

Market segmentation

Market segmentation in marketing refers to the practice of categorizing a broad market of consumers or businesses into smaller, more homogeneous groups based on shared characteristics or traits. This division enables businesses to tailor their marketing strategies and offerings to better meet the specific needs and preferences of each segment. By understanding the distinct behaviors, preferences, demographics, and psychographics of different segments, companies can more effectively target their marketing efforts and optimize their resources to attract and retain customers.

My jupyter notebook:

https://github.com/alex80ds/Boulder-CU/blob/main/Market_segmentation.ipynb

My PDF file: https://github.com/alex80ds/Boulder-CU/blob/main/Market_segmentation.pdf

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import seaborn as sns
```

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

```
df=pd.read_csv('https://raw.githubusercontent.com/alex80ds/Boulder-
CU/main/Market_segmentation.csv')
```

```
df.head()
```

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES
\					
0	C10001	40.900749	0.818182	95.40	0.00
1	C10002	3202.467416	0.909091	0.00	0.00
2	C10003	2495.148862	1.000000	773.17	773.17
3	C10004	1666.670542	0.636364	1499.00	1499.00
4	C10005	817.714335	1.000000	16.00	16.00

	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
0	95.4	0.000000	0.166667	
1	0.0	6442.945483	0.000000	
2	0.0	0.000000	1.000000	
3	0.0	205.788017	0.083333	
4	0.0	0.000000	0.083333	

ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
----------------------------	----------------------------------	---

0	0.000000	0.083333
1	0.000000	0.000000
2	1.000000	0.000000
3	0.083333	0.000000
4	0.083333	0.000000

	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX
CREDIT_LIMIT \			
0	0.000000	0	2
1000.0			
1	0.250000	4	0
7000.0			
2	0.000000	0	12
7500.0			
3	0.083333	1	1
7500.0			
4	0.000000	0	1
1200.0			

	PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE
0	201.802084	139.509787	0.000000	12
1	4103.032597	1072.340217	0.222222	12
2	622.066742	627.284787	0.000000	12
3	0.000000	NaN	0.000000	12
4	678.334763	244.791237	0.000000	12

EDA

```
df.shape
```

```
(8950, 18)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
```

```
RangeIndex: 8950 entries, 0 to 8949
```

```
Data columns (total 18 columns):
```

#	Column	Non-Null Count	Dtype
---	-----	-----	-----
0	CUST_ID	8950 non-null	object
1	BALANCE	8950 non-null	float64
2	BALANCE_FREQUENCY	8950 non-null	float64
3	PURCHASES	8950 non-null	float64
4	ONEOFF_PURCHASES	8950 non-null	float64
5	INSTALLMENTS_PURCHASES	8950 non-null	float64
6	CASH_ADVANCE	8950 non-null	float64
7	PURCHASES_FREQUENCY	8950 non-null	float64
8	ONEOFF_PURCHASES_FREQUENCY	8950 non-null	float64

9	PURCHASES_INSTALLMENTS_FREQUENCY	8950	non-null	float64
10	CASH_ADVANCE_FREQUENCY	8950	non-null	float64
11	CASH_ADVANCE_TRX	8950	non-null	int64
12	PURCHASES_TRX	8950	non-null	int64
13	CREDIT_LIMIT	8949	non-null	float64
14	PAYMENTS	8950	non-null	float64
15	MINIMUM_PAYMENTS	8637	non-null	float64
16	PRC_FULL_PAYMENT	8950	non-null	float64
17	TENURE	8950	non-null	int64

dtypes: float64(14), int64(3), object(1)

memory usage: 1.2+ MB

df.describe()

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES
\				
count	8950.000000	8950.000000	8950.000000	8950.000000
mean	1564.474828	0.877271	1003.204834	592.437371
std	2081.531879	0.236904	2136.634782	1659.887917
min	0.000000	0.000000	0.000000	0.000000
25%	128.281915	0.888889	39.635000	0.000000
50%	873.385231	1.000000	361.280000	38.000000
75%	2054.140036	1.000000	1110.130000	577.405000
max	19043.138560	1.000000	49039.570000	40761.250000

	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
count	8950.000000	8950.000000	8950.000000	
mean	411.067645	978.871112	0.490351	
std	904.338115	2097.163877	0.401371	
min	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.083333	
50%	89.000000	0.000000	0.500000	
75%	468.637500	1113.821139	0.916667	
max	22500.000000	47137.211760	1.000000	

	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
count	8950.000000	8950.000000	
mean	0.202458	0.364437	
std	0.298336	0.397448	
min	0.000000	0.000000	
25%	0.000000	0.000000	
50%	0.083333	0.166667	
75%	0.300000	0.750000	

max	1.000000	1.000000
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	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX
CREDIT_LIMIT \			
count	8950.000000	8950.000000	8950.000000
8949.000000			
mean	0.135144	3.248827	14.709832
4494.449450			
std	0.200121	6.824647	24.857649
3638.815725			
min	0.000000	0.000000	0.000000
50.000000			
25%	0.000000	0.000000	1.000000
1600.000000			
50%	0.000000	0.000000	7.000000
3000.000000			
75%	0.222222	4.000000	17.000000
6500.000000			
max	1.500000	123.000000	358.000000
30000.000000			

	PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE
count	8950.000000	8637.000000	8950.000000	8950.000000
mean	1733.143852	864.206542	0.153715	11.517318
std	2895.063757	2372.446607	0.292499	1.338331
min	0.000000	0.019163	0.000000	6.000000
25%	383.276166	169.123707	0.000000	12.000000
50%	856.901546	312.343947	0.000000	12.000000
75%	1901.134317	825.485459	0.142857	12.000000
max	50721.483360	76406.207520	1.000000	12.000000

df.isnull().sum()

CUST_ID	0
BALANCE	0
BALANCE_FREQUENCY	0
PURCHASES	0
ONEOFF_PURCHASES	0
INSTALLMENTS_PURCHASES	0
CASH_ADVANCE	0
PURCHASES_FREQUENCY	0
ONEOFF_PURCHASES_FREQUENCY	0
PURCHASES_INSTALLMENTS_FREQUENCY	0
CASH_ADVANCE_FREQUENCY	0
CASH_ADVANCE_TRX	0
PURCHASES_TRX	0
CREDIT_LIMIT	1
PAYMENTS	0
MINIMUM_PAYMENTS	313
PRC_FULL_PAYMENT	0

```
TENURE                                0
dtype: int64

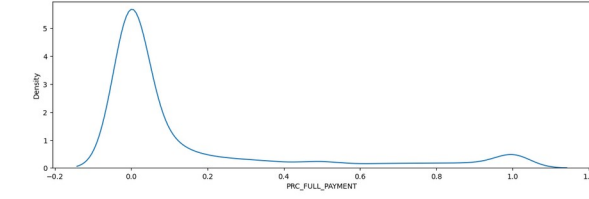
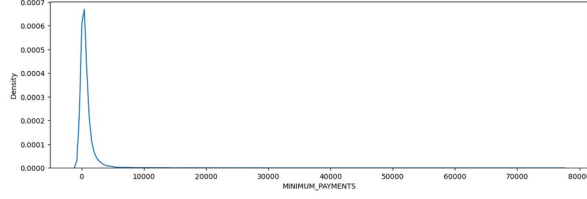
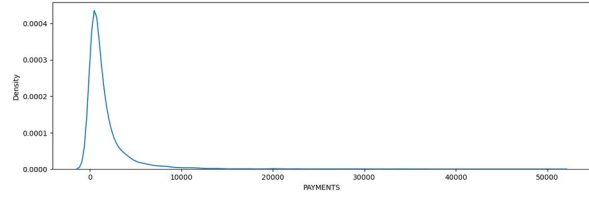
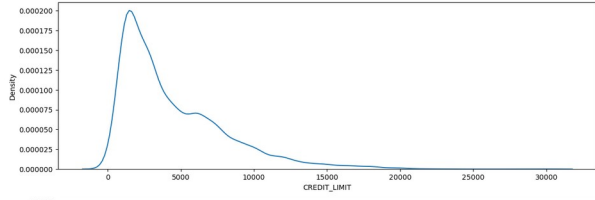
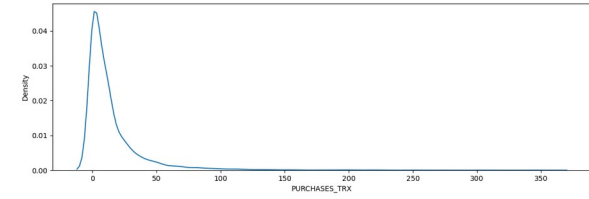
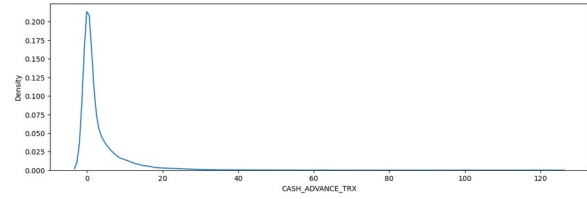
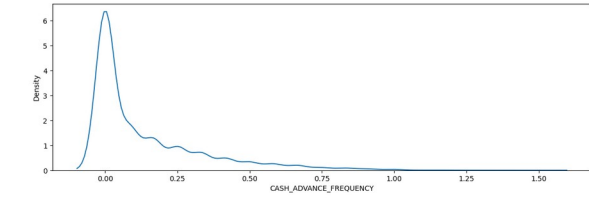
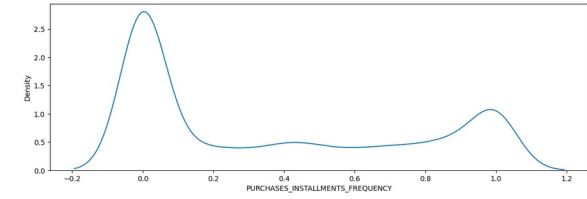
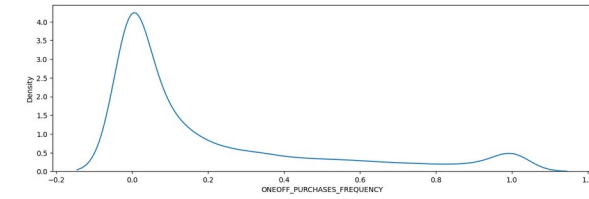
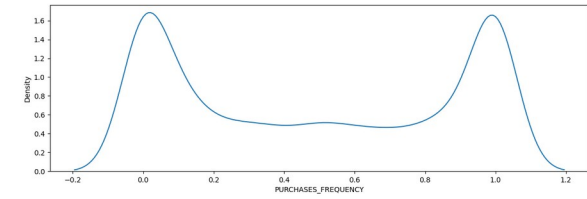
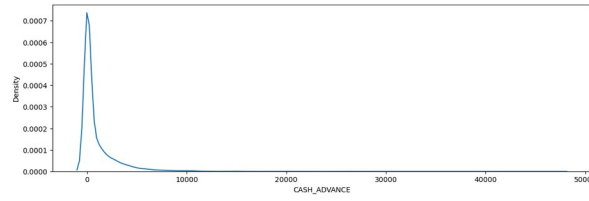
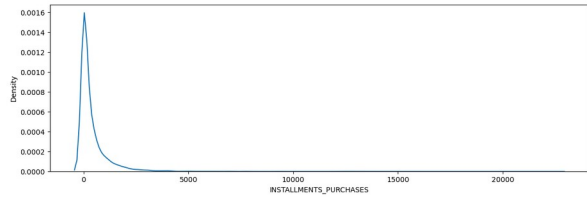
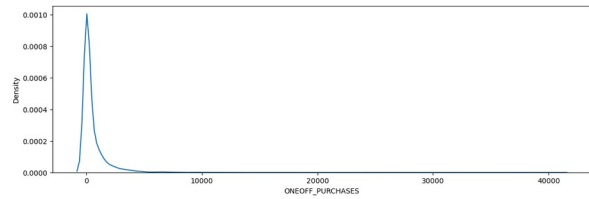
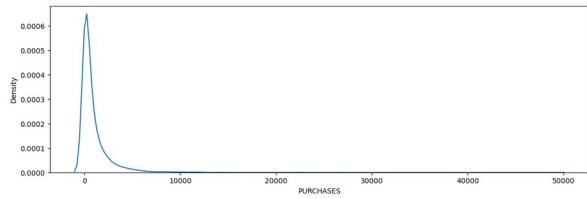
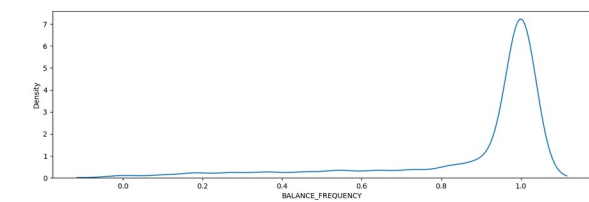
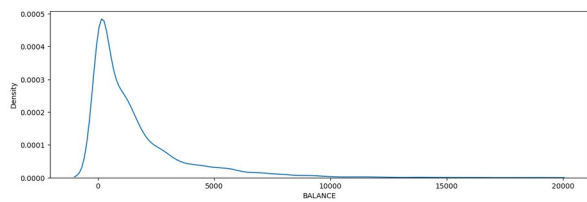
df["MINIMUM_PAYMENTS"] =
df["MINIMUM_PAYMENTS"].fillna(df["MINIMUM_PAYMENTS"].mean())
df["CREDIT_LIMIT"] =
df["CREDIT_LIMIT"].fillna(df["CREDIT_LIMIT"].mean())

df.drop(columns=["CUST_ID"],axis=1,inplace=True)
```

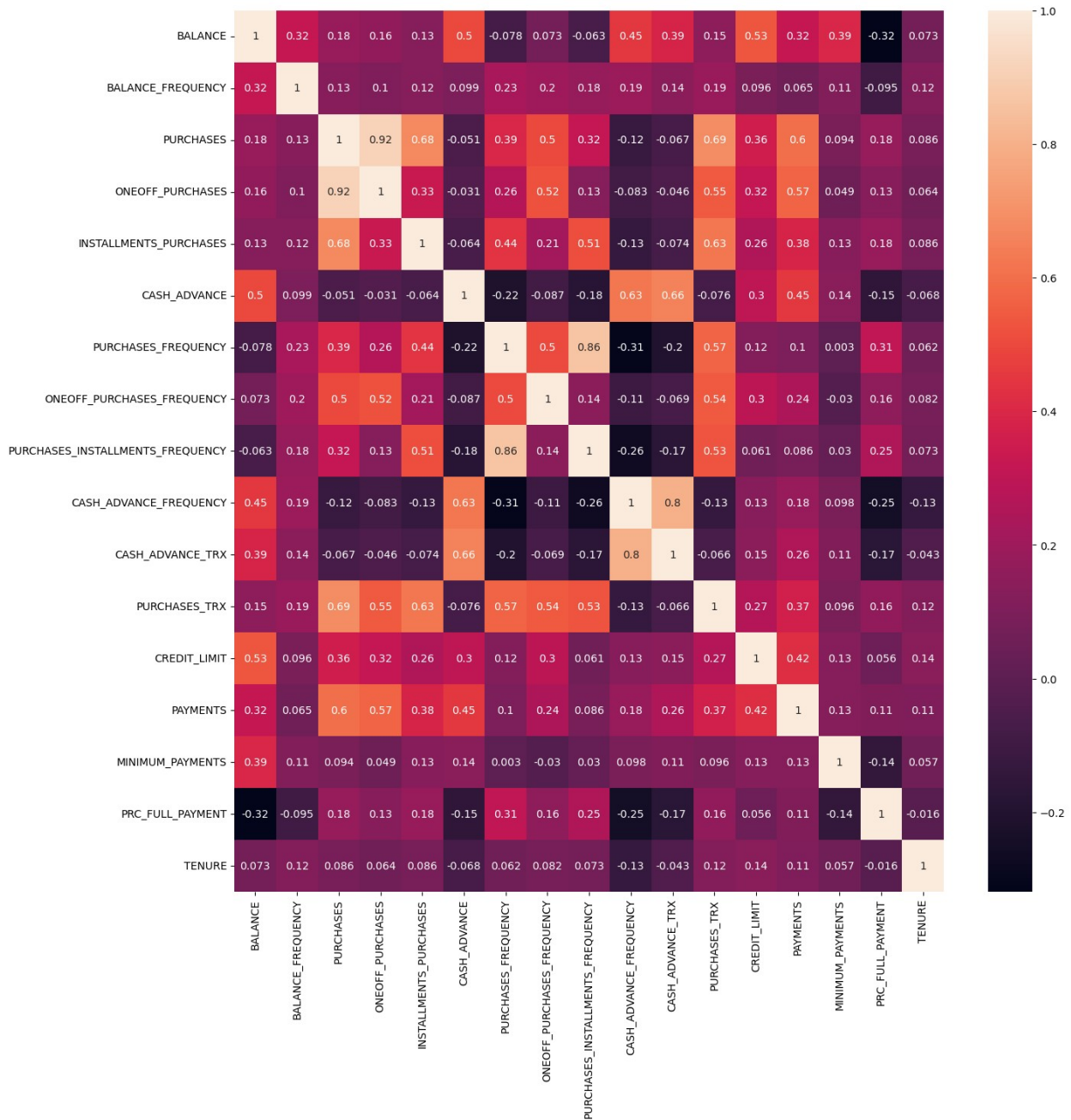
Visualization

```
plt.figure(figsize=(30,45))
for i, col in enumerate(df.columns):
    if df[col].dtype != 'object':
        ax = plt.subplot(9, 2, i+1)
        sns.kdeplot(df[col], ax=ax)
        plt.xlabel(col)

plt.show()
```



```
plt.figure(figsize=(15,15))
sns.heatmap(df.corr(), annot=True)
plt.show()
```



Data preprocessing

```
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
```

```

from sklearn.cluster import
KMeans,AgglomerativeClustering,DBSCAN,SpectralClustering
from sklearn.mixture import GaussianMixture
from sklearn.metrics import silhouette_samples, silhouette_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import classification_report
from sklearn import tree
from sklearn import metrics

```

```

scalar=StandardScaler()

```

```

scaled_df = scalar.fit_transform(df)

```

```

pca = PCA(n_components=2)
principal_components = pca.fit_transform(scaled_df)
pca_df =
pd.DataFrame(data=principal_components ,columns=["PCA1","PCA2"])
pca_df

```

	PCA1	PCA2
0	-1.682221	-1.076442
1	-1.138303	2.506541
2	0.969687	-0.383541
3	-0.873625	0.043134
4	-1.599436	-0.688562
...
8945	-0.359628	-2.016154
8946	-0.564365	-1.639156
8947	-0.926202	-1.810796
8948	-2.336553	-0.657949
8949	-0.556424	-0.400455

```

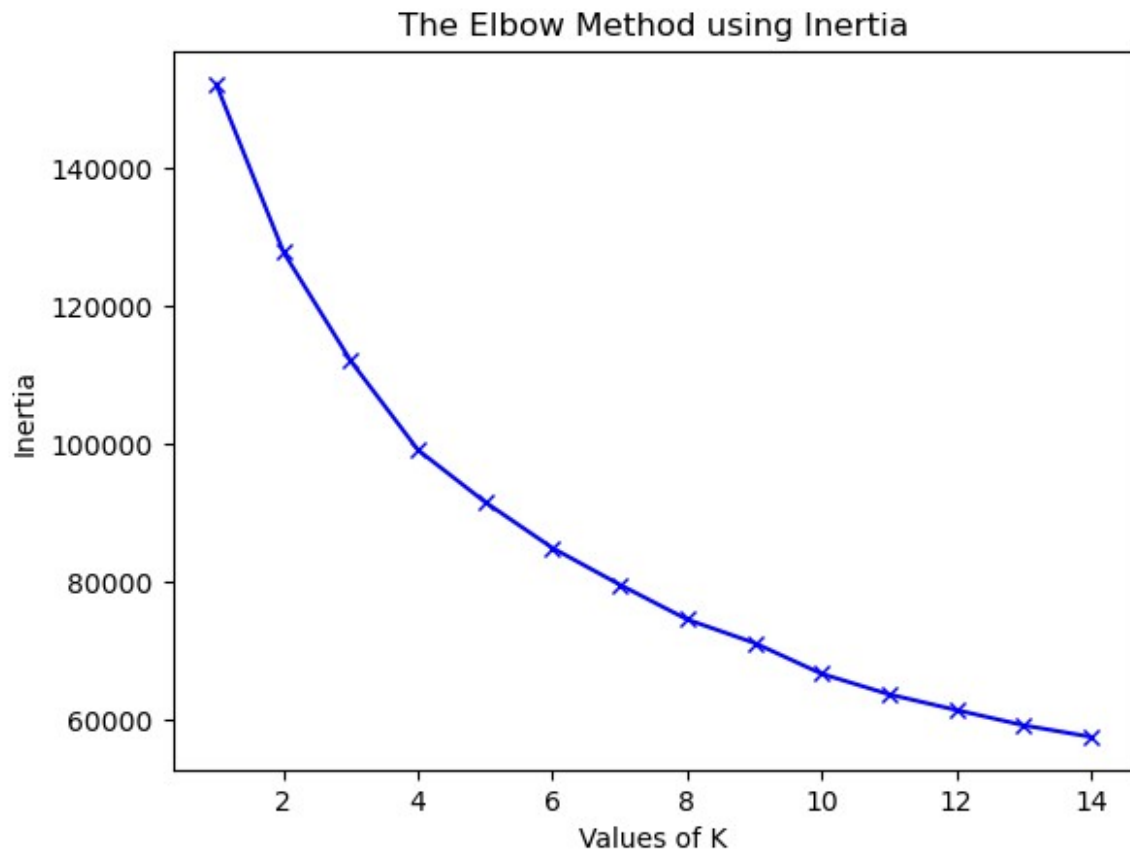
[8950 rows x 2 columns]

```

```

inertia = []
range_val = range(1,15)
for i in range_val:
    kmean = KMeans(n_clusters=i)
    kmean.fit_predict(pd.DataFrame(scaled_df))
    inertia.append(kmean.inertia_)
plt.plot(range_val,inertia,'bx-')
plt.xlabel('Values of K')
plt.ylabel('Inertia')
plt.title('The Elbow Method using Inertia')
plt.show()

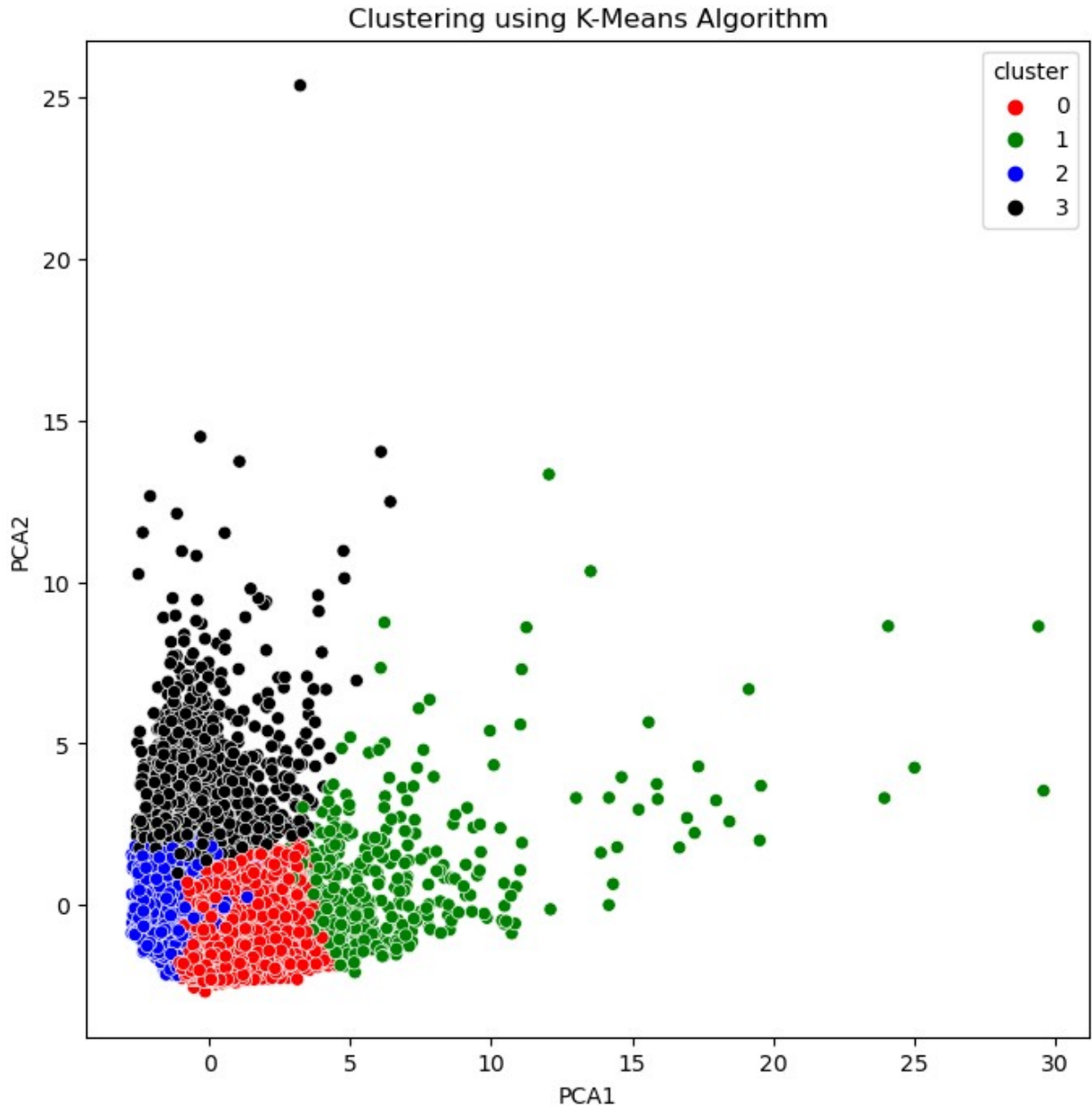
```

Model building

```
kmeans_model=KMeans(4)
kmeans_model.fit_predict(scaled_df)
pca_df_kmeans=
pd.concat([pca_df,pd.DataFrame({'cluster':kmeans_model.labels_})],axis
=1)

plt.figure(figsize=(8,8))
ax=sns.scatterplot(x="PCA1",y="PCA2",hue="cluster",data=pca_df_kmeans,
palette=['red','green','blue','black'])
plt.title("Clustering using K-Means Algorithm")
plt.show()
```



```
cluster_centers =
pd.DataFrame(data=kmeans_model.cluster_centers_,columns=[df.columns])

cluster_centers = scalar.inverse_transform(cluster_centers)
cluster_centers =
pd.DataFrame(data=cluster_centers,columns=[df.columns])
cluster_centers
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	\
0	897.456372	0.935846	1238.779285	595.851281	
1	3556.148177	0.986911	7680.432073	5099.738293	
2	1004.071622	0.788666	271.249733	209.972733	

3	4577.199684	0.968513	491.071544	311.745004
	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
0	643.203117	211.260815	0.885991	
1	2582.157195	686.680975	0.946548	
2	61.544224	588.473350	0.171839	
3	179.410495	4485.847516	0.284436	

	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
0	0.297970	0.712244	
1	0.739667	0.788577	
2	0.086325	0.082144	
3	0.136892	0.183111	

	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX	
	CREDIT_LIMIT	\		
0	0.042713	0.792610	22.133492	4217.363007
1	0.073149	2.170732	89.309756	9711.097561
2	0.113588	2.092122	2.928769	3274.061863
3	0.483006	14.215524	7.530966	7499.962465

	PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE
0	1334.890105	651.454148	0.269643	11.597437
1	7301.419079	1977.054411	0.286211	11.951220
2	970.071857	584.198510	0.078333	11.445004
3	3455.052828	1995.669235	0.034898	11.385632

```
cluster_df =
pd.concat([df,pd.DataFrame({'Cluster':kmeans_model.labels_})],axis=1)
cluster_df
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	\
0	40.900749	0.818182	95.40	0.00	
1	3202.467416	0.909091	0.00	0.00	
2	2495.148862	1.000000	773.17	773.17	
3	1666.670542	0.636364	1499.00	1499.00	
4	817.714335	1.000000	16.00	16.00	
...	
8945	28.493517	1.000000	291.12	0.00	
8946	19.183215	1.000000	300.00	0.00	
8947	23.398673	0.833333	144.40	0.00	
8948	13.457564	0.833333	0.00	0.00	
8949	372.708075	0.666667	1093.25	1093.25	

	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
0	95.40	0.000000	0.166667	
1	0.00	6442.945483	0.000000	

2	0.00	0.000000	1.000000
3	0.00	205.788017	0.083333
4	0.00	0.000000	0.083333
...
8945	291.12	0.000000	1.000000
8946	300.00	0.000000	1.000000
8947	144.40	0.000000	0.833333
8948	0.00	36.558778	0.000000
8949	0.00	127.040008	0.666667
	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
0	0.000000	0.083333	
1	0.000000	0.000000	
2	1.000000	0.000000	
3	0.083333	0.000000	
4	0.083333	0.000000	
...	
8945	0.000000	0.833333	
8946	0.000000	0.833333	
8947	0.000000	0.666667	
8948	0.000000	0.000000	
8949	0.666667	0.000000	
	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX
CREDIT_LIMIT \			
0	0.000000	0	2
1000.0			
1	0.250000	4	0
7000.0			
2	0.000000	0	12
7500.0			
3	0.083333	1	1
7500.0			
4	0.000000	0	1
1200.0			
...
...			
8945	0.000000	0	6
1000.0			
8946	0.000000	0	6
1000.0			
8947	0.000000	0	5
1000.0			
8948	0.166667	2	0
500.0			
8949	0.333333	2	23
1200.0			
PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE Cluster

0	201.802084	139.509787	0.000000	12	2
1	4103.032597	1072.340217	0.222222	12	3
2	622.066742	627.284787	0.000000	12	0
3	0.000000	864.206542	0.000000	12	2
4	678.334763	244.791237	0.000000	12	2
...
8945	325.594462	48.886365	0.500000	6	0
8946	275.861322	864.206542	0.000000	6	0
8947	81.270775	82.418369	0.250000	6	0
8948	52.549959	55.755628	0.250000	6	2
8949	63.165404	88.288956	0.000000	6	2

[8950 rows x 18 columns]

```
cluster_1_df = cluster_df[cluster_df["Cluster"]==0]
cluster_1_df
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	\
2	2495.148862	1.000000	773.17	773.17	
5	1809.828751	1.000000	1333.28	0.00	
7	1823.652743	1.000000	436.20	0.00	
10	1293.124939	1.000000	920.12	0.00	
12	1516.928620	1.000000	3217.99	2500.23	
...	
8940	130.838554	1.000000	591.24	0.00	
8942	40.829749	1.000000	113.28	0.00	
8945	28.493517	1.000000	291.12	0.00	
8946	19.183215	1.000000	300.00	0.00	
8947	23.398673	0.833333	144.40	0.00	
	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\	
2	0.00	0.0	1.000000		
5	1333.28	0.0	0.666667		
7	436.20	0.0	1.000000		
10	920.12	0.0	1.000000		
12	717.76	0.0	1.000000		
...		
8940	591.24	0.0	1.000000		
8942	113.28	0.0	1.000000		
8945	291.12	0.0	1.000000		

8946	300.00	0.0	1.000000		
8947	144.40	0.0	0.833333		
ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY \				
2	1.00	0.000000			
5	0.00	0.583333			
7	0.00	1.000000			
10	0.00	1.000000			
12	0.25	0.916667			
...			
8940	0.00	0.833333			
8942	0.00	0.833333			
8945	0.00	0.833333			
8946	0.00	0.833333			
8947	0.00	0.666667			
CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX			
CREDIT_LIMIT \					
2	0.0	0	12		
7500.0					
5	0.0	0	8		
1800.0					
7	0.0	0	12		
2300.0					
10	0.0	0	12		
1200.0					
12	0.0	0	26		
3000.0					
...		
...					
8940	0.0	0	6		
1000.0					
8942	0.0	0	6		
1000.0					
8945	0.0	0	6		
1000.0					
8946	0.0	0	6		
1000.0					
8947	0.0	0	5		
1000.0					
PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE	Cluster	
2	622.066742	627.284787	0.00	12	0
5	1400.057770	2407.246035	0.00	12	0
7	679.065082	532.033990	0.00	12	0
10	1083.301007	2172.697765	0.00	12	0

12	608.263689	490.207013	0.25	12	0
...
8940	475.523262	82.771320	1.00	6	0
8942	94.488828	86.283101	0.25	6	0
8945	325.594462	48.886365	0.50	6	0
8946	275.861322	864.206542	0.00	6	0
8947	81.270775	82.418369	0.25	6	0

[3356 rows x 18 columns]

```
cluster_2_df = cluster_df[cluster_df["Cluster"]==1]
cluster_2_df
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	\
6	627.260806	1.000000	7091.01	6402.63	
21	6369.531318	1.000000	6359.95	5910.04	
57	2386.330629	1.000000	5217.62	4789.09	
84	1935.362486	1.000000	4915.60	4515.34	
90	9381.255094	1.000000	5100.07	1147.83	
...	
8215	4436.557694	1.000000	6005.90	5838.38	
8541	3326.323283	1.000000	8209.77	2218.28	
8662	599.909949	1.000000	4947.32	3149.59	
8689	368.318662	0.909091	8053.95	8053.95	
8737	2533.618119	0.909091	5633.83	2985.92	

	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
6	688.38	0.000000	1.000000	
21	449.91	229.028245	1.000000	
57	428.53	0.000000	0.916667	
84	400.26	293.844792	1.000000	
90	3952.24	370.737197	1.000000	
...	
8215	167.52	567.971877	1.000000	
8541	5991.49	0.000000	1.000000	
8662	1797.73	0.000000	1.000000	
8689	0.00	0.000000	0.833333	
8737	2647.91	2451.807788	0.916667	

	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
6	1.000000	1.000000	
21	0.916667	1.000000	
57	0.916667	0.500000	

84	1.000000	0.333333
90	0.250000	0.916667
...
8215	0.583333	0.916667
8541	0.416667	1.000000
8662	1.000000	0.916667
8689	0.833333	0.000000
8737	0.500000	0.750000

	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX
CREDIT_LIMIT \			
6	0.000000	0	64
13500.0			
21	0.333333	6	92
11250.0			
57	0.000000	0	42
7500.0			
84	0.083333	1	50
9000.0			
90	0.083333	1	46
9000.0			
...
...			
8215	0.083333	1	61
10500.0			
8541	0.000000	0	130
10000.0			
8662	0.000000	0	73
3000.0			
8689	0.000000	0	46
2000.0			
8737	0.333333	16	82
9000.0			

	PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE	Cluster
6	6354.314328	198.065894	1.000000	12	1
21	2077.959051	1659.775075	0.000000	12	1
57	5678.729613	1311.514878	0.083333	12	1
84	4921.066897	594.756686	0.000000	12	1
90	6409.496345	9827.045323	0.000000	12	1
...
8215	1650.425296	1067.515656	0.000000	12	1

8541	1942.074765	702.905059	0.083333	12	1
8662	5024.430008	218.172915	0.083333	12	1
8689	7966.582037	219.761189	0.777778	12	1
8737	8176.953944	602.963244	0.000000	12	1

[410 rows x 18 columns]

```
cluster_3_df = cluster_df[cluster_df["Cluster"]==2]
cluster_3_df
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	\
0	40.900749	0.818182	95.40	0.00	
3	1666.670542	0.636364	1499.00	1499.00	
4	817.714335	1.000000	16.00	16.00	
8	1014.926473	1.000000	861.49	661.49	
9	152.225975	0.545455	1281.60	1281.60	
...	
8939	728.352548	1.000000	734.40	734.40	
8943	5.871712	0.500000	20.90	20.90	
8944	193.571722	0.833333	1012.73	1012.73	
8948	13.457564	0.833333	0.00	0.00	
8949	372.708075	0.666667	1093.25	1093.25	

	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
0	95.4	0.000000	0.166667	
3	0.0	205.788017	0.083333	
4	0.0	0.000000	0.083333	
8	200.0	0.000000	0.333333	
9	0.0	0.000000	0.166667	
...	
8939	0.0	239.891038	0.333333	
8943	0.0	0.000000	0.166667	
8944	0.0	0.000000	0.333333	
8948	0.0	36.558778	0.000000	
8949	0.0	127.040008	0.666667	

	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
0	0.000000	0.083333	
3	0.083333	0.000000	
4	0.083333	0.000000	
8	0.083333	0.250000	
9	0.166667	0.000000	
...	
8939	0.333333	0.000000	
8943	0.166667	0.000000	
8944	0.333333	0.000000	

8948	0.000000	0.000000
8949	0.666667	0.000000
CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX
CREDIT_LIMIT \		
0	0.000000	0 2
1000.0		
3	0.083333	1 1
7500.0		
4	0.000000	0 1
1200.0		
8	0.000000	0 5
7000.0		
9	0.000000	0 3
11000.0		
...
...		
8939	0.166667	2 2
1000.0		
8943	0.000000	0 1
500.0		
8944	0.000000	0 2
4000.0		
8948	0.166667	2 0
500.0		
8949	0.333333	2 23
1200.0		
PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT
TENURE	Cluster	
0	201.802084	139.509787 0.00 12 2
3	0.000000	864.206542 0.00 12 2
4	678.334763	244.791237 0.00 12 2
8	688.278568	311.963409 0.00 12 2
9	1164.770591	100.302262 0.00 12 2
...
...
8939	72.530037	110.950798 0.00 6 2
8943	58.644883	43.473717 0.00 6 2
8944	0.000000	864.206542 0.00 6 2
8948	52.549959	55.755628 0.25 6 2

8949	63.165404	88.288956	0.00	6	2
------	-----------	-----------	------	---	---

[3973 rows x 18 columns]

```
cluster_4_df = cluster_df[cluster_df["Cluster"] == 3]
cluster_4_df
```

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	\
1	3202.467416	0.909091	0.00	0.00	
15	6886.213231	1.000000	1611.70	0.00	
23	3800.151377	0.818182	4248.35	3454.56	
24	5368.571219	1.000000	0.00	0.00	
28	7152.864372	1.000000	387.05	204.55	
...	
8857	2330.222764	1.000000	1320.00	0.00	
8858	812.934042	1.000000	50.00	50.00	
8869	2171.222526	1.000000	791.18	791.18	
8915	381.341657	1.000000	78.00	0.00	
8941	5967.475270	0.833333	214.55	0.00	

	INSTALLMENTS_PURCHASES	CASH_ADVANCE	PURCHASES_FREQUENCY	\
1	0.00	6442.945483	0.000000	
15	1611.70	2301.491267	0.500000	
23	793.79	7974.415626	1.000000	
24	0.00	798.949863	0.000000	
28	182.50	2236.145259	0.666667	
...	
8857	1320.00	14926.790590	0.428571	
8858	0.00	2185.500596	0.142857	
8869	0.00	2056.602480	0.428571	
8915	78.00	934.808869	1.000000	
8941	214.55	8555.409326	0.833333	

	ONEOFF_PURCHASES_FREQUENCY	PURCHASES_INSTALLMENTS_FREQUENCY	\
1	0.000000	0.000000	
15	0.000000	0.500000	
23	0.083333	0.916667	
24	0.000000	0.000000	
28	0.166667	0.416667	
...	
8857	0.000000	0.285714	
8858	0.142857	0.000000	
8869	0.428571	0.000000	
8915	0.000000	0.833333	
8941	0.000000	0.666667	

	CASH_ADVANCE_FREQUENCY	CASH_ADVANCE_TRX	PURCHASES_TRX	CREDIT_LIMIT	\
1	0.250000	4	0		

```

7000.0
15          0.166667          4          11
8000.0
23          0.333333          13          13
9000.0
24          0.363636          4           0
6000.0
28          0.833333          16           8
10500.0
...          ...          ...          ...
...
8857          0.571429          10           3
10000.0
8858          1.000000          16           1
3000.0
8869          0.571429           6           8
3000.0
8915          0.666667          16           6
1000.0
8941          0.666667          13           5
9000.0

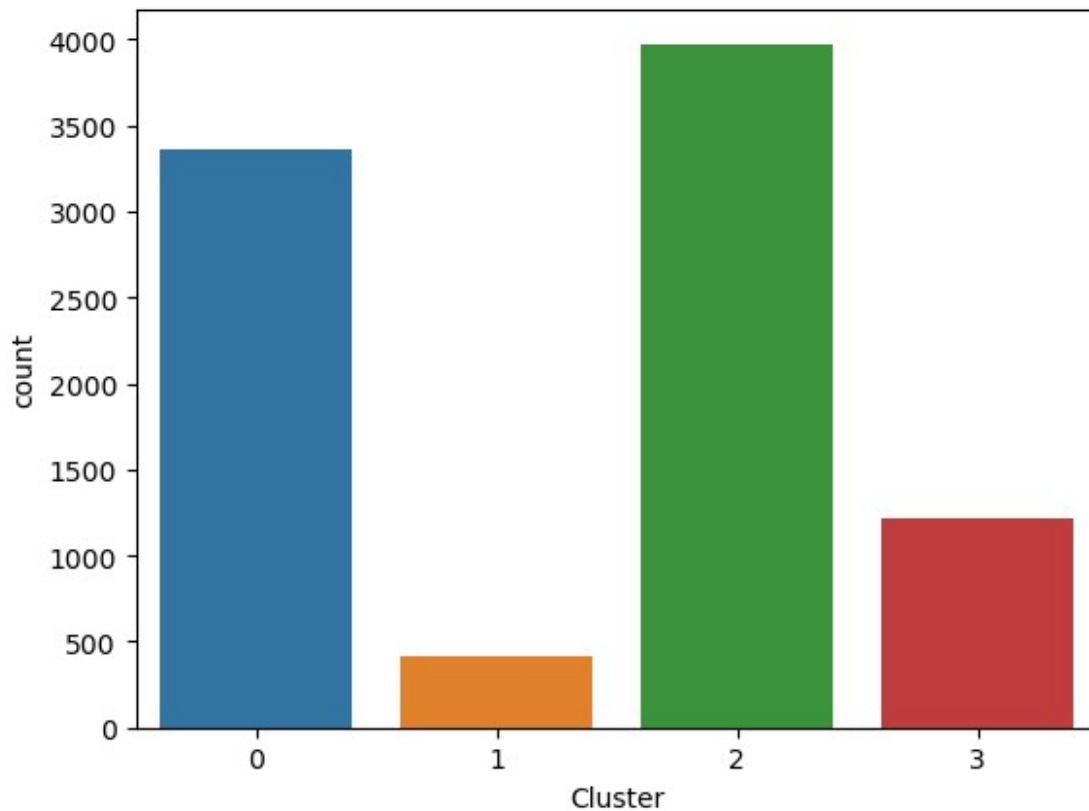
```

	PAYMENTS	MINIMUM_PAYMENTS	PRC_FULL_PAYMENT	TENURE	Cluster
1	4103.032597	1072.340217	0.222222	12	3
15	1993.439277	2109.906490	0.000000	12	3
23	9479.043842	1425.426525	0.000000	12	3
24	1422.726707	1657.002877	0.000000	11	3
28	1601.448347	1648.851345	0.000000	12	3
...
8857	8157.666434	283.362434	0.200000	7	3
8858	726.683966	127.843735	0.000000	7	3
8869	300.088696	453.100425	0.000000	7	3
8915	143.118373	85.152441	0.000000	6	3
8941	966.202912	861.949906	0.000000	6	3

```
[1211 rows x 18 columns]
```

```
sns.countplot(x='Cluster', data=cluster_df)
```

<AxesSubplot:xlabel='Cluster', ylabel='count'>



Result

```
X = cluster_df.drop(['Cluster'],axis=1)
y = cluster_df[['Cluster']]
X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.3,random_state=3)
```

```
model= DecisionTreeClassifier(criterion="entropy")
model.fit(X_train, y_train)
y_pred = model.predict(X_test)
```

```
print(metrics.confusion_matrix(y_test, y_pred))
print(classification_report(y_test, y_pred))
```

```
[[ 973    9   28   11]
 [   10  107    3    1]
 [   35    2 1102   25]
 [   11    0   31  337]]
      precision    recall  f1-score   support

     0       0.95      0.95      0.95     1021
```

1	0.91	0.88	0.90	121
2	0.95	0.95	0.95	1164
3	0.90	0.89	0.90	379
accuracy			0.94	2685
macro avg	0.93	0.92	0.92	2685
weighted avg	0.94	0.94	0.94	2685

Conclusion

An accuracy of 94% in the context of customer segmentation suggests that the clustering model has been highly effective in distinguishing between different customer behaviors and preferences based on the provided dataset. This high level of accuracy indicates a strong correspondence between the model's segmentation and the underlying patterns in the credit card usage behavior of about 9,000 active cardholders over the last 6 months. Such a result is highly promising for targeted marketing strategies and personalized financial product offerings. Here's a wider perspective on the conclusion and its implications:

Detailed Insights and Strategic Applications Targeted Marketing Efficiency: With distinct customer segments identified so accurately, marketing campaigns can be designed to specifically address the needs, preferences, and behaviors of each segment. This precision in targeting is likely to significantly increase the effectiveness of marketing efforts, reduce costs associated with broad-spectrum campaigns, and improve customer response rates.

Personalized Product Offerings: Financial institutions can tailor their product offerings to meet the unique needs of each segment. For example, customers who frequently make installment purchases might be offered special installment plans with lower interest rates or rewards for installment purchases. Similarly, those using their credit card primarily for cash advances could be targeted with products that offer lower cash advance fees or better terms for short-term liquidity.

Enhanced Customer Experience and Loyalty: By understanding the distinct needs and preferences of each segment, financial institutions can not only offer more relevant products but also communicate in a way that resonates with each group. This personalized approach is likely to enhance customer satisfaction, foster loyalty, and reduce churn rates. Customers are more likely to stay with a bank that understands their needs and offers solutions that are tailored to them.

Strategic Decision Making: The insights gained from this segmentation can inform strategic decisions at higher levels of management. Understanding the different segments can help in allocating resources more efficiently, developing new products, and even entering new markets. For instance, if a significant segment of customers shows a preference for digital banking solutions, the institution might prioritize digital transformation initiatives.

Competitive Advantage: In a highly competitive financial services market, the ability to accurately segment and target customers can provide a significant competitive edge. It allows

an institution to differentiate itself by offering personalized experiences and products that competitors may not.

Future Opportunities: Beyond immediate marketing and product development implications, this segmentation can be used to predict future trends and customer needs. As customer behavior evolves, the model can be updated and refined to maintain high levels of accuracy and relevance, ensuring that the financial institution remains ahead of the curve in understanding and meeting customer demands.

Achieving a 94% accuracy rate in customer segmentation is a remarkable achievement that opens up numerous opportunities for targeted marketing, personalized product offerings, and strategic decision-making. By leveraging these insights, financial institutions can enhance customer experiences, improve loyalty, and gain a competitive advantage in the market. This approach not only maximizes the effectiveness of marketing and product development efforts but also paves the way for anticipating and adapting to future customer needs and market trends.