# cc_lead_prediction

February 11, 2022

Credit Card Lead Prediction

## 0.1 Problem Statement

**Description:** Happy Customer Bank is a mid-sized private bank that deals in all kinds of banking products, like Savings accounts, Current accounts, investment products, credit products, among other offerings.

The bank also cross-sells products to its existing customers and to do so they use different kinds of communication like tele-calling, e-mails, recommendations on net banking, mobile banking, etc.

In this case, the Happy Customer Bank wants to cross sell its credit cards to its existing customers. The bank has identified a set of customers that are eligible for taking these credit cards.

Now, the bank is looking for your help in identifying customers that could show higher intent towards a recommended credit card, given:

- Customer details (gender, age, region etc.)
- Details of his/her relationship with the bank (Channel_Code,Vintage, 'Avg_Asset_Value etc.)

### 0.1.1 Data Dictionary

### 0.1.2 Public and Private Split

Test data is further divided into Public 30% and Private 70%

### 0.1.3 Evaluation

The evaluation metric for this competition is **roc_auc_score** across all entries in the test set.

[2]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from tqdm import tqdm
from sklearn.linear_model import LogisticRegression,SGDClassifier
from sklearn.svm import LinearSVC
from sklearn.ensemble import StackingClassifier,RandomForestClassifier
from xgboost.sklearn import XGBClassifier
from sklearn.model_selection import train_test_split
```

```
from sklearn.preprocessing import OneHotEncoder,StandardScaler,Normalizer
from sklearn.calibration import CalibratedClassifierCV
from sklearn.model_selection import GridSearchCV
from sklearn.naive_bayes import MultinomialNB
from sklearn.metrics import roc_auc_score,confusion_matrix
from sklearn.ensemble import StackingClassifier
from imblearn.over_sampling import SMOTE,RandomOverSampler
from sklearn.svm import SVC
import tensorflow as tf
from scipy.sparse import hstack
warnings.filterwarnings(action="ignore")
```

[3]:
```
#loading training datasets
train_df=pd.read_csv("data/train_s3TEQDk.csv")
train_df.head()
```

[3]:
```
        ID  Gender  Age Region_Code     Occupation Channel_Code  Vintage  \
0  NNVBBKZB  Female   73       RG268          Other           X3       43
1  IDD62UNG  Female   30       RG277       Salaried           X1       32
2  HD3DSEMC  Female   56       RG268  Self_Employed           X3       26
3  BF3NC7KV    Male   34       RG270       Salaried           X1       19
4  TEASRWXV  Female   30       RG282       Salaried           X1       33

  Credit_Product  Avg_Account_Balance Is_Active  Is_Lead
0             No              1045696        No        0
1             No               581988        No        0
2             No              1484315       Yes        0
3             No               470454        No        0
4             No               886787        No        0
```

[4]:
```
print("List of columns::",train_df.columns.values)
```

```
List of columns:: ['ID' 'Gender' 'Age' 'Region_Code' 'Occupation' 'Channel_Code'
'Vintage'
 'Credit_Product' 'Avg_Account_Balance' 'Is_Active' 'Is_Lead']
```

[5]:
```
duplicated_rows=sum(train_df.duplicated(subset=['Gender', 'Age', 'Region_Code',␣
↪'Occupation', 'Channel_Code',
       'Vintage', 'Credit_Product', 'Avg_Account_Balance',␣
↪'Is_Active','Is_Lead']))
print("Number of duplicate rows based on sub groups of columns::␣
↪",duplicated_rows)
```

```
Number of duplicate rows based on sub groups of columns::  21
```

[6]:
```
# Deleting duplicates rows
train_df.drop_duplicates(subset=['Gender', 'Age', 'Region_Code', 'Occupation',␣
↪'Channel_Code',
```

```
    'Vintage', 'Credit_Product', 'Avg_Account_Balance',␣
↪'Is_Active','Is_Lead'],keep="first",inplace=True)
```

[7]:
```
#  training data infomation
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 245704 entries, 0 to 245724
Data columns (total 11 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   ID                   245704 non-null  object
 1   Gender               245704 non-null  object
 2   Age                  245704 non-null  int64
 3   Region_Code          245704 non-null  object
 4   Occupation           245704 non-null  object
 5   Channel_Code         245704 non-null  object
 6   Vintage              245704 non-null  int64
 7   Credit_Product       216379 non-null  object
 8   Avg_Account_Balance  245704 non-null  int64
 9   Is_Active            245704 non-null  object
 10  Is_Lead              245704 non-null  int64
dtypes: int64(4), object(7)
memory usage: 22.5+ MB
```

[8]:
```
# Ques: How much data points are missing in every feature(percentage)
train_df.isna().sum()/train_df.shape[0]
```

[8]:
```
ID                     0.000000
Gender                 0.000000
Age                    0.000000
Region_Code            0.000000
Occupation             0.000000
Channel_Code           0.000000
Vintage                0.000000
Credit_Product         0.119351
Avg_Account_Balance    0.000000
Is_Active              0.000000
Is_Lead                0.000000
dtype: float64
```

**Observation** * Number of data points in train datasets: 245725 * Only credit_product column has missing data points. * Around 12% of data points are missing in Credit Product feature

**Ques:** How can we fill this missing this value

There are many way to fill Missing value. * most common category * Predict with trained model * With Domain knowledge * Assume NaN as another category

[9]:
```
#trying to find pattern how can we fill NaN values
train_df[train_df["Credit_Product"].isna()].head()
```

[9]:
```
          ID  Gender  Age Region_Code     Occupation Channel_Code  Vintage  \
6   ETQCZFEJ    Male   62       RG282          Other           X3       20
15  UJ2NJKKL    Male   33       RG268  Self_Employed           X2       69
31  ABPMK4WU  Female   32       RG279       Salaried           X4       15
36  MTEIXMB9  Female   41       RG268  Self_Employed           X3       62
40  6WX9JDVK  Female   63       RG254          Other           X3      103

   Credit_Product  Avg_Account_Balance Is_Active  Is_Lead
6             NaN              1056750       Yes        1
15            NaN               517063       Yes        1
31            NaN              1072850       Yes        1
36            NaN               962383        No        1
40            NaN              1249319       Yes        1
```

[10]:
```
train_df[train_df['Credit_Product']=="Yes"].head()
```

[10]:
```
          ID  Gender  Age Region_Code     Occupation Channel_Code  Vintage  \
9   NVKTFBA2  Female   55       RG268  Self_Employed           X2       49
11  GZ5TMYIR    Male   27       RG270  Self_Employed           X1       14
13  KCE7JSFN    Male   31       RG254       Salaried           X1       31
16  CNGSPYWS  Female   46       RG268          Other           X3       97
17  VH7NBNNQ  Female   59       RG283          Other           X3       15

   Credit_Product  Avg_Account_Balance Is_Active  Is_Lead
9             Yes              2014239        No        0
11            Yes               502787        No        0
13            Yes               938754        No        0
16            Yes              2282502        No        1
17            Yes              2384692        No        1
```

[11]:
```
train_df[train_df['Credit_Product']=="No"].head()
```

[11]:
```
         ID  Gender  Age Region_Code     Occupation Channel_Code  Vintage  \
0  NNVBBKZB  Female   73       RG268          Other           X3       43
1  IDD62UNG  Female   30       RG277       Salaried           X1       32
2  HD3DSEMC  Female   56       RG268  Self_Employed           X3       26
3  BF3NC7KV    Male   34       RG270       Salaried           X1       19
4  TEASRWXV  Female   30       RG282       Salaried           X1       33

  Credit_Product  Avg_Account_Balance Is_Active  Is_Lead
0             No              1045696        No        0
1             No               581988        No        0
2             No              1484315       Yes        0
3             No               470454        No        0
```

```
4              No                 886787        No          0
```

[12]:
```
#Let see value count
train_df['Credit_Product'].value_counts(normalize=True)
```

[12]:
```
No      0.667075
Yes     0.332925
Name: Credit_Product, dtype: float64
```

**Observation:**

- Above we can see that around 66% of data points have "No" as value so we can fill missing value with "No"
- or we can use some model which will train with other feature as independent variable and credit product as dependent variable
- or we can consider "NaN" as category if above idea doesn't work well for training Models

## 0.2 Exploratory Data Analysis [EDA]

### 0.2.1 Balanced or Imbalanced Dataset

[13]:
```
train_df.Is_Lead.value_counts(normalize=True)
```

[13]:
```
0    0.762771
1    0.237229
Name: Is_Lead, dtype: float64
```

**Observation**

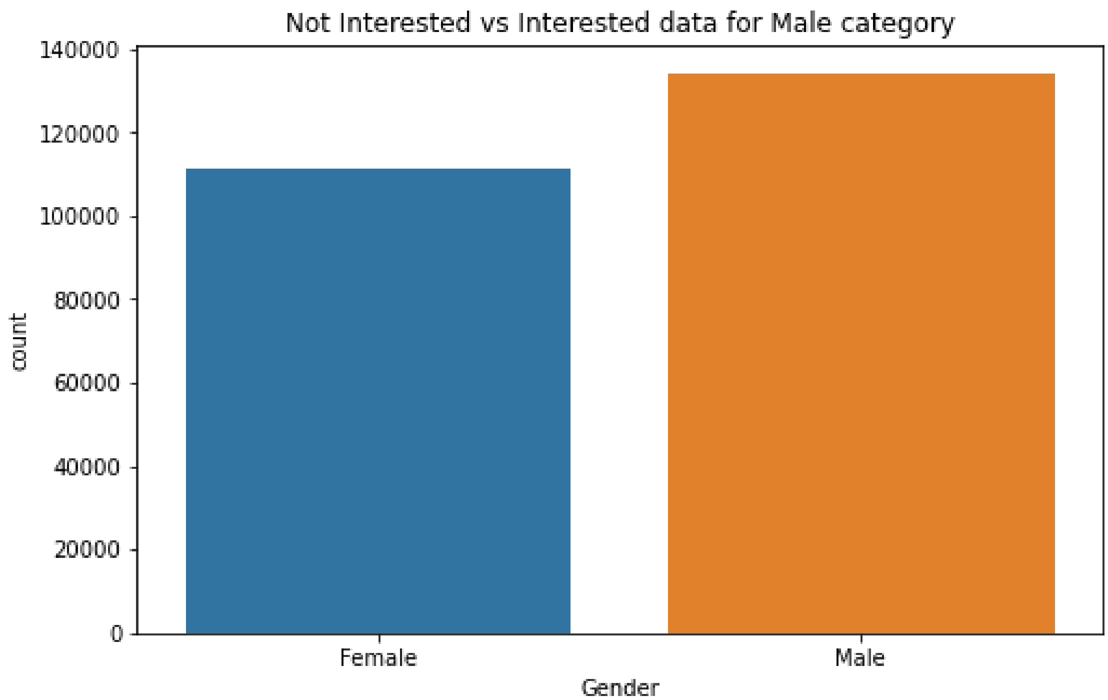
- It's Imbalanced Dataset so we can try SMOTE technique as Over sampling.
- Or we can try class_weight parameter in models

### 0.2.2 Gender Feature Analysis

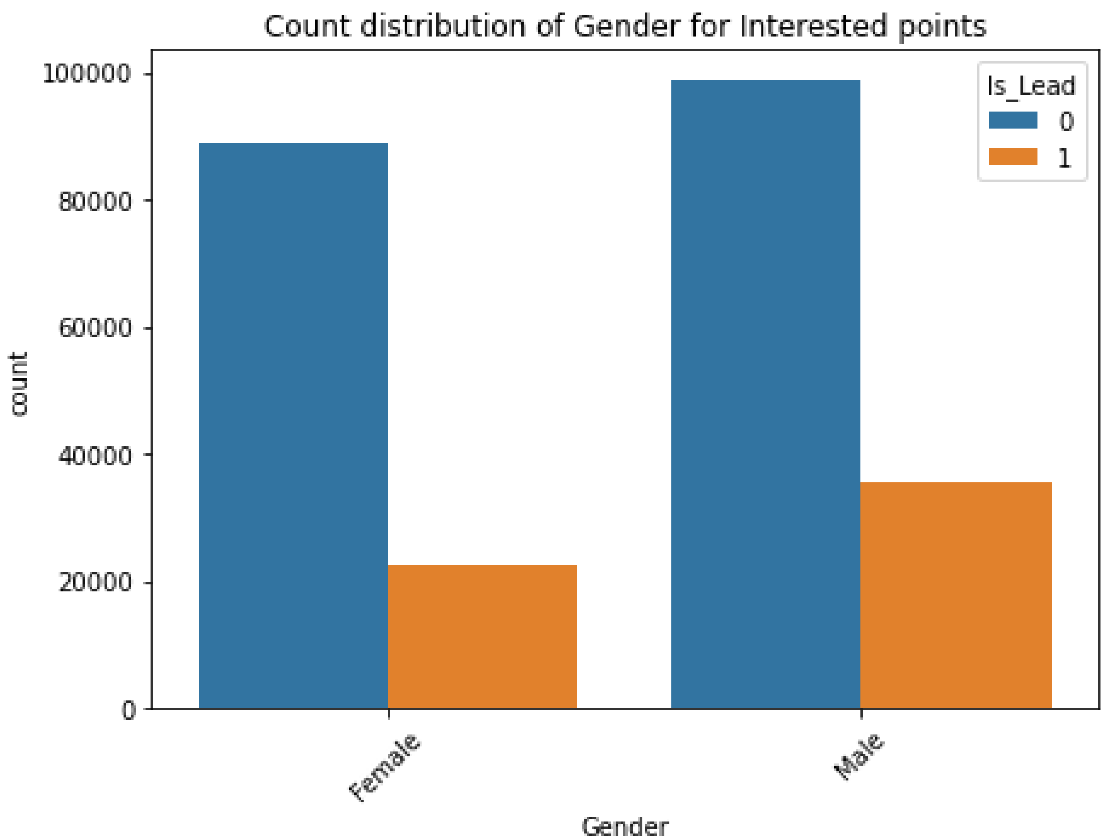
[14]:
```
# Gender Feature distribution
print("{}% of Male data present in this dataset.".
 ↪format(round(train_df["Gender"].value_counts(normalize=True)[0]*100)))
print("{}% of Female data present in this dataset.".
 ↪format(round(train_df["Gender"].value_counts(normalize=True)[1]*100)))
```

```
55% of Male data present in this dataset.
45% of Female data present in this dataset.
```

[15]:
```
plt.figure(figsize=(8,5))
plt.title("Not Interested vs Interested data for Male category")
sns.countplot(train_df["Gender"])
plt.show()
```



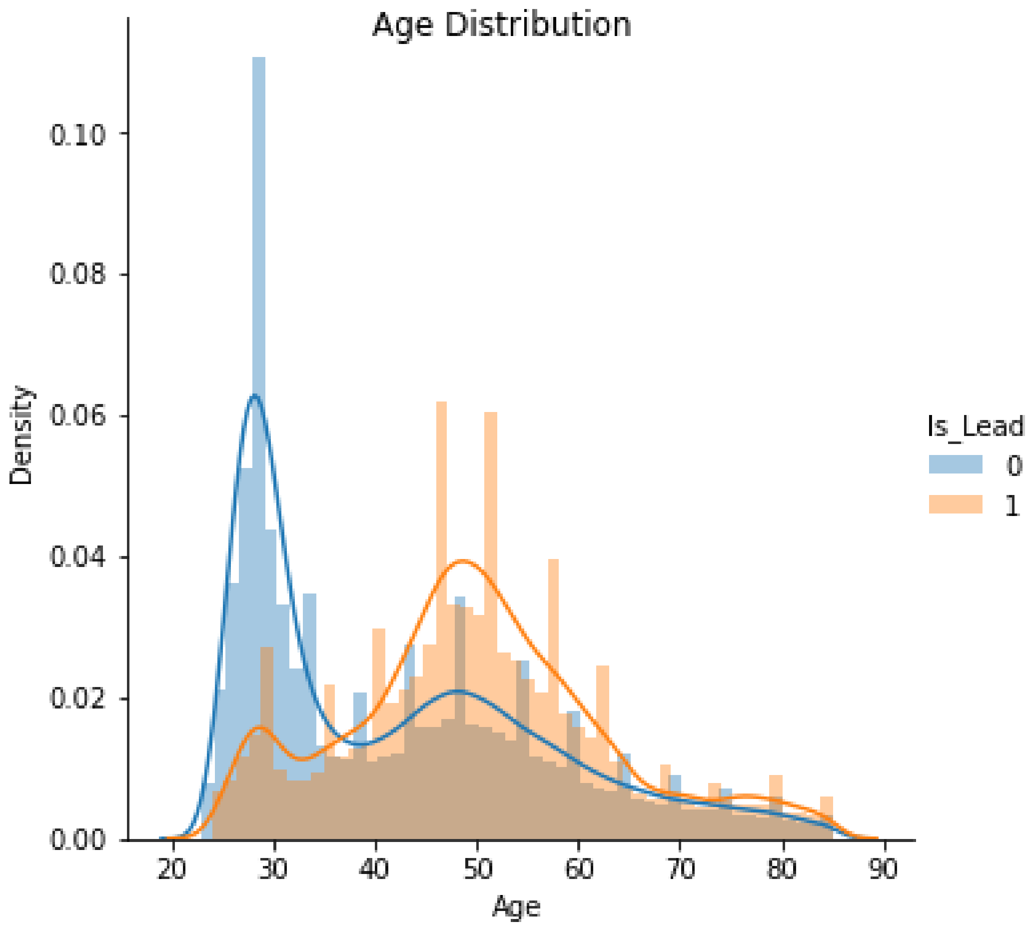

[16]:
```
plt.figure(figsize=(7,5))
plt.title("Count distribution of Gender for Interested points")
sns.countplot(x=train_df["Gender"],hue=train_df["Is_Lead"])
plt.xticks(rotation=45)
plt.show()
```




**Observation** * this dataset has 55% of male and 45% of female data points * Female are less interested than Male

#### 0.2.3 Age Feature Analysis

[17]:
```
g=sns.FacetGrid(train_df,height=5,hue="Is_Lead").map(sns.distplot,"Age").
↪add_legend()
g.fig.suptitle("Age Distribution")
plt.show()
```

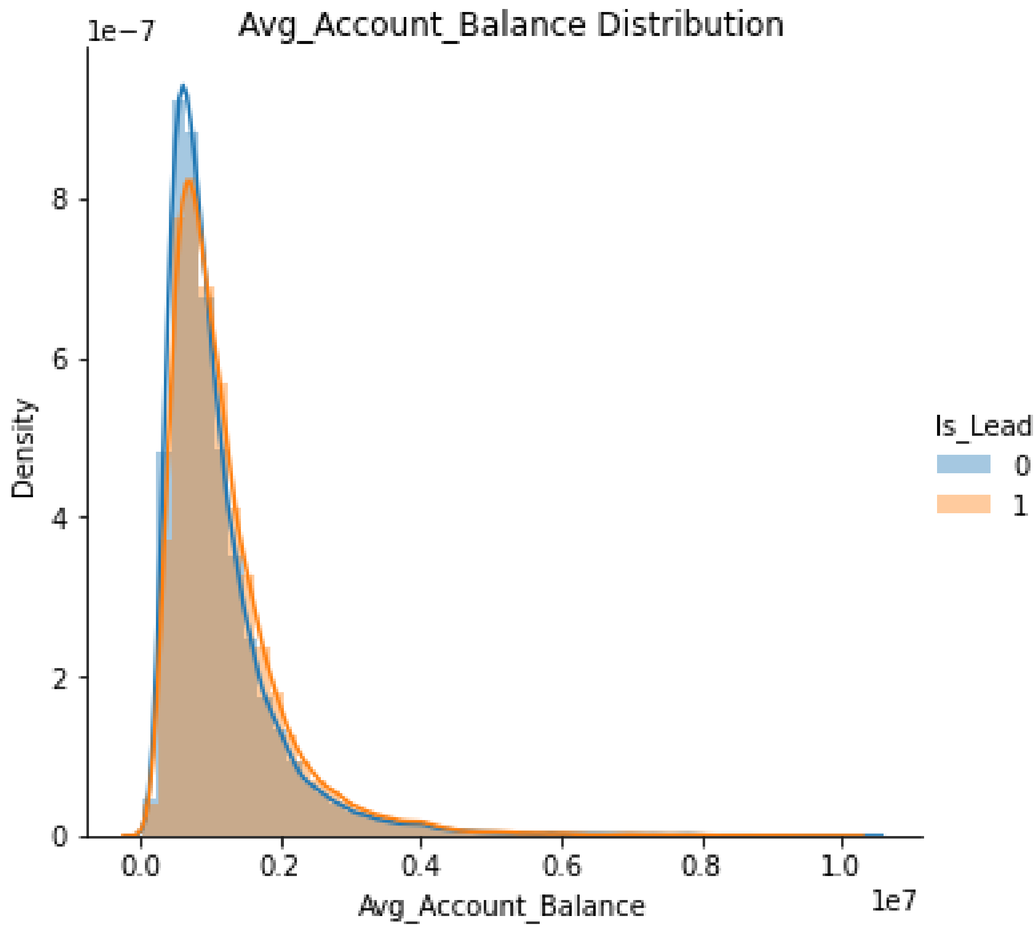



**Observation:** * Age distribution for "Not Interested" and "Inrerested" are overlapping. * It seems that who has age less than 35 is more "not intereseted" for credit card. * who have age >35 and age < 65 are more "Interested" for credit card. * and Age > 65 have almost equal interest for creadit card. * Based on this analogy we can convert this feature into categorical variable.

**Convert to category** * based on above analogy, this feature will be converted into category with below strategy. * 0-35='age_grp1',35-42:'age_grp2',42-65:'age_grp3',65-above:'age_grp4'

### 0.2.4 Avg_Account_Balance Feature Analysis

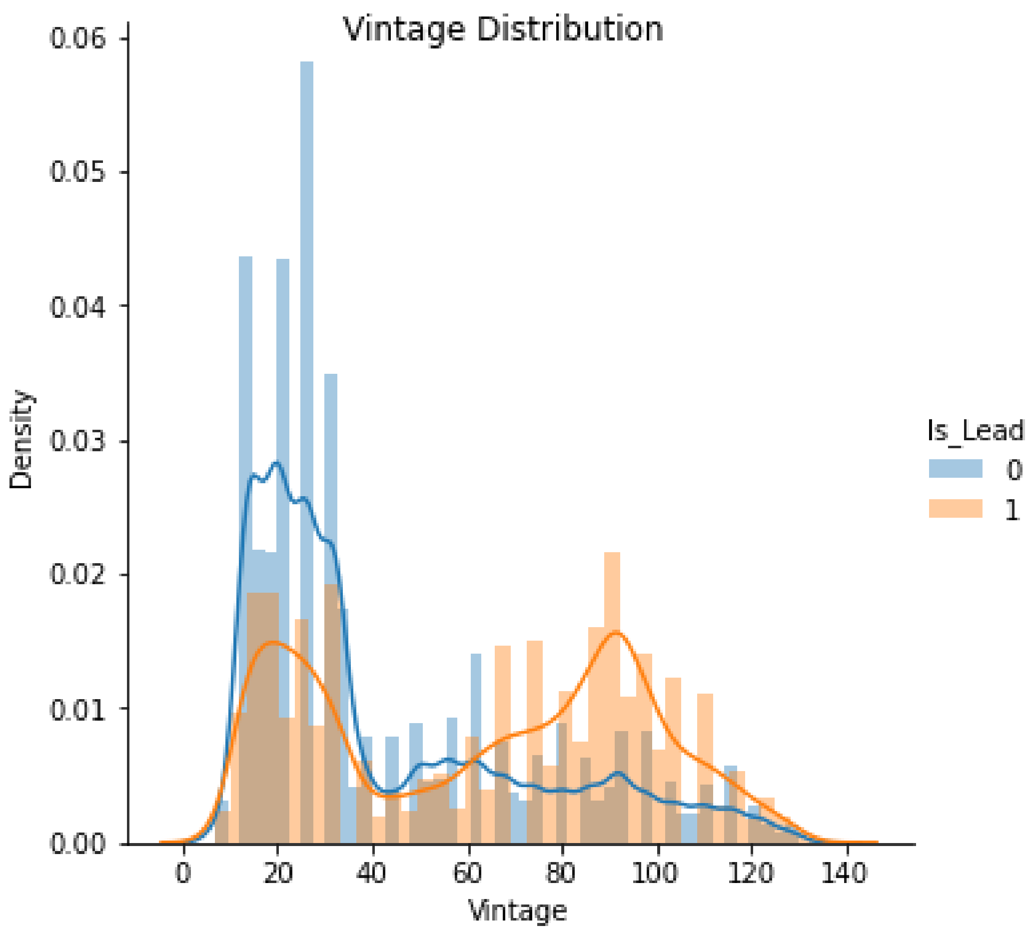
[18]:
```
g=sns.FacetGrid(train_df,height=5,hue="Is_Lead").map(sns.
 ↪distplot,"Avg_Account_Balance").add_legend()
g.fig.suptitle("Avg_Account_Balance Distribution")
plt.show()
```




**Observation:** * distribution of Avg_Account_Balance for both Is_Lead categories are almost same. * we can see a little pick for "not interested" person who belongs between 0.0 and 0.2 range of avg acc balanced(x-axis). * so we will add this feature for training the model and will see it is helping to improve model or not.

### 0.2.5 Vintage Feature Analysis

[19]:
```
g=sns.FacetGrid(train_df,height=5,hue="Is_Lead").map(sns.distplot,"Vintage").
 ↪add_legend()
g.fig.suptitle("Vintage Distribution")
plt.show()
```




**Observation:** * Vintage distribution for "Not Interested" and "Inrerested" are overlapping. * between vintage >0 and vintage <40 has more probability to "Not Interested" for credit card. * between vintage >40 and vintage <60 has bit more probability to "Not Interested" for credit card but alomost overlapping. * between vintage >40 and vintage <120 has more probability to "Interested" for credit card. * between vintage >120 and above has almost same probabilty for both Is_lead category. * Based on this analogy we can convert this feature into categorical variable.

**Convert to category** * based on above analogy, this feature will be converted into category with below strategy. * 0-40='vint_g1',40-60='vint_g2',60-80='vint_g3',80-100='vint_g4',100-120='vint_g5',120-above='vint_g6']

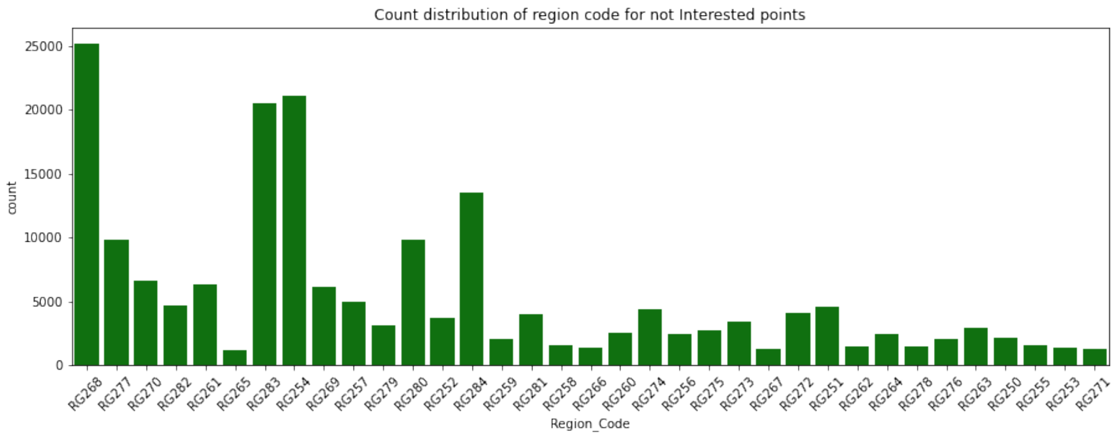
#### 0.2.6 Region_Code feature

[20]:
```
print("Number of Unique Region_Code :",len(train_df['Region_Code'].unique()))
```

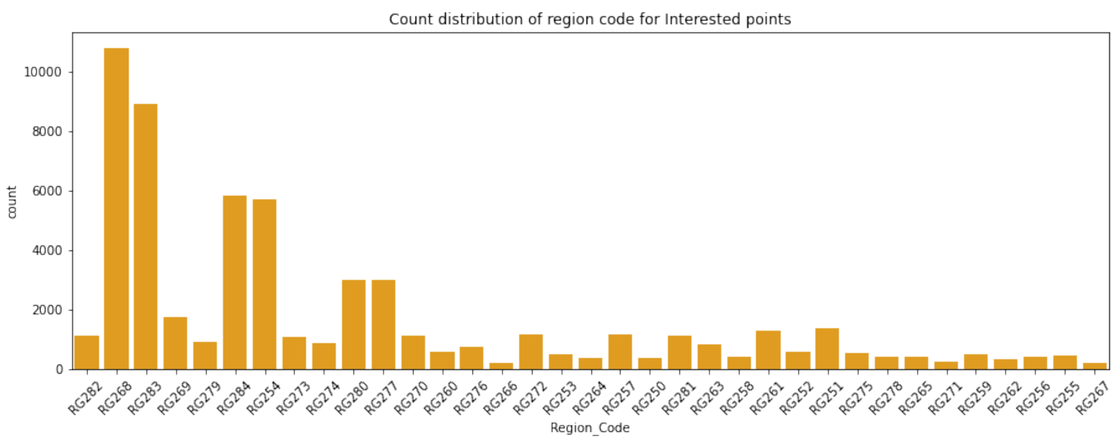
```
Number of Unique Region_Code : 35
```

[21]:
```
plt.figure(figsize=(15,5))
plt.title("Count distribution of region code for not Interested points")
```

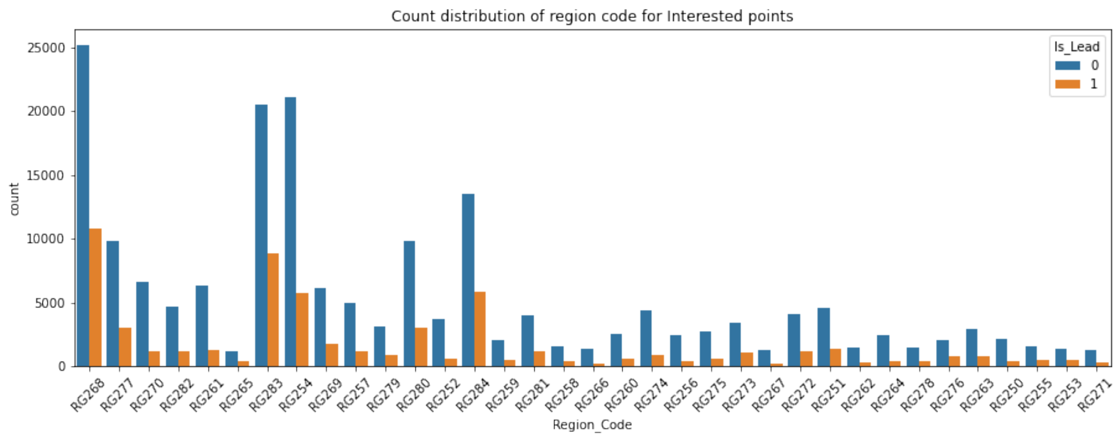
```
sns.countplot(x=train_df[train_df["Is_Lead"]==0]["Region_Code"],color='green')
plt.xticks(rotation=45)
plt.show()
```



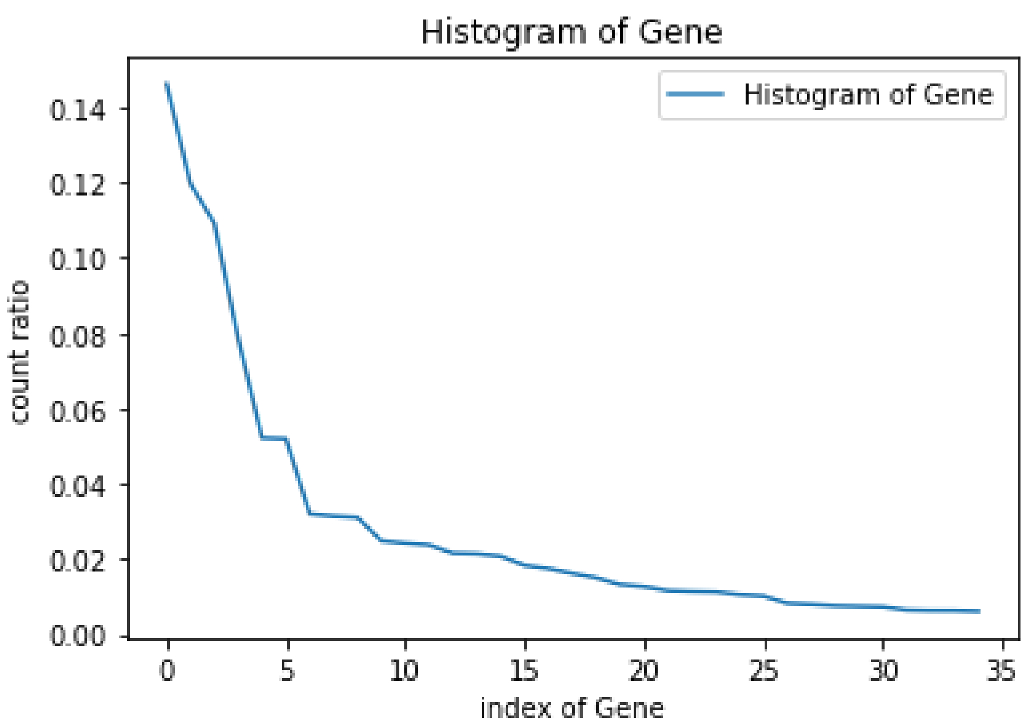

[22]:
```
plt.figure(figsize=(15,5))
plt.title("Count distribution of region code for Interested points")
sns.countplot(x=train_df[train_df["Is_Lead"]==1]["Region_Code"],color='orange')
plt.xticks(rotation=45)
plt.show()
```




[23]:
```
plt.figure(figsize=(15,5))
plt.title("Count distribution of region code for Interested points")
sns.countplot(x=train_df["Region_Code"],hue=train_df["Is_Lead"])
plt.xticks(rotation=45)
plt.show()
```




[24]:
```
unique_gene_count=train_df['Region_Code'].value_counts(normalize=True,sort=True)
plt.plot(unique_gene_count.values,label="Histogram of Gene")
plt.title("Histogram of Gene")
plt.xlabel("index of Gene")
plt.ylabel("count ratio")
# plt.xticks([0,50,100,150,200,250])
plt.legend()
plt.show()
```



**Observation:** * In few region, counts are very high and the number of "not Interested" and "Interested" counts are also high in those region. * we will convert it into vector using **One Hot Encoding** and will see how much helpful for models. * And also we can trying by converting into category region group and will see how much helpful for our models.

[25]:
```
#Creating reference region group category dictionary
ref_reg=train_df["Region_Code"].value_counts()
ref_reg_ind=ref_reg.index
reg_cat_dict=dict()
[reg_cat_dict.update({i:"reg_cat1"}) for i in ref_reg_ind[:5]]
[reg_cat_dict.update({i:"reg_cat2"}) for i in ref_reg_ind[5:15]]
[reg_cat_dict.update({i:"reg_cat3"}) for i in ref_reg_ind[15:25]]
[reg_cat_dict.update({i:"reg_cat4"}) for i in ref_reg_ind[25:]]
print("Tried these category but It does not work well for models")
```

```
Tried these category but It does not work well for models
```

### 0.2.7 Occupation Analysis

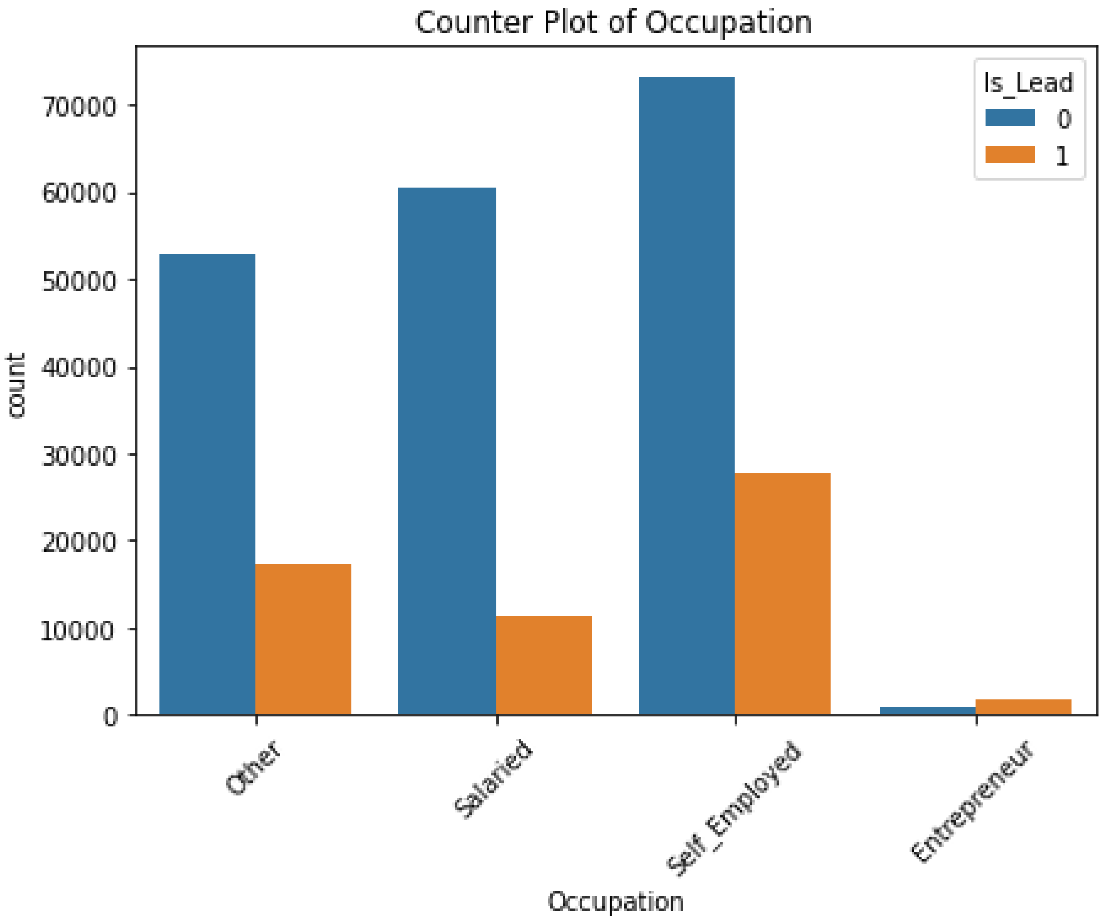
[26]:
```
train_df.Occupation.value_counts(normalize=True)
```

[26]:
```
Self_Employed    0.410583
Salaried         0.292970
Other            0.285592
Entrepreneur     0.010855
Name: Occupation, dtype: float64
```

[27]:
```
print("Number of Unique Region_Code :",len(train_df['Occupation'].unique()))
```

```
Number of Unique Region_Code : 4
```

[28]:
```
plt.figure(figsize=(7,5))
plt.title("Counter Plot of Occupation")
sns.countplot(x=train_df["Occupation"],hue=train_df["Is_Lead"])
plt.xticks(rotation=45)
plt.show()
```




**Observation** * Entrepreneur are more interested for credit card over not interested Entrepreneur * Other category are more likely to interested for credit card than salaried category

#### 0.2.8 Channel_Code Analysis

[29]:
```
print("Number of Unique Region_Code :",len(train_df['Channel_Code'].unique()))
```

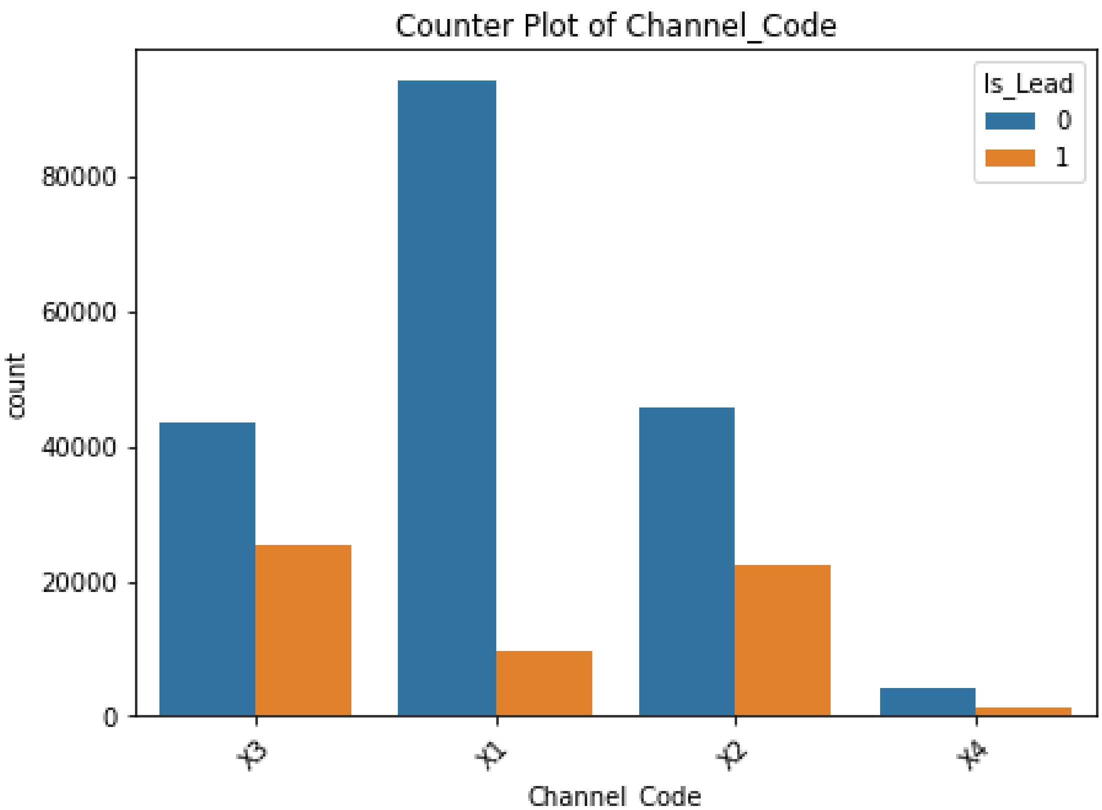
```
Number of Unique Region_Code : 4
```

[30]:
```
train_df.Channel_Code.value_counts(normalize=True)
```

[30]:
```
X1    0.422061
X3    0.279645
X2    0.275628
X4    0.022665
Name: Channel_Code, dtype: float64
```

[31]:
```
plt.figure(figsize=(7,5))
plt.title("Counter Plot of Channel_Code")
```

```
sns.countplot(x=train_df["Channel_Code"],hue=train_df["Is_Lead"])
plt.xticks(rotation=45)
plt.show()
```



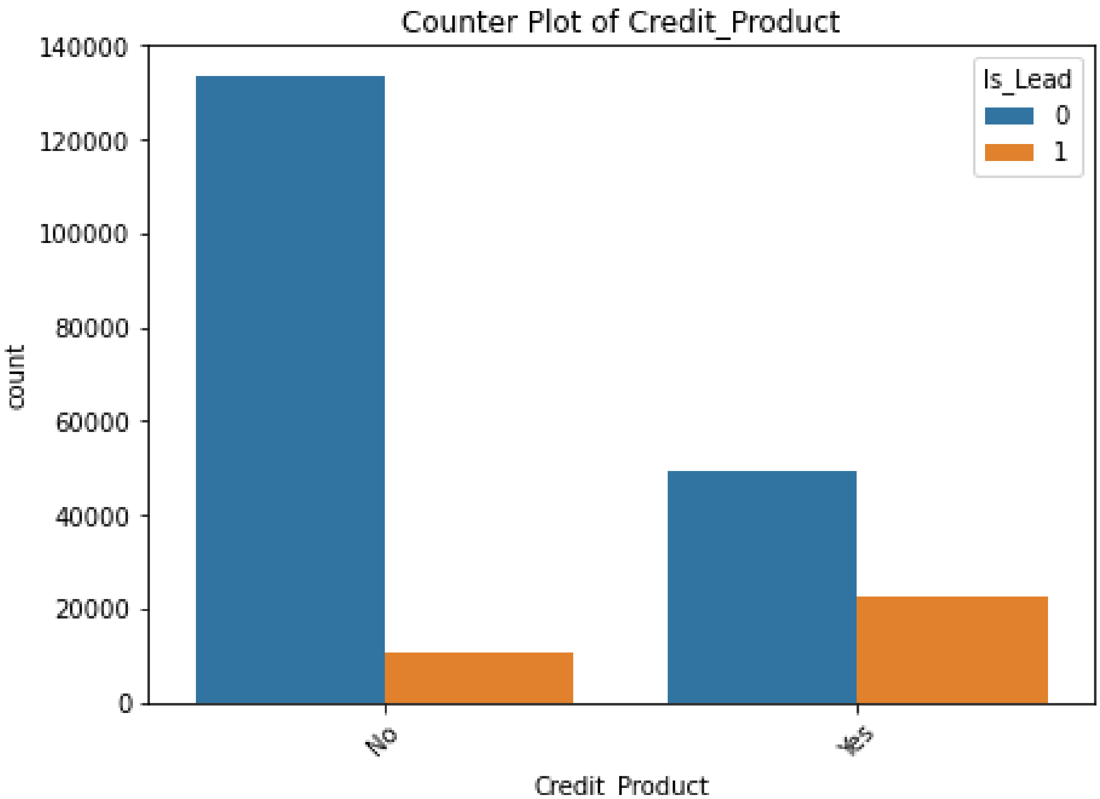

**Observation** * We have very less data points for category X4.It's around 2 % of whole data. * users who belongs to X1 channel are more likely to "Not interested" for credit card over "interested" X1 Channel

### 0.2.9 Credit_Product analysis

[32]:
```
print("Number of Unique Region_Code :",len(train_df['Credit_Product'].unique()))
```

```
Number of Unique Region_Code : 3
```

[33]:
```
plt.figure(figsize=(7,5))
plt.title("Counter Plot of Credit_Product")
sns.countplot(x=train_df["Credit_Product"],hue=train_df["Is_Lead"])
plt.xticks(rotation=45)
plt.show()
```



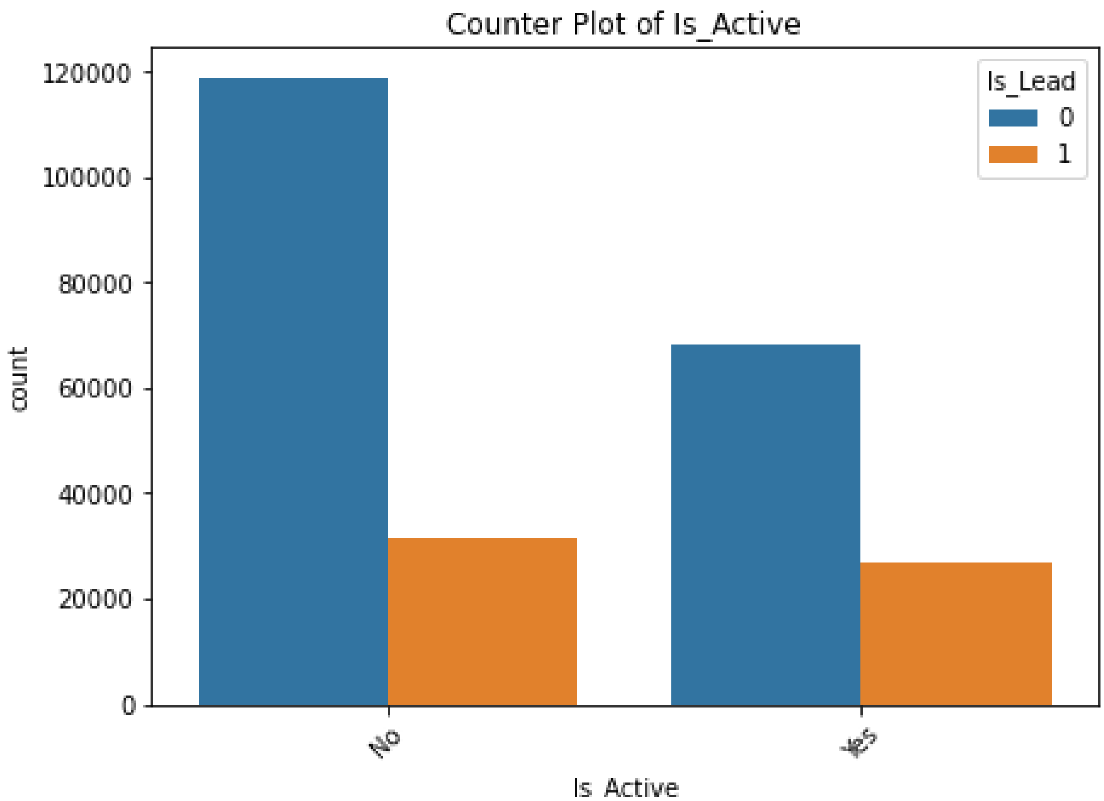

**Obsevation:** * There are two categories for credit product ("Yes" and "No") along with some missing value * so for filling missing data points, we will consider third category which will be NaN. * user who have any active product(like Home Loan) are more likely to "Interested" for credit card rather than who have not any active product.

#### 0.2.10 Is_Active analysis

[34]:
```
print("Number of Unique Region_Code :",len(train_df['Is_Active'].unique()))
```

```
Number of Unique Region_Code : 2
```

[35]:
```
plt.figure(figsize=(7,5))
plt.title("Counter Plot of Is_Active")
sns.countplot(x=train_df["Is_Active"],hue=train_df["Is_Lead"])
plt.xticks(rotation=45)
plt.show()
```




**Observation:** * user who is active < 3 months are more likely to Interested for credit card rather than who is not active.

### 0.3 Preparing Data

[36]:
```
train_df[train_df.Is_Lead==1]["Credit_Product"].value_counts()
```

[36]:
```
Yes     22690
No      10623
Name: Credit_Product, dtype: int64
```

[37]:
```
train_df[train_df.Is_Lead==0]["Credit_Product"].value_counts()
```

[37]:
```
No      133718
Yes      49348
Name: Credit_Product, dtype: int64
```

**Note:** * most frequent category of credit_product for not interested people is "No" * most frequent category of credit_product for Interested people is "Yes" * we can fill data point with this observation but it dooes not work well so I choose "NaN" as third category for all missing datapoints

[38]:
```
# Defining function for preprocessing and Feature Engineering
def preprocessed_data(data):
    #Converted Age into category feature
    data["Age_group"]=pd.cut(data.
 ↪Age,bins=[0,35,45,65,120],labels=['age_grp1','age_grp2','age_grp3','age_grp4'])
    #Converted Vintage into category feature
    data["Vint_group"]=pd.cut(data.
 ↪Vintage,bins=[0,40,60,80,100,120,200],labels=['vint_g1','vint_g2','vint_g3','vint_g4','vint
    #Concating Two feature that may help to imporve model accuracy
    data["Credit_Product"]=data["Credit_Product"].fillna("Nan")
    data["age_vintage"]=[temp[0]+"_"+temp[1] for temp in␣
 ↪data[["Age_group","Vint_group"]].values]
    data["age_credit"]=[temp[0]+"_"+temp[1] for temp in␣
 ↪data[["Age_group","Credit_Product"]].values]
    data["region_credit"]=[temp[0]+"_"+temp[1] for temp in␣
 ↪data[["Region_Code","Credit_Product"]].values]

    #dropping Age and Vintage after converted into category features
    data.drop(columns=["Age","Vintage"],inplace=True)
    return data
```

[39]:
```
#Preprocessing training data
train_df=preprocessed_data(train_df)
train_df.head()
```

[39]:
```
         ID  Gender Region_Code     Occupation Channel_Code Credit_Product  \
0  NNVBBKZB  Female       RG268          Other           X3             No
1  IDD62UNG  Female       RG277       Salaried           X1             No
2  HD3DSEMC  Female       RG268  Self_Employed           X3             No
3  BF3NC7KV    Male       RG270       Salaried           X1             No
4  TEASRWXV  Female       RG282       Salaried           X1             No

   Avg_Account_Balance Is_Active  Is_Lead Age_group Vint_group  \
0              1045696        No        0  age_grp4    vint_g2
1               581988        No        0  age_grp1    vint_g1
2              1484315       Yes        0  age_grp3    vint_g1
3               470454        No        0  age_grp1    vint_g1
4               886787        No        0  age_grp1    vint_g1

        age_vintage   age_credit region_credit
0  age_grp4_vint_g2  age_grp4_No      RG268_No
1  age_grp1_vint_g1  age_grp1_No      RG277_No
2  age_grp3_vint_g1  age_grp3_No      RG268_No
3  age_grp1_vint_g1  age_grp1_No      RG270_No
4  age_grp1_vint_g1  age_grp1_No      RG282_No
```

[40]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 245704 entries, 0 to 245724
Data columns (total 14 columns):
 #   Column               Non-Null Count   Dtype
---  ------               --------------   -----
 0   ID                   245704 non-null  object
 1   Gender               245704 non-null  object
 2   Region_Code          245704 non-null  object
 3   Occupation           245704 non-null  object
 4   Channel_Code         245704 non-null  object
 5   Credit_Product       245704 non-null  object
 6   Avg_Account_Balance  245704 non-null  int64
 7   Is_Active            245704 non-null  object
 8   Is_Lead              245704 non-null  int64
 9   Age_group            245704 non-null  category
 10  Vint_group           245704 non-null  category
 11  age_vintage          245704 non-null  object
 12  age_credit           245704 non-null  object
 13  region_credit        245704 non-null  object
dtypes: category(2), int64(2), object(10)
memory usage: 32.9+ MB
```

[41]:
```
X=train_df.drop(columns=["Is_Lead","ID"])
y=train_df.Is_Lead.values
```

[ ]:
```

```

### 0.3.1 Split into Train and CV data

[42]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.
 ↪25,stratify=y,random_state=8)
```

[43]:
```
# X_train=X
# y_train=y
```

[44]:
```
#Creating List of columns of all category features
category_var=list(X_train.select_dtypes(include=["object","category"]).columns.
 ↪values)
```

[45]:
```
#Fitting Encoder and Normalizer so that we can use it to transform train, cv␣
 ↪and test data
encoder=OneHotEncoder(drop="first")
encoder.fit(X_train[category_var])
#Normalizer fitting
# we can also  use StandardScaler here
norm=Normalizer()
norm.fit(X_train["Avg_Account_Balance"].values.reshape(-1,1))
```

[45]: Normalizer()

[46]:
```
## Making list of All features
features_name=list(encoder.get_feature_names())
features_name.append("Avg_Account_Balance")
```

[47]:
```
# create a function to convert cotegory data to vector and Normalized the␣
↪continuous variables
def encode_dataset(data):
    category_data=encoder.transform(data[category_var])
    numeric_norm=norm.transform(data["Avg_Account_Balance"].values.
↪reshape(-1,1))
    # concating category data and Numerical feature
    data=hstack((category_data,numeric_norm))
    print("data shape: ",data.shape)
    return data
```

[48]:
```
X_train=encode_dataset(X_train)
X_test=encode_dataset(X_test)
```

```
data shape:  (184278, 189)
data shape:  (61426, 189)
```

[49]:
```
print("X_train shape:",X_train.shape)
print("X_test shape:",X_test.shape)
```

```
X_train shape: (184278, 189)
X_test shape: (61426, 189)
```

[50]:
```
#define a function which helps to preprocess ,feature engineering and encode␣
↪into vectors
def preprocess_and_encode_test_data(data):
    data=preprocessed_data(data)
    data=encode_dataset(data)
    return data
```

## 0.4 Model Training

### 0.4.1 Random Forest Classifier

[51]:
```
#Hyper parameter tunning to RandomForestClassifier
param={"n_estimators":[100,120,150,200]}
model=RandomForestClassifier(class_weight="balanced",max_depth=10,n_jobs=-1)
# model.fit(X_train,y_train)
clf=GridSearchCV(estimator=model,param_grid=param,scoring="roc_auc",verbose=1)
clf.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 4 candidates, totalling 20 fits
```

[51]:
```
GridSearchCV(estimator=RandomForestClassifier(class_weight='balanced',
                                              max_depth=10, n_jobs=-1),
             param_grid={'n_estimators': [100, 120, 150, 200]},
             scoring='roc_auc', verbose=1)
```

[52]:
```
rf_param=clf.best_params_
print("Tunned Parameter of RF:",rf_param)
model=RandomForestClassifier(max_depth=10
 ,→,n_estimators=rf_param["n_estimators"],class_weight="balanced",n_jobs=-1)
model.fit(X_train,y_train)
```

```
Tunned Parameter of RF: {'n_estimators': 150}
```

[52]:
```
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=150,
                       n_jobs=-1)
```

**Top 50 Feature (Featuere_Important)**

[53]:
```
## Selecting Top 50 Features
no_of_features=50
features_dict=dict(zip(features_name,model.feature_importances_))
features_dict=sorted(features_dict.items(), key=lambda x: x[1], reverse=True)
def get_important_feature(top=10):
    features=[feat[0] for feat in features_dict[:top]]
    return features
important_feature=get_important_feature(no_of_features)
important_feature_index=[features_name.index(item) for item in␣
 ,→important_feature]
```

[54]:
```
print("#"*10,"Top Features","#"*10)
print(important_feature)
```

```
########## Top Features ##########
['x4_No', 'x9_age_grp1_No', 'x9_age_grp3_Nan', 'x6_age_grp3', 'x7_vint_g4',
'x9_age_grp3_No', 'x9_age_grp2_Nan', 'x4_Yes', 'x3_X3', 'x8_age_grp3_vint_g4',
'x10_RG268_Nan', 'x9_age_grp3_Yes', 'x2_Salaried', 'x9_age_grp4_Nan', 'x3_X2',
'x9_age_grp2_No', 'x9_age_grp1_Yes', 'x10_RG283_Nan', 'x5_Yes', 'x10_RG268_No',
'x6_age_grp2', 'x9_age_grp2_Yes', 'x10_RG284_Nan', 'x10_RG283_No',
'x10_RG254_Nan', 'x10_RG254_No', 'x7_vint_g3', 'x9_age_grp4_No',
'x2_Self_Employed', 'x8_age_grp3_vint_g5', 'x8_age_grp2_vint_g1', 'x7_vint_g2',
'x8_age_grp3_vint_g3', 'x8_age_grp4_vint_g4', 'x6_age_grp4', 'x10_RG284_No',
'x10_RG280_Nan', 'x8_age_grp3_vint_g2', 'x8_age_grp3_vint_g1', 'x0_Male',
'x7_vint_g5', 'x8_age_grp2_vint_g4', 'x2_Other', 'x10_RG277_Nan', 'x1_RG268',
'x10_RG268_Yes', 'x10_RG277_No', 'x10_RG280_No', 'x8_age_grp2_vint_g3',
'x9_age_grp4_Yes']
```

[55]:
```
#Extracting top 50 features
def extract_important_features(data):
```

```
    return data.tocsr()[:,important_feature_index]
X_train_imp=extract_important_features(X_train)
X_test_imp=extract_important_features(X_test)
```

### 1. RandomForestClassifier on all data

[56]:
```
model=RandomForestClassifier(max_depth=10
                    ␣
↪,n_estimators=rf_param["n_estimators"],class_weight="balanced",n_jobs=-1)
model.fit(X_train,y_train)
```

[56]:
```
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=150,
                       n_jobs=-1)
```

[57]:
```
#AUC on training data
pred=model.predict_proba(X_train)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8659737803098613
```

[58]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test)
auc=roc_auc_score(y_test,pred[:, 1])
print("Test AUC:",auc)
```

```
Test AUC: 0.8664393102039625
```

### 2. RandomForestClassifier on Top 50 features

[59]:
```
model=RandomForestClassifier(max_depth=10
                    ␣
↪,n_estimators=rf_param["n_estimators"],class_weight="balanced",n_jobs=-1)
model.fit(X_train_imp,y_train)
```

[59]:
```
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=150,
                       n_jobs=-1)
```

[60]:
```
#AUC on training data
pred=model.predict_proba(X_train_imp)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8708094403670058
```

[61]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test_imp)
auc=roc_auc_score(y_test,pred[:, 1])
print("Test AUC:",auc)
```

```
Test AUC: 0.8709047009451487
```

[ ]:

```

```

### 0.4.2 SGDClassifier

[62]:

```
alpha=[10**i for i in range(-4,0)]
param={"alpha":alpha,"penalty":['l2', 'l1', 'elasticnet']}
model=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal")
#     model.fit(X_train,y_train)
clf=GridSearchCV(estimator=model,param_grid=param,scoring="roc_auc",verbose=1)
clf.fit(X_train,y_train)
```

```
Fitting 5 folds for each of 12 candidates, totalling 60 fits
```

[62]:

```
GridSearchCV(estimator=SGDClassifier(class_weight='balanced', loss='log'),
             param_grid={'alpha': [0.0001, 0.001, 0.01, 0.1],
                         'penalty': ['l2', 'l1', 'elasticnet']},
             scoring='roc_auc', verbose=1)
```

[63]:

```
sgd_param=clf.best_params_
sgd_param
```

[63]:

```
{'alpha': 0.001, 'penalty': 'l2'}
```

**1. SGDClassifier on All features**

[64]:

```
model=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sgd_param
model.fit(X_train,y_train)
```

[64]:

```
SGDClassifier(alpha=0.001, class_weight='balanced', loss='log')
```

[65]:

```
#AUC on training data
pred=model.predict_proba(X_train)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8645218412206594
```

[66]:

```
#AUC on cross validation data
pred=model.predict_proba(X_test)
auc=roc_auc_score(y_test,pred[:, 1])
print("Test AUC:",auc)
```

```
Test AUC: 0.8674847268533024
```

**2. SGDClassifier on Top 50 features**

[67]:

```
model=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sgd_param
model.fit(X_train_imp,y_train)
```

[67]:

```
SGDClassifier(alpha=0.001, class_weight='balanced', loss='log')
```

[68]:
```
#AUC on training data
pred=model.predict_proba(X_train_imp)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8629184442762036
```

[69]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test_imp)
auc=roc_auc_score(y_test,pred[:, 1])
print("Test AUC:",auc)
```

```
Test AUC: 0.8659755233259679
```

### 0.4.3 XGBOOST Classifier

[70]:
```
#Hyper Tunning for XGBoostClassifier
param={"n_estimators":[100,120,150],"reg_lambda":[0.1,0.05]}
model=XGBClassifier(scale_pos_weight=3,eval_metric="logloss",learning_rate=0.
 ↪1,max_depth=5)

clf=GridSearchCV(estimator=model,param_grid=param,scoring="roc_auc",verbose=1)
clf.fit(X_train_imp,y_train)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits
```

[70]:
```
GridSearchCV(estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     enable_categorical=False,
                                     eval_metric='logloss', gamma=None,
                                     gpu_id=None, importance_type=None,
                                     interaction_constraints=None,
                                     learning_rate=0.1, max_delta_step=None,
                                     max_depth=5, min_child_weight=None,
                                     missing=nan, monotone_constraints=None,
                                     n_estimators=100, n_jobs=None,
                                     num_parallel_tree=None, predictor=None,
                                     random_state=None, reg_alpha=None,
                                     reg_lambda=None, scale_pos_weight=3,
                                     subsample=None, tree_method=None,
                                     validate_parameters=None, verbosity=None),
             param_grid={'n_estimators': [100, 120, 150],
                         'reg_lambda': [0.1, 0.05]},
             scoring='roc_auc', verbose=1)
```

[71]:
```
xgb_param=clf.best_params_
xgb_param
```

[71]: {'n_estimators': 100, 'reg_lambda': 0.1}

**1. XGBClassifier on all Features**

[72]:
```
model=XGBClassifier(eval_metric="logloss",max_depth=5,reg_lambda=xgb_param["reg_lambda"]
                    ,learning_rate=0.1,n_estimators=xgb_param["n_estimators"])
model.fit(X_train,y_train)
```

[72]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              eval_metric='logloss', gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=5, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=12,
              num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=0.1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[73]:
```
#AUC on training data
pred=model.predict_proba(X_train)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8736070816282663
```

[74]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test)
auc=roc_auc_score(y_test,pred[:, 1])
print("CV AUC:",auc)
```

```
CV AUC: 0.87362973327029
```

**2. XGBClassifier on Top 50 Features**

[75]:
```
model=XGBClassifier(eval_metric="logloss",max_depth=5,reg_lambda=xgb_param["reg_lambda"]
                    ,learning_rate=0.1,n_estimators=xgb_param["n_estimators"])
model.fit(X_train_imp,y_train)
```

[75]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              eval_metric='logloss', gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=5, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=12,
              num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=0.1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[76]:
```
#AUC on training data
pred=model.predict_proba(X_train_imp)
```

```
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8730313223410271
```

[77]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test_imp)
auc=roc_auc_score(y_test,pred[:, 1])
print("CV AUC:",auc)
```

```
CV AUC: 0.873803272448727
```

### 0.4.4 StackingClassifier

**1. StackingClassifier on all features**

[78]:
```
# param={"n_estimators":[50,100],"max_depth":[5,10,15]}
clf1=model=XGBClassifier(eval_metric="auc",learning_rate=0.1,max_depth=5
                    ␣
 ↪,n_estimators=xgb_param["n_estimators"],reg_lambda=xgb_param["reg_lambda"])
clf2=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sgd_param[

clf3=RandomForestClassifier(max_depth=10
                   ,n_estimators=100,class_weight="balanced",n_jobs=-1)

lr_clf=LogisticRegression()
model=StackingClassifier(estimators=[("xgb",clf1),("sgd",clf2),("rf",clf3)],final_estimator=lr
model.fit(X_train,y_train)
# clf=GridSearchCV(estimator=model,param_grid=param,scoring="roc_auc",verbose=1)
# clf.fit(X_train,y_train)
```

[78]:
```
StackingClassifier(estimators=[('xgb',
                                XGBClassifier(base_score=None, booster=None,
                                              colsample_bylevel=None,
                                              colsample_bynode=None,
                                              colsample_bytree=None,
                                              enable_categorical=False,
                                              eval_metric='auc', gamma=None,
                                              gpu_id=None, importance_type=None,
                                              interaction_constraints=None,
                                              learning_rate=0.1,
                                              max_delta_step=None, max_depth=5,
                                              min_child_weight=None,
                                              missing=nan,
                                              mo…
                                              num_parallel_tree=None,
                                              predictor=None, random_state=None,
                                              reg_alpha=None, reg_lambda=0.1,
                                              scale_pos_weight=None,
```

```
                              subsample=None, tree_method=None,
                              validate_parameters=None,
                              verbosity=None)),
               ('sgd',
                SGDClassifier(alpha=0.001,
                              class_weight='balanced',
                              loss='log')),
               ('rf',
                RandomForestClassifier(class_weight='balanced',
                                       max_depth=10,
                                       n_jobs=-1))],
   final_estimator=LogisticRegression())
```

[79]:
```
#AUC on training data
pred=model.predict_proba(X_train)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8724306720416939
```

[80]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test)
auc=roc_auc_score(y_test,pred[:, 1])
print("CV AUC:",auc)
```

```
CV AUC: 0.8729916565802007
```

**2. StackingClassifier on Top 50 Features**

[81]:
```
# param={"n_estimators":[50,100],"max_depth":[5,10,15]}
clf1=model=XGBClassifier(eval_metric="auc",learning_rate=0.1,max_depth=5
                   ␣
 ↪,n_estimators=xgb_param["n_estimators"],reg_lambda=xgb_param["reg_lambda"])
clf2=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sgd_param[

clf3=RandomForestClassifier(max_depth=10
                   ,n_estimators=100,class_weight="balanced",n_jobs=-1)

lr_clf=LogisticRegression()
model=StackingClassifier(estimators=[("xgb",clf1),("sgd",clf2),("rf",clf3)],final_estimator=lr
model.fit(X_train_imp,y_train)
# clf=GridSearchCV(estimator=model,param_grid=param,scoring="roc_auc",verbose=1)
# clf.fit(X_train,y_train)
```

[81]:
```
StackingClassifier(estimators=[('xgb',
                XGBClassifier(base_score=None, booster=None,
                              colsample_bylevel=None,
                              colsample_bynode=None,
                              colsample_bytree=None,
```

```
                                            enable_categorical=False,
                                            eval_metric='auc', gamma=None,
                                            gpu_id=None, importance_type=None,
                                            interaction_constraints=None,
                                            learning_rate=0.1,
                                            max_delta_step=None, max_depth=5,
                                            min_child_weight=None,
                                            missing=nan,
                                            mo…
                                            num_parallel_tree=None,
                                            predictor=None, random_state=None,
                                            reg_alpha=None, reg_lambda=0.1,
                                            scale_pos_weight=None,
                                            subsample=None, tree_method=None,
                                            validate_parameters=None,
                                            verbosity=None)),
                              ('sgd',
                               SGDClassifier(alpha=0.001,
                                            class_weight='balanced',
                                            loss='log')),
                              ('rf',
                               RandomForestClassifier(class_weight='balanced',
                                                      max_depth=10,
                                                      n_jobs=-1))],
                   final_estimator=LogisticRegression())
```

[82]:
```
#AUC on training data
pred=model.predict_proba(X_train_imp)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8729316136176766
```

[83]:
```
#AUC on cross validation data
pred=model.predict_proba(X_test_imp)
auc=roc_auc_score(y_test,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8731234993405145
```

## 0.5 Summary

[97]:
```
from tabulate import tabulate
columns=["Model","Top_50 or All","Train auc","CV auc"]
summary=[["RandomForestClassifier","All",0.8659,0.8664],
         ["RandomForestClassifier","Top_50",0.8708,0.8709],
         ["SGDClassifier","All",0.8645,0.8674],
         ["SGDClassifier","Top_50",0.8629,0.8659],
```

```
        ["XGBClassifier","All",0.8736,0.8736],
        ["XGBClassifier","Top_50",0.8730,0.8738],
        ["StackingClassifier","All",0.8724,0.8729],
        ["StackingClassifier","Top_50",0.8729,0.8731],
       ]
summary_df=pd.DataFrame(summary,columns=columns)
#https://www.geeksforgeeks.org/display-the-pandas-dataframe-in-table-style/
print(tabulate(summary_df,headers="keys",tablefmt = 'psql'))
```

```
+----+------------------------+-----------------+-------------+----------+
|    | Model                  | Top_50 or All   |   Train auc |   CV auc |
|----+------------------------+-----------------+-------------+----------|
|  0 | RandomForestClassifier | All             |      0.8659 |   0.8664 |
|  1 | RandomForestClassifier | Top_50          |      0.8708 |   0.8709 |
|  2 | SGDClassifier          | All             |      0.8645 |   0.8674 |
|  3 | SGDClassifier          | Top_50          |      0.8629 |   0.8659 |
|  4 | XGBClassifier          | All             |      0.8736 |   0.8736 |
|  5 | XGBClassifier          | Top_50          |      0.873  |   0.8738 |
|  6 | StackingClassifier     | All             |      0.8724 |   0.8729 |
|  7 | StackingClassifier     | Top_50          |      0.8729 |   0.8731 |
+----+------------------------+-----------------+-------------+----------+
```

## 0.6 Conclution

- Have trained many model where XGBClassifier works well
- So I have chose XGBClassifier for predicting test data

### 0.6.1 Best Model

[89]:
```
model=XGBClassifier(eval_metric="logloss",max_depth=5,reg_lambda=xgb_param["reg_lambda"]
                    ,learning_rate=0.1,n_estimators=xgb_param["n_estimators"])
model.fit(X_train,y_train)
```

[89]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, enable_categorical=False,
              eval_metric='logloss', gamma=0, gpu_id=-1, importance_type=None,
              interaction_constraints='', learning_rate=0.1, max_delta_step=0,
              max_depth=5, min_child_weight=1, missing=nan,
              monotone_constraints='()', n_estimators=100, n_jobs=12,
              num_parallel_tree=1, predictor='auto', random_state=0,
              reg_alpha=0, reg_lambda=0.1, scale_pos_weight=1, subsample=1,
              tree_method='exact', validate_parameters=1, verbosity=None)
```

[90]:
```
pred=model.predict_proba(X_test)
auc=roc_auc_score(y_test,pred[:, 1])
print("CV AUC:",auc)
```

```
CV AUC: 0.87362973327029
```

## 0.7 Creating Submission File

[91]:
```
#reading Test datasets
test_data=pd.read_csv("data/test_mSzZ8RL.csv")
print("Shape of test data::",test_data.shape)
```

```
Shape of test data:: (105312, 10)
```

[92]:
```
#Test data preprocessing,feature engineering and converting into vectors
test_df=preprocess_and_encode_test_data(test_data)
```

```
data shape:  (105312, 189)
```

[93]:
```
y_pred=model.predict_proba(test_df)[:,1]
test_data["Is_Lead"]=y_pred
```

[94]:
```
test_data=test_data[["ID","Is_Lead"]]
```

[96]:
```
test_data.to_csv("output/final_submission.csv",index=False)
```