Class Weight+FE+Standardization+Model

1. Import necessary Libraries

In [ ]:

```
### For computational and random seed purpose
import numpy as np
np.random.seed(42)
#to read csv file
import pandas as pd
#To split into train and cv data
from sklearn.model_selection import train_test_split
#To compute AUROC
from sklearn.metrics import auc,roc_auc_score
#for AUROC graph
import matplotlib.pyplot as plt
#for oversampling technique
from imblearn.over_sampling import SMOTE # (https://imbalanced-learn.org/stable/references/generated/imblearn.ove
r_sampling.SMOTE.html)
#Data is imbalanced, we need calibrated model
from sklearn.calibration import CalibratedClassifierCV
#for hyperparameter tuning and Cross-validation fold
from sklearn.model_selection import GridSearchCV,StratifiedKFold,RepeatedStratifiedKFold
#to ignore the error message
import warnings
warnings.filterwarnings("ignore")
#for heatmap and other plotting technique
import seaborn as sns
#to strandize the real value data
from sklearn.preprocessing import StandardScaler,MinMaxScaler
from sklearn.preprocessing import LabelEncoder
#To create Knn model on datasets
from sklearn.neighbors import KNeighborsClassifier
#for roc_curve
from sklearn.metrics import roc_curve,roc_auc_score,accuracy_score

import eli5
from eli5.sklearn import PermutationImportance
import joblib
import sys
sys.modules['sklearn.externals.joblib'] = joblib
from mlxtend.feature_selection import SequentialFeatureSelector
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import RFE
from scipy.stats import kurtosis
from scipy.stats import skew
import warnings
warnings.filterwarnings('ignore')
from catboost import CatBoostClassifier
from sklearn.preprocessing import RobustScaler
```

In [5]:

```
#locate parent directory
data_dir = "./"

#Read the training data
df_train = pd.read_csv('train.csv')
print(df_train)
```

```
      id  target      0      1      2  ...    295    296    297    298    299
0      0     1.0 -0.098  2.165  0.681  ... -2.097  1.051 -0.414  1.038 -1.065
1      1     0.0  1.081 -0.973 -0.383  ... -1.624 -0.458 -1.099 -0.936  0.973
2      2     1.0 -0.523 -0.089 -0.348  ... -1.165 -1.544  0.004  0.800 -1.211
3      3     1.0  0.067 -0.021  0.392  ...  0.467 -0.562 -0.254 -0.533  0.238
4      4     1.0  2.347 -0.831  0.511  ...  1.378  1.246  1.478  0.428  0.253
..   ...     ...    ...    ...    ...  ...    ...    ...    ...    ...    ...
245  245     0.0 -1.199  0.466 -0.908  ... -0.243  0.525  0.281 -0.255 -1.136
246  246     0.0  0.237  0.233 -0.380  ...  1.004 -0.979  0.007  0.112 -0.558
247  247     0.0  1.411 -1.465  0.119  ... -0.727  0.461  0.760  0.168 -0.719
248  248     1.0  0.620  1.040  0.184  ...  0.478 -0.910 -0.805  2.029 -0.423
249  249     0.0  0.489  0.403  0.139  ...  0.812  0.269 -1.454 -0.625  1.474

[250 rows x 302 columns]
```

In [6]:

```
#Read test data
df_test = pd.read_csv('test.csv')
df_test
```

Out[6]:

	id	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
0	250	0.500	-1.033	-1.595	0.309	-0.714	0.502	0.535	-0.129	-0.687	1.291	0.507	-0.317	1.848	-0.232	-0.340	-0.0
1	251	0.776	0.914	-0.494	1.347	-0.867	0.480	0.578	-0.313	0.203	1.356	-1.086	0.322	0.876	-0.563	-1.394	0.3
2	252	1.750	0.509	-0.057	0.835	-0.476	1.428	-0.701	-2.009	-1.378	0.167	-0.132	0.459	-0.341	0.014	0.184	-0.4
3	253	-0.556	-1.855	-0.682	0.578	1.592	0.512	-1.419	0.722	0.511	0.567	0.356	-0.060	0.767	-0.196	0.359	0.0
4	254	0.754	-0.245	1.173	-1.623	0.009	0.370	0.781	-1.763	-1.432	-0.930	-0.098	0.896	0.293	-0.259	0.030	-0.6
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
19745	19995	1.069	0.517	-0.690	0.241	0.913	-0.859	0.093	-0.359	-0.047	0.713	2.191	0.774	-0.110	-0.721	0.375	0.5
19746	19996	-0.529	0.438	0.672	1.436	-0.720	0.698	-0.350	2.150	-1.241	-0.167	-0.188	0.541	-0.392	1.727	-0.965	0.5
19747	19997	-0.554	-0.936	-1.427	0.027	-0.539	0.994	-1.832	-1.156	0.474	1.483	1.524	0.143	-0.607	-1.142	2.786	-0.3
19748	19998	-0.746	1.205	0.750	-0.236	1.139	-1.727	-0.677	-1.254	-0.099	-0.724	0.014	-0.575	-0.142	1.171	-0.198	0.3
19749	19999	0.736	-0.216	-0.110	-1.404	-0.265	-1.770	0.715	0.469	1.077	0.333	-0.994	-0.331	1.009	0.607	-1.729	1.4

19750 rows × 301 columns

In [7]:

```
df_train.dropna(inplace=True)
df_test.dropna(inplace=True)
```

In [8]:

```
def feature_engg(df,test=False):
  '''
  perform feature Engieering in basic statistics, trignometory, hyperbolic and exponential function

  parameters:

  '''
  if test:
    data = df.drop(['id'],axis=1)
  else:
    data = df.drop(['id','target'],axis=1)

  #mean and std
  df['mean'] = np.mean(data,axis=1) # taking mean value along with column
  df['std'] = np.std(data,axis=1) # taking std along with column
  df['median'] = np.median(data,axis=1)
  df['min'] = np.min(data,axis=1)
  df['max'] = np.max(data,axis=1)


  # applying trignometric function
  df['sin_mean'] = np.sin(df['mean'])
  df['cos_mean'] = np.cos(df['mean'])
  df['tan_mean'] = np.tan(df['mean'])
  df['sin_std'] = np.sin(df['std'])
  df['cos_std'] = np.cos(df['std'])
  df['tan_std'] = np.tan(df['std'])

  df['sin_median'] = np.sin(df['median'])
  df['cos_median'] = np.cos(df['median'])
  df['tan_median'] = np.tan(df['median'])
  sin_data = np.sin(data) #calculated the sin_data
  cos_data = np.cos(data) #calculated the cos_data
  tan_data = np.tan(data) #calculated the tan_data

  df['mean_sin'] = np.mean(sin_data,axis=1) #calculating the mean of sin_data
  df['mean_cos'] = np.mean(cos_data,axis=1) #calculating the mean of cos_data
  df['mean_tan'] = np.mean(tan_data,axis=1) #calculating the mean of tan_data

  #hyperbolic function

  sinh_data = np.sinh(data)
  cosh_data = np.cosh(data)
  tanh_data = np.tanh(data)
```

```
  tanh_data = np.tanh(data)
  arcsinh_data = np.arcsinh(data)
  arccosh_data = np.arccosh(data)

  df['mean_sinh'] = np.mean(sinh_data,axis=1)
  df['mean_cosh'] = np.mean(cosh_data,axis=1)
  df['mean_tanh'] = np.mean(tanh_data,axis=1)
  df['mean_arsinh'] = np.mean(arcsinh_data,axis=1)
  df['mean_arcosh'] = np.mean(arccosh_data,axis=1)
  df['sinh_mean'] = np.sinh(df['mean'])

  df['tanh_mean'] = np.tanh(df['mean'])
  df['arsinh_mean'] = np.arcsinh(df['mean'])
  df['sinh_std'] = np.sinh(df['std'])
  df['cosh_std'] = np.cosh(df['std'])
  df['tanh_std'] = np.tanh(df['std'])
  df['sinh_median'] = np.sinh(df['median'])
  df['cosh_median'] = np.cosh(df['median'])
  df['tanh_median'] = np.tanh(df['median'])

#exponential function


  exp_data = np.exp(data)
  expm1_data = np.expm1(data)
  exp2_data = np.exp2(data)

  df['mean_exp'] = np.mean(exp_data,axis=1)
  df['mean_expm1'] = np.mean(expm1_data,axis=1)
  df['mean_exp2'] = np.mean(exp2_data,axis=1)
  df['exp1_mean'] = np.exp(df['mean'])
  df['expm1_mean'] = np.expm1(df['mean'])
  df['exp2_mean'] = np.exp2(df['mean'])
  df['exp1_median'] = np.exp(df['median'])
  df['expm1_median'] = np.expm1(df['median'])
  df['exp2_median'] = np.exp2(df['median'])

  df['exp1_std'] = np.exp(df['std'])
  df['expm1_std'] = np.expm1(df['std'])
  df['exp2_std'] = np.exp2(df['std'])
  # Polynomial FE
  # X**2
  df['mean_x2'] = np.mean(np.power(data,2), axis=1)
  # X**3
  df['mean_x3'] = np.mean(np.power(data,3), axis=1)
  # X**4
  df['mean_x4'] = np.mean(np.power(data,4), axis=1)
  # X**5
  df['mean_x5'] = np.mean(np.power(data,5), axis=1)
  # X**6
  df['mean_x6'] = np.mean(np.power(data,6), axis=1)
  # X**7
  df['mean_x7'] = np.mean(np.power(data,7), axis=1)
  #logithm FE
  df['x2_mean'] = np.power(df['mean'],2)
  # X**3
  df['x3_mean'] = np.power(df['mean'],3)
  # X**4
  df['x4_mean'] = np.power(df['mean'],4)
  # X**5
  df['x5_mean'] = np.power(df['mean'],5)
  # X**6
  df['x6_mean'] = np.power(df['mean'],6)
  # X**7
  df['x7_mean'] = np.power(df['mean'],7)
  #skewness and kurtosis
  skew_data = skew(data)
  kurtosis_data = kurtosis(data)
  df['skewness'] = np.mean(skew_data)

  df['kurtosis'] = np.mean(kurtosis_data)
  data['mean_skewness'] = skew(df['mean'])
  data['mean_kurtosis'] = kurtosis(df['mean'])
  df['x2_median'] = np.power(df['median'],2)
  # X**3
  df['x3_median'] = np.power(df['median'],3)
  # X**4
  df['x4_median'] = np.power(df['median'],4)
  # X**5
  df['x5_median'] = np.power(df['median'],5)
  # X**6
  df['x6_median'] = np.power(df['median'],6)
  # X**7
  df['x7_median'] = np.power(df['median'],7)
```

```
    return df
```

In [9]:

```
df_train = feature_engg(df_train)
df_train.head(5)
```

Out[9]:

	id	target	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	
0	0	1.0	-0.098	2.165	0.681	-0.614	1.309	-0.455	-0.236	0.276	-2.246	1.825	-0.912	-0.107	0.305	0.102	0.826	0.4
1	1	0.0	1.081	-0.973	-0.383	0.326	-0.428	0.317	1.172	0.352	0.004	-0.291	2.907	1.085	2.144	1.540	0.584	1.1
2	2	1.0	-0.523	-0.089	-0.348	0.148	-0.022	0.404	-0.023	-0.172	0.137	0.183	0.459	0.478	-0.425	0.352	1.095	0.3
3	3	1.0	0.067	-0.021	0.392	-1.637	-0.446	-0.725	-1.035	0.834	0.503	0.274	0.335	-1.148	0.067	-1.010	1.048	-1.
4	4	1.0	2.347	-0.831	0.511	-0.021	1.225	1.594	0.585	1.509	-0.012	2.198	0.190	0.453	0.494	1.478	-1.412	0.2

5 rows × 365 columns

In [10]:

```
df_test = feature_engg(df_test,True)
df_test.head(5)
```

Out[10]:

	id	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	
0	250	0.500	-1.033	-1.595	0.309	-0.714	0.502	0.535	-0.129	-0.687	1.291	0.507	-0.317	1.848	-0.232	-0.340	-0.051	0.
1	251	0.776	0.914	-0.494	1.347	-0.867	0.480	0.578	-0.313	0.203	1.356	-1.086	0.322	0.876	-0.563	-1.394	0.385	1.
2	252	1.750	0.509	-0.057	0.835	-0.476	1.428	-0.701	-2.009	-1.378	0.167	-0.132	0.459	-0.341	0.014	0.184	-0.460	-0
3	253	-0.556	-1.855	-0.682	0.578	1.592	0.512	-1.419	0.722	0.511	0.567	0.356	-0.060	0.767	-0.196	0.359	0.080	-0
4	254	0.754	-0.245	1.173	-1.623	0.009	0.370	0.781	-1.763	-1.432	-0.930	-0.098	0.896	0.293	-0.259	0.030	-0.661	0.

5 rows × 364 columns

In [11]:

```
X_train = (df_train.drop(['id','target'],axis = 1))
X_test = (df_test.drop(['id'],axis = 1))

y_train = df_train['target']

#n_fold = 20
#folds = StratifiedKFold(n_splits=n_fold, shuffle=True, random_state=42)
#repeated_folds = RepeatedStratifiedKFold(n_splits=20, n_repeats=20, random_state=42)
```

In [12]:

```
X_train.shape
```

Out[12]:

(250, 363)

Normalization

In [15]:

```
stand = MinMaxScaler()
X_train = stand.fit_transform(X_train)
X_test = stand.transform(X_test)
```

In [16]:

```
X_train.shape
```

Out[16]:

```
(250, 363)
```

In [17]:

```
X_train.shape
```

Out[17]:

```
(250, 363)
```

Used Grid Search for hyper-parameter tuning

In [18]:

```
def hyperparameter_model(models, params):
  '''
  Hyperparameter tuning with StratifiedKFold follow by GridSearchCV follow by␣
  ,→CalibratedClassifier
  Parameters:
  models: Instance of the model
  params: list of parameters with value fr tuning (dict)
  Return:
  grid_clf: return gridsearch model
  '''
  # Perform KCrossValidation with stratified target
  str_cv = StratifiedKFold(n_splits=11, random_state=42,shuffle=True)
  # Perform Hyperparamter using GridSearchCV
  grid_clf = GridSearchCV(models, params, cv=str_cv, return_train_score=True,scoring='roc_auc')
  # Fit the train model to evaluate score
  grid_clf.fit(X_train, y_train)
  return grid_clf
```

In [19]:

```
#kNN (See Docs: https://scikit-learn.org/stable/modules/generated/sklearn.→neighbors.KNeighborsClassifier.html)
# List of params
# List of params
params = {'n_neighbors':np.arange(3,51,2).tolist(), 'algorithm': ['kd_tree','brute']}

# Instance of knn model
knn_model = KNeighborsClassifier()
# Call hyperparameter for find the best params as possible
knn_clf = hyperparameter_model(knn_model, params)
```

In [20]:

```
print(knn_clf.best_params_)
```

```
{'algorithm': 'kd_tree', 'n_neighbors': 45}
```

In [21]:

```
knn_model = KNeighborsClassifier(**knn_clf.best_params_)
knn_model.fit(X_train,y_train)
```

Out[21]:

```
KNeighborsClassifier(algorithm='kd_tree', n_neighbors=45)
```

In [22]:

```
y_pred = knn_model.predict(X_train)
print(y_pred)
```

```
[1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1.]
```

In [23]:

```
train_auc = roc_auc_score(y_train,y_pred)
print(train_auc)
```

```
0.5375
```

In [24]:

```
y_predict = knn_model.predict_proba(X_test)[:,1]
```

In [25]:

```
y_pred_lr_test = pd.DataFrame({"ID": df_test['id'],"Target": y_predict})


y_pred_lr_test.to_csv('submission_knn1.csv', index=False)
y_pred_lr_test.head(20)
```

Out[25]:

	ID	Target
0	250	0.533333
1	251	0.711111
2	252	0.600000
3	253	0.600000
4	254	0.577778
5	255	0.555556
6	256	0.622222
7	257	0.733333
8	258	0.688889
9	259	0.600000
10	260	0.666667
11	261	0.577778
12	262	0.377778
13	263	0.622222
14	264	0.666667
15	265	0.600000
16	266	0.688889
17	267	0.666667
18	268	0.511111
19	269	0.511111

Name	Submitted	Wait time	Execution time	Score
submission_knn1.csv	just now	1 seconds	0 seconds	0.625

Complete

Jump to your position on the leaderboard

test_auc = 0.63

Logistic Regresstion Applied

In [33]:

```
#ref= https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LogisticRegression.html

params = {'penalty':['l1','l2','elasticnet'],'C':[10**i for i in range(-4,5)], 'solver':['liblinear','sag','saga'
]}

#the instance  of Logistic Regression

log_model = LogisticRegression(class_weight='balanced',random_state=42)

#Call Hyper-parameter function to get best hyperparameter tuning

log_clf = hyperparameter_model(log_model,params)
```

In [34]:

```
print(log_clf.best_params_)
```

```
{'C': 10000, 'penalty': 'l1', 'solver': 'liblinear'}
```

In [28]:

```
from sklearn import linear_model

model = LogisticRegression(penalty='l1', C=10000, solver='liblinear')

model.fit(X_train,y_train)
```

Out[28]:

```
LogisticRegression(C=10000, penalty='l1', solver='liblinear')
```

In [29]:

```
y_pred = model.predict(X_train)
print(y_pred)
```

```
[1. 0. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 0. 0. 1. 1. 0. 1. 1. 1. 1. 0. 1.
 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1.
 0. 0. 1. 1. 0. 1. 0. 1. 0. 1. 0. 0. 1. 1. 0. 0. 0. 1. 0. 1. 1. 1. 0. 1.
 1. 1. 1. 0. 1. 1. 0. 1. 1. 0. 0. 1. 1. 1. 0. 1. 1. 1. 1. 0. 1. 1. 1. 1.
 0. 1. 1. 1. 1. 0. 0. 1. 0. 1. 1. 0. 0. 1. 1. 1. 1. 1. 0. 1. 1. 0. 0. 1.
 0. 1. 0. 1. 0. 1. 0. 0. 0. 1. 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 1. 0. 1. 0.
 1. 1. 1. 1. 0. 1. 0. 1. 1. 0. 0. 1. 1. 0. 0. 1. 1. 0. 1. 1. 0. 1. 1. 1.
 0. 0. 0. 0. 0. 1. 1. 1. 1. 0. 0. 1. 1. 0. 0. 0. 1. 1. 1. 1. 1. 0. 1. 1.
 1. 0. 0. 1. 1. 1. 0. 1. 1. 0. 1. 1. 1. 0. 1. 0. 1. 0. 0. 0. 0. 1. 1. 0.
 1. 1. 0. 1. 1. 1. 1. 1. 1. 0. 1. 0. 0. 1. 1. 1. 1. 0. 0. 1. 1. 1. 1. 0.
 0. 1. 1. 0. 0. 0. 0. 0. 1. 0.]
```

In [30]:

```
train_auc_lr = roc_auc_score(y_train,y_pred)
print(train_auc_lr)
```

```
1.0
```

In [31]:

```
y_pred_lr_test = model.predict_proba(X_test)[:,1]
print(y_pred_lr_test)
```

```
[5.82938872e-07 2.58333864e-02 9.75004007e-01 ... 9.98808911e-01
 9.99999484e-01 1.90449945e-02]
```

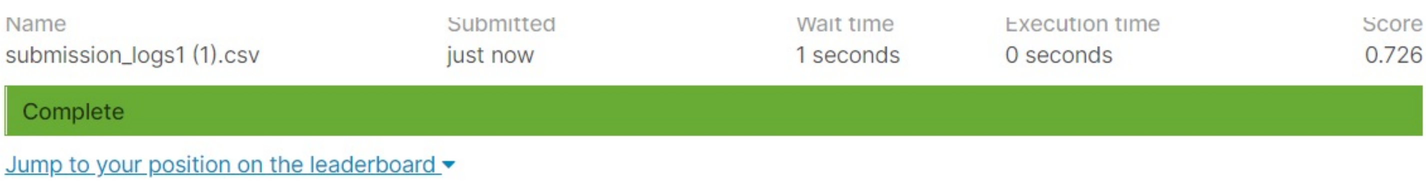
In [32]:

```
y_pred_lr_test = pd.DataFrame({"ID": df_test['id'],"Target": y_pred_lr_test})


y_pred_lr_test.to_csv('submission_logs1.csv', index=False)
y_pred_lr_test.head(20)
```

Out[32]:

	ID	Target
0	250	5.829389e-07
1	251	2.583339e-02
2	252	9.750040e-01
3	253	1.000000e+00
4	254	2.125819e-01
5	255	7.975479e-01
6	256	4.434680e-05
7	257	9.975409e-01
8	258	9.999624e-01
9	259	3.107310e-03
10	260	9.800100e-01
11	261	1.593746e-03
12	262	6.503353e-04
13	263	9.930242e-01
14	264	2.692324e-01
15	265	9.591362e-01
16	266	9.992945e-01
17	267	1.062056e-01
18	268	6.084120e-03
19	269	6.981383e-01



logistic_test_auc = 0.73

Support Vector Machine

In [35]:

```
from sklearn.svm import SVC
```

In [36]:

```
#ref = https://scikit-learn.org/stable/modules/svm.html

params = {'C':[10**i for i in range(-4,5)],'kernel':['linear','poly','sigmoid','rdf']}

#The instance of SVC

svc_model = SVC(class_weight='balanced',random_state=42)
#call the hyper-parameter function to get best parameters

svc_clf = hyperparameter_model(svc_model,params)
```

In [37]:

```
print(svc_clf.best_params_)
```

```
{'C': 0.1, 'kernel': 'poly'}
```

In [38]:

```
svc_clf = SVC(C = 0.1, kernel = 'poly',probability=True)
svc_clf.fit(X_train,y_train)
```

Out[38]:

```
SVC(C=0.1, kernel='poly', probability=True)
```

In [39]:

```
y_pred = svc_clf.predict(X_train)
train_svm_auc = roc_auc_score(y_train,y_pred)
print(train_svm_auc)
```

```
1.0
```

In [40]:

```
y_pred_svc_test = svc_clf.predict_proba(X_test)[:,1]
```

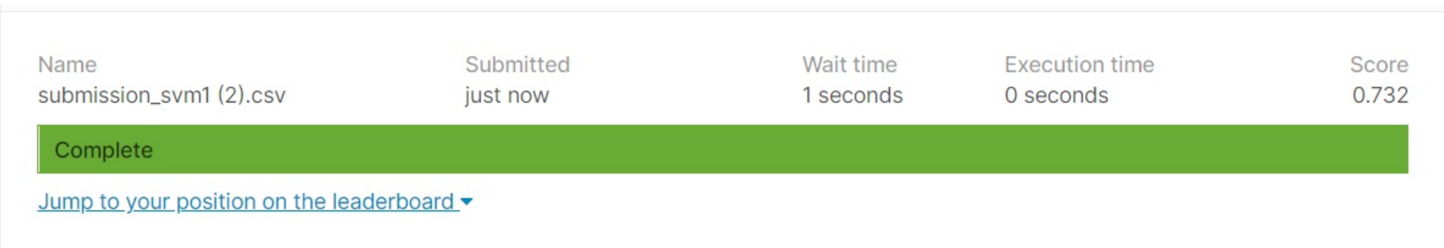
In [41]:

```
y_pred_svc_test = pd.DataFrame({"ID": df_test['id'],"Target": y_pred_svc_test})


y_pred_svc_test.to_csv('submission_svm1.csv', index=False)
y_pred_svc_test.head(10)
```

Out[41]:

	ID	Target
0	250	0.201923
1	251	0.455340
2	252	0.684746
3	253	0.933575
4	254	0.588955
5	255	0.645255
6	256	0.309197
7	257	0.649187
8	258	0.825740
9	259	0.447801



Test_SVM_auc = 0.73

Ensemble Model : Random Forest

In [43]:

```
from sklearn.ensemble import RandomForestClassifier
```

In [49]:

```
#https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
params = {'n_estimators': [10,20,30,40,50,60,100,200,300,400,500],'max_depth':[2,3,5,7,9]}

#The instance of model

rdf_model = RandomForestClassifier(class_weight='balanced',random_state=42)

# Call the hyperparameter function  to get best parameter
rdf_clf = hyperparameter_model(rdf_model,params)
```

In [50]:

```
print(rdf_clf.best_params_)
```

{'max_depth': 9, 'n_estimators': 200}

In [51]:

```
rdf_clf = RandomForestClassifier(**rdf_clf.best_params_,bootstrap=True)
rdf_clf.fit(X_train,y_train)
```

Out[51]:

RandomForestClassifier(max_depth=9, n_estimators=200)

In [52]:

```
y_pred = rdf_clf.predict(X_train)
train_rdf_auc = roc_auc_score(y_train,y_pred)
print(train_rdf_auc)
```

1.0

In [53]:

```
y_pred_rdf_test = rdf_clf.predict_proba(X_test)[:,1]
```

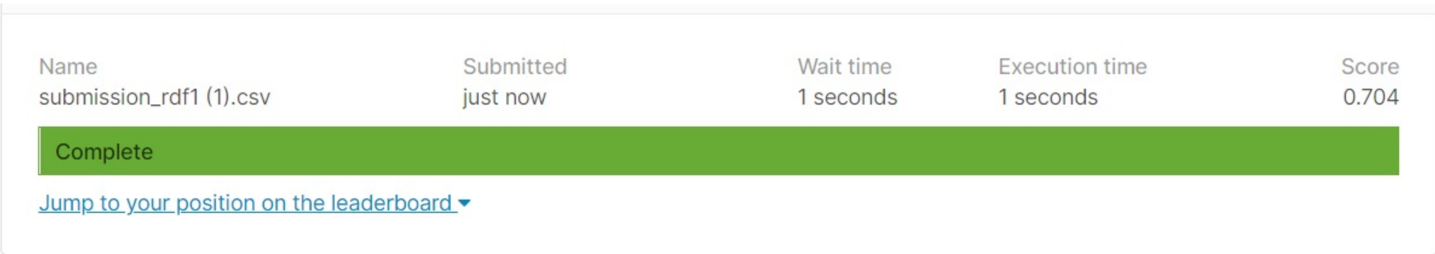
In [54]:

```
y_pred_rdf_test = pd.DataFrame({"ID": df_test['id'],"Target": y_pred_rdf_test})


y_pred_rdf_test.to_csv('submission_rdf1.csv', index=False)
y_pred_rdf_test.head(20)
```

Out[54]:

	ID	Target
0	250	0.464459
1	251	0.656186
2	252	0.664916
3	253	0.750082
4	254	0.510925
5	255	0.611556
6	256	0.548641
7	257	0.710989
8	258	0.761312
9	259	0.588592
10	260	0.606752
11	261	0.578772
12	262	0.561799
13	263	0.590617
14	264	0.560631
15	265	0.755405
16	266	0.588609
17	267	0.619911
18	268	0.548629
19	269	0.546993



Test_rdf_auc : 0.704

Decision Tree Classifier

In [70]:

```
from sklearn.tree import DecisionTreeClassifier
```

In [71]:

```
#ref =https://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html

params =  {'max_depth':[2,3,5,7,9]}

#The instance of Decision Tree Classifier

tree_model = DecisionTreeClassifier(class_weight='balanced',random_state=42)

#Call Hyperparameter function to get best parameter

tree_clf = hyperparameter_model(tree_model,params)
```

In [72]:

```
print(tree_clf.best_params_)
```

```
{'max_depth': 2}
```

In [73]:

```
tree_clf = DecisionTreeClassifier(**tree_clf.best_params_)
tree_clf.fit(X_train,y_train)
```

Out[73]:

```
DecisionTreeClassifier(max_depth=2)
```

In [74]:

```
y_pred = tree_clf.predict(X_train)
train_tree_auc = roc_auc_score(y_train,y_pred)
print(train_tree_auc)
```

```
0.6621527777777778
```

In [75]:

```
y_pred_tree_test = tree_clf.predict_proba(X_test)[:,1]
```

In [76]:

```
y_pred_tree_test = pd.DataFrame({"ID": df_test['id'],"Target": y_pred_tree_test})


y_pred_tree_test.to_csv('submission_tree1.csv', index=False)
y_pred_tree_test.head(20)
```

Out[76]:

	ID	Target
0	250	0.846774
1	251	0.846774
2	252	0.561798
3	253	0.846774
4	254	0.846774
5	255	0.561798
6	256	0.846774
7	257	0.846774
8	258	0.846774
9	259	0.561798
10	260	0.142857
11	261	0.561798
12	262	0.846774
13	263	0.561798
14	264	0.561798
15	265	0.846774
16	266	0.846774
17	267	0.561798
18	268	0.133333
19	269	0.133333

Name	Submitted	Wait time	Execution time	Score
submission_tree1 (2).csv	just now	1 seconds	0 seconds	0.614

Complete

Jump to your position on the leaderboard

test_auc = 0.614

XGBoost Classifier

In [77]:

```
from xgboost import XGBClassifier
```

In [78]:

```
#list of hyper-parameter

params = {'max_depth':[2,3,5,7,9],'n_estimators':[10,20,30,40,50,100,200,400,500]}

# The instance of XGBClassifier

xg_model = XGBClassifier(scale_pos_weight=0.5)
# call hyparameter function to get best parameter

xg_clf = hyperparameter_model(xg_model,params)
```

In [79]:

```
print(xg_clf.best_params_)
```

```
{'max_depth': 2, 'n_estimators': 500}
```

In [80]:

```
xg_clf = XGBClassifier(**xg_clf.best_params_)
xg_clf.fit(X_train,y_train)
```

Out[80]:

```
XGBClassifier(max_depth=2, n_estimators=500)
```

In [81]:

```
y_pred = xg_clf.predict(X_train)
```

In [82]:

```
train_xgboost_auc = roc_auc_score(y_train,y_pred)
print(train_xgboost_auc)
```

```
1.0
```

In [83]:

```
y_pred_xg_test = xg_clf.predict_proba(X_test)[:,1]
print(y_pred_xg_test)
```

```
[0.6067806  0.8061706  0.5926346  ... 0.23538436 0.98913246 0.20229056]
```

In [84]:

```
y_pred_xg_test = pd.DataFrame({"ID": df_test['id'],"Target": y_pred_xg_test})


y_pred_xg_test.to_csv('submission_xgboost1.csv', index=False)
y_pred_xg_test.head(10)
```

Out[84]:

	ID	Target
0	250	0.606781
1	251	0.806171
2	252	0.592635
3	253	0.998114
4	254	0.786182
5	255	0.507155
6	256	0.293211
7	257	0.383449
8	258	0.996120
9	259	0.372154

Name	Submitted	Wait time	Execution time	Score
submission_xgboost1 (1).csv	just now	1 seconds	0 seconds	0.795

Complete

Jump to your position on the leaderboard ▾

xgboost_test_auc = 0.795

Stacking Classifier

In [86]:

```
import six
import sys
sys.modules['sklearn.externals.six'] = six
```

In [87]:

```
from mlxtend.classifier import StackingClassifier
```

In [89]:

```
#classifier 1
knn_model = KNeighborsClassifier(algorithm ='kd_tree',n_neighbors = 45)
knn_model.fit(X_train,y_train)

#Classifier 2
model = LogisticRegression(C= 10000, penalty = 'l1', solver = 'liblinear')
model.fit(X_train,y_train)

#Classifier 3
svc_clf = SVC(C = 0.1, kernel = 'poly',probability=True)
svc_clf.fit(X_train,y_train)

#classifier 3

rdf_clf = RandomForestClassifier(max_depth=9, n_estimators=200)
rdf_clf.fit(X_train,y_train)
#classifier 4

tree_clf = DecisionTreeClassifier(max_depth = 2)
tree_clf.fit(X_train,y_train)

#classifier 5
xg_clf = XGBClassifier(max_depth = 2, n_estimators = 500)
xg_clf.fit(X_train,y_train)


#Stacking Classifer

sclf = StackingClassifier(classifiers=[knn_model,model,svc_clf,rdf_clf,tree_clf,xg_clf],meta_classifier=model,use
_probas=True)

#fit the model
sclf.fit(X_train,y_train)

#predict in probabilities

y_pred = sclf.predict(X_train)
```

In [90]:

```
train_auc = roc_auc_score(y_train,y_pred)
print(train_auc)
```

1.0

In [91]:

```
y_pred_stack_test = sclf.predict_proba(X_test)[:,1]
```

In [92]:

```
y_pred_stack_test = pd.DataFrame({"ID": df_test['id'],"Target": y_pred_stack_test})


y_pred_stack_test.to_csv('submission_stack1.csv', index=False)
y_pred_stack_test.head(20)
```

Out[92]:

	ID	Target
0	250	0.001383
1	251	0.105695
2	252	0.998640
3	253	0.999989
4	254	0.286169
5	255	0.988268
6	256	0.000815
7	257	0.994528
8	258	0.999980
9	259	0.005618
10	260	0.999522
11	261	0.011635
12	262	0.000444
13	263	0.999879
14	264	0.073121
15	265	0.999924
16	266	0.997855
17	267	0.496824
18	268	0.015918
19	269	0.997534

Name	Submitted	Wait time	Execution time	Score
submission_stack1 (1).csv	just now	1 seconds	0 seconds	0.772

Complete

Jump to your position on the leaderboard

Test_auc = 0.772

Summary of All Models

In [1]:

```
from texttable import Texttable
t = Texttable()
t.add_rows([['Model','Hyper-parameter','Train AUC','Test AUC'],['Knn_Model',r"{'algorithm': 'kd_tree', 'n_neighbo
rs': 45}",0.54,0.63],
           ['logistic Regresstion',r"{'C': 10000, 'penalty': 'l1', 'solver': 'liblinear'}",1.0,0.73],['Support Ve
ctor Machine',
           r"{'C': 0.1, 'kernel': 'poly'}",1.0,0.73],['XGBoost Classifier',r"{'max_depth': 2, 'n_estimators': 500
}",1.00,0.80],
            ['Random forest',r"{'max_depth': 9, 'n_estimators': 200}",1.0,0.70], ['DecisionTree',r"{'max_depth':
2}",0.66,0.61],
            ['Calibrated Model',"--",1.00,0.77]])

print(t.draw())
```

```
+-------------------------+-----------------------------+-----------+----------+
|         Model           |       Hyper-parameter       | Train AUC | Test AUC |
+=========================+=============================+===========+==========+
| Knn_Model               | {'algorithm': 'kd_tree',    | 0.540     | 0.630    |
|                         | 'n_neighbors': 45}          |           |          |
+-------------------------+-----------------------------+-----------+----------+
| logistic Regresstion    | {'C': 10000, 'penalty':     | 1         | 0.730    |
|                         | 'l1', 'solver': 'liblinear'} |           |          |
+-------------------------+-----------------------------+-----------+----------+
| Support Vector Machine  | {'C': 0.1, 'kernel': 'poly'} | 1         | 0.730    |
+-------------------------+-----------------------------+-----------+----------+
| XGBoost Classifier      | {'max_depth': 2,            | 1         | 0.800    |
|                         | 'n_estimators': 500}        |           |          |
+-------------------------+-----------------------------+-----------+----------+
| Random forest           | {'max_depth': 9,            | 1         | 0.700    |
|                         | 'n_estimators': 200}        |           |          |
+-------------------------+-----------------------------+-----------+----------+
| DecisionTree            | {'max_depth': 2}            | 0.660     | 0.610    |
+-------------------------+-----------------------------+-----------+----------+
| Calibrated Model        | --                          | 1         | 0.770    |
+-------------------------+-----------------------------+-----------+----------+
```

Observation

1.We have read the training and test dataset. After reading both of dataset, we got it know that test dataset is having more features compare to training dataset.

1. Applied Feature Engineering and came up with new Features.
2. Dropped the labled data from both train and test datasets.
3. Standardized the Features using StandScaler()
4. Used GridSerach Validation for hyper-parameter tuning.
5. We have applied following machine learning algorithm: 1.KNN : The KNN algorithm trained the model along with parameter(algorithm = 'kd_tree', and n_neighbors=45) and Class_weight, and gave train_AUC=0.54 and Test Auc = 0.63 . Model is less accurate but it is not overfitted.

   2.Logistic Regression : The Logistic regression algorithm trained the model with parameter(C=1000,penalty=l1,solver=liblinear) and class_weight, and gave train_AUC = 1.00 and Test_auc=0.73. Model is not overfitted.

   3.Support Vector Machine: The SVM algorithm trained the model with parameter(C=0.1,kernel=Poly) and class_weight, and got the train_AUC=0.1 and Test_AUC = 0.73.Model is not overfitted.

   4.XGBoost Classifier: The XGBoost classifier trained the model with parameter(max_depth=2,n_estimators=500) and class_weight, and got the train_AUC= 1.0 and Test_AUC=0.80. Model is accurate and not overfitted

   5.Random Forest : The Random Forest classifier trained the model with parameter(max_depth=9,n_estimators=200) and class_weight, and got the train_AUC = 1.00 and test_AUC = 0.70. Model is not overfitted

   6.DecisionTree : The Decision Tree classifier trained the model with parameter(max_depth=2) and got the train_AUC = 0.66 and test_AUC=0.61 .Model is comparable less accurate but it is not overfitted.

   7.Calibrated model gave train_AUC = 1.0 and Test_AUC = 0.77. Model is not overfitted.

XGBoost is giving good accuracy from above applied model