This project analyze the online retail sales data (http://archive.ics.uci.edu/ml/datasets/online+retail) to understand the possible group of customers based on recency, frequency, and monetary values using K-means clustering.

In [1]:
```
# Import necessary libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

from scipy import stats
from sklearn.preprocessing import StandardScaler
from sklearn.manifold import TSNE
from sklearn.cluster import KMeans

import datetime as dt

import warnings
warnings.filterwarnings("ignore")
```

In [2]:
```
# read data
xls = pd.ExcelFile('Online Retail.xlsx')
data = pd.read_excel(xls, 'Online Retail')
```

In [3]:
```
print(data.head())
print(data.tail())
```

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

          InvoiceDate  UnitPrice  CustomerID         Country
0 2010-12-01 08:26:00       2.55     17850.0  United Kingdom
1 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
2 2010-12-01 08:26:00       2.75     17850.0  United Kingdom
3 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
4 2010-12-01 08:26:00       3.39     17850.0  United Kingdom
       InvoiceNo StockCode                       Description  Quantity  \
541904    581587     22613      PACK OF 20 SPACEBOY NAPKINS        12
541905    581587     22899     CHILDREN'S APRON DOLLY GIRL          6
541906    581587     23254    CHILDRENS CUTLERY DOLLY GIRL          4
541907    581587     23255  CHILDRENS CUTLERY CIRCUS PARADE         4
541908    581587     22138    BAKING SET 9 PIECE RETROSPOT          3

               InvoiceDate  UnitPrice  CustomerID Country
541904 2011-12-09 12:50:00       0.85     12680.0  France
541905 2011-12-09 12:50:00       2.10     12680.0  France
541906 2011-12-09 12:50:00       4.15     12680.0  France
541907 2011-12-09 12:50:00       4.15     12680.0  France
541908 2011-12-09 12:50:00       4.95     12680.0  France
```

In [4]:
```
data.shape
```

Out[4]: (541909, 8)

Exploratory Data Analysis

In [5]:
```
def summary(data, pred=None):
    obs = data.shape[0]
    types = data.dtypes
    counts = data.apply(lambda x: x.count())
    min = data.min()
    uniques = data.apply(lambda x: x.unique().shape[0])
    nulls = data.apply(lambda x: x.isnull().sum())
    print('Data shape:', data.shape)

    if pred is None:
        cols = ['types', 'counts', 'uniques', 'nulls', 'min']
        str = pd.concat([types, counts, uniques, nulls, min], axis = 1, sort = True)

    str.columns = cols
    #dtypes = str.types.value_counts()
    print('_____________________\nData types:')
    print(str.types.value_counts())
    print('_____________________')
    return str

details = summary(data)
display(details.sort_values(by='nulls', ascending=False))
```

```
Data shape: (541909, 8)
_____________________
Data types:
object            4
float64           2
int64             1
datetime64[ns]    1
Name: types, dtype: int64
_____________________
```

	types	counts	uniques	nulls	min
CustomerID	float64	406829	4373	135080	12346.0
Description	object	540455	4224	1454	NaN
Country	object	541909	38	0	Australia
InvoiceDate	datetime64[ns]	541909	23260	0	2010-12-01 08:26:00
InvoiceNo	object	541909	25900	0	NaN
Quantity	int64	541909	722	0	-80995
StockCode	object	541909	4070	0	NaN
UnitPrice	float64	541909	1630	0	-11062.06

In [6]:
```
data.describe()
```

Out[6]:

	Quantity	UnitPrice	CustomerID
count	541909.000000	541909.000000	406829.000000
mean	9.552250	4.611114	15287.690570
std	218.081158	96.759853	1713.600303
min	-80995.000000	-11062.060000	12346.000000
25%	1.000000	1.250000	13953.000000
50%	3.000000	2.080000	15152.000000
75%	10.000000	4.130000	16791.000000
max	80995.000000	38970.000000	18287.000000

The negative values of Quantity & UnitPrice might be due to cancellation of orders. So, lets check the rows with negative UnitPrice & Quantity.

In [7]:
```
data.loc[(data.UnitPrice<0)]
```

Out[7]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
299983	A563186	B	Adjust bad debt	1	2011-08-12 14:51:00	-11062.06	NaN	United Kingdom
299984	A563187	B	Adjust bad debt	1	2011-08-12 14:52:00	-11062.06	NaN	United Kingdom

In [8]:
```
data.loc[(data.Quantity<0)]
```

Out[8]:

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
141	C536379	D	Discount	-1	2010-12-01 09:41:00	27.50	14527.0	United Kingdom
154	C536383	35004C	SET OF 3 COLOURED FLYING DUCKS	-1	2010-12-01 09:49:00	4.65	15311.0	United Kingdom
235	C536391	22556	PLASTERS IN TIN CIRCUS PARADE	-12	2010-12-01 10:24:00	1.65	17548.0	United Kingdom
236	C536391	21984	PACK OF 12 PINK PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom
237	C536391	21983	PACK OF 12 BLUE PAISLEY TISSUES	-24	2010-12-01 10:24:00	0.29	17548.0	United Kingdom
...	...	...	...	...	...	...	...	...

	InvoiceNo	StockCode	Description	Quantity	InvoiceDate	UnitPrice	CustomerID	Country
540449	C581490	23144	ZINC T-LIGHT HOLDER STARS SMALL	-11	2011-12-09 09:57:00	0.83	14397.0	United Kingdom
541541	C581499	M	Manual	-1	2011-12-09 10:28:00	224.69	15498.0	United Kingdom
541715	C581568	21258	VICTORIAN SEWING BOX LARGE	-5	2011-12-09 11:57:00	10.95	15311.0	United Kingdom
541716	C581569	84978	HANGING HEART JAR T-LIGHT HOLDER	-1	2011-12-09 11:58:00	1.25	17315.0	United Kingdom
541717	C581569	20979	36 PENCILS TUBE RED RETROSPOT	-5	2011-12-09 11:58:00	1.25	17315.0	United Kingdom

10624 rows × 8 columns

There are 10624 rows with negative quantity and 2 rows with negative Unit Price.

In [9]:
```
# lets check the null values
data.isnull().mean()*100
```

Out[9]:
```
InvoiceNo       0.000000
StockCode       0.000000
Description     0.268311
Quantity        0.000000
InvoiceDate     0.000000
UnitPrice       0.000000
CustomerID     24.926694
Country         0.000000
dtype: float64
```

25% rows don't have CustomerID, can we drop them? Description we can fill?

In [10]:
```
# find customer counts based on countries
data.Country.value_counts(normalize=True)
```

Out[10]:
```
United Kingdom          0.914320
Germany                 0.017521
France                  0.015790
EIRE                    0.015124
Spain                   0.004674
Netherlands             0.004375
Belgium                 0.003818
Switzerland             0.003694
Portugal                0.002803
Australia               0.002323
Norway                  0.002004
Italy                   0.001482
Channel Islands         0.001399
Finland                 0.001283
```

```
Cyprus                  0.001148
Sweden                  0.000853
Unspecified             0.000823
Austria                 0.000740
Denmark                 0.000718
Japan                   0.000661
Poland                  0.000629
Israel                  0.000548
USA                     0.000537
Hong Kong               0.000531
Singapore               0.000423
Iceland                 0.000336
Canada                  0.000279
Greece                  0.000269
Malta                   0.000234
United Arab Emirates    0.000125
European Community      0.000113
RSA                     0.000107
Lebanon                 0.000083
Lithuania               0.000065
Brazil                  0.000059
Czech Republic          0.000055
Bahrain                 0.000035
Saudi Arabia            0.000018
Name: Country, dtype: float64
```

United Kingdom contribute 91% rows, lets only keep data for United Kingdom for easyness to analyze customer behaviors

In [11]:
```
data = data[data.Country == 'United Kingdom']
```

Lets remove the rows with negative value of Unit Price and Quantity

In [12]:
```
data = data[data.Quantity > 0]
data = data[data.UnitPrice > 0]
```

Remove the rows with CustomerID as null

In [13]:
```
data = data[pd.notnull(data['CustomerID'])]
```

Lets convert the dateteime to the date we can use in our analysis

In [14]:
```
data['InvoiceDate'] = pd.to_datetime(data['InvoiceDate'])
data['InvoiceYearMonth'] = data['InvoiceDate'].map(lambda date: 100*date.year + date.mo
data['Date'] = data['InvoiceDate'].dt.strftime('%Y-%m')
```

In [15]:
```
# Lets check the null values.
print(data.isnull().mean()*100)

print('_____________________\nData types:')

# lets see the number of table rows and columns
print(data.shape)
```

```
InvoiceNo           0.0
StockCode           0.0
Description         0.0
```

```
Quantity            0.0
InvoiceDate         0.0
UnitPrice           0.0
CustomerID          0.0
Country             0.0
InvoiceYearMonth    0.0
Date                0.0
dtype: float64

____________________
Data types:
(354321, 10)
```

In [16]:

```
# Aggregate the orders by Month

data_agg_month = data.groupby("Date").Quantity.sum()
data_agg_month
```

Out[16]:

```
Date
2010-12    267767
2011-01    278251
2011-02    213375
2011-03    276304
2011-04    260448
2011-05    301824
2011-06    280974
2011-07    303601
2011-08    310831
2011-09    454559
2011-10    476984
2011-11    571215
2011-12    260607
Name: Quantity, dtype: int64
```

In [17]:

```
# convert above data into a dataframe so we can plot graph
data_agg_month = pd.DataFrame(data_agg_month)
data_agg_month = data_agg_month.reset_index()
data_agg_month.head()
```

Out[17]:

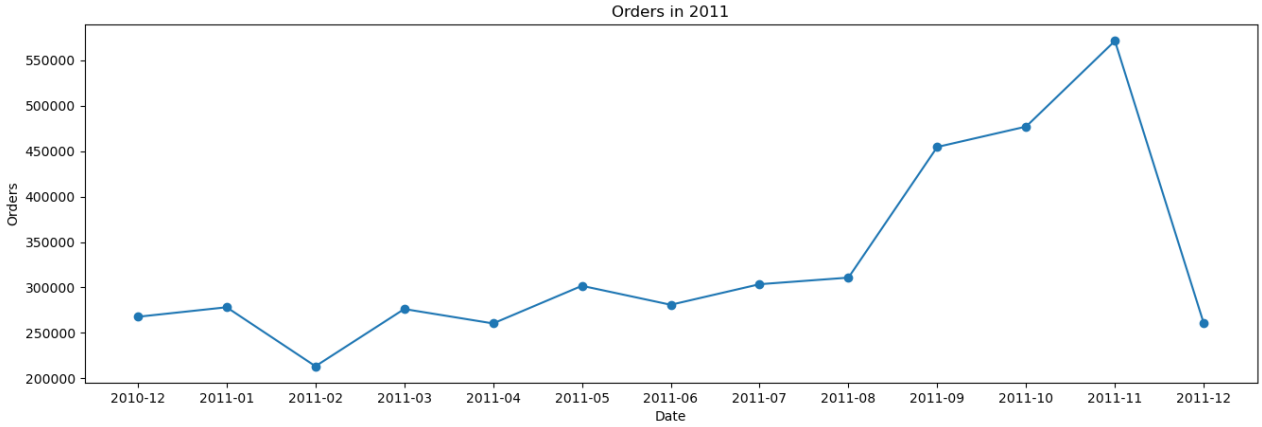
	Date	Quantity
0	2010-12	267767
1	2011-01	278251
2	2011-02	213375
3	2011-03	276304
4	2011-04	260448

How about plotting the quantity (orders) by month?

In [18]:

```
# lets first a function for plotting:

def plot_data(data, x, y, title="", xlabel = 'Date', ylabel = 'Orders', dpi = 100):
    plt.figure(figsize=(16,5), dpi=dpi)
    plt.gca().set(title=title, xlabel=xlabel, ylabel=ylabel)
    plt.plot(x,y, color='tab:Blue', marker='o')
    plt.show()
```

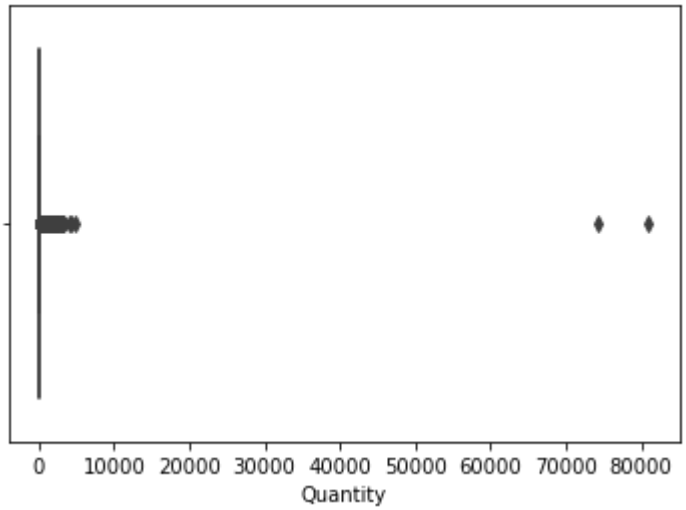
In [19]:
```
# Plot Quantity vs Month

plot_data(data_agg_month, x=data_agg_month.Date, y=data_agg_month.Quantity, title='Orde
```



What about Revenue by month?

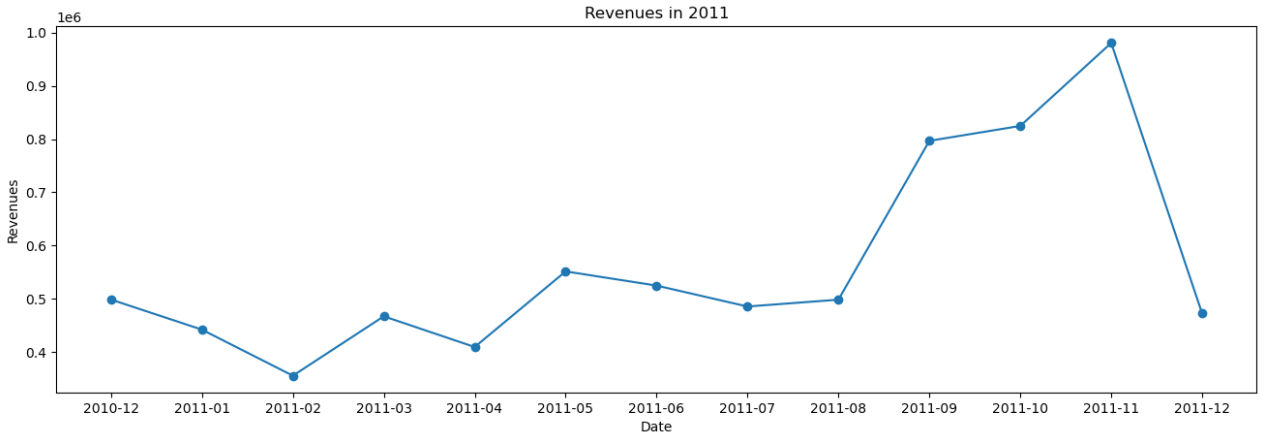
In [20]:
```
# Lets create 'Revenue' from 'Quantity' & 'UnitPrice'

data['Revenue'] = data['Quantity']*data['UnitPrice']
sns.boxplot(x=data['Quantity'])
```

Out[20]: <AxesSubplot:xlabel='Quantity'>



In [21]:
```
# Lets create a table of date with Revenue and plot:

data_revenue = data.groupby(['Date'])['Revenue'].sum().reset_index()
print(data_revenue.head())

plot_data(data_revenue, x=data_revenue.Date, y=data_revenue.Revenue, xlabel = 'Date', y
```

```
      Date     Revenue
0  2010-12  498661.850
1  2011-01  442190.060
2  2011-02  355655.630
3  2011-03  467198.590
4  2011-04  409559.141
```



Both Quantity and Revenue plot follows the same pattern, higher in November.

RFM (Recency - Frequency - Monetary) Analysis

In [22]:
```
# The RFM Analysis clusters/segments customers based on their recent purchase behavior,
# the total money spent by each customers.

# Last date in our data is 2011-12-09, and this will be used to calculate the recency
NOW = dt.date(2011,12,9)
data['Date'] = pd.DatetimeIndex(data.InvoiceDate).date
```

Recency

In [23]:
```
data_recency = data.groupby(['CustomerID'], as_index=False)['Date'].max()
data_recency.columns = ['CustomerID', 'Last_Purchase_Date']

data_recency['Recency'] = data_recency.Last_Purchase_Date.apply(lambda x:(NOW - x).days
data_recency.drop(columns=['Last_Purchase_Date'], inplace=True)
data_recency.head()
```

Out[23]:

	CustomerID	Recency
0	12346.0	325
1	12747.0	2
2	12748.0	0
3	12749.0	3
4	12820.0	3

Frequency-Monetary

In [24]:
```
FM_Table = data.groupby('CustomerID').agg({'InvoiceNo': lambda x:len(x),
                                           'Revenue': lambda x:x.sum()})
```

```
FM_Table.rename(columns = {'InvoiceNo': 'Frequency',
                           'Revenue': 'Monetary'}, inplace=True)

FM_Table.head()
```

Out[24]:

CustomerID	Frequency	Monetary
12346.0	1	77183.60
12747.0	103	4196.01
12748.0	4595	33719.73
12749.0	199	4090.88
12820.0	59	942.34

In [25]:

```
# Lets create one table from Recency, Frequency, and Monetary variables

RFM_Table = data_recency.merge(FM_Table, left_on = 'CustomerID', right_on = 'CustomerID
RFM_Table.head()
```

Out[25]:

	CustomerID	Recency	Frequency	Monetary
0	12346.0	325	1	77183.60
1	12747.0	2	103	4196.01
2	12748.0	0	4595	33719.73
3	12749.0	3	199	4090.88
4	12820.0	3	59	942.34

In [26]:

```
(NOW - dt.date(2011,1,18)).days == 325
```

Out[26]: True

Now we have a table of Recency, Frequency, and Monetary value for each Customers. we can give value from 1 to 4 for each Recency, Frequency, and Monetary. 1 for highest value and 4 to the lowest. we can later calculate the RFM Score by combining individual RFM score numbers.

In [27]:

```
# Lets create quantiles

quantiles = RFM_Table.quantile(q=[0.25, 0.50, 0.75])
quantiles = quantiles.to_dict()

segmented_rfm = RFM_Table.copy()
```

In [28]:

```
# create scores for the quantiles

def RScore(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 [29]:

```
# Give scores to the RFM Values created

segmented_rfm['R_quartile'] = segmented_rfm['Recency'].apply(RScore, args=('Recency', q
segmented_rfm['F_quartile'] = segmented_rfm['Frequency'].apply(FMScore, args=('Frequenc
segmented_rfm['M_quartile'] = segmented_rfm['Monetary'].apply(FMScore, args=('Monetary'
segmented_rfm.head()
```

Out[29]:

	CustomerID	Recency	Frequency	Monetary	R_quartile	F_quartile	M_quartile
0	12346.0	325	1	77183.60	4	4	1
1	12747.0	2	103	4196.01	1	1	1
2	12748.0	0	4595	33719.73	1	1	1
3	12749.0	3	199	4090.88	1	1	1
4	12820.0	3	59	942.34	1	2	2

Now, it is time to create total RFM score based on: RFM_Score = R_quartile + F_quartile + M_quartile

In [30]:

```
segmented_rfm['RFM_Segment'] = segmented_rfm.R_quartile.map(str) + segmented_rfm.F_quar

segmented_rfm.head()
```

Out[30]:

	CustomerID	Recency	Frequency	Monetary	R_quartile	F_quartile	M_quartile	RFM_Segment
0	12346.0	325	1	77183.60	4	4	1	441
1	12747.0	2	103	4196.01	1	1	1	111
2	12748.0	0	4595	33719.73	1	1	1	111
3	12749.0	3	199	4090.88	1	1	1	111
4	12820.0	3	59	942.34	1	2	2	122

In [31]:

```
segmented_rfm['RFM_Score'] = segmented_rfm[['R_quartile','F_quartile','M_quartile']].su
```

```
segmented_rfm.head()
```

Out[31]:

	CustomerID	Recency	Frequency	Monetary	R_quartile	F_quartile	M_quartile	RFM_Segment	RFM_
0	12346.0	325	1	77183.60	4	4	1	441	
1	12747.0	2	103	4196.01	1	1	1	111	
2	12748.0	0	4595	33719.73	1	1	1	111	
3	12749.0	3	199	4090.88	1	1	1	111	
4	12820.0	3	59	942.34	1	2	2	122	

In [32]:
```
segmented_rfm['RFM_Score'].unique()
```

Out[32]:
```
array([ 9,  3,  5, 12,  7,  8,  6, 10, 11,  4], dtype=int64)
```

In [33]:
```
segmented_rfm.groupby('RFM_Score').agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'Monetary': ['mean', 'count'] }).round(1)
```

Out[33]:

	Recency	Frequency	Monetary	
	mean	mean	mean	count
RFM_Score				
3	6.6	363.7	8218.2	409
4	20.3	187.0	3492.1	345
5	32.0	113.3	1909.4	386
6	47.0	78.9	1806.6	380
7	60.5	55.4	917.1	408
8	78.1	38.5	733.0	393
9	96.7	28.4	829.5	424
10	153.0	21.0	357.0	470
11	174.0	13.7	234.2	362
12	257.9	8.1	152.3	343

K-Means Clustering for RFM Customer Segmentation

K-means gives best result under the following conditions:

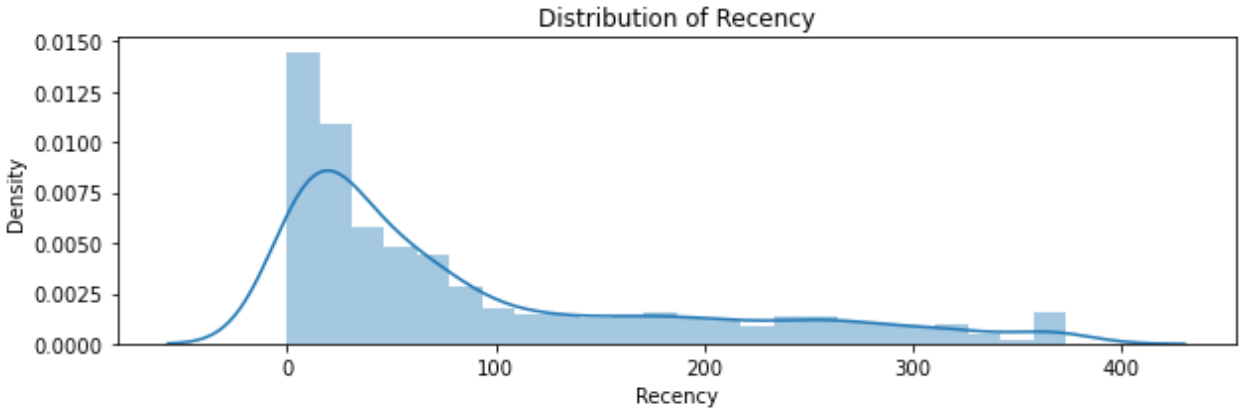
. Data's distribution is not skewed (i.e. long-tail distribution)
. Data is standardised (i.e. mean of 0 and standard deviation of 1)

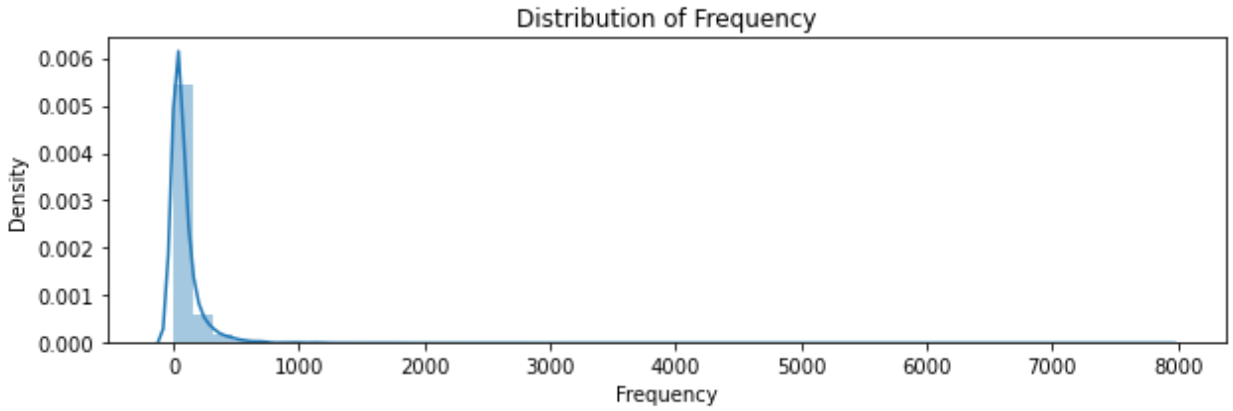
Lets plot chart to understand data skewness

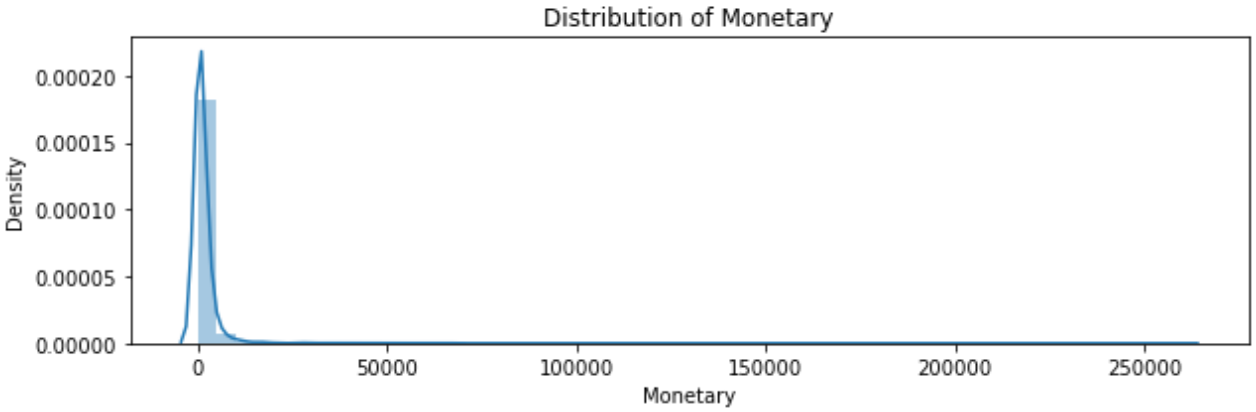
In [34]:
```
## Function to check skewness:

def check_skew(data_skew, column):
    skew = stats.skew(data_skew[column])
    skewtest = stats.skewtest(data_skew[column])
    plt.title('Distribution of ' + column)
    sns.distplot(data_skew[column])
    print("{}'s: Skew: {}, : {}".format(column, skew, skewtest))
    return
```

In [35]:
```
# Plot all 3 graphs together for summary findings
plt.figure(figsize=(9, 9))

plt.subplot(3, 1, 1)
check_skew(RFM_Table,'Recency')

plt.subplot(3, 1, 2)
check_skew(RFM_Table,'Frequency')

plt.subplot(3, 1, 3)
check_skew(RFM_Table,'Monetary')

plt.tight_layout()
```

```
Recency's: Skew: 1.244516494686479, : SkewtestResult(statistic=25.283720058978158, pvalu
e=4.8246481722257944e-141)
Frequency's: Skew: 18.66163311873067, : SkewtestResult(statistic=80.10349526126947, pval
ue=0.0)
Monetary's: Skew: 20.190728787200957, : SkewtestResult(statistic=81.75346911703686, pval
ue=0.0)
```







In [36]:
```
# the data are highly skewed. log scale are used to remove/fix the skewness

data_rfm_log = RFM_Table.copy()
data_rfm_log.head()
```

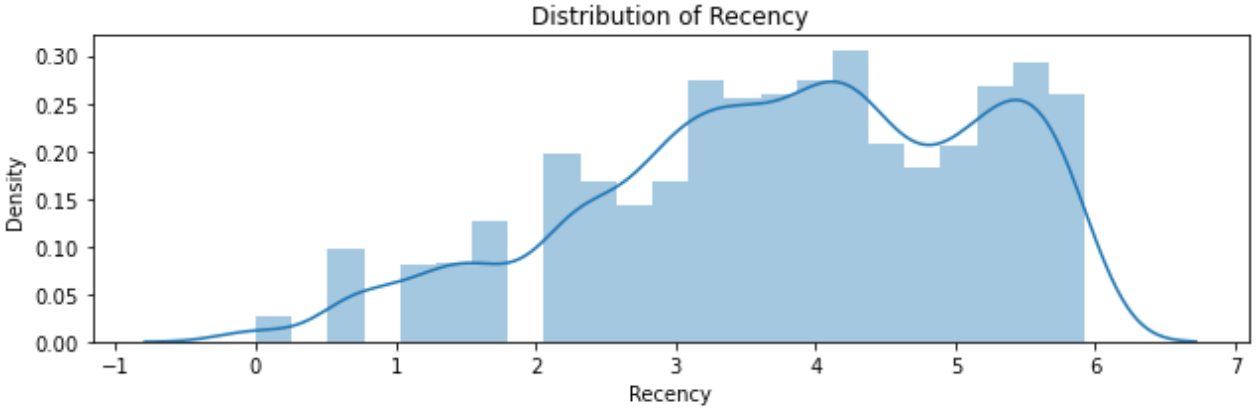
Out[36]:

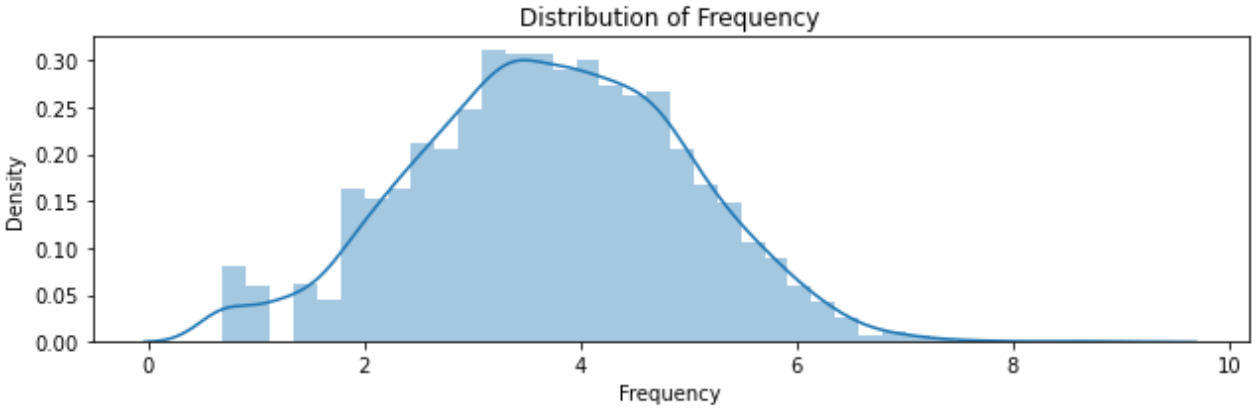
	CustomerID	Recency	Frequency	Monetary
0	12346.0	325	1	77183.60
1	12747.0	2	103	4196.01
2	12748.0	0	4595	33719.73
3	12749.0	3	199	4090.88
4	12820.0	3	59	942.34

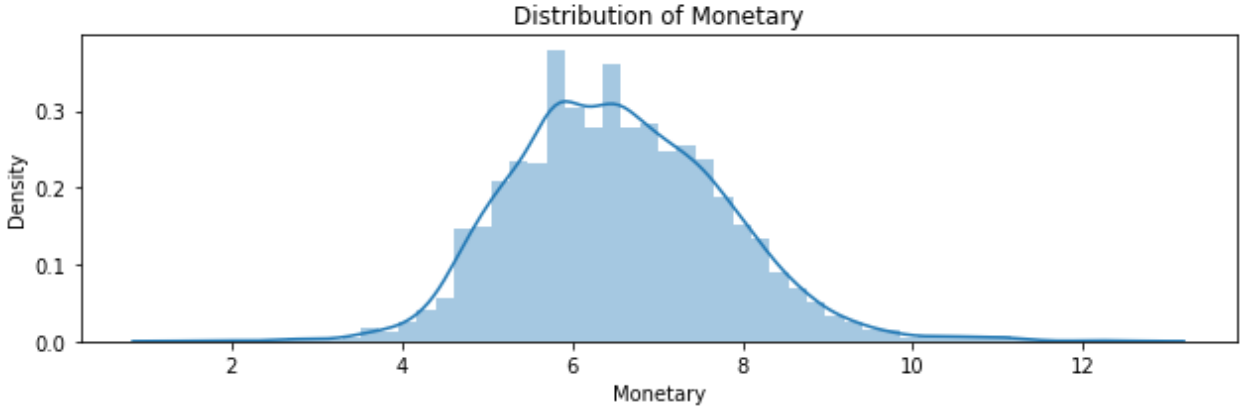
In [37]:
```
data_rfm_log = np.log(data_rfm_log+1)
```

```
plt.figure(figsize=(9, 9))

plt.subplot(3, 1, 1)
check_skew(data_rfm_log,'Recency')

plt.subplot(3, 1, 2)
check_skew(data_rfm_log,'Frequency')
plt.subplot(3, 1, 3)
check_skew(data_rfm_log,'Monetary')

plt.tight_layout()
```

```
Recency's: Skew: -0.4635591539552193, : SkewtestResult(statistic=-11.314301280234206, pv
alue=1.114869536941138e-29)
Frequency's: Skew: -0.02600696239989871, : SkewtestResult(statistic=-0.6659021000684195,
pvalue=0.5054736781086501)
Monetary's: Skew: 0.3694308288045071, : SkewtestResult(statistic=9.166088768517884, pval
ue=4.904929990328552e-20)
```







In [38]:

```
# now lets standardise the data by centring and scaling, all variables will have a mean

scaler = StandardScaler()
scaler.fit(data_rfm_log)
RFM_Table_scaled = scaler.transform(data_rfm_log)
```

In [76]:
```
RFM_Table_scaled = pd.DataFrame(RFM_Table_scaled, columns=data_rfm_log.columns)
RFM_Table_scaled.head()
```

Out[76]:

	CustomerID	Recency	Frequency	Monetary
0	-2.216570	1.438428	-2.403387	3.785914
1	-1.903521	-1.953555	0.732578	1.444280
2	-1.902753	-2.748403	3.739419	3.119983
3	-1.901985	-1.745416	1.251577	1.423880
4	-1.847594	-1.745416	0.296025	0.243880

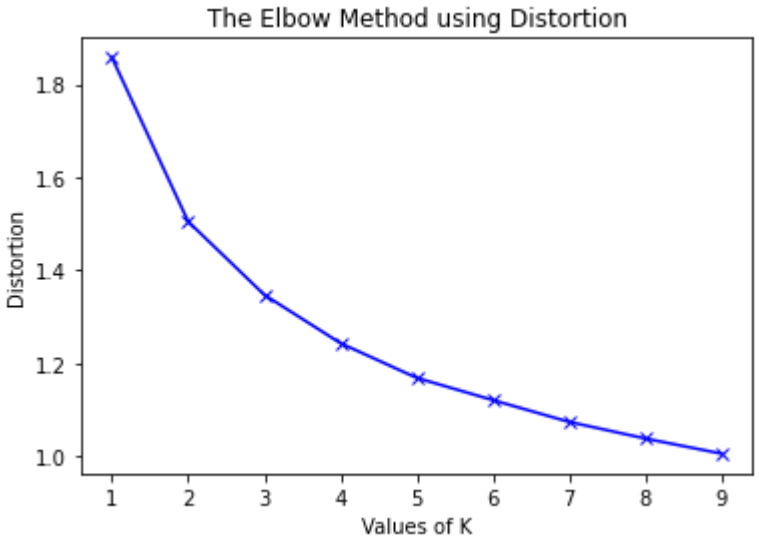
K-Means Clustering

Find the optimal number of clusters

In [39]:
```
from scipy.spatial.distance import cdist
```

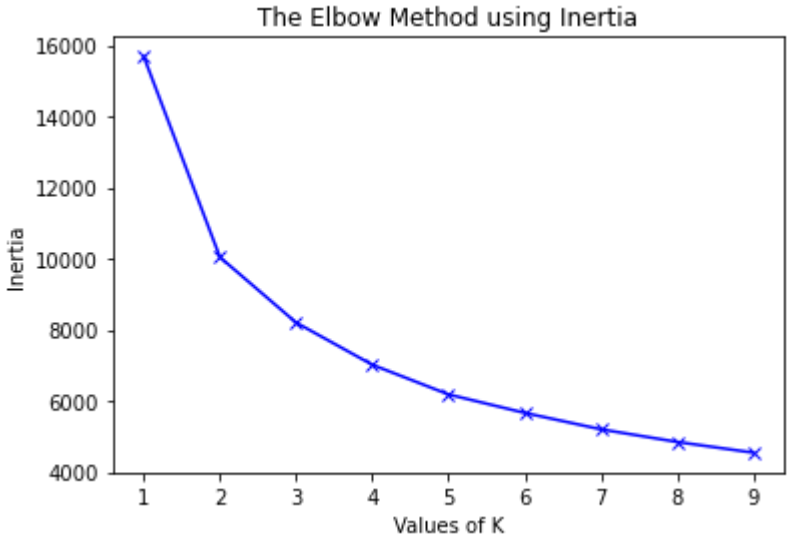
In [40]:
```
distortions = []
inertias = []
mapping1 = {}
mapping2 = {}
K = range(1,10)

for k in K:
    #Building and fitting the model
    kmeanModel = KMeans(n_clusters=k).fit(RFM_Table_scaled)
    kmeanModel.fit(RFM_Table_scaled)

    distortions.append(sum(np.min(cdist(RFM_Table_scaled, kmeanModel.cluster_centers_,
                      'euclidean'),axis=1)) / RFM_Table_scaled.shape[0])
    inertias.append(kmeanModel.inertia_)

    mapping1[k] = sum(np.min(cdist(RFM_Table_scaled, kmeanModel.cluster_centers_,
                 'euclidean'),axis=1)) / RFM_Table_scaled.shape[0]
    mapping2[k] = kmeanModel.inertia_
```

In [41]:
```
# Elbow method with distortion

plt.plot(K, distortions, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Distortion')
plt.title('The Elbow Method using Distortion')
plt.show()
```



In [42]:

```
# Elbow with Inertia

plt.plot(K, inertias, 'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()
```



From both elbow method using distortion and intertia, first drop is in cluster 2 and then gradual decrease. lets use other plots to better understand the optimal number of clusters. From above plots, clusters around 4-5 can be optimum numbers.

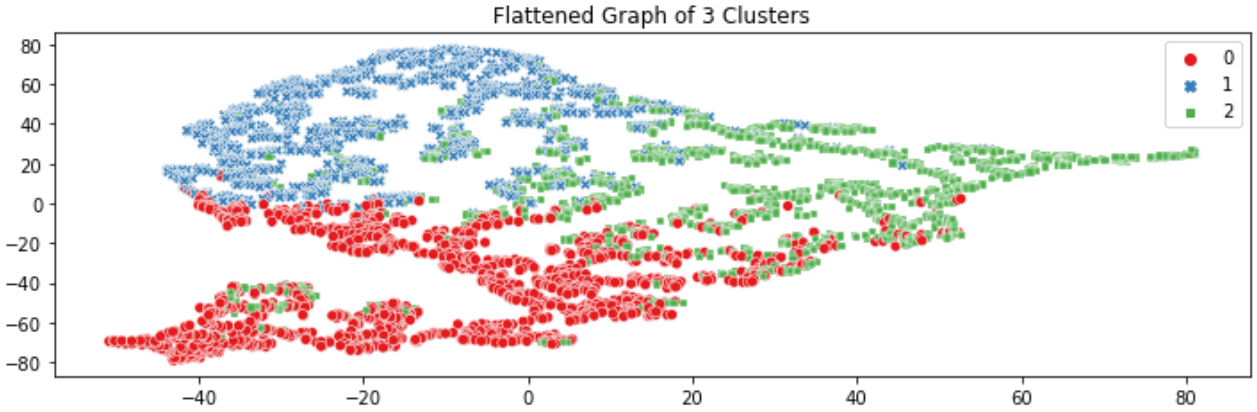
In [43]:

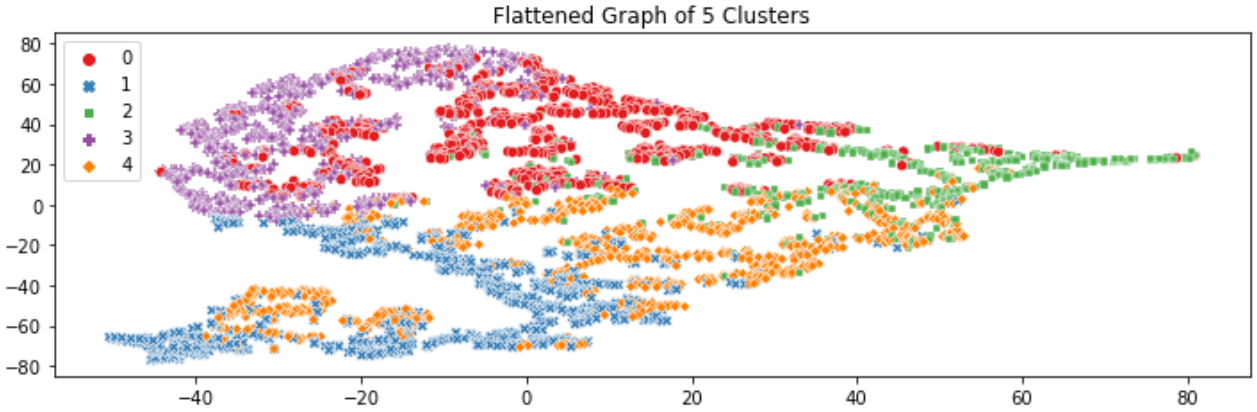
```
def kmeans(normalised_data_rfm, clusters_number, original_data_rfm):

    kmeans = KMeans(n_clusters = clusters_number, random_state = 1)
    kmeans.fit(normalised_data_rfm)

    # Extract cluster labels
    cluster_labels = kmeans.labels_

    # Create a cluster label column in original dataset
```

```
    data_new = original_data_rfm.assign(Cluster = cluster_labels)

    # Initialise TSNE
    model = TSNE(random_state=1)
    transformed = model.fit_transform(data_new)

    # Plot t-SNE
    plt.title('Flattened Graph of {} Clusters'.format(clusters_number))
    sns.scatterplot(x=transformed[:,0], y=transformed[:,1], hue=cluster_labels, style=c

    return data_new
```

In [44]:

```
plt.figure(figsize=(10, 10))

plt.subplot(3, 1, 1)
data_rfm_k3 = kmeans(RFM_Table_scaled, 3, RFM_Table)

plt.subplot(3, 1, 2)
data_rfm_k4 = kmeans(RFM_Table_scaled, 4, RFM_Table)

plt.subplot(3, 1, 3)
data_rfm_k5 = kmeans(RFM_Table_scaled, 5, RFM_Table)

plt.tight_layout()
```



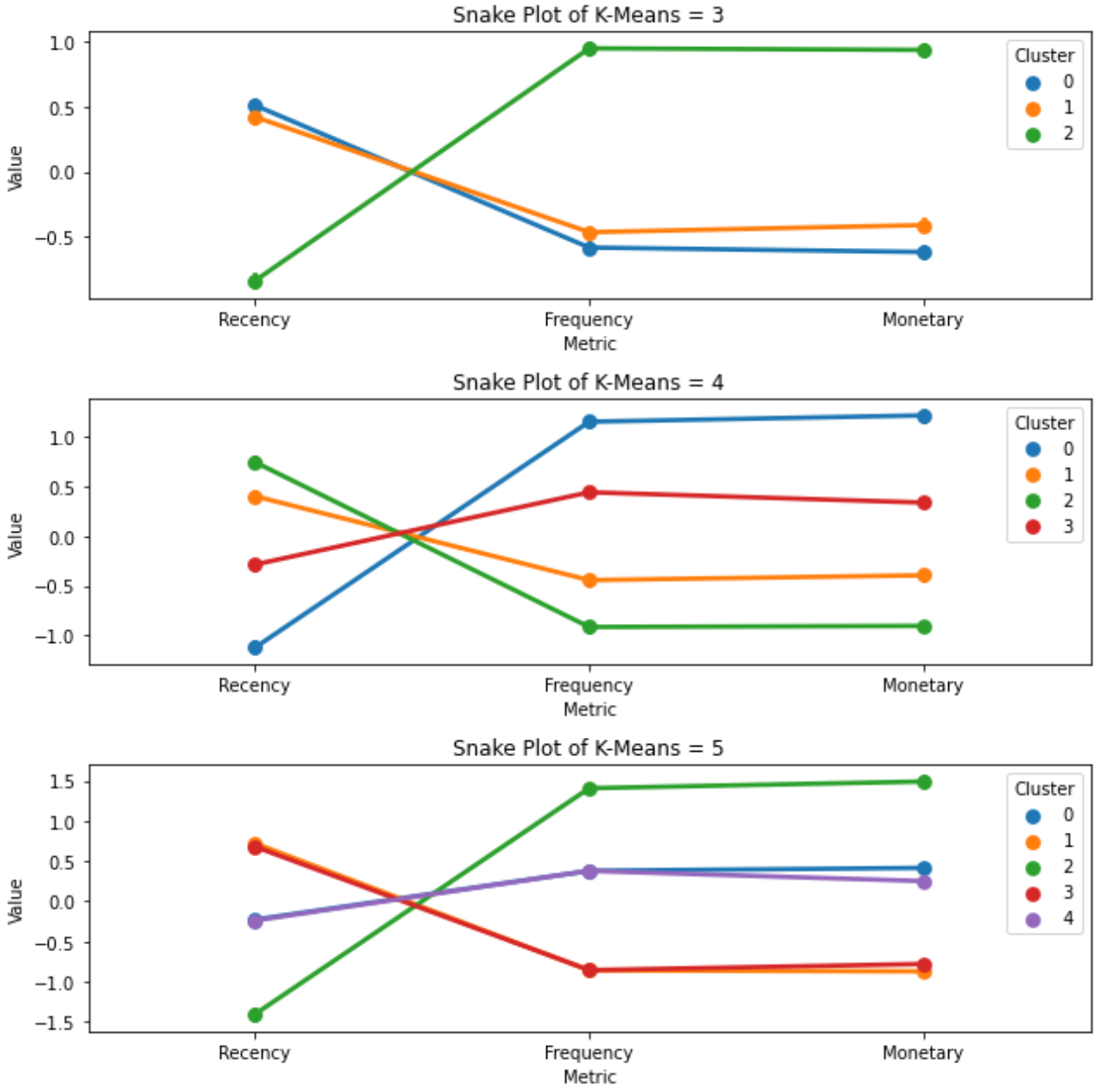


In [45]:

```
def snake_plot(normalised_data_rfm, data_rfm_kmeans, data_rfm_original):

    normalised_data_rfm = pd.DataFrame(normalised_data_rfm,
                                       index=RFM_Table.index,
                                       columns=RFM_Table.columns)
    normalised_data_rfm['Cluster'] = data_rfm_kmeans['Cluster']

    # Melt data into long format
    data_melt = pd.melt(normalised_data_rfm.reset_index(),
                        id_vars=['CustomerID', 'Cluster'],
                        value_vars=['Recency', 'Frequency', 'Monetary'],
                        var_name='Metric',
                        value_name='Value')

    plt.xlabel('Metric')
    plt.ylabel('Value')
    sns.pointplot(data=data_melt, x='Metric', y='Value', hue='Cluster')

    return
```

In [46]:

```
plt.figure(figsize=(9, 9))

plt.subplot(3, 1, 1)
plt.title('Snake Plot of K-Means = 3')
snake_plot(RFM_Table_scaled, data_rfm_k3, RFM_Table)

plt.subplot(3, 1, 2)
plt.title('Snake Plot of K-Means = 4')
snake_plot(RFM_Table_scaled, data_rfm_k4, RFM_Table)

plt.subplot(3, 1, 3)
plt.title('Snake Plot of K-Means = 5')
snake_plot(RFM_Table_scaled, data_rfm_k5, RFM_Table)

plt.tight_layout()
```



From the flattened graph and Snake plot, 4 clusters / segments are the perfect representation of the data.

Clusters interpreations:

In [47]:
```
def rfm_values(data):

    data_new = data.groupby(['Cluster']).agg({
        'Recency': 'mean',
        'Frequency': 'mean',
        'Monetary': ['mean', 'count']
    }).round(0)

    return data_new
```

In [48]:
```
rfm_values(data_rfm_k4)
```

Out[48]:

	Recency	Frequency	Monetary	
	mean	mean	mean	count
Cluster				
0	16.0	264.0	6138.0	763
1	118.0	32.0	691.0	1108
2	171.0	17.0	296.0	959
3	48.0	93.0	1446.0	1090

Cluster 0 represents best customers in terms of recent, frequent, and higher monetary value.

Cluster 1 represents customers who purchased long time ago, with the 3rd lowest frequency, and 3rd lowest monetary value.

Cluster 2 represents group of customers whose last purchased date is the longest time ago, with the lowest frequency, and the lowest monetary value. These customers are of low value customers or purchase/spend the least amounts of money.

Cluster 3 is the second best customer group in terms of the three values. This group got second highest number of customers.

In [ ]:

In [ ]: