Title: Bank Customer Churn Prediction

Objective:

Our objective is to build a machine learning model to predict whether the customer will churn or not in the next six months.

Data Source: Kaggle dataset

About dataset:

The bank customer churn dataset is a commonly used dataset for predicting customer churn in the banking industry. It contains information on bank customers who either left the bank or continue to be a customer. The dataset includes the following attributes:

Variable

ID: Unique Identifier of a row

Age: Age of the customer

Gender: Gender of the customer (Male and Female)

Income: Yearly income of the customer

Balance: Average quarterly balance of the customer

Vintage: No. of years the customer is associated with bank

Transaction_Status: Whether the customer has done any transaction in the past 3 months or not

Product_Holdings: No. of product holdings with the bank

Credit_Card: Whether the customer has a credit card or not

Credit_Category: Category of a customer based on the credit score

Is_Churn: Whether the customer will churn in next 6 months or not

The goal of the dataset is to predict which customers are likely to churn, based on the input features provided. By predicting customer churn, banks can take appropriate measures to retain their customers and reduce customer turnover.

Required Libraries

In [1]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import plotly.graph_objects as go

from sklearn.preprocessing import LabelEncoder
from sklearn.preprocessing import StandardScaler

from imblearn.over_sampling import RandomOverSampler
from sklearn.model_selection import train_test_split

from sklearn.svm import SVC
from sklearn.ensemble import AdaBoostClassifier, RandomForestClassifier
from sklearn.linear_model import LogisticRegression, SGDClassifier
from xgboost import XGBClassifier
from sklearn.model_selection import GridSearchCV

import re
from sklearn.metrics import roc_auc_score, roc_curve,accuracy_score, precision_score, recall_score, make_scorer
from sklearn.metrics import classification_report,confusion_matrix
```

Import Data

In [2]:
```
# Training data
train=pd.read_csv('train_churn.csv')
train.head()
```

Out[2]:

	ID	Age	Gender	Income	Balance	Vintage	Transaction_Status	Product_Holdings	Credit_Card	Credit_Category	Is_Churn
0	84e2fcc9	36	Female	5L - 10L	563266.44	4	0	1	0	Average	1
1	57fea15e	53	Female	Less than 5L	875572.11	2	1	1	1	Poor	0
2	8df34ef3	35	Female	More than 15L	701607.06	2	1	2	0	Poor	0
3	c5c0788b	43	Female	More than 15L	1393922.16	0	1	2	1	Poor	1
4	951d69c4	39	Female	More than 15L	893146.23	1	1	1	1	Good	1

In [3]:

```
# Testing data
test=pd.read_csv('test_churn.csv')
test.head()
```

Out[3]:

	ID	Age	Gender	Income	Balance	Vintage	Transaction_Status	Product_Holdings	Credit_Card	Credit_Category
0	55480787	50	Female	More than 15L	1008636.39	2	1	2	1	Average
1	9aededf2	36	Male	5L - 10L	341460.72	2	0	2	1	Average
2	a5034a09	25	Female	10L - 15L	439460.10	0	0	2	1	Good
3	b3256702	41	Male	Less than 5L	28581.93	0	1	2	1	Poor
4	dc28adb5	48	Male	More than 15L	1104540.03	2	1	3+	0	Good

In [4]:

```
train.shape,test.shape
```

Out[4]:

```
((6650, 11), (2851, 10))
```

In [5]:

```
## Cheaking total row, total column, null-value, Dtypes
train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 6650 entries, 0 to 6649
Data columns (total 11 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   ID                  6650 non-null   object 
 1   Age                 6650 non-null   int64  
 2   Gender              6650 non-null   object 
 3   Income              6650 non-null   object 
 4   Balance             6650 non-null   float64
 5   Vintage             6650 non-null   int64  
 6   Transaction_Status  6650 non-null   int64  
 7   Product_Holdings    6650 non-null   object 
 8   Credit_Card         6650 non-null   int64  
 9   Credit_Category     6650 non-null   object 
 10  Is_Churn            6650 non-null   int64  
dtypes: float64(1), int64(5), object(5)
memory usage: 571.6+ KB
```

Solution approach

1. There are continuous variable as well as categorical variables.
2. categorical variables need to be chnaged into numerical discrete values.
3. Continuous variables need to be checked for their distribution type.
4. All the variables need to be standardized to make them fall in same range
5. Then the classification algorithms is used

In [6]:

```
train.describe()
```

Out[6]:

	Age	Balance	Vintage	Transaction_Status	Credit_Card	Is_Churn
count	6650.000000	6.650000e+03	6650.000000	6650.000000	6650.000000	6650.000000
mean	41.130226	8.045954e+05	2.250226	0.515789	0.664361	0.231128
std	9.685747	5.157549e+05	1.458795	0.499788	0.472249	0.421586
min	21.000000	6.300000e+01	0.000000	0.000000	0.000000	0.000000
25%	34.000000	3.922642e+05	1.000000	0.000000	0.000000	0.000000
50%	40.000000	7.649386e+05	2.000000	1.000000	1.000000	0.000000
75%	47.000000	1.147124e+06	3.000000	1.000000	1.000000	0.000000
max	72.000000	2.436616e+06	5.000000	1.000000	1.000000	1.000000

In [7]:

```
## Cheaking wheather any duplicate record present or not
train['ID'].duplicated().sum()
```

Out[7]:

```
0
```

In [8]:

```
train['Gender'].value_counts()
```

Out[8]:
```
Gender
Male      3612
Female    3038
Name: count, dtype: int64
```

In [9]:
```
train['Income'].value_counts()
```

Out[9]:
```
Income
10L - 15L        1885
5L - 10L         1847
Less than 5L     1573
More than 15L    1345
Name: count, dtype: int64
```

In [10]:
```
train['Vintage'].value_counts()
```

Out[10]:
```
Vintage
3    1405
1    1354
2    1328
4    1296
0     956
5     311
Name: count, dtype: int64
```

In [11]:
```
train['Transaction_Status'].value_counts()
```

Out[11]:
```
Transaction_Status
1    3430
0    3220
Name: count, dtype: int64
```

In [12]:
```
train['Product_Holdings'].value_counts()
```

Out[12]:
```
Product_Holdings
1     3200
2     3182
3+     268
Name: count, dtype: int64
```

In [13]:
```
train['Credit_Card'].value_counts()
```

Out[13]:
```
Credit_Card
1    4418
0    2232
Name: count, dtype: int64
```

In [14]:
```
train['Credit_Category'].value_counts()
```

Out[14]:
```
Credit_Category
Poor       3076
Average    2043
Good       1531
Name: count, dtype: int64
```

In [15]:
```
train['Is_Churn'].value_counts()
```

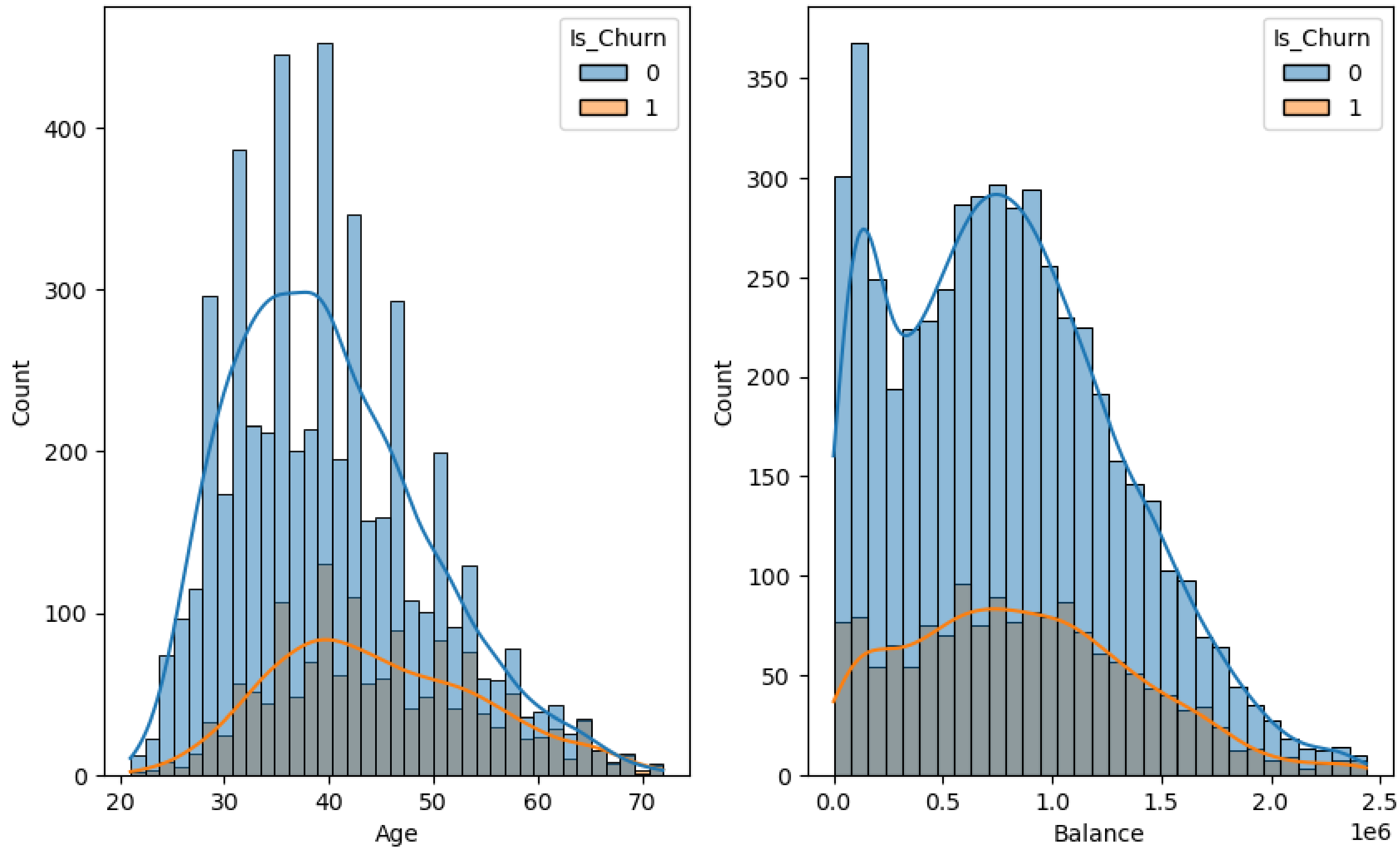
Out[15]:
```
Is_Churn
0    5113
1    1537
Name: count, dtype: int64
```

Clearly the data is imbalanced

Data Visualization

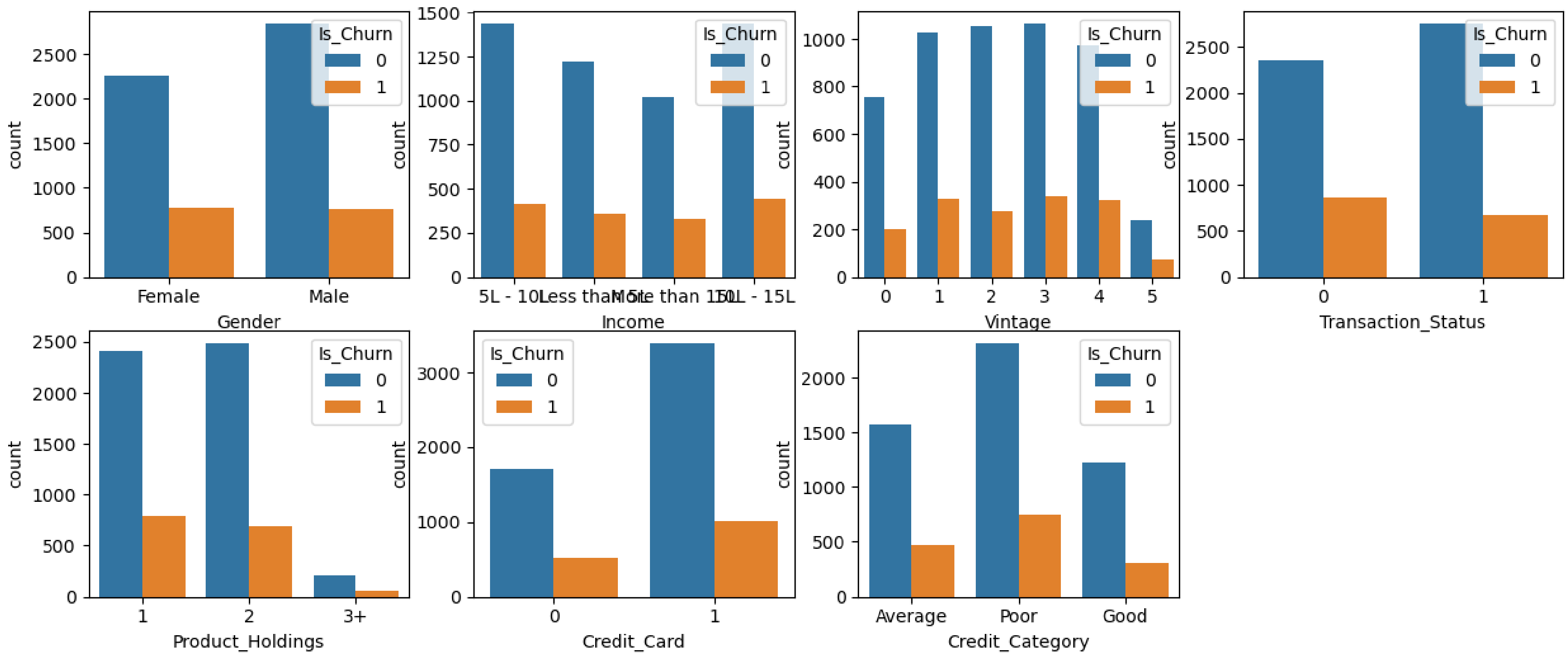
In [16]:
```
# let check the distribution of the continuous variable 'age' and 'Balance'
plt.figure(figsize= (10,6))
plt.subplot(1,2,1)
sns.histplot(data=train, x = 'Age', hue='Is_Churn', kde=True)
plt.subplot(1,2,2)
sns.histplot(data=train, x = 'Balance', hue='Is_Churn', kde=True)
```

Out[16]:
```
<AxesSubplot:xlabel='Balance', ylabel='Count'>
```



observation:Both features follows right or positively skewed distribution

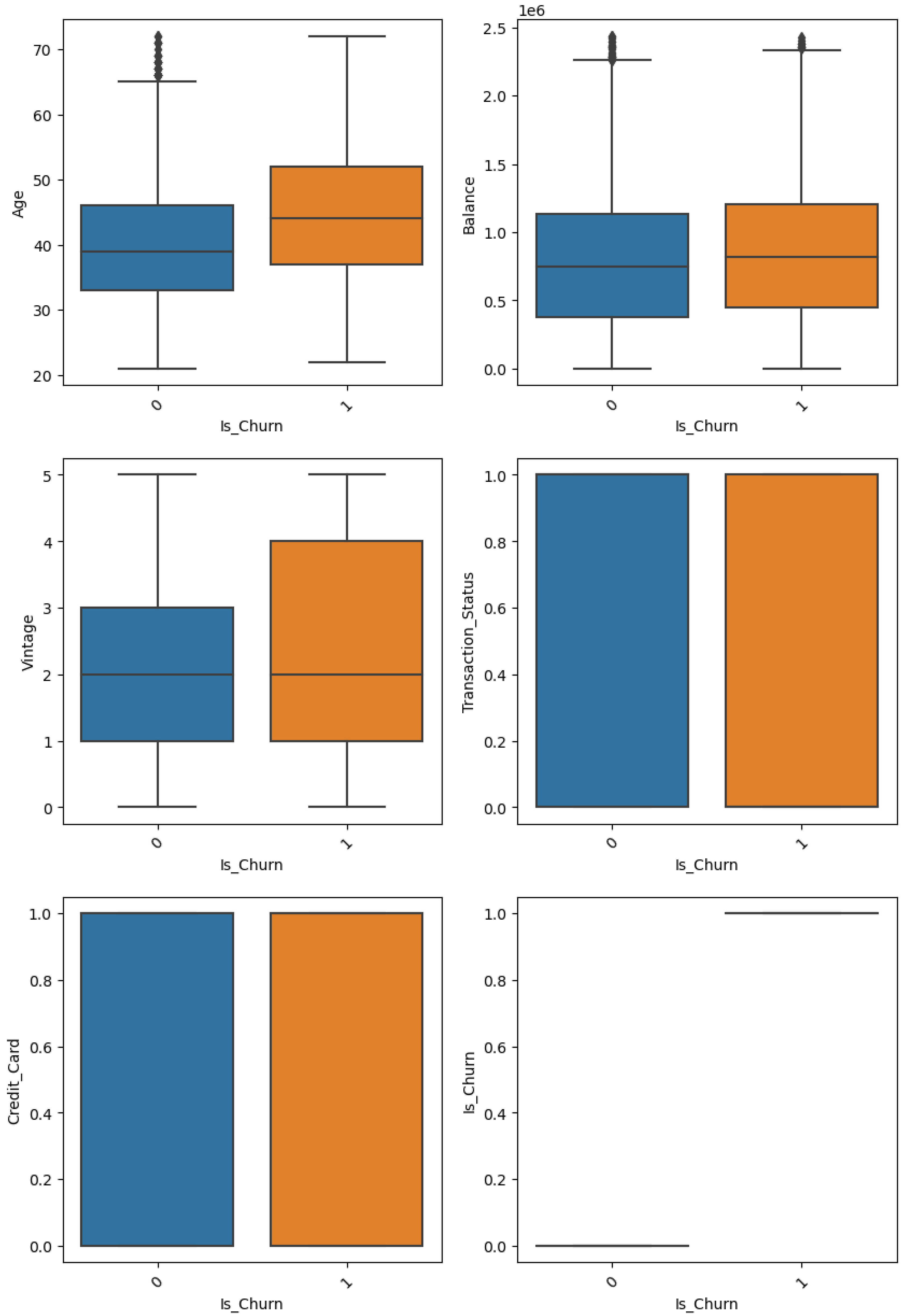
In [17]:
```
# lets check the counts of each categorical variable.
list = ['Gender','Income','Vintage','Transaction_Status','Product_Holdings','Credit_Card','Credit_Category']
plt.figure(figsize=(15,6))
for i,x in enumerate(list):
    plt.subplot(2,4,i+1)
    sns.countplot(data= train, x=train[x], hue='Is_Churn')
```



Observation:

```
1.Greater percentage of females are likely to churn
2.Higher Income customers with earnings greater than 10 Lakhs are more likely to churn
3.Almost equal number of customers have 1 to 2 products holdings. It's rare for a customer to have 3 or more
product holdings. Also, there is no such distinction in churn rate based on number of product holdings.
4.Customers who has not done any transaction in the past 3 months are more likely to churn
5. Customers with credit card are more in number and are more likely to churn
6.Customers with poor credit ratings dominate the dataset and are also more likely to exit
```

In [18]:
```
numerical_features =train.select_dtypes(include=['int64','float64']).columns.tolist()
# Plots between Target Categorical and Numerical Variable
fig = plt.figure(figsize=(10,15))
for index,var in enumerate(numerical_features):
    plt.subplot(3,2,index+1)
    plt.xticks(rotation=45)
    sns.boxplot(x="Is_Churn",y = var, data=train)
    plt.plot()
```

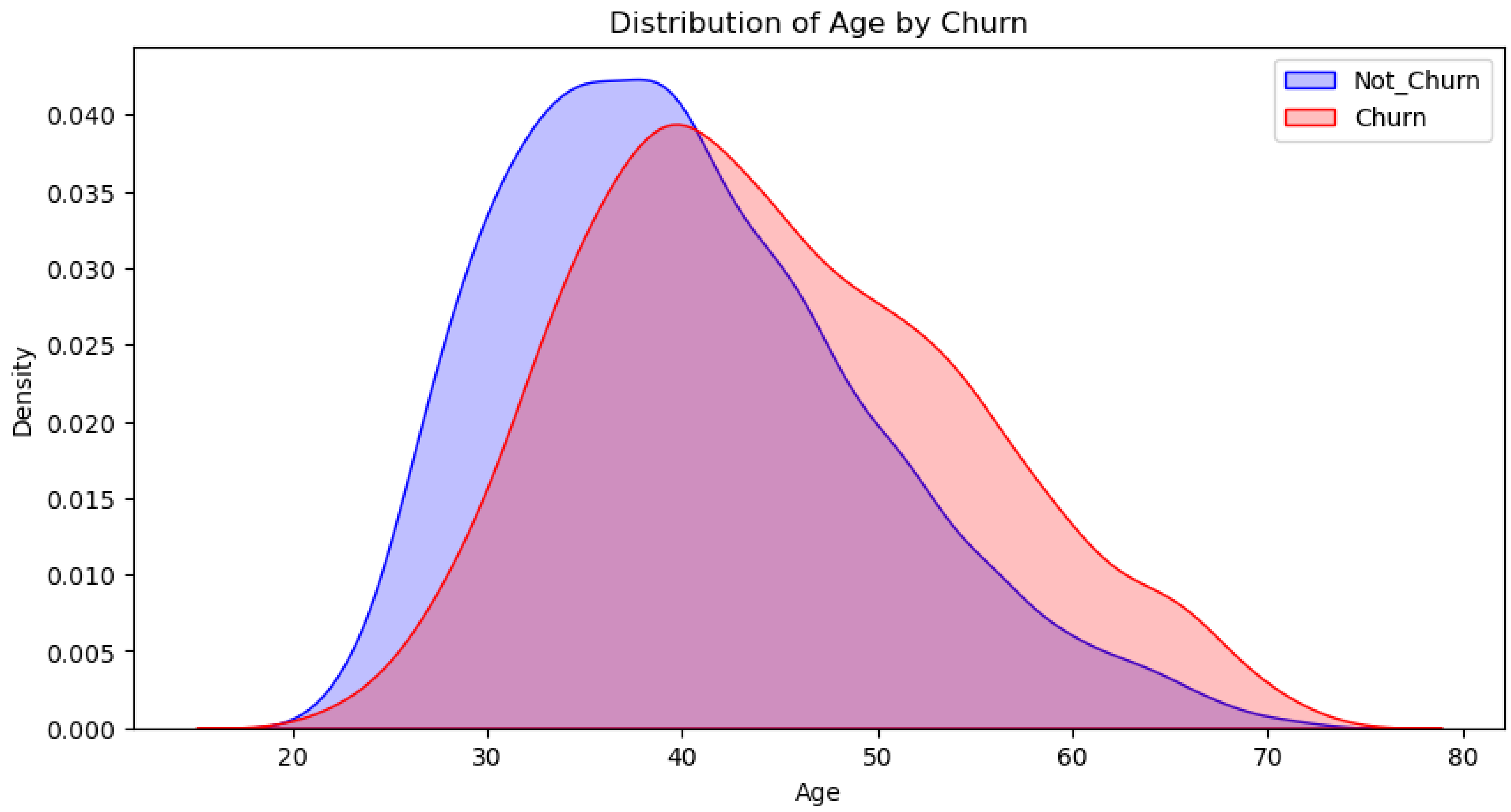


Observation:

```
We see a couple of outliers in the Age feature whereas there are a few in Balance feature
```

In [19]:
```
# Variation of churn rate with age of customers

plt.figure(figsize=(10,5))
ax = sns.kdeplot(train['Age'][(train['Is_Churn'] == 0)], color = 'Blue', fill=True)
ax = sns.kdeplot(train['Age'][(train['Is_Churn'] == 1)], color = 'Red', fill=True)

ax.legend(['Not_Churn', 'Churn'], loc = 'upper right')
ax.set_ylabel("Density")
ax.set_xlabel('Age')
```

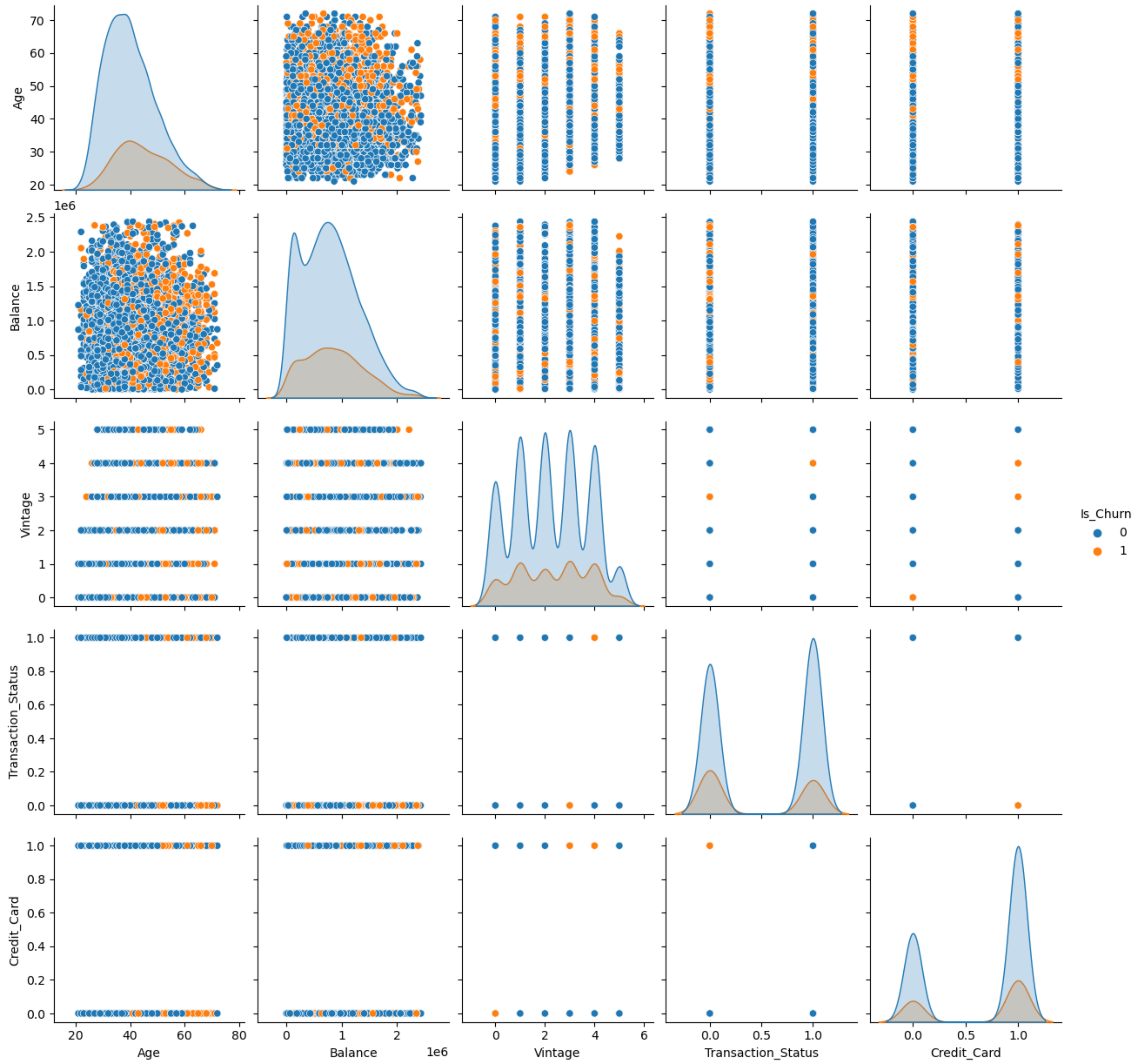
```
ax.set_title('Distribution of Age by Churn')
plt.show()
```



Observation:

```
The above plot shows that elder people are more likely to churn. The blue region (Not_Churned) is centered
around 35 and is slightly right skewed whereas the red region (Churned) is centered around 40 and right
skewed.
```

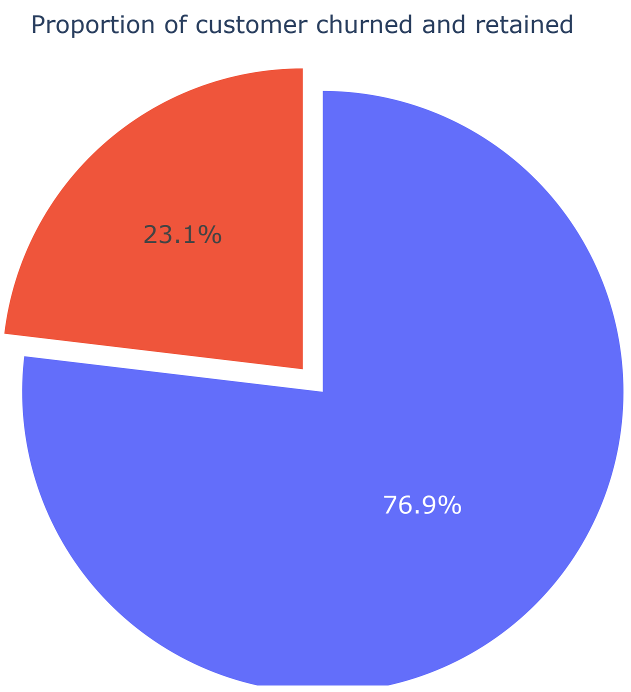
In [20]:
```
#Variation of each feature with respect to other features
sns.pairplot(train, hue='Is_Churn')
plt.show()
```



Observation:

The above pairplot shows that no two feature has linear relation. It also confirms our earlier findings that elderly people are more likely to churn and new customers who have been served for less than 2 years are more likely to churn. Long term customers seem to be happy with the service and are less likely to leave.

In [21]:
```
# Percent of churned vs not-churned customers

labels = ['Churned', 'Retained']
values = [train.Is_Churn[train['Is_Churn']==1].count(), train.Is_Churn[train['Is_Churn']==0].count()]

fig = go.Figure(data=[go.Pie(labels=labels, values=values, pull=[0, 0.1], title='Proportion of customer churned and retained')])
fig.show()
```



Observation:

```
We have imbalance in our target attribute.
```

Data Preprocessing

We have a good understanding of the data from the previous section. Here, we will make some changes to the dataset to make it model ready. We are going to perform the following operations:

1.Handle Missing Values

2.Handle Outliers

3.Encode Categorical Features

4.Feature Scaling

5.Handling Imbalanced Class

1. Missing Values

In [22]:
```
train.isna().sum()
```

Out[22]:
```
ID                    0
Age                   0
Gender                0
Income                0
Balance               0
Vintage               0
Transaction_Status    0
Product_Holdings      0
Credit_Card           0
Credit_Category       0
Is_Churn              0
dtype: int64
```

In [23]:
```
test.isna().sum()
```

Out[23]:
```
ID                    0
Age                   0
Gender                0
Income                0
Balance               0
Vintage               0
Transaction_Status    0
Product_Holdings      0
Credit_Card           0
Credit_Category       0
dtype: int64
```

So both the dataset don't have any missing value

2. Handling Outliers

In the EDA section we identified that Age and Balance features do have a couple of outliers and since, all are beyond the upper limit we will consider the upper range only to detect the outliers in this scenario.

In [24]:
```
def upper_bound(df, feat):
    ''' Calculate IQR and the respective upper and lower bounds '''
    upper= lower = per25 = per75 = iqr = 0
    per25 = np.percentile(df[feat], 25)
    per75 = np.percentile(df[feat], 75)
    iqr = per75 - per25
    #lower = per25 - (1.5*iqr)
    upper = per75 + (1.5*iqr)
    return upper
```

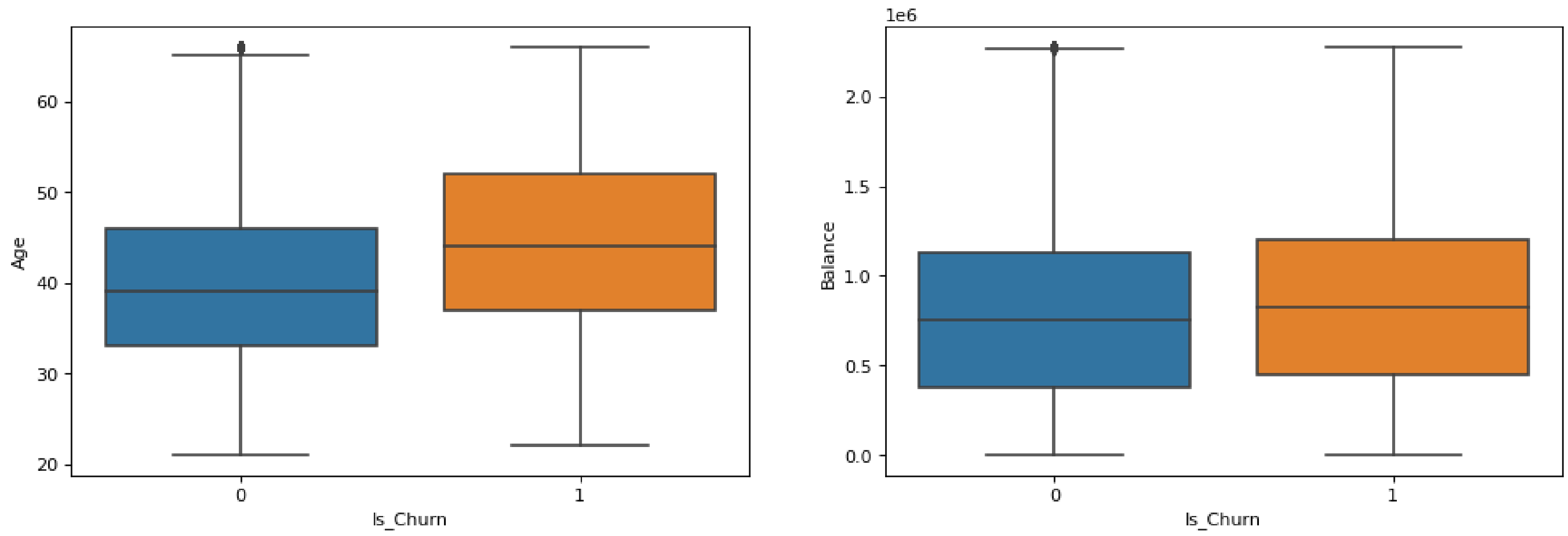
In [25]:
```
# Count of outliers for each feature in train as well as test set

print("Train: In Age", train[train['Age']>upper_bound(train, 'Age')].shape[0], ' In Balance: ', train[train['Balance']>upper_bou
print("Test: In Age", test[test['Age']>upper_bound(test, 'Age')].shape[0], ' In Balance: ', test[test['Balance']>upper_bound(tes
```

```
Train: In Age 57  In Balance:  38
Test: In Age 25  In Balance:  18
```

In [26]:
```
# Replacing the outliers with the upper limit values

train['Age'] = train['Age'].apply(lambda x: round(upper_bound(train, 'Age')) if (x > upper_bound(train, 'Age')) else x)
test['Age'] = test['Age'].apply(lambda x: round(upper_bound(test, 'Age')) if (x > upper_bound(test, 'Age')) else x)

train['Balance'] = train['Balance'].apply(lambda x: round(upper_bound(train, 'Balance')) if (x > upper_bound(train, 'Balance')) e
test['Balance'] = test['Balance'].apply(lambda x: round(upper_bound(test, 'Balance')) if (x > upper_bound(test, 'Balance')) else
```

We see that there are 57 and 25 outliers in Age feature and 38 and 18 in Balance feature in train and test set respectively. Replacing these values with the upper bound value will be advantageous while Binning these features in the later section.

In [27]:
```
# Verifying if any outliers exist:
plt.figure(figsize=(15, 10), dpi=80)

plt.subplot(221)
sns.boxplot(train,x="Is_Churn",y = 'Age')

plt.subplot(222)
sns.boxplot(train,x="Is_Churn",y = 'Balance')
plt.show()
```



3. Encoding

```
Model understands only numerical values, so we have to assign numerical values to each categorical values.
```

In [28]:
```
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
var = ['Product_Holdings','Income','Gender','Credit_Category']
for i in var:
    train[i] = le.fit_transform(train[i])
    test[i] = le.transform(test[i])
```

In [29]:
```
train.head()
```

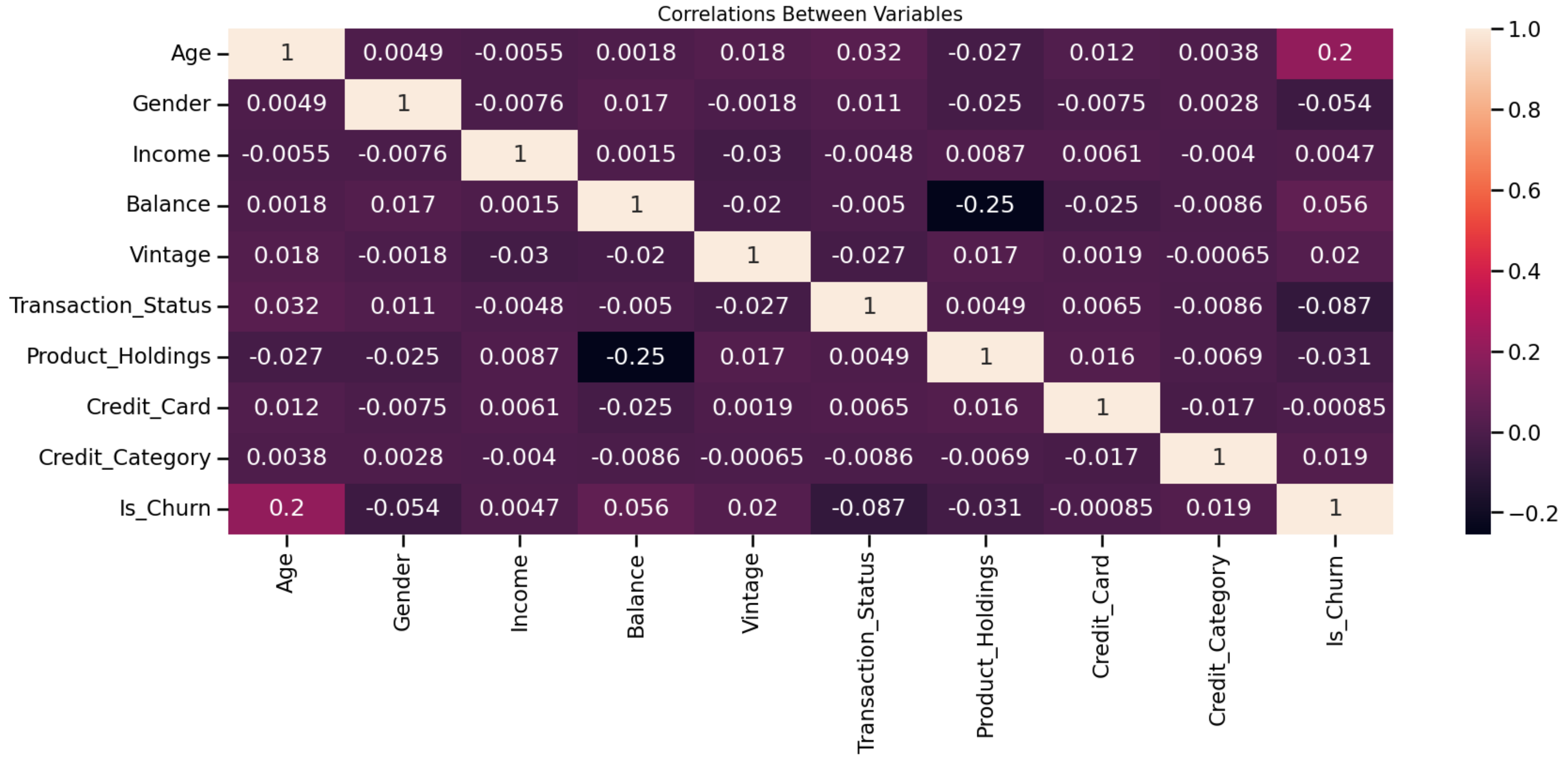
Out[29]:

	ID	Age	Gender	Income	Balance	Vintage	Transaction_Status	Product_Holdings	Credit_Card	Credit_Category	Is_Churn
0	84e2fcc9	36	0	1	563266.44	4	0	0	0	0	1
1	57fea15e	53	0	2	875572.11	2	1	0	1	2	0
2	8df34ef3	35	0	3	701607.06	2	1	1	0	2	0
3	c5c0788b	43	0	3	1393922.16	0	1	1	1	2	1
4	951d69c4	39	0	3	893146.23	1	1	0	1	1	1

In [30]:
```
train.dtypes
```

Out[30]:
```
ID                    object
Age                    int64
Gender                 int32
Income                 int32
Balance              float64
Vintage                int64
Transaction_Status     int64
Product_Holdings       int32
Credit_Card            int64
Credit_Category        int32
Is_Churn               int64
dtype: object
```

In [109…
```
## visulation for correlation beetween variables
plt.figure(figsize=(20,7))
sns.heatmap(train.drop('ID',axis=1).corr(),annot=True)
plt.title("Correlations Between Variables",size=15)
plt.show()
```



Observation:

whether a customer leaves or not is strongly Correlated with Customer's Age followed by his transaction status and account balance

4.Scaling

Scaling is an important part of Feature Engineering. The idea behind scaling is to bring down all the values in a feature within a certain range. Here, we have used StandardScaler on Age, Balance, Vintage features to bring down the mean to 0 and the varience to 1 of these features.

In [31]:
```
from sklearn.preprocessing import StandardScaler
sc=StandardScaler()
```

In [32]:
```
num_features = ['Age', 'Balance','Vintage']
train[num_features] = sc.fit_transform(train[num_features])
test[num_features] = sc.fit_transform(test[num_features])
```

In [33]:
```
train.head()
```

Out[33]:

	ID	Age	Gender	Income	Balance	Vintage	Transaction_Status	Product_Holdings	Credit_Card	Credit_Category	Is_Churn
0	84e2fcc9	-0.530860	0	1	-0.468255	1.199556	0	0	0	0	1
1	57fea15e	1.236432	0	2	0.138740	-0.171542	1	0	1	2	0
2	8df34ef3	-0.634818	0	3	-0.199377	-0.171542	1	1	0	2	0
3	c5c0788b	0.196849	0	3	1.146201	-1.542639	1	1	1	2	1
4	951d69c4	-0.218985	0	3	0.172897	-0.857091	1	0	1	1	1

5.Handling Imbalanced Class

Since our target attribute is highly imbalanced, we will use RandomOverSampling technique to balance the imbalance.

In [34]:
```
# Define Target Variable (y) and Input Variables (X)
X=train.drop(['Is_Churn','ID'], axis=1)
y=train['Is_Churn']
```

In [35]:
```
X.shape,y.shape
```

Out[35]:
```
((6650, 9), (6650,))
```

In [36]:
```
from imblearn.over_sampling import RandomOverSampler
ros=RandomOverSampler(random_state=2529)
```

In [37]:
```
X_ros,y_ros=ros.fit_resample(X,y)
```

In [38]:
```
X_ros.shape,y_ros.shape,X.shape,y.shape
```

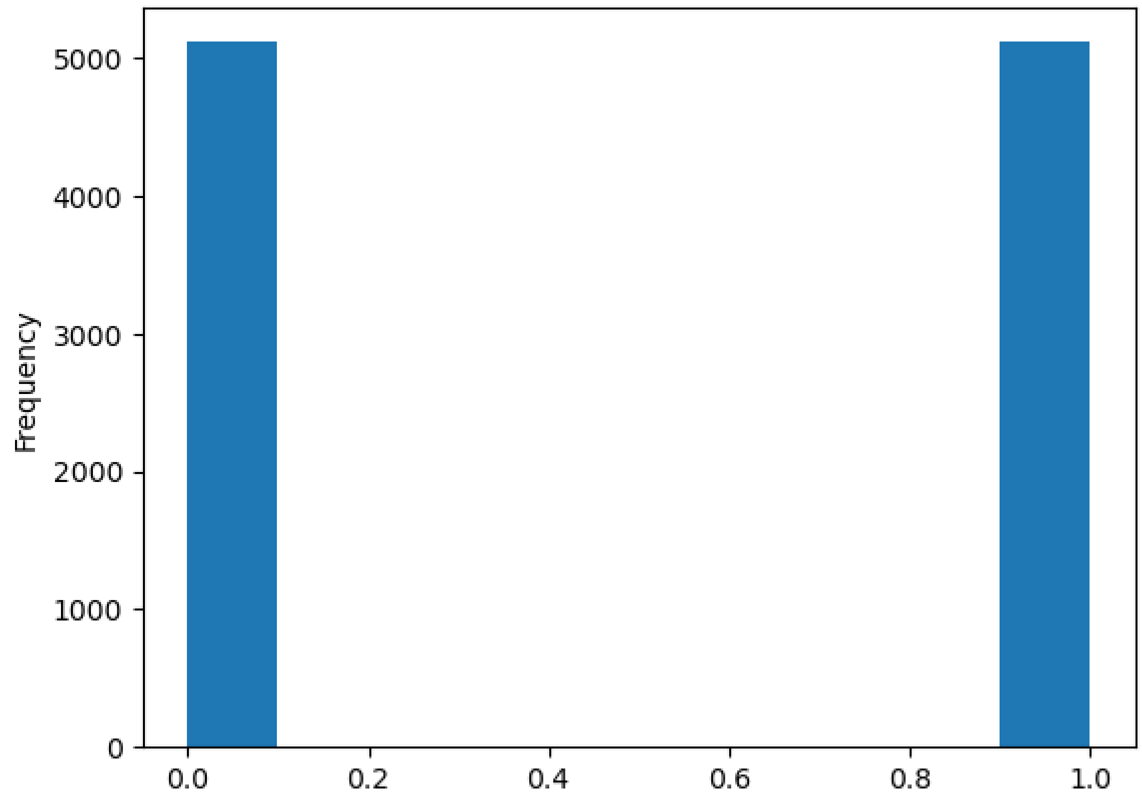
Out[38]:
```
((10226, 9), (10226,), (6650, 9), (6650,))
```

In [39]:
```
y_ros.value_counts()
```

Out[39]:
```
Is_Churn
1    5113
0    5113
Name: count, dtype: int64
```

In [40]:
```
y_ros.plot(kind='hist')
```

Out[40]:
```
<AxesSubplot:ylabel='Frequency'>
```



Train_Test_Split

In [41]:
```
from sklearn.model_selection import train_test_split
```

In [42]:
```
# Split random over sample data
X_ros_train,X_ros_test,y_ros_train,y_ros_test=train_test_split(X_ros,y_ros,test_size=0.3,random_state=2529)
```

Model Building and Evaluation

In [43]:
```
def pipeline(learner_list,train_x,train_y,test_x,test_y):
    '''
    inputs:
       - learner: the learning algorithm to be trained and predicted on
       - X_train: features training set
       - y_train: outcome training set
       - X_test: features testing set
       - y_test: outcome testing set
    '''

    # Get length of Training Data:
    size = len(train_y)

    results = {}
    final_results = []

    for learner in learner_list:

        # Store the learner name:
        results['Algorithm'] = learner.__class__.__name__

        # Fit the learner:
        start = time() # Get start time
        print("Training {}".format(learner.__class__.__name__))
        learner = learner.fit(train_x,train_y)
        end = time() # Get end time

        # Store the training time
```

```
        results['Training Time'] = end - start

        start = time() # Get start time
        predictions_test = learner.predict(test_x)
        predictions_train = learner.predict(train_x)
        end = time() # Get end time

        # Store the prediction time
        results['Prediction Time'] = end - start

        # Compute the Accuracy on Test Set
        results['Accuracy: Test'] = accuracy_score(test_y, predictions_test)

        # Compute the Accuracy on Training Set
        results['Accuracy: Train'] = accuracy_score(train_y, predictions_train)

        # Success
        print("Training {} finished in {:.2f} sec".format(learner.__class__.__name__, results['Training Time']))
        print('----------------------------------------------------')

        final_results.append(results.copy())
    # Return a dataframe of the results
    return final_results
```

In [44]:
```
models = [ XGBClassifier(),
           RandomForestClassifier(),
          SVC(max_iter=10000), AdaBoostClassifier(),
         LogisticRegression(), SGDClassifier()]
```

In [45]:
```
from time import time
re = pipeline(models, X_ros_train, y_ros_train, X_ros_test,y_ros_test)
result = pd.DataFrame(re)
result = result.reindex(columns = ['Algorithm', 'Accuracy: Test', 'Prediction Time','Accuracy: Train', 'Training Time'])
```

```
Training XGBClassifier
Training XGBClassifier finished in 0.68 sec
----------------------------------------------------
Training RandomForestClassifier
Training RandomForestClassifier finished in 1.09 sec
----------------------------------------------------
Training SVC
Training SVC finished in 4.26 sec
----------------------------------------------------
Training AdaBoostClassifier
Training AdaBoostClassifier finished in 0.55 sec
----------------------------------------------------
Training LogisticRegression
Training LogisticRegression finished in 0.05 sec
----------------------------------------------------
Training SGDClassifier
Training SGDClassifier finished in 0.05 sec
----------------------------------------------------
```

In [46]:
```
result.sort_values(by = 'Accuracy: Test', inplace = True, ascending = False)
result.reset_index(drop = True)
```

Out[46]:

	Algorithm	Accuracy: Test	Prediction Time	Accuracy: Train	Training Time
0	RandomForestClassifier	0.887549	0.304648	1.000000	1.092632
1	XGBClassifier	0.785202	0.025000	0.930008	0.682189
2	SVC	0.635593	15.450867	0.653674	4.258128
3	AdaBoostClassifier	0.619296	0.177999	0.617770	0.551849
4	LogisticRegression	0.615711	0.006946	0.612182	0.045049
5	SGDClassifier	0.574967	0.010994	0.575580	0.053005

Approach:

```
1.Based on descending order of test accuracy we are choosing top 3 models.
2.Performing paramerer tuning using GridSearchCV we are going to find most suitable paramerer combination.
3.Then we will compare these 3 models performance based on classification report and AUC Score.
```

In [ ]:

In [47]:
```
# We are going to create a function to print classification report and confusion matrix for each model
def model_score(model):
    y_pred = model.predict(X_ros_test)
    print(classification_report(y_ros_test, y_pred,digits=4))
    cm = confusion_matrix(y_ros_test, y_pred)
    sns.set_context('talk')
    sns.heatmap(cm, annot=True, fmt='d')
    plt.show()
```

In [48]:
```
# Available parameter keys of RandomForest
RandomForestClassifier().get_params().keys()
```

Out[48]:
```
dict_keys(['bootstrap', 'ccp_alpha', 'class_weight', 'criterion', 'max_depth', 'max_features', 'max_leaf_nodes', 'max_samples', 'min_impurity_decrease', 'min_samples_leaf', 'min_samples_split', 'min_weight_fraction_leaf', 'n_estimators', 'n_jobs', 'oob_score', 'random_state', 'verbose', 'warm_start'])
```

In [49]:
```
from sklearn.model_selection import GridSearchCV
# RandomForestClassifier parameter tuning
param_grid = {
    'bootstrap': [True],
    'max_depth': [13,20,30],
    'max_features': [3,5,8],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [5,8],
    'n_estimators': [200,300, 400,500]
}
#Create a based model
rf = RandomForestClassifier()
#Instantiate the grid search model
gs1 = GridSearchCV(estimator = rf, param_grid = param_grid,
                          cv = 2, n_jobs = -1, verbose = 2, error_score='raise')
```

In [50]:
```
# Fit the grid search to the data
gs1.fit(X_ros_train,y_ros_train)
```

```
Fitting 2 folds for each of 216 candidates, totalling 432 fits
```

Out[50]:
```
GridSearchCV(cv=2, error_score='raise', estimator=RandomForestClassifier(),
             n_jobs=-1,
             param_grid={'bootstrap': [True], 'max_depth': [13, 20, 30],
                         'max_features': [3, 5, 8],
                         'min_samples_leaf': [3, 4, 5],
                         'min_samples_split': [5, 8],
                         'n_estimators': [200, 300, 400, 500]},
             verbose=2)
```

In [51]:
```
print(gs1.best_estimator_)
```

```
RandomForestClassifier(max_depth=20, max_features=8, min_samples_leaf=3,
                       min_samples_split=5, n_estimators=500)
```

In [52]:
```
print('Best score:', gs1.best_score_)
```

```
Best score: 0.7341436155350657
```

In [53]:
```
rf=RandomForestClassifier(max_depth=20, max_features=5, min_samples_leaf=3,
                       min_samples_split=5, n_estimators=500)
```

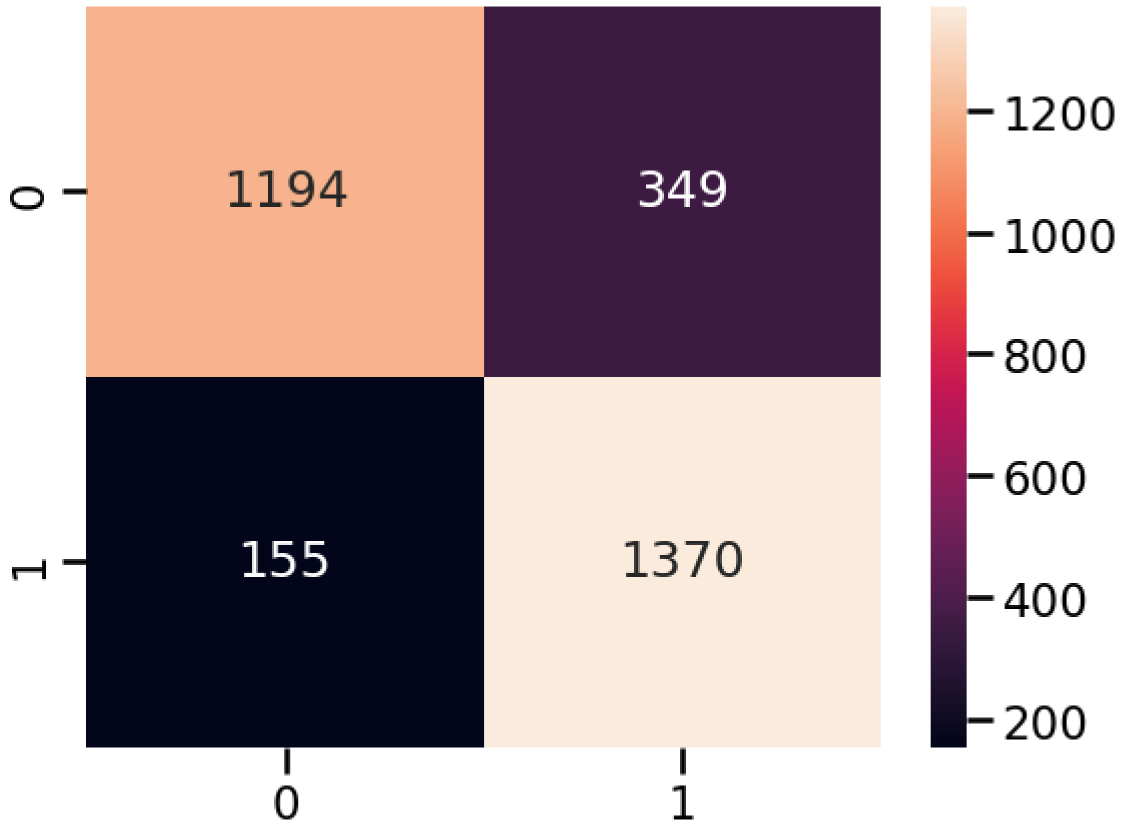
In [54]:
```
rf.fit(X_ros_train,y_ros_train)
```

Out[54]:
```
RandomForestClassifier(max_depth=20, max_features=5, min_samples_leaf=3,
                       min_samples_split=5, n_estimators=500)
```

In [55]:
```
rf_pred=rf.predict(X_ros_test)
```

In [56]:
```
# classification report and confution matrix for RandomForestClassifier model
model_score(rf)
```

```
              precision    recall  f1-score   support

           0     0.8851    0.7738    0.8257      1543
           1     0.7970    0.8984    0.8446      1525

    accuracy                         0.8357      3068
   macro avg     0.8410    0.8361    0.8352      3068
weighted avg     0.8413    0.8357    0.8351      3068
```



In [ ]:

In [ ]:

In [57]:
```
# Available parameter keys of XGBClassifier
XGBClassifier().get_params().keys()
```

Out[57]:
```
dict_keys(['objective', 'use_label_encoder', 'base_score', 'booster', 'callbacks', 'colsample_bylevel', 'colsample_bynode', 'col
sample_bytree', 'early_stopping_rounds', 'enable_categorical', 'eval_metric', 'feature_types', 'gamma', 'gpu_id', 'grow_policy',
'importance_type', 'interaction_constraints', 'learning_rate', 'max_bin', 'max_cat_threshold', 'max_cat_to_onehot', 'max_delta_s
tep', 'max_depth', 'max_leaves', 'min_child_weight', 'missing', 'monotone_constraints', 'n_estimators', 'n_jobs', 'num_parallel_
tree', 'predictor', 'random_state', 'reg_alpha', 'reg_lambda', 'sampling_method', 'scale_pos_weight', 'subsample', 'tree_metho
d', 'validate_parameters', 'verbosity'])
```

In [58]:
```
# XGBClassifier parameter tuning
# n_jobs=-1 to allow run it on all cores
params = {
    'n_estimators': [100, 200, 500],
    'learning_rate': [0.01,0.05,0.1],
    'booster': ['gbtree', 'gblinear'],
    'gamma': [0, 0.5, 1],
    'reg_alpha': [0, 0.5, 1],
    'reg_lambda': [0.5, 1, 5],
    'base_score': [0.2, 0.5, 0.9]
}
#Instantiate the grid search model
gs2 = GridSearchCV(XGBClassifier(n_jobs=-1), params, n_jobs=-1, cv=2, scoring='roc_auc',error_score='raise')
gs2.fit(X_ros_train, y_ros_train)
```

Out[58]:
```
GridSearchCV(cv=2, error_score='raise',
             estimator=XGBClassifier(base_score=None, booster=None,
                                     callbacks=None, colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     early_stopping_rounds=None,
                                     enable_categorical=False, eval_metric=None,
                                     feature_types=None, gamma=None,
                                     gpu_id=None, grow_policy=None,
                                     importance_type=None,
                                     interaction_constraints=None...
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs=-1,
                                     num_parallel_tree=None, predictor=None,
                                     random_state=None, ...),
             n_jobs=-1,
             param_grid={'base_score': [0.2, 0.5, 0.9],
                         'booster': ['gbtree', 'gblinear'],
                         'gamma': [0, 0.5, 1],
                         'learning_rate': [0.01, 0.05, 0.1],
                         'n_estimators': [100, 200, 500],
                         'reg_alpha': [0, 0.5, 1], 'reg_lambda': [0.5, 1, 5]},
             scoring='roc_auc')
```

In [59]:
```
print('Best score:', gs2.best_score_)
```

```
Best score: 0.8107223268348589
```

In [60]:
```
print(gs2.best_params_)
```

```
{'base_score': 0.9, 'booster': 'gbtree', 'gamma': 0, 'learning_rate': 0.1, 'n_estimators': 500, 'reg_alpha': 0, 'reg_lambda': 0.
5}
```

In [61]:
```
xgb=XGBClassifier(base_score= 0.9, booster= 'gbtree', gamma= 0, learning_rate= 0.1, n_estimators= 500, reg_alpha= 0, reg_lambda=
```

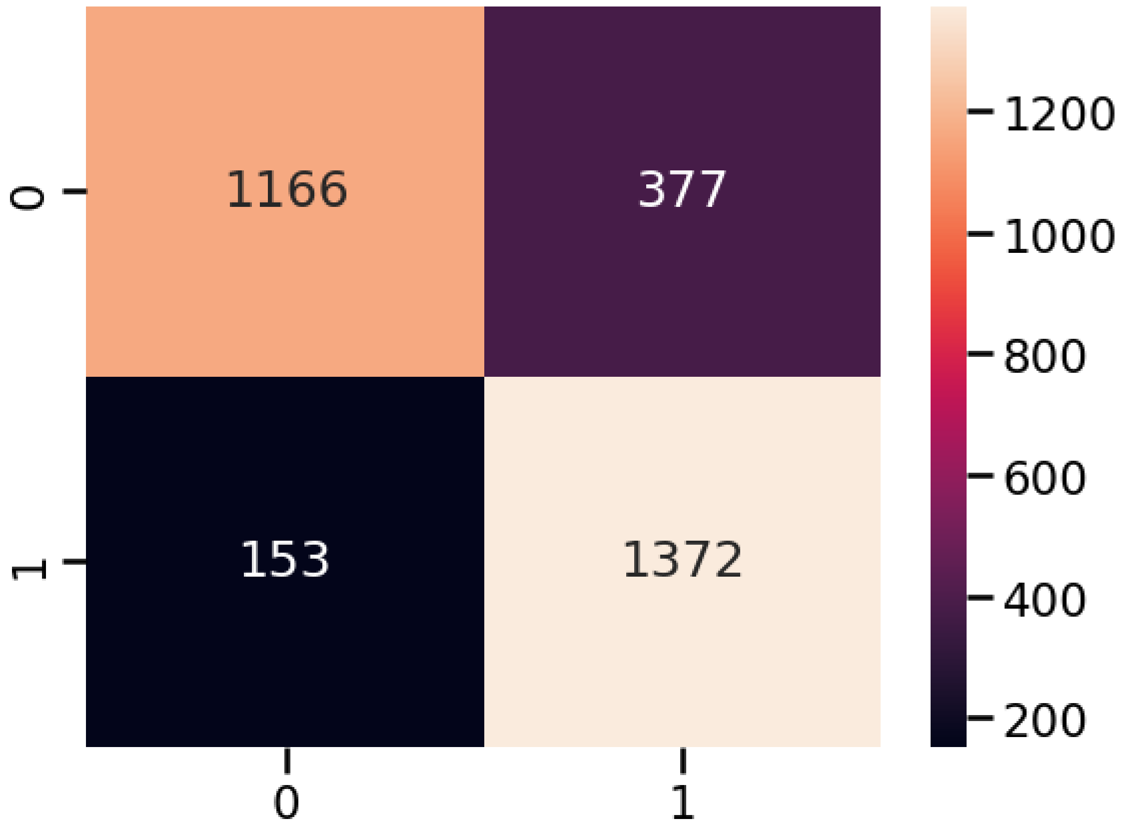
In [62]:
```
xgb.fit(X_ros_train, y_ros_train)
```

Out[62]:
```
XGBClassifier(base_score=0.9, booster='gbtree', callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=0, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=0.1, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=500, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [63]:
```
xgb_pred=xgb.predict(X_ros_test)
```

In [64]:
```
model_score(xgb)
```

```
              precision    recall  f1-score   support

           0     0.8840    0.7557    0.8148      1543
           1     0.7844    0.8997    0.8381      1525

    accuracy                         0.8272      3068
   macro avg     0.8342    0.8277    0.8265      3068
weighted avg     0.8345    0.8272    0.8264      3068
```



In [ ]:

In [ ]:

In [65]:
```
# Available parameter keys of SVM
SVC().get_params().keys()
```

Out[65]:
```
dict_keys(['C', 'break_ties', 'cache_size', 'class_weight', 'coef0', 'decision_function_shape', 'degree', 'gamma', 'kernel', 'ma
x_iter', 'probability', 'random_state', 'shrinking', 'tol', 'verbose'])
```

In [66]:
```
# SVM classifier parameter tuning
param_grid={'C':[0.1,1,10],
           'gamma':[1,0.1,0.01],
           'kernel':['rbf'],
           'class_weight':['balanced']}
gs3=GridSearchCV(SVC(),param_grid,refit=True,verbose=2,cv=2)
gs3.fit(X_ros_train,y_ros_train)
```

```
Fitting 2 folds for each of 9 candidates, totalling 18 fits
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.4s
[CV] END ..C=0.1, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.4s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   2.9s
[CV] END C=0.1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   2.9s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   3.1s
[CV] END C=0.1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   3.1s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.3s
[CV] END ....C=1, class_weight=balanced, gamma=1, kernel=rbf; total time=   3.1s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   2.8s
[CV] END ..C=1, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   3.0s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.9s
[CV] END .C=1, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.9s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   2.6s
[CV] END ...C=10, class_weight=balanced, gamma=1, kernel=rbf; total time=   2.6s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   3.0s
[CV] END .C=10, class_weight=balanced, gamma=0.1, kernel=rbf; total time=   3.1s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.8s
[CV] END C=10, class_weight=balanced, gamma=0.01, kernel=rbf; total time=   2.8s
```

Out[66]:
```
GridSearchCV(cv=2, estimator=SVC(),
             param_grid={'C': [0.1, 1, 10], 'class_weight': ['balanced'],
                         'gamma': [1, 0.1, 0.01], 'kernel': ['rbf']},
             verbose=2)
```

In [67]:
```
print(gs3.best_estimator_)
```

```
SVC(C=10, class_weight='balanced', gamma=1)
```

In [68]:
```
svc=SVC(C=10, class_weight='balanced', gamma=1, probability=True)
```

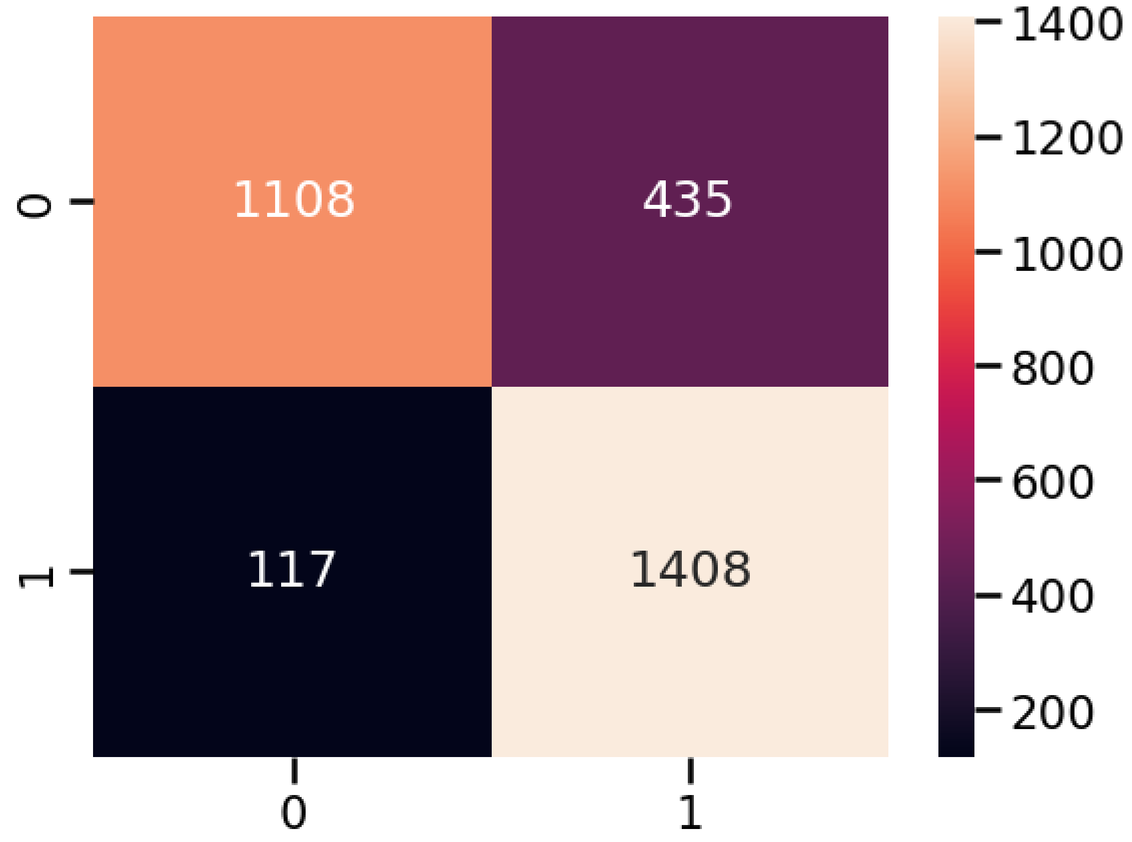
In [69]:
```
svc.fit(X_ros_train,y_ros_train)
```

Out[69]:
```
SVC(C=10, class_weight='balanced', gamma=1, probability=True)
```

In [70]:
```
svc_pred=svc.predict(X_ros_test)
```

In [71]:
```
# classification report and confution matrix for SVM model
model_score(svc)
```

```
              precision    recall  f1-score   support

           0     0.9045    0.7181    0.8006      1543
           1     0.7640    0.9233    0.8361      1525

    accuracy                         0.8201      3068
   macro avg     0.8342    0.8207    0.8183      3068
weighted avg     0.8346    0.8201    0.8182      3068
```



In [ ]:

Model Comparison

In [72]:

```
# calculating the false positive and true positive rate for each of the models
fpr1, tpr1, thresh1 = roc_curve(y_ros_test, rf.predict_proba(X_ros_test)[:, 1], pos_label=1)
fpr2, tpr2, thresh2 = roc_curve(y_ros_test, xgb.predict_proba(X_ros_test)[:, 1], pos_label=1)
fpr3, tpr3, thresh3 = roc_curve(y_ros_test, svc.predict_proba(X_ros_test)[:, 1], pos_label=1)
```

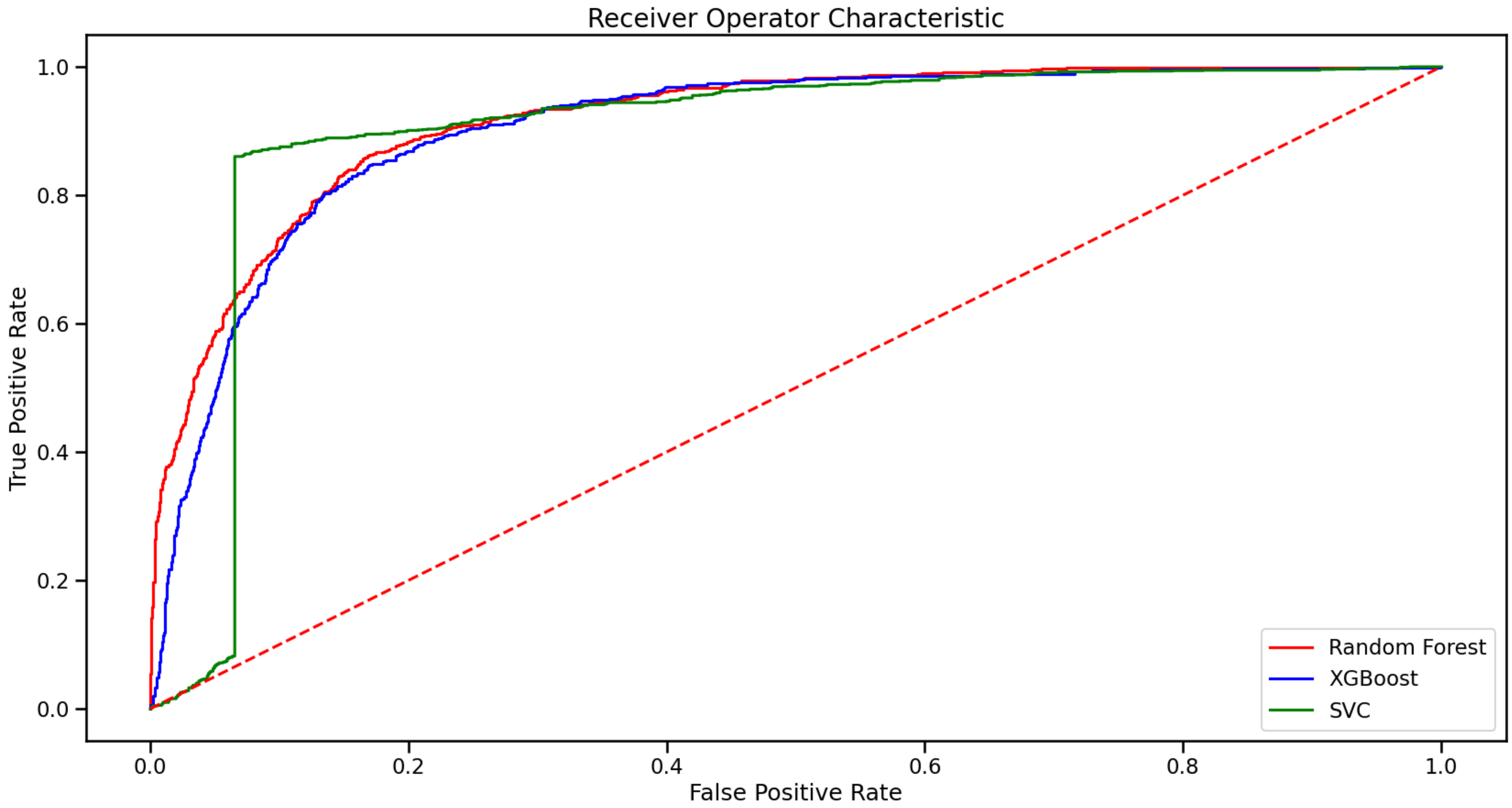
In [73]:

```
# Fething the Area under the curve
auc_score1 = roc_auc_score(y_ros_test, rf.predict_proba(X_ros_test)[:, 1])
auc_score2 = roc_auc_score(y_ros_test, xgb.predict_proba(X_ros_test)[:,1])
auc_score3 = roc_auc_score(y_ros_test, svc.predict_proba(X_ros_test)[:, 1])

print("Random Forest(AUC_Score): ", auc_score1)
print("XGBoost(AUC_Score): ", auc_score2)
print("SVC(AUC_Score):", auc_score3)
```

```
Random Forest(AUC_Score):  0.9170787161480188
XGBoost(AUC_Score):  0.904553828501004
SVC(AUC_Score): 0.8973715244945445
```

In [74]:

```
# Plotting ROC curve
plt.figure(figsize=(20,10))
plt.plot(fpr1, tpr1,  color = 'red', label='Random Forest')
plt.plot(fpr2, tpr2, color = 'blue', label='XGBoost')
plt.plot(fpr3, tpr3, color = 'green', label='SVC')

plt.title('Receiver Operator Characteristic', fontsize=20)
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.plot([0, 1], [0, 1],'r--')
plt.legend(loc = 'best')
plt.show()
```



Model Comparison Results:

```
ROC-AUC curve shows the model performance by plotting the false positive rate to true positive rate
More the skewness of the curve towards the upper left corner higher is the area under the roc curve and
better is the model performance.
From the ROC-AUC curve it is clear that all three model performances are very close.
Random Forest showed a tremendous performance but it is likely to overfit.

Both Random Forest(Bagging) and XGBoost(Boosting) are ensemble techniques and their performances are very
close.
All of the models have achived above 80% accuracy and above 0.80 f1-score and around 0.90 AUC_Score.
```

RandomForestClassifier has got highest score in every aspect. So,we are choosing Randomforest as our final model for prediction purpose

In [ ]:

Prediction

In [75]:
```
test_new=test.drop('ID',axis=1)
```

In [76]:
```
test_new.head()
```

Out[76]:

	Age	Gender	Income	Balance	Vintage	Transaction_Status	Product_Holdings	Credit_Card	Credit_Category
0	0.918856	0	3	0.380308	-0.148337	1	1	1	0
1	-0.547566	1	1	-0.893472	-0.148337	0	1	1	0
2	-1.699756	0	0	-0.706370	-1.490908	0	1	1	1
3	-0.023844	1	2	-1.490824	-1.490908	1	1	1	2
4	0.709367	1	3	0.563408	-0.148337	1	2	0	1

In [77]:
```
test_new.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2851 entries, 0 to 2850
Data columns (total 9 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Age                 2851 non-null   float64
 1   Gender              2851 non-null   int32  
 2   Income              2851 non-null   int32  
 3   Balance             2851 non-null   float64
 4   Vintage             2851 non-null   float64
 5   Transaction_Status  2851 non-null   int64  
 6   Product_Holdings    2851 non-null   int32  
 7   Credit_Card         2851 non-null   int64  
 8   Credit_Category     2851 non-null   int32  
dtypes: float64(3), int32(4), int64(2)
memory usage: 156.0 KB
```

In [79]:
```
# Predicting Target Dataset
prediction=rf.predict(test_new)
```

In [80]:
```
prediction
```
Out[80]:
```
array([0, 1, 0, ..., 1, 1, 1], dtype=int64)
```

In [81]:
```
prediction.shape, test.shape
```
Out[81]:
```
((2851,), (2851, 10))
```

In [95]:
```
ID=test['ID'].values
```

In [97]:
```
ID
```
Out[97]:
```
array(['55480787', '9aededf2', 'a5034a09', ..., 'f708121b', 'f008715d',
       '36b81f59'], dtype=object)
```

In [96]:
```
type(ID)
```
Out[96]:
```
numpy.ndarray
```

In [90]:
```
type(prediction)
```
Out[90]:
```
numpy.ndarray
```

In [100…
```
df=pd.DataFrame({'Customer_ID':ID, 'Is_Churn':prediction})
```

In [101…
```
df
```
Out[101]:

	Customer_ID	Is_Churn
0	55480787	0
1	9aededf2	1
2	a5034a09	0
3	b3256702	0
4	dc28adb5	0
...	...	...
2846	19e40adf	1
2847	52d5bc8d	0
2848	f708121b	1
2849	f008715d	1
2850	36b81f59	1

2851 rows × 2 columns

This is our final predicted classification along with customer_ID

In [102…
```
# Saving Target classification dataframe as csv file
df.to_csv('Target_classification.csv')
```

In [ ]:
```

```

Explaination

In this classification problem, a lot of information about the consumers was provided, and the dataset was pretty clean with no missing values and no duplicate values.

With only two classes in the objective feature (0: not churned, 1: churned), it was a binary classification challenge. The classes were imbalanced and the models were predicting all 0s in the target feature. We had employed the over-sampling technique to address this.

we found repeated categorical values in some of the columns, We used LabelEncoder() to assign numerical values for categorical values.Later on, the Age, Balance and Vintage columns were scaled using standardscalar by projecting mean to zero and varience to one.

We created a pipeline to compare testing accauracy of six different models, then we choose top 3 of them, tuned parameters of them compared Classification report and AUC_Score, choosed most suitable model, RandomForestClassifier().

Some key lessons that the Bank can focus to bring down the churn rate--------

1.Greater percentage of females are likely to churn

2.Customers who has not done any transaction in the past 3 months are more likely to churn

3.Customers with credit card are more in number and are more likely to churn

4.Customers with poor credit ratings dominate the dataset and are also more likely to exit

5.High-income customers are difficult to keep as they are more prone to churn

Scope for Improvement

To improve the model performance and to get higher accuracy the below things can be done:

1.A model's performance increases with increase in data (clean and relevant). If we can increase our training data we can achieve higher accuracy.

2.Experimenting with under-sampling to see whether there is any change in model performance

3.Trying other ensemble techniques like StackingCVClassifier and CatBoost might also help

4.Trying Deep Learning approach, training Artificial Neural Network