RFM Analysis for Online Retail Business

Problem Statement

- It is a critical requirement for business to understand the value derived from a customer. RFM is a method used for analyzing customer value.
- Customer segmentation is the practice of segregating the customer base into groups of individuals based on some common characteristics such as age, gender, interests, and spending habits
- Perform customer segmentation using RFM analysis. The resulting segments can be ordered from most valuable (highest recency, frequency, and value) to least valuable (lowest recency, frequency, and value).

Dataset Description

This is a transnational data set which contains all the transactions that occurred between 01/12/2010 and 09/12/2011 for a UK-based and registered non-store online retail. The company mainly sells unique and all-occasion gifts.

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

Project Task: Week 1

Data Cleaning:

1. Perform a preliminary data inspection and data cleaning.

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

b. Remove duplicate data records.

c. Perform descriptive analytics on the given data.

Data Transformation:

2. Perform cohort analysis (a cohort is a group of subjects that share a defining characteristic). Observe how a cohort behaves across time and compare it to other cohorts.

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

b. Analyze the retention rate of customers.

Project Task: Week 2

Data Modeling :

1. Build a RFM (Recency Frequency Monetary) model. Recency means the number of days since a customer made the last purchase. Frequency is the number of purchase in a given period. It could be 3 months, 6 months or 1 year. Monetary is the total amount of money a customer spent in that given period. Therefore, big spenders will be differentiated among other customers such as MVP (Minimum Viable Product) or VIP.

2. Calculate RFM metrics.

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

b1. Combine three ratings to get a RFM segment (as strings).

b2. Get the RFM score by adding up the three ratings.

b3. Analyze the RFM segments by summarizing them and comment on the findings.

Note: Rate “recency" for customer who has been active more recently higher than the less recent customer, because each company wants its customers to be recent.

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

Project Task: Week 3

Data Modeling :

1. Create clusters using k-means clustering algorithm.

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

b. Decide the optimum number of clusters to be formed.

c. Analyze these clusters and comment on the results.

Project Task: Week 4

Data Reporting:

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

a. Country-wise analysis to demonstrate average spend. Use a bar chart to show the monthly figures

b. Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold

c. Bar graph to show the count of orders vs. hours throughout the day

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

e. Plot error (cost) vs. number of clusters selected

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

RFM Analysis for Online Retail Business

In [1]:
```
# First importing the necessary library.
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
from pandas import ExcelWriter
%matplotlib inline
```

In [2]:
```
# Now ignoring the unusual warnings.
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```
# Now Importing the dataset to perform further action.
retail_df = pd.read_excel("Online Retail.xlsx")
```

In [4]:
```
retail_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]:
```
retail_df.shape
```

Out[5]: (541909, 8)

In [6]:
```
retail_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
```

Project Task: Week 1

Data Cleaning:

1. Perform a preliminary data inspection and data cleaning.

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

In [7]:
```
# Now checking the missing value in the data set.
retail_df.isnull().sum()
```

Out[7]:
```
InvoiceNo           0
StockCode           0
Description      1454
Quantity            0
InvoiceDate         0
UnitPrice           0
CustomerID     135080
Country             0
dtype: int64
```

In [8]:
```
# Checking the missing value in the percentage.
round((retail_df.isnull().sum()/len(retail_df))*100,2)
```

Out[8]:
```
InvoiceNo       0.00
StockCode       0.00
Description     0.27
Quantity        0.00
InvoiceDate     0.00
UnitPrice       0.00
CustomerID     24.93
Country         0.00
dtype: float64
```

We have two columns which contain the null values but both column has the unique identity so we can not replace them with the mean, median or mode.

So for deal with null value of customerID column. we will check with respect to customerID is any invoice no is present so with respect to that we can fill customer name.

In [9]:
```
custid_null_treat = retail_df[retail_df['CustomerID'].isnull()]['InvoiceNo']
```

In [10]:
```
(retail_df["CustomerID"].isin(retail_df) & retail_df['InvoiceNo'].isin(custid_null_treat)).any
```

Out[10]:
```
False
```

We have checked that with repect to invoice no there is no customer id in the data set so we have to treat the null value by dropping the row.

In [11]:
```
retail_df.drop('Description', axis=1, inplace=True)
retail_df.dropna(inplace=True)
```

In [12]:
```
retail_df.shape
```

Out[12]:
```
(406829, 7)
```

b. Remove duplicate data records.

In [13]:
```
retail_df[retail_df.duplicated()]
```

Out[13]:

	InvoiceNo	StockCode	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
517	536409	21866	1	2010-12-01 11:45:00	1.25	17908.0	United Kingdom
527	536409	22866	1	2010-12-01 11:45:00	2.10	17908.0	United Kingdom
537	536409	22900	1	2010-12-01 11:45:00	2.95	17908.0	United Kingdom
539	536409	22111	1	2010-12-01 11:45:00	4.95	17908.0	United Kingdom
555	536412	22327	1	2010-12-01 11:49:00	2.95	17920.0	United Kingdom
...	...	...	...	...	...	...	...
541675	581538	22068	1	2011-12-09 11:34:00	0.39	14446.0	United Kingdom
541689	581538	23318	1	2011-12-09 11:34:00	2.49	14446.0	United Kingdom
541692	581538	22992	1	2011-12-09 11:34:00	1.95	14446.0	United Kingdom
541699	581538	22694	1	2011-12-09 11:34:00	2.10	14446.0	United Kingdom
541701	581538	23343	1	2011-12-09 11:34:00	2.08	14446.0	United Kingdom

5227 rows × 7 columns

It is clear from the above observation that there is duplicate values in the data set so we will drop all duplicate values.

In [14]:
```
retail_df = retail_df.drop_duplicates()
retail_df.shape
```

Out[14]: (401602, 7)

c. Perform descriptive analytics on the given data.

In [15]:
```
retail_df.describe(datetime_is_numeric=True)
```

Out[15]:

	Quantity	InvoiceDate	UnitPrice	CustomerID
count	401602.000000	401602	401602.000000	401602.000000
mean	12.182579	2011-07-10 12:08:08.129839872	3.474064	15281.172576
min	-80995.000000	2010-12-01 08:26:00	0.000000	12346.000000
25%	2.000000	2011-04-06 15:02:00	1.250000	13939.000000
50%	5.000000	2011-07-29 15:40:00	1.950000	15145.000000
75%	12.000000	2011-10-20 11:58:00	3.750000	16784.000000
max	80995.000000	2011-12-09 12:50:00	38970.000000	18287.000000
std	250.283248	NaN	69.764209	1714.002257

In [16]:
```
# we will also analysis the object type field in term of count, freq etc..
retail_df.describe(include = ['O'])
```

Out[16]:

	InvoiceNo	StockCode	Country
count	401602	401602	401602
unique	22190	3684	37
top	576339	85123A	United Kingdom
freq	542	2065	356726

Data Transformation:

2. Perform cohort analysis (a cohort is a group of subjects that share a defining characteristic). Observe how a cohort behaves across time and compare it to other cohorts.

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

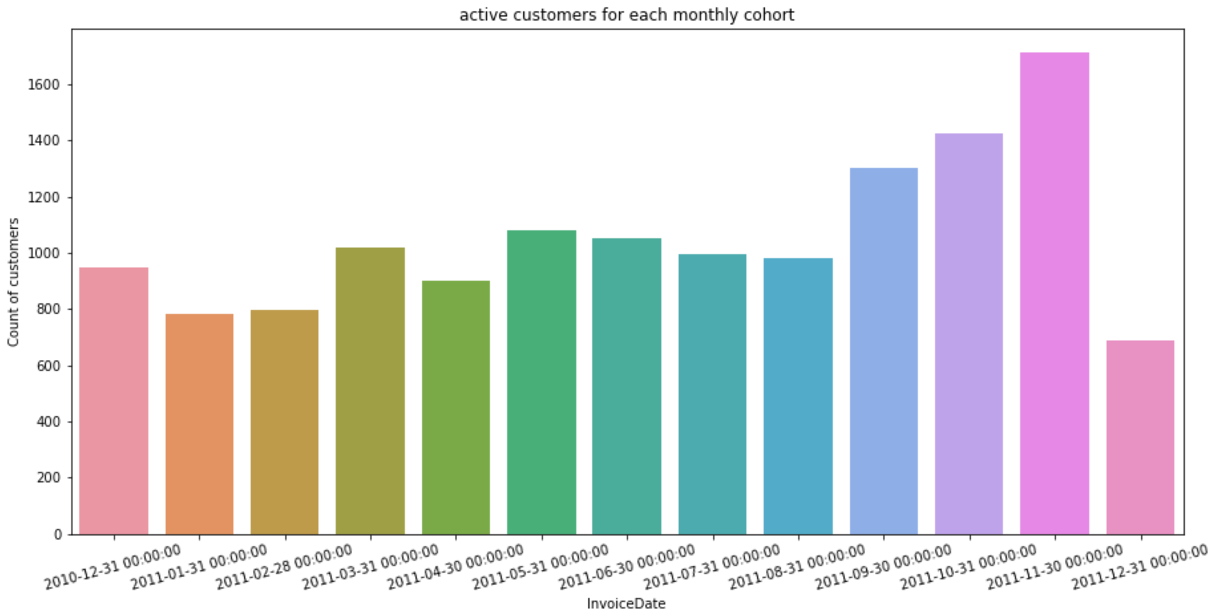
In [17]:
```
df = retail_df.groupby(pd.Grouper(key="InvoiceDate", axis=0, freq="M")).nunique()
```

In [18]:
```
monthwise_cohort = df['CustomerID']
```

In [19]:
```
monthwise_cohort
```

Out[19]:
```
InvoiceDate
2010-12-31     948
2011-01-31     783
2011-02-28     798
2011-03-31    1020
2011-04-30     899
2011-05-31    1079
2011-06-30    1051
2011-07-31     993
2011-08-31     980
2011-09-30    1302
2011-10-31    1425
2011-11-30    1711
2011-12-31     686
Freq: M, Name: CustomerID, dtype: int64
```

In [20]:
```
plt.figure(figsize=(15,7))
sns.barplot(x = monthwise_cohort.index, y = monthwise_cohort.values)
plt.xticks(rotation = 15)
plt.title("active customers for each monthly cohort")
plt.ylabel("Count of customers")
plt.show()
```



b. Analyze the retention rate of customers.

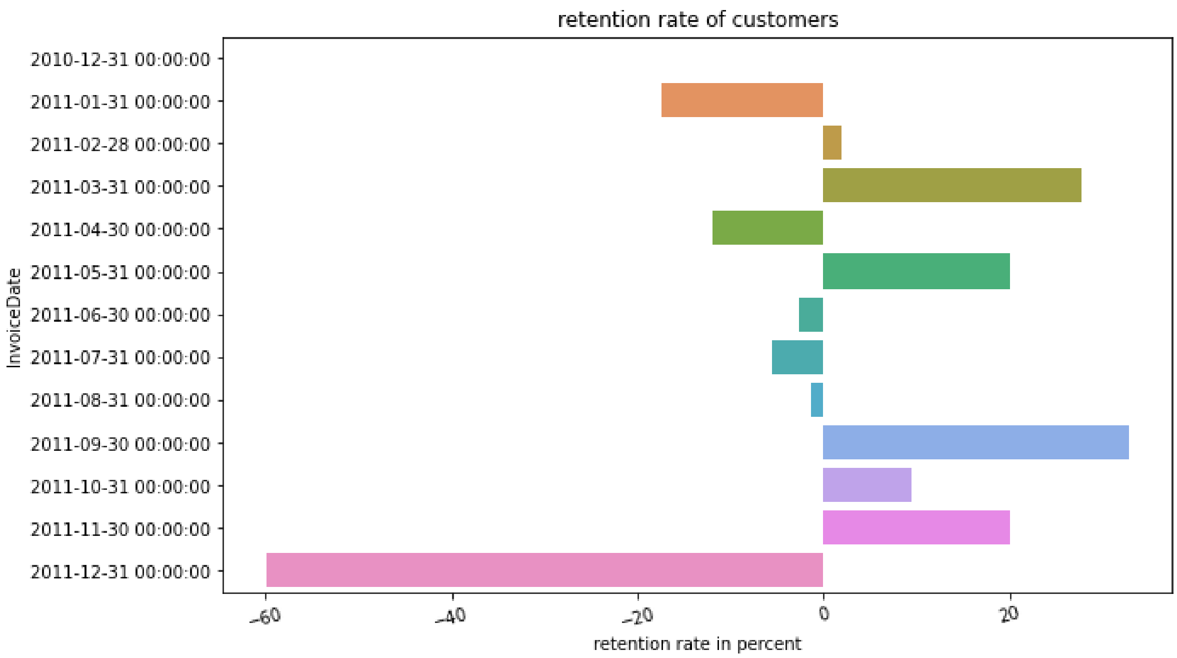
In [21]:
```
# Now we analyze the retention rate of the customer.
monthwise_cohort - monthwise_cohort.shift(1)
```

Out[21]:
```
InvoiceDate
2010-12-31       NaN
2011-01-31    -165.0
2011-02-28      15.0
2011-03-31     222.0
2011-04-30    -121.0
2011-05-31     180.0
2011-06-30     -28.0
2011-07-31     -58.0
2011-08-31     -13.0
2011-09-30     322.0
2011-10-31     123.0
2011-11-30     286.0
2011-12-31   -1025.0
Freq: M, Name: CustomerID, dtype: float64
```

In [22]:
```
retention_rate = round((monthwise_cohort.pct_change())*100,2)
retention_rate
```

Out[22]:
```
InvoiceDate
2010-12-31      NaN
2011-01-31   -17.41
2011-02-28     1.92
2011-03-31    27.82
2011-04-30   -11.86
2011-05-31    20.02
2011-06-30    -2.59
2011-07-31    -5.52
2011-08-31    -1.31
2011-09-30    32.86
2011-10-31     9.45
2011-11-30    20.07
2011-12-31   -59.91
Freq: M, Name: CustomerID, dtype: float64
```

In [23]:
```
# lets visualize the retention rate.
plt.figure(figsize=(10,6))
sns.barplot(x = retention_rate.values, y = retention_rate.index)
plt.xticks(rotation = 15)
plt.title("retention rate of customers")
plt.xlabel("retention rate in percent")
plt.show()
```



Project Task: Week 2

Data Modeling :

1. Build a RFM (Recency Frequency Monetary) model. Recency means the number of days since a customer made the last purchase. Frequency is the number of purchase in a given period. It could be 3 months, 6 months or 1 year. Monetary is the total amount of money a customer spent in that given period. Therefore, big spenders will be differentiated among other customers such as MVP (Minimum Viable Product) or VIP.

In [24]:
```
# First calculating the total price
retail_df["TotalPrice"] = retail_df["Quantity"] * retail_df["UnitPrice"]
```

In [25]:
```
# We will make the refrence date +1 because we will get the transaction done on the last date.
from datetime import timedelta
refrence_date = (retail_df["InvoiceDate"].max()) + timedelta(days=1)
print("refrence Date: ", refrence_date)
```

```
refrence Date:  2011-12-10 12:50:00
```

In [26]:
```
RFM = retail_df.groupby(['CustomerID']).agg({'InvoiceDate': lambda x : (refrence_date-x.max())
                                            "InvoiceNo": "count",
                                            "TotalPrice": 'sum'})
```

2. Calculate RFM metrics.

In [27]:
```
RFM.rename(columns = {'InvoiceDate':"Recency", "InvoiceNo": "Frequency", "TotalPrice": "Moneta
```

In [28]:
```
RFM
```

Out[28]:

CustomerID	Recency	Frequency	MonetaryValue
12346.0	326	2	0.00
12347.0	2	182	4310.00
12348.0	75	31	1797.24
12349.0	19	73	1757.55
12350.0	310	17	334.40
...	...	...	...
18280.0	278	10	180.60
18281.0	181	7	80.82
18282.0	8	13	176.60
18283.0	4	721	2045.53
18287.0	43	70	1837.28

4372 rows × 3 columns

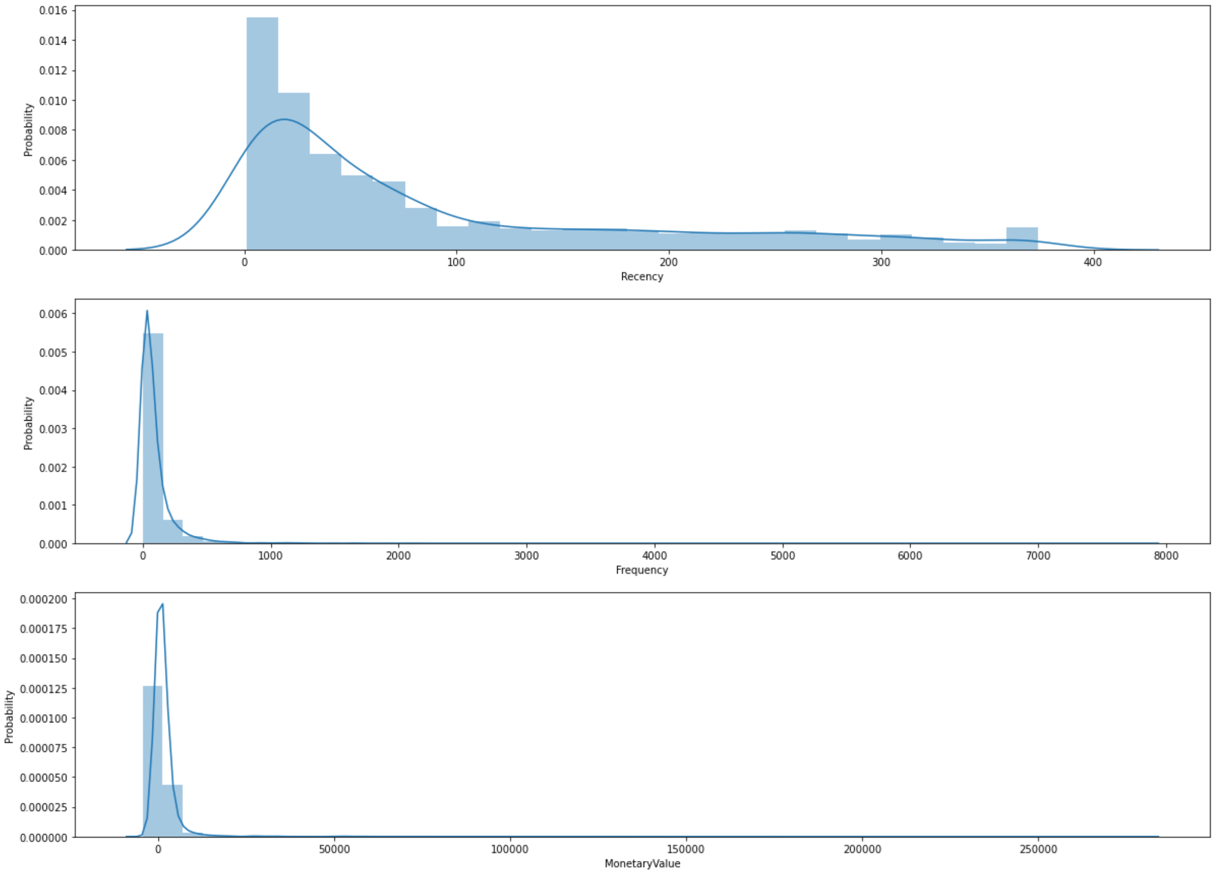
In [29]:
```
# Plot the RFM distribution
plt.figure(figsize=(20,15))

plt.subplot(3,1,1)
sns.distplot(RFM['Recency'])
plt.xlabel('Recency')
plt.ylabel('Probability')

plt.subplot(3,1,2)
sns.distplot(RFM['Frequency'])
plt.xlabel('Frequency')
plt.ylabel('Probability')

plt.subplot(3,1,3)
sns.distplot(RFM['MonetaryValue'])
plt.xlabel('MonetaryValue')
plt.ylabel('Probability')

plt.show()
```



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

b1. Combine three ratings to get a RFM segment (as strings).

b2. Get the RFM score by adding up the three ratings.

b3. Analyze the RFM segments by summarizing them and comment on the findings.

In [30]:
```
# Creating the rating by using the quartile function
rlabel = range(4,0,-1)
flabel = range(1,5)
mlabel = range(1,5)

# Using the quartile function and give rating.
r = pd.qcut(RFM["Recency"], q =4, labels = rlabel)
f = pd.qcut(RFM["Frequency"],q = 4, labels=flabel)
m = pd.qcut(RFM["MonetaryValue"],q = 4, labels=mlabel)

RFM["R"] = r.values
RFM["F"] = f.values
RFM["M"] = m.values
```

In [31]:
```
RFM.head()
```

Out[31]:

CustomerID	Recency	Frequency	MonetaryValue	R	F	M
12346.0	326	2	0.00	1	1	1
12347.0	2	182	4310.00	4	4	4
12348.0	75	31	1797.24	2	2	4
12349.0	19	73	1757.55	3	3	4
12350.0	310	17	334.40	1	1	2

In [32]:
```
RFM['RFM_concat'] = RFM.apply(lambda x: str(x["R"]) + str(x["F"]) + str(x["M"]), axis=1)
```

In [33]:
```
RFM.head()
```

Out[33]:

CustomerID	Recency	Frequency	MonetaryValue	R	F	M	RFM_concat
12346.0	326	2	0.00	1	1	1	1.01.01.0
12347.0	2	182	4310.00	4	4	4	4.04.04.0
12348.0	75	31	1797.24	2	2	4	2.02.04.0
12349.0	19	73	1757.55	3	3	4	3.03.04.0
12350.0	310	17	334.40	1	1	2	1.01.02.0

In [34]:
```
RFM["RFM_score"] = RFM.apply(lambda x: x['R'] + x['F'] + x['M'], axis=1)
```

In [35]:
```
RFM.head()
```

Out[35]:

CustomerID	Recency	Frequency	MonetaryValue	R	F	M	RFM_concat	RFM_score
12346.0	326	2	0.00	1	1	1	1.01.01.0	3
12347.0	2	182	4310.00	4	4	4	4.04.04.0	12
12348.0	75	31	1797.24	2	2	4	2.02.04.0	8
12349.0	19	73	1757.55	3	3	4	3.03.04.0	10
12350.0	310	17	334.40	1	1	2	1.01.02.0	4

In [36]:
```
# Now on the basis of the score we will make the segment.
def segment(df):
    if df['RFM_score']>9:
        return "premiere"
    elif df['RFM_score']>7 and df['RFM_score']<10:
        return "Champions"
    elif df['RFM_score']>5 and df['RFM_score']<8:
        return "Loyal"
    elif df['RFM_score']>4 and df['RFM_score']<=5:
        return "Potential"
    elif df['RFM_score']>3 and df['RFM_score']<=4:
        return "Promissing"
    elif df['RFM_score']>2 and df['RFM_score']<=3:
        return "Need Atention"
    else:
        return "Require Activation"
```

In [37]:
```
RFM["RFM_segment"] = RFM.apply(segment, axis=1)
```

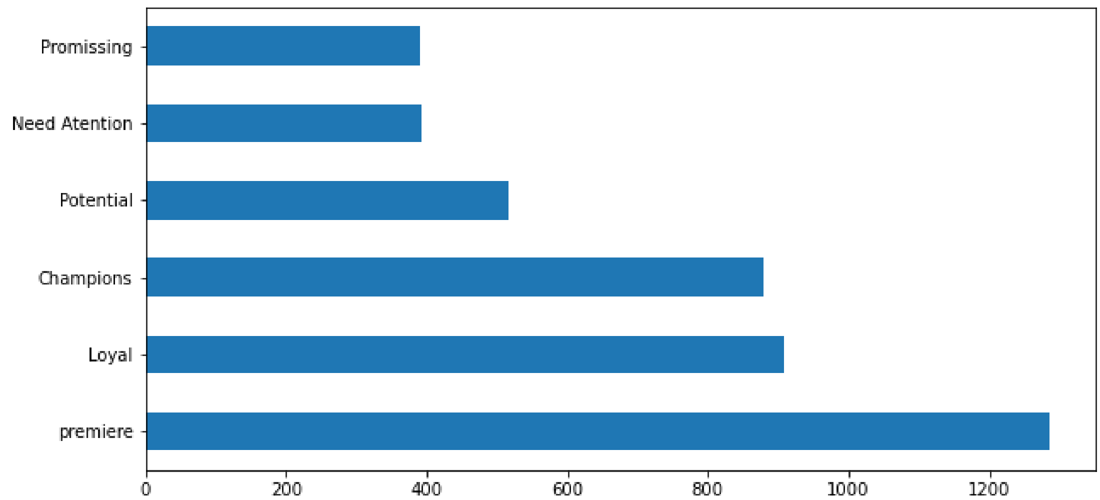
In [38]:
```
RFM.head()
```

Out[38]:

CustomerID	Recency	Frequency	MonetaryValue	R	F	M	RFM_concat	RFM_score	RFM_segment
12346.0	326	2	0.00	1	1	1	1.01.01.0	3	Need Atention
12347.0	2	182	4310.00	4	4	4	4.04.04.0	12	premiere
12348.0	75	31	1797.24	2	2	4	2.02.04.0	8	Champions
12349.0	19	73	1757.55	3	3	4	3.03.04.0	10	premiere
12350.0	310	17	334.40	1	1	2	1.01.02.0	4	Promissing

In [39]:
```
RFM["RFM_segment"].value_counts().plot(kind = "barh", figsize=(10, 5))
```

Out[39]: <AxesSubplot:>



Project Task: Week 3

Data Modeling :

1. Create clusters using k-means clustering algorithm.

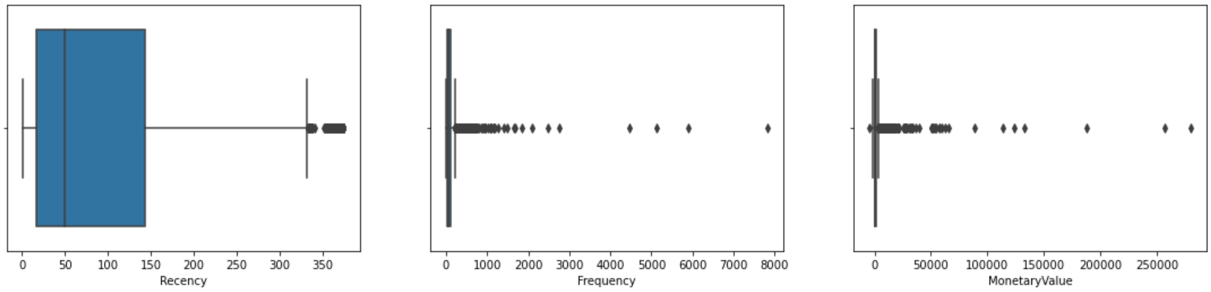
a. Prepare the data for the algorithm. If the data is asymmetrically distributed, manage the skewness with appropriate transformation. Standardize the data.

In [40]:
```
# First check the outlier
plt.figure(figsize=(19,4))
plt.subplot(1,3,1)
sns.boxplot(RFM['Recency'])

plt.subplot(1,3,2)
sns.boxplot(RFM['Frequency'])

plt.subplot(1,3,3)
sns.boxplot(RFM['MonetaryValue'])
```

Out[40]: <AxesSubplot:xlabel='MonetaryValue'>



There is otlier in our data set so we will drop the outlier

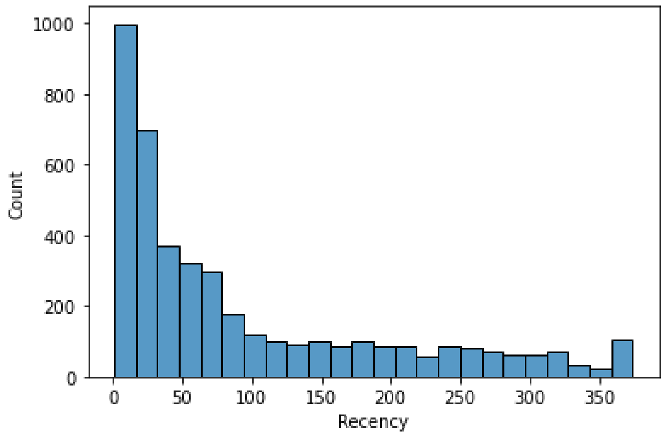
In [41]:
```
RFM_clust = RFM[(RFM['Frequency']<500) & (RFM['MonetaryValue']<50000)]
```

In [42]:
```
RFM_clust.shape
```

Out[42]: (4283, 9)

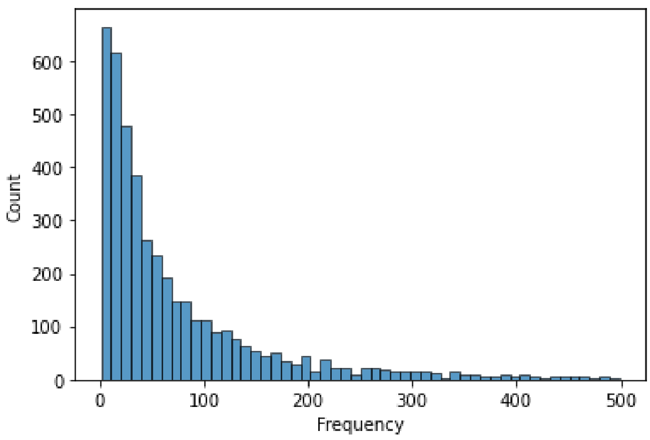
In [43]:
```
# let's first check the data is asymmetrically distributed or not.
sns.histplot(RFM_clust['Recency'])
```

Out[43]: <AxesSubplot:xlabel='Recency', ylabel='Count'>

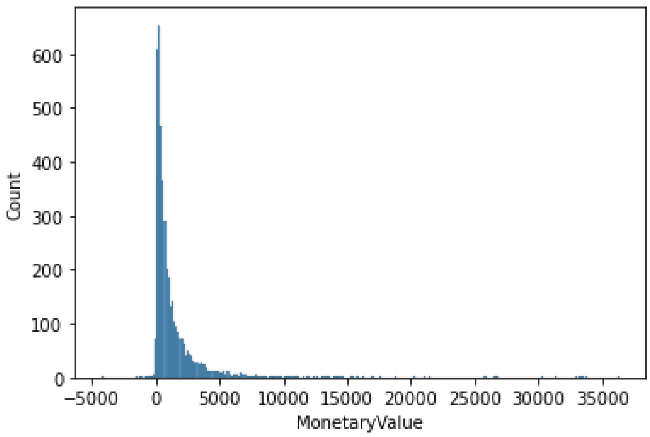


In [44]:
```
sns.histplot(RFM_clust['Frequency'])
```

Out[44]:
```
<AxesSubplot:xlabel='Frequency', ylabel='Count'>
```



In [45]:
```
sns.histplot(RFM_clust['MonetaryValue'])
plt.show()
```



Form above graph it is clear data is highly skewed so we will apply log transformation to make data symmetric the data.

In [46]:
```
transform_rfm = pd.DataFrame()
transform_rfm["Recency"] = np.log(RFM_clust['Recency'])
transform_rfm["Frequency"] = np.log(RFM_clust['Frequency'])
transform_rfm["MonetaryValue"] = np.log(RFM_clust['MonetaryValue']-RFM_clust['MonetaryValue'].
```

In [47]:
```
# Let's make the standardize.
from sklearn.preprocessing import StandardScaler
```

In [48]:
```
sc = StandardScaler()
```

In [49]:
```
scaled_rfm = sc.fit_transform(transform_rfm)
```

In [50]:
```
scaled_rfm = pd.DataFrame(scaled_rfm, columns = ["Recency", "Frequency", "MonetaryValue"])
scaled_rfm.head()
```

Out[50]:

	Recency	Frequency	MonetaryValue
0	1.397441	-2.290339	-0.767370
1	-2.141630	1.246250	1.571477
2	0.376515	-0.141475	0.409398
3	-0.577462	0.530013	0.387400
4	1.362476	-0.612492	-0.514928

b. Decide the optimum number of clusters to be formed.

In [51]:
```
from sklearn.cluster import KMeans
```

In [52]:
```
km = KMeans(n_clusters = 4, init = "k-means++", max_iter = 500, random_state=10)
```

In [53]:
```
clusters = km.fit_predict(scaled_rfm)
```

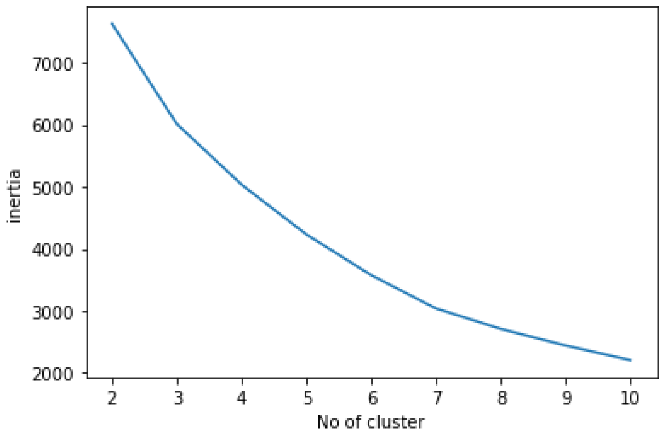
In [54]:
```
from sklearn.metrics import silhouette_score

silhouette_score(scaled_rfm, clusters)
```

Out[54]: 0.2886421085562689

In [55]:
```
# Nom by using the elbow method we will get the optimul no of cluster.
inertia_list = []
for i in range(2,11):
    km = KMeans(n_clusters = i, random_state = 10)
    km.fit(scaled_rfm)
    inertia_list.append(km.inertia_)
```

In [56]:
```
# Now plot the elbow curve.
plt.plot(range(2,11), inertia_list)
plt.xlabel("No of cluster")
plt.ylabel("inertia")
plt.show()
```



In [57]:
```
n_cluster = list(range(2,11))
inertia = pd.DataFrame(zip(n_cluster, inertia_list), columns = ["cluster", "inertia"])
inertia
```

Out[57]:

	cluster	inertia
0	2	7627.132134
1	3	6013.142026
2	4	5034.654335
3	5	4231.276699
4	6	3576.477580
5	7	3038.846349
6	8	2710.213140
7	9	2443.021897
8	10	2207.119238

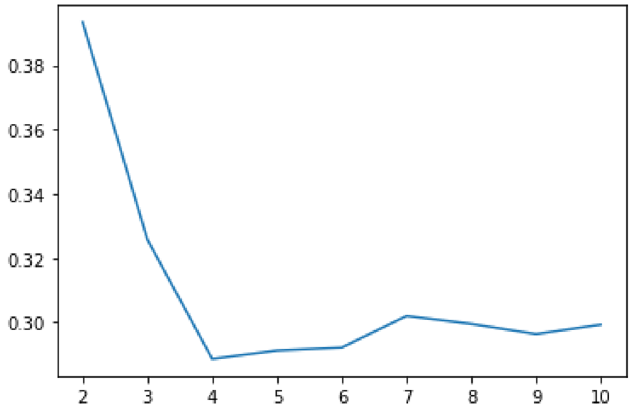
By analysis of grapg its getting difficult which would be optimul no of cluster because elbow bend is not clear.

In [58]:
```
silhouete_score = []

for i in range(2,11):
    km = KMeans(n_clusters = i, max_iter = 500, random_state = 10)
    cluster = km.fit_predict(scaled_rfm)
    score = silhouette_score(scaled_rfm, cluster)
    silhouete_score.append(score)
```

In [59]:
```
# Let's plot the silhouete_score graph.
plt.plot(range(2,11), silhouete_score)
```

Out[59]: [<matplotlib.lines.Line2D at 0x26ff78a8190>]



In [60]:
```
km = KMeans(n_clusters = 2, init= "k-means++", max_iter=500, random_state= 500)
```

In [61]:
```
cluster = km.fit_predict(scaled_rfm)
```

In [62]:
```
silhouette_score(scaled_rfm, cluster)
```

Out[62]: 0.3934322038543268

In [63]:
```
RFM_clust['labeled'] = km.labels_
```

In [64]:
```
RFM_clust
```

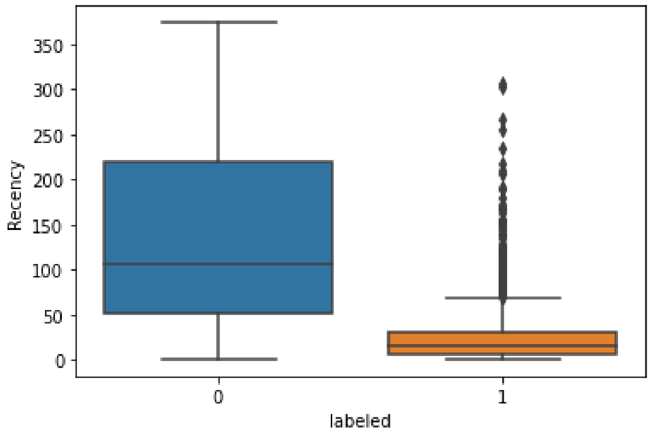
Out[64]:

	Recency	Frequency	MonetaryValue	R	F	M	RFM_concat	RFM_score	RFM_segment	labeled
CustomerID										
12346.0	326	2	0.00	1	1	1	1.01.01.0	3	Need Atention	0
12347.0	2	182	4310.00	4	4	4	4.04.04.0	12	premiere	1
12348.0	75	31	1797.24	2	2	4	2.02.04.0	8	Champions	0
12349.0	19	73	1757.55	3	3	4	3.03.04.0	10	premiere	1
12350.0	310	17	334.40	1	1	2	1.01.02.0	4	Promissing	0
...	...	...	...	...	...	...	...	...	...	...
18278.0	74	9	173.90	2	1	1	2.01.01.0	4	Promissing	0
18280.0	278	10	180.60	1	1	1	1.01.01.0	3	Need Atention	0
18281.0	181	7	80.82	1	1	1	1.01.01.0	3	Need Atention	0
18282.0	8	13	176.60	4	1	1	4.01.01.0	6	Loyal	0
18287.0	43	70	1837.28	3	3	4	3.03.04.0	10	premiere	1

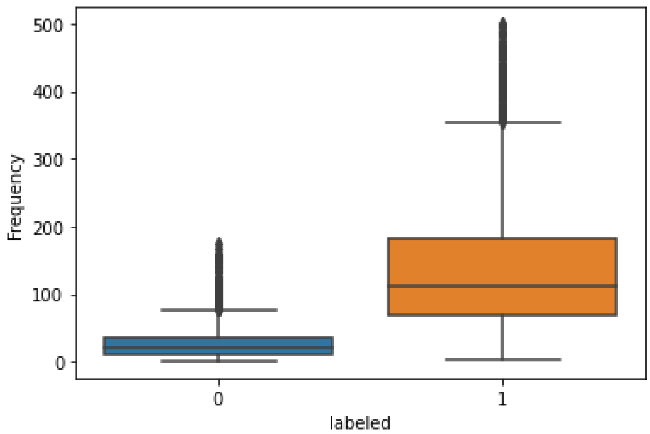
4283 rows × 10 columns

c. Analyze these clusters and comment on the results.

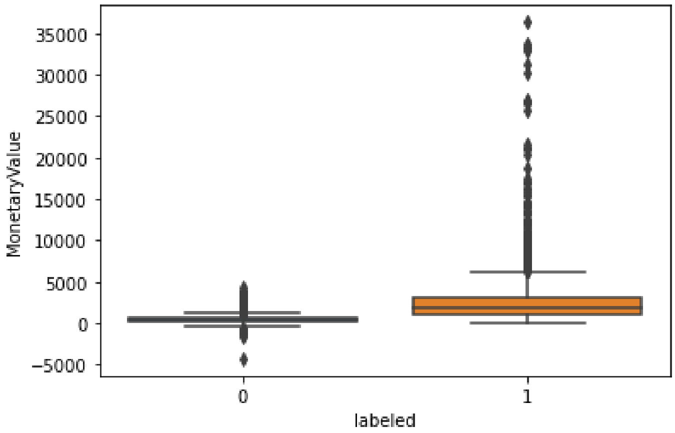
In [65]:
```
sns.boxplot(x='labeled', y='Recency', data=RFM_clust);
```



In [66]:
```
sns.boxplot(x='labeled', y='Frequency', data=RFM_clust);
```



In [67]:
```
sns.boxplot(x='labeled', y='MonetaryValue', data=RFM_clust);
```



Result analysis

After analysing the customer it is clear that the customer in cluster 1 is loyal and frequently buy the product and also spend good amount whereas the customer in cluster 1 is week customer on which we need to give attention.

Project Task: Week 4

Data Reporting:

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

a. Country-wise analysis to demonstrate average spend. Use a bar chart to show the monthly figures

b. Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold

c. Bar graph to show the count of orders vs. hours throughout the day

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

e. Plot error (cost) vs. number of clusters selected

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

In [68]:
```
# Converting the data frame into the excel to make dashboard in the tableau
retail_df.to_excel('master_data.xlsx', sheet_name='master_data', index=False)
RFM_clust.to_excel('rfm_data.xlsx', sheet_name='rfm_data', index=False)
inertia.to_excel('inertia_data.xlsx', sheet_name='inertia', index=False)
```

Please refer Tableau Dashboard for visualization and graphs

In [ ]:

In [ ]:

Retail.

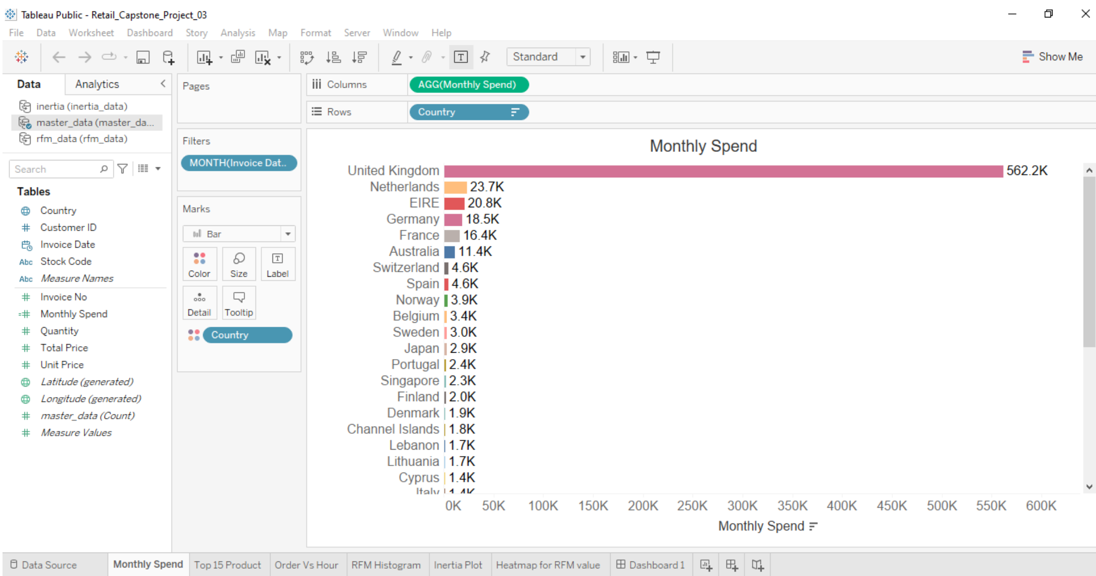
Course-end Project 3

Project Task: Week 4

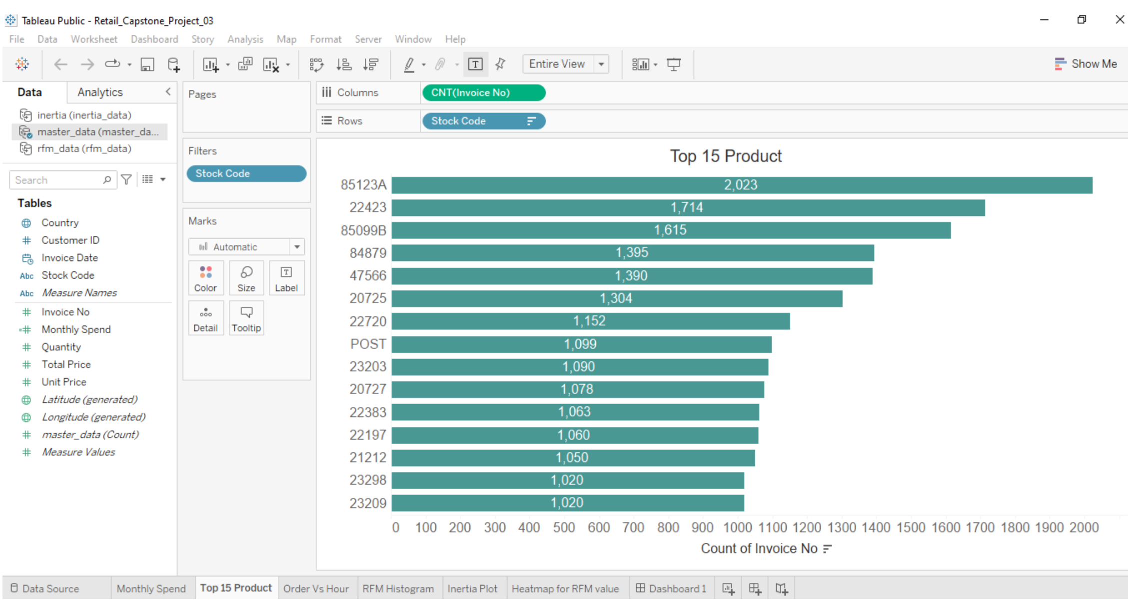
Data Reporting:

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

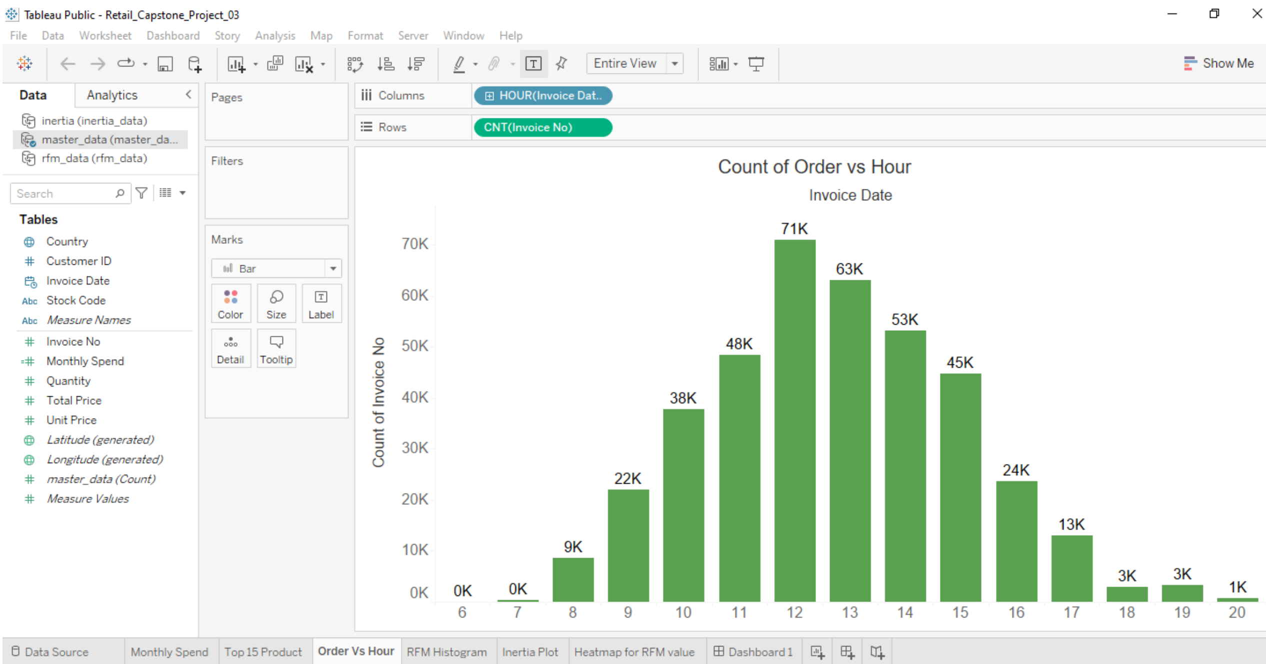
a. Country-wise analysis to demonstrate average spend. Use a bar chart to show the monthly figures



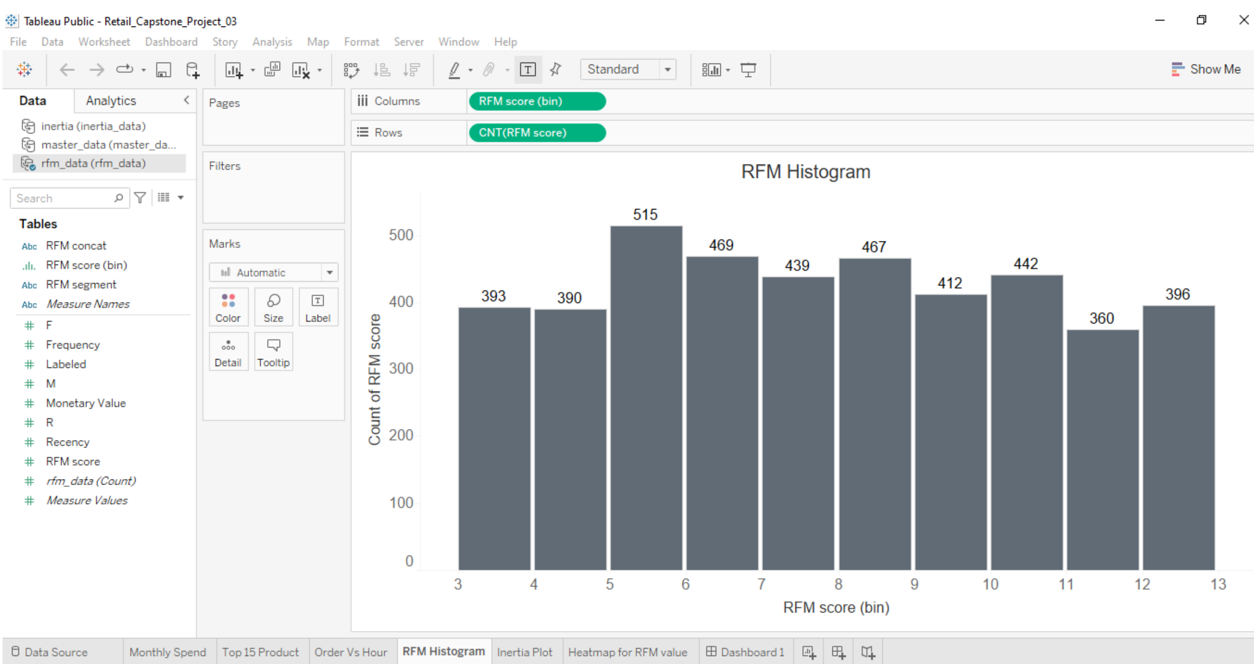
b. Bar graph of top 15 products which are mostly ordered by the users to show the number of products sold



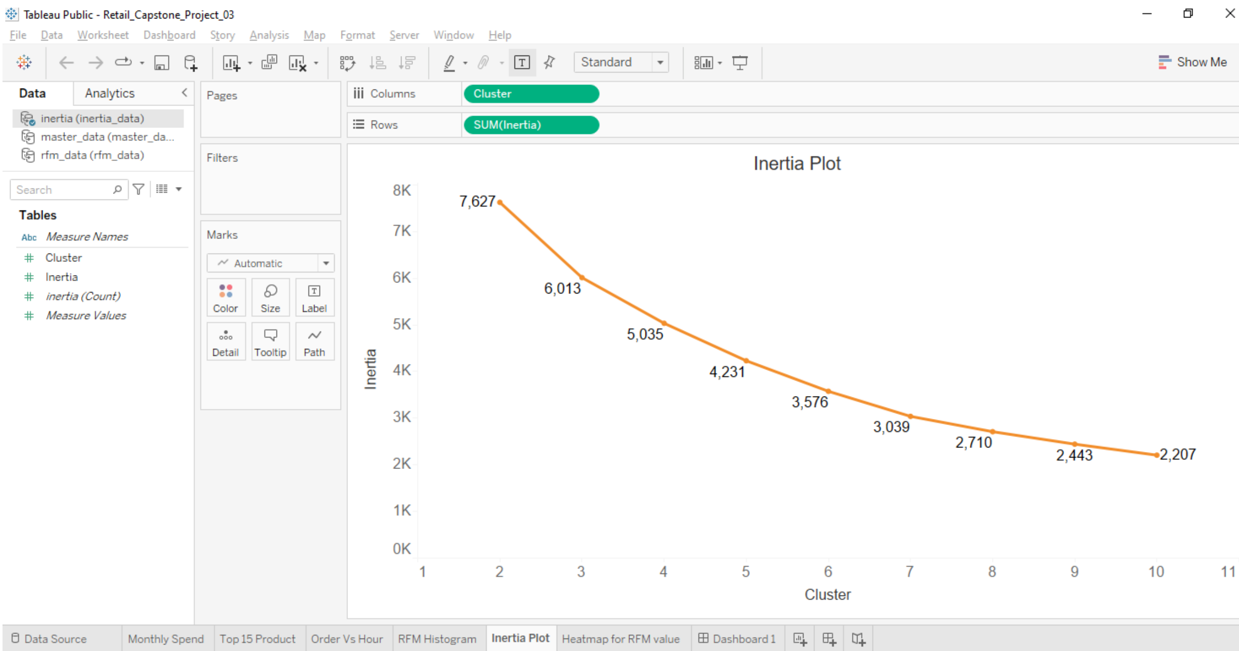
c. Bar graph to show the count of orders vs. hours throughout the day



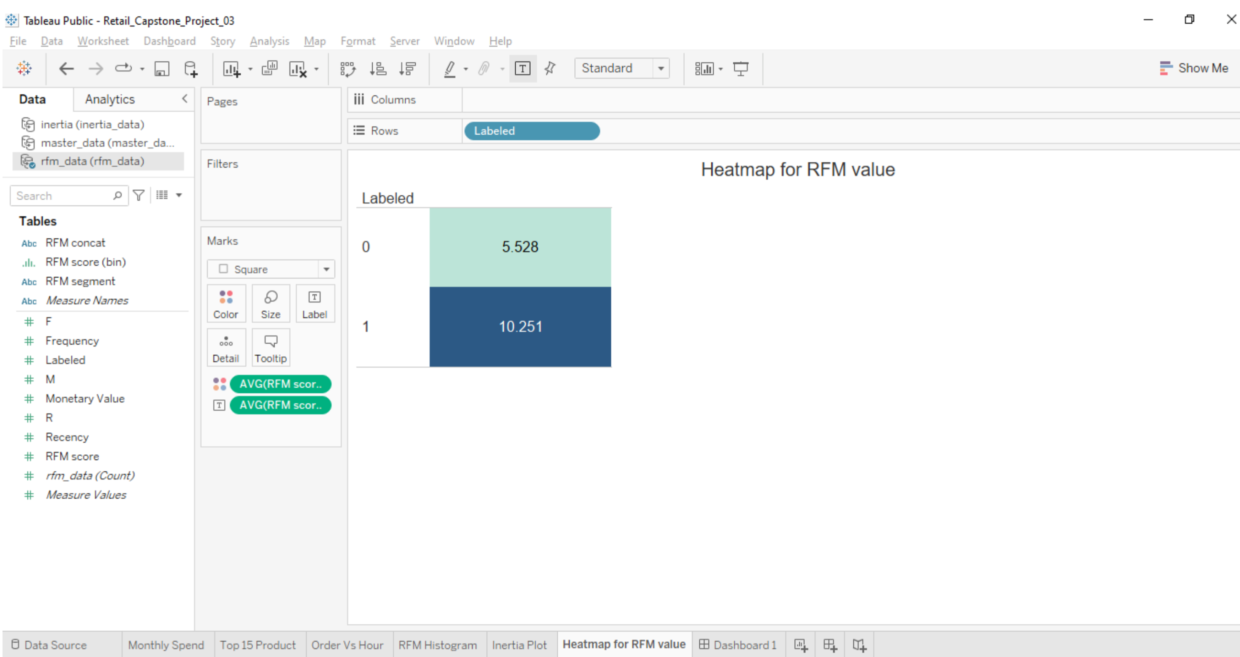
d. Plot the distribution of RFM values using histogram and frequency charts



e. Plot error (cost) vs. number of clusters selected



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



** FINAL DASHBOARD**