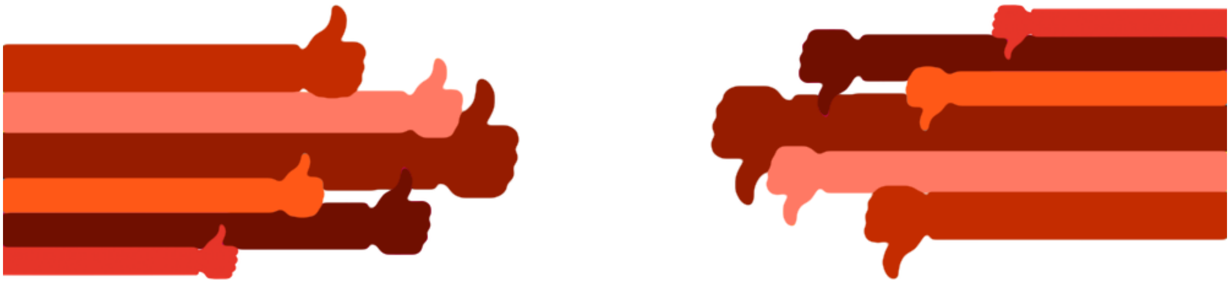
Santander Customer Satisfaction:

In [ ]:

Out[ ]:



Introduction:

Santander Bank is a retail banking company, meant for providing banking services to the general public. Customer satisfaction is of utmost priority for any business and it is very important for a bank to identify all the unsatisfied customers so that management can take care of their needs and prevent them from leaving the bank. But the problem lies in identification of these unsatisfied customers because the unsatisfied customers don't express their reason of dissatisfaction with the bank directly. In addition to that it is just not possible for banking management to identify unsatisfied customers by just looking at their banking records because it is very difficult for a human being to identify a pattern from so many variables present in the customer's banking record. Also doing that is not possible for each customer as the number of customers is very high.

So for the given problem employing a machine learning model is the only solution by which unsatisfied customers can be identified in very less time. Using Machine Learning, a model can be created that can identify unsatisfied customers. After which the bank can directly approach those customers and resolve their issue or take appropriate action like offering them exclusive offers to prevent the customer from leaving the bank.

Data Analysis:

All relevant data can be obtained from the following link:

https://www.kaggle.com/c/santander-customer-satisfaction/data

Brief Description of dataset:

For the dataset we are given, each row represents a customer. We are given two datasets 'train.csv' and 'test.csv' with 371 and 370 features respectively. Since it is a competition only train dataset has an extra column called 'TARGET' which isn't present in test dataset. 'TARGET' column show's customer's satisfaction. Value '0' in TARGET column means the customer is satisfied, value '1' means customer is unsatisfied. Column names don't really convey a meaning about what they represent, maybe the column names are renamed on purpose for security/privacy reasons. Data is highly unbalanced with only 3.957% belonging to class '1' that is unsatisfied customers.

Importing Packages

In [ ]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [ ]:

```
train_df= pd.read_csv("train.csv")
test_df= pd.read_csv("test.csv")
```

In [ ]:

```
train_df
```

Out[ ]:

	ID	var3	var15	imp_ent_var16_ult1	imp_op_var39_comer_ult1	imp_op_var39_comer_u
0	1	2	23	0.0	0.0	
1	3	2	34	0.0	0.0	
2	4	2	23	0.0	0.0	
3	8	2	37	0.0	195.0	19
4	10	2	39	0.0	0.0	
...	...	...	...	...	...	
76015	151829	2	48	0.0	0.0	
76016	151830	2	39	0.0	0.0	
76017	151835	2	23	0.0	0.0	
76018	151836	2	25	0.0	0.0	
76019	151838	2	46	0.0	0.0	

76020 rows × 371 columns

In [ ]:

```
test_df
```

Out[ ]:

	ID	var3	var15	imp_ent_var16_ult1	imp_op_var39_comer_ult1	imp_op_var39_comer_u
0	2	2	32	0.0	0.0	
1	5	2	35	0.0	0.0	
2	6	2	23	0.0	0.0	
3	7	2	24	0.0	0.0	
4	9	2	23	0.0	0.0	
...	...	...	...	...	...	
75813	151831	2	23	0.0	0.0	
75814	151832	2	26	0.0	0.0	
75815	151833	2	24	0.0	0.0	
75816	151834	2	40	0.0	0.0	
75817	151837	2	23	0.0	0.0	

75818 rows × 370 columns

In [ ]:

```
train_id= train_df['ID']
test_id= test_df['ID']

train_df.drop(['ID'], axis=1, inplace= True)
test_df.drop(['ID'], axis=1, inplace= True)
```

In [ ]:

```
y_train= train_df['TARGET']
train_df= train_df.drop('TARGET', axis=1)
```

Exploratory data analysis (EDA)

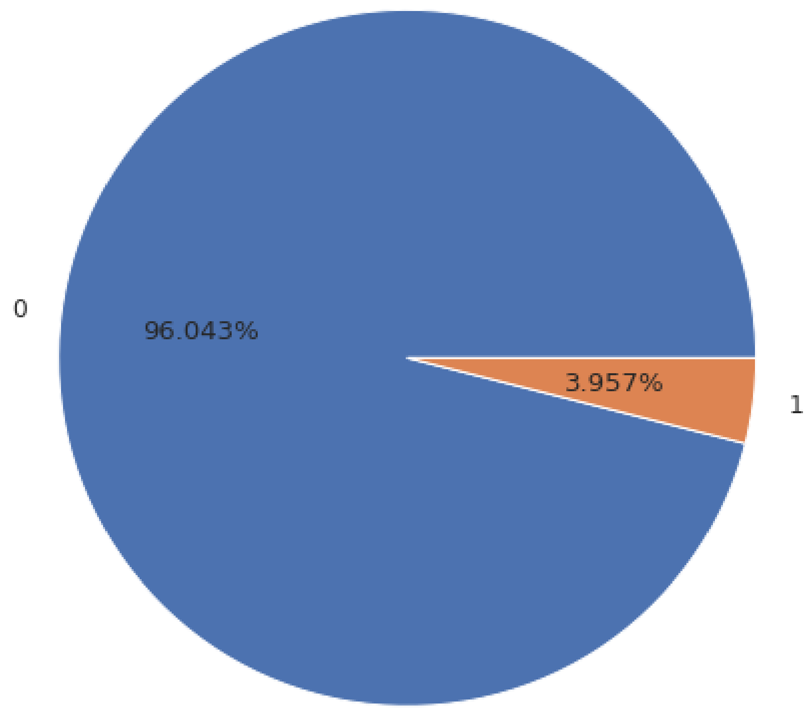
Checking class imbalance if any:

In [ ]:

```
zero= train_df['TARGET'].value_counts()[0]
one= train_df['TARGET'].value_counts()[1]
my_labels=[0,1]
plt.rcParams["figure.figsize"] = (8,8)

plt.pie([zero,one], labels= my_labels, autopct='%1.3f%%')
plt.show()

print("Number of Positive data points are: {}  ({:.3f}{})".format(one, one/(c
print("Number of Negative data points are: {} ({:.3f}{})".format(zero, zero/(
```




```
Number of Positive data points are: 3008  (3.957%)
Number of Negative data points are: 73012 (96.043%)
```

As we can see from the pie chart above that this is very highly imbalanced dataset. We can see in above plot that there are 3.95% TARGET label which are '0' i.e those customers who are unsatisfied from the bank. To compensate this data imbalance we can use SMOTE to oversample and balance this dataset.

Checking for null values and infinity values:

In [ ]:

```
print("Number of Null values {}".format(train_df.isnull().sum().sum()))
print("Number of Infinite values {}".format(train_df.isin([np.inf, -np.inf]).
```

```
Number of Null values 0
Number of Infinite values 0
```

Great! There are No null or infinite values in our dataset.

Now lets look at Constant, Quassi constant and Sparse features:

Presence of constant features:

In [ ]:

```
from sklearn.feature_selection import VarianceThreshold

vt= VarianceThreshold(threshold= 0) #threshold: features with set-variance 0
vt.fit(train_df)
const_feat= [x for x in train_df.columns if (x !='TAREGT') and (x not in trai
print("There are {} constant features".format(len(const_feat)))
```

```
There are 34 constant features
```

Presence Quassi constant features:

In [ ]:

```
from sklearn.feature_selection import VarianceThreshold
vt= VarianceThreshold(threshold= 0.02) #threshold: features with set-variance
vt.fit(train_df)

quasi_const_feat= [x for x in train_df.columns if ((x!='TARGET') and (x not i

print("There are {} quassi-constant features".format(len(quasi_const_feat)))
```

```
There are 106 quassi-constant features
```

Identifying Sparse features:

In [ ]:

```
zeros= (train_df == 0).astype(int).sum()
not_zeros= (train_df != 0).astype(int).sum()

sparse_columns=[]

for i in range(len(train_df.columns)):
  if (zeros[i]/(zeros[i]+not_zeros[i])) > 0.998:
    sparse_columns.append(train_df.columns[i])
print("There are {} sparse features".format(len(sparse_columns)))
```

```
There are 177 sparse features
```

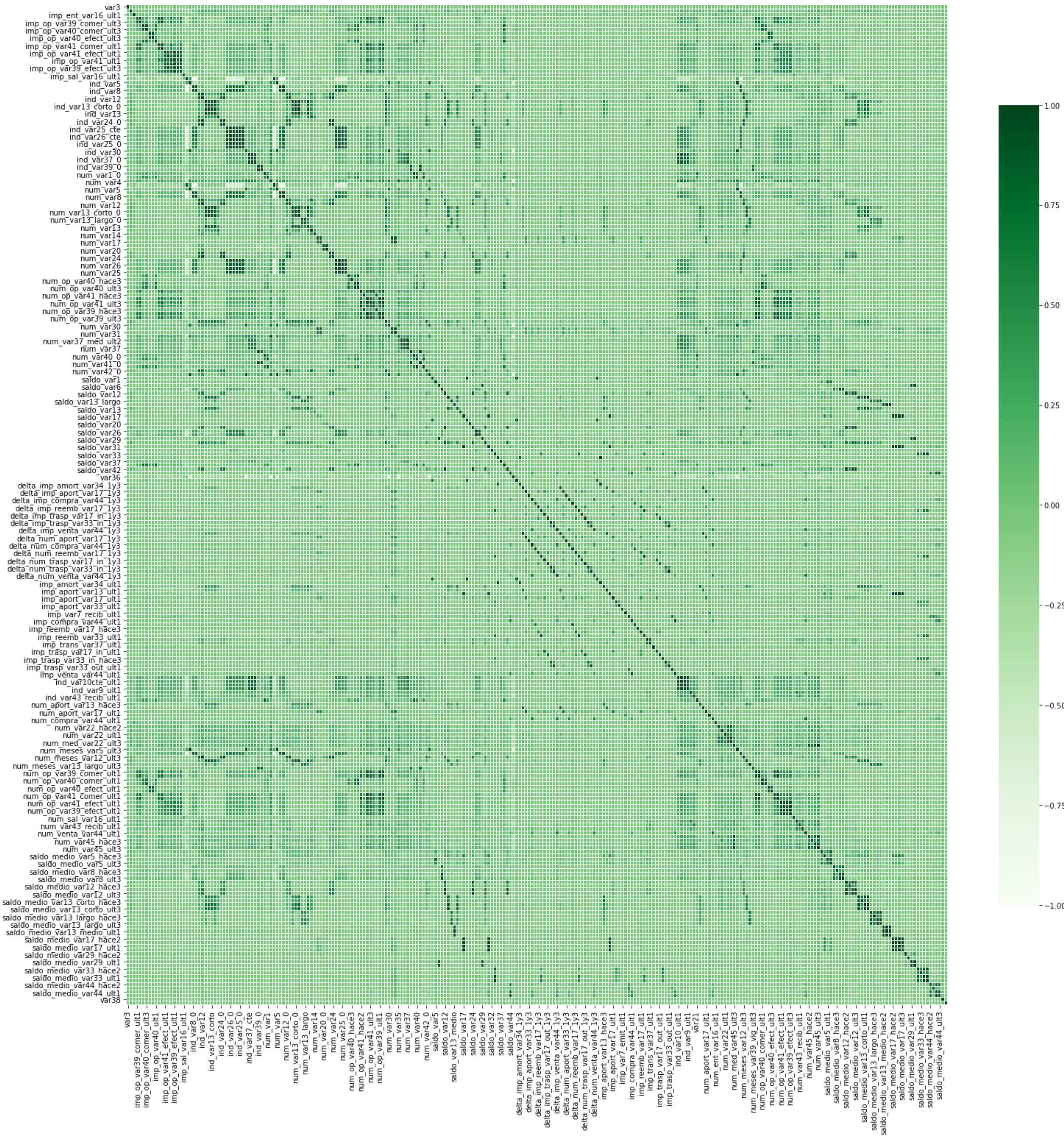
Correlations of features with heatmap:

In [ ]:

```
fig, ax_1 = plt.subplots(figsize=(25, 25))
```

```
# plot heatmap
sns.heatmap(train_df.corr(), vmin= -1, vmax=1.00,
            linewidth=0.01,cmap="Greens", cbar_kws={"shrink": .8}, ax=ax_1)

plt.show()
```



Above heatmap shows that there are features which are correlated. Correlated features are similar and don't really help in classification. That means we later on while data preprocessing we need to remove these correlated features.

Based on various thresholds selected above, our dataset has:

- 34 Constant features
- 106 quassi constant features
- 117 sparse features
- Lots of correlated features

Later on we will remove the above features as they are less likely to contribute in classification process

Lets look at the description of dataset:

In [ ]:
```
train_df.describe()
```

Out[ ]:

	var3	var15	imp_ent_var16_ult1	imp_op_var39_comer_ult1	imp_op_var39_
count	76020.000000	76020.000000	76020.000000	76020.000000	7
mean	-1523.199277	33.212865	86.208265	72.363067	
std	39033.462364	12.956486	1614.757313	339.315831	
min	-999999.000000	5.000000	0.000000	0.000000	
25%	2.000000	23.000000	0.000000	0.000000	
50%	2.000000	28.000000	0.000000	0.000000	
75%	2.000000	40.000000	0.000000	0.000000	
max	238.000000	105.000000	210000.000000	12888.030000	2

8 rows × 370 columns

Correlation between continuos and categorical features

In [ ]:
```
from scipy import stats

F,p= stats.f_oneway(train_df[train_df.TARGET==1].var15,
                    train_df[train_df.TARGET==0].var15)

F,p
```

Out[ ]:
```
(788.5084933218477, 1.3022841332153018e-172)
```

Univariate Analysis:

Analysing feature 'var15'

We can see in the description of dataset above particularly at column 'var15' which has minimum value 5 and maximum value 105. We should take a close look at this feature which according to some literature surveys can be age, and also considered an important feature, so if we can find any pattern in distribution of this feature then later we can use this feature in feature engineering.

In [ ]:
```
np.sort(pd.unique(train_df['var15']))
```

Out[ ]:
```
array([  5,   6,   7,   8,   9,  10,  11,  12,  13,  14,  15,  16,  17,
        18,  19,  20,  21,  22,  23,  24,  25,  26,  27,  28,  29,  30,
        31,  32,  33,  34,  35,  36,  37,  38,  39,  40,  41,  42,  43,
        44,  45,  46,  47,  48,  49,  50,  51,  52,  53,  54,  55,  56,
        57,  58,  59,  60,  61,  62,  63,  64,  65,  66,  67,  68,  69,
        70,  71,  72,  73,  74,  75,  76,  77,  78,  79,  80,  81,  82,
        83,  84,  85,  86,  87,  88,  89,  90,  91,  92,  93,  94,  95,
        96,  97,  98,  99, 100, 101, 102, 104, 105])
```

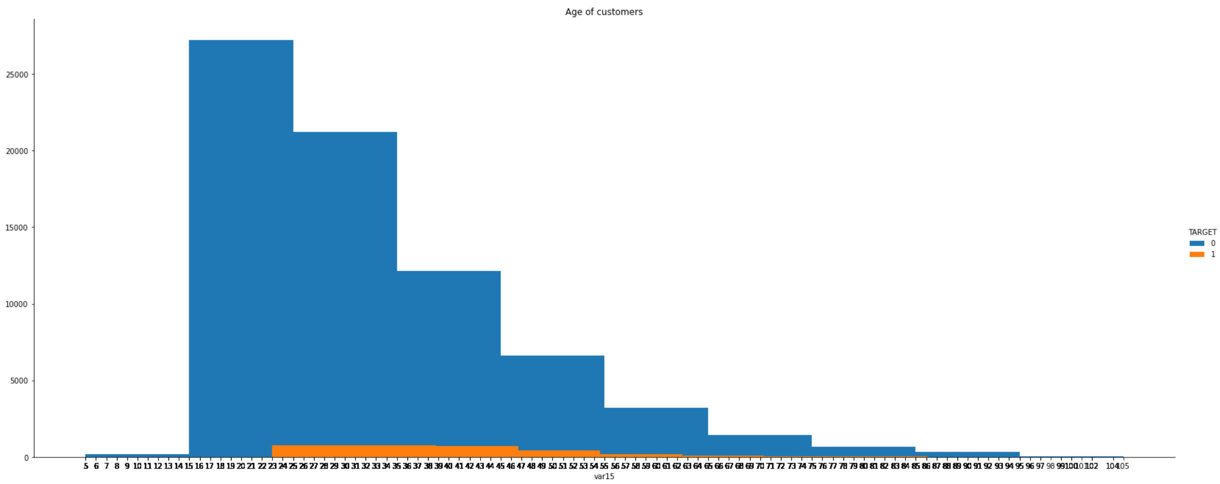
All the unique values range from 5 to 105, it looks like this features 'var15' could really be age of the customers. So let's plot some graph and check their distribution over the data.

In [ ]:

```
import seaborn as sns
counts, bins = np.histogram(train_df)

g= sns.FacetGrid(train_df, hue="TARGET", height=9, aspect=2.5).map(plt.hist,
g.set(xticks=train_df.var15)
#g.set_xticklabels(g.get_xticklabels(), rotation=90)

plt.title('Age of customers')
plt.show()
```



From above plot we can see that majority of customers are young and most of them are under the age of 30. And we can also see from the above graph that customers below age '23' are never unsatisfied.

So we can create a new feature which willbe categorical denoting whether age is less than 23 or not.

Further we can see that there are no unsatisfied customer at age above 80, lets check this through a code.

In [ ]:

```
for age in [79,80]:
  cnt= 0
  for i in train_df['var15']:
    if (i > age) and (train_df['TARGET'][i]==1):
      cnt +=1
  print("Number of unsatisfied customers of more than {} age: {}".format(age,
```

```
Number of unsatisfied customers of more than 79 age: 57
Number of unsatisfied customers of more than 80 age: 0
```

As we can see that there aren't any unsatisfied customers above age 80. This too can be made into a categorical feature whether customer's age is above 80 or not.

Analysing 'num_var4'

'num_var4' feature according to some literature is believed to be number of banking products customer is having with the bank.

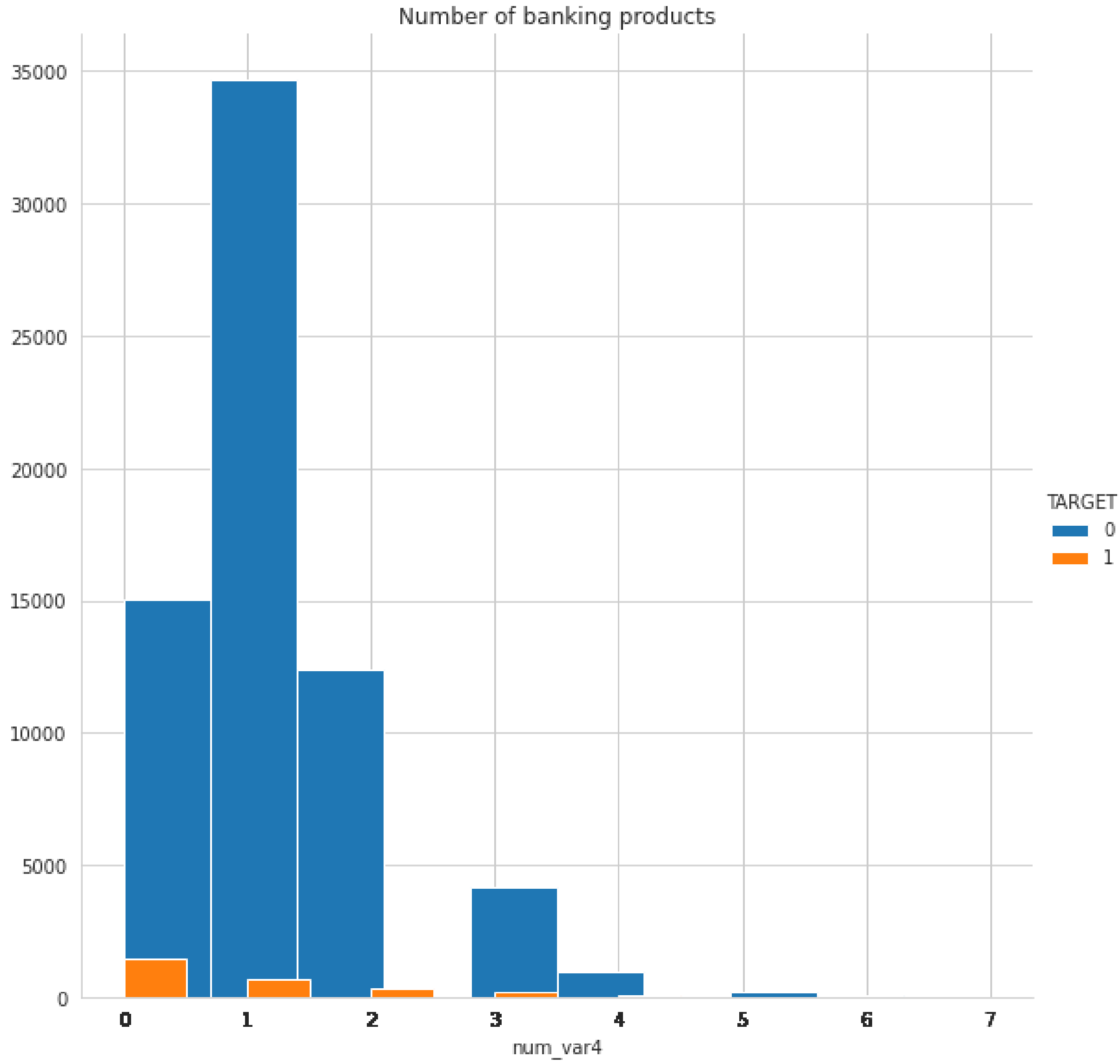
In [ ]:

```
import seaborn as sns

g= sns.FacetGrid(train_df, hue="TARGET", height=8, aspect=1).map(plt.hist, "r
```

```
g.set(xticks=train_df.num_var4)
#g.set_xticklabels(g.get_xticklabels(), rotation=90)

plt.title('Number of banking products')
plt.show()
```



From the above plot we can see that majority of Unsatisfied Customers don't tend to buy any banking products. Maybe this is because of the fact that they are unsatisfied and aren't interested in continuing with the bank.

On the other hand very few people tend to have more than 2 banking products. This plot gives an overview, lets get the actual data for further analysis.

In [ ]:

```
train_df['num_var4'].value_counts()
```

Out[ ]:

```
1    35348
0    16536
2    12692
3     4377
4     1031
5      203
6       36
7        6
Name: num_var4, dtype: int64
```

In [ ]:

```
train_df.loc[train_df['TARGET']==1]['num_var4'].value_counts()
```

Out[ ]:
```
0    1482
1     692
2     333
3     182
4      58
5       6
Name: num_var4, dtype: int64
```

Number of banking products 6 and 7 didn't make it in the series above. So it is clear that customers who have 6 or more than 6 banking products with the bank are all satisfied. This could be used to make a new feature while feature engineering whether value of 'num_var4' is 6 or more than 6.

Feature importance:

From literature surveys we know what some of the features mean, besides that it is difficult to find meaning of features, so for further features analysis we will find feature importance and use the top feature for analysis purpose.

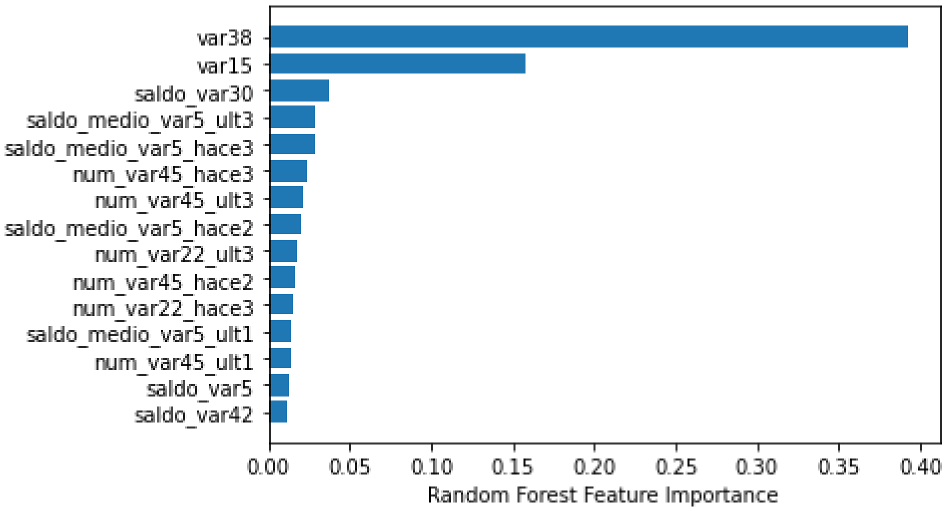
In [ ]:
```
# decissiontree for feature importance:
from sklearn.tree import DecisionTreeRegressor
from sklearn.tree import DecisionTreeClassifier

model = DecisionTreeClassifier()
model.fit(train_df, y_train)

# get importance
importance_dt = model.feature_importances_

# before feat engg
sorted_idx = importance_dt.argsort()[-15:]
plt.barh(train_df.columns[sorted_idx], importance_dt[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

Out[ ]:
```
Text(0.5, 0, 'Random Forest Feature Importance')
```



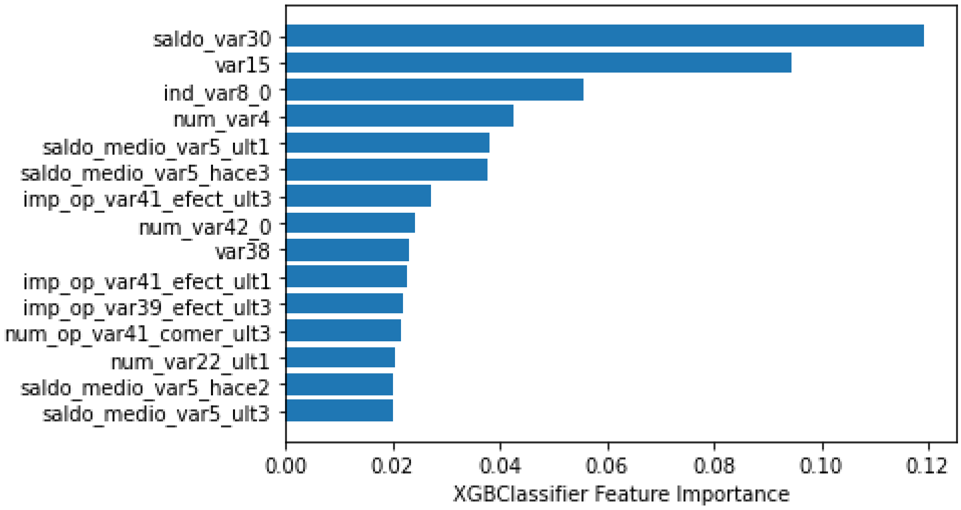
In [ ]:
```
# xgbclassifier for feature importance:
from xgboost import XGBClassifier

model = XGBClassifier()
model.fit(train_df, y_train)
```

```
# get importance
importance_xgb = model.feature_importances_

# before feat engg
sorted_idx = importance_xgb.argsort()[-15:]
plt.barh(train_df.columns[sorted_idx], importance_xgb[sorted_idx])
plt.xlabel("XGBClassifier Feature Importance")
```

Out[ ]:
```
Text(0.5, 0, 'XGBClassifier Feature Importance')
```



Bivariate analysis:

Bivariate Analysis with top 5 features obtained from decissiontreeclassifier and xgbclassifier:

Bivariate analysis of top 5 features obtained from DecissionTreeClassifier:

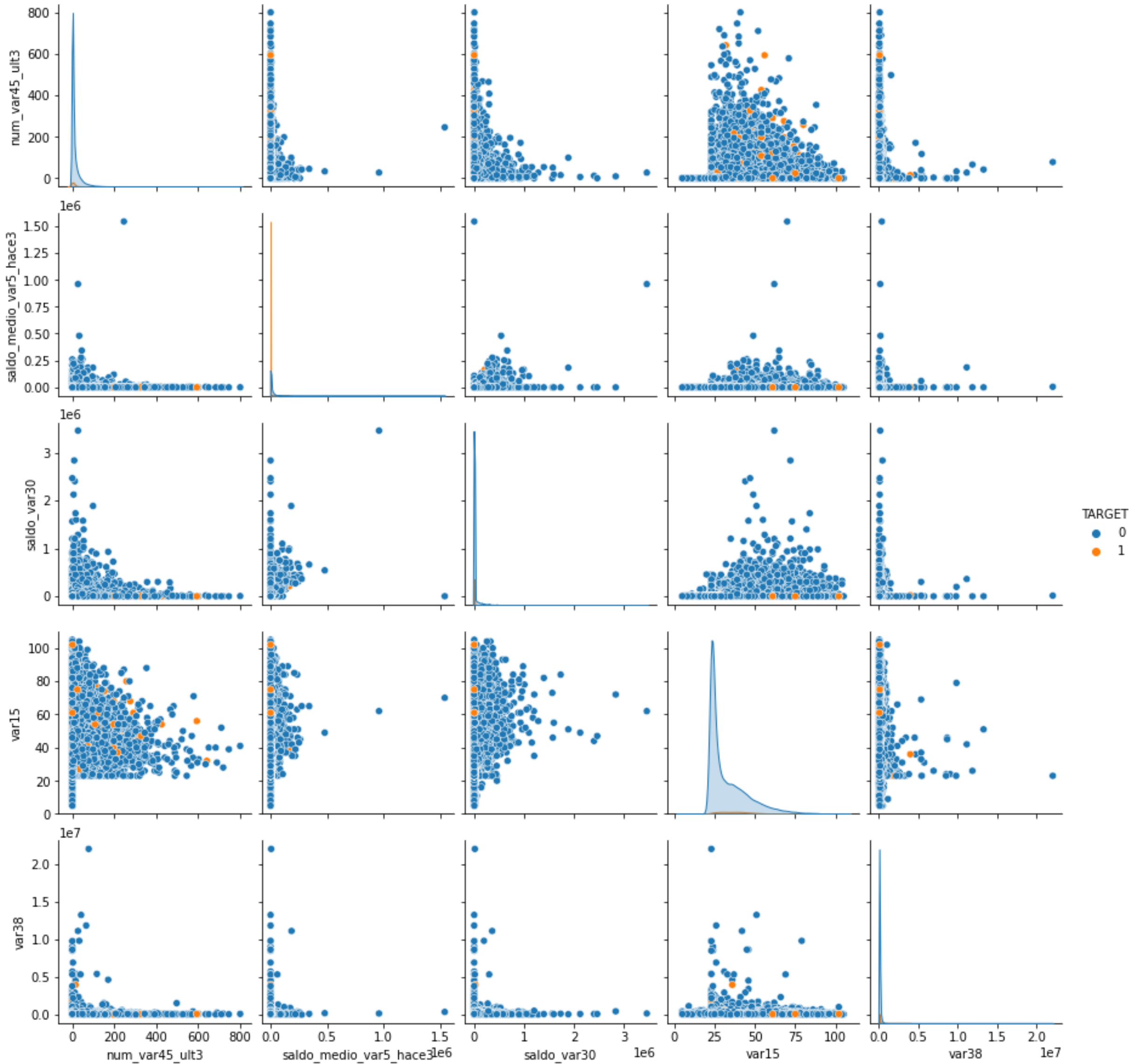
In [ ]:
```
sorted_idx = importance_dt.argsort()[-5:]
top_feat= list(train_df.columns[sorted_idx])

train_df_2= train_df[top_feat]
train_df_2['TARGET']= y_train

plt.figure(figsize=(100, 100))
sns.pairplot(train_df_2, diag_kind='kde',hue='TARGET');
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCo
pyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
<Figure size 7200x7200 with 0 Axes>
```



From the above plots we can see that there aren't any features which can efficiently seperate two classes, however some pattern is vissible in some of the plots like in plot 'saldo_var30 vs var15' we can see that TARGET with value 1 tend to be vissible at very low values of saldo_var30.

Similarly in plot 'saldo_medio_var5_hace3' vs 'var15' we can see that positive datapoints tend to have lower values.

Based on the above three features (saldo_var_30, var15, var38) we can further perfom multivariate analysis to see relations between them simultaneously.

In [ ]:

```
sorted_idx = importance_xgb.argsort()[-5:]
top_feat= list(train_df.columns[sorted_idx])

train_df_2= train_df[top_feat]
train_df_2['TARGET']= y_train

plt.figure(figsize=(100, 100))
sns.pairplot(train_df_2, diag_kind='kde',hue='TARGET');
```

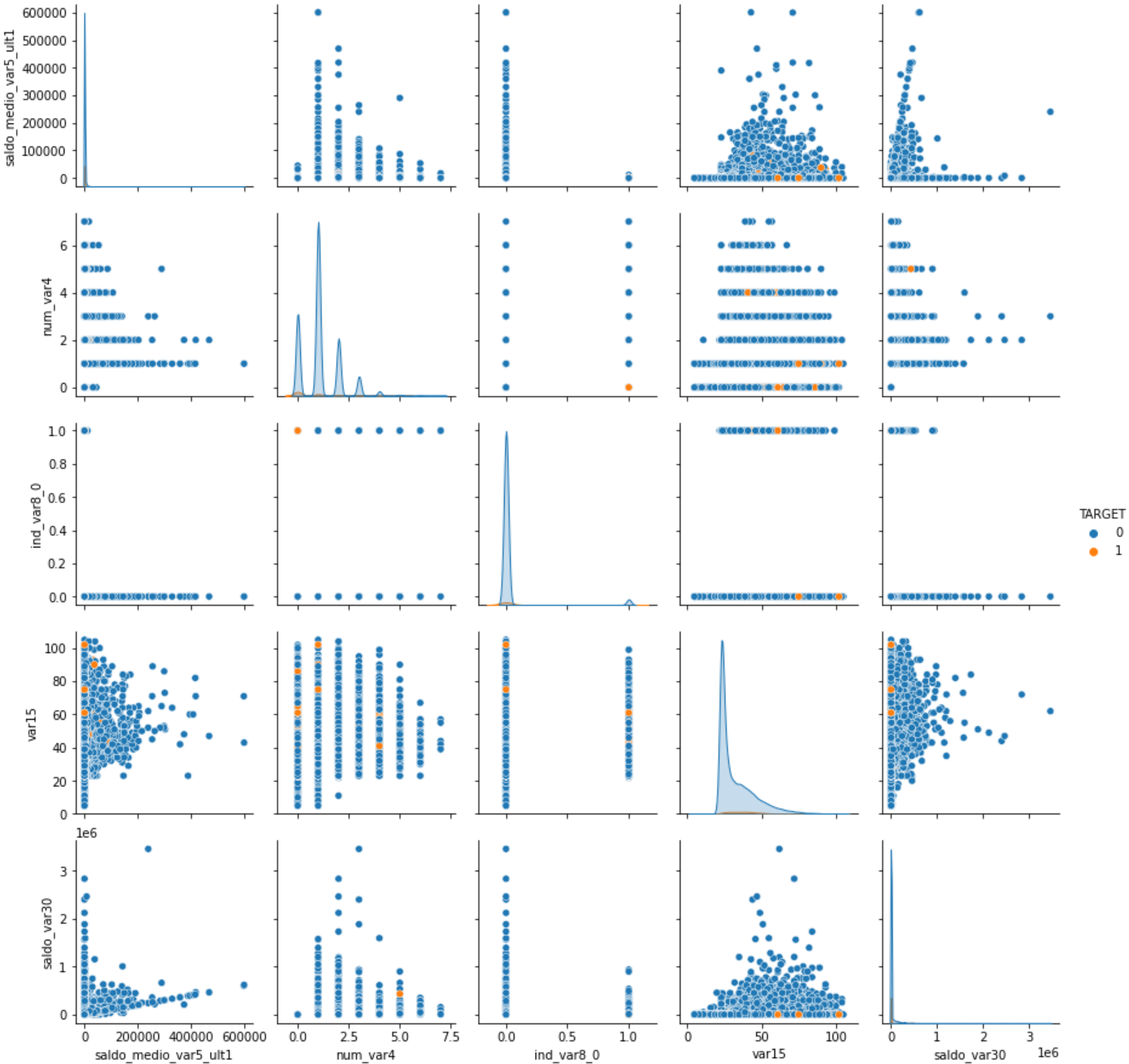
```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCopyWarning:


A value is trying to be set on a copy of a slice from a DataFrame.
```

```
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy

<Figure size 7200x7200 with 0 Axes>
```



We can't see anything valuable from the above plots except for saldo_var30 and var15 which we have discussed earlier. So lets do multivariate analysis for further analysis.

Multivariate analysis:

Since there are lots of features, we will be doing analysis of those features which are considered important in feature importance earlier.

saldo_medio_var5_ult3, saldo_var30, num_var45_hace3

Lets plot a 3d scatter plot between the top three features (var15, saldo_var30, var38) obtained earlier and see if we can find a pattern which might help in classification porcess.

In [ ]:

```
sorted_idx = importance_dt.argsort()[-10:]
top_feat= list(train_df.columns[sorted_idx])

train_df_1= train_df[top_feat]
train_df_1['TARGET']= y_train
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:5: SettingWithCo
pyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/s
table/user_guide/indexing.html#returning-a-view-versus-a-copy
  """
```

In [ ]:

```
import plotly.express as px

fig = px.scatter_3d(train_df_1, x='saldo_medio_var5_ult3', y='saldo_var30', z
              color='TARGET')
fig.show()
```

As we can see from the 3-D scatter plot, a large number of datapoints with class label '1' seems to be cornered in single place i.e majority of occurance of class variable 'TARGET'=1 happens where the values of saldo_var_30 and saldo_medio_var5_ult3 is very low.

Lets check at what values of saldo_var_30 we can mostly observe the values of TARGET=1

In [ ]:

```
# saldo_var30
value=[]
count=[]

for i in (train_df_1.saldo_var30.unique()):
  count.append(train_df_1[(train_df_1.saldo_var30==i) & (train_df_1.TARGET==1
  value.append(i)
```

```
sorted_index= np.argsort(np.array(count))[-5:]

for i in sorted_index:
  print("for value {}, there are {} datapoints with TARGET values =1".format(
```

```
for value 30.0, there are 39 datapoints with TARGET values =1
for value 90.0, there are 39 datapoints with TARGET values =1
for value 15.0, there are 39 datapoints with TARGET values =1
for value 3.0, there are 320 datapoints with TARGET values =1
for value 0.0, there are 1786 datapoints with TARGET values =1
```

As we can see from the above code that more than 50% of unsatisfied customers have the value of variable 'saldo_var30' =0. We can make a new feature out of this based on value of saldo_var30 whether it is equal to any of the values 0 or 3.

In the following code, lets check at what values of saldo_medio_var5_ult3 we can mostly observe the values of TARGET=1:

In [ ]:

```
#saldo_medio_var5_ult3
value=[]
count=[]

for i in (train_df_1.saldo_medio_var5_ult3.unique()):
  count.append(train_df_1[(train_df_1.saldo_medio_var5_ult3==i) & (train_df_1
  value.append(i)

sorted_index= np.argsort(np.array(count))[-5:]

for i in sorted_index:
  print("for value {}, there are {} datapoints with TARGET values =1".format(
```

```
for value 2.88, there are 18 datapoints with TARGET values =1
for value 2.28, there are 18 datapoints with TARGET values =1
for value 2.04, there are 19 datapoints with TARGET values =1
for value 2.34, there are 22 datapoints with TARGET values =1
for value 0.0, there are 1929 datapoints with TARGET values =1
```

As we can see from the above code that about 65% of unsatisfied customers have the value of variable 'saldo_medio_var5_ult3'= 0.0. We can make a new feature out of this based on value of saldo_medio_var5_ult3 whether it is equal to 0 or not.

var15, saldo_medio_var5_hace3, var38

In [ ]:

```
import plotly.express as px

fig = px.scatter_3d(train_df_1, x='var15', y='saldo_medio_var5_hace3', z='var
              color='TARGET')
fig.show()
```

In [ ]:
```
value=[]
count=[]

for i in (train_df_1.var38.unique()):
  count.append(train_df_1[(train_df_1.var38==i) & (train_df_1.TARGET==1)].cou
  value.append(i)

sorted_index= np.argsort(np.array(count))[-5:]

for i in sorted_index:
  print("for value {}, there are {} datapoints with TARGET values =1".format(
```

```
for value 51769.17, there are 2 datapoints with TARGET values =1
for value 60170.88, there are 2 datapoints with TARGET values =1
for value 118720.26, there are 2 datapoints with TARGET values =1
for value 105318.6, there are 2 datapoints with TARGET values =1
for value 117310.979016494, there are 614 datapoints with TARGET values =1
```

As we can see that a large number of datapoints which have value of 'TARGET'=1, tend to have 'var38' value equal to 117310.979016494. While feature engineering we will make a new feature based on this.

Feature preprocessing

Most of the feature processing will be done based on EDA done earlier such as constant, quassi constant, sparse features removal.

Removing constant features (features with no variance):

Features with no variance don't contribute at all in classification process. So in next cell we will identify such features and remove them.

In [ ]:
```
def remove_const_feature(train= train_df, test=test_df, threshold=0):
  from sklearn.feature_selection import VarianceThreshold

  vt= VarianceThreshold(threshold= threshold) #threshold: features with set-v
  vt.fit(train_df)
  const_feat= [x for x in train_df.columns if (x !='TAREGT') and (x not in tr
```

```
    print("Number of columns before: {} ".format(train_df.shape[1]))
    train_df.drop(const_feat, axis=1, inplace=True)
    test_df.drop(const_feat, axis=1, inplace=True)

    print("{} features with 0 variance have been removed".format(len(const_feat
    print("Number of columns in train dataset after: {} ".format(train_df.shape
    print("Number of columns in test dataset after: {} ".format(test_df.shape[1
    print("----------------------------------------")
```

In [ ]:

```
remove_const_feature(train_df,test_df)
```

```
Number of columns before: 369
34 features with 0 variance have been removed
Number of columns in train dataset after: 335
Number of columns in test dataset after: 335
----------------------------------------
```

Removing Quassi constant features (features with very little variance):

Just like features with 0 variance, we can also eliminate features with very little variance also known as quassi constant features..

In [ ]:

```
def remove_quassi_const_feat(train= train_df, test= test_df, threshold=0.0005
    from sklearn.feature_selection import VarianceThreshold

    vt= VarianceThreshold(threshold= threshold) #threshold: features with set-v
    vt.fit(train_df)

    quasi_const_feat= [x for x in train_df.columns if ((x!='TARGET') and (x not

    print("Number of columns before: {} ".format(train_df.shape[1]))

    train_df.drop(quasi_const_feat, axis=1, inplace= True)
    test_df.drop(quasi_const_feat, axis=1, inplace= True)

    print("{} features with very little variance have been removed".format(len(
    print("Number of columns in train dataset after: {} ".format(train_df.shape
    print("Number of columns in test dataset after: {} ".format(test_df.shape[1
    print("----------------------------------------")
```

In [ ]:

```
remove_quassi_const_feat(train_df)
```

```
Number of columns before: 369
97 features with very little variance have been removed
Number of columns in train dataset after: 272
Number of columns in test dataset after: 272
----------------------------------------
```

From the heatmap of features in EDA it is clear that there are lots of features which are correlated to each other. Lets remove the features which are highly correlated to each other. Lets take the threshold to be 0.97. If two features have correlation greater than 0.97, then second feature will be dropped and first one will be kept.

Removing features which are highly correlated to each other:

In [ ]:

```
def del_correlated_feats(train= train_df, test=test_df, threshold=0.98):

  correlated_columns=  []
  correlations= train_df.corr() #computes pairwise correlation of columns

  for i in range(len(train_df.columns)):
    for j in range(i):
      if (correlations.iloc[i,j] >= threshold) and (correlations.columns[j] r
        correlated_columns.append(correlations.columns[i]) #add that column r

  print("Number of columns before: {} ".format(train_df.shape[1]))
  print("Number of columns before: {} ".format(test_df.shape[1]))

  print("Number of correlated features being removed: {}".format(len(correlat

  train_df.drop(set(correlated_columns), axis=1, inplace= True)
  test_df.drop(set(correlated_columns), axis=1, inplace= True)

  print("Number of columns in train dataset after: {} ".format(train_df.shape
  print("Number of columns in test dataset after: {} ".format(test_df.shape[1
  print("----------------------------------------")
```

In [ ]:

```
del_correlated_feats(train_df, test_df)
```

```
Number of columns before: 272
Number of columns before: 272
Number of correlated features being removed: 78
Number of columns in train dataset after: 194
Number of columns in test dataset after: 194
----------------------------------------
```

Removing Sparse features:

In [ ]:

```
def remove_sparse_feats(train= train_df, test= test_df, threshold= 0.998):
  zeros= (train_df == 0).astype(int).sum()
  not_zeros= (train_df != 0).astype(int).sum()

  sparse_columns=[]

  for i in range(len(train_df.columns)):
    if (zeros[i]/(zeros[i]+not_zeros[i])) > threshold:
      sparse_columns.append(train_df.columns[i])

  print("number of columns before: {}".format(train_df.shape[1]))
  print("number of columns before: {}".format(test_df.shape[1]))

  train_df.drop(sparse_columns, axis=1, inplace= True)
  test_df.drop(sparse_columns, axis=1, inplace= True)

  print("number of columns in train dataset after: {}".format(train_df.shape[
  print("number of columns in test dataset after: {}".format(test_df.shape[1]
  print("----------------------------------------")
```

In [ ]:

```
remove_sparse_feats(train_df, test_df)
```

```
number of columns before: 194
number of columns before: 194
number of columns in train dataset after: 130
number of columns in test dataset after: 130
----------------------------------------
```

Feature Engineering

Just a general look at the data made me realise that there are lots and lots of zeros. Maybe the count of zeros and non zeros add value to our classification process while modeling. So let's just create two new feature that will give count of number of zeros and non zeros.

Count of number of zeros and count of non_zeros:

In [ ]:

```
def count_of_zeros(train= train_df, test= test_df):
  for df in [train, test]:
    df.insert((df.shape[1]), 'count_zeros', (df == 0).astype(int).sum(axis=1)
    print("new feature:'count_zeros' added to dataframe")
    print("----------------------------------------")

def count_of_non_zeros(train= train_df, test= test_df):
  for df in [train, test]:
    df.insert((df.shape[1]), 'count_non_zeros', (df != 0).astype(int).sum(axi
    print("new feature:'count_non_zeros' added to dataframe")
    print("----------------------------------------")
```

In [ ]:

```
count_of_zeros(train_df, test_df)
count_of_non_zeros(train_df, test_df)
```

```
new feature:'count_zeros' added to dataframe
----------------------------------------
new feature:'count_zeros' added to dataframe
----------------------------------------
new feature:'count_non_zeros' added to dataframe
----------------------------------------
new feature:'count_non_zeros' added to dataframe
----------------------------------------
```

New feature: Age below 23 or not:

In [ ]:

```
def age_below_23(train= train_df, test= test_df):
  for df in [train, test]:
    below_23= []
    for i in (df['var15']):
      if i < 23:
        below_23.append(1)
      else:
        below_23.append(0)

    df['below_23']= below_23
    print ("added new feature whether age is below 23 or not")
    print("----------------------------------------")
```

In [ ]:

```
age_below_23(train_df,test_df)
```

```
added new feature whether age is below 23 or not
----------------------------------------
added new feature whether age is below 23 or not
----------------------------------------
```

New feature: Age above 80 or not:

In [ ]:

```
def age_above_80(train= train_df, test= test_df):
  for df in [train, test]:
    above_80= []
    for i in (df['var15']):
      if i > 80:
        above_80.append(1)
      else:
        above_80.append(0)

    df['above_80']= above_80
    print ("added new feature whether age is above 80 or not")
    print("----------------------------------------")
```

In [ ]:

```
age_above_80(train_df,test_df)
```

```
added new feature whether age is above 80 or not
----------------------------------------
added new feature whether age is above 80 or not
----------------------------------------
```

New feature: value of 'saldo_var30' equal to 0 or 3 or not:

In [ ]:

```
def saldo_var30_0_3(train= train_df, test= test_df):
  for df in [train, test]:
    saldo_var30_0_3= []
    for i in (df['saldo_var30']):
      if ((i == 0)or(i ==3)):
        saldo_var30_0_3.append(1)
      else:
        saldo_var30_0_3.append(0)

    df['saldo_var30_0_3']= saldo_var30_0_3
    print ("added new feature whether value of saldo_var30 is equal to 0/3 or
    print("----------------------------------------")
```

In [ ]:

```
saldo_var30_0_3(train_df,test_df)
```

```
added new feature whether value of saldo_var30 is equal to 0/3 or not
----------------------------------------
added new feature whether value of saldo_var30 is equal to 0/3 or not
----------------------------------------
```

New feature: value of 'var38' equal to 117310.979016494 or not:

In [ ]:

```
def value_var38(train= train_df, test= test_df):
  for df in [train, test]:
    value_var38= []
    for i in (df['var38']):
      if (i == 117310.979016494):
        value_var38.append(1)
      else:
        value_var38.append(0)

    df['value_var38']= value_var38
    print ("added new feature whether value of var38 is equal to 117310.97901
    print("----------------------------------------")
```

In [ ]:
```
value_var38(train_df,test_df)
```

```
added new feature whether value of var38 is equal to 117310.979016494 or not
----------------------------------------
added new feature whether value of var38 is equal to 117310.979016494 or not
----------------------------------------
```

New feature: value of 'saldo_medio_var5_ult3' equal to 0.0 or not:

In [ ]:
```
def value_saldo_medio_var5_ult3(train= train_df, test= test_df):
  for df in [train, test]:
    value_saldo_medio_var5_ult3= []
    for i in (df['saldo_medio_var5_ult3']):
      if (i == 0.0):
        value_saldo_medio_var5_ult3.append(1)
      else:
        value_saldo_medio_var5_ult3.append(0)

    df['value_saldo_medio_var5_ult3']= value_saldo_medio_var5_ult3
    print ("added new feature whether value of saldo_medio_var5_ult3 is equal
    print("----------------------------------------")
```

In [ ]:
```
value_saldo_medio_var5_ult3(train_df,test_df)
```

```
added new feature whether value of saldo_medio_var5_ult3 is equal to 0 or not
----------------------------------------
added new feature whether value of saldo_medio_var5_ult3 is equal to 0 or not
----------------------------------------
```

In [ ]:
```
print (train_df.shape)
print (y_train.shape)
print (test_df.shape)
```

```
(76020, 152)
(76020,)
(75818, 152)
```

Feature importances

Now that the feature processing and feature engineering is done, lets do a quick feature importance using xgbclassifier and Decission tree to see which of the new features we included in feature engineering are important.

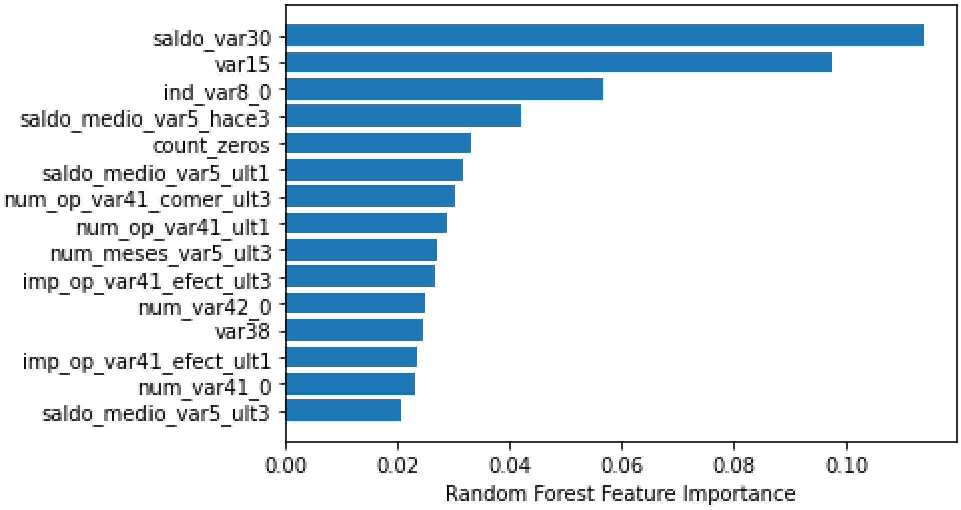
In [ ]:
```
# xgboost for feature importance on a regression problem
from sklearn.datasets import make_regression
from xgboost import XGBRegressor
from matplotlib import pyplot
from tqdm import tqdm
from xgboost import XGBClassifier

model = XGBClassifier()
model.fit(train_df, y_train)

# get importance
feat_importance = model.feature_importances_
```

```
sorted_idx = feat_importance.argsort()[-15:]
plt.barh(train_df.columns[sorted_idx], feat_importance[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

Out[ ]: Text(0.5, 0, 'Random Forest Feature Importance')



In [ ]:

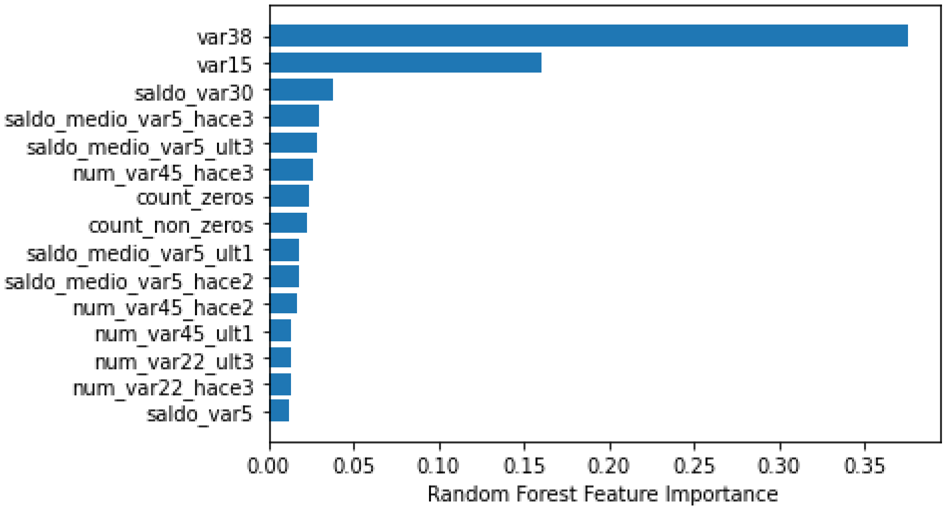
```
# decissiontree for feature importance:
from sklearn.tree import DecisionTreeRegressor

model = DecisionTreeRegressor()
model.fit(train_df, y_train)

# get importance
importance = model.feature_importances_

# before feat engg
sorted_idx = importance.argsort()[-15:]
plt.barh(train_df.columns[sorted_idx], importance[sorted_idx])
plt.xlabel("Random Forest Feature Importance")
```

Out[ ]: Text(0.5, 0, 'Random Forest Feature Importance')



MODELING:

Random Forest:

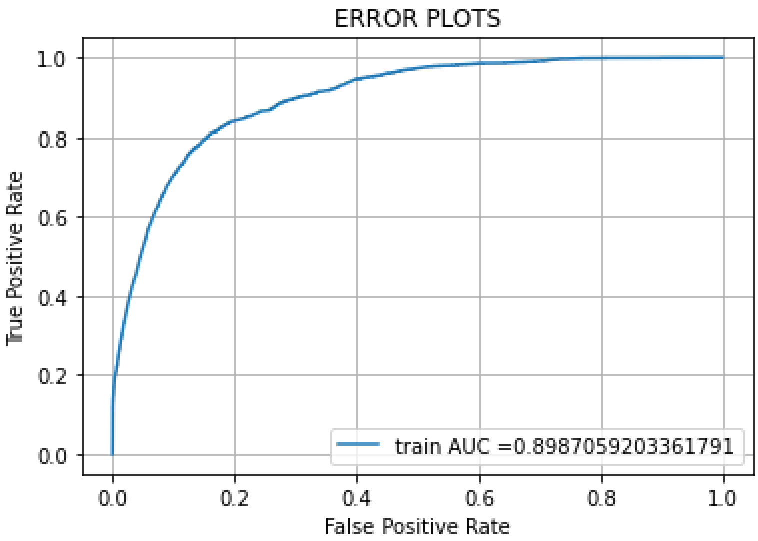
In [ ]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve
from sklearn.metrics import roc_curve, auc
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import cross_val_score

clf_rf= RandomForestClassifier(n_estimators= 150, max_depth= 13, min_samples_
#sets max_depth= 10 and n_estimators= 1000 i.e best parameters
clf_rf.fit(train_df, y_train)
# roc_auc_score(y_true, y_score) the 2nd parameter should be probability esti
# not the predicted outputs

y_train_pred = clf_rf.predict_proba(train_df) [:,1]

train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_t
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
plt.show()
```



XGBRFClassifier

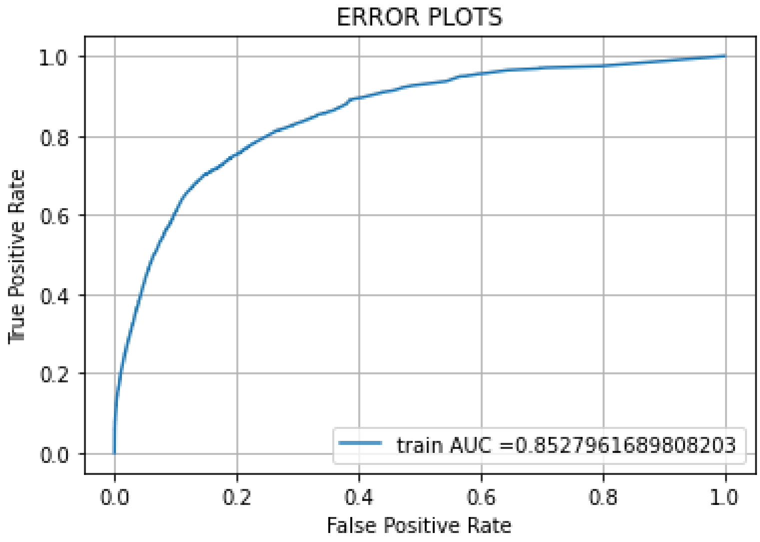
In [ ]:
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve
from xgboost import XGBRFClassifier
from sklearn.metrics import roc_curve, auc

xgb= XGBRFClassifier
clf_xgbrf = xgb(max_depth=10, n_estimators=200, subsample=0.8, colsample_bytr
clf_xgbrf.fit(train_df, y_train)

y_train_pred = clf_xgbrf.predict_proba(train_df) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_t

plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
plt.show()
```



XGBClassifier

In [ ]:

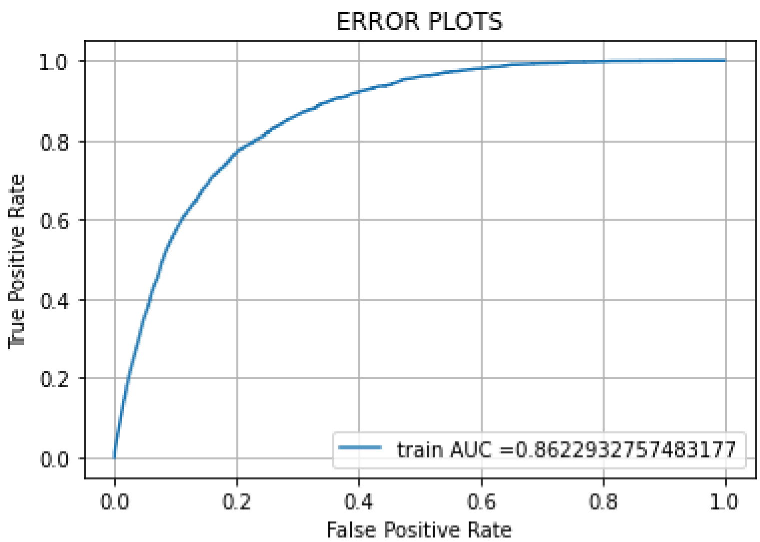
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve
from xgboost import XGBClassifier
from sklearn.metrics import roc_curve, auc

xgb= XGBClassifier
clf_xgb = xgb(max_depth=4, n_estimators=50, scale_pos_weight=22, subsample=0.
clf_xgb.fit(train_df, y_train)

y_train_pred = clf_xgb.predict_proba(train_df) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_t

plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
plt.show()
```



LGBM

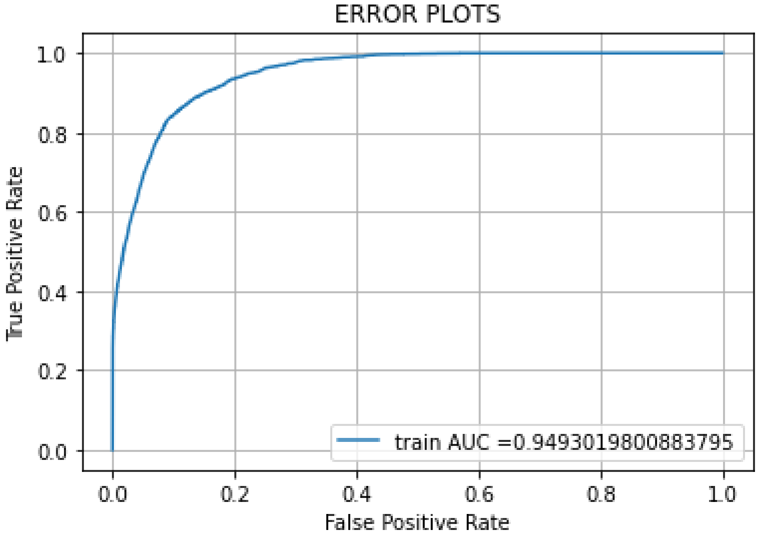
In [ ]:

```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve
from xgboost import XGBClassifier
from sklearn.metrics import roc_curve, auc
from lightgbm import LGBMClassifier

lgbm= LGBMClassifier
clf_lgbm = lgbm(max_depth=-1, n_estimators=200, class_weight=None, subsample=
clf_lgbm.fit(train_df, y_train)

y_train_pred = clf_lgbm.predict_proba(train_df) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_t
plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
plt.grid(True)
plt.show()
```



ADABoost

In [ ]:

```
from sklearn.ensemble import AdaBoostClassifier

clf_adb = AdaBoostClassifier(n_estimators=350, learning_rate=1, random_state=
clf_adb.fit(train_df, y_train)
```

Out[ ]:

```
AdaBoostClassifier(algorithm='SAMME.R', base_estimator=None, learning_rate=1,
                   n_estimators=350, random_state=0)
```

In [ ]:

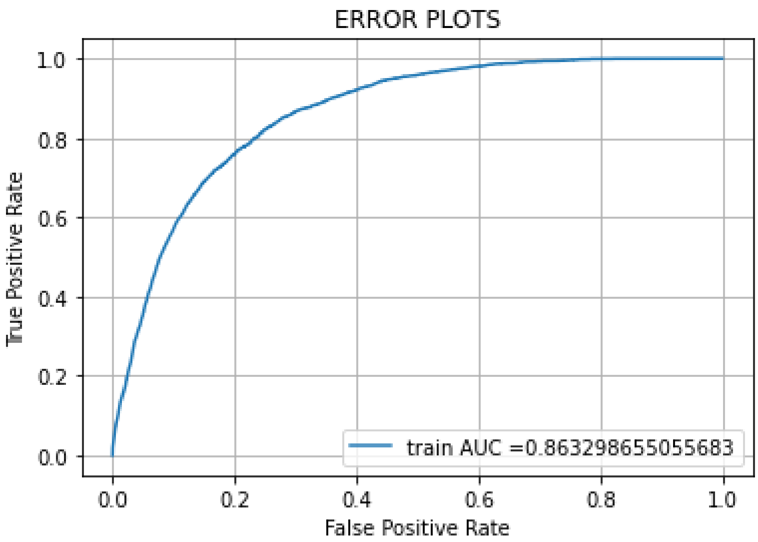
```
# https://scikit-learn.org/stable/modules/generated/sklearn.metrics.roc_curve
from xgboost import XGBClassifier
from sklearn.metrics import roc_curve, auc

y_train_pred = clf_adb.predict_proba(train_df) [:,1]
train_fpr, train_tpr, tr_thresholds = roc_curve(y_train, y_train_pred)

plt.plot(train_fpr, train_tpr, label="train AUC ="+str(auc(train_fpr, train_t

plt.legend()
plt.xlabel("False Positive Rate")
plt.ylabel("True Positive Rate")
plt.title("ERROR PLOTS")
```

```
plt.grid(True)
plt.show()
```



Deep Learning:

In [ ]:

```
import tensorflow as tf
import keras
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Dropout, Flatten, BatchNormalizati
from tensorflow.keras import Input
from tensorflow.keras.callbacks import ModelCheckpoint
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

In [ ]:

```
# train_test_split
X_train, X_val, y_train, y_val= train_test_split(train_df, y_train, test_size
```

In [ ]:

```
#Scaling
scaler = StandardScaler()

X_train= scaler.fit_transform(X_train)
X_val= scaler.transform(X_val)
test_df_dl= scaler.transform(test_df)
```

In [ ]:

```
print(X_train.shape)
print(X_val.shape)
print(test_df_dl.shape)
```

```
(53214, 149)
(22806, 149)
(75818, 149)
```

In [ ]:

```
y_train=y_train.to_numpy()
y_val=y_val.to_numpy()

# reshaping as per neural network requires
X_train = X_train.reshape(X_train.shape[0], X_train.shape[1], 1)
X_val= X_val.reshape(X_val.shape[0], X_val.shape[1], 1)
X_test_dl = test_df_dl.reshape(test_df.shape[0], test_df.shape[1], 1)
```

In [ ]:
```
print(X_train.shape)
print(X_val.shape)
print(X_test_dl.shape)
```

```
(53214, 149, 1)
(22806, 149, 1)
(75818, 149, 1)
```

In [ ]:
```
#final
train_input= X_train[0].shape

model=Sequential()

model.add(Conv1D(64, 3, strides=1, padding='valid', activation='relu', input_
model.add(BatchNormalization())

model.add(Flatten())

model.add(Dense(256, activation='relu'))
model.add(Dropout(0.3))

model.add(Dense(128, activation='relu'))
model.add(Dropout(0.3))

model.add(Dense(64, activation='relu'))
model.add(Dropout(0.3))

model.add(Dense(32, activation='relu'))
model.add(Dropout(0.3))

model.add(Dense(1, activation='sigmoid'))
```

In [ ]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_1 (Conv1D)            (None, 147, 64)           256
_________________________________________________________________
batch_normalization_1 (Batch (None, 147, 64)           256
_________________________________________________________________
flatten_1 (Flatten)          (None, 9408)              0
_________________________________________________________________
dense_5 (Dense)              (None, 256)               2408704
_________________________________________________________________
dropout_4 (Dropout)          (None, 256)               0
_________________________________________________________________
dense_6 (Dense)              (None, 128)               32896
_________________________________________________________________
dropout_5 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_7 (Dense)              (None, 64)                8256
_________________________________________________________________
dropout_6 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_8 (Dense)              (None, 32)                2080
_________________________________________________________________
dropout_7 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 33
=================================================================
Total params: 2,452,481
Trainable params: 2,452,353
```

```
Non-trainable params: 128
```

In [ ]:

```
epochs= 50
chkpoint = ModelCheckpoint('/content/drive/MyDrive/Santander/chk/July_23.h5',
                             monitor='val_auc',
                             mode='max',
                             verbose=1,
                             save_best_only=True,
                             save_weights_only = True)
```

In [ ]:

```
model.compile(optimizer='adam', loss='binary_crossentropy', metrics=['AUC'])
```

In [ ]:

```
model.save("/content/drive/MyDrive/Santander/pickle/models/dl_model")
```

In [ ]:

```
history=model.fit(X_train, y_train, validation_data=(X_val, y_val), epochs=ep
```

```
Epoch 1/50
1663/1663 [==============================] - 45s 10ms/step - loss: 0.1956 - a
uc: 0.6830 - val_loss: 0.1498 - val_auc: 0.7939

Epoch 00001: val_auc improved from -inf to 0.79395, saving model to /content/
drive/MyDrive/Santander/chk/July_23.h5
Epoch 2/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1561 - au
c: 0.7560 - val_loss: 0.1523 - val_auc: 0.8086

Epoch 00002: val_auc improved from 0.79395 to 0.80862, saving model to /conte
nt/drive/MyDrive/Santander/chk/July_23.h5
Epoch 3/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1486 - au
c: 0.7811 - val_loss: 0.1397 - val_auc: 0.8147

Epoch 00003: val_auc improved from 0.80862 to 0.81466, saving model to /conte
nt/drive/MyDrive/Santander/chk/July_23.h5
Epoch 4/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1468 - au
c: 0.7901 - val_loss: 0.1412 - val_auc: 0.8144

Epoch 00004: val_auc did not improve from 0.81466
Epoch 5/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1453 - au
c: 0.7959 - val_loss: 0.1404 - val_auc: 0.8161

Epoch 00005: val_auc improved from 0.81466 to 0.81613, saving model to /conte
nt/drive/MyDrive/Santander/chk/July_23.h5
Epoch 6/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1432 - au
c: 0.8045 - val_loss: 0.1483 - val_auc: 0.8210

Epoch 00006: val_auc improved from 0.81613 to 0.82095, saving model to /conte
nt/drive/MyDrive/Santander/chk/July_23.h5
Epoch 7/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1432 - au
c: 0.8053 - val_loss: 0.1416 - val_auc: 0.8207

Epoch 00007: val_auc did not improve from 0.82095
Epoch 8/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1428 - au
c: 0.8056 - val_loss: 0.1487 - val_auc: 0.8020

Epoch 00008: val_auc did not improve from 0.82095
Epoch 9/50
```

```
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1412 - au
c: 0.8117 - val_loss: 0.1422 - val_auc: 0.8237

Epoch 00009: val_auc improved from 0.82095 to 0.82373, saving model to /conte
nt/drive/MyDrive/Santander/chk/July_23.h5
Epoch 10/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1413 - au
c: 0.8126 - val_loss: 0.1392 - val_auc: 0.8265

Epoch 00010: val_auc improved from 0.82373 to 0.82655, saving model to /conte
nt/drive/MyDrive/Santander/chk/July_23.h5
Epoch 11/50
1663/1663 [==============================] - 16s 9ms/step - loss: 0.1417 - au
c: 0.8129 - val_loss: 0.1385 - val_auc: 0.8258

Epoch 00011: val_auc did not improve from 0.82655
Epoch 12/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1403 - au
c: 0.8184 - val_loss: 0.1409 - val_auc: 0.8239

Epoch 00012: val_auc did not improve from 0.82655
Epoch 13/50
1663/1663 [==============================] - 16s 9ms/step - loss: 0.1401 - au
c: 0.8178 - val_loss: 0.1411 - val_auc: 0.8199

Epoch 00013: val_auc did not improve from 0.82655
Epoch 14/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1395 - au
c: 0.8203 - val_loss: 0.1416 - val_auc: 0.8228

Epoch 00014: val_auc did not improve from 0.82655
Epoch 15/50
1663/1663 [==============================] - 16s 9ms/step - loss: 0.1393 - au
c: 0.8215 - val_loss: 0.1464 - val_auc: 0.8111

Epoch 00015: val_auc did not improve from 0.82655
Epoch 16/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1383 - au
c: 0.8248 - val_loss: 0.1447 - val_auc: 0.8211

Epoch 00016: val_auc did not improve from 0.82655
Epoch 17/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1383 - au
c: 0.8246 - val_loss: 0.1467 - val_auc: 0.8187

Epoch 00017: val_auc did not improve from 0.82655
Epoch 18/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1390 - au
c: 0.8238 - val_loss: 0.1452 - val_auc: 0.8215

Epoch 00018: val_auc did not improve from 0.82655
Epoch 19/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1381 - au
c: 0.8258 - val_loss: 0.1453 - val_auc: 0.8229

Epoch 00019: val_auc did not improve from 0.82655
Epoch 20/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1378 - au
c: 0.8285 - val_loss: 0.1500 - val_auc: 0.8179

Epoch 00020: val_auc did not improve from 0.82655
Epoch 21/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1375 - au
c: 0.8269 - val_loss: 0.1467 - val_auc: 0.8246

Epoch 00021: val_auc did not improve from 0.82655
Epoch 22/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1377 - au
c: 0.8278 - val_loss: 0.1438 - val_auc: 0.8255
```

```
Epoch 00022: val_auc did not improve from 0.82655
Epoch 23/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1375 - au
c: 0.8290 - val_loss: 0.1548 - val_auc: 0.8191

Epoch 00023: val_auc did not improve from 0.82655
Epoch 24/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1383 - au
c: 0.8248 - val_loss: 0.1464 - val_auc: 0.8196

Epoch 00024: val_auc did not improve from 0.82655
Epoch 25/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1376 - au
c: 0.8290 - val_loss: 0.1525 - val_auc: 0.8196

Epoch 00025: val_auc did not improve from 0.82655
Epoch 26/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1366 - au
c: 0.8320 - val_loss: 0.1471 - val_auc: 0.8244

Epoch 00026: val_auc did not improve from 0.82655
Epoch 27/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1378 - au
c: 0.8273 - val_loss: 0.1450 - val_auc: 0.8220

Epoch 00027: val_auc did not improve from 0.82655
Epoch 28/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1385 - au
c: 0.8251 - val_loss: 0.1489 - val_auc: 0.8153

Epoch 00028: val_auc did not improve from 0.82655
Epoch 29/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1367 - au
c: 0.8318 - val_loss: 0.1613 - val_auc: 0.8153

Epoch 00029: val_auc did not improve from 0.82655
Epoch 30/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1377 - au
c: 0.8265 - val_loss: 0.1521 - val_auc: 0.8202

Epoch 00030: val_auc did not improve from 0.82655
Epoch 31/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1366 - au
c: 0.8301 - val_loss: 0.1512 - val_auc: 0.8204

Epoch 00031: val_auc did not improve from 0.82655
Epoch 32/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1365 - au
c: 0.8320 - val_loss: 0.1501 - val_auc: 0.8219

Epoch 00032: val_auc did not improve from 0.82655
Epoch 33/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1368 - au
c: 0.8303 - val_loss: 0.1504 - val_auc: 0.8188

Epoch 00033: val_auc did not improve from 0.82655
Epoch 34/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1366 - au
c: 0.8300 - val_loss: 0.1498 - val_auc: 0.8140

Epoch 00034: val_auc did not improve from 0.82655
Epoch 35/50
1663/1663 [==============================] - 16s 9ms/step - loss: 0.1362 - au
c: 0.8319 - val_loss: 0.1469 - val_auc: 0.8216

Epoch 00035: val_auc did not improve from 0.82655
Epoch 36/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1372 - au
```

```
c: 0.8291 - val_loss: 0.1436 - val_auc: 0.8169

Epoch 00036: val_auc did not improve from 0.82655
Epoch 37/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1377 - au
c: 0.8270 - val_loss: 0.1443 - val_auc: 0.8171

Epoch 00037: val_auc did not improve from 0.82655
Epoch 38/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1365 - au
c: 0.8319 - val_loss: 0.1471 - val_auc: 0.8153

Epoch 00038: val_auc did not improve from 0.82655
Epoch 39/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1374 - au
c: 0.8278 - val_loss: 0.1541 - val_auc: 0.8175

Epoch 00039: val_auc did not improve from 0.82655
Epoch 40/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1385 - au
c: 0.8274 - val_loss: 0.1492 - val_auc: 0.8224

Epoch 00040: val_auc did not improve from 0.82655
Epoch 41/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1370 - au
c: 0.8286 - val_loss: 0.1645 - val_auc: 0.8186

Epoch 00041: val_auc did not improve from 0.82655
Epoch 42/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1368 - au
c: 0.8304 - val_loss: 0.1757 - val_auc: 0.8090

Epoch 00042: val_auc did not improve from 0.82655
Epoch 43/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1371 - au
c: 0.8301 - val_loss: 0.1555 - val_auc: 0.8197

Epoch 00043: val_auc did not improve from 0.82655
Epoch 44/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1366 - au
c: 0.8319 - val_loss: 0.1498 - val_auc: 0.8242

Epoch 00044: val_auc did not improve from 0.82655
Epoch 45/50
1663/1663 [==============================] - 16s 9ms/step - loss: 0.1378 - au
c: 0.8273 - val_loss: 0.1470 - val_auc: 0.8197

Epoch 00045: val_auc did not improve from 0.82655
Epoch 46/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1373 - au
c: 0.8305 - val_loss: 0.1666 - val_auc: 0.8175

Epoch 00046: val_auc did not improve from 0.82655
Epoch 47/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1363 - au
c: 0.8324 - val_loss: 0.1676 - val_auc: 0.8200

Epoch 00047: val_auc did not improve from 0.82655
Epoch 48/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1368 - au
c: 0.8315 - val_loss: 0.1674 - val_auc: 0.8150

Epoch 00048: val_auc did not improve from 0.82655
Epoch 49/50
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1406 - au
c: 0.8171 - val_loss: 0.1610 - val_auc: 0.8173

Epoch 00049: val_auc did not improve from 0.82655
Epoch 50/50
```

```
1663/1663 [==============================] - 15s 9ms/step - loss: 0.1391 - au
c: 0.8186 - val_loss: 0.1738 - val_auc: 0.8165

Epoch 00050: val_auc did not improve from 0.82655
```

Ensemble

We will just take average of the outputs from all six models and use them as our final output.

In [ ]:

```
y_test_pred_rf = clf_rf.predict_proba(test_df)[:,1]
y_test_pred_xgbrf = clf_xgbrf.predict_proba(test_df)[:,1]
y_test_pred_xgb = clf_xgb.predict_proba(test_df)[:,1]
y_test_pred_lgbm = clf_lgbm.predict_proba(test_df)[:,1]
y_test_pred_adb = clf_adb.predict_proba(test_df) [:,1]

y_test_pred= model.predict(X_test_dl) #dl model
y_test_pred_dl= []
for i in range(y_test_pred.shape[0]):
  y_test_pred_dl.append(y_test_pred[i][0])

y_test_pred= (y_test_pred_rf+ y_test_pred_xgbrf+ y_test_pred_xgb+ y_test_pred

submission = pd.DataFrame({"ID":test_id, "TARGET": y_test_pred})
submission.to_csv("submission.csv", index=False)
```

Best score I got is from ENSEMBLE of all the models i.e 'RandomForest', 'XGClassifier', 'XGBRFClassifier', 'LightGBMClassifier', 'ADAboostClassifier' and a 'Deep Learning Model' a score of 0.83968.

Individually all the models turned out to give a Kaggle score of 0.82-0.83, but ensemble of all the six models turned out to be the best.

Saving models to pickle

In [ ]:

```
# save pickle
import pickle

with open('models/clf_rf.pkl','wb') as w:
  pickle.dump(clf_rf, w)
with open('models/clf_xgbrf.pkl','wb') as w:
  pickle.dump(clf_xgbrf, w)
with open('models/clf_xgb.pkl','wb') as w:
  pickle.dump(clf_xgb, w)
with open('models/clf_lgbm.pkl','wb') as w:
  pickle.dump(clf_lgbm, w)
with open('models/clf_adb.pkl','wb') as w:
  pickle.dump(clf_adb, w)
with open('scaler.pkl','wb') as w:
  pickle.dump(scaler, w)
```

Load Models and get output:

In [ ]:

```
#load models:
import pickle

with open('clf_rf.pkl', 'rb') as o: #random_forest
```

```
    clf_rf = pickle.load(o)
with open('clf_xgbrf.pkl', 'rb') as o: #xgbrfclassifier
    clf_xgbrf = pickle.load(o)
with open('clf_xgb.pkl', 'rb') as o:#xgboost
    clf_xgb = pickle.load(o)
with open('clf_lgbm.pkl', 'rb') as o:#lgbmclassifier
    clf_lgbm = pickle.load(o)
with open('clf_adb.pkl', 'rb') as o:#adbclassifier
    clf_adb = pickle.load(o)
model = tf.keras.models.load_model('dl_model')#neuaral network model

with open('scaler.pkl', 'rb') as o:
    scaler = pickle.load(o)

#preparing data for deep learning:
test_df_dl= scaler.transform(test_df)
X_test_dl = test_df_dl.reshape(test_df.shape[0], test_df.shape[1], 1)

# prediction:
y_test_pred_rf = clf_rf.predict_proba(test_df)[:,1]
y_test_pred_xgbrf = clf_xgbrf.predict_proba(test_df)[:,1]
y_test_pred_xgb = clf_xgb.predict_proba(test_df)[:,1]
y_test_pred_lgbm = clf_lgbm.predict_proba(test_df)[:,1]
y_test_pred_adb = clf_adb.predict_proba(test_df) [:,1]

y_test_pred= model.predict(X_test_dl) #dl model
y_test_pred_dl= []
for i in range(y_test_pred.shape[0]):
  y_test_pred_dl.append(y_test_pred[i][0])

y_test_pred= (y_test_pred_rf+ y_test_pred_xgbrf+ y_test_pred_xgb+ y_test_pred

submission = pd.DataFrame({"ID":test_id, "TARGET": y_test_pred})
submission.to_csv("submission.csv", index=False)
```