

# Customer\_Segmentation using RFM Clustering

Customer segmentation is the process of separating customers into groups on the basis of their shared behavior or other attributes. The groups should be homogeneous within themselves and should also be heterogeneous to each other. The overall aim of this process is to identify high-value customer base i.e. customers that have the highest growth potential or are the most profitable.

```
In [1]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

## Understanding Business Question

### RFM Segmentation

RFM stands for Recency, Frequency, and Monetary. RFM analysis is a commonly used technique to generate and assign a score to each customer based on how recent their last transaction was (Recency), how many transactions they have made in the last year (Frequency), and what the monetary value of their transaction was (Monetary).

```
In [65]: df = pd.read_csv('CS_08.csv')
```

```
In [66]: df.head()
```

```
Out[66]:
```

	order_id	created_ts	shamsy_date	customer_id	total_purchase
0	5c92a3d9a7b11b0001e4ec46	3/21/2019 0:04	1398-Farvardin-1	5bf1092b24aa9a000135ac7c	240000.0
1	5c92af8024aa9a00015b536d	3/21/2019 0:54	1398-Farvardin-1	58d2fe9b46e0fb0001e432c0	620000.0
2	5c930b0ea7b11b0001e4f07e	3/21/2019 7:24	1398-Farvardin-1	5c85f140a7b11b0001e65ec1	320000.0
3	5c93157324aa9a00015b5750	3/21/2019 8:09	1398-Farvardin-1	59c52fe152faff00014e4932	220000.0
4	5c93250024aa9a00015b5884	3/21/2019 9:15	1398-Farvardin-1	58eba26fd601800001b98a34	360000.0

```
In [67]: df.tail()
```

```
Out[67]:
```

	order_id	created_ts	shamsy_date	customer_id	total_purchase
40532	5d35fd03b2cf38d2d17b11c9	7/22/2019 22:44	1398-Tir-31	58d2972b46e0fb0001e42133	280000.0
40533	5d35fe44ec2c893461deb4e0	7/22/2019 22:49	1398-Tir-31	597009a6c9e77c00018c27d9	300000.0
40534	5d35ff28b2cf38d2d17b1228	7/22/2019 22:53	1398-Tir-31	59222bce52faff00016c59cc	180000.0
40535	5d360499b2cf38d2d17b12f6	7/22/2019 23:16	1398-Tir-31	5d19f78ab2cf38e5e4deddd6	180000.0
40536	5d360b2eec2c893461deb667	7/22/2019 23:44	1398-Tir-31	5c46e8fe24aa9a00019af009	180000.0

```
In [68]: df.shape
```

```
Out[68]: (40537, 5)
```

```
In [69]: df.info()
```

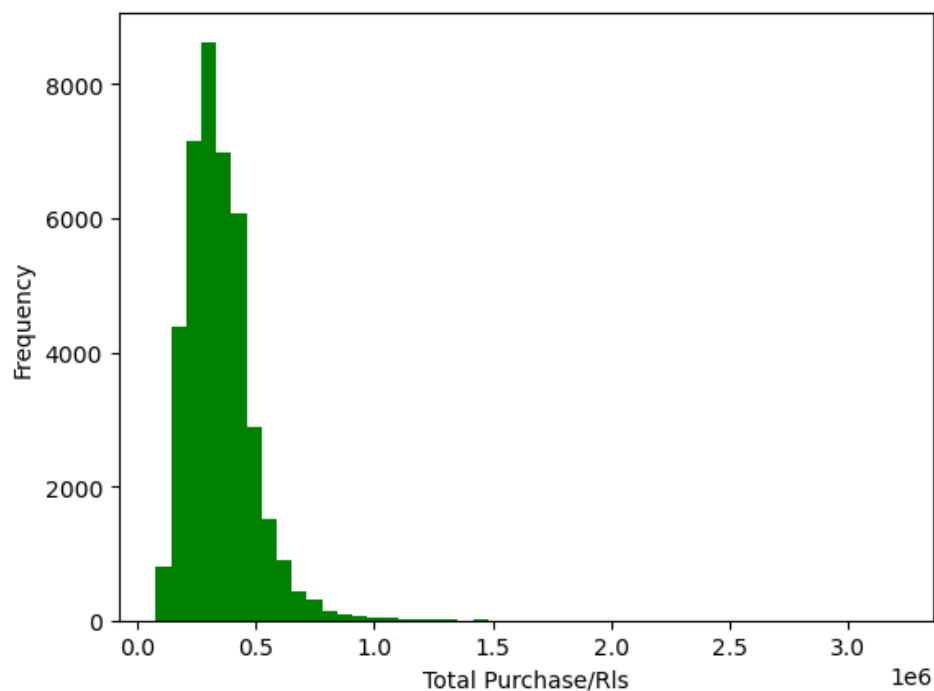
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40537 entries, 0 to 40536
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   order_id        40537 non-null  object
1   created_ts      40537 non-null  object
2   shamsy_date     40537 non-null  object
3   customer_id     40537 non-null  object
4   total_purchase  40537 non-null  float64
dtypes: float64(1), object(4)
memory usage: 1.5+ MB
```

```
In [74]: df.describe()
```

```
Out[74]:
```

	total_purchase
count	4.053700e+04
mean	3.488023e+05
std	1.414450e+05
min	8.000000e+04
25%	2.600000e+05
50%	3.200000e+05
75%	4.200000e+05
max	3.200000e+06

```
In [75]: #Histogram of total purchase
plt.hist(df['total_purchase'],
         color = 'green',
         bins = np.linspace(df['total_purchase'].min(),
                             df['total_purchase'].max(), 50))
plt.xlabel('Total Purchase/Rls')
plt.ylabel('Frequency')
plt.show()
```



```
In [76]: #daily demand
df['created_ts'] = pd.to_datetime(df['created_ts'])
```

```
In [77]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40537 entries, 0 to 40536
Data columns (total 5 columns):
#   Column          Non-Null Count  Dtype
---  -
0   order_id        40537 non-null  object
1   created_ts      40537 non-null  datetime64[ns]
2   shamsy_date     40537 non-null  object
3   customer_id    40537 non-null  object
4   total_purchase  40537 non-null  float64
dtypes: datetime64[ns](1), float64(1), object(3)
memory usage: 1.5+ MB
```

```
In [31]: df.iloc[0, 1]
```

```
Out[31]: Timestamp('2019-03-21 00:04:00')
```

```
In [78]: df['created_ts'].dt.date
```

```
Out[78]: 0      2019-03-21
1      2019-03-21
2      2019-03-21
3      2019-03-21
4      2019-03-21
...
40532   2019-07-22
40533   2019-07-22
40534   2019-07-22
40535   2019-07-22
40536   2019-07-22
Name: created_ts, Length: 40537, dtype: object
```

```
In [79]: df['date'] = df['created_ts'].dt.date
```

```
In [35]: df.info()
```

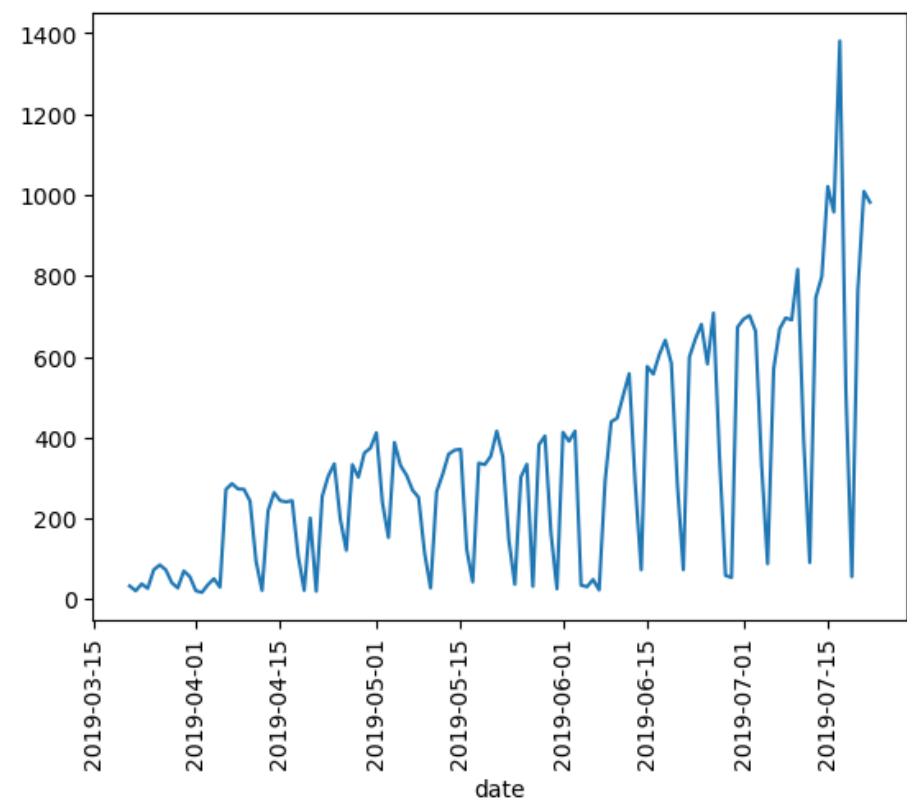
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 40537 entries, 0 to 40536
Data columns (total 6 columns):
#   Column          Non-Null Count  Dtype
---  -
0   order_id        40537 non-null  object
1   created_ts      40537 non-null  datetime64[ns]
2   shamsy_date     40537 non-null  object
3   customer_id     40537 non-null  object
4   total_purchase  40537 non-null  float64
5   date            40537 non-null  object
dtypes: datetime64[ns](1), float64(1), object(4)
memory usage: 1.9+ MB
```

```
In [80]: daily_demand = df.groupby(by = ['date'])['order_id'].count()
```

```
In [81]: daily_demand
```

```
Out[81]: date
2019-03-21      33
2019-03-22      21
2019-03-23      38
2019-03-24      27
2019-03-25      73
...
2019-07-18     517
2019-07-19      56
2019-07-20     765
2019-07-21    1009
2019-07-22     982
Name: order_id, Length: 124, dtype: int64
```

```
In [38]: daily_demand.plot()  
plt.xticks(rotation = 90)  
plt.show()
```



## Create RFM Dataset

### Frequency

```
In [82]: customer_f = pd.DataFrame({'freq': df.groupby(by = ['customer_id'])['order_id'].count()})  
customer_f
```

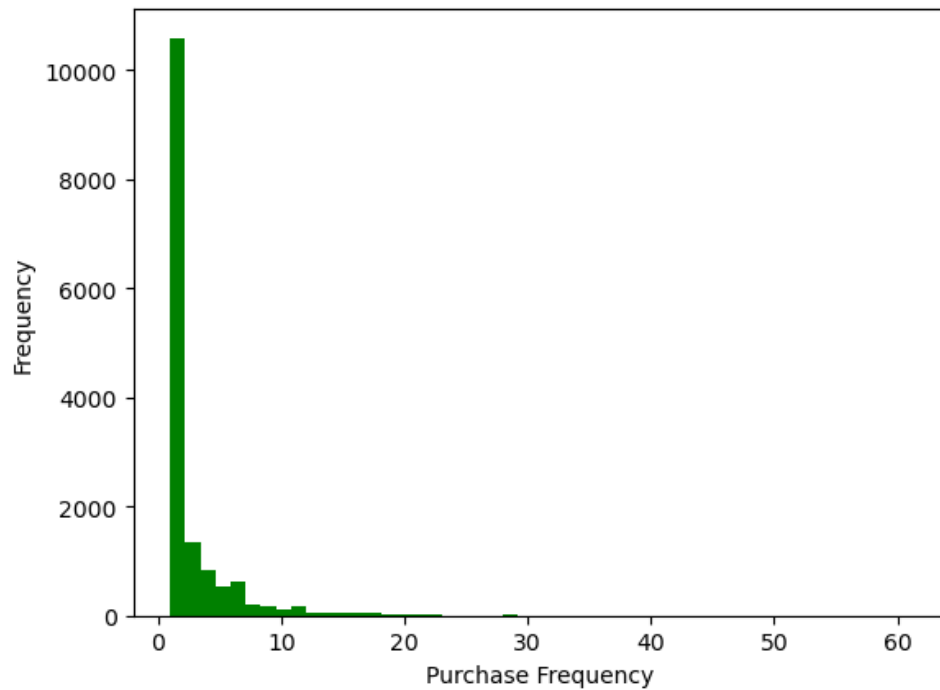
Out[82]:

customer_id	freq
5.94687E+23	2
5.94772E+23	1
5.94773E+23	5
5.95E+25	1
58a4b0e452faff000179dbd0	7
...	...
5d3584f8b2cf38d2d17aafba	1
5d359600b2cf38d2d17ac0e7	1
5d35a06bb2cf38d2d17acbc3	1
5d35ae07b2cf38d2d17adb54	1
5d35cf29b2cf38d2d17afcda	1

14964 rows × 1 columns

```
In [83]: #Histogram of purchase frequency
plt.hist(customer_f['freq'],
         color = 'green',
         bins = np.linspace(customer_f['freq'].min(), customer_f['freq'].max(), 50))
plt.xlabel('Purchase Frequency')
plt.ylabel('Frequency')
```

```
Out[83]: Text(0, 0.5, 'Frequency')
```



```
In [84]: customer_f.describe()
```

```
Out[84]:
```

	freq
count	14964.000000
mean	2.708968
std	3.425412
min	1.000000
25%	1.000000
50%	1.000000
75%	3.000000
max	61.000000

```
In [85]: df.tail()
```

```
Out[85]:
```

	order_id	created_ts	shamsy_date	customer_id	total_purchase	date
40532	5d35fd03b2cf38d2d17b11c9	2019-07-22 22:44:00	1398-Tir-31	58d2972b46e0fb0001e42133	280000.0	2019-07-22
40533	5d35fe44ec2c893461deb4e0	2019-07-22 22:49:00	1398-Tir-31	597009a6c9e77c00018c27d9	300000.0	2019-07-22
40534	5d35ff28b2cf38d2d17b1228	2019-07-22 22:53:00	1398-Tir-31	59222bce52faff00016c59cc	180000.0	2019-07-22
40535	5d360499b2cf38d2d17b12f6	2019-07-22 23:16:00	1398-Tir-31	5d19f78ab2cf38e5e4deddd6	180000.0	2019-07-22
40536	5d360b2eec2c893461deb667	2019-07-22 23:44:00	1398-Tir-31	5c46e8fe24aa9a00019af009	180000.0	2019-07-22

```
In [86]: r_date = pd.to_datetime('2019-07-23').date() - df['date']
```

```
In [87]: r_date[0]
```

```
Out[87]: Timedelta('124 days 00:00:00')
```

```
In [48]: r_date.dt.days
```

Out[48]:

0	124
1	124
2	124
3	124
4	124
...	...
40532	1
40533	1
40534	1
40535	1
40536	1

Name: date, Length: 40537, dtype: int64

```
In [88]: df['r_date'] = r_date.dt.days
df
```

Out[88]:

	order_id	created_ts	shamsy_date	customer_id	total_purchase	date	r_date
0	5c92a3d9a7b11b0001e4ec46	2019-03-21 00:04:00	1398-Farvardin-1	5bf1092b24aa9a000135ac7c	240000.0	2019-03-21	124
1	5c92af8024aa9a00015b536d	2019-03-21 00:54:00	1398-Farvardin-1	58d2fe9b46e0fb0001e432c0	620000.0	2019-03-21	124
2	5c930b0ea7b11b0001e4f07e	2019-03-21 07:24:00	1398-Farvardin-1	5c85f140a7b11b0001e65ec1	320000.0	2019-03-21	124
3	5c93157324aa9a00015b5750	2019-03-21 08:09:00	1398-Farvardin-1	59c52fe152faff00014e4932	220000.0	2019-03-21	124
4	5c93250024aa9a00015b5884	2019-03-21 09:15:00	1398-Farvardin-1	58eba26fd601800001b98a34	360000.0	2019-03-21	124
...	...	...	...	...	...	...	...
40532	5d35fd03b2cf38d2d17b11c9	2019-07-22 22:44:00	1398-Tir-31	58d2972b46e0fb0001e42133	280000.0	2019-07-22	1
40533	5d35fe44ec2c893461deb4e0	2019-07-22 22:49:00	1398-Tir-31	597009a6c9e77c00018c27d9	300000.0	2019-07-22	1
40534	5d35ff28b2cf38d2d17b1228	2019-07-22 22:53:00	1398-Tir-31	59222bce52faff00016c59cc	180000.0	2019-07-22	1
40535	5d360499b2cf38d2d17b12f6	2019-07-22 23:16:00	1398-Tir-31	5d19f78ab2cf38e5e4deddd6	180000.0	2019-07-22	1
40536	5d360b2eec2c893461deb667	2019-07-22 23:44:00	1398-Tir-31	5c46e8fe24aa9a00019af009	180000.0	2019-07-22	1

40537 rows × 7 columns

```
In [89]: customer_r = pd.DataFrame({'recency': df.groupby(by = ['customer_id'])['r_date'].min()})
customer_r
```

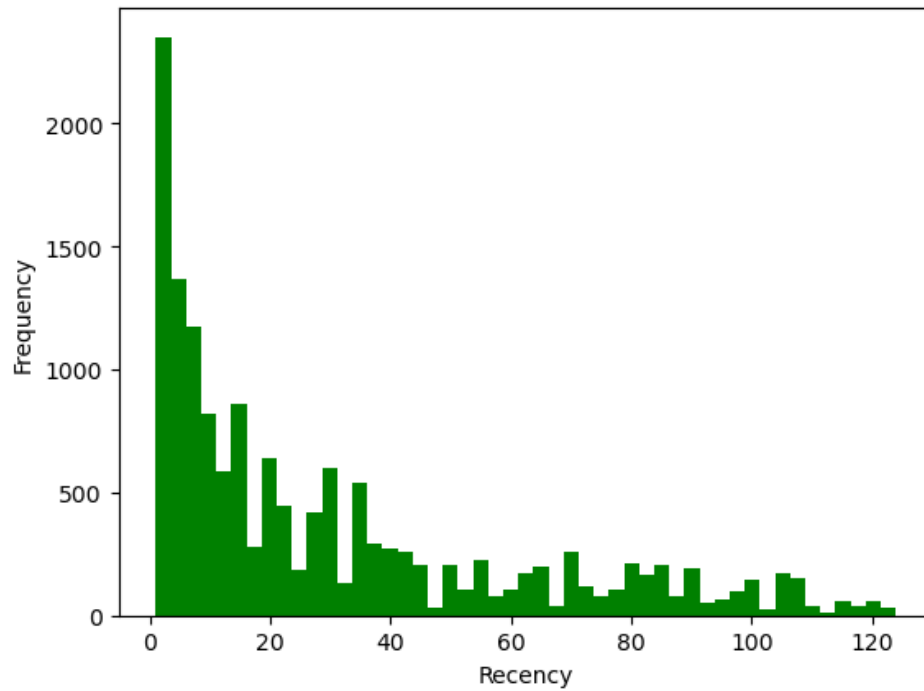
Out[89]:

	recency
customer_id	
5.94687E+23	9
5.94772E+23	64
5.94773E+23	9
5.95E+25	5
58a4b0e452faff000179dbd0	7
...	...
5d3584f8b2cf38d2d17aafba	1
5d359600b2cf38d2d17ac0e7	1
5d35a06bb2cf38d2d17acbc3	1
5d35ae07b2cf38d2d17adb54	1
5d35cf29b2cf38d2d17afcda	1

14964 rows × 1 columns

```
In [52]: #Histogram of recency
plt.hist(customer_r['recency'], color = 'green',
         bins = np.linspace(customer_r['recency'].min(), customer_r['recency'].max(), 50))
plt.xlabel('Recency')
plt.ylabel('Frequency')
```

Out[52]: Text(0, 0.5, 'Frequency')



```
In [90]: customer_r.describe()
```

Out[90]:

	recency
count	14964.000000
mean	30.497995
std	30.833106
min	1.000000
25%	7.000000
50%	19.000000
75%	43.000000
max	124.000000

# Monetary

```
In [91]: customer_m = pd.DataFrame({'monetary': df.groupby(by = ['customer_id'])['total_purchase'].sum()})
customer_m
```

Out[91]:

monetary	
customer_id	
5.94687E+23	680000.0
5.94772E+23	600000.0
5.94773E+23	1700000.0
5.95E+25	320000.0
58a4b0e452faff000179dbd0	1480000.0
...	...
5d3584f8b2cf38d2d17aafba	200000.0
5d359600b2cf38d2d17ac0e7	520000.0
5d35a06bb2cf38d2d17acbc3	440000.0
5d35ae07b2cf38d2d17adb54	200000.0
5d35cf29b2cf38d2d17afcda	420000.0

14964 rows × 1 columns

# RFM Dataframe for Customers

```
In [92]: df = customer_f.merge(customer_r, left_index = True, right_index = True)
df
```

Out[92]:

freq recency		
customer_id		
5.94687E+23	2	9
5.94772E+23	1	64
5.94773E+23	5	9
5.95E+25	1	5
58a4b0e452faff000179dbd0	7	7
...	...	...
5d3584f8b2cf38d2d17aafba	1	1
5d359600b2cf38d2d17ac0e7	1	1
5d35a06bb2cf38d2d17acbc3	1	1
5d35ae07b2cf38d2d17adb54	1	1
5d35cf29b2cf38d2d17afcda	1	1

14964 rows × 2 columns

```
In [93]: rfm_customer = df.merge(customer_m, left_index = True, right_index = True)
```



In [94]: rfm\_customer

Out [94]:

	freq	recency	monetary
customer_id			
5.94687E+23	2	9	680000.0
5.94772E+23	1	64	600000.0
5.94773E+23	5	9	1700000.0
5.95E+25	1	5	320000.0
58a4b0e452faff000179dbd0	7	7	1480000.0
...	...	...	...
5d3584f8b2cf38d2d17aafba	1	1	200000.0
5d359600b2cf38d2d17ac0e7	1	1	520000.0
5d35a06bb2cf38d2d17acbc3	1	1	440000.0
5d35ae07b2cf38d2d17adb54	1	1	200000.0
5d35cf29b2cf38d2d17afcda	1	1	420000.0

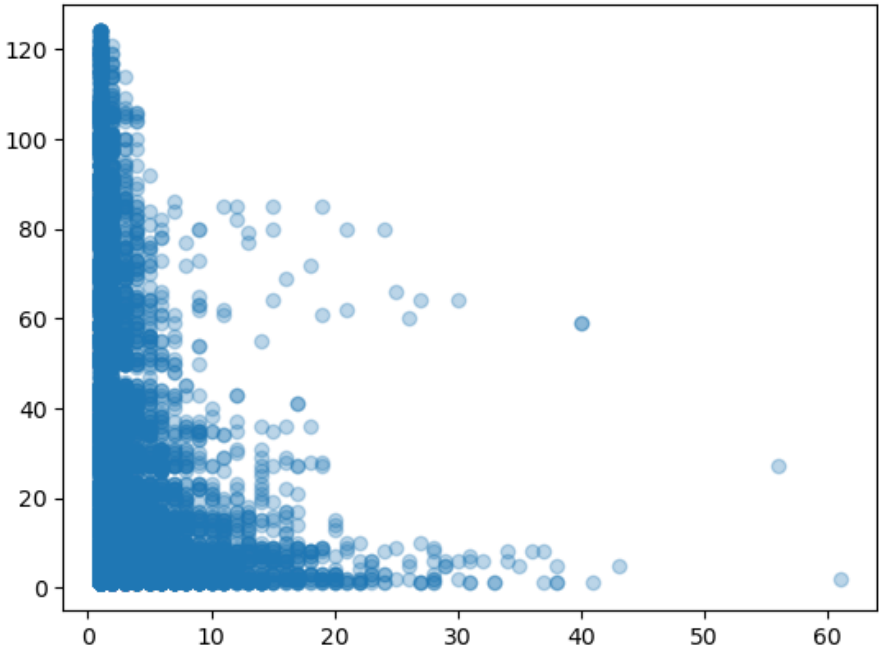
14964 rows × 3 columns

In [96]: `#Remove some dataframes to free RAM`  
`del(customer_r, customer_f, customer_m, df, data)`

-----  
**NameError** Traceback (most recent call last)  
Cell In[96], line 2  
1 #Remove some dataframes to free RAM  
----> 2 del(customer\_r, customer\_f, customer\_m, df, data)  
  
**NameError**: name 'customer\_r' is not defined

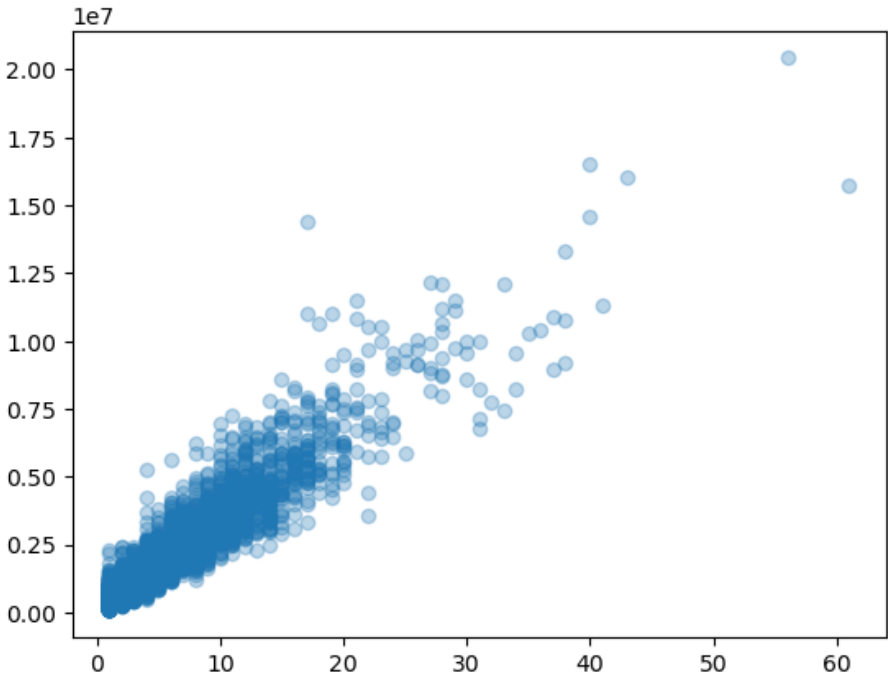
In [97]: `plt.scatter(x = rfm_customer['freq'],`  
`y = rfm_customer['recency'], alpha = 0.3)`

Out [97]: <matplotlib.collections.PathCollection at 0x174137588d0>



```
In [98]: plt.scatter(x = rfm_customer['freq'],
                    y = rfm_customer['monetary'], alpha = 0.3)
```

Out[98]: <matplotlib.collections.PathCollection at 0x17413d62d90>



```
In [99]: rfm_customer[['freq', 'monetary']].corr(method = 'pearson')
```

Out[99]:

	freq	monetary
freq	1.000000	0.947786
monetary	0.947786	1.000000

```
In [100]: rfm_customer_2 = rfm_customer.loc[:, ['freq', 'recency']]
```

```
In [101]: rfm_customer_2
```

Out[101]:

	freq	recency
customer_id		
5.94687E+23	2	9
5.94772E+23	1	64
5.94773E+23	5	9
5.95E+25	1	5
58a4b0e452faff000179dbd0	7	7
...	...	...
5d3584f8b2cf38d2d17aafba	1	1
5d359600b2cf38d2d17ac0e7	1	1
5d35a06bb2cf38d2d17acbc3	1	1
5d35ae07b2cf38d2d17adb54	1	1
5d35cf29b2cf38d2d17afcda	1	1

14964 rows × 2 columns

```
In [102]: #Scale features
from sklearn.preprocessing import StandardScaler
```

```
In [103]: scaled_data = StandardScaler().fit_transform(rfm_customer_2)
scaled_data
```

```
Out[103]: array([[ -0.20698004, -0.69726072],
        [-0.49892549,  1.08659584],
        [ 0.66885632, -0.69726072],
        ...,
        [-0.49892549, -0.95673077],
        [-0.49892549, -0.95673077],
        [-0.49892549, -0.95673077]])
```

```
In [104]: scaled_data = pd.DataFrame(scaled_data,
                                     columns = rfm_customer_2.columns,
                                     index = rfm_customer_2.index)

scaled_data
```

```
Out[104]:
```

	freq	recency
customer_id		
5.94687E+23	-0.206980	-0.697261
5.94772E+23	-0.498925	1.086596
5.94773E+23	0.668856	-0.697261
5.95E+25	-0.498925	-0.826996
58a4b0e452faff000179dbd0	1.252747	-0.762128
...	...	...
5d3584f8b2cf38d2d17aafba	-0.498925	-0.956731
5d359600b2cf38d2d17ac0e7	-0.498925	-0.956731
5d35a06bb2cf38d2d17acbc3	-0.498925	-0.956731
5d35ae07b2cf38d2d17adb54	-0.498925	-0.956731
5d35cf29b2cf38d2d17afcda	-0.498925	-0.956731

14964 rows × 2 columns

```
In [105]: scaled_data.describe()
```

```
Out[105]:
```

	freq	recency
count	1.496400e+04	1.496400e+04
mean	2.659075e-17	-1.139603e-17
std	1.000033e+00	1.000033e+00
min	-4.989255e-01	-9.567308e-01
25%	-4.989255e-01	-7.621282e-01
50%	-4.989255e-01	-3.729232e-01
75%	8.496541e-02	4.054870e-01
max	1.701780e+01	3.032621e+00

## K-means Clustering

```
In [106]: #First try
from sklearn.cluster import KMeans
seg_kml = KMeans(n_clusters = 5,
                 init = 'random',
                 random_state = 123,
                 n_init = 1).fit(scaled_data)
```

```
In [107]: rfm_customer['seg_km1'] = seg_km1.predict(scaled_data)
rfm_customer
```

Out[107]:

	freq	recency	monetary	seg_km1
customer_id				
5.94687E+23	2	9	680000.0	0
5.94772E+23	1	64	600000.0	2
5.94773E+23	5	9	1700000.0	4
5.95E+25	1	5	320000.0	0
58a4b0e452fa00179dbd0	7	7	1480000.0	4
...	...	...	...	...
5d3584f8b2cf38d2d17aafba	1	1	200000.0	0
5d359600b2cf38d2d17ac0e7	1	1	520000.0	0
5d35a06bb2cf38d2d17acbc3	1	1	440000.0	0
5d35ae07b2cf38d2d17adb54	1	1	200000.0	0
5d35cf29b2cf38d2d17afcda	1	1	420000.0	0

14964 rows × 4 columns

```
In [108]: rfm_customer['seg_km1'].isnull().sum()
```

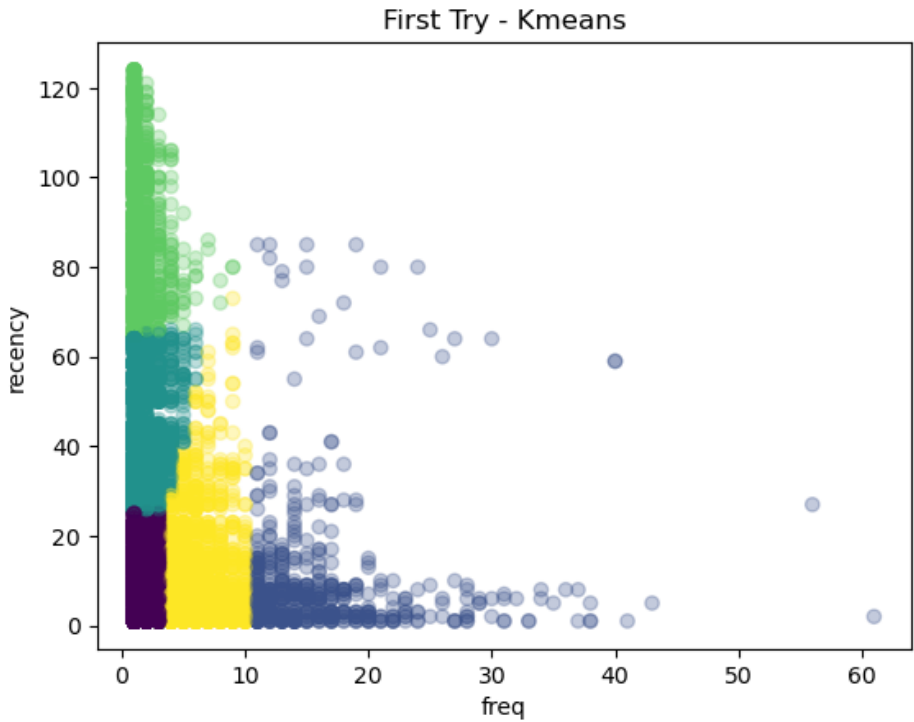
Out[108]: 0

```
In [109]: #Results
rfm_customer.groupby(['seg_km1'])[['freq', 'recency', 'monetary']].mean()
```

Out[109]:

	freq	recency	monetary
seg_km1			
0	1.600363	9.873286	5.718949e+05
1	15.992832	9.996416	5.461541e+06
2	1.512330	40.665558	5.341036e+05
3	1.288755	88.822892	4.376867e+05
4	5.882431	10.248447	2.046477e+06

```
In [110]: #Scatter Plot - First Try
plt.scatter(x = rfm_customer['freq'],
            y = rfm_customer['recency'],
            c = rfm_customer['seg_km1'], alpha = 0.3)
plt.xlabel('freq')
plt.ylabel('recency')
plt.title('First Try - Kmeans')
plt.show()
```



```
In [111]: #Second try
from sklearn.cluster import KMeans
seg_km2 = KMeans(n_clusters = 5,
                 init = 'random',
                 random_state = 1000,
                 n_init = 1).fit(scaled_data)
```

```
In [112]: rfm_customer['seg_km2'] = seg_km2.predict(scaled_data)
rfm_customer
```

Out[112]:

	freq	recency	monetary	seg_km1	seg_km2
customer_id					
5.94687E+23	2	9	680000.0	0	3
5.94772E+23	1	64	600000.0	2	4
5.94773E+23	5	9	1700000.0	4	2
5.95E+25	1	5	320000.0	0	3
58a4b0e452faff000179dbd0	7	7	1480000.0	4	2
...	...	...	...	...	...
5d3584f8b2cf38d2d17aafba	1	1	200000.0	0	3
5d359600b2cf38d2d17ac0e7	1	1	520000.0	0	3
5d35a06bb2cf38d2d17acbc3	1	1	440000.0	0	3
5d35ae07b2cf38d2d17adb54	1	1	200000.0	0	3
5d35cf29b2cf38d2d17afcda	1	1	420000.0	0	3

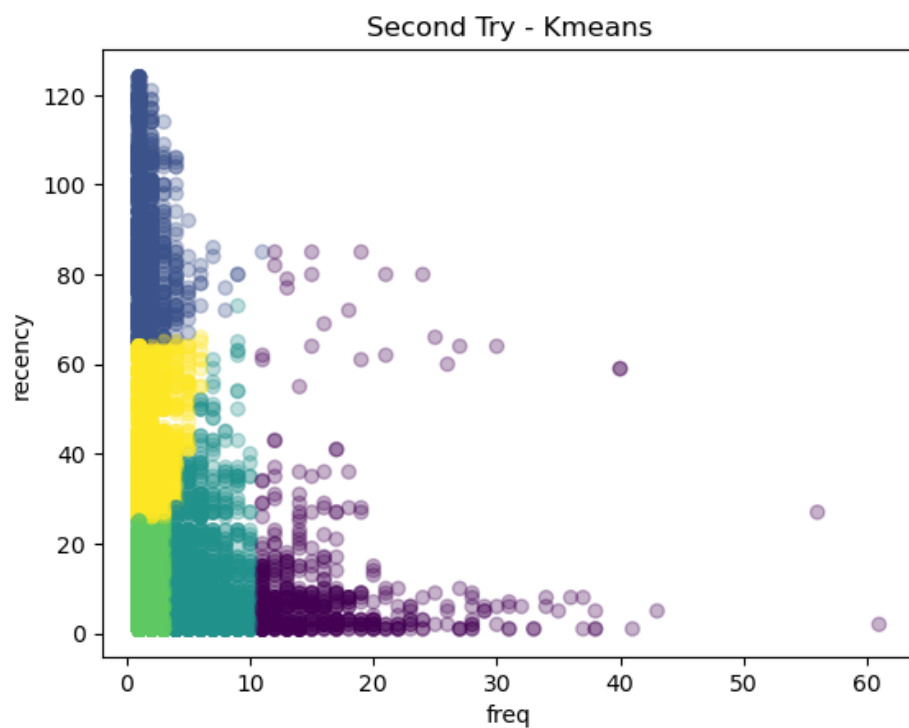
14964 rows × 5 columns

```
In [113]: #Results
rfm_customer.groupby(['seg_km2'])[['freq', 'recency', 'monetary']].mean()
```

```
Out[113]:
```

	freq	recency	monetary
seg_km2			
0	16.001795	9.861759	5.464201e+06
1	1.297686	88.679170	4.410694e+05
2	5.889978	10.173274	2.049149e+06
3	1.600363	9.873286	5.718949e+05
4	1.515959	40.534832	5.352484e+05

```
In [114]: #Scatter Plot - Second Try
plt.scatter(x = rfm_customer['freq'],
            y = rfm_customer['recency'],
            c = rfm_customer['seg_km2'], alpha = 0.3)
plt.xlabel('freq')
plt.ylabel('recency')
plt.title('Second Try - Kmeans')
plt.show()
```



## K-means ++

`n_init`: sets the number of initializations to perform. The default behavior for the scikit-learn algorithm is to perform ten k-means runs and return the results of the one with the lowest SSE.

```
In [115]: #First Try
from sklearn.cluster import KMeans
seg_km3 = KMeans(n_clusters = 5,
                 init = 'k-means++',
                 random_state = 1000,
                 n_init = 15).fit(scaled_data)
```

```
In [116]: rfm_customer['seg_km3'] = seg_km3.predict(scaled_data)
rfm_customer
```

Out[116]:

	freq	recency	monetary	seg_km1	seg_km2	seg_km3
customer_id						
5.94687E+23	2	9	680000.0	0	3	0
5.94772E+23	1	64	600000.0	2	4	4
5.94773E+23	5	9	1700000.0	4	2	1
5.95E+25	1	5	320000.0	0	3	0
58a4b0e452faff000179dbd0	7	7	1480000.0	4	2	1
...	...	...	...	...	...	...
5d3584f8b2cf38d2d17aafba	1	1	200000.0	0	3	0
5d359600b2cf38d2d17ac0e7	1	1	520000.0	0	3	0
5d35a06bb2cf38d2d17acbc3	1	1	440000.0	0	3	0
5d35ae07b2cf38d2d17adb54	1	1	200000.0	0	3	0
5d35cf29b2cf38d2d17afcda	1	1	420000.0	0	3	0

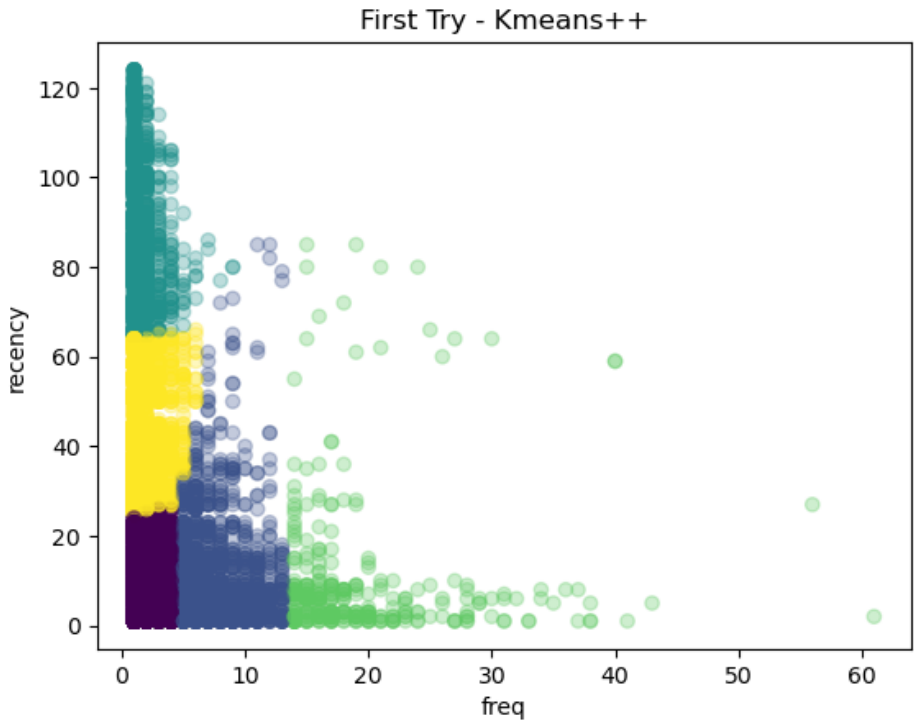
14964 rows × 6 columns

```
In [117]: #Results
rfm_customer.groupby(['seg_km3'])[['freq', 'recency', 'monetary']].mean()
```

Out[117]:

	freq	recency	monetary
seg_km3			
0	1.833882	9.707273	6.540527e+05
1	7.409015	10.050640	2.575548e+06
2	1.291134	88.687300	4.391454e+05
3	19.317308	10.339744	6.512821e+06
4	1.556010	40.378305	5.475988e+05

```
In [118]: #Scatter Plot - First Try
plt.scatter(x = rfm_customer['freq'],
            y = rfm_customer['recency'],
            c = rfm_customer['seg_km3'], alpha = 0.3)
plt.xlabel('freq')
plt.ylabel('recency')
plt.title('First Try - Kmeans++')
plt.show()
```



```
In [119]: #Second Try
from sklearn.cluster import KMeans
seg_km4 = KMeans(n_clusters = 5,
                 init = 'k-means++',
                 random_state = 1234,
                 n_init = 15).fit(scaled_data)
```

```
In [120]: rfm_customer['seg_km4'] = seg_km4.predict(scaled_data)
rfm_customer
```

```
Out[120]:
```

	freq	recency	monetary	seg_km1	seg_km2	seg_km3	seg_km4
customer_id							
5.94687E+23	2	9	680000.0	0	3	0	1
5.94772E+23	1	64	600000.0	2	4	4	0
5.94773E+23	5	9	1700000.0	4	2	1	2
5.95E+25	1	5	320000.0	0	3	0	1
58a4b0e452faff000179dbd0	7	7	1480000.0	4	2	1	2
...	...	...	...	...	...	...	...
5d3584f8b2cf38d2d17aafba	1	1	200000.0	0	3	0	1
5d359600b2cf38d2d17ac0e7	1	1	520000.0	0	3	0	1
5d35a06bb2cf38d2d17acbc3	1	1	440000.0	0	3	0	1
5d35ae07b2cf38d2d17adb54	1	1	200000.0	0	3	0	1
5d35cf29b2cf38d2d17afcda	1	1	420000.0	0	3	0	1

14964 rows × 7 columns

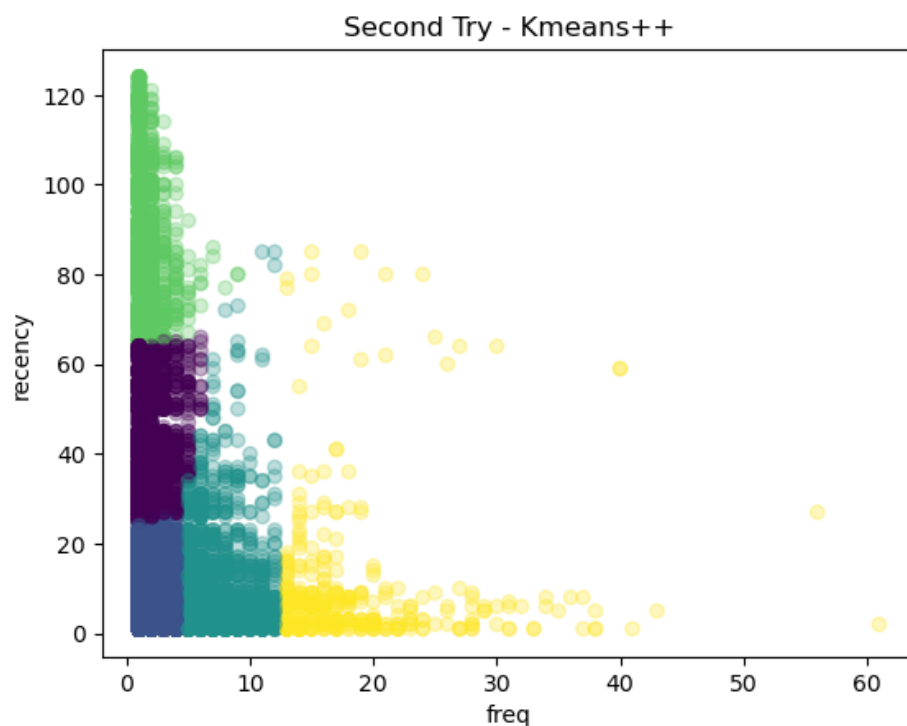


```
In [121]: #Results
rfm_customer.groupby(['seg_km4'])[['freq', 'recency', 'monetary']].mean()
```

```
Out[121]:
```

	freq	recency	monetary
seg_km4			
0	1.550369	40.388752	5.459023e+05
1	1.833882	9.707273	6.540527e+05
2	7.208262	10.183592	2.507229e+06
3	1.291134	88.687300	4.391454e+05
4	18.298387	10.056452	6.181882e+06

```
In [122]: #Scatter Plot - Second Try
plt.scatter(x = rfm_customer['freq'], y = rfm_customer['recency'],
            c = rfm_customer['seg_km4'], alpha = 0.3)
plt.xlabel('freq')
plt.ylabel('recency')
plt.title('Second Try - Kmeans++')
plt.show()
```



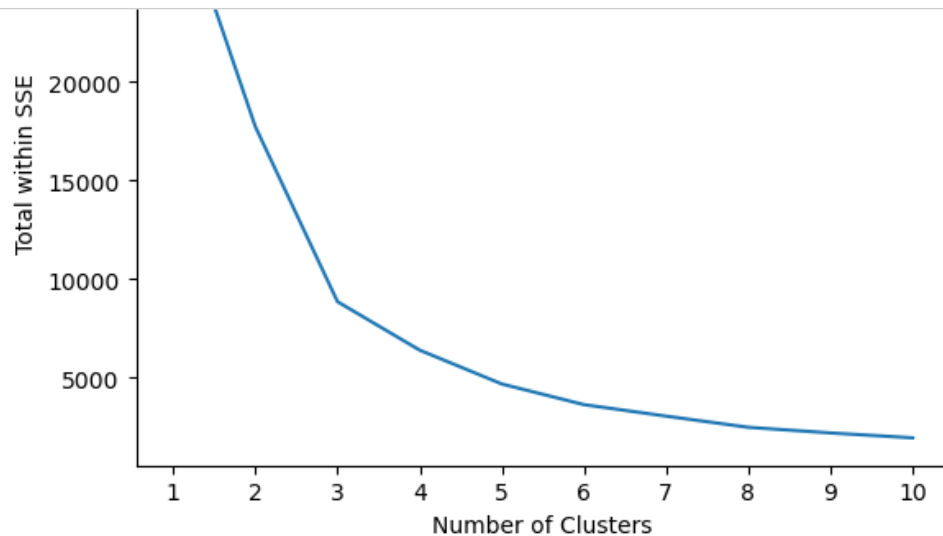
## Optimal Number of Clusters

### Perform Elbow Method to find Optimal No. of Clusters

```
In [7]: from sklearn.cluster import KMeans
```

```
In [123]: sse = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters = k,
                    init = 'k-means++',
                    random_state = 1234,
                    n_init = 10)
    kmeans.fit(scaled_data)
    sse.append(kmeans.inertia_)
```

```
In [124]: plt.plot(range(1, 11), sse)
plt.xticks(range(1, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("Total within SSE")
plt.show()
```

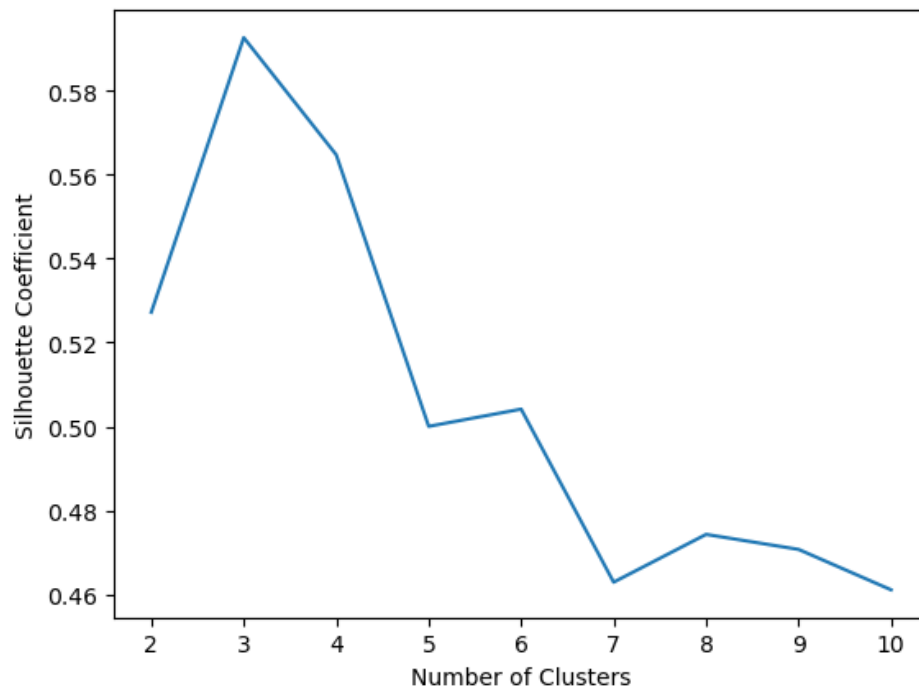


## Silhouette Coefficient

```
In [125]: from sklearn.metrics import silhouette_score
```

```
In [126]: silhouette_coefficients = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters = k,
                    init = 'k-means++',
                    random_state = 1234,
                    n_init = 10)
    kmeans.fit(scaled_data)
    score = silhouette_score(scaled_data, kmeans.labels_)
    silhouette_coefficients.append(score)
```

```
In [127]: plt.plot(range(2, 11), silhouette_coefficients)
plt.xticks(range(2, 11))
plt.xlabel("Number of Clusters")
plt.ylabel("Silhouette Coefficient")
plt.show()
```



**GitHub:** [https://github.com/elihe90/Customer\\_Segmentation-using-RFM-Clustering](https://github.com/elihe90/Customer_Segmentation-using-RFM-Clustering)  
([https://github.com/elihe90/Customer\\_Segmentation-using-RFM-Clustering](https://github.com/elihe90/Customer_Segmentation-using-RFM-Clustering))

In [ ]: