Machine Learning Project using Online Retail dataset

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Marketing Analytics -Unsupervised Learning clustering algorithm.

Objective : We are performing customer segmentation based on key attributes Recency, Frequency & Monetary (RFM) using K-means.

What is customer segmentation and why bother ?

What is customer segmentation ? Customer segmentation is the division of customers into various groups based on specific attributes. Segmentation types may vary based on these four main characteristics/variable-types:

1. Demographics (eg. age, income, gender etc.)
2. Geographic regions (eg. country, region, city, town etc.)
3. Psychographic (eg. interests, personality traits, attitudes, views)
4. Behaviour (eg. actual spending pattern/actual purchases)

Benefits of Segmentation

Marketers segment customers because it allows them to better understand the various types of customers and hence better serve their needs to ultimately yield increase in revenue. Better served customers are happier customers and happier customers spend more leading to a more favourle company bottom-line.

So, in short, if we adopt a more tailored approach to they way we market products/services to our customer the customers feel more valued and the company benefits financially. This bets the one-size fits all approach (when no differentiation is made among customers).

This segmentation of customers also helps companies to identify customers that are their most valuable customers and hence direct more efforts at those customers and less on the customers that have been the least profitable. Segmentation based on behaviour (type #4 above) offers this approach where, based on attributes such as : (i) Recency (R) - the last time a purchase was made (ii) Frequency (F) - the cummulative number of transactions conducted. (iii) Monetary Value (M) - the total cummulative amount spent.

This is known as **RFM segmentation and scoring.**

Our work will be focused on RFM using K-Means Machine Learning Clustering technique.

Methodology for Model Building

Steps :

1. Problem Definition
2. Data Collection
    - Dataset : Online retail dataset (source:http://archive.ics.uci.edu/ml/datasets/online+retail (http://archive.ics.uci.edu/ml/datasets/online+retail))
3. Data Preparation

    (i) Data Exloration

    (ii) Data Cleaning

    (iii) Data Analysis

    (iv) Feature Selection

```
- Identify Recency, Frequency & Monetary Value features (RFM)
```

    (v) Data Preprocessing

```
- Scale features
```

5. Perform K-Means clustering based on RFM features
6. Choose optimal K clusters

```
- uses Elbow method (visualization of average distance across clus
ters for k number of clusters,
    choosing the cluster kn where kn+1 reflects a marginal decrease
 in the avg. distance )
```

7. Identify best customers, valuable customers at highest risk of churn

Main Python Libraries used:

1. pandas - mainly for EDA
2. numpy - mainly for EDA
3. sklearn - machine learning
4. Matplotlib - visualizations

About the dataset

According to the website for the UCI repository (ref. https://archive.ics.uci.edu/ml/datasets/Online+Retail) (https://archive.ics.uci.edu/ml/datasets/Online+Retail)), this transactional dataset reflects transactions (approx. 1 year's worth) effected between 01/12/2010 and 09/12/2011 for a registered non-store online retail based in the UK.

Attributes :

```
1. InvoiceNo   : Invoice number -uniquely identifies the transaction.
                 - Nominal, a 6-digit integral number; Code starting with
letter 'c' indicates a cancellation.

2. StockCode   : Product (item) code - uniquely identifies each product.
                 - Nominal, a 5-digit integral number
3. Description: Name of the product. Nominal.

4. Quantity    : # of units of the product per transaction. Numeric.

5. InvoiceDate : Date and time of the invoice (transaction date & time).
 Numeric.

6. UnitPrice   : Selling price per unit in sterling.- Numeric

7. CustomerID  : Unique indentifier for each customer. Nominal, a 5-digit
integral number.
8. Country     : Country name. Nominal, Customer's country of residence.
```

Data Collection

Let's load the data

In [1]:
```
# Ref.: https://www.blastam.com/blog/rfm-analysis-boosts-sales
#      https://towardsdatascience.com/find-your-best-customers-with-customer-segme

# Main Ref. : https://towardsdatascience.com/apply-rfm-principles-to-cluster-custo
# Ref. : "Marketing Data Science: Modeling Techniques in Predictive Analytics wit

import pandas as pd
import numpy as np
import sklearn
import matplotlib.pyplot as plt
import os
```

In [2]:
```
os.getcwd()
```

Out[2]:
```
'C:\\Users\\Kisha\\Documents\\Python Scripts\\Class Imbalance Prob'
```

In [3]:
```
path =  "C:/Users/Kisha/Documents/Datasets/Online Retail.xlsx"
df = pd.read_excel(path)
```

Data Preparation

Data Exploration

In [4]:
```
df.head(5)
```

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

What is our dataset size? How big is it (# rows)?

In [5]:
```
df.shape
```

Out[5]:
```
(541909, 8)
```

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
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

Checking to see how many transaction have a neg unit price

In [7]:
```
len(df[df["UnitPrice"]<0])
```

Out[7]:
```
2
```

Let's delete those or rather subset for only those that have a non-negative UnitPrice

In [8]:
```
df = df[df["UnitPrice"]>=0]
```

In [9]:
```
### Let's look to see if we hae any missing values per feature
df.isnull().sum()
```

Out[9]:
```
InvoiceNo          0
StockCode          0
Description     1454
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     135078
Country            0
dtype: int64
```

We note that we have missing values for the description and for customer ID.

In [10]:
```
#### Let's examine rows where CustomerID is missing more closely. Looking at the j

df.loc[np.where(df["CustomerID"].isnull())].head(5)
```

Out[10]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
622	536414	22139	NaN	56	2010-12-01 11:52:00	0.00	NaN	United Kingdom
1443	536544	21773	DECORATIVE ROSE BATHROOM BOTTLE	1	2010-12-01 14:32:00	2.51	NaN	United Kingdom
1444	536544	21774	DECORATIVE CATS BATHROOM BOTTLE	2	2010-12-01 14:32:00	2.51	NaN	United Kingdom
1445	536544	21786	POLKADOT RAIN HAT	4	2010-12-01 14:32:00	0.85	NaN	United Kingdom
1446	536544	21787	RAIN PONCHO RETROSPOT	2	2010-12-01 14:32:00	1.66	NaN	United Kingdom

We cannot use these rows that are missing customerID in our analysis. So for now we will filter out these rows.

In [26]:
```
newdf = df[pd.notnull(df["CustomerID"])]
```

Note missing values checked again after filtering out those rows with missing values for CustomerID

In [27]:
```
newdf.isnull().sum()
```

Out[27]:
```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

In [28]:
```
newdf.shape
```

Out[28]:
```
(406829, 8)
```

We lost the following % of our data due to missing info. :

In [29]:
```
(df.shape[0]-newdf.shape[0])*100/df.shape[0]
```

Out[29]:
```
24.92641726347879
```

Let's get more familiar with our data by getting a feel for :

(i) the number of different products
(ii) Range of quantities purchased
(iii) Range of prices
(iv) Number of Countries
(iv) Groupings of customers by country and or by products purchased

Number of different products

In [30]:
```
len(newdf["StockCode"].unique())
```

Out[30]:
```
3684
```

In [31]:
```
newdf["StockCode"].head(5)
```

Out[31]:
```
0    85123A
1     71053
2    84406B
3    84029G
4    84029E
Name: StockCode, dtype: object
```

Top 5 products sold (by count)

In [32]:
```
ProdSales = newdf.groupby(["StockCode","Description"])["Quantity"].aggregate('sum
ProdSales.columns = ["StockCode","Description","Sum of Qty sold"]
ProdSales.head(5)
```

Out[32]:

	StockCode	Description	Sum of Qty sold
2712	84077	WORLD WAR 2 GLIDERS ASSTD DESIGNS	53215
3586	85099B	JUMBO BAG RED RETROSPOT	45066
2818	84879	ASSORTED COLOUR BIRD ORNAMENT	35314
3593	85123A	WHITE HANGING HEART T-LIGHT HOLDER	34147
361	21212	PACK OF 72 RETROSPOT CAKE CASES	33409

In [33]:
```
CustCountry = newdf.groupby(["Country"])["InvoiceNo"].count().reset_index().sort_
CustCountry.columns = ["Country", "Count of transactions per country"]
CustCountry.head(5)
```

Out[33]:

	Country	Count of transactions per country
35	United Kingdom	361878
14	Germany	9495
13	France	8491
10	EIRE	7485
30	Spain	2533

Top 5 sales (revenue) by country

In [34]:
```
newdf["SalesAmt_per_Invoice"] = newdf["UnitPrice"] * newdf["Quantity"]
CountrySales = newdf.groupby("Country")["SalesAmt_per_Invoice"].aggregate("sum").
CountrySales.columns =["Country", "Total Sales $"]
CountrySales.head(5)
```

```
C:\Users\Kisha\Anaconda3\lib\site-packages\ipykernel_launcher.py:1: SettingWith
CopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: http://pandas.pydata.org/pandas-docs/stab
le/indexing.html#indexing-view-versus-copy (http://pandas.pydata.org/pandas-doc
s/stable/indexing.html#indexing-view-versus-copy)
  """Entry point for launching an IPython kernel.
```

Out[34]:

	Country	Total Sales $
35	United Kingdom	6.767873e+06
23	Netherlands	2.846615e+05
10	EIRE	2.502852e+05
14	Germany	2.216982e+05
13	France	1.967128e+05

Group by product type & count of customers

In [35]:
```
pd.DataFrame(newdf.groupby(["StockCode","Description"])["CustomerID"].count()).so
#CountrySales.columns =["Country", "Total Sales $"]
#CountrySales.head(5)
```

Out[35]:

		CustomerID
StockCode	**Description**	
85123A	**WHITE HANGING HEART T-LIGHT HOLDER**	2070
22423	**REGENCY CAKESTAND 3 TIER**	1905
85099B	**JUMBO BAG RED RETROSPOT**	1662
84879	**ASSORTED COLOUR BIRD ORNAMENT**	1418
47566	**PARTY BUNTING**	1416
20725	**LUNCH BAG RED RETROSPOT**	1358
22720	**SET OF 3 CAKE TINS PANTRY DESIGN**	1232
POST	**POSTAGE**	1196
20727	**LUNCH BAG BLACK SKULL.**	1126
21212	**PACK OF 72 RETROSPOT CAKE CASES**	1080

Top 5 Selling products

In [36]:
```
pd.DataFrame(newdf.groupby(["StockCode","Description"])["Quantity"].sum()).sort_v
```

Out[36]:

StockCode	Description	Quantity
84077	WORLD WAR 2 GLIDERS ASSTD DESIGNS	53215
85099B	JUMBO BAG RED RETROSPOT	45066
84879	ASSORTED COLOUR BIRD ORNAMENT	35314
85123A	WHITE HANGING HEART T-LIGHT HOLDER	34147
21212	PACK OF 72 RETROSPOT CAKE CASES	33409
22197	POPCORN HOLDER	30504
23084	RABBIT NIGHT LIGHT	27094
22492	MINI PAINT SET VINTAGE	25880
22616	PACK OF 12 LONDON TISSUES	25321
21977	PACK OF 60 PINK PAISLEY CAKE CASES	24163

Products that have been returned in a different period from which they were purchsed would have an overal negative qty.

This the five (5) worst selling products (reflecting net returns for that period)

In [37]:
```
pd.DataFrame(newdf.groupby(["StockCode","Description"])["Quantity"].sum()).sort_v
```

Out[37]:

StockCode	Description	Quantity
84347	ROTATING SILVER ANGELS T-LIGHT HLDR	-1460
D	Discount	-1194
21645	ASSORTED TUTTI FRUTTI ROUND BOX	-24
CRUK	CRUK Commission	-16
21144	PINK POODLE HANGING DECORATION	-12

In [38]:
```
newdf["Quantity"].describe()
```

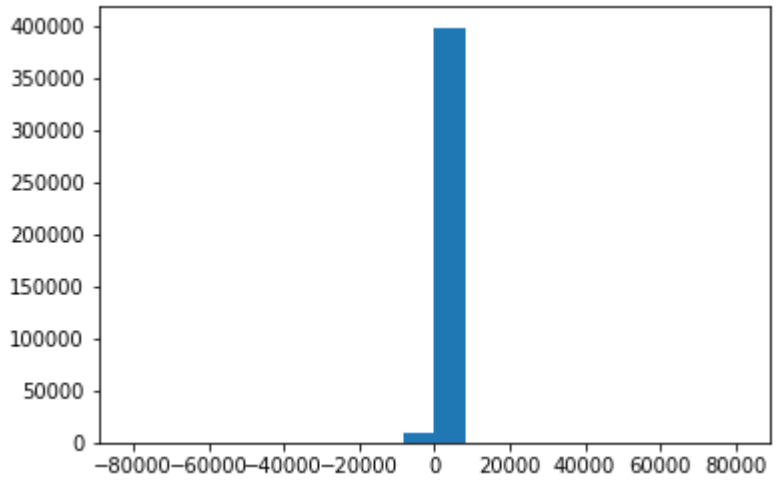
Out[38]:
```
count    406829.000000
mean         12.061303
std         248.693370
min      -80995.000000
25%           2.000000
50%           5.000000
75%          12.000000
max       80995.000000
Name: Quantity, dtype: float64
```

Note from above, most transaction have a purchase quantity below 12 (since 12 is at the 75th

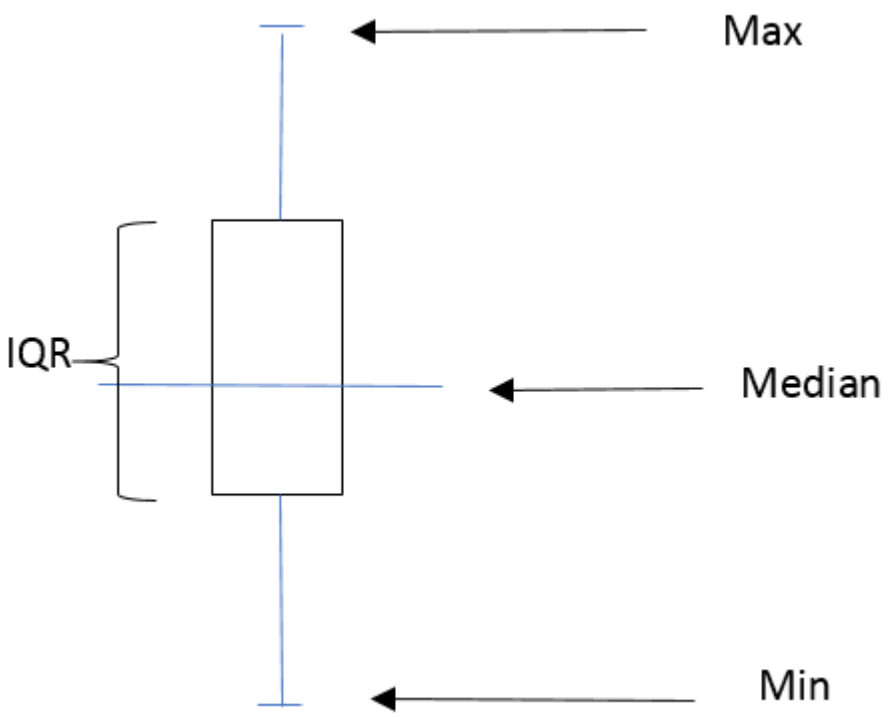
percentile)

Visual of the range of quantity values, reflecting most transactions with the range 0 to below 10,000

In [39]:
```
plt.hist(newdf["Quantity"],bins=20)
plt.show()
```

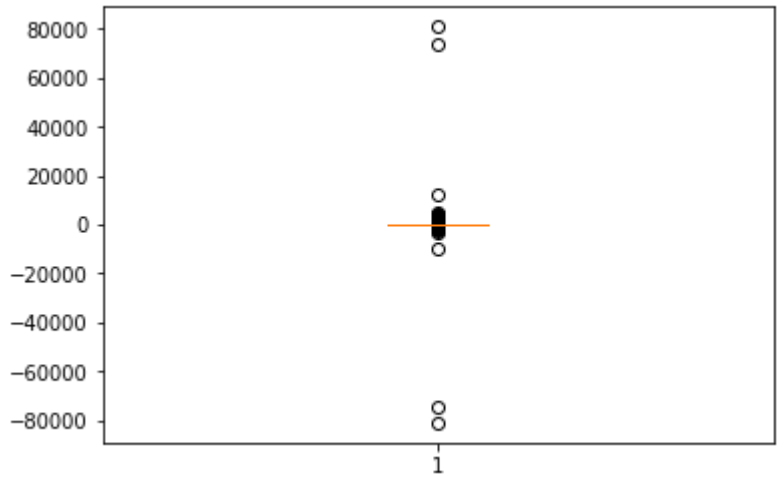


Recall boxplot diagrams



This boxplot visualization (below) confirms that the transactions (qty.) typically range below 20k positve and negative. Note the outliers are in the 70k to 80k range with the median close to zero.

In [40]:
```
plt.boxplot(newdf["Quantity"])
plt.show()
```



Range of prices

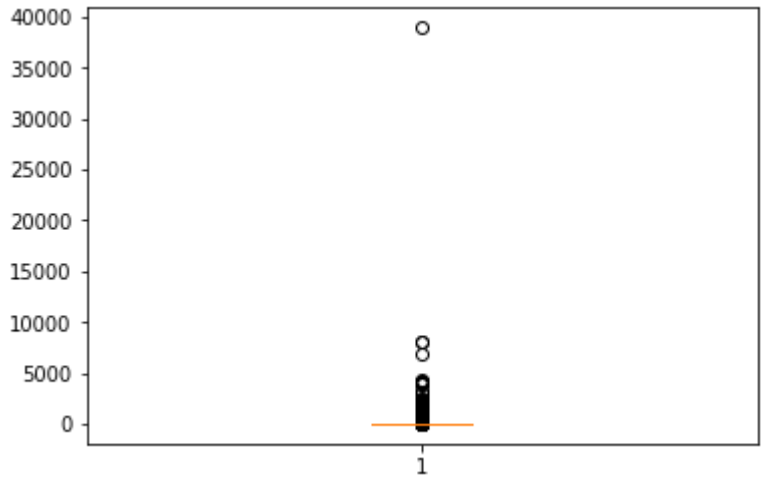
In [41]:
```
newdf["UnitPrice"].describe()
```

Out[41]:
```
count    406829.000000
mean          3.460471
std          69.315162
min           0.000000
25%           1.250000
50%           1.950000
75%           3.750000
max       38970.000000
Name: UnitPrice, dtype: float64
```

Note from statsistical description above for Unit Price 75% of all products are priced below $3.75.

The mean unit price is $3.46 and 50% of all products are priced below $1.95.

In [42]:
```
plt.boxplot(newdf["UnitPrice"])
plt.show()
```



Number of different countries

In [43]:
```
len(newdf["Country"].unique())
```

Out[43]: 37

Groupings of customers by country (Percentage)

In [44]:
```
CustCountry = newdf.groupby(["Country"])["CustomerID"].aggregate('count').reset_i
CustCountry.columns = ["Country","CustomerID-Count"]
CustCountry["CustomerID-Count in Perc %"] = CustCountry["CustomerID-Count"]*100/s
CustCountry.head(10)
```

Out[44]:

	Country	CustomerID-Count	CustomerID-Count in Perc %
35	United Kingdom	361878	88.950886
14	Germany	9495	2.333904
13	France	8491	2.087118
10	EIRE	7485	1.839839
30	Spain	2533	0.622620
23	Netherlands	2371	0.582800
3	Belgium	2069	0.508567
32	Switzerland	1877	0.461373
26	Portugal	1480	0.363789
0	Australia	1259	0.309467

We will calculate each required feature starting with:

- Recency Let's calculate using the report date as 1 day after the last invoice date

In [45]:
```
# Last invoice date
import datetime as dt

newdf["InvoiceDate"].max()
```

Out[45]:
```
Timestamp('2011-12-09 12:50:00')
```

In [46]:
```
# So, let's set our report date, from which calculations will be done to 1 day ah
reportdate = dt.datetime(2011,12,10)
reportdate
```

Out[46]:
```
datetime.datetime(2011, 12, 10, 0, 0)
```

In [47]:
```
newdf.head(2)
```

Out[47]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country	Sale
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	

In [48]:
```
#newdf['InvoiceDate'] = pd.to_datetime(newdf['InvoiceDate'])
RFM_df =newdf.groupby("CustomerID").aggregate({"InvoiceDate" : lambda x:(reportda
RFM_df.columns = ["CustID","R","F","M"]
RFM_df.head(5)
```

Out[48]:

	CustID	R	F	M
0	12346.0	325	2	0.00
1	12347.0	2	182	4310.00
2	12348.0	75	31	1797.24
3	12349.0	18	73	1757.55
4	12350.0	310	17	334.40

Let's now calculate the RFM metric (scores) for each customer.

We will do this by first splitting into quantiles then ranking the quantiles for each sub-metric (R, F & M).

Recency ranking Let's rank by quartiles where the upper quartiles for the recency defned as being worse than the lower quartiles. This means that for Q1 that represents the group the lowest 25% recency score this group is the better than the Q2 which has higher recency scores. Recall, we place a higher value on customers who have purchased from us more recently (as depicted by their recency score) than customers who have purchased from us less recently.

Frequency & Monetary value ranking These scores will be ranked opposite to recency since the greater the score the better or more highly we value that customer.

In [49]:
```
newdf.columns
```

Out[49]:
```
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity', 'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country', 'SalesAmt_per_Invoice'],
      dtype='object')
```

Let's find out the levels of Recency , Freq. & Monetray value for each quantile Q1,Q2 & Q3

In [50]:
```
qrt = RFM_df.quantile(q=[0.25,0.5,0.75])
qrt.columns =["CustID","R","F","M"]

Rqrt = qrt["R"]
Fqrt = qrt["F"]
MVqrt = qrt["M"]

print(qrt)
print("\n")

print("RFM scores\n",RFM_df.head(2))
```

```
        CustID      R      F          M
0.25  13812.75   16.0   17.0   293.3625
0.50  15300.50   50.0   42.0   648.0750
0.75  16778.25  143.0  102.0  1611.7250


RFM scores
     CustID    R    F       M
0  12346.0  325    2     0.0
1  12347.0    2  182  4310.0
```

Let's further rank 1 to 4 for the quantiles as described earlier.

In [51]:
```
copyRFM = RFM_df
print(copyRFM.head(5))
```

```
    CustID    R    F        M
0  12346.0  325    2     0.00
1  12347.0    2  182  4310.00
2  12348.0   75   31  1797.24
3  12349.0   18   73  1757.55
4  12350.0  310   17   334.40
```

In [53]:
```
rk = RFM_df
print(rk.head(5))
print(RFM_df.head(5))
```

```
    CustID    R    F        M
0  12346.0  325    2     0.00
1  12347.0    2  182  4310.00
2  12348.0   75   31  1797.24
3  12349.0   18   73  1757.55
4  12350.0  310   17   334.40
    CustID    R    F        M
0  12346.0  325    2     0.00
1  12347.0    2  182  4310.00
2  12348.0   75   31  1797.24
3  12349.0   18   73  1757.55
4  12350.0  310   17   334.40
```

Recall, as explained earlier, the lowest rank is the best for each metric

In [54]:
```
def myfun(x,mtype):

    if mtype == "R":
        if (x <= qrt.loc[0.25][mtype]):
            rank = 1
            return(rank)

        elif ((x > qrt.loc[0.25][mtype]) & (x <= qrt.loc[0.5][mtype])):
            rank = 2
            return(rank)

        elif ((x > qrt.loc[0.5][mtype]) & (x <= qrt.loc[0.75][mtype])):
            rank = 3
            return(rank)

        elif (x > qrt.loc[0.75][mtype]) :
            rank = 4
            return(rank)
    else:
        if (x <= qrt.loc[0.25][mtype]):
            rank = 4
            return(rank)

        elif ((x > qrt.loc[0.25][mtype]) & (x <= qrt.loc[0.5][mtype])):
            rank = 3
            return(rank)

        elif ((x > qrt.loc[0.5][mtype]) & (x <= qrt.loc[0.75][mtype])):
            rank = 2
            return(rank)

        elif (x > qrt.loc[0.75][mtype]) :
            rank = 1
            return(rank)

rk["R"] = rk["R"].apply(myfun,args="R").values
rk["F"] = rk["F"].apply(myfun,args="F").values
rk["M"] = rk["M"].apply(myfun,args="M").values
```

In [55]:
```
#rk.head(5)

rk["RFM"] = rk["R"].map(str)+ rk["F"].map(str) + rk["M"].map(str)
```

In [56]:
```
rk.head(5)
```

Out[56]:

	CustID	R	F	M	RFM
0	12346.0	4	4	4	444
1	12347.0	1	1	1	111
2	12348.0	3	3	1	331
3	12349.0	2	2	1	221
4	12350.0	4	4	3	443

In [57]:
```
from sklearn.cluster import KMeans

kmeans = KMeans(n_clusters=4, init='k-means++', random_state=0)

clusters = kmeans.fit_predict(rk.iloc[:,1:5])
clusters
```

Out[57]:
```
array([3, 2, 1, ..., 2, 2, 0])
```

In [58]:
```
rk["ClusterIndx"] = clusters
rk.head(5)
```

Out[58]:

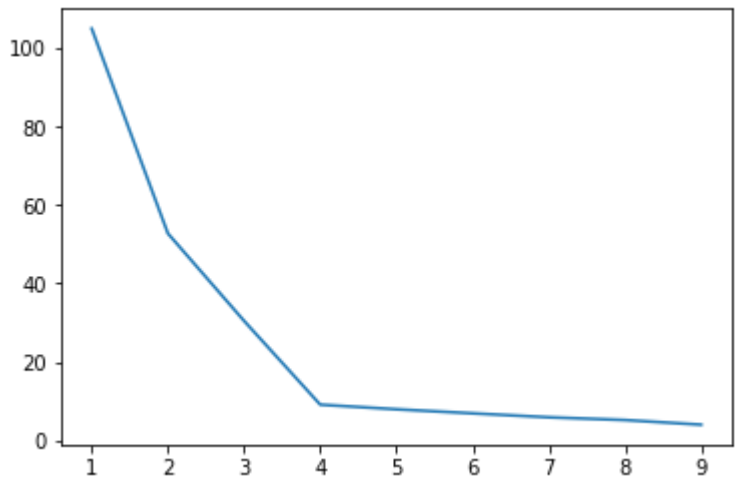
	CustID	R	F	M	RFM	ClusterIndx
0	12346.0	4	4	4	444	3
1	12347.0	1	1	1	111	2
2	12348.0	3	3	1	331	1
3	12349.0	2	2	1	221	0
4	12350.0	4	4	3	443	3

Choosing optimal K clusters :

```
        - uses Elbow method (visualization of average distance across clus
ters for k number of clusters,
          choosing the cluster kn where kn+1 reflects a marginal decrease
 in the avg. distance )
```

In [59]:
```
# Finding Optimal clusters
# Using elbow method
#https://www.geeksforgeeks.org/elbow-method-for-optimal-value-of-k-in-kmeans/
from scipy.spatial.distance import cdist

TotDist = []
X = rk.iloc[:,1:5]
Npts = X.shape[0]

K = range(1,10)

for k in K:
    kM = KMeans(n_clusters=k).fit(X)
    kM.fit(X)
    TotDist.append(sum(np.min(cdist(X, kM.cluster_centers_,
                      'euclidean'),axis=1)) / Npts)

print(TotDist)
plt.plot(K,TotDist)
plt.show()
```

```
[105.01030869294542, 52.74187689279378, 30.424566307170487, 9.053430012633756,
7.872599089379112, 6.838711380099015, 5.829369723762046, 5.129785658136272, 3.9
452358631617064]
```



Optimal K is the pt after which the avg. of TotDist does not decrease by much, soon flattens out "at the elbow".

This optmal K for us is K= 4 (as shown in the graph above)

In [60]:
```
rk.head(10).sort_values("ClusterIndx")
```

Out[60]:

	CustID	R	F	M	RFM	ClusterIndx
3	12349.0	2	2	1	221	0
5	12352.0	2	2	2	222	0
9	12356.0	2	2	1	221	0
2	12348.0	3	3	1	331	1
1	12347.0	1	1	1	111	2
0	12346.0	4	4	4	444	3
4	12350.0	4	4	3	443	3
6	12353.0	4	4	4	444	3
7	12354.0	4	2	2	422	3
8	12355.0	4	4	3	443	3

In [65]:
```
rk["ClusterName"]  =  rk["ClusterIndx"]
rk.loc[rk["ClusterIndx"]==3,"ClusterName"] = 4
rk.loc[rk["ClusterIndx"]==2,"ClusterName"] = 1
rk.loc[rk["ClusterIndx"]==1,"ClusterName"] = 3
rk.loc[rk["ClusterIndx"]==0,"ClusterName"] = 2

rk["ClusterDesc"]  =  rk["ClusterIndx"]
rk.loc[rk["ClusterIndx"]==3,"ClusterDesc"] = "Worst- Low Budget, rare shopper & n
rk.loc[rk["ClusterIndx"]==2,"ClusterDesc"] = "Best - Gotta Keep"
rk.loc[rk["ClusterIndx"]==1,"ClusterDesc"] = "Low Budget, rare shopper"
rk.loc[rk["ClusterIndx"]==0,"ClusterDesc"] = "2nd Best - Loyal Low Budget Spender
```

In [66]:
```
rk.head(10).sort_values("ClusterDesc")
```

Out[66]:

	CustID	R	F	M	RFM	ClusterIndx	ClusterName	ClusterDesc
3	12349.0	2	2	1	221	0	2	2nd Best - Loyal Low Budget Spender
5	12352.0	2	2	2	222	0	2	2nd Best - Loyal Low Budget Spender
9	12356.0	2	2	1	221	0	2	2nd Best - Loyal Low Budget Spender
1	12347.0	1	1	1	111	2	1	Best - Gotta Keep
2	12348.0	3	3	1	331	1	3	Low Budget, rare shopper
0	12346.0	4	4	4	444	3	4	Worst- Low Budget, rare shopper & near churn
4	12350.0	4	4	3	443	3	4	Worst- Low Budget, rare shopper & near churn
6	12353.0	4	4	4	444	3	4	Worst- Low Budget, rare shopper & near churn
7	12354.0	4	2	2	422	3	4	Worst- Low Budget, rare shopper & near churn
8	12355.0	4	4	3	443	3	4	Worst- Low Budget, rare shopper & near churn

In [67]:
```
# Let's count the number of customers in each segment
rf_df = rk.groupby(["ClusterDesc"])["CustID"].aggregate("count").reset_index().so
rf_df.columns = ["ClusterDesc","Count_Of_CustID"]
rf_df["Perc_Cust"] = rf_df["Count_Of_CustID"]*100/rf_df["Count_Of_CustID"].sum()
```

In [68]:
```
rf_df
```

Out[68]:

	ClusterDesc	Count_Of_CustID	Perc_Cust
2	Low Budget, rare shopper	1064	24.336688
3	Worst- Low Budget, rare shopper & near churn	1085	24.817017
1	Best - Gotta Keep	1096	25.068618
0	2nd Best - Loyal Low Budget Spender	1127	25.777676

Conclusion

We have segmented our customer base into 4 distinct groups shown above. The group names indicate the value of the customer.

Note also, that the groups are roughly evenly divided. We can now focus our marketing efforts mainly towrds our higher valued customer groups : (i) "Best- Gotta keep" (ii) "2nd Best - Loyal Low Budget Spender" Given that we now know the recency, frequency and total spent amount for these customers we can tailor our marketing accordingly.

The End

In [ ]:
```
```