# Retail

## Data Cleaning:

## Week 1

In [4]:

```
import pandas as pd
import numpy as np
import seaborn as sns
from operator import attrgetter
import matplotlib.colors as mcolors
import matplotlib.pyplot as plt
import datetime as dt
from scipy.stats import skewnorm
import scipy.stats as stats
from sklearn.preprocessing import LabelEncoder
import pylab as p
from sklearn.preprocessing import StandardScaler
```

In [5]:

```
df=pd.read_excel('Online Retail.xlsx',sheet_name='Online Retail')
```

In [6]:

```
df.head()
```

Out[6]:

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

## Data Cleaning

### 1. Perform a preliminary data inspection and data cleaning.

#### a) Check For missing Data and formulate an apt strategy to treat them.

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
InvoiceNo            0
StockCode            0
Description       1454
Quantity             0
InvoiceDate          0
UnitPrice            0
CustomerID      135080
Country              0
dtype: int64
```

In [8]:

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

In [9]:

```
df.isnull().sum()
```

Out[9]:

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

### b) Remove duplicate data records.

In [10]:

```
df.duplicated().sum()
```

Out[10]:

```
5225
```

In [11]:

```
df=df.drop_duplicates()
```

In [12]:

```
df.duplicated().sum()
```

Out[12]:

```
0
```

### c) Perform descriptive analytics on the given data.

#### Country

In [13]:

```
pd.DataFrame(df['Country'].unique())
```

Out[13]:

| | 0 |
|---|---|
| 0 | United Kingdom |
| 1 | France |
| 2 | Australia |
| 3 | Netherlands |
| 4 | Germany |

| | |
|---|---|
| 5 | Norway |
| 6 | EIRE |
| 7 | Switzerland |
| 8 | Spain |
| 9 | Poland |
| 10 | Portugal |
| 11 | Italy |
| 12 | Belgium |
| 13 | Lithuania |
| 14 | Japan |
| 15 | Iceland |
| 16 | Channel Islands |
| 17 | Denmark |
| 18 | Cyprus |
| 19 | Sweden |
| 20 | Austria |
| 21 | Israel |
| 22 | Finland |
| 23 | Greece |
| 24 | Singapore |
| 25 | Lebanon |
| 26 | United Arab Emirates |
| 27 | Saudi Arabia |
| 28 | Czech Republic |
| 29 | Canada |
| 30 | Unspecified |
| 31 | Brazil |
| 32 | USA |
| 33 | European Community |
| 34 | Bahrain |
| 35 | Malta |
| 36 | RSA |

## Total Customers

In [14]:

In [14]:
```
len(df['CustomerID'].unique())
```

Out[14]:
```
4372
```

## Majority of Customer country wise

In [15]:
```
c=pd.DataFrame(df.groupby('Country')['CustomerID'].nunique())
```

In [16]:
```
customercoutrywise=pd.DataFrame(c).sort_values(by='CustomerID', ascending=False)
```

In [17]:
```
customercoutrywise
```

Out[17]:

| Country | CustomerID |
|---|---|
| United Kingdom | 3950 |
| Germany | 95 |
| France | 87 |
| Spain | 31 |
| Belgium | 25 |
| Switzerland | 21 |
| Portugal | 19 |
| Italy | 15 |
| Finland | 12 |
| Austria | 11 |
| Norway | 10 |
| Netherlands | 9 |
| Australia | 9 |
| Denmark | 9 |
| Channel Islands | 9 |
| Cyprus | 8 |
| Sweden | 8 |
| Japan | 8 |
| Poland | 6 |
| USA | 4 |
| Canada | 4 |
| Unspecified | 4 |
| Israel | 4 |

| | |
|---|---|
| **Greece** | 4 |
| **EIRE** | 3 |
| **Malta** | 2 |
| **United Arab Emirates** | 2 |
| **Bahrain** | 2 |
| **Czech Republic** | 1 |
| **Lithuania** | 1 |
| **Lebanon** | 1 |
| **RSA** | 1 |
| **Saudi Arabia** | 1 |
| **Singapore** | 1 |
| **Iceland** | 1 |
| **Brazil** | 1 |
| **European Community** | 1 |

### Customer Order More than one item

In [18]:

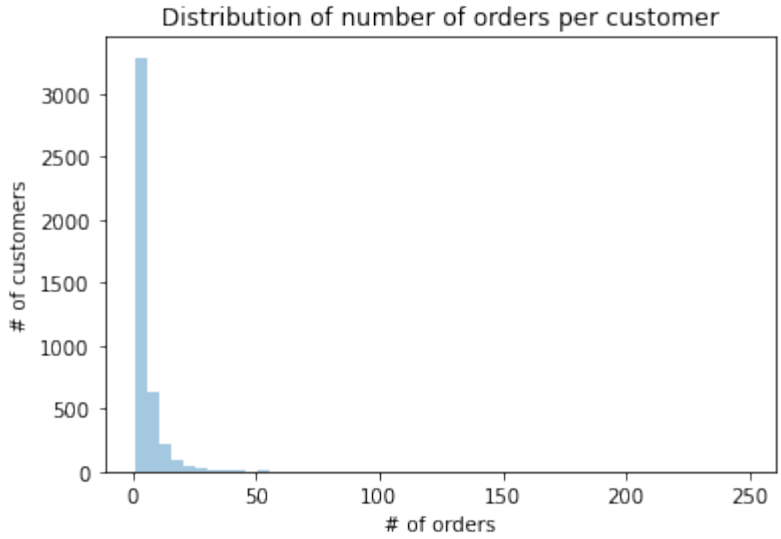
```
n_orders = df.groupby(['CustomerID'])['InvoiceNo'].nunique()
mult_orders_perc = np.sum(n_orders > 1) / df['CustomerID'].nunique()
print(f'{100 * mult_orders_perc:.2f}% of customers ordered more than one item.')
```

```
69.97% of customers ordered more than one item.
```

In [25]:

```
ax = sns.distplot(n_orders, kde=False, hist=True)
ax.set(title='Distribution of number of orders per customer',
       xlabel='# of orders',
       ylabel='# of customers');
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt your c
ode to use either `displot` (a figure-level function with similar flexibility) or `histplot`
 (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```




# Data Transformation

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

In [26]:

```
df['order_month'] = df['InvoiceDate'].dt.to_period('M')
```

In [27]:

```
df['cohort'] = df.groupby('CustomerID')['InvoiceDate'] \
                 .transform('min') \
                 .dt.to_period('M')
```

In [28]:

```
df_cohort=pd.DataFrame(df.groupby(['cohort', 'order_month']) \
              .agg(n_customers=('CustomerID', 'nunique')) \
              .reset_index(drop=False))
```

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

In [29]:

```
df_cohort['period_number'] = (df_cohort.order_month -
df_cohort.cohort).apply(attrgetter('n'))
df_cohort
```

Out[29]:

| | cohort | order_month | n_customers | period_number |
|---|---|---|---|---|
| **0** | 2010-12 | 2010-12 | 948 | 0 |
| **1** | 2010-12 | 2011-01 | 362 | 1 |
| **2** | 2010-12 | 2011-02 | 317 | 2 |
| **3** | 2010-12 | 2011-03 | 367 | 3 |
| **4** | 2010-12 | 2011-04 | 341 | 4 |

| | | | | |
|---|---|---|---|---|
| ... | ... | ... | ... | ... |
| **86** | 2011-10 | 2011-11 | 93 | 1 |
| **87** | 2011-10 | 2011-12 | 46 | 2 |
| **88** | 2011-11 | 2011-11 | 321 | 0 |
| **89** | 2011-11 | 2011-12 | 43 | 1 |
| **90** | 2011-12 | 2011-12 | 41 | 0 |

91 rows × 4 columns

In [30]:

```
cohort_pivot = df_cohort.pivot_table(index = 'cohort',
                                     columns = 'period_number',
                                     values = 'n_customers')
cohort_pivot
```

Out[30]:

| period_number | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **cohort** | | | | | | | | | | | | | |
| **2010-12** | 948.0 | 362.0 | 317.0 | 367.0 | 341.0 | 376.0 | 360.0 | 336.0 | 336.0 | 374.0 | 354.0 | 474.0 | 260.0 |
| **2011-01** | 421.0 | 101.0 | 119.0 | 102.0 | 138.0 | 126.0 | 110.0 | 108.0 | 131.0 | 146.0 | 155.0 | 63.0 | NaN |
| **2011-02** | 380.0 | 94.0 | 73.0 | 106.0 | 102.0 | 94.0 | 97.0 | 107.0 | 98.0 | 119.0 | 35.0 | NaN | NaN |
| **2011-03** | 440.0 | 84.0 | 112.0 | 96.0 | 102.0 | 78.0 | 116.0 | 105.0 | 127.0 | 39.0 | NaN | NaN | NaN |
| **2011-04** | 299.0 | 68.0 | 66.0 | 63.0 | 62.0 | 71.0 | 69.0 | 78.0 | 25.0 | NaN | NaN | NaN | NaN |
| **2011-05** | 279.0 | 66.0 | 48.0 | 48.0 | 60.0 | 68.0 | 74.0 | 29.0 | NaN | NaN | NaN | NaN | NaN |
| **2011-06** | 235.0 | 49.0 | 44.0 | 64.0 | 58.0 | 79.0 | 24.0 | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-07** | 191.0 | 40.0 | 39.0 | 44.0 | 52.0 | 22.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-08** | 167.0 | 42.0 | 42.0 | 42.0 | 23.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-09** | 298.0 | 89.0 | 97.0 | 36.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-10** | 352.0 | 93.0 | 46.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-11** | 321.0 | 43.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-12** | 41.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

In [31]:

```
cohort_size = cohort_pivot.iloc[:,0]
retention_matrix = cohort_pivot.divide(cohort_size, axis = 0)
```

## b. Analyze the retention rate of customers.

In [34]:

```
retention_matrix
```

Out[34]:

| period_number | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|

| cohort | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **2010-12** | 1.0 | 0.381857 | 0.334388 | 0.387131 | 0.359705 | 0.396624 | 0.379747 | 0.354430 | 0.354430 | 0.394515 | 0.373418 | 0.500000 |
| **2011-01** | 1.0 | 0.239905 | 0.282660 | 0.242280 | 0.327791 | 0.299287 | 0.261283 | 0.256532 | 0.311164 | 0.346793 | 0.368171 | 0.149644 |
| **2011-02** | 1.0 | 0.247368 | 0.192105 | 0.278947 | 0.268421 | 0.247368 | 0.255263 | 0.281579 | 0.257895 | 0.313158 | 0.092105 | NaN |
| **2011-03** | 1.0 | 0.190909 | 0.254545 | 0.218182 | 0.231818 | 0.177273 | 0.263636 | 0.238636 | 0.288636 | 0.088636 | NaN | NaN |
| **2011-04** | 1.0 | 0.227425 | 0.220736 | 0.210702 | 0.207358 | 0.237458 | 0.230769 | 0.260870 | 0.083612 | NaN | NaN | NaN |
| **2011-05** | 1.0 | 0.236559 | 0.172043 | 0.172043 | 0.215054 | 0.243728 | 0.265233 | 0.103943 | NaN | NaN | NaN | NaN |
| **2011-06** | 1.0 | 0.208511 | 0.187234 | 0.272340 | 0.246809 | 0.336170 | 0.102128 | NaN | NaN | NaN | NaN | NaN |
| **2011-07** | 1.0 | 0.209424 | 0.204188 | 0.230366 | 0.272251 | 0.115183 | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-08** | 1.0 | 0.251497 | 0.251497 | 0.251497 | 0.137725 | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-09** | 1.0 | 0.298658 | 0.325503 | 0.120805 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-10** | 1.0 | 0.264205 | 0.130682 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-11** | 1.0 | 0.133956 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |
| **2011-12** | 1.0 | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN | NaN |

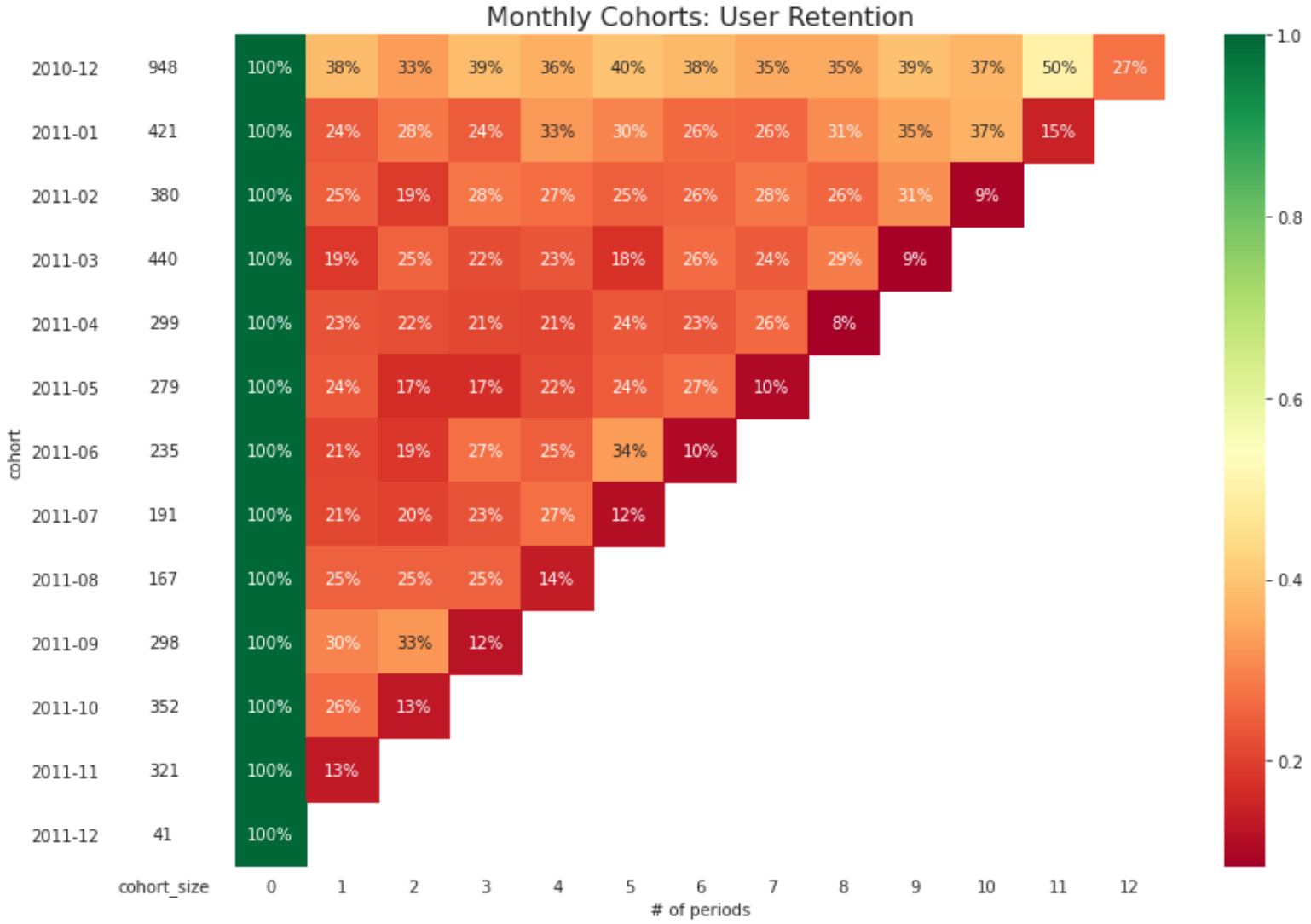
In [35]:

```
with sns.axes_style("white"):
    fig, ax = plt.subplots(1, 2, figsize=(12, 8), sharey=True,
gridspec_kw={'width_ratios': [1, 11]})

    # retention matrix
    sns.heatmap(retention_matrix,
                mask=retention_matrix.isnull(),
                annot=True,
                fmt='.0%',
                cmap='RdYlGn',
                ax=ax[1])
    ax[1].set_title('Monthly Cohorts: User Retention', fontsize=16)
    ax[1].set(xlabel='# of periods',
              ylabel='')

    # cohort size
    cohort_size_df = pd.DataFrame(cohort_size).rename(columns={0: 'cohort_size'})
    white_cmap = mcolors.ListedColormap(['white'])
    sns.heatmap(cohort_size_df,
                annot=True,
                cbar=False,
                fmt='g',
                cmap=white_cmap,
                ax=ax[0])

    fig.tight_layout()
```




# Week 2

Build RFM model

In [36]:

```
df['InvoiceDate'].max()
```

Out[36]:

```
Timestamp('2011-12-09 12:50:00')
```

Latest Date is 2011-12-09 so in order to calculate recency we will use 2011-12-10

## RFM metrics

In [37]:

```
latestdate = dt.datetime(2011,12,10)
rfmtable=df.groupby('CustomerID').agg({'InvoiceDate': lambda x: (latestdate -
x.max()).days, 'InvoiceNo': lambda x: len(x),'UnitPrice': lambda x: x.sum()})
rfmtable=rfmtable.rename(columns={'InvoiceDate': 'recency',
                        'InvoiceNo': 'frequency',
                        'UnitPrice': 'monetary_value'})
rfmtable
```

Out[37]:

| CustomerID | recency | frequency | monetary_value |
|---|---|---|---|
| **12346.0** | 325 | 2 | 2.08 |
| **12347.0** | 2 | 182 | 481.21 |
| **12348.0** | 75 | 31 | 178.71 |
| **12349.0** | 18 | 73 | 605.10 |
| **12350.0** | 310 | 17 | 65.30 |
| **...** | ... | ... | ... |
| **18280.0** | 277 | 10 | 47.65 |
| **18281.0** | 180 | 7 | 39.36 |
| **18282.0** | 7 | 13 | 62.68 |
| **18283.0** | 3 | 721 | 1174.33 |
| **18287.0** | 42 | 70 | 104.55 |

4372 rows × 3 columns

# RFM segments

Quantile

In [38]:

```
quantiles = rfmtable.quantile(q=[0.25,0.5,0.75])
quantiles.to_dict()
```

Out[38]:

```
{'recency': {0.25: 16.0, 0.5: 50.0, 0.75: 143.0},
 'frequency': {0.25: 17.0, 0.5: 41.0, 0.75: 99.25},
 'monetary value': {0.25: 52.730000000000004, 0.5: 128.925, 0.75: 299.0975}}
```

In [39]:

```
segmented_rfm = rfmtable
```

Recency must be low

In [40]:

```
def recencyscore(x,p,d):
    if x <= d[p][0.25]:
        return 1
    elif x <= d[p][0.50]:
        return 2
    elif x <= d[p][0.75]:
        return 3
    else:
        return 4

def fmscore(x,p,d):
    if x <= d[p][0.25]:
        return 4
    elif x <= d[p][0.50]:
        return 3
```

```
    elif x <= d[p][0.75]:
        return 2
    else:
        return 1
```

In [41]:

```
segmented_rfm['r_quartile'] = segmented_rfm['recency'].apply(recencyscore,
args=('recency',quantiles,))
segmented_rfm['f_quartile'] = segmented_rfm['frequency'].apply(fmscore,
args=('frequency',quantiles,))
segmented_rfm['m_quartile'] = segmented_rfm['monetary_value'].apply(fmscore,
args=('monetary_value',quantiles,))
```

```
segmented_rfm.head()
```

Out[41]:

| CustomerID | recency | frequency | monetary_value | r_quartile | f_quartile | m_quartile |
|---|---|---|---|---|---|---|
| **12346.0** | 325 | 2 | 2.08 | 4 | 4 | 4 |
| **12347.0** | 2 | 182 | 481.21 | 1 | 1 | 1 |
| **12348.0** | 75 | 31 | 178.71 | 3 | 3 | 2 |
| **12349.0** | 18 | 73 | 605.10 | 2 | 2 | 1 |
| **12350.0** | 310 | 17 | 65.30 | 4 | 4 | 3 |

In [42]:

```
segmented_rfm.to_csv('SegmentedRFM.csv')
segmented_rfm['RFMScore'] =
segmented_rfm.r_quartile.map(str)+segmented_rfm.f_quartile.map(str)+segmented_rfm.m_quartile
```

```
segmented_rfm.head()
```

Out[42]:

| CustomerID | recency | frequency | monetary_value | r_quartile | f_quartile | m_quartile | RFMScore |
|---|---|---|---|---|---|---|---|
| **12346.0** | 325 | 2 | 2.08 | 4 | 4 | 4 | 444 |
| **12347.0** | 2 | 182 | 481.21 | 1 | 1 | 1 | 111 |
| **12348.0** | 75 | 31 | 178.71 | 3 | 3 | 2 | 332 |
| **12349.0** | 18 | 73 | 605.10 | 2 | 2 | 1 | 221 |
| **12350.0** | 310 | 17 | 65.30 | 4 | 4 | 3 | 443 |

## Customer Segementation according to RFM

In [43]:

```
pd.set_option("display.max_colwidth", 10000)
data = {'Customer Segement':['Best Customers', 'Loyal Customers', 'Big Spender', 'Almost
```

```
Lost','Lost Customers','Lost Cheap Customers'], 'RFM':['111', 'X1X', 'XX1',
'311','411','444'],'Desrciption':['Bought Most Recently and More Often', 'Buy Most
Frequently', 'Spend The Most', 'Did not purchased for some time but purchased frequently
and most','Did not purchased for some time but purchased frequently and most','Last
purchased long ago,purchased few and spent little']}
pd.DataFrame(data)
```

Out[43]:

| | Customer Segement | RFM | Desrciption |
|---|---|---|---|
| **0** | Best Customers | 111 | Bought Most Recently and More Often |
| **1** | Loyal Customers | X1X | Buy Most Frequently |
| **2** | Big Spender | XX1 | Spend The Most |
| **3** | Almost Lost | 311 | Did not purchased for some time but purchased frequently and most |
| **4** | Lost Customers | 411 | Did not purchased for some time but purchased frequently and most |
| **5** | Lost Cheap Customers | 444 | Last purchased long ago,purchased few and spent little |

# Week 3

## 1. Create clusters using k-means clustering algorithm.

In [44]:

```
cluster = segmented_rfm
cluster = cluster.reset_index(level=0).iloc[:,[2,3]].values

pd.DataFrame(cluster)
```

Out[44]:

| | 0 | 1 |
|---|---|---|
| **0** | 2.0 | 2.08 |
| **1** | 182.0 | 481.21 |
| **2** | 31.0 | 178.71 |
| **3** | 73.0 | 605.10 |
| **4** | 17.0 | 65.30 |
| **...** | ... | ... |
| **4367** | 10.0 | 47.65 |
| **4368** | 7.0 | 39.36 |
| **4369** | 13.0 | 62.68 |
| **4370** | 721.0 | 1174.33 |
| **4371** | 70.0 | 104.55 |

4372 rows × 2 columns

In [45]:

```
sc= StandardScaler()
```

```
cluster = sc.fit_transform(cluster)
```

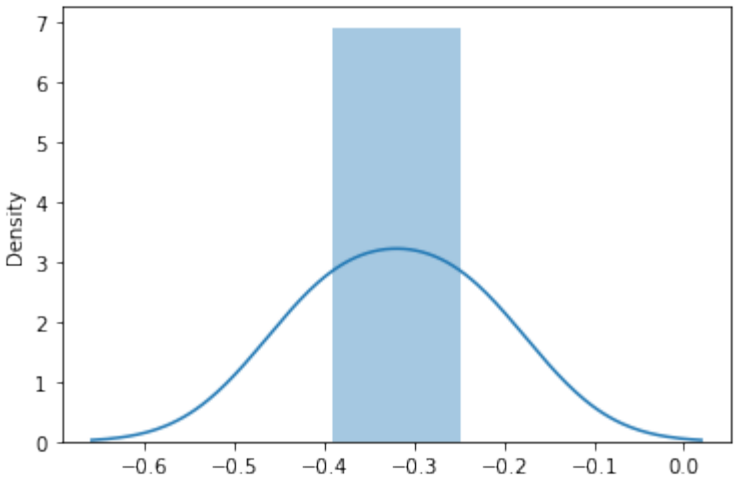
In [46]:

```
sns.distplot(cluster[0])
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt your c
ode to use either `displot` (a figure-level function with similar flexibility) or `histplot`
 (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[46]:

```
<AxesSubplot:ylabel='Density'>
```



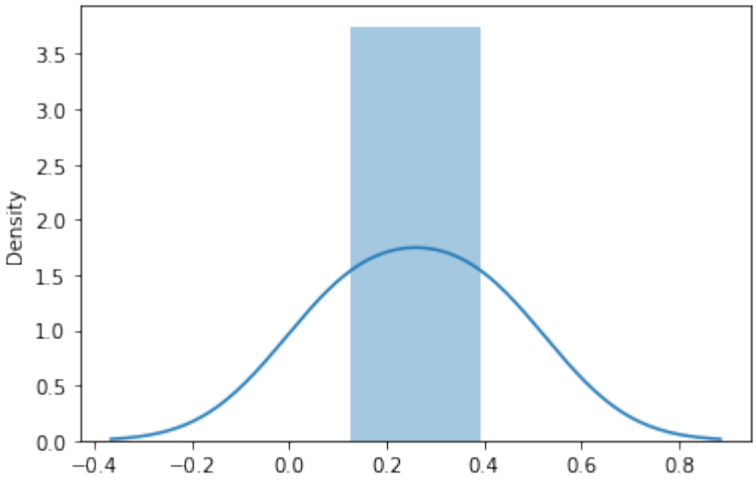

In [47]:

```
sns.distplot(cluster[1])
```

```
C:\Users\User\anaconda3\lib\site-packages\seaborn\distributions.py:2551: FutureWarning: `dis
tplot` is a deprecated function and will be removed in a future version. Please adapt your c
ode to use either `displot` (a figure-level function with similar flexibility) or `histplot`
 (an axes-level function for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[47]:

```
<AxesSubplot:ylabel='Density'>
```

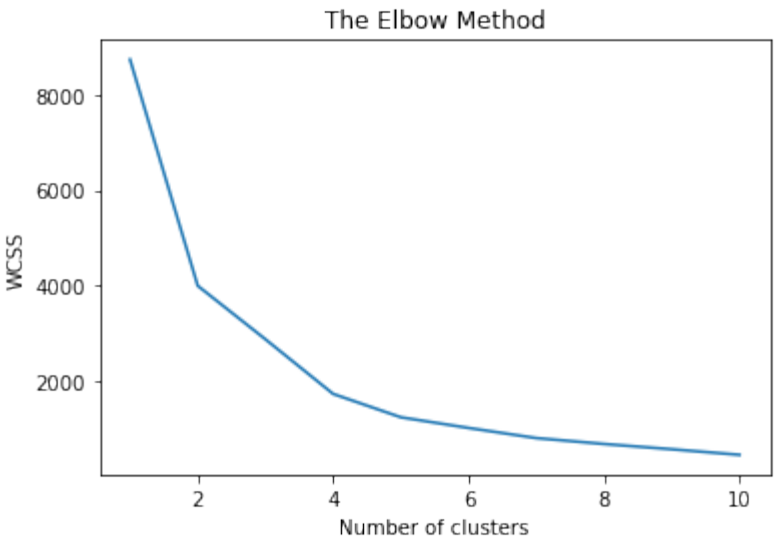



WCSS

In [48]:

```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    kmeans = KMeans(n_clusters = i, init = 'k-means++')
    kmeans.fit(cluster)
```

```
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS')
plt.show()
```




Optimum number of clusters to be formed is 4

In [49]:

```
kmeans = KMeans(n_clusters = 4, init = 'k-means++')
y_kmeans = kmeans.fit_predict(cluster)
plt.scatter(cluster[y_kmeans == 0, 0], cluster[y_kmeans == 0, 1], s = 5, c = 'red', label
= 'Lost Customer')
plt.scatter(cluster[y_kmeans == 1, 0], cluster[y_kmeans == 1, 1], s = 5, c = 'blue', label
= 'Loyal customer')
plt.scatter(cluster[y_kmeans == 2, 0], cluster[y_kmeans == 2, 1], s = 5, c = 'green',
label = 'Average Customers')
plt.scatter(cluster[y_kmeans == 3, 0], cluster[y_kmeans == 3, 1], s = 5, c = 'cyan', label
= 'Bought frequently but Spend less')
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s = 20, c =
'yellow', label = 'Centroids')
plt.title('Clusters of customers')
plt.xlabel('Total Spending')
plt.ylabel('Buying Frequency')
plt.legend()
plt.show()
```


Clusters of customers
Buying Frequency
Total Spending
Lost Customer
Loyal customer
Average Customers
Bought frequently but Spend less
Centroids
0
5
10
15
20
25
30
35

In [ ]: