Consolidated Segmentation and Churn Analysis of Ba Clients

By: Tamjid Ahsan

As capstone project of Flatiron Data Science Bootcamp.

- Student pace: Full Time
- Scheduled project review date/time: July 22, 2021, 05:00 PM [DST]
- Instructor name: James Irving

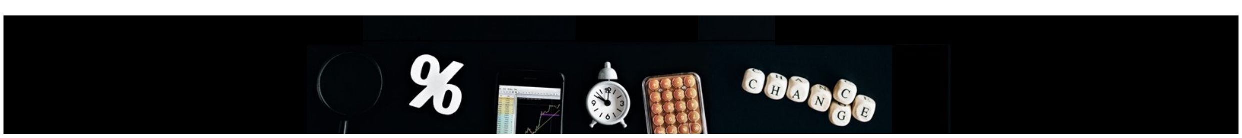
ABSTRACT

Attracting new customers is no longer a good strategy for mature businesses since the cost of retaining existin customers is much lower. For this reason, customer churn management becomes instrumental for any service industry.

This analysis is combining churn prediction and customer segmentation and aims to come up with an integrate customer analytics outline for churn management. There are six components in this analysis, starting with data processing, exploratory data analysis, customer segmentation, customer characteristics analytics, churn predict and factor analysis. This analysis is adapting OESMiN framework for data science.

Customer data of a bank is used for this analysis. After preprocessing and exploratory data analysis, customer segmentation is carried out using K-means clustering. A Random Forest model is used focusing on optimizing score to validate the clustering and get feature importance. By using this model, customers are segmented intc different groups, which sanctions marketers and decision makers to implement existing customer retention stra more precisely. Then different machine learning models are used with the preprocessed data along with the segmentation prediction from the K-means clustering model. For this type of modeling, models were optimize precision. To address class imbalance Synthetic Minority Oversampling Technique (SMOTE) is applied to the tra set. For factor analysis feature importance of models are used. Based on cluster characteristics, clients are label `Low value frequent users of services`, `High risk clients`, `Regular clients`, `Mos loyal clients`, and `High value clients`. Final model accuracy is 0.97 with good precision of predi churn at around 0.93.

OVERVIEW



cost of obtaining a new one.

When it comes to customers, the financial crisis of 2008 changed the banking sector's strategy. Prior to the fina crisis, banks were mostly focused on acquiring more and more clients. However, once the market crashed after market imploded, banks realized rapidly that the expense of attracting new clients is multiple times higher thar holding existing ones, which means losing clients can be monetarily unfavorable. Fast forward to today, and th global banking sector has a market capitalization of $7.6 trillion, with technology and laws making things easie ever to transfer assets and money between institutions. Furthermore, it has given rise to new forms of competi banks, such as open banking, neo-banks, and fin-tech businesses (Banking as a Service (BaaS))[1]. Overall, toda consumers have more options than ever before, making it easier than ever to transfer or quit banks altogether. According to studies, repeat customers seem to be more likely to spend 67 percent more on a bank's products services, emphasizing the necessity of knowing why clients churn and how it varies across different characterist Banking is one of those conventional sectors that has undergone continuous development throughout the yea Nonetheless, many banks today with a sizable client base expecting to gain a competitive advantage have not into the huge amounts of data they have, particularly in tackling one of the most well-known challenges, custo turnover.

Churn can be expressed as a level of customer inactivity or disengagement seen over a specific period. This exp itself in the data in a variety of ways e.g., frequent balance transfers to another account or unusual drop in aver balance over time. But how can anyone look for churn indicators? Collecting detailed feedback on the custome experience might be difficult. For one thing, surveys are both rare and costly. Furthermore, not all clients receiv bother to reply to it. So, where else can you look for indicators of future client dissatisfaction? The solution con identifying early warning indicators from existing data. Advanced machine learning and data science technique learn from previous customer behavior and external events that lead to churn and use this knowledge to antici the possibility of a churn-like event in the future.

Ref:

[1] Business Insider

[2] Stock images from PEXELS

BUSINESS PROBLEM

value, there is very little banks can do about customer churn when they don't anticipate it coming in the first pl
Predicting attrition becomes critical in this situation, especially when unambiguous consumer feedback is lackir
Precise prediction enables advertisers and client experience groups to be imaginative and proactive in their off
to the client.

XYZ Bank (read: fictional) is a mature financial institution based in Eastern North America. Recent advance in technology and rise in BaaS is a real threat for them as they can lure away the existing clientele. The bank has e
data of their clients. Based on the data available, the bank wants to know whom of them are in risk of churning

This analysis focuses on the behavior of bank clients who are more likely to leave the bank (**i.e. close their bar
account**, churn).

IMPORTS

In [1]:
```
%load_ext autoreload
%autoreload 2
```

In [2]:
```
from imports_and_functions.packages import *
import imports_and_functions as fn
```

In [3]:
```
# notebook styling
try:
    from jupyterthemes import jtplot
except:
    !pip install jupyterthemes
    from jupyterthemes import jtplot
# jtplot.reset() # reset notebook styling
jtplot.style(theme='monokai', context='notebook', ticks='True',
grid='False')
```

OBTAIN

The data for this analysis is obtained from *Kaggle*, titled **"Credit Card customers"** uploaded by Sakshi Goyal. V
can be found here, this dataset was originally obtained from LEAPS Analyttica. A copy of the data is in this rep
at `/data/BankChurners.csv` .

This dataset contains data of more than 10000 credit card accounts with around 19 variables of different types
time point and their attrition indicator over the next 6 months.

Data description is as below:

Variable	Type	Description
Clientnum	Num	Client number. Unique identifier for the customer holding the account

Variable	Type	Description
Education_Level	obj	Demographic variable - Educational Qualification of the account holder (example: high sc college graduate, etc.)
Marital_Status	obj	Demographic variable - Married, Single, Divorced, Unknown
Income_Category	obj	Demographic variable - Annual Income Category of the account holder (< $40K$,40K - 60K, (80K, $80K-$120K, > $120K, Unknown)
Card_Category	obj	Product Variable - Type of Card (Blue, Silver, Gold, Platinum)
Months_on_book	Num	Months on book (Time of Relationship)
Total_Relationship_Count	Num	Total no. of products held by the customer
Months_Inactive_12_mon	Num	No. of months inactive in the last 12 months
Contacts_Count_12_mon	Num	No. of Contacts in the last 12 months
Credit_Limit	Num	Credit Limit on the Credit Card
Total_Revolving_Bal	Num	Total Revolving Balance on the Credit Card
Avg_Open_To_Buy	Num	Open to Buy Credit Line (Average of last 12 months)
Total_Amt_Chng_Q4_Q1	Num	Change in Transaction Amount (Q4 over Q1)
Total_Trans_Amt	Num	Total Transaction Amount (Last 12 months)
Total_Trans_Ct	Num	Total Transaction Count (Last 12 months)
Total_Ct_Chng_Q4_Q1	Num	Change in Transaction Count (Q4 over Q1)
Avg_Utilization_Ratio	Num	Average Card Utilization Ratio

There are unknown category in Education Level, Marital Status, and Income Category. Imputing values for thos features does not make sense. And it is understandable why those are unknown in the first place. Information a Education and Marital status is often complicated and confidential; and customers are reluctant to share those information. Same for the income level. It is best for the model to be able to handle when those information is available and still produce prediction.

In [4]:

```
# loading dataset
raw_df = pd.read_csv('./data/BankChurners.csv')
# first view of the dataset
raw_df
```

Out[4]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	I
0	768805383	Existing Customer	45	M	3	High School	Married	
1	818770008	Existing Customer	49	F	5	Graduate	Single	
2	713982108	Existing Customer	51	M	3	Graduate	Married	
3	769911858	Existing Customer	40	F	4	High School	Unknown	
4	709106358	Existing	40	M	3	Uneducated	Married	

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	I
10123	710638233	Attrited Customer	41	M	2	Unknown	Divorced	
10124	716506083	Attrited Customer	44	F	1	High School	Married	
10125	717406983	Attrited Customer	30	M	2	Graduate	Unknown	
10126	714337233	Attrited Customer	43	F	2	Graduate	Married	

In [5]:

```
# columns of the dataset
raw_df.columns
```

Out[5]:

```
Index(['CLIENTNUM', 'Attrition_Flag', 'Customer_Age', 'Gender',
       'Dependent_count', 'Education_Level', 'Marital_Status',
       'Income_Category', 'Card_Category', 'Months_on_book',
       'Total_Relationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal',
       'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio',
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Deper
unt_Education_Level_Months_Inactive_12_mon_1',
       'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Deper
unt_Education_Level_Months_Inactive_12_mon_2'],
      dtype='object')
```

In [6]:

```
# no duplicates in the dataset
raw_df.CLIENTNUM.duplicated().value_counts()
```

Out[6]:

```
False    10127
Name: CLIENTNUM, dtype: int64
```

In [7]:

```
# dropping customer identifier and unnecessary feature
raw_df.drop(columns=[
    'CLIENTNUM',

'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12

'Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12
],
        inplace=True)
raw_df
```

Out[7]:

	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Catego
0	Existing Customer	45	M	3	High School	Married	$60K-8$
1	Existing Customer	49	F	5	Graduate	Single	Less than $4(

	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Catego
4	Existing Customer	40	M	3	Uneducated	Married	$60K-8$
...	...	...	...	...	...	...	
10122	Existing Customer	50	M	2	Graduate	Single	$40K-6$
10123	Attrited Customer	41	M	2	Unknown	Divorced	$40K-6$
10124	Attrited Customer	44	F	1	High School	Married	Less than $4(
10125	Attrited Customer	30	M	2	Graduate	Unknown	$40K-6$
10126	Attrited Customer	43	F	2	Graduate	Married	Less than $4(

In [8]:

```
# looking at the distribution for changing labels to more notebook
friendly description
raw_df['Income_Category'].value_counts()
```

Out[8]:

```
Less than $40K    3561
$40K - $60K       1790
$80K - $120K      1535
$60K - $80K       1402
Unknown           1112
$120K +            727
Name: Income_Category, dtype: int64
```

In [9]:

```
# cleaning text in 'Income_Category'
raw_df['Income_Category'] = raw_df['Income_Category'].apply(
    lambda x: x.replace("$", "")).apply(
        lambda x: x.replace(" - ", "_to_")).apply(
            lambda x: x.replace("120K +", "Above_120K")).apply(
                lambda x: x.replace("Less than 40K", "Less_than_40K"))
raw_df
```

Out[9]:

	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Catego
0	Existing Customer	45	M	3	High School	Married	60K_to_8(
1	Existing Customer	49	F	5	Graduate	Single	Less_than_4(
2	Existing Customer	51	M	3	Graduate	Married	80K_to_12(
3	Existing Customer	40	F	4	High School	Unknown	Less_than_4(
4	Existing Customer	40	M	3	Uneducated	Married	60K_to_8(

	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Catego
10124	Attrited Customer	44	F	1	High School	Married	Less_than_4
10125	Attrited Customer	30	M	2	Graduate	Unknown	40K_to_6
10126	Attrited Customer	43	F	2	Graduate	Married	Less_than_4

In [10]:

```
# distribution of target
(raw_df.Attrition_Flag.value_counts(1)*100).round(2)
```

Out[10]:

```
Existing Customer    83.93
Attrited Customer    16.07
Name: Attrition_Flag, dtype: float64
```

There is major class imbalance spotted in the target column.

In [11]:

```
df = raw_df.copy()
print(f'"df" statistical description: \n{"+"*30}')
display(fn.describe_dataframe(df))
print(f'"df" feature details: \n{"+"*30}\n')
fn.check_duplicates(df, verbose=2, limit_num=50)
```

```
"df" statistical description:
++++++++++++++++++++++++++++++
```

	count	unique	top	freq	mean	std	min	25%	50%	75%
Attrition_Flag	10127.0	2	Existing Customer	8500						
Customer_Age	10127.0				46.33	8.02	26.0	41.0	46.0	52.0
Gender	10127.0	2	F	5358						
Dependent_count	10127.0				2.35	1.3	0.0	1.0	2.0	3.0
Education_Level	10127.0	7	Graduate	3128						
Marital_Status	10127.0	4	Married	4687						
Income_Category	10127.0	6	Less_than_40K	3561						
Card_Category	10127.0	4	Blue	9436						
Months_on_book	10127.0				35.93	7.99	13.0	31.0	36.0	40.0
Total_Relationship_Count	10127.0				3.81	1.55	1.0	3.0	4.0	5.0
Months_Inactive_12_mon	10127.0				2.34	1.01	0.0	2.0	2.0	3.0
Contacts_Count_12_mon	10127.0				2.46	1.11	0.0	2.0	2.0	3.0
Credit_Limit	10127.0				8631.95	9088.78	1438.3	2555.0	4549.0	11067.5
Total_Revolving_Bal	10127.0				1162.81	814.99	0.0	359.0	1276.0	1784.0
Avg_Open_To_Buy	10127.0				7469.14	9090.69	3.0	1324.5	3474.0	9859.0

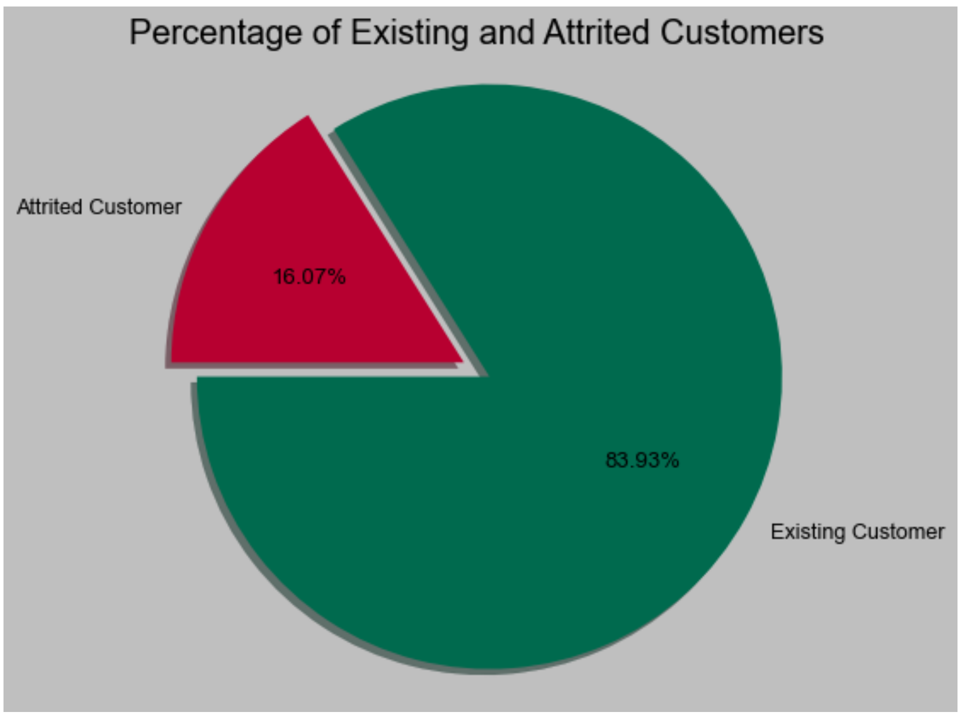
count	unique	top	freq	mean	std	min	25%	50%	75%

```
"df" feature details:
++++++++++++++++++++++++++++++

Attrition_Flag >> number of uniques: 2
Values:
['Existing Customer' 'Attrited Customer']
____________________________________________________________

Customer_Age >> number of uniques: 45
Values:
[45 49 51 40 44 32 37 48 42 65 56 35 57 41 61 47 62 54 59 63 53 58 55 66
 50 38 46 52 39 43 64 68 67 60 73 70 36 34 33 26 31 29 30 28 27]
____________________________________________________________

Gender >> number of uniques: 2
Values:
['M' 'F']
____________________________________________________________

Dependent_count >> number of uniques: 6
Values:
[3 5 4 2 0 1]
____________________________________________________________

Education_Level >> number of uniques: 7
Values:
['High School' 'Graduate' 'Uneducated' 'Unknown' 'College' 'Post-Graduate'
 'Doctorate']
____________________________________________________________

Marital_Status >> number of uniques: 4
Values:
['Married' 'Single' 'Unknown' 'Divorced']
____________________________________________________________

Income_Category >> number of uniques: 6
Values:
['60K_to_80K' 'Less_than_40K' '80K_to_120K' '40K_to_60K' 'Above_120K'
 'Unknown']
____________________________________________________________

Card_Category >> number of uniques: 4
Values:
['Blue' 'Gold' 'Silver' 'Platinum']
____________________________________________________________

Months_on_book >> number of uniques: 44
Values:
[39 44 36 34 21 46 27 31 54 30 48 37 56 42 49 33 28 38 41 43 45 52 40 50
 35 47 32 20 29 25 53 24 55 23 22 26 13 51 19 15 17 18 16 14]
____________________________________________________________

Total_Relationship_Count >> number of uniques: 6
Values:
[5 6 4 3 2 1]
____________________________________________________________

Months_Inactive_12_mon >> number of uniques: 7
Values:
[1 4 2 3 6 0 5]
____________________________________________________________

Contacts_Count_12_mon >> number of uniques: 7
Values:
[3 2 0 1 4 5 6]
____________________________________________________________
```

```
____________________________________________________________

Total_Revolving_Bal >> number of uniques: 1974, showing top 50 values
Top 50 Values:
[ 777  864    0 2517 1247 2264 1396 1677 1467 1587 1666  680  972 2362
 1291 1157 1800 1560 1669 1374 1010 1362 1811 1690 1490 1696 1914 2298
  886  605  578 2204 2055 1430 2020 1435 1227 1549  808 2179 2200 2363
 1880  978 1753 2016 1251 2102 1634 1515]

____________________________________________________________

Avg_Open_To_Buy >> number of uniques: 6813, showing top 50 values
Top 50 Values:
[11914.   7392.   3418.    796.   4716.   2763.  32252.  27685.  19835.
  9979.   5281.   7508.  11751.   6881.   1756.   3262.  28005.  12244.
   676.  13313.  19179.   1438.3  3790.    932.  12217.   6099.  13410.
  9205.  10100.   3423.    942.    761.   6406.   1160.  10859.   1606.
   737.  15433.   2786.   7277.  31848.   4001.  14787.   3906.   7775.
 34516.    853.    528.  18023.   3518. ]

____________________________________________________________

Total_Amt_Chng_Q4_Q1 >> number of uniques: 1158, showing top 50 values
Top 50 Values:
[1.335 1.541 2.594 1.405 2.175 1.376 1.975 2.204 3.355 1.524 0.831 1.433
 3.397 1.163 1.19  1.707 1.708 0.653 1.831 0.966 0.906 1.047 1.608 0.573
 1.075 0.797 0.921 0.843 0.525 0.739 0.977 1.323 1.726 1.75  0.519 0.51
 1.724 0.865 1.32  1.052 1.042 0.803 1.449 1.214 1.621 2.316 2.357 0.787
 0.624 1.321]

____________________________________________________________

Total_Trans_Amt >> number of uniques: 5033, showing top 50 values
Top 50 Values:
[1144 1291 1887 1171  816 1088 1330 1538 1350 1441 1201 1314 1539 1311
 1570 1348 1671 1028 1336 1207 1178  692  931 1126 1110 1051 1197 1904
 1052 1045 1038 1596 1589 1411 1407 1877  966 1464  704 1109 1347 1756
 1042 1444 1741 1719 1217 1140 1878  705]

____________________________________________________________

Total_Trans_Ct >> number of uniques: 126, showing top 50 values
Top 50 Values:
[42 33 20 28 24 31 36 32 26 17 29 27 21 30 16 18 23 22 40 38 25 43 37 19
 35 15 41 57 12 14 34 44 13 47 10 39 53 50 52 48 49 45 11 55 46 54 60 51
 63 58]

____________________________________________________________

Total_Ct_Chng_Q4_Q1 >> number of uniques: 830, showing top 50 values
Top 50 Values:
[1.625 3.714 2.333 2.5   0.846 0.722 0.714 1.182 0.882 0.68  1.364 3.25
 2.    0.611 1.7   0.929 1.143 0.909 0.6   1.571 0.353 0.75  0.833 1.3
 1.    0.9   2.571 1.6   1.667 0.483 1.176 1.2   0.556 0.143 0.474 0.917
 1.333 0.588 0.8   1.923 0.25  0.364 1.417 1.083 1.25  0.5   1.154 0.733
 0.667 2.4  ]

____________________________________________________________

Avg_Utilization_Ratio >> number of uniques: 964, showing top 50 values
Top 50 Values:
[0.061 0.105 0.    0.76  0.311 0.066 0.048 0.113 0.144 0.217 0.174 0.195
 0.279 0.23  0.078 0.095 0.788 0.08  0.086 0.152 0.626 0.215 0.093 0.099
 0.285 0.658 0.69  0.282 0.562 0.135 0.544 0.757 0.241 0.077 0.018 0.355
 0.145 0.209 0.793 0.074 0.259 0.591 0.687 0.127 0.667 0.843 0.422 0.156
 0.525 0.587]
```

In [12]:

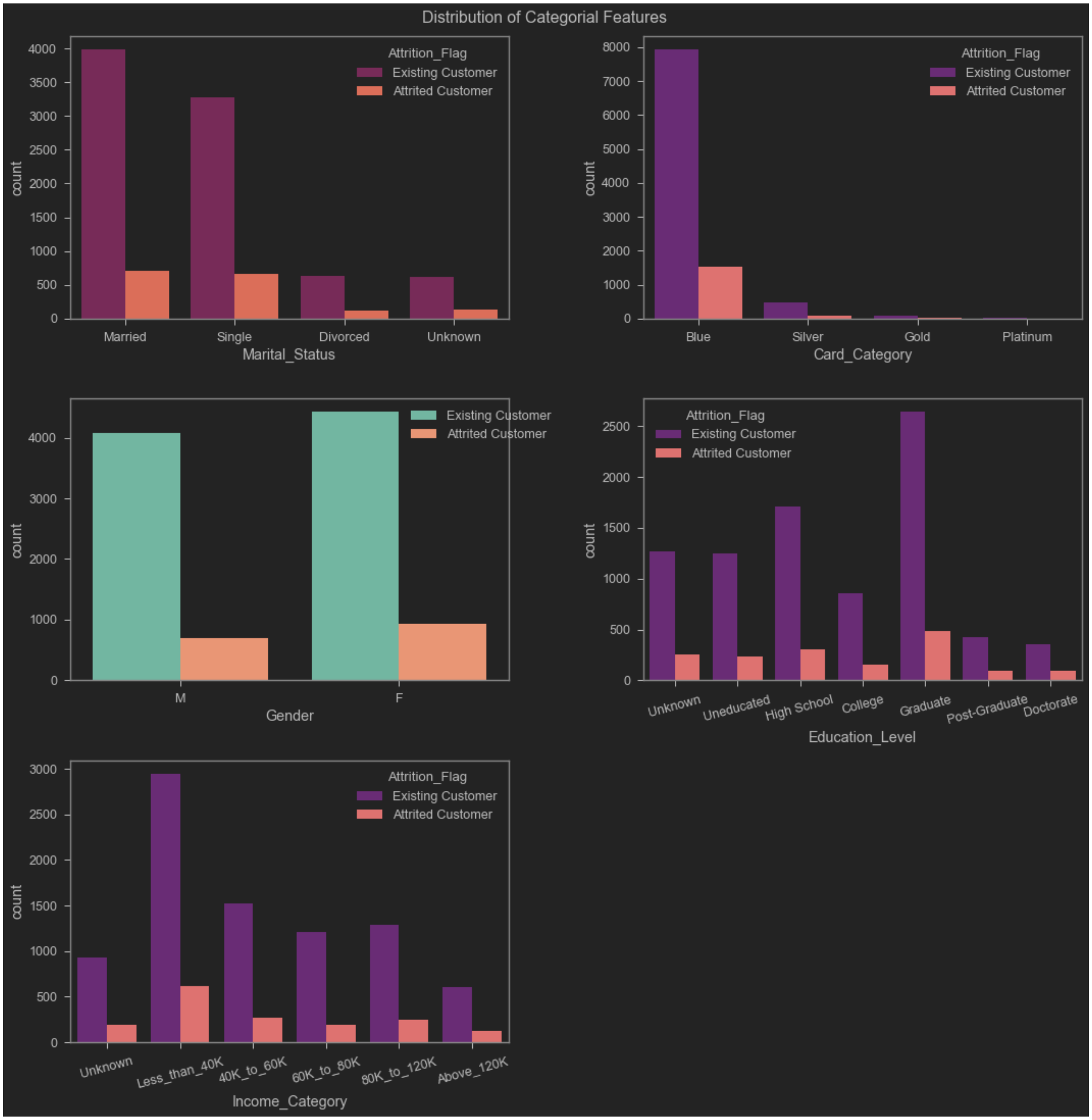
```
with plt.style.context('grayscale'): # seaborn-deep
    plt.pie([
        df.Attrition_Flag[df.Attrition_Flag == 'Existing 
Customer'].count(),
        df.Attrition_Flag[df.Attrition_Flag == 'Attrited 
Customer'].count()
    ],
            labels=['Existing Customer', 'Attrited Customer'],
            colors=['#006a4e', '#b70030'],
            explode=[0.1, 0],
            autopct='%1.2f%%',
            shadow=True,
            startangle=180)
    plt.title("Percentage of Existing and Attrited Customers", size=2(
    plt.axis('equal')
    plt.show()
```



In this dataset, around 16% clients has halted their affiliation with the bank.

In [13]:

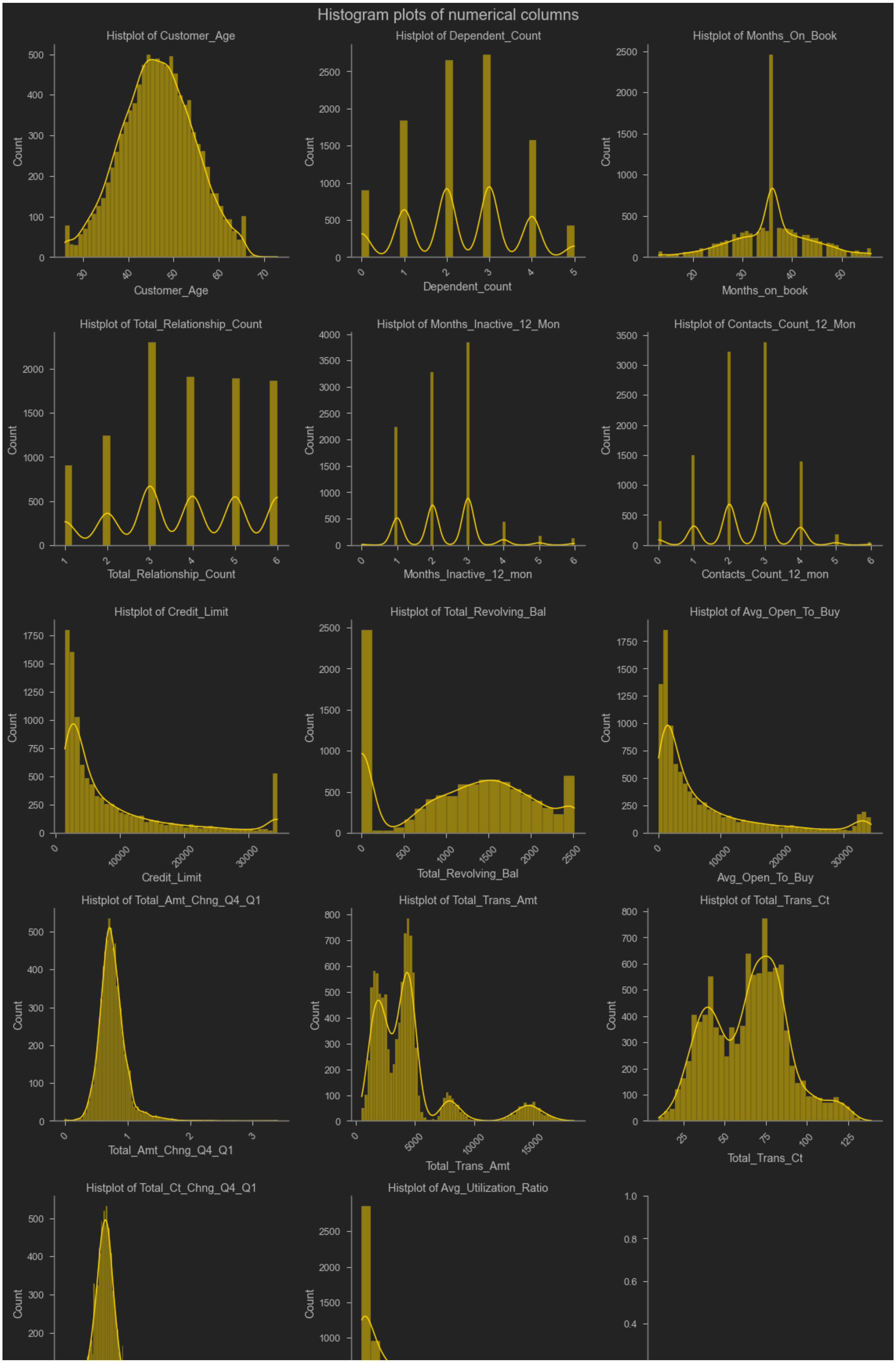
```
plt.figure(figsize=(15, 15))
plt.subplot(3, 2, 1)
sns.countplot(x=df['Marital_Status'],
              hue=df['Attrition_Flag'],
              palette='rocket',
              order=['Married', 'Single', 'Divorced', 'Unknown'])
plt.subplot(3, 2, 2)
sns.countplot(x=df['Card_Category'],
              hue=df['Attrition_Flag'],
              palette='magma',
              order=['Blue', 'Silver', 'Gold', 'Platinum'])
plt.subplot(3, 2, 3)
sns.countplot(x=df['Gender'], hue=df['Attrition_Flag'], palette='Set2'
plt.legend(bbox_to_anchor=(.75, 1))
plt.subplot(3, 2, 4)
sns.countplot(x=df['Education_Level'],
              hue=df['Attrition_Flag'],
              palette='magma',
              order=[
                  'Unknown', 'Uneducated', 'High School', 'College',
                  'Graduate', 'Post-Graduate', 'Doctorate'
              ])
plt.xticks(rotation=15)
plt.subplot(3, 2, 5)
sns.countplot(x=df['Income_Category'],
              hue=df['Attrition_Flag'],
              palette='magma',
              order=[
                  'Unknown', 'Less_than_40K', '40K_to_60K', '60K_to_8(
                  '80K_to_120K', 'Above_120K'
              ])
plt.xticks(rotation=15)
plt.tight_layout()
plt.suptitle(f'Distribution of Categorial Features \n', va='bottom')
plt.show()
```

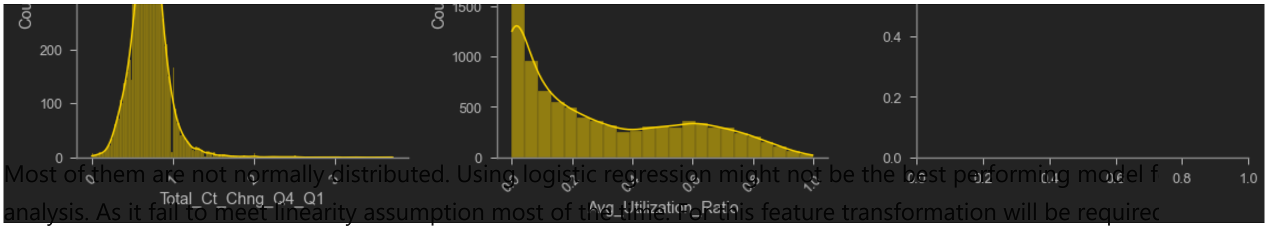


Category	Observation
Marital Status	Being married or single has little impact on them churning
Card Category	Blue category severely out weighs the other card categories
Gender	Slightly more female clients than men, overall almost similar churning possibility
Education Level	Most of the clients of the bank are graduate, given the size of each class, churn rate is very similar
Income Category	Most of the clients earn less than 40K.

In [14]:

```
fn.plot_distribution(df.select_dtypes('number'),
                     plot_title='Histogram plots of numerical columns'
```


Histogram plots of numerical columns
Histplot of Customer_Age
Customer_Age
Histplot of Dependent_Count
Dependent_count
Histplot of Months_On_Book
Months_on_book
Histplot of Total_Relationship_Count
Total_Relationship_Count
Histplot of Months_Inactive_12_Mon
Months_Inactive_12_mon
Histplot of Contacts_Count_12_Mon
Contacts_Count_12_mon
Histplot of Credit_Limit
Credit_Limit
Histplot of Total_Revolving_Bal
Total_Revolving_Bal
Histplot of Avg_Open_To_Buy
Avg_Open_To_Buy
Histplot of Total_Amt_Chng_Q4_Q1
Total_Amt_Chng_Q4_Q1
Histplot of Total_Trans_Amt
Total_Trans_Amt
Histplot of Total_Trans_Ct
Total_Trans_Ct
Histplot of Total_Ct_Chng_Q4_Q1
Histplot of Avg_Utilization_Ratio
Count



Most of them are not normally distributed. Using logistic regression might not be the best performing model f
analysis. As it fail to meet linearity assumption most of the time. For this feature transformation will be requirec

Feature	Observation
Customer Age	Normal distribution for age
Dependent count	ordinal variable ranging one to five
Months on book	Almost normal distribution except a huge spike at 36 moth point and a gap at every 6 month inte
Total Relationship Count	ordinal variable, majority of clients have 3 or more relationship
Months_Inactive_12_mon	most customers don't stay inactive more than 3 months
Contacts_Count_12_mon	ordinal variable, most values in 2 and 3
Credit Limit	Almost log normal distribution, maximum credit limit offered is 35k.
Total Revolving Bal	ignoring a spike of 0, this distribution has almost normal distribution, with a fat tail at the right e
Avg Open To Buy	log normal distribution
Total_Amt_Chng_Q4_Q1	normal distribution with skinny ling tail towards right
Total Trans Amt	seems like there are four normal distribution here, this can be a strong deciding feature for use segmentation
Total Trans Ct	normal distribution with skinny ling tail towards right
Total_Ct_Chng_Q4_Q1	good distribution but far from being normal distribution
Avg Utilization Ratio	Log normal distribution, a very few people are using their total credit limit. This expected as very people does so.

In [15]:

```
print(f'Minimum customer age: {df.Customer_Age.unique().min()}')
print(f'Maximum customer age: {df.Customer_Age.unique().max()}')
```

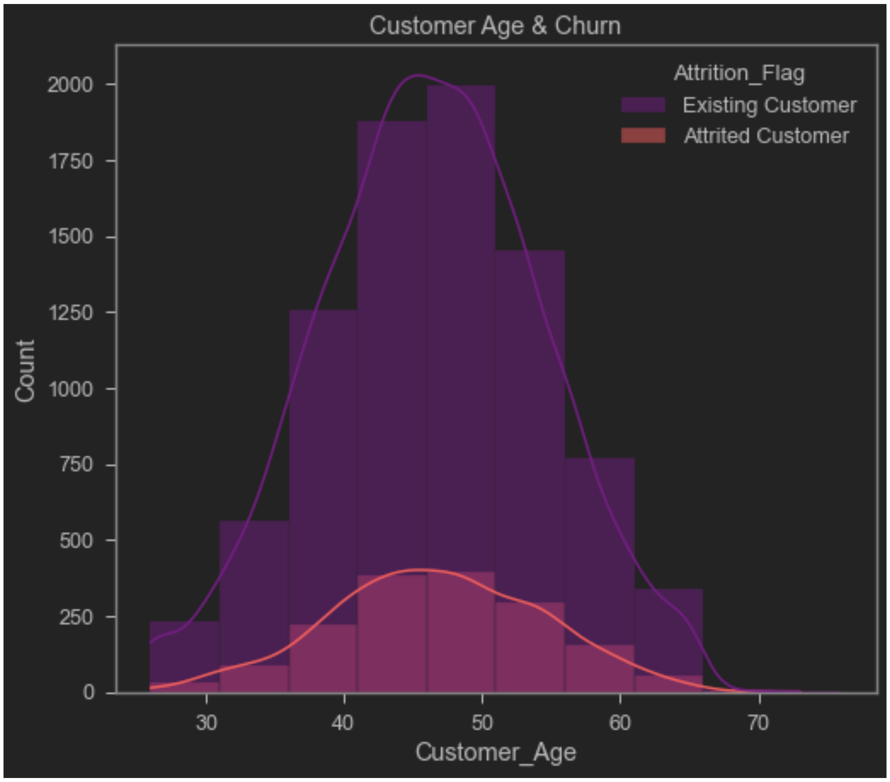
```
Minimum customer age: 26
Maximum customer age: 73
```

In [16]:

```
# pairweise eda
```

In [17]:

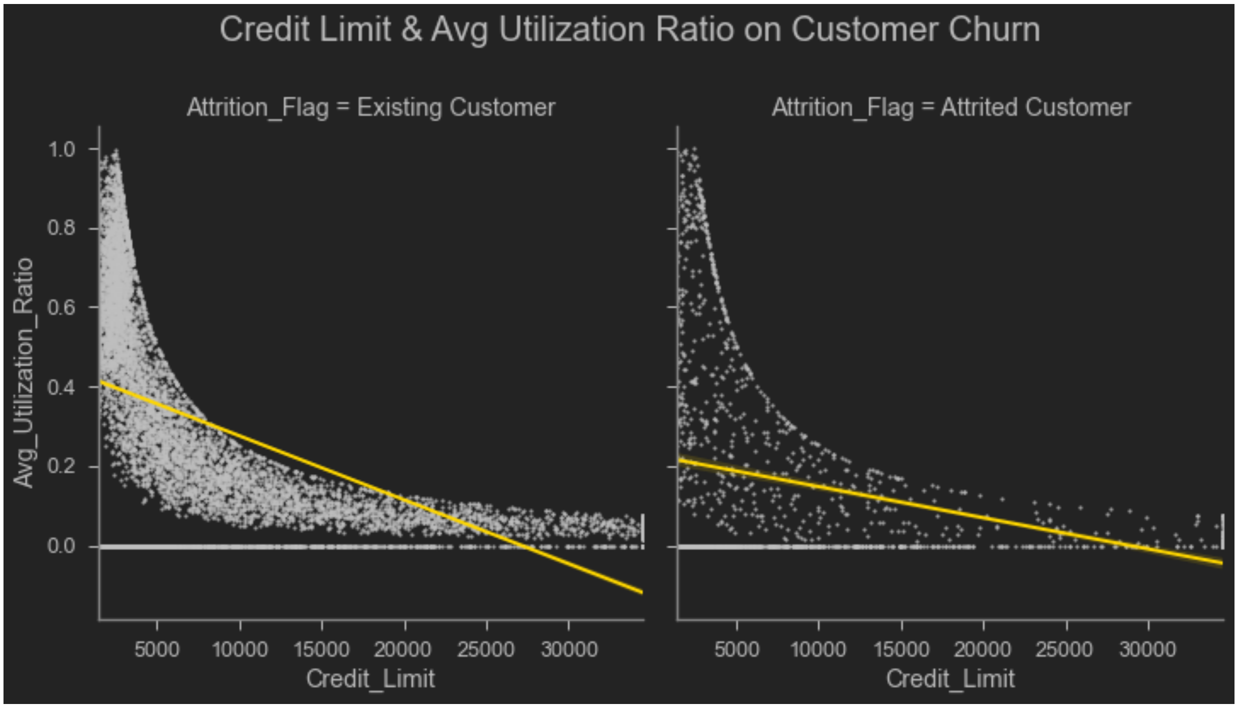
```
sns.histplot(x=df.Customer_Age,
             hue=df.Attrition_Flag,
             kde=True,
             binwidth=5,
             palette='magma')
plt.title('Customer Age & Churn')
plt.show()
```



There is no clear pattern spotted. Every client age group is similarly likely to churn.

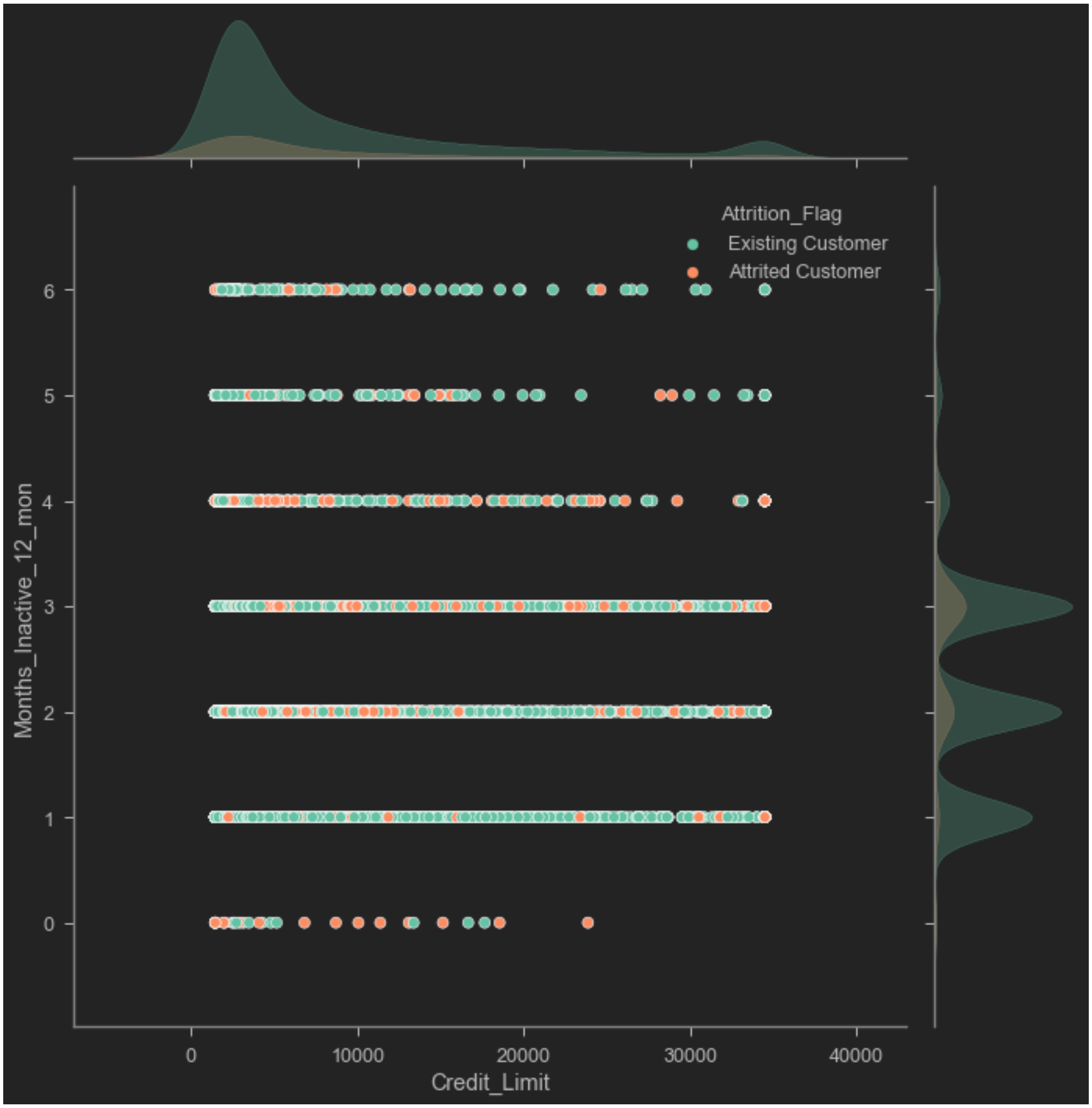
In [18]:

```
sns.lmplot(x='Credit_Limit',
           y='Avg_Utilization_Ratio',
           data=df,
           col='Attrition_Flag',
           palette='Set2',
           scatter_kws={
               "s": 5,
               "color": 'silver'
           },
           line_kws={
               'lw': 2,
               'color': 'gold'
           })
plt.suptitle('Credit Limit & Avg Utilization Ratio on Customer Churn \
             va='bottom',
             fontsize=20)
plt.show()
```



Clients with lower credit limit utilization ratio is more likely to churn. They have a less steep regression line. Als
Clients with lower credit limit with high utilization has more risk of churning.

In [19]:
```
g = sns.jointplot(data=df,
                  x='Credit_Limit',
                  y='Months_Inactive_12_mon',
                  hue='Attrition_Flag',
                  palette='Set2',
                  height=10)
```



Clients inactive for 3 to 4 month has a higher risk of churning.

SCRUB

In [20]:

```
(df.Attrition_Flag.value_counts(1)*100).round(2)
```

Out[20]:

```
Existing Customer    83.93
Attrited Customer    16.07
Name: Attrition_Flag, dtype: float64
```

As spotted before, class imbalance in the target column will be addressed by synthetic oversampling later in th section.

Label encoding

In [22]:

```
X = df.drop(columns='Attrition_Flag').copy()
y = df.Attrition_Flag.map(churn_map).copy()
```

Train-Test split

In [23]:

```
X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=.
```

Encoding & Scaling

Pipeline

In [24]:

```
# isolating numerical cols
nume_col = list(X.select_dtypes('number').columns)
# isolating categorical cols
cate_col = list(X.select_dtypes('object').columns)
# pipeline for processing categorical features
pipe_cate = Pipeline([('ohe', OneHotEncoder(sparse=False, drop=None))]
# pipeline for processing numerical features
pipe_nume = Pipeline([('scaler', StandardScaler())])
# transformer
preprocessor = ColumnTransformer([('nume_feat', pipe_nume, nume_col),
                                  ('cate_feat', pipe_cate, cate_col)])
# creating dataframes
# X_train
X_train_pr = pd.DataFrame(preprocessor.fit_transform(X_train),
                          columns=nume_col +

list(preprocessor.named_transformers_['cate_feat'].

named_steps['ohe'].get_feature_names(cate_col)))
# X_test
X_test_pr = pd.DataFrame(preprocessor.transform(X_test),
                         columns=nume_col +

list(preprocessor.named_transformers_['cate_feat'].

named_steps['ohe'].get_feature_names(cate_col)))
```

In [25]:

```
# # preprocessor, nume_col, cate_col are saved for later use
# joblib.dump(preprocessor, filename='./model/preprocessor.joblib',
compress=9)
# joblib.dump(nume_col, filename='./model/nume_col.joblib', compress=9
# joblib.dump(cate_col, filename='./model/cate_col.joblib', compress=9
```

SMOTENC

In [26]:

```
# yvalue count
y_train_value_counts = pd.DataFrame([y_train.value_counts(),
round(y_train.value_counts(1),2)]).T
y_train_value_counts.columns = ['Attrition_Flag_count',
'Attrition_Flag_%']
y_train_value_counts
```

Out[26]:

	Attrition_Flag_count	Attrition_Flag_%
0	6783.0	0.84
1	1318.0	0.16

In [27]:

```
# peeking into train independent variables
X_train_pr
```

Out[27]:

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	Cc
0	-1.413331	-0.274533	-2.608861	0.118180	-0.333760	
1	1.205726	-1.048364	0.753948	0.765056	-0.333760	
2	-1.039180	-1.048364	-0.491537	0.118180	-0.333760	
3	-0.415595	2.046961	0.255754	-0.528696	0.655552	
4	-0.041444	0.499298	0.006657	0.765056	-0.333760	
...	...	...	...	...	...	
8096	0.831575	-1.048364	-0.117891	0.118180	0.655552	
8097	-0.166161	0.499298	0.006657	0.118180	1.644864	
8098	-0.290878	0.499298	0.006657	-1.822448	-1.323072	
8099	2.328179	-1.822196	1.750336	-0.528696	1.644864	
8100	-1.912199	-1.822196	-2.235216	-0.528696	-0.333760	

8101 rows × 37 columns

In [28]:

```
smotenc features = [False] * len(nume col) + [True] * (
```

In [30]:
```
X_train_pr_os, y_train_encoded_os = oversampling.fit_sample(
                                                        X_train_pr,
y_train)
```

In [31]:
```
# oversampled y_train
y_train_value_counts = pd.DataFrame([y_train_encoded_os.value_counts()
round(y_train_encoded_os.value_counts(1),2)]).T
y_train_value_counts.columns = ['Attrition_Flag_count',
'Attrition_Flag_%']
y_train_value_counts
```

Out[31]:

	Attrition_Flag_count	Attrition_Flag_%
0	6783.0	0.5
1	6783.0	0.5

In [32]:
```
# oversampled X_train
X_train_pr_os
```

Out[32]:

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	C
0	-1.413331	-0.274533	-2.608861	0.118180	-0.333760	
1	1.205726	-1.048364	0.753948	0.765056	-0.333760	
2	-1.039180	-1.048364	-0.491537	0.118180	-0.333760	
3	-0.415595	2.046961	0.255754	-0.528696	0.655552	
4	-0.041444	0.499298	0.006657	0.765056	-0.333760	
...	...	...	...	...	...	
13561	0.852873	0.499298	1.380746	-0.618097	1.508136	
13562	1.470704	-1.651038	0.740757	0.621978	0.436734	
13563	0.058571	-0.223444	0.098315	-1.175572	0.655552	
13564	-0.637032	-0.274533	-0.450868	-1.822448	0.655552	
13565	0.291227	-0.102666	0.006657	-0.528696	-0.553485	

13566 rows × 37 columns

Oversampled to have around 13K samples for training prediction model.

MODEL

Client Segmentation

Performance is mostly indifferent, following is the data preparation steps for segmentation model.

In [33]:
```
# # First Approach
# # lable Encoding
# Education_Level_map = {
#     'High School': 2,
#     'Graduate': 4,
#     'Uneducated': 0,
#     'Unknown': 1,
#     'College': 3,
#     'Post-Graduate': 5,
#     'Doctorate': 6
# }
# Income_Category_map = {
#     '60K_to_80K': 3,
#     'Less_than_40K': 1,
#     '80K_to_120K': 4,
#     '40K_to_60K': 3,
#     'Above_120K': 5,
#     'Unknown': 0
# }
# Card_Category_map = {'Blue': 0, 'Gold': 2, 'Silver': 1, 'Platinum':

# # OHE
# Marital_Status_map = {'Married': 2, 'Single': 1, 'Unknown': 0,
'Divorced': 3}
# Gender_map = {'M': 1, 'F': 0}

# X.Education_Level = X.Education_Level.map(Education_Level_map)
# X.Income_Category = X.Income_Category.map(Income_Category_map)
# X.Card_Category = X.Card_Category.map(Card_Category_map)

# X.Marital_Status = X.Marital_Status.map(Marital_Status_map)
# X.Gender = X.Gender.map(Gender_map)
# display("X",X)

# seg_scaler = StandardScaler()
```

In [34]:
```python
# # Second Approach: trying diffrent scalers and one-hot-encoding
# # check doctsring for details
# X_segmentation = fn.dataset_processor_segmentation(X, verbose=2)
```

In [35]:
```python
X_segmentation = pd.DataFrame(preprocessor.transform(X),
                              columns=nume_col +

list(preprocessor.named_transformers_['cate_feat'].

named_steps['ohe'].get_feature_names(cate_col)))
X_segmentation
```

Out[35]:

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	C
0	-0.166161	0.499298	0.380303	0.765056	-1.323072	
1	0.332707	2.046961	1.003045	1.411932	-1.323072	
2	0.582141	0.499298	0.006657	0.118180	-1.323072	
3	-0.789746	1.273130	-0.242440	-0.528696	1.644864	
4	-0.789746	0.499298	-1.861570	0.765056	-1.323072	
...	...	...	...	...	...	
10122	0.457424	-0.274533	0.504851	-0.528696	-0.333760	
10123	-0.665029	-0.274533	-1.363376	0.118180	-0.333760	
10124	-0.290878	-1.048364	0.006657	0.765056	0.655552	
10125	-2.036916	-0.274533	0.006657	0.118180	0.655552	
10126	-0.415595	-0.274533	-1.363376	1.411932	-0.333760	

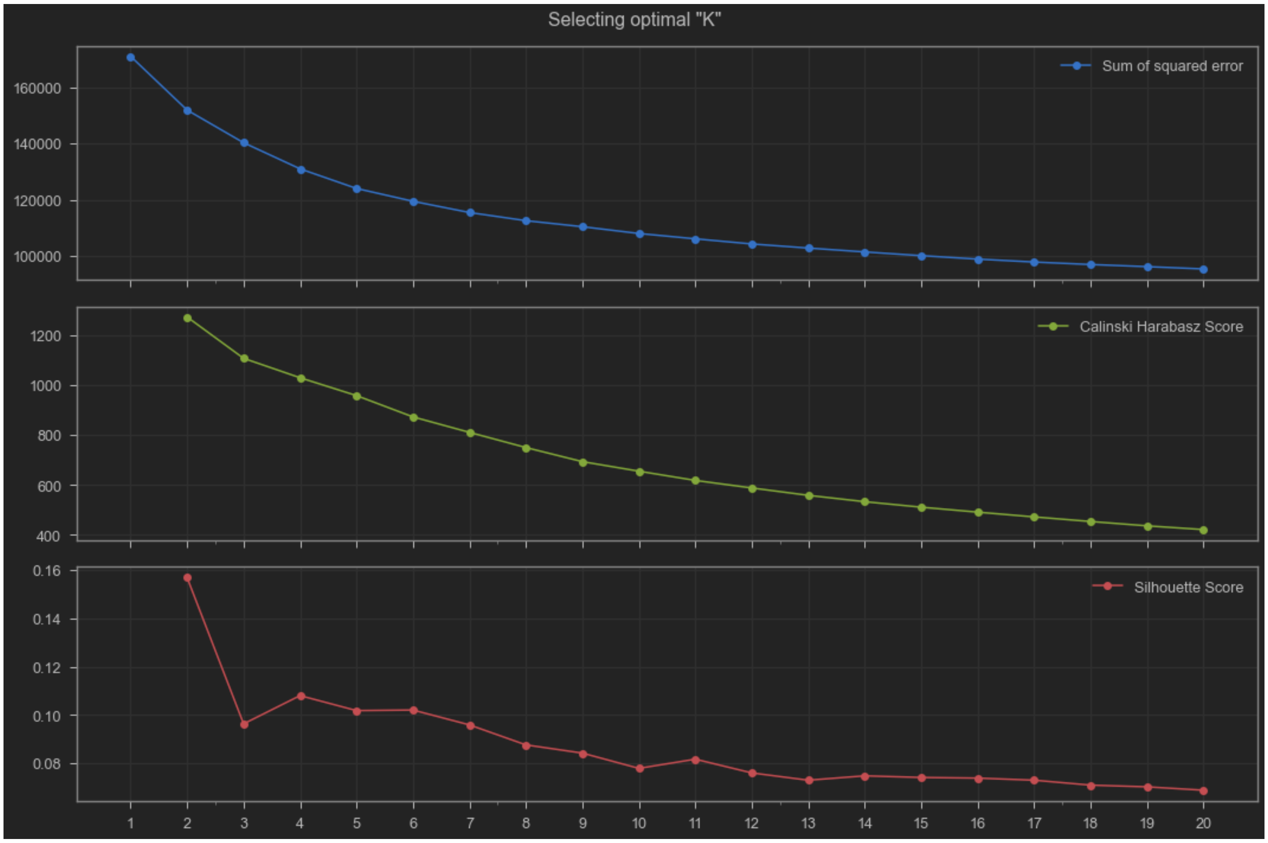
10127 rows × 37 columns

Finding "K"

Several k-means models were used to deduce optimal number of segmentation. Number of cluster size used ra
from 1 to 20.

In [36]:

```
search_range = range(1, 21)
report = {}
for k in search_range:
    temp_dict = {}
    kmeans = KMeans(init='k-means++',
                    algorithm='auto',
                    n_clusters=k,
                    max_iter=1000,
                    random_state=1,
                    verbose=0).fit(X_segmentation)
    inertia = kmeans.inertia_
    temp_dict['Sum of squared error'] = inertia
    try:
        cluster = kmeans.predict(X_segmentation)
        chs = metrics.calinski_harabasz_score(X_segmentation, cluster)
        ss = metrics.silhouette_score(X_segmentation, cluster)
        temp_dict['Calinski Harabasz Score'] = chs
        temp_dict['Silhouette Score'] = ss
        report[k] = temp_dict
    except:
        report[k] = temp_dict

report_df = pd.DataFrame(report).T
report_df.plot(figsize=(15, 10),
               xticks=search_range,
               grid=True,
               title=f'Selecting optimal "K"',
               subplots=True,
               marker='o',
               sharex=True)
plt.tight_layout()
```



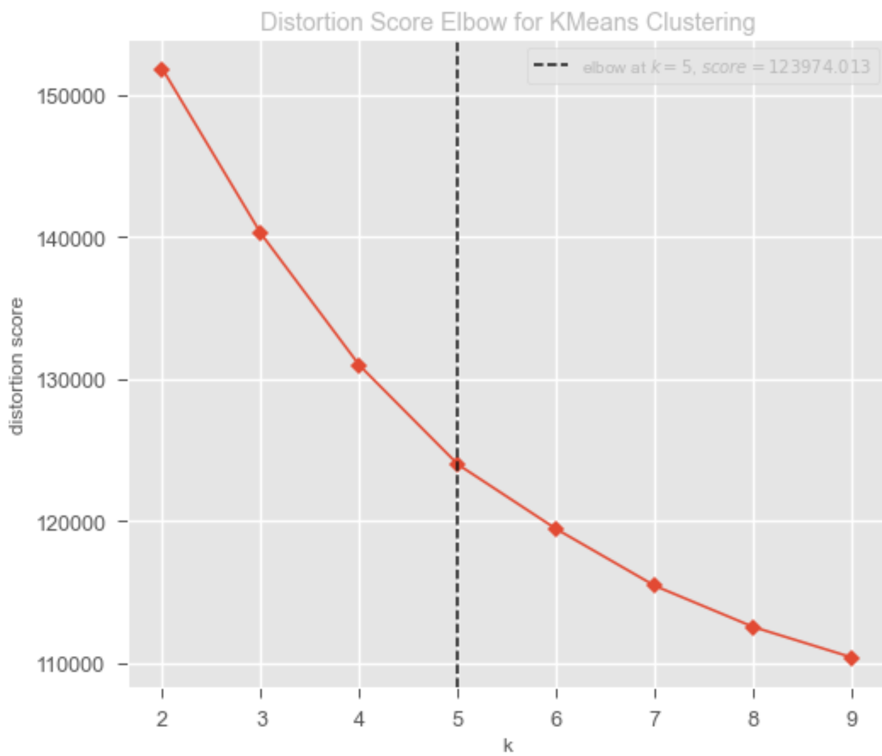
Higher Silhouette Coefficient score relates to a model with better defined clusters. And higher Calinski-Harabas score relates to a model with better defined clusters.

Although by looking at the visual no obvious optimal K can not be spotted. Based on the `Silhouette Sco` and `Sum of squared error` (a.k.a. Elbow plot), 5 segmentation seemed optimal for initial model. `Cali Harabasz Score` also supports this segmentation.

Customers are segmented by 5 groups by their characteristics.

In [37]:

```
# using yellowbrick to get an idea about the choice of K=5
with plt.style.context('ggplot'):
    kelbow_visualizer(KMeans(random_state=1),
                      X_segmentation,
                      k=(2, 10),
                      timings=False)
```



Among models run for K from a range of 2 to 10, 5 is recommended by yellowbrick package.

In [38]:

```
# using MeanShift to get an estimate
bandwidth = estimate_bandwidth(X_segmentation, quantile=0.3, n_jobs=-1
ms = MeanShift(bandwidth=bandwidth, bin_seeding=False, n_jobs=-1,
max_iter=500)
ms.fit(X_segmentation)
labels = ms.labels_
cluster_centers = ms.cluster_centers_
labels_unique = np.unique(labels)
n_clusters_ = len(labels_unique)
print(f"Number of estimated clusters : {n_clusters_}")
```

```
Number of estimated clusters : 5
```

Mean shift clustering aims to discover "blobs" in a smooth density of samples. It is a centroid-based algorithm, works by updating candidates for centroids to be the mean of the points within a given region. These candidat then filtered in a post-processing stage to eliminate near-duplicates to form the final set of centroids. (From sc learn documentation)

Suggestion of MeanShift supports the initial choice of K=5.

Selecting "K"

In [39]:

```
```

In [40]:
```
kmeans = KMeans(
    init='k-means++',
    algorithm='auto',
    n_clusters=n_clusters,
    max_iter=1000,
    random_state=1,  # selecting random_state=1 for reproducibility
    verbose=0).fit(X_segmentation)
```

In [41]:
```
# using prediction to create a dataframe
clusters = kmeans.predict(X_segmentation)
cluster_df = X_segmentation.copy()
cluster_df['Clusters'] = clusters
cluster_df
```

Out[41]:

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	C
0	-0.166161	0.499298	0.380303	0.765056	-1.323072	
1	0.332707	2.046961	1.003045	1.411932	-1.323072	
2	0.582141	0.499298	0.006657	0.118180	-1.323072	
3	-0.789746	1.273130	-0.242440	-0.528696	1.644864	
4	-0.789746	0.499298	-1.861570	0.765056	-1.323072	
...	...	...	...	...	...	
10122	0.457424	-0.274533	0.504851	-0.528696	-0.333760	
10123	-0.665029	-0.274533	-1.363376	0.118180	-0.333760	
10124	-0.290878	-1.048364	0.006657	0.765056	0.655552	
10125	-2.036916	-0.274533	0.006657	0.118180	0.655552	
10126	-0.415595	-0.274533	-1.363376	1.411932	-0.333760	

10127 rows × 38 columns

In [73]:
```
# # cluster_df is saved for reproducibilty of the analysis insight
# cluster_df = joblib.load('./model/scaled_data.joblib')
```

In [62]:
```
# distribution of classes (%)
(cluster_df.Clusters.value_counts(1)*100).round(2)
```

Out[62]:
```
2    30.23
1    26.83
3    19.75
4    13.55
0     9.65
```

In [63]:

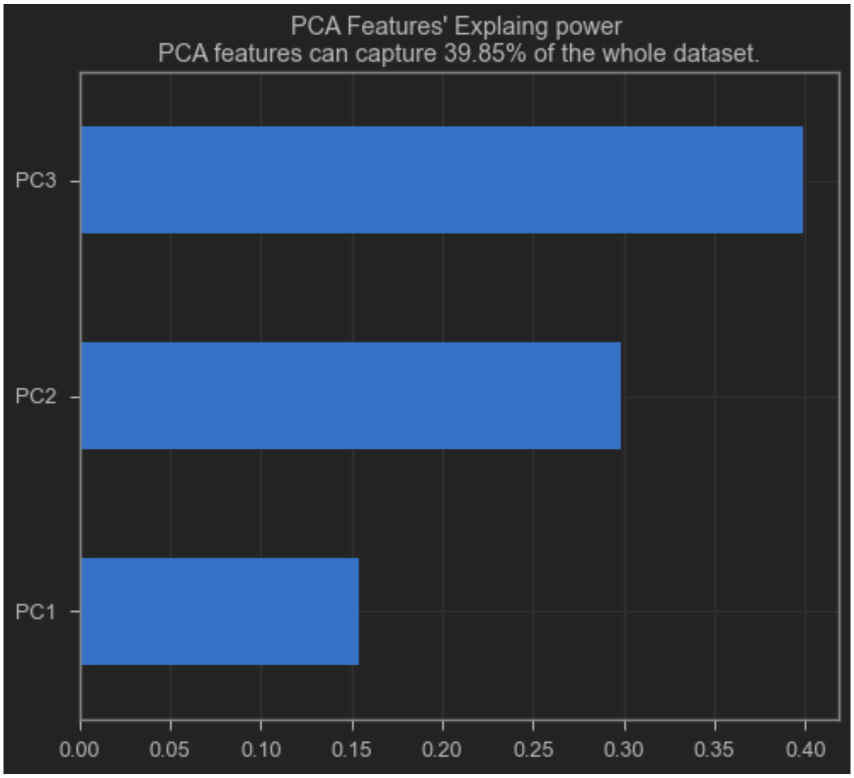
```
@interact(df=fixed(cluster_df),
          x=cluster_df.columns,
          y=cluster_df.columns,
          z=cluster_df.columns)
def plot_segments(df=cluster_df,
                  x='Customer_Age',
                  y='Months_on_book',
                  z='Credit_Limit'):
    df['Clusters'] = df['Clusters'].astype('str')
    fig = px.scatter_3d(
        df,
        x=x,
        y=y,
        z=z,
        title=
        f'{x.replace("_", " ")}, {y.replace("_", " ")} and,
{z.replace("_", " ")} by Clusters',
        color='Clusters',
        template='plotly_dark')
    fig.update_traces(marker=dict(size=2))
    df['Clusters'] = df['Clusters'].astype('int')
    fig.show()
```

Segmentation is not immediately apparent in this visualization. More insights on the segmentation is in the INTERPRET part of this analysis. Using PCA to explore the segmentation.

Using principal component analysis concept for reducing features to visualize the clusters in a three dimension space.

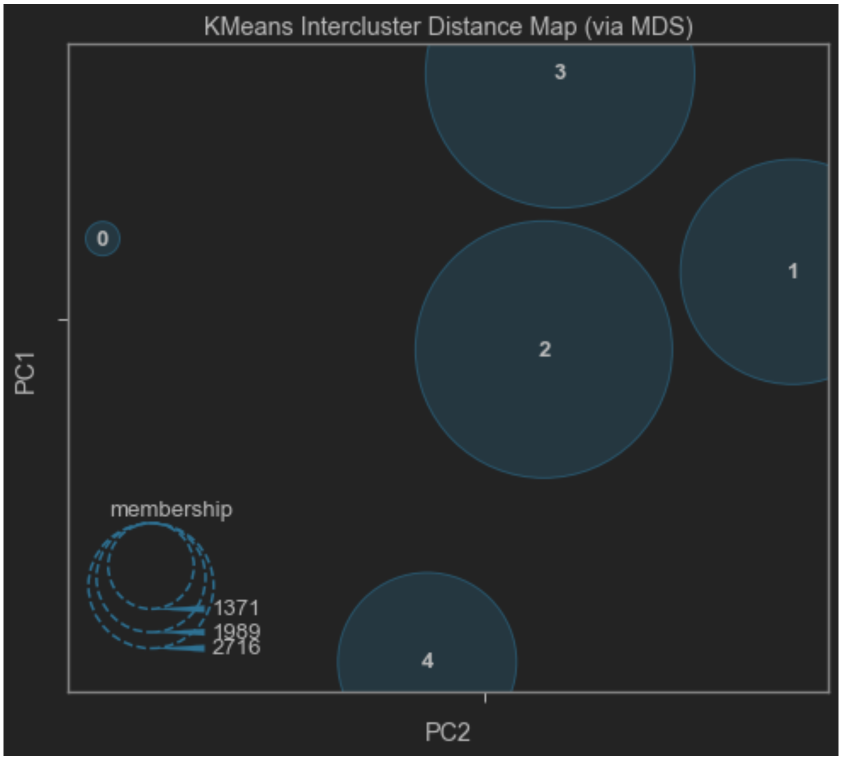
In [64]:

```
pca = PCA(n_components=3)
pc_feature_names = [f"PC{x}" for x in range(1, pca.n_components + 1)]
pca_data = pca.fit_transform(cluster_df)
pca_df = pd.DataFrame(pca_data, columns=pc_feature_names)
pd.Series(pca.explained_variance_ratio_.cumsum(),
index=pc_feature_names).plot(
    kind='barh',
    title=
    f"""PCA Features' Explaing power \nPCA features can capture
{((pca.explained_variance_ratio_.cumsum()[-1])*100).round(2)}% of the
whole dataset."""
)
plt.grid()
plt.show()
pca_df['Clusters'] = clusters.astype('str')
fig = px.scatter_3d(pca_df,
                    x='PC1',
                    y='PC2',
                    z='PC3',
                    color='Clusters',
                    title='Cluster visualization with the help of PCA'
                    template='plotly_dark')
fig.update_traces(marker=dict(size=2))
fig.update_layout(width=700, height=500, bargap=0.05)
fig.show()
```



With only forty percent explainability of the entire dataset by PCA, the clusters exhibit a clear separation betwe them in a three dimensional space. And thre is a clear separation between clusters in a two dimensional space.

In [45]:
```
# Using two PC
intercluster_distance(kmeans, X_segmentation, embedding='mds',
random_state=12); # 'tsne'
```



Clustering Feature importance

Newly created `cluster_df` is used to get the feature importance to get insights which features were often for determining the segmentation. A Random Forest model is used to get feature importance alongside a permutation importance analysis to get the most important features.

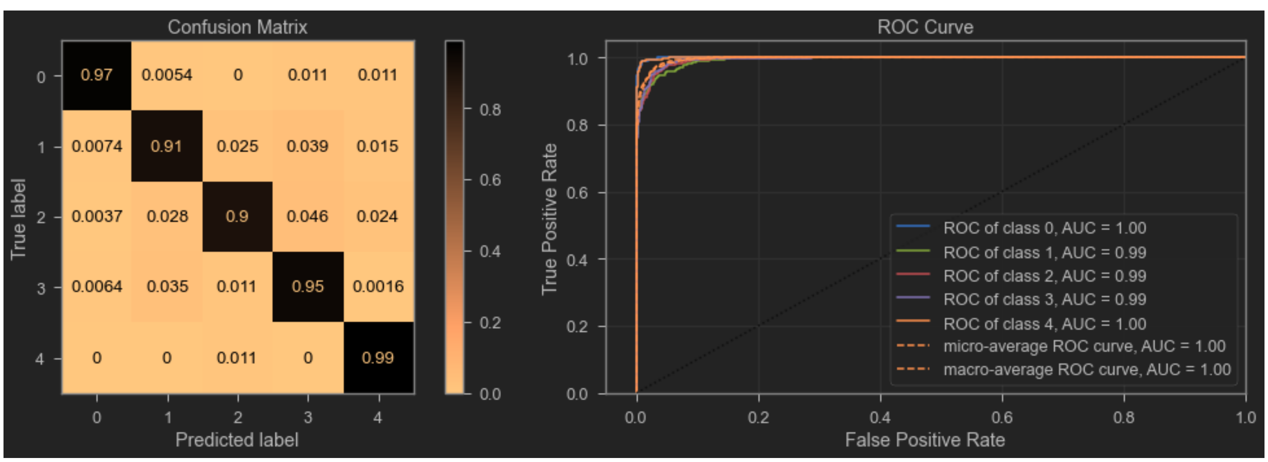
In [46]:
```
X_feat_imp = cluster_df.drop(columns='Clusters').copy()
y_feat_imp = cluster_df.Clusters.copy()
```

In [47]:
```
X_feat_imp_train, X_feat_imp_test, y_feat_imp_train, y_feat_imp_test =
train_test_split(
    X_feat_imp, y_feat_imp, train_size=.8)
```

```
In [48]:
# Random Forest
clf_rf = RandomForestClassifier(
    n_jobs=-1,
    criterion='entropy',
    min_samples_leaf=5,
    min_samples_split=6,
    class_weight='balanced_subsample',
)
fn.model_report_multiclass(clf_rf,
                           X_feat_imp_train,
                           y_feat_imp_train,
                           X_feat_imp_test,
                           y_feat_imp_test,
                           show_train_report=False)
```

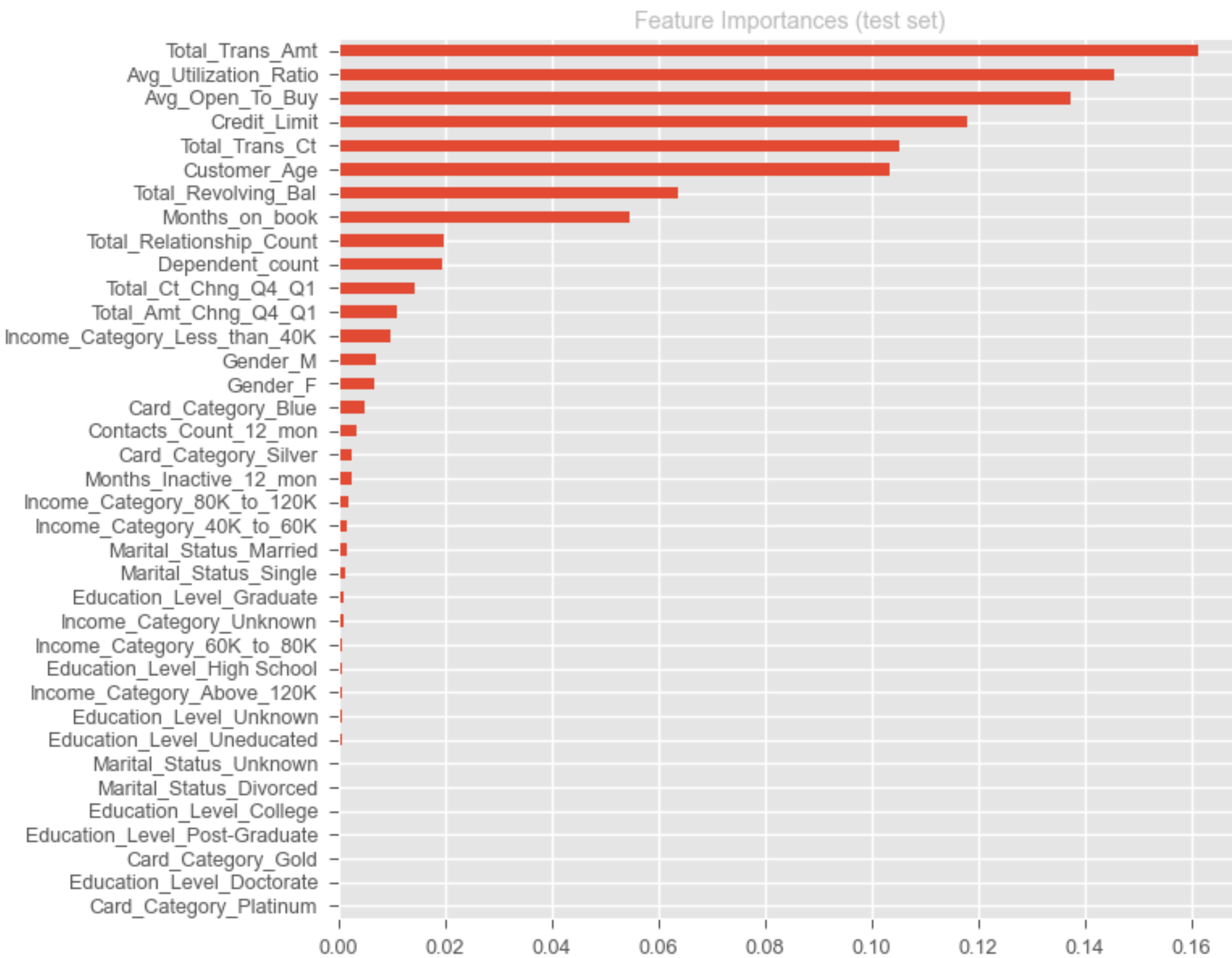
Report of RandomForestClassifier type model using train-test split dataset.

```
*****************************************************************************************
Train accuracy score: 0.9825
Test accuracy score: 0.9348
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*****************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.95      0.97      0.96       185
           1       0.91      0.91      0.91       407
           2       0.96      0.90      0.93       540
           3       0.93      0.95      0.94       621
           4       0.92      0.99      0.96       273

    accuracy                           0.93      2026
   macro avg       0.94      0.94      0.94      2026
weighted avg       0.94      0.93      0.93      2026

************************************************************
```



In [49]:

```
# Feature Importance
with plt.style.context('ggplot'):
    pd.Series(clf_rf.feature_importances_,
          index=X_feat_imp_test.columns).sort_values().plot(kind='barh
                                                            figsize=(10,
10))
    plt.title('Feature Importances (test set)')
```



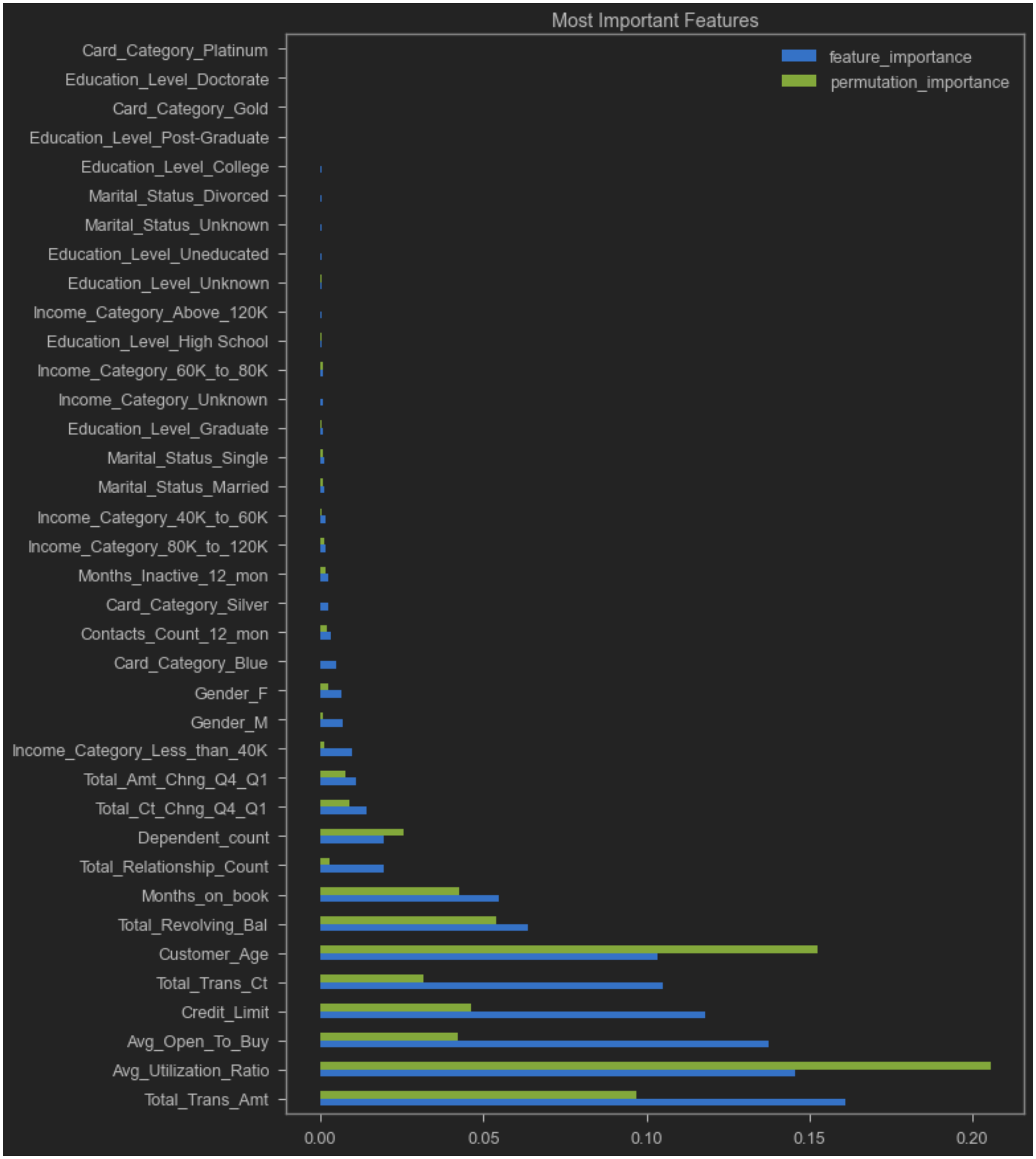
In [50]:

```
# Permutation Feature Importance
result = permutation_importance(clf_rf,
                                X_feat_imp_test,
                                y_feat_imp_test,
                                n_repeats=30,
                                random_state=42,
                                n_jobs=-1)
sorted_idx = result.importances_mean.argsort()
with plt.style.context('ggplot'):
    fig, ax = plt.subplots(figsize=(10, 10))
    ax.boxplot(result.importances[sorted_idx].T,
               notch=True,
               vert=False,
               labels=X_feat_imp_test.columns[sorted_idx])
    ax.set_title("Feature Importances by Permutation (test set)")
    fig.tight_layout()
    plt.show()
```

Feature Importances by Permutation (test set)
Avg_Utilization_Ratio
Customer_Age
Total_Trans_Amt
Total_Revolving_Bal
Credit_Limit
Months_on_book
Avg_Open_To_Buy
Total_Trans_Ct
Dependent_count
Total_Ct_Chng_Q4_Q1
Total_Amt_Chng_Q4_Q1
Total_Relationship_Count
Gender_F
Contacts_Count_12_mon
Months_Inactive_12_mon
Income_Category_80K_to_120K
Income_Category_Less_than_40K
Marital_Status_Single
Income_Category_60K_to_80K
Marital_Status_Married
Gender_M
Education_Level_Unknown
Education_Level_High School
Income_Category_40K_to_60K
Education_Level_Graduate
Income_Category_Above_120K
Income_Category_Unknown
Education_Level_Uneducated
Marital_Status_Unknown
Education_Level_Doctorate
Card_Category_Gold
Card_Category_Platinum
Marital_Status_Divorced
Card_Category_Silver
Education_Level_Post-Graduate
Card_Category_Blue
Education_Level_College
0.00
0.05
0.10
0.15
0.20

In [51]:

```
# fatures from the model
feature_importance = pd.Series(
    clf_rf.feature_importances_,
    index=X_feat_imp_test.columns).sort_values(ascending=False)

permutation_importance = pd.DataFrame(
    result.importances[sorted_idx].T,
    columns=X_feat_imp_test.columns[sorted_idx]).mean().sort_values(
        ascending=False)

important_features = pd.DataFrame([feature_importance,
                                   permutation_importance]).T
important_features.columns = ['feature_importance',
'permutation_importance']
important_features.plot(kind='barh',
                        figsize=(10, 15),
                        title="Most Important Features")
plt.show()
```



By looking at the above chart, these 10 features are selected as the most important features. Those will be expl
the later part of the notebook.

In [52]:

```
top_most_features = list(important_features[:10].index)
top_most_features
```

Out[52]:

```
['Total_Trans_Amt',
 'Avg_Utilization_Ratio',
```

Segmentation Characteristics

In [53]:

```
characteristics_df = X.copy()
characteristics_df['target'] = y.copy()
characteristics_df['Clusters'] = cluster_df.Clusters
characteristics_df
```

Out[53]:

	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Categ
0	45	M	3	High School	Married	60K_to_80K	B
1	49	F	5	Graduate	Single	Less_than_40K	B
2	51	M	3	Graduate	Married	80K_to_120K	B
3	40	F	4	High School	Unknown	Less_than_40K	B
4	40	M	3	Uneducated	Married	60K_to_80K	B
...	...	...	...	...	...	...	
10122	50	M	2	Graduate	Single	40K_to_60K	B
10123	41	M	2	Unknown	Divorced	40K_to_60K	B
10124	44	F	1	High School	Married	Less_than_40K	B
10125	30	M	2	Graduate	Unknown	40K_to_60K	B
10126	43	F	2	Graduate	Married	Less_than_40K	Si

10127 rows × 21 columns

In [66]:

```
# # data is saved and reused
# characteristics_df = joblib.load('./model/unscaled_data.joblib')
```

In [67]:

```python
print(f'Most frequent values in all the clusters: ')
# store data
out_dict = {}
# loop through all clusters
for cluster in range(0, n_clusters):
    # get cluster
    temp_df = characteristics_df.groupby(by='Clusters').get_group(clus
    # store temp data
    temp_dict = {}
    # loop though all columns
    for i in temp_df.columns:
        # get most frequent value and append
        temp_dict[i] = temp_df[i].value_counts().idxmax()
    # store in dict with cluster as key
    out_dict[cluster] = temp_dict
# convert to pandas dataframe
pd.DataFrame(out_dict)
```

```
Most frequent values in all the clusters:
```

Out[67]:

	0	1	2	3	4
Customer_Age	49	46	45	53	50
Gender	M	F	F	F	M
Dependent_count	2	3	3	1	3
Education_Level	Graduate	Graduate	Graduate	Graduate	Graduate
Marital_Status	Married	Married	Married	Married	Single
Income_Category	Less_than_40K	Less_than_40K	Less_than_40K	Less_than_40K	80K_to_120K
Card_Category	Blue	Blue	Blue	Blue	Blue
Months_on_book	36	36	36	36	36
Total_Relationship_Count	2	3	3	3	3
Months_Inactive_12_mon	3	3	3	3	3
Contacts_Count_12_mon	2	3	2	3	2
Credit_Limit	34516.0	1438.3	1438.3	1438.3	34516.0
Total_Revolving_Bal	0	0	2517	0	0
Avg_Open_To_Buy	34516.0	1438.3	463.0	1438.3	34516.0
Total_Amt_Chng_Q4_Q1	0.749	0.699	0.744	0.791	0.791
Total_Trans_Amt	14802	2473	4275	1627	3819
Total_Trans_Ct	99	74	79	69	65

In [68]:

```python
# statistical info of each clusters
cluster_dict = dict(tuple(characteristics_df.groupby('Clusters')))
for i in range(n_clusters):
    print("Cluster " + str(i) + ' description:')
    display(fn.describe_dataframe(eval("cluster_dict[" + str(i) + "]")))
```

```
Cluster 0 description:
```

	count	unique	top	freq	mean	std	min	25%	50%	75
Customer_Age	977.0				45.34	7.64	27.0	41.0	46.0	51.
Gender	977.0	2	M	588						
Dependent_count	977.0				2.34	1.29	0.0	1.0	2.0	3.
Education_Level	977.0	7	Graduate	312						
Marital_Status	977.0	4	Married	439						
Income_Category	977.0	6	Less_than_40K	272						
Card_Category	977.0	4	Blue	778						
Months_on_book	977.0				35.21	7.66	13.0	31.0	36.0	40.
Total_Relationship_Count	977.0				2.18	1.19	1.0	1.0	2.0	3.
Months_Inactive_12_mon	977.0				2.22	0.98	1.0	1.0	2.0	3.
Contacts_Count_12_mon	977.0				2.18	0.95	0.0	1.0	2.0	3.
Credit_Limit	977.0				13507.58	9921.81	2019.0	5282.0	10353.0	18341.
Total_Revolving_Bal	977.0				1402.45	708.53	0.0	1060.0	1481.0	1907.
Avg_Open_To_Buy	977.0				12105.13	9935.95	553.0	3936.0	9027.0	17328.
Total_Amt_Chng_Q4_Q1	977.0				0.78	0.11	0.51	0.7	0.76	0.8
Total_Trans_Amt	977.0				13144.04	2954.38	4957.0	12575.0	14242.0	15124.
Total_Trans_Ct	977.0				106.0	13.03	63.0	97.0	106.0	116.
Total_Ct_Chng_Q4_Q1	977.0				0.73	0.1	0.41	0.66	0.73	0.
Avg_Utilization_Ratio	977.0				0.18	0.17	0.0	0.06	0.13	0.2
target	977.0				0.02	0.13	0.0	0.0	0.0	0.
Clusters	977.0				0.0	0.0	0.0	0.0	0.0	0.

```
Cluster 1 description:
```

	count	unique	top	freq	mean	std	min	25%	50%	75%
Customer_Age	2717.0				44.33	6.61	26.0	40.0	45.0	49.0
Gender	2717.0	2	F	1583						
Dependent_count	2717.0				2.58	1.22	0.0	2.0	3.0	3.0
Education_Level	2717.0	7	Graduate	840						
Marital_Status	2717.0	4	Married	1207						

	count	unique	top	freq	mean	std	min	25%	50%	75%
Months_Inactive_12_mon	2717.0				2.42	0.98	0.0	2.0	2.0	3.0
Contacts_Count_12_mon	2717.0				2.62	1.12	0.0	2.0	3.0	3.0
Credit_Limit	2717.0				5804.87	4223.77	1438.3	2054.0	4532.0	8621.0
Total_Revolving_Bal	2717.0				310.39	496.68	0.0	0.0	0.0	672.0
Avg_Open_To_Buy	2717.0				5494.48	4069.77	552.3	1950.0	4263.0	8017.0
Total_Amt_Chng_Q4_Q1	2717.0				0.71	0.19	0.0	0.59	0.71	0.82
Total_Trans_Amt	2717.0				3391.27	1616.66	510.0	2131.0	3350.0	4447.0
Total_Trans_Ct	2717.0				59.18	19.36	10.0	42.0	62.0	75.0
Total_Ct_Chng_Q4_Q1	2717.0				0.65	0.21	0.0	0.51	0.65	0.78
Avg_Utilization_Ratio	2717.0				0.05	0.09	0.0	0.0	0.0	0.09
target	2717.0				0.33	0.47	0.0	0.0	0.0	1.0

```
Cluster 2 description:
```

	count	unique	top	freq	mean	std	min	25%	50%	75%
Customer_Age	3061.0				42.12	6.26	26.0	38.0	43.0	47.0
Gender	3061.0	2	F	2090						
Dependent_count	3061.0				2.65	1.25	0.0	2.0	3.0	4.0
Education_Level	3061.0	7	Graduate	961						
Marital_Status	3061.0	4	Married	1412						
Income_Category	3061.0	6	Less_than_40K	1495						
Card_Category	3061.0	3	Blue	3039						
Months_on_book	3061.0				31.99	6.51	13.0	28.0	34.0	36.0
Total_Relationship_Count	3061.0				4.0	1.49	1.0	3.0	4.0	5.0
Months_Inactive_12_mon	3061.0				2.28	1.01	0.0	2.0	2.0	3.0
Contacts_Count_12_mon	3061.0				2.34	1.08	0.0	2.0	2.0	3.0
Credit_Limit	3061.0				3860.53	2568.21	1438.3	2289.0	2900.0	4502.0
Total_Revolving_Bal	3061.0				1680.51	503.87	0.0	1305.0	1662.0	2053.0
Avg_Open_To_Buy	3061.0				2180.02	2447.88	3.0	694.0	1102.0	2736.0
Total_Amt_Chng_Q4_Q1	3061.0				0.8	0.23	0.0	0.66	0.76	0.89
Total_Trans_Amt	3061.0				3709.21	1479.44	643.0	2441.0	4074.0	4625.0
Total_Trans_Ct	3061.0				64.95	18.42	12.0	51.0	69.0	79.0
Total_Ct_Chng_Q4_Q1	3061.0				0.76	0.25	0.0	0.63	0.74	0.86
Avg_Utilization_Ratio	3061.0				0.54	0.21	0.0	0.36	0.56	0.7
target	3061.0				0.08	0.27	0.0	0.0	0.0	0.0
Clusters	3061.0				2.0	0.0	2.0	2.0	2.0	2.0

```
Cluster 3 description:
```

	count	unique	top	freq	mean	std	min	25%	50%	75%

	count	unique	top	freq	mean	std	min	25%	50%	75%
Marital_Status	2000.0	4	Married	1072						
Income_Category	2000.0	6	Less_than_40K	781						
Card_Category	2000.0	3	Blue	1969						
Months_on_book	2000.0				44.59	6.08	30.0	40.0	45.0	49.0
Total_Relationship_Count	2000.0				4.17	1.43	1.0	3.0	4.0	5.0
Months_Inactive_12_mon	2000.0				2.41	1.08	0.0	2.0	2.0	3.0
Contacts_Count_12_mon	2000.0				2.48	1.11	0.0	2.0	3.0	3.0
Credit_Limit	2000.0				5120.82	3763.12	1438.3	2422.5	3517.5	6909.25
Total_Revolving_Bal	2000.0				1391.41	697.38	0.0	975.0	1456.5	1892.0
Avg_Open_To_Buy	2000.0				3729.41	3725.14	10.0	962.0	2160.0	5471.25
Total_Amt_Chng_Q4_Q1	2000.0				0.76	0.25	0.0	0.61	0.73	0.86
Total_Trans_Amt	2000.0				3108.56	1588.81	530.0	1618.75	3075.0	4363.75
Total_Trans_Ct	2000.0				55.96	20.74	10.0	37.0	58.0	74.0
Total_Ct_Chng_Q4_Q1	2000.0				0.71	0.26	0.0	0.56	0.69	0.83
Avg_Utilization_Ratio	2000.0				0.38	0.26	0.0	0.17	0.35	0.59
target	2000.0				0.13	0.34	0.0	0.0	0.0	0.0

```
Cluster 4 description:
```

	count	unique	top	freq	mean	std	min	25%	50%	7
Customer_Age	1372.0				46.34	6.6	26.0	42.0	46.0	5
Gender	1372.0	2	M	1231						
Dependent_count	1372.0				2.58	1.22	0.0	2.0	3.0	
Education_Level	1372.0	7	Graduate	399						
Marital_Status	1372.0	4	Single	565						
Income_Category	1372.0	6	80K_to_120K	569						
Card_Category	1372.0	4	Blue	1004						
Months_on_book	1372.0				35.96	6.72	13.0	32.0	36.0	3
Total_Relationship_Count	1372.0				3.93	1.52	1.0	3.0	4.0	
Months_Inactive_12_mon	1372.0				2.31	0.97	0.0	2.0	2.0	
Contacts_Count_12_mon	1372.0				2.54	1.15	0.0	2.0	3.0	
Credit_Limit	1372.0				26522.13	6887.51	12691.0	20229.75	26158.0	3451
Total_Revolving_Bal	1372.0				1192.01	792.14	0.0	653.5	1291.0	175
Avg_Open_To_Buy	1372.0				25330.12	6965.65	10848.0	19084.0	25086.0	3260
Total_Amt_Chng_Q4_Q1	1372.0				0.76	0.24	0.0	0.62	0.74	0
Total_Trans_Amt	1372.0				3624.9	2162.81	597.0	1809.0	3420.0	4367
Total_Trans_Ct	1372.0				59.58	20.18	10.0	43.0	62.0	7

intra cluster EDA

Exploration of clusters with an interactive plot.

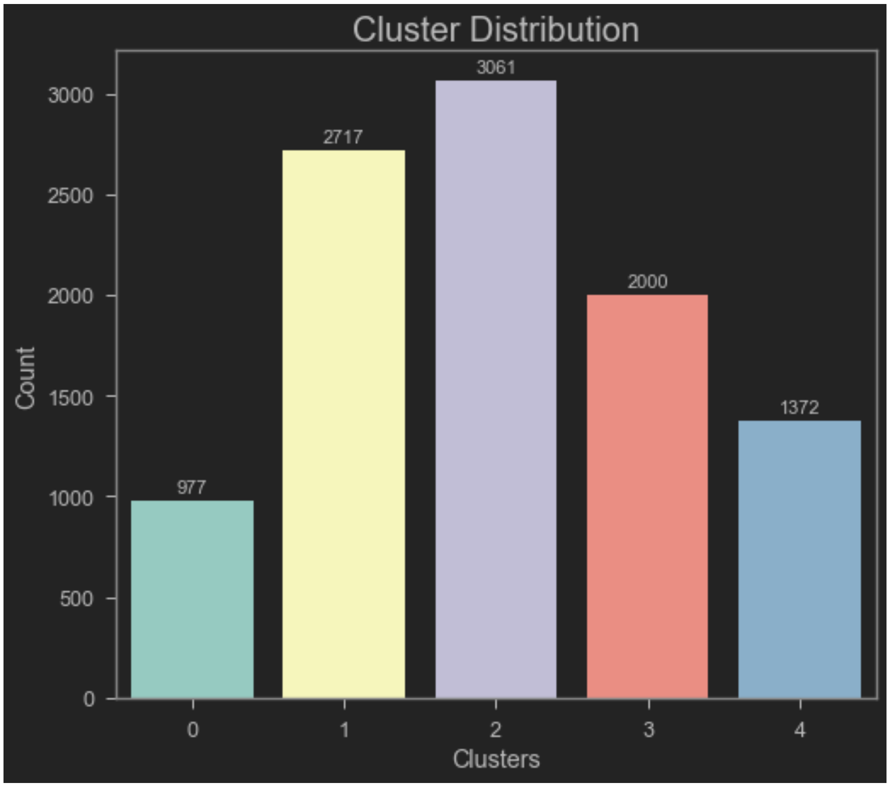
In [69]:
```
@interact(Cluster=cluster_dict.keys())
def show_clusters(Cluster):
    fn.cluster_insights(cluster_dict[Cluster])
```

inter cluster EDA

Exploring features among clusters based on the insights from the feature importance from the previous part of analysis. Only the most important features decided at the previous part are explored.

Cluster Distribution

In [70]:
```
plot_data = characteristics_df.groupby(
    'Clusters').count()
['target'].sort_index(ascending=False).reset_index()
plots = sns.barplot(y='target',
                    x='Clusters',
                    data=plot_data,
                    orient='v',
                    palette='Set3')
for bar in plots.patches:
    plots.annotate(format(bar.get_height(), '.0f'),
                   (bar.get_x() + bar.get_width() / 2, bar.get_height
                   ha='center',
                   va='center',
                   size=11,
                   xytext=(0, 8),
                   textcoords='offset points')
plt.ylabel("Count")
plt.title("Cluster Distribution", size=20)
plt.show()
```



Cluster 0 has the lowest member. Cluster 1 and 2 are fairly similar sized. Cluster 3 and 4 have moderate membe

In [71]:

```
plot_data = characteristics_df.groupby(['Clusters', 'target'
                                         ]).count()['Gender'].reset_inc
plot_data['target'] = plot_data['target'].map({
    0: 'Existing Customer',
    1: 'Attrited Customer'
})
plot_data['Clusters'] = plot_data['Clusters'].astype('str')
fig = px.bar(plot_data,
             x='target',
             y='Gender',
             color='Clusters',
             template='presentation',
             barmode='group',
             text='Gender',
             color_discrete_sequence=[
                 '#E0BBE4', '#957DAD', '#D291BC', '#FEC8D8', '#FFDFD3'
             ],
             title='Cluster Size by Chruning')
fig.update_xaxes(showline=True,
                 linewidth=2,
                 linecolor='black',
                 mirror=True,
                 title={'text': ''})
fig.update_yaxes(showline=True, linewidth=2, linecolor='black',
mirror=True, title={'text': 'Counts'})
fig.show()
```

Customer Age

In [76]:
```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
                                       x='Customer_Age',
                                       facet_col='Clusters',
                                       n_clusters=n_clusters,
                                       nbins=10)
fig.update_xaxes(tickmode='linear', tick0=20, dtick=10)
```

Cluster 4 and 1 has similar distribution. Cluster 0 is younger. Cluster 3 is distinct as it is mostly comprised of olc clients. Others have similar distribution.

Credit Limit

In [60]:

```
fig = fn.feature_analysis_intracluster(
    data_frame=characteristics_df,
    x='Credit_Limit',
    facet_col='Clusters',
    n_clusters=n_clusters,
    color_discrete_sequence=px.colors.qualitative.Dark2,
    nbins=25)
fig.show()
```

- Cluster 0 has a well balanced distribution, it does not have lower credit limit clients.
- Cluster 1 has mostly lower credit limit clients.
- Cluster 2 and 3 has mostly same characteristics.
- Cluster 4 has the clients with mostly high credit limit.

Avg Utilization Ratio

In [61]:
```
fig = fn.feature_analysis_intracluster(
    data_frame=characteristics_df,
    x='Avg_Utilization_Ratio',
    facet_col = characteristics_df.Clusters,
    n_clusters=n_clusters,
    color_discrete_sequence=['#ff0000'],
    nbins=10)
fig.update_xaxes(tickmode='linear', tick0=0, dtick=.20)
fig.show()
```

- Cluster 0 shows good utilization ratio, with some 0.
- Cluster 1 has mostly less utilization ratio.
- Cluster 2 and 3 has similar utilization. Cluster 2 does not have many 0's.
- Cluster 4 has low utilization of credit.

Months on book

In [56]:
```
fig = fn.feature_analysis_intracluster(
    data_frame=characteristics_df,
    x='Months_on_book',
    facet_col='Clusters',
    n_clusters=n_clusters,
    color_discrete_sequence=['rgb(135, 197, 95)'])
fig.update_xaxes(tickmode='linear', tick0=10, dtick=10)
fig.show()
```

All of them show similar spread except Cluster 3, they are the most loyal clients.

Total_Trans_Amt

In [57]:
```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
    x='Total_Trans_Amt',
    facet_col='Clusters',
    n_clusters=n_clusters,
    color_discrete_sequence=['rgb(201, 219, 116)'])
fig.show()
```

Cluster 0 has highest transaction amount. Rest of the has similar pattern.

Avg_Open_To_Buy

In [58]:

```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
                                       x='Avg_Open_To_Buy',
                                       facet_col='Clusters',
                                       n_clusters=n_clusters,
                                       color_discrete_sequence=
['chocolate'])
fig.show()
```

- Cluster 0 has a well spread.
- Cluster 1, 2, 3 are mostly similar.
- Cluster 4 has most open to buy available.

Total_Trans_Ct

In [59]:
```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
                                       x='Total_Trans_Ct',
                                       facet_col='Clusters',
                                       n_clusters=n_clusters,
                                       color_discrete_sequence=
['skyblue'])
fig.update_xaxes(tickmode='linear', tick0=0, dtick=10)
fig.show()
```

In [60]:

```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
                                       x='Total_Revolving_Bal',

facet_col='Clusters',histnorm='density',
                                       n_clusters=n_clusters,
                                       nbins=10,
                                       color_discrete_sequence=['tomat
fig.update_xaxes(tickmode='linear', tick0=0, dtick=500)
fig.show()
```

- Cluster 0 has even distribution.
- Cluster 1 has mostly low revolving balance.
- Cluster 2 does not include low revolving balance clients.
- Cluster 3 and 4 has similar distribution.

Total_Relationship_Count

In [61]:
```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
                                       x='Total_Relationship_Count',
                                       facet_col='Clusters',
                                       n_clusters=n_clusters,
                                       color_discrete_sequence=
['turquoise'])
fig.update_xaxes(tickmode='linear', tick0=0, dtick=1)
fig.show()
```

Cluster 0 mostly comprised of lower relationship count clients. Rest of the Clusters has similar distributions.

Dependent_count

In [62]:
```
fig = fn.feature_analysis_intracluster(data_frame=characteristics_df,
                                       x='Dependent_count',
                                       facet_col='Clusters',
                                       n_clusters=n_clusters,
                                       color_discrete_sequence=
['orangered'])
```

All of them are mostly similar.

with churn info

All the features are explored with respect of churning.

In [79]:

```
@interact(Cluster=fixed(characteristics_df),
          feature=characteristics_df.columns)
def show_clusters(Cluster, feature='Customer_Age'):
    fig = px.histogram(Cluster,
                       x=feature,
                       marginal="box",
                       template='presentation',
                       color='Clusters',
                       facet_col='target',

color_discrete_sequence=px.colors.qualitative.Dark2,
                       barmode='group',
                       title=f'"{feature}" seperated by Clusters',
                       hover_data=Cluster)
    fig.show()
```

In [64]:

```
@interact(Cluster=fixed(characteristics_df),
          feature=characteristics_df.columns)
def show_clusters(Cluster, feature='Customer_Age'):
    fig = px.histogram(
        data_frame=Cluster,
        x=feature,
        marginal="box",
        template='presentation',
        color='target',
        facet_col='Clusters',
        color_discrete_sequence=px.colors.qualitative.Dark2,
        barmode='group',
        category_orders={'Clusters': list(np.arange(0, n_clusters))},
        title=f'"{feature.replace("_"," ")}" seperated by Clusters',
        hover_data=Cluster)
    fig.update_xaxes(showline=True,
                     linewidth=1,
                     linecolor='black', title={'text': ''})
#     fig.update_yaxes(title={'text': ''})
    fig.update_layout(annotations=list(fig.layout.annotations) + [
        go.layout.Annotation(x=0.5,
                             y=-0.22,
                             font=dict(size=14),
                             showarrow=False,
                             text=f"{feature}s",
                             textangle=0,
                             xref="paper",
                             yref="paper")
    ])
    fig.show()
    pass
```

Summary of exploring clusters by the most important features. This is done by interpreting results and taking r
create a summary table. All the intra-cluster and intra-cluster plots are considered for this. For this purpose Mic
Excel is used.

Variable	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Churn	Commer
Avg_Utilization_Ratio	low utilization	minimal low utilization	no low utilization ratio	med utilization	low utilization	1	Majority values a
Card_Category						1	High class imbal comment
Contacts_Count_12_mon						1	3
Credit_Limit	all clients from2k	mostly low limit	2k to 4k, no high limit		high limit, above 14k	1	
Customer_Age	similar	similar	similar	older	similar	3	
Dependent_count	spread	spread	spread	low	spread	1	count 3 and 4 is
Education_Level	Graduate	Graduate	College	College	Uneducated	1	Graduates >HS : Unknown>=Une PG and PhD is le
Gender	M	F	F	F	M	1	Females is risky
Income_Category	Less_than_40K	40K_to_60K	40K_to_60K	Less_than_40K	Unknown	1	Less than 40K
Marital_Status	Unknown	Single	Married	Married	Unknown	1	Majority values i Married
Months_Inactive_12_mon						1	3
Months_on_book	good	similar	similar	loyal customer	similar	3	

Variable	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Churn	Commen
Total_Ct_Chng_Q4_Q1						1	
Total_Relationship_Count	low	high	high	high	high	1	2 and 3 are mos frequent
Total_Revolving_Bal	spread	low	mod	spread	spread	1	Majority values a
Total_Trans_Amt	High transaction amount	low	mid amount till 5k high feq transaction	mid amount till 5k high feq transaction	mid amount till 5k med feq transaction	1	low amounts

Churn Prediction

Prediction from the clustering model is used as a feature for modeling churn prediction model. Models withou feature was also experimented. Those models had a slightly worse performance. For the final modeling approa dataset containing predictions from the kmeans model is used.

In [65]:

```
# appending churn labels as 'target'
cluster_df['target'] = df.Attrition_Flag.map(churn_map).copy()
cluster_df
```

Out[65]:

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Inactive_12_mon	C
0	-0.165406	0.503368	0.384621	0.763943	-1.327136	
1	0.333570	2.043199	1.010715	1.407306	-1.327136	
2	0.583058	0.503368	0.008965	0.120579	-1.327136	
3	-0.789126	1.273283	-0.241473	-0.522785	1.641478	
4	-0.789126	0.503368	-1.869317	0.763943	-1.327136	
...	...	...	...	...	...	
10122	0.458314	-0.266547	0.509840	-0.522785	-0.337598	
10123	-0.664382	-0.266547	-1.368442	0.120579	-0.337598	
10124	-0.290150	-1.036462	0.008965	0.763943	0.651940	
10125	-2.036565	-0.266547	0.008965	0.120579	0.651940	
10126	-0.414894	-0.266547	-1.368442	1.407306	-0.337598	

10127 rows × 39 columns

In [66]:

```
characteristics_df
```

	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	Income_Category	Card_Catego
2	51	M	3	Graduate	Married	80K_to_120K	B
3	40	F	4	High School	Unknown	Less_than_40K	B
4	40	M	3	Uneducated	Married	60K_to_80K	B
...	...	...	...	...	...	...	
10122	50	M	2	Graduate	Single	40K_to_60K	B
10123	41	M	2	Unknown	Divorced	40K_to_60K	B
10124	44	F	1	High School	Married	Less_than_40K	B
10125	30	M	2	Graduate	Unknown	40K_to_60K	B
10126	43	F	2	Graduate	Married	Less_than_40K	Si

In [67]:

```
# # exporting data
# characteristics_df.to_csv(path_or_buf=f'./data/unscaled_data.csv',
index=False)
# cluster_df.to_csv(path_or_buf=f'./data/scaled_data.csv', index=False
# joblib.dump(cluster_df, filename=f'./model/scaled_data.joblib',
compress=9)
# joblib.dump(characteristics_df,
#             filename=f'./model/unscaled_data.joblib',
#             compress=9)
```

In [68]:

```
# preparing X (independent variable), and y (dependent) for the model
X_additional_col = cluster_df.drop(columns='target').copy()
y_additional_col = cluster_df.target.copy()
```

In [69]:

```
# train test split size of 80%
X_train_pr, X_test_pr, y_train, y_test =
train_test_split(X_additional_col,

y_additional_col,
                                                          train_size=.
```

In [70]:

```
# creating an instance of SMOTENC using feature list defined at the S(
section
oversampling1 = SMOTENC(categorical_features=smotenc_features, n_jobs=
```

In [71]:

```
# oversampling X based on y
```

In [72]:

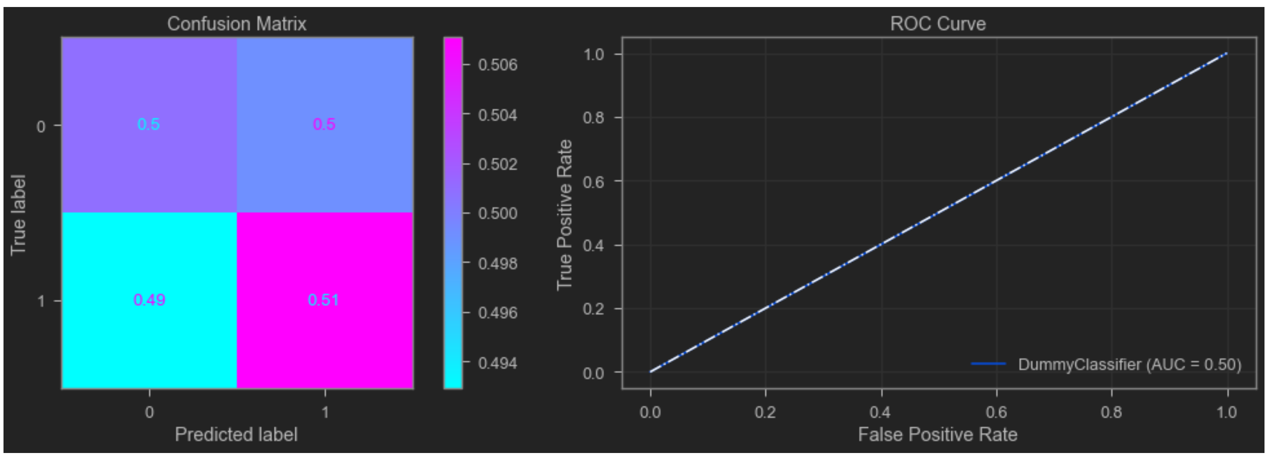
```python
base_model = DummyClassifier(strategy='stratified')
```

In [73]:

```python
# using oversampled data
fn.model_report(base_model, X_train_pr_os, y_train_encoded_os, X_test_
                y_test)
```

Report of DummyClassifier type model using train-test split dataset.

```
*************************************************************************************
Train accuracy score: 0.4989
Test accuracy score: 0.4941
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*************************************************************************************

Train Report:
************************************************************
              precision    recall  f1-score   support

           0       0.50      0.50      0.50      6786
           1       0.50      0.50      0.50      6786

    accuracy                           0.50     13572
   macro avg       0.50      0.50      0.50     13572
weighted avg       0.50      0.50      0.50     13572

************************************************************
```



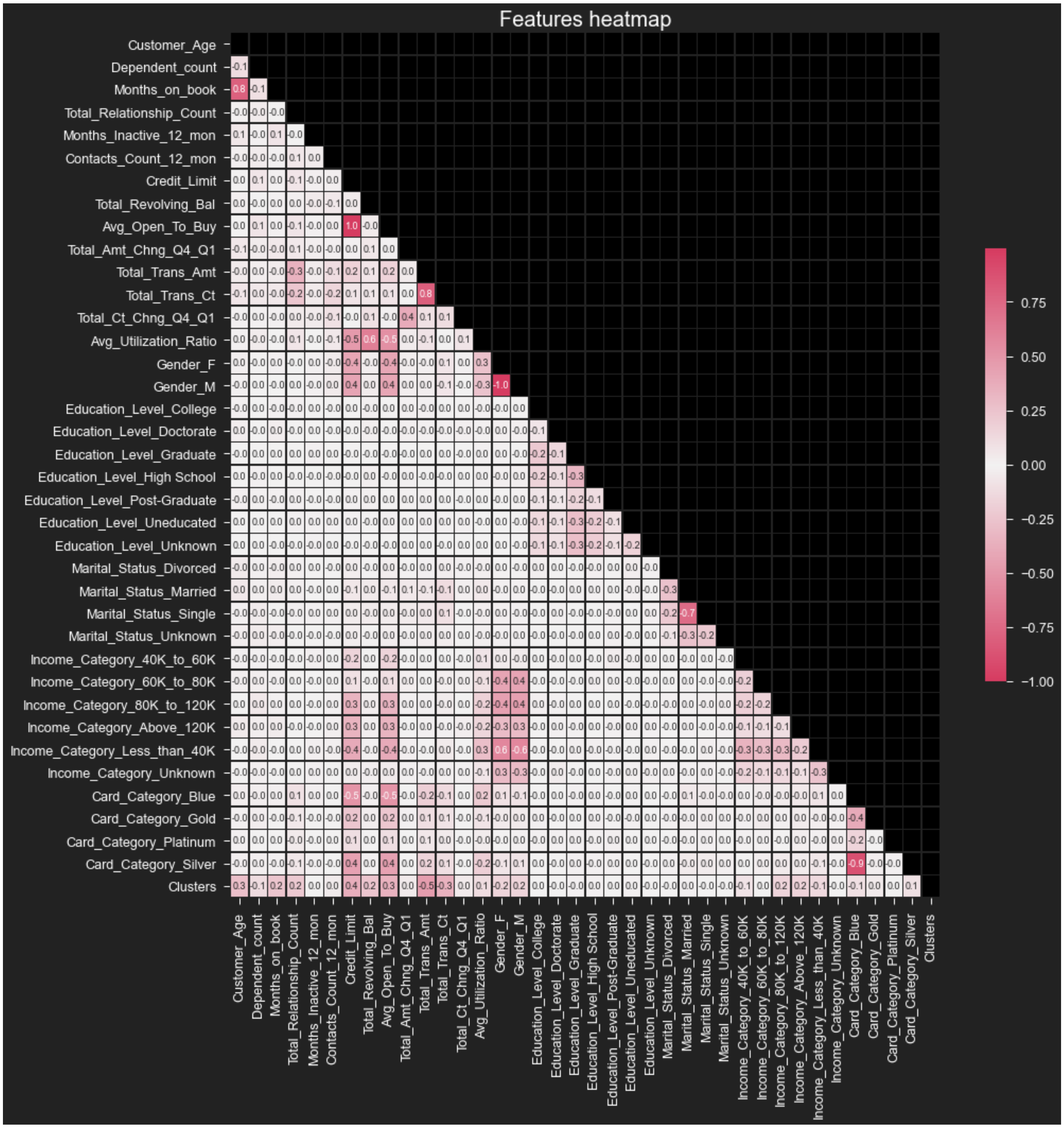

```
Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.86      0.53      0.65      1714
           1       0.17      0.52      0.25       312

    accuracy                           0.52      2026
   macro avg       0.51      0.52      0.45      2026
weighted avg       0.75      0.52      0.59      2026

************************************************************
```

The baseline model is performing as par as random chance of flipping a coin for prediction.

Logistic Regression

In [78]:

```
fn.heatmap_of_features(X_additional_col);
```



`'Avg_Open_To_Buy'` with `Credit_limit`, `'Card_Category_Silver'` with `'Card_Category_Blue`, `'Gender_M'` with `'Gender_F`, `'Months_on_book'` with

- `'Card_Category_Silver'` with `'Card_Category_Blue` : This is interesting. Blue and Silver carc the two most common type of credit card. There is a strong negative relationship.
- `'Gender_M'` with `'Gender_F` : Binary category.
- `'Months_on_book'` with `'Customer_Age'` : Customers age has a impact on how long they can be customer of the bank. Older they are, more time they have to be a customer. - `'Total_Trans_Ct'` wi `'Total_Trans_Amt` : Very closely related feature. 80% correlation is not that horrible.

In [79]:
```
fn.drop_features_based_on_correlation(X_additional_col)
```

Out[79]:
```
{'Avg_Open_To_Buy',
 'Card_Category_Silver',
 'Gender_M',
 'Months_on_book',
 'Total_Trans_Ct'}
```

Multicollinearity undermines the statistical significance of an independent variable. Here it is important to poin that multicollinearity does not affect the model's predictive accuracy. Choosing not to deal with this issue right

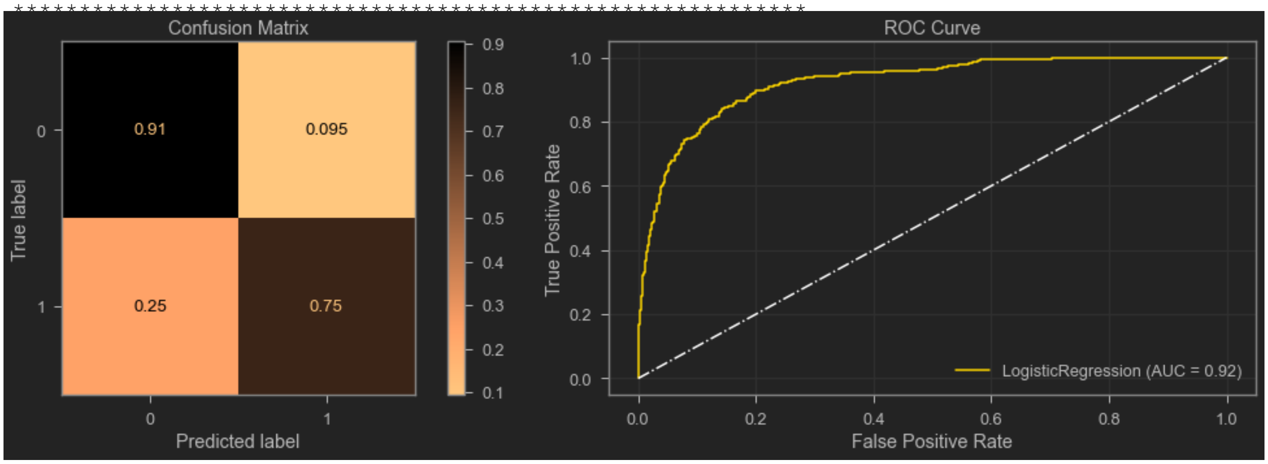
In [80]:
```
# dropped first from OHE using cluster prediction
X_log_reg = X.copy()
X_log_reg['cluster'] = clusters
X_log_reg['cluster'] = X_log_reg['cluster'].astype('str')

X_train_log_reg, y_train_log_reg, X_test_log_reg, y_test_log_reg = 
fn.dataset_processor(
    X_log_reg, y, verbose=0, OHE_drop_option='first')
```

In [81]:
```
# with all data
logreg = LogisticRegression(max_iter=1000, class_weight='balanced')
# score of logistic regression classifier
fn.model_report(logreg,
                X_train_log_reg,
                y_train_log_reg,
                X_test_log_reg,
                y_test_log_reg,
                show_train_report=False)
```

Report of LogisticRegression type model using train-test split dataset.

```
****************************************************************************
Train accuracy score: 0.9046
Test accuracy score: 0.8801
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
****************************************************************************

Test Report:
************************************************************
```

```
************************************************************
```



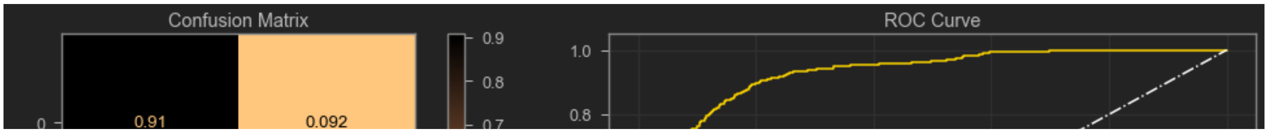
Model is not good enough to predict target class 1, churned customer. Although accuracy is good.

In [84]:

```python
# dropping all the correlated features
logreg_1 = LogisticRegression(max_iter=1000, class_weight='balanced')
# score of logistic regression classifier
fn.model_report(logreg_1,
                X_train_log_reg.drop(columns=['Gender_M',
'Months_on_book']),
                y_train_log_reg,
                X_test_log_reg.drop(columns=['Gender_M',
'Months_on_book']),
                y_test_log_reg,
                show_train_report=False)
```

Report of LogisticRegression type model using train-test split dataset.

```
***************************************************************************************
Train accuracy score: 0.9032
Test accuracy score: 0.8825
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
***************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.95      0.91      0.93      1689
           1       0.62      0.75      0.68       337

    accuracy                           0.88      2026
   macro avg       0.78      0.83      0.80      2026
weighted avg       0.89      0.88      0.89      2026

************************************************************
```



The accuracy is good enough. But the the residual must be crazy as indicated by the f-1 and precision values. Supports my previous point about model performance. Outlier removal is next. Not pursuing that because data will be very high as there are lots of recurring values for the numeric values (lots of zeros) for both IQR and Z-s based approach for outlier removal.

Critical features for churning:

Odds ratios are used to measure the relative odds of the occurrence of the outcome, given a factor of interest JM, Altman DG.(2000), The odds ratio]. The odds ratio is used to determine whether a particular attribute is a r factor or protective factor for a particular class and the magnitude of percentage effect is used to compare the various risk factors for that class. The positive percentage effect means that the factor is positively correlated w churn and vice versa.

The odds ratio and percentage effect of each feature are estimated as $\mathbf{OddsRatio} = e^{\Theta}$ and $\mathbf{Effect(\%)} = 100 * (OddsRatio - 1)$, where Θ is the value of weight of each feature in Logistic Regressior model. If the effect is positive, the greater the factor, the likely that the client will churn, those factors are consi as risk factors. While if the effect is negative, the greater the factor, the greater the possibility that the custome not churn, and can be considered as protective factors. This is a Bayesian approach for identifying feature impc

In [85]:

```
churn_feature = pd.DataFrame(
    logreg.coef_,columns=X_train_log_reg.columns).T
churn_feature.columns = ['weights']
churn_feature['odds_ratio'] = np.exp(churn_feature['weights'])
churn_feature['effect'] = 100 * (churn_feature['odds_ratio'] - 1)
churn_feature
```

Out[85]:

	weights	odds_ratio	effect
Customer_Age	0.202600	1.224583	22.458276
Dependent_count	0.076432	1.079428	7.942849
Months_on_book	-0.071580	0.930922	-6.907836
Total_Relationship_Count	-0.713739	0.489809	-51.019067
Months_Inactive_12_mon	0.538011	1.712598	71.259752
Contacts_Count_12_mon	0.535978	1.709119	70.911902
Credit_Limit	0.268250	1.307675	30.767457
Total_Revolving_Bal	-0.437024	0.645956	-35.404405
Avg_Open_To_Buy	0.307464	1.359971	35.997135
Total_Amt_Chng_Q4_Q1	-0.200003	0.818729	-18.127130
Total_Trans_Amt	2.683227	14.632238	1363.223757
Total_Trans_Ct	-3.411589	0.032989	-96.701126

	weights	odds_ratio	effect
Education_Level_Graduate	-1.914202	0.147459	-85.254051
Education_Level_High School	-2.188521	0.112082	-88.791758
Education_Level_Post-Graduate	-2.752172	0.063789	-93.621085
Education_Level_Uneducated	-2.348607	0.095502	-90.449786
Education_Level_Unknown	-2.320679	0.098207	-90.179308
Marital_Status_Married	-1.153530	0.315521	-68.447898
Marital_Status_Single	-0.851991	0.426565	-57.343500
Marital_Status_Unknown	-1.626720	0.196573	-80.342665
Income_Category_60K_to_80K	-1.828942	0.160583	-83.941663
Income_Category_80K_to_120K	-1.435637	0.237964	-76.203628
Income_Category_Above_120K	-1.497907	0.223598	-77.640225
Income_Category_Less_than_40K	-0.557948	0.572382	-42.761784
Income_Category_Unknown	-1.734102	0.176559	-82.344124
Card_Category_Gold	-0.928712	0.395062	-60.493777
Card_Category_Platinum	-0.376188	0.686473	-31.352708
Card_Category_Silver	-1.325415	0.265693	-73.430735
cluster_1	3.747758	42.425861	4142.586081
cluster_2	3.222978	25.102754	2410.275377
cluster_3	2.588146	13.305075	1230.507459

Greater risk factors are `Customer_Age`, `Credit_Limit`, `Avg_Open_To_Buy`, `Contacts_Count_12_mon`, `Months_Inactive_12_mon`. Cluster 1 is the most likely to churn.

In [87]:

```
churn_feature = pd.DataFrame(
    logreg_1.coef_,
    columns=X_train_log_reg.drop(
        columns=['Gender_M', 'Months_on_book']).columns).T
churn_feature.columns = ['weights']
churn_feature['odds_ratio'] = np.exp(churn_feature['weights'])
churn_feature['effect'] = 100 * (churn_feature['odds_ratio'] - 1)
churn_feature
```

Out[87]:

	weights	odds_ratio	effect
Customer_Age	0.169362	1.184549	18.454939
Dependent_count	0.092034	1.096402	9.640225
Total_Relationship_Count	-0.708161	0.492549	-50.745066
Months_Inactive_12_mon	0.533956	1.705667	70.566652

	weights	odds_ratio	effect
Avg_Open_To_Buy	0.286892	1.332280	33.228012
Total_Amt_Chng_Q4_Q1	-0.201614	0.817411	-18.258924
Total_Trans_Amt	2.642947	14.054559	1305.455938
Total_Trans_Ct	-3.384232	0.033904	-96.609631
Total_Ct_Chng_Q4_Q1	-0.700182	0.496495	-50.350498
Avg_Utilization_Ratio	-0.015595	0.984526	-1.547386
Education_Level_Doctorate	-2.401720	0.090562	-90.943796
Education_Level_Graduate	-1.935874	0.144298	-85.570196
Education_Level_High School	-2.209761	0.109727	-89.027314
Education_Level_Post-Graduate	-2.767894	0.062794	-93.720590
Education_Level_Uneducated	-2.360638	0.094360	-90.564004
Education_Level_Unknown	-2.332958	0.097008	-90.299161
Marital_Status_Married	-1.140814	0.319559	-68.044108
Marital_Status_Single	-0.835330	0.433732	-56.626846
Marital_Status_Unknown	-1.628805	0.196164	-80.383616
Income_Category_60K_to_80K	-2.123131	0.119656	-88.034361
Income_Category_80K_to_120K	-1.700958	0.182509	-81.749136
Income_Category_Above_120K	-1.757053	0.172553	-82.744741
Income_Category_Less_than_40K	-0.327268	0.720891	-27.910944
Income_Category_Unknown	-1.453010	0.233865	-76.613460
Card_Category_Gold	-0.857378	0.424273	-57.572696
Card_Category_Platinum	-0.331995	0.717491	-28.250902
Card_Category_Silver	-1.295133	0.273862	-72.613844
cluster_1	3.674570	39.431683	3843.168338
cluster_2	3.190118	24.291300	2329.129958
cluster_3	2.494671	12.117746	1111.774608

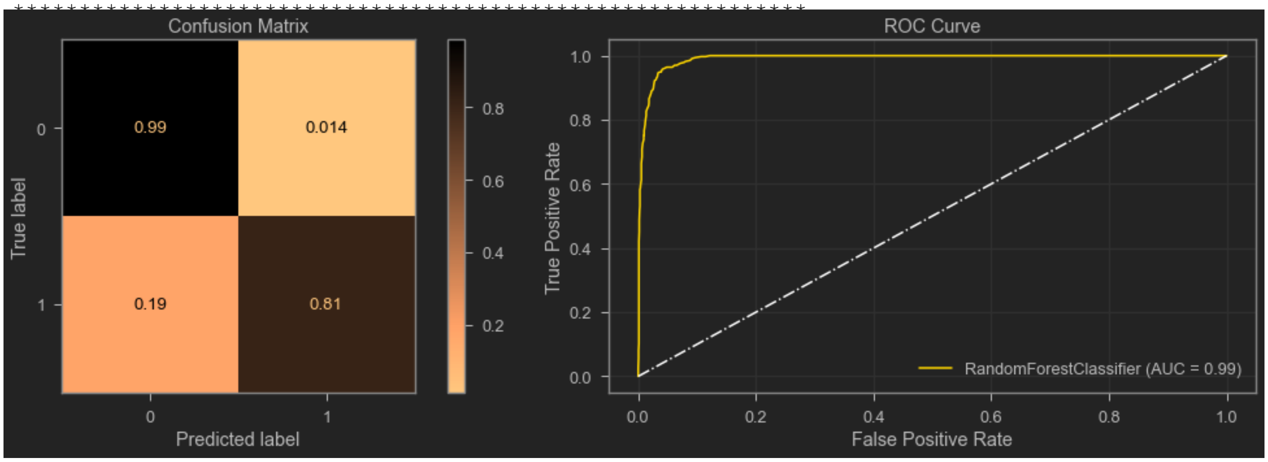
Random Forest

OG data

In [88]:

```
# not using oversampled data
clf_rf = RandomForestClassifier(n_jobs=-1)
fn.model_report(clf_rf,
             X_train_pr,
             y_train,
             X_test_pr,
             y_test
```

```
Test accuracy score: 0.958
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*****************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.96      0.99      0.98      1693
           1       0.92      0.81      0.86       333

    accuracy                           0.96      2026
   macro avg       0.94      0.90      0.92      2026
weighted avg       0.96      0.96      0.96      2026

************************************************************
```



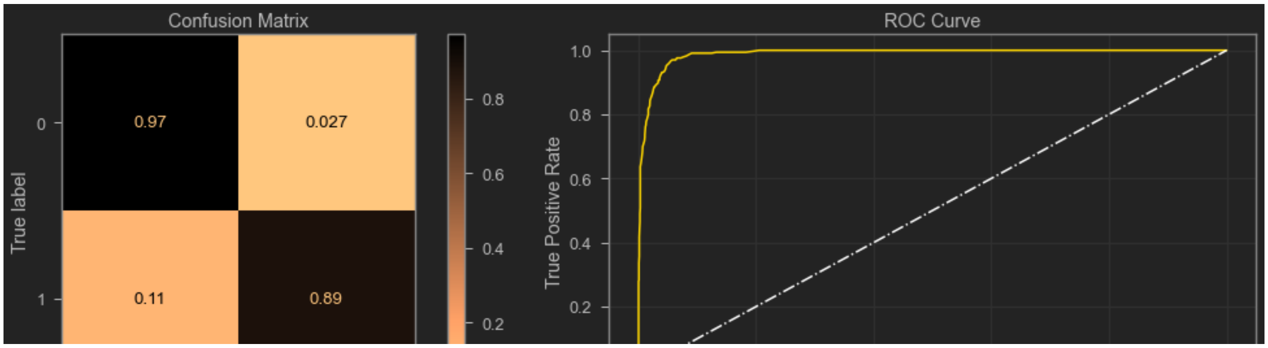
OS data

In [89]:

```python
# using oversampled data
clf_rf = RandomForestClassifier(n_jobs=-1)
fn.model_report(clf_rf,
                X_train_pr_os,
                y_train_encoded_os,
                X_test_pr,
                y_test,
                show_train_report=False)
```

Report of RandomForestClassifier type model using train-test split dataset.

```
*****************************************************************************************
Train accuracy score: 1.0
Test accuracy score: 0.9585
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*****************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.98      0.97      0.98      1693
           1       0.87      0.89      0.88       333

    accuracy                           0.96      2026
   macro avg       0.92      0.93      0.93      2026
```



Grid Search

In [90]:

```
rf_clf_gs = RandomForestClassifier(n_jobs=-1, verbose=0)
params = {
    'criterion': ["gini", "entropy"],
    'max_depth': [5, 6, 7, 8, 9, 10],
    'min_samples_leaf': [2, 3, 4],
    #      'class_weight': ["balanced", "balanced_subsample"]
}
gridsearch_rf_clf = GridSearchCV(estimator=rf_clf_gs,
                                 param_grid=params,
                                 n_jobs=-1,
                                 scoring='f1_macro')
gridsearch_rf_clf
```

Out[90]:

```
GridSearchCV(estimator=RandomForestClassifier(n_jobs=-1), n_jobs=-1,
             param_grid={'criterion': ['gini', 'entropy'],
                         'max_depth': [5, 6, 7, 8, 9, 10],
                         'min_samples_leaf': [2, 3, 4]},
             scoring='f1_macro')
```

In [91]:

```
with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    gridsearch_rf_clf.fit(X_train_pr_os, y_train_encoded_os)
print(f"Best Parameters by gridsearch:\t{gridsearch_rf_clf.best_params
print(f"Best Estimator by
gridsearch:\t{gridsearch_rf_clf.best_estimator_}")


rf_clf_gs_best = gridsearch_rf_clf.best_estimator_
```

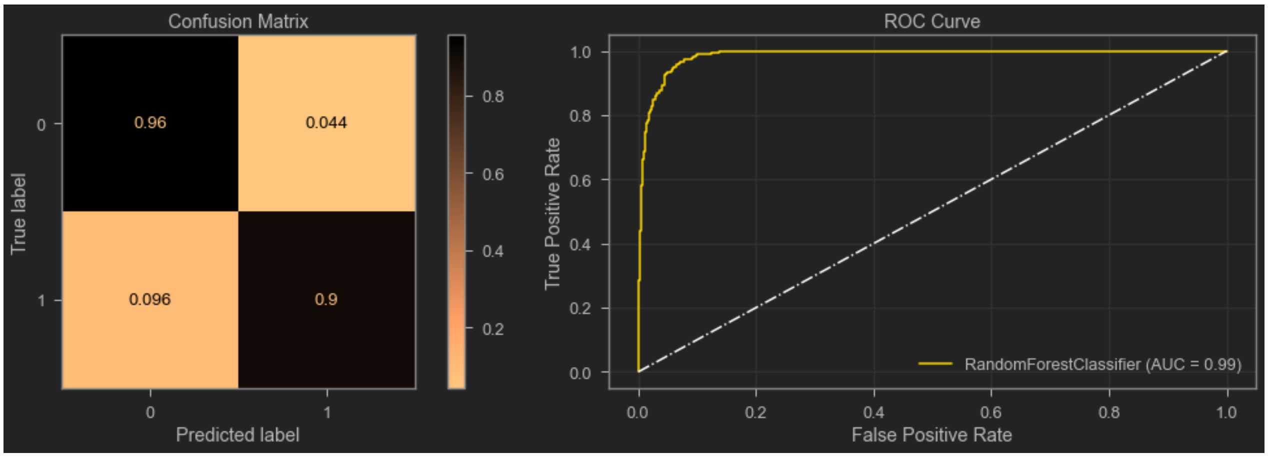
```
Best Parameters by gridsearch:  {'criterion': 'gini', 'max_depth': 10, 'min_samples_lea
Best Estimator by gridsearch:   RandomForestClassifier(max_depth=10, min_samples_leaf=2
s=-1)
```

In [93]:

```
fn.model_report(rf_clf_gs_best, X_train_pr_os, y_train_encoded_os,
```

Report of RandomForestClassifier type model using train-test split dataset.

```
*************************************************************************************
Train accuracy score: 0.9854
Test accuracy score: 0.9472
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.98      0.96      0.97      1693
           1       0.80      0.90      0.85       333

    accuracy                           0.95      2026
   macro avg       0.89      0.93      0.91      2026
weighted avg       0.95      0.95      0.95      2026

************************************************************
```



Gridsearch did not find better model. precision for target class of 0 is worse than previous model.

XGBoost

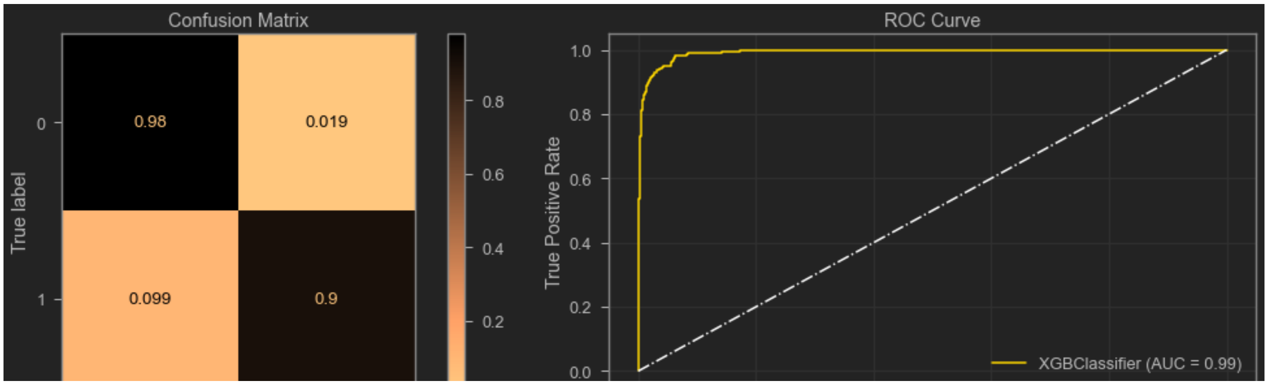
XGBClassifier

In [74]:

```python
clf_xg = XGBClassifier(n_jobs=-1)
fn.model_report(clf_xg, X_train_pr_os, y_train_encoded_os, X_test_pr,
y_test,
                show_train_report=False)
```

Report of XGBClassifier type model using train-test split dataset.

```
*************************************************************************************
Train accuracy score: 1.0
Test accuracy score: 0.9684
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1714
           1       0.89      0.90      0.90       312
```



Model is not overfitting. Good test accuracy and the highest precision for target class of 1, which represents ch

(Numbers vary sightly between runs)

Grid search

In [75]:

```
xgg_clf_gs = XGBClassifier(
    n_jobs=-1, verbosity=0, objective='binary:logistic',
    eval_metric='error')   #"rank:pairwise","count:poisson"
#'logloss','auc'
params = {
    'criterion': ["gini", "entropy"],
    'max_depth': [2, 3, 4],
    'min_samples_leaf': [1, 2, 3, 4],
    'class_weight': ["balanced", "balanced_subsample"],
    'ccp_alpha': [0.0, 0.05, 0.1, 0.2, 0.3],
    'importance_type':
    ["gain", "weight", "cover", "total_gain", "total_cover"],
}
gridsearch_xgg_clf_gs = GridSearchCV(
    estimator=xgg_clf_gs, param_grid=params, n_jobs=-1,
    scoring='precision')   #'roc_auc_ovr_weighted'
gridsearch_xgg_clf_gs
```

Out[75]:

```
GridSearchCV(estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None, eval_metric='error',
                                     gamma=None, gpu_id=None,
                                     importance_type='gain',
                                     interaction_constraints=None,
                                     learning_rate=None, max_delta_step=None,
                                     max_depth=None, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_estima...
                                     scale_pos_weight=None, subsample=None,
                                     tree_method=None, validate_parameters=None,
                                     verbosity=0),
```

```
                    scoring='precision')
```

In [76]:

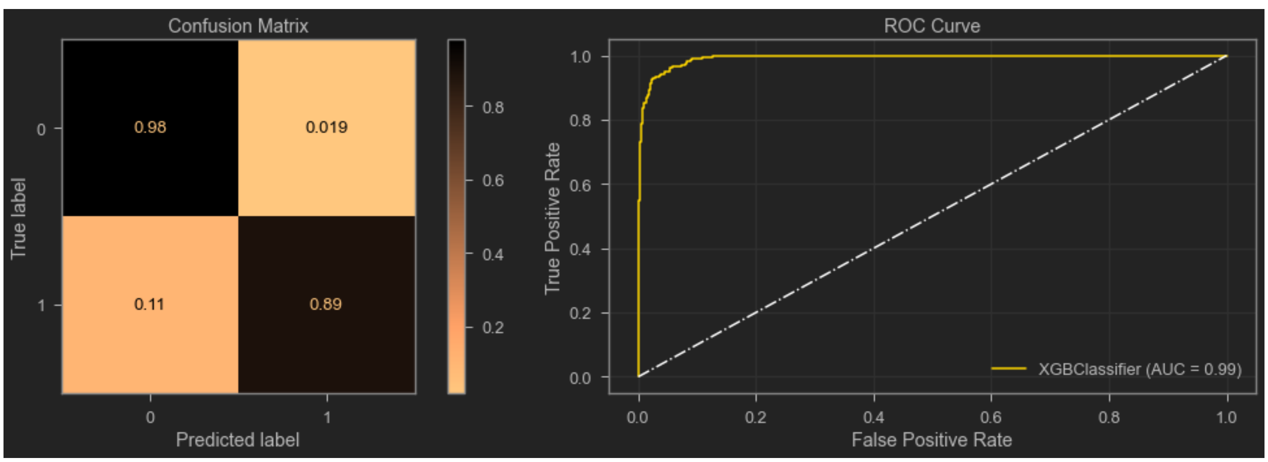
```
with warnings.catch_warnings():
    warnings.simplefilter("ignore")
    gridsearch_xgg_clf_gs.fit(X_train_pr_os, y_train_encoded_os)

xgg_clf_gs_best = gridsearch_xgg_clf_gs.best_estimator_
```

In [77]:

```
fn.model_report(xgg_clf_gs_best, X_train_pr_os, y_train_encoded_os,
X_test_pr, y_test,
                show_train_report=False)
```

Report of XGBClassifier type model using train-test split dataset.

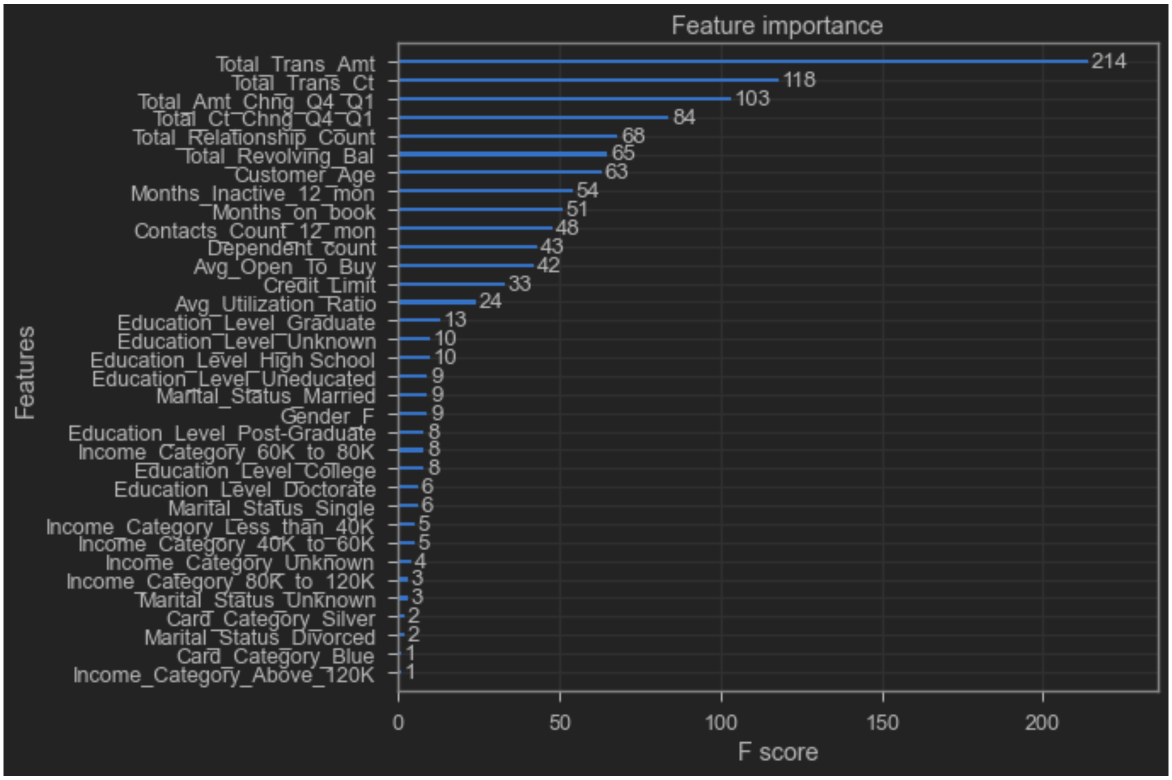
```
*************************************************************************************
Train accuracy score: 0.9968
Test accuracy score: 0.9674
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.98      0.98      0.98      1717
           1       0.89      0.89      0.89       309

    accuracy                           0.97      2026
   macro avg       0.94      0.94      0.94      2026
weighted avg       0.97      0.97      0.97      2026

************************************************************
```



Model performance is mostly similar with all the extensive (expensive in term of runtime) grid search.

In [78]:

```
# looking what the model used for its prediction
xgb.plot_importance(xgg_clf_gs_best);
```



XGBRFClassifier

In [100…

```
clf_xg_rf = XGBRFClassifier(n_jobs=-1)
fn.model_report(clf_xg_rf, X_train_pr_os, y_train_encoded_os, X_test_p
y_test,
                show_train_report=False)
```

Report of XGBRFClassifier type model using train-test split dataset.

```
*************************************************************************
Train accuracy score: 0.9489
Test accuracy score: 0.9413
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.98      0.95      0.96      1693
           1       0.78      0.89      0.83       333

    accuracy                           0.94      2026
   macro avg       0.88      0.92      0.90      2026
weighted avg       0.95      0.94      0.94      2026

************************************************************
```

Significantly worse performance for predicting target class than previous model.

Best model

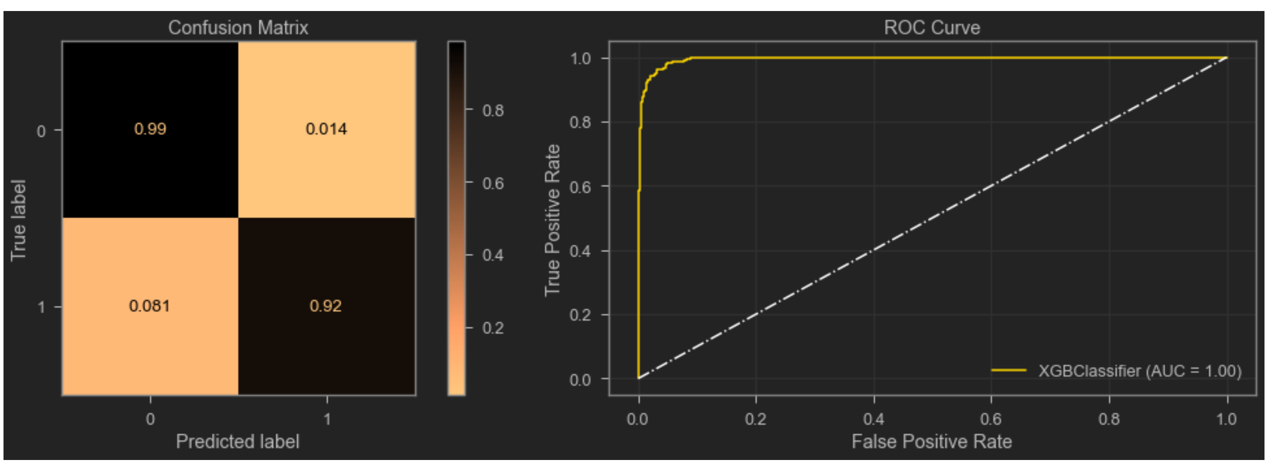
`XGBClassifier` type model deemed the best model type for predicting churning. It shows best fit and mo performance. Here is the model report for that model.

In [101…

```
fn.model_report(clf_xg,
                X_train_pr_os,
                y_train_encoded_os,
                X_test_pr,
                y_test,
                show_train_report=False,
                fitted_model=True)
```

Report of XGBClassifier type model using train-test split dataset.

```
*************************************************************************************
Train accuracy score: 1.0
Test accuracy score: 0.9753
    No over or underfitting detected, diffrence of scores did not cross 5% thresh hold.
*************************************************************************************

Test Report:
************************************************************
              precision    recall  f1-score   support

           0       0.98      0.99      0.99      1693
           1       0.93      0.92      0.92       333

    accuracy                           0.98      2026
   macro avg       0.96      0.95      0.95      2026
weighted avg       0.98      0.98      0.98      2026

************************************************************
```



Additional interpretation with insights can be found in the `INTERPRET` section of the analysis.

In [134…

```
# # Save segmentation model
# joblib.dump(kmeans,
#             filename=f'./model/kmeans_segmentation_model.joblib',
#             compress=9)
# # save params of best model
# joblib.dump(clf_xg.get_params(),
#             filename=f'./model/best_model_parameters_xgb.joblib',
#             compress=9)
```

In [133…

```
# # save model after fitting on entire dataset
# xgb_clf = XGBClassifier(**clf_xg.get_params())
# xgb_clf.fit(X_additional_col, y_additional_col)
# joblib.dump(xgb_clf,
#             filename=f'./model
/xgb_clf_churn_prediction_all_data.joblib',
#             compress=9)
```

INTERPRET

Customer Segmentation model

Based on analysis from the segmentation part and exploration of the clusters, they can be be identified as follo

- Cluster 0: Low value frequent users of services.
- Cluster 1: High risk clients segmentation.
- Cluster 2: Regular clients.
- Cluster 3: Most loyal clients. (mostly consists of older clients)
- Cluster 4: High value clients.

NOTE: labels can change on different runs.

Churn Prediction model

Using SHAPely values to explain this model. SHAP (SHapley Additive exPlanations) is a game-theoretic approac explain the output of any machine learning model. (source)

In [102…

```
# init shap
shap.initjs()
```

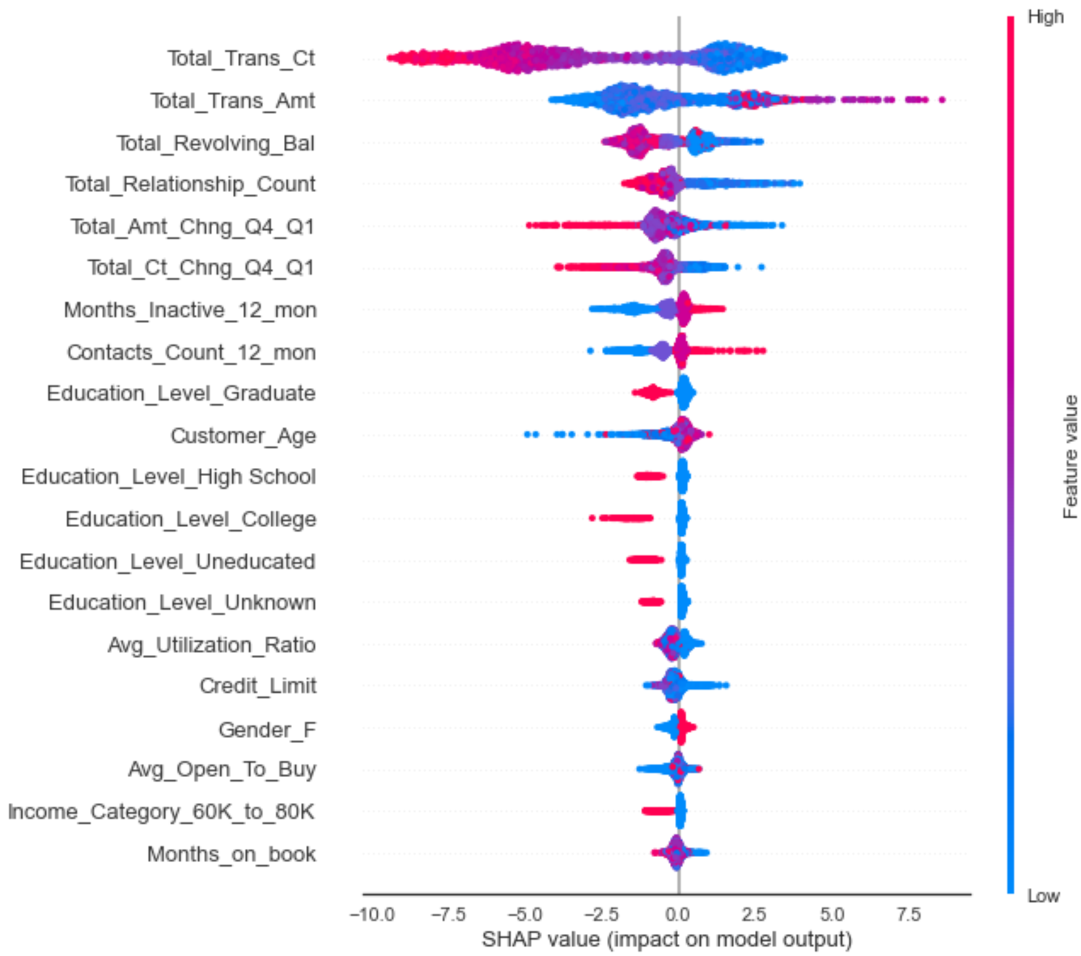
In [103…

```
explainer = shap.TreeExplainer(clf_xg)
```

- red indicating high
- blue indicating low.

In [104…

```
with plt.style.context('seaborn-white'):
    shap.summary_plot(shap_values, X_test_pr)
```



Feature	Observation
Total_Trans_Ct	Low value means higher risk of churning
Total_Trans_Amt	Above agerage value means higher risk of churning
Total_Revolving_Bal	Low value means higher risk of churning
Total_Relationship_Count	More relationship indicates more chance of churning
Total_Amt_Chng_Q4_Q1	Low value means higher risk of churning
Total_Ct_Chng_Q4_Q1	Low value means higher risk of churning
Months_Inactive_12_mon	Higher value means higher risk of churning
Contacts_Count_12_mon	Higher value means higher risk of churning

These attributes can be considered as warning sign.

In [105…

```
# feature wights used by the XGBClassifier model
eli5.format_as_dataframe(eli5.explain_weights(
    clf_xg, feature_names=list(X_test_pr.columns)))
```

Out[105…

	feature	weight
0	Total_Trans_Ct	0.250433
1	Total_Revolving_Bal	0.079447
2	Total_Relationship_Count	0.079296
3	Total_Trans_Amt	0.052821
4	Months_Inactive_12_mon	0.046896
5	Education_Level_Unknown	0.042242
6	Gender_F	0.039837
7	Income_Category_80K_to_120K	0.033957
8	Education_Level_College	0.032579
9	Total_Ct_Chng_Q4_Q1	0.030267
10	Contacts_Count_12_mon	0.030240
11	Education_Level_Uneducated	0.023423
12	Income_Category_60K_to_80K	0.022967
13	Education_Level_High School	0.021457
14	Education_Level_Graduate	0.018247
15	Education_Level_Post-Graduate	0.017746
16	Total_Amt_Chng_Q4_Q1	0.017545
17	Customer_Age	0.017284
18	Education_Level_Doctorate	0.014393
19	Income_Category_Less_than_40K	0.014263

RECOMMENDATION & CONCLUSION

Cluster 1 is the most riskiest client segmentation. They should be offered deals to make them stick with the bar

- Their utilization ratio is low. By offering incentives like cash back offer is a viable option.
- Their credit limits are low. Based on their credit habit, they can be offered a larger credit limit.

As a rule of thumb:

- Most loyal and at risk clients are female. Marketers should target them with specific package.
- frequent smaller amount of transaction can be perceived as a red flag. When spotted, customer relationsh must act on it.
- large expenditure can be a signal for cross selling products and it is also a sign of churn.

NEXT STEPS

Modeling aspect: Gaussian Mixture Models for segmentation modeling, and Neural Network based approach prediction model.

Business need aspect: A part of the business challenge is determining how soon you want the model to foreca prediction that is made too long in advance may be less accurate. A narrow prediction horizon, on the other ha may perform better in terms of accuracy, but it may be too late to act after the consumer has made her decisio

Finally, it is critical to establish whether churn should be characterized at the product level (customers who are to discontinue using a certain product, such as a credit card) or at the relationship level (client likely to extricate the bank itself). When data is evaluated at the relationship level, you gain a wider insight of the customer's perspective. Excessive withdrawals from a savings account, for example, may be used to pay for a deposit on a or education costs. Such insights into client life events are extremely effective not just for preventing churn, bu for cross-selling complementary items that may enhance the engagement even further. This can be done with information about the customers if there is product level data is available.

APPENDIX

Environment setup

For running this locally please follow instructions from `'./assets/req/README.md'` .

all functions and imports from the `functions.py` and `packages.py`

In [110…

```
# functions used in various steps of this analysis
fn.show_py_file_content(file='./imports_and_functions/functions.py')
```

```
# imports
import plotly.graph_objs as go
import matplotlib.pyplot as plt
# import plotly
# from plotly import graph_objs
from sklearn import metrics
from IPython.display import display, HTML, Markdown
import pandas as pd
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler, StandardScaler
from sklearn.compose import ColumnTransformer
from yellowbrick.classifier.rocauc import roc_auc
import seaborn as sns
import numpy as np
import plotly.express as px

# functions


def model_report(model,
                 X_train,
```

```
                 cmap=['cool', 'copper_r'],
                 normalize='true',
                 figsize=(15, 5)):
    """
    Dispalys classification model report.
    Report of model performance using train-test split dataset.
    Shows train and test score, Confusion Matrix and, ROC Curve of performane of test da
    Uses sklearn for plotting.

    Intended to work ONLY on model where target has properly encoded binomial class valu

    Parameters:
    -----------
    model : object, scikit-learn model object; no default.
    X_train : pandas.DataFrame, predictor variable training data split; no default,
    y_train : pandas.DataFrame, target variable training data split; no default,
    X_test : pandas.DataFrame, predictor variable test data split; no default,
    y_test : pandas.DataFrame, target variable test data split; no default,
    cmap : {NOT IMPLIMENTED} list of str, colormap of Confusion Matrix; default: ['cool'
opper_r'],
        cmap of train and test data
    normalize : {NOT IMPLIMENTED} str, normalize count of Confusion Matrix; default: 'tr
        - `true` to normalize counts.
        - `false` to show raw counts.
    figsize : tuple ``(lenght, height) in inchs``, figsize of output; default: (16, 6),
    show_train_report : boolean; default: False,
        - True, to show report.
        - False, to turn off report.
    fitted_model : bool; default: False,
        - if True, fits model to train data and generates report.
        - if False, does not fits model and generates report.
        Use False for previously fitted model.

    ---version 0.9.14---
    """
    if fitted_model is False:
        model.fit(X_train, y_train)
    train = model.score(X_train, y_train)
    test = model.score(X_test, y_test)

    def str_model_(model):
        """Helper function to get model class display statement, this text conversion br
code if
        performed in ``model_report`` function's local space. This function is to isolat
om the
        previous function's local space."""
        str_model = str(model.__class__).split('.')[-1][:-2]
        display(
            HTML(
                f"""<strong>Report of {str_model} type model using train-test split data
t.</strong>"""
            ))

    str_model_(model)
    print(f"{'*'*90}")
```

```
        )
    elif (train - test) > .05:
        print(
            f"    Possible Overfitting, diffrence of scores {round(abs(train-test)*100,2
crossed 5% thresh hold."
        )
    elif (train - test) < -.05:
        print(
            f"    Possible Underfitting, diffrence of scores {round(abs(train-test)*100,
crossed 5% thresh hold."
        )
    print(f"{'*'*90}")
    print("")

    if show_train_report:
        print(f'Train Report: ')
        print(f"{'*'*60}")
        # train report
        # classification report
        print(
            metrics.classification_report(y_train,
                                          model.predict(X_train)))
        print(f"{'*'*60}")
        # Confusion matrix
        fig, ax = plt.subplots(ncols=2, figsize=figsize)
        metrics.plot_confusion_matrix(model,
                                      X_train,
                                      y_train,
                                      cmap='cool',
                                      normalize='true',
                                      ax=ax[0])
        ax[0].title.set_text('Confusion Matrix')
        # ROC curve
        metrics.plot_roc_curve(model,
                               X_train,
                               y_train,
                               color='#0450E7',
                               ax=ax[1])
        ax[1].plot([0, 1], [0, 1], ls='-.', color='white')
        ax[1].title.set_text('ROC Curve')
        plt.grid()
        plt.tight_layout()
        plt.show()

    if show_test_report:
        # train report
        # classification report
        print(f'Test Report: ')
        print(f"{'*'*60}")
        print(metrics.classification_report(y_test,
                                            model.predict(X_test)))
        print(f"{'*'*60}")
        # Confusion matrix
        fig, ax = plt.subplots(ncols=2, figsize=figsize)
        metrics.plot_confusion_matrix(model,
```

```
        # ROC curve
        metrics.plot_roc_curve(model,
                               X_test,
                               y_test,
                               color='gold',
                               ax=ax[1])
        ax[1].plot([0, 1], [0, 1], ls='-.', color='white')
        ax[1].title.set_text('ROC Curve')
        plt.grid()
        plt.tight_layout()
        plt.show()
    pass


def dataset_processor_segmentation(X, OHE_drop_option=None, verbose=0, scaler=None):
    """Prepares data for use in Kmeans clustering algorithm.

    +++++++++++++++++++++
     predefined function
    +++++++++++++++++++++

    Parameters:
    -----------
    X : pandas.core.frame.DataFrame; no defalut, independent variables,
    scaler : sklearn.preprocessing; default = None,
        None uses ```StandardScaler
```

OHE_drop_option : str; default = None,

for use in sklearn.preprocessing._encoders.OneHotEncoder

drop : {'first', 'if_binary'} or a array-like of shape (n_features,),

default=None, Specifies a methodology to use to drop one of the

categories per feature. This is useful in situations where perfectly

collinear features cause problems, such as when feeding the resulting

data into a neural network or an unregularized regression.

However, dropping one category breaks the symmetry of the original

representation and can therefore induce a bias in downstream models,

for instance for penalized linear classification or regression models.

- None : retain all features (the default).
- 'first' : drop the first category in each feature. If only one category is present, the feature will be dropped entirely.
- 'if_binary' : drop the first category in each feature with two categories. Features with 1 or more than 2 categories are left intact.
- array : ``drop[i]`` is the category in feature ``X[:, i]`` that

```
Returns:
--------
X  : pandas.core.frame.DataFrame,

--- version 0.1 ---
"""
# isolating numerical cols
nume_col = list(X.select_dtypes('number').columns)
if verbose > 0:
    print("Numerical columns: \n---------------------\n", nume_col)

# isolating categorical cols
cate_col = list(X.select_dtypes('object').columns)
if verbose > 0:
    print('')
    print("Categorical columns: \n---------------------\n", cate_col)

# pipeline for processing categorical features
pipe_cate = Pipeline([('ohe',
                       OneHotEncoder(sparse=False, drop=OHE_drop_option))])
# pipeline for processing numerical features
if scaler is None:
    scaler = StandardScaler()
pipe_nume = Pipeline([('scaler', scaler)])
# transformer
preprocessor = ColumnTransformer([('nume_feat', pipe_nume, nume_col),
                                  ('cate_feat', pipe_cate, cate_col)])
# creating dataframes
try:
    X_pr = pd.DataFrame(
        preprocessor.fit_transform(X),
        columns=nume_col +
        list(preprocessor.named_transformers_['cate_feat'].
             named_steps['ohe'].get_feature_names(cate_col)))
    if verbose > 1:
        print("\n\n------")
        print(
```

```
        print(
            f"Encoder: {str(preprocessor.named_transformers_['cate_feat'].name
eps['ohe'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_tra
rmers_['cate_feat'].named_steps['ohe'].get_params()}"
        )
        print("------")
except:
    if verbose > 1:
        print("\n\n------")
        print(
            f"Scaler: {str(preprocessor.named_transformers_['nume_feat'].named
ps['scaler'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_t
formers_['nume_feat'].named_steps['scaler'].get_params()}"
        )
        print(
            f"Encoder: {str(preprocessor.named_transformers_['cate_feat'].name
eps['ohe'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_tra
rmers_['cate_feat'].named_steps['ohe'].get_params()}"
        )
        print("------")
        print("No Categorical columns found")
    X_pr = pd.DataFrame(preprocessor.fit_transform(X), columns=nume_col)
return X_pr
```

def show_py_file_content(file='./imports_and_functions/functions.py'): """ displays content of a py file output formatted as python code in jupyter notebook.

```
Parameter:
==========
file : `str`; default: './imports_and_functions/functions.py',
    path to the py file.
"""
with open(file, 'r', encoding="utf8") as f:
    x = f"""```python
```

{f.read()}

```
"""
        display(Markdown(x))
```

```
                        y_train,
                        X_test,
                        y_test,
                        show_train_report=True,
                        show_test_report=True,
                        fitted_model=False,
                        cmap=['cool', 'copper_r'],
                        normalize='true',
                        figsize=(15, 5)):
    """
    Dispalys model report of multiclass classification model.
    Report of model performance using train-test split dataset.
    Shows train and test score, Confusion Matrix and, ROC Curve of performane
est data.
    Uses sklearn and yellowbrick for plotting.

    Parameters:
    -----------
    model : object, scikit-learn model object; no default.
    X_train : pandas.DataFrame, predictor variable training data split; no de
t,
    y_train : pandas.DataFrame, target variable training data split; no defau
    X_test : pandas.DataFrame, predictor variable test data split; no default
    y_test : pandas.DataFrame, target variable test data split; no default,
    cmap : {NOT IMPLIMENTED} list of str, colormap of Confusion Matrix; defau
['cool', 'copper_r'],
        cmap of train and test data
    normalize : {NOT IMPLIMENTED} str, normalize count of Confusion Matrix; de
t: 'true',
        - `true` to normalize counts.
        - `false` to show raw counts.
    figsize : tuple ``(lenght, height) in inchs``, figsize of output; default
6, 6),
    show_train_report : boolean; default: False,
        - True, to show report.
        - False, to turn off report.
    fitted_model : bool; default: False,
```

```
    ---version 0.9.14---
    """
    if fitted_model is False:
        model.fit(X_train, y_train)
    train = model.score(X_train, y_train)
    test = model.score(X_test, y_test)

    def str_model_(model):
        """Helper function to get model class display statement, this text co
ion breaks code if
        performed in ``model_report`` function's local space. This function i
isolate from the
        previous function's local space."""
        str_model = str(model.__class__).split('.')[-1][:-2]
        display(
            HTML(
                f"""<strong>Report of {str_model} type model using train-test
t dataset.</strong>"""
            ))

    str_model_(model)
    print(f"{'*'*90}")
    print(f"""Train accuracy score: {train.round(4)}""")
    print(f"""Test accuracy score: {test.round(4)}""")
    if abs(train - test) <= .05:
        print(
            f"    No over or underfitting detected, diffrence of scores did n
oss 5% thresh hold."
        )
    elif (train - test) > .05:
        print(
            f"    Possible Overfitting, diffrence of scores {round(abs(train-
*100,2)}% crossed 5% thresh hold."
        )
    elif (train - test) < -.05:
        print(
            f"    Possible Underfitting, diffrence of scores {round(abs(train
```

```
if show_train_report:
    print(f'Train Report: ')
    print(f"{'*'*60}")
    # train report
    # classification report
    print(
        metrics.classification_report(y_train,
                                      model.predict(X_train)))
    print(f"{'*'*60}")
    # Confusion matrix
    fig, ax = plt.subplots(ncols=2, figsize=figsize)
    metrics.plot_confusion_matrix(model,
                                  X_train,
                                  y_train,
                                  cmap='cool',
                                  normalize='true',
                                  ax=ax[0])
    ax[0].title.set_text('Confusion Matrix')
    # ROC curve
    _ = roc_auc(model,
                X_train,
                y_train,
                classes=None,
                is_fitted=True,
                show=False,
                ax=ax[1])

    ax[1].grid()
    ax[1].title.set_text('ROC Curve')
    plt.xlim([-.05, 1])
    plt.ylim([0, 1.05])
    plt.tight_layout()
    plt.show()

if show_test_report:
    # train report
```

```
                                            model.predict(X_test)))
        print(f"{'*'*60}")
        # Confusion matrix
        fig, ax = plt.subplots(ncols=2, figsize=figsize)
        metrics.plot_confusion_matrix(model,
                                      X_test,
                                      y_test,
                                      cmap='copper_r',
                                      normalize='true',
                                      ax=ax[0])
        ax[0].title.set_text('Confusion Matrix')
        # ROC curve
        _ = roc_auc(model,
                    X_test,
                    y_test,
                    classes=None,
                    is_fitted=True,
                    show=False,
                    ax=ax[1])
        plt.xlim([-.05, 1])
        plt.ylim([0, 1.05])
        ax[1].grid()
        ax[1].title.set_text('ROC Curve')
        plt.tight_layout()
        plt.show()
    pass


def plot_distribution(df,
                      color='gold',
                      figsize=(16, 26),
                      fig_col=3,
                      labelrotation=45,
                      plot_title='Histogram plots of the dataset'):
    """Plots distribution of features

    +++++++++++++++++
```

```
    -----------
    df : pandas.DataFrame, predictor variable training data split; no default,
    color : str, default = 'gold',
        color of bars, takes everything that seaborn takes as color option,
    figsize : tuple ``(lenght, height) in inchs``, figsize of output; default
6, 26),
    fig_col : int; defalut = 3, Controls how many colums to plot in one row,
    labelrotation : int; default = 45, xlabel tick rotation,
    plot_title : str; default = 'Histogram plots of the dataset',
    """
    def num_col_for_plotting(row, col=fig_col):
        """
        +++ formatting helper function +++
        __________________________________
        Returns number of rows to plot

        Parameters:
        ===========
        row = int;
        col = int; default col: 3
        """
        if row % col != 0:
            return (row // col) + 1
        else:
            return row // col

    fig, axes = plt.subplots(nrows=num_col_for_plotting(len(df.columns),
                                                           col=fig_col),
                             ncols=fig_col,
                             figsize=figsize,
                             sharey=False)
    for ax, column in zip(axes.flatten(), df):
        sns.histplot(x=column, data=df, color=color, ax=ax, kde=True)
        ax.set_title(f'Histplot of {column.title()}')
        ax.tick_params('x', labelrotation=labelrotation)
        sns.despine()
        plt.tight_layout()
```

```python
def heatmap_of_features(df, figsize=(15, 15), annot_format='.1f'):
    """
    Return a masked heatmap of the given DataFrame

    Parameters:
    -----------
    df : pandas.DataFrame object.
    annot_format : str, for formatting; default: '.1f'

    Example of `annot_format`:
    --------------------------
    .1e = scientific notation with 1 decimal point (standard form)
    .2f = 2 decimal places
    .3g = 3 significant figures
    .4% = percentage with 4 decimal places

    Note:
    -----
    Rounding error can happen if '.1f' is used.

    -- version: 1.1 --
    """
    with plt.style.context('dark_background'):
        plt.figure(figsize=figsize, facecolor='k')
        mask = np.triu(np.ones_like(df.corr(), dtype=bool))
        cmap = sns.diverging_palette(3, 3, as_cmap=True)
        ax = sns.heatmap(df.corr(),
                         mask=mask,
                         cmap=cmap,
                         annot=True,
                         fmt=annot_format,
                         linecolor='k',
                         annot_kws={"size": 9},
                         square=False,
                         linewidths=.5,
                         cbar_kws={"shrink": .5})
```

```
def drop_features_based_on_correlation(df, threshold=0.75):
    """
    Returns features with high collinearity.

    Parameters:
    ===========
    df = pandas.DataFrame; no default.
            data to work on.
    threshold = float; default: .75.
            Cut off value of check of collinearity.

    -- ver: 1.0 --
    """
    # Set of all the names of correlated columns
    feature_corr = set()
    corr_matrix = df.corr()
    for i in range(len(corr_matrix.columns)):
        for j in range(i):
            # absolute coeff value
            if abs(corr_matrix.iloc[i, j]) > threshold:
                # getting the name of column
                colname = corr_matrix.columns[i]
                feature_corr.add(colname)
    return feature_corr


def cluster_insights(df, color=px.colors.qualitative.Pastel):
    """Plots plotly plots.

    +++++++++++++++++
     Helper function
    +++++++++++++++++
    """
    # fig 1 Age
    financials = [
        'Months_on_book', 'Total_Relationship_Count', 'Months_Inactive_12_mon
```

```
fig = px.histogram(df,
                   x='Customer_Age',
                   marginal="box",
                   template='presentation',
                   nbins=10,
                   color='Gender',
                   barmode='group', color_discrete_sequence=color,
                   title='Customer Demographics',
                   hover_data=df)
fig.update_traces(opacity=0.8)
fig.update_layout(bargap=0.05)
fig.show()
# fig 2 Education
fig = px.histogram(df,
                   color='Education_Level',
                   marginal="box",
                   template='presentation', color_discrete_sequence=color
                   category_orders=dict(Income_Category=[
                       'Unknown', 'Less_than_40K', '40K_to_60K',
                       '60K_to_80K', '80K_to_120K', 'Above_120K'
                   ]),
                   title='Education Level by Income Category',
                   x='Income_Category',
                   barmode='group',
                   hover_data=df)
# fig.update_layout(width=700, height=500, bargap=0.05)
fig.show()
# fig 4 dependent count
fig = px.histogram(df,
                   x='Dependent_count',
                   marginal="box",
                   template='presentation', color_discrete_sequence=color
                   title='Marital Status & Dependent count',
                   color='Marital_Status',
                   barmode='group',
                   hover_data=df)
fig.update_traces(opacity=0.8)
```

```
                 color='Card_Category',
                 data_frame=df,
                 template='presentation',
                 title='Card Category',
                 color_discrete_sequence=["#4169e1", "#fdff00", "#797979", "#e
5"])
    fig.update_layout(width=700, height=500, bargap=0.05)
    fig.show()
    # fig 6
    plot_distribution(df[financials], color='silver', figsize=(
        16, 16), plot_title='Histogram of Numreical features')
    plt.show()
    pass


def describe_dataframe(df):
    """Statistical description of the pandas.DataFrame."""
    left = df.describe(include='all').round(2).T
    right = pd.DataFrame(df.dtypes)
    right.columns = ['dtype']
    ret_df = pd.merge(left=left, right=right,
                      left_index=True, right_index=True)
    na_df = pd.DataFrame(df.isna().sum())
    na_df.columns = ['nulls']
    ret_df = pd.merge(left=ret_df, right=na_df,
                      left_index=True, right_index=True)
    ret_df.fillna('', inplace=True)
    return ret_df


def check_duplicates(df, verbose=0, limit_output=True, limit_num=150):
    """
    Checks for duplicates in the pandas DataFrame and return a Dataframe of re
t.

    Parameters:
    ===========
```

```
                `False` details of unique features.
    limit_num = `int`, limit number of uniques; default: 150,

    Returns:
    ========
    pandas.DataFrame, if verbose = 1.

    ---version 1.3---
    """
    dup_checking = []
    for column in df.columns:
        not_duplicated = df[column].duplicated().value_counts()[0]
        try:
            duplicated = df[column].duplicated().value_counts()[1]
        except:
            duplicated = 0
        temp_dict = {
            'name': column,
            'duplicated': duplicated,
            'not_duplicated': not_duplicated
        }
        dup_checking.append(temp_dict)
    df_ = pd.DataFrame(dup_checking)

    if verbose > 0:
        if limit_output:
            for col in df:
                if (len(df[col].unique())) <= limit_num:
                    print(
                        f"{col} >> number of uniques: {len(df[col].unique())}
ues:\n{df[col].unique()}")
                else:
                    print(
                        f"{col} >> number of uniques: {len(df[col].unique())}
wing top {limit_num} values\nTop {limit_num} Values:\n{df[col].unique()[:limi
m]}\n")
                print(f"{'_'*60}\n")
```

```
s:\n{df[col].unique()}")
    if 1 > verbose >= 0:
        return df_


def unseen_data_processor(X, preprocessor, nume_col, cate_col):
    """
    ++++++++++++++++++
     Helper function
    ++++++++++++++++++
    """
    ret_df = pd.DataFrame(preprocessor.transform(X),
                          columns=nume_col +
                          list(preprocessor.named_transformers_['cate_feat'].
                               named_steps['ohe'].get_feature_names(cate_col)
    return ret_df


def show_px_color_options(type='qualitative'):
    """Shows available options for plotly express."""
    if type == 'qualitative':
        display(dir(px.colors.qualitative))
    elif type == 'sequential':
        display(dir(px.colors.sequential))
    pass


def dataset_processor(X, y, train_size=.8, scaler=None,  OHE_drop_option=None
rsample=True, random_state=None, verbose=0, output='default'):
    """All data processing steps in one. Train test split, scale, OHE, Oversa

    Parameters:
    -----------
    X : pandas.core.frame.DataFrame; no defalut, independent variables,
    y : pandas.core.series.Series, no defalut, dependent variables,
    train_size : float or int; default = .8,
        For use in train_test_split module from sklearn.model_selection
```

```
    scaler : sklearn.preprocessing; default = None,
        None uses ```StandardScaler
OHE_drop_option : str; default = None,
    for use in sklearn.preprocessing._encoders.OneHotEncoder
    drop : {'first', 'if_binary'} or a array-like of shape (n_features,),
    default=None, Specifies a methodology to use to drop one of the
    categories per feature. This is useful in situations where perfectly
    collinear features cause problems, such as when feeding the resulting
    data into a neural network or an unregularized regression.

    However, dropping one category breaks the symmetry of the original
    representation and can therefore induce a bias in downstream models,
    for instance for penalized linear classification or regression models.

        - None : retain all features (the default).
        - 'first' : drop the first category in each feature. If only one
        category is present, the feature will be dropped entirely.
        - 'if_binary' : drop the first category in each feature with two
        categories. Features with 1 or more than 2 categories are
        left intact.
        - array : ``drop[i]`` is the category in feature ``X[:, i]`` that
        should be dropped.
oversample : bool; default = True,
    - ```True``` oversamples train data
    - ```False``` does not oversample train data
random_state : int; defult = None,
    for use in ```train_test_split``` and ```SMOTENC```
verbose : int; default = 0,
    verbosity control. Larger value means more report.
output : str; default = 'default',
    output control, options == ```'default' , 'all'```
    - 'default' returns {X_train, y_train, X_test, y_test}
    - 'all' returns {X_train, y_train, X_test, y_test, preprocessor, nume_col
e_col}

Returns:
--------
```

```
y_test : pandas.core.series.Series,
preprocessor : ColumnTransformer object,
nume_col : list,
cate_col : list,

--- version 0.1 ---
"""
from sklearn.model_selection import train_test_split
# isolating numerical cols
nume_col = list(X.select_dtypes('number').columns)
if verbose > 0:
    print("Numerical columns: \n---------------------\n", nume_col)

# isolating categorical cols
cate_col = list(X.select_dtypes('object').columns)
if verbose > 0:
    print('')
    print("Categorical columns: \n---------------------\n", cate_col)
# train_test_split
X_train, X_test, y_train, y_test = train_test_split(
    X, y, train_size=train_size, random_state=random_state)

# pipeline for processing categorical features
pipe_cate = Pipeline([('ohe',
                       OneHotEncoder(sparse=False, drop=OHE_drop_option))])
# pipeline for processing numerical features
if scaler is None:
    scaler = StandardScaler()
pipe_nume = Pipeline([('scaler', scaler)])
# transformer
preprocessor = ColumnTransformer([('nume_feat', pipe_nume, nume_col),
                                  ('cate_feat', pipe_cate, cate_col)])
# creating dataframes
try:
    X_train = pd.DataFrame(
        preprocessor.fit_transform(X_train),
        columns=nume_col +
```

```
        columns=nume_col +
        list(preprocessor.named_transformers_['cate_feat'].
             named_steps['ohe'].get_feature_names(cate_col)))
    if verbose > 2:
        print("\n\n------")
        print(
            f"Scaler: {str(preprocessor.named_transformers_['nume_feat'].namec
ps['scaler'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_t
formers_['nume_feat'].named_steps['scaler'].get_params()}"
        )
        print(
            f"Encoder: {str(preprocessor.named_transformers_['cate_feat'].name
eps['ohe'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_tra
rmers_['cate_feat'].named_steps['ohe'].get_params()}"
        )
        print("------")
except:
    # if no categorical cols found
    if verbose > 2:
        print("\n\n------")
        print(
            f"Scaler: {str(preprocessor.named_transformers_['nume_feat'].namec
ps['scaler'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_t
formers_['nume_feat'].named_steps['scaler'].get_params()}"
        )
        print(
            f"Encoder: {str(preprocessor.named_transformers_['cate_feat'].name
eps['ohe'].__class__)[1:-2].split('.')[-1]}, settings: {preprocessor.named_tra
rmers_['cate_feat'].named_steps['ohe'].get_params()}"
        )
        print("------")
    print("No Categorical columns found")
    X_train = pd.DataFrame(
        preprocessor.fit_transform(X_train), columns=nume_col)
    X_test = pd.DataFrame(preprocessor.transform(X_test), columns=nume_col)
if oversample:
    from imblearn.over_sampling import SMOTENC
```

```
    smotenc_features = [
        False] * len(nume_col) + [True] * (len(X_train.columns) - len(nume_co
    if verbose > 3:
        print(
            f'debug mode: oversampling, based on X_train, check dtype of overs
ed data')
        print(f'smotenc_features: {smotenc_features}')
    oversampling = SMOTENC(
        categorical_features=smotenc_features, random_state=random_state, n_jo
1)
    X_train, y_train = oversampling.fit_sample(X_train, y_train)

if output == 'default':
    return X_train, y_train, X_test, y_test
elif output == 'all':
    return X_train, y_train, X_test, y_test, preprocessor, nume_col, cate_col
```

def feature_analysis_intracluster(x, facet_col, n_clusters, data_frame=None, title=None, nbins=None, marginal=
histnorm='probability density', color_discrete_sequence=px.colors.qualitative.Pastel, template='presentation'):
"""produces plots for use in analysis intracluster Parameters follows conventional plotly express histogram opti

```
+++++++++++++++++
 Helper function
+++++++++++++++++

Parameters:
-----------
data_frame: DataFrame or array-like or dict
    This argument needs to be passed for column names (and not keyword
    names) to be used. Array-like and dict are tranformed internally to a
    pandas DataFrame. Optional: if missing, a DataFrame gets constructed
    under the hood using the other arguments.
x: str or int or Series or array-like
    Either a name of a column in `data_frame`, or a pandas Series or
    array_like object. Values from this column or array_like are used to
    position marks along the x axis in cartesian coordinates. If
    `orientation` is `'h'`, these values are used as inputs to `histfunc`.
```

```
    Either a name of a column in `data_frame`, or a pandas Series or
    array_like object. Values from this column or array_like are used to
    assign marks to facetted subplots in the horizontal direction.
color_discrete_sequence: list of str
    Strings should define valid CSS-colors. When `color` is set and the
    values in the corresponding column are not numeric, values in that
    column are assigned colors by cycling through `color_discrete_sequence`
    in the order described in `category_orders`, unless the value of
    `color` is a key in `color_discrete_map`. Various useful color
    sequences are available in the `plotly.express.colors` submodules,
    specifically `plotly.express.colors.qualitative`.
marginal: str
    One of `'rug'`, `'box'`, `'violin'`, or `'histogram'`. If set, a
    subplot is drawn alongside the main plot, visualizing the distribution.
histnorm: str (default `None`)
    One of `'percent'`, `'probability'`, `'density'`, or `'probability
    density'` If `None`, the output of `histfunc` is used as is. If
    `'probability'`, the output of `histfunc` for a given bin is divided by
    the sum of the output of `histfunc` for all bins. If `'percent'`, the
    output of `histfunc` for a given bin is divided by the sum of the
    output of `histfunc` for all bins and multiplied by 100. If
    `'density'`, the output of `histfunc` for a given bin is divided by the
    size of the bin. If `'probability density'`, the output of `histfunc`
    for a given bin is normalized such that it corresponds to the
    probability that a random event whose distribution is described by the
    output of `histfunc` will fall into that bin.
nbins: int
    Positive integer. Sets the number of bins.
title: str
    The figure title.
template: str or dict or plotly.graph_objects.layout.Template instance
    The figure template name (must be a key in plotly.io.templates) or
    definition.
"""
if title is None:
    if data_frame is None:
        title = f'{x.name.replace("_"," ")}'
```

```
    x=x,
    facet_col=facet_col,
    marginal=marginal,
    histnorm=histnorm,
    nbins=nbins,
    # labels={'count':histnorm},
    color_discrete_sequence=color_discrete_sequence,
    template=template,
    title=title,
    facet_col_spacing=0.005,
    category_orders={'Clusters': list(np.arange(0, n_clusters))})
fig.update_xaxes(showline=True,
                 linewidth=1,
                 linecolor=color_discrete_sequence[0],
                 mirror=True,
                 title={'text': ''})
fig.update_yaxes(showline=True,
                 linewidth=1,
                 linecolor=color_discrete_sequence[0],
                 mirror=True)

fig.update_yaxes(title={'font': {'size': 8}, 'text': ''})
fig.for_each_annotation(
    lambda a: a.update(text=f'Cluster: {a.text.split("=")[1]}'))

fig.update_layout(
    # keep the original annotations and add a list of new annotations:
    annotations=list(fig.layout.annotations) +
    [go.layout.Annotation(x=-0.06, y=0.5, font=dict(size=12),
                          showarrow=False,
                          text=histnorm,
                          textangle=-90,
                          xref="paper",
                          yref="paper")])
return fig
```

```
fig : plotly figure object; no default,
filename : str; default = None,
ext : str; default = '.png', extension of the file to save. options == ``'pdf
ng', 'jpg'``,
width : int; default = 1400, width in pixels,
height : int: default = 700, height in pixels,
"""
import plotly.io as pio
pio.write_image(
    fig, f'./assets/{filename}{ext}', width=width, height=height)
pass
```

def get_variable_name(*args): """modified from: https://stackoverflow.com/questions/32000934/python-print-a-variables-name-and-value

```
+++++++++++++++++
 Helper function
+++++++++++++++++

Gets variable name for use in function (with eval()).

Parameter:
----------
*args : vairable

Returns:
--------
str

+++ version: 0.0.1 +++
"""
```

In [76]:

```
# imports for this analysis
fn.show_py_file_content(file='./imports_and_functions/packages.py')
```

```
import pandas as pd
import scipy.stats as sts
import numpy as np
from ipywidgets import interact, fixed
```

```python
from sklearn.preprocessing import OrdinalEncoder
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.cluster import KMeans
from sklearn.model_selection import GridSearchCV
from imblearn.over_sampling import SMOTENC
from sklearn.decomposition import PCA
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier
from sklearn.compose import ColumnTransformer
from sklearn.cluster import MeanShift, estimate_bandwidth
from sklearn.inspection import permutation_importance
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler, StandardScaler
from sklearn import metrics
from sklearn.dummy import DummyClassifier
from sklearn.model_selection import train_test_split
from xgboost import XGBClassifier, XGBRFClassifier
import xgboost as xgb
from yellowbrick.cluster import intercluster_distance
from yellowbrick.cluster.elbow import kelbow_visualizer
import seaborn as sns
import matplotlib.pyplot as plt
import joblib
```

Dashboard

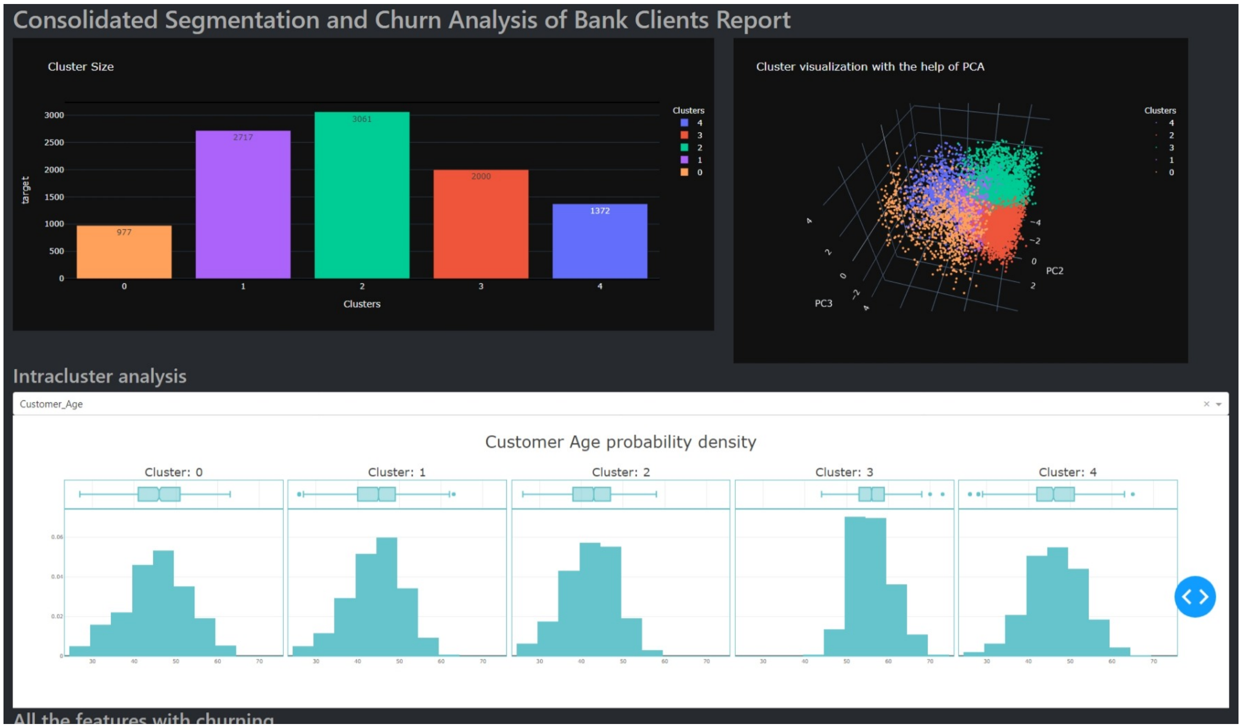
Online

COMING SOON

Local

run `viz_dash.py` for dashboard with insight and prediction. `Dashboard_jupyter.ipynb` contains JupyterDash version for running dash inside jupyter notebook.

Snapshot:


Consolidated Segmentation and Churn Analysis of Bank Clients Report
Cluster Size
target
Clusters
977
2717
3061
2000
1372
Cluster visualization with the help of PCA
PC2
PC3
Intracluster analysis
Customer_Age
Customer Age probability density
Cluster: 0
Cluster: 1
Cluster: 2
Cluster: 3
Cluster: 4
All the features with churning