

In [1]:

```

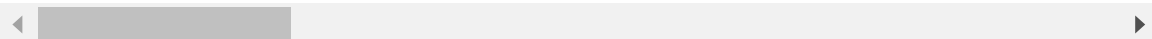
1  #importing libraries
2  import pandas as pd
3  import numpy as np
4  import seaborn as sns
5  import matplotlib.pyplot as plt
6  from sklearn.preprocessing import StandardScaler, normalize
7  from sklearn.cluster import KMeans
8  from sklearn.decomposition import PCA
9  #importing dataset
10 creditcard_df = pd.read_csv('D:\\Data Science for Business Package\\2. Marketing Dep
11 creditcard_df

```

Out[1]:

| | CUST_ID | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | I |
|------|---------|-------------|-------------------|-----------|------------------|-----|
| 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 | |
| ... | ... | ... | ... | ... | ... | ... |
| 8945 | C19186 | 28.493517 | 1.000000 | 291.12 | 0.00 | |
| 8946 | C19187 | 19.183215 | 1.000000 | 300.00 | 0.00 | |
| 8947 | C19188 | 23.398673 | 0.833333 | 144.40 | 0.00 | |
| 8948 | C19189 | 13.457564 | 0.833333 | 0.00 | 0.00 | |
| 8949 | C19190 | 372.708075 | 0.666667 | 1093.25 | 1093.25 | |

8950 rows × 18 columns



In [2]:

```

1 #features
2 # CUSTID: Identification of Credit Card holder
3 # BALANCE: Balance amount left in customer's account to make purchases
4 # BALANCE_FREQUENCY: How frequently the Balance is updated, score between 0 and 1 (1 =
5 # PURCHASES: Amount of purchases made from account
6 # ONEOFFPURCHASES: Maximum purchase amount done in one-go
7 # INSTALLMENTS_PURCHASES: Amount of purchase done in installment
8 # CASH_ADVANCE: Cash in advance given by the user
9 # PURCHASES_FREQUENCY: How frequently the Purchases are being made, score between 0
10 # ONEOFF_PURCHASES_FREQUENCY: How frequently Purchases are happening in one-go (1 =
11 # PURCHASES_INSTALLMENTS_FREQUENCY: How frequently purchases in installments are bei
12 # CASH_ADVANCE_FREQUENCY: How frequently the cash in advance being paid
13 # CASH_ADVANCE_TRX: Number of Transactions made with "Cash in Advance"
14 # PURCHASES_TRX: Number of purchase transactions made
15 # CREDIT_LIMIT: Limit of Credit Card for user
16 # PAYMENTS: Amount of Payment done by user
17 # MINIMUM_PAYMENTS: Minimum amount of payments made by user
18 # PRC_FULL_PAYMENT: Percent of full payment paid by user
19 # TENURE: Tenure of credit card service for user

```

In [3]:

```
1 creditcard_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)
```

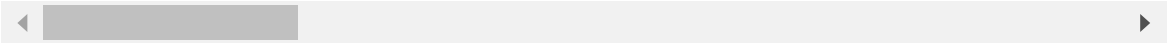
```
memory usage: 1.2+ MB
```

In [4]:

```
1 creditcard_df.describe()
```

Out[4]:

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

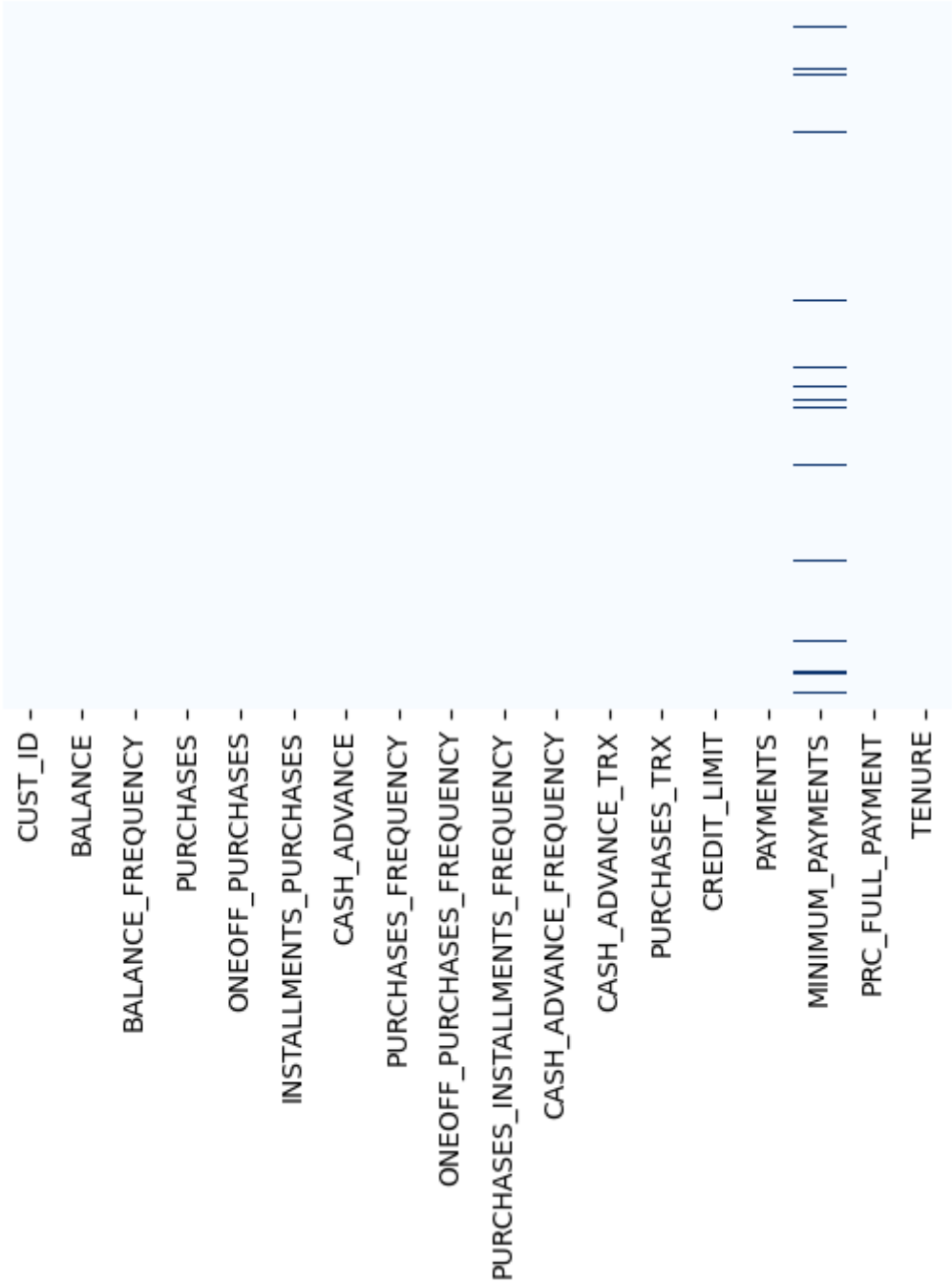


In [5]:

```
1 #visualizing null values
2 sns.heatmap(creditcard_df.isnull(), yticklabels = False, cbar = False, cmap="Blues")
3
```

Out[5]:

<AxesSubplot: >



In [6]:

```
1 creditcard_df.isnull().sum()
```

Out[6]:

| | |
|----------------------------------|-----|
| 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

In [7]:

```
1 # Fill up the missing elements
2 creditcard_df.loc[(creditcard_df['MINIMUM_PAYMENTS'].isnull() == True), 'MINIMUM_PAYMENTS'] = 313
3
```

In [8]:

```
1 # Fill up the missing elements
2 creditcard_df.loc[(creditcard_df['CREDIT_LIMIT'].isnull() == True), 'CREDIT_LIMIT'] = 1
```

In [9]:

```
1 # checking duplicate values
2 creditcard_df.duplicated().sum()
```

Out[9]:

0

In [10]:

```
1 creditcard_df.head()
```

Out[10]:

| | CUST_ID | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INS |
|---|---------|-------------|-------------------|-----------|------------------|-----|
| 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 | |

In [11]:

```
1 #dropping feature
2 creditcard_df.drop("CUST_ID", axis = 1, inplace= True)
3 creditcard_df
```

Out[11]:

| | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INSTALLME |
|------|-------------|-------------------|-----------|------------------|-----------|
| 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 | |

8950 rows × 5 columns

In [12]:

```
1 plt.figure(figsize=(10,50))
2 for i in range(len(creditcard_df.columns)):
3     plt.subplot((len(creditcard_df.columns)), 1, i+1)
4     sns.distplot(creditcard_df[creditcard_df.columns[i]], kde_kws={"color": "b", "lw": 3, "label": "KDE"}, hist_kws={"color": "g"})
5     plt.title(creditcard_df.columns[i])
6
7 plt.tight_layout()
8
```

C:\Users\Pradeep\AppData\Local\Temp\ipykernel_25616\747322071.py:4: Use
rWarning:

`distplot` is a deprecated function and will be removed in seaborn v0.14.0.

Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histograms).

For a guide to updating your code to use the new functions, please see <https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751> (<https://gist.github.com/mwaskom/de44147ed2974457ad6372750bbe5751>)

```
sns.distplot(creditcard_df[creditcard_df.columns[i]], kde_kws={"color": "b", "lw": 3, "label": "KDE"}, hist_kws={"color": "g"})
```

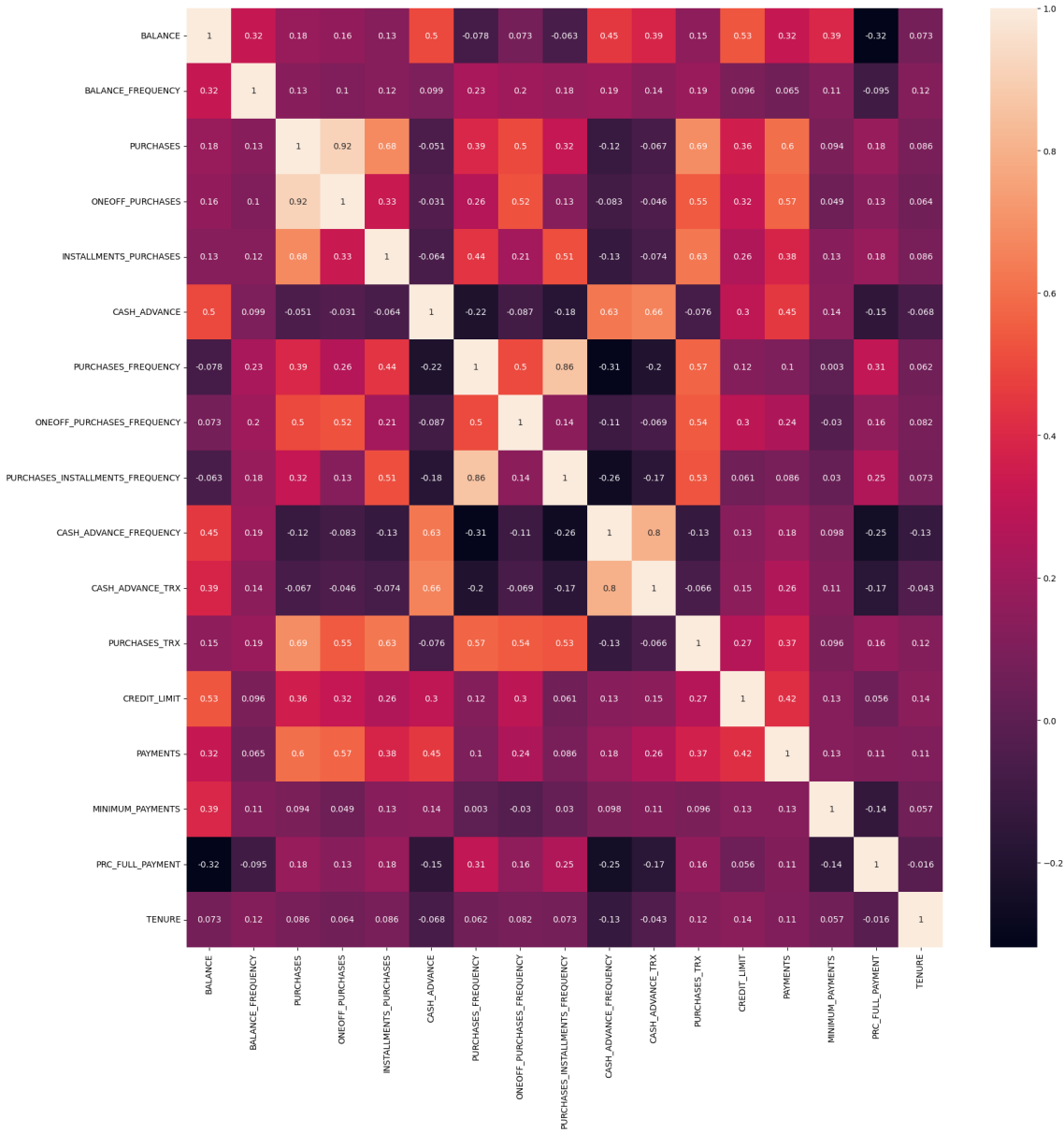
C:\Users\Pradeep\AppData\Local\Temp\ipykernel_25616\747322071.py:4: Use
rWarning:

In [13]:

```
1 #correlation plot
2 f, ax = plt.subplots(figsize = (20, 20))
3 sns.heatmap(creditcard_df.corr(), annot = True)
4
```

Out[13]:

<AxesSubplot: >



In [14]:

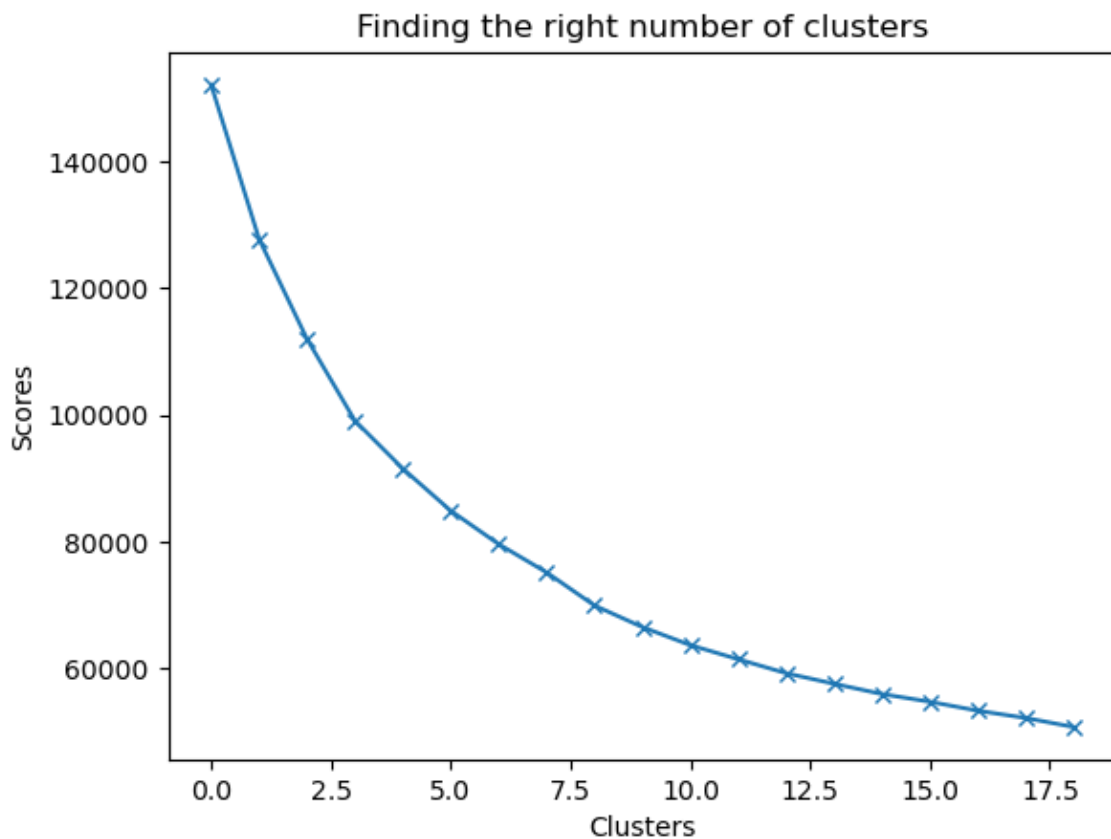
```
1 #scaling the data
2 scaler = StandardScaler()
3 creditcard_df_scaled = scaler.fit_transform(creditcard_df)
```


In [15]:

```
1  #elbow plot for no of clusters
2  scores_1 = []
3
4  range_values = range(1, 20)
5
6  for i in range_values:
7      kmeans = KMeans(n_clusters = i)
8      kmeans.fit(creditcard_df_scaled)
9      scores_1.append(kmeans.inertia_)
10
11 plt.plot(scores_1, 'x-')
12 plt.title('Finding the right number of clusters')
13 plt.xlabel('Clusters')
14 plt.ylabel('Scores')
15 plt.show()
16
```

localhost:8888/notebooks/marketing.ipynb

```
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
```



In [16]:

```
1 #apply KMEANS
2 kmeans = KMeans(8)
3 kmeans.fit(creditcard_df_scaled)
4 labels = kmeans.labels_
```

```
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
```

In [17]:

```
1 print(kmeans.cluster_centers_.shape)
2 print("centroid point\n",kmeans.cluster_centers_)
```

(8, 17)

centroid point

```
[[-1.20442106e-01  4.02699267e-01  5.79851494e-01  7.03609956e-01
  7.81975316e-02 -3.33108401e-01  9.98102693e-01  1.91406317e+00
  2.13137767e-01 -4.22686809e-01 -3.36697878e-01  6.64851547e-01
  4.68463996e-01  1.72617202e-01 -1.56173965e-01  4.63366546e-01
  2.74995888e-01]
 [-7.00762713e-01 -2.14030902e+00 -3.09740586e-01 -2.34356396e-01
 -3.01708455e-01 -3.20376411e-01 -5.53141715e-01 -4.41318119e-01
 -4.38249132e-01 -5.21411574e-01 -3.76356028e-01 -4.18151679e-01
 -1.73838959e-01 -1.91518868e-01 -2.56660487e-01  2.88039803e-01
  2.02767206e-01]
 [ 5.45478694e-03  4.03039463e-01 -3.54119574e-01 -2.38698657e-01
 -3.98669620e-01 -1.04268851e-01 -8.40918849e-01 -3.82633698e-01
 -7.51078473e-01  8.72301669e-02 -3.96464753e-02 -4.77542444e-01
 -3.07989926e-01 -2.53183607e-01 -1.31176639e-02 -4.55115693e-01
  2.73532981e-01]
 [ 1.10639616e+00  4.75193093e-01  2.59960254e+00  1.86486936e+00
  2.72075736e+00 -1.22047896e-01  1.16917640e+00  1.57834607e+00
  1.29097192e+00 -2.61630966e-01 -1.21752321e-01  3.25571270e+00
  1.34920399e+00  1.53000655e+00  6.17127927e-01  2.47010309e-01
  3.35231702e-01]
 [ 1.66021988e+00  3.96119231e-01 -2.22143812e-01 -1.57786787e-01
 -2.35440730e-01  1.98178259e+00 -4.83145870e-01 -2.11910088e-01
 -4.24003122e-01  1.91150544e+00  1.90809584e+00 -2.71298441e-01
  1.00452777e+00  7.89642588e-01  5.41194989e-01 -3.95893013e-01
  7.50189565e-02]
 [-3.58012219e-01  3.32525127e-01 -2.95407248e-02 -2.40512089e-01
  3.71816764e-01 -3.61514344e-01  9.96780085e-01 -3.80547652e-01
  1.20778087e+00 -4.71384129e-01 -3.59029975e-01  1.95018510e-01
 -2.59745161e-01 -2.12570099e-01 -2.98669130e-02  3.13075087e-01
  2.55465614e-01]
 [-3.34901439e-01 -3.49885235e-01 -2.87298367e-01 -2.12974259e-01
 -2.87679154e-01  6.80198997e-02 -2.03948289e-01 -2.84236496e-01
 -2.27466186e-01  3.07808330e-01 -1.79210756e-04 -3.87811550e-01
 -5.62208511e-01 -3.91666335e-01 -2.08921003e-01  1.27483622e-02
 -3.19766866e+00]
 [ 1.86590651e+00  3.32878117e-01  1.25968437e+01  1.31111821e+01
  5.69638874e+00 -4.17760945e-03  1.03332159e+00  2.17063444e+00
  8.66220718e-01 -4.76183389e-01 -2.14853617e-01  4.56655817e+00
  3.17419740e+00  8.99113558e+00  1.06481726e+00  1.23631700e+00
  2.95702050e-01]]
```

In [18]:

```

1 cluster_centers = pd.DataFrame(data = kmeans.cluster_centers_, columns = [creditcard
2 cluster_centers
3

```

Out[18]:

| | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INSTALLMENTS_ |
|---|-----------|-------------------|-----------|------------------|---------------|
| 0 | -0.120442 | 0.402699 | 0.579851 | 0.703610 | |
| 1 | -0.700763 | -2.140309 | -0.309741 | -0.234356 | |
| 2 | 0.005455 | 0.403039 | -0.354120 | -0.238699 | |
| 3 | 1.106396 | 0.475193 | 2.599603 | 1.864869 | |
| 4 | 1.660220 | 0.396119 | -0.222144 | -0.157787 | |
| 5 | -0.358012 | 0.332525 | -0.029541 | -0.240512 | |
| 6 | -0.334901 | -0.349885 | -0.287298 | -0.212974 | |
| 7 | 1.865907 | 0.332878 | 12.596844 | 13.111182 | |

In [19]:

```

1 # In order to understand what these numbers mean, let's perform inverse transformati
2 cluster_centers = scaler.inverse_transform(cluster_centers)
3 cluster_centers = pd.DataFrame(data = cluster_centers, columns = [creditcard_df.colu
4 cluster_centers
5

```

Out[19]:

| | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INSTALLMENT |
|---|-------------|-------------------|--------------|------------------|-------------|
| 0 | 1313.784751 | 0.972666 | 2242.066489 | 1760.285787 | |
| 1 | 105.896392 | 0.370251 | 341.439298 | 203.453753 | |
| 2 | 1575.828506 | 0.972747 | 246.622905 | 196.246490 | |
| 3 | 3867.345034 | 0.989840 | 6557.295728 | 3687.738545 | |
| 4 | 5020.082361 | 0.971108 | 528.591155 | 330.543621 | |
| 5 | 819.302614 | 0.956043 | 940.090620 | 193.236564 | |
| 6 | 867.405752 | 0.794386 | 389.387444 | 238.943722 | |
| 7 | 5448.201718 | 0.956126 | 27916.555652 | 22354.314348 | |

In [20]:

```

1 # concatenate the clusters labels to our original dataframe
2 creditcard_df_cluster = pd.concat([creditcard_df, pd.DataFrame({'cluster':labels})],
3 creditcard_df_cluster.head()

```

Out[20]:

| | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INSTALLMENT |
|---|-------------|-------------------|-----------|------------------|-------------|
| 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 | |

In [21]:

```

1 # Obtain the principal components
2 pca = PCA(n_components=2)
3 principal_comp = pca.fit_transform(creditcard_df_scaled)
4 principal_comp

```

Out[21]:

```

array([[ -1.68222111, -1.07644631],
       [ -1.13829816,  2.50649826],
       [  0.96968089, -0.38350334],
       ...,
       [-0.92620277, -1.8107928 ],
       [-2.33654826, -0.65798708],
       [-0.55641888, -0.40048456]])

```

In [22]:

```

1 # Create a dataframe with the two components
2 pca_df = pd.DataFrame(data = principal_comp, columns = ['pca1', 'pca2'])
3 pca_df.head()

```

Out[22]:

| | pca1 | pca2 |
|---|-----------|-----------|
| 0 | -1.682221 | -1.076446 |
| 1 | -1.138298 | 2.506498 |
| 2 | 0.969681 | -0.383503 |
| 3 | -0.873629 | 0.043177 |
| 4 | -1.599434 | -0.688579 |

In [23]:

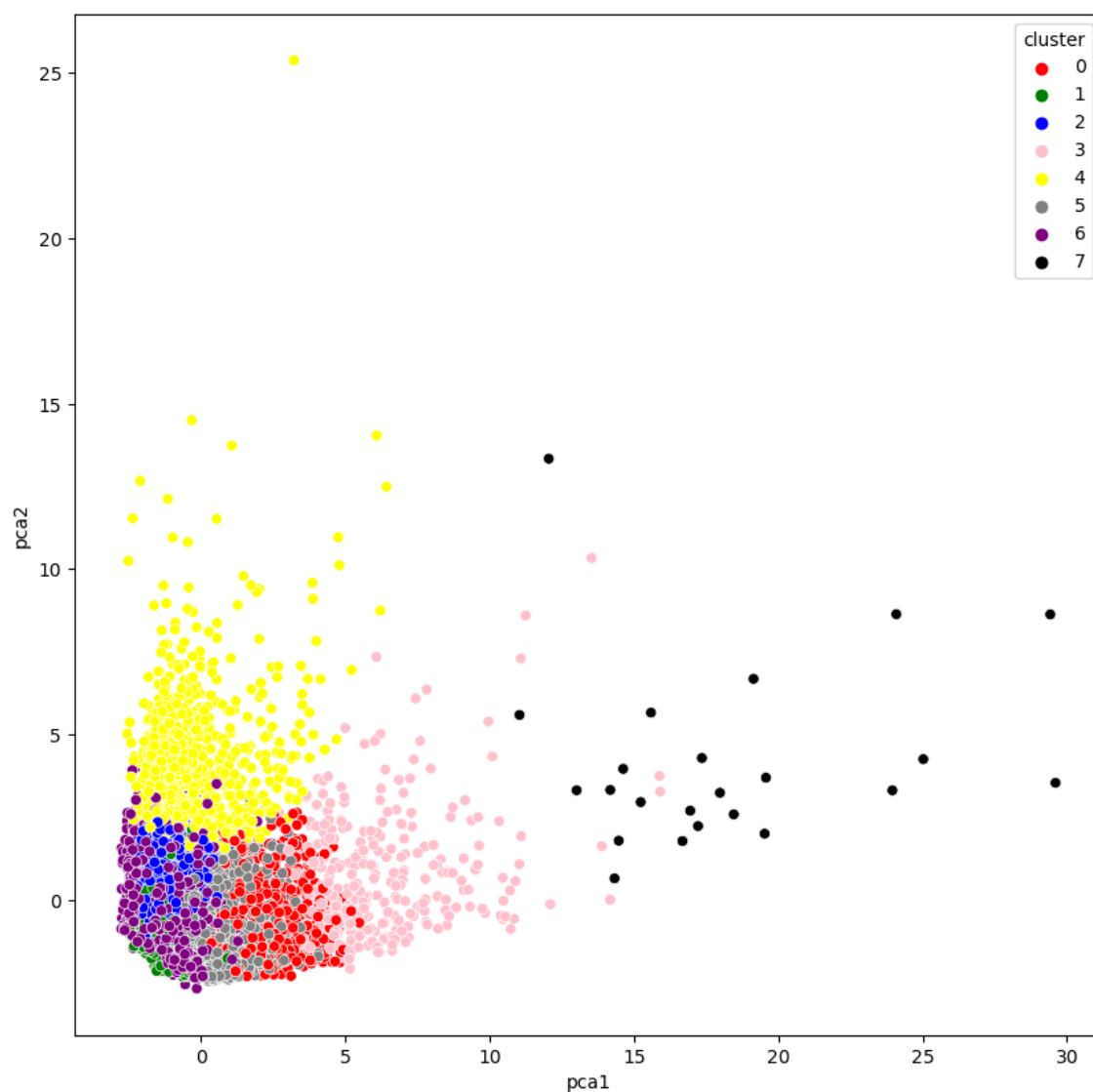
```
1 # Concatenate the clusters labels to the dataframe
2 pca_df = pd.concat([pca_df, pd.DataFrame({'cluster': labels})], axis = 1)
3 pca_df.head()
```

Out[23]:

| | pca1 | pca2 | cluster |
|---|-----------|-----------|---------|
| 0 | -1.682221 | -1.076446 | 2 |
| 1 | -1.138298 | 2.506498 | 4 |
| 2 | 0.969681 | -0.383503 | 0 |
| 3 | -0.873629 | 0.043177 | 2 |
| 4 | -1.599434 | -0.688579 | 2 |

In [24]:

```
1 plt.figure(figsize=(10,10))
2 ax = sns.scatterplot(x="pca1", y="pca2", hue = "cluster", data = pca_df, palette = '
3 plt.show()
```



In [25]:

```
1 from tensorflow.keras.layers import Input, Add, Dense, Activation, ZeroPadding2D, Ba
2 from tensorflow.keras.models import Model, load_model
3 from tensorflow.keras.initializers import glorot_uniform
4 from keras.optimizers import SGD
5
6 encoding_dim = 7
7
8 input_df = Input(shape=(17,))
9
10
11 # Glorot normal initializer (Xavier normal initializer) draws samples from a truncat
12
13 x = Dense(encoding_dim, activation='relu')(input_df)
14 x = Dense(500, activation='relu', kernel_initializer = 'glorot_uniform')(x)
15 x = Dense(500, activation='relu', kernel_initializer = 'glorot_uniform')(x)
16 x = Dense(2000, activation='relu', kernel_initializer = 'glorot_uniform')(x)
17
18 encoded = Dense(10, activation='relu', kernel_initializer = 'glorot_uniform')(x)
19
20 x = Dense(2000, activation='relu', kernel_initializer = 'glorot_uniform')(encoded)
21 x = Dense(500, activation='relu', kernel_initializer = 'glorot_uniform')(x)
22
23 decoded = Dense(17, kernel_initializer = 'glorot_uniform')(x)
24
25 # autoencoder
26 autoencoder = Model(input_df, decoded)
27
28 #encoder - used for our dimention reduction
29 encoder = Model(input_df, encoded)
30
31 autoencoder.compile(optimizer= 'adam', loss='mean_squared_error')
32
```


In [26]:

```
1 autoencoder.fit(creditcard_df_scaled, creditcard_df_scaled, batch_size = 128, epochs
```

```
Epoch 1/25
70/70 [=====] - 5s 38ms/step - loss: 0.5431
Epoch 2/25
70/70 [=====] - 3s 43ms/step - loss: 0.2705
Epoch 3/25
70/70 [=====] - 3s 39ms/step - loss: 0.2065
Epoch 4/25
70/70 [=====] - 3s 44ms/step - loss: 0.1836
Epoch 5/25
70/70 [=====] - 3s 45ms/step - loss: 0.1544
Epoch 6/25
70/70 [=====] - 3s 45ms/step - loss: 0.1404
Epoch 7/25
70/70 [=====] - 3s 46ms/step - loss: 0.1321
Epoch 8/25
70/70 [=====] - 4s 58ms/step - loss: 0.1238
Epoch 9/25
70/70 [=====] - 4s 54ms/step - loss: 0.1278
Epoch 10/25
70/70 [=====] - 3s 43ms/step - loss: 0.1199
Epoch 11/25
70/70 [=====] - 3s 47ms/step - loss: 0.1081
Epoch 12/25
70/70 [=====] - 3s 46ms/step - loss: 0.0996
Epoch 13/25
70/70 [=====] - 3s 43ms/step - loss: 0.0973
Epoch 14/25
70/70 [=====] - 3s 40ms/step - loss: 0.0900
Epoch 15/25
70/70 [=====] - 2s 36ms/step - loss: 0.0834
Epoch 16/25
70/70 [=====] - 3s 39ms/step - loss: 0.0862
Epoch 17/25
70/70 [=====] - 3s 42ms/step - loss: 0.0789
Epoch 18/25
70/70 [=====] - 3s 41ms/step - loss: 0.0712
Epoch 19/25
70/70 [=====] - 3s 42ms/step - loss: 0.0705
Epoch 20/25
70/70 [=====] - 3s 40ms/step - loss: 0.0664
Epoch 21/25
70/70 [=====] - 3s 47ms/step - loss: 0.0646
Epoch 22/25
70/70 [=====] - 3s 44ms/step - loss: 0.0690
Epoch 23/25
70/70 [=====] - 3s 43ms/step - loss: 0.0606
Epoch 24/25
70/70 [=====] - 4s 51ms/step - loss: 0.0616
Epoch 25/25
70/70 [=====] - 3s 45ms/step - loss: 0.0547
```

Out[26]:

```
<keras.callbacks.History at 0x218ceb769a0>
```

In [27]:

```
1 pred = encoder.predict(creditcard_df_scaled)
2 print(len(pred))
```

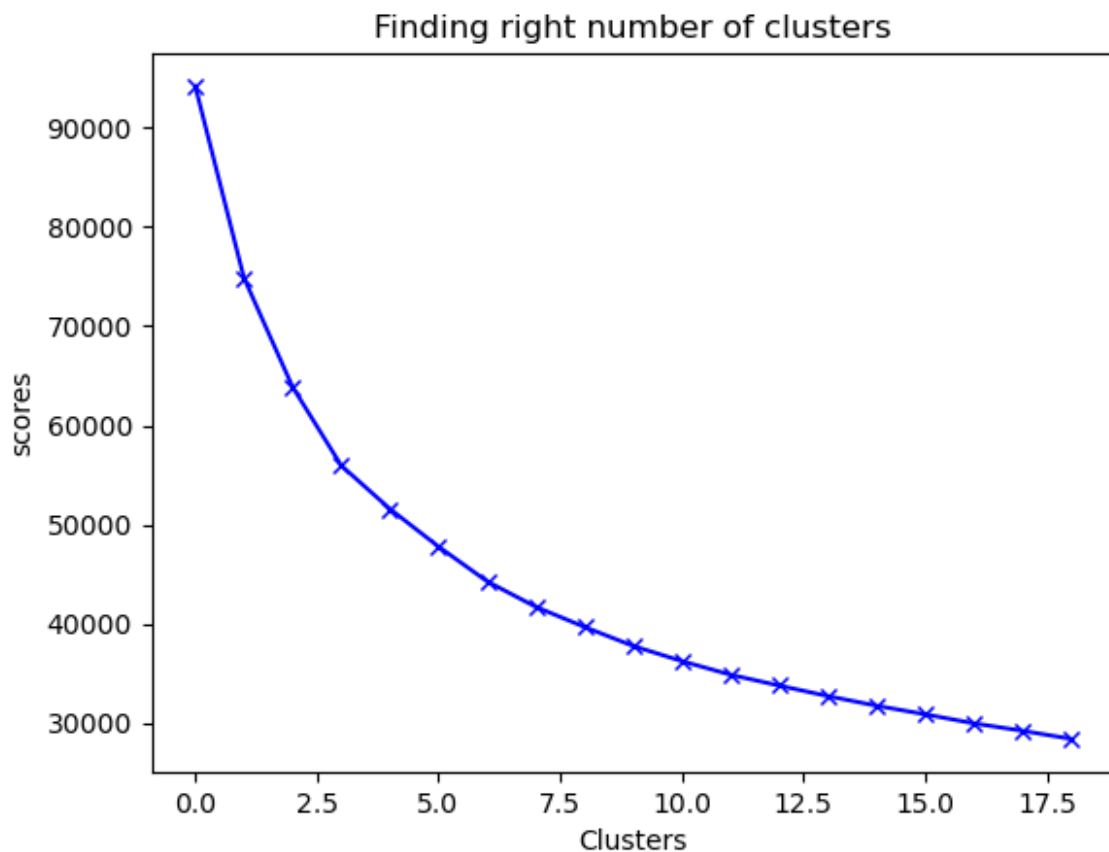
280/280 [=====] - 2s 7ms/step
8950

In [28]:

```
1 scores_2 = []
2
3 range_values = range(1, 20)
4
5 for i in range_values:
6     kmeans = KMeans(n_clusters= i)
7     kmeans.fit(pred)
8     scores_2.append(kmeans.inertia_)
9
10 plt.plot(scores_2, 'bx-')
11 plt.title('Finding right number of clusters')
12 plt.xlabel('Clusters')
13 plt.ylabel('scores')
14 plt.show()
```

localhost:8888/notebooks/marketing.ipynb

```
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster\_kmeans.py:87
0: FutureWarning: The default value of `n_init` will change from 10 to 'au
to' in 1.4. Set the value of `n_init` explicitly to suppress the warning
warnings.warn(
```



In [29]:

```
1 plt.plot(scores_1, 'bx-', color = 'r')
2 plt.plot(scores_2, 'bx-', color = 'g')
```

C:\Users\Pradeep\AppData\Local\Temp\ipykernel_25616\3067751309.py:1: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "bx-" (-> color='b'). The keyword argument will take precedence.

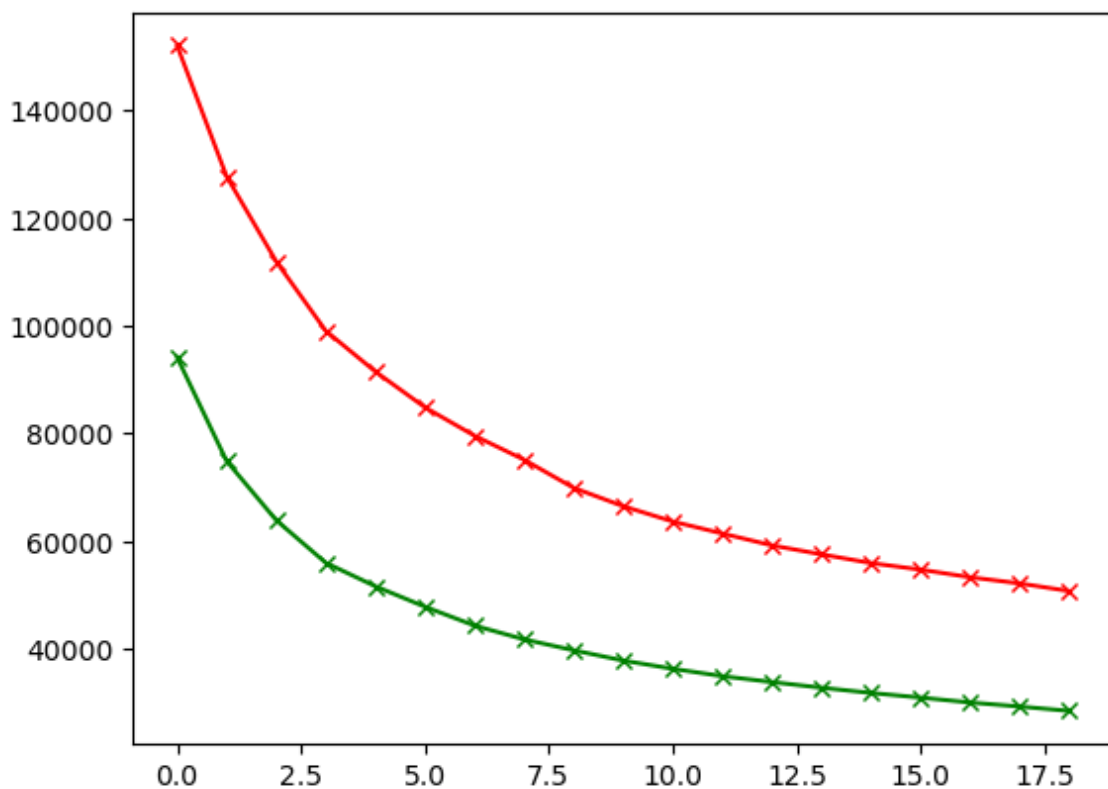
```
plt.plot(scores_1, 'bx-', color = 'r')
```

C:\Users\Pradeep\AppData\Local\Temp\ipykernel_25616\3067751309.py:2: UserWarning: color is redundantly defined by the 'color' keyword argument and the fmt string "bx-" (-> color='b'). The keyword argument will take precedence.

```
plt.plot(scores_2, 'bx-', color = 'g')
```

Out[29]:

```
[<matplotlib.lines.Line2D at 0x218d08d96d0>]
```



In [30]:

```
1 kmeans = KMeans(4)
2 kmeans.fit(pred)
3 labels = kmeans.labels_
4 y_kmeans = kmeans.fit_predict(creditcard_df_scaled)
```

C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:870: FutureWarning: The default value of 'n_init' will change from 10 to 'auto' in 1.4. Set the value of 'n_init' explicitly to suppress the warning
 warnings.warn(

C:\Users\Pradeep\anaconda3\lib\site-packages\sklearn\cluster_kmeans.py:870: FutureWarning: The default value of 'n_init' will change from 10 to 'auto' in 1.4. Set the value of 'n_init' explicitly to suppress the warning
 warnings.warn(

In [31]:

```
1 df_cluster_dr = pd.concat([creditcard_df, pd.DataFrame({'cluster':labels})], axis =
2 df_cluster_dr.head()
```

Out[31]:

| | BALANCE | BALANCE_FREQUENCY | PURCHASES | ONEOFF_PURCHASES | INSTALLMENTP |
|---|-------------|-------------------|-----------|------------------|--------------|
| 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 | |

In [32]:

```
1 pca = PCA(n_components=2)
2 prin_comp = pca.fit_transform(pred)
3 pca_df = pd.DataFrame(data = prin_comp, columns = ['pca1','pca2'])
4 pca_df.head()
```

Out[32]:

| | pca1 | pca2 |
|---|-----------|-----------|
| 0 | -1.792409 | -0.329980 |
| 1 | 0.594816 | 1.449199 |
| 2 | -0.427213 | -0.965590 |
| 3 | -0.833271 | 0.035266 |
| 4 | -1.744368 | -0.176150 |

In [33]:

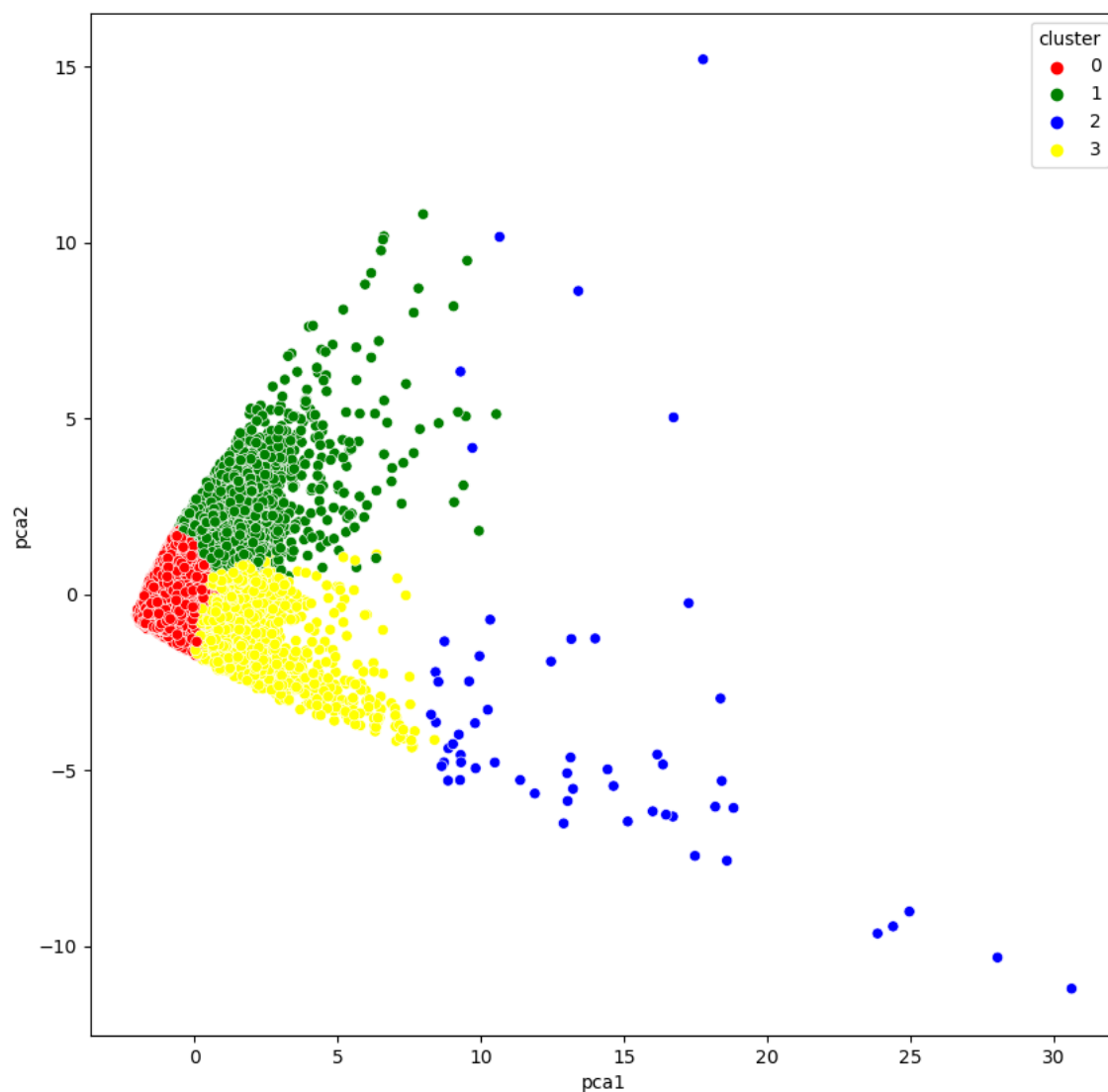
```
1 pca_df = pd.concat([pca_df,pd.DataFrame({'cluster':labels})], axis = 1)
2 pca_df.head()
```

Out[33]:

| | pca1 | pca2 | cluster |
|---|-----------|-----------|---------|
| 0 | -1.792409 | -0.329980 | 0 |
| 1 | 0.594816 | 1.449199 | 1 |
| 2 | -0.427213 | -0.965590 | 0 |
| 3 | -0.833271 | 0.035266 | 0 |
| 4 | -1.744368 | -0.176150 | 0 |

In [34]:

```
1 plt.figure(figsize=(10,10))
2 ax = sns.scatterplot(x="pca1", y="pca2", hue = "cluster", data = pca_df, palette = '
3 plt.show()
```



In []:

1