```
import pandas as pd
import datetime as dt
import string
import random
import math
import matplotlib.pyplot as plt
import seaborn as sns
from IPython.display import HTML
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
```

Week 1 Tasks

```
Retail_train = pd.read_excel("train.xlsx")
Retail_test = pd.read_excel("test.xlsx")
```

Data Analysis of train and test datasets

```
Retail_train.head(10)
```

```
  InvoiceNo StockCode                          Description  Quantity  \
0    558904     22292    HANGING CHICK  YELLOW DECORATION         1
1    556072     20970  PINK FLORAL FELTCRAFT SHOULDER BAG         8
2    551739     21559   STRAWBERRY LUNCH BOX WITH CUTLERY         2
3    541658     21988        PACK OF 6 SKULL PAPER PLATES         1
4    538364    85099C      JUMBO  BAG BAROQUE BLACK WHITE        10
5    552306     84789           ENCHANTED BIRD PLANT CAGE         4
6    561513    72351B      SET/6 PINK  BUTTERFLY T-LIGHTS         1
7    566591     23057    BEADED CHANDELIER T-LIGHT HOLDER         4
8    564516    84970l    SINGLE HEART ZINC T-LIGHT HOLDER         3
9    573582     23082   SET 6 PAPER TABLE LANTERN HEARTS          6

           InvoiceDate  UnitPrice  CustomerID         Country
0 2011-07-04 16:18:00       1.25         NaN  United Kingdom
1 2011-06-08 14:57:00       3.75     16126.0  United Kingdom
2 2011-05-04 10:58:00       2.55     18118.0  United Kingdom
3 2011-01-20 12:16:00       0.85     15529.0  United Kingdom
4 2010-12-10 17:26:00       1.95     14448.0  United Kingdom
5 2011-05-08 15:20:00       3.75     13911.0  United Kingdom
6 2011-07-27 15:12:00       4.13         NaN  United Kingdom
7 2011-09-13 14:53:00       4.95     16036.0  United Kingdom
8 2011-08-25 14:45:00       2.08         NaN  United Kingdom
9 2011-10-31 14:23:00       3.75     16633.0  United Kingdom
```

```
Retail_test.head(10)
```

```
  InvoiceNo StockCode                          Description  Quantity  \
0    562955    84660c            PINK STITCHED WALL CLOCK         3
1    548451     22707                  WRAP MONSTER FUN          50
2    568180     22534       MAGIC DRAWING SLATE SPACEBOY         12
3    577078    47369B  BLUE GREEN EMBROIDERY COSMETIC BAG         1
4   C569891     22720   SET OF 3 CAKE TINS PANTRY DESIGN         -2
```

```
5    544812     22420             LIPSTICK PEN BABY PINK        12
6    538795     82482   WOODEN PICTURE FRAME WHITE FINISH         6
7    548203     22672     FRENCH BATHROOM SIGN BLUE METAL         8
8    561968     23077                  DOUGHNUT LIP GLOSS        20
9    581450     20725              LUNCH BAG RED RETROSPOT         1

          InvoiceDate  UnitPrice  CustomerID         Country
0 2011-08-11 10:14:00       7.46         NaN  United Kingdom
1 2011-03-31 11:25:00       0.42     17365.0  United Kingdom
2 2011-09-25 13:42:00       0.42     15429.0  United Kingdom
3 2011-11-17 15:17:00       5.79         NaN  United Kingdom
4 2011-10-06 15:46:00       4.95     13924.0  United Kingdom
5 2011-02-23 15:58:00       0.83         NaN  United Kingdom
6 2010-12-14 11:42:00       2.55     13267.0  United Kingdom
7 2011-03-29 16:40:00       4.95         NaN  United Kingdom
8 2011-08-01 13:29:00       1.25     16332.0  United Kingdom
9 2011-12-08 17:54:00       1.65     16794.0  United Kingdom
```

```
print('No. of rows and columns of train dataset :')
print(Retail_train.shape, '\n')
print('No. of rows and columns of test dataset :')
print(Retail_test.shape)
```

```
No. of rows and columns of train dataset :
(379336, 8)

No. of rows and columns of test dataset :
(162573, 8)
```

```
print("Column names of train set :")
print('============================')
print(Retail_train.columns,'\n')
print("Column names of test set :")
print('============================')
print(Retail_test.columns)
```

```
Column names of train set :
============================
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity',
'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')

Column names of test set :
============================
Index(['InvoiceNo', 'StockCode', 'Description', 'Quantity',
'InvoiceDate',
       'UnitPrice', 'CustomerID', 'Country'],
      dtype='object')
```

```
print('Train dataset structure information :')
print('====================================')
print(Retail_train.info(), '\n')
print('Test dataset structure information :')
print('====================================')
print(Retail_test.info())
```

```
Train dataset structure information :
====================================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 379336 entries, 0 to 379335
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    379336 non-null  object
 1   StockCode    379336 non-null  object
 2   Description  378373 non-null  object
 3   Quantity     379336 non-null  int64
 4   InvoiceDate  379336 non-null  datetime64[ns]
 5   UnitPrice    379336 non-null  float64
 6   CustomerID   285076 non-null  float64
 7   Country      379336 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 23.2+ MB
None

Test dataset structure information :
====================================
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 162573 entries, 0 to 162572
Data columns (total 8 columns):
 #   Column       Non-Null Count   Dtype
---  ------       --------------   -----
 0   InvoiceNo    162573 non-null  object
 1   StockCode    162573 non-null  object
 2   Description  162082 non-null  object
 3   Quantity     162573 non-null  int64
 4   InvoiceDate  162573 non-null  datetime64[ns]
 5   UnitPrice    162573 non-null  float64
 6   CustomerID   121753 non-null  float64
 7   Country      162573 non-null  object
dtypes: datetime64[ns](1), float64(2), int64(1), object(4)
memory usage: 9.9+ MB
None
```

```
print('Count of each unique value in each column in train set :')
print('=======================================================')
print(Retail_train.nunique(), '\n')
print('Count of each unique value in each column in test set :')
```

```
print('=========================================================')
print(Retail_test.nunique())
```

```
Count of each unique value in each column in train set :
=========================================================
InvoiceNo      23857
StockCode       4008
Description     4132
Quantity         619
InvoiceDate    21712
UnitPrice       1267
CustomerID      4353
Country           38
dtype: int64

Count of each unique value in each column in test set :
=========================================================
InvoiceNo      20166
StockCode       3759
Description     3825
Quantity         434
InvoiceDate    18686
UnitPrice        792
CustomerID      4224
Country           38
dtype: int64
```

```
print('Train dataset description :')
print('============================')
print(Retail_train.describe(), '\n')
print('Test dataset description :')
print('============================')
print(Retail_test.describe())
```

```
Train dataset description :
============================
            Quantity      UnitPrice     CustomerID
count  379336.000000  379336.000000  285076.000000
mean        9.517272       4.681474   15288.302463
std       259.070548     105.799352    1712.323663
min    -80995.000000  -11062.060000   12346.000000
25%         1.000000       1.250000   13958.750000
50%         3.000000       2.080000   15152.000000
75%        10.000000       4.130000   16791.000000
max     80995.000000   38970.000000   18287.000000

Test dataset description :
============================
            Quantity      UnitPrice     CustomerID
count  162573.000000  162573.000000  121753.000000
mean        9.633863       4.446940   15286.257866
```

```
std        43.862669      71.344746    1716.591938
min     -3667.000000  -11062.060000   12347.000000
25%         1.000000       1.250000   13940.000000
50%         3.000000       2.080000   15150.000000
75%        10.000000       4.130000   16794.000000
max      3114.000000   13541.330000   18287.000000
```

Checking and removing duplicate values in both datasets :

```
Is_Duplicate = Retail_train.duplicated()
Is_Duplicate.value_counts()
```

```
False    376663
True       2673
dtype: int64
```

```
Is_Duplicate = Retail_test.duplicated()
Is_Duplicate.value_counts()
```

```
False    162103
True        470
dtype: int64
```

```
Retail_train.drop_duplicates(keep = 'first', inplace = True)
Retail_train.duplicated().value_counts()
```

```
False    376663
dtype: int64
```

```
Retail_test.drop_duplicates(keep = 'first', inplace = True)
Retail_test.duplicated().value_counts()
```

```
False    162103
dtype: int64
```

```
Retail_train.shape, Retail_test.shape
```

```
((376663, 8), (162103, 8))
```

Checking that removing duplicate values has not inadvertently removed any unique value from the columns, if so then the unique count will be different from the previous one we perform.

```
print('Count of unique values in each Column in train dataset :')
print('=========================================================')
print(Retail_train.nunique(), '\n')
print('Count of unique values in each Column in test dataset :')
print('=========================================================')
print(Retail_test.nunique())
```

```
Count of unique values in each Column in train dataset :
=========================================================
InvoiceNo      23857
```

```
StockCode       4008
Description     4132
Quantity         619
InvoiceDate    21712
UnitPrice       1267
CustomerID      4353
Country           38
dtype: int64

Count of unique values in each Column in test dataset :
=======================================================
InvoiceNo      20166
StockCode       3759
Description     3825
Quantity         434
InvoiceDate    18686
UnitPrice        792
CustomerID      4224
Country           38
dtype: int64
```

Missing value treatment in both dataset :

Counting no. of missing values in each column

```
print('No. of null values in each column in train dataset :')
print('=====================================================')
Retail_train.isnull().sum()
```

```
No. of null values in each column in train dataset :
=====================================================

InvoiceNo          0
StockCode          0
Description      963
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     94243
Country            0
dtype: int64
```

```
print('No. of null values in each column in test dataset :')
print('====================================================')
Retail_test.isnull().sum()
```

```
No. of null values in each column in test dataset :
====================================================

InvoiceNo          0
StockCode          0
Description      491
```

```
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     40818
Country            0
dtype: int64
```

So, there are 2 columns with missing values - 'Description' and 'CustomerID'

I have also noticed that few rows of 'UnitPrice' column has value as 0, which doesnot make sense. An item with unit price 0 is same as no item. It also won't effect the overall calculation of total amount. And the description column has null value where unit price is 0. So, I removed all those rows with UnitPrice as 0.

```
Retail_train.UnitPrice.sort_values()
```

```
173043   -11062.06
159270        0.00
288590        0.00
159274        0.00
353564        0.00
             ...
101732    13541.33
191530    16453.71
266443    16888.02
3743      17836.46
302181    38970.00
Name: UnitPrice, Length: 376663, dtype: float64
```

```
Retail_test.UnitPrice.sort_values()
```

```
152119   -11062.06
161979        0.00
64354         0.00
113428        0.00
138856        0.00
             ...
73468      7006.83
96054      7427.97
161819     8142.75
126924     8286.22
131131    13541.33
Name: UnitPrice, Length: 162103, dtype: float64
```

```
Retail_train =
Retail_train.drop(Retail_train[Retail_train['UnitPrice'] == 0].index,
axis=0)
Retail_train.UnitPrice.sort_values()
```

```
173043   -11062.060
13898         0.001
361772        0.001
```

```
38037         0.030
110196        0.030
             ...
101732    13541.330
191530    16453.710
266443    16888.020
3743      17836.460
302181    38970.000
Name: UnitPrice, Length: 374959, dtype: float64
```

```
Retail_test = Retail_test.drop(Retail_test[Retail_test['UnitPrice'] ==
0].index, axis=0)
Retail_test.UnitPrice.sort_values()
```

```
152119   -11062.060
60598         0.001
72380         0.001
149071        0.010
141021        0.040
             ...
73468      7006.830
96054      7427.970
161819     8142.750
126924     8286.220
131131    13541.330
Name: UnitPrice, Length: 161294, dtype: float64
```

Checked the count of missing value again and found that the 'Description' column has no missing value for both sets

```
Retail_train.isnull().sum()
```

```
InvoiceNo          0
StockCode          0
Description        0
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     92570
Country            0
dtype: int64
```

```
Retail_test.isnull().sum()
```

```
InvoiceNo          0
StockCode          0
Description        0
Quantity           0
InvoiceDate        0
UnitPrice          0
CustomerID     40018
```

```
Country            0
dtype: int64
```

I have noticed and verified that for every cancelled item, a new invoice number prefixed with 'C' is generated and Quantity is marked as a negative value. Only with CustomerID value we can identify who had made the cancellation but with null CustomerID there is no way of knowing who made the cancellation. So, if we generate a new customer ID for these cancelled trsactions, it will look as if the customer has made only cancellation and no purchase. Thus I removed all those rows with Quantity in negative (ie, item cancelled) and CustomerID as null.

```
Retail_train[(Retail_train['Quantity']<0) &
Retail_train['CustomerID'].isnull()]
```

```
       InvoiceNo     StockCode                  Description
Quantity  \
1732     C577346             M                       Manual        -1

3743     C580605     AMAZONFEE                   AMAZON FEE        -1

5231     C564498  BANK CHARGES                Bank Charges        -1

8876     C553854         22053       EMPIRE DESIGN ROSETTE        -1

9334     C547904     AMAZONFEE                   AMAZON FEE        -1

...          ...           ...                          ...       ...

371988   C544580             S                     SAMPLES        -1

373462   C540854         22461        SAVOY ART DECO CLOCK        -1

377377   C566578             M                       Manual        -1

377581   C575153         22947  WOODEN ADVENT CALENDAR RED        -1

378676   C567518             M                       Manual        -1


               InvoiceDate  UnitPrice  CustomerID         Country
1732   2011-11-18 15:25:00     530.25         NaN  United Kingdom
3743   2011-12-05 11:36:00   17836.46         NaN  United Kingdom
5231   2011-08-25 14:22:00      77.63         NaN  United Kingdom
8876   2011-05-19 13:13:00       1.25         NaN  United Kingdom
9334   2011-03-28 12:02:00     219.76         NaN  United Kingdom
...                    ...        ...         ...             ...
371988 2011-02-21 14:25:00      20.55         NaN  United Kingdom
373462 2011-01-12 09:54:00      12.75         NaN  United Kingdom
377377 2011-09-13 13:33:00      92.93         NaN  United Kingdom
```

```
377581 2011-11-08 16:15:00      33.17         NaN  United Kingdom
378676 2011-09-20 16:28:00       5.95         NaN            EIRE

[262 rows x 8 columns]
```

```
Retail_train =
Retail_train.drop(Retail_train[(Retail_train['Quantity']<0)
                                                &
Retail_train['CustomerID'].isnull()].index).reset_index(drop=True)
```

```
Retail_train
```

```
       InvoiceNo StockCode                          Description
Quantity  \
0         558904     22292    HANGING CHICK  YELLOW DECORATION
1
1         556072     20970  PINK FLORAL FELTCRAFT SHOULDER BAG
8
2         551739     21559   STRAWBERRY LUNCH BOX WITH CUTLERY
2
3         541658     21988        PACK OF 6 SKULL PAPER PLATES
1
4         538364    85099C      JUMBO  BAG BAROQUE BLACK WHITE
10
...          ...       ...                                ...       .
..
374692   C554864     22962               JAM JAR WITH PINK LID
-4
374693    539451     20749          ASSORTED COLOUR MINI CASES
1
374694    572302     22091                    EMPIRE TISSUE BOX
1
374695    559339     84946        ANTIQUE SILVER T-LIGHT GLASS
60
374696    576771     23159        SET OF 5 PANCAKE DAY MAGNETS
12

               InvoiceDate  UnitPrice  CustomerID         Country
0      2011-07-04 16:18:00       1.25         NaN  United Kingdom
1      2011-06-08 14:57:00       3.75     16126.0  United Kingdom
2      2011-05-04 10:58:00       2.55     18118.0  United Kingdom
3      2011-01-20 12:16:00       0.85     15529.0  United Kingdom
4      2010-12-10 17:26:00       1.95     14448.0  United Kingdom
...                    ...        ...         ...             ...
374692 2011-05-27 10:36:00       0.85     15122.0  United Kingdom
374693 2010-12-17 16:59:00      16.98         NaN  United Kingdom
374694 2011-10-23 14:47:00       0.39     15427.0  United Kingdom
374695 2011-07-07 16:49:00       1.25     13752.0  United Kingdom
374696 2011-11-16 13:19:00       2.08     13285.0  United Kingdom
```

```
[374697 rows x 8 columns]
```

```
print(Retail_train[(Retail_train['Quantity']<0) &
Retail_train['CustomerID'].isnull()])
```

```
Empty DataFrame
Columns: [InvoiceNo, StockCode, Description, Quantity, InvoiceDate,
UnitPrice, CustomerID, Country]
Index: []
```

```
Retail_test[(Retail_test['Quantity']<0) &
Retail_test['CustomerID'].isnull()]
```

```
       InvoiceNo     StockCode                          Description
Quantity  \
210      C544580             S                             SAMPLES
-1
438      C544581             S                             SAMPLES
-1
944      C537251         22418             10 COLOUR SPACEBOY PEN
-7
2379     C547725         22710                WRAP I LOVE LONDON
-25
5066     C579907         22169  FAMILY ALBUM WHITE PICTURE FRAME
-2
...          ...           ...                                ...
...
153598   C544580             S                             SAMPLES
-1
153743   C546943  BANK CHARGES                       Bank Charges
-1
158202   C559949         22699  ROSES REGENCY TEACUP AND SAUCER
-2
159485   C546948             S                             SAMPLES
-1
161544   C537251         22747        POPPY'S PLAYHOUSE BATHROOM
-6

                InvoiceDate  UnitPrice  CustomerID         Country
210    2011-02-21 14:25:00       9.74         NaN  United Kingdom
438    2011-02-21 14:32:00      92.00         NaN  United Kingdom
944    2010-12-06 10:45:00       0.85         NaN  United Kingdom
2379   2011-03-25 10:43:00       0.42         NaN  United Kingdom
5066   2011-12-01 08:48:00       7.65         NaN            EIRE
...                    ...        ...         ...             ...
153598 2011-02-21 14:25:00       7.00         NaN  United Kingdom
153743 2011-03-18 11:11:00      56.93         NaN  United Kingdom
158202 2011-07-14 10:42:00       2.95         NaN            EIRE
159485 2011-03-18 11:20:00      50.99         NaN  United Kingdom
161544 2010-12-06 10:45:00       2.10         NaN  United Kingdom
```

```
[120 rows x 8 columns]
```

```
Retail_test = Retail_test.drop(Retail_test[(Retail_test['Quantity']<0)
                                           &
Retail_test['CustomerID'].isnull()].index).reset_index(drop=True)
```

```
Retail_test
```

```
       InvoiceNo StockCode                          Description
Quantity  \
0         562955    84660c              PINK STITCHED WALL CLOCK
3
1         548451     22707                     WRAP MONSTER FUN
50
2         568180     22534         MAGIC DRAWING SLATE SPACEBOY
12
3         577078    47369B  BLUE GREEN EMBROIDERY COSMETIC BAG
1
4        C569891     22720   SET OF 3 CAKE TINS PANTRY DESIGN
-2
...          ...       ...                                 ...       .
..
161169    574102     22866         HAND WARMER SCOTTY DOG DESIGN
24
161170    545226     22919                     HERB MARKER MINT
12
161171    573160     22077               6 RIBBONS RUSTIC CHARM
12
161172    552321     23204          CHARLOTTE BAG APPLES DESIGN
10
161173    573359     21983    PACK OF 12 BLUE PAISLEY TISSUES
4

               InvoiceDate  UnitPrice  CustomerID         Country
0      2011-08-11 10:14:00       7.46         NaN  United Kingdom
1      2011-03-31 11:25:00       0.42     17365.0  United Kingdom
2      2011-09-25 13:42:00       0.42     15429.0  United Kingdom
3      2011-11-17 15:17:00       5.79         NaN  United Kingdom
4      2011-10-06 15:46:00       4.95     13924.0  United Kingdom
...                    ...        ...         ...             ...
161169 2011-11-03 10:27:00       2.10     16128.0  United Kingdom
161170 2011-03-01 09:33:00       0.65     12428.0         Finland
161171 2011-10-28 08:58:00       1.95     14359.0  United Kingdom
161172 2011-05-09 09:15:00       0.85     17049.0  United Kingdom
161173 2011-10-30 12:48:00       0.39     14178.0  United Kingdom

[161174 rows x 8 columns]
```

```
print(Retail_test[(Retail_test['Quantity']<0) &
Retail_test['CustomerID'].isnull()])
```

```
Empty DataFrame
Columns: [InvoiceNo, StockCode, Description, Quantity, InvoiceDate,
UnitPrice, CustomerID, Country]
Index: []
```

Here, I am checking whether there are any invoices that has CustomerID in some rows and missing in others. So that I can replace the missing ones with available ones.

Creating 2 dataframe, 1 with all rows with null customerID and the other with no null CustomerID

```
All_CustomerID1 = Retail_train.copy()
No_CustomerID1 =
pd.DataFrame(Retail_train[Retail_train['CustomerID'].isnull()])
All_CustomerID1 =
All_CustomerID1.drop(All_CustomerID1[All_CustomerID1['CustomerID'].isn
ull()].index, axis=0)
print('No. of Invoices that are missing Customer ID for train dataset
= ', No_CustomerID1.InvoiceNo.nunique())
```

```
No. of Invoices that are missing Customer ID for train dataset =  1329
```

There are 1329 unique Invoices that are missing CustomerID in train dataset. So we have to generate 1329 new CustomerID for train dataset.

Checking for common invoice in both dataset, which came as empty, meaning no common InvoiceNo

```
Invoice_set1 = set(All_CustomerID1.InvoiceNo.unique())
Invoice_set2 = set(No_CustomerID1.InvoiceNo.unique())
print('Any common InvoiceNo for train dataset = ', Invoice_set1 &
Invoice_set2)
```

```
Any common InvoiceNo for train dataset =  set()
```

Did same for test dataset

```
All_CustomerID2 =Retail_test.copy()
No_CustomerID2 =
pd.DataFrame(Retail_test[Retail_test['CustomerID'].isnull()])
All_CustomerID2 =
All_CustomerID2.drop(All_CustomerID2[All_CustomerID2['CustomerID'].isn
ull()].index, axis=0)
print('No. of Invoice missing Customer ID for test dataset = ',
No_CustomerID2.InvoiceNo.nunique())
```

```
No. of Invoice missing Customer ID for test dataset =  1182
```

```
Invoice_set1 = set(All_CustomerID2.InvoiceNo.unique())
Invoice_set2 = set(No_CustomerID2.InvoiceNo.unique())
print('Any common InvoiceNo for test dataset = ', Invoice_set1 &
Invoice_set2)
```

```
Any common InvoiceNo for test dataset =  set()
```

Checking for common invoices in train and test dataset.

```
Invoice_set1 = set(No_CustomerID1.InvoiceNo.unique())
Invoice_set2 = set(No_CustomerID2.InvoiceNo.unique())
Common_invoice_null = Invoice_set1 & Invoice_set2
print('No of InvoiceNo common for train and test datasets with missing
CustomerID = ', len(Common_invoice_null))
```

```
No of InvoiceNo common for train and test datasets with missing
CustomerID =  1081
```

```
Invoice_set1 = set(All_CustomerID1.InvoiceNo.unique())
Invoice_set2 = set(All_CustomerID2.InvoiceNo.unique())
Common_invoice_not_null = Invoice_set1 & Invoice_set2
print('No of InvoiceNo common for train and test datasets without
missing CustomerID = ', len(Common_invoice_not_null))
```

```
No of InvoiceNo common for train and test datasets without missing
CustomerID =  16994
```

Though train and test are seperate and it doensn't matter whether they have same or different invoice numbers. But since they are the part of same dataset, I have generated the same CustomerID number for invoices that are common in both the train and test dataset. Only invoices that are unique to both sets have different CustomerID.

```
def find_random():
    random_str = ""
    first_digit = random.randint(1, 9)
    random_str += str(first_digit)

    for i in range(4):
        random_str += str(random.randint(0, 9))
    random_str = int(random_str)
    return random_str

def generate_custID():
    lst2 = list(Retail_train.CustomerID.unique())
    lst3 = list(Retail_test.CustomerID.unique())
    random_no = find_random()
    while (random_no in lst2 or random_no in lst3):
        random_no = find_random()
    lst2.append(random_no)
    lst3.append(random_no)
    return random_no
```

```
lst1 = No_CustomerID1.InvoiceNo.unique()
for i in lst1:
    cust_id = generate_custID()
    for j, k in enumerate(Retail_train.InvoiceNo):
        if i == k:
            Retail_train.loc[j, 'CustomerID'] = cust_id
    if i in Common_invoice_null:
        for l, m in enumerate(Retail_test.InvoiceNo):
            if i == m:
                Retail_test.loc[l, 'CustomerID'] = cust_id
```

```
Retail_train.isnull().sum()
```

```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

```
Retail_test.isnull().sum()
```

```
InvoiceNo        0
StockCode        0
Description      0
Quantity         0
InvoiceDate      0
UnitPrice        0
CustomerID     119
Country          0
dtype: int64
```

```
Null_CustomerID2 =
pd.DataFrame(Retail_test[Retail_test['CustomerID'].isnull()])
Null_CustomerID2.InvoiceNo.nunique()
```

```
101
```

I have sucessfully replaced all null customer id with new id in train set but test set still have 101 invoices that have null customer id. So generate different set if ids for test set.

```
lst1 = Null_CustomerID2.InvoiceNo.unique()
for i in lst1:
    cust_id = generate_custID()
    for j, k in enumerate(Retail_test.InvoiceNo):
        if i == k:
            Retail_test.loc[j, 'CustomerID'] = cust_id
```

```
Retail_test.isnull().sum()
```

```
InvoiceNo      0
StockCode      0
Description    0
Quantity       0
InvoiceDate    0
UnitPrice      0
CustomerID     0
Country        0
dtype: int64
```

Missing value treatment is complete. Lets' check one last time.

```
print('Total number of rows and columns after processing in train
set :')
print('================================================================
=')
print(Retail_train.shape, '\n')
print('Total number of rows and columns after processing in test
set :')
print('================================================================
')
print(Retail_test.shape)
```

```
Total number of rows and columns after processing in train set :
================================================================
(374697, 8)

Total number of rows and columns after processing in test set :
================================================================
(161174, 8)
```

```
print('Is there any missing value left in train set ? ')
print('================================================')
print(Retail_train.isnull().any(), '\n')
print('Is there any missing value left in test set ? ')
print('================================================')
print(Retail_test.isnull().any())
```

```
Is there any missing value left in train set ?
================================================
InvoiceNo      False
StockCode      False
Description    False
Quantity       False
InvoiceDate    False
UnitPrice      False
CustomerID     False
Country        False
dtype: bool

Is there any missing value left in test set ?
```

```
================================================
InvoiceNo      False
StockCode      False
Description    False
Quantity       False
InvoiceDate    False
UnitPrice      False
CustomerID     False
Country        False
dtype: bool
```

Changing datatype of 'CustomerID' to integer from float. Float doesn't make sense.

```
Retail_train.CustomerID = Retail_train.CustomerID.astype('int64')
Retail_train.CustomerID.dtype
```

```
dtype('int64')
```

```
Retail_test.CustomerID = Retail_test.CustomerID.astype('int64')
Retail_test.CustomerID.dtype
```

```
dtype('int64')
```

Removing dates from 2011-12-01 to 2011-12-09

```
D = Retail_train.InvoiceDate.astype(str)
D = [d.split()[0] for d in D]
D = pd.to_datetime(D)
Retail_train['D'] = D
D = pd.Series(pd.date_range('20111201', periods=9))
Retail_train =
Retail_train.drop(Retail_train[Retail_train['D'].isin(D)].index,
axis=0).reset_index(drop=True)
Retail_train.drop(columns='D', axis=1, inplace=True)
Retail_train
```

```
       InvoiceNo StockCode                          Description
Quantity  \
0         558904     22292    HANGING CHICK  YELLOW DECORATION
1
1         556072     20970  PINK FLORAL FELTCRAFT SHOULDER BAG
8
2         551739     21559   STRAWBERRY LUNCH BOX WITH CUTLERY
2
3         541658     21988        PACK OF 6 SKULL PAPER PLATES
1
4         538364    85099C      JUMBO  BAG BAROQUE BLACK WHITE
10
...          ...       ...                                 ...       .
..
357173   C554864     22962              JAM JAR WITH PINK LID
-4
```

```
357174    539451     20749          ASSORTED COLOUR MINI CASES
1
357175    572302     22091                   EMPIRE TISSUE BOX
1
357176    559339     84946        ANTIQUE SILVER T-LIGHT GLASS
60
357177    576771     23159        SET OF 5 PANCAKE DAY MAGNETS
12

               InvoiceDate  UnitPrice  CustomerID         Country
0      2011-07-04 16:18:00       1.25       93842  United Kingdom
1      2011-06-08 14:57:00       3.75       16126  United Kingdom
2      2011-05-04 10:58:00       2.55       18118  United Kingdom
3      2011-01-20 12:16:00       0.85       15529  United Kingdom
4      2010-12-10 17:26:00       1.95       14448  United Kingdom
...                    ...        ...         ...             ...
357173 2011-05-27 10:36:00       0.85       15122  United Kingdom
357174 2010-12-17 16:59:00      16.98       84509  United Kingdom
357175 2011-10-23 14:47:00       0.39       15427  United Kingdom
357176 2011-07-07 16:49:00       1.25       13752  United Kingdom
357177 2011-11-16 13:19:00       2.08       13285  United Kingdom

[357178 rows x 8 columns]
```

Checking for minimum and maximum date

```
Retail_train.InvoiceDate.min(), Retail_train.InvoiceDate.max()
```

```
(Timestamp('2010-12-01 08:26:00'), Timestamp('2011-11-30 17:42:00'))
```

Creating Total_Amount column for train set

```
Retail_train['Total_Amount'] = Retail_train['Quantity'] *
Retail_train['UnitPrice']
Retail_train
```

```
       InvoiceNo StockCode                          Description
Quantity  \
0         558904     22292    HANGING CHICK  YELLOW DECORATION
1
1         556072     20970  PINK FLORAL FELTCRAFT SHOULDER BAG
8
2         551739     21559   STRAWBERRY LUNCH BOX WITH CUTLERY
2
3         541658     21988        PACK OF 6 SKULL PAPER PLATES
1
4         538364    85099C      JUMBO  BAG BAROQUE BLACK WHITE
10
...          ...       ...                                 ...       .
..
357173   C554864     22962              JAM JAR WITH PINK LID
```

```
-4
357174    539451     20749          ASSORTED COLOUR MINI CASES
1
357175    572302     22091                   EMPIRE TISSUE BOX
1
357176    559339     84946        ANTIQUE SILVER T-LIGHT GLASS
60
357177    576771     23159        SET OF 5 PANCAKE DAY MAGNETS
12

               InvoiceDate  UnitPrice  CustomerID         Country  \
0      2011-07-04 16:18:00       1.25       93842  United Kingdom
1      2011-06-08 14:57:00       3.75       16126  United Kingdom
2      2011-05-04 10:58:00       2.55       18118  United Kingdom
3      2011-01-20 12:16:00       0.85       15529  United Kingdom
4      2010-12-10 17:26:00       1.95       14448  United Kingdom
...                    ...        ...         ...             ...
357173 2011-05-27 10:36:00       0.85       15122  United Kingdom
357174 2010-12-17 16:59:00      16.98       84509  United Kingdom
357175 2011-10-23 14:47:00       0.39       15427  United Kingdom
357176 2011-07-07 16:49:00       1.25       13752  United Kingdom
357177 2011-11-16 13:19:00       2.08       13285  United Kingdom

        Total_Amount
0               1.25
1              30.00
2               5.10
3               0.85
4              19.50
...              ...
357173         -3.40
357174         16.98
357175          0.39
357176         75.00
357177         24.96

[357178 rows x 9 columns]
```

Saving the processed train dataset to Retail_train.csv file inorder to use it for tableau dashboard creation.

```
Retail_train.to_csv('Retail_train.csv')
```

Data preprocessing complete and now it is ready for further analysis.

Cohort Analysis

I have used only columns (InvoiceNO, Quantity, InvoiceDate, UnitPrice, CustomerID) of train dataset.

```
Retail_Cohort = pd.DataFrame(Retail_train.iloc[:, [0, 4, 6, 8]])
Retail_Cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
0         558904 2011-07-04 16:18:00       93842          1.25
1         556072 2011-06-08 14:57:00       16126         30.00
2         551739 2011-05-04 10:58:00       18118          5.10
3         541658 2011-01-20 12:16:00       15529          0.85
4         538364 2010-12-10 17:26:00       14448         19.50
...          ...                 ...         ...           ...
357173   C554864 2011-05-27 10:36:00       15122         -3.40
357174    539451 2010-12-17 16:59:00       84509         16.98
357175    572302 2011-10-23 14:47:00       15427          0.39
357176    559339 2011-07-07 16:49:00       13752         75.00
357177    576771 2011-11-16 13:19:00       13285         24.96

[357178 rows x 4 columns]
```

```
Retail_Cohort['Month'] = [m.strftime('%B') for m in
Retail_Cohort.InvoiceDate]
Retail_Cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
Month
0         558904 2011-07-04 16:18:00       93842          1.25
July
1         556072 2011-06-08 14:57:00       16126         30.00
June
2         551739 2011-05-04 10:58:00       18118          5.10
May
3         541658 2011-01-20 12:16:00       15529          0.85
January
4         538364 2010-12-10 17:26:00       14448         19.50
December
...          ...                 ...         ...           ...       .
..
357173   C554864 2011-05-27 10:36:00       15122         -3.40
May
357174    539451 2010-12-17 16:59:00       84509         16.98
December
357175    572302 2011-10-23 14:47:00       15427          0.39
October
357176    559339 2011-07-07 16:49:00       13752         75.00
July
357177    576771 2011-11-16 13:19:00       13285         24.96
November

[357178 rows x 5 columns]
```

Weekly Retention Rate

Here I doing a weekly cohort analysis of number of customer.

```
weekly_cohort = Retail_Cohort.copy()
weekly_cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
Month
0         558904 2011-07-04 16:18:00       93842          1.25
July
1         556072 2011-06-08 14:57:00       16126         30.00
June
2         551739 2011-05-04 10:58:00       18118          5.10
May
3         541658 2011-01-20 12:16:00       15529          0.85
January
4         538364 2010-12-10 17:26:00       14448         19.50
December
...          ...                 ...         ...           ...       .
..
357173   C554864 2011-05-27 10:36:00       15122         -3.40
May
357174    539451 2010-12-17 16:59:00       84509         16.98
December
357175    572302 2011-10-23 14:47:00       15427          0.39
October
357176    559339 2011-07-07 16:49:00       13752         75.00
July
357177    576771 2011-11-16 13:19:00       13285         24.96
November

[357178 rows x 5 columns]
```

```
def week_number_of_month(date_value):
    wn = str(((date_value.day - 1)//7)+1)
    w = 'Week ' + wn
    return w

week =
weekly_cohort['InvoiceDate'].apply(week_number_of_month).astype(str)
weekly_cohort['Week_No.'] = week
weekly_cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
Month  \
0         558904 2011-07-04 16:18:00       93842          1.25
July
1         556072 2011-06-08 14:57:00       16126         30.00
June
2         551739 2011-05-04 10:58:00       18118          5.10
May
3         541658 2011-01-20 12:16:00       15529          0.85
```

```
January
4         538364 2010-12-10 17:26:00       14448         19.50
December
...          ...                 ...         ...           ...       .
..
357173   C554864 2011-05-27 10:36:00       15122         -3.40
May
357174    539451 2010-12-17 16:59:00       84509         16.98
December
357175    572302 2011-10-23 14:47:00       15427          0.39
October
357176    559339 2011-07-07 16:49:00       13752         75.00
July
357177    576771 2011-11-16 13:19:00       13285         24.96
November

       Week_No.
0        Week 1
1        Week 2
2        Week 1
3        Week 3
4        Week 2
...         ...
357173   Week 4
357174   Week 3
357175   Week 4
357176   Week 1
357177   Week 3

[357178 rows x 6 columns]
```

```
weekly_cohort_data = weekly_cohort.groupby(['Month', 'Week_No.'])
['CustomerID'].nunique().reset_index()
weekly_cohort_data.rename(columns = {'CustomerID': 'No_of_Customers'},
inplace=True)
weekly_cohort_data['Month_Index'] =
weekly_cohort_data.Month.map({'December' : 1, 'January' : 2,
'February' : 3,

'March' : 4, 'April' : 5, 'May' : 6, 'June' : 7,

'July' : 8, 'August' : 9, 'September' : 10,

'October' : 11, 'November' : 12}).astype(int)
weekly_cohort_data
```

```
        Month Week_No.  No_of_Customers  Month_Index
0       April   Week 1              300            5
1       April   Week 2              353            5
2       April   Week 3              347            5
```

3	April	Week 4	190	5
4	August	Week 1	306	9
5	August	Week 2	282	9
6	August	Week 3	303	9
7	August	Week 4	335	9
8	August	Week 5	114	9
9	December	Week 1	479	1
10	December	Week 2	438	1
11	December	Week 3	366	1
12	December	Week 4	50	1
13	February	Week 1	264	3
14	February	Week 2	248	3
15	February	Week 3	270	3
16	February	Week 4	287	3
17	January	Week 1	203	2
18	January	Week 2	273	2
19	January	Week 3	226	2
20	January	Week 4	294	2
21	January	Week 5	88	2
22	July	Week 1	318	8
23	July	Week 2	308	8
24	July	Week 3	340	8
25	July	Week 4	323	8
26	July	Week 5	95	8
27	June	Week 1	338	7
28	June	Week 2	355	7
29	June	Week 3	344	7
30	June	Week 4	285	7
31	June	Week 5	107	7
32	March	Week 1	299	4
33	March	Week 2	260	4
34	March	Week 3	330	4
35	March	Week 4	308	4
36	March	Week 5	205	4
37	May	Week 1	296	6
38	May	Week 2	393	6
39	May	Week 3	362	6
40	May	Week 4	357	6
41	May	Week 5	72	6
42	November	Week 1	497	12
43	November	Week 2	600	12
44	November	Week 3	615	12
45	November	Week 4	524	12
46	November	Week 5	242	12
47	October	Week 1	455	11
48	October	Week 2	417	11
49	October	Week 3	413	11
50	October	Week 4	442	11
51	October	Week 5	156	11
52	September	Week 1	321	10

```
53  September   Week 2              384           10
54  September   Week 3              362           10
55  September   Week 4              452           10
56  September   Week 5              167           10
```

```
weekly_cohort_pivot =
pd.DataFrame(weekly_cohort_data.pivot_table(index = ['Month_Index',
'Month'],
                                                    columns =
'Week_No.',
                                                    values =
'No_of_Customers'))
weekly_cohort_pivot
```

Week_No.		Week 1	Week 2	Week 3	Week 4	Week 5
Month_Index	Month					
1	December	479.0	438.0	366.0	50.0	NaN
2	January	203.0	273.0	226.0	294.0	88.0
3	February	264.0	248.0	270.0	287.0	NaN
4	March	299.0	260.0	330.0	308.0	205.0
5	April	300.0	353.0	347.0	190.0	NaN
6	May	296.0	393.0	362.0	357.0	72.0
7	June	338.0	355.0	344.0	285.0	107.0
8	July	318.0	308.0	340.0	323.0	95.0
9	August	306.0	282.0	303.0	335.0	114.0
10	September	321.0	384.0	362.0	452.0	167.0
11	October	455.0	417.0	413.0	442.0	156.0
12	November	497.0	600.0	615.0	524.0	242.0

```
total = [weekly_cohort_pivot.iloc[i, 0:6].sum().astype(int) for i in
range(len(weekly_cohort_pivot))]
print("Total no. of customers in each month :")
print('====================================')
print(total)
```

```
Total no. of customers in each month :
====================================
[1333, 1084, 1069, 1402, 1190, 1480, 1429, 1384, 1340, 1686, 1883,
2478]
```

Above pivot table showing the weekly distribution of customers for each month. Eg. In month of December there were total 1333 customers, of which there were 479, 438, 366 and 50 customers in week 1, week 2, week 3 and week 4 repectively. Week 5 as NaN means there were no transactions.

Below table shows the percentage of total customers in each week.

```
weekly_cohort_pct = weekly_cohort_pivot.divide(total, axis=0)
weekly_cohort_pct.round(3)*100
```

Week_No.		Week 1	Week 2	Week 3	Week 4	Week 5
Month_Index	Month					

```
1           December     35.9    32.9    27.5     3.8     NaN
2           January      18.7    25.2    20.8    27.1     8.1
3           February     24.7    23.2    25.3    26.8     NaN
4           March        21.3    18.5    23.5    22.0    14.6
5           April        25.2    29.7    29.2    16.0     NaN
6           May          20.0    26.6    24.5    24.1     4.9
7           June         23.7    24.8    24.1    19.9     7.5
8           July         23.0    22.3    24.6    23.3     6.9
9           August       22.8    21.0    22.6    25.0     8.5
10          September    19.0    22.8    21.5    26.8     9.9
11          October      24.2    22.1    21.9    23.5     8.3
12          November     20.1    24.2    24.8    21.1     9.8
```

Formatting the dataframe for proper visualization.

```
cohort_style = weekly_cohort_pct.style
cohort_style = cohort_style.format("{:.1%}")
cohort_style
```

```
<pandas.io.formats.style.Styler at 0x24b609c4e90>
```

```
styles = [dict(selector="th", props=[("font-size", "150%"), ("text-
align", "center"), ('border', '2px solid black')]),
          dict(selector='td', props= [('border-color', 'grey'),
('border', '2px solid black')]),
          dict(selector="caption", props=[("caption-side", "top"),
("text-align", "center"), ("font-size", "170%")])]

cohort_style =
(cohort_style.set_table_styles(styles).set_caption("Weekly Retention
Rate"))

cm = sns.light_palette("orange", as_cmap=True)
cohort_style.background_gradient(cmap=cm, axis=1)
```

```
<pandas.io.formats.style.Styler at 0x24b609c4e90>
```

Yearly Retention

```
yearly_cohort = Retail_Cohort.copy()
```

Below I an finding the month for each invoice and also the month in which a customer has made the first transaction.

```
def get_month(x):
    return dt.datetime(x.year, x.month, 1)

yearly_cohort['Invoice_Month'] =
yearly_cohort['InvoiceDate'].apply(get_month)
yearly_cohort['Cohort_Join_Month'] =
yearly_cohort.groupby('CustomerID')['Invoice_Month'].transform('min')
```

```
yearly_cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
Month  \
0         558904 2011-07-04 16:18:00       93842          1.25
July
1         556072 2011-06-08 14:57:00       16126         30.00
June
2         551739 2011-05-04 10:58:00       18118          5.10
May
3         541658 2011-01-20 12:16:00       15529          0.85
January
4         538364 2010-12-10 17:26:00       14448         19.50
December
...          ...                 ...         ...           ...       .
..
357173   C554864 2011-05-27 10:36:00       15122         -3.40
May
357174    539451 2010-12-17 16:59:00       84509         16.98
December
357175    572302 2011-10-23 14:47:00       15427          0.39
October
357176    559339 2011-07-07 16:49:00       13752         75.00
July
357177    576771 2011-11-16 13:19:00       13285         24.96
November

       Invoice_Month Cohort_Join_Month
0         2011-07-01        2011-07-01
1         2011-06-01        2011-02-01
2         2011-05-01        2011-12-01
3         2011-01-01        2010-12-01
4         2010-12-01        2010-12-01
...              ...               ...
357173    2011-05-01        2011-02-01
357174    2010-12-01        2010-12-01
357175    2011-10-01        2011-10-01
357176    2011-07-01        2011-04-01
357177    2011-11-01        2011-02-01

[357178 rows x 7 columns]
```

Next I am finding the difference of months of the customer's first and last transactions. So that I know how long the customer is being active.

```
def get_date(df, column):
    year = df[column].dt.year
    month = df[column].dt.month
    return year, month
```

```
invoice_year, invoice_month = get_date(yearly_cohort, 'Invoice_Month')
cohort_year, cohort_month  = get_date(yearly_cohort,
'Cohort_Join_Month')

year_diff = invoice_year - cohort_year
month_diff = invoice_month - cohort_month

yearly_cohort['Cohort_Index'] = year_diff * 12 + month_diff + 1
yearly_cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
Month  \
0         558904 2011-07-04 16:18:00       93842          1.25
July
1         556072 2011-06-08 14:57:00       16126         30.00
June
2         551739 2011-05-04 10:58:00       18118          5.10
May
3         541658 2011-01-20 12:16:00       15529          0.85
January
4         538364 2010-12-10 17:26:00       14448         19.50
December
...          ...                 ...         ...           ...       .
..
357173   C554864 2011-05-27 10:36:00       15122         -3.40
May
357174    539451 2010-12-17 16:59:00       84509         16.98
December
357175    572302 2011-10-23 14:47:00       15427          0.39
October
357176    559339 2011-07-07 16:49:00       13752         75.00
July
357177    576771 2011-11-16 13:19:00       13285         24.96
November

       Invoice_Month Cohort_Join_Month  Cohort_Index
0         2011-07-01        2011-07-01             1
1         2011-06-01        2011-02-01             5
2         2011-05-01        2010-12-01             6
3         2011-01-01        2010-12-01             2
4         2010-12-01        2010-12-01             1
...              ...               ...           ...
357173    2011-05-01        2011-02-01             4
357174    2010-12-01        2010-12-01             1
357175    2011-10-01        2011-10-01             1
357176    2011-07-01        2011-04-01             4
357177    2011-11-01        2011-02-01            10

[357178 rows x 8 columns]
```

```
yearly_cohort.Cohort_Index.unique()
```

```
array([ 1,  5,  6,  2,  4,  7,  8,  9, 11, 12,  3, 10], dtype=int64)
```

From above we can see that there are 12 cohort indexes, which means a customer was active for that many months from making first transaction. Eg. If a customer has a Cohort_Index of 5 then that means the customer was active for next 5 months from making his/her first transaction.

```
yearly_cohort_data = yearly_cohort.groupby(['Cohort_Join_Month',
'Cohort_Index'])['CustomerID'].apply(pd.Series.nunique).reset_index()
yearly_cohort_data['Join_Month'] = [m.strftime('%B') for m in
yearly_cohort_data.Cohort_Join_Month]
yearly_cohort_data.rename(columns = {'CustomerID': 'No_of_Customer'},
inplace=True)
yearly_cohort_data
```

```
   Cohort_Join_Month  Cohort_Index  No_of_Customer Join_Month
0         2010-12-01             1            1073   December
1         2010-12-01             2             350   December
2         2010-12-01             3             297   December
3         2010-12-01             4             353   December
4         2010-12-01             5             332   December
..               ...           ...             ...        ...
73        2011-09-01             2              86  September
74        2011-09-01             3              97  September
75        2011-10-01             1             450    October
76        2011-10-01             2              91    October
77        2011-11-01             1             424   November

[78 rows x 4 columns]
```

```
yearly_cohort_data['Month_Index'] =
yearly_cohort_data.Join_Month.map({'December' : 1, 'January' : 2,
'February' : 3,

'March' : 4, 'April' : 5, 'May' : 6, 'June' : 7,

'July' : 8, 'August' : 9, 'September' : 10,

'October' : 11, 'November' : 12}).astype(int)
yearly_cohort_data
```

```
   Cohort_Join_Month  Cohort_Index  No_of_Customer Join_Month
Month_Index
0         2010-12-01             1            1073   December
1
1         2010-12-01             2             350   December
1
2         2010-12-01             3             297   December
```

```
1
3         2010-12-01             4             353   December
1
4         2010-12-01             5             332   December
1
..               ...           ...             ...        ...
...
73        2011-09-01             2              86  September
10
74        2011-09-01             3              97  September
10
75        2011-10-01             1             450    October
11
76        2011-10-01             2              91    October
11
77        2011-11-01             1             424   November
12

[78 rows x 5 columns]
```

```
yearly_cohort_pivot = yearly_cohort_data.pivot_table(index =
['Month_Index', 'Join_Month'],
                                        columns = 'Cohort_Index',
                                        values = 'No_of_Customer')
yearly_cohort_pivot
```

```
Cohort_Index                1      2      3      4      5      6
7   \
Month_Index Join_Month

1           December    1073.0  350.0  297.0  353.0  332.0  367.0
351.0
2           January      515.0  102.0  120.0  104.0  141.0  122.0
113.0
3           February     475.0   91.0   72.0  101.0  102.0   91.0
95.0
4           March        563.0   81.0  110.0   93.0  101.0   76.0
113.0
5           April        393.0   67.0   65.0   60.0   61.0   71.0
69.0
6           May          392.0   60.0   48.0   48.0   59.0   69.0
74.0
7           June         371.0   46.0   43.0   62.0   57.0   80.0
NaN
8           July         330.0   39.0   38.0   45.0   55.0    NaN
NaN
9           August       242.0   38.0   41.0   41.0    NaN    NaN
NaN
10          September    374.0   86.0   97.0    NaN    NaN    NaN
NaN
```

```
11           October      450.0   91.0    NaN    NaN    NaN    NaN
NaN
12           November     424.0    NaN    NaN    NaN    NaN    NaN
NaN
```

```
Cohort_Index                8      9      10     11     12
Month_Index Join_Month
1           December    322.0  325.0  361.0  344.0  459.0
2           January     109.0  132.0  148.0  157.0    NaN
3           February    101.0   97.0  117.0    NaN    NaN
4           March       103.0  125.0    NaN    NaN    NaN
5           April        78.0    NaN    NaN    NaN    NaN
6           May           NaN    NaN    NaN    NaN    NaN
7           June          NaN    NaN    NaN    NaN    NaN
8           July          NaN    NaN    NaN    NaN    NaN
9           August        NaN    NaN    NaN    NaN    NaN
10          September     NaN    NaN    NaN    NaN    NaN
11          October       NaN    NaN    NaN    NaN    NaN
12          November      NaN    NaN    NaN    NaN    NaN
```

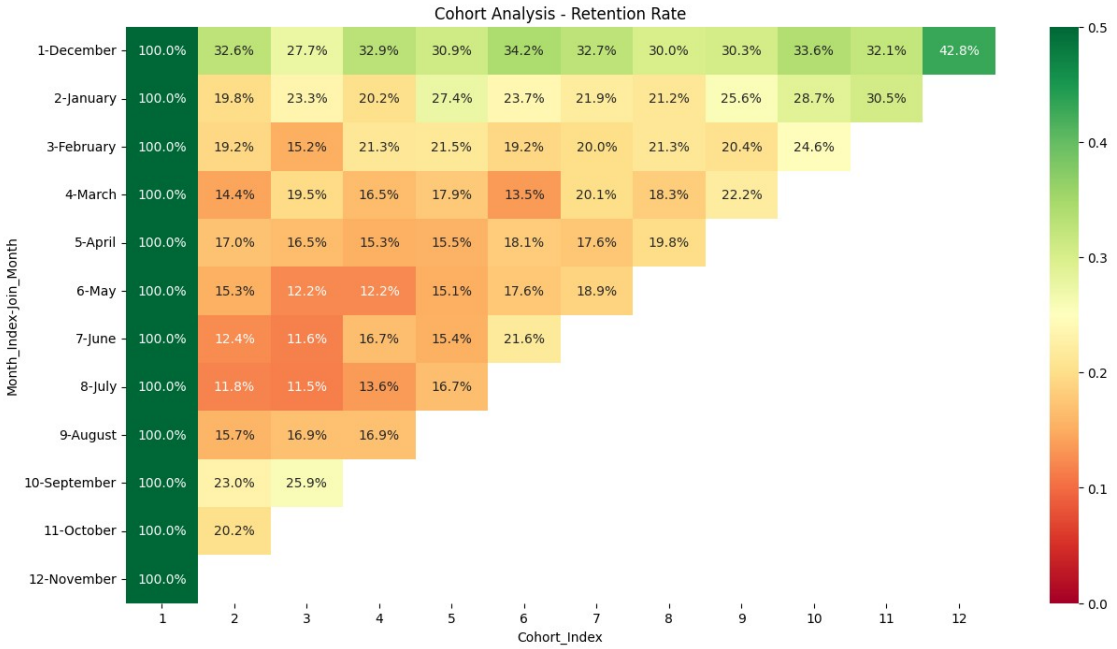
Above pivot table shows the retention of customer through the year. Eg. In December month, there were 1037 active customers, of which 350 were active next month, ie, January also and so on. Since there are 12 months from December to November, so December has 12 cohort index. January to November has 11 months so it has 11 cohort index and so on.

```
total = yearly_cohort_pivot.iloc[:,0]
yearly_cohort_pct = yearly_cohort_pivot.divide(total, axis = 0)
yearly_cohort_pct.round(3)*100
```

```
Cohort_Index                1     2     3     4     5     6     7     8
9   \
Month_Index Join_Month

1           December    100.0  32.6  27.7  32.9  30.9  34.2  32.7
30.0  30.3
2           January     100.0  19.8  23.3  20.2  27.4  23.7  21.9
21.2  25.6
3           February    100.0  19.2  15.2  21.3  21.5  19.2  20.0
21.3  20.4
4           March       100.0  14.4  19.5  16.5  17.9  13.5  20.1
18.3  22.2
5           April       100.0  17.0  16.5  15.3  15.5  18.1  17.6
19.8   NaN
6           May         100.0  15.3  12.2  12.2  15.1  17.6  18.9
NaN   NaN
7           June        100.0  12.4  11.6  16.7  15.4  21.6   NaN
NaN   NaN
8           July        100.0  11.8  11.5  13.6  16.7   NaN   NaN
NaN   NaN
9           August      100.0  15.7  16.9  16.9   NaN   NaN   NaN
```

```
NaN   NaN
10           September   100.0  23.0  25.9   NaN   NaN   NaN   NaN
NaN   NaN
11           October     100.0  20.2   NaN   NaN   NaN   NaN   NaN
NaN   NaN
12           November    100.0   NaN   NaN   NaN   NaN   NaN   NaN
NaN   NaN

Cohort_Index                10    11    12
Month_Index Join_Month
1            December    33.6  32.1  42.8
2            January     28.7  30.5   NaN
3            February    24.6   NaN   NaN
4            March        NaN   NaN   NaN
5            April        NaN   NaN   NaN
6            May          NaN   NaN   NaN
7            June         NaN   NaN   NaN
8            July         NaN   NaN   NaN
9            August       NaN   NaN   NaN
10           September    NaN   NaN   NaN
11           October      NaN   NaN   NaN
12           November     NaN   NaN   NaN
```

```
def yearly_retention():
    plt.figure(figsize = (15,8))
    plt.title('Cohort Analysis - Retention Rate')
    sns.heatmap(data = yearly_cohort_pct, annot = True, fmt = '.1%',
vmin = 0.0, vmax = 0.5, cmap = "RdYlGn")
    plt.show()

yearly_retention()
```



Lets' find the total customer retention rate over the year.

```
user_retention = pd.DataFrame()
Total_Users = yearly_cohort_pivot.iloc[:,0].sum()
user_retention['All Users'] = pd.Series(Total_Users)
j=0
for i in yearly_cohort_data.Join_Month.unique():
    user_retention[i] = pd.Series(yearly_cohort_pivot.iloc[:,j].sum())
    j+=1

user_retention
```

```
   All Users  December  January  February  March  April    May   June
July  \
0     5602.0    5602.0   1051.0     931.0  907.0  908.0  876.0  815.0
713.0

   August  September  October  November
0   679.0      626.0    501.0     459.0
```

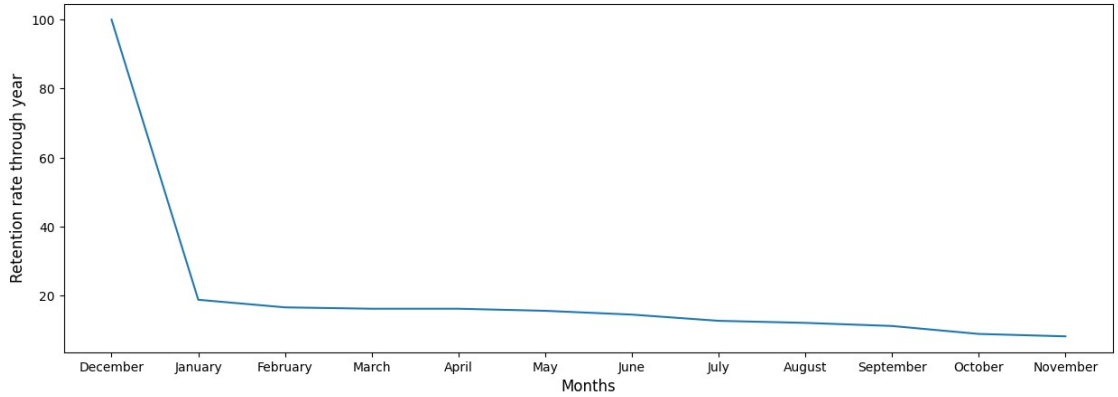
```
User_Retention_Rate = pd.DataFrame()
tot = user_retention['All Users']
user_retention_rate = round((user_retention.divide(tot, axis =
0)*100), 1)
user_retention_rate
```

```
   All Users  December  January  February  March  April   May  June
July  \
0      100.0     100.0     18.8      16.6   16.2   16.2  15.6  14.5
12.7
```

```
   August  September  October  November
0    12.1       11.2      8.9       8.2
```

```
plt.figure(figsize = (15, 5))
plt.plot(user_retention_rate.iloc[0, 1:13])
plt.xlabel('Months', fontsize = 12)
plt.ylabel('Retention rate through year', fontsize = 12)
```

```
Text(0, 0.5, 'Retention rate through year')
```



The above plot shows the retention rate of customer over the whole year. The graph doesn't look good at all. Company needs to do a lot of serious thinking and planning :)

Spent Analysis

```
spent_cohort = yearly_cohort.copy()
spent_cohort
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
Month  \
0         558904 2011-07-04 16:18:00       93842          1.25
July
1         556072 2011-06-08 14:57:00       16126         30.00
June
2         551739 2011-05-04 10:58:00       18118          5.10
May
3         541658 2011-01-20 12:16:00       15529          0.85
January
4         538364 2010-12-10 17:26:00       14448         19.50
December
...          ...                 ...         ...           ...       .
..
357173   C554864 2011-05-27 10:36:00       15122         -3.40
May
357174    539451 2010-12-17 16:59:00       84509         16.98
December
357175    572302 2011-10-23 14:47:00       15427          0.39
October
357176    559339 2011-07-07 16:49:00       13752         75.00
```

```
July
357177    576771 2011-11-16 13:19:00       13285         24.96
November

       Invoice_Month Cohort_Join_Month  Cohort_Index
0         2011-07-01        2011-07-01             1
1         2011-06-01        2011-02-01             5
2         2011-05-01        2010-12-01             6
3         2011-01-01        2010-12-01             2
4         2010-12-01        2010-12-01             1
...              ...               ...           ...
357173    2011-05-01        2011-02-01             4
357174    2010-12-01        2010-12-01             1
357175    2011-10-01        2011-10-01             1
357176    2011-07-01        2011-04-01             4
357177    2011-11-01        2011-02-01            10

[357178 rows x 8 columns]
```

```
spent_cohort_data = spent_cohort.groupby(['Cohort_Join_Month',
'Cohort_Index'])['Total_Amount'].sum().round(1).reset_index()
spent_cohort_data['Join_Month'] = [m.strftime('%B') for m in
spent_cohort_data.Cohort_Join_Month]
spent_cohort_data.rename(columns = {'Total_Amount': 'Amount_Spent'},
inplace=True)
spent_cohort_data
```

```
   Cohort_Join_Month  Cohort_Index  Amount_Spent Join_Month
0         2010-12-01             1      557308.6   December
1         2010-12-01             2      189452.7   December
2         2010-12-01             3      158767.4   December
3         2010-12-01             4      199869.7   December
4         2010-12-01             5      139649.0   December
..               ...           ...           ...        ...
73        2011-09-01             2       17443.5  September
74        2011-09-01             3       24658.4  September
75        2011-10-01             1      184442.3    October
76        2011-10-01             2       27303.8    October
77        2011-11-01             1      340265.2   November

[78 rows x 4 columns]
```

```
spent_cohort_data['Month_Index'] =
spent_cohort_data.Join_Month.map({'December' : 1, 'January' : 2,
'February' : 3,

'March' : 4, 'April' : 5, 'May' : 6, 'June' : 7,

'July' : 8, 'August' : 9, 'September' : 10,
```

```
'October' : 11, 'November' : 12}).astype(int)
spent_cohort_data
```

```
   Cohort_Join_Month  Cohort_Index  Amount_Spent Join_Month
Month_Index
0         2010-12-01             1      557308.6   December
1
1         2010-12-01             2      189452.7   December
1
2         2010-12-01             3      158767.4   December
1
3         2010-12-01             4      199869.7   December
1
4         2010-12-01             5      139649.0   December
1
..               ...           ...           ...        ...          .
..
73        2011-09-01             2       17443.5  September
10
74        2011-09-01             3       24658.4  September
10
75        2011-10-01             1      184442.3    October
11
76        2011-10-01             2       27303.8    October
11
77        2011-11-01             1      340265.2   November
12

[78 rows x 5 columns]
```

```
spent_cohort_pivot = spent_cohort_data.pivot_table(index =
['Month_Index', 'Join_Month'],
                                          columns = 'Cohort_Index',
                                          values = 'Amount_Spent')
spent_cohort_pivot
```

```
Cohort_Index                   1         2         3         4
5   \
Month_Index Join_Month

1           December    557308.6  189452.7  158767.4  199869.7
139649.0
2           January     236648.7   44659.3   53506.7   25542.1
60601.8
3           February    161589.8   17257.4   28580.4   32355.3
24717.4
4           March       220875.0   16026.0   37769.6   28135.3
32383.6
5           April       130045.3   20184.9   18511.9   16852.8
18406.6
6           May         147734.5   13410.6   13434.8   13734.5
```

19015.0
7 June 132900.2 9540.7 9811.1 20936.6
18688.5
8 July 132630.8 8580.4 15264.6 15666.4
15377.3
9 August 124307.4 13106.3 21900.2 27784.0
NaN
10 September 182970.1 17443.5 24658.4 NaN
NaN
11 October 184442.3 27303.8 NaN NaN
NaN
12 November 340265.2 NaN NaN NaN
NaN

Cohort_Index		6	7	8	9	10 \
Month_Index	Join_Month					
1	December	202535.7	196629.5	202312.3	216380.8	305675.2
2	January	73827.7	61852.9	53697.2	59686.6	75679.4
3	February	22395.5	33930.9	38149.0	37748.2	41799.7
4	March	26928.2	44082.9	43880.2	42552.0	NaN
5	April	19764.3	20408.0	23634.8	NaN	NaN
6	May	23505.5	21821.3	NaN	NaN	NaN
7	June	29604.0	NaN	NaN	NaN	NaN
8	July	NaN	NaN	NaN	NaN	NaN
9	August	NaN	NaN	NaN	NaN	NaN
10	September	NaN	NaN	NaN	NaN	NaN
11	October	NaN	NaN	NaN	NaN	NaN
12	November	NaN	NaN	NaN	NaN	NaN

Cohort_Index		11	12
Month_Index	Join_Month		
1	December	294167.1	348983.6
2	January	85448.1	NaN
3	February	NaN	NaN
4	March	NaN	NaN
5	April	NaN	NaN

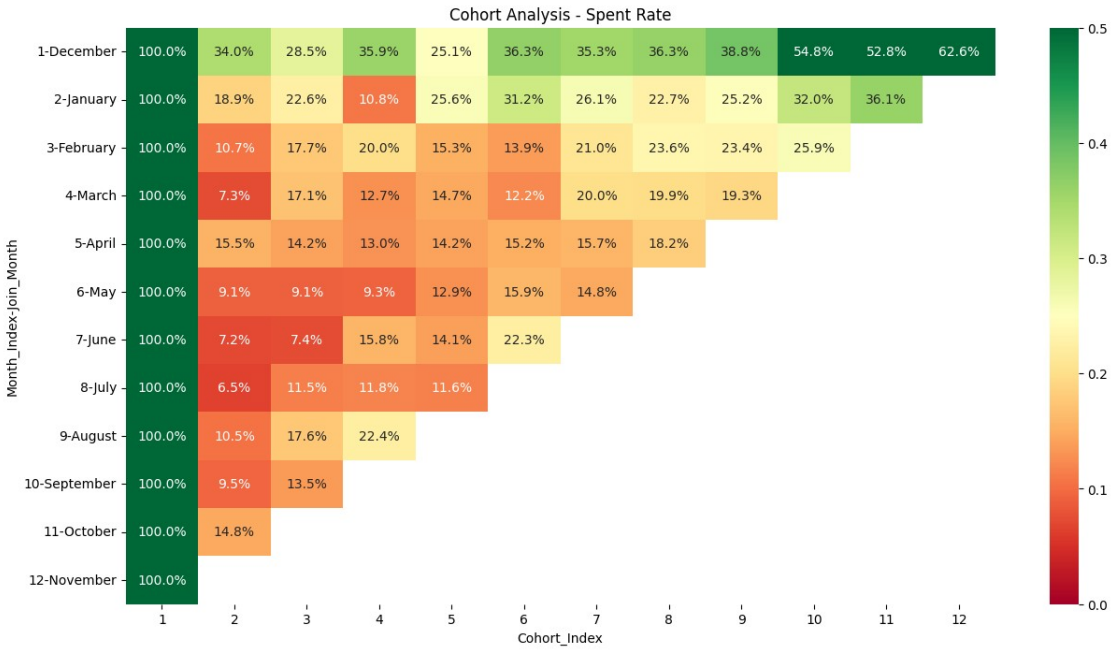
```
6           May              NaN       NaN
7           June             NaN       NaN
8           July             NaN       NaN
9           August           NaN       NaN
10          September        NaN       NaN
11          October          NaN       NaN
12          November         NaN       NaN
```

```
total = spent_cohort_pivot.iloc[:,0]
spent_rate = spent_cohort_pivot.divide(total, axis = 0)
spent_rate.round(3)*100
```

```
Cohort_Index                1     2     3     4     5     6     7     8
9   \
Month_Index Join_Month

1           December    100.0  34.0  28.5  35.9  25.1  36.3  35.3
36.3  38.8
2           January     100.0  18.9  22.6  10.8  25.6  31.2  26.1
22.7  25.2
3           February    100.0  10.7  17.7  20.0  15.3  13.9  21.0
23.6  23.4
4           March       100.0   7.3  17.1  12.7  14.7  12.2  20.0
19.9  19.3
5           April       100.0  15.5  14.2  13.0  14.2  15.2  15.7
18.2   NaN
6           May         100.0   9.1   9.1   9.3  12.9  15.9  14.8
NaN   NaN
7           June        100.0   7.2   7.4  15.8  14.1  22.3   NaN
NaN   NaN
8           July        100.0   6.5  11.5  11.8  11.6   NaN   NaN
NaN   NaN
9           August      100.0  10.5  17.6  22.4   NaN   NaN   NaN
NaN   NaN
10          September   100.0   9.5  13.5   NaN   NaN   NaN   NaN
NaN   NaN
11          October     100.0  14.8   NaN   NaN   NaN   NaN   NaN
NaN   NaN
12          November    100.0   NaN   NaN   NaN   NaN   NaN   NaN
NaN   NaN

Cohort_Index               10    11    12
Month_Index Join_Month
1           December    54.8  52.8  62.6
2           January     32.0  36.1   NaN
3           February    25.9   NaN   NaN
4           March        NaN   NaN   NaN
5           April        NaN   NaN   NaN
6           May          NaN   NaN   NaN
7           June         NaN   NaN   NaN
```

```
8           July          NaN   NaN   NaN
9           August        NaN   NaN   NaN
10          September     NaN   NaN   NaN
11          October       NaN   NaN   NaN
12          November      NaN   NaN   NaN
```

```
def spent_Retention():
    plt.figure(figsize = (15,8))
    plt.title('Cohort Analysis - Spent Rate')
    sns.heatmap(data = spent_rate, annot = True, fmt = '.1%', vmin =
0.0, vmax = 0.5, cmap = "RdYlGn")
    plt.show()

spent_Retention()
```



RMF Modeling

```
Retail_RFM = pd.DataFrame(Retail_train.iloc[:, [0, 4, 6, 8]])
Retail_RFM
```

```
       InvoiceNo         InvoiceDate  CustomerID  Total_Amount
0         558904 2011-07-04 16:18:00       93842          1.25
1         556072 2011-06-08 14:57:00       16126         30.00
2         551739 2011-05-04 10:58:00       18118          5.10
3         541658 2011-01-20 12:16:00       15529          0.85
4         538364 2010-12-10 17:26:00       14448         19.50
...          ...                 ...         ...           ...
357173   C554864 2011-05-27 10:36:00       15122         -3.40
357174    539451 2010-12-17 16:59:00       84509         16.98
357175    572302 2011-10-23 14:47:00       15427          0.39
357176    559339 2011-07-07 16:49:00       13752         75.00
```

```
357177    576771 2011-11-16 13:19:00       13285         24.96

[357178 rows x 4 columns]
```

There are few customers whose transactions are divided in train and test, ie, few of their transactions are in train set and others in test set. This has led to a few discrepencies. For eg. for CustomerID = 12454, there are 2 invoices, 1 for items purchased and other for cancelled items. If we look at the codes below, it seems the customer has returned more items than he had purchased. In actual, the rest of the transaction details are in test set. So, when we calculate the monetary value for this customer it will be negative, as if the company owe the customer money. There are few records of this category.

I don't know how to deal with these records and I don't want to remove these records as these are genuine transactions with all the details available. So I left it as it is.

```
temp = Retail_train[(Retail_train['CustomerID'] == 12454) &
(Retail_train['Quantity']<0)]
print(temp.loc[:, ['InvoiceNo', 'Quantity', 'InvoiceDate',
'CustomerID', 'Total_Amount']])
print('\nNo. of Items returned : ', len(temp))
```

```
       InvoiceNo  Quantity         InvoiceDate  CustomerID
Total_Amount
12024    C571499       -32 2011-10-17 15:07:00       12454        -
88.00
41978    C571499       -72 2011-10-17 15:07:00       12454       -
183.60
70205    C571499       -72 2011-10-17 15:07:00       12454       -
183.60
75807    C571499      -200 2011-10-17 15:07:00       12454       -
250.00
131774   C571499       -16 2011-10-17 15:07:00       12454        -
66.40
163143   C571499       -48 2011-10-17 15:07:00       12454       -
258.72
169555   C571499       -12 2011-10-17 15:07:00       12454        -
97.80
170159   C571499       -48 2011-10-17 15:07:00       12454       -
312.00
181955   C571499       -32 2011-10-17 15:07:00       12454       -
190.40
273050   C571499       -48 2011-10-17 15:07:00       12454       -
258.72
288198   C571499       -48 2011-10-17 15:07:00       12454       -
312.00
305259   C571499       -48 2011-10-17 15:07:00       12454       -
199.20
333040   C571499       -10 2011-10-17 15:07:00       12454       -
417.50
346570   C571499       -32 2011-10-17 15:07:00       12454       -
```

```
350.40

No. of Items returned :  14
```

```
temp = Retail_train[(Retail_train['CustomerID'] == 12454) &
(Retail_train['Quantity']>0)]
print(temp.loc[:, ['InvoiceNo', 'Quantity', 'InvoiceDate',
'CustomerID', 'Total_Amount']])
print('\nNo. of Items Purchased : ', len(temp))
```

```
       InvoiceNo  Quantity         InvoiceDate  CustomerID
Total_Amount
98734     571255        12 2011-10-14 17:13:00       12454
97.80
111986    571255        32 2011-10-14 17:13:00       12454
350.40
115489    571255        48 2011-10-14 17:13:00       12454
312.00
156596    571255        48 2011-10-14 17:13:00       12454
258.72
189621    571255        10 2011-10-14 17:13:00       12454
417.50
203052    571255        16 2011-10-14 17:13:00       12454
66.40
229496    571255        32 2011-10-14 17:13:00       12454
190.40
273817    571255        48 2011-10-14 17:13:00       12454
258.72
298591    571255        48 2011-10-14 17:13:00       12454
199.20
321284    571255        48 2011-10-14 17:13:00       12454
312.00
335926    571255        72 2011-10-14 17:13:00       12454
183.60
356179    571255        72 2011-10-14 17:13:00       12454
183.60

No. of Items Purchased :  12
```

RFM Calculations

```
Retail_RFM['InvoiceDate'] = [d.date() for d in
Retail_RFM['InvoiceDate']]
Retail_RFM
```

```
       InvoiceNo InvoiceDate  CustomerID  Total_Amount
0         558904  2011-07-04       93842          1.25
1         556072  2011-06-08       16126         30.00
2         551739  2011-05-04       18118          5.10
3         541658  2011-01-20       15529          0.85
```

```
4         538364  2010-12-10       14448         19.50
...          ...         ...         ...           ...
357173   C554864  2011-05-27       15122         -3.40
357174    539451  2010-12-17       84509         16.98
357175    572302  2011-10-23       15427          0.39
357176    559339  2011-07-07       13752         75.00
357177    576771  2011-11-16       13285         24.96

[357178 rows x 4 columns]
```

```
Recent_Date = Retail_RFM.InvoiceDate.max()
print('Most recent date : ', Recent_Date)
```

```
Most recent date :  2011-11-30
```

Recency Calculation

```
Recency = Recent_Date - Retail_RFM.groupby('CustomerID')
['InvoiceDate'].max()
Recency = Recency.astype(str)
index = Recency.index
for i, a in enumerate(Recency):
    Recency[index[i]] = a.split()[0]

Recency = Recency.astype(int)
Recency
```

```
CustomerID
10044     92
10115    208
10156      5
10217    168
10421    246
        ...
99711    275
99764    356
99821    209
99880     33
99881     50
Name: InvoiceDate, Length: 5602, dtype: int32
```

Frequency Claculation

```
Frequency = Retail_RFM.groupby('CustomerID')['InvoiceNo'].count()
Frequency
```

```
CustomerID
10044    153
10115      1
10156      6
10217      7
10421     44
```

```
        ...
99711      1
99764    465
99821      2
99880      3
99881     47
Name: InvoiceNo, Length: 5602, dtype: int64
```

Monetary Calculation

```
Monetary = Retail_RFM.groupby('CustomerID')['Total_Amount'].sum()
Monetary
```

```
CustomerID
10044    1014.98
10115       6.20
10156      10.00
10217      57.92
10421     577.05
           ...
99711     764.12
99764    5489.81
99821      17.50
99880       2.09
99881    1575.67
Name: Total_Amount, Length: 5602, dtype: float64
```

```
RFM_Data = pd.DataFrame(columns = ['CustomerID', 'Recency',
'Frequency', 'Monetary'])
RFM_Data['CustomerID'] = sorted(Retail_RFM.CustomerID.unique())
RFM_Data['Recency'] = Recency.values
RFM_Data['Frequency'] = Frequency.values
RFM_Data['Monetary'] = Monetary.values
RFM_Data
```

```
      CustomerID  Recency  Frequency  Monetary
0          10044       92        153   1014.98
1          10115      208          1      6.20
2          10156        5          6     10.00
3          10217      168          7     57.92
4          10421      246         44    577.05
...          ...      ...        ...       ...
5597       99711      275          1    764.12
5598       99764      356        465   5489.81
5599       99821      209          2     17.50
5600       99880       33          3      2.09
5601       99881       50         47   1575.67

[5602 rows x 4 columns]
```

Computing Qurantiles : Dividing into 4 quantiles

For Recency, the lower it is, the better it is. So, lower values get higher quantile.

```
RFM_Data['Recency_Quantile'] = pd.qcut(RFM_Data['Recency'], 4, [4, 3,
2, 1])
RFM_Data
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5597       99711      275          1    764.12                1
5598       99764      356        465   5489.81                1
5599       99821      209          2     17.50                1
5600       99880       33          3      2.09                3
5601       99881       50         47   1575.67                3

[5602 rows x 5 columns]
```

For Frequency, the higher it is, the better it is. So higher values get higher quantile.

```
RFM_Data['Frequency_Quantile'] = pd.qcut(RFM_Data['Frequency'], 4, [1,
2, 3, 4])
RFM_Data
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5597       99711      275          1    764.12                1
5598       99764      356        465   5489.81                1
5599       99821      209          2     17.50                1
5600       99880       33          3      2.09                3
5601       99881       50         47   1575.67                3

     Frequency_Quantile
0                     4
1                     1
2                     1
3                     1
4                     3
...                 ...
5597                  1
5598                  4
5599                  1
5600                  1
```

```
5601                  3

[5602 rows x 6 columns]
```

For Monetary, the higher it is, the better it is. So higher values get higher quantile.

```
RFM_Data['Monetary_Quantile'] = pd.qcut(RFM_Data['Monetary'], 4, [1,
2, 3, 4])
RFM_Data
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5597       99711      275          1    764.12                1
5598       99764      356        465   5489.81                1
5599       99821      209          2     17.50                1
5600       99880       33          3      2.09                3
5601       99881       50         47   1575.67                3

     Frequency_Quantile Monetary_Quantile
0                     4                 3
1                     1                 1
2                     1                 1
3                     1                 1
4                     3                 3
...                 ...               ...
5597                  1                 3
5598                  4                 4
5599                  1                 1
5600                  1                 1
5601                  3                 4

[5602 rows x 7 columns]
```

```
print('Recency Quantile Counts :')
print(RFM_Data.Recency_Quantile.value_counts(), '\n')
print('Frequency Quantile Counts :')
print(RFM_Data.Frequency_Quantile.value_counts(), '\n')
print('Monetary Quantile Counts :')
print(RFM_Data.Monetary_Quantile.value_counts())
```

```
Recency Quantile Counts :
4    1424
1    1400
3    1393
2    1385
Name: Recency_Quantile, dtype: int64
```

```
Frequency Quantile Counts :
1    1420
4    1399
3    1395
2    1388
Name: Frequency_Quantile, dtype: int64

Monetary Quantile Counts :
1    1401
4    1401
2    1400
3    1400
Name: Monetary_Quantile, dtype: int64
```

Calculating RFM Score for each customer based on the quantiles of Recency, Frequency and Monetary.

```
RFM_Data['RFM_Score'] = RFM_Data.Recency_Quantile.astype(str) +
RFM_Data.Frequency_Quantile.astype(str) +
RFM_Data.Monetary_Quantile.astype(str)
RFM_Data.RFM_Score = RFM_Data.RFM_Score.astype('int64')
RFM_Data
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5597       99711      275          1    764.12                1
5598       99764      356        465   5489.81                1
5599       99821      209          2     17.50                1
5600       99880       33          3      2.09                3
5601       99881       50         47   1575.67                3

     Frequency_Quantile Monetary_Quantile  RFM_Score
0                     4                 3        243
1                     1                 1        111
2                     1                 1        411
3                     1                 1        211
4                     3                 3        133
...                 ...               ...        ...
5597                  1                 3        113
5598                  4                 4        144
5599                  1                 1        111
5600                  1                 1        311
5601                  3                 4        334
```

```
[5602 rows x 8 columns]
```

For the above table RFM_Score value 111 means the customer has highest recency, frequenct and monetary value. The highest in all scores. Similarly, RFM_Score value 444 means the customer has lowest recency, frequency and monetary value.

```
Score = RFM_Data.RFM_Score.value_counts().sort_index()
print('Count of customers in each RFM Score value :')
print('============================================')
print(Score)
```

```
Count of customers in each RFM Score value :
============================================
111    481
112     88
113     21
114      7
121    102
      ...
434    113
441      1
442     19
443    106
444    489
Name: RFM_Score, Length: 62, dtype: int64
```

Lets' find the percentage of total of customer in each RFM score group.

```
Tot = RFM_Data.RFM_Score.value_counts().sum()
print('Total no. of customers : ', Tot)
```

```
Total no. of customers :  5602
```

```
x = lambda x: x/Tot * 100
pct = RFM_Data.RFM_Score.value_counts().apply(x).sort_index()
print('Percentage of customers in RFM score group :')
print('============================================')
print(pct)
```

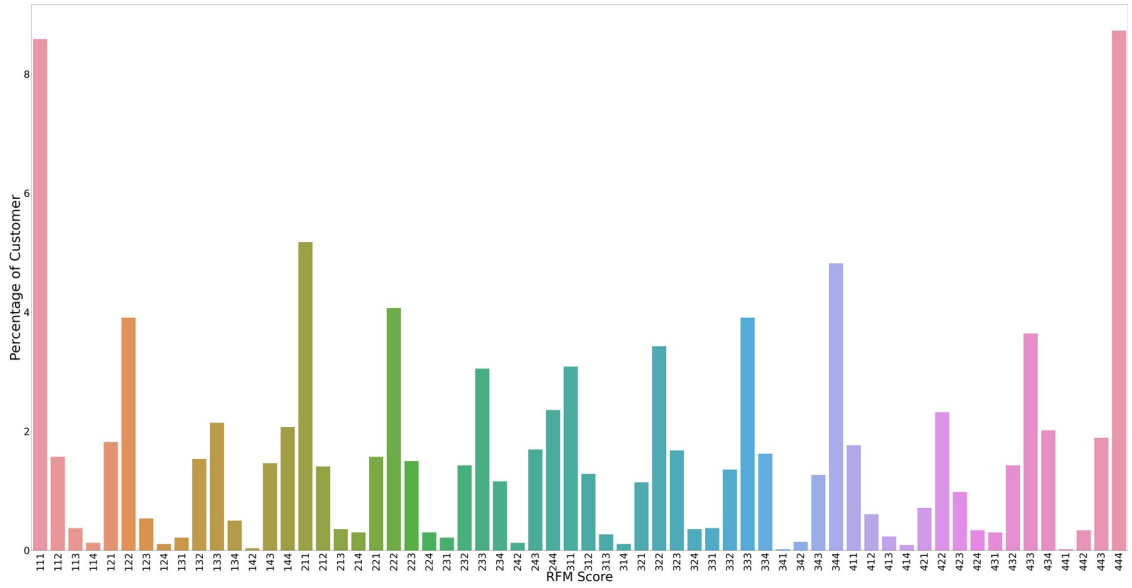
```
Percentage of customers in RFM score group :
============================================
111    8.586219
112    1.570868
113    0.374866
114    0.124955
121    1.820778
         ...
434    2.017137
441    0.017851
442    0.339165
443    1.892181
```

```
444    8.729025
Name: RFM_Score, Length: 62, dtype: float64
```

Plotting the count of customers in each RFM score value

```
plt.figure(figsize = (100, 50))
sns.barplot(x=pct.index, y=pct.values)
plt.xticks(rotation = 'vertical', fontsize = 50)
plt.yticks(fontsize = 50)
plt.xlabel('RFM Score', fontsize = 65)
plt.ylabel('Percentage of Customer', fontsize = 70)
```

```
Text(0, 0.5, 'Percentage of Customer')
```



Customer Segmentation Customers are divided into the following 6 segments: 1.) Best Customers – This group consists of those customers who are found in R-Tier-4, F-Tier-4 and M-Tier-3 or 4, meaning that they transacted recently, do so often and spend more than other customers. The shortened notations for this segment are 4-4-3 and 4-4-4; we'll use these notation going forward.

2.) High-Spending New Customers – This group consists of those customers in 4-1-3 and 4-1-4. These are customers who transacted only once, but very recently and they spent a lot.

3.) Lowest-Spending Active Loyal Customers – This group consists of those customers in segments 4-3-1, 4-3-2, 4-4-1 and 4-4-2 (they transacted recently and do so often, but spend the least).

4.) Churned Best Customers – This segment consists of those customers in groups 1-1-3, 1-1-4, 1-2-3 and 1-2-4 (they transacted frequently and spent a lot, but it's been a long time since they've transacted).

5.) Average Spending Active Loyal Customers - This is a group of people who are regular customers but they don't buy often and they spend average. They belong to groups 3-4-2, 3-4-3 and 4-3-3

6.) Other Customers or MVC (Minimum Viable Customers) - These are those customers who do not fall under any of the above customer classifications.

```
def cust_seg(score):
    if score in [444, 443]:
        seg = 'BC'
        name = 'Best Customers'
    elif score in [414, 413]:
        seg = 'HSNC'
        name = 'High-spending New Customers'
    elif score in [431, 432, 441, 442]:
        seg = 'LSALC'
        name = 'Lowest-Spending Active Loyal Customers'
    elif score in [113, 11,4, 123, 124]:
        seg = 'CBC'
        name = 'Churned Best Customers'
    elif score in [342, 343, 433]:
        seg = 'ASALC'
        name = 'Average Spending Active Loyal Customers'
    else:
        seg = 'MVC'
        name = 'Minimum Viable Customers'
    return seg, name

segment = []
names = []
for i in range(len(RFM_Data)):
    seg, name = cust_seg(RFM_Data.RFM_Score[i])
    segment.append(seg)
    names.append(name)

RFM_Data['RFM_Segment'] = segment
RFM_Data['Segment_name'] = names
RFM_Data
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5597       99711      275          1    764.12                1
5598       99764      356        465   5489.81                1
5599       99821      209          2     17.50                1
5600       99880       33          3      2.09                3
5601       99881       50         47   1575.67                3
```

```
     Frequency_Quantile Monetary_Quantile  RFM_Score RFM_Segment  \
0                     4                 3        243         MVC
1                     1                 1        111         MVC
2                     1                 1        411         MVC
3                     1                 1        211         MVC
4                     3                 3        133         MVC
...                 ...               ...        ...         ...
5597                  1                 3        113         CBC
5598                  4                 4        144         MVC
5599                  1                 1        111         MVC
5600                  1                 1        311         MVC
5601                  3                 4        334         MVC

                  Segment_name
0     Minimum Viable Customers
1     Minimum Viable Customers
2     Minimum Viable Customers
3     Minimum Viable Customers
4     Minimum Viable Customers
...                        ...
5597    Churned Best Customers
5598  Minimum Viable Customers
5599  Minimum Viable Customers
5600  Minimum Viable Customers
5601  Minimum Viable Customers

[5602 rows x 10 columns]
```

```
print('Count of Customers in each Segment :')
print('====================================')
RFM_Data.RFM_Segment.value_counts()
```

```
Count of Customers in each Segment :
====================================

MVC      4532
BC        595
ASALC     283
LSALC     117
CBC        57
HSNC       18
Name: RFM_Segment, dtype: int64
```

```
RFM_Data.to_csv('RFM_Data.csv')
```

```
plt.figure(figsize = (50, 20))
sns.countplot(RFM_Data.Segment_name)
plt.xticks(fontsize = 30, rotation=35)
plt.yticks(fontsize = 30)
```

```
plt.xlabel('Customer Segment', fontsize = 35)
plt.ylabel('No. of Customers', fontsize = 35)

---------------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
last)
Cell In[105], line 2
      1 plt.figure(figsize = (50, 20))
----> 2 sns.countplot(RFM_Data.Segment_name)
      3 plt.xticks(fontsize = 30, rotation=35)
      4 plt.yticks(fontsize = 30)

File c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\seaborn\categorical.py:2943, in countplot(data, x, y, hue,
order, hue_order, orient, color, palette, saturation, width, dodge,
ax, **kwargs)
   2940 elif x is not None and y is not None:
   2941     raise ValueError("Cannot pass values for both `x` and
`y`")
-> 2943 plotter = _CountPlotter(
   2944     x, y, hue, data, order, hue_order,
   2945     estimator, errorbar, n_boot, units, seed,
   2946     orient, color, palette, saturation,
   2947     width, errcolor, errwidth, capsize, dodge
   2948 )
   2950 plotter.value_label = "count"
   2952 if ax is None:

File c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\seaborn\categorical.py:1530, in _BarPlotter.__init__(self, x,
y, hue, data, order, hue_order, estimator, errorbar, n_boot, units,
seed, orient, color, palette, saturation, width, errcolor, errwidth,
capsize, dodge)
   1525 def __init__(self, x, y, hue, data, order, hue_order,
   1526              estimator, errorbar, n_boot, units, seed,
   1527              orient, color, palette, saturation, width,
   1528              errcolor, errwidth, capsize, dodge):
   1529     """Initialize the plotter."""
-> 1530     self.establish_variables(x, y, hue, data, orient,
   1531                              order, hue_order, units)
   1532     self.establish_colors(color, palette, saturation)
   1533     self.estimate_statistic(estimator, errorbar, n_boot, seed)

File c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\seaborn\categorical.py:516, in
_CategoricalPlotter.establish_variables(self, x, y, hue, data, orient,
order, hue_order, units)
    513     plot_data = data
    515 # Convert to a list of arrays, the common representation
```

```
--> 516 plot_data = [np.asarray(d, float) for d in plot_data]
    518 # The group names will just be numeric indices
    519 group_names = list(range(len(plot_data)))

File c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\seaborn\categorical.py:516, in <listcomp>(.0)
    513     plot_data = data
    515 # Convert to a list of arrays, the common representation
--> 516 plot_data = [np.asarray(d, float) for d in plot_data]
    518 # The group names will just be numeric indices
    519 group_names = list(range(len(plot_data)))

File c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\pandas\core\series.py:893, in Series.__array__(self, dtype)
    846 def __array__(self, dtype: npt.DTypeLike | None = None) ->
np.ndarray:
    847     """
    848     Return the values as a NumPy array.
    849
   (...)
    891           dtype='datetime64[ns]')
    892     """
--> 893     return np.asarray(self._values, dtype)

ValueError: could not convert string to float: 'Minimum Viable
Customers'

<Figure size 5000x2000 with 0 Axes>
```

Data Modeling : K-Means

```
KMeans_X = RFM_Data.copy()
KMeans_X
```

	CustomerID	Recency	Frequency	Monetary	Recency_Quantile	\
0	10044	92	153	1014.98	2	
1	10115	208	1	6.20	1	
2	10156	5	6	10.00	4	
3	10217	168	7	57.92	2	
4	10421	246	44	577.05	1	
...	...	...	...	...	...	
5597	99711	275	1	764.12	1	
5598	99764	356	465	5489.81	1	
5599	99821	209	2	17.50	1	
5600	99880	33	3	2.09	3	
5601	99881	50	47	1575.67	3	

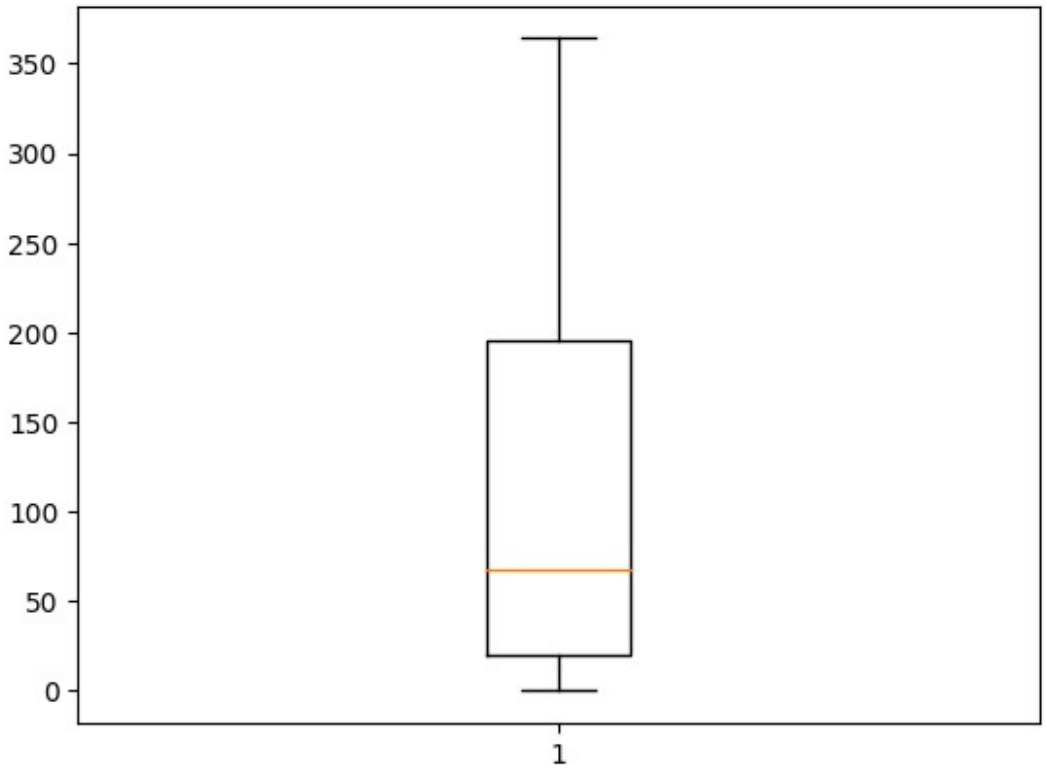
	Frequency_Quantile	Monetary_Quantile	RFM_Score	RFM_Segment	\
0	4	3	243	MVC	
1	1	1	111	MVC	
2	1	1	411	MVC	

```
3                    1                  1        211         MVC
4                    3                  3        133         MVC
...                ...                ...        ...         ...
5597                 1                  3        113         CBC
5598                 4                  4        144         MVC
5599                 1                  1        111         MVC
5600                 1                  1        311         MVC
5601                 3                  4        334         MVC

                  Segment_name
0     Minimum Viable Customers
1     Minimum Viable Customers
2     Minimum Viable Customers
3     Minimum Viable Customers
4     Minimum Viable Customers
...                        ...
5597    Churned Best Customers
5598  Minimum Viable Customers
5599  Minimum Viable Customers
5600  Minimum Viable Customers
5601  Minimum Viable Customers

[5602 rows x 10 columns]
```

Removing the extremes from Recency, Frequency and Monetary

```
plt.boxplot(KMeans_X.Recency)
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x24b611966d0>,
  <matplotlib.lines.Line2D at 0x24b60484310>],
 'caps': [<matplotlib.lines.Line2D at 0x24b604736d0>,
  <matplotlib.lines.Line2D at 0x24b6150f490>],
 'boxes': [<matplotlib.lines.Line2D at 0x24b611b2510>],
 'medians': [<matplotlib.lines.Line2D at 0x24b5ee80fd0>],
 'fliers': [<matplotlib.lines.Line2D at 0x24b61507310>],
 'means': []}
```




```
Q1 = KMeans_X.Recency.quantile(.25)
Q3 = KMeans_X.Recency.quantile(.75)
IQR = Q3 - Q1
print('25% Quantile of Recency = ', Q1)
print('75% Quantile of Recency = ', Q3)
print('Interquantile Range of Recency =', IQR)
```

```
25% Quantile of Recency =  20.0
75% Quantile of Recency =  195.0
Interquantile Range of Recency = 175.0
```

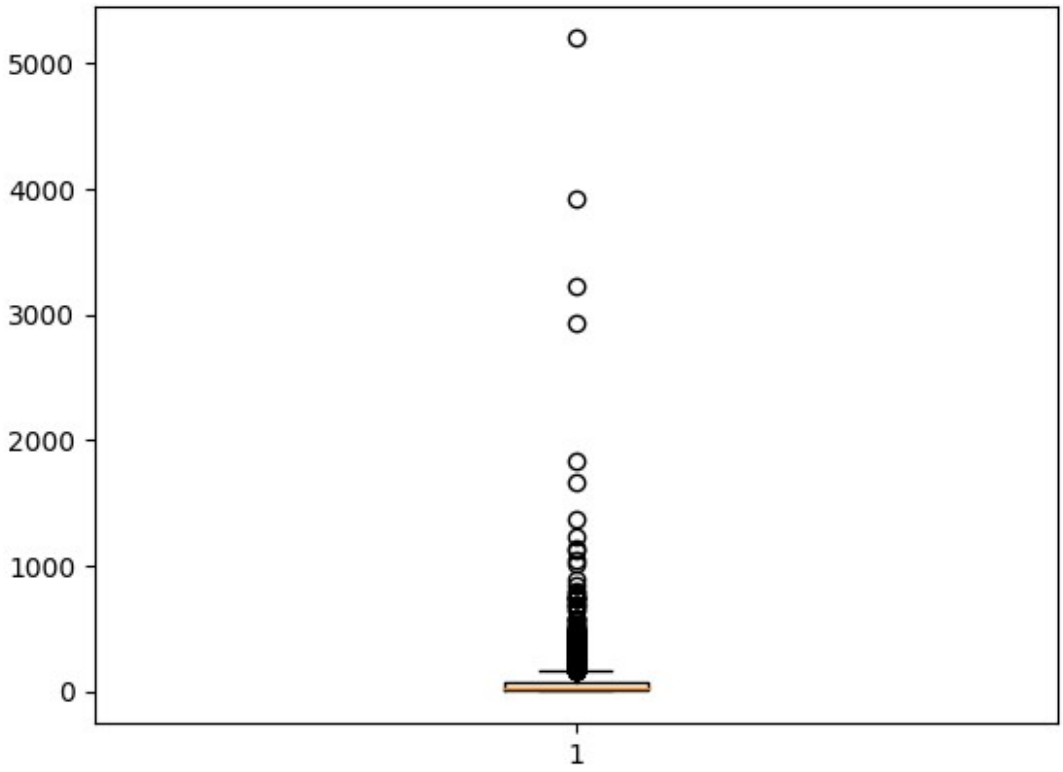
```
KMeans_X = KMeans_X[(KMeans_X.Recency >= Q1-1.5*IQR) &
(KMeans_X.Recency <= Q3+1.5*IQR)]
KMeans_X
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5597       99711      275          1    764.12                1
5598       99764      356        465   5489.81                1
5599       99821      209          2     17.50                1
5600       99880       33          3      2.09                3
5601       99881       50         47   1575.67                3
```

```
     Frequency_Quantile Monetary_Quantile  RFM_Score RFM_Segment  \
0                     4                 3        243         MVC
1                     1                 1        111         MVC
2                     1                 1        411         MVC
3                     1                 1        211         MVC
4                     3                 3        133         MVC
...                 ...               ...        ...         ...
5597                  1                 3        113         CBC
5598                  4                 4        144         MVC
5599                  1                 1        111         MVC
5600                  1                 1        311         MVC
5601                  3                 4        334         MVC

                  Segment_name
0     Minimum Viable Customers
1     Minimum Viable Customers
2     Minimum Viable Customers
3     Minimum Viable Customers
4     Minimum Viable Customers
...                        ...
5597    Churned Best Customers
5598  Minimum Viable Customers
5599  Minimum Viable Customers
5600  Minimum Viable Customers
5601  Minimum Viable Customers

[5602 rows x 10 columns]
```

```
plt.boxplot(KMeans_X.Frequency)
```

```
{'whiskers': [<matplotlib.lines.Line2D at 0x24b60775210>,
  <matplotlib.lines.Line2D at 0x24b605029d0>],
 'caps': [<matplotlib.lines.Line2D at 0x24b60502e50>,
  <matplotlib.lines.Line2D at 0x24b60503850>],
 'boxes': [<matplotlib.lines.Line2D at 0x24b61581a10>],
 'medians': [<matplotlib.lines.Line2D at 0x24b60500ad0>],
 'fliers': [<matplotlib.lines.Line2D at 0x24b60500850>],
 'means': []}
```



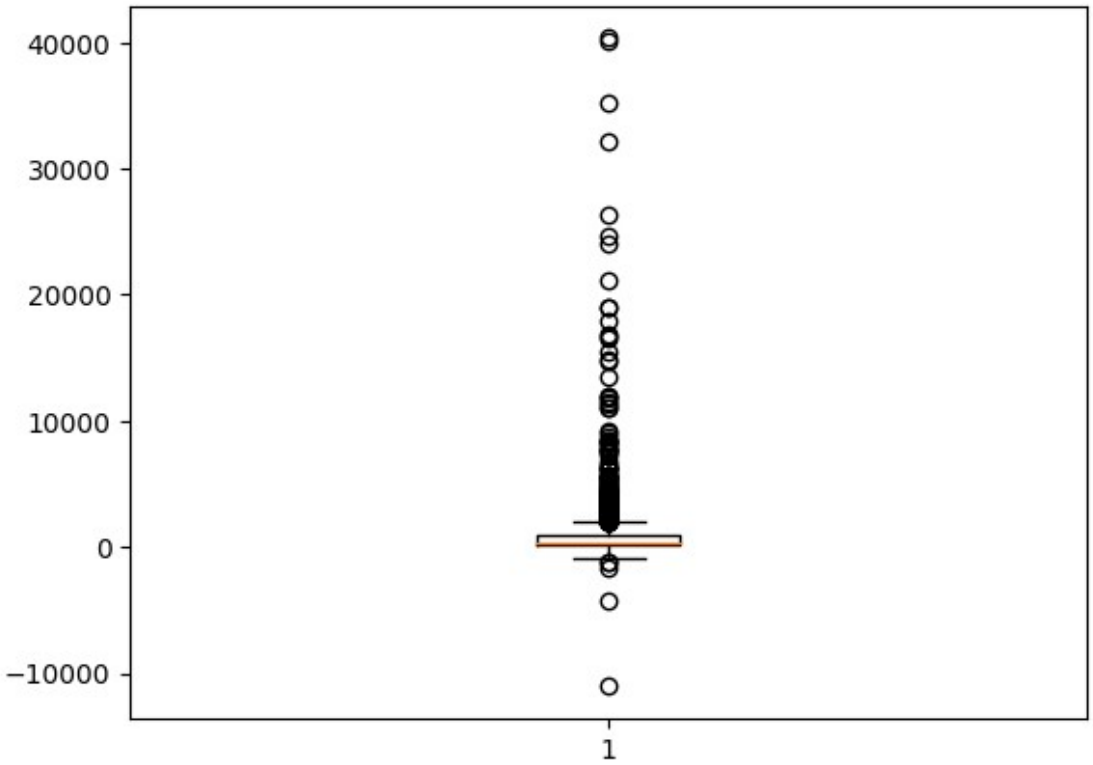

```
Q1 = KMeans_X.Frequency.quantile(.25)
Q3 = KMeans_X.Frequency.quantile(.75)
IQR = Q3 - Q1
print('25% Quantile of Frequency = ', Q1)
print('75% Quantile of Frequency = ', Q3)
print('Interquantile Range of Frequency =', IQR)
```

```
25% Quantile of Frequency =  10.0
75% Quantile of Frequency =  73.0
Interquantile Range of Frequency = 63.0
```

```
KMeans_X = KMeans_X[(KMeans_X.Frequency >= Q1-1.5*IQR) &
(KMeans_X.Frequency <= Q3+1.5*IQR)]
KMeans_X
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
5596       99707       61          1      4.15                3
5597       99711      275          1    764.12                1
```

```
5599       99821      209           2     17.50                1
5600       99880       33           3      2.09                3
5601       99881       50          47   1575.67                3

     Frequency_Quantile Monetary_Quantile  RFM_Score RFM_Segment  \
0                      4                 3        243         MVC
1                      1                 1        111         MVC
2                      1                 1        411         MVC
3                      1                 1        211         MVC
4                      3                 3        133         MVC
...                  ...               ...        ...         ...
5596                   1                 1        311         MVC
5597                   1                 3        113         CBC
5599                   1                 1        111         MVC
5600                   1                 1        311         MVC
5601                   3                 4        334         MVC

                  Segment_name
0     Minimum Viable Customers
1     Minimum Viable Customers
2     Minimum Viable Customers
3     Minimum Viable Customers
4     Minimum Viable Customers
...                        ...
5596  Minimum Viable Customers
5597    Churned Best Customers
5599  Minimum Viable Customers
5600  Minimum Viable Customers
5601  Minimum Viable Customers

[5123 rows x 10 columns]

plt.boxplot(KMeans_X.Monetary)

{'whiskers': [<matplotlib.lines.Line2D at 0x24b5f23df50>,
  <matplotlib.lines.Line2D at 0x24b5f23f190>],
 'caps': [<matplotlib.lines.Line2D at 0x24b64156750>,
  <matplotlib.lines.Line2D at 0x24b603fea10>],
 'boxes': [<matplotlib.lines.Line2D at 0x24b5ee34050>],
 'medians': [<matplotlib.lines.Line2D at 0x24b5f259d50>],
 'fliers': [<matplotlib.lines.Line2D at 0x24b5f258b10>],
 'means': []}
```




```
Q1 = KMeans_X.Monetary.quantile(.25)
Q3 = KMeans_X.Monetary.quantile(.75)
IQR = Q3 - Q1
print('25% Quantile of Monetary = ', Q1)
print('75% Quantile of Monetary = ', round((Q3),1))
print('Interquantile Range of Monetary =', round((IQR),1))
```

```
25% Quantile of Monetary =  150.275
75% Quantile of Monetary =  884.8
Interquantile Range of Monetary = 734.5
```

```
KMeans_X = KMeans_X[(KMeans_X.Monetary >= Q1-1.5*IQR) &
(KMeans_X.Monetary <= Q3+1.5*IQR)]
KMeans_Data = KMeans_X.copy().reset_index(drop=True)
KMeans_Data
```

```
      CustomerID  Recency  Frequency  Monetary Recency_Quantile  \
0          10044       92        153   1014.98                2
1          10115      208          1      6.20                1
2          10156        5          6     10.00                4
3          10217      168          7     57.92                2
4          10421      246         44    577.05                1
...          ...      ...        ...       ...              ...
4755       99707       61          1      4.15                3
4756       99711      275          1    764.12                1
4757       99821      209          2     17.50                1
4758       99880       33          3      2.09                3
```

```
4759       99881       50         47   1575.67                3

     Frequency_Quantile Monetary_Quantile  RFM_Score RFM_Segment  \
0                     4                 3        243         MVC
1                     1                 1        111         MVC
2                     1                 1        411         MVC
3                     1                 1        211         MVC
4                     3                 3        133         MVC
...                 ...               ...        ...         ...
4755                  1                 1        311         MVC
4756                  1                 3        113         CBC
4757                  1                 1        111         MVC
4758                  1                 1        311         MVC
4759                  3                 4        334         MVC

                  Segment_name
0     Minimum Viable Customers
1     Minimum Viable Customers
2     Minimum Viable Customers
3     Minimum Viable Customers
4     Minimum Viable Customers
...                        ...
4755  Minimum Viable Customers
4756    Churned Best Customers
4757  Minimum Viable Customers
4758  Minimum Viable Customers
4759  Minimum Viable Customers

[4760 rows x 10 columns]
```

Scaling Data

```
scaler = StandardScaler()
Scaled_Data = pd.DataFrame(scaler.fit_transform(KMeans_Data.iloc[:,
1:4]))
Scaled_Data
```

```
             0         1         2
0    -0.289332  3.250668  1.134169
1     0.772583 -0.937759 -1.039943
2    -1.085768 -0.799982 -1.031753
3     0.406405 -0.772426 -0.928476
4     1.120451  0.247125  0.190347
...        ...       ...       ...
4755 -0.573120 -0.937759 -1.044361
4756  1.385930 -0.937759  0.593519
4757  0.781737 -0.910204 -1.015589
4758 -0.829444 -0.882648 -1.048800
4759 -0.673819  0.329791  2.342563
```

```
[4760 rows x 3 columns]
```

Elbow method to fid the optimum value of K

```
Inertia = []
for i in range(1, 26):
    model = KMeans(n_clusters = i, init = 'k-means++', random_state =
0)
    model.fit(Scaled_Data)
    Inertia.append(model.inertia_)
```

```
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
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packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
```

```
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value of `n_init` explicitly to suppress the warning
```

```
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
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  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
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of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
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c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
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  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
```

```python
clusters = range(1, 26)
df_elbow = pd.DataFrame(columns = ['No_of_Clusters', 'Cost'])
df_elbow['No_of_Clusters'] = clusters
df_elbow['Cost'] = Inertia

df_elbow.to_csv('Cost_Clusters.csv')

plt.figure(figsize = (15, 5))
plt.plot(range(1, 26), Inertia)
plt.xlabel('No. of Clusters')
plt.ylabel('Inertia')
```

The last elbow is at 3.

```
KMeans_model = KMeans(n_clusters = 3, init = 'k-means++', random_state
= 0)
Clusters = KMeans_model.fit_predict(Scaled_Data)
```

```
c:\Users\ADMIN\AppData\Local\Programs\Python\Python311\Lib\site-
packages\sklearn\cluster\_kmeans.py:870: FutureWarning: The default
value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
```

```
KMeans_model.labels_
```

```
array([2, 1, 0, ..., 1, 0, 2])
```

```
KMeans_model.inertia_
```

```
5101.027360596687
```

```
KMeans_model.cluster_centers_
```

```
array([[-0.6372947 , -0.34649842, -0.31513304],
       [ 1.18535916, -0.54945803, -0.59520279],
       [-0.39248443,  1.43766038,  1.43956073]])
```

```
KMeans_Data['Cluster_ID'] = KMeans_model.labels_
KMeans_Data
```

	CustomerID	Recency	Frequency	Monetary	Recency_Quantile	\
0	10044	92	153	1014.98	2	
1	10115	208	1	6.20	1	
2	10156	5	6	10.00	4	
3	10217	168	7	57.92	2	
4	10421	246	44	577.05	1	
...	...	...	...	...	...	
4755	99707	61	1	4.15	3	
4756	99711	275	1	764.12	1	
4757	99821	209	2	17.50	1	
4758	99880	33	3	2.09	3	
4759	99881	50	47	1575.67	3	

	Frequency_Quantile	Monetary_Quantile	RFM_Score	RFM_Segment	\
0	4	3	243	MVC	
1	1	1	111	MVC	
2	1	1	411	MVC	
3	1	1	211	MVC	
4	3	3	133	MVC	
...	...	...	...	...	
4755	1	1	311	MVC	
4756	1	3	113	CBC	
4757	1	1	111	MVC	
4758	1	1	311	MVC	
4759	3	4	334	MVC	

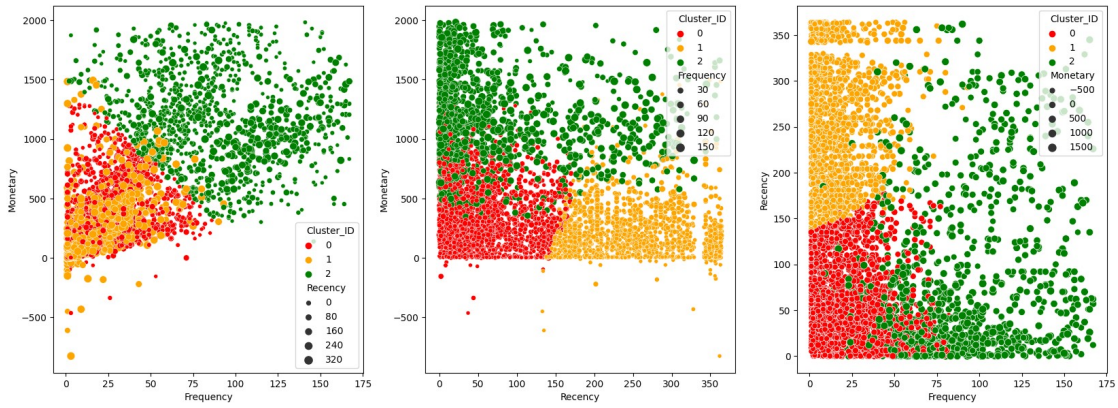
```
                  Segment_name  Cluster_ID
0     Minimum Viable Customers           2
1     Minimum Viable Customers           1
2     Minimum Viable Customers           0
3     Minimum Viable Customers           1
4     Minimum Viable Customers           1
...                        ...         ...
4755  Minimum Viable Customers           0
4756    Churned Best Customers           1
4757  Minimum Viable Customers           1
4758  Minimum Viable Customers           0
4759  Minimum Viable Customers           2

[4760 rows x 11 columns]
```

```
print('Count of Customers in each Clusters :')
print('====================================')
KMeans_Data.Cluster_ID.value_counts()
```

```
Count of Customers in each Clusters :
====================================

0    2146
1    1519
2    1095
Name: Cluster_ID, dtype: int64
```

```
fig, axs = plt.subplots(1,3, figsize=(20, 7))
sns.scatterplot(data=KMeans_Data, x='Frequency', y='Monetary',
hue='Cluster_ID', size='Recency',
                palette=['Red', 'Orange', 'Green'] , ax=axs[0])

sns.scatterplot(data=KMeans_Data, x='Recency', y='Monetary',
hue='Cluster_ID', size='Frequency',
                palette=['Red', 'Orange', 'Green'] ,ax=axs[1])

sns.scatterplot(data=KMeans_Data, x='Frequency', y='Recency',
hue='Cluster_ID', size='Monetary',
                palette=['Red', 'Orange', 'Green'] ,ax=axs[2])
```

```
<AxesSubplot: xlabel='Frequency', ylabel='Recency'>
```




```
Avg = pd.DataFrame(KMeans_Data.groupby('Cluster_ID',
as_index=False).aggregate({'Recency': 'mean',

'Frequency':'mean',

'Monetary':'mean'}))
Avg.rename(columns={'Recency':'Avg_Recency',
'Frequency':'Avg_Frequency', 'Monetary':'Avg_Monetary'}, inplace=True)
Avg
```

	Cluster_ID	Avg_Recency	Avg_Frequency	Avg_Monetary
0	0	53.875582	22.491612	343.343370
1	1	252.942067	15.080974	212.308934
2	2	80.846575	87.284018	1157.114530

```
fig, axs = plt.subplots(1,3, figsize=(20,5))
sns.barplot(x="Cluster_ID", y="Avg_Recency", data=Avg, palette=['Red',
'Orange', 'Green'], ax=axs[0])
sns.barplot(x="Cluster_ID", y="Avg_Frequency", data=Avg,
palette=['Red', 'Orange', 'Green'], ax=axs[1])
sns.barplot(x="Cluster_ID", y="Avg_Monetary", data=Avg,
palette=['Red', 'Orange', 'Green'], ax=axs[2])
```

```
<AxesSubplot: xlabel='Cluster_ID', ylabel='Avg_Monetary'>
```