Customer Clustering based on Relationship with Card Providers

0. Setup Google Drive Environment and Get Data

```
!pip install -U -q PyDrive

from pydrive.auth import GoogleAuth
from pydrive.drive import GoogleDrive
from google.colab import auth
from oauth2client.client import GoogleCredentials

auth.authenticate_user()
gauth = GoogleAuth()
gauth.credentials = GoogleCredentials.get_application_default()
drive = GoogleDrive(gauth)

file = drive.CreateFile({'id':'1NWnmneol2ApYRv18uBYtFsNNbSDVWiz6'})  # replace the id with id of file you want to access
file.GetContentFile('data.csv')
```

1. Data Overview

```
import pandas as pd
import numpy as np
df = pd.read_csv('data.csv')
df.head()
```

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Statu
0	768805383	Existing Customer	45	М	3	High School	Marrie
1	818770008	Existing Customer	49	F	5	Graduate	Singl
2	713982108	Existing Customer	51	М	3	Graduate	Marrie
3	769911858	Existing Customer	40	F	4	High School	Unknow
4	709106358	Existing Customer	40	М	3	Uneducated	Marrie

5 rows × 23 columns



df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 23 columns):
# Column
                                                                                                                                         Non-Nu1
O CLIENTNUM
                                                                                                                                         10127 n
    Attrition_Flag
                                                                                                                                         10127 n
    Customer_Age
                                                                                                                                         10127 n
                                                                                                                                         10127 n
    Gender
                                                                                                                                         10127 n
    Dependent count
                                                                                                                                         10127 n
    Education_Level
    Marital_Status
                                                                                                                                         10127 n
    Income_Category
                                                                                                                                         10127 n
    Card_Category
                                                                                                                                         10127 n
                                                                                                                                         10127 n
    Months_on_book
                                                                                                                                         10127 n
 10 Total Relationship Count
 11 Months_Inactive_12_mon
                                                                                                                                         10127 n
 12 Contacts_Count_12_mon
                                                                                                                                         10127 n
 13 Credit Limit
                                                                                                                                         10127 n
 14 Total_Revolving_Bal
                                                                                                                                         10127 n
 15 Avg_Open_To_Buy
                                                                                                                                         10127 n
 16 Total_Amt_Chng_Q4_Q1
                                                                                                                                         10127 n
 17
    Total_Trans_Amt
                                                                                                                                         10127 n
 18 Total_Trans_Ct
                                                                                                                                         10127 n
    Total_Ct_Chng_Q4_Q1
                                                                                                                                         10127 n
 20 Avg_Utilization_Ratio
    Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1
                                                                                                                                        10127 n
    Naive Bayes Classifier Attrition Flag Card Category Contacts Count 12 mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2
                                                                                                                                        10127 n
```

dtypes: float64(7), int64(10), object(6) memory usage: 1.8+ $\rm MB$

df. nunique() CLIENTNUM 10127 Attrition_Flag Customer_Age 45 2 Gender 6 Dependent count 7 Education Level ${\tt Marital_Status}$ Income_Category 6 Card_Category Months_on_book Total_Relationship_Count Months_Inactive_12_mon Contacts_Count_12_mon 6205 Credit Limit Total Revolving Bal 1974 Avg_Open_To_Buy 6813 ${\tt Total_Amt_Chng_Q4_Q1}$ 1158 ${\tt Total_Trans_Amt}$ 5033 ${\tt Total_Trans_Ct}$ 126 ${\tt Total_Ct_Chng_Q4_Q1}$ 830 Avg_Utilization_Ratio 964 Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1 1704 $Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2$ 640 dtype: int64 df.isnull().sum() CLIENTNIM 0 Attrition_Flag 0 ${\tt Customer_Age}$ 0 Gender 0 Dependent_count Education_Level Marital Status 0 0 Income Category Card_Category 0 Months_on_book 0 Total_Relationship_Count 0 Months_Inactive_12_mon 0 Contacts_Count_12_mon 0 ${\tt Credit_Limit}$ Total_Revolving_Bal Avg Open To Buy Total Amt Chng Q4 Q1 Total_Trans_Amt 0 Total Trans Ct 0 Total Ct Chng Q4 Q1 0 Avg_Utilization_Ratio Λ Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1 0 $Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_Dependent_count_Education_Level_Months_Count_Co$ dtype: int64

As shown above, this data set has 10127 rows and 22 columns from 3 categories:

1.Demographic Information

CLIENTNUM: Unique identifier for each customer.

Customer_Age: Age of customer.

Gender: Gender of customer.

Dependent_count: Number of dependents that customer has.

Education_Level: Education level of customer.

Marital_Status: Marital status of customer.

Income_Category: Income category of customer.

2. Relationship with Card Provider

Card_Category: Type of card held by customer.

Months_on_book: How long customer has been on the books.

Total_Relationship_Count: Total number of relationships customer has with the credit card provider.

Months_Inactive_12_mon: Number of months customer has been inactive in the last twelve months.

Contacts_Count_12_mon: Number of contacts customer has had in the last twelve months.

Credit_Limit: Credit limit of customer.

3. Spending Behavior

Total_Revolving_Bal: Total revolving balance of customer.

Avg_Open_To_Buy: Average open to buy ratio of customer.

Total_Amt_Chng_Q4_Q1: Total amount changed from quarter 4 to quarter 1.

Total_Trans_Amt: Total transaction amount.

Total_Trans_Ct: Total transaction count.

Total_Ct_Chng_Q4_Q1: Total count changed from quarter 4 to quarter 1.

Avg_Utilization_Ratio: Average utilization ratio of customer.

4.Information for Prediction

Attrition_Flag: Flag indicating whether or not the customer has churned out.

 $Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon: \\$

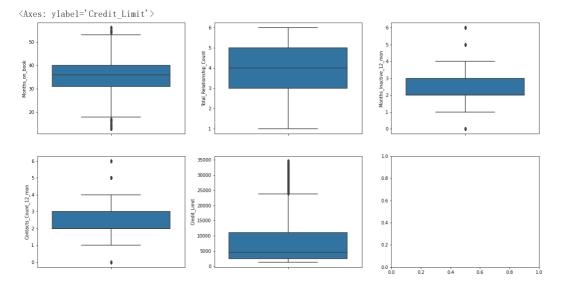
Naive Bayes classifier for predicting whether or not someone will churn

2. Relationship with Card Provider Preprocessing

 $df_cp = df[['Card_Category', 'Months_on_book', 'Total_Relationship_Count', 'Months_Inactive_12_mon', 'Contacts_Count_12_mon', 'Credit_Limit']] \\ df_cp.head()$

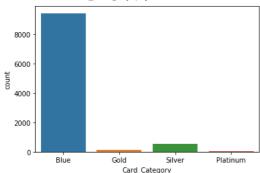
	Card_Category	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	${\tt Contacts_Count_}$
0	Blue	39	5	1	
1	Blue	44	6	1	
2	Blue	36	4	1	
3	Blue	34	3	4	
4	Blue	21	5	1	

```
import matplotlib.pyplot as plt
import seaborn as sns
_,axss = plt.subplots(2,3, figsize=[20,10])
sns.boxplot(y ='Months_on_book', data=df_cp, ax=axss[0][0])
sns.boxplot(y ='Total_Relationship_Count', data=df_cp, ax=axss[0][1])
sns.boxplot(y ='Months_Inactive_12_mon', data=df_cp, ax=axss[0][2])
sns.boxplot(y ='Contacts_Count_12_mon', data=df_cp, ax=axss[1][0])
sns.boxplot(y ='Credit_Limit', data=df_cp, ax=axss[1][1])
```



```
sns. \, countplot(x = "Card_Category", \, data=df\_cp) \\
```

<Axes: xlabel='Card_Category', ylabel='count'>



Although we have a lot of outliers here, we choose not to drop them for they can be important evidence for clustering.

Encoding Card Categories

```
num_cols = df_cp.columns[(df_cp.dtypes == 'float64') | (df_cp.dtypes == 'int64')]
cat_cols = df_cp.columns[df_cp.dtypes == 'object']

from sklearn.preprocessing import OrdinalEncoder

df_cp_Encoded = df_cp.copy()
categories = ['Card_Category']
enc_oe = OrdinalEncoder()
enc_oe.fit(df_cp_Encoded[categories])
df_cp_Encoded[categories] = enc_oe.transform(df_cp_Encoded[categories])
df_cp_Encoded.head()
```

	Card_Category	Months_on_book	${\tt Total_Relationship_Count}$	${\tt Months_Inactive_12_mon}$	${\tt Contacts_Count_}$
0	0.0	39	5	1	
1	0.0	44	6	1	
2	0.0	36	4	1	
3	0.0	34	3	4	
4	0.0	21	5	1	

 $df_{cp.}$ head()

	Card_Category	Months_on_book	$Total_Relationship_Count$	${\tt Months_Inactive_12_mon}$	${\tt Contacts_Count_}$
0	Blue	39	5	1	
1	Blue	44	6	1	
2	Blue	36	4	1	
3	Blue	34	3	4	
4	Blue	21	5	1	

 ${\tt df_cp_Encoded.\,info()}$

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 6 columns):

#	Column	Non-Null Count	Dtype
0	Card_Category	10127 non-null	float64
1	Months_on_book	10127 non-null	int64
2	Total_Relationship_Count	10127 non-null	int64
3	Months_Inactive_12_mon	10127 non-null	int64
4	Contacts_Count_12_mon	10127 non-null	int64
5	Credit_Limit	10127 non-null	float64
dtvn	oc: float64(2) int64(4)		

memory usage: 474.8 KB

df_cp_Encoded.describe()

	Card_Category	Months_on_book	${\tt Total_Relationship_Count}$	${\tt Months_Inactive_12_mon}$	Contacts_Co
count	10127.000000	10127.000000	10127.000000	10127.000000	1(
mean	0.179816	35.928409	3.812580	2.341167	
std	0.693039	7.986416	1.554408	1.010622	
min	0.000000	13.000000	1.000000	0.000000	
25%	0.000000	31.000000	3.000000	2.000000	
50%	0.000000	36.000000	4.000000	2.000000	
75%	0.000000	40.000000	5.000000	3.000000	
max	3.000000	56.000000	6.000000	6.000000	

3. K-means Clustering Model

K-means Clustering Model with 5 Clusters

```
from sklearn.cluster import KMeans
num_clusters = 5 # this number is randomly choosed
# number of clusters
km = KMeans(n_clusters=num_clusters)
km.fit(df_cp_Encoded)
clusters = km.labels_.tolist()
clusters = pd.DataFrame(clusters)
```

/usr/local/lib/python3.9/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from 10 to 'auto warnings.warn(

```
df_cp['Cluster'] = clusters[0]
df_cp.head()
```

<ipython-input-9-9de0d0e88cbe>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer, col_indexer] = value instead

See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#retur_df_cp['Cluster'] = clusters[0]

	Card_Category	Months_on_book	$Total_Relationship_Count$	Months_Inactive_12_mon	Contacts_Count_
0	Blue	39	5	1	
1	Blue	44	6	1	
2	Blue	36	4	1	
3	Blue	34	3	4	
4	Blue	21	5	1	

Number of reviews included in each cluster:

	Cluster	1
2	5428	
0	2089	
3	1167	
4	754	
1	689	

The five cluster we get from the model

```
cluster_0 = df_cp[df_cp["Cluster"] == 0]
cluster_0.head()
```

	Card_Category	Months_on_book	${\tt Total_Relationship_Count}$	${\tt Months_Inactive_12_mon}$	${\tt Contacts_Count}$		
2	Blue	36	4	1			
3	Blue	34	3	4			
4	Blue	21	5	1			
cluster_1 = df_cp[df_cp["Cluster"] == 1] cluster l.head()							

	Card_Category	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Contacts_Count
6	Gold	46	6	1	
7	Silver	27	2	2	
16	Blue	36	6	2	
40	Blue	41	2	2	
45	Blue	30	3	2	

cluster_2 = df_cp[df_cp["Cluster"] == 2]
cluster_2.head()

	Card_Category	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Contacts_Count
0	Blue	39	5	1	
9	Blue	36	6	3	
12	Blue	36	3	6	
17	Blue	34	4	4	
19	Blue	37	6	1	

 $\begin{array}{lll} cluster_3 &=& df_cp[df_cp["Cluster"] &==& 3] \\ cluster_3.\,head() & & \end{array}$

	Card_Category	${\tt Months_on_book}$	${\tt Total_Relationship_Count}$	${\tt Months_Inactive_12_mon}$	${\tt Contacts_Count}$
8	Blue	36	5	2	
20	Blue	42	5	2	
48	Blue	40	4	3	
53	Blue	36	4	2	
63	Blue	32	2	4	

 $\begin{array}{lll} cluster_4 &=& df_cp[df_cp["Cluster"] &==& 4] \\ cluster_4.\,head() & & \end{array}$

	Card_Category	Months_on_book	${\tt Total_Relationship_Count}$	${\tt Months_Inactive_12_mon}$	${\tt Contacts_Count}$
1	Blue	44	6	1	
10	Blue	31	5	3	
11	Blue	54	6	2	
13	Blue	30	5	1	
25	Blue	28	6	1	

4. Model Insight: K-Means

Use PCA Transform to project customer to 2D plot

```
from sklearn.decomposition import PCA

pca = PCA(n_components=2)

c_0_index = list(cluster_0.index)
c_0 = pca.fit_transform(df_cp_Encoded.loc[c_0_index])

c_1_index = list(cluster_1.index)
c_1 = pca.fit_transform(df_cp_Encoded.loc[c_1_index])

c_2_index = list(cluster_2.index)
```

```
c_2 = pca.fit_transform(df_cp_Encoded.loc[c_2_index])
c_3_index = list(cluster_3.index)
c 3 = pca.fit transform(df cp Encoded.loc[c 3 index])
c_4_{index} = list(cluster_4.index)
c_4 = pca.fit_transform(df_cp_Encoded.loc[c_4_index])
fig = plt.figure(figsize = [15,10])
                                    'r', s = 20,
plt.scatter(c_0[:,0], c_0[:,1], c =
                                                   lahe1 =
                                                             'cluster 0')
plt.scatter(c_1[:,0], c_1[:,1], c = 'b', s = 20, label = 'cluster 1')
                                    'y', s = 20,
plt.scatter(c_2[:,0], c_2[:,1], c =
                                                   labe1 =
                                                             'cluster 2')
plt.scatter(c_3[:,0], c_3[:,1], c = 'g',
                                                   label = 'cluster 3')
                                            =
                                               20,
plt.scatter(c 4[:,0], c 4[:,1], c = 'brown', s = 20, label = 'cluster 4')
```

(matplotlib.collections.PathCollection at 0x7f7894d4b790)



Unfortunately, we didn't find clear clusters in the 2D plot. The reason is that K means is good for clustering data that can form a ball in hyper dimension. If we project featuers of our data into 2D plots, we can see that all the data points are nearly uniformly distributed in the 2D plots. They do not have potential to form clusters. That is probably the reason that we cannot form clear clusters from the data set. I also make plots that shows distributions of each pair of features. If you are interested, I put those plots in part 2 of the report.

5. Latent Dirichlet Allocation(LDA) Model

```
2023/3/22 21:18
                        9.55318991e+02 1.80585056e+07]
                      [1.68995839e+02 5.55465441e+03 5.27359135e+02 5.15211230e+02
                        6.53134723e+02 1.81498759e+07]]
        # column names
        cluster number = ["Cluster" + str(i) for i in range(lda.n components)]
        df_document_cluster = pd.DataFrame(np.round(lda_output, 2), columns=cluster_number)
        # get dominant topic for each document
        cluster = np.argmax(df_document_cluster.values, axis=1)
        df_document_cluster['cluster'] = cluster
        df_document_cluster.head(15)
                               ClusterO Cluster1 Cluster2 Cluster3 Cluster4 cluster
                       0
                                          0.22
                                                                 0.21
                                                                                        0.14
                                                                                                                0.22
                                                                                                                                       0.22
                                                                                                                                                                 0
                                          0.19
                                                                 0.19
                                                                                        0.23
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                       1
                                                                                                               0.19
                                                                                                                                       0.19
                       2
                                          0.15
                                                                 0.16
                                                                                        0.40
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                                                                                                                                                                 2
                       3
                                                                                                                                                                  2
                                          0.14
                                                                 0.15
                                                                                        0.42
                                                                                                               0.14
                                                                                                                                       0.14
                       4
                                          0.20
                                                                 0.20
                                                                                        0.20
                                                                                                               0.20
                                                                                                                                      0.20
                                                                                                                                                                 0
                       5
                                          0.16
                                                                 0.17
                                                                                        0.36
                                                                                                                0.16
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                                                                                                                                                                  2
                                          0.24
                                                                 0.22
                                                                                        0.07
                                                                                                               0.23
                                                                                                                                      0.24
                       6
                                                                                                                                                                 Λ
                                          0.25
                                                                 0.22
                                                                                        0.05
                                                                                                               0.24
                                                                                                                                      0.24
                                                                                                                                                                 0
                       7
                       8
                                          0.24
                                                                 0.22
                                                                                        0.08
                                                                                                               0.23
                                                                                                                                       0.23
                                                                                                                                                                 0
                       9
                                          0.22
                                                                 0.21
                                                                                                                                      0.21
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                                                                 0.20
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                                                                                                                0.20
                                                                                                                                       0.20
                                                                                                                                                                  2
                                          0.19
                                                                 0.19
                                                                                        0.25
                                                                                                               0.19
                                                                                                                                       0.19
                                                                                                                                                                  2
                      11
                                                                                                                                                                 0
                      12
                                          0.22
                                                                 0.21
                                                                                        0.14
                                                                                                                0.21
                                                                                                                                      0.22
                      13
                                          0.21
                                                                 0.21
                                                                                        0.16
                                                                                                                0.21
                                                                                                                                       0.21
                                                                                                                                                                 0
                      14
                                          0.07
                                                                 0.09
                                                                                        0.69
                                                                                                               0.08
                                                                                                                                       0.08
                                                                                                                                                                 2
        cluster_number = [i for i in range(lda.n_components)]
        df_document_cluster = pd.DataFrame(np.round(lda_output, 2), columns=cluster_number)
        cluster = np.argmax(df_document_cluster.values, axis=1)
        df_cp['Cluster'] = cluster
        df_cp. head(10)
                    <ipython-input-14-63f1fadb831a>:4: SettingWithCopyWarning:
                    A value is trying to be set on a copy of a slice from a DataFrame.
                    Try using .loc[row_indexer, col_indexer] = value instead
                    See the caveats in the documentation: <a href="https://pandas.pydata.org/pandas-docs/stable/user-guide">https://pandas.pydata.org/pandas-docs/stable/user-guide</a>
                        df_cp['Cluster'] = cluster
                            Card_Category Months_on_book Total_Relationship_Count Months_Inactive_12_months_on_book Total_Relationship_Count Months_On_book Months_On_boo
                      0
                                                                                                                                                            5
                                                   Blue
                                                                                            39
                      1
                                                   Blue
                                                                                             44
                                                                                                                                                            6
                      2
                                                   Blue
                                                                                            36
                                                                                                                                                            4
                      3
                                                   Blue
                                                                                             34
                                                                                                                                                            3
                      4
                                                   Blue
                                                                                             21
                                                                                                                                                            5
                      5
                                                   Blue
                                                                                             36
                                                                                                                                                            3
                      6
                                                                                                                                                            6
                                                  Gold
                                                                                             46
                      7
                                                 Silver
                                                                                            27
                                                                                                                                                            2
                      8
                                                   Blue
                                                                                             36
                                                                                                                                                            5
        cluster\_0 = df\_cp[df\_cp["Cluster"] == 0]
        cluster_1 = df_cp[df_cp["Cluster"] == 1]
        cluster_2 = df_cp[df_cp["Cluster"] == 2]
```

```
cluster_3 = df_cp[df_cp["Cluster"] == 3]
cluster_4 = df_cp[df_cp["Cluster"] == 4]
```

```
print ("Number of reviews included in each cluster:")
df_cp['Cluster'].value_counts().to frame()
```

Number of reviews included in each cluster:

```
Cluster
2
      6560
0
      3480
3
        84
4
          3
```

We can see that cluster 1 and cluster 2, as well as cluster 3 and cluster 4 are always having similar probabilities. They may be similar clusters. Besides, there is no element in cluster 1. As a result, in this case, 5 may not be a good cluster number. Let's try other cluster numbers.

```
1da2 = LatentDirichletAllocation(n components=3)
1da2_output = 1da2.fit_transform(df_cp_Encoded)
# column names
cluster_number = ["Cluster" + str(i) for i in range(1da2.n_components)]
df_document_cluster = pd.DataFrame(np.round(1da2_output, 2), columns=cluster_number)
# get dominant topic for each document
cluster = np.argmax(df_document_cluster.values, axis=1)
df_document_cluster['cluster'] = cluster
df_document_cluster.head(10)
```

Cluster0 Cluster1 Cluster2 cluster 0 0.38 0.37 0.25 0 0.32 1 0.32 0.36 2 2 0.22 0.23 0.55 2 3 0.21 0.22 0.57 2 4 0.33 0.34 0.33 1 5 0.24 0.26 0.50 2 6 0.43 0.40 0.16 0 7 0.41 0.14

0.40

0.36

0.45

0.42

0.37

8

9

```
cluster_number = [i for i in range(lda2.n_components)]
df_document_cluster = pd.DataFrame(np.round(1da2_output, 2), columns=cluster_number)
cluster = np.argmax(df_document_cluster.values, axis=1)
df cp['Cluster'] = cluster
df_cp. head (10)
```

<ipython-input-36-cd572c7e8d63>:4: SettingWithCopyWarning: A value is trying to be set on a copy of a slice from a DataFrame. Try using .loc[row_indexer, col_indexer] = value instead

0.18

0.27

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide df_cp['Cluster'] = cluster Card Category Months on book Total Relationship Count Months Inactive 12 mo

0

0

0

	Card_Category	months_on_book	lotal_Kelationship_Count	months_Inactive_12_mol
0	Blue	39	5	
1	Blue	44	6	
2	Blue	36	4	
3	Blue	34	3	
4	Blue	21	5	
5	Blue	36	3	
6	Gold	46	6	
7	Silver	27	2	;
8	Blue	36	5	;
4	Dlug	26	£	.

```
print ("Number of reviews included in each cluster:")
df_cp['Cluster'].value_counts().to_frame()

Number of reviews included in each cluster:
```

Cluster

3573

2 6552

1 2

0

Similar to the first case where cluster number is 5, there is a cluster that is very small. In this case, we can change cluster number to 2.

```
lda3 = LatentDirichletAllocation(n_components=2)
lda3_output = lda3.fit_transform(df_cp_Encoded)

# column names
cluster_number = ["Cluster" + str(i) for i in range(lda3.n_components)]

df_document_cluster = pd.DataFrame(np.round(lda3_output, 2), columns=cluster_number)

# get dominant topic for each document
cluster = np.argmax(df_document_cluster.values, axis=1)
df_document_cluster['cluster'] = cluster
```

df_document_cluster.head(10)

	Cluster0	Cluster1	cluster
0	0.57	0.43	0
1	0.47	0.53	1
2	0.31	0.69	1
3	0.29	0.71	1
4	0.49	0.51	1
5	0.34	0.66	1
6	0.66	0.34	0
7	0.68	0.32	0
8	0.65	0.35	0
9	0.55	0.45	0

```
df_cp['Cluster'] = cluster
df_cp.head(10)
```

<ipython-input-42-e58de5a68fb7>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer, col_indexer] = value instead

	Card_Category	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon
0	Blue	39	5	;
1	Blue	44	6	
2	Blue	36	2	
3	Blue	34	3	,
4	Blue	21	5	
5	Blue	36	3	
6	Gold	46	6	
7	Silver	27	2	2
8	Blue	36	5	5
△	Dlug	26		.

Number of reviews included in each cluster:

```
Cluster
```

1 6627

6. Model Insight: LDA

```
cluster_0 = df_cp[df_cp["Cluster"] == 0]
cluster_1 = df_cp[df_cp["Cluster"] == 1]

from sklearn.decomposition import PCA

pca = PCA(n_components=2)

c_0_index = list(cluster_0.index)
c_0 = pca.fit_transform(df_cp_Encoded.loc[c_0_index])

c_1_index = list(cluster_1.index)
c_1 = pca.fit_transform(df_cp_Encoded.loc[c_1_index])

fig = plt.figure(figsize = [15,10])

plt.scatter(c_0[:,0], c_0[:,1], c = 'r', s = 20, label = 'cluster 0')
plt.scatter(c_1[:,0], c_1[:,1], c = 'g', s = 20, label = 'cluster 1')
```

$\verb|\langle matplotlib.collections.PathCollection| at 0x7f788e2673d0 > \\$

