Project - Unsupervised Learning

Name: Panagam Mohitha

Domain: Banking, Finance

Context: This case requires to develop a customer segmentation to define marketing strategy. The sample Dataset summarizes the usage behavior of about 9000 active credit card holders during the last 6 months. The file is at a customer level with 18 behavioral variables.

Attribute Information:

- **CUSTID** : Identification of Credit Card holder (Categorical)
- **BALANCE**: Balance amount left in their account to make purchases
- **BALANCEFREQUENCY** : How frequently the Balance is updated, score between 0 and 1 (1 = frequently updated, 0 = not frequently updated)
- **PURCHASES** : Amount of purchases made from account
- **ONEOFFPURCHASES** : Maximum purchase amount done in one-go
- **INSTALLMENTSPURCHASES** : Amount of purchase done in installment
- **CASHADVANCE** : Cash in advance given by the user
- **PURCHASESFREQUENCY** : How frequently the Purchases are being made, score between 0 and 1 (1 = frequently purchased, 0 = not frequently purchased)
- **ONEOFFPURCHASESFREQUENCY** : How frequently Purchases are happening in one-go (1 = frequently purchased, 0 = not frequently purchased)
- **PURCHASESINSTALLMENTSFREQUENCY**: How frequently purchases in installments are being done (1 = frequently done, 0 = not frequently done)
- **CASHADVANCEFREQUENCY** : How frequently the cash in advance being paid
- **CASHADVANCETRX** : Number of Transactions made with "Cash in Advance"
- **PURCHASESTRX** : Number of purchase transactions made
- **CREDITLIMIT** : Limit of Credit Card for user
- **PAYMENTS** : Amount of Payment done by user
- **MINIMUM_PAYMENTS** : Minimum amount of payments made by user
- **PRCFULLPAYMENT** : Percent of full payment paid by user
- **TENURE** : Tenure of credit card service for user

1. Preprocessing the data

In [559…

```
# used to supress display of warnings
import warnings

# os is used to provide a way of using operating system dependent functionality
```

```
# We use it for setting working folder
import os

# Pandas is used for data manipulation and analysis
import pandas as pd

# Numpy is used for large, multi-dimensional arrays and matrices, along with mathen
import numpy as np

# Matplotlib is a data visualization library for 2D plots of arrays, built on NumPy
# and designed to work with the broader SciPy stack
import matplotlib.pyplot as plt
%matplotlib inline

# Seaborn is based on matplotlib, which aids in drawing attractive and informative
import seaborn as sns


## Scikit-learn features various classification, regression and clustering algorit
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn import metrics
from sklearn import preprocessing
from sklearn.metrics import average_precision_score, confusion_matrix, accuracy_sc

from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram
from scipy.cluster.hierarchy import cut_tree
```

In [560…

```
# suppress display of warnings
warnings.filterwarnings('ignore')

# display all dataframe columns
pd.options.display.max_columns = None

# to set the limit to 3 decimals
pd.options.display.float_format = '{:.3f}'.format

# display all dataframe rows
pd.options.display.max_rows = None
```

a. Check a few observations and get familiar with the data.

In [561…

```
# reading the CSV file into pandas dataframe
cc_data = pd.read_csv('C:\\Users\\Mohitha Panagam\\Downloads\\Project\\data_credit_
```

In [562…

```
# to display the top 10 rows of the dataframe
cc_data.head(10)
```

Out[562]:

	CUST_ID	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS
0	C10001	40.901	0.818	95.400	0.000	
1	C10002	3202.467	0.909	0.000	0.000	
2	C10003	2495.149	1.000	773.170	773.170	
3	C10004	1666.671	0.636	1499.000	1499.000	
4	C10005	817.714	1.000	16.000	16.000	
5	C10006	1809.829	1.000	1333.280	0.000	
6	C10007	627.261	1.000	7091.010	6402.630	
7	C10008	1823.653	1.000	436.200	0.000	
8	C10009	1014.926	1.000	861.490	661.490	
9	C10010	152.226	0.545	1281.600	1281.600	

b. Check the size and info of the data set.

In [563…

```
# to display the dimension of the dataframe
cc_data.shape
```

Out[563]:

```
(8950, 18)
```

Inference:

- There are 8950 Observations / Rows and 18 Attributes / Columns.

In [564…

```
cc_data.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
```

Inference:

- All the variables are numerical attributes except CUST_ID is a categorical attribute.

In [565…

```
# to display the column names of the dataframe
cc_data.columns
```

Out[565]:

```
Index(['CUST_ID', 'BALANCE', 'BALANCE_FREQUENCY', 'PURCHASES',
       'ONEOFF_PURCHASES', 'INSTALLMENTS_PURCHASES', 'CASH_ADVANCE',
       'PURCHASES_FREQUENCY', 'ONEOFF_PURCHASES_FREQUENCY',
       'PURCHASES_INSTALLMENTS_FREQUENCY', 'CASH_ADVANCE_FREQUENCY',
       'CASH_ADVANCE_TRX', 'PURCHASES_TRX', 'CREDIT_LIMIT', 'PAYMENTS',
       'MINIMUM_PAYMENTS', 'PRC_FULL_PAYMENT', 'TENURE'],
      dtype='object')
```

In [566…

```
# check the datatypes
cc_data.dtypes
```

Out[566]:

```
CUST_ID                              object
BALANCE                             float64
BALANCE_FREQUENCY                   float64
PURCHASES                           float64
ONEOFF_PURCHASES                    float64
INSTALLMENTS_PURCHASES              float64
CASH_ADVANCE                        float64
PURCHASES_FREQUENCY                 float64
ONEOFF_PURCHASES_FREQUENCY          float64
PURCHASES_INSTALLMENTS_FREQUENCY    float64
CASH_ADVANCE_FREQUENCY              float64
CASH_ADVANCE_TRX                      int64
PURCHASES_TRX                         int64
CREDIT_LIMIT                        float64
PAYMENTS                            float64
MINIMUM_PAYMENTS                    float64
PRC_FULL_PAYMENT                    float64
TENURE                                int64
dtype: object
```

c. Check for missing values. Impute the missing values if there is any.

In [567…

```
#check the missing values.
cc_data.isnull().any()
```

Out[567]:

```
CUST_ID                             False
BALANCE                             False
BALANCE_FREQUENCY                   False
PURCHASES                           False
ONEOFF_PURCHASES                    False
INSTALLMENTS_PURCHASES              False
CASH_ADVANCE                        False
PURCHASES_FREQUENCY                 False
ONEOFF_PURCHASES_FREQUENCY          False
PURCHASES_INSTALLMENTS_FREQUENCY    False
CASH_ADVANCE_FREQUENCY              False
CASH_ADVANCE_TRX                    False
PURCHASES_TRX                       False
CREDIT_LIMIT                         True
PAYMENTS                            False
MINIMUM_PAYMENTS                     True
PRC_FULL_PAYMENT                    False
TENURE                              False
dtype: bool
```

In [568…
```
# CREDIT_LIMIT  and MINIMUM_PAYMENTS has missing values so we need to remove with r
cc_data['CREDIT_LIMIT'].fillna(cc_data['CREDIT_LIMIT'].median(),inplace=True)

cc_data['CREDIT_LIMIT'].count()


cc_data['MINIMUM_PAYMENTS'].median()
cc_data['MINIMUM_PAYMENTS'].fillna(cc_data['MINIMUM_PAYMENTS'].median(),inplace=Tru
```

In [569…
```
# Now again check the missing values.
cc_data.isnull().any()
```

Out[569]:
```
CUST_ID                             False
BALANCE                             False
BALANCE_FREQUENCY                   False
PURCHASES                           False
ONEOFF_PURCHASES                    False
INSTALLMENTS_PURCHASES              False
CASH_ADVANCE                        False
PURCHASES_FREQUENCY                 False
ONEOFF_PURCHASES_FREQUENCY          False
PURCHASES_INSTALLMENTS_FREQUENCY    False
CASH_ADVANCE_FREQUENCY              False
CASH_ADVANCE_TRX                    False
PURCHASES_TRX                       False
CREDIT_LIMIT                        False
PAYMENTS                            False
MINIMUM_PAYMENTS                    False
PRC_FULL_PAYMENT                    False
TENURE                              False
dtype: bool
```

Inference:

- Since there are missing values in the data so those attributes are imputing them with median.

d. Drop unnecessary columns.

In [570…
```
cols_to_drop = ['CUST_ID']
cc_data = cc_data.drop(cols_to_drop, axis=1)
```

In [571…
```
cc_data.columns
```

Out[571]:
```
Index(['BALANCE', 'BALANCE_FREQUENCY', 'PURCHASES', 'ONEOFF_PURCHASES',
       'INSTALLMENTS_PURCHASES', 'CASH_ADVANCE', 'PURCHASES_FREQUENCY',
       'ONEOFF_PURCHASES_FREQUENCY', 'PURCHASES_INSTALLMENTS_FREQUENCY',
       'CASH_ADVANCE_FREQUENCY', 'CASH_ADVANCE_TRX', 'PURCHASES_TRX',
       'CREDIT_LIMIT', 'PAYMENTS', 'MINIMUM_PAYMENTS', 'PRC_FULL_PAYMENT',
       'TENURE'],
      dtype='object')
```

Inference:

- CUST_ID is an unnecessary column for building model so it is dropped.

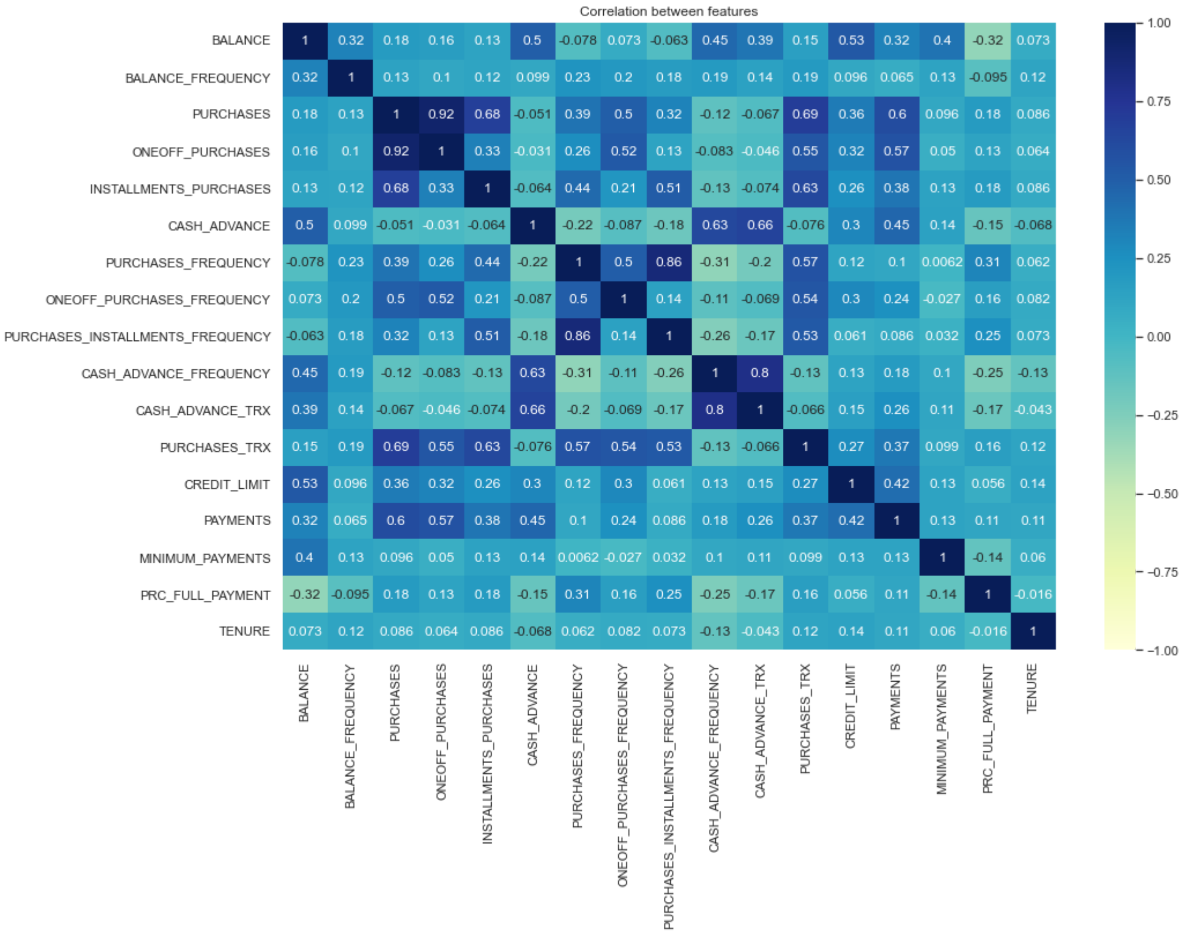
e. Check correlation among features and comment your findings.

In [502…

```
# To get a correlation matrix
# Ploting correlation plot
corr = cc_data.iloc[:, :17].corr()
plt.figure(figsize=(15, 10))

sns.heatmap(corr, cmap='YlGnBu', vmax=1.0, vmin=-1.0, annot = True, annot_kws={"si

# specify name of the plot
plt.title('Correlation between features')
plt.show()
```



Inference:

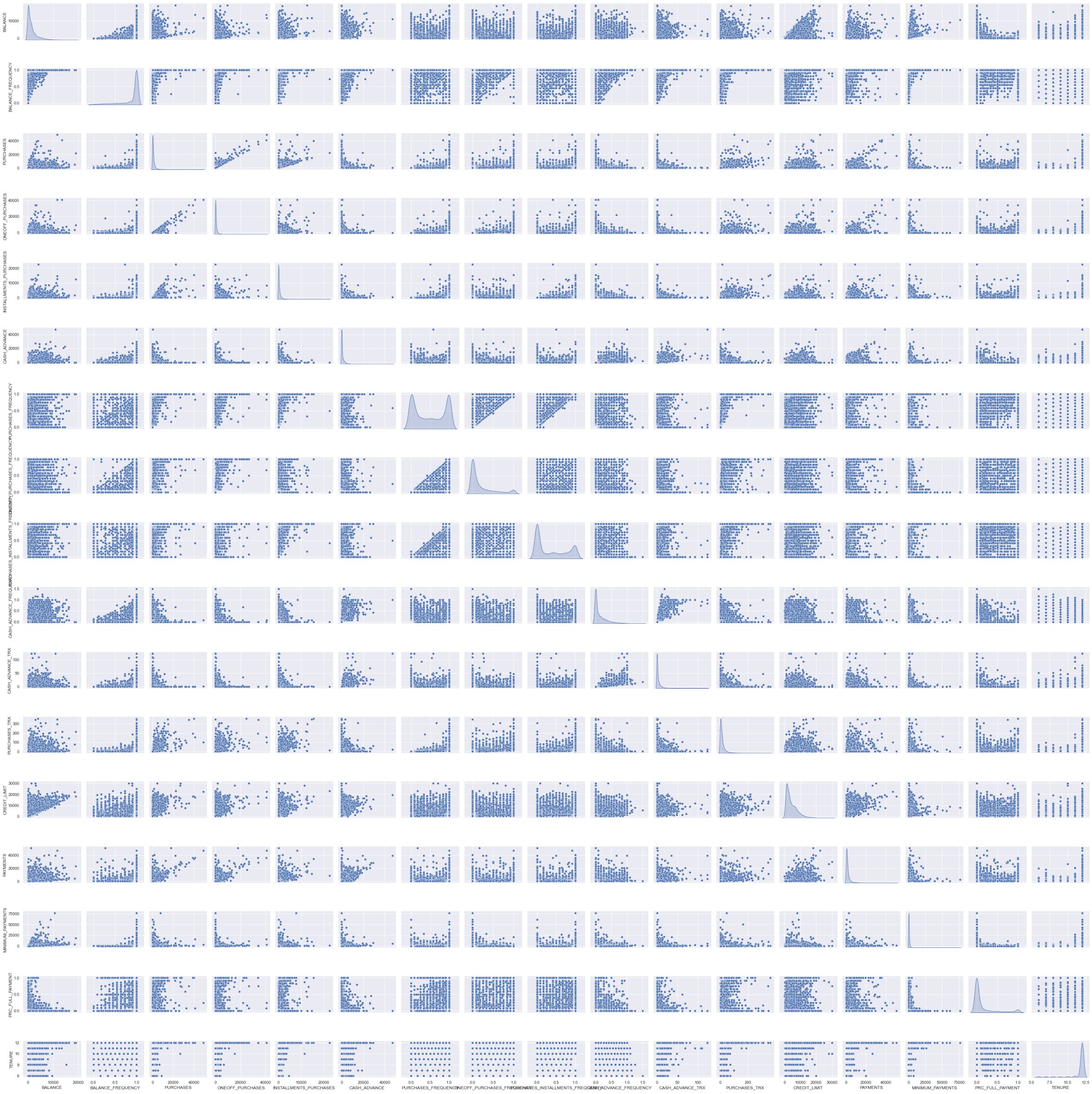
- ONEOFF_PURCHASES and PURCHASES have highest correlation
- PURCHASES_INSTALLMENTS_FREQUENCY and PURCHASES_FREQUENCY have high correlation
- There is positive correlation between attributes of transcation and frequency such as CASH_ADVANCE_FREQUENCY, CASH_ADVANCE_TRX

In [503…

```
sns.pairplot(cc_data.iloc[:,:17], diag_kind='kde')
```

Out[503]:

```
<seaborn.axisgrid.PairGrid at 0x219bae4f160>
```



f. Check distribution of features and comment your findings.

In [504…

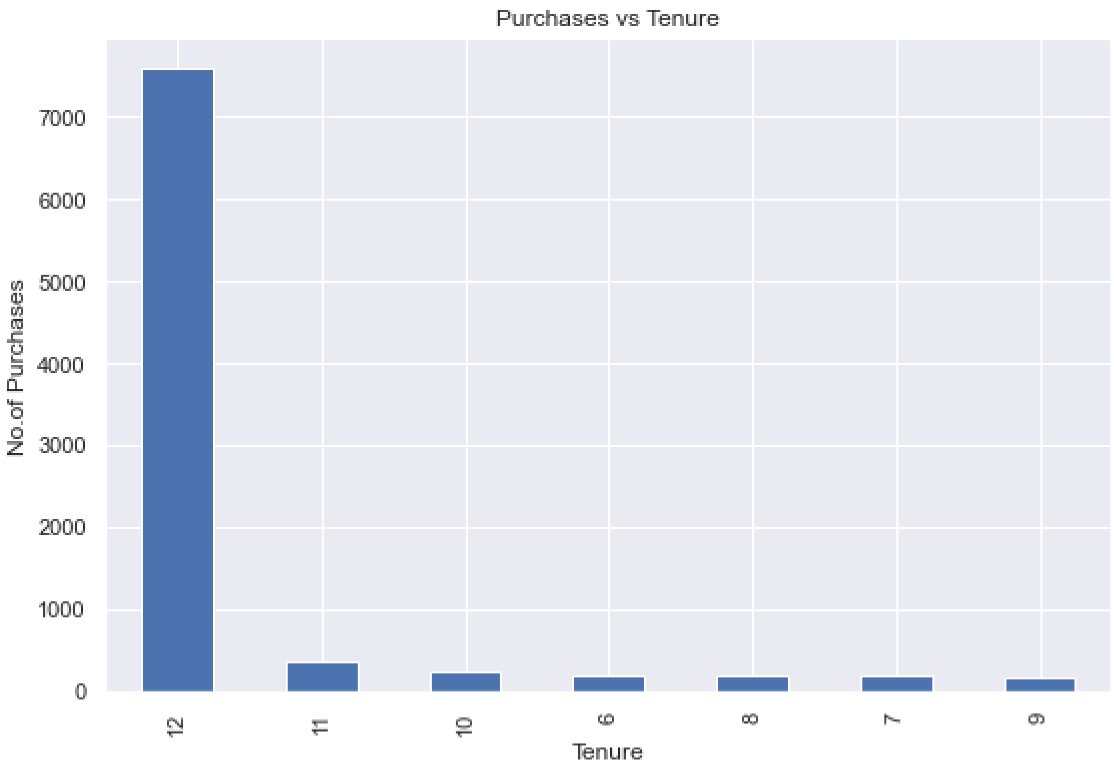
```
# describe the numerical data
cc_data.describe()
```

Out[504]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURC
count	8950.000	8950.000	8950.000	8950.000	8
mean	1564.475	0.877	1003.205	592.437	
std	2081.532	0.237	2136.635	1659.888	
min	0.000	0.000	0.000	0.000	
25%	128.282	0.889	39.635	0.000	
50%	873.385	1.000	361.280	38.000	
75%	2054.140	1.000	1110.130	577.405	
max	19043.139	1.000	49039.570	40761.250	22

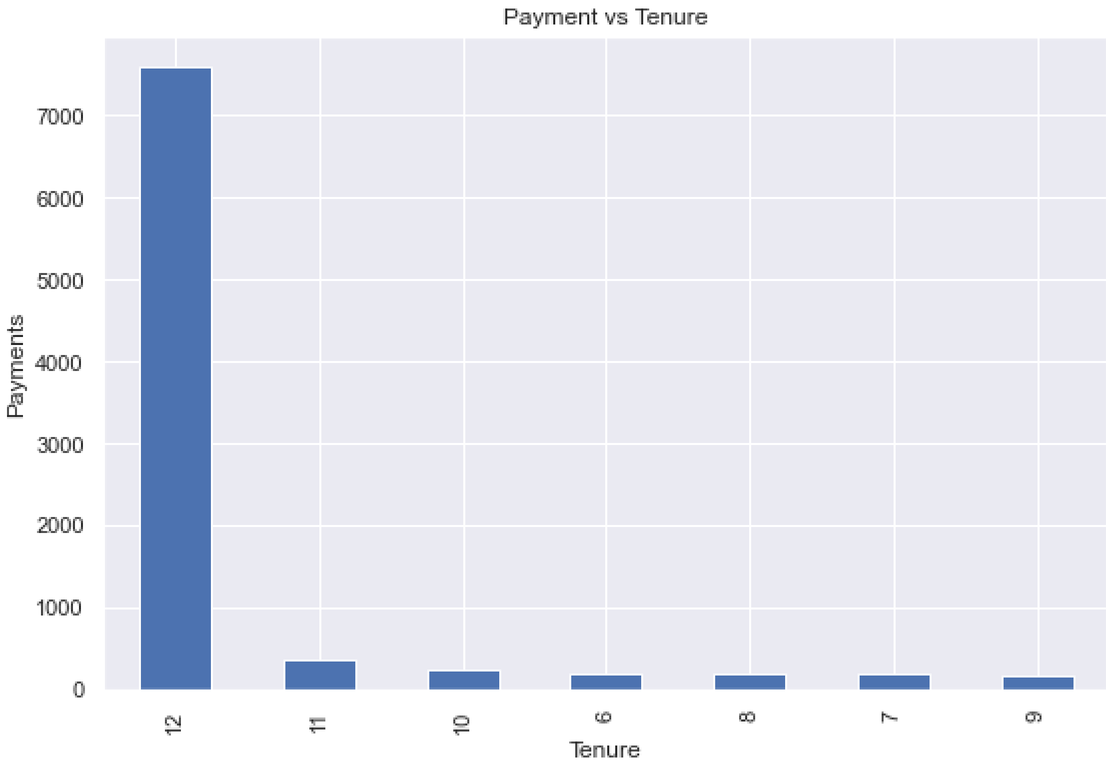
In [505…

```
plt.figure(figsize=(9,6))
top_cities = cc_data.groupby(['TENURE'])['PURCHASES'].count().sort_values(ascending
top_cities.plot(kind = 'bar')
plt.title('Purchases vs Tenure')
plt.xlabel('Tenure')
plt.ylabel('No.of Purchases')
plt.show()
```



In [506…

```
plt.figure(figsize=(9,6))
top_cities = cc_data.groupby(['TENURE'])['PAYMENTS'].count().sort_values(ascending
top_cities.plot(kind = 'bar')
plt.title('Payment vs Tenure')
plt.xlabel('Tenure')
plt.ylabel('Payments')
plt.show()
```

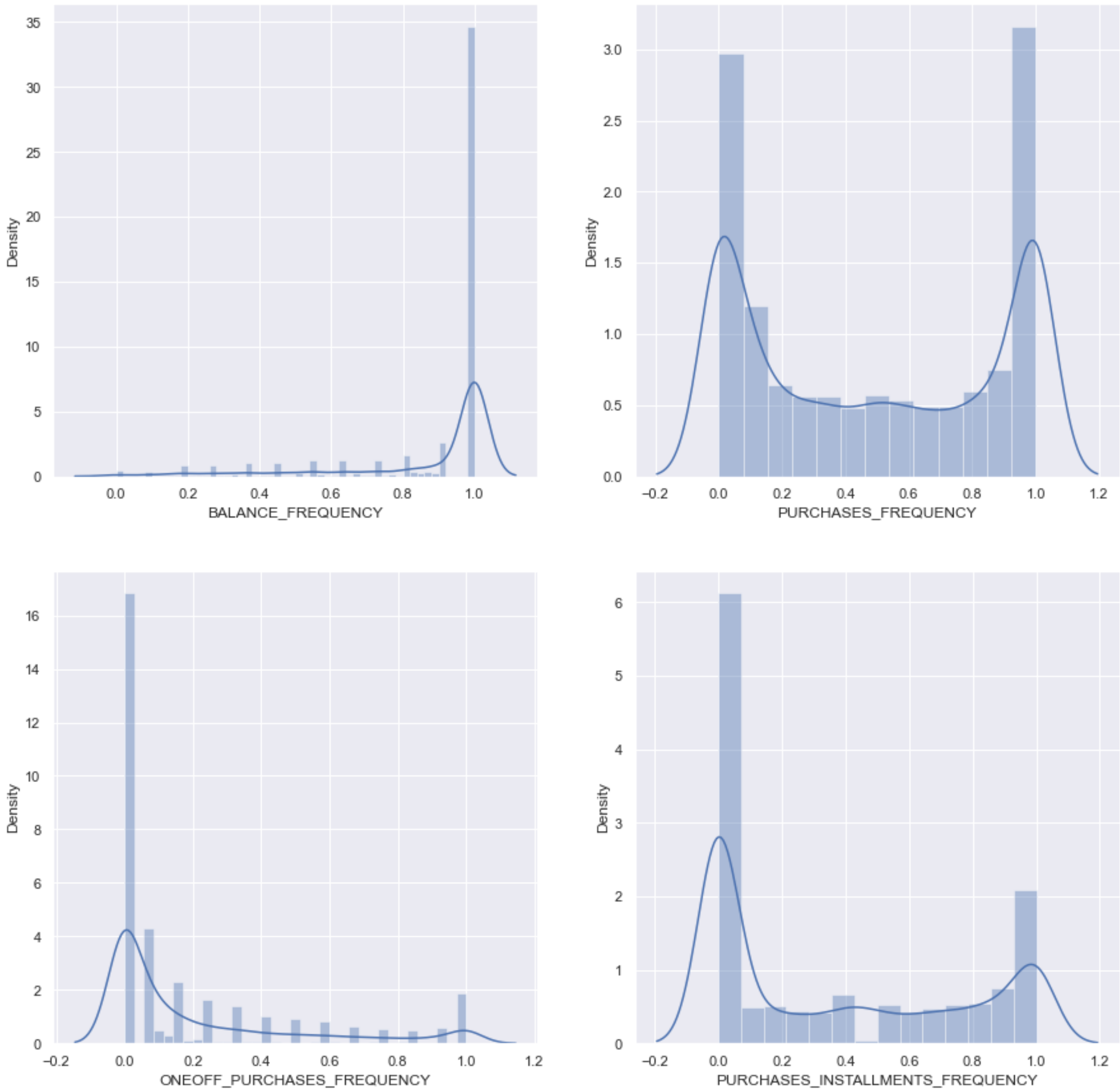


In [507…

```
sns.set()
fig, axes = plt.subplots(2, 2, figsize=(15, 15))
sns.distplot(cc_data['BALANCE_FREQUENCY'], ax=axes[0,0])
sns.distplot(cc_data['PURCHASES_FREQUENCY'],ax=axes[0,1])
sns.distplot(cc_data['ONEOFF_PURCHASES_FREQUENCY'], ax=axes[1,0])
sns.distplot(cc_data['PURCHASES_INSTALLMENTS_FREQUENCY'], ax=axes[1,1])
```

Out[507]:

```
<AxesSubplot:xlabel='PURCHASES_INSTALLMENTS_FREQUENCY', ylabel='Density'>
```



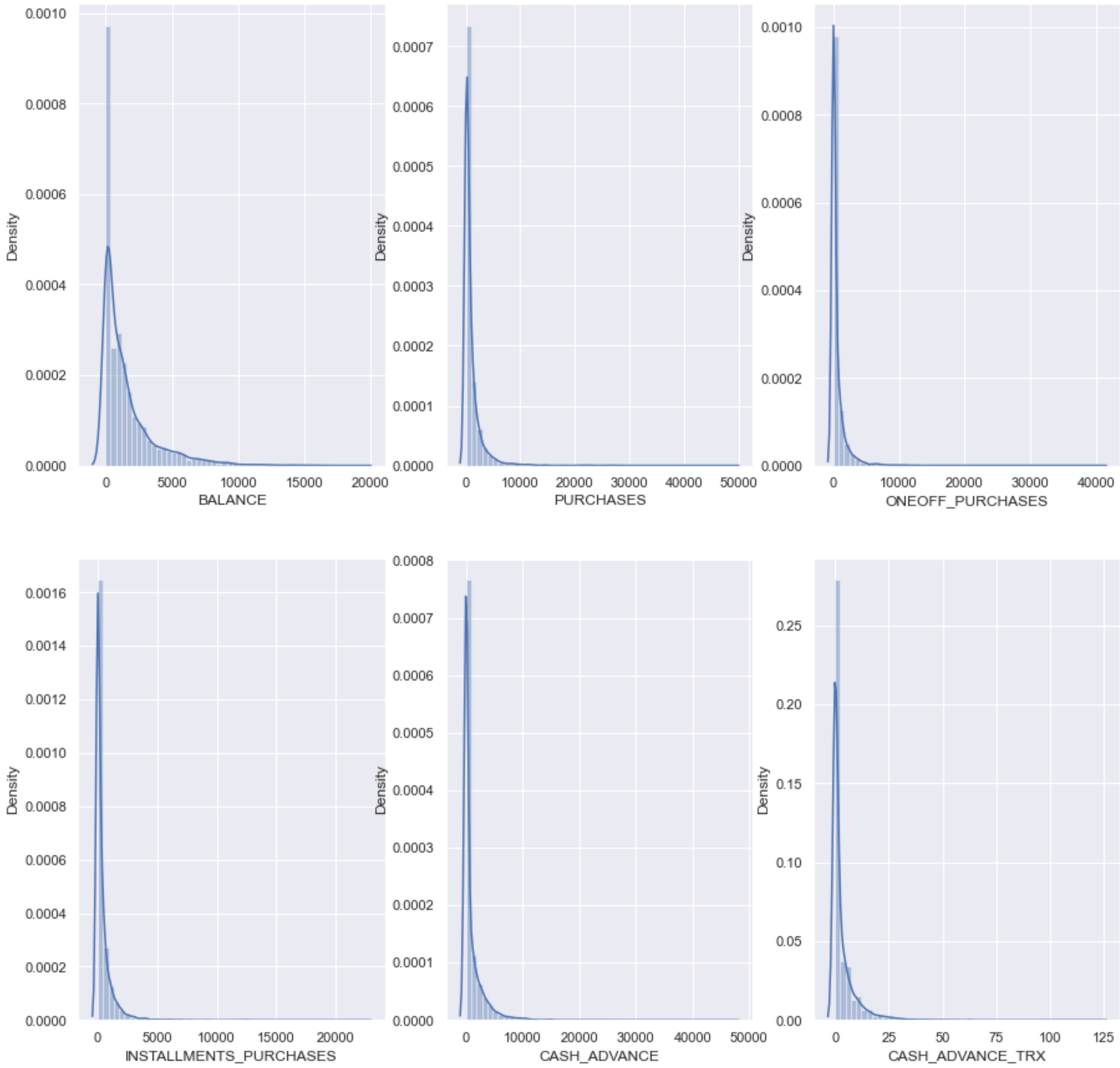
In [508…

```
sns.set()

fig, axes = plt.subplots(2, 3, figsize=(15, 15))
sns.distplot(cc_data['BALANCE'], ax=axes[0,0])
sns.distplot(cc_data['PURCHASES'],ax=axes[0,1])
sns.distplot(cc_data['ONEOFF_PURCHASES'], ax=axes[0,2])
sns.distplot(cc_data['INSTALLMENTS_PURCHASES'], ax=axes[1,0])
sns.distplot(cc_data['CASH_ADVANCE'], ax=axes[1,1])
sns.distplot(cc_data['CASH_ADVANCE_TRX'], ax=axes[1,2])
```

Out[508]:

```
<AxesSubplot:xlabel='CASH_ADVANCE_TRX', ylabel='Density'>
```



Inference:

- Most of the payments and purchases done with the tenure of 12.
- Balance_frequency is right skewed and ONEOFF_PURCHASES_FREQUENCY is left skewed. This explains that users update their balance frequently but rarely opt for one go purchases.
- Major share of users fall below 10k in purchases and oneoff_purchases.Very few use cash_advance for more than 10k purchase.

g. Standardize the data using appropriate methods.

In [572…

```
# To put data on the same scale
from sklearn.preprocessing import StandardScaler
features = cc_data.columns
sc = StandardScaler()
cc_data_scaled = sc.fit_transform(cc_data)
data = pd.DataFrame(cc_data_scaled, columns=cc_data.columns)
data.head()
```

Out[572]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHAS
0	-0.732	-0.249	-0.425	-0.357	-0.3
1	0.787	0.134	-0.470	-0.357	-0.4
2	0.447	0.518	-0.108	0.109	-0.4
3	0.049	-1.017	0.232	0.546	-0.4
4	-0.359	0.518	-0.462	-0.347	-0.4

3. Apply PCA to the dataset and perform all steps from Q2 on the new features generated using PCA.

In [573…
```
# With the help of principal component analysis we will reduce features
from sklearn.decomposition import PCA
```

In [574…
```
cc_data.shape
```

Out[574]:
```
(8950, 17)
```

In [575…
```
#We have 17 features so our n_component will be 17.
pc=PCA(n_components=17)
cc_data_pca=pc.fit(cc_data_scaled)
```

In [576…
```
sum(cc_data_pca.explained_variance_ratio_)
```

Out[576]:
```
1.0000000000000002
```

In [577…
```
var_ratio={}
for n in range(2,18):
    pc=PCA(n_components=n)
    cc_data_pca=pc.fit(cc_data_scaled)
    var_ratio[n]=sum(cc_data_pca.explained_variance_ratio_)
```

In [578…
```
var_ratio
```

Out[578]:
```
{2: 0.4761145096038464,
 3: 0.5642463262126608,
 4: 0.6390415683340281,
 5: 0.7012888630326691,
 6: 0.7586894275299021,
 7: 0.8075236830564568,
 8: 0.850515715540971,
 9: 0.8884983024975869,
 10: 0.9192983251775998,
 11: 0.9430208355910034,
 12: 0.960754531954597,
 13: 0.9750331004392295,
 14: 0.9872022960817174,
 15: 0.9973289663784978,
 16: 0.9999993147732045,
 17: 1.0000000000000002}
```

In [579…
```
#Since 10 components are explaining about 90% variance so we select 9 components
pc=PCA(n_components=10)
```

In [580…
```
p=pc.fit(cc_data_scaled)
```

In [581…
```
cc_data_scaled.shape
```

Out[581]:
```
(8950, 17)
```

In [582…
```
p.explained_variance_
```

Out[582]:
```
array([4.64112269, 3.45372843, 1.49840831, 1.27166123, 1.05832222,
       0.97591864, 0.83027511, 0.73094622, 0.64577613, 0.52365889])
```

In [583…
```
np.sum(p.explained_variance_)
```

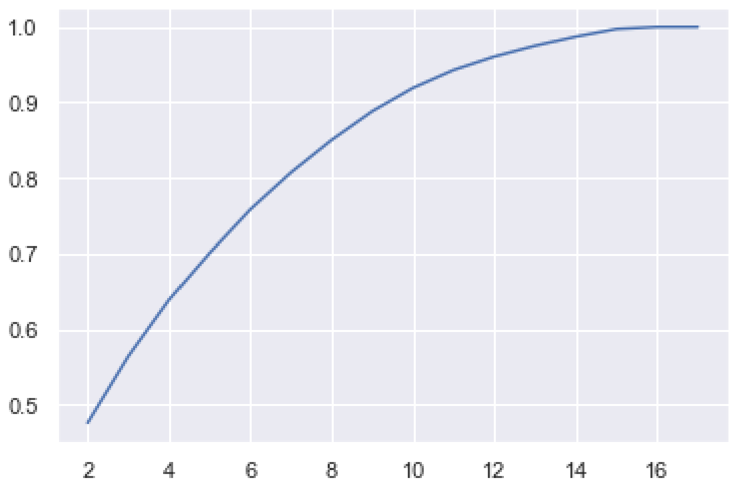
Out[583]:
```
15.629817876385282
```

In [584…
```
var_ratio
```

Out[584]:
```
{2: 0.4761145096038464,
 3: 0.5642463262126608,
 4: 0.6390415683340281,
 5: 0.7012888630326691,
 6: 0.7586894275299021,
 7: 0.8075236830564568,
 8: 0.850515715540971,
 9: 0.8884983024975869,
 10: 0.9192983251775998,
 11: 0.9430208355910034,
 12: 0.960754531954597,
 13: 0.9750331004392295,
 14: 0.9872022960817174,
 15: 0.9973289663784978,
 16: 0.9999993147732045,
 17: 1.0000000000000002}
```

In [585…
```
pd.Series(var_ratio).plot()
```

Out[585]:
```
<AxesSubplot:>
```



In [586…
```
#Since 9 components are explaining about 88% variance so we select 9 components
cc_data_scaled.shape
```

Out[586]:
```
(8950, 17)
```

In [587…
```
pc_final=PCA(n_components=10).fit(cc_data_scaled)

reduced_cc_data=pc_final.fit_transform(cc_data_scaled)
```

In [588…
```
dd=pd.DataFrame(reduced_cc_data)
```

In [589…
```
dd.head()
```

Out[589]:

	0	1	2	3	4	5	6	7	8	9
0	-1.684	-1.072	0.476	0.680	0.043	0.068	0.822	-0.019	0.118	-0.078
1	-1.134	2.509	0.602	-0.110	0.663	-1.102	-0.384	0.176	0.674	-0.778
2	0.969	-0.384	0.091	1.238	-2.167	-0.320	-1.542	-0.229	-0.868	-0.002
3	-0.888	0.005	1.500	1.075	0.226	-0.172	-0.237	-0.690	-0.064	0.394
4	-1.600	-0.684	0.348	1.014	-0.454	0.077	0.698	0.245	0.578	-0.122

In [590…
```
# initially we had 17 variables now its 9 so our variable go reduced
dd.shape
```

Out[590]:
```
(8950, 10)
```

In [591…
```
col_list=cc_data.columns
```

In [592…
```
col_list
```

Out[592]:
```
Index(['BALANCE', 'BALANCE_FREQUENCY', 'PURCHASES', 'ONEOFF_PURCHASES',
       'INSTALLMENTS_PURCHASES', 'CASH_ADVANCE', 'PURCHASES_FREQUENCY',
       'ONEOFF_PURCHASES_FREQUENCY', 'PURCHASES_INSTALLMENTS_FREQUENCY',
       'CASH_ADVANCE_FREQUENCY', 'CASH_ADVANCE_TRX', 'PURCHASES_TRX',
       'CREDIT_LIMIT', 'PAYMENTS', 'MINIMUM_PAYMENTS', 'PRC_FULL_PAYMENT',
       'TENURE'],
      dtype='object')
```

In [593…
```
pd.DataFrame(pc_final.components_.T, columns=['PC_' +str(i) for i in range(10)],in
```

Out[593]:

	PC_0	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC
BALANCE	0.102	0.404	-0.162	0.279	0.051	0.043	-0.254	-0.1
BALANCE_FREQUENCY	0.120	0.131	-0.423	0.156	-0.477	0.022	0.101	0.2
PURCHASES	0.412	0.040	0.257	0.042	0.028	0.180	0.200	0.0
ONEOFF_PURCHASES	0.346	0.062	0.391	0.085	-0.161	0.180	0.121	0.1
INSTALLMENTS_PURCHASES	0.337	-0.019	-0.109	-0.058	0.361	0.096	0.252	-0.1
CASH_ADVANCE	-0.023	0.439	-0.023	-0.257	0.098	-0.145	-0.049	-0.0
PURCHASES_FREQUENCY	0.321	-0.191	-0.371	-0.195	-0.100	-0.047	-0.151	-0.0
ONEOFF_PURCHASES_FREQUENCY	0.294	-0.019	0.116	0.034	-0.540	-0.004	-0.281	0.0
PURCHASES_INSTALLMENTS_FREQUENCY	0.274	-0.179	-0.470	-0.225	0.177	-0.048	0.038	-0.1
CASH_ADVANCE_FREQUENCY	-0.089	0.434	-0.105	-0.265	-0.145	0.058	0.144	0.0
CASH_ADVANCE_TRX	-0.048	0.420	-0.110	-0.328	-0.084	-0.065	0.199	0.1
PURCHASES_TRX	0.391	-0.020	-0.076	-0.021	-0.036	0.101	0.109	-0.1
CREDIT_LIMIT	0.212	0.238	0.101	0.132	0.086	-0.320	-0.557	-0.3
PAYMENTS	0.266	0.257	0.277	-0.112	0.201	-0.116	0.157	0.0
MINIMUM_PAYMENTS	0.063	0.169	-0.235	0.393	0.415	0.290	-0.200	0.5
PRC_FULL_PAYMENT	0.132	-0.190	0.126	-0.420	0.143	-0.353	-0.300	0.5
TENURE	0.081	-0.004	-0.068	0.438	-0.002	-0.745	0.404	0.0

Inference:

- So above data gave us eigen vector for each component we had all eigen vector value very small we can remove those variable but in this case its not.

In [594…

```
# Factor Analysis : variance explained by each component-
pd.Series(pc_final.explained_variance_ratio_,index=['PC_'+ str(i) for i in range(1(
```

Out[594]:

```
PC_0    0.273
PC_1    0.203
PC_2    0.088
PC_3    0.075
PC_4    0.062
PC_5    0.057
PC_6    0.049
PC_7    0.043
PC_8    0.038
PC_9    0.031
dtype: float64
```

2. Build a k-means algorithm for clustering credit card data. Kindly follow the below steps and answer the following.

In [595…

```
#Assuming no.of clusters =4
from sklearn.cluster import KMeans
```

In [596...
```
km_4=KMeans(n_clusters=4,random_state=123)
```

In [597...
```
km_4.fit(data)
```

Out[597]:
```
KMeans(n_clusters=4, random_state=123)
```

In [598...
```
km_4.labels_
```

Out[598]:
```
array([2, 1, 3, ..., 3, 2, 2])
```

In [599...
```
pd.Series(km_4.labels_).value_counts()
```

Out[599]:
```
2    3977
3    3367
1    1197
0     409
dtype: int64
```

a. Build k means model on various k values and plot the inertia against various k values.

In [600...
```
cluster_range = range( 1, 21 )
cluster_errors = []

for num_clusters in cluster_range:
    clusters = KMeans( num_clusters )
    clusters.fit( data )
    cluster_errors.append( clusters.inertia_ )
```

In [601...
```
clusters_df = pd.DataFrame( { "num_clusters":cluster_range, "cluster_errors": clus

clusters_df[0:21]
```

Out[601]:

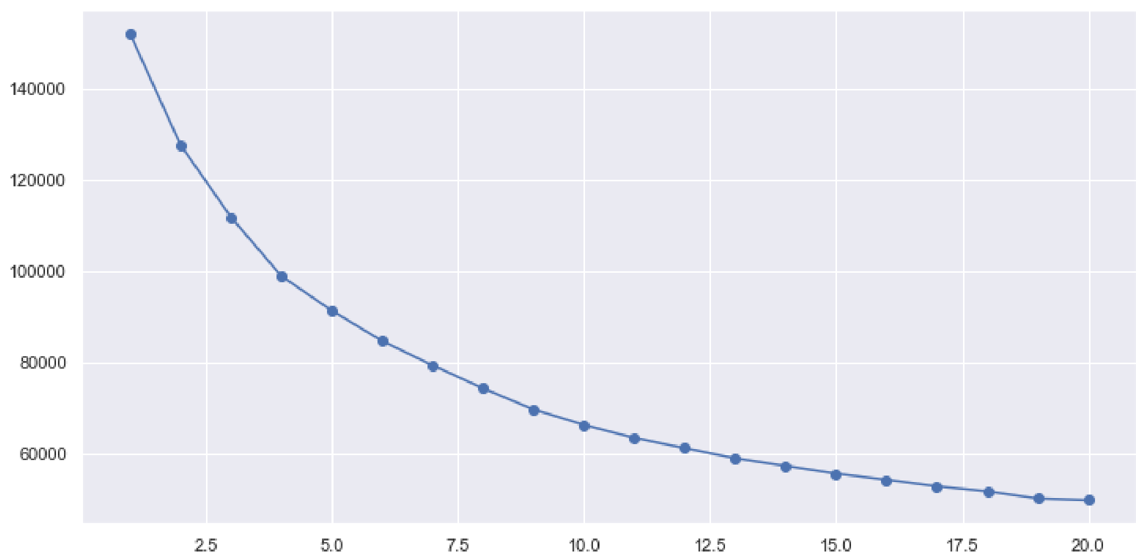
	num_clusters	cluster_errors
0	1	152150.000
1	2	127784.573
2	3	111973.990
3	4	99061.940
4	5	91491.608
5	6	84826.621
6	7	79506.847
7	8	74465.983
8	9	69840.515
9	10	66459.760
10	11	63618.827
11	12	61357.139
12	13	59133.096
13	14	57481.073
14	15	55815.648
15	16	54426.358
16	17	53002.692
17	18	51906.246
18	19	50348.935
19	20	49972.905

In [602…

```
# allow plots to appear in the notebook
%matplotlib inline
import matplotlib.pyplot as plt
plt.figure(figsize=(12,6))
sns.set(style="darkgrid")
plt.plot( clusters_df.num_clusters, clusters_df.cluster_errors, marker = "o" )
```

Out[602]:

```
[<matplotlib.lines.Line2D at 0x219d546fd00>]
```



b. Evaluate the model using Silhouette coefficient

In [603…
```
from sklearn import metrics
```

In [604…
```
#using silhouette score: Higher the value, better the cluster.
from sklearn.metrics import silhouette_score

# create a list for different values of K
n_clusters = [2, 3, 4, 5, 6,7,8,9]

for K in n_clusters:
    cluster = KMeans (n_clusters= K, random_state= 10)
    predict = cluster.fit_predict(data)
    score = silhouette_score(data, predict, random_state= 10)
    print ("For n_clusters = {}, silhouette score is {})".format(K, score))
```

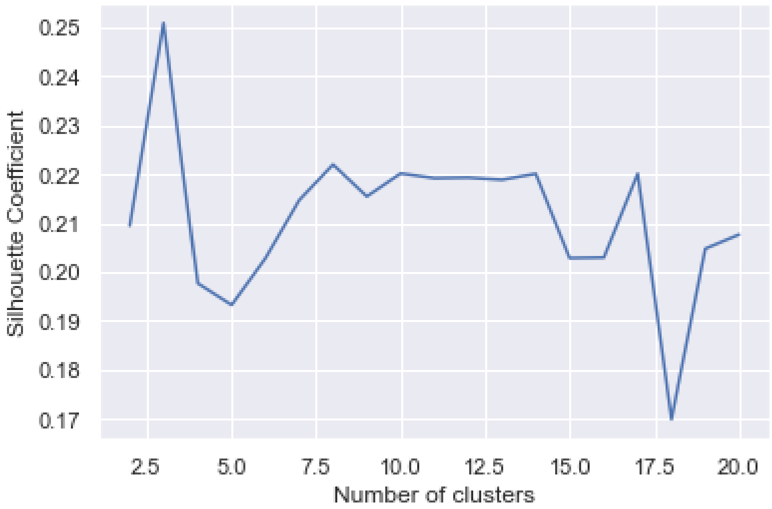
```
For n_clusters = 2, silhouette score is 0.20951117145873602)
For n_clusters = 3, silhouette score is 0.2506116638886035)
For n_clusters = 4, silhouette score is 0.1976791965228765)
For n_clusters = 5, silhouette score is 0.19325195080511473)
For n_clusters = 6, silhouette score is 0.20286011584987834)
For n_clusters = 7, silhouette score is 0.21456513775079983)
For n_clusters = 8, silhouette score is 0.22193282658122515)
For n_clusters = 9, silhouette score is 0.21569986719782255)
```

In [605…
```
# calculate SC for K=3 through K=21
k_range = range(2, 21)
scores = []
for k in k_range:
    km = KMeans(n_clusters=k, random_state=1)
    km.fit(data)
    scores.append(metrics.silhouette_score(data, km.labels_))
```

In [606…
```
scores
```

Out[606]:
```
[0.20949692655850133,
 0.25094878327513914,
 0.1976911456779212,
 0.19325195080511473,
 0.20282934577578765,
 0.21474509359961605,
 0.22204404116809873,
 0.21549380253155773,
 0.22020848165025195,
 0.21924048257110365,
 0.2193433960056921,
 0.21891552422536958,
 0.220144936068657,
 0.20286428711384824,
 0.20297722558281397,
 0.22016598510750354,
 0.16991219754345324,
 0.20478753738317101,
 0.20769150746882784]
```

In [607…
```
# plot the results
plt.plot(k_range, scores)
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Coefficient')
plt.grid(True)
```



Inference:

- using silhouette score: Higher the value, better the cluster.
- silhouette score is high at 3 and 8

c. Plot a elbow plot to find the optimal value of k

In [608…

```
from scipy.stats import zscore

cc_attributes=cc_data.iloc[:,1:]
cc_datascaled=cc_attributes.apply(zscore)
```

In [609…

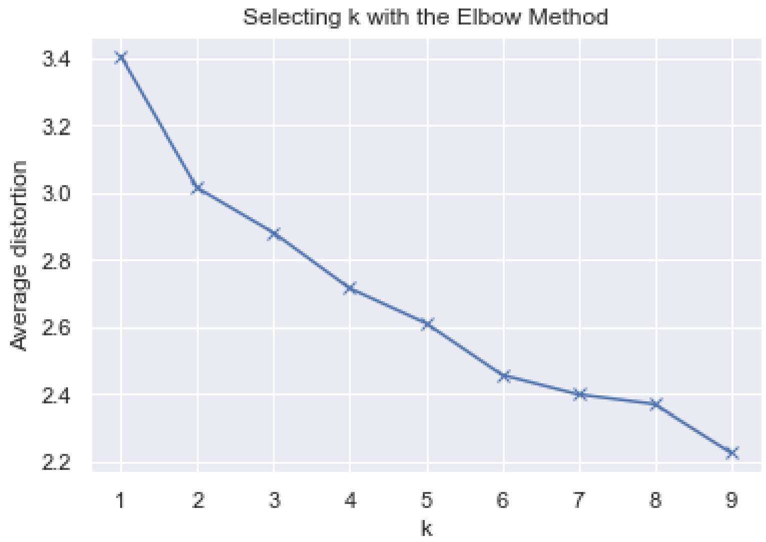
```
#Finding optimal no. of clusters
from scipy.spatial.distance import cdist
clusters=range(1,10)
meanDistortions=[]

for k in clusters:
    model=KMeans(n_clusters=k)
    model.fit(cc_datascaled)
    prediction=model.predict(cc_datascaled)
    meanDistortions.append(sum(np.min(cdist(cc_datascaled, model.cluster_centers_,


plt.plot(clusters, meanDistortions, 'bx-')
plt.xlabel('k')
plt.ylabel('Average distortion')
plt.title('Selecting k with the Elbow Method')
```

Out[609]:

```
Text(0.5, 1.0, 'Selecting k with the Elbow Method')
```



Inference:

- from the above graph, it bends at 2, 6
- Though the bend is not coming out clearly as there are many bends, let us look at 2 clusters and 6 clusters

d. Which k value gives the best result?

In [610…

```
# Let us first start with K = 2 from elbow point
final_model=KMeans(2)
final_model.fit(cc_datascaled)
prediction=final_model.predict(cc_datascaled)

#Append the prediction
cc_data["GROUP"] = prediction
cc_datascaled["GROUP"] = prediction
print("Groups Assigned : \n")
cc_data.head()
```

```
Groups Assigned :
```

Out[610]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHAS
0	40.901	0.818	95.400	0.000	95.4
1	3202.467	0.909	0.000	0.000	0.0
2	2495.149	1.000	773.170	773.170	0.0
3	1666.671	0.636	1499.000	1499.000	0.0
4	817.714	1.000	16.000	16.000	0.0

In [611…

```
cc_cluster = cc_data.groupby(['GROUP'])
cc_cluster.mean()
```

Out[611]:

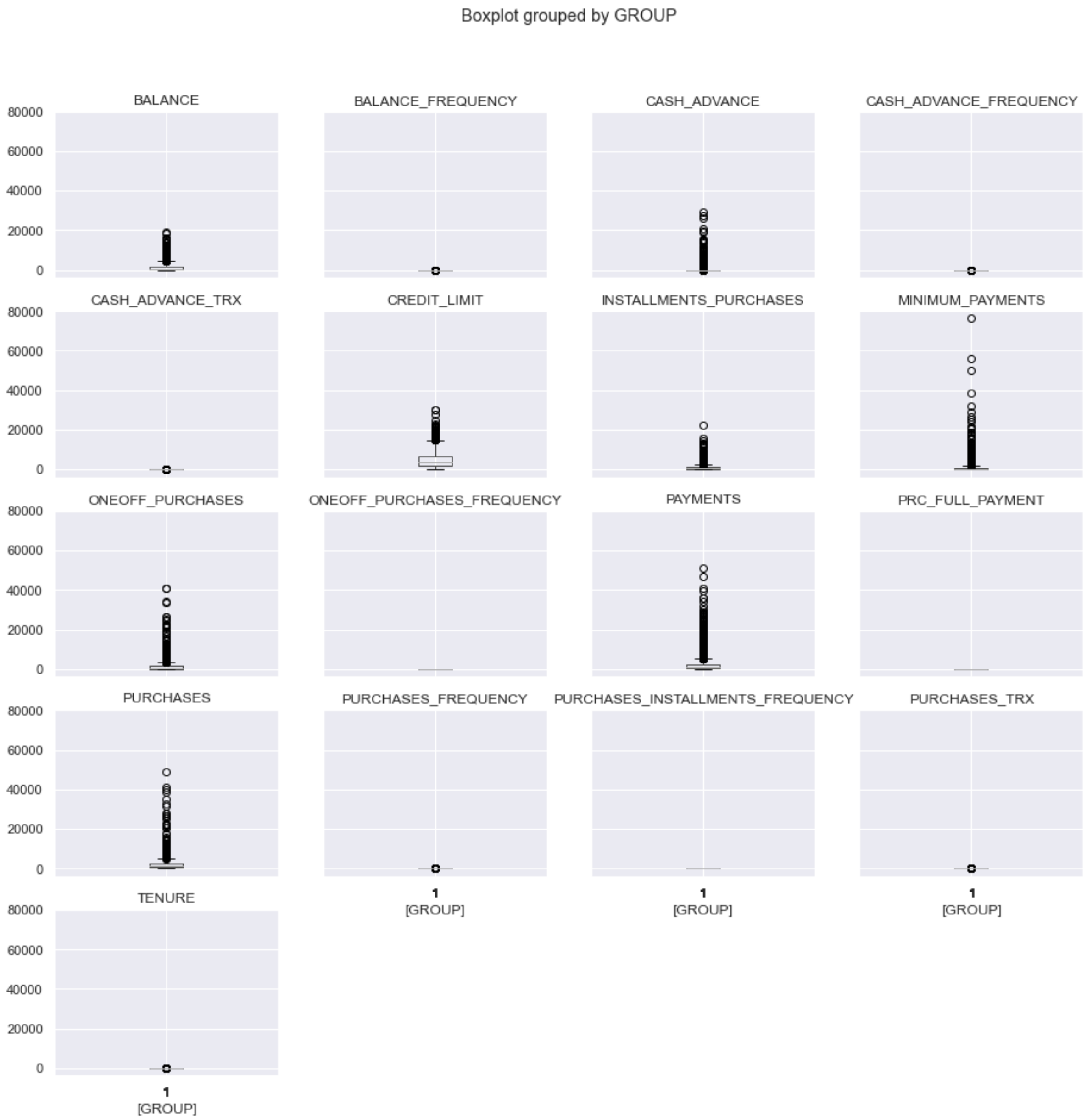
GROUP	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PUI
0	1671.096	0.828	277.894	201.238	
1	1411.645	0.948	2042.857	1153.177	

In [612...

```
cc_cluster.boxplot(by='GROUP', layout = (3,3),figsize=(15,15))
```

Out[612]:

```
0    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
1    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
dtype: object
```



In [613...

```
# Let us first start with K = 3 from silhouette score
final_model=KMeans(3)
final_model.fit(cc_datascaled)
prediction=final_model.predict(cc_datascaled)

#Append the prediction
cc_data["GROUP"] = prediction
cc_datascaled["GROUP"] = prediction
print("Groups Assigned : \n")
cc_data.head()
```

```
Groups Assigned :
```

Out[613]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHAS
0	40.901	0.818	95.400	0.000	95.4
1	3202.467	0.909	0.000	0.000	0.0
2	2495.149	1.000	773.170	773.170	0.0
3	1666.671	0.636	1499.000	1499.000	0.0
4	817.714	1.000	16.000	16.000	0.0

In [614…

```
cc_cluster = cc_data.groupby(['GROUP'])
cc_cluster.mean()
```

Out[614]:

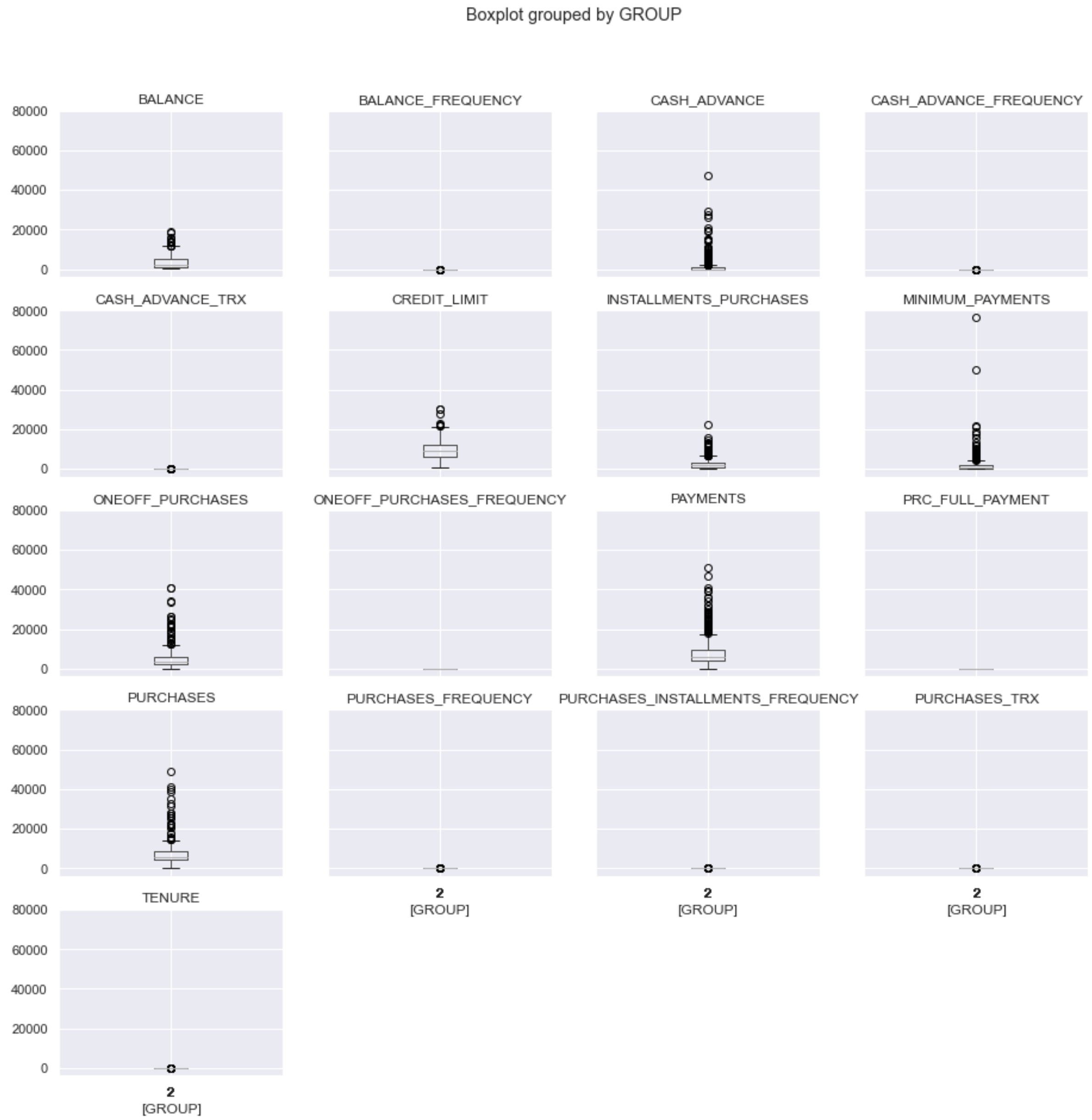
GROUP	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PUI
0	1733.813	0.830	266.530	202.868	
1	1097.017	0.931	1264.568	619.864	
2	3547.524	0.985	7587.562	5025.297	

In [615…

```
cc_cluster.boxplot(by='GROUP', layout = (3,3),figsize=(15,15))
```

Out[615]:

```
0    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
1    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
2    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
dtype: object
```



In [616…

```
# Let us first start with K = 6 from elbow point
final_model=KMeans(6)
final_model.fit(cc_datascaled)
prediction=final_model.predict(cc_datascaled)

#Append the prediction
cc_data["GROUP"] = prediction
cc_datascaled["GROUP"] = prediction
print("Groups Assigned : \n")
cc_data.head()
```

```
Groups Assigned :
```

Out[616]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHAS
0	40.901	0.818	95.400	0.000	95.4
1	3202.467	0.909	0.000	0.000	0.0
2	2495.149	1.000	773.170	773.170	0.0
3	1666.671	0.636	1499.000	1499.000	0.0
4	817.714	1.000	16.000	16.000	0.0

In [617…

```
cc_cluster = cc_data.groupby(['GROUP'])
cc_cluster.mean()
```

Out[617]:

GROUP	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PUI
0	117.037	0.362	323.580	208.114	
1	1657.223	0.965	260.371	211.757	
2	852.401	0.946	880.077	198.654	
3	4301.415	0.956	499.996	317.838	
4	4456.574	0.976	16039.635	10886.014	
5	1848.679	0.978	2988.792	2062.421	

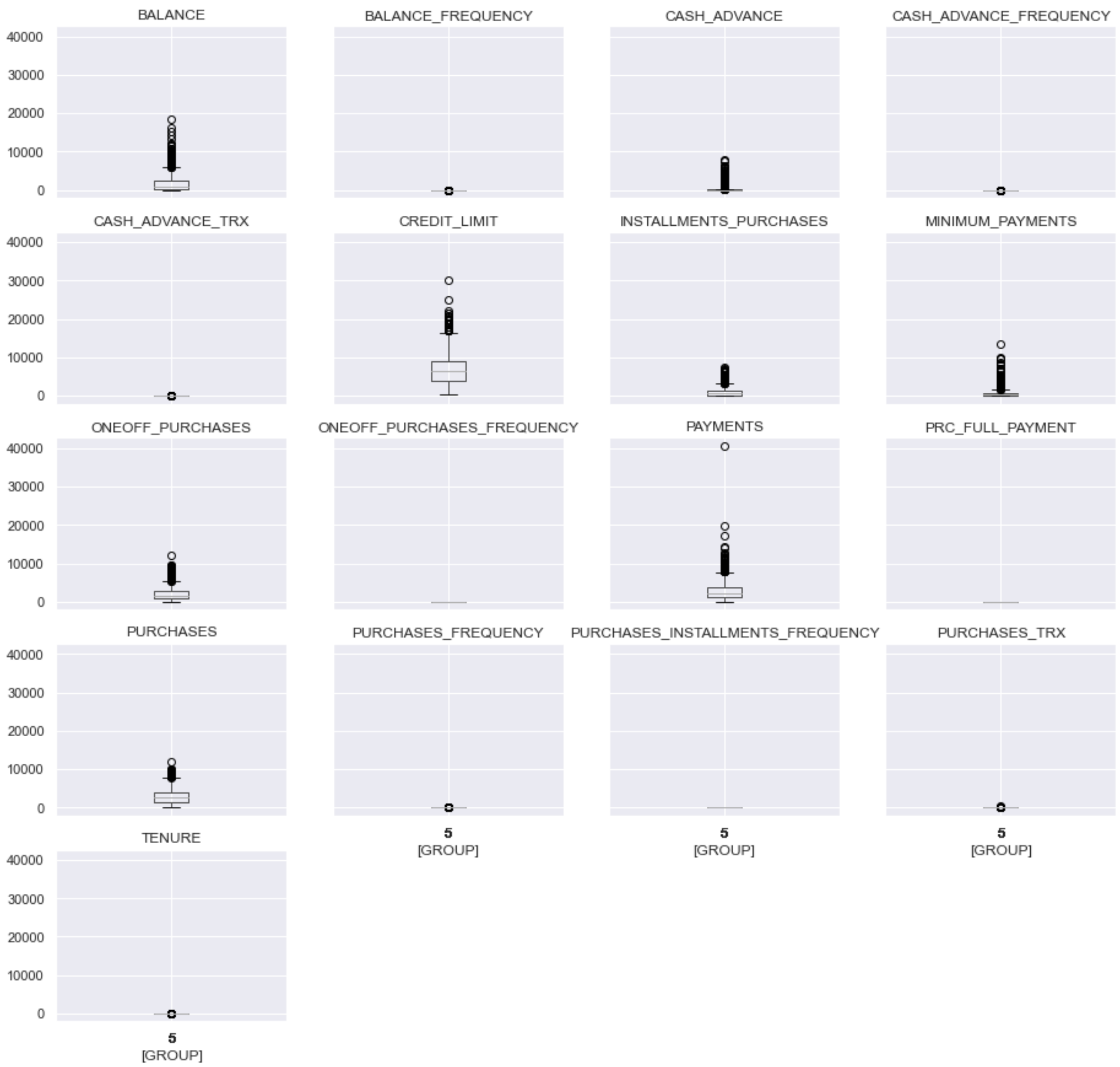
In [620…

```
cc_cluster.boxplot(by='GROUP', layout = (3,3),figsize=(15,15))
```

Out[620]:

```
0    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
1    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
2    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
3    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
4    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
5    [[AxesSubplot(0.1,0.77069;0.173913x0.12931), A...
dtype: object
```

Boxplot grouped by GROUP



Inference:

- Comparing the box plots of attributes, k=3 is the optimal no.of clusters

4. Create a new column as a cluster label in the original data frame and perform cluster analysis. Check the correlation of cluster labels with various features and mention your inferences

In [621...

```
# add a column 'cluster' in the data giving cluster number corresponding to each ol
cc_data['cluster'] = kmeans.labels_
cc_data.head(5)
```

Out[621]:

	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURCHAS
0	40.901	0.818	95.400	0.000	95.4
1	3202.467	0.909	0.000	0.000	0.0
2	2495.149	1.000	773.170	773.170	0.0
3	1666.671	0.636	1499.000	1499.000	0.0
4	817.714	1.000	16.000	16.000	0.0

In [622…

```
cc_data['cluster'].value_counts()
```

Out[622]:

```
0     2214
1     1486
11    1069
7      727
4      715
6      650
9      576
3      466
10     455
2      357
8      104
5       75
13      36
12      20
Name: cluster, dtype: int64
```

In [623…

```
# get summary for observations in the cluster
cc_data[cc_data.cluster==0].describe()
```

Out[623]:

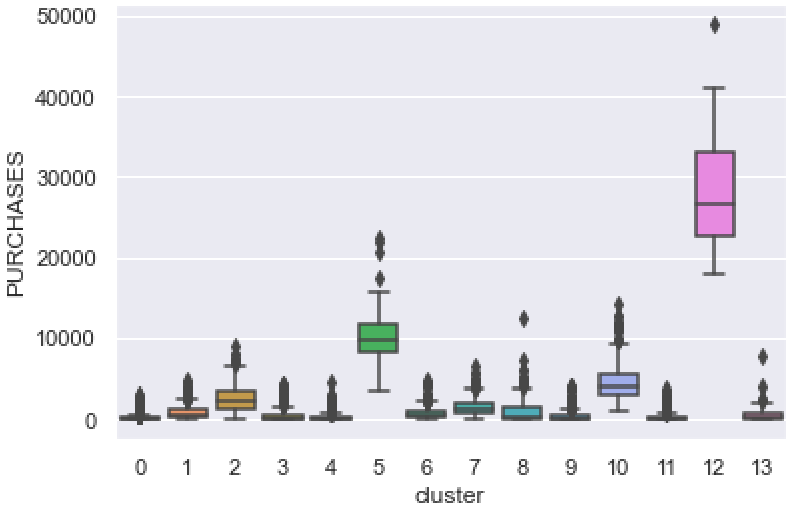
	BALANCE	BALANCE_FREQUENCY	PURCHASES	ONEOFF_PURCHASES	INSTALLMENTS_PURC
count	2214.000	2214.000	2214.000	2214.000	2
mean	1378.859	0.970	205.247	162.625	
std	1066.178	0.077	373.041	343.637	
min	0.488	0.545	0.000	0.000	
25%	598.425	1.000	0.000	0.000	
50%	1156.641	1.000	37.770	0.000	
75%	1845.187	1.000	246.415	160.360	
max	5934.611	1.000	3183.000	3183.000	3

In [624…

```
sns.boxplot(cc_data['cluster'],cc_data['PURCHASES'])
```

Out[624]:

```
<AxesSubplot:xlabel='cluster', ylabel='PURCHASES'>
```

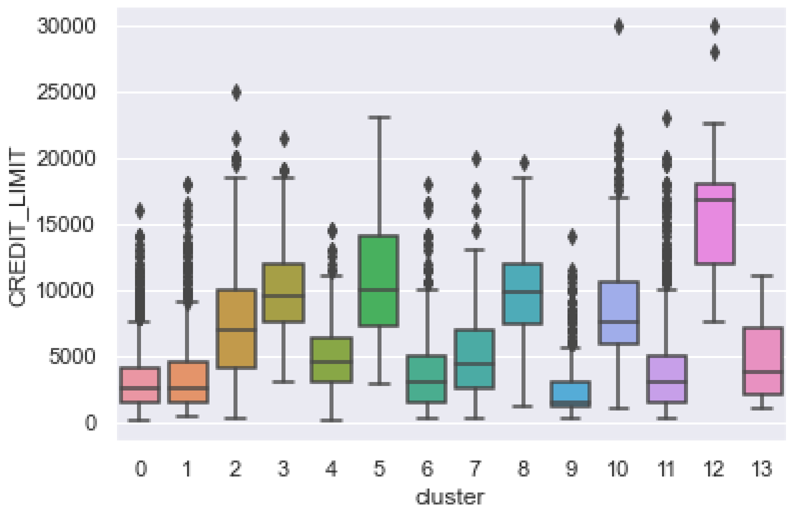


In [625…

```
sns.boxplot(cc_data['cluster'],cc_data['CREDIT_LIMIT'])
```

Out[625]:

```
<AxesSubplot:xlabel='cluster', ylabel='CREDIT_LIMIT'>
```



In [626…

```
df_pair_plot=pd.DataFrame(reduced_cc_data,columns=['PC_' +str(i) for i in range(10
```

In [627…

```
df_pair_plot['Cluster']=km_4.labels_ #Add cluster column in the data frame
```

In [628…

```
df_pair_plot.head()
```

Out[628]:

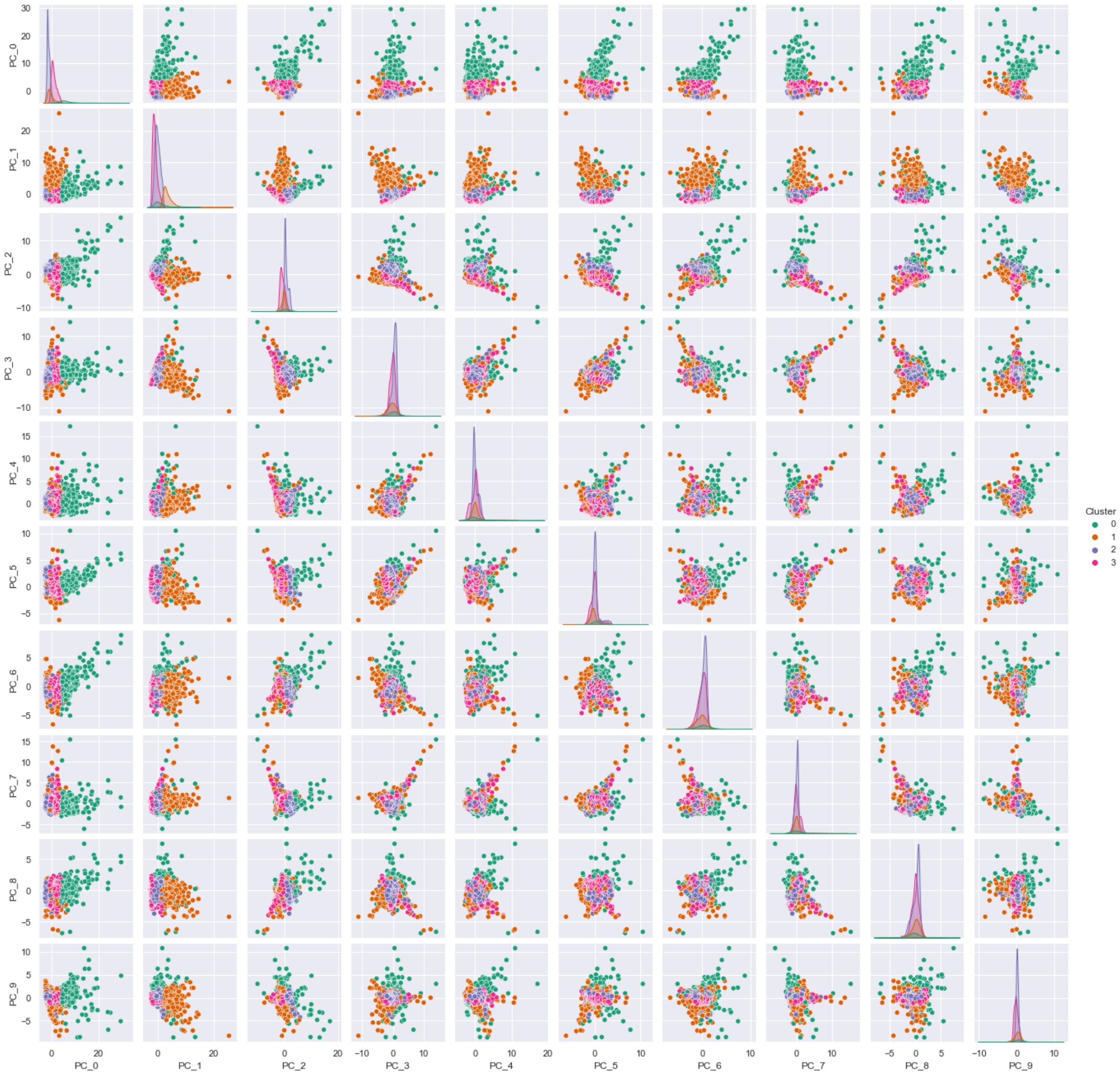
	PC_0	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7	PC_8	PC_9	Cluster
0	-1.684	-1.072	0.476	0.680	0.043	0.068	0.822	-0.019	0.118	-0.078	2
1	-1.134	2.509	0.602	-0.110	0.663	-1.102	-0.384	0.176	0.674	-0.778	1
2	0.969	-0.384	0.091	1.238	-2.167	-0.320	-1.542	-0.229	-0.868	-0.002	3
3	-0.888	0.005	1.500	1.075	0.226	-0.172	-0.237	-0.690	-0.064	0.394	2
4	-1.600	-0.684	0.348	1.014	-0.454	0.077	0.698	0.245	0.578	-0.122	2

In [629…

```
sns.pairplot(df_pair_plot,hue='Cluster', palette= 'Dark2', diag_kind='kde',size=1.
```

Out[629]:

```
<seaborn.axisgrid.PairGrid at 0x219e49c68e0>
```



5. Comment your findings and inferences and compare the performance. Does applying PCA give a better result in comparison to earlier?

- From K-means algorithm, the optimal no.of clusters from siloutte score can be 3
- from elbow method it is 2 or 6 clusters
- But from PCA there are 9 components to be formed.