Context:

This is a transnational data set which contains all the transactions occurring between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail.The company mainly sells unique all-occasion gifts. Many customers of the company are wholesalers. Data Description: InvoiceNo: Invoice number. Nominal, a 6-digit integral number uniquely assigned to each transaction. If this code starts with letter 'c', it indicates a cancellation. StockCode: Product (item) code. Nominal, a 5-digit integral number uniquely assigned to each distinct product. Description: Product (item) name. Nominal. Quantity: The quantities of each product (item) per transaction. Numeric. InvoiceDate: Invoice Date and time. Numeric, the day and time when each transaction was generated. UnitPrice: Unit price. Numeric, Product price per unit in sterling. CustomerID: Customer number. Nominal, a 5-digit integral number uniquely assigned to each customer. Country: Country name. Nominal, the name of the country where each customer resides.

Problem statement

It is a business critical requirement to understand the value derived from a customer. RFM is a method used for analyzing customer value. 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). Identifying the most valuable RFM segments can capitalize on chance relationships in the data used for this analysis. Approach:

Following pointers will be helpful to structure your findings.

1. Perform a preliminary data inspection and Data cleaning

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

b. Are there any duplicate data records? Remove them if present.

c. Perform Descriptive analytics on the given data.

2. Cohort Analysis: A cohort is a group of subjects who share a defining characteristic. We can observe how a cohort behaves across time and compare it to other cohorts.

a. Create month cohorts and analyse active customers for each cohort.

b. Also Analyse the retention rate of customers. Comment.

3. Build a RFM model – Recency Frequency and Monetary based on their behaviour.

Recency is about when was the last order of a customer. It means the number of days since a customer made the last purchase. If it's a case for a website or an app, this could be interpreted as the last visit day or the last login time. Frequency is about the number of purchase in a given period. It could be 3 months, 6 months or 1 year. So we can understand this value as for how often or how many a customer used the product of a company. The bigger the value is, the more engaged the customers are. Could we say them as our VIP? Not necessary. Cause we also have to think about how much they actually paid for each purchase, which means monetary value. 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.

a. Calculate RFM metrics.

i. Recency as the time in no. of days since last transaction

ii. Frequency as count of purchases done

iii. Monetary value as total amount spend

b. Build RFM Segments.

i. Give Recency Frequency and Monetary scores individually by dividing them in to quartiles. Note: Rate "Recency" for customer who have been active more recently better than the less recent customer, because each company wants its customers to be recent Rate "Frequency" and "Monetary Value" higher label because we want Customer to spend more money and visit more often.

ii. Combine three ratings to get a RFM segment (as strings)

iii. Get the RFM score by adding up the three ratings.

c. Analyse the RFM Segments by summarizing them and comment on the findings.

4. Create clusters using k means clustering algorithm.

a. Prepare the data for the algorithm.

i. If the data is Un Symmetrically distributed, manage the skewness with appropriate transformation.

ii. Standardize / scale the data.

b. Decide the optimum number of clusters to be formed c. Analyse these clusters and

comment on the results.

5. 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 show 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. What are the peak hours per your chart?

d) Plot the distribution of RFM values using histogram and frequency-charts.

e) Plot error(cost) vs no of clusters selected

f) Visualize to compare the RFM values of the clusters using heatmap

Project Task: Week 1

Data Cleaning:

- Perform a preliminary data inspection and data cleaning.

In [1]:
```
import pandas as pd
import numpy as np

import warnings
warnings.filterwarnings("ignore")

import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns
```

In [2]:
```
df = pd.read_excel('Online Retail.xlsx')
```

In [3]:
```
df.shape
```

Out[3]:
```
(541909, 8)
```

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

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

In [5]:
```
df.head()
```

Out[5]:

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

In [6]:
```
df.describe(include='all')
```

Out[6]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	4(
count	541909.0	541909	540455	541909.000000	541909	541909.000000	
unique	25900.0	4070	4223	NaN	23260	NaN	
top	573585.0	85123A	WHITE HANGING HEART T-LIGHT HOLDER	NaN	2011-10-31 14:41:00	NaN	
freq	1114.0	2313	2369	NaN	1114	NaN	
first	NaN	NaN	NaN	NaN	2010-12-01 08:26:00	NaN	
last	NaN	NaN	NaN	NaN	2011-12-09 12:50:00	NaN	
mean	NaN	NaN	NaN	9.552250	NaN	4.611114	
std	NaN	NaN	NaN	218.081158	NaN	96.759853	
min	NaN	NaN	NaN	-80995.000000	NaN	-11062.060000	
25%	NaN	NaN	NaN	1.000000	NaN	1.250000	
50%	NaN	NaN	NaN	3.000000	NaN	2.080000	
75%	NaN	NaN	NaN	10.000000	NaN	4.130000	
max	NaN	NaN	NaN	80995.000000	NaN	38970.000000	

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

Out[7]:

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

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

In [8]:
```
df.isna().sum().any()
```

Out[8]:
```
True
```

In [9]:
```
df.isnull().sum()
```

Out[9]:
```
InvoiceNo          0
StockCode          0
Description     1454
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     135080
Country            0
dtype: int64
```

In [10]:
```
#Transactions with negative quantity (cancelled orders)

df[df['InvoiceNo'].str.startswith('C')==True]
```

Out[10]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
141	C536379	D	Discount	-1	2010-12-01 09:41:00	27.50	14527.0
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2010-12-01 09:49:00	4.65	15311.0
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2010-12-01 10:24:00	1.65	17548.0
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0
...	...	...	...	...	...	...	...
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2011-12-09 09:57:00	0.83	14397.0
541541	C581499	M	Manual	-1	2011-12-09 10:28:00	224.69	15498.0
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2011-12-09 11:57:00	10.95	15311.0
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2011-12-09 11:58:00	1.25	17315.0
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2011-12-09 11:58:00	1.25	17315.0

9288 rows × 8 columns

In [11]:

```
#removing these cancelled orders entries

df = df[df['InvoiceNo'].str.startswith('C')!=True]
df.shape
```

Out[11]:

```
(532621, 8)
```

In [12]:
```
df.InvoiceNo.nunique()
```

Out[12]:
```
22064
```

In [13]:
```
df.StockCode.nunique()
```

Out[13]:
```
4059
```

In [14]:
```
df.StockCode.value_counts().head(10) #top 10 stock id's that sold the most
```

Out[14]:
```
85123A    2271
85099B    2115
22423     2022
47566     1707
20725     1595
84879     1490
22197     1426
22720     1403
21212     1370
20727     1328
Name: StockCode, dtype: int64
```

In [15]:
```
df.Quantity.describe()
```

Out[15]:
```
count    532621.000000
mean         10.239972
std         159.593551
min       -9600.000000
25%           1.000000
50%           3.000000
75%          10.000000
max       80995.000000
Name: Quantity, dtype: float64
```

In [16]:
```
df[df['Quantity']<0]
```

Out[16]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
2406	536589	21777	NaN	-10	2010-12-01 16:50:00	0.0	NaN
4347	536764	84952C	NaN	-38	2010-12-02 14:42:00	0.0	NaN
7188	536996	22712	NaN	-20	2010-12-03 15:30:00	0.0	NaN
7189	536997	22028	NaN	-20	2010-12-03 15:30:00	0.0	NaN
7190	536998	85067	NaN	-6	2010-12-03 15:30:00	0.0	NaN
...	...	...	...	...	...	...	...
535333	581210	23395	check	-26	2011-12-07 18:36:00	0.0	NaN
535335	581212	22578	lost	-1050	2011-12-07 18:38:00	0.0	NaN
535336	581213	22576	check	-30	2011-12-07 18:38:00	0.0	NaN
536908	581226	23090	missing	-338	2011-12-08 09:56:00	0.0	NaN
538919	581422	23169	smashed	-235	2011-12-08 15:24:00	0.0	NaN

1336 rows × 8 columns

In [17]:

```
df = df[df['Quantity']>=0]
df.shape
```

Out[17]:

```
(531285, 8)
```

In [18]:

```
#This is a transnational data set which contains all the transactions occu
#01/12/2010 and 09/12/2011 for a UK-based and registered non-store online
print('The minimum date is:', df.InvoiceDate.min())
print('The maximum date is:', df.InvoiceDate.max())
```

```
The minimum date is: 2010-12-01 08:26:00
The maximum date is: 2011-12-09 12:50:00
```

In [19]:

```
#checking distribution of unit price
df.UnitPrice.describe()
```

Out[19]:
```
count    531285.000000
mean          3.857296
std          41.810047
min      -11062.060000
25%          1.250000
50%          2.080000
75%          4.130000
max      13541.330000
Name: UnitPrice, dtype: float64
```

In [20]:
```
df.UnitPrice.describe(percentiles=[0.25,0.5,0.75,0.9,0.95,0.99])
```

Out[20]:
```
count    531285.000000
mean          3.857296
std          41.810047
min      -11062.060000
25%          1.250000
50%          2.080000
75%          4.130000
90%          7.950000
95%          9.950000
99%         16.980000
max      13541.330000
Name: UnitPrice, dtype: float64
```

In [21]:
```
df.Country.value_counts()
```

Out[21]:
```
United Kingdom          486286
Germany                   9042
France                    8408
EIRE                      7894
Spain                     2485
Netherlands               2363
Belgium                   2031
Switzerland               1967
Portugal                  1501
Australia                 1185
Norway                    1072
Italy                      758
Channel Islands            748
Finland                    685
Cyprus                     614
Sweden                     451
Unspecified                446
Austria                    398
Denmark                    380
Poland                     330
Japan                      321
Israel                     295
Hong Kong                  284
Singapore                  222
Iceland                    182
USA                        179
Canada                     151
Greece                     145
Malta                      112
United Arab Emirates        68
European Community          60
RSA                         58
Lebanon                     45
Lithuania                   35
Brazil                      32
Czech Republic              25
Bahrain                     18
Saudi Arabia                 9
Name: Country, dtype: int64
```

In [22]:
```
df.Country.value_counts(normalize=True)
```

Out[22]:
```
United Kingdom          0.915302
Germany                 0.017019
France                  0.015826
EIRE                    0.014858
Spain                   0.004677
Netherlands             0.004448
Belgium                 0.003823
Switzerland             0.003702
Portugal                0.002825
Australia               0.002230
Norway                  0.002018
Italy                   0.001427
Channel Islands         0.001408
Finland                 0.001289
Cyprus                  0.001156
Sweden                  0.000849
Unspecified             0.000839
Austria                 0.000749
Denmark                 0.000715
Poland                  0.000621
Japan                   0.000604
Israel                  0.000555
Hong Kong               0.000535
Singapore               0.000418
Iceland                 0.000343
USA                     0.000337
Canada                  0.000284
Greece                  0.000273
Malta                   0.000211
United Arab Emirates    0.000128
European Community      0.000113
RSA                     0.000109
Lebanon                 0.000085
Lithuania               0.000066
Brazil                  0.000060
Czech Republic          0.000047
Bahrain                 0.000034
Saudi Arabia            0.000017
Name: Country, dtype: float64
```

In [23]:
```
#Valuecount of Country shows that we have values more than 90% for UK, so
#So, Combining rest of the countries to one category

df['Country'] = df['Country'].apply(lambda x:'United Kingdom' if x=='Unite
df.Country.value_counts(normalize=True)
```

Out[23]:
```
United Kingdom    0.915302
Others            0.084698
Name: Country, dtype: float64
```

In [24]:
```
df.Description.nunique()
```

Out[24]:
```
4077
```

In [132…
```
df.Description.value_counts().head(15)
```

Out[132…
```
WHITE HANGING HEART T-LIGHT HOLDER    2016
REGENCY CAKESTAND 3 TIER              1714
JUMBO BAG RED RETROSPOT               1615
ASSORTED COLOUR BIRD ORNAMENT         1395
PARTY BUNTING                         1390
LUNCH BAG RED RETROSPOT               1303
SET OF 3 CAKE TINS PANTRY DESIGN      1152
POSTAGE                               1099
LUNCH BAG  BLACK SKULL.               1078
PACK OF 72 RETROSPOT CAKE CASES       1050
SPOTTY BUNTING                        1014
PAPER CHAIN KIT 50'S CHRISTMAS        1003
LUNCH BAG SPACEBOY DESIGN              993
HEART OF WICKER SMALL                  979
LUNCH BAG CARS BLUE                    977
Name: Description, dtype: int64
```

In [26]:
```
df[df['Description'].str.startswith('?')==True]
```

Out[26]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
38261	539494	21479	?	752	2010-12-20 10:36:00	0.0	NaN
115807	546139	84988	?	3000	2011-03-09 16:35:00	0.0	NaN
220843	556231	85123A	?	4000	2011-06-09 15:04:00	0.0	NaN
282882	561665	22171	?	142	2011-07-28 16:55:00	0.0	NaN
323315	565288	23135	?	101	2011-09-02 11:43:00	0.0	NaN
421093	572920	72803A	?	117	2011-10-26 16:52:00	0.0	NaN

In [27]:
```
#as where there is ? in description there unitprice is 0 so removing these

df=df[df['Description'].str.startswith('?')!=True]
df.shape
```

Out[27]:
```
(531279, 8)
```

In [28]:
```
df[df['Description'].str.startswith('*')==True]
```

Out[28]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	C
20749	538071	21120	*Boombox Ipod Classic	1	2010-12-09 14:09:00	16.98	NaN	K
35675	539437	20954	*USB Office Mirror Ball	1	2010-12-17 14:54:00	8.47	NaN	K
37095	539453	20954	*USB Office Mirror Ball	1	2010-12-17 17:08:00	8.47	NaN	K

In [29]:

```
# where we have desc. starting with * in description there customer id is
#replacing them with appropriate name

df['Description'] = df['Description'].replace(('*Boombox Ipod Classic','*U
```

In [30]:

```
df[df['Description'].str.islower()==True]['Description'].value_counts()
```

Out[30]:

```
check                                  39
found                                  25
adjustment                             14
amazon                                  8
had been put aside                      5
dotcom                                  4
mailout                                 3
taig adjust                             2
returned                                2
test                                    2
wrongly marked 23343                    1
michel oops                             1
wrongly coded 20713                     1
wrongly marked                          1
wrongly coded 23343                     1
damaged                                 1
amazon adjust                           1
dotcomstock                             1
dotcom adjust                           1
website fixed                           1
allocate stock for dotcom orders ta     1
found box                               1
for online retail orders                1
add stock to allocate online orders     1
amazon sales                            1
alan hodge cant mamage this section     1
came coded as 20713                     1
to push order througha s stock was      1
on cargo order                          1
mailout                                 1
did  a credit  and did not tick ret     1
rcvd be air temp fix for dotcom sit     1
wrongly sold (22719) barcode            1
check?                                  1
Name: Description, dtype: int64
```

In [31]:
```
#removing all the above noises
df = df[df['Description'].str.islower()!=True]
df.shape
```

Out[31]:
```
(531151, 8)
```

In [32]:
```
#Description have actual entries in uppercase words, those don't have uppe
#they have some noises in the data set

df[df['Description'].str.istitle()==True]['Description'].value_counts()
```

Out[32]:
```
Manual                                  328
Next Day Carriage                        79
Bank Charges                             12
Dotcomgiftshop Gift Voucher £20.00        9
Found                                     8
Dotcomgiftshop Gift Voucher £10.00        8
Dotcomgiftshop Gift Voucher £30.00        7
Amazon                                    7
Dotcomgiftshop Gift Voucher £50.00        4
Dotcomgiftshop Gift Voucher £40.00        3
High Resolution Image                     3
Adjustment                                2
Boombox Ipod Classic                      1
Dotcomgiftshop Gift Voucher £100.00       1
Amazon Adjustment                         1
John Lewis                                1
Name: Description, dtype: int64
```

In [33]:
```
#removing
df=df[df['Description'].str.istitle()!=True]
df.shape
```

Out[33]:
```
(530677, 8)
```

In [34]:
```
df['Description'] = df['Description'].str.strip()
```

In [35]:
```
df.CustomerID.nunique()
```

Out[35]:
```
4335
```

In [36]:
```
#removing all entries where customer id is null
df = df[~df.CustomerID.isnull()]
df.shape
```

Out[36]:
```
(397540, 8)
```

In [37]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 397540 entries, 0 to 541908
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    397540 non-null  object        
 1   StockCode    397540 non-null  object        
 2   Description  397540 non-null  object        
 3   Quantity     397540 non-null  int64         
 4   InvoiceDate  397540 non-null  datetime64[ns]
 5   UnitPrice    397540 non-null  float64       
 6   CustomerID   397540 non-null  float64       
 7   Country      397540 non-null  object        
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 27.3+ MB
```

In [38]:
```
df.isnull().sum().any()
```

Out[38]:
```
False
```

In [39]:
```
df.sample(3)
```

Out[39]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
453557	575485	84509A	SET OF 4 ENGLISH ROSE PLACEMATS	4	2011-11-09 17:03:00	3.75	18274.0
444161	574721	23177	TREASURE ISLAND BOOK BOX	1	2011-11-06 14:43:00	2.25	17920.0
494985	578289	23406	HOME SWEET HOME KEY HOLDER	1	2011-11-23 14:07:00	6.25	17841.0

- Remove duplicate data records.

In [40]:
```
df.duplicated().sum().any()
```

Out[40]:
```
True
```

In [41]:
```
df.duplicated().sum()
```

Out[41]:
```
5187
```

In [42]:
```
df.drop_duplicates(inplace=True)
```

In [43]:
```
df.duplicated().sum().any()
```

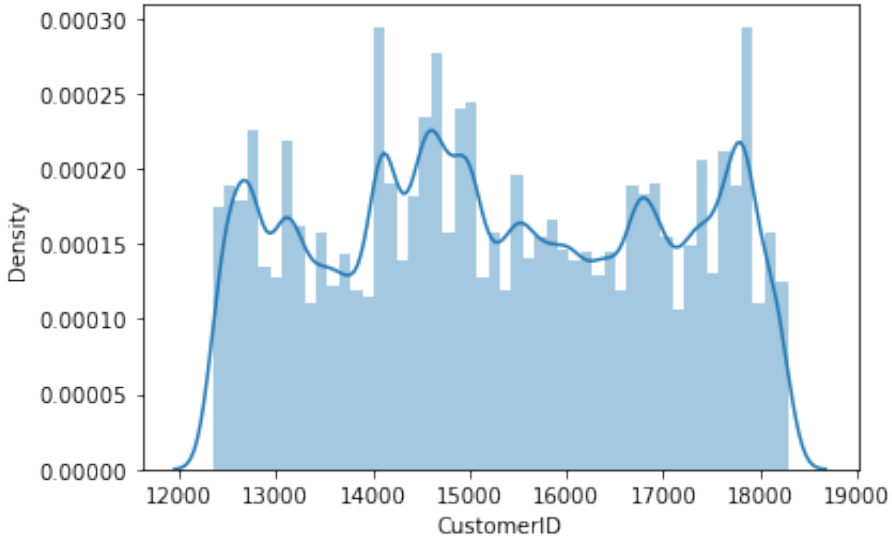
Out[43]:
```
False
```

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

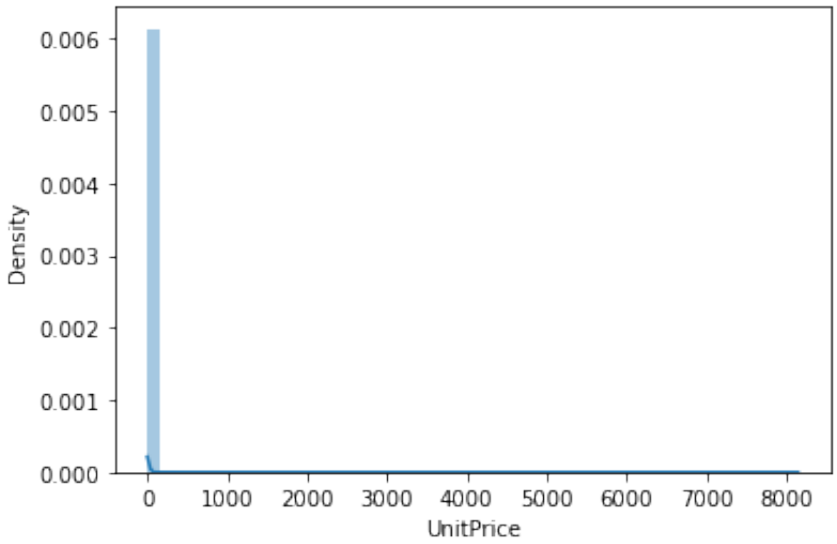
Out[44]:
```
(392353, 8)
```

- Perform descriptive analytics on the given data.

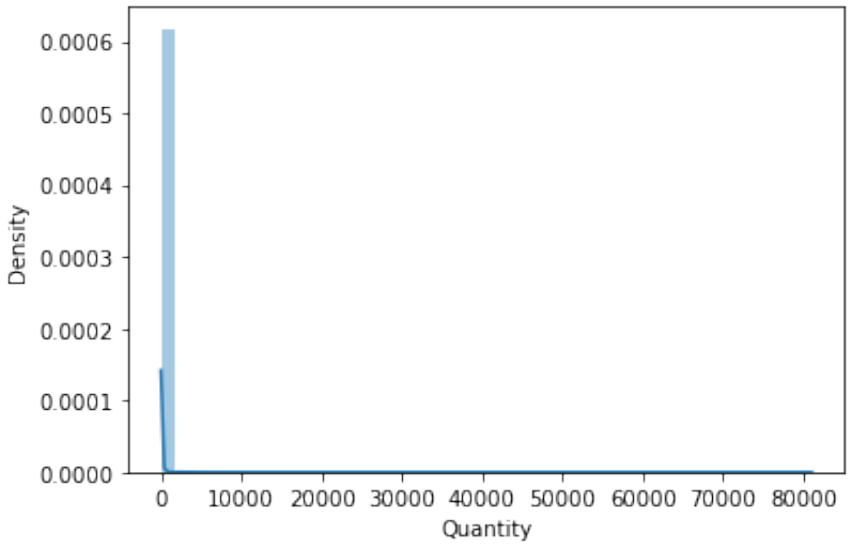
In [45]:
```
sns.distplot(df.CustomerID);
```



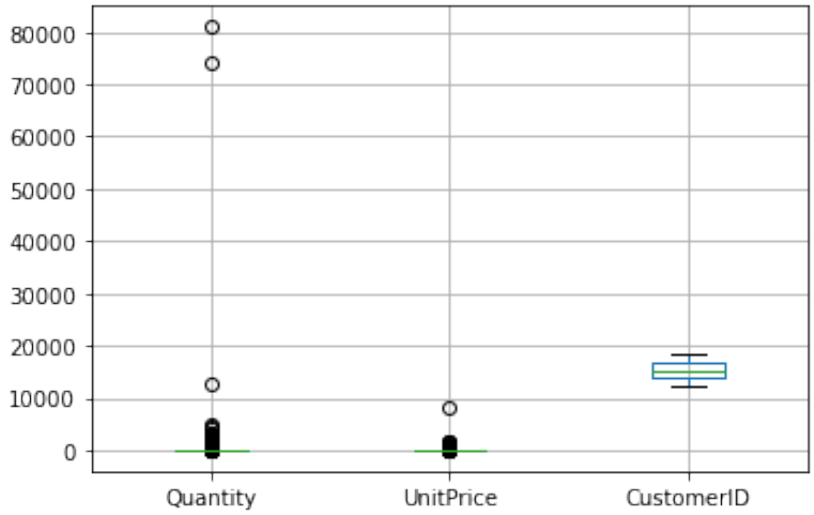
In [46]:
```
sns.distplot(df.UnitPrice);
```



In [47]:
```
sns.distplot(df.Quantity);
```



In [48]:
```
df.boxplot();
```



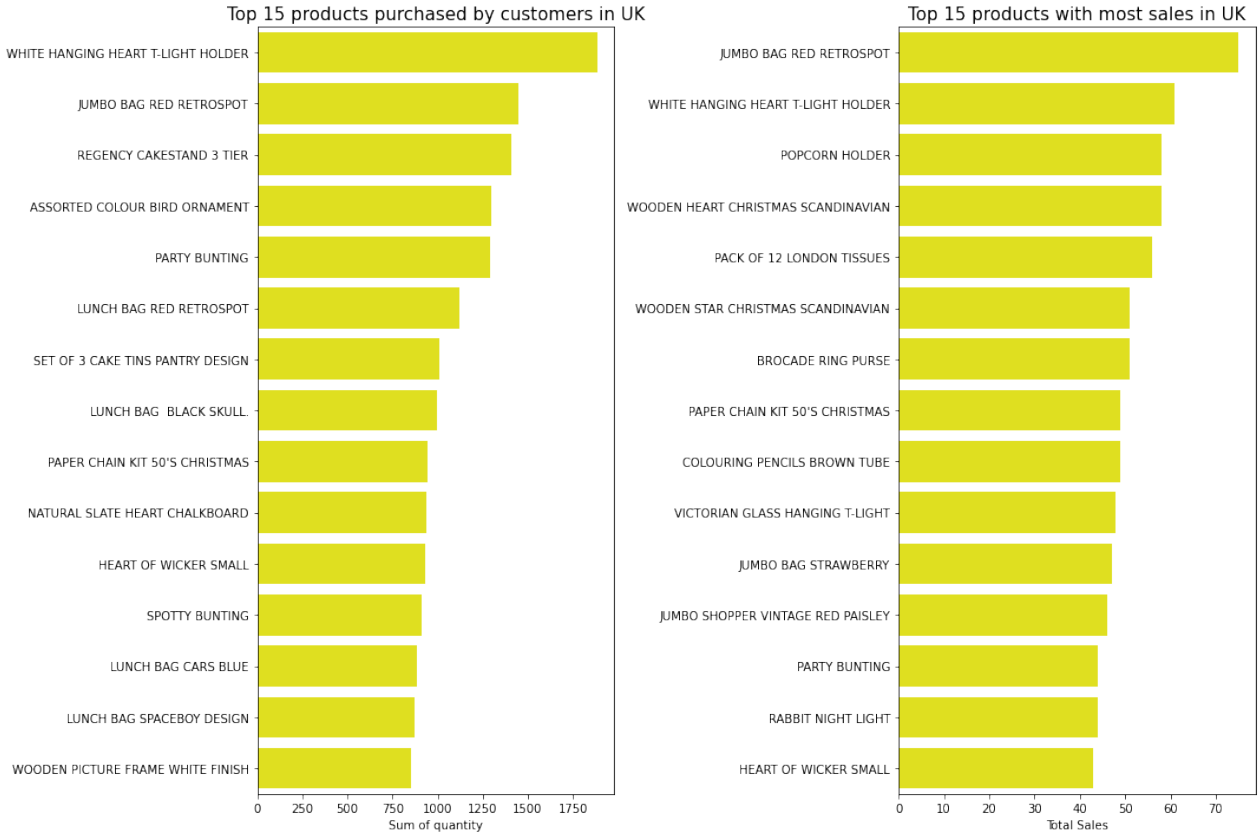
In [49]:
```
#creating cols for further exploration

df['Amount'] = df['Quantity']*df['UnitPrice']

df['Year'] = df['InvoiceDate'].dt.year

df['Month'] = df['InvoiceDate'].dt.month

df['Day'] = df['InvoiceDate'].dt.day

df['Hour'] = df['InvoiceDate'].dt.hour

df['Day_Of_Week'] = df['InvoiceDate'].dt.dayofweek
```

In [50]:
```
df.head(2)
```

Out[50]:

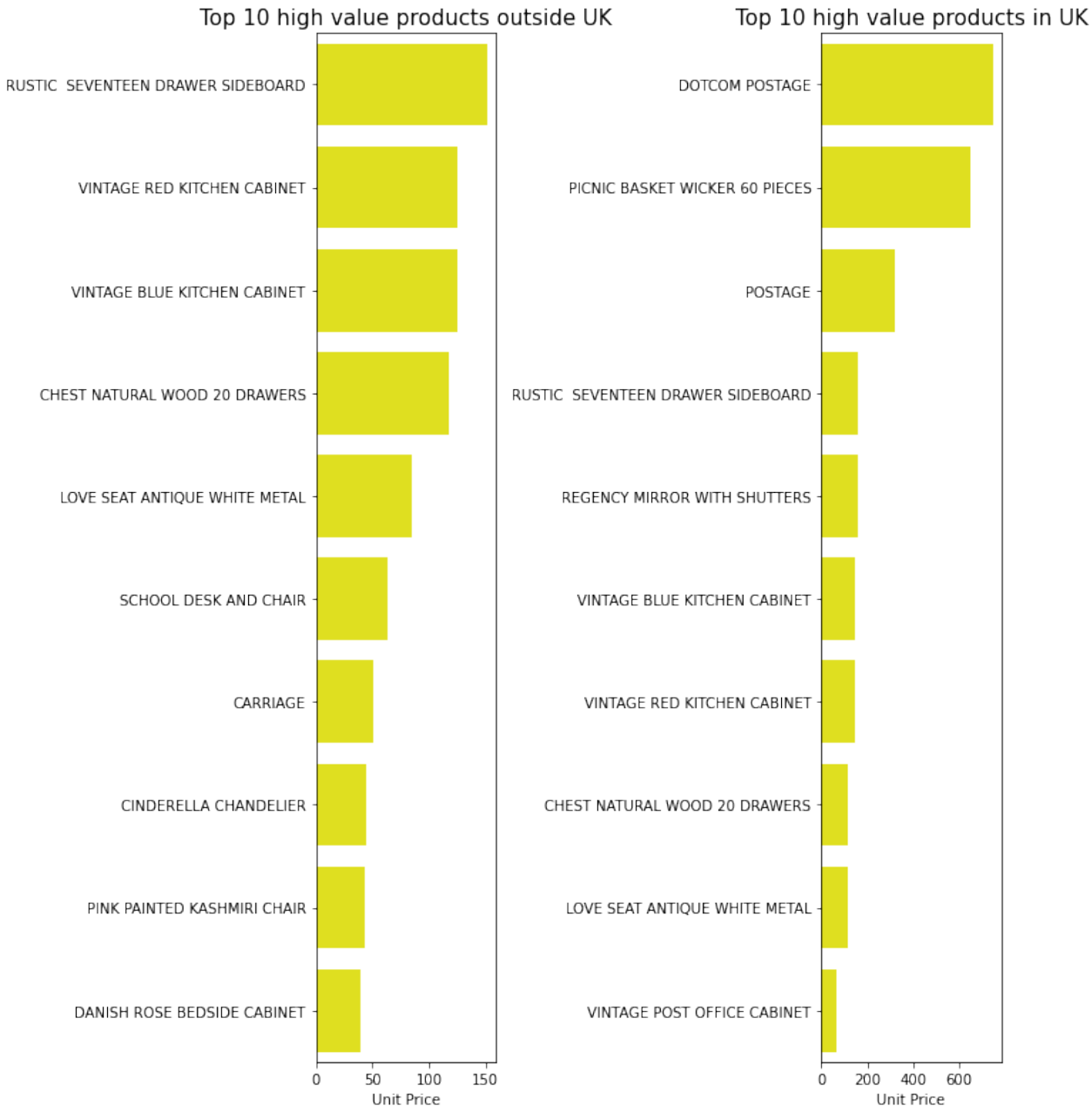
	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Count
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	Unit Kingdo
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	Unit Kingdo

In [131…
```
column = ['InvoiceNo','Amount']

plt.figure(figsize=(15,10))
for i,j in enumerate(column):
    plt.subplot(1,2,i+1)
    sns.barplot(x = df[df['Country']=='United Kingdom'].groupby('Descriptio
                y = df[df['Country']=='United Kingdom'].groupby('Descriptio
                color='yellow')
    plt.ylabel('')
    if i==0:
        plt.xlabel('Sum of quantity')
        plt.title('Top 15 products purchased by customers in UK',size=15)
    else:
        plt.xlabel('Total Sales')
        plt.title('Top 15 products with most sales in UK',size=15)

plt.tight_layout()
plt.show()
```



In [52]:

```
column = ['Others','United Kingdom']

plt.figure(figsize=(10,11))
for i,j in enumerate(column):
    plt.subplot(1,2,i+1)
    sns.barplot(x = df[df['Country']==j].groupby('Description')['UnitPrice
                y = df[df['Country']==j].groupby('Description')['UnitPrice
                color='yellow')
    plt.ylabel('')
    if i==0:
        plt.xlabel('Unit Price')
        plt.title('Top 10 high value products outside UK',size=15)
    else:
        plt.xlabel('Unit Price')
        plt.title('Top 10 high value products in UK',size=15)

plt.tight_layout()
plt.show()
```



In [53]:
```
df.skew()
```

Out[53]:
```
InvoiceNo       -0.175370
Quantity       400.874873
UnitPrice      417.305256
CustomerID       0.030312
Amount         450.165574
Year            -3.517019
Month           -0.440268
Day              0.114336
Hour             0.187199
Day_Of_Week      0.399060
dtype: float64
```

In [54]:
```
df.kurtosis()
```

Out[54]:
```
InvoiceNo          -1.198858
Quantity       171754.563034
UnitPrice      219479.429625
CustomerID         -1.180573
Amount         230220.747017
Year               10.369476
Month              -1.076601
Day                -1.171654
Hour               -0.220062
Day_Of_Week        -0.819281
dtype: float64
```

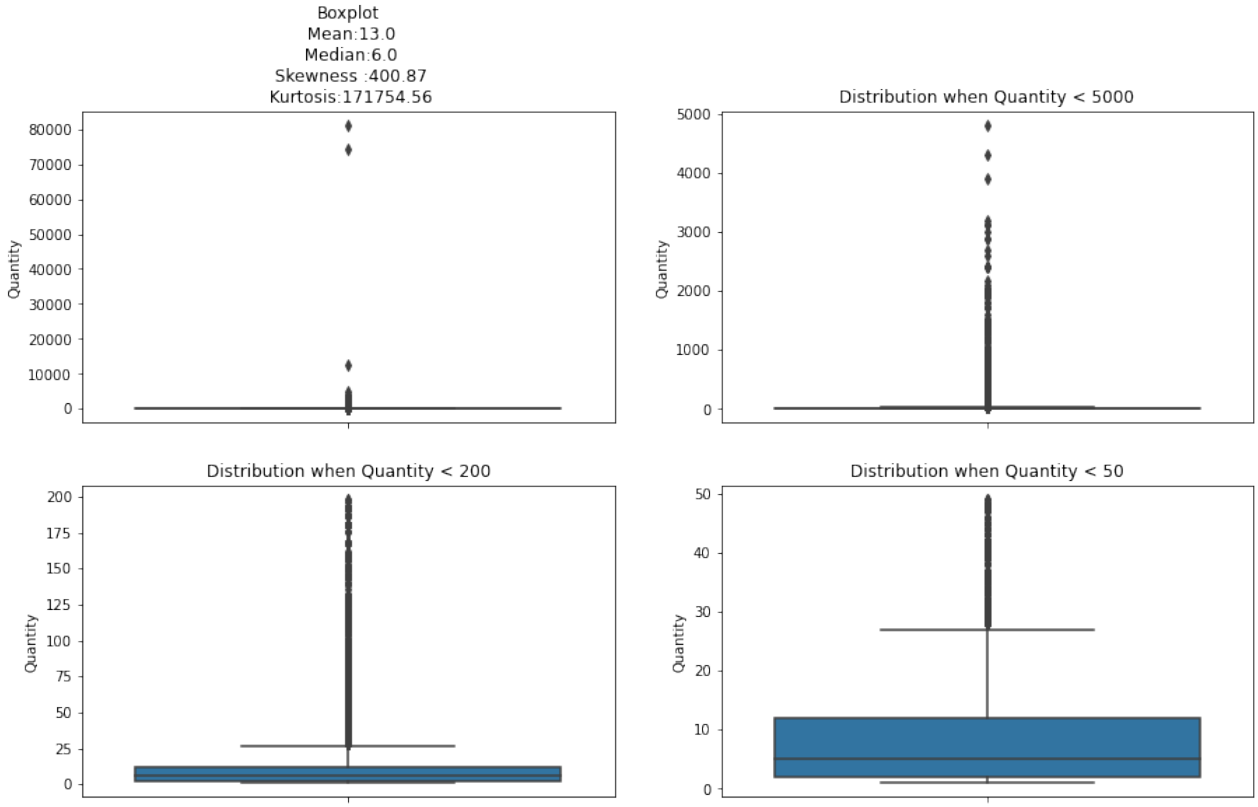
In [55]:
```
df.describe()
```

Out[55]:

	Quantity	UnitPrice	CustomerID	Amount	Year	
count	392353.000000	392353.000000	392353.000000	392353.000000	392353.000000	39
mean	13.148496	2.998207	15287.636335	22.511353	2010.934638	
std	181.636906	15.045821	1713.455965	310.803717	0.247164	
min	1.000000	0.000000	12346.000000	0.000000	2010.000000	
25%	2.000000	1.250000	13955.000000	4.950000	2011.000000	
50%	6.000000	1.950000	15150.000000	12.390000	2011.000000	
75%	12.000000	3.750000	16791.000000	19.800000	2011.000000	
max	80995.000000	8142.750000	18287.000000	168469.600000	2011.000000	

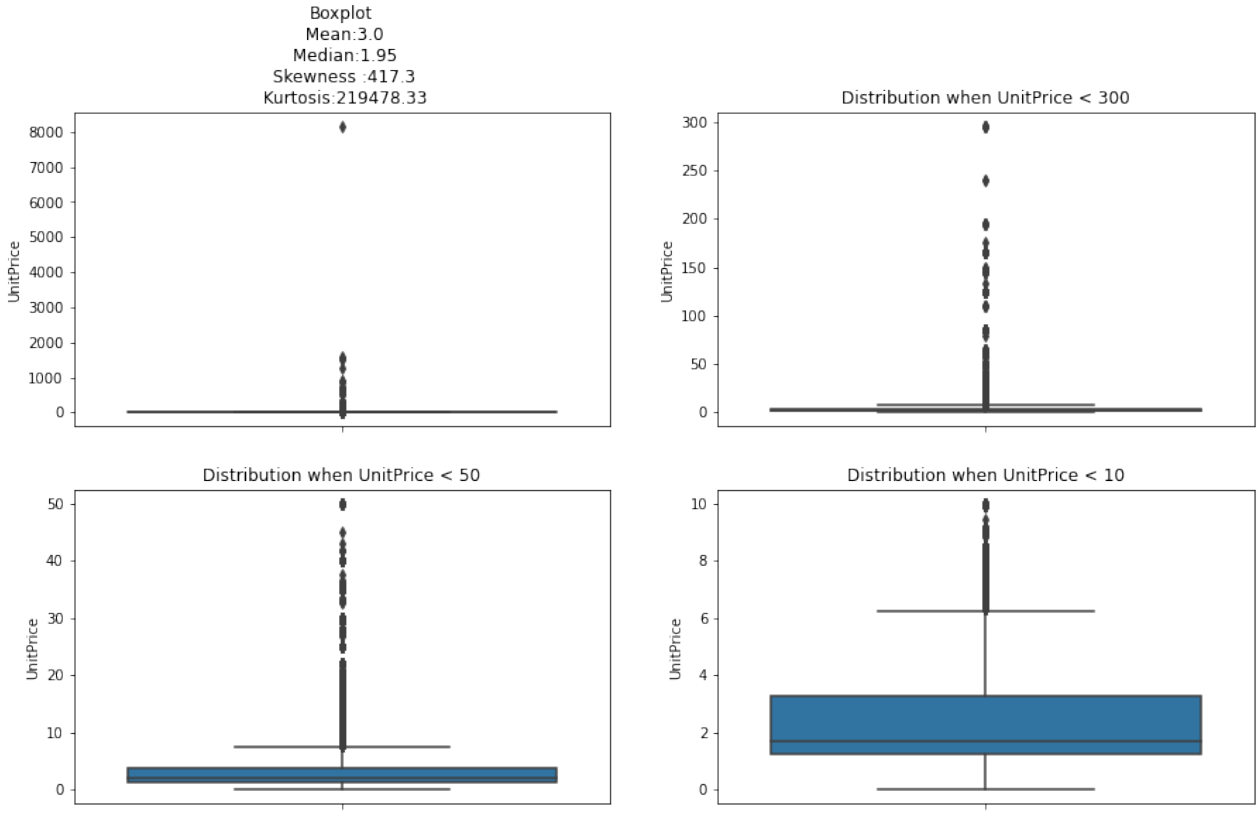
In [56]:

```
#distribution of Quantity

plt.figure(figsize=(15,9))

skewness = round(df.Quantity.skew(),2)
kurtosis = round(df.Quantity.kurtosis(),2)
mean = round(np.mean(df.Quantity),0)
median = np.median(df.Quantity)

plt.subplot(2,2,1)
sns.boxplot(y=df.Quantity)
plt.title('Boxplot\n Mean:{}\n Median:{}\n Skewness :{}\n Kurtosis:{}'.forr

plt.subplot(2,2,2)
sns.boxplot(y=df[df.Quantity<5000]['Quantity'])
plt.title('Distribution when Quantity < 5000')

plt.subplot(2,2,3)
sns.boxplot(y=df[df.Quantity<200]['Quantity'])
plt.title('Distribution when Quantity < 200')

plt.subplot(2,2,4)
sns.boxplot(y=df[df.Quantity<50]['Quantity'])
plt.title('Distribution when Quantity < 50')

plt.show()
```



In [57]:
```
#removing Quantitites > 70000

df = df[df['Quantity']<70000]
```

In [58]:
```
#distribution of UnitPrice

plt.figure(figsize=(15,9))

skewness = round(df.UnitPrice.skew(),2)
kurtosis = round(df.UnitPrice.kurtosis(),2)
mean = round(np.mean(df.UnitPrice),0)
median = np.median(df.UnitPrice)

plt.subplot(2,2,1)
sns.boxplot(y=df.UnitPrice)
plt.title('Boxplot\n Mean:{}\n Median:{}\n Skewness :{}\n Kurtosis:{}'.forr

plt.subplot(2,2,2)
sns.boxplot(y=df[df.UnitPrice<300]['UnitPrice'])
plt.title('Distribution when UnitPrice < 300')

plt.subplot(2,2,3)
sns.boxplot(y=df[df.UnitPrice<50]['UnitPrice'])
plt.title('Distribution when UnitPrice < 50')

plt.subplot(2,2,4)
sns.boxplot(y=df[df.UnitPrice<10]['UnitPrice'])
plt.title('Distribution when UnitPrice < 10')

plt.show()
```

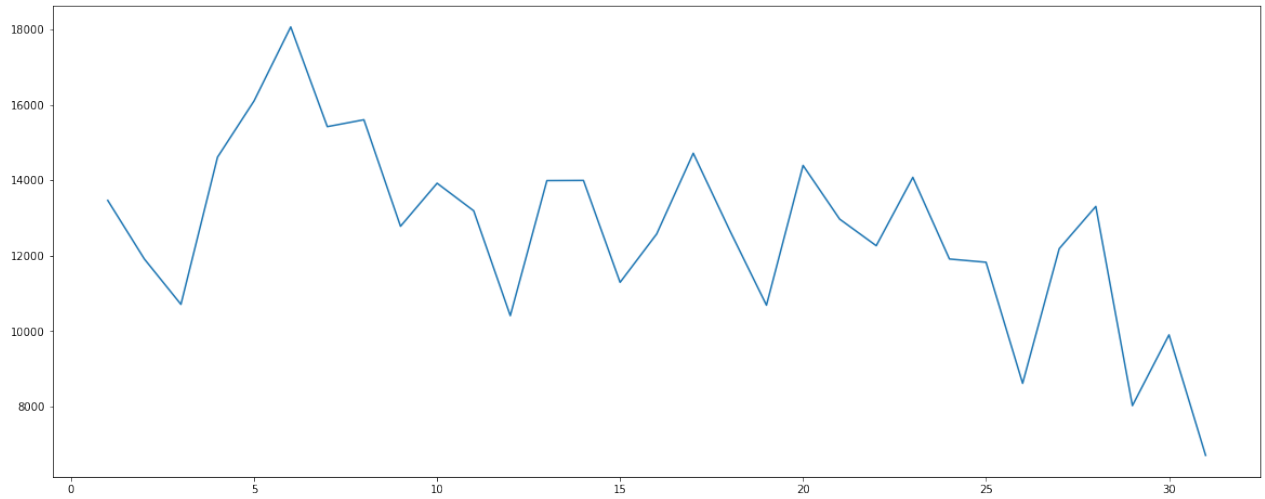


In [59]:
```
df.head(1)
```

Out[59]:

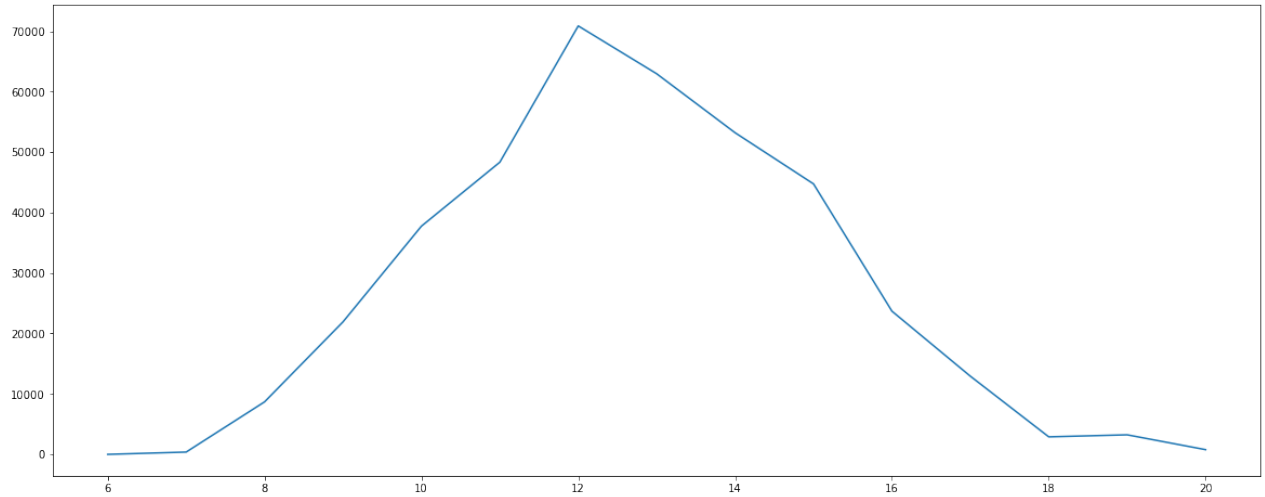
	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Count
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	Unit Kingdo

In [60]:
```
#time series transactions for day
active_transactions=df.groupby('Day')['InvoiceNo'].agg(np.size)
plt.figure(figsize=(20,8))
plt.plot(active_transactions)
plt.show()
```



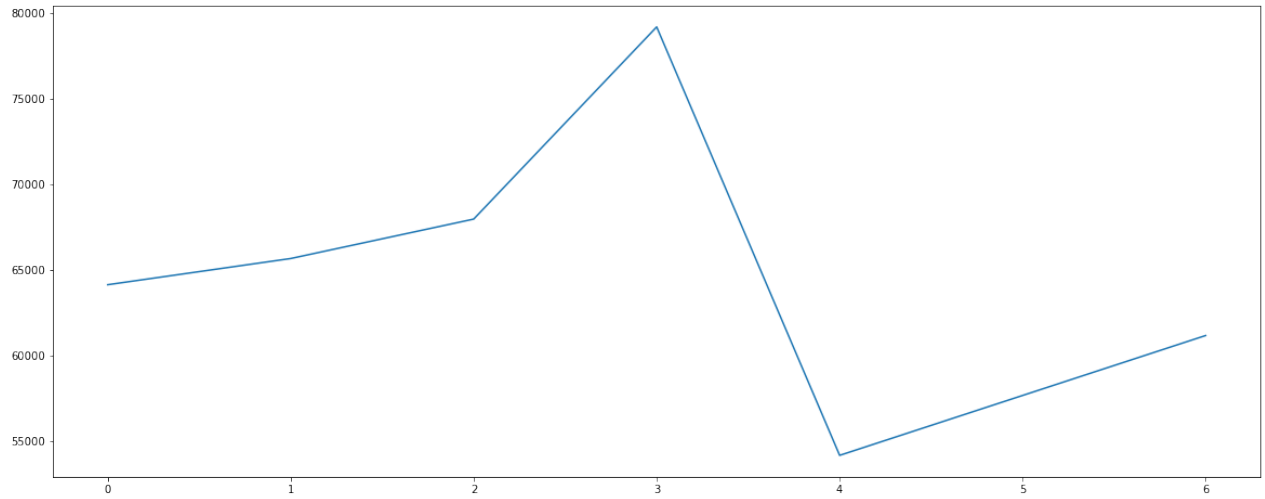
In [61]:

```
#time series transactions for hour
active_transactions=df.groupby('Hour')['InvoiceNo'].agg(np.size)
plt.figure(figsize=(20,8))
plt.plot(active_transactions)
plt.show()
```



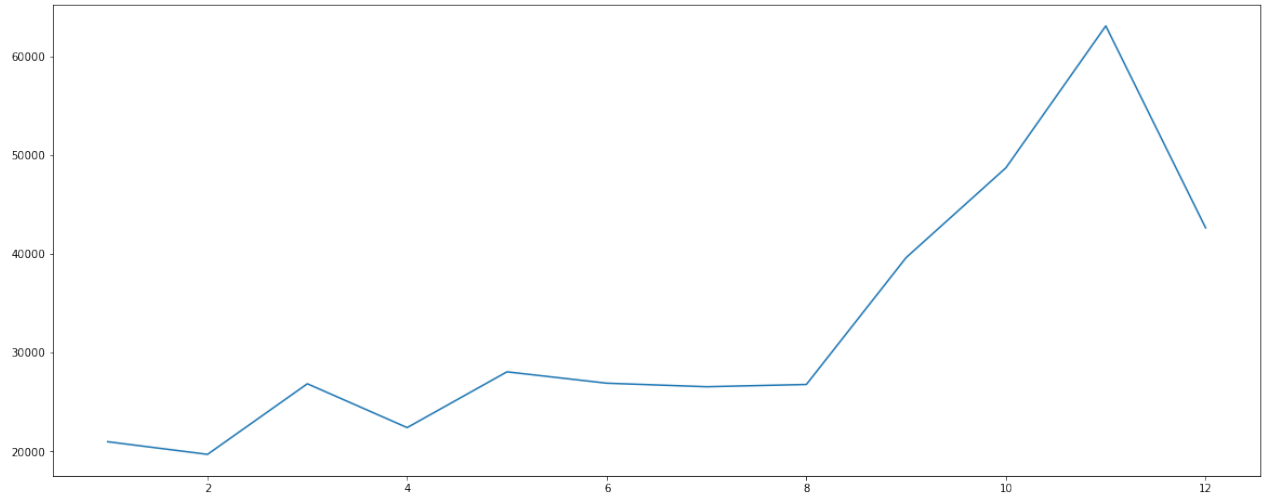
In [62]:

```
#time series transactions for Day_Of_Week
active_transactions=df.groupby('Day_Of_Week')['InvoiceNo'].agg(np.size)
plt.figure(figsize=(20,8))
plt.plot(active_transactions)
plt.show()
```



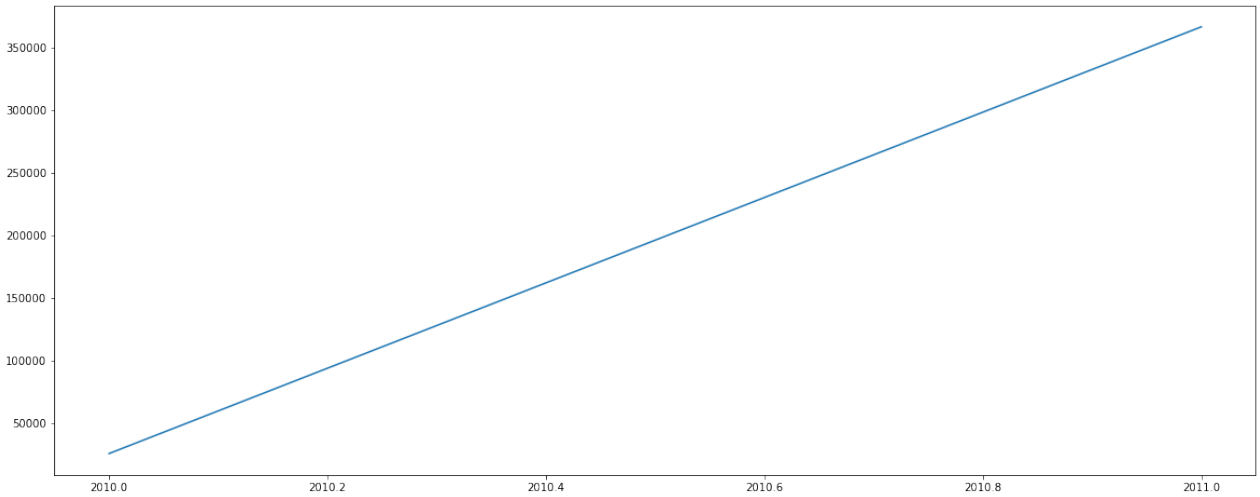
In [63]:

```
#time series transactions for Month
active_transactions=df.groupby('Month')['InvoiceNo'].agg(np.size)
plt.figure(figsize=(20,8))
plt.plot(active_transactions)
plt.show()
```



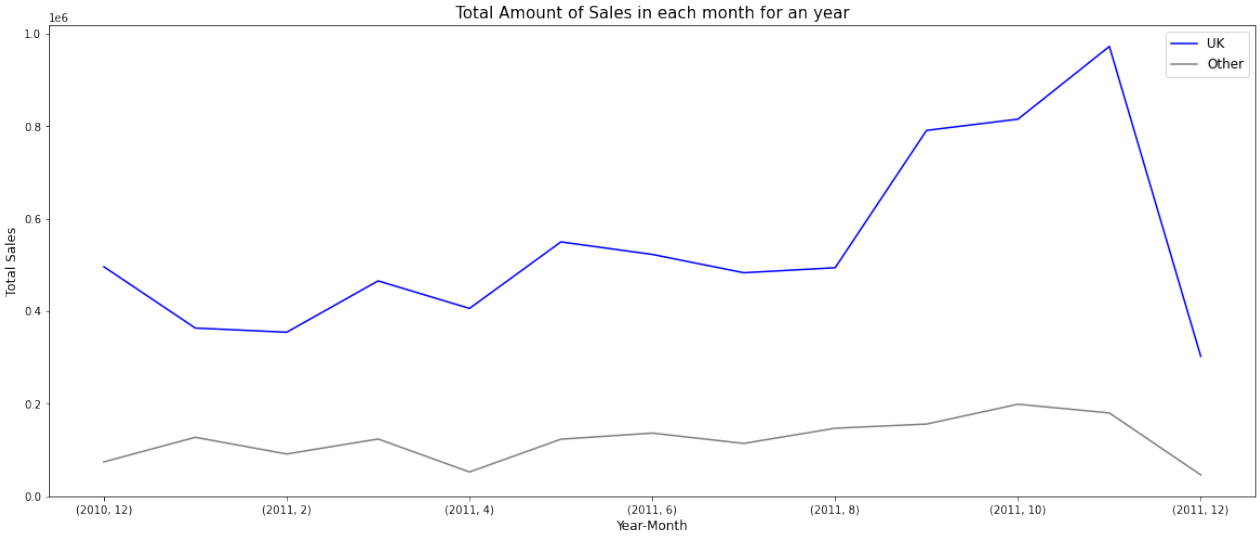
In [64]:

```
#time series transactions for Year
active_transactions=df.groupby('Year')['InvoiceNo'].agg(np.size)
plt.figure(figsize=(20,8))
plt.plot(active_transactions)
plt.show()
```



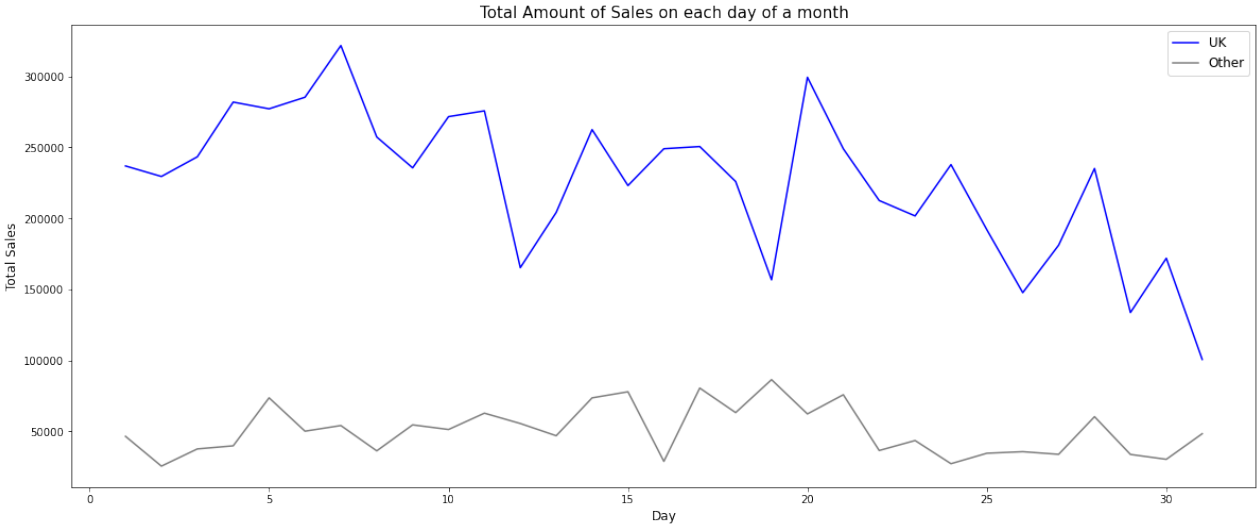
In [65]:

```
plt.figure(figsize=(20,8))
df[df['Country']=='United Kingdom'].groupby(['Year','Month'])['Amount'].sur
df[df['Country']=='Others'].groupby(['Year','Month'])['Amount'].sum().plot
plt.xlabel('Year-Month',size=12)
plt.ylabel('Total Sales', size=12)
plt.title('Total Amount of Sales in each month for an year', size=15)
plt.legend(fontsize=12)
plt.show()
```



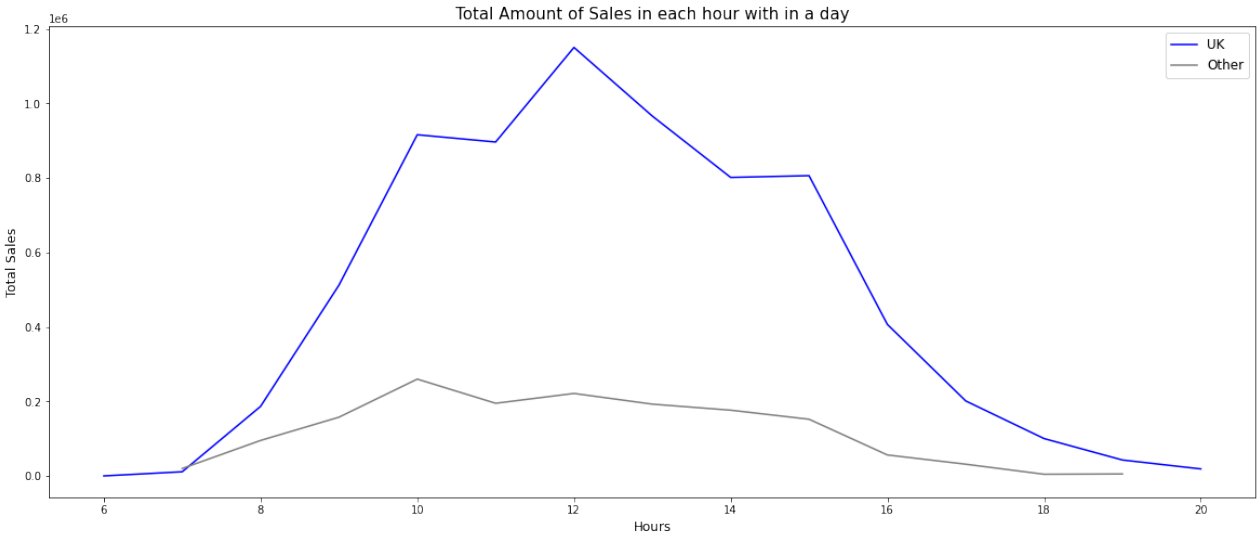
In [66]:

```
plt.figure(figsize=(20,8))
df[df['Country']=='United Kingdom'].groupby(['Day'])['Amount'].sum().plot(l
df[df['Country']=='Others'].groupby(['Day'])['Amount'].sum().plot(kind='li
plt.xlabel('Day',size=12)
plt.ylabel('Total Sales', size=12)
plt.title('Total Amount of Sales on each day of a month', size=15)
plt.legend(fontsize=12)
plt.show()
```



In [67]:

```
plt.figure(figsize=(20,8))
df[df['Country']=='United Kingdom'].groupby(['Hour'])['Amount'].sum().plot
df[df['Country']=='Others'].groupby(['Hour'])['Amount'].sum().plot(kind='l
plt.xlabel('Hours',size=12)
plt.ylabel('Total Sales', size=12)
plt.title('Total Amount of Sales in each hour with in a day', size=15)
plt.legend(fontsize=12)
plt.show()
```



Data Transformation:

- 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.
- Create month cohorts and analyze active customers for each cohort.
- Analyze the retention rate of customers.

In [68]:
```
df_cohort = df.copy()
#selecting limited cols
df_cohort = df_cohort.iloc[:,:9]
df_cohort.head()
```

Out[68]:

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

In [69]:
```
df_cohort.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 392351 entries, 0 to 541908
Data columns (total 9 columns):
 #   Column       Non-Null Count   Dtype         
---  ------       --------------   -----         
 0   InvoiceNo    392351 non-null  object        
 1   StockCode    392351 non-null  object        
 2   Description  392351 non-null  object        
 3   Quantity     392351 non-null  int64         
 4   InvoiceDate  392351 non-null  datetime64[ns]
 5   UnitPrice    392351 non-null  float64       
 6   CustomerID   392351 non-null  float64       
 7   Country      392351 non-null  object        
 8   Amount       392351 non-null  float64       
dtypes: datetime64[ns](1), float64(3), int64(1), object(4)
memory usage: 29.9+ MB
```

In [70]:
```
#creating 1st variable InvoiceMonth
df_cohort['InvoiceMonth'] = df_cohort['InvoiceDate'].dt.strftime('%Y-%m')

df_cohort['InvoiceMonth'] = pd.to_datetime(df_cohort['InvoiceMonth'])
```

In [71]:
```
#creating 2nd variable CohortMonth

df_cohort['CohortMonth'] = df_cohort.groupby('CustomerID')['InvoiceMonth']

df_cohort['CohortMonth'] = pd.to_datetime(df_cohort['CohortMonth'])
```

In [72]:
```
df_cohort.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 392351 entries, 0 to 541908
Data columns (total 11 columns):
 #   Column        Non-Null Count   Dtype         
---  ------        --------------   -----         
 0   InvoiceNo     392351 non-null  object        
 1   StockCode     392351 non-null  object        
 2   Description   392351 non-null  object        
 3   Quantity      392351 non-null  int64         
 4   InvoiceDate   392351 non-null  datetime64[ns]
 5   UnitPrice     392351 non-null  float64       
 6   CustomerID    392351 non-null  float64       
 7   Country       392351 non-null  object        
 8   Amount        392351 non-null  float64       
 9   InvoiceMonth  392351 non-null  datetime64[ns]
 10  CohortMonth   392351 non-null  datetime64[ns]
dtypes: datetime64[ns](3), float64(3), int64(1), object(4)
memory usage: 35.9+ MB
```

In [73]:
```
#creating 3nd variable CohortPeriod

def diff_month(d1,d2):
    return((d1.dt.year - d2.dt.year)*12+d1.dt.month-d2.dt.month)

df_cohort['CohortPeriod'] = diff_month(df_cohort['InvoiceMonth'],df_cohort
```

In [74]:
```
df_cohort.sample(10)
```

Out[74]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID
144007	548715	84251C	GREETING CARD, TWO SISTERS.	12	2011-04-03 15:22:00	0.19	17758.0
119762	546580	84692	BOX OF 24 COCKTAIL PARASOLS	25	2011-03-15 11:09:00	0.42	14911.0
462574	575982	22307	GOLD MUG BONE CHINA TREE OF LIFE	6	2011-11-13 13:42:00	1.06	13798.0
152970	549718	23049	RECYCLED ACAPULCO MAT RED	2	2011-04-11 15:03:00	8.25	13846.0
483822	577508	85123A	WHITE HANGING HEART T-LIGHT HOLDER	2	2011-11-20 12:45:00	2.95	18127.0
41177	539754	82600	NO SINGING METAL SIGN	1	2010-12-21 16:06:00	2.10	12748.0
506800	579155	20956	PORCELAIN T-LIGHT HOLDERS ASSORTED	4	2011-11-28 13:37:00	1.25	18101.0
464122	576078	21108	FAIRY CAKE FLANNEL ASSORTED COLOUR	18	2011-11-13 16:22:00	0.79	14432.0
507232	579170	21172	PARTY METAL SIGN	4	2011-11-28 14:26:00	1.45	17811.0
122071	546850	21382	SET/4 SPRING FLOWER DECORATION	1	2011-03-17 13:20:00	2.95	13268.0

In [75]:
```
Customer_Cohort = df_cohort.pivot_table(index='CohortMonth',columns='Cohor
```

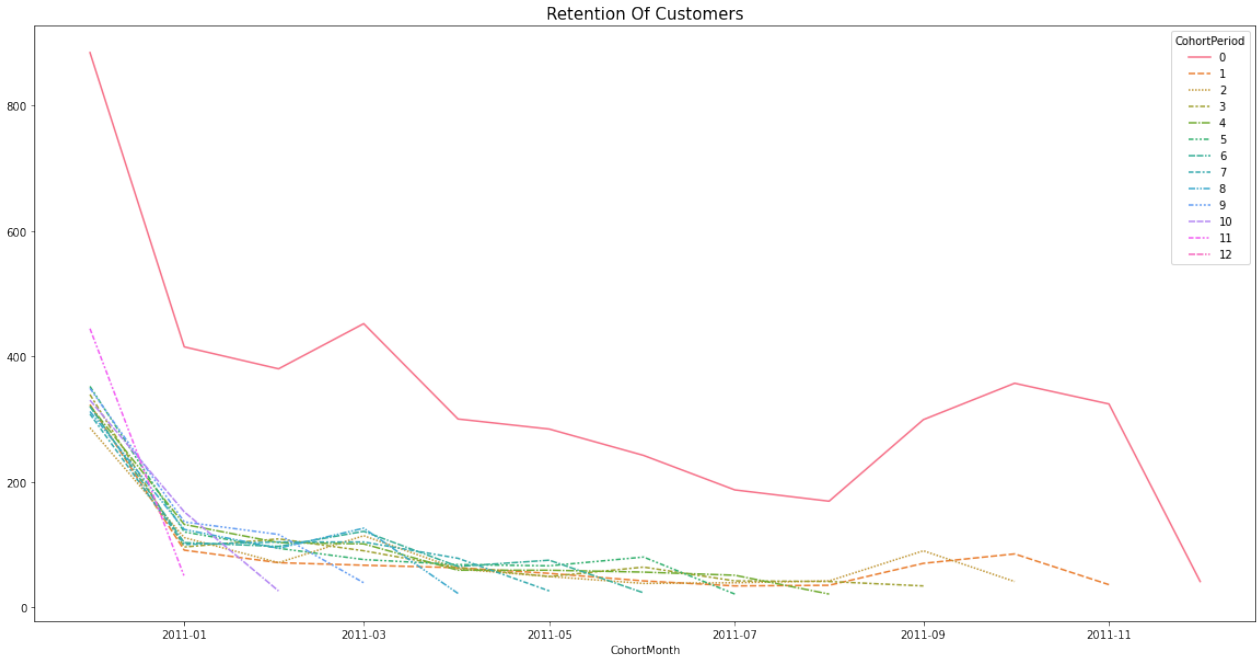
In [76]:
```
Customer_Cohort
```

Out[76]:

CohortPeriod	0	1	2	3	4	5	6	7	8	9	10
CohortMonth											
2010-12-01	884.0	323.0	286.0	339.0	321.0	352.0	320.0	308.0	312.0	349.0	330.0
2011-01-01	415.0	91.0	111.0	96.0	132.0	120.0	103.0	100.0	124.0	136.0	152.0
2011-02-01	380.0	71.0	71.0	109.0	103.0	94.0	97.0	104.0	94.0	116.0	26.0
2011-03-01	452.0	67.0	114.0	90.0	101.0	76.0	121.0	104.0	126.0	39.0	NaN
2011-04-01	300.0	63.0	61.0	63.0	59.0	68.0	65.0	78.0	22.0	NaN	NaN
2011-05-01	284.0	54.0	49.0	49.0	59.0	66.0	75.0	26.0	NaN	NaN	NaN
2011-06-01	242.0	42.0	38.0	64.0	56.0	80.0	23.0	NaN	NaN	NaN	NaN
2011-07-01	187.0	34.0	39.0	42.0	51.0	21.0	NaN	NaN	NaN	NaN	NaN
2011-08-01	169.0	35.0	42.0	41.0	21.0	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	299.0	70.0	90.0	34.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	357.0	85.0	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	324.0	36.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [77]:

```
plt.figure(figsize=(20,10))
plt.title('Retention Of Customers', size=15)
sns.lineplot(data=Customer_Cohort);
```

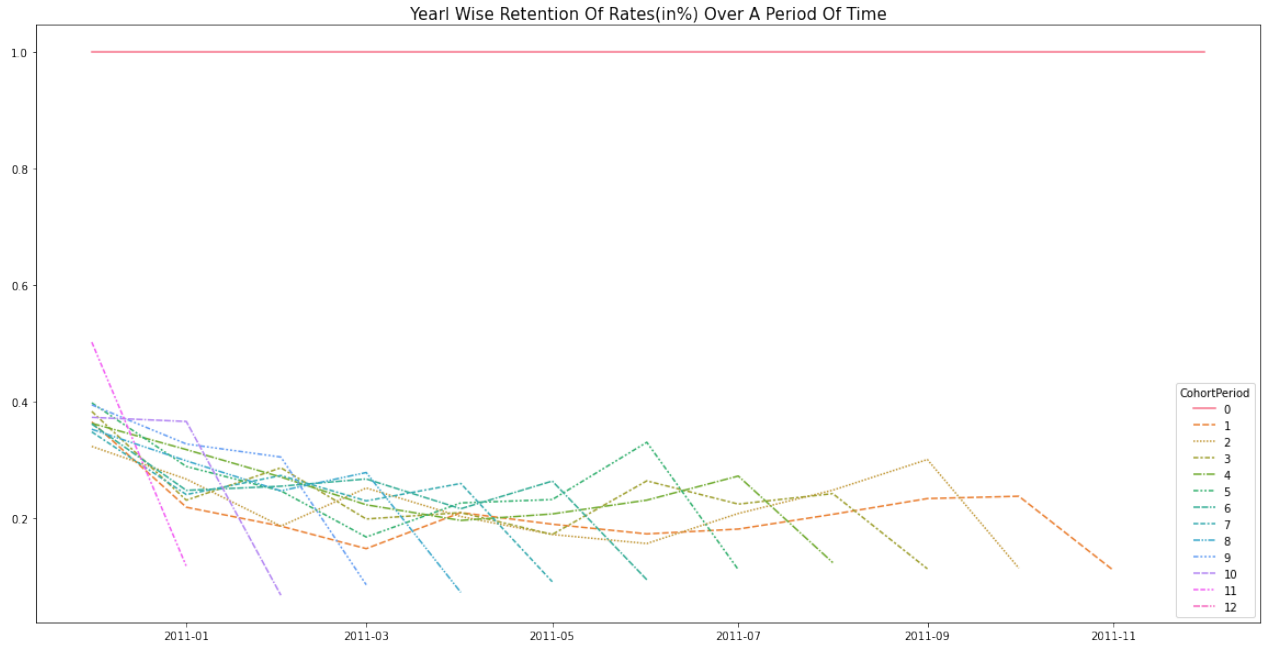


In [78]:
```
# retention table

cohort_size = Customer_Cohort.iloc[:,0]
retention = Customer_Cohort.divide(cohort_size, axis=0)

retention.index = pd.to_datetime(retention.index).date
retention.round(3)*100
```

Out[78]:

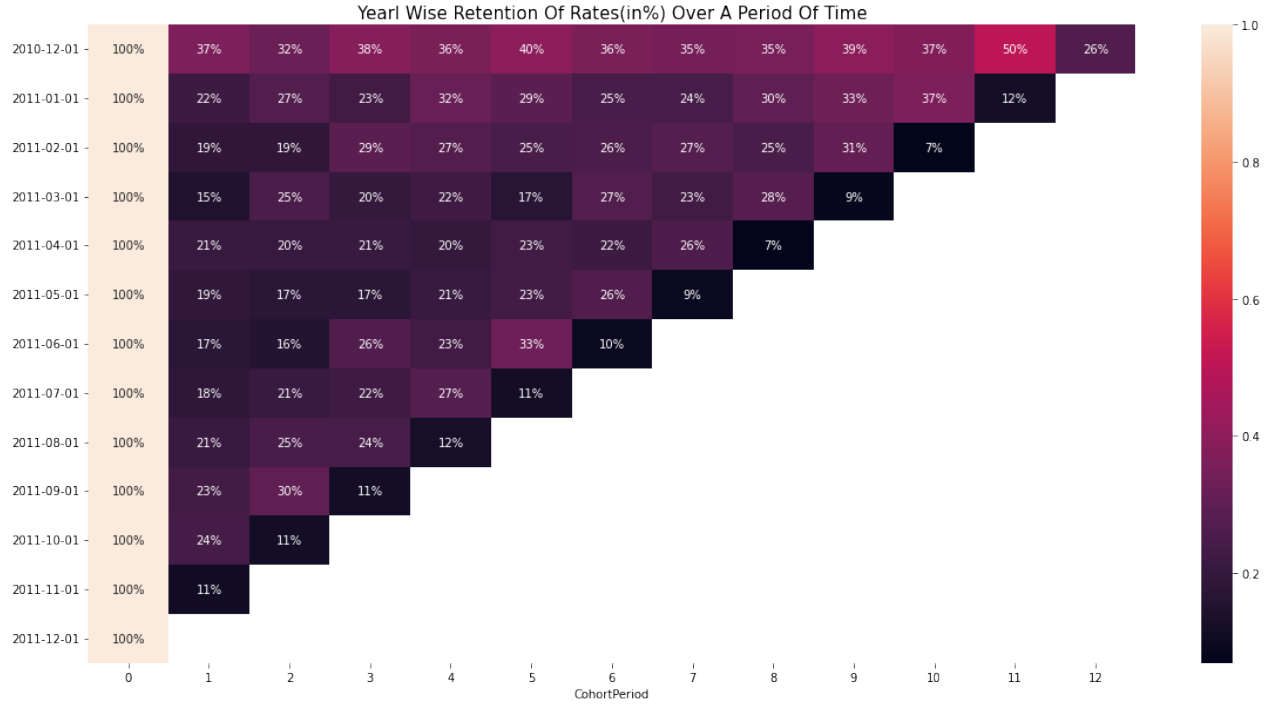
CohortPeriod	0	1	2	3	4	5	6	7	8	9	10	11	12
2010-12-01	100.0	36.5	32.4	38.3	36.3	39.8	36.2	34.8	35.3	39.5	37.3	50.2	26.5
2011-01-01	100.0	21.9	26.7	23.1	31.8	28.9	24.8	24.1	29.9	32.8	36.6	11.8	NaN
2011-02-01	100.0	18.7	18.7	28.7	27.1	24.7	25.5	27.4	24.7	30.5	6.8	NaN	NaN
2011-03-01	100.0	14.8	25.2	19.9	22.3	16.8	26.8	23.0	27.9	8.6	NaN	NaN	NaN
2011-04-01	100.0	21.0	20.3	21.0	19.7	22.7	21.7	26.0	7.3	NaN	NaN	NaN	NaN
2011-05-01	100.0	19.0	17.3	17.3	20.8	23.2	26.4	9.2	NaN	NaN	NaN	NaN	NaN
2011-06-01	100.0	17.4	15.7	26.4	23.1	33.1	9.5	NaN	NaN	NaN	NaN	NaN	NaN
2011-07-01	100.0	18.2	20.9	22.5	27.3	11.2	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-08-01	100.0	20.7	24.9	24.3	12.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	100.0	23.4	30.1	11.4	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	100.0	23.8	11.5	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	100.0	11.1	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	100.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [79]:
```
plt.figure(figsize=(20,10))
plt.title('Yearl Wise Retention Of Rates(in%) Over A Period Of Time', size=
sns.lineplot(data=retention);
```



In [80]:

```
#periodical representation
plt.figure(figsize=(20,10))
plt.title('Yearl Wise Retention Of Rates(in%) Over A Period Of Time', size=
sns.heatmap(data=retention, annot=True, fmt='.0%')
plt.show()
```



In [81]:

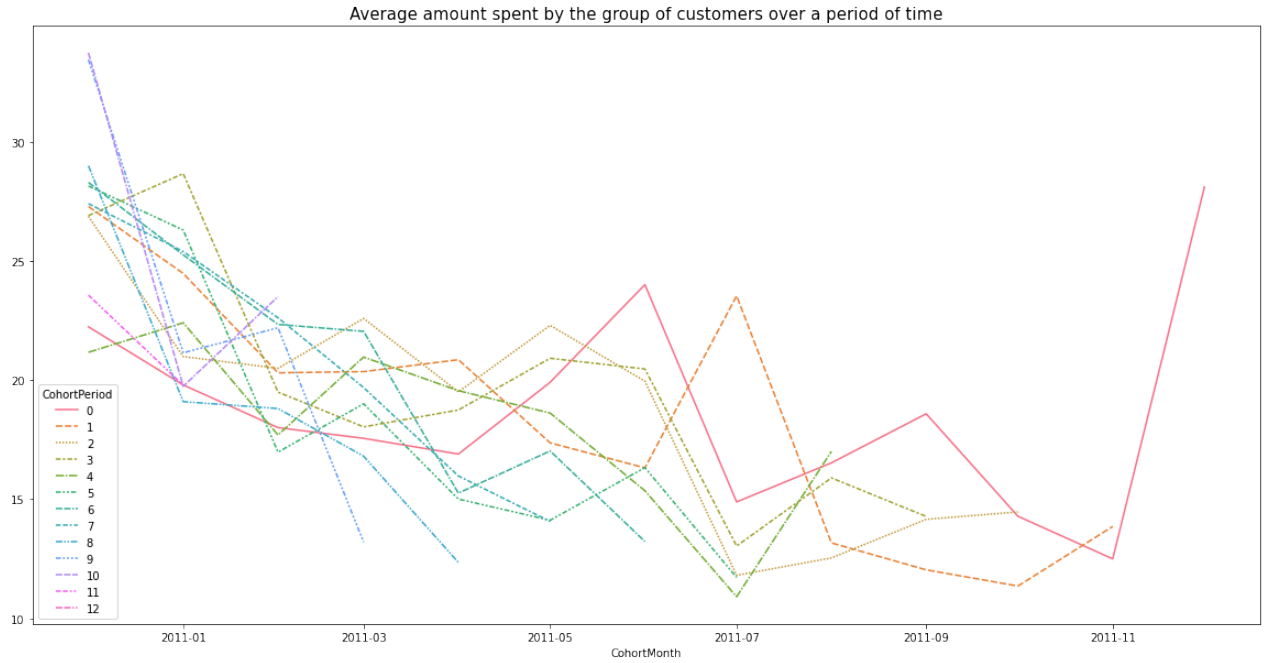
```
amnt_Cohort = df_cohort.pivot_table(index='CohortMonth', columns='CohortPer
amnt_Cohort

#this table shows the average amount spent by the group of customers over
```

Out[81]:

CohortPeriod	0	1	2	3	4	5	6	7	8	9	10
CohortMonth											
2010-12-01	22.23	27.28	26.87	26.90	21.16	28.14	28.29	27.40	28.99	33.44	33.73
2011-01-01	19.79	24.47	20.98	28.66	22.40	26.29	25.25	25.39	19.09	21.14	19.73
2011-02-01	18.00	20.30	20.49	19.49	17.69	16.97	22.33	22.61	18.80	22.19	23.50
2011-03-01	17.55	20.35	22.58	18.03	20.96	19.00	22.04	19.68	16.80	13.19	NaN
2011-04-01	16.89	20.85	19.50	18.74	19.55	15.00	15.25	15.97	12.34	NaN	NaN
2011-05-01	19.90	17.36	22.29	20.91	18.61	14.11	17.02	14.06	NaN	NaN	NaN
2011-06-01	24.00	16.31	19.95	20.46	15.35	16.32	13.22	NaN	NaN	NaN	NaN
2011-07-01	14.88	23.53	11.80	13.03	10.90	11.71	NaN	NaN	NaN	NaN	NaN
2011-08-01	16.52	13.16	12.53	15.89	17.00	NaN	NaN	NaN	NaN	NaN	NaN
2011-09-01	18.58	12.03	14.15	14.27	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-10-01	14.28	11.35	14.46	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-11-01	12.49	13.85	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12-01	28.10	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

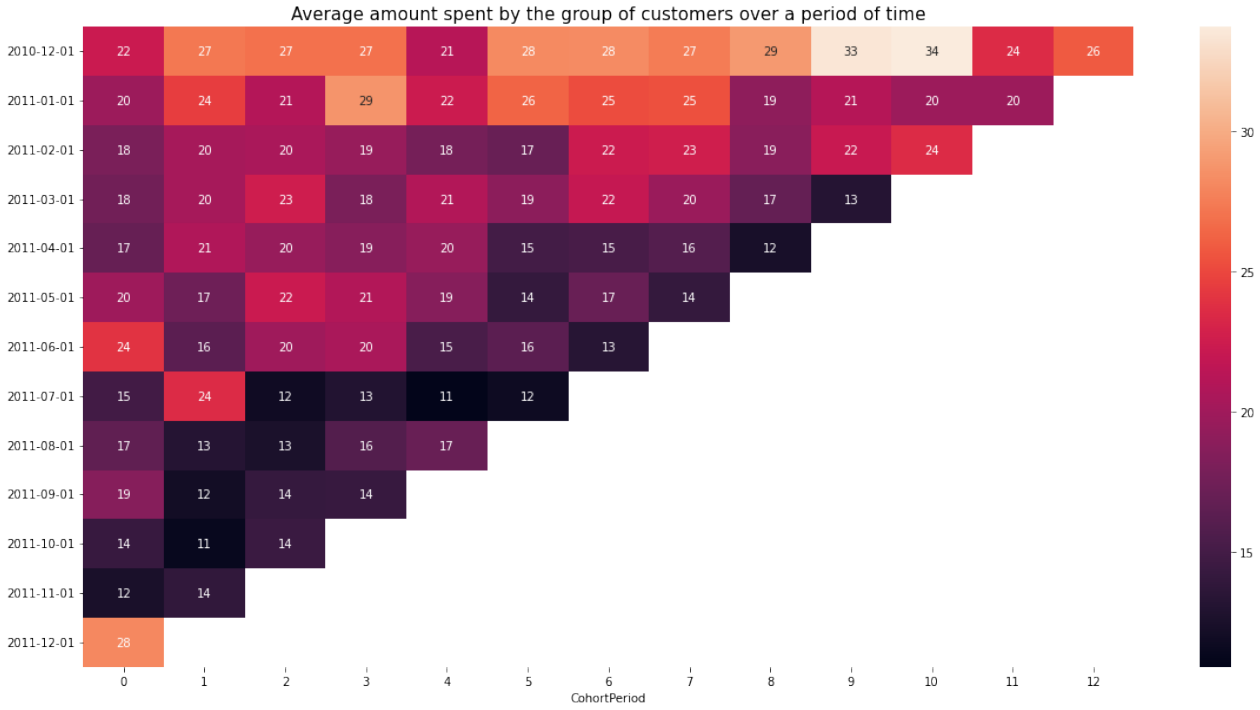
In [82]:

```
plt.figure(figsize=(20,10))
plt.title('Average amount spent by the group of customers over a period of
sns.lineplot(data=amnt_Cohort);
```



In [83]:

```
amnt_Cohort.index = pd.to_datetime(amnt_Cohort.index).date
plt.figure(figsize=(20, 10))
plt.title('Average amount spent by the group of customers over a period of
sns.heatmap(data = amnt_Cohort, annot = True)
plt.show()
```



Data Modeling :

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.

Calculate RFM metrics.

Build RFM Segments. Give recency, frequency, and monetary scores individually by dividing them into quartiles.

Combine three ratings to get a RFM segment (as strings).

Get the RFM score by adding up the three ratings.

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.

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

In [84]:

```
R_F_M = df.copy()

R_F_M = R_F_M.iloc[:,:9]

R_F_M.head()
```

Out[84]:

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

In [85]:

```
Recency = pd.DataFrame(R_F_M.groupby('CustomerID')['InvoiceDate'].max().res

Recency['InvoiceDate'] = pd.to_datetime(Recency['InvoiceDate']).dt.date

Recency['MaxDate'] = (Recency['InvoiceDate'].max())

Recency['Recency'] = (Recency['MaxDate']-Recency['InvoiceDate']).dt.days +

Recency = Recency[['CustomerID','Recency']]

Recency.head()
```

Out[85]:

	CustomerID	Recency
0	12347.0	3
1	12348.0	76
2	12349.0	19
3	12350.0	311
4	12352.0	37

In [86]:
```
Frequency = pd.DataFrame(R_F_M.groupby('CustomerID')['InvoiceNo'].nunique(

Frequency.columns = ['FreqCustomerID','Frequency']

Frequency.head()
```

Out[86]:

	FreqCustomerID	Frequency
0	12347.0	7
1	12348.0	4
2	12349.0	1
3	12350.0	1
4	12352.0	7

In [87]:
```
Monetary = pd.DataFrame(R_F_M.groupby('CustomerID')['Amount'].sum().reset_

Monetary.columns = ['MCustomerID','Monetary']

Monetary.head()
```

Out[87]:

	MCustomerID	Monetary
0	12347.0	4310.00
1	12348.0	1797.24
2	12349.0	1757.55
3	12350.0	334.40
4	12352.0	1665.74

In [88]:
```
R_F_M = pd.concat([Recency,Frequency,Monetary], axis=1)

R_F_M.drop(['FreqCustomerID','MCustomerID'], axis=1,inplace=True)

R_F_M.head(10)
```

Out[88]:

	CustomerID	Recency	Frequency	Monetary
0	12347.0	3	7	4310.00
1	12348.0	76	4	1797.24
2	12349.0	19	1	1757.55
3	12350.0	311	1	334.40
4	12352.0	37	7	1665.74
5	12353.0	205	1	89.00
6	12354.0	233	1	1079.40
7	12355.0	215	1	459.40
8	12356.0	23	3	2811.43
9	12357.0	34	1	6207.67

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.

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

In [89]:

```
R_F_M['Recency_Score'] = pd.cut(R_F_M['Recency'],bins=[0,18,51,143,264,375
R_F_M['Recency_Score'] = R_F_M['Recency_Score'].astype('int')
R_F_M['Frequency_Score'] = pd.cut(R_F_M['Frequency'],bins=[0,1,2,5,9,210],
R_F_M['Frequency_Score'] = R_F_M['Frequency_Score'].astype('int')
R_F_M['Monetary_Score'] = pd.cut(R_F_M['Monetary'],bins=[-1,306,667,1650,3
R_F_M['Monetary_Score'] = R_F_M['Monetary_Score'].astype('int')
```

In [90]:

```
R_F_M.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4334 entries, 0 to 4333
Data columns (total 7 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   CustomerID       4334 non-null   float64
 1   Recency          4334 non-null   int64  
 2   Frequency        4334 non-null   int64  
 3   Monetary         4334 non-null   float64
 4   Recency_Score    4334 non-null   int64  
 5   Frequency_Score  4334 non-null   int64  
 6   Monetary_Score   4334 non-null   int64  
dtypes: float64(2), int64(5)
memory usage: 237.1 KB
```

In [91]:
```
R_F_M.head()
```

Out[91]:

	CustomerID	Recency	Frequency	Monetary	Recency_Score	Frequency_Score	Monetar
0	12347.0	3	7	4310.00	5	4	
1	12348.0	76	4	1797.24	3	3	
2	12349.0	19	1	1757.55	4	1	
3	12350.0	311	1	334.40	1	1	
4	12352.0	37	7	1665.74	4	4	

In [92]:
```
R_F_M['TScore'] = R_F_M.Frequency_Score + R_F_M.Monetary_Score + R_F_M.Rece
```

In [93]:
```
R_F_M.head()
```

Out[93]:

	CustomerID	Recency	Frequency	Monetary	Recency_Score	Frequency_Score	Monetar
0	12347.0	3	7	4310.00	5	4	
1	12348.0	76	4	1797.24	3	3	
2	12349.0	19	1	1757.55	4	1	
3	12350.0	311	1	334.40	1	1	
4	12352.0	37	7	1665.74	4	4	

In [94]:
```
R_F_M.TScore.describe(percentiles=[0.25,0.5,0.75,0.9,0.95,0.99])
```

Out[94]:
```
count    4334.000000
mean        8.413013
std         3.309021
min         3.000000
25%         6.000000
50%         8.000000
75%        11.000000
90%        13.000000
95%        15.000000
99%        15.000000
max        15.000000
Name: TScore, dtype: float64
```

In [95]:
```
R_F_M['Customer_Type'] = pd.cut(R_F_M['TScore'],bins=[0,6,8,11,13,16], labe
```

In [96]:
```
R_F_M.head()
```

Out[96]:

	CustomerID	Recency	Frequency	Monetary	Recency_Score	Frequency_Score	Monetar
0	12347.0	3	7	4310.00	5	4	
1	12348.0	76	4	1797.24	3	3	
2	12349.0	19	1	1757.55	4	1	
3	12350.0	311	1	334.40	1	1	
4	12352.0	37	7	1665.74	4	4	

In [97]:
```
round(R_F_M.Customer_Type.value_counts(normalize=True)*100,0)
```

Out[97]:
```
Bad         33.0
Silver      28.0
Bronze      20.0
Gold        10.0
Platinum     9.0
Name: Customer_Type, dtype: float64
```

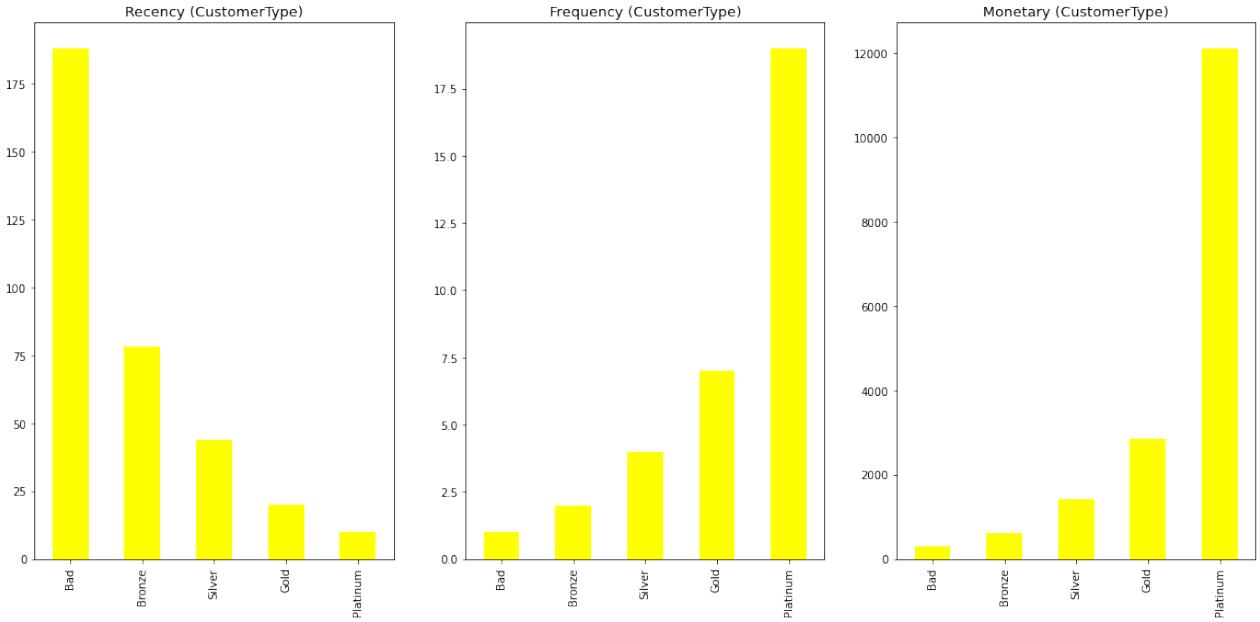
In [98]:
```
R_F_M.groupby('Customer_Type')['Recency','Frequency','Monetary'].mean().rou
```

Out[98]:

Customer_Type	Recency	Frequency	Monetary
Bad	188.0	1.0	297.0
Bronze	78.0	2.0	621.0
Silver	44.0	4.0	1416.0
Gold	20.0	7.0	2863.0
Platinum	10.0	19.0	12111.0

In [99]:

```
column = ['Recency','Frequency','Monetary']
plt.figure(figsize=(20,9))

for i,j in enumerate(column):
    plt.subplot(1,3,i+1)
    R_F_M.groupby('Customer_Type')[j].mean().round(0).plot(kind='bar',colo
    plt.title('{} (CustomerType)'.format(j),size=13)
    plt.xlabel('')

plt.show()
```



Data Modeling :

Create clusters using k-means clustering algorithm.

Prepare the data for the algorithm. If the data is asymmetrically distributed, manage the skewness with appropriate transformation. Standardize the data.

Decide the optimum number of clusters to be formed.

Analyze these clusters and comment on the results.

In [100…

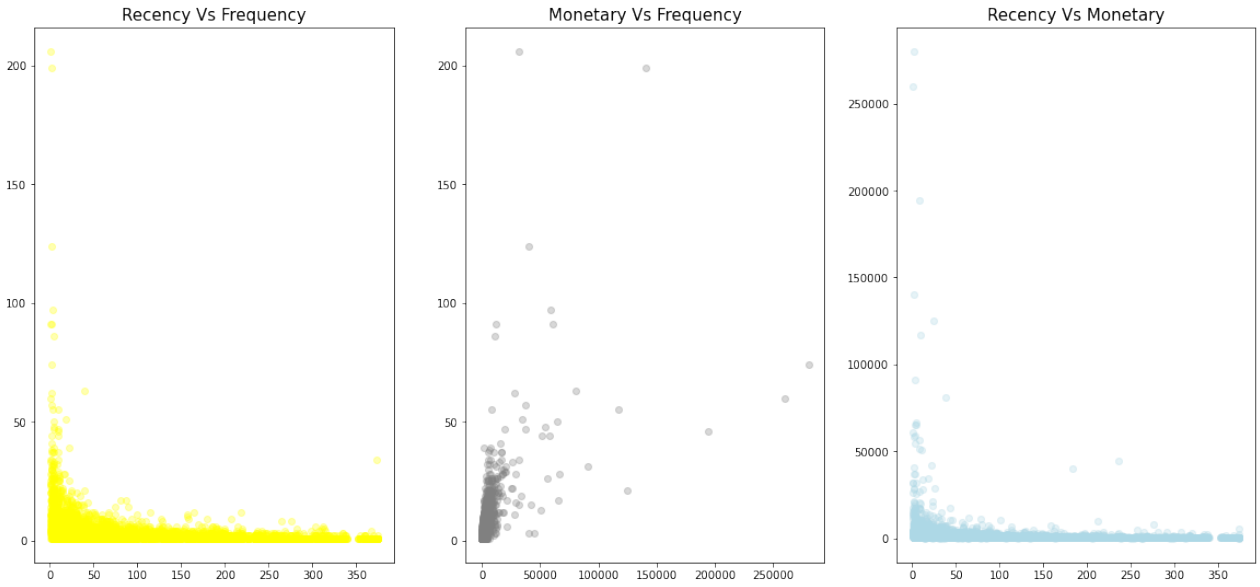
```
kmeans_df = R_F_M.copy()

kmeans_df = kmeans_df.iloc[:,:4]
kmeans_df.head()
```

Out[100…

	CustomerID	Recency	Frequency	Monetary
0	12347.0	3	7	4310.00
1	12348.0	76	4	1797.24
2	12349.0	19	1	1757.55
3	12350.0	311	1	334.40
4	12352.0	37	7	1665.74

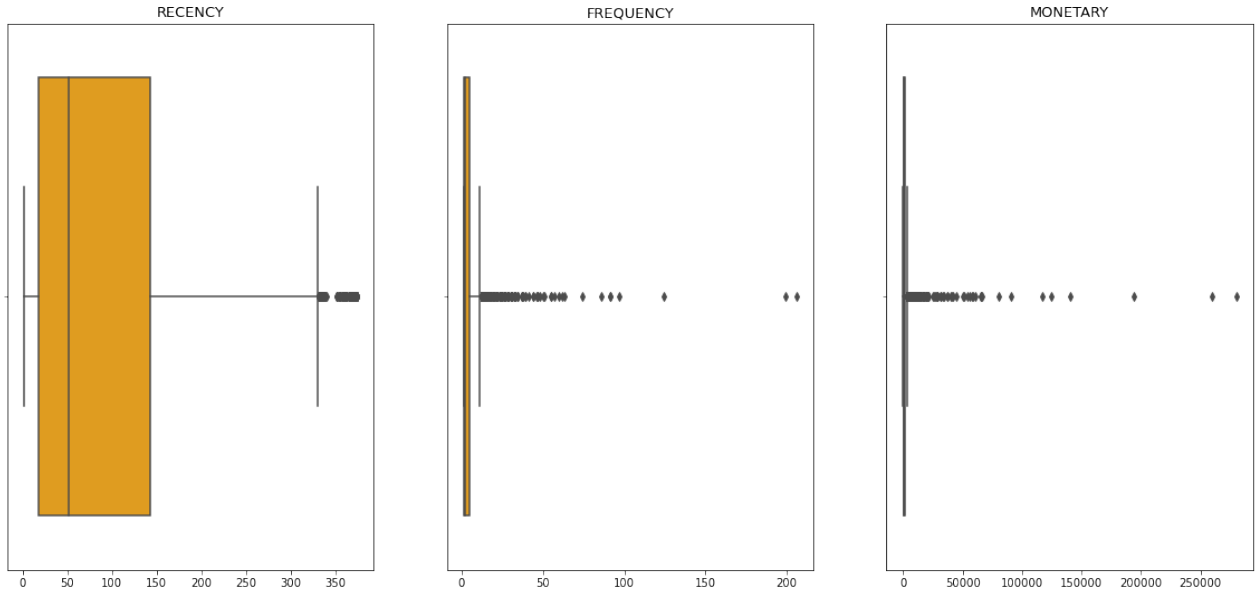
In [101…

```
plt.figure(figsize=(20,9))

plt.subplot(1,3,1)
plt.scatter(kmeans_df.Recency, kmeans_df.Frequency, color = 'yellow', alpha
plt.title('Recency Vs Frequency', size=15)

plt.subplot(1,3,2)
plt.scatter(kmeans_df.Monetary, kmeans_df.Frequency, color = 'grey', alpha=
plt.title('Monetary Vs Frequency', size=15)

plt.subplot(1,3,3)
plt.scatter(kmeans_df.Recency, kmeans_df.Monetary, color = 'lightblue', alp
plt.title('Recency Vs Monetary', size=15)

plt.show()
```



In [102…

```
#distribution of variables

column = ['Recency','Frequency','Monetary']

plt.figure(figsize=(20,9))

for i,j in enumerate(column):
    plt.subplot(1,3,i+1)
    sns.boxplot(kmeans_df[j], color='orange')
    plt.xlabel('')
    plt.title('{}'.format(j.upper()),size=13)

plt.show()
```



In [103…

```
#Treating Outliers
# For Monetary
Q1 = kmeans_df.Monetary.quantile(0.05)

Q3 = kmeans_df.Monetary.quantile(0.95)

IQR = Q3 - Q1

kmeans_df = kmeans_df[(kmeans_df.Monetary >= Q1 - 1.5 * IQR) & (kmeans_df.M
```

In [104…

```
# For Monetary
Q1 = kmeans_df.Recency.quantile(0.05)

Q3 = kmeans_df.Recency.quantile(0.95)

IQR = Q3 - Q1

kmeans_df = kmeans_df[(kmeans_df.Recency >= Q1 - 1.5 * IQR) & (kmeans_df.Re
```

In [105…
```
# For Monetary
Q1 = kmeans_df.Frequency.quantile(0.05)

Q3 = kmeans_df.Frequency.quantile(0.95)

IQR = Q3 - Q1

kmeans_df = kmeans_df[(kmeans_df.Frequency >= Q1 - 1.5 * IQR) & (kmeans_df
```

In [106…
```
kmeans_df = kmeans_df.reset_index(drop=True)
kmeans_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4259 entries, 0 to 4258
Data columns (total 4 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   CustomerID  4259 non-null   float64
 1   Recency     4259 non-null   int64  
 2   Frequency   4259 non-null   int64  
 3   Monetary    4259 non-null   float64
dtypes: float64(2), int64(2)
memory usage: 133.2 KB
```

In [107…
```
kmeans_df.sample(5)
```

Out[107…

	CustomerID	Recency	Frequency	Monetary
2250	15471.0	3	1	454.48
3360	17015.0	29	3	1838.61
2431	15716.0	146	4	1101.11
4210	18221.0	23	5	1041.61
2935	16425.0	303	1	302.70

In [108…
```
kmeans_df = kmeans_df.iloc[:,1:]
```

In [109…
```
from sklearn.preprocessing import StandardScaler
```

In [110…
```
SC = StandardScaler()
```

In [111…
```
kmeans_df_norm = SC.fit_transform(kmeans_df)
```

In [112…
```
kmeans_df_norm = pd.DataFrame(kmeans_df_norm)
kmeans_df_norm.columns = ['Recency','Frequency','Monetary']
kmeans_df_norm.head()
```

Out[112…

	Recency	Frequency	Monetary
0	-0.912760	0.877595	1.680623
1	-0.184490	0.098534	0.272852
2	-0.753139	-0.680528	0.250616
3	2.159940	-0.680528	-0.546702
4	-0.573566	0.877595	0.199179

In [113…
```
from sklearn.cluster import KMeans
```

In [114…
```
Kmeans = KMeans(n_clusters=5)
Kmeans.fit(kmeans_df_norm)
```

Out[114…
```
KMeans(n_clusters=5)
```

In [115…
```
Kmeans.labels_
```

Out[115…
```
array([4, 0, 3, ..., 3, 4, 0], dtype=int32)
```

In [116…
```
Kmeans.cluster_centers_
```

Out[116…
```
array([[-0.60259196,  0.50101857,  0.3960702 ],
       [ 1.59606641, -0.55700248, -0.49063499],
       [-0.79919799,  3.66619854,  4.18212942],
       [-0.39766469, -0.42333904, -0.41262776],
       [-0.70422941,  1.85985342,  1.68866528]])
```

In [117…
```
print (Kmeans.labels_)
print (len(Kmeans.labels_))
```

```
[4 0 3 ... 3 4 0]
4259
```

In [118…
```
print (type(Kmeans.labels_))
unique, counts = np.unique(Kmeans.labels_, return_counts=True)
print(dict(zip(unique, counts)))
```

```
<class 'numpy.ndarray'>
{0: 862, 1: 1007, 2: 107, 3: 1975, 4: 308}
```

In [119…

```
kmeans_df['clusters'] = Kmeans.labels_
kmeans_df.head()
```

Out[119…

	Recency	Frequency	Monetary	clusters
0	3	7	4310.00	4
1	76	4	1797.24	0
2	19	1	1757.55	3
3	311	1	334.40	1
4	37	7	1665.74	0

In [120…

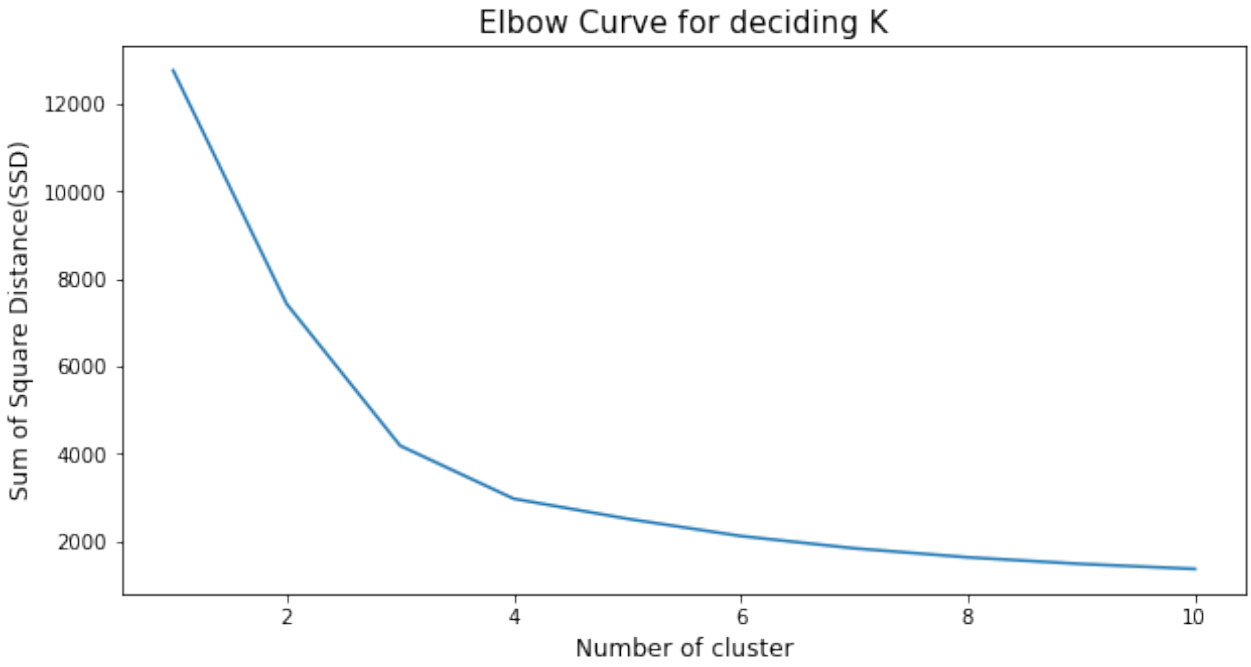
```
kmeans_df.groupby('clusters').mean().round(0)
```

Out[120…

clusters	Recency	Frequency	Monetary
0	34.0	6.0	2017.0
1	254.0	1.0	434.0
2	14.0	18.0	8775.0
3	55.0	2.0	574.0
4	24.0	11.0	4324.0

In [121…

```
# Elbow-curve/SSD

ssd = []
for num_clusters in list(range(1,11)):
    model_clus = KMeans(n_clusters = num_clusters, max_iter=50)
    model_clus.fit(kmeans_df_norm)
    ssd.append(model_clus.inertia_)

# plot the SSDs for each n_clusters
plt.figure(figsize=(10,5))
plt.plot(np.arange(1,11,1), ssd)
plt.xlabel('Number of cluster', size=12)
plt.ylabel('Sum of Square Distance(SSD)', size=12)
plt.title('Elbow Curve for deciding K', size=15)
plt.show()
```



In [122…

```
from sklearn.metrics import silhouette_samples, silhouette_score


for num_clusters in list(range(2,11)):
    # intialise kmeans
    model_clus = KMeans(n_clusters = num_clusters, max_iter=50)
    model_clus.fit(kmeans_df_norm)

    cluster_labels = model_clus.labels_

    # silhouette score
    silhouette_avg = silhouette_score(kmeans_df_norm, cluster_labels)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clus
```

```
For n_clusters=2, the silhouette score is 0.5460929706945657
For n_clusters=3, the silhouette score is 0.5105004334604668
For n_clusters=4, the silhouette score is 0.4865715970728021
For n_clusters=5, the silhouette score is 0.44185916176884094
For n_clusters=6, the silhouette score is 0.4169656865593138
For n_clusters=7, the silhouette score is 0.41751507836186597
For n_clusters=8, the silhouette score is 0.38667007992559166
For n_clusters=9, the silhouette score is 0.39012889737040457
For n_clusters=10, the silhouette score is 0.38224842379456425
```

In [123…

```
# Kmeans with K=3
Kmeans = KMeans(n_clusters = 2)
Kmeans.fit(kmeans_df_norm)
```

Out[123…

```
KMeans(n_clusters=2)
```

In [124…

```
kmeans_df['clusters'] = Kmeans.labels_
kmeans_df.head()
```

Out[124...

	Recency	Frequency	Monetary	clusters
0	3	7	4310.00	1
1	76	4	1797.24	0
2	19	1	1757.55	0
3	311	1	334.40	0
4	37	7	1665.74	0

In [125...

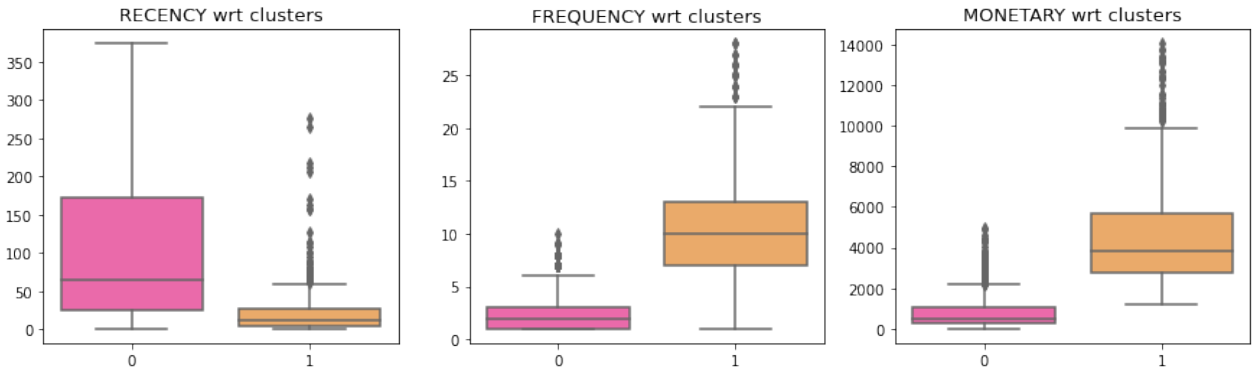
```
kmeans_df.groupby('clusters').mean().round(0)
```

Out[125...

clusters	Recency	Frequency	Monetary
0	106.0	2.0	758.0
1	23.0	11.0	4614.0

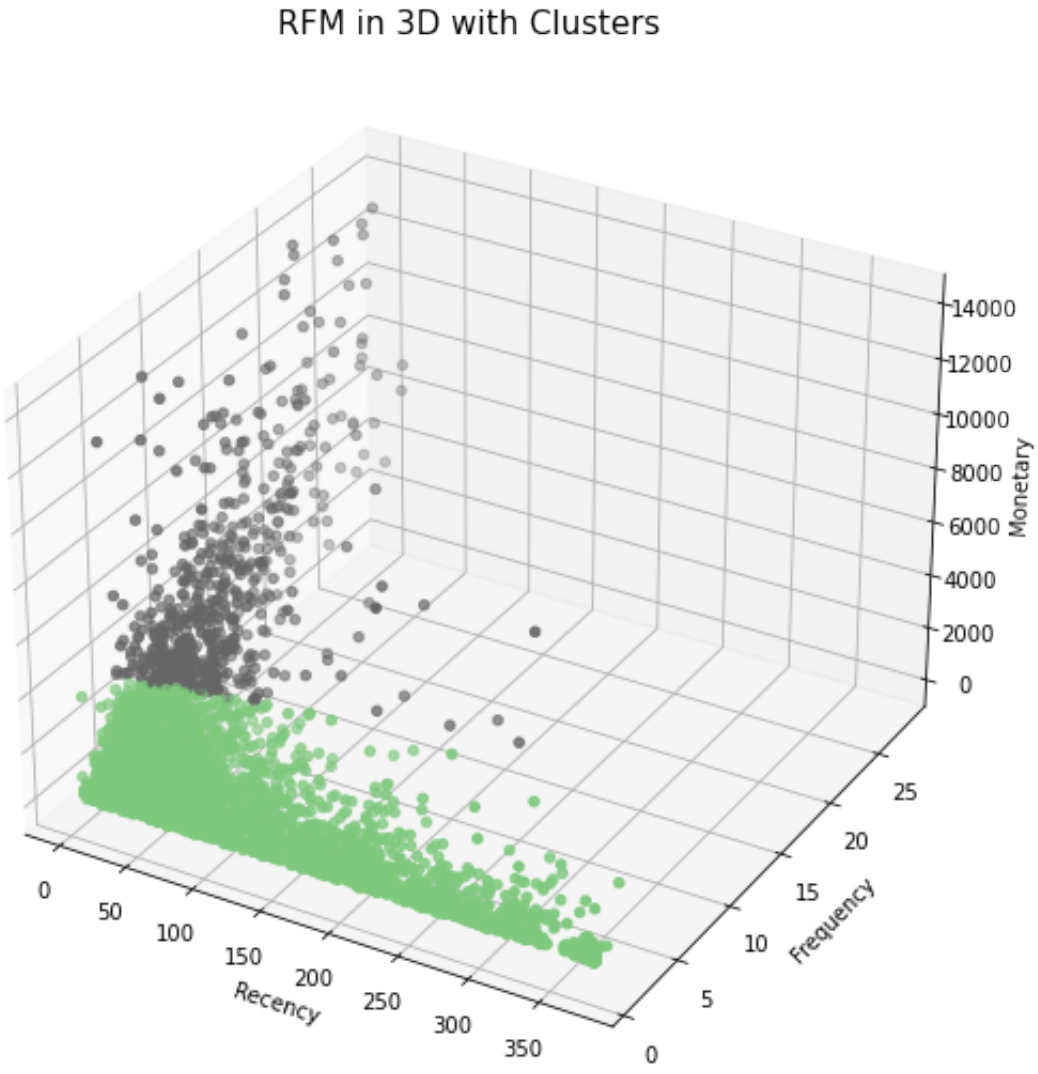
In [126...

```
column = ['Recency','Frequency','Monetary']
plt.figure(figsize=(15,4))
for i,j in enumerate(column):
    plt.subplot(1,3,i+1)
    sns.boxplot(y=kmeans_df[j], x=kmeans_df['clusters'], palette='spring')
    plt.title('{} wrt clusters'.format(j.upper()), size=13)
    plt.ylabel('')
    plt.xlabel('')

plt.show()
```



In [127…

```
# Creating figure
fig = plt.figure(figsize = (20, 9))
ax = plt.axes(projection ="3d")



# Creating plot
ax.scatter3D(kmeans_df.Recency, kmeans_df.Frequency, kmeans_df.Monetary, c=
ax.set_xlabel('Recency')
ax.set_ylabel('Frequency')
ax.set_zlabel('Monetary')
plt.title('RFM in 3D with Clusters', size=15)
ax.set(facecolor='white')
plt.show()
```



Create a dashboard in tableau by choosing appropriate chart types and metrics useful for the business. The dashboard must entail the following:

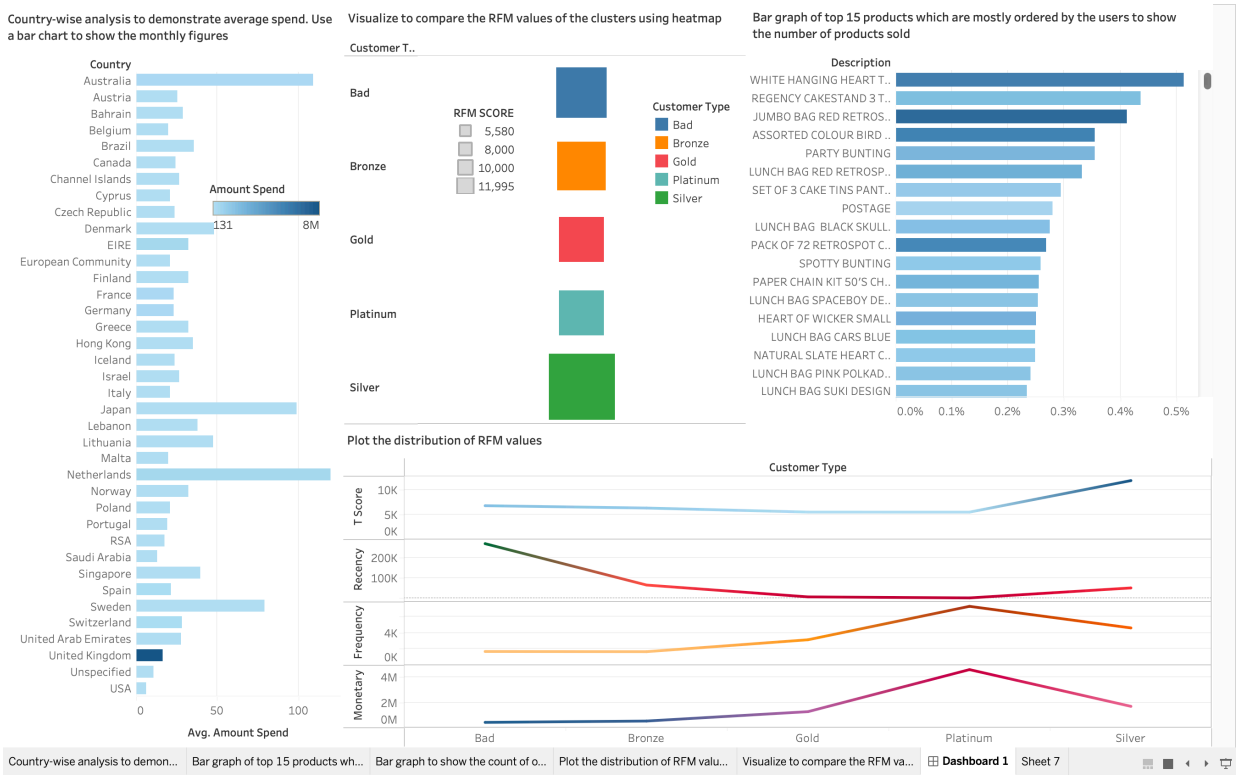
- Country-wise analysis to demonstrate average spend. Use a bar chart to show the monthly figures
- Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold
- Bar graph to show the count of orders vs. hours throughout the day
- Plot the distribution of RFM values using histogram and frequency charts
- Plot error (cost) vs. number of clusters selected
- Visualize to compare the RFM values of the clusters using heatmap

In [129...
```
df.to_excel('df_.xlsx')
```

In [134...
```
R_F_M.to_excel('R_F_M.xlsx')
```

In [135...
```
kmeans_df_norm.to_excel('kmeans_df_norm.xlsx')
```

In [139...
```
kmeans_df.to_excel('kmeans_df.xlsx')
```



https://public.tableau.com/app/profile/rushikesh.khankar/viz/RetailCohortRFM
publish=yes

In [ ]: