Customer Segmentation

Customer segmentation is the activity of dividing a broad consumer or business market, normally consisting of existing and potential customers, into sub-groups of consumers (known as segments) based on some type of shared characteristics. The overall aim of segmentation is to identify high yield segments – that is, those segments that are likely to be the most profitable or that have growth potential – so that these can be selected for special attention ([Reference])

What is in this Kernel?

- **Cleaning/Transforming the Data**
- **Univariate Analysis**
- **Analyzing the KPIs**
  1. **Annual Revenue**
  2. **Monthly Revenue**
  3. **Monthly Revenue growth rate**
  4. **Monthly Active Customers**
  5. **Average Sales per Order**
  6. **New Customers Growth Rate**
- **Clustering with arbitrary number of clusters**
  1. **Calculating Recency, Frequency and Monetary value for each customer**
  2. **Calculating RFM Score**
  3. **Dividing the customers into segments**
- **KMeans Clustering**
  1. **Data Preprocessing for KMeans**
     A. **Removing the Skewness for achieving Normal distribution using Log Transformation**
     B. **Standardizing the variables using Standard Scaler for eual variance and equal mean**
     C. **Choosing the number of clusters using Elbow Method**
     D. **Implementing KMeans**
     E. **Building Customer Personas**
        a. **Snake Plot**
        b. **Calculation relative importance of each cluster compared to the population**

In [1]:

```
#importing the required libraries
import pandas as pd
import numpy as np

#viz Libraries
import matplotlib.pyplot as plt

plt.style.use('ggplot')
import seaborn as sns

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

#datetime
import datetime as dt

#StandardSccaler
from sklearn.preprocessing import StandardScaler

#KMeans
from sklearn.cluster import KMeans

#file directoryy
import os
```

In [2]:

```
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))
```

```
/kaggle/input/sample-sales-data/sales_data_sample.csv
```

Reading the data

In [3]:

```
#reading the data
df = pd.read_csv('../input/sample-sales-data/sales_data_sample.csv', encoding = 'unicode_escape')
```

In [4]:

```
df.shape #Dimensions of the data
```

Out[4]:

```
(2823, 25)
```

In [5]:

```
df.head() #Glimpse of the data
```

Out[5]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONT
0	10107	30	95.70	2	2871.00	2/24/2003 0:00	Shipped	1	
1	10121	34	81.35	5	2765.90	5/7/2003 0:00	Shipped	2	
2	10134	41	94.74	2	3884.34	7/1/2003 0:00	Shipped	3	
3	10145	45	83.26	6	3746.70	8/25/2003 0:00	Shipped	3	
4	10159	49	100.00	14	5205.27	10/10/2003 0:00	Shipped	4	

5 rows × 25 columns

Dropping columns

In [6]:

```
#Removing the variables which dont add significant value fot the analysis.
to_drop = ['PHONE','ADDRESSLINE1','ADDRESSLINE2','STATE','POSTALCODE']
df = df.drop(to_drop, axis=1)
```

Checking for null values

In [7]:

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

Out[7]:

```
ORDERNUMBER           0
QUANTITYORDERED       0
PRICEEACH             0
ORDERLINENUMBER       0
SALES                 0
ORDERDATE             0
```

```
STATUS                  0
QTR_ID                  0
MONTH_ID                0
YEAR_ID                 0
PRODUCTLINE             0
MSRP                    0
PRODUCTCODE             0
CUSTOMERNAME            0
CITY                    0
COUNTRY                 0
TERRITORY            1074
CONTACTLASTNAME         0
CONTACTFIRSTNAME        0
DEALSIZE                0
dtype: int64
```

Not dealing with the mising values of 'Territory' Variable as it may not have a significant effect on the analysis.

Checking for inconsistent data types

In [8]:

```
df.dtypes
```

Out[8]:

```
ORDERNUMBER           int64
QUANTITYORDERED       int64
PRICEEACH           float64
ORDERLINENUMBER       int64
SALES               float64
ORDERDATE            object
STATUS               object
QTR_ID                int64
MONTH_ID              int64
YEAR_ID               int64
PRODUCTLINE          object
MSRP                  int64
PRODUCTCODE          object
CUSTOMERNAME         object
CITY                 object
COUNTRY              object
TERRITORY            object
CONTACTLASTNAME      object
CONTACTFIRSTNAME     object
DEALSIZE             object
dtype: object
```

Changing the data type of variable 'ORDERDATE' from object to datetime

In [9]:

```
df['ORDERDATE'] = pd.to_datetime(df['ORDERDATE'])
```

Summary stats of Quantitative variables

In [10]:

```
quant_vars = ['QUANTITYORDERED','PRICEEACH','SALES','MSRP']
df[quant_vars].describe()
```

Out[10]:

	QUANTITYORDERED	PRICEEACH	SALES	MSRP
count	2823.000000	2823.000000	2823.000000	2823.000000
mean	35.092809	83.658544	3553.889072	100.715551
std	9.741443	20.174277	1841.865106	40.187912

	QUANTITYORDERED	PRICEEACH	SALES	MSRP
min	6.000000	26.880000	482.130000	33.000000
25%	27.000000	68.860000	2203.430000	68.000000
50%	35.000000	95.700000	3184.800000	99.000000
75%	43.000000	100.000000	4508.000000	124.000000
max	97.000000	100.000000	14082.800000	214.000000

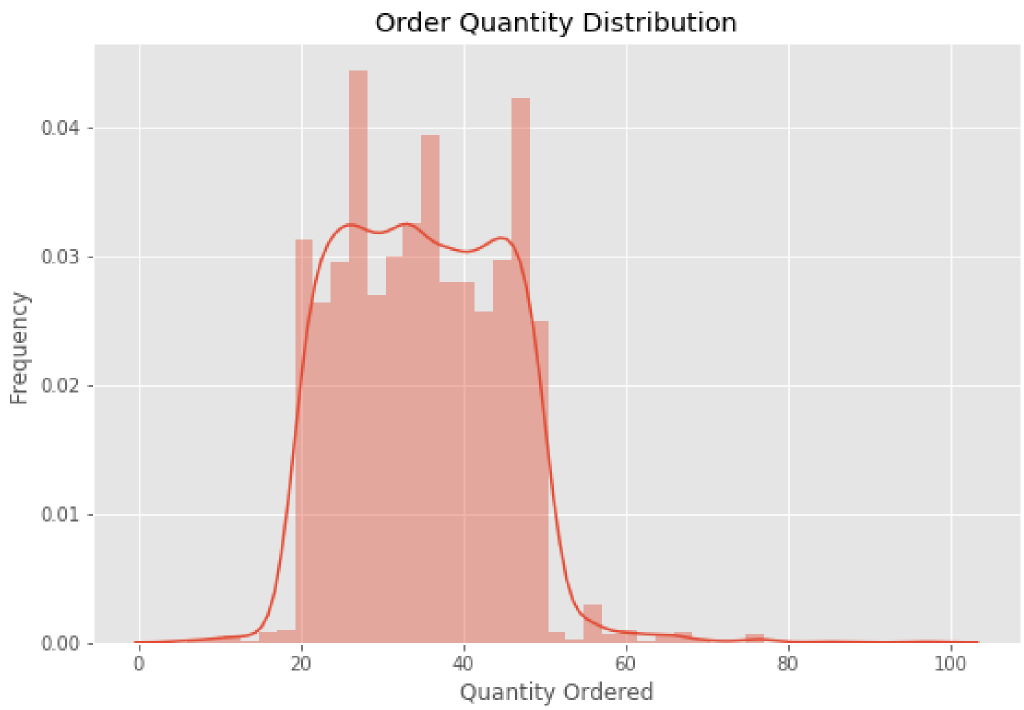
It is observed that there are no negative values for the quantitative variables, which is a good sign because we cannot have negative prices or quantities.

Exploring the variables

Order Quantity Distribution

In [11]:

```
plt.figure(figsize=(9,6))
sns.distplot(df['QUANTITYORDERED'])
plt.title('Order Quantity Distribution')
plt.xlabel('Quantity Ordered')
plt.ylabel('Frequency')
plt.show()
```

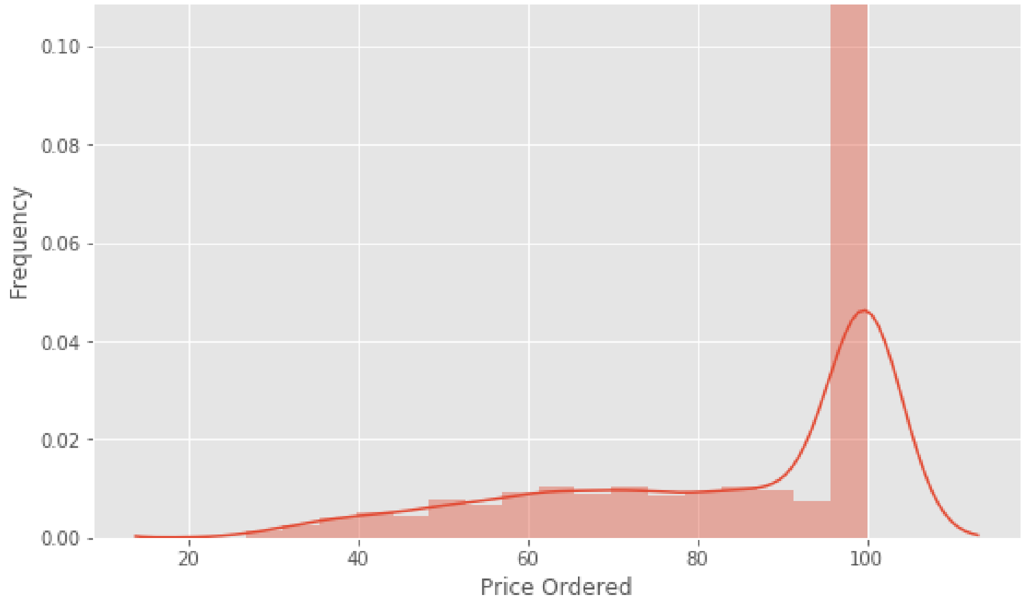


From the distribution plot of quantity, we can infer that the orders are bulk orders. Majority of the order's quantity are between 20 -40 units.

Price Distribution

In [12]:

```
plt.figure(figsize=(9,6))
sns.distplot(df['PRICEEACH'])
plt.title('Price Distribution')
plt.xlabel('Price Ordered')
plt.ylabel('Frequency')
plt.show()
```

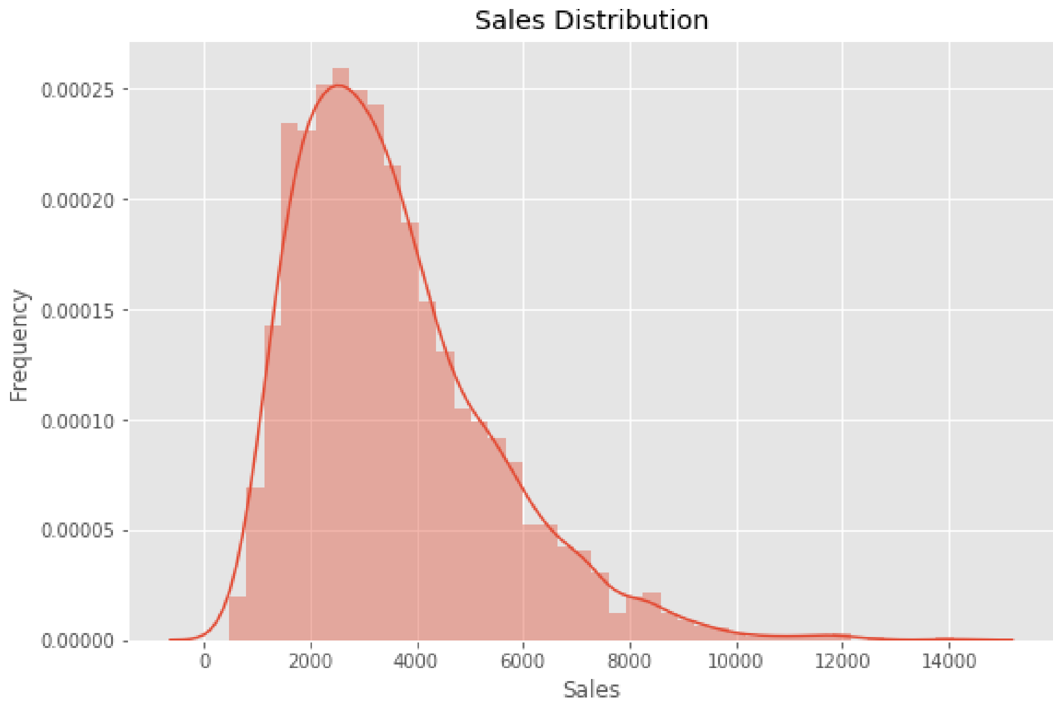


The distribution of Price is Left Skewed with max price of 100$. Interestingly, many of the orders recieved are of this price. Not investigating further about this particular product line which has the highest price beacuse the target is to segment the customers.

Sales Distribution

In [13]:

```
plt.figure(figsize=(9,6))
sns.distplot(df['SALES'])
plt.title('Sales Distribution')
plt.xlabel('Sales')
plt.ylabel('Frequency')
plt.show()
```



Analyzing the STATUS variable

In [14]:

```
df['STATUS'].value_counts(normalize = True)
```

Out[14]:

```
Shipped       0.927028
Cancelled     0.021254
```

```
Resolved      0.016649
On Hold       0.015586
In Process    0.014524
Disputed      0.004959
Name: STATUS, dtype: float64
```

Checking the time range of the data

In [15]:

```
df.groupby(['YEAR_ID'])['MONTH_ID'].nunique()
```

Out[15]:

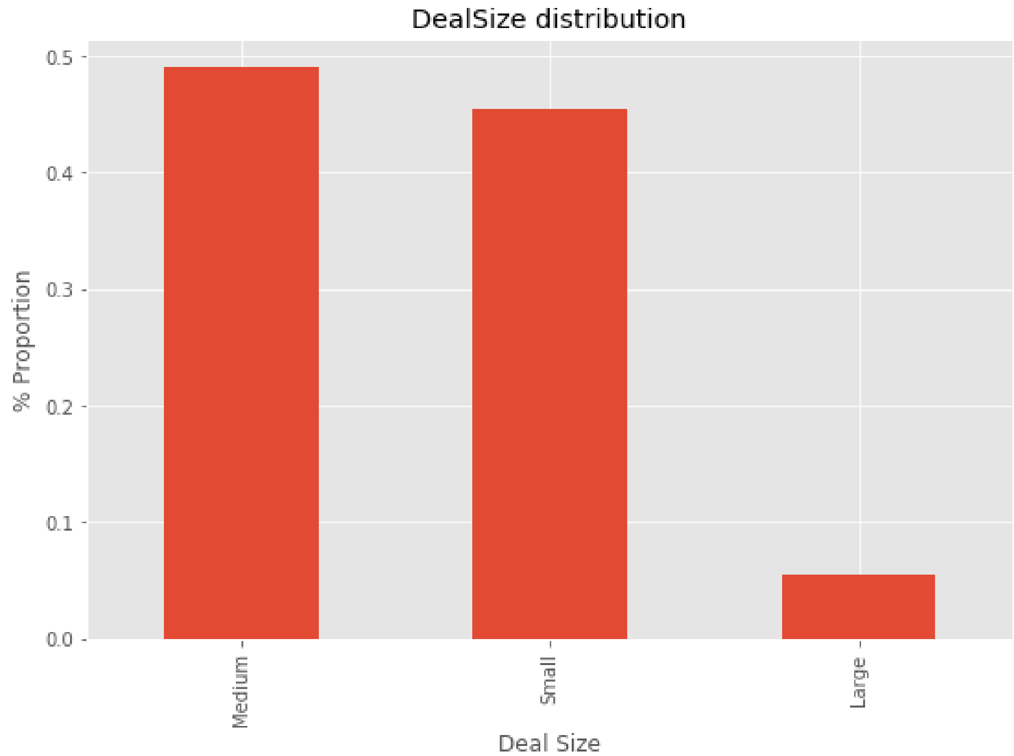
```
YEAR_ID
2003    12
2004    12
2005     5
Name: MONTH_ID, dtype: int64
```

We dont have the complete data for 2005.

Dealsize Distribution

In [16]:

```
plt.figure(figsize=(9,6))
df['DEALSIZE'].value_counts(normalize = True).plot(kind = 'bar')
plt.title('DealSize distribution')
plt.xlabel('Deal Size')
plt.ylabel('% Proportion')
plt.show()
```



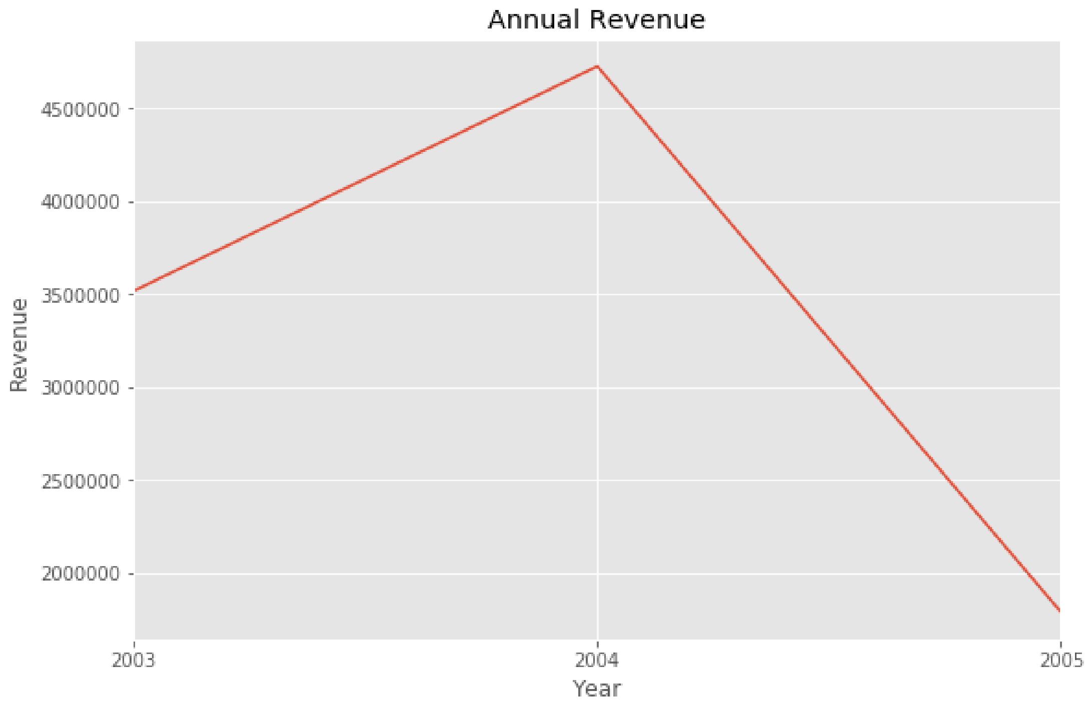
Analyzing KPIs

Annual Revenue

In [17]:

```
#Annual Revenue
```

```
plt.figure(figsize=(9,6))
df.groupby(['YEAR_ID'])['SALES'].sum().plot()
plt.xlabel('Year')
plt.ylabel('Revenue')
plt.title('Annual Revenue')
plt.xticks(np.arange(2003,2006,1))
plt.show()
```

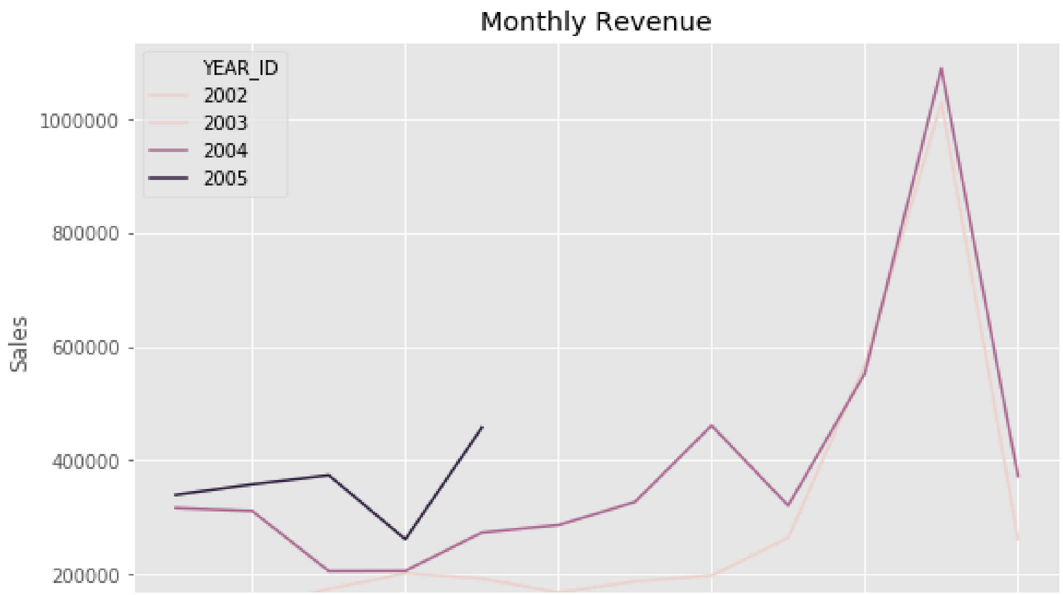


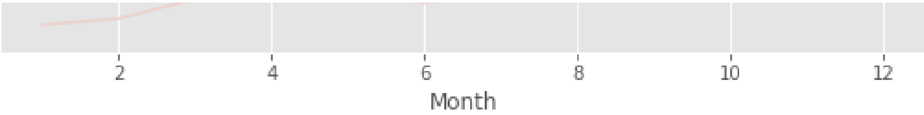
As we dont have the complete data for 2005, analyzing the Annual Revenue can be misleading. Instead, we can analyze Monthy Revenue.

Monthly Revenue

In [18]:

```
#Monthly Revenue
plt.figure(figsize=(9,6))

monthly_revenue = df.groupby(['YEAR_ID','MONTH_ID'])['SALES'].sum().reset_index()
monthly_revenue
sns.lineplot(x="MONTH_ID", y="SALES",hue="YEAR_ID", data=monthly_revenue)
plt.xlabel('Month')
plt.ylabel('Sales')
plt.title('Monthly Revenue')
plt.show()
```





This clearly shows that the revenue is growing especially in October and November. It can be the result of the seasonality(Thnaks Giving and other festivitues). We can also observe that 2005 is performing better than the other years in terms of revenue having the maximum sales in all the months(Jan - May). The reason behind this spike of sales in 2005 can be further investigated to maintain high sales in future.

Monthly Revenue Growth Rate:

In [19]:

```
monthly_revenue['MONTHLY GROWTH'] = monthly_revenue['SALES'].pct_change()
```

In [20]:

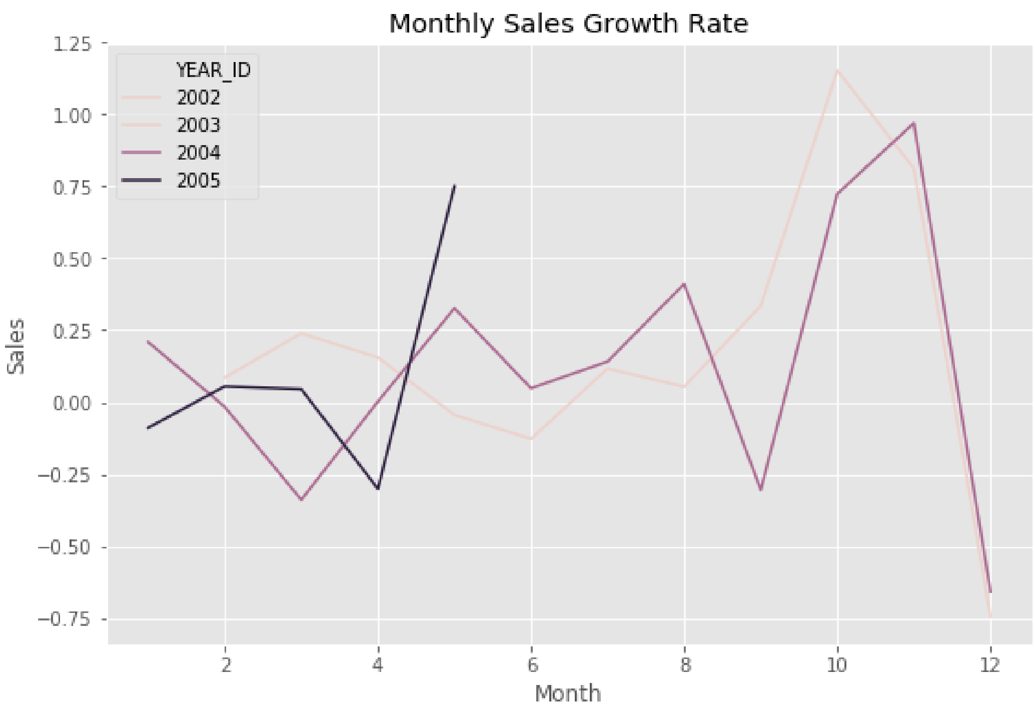
```
monthly_revenue.head()
```

Out[20]:

	YEAR_ID	MONTH_ID	SALES	MONTHLY GROWTH
0	2003	1	129753.60	NaN
1	2003	2	140836.19	0.085413
2	2003	3	174504.90	0.239063
3	2003	4	201609.55	0.155323
4	2003	5	192673.11	-0.044325

In [21]:

```
#Monthly Sales Growth Rate
plt.figure(figsize=(9,6))
sns.lineplot(x="MONTH_ID", y="MONTHLY GROWTH",hue="YEAR_ID", data=monthly_revenue)
plt.xlabel('Month')
plt.ylabel('Sales')
plt.title('Monthly Sales Growth Rate')
plt.show()
```



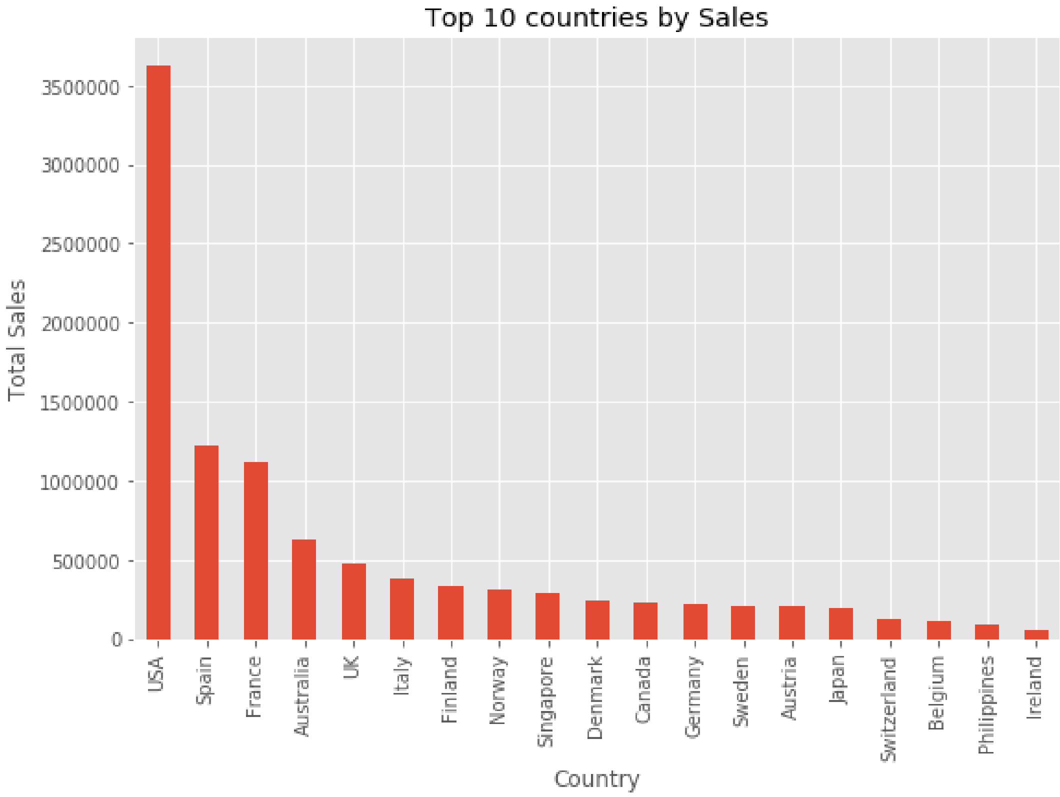
Apart from expected high/low growth rates during the seasonal months, there is hig growth rate from Apr 2005

to May 2005.

Top 10 countries by Sales

In [22]:

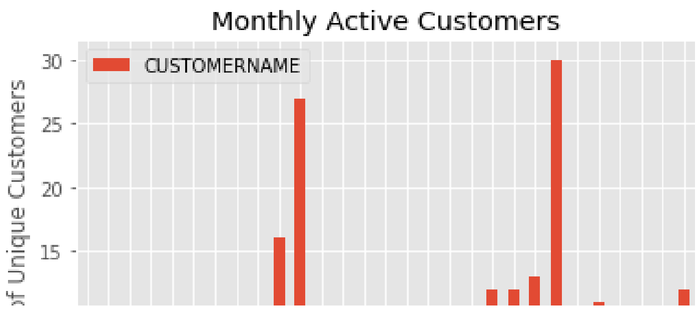
```
plt.figure(figsize=(9,6))
top_cities = df.groupby(['COUNTRY'])['SALES'].sum().sort_values(ascending=False)
top_cities.plot(kind = 'bar')
plt.title('Top 10 countries by Sales')
plt.xlabel('Country')
plt.ylabel('Total Sales')
plt.show()
```

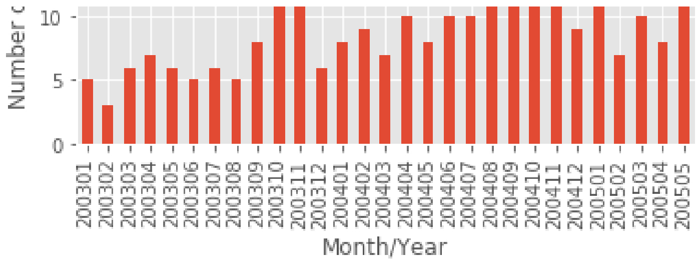


Monthly Active Customers

In [23]:

```
#plt.figure(figsize=(10,8))
df['YEAR_MONTH'] = df['YEAR_ID'].map(str)+df['MONTH_ID'].map(str).map(lambda x: x.rjust(
2,'0'))
monthly_active = df.groupby(['YEAR_MONTH'])['CUSTOMERNAME'].nunique().reset_index()
monthly_active.plot(kind='bar',x='YEAR_MONTH',y='CUSTOMERNAME')
#plt.figure(figsize=(10,8))
plt.title('Monthly Active Customers')
plt.xlabel('Month/Year')
plt.ylabel('Number of Unique Customers')
plt.xticks(rotation=90)
#plt.figure(figsize=(10,8))
plt.show()
```





As expected, customers are highly active during the months of November and October. The number of active customers increased from 2003 to 2004 which indicates that the company is successful in retention/acquisition of ol/new customers.

Average Sales per Order

In [24]:

```
#Average Sales per Order
average_revenue = df.groupby(['YEAR_ID','MONTH_ID'])['SALES'].mean().reset_index()
plt.figure(figsize=(10,6))
sns.lineplot(x="MONTH_ID", y="SALES",hue="YEAR_ID", data=average_revenue)
plt.xlabel('Month')
plt.ylabel('Average Sales')
plt.title('Average Sales per Order')
plt.show()
```

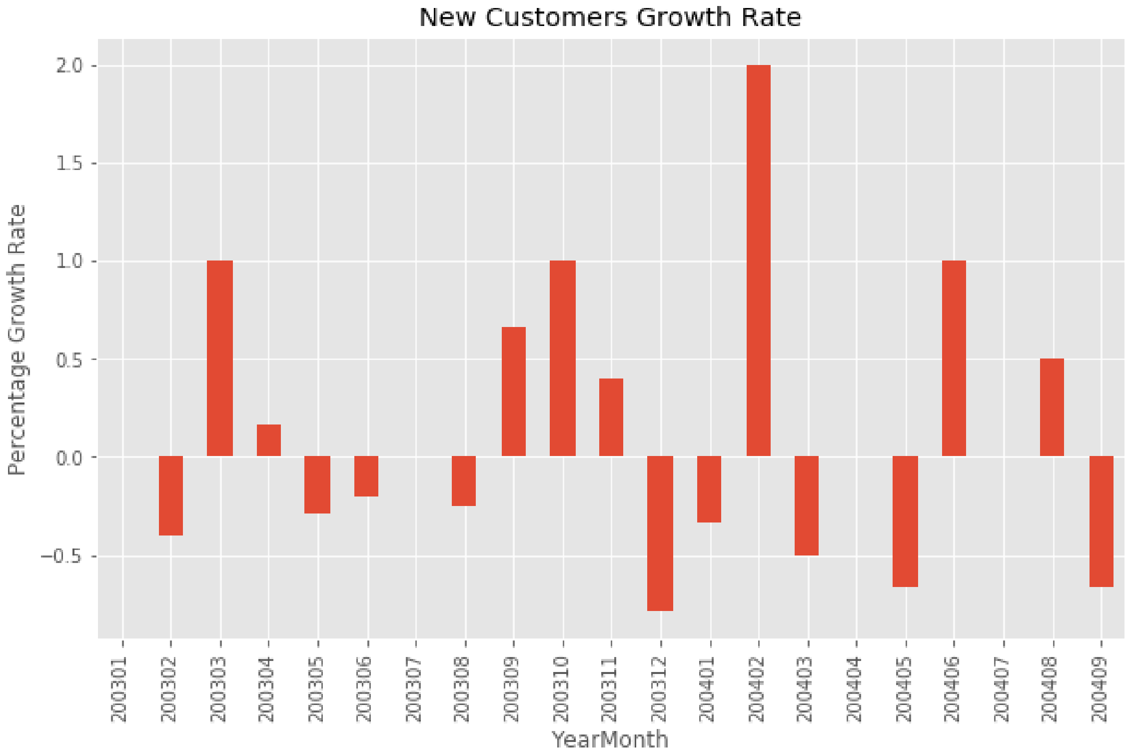
New Customers Growth Rate

New customer is whoever did his/her first purchase in the time window we defined, i.e., Mothly in this analysis.

In [25]:

```
#New Customers Growth Rate
df_first_purchase = df.groupby('CUSTOMERNAME').YEAR_MONTH.min().reset_index()
df_first_purchase.columns = ['CUSTOMERNAME','FirstPurchaseDate']

plt.figure(figsize=(10,6))
df_first_purchase.groupby(['FirstPurchaseDate'])['CUSTOMERNAME'].nunique().pct_change().
plot(kind='bar')
plt.title('New Customers Growth Rate')
plt.xlabel('YearMonth')
```

```
plt.ylabel('Percentage Growth Rate')
plt.show()
```



The highest growth rate is observed in February 2002. This can be investigated further to betetr understand what factors contributed the growth.

Segmentation with number of clusters chosen randomly

In [26]:

```
df['ORDERDATE'] = [d.date() for d in df['ORDERDATE']]
df.head()
```

Out[26]:

	ORDERNUMBER	QUANTITYORDERED	PRICEEACH	ORDERLINENUMBER	SALES	ORDERDATE	STATUS	QTR_ID	MONT
0	10107	30	95.70	2	2871.00	2003-02-24	Shipped	1	
1	10121	34	81.35	5	2765.90	2003-05-07	Shipped	2	
2	10134	41	94.74	2	3884.34	2003-07-01	Shipped	3	
3	10145	45	83.26	6	3746.70	2003-08-25	Shipped	3	
4	10159	49	100.00	14	5205.27	2003-10-10	Shipped	4	

5 rows × 21 columns

Calculate Recency, Frequency and Monetary value for each customer

Assuming that we are analyzing the next day of latest order date in the data set. Creating a variable ' ***snapshot date**'*** **which is the latest date in data set.**

Recency : Recency is the number of days between the customer's latest order date and the snapshot date
Frequency: Number of purchases made by the customer
MonetaryValue: Revenue generated by the customer

In [27]:

```
# Calculate Recency, Frequency and Monetary value for each customer
```

```
# calculate Recency, Frequency and Monetary value for each customer
snapshot_date = df['ORDERDATE'].max() + dt.timedelta(days=1) #latest date in the data set
df_RFM = df.groupby(['CUSTOMERNAME']).agg({
    'ORDERDATE': lambda x: (snapshot_date - x.max()).days,
    'ORDERNUMBER': 'count',
    'SALES':'sum'})

#Renaming the columns
df_RFM.rename(columns={'ORDERDATE': 'Recency',
                       'ORDERNUMBER': 'Frequency',
                       'SALES': 'MonetaryValue'}, inplace=True)
```

In [28]:

```
df_RFM.head()
```

Out[28]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue
AV Stores, Co.	196	51	157807.81
Alpha Cognac	65	20	70488.44
Amica Models & Co.	265	26	94117.26
Anna's Decorations, Ltd	84	46	153996.13
Atelier graphique	188	7	24179.96

Dividing the customer into 4 segments(Randomly Chosen)

Recency/Frequency/MonetaryValue : Level 4 > Level 3> Level 2 > Level 1

- **Lower the recency, higher the Recency level**
- **Higher the number of orders, higher the Frequency level**
- **Higher the monetary value, higher the MonetaryValue level**

In [29]:

```
#Dividing into segments

# Create a spend quartile with 4 groups - a range between 1 and 5
MonetaryValue_quartile = pd.qcut(df_RFM['MonetaryValue'], q=4, labels=range(1,5))
Recency_quartile = pd.qcut(df_RFM['Recency'], q=4, labels=list(range(4, 0, -1)))
Frequency_quartile = pd.qcut(df_RFM['Frequency'], q=4, labels=range(1,5))


# Assign the quartile values to the Spend_Quartile column in data
df_RFM['R'] = Recency_quartile
df_RFM['F'] = Frequency_quartile
df_RFM['M'] = MonetaryValue_quartile

#df_RFM[['MonetaryValue_Quartile','Recency_quartile','Frequency_quartile']] = [MonetaryValue_quartile,Recency_quartile,Frequency_quartile]

# Print data with sorted Spend values
#print(df_RFM.sort_values('MonetaryValue'))

df_RFM.head()
```

Out[29]:

CUSTOMERNAME	Recency	Frequency	MonetaryValue	R	F	M
AV Stores, Co.	196	51	157807.81	2	4	4

	Recency	Frequency	MonetaryValue	R	F	M
CUSTOMERNAME						
Alpha Cognac	65	20	70488.44	4	2	2
Amica Models & Co.	265	26	94117.26	1	2	3
Anna's Decorations, Ltd	84	46	153996.13	3	4	4
Atelier graphique	188	7	24179.96	2	1	1

Calculating RFM Score

In [30]:

```
# Calculate RFM_Score
df_RFM['RFM_Score'] = df_RFM[['R','F','M']].sum(axis=1)
df_RFM.head()
```

Out[30]:

	Recency	Frequency	MonetaryValue	R	F	M	RFM_Score
CUSTOMERNAME							
AV Stores, Co.	196	51	157807.81	2	4	4	10.0
Alpha Cognac	65	20	70488.44	4	2	2	8.0
Amica Models & Co.	265	26	94117.26	1	2	3	6.0
Anna's Decorations, Ltd	84	46	153996.13	3	4	4	11.0
Atelier graphique	188	7	24179.96	2	1	1	4.0

Labelling the levels

- **RFM Score > 10 - High Value Customer**
- **RFM SCore < 10 and RFM Score >= 6 - Mid Value Customer**
- **RFM Score < 6 - Low Value Customer**

In [31]:

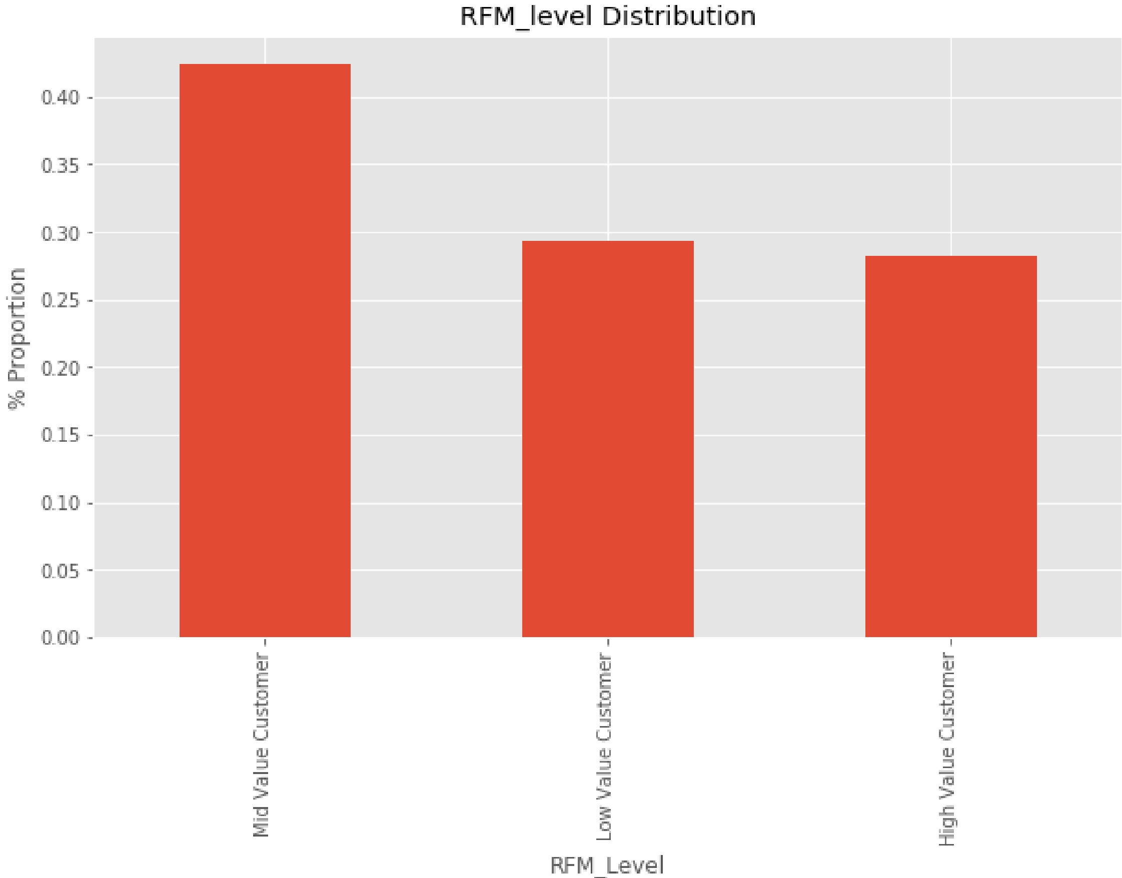
```
#Naming Levels
# Define rfm_level function
def rfm_level(df):
    if np.bool(df['RFM_Score'] >= 10):
        return 'High Value Customer'
    elif np.bool((df['RFM_Score'] < 10) & (df['RFM_Score'] >= 6)):
        return 'Mid Value Customer'
    else:
        return 'Low Value Customer'

# Create a new variable RFM_Level
df_RFM['RFM_Level'] = df_RFM.apply(rfm_level, axis=1)

# Print the header with top 5 rows to the console
df_RFM.head()
```

Out[31]:

	Recency	Frequency	MonetaryValue	R	F	M	RFM_Score	RFM_Level
CUSTOMERNAME								
AV Stores, Co.	196	51	157807.81	2	4	4	10.0	High Value Customer
Alpha Cognac	65	20	70488.44	4	2	2	8.0	Mid Value Customer
Amica Models & Co.	265	26	94117.26	1	2	3	6.0	Mid Value Customer
Anna's Decorations, Ltd	84	46	153996.13	3	4	4	11.0	High Value Customer
Atelier graphique	188	7	24179.96	2	1	1	4.0	Low Value Customer

In [32]:

```
plt.figure(figsize=(10,6))
df_RFM['RFM_Level'].value_counts(normalize = True).plot(kind='bar')
plt.title('RFM_level Distribution')
plt.xlabel('RFM_Level')
plt.ylabel('% Proportion')
plt.show()
```



Higher the monetary value, higher the MonetaryValue level

In [33]:

```
#Analyzing customer segments
# Calculate average values for each RFM_Level, and return a size of each segment
rfm_level_agg = df_RFM.groupby(['RFM_Level']).agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue':['mean','count']}).round(1)

# Print the aggregated dataset
print(rfm_level_agg)
```

```
                    Recency Frequency MonetaryValue
                       mean      mean          mean count
RFM_Level
High Value Customer    85.0      54.3      193532.1    26
Low Value Customer    293.8      15.0       52414.6    27
Mid Value Customer    171.2      25.8       91938.5    39
```

Segmentation using KMeans Clustering

Data Preprocessing for KMeans

K Means Assumptions

- **All variables have symmetrical (Normal) Distribution**
- **All Variables have same average value(approx)**
- **All Variables have same variance(approx)**

Check the distribution of the variables

In [34]:

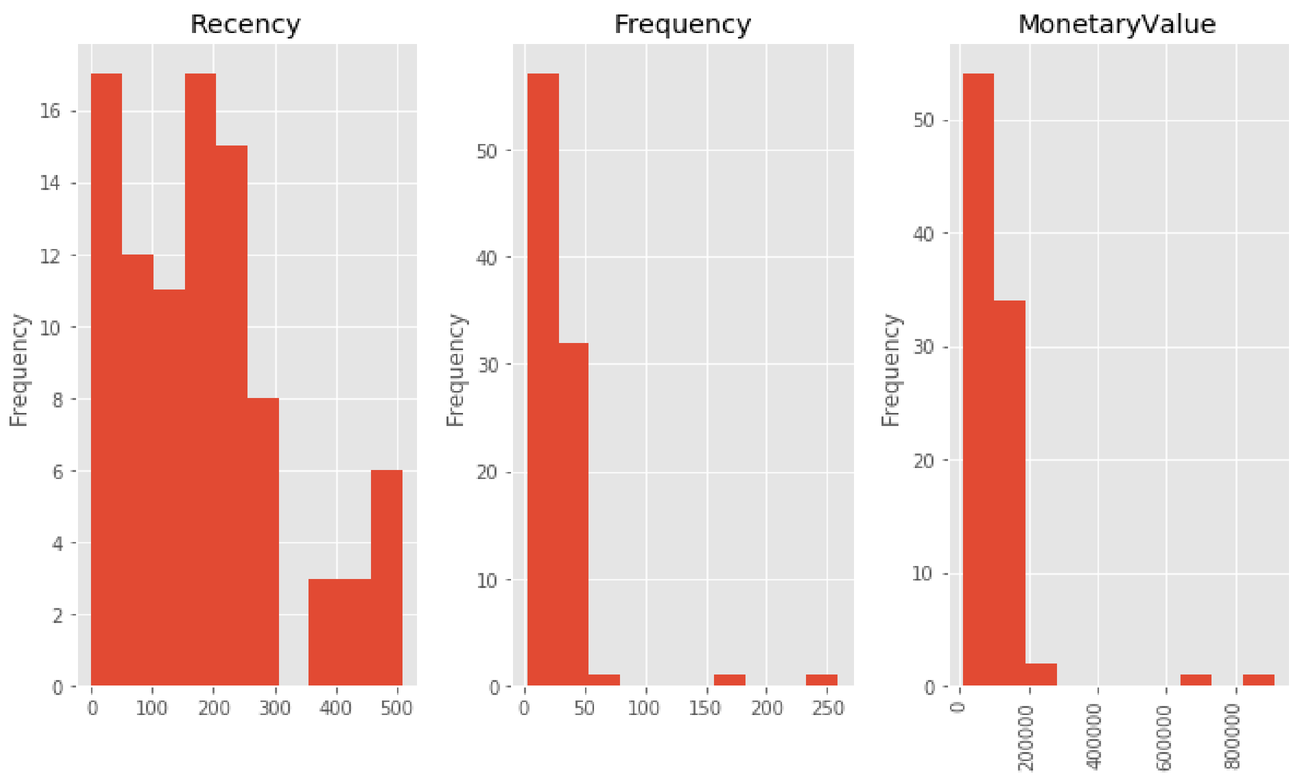
```
data = df_RFM[['Recency','Frequency','MonetaryValue']]
data.head()
```

Out[34]:

	Recency	Frequency	MonetaryValue
CUSTOMERNAME			
AV Stores, Co.	196	51	157807.81
Alpha Cognac	65	20	70488.44
Amica Models & Co.	265	26	94117.26
Anna's Decorations, Ltd	84	46	153996.13
Atelier graphique	188	7	24179.96

In [35]:

```
plt.figure(figsize=(10,6))

plt.subplot(1,3,1)
data['Recency'].plot(kind='hist')
plt.title('Recency')

plt.subplot(1,3,2)
data['Frequency'].plot(kind='hist')
plt.title('Frequency')

plt.subplot(1,3,3)
data['MonetaryValue'].plot(kind='hist')
plt.xticks(rotation = 90)
plt.title('MonetaryValue')

plt.tight_layout()
plt.show()
```



Removing the skewness by performing log transformation on the variables

In [36]:

```
data_log = np.log(data)
```

In [37]:

```
data_log.head()
```

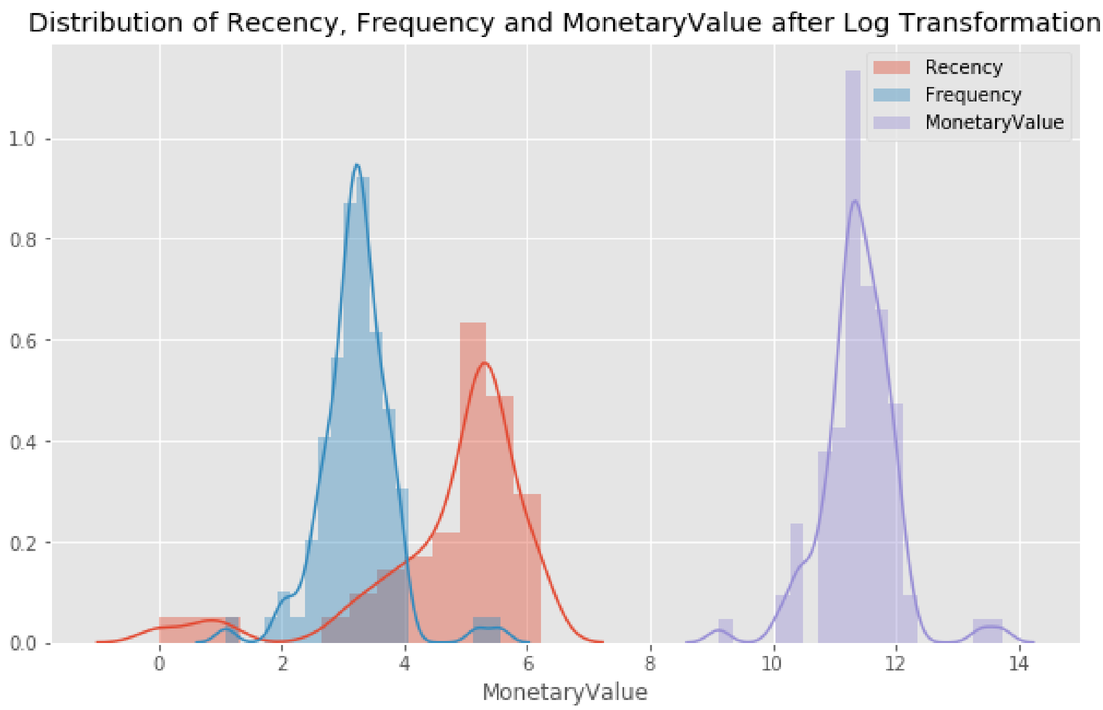
Out[37]:

	Recency	Frequency	MonetaryValue
CUSTOMERNAME			
AV Stores, Co.	5.278115	3.931826	11.969133
Alpha Cognac	4.174387	2.995732	11.163204
Amica Models & Co.	5.579730	3.258097	11.452297
Anna's Decorations, Ltd	4.430817	3.828641	11.944683
Atelier graphique	5.236442	1.945910	10.093279

Distribution of Recency, Frequency and MonetaryValue after Log Transformation

In [38]:

```
plt.figure(figsize=(10,6))

#plt.subplot(1,3,1)
sns.distplot(data_log['Recency'],label='Recency')

#plt.subplot(1,3,1)
sns.distplot(data_log['Frequency'],label='Frequency')

#plt.subplot(1,3,1)
sns.distplot(data_log['MonetaryValue'],label='MonetaryValue')

plt.title('Distribution of Recency, Frequency and MonetaryValue after Log Transformation'
)
plt.legend()
plt.show()
```



Standardizing the variables using StandardScaler() for equal variance and mean

In [39]:

In [39]:

```
# Initialize a scaler
scaler = StandardScaler()

# Fit the scaler
scaler.fit(data_log)

# Scale and center the data
data_normalized = scaler.transform(data_log)

# Create a pandas DataFrame
data_normalized = pd.DataFrame(data_normalized, index=data_log.index, columns=data_log.c
olumns)

# Print summary statistics
data_normalized.describe().round(2)
```

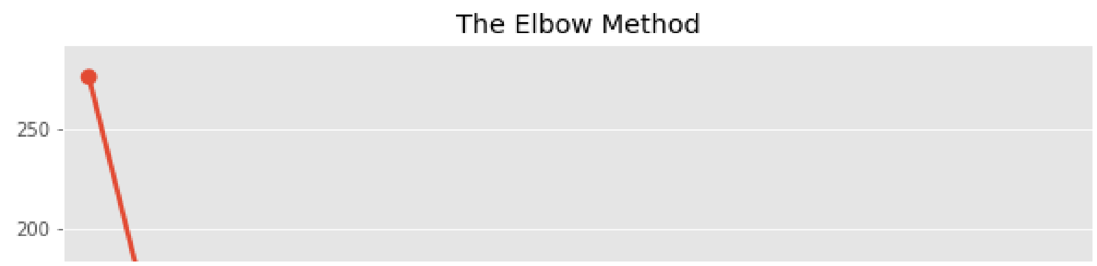
Out[39]:

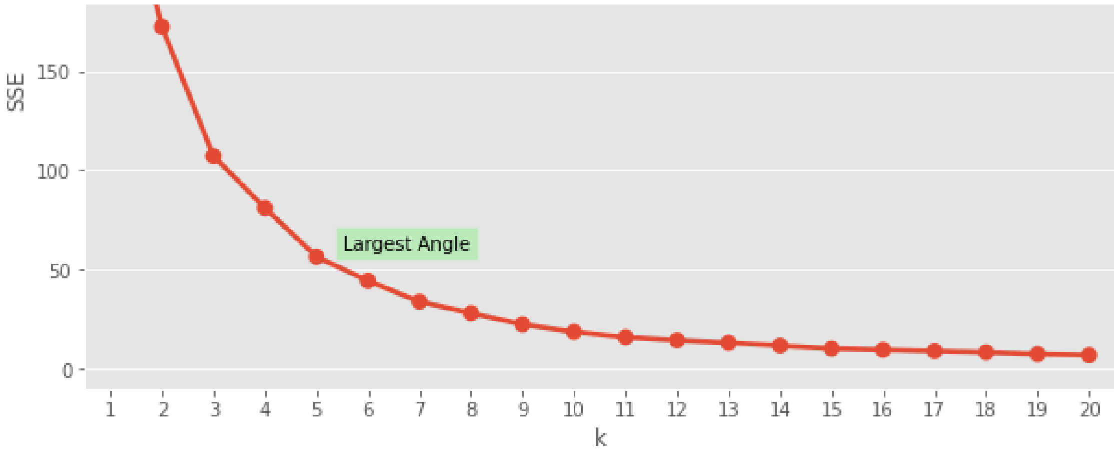
	Recency	Frequency	MonetaryValue
count	92.00	92.00	92.00
mean	0.00	-0.00	0.00
std	1.01	1.01	1.01
min	-3.51	-3.67	-3.82
25%	-0.24	-0.41	-0.39
50%	0.37	0.06	-0.04
75%	0.53	0.45	0.52
max	1.12	4.03	3.92

Choosing number of Clusters using Elbow Method

In [40]:

```
# Fit KMeans and calculate SSE for each k
sse={}
for k in range(1, 21):
    kmeans = KMeans(n_clusters=k, random_state=1)
    kmeans.fit(data_normalized)
    sse[k] = kmeans.inertia_


plt.figure(figsize=(10,6))
# Add the plot title "The Elbow Method"
plt.title('The Elbow Method')

# Add X-axis label "k"
plt.xlabel('k')

# Add Y-axis label "SSE"
plt.ylabel('SSE')

# Plot SSE values for each key in the dictionary
sns.pointplot(x=list(sse.keys()), y=list(sse.values()))
plt.text(4.5,60,"Largest Angle",bbox=dict(facecolor='lightgreen', alpha=0.5))
plt.show()
```





Running KMeans with 5 clusters

In [41]:

```
# Initialize KMeans
kmeans = KMeans(n_clusters=5, random_state=1)

# Fit k-means clustering on the normalized data set
kmeans.fit(data_normalized)

# Extract cluster labels
cluster_labels = kmeans.labels_

# Assigning Cluster Labels to Raw Data
# Create a DataFrame by adding a new cluster label column
data_rfm = data.assign(Cluster=cluster_labels)
data_rfm.head()
```

Out[41]:

	Recency	**Frequency**	**MonetaryValue**	**Cluster**
CUSTOMERNAME				
AV Stores, Co.	196	51	157807.81	3
Alpha Cognac	65	20	70488.44	0
Amica Models & Co.	265	26	94117.26	0
Anna's Decorations, Ltd	84	46	153996.13	3
Atelier graphique	188	7	24179.96	2

In [42]:

```
# Group the data by cluster
grouped = data_rfm.groupby(['Cluster'])

# Calculate average RFM values and segment sizes per cluster value
grouped.agg({
    'Recency': 'mean',
    'Frequency': 'mean',
    'MonetaryValue': ['mean', 'count']
  }).round(1)
```

Out[42]:

	Recency	**Frequency**	**MonetaryValue**	
	mean	**mean**	**mean**	**count**
Cluster				
0	209.2	22.1	78633.2	43
1	2.0	38.8	132201.6	4

	Recency	Frequency	MonetaryValue	
	mean	mean	mean	count
Cluster				
2	324.2	10.7	35628.7	12
3	126.5	37.1	133158.0	31
4	2.0	219.5	783576.1	2

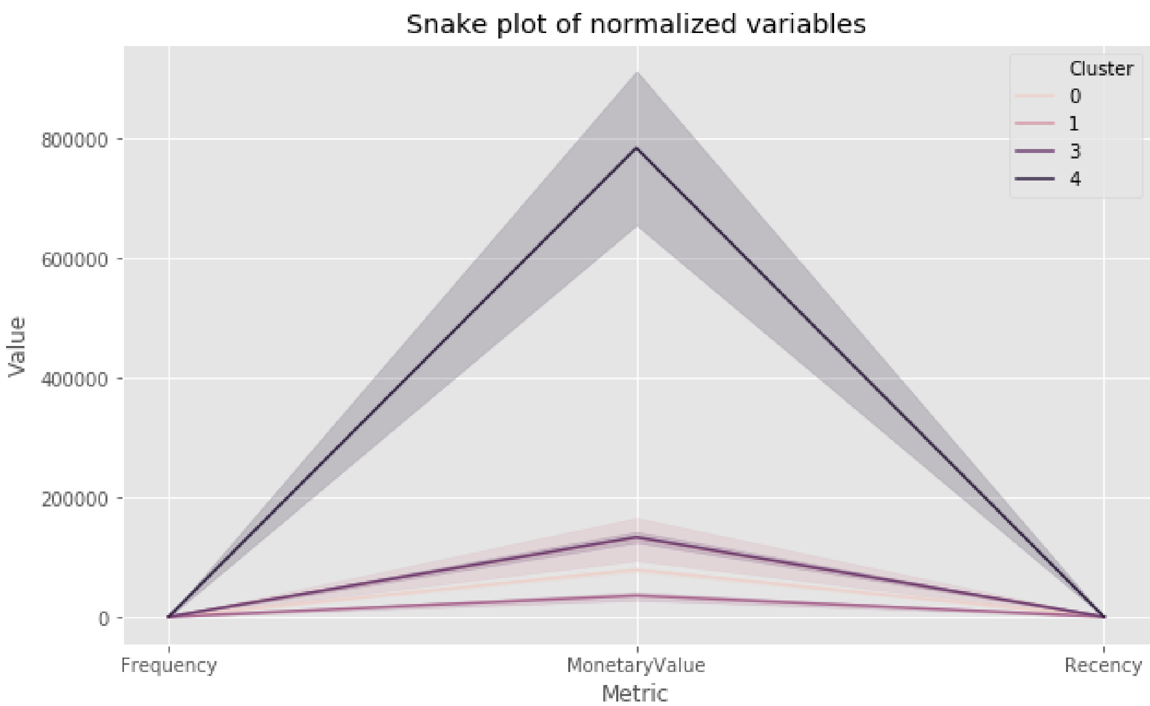
Building Customer Personas

Customer Pesonas can build by determining the summary stats of RFM values or Snake Plot. Snake Plots is a Market Research technique used to compare segments. Visual representation of each segment's attributes helps us to determine the relative Importance of segment attributes

Snake Plot

In [43]:

```
data_rfm_melt = pd.melt(data_rfm.reset_index(), id_vars=['CUSTOMERNAME', 'Cluster'],
                        value_vars=['Recency', 'Frequency', 'MonetaryValue'],
                        var_name='Metric', value_name='Value')

plt.figure(figsize=(10,6))
# Add the plot title
plt.title('Snake plot of normalized variables')

# Add the x axis label
plt.xlabel('Metric')

# Add the y axis label
plt.ylabel('Value')

# Plot a line for each value of the cluster variable
sns.lineplot(data=data_rfm_melt, x='Metric', y='Value', hue='Cluster')
plt.show()
```



Calculating relative importance of each attribute

In [44]:

```
# Calculate average RFM values for each cluster
cluster_avg = data_rfm.groupby(['Cluster']).mean()
```

```
print(cluster_avg)
```

```
           Recency   Frequency  MonetaryValue
Cluster
0       209.162791   22.093023   78633.205814
1         2.000000   38.750000  132201.635000
2       324.250000   10.666667   35628.653333
3       126.548387   37.129032  133158.014516
4         2.000000  219.500000  783576.085000
```

In [45]:

```
# Calculate average RFM values for the total customer population
population_avg = data.mean()
print(population_avg)
```

```
Recency             182.826087
Frequency            30.684783
MonetaryValue    109050.313587
dtype: float64
```

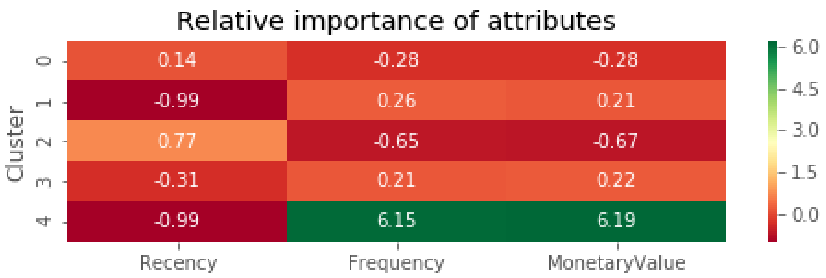
In [46]:

```
# Calculate relative importance of cluster's attribute value compared to population
relative_imp = cluster_avg / population_avg - 1

# Print relative importance score rounded to 2 decimals
print(relative_imp.round(2))
```

```
         Recency  Frequency  MonetaryValue
Cluster
0           0.14      -0.28          -0.28
1          -0.99       0.26           0.21
2           0.77      -0.65          -0.67
3          -0.31       0.21           0.22
4          -0.99       6.15           6.19
```

In [47]:

```
#Plot Relative Importance

# Initialize a plot with a figure size of 8 by 2 inches
plt.figure(figsize=(8, 2))

# Add the plot title
plt.title('Relative importance of attributes')

# Plot the heatmap
sns.heatmap(data=relative_imp, annot=True, fmt='.2f', cmap='RdYlGn')
plt.show()
```



In [ ]: