Credit Card Lead Prediction

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.)

Data Dictionary

Train Data

Variable	Definition
ID	Unique Identifier for a row
Gender	Gender of the Customer
Age	Age of the Customer (in Years)
Region_Code	Code of the Region for the customers
Occupation	Occupation Type for the customer
Channel_Code	Acquisition Channel Code for the Customer (Encoded)
Vintage	Vintage for the Customer (In Months)
Credit_Product	If the Customer has any active credit product (Home loan, Personal loan, Credit Card etc.)
Avg_Account_Balance	Average Account Balance for the Customer in last 12 Months
Is_Active	If the Customer is Active in last 3 Months
Is_Lead(Target)	If the Customer is interested for the Credit Card 0 : Customer is not interested 1 : Customer is interested

Test Data

Variable	Definition
ID	Unique Identifier for a row
Gender	Gender of the Customer
Age	Age of the Customer (in Years)
Region_Code	Code of the Region for the customers
Occupation	Occupation Type for the customer
Channel_Code	Acquisition Channel Code for the Customer (Encoded)
Vintage	Vintage for the Customer (In Months)
Credit_Product	If the Customer has any active credit product (Home loan, Personal loan, Credit Card etc.)
Avg_Account_Balance	Average Account Balance for the Customer in last 12 Months
Is_Active	If the Customer is Active in last 3 Months

ref: https://datahack.analyticsvidhya.com/contest/job-a-thon-2/?utm_source=datahack&utm_medium=Navbar&utm_campaign=Jobathon#ProblemStatement

Public and Private Split

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

- Your initial responses will be checked and scored on the Public data.
- The final rankings would be based on your private score which will be published once the competition is over.

Evaluation

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

In [259...

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from tqdm import tqdm
from tensorflow.keras.layers import Dense,Flatten,Dropout,Input
from tensorflow.keras.models import Sequential
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")
```

In [227...

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

Out[227...

	ID	Gender	Age	Region_Code	Occupation	Channel_Code	Vintage	Credit_Product	Avg_
0	NNVBBKZB	Female	73	RG268	Other	X3	43	No	
1	IDD62UNG	Female	30	RG277	Salaried	X1	32	No	
2	HD3DSEMC	Female	56	RG268	Self_Employed	X3	26	No	
3	BF3NC7KV	Male	34	RG270	Salaried	X1	19	No	
4	TEASRWXV	Female	30	RG282	Salaried	X1	33	No	

In [229...

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

```
List of columns:: ['ID' 'Gender' 'Age' 'Region_Code' 'Occupation' 'Channel_Code' 'Vintag
e'
```

```
'Credit_Product' 'Avg_Account_Balance' 'Is_Active' 'Is_Lead']
```

In [230…

```
duplicated_rows=sum(train_df.duplicated(subset=['Gender', 'Age', 'Region_Code', 'Occupa
       '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 column groups::  21
```

In [231…

```
# Deleting duplicates rows
train_df.drop_duplicates(subset=['Gender', 'Age', 'Region_Code', 'Occupation', 'Channel
       'Vintage', 'Credit_Product', 'Avg_Account_Balance', 'Is_Active','Is_Lead'],keep=
```

In [232…

```
#  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
```

In [7]:

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

Out[7]:

```
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

In [8]:
```
#trying to find pattern how can we fill NaN values
train_df[train_df["Credit_Product"].isna()].head()
```

Out[8]:

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

In [9]:
```
train_df[train_df['Credit_Product']=="Yes"].head()
```

Out[9]:

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

In [10]:
```
train_df[train_df['Credit_Product']=="No"].head()
```

Out[10]:

	ID	Gender	Age	Region_Code	Occupation	Channel_Code	Vintage	Credit_Product	Avg_
0	NNVBBKZB	Female	73	RG268	Other	X3	43	No	
1	IDD62UNG	Female	30	RG277	Salaried	X1	32	No	
2	HD3DSEMC	Female	56	RG268	Self_Employed	X3	26	No	
3	BF3NC7KV	Male	34	RG270	Salaried	X1	19	No	
4	TEASRWXV	Female	30	RG282	Salaried	X1	33	No	

In [11]:
```
#Let see value count
train_df['Credit_Product'].value_counts(normalize=True)
```

Out[11]:
```
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

Exploratory Data Analysis [EDA]

Balanced or Imbalanced Dataset

In [12]:
```
train_df.Is_Lead.value_counts(normalize=True)
```

Out[12]:
```
0    0.762771
1    0.237229
Name: Is_Lead, dtype: float64
```

Observation

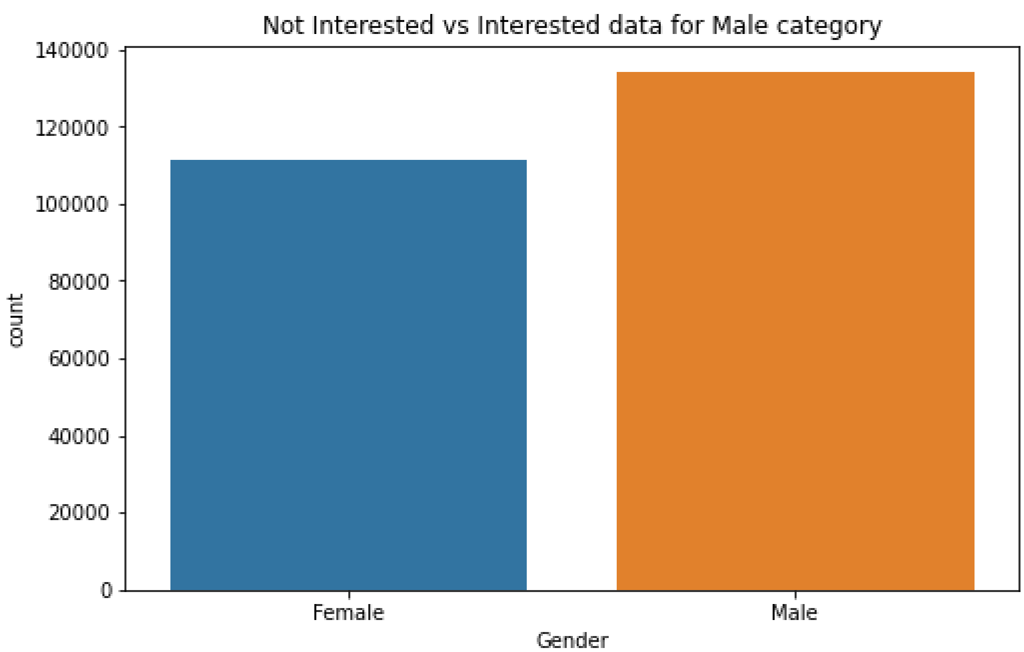
- It's Imbalanced Dataset so we can try SMOTE technique as Over sampling.
- Or we can try class_weight parameter in models

Gender Feature Analysis

In [233…
```
# Gender Feature distribution
print("{}% of Male data present in this dataset.".format(round(train_df["Gender"].value
print("{}% of Female data present in this dataset.".format(round(train_df["Gender"].val
```

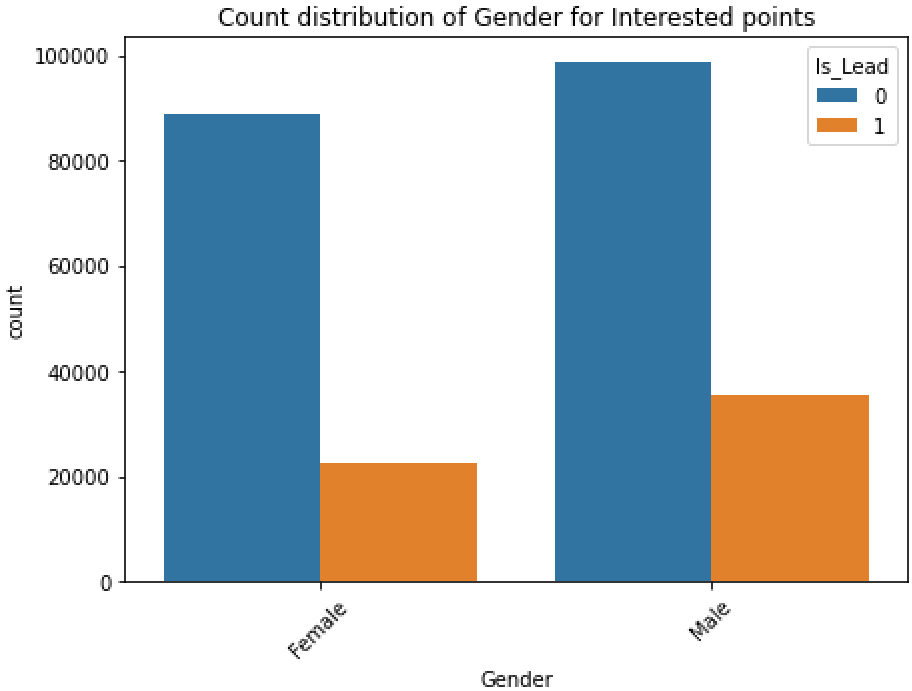
```
55% of Male data present in this dataset.
45% of Female data present in this dataset.
```

In [234…
```
plt.figure(figsize=(8,5))
plt.title("Not Interested vs Interested data for Male category")
sns.countplot(train_df["Gender"])
plt.show()
```



In [237…

```
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()
```



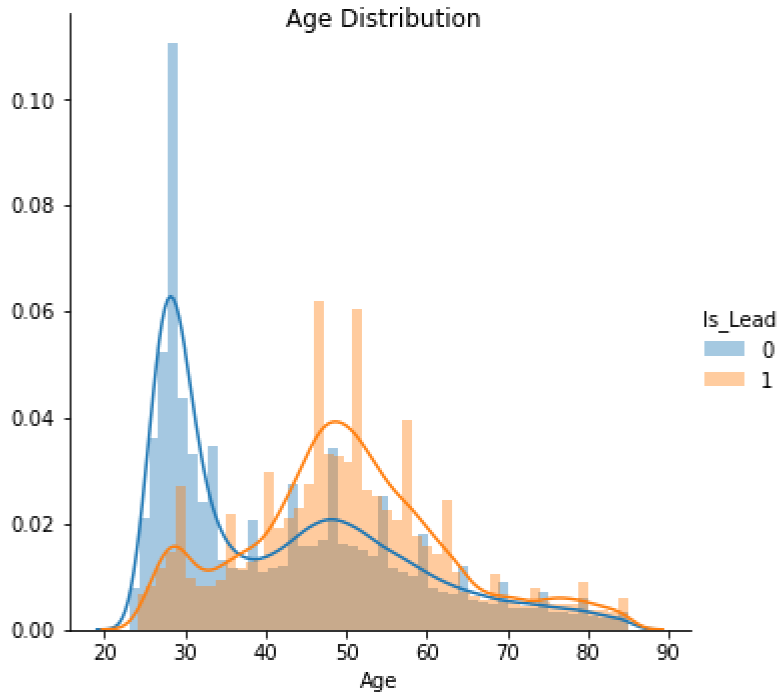
Observation

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

Age Feature Analysis

In [18]:

```
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.

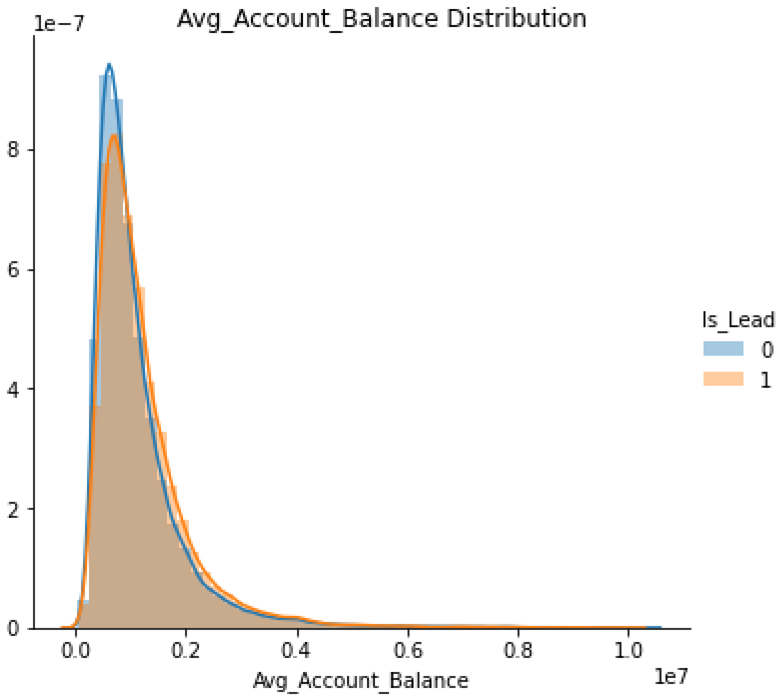
Convert to category

- 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'

Avg_Account_Balance Feature Analysis

In [238...

```
g=sns.FacetGrid(train_df,height=5,hue="Is_Lead").map(sns.distplot,"Avg_Account_Balance"
g.fig.suptitle("Avg_Account_Balance Distribution")
plt.show()
```

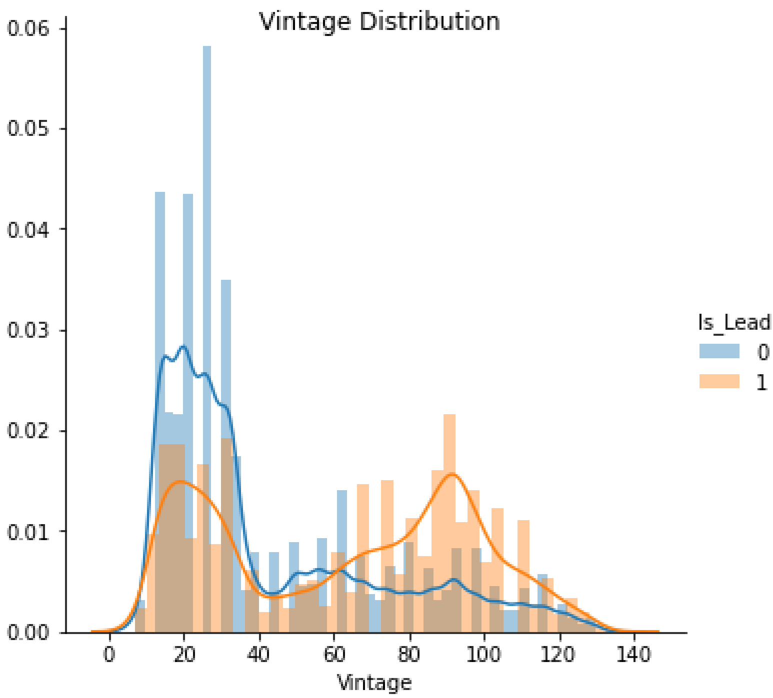


Observation:

- 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.

Vintage Feature Analysis

In [20]:
```
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

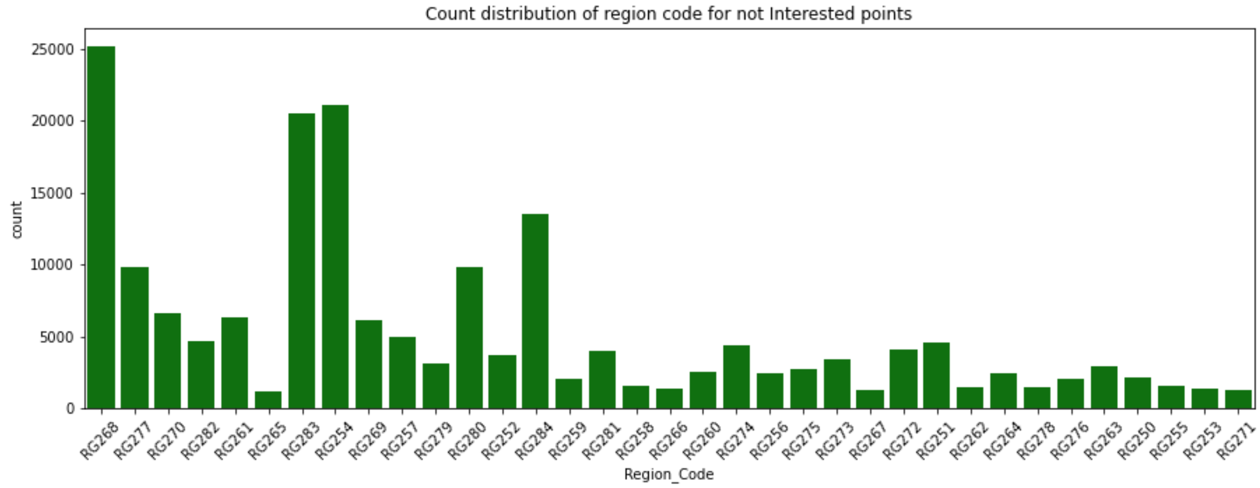
- based on above analogy, this feature will be converted into category with below strategy.
- 0-40='vint_g1',40-60='vint_g2',60-80='vint_g3',80-100='vint_g4',100-120='vint_g5',120-above='vint_g6']

Region_Code feature

In [239…
```
print("Number of Unique Region_Code :",len(train_df['Region_Code'].unique()))
```

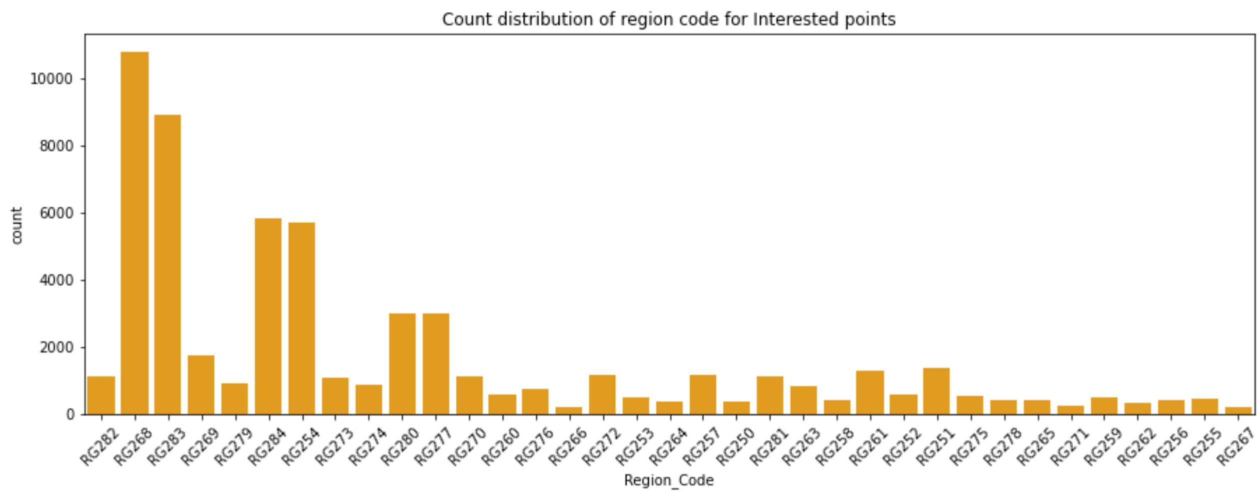
```
Number of Unique Region_Code : 35
```

In [240…
```
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()
```



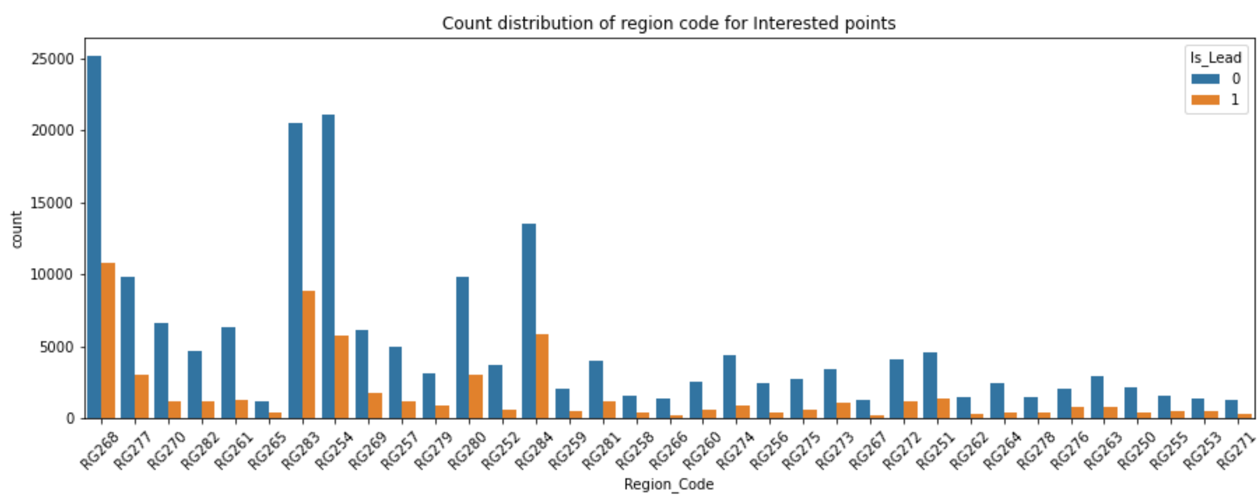
In [241…

```
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()
```

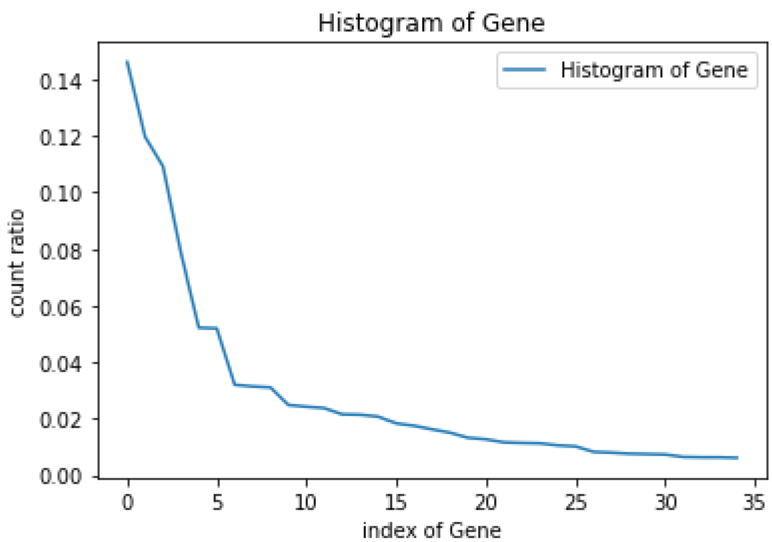


In [242…

```
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()
```



In [25]:
```
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.

In [244…
```
#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
```

Occupation Analysis

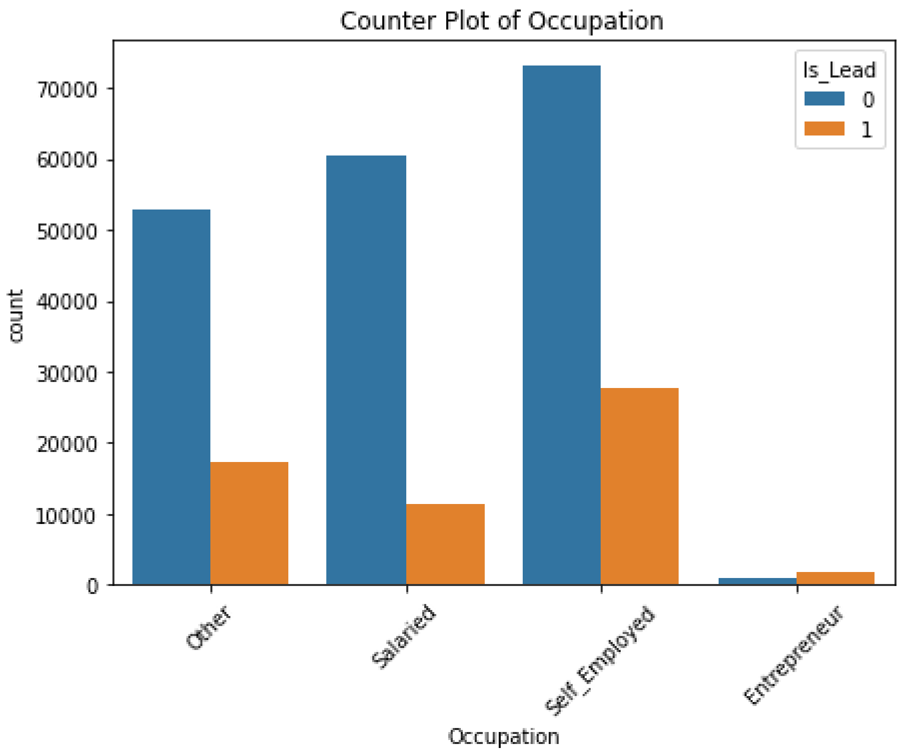
In [249…
```
train_df.Occupation.value_counts(normalize=True)
```

Out[249…
```
Self_Employed    0.410583
Salaried         0.292970
Other            0.285592
Entrepreneur     0.010855
Name: Occupation, dtype: float64
```

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

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

In [247…
```
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

Channel_Code Analysis

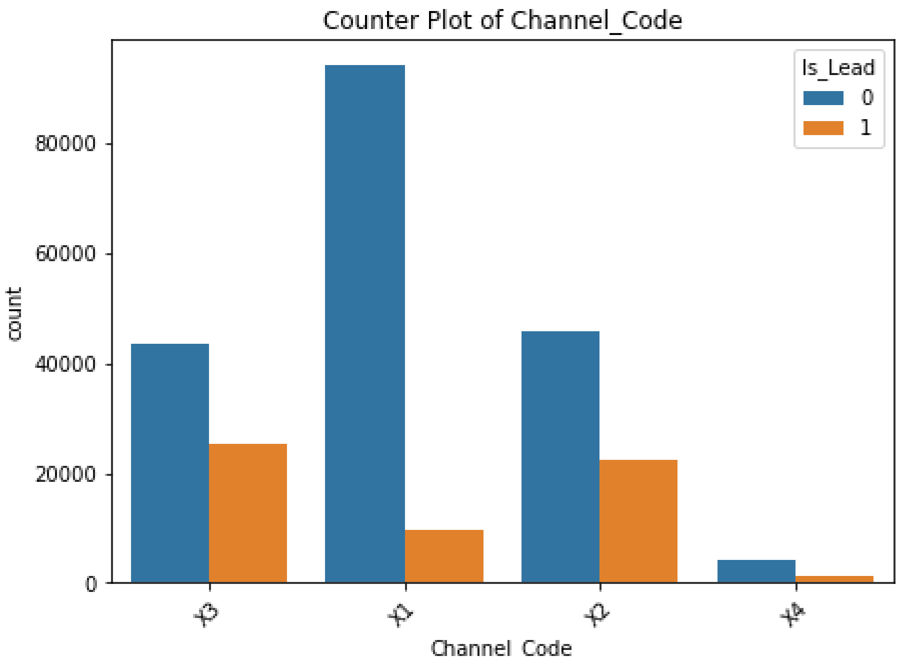
In [29]:
```
print("Number of Unique Region_Code :",len(train_df['Channel_Code'].unique()))
```

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

In [250…
```
train_df.Channel_Code.value_counts(normalize=True)
```

Out[250…
```
X1    0.422061
X3    0.279645
X2    0.275628
X4    0.022665
Name: Channel_Code, dtype: float64
```

In [248…
```
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

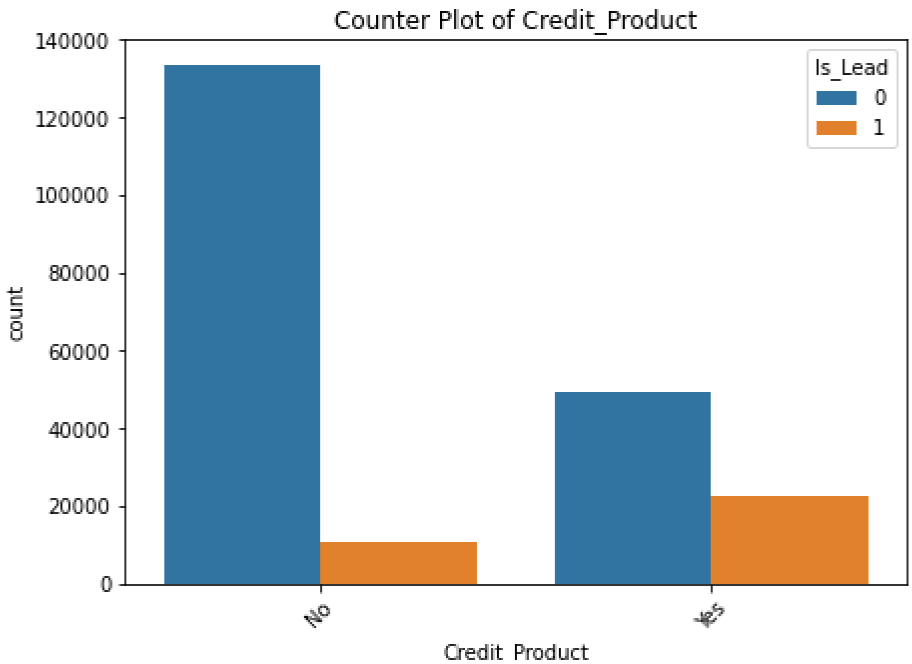
- We have very less data points for category X4.It's around 2 % of whole data.
- users who belongs to X1 channel are more likely to "Not interested" for credit card over "interested" X1 Channel

Credit_Product analysis

In [31]:
```
print("Number of Unique Region_Code :",len(train_df['Credit_Product'].unique()))
```

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

In [251…
```
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:

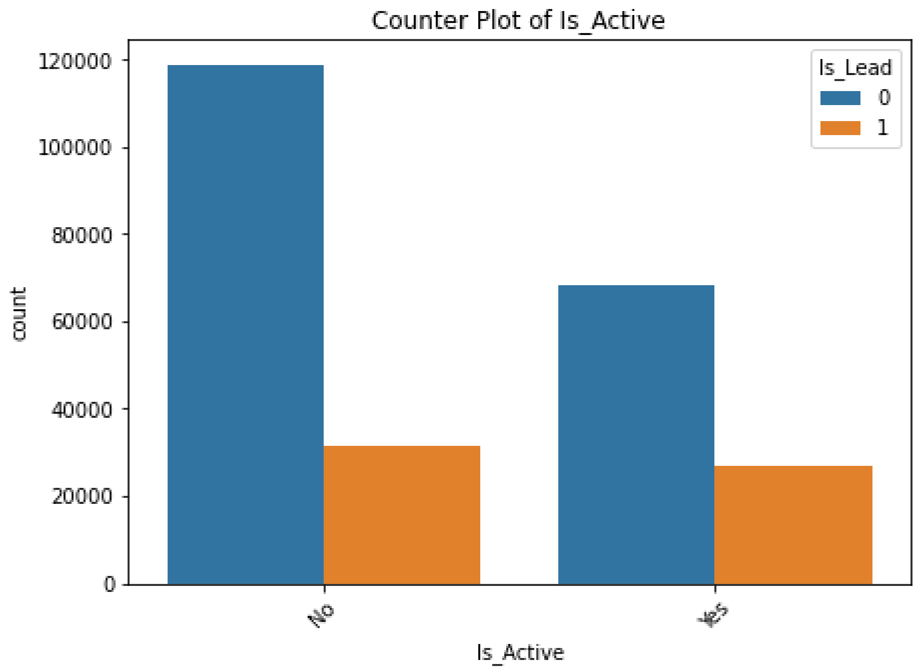
- There are two categories for credit product ("Yes" and "No") along with some missing value
- so for filling missing data points, we will consider third category which will be NaN.
- user who have any active product(like Home Loan) are more likely to "Interested" for credit card rather than who have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

Is_Active analysis

In [33]:
```
print("Number of Unique Region_Code :",len(train_df['Is_Active'].unique()))
```

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

In [252…
```
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.

Preparing Data

In [253…

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

Out[253…

```
Yes     22690
No      10623
Name: Credit_Product, dtype: int64
```

In [36]:

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

Out[36]:

```
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

In [257…

```
# 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_grp
    #Converted Vintage into category feature
    data["Vint_group"]=pd.cut(data.Vintage,bins=[0,40,60,80,100,120,200],labels=['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"
    data["age_credit"]=[temp[0]+"_"+temp[1] for temp in data[["Age_group","Credit_Produ
```

```
    data["region_credit"]=[temp[0]+"_"+temp[1] for temp in data[["Region_Code","Credit_

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

In [256…

```
#Preprocessing training data
train_df=preprocessed_data(train_df)
train_df.head()
```

Out[256…

	ID	Gender	Region_Code	Occupation	Channel_Code	Credit_Product	Avg_Account_Balanc
0	NNVBBKZB	Female	RG268	Other	X3	No	104569
1	IDD62UNG	Female	RG277	Salaried	X1	No	58198
2	HD3DSEMC	Female	RG268	Self_Employed	X3	No	148431
3	BF3NC7KV	Male	RG270	Salaried	X1	No	47045
4	TEASRWXV	Female	RG282	Salaried	X1	No	88678

In [258…

```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 245725 entries, 0 to 245724
Data columns (total 14 columns):
 #   Column               Non-Null Count   Dtype   
---  ------               --------------   -----   
 0   ID                   245725 non-null  object  
 1   Gender               245725 non-null  object  
 2   Region_Code          245725 non-null  object  
 3   Occupation           245725 non-null  object  
 4   Channel_Code         245725 non-null  object  
 5   Credit_Product       245725 non-null  object  
 6   Avg_Account_Balance  245725 non-null  int64   
 7   Is_Active            245725 non-null  object  
 8   Is_Lead              245725 non-null  int64   
 9   Age_group            245725 non-null  category
 10  Vint_group           245725 non-null  category
 11  age_vintage          245725 non-null  object  
 12  age_credit           245725 non-null  object  
 13  region_credit        245725 non-null  object  
dtypes: category(2), int64(2), object(10)
memory usage: 23.0+ MB
```

In [261…

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

In [ ]:

```

```

Split into Train and CV data

In [262…

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.25,stratify=y,ran
```

In [263…

```
# X_train=X
# y_train=y
```

In [264...
```
#Creating List of columns of all category features
category_var=list(X_train.select_dtypes(include=["object","category"]).columns.values)
```

In [267...
```
#Fitting Encoder and Normalizer so that we can use it to transform train, cv and test d
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))
```

Out[267... Normalizer()

In [268...
```
## Making list of All features
features_name=list(encoder.get_feature_names())
features_name.append("Avg_Account_Balance")
```

In [269...
```
# create a function to convert cotegory data to vector and Normalized the continuous va
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
```

In [270...
```
X_train=encode_dataset(X_train)
X_test=encode_dataset(X_test)
```

```
data shape:  (184293, 189)
data shape:  (61432, 189)
```

In [271...
```
print("X_train shape:",X_train.shape)
print("X_test shape:",X_test.shape)
```

```
X_train shape: (184293, 189)
X_test shape: (61432, 189)
```

In [273...
```
#define a function which helps to preprocess ,feature engineering and encode into vecto
def preprocess_and_encode_test_data(data):
    data=preprocessed_data(data)
    data=encode_dataset(data)
    return data
```

Model Training

Random Forest Classifier

In [274...
```
#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
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  20 out of  20 | elapsed:  3.9min finished
```

Out[274…
```
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)
```

In [169…
```
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_job
model.fit(X_train,y_train)
```

```
Tunned Parameter of RF: {'n_estimators': 120}
```

Out[169…
```
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=120,
                       n_jobs=-1)
```

Top 50 Feature (Featuere_Important)

In [172…
```
## 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]
```

In [173…
```
print("#"*10,"Top Features","#"*10)
print(important_feature)
```

```
########## Top Features ##########
['x4_No', 'x9_age_grp1_No', 'x9_age_grp3_Nan', 'x7_vint_g4', 'x9_age_grp2_Nan', 'x6_age_
grp3', 'x3_X3', 'x9_age_grp3_No', 'x4_Yes', 'x10_RG268_Nan', 'x8_age_grp3_vint_g4', 'x3_
X2', 'x10_RG283_Nan', 'x9_age_grp2_No', 'x2_Salaried', 'x9_age_grp3_Yes', 'x9_age_grp4_N
an', 'x9_age_grp1_Yes', 'x5_Yes', 'x10_RG268_No', 'x10_RG284_Nan', 'x10_RG254_No', 'x6_a
ge_grp2', 'x10_RG283_No', 'x9_age_grp4_No', 'x9_age_grp2_Yes', 'x10_RG254_Nan', 'x2_Self
_Employed', 'x7_vint_g3', 'x7_vint_g5', 'x7_vint_g2', 'x8_age_grp4_vint_g4', 'x8_age_grp
3_vint_g5', 'x8_age_grp3_vint_g2', 'x10_RG284_No', 'x6_age_grp4', 'x8_age_grp3_vint_g3',
'x0_Male', 'x2_Other', 'x8_age_grp2_vint_g1', 'x10_RG280_Nan', 'x10_RG277_Nan', 'x10_RG2
77_No', 'x8_age_grp3_vint_g1', 'x9_age_grp4_Yes', 'x10_RG270_No', 'x10_RG283_Yes', 'x8_a
ge_grp2_vint_g4', 'x10_RG268_Yes', 'x1_RG268']
```

In [174…
```
#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

In [175…
```
model=RandomForestClassifier(max_depth=10
                   ,n_estimators=rf_param["n_estimators"],class_weight="balanced",n_job
model.fit(X_train,y_train)
```

Out[175…
```
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=120,
                       n_jobs=-1)
```

In [176…
```
#AUC on training data
pred=model.predict_proba(X_train)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8674998275134347
```

In [98]:
```
#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: 0.867739274152137
```

2. RandomForestClassifier on Top 50 features

In [177…
```
model=RandomForestClassifier(max_depth=10
                   ,n_estimators=rf_param["n_estimators"],class_weight="balanced",n_job
model.fit(X_train_imp,y_train)
```

Out[177…
```
RandomForestClassifier(class_weight='balanced', max_depth=10, n_estimators=120,
                       n_jobs=-1)
```

In [178…
```
#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: 0.8729368263767127
```

In [179…
```
#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: 0.8651157851709363
```

In [ ]:

SGDClassifier

In [180…
```
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
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  60 out of  60 | elapsed:   23.0s finished
```

Out[180…
```
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)
```

In [181…
```
sgd_param=clf.best_params_
sgd_param
```

Out[181…
```
{'alpha': 0.001, 'penalty': 'l2'}
```

1. SGDClassifier on All features

In [182…
```
model=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sg
model.fit(X_train,y_train)
```

Out[182…
```
SGDClassifier(alpha=0.001, class_weight='balanced', loss='log')
```

In [183…
```
#AUC on training data
pred=model.predict_proba(X_train)
auc=roc_auc_score(y_train,pred[:, 1])
print("Train AUC:",auc)
```

```
Train AUC: 0.8664527422385417
```

In [184…
```
#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: 0.8616602297637795
```

2. SGDClassifier on Top 50 features

In [185…
```
model=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sg
model.fit(X_train_imp,y_train)
```

Out[185…
```
SGDClassifier(alpha=0.001, class_weight='balanced', loss='log')
```

In [186…
```
#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: 0.8651969040570424
```

In [109…
```
#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: 0.8683482910706739
```

XGBOOST Classifier

In [110…
```
#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_dept

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
[Parallel(n_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.
[Parallel(n_jobs=1)]: Done  30 out of  30 | elapsed:  1.4min finished
```

Out[110…
```
GridSearchCV(estimator=XGBClassifier(base_score=None, booster=None,
                                     colsample_bylevel=None,
                                     colsample_bynode=None,
                                     colsample_bytree=None,
                                     eval_metric='logloss', gamma=None,
                                     gpu_id=None, importance_type='gain',
                                     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, 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)
```

In [111…

```
xgb_param=clf.best_params_
xgb_param
```

Out[111…

```
{'n_estimators': 100, 'reg_lambda': 0.05}
```

1. XGBClassifier on all Features

In [112…

```
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)
```

Out[112…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='logloss',
              gamma=0, gpu_id=-1, importance_type='gain',
              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=8,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=0.05,
              scale_pos_weight=1, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

In [113…

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

```
Train AUC: 0.8730037111540334
```

In [114…

```
#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: 0.8757950601654328
```

2. XGBClassifier on Top 50 Features

In [115…

```
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)
```

Out[115…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='logloss',
              gamma=0, gpu_id=-1, importance_type='gain',
              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=8,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=0.05,
              scale_pos_weight=1, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

In [116…

```
#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: 0.8726602517415849
```

In [117…

```
#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: 0.8761084355851041
```

StackingClassifier

1. StackingClassifier on all features

In [118…

```
# 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_la
clf2=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sgd

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

Out[118…

```
StackingClassifier(estimators=[('xgb',
                                XGBClassifier(base_score=None, booster=None,
                                              colsample_bylevel=None,
                                              colsample_bynode=None,
                                              colsample_bytree=None,
                                              eval_metric='auc', gamma=None,
                                              gpu_id=None,
                                              importance_type='gain',
                                              interaction_constraints=None,
                                              learning_rate=0.1,
                                              max_delta_step=None, max_depth=5,
                                              min_child_weight=None,
                                              missing=nan,
                                              monotone_constraints=None...
                                              num_parallel_tree=None,
                                              random_state=None, reg_alpha=None,
                                              reg_lambda=0.05,
                                              scale_pos_weight=None,
                                              subsample=None, tree_method=None,
                                              validate_parameters=None,
                                              verbosity=None)),
                               ('sgd',
                                SGDClassifier(class_weight='balanced',
                                              loss='log', penalty='l1')),
                               ('rf',
                                RandomForestClassifier(class_weight='balanced',
                                                       max_depth=10,
                                                       n_jobs=-1))],
                   final_estimator=LogisticRegression())
```

In [119…

```
#AUC on training data
pred=model.predict_proba(X_train)
```

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

Train AUC: 0.8717663142973169

In [120…

```
#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: 0.8746653993785285

2. StackingClassifier on Top 50 Features

In [121…

```
# 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_la
clf2=SGDClassifier(loss="log",class_weight="balanced",learning_rate="optimal",alpha=sgd

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_estim
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)
```

Out[121…

```
StackingClassifier(estimators=[('xgb',
                                XGBClassifier(base_score=None, booster=None,
                                              colsample_bylevel=None,
                                              colsample_bynode=None,
                                              colsample_bytree=None,
                                              eval_metric='auc', gamma=None,
                                              gpu_id=None,
                                              importance_type='gain',
                                              interaction_constraints=None,
                                              learning_rate=0.1,
                                              max_delta_step=None, max_depth=5,
                                              min_child_weight=None,
                                              missing=nan,
                                              monotone_constraints=None...
                                              num_parallel_tree=None,
                                              random_state=None, reg_alpha=None,
                                              reg_lambda=0.05,
                                              scale_pos_weight=None,
                                              subsample=None, tree_method=None,
                                              validate_parameters=None,
                                              verbosity=None)),
                               ('sgd',
                                SGDClassifier(class_weight='balanced',
                                              loss='log', penalty='l1')),
                               ('rf',
                                RandomForestClassifier(class_weight='balanced',
                                                       max_depth=10,
                                                       n_jobs=-1))],
                   final_estimator=LogisticRegression())
```

In [122…

```
#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: 0.8722698481124256

In [123…
```
#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: 0.8750227621562479
```

Sequencial Model (ANN)

In [673…
```
X_train.shape[1]
```

Out[673… 189

In [124…
```
model=Sequential()
model.add(Input(shape=(50,)))
model.add(Dense(16,activation="relu"))
model.add(Dropout(0.2))
model.add(Dense(8,activation="relu"))
# model.add(Dropout(0.2))
model.add(Dense(1,activation="sigmoid"))

callback = tf.keras.callbacks.EarlyStopping(monitor='loss', patience=2)
model.compile(optimizer='adam',
              loss=tf.keras.losses.binary_crossentropy,
              metrics=[tf.keras.metrics.AUC()])
```

In [125…
```
model.fit(X_train_imp,y_train,batch_size=512,validation_data=(X_test_imp,y_test),epochs
```

```
Epoch 1/20
360/360 [==============================] - 3s 6ms/step - loss: 0.4925 - auc: 0.7371 - va
l_loss: 0.3594 - val_auc: 0.8678
Epoch 2/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3851 - auc: 0.8478 - va
l_loss: 0.3541 - val_auc: 0.8709
Epoch 3/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3751 - auc: 0.8523 - va
l_loss: 0.3514 - val_auc: 0.8720
Epoch 4/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3718 - auc: 0.8547 - va
l_loss: 0.3498 - val_auc: 0.8729
Epoch 5/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3695 - auc: 0.8561 - va
l_loss: 0.3493 - val_auc: 0.8735
Epoch 6/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3655 - auc: 0.8584 - va
l_loss: 0.3486 - val_auc: 0.8737
Epoch 7/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3673 - auc: 0.8594 - va
l_loss: 0.3477 - val_auc: 0.8742
Epoch 8/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3646 - auc: 0.8598 - va
l_loss: 0.3475 - val_auc: 0.8747
Epoch 9/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3666 - auc: 0.8581 - va
l_loss: 0.3474 - val_auc: 0.8747
Epoch 10/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3635 - auc: 0.8610 - va
l_loss: 0.3471 - val_auc: 0.8750
Epoch 11/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3665 - auc: 0.8598 - va
l_loss: 0.3468 - val_auc: 0.8749
```

```
Epoch 12/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3643 - auc: 0.8599 - va
l_loss: 0.3465 - val_auc: 0.8748
Epoch 13/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3643 - auc: 0.8608 - va
l_loss: 0.3466 - val_auc: 0.8750
Epoch 14/20
360/360 [==============================] - 2s 5ms/step - loss: 0.3629 - auc: 0.8612 - va
l_loss: 0.3463 - val_auc: 0.8752
```

Out[125…

```
<tensorflow.python.keras.callbacks.History at 0x1c6e3f171c0>
```

In [137…

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

```
Train AUC: 0.8752110745893438
```

Summary

In [275…

```python
from tabulate import tabulate
columns=["Model","Top_50 or All","Train auc","CV auc"]
summary=[["RandomForestClassifier","All",0.86610,0.86517],
         ["RandomForestClassifier","Top_50",0.87158,0.86882],
         ["XGBClassifier","All",0.87428,0.87251],
         ["XGBClassifier","Top_50",0.87283,0.87205],
         ["SGDClassifier","All",0.86512,0.86570],
         ["SGDClassifier","Top_50",0.86374,0.86484],
         ["StackingClassifier","All",0.87278,0.87173],
         ["StackingClassifier","Top_50",0.87376,0.87193],
         ["ANN Sequencial Model","Top_50",0.8612,0.87521],
        ]
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             |     0.8661  |  0.86517 |
|  1 | RandomForestClassifier | Top_50          |     0.87158 |  0.86882 |
|  2 | XGBClassifier          | All             |     0.87428 |  0.87251 |
|  3 | XGBClassifier          | Top_50          |     0.87283 |  0.87205 |
|  4 | SGDClassifier          | All             |     0.86512 |  0.8657  |
|  5 | SGDClassifier          | Top_50          |     0.86374 |  0.86484 |
|  6 | StackingClassifier     | All             |     0.87278 |  0.87173 |
|  7 | StackingClassifier     | Top_50          |     0.87376 |  0.87193 |
|  8 | ANN Sequencial Model   | Top_50          |     0.8612  |  0.87521 |
+----+------------------------+-----------------+-------------+----------+
```

Conclution

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

Best Model

In [284…

```python
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)
```

Out[284…

```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, eval_metric='logloss',
              gamma=0, gpu_id=-1, importance_type='gain',
              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=8,
              num_parallel_tree=1, random_state=0, reg_alpha=0, reg_lambda=0.05,
              scale_pos_weight=1, subsample=1, tree_method='exact',
              validate_parameters=1, verbosity=None)
```

In [285…

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

```
CV AUC: 0.8752815335896964
```

Creating Submission File

In [286…

```
#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)
```

In [287…

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

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

In [288…

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

In [216…

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

In [217…

```
test_data.to_csv("output/final_submission.csv",index=False)
```

In [ ]: