Customers_Attraction

December 6, 2022

1 Importing Libraries and Dataset

[41]:
```
#import the libraries that will use
import pandas as pd
from google.colab import files
import io
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import preprocessing
import numpy as np
import copy
import matplotlib.style as style
import os
import math
from scipy import stats
from collections import Counter
from sklearn.datasets import make_classification
from sklearn.model_selection import train_test_split as tts
from sklearn.decomposition import PCA
from sklearn.neighbors import KNeighborsClassifier as KNN
from sklearn.metrics import classification_report
from imblearn.over_sampling import SMOTE
from imblearn.pipeline import Pipeline
from sklearn.metrics import roc_auc_score
```

[42]:
```
pip install dython
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
Requirement already satisfied: dython in /usr/local/lib/python3.7/dist-packages
(0.7.2)
Requirement already satisfied: seaborn>=0.11.0 in /usr/local/lib/python3.7/dist-
packages (from dython) (0.11.2)
Collecting matplotlib>=3.4.3
  Using cached
matplotlib-3.5.3-cp37-cp37m-manylinux_2_5_x86_64.manylinux1_x86_64.whl (11.2 MB)
Requirement already satisfied: scikit-learn>=0.24.2 in
```

```
/usr/local/lib/python3.7/dist-packages (from dython) (1.0.2)
Requirement already satisfied: psutil>=5.9.1 in /usr/local/lib/python3.7/dist-
packages (from dython) (5.9.4)
Requirement already satisfied: pandas>=1.3.2 in /usr/local/lib/python3.7/dist-
packages (from dython) (1.3.5)
Requirement already satisfied: scikit-plot>=0.3.7 in
/usr/local/lib/python3.7/dist-packages (from dython) (0.3.7)
Requirement already satisfied: numpy>=1.19.5 in /usr/local/lib/python3.7/dist-
packages (from dython) (1.21.6)
Requirement already satisfied: scipy>=1.7.1 in /usr/local/lib/python3.7/dist-
packages (from dython) (1.7.3)
Requirement already satisfied: pyparsing>=2.2.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.4.3->dython) (3.0.9)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.7/dist-
packages (from matplotlib>=3.4.3->dython) (21.3)
Requirement already satisfied: fonttools>=4.22.0 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.4.3->dython) (4.38.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib>=3.4.3->dython) (0.11.0)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.7/dist-
packages (from matplotlib>=3.4.3->dython) (7.1.2)
Requirement already satisfied: python-dateutil>=2.7 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.4.3->dython) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib>=3.4.3->dython) (1.4.4)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from
kiwisolver>=1.0.1->matplotlib>=3.4.3->dython) (4.1.1)
Requirement already satisfied: pytz>=2017.3 in /usr/local/lib/python3.7/dist-
packages (from pandas>=1.3.2->dython) (2022.6)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.7->matplotlib>=3.4.3->dython) (1.15.0)
Requirement already satisfied: joblib>=0.11 in /usr/local/lib/python3.7/dist-
packages (from scikit-learn>=0.24.2->dython) (1.2.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn>=0.24.2->dython)
(3.1.0)
Installing collected packages: matplotlib
  Attempting uninstall: matplotlib
    Found existing installation: matplotlib 3.1.1
    Uninstalling matplotlib-3.1.1:
      Successfully uninstalled matplotlib-3.1.1
Successfully installed matplotlib-3.5.3
```

[43]:
```
pip install matplotlib==3.1.1
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-
wheels/public/simple/
```

```
Collecting matplotlib==3.1.1
  Using cached matplotlib-3.1.1-cp37-cp37m-manylinux1_x86_64.whl (13.1 MB)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib==3.1.1) (3.0.9)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.7/dist-
packages (from matplotlib==3.1.1) (0.11.0)
Requirement already satisfied: python-dateutil>=2.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib==3.1.1) (2.8.2)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib==3.1.1) (1.4.4)
Requirement already satisfied: numpy>=1.11 in /usr/local/lib/python3.7/dist-
packages (from matplotlib==3.1.1) (1.21.6)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from
kiwisolver>=1.0.1->matplotlib==3.1.1) (4.1.1)
Requirement already satisfied: six>=1.5 in /usr/local/lib/python3.7/dist-
packages (from python-dateutil>=2.1->matplotlib==3.1.1) (1.15.0)
Installing collected packages: matplotlib
  Attempting uninstall: matplotlib
    Found existing installation: matplotlib 3.5.3
    Uninstalling matplotlib-3.5.3:
      Successfully uninstalled matplotlib-3.5.3
ERROR: pip's dependency resolver does not currently take into account all
the packages that are installed. This behaviour is the source of the following
dependency conflicts.
dython 0.7.2 requires matplotlib>=3.4.3, but you have matplotlib 3.1.1 which is
incompatible.
Successfully installed matplotlib-3.1.1
```

[49]:
```
from dython.nominal import associations
```

[44]:
```
# Read the data with the Pandas libray in this stage
data = pd.read_csv('https://raw.githubusercontent.com/AlaaAli968/Bank-Churn/
↪main/BankChurners%20(1).csv',sep = ',')
```

2 Exploratory Data Analysis

[5]:
```
# To check the datatypes as we can see do not have any null value
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                    Non-Null Count  Dtype
```

```
---  ------                    --------------  -----
 0   CLIENTNUM                 10127 non-null  int64
 1   Attrition_Flag            10127 non-null  object
 2   Customer_Age              10127 non-null  int64
 3   Gender                    10127 non-null  object
 4   Dependent_count           10127 non-null  int64
 5   Education_Level           10127 non-null  object
 6   Marital_Status            10127 non-null  object
 7   Income_Category           10127 non-null  object
 8   Card_Category             10127 non-null  object
 9   Months_on_book            10127 non-null  int64
 10  Total_Relationship_Count  10127 non-null  int64
 11  Months_Inactive_12_mon    10127 non-null  int64
 12  Contacts_Count_12_mon     10127 non-null  int64
 13  Credit_Limit              10127 non-null  float64
 14  Total_Revolving_Bal       10127 non-null  int64
 15  Avg_Open_To_Buy           10127 non-null  float64
 16  Total_Amt_Chng_Q4_Q1      10127 non-null  float64
 17  Total_Trans_Amt           10127 non-null  int64
 18  Total_Trans_Ct            10127 non-null  int64
 19  Total_Ct_Chng_Q4_Q1       10127 non-null  float64
 20  Avg_Utilization_Ratio     10127 non-null  float64
dtypes: float64(5), int64(10), object(6)
memory usage: 1.6+ MB
```

[6]:
```python
# To check the data we can use the head() function to see first 5 rows.
data.head()
```

[6]:
```
   CLIENTNUM     Attrition_Flag  Customer_Age Gender  Dependent_count  \
0  768805383  Existing Customer            45      M                3
1  818770008  Existing Customer            49      F                5
2  713982108  Existing Customer            51      M                3
3  769911858  Existing Customer            40      F                4
4  709106358  Existing Customer            40      M                3

  Education_Level Marital_Status Income_Category Card_Category  \
0     High School        Married     $60K - $80K          Blue
1        Graduate         Single  Less than $40K          Blue
2        Graduate        Married    $80K - $120K          Blue
3     High School        Unknown  Less than $40K          Blue
4      Uneducated        Married     $60K - $80K          Blue

   Months_on_book  …  Months_Inactive_12_mon  Contacts_Count_12_mon  \
0              39  …                       1                      3
1              44  …                       1                      2
2              36  …                       1                      0
3              34  …                       4                      1
```

```
4              21  …                       1                      0

   Credit_Limit  Total_Revolving_Bal  Avg_Open_To_Buy  Total_Amt_Chng_Q4_Q1  \
0       12691.0                  777          11914.0                 1.335
1        8256.0                  864           7392.0                 1.541
2        3418.0                    0           3418.0                 2.594
3        3313.0                 2517            796.0                 1.405
4        4716.0                    0           4716.0                 2.175

   Total_Trans_Amt  Total_Trans_Ct  Total_Ct_Chng_Q4_Q1  Avg_Utilization_Ratio
0             1144              42                1.625                  0.061
1             1291              33                3.714                  0.105
2             1887              20                2.333                  0.000
3             1171              20                2.333                  0.760
4              816              28                2.500                  0.000

[5 rows x 21 columns]
```

[7]:

```
d=data.describe().T
d
```

[7]:

```
                            count          mean           std          min  \
CLIENTNUM                 10127.0  7.391776e+08  3.690378e+07  708082083.0
Customer_Age              10127.0  4.632596e+01  8.016814e+00         26.0
Dependent_count           10127.0  2.346203e+00  1.298908e+00          0.0
Months_on_book            10127.0  3.592841e+01  7.986416e+00         13.0
Total_Relationship_Count  10127.0  3.812580e+00  1.554408e+00          1.0
Months_Inactive_12_mon    10127.0  2.341167e+00  1.010622e+00          0.0
Contacts_Count_12_mon     10127.0  2.455317e+00  1.106225e+00          0.0
Credit_Limit              10127.0  8.631954e+03  9.088777e+03       1438.3
Total_Revolving_Bal       10127.0  1.162814e+03  8.149873e+02          0.0
Avg_Open_To_Buy           10127.0  7.469140e+03  9.090685e+03          3.0
Total_Amt_Chng_Q4_Q1      10127.0  7.599407e-01  2.192068e-01          0.0
Total_Trans_Amt           10127.0  4.404086e+03  3.397129e+03        510.0
Total_Trans_Ct            10127.0  6.485869e+01  2.347257e+01         10.0
Total_Ct_Chng_Q4_Q1       10127.0  7.122224e-01  2.380861e-01          0.0
Avg_Utilization_Ratio     10127.0  2.748936e-01  2.756915e-01          0.0

                                   25%           50%           75%  \
CLIENTNUM                 7.130368e+08  7.179264e+08  7.731435e+08
Customer_Age              4.100000e+01  4.600000e+01  5.200000e+01
Dependent_count           1.000000e+00  2.000000e+00  3.000000e+00
Months_on_book            3.100000e+01  3.600000e+01  4.000000e+01
Total_Relationship_Count  3.000000e+00  4.000000e+00  5.000000e+00
Months_Inactive_12_mon    2.000000e+00  2.000000e+00  3.000000e+00
Contacts_Count_12_mon     2.000000e+00  2.000000e+00  3.000000e+00
Credit_Limit              2.555000e+03  4.549000e+03  1.106750e+04
```

```
Total_Revolving_Bal       3.590000e+02  1.276000e+03  1.784000e+03
Avg_Open_To_Buy           1.324500e+03  3.474000e+03  9.859000e+03
Total_Amt_Chng_Q4_Q1      6.310000e-01  7.360000e-01  8.590000e-01
Total_Trans_Amt           2.155500e+03  3.899000e+03  4.741000e+03
Total_Trans_Ct            4.500000e+01  6.700000e+01  8.100000e+01
Total_Ct_Chng_Q4_Q1       5.820000e-01  7.020000e-01  8.180000e-01
Avg_Utilization_Ratio     2.300000e-02  1.760000e-01  5.030000e-01

                                   max
CLIENTNUM                 8.283431e+08
Customer_Age              7.300000e+01
Dependent_count           5.000000e+00
Months_on_book            5.600000e+01
Total_Relationship_Count  6.000000e+00
Months_Inactive_12_mon    6.000000e+00
Contacts_Count_12_mon     6.000000e+00
Credit_Limit              3.451600e+04
Total_Revolving_Bal       2.517000e+03
Avg_Open_To_Buy           3.451600e+04
Total_Amt_Chng_Q4_Q1      3.397000e+00
Total_Trans_Amt           1.848400e+04
Total_Trans_Ct            1.390000e+02
Total_Ct_Chng_Q4_Q1       3.714000e+00
Avg_Utilization_Ratio     9.990000e-01
```

[8]:
```
# Double check for the null-values
data.isnull().sum()
```

[8]:
```
CLIENTNUM                   0
Attrition_Flag              0
Customer_Age                0
Gender                      0
Dependent_count             0
Education_Level             0
Marital_Status              0
Income_Category             0
Card_Category               0
Months_on_book              0
Total_Relationship_Count    0
Months_Inactive_12_mon      0
Contacts_Count_12_mon       0
Credit_Limit                0
Total_Revolving_Bal         0
Avg_Open_To_Buy             0
Total_Amt_Chng_Q4_Q1        0
Total_Trans_Amt             0
Total_Trans_Ct              0
```

```
Total_Ct_Chng_Q4_Q1          0
Avg_Utilization_Ratio        0
dtype: int64
```

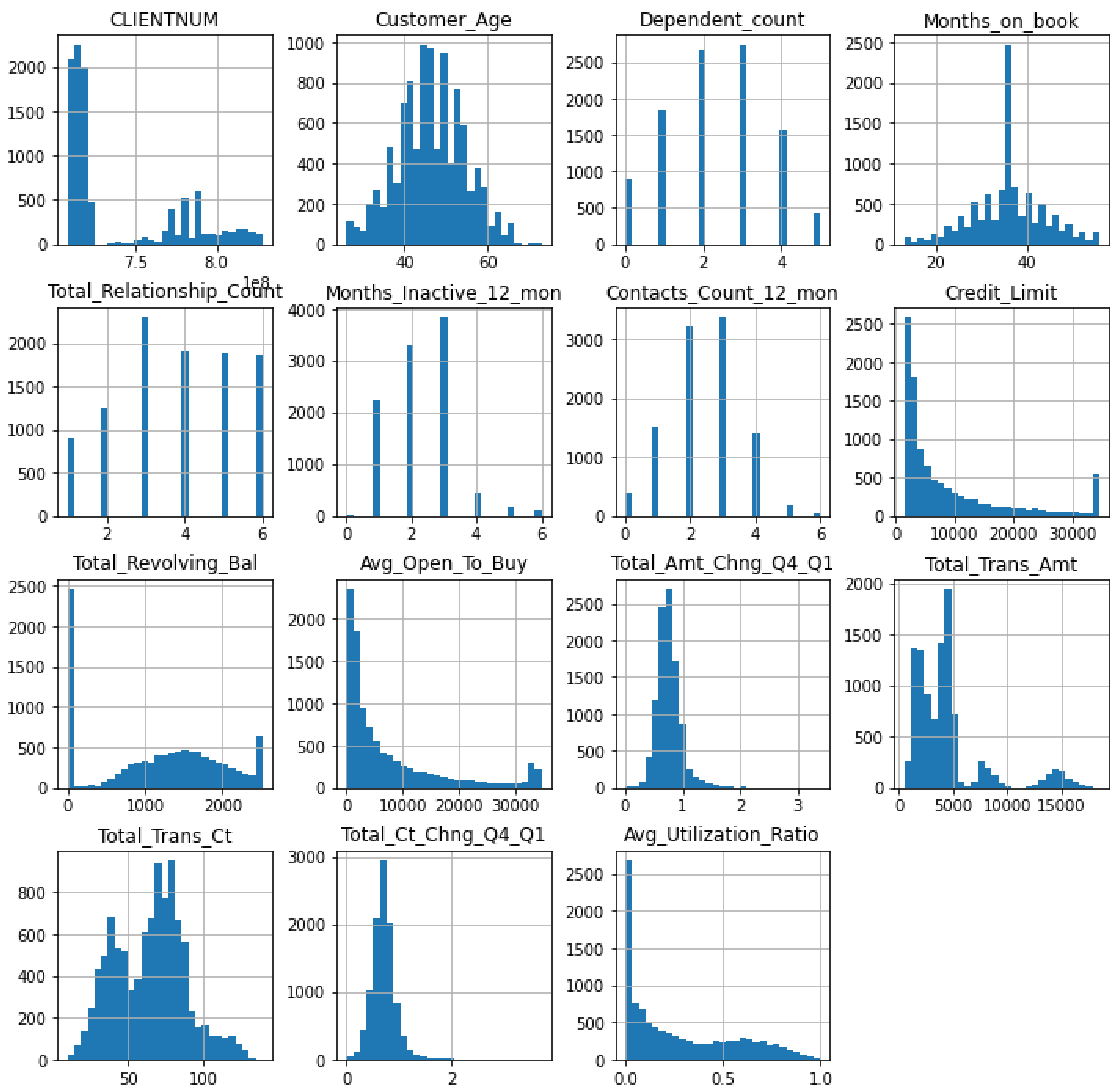
[25]:
```
data.duplicated().sum()
```

[25]:
```
0
```

[9]:
```
cat_cols = ['Attrition_Flag','Gender','Education_Level', 'Marital_Status',␣
 ↪'Income_Category', 'Card_Category']
from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy='most_frequent', missing_values='Unknown')

data[cat_cols] = imputer.fit_transform(data[cat_cols])

for i in cat_cols:
  print(i)
  print(data[i].unique())
  print('-'*25)
```

```
Attrition_Flag
['Existing Customer' 'Attrited Customer']
-------------------------
Gender
['M' 'F']
-------------------------
Education_Level
['High School' 'Graduate' 'Uneducated' 'College' 'Post-Graduate'
 'Doctorate']
-------------------------
Marital_Status
['Married' 'Single' 'Divorced']
-------------------------
Income_Category
['$60K - $80K' 'Less than $40K' '$80K - $120K' '$40K - $60K' '$120K +']
-------------------------
Card_Category
['Blue' 'Gold' 'Silver' 'Platinum']
-------------------------
```

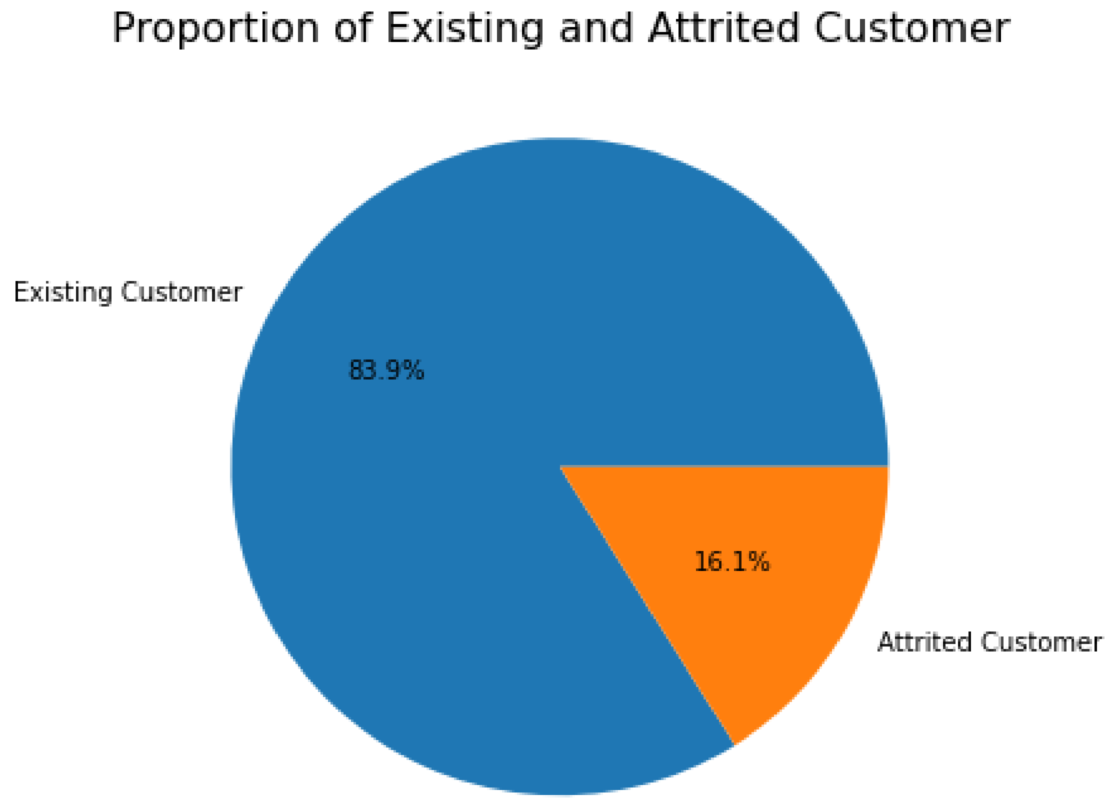
[11]:
```
# distribution of numerical features
axList = data.hist(bins=29, figsize = (12, 12))
plt.savefig("Hist.png")
```



[12]:
```
table=data['Attrition_Flag'].value_counts(normalize=True) * 100
print(table)
churn=data['Attrition_Flag'].value_counts()
churn
plt.figure(figsize = (6,6))
piechart=plt.pie(x=churn,labels=churn.keys(),autopct="%.1f%%")
plt.title('Proportion of Existing and Attrited Customer', fontsize = 16)
# as we see data is  imbalanced so we will apply some and random oversamling␣
↪techniques later to balance it before running the models
```

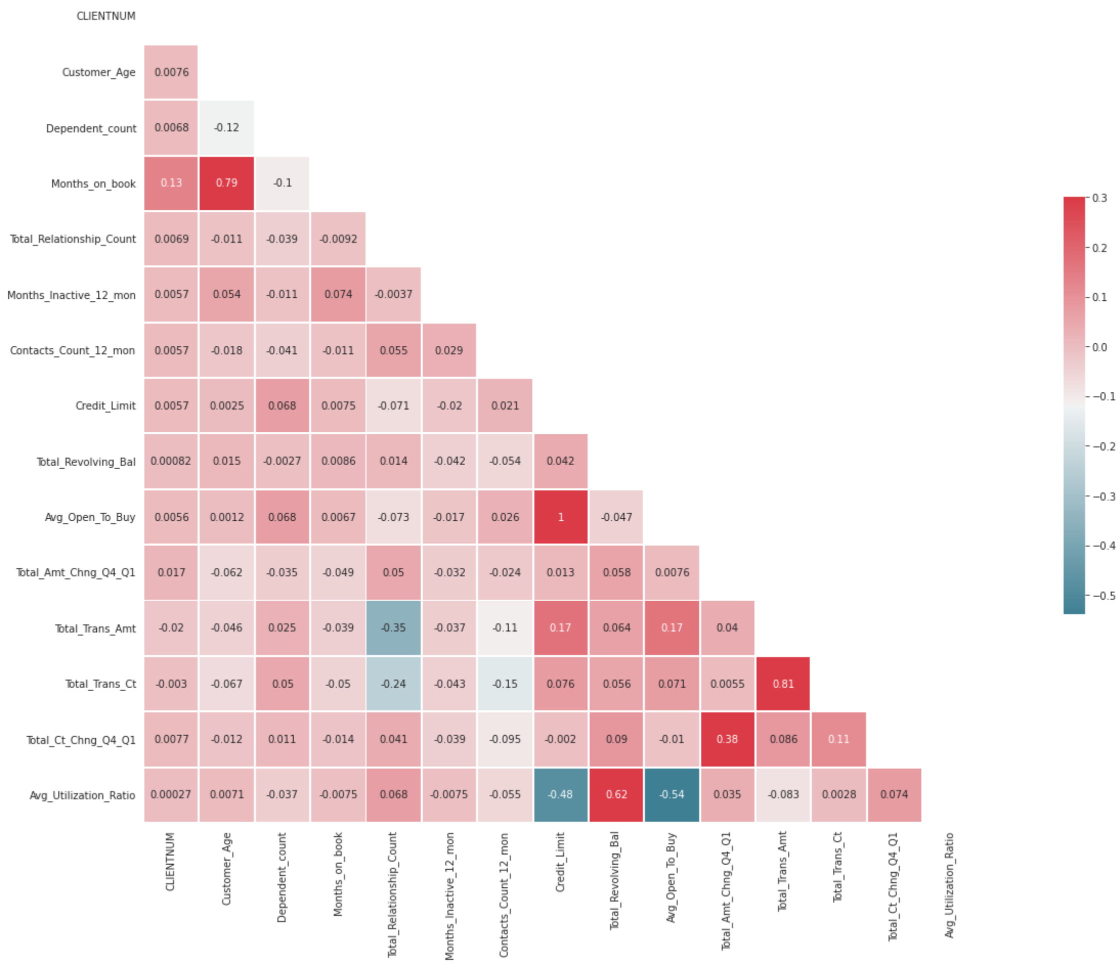
```
Existing Customer     83.934038
Attrited Customer     16.065962
Name: Attrition_Flag, dtype: float64
```

[12]: Text(0.5, 1.0, 'Proportion of Existing and Attrited Customer')

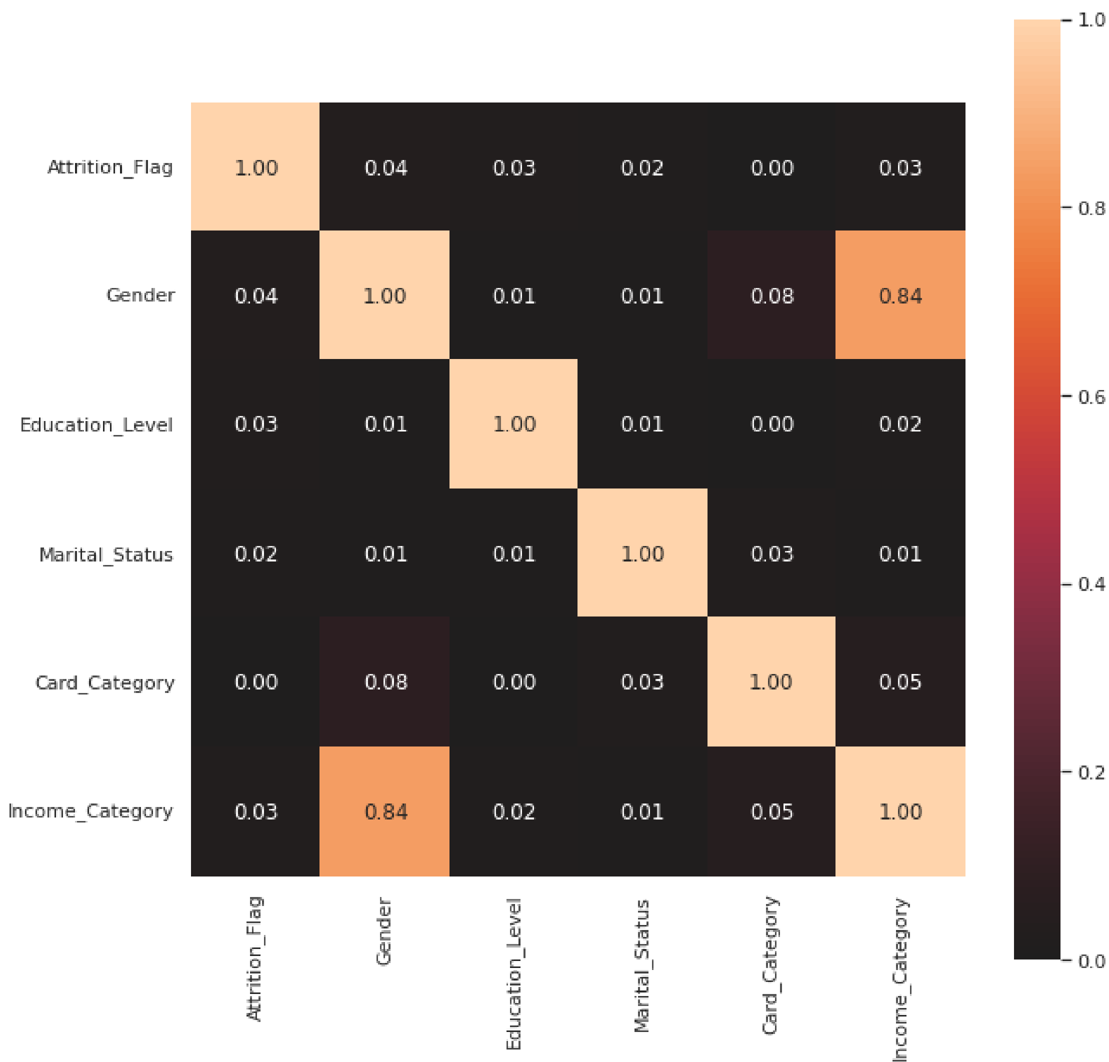


[18]:
```
# correlation matrix for numeric data using Pearson correlation coefficient
new_data= copy.copy(data)

new_data['Attrition_Flag'].replace({'Existing Customer':0, 'Attrited Customer':
 ↪1})
corr = new_data.corr()
corr

mask = np.zeros_like(corr)
mask[np.triu_indices_from(mask)] = True

# Generate a custom diverging colormap
cmap = sns.diverging_palette(220, 10, as_cmap=True)

with sns.axes_style("white"):
    # Set up the matplotlib figure
    f, ax = plt.subplots(figsize=(30, 15))
```

```
ax = sns.heatmap(corr, cmap=cmap, mask=mask, vmax=.3, square=True,␣
↪linewidths=.9, cbar_kws={"shrink": .5}, annot=True)
```

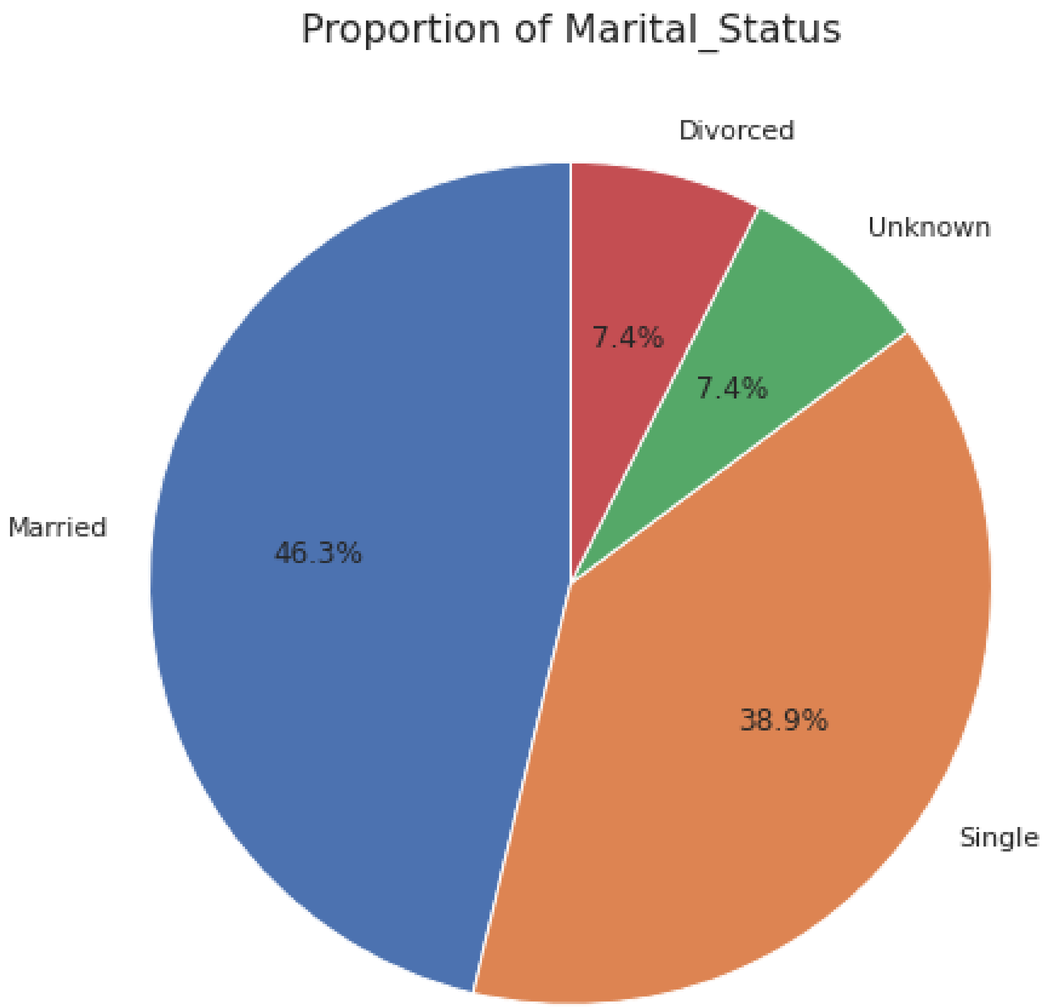


[50]:
```
#correlation for categorical data (Cramer's coefficient)
selected_column=␣
↪data[["Attrition_Flag","Gender","Education_Level","Marital_Status","Card_Category","Income_
categorical_df = selected_column.copy()
categorical_correlation= associations(categorical_df, filename=␣
↪'categorical_correlation.png', figsize=(10,10))
```

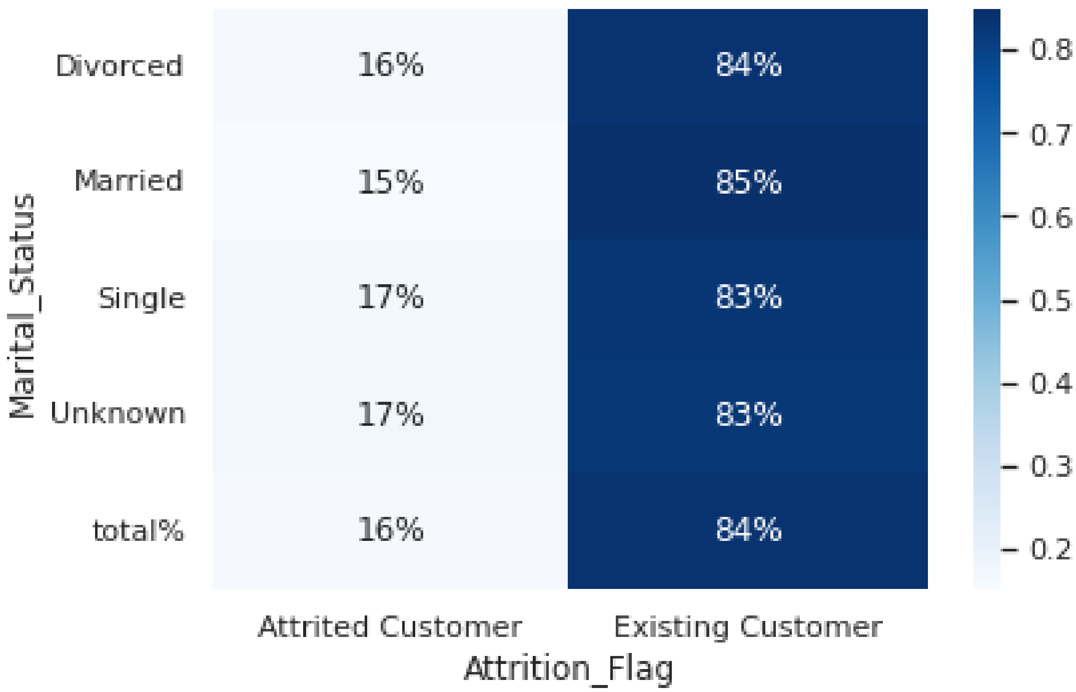


[47]:
```
# Customers' Distribution  based on Marital status
plt.figure(figsize = (8,8))
plt.pie(data['Marital_Status'].value_counts(),
        labels = ['Married', 'Single', 'Unknown', 'Divorced'],
        autopct='%1.1f%%', startangle = 90)
plt.title('Proportion of Marital_Status', fontsize = 16)
plt.show()

# Attrition proportion between genders to see the probability of churning  in␣
 ↪each education level category
cross = pd.crosstab(data['Marital_Status'],
            data['Attrition_Flag'],
            margins = True,
            margins_name = "total%",
```

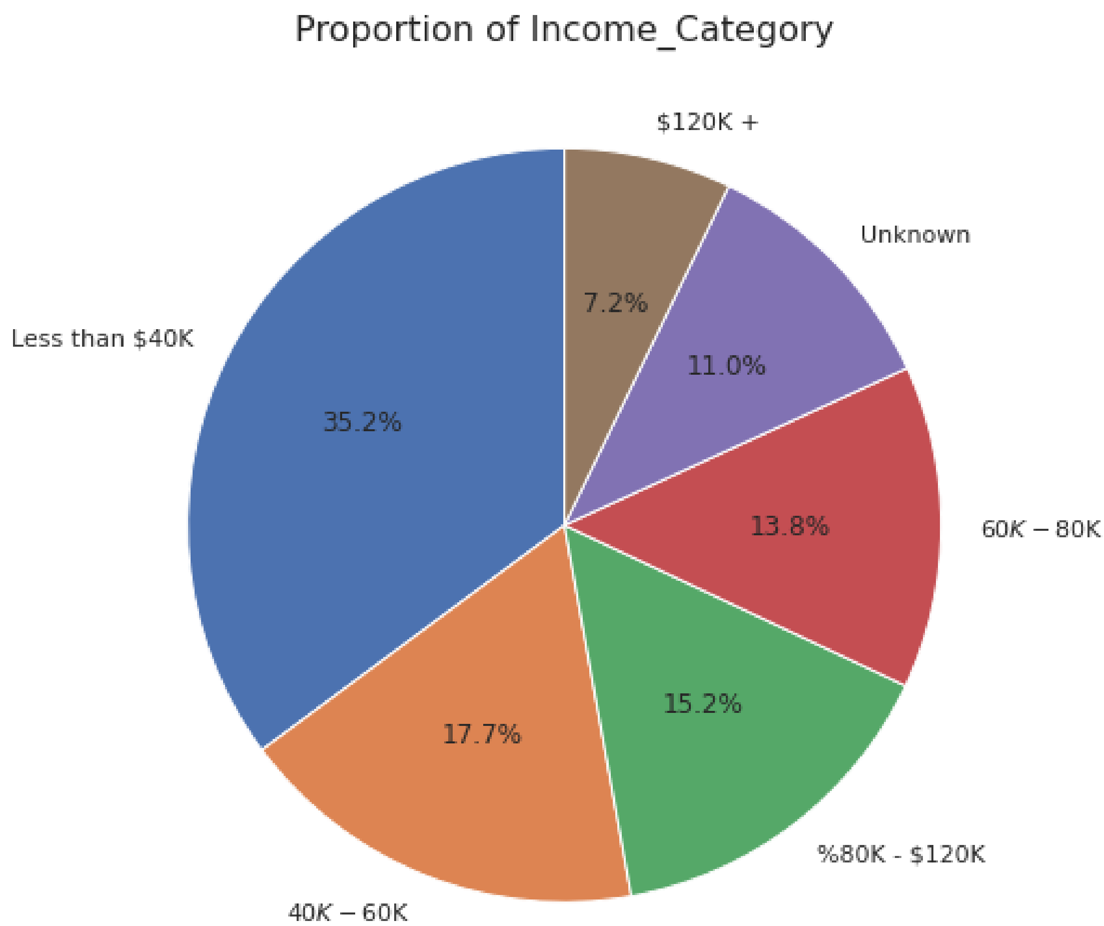
```
            normalize='index')
sns.heatmap(cross, annot=True, fmt='.0%', cmap='Blues')
```



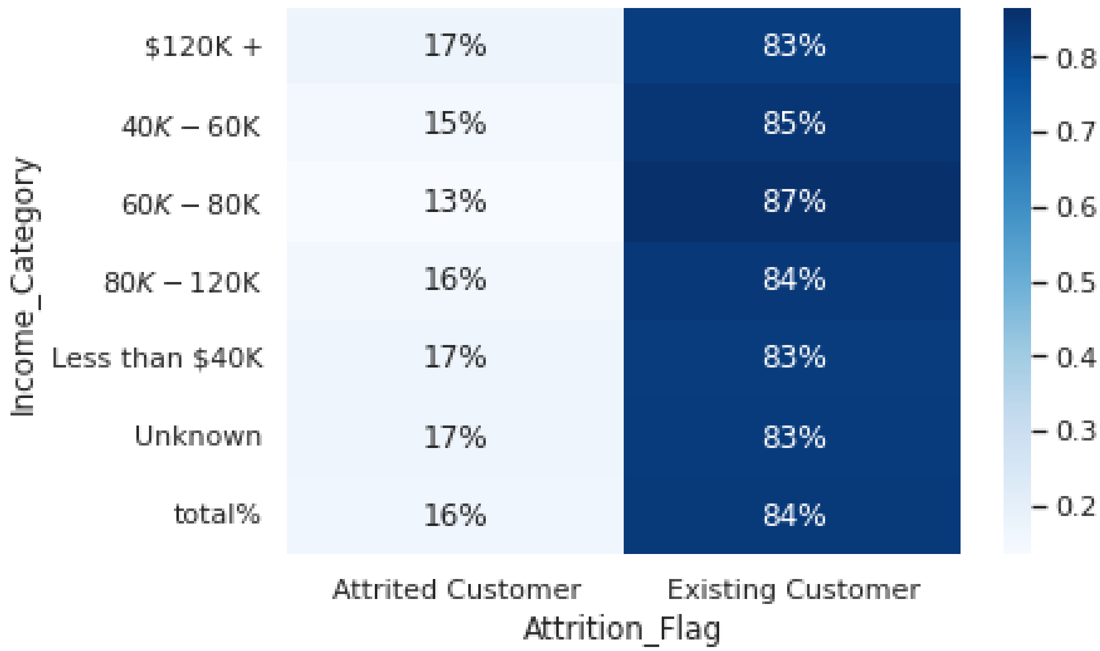
[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb8bb6e390>



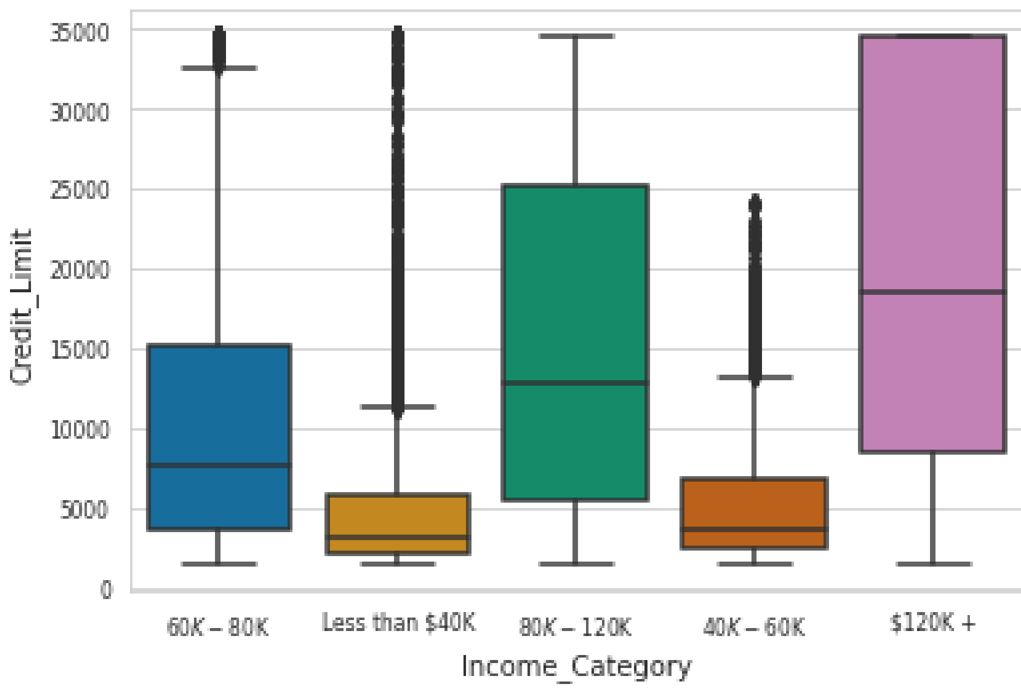
[45]:
```
# Customers' Distribution based on Income Category
plt.figure(figsize = (8,8))
plt.pie(data['Income_Category'].value_counts(),
        labels = ['Less than $40K', '$40K - $60K', '%80K - $120K', '$60K -␣
↪$80K', 'Unknown','$120K +'],
        autopct='%1.1f%%', startangle = 90)
plt.title('Proportion of Income_Category', fontsize = 16)
plt.show()

# Attrition proportion between genders to see the probability of churning  in␣
↪each education level category
cross = pd.crosstab(data['Income_Category'],
            data['Attrition_Flag'],
            margins = True,
            margins_name = "total%",
            normalize='index')
sns.heatmap(cross, annot=True, fmt='.0%', cmap='Blues')
```



[45]: <matplotlib.axes._subplots.AxesSubplot at 0x7ffb865f4850>

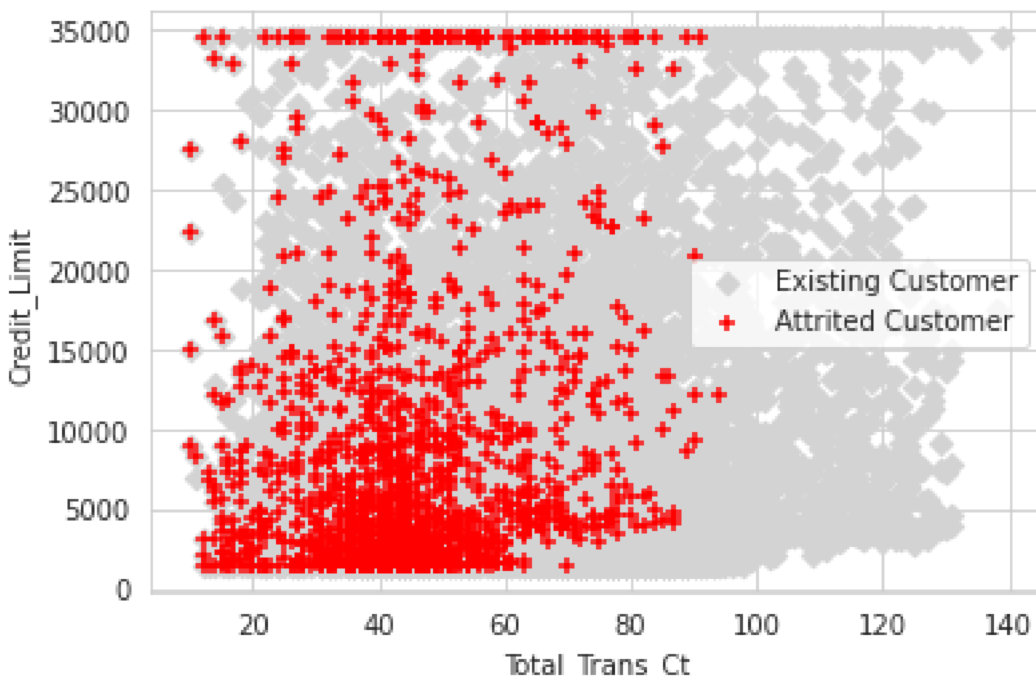


[28]:
```
#Income_Category and Credit_Limit
sns.set_style("whitegrid")
s=sns.boxplot(x = 'Income_Category', y = 'Credit_Limit', data =␣
 ↪data,palette="colorblind")
s.tick_params(labelsize=7.5)
```



[30]:

```
#Existing Customer Attrited Customer
plt.scatter(data['Total_Trans_Ct'][(data.Attrition_Flag == 'Existing Customer')␣
 ↪| (data.Attrition_Flag == 'Attrited Customer')],
            data['Credit_Limit'][(data.Attrition_Flag == 'Existing Customer') |␣
 ↪(data.Attrition_Flag == 'Attrited Customer')],
           marker='D',
           color='lightgray',
           label='Existing Customer')
plt.scatter(data['Total_Trans_Ct'][data.Attrition_Flag == 'Attrited Customer'],
            data['Credit_Limit'][data.Attrition_Flag == 'Attrited Customer'],
           marker='+',
           color='red',
           label='Attrited Customer')
plt.xlabel('Total_Trans_Ct')
plt.ylabel('Credit_Limit')
plt.legend()
plt.show()
```



3 Data Preprocessing

[51]:
```python
df = data.copy()
```

3.1 Converting Categorical Columns to Numeric Columns

Machine learning algorithms work best with numerical data. However, in my dataset, I have some categorical columns, I need to convert them to numeric columns.

[52]:
```python
# Encoding our target: Attrition_Flag
df = df.replace({'Attrition_Flag':{'Existing Customer':0, 'Attrited Customer':
 ↪1}})
# Selecting all the categorical features to one hot encode
df_cat = df.select_dtypes('object')

# One hot encoding
df = pd.get_dummies(df, df_cat.columns, drop_first = False)
df.dtypes
```

[52]:
```
CLIENTNUM                            int64
Attrition_Flag                       int64
Customer_Age                         int64
Dependent_count                      int64
Months_on_book                       int64
Total_Relationship_Count             int64
Months_Inactive_12_mon               int64
Contacts_Count_12_mon                int64
Credit_Limit                       float64
Total_Revolving_Bal                  int64
Avg_Open_To_Buy                    float64
Total_Amt_Chng_Q4_Q1               float64
Total_Trans_Amt                      int64
Total_Trans_Ct                       int64
Total_Ct_Chng_Q4_Q1                float64
Avg_Utilization_Ratio              float64
Gender_F                             uint8
Gender_M                             uint8
Education_Level_College              uint8
Education_Level_Doctorate            uint8
Education_Level_Graduate             uint8
Education_Level_High School          uint8
Education_Level_Post-Graduate        uint8
Education_Level_Uneducated           uint8
Education_Level_Unknown              uint8
Marital_Status_Divorced              uint8
Marital_Status_Married               uint8
```

```
Marital_Status_Single                 uint8
Marital_Status_Unknown                uint8
Income_Category_$120K +               uint8
Income_Category_$40K - $60K           uint8
Income_Category_$60K - $80K           uint8
Income_Category_$80K - $120K          uint8
Income_Category_Less than $40K        uint8
Income_Category_Unknown               uint8
Card_Category_Blue                    uint8
Card_Category_Gold                    uint8
Card_Category_Platinum                uint8
Card_Category_Silver                  uint8
dtype: object
```

4 Split Data

I split the model into 70% training and 30% testing as it's the most popular ratio

[53]:
```python
from sklearn.model_selection import train_test_split
x = df.drop(['CLIENTNUM', 'Attrition_Flag'], axis = 1)
y = df['Attrition_Flag']
x_train, x_test, y_train, y_test = train_test_split(
                                    x,
                                    y,
                                    test_size = 0.3,
                                    random_state = 1999)
```

5 Model Training

After splitting the data, I will create various machine learning classifiers and identify the best model out of three(in trining set)

I will train different classifiers and try to best model. We will utilize:

1. Random Forest
2. Decision Tree
3. Logistic Regression

I chose these models because they are popular in binry classification problem also as I saw in Kaggle many people who have the same dataset and used these models got more accurate results.As well as I mentioned in the literature review in the related studies section most of them used Random Forest and was the best model, those studies have binary classification problems like my problem.so based on these I think Random Forest will be the best model.

I will train these models on imbalanced data then with oversampling, I used 2 techniques for oversampling (SMOTE and Random Oversampling) and compare between them.

6 Imbalanced

6.1 Confusion Metric

A confusion matrix is a technique for summarizing the performance of a classification algorithm. It is a table with combinations of predicted and actual values. For my case target is :

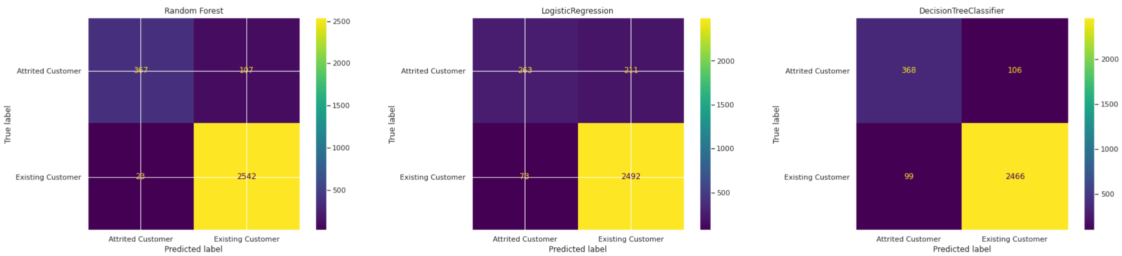
0 : Existing Customer

1 : Attrited Customer

[76]:
```
model1 = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model2 =ensemble.RandomForestClassifier(random_state=2002)
model3 = tree.DecisionTreeClassifier(random_state=2002)

model2.fit(x_train, y_train)
model1.fit(x_train, y_train)
model3.fit(x_train, y_train)

from sklearn.metrics import plot_confusion_matrix
fig,ax=plt.subplots(ncols=3, figsize=(30,6))
plt.grid(False)
plot_confusion_matrix(model2, x_test,␣
 ↪y_test,labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
 ↪Customer'], ax=ax[0])
ax[0].title.set_text('Random Forest')

plot_confusion_matrix(model1, x_test,␣
 ↪y_test,labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
 ↪Customer'],ax=ax[1])
ax[1].title.set_text('LogisticRegression')



plot_confusion_matrix(model3, x_test, y_test,labels=[1,0]␣
 ↪,display_labels=["Attrited Customer", 'Existing Customer'],ax=ax[2])
ax[2].title.set_text('DecisionTreeClassifier')
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
```

```
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
```



6.2 Build and Evaluate the Models for Imbalanced Data

[54]:
```python
from sklearn.metrics import roc_curve,roc_auc_score,accuracy_score,recall_score,f1_score,brier_score_loss,matthews_corrcoef
import time
from sklearn import tree,ensemble,linear_model
#Build the 3 models
models = [tree.DecisionTreeClassifier(random_state=2002),
       ensemble.RandomForestClassifier(random_state=2002),
       linear_model.LogisticRegression(solver="liblinear",random_state=2002)]#liblinear is a good choice for small dataset



name = []

Accuracy = []#= TP+TN/TP+FP+FN+TN

Specificity=[]#true negative rate

Sensetivity=[]#true positive rate

auc=[]#evaluates the the model's performance across different threshold
f1=[]#
mcc=[]#Matthews correlation coefficient -1 to 1
brier=[]#1-Acc
ptime=[]#
```

```
ttime=[]#

for i in models:

    name.append(i.__class__.__name__)

    start_f=time.time()

    i.fit(x_train, y_train)
    end_f=time.time()
    start_p=time.time()



    y_predicted=i.predict(x_test)

    end_p=time.time()

    train_t=end_f - start_f
    pre_t=end_f - start_f

    Accuracy.append(accuracy_score(y_test,y_predicted))

    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))#true␣
 ↪positive rate.

    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))#true␣
 ↪positive rate.

    i_probs= i.predict_proba(x_test)

    i_probs=i_probs[:,1]
    mcc.append(matthews_corrcoef(y_test,y_predicted))
    auc.append(roc_auc_score(y_test,i_probs))
    f1.append(f1_score(y_test,y_predicted))
    brier.append(brier_score_loss(y_test,y_predicted))#1-ACC
    ptime.append(pre_t)
    ttime.append(train_t)






models_evaluation = pd.DataFrame({"Model": name, "MCC":mcc,"Brier":
 ↪brier,"Accuracy": Accuracy,"Sensetivity":Sensetivity,"Specificity":
 ↪Specificity,"F1":f1,"AUC":auc,"Predict Time":ptime,"Training Time":ttime})
```

```
display(models_evaluation)
```

```
                    Model       MCC     Brier  Accuracy  Sensetivity  \
0  DecisionTreeClassifier  0.742271  0.067456  0.932544     0.776371
1  RandomForestClassifier  0.830211  0.042777  0.957223     0.774262
2      LogisticRegression  0.609045  0.093452  0.906548     0.554852

   Specificity        F1       AUC  Predict Time  Training Time
0     0.961404  0.782147  0.868887      0.087921       0.087921
1     0.991033  0.849537  0.987695      1.191323       1.191323
2     0.971540  0.649383  0.922995      0.093405       0.093405
```

from the table we can see that Random Forest model the best model with really high values for Accuracy, MCC, and AUC. Also lowest value with Brier

6.3 ROC curve for Imbalanced data

Next step will show ROC curve (receiver operating characteristic curve) a graph showing the performance of a classification model at all classification thresholds(defult 0.5). This curve plots two parameters:

1. True Positive Rate
2. False Positive Rate

Area Under ROC Curve (or ROC AUC for short) is a performance metric for binary classification problems.

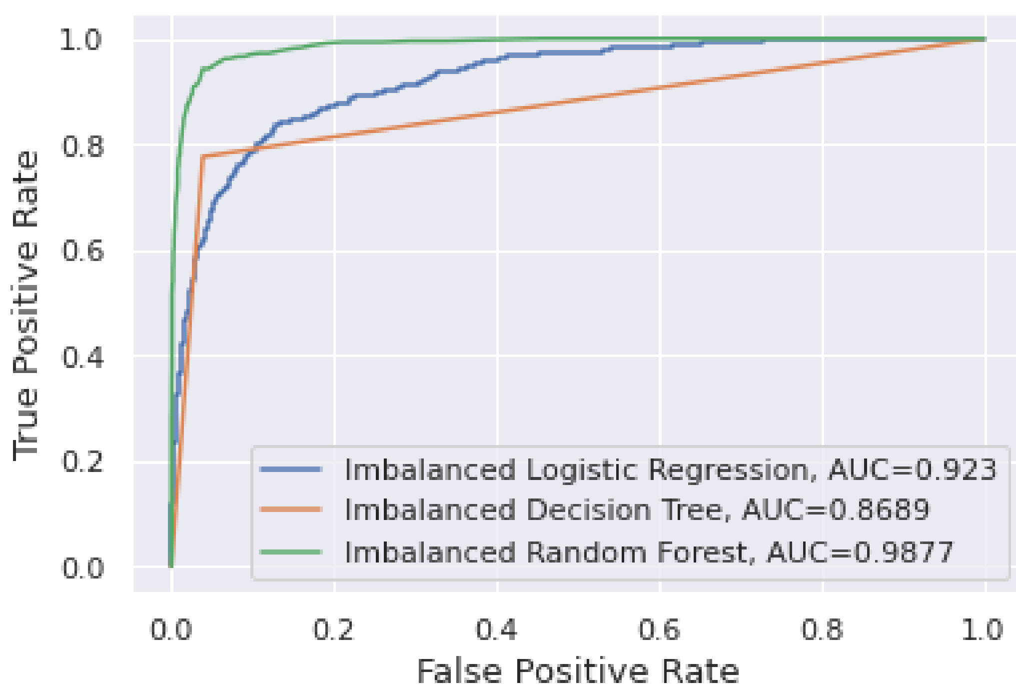
The AUC represents a model's ability to discriminate between positive and negative classes. An area of 1.0 represents a model that made all predictions perfectly. An area of 0.5 represents a model as good as random.

A ROC Curve is a plot of the true positive rate and the false positive rate for a given set of probability predictions at different thresholds used to map the probabilities to class labels. The area under the curve is then the approximate integral under the ROC Curve.

[56]:
```
from sklearn import metrics
from sklearn import datasets
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt
#plt.figure(0).clf()
#fit logistic regression model and plot ROC curve
model = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model.fit(x_train, y_train)
y_pred = model.predict_proba(x_test)[:, 1]# prob number of classes
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)#fpr:False Positive Rates, tpr:
 ↪True Positive Rates, _:threshold
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
```

```
plt.plot(fpr,tpr,label="Imbalanced Logistic Regression, AUC="+str(auc))


#fit Decision Tree model and plot ROC curve
model = tree.DecisionTreeClassifier(random_state=2002)
model.fit(x_train, y_train)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="Imbalanced Decision Tree, AUC="+str(auc))

#fit Random Forest model and plot ROC curve
model = ensemble.RandomForestClassifier(random_state=2002)
model.fit(x_train, y_train)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="Imbalanced Random Forest, AUC="+str(auc))


#add legend
plt.legend()
plt.ylabel('True Positive Rate', size = 13)
plt.xlabel('False Positive Rate', size = 13)
```

[56]: Text(0.5, 0, 'False Positive Rate')



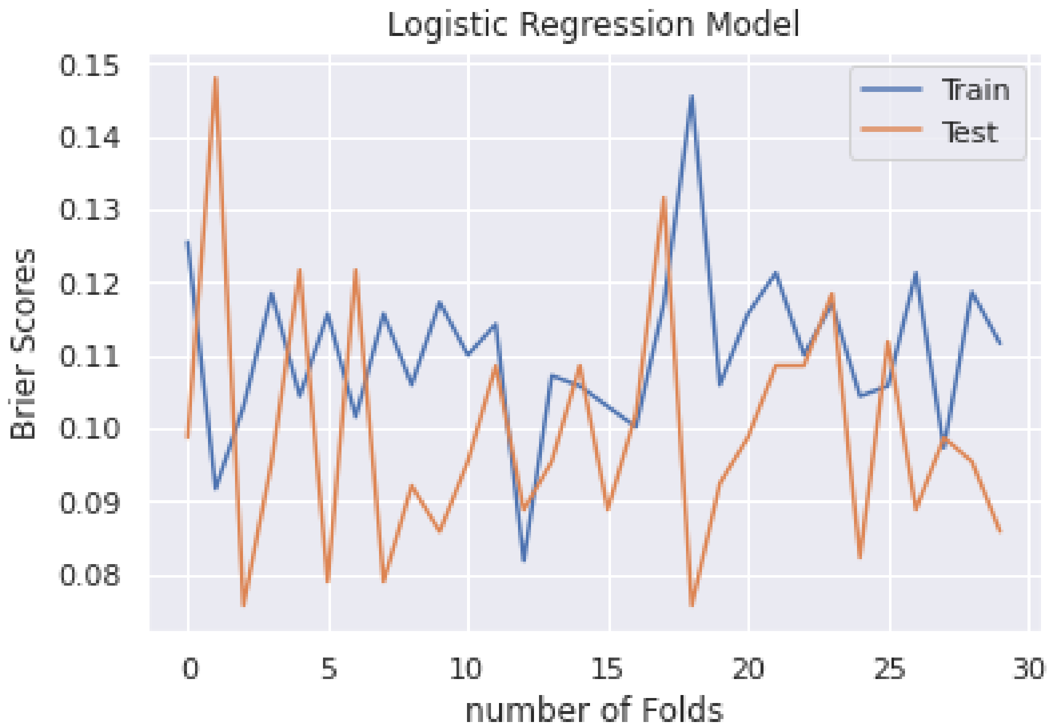
6.4 k-fold cross-validation for Imbalanced data

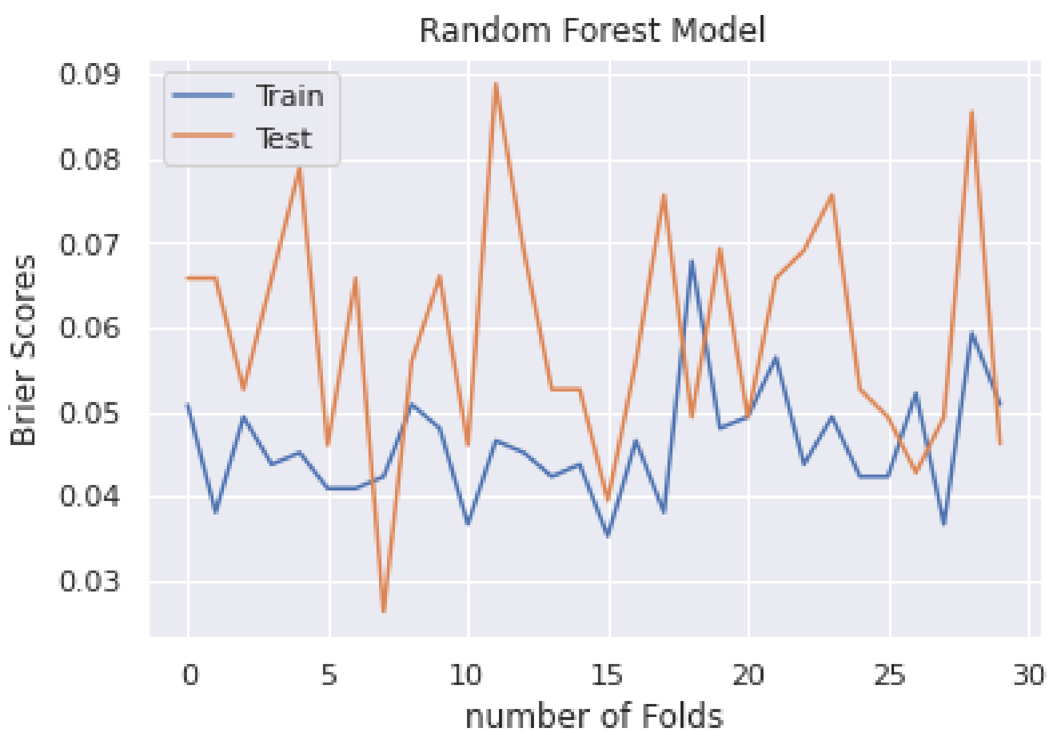
To ckeck overfitting and underfitting I used Brier score which is similar to mean squared error

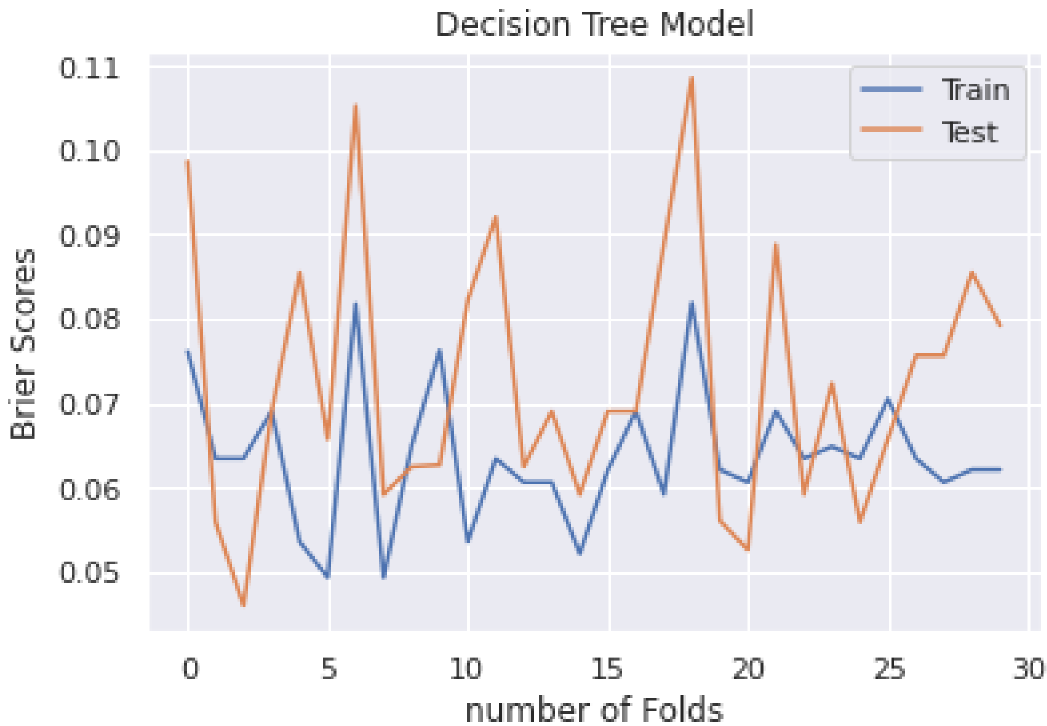
[57]:
```
# Evaluate a logistic regression model using repeated k-fold cross-validation

from numpy import mean

from numpy import std

from sklearn.datasets import make_classification

from sklearn.model_selection import RepeatedKFold

from sklearn.model_selection import cross_val_score

from sklearn.linear_model import LogisticRegression



# prepare the cross-validation procedure Repeats 10-Fold 3 times

cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

# create models

model1 = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model2 =ensemble.RandomForestClassifier(random_state=2002)
model3 = tree.DecisionTreeClassifier(random_state=2002)

# evaluate models by Brier score which is = 1-Accuracy
scores1 = 1-cross_val_score(model1, x_train, y_train, scoring='accuracy',␣
↪cv=cv, n_jobs=-1) #n_job=-1 means using all processors
scores2 =1- cross_val_score(model2, x_train, y_train, scoring='accuracy',␣
↪cv=cv, n_jobs=-1)
scores3 = 1-cross_val_score(model3,x_train, y_train, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)

#to compare with test set
log_test = 1-cross_val_score(model1, x_test, y_test, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)
rf_test =1- cross_val_score(model2, x_test, y_test, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)
```

```
dt_test = 1-cross_val_score(model3, x_test, y_test, scoring='accuracy', cv=cv,␣
 ↪n_jobs=-1)


# report performance

print('Brier for Logistic Regression : %.3f (%.3f)' %␣
 ↪(mean(scores1),std(scores2)))
print('Brier Random Forest: %.3f (%.3f)' % (mean(scores2), std(scores2)))
print('Brier Decision Tree: %.3f (%.3f)' % (mean(scores3), std(scores3)))
#plot performance for Logistic Regression Model
plt.plot(scores1,  label='Train')
plt.plot(log_test ,label='Test')
plt.legend(loc='best')
plt.title('Logistic Regression Model')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()

#plot performance for Random Forest Model
plt.plot(scores2,  label='Train')
plt.plot(rf_test ,label='Test')
plt.legend(loc='best')
plt.title('Random Forest Model')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()
#plot performance for Decision Tree Model
plt.plot(scores3,  label='Train')
plt.plot(dt_test ,label='Test')
plt.legend(loc='best')
plt.title('Decision Tree Model')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()
```

```
Brier for Logistic Regression : 0.110 (0.007)
Brier Random Forest: 0.046 (0.007)
Brier Decision Tree: 0.064 (0.008)
```


Logistic Regression Model
Train
Test
Brier Scores
number of Folds


Random Forest Model
Train
Test
Brier Scores
number of Folds



7 SMOTE

Now I will apply SMOTE oversampling technique to fix the imbalanced data

[58]:
```
sm = SMOTE(sampling_strategy='minority', random_state=42)
x_train_res, y_train_res = sm.fit_resample(x_train, y_train)
```

[59]:
```
#Before SMOTE
unique,count=np.unique(y_train,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
print(y_train_dict_value_count)

#After SMOTE
unique,count=np.unique(y_train_res,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
print(y_train_dict_value_count)
```

```
{0: 5935, 1: 1153}
{0: 5935, 1: 5935}
```

7.1 Confusion Metric

[92]:
```
model1 = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model2 =ensemble.RandomForestClassifier(random_state=2002)
model3 = tree.DecisionTreeClassifier(random_state=2002)

model2.fit(x_train_res, y_train_res)
model1.fit(x_train_res, y_train_res)
model3.fit(x_train_res, y_train_res)

from sklearn.metrics import plot_confusion_matrix
fig,ax=plt.subplots(ncols=3, figsize=(20,6))
plot_confusion_matrix(model2, x_test,␣
 ↪y_test,labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
 ↪Customer'], ax=ax[0])
ax[0].title.set_text('Random Forest')
plot_confusion_matrix(model1, x_test, y_test,␣
 ↪labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
 ↪Customer'],ax=ax[1])
ax[1].title.set_text('LogisticRegression')
plot_confusion_matrix(model3, x_test, y_test,␣
 ↪labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
 ↪Customer'],ax=ax[2])
ax[2].title.set_text('DecisionTreeClassifier')
plt.grid(b=None)
fig.tight_layout(pad=53)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:18: UserWarning:
Tight layout not applied. The bottom and top margins cannot be made large enough
```

```
to accommodate all axes decorations.
```

7.2 Build and Evaluate the Models for balanced Data (SMOTE)

[61]:
```python
from sklearn.metrics import roc_curve,␣
 ↪roc_auc_score,accuracy_score,recall_score,f1_score

from sklearn import tree,ensemble
import time

models = [tree.DecisionTreeClassifier(random_state=2002),
       ensemble.RandomForestClassifier(random_state=2002),
       linear_model.LogisticRegression(solver="liblinear",random_state=2002)]

name = []

Accuracy = []

Specificity=[]

Sensetivity=[]

auc=[]

f1=[]

mcc=[]

brier=[]
ptime=[]
ttime=[]

for i in models:
```

```
    name.append(i.__class__.__name__)

    start_f=time.time()

    i.fit(x_train_res, y_train_res)

    end_f=time.time()
    start_p=time.time()


    y_predicted=i.predict(x_test)
    end_p=time.time()

    train_t=end_f - start_f
    pre_t=end_f - start_f

    Accuracy.append(accuracy_score(y_test,y_predicted))

    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))

    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))

    i_probs= i.predict_proba(x_test)

    i_probs=i_probs[:,1]
    mcc.append(matthews_corrcoef(y_test,y_predicted))


    auc.append(roc_auc_score(y_test,i_probs))
    f1.append(f1_score(y_test,y_predicted))
    brier.append(brier_score_loss(y_test,y_predicted))
    ptime.append(pre_t)
    ttime.append(train_t)




models_evaluation1= pd.DataFrame({"Model": name,"MCC":mcc,"Brier":brier,␣
 ↪"Accuracy": Accuracy,"Sensetivity":Sensetivity,"Specificity":
 ↪Specificity,"F1":f1,"AUC":auc,"Predict Time":ptime,"Training Time":ttime})#.
 ↪style.set_caption("After SMOTE OverSampling")

display(models_evaluation1)
```

```
                    Model       MCC     Brier  Accuracy  Sensetivity  \
0  DecisionTreeClassifier  0.727393  0.074696  0.925304     0.805907
1  RandomForestClassifier  0.831757  0.043764  0.956236     0.843882
```

```
2      LogisticRegression  0.647079  0.086542  0.913458     0.620253

   Specificity        F1       AUC  Predict Time  Training Time
0     0.947368  0.770938  0.876638      0.736316       0.736316
1     0.976998  0.857449  0.985499      3.190659       3.190659
2     0.967641  0.690952  0.931549      0.275132       0.275132
```

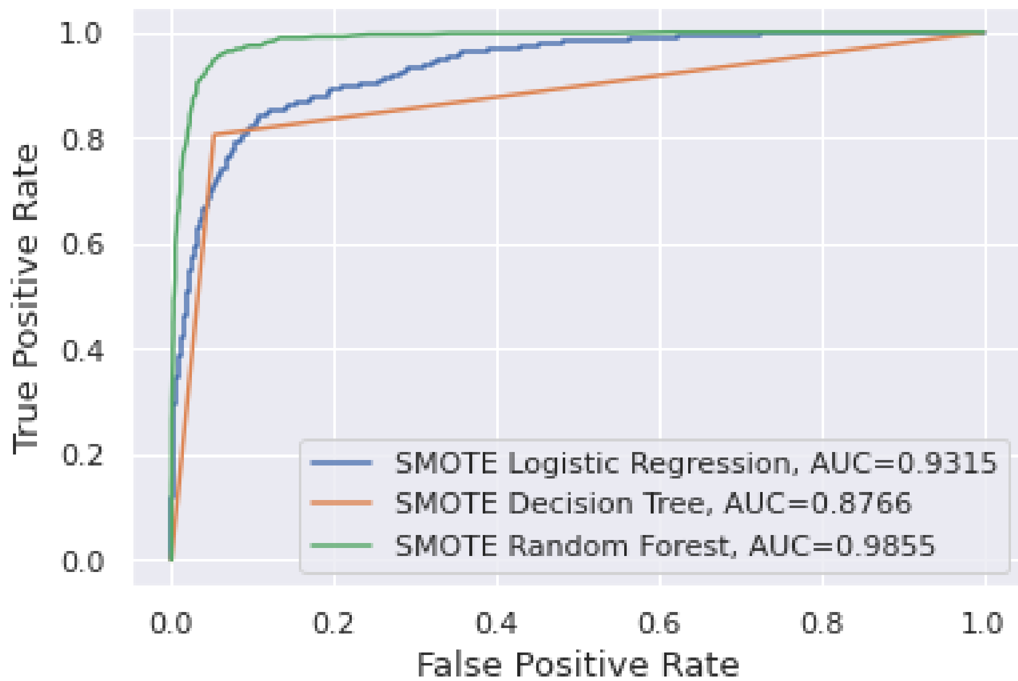
As we can see, Random Forest is still the best model, but there is a slight decrease in the Accuracy, Auc and true negative rate after using SMOTE. On the other hand F1, true positive rate and MCC increased.

7.3 ROC curve for balanced Data (SMOTE)

[62]:
```python
from sklearn import metrics
from sklearn import datasets
from sklearn.model_selection import train_test_split
import matplotlib.pyplot as plt

#fit logistic regression model and plot ROC curve
model = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model.fit(x_train_res, y_train_res)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="SMOTE Logistic Regression, AUC="+str(auc))

#fit Decision Tree model and plot ROC curve
model = tree.DecisionTreeClassifier(random_state=2002)
model.fit(x_train_res, y_train_res)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="SMOTE Decision Tree, AUC="+str(auc))

#fit Random Forest model and plot ROC curve
model = ensemble.RandomForestClassifier(random_state=2002)
model.fit(x_train_res, y_train_res)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)#thrushhold
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="SMOTE Random Forest, AUC="+str(auc))


#add legend
plt.legend()
plt.ylabel('True Positive Rate', size = 13)
```

```
plt.xlabel('False Positive Rate', size = 13)
```

[62]: Text(0.5, 0, 'False Positive Rate')



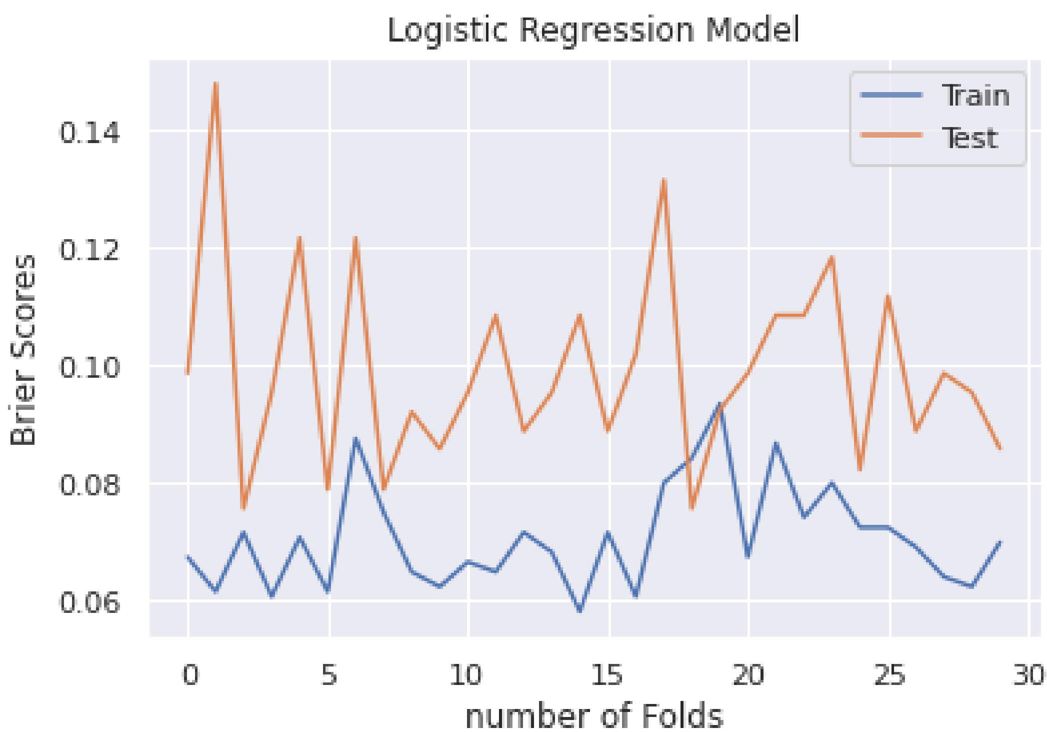
7.4 k-fold cross-validation for balanced data(SMOTE)

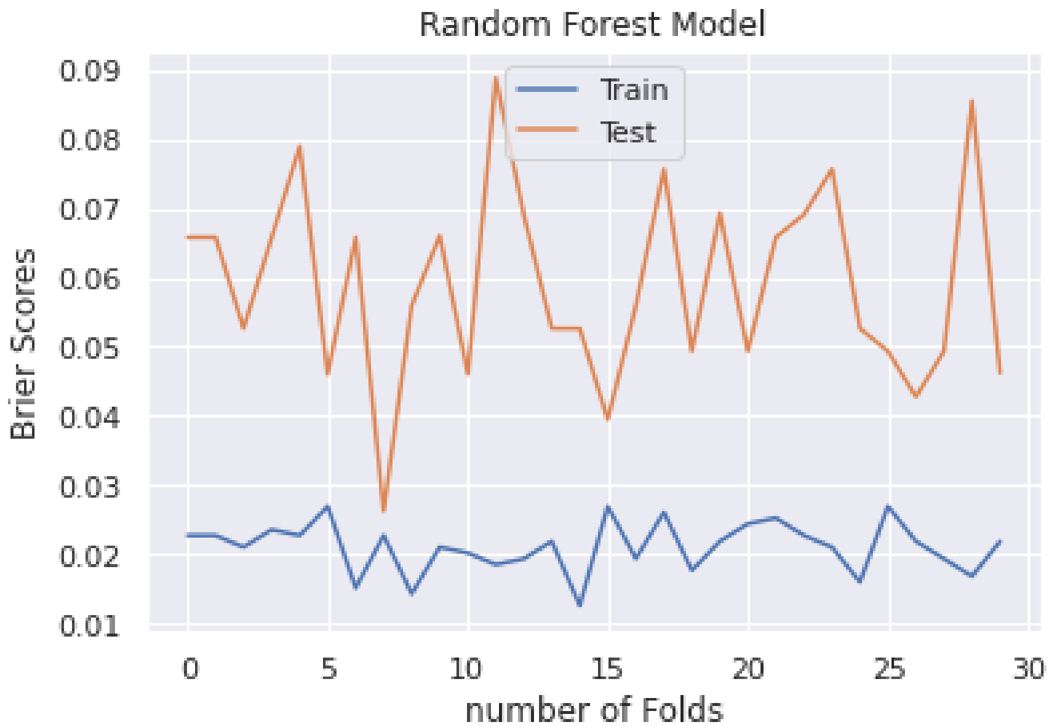
[63]:
```
from sklearn.datasets import make_classification

from sklearn.model_selection import RepeatedKFold

from sklearn.model_selection import cross_val_score

from sklearn.linear_model import LogisticRegression



# prepare the cross-validation procedure Repeats 10-Fold 3 times

cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)#

# create models

model1 = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
```

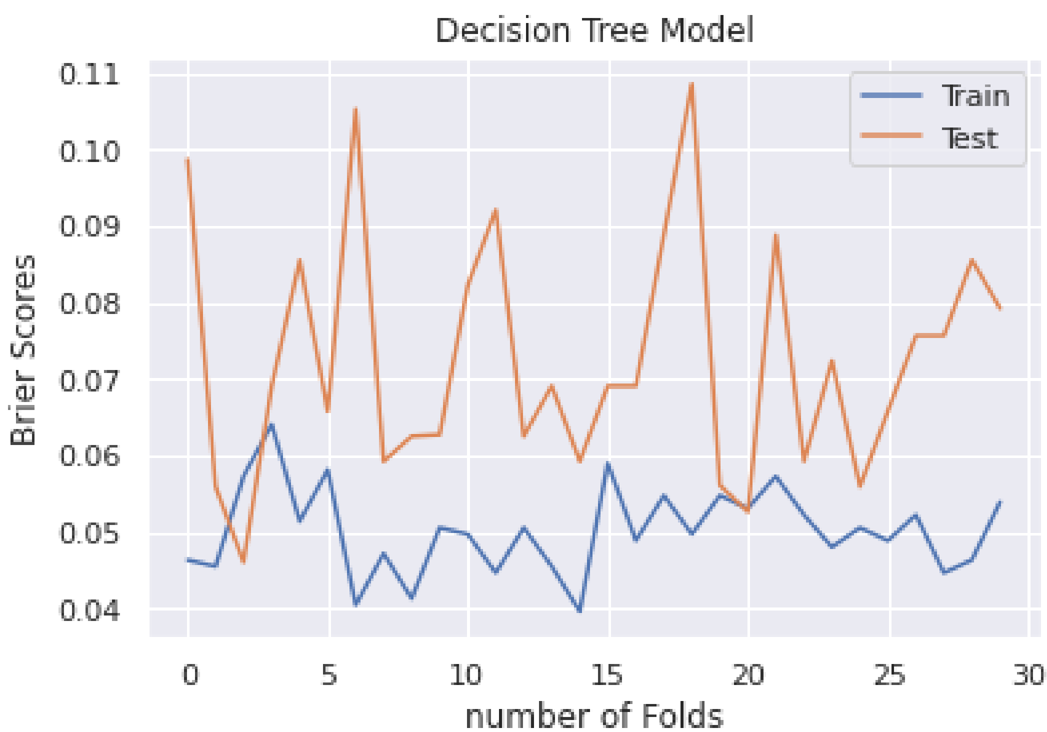
```python
model2 =ensemble.RandomForestClassifier(random_state=2002)
model3 = tree.DecisionTreeClassifier(random_state=2002)

# evaluate models by Brier score which is = 1-Accuracy
scores1 = 1-cross_val_score(model1, x_train_res, y_train_res,␣
 ↪scoring='accuracy', cv=cv, n_jobs=-1) #n_job=-1 -1 means using all processors
scores2 =1- cross_val_score(model2, x_train_res, y_train_res,␣
 ↪scoring='accuracy', cv=cv, n_jobs=-1)
scores3 = 1-cross_val_score(model3,x_train_res, y_train_res,␣
 ↪scoring='accuracy', cv=cv, n_jobs=-1)
# to compare with test set
log_test = 1-cross_val_score(model1, x_test, y_test, scoring='accuracy', cv=cv,␣
 ↪n_jobs=-1)
rf_test =1- cross_val_score(model2, x_test, y_test, scoring='accuracy', cv=cv,␣
 ↪n_jobs=-1)
dt_test = 1-cross_val_score(model3, x_test, y_test, scoring='accuracy', cv=cv,␣
 ↪n_jobs=-1)

#print(scores)

# report performance

print('Brier for Logistic Regression : %.3f (%.3f)' %␣
 ↪(mean(scores1),std(scores2)))
print('Brier for Random Forest: %.3f (%.3f)' % (mean(scores2), std(scores2)))
print('Brier for Decision Tree: %.3f (%.3f)' % (mean(scores3), std(scores3)))
#plot performance for Logistic Regression Model
plt.plot(scores1,  label='Train')
plt.plot(log_test ,label='Test')
plt.legend(loc='best')
plt.title('Logistic Regression Model')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()
#plot performance for Random Forest Model

plt.plot(scores2,  label='Train')
plt.plot(rf_test ,label='Test')
plt.legend(loc='best')
plt.title('Random Forest Model')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()
#plot performance for Decision Tree Model
```

```
plt.plot(scores3,  label='Train')
plt.plot(dt_test ,label='Test')
plt.legend(loc='best')
plt.title('Decision Tree Model')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()
```

```
Brier for Logistic Regression : 0.071 (0.004)
Brier for Random Forest: 0.021 (0.004)
Brier for Decision Tree: 0.050 (0.006)
```




Random Forest Model
Train
Test
Brier Scores
number of Folds
0.09
0.08
0.07
0.06
0.05
0.04
0.03
0.02
0.01
0
5
10
15
20
25
30


Decision Tree Model
Train
Test
Brier Scores
number of Folds
0.11
0.10
0.09
0.08
0.07
0.06
0.05
0.04
0
5
10
15
20
25
30

8 Random OverSampling

[64]:
```
from sklearn.datasets import make_classification
from imblearn.over_sampling import RandomOverSampler

# define oversampling strategy
oversample = RandomOverSampler(sampling_strategy='minority',random_state=2002)
# fit and apply the transform
x_over, y_over = oversample.fit_resample(x_train, y_train)
```

[65]:
```
#Before Random OverSampling
unique,count=np.unique(y_train,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
print(y_train_dict_value_count)

#After Random OverSampling
unique,count=np.unique(y_over,return_counts=True)
y_train_dict_value_count={k:v for (k,v) in zip(unique,count)}
print(y_train_dict_value_count)
```

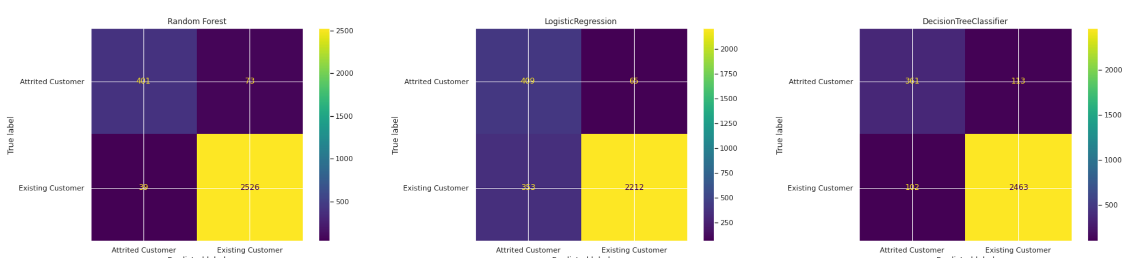
```
{0: 5935, 1: 1153}
{0: 5935, 1: 5935}
```

8.1 Confusion Metric

[79]:
```
model1 = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model2 =ensemble.RandomForestClassifier(random_state=2002)
model3 = tree.DecisionTreeClassifier(random_state=2002)

model2.fit(x_over, y_over)
model1.fit(x_over, y_over)
model3.fit(x_over, y_over)

from sklearn.metrics import plot_confusion_matrix
fig,ax=plt.subplots(ncols=3, figsize=(30,6))
plot_confusion_matrix(model2, x_test, y_test,␣
 ↪labels=[1,0],display_labels=["Attrited Customer", 'Existing Customer'],␣
 ↪ax=ax[0])

ax[0].title.set_text('Random Forest')
plot_confusion_matrix(model1, x_test, y_test,␣
 ↪labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
 ↪Customer'],ax=ax[1])
ax[1].title.set_text('LogisticRegression')
```

```
plot_confusion_matrix(model3, x_test, y_test,␣
↪labels=[1,0],display_labels=["Attrited Customer", 'Existing␣
↪Customer'],ax=ax[2])
ax[2].title.set_text('DecisionTreeClassifier')
fig.tight_layout(pad=53)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87:
FutureWarning: Function plot_confusion_matrix is deprecated; Function
`plot_confusion_matrix` is deprecated in 1.0 and will be removed in 1.2. Use one
of the class methods: ConfusionMatrixDisplay.from_predictions or
ConfusionMatrixDisplay.from_estimator.
  warnings.warn(msg, category=FutureWarning)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:18: UserWarning:
Tight layout not applied. The bottom and top margins cannot be made large enough
to accommodate all axes decorations.
```



8.2 Build and Evaluate the Models for balanced Data (ROS)

[80]:
```
from sklearn.metrics import roc_curve,␣
↪roc_auc_score,accuracy_score,recall_score,f1_score

from sklearn import tree,ensemble
import time
```

```
models = [tree.DecisionTreeClassifier(random_state=2002),
       ensemble.RandomForestClassifier(random_state=2002),
       linear_model.LogisticRegression(solver="liblinear",random_state=2002)]

name = []

Accuracy = []

Specificity=[]

Sensetivity=[]

auc=[]

f1=[]

mcc=[]

brier=[]
ptime=[]
ttime=[]

for i in models:

    name.append(i.__class__.__name__)

    start_f=time.time()

    i.fit(x_over, y_over)

    end_f=time.time()
    start_p=time.time()


    y_predicted=i.predict(x_test)
    end_p=time.time()

    train_t=end_f - start_f
    pre_t=end_f - start_f

    Accuracy.append(accuracy_score(y_test,y_predicted))

    Specificity.append(recall_score(y_test, y_predicted, pos_label=0))

    Sensetivity.append(recall_score(y_test, y_predicted, pos_label=1))
```

```
    i_probs= i.predict_proba(x_test)

    i_probs=i_probs[:,1]
    mcc.append(matthews_corrcoef(y_test,y_predicted))


    auc.append(roc_auc_score(y_test,i_probs))
    f1.append(f1_score(y_test,y_predicted))
    brier.append(brier_score_loss(y_test,y_predicted))
    ptime.append(pre_t)
    ttime.append(train_t)





models_evaluation = pd.DataFrame({"Model": name,"MCC":mcc,"Brier":brier,␣
 ↪"Accuracy": Accuracy,"Sensetivity":Sensetivity,"Specificity":
 ↪Specificity,"F1":f1,"AUC":auc,"Predict Time":ptime,"Training Time":ttime}).
 ↪style.set_caption("After Random OverSampling")

display(models_evaluation)
```

```
<pandas.io.formats.style.Styler at 0x7ffb8623cbd0>
```

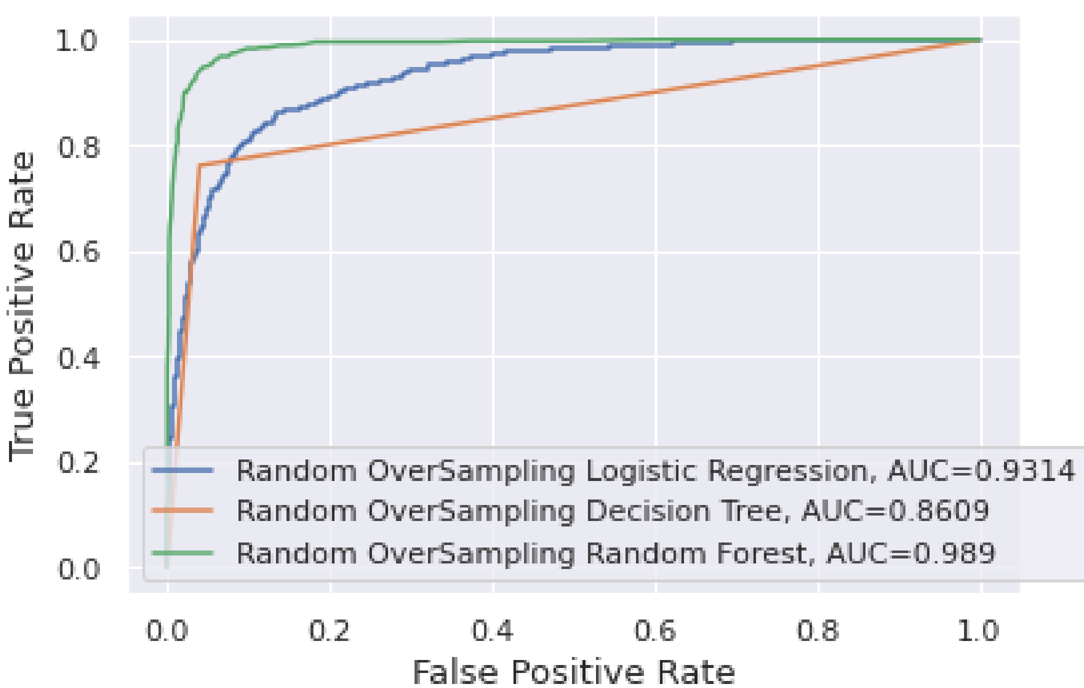
Random Forest with Random Oversampling gave the best results compared with SMOTE and imbalanced data with all results. MCC 0.856629 which is close to 1 our target. Brier scores very close to zero. Accuracy, Sensitivity, Specificity, F1 and AUC increased.

8.3 ROC curve for balanced Data (Random OverSampling)

[81]:
```
#plt.figure(0).clf()
#fit logistic regression model and plot ROC curve
model = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model.fit(x_over, y_over)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="Random OverSampling Logistic Regression, AUC="+str(auc))

#fit Decision Tree model and plot ROC curve
model = tree.DecisionTreeClassifier(random_state=2002)
model.fit(x_over, y_over)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
```

```
plt.plot(fpr,tpr,label="Random OverSampling Decision Tree, AUC="+str(auc))

#fit Random Forest model and plot ROC curve
model = ensemble.RandomForestClassifier(random_state=2002)
model.fit(x_over, y_over)
y_pred = model.predict_proba(x_test)[:, 1]
fpr, tpr, _ = metrics.roc_curve(y_test, y_pred)
auc = round(metrics.roc_auc_score(y_test, y_pred), 4)
plt.plot(fpr,tpr,label="Random OverSampling Random Forest, AUC="+str(auc))


#add legend
plt.legend()
plt.ylabel('True Positive Rate', size = 13)
plt.xlabel('False Positive Rate', size = 13)
```

[81]: Text(0.5, 0, 'False Positive Rate')

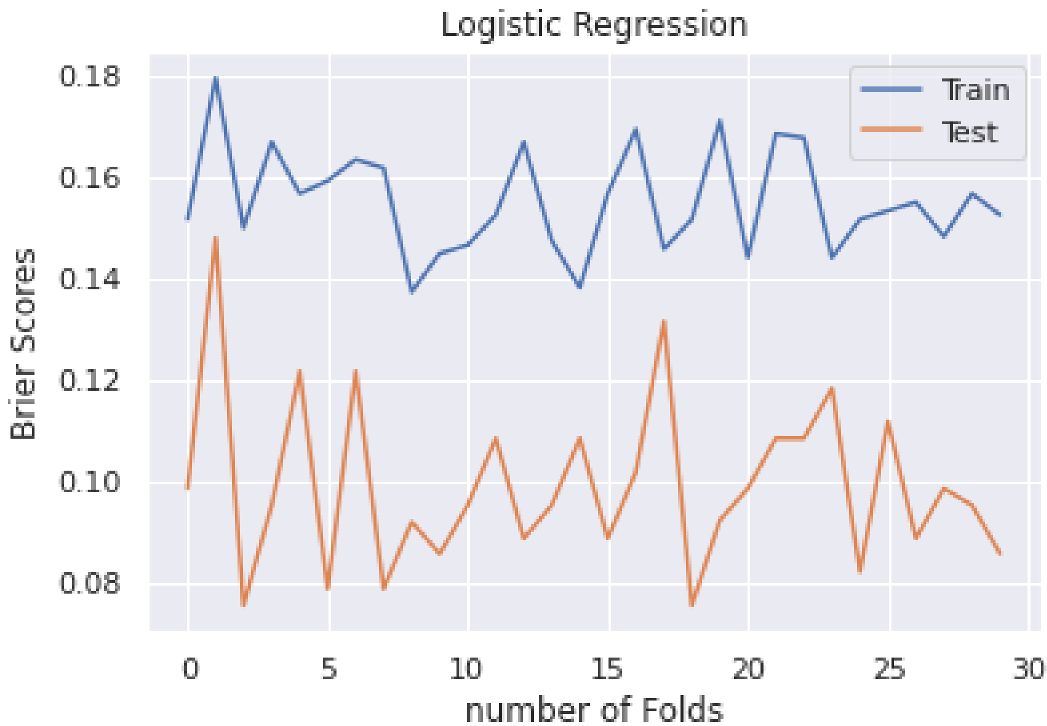


8.4 k-fold cross-validation for balanced data(Random OverSampling)

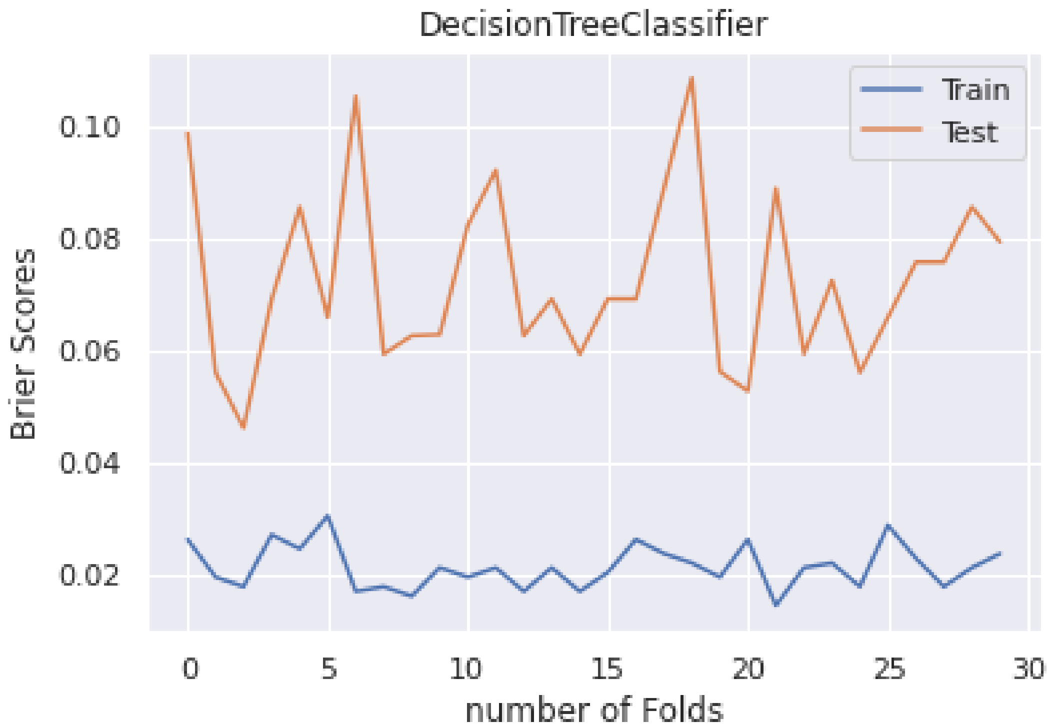
[82]:
```
# evaluate a logistic regression model using repeated k-fold cross-validation

from numpy import mean

from numpy import std

from sklearn.datasets import make_classification

from sklearn.model_selection import RepeatedKFold

from sklearn.model_selection import cross_val_score

from sklearn.linear_model import LogisticRegression



# prepare the cross-validation procedure

cv = RepeatedKFold(n_splits=10, n_repeats=3, random_state=1)

# create models
model1 = linear_model.LogisticRegression(solver="liblinear",random_state=2002)
model2 =ensemble.RandomForestClassifier(random_state=2002)
model3 = tree.DecisionTreeClassifier(random_state=2002)

#evaluate models by Brier score which is = 1-Accuracy
scores1 = 1-cross_val_score(model1, x_over, y_over, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)
scores2 = 1-cross_val_score(model2, x_over, y_over, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)
scores3 = 1-cross_val_score(model3, x_over, y_over, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)

log_test = 1-cross_val_score(model1, x_test, y_test, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)
rf_test = 1-cross_val_score(model2, x_test, y_test, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)
dt_test =1- cross_val_score(model3, x_test, y_test, scoring='accuracy', cv=cv,␣
↪n_jobs=-1)

#print(scores)

# report performance
```

```
print('Average Brier for Logistic Regression : %.3f (%.3f)' %␣
↪(mean(scores1),std(scores2)))
print('Average Brier Random Forest: %.3f (%.3f)' % (mean(scores2),␣
↪std(scores2)))
print('Average Brier Decision Tree: %.3f (%.3f)' % (mean(scores3),␣
↪std(scores3)))


plt.plot(scores1,  label='Train')
plt.plot(log_test ,label='Test')
plt.legend(loc='best')
plt.title('Logistic Regression')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()


plt.plot(scores2,  label='Train')
plt.plot(rf_test ,label='Test')
plt.legend(loc='best')
plt.title('RF')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()

plt.plot(scores3,  label='Train')
plt.plot(dt_test ,label='Test')
plt.legend(loc='best')
plt.title('DecisionTreeClassifier')
plt.xlabel('number of Folds')
plt.ylabel('Brier Scores')
plt.savefig('number-of-cv.png')
plt.show()
```

```
Average Brier for Logistic Regression : 0.155 (0.003)
Average Brier Random Forest: 0.011 (0.003)
Average Brier Decision Tree: 0.021 (0.004)
```


Logistic Regression
Train
Test
Brier Scores
0.18
0.16
0.14
0.12
0.10
0.08
0
5
10
15
20
25
30
number of Folds


RF
Train
Test
Brier Scores
0.08
0.06
0.04
0.02
0.00
0
5
10
15
20
25
30
number of Folds



9 Feature Importance

feature importance based on best model Random Forest

[84]:
```
forest = ensemble.RandomForestClassifier(random_state=2002)
forest.fit(x_over, y_over)
forest.feature_importances_
```

[84]:
```
array([2.66571716e-02, 1.20702993e-02, 2.20177340e-02, 4.22616346e-02,
       2.93858338e-02, 2.41002413e-02, 2.92718725e-02, 1.07260195e-01,
       3.28002949e-02, 6.42345574e-02, 2.02364333e-01, 1.92517799e-01,
       9.02309290e-02, 6.67051075e-02, 5.72714304e-03, 5.21913643e-03,
       2.43197464e-03, 1.47419096e-03, 2.92736879e-03, 2.72334752e-03,
       1.59999867e-03, 2.55699191e-03, 3.01333341e-03, 1.43272535e-03,
       4.81516105e-03, 4.45981251e-03, 1.75512984e-03, 1.80624571e-03,
       2.64406387e-03, 3.04884972e-03, 2.49432642e-03, 2.46549752e-03,
       1.85752028e-03, 1.47811392e-03, 7.34117665e-04, 1.11980758e-04,
       1.34496734e-03])
```

[26]:
```
# feature importance dataframe
feat_imp = pd.DataFrame({'Feature': x_over.columns,
                         'Importance': forest.feature_importances_})
```

```python
feat_imp_sort = feat_imp.sort_values(by='Importance', ascending=False)
feat_imp_sort
```

[26]:

	Feature	Importance
10	Total_Trans_Amt	0.202364
11	Total_Trans_Ct	0.192518
7	Total_Revolving_Bal	0.107260
12	Total_Ct_Chng_Q4_Q1	0.090231
13	Avg_Utilization_Ratio	0.066705
9	Total_Amt_Chng_Q4_Q1	0.064235
3	Total_Relationship_Count	0.042262
8	Avg_Open_To_Buy	0.032800
4	Months_Inactive_12_mon	0.029386
6	Credit_Limit	0.029272
0	Customer_Age	0.026657
5	Contacts_Count_12_mon	0.024100
2	Months_on_book	0.022018
1	Dependent_count	0.012070
14	Gender_F	0.005727
15	Gender_M	0.005219
24	Marital_Status_Married	0.004815
25	Marital_Status_Single	0.004460
29	Income_Category_$60K - $80K	0.003049
22	Education_Level_Unknown	0.003013
18	Education_Level_Graduate	0.002927
19	Education_Level_High School	0.002723
28	Income_Category_$40K - $60K	0.002644
21	Education_Level_Uneducated	0.002557
30	Income_Category_$80K - $120K	0.002494
31	Income_Category_Less than $40K	0.002465
16	Education_Level_College	0.002432
32	Income_Category_Unknown	0.001858
27	Income_Category_$120K +	0.001806
26	Marital_Status_Unknown	0.001755
20	Education_Level_Post-Graduate	0.001600
33	Card_Category_Blue	0.001478
17	Education_Level_Doctorate	0.001474
23	Marital_Status_Divorced	0.001433
36	Card_Category_Silver	0.001345
34	Card_Category_Gold	0.000734
35	Card_Category_Platinum	0.000112

[86]:

```python
from sklearn.feature_selection import SelectFromModel

sel = SelectFromModel(ensemble.RandomForestClassifier(random_state=2002))
```

```
#removed if the corresponding importance of the feature values are below the␣
↪provided threshold parameter
sel.fit(x_over, y_over)
sel.get_support()

selected_feat= x_over.columns[(sel.get_support())]
print(len(selected_feat))
print(selected_feat)
```

```
10
Index(['Total_Relationship_Count', 'Months_Inactive_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'],
      dtype='object')
```

[ ]:

```

```

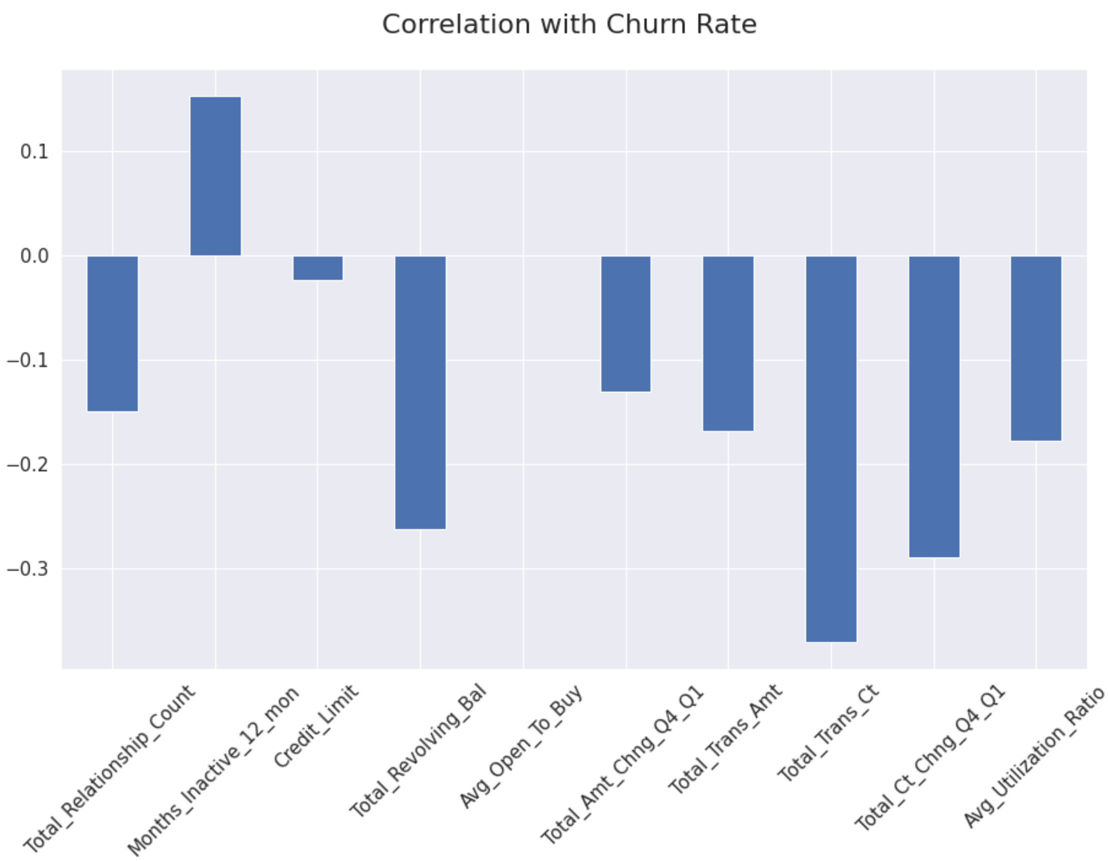
9.1 Relationship between the churn rate and important features

[88]:

```
dataset2=df[['Total_Relationship_Count', 'Months_Inactive_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']]

correlations = dataset2.corrwith(df.Attrition_Flag)

correlations = correlations[correlations!=1]
correlations.plot.bar(
        figsize = (15, 9),
        fontsize = 15,
        #color = '#ec838a',
        rot = 45, grid = True)
plt.title('Correlation with Churn Rate \n',
horizontalalignment="center", fontstyle = "normal",
fontsize = "22", fontfamily = "sans-serif")
```

[88]:

```
Text(0.5, 1.0, 'Correlation with Churn Rate \n')
```



[5]:
```
!sudo apt-get install texlive-xetex texlive-fonts-recommended␣
↪texlive-plain-generic
```

```
Reading package lists… Done
Building dependency tree
Reading state information… Done
texlive-fonts-recommended is already the newest version (2017.20180305-1).
texlive-plain-generic is already the newest version (2017.20180305-2).
texlive-xetex is already the newest version (2017.20180305-1).
The following package was automatically installed and is no longer required:
  libnvidia-common-460
Use 'sudo apt autoremove' to remove it.
0 upgraded, 0 newly installed, 0 to remove and 5 not upgraded.
```

[7]:
```
!jupyter nbconvert --to pdf /Customers_Attraction.ipynb
```

```
[NbConvertApp] WARNING | pattern '/Customers_Attraction.ipynb' matched no files
This application is used to convert notebook files (*.ipynb)
        to various other formats.
```

```
        WARNING: THE COMMANDLINE INTERFACE MAY CHANGE IN FUTURE RELEASES.

Options
=======
The options below are convenience aliases to configurable class-options,
as listed in the "Equivalent to" description-line of the aliases.
To see all configurable class-options for some <cmd>, use:
    <cmd> --help-all

--debug
    set log level to logging.DEBUG (maximize logging output)
    Equivalent to: [--Application.log_level=10]
--show-config
    Show the application's configuration (human-readable format)
    Equivalent to: [--Application.show_config=True]
--show-config-json
    Show the application's configuration (json format)
    Equivalent to: [--Application.show_config_json=True]
--generate-config
    generate default config file
    Equivalent to: [--JupyterApp.generate_config=True]
-y
    Answer yes to any questions instead of prompting.
    Equivalent to: [--JupyterApp.answer_yes=True]
--execute
    Execute the notebook prior to export.
    Equivalent to: [--ExecutePreprocessor.enabled=True]
--allow-errors
    Continue notebook execution even if one of the cells throws an error and
include the error message in the cell output (the default behaviour is to abort
conversion). This flag is only relevant if '--execute' was specified, too.
    Equivalent to: [--ExecutePreprocessor.allow_errors=True]
--stdin
    read a single notebook file from stdin. Write the resulting notebook with
default basename 'notebook.*'
    Equivalent to: [--NbConvertApp.from_stdin=True]
--stdout
    Write notebook output to stdout instead of files.
    Equivalent to: [--NbConvertApp.writer_class=StdoutWriter]
--inplace
    Run nbconvert in place, overwriting the existing notebook (only
            relevant when converting to notebook format)
    Equivalent to: [--NbConvertApp.use_output_suffix=False
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=]
--clear-output
    Clear output of current file and save in place,
            overwriting the existing notebook.
    Equivalent to: [--NbConvertApp.use_output_suffix=False
```

```
--NbConvertApp.export_format=notebook --FilesWriter.build_directory=
--ClearOutputPreprocessor.enabled=True]
--no-prompt
    Exclude input and output prompts from converted document.
    Equivalent to: [--TemplateExporter.exclude_input_prompt=True
--TemplateExporter.exclude_output_prompt=True]
--no-input
    Exclude input cells and output prompts from converted document.
            This mode is ideal for generating code-free reports.
    Equivalent to: [--TemplateExporter.exclude_output_prompt=True
--TemplateExporter.exclude_input=True]
--log-level=<Enum>
    Set the log level by value or name.
    Choices: any of [0, 10, 20, 30, 40, 50, 'DEBUG', 'INFO', 'WARN', 'ERROR',
'CRITICAL']
    Default: 30
    Equivalent to: [--Application.log_level]
--config=<Unicode>
    Full path of a config file.
    Default: ''
    Equivalent to: [--JupyterApp.config_file]
--to=<Unicode>
    The export format to be used, either one of the built-in formats
            ['asciidoc', 'custom', 'html', 'latex', 'markdown', 'notebook',
'pdf', 'python', 'rst', 'script', 'slides']
            or a dotted object name that represents the import path for an
            `Exporter` class
    Default: 'html'
    Equivalent to: [--NbConvertApp.export_format]
--template=<Unicode>
    Name of the template file to use
    Default: ''
    Equivalent to: [--TemplateExporter.template_file]
--writer=<DottedObjectName>
    Writer class used to write the
                                    results of the conversion
    Default: 'FilesWriter'
    Equivalent to: [--NbConvertApp.writer_class]
--post=<DottedOrNone>
    PostProcessor class used to write the
                                    results of the conversion
    Default: ''
    Equivalent to: [--NbConvertApp.postprocessor_class]
--output=<Unicode>
    overwrite base name use for output files.
                can only be used when converting one notebook at a time.
    Default: ''
    Equivalent to: [--NbConvertApp.output_base]
```

```
--output-dir=<Unicode>
    Directory to write output(s) to. Defaults
                                  to output to the directory of each notebook.
To recover
                                  previous default behaviour (outputting to the
current
                                  working directory) use . as the flag value.
    Default: ''
    Equivalent to: [--FilesWriter.build_directory]
--reveal-prefix=<Unicode>
    The URL prefix for reveal.js (version 3.x).
            This defaults to the reveal CDN, but can be any url pointing to a
copy
            of reveal.js.
            For speaker notes to work, this must be a relative path to a local
            copy of reveal.js: e.g., "reveal.js".
            If a relative path is given, it must be a subdirectory of the
            current directory (from which the server is run).
            See the usage documentation
            (https://nbconvert.readthedocs.io/en/latest/usage.html#reveal-js-
html-slideshow)
            for more details.
    Default: ''
    Equivalent to: [--SlidesExporter.reveal_url_prefix]
--nbformat=<Enum>
    The nbformat version to write.
            Use this to downgrade notebooks.
    Choices: any of [1, 2, 3, 4]
    Default: 4
    Equivalent to: [--NotebookExporter.nbformat_version]

Examples
--------

    The simplest way to use nbconvert is

            > jupyter nbconvert mynotebook.ipynb

            which will convert mynotebook.ipynb to the default format (probably
HTML).

            You can specify the export format with `--to`.
            Options include ['asciidoc', 'custom', 'html', 'latex', 'markdown',
'notebook', 'pdf', 'python', 'rst', 'script', 'slides'].

            > jupyter nbconvert --to latex mynotebook.ipynb

            Both HTML and LaTeX support multiple output templates. LaTeX
```

```
includes
              'base', 'article' and 'report'.  HTML includes 'basic' and 'full'.
You
              can specify the flavor of the format used.

              > jupyter nbconvert --to html --template basic mynotebook.ipynb

              You can also pipe the output to stdout, rather than a file

              > jupyter nbconvert mynotebook.ipynb --stdout

              PDF is generated via latex

              > jupyter nbconvert mynotebook.ipynb --to pdf

              You can get (and serve) a Reveal.js-powered slideshow

              > jupyter nbconvert myslides.ipynb --to slides --post serve

              Multiple notebooks can be given at the command line in a couple of
              different ways:

              > jupyter nbconvert notebook*.ipynb
              > jupyter nbconvert notebook1.ipynb notebook2.ipynb

              or you can specify the notebooks list in a config file, containing::

                  c.NbConvertApp.notebooks = ["my_notebook.ipynb"]

              > jupyter nbconvert --config mycfg.py

To see all available configurables, use `--help-all`.
```

[1]:
```python
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```