```
#importing required libraries
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
import matplotlib.pyplot as plt
%matplotlib inline
```

```
#importing the dataset
data = pd.read_excel('Dataset.xlsx')
```

first 5 rows of the data
data.head()

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Coι |
|--------------------------------|-----------|-----------|---|----------|------------------------|-----------|------------|----------|
| 0 | 536365 | 85123A | WHITE HANGING HEART T- LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 | L Kin |
| 1 | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | L Kin |
| 2 | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER KNITTED | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 | L Kin |
| # shape of the data data.shape | | | | | | | | |

(541909, 8)

Cleaning the Dataset

```
# Checking missing values
round(100*data.isnull().sum()/len(data))
```

InvoiceNo 0.0 StockCode 0.0

| Jedenedae | 0.0 |
|----------------|------|
| Description | 0.0 |
| Quantity | 0.0 |
| InvoiceDate | 0.0 |
| UnitPrice | 0.0 |
| CustomerID | 25.0 |
| Country | 0.0 |
| dtyne: float64 | |

Here, CustomerID column having 25% missing values. but, the column is very important for modelling. we can't impute those missing values, we simply dropping all the rows having missing values

```
# dropping missing values using dropna()
data = data.dropna()
data.shape

   (406829, 8)

# viewing the dataset
data.head()
```

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerII |
|---|-----------|-----------|---|----------|------------------------|-----------|------------|
| 0 | 536365 | 85123A | WHITE HANGING HEART T- LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.(|
| 1 | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.(|
| 2 | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 |
| | | | KNITTED | | | | |

Data Preparation

based on anlysis the retail store customers segmented by using 'RFM',

```
* R (Recency): Number of days since last purchase

* F (Frequency): Number of tracsactions
```

* M (Monetary): Total amount of transactions (revenue contributed)

→ 1. Monetary

```
# finding monetary
data['Amount'] = data['UnitPrice']*data['Quantity']
data.head()
```

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerII |
|---|-----------|-----------|---|----------|------------------------|-----------|------------|
| 0 | 536365 | 85123A | WHITE HANGING HEART T- LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.(|
| 1 | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.(|
| 2 | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.(|
| | | | KNITTED | | | | |

```
# Grouping 'CustomerId' and 'Amount'
grouped_data = data.groupby('CustomerID')['Amount'].sum()
grouped_data = grouped_data.reset_index()
grouped_data.head()
```

| | CustomerID | Amount | 1 |
|---|------------|---------|---|
| 0 | 12346.0 | 0.00 | |
| 1 | 12347.0 | 4310.00 | |
| 2 | 12348.0 | 1797.24 | |
| 3 | 12349.0 | 1757.55 | |
| 4 | 12350.0 | 334.40 | |

→ 2. Frequency

```
# Finding Frequency
frequency = data.groupby('CustomerID')['InvoiceNo'].count()
frequency = frequency.reset_index()
frequency.columns = ['CustomerID', 'frequency']
frequency.head()
```

| | CustomerID | frequency | 1 |
|---|------------|-----------|---|
| 0 | 12346.0 | 2 | |
| 1 | 12347.0 | 182 | |
| 2 | 12348.0 | 31 | |
| 3 | 12349.0 | 73 | |
| 4 | 12350.0 | 17 | |

```
# Merge the two dataframes
grouped_data = pd.merge(grouped_data, frequency, on='CustomerID', how='inner')
grouped_data.head()
```

| | CustomerID | Amount | frequency |
|---|------------|---------|-----------|
| 0 | 12346.0 | 0.00 | 2 |
| 1 | 12347.0 | 4310.00 | 182 |
| 2 | 12348.0 | 1797.24 | 31 |
| 3 | 12349.0 | 1757.55 | 73 |
| 4 | 12350.0 | 334.40 | 17 |

→ 3. Recency

Checking datatypes
data.dtypes

| InvoiceNo | object |
|---------------|---------------------------|
| StockCode | object |
| Description | object |
| Quantity | int64 |
| InvoiceDate | <pre>datetime64[ns]</pre> |
| UnitPrice | float64 |
| CustomerID | float64 |
| Country | object |
| Amount | float64 |
| dtype: object | |

```
# compute the max date
max_date = max(data['InvoiceDate'])
max_date
```

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

```
# compute the Recency
data['Recency'] = max_date - data['InvoiceDate']
data.head()
```

| | InvoiceNo | StockCode | Description | Quantity | InvoiceDate | UnitPrice | CustomerID | Coι |
|---|-----------|-----------|---|----------|------------------------|-----------|------------|-----------------------|
| 0 | 536365 | 85123A | WHITE HANGING HEART T- LIGHT HOLDER | 6 | 2010-12-01 08:26:00 | 2.55 | 17850.0 | L Kin |
| 1 | 536365 | 71053 | WHITE METAL LANTERN | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | L Kin |
| 2 | 536365 | 84406B | CREAM CUPID HEARTS COAT HANGER | 8 | 2010-12-01 08:26:00 | 2.75 | 17850.0 | L Kin |
| 3 | 536365 | 84029G | KNITTED UNION FLAG HOT WATER | 6 | 2010-12-01 08:26:00 | 3.39 | 17850.0 | L Kin _i |

```
# Recency
last_purchase = data.groupby('CustomerID')['Recency'].min()
last_purchase = last_purchase.reset_index()
last_purchase.head()
```

```
# merging the datasets
grouped_data = pd.merge(grouped_data, last_purchase, on='CustomerID', how='inner')
```

grouped_data.head()

| | CustomerID | Amount | frequency | Recency |
|---|------------|---------|-----------|-------------------|
| 0 | 12346.0 | 0.00 | 2 | 325 days 02:33:00 |
| 1 | 12347.0 | 4310.00 | 182 | 1 days 20:58:00 |
| 2 | 12348.0 | 1797.24 | 31 | 74 days 23:37:00 |
| 3 | 12349.0 | 1757.55 | 73 | 18 days 02:59:00 |
| 4 | 12350.0 | 334.40 | 17 | 309 days 20:49:00 |

```
# getting number of days only
grouped_data['Recency'] = grouped_data['Recency'].dt.days
grouped_data.head()
```

| | CustomerID | Amount | frequency | Recency |
|---|------------|---------|-----------|---------|
| 0 | 12346.0 | 0.00 | 2 | 325 |
| 1 | 12347.0 | 4310.00 | 182 | 1 |
| 2 | 12348.0 | 1797.24 | 31 | 74 |
| 3 | 12349.0 | 1757.55 | 73 | 18 |
| 4 | 12350.0 | 334.40 | 17 | 309 |

Checking Outliers

• 'RFM' values may have some Extreme points

```
# 1. outlier treatment
plt.boxplot(grouped_data['Recency'])
```

```
tilers : [<matplotlib.lines.Linezv at ux/t65bct2115u>],
      'means': [],
      'medians': [<matplotlib.lines.Line2D at 0x7f65bb367a10>],
      'whiskers': [<matplotlib.lines.Line2D at 0x7f65bbdc8a50>,
       <matplotlib.lines.Line2D at 0x7f65bbdc8090>]}
      350
      300
# removing (statistical) outliers
Q1 = grouped_data.Amount.quantile(0.05)
Q3 = grouped data.Amount.quantile(0.95)
```

```
IQR = Q3 - Q1
grouped_data = grouped_data[(grouped_data.Amount >= Q1 - 1.5*IQR) & (grouped_data.Amount <= (</pre>
# outlier treatment for Recency
Q1 = grouped data.Recency.quantile(0.05)
Q3 = grouped data.Recency.quantile(0.95)
IQR = Q3 - Q1
grouped data = grouped data[(grouped data.Recency >= Q1 - 1.5*IQR) & (grouped data.Recency <=
# outlier treatment for frequency
Q1 = grouped_data.frequency.quantile(0.05)
Q3 = grouped data.frequency.quantile(0.95)
IQR = Q3 - Q1
grouped_data = grouped_data[(grouped_data.frequency >= Q1 - 1.5*IQR) & (grouped_data.frequenc
```

Scaling

Kmeans clustering is distance based algorithm scaling the data is more important

```
# Scaling
from sklearn.preprocessing import StandardScaler
data_scaled= grouped_data[['Amount', 'frequency', 'Recency']]
# instantiate
scaler = StandardScaler()
# fit transform
df scaled = scaler.fit transform(data scaled)
df_scaled.shape
     (4293, 3)
df_scaled = pd.DataFrame(df_scaled)
df_scaled.columns = ['Amount', 'Frequency', 'Recency']
df_scaled.head()
```

| | Amount | Frequency | Recency |
|---|-----------|-----------|-----------|
| 0 | -0.723738 | -0.752888 | 2.301611 |
| 1 | 1.731617 | 1.042467 | -0.906466 |
| 2 | 0.300128 | -0.463636 | -0.183658 |
| 3 | 0.277517 | -0.044720 | -0.738141 |
| 4 | -0.533235 | -0.603275 | 2.143188 |

KMeans Clustering

for cluster in range(1 20).

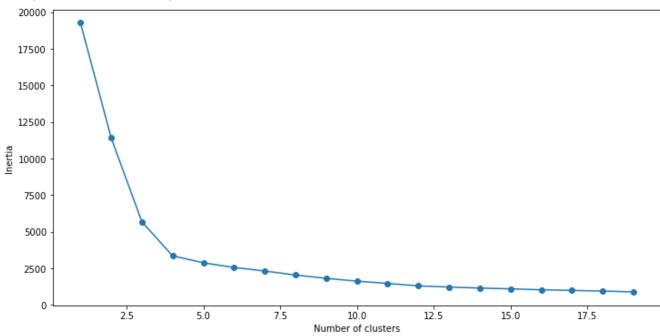
```
# importing KMeans
from sklearn.cluster import KMeans
# k-means with k value 2
kmeans = KMeans(n_clusters=2)
kmeans.fit(df_scaled)
     KMeans(n_clusters=2)
pred=kmeans.predict(df_scaled)
pred
     array([0, 1, 0, ..., 0, 0, 0], dtype=int32)
pd.Series(pred).value_counts()
     0
          3282
          1011
     dtype: int64
kmeans.inertia_
     11408.667844165004
kmeans.score(df_scaled)
     -11408.667844165004
SSE = []
```

```
kmeans = KMeans(n_clusters = cluster)
kmeans.fit(df_scaled)
SSE.append(kmeans.inertia_)
```

```
frame = pd.DataFrame({'Cluster':range(1,20), 'SSE':SSE})
```

```
# Elbow curve
plt.figure(figsize=(12,6))
plt.plot(frame['Cluster'], frame['SSE'], marker='o')
plt.xlabel('Number of clusters')
plt.ylabel('Inertia')
```

Text(0, 0.5, 'Inertia')



```
# from elbow curve we setting the k value to '4'
kmeans = KMeans(n_clusters = 4)
kmeans.fit(df_scaled)
pred = kmeans.predict(df_scaled)
```

pred

```
array([0, 2, 1, ..., 0, 1, 1], dtype=int32)
```

```
frame = pd.DataFrame(df_scaled)
```

```
frame['cluster'] = pred
```

frame['cluster'].value_counts()

1 2250 0 1035 2 782 3 226

Name: cluster, dtype: int64

Here, we segmented the customers into 4 groups or clusters

✓ 0s completed at 12:12 PM

×