RFM_Solution

April 30, 2022

0.1 RFM Analysis

F:- Frequency of transactions/login by a particular customer.

R:- Recency. How recently the customer has visited/transacted on the store.

M:- Monetory. The amount spent by the customer on the store.

0.2 Data Info

CustomerID is customer Identifier

InvoiceNo is transaction identifier (bill).

0.3 Objective

Build an RFM segmentation of these customers. The segmentation should build relevant clusters, show how these segments differ from each other (KPIs) and explain the engagement strategy for each segment, i.e. how should the brand be engaging these customers, what type of campaigns they should run, how will this affect the KPIs.

[1]:
```python
import pandas as pd
import numpy as np
import utility_functions as uf
import os
import datetime as dt
from collections import Counter

import warnings
warnings.filterwarnings('ignore')

#Plotting Libraries
import seaborn as sns
import matplotlib.pyplot as plt

#Clustering
from sklearn.cluster import KMeans
```

[2]:
```python
data = pd.read_csv("data.csv")
```

[3]:
```
data.head()
```

[3]:
```
  InvoiceNo StockCode                          Description  Quantity  \
0    536365    85123A   WHITE HANGING HEART T-LIGHT HOLDER         6
1    536365     71053                  WHITE METAL LANTERN         6
2    536365    84406B       CREAM CUPID HEARTS COAT HANGER         8
3    536365    84029G  KNITTED UNION FLAG HOT WATER BOTTLE         6
4    536365    84029E       RED WOOLLY HOTTIE WHITE HEART.         6

      InvoiceDate  UnitPrice  CustomerID         Country
0  12/1/2010 8:26       2.55     17850.0  United Kingdom
1  12/1/2010 8:26       3.39     17850.0  United Kingdom
2  12/1/2010 8:26       2.75     17850.0  United Kingdom
3  12/1/2010 8:26       3.39     17850.0  United Kingdom
4  12/1/2010 8:26       3.39     17850.0  United Kingdom
```

[4]:
```
#Create an object for the entire data
data_obj = uf.GetStats(data)

#Distribution of All Countries
data_obj.categorical_distribution('Country').head()
```

[4]:
```
          Category  Counts  Percentage
34  United Kingdom  495478       91.43
11         Germany    9495        1.75
30          France    8557        1.58
22            EIRE    8196        1.51
37           Spain    2533        0.47
```

0.4 UK Data

91.43 % of the data belongs to UK

[5]:
```
uk_data = data.loc[data['Country']=='United Kingdom', :]
print("Record size:-\nOverall:- {}\t UK Specific:- {}" .format(data.shape,␣
 ↪uk_data.shape))
```

```
Record size:-
Overall:- (541909, 8)    UK Specific:- (495478, 8)
```

[6]:
```
uk_data_obj = uf.GetStats(uk_data)
```

[7]:
```
#Get the statistics
uk_data_stats = uk_data_obj.driver()
uk_data_stats
#Write the stats to a file
```

```
#uk_data_stats.to_csv(os.getcwd() + "/Statistics/Descriptive Statistics.csv")
```

[7]:

```
      Features  Missing Value Count  Missing Value Percentage Data Types  \
0   CustomerID               133600                  0.269639    float64
1  Description                 1454                  0.002935     object
2    InvoiceNo                    0                  0.000000     object
3    StockCode                    0                  0.000000     object
4     Quantity                    0                  0.000000      int64
5  InvoiceDate                    0                  0.000000     object
6    UnitPrice                    0                  0.000000    float64
7      Country                    0                  0.000000     object

      count          mean          std       min       25%      50%       75%  \
0  361878.0  15547.871368  1594.402590  12346.00  14194.00  15514.0  16931.00
1       NaN           NaN          NaN       NaN       NaN      NaN       NaN
2       NaN           NaN          NaN       NaN       NaN      NaN       NaN
3       NaN           NaN          NaN       NaN       NaN      NaN       NaN
4  495478.0      8.605486   227.588756 -80995.00      1.00      3.0     10.00
5       NaN           NaN          NaN       NaN       NaN      NaN       NaN
6  495478.0      4.532422    99.315438 -11062.06      1.25      2.1      4.13
7       NaN           NaN          NaN       NaN       NaN      NaN       NaN

       max  # Categories
0  18287.0           NaN
1      NaN        4203.0
2      NaN       23494.0
3      NaN        4065.0
4  80995.0           NaN
5      NaN       21220.0
6  38970.0           NaN
7      NaN           1.0
```

0.4.1 Dealing with Missing CustomerID

1. Drop the records with missing values. ~27% data loss.
2. Drop the column. Not feasible. CustomerID is the identifier.
3. Imputation. Customer Count = 3,61,878

#Chosing option 1 in the interest of time

[8]:

```
#26.96 % of rows for CustomerIDs is missing
print("Missing Customer Records:- %d\nNA Free Customer Records:- %d\nTotal:-␣
↪%d" \
      %(133600, 495478-133600, 495478))
print("Missing Customer Records Percentage:- %.2f" %((133600*100)/495478))
```

```
Missing Customer Records:- 133600
NA Free Customer Records:- 361878
```

```
Total:- 495478
Missing Customer Records Percentage:- 26.96
```

[9]:
```python
#Check a few observations belonging to Missing CustomerID
uk_data_NA_cust = uk_data.loc[uk_data['CustomerID'].isnull(), :]
uk_data_NA_free_cust = uk_data.loc[~uk_data['CustomerID'].isnull(), :]

#Check the stats for uk_data_NA_free_cust
uk_data_NA_free_obj = uf.GetStats(uk_data_NA_free_cust)
uk_data_NA_free_obj.driver()
```

[9]:
```
      Features  Missing Value Count  Missing Value Percentage Data Types  \
0    InvoiceNo                    0                       0.0     object
1    StockCode                    0                       0.0     object
2  Description                    0                       0.0     object
3     Quantity                    0                       0.0      int64
4  InvoiceDate                    0                       0.0     object
5    UnitPrice                    0                       0.0    float64
6   CustomerID                    0                       0.0    float64
7      Country                    0                       0.0     object

      count          mean          std      min       25%       50%       75%  \
0       NaN           NaN          NaN      NaN       NaN       NaN       NaN
1       NaN           NaN          NaN      NaN       NaN       NaN       NaN
2       NaN           NaN          NaN      NaN       NaN       NaN       NaN
3  361878.0     11.077029   263.129266 -80995.0      2.00      4.00     12.00
4       NaN           NaN          NaN      NaN       NaN       NaN       NaN
5  361878.0      3.256007    70.654731      0.0      1.25      1.95      3.75
6  361878.0  15547.871368  1594.402590  12346.0  14194.00  15514.00  16931.00
7       NaN           NaN          NaN      NaN       NaN       NaN       NaN

       max  # Categories
0      NaN       19857.0
1      NaN        3661.0
2      NaN        3860.0
3  80995.0           NaN
4      NaN       18441.0
5  38970.0           NaN
6  18287.0           NaN
7      NaN           1.0
```

[10]:
```python
# uk_data
# uk_data_NA_cust
# uk_data_NA_free_cust
def data_manipulation(data):
    '''
    Creating derived variables related to Invoice Date and Amount.
```

```
    '''
    data['InvoiceNo_Date'] = data['InvoiceNo'] + '_' + data['InvoiceDate']
    data['InvoiceDateExclusive'] = list(map(lambda date_time: date_time.
 ↪split()[0], \
                                             data['InvoiceDate'].tolist()))
    data['InvoiceTimeExclusive'] = list(map(lambda date_time: date_time.
 ↪split()[1], \
                                             data['InvoiceDate'].tolist()))

    #Convert to date
    data['InvoiceDate_new'] = pd.to_datetime(data['InvoiceDate'])
    data['InvoiceDateExclusive'] = pd.to_datetime(data['InvoiceDateExclusive'])

    #Get the total amount
    data['Total Amount'] = data['Quantity'] * data['UnitPrice']

    return data
```

[11]:
```
#Check count of unique InvoiceNo for Null Customers
#InvoiceNo does not contain Missing Values
len(set(uk_data_NA_free_cust['InvoiceNo'])) #19,857
```

[11]: 19857

[66]:
```
#Check the unique combination of InvoiceNo and InvoiceDate
#Check both NA Customers(uk_data_NA_cust_data) and Filled Customers
uk_data_NA_free_cust = data_manipulation(uk_data_NA_free_cust)

#Write the data free from missing values to a file
uk_data_NA_free_cust.to_csv(os.getcwd() + '/Statistics/UK_data_NA_free.csv')
```

[13]:
```
uk_data_NA_free_cust[['InvoiceNo', 'InvoiceDate_new', 'InvoiceTimeExclusive', \
         'InvoiceDateExclusive', 'InvoiceNo_Date', 'Quantity', \
         'UnitPrice', 'Total Amount']].head()
```

[13]:
```
  InvoiceNo     InvoiceDate_new InvoiceTimeExclusive InvoiceDateExclusive  \
0    536365 2010-12-01 08:26:00                 8:26           2010-12-01
1    536365 2010-12-01 08:26:00                 8:26           2010-12-01
2    536365 2010-12-01 08:26:00                 8:26           2010-12-01
3    536365 2010-12-01 08:26:00                 8:26           2010-12-01
4    536365 2010-12-01 08:26:00                 8:26           2010-12-01

          InvoiceNo_Date  Quantity  UnitPrice  Total Amount
0  536365_12/1/2010 8:26         6       2.55         15.30
1  536365_12/1/2010 8:26         6       3.39         20.34
2  536365_12/1/2010 8:26         8       2.75         22.00
```

```
3  536365_12/1/2010 8:26          6        3.39          20.34
4  536365_12/1/2010 8:26          6        3.39          20.34
```

0.5 Analyze Customer Behaviour

[14]:
```
#Check unique customer counts
#Distinct Customers:-    3,950
#Total transactions:- 4,95,478
customer_grp = uk_data_NA_free_cust.groupby('CustomerID')
```

0.6 R

Recency:- The amount of time since the last transaction of a customer

[15]:
```
def get_recency():
    #Select the recent date of transaction for each and every customer
    #1-Date  per Customer. Time in  days
    recency = customer_grp.apply(lambda df: \
                                 df.sort_values(by='InvoiceDate_new',␣
 ↪ascending=False)\
                                 .iloc[0, :])

    recency = pd.DataFrame(recency)
    if('CustomerID' in recency.columns):
        recency = recency.drop('CustomerID', axis=1)

    #Sort in descending order of InvoiceDate_new
    recency = recency.sort_values(by='InvoiceDate_new', ascending=False)

    #Time since the last transaction = Current Date - Maximum Invoice Date
    recency['TimeSinceLastTxn'] = pd.Timestamp(dt.datetime.now()) -␣
 ↪recency['InvoiceDate_new']

    #Extract days from the above
    recency['Days_SinceLastTxn'] = recency['TimeSinceLastTxn'].apply(lambda␣
 ↪diff:diff.days)
    recency['Years_SinceLastTxn'] = recency['Days_SinceLastTxn']/365
    recency['Months_SinceLastTxn'] = recency['Years_SinceLastTxn']*12
    #Recent will be at the top

    #Most recent transactions(InvoiceDate_new) will be at the top
    recency = recency[['Days_SinceLastTxn', 'Years_SinceLastTxn',\
                       'Months_SinceLastTxn']].reset_index() #CustomerID will␣
 ↪become a column
    recency.to_csv(os.getcwd() + "/Statistics/Recency_Customers.csv")
```

```
    return recency

recency = get_recency()
recency.head()
#(3950, 12)
```

[15]:

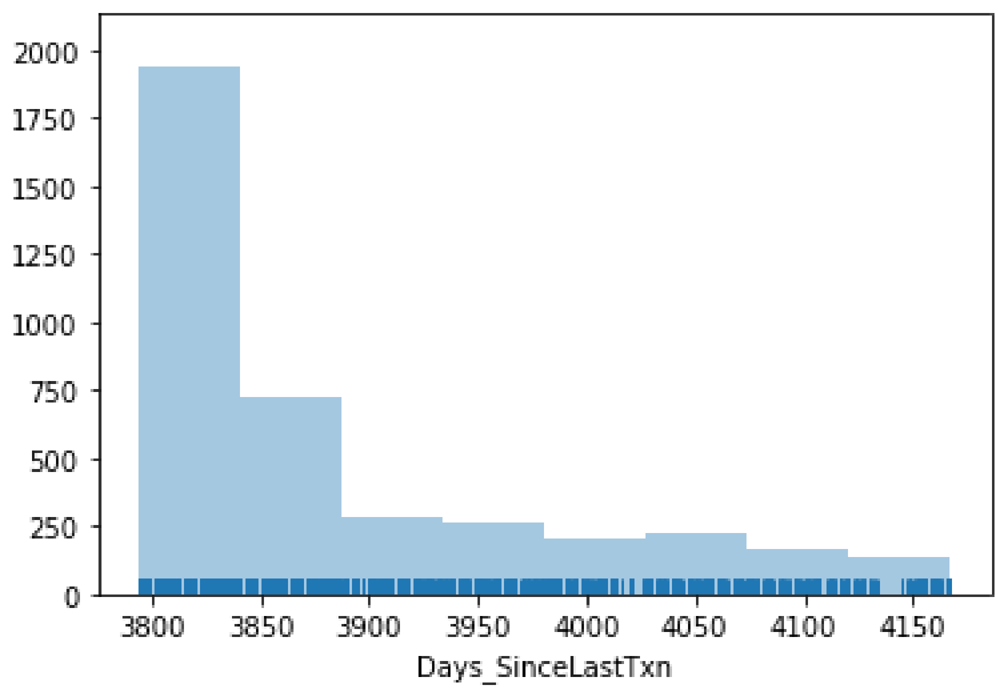
	CustomerID	Days_SinceLastTxn	Years_SinceLastTxn	Months_SinceLastTxn
0	13113.0	3794	10.394521	124.734247
1	15804.0	3794	10.394521	124.734247
2	13777.0	3794	10.394521	124.734247
3	17581.0	3794	10.394521	124.734247
4	12748.0	3794	10.394521	124.734247

[16]:

```
#Plot Recency
def plotting_dist(cust_data, var, plot_name):
    sns_plt = sns.distplot(cust_data[var],bins=8,kde=False,rug=True)
    fig = sns_plt.get_figure()
    fig.savefig(os.getcwd() + '/Plots/' + plot_name + '.png')
```

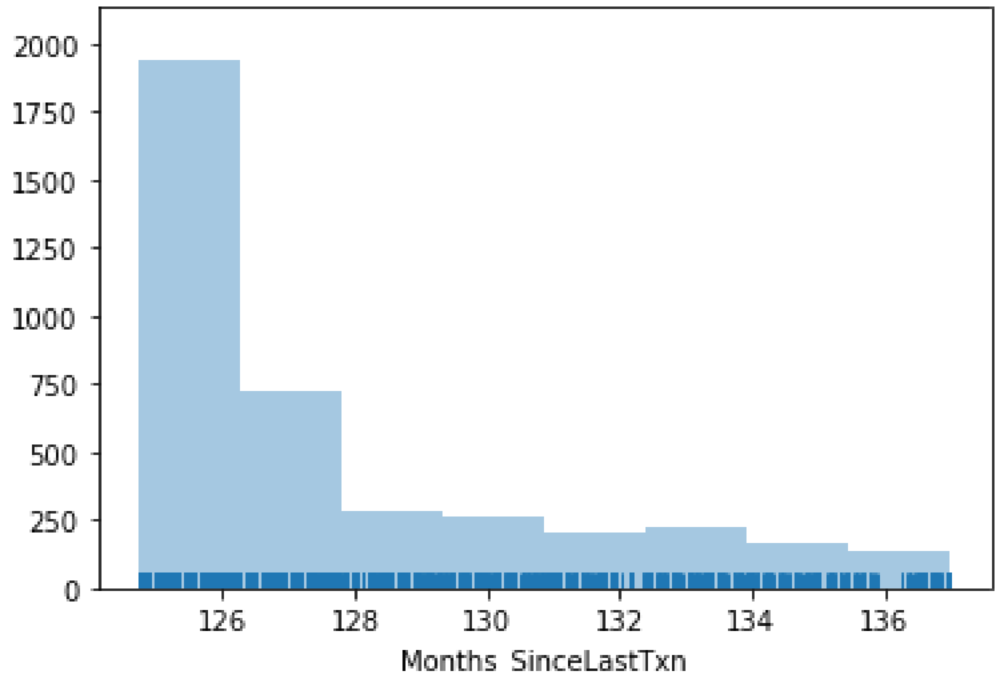
[17]:

```
#Distribution of Days Since Last Transaction
plotting_dist(recency, 'Days_SinceLastTxn', 'Recency_Plot_Days')
```

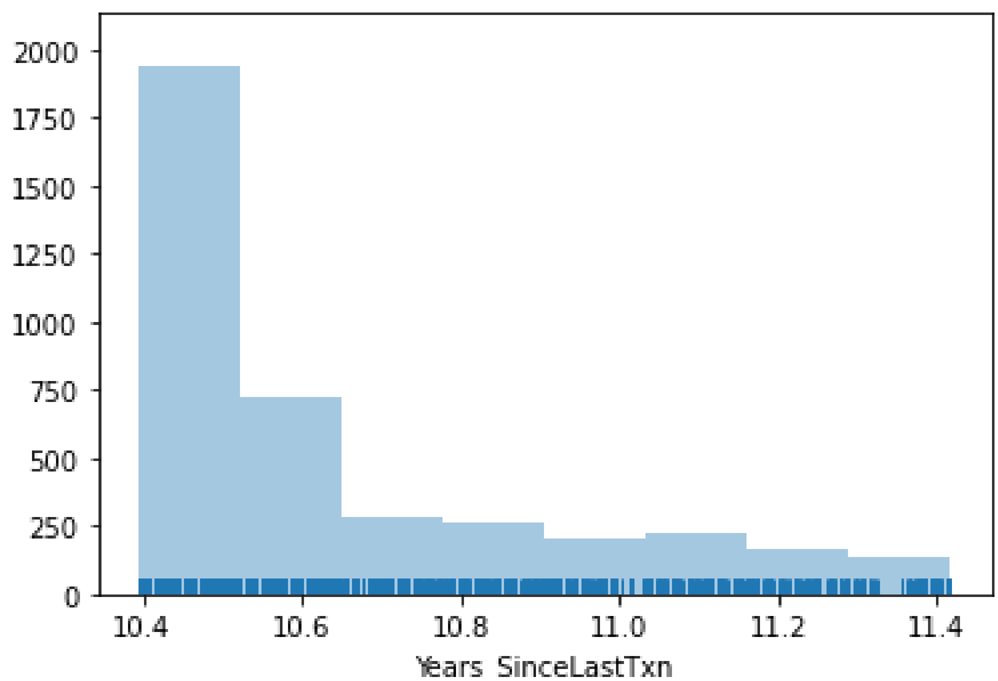


[18]:

```
#Distribution of Months Since Last Transaction
plotting_dist(recency, 'Months_SinceLastTxn', 'Recency_Plot_Months')
```



[19]:
```
#Distribution of Years Since Last Transaction
plotting_dist(recency, 'Years_SinceLastTxn', 'Recency_Plot_Years')
```



0.7 F

Frequency:- The total number of transactions carried out by a customer

0.7.1 Customer wise InvoiceDate and InvoiceNo

Check for same customers, same InvoiceNo and different InvoiceDate. –> Suspecious.

Check for same customers, same InvoiceDate and different InvoiceNo. –> Multiple Transaction on the day

[20]:
```
def get_frequency():
    #A particular customer can have multiple invoices on the same day.
    #Count Unique Invoices for each customer

    unique_invoices_count = pd.DataFrame(customer_grp.apply(lambda df: len(np.
 ↪unique(df['InvoiceNo']))))
    unique_invoices_count = unique_invoices_count.rename(columns={0:'InvoiceNo␣
 ↪Counts'})
    unique_invoices_count = unique_invoices_count.sort_values(by='InvoiceNo␣
 ↪Counts', ascending=False)

    #Count Unique InvoiceNo_Date combination for each customer
    unique_invoice_date_count = pd.DataFrame(customer_grp.apply(lambda df:␣
 ↪len(np.unique(df['InvoiceNo_Date']))))
    unique_invoice_date_count = unique_invoice_date_count.rename(columns={0:
 ↪'InvoiceNo_Date Counts'})
    unique_invoice_date_count = unique_invoice_date_count.
 ↪sort_values(by='InvoiceNo_Date Counts', ascending=False)

    #Join the 2 data frames
    unique_invoices_count = unique_invoices_count.reset_index()
    unique_invoice_date_count = unique_invoice_date_count.reset_index()

    frequency = pd.merge(unique_invoices_count, unique_invoice_date_count,␣
 ↪on='CustomerID', how='left')

    #Difference in Counts
    frequency["Difference"] = frequency['InvoiceNo_Date Counts'] -␣
 ↪frequency['InvoiceNo Counts']
    frequency.to_csv(os.getcwd() + "/Statistics/Frequency_Customers.csv")

    return frequency

frequency = get_frequency()
frequency.head()
```

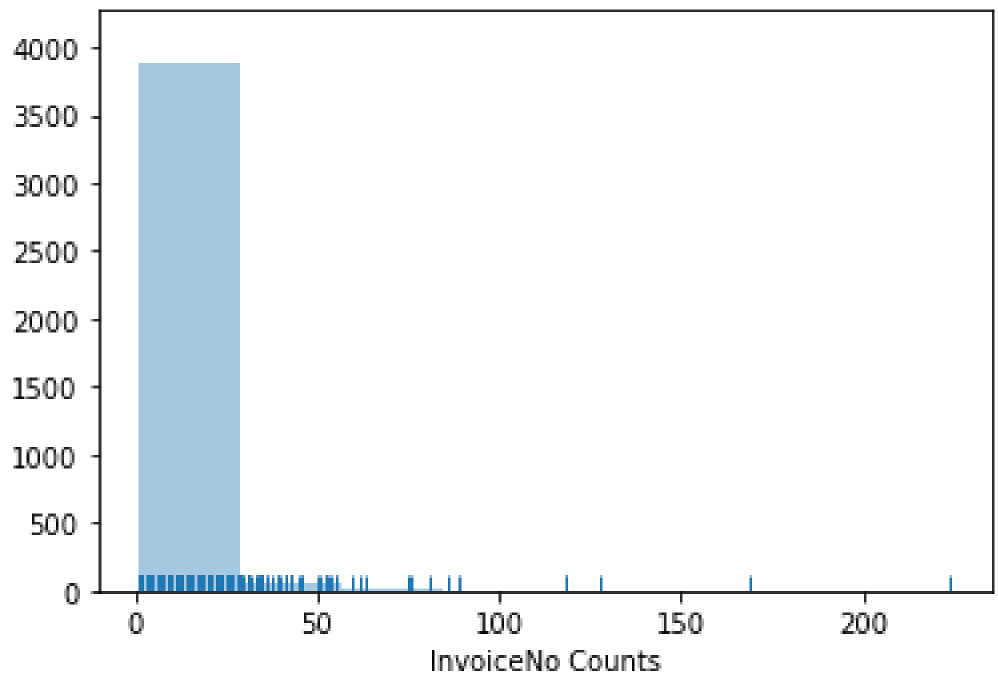
[20]:

	CustomerID	InvoiceNo Counts	InvoiceNo_Date Counts	Difference
0	12748.0	224	225	1
1	17841.0	169	169	0
2	14606.0	128	130	2
3	13089.0	118	118	0
4	15311.0	118	118	0

[21]:
```
#Count of Difference
#Counter({1: 24, 0: 3924, 2: 2}):- 26(24+2) Customers
Counter(frequency['Difference'])
```

[21]: Counter({1: 24, 0: 3924, 2: 2})

[22]:
```
plotting_dist(frequency, 'InvoiceNo Counts', 'Frequency_Plot')
```



[23]:
```
#Group By ['CustomerID', 'InvoiceNo']
#Obtain the counts, InvoiceNo_Date Counts and the values
# cust_invoice_grp = pd.DataFrame(uk_data.groupby('CustomerID', 'InvoiceNo'))
# cust_invoice_grp
```

0.8 M

Monetory:- The total value of the transactions carried out by a customer across all it's transactions

0.8.1 Negative Amount

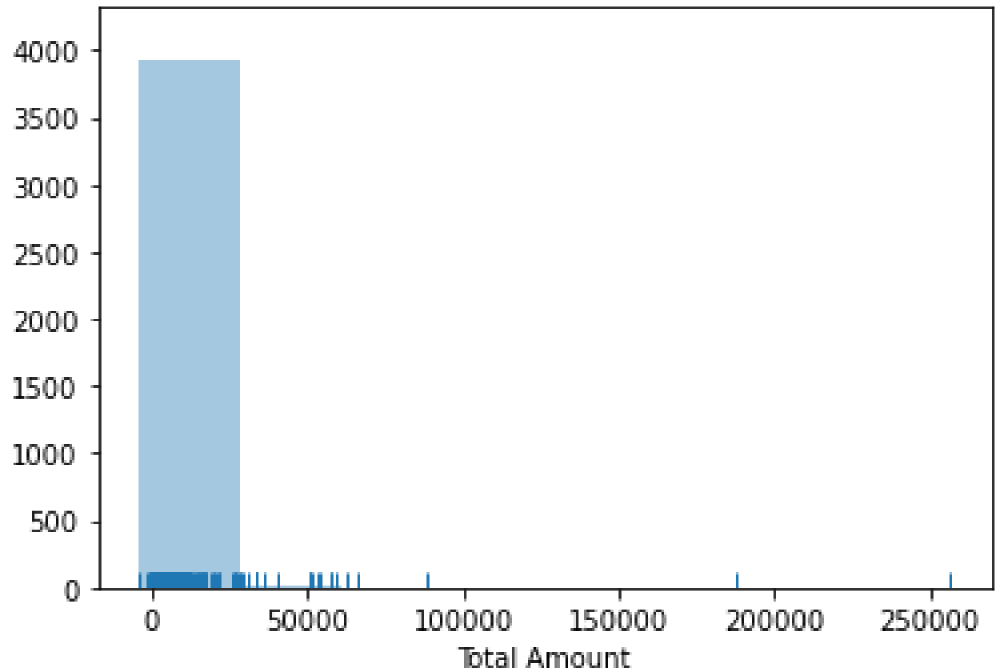
Negative Total Amount is corresponding to Cancelled item indicated by InvoiceNo begining with C

[24]:
```
#ATS of each customer
#'Total Amount'

'''
def get_monetary():
    #Monetary
    monetary = customer_grp.apply(lambda df: max(df['Total Amount']))

def compute_ATS(df):

#     ATS is the Average Transaction Size for each customer
#     ATS = (Total Transaction Amount)/(Number of Transactions)

    sum(df[])/df.shape[0]

'''
def get_monetary():
    monetary = pd.DataFrame(customer_grp.apply(lambda df: sum(df['Total␣
 ↪Amount'])))#, max(df['Total Amount'])]))
    monetary = monetary.rename(columns={0:'Total Amount'})

    monetary = monetary.reset_index()
    return monetary

monetary = get_monetary()
monetary.head()
```

[24]:

	CustomerID	Total Amount
0	12346.0	0.00
1	12747.0	4196.01
2	12748.0	29072.10
3	12749.0	3868.20
4	12820.0	942.34

[25]:
```
plotting_dist(monetary, 'Total Amount', 'Monetary_Plot')
```

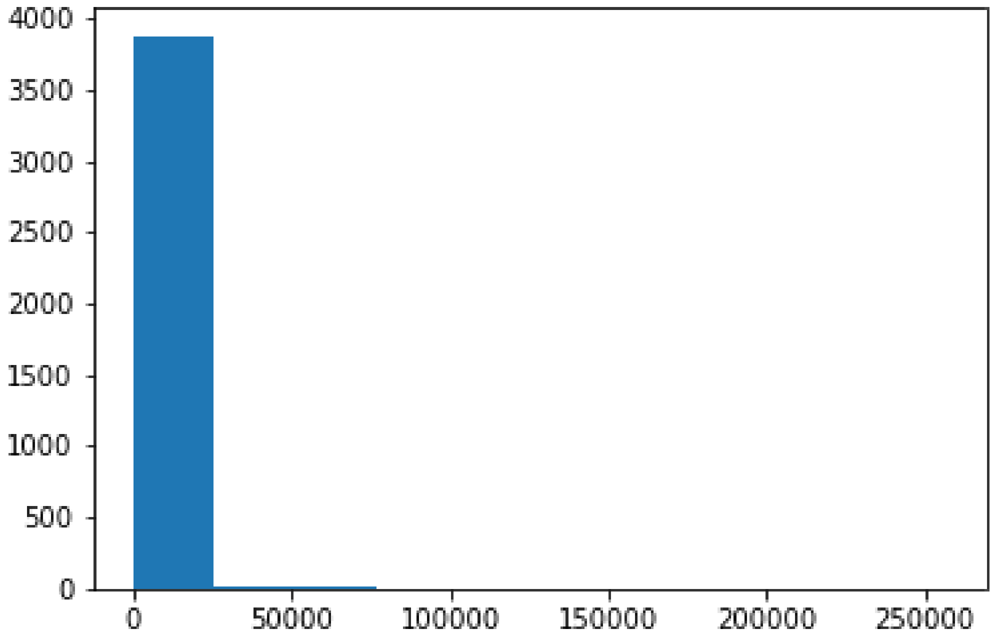


[26]:

```python
#>0 Total Amount
monetary_non_zero = monetary.loc[monetary['Total Amount']>0, :]
plt.hist(monetary_non_zero['Total Amount'])
```

[26]:

```
(array([3.876e+03, 1.800e+01, 8.000e+00, 1.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 1.000e+00, 0.000e+00, 1.000e+00]),
 array([1.24344979e-14, 2.56438490e+04, 5.12876980e+04, 7.69315470e+04,
        1.02575396e+05, 1.28219245e+05, 1.53863094e+05, 1.79506943e+05,
        2.05150792e+05, 2.30794641e+05, 2.56438490e+05]),
 <BarContainer object of 10 artists>)
```



[27]:
```
monetary_non_zero.shape, monetary.shape
```

[27]:
```
((3905, 2), (3950, 2))
```

0.9 Total Amount = 0

Aggregated:- The sum of total amount for a customer can be 0 because of cancellation of purchased items.

Total Amount can also be 0 due to UnitPrice = 0

[28]:
```
#Check for customers with Total Amount = 0
#[12346.0, 13256.0, 14557.0, 14792.0, 16742.0, 16878.0, 18268.0]
customers_zero_M = monetary.loc[monetary['Total Amount']==0, 'CustomerID'].
 ↪tolist()
customers_zero_M
```

[28]:
```
[12346.0, 13256.0, 14557.0, 14792.0, 16742.0, 16878.0, 18268.0]
```

[29]:
```
#12346.0, 13256.0, 14557.0, 14792.0, 16742.0, 16878.0, 18268.0]]

uk_data_NA_free_cust_index = uk_data_NA_free_cust.set_index('CustomerID')
uk_data_NA_free_cust_index.loc[customers_zero_M, :].
 ↪sort_values(by='CustomerID', axis=0)
```

[29]:
```
           InvoiceNo StockCode                         Description  Quantity  \
CustomerID
12346.0       541431     23166      MEDIUM CERAMIC TOP STORAGE JAR     74215
12346.0      C541433     23166      MEDIUM CERAMIC TOP STORAGE JAR    -74215
13256.0       578841     84826      ASSTD DESIGN 3D PAPER STICKERS     12540
14557.0      C569995     23301   GARDENERS KNEELING PAD KEEP CALM        -48
14557.0      C569995     23267     SET OF 4 SANTA PLACE SETTINGS         -48
14557.0      C569995     23154          SET OF 4 JAM JAR MAGNETS         -48
14557.0      C569995     23120       PACK OF 6 SMALL FRUIT STRAWS        -48
14557.0      C569995     22960           JAM MAKING SET WITH JARS        -12
14557.0      C569995     22952     60 CAKE CASES VINTAGE CHRISTMAS       -24
14557.0      C569995     22910   PAPER CHAIN KIT VINTAGE CHRISTMAS       -24
14557.0      C569995     23318       BOX OF 6 MINI VINTAGE CRACKERS      -24
14557.0      C569995     22909 SET OF 20 VINTAGE CHRISTMAS NAPKINS       -24
14557.0      C569995     22737      RIBBON REEL CHRISTMAS PRESENT        -30
14557.0      C569995     22439                 6 ROCKET BALLOONS         -24
14557.0      C569995     22436          12 COLOURED PARTY BALLOONS       -20
14557.0      C569995     22086       PAPER CHAIN KIT 50'S CHRISTMAS      -40
14557.0      C569995     22950          36 DOILIES VINTAGE CHRISTMAS     -24
14557.0      C569995     23319          BOX OF 6 MINI 50'S CRACKERS      -48
14557.0      C569995     23119        PACK OF 6 LARGE FRUIT STRAWS       -24
14557.0       566938     22436          12 COLOURED PARTY BALLOONS        20
14557.0       566938     23119        PACK OF 6 LARGE FRUIT STRAWS        24
14557.0       566938     22086       PAPER CHAIN KIT 50'S CHRISTMAS       40
14557.0       566938     23319          BOX OF 6 MINI 50'S CRACKERS       48
14557.0       566938     22910   PAPER CHAIN KIT VINTAGE CHRISTMAS        24
14557.0       566938     22909 SET OF 20 VINTAGE CHRISTMAS NAPKINS        24
14557.0       566938     23267     SET OF 4 SANTA PLACE SETTINGS          48
14557.0       566938     22950          36 DOILIES VINTAGE CHRISTMAS      24
14557.0       566938     23301   GARDENERS KNEELING PAD KEEP CALM         48
14557.0       566938     22952     60 CAKE CASES VINTAGE CHRISTMAS        24
14557.0       566938     22737      RIBBON REEL CHRISTMAS PRESENT         30
14557.0       566938     22960           JAM MAKING SET WITH JARS         12
14557.0       566938     23154          SET OF 4 JAM JAR MAGNETS          48
14557.0       566938     23120       PACK OF 6 SMALL FRUIT STRAWS         48
14557.0       566938     22439                 6 ROCKET BALLOONS          24
14557.0       566938     23318       BOX OF 6 MINI VINTAGE CRACKERS       24
14792.0      C569954    47594A            CAROUSEL DESIGN WASHBAG         -1
14792.0      C569954     22371        AIRLINE BAG VINTAGE TOKYO 78        -1
14792.0       570003    47594A            CAROUSEL DESIGN WASHBAG          1
14792.0       570003     22371        AIRLINE BAG VINTAGE TOKYO 78         1
16742.0       572423         M                              Manual         1
16742.0      C572410     23170             REGENCY TEA PLATE ROSES       -20
16742.0      C572410     23174             REGENCY SUGAR BOWL GREEN       -2
16742.0      C572410     22699      ROSES REGENCY TEACUP AND SAUCER     -168
16878.0       567158     21034         REX CASH+CARRY JUMBO SHOPPER       10
16878.0       567158     22583         PACK OF 6 HANDBAG GIFT BOXES        1
```

```
16878.0       567158     22585            PACK OF 6 BIRDY GIFT TAGS          1
16878.0      C576375     22585            PACK OF 6 BIRDY GIFT TAGS         -1
16878.0      C576375     22583         PACK OF 6 HANDBAG GIFT BOXES         -1
16878.0      C576375     21034         REX CASH+CARRY JUMBO SHOPPER        -10
18268.0      C561590    84968A       SET OF 16 VINTAGE ROSE CUTLERY         -2
18268.0       561680    84968A       SET OF 16 VINTAGE ROSE CUTLERY          2

                 InvoiceDate  UnitPrice         Country  \
CustomerID
12346.0      1/18/2011 10:01       1.04  United Kingdom
12346.0      1/18/2011 10:17       1.04  United Kingdom
13256.0     11/25/2011 15:57       0.00  United Kingdom
14557.0      10/6/2011 20:36       1.45  United Kingdom
14557.0      10/6/2011 20:36       1.25  United Kingdom
14557.0      10/6/2011 20:36       2.08  United Kingdom
14557.0      10/6/2011 20:36       0.42  United Kingdom
14557.0      10/6/2011 20:36       3.75  United Kingdom
14557.0      10/6/2011 20:36       0.55  United Kingdom
14557.0      10/6/2011 20:36       2.95  United Kingdom
14557.0      10/6/2011 20:36       2.49  United Kingdom
14557.0      10/6/2011 20:36       0.85  United Kingdom
14557.0      10/6/2011 20:36       1.65  United Kingdom
14557.0      10/6/2011 20:36       0.65  United Kingdom
14557.0      10/6/2011 20:36       0.65  United Kingdom
14557.0      10/6/2011 20:36       2.55  United Kingdom
14557.0      10/6/2011 20:36       1.45  United Kingdom
14557.0      10/6/2011 20:36       2.08  United Kingdom
14557.0      10/6/2011 20:36       0.62  United Kingdom
14557.0      9/15/2011 15:48       0.65  United Kingdom
14557.0      9/15/2011 15:48       0.62  United Kingdom
14557.0      9/15/2011 15:48       2.55  United Kingdom
14557.0      9/15/2011 15:48       2.08  United Kingdom
14557.0      9/15/2011 15:48       2.95  United Kingdom
14557.0      9/15/2011 15:48       0.85  United Kingdom
14557.0      9/15/2011 15:48       1.25  United Kingdom
14557.0      9/15/2011 15:48       1.45  United Kingdom
14557.0      9/15/2011 15:48       1.45  United Kingdom
14557.0      9/15/2011 15:48       0.55  United Kingdom
14557.0      9/15/2011 15:48       1.65  United Kingdom
14557.0      9/15/2011 15:48       3.75  United Kingdom
14557.0      9/15/2011 15:48       2.08  United Kingdom
14557.0      9/15/2011 15:48       0.42  United Kingdom
14557.0      9/15/2011 15:48       0.65  United Kingdom
14557.0      9/15/2011 15:48       2.49  United Kingdom
14792.0      10/6/2011 18:34       1.95  United Kingdom
14792.0      10/6/2011 18:34       4.25  United Kingdom
14792.0       10/7/2011 9:19       1.95  United Kingdom
```

```
14792.0       10/7/2011 9:19       4.25  United Kingdom
16742.0     10/24/2011 12:02     464.90  United Kingdom
16742.0     10/24/2011 11:58       1.45  United Kingdom
16742.0     10/24/2011 11:58       3.75  United Kingdom
16742.0     10/24/2011 11:58       2.55  United Kingdom
16878.0      9/16/2011 17:39       0.95  United Kingdom
16878.0      9/16/2011 17:39       2.55  United Kingdom
16878.0      9/16/2011 17:39       1.25  United Kingdom
16878.0      11/15/2011 8:52       1.25  United Kingdom
16878.0      11/15/2011 8:52       2.55  United Kingdom
16878.0      11/15/2011 8:52       0.95  United Kingdom
18268.0      7/28/2011 11:16      12.75  United Kingdom
18268.0      7/28/2011 19:13      12.75  United Kingdom

                      InvoiceNo_Date InvoiceDateExclusive  \
CustomerID
12346.0       541431_1/18/2011 10:01           2011-01-18
12346.0      C541433_1/18/2011 10:17           2011-01-18
13256.0      578841_11/25/2011 15:57           2011-11-25
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0      C569995_10/6/2011 20:36           2011-10-06
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
14557.0       566938_9/15/2011 15:48           2011-09-15
```

```
14557.0       566938_9/15/2011 15:48          2011-09-15
14557.0       566938_9/15/2011 15:48          2011-09-15
14557.0       566938_9/15/2011 15:48          2011-09-15
14557.0       566938_9/15/2011 15:48          2011-09-15
14792.0      C569954_10/6/2011 18:34          2011-10-06
14792.0      C569954_10/6/2011 18:34          2011-10-06
14792.0        570003_10/7/2011 9:19          2011-10-07
14792.0        570003_10/7/2011 9:19          2011-10-07
16742.0      572423_10/24/2011 12:02          2011-10-24
16742.0     C572410_10/24/2011 11:58          2011-10-24
16742.0     C572410_10/24/2011 11:58          2011-10-24
16742.0     C572410_10/24/2011 11:58          2011-10-24
16878.0       567158_9/16/2011 17:39          2011-09-16
16878.0       567158_9/16/2011 17:39          2011-09-16
16878.0       567158_9/16/2011 17:39          2011-09-16
16878.0      C576375_11/15/2011 8:52          2011-11-15
16878.0      C576375_11/15/2011 8:52          2011-11-15
16878.0      C576375_11/15/2011 8:52          2011-11-15
18268.0      C561590_7/28/2011 11:16          2011-07-28
18268.0       561680_7/28/2011 19:13          2011-07-28

           InvoiceTimeExclusive     InvoiceDate_new  Total Amount
CustomerID
12346.0                   10:01 2011-01-18 10:01:00      77183.60
12346.0                   10:17 2011-01-18 10:17:00     -77183.60
13256.0                   15:57 2011-11-25 15:57:00          0.00
14557.0                   20:36 2011-10-06 20:36:00        -69.60
14557.0                   20:36 2011-10-06 20:36:00        -60.00
14557.0                   20:36 2011-10-06 20:36:00        -99.84
14557.0                   20:36 2011-10-06 20:36:00        -20.16
14557.0                   20:36 2011-10-06 20:36:00        -45.00
14557.0                   20:36 2011-10-06 20:36:00        -13.20
14557.0                   20:36 2011-10-06 20:36:00        -70.80
14557.0                   20:36 2011-10-06 20:36:00        -59.76
14557.0                   20:36 2011-10-06 20:36:00        -20.40
14557.0                   20:36 2011-10-06 20:36:00        -49.50
14557.0                   20:36 2011-10-06 20:36:00        -15.60
14557.0                   20:36 2011-10-06 20:36:00        -13.00
14557.0                   20:36 2011-10-06 20:36:00       -102.00
14557.0                   20:36 2011-10-06 20:36:00        -34.80
14557.0                   20:36 2011-10-06 20:36:00        -99.84
14557.0                   20:36 2011-10-06 20:36:00        -14.88
14557.0                   15:48 2011-09-15 15:48:00         13.00
14557.0                   15:48 2011-09-15 15:48:00         14.88
14557.0                   15:48 2011-09-15 15:48:00        102.00
14557.0                   15:48 2011-09-15 15:48:00         99.84
14557.0                   15:48 2011-09-15 15:48:00         70.80
```

```
14557.0                          15:48 2011-09-15 15:48:00         20.40
14557.0                          15:48 2011-09-15 15:48:00         60.00
14557.0                          15:48 2011-09-15 15:48:00         34.80
14557.0                          15:48 2011-09-15 15:48:00         69.60
14557.0                          15:48 2011-09-15 15:48:00         13.20
14557.0                          15:48 2011-09-15 15:48:00         49.50
14557.0                          15:48 2011-09-15 15:48:00         45.00
14557.0                          15:48 2011-09-15 15:48:00         99.84
14557.0                          15:48 2011-09-15 15:48:00         20.16
14557.0                          15:48 2011-09-15 15:48:00         15.60
14557.0                          15:48 2011-09-15 15:48:00         59.76
14792.0                          18:34 2011-10-06 18:34:00         -1.95
14792.0                          18:34 2011-10-06 18:34:00         -4.25
14792.0                           9:19 2011-10-07 09:19:00          1.95
14792.0                           9:19 2011-10-07 09:19:00          4.25
16742.0                          12:02 2011-10-24 12:02:00        464.90
16742.0                          11:58 2011-10-24 11:58:00        -29.00
16742.0                          11:58 2011-10-24 11:58:00         -7.50
16742.0                          11:58 2011-10-24 11:58:00       -428.40
16878.0                          17:39 2011-09-16 17:39:00          9.50
16878.0                          17:39 2011-09-16 17:39:00          2.55
16878.0                          17:39 2011-09-16 17:39:00          1.25
16878.0                           8:52 2011-11-15 08:52:00         -1.25
16878.0                           8:52 2011-11-15 08:52:00         -2.55
16878.0                           8:52 2011-11-15 08:52:00         -9.50
18268.0                          11:16 2011-07-28 11:16:00        -25.50
18268.0                          19:13 2011-07-28 19:13:00         25.50
```

[30]:
```
#(51, 12). 51 records belong to customers having No net purchase.(Includes␣
↪cancellation)
#Records with customers having 0 Aggregated Total Amount = 51
uk_data_NA_free_cust_index.loc[customers_zero_M, :].shape
```

[30]:
```
(51, 12)
```

[31]:
```
#(24, 12). 24 Records have 0 Unit Price and hence 0 Total Amount
uk_data_NA_free_cust_index.loc[(uk_data_NA_free_cust_index['UnitPrice']==0), :].
↪shape# &\
                  #(set(uk_data_NA_free_cust_index.index).
↪intersection(set(customers_zero_M))!=set()), :]
```

[31]:
```
(24, 12)
```

0.10 Assigning Order to R, F and M

Creating groups of customers for Recency, Frequency and Monetory.

It's recommended to divide the customers into four tiers for each dimension, such that each customer will be assigned to one tier in each dimension

Recency Frequency Monetary

R-Tier-1 (most recent) F-Tier-1 (most frequent) M-Tier-1 (highest spend)

R-Tier-2 F-Tier-2 M-Tier-2

R-Tier-3 F-Tier-3 M-Tier-3

R-Tier-4 (least recent)F-Tier-4 (only one transaction)M-Tier-4 (lowest spend)

0.11 Understanding the Customer Segments

1. Most Recent Very Active High Spending Customers(Present in (R-Tier-1) AND (F-Tier-1) AND (M-Tier-1))
2. Most Recent Very Active Medium Spending Customers(Present in (R-Tier-1) AND (F-Tier-1) AND (M-Tier-2))
3. Churned:- (R-4, F-4, M-1) (R-4, F-4, M-2)

[32]:
```
#Merge the 3 values into a Single Data Frame
#['Days_SinceLastTxn', 'Years_SinceLastTxn', 'Months_SinceLastTxn', 'InvoiceNo␣
↪Counts', 'Total Amount']
#print(list(map(lambda df:df.shape, [recency, frequency, monetary])))
#[(3950, 4), (3950, 4), (3950, 2)]

def normalize_min_max(data, variable):
    minimum, maximum = min(data[variable]), max(data[variable])
    normalized_variable = list(map(lambda value:(value-minimum)/
↪(maximum-minimum), \
                                  data[variable].tolist()))

    return normalized_variable

def get_combined_RFM():
    '''
    Combine the 3 fields R, F and M respectively for the customers.
    Normalize the values of R, F and M in ordr to produce a combined RFM score.
    '''
    #Join the 3 data frames [recency, frequency, monetary]
    RFM = recency[['CustomerID', 'Days_SinceLastTxn']]

    RFM = pd.merge(RFM, frequency[['CustomerID', 'InvoiceNo Counts']], \
                   how='left', on='CustomerID')

    RFM = pd.merge(RFM, monetary, how='left', on='CustomerID')

    #Obtain the Ranks
```

```
    RFM['R_Rank'] = RFM['Days_SinceLastTxn'].rank(ascending=True) #Lesser =␣
↪Most Recent
    RFM['F_Rank'] = RFM['InvoiceNo Counts'].rank(ascending=False) #Higher =␣
↪Most Frequent
    RFM['M_Rank'] = RFM['Total Amount'].rank(ascending=False) #Higher = Most␣
↪Valued Purchase

    #Ranks to be Normalized. Since we want to cluster the customers on the␣
↪basis of Ranks
    for col in ['R_Rank', 'F_Rank', 'M_Rank']:
        RFM[col + '_nrm'] = normalize_min_max(RFM, col)
        #Bringing the numbers in the range [1, 5]
        RFM[col + '_score'] = list(map(lambda val: (int(val)+5)%5,RFM[col +␣
↪'_nrm'].tolist()))

    RFM['RFM_score'] = RFM['R_Rank_score'] + RFM['F_Rank_score'] +␣
↪RFM['M_Rank_score']

    return RFM
    '''
    [['CustomerID', 'R_Rank', 'F_Rank', 'M_Rank', 'R_Rank_nrm',\
      'F_Rank_nrm', 'M_Rank_nrm', 'R_Rank_score', 'F_Rank_score', \
      'M_Rank_score', 'RFM_score']]
    '''
```

[33]:
```
RFM = get_combined_RFM()

RFM.tail()
```

[33]:
```
      CustomerID  Days_SinceLastTxn  InvoiceNo Counts  Total Amount  R_Rank  \
3945     17968.0               4167                 1        277.35  3943.5
3946     16583.0               4167                 1        233.45  3943.5
3947     17908.0               4167                 1        243.28  3943.5
3948     13747.0               4167                 1         79.60  3943.5
3949     18074.0               4167                 1        489.60  3943.5

      F_Rank  M_Rank  R_Rank_nrm  R_Rank_score  F_Rank_nrm  F_Rank_score  \
3945  3356.5  2978.0         1.0             1         1.0             1
3946  3356.5  3137.0         1.0             1         1.0             1
3947  3356.5  3107.0         1.0             1         1.0             1
3948  3356.5  3807.0         1.0             1         1.0             1
3949  3356.5  2269.0         1.0             1         1.0             1

      M_Rank_nrm  M_Rank_score  RFM_score
3945    0.753862             0          2
3946    0.794125             0          2
```

```
3947    0.786528            0           2
3948    0.963788            0           2
3949    0.574323            0           2
```

[34]:
```
RFM[['R_Rank_score', 'F_Rank_score', 'M_Rank_score','RFM_score']].describe()
```

[34]:

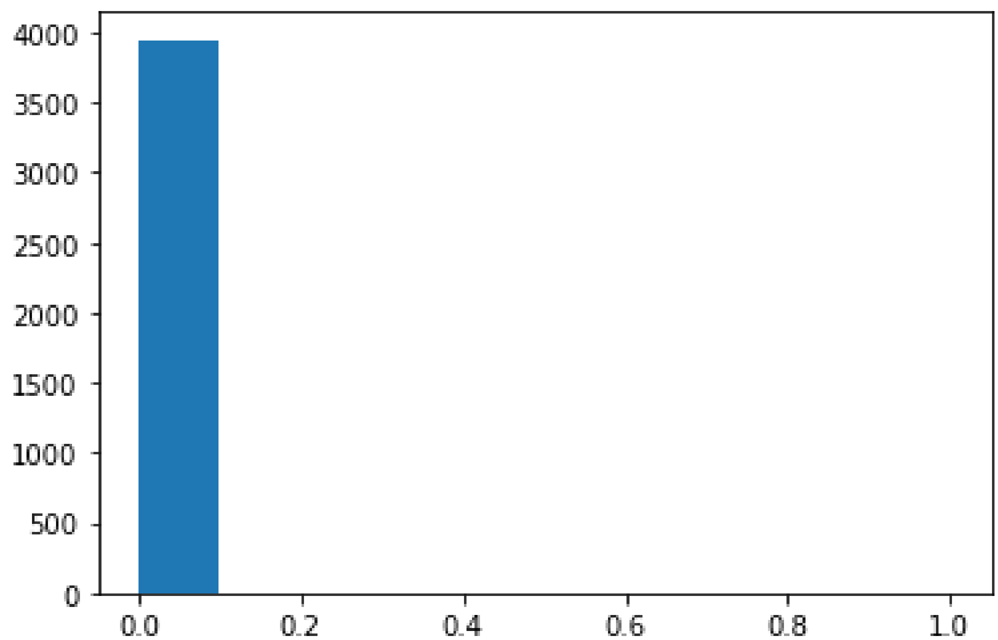
	R_Rank_score	F_Rank_score	M_Rank_score	RFM_score
count	3950.000000	3950.000000	3950.000000	3950.000000
mean	0.003544	0.300759	0.000253	0.304557
std	0.059436	0.458646	0.015911	0.468458
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	0.000000	0.000000	0.000000	0.000000
75%	0.000000	1.000000	0.000000	1.000000
max	1.000000	1.000000	1.000000	2.000000

[35]:
```
RFM[['R_Rank_score', 'F_Rank_score', 'M_Rank_score','RFM_score']].
 ↪describe()['RFM_score']
```

[35]:
```
count    3950.000000
mean        0.304557
std         0.468458
min         0.000000
25%         0.000000
50%         0.000000
75%         1.000000
max         2.000000
Name: RFM_score, dtype: float64
```

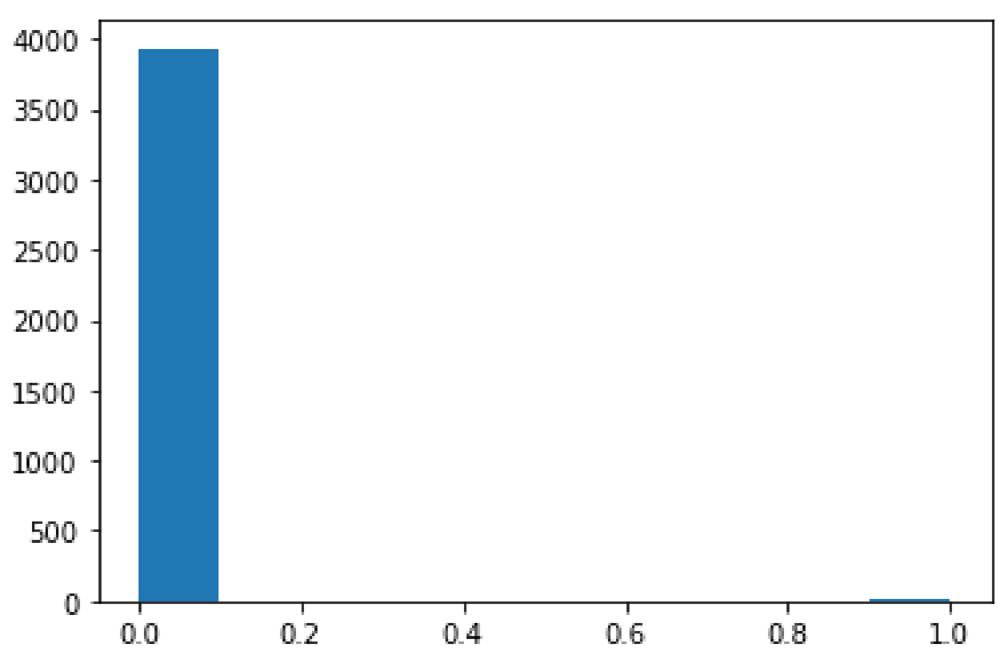
[36]:
```
plt.hist(RFM['M_Rank_score'])
```

[36]:
```
(array([3.949e+03, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00, 0.000e+00,
        0.000e+00, 0.000e+00, 0.000e+00, 1.000e+00]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```



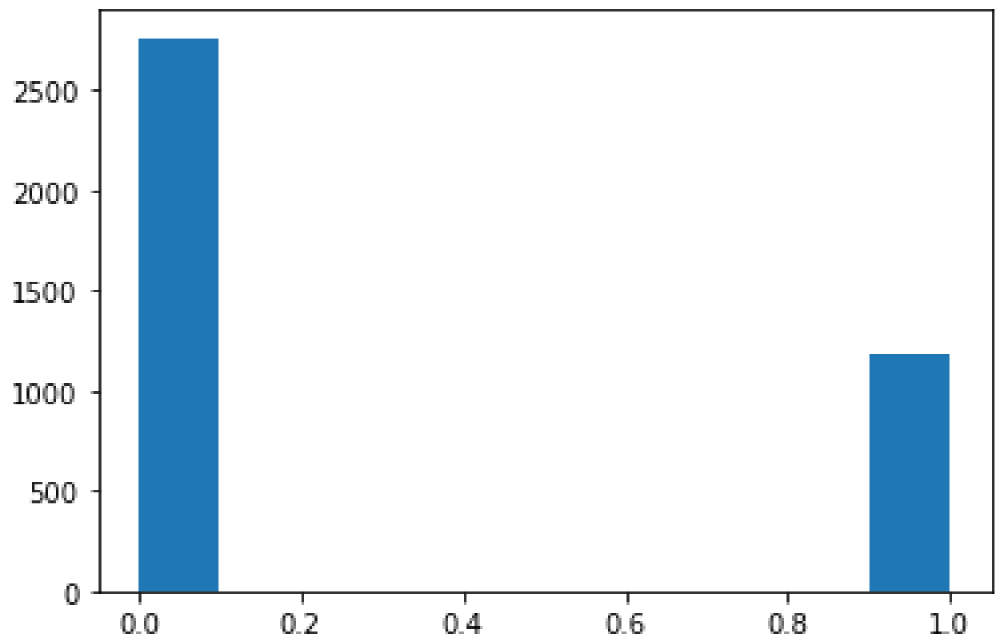
[37]:
```
plt.hist(RFM['R_Rank_score'])
```

[37]:
```
(array([3936.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,
          14.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```



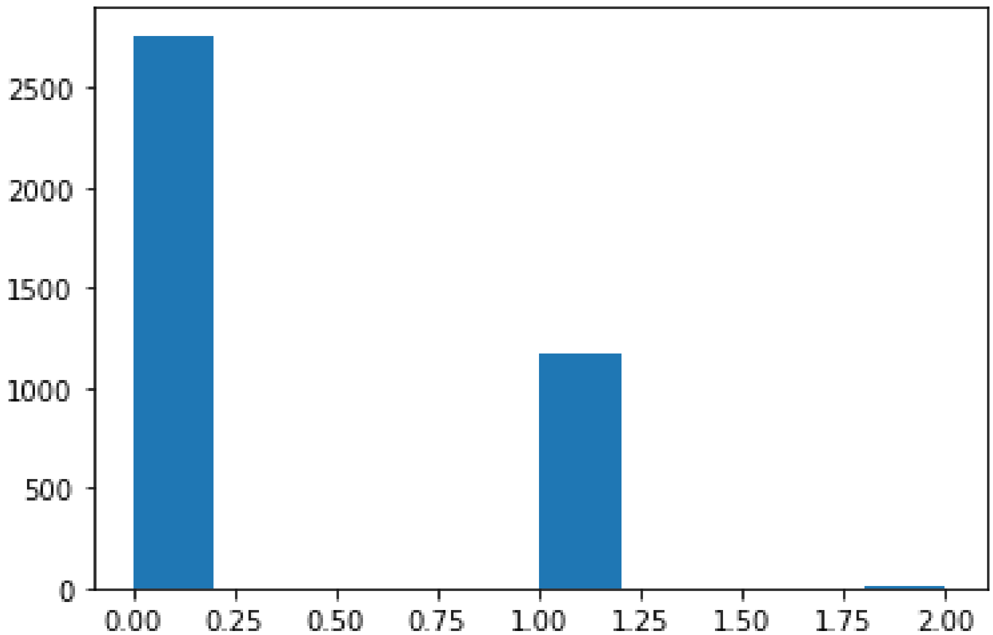
[38]:
```
plt.hist(RFM['F_Rank_score'])
```

[38]:
```
(array([2762.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,    0.,
        1188.]),
 array([0. , 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1. ]),
 <BarContainer object of 10 artists>)
```



[39]:
```
plt.hist(RFM['RFM_score'])
```

[39]:
```
(array([2762.,    0.,    0.,    0.,    0., 1173.,    0.,    0.,    0.,
          15.]),
 array([0. , 0.2, 0.4, 0.6, 0.8, 1. , 1.2, 1.4, 1.6, 1.8, 2. ]),
 <BarContainer object of 10 artists>)
```



0.12 Optimum Number of Clusters

Find the optimum number of clusters using the Elbow method. Apply K-Means clustering algorithm. Cluster the RFM normalized variables into clusters.

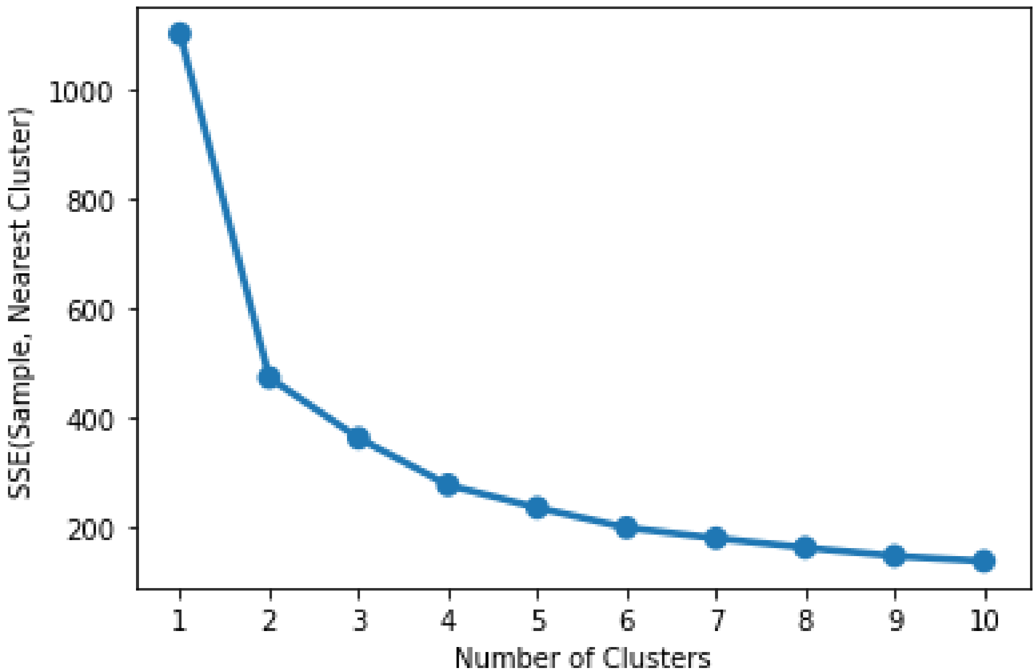
[40]:
```
#Input to KMeans Clustering
RFM[['R_Rank_nrm', 'F_Rank_nrm', 'M_Rank_nrm']].describe()
```

[40]:

	R_Rank_nrm	F_Rank_nrm	M_Rank_nrm
count	3950.000000	3950.000000	3950.000000
mean	0.498918	0.588437	0.500000
std	0.290346	0.333637	0.288785
min	0.000000	0.000000	0.000000
25%	0.241630	0.329906	0.250000
50%	0.502992	0.536582	0.500000
75%	0.750223	1.000000	0.750000
max	1.000000	1.000000	1.000000

[41]:
```
#Inertia: It is the sum of squared distances of samples to their closest␣
↪cluster center.
SSE = []
for k in range(0, 10): #10 possible clusters
    #RFM['R_Rank_nrm']
    RFM_normalized = RFM[['R_Rank_nrm', 'F_Rank_nrm', 'M_Rank_nrm']]

    kmeans = KMeans(n_clusters=k+1, random_state=1231).fit(RFM_normalized)
```

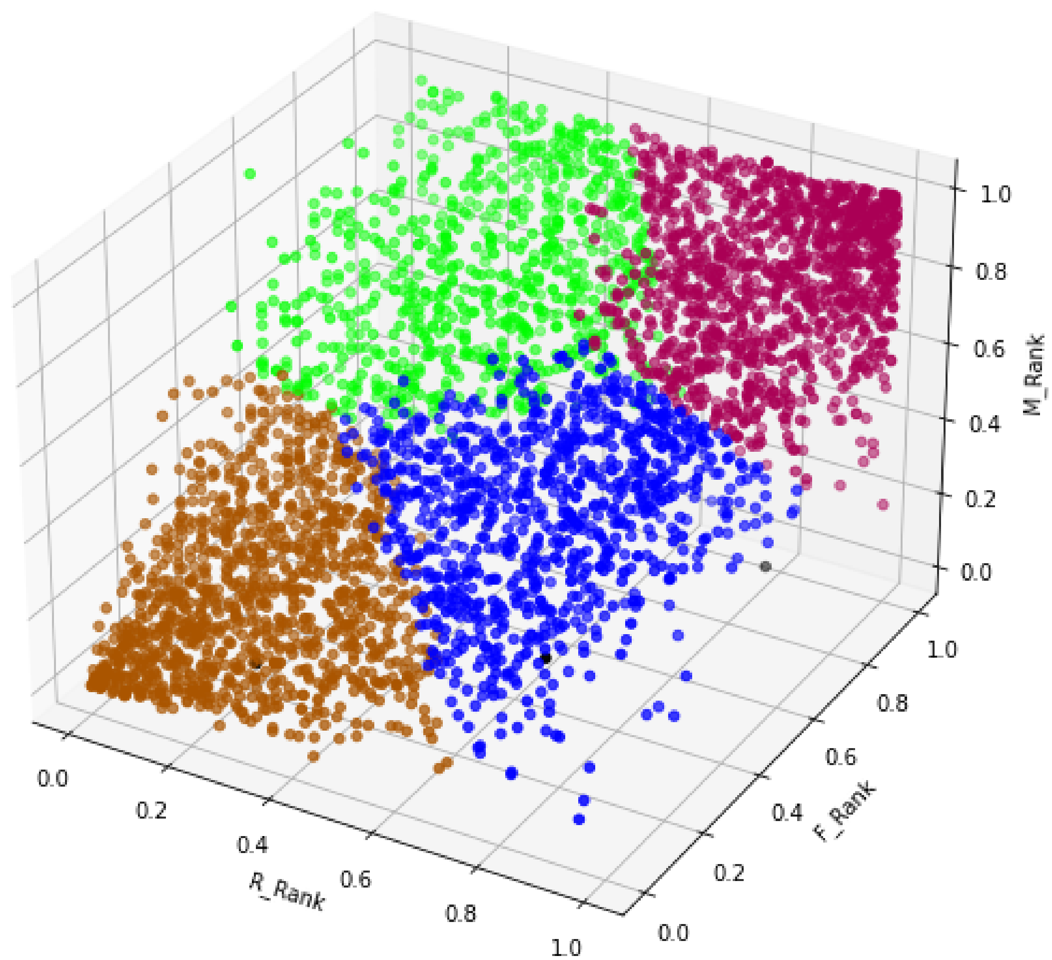
```
    SSE.append(kmeans.inertia_)

sns.pointplot(x=list(range(1,11)), y=SSE)
plt.xlabel('Number of Clusters')
plt.ylabel('SSE(Sample, Nearest Cluster)')
plt.savefig(os.getcwd() + '/Plots/Elbow_Method_K_Means.png')
plt.show()
```



Choosing 4 Clusters as the optimum number of clusters. There is no significant decrease in the error from 5-th Clusters onwards on the x-axis.

[61]:
```
model = KMeans(n_clusters=4, random_state = 1231).fit(RFM_normalized)
centroids = model.cluster_centers_

customer_tags = {0: 'New Customer', 1:'Best Customer', \
                 2:'Churned Customer', 3:'Risk of Leaving'}

predicted_labels = model.predict(RFM_normalized)

fig = plt.figure(figsize=(9,9))
ax = fig.add_subplot(111, projection='3d')

ax.scatter(RFM_normalized['R_Rank_nrm'], RFM_normalized['F_Rank_nrm'],␣
↪RFM_normalized['M_Rank_nrm'], \
           cmap='brg', c=predicted_labels)
```

```
#print("Unique Predictions Classes:- {}" .format(set(model.
↪predict(RFM_normalized))))

ax.set_xlabel("R_Rank")
ax.set_ylabel("F_Rank")
ax.set_zlabel("M_Rank")

#ax.legend([customer_tags[class_label] for class_label in predicted_labels])
ax.scatter(centroids[:, 0], centroids[:, 1], c='black')
plt.savefig(os.getcwd() + '/Plots/KMeans Clusters.png')
```



0.13 Obtain Cluster Labels

[56]:
```
RFM['Customer_Segments'] = model.labels_

#Write the final data to a file
RFM.to_csv(os.getcwd() + '/Final_Data.csv')

RFM[['CustomerID', 'Customer_Segments', 'R_Rank_nrm', 'F_Rank_nrm',␣
↪'M_Rank_nrm']].head()
```

[56]:

	CustomerID	Customer_Segments	R_Rank_nrm	F_Rank_nrm	M_Rank_nrm
0	13113.0	2	0.0	0.010133	0.017726
1	15804.0	2	0.0	0.044107	0.078501
2	13777.0	2	0.0	0.009388	0.007090
3	17581.0	2	0.0	0.016093	0.016713
4	12748.0	2	0.0	0.000000	0.005318

[57]:
```
#Statistics of R_Rank, F_Rank, M_Rank
RFM_Stats = RFM.groupby('Customer_Segments').agg({
    'R_Rank':['min', 'mean', 'max', 'count'],
    'F_Rank':['min', 'mean', 'max', 'count'],
    'M_Rank':['min', 'mean', 'max', 'count']
})

RFM_Stats
```

[57]:

	R_Rank				F_Rank		\
	min	mean	max	count	min	mean	
Customer_Segments							
0	965.0	2465.480937	3865.5	918	43.5	1566.259259	
1	1945.0	3195.162186	3943.5	1153	892.0	3096.190373	
2	16.0	811.124666	2631.0	1123	1.0	684.082369	
3	16.0	1249.998016	2430.0	756	609.0	2681.570106	

			M_Rank			
	max	count	min	mean	max	count
Customer_Segments						
0	3356.5	918	30.0	1516.827342	3836.0	918
1	3356.5	1153	728.0	3057.633131	3950.0	1153
2	2392.0	1123	1.0	745.539626	2860.0	1123
3	3356.5	756	310.0	2709.107804	3947.0	756

0.14 Observations from Clusters

Mean Comparison

1. Segment 0:- New Customers. Send mail, push notifications saying:- 'You viewd these items, you might be interested in one of these similar items[Item 1, Item 2, ...]'. Make these customes

frequent visitors. Count(918)

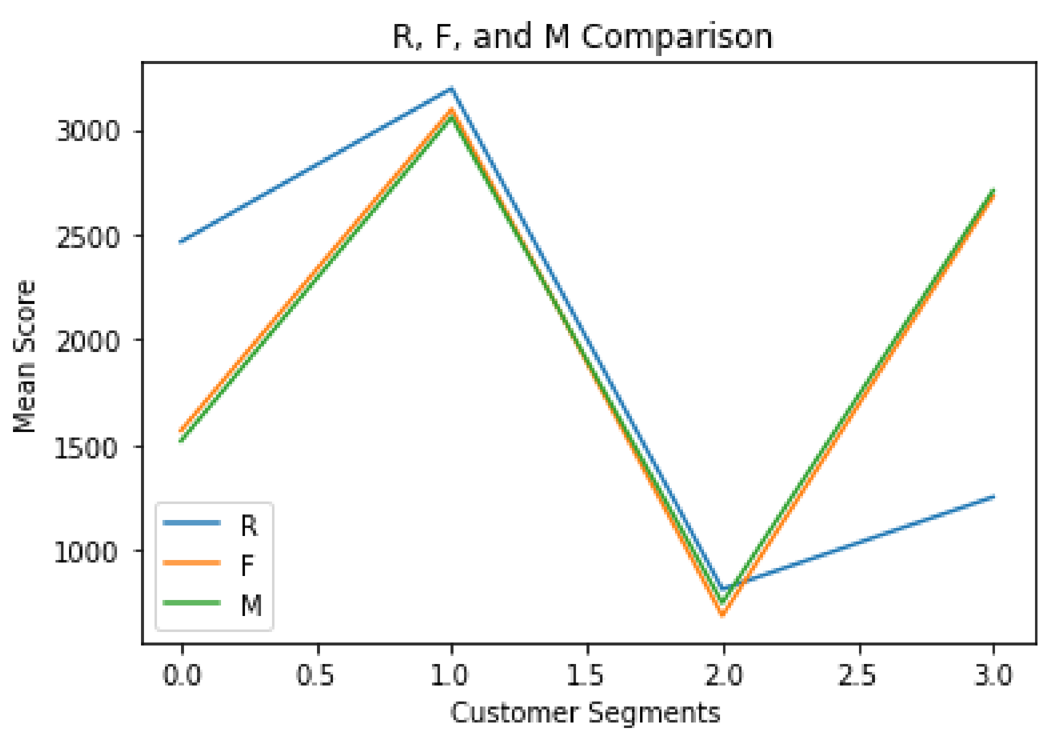
2. Segment 3:- Second Most Valuable set(Risk of Leaving). Frequently visiting customers, spending significant amount. But have not recently visited. The marketing team can send reminders about various items present in the stores. Provide coupons and Promo Codes to these Customers. Count(756).

–>Previous R(811.9), F(687.4), M(747.9) 3. Segment 2:- R(811.12), F(684.08), M(745.53) –> Less Recent, Less Frequent and Less Purchase Value —> Churned(/Lost) Customers. Count(1123)

4. Segment 1:- Most Valuable set. Recently Visited,Frequently Visiting and High Value Purchase. These bring large profits to the stores. Maximum Count(1153).

0.15 Plot the means of R_Rank, F_Rank and M_Rank for each cluster

[58]:
```
plt.plot(RFM_Stats.index.tolist(), RFM_Stats[('R_Rank',   'mean')])

plt.plot(RFM_Stats.index.tolist(), RFM_Stats[('F_Rank',   'mean')])

plt.plot(RFM_Stats.index.tolist(), RFM_Stats[('M_Rank',   'mean')])

plt.xlabel('Customer Segments')
plt.ylabel('Mean Score')
plt.title('R, F, and M Comparison ')
plt.legend(['R', 'F', 'M'])
plt.savefig(os.getcwd() + '/Plots/RFM_Comparison')
plt.show()
```



[59]:
```
#Distribution of Customer_Segments(Target)
cust_seg_obj = uf.GetStats(RFM[['CustomerID', 'Customer_Segments']])

cust_seg_obj.categorical_distribution('Customer_Segments')
```

[59]:

	Category	Counts	Percentage
1	1	1153	29.19
2	2	1123	28.43
0	0	918	23.24
3	3	756	19.14

0.16 Create Customer Tags

0 –> New Customer

1 –> Best Customer

2 –> Churned Customer

3 –> Risk of Leaving

[62]:
```
RFM['Customer Tags'] = RFM['Customer_Segments'].map(customer_tags)

cust_seg_obj = uf.GetStats(RFM[['CustomerID', 'Customer Tags']])

cust_seg_obj.categorical_distribution('Customer Tags')
```

[62]:

	Category	Counts	Percentage
0	Best Customer	1153	29.19
2	Churned Customer	1123	28.43
3	New Customer	918	23.24
1	Risk of Leaving	756	19.14

0.17 Create Customer Segments

Based on the Quartile values of RFM Score

`rfm score > 2.25 : Top Customer`

`2.25 >= rfm score > 1.62  : High Value Customer`

`1.62 >= rfm score > 0.95 : Medium value customer`

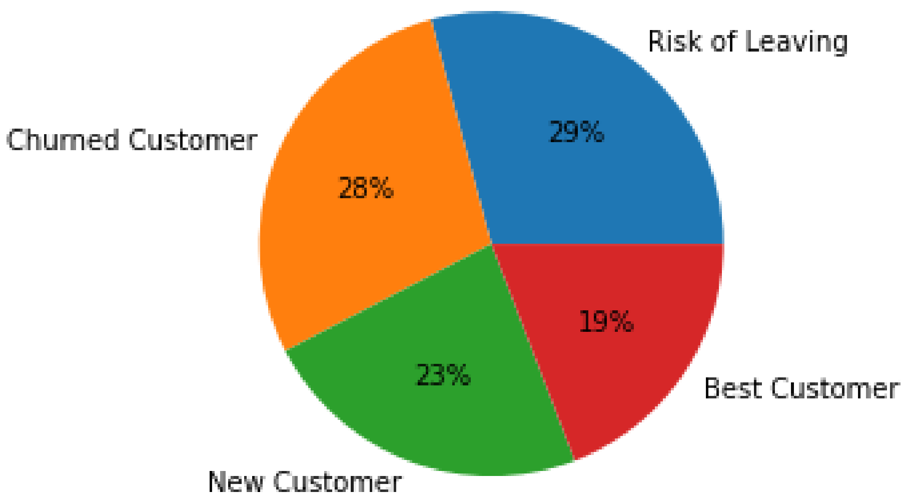
`0.95 >= rfm score > 0.45 : Low-value customer`

`rfm score =< 0.45 :Lost Customer`

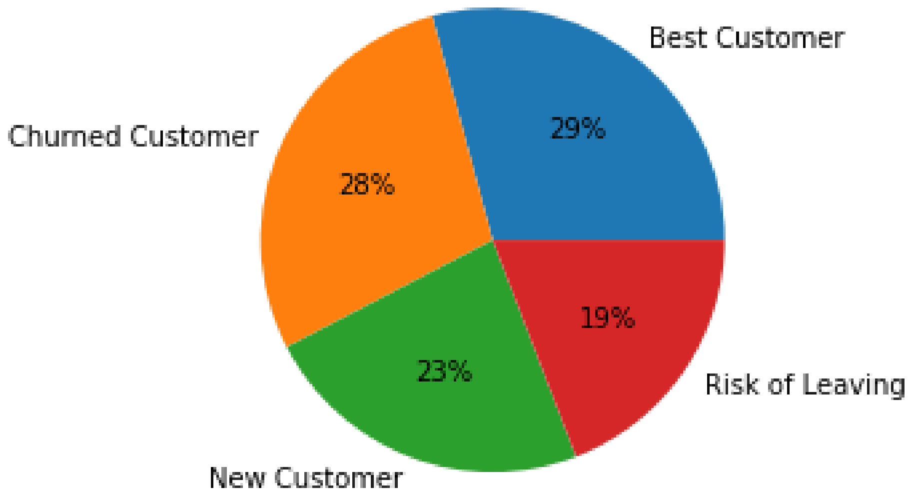
”’ RFM Score count 3950.000000 mean 1.587355 std 0.790757 min 0.002309 255075max 2.993015 ”’

0.18 Distribution of Customer Segments

[49]:
```
#Based on the Quartiles of RFM_score
plt.pie(RFM['Customer Tags'].value_counts(),
        labels=RFM['Customer Tags'].value_counts().index,
        autopct='%.0f%%')

plt.savefig(os.getcwd() + '/Plots/New_Customer_Distribution.png')
plt.show()
```



[64]:
```
##Based on randomly selected thresholds of RFM_score

plt.pie(RFM['Customer Tags'].value_counts(),
        labels=RFM['Customer Tags'].value_counts().index,
        autopct='%.0f%%')

plt.savefig(os.getcwd() + '/Plots/Customer_Distribution.png')
plt.show()
```




```
[51]: #Final Data Dimensions
      #RFM.shape #(3950, 11)
```

```
[52]: RFM.head()
```

```
[52]:    CustomerID  Days_SinceLastTxn  InvoiceNo Counts  Total Amount  R_Rank  \
      0     13113.0               3794                40      10510.00    16.0
      1     15804.0               3794                19       3848.55    16.0
      2     13777.0               3794                41      25748.35    16.0
      3     17581.0               3794                31      10736.11    16.0
      4     12748.0               3794               224      29072.10    16.0

         F_Rank  M_Rank  R_Rank_nrm  R_Rank_score  F_Rank_nrm  F_Rank_score  \
      0    35.0    71.0         0.0             0    0.010133             0
      1   149.0   311.0         0.0             0    0.044107             0
      2    32.5    29.0         0.0             0    0.009388             0
      3    55.0    67.0         0.0             0    0.016093             0
      4     1.0    22.0         0.0             0    0.000000             0

         M_Rank_nrm  M_Rank_score  RFM_score  Customer_Segments     Customer Tags
      0    0.017726             0          0                  2  Churned Customer
      1    0.078501             0          0                  2  Churned Customer
      2    0.007090             0          0                  2  Churned Customer
      3    0.016713             0          0                  2  Churned Customer
      4    0.005318             0          0                  2  Churned Customer
```

0.19 Check Cluster Relevance

1. Less Intra-Cluster Distance
2. More Inter-Cluster DIstance

[53]:
```
#help(pd.cut)
```

[ ]:
```

```