Problem Statement

Variables Description InvoiceNo Invoice number. Nominal, a six 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 five 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 six digit integral number uniquely assigned to each customer Country Country name. Nominal, the name of the country where each customer resides

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.

Variables Description

- InvoiceNo- Invoice number. Nominal, a six 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 five 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 six digit integral number uniquely assigned to each customer
- Country Country name. Nominal, the name of the country where each customer resides

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
from PIL import Image as PILImage
from operator import attrgetter
import datetime as dt
from sklearn.preprocessing import StandardScaler
from sklearn.cluster import KMeans
```

In [2]:
```
df = pd.read_excel('C:/Users/vipul/Downloads/Project 3/Online Retail.xlsx')
```

In [3]:
```
Rows,Columns = df.shape
print('Data frame has {} rows and {} columns'.format(Rows,Columns))
```

```
Data frame has 541909 rows and 8 columns
```

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

Out[4]:

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

In [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
```

In [6]:
```
df.describe()
```

Out[6]:

	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

	Quantity	UnitPrice	CustomerID
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

- Dataset has 'Quantity' and 'UnitPrice' value starting from negative values which doesn't reallt make any sense.
- Let's explore the data more and see how this could be managed.

In [7]:
```
df[df['UnitPrice']<0]
```

Out[7]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
299983	A563186	B	Adjust bad debt	1	2011-08-12 14:51:00	-11062.06	NaN	Unitec Kingdom
299984	A563187	B	Adjust bad debt	1	2011-08-12 14:52:00	-11062.06	NaN	Unitec Kingdom

In [8]:
```
df[df['Quantity']<0]
```

Out[8]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
141	C536379	D	Discount	-1	2010-12-01 09:41:00	27.50	14527.0	United Kingdom
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2010-12-01 09:49:00	4.65	15311.0	United Kingdom
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2010-12-01 10:24:00	1.65	17548.0	United Kingdom
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom
...	...	...	...	...	...	...	...	...
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2011-12-09 09:57:00	0.83	14397.0	United Kingdom
541541	C581499	M	Manual	-1	2011-12-09 10:28:00	224.69	15498.0	United Kingdom

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2011-12-09 11:57:00	10.95	15311.0	United Kingdom
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2011-12-09 11:58:00	1.25	17315.0	United Kingdom
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2011-12-09 11:58:00	1.25	17315.0	United Kingdom

10624 rows × 8 columns

Checking Null values

In [9]:
```
df[df['Quantity']<0].isnull().sum()
```

Out[9]:
```
InvoiceNo         0
StockCode         0
Description     862
Quantity          0
InvoiceDate       0
UnitPrice         0
CustomerID     1719
Country           0
dtype: int64
```

In [ ]:

In [10]:
```
df.columns
```

Out[10]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')
```

As per the data definition the 'InvoiceNo' starting with 'C' means cancelled order and they are not required for the model

In [11]:
```
df[df['InvoiceNo'].str.startswith('C',na=False)]
```

Out[11]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
141	C536379	D	Discount	-1	2010-12-01 09:41:00	27.50	14527.0	United Kingdom
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2010-12-01 09:49:00	4.65	15311.0	United Kingdom
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2010-12-01 10:24:00	1.65	17548.0	United Kingdom
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom
...	...	...	...	...	...	...	...	...
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2011-12-09 09:57:00	0.83	14397.0	United Kingdom
541541	C581499	M	Manual	-1	2011-12-09 10:28:00	224.69	15498.0	United Kingdom
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2011-12-09 11:57:00	10.95	15311.0	United Kingdom
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2011-12-09 11:58:00	1.25	17315.0	United Kingdom
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2011-12-09 11:58:00	1.25	17315.0	United Kingdom

9288 rows × 8 columns

In [12]:
```
df = df[~df['InvoiceNo'].str.startswith('C',na=False)]
```

In [13]:
```
df.describe()
```

Out[13]:

	Quantity	UnitPrice	CustomerID
count	532621.000000	532621.000000	397924.000000
mean	10.239972	3.847621	15294.315171
std	159.593551	41.758023	1713.169877
min	-9600.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13969.000000
50%	3.000000	2.080000	15159.000000
75%	10.000000	4.130000	16795.000000
max	80995.000000	13541.330000	18287.000000

Duplicate data check

In [14]:
```
df.duplicated().sum()
```

Out[14]: 5231

In [15]:
```
df.drop_duplicates(inplace=True,keep = 'first')
```

In [16]:
```
df.duplicated().sum()
```

Out[16]: 0

Handeling missing values

In [17]:
```
df.isnull().sum()
```

Out[17]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     134658
Country             0
dtype: int64
```

In [18]:
```
df[(df['Description'].isnull()) & (df['CustomerID'].isnull())]
```

Out[18]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	NaN	56	2010-12-01 11:52:00	0.0	NaN	United Kingdom
1970	536545	21134	NaN	1	2010-12-01 14:32:00	0.0	NaN	United Kingdom
1971	536546	22145	NaN	1	2010-12-01 14:33:00	0.0	NaN	United Kingdom
1972	536547	37509	NaN	1	2010-12-01 14:33:00	0.0	NaN	United Kingdom
1987	536549	85226A	NaN	1	2010-12-01 14:34:00	0.0	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
535322	581199	84581	NaN	-2	2011-12-07 18:26:00	0.0	NaN	United Kingdom
535326	581203	23406	NaN	15	2011-12-07 18:31:00	0.0	NaN	United Kingdom
535332	581209	21620	NaN	6	2011-12-07 18:35:00	0.0	NaN	United Kingdom
536981	581234	72817	NaN	27	2011-12-08 10:33:00	0.0	NaN	United Kingdom
538554	581408	85175	NaN	20	2011-12-08 14:06:00	0.0	NaN	United Kingdom

1454 rows × 8 columns

In [19]:
```
df[(df['Description'].isnull())]
```

Out[19]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	NaN	56	2010-12-01 11:52:00	0.0	NaN	United Kingdom
1970	536545	21134	NaN	1	2010-12-01 14:32:00	0.0	NaN	United Kingdom

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
1971	536546	22145	NaN	1	2010-12-01 14:33:00	0.0	NaN	United Kingdom
1972	536547	37509	NaN	1	2010-12-01 14:33:00	0.0	NaN	United Kingdom
1987	536549	85226A	NaN	1	2010-12-01 14:34:00	0.0	NaN	United Kingdom
...	...	...	...	...	...	...	...	...
535322	581199	84581	NaN	-2	2011-12-07 18:26:00	0.0	NaN	United Kingdom
535326	581203	23406	NaN	15	2011-12-07 18:31:00	0.0	NaN	United Kingdom
535332	581209	21620	NaN	6	2011-12-07 18:35:00	0.0	NaN	United Kingdom
536981	581234	72817	NaN	27	2011-12-08 10:33:00	0.0	NaN	United Kingdom
538554	581408	85175	NaN	20	2011-12-08 14:06:00	0.0	NaN	United Kingdom

1454 rows × 8 columns

In [20]:
```
df.dropna(subset=['CustomerID'],inplace=True)
```

In [21]:
```
df.describe()
```

Out[21]:

	Quantity	UnitPrice	CustomerID
count	392732.000000	392732.000000	392732.000000
mean	13.153718	3.125596	15287.734822
std	181.588420	22.240725	1713.567773
min	1.000000	0.000000	12346.000000
25%	2.000000	1.250000	13955.000000
50%	6.000000	1.950000	15150.000000
75%	12.000000	3.750000	16791.000000
max	80995.000000	8142.750000	18287.000000

Now the data is clean from all negative values and null values. But the UnitPrice have some values zero values which again really don't make any sense.

In [22]:
```
df = df[df['UnitPrice']!=0]
```

In [23]:
```
df.isnull().sum()
```

Out[23]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
```

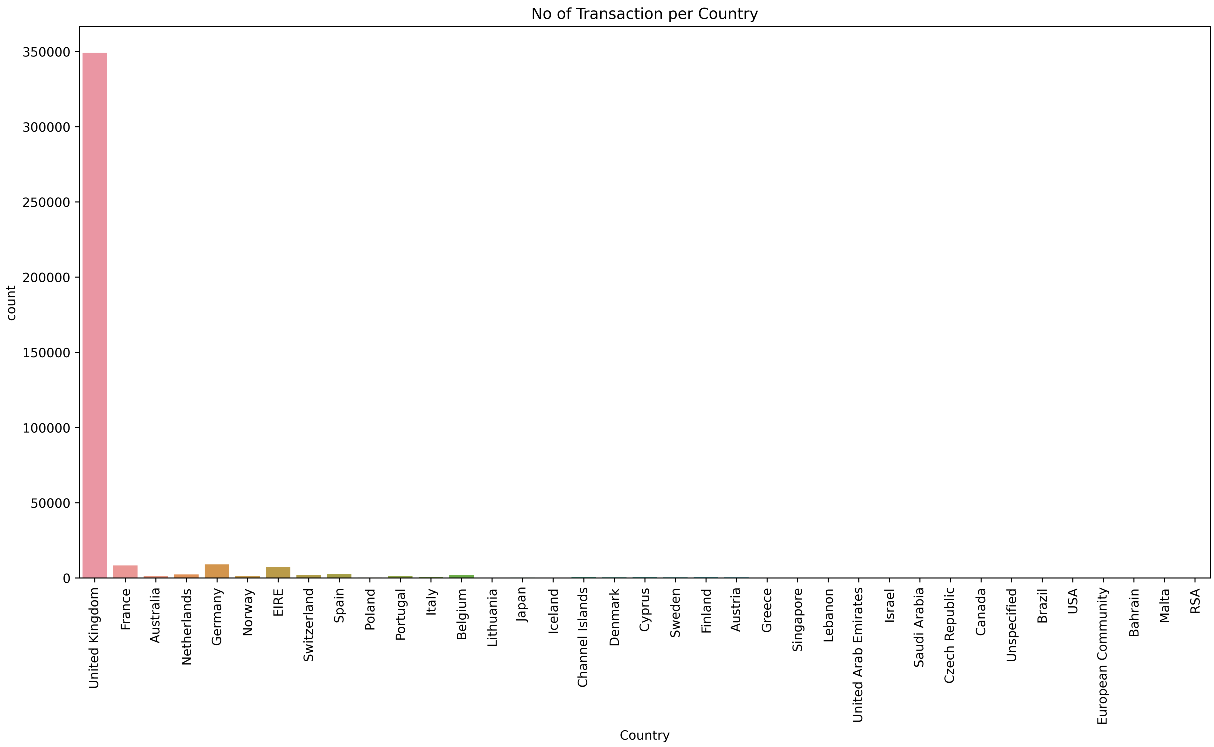
```
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

In [24]:
```
df.shape
```

Out[24]:
```
(392692, 8)
```

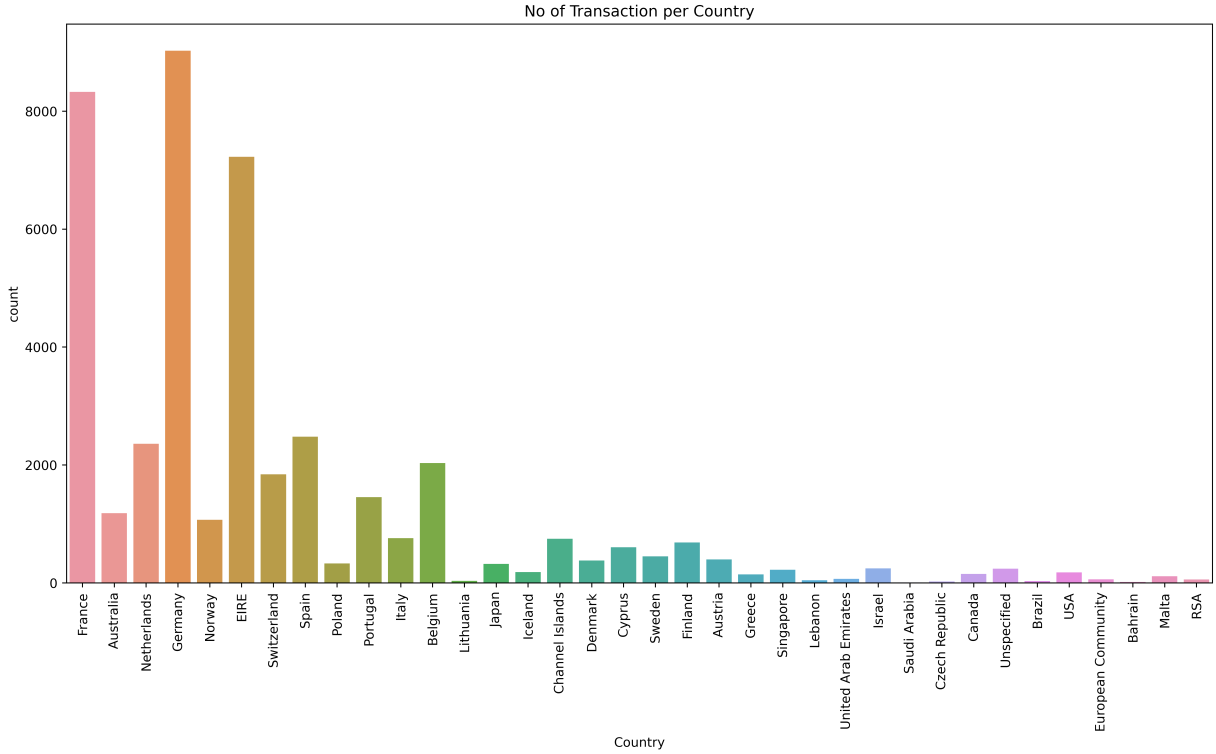
In [25]:
```
plt.figure(figsize=(16,8),dpi = 600)
sns.countplot(x = df['Country'])
plt.xticks(rotation = 90);
plt.title("No of Transaction per Country")
```

Out[25]:
```
Text(0.5, 1.0, 'No of Transaction per Country')
```



In [26]:
```
plt.figure(figsize=(16,8),dpi = 600)
sns.countplot(x = df[df['Country']!='United Kingdom']['Country'])
plt.xticks(rotation = 90);
plt.title("No of Transaction per Country")
```

Out[26]:
```
Text(0.5, 1.0, 'No of Transaction per Country')
```



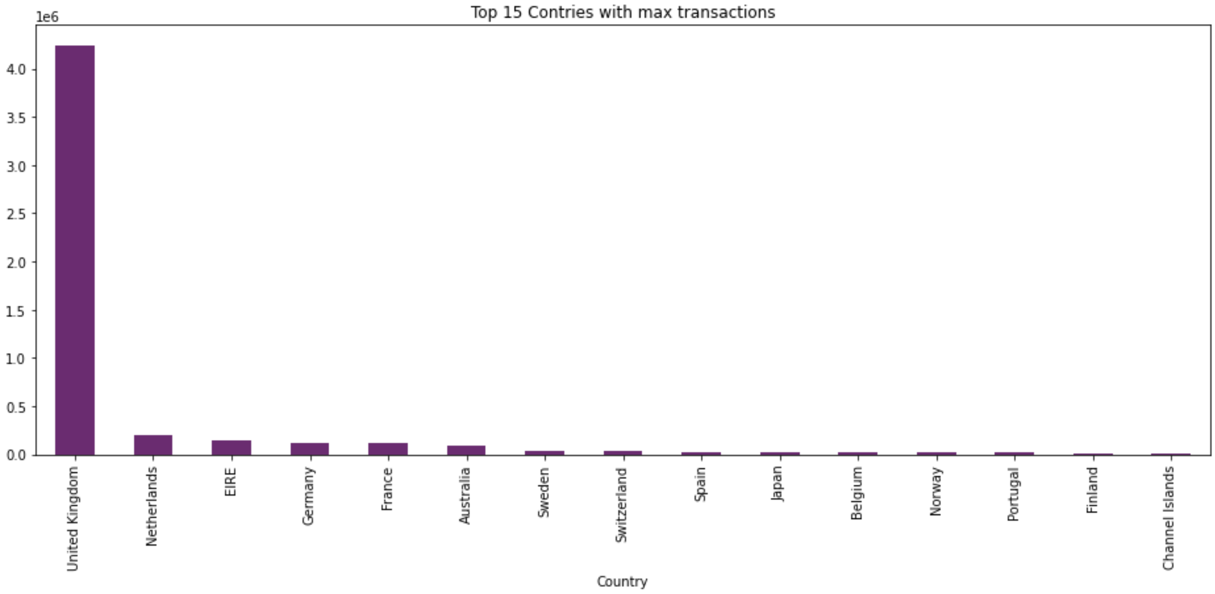
In [27]:

```
df.groupby(['Country'])['Quantity'].sum().sort_values()
```

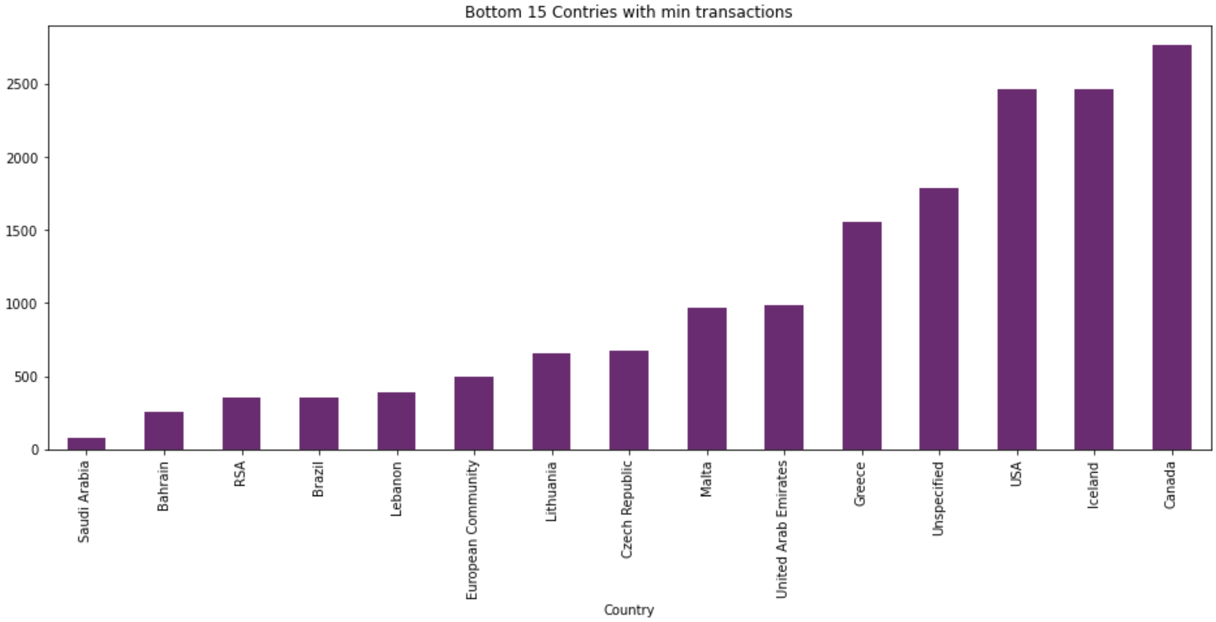
Out[27]:

```
Country
Saudi Arabia                80
Bahrain                    260
RSA                        351
Brazil                     356
Lebanon                    386
European Community         499
Lithuania                  652
Czech Republic             671
Malta                      970
United Arab Emirates       982
Greece                    1557
Unspecified               1785
USA                       2458
Iceland                   2458
Canada                    2763
Poland                    3684
Israel                    4043
Austria                   4881
Singapore                 5241
Cyprus                    6340
Italy                     8112
Denmark                   8235
Channel Islands           9485
Finland                  10704
Portugal                 16095
Norway                   19336
Belgium                  23237
Japan                    26016
Spain                    27933
Switzerland              30082
Sweden                   36078
Australia                83891
France                  111428
Germany                 119154
EIRE                    140133
Netherlands             200361
United Kingdom         4241305
Name: Quantity, dtype: int64
```

In [28]:
```
df.groupby('Country')['Quantity'].sum().sort_values(ascending = False).head(15).plot
plt.title('Top 15 Contries with max transactions');
```



In [29]:
```
df.groupby('Country')['Quantity'].sum().sort_values(ascending = True).head(15).plot(
plt.title('Bottom 15 Contries with min transactions');
```



In [30]:
```
df.head(1)
```

Out[30]:

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

Let's count the how many people have ordered multiple times and how many have ordered only once.

In [31]:
```
n_orders = df.groupby('CustomerID')['InvoiceNo'].nunique()
multi_order_percent = np.sum(n_orders>1)/len(df['CustomerID'].unique())
print( '{}% of people orderd more than once'.format((100*multi_order_percent).round(
```

```
65.58% of people orderd more than once and 34.42% of people ordered just once
```

Cohort Analysis

In [32]:
```
df['order_month'] = df['InvoiceDate'].dt.to_period('M')
df['cohort'] = df.groupby('CustomerID')['InvoiceDate'].transform('min').dt.to_period
df
```

Out[32]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
0	536365	85123A	WHITE HANGING HEART T-LIGHT HOLDER	6	2010-12-01 08:26:00	2.55	17850.0	United Kingdom
1	536365	71053	WHITE METAL LANTERN	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
2	536365	84406B	CREAM CUPID HEARTS COAT HANGER	8	2010-12-01 08:26:00	2.75	17850.0	United Kingdom
3	536365	84029G	KNITTED UNION FLAG HOT WATER BOTTLE	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
4	536365	84029E	RED WOOLLY HOTTIE WHITE HEART.	6	2010-12-01 08:26:00	3.39	17850.0	United Kingdom
...	...	...	...	...	...	...	...	...
541904	581587	22613	PACK OF 20 SPACEBOY NAPKINS	12	2011-12-09 12:50:00	0.85	12680.0	France
541905	581587	22899	CHILDREN'S APRON DOLLY GIRL	6	2011-12-09 12:50:00	2.10	12680.0	France
541906	581587	23254	CHILDRENS CUTLERY DOLLY GIRL	4	2011-12-09 12:50:00	4.15	12680.0	France
541907	581587	23255	CHILDRENS CUTLERY CIRCUS PARADE	4	2011-12-09 12:50:00	4.15	12680.0	France
541908	581587	22138	BAKING SET 9 PIECE RETROSPOT	3	2011-12-09 12:50:00	4.95	12680.0	France

392692 rows × 10 columns

In [ ]:

In [33]:
```
df_cohort = df.groupby(['cohort', 'order_month']).agg(n_customers=('CustomerID', 'nu
df_cohort['period_number'] = (df_cohort.order_month - df_cohort.cohort).apply(attrge
```

In [34]:
```
df_cohort
```

Out[34]:

	cohort	order_month	n_customers	period_number
0	2010-12	2010-12	885	0
1	2010-12	2011-01	324	1
2	2010-12	2011-02	286	2
3	2010-12	2011-03	340	3
4	2010-12	2011-04	321	4
...	...	...	...	...
86	2011-10	2011-11	86	1
87	2011-10	2011-12	41	2
88	2011-11	2011-11	323	0
89	2011-11	2011-12	36	1
90	2011-12	2011-12	41	0

91 rows × 4 columns

In [35]:
```
cohort_pivot = df_cohort.pivot_table(index = 'cohort',
                                     columns = 'period_number',
                                     values = 'n_customers')
```

In [36]:
```
cohort_pivot
```

Out[36]:

period_number	0	1	2	3	4	5	6	7	8	9	10	11	
cohort													
2010-12	885.0	324.0	286.0	340.0	321.0	352.0	321.0	309.0	313.0	350.0	331.0	445.0	23
2011-01	417.0	92.0	111.0	96.0	134.0	120.0	103.0	101.0	125.0	136.0	152.0	49.0	N
2011-02	380.0	71.0	71.0	108.0	103.0	94.0	96.0	106.0	94.0	116.0	26.0	NaN	N
2011-03	452.0	68.0	114.0	90.0	101.0	76.0	121.0	104.0	126.0	39.0	NaN	NaN	N
2011-04	300.0	64.0	61.0	63.0	59.0	68.0	65.0	78.0	22.0	NaN	NaN	NaN	N
2011-05	284.0	54.0	49.0	49.0	59.0	66.0	75.0	27.0	NaN	NaN	NaN	NaN	N
2011-06	242.0	42.0	38.0	64.0	56.0	81.0	23.0	NaN	NaN	NaN	NaN	NaN	N
2011-07	188.0	34.0	39.0	42.0	51.0	21.0	NaN	NaN	NaN	NaN	NaN	NaN	N
2011-08	169.0	35.0	42.0	41.0	21.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
2011-09	299.0	70.0	90.0	34.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
2011-10	358.0	86.0	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
2011-11	323.0	36.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N
2011-12	41.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN	N

In [37]:
```
cohort_pivot.iloc[:,0]
```

Out[37]:
```
cohort
2010-12    885.0
2011-01    417.0
2011-02    380.0
2011-03    452.0
2011-04    300.0
2011-05    284.0
2011-06    242.0
2011-07    188.0
2011-08    169.0
2011-09    299.0
2011-10    358.0
2011-11    323.0
2011-12     41.0
Freq: M, Name: 0, dtype: float64
```

In [38]:
```
cohort_pivot.divide(cohort_pivot.iloc[:,0], axis = 0)
```

Out[38]:

period_number cohort	0	1	2	3	4	5	6	7	8
2010-12	1.0	0.366102	0.323164	0.384181	0.362712	0.397740	0.362712	0.349153	0.353672
2011-01	1.0	0.220624	0.266187	0.230216	0.321343	0.287770	0.247002	0.242206	0.299760
2011-02	1.0	0.186842	0.186842	0.284211	0.271053	0.247368	0.252632	0.278947	0.247368
2011-03	1.0	0.150442	0.252212	0.199115	0.223451	0.168142	0.267699	0.230088	0.278761
2011-04	1.0	0.213333	0.203333	0.210000	0.196667	0.226667	0.216667	0.260000	0.073333
2011-05	1.0	0.190141	0.172535	0.172535	0.207746	0.232394	0.264085	0.095070	NaN
2011-06	1.0	0.173554	0.157025	0.264463	0.231405	0.334711	0.095041	NaN	NaN
2011-07	1.0	0.180851	0.207447	0.223404	0.271277	0.111702	NaN	NaN	NaN
2011-08	1.0	0.207101	0.248521	0.242604	0.124260	NaN	NaN	NaN	NaN
2011-09	1.0	0.234114	0.301003	0.113712	NaN	NaN	NaN	NaN	NaN
2011-10	1.0	0.240223	0.114525	NaN	NaN	NaN	NaN	NaN	NaN
2011-11	1.0	0.111455	NaN	NaN	NaN	NaN	NaN	NaN	NaN
2011-12	1.0	NaN	NaN	NaN	NaN	NaN	NaN	NaN	NaN

In [39]:
```
plt.figure(figsize = (16,8))
sns.heatmap(data =cohort_pivot.divide(cohort_pivot.iloc[:,0], axis = 0),annot=True,c
```

Out[39]:
```
<AxesSubplot:xlabel='period_number', ylabel='cohort'>
```

In [ ]:

In [40]:
```
df['Total Price'] = df['Quantity']*df['UnitPrice']
```

Extract Recency, Frequency, Monetary (RFM) Metrics¶

Lets find out RFM values

- Recency: Number of days since a customer's last purchase
- Frequency: Number of purchases by the customer
- Monetary(Total Price): Total amount of money spent by the customer on his purchases

In [41]:
```
df_Monetary = df[['CustomerID','Total Price']].groupby("CustomerID", as_index=False)
df_Monetary
```

Out[41]:

	CustomerID	Total Price
0	12346.0	77183.60
1	12347.0	4310.00
2	12348.0	1797.24
3	12349.0	1757.55
4	12350.0	334.40
...	...	...
4333	18280.0	180.60
4334	18281.0	80.82
4335	18282.0	178.05
4336	18283.0	2045.53

	CustomerID	Total Price
4337	18287.0	1837.28

4338 rows × 2 columns

In [42]:
```
df_Frequency = df[['CustomerID','InvoiceNo']].groupby("CustomerID", as_index=False)[
df_Frequency
```

Out[42]:

	CustomerID	InvoiceNo
0	12346.0	1
1	12347.0	182
2	12348.0	31
3	12349.0	73
4	12350.0	17
...	...	...
4333	18280.0	10
4334	18281.0	7
4335	18282.0	12
4336	18283.0	721
4337	18287.0	70

4338 rows × 2 columns

In [43]:
```
df_Last_Purchase = df[["CustomerID","InvoiceDate"]].groupby(['CustomerID'], as_index
df_Last_Purchase
```

Out[43]:

	CustomerID	InvoiceDate
0	12346.0	2011-01-18 10:01:00
1	12347.0	2011-12-07 15:52:00
2	12348.0	2011-09-25 13:13:00
3	12349.0	2011-11-21 09:51:00
4	12350.0	2011-02-02 16:01:00
...	...	...
4333	18280.0	2011-03-07 09:52:00
4334	18281.0	2011-06-12 10:53:00
4335	18282.0	2011-12-02 11:43:00
4336	18283.0	2011-12-06 12:02:00
4337	18287.0	2011-10-28 09:29:00

4338 rows × 2 columns

In [44]:
```
df_Last_Purchase['InvoiceDate'] = pd.to_datetime(df_Last_Purchase['InvoiceDate'])
```

In [45]:
```
df['InvoiceDate'] = pd.to_datetime(df['InvoiceDate'])
```

In [46]:
```
days_since_last_purchase = df['InvoiceDate'].max() - df_Last_Purchase['InvoiceDate']
days_since_last_purchase = days_since_last_purchase + pd.Timedelta("1 days")
days_since_last_purchase
```

Out[46]:
```
0       326 days 02:49:00
1         2 days 20:58:00
2        75 days 23:37:00
3        19 days 02:59:00
4       310 days 20:49:00
                ...
4333    278 days 02:58:00
4334    181 days 01:57:00
4335      8 days 01:07:00
4336      4 days 00:48:00
4337     43 days 03:21:00
Name: InvoiceDate, Length: 4338, dtype: timedelta64[ns]
```

In [47]:
```
df['InvoiceDate'].max()
```

Out[47]:
```
Timestamp('2011-12-09 12:50:00')
```

In [48]:
```
time_diff_in_days = pd.Series(data = [d.days for d in days_since_last_purchase])
time_diff_in_days
```

Out[48]:
```
0       326
1         2
2        75
3        19
4       310
       ...
4333    278
4334    181
4335      8
4336      4
4337     43
Length: 4338, dtype: int64
```

In [49]:
```
df_final = pd.merge(df_Monetary, df_Frequency, on="CustomerID")
df_final['Recency'] = time_diff_in_days
df_final.rename(columns={"Total Price": "Monetary", "InvoiceNo": "Frequency"}, inpla
df_final
```

Out[49]:

	CustomerID	Monetary	Frequency	Recency
0	12346.0	77183.60	1	326
1	12347.0	4310.00	182	2
2	12348.0	1797.24	31	75
3	12349.0	1757.55	73	19
4	12350.0	334.40	17	310
...	...	...	...	...
4333	18280.0	180.60	10	278
4334	18281.0	80.82	7	181
4335	18282.0	178.05	12	8
4336	18283.0	2045.53	721	4
4337	18287.0	1837.28	70	43

4338 rows × 4 columns

In [50]:
```
df_final['R Score'] = pd.qcut(df_final['Recency'], 4, ['4','3','2','1'])
df_final['F Score'] = pd.qcut(df_final['Frequency'], 4, ['1','2','3','4'])
df_final['M Score'] = pd.qcut(df_final['Monetary'], 4, ['1','2','3','4'])

df_final
```

Out[50]:

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score
0	12346.0	77183.60	1	326	1	1	4
1	12347.0	4310.00	182	2	4	4	4
2	12348.0	1797.24	31	75	2	2	4
3	12349.0	1757.55	73	19	3	3	4
4	12350.0	334.40	17	310	1	1	2
...	...	...	...	...	...	...	...
4333	18280.0	180.60	10	278	1	1	1
4334	18281.0	80.82	7	181	1	1	1
4335	18282.0	178.05	12	8	4	1	1
4336	18283.0	2045.53	721	4	4	4	4
4337	18287.0	1837.28	70	43	3	3	4

4338 rows × 7 columns

In [51]:
```
df_final['RFM Segment'] = df_final['R Score'].astype(str) + df_final['F Score'].asty
```

In [52]:
```
df_final
```

Out[52]:

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment
0	12346.0	77183.60	1	326	1	1	4	114
1	12347.0	4310.00	182	2	4	4	4	444
2	12348.0	1797.24	31	75	2	2	4	224
3	12349.0	1757.55	73	19	3	3	4	334
4	12350.0	334.40	17	310	1	1	2	112
...	...	...	...	...	...	...	...	...
4333	18280.0	180.60	10	278	1	1	1	111
4334	18281.0	80.82	7	181	1	1	1	111
4335	18282.0	178.05	12	8	4	1	1	411
4336	18283.0	2045.53	721	4	4	4	4	444
4337	18287.0	1837.28	70	43	3	3	4	334

4338 rows × 8 columns

In [53]:
```
df_final[df_final['RFM Segment']=='144']
```

Out[53]:

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment
31	12383.0	1850.560	99	185	1	4	4	144
123	12501.0	2169.390	149	337	1	4	4	144
263	12669.0	2744.030	101	151	1	4	4	144
390	12840.0	2726.770	113	144	1	4	4	144
566	13093.0	7832.470	159	276	1	4	4	144
1185	13952.0	3251.071	137	218	1	4	4	144
1230	14016.0	4341.210	161	162	1	4	4	144
1399	14245.0	1693.450	108	220	1	4	4	144
1550	14461.0	2103.060	180	148	1	4	4	144
2118	15235.0	2247.510	143	218	1	4	4	144
2225	15379.0	3703.290	194	169	1	4	4	144
2440	15665.0	2222.210	115	168	1	4	4	144
2546	15808.0	3651.270	195	306	1	4	4	144
3355	16919.0	2592.250	326	156	1	4	4	144
3639	17337.0	1981.060	521	151	1	4	4	144
3695	17406.0	2184.420	111	333	1	4	4	144
3724	17444.0	2940.040	135	148	1	4	4	144
3764	17504.0	2997.030	127	206	1	4	4	144
3977	17787.0	1817.540	128	153	1	4	4	144
4016	17850.0	5391.210	297	372	1	4	4	144
4299	18231.0	2071.770	123	192	1	4	4	144
4319	18260.0	2628.350	133	173	1	4	4	144

In [54]:

```
df_final['RFM Score'] = df_final['R Score'].astype(int) + df_final['F Score'].astype
```

In [55]:

```
df_final
```

Out[55]:

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment	RFM Score
0	12346.0	77183.60	1	326	1	1	4	114	6
1	12347.0	4310.00	182	2	4	4	4	444	12
2	12348.0	1797.24	31	75	2	2	4	224	8
3	12349.0	1757.55	73	19	3	3	4	334	10
4	12350.0	334.40	17	310	1	1	2	112	4
...	...	...	...	...	...	...	...	...	...
4333	18280.0	180.60	10	278	1	1	1	111	3
4334	18281.0	80.82	7	181	1	1	1	111	3
4335	18282.0	178.05	12	8	4	1	1	411	6

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment	RFM Score
4336	18283.0	2045.53	721	4	4	4	4	444	12
4337	18287.0	1837.28	70	43	3	3	4	334	10

4338 rows × 9 columns

In [56]:
```
df_final['RFM Level'] = pd.qcut(df_final['RFM Score'],4,labels = ('Bronze','Silver',
```

In [57]:
```
df_final
```

Out[57]:

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment	RFM Score	RFM Level
0	12346.0	77183.60	1	326	1	1	4	114	6	Silver
1	12347.0	4310.00	182	2	4	4	4	444	12	Platinum
2	12348.0	1797.24	31	75	2	2	4	224	8	Gold
3	12349.0	1757.55	73	19	3	3	4	334	10	Gold
4	12350.0	334.40	17	310	1	1	2	112	4	Bronze
...	...	...	...	...	...	...	...	...	...	...
4333	18280.0	180.60	10	278	1	1	1	111	3	Bronze
4334	18281.0	80.82	7	181	1	1	1	111	3	Bronze
4335	18282.0	178.05	12	8	4	1	1	411	6	Silver
4336	18283.0	2045.53	721	4	4	4	4	444	12	Platinum
4337	18287.0	1837.28	70	43	3	3	4	334	10	Gold

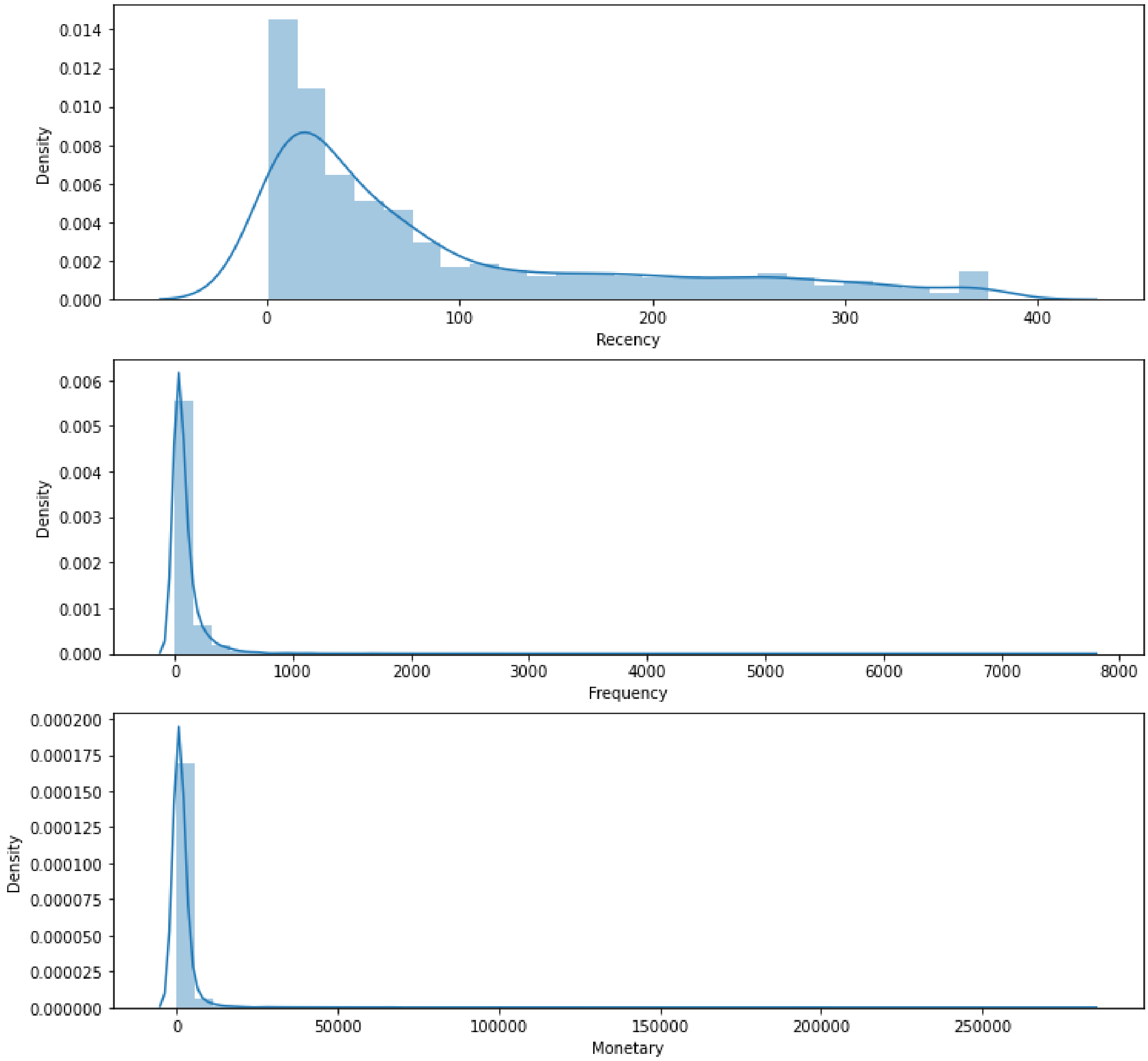
4338 rows × 10 columns

In [58]:
```
# df_final['RFM Score'].value_counts()
```

Plotting recency, frequency and monetary values to check the skewness in data

In [59]:
```
fig,axes = plt.subplots(nrows = 3,ncols = 1,figsize =(12,12))
axes1 = axes[0]
axes2 = axes[1]
axes3 = axes[2]
sns.distplot(df_final['Recency'],ax=axes1)
sns.distplot(df_final['Frequency'],ax=axes2)
sns.distplot(df_final['Monetary'],ax=axes3)
```

Out[59]: <AxesSubplot:xlabel='Monetary', ylabel='Density'>



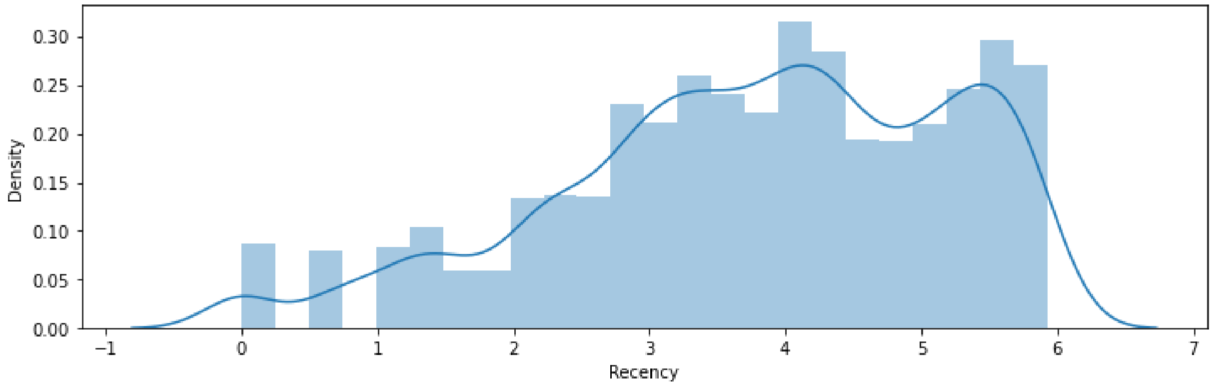
To fix the skewness in the data we'll do log transformation.

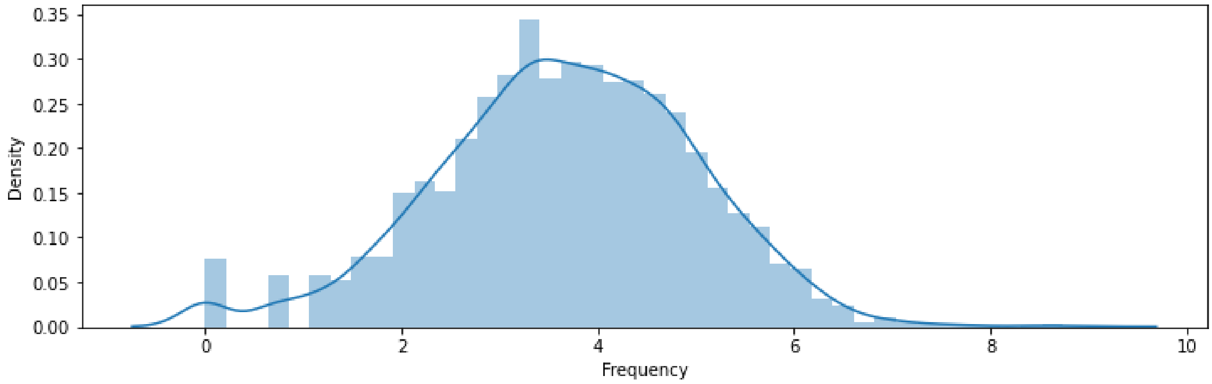
In [60]:
```
df_log = df_final.copy()
```

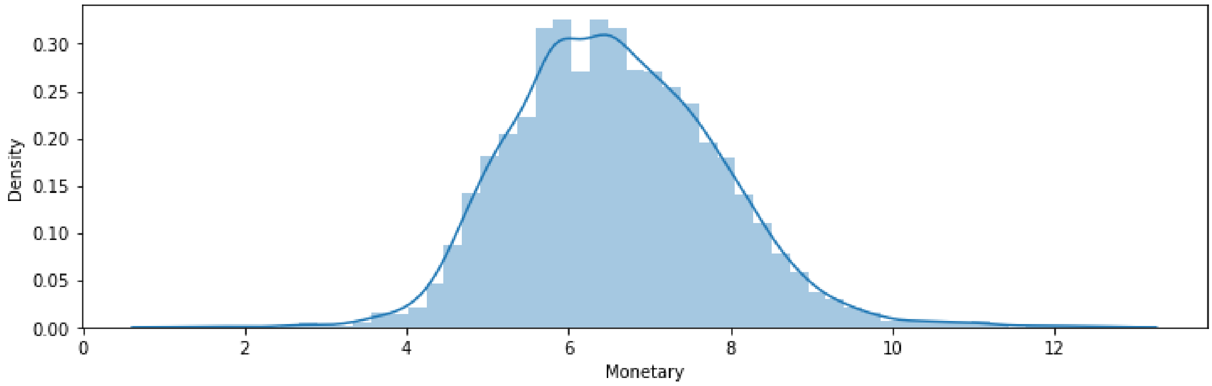
In [61]:
```
df_log = df_log[['Recency','Frequency','Monetary']].apply(np.log,axis=1)
```

In [62]:
```
fig,axes = plt.subplots(nrows = 3,ncols = 1,figsize =(12,12))
axes1 = axes[0]
axes2 = axes[1]
axes3 = axes[2]
sns.distplot(df_log['Recency'],ax=axes1)
sns.distplot(df_log['Frequency'],ax=axes2)
sns.distplot(df_log['Monetary'],ax=axes3)
```

Out[62]: <AxesSubplot:xlabel='Monetary', ylabel='Density'>







Let's Standardize the data to bring the data at the same scale.

In [63]:
```
scaler = StandardScaler()
```

In [64]:
```
df_log_scaled = scaler.fit_transform(df_log)
```

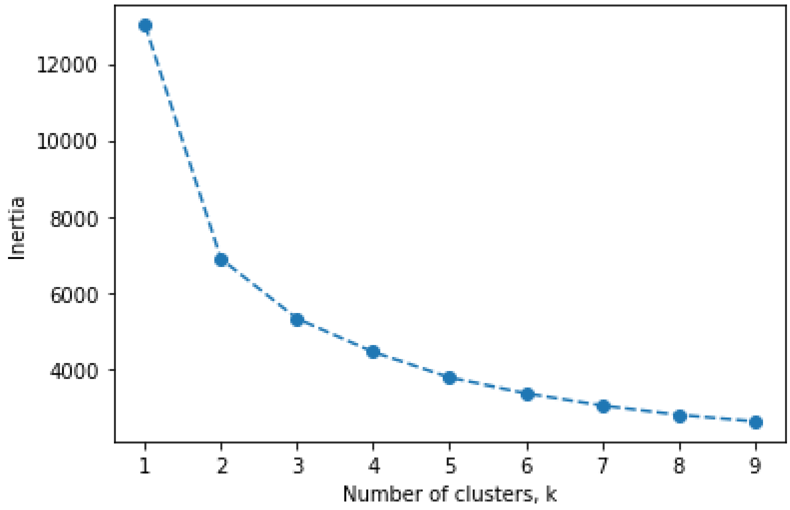
Model Building

In [65]:
```
ssd = []

for k in range(1,10):

    model = KMeans(n_clusters=k)


    model.fit(df_log_scaled)

    #Sum of squared distances of samples to their closest cluster center.
    ssd.append(model.inertia_)
```

In [66]:
```
plt.plot(range(1,10),ssd,'o--')
plt.xlabel("K Value")
plt.ylabel(" Sum of Squared Distances")
```

```
plt.style.use('ggplot')
plt.xlabel('Number of clusters, k')
plt.ylabel('Inertia')
```

Out[66]: Text(0, 0.5, 'Inertia')



In [67]:
```
ssd
```

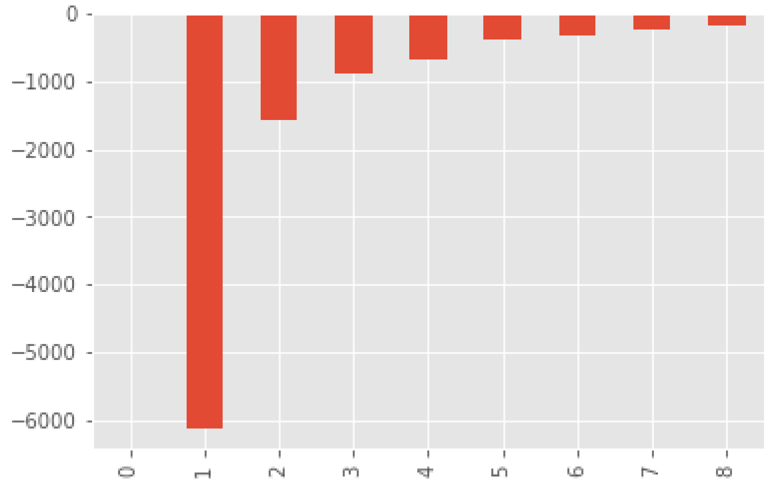
Out[67]:
```
[13014.000000000002,
 6883.679444650629,
 5314.619000863782,
 4440.186305838019,
 3766.384321223561,
 3366.8491936076134,
 3046.7406605841243,
 2802.375185164407,
 2629.6361801308053]
```

In [68]:
```
pd.Series(ssd).diff()
```

Out[68]:
```
0            NaN
1   -6130.320555
2   -1569.060444
3    -874.432695
4    -673.801985
5    -399.535128
6    -320.108533
7    -244.365475
8    -172.739005
dtype: float64
```

In [69]:
```
pd.Series(ssd).diff().plot(kind = 'bar')
```

Out[69]: <AxesSubplot:>



It could be concluded from above three plots that the best results could be found with 4 clusters. So we'll take n_clusters = 4 for final model.

In [70]:
```
final_model = KMeans(n_clusters=4)
```

In [71]:
```
final_model.fit(df_log_scaled)
```

Out[71]: KMeans(n_clusters=4)

In [72]:
```
labels = final_model.labels_
```

In [73]:
```
rfm_ = df_final.assign(K_Cluster = labels)
```

In [74]:
```
rfm_['K_Cluster'].unique()
```

Out[74]: array([3, 1, 0, 2])

In [75]:
```
rfm_.groupby('K_Cluster')[['Monetary','Frequency','Recency']].count()
```

Out[75]:

K_Cluster	Monetary	Frequency	Recency
0	1378	1378	1378
1	836	836	836
2	832	832	832
3	1292	1292	1292

In [76]:
```
rfm_['K_Cluster'] = rfm_['K_Cluster']+1
```

In [77]:
```
rfm_
```

Out[77]:

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment	RFM Score	RFM Level
0	12346.0	77183.60	1	326	1	1	4	114	6	Silver
1	12347.0	4310.00	182	2	4	4	4	444	12	Platinum
2	12348.0	1797.24	31	75	2	2	4	224	8	Gold
3	12349.0	1757.55	73	19	3	3	4	334	10	Gold

	CustomerID	Monetary	Frequency	Recency	R Score	F Score	M Score	RFM Segment	RFM Score	RFM Level
4	12350.0	334.40	17	310	1	1	2	112	4	Bronze
...	...	...	...	...	...	...	...	...	...	...
4333	18280.0	180.60	10	278	1	1	1	111	3	Bronze
4334	18281.0	80.82	7	181	1	1	1	111	3	Bronze
4335	18282.0	178.05	12	8	4	1	1	411	6	Silver
4336	18283.0	2045.53	721	4	4	4	4	444	12	Platinum
4337	18287.0	1837.28	70	43	3	3	4	334	10	Gold

4338 rows × 11 columns

In [81]:
```
# assign cluster column
df_log_scaled = pd.DataFrame(df_log_scaled, columns=['Monetary','Frequency','Recency
df_log_scaled['K_Cluster'] = model.labels_
df_log_scaled['RFM_Level'] = df_final['RFM Level']
df_log_scaled.reset_index(inplace = True)

# melt the dataframe
rfm_melted = pd.melt(frame= df_log_scaled, id_vars= ['RFM_Level', 'K_Cluster'], var_
rfm_melted.head()
```

Out[81]:

	RFM_Level	K_Cluster	Metrics	Value
0	Silver	5	index	0.0
1	Platinum	8	index	1.0
2	Gold	5	index	2.0
3	Gold	7	index	3.0
4	Bronze	1	index	4.0

In [82]:
```
df_final.iloc[:, 1:4].mean()
```

Out[82]:
```
Monetary     2048.688081
Frequency      90.523744
Recency        92.536422
dtype: float64
```

In [83]:
```
df_final.groupby('RFM Level').mean().iloc[:, 1:4]
```

Out[83]:

RFM Level	Monetary	Frequency	Recency
Bronze	266.505704	15.060606	192.165501
Silver	789.257001	32.959783	87.686957
Gold	1597.725141	81.236476	47.848532
Platinum	6870.541553	284.188769	13.761051

In [84]:
```
df_final.groupby('RFM Level').mean().iloc[:, 1:4]/df_final.iloc[:, 1:4].mean()
```

Out[84]:

RFM Level	Monetary	Frequency	Recency
Bronze	0.130086	0.166372	2.076647
Silver	0.385250	0.364101	0.947594
Gold	0.779877	0.897405	0.517078
Platinum	3.353630	3.139384	0.148710

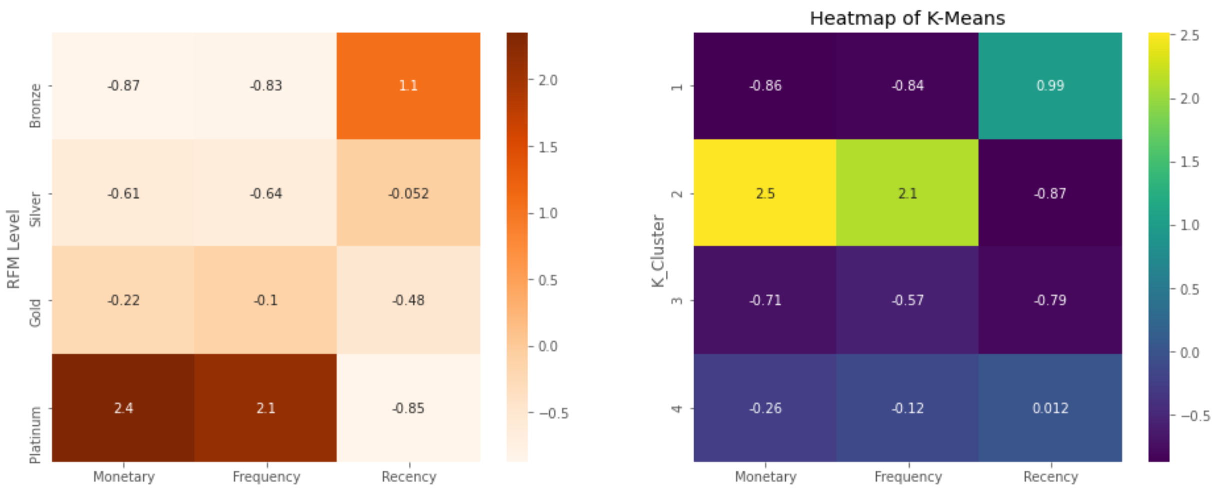
In [85]:

```python
# the mean value in total
total_avg = df_final.iloc[:, 1:4].mean()
total_avg

# calculate the proportional gap with total mean
cluster_avg = df_final.groupby('RFM Level').mean().iloc[:, 1:4]
prop_rfm = cluster_avg/total_avg - 1

# calculate the proportional gap with total mean
cluster_avg_K = rfm_.groupby('K_Cluster').mean().iloc[:, 1:4]
prop_rfm_K = cluster_avg_K/total_avg - 1
```

In [86]:

```python
f,ax = plt.subplots(nrows=1,ncols=2,figsize = (16,6))

ax1 = ax[0]
ax2 = ax[1]


sns.heatmap(prop_rfm, cmap= 'Oranges',  annot = True,ax=ax1)
plt.title('Heatmap of RFM quantile')
plt.plot()

sns.heatmap(prop_rfm_K, cmap= 'viridis', annot = True,ax=ax2)
plt.title('Heatmap of K-Means')
plt.plot()
```

Out[86]: []



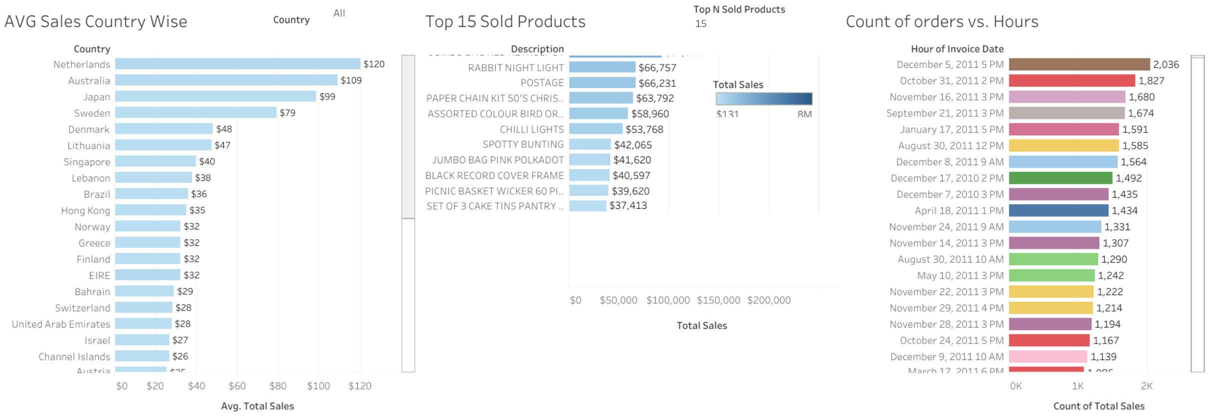
From the values above in each box it could be concluded that the green group corresponds to group 2 and from the given dataset we made two metrics one using RFM segmentation and one from K-Means and found that the customers belonging to Green category are the most profitable customers and those are the same customers from grouo 2.

Tableau Visualization

In [88]:

```
image1 = PILImage.open('C:/Users/vipul/ML project 1/Tableau Dashboard/Retail/Retail
image1
```

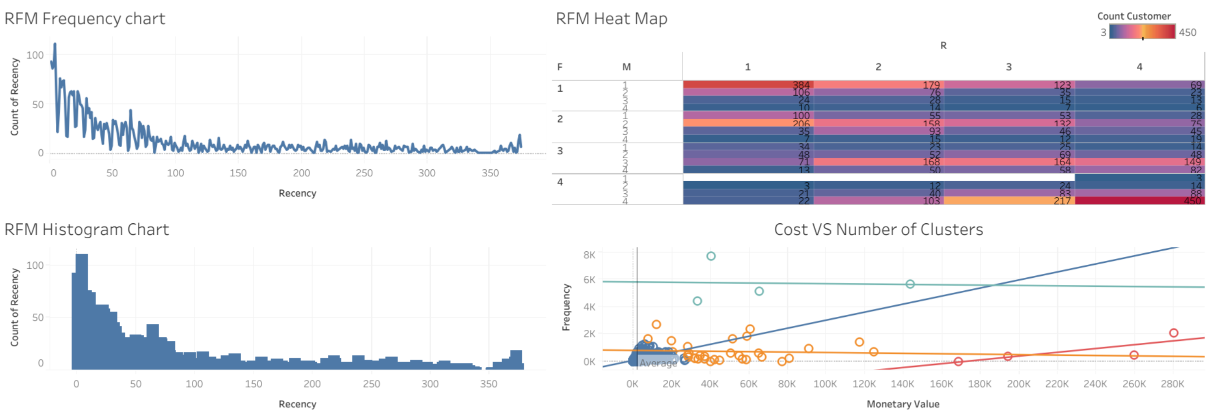
Out[88]:



In [89]:

```
image2 = PILImage.open('C:/Users/vipul/ML project 1/Tableau Dashboard/Retail/RFM Fre
image2
```

Out[89]:



In [ ]: