Credit card customer analysis, Churn Prediction

Group 1

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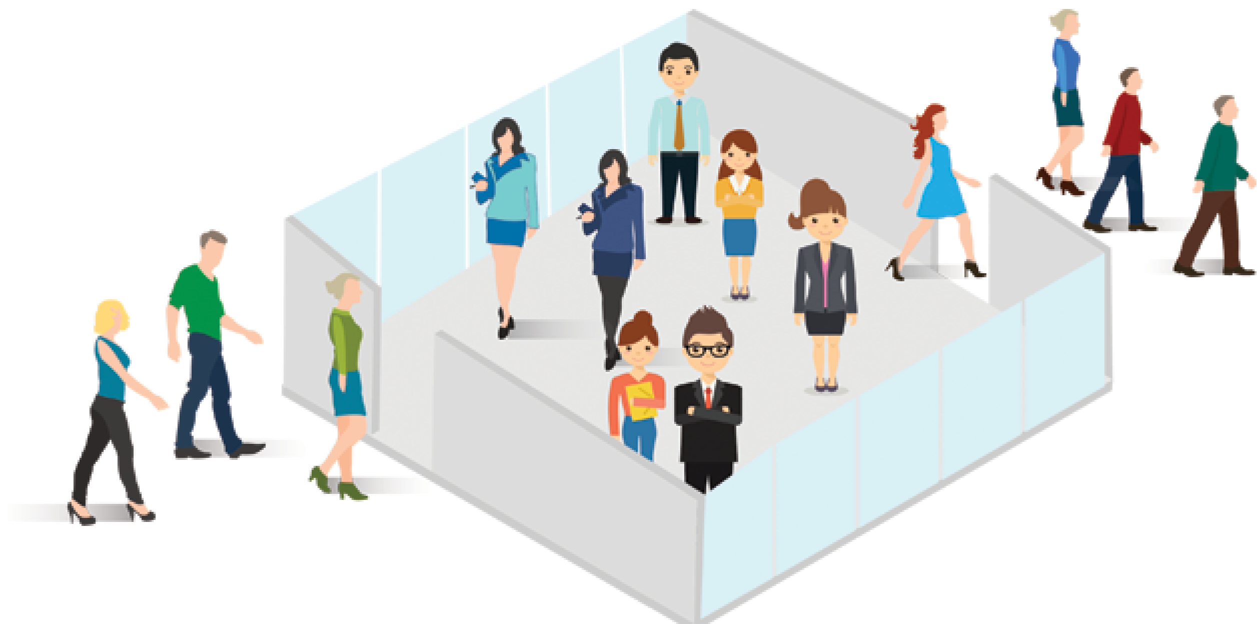


1. Business Problem

Section 1:

1. Business Problem

1.1 Problem Description

A manager at the bank is disturbed with more and more customers leaving their credit card services. They would really appreciate it if we could predict for them who is going to get churned so they can proactively go to the customer to provide them better services and turn customers' decisions in the opposite direction. This dataset is from a website with the URL [https://leaps.analyttica.com/home (https://leaps.analyttica.com/home)](https://leaps.analyttica.com/home)

2. Business Question

Which customers are more likely to leave the bank?

3. Analytical Problem & Approach

This project is done in a series of phases, the first of which involves an exploratory data analysis, where the objective is to know the nature of the variables and to examine attributes that indicate a strong relationship with leaving credit card services. The next phase involves applying a machine-learning algorithm to find the best properties for building the model. At the end of the project, after finishing all steps, a machine learning model will be utilized, adept at predicting, based on the data of a structure, whether a customer will cancel the credit card service or not.

4. Dataset & Target Variable

We have 10,127 customers and out of those 8500 customers are existing and 1627 are attritted customers which gives us percentages or 84.9% for existing customers vs 16.1% of attrited customers since we only 16% of the customers who have churned. Thus, it's a bit difficult to train our model to predict churning customers since the sample is very small comparing the total number of customers.

Target Variable:

The data has 20 features. Of the features provided, 6 are categorical variables (including the target which is the attrition flag), 13 are continuous variables, and one is a ratio. The data has numerous demographic data, as well as data about the relationship the bank currently has with its customer. The information would be of particular use to the customer retention department, whose success is measured by the number of customers that can retain. The bank currently has limited solutions in place to predict whether a customer will churn or not, and our goal is to predict which customers are more likely to leave the bank. The initial success of the model will be assessed by its accuracy on a train/test split, but ultimately the success of the model is measured by how accurately it can predict whether a customer will leave the bank.

5. Importing all necessary libraries

In [1]:
```
import pandas as pd
import numpy as np
import statsmodels.api as sm
import sklearn
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.graph_objects as go
from sklearn.metrics import confusion_matrix, classification_report
import sklearn.metrics as metrics
from sklearn.impute import KNNImputer
from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import classification_report
from sklearn.metrics import mean_squared_error
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model_selection import GridSearchCV
from sklearn import neighbors
from math import sqrt
#To perfom Exploratory Data Analysis (EDA) in just one line of a code
import pandas_profiling
from imblearn.over_sampling import SMOTE
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score, precision_score, recall_score
from sklearn.model_selection import train_test_split
from sklearn.metrics import precision_recall_curve, auc, log_loss
from sklearn import utils
import warnings
warnings.filterwarnings('ignore')
%matplotlib inline
#import warnings
#import numpy as np
#warnings.simplefilter(action='ignore', category=FutureWarning)
#print('x' in np.arange(5))   #returns False, without Warning
#Makes the notebook full width for preference
#from IPython.core.display import display, HTML
#display(HTML("<style>.container { width:100% !important; }</style>"))
```

6. Loading the data

In [2]:
```
df = pd.read_csv('BankChurners.csv')
```

In [3]:
```
df.shape
```

Out[3]: (10127, 23)

In [4]:
```
df
```

Out[4]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level
0	768805383	Existing Customer	45	M	3	High School
1	818770008	Existing Customer	49	F	5	Graduate
2	713982108	Existing Customer	51	M	3	Graduate
3	769911858	Existing Customer	40	F	4	High School
4	709106358	Existing Customer	40	M	3	Uneducated
...	...	...	...	...	...	...
10122	772366833	Existing Customer	50	M	2	Graduate
10123	710638233	Attrited Customer	41	M	2	Unknown
10124	716506083	Attrited Customer	44	F	1	High School
10125	717406983	Attrited Customer	30	M	2	Graduate
10126	714337233	Attrited Customer	43	F	2	Graduate

10127 rows × 23 columns

7. Exploratory Data Analysis (EDA)

The objective of this step is to dig deep into the data to discover the main elements that are contributing to the cancellation of credit card service bank customers. For this step we will use panda profiling to derive statistical information of each variable (Descriptive Analysis & Visualization) and to check the correlation between features which will provide important insights to carry on with the rest of the analysis in this project

8. Preperation

8.1 Part1:

We start preparing the dataset by removing the last two columns because the two columns have irrelevant information will cause problems to the models. We will also drop the first column because it is very insignificant to the dataset and analysis.

In [5]:
```
#Deleting unnecessary columns
del df['Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_1']
del df['Naive_Bayes_Classifier_Attrition_Flag_Card_Category_Contacts_Count_12_mon_Dependent_count_Education_Level_Months_Inactive_12_mon_2']
df.head()
```

Out[5]:

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

5 rows × 21 columns

In [6]:
```
#Copying the dataframe
df1 = df
```

In [7]:
```
df.info()
df.shape
```

```
<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
```

Out[7]:
```
(10127, 21)
```

In [8]:
```
pandas_profiling.ProfileReport(df, title = 'Credit Card Churn', html={'style':
{'full_width':True}})
```

Overview

Dataset statistics

Number of variables	21
Number of observations	10127
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	1.6 MiB
Average record size in memory	168.0 B

Variable types

Numeric	15
Categorical	6

Warnings

`Credit_Limit` is highly correlated with `Avg_Open_To_Buy`	**High correlation**
`Avg_Open_To_Buy` is highly correlated with `Credit_Limit`	**High correlation**
`CLIENTNUM` has unique values	**Unique**
`Dependent_count` has 904 (8.9%) zeros	**Zeros**

Out[8]:

8.2 Part 2:

The dataset is fairly clean and has no missing values, no duplicated rows, and no NaN values, however there are significant “unknowns”. We start preparing the dataset by removing the last two columns because the two columns have irrelevant information Since machine learning algorithms cannot work directly with categorical data and so we do need to do some engineering and transformations on this data before we can start modeling our dataset. The engineering required is dependent on the type of model used.

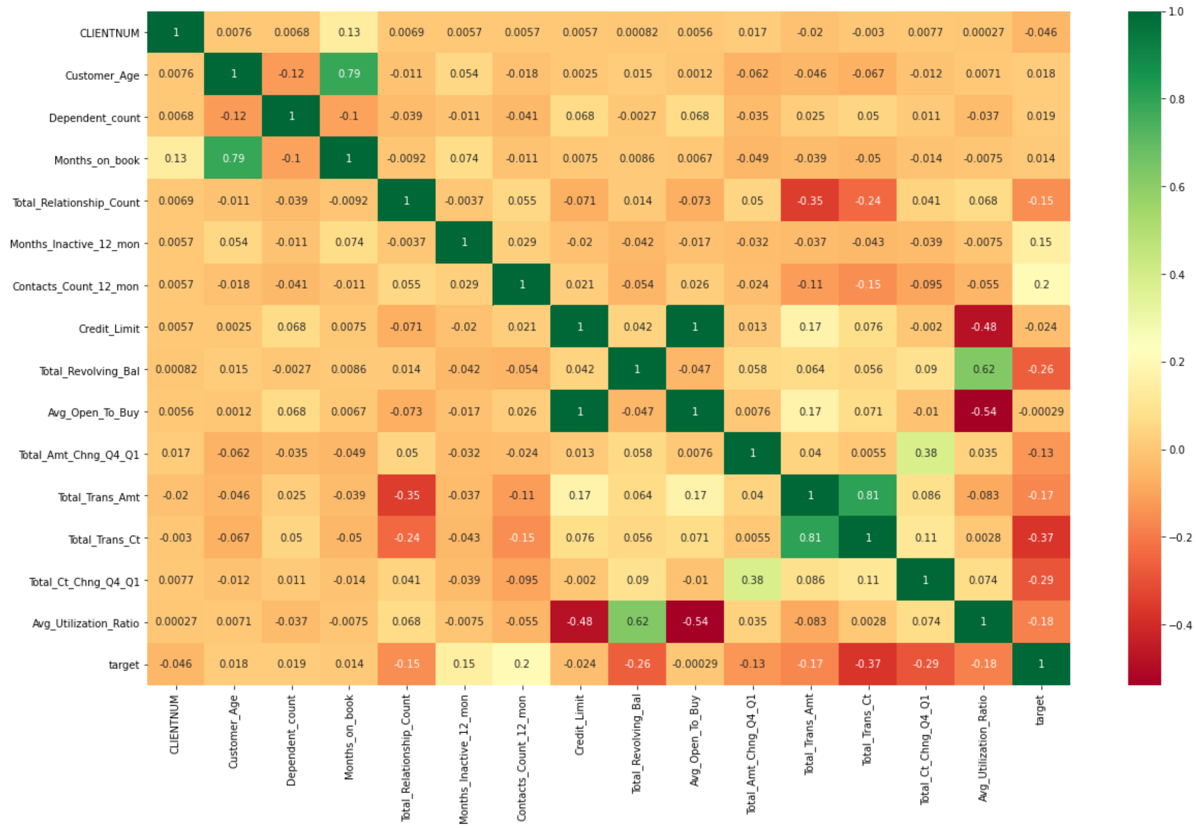
In [9]:
```
df.columns
```

Out[9]:
```
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'],
      dtype='object')
```

In [10]:
```
df['target'] = (df.Attrition_Flag == 'Attrited Customer').astype(int)
#target is the attrited customer under the attrited flag variable
```

```
In [11]: feats = ['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']

         plt.subplots(figsize=(20, 12))
         sns.heatmap(df.corr(), annot=True, cmap="RdYlGn")
```

```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x21a307d8a60>
```



correlation between variables on each axis

plt.figure(figsize = (30,30)) sns.heatmap(df.corr(), annot = True, cmap = 'RdYlGn')

8.3 Part 3:

Correlation Analysis - Spearman's Rank Correlation

The Spearman's rank correlation coefficient (ρ) is a measure of monotonic correlation between two variables, and is therefore better in catching nonlinear monotonic correlations than Pearson's r. It's value lies between -1 and +1, -1 indicating total negative monotonic correlation, 0 indicating no monotonic correlation and 1 indicating total positive monotonic correlation.

To calculate ρ for two variables X and Y, one divides the covariance of the rank variables of X and Y by the product of their standard deviations.

Spearman Correlation evaluates statistical relationship between two variables. We observe that we can't confirm from the start which variables should be given the most consideration, saving time in analyzing variables that do not have a strong impact on the rate of the attrited customers variables that show a sizeable negative relationship in relative to the dependent attribute, and that are the target of investigation, are: Total_Trans_Ct, Total_Ct_Chng_Q4_Q1, Total_Revolving_Bal and Avg_Utilization_Ratio. A negative association (<0) indicates that the attribute has a relevant level of importance in the customer's permanence.

In [12]:

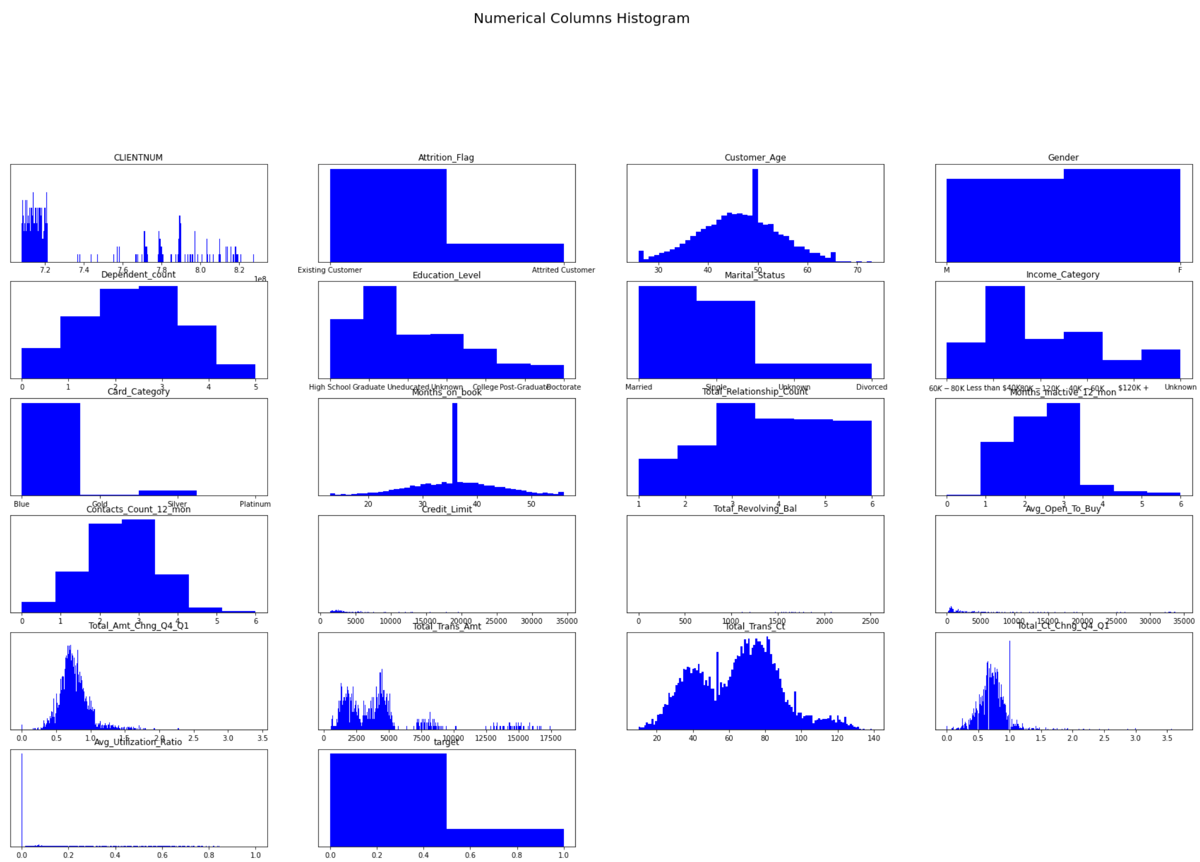
```
df
```

Out[12]:

	CLIENTNUM	Attrition_Flag	Customer_Age	Gender	Dependent_count	Education_Level
0	768805383	Existing Customer	45	M	3	High School
1	818770008	Existing Customer	49	F	5	Graduate
2	713982108	Existing Customer	51	M	3	Graduate
3	769911858	Existing Customer	40	F	4	High School
4	709106358	Existing Customer	40	M	3	Uneducated
...	...	...	...	...	...	...
10122	772366833	Existing Customer	50	M	2	Graduate
10123	710638233	Attrited Customer	41	M	2	Unknown
10124	716506083	Attrited Customer	44	F	1	High School
10125	717406983	Attrited Customer	30	M	2	Graduate
10126	714337233	Attrited Customer	43	F	2	Graduate

10127 rows × 22 columns

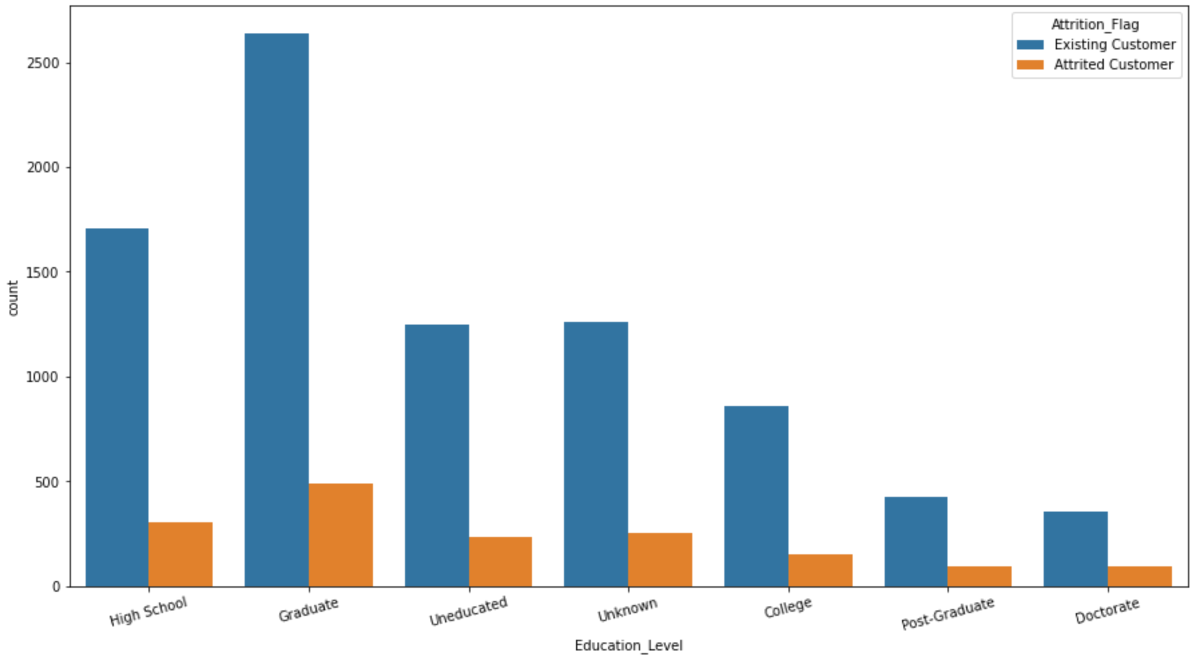
In [13]:
```
fig = plt.figure(figsize=(30, 30))
plt.suptitle('Numerical Columns Histogram', fontsize=20)
for i in range(1, df.shape[1] + 1):
    plt.subplot(10, 4, i)
    f = plt.gca()
    f.axes.get_yaxis().set_visible(False)
    f.set_title(df.columns.values[i - 1])

    vals = np.size(df.iloc[:, i - 1].unique())

    plt.hist(df.iloc[:, i - 1], bins=vals, color='Blue')
```



9. Visualizing data and checking for outliers

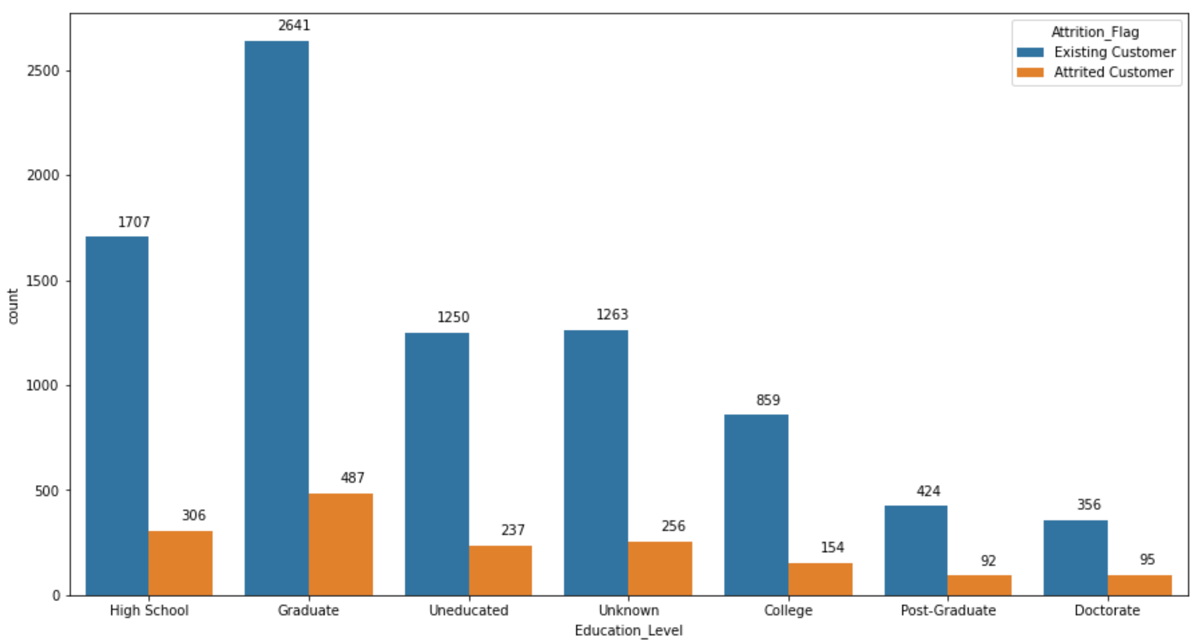
In [14]:

```
fig_dims = (15, 8)
fig, sns_plot = plt.subplots(figsize=fig_dims)
sns_plot = sns.countplot(x = "Education_Level", hue = "Attrition_Flag", data =
df)
sns_plot.set_xticklabels(sns_plot.get_xticklabels(), rotation = 15)
sns_plot.figure.savefig("Education_Level.png") #Save it as a png file for easi
er use in a report
```

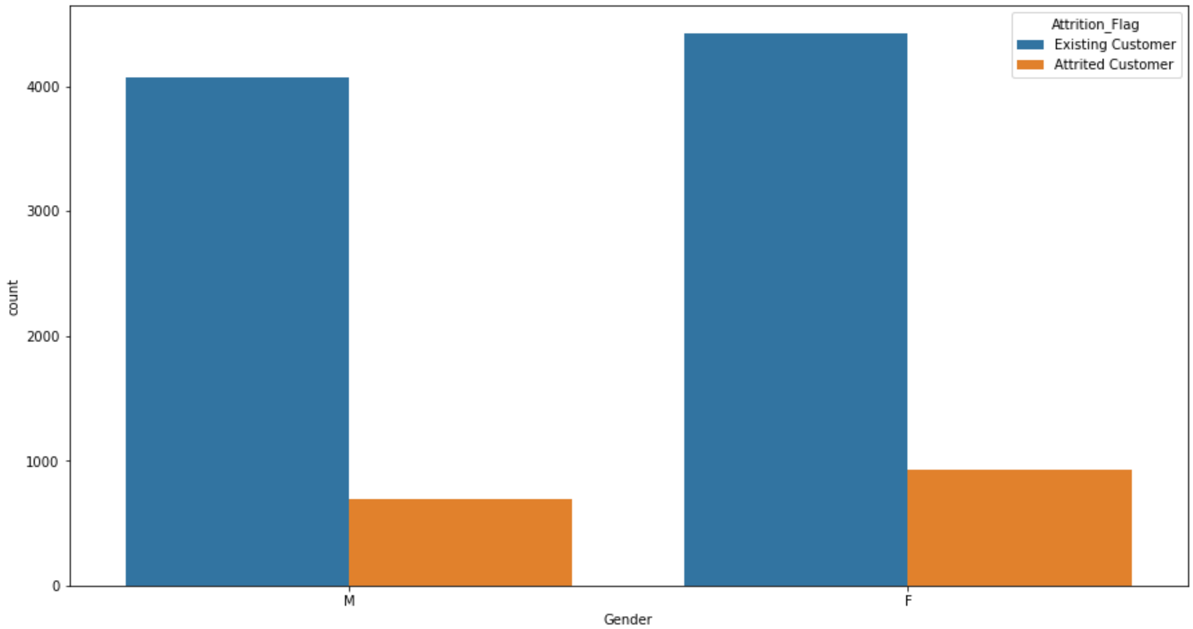


In [15]:

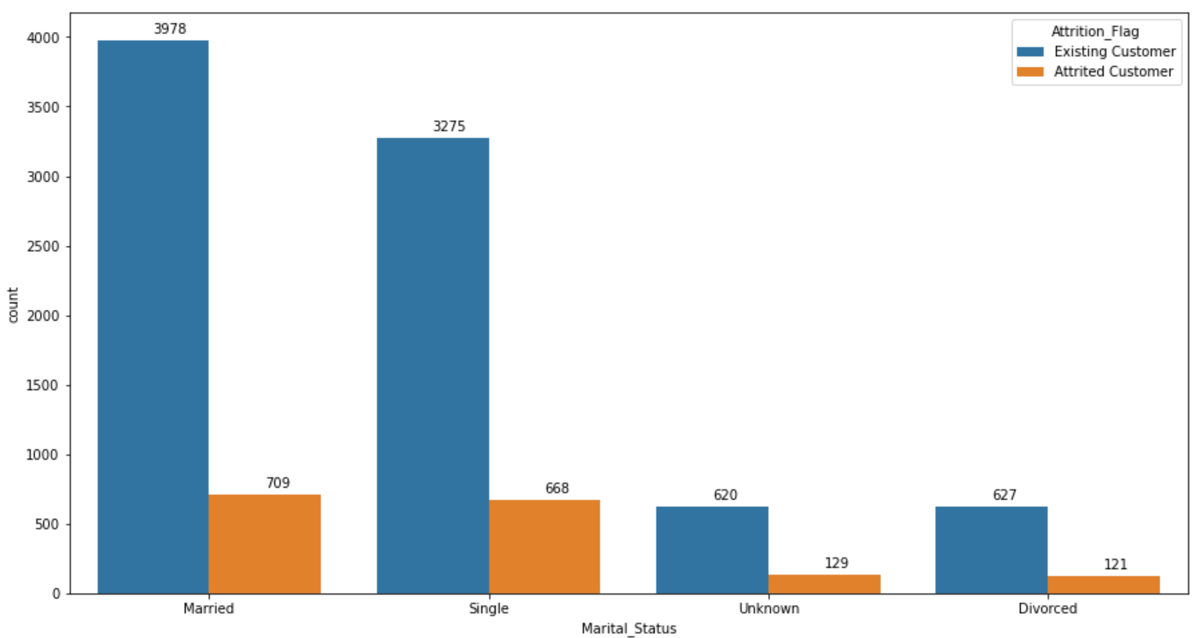
```
plt.figure(figsize=(15,8))
plot=sns.countplot(x=df.Education_Level,hue=df.Attrition_Flag)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```



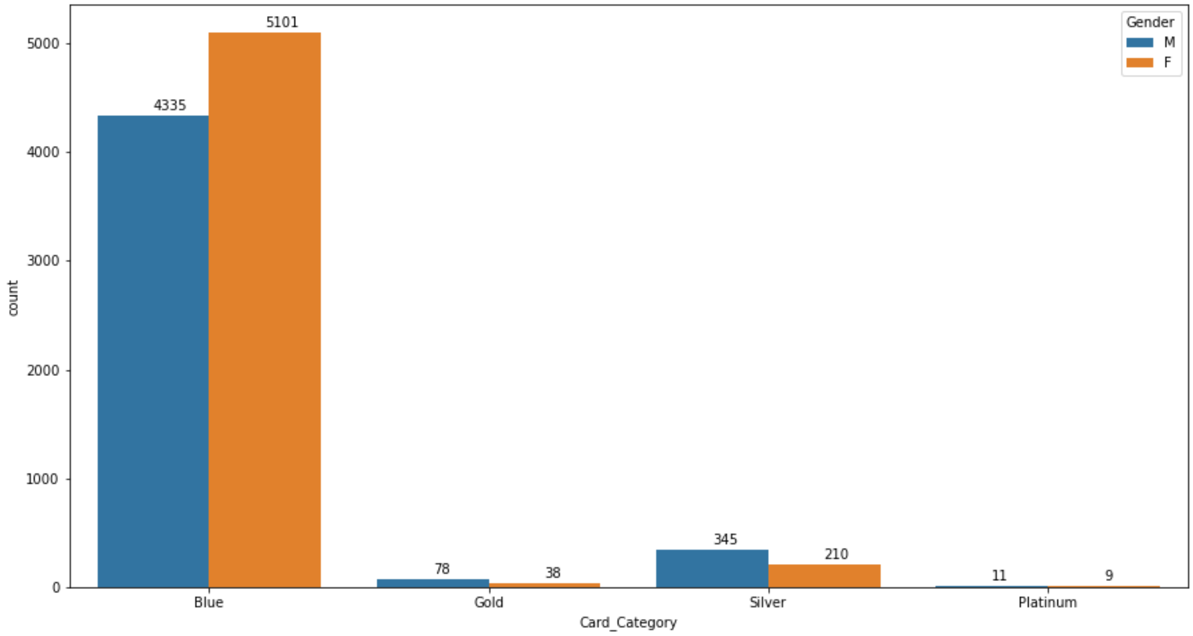
In [16]:
```
#Visualize the churn count for both Males and Females
plt.figure(figsize=(15,8))
sns.countplot(x=df.Gender, hue=df.Attrition_Flag,data = df)
sns_plot.set_xticklabels(sns_plot.get_xticklabels(), rotation = 15)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```



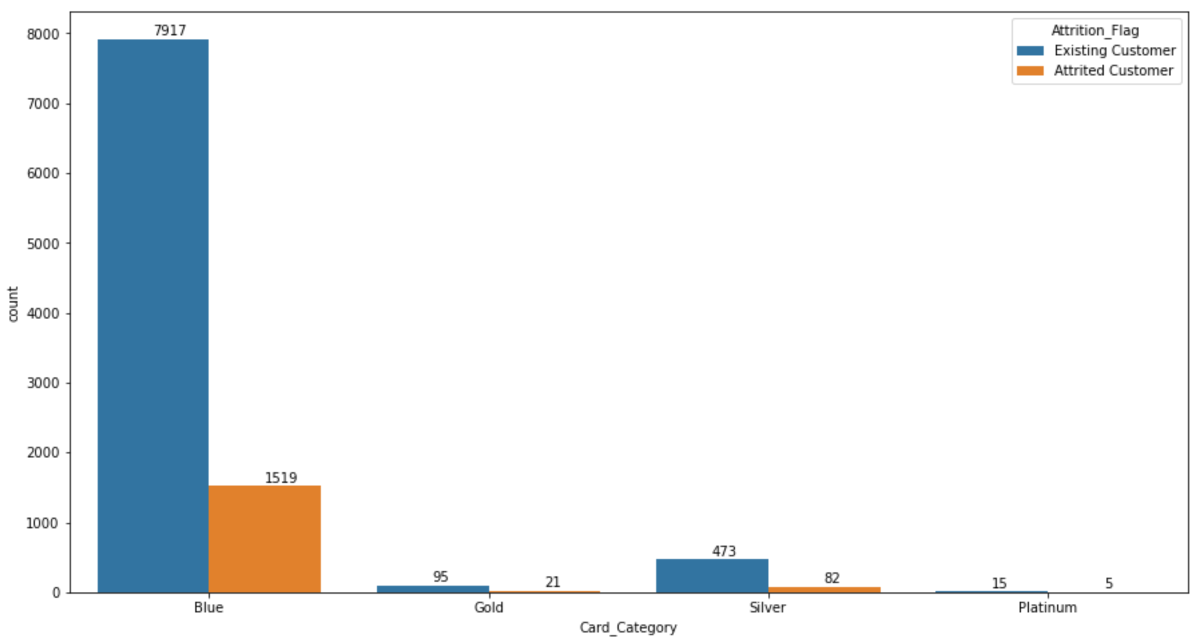
In [17]:
```
plt.figure(figsize=(15,8))
plot=sns.countplot(x=df.Marital_Status,hue=df.Attrition_Flag)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```



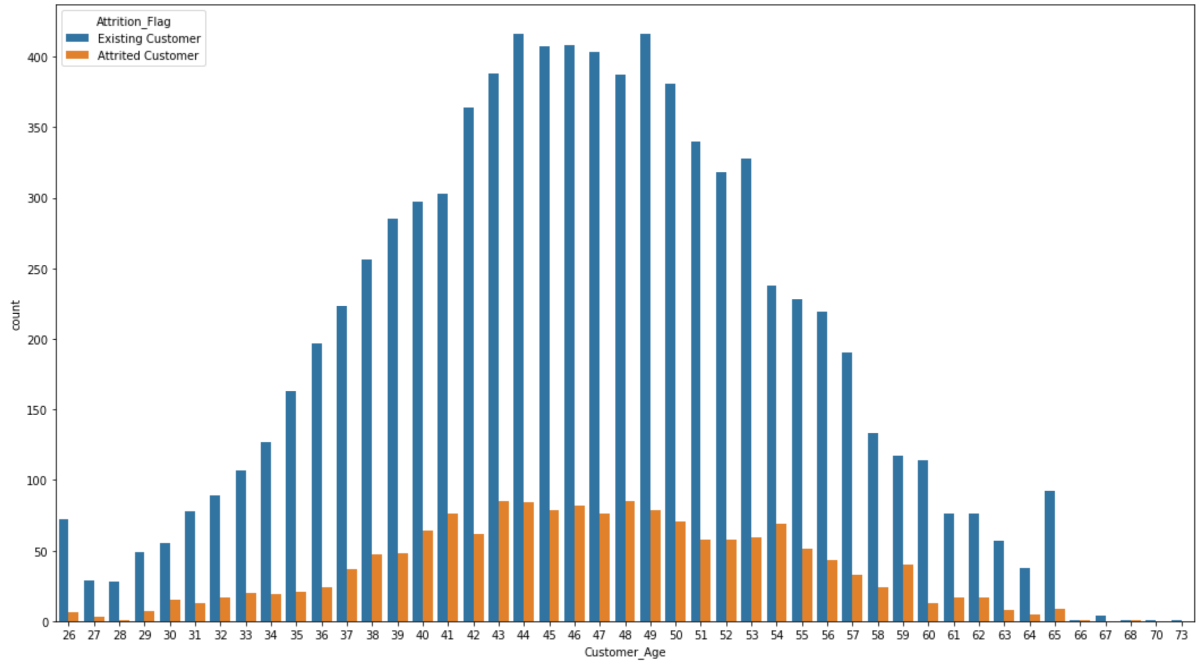
In [18]:
```
plt.figure(figsize=(15,8))
plot=sns.countplot(x=df.Card_Category,hue=df.Gender)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```



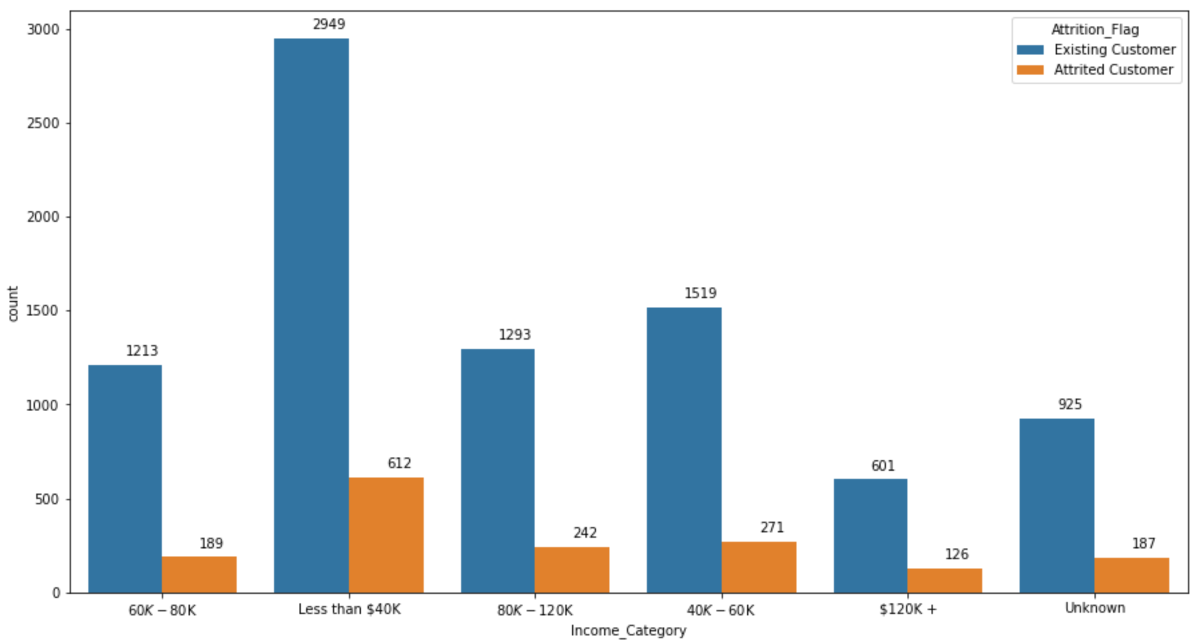
In [19]:
```
plt.figure(figsize=(15,8))
plot=sns.countplot(x=df.Card_Category,hue=df.Attrition_Flag)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```



In [20]:
```python
plt.figure(figsize=(18,10))
plot=sns.countplot(x=df.Customer_Age,hue=df.Attrition_Flag)
plt.show()
```

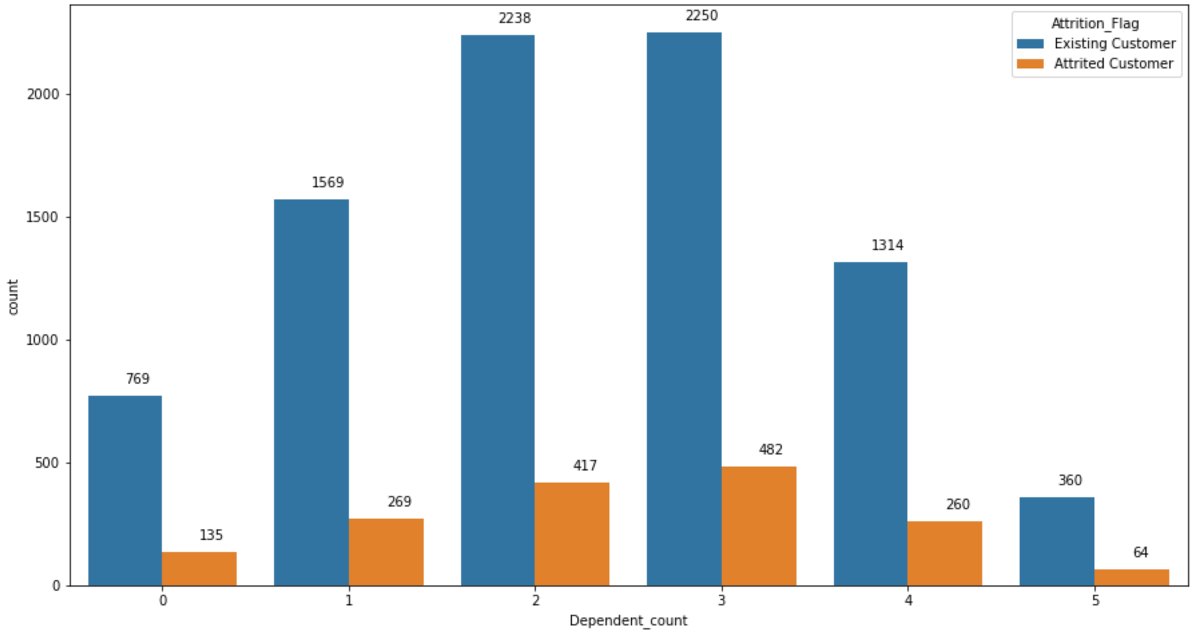


In [21]:
```python
plt.figure(figsize=(15,8))
plot=sns.countplot(x=df.Income_Category,hue=df.Attrition_Flag)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```



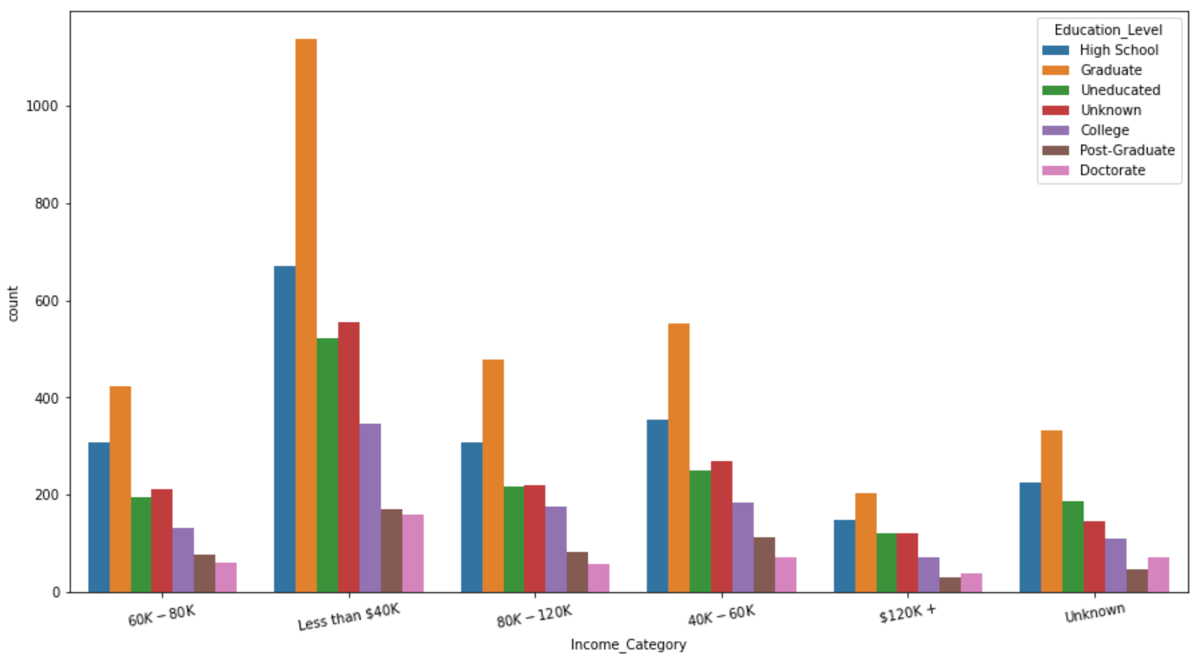
In [22]:

```
plt.figure(figsize=(15,8))
plot=sns.countplot(x=df.Dependent_count,hue=df.Attrition_Flag)
for i in plot.patches:
    plot.annotate(i.get_height(),(i.get_x()+i.get_width()/2,i.get_height()+50
))
plt.show()
```

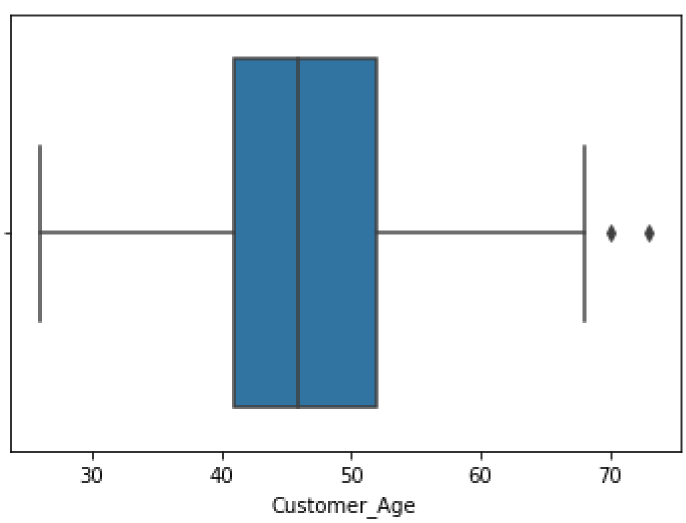


In [23]:
```python
#plt.figure(figsize=(15,8))
#plot=sns.countplot(x=df.Income_Category,hue=df.Education_Level)
#plt.show()
fig_dims = (15, 8)
fig, sns_plot = plt.subplots(figsize=fig_dims)
sns_plot = sns.countplot(x="Income_Category", hue = "Education_Level", data =
df)
sns_plot.set_xticklabels(sns_plot.get_xticklabels(), rotation = 10)
```

Out[23]:
```
[Text(0, 0, '$60K - $80K'),
 Text(0, 0, 'Less than $40K'),
 Text(0, 0, '$80K - $120K'),
 Text(0, 0, '$40K - $60K'),
 Text(0, 0, '$120K +'),
 Text(0, 0, 'Unknown')]
```

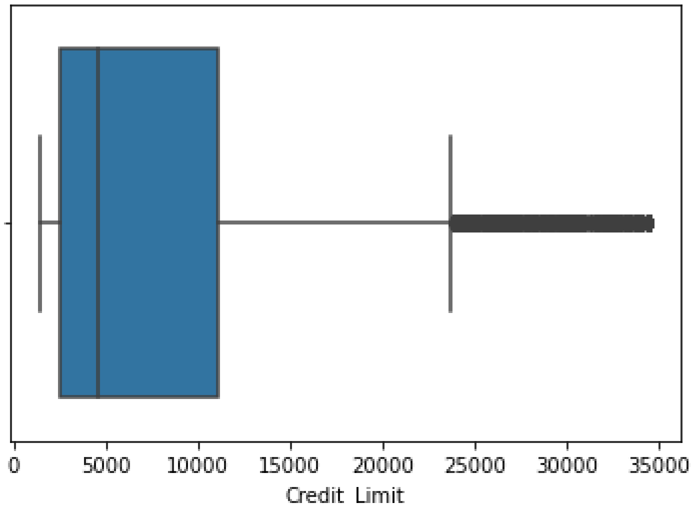


In [24]:
```python
sns_plot=sns.boxplot(x='Customer_Age',data=df)
sns_plot.figure.savefig("Customer_Age.png")
```



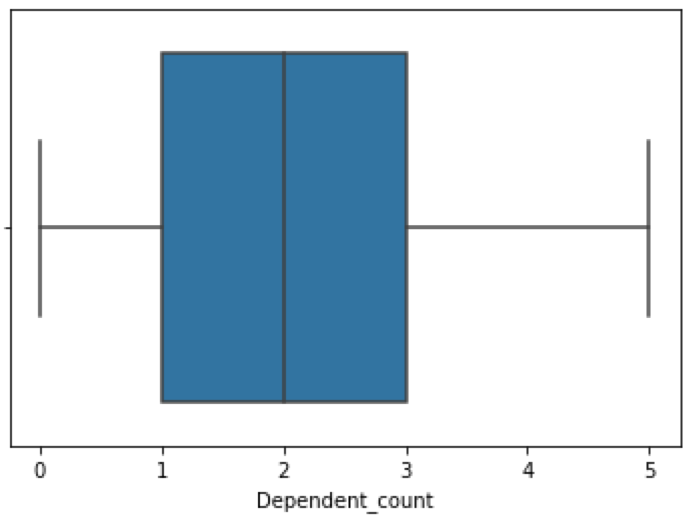
In [25]:

```
sns_plot=sns.boxplot(x='Credit_Limit',data=df)
sns_plot.figure.savefig("Credit_Limit.png")
```

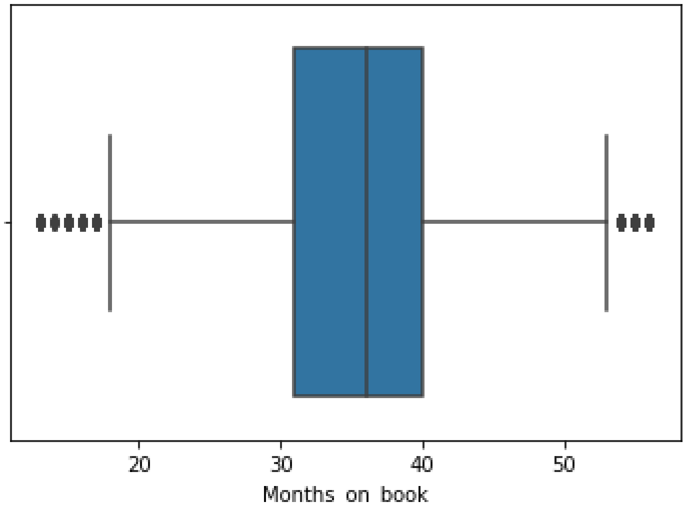


In [26]:

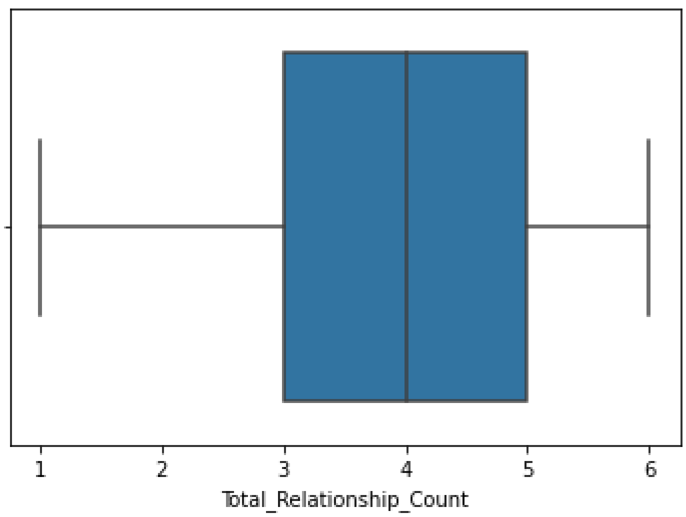
```
sns_plot=sns.boxplot(x='Dependent_count',data=df)
sns_plot.figure.savefig("Dependent_count.png")
```



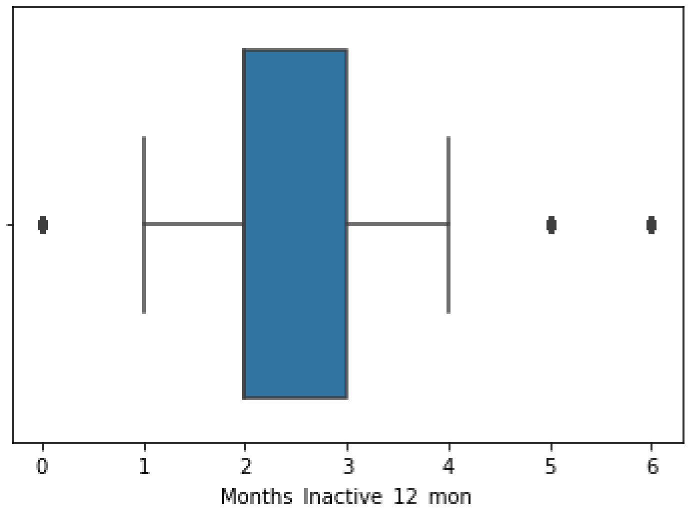
In [27]:
```
sns_plot=sns.boxplot(x='Months_on_book',data=df)
sns_plot.figure.savefig("Months_on_book.png")
```



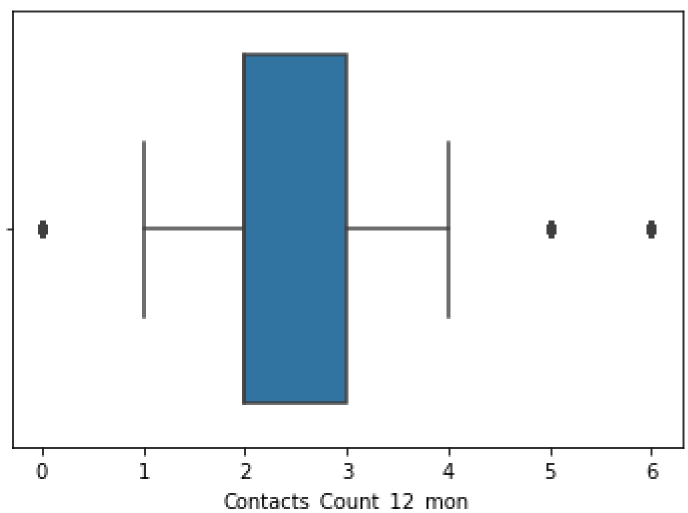
In [28]:
```
sns_plot=sns.boxplot(x='Total_Relationship_Count',data=df)
sns_plot.figure.savefig("Total_Relationship_Count.png")
```



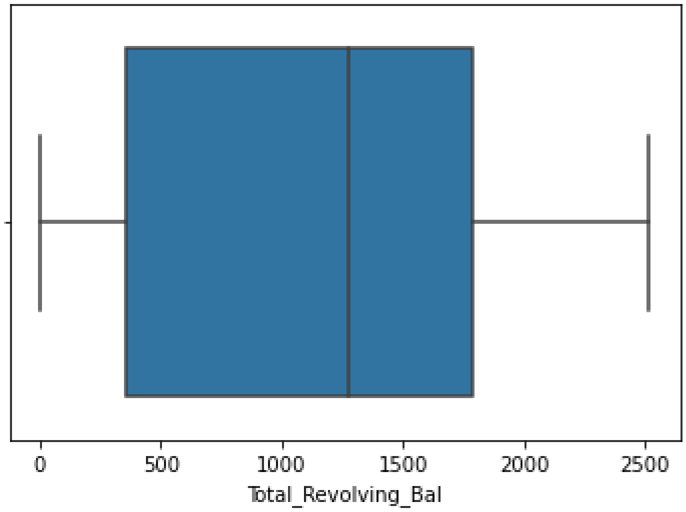
In [29]:
```
sns_plot=sns.boxplot(x='Months_Inactive_12_mon',data=df)
sns_plot.figure.savefig("Months_Inacative_12_mon.png")
```



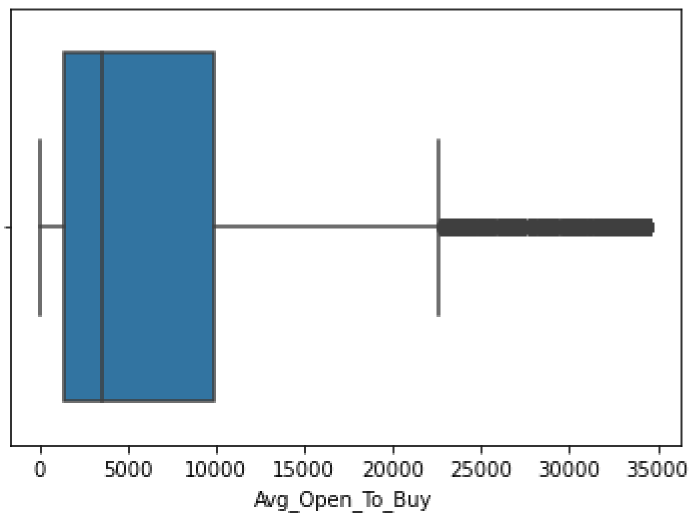
In [30]:
```
sns_plot=sns.boxplot(x='Contacts_Count_12_mon',data=df)
sns_plot.figure.savefig("Contacts_Count_12_mon.png")
```



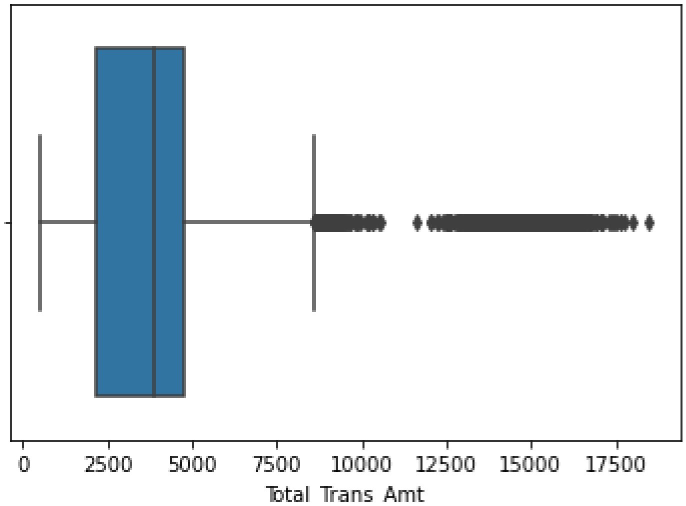
In [31]:
```
sns_plot=sns.boxplot(x='Total_Revolving_Bal',data=df)
sns_plot.figure.savefig("Total_Revolving_Bal.png")
```



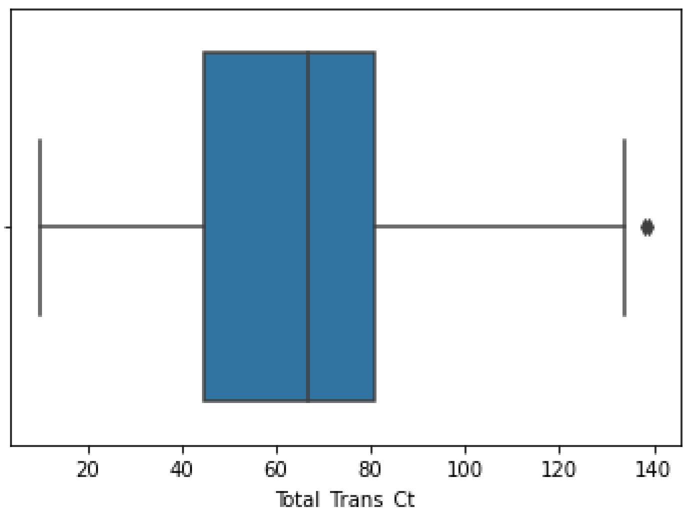
In [32]:
```
sns_plot=sns.boxplot(x='Avg_Open_To_Buy',data=df)
sns_plot.figure.savefig("Avg_Open_To_Buy.png")
```



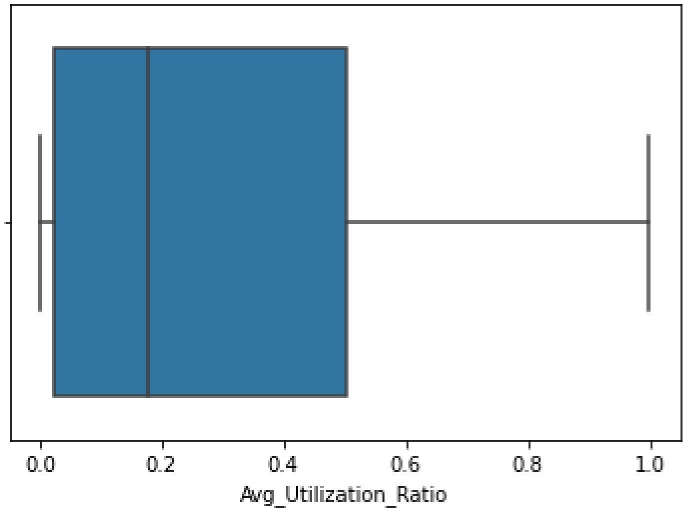
In [33]:
```
sns_plot=sns.boxplot(x='Total_Trans_Amt',data=df)
sns_plot.figure.savefig("Total_Trans_Amt.png")
```



In [34]:
```
sns_plot=sns.boxplot(x='Total_Trans_Ct',data=df)
sns_plot.figure.savefig("Total_Trans_Ct.png")
```



In [35]:
```
sns_plot=sns.boxplot(x='Avg_Utilization_Ratio',data=df)
sns_plot.figure.savefig("Avg_Utilization_Ratio.png")
```



10. Encoding the target variable

In [36]:
```
#df['target'] = (df['Attrition_Flag'] == 'Attrited Customer').astype(int)
#target is the attrited customer under the attrited flag variable
```

11. Split the data into Train Test

Stratify parameter is dirserabel to split the dataset to train and test in a way to retain the same proportion of classes in the train and test classes that are found in the entire original dataset.

In [37]:
```
#creating two Variables X & y and assigning to them and assin split train perc
entages as 20%  of data test and 80% train
X = df.drop(['Attrition_Flag', 'target'], axis=1)
y = df['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, strat
ify=y)
```

In [38]:
```
y_test.value_counts() / len(y_test)
```

Out[38]:
```
0    0.839585
1    0.160415
Name: target, dtype: float64
```

In [39]:
```
y_train.value_counts() / len(y_train)
```

Out[39]:
```
0    0.839279
1    0.160721
Name: target, dtype: float64
```

It is clear now the test and train datasets have the same proportion. This was achieve this by setting the “stratify” argument to the y component of the original dataset

In [40]:
```
# Combining both X_train and y_train
df2 = pd.concat((X_train, y_train), axis=1)
df2.shape
df2
```

Out[40]:

	CLIENTNUM	Customer_Age	Gender	Dependent_count	Education_Level	Marital_Status	I
2190	709149408	36	M	2	Uneducated	Married	
9590	715132758	52	F	2	College	Divorced	
2419	721467258	58	M	1	High School	Married	
1024	813952233	44	M	3	Graduate	Unknown	
5990	710929233	33	F	2	Doctorate	Single	
...	...	...	...	...	...	...	
2571	714514983	43	F	5	Graduate	Married	
128	718039683	52	M	2	High School	Single	
8095	794576058	42	M	3	Graduate	Married	
7270	827123883	53	M	4	High School	Single	
9307	717571683	47	F	4	Uneducated	Married	

8101 rows × 21 columns

11. Data Analysis & Processing

In [41]:
```
#classify our variables, the following categories can be calssified as ordinal
ordinal_cat = {
    'Education_Level': ['Uneducated', 'High School', 'College', 'Graduate', 'P
ost-Graduate', 'Doctorate'],
    'Income_Category': ['Less than $40K', '$40K - $60K', '$60K - $80K', '$80K
 - $120K', '$120K +'],
    'Card_Category': ['Blue', 'Silver', 'Gold', 'Platinum']
}

def encode_ordinals(df, ordinal_cat):
    s = df.copy()
    for var, values in ordinal_cat.items():
        s[var] = s[var].apply(lambda x: values.index(x) + 1
                                  if x is not np.nan else x)
    return s
```

In [42]:
```
X_train.columns
```

Out[42]:
```
Index(['CLIENTNUM', 'Customer_Age', 'Gender', 'Dependent_count',
       'Education_Level', 'Marital_Status', 'Income_Category', 'Card_Categor
y',
       'Months_on_book', 'Total_Relationship_Count', 'Months_Inactive_12_mo
n',
       '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'],
      dtype='object')
```

In [43]:
```
#classify and split the variables

ordinal_vars = ['Income_Category','Education_Level','Card_Category']
categor_vars = ['Marital_Status','Gender']
num_vars = ['Customer_Age', 'Months_on_book', 'Dependent_count', 'Total_Relati
onship_Count',
             'Months_Inactive_12_mon',  'Credit_Limit', 'Contacts_Count_12_mo
n',
             'Total_Revolving_Bal', 'Avg_Open_To_Buy', 'Total_Amt_Chng_Q4_Q1',
             'Total_Trans_Amt', 'Total_Trans_Ct','Avg_Utilization_Ratio','Tota
l_Ct_Chng_Q4_Q1']
```

In [44]:
```
#Checking to make sure we have all the variables and we're not missing any
[col for col in X_train.columns
if col not in categor_vars + ordinal_vars + num_vars]
```

Out[44]:
```
['CLIENTNUM']
```

12. Encoding & Imputation

Using OneHotEncoder for the encoding & SimpleImputer function for imputation

In [45]:
```
def train_data(X):

    #looking for Unknown and replacing with nan
    X = X.replace('Unknown', np.nan)

    #encoding ordinal category
    X = encode_ordinals(X, ordinal_cat)

    #selecting Variables
    X_categor = X[categor_vars]
    X_ordinal = X[ordinal_vars]
    X_num = X[num_vars]

    #Imputing
    from sklearn.impute import SimpleImputer
    cat_imputer = SimpleImputer(strategy="most_frequent")
    ord_imputer = SimpleImputer(strategy="median")
    num_imputer = SimpleImputer(strategy="median")

    X_categor = cat_imputer.fit_transform(X_categor)
    X_ordinal = ord_imputer.fit_transform(X_ordinal)
    X_num = num_imputer.fit_transform(X_num)

    #encoding categorical variables using oneHotEncoder function
    from sklearn.preprocessing import OneHotEncoder
    one_hot_encoder = OneHotEncoder()
    X_categor = one_hot_encoder.fit_transform(X_categor).toarray()

    p = [cat_imputer, ord_imputer, num_imputer, one_hot_encoder]
    X_prep = np.concatenate([X_categor, X_ordinal, X_num], axis=1)

    return X_prep, p
```

In [46]:
```
def test_data(X, p):

    cat_imputer, ord_imputer, num_imputer, one_hot_encoder = p

    #Looking for Unknown and replacing with nan
    X = X.replace('Unknown', np.nan)

    #encoding ordinal category
    X = encode_ordinals(X, ordinal_cat)

    #selecting Variables
    X_cat = X[categor_vars]
    X_ord = X[ordinal_vars]
    X_num = X[num_vars]

    #Imputing
    X_cat = cat_imputer.transform(X_cat)
    X_ord = ord_imputer.transform(X_ord)
    X_num = num_imputer.transform(X_num)

    #encode categorical vars
    X_cat = one_hot_encoder.transform(X_cat).toarray()
    X_prep = np.concatenate([X_cat, X_ord, X_num], axis=1)

    return X_prep
```

13. Model building

In [47]:
```
X_train_prep, p = train_data(X_train)
X_test_prep = test_data(X_test, p)
```

In [48]:
```
X_train_prep.shape, X_test_prep.shape
```

Out[48]:
```
((8101, 22), (2026, 22))
```

14. Checking model Accuracy and F1 Score

In [49]:
```
from sklearn.metrics import accuracy_score, f1_score
from sklearn.metrics import make_scorer

score = make_scorer(f1_score)
```

15. Random Forest Classifier

In [50]:
```
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV

params = {
    'min_samples_leaf': [1, 2, 4, 6, 8, 10, 12],
    'n_estimators': [120, 130, 140, 150, 160, 170]
}

rfc = RandomForestClassifier(random_state=42)

rfc_grid = GridSearchCV(rfc,
                        params,
                        scoring=score,)

rfc_grid.fit(X_train_prep, y_train)
```

Out[50]:
```
GridSearchCV(estimator=RandomForestClassifier(random_state=42),
             param_grid={'min_samples_leaf': [1, 2, 4, 6, 8, 10, 12],
                         'n_estimators': [120, 130, 140, 150, 160, 170]},
             scoring=make_scorer(f1_score))
```

In [51]:
```
rfc_grid.best_params_
```

Out[51]:
```
{'min_samples_leaf': 1, 'n_estimators': 150}
```

In [52]:
```
rfc = RandomForestClassifier(**rfc_grid.best_params_,
                             random_state=42)
rfc.fit(X_train_prep, y_train)
```

Out[52]:
```
RandomForestClassifier(n_estimators=150, random_state=42)
```

```
In [53]: from sklearn.model_selection import cross_val_score
         scores = cross_val_score(rfc, X_train_prep, y_train, cv=5, verbose=2, scoring=
         score)
         print(scores)
         print('Scores Mean = ', scores.mean(), ' Scores Standard Deviation = ', scores
         .std())
```

```
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent worke
rs.

[CV]  ................................................................
[CV] ................................................. , total=   1.4s
[CV]  ................................................................

[Parallel(n_jobs=1)]: Done   1 out of   1 | elapsed:    1.3s remaining:    0.
0s

[CV] ................................................. , total=   1.3s
[CV]  ................................................................
[CV] ................................................. , total=   1.3s
[CV]  ................................................................
[CV] ................................................. , total=   1.3s
[CV]  ................................................................
[CV] ................................................. , total=   1.3s
[0.88752556 0.87804878 0.83789474 0.84599589 0.86409736]
Scores Mean =  0.8627124672018164  Scores Standard Deviation =  0.01869852250
586271

[Parallel(n_jobs=1)]: Done   5 out of   5 | elapsed:    6.5s finished
```

16. Final accuracy and F1 score

```
In [54]: from sklearn.metrics import accuracy_score
         y_test_pred = rfc.predict(X_test_prep)
         RF_ac = print("RF Accuracy Score = ",accuracy_score(y_test_pred, y_test))
```

```
RF Accuracy Score =  0.9536031589338598
```

```
In [55]: y_test_pred = rfc.predict(X_test_prep)
         RF_f1= print('RF F1 Score = ',f1_score(y_test_pred, y_test))
```

```
RF F1 Score =  0.84640522875817
```

In [56]:
```
# Build a confusion matrix, which will provide insights into the accuracy of t
he model.
confusion_matrixRF = pd.crosstab(y_test, y_test_pred, rownames=['Actual'], col
names=['Predicted'])
print(confusion_matrixRF)
print('Accuracy: ',metrics.accuracy_score(y_test, y_test_pred))
plt.show()
```

```
Predicted     0    1
Actual
0          1673   28
1            66  259
Accuracy:  0.9536031589338598
```

17. Feature importances

In [57]:
```
rfc.feature_importances_
```

Out[57]:
```
array([0.00225109, 0.0051473 , 0.00457561, 0.00645994, 0.00710344,
       0.00933276, 0.01162648, 0.0026852 , 0.03181216, 0.02697822,
       0.01370493, 0.06490266, 0.02489387, 0.03436559, 0.02811725,
       0.11434273, 0.03487793, 0.05660342, 0.17819413, 0.16767331,
       0.06304179, 0.11131019])
```

In [58]:
```
#we're trying to get the index of every attribute in our decision trees
#our categorical attributes are one hot encoded, so our model looks at them as
multiple attributes

features ={'Gender': [0, 1],
           'Marital_Status': [2, 3, 4]
          }

start = 5

for f in ordinal_vars + num_vars:
    features[f] = [start]
    start += 1

print(features)
```

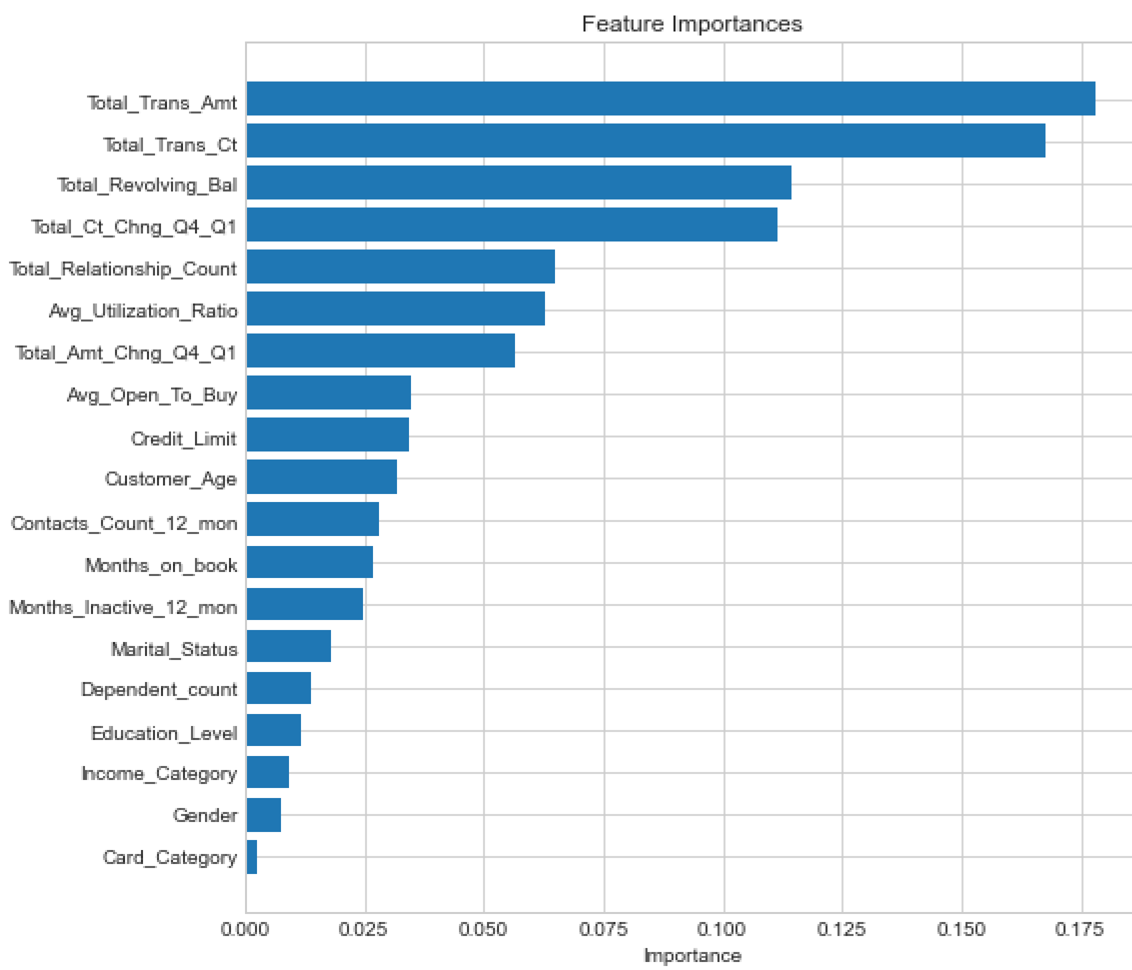
```
{'Gender': [0, 1], 'Marital_Status': [2, 3, 4], 'Income_Category': [5], 'Educ
ation_Level': [6], 'Card_Category': [7], 'Customer_Age': [8], 'Months_on_boo
k': [9], 'Dependent_count': [10], 'Total_Relationship_Count': [11], 'Months_I
nactive_12_mon': [12], 'Credit_Limit': [13], 'Contacts_Count_12_mon': [14],
'Total_Revolving_Bal': [15], 'Avg_Open_To_Buy': [16], 'Total_Amt_Chng_Q4_Q1':
[17], 'Total_Trans_Amt': [18], 'Total_Trans_Ct': [19], 'Avg_Utilization_Rati
o': [20], 'Total_Ct_Chng_Q4_Q1': [21]}
```

In [59]:

```
#Now we aggregate the importances of the one hot encoded attributes (features)

f_importances = [(feature, sum([rfc.feature_importances_[index]
                  for index in indexes]))
                    for feature, indexes in features.items()]

f_importances = sorted(f_importances, key=lambda x: x[1], reverse=True)
```

In [60]:

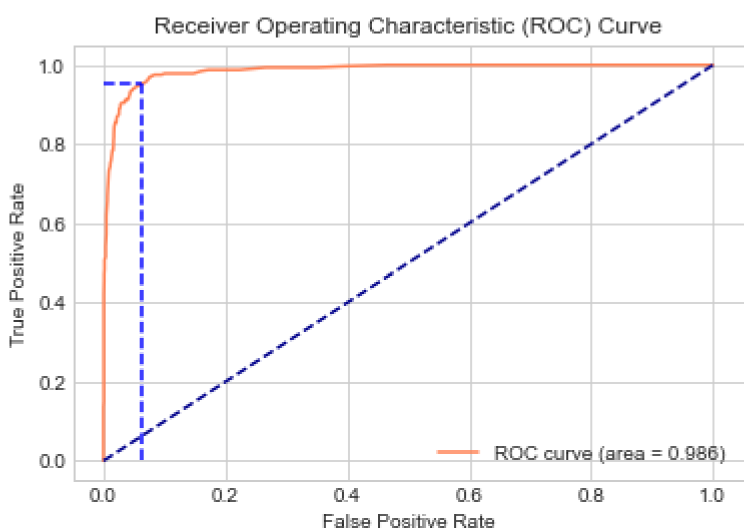
```
plt.style.use('seaborn-whitegrid')

features, importances = zip(*f_importances)

y_pos = np.arange(len(features))

fig, ax = plt.subplots(figsize=(8, 8))

ax.barh(y_pos, importances, align='center')
ax.set_yticks(y_pos)
ax.set_yticklabels(features)
ax.invert_yaxis()  # Labels in the graph are flipped
ax.set_xlabel('Importance')
ax.set_title('Feature Importances')

plt.show()
```



In [61]:
```
#calculate AUC score for RF model
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
probs = rfc.predict_proba(X_test_prep)
probs = probs[:, 1]
RF_auc = print("AUC = ",roc_auc_score(y_test, probs))
```

```
AUC =  0.985819201374757
```

In [62]:
```
fpr, tpr, thresholds = roc_curve(y_test, probs)
idx = np.min(np.where(tpr > 0.95)) # index of the first threshold for which th
e sensibility > 0.95

def plot_roc_curve(fpr, tpr):
    plt.plot(fpr, tpr, color='coral', label='ROC curve (area = %0.3f)' % auc(f
pr, tpr))
    plt.plot([0, 1], [0, 1], color='darkblue', linestyle='--')
    plt.plot([0,fpr[idx]], [tpr[idx],tpr[idx]], 'k--', color='blue')
    plt.plot([fpr[idx],fpr[idx]], [0,tpr[idx]], 'k--', color='blue')
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title('Receiver Operating Characteristic (ROC) Curve')
    plt.legend()
    plt.show()

plot_roc_curve(fpr, tpr)
```



Section2:

Logistic Regression:

In [63]:
```python
#Replacing the "unknowns" with NaNs
df1=df1.replace('Unknown', np.nan)
```

In [64]:
```python
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 22 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           8608 non-null   object 
 6   Marital_Status            9378 non-null   object 
 7   Income_Category           9015 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
 21  target                    10127 non-null  int32  
dtypes: float64(5), int32(1), int64(10), object(6)
memory usage: 1.7+ MB
```

In [65]:
```python
#Creating a DF with just the categorical data
obj_df = df1.select_dtypes(include=['object']).copy()
obj_df.head()
```

Out[65]:

	Attrition_Flag	Gender	Education_Level	Marital_Status	Income_Category	Card_Category
0	Existing Customer	M	High School	Married	$60K -$80K	Blue
1	Existing Customer	F	Graduate	Single	Less than $40K	Blue
2	Existing Customer	M	Graduate	Married	$80K -$120K	Blue
3	Existing Customer	F	High School	NaN	Less than $40K	Blue
4	Existing Customer	M	Uneducated	Married	$60K -$80K	Blue

In [66]:
```
#Creating classes of columns (numerical and categorical)

numerical_cols = ['Customer_Age', 'Dependent_count', 'Months_on_book','Total_R
elationship_Count', 'Months_Inactive_12_mon',
       'Contacts_Count_12_mon', 'Credit_Limit', 'Total_Revolving_Bal','Avg_Ope
n_To_Buy', 'Total_Amt_Chng_Q4_Q1', 'Total_Trans_Amt',
       'Total_Trans_Ct', 'Total_Ct_Chng_Q4_Q1', 'Avg_Utilization_Ratio']

category_cols = [x for x in df1.columns if x not in ['CLIENTNUM']+numerical_co
ls] #Everything else is a categorical column
```

In [67]:
```
#Creating a dictionary to encode the categorical variables
cleanup_nums = {"Education_Level":{"Uneducated": 1, "High School": 2, "Graduat
e": 3, "Post-Graduate": 4, "College": 5, "Doctorate": 6},
                "Marital_Status": {"Single": 1, "Married": 2, "Divorced": 3},
               "Income_Category": {"Less than $40K": 1, '$40K - $60K': 2, '$60
K - $80K': 3, '$80K - $120K': 4, "$120K +": 5},
               "Gender": {"M": 1, "F": 2},
               "Card_Category": {"Blue": 1, "Silver": 2, "Gold": 3, "Platinum"
: 4}}
```

In [68]:
```
#Creating a new DF with the encoded categorical variables
#Attrition Flag was left as is because that will be converted to dummies to be
tter evaluate a model
obj_df = obj_df.replace(cleanup_nums)
obj_df.head()
```

Out[68]:

	Attrition_Flag	Gender	Education_Level	Marital_Status	Income_Category	Card_Category
0	Existing Customer	1	2.0	2.0	3.0	1
1	Existing Customer	2	3.0	1.0	1.0	1
2	Existing Customer	1	3.0	2.0	4.0	1
3	Existing Customer	2	2.0	NaN	1.0	1
4	Existing Customer	1	1.0	2.0	3.0	1

In [69]:
```
obj_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 6 columns):
 #   Column           Non-Null Count  Dtype  
---  ------           --------------  -----  
 0   Attrition_Flag   10127 non-null  object 
 1   Gender           10127 non-null  int64  
 2   Education_Level  8608 non-null   float64
 3   Marital_Status   9378 non-null   float64
 4   Income_Category  9015 non-null   float64
 5   Card_Category    10127 non-null  int64  
dtypes: float64(3), int64(2), object(1)
memory usage: 474.8+ KB
```

In [70]:
```
#Putting dummies in the Attrition Flag column
obj_df=pd.get_dummies(obj_df, prefix=['Attrition_Flag'], columns=['Attrition_F
lag'])
```

In [71]:
```
#Creating a new DF with the categorical features removed
#Will later be replaced with encoded and imputed features
df2 = df1.drop(['Education_Level', 'Marital_Status', 'Income_Category','Attrit
ion_Flag', 'Gender', 'Card_Category', 'CLIENTNUM','target'], axis=1)
df2
```

Out[71]:

	Customer_Age	Dependent_count	Months_on_book	Total_Relationship_Count	Months_Ina
0	45	3	39	5	
1	49	5	44	6	
2	51	3	36	4	
3	40	4	34	3	
4	40	3	21	5	
...	...	...	...	...	
10122	50	2	40	3	
10123	41	2	25	4	
10124	44	1	36	5	
10125	30	2	36	4	
10126	43	2	25	6	

10127 rows × 14 columns

In [72]:
```
#New DF with the encoded categorical variables added
df3 = pd.concat([obj_df, df2], axis=1)
df3
```

Out[72]:

	Gender	Education_Level	Marital_Status	Income_Category	Card_Category	Attrition_Flag_ C
0	1	2.0	2.0	3.0	1	
1	2	3.0	1.0	1.0	1	
2	1	3.0	2.0	4.0	1	
3	2	2.0	NaN	1.0	1	
4	1	1.0	2.0	3.0	1	
...	...	...	...	...	...	
10122	1	3.0	1.0	2.0	1	
10123	1	NaN	3.0	2.0	1	
10124	2	2.0	2.0	1.0	1	
10125	1	3.0	NaN	2.0	1	
10126	2	3.0	2.0	1.0	2	

10127 rows × 21 columns

In [73]:
```
df3.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10127 entries, 0 to 10126
Data columns (total 21 columns):
 #   Column                              Non-Null Count  Dtype  
---  ------                              --------------  -----  
 0   Gender                              10127 non-null  int64  
 1   Education_Level                     8608 non-null   float64
 2   Marital_Status                      9378 non-null   float64
 3   Income_Category                     9015 non-null   float64
 4   Card_Category                       10127 non-null  int64  
 5   Attrition_Flag_Attrited Customer    10127 non-null  uint8  
 6   Attrition_Flag_Existing Customer    10127 non-null  uint8  
 7   Customer_Age                        10127 non-null  int64  
 8   Dependent_count                     10127 non-null  int64  
 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(8), int64(11), uint8(2)
memory usage: 1.5 MB
```

In [74]:
```
#Setting up a KNN imputer
imputer = KNNImputer(n_neighbors=10) #k=10 is arbitrary at this point
imputed = imputer.fit_transform(df3)
df_imputed = pd.DataFrame(imputed, columns=df3.columns) #Renaming the imputed
 DF
```

In [75]:
```
df_imputed
```

Out[75]:

	Gender	Education_Level	Marital_Status	Income_Category	Card_Category	Attrition_Flag_ Cu
0	1.0	2.0	2.0	3.0	1.0	
1	2.0	3.0	1.0	1.0	1.0	
2	1.0	3.0	2.0	4.0	1.0	
3	2.0	2.0	1.8	1.0	1.0	
4	1.0	1.0	2.0	3.0	1.0	
...	...	...	...	...	...	
10122	1.0	3.0	1.0	2.0	1.0	
10123	1.0	3.4	3.0	2.0	1.0	
10124	2.0	2.0	2.0	1.0	1.0	
10125	1.0	3.0	1.5	2.0	1.0	
10126	2.0	3.0	2.0	1.0	2.0	

10127 rows × 21 columns

In [76]:
```
#Rounded the values to the nearest number
df_imputed=df_imputed.round(0)
df_imputed.head()
```

Out[76]:

	Gender	Education_Level	Marital_Status	Income_Category	Card_Category	Attrition_Flag_Attri Custor
0	1.0	2.0	2.0	3.0	1.0	
1	2.0	3.0	1.0	1.0	1.0	
2	1.0	3.0	2.0	4.0	1.0	
3	2.0	2.0	2.0	1.0	1.0	
4	1.0	1.0	2.0	3.0	1.0	

5 rows × 21 columns

In [77]:
```
df_imputed10 = df_imputed # we can use this copy for KNN dataset
```

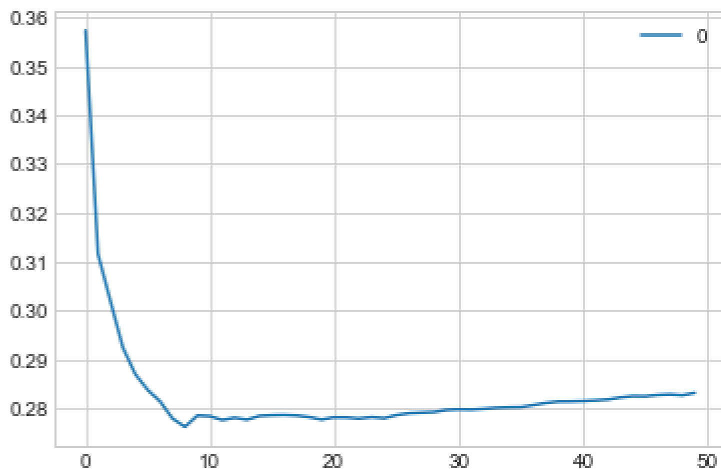
In [78]:
```
#Setting up a train/test split to evaluate the KNN imputation
y=df_imputed['Attrition_Flag_Attrited Customer']
X=df_imputed.drop(['Attrition_Flag_Attrited Customer', 'Attrition_Flag_Existin
g Customer'], axis=1)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.3, r
andom_state=0)
columns =X_train2.columns
```

In [79]:
```
#Checking to see what the optimum number of K for KNN imputation actually is

rmse_val = [] #to store rmse values for different k
for K in range(50): #Use up to 50 nearest neighbours
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K)

    model.fit(X_train2, y_train2)  #fit the model
    pred=model.predict(X_test2) #make prediction on test set
    error = sqrt(mean_squared_error(y_test2,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 0.3573143949444033
RMSE value for k=  2 is: 0.31156284288640135
RMSE value for k=  3 is: 0.3019079397437066
RMSE value for k=  4 is: 0.29239145127135857
RMSE value for k=  5 is: 0.2869315488433068
RMSE value for k=  6 is: 0.2836926471433759
RMSE value for k=  7 is: 0.28132051473553615
RMSE value for k=  8 is: 0.2778110241155043
RMSE value for k=  9 is: 0.2761000116061324
RMSE value for k=  10 is: 0.2784281078729335
RMSE value for k=  11 is: 0.2782991995982396
RMSE value for k=  12 is: 0.2775075465193632
RMSE value for k=  13 is: 0.27796719600664976
RMSE value for k=  14 is: 0.27757467397561053
RMSE value for k=  15 is: 0.2783473375483962
RMSE value for k=  16 is: 0.2784949472964064
RMSE value for k=  17 is: 0.2785435887053008
RMSE value for k=  18 is: 0.2784314636756696
RMSE value for k=  19 is: 0.27810710910929876
RMSE value for k=  20 is: 0.2775966284397065
RMSE value for k=  21 is: 0.2780550981412249
RMSE value for k=  22 is: 0.27802667887116655
RMSE value for k=  23 is: 0.2778050940633063
RMSE value for k=  24 is: 0.278103899818036
RMSE value for k=  25 is: 0.2778746962654451
RMSE value for k=  26 is: 0.2785287553053484
RMSE value for k=  27 is: 0.2788985712683346
RMSE value for k=  28 is: 0.27902850717699285
RMSE value for k=  29 is: 0.27914164062107133
RMSE value for k=  30 is: 0.2795727897260733
RMSE value for k=  31 is: 0.2796925469704104
RMSE value for k=  32 is: 0.27963838005809155
RMSE value for k=  33 is: 0.27980108098863027
RMSE value for k=  34 is: 0.2800046836762504
RMSE value for k=  35 is: 0.28011339090100495
RMSE value for k=  36 is: 0.280157351877085
RMSE value for k=  37 is: 0.2805682853611082
RMSE value for k=  38 is: 0.2810085879944278
RMSE value for k=  39 is: 0.28129243618939653
RMSE value for k=  40 is: 0.28132478165625363
RMSE value for k=  41 is: 0.2813996004891476
RMSE value for k=  42 is: 0.28154222935632395
RMSE value for k=  43 is: 0.28171391860170925
RMSE value for k=  44 is: 0.28213384052442797
RMSE value for k=  45 is: 0.28241523960151166
RMSE value for k=  46 is: 0.28237749178595617
RMSE value for k=  47 is: 0.2826445986603902
RMSE value for k=  48 is: 0.28276380926992717
RMSE value for k=  49 is: 0.28258963884055965
RMSE value for k=  50 is: 0.28308622094626
```

In [80]:
```
#plotting the rmse values against k values for visuals
curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

Out[80]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21a5fddc1f0>
```



In [81]:
```
#Creating a Train/Test Split

y=df_imputed['Attrition_Flag_Attrited Customer']
X=df_imputed.drop(['Attrition_Flag_Attrited Customer', 'Attrition_Flag_Existin
g Customer'], axis=1)
X_train2, X_test2, y_train2, y_test2 = train_test_split(X, y, test_size=0.3, r
andom_state=0)
columns =X_train2.columns
```

In [82]:
```
#Creating SMOTE'd data for the model

os = SMOTE(random_state=41)

os_data_X,os_data_y=os.fit_sample(X_train2,y_train2)
os_data_X = pd.DataFrame(data=os_data_X,columns=columns )
os_data_y= pd.DataFrame(data=os_data_y,columns=["Attrition_Flag_Attrited Custo
mer"])
# we can Check the numbers of our data
print("length of oversampled data is ",len(os_data_X))
print("Number of yes in oversampled data",len(os_data_y[os_data_y["Attrition_F
lag_Attrited Customer"]=='Yes']))
print("No.of No transcation",len(os_data_y[os_data_y["Attrition_Flag_Attrited
 Customer"]=='No']))
print("Proportion of churn yes data in oversampled data is ",len(os_data_y[os_
data_y["Attrition_Flag_Attrited Customer"]=='Yes'])/len(os_data_X))
print("Proportion of no data in oversampled data is ",len(os_data_y[os_data_y[
"Attrition_Flag_Attrited Customer"]=='No'])/len(os_data_X))
```

```
length of oversampled data is  11834
Number of yes in oversampled data 0
No.of No transcation 0
Proportion of churn yes data in oversampled data is  0.0
Proportion of no data in oversampled data is  0.0
```

In [83]:
```
#Using logistic regression on a train/test split
X=os_data_X #The independent variable
y=os_data_y #What we are trying to predict
X_train2,X_test2,y_train2,y_test2=train_test_split(X,y, test_size=0.3, random_
state=0) #Train/Test Split

model=LogisticRegression(max_iter=50000) #Max iter is high just so the entire
 dataset is used
model.fit(X_train2, np.ravel(y_train2))


print('Logistic Regression:')
print('Training Model accuracy: {:.2%}'.format(model.score(X_train2,y_train2
)))
print('Test Model accuracy: {:.2%}'.format(model.score(X_test2,y_test2['Attrit
ion_Flag_Attrited Customer'])))
```

```
Logistic Regression:
Training Model accuracy: 83.97%
Test Model accuracy: 83.47%
```

In [84]:
```
#Printing a classification report and confusion matrix from the logistic regre
ssion model

predictions = model.predict(X_test2)
print(classification_report(y_test2,predictions))
print ("Confusion Matrix")
print(confusion_matrix(y_test2, predictions))
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.82      0.83      1758
         1.0       0.83      0.85      0.84      1793

    accuracy                           0.83      3551
   macro avg       0.84      0.83      0.83      3551
weighted avg       0.83      0.83      0.83      3551

Confusion Matrix
[[1436  322]
 [ 265 1528]]
```

In [85]:
```
clf_reg = LogisticRegression(max_iter=20000);
clf_reg.fit(X_train2, y_train2);
```

In [86]:
```
 y_score2 = clf_reg.predict_proba(X_test2)[:,1]
```

In [87]:
```
false_positive_rate2, true_positive_rate2, threshold2 = roc_curve(y_test2, y_s
core2)
```

In [88]:
```
print('roc_auc_score for Logistic Regression: ', roc_auc_score(y_test2, y_score2))
```

```
roc_auc_score for Logistic Regression:  0.9149733478760468
```

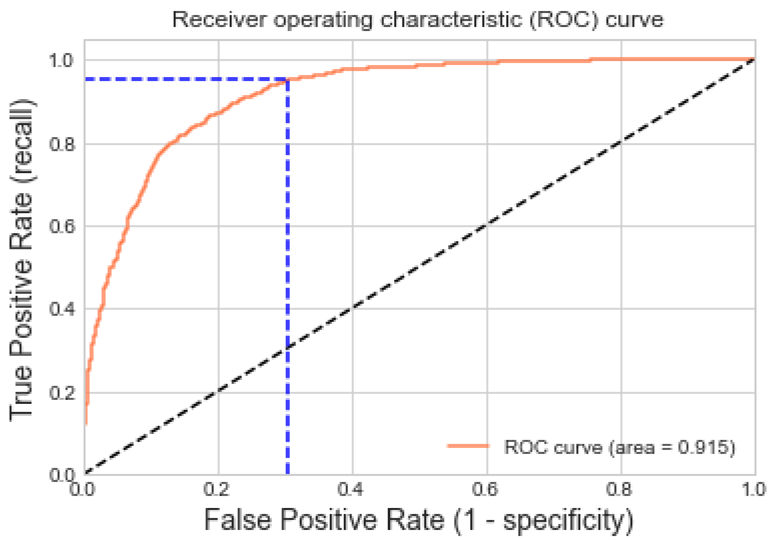
In [89]:
```
'''plt.subplots(1, figsize=(4,4))
plt.title('Receiver Operating Characteristic - Logistic regression')
plt.plot(false_positive_rate2, true_positive_rate2)
plt.plot([0, 1], ls="--")
plt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()'''
```

Out[89]:
```
'plt.subplots(1, figsize=(4,4))\nplt.title(\'Receiver Operating Characteristic - Logistic regression\')\nplt.plot(false_positive_rate2, true_positive_rate2)\nplt.plot([0, 1], ls="--")\nplt.plot([0, 0], [1, 0] , c=".7"), plt.plot([1, 1] , c=".7")\nplt.ylabel(\'True Positive Rate\')\nplt.xlabel(\'False Positive Rate\')\nplt.show()'
```

In [90]:

```
# create X (features) and y (response)
X = os_data_X
y = os_data_y

# use train/test split with different random_state values
# we can change the random_state values that changes the accuracy scores
# the scores change a lot, this is why testing scores is a high-variance estim
ate
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, rando
m_state=0)

# check classification scores of logistic regression
logreg = LogisticRegression(max_iter=20000)
logreg.fit(X_train, y_train)
y_pred = logreg.predict(X_test)
y_pred_proba = logreg.predict_proba(X_test)[:, 1]
[fpr, tpr, thr] = roc_curve(y_test, y_pred_proba)
print('Train/Test split results:')
LR_ac = print(logreg.__class__.__name__+" accuracy is %2.3f" % accuracy_score(
y_test, y_pred))
print(logreg.__class__.__name__+" log_loss is %2.3f" % log_loss(y_test, y_pred
_proba))
print(logreg.__class__.__name__+" auc is %2.3f" % auc(fpr, tpr))

idx = np.min(np.where(tpr > 0.95)) # index of the first threshold for which th
e sensibility > 0.95

plt.figure()
plt.plot(fpr, tpr, color='coral', label='ROC curve (area = %0.3f)' % auc(fpr,
tpr))
plt.plot([0, 1], [0, 1], 'k--')
plt.plot([0,fpr[idx]], [tpr[idx],tpr[idx]], 'k--', color='blue')
plt.plot([fpr[idx],fpr[idx]], [0,tpr[idx]], 'k--', color='blue')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate (1 - specificity)', fontsize=14)
plt.ylabel('True Positive Rate (recall)', fontsize=14)
plt.title('Receiver operating characteristic (ROC) curve')
plt.legend(loc="lower right")
plt.show()

print("Using a threshold of %.3f " % thr[idx] + "guarantees a sensitivity of
%.3f " % tpr[idx] +
      "and a specificity of %.3f" % (1-fpr[idx]) +
      ", i.e. a false positive rate of %.2f%%." % (np.array(fpr[idx])*100))
```

```
Train/Test split results:
LogisticRegression accuracy is 0.835
LogisticRegression log_loss is 0.367
LogisticRegression auc is 0.915
```




```
Using a threshold of 0.281 guarantees a sensitivity of 0.950 and a specificit
y of 0.693, i.e. a false positive rate of 30.66%.
```

Section 3:

K Nearest Neighbour (KNN)

In [91]:
```
df_imputed10.head()
```

Out[91]:

	Gender	Education_Level	Marital_Status	Income_Category	Card_Category	Attrition_Flag_Attri Custor
0	1.0	2.0	2.0	3.0	1.0	
1	2.0	3.0	1.0	1.0	1.0	
2	1.0	3.0	2.0	4.0	1.0	
3	2.0	2.0	2.0	1.0	1.0	
4	1.0	1.0	2.0	3.0	1.0	

5 rows × 21 columns

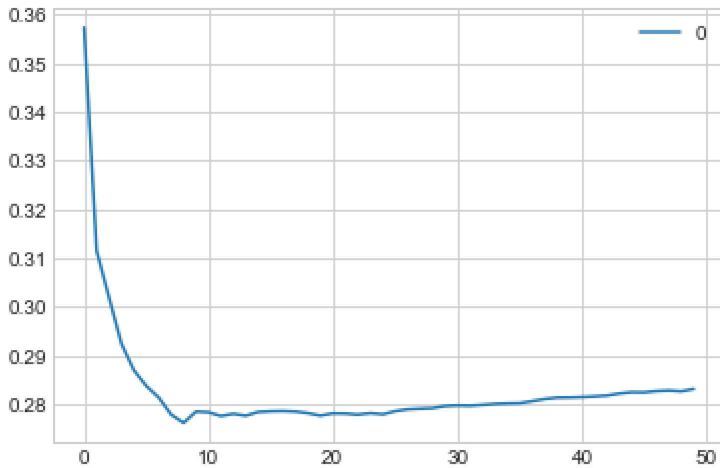
In [92]:
```
#Setting up a train/test split to evaluate the KNN imputation
y=df_imputed10['Attrition_Flag_Attrited Customer']
X=df_imputed10.drop(['Attrition_Flag_Attrited Customer', 'Attrition_Flag_Exist
ing Customer'], axis=1)
X_train10, X_test10, y_train10, y_test10 = train_test_split(X, y, test_size=0.
3, random_state=0)
columns =X_train10.columns
```

In [93]:
```
#Checking to see what the optimum number of K for KNN imputation actually is

rmse_val = [] #to store rmse values for different k
for K in range(50): #Use up to 50 nearest neighbours
    K = K+1
    model = neighbors.KNeighborsRegressor(n_neighbors = K)

    model.fit(X_train10, y_train10)  #fit the model
    pred=model.predict(X_test10) #make prediction on test set
    error = sqrt(mean_squared_error(y_test10,pred)) #calculate rmse
    rmse_val.append(error) #store rmse values
    print('RMSE value for k= ' , K , 'is:', error)
```

```
RMSE value for k=  1 is: 0.3573143949444033
RMSE value for k=  2 is: 0.31156284288640135
RMSE value for k=  3 is: 0.3019079397437066
RMSE value for k=  4 is: 0.29239145127135857
RMSE value for k=  5 is: 0.2869315488433068
RMSE value for k=  6 is: 0.2836926471433759
RMSE value for k=  7 is: 0.28132051473553615
RMSE value for k=  8 is: 0.2778110241155043
RMSE value for k=  9 is: 0.2761000116061324
RMSE value for k=  10 is: 0.2784281078729335
RMSE value for k=  11 is: 0.2782991995982396
RMSE value for k=  12 is: 0.2775075465193632
RMSE value for k=  13 is: 0.27796719600664976
RMSE value for k=  14 is: 0.27757467397561053
RMSE value for k=  15 is: 0.2783473375483962
RMSE value for k=  16 is: 0.2784949472964064
RMSE value for k=  17 is: 0.2785435887053008
RMSE value for k=  18 is: 0.2784314636756696
RMSE value for k=  19 is: 0.27810710910929876
RMSE value for k=  20 is: 0.2775966284397065
RMSE value for k=  21 is: 0.2780550981412249
RMSE value for k=  22 is: 0.27802667887116655
RMSE value for k=  23 is: 0.2778050940633063
RMSE value for k=  24 is: 0.278103899818036
RMSE value for k=  25 is: 0.2778746962654451
RMSE value for k=  26 is: 0.2785287553053484
RMSE value for k=  27 is: 0.2788985712683346
RMSE value for k=  28 is: 0.27902850717699285
RMSE value for k=  29 is: 0.27914164062107133
RMSE value for k=  30 is: 0.2795727897260733
RMSE value for k=  31 is: 0.2796925469704104
RMSE value for k=  32 is: 0.27963838005809155
RMSE value for k=  33 is: 0.27980108098863027
RMSE value for k=  34 is: 0.2800046836762504
RMSE value for k=  35 is: 0.28011339090100495
RMSE value for k=  36 is: 0.280157351877085
RMSE value for k=  37 is: 0.2805682853611082
RMSE value for k=  38 is: 0.2810085879944278
RMSE value for k=  39 is: 0.28129243618939653
RMSE value for k=  40 is: 0.28132478165625363
RMSE value for k=  41 is: 0.2813996004891476
RMSE value for k=  42 is: 0.28154222935632395
RMSE value for k=  43 is: 0.28171391860170925
RMSE value for k=  44 is: 0.28213384052442797
RMSE value for k=  45 is: 0.28241523960151166
RMSE value for k=  46 is: 0.28237749178595617
RMSE value for k=  47 is: 0.2826445986603902
RMSE value for k=  48 is: 0.28276380926992717
RMSE value for k=  49 is: 0.28258963884055965
RMSE value for k=  50 is: 0.28308622094626
```

In [94]:
```
#plotting the rmse values against k values for visuals
curve = pd.DataFrame(rmse_val) #elbow curve
curve.plot()
```

Out[94]: <matplotlib.axes._subplots.AxesSubplot at 0x21a5fe96be0>



In [95]:
```
#Creating a Train/Test Split

y=df_imputed10['Attrition_Flag_Attrited Customer']
X=df_imputed10.drop(['Attrition_Flag_Attrited Customer', 'Attrition_Flag_Exist
ing Customer'], axis=1)
X_train11, X_test11, y_train11, y_test11 = train_test_split(X, y, test_size=0.
3, random_state=0)
columns =X_train11.columns
```

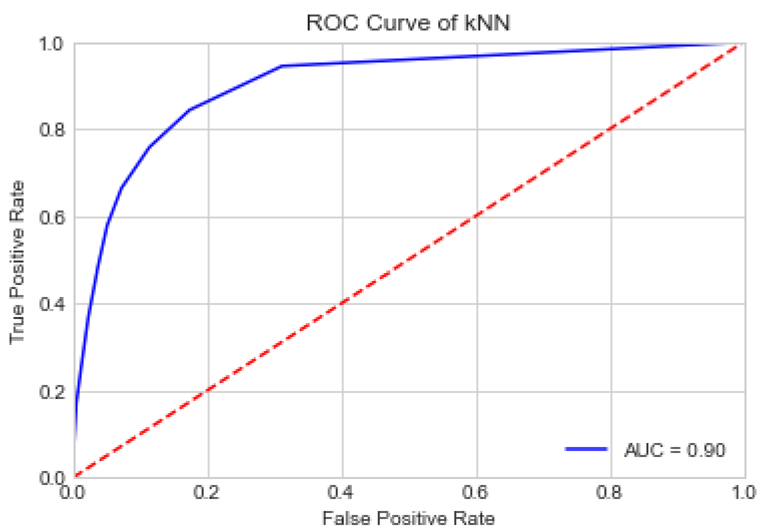
In [96]:
```
#Creating SMOTE'd data for the model

os1 = SMOTE(random_state=41)

os_data_X1,os_data_y=os1.fit_sample(X_train11,y_train11)
os_data_X1 = pd.DataFrame(data=os_data_X1,columns=columns )
os_data_y1= pd.DataFrame(data=os_data_y,columns=["Attrition_Flag_Attrited Cust
omer"])
# we can Check the numbers of our data
print("length of oversampled data is ",len(os_data_X1))
print("Number of yes in oversampled data",len(os_data_y1[os_data_y1["Attrition
_Flag_Attrited Customer"]=='Yes']))
print("No.of No transcation",len(os_data_y1[os_data_y1["Attrition_Flag_Attrite
d Customer"]=='No']))
print("Proportion of churn yes data in oversampled data is ",len(os_data_y1[os
_data_y1["Attrition_Flag_Attrited Customer"]=='Yes'])/len(os_data_X1))
print("Proportion of no data in oversampled data is ",len(os_data_y1[os_data_y
1["Attrition_Flag_Attrited Customer"]=='No'])/len(os_data_X1))
```

```
length of oversampled data is  11834
Number of yes in oversampled data 0
No.of No transcation 0
Proportion of churn yes data in oversampled data is  0.0
Proportion of no data in oversampled data is  0.0
```

In [97]:
```python
knn = KNeighborsClassifier()

## Set up hyperparameter grid for tuning
knn_param_grid = {'n_neighbors' : np.arange(5,26),
                  'weights' : ['uniform', 'distance']}

## Tune hyperparameters
knn_cv = GridSearchCV(knn, param_grid = knn_param_grid, cv = 5)

## Fit knn to training data
knn_cv.fit(X_train11, y_train11)

## Get info about best hyperparameters
print("Tuned KNN Parameters: {}".format(knn_cv.best_params_))
print("Best KNN Training Score:{}".format(knn_cv.best_score_))

## Predict knn on test data
print("KNN Test Performance: {}".format(knn_cv.score(X_test11, y_test11)))

## Obtain model performance metrics
knn_pred_prob = knn_cv.predict_proba(X_test11)[:,1]
knn_auroc = roc_auc_score(y_test11, knn_pred_prob)
print("KNN AUROC: {}".format(knn_auroc))
knn_y_pred = knn_cv.predict(X_test11)
print(classification_report(y_test11, knn_y_pred))


#predictions = model.predict(X_test11)
#print ("Confusion Matrix")
#print(confusion_matrix(y_test11, predictions))
```

```
Tuned KNN Parameters: {'n_neighbors': 16, 'weights': 'distance'}
Best KNN Training Score:0.8944691351143131
KNN Test Performance: 0.8970055939453768
KNN AUROC: 0.9119075636245085
              precision    recall  f1-score   support

         0.0       0.92      0.96      0.94      2583
         1.0       0.70      0.55      0.61       456

    accuracy                           0.90      3039
   macro avg       0.81      0.75      0.78      3039
weighted avg       0.89      0.90      0.89      3039
```

In [98]:
```
knn = KNeighborsClassifier(n_neighbors = 10)
knn.fit(X_train11,y_train11)

y_scores = knn.predict_proba(X_test11)
fpr, tpr, threshold = roc_curve(y_test11, y_scores[:, 1])
roc_auc = auc(fpr, tpr)

plt.title('Receiver Operating Characteristic')
plt.plot(fpr, tpr, 'b', label = 'AUC = %0.2f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.title('ROC Curve of kNN')
plt.show()
```



Comparison between Models

Model	Evaluation Metrics (Accuracy)	Evaluation Metrics (AUC score)
Logistic Regression	83.47%	0.900
Random Forest	95.36%	0.986
k-Nearest Neighbours	90.00%	0.912

In [ ]: