Credit Card Clustering

Credit card clustering means grouping credit card holders based on their buying habits, credit limits, and many more financial factors. It is also known as credit card segmentation. Such clustering analysis helps businesses find their potential customers and many more marketing strategies.

For the task of credit card clustering with Machine Learning, we need to have a dataset based on buying history of credit card holders.

- Data Source: https://statso.io/customer-segmentation-case-study/ (https://statso.io/customer-segmentation-case-study/)
- Project Source: https://thecleverprogrammer.com/2022/10/03/credit-card-clustering-with-machine-learning/ (https://thecleverprogrammer.com/2022/10/03/credit-card-clustering-with-machine-learning/)

ABOUT DATA

`CUST_ID` : Unique identification number of the customer

`BALANCE` : Balance in the bank account of the customer

`BALANCE_FREQUENCY` : How frequently the balance is updated in the account of the customer (1 means frequently updated, and 0 means not frequently updated)

`PURCHASES` : The number of purchases made by the customer

`ONEOFF_PURCHASES` : Maximum amount of one-time purchase

`INSTALLMENTS_PURCHASES` : Amount of purchases on instalments

`CASH_ADVANCE` : Cash in advance paid by the customer

`PURCHASES_FREQUENCY` : The frequency of purchases (1 means high frequency, 0 means low frequency)

`ONEOFF_PURCHASES_FREQUENCY` : The frequency of one-time payment purchases (1 means high frequency, 0 means low frequency)

`PURCHASES_INSTALLMENTS_FREQUENCY` : The frequency of purchases on instalments (1 means high frequency, 0 means low frequency)

`CASH_ADVANCE_FREQUENCY` : Frequency of cash in advance payments

`CASH_ADVANCE_TRX` : Number of cash in advance transactions

`PURCHASES_TRX` : Number of transactions on purchases

`CREDIT_LIMIT` : Credit limit of the customer

`PAYMENTS` : Amount of payments made by the customer

`MINIMUM_PAYMENTS` : Amount of minimum payments made by the customer

`PRC_FULL_PAYMENT` : Percentage of full payment made by the customer

`TENURE` : The tenure of the credit card service of the customer

In [34]:
```
from sklearn.cluster import KMeans, DBSCAN
import pandas as pd
import numpy as np
import seaborn as sns
import plotly.express as px
import matplotlib.pyplot as plt
pd.options.display.max_columns =1000
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.datasets import load_iris
from sklearn.metrics import silhouette_score

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

In [85]:
```
data = pd.read_csv("/Users/USER/Documents/DATASETS/Credit_card_clustering.csv")
```

In [86]:
```
df = data.copy()
df = df.iloc[:,1:]
```

In [87]:
```
df.head()
```

Out[87]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_AI
0	40.900749	0.818182	95.40	0.00	95.4	(
1	3202.467416	0.909091	0.00	0.00	0.0	6442
2	2495.148862	1.000000	773.17	773.17	0.0	(
3	1666.670542	0.636364	1499.00	1499.00	0.0	205
4	817.714335	1.000000	16.00	16.00	0.0	(

In [88]:
```
df.shape
```

Out[88]: (8950, 17)

In [89]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 8950 entries, 0 to 8949
Data columns (total 17 columns):
 #   Column                            Non-Null Count  Dtype  
---  ------                            --------------  -----  
 0   BALANCE                           8950 non-null   float64
 1   BALANCE_FREQUENCY                 8950 non-null   float64
 2   PURCHASES                         8950 non-null   float64
 3   ONEOFF_PURCHASES                  8950 non-null   float64
 4   INSTALLMENTS_PURCHASES            8950 non-null   float64
 5   CASH_ADVANCE                      8950 non-null   float64
 6   PURCHASES_FREQUENCY               8950 non-null   float64
 7   ONEOFF_PURCHASES_FREQUENCY        8950 non-null   float64
 8   PURCHASES_INSTALLMENTS_FREQUENCY  8950 non-null   float64
 9   CASH_ADVANCE_FREQUENCY            8950 non-null   float64
 10  CASH_ADVANCE_TRX                  8950 non-null   int64  
 11  PURCHASES_TRX                     8950 non-null   int64  
 12  CREDIT_LIMIT                      8949 non-null   float64
 13  PAYMENTS                          8950 non-null   float64
 14  MINIMUM_PAYMENTS                  8637 non-null   float64
 15  PRC_FULL_PAYMENT                  8950 non-null   float64
 16  TENURE                            8950 non-null   int64  
dtypes: float64(14), int64(3)
memory usage: 1.2 MB
```

Check for Duplicates

In [90]:
```
df[df.duplicated()]
```

Out[90]:

BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHASES	CASH_ADVA

Check for whitespaces

In [91]:
```
[i for i in df.columns if i.startswith(' ' or i.endswith(' '))]
```

Out[91]: []

In [92]:
```
for i in df.columns:
    print(df[df[i]==' '])
```

```
NIMUM_PAYMENTS, PRC_FULL_PAYMENT, TENURE]
Index: []
Empty DataFrame
Columns: [BALANCE, BALANCE_FREQUENCY, PURCHASES, ONEOFF_PURCHASES, INSTALLMENTS_PURCHASES,
CASH_ADVANCE, PURCHASES_FREQUENCY, ONEOFF_PURCHASES_FREQUENCY, PURCHASES_INSTALLMENTS_FREQ
UENCY, CASH_ADVANCE_FREQUENCY, CASH_ADVANCE_TRX, PURCHASES_TRX, CREDIT_LIMIT, PAYMENTS, MI
NIMUM_PAYMENTS, PRC_FULL_PAYMENT, TENURE]
Index: []
Empty DataFrame
Columns: [BALANCE, BALANCE_FREQUENCY, PURCHASES, ONEOFF_PURCHASES, INSTALLMENTS_PURCHASES,
CASH_ADVANCE, PURCHASES_FREQUENCY, ONEOFF_PURCHASES_FREQUENCY, PURCHASES_INSTALLMENTS_FREQ
UENCY, CASH_ADVANCE_FREQUENCY, CASH_ADVANCE_TRX, PURCHASES_TRX, CREDIT_LIMIT, PAYMENTS, MI
NIMUM_PAYMENTS, PRC_FULL_PAYMENT, TENURE]
Index: []
Empty DataFrame
Columns: [BALANCE, BALANCE_FREQUENCY, PURCHASES, ONEOFF_PURCHASES, INSTALLMENTS_PURCHASES,
CASH_ADVANCE, PURCHASES_FREQUENCY, ONEOFF_PURCHASES_FREQUENCY, PURCHASES_INSTALLMENTS_FREQ
UENCY, CASH_ADVANCE_FREQUENCY, CASH_ADVANCE_TRX, PURCHASES_TRX, CREDIT_LIMIT, PAYMENTS, MI
NIMUM_PAYMENTS, PRC_FULL_PAYMENT, TENURE]
Index: []
```

Check for null values

In [93]:
```
total = np.product(df.shape)
null = df.isnull().sum().sum()

(null/total) * 100
```

Out[93]:
```
0.20637528754518566
```

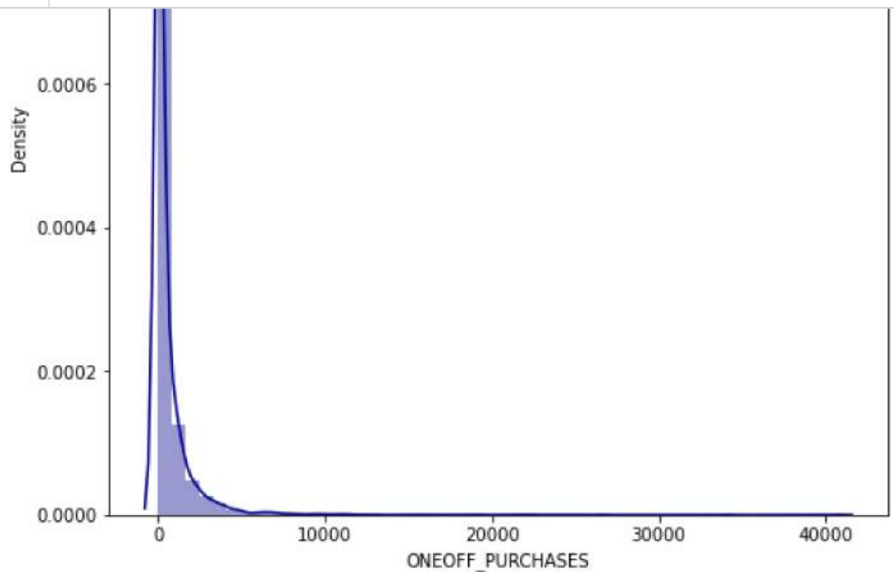
In [94]:
```
df.isnull().sum()
```

Out[94]:
```
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
```

In [95]:
```
df.isnull().mean()
```

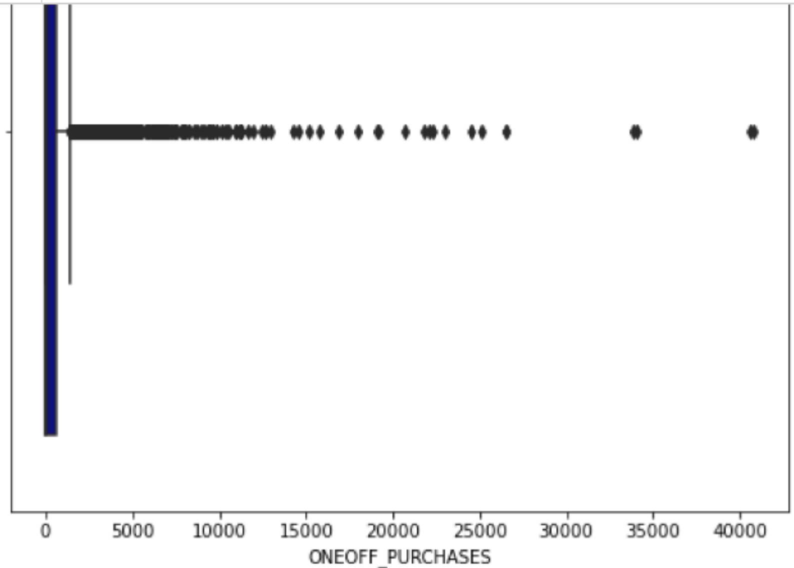
Out[95]:
```
BALANCE                             0.000000
BALANCE_FREQUENCY                   0.000000
PURCHASES                           0.000000
ONEOFF_PURCHASES                    0.000000
INSTALLMENTS_PURCHASES              0.000000
CASH_ADVANCE                        0.000000
PURCHASES_FREQUENCY                 0.000000
ONEOFF_PURCHASES_FREQUENCY          0.000000
PURCHASES_INSTALLMENTS_FREQUENCY    0.000000
CASH_ADVANCE_FREQUENCY              0.000000
CASH_ADVANCE_TRX                    0.000000
PURCHASES_TRX                       0.000000
CREDIT_LIMIT                        0.000112
PAYMENTS                            0.000000
MINIMUM_PAYMENTS                    0.034972
PRC_FULL_PAYMENT                    0.000000
TENURE                              0.000000
dtype: float64
```

In [96]:
```
for i in df.columns:
    plt.figure(figsize=(8,8))

    sns.distplot(x =df[i], color='darkblue')
    plt.xlabel(i.upper())
```



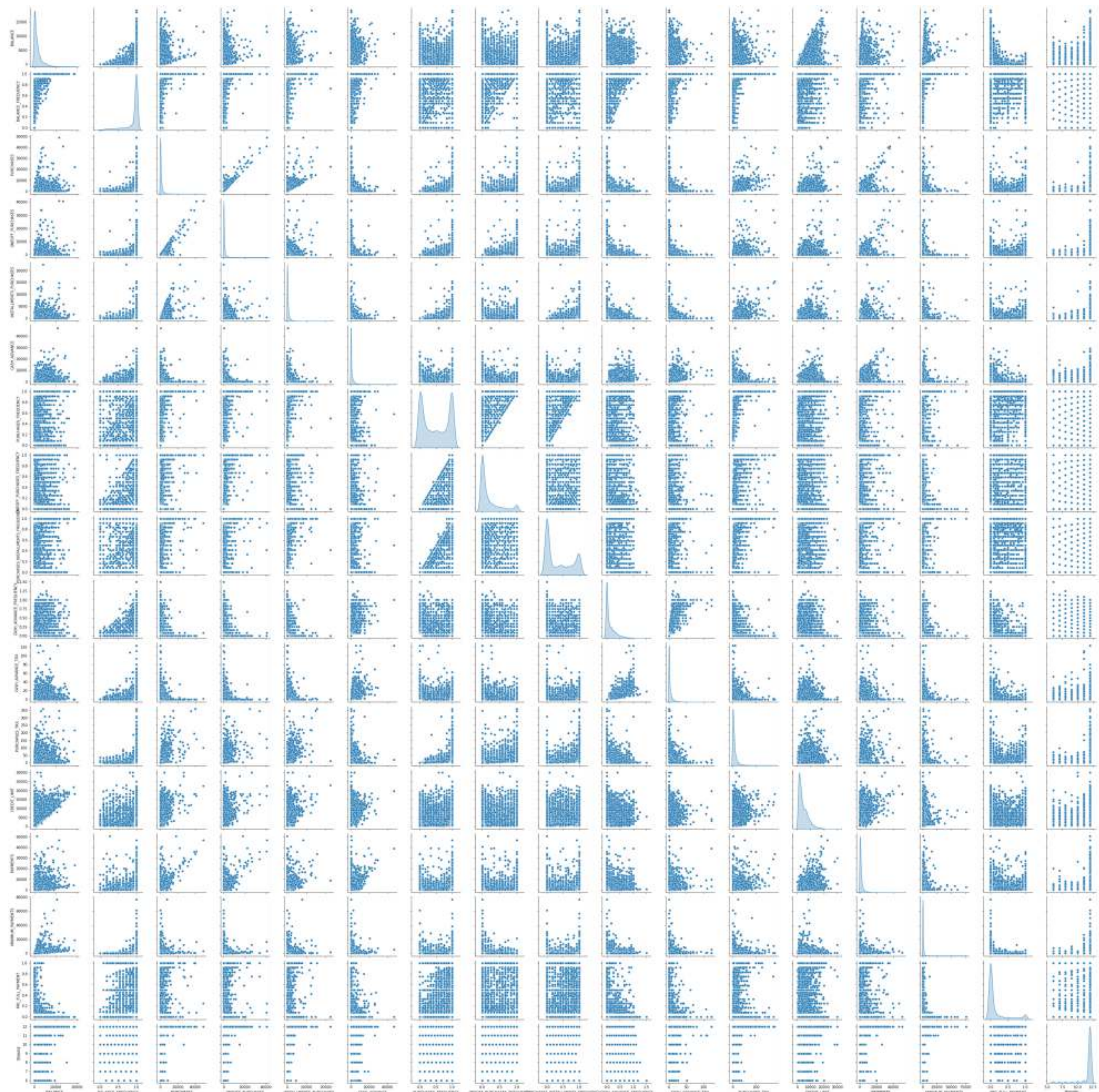
In [97]:

```
for i in df.columns:
    plt.figure(figsize=(8,8))

    sns.boxplot(x =df[i], color='darkblue')
    plt.xlabel(i.upper())
```



In [98]:
```
sns.pairplot(df, diag_kind='kde')
```

Out[98]: <seaborn.axisgrid.PairGrid at 0x28c2a01d310>



STATS

In [99]:
```
def stats():

    skews = []
    kurts = []
    means = []
    medians = []
    type_skewss = []
    column_name = []

    for i in df.columns:
        skew = df[i].skew()
        kurt = df[i].kurt()
        mean = df[i].mean()
        median = df[i].median()

        if mean>median:
            type_skew = 'left_skewed'
        elif mean==median:
            type_skew = 'normal'
        else:
            type_skew = 'right_skewed'

        skews.append(skew)
        kurts.append(kurt)
        means.append(mean)
        medians.append(median)
        type_skewss.append(type_skew)
        column_name.append(i)

    return pd.DataFrame({'Feature':column_name,
                         'Skew':skews,
                         'Kurtosis':kurts,
                         'Mean':means,
                         'Median':medians,
                         'Type_of_skew':type_skewss})

stats()
```

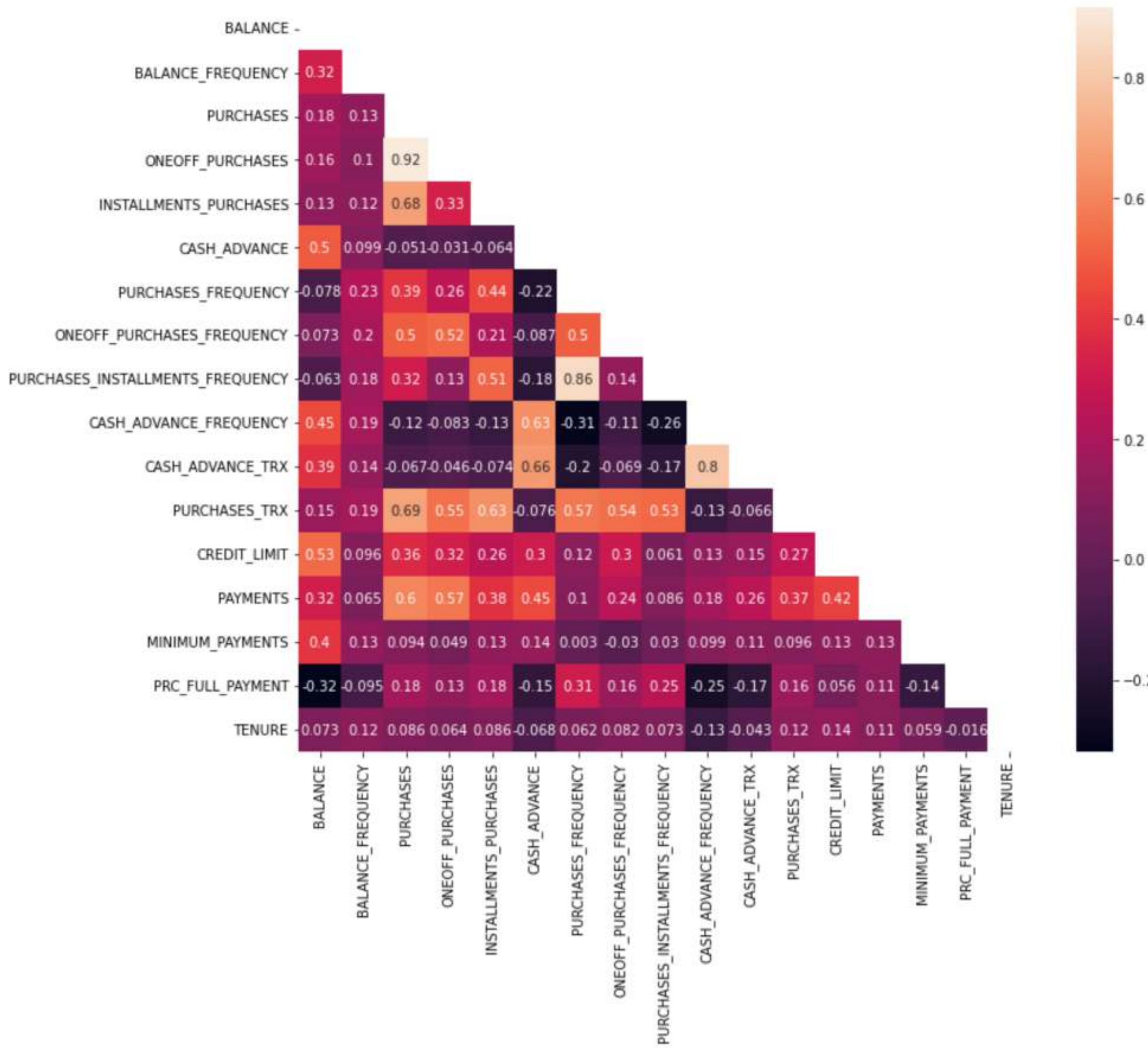
Out[99]:

	Feature	Skew	Kurtosis	Mean	Median	Type_of_skew
0	BALANCE	2.393386	7.674751	1564.474828	873.385231	left_skewed
1	BALANCE_FREQUENCY	-2.023266	3.092370	0.877271	1.000000	right_skewed
2	PURCHASES	8.144269	111.388771	1003.204834	361.280000	left_skewed
3	ONEOFF_PURCHASES	10.045083	164.187572	592.437371	38.000000	left_skewed
4	INSTALLMENTS_PURCHASES	7.299120	96.575178	411.067645	89.000000	left_skewed
5	CASH_ADVANCE	5.166609	52.899434	978.871112	0.000000	left_skewed
6	PURCHASES_FREQUENCY	0.060164	-1.638631	0.490351	0.500000	right_skewed
7	ONEOFF_PURCHASES_FREQUENCY	1.535613	1.161846	0.202458	0.083333	left_skewed
8	PURCHASES_INSTALLMENTS_FREQUENCY	0.509201	-1.398632	0.364437	0.166667	left_skewed
9	CASH_ADVANCE_FREQUENCY	1.828686	3.334734	0.135144	0.000000	left_skewed
10	CASH_ADVANCE_TRX	5.721298	61.646862	3.248827	0.000000	left_skewed
11	PURCHASES_TRX	4.630655	34.793100	14.709832	7.000000	left_skewed
12	CREDIT_LIMIT	1.522464	2.836656	4494.449450	3000.000000	left_skewed
13	PAYMENTS	5.907620	54.770736	1733.143852	856.901546	left_skewed
14	MINIMUM_PAYMENTS	13.622797	283.989986	864.206542	312.343947	left_skewed
15	PRC_FULL_PAYMENT	1.942820	2.432395	0.153715	0.000000	left_skewed
16	TENURE	-2.943017	7.694823	11.517318	12.000000	right_skewed

Correlation

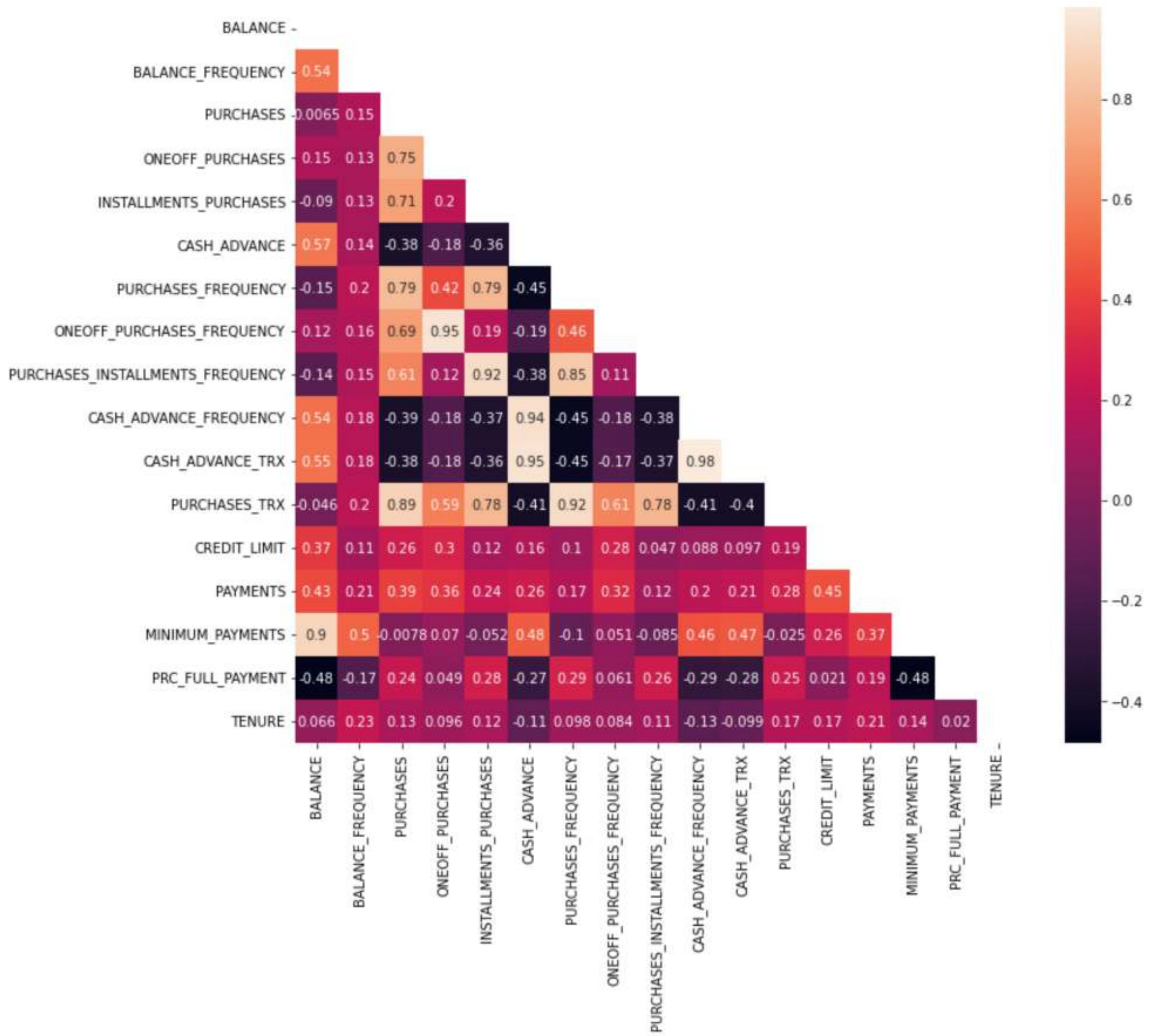
In [100]:
```
plt.figure(figsize=(12, 10))
sns.heatmap(df.corr(), mask = np.triu(df.corr()), annot=True)
```

Out[100]: <AxesSubplot:>



In [101]:
```
plt.figure(figsize=(12, 10))
sns.heatmap(df.corr(method='spearman'), mask = np.triu(df.corr(method='spearman')), annot=
```

Out[101]: <AxesSubplot:>



FEATURE SELECTION

In [102]:
```
df = df[['BALANCE','PURCHASES','CREDIT_LIMIT']]
```

EXPERIMENT 0

- StandardScaler
- Dropping null values

In [103]:
```
df_copy = df.dropna()
```

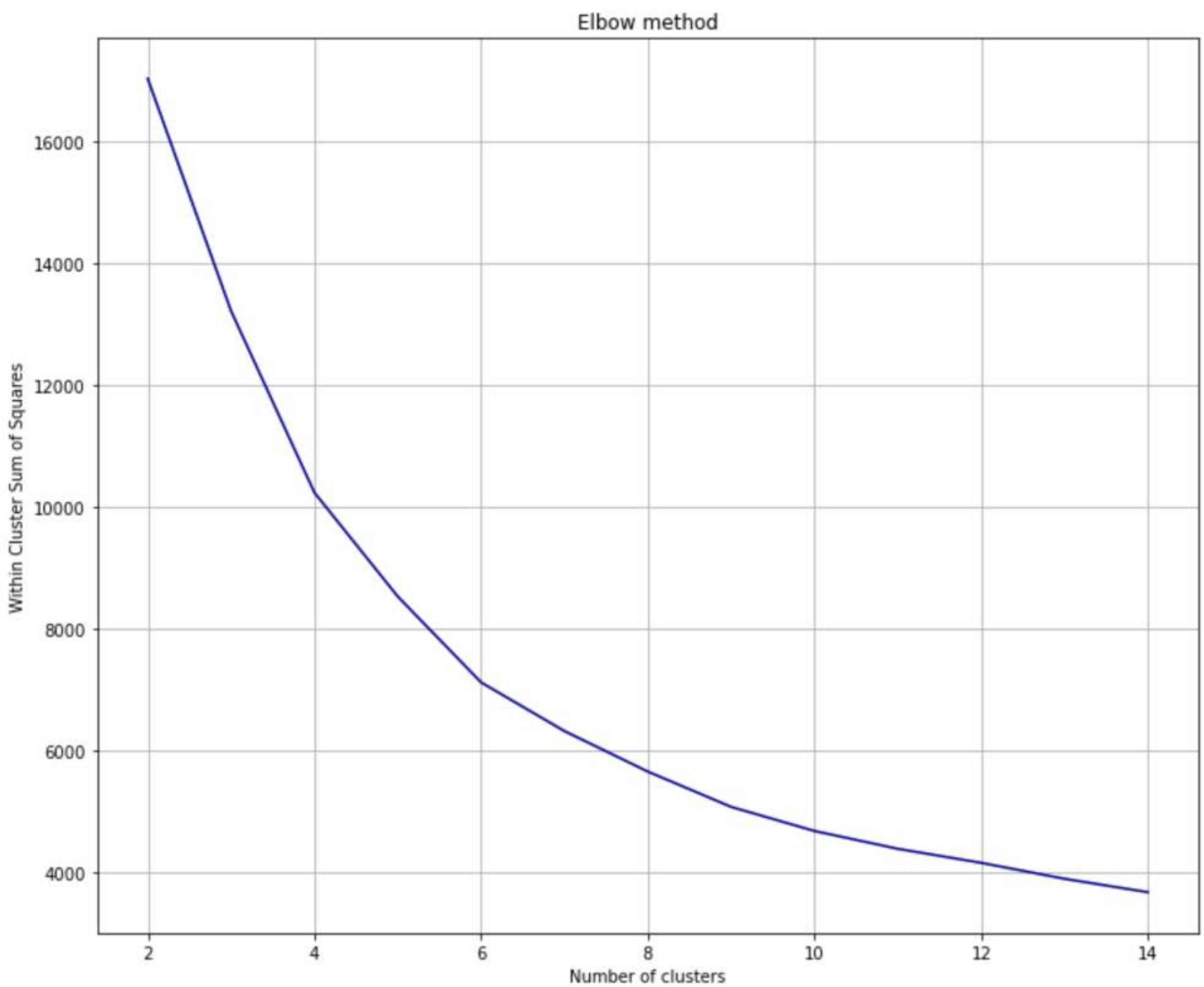
In [104]:
```
scaler = StandardScaler()
```

In [105]:
```
scaled_data = scaler.fit_transform(df_copy)
```

ELBOW METHOD

In [106]:
```
wcss = []

for i in range(2, 15):
    kmeans = KMeans(n_clusters =i)
    kmeans.fit(scaled_data)

    wcss.append(kmeans.inertia_)
```

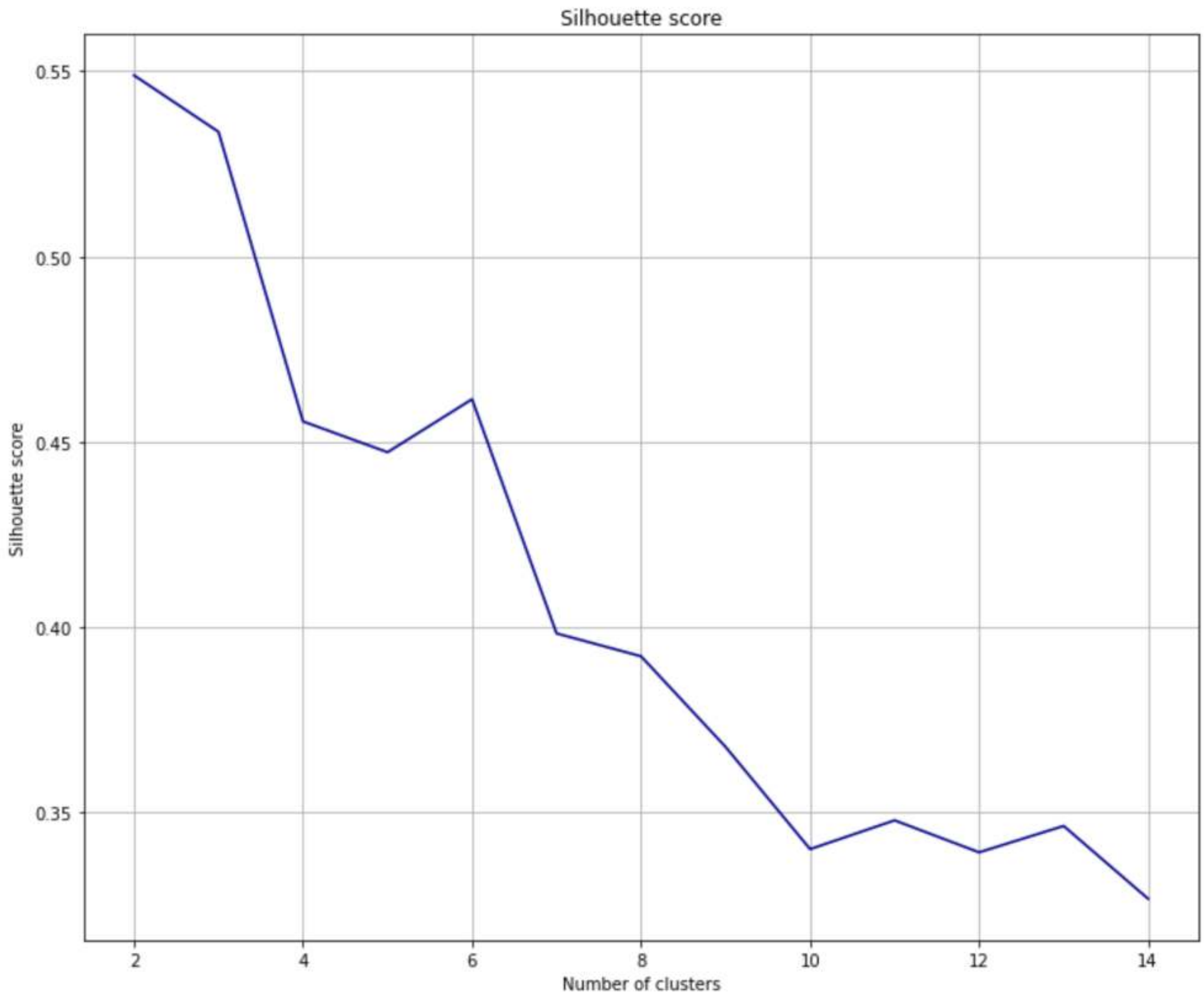
In [107]:
```
plt.figure(figsize=(12, 10))
plt.plot(range(2, 15), wcss, color='darkblue')
plt.title('Elbow method')

plt.xlabel('Number of clusters');plt.ylabel('Within Cluster Sum of Squares');plt.grid(True)
```



SILHOUETTE SCORE

In [108]:
```
silhouette_scores = []

for i in range(2, 15):
    kmeans = KMeans(n_clusters =i)
    kmeans.fit(scaled_data)

    score = silhouette_score(scaled_data, kmeans.labels_)

    silhouette_scores.append(score)
```

In [109]:
```
plt.figure(figsize=(12, 10))
plt.plot(range(2, 15), silhouette_scores, color='darkblue')
plt.title('Silhouette score')

plt.xlabel('Number of clusters');plt.ylabel('Silhouette score');plt.grid(True)
```



KMEANS

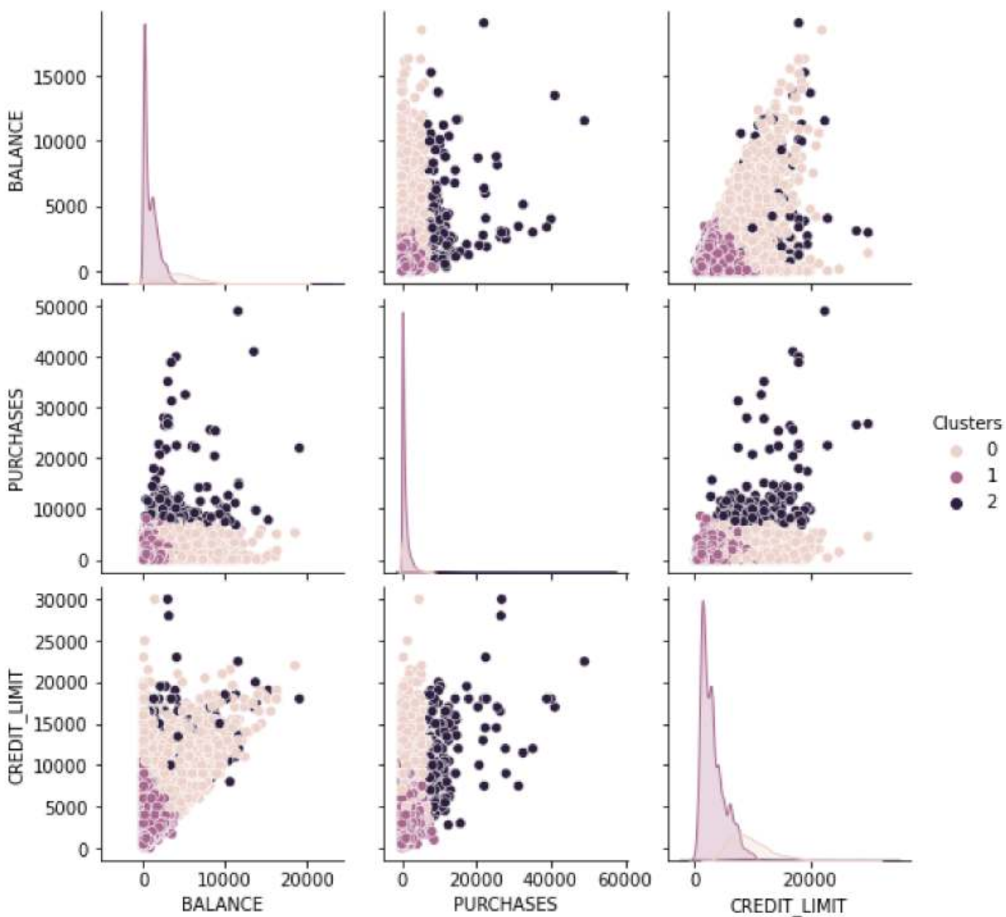
In [115]:
```
kmeans = KMeans(n_clusters= 3)
clusters = kmeans.fit_predict(scaled_data)
```

In [116]:
```
centroids = kmeans.cluster_centers_
```

In [117]:
```
df_copy['Clusters'] = clusters
```

In [118]:
```
sns.pairplot(df_copy, hue='Clusters', diag_kind='kde')
```

Out[118]: <seaborn.axisgrid.PairGrid at 0x28c0b505970>



DBSCAN

In [127]:
```
dbscan = DBSCAN(eps = 0.05, min_samples= 8)
dbscan.fit(scaled_data)
```

Out[127]:
```
DBSCAN
DBSCAN(eps=0.05, min_samples=8)
```

In [128]:
```
dbscan.labels_
```

Out[128]:
```
array([ 0, -1, -1, ...,  0, 21, -1], dtype=int64)
```

In [129]:
```
len(dbscan.core_sample_indices_)
```

Out[129]: 3536

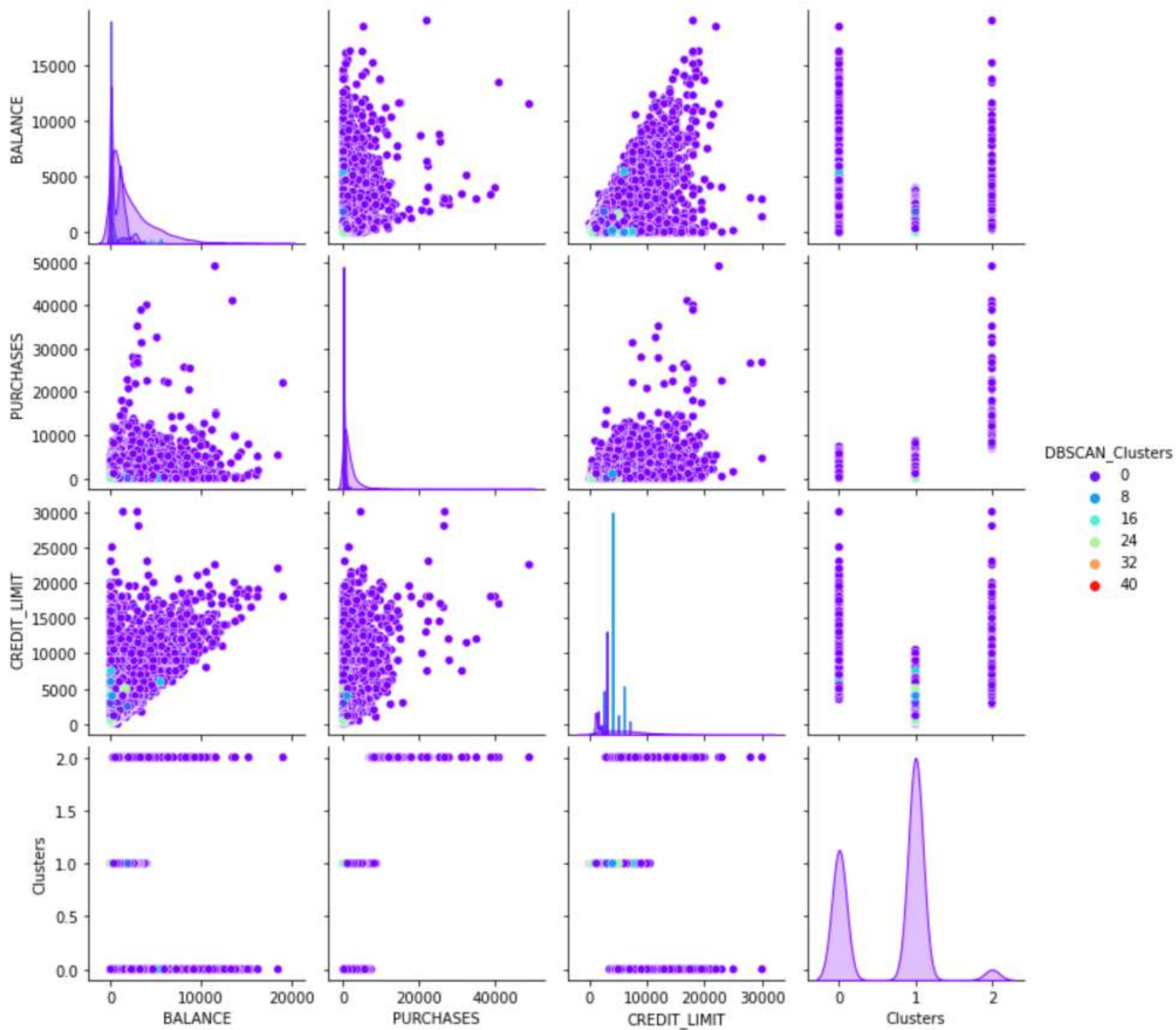
In [130]:
```
centroids = dbscan.components_
centroids
```

Out[130]:
```
array([[-0.73205404, -0.4249337 , -0.96037969],
       [-0.35884931, -0.4620954 , -0.90541368],
       [ 0.58041983, -0.4695839 , -0.4107196 ],
       ...,
       [-0.7424878 , -0.32917446, -0.96037969],
       [-0.74046257, -0.40200016, -0.96037969],
       [-0.74523857, -0.4695839 , -1.09779471]])
```

In [131]:
```
df_copy['DBSCAN_Clusters'] = dbscan.labels_
```

In [132]:
```
sns.pairplot(df_copy, hue='DBSCAN_Clusters', diag_kind='kde', palette = 'rainbow')
```

Out[132]:
```
<seaborn.axisgrid.PairGrid at 0x28c2b980730>
```



DBSCAN does not have a predict method so it cant predict for new instances, we have to use a classifcation algorithm here to predict clusters of new instances.

In [133]:
```
from sklearn.neighbors import KNeighborsClassifier
```

In [134]:
```
kn = KNeighborsClassifier(n_neighbors = 50)
kn.fit(dbscan.components_, dbscan.labels_[dbscan.core_sample_indices_])
#we only trained with for core instances, we can choose to train with all instances
```

Out[134]:
```
▾ KNeighborsClassifier
KNeighborsClassifier(n_neighbors=50)
```

In [136]:
```
kn.predict(scaled_data)
```

Out[136]:
```
array([ 0, 13, 12, ...,  0, 21,  0], dtype=int64)
```

EXPERIMENT 1

- Without scaling
- Imputing null values

In [137]:
```
df_copy_2 = df.copy()
```

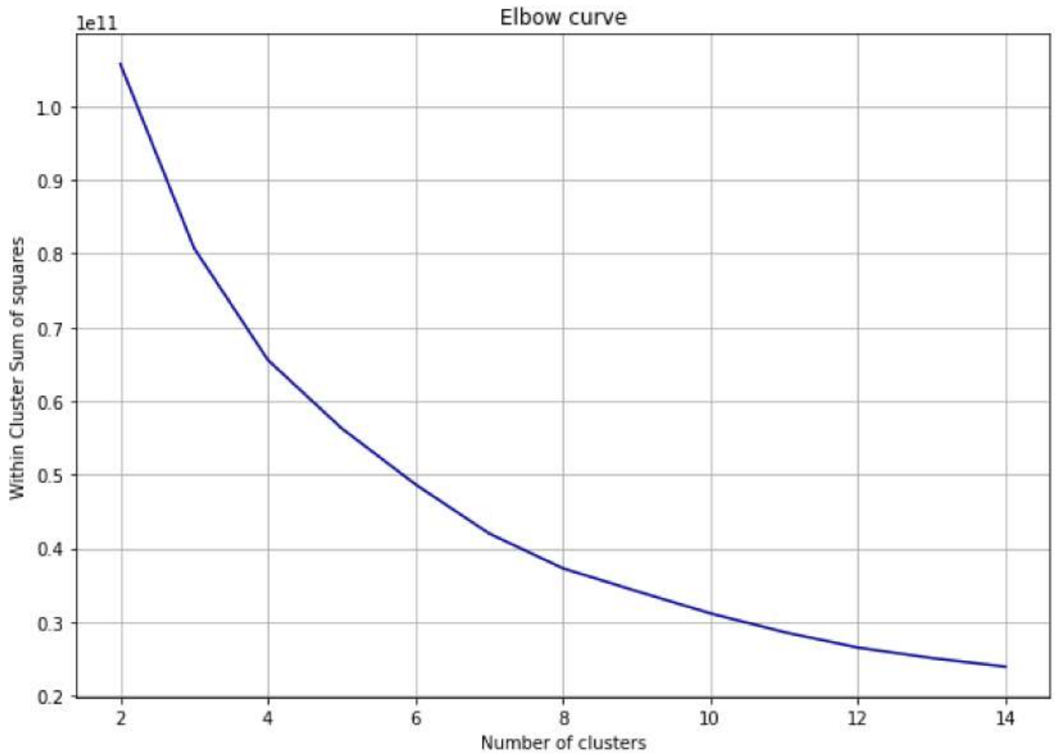
In [139]:
```
median_imputer = SimpleImputer(strategy = 'median')
```

In [140]:
```
data_imputed = median_imputer.fit_transform(df_copy_2)
```

ELBOW METHOD

In [144]:
```
wcss = []

for i in range(2, 15):
    kmeans = KMeans(n_clusters = i)

    kmeans.fit(data_imputed)

    wcss.append(kmeans.inertia_)
```

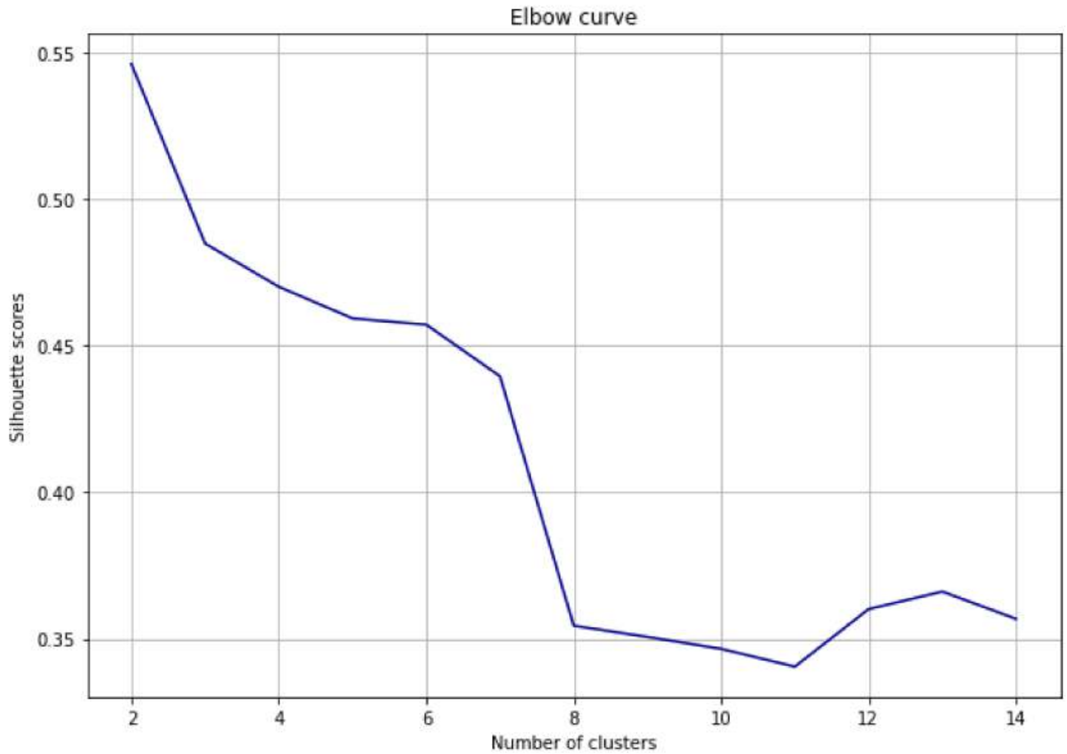
In [145]:
```
plt.figure(figsize=(10,7))
plt.plot(range(2, 15), wcss, color='darkblue')
plt.title('Elbow curve')
plt.xlabel('Number of clusters');plt.ylabel('Within Cluster Sum of squares');plt.grid(True
```



SILHOUETTE SCORE

In [147]:
```
scores = []
for i in range(2, 15):
    kmeans = KMeans(n_clusters= i)
    kmeans.fit(data_imputed)
    score = silhouette_score(data_imputed, kmeans.labels_)
    scores.append(score)
```

In [148]:
```
plt.figure(figsize=(10,7))
plt.plot(range(2, 15), scores, color='darkblue')
plt.title('Elbow curve')
plt.xlabel('Number of clusters');plt.ylabel('Silhouette scores');plt.grid(True)
```



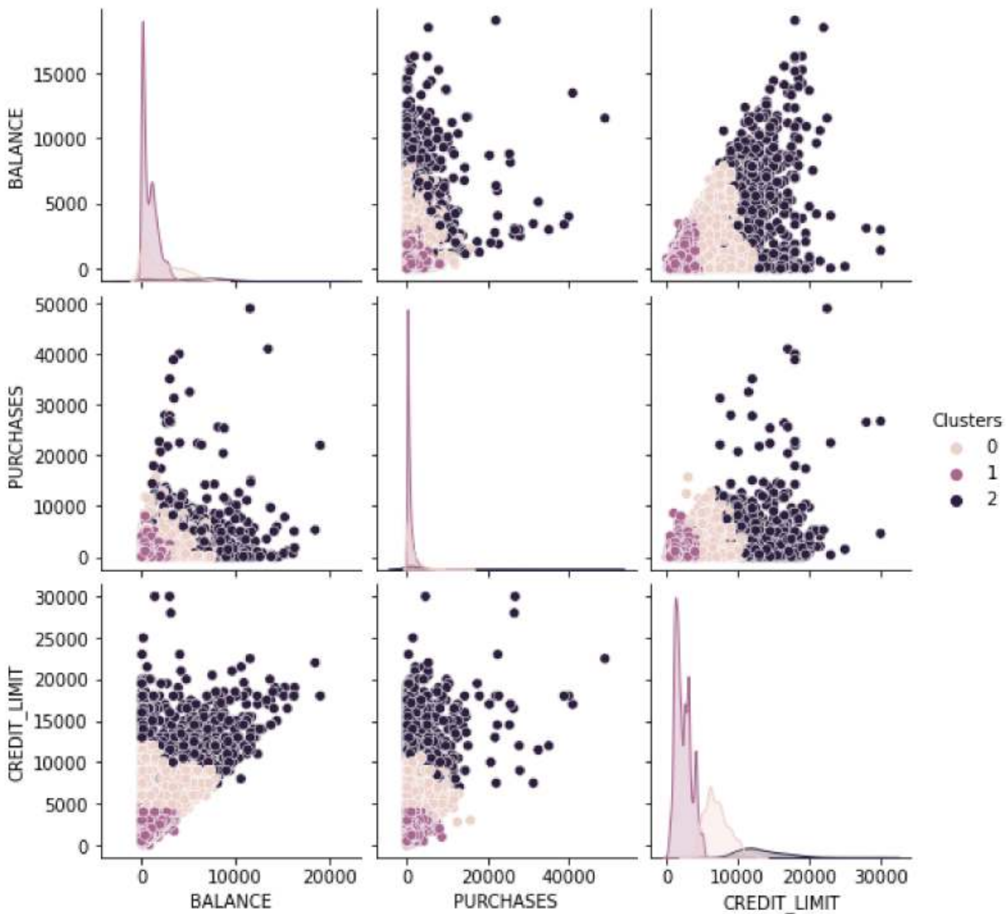
KMEANS

In [153]:
```
kmeans = KMeans(n_clusters =3 )
clusters = kmeans.fit_predict(data_imputed)
```

In [154]:
```
df_copy_2['Clusters'] = clusters
```

In [155]:
```
sns.pairplot(df_copy_2, hue = 'Clusters', diag_kind='kde')
```

Out[155]: <seaborn.axisgrid.PairGrid at 0x28c004d1400>



DBSCAN

In [163]:
```
dbscan = DBSCAN(eps=0.1, min_samples=10)
dbscan.fit(data_imputed)
```

Out[163]:
```
DBSCAN
DBSCAN(eps=0.1, min_samples=10)
```

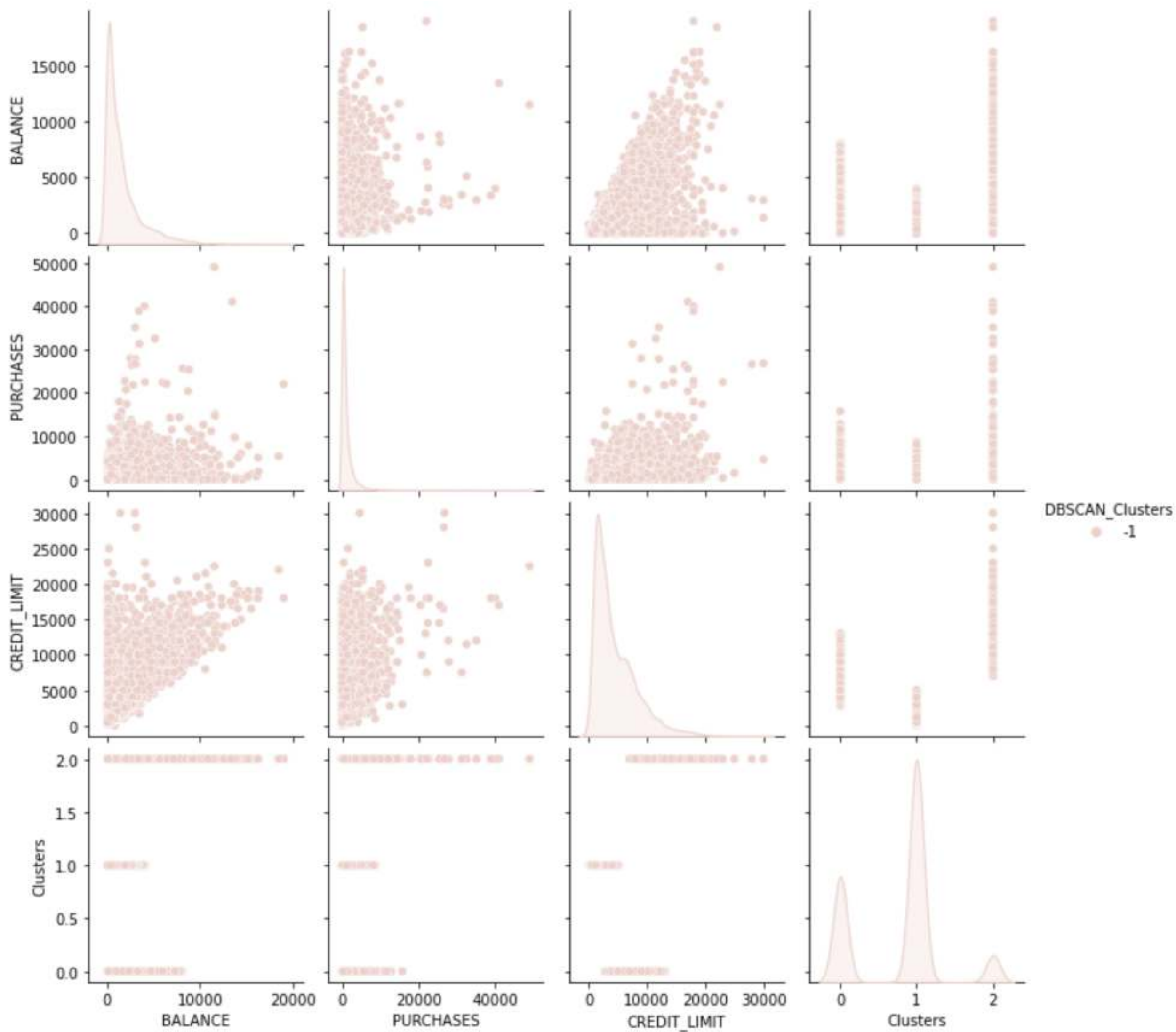
In [164]:
```
dbscan.labels_
```

Out[164]: array([-1, -1, -1, ..., -1, -1, -1], dtype=int64)

In [165]:
```
df_copy_2['DBSCAN_Clusters'] = dbscan.labels_
```

In [166]:
```
sns.pairplot(df_copy_2, hue = 'DBSCAN_Clusters', diag_kind='kde')
```

Out[166]: <seaborn.axisgrid.PairGrid at 0x28c0405b100>



EXPERIMENT 2

- StandardScaler
- SimpleImputer

In [168]:
```
df_copy_3 = df.copy()
```

In [169]:
```
from sklearn.pipeline import Pipeline
```

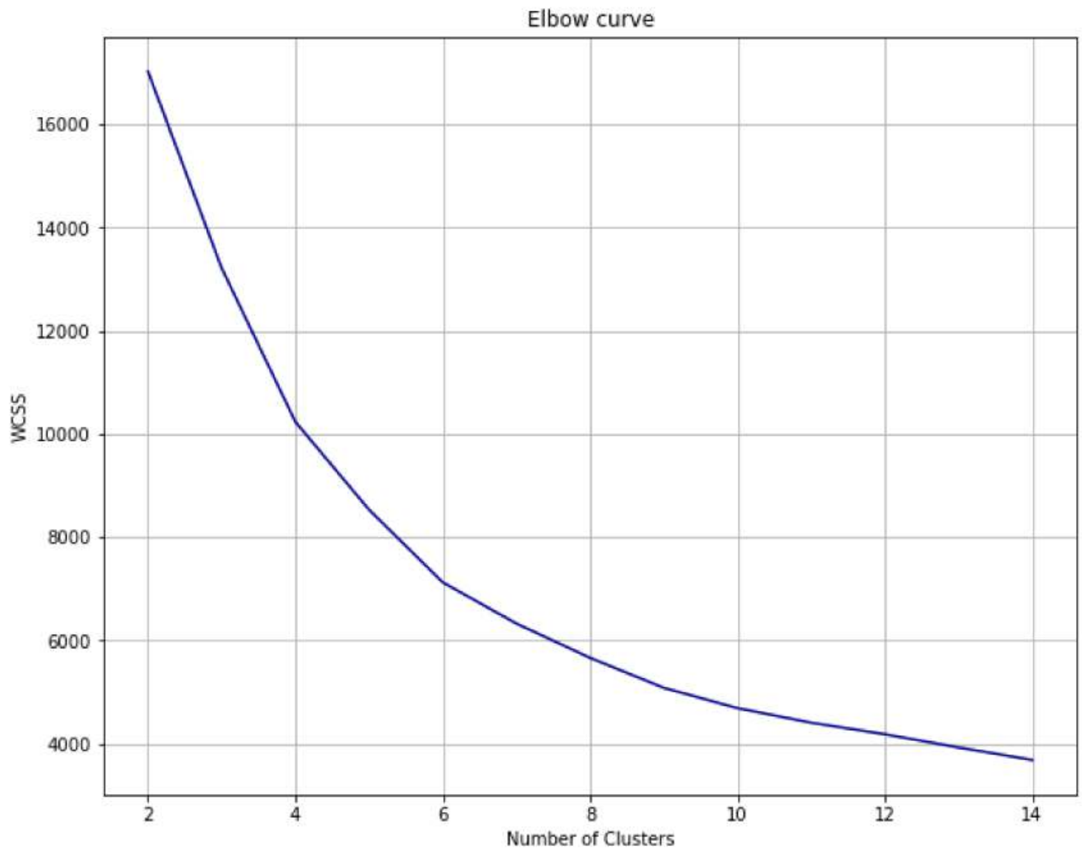
In [170]:
```
preprocessor = Pipeline([('imputer',SimpleImputer(strategy='median')),
                         ('scaler',StandardScaler())])
```

In [171]:
```
df_processed = preprocessor.fit_transform(df_copy_3)
```

ELBOW METHOD

In [177]:
```
wcss = []

for i in range(2, 15):
    kmeans = KMeans(n_clusters = i)

    kmeans.fit(df_processed)

    wcss.append(kmeans.inertia_)
```

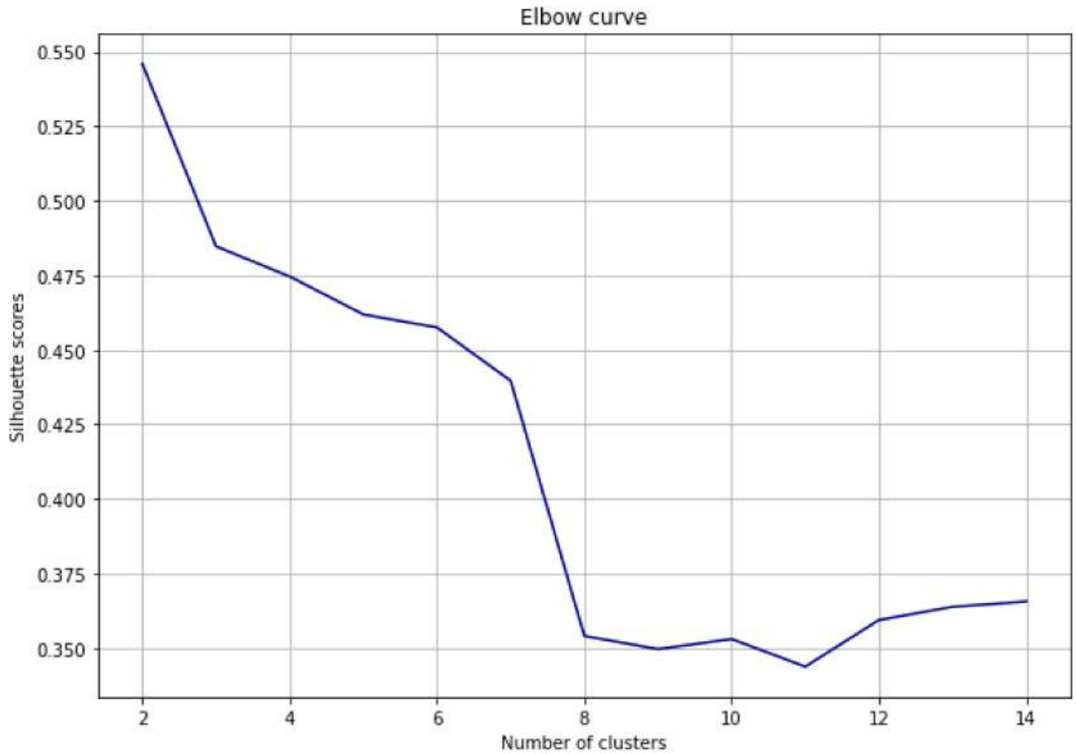
In [178]:
```
plt.figure(figsize=(10,8))
plt.plot(range(2, 15), wcss, color='darkblue')
plt.title('Elbow curve')
plt.xlabel('Number of Clusters');plt.ylabel('WCSS');plt.grid(True)
```



SILHOUETTE SCORE

In [174]:
```
scores = []

for i in range(2, 15):

    kmeans = KMeans(n_clusters= i)

    kmeans.fit(data_imputed)

    score = silhouette_score(data_imputed, kmeans.labels_)
    scores.append(score)
```

In [175]:
```
plt.figure(figsize=(10,7))
plt.plot(range(2, 15), scores, color='darkblue')
plt.title('Elbow curve')
plt.xlabel('Number of clusters');plt.ylabel('Silhouette scores');plt.grid(True)
```



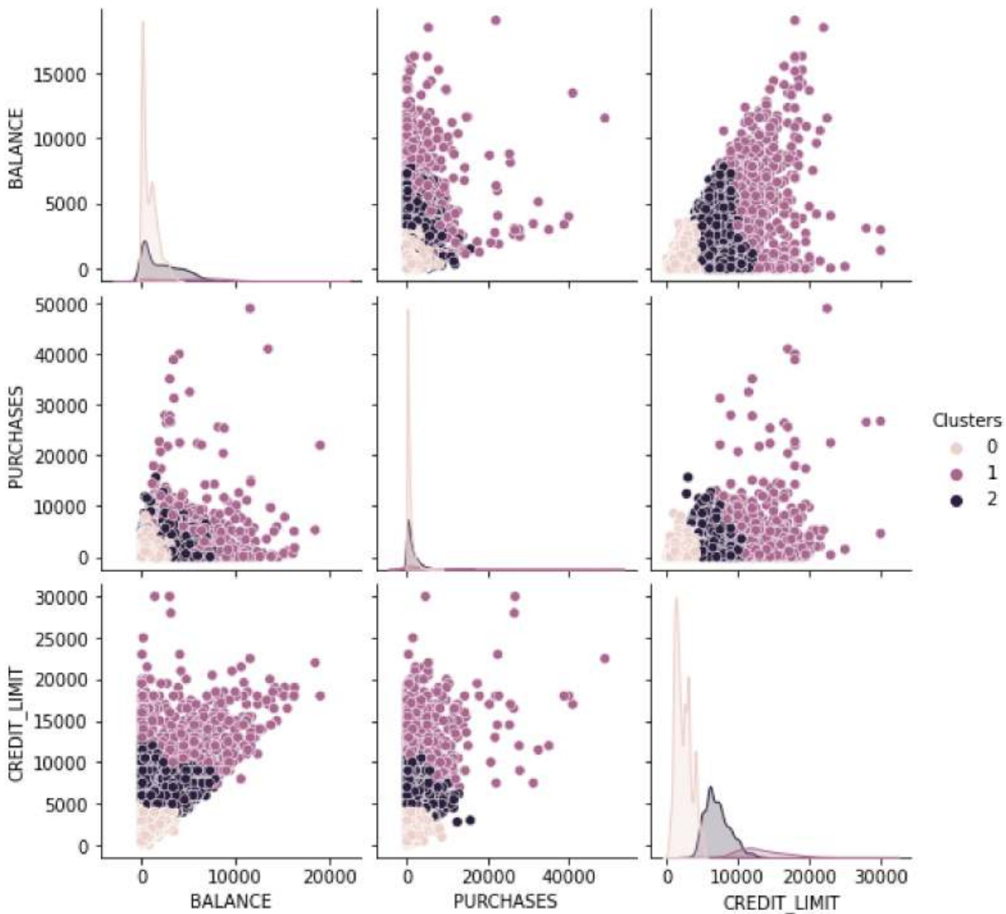
KMEANS

In [179]:
```
kmeans = KMeans(n_clusters = 3)
clusters = kmeans.fit_predict(data_imputed)
```

In [180]:
```
df_copy_3['Clusters'] = clusters
```

In [181]:
```
sns.pairplot(df_copy_3, hue = 'Clusters', diag_kind='kde')
```

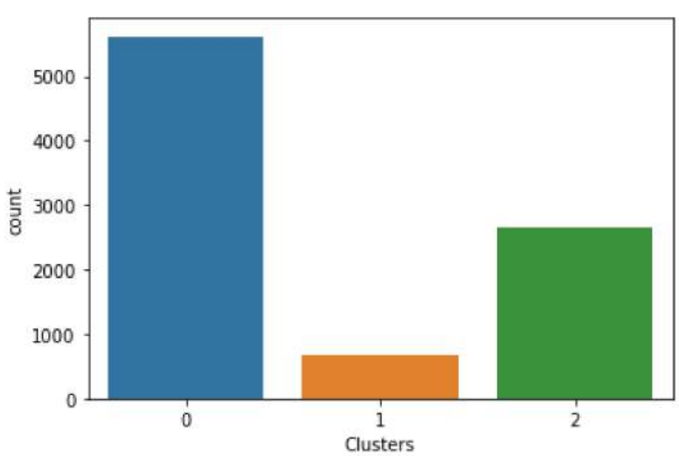
Out[181]: <seaborn.axisgrid.PairGrid at 0x28c3c3060d0>



EDA

In [182]:
```
sns.countplot(x=df_copy_3['Clusters'])
```

Out[182]: <AxesSubplot:xlabel='Clusters', ylabel='count'>



In [183]:

```
df_copy_3.groupby('Clusters').median()
```

Out[183]:

Clusters	BALANCE	PURCHASES	CREDIT_LIMIT
0	545.767741	258.900	2000.0
1	5643.992345	1490.940	12500.0
2	1727.957186	665.355	7000.0

In [184]:

```
df_copy_3.groupby('Clusters').mean()
```

Out[184]:

Clusters	BALANCE	PURCHASES	CREDIT_LIMIT
0	805.059624	548.540514	2247.987050
1	5489.730712	3681.097748	13185.555556
2	2174.544585	1285.077638	7041.028979

In [193]:

```
for i in df_copy_3.iloc[:,:-1].columns:
    plt.figure()
    sns.barplot(data=df_copy_3,y = i, x='Clusters')
```