3f548>:12: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['Month'] = grouping.transform('min')
```

Calculate time offset in months Calculating time offset for each transaction allows you to report the metrics for each cohort in a comparable fashion.

First, we will create some variables that capture the integer value of years and months for Invoice and Cohort Date

[46]:
```
def get_date_int(df, column):
    year = df[column].dt.year
    month = df[column].dt.month
    return year, month

# Get the integers for date parts from the `InvoiceMonth` column
invoice_year, invoice_month = get_date_int(df,'InvoiceMonth')

# Get the integers for date parts from the `CohortMonth` column
cohort_year, cohort_month = get_date_int(df,'Month')

# Calculate difference in years
years_diff = invoice_year - cohort_year

# Calculate difference in months
months_diff = invoice_month - cohort_month

# Extract the difference in months from all previous values
df['CohortIndex'] = years_diff * 12 + months_diff + 1
```

```
<ipython-input-46-5c78512d06d5>:19: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df['CohortIndex'] = years_diff * 12 + months_diff + 1
```

[47]:
```
#Sanity Check to see if the Cohort Index is of different number
df['CohortIndex']
```

[47]:
```
0         8
1         1
4         1
10        4
20        4
         ..
541903    1
541904    8
541906    1
541907    1
541908    8
Name: CohortIndex, Length: 401604, dtype: int64
```

[48]:
```
df.head()
```

[48]:
```
  InvoiceNo StockCode                      Description  Quantity  \
0   C581484     23843      PAPER CRAFT , LITTLE BIRDIE    -80995
```

```
1    C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
4    C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
10   C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
20   C550456     21175          GIN + TONIC DIET METAL SIGN     -2000

           InvoiceDate  UnitPrice  CustomerID        Country InvoiceMonth  \
0  2011-12-09 09:27:00       2.08     16446.0 United Kingdom   2011-12-01
1  2011-01-18 10:17:00       1.04     12346.0 United Kingdom   2011-01-01
4  2010-12-02 14:23:00       0.03     15838.0 United Kingdom   2010-12-01
10 2011-04-18 13:08:00       2.10     15749.0 United Kingdom   2011-04-01
20 2011-04-18 13:08:00       1.85     15749.0 United Kingdom   2011-04-01

    Total_cost      Month  CohortIndex
0    -168469.6 2011-05-01            8
1     -77183.6 2011-01-01            1
4       -280.8 2010-12-01            1
10     -6539.4 2011-01-01            4
20     -3700.0 2011-01-01            4
```

[49]:
```
#retention rate or Active Customers
grouping = df.groupby(['Month', 'CohortIndex'])
```

[50]:
```
# Count the number of unique values per customer ID
cohort_data = grouping['CustomerID'].apply(pd.Series.nunique).reset_index()
```

[51]:
```
# Create a pivot
cohort_counts = cohort_data.pivot(index='Month', columns='CohortIndex',␣
↪values='CustomerID')
```

[52]:
```
cohort_counts
```

[52]:
```
CohortIndex     1      2      3      4      5      6      7      8      9   \
Month
2010-12-01   948.0  362.0  317.0  367.0  341.0  376.0  360.0  336.0  336.0
2011-01-01   421.0  101.0  119.0  102.0  138.0  126.0  110.0  108.0  131.0
2011-02-01   380.0   94.0   73.0  106.0  102.0   94.0   97.0  107.0   98.0
2011-03-01   440.0   84.0  112.0   96.0  102.0   78.0  116.0  105.0  127.0
2011-04-01   299.0   68.0   66.0   63.0   62.0   71.0   69.0   78.0   25.0
2011-05-01   279.0   66.0   48.0   48.0   60.0   68.0   74.0   29.0    NaN
2011-06-01   235.0   49.0   44.0   64.0   58.0   79.0   24.0    NaN    NaN
2011-07-01   191.0   40.0   39.0   44.0   52.0   22.0    NaN    NaN    NaN
2011-08-01   167.0   42.0   42.0   42.0   23.0    NaN    NaN    NaN    NaN
2011-09-01   298.0   89.0   97.0   36.0    NaN    NaN    NaN    NaN    NaN
2011-10-01   352.0   93.0   46.0    NaN    NaN    NaN    NaN    NaN    NaN
2011-11-01   321.0   43.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN
2011-12-01    41.0    NaN    NaN    NaN    NaN    NaN    NaN    NaN    NaN
```

```
CohortIndex     10     11     12     13
Month
2010-12-01   374.0  354.0  474.0  260.0
2011-01-01   146.0  155.0   63.0    NaN
2011-02-01   119.0   35.0    NaN    NaN
2011-03-01    39.0    NaN    NaN    NaN
2011-04-01     NaN    NaN    NaN    NaN
2011-05-01     NaN    NaN    NaN    NaN
2011-06-01     NaN    NaN    NaN    NaN
2011-07-01     NaN    NaN    NaN    NaN
2011-08-01     NaN    NaN    NaN    NaN
2011-09-01     NaN    NaN    NaN    NaN
2011-10-01     NaN    NaN    NaN    NaN
2011-11-01     NaN    NaN    NaN    NaN
2011-12-01     NaN    NaN    NaN    NaN
```

[53]:
```
# Select the first column and store it to cohort_sizes
cohort_sizes = cohort_counts.iloc[:,0]
cohort_sizes
```

[53]:
```
Month
2010-12-01    948.0
2011-01-01    421.0
2011-02-01    380.0
2011-03-01    440.0
2011-04-01    299.0
2011-05-01    279.0
2011-06-01    235.0
2011-07-01    191.0
2011-08-01    167.0
2011-09-01    298.0
2011-10-01    352.0
2011-11-01    321.0
2011-12-01     41.0
Name: 1, dtype: float64
```

[54]:
```
# Divide the cohort count by cohort sizes along the rows
retention = cohort_counts.divide(cohort_sizes, axis=0)*100
```

[55]:
```
retention
```

[55]:
```
CohortIndex     1          2          3          4          5          6   \
Month
2010-12-01   100.0  38.185654  33.438819  38.713080  35.970464  39.662447
2011-01-01   100.0  23.990499  28.266033  24.228029  32.779097  29.928741
2011-02-01   100.0  24.736842  19.210526  27.894737  26.842105  24.736842
2011-03-01   100.0  19.090909  25.454545  21.818182  23.181818  17.727273
```

```
2011-04-01   100.0  22.742475  22.073579  21.070234  20.735786  23.745819
2011-05-01   100.0  23.655914  17.204301  17.204301  21.505376  24.372760
2011-06-01   100.0  20.851064  18.723404  27.234043  24.680851  33.617021
2011-07-01   100.0  20.942408  20.418848  23.036649  27.225131  11.518325
2011-08-01   100.0  25.149701  25.149701  25.149701  13.772455        NaN
2011-09-01   100.0  29.865772  32.550336  12.080537        NaN        NaN
2011-10-01   100.0  26.420455  13.068182        NaN        NaN        NaN
2011-11-01   100.0  13.395639        NaN        NaN        NaN        NaN
2011-12-01   100.0        NaN        NaN        NaN        NaN        NaN

CohortIndex         7          8          9          10         11         12  \
Month
2010-12-01   37.974684  35.443038  35.443038  39.451477  37.341772  50.000000
2011-01-01   26.128266  25.653207  31.116390  34.679335  36.817102  14.964371
2011-02-01   25.526316  28.157895  25.789474  31.315789   9.210526        NaN
2011-03-01   26.363636  23.863636  28.863636   8.863636        NaN        NaN
2011-04-01   23.076923  26.086957   8.361204        NaN        NaN        NaN
2011-05-01   26.523297  10.394265        NaN        NaN        NaN        NaN
2011-06-01   10.212766        NaN        NaN        NaN        NaN        NaN
2011-07-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-08-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-09-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-10-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-11-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-12-01         NaN        NaN        NaN        NaN        NaN        NaN

CohortIndex        13
Month
2010-12-01   27.42616
2011-01-01        NaN
2011-02-01        NaN
2011-03-01        NaN
2011-04-01        NaN
2011-05-01        NaN
2011-06-01        NaN
2011-07-01        NaN
2011-08-01        NaN
2011-09-01        NaN
2011-10-01        NaN
2011-11-01        NaN
2011-12-01        NaN
```

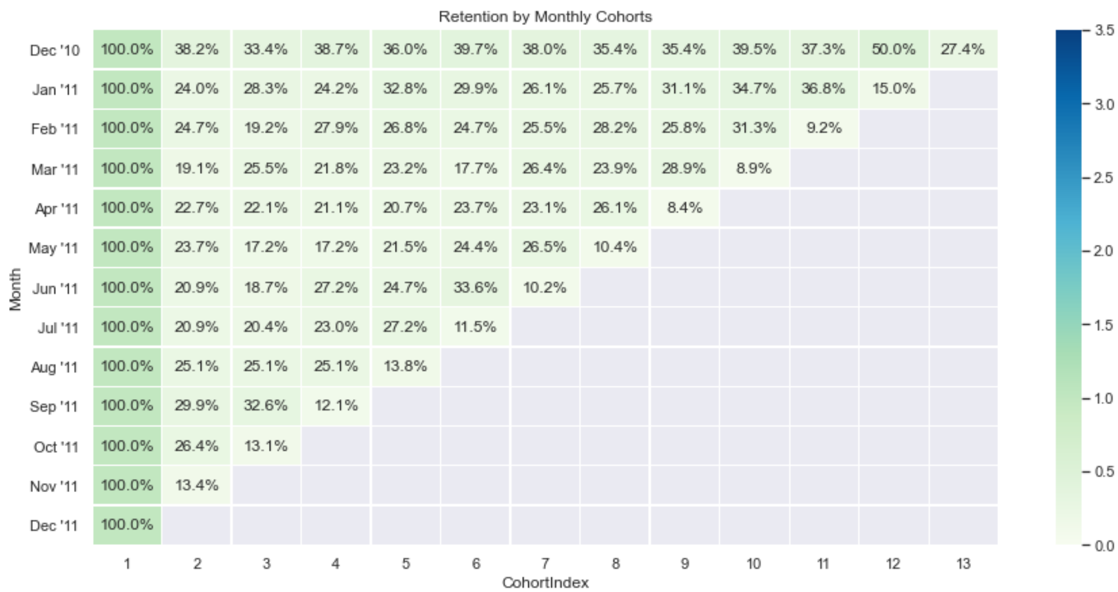
[56]:
```
retention.min(), retention.max()
```

[56]:
```
(CohortIndex
 1     100.000000
 2      13.395639
```

```
3       13.068182
4       12.080537
5       13.772455
6       11.518325
7       10.212766
8       10.394265
9        8.361204
10       8.863636
11       9.210526
12      14.964371
13      27.426160
dtype: float64,
CohortIndex
1      100.000000
2       38.185654
3       33.438819
4       38.713080
5       35.970464
6       39.662447
7       37.974684
8       35.443038
9       35.443038
10      39.451477
11      37.341772
12      50.000000
13      27.426160
dtype: float64)
```

[57]:
```
month_list = ["Dec '10", "Jan '11", "Feb '11", "Mar '11", "Apr '11",\
              "May '11", "Jun '11", "Jul '11", "Aug '11", "Sep '11", \
              "Oct '11", "Nov '11", "Dec '11"]

retention = retention/100
# Initialize inches plot figure
plt.figure(figsize=(15,7))

# Add a title
plt.title('Retention by Monthly Cohorts')

# Create the heatmap
sns.heatmap(data=retention,
            annot = True,
            #fmt= '.0%',
            cmap = "GnBu",
            vmin = 0.0,
            vmax = list(retention.max().sort_values(ascending = False))[1]+3,
            fmt = '.1%',
```

```
             linewidth = 0.3,
             yticklabels=month_list)

plt.show();
```



[58]:

```
#average price per cohort
# Create a groupby object and pass the monthly cohort and cohort index as a list
grouping = df.groupby(['Month', 'CohortIndex'])


# Calculate the average of the unit price column
cohort_data = grouping['UnitPrice'].mean()

# Reset the index of cohort_data
cohort_data = cohort_data.reset_index()

# Create a pivot
average_price = cohort_data.pivot(index='Month', columns='CohortIndex',␣
 ↪values='UnitPrice')
average_price.round(1)
average_price.index = average_price.index.date
```

[59]:

```
average_price
```

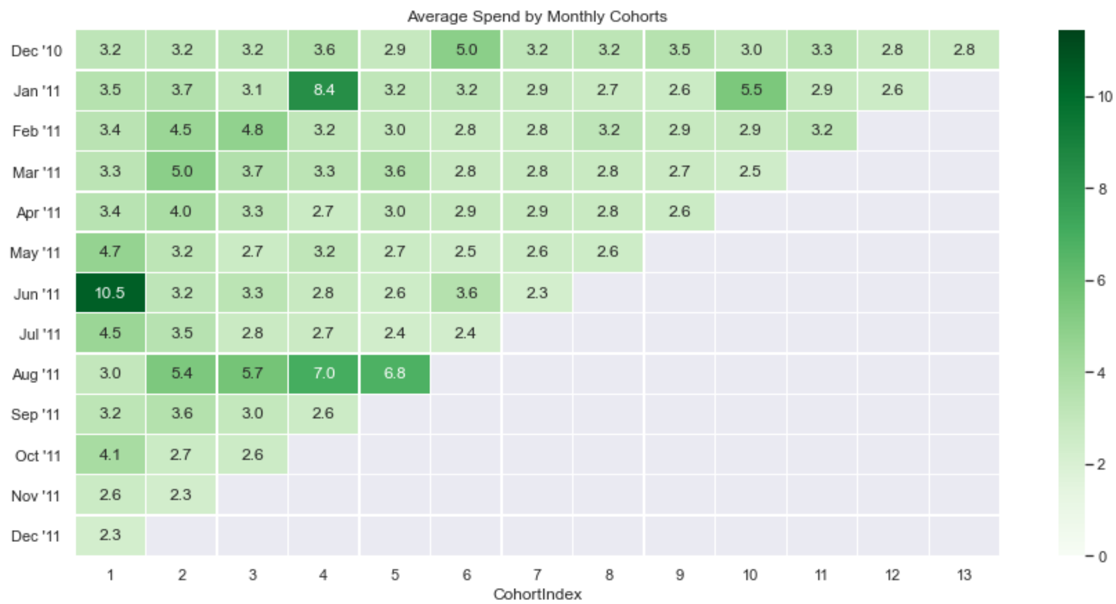
[59]:

```
CohortIndex         1         2         3         4         5         6  \
2010-12-01   3.216682  3.182040  3.207467  3.603758  2.937803  4.996508
2011-01-01   3.505492  3.653572  3.069534  8.439024  3.157803  3.172919
```

```
2011-02-01    3.355968  4.469638  4.824106  3.150045  2.987616  2.792577
2011-03-01    3.302802  4.990095  3.655094  3.289768  3.616562  2.758381
2011-04-01    3.431172  3.958074  3.300128  2.673439  3.028297  2.867185
2011-05-01    4.662054  3.243691  2.652761  3.167391  2.667158  2.495751
2011-06-01   10.490030  3.205283  3.343994  2.835952  2.553037  3.550657
2011-07-01    4.493676  3.480495  2.752121  2.701985  2.403989  2.366635
2011-08-01    3.028246  5.425904  5.714033  7.046410  6.830066       NaN
2011-09-01    3.235116  3.584834  2.957893  2.625593       NaN       NaN
2011-10-01    4.053162  2.678140  2.596869       NaN       NaN       NaN
2011-11-01    2.641554  2.335018       NaN       NaN       NaN       NaN
2011-12-01    2.288479       NaN       NaN       NaN       NaN       NaN

CohortIndex         7         8         9        10        11        12  \
2010-12-01   3.184572  3.235695  3.511560  3.035982  3.309705  2.835557
2011-01-01   2.918498  2.749649  2.641686  5.489040  2.886220  2.635897
2011-02-01   2.812985  3.214380  2.894988  2.946092  3.217742       NaN
2011-03-01   2.843273  2.809136  2.707846  2.466172       NaN       NaN
2011-04-01   2.902668  2.812492  2.636564       NaN       NaN       NaN
2011-05-01   2.615408  2.560400       NaN       NaN       NaN       NaN
2011-06-01   2.293928       NaN       NaN       NaN       NaN       NaN
2011-07-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-08-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-09-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-10-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-11-01        NaN       NaN       NaN       NaN       NaN       NaN
2011-12-01        NaN       NaN       NaN       NaN       NaN       NaN

CohortIndex        13
2010-12-01   2.759449
2011-01-01        NaN
2011-02-01        NaN
2011-03-01        NaN
2011-04-01        NaN
2011-05-01        NaN
2011-06-01        NaN
2011-07-01        NaN
2011-08-01        NaN
2011-09-01        NaN
2011-10-01        NaN
2011-11-01        NaN
2011-12-01        NaN
```

[60]:
```
plt.figure(figsize=(15, 7))

# Add a title
plt.title('Average Spend by Monthly Cohorts')
```

```
# Create the heatmap
sns.heatmap(data = average_price,
            annot=True,
            vmin = 0.0,
#               vmax =20,
            cmap='Greens',
            vmax = list(average_price.max().sort_values(ascending =␣
 ↪False))[1]+3,
            fmt = '.1f',
            linewidth = 0.3,
            yticklabels=month_list)
plt.show();
```




```
[61]: #average quantity per cohort

# Create a groupby object and pass the monthly cohort and cohort index as a list
grouping = df.groupby(['Month', 'CohortIndex'])

# Calculate the average of the Quantity column
cohort_data = grouping['Quantity'].mean()

# Reset the index of cohort_data
cohort_data = cohort_data.reset_index()

# Create a pivot
average_quantity = cohort_data.pivot(index='Month', columns='CohortIndex',␣
 ↪values='Quantity')
```

```
average_quantity
```

[61]:

```
CohortIndex         1          2          3          4          5          6   \
Month
2010-12-01   11.200463  14.691852  15.108447  14.954097  13.054649  14.416287
2011-01-01   10.127231  12.704190  12.429557  11.032382  12.288608  15.006101
2011-02-01   10.924450  12.251366  18.563808  12.018144  11.167271  11.476727
2011-03-01    9.818050   9.972109  12.249296   9.483094  13.037510  12.369617
2011-04-01    9.803935  10.130252   9.432453  11.622102  11.645560   8.315994
2011-05-01   10.977360   9.138087  14.023864  11.805435  10.973613   8.740725
2011-06-01   10.411028  13.859783  10.509642  13.384102  10.360800   9.901184
2011-07-01    9.804225  12.700952   7.229385   7.929151   6.101961   7.111538
2011-08-01    9.941459   5.983114   5.371409   5.972992   6.980110        NaN
2011-09-01   12.003023   5.551129   7.657590   8.873418        NaN        NaN
2011-10-01    8.553545   7.056196   8.079686        NaN        NaN        NaN
2011-11-01    8.901297   9.508021        NaN        NaN        NaN        NaN
2011-12-01   14.795478        NaN        NaN        NaN        NaN        NaN

CohortIndex         7          8          9         10         11         12   \
Month
2010-12-01   15.306910  14.879447  16.764934  16.809158  17.528956  13.019471
2011-01-01   14.302480  14.519414  11.451025   9.982762   9.256968   9.737305
2011-02-01   13.378526  12.448602  10.381961  12.043074  12.702765        NaN
2011-03-01   13.221102  12.263293  10.662973   9.091004        NaN        NaN
2011-04-01    9.777895   9.480778   7.403071        NaN        NaN        NaN
2011-05-01   10.275862   7.576774        NaN        NaN        NaN        NaN
2011-06-01    9.348609        NaN        NaN        NaN        NaN        NaN
2011-07-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-08-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-09-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-10-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-11-01         NaN        NaN        NaN        NaN        NaN        NaN
2011-12-01         NaN        NaN        NaN        NaN        NaN        NaN

CohortIndex         13
Month
2010-12-01   14.901201
2011-01-01         NaN
2011-02-01         NaN
2011-03-01         NaN
2011-04-01         NaN
2011-05-01         NaN
2011-06-01         NaN
2011-07-01         NaN
2011-08-01         NaN
2011-09-01         NaN
2011-10-01         NaN
```

```
2011-11-01          NaN
2011-12-01          NaN
```

[62]:
```
plt.figure(figsize=(15, 7))
plt.title('Average Quantity per Monthly Cohorts')

# Create the heatmap
sns.heatmap(data = average_quantity,
            annot=True,
            vmin = 0.0,
            cmap='Greens',
            vmax = list(average_quantity.max().sort_values(ascending =
 ↪False))[1]+3,
            fmt = '.1f',
            linewidth = 0.3,
            yticklabels=month_list)
plt.show();
```

Week 2 Data Modeling : 1. Build a RFM (Recency Frequency Monetary) model. Recency means the number of days since a customer made the last purchase. Frequency is the number of purchase in a given period. It could be 3 months, 6 months or 1 year. Monetary is the total amount of money a customer spent in that given period. Therefore, big spenders will be differentiated among other customers such as MVP (Minimum Viable Product) or VIP. 2. Calculate RFM metrics. 3. Build RFM Segments. Give recency, frequency, and monetary scores individually by dividing them into quartiles. b1. Combine three ratings to get a RFM segment (as strings). b2. Get the RFM score by adding up the three ratings. b3. Analyze the RFM segments by summarizing them and comment on the findings. Note: Rate "recency" for customer who has been active more recently higher than the less recent customer, because each company wants its customers to be recent. Note:

Rate "frequency" and "monetary" higher, because the company wants the customer to visit more often and spend more money

RFM Analysis RFM analysis is a customer segmentation technique that uses past purchase behavior to divide customers into groups. RFM helps divide customers into various categories or clusters to identify customers who are more likely to respond to promotions and also for future personalization services.

Recency (R): Time since last purchase Frequency (F): Total number of purchases Monetary (M): Total purchase value

For RFM need to divide customers into four equal groups according to the distribution of values for recency, frequency, and monetary value. Four equal groups across three variables create 64 (4x4x4) different customer segments.

For example: Customer with most recent purchase (R=4), is Customer with most quantity (F=4), Customer who spent the most (M=4) This customer belongs to RFM segment 4-4-4 (Best Customers), (R=4, F=4, M=4)

[63]:
```
#Creating a copy of df as safe copy. Will be using df1 for changes

df1 = df
df1

#For recency, need to get the date difference since the last purchase.
#For this using the last purchase date on the database as today's date
```

[63]:
```
       InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
4        C536757     84347   ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
10       C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
20       C550456     21175          GIN + TONIC DIET METAL SIGN     -2000
…            …        …                                    …        …
541903    554868     22197                  SMALL POPCORN HOLDER      4300
541904    573008     84077    WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
541906    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
541907    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
541908    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
4      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
10     2011-04-18 13:08:00       2.10     15749.0  United Kingdom
20     2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                      …        …           …              …
541903 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
541904 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
```

```
541906 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
541907 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
541908 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost       Month  CohortIndex
0        2011-12-01   -168469.6 2011-05-01            8
1        2011-01-01    -77183.6 2011-01-01            1
4        2010-12-01      -280.8 2010-12-01            1
10       2011-04-01     -6539.4 2011-01-01            4
20       2011-04-01     -3700.0 2011-01-01            4
…             …          …         …          …
541903   2011-05-01      3096.0 2011-05-01            1
541904   2011-10-01      1008.0 2011-03-01            8
541906   2011-11-01         0.0 2011-11-01            1
541907   2011-01-01     77183.6 2011-01-01            1
541908   2011-12-01    168469.6 2011-05-01            8

[401604 rows x 12 columns]
```

[64]:
```
#last date available in our dataset
df1['InvoiceDate'].max()
```

[64]:
```
Timestamp('2011-12-09 12:50:00')
```

[65]:
```
current_date = df1['InvoiceDate'].max()
current_date = pd.to_datetime(current_date).date()
current_date
```

[65]:
```
datetime.date(2011, 12, 9)
```

[66]:
```
# Lets create a date column for date values only
df1['Purchase_Date'] = df1.InvoiceDate.dt.date
```

```
<ipython-input-66-3f5c8d7b2332>:2: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-
docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
  df1['Purchase_Date'] = df1.InvoiceDate.dt.date
```

[67]:
```
recency = df1.groupby('CustomerID')['Purchase_Date'].max().reset_index()
# Creating a separate column for this date.
recency = recency.assign(Current_Date = current_date)
# Compute the number of days since last purchase
recency['Recency'] = recency.Purchase_Date.apply(lambda x: (current_date - x).
 ↪days)
recency
```

[67]:
```
      CustomerID Purchase_Date Current_Date  Recency
0        12346.0    2011-01-18   2011-12-09      325
1        12347.0    2011-12-07   2011-12-09        2
2        12348.0    2011-09-25   2011-12-09       75
3        12349.0    2011-11-21   2011-12-09       18
4        12350.0    2011-02-02   2011-12-09      310
…           …           …           …     …
4367     18280.0    2011-03-07   2011-12-09      277
4368     18281.0    2011-06-12   2011-12-09      180
4369     18282.0    2011-12-02   2011-12-09        7
4370     18283.0    2011-12-06   2011-12-09        3
4371     18287.0    2011-10-28   2011-12-09       42

[4372 rows x 4 columns]
```

[68]:
```
# Drop Current tdate that we took for calculation. That is no more required
recency.drop(['Purchase_Date','Current_Date'], axis=1, inplace=True)

#Now finiding out Frequency - how often or how many a customer used the product␣
↪of a company.

frequency = df1.groupby('CustomerID').InvoiceNo.nunique().reset_index().
↪rename(columns={'InvoiceNo':'Frequency'})
frequency
```

[68]:
```
      CustomerID  Frequency
0        12346.0          2
1        12347.0          7
2        12348.0          4
3        12349.0          1
4        12350.0          1
…           …          …
4367     18280.0          1
4368     18281.0          1
4369     18282.0          3
4370     18283.0         16
4371     18287.0          3

[4372 rows x 2 columns]
```

Doing the same on the Spending or Monetary Monetary is the total amount of money a customer spent in that given period. Therefore big spenders will be differentiated with other customers such as MVP or VIP.

[69]:
```
#We had already calculated Total Cost Earlier, using that

monetary = df1.groupby('CustomerID').Total_cost.sum().reset_index().
↪rename(columns={'Total_cost':'Monetary'})
```

```
monetary
```

[69]:

	CustomerID	Monetary
0	12346.0	0.00
1	12347.0	4310.00
2	12348.0	1797.24
3	12349.0	1757.55
4	12350.0	334.40
…	…	…
4367	18280.0	180.60
4368	18281.0	80.82
4369	18282.0	176.60
4370	18283.0	2045.53
4371	18287.0	1837.28

[4372 rows x 2 columns]

[70]:

```
#Also creating a seperate table for Customers for RFM. First merging frequency␣
↪with recgency and then that table with monetary
temp_ = recency.merge(frequency, on='CustomerID')
rfm_table = temp_.merge(monetary, on='CustomerID')
```

[71]:

```
rfm_table
```

[71]:

	CustomerID	Recency	Frequency	Monetary
0	12346.0	325	2	0.00
1	12347.0	2	7	4310.00
2	12348.0	75	4	1797.24
3	12349.0	18	1	1757.55
4	12350.0	310	1	334.40
…	…	…	…	…
4367	18280.0	277	1	180.60
4368	18281.0	180	1	80.82
4369	18282.0	7	3	176.60
4370	18283.0	3	16	2045.53
4371	18287.0	42	3	1837.28

[4372 rows x 4 columns]

[72]:

```
#RFM Table integrity Check
# Fetch the records corresponding to the first customer id in above table
df1.groupby('CustomerID').Total_cost.sum()
#Data matches
```

[72]:

```
CustomerID
12346.0       0.00
12347.0    4310.00
```

```
12348.0    1797.24
12349.0    1757.55
12350.0     334.40
             …
18280.0     180.60
18281.0      80.82
18282.0     176.60
18283.0    2045.53
18287.0    1837.28
Name: Total_cost, Length: 4372, dtype: float64
```

[73]:
```
temp = df1.groupby('CustomerID').InvoiceDate.max().dt.date
temp = current_date - temp
temp
#Data Matches
```

[73]:
```
CustomerID
12346.0   325 days
12347.0     2 days
12348.0    75 days
12349.0    18 days
12350.0   310 days
             …
18280.0   277 days
18281.0   180 days
18282.0     7 days
18283.0     3 days
18287.0    42 days
Name: InvoiceDate, Length: 4372, dtype: timedelta64[ns]
```

[74]:
```
# RFM Quantiles
quantiles = rfm_table.quantile(q=[0.25,0.5,0.75, 1])
quantiles
```

[74]:

	CustomerID	Recency	Frequency	Monetary
0.25	13812.75	16.0	1.0	291.795
0.50	15300.50	50.0	3.0	644.070
0.75	16778.25	143.0	5.0	1608.335
1.00	18287.00	373.0	248.0	279489.020

[75]:
```
#convert quartile information into a dictionary so that cutoffs can be picked␣
↪up. Like a lookup table
quantiles=quantiles.to_dict()
quantiles
```

[75]:
```
{'CustomerID': {0.25: 13812.75, 0.5: 15300.5, 0.75: 16778.25, 1.0: 18287.0},
 'Recency': {0.25: 16.0, 0.5: 50.0, 0.75: 143.0, 1.0: 373.0},
```

```
 'Frequency': {0.25: 1.0, 0.5: 3.0, 0.75: 5.0, 1.0: 248.0},
 'Monetary': {0.25: 291.795,
  0.5: 644.0700000000002,
  0.75: 1608.335,
  1.0: 279489.0199999991}}
```

[76]:
```
#RFM Segments
# Arguments (x = value, p = recency, monetary_value, frequency, d = quantiles␣
↪dict)
def RScore(x,p,d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1

# Arguments (x = value, p = recency, monetary_value, frequency, k = quantiles␣
↪dict)
def FMScore(x,p,d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.50]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4
```

[77]:
```
#rfm_table['segment'] = rfm_table.copy()
rfm_table['R_Quartile'] = rfm_table['Recency'].apply(RScore,␣
↪args=('Recency',quantiles,))
rfm_table['F_Quartile'] = rfm_table['Frequency'].apply(FMScore,␣
↪args=('Frequency',quantiles,))
rfm_table['M_Quartile'] = rfm_table['Monetary'].apply(FMScore,␣
↪args=('Monetary',quantiles,))
rfm_table
```

[77]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0        12346.0      325          2      0.00           1           2
1        12347.0        2          7   4310.00           4           4
2        12348.0       75          4   1797.24           2           3
3        12349.0       18          1   1757.55           3           1
4        12350.0      310          1    334.40           1           1
…            …        …          …         …           …           …
```

```
4367     18280.0      277          1    180.60          1           1
4368     18281.0      180          1     80.82          1           1
4369     18282.0        7          3    176.60          4           2
4370     18283.0        3         16   2045.53          4           4
4371     18287.0       42          3   1837.28          3           2

      M_Quartile
0              1
1              4
2              4
3              4
4              2
…            …
4367           1
4368           1
4369           1
4370           4
4371           4

[4372 rows x 7 columns]
```

[78]:
```
rfm_table['RFMScore'] = rfm_table.R_Quartile.map(str) \
                            + rfm_table.F_Quartile.map(str) \
                            + rfm_table.M_Quartile.map(str)
rfm_table
```

[78]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0        12346.0      325          2      0.00           1           2
1        12347.0        2          7   4310.00           4           4
2        12348.0       75          4   1797.24           2           3
3        12349.0       18          1   1757.55           3           1
4        12350.0      310          1    334.40           1           1
…            …        …         …        …          …          …
4367     18280.0      277          1    180.60           1           1
4368     18281.0      180          1     80.82           1           1
4369     18282.0        7          3    176.60           4           2
4370     18283.0        3         16   2045.53           4           4
4371     18287.0       42          3   1837.28           3           2

      M_Quartile RFMScore
0              1      121
1              4      444
2              4      234
3              4      314
4              2      112
…            …        …
4367           1      111
```

```
4368            1      111
4369            1      421
4370            4      444
4371            4      324

[4372 rows x 8 columns]
```

[79]:
```
#Integrity Check - Passed
rfm_table.iloc[0,7] < rfm_table.iloc[1,7]
```

[79]:
```
True
```

[80]:
```
rfm_table['RFM_Score'] = rfm_table[['R_Quartile','F_Quartile','M_Quartile']].
 ↪sum(axis=1)
#Assigning Score to the RFM before categorization. Will help later in plotting
rfm_table
```

[80]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0        12346.0      325          2      0.00           1           2
1        12347.0        2          7   4310.00           4           4
2        12348.0       75          4   1797.24           2           3
3        12349.0       18          1   1757.55           3           1
4        12350.0      310          1    334.40           1           1
…            …       …          …         …           …
4367     18280.0      277          1    180.60           1           1
4368     18281.0      180          1     80.82           1           1
4369     18282.0        7          3    176.60           4           2
4370     18283.0        3         16   2045.53           4           4
4371     18287.0       42          3   1837.28           3           2

      M_Quartile RFMScore  RFM_Score
0              1      121          4
1              4      444         12
2              4      234          9
3              4      314          8
4              2      112          4
…            …       …          …
4367           1      111          3
4368           1      111          3
4369           1      421          7
4370           4      444         12
4371           4      324          9

[4372 rows x 9 columns]
```

[81]:
```
# Create a dictionary for each segment to map them against each customer
segment_dict = {
```

```
    'Best Customers':'444',      # Highest frequency as well as monetary value␣
↪with least recency
    'Loyal Customers':'344',     # High frequency as well as monetary value␣
↪with good recency
    'Big Spenders':'334',        # High monetary value but good recency and␣
↪frequency values
    'Almost Lost':'244',         # Customer's shopping less often now who used␣
↪to shop a lot
    'Lost Customers':'144',      # Customer's shopped long ago who used to shop␣
↪a lot.
    'Recent Customers':'443',    # Customer's who recently started shopping a␣
↪lot but with less monetary value
    'Lost Cheap Customers':'122', # Customer's shopped long ago but with less␣
↪frequency and monetary value
    'No Harm to Lose Cheap Customers':'211' # Customer's shopped sometime back␣
↪ago but with less frequency and monetary value
}
```

[82]:
```
# Swap the key and value of dictionary. So that Lookup is from value to␣
↪Customer type and not vie-versa
dict_segment = dict(zip(segment_dict.values(),segment_dict.keys()))
rfm_table['Segment'] = rfm_table.RFMScore.map(lambda x: dict_segment.get(x))
```

[83]:
```
rfm_table
```

[83]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0        12346.0      325          2      0.00           1           2
1        12347.0        2          7   4310.00           4           4
2        12348.0       75          4   1797.24           2           3
3        12349.0       18          1   1757.55           3           1
4        12350.0      310          1    334.40           1           1
…            …      …         …         …          …
4367     18280.0      277          1    180.60           1           1
4368     18281.0      180          1     80.82           1           1
4369     18282.0        7          3    176.60           4           2
4370     18283.0        3         16   2045.53           4           4
4371     18287.0       42          3   1837.28           3           2

      M_Quartile RFMScore  RFM_Score         Segment
0              1      121          4            None
1              4      444         12  Best Customers
2              4      234          9            None
3              4      314          8            None
4              2      112          4            None
…           …      …         …           …
4367           1      111          3            None
```

```
4368           1      111          3          None
4369           1      421          7          None
4370           4      444         12  Best Customers
4371           4      324          9          None

[4372 rows x 10 columns]
```

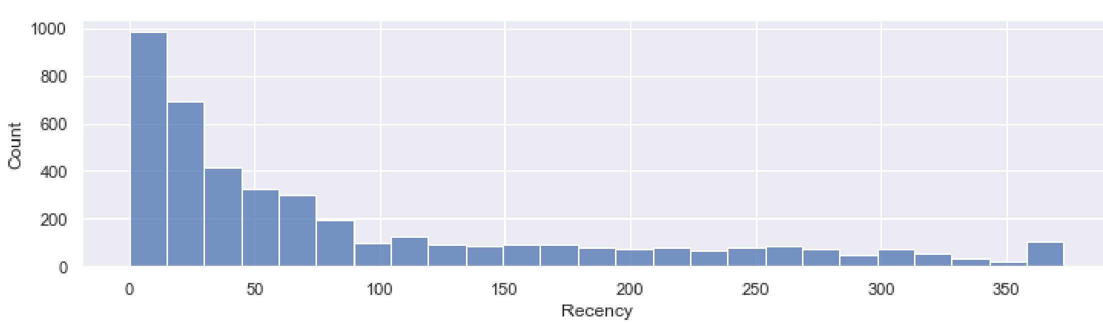
[84]:
```
rfm_table.groupby('Segment').CustomerID.count()
```

[84]:
```
Segment
Almost Lost                        90
Best Customers                    482
Big Spenders                       55
Lost Cheap Customers              151
Lost Customers                     13
Loyal Customers                   225
No Harm to Lose Cheap Customers   177
Recent Customers                   99
Name: CustomerID, dtype: int64
```

Almost Lost 90 Best Customers 482 - These need Promotion materials and other engagement Big Spenders 55 These need exclusive product - high end newsletters Lost Cheap Customers 151 They may come back but focus spening is not recommended Lost Customers 13 No effort to win them back Loyal Customers 225 They need focused product list and AI buil-in recommendation No Harm to Lose Cheap Customers 177 Won't spend of this category Recent Customers 99 Need to keep their interest alive - promote newer things on their spending using product recommendation

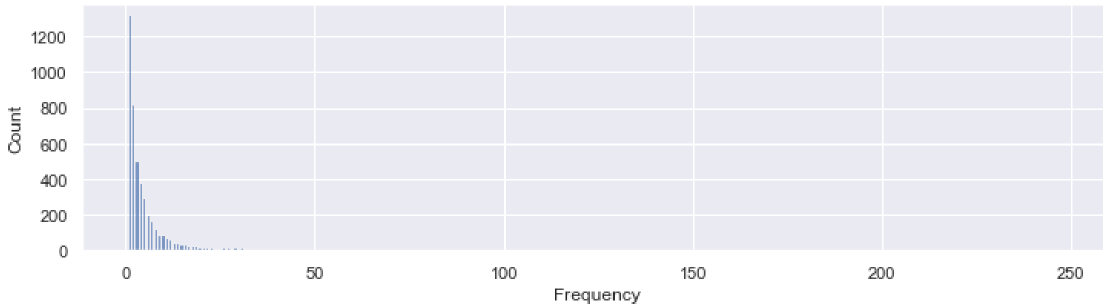
[85]:
```
# Checking the distribution of variables.
plt.figure(figsize=(12,10))
# Plot distribution of Recency
plt.subplot(3, 1, 1); sns.histplot(rfm_table['Recency'])
```

[85]: <AxesSubplot:xlabel='Recency', ylabel='Count'>



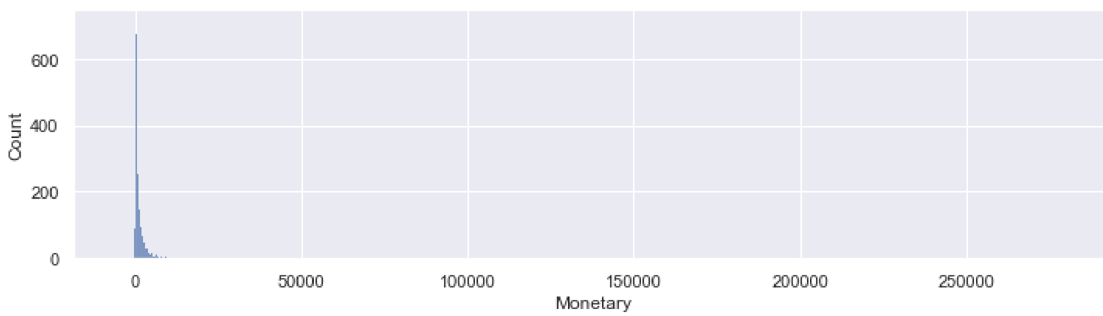
[86]:
```python
# Plot distribution of Frequency
plt.figure(figsize=(12,10))
plt.subplot(3, 1, 2); sns.histplot(rfm_table['Frequency'])
```

[86]: <AxesSubplot:xlabel='Frequency', ylabel='Count'>



[87]:
```python
# Checking the distribution of variables.
plt.figure(figsize=(12,10))
# Plot distribution of Monetary
plt.subplot(3, 1, 3); sns.histplot(rfm_table['Monetary'])
```

[87]: <AxesSubplot:xlabel='Monetary', ylabel='Count'>



[88]:
```python
# Checking the distribution of variables.
plt.figure(figsize=(12,10))
# Plot distribution of RFM_Score Segment
plt.subplot(3, 1, 3); sns.histplot(rfm_table['RFM_Score'])
```

[88]: <AxesSubplot:xlabel='RFM_Score', ylabel='Count'>

[89]:
```
rfm_table.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4372 entries, 0 to 4371
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   CustomerID  4372 non-null   float64
 1   Recency     4372 non-null   int64
 2   Frequency   4372 non-null   int64
 3   Monetary    4372 non-null   float64
 4   R_Quartile  4372 non-null   int64
 5   F_Quartile  4372 non-null   int64
 6   M_Quartile  4372 non-null   int64
 7   RFMScore    4372 non-null   object
 8   RFM_Score   4372 non-null   int64
 9   Segment     1292 non-null   object
dtypes: float64(2), int64(6), object(2)
memory usage: 375.7+ KB
```

[90]:
```
rfm_table.describe()
```

[90]:
```
        CustomerID      Recency    Frequency       Monetary   R_Quartile  \
count  4372.000000  4372.000000  4372.000000    4372.000000  4372.000000
mean  15299.677722    91.581199     5.075480    1893.531433     2.510979
std    1722.390705   100.772139     9.338754    8218.696204     1.117084
min   12346.000000     0.000000     1.000000   -4287.630000     1.000000
25%   13812.750000    16.000000     1.000000     291.795000     2.000000
50%   15300.500000    50.000000     3.000000     644.070000     3.000000
75%   16778.250000   143.000000     5.000000    1608.335000     4.000000
max   18287.000000   373.000000   248.000000  279489.020000     4.000000

        F_Quartile   M_Quartile    RFM_Score
count  4372.000000  4372.000000  4372.000000
mean      2.349039     2.500000     7.360018
```

```
std        1.151264     1.118162     2.872703
min        1.000000     1.000000     3.000000
25%        1.000000     1.750000     5.000000
50%        2.000000     2.500000     7.000000
75%        3.000000     3.250000    10.000000
max        4.000000     4.000000    12.000000
```

K-Means Clustering From the above plots and rfm_table, we see that data is highly skewed. It needs to be transformed and scale the data first because K-Means assumes that the variables should have a symmetric distributions(not skewed) and they should have same average values as well as same variance.

Also, noticed, -ve value in monetery. minimum range of value starts from 1 otherwise log transformation may lead to errors in graph plotting as well as K-Means clustering. After that we will utilize log transformation and scaling to make data available for for K-Means clustering.

The k-means algorithm is an unsupervised clustering algorithm. It takes a bunch of unlabeled points and tries to group them into "k" number of clusters. It is unsupervised because the points have no external classification.

Step 0: Preparing the data; scaling and removal of -ve values Step 1: Determine K value by Elbow method and specify the number of clusters K Step 2: Randomly assign each data point to a cluster Step 3: Determine the cluster centroid coordinates Step 4: Determine the distances of each data point to the centroids and re-assign each point to the closest cluster centroid based upon minimum distance Step 5: Calculate cluster centroids again Step 6: Repeat steps 4 and 5 until we reach global optima where no improvements are possible and no switching of data points from one cluster to other.

[91]:
```python
# Create a copy of rfm table for scaled calculation
rfm_s = rfm_table.copy()

# Shift all values in the column by adding absolute of minimum value to each␣
↪value, thereby making each value positive.
rfm_s.Monetary = rfm_s.Monetary + abs(rfm_s.Monetary.min()) + 1
rfm_s.Recency = rfm_s.Recency + abs(rfm_s.Recency.min()) + 1

# Check the summary of new values
rfm_s.describe()
```

[91]:
```
        CustomerID      Recency    Frequency       Monetary   R_Quartile  \
count  4372.000000  4372.000000  4372.000000    4372.000000  4372.000000
mean  15299.677722    92.581199     5.075480    6182.161433     2.510979
std    1722.390705   100.772139     9.338754    8218.696204     1.117084
min   12346.000000     1.000000     1.000000       1.000000     1.000000
25%   13812.750000    17.000000     1.000000    4580.425000     2.000000
50%   15300.500000    51.000000     3.000000    4932.700000     3.000000
75%   16778.250000   144.000000     5.000000    5896.965000     4.000000
max   18287.000000   374.000000   248.000000  283777.650000     4.000000
```

```
       F_Quartile   M_Quartile    RFM_Score
count  4372.000000  4372.000000  4372.000000
mean      2.349039     2.500000     7.360018
std       1.151264     1.118162     2.872703
min       1.000000     1.000000     3.000000
25%       1.000000     1.750000     5.000000
50%       2.000000     2.500000     7.000000
75%       3.000000     3.250000    10.000000
max       4.000000     4.000000    12.000000
```

[92]:
```
rfm_s.head()
```

[92]:
```
   CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0     12346.0      326          2   4288.63           1           2
1     12347.0        3          7   8598.63           4           4
2     12348.0       76          4   6085.87           2           3
3     12349.0       19          1   6046.18           3           1
4     12350.0      311          1   4623.03           1           1

   M_Quartile RFMScore  RFM_Score         Segment
0           1      121          4            None
1           4      444         12  Best Customers
2           4      234          9            None
3           4      314          8            None
4           2      112          4            None
```

Since it is unsupervised learning, we do not need to define the the Segment & RFM_Score. We need the raw 3 components to find the clusters. Later we would add it in main table to see which cluster the cusomer belongs to.

Seperating the three main inputs for K-CLustering and scale it

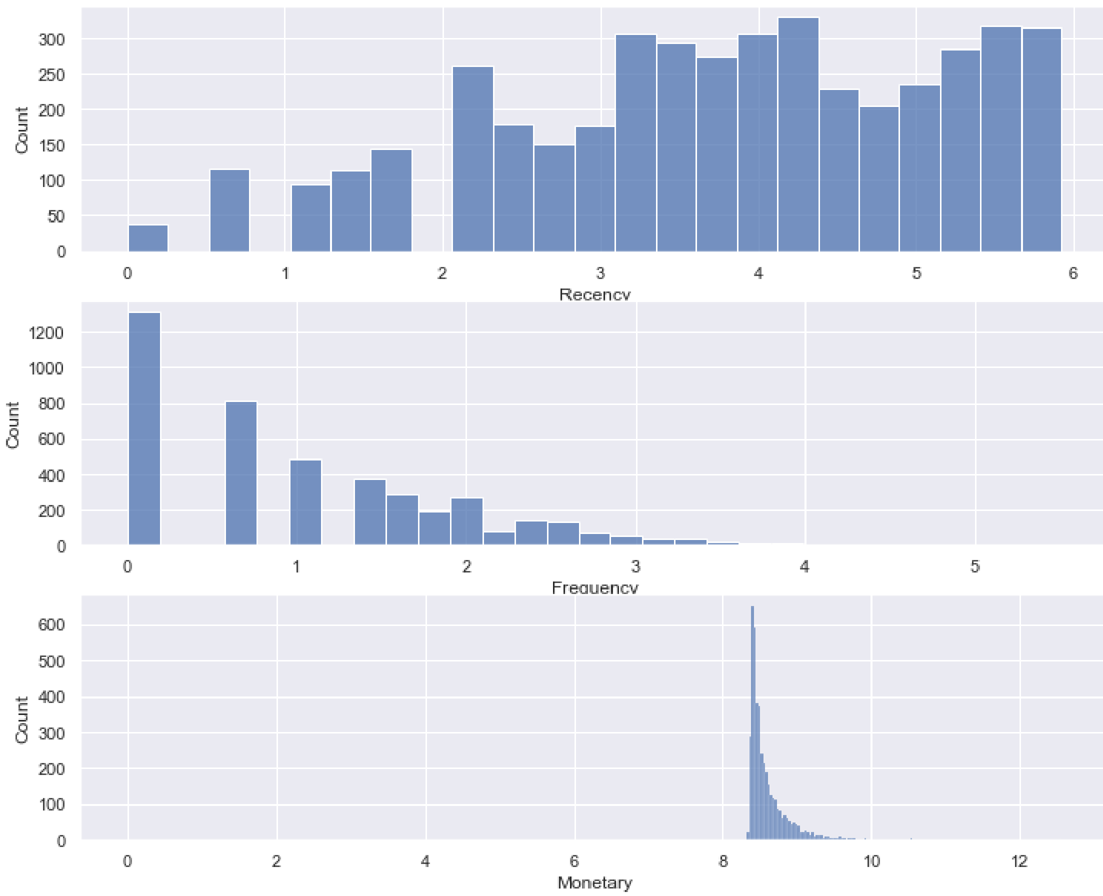
[93]:
```
raw_data = rfm_s[['Recency','Frequency','Monetary']]
data_log = np.log(raw_data)

# Initialize a standard scaler and fit it
scaler = StandardScaler()
scaler.fit(data_log)

# Scale and center the data
data_normalized = scaler.transform(data_log)

# Create a pandas DataFrame
data_norm = pd.DataFrame(data=data_log, index=raw_data.index, columns=raw_data.
 ↪columns)

data_norm.head()
```

[93]:

	Recency	Frequency	Monetary
0	5.786897	0.693147	8.363723
1	1.098612	1.945910	9.059358
2	4.330733	1.386294	8.713725
3	2.944439	0.000000	8.707182
4	5.739793	0.000000	8.438806

[94]:

```
#Plotting the figures again to see if it is normalized

plt.figure(figsize=(12,10))

# Plot recency distribution
plt.subplot(3, 1, 1); sns.histplot(data_norm['Recency'])

# Plot frequency distribution
plt.subplot(3, 1, 2); sns.histplot(data_norm['Frequency'])

# Plot monetary value distribution
plt.subplot(3, 1, 3); sns.histplot(data_norm['Monetary'])

# Show the plot
plt.show()
```



Finding out the optimum value of the clusters using elbow method and using the feature in Kmean called inertia_

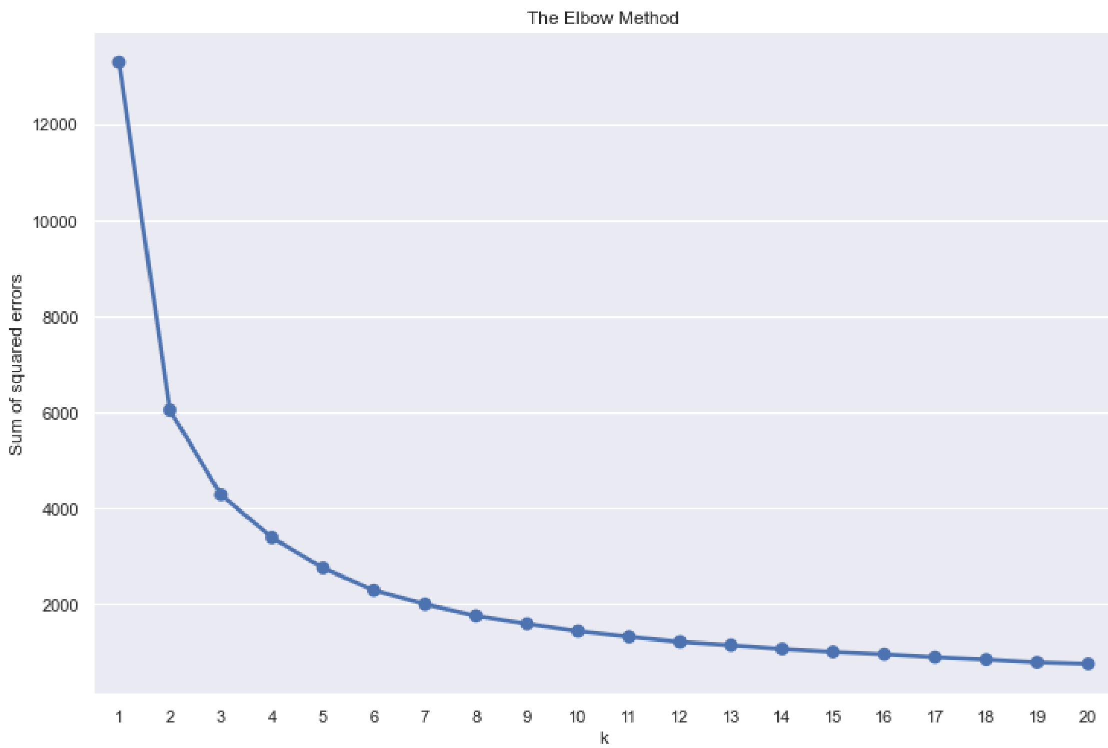
Inertia measures how well a dataset was clustered by K-Means. It is calculated by measuring the distance between each data point and its centroid, squaring this distance, and summing these squares across one cluster.

A good model is one with low inertia AND a low number of clusters (K). However, this is a tradeoff because as K increases, inertia decreases.

In Figure below the slowdown occurs at 5 but sharp cut starts at 3. So, we take 5 or 3 as the number of cluster = k = 5

[137]:
```
sse = {}

# Fit KMeans and calculate SSE for each k
for k in range(1, 21):

    # Initialize KMeans with k clusters
    kmeans = KMeans(n_clusters=k, random_state=1)

```

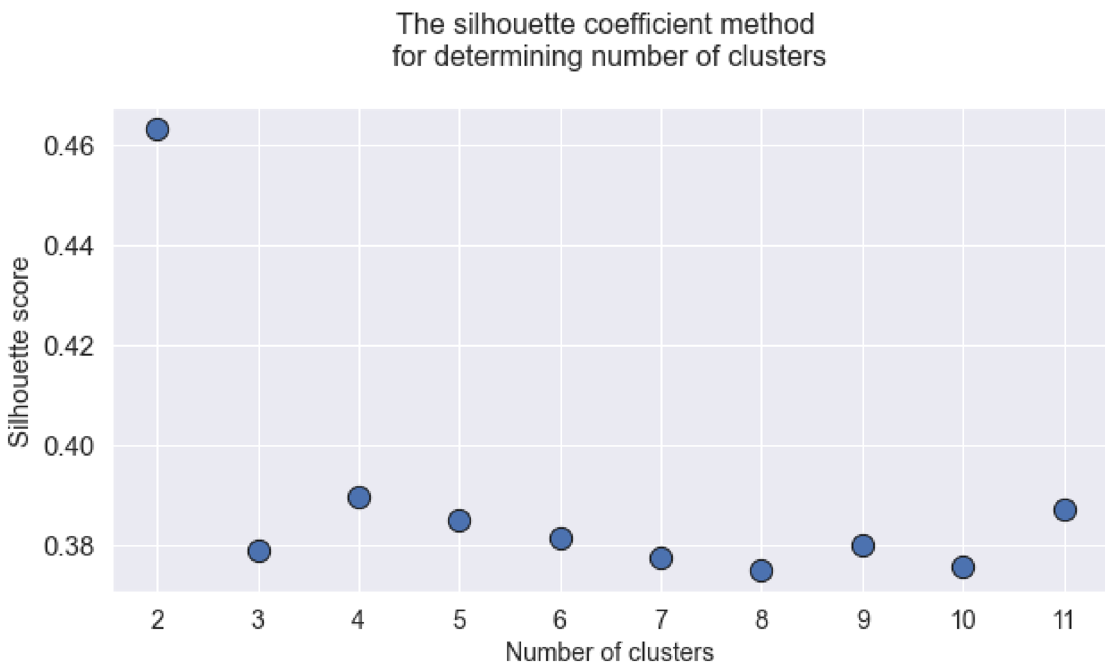
```
    # Fit KMeans on the normalized dataset
    kmeans.fit(data_norm)

    # Assign sum of squared distances to k element of dictionary
    sse[k] = kmeans.inertia_

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

plt.title('The Elbow Method')
plt.xlabel('k');
plt.ylabel('Sum of squared errors')
sns.pointplot(x=list(sse.keys()), y=list(sse.values()))
plt.show()
```



[140]:
```
#Confirming as the same
from sklearn.metrics import silhouette_score
wcss_silhouette = []
for i in range(2,12):
    km = KMeans(n_clusters=i, random_state=0,init='k-means++').fit(data_norm)
    preds = km.predict(data_norm)
    silhouette = silhouette_score(data_norm,preds)
    wcss_silhouette.append(silhouette)
```

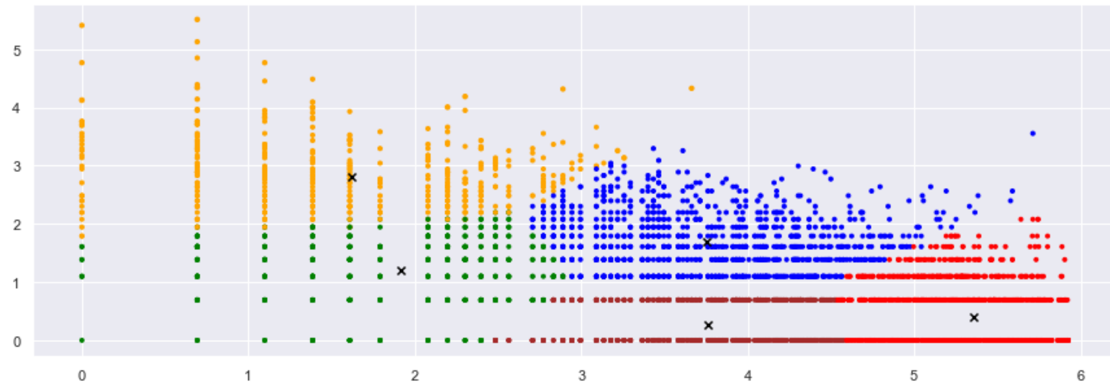
```
    print("Silhouette score for number of cluster(s) {}: {}".
 ↪format(i,silhouette))
                                                                        ␣
 ↪                                                                      ␣
 ↪                                                                      ␣
 ↪                                                                      ␣
 ↪                                                                      ␣
 ↪                                                                      ␣
 ↪                                                                      ␣
 ↪                                                                      ␣
 ↪5-
plt.figure(figsize=(10,5))
plt.title("The silhouette coefficient method \nfor determining number of␣
 ↪clusters\n",fontsize=16)
plt.scatter(x=[i for i in range(2,12)],y=wcss_silhouette,s=150,edgecolor='k')
plt.grid(True)
plt.xlabel("Number of clusters",fontsize=14)
plt.ylabel("Silhouette score",fontsize=15)
plt.xticks([i for i in range(2,12)],fontsize=14)
plt.yticks(fontsize=15)
plt.show()
```

```
Silhouette score for number of cluster(s) 2: 0.46320292333881263
Silhouette score for number of cluster(s) 3: 0.37882385562792953
Silhouette score for number of cluster(s) 4: 0.38942882326747985
Silhouette score for number of cluster(s) 5: 0.38480602348390036
Silhouette score for number of cluster(s) 6: 0.3814620438903689
Silhouette score for number of cluster(s) 7: 0.37740088768033014
Silhouette score for number of cluster(s) 8: 0.3749214782348163
Silhouette score for number of cluster(s) 9: 0.379746242901208
Silhouette score for number of cluster(s) 10: 0.37572690058058267
Silhouette score for number of cluster(s) 11: 0.3869596058631919
```



[141]:
```
#Implementation of K-Means Clustering

plt.figure(figsize=(15,5))

model = KMeans(n_clusters = 5)
model.fit(data_norm)

#Extract cluster labels from labels_ attribute
cluster_labels = model.labels_
centers = np.array(model.cluster_centers_)

plt.plot()


colormap = np.array(['Red', 'Blue', 'Green', 'Orange', 'Brown', 'Black'])
z = plt.scatter(data_norm.Recency, data_norm.Frequency, data_norm.Monetary,  c␣
↪= colormap[cluster_labels])
plt.scatter(centers[:,0], centers[:,1], marker="x", color='Black')
```

[141]:
```
<matplotlib.collections.PathCollection at 0x2cae3bece50>
```



[100]:
```python
# Create a cluster label column in the original DataFrame
data_norm_k5 = data_norm.assign(Cluster = model.labels_)
data_k5 = raw_data.assign(Cluster = model.labels_)

# Calculate average RFM values and size for each cluster
summary_k5 = data_k5.groupby(['Cluster']).agg({'Recency': 'mean',
                                                 'Frequency': 'mean',
                                                 'Monetary': ['mean',␣
 ↪'count'],}).round(0)

summary_k5
```

[100]:

	Recency	Frequency	Monetary	
	mean	mean	mean	count
Cluster				
0	229.0	2.0	4743.0	1279
1	9.0	4.0	5404.0	646
2	51.0	1.0	4751.0	873
3	53.0	6.0	6197.0	1120
4	7.0	21.0	14061.0	454

[101]:
```python
data_norm_k5.index = rfm_s['CustomerID'].astype(int)
data_norm_k5
```

[101]:

	Recency	Frequency	Monetary	Cluster
CustomerID				
12346	5.786897	0.693147	8.363723	0
12347	1.098612	1.945910	9.059358	4
12348	4.330733	1.386294	8.713725	3
12349	2.944439	0.000000	8.707182	2
12350	5.739793	0.000000	8.438806	0
…	…	…	…	…
18280	5.627621	0.000000	8.404971	0

```
18281        5.198497   0.000000  8.382392        0
18282        2.079442   1.098612  8.404076        1
18283        1.386294   2.772589  8.753712        4
18287        3.761200   1.098612  8.720283        3

[4372 rows x 4 columns]
```

[102]:
```python
# Assign the clusters as column to each customer

Cluster_table = rfm_s.assign(Cluster = cluster_labels)
Cluster_table
```

[102]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
0        12346.0      326          2   4288.63           1           2
1        12347.0        3          7   8598.63           4           4
2        12348.0       76          4   6085.87           2           3
3        12349.0       19          1   6046.18           3           1
4        12350.0      311          1   4623.03           1           1
…            …        …          …        …           …
4367     18280.0      278          1   4469.23           1           1
4368     18281.0      181          1   4369.45           1           1
4369     18282.0        8          3   4465.23           4           2
4370     18283.0        4         16   6334.16           4           4
4371     18287.0       43          3   6125.91           3           2

      M_Quartile RFMScore  RFM_Score         Segment  Cluster
0              1      121          4            None        0
1              4      444         12  Best Customers        4
2              4      234          9            None        3
3              4      314          8            None        2
4              2      112          4            None        0
…            …        …          …             …      …
4367           1      111          3            None        0
4368           1      111          3            None        0
4369           1      421          7            None        1
4370           4      444         12  Best Customers        4
4371           4      324          9            None        3

[4372 rows x 11 columns]
```

[103]:
```python
# Check counts of records assigned to different clusters
Cluster_table.Cluster.value_counts()
```

[103]:
```
0    1279
3    1120
2     873
1     646
```

```
4     454
Name: Cluster, dtype: int64
```

[104]:
```
#Cluster_table
Inference = Cluster_table.groupby(['Cluster']).agg({'RFM_Score': 'mean'}).
↪round(0)
Inference
#summary_k5 = data_k5.groupby(['Cluster'])
```

[104]:
```
         RFM_Score
Cluster
0              4.0
1              9.0
2              6.0
3              9.0
4             12.0
```

[105]:
```
Cluster_table[Cluster_table.Cluster == 0].sample(10)
```

[105]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
4081     17890.0      323          2   4875.52           1           2
2016     15083.0      257          1   4376.83           1           1
3223     16714.0      219          4   5167.69           1           3
1826     14816.0      198          1   4560.48           1           1
2550     15789.0      359          1   4639.93           1           1
2765     16093.0      107          1   4305.63           2           1
242      12641.0      116          1   4474.53           2           1
758      13343.0      173          2   4592.56           1           2
841      13466.0      101          2   4586.58           2           2
3798     17508.0      281          1   4675.94           1           1

      M_Quartile RFMScore  RFM_Score                          Segment  Cluster
4081           2      122          5            Lost Cheap Customers        0
2016           1      111          3                            None        0
3223           3      133          7                            None        0
1826           1      111          3                            None        0
2550           2      112          4                            None        0
2765           1      211          4  No Harm to Lose Cheap Customers        0
242            1      211          4  No Harm to Lose Cheap Customers        0
758            2      122          5            Lost Cheap Customers        0
841            2      222          6                            None        0
3798           2      112          4                            None        0
```

[106]:
```
Cluster_table[Cluster_table.Cluster == 1].sample(10)
```

[106]:
```
      CustomerID  Recency  Frequency  Monetary  R_Quartile  F_Quartile  \
520      13017.0        8          1   4492.63           4           1
```

3890	17631.0	2	3	4816.96	4	2
3885	17624.0	15	2	5132.11	4	2
232	12627.0	11	7	8767.16	4	4
4280	18167.0	4	6	5644.14	4	4
566	13083.0	5	2	4592.38	4	2
3931	17682.0	11	7	6747.96	4	4
1471	14335.0	17	2	4743.49	4	2
1346	14157.0	20	3	4681.07	3	2
247	12646.0	5	2	5635.60	4	2

	M_Quartile	RFMScore	RFM_Score	Segment	Cluster
520	1	411	6	None	1
3890	2	422	8	None	1
3885	3	423	9	None	1
232	4	444	12	Best Customers	1
4280	3	443	11	Recent Customers	1
566	2	422	8	None	1
3931	4	444	12	Best Customers	1
1471	2	422	8	None	1
1346	2	322	7	None	1
247	3	423	9	None	1

[107]:
```
Cluster_table[Cluster_table.Cluster == 2].sample(10)
```

[107]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile \
570	13091.0	22	2	4608.45	3	2
4188	18040.0	20	2	4645.83	3	2
1602	14508.0	23	2	4556.68	3	2
1202	13960.0	22	2	4518.85	3	2
1249	14029.0	64	2	4756.29	2	2
1404	14236.0	81	2	4779.49	2	2
2381	15565.0	51	2	4461.79	3	2
58	12420.0	64	1	4889.02	2	1
3446	17011.0	31	1	4559.53	3	1
3349	16878.0	25	2	4288.63	3	2

	M_Quartile	RFMScore	RFM_Score	Segment	Cluster
570	2	322	7	None	2
4188	2	322	7	None	2
1602	1	321	6	None	2
1202	1	321	6	None	2
1249	2	222	6	None	2
1404	2	222	6	None	2
2381	1	321	6	None	2
58	2	212	5	None	2
3446	1	311	5	None	2
3349	1	321	6	None	2

[108]:
```
Cluster_table[Cluster_table.Cluster == 3].sample(10)
```

[108]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile
3556	17166.0	39	3	4478.12	3	2
1430	14273.0	52	4	4848.60	2	3
3147	16609.0	16	9	9739.59	4	4
2310	15468.0	36	5	4727.09	3	3
1477	14342.0	22	6	4896.34	3	4
1338	14147.0	50	3	4757.03	3	2
3246	16743.0	30	8	6455.51	3	4
3769	17462.0	52	3	4951.57	2	2
4208	18069.0	27	7	6283.02	3	4
1336	14145.0	47	5	7436.83	3	3

	M_Quartile	RFMScore	RFM_Score	Segment	Cluster
3556	1	321	6	None	3
1430	2	232	7	None	3
3147	4	444	12	Best Customers	3
2310	2	332	8	None	3
1477	2	342	9	None	3
1338	2	322	7	None	3
3246	4	344	11	Loyal Customers	3
3769	3	223	7	None	3
4208	4	344	11	Loyal Customers	3
1336	4	334	10	Big Spenders	3

[109]:
```
Cluster_table[Cluster_table.Cluster == 4].sample(10)
```

[109]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile
2590	15838.0	12	21	37639.39	4	4
3215	16705.0	1	29	18234.76	4	4
3923	17673.0	2	7	5876.70	4	4
3985	17754.0	1	6	5920.94	4	4
4340	18241.0	10	18	6346.72	4	4
3537	17139.0	16	15	14856.50	4	4
3014	16422.0	18	75	38094.32	3	4
115	12490.0	6	10	9706.56	4	4
277	12682.0	4	31	16568.45	4	4
4192	18044.0	5	11	6374.28	4	4

	M_Quartile	RFMScore	RFM_Score	Segment	Cluster
2590	4	444	12	Best Customers	4
3215	4	444	12	Best Customers	4
3923	3	443	11	Recent Customers	4
3985	4	444	12	Best Customers	4
4340	4	444	12	Best Customers	4
3537	4	444	12	Best Customers	4

```
3014            4      344          11   Loyal Customers        4
115             4      444          12    Best Customers        4
277             4      444          12    Best Customers        4
4192            4      444          12    Best Customers        4
```

CLuster 0 & 4 does not matter for us. Their RFM Score avg is low, and as we see they do not fall under any specialized marketing plan. They are the ones, who have very low RF&M. Though their number is high. They may be chaced customer who happen to drop in by some add etc.

1 & 3 has few categories that we had defined. Still a lot of effort is not to be directed on this cluster. Normal exposure to brand is good enough.

2 is the category we should be foucsing out attention to. Their RFM avg is 12

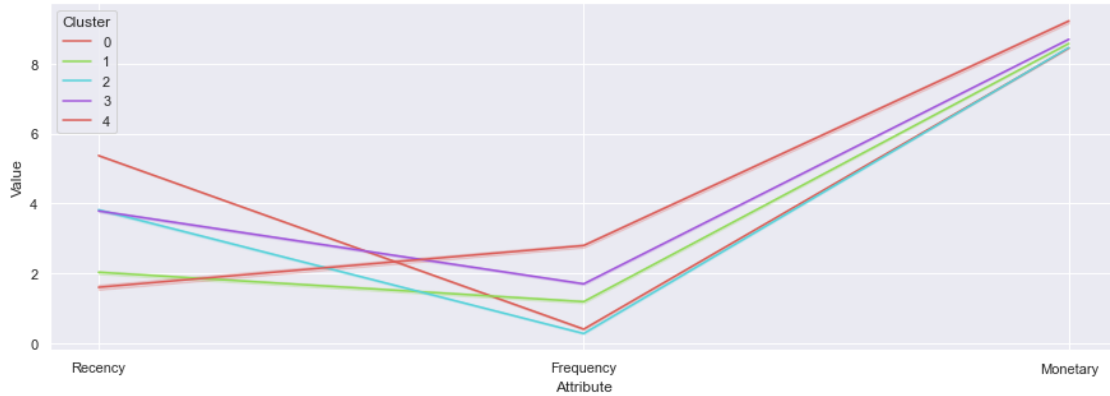
Snake plots Market research technique to compare different segments Visual representation of each segment's attributes Plot each cluster's average normalized values of each attribute To plot this we should have normalized data distribution and all the attributes in a single column. We will use pandas melt facility to achieve that

[110]:
```
#Melt the data into along format so RFM values and metric names are stored in 1␣
↪column each
data_melt = pd.melt(data_norm_k5.reset_index(),
                    id_vars=['CustomerID', 'Cluster'],
                    value_vars=['Recency', 'Frequency', 'Monetary'],
                    var_name='Attribute',
                    value_name='Value')
data_melt
```

[110]:
```
       CustomerID  Cluster Attribute     Value
0           12346        0   Recency  5.786897
1           12347        4   Recency  1.098612
2           12348        3   Recency  4.330733
3           12349        2   Recency  2.944439
4           12350        0   Recency  5.739793
…             …       …        …         …
13111       18280        0  Monetary  8.404971
13112       18281        0  Monetary  8.382392
13113       18282        1  Monetary  8.404076
13114       18283        4  Monetary  8.753712
13115       18287        3  Monetary  8.720283

[13116 rows x 4 columns]
```

[111]:
```
plt.figure(figsize=(15,5))
sns.lineplot(x="Attribute", y="Value", hue='Cluster', palette = 'hls',␣
↪data=data_melt)
```

[111]: <AxesSubplot:xlabel='Attribute', ylabel='Value'>



0, 1, 2, & 3 show similar spending. 4 & 3 have are very infrequent. 0 shows average frequency of vist, - These are low spending but have a good volume of transaction. 0 cannot be ignores, thought a lot of effort or resources may not be given. but hightest is 2, followed by 1 - they are good spender with good frequency. We would need to make sure we retain them.

Surprizingly 2 shows low recency. So these are planned buyers, not impulsive ones, whole 0 are the impulsive ones.

Now we get cluster average and population av erage to see the relative importance of each cluster Then plot it in heat map

[112]:
```
cluster_avg = data_k5.groupby(['Cluster']).mean()
population_avg = raw_data.head().mean()
```

[113]:
```
population_avg
```

[113]:
```
Recency       147.000
Frequency       3.000
Monetary     5928.468
dtype: float64
```

[114]:
```
cluster_avg
```

[114]:

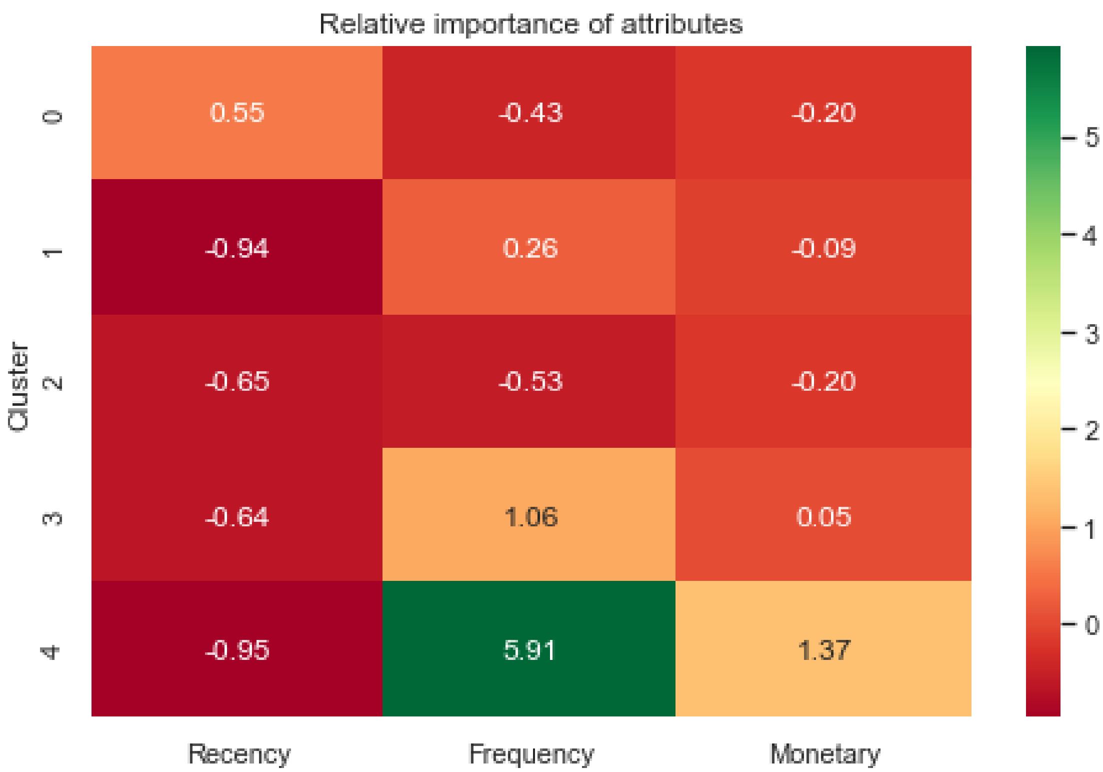
Cluster	Recency	Frequency	Monetary
0	228.553557	1.718530	4742.588234
1	9.105263	3.773994	5404.087043
2	50.983963	1.395189	4750.991639
3	52.691071	6.180357	6196.646055
4	6.696035	20.735683	14061.101145

[115]:
```
relative_imp = cluster_avg / population_avg - 1
relative_imp.round(2)
```

[115]:

	Recency	Frequency	Monetary
Cluster			
0	0.55	-0.43	-0.20
1	-0.94	0.26	-0.09
2	-0.65	-0.53	-0.20
3	-0.64	1.06	0.05
4	-0.95	5.91	1.37

[119]:
```
# Plot heatmap
plt.figure(figsize=(8, 5))
plt.title('Relative importance of attributes')
sns.heatmap(data=relative_imp, annot=True, fmt='.2f', cmap='RdYlGn')
plt.show()
```



#Heat map confirms the findings. Now Reporting Instead of taking to Tableau and merging the data set, creating one excel file here with all the data points required. This file will be used in Tableau for Visulalization

[116]:
```
Cluster_table
```

[116]:

	CustomerID	Recency	Frequency	Monetary	R_Quartile	F_Quartile	\
0	12346.0	326	2	4288.63	1	2	
1	12347.0	3	7	8598.63	4	4	

```
2         12348.0       76          4   6085.87          2            3
3         12349.0       19          1   6046.18          3            1
4         12350.0      311          1   4623.03          1            1
…            …       …        …       …        …          …
4367      18280.0      278          1   4469.23          1            1
4368      18281.0      181          1   4369.45          1            1
4369      18282.0        8          3   4465.23          4            2
4370      18283.0        4         16   6334.16          4            4
4371      18287.0       43          3   6125.91          3            2

      M_Quartile RFMScore  RFM_Score         Segment  Cluster
0              1      121          4            None        0
1              4      444         12  Best Customers        4
2              4      234          9            None        3
3              4      314          8            None        2
4              2      112          4            None        0
…           …       …        …             …       …
4367           1      111          3            None        0
4368           1      111          3            None        0
4369           1      421          7            None        1
4370           4      444         12  Best Customers        4
4371           4      324          9            None        3

[4372 rows x 11 columns]
```

[120]:
```
df1
```

[120]:
```
       InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
4        C536757     84347   ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
10       C550456     21108    FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
20       C550456     21175          GIN + TONIC DIET METAL SIGN     -2000
…            …       …                                …       …
541903    554868     22197                SMALL POPCORN HOLDER      4300
541904    573008     84077     WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
541906    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
541907    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
541908    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
4      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
10     2011-04-18 13:08:00       2.10     15749.0  United Kingdom
20     2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                     …         …          …               …
```

```
541903 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
541904 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
541906 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
541907 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
541908 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost      Month  CohortIndex Purchase_Date
0        2011-12-01   -168469.6 2011-05-01            8    2011-12-09
1        2011-01-01    -77183.6 2011-01-01            1    2011-01-18
4        2010-12-01      -280.8 2010-12-01            1    2010-12-02
10       2011-04-01     -6539.4 2011-01-01            4    2011-04-18
20       2011-04-01     -3700.0 2011-01-01            4    2011-04-18
…             …           …          …          …           …
541903   2011-05-01      3096.0 2011-05-01            1    2011-05-27
541904   2011-10-01      1008.0 2011-03-01            8    2011-10-27
541906   2011-11-01         0.0 2011-11-01            1    2011-11-25
541907   2011-01-01     77183.6 2011-01-01            1    2011-01-18
541908   2011-12-01    168469.6 2011-05-01            8    2011-12-09

[401604 rows x 13 columns]
```

[121]:
```python
FinalFile = pd.merge(df1, Cluster_table, how = 'left', on='CustomerID')
```

[122]:
```python
FinalFile
```

[122]:
```
       InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
2        C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
3        C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
4        C550456     21175          GIN + TONIC DIET METAL SIGN     -2000
…            …        …                                   …        …
401599    554868     22197                  SMALL POPCORN HOLDER      4300
401600    573008     84077     WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
401601    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
401602    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
401603    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
2      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
3      2011-04-18 13:08:00       2.10     15749.0  United Kingdom
4      2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                      …        …          …              …
401599 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
401600 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
```

```
401601 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
401602 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
401603 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost  … Recency  Frequency  Monetary  R_Quartile  \
0        2011-12-01   -168469.6  …       1          3   4291.53           4
1        2011-01-01    -77183.6  …     326          2   4288.63           1
2        2010-12-01      -280.8  …      12         21  37639.39           4
3        2011-04-01     -6539.4  …     236          4  25824.53           1
4        2011-04-01     -3700.0  …     236          4  25824.53           1
…               …          …  …  …       …          …         …
401599   2011-05-01      3096.0  …     197          1   7384.63           1
401600   2011-10-01      1008.0  …       9         36  20581.73           4
401601   2011-11-01         0.0  …      15          1   4288.63           4
401602   2011-01-01     77183.6  …     326          2   4288.63           1
401603   2011-12-01    168469.6  …       1          3   4291.53           4

        F_Quartile  M_Quartile  RFMScore  RFM_Score         Segment Cluster
0                2           1       421          7            None       1
1                2           1       121          4            None       0
2                4           4       444         12  Best Customers       4
3                3           4       134          8            None       0
4                3           4       134          8            None       0
…             …          …       …        …              …      …
401599           1           4       114          6            None       0
401600           4           4       444         12  Best Customers       4
401601           1           1       411          6            None       2
401602           2           1       121          4            None       0
401603           2           1       421          7            None       1

[401604 rows x 23 columns]
```

[128]:
```python
relative_imp.round(2)
```

[128]:
```
         Recency  Frequency  Monetary
Cluster
0           0.55      -0.43     -0.20
1          -0.94       0.26     -0.09
2          -0.65      -0.53     -0.20
3          -0.64       1.06      0.05
4          -0.95       5.91      1.37
```

[129]:
```python
FF = pd.merge(FinalFile, relative_imp, how = 'left', on='Cluster')
```

[130]:
```python
FF
```

[130]:

```
        InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
2        C536757     84347  ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
3        C550456     21108   FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
4        C550456     21175          GIN + TONIC DIET METAL SIGN     -2000
…             …       …                                    …        …
401599    554868     22197                 SMALL POPCORN HOLDER      4300
401600    573008     84077    WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
401601    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
401602    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
401603    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
2      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
3      2011-04-18 13:08:00       2.10     15749.0  United Kingdom
4      2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                      …         …          …              …
401599 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
401600 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
401601 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
401602 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
401603 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost  … R_Quartile  F_Quartile M_Quartile  \
0        2011-12-01   -168469.6  …          4           2          1
1        2011-01-01    -77183.6  …          1           2          1
2        2010-12-01      -280.8  …          4           4          4
3        2011-04-01     -6539.4  …          1           3          4
4        2011-04-01     -3700.0  …          1           3          4
…               …         …   …        …          …         …
401599   2011-05-01      3096.0  …          1           1          4
401600   2011-10-01      1008.0  …          4           4          4
401601   2011-11-01         0.0  …          4           1          1
401602   2011-01-01     77183.6  …          1           2          1
401603   2011-12-01    168469.6  …          4           2          1

        RFMScore  RFM_Score         Segment  Cluster  Recency_y  Frequency_y  \
0            421          7            None        1  -0.938059     0.257998
1            121          4            None        0   0.554786    -0.427157
2            444         12  Best Customers        4  -0.954449     5.911894
3            134          8            None        0   0.554786    -0.427157
4            134          8            None        0   0.554786    -0.427157
…            …        …              …      …        …          …
401599       114          6            None        0   0.554786    -0.427157
```

```
401600       444          12  Best Customers          4  -0.954449     5.911894
401601       411           6            None          2  -0.653170    -0.534937
401602       121           4            None          0   0.554786    -0.427157
401603       421           7            None          1  -0.938059     0.257998

        Monetary_y
0        -0.088451
1        -0.200031
2         1.371793
3        -0.200031
4        -0.200031
…              …
401599   -0.200031
401600    1.371793
401601   -0.198614
401602   -0.200031
401603   -0.088451

[401604 rows x 26 columns]
```

[131]:

```
FF.rename(columns = {'Recency_y':'Recency_Imp'}, inplace = True)
FF.rename(columns = {'Frequency_y':'Frequency_Imp'}, inplace = True)
FF.rename(columns = {'Monetary_y':'Monetary_Imp'}, inplace = True)
FF
```

[131]:

```
       InvoiceNo StockCode                          Description  Quantity  \
0        C581484     23843          PAPER CRAFT , LITTLE BIRDIE    -80995
1        C541433     23166       MEDIUM CERAMIC TOP STORAGE JAR    -74215
2        C536757     84347   ROTATING SILVER ANGELS T-LIGHT HLDR     -9360
3        C550456     21108    FAIRY CAKE FLANNEL ASSORTED COLOUR     -3114
4        C550456     21175          GIN + TONIC DIET METAL SIGN      -2000
…           …        …                                   …        …
401599    554868     22197                 SMALL POPCORN HOLDER      4300
401600    573008     84077     WORLD WAR 2 GLIDERS ASSTD DESIGNS      4800
401601    578841     84826       ASSTD DESIGN 3D PAPER STICKERS     12540
401602    541431     23166       MEDIUM CERAMIC TOP STORAGE JAR     74215
401603    581483     23843          PAPER CRAFT , LITTLE BIRDIE     80995

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-12-09 09:27:00       2.08     16446.0  United Kingdom
1      2011-01-18 10:17:00       1.04     12346.0  United Kingdom
2      2010-12-02 14:23:00       0.03     15838.0  United Kingdom
3      2011-04-18 13:08:00       2.10     15749.0  United Kingdom
4      2011-04-18 13:08:00       1.85     15749.0  United Kingdom
…                       …        …           …             …
401599 2011-05-27 10:52:00       0.72     13135.0  United Kingdom
401600 2011-10-27 12:26:00       0.21     12901.0  United Kingdom
```

```
401601 2011-11-25 15:57:00       0.00     13256.0  United Kingdom
401602 2011-01-18 10:01:00       1.04     12346.0  United Kingdom
401603 2011-12-09 09:15:00       2.08     16446.0  United Kingdom

       InvoiceMonth  Total_cost  … R_Quartile  F_Quartile M_Quartile  \
0        2011-12-01   -168469.6  …          4           2          1
1        2011-01-01    -77183.6  …          1           2          1
2        2010-12-01      -280.8  …          4           4          4
3        2011-04-01     -6539.4  …          1           3          4
4        2011-04-01     -3700.0  …          1           3          4
…               …           …  …        …          …          …
401599   2011-05-01      3096.0  …          1           1          4
401600   2011-10-01      1008.0  …          4           4          4
401601   2011-11-01         0.0  …          4           1          1
401602   2011-01-01     77183.6  …          1           2          1
401603   2011-12-01    168469.6  …          4           2          1

        RFMScore  RFM_Score         Segment  Cluster  Recency_Imp  \
0            421          7            None        1    -0.938059
1            121          4            None        0     0.554786
2            444         12  Best Customers        4    -0.954449
3            134          8            None        0     0.554786
4            134          8            None        0     0.554786
…          …         …              …      …          …
401599       114          6            None        0     0.554786
401600       444         12  Best Customers        4    -0.954449
401601       411          6            None        2    -0.653170
401602       121          4            None        0     0.554786
401603       421          7            None        1    -0.938059

        Frequency_Imp Monetary_Imp
0            0.257998    -0.088451
1           -0.427157    -0.200031
2            5.911894     1.371793
3           -0.427157    -0.200031
4           -0.427157    -0.200031
…                 …            …
401599      -0.427157    -0.200031
401600       5.911894     1.371793
401601      -0.534937    -0.198614
401602      -0.427157    -0.200031
401603       0.257998    -0.088451

[401604 rows x 26 columns]
```

[222]:
```
i= 0
wcss_silhouette
```

```python
sse = pd.DataFrame(wcss_silhouette)
sse
```

[222]:

	0
0	0.463203
1	0.378824
2	0.389429
3	0.384806
4	0.381462
5	0.377401
6	0.374921
7	0.379746
8	0.375727
9	0.386960

[223]:
```python
sse.to_excel(r'D:\OneDrive\Studies\AI - ML\Capstone Project\SSE.xlsx')
```

[132]:
```python
FF.to_excel('Cluster_file.xlsx')
```

SSE file is to create the SSE in Tableau. These two Tables are picked added as source in Tableau as independent tables. The last part is in Tableau Public. Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following: a. Country-wise analysis to demonstrate average spend. - Use a bar chart to show the monthly figures b. Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold c. Bar graph to show the count of orders vs. hours throughout the day d. Plot the distribution of RFM values using histogram and frequency charts e. Plot error (cost) vs. number of clusters selected f. Visualize to compare the RFM values of the clusters using heatmap

Link to Tabelau DAshboard is https://public.tableau.com/app/profile/naseha/viz/CapstoneProject3v1_0-SimpiliLearnOnlineRetail/Country-wiseMonthwiseDetailedDashboard