PREDICT FRAUDS WITH MACHINE LEARNING MODELS

Introduction

Project Overview

In this project, we will build various predictive models to see how accurate they are in detecting whether a transaction is a normal payment or a fraud. As described in the data set, the features are scaled and the names of the features are not shown due to privacy reasons. The models we build are important because credit card companies will be able to recognize fraudulent credit card transactions through the models, and customers will not be charged for items that they did not purchase.

Data Description

We'll train our model with a data set which has 26 variables and 10,800 transactions record. The feature 'Y' is response variable and it takes value 1 in case of fraud and 0 otherwise. The other 25 variables are numerical predictors, to attempt to predict fraudulent credit card transactions. Throughput analysis, the feature 'Y' in training data set has 1062 frauds record out of 10,800 transactions, which is somehow unbalanced. The positive class (frauds) account for 9.83% of all transactions. Most of our variables have Na values, and the distribution of Na values is pretty balanced. Except Var22-25 don't have any NA values, every other feature have about 2300 NA values.

Starter Code

Loading Package

```
# General
from sklearn.model_selection import cross_val_score
from sklearn.impute import SimpleImputer, KNNImputer
import numpy as np
import pandas as pd
from google.colab import drive
import matplotlib.pyplot as plt
import seaborn as sns

#Data Processing
from sklearn.preprocessing import OneHotEncoder,OrdinalEncoder
from sklearn.impute import SimpleImputer
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import PolynomialFeatures, StandardScaler
from sklearn.pipeline import make_pipeline
from sklearn.compose import ColumnTransformer
from sklearn.preprocessing import StandardScaler
from sklearn import metrics
from sklearn.metrics import confusion_matrix
from sklearn.metrics import classification_report, plot_confusion_matrix
from sklearn.metrics import roc_auc_score
from imblearn.over_sampling import SMOTE

#Data Modeling
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression, LogisticRegressionCV
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier, HistGradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.model_selection import GridSearchCV
```

Loading Data

```
train = pd.read_csv('/content/fraud_train.csv')
test = pd.read_csv('/content/fraud_test.csv')
```

Data Pre-processing

Data Analysis

```
train.head()
```

	Y	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	...	Var16	Var17	Var18	Var19	V
0	0	11.9967	0.6640	9.4284	NaN	9.5841	-8.8909	6.8590	20.6198	-1.6497	...	14.6973	NaN	-3.3983	7.7124	4.
1	1	7.3841	-5.8628	13.4809	4.0597	9.3176	NaN	NaN	NaN	-3.5666	...	14.8458	NaN	NaN	31.4884	21.
2	0	7.1921	-1.0867	9.2162	6.6952	12.1916	5.3659	5.2984	17.2626	-2.4231	...	NaN	9.3673	-5.1032	NaN	
3	0	4.9825	NaN	NaN	7.1418	10.3485	-2.2850	NaN	NaN	NaN	...	NaN	10.3258	3.7540	15.4096	-1.
4	0	14.0560	NaN	8.8360	NaN	9.0164	-12.6593	4.5088	13.4253	NaN	...	15.4690	10.7742	-11.3350	9.6330	23.

```
test.head()
```

	ID	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	...	Var16	Var17	Var18	Var19	Va
0	1	8.2781	-2.4840	NaN	7.7391	8.4642	6.2852	7.2324	18.1359	NaN	...	14.1446	11.0192	-16.1145	NaN	8.2
1	3	10.3614	-4.2579	16.7134	5.6450	NaN	NaN	6.6844	NaN	NaN	...	14.1765	4.9560	-7.9790	23.5552	N
2	4	10.9930	NaN	12.3683	8.3846	12.4445	-7.1959	NaN	NaN	NaN		NaN	NaN	1.9167	17.4225	5.2

```
train.describe()
```

	Y	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8
count	10800.000000	8431.000000	8429.000000	8424.000000	8372.000000	8438.000000	8357.000000	8401.000000	8416.000000
mean	0.098333	10.692028	-1.539602	10.700727	6.819757	11.072874	-4.985175	5.405046	16.501264
std	0.297779	3.025084	4.025577	2.608815	2.070841	1.617926	7.878781	0.869471	3.427696
min	0.000000	0.893500	-13.006000	3.343500	1.243900	6.154700	-27.687900	2.963200	5.749400
25%	0.000000	8.493150	-4.622800	8.737525	5.252425	9.879150	-11.082500	4.766200	13.870875
50%	0.000000	10.525200	-1.482300	10.583200	6.822050	11.131200	-4.539400	5.389200	16.378200
75%	0.000000	12.766500	1.400900	12.490425	8.366050	12.229175	1.004200	6.008900	19.028450
max	1.000000	20.315000	8.803000	18.405500	12.870000	15.558900	16.128700	7.986200	26.928200

8 rows × 26 columns

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

```
0    9738
1    1062
Name: Y, dtype: int64
```

```
train.columns
```

```
Index(['Y', 'Var1', 'Var2', 'Var3', 'Var4', 'Var5', 'Var6', 'Var7', 'Var8',
       'Var9', 'Var10', 'Var11', 'Var12', 'Var13', 'Var14', 'Var15', 'Var16',
       'Var17', 'Var18', 'Var19', 'Var20', 'Var21', 'Var22', 'Var23', 'Var24',
       'Var25'],
      dtype='object')
```

```
##Check if there is null values
train.isna().sum()
```

```
Y           0
Var1     2369
Var2     2371
Var3     2376
Var4     2428
Var5     2362
Var6     2443
Var7     2399
Var8     2384
Var9     2353
Var10    2419
Var11    2406
Var12    2421
Var13    2340
Var14    2376
Var15    2398
Var16    2395
Var17    2351
Var18    2371
Var19    2435
Var20    2401
Var21    2377
Var22       0
Var23       0
Var24       0
Var25       0
dtype: int64
```

```
X = train.drop("Y", axis = 1)
```

```
y = train["Y"]
print(X.shape)
print(y.shape)
```

```
(10800, 25)
(10800,)
```

There are 25 vairables and 10800 observations in the train dataset. In each 21 columns of the 25 variables, there are 2300-2500 observations with null values and the data is unbalanced, the positive class ('Y'=1) account for 10% of all transactions

Visualizing Data

Observe the Data Balance

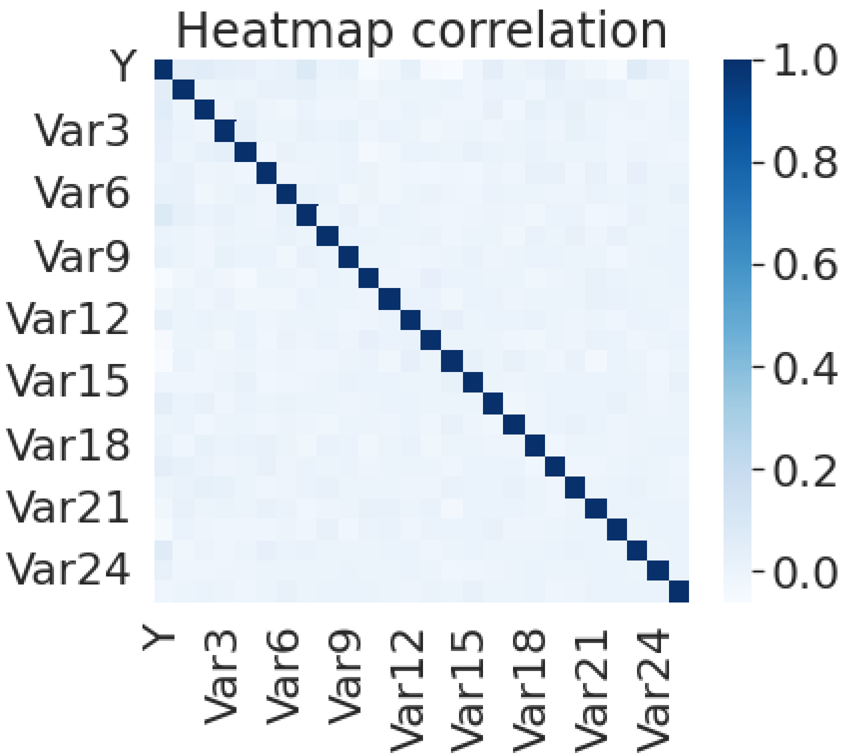
```
sns.countplot(x = y)
plt.title("Bar Graph of 0 and 1 in Fraud Class")
```

```
Text(0.5, 1.0, 'Bar Graph of 0 and 1 in Fraud Class')
```

Visualizing Correlation Matrix of features

```
df = pd.DataFrame(train)
df_corr = df.corr()
plt.figure(figsize=(6,5))
sns.heatmap(df_corr, cmap='Blues')
sns.set(font_scale=2,style='white')

plt.title('Heatmap correlation')
plt.show()
```



As we can see, there is very less correlation between main features (Var1 to Var25)

Scale the data

There are many missing values in the data, which could cause problems with the training of our model later on. The features are all numeric data and the dataset is medium, as we observed before, therefore, we choose to replace missing values with columns' median.

```
num_cols = ['Var1', 'Var2', 'Var3', 'Var4', 'Var5', 'Var6', 'Var7', 'Var8',
             'Var9', 'Var10', 'Var11', 'Var12', 'Var13', 'Var14', 'Var15', 'Var16',
             'Var17', 'Var18', 'Var19', 'Var20', 'Var21', 'Var22', 'Var23', 'Var24',
             'Var25']
num_si_step = ('si', SimpleImputer(strategy='median'))
num_ss_step = ('ss', StandardScaler())
num_steps = [num_si_step, num_ss_step]

num_pipe = Pipeline(num_steps)
num_transformers = [('num', num_pipe, num_cols)]

ct = ColumnTransformer(transformers=num_transformers)

X_num_transformed = ct.fit_transform(train)
X_num_transformed.shape
```

```
(10800, 25)
```

```
labels = train['Y'].values
labels.shape
```

```
(10800,)
```

Feature Selection

Feature importance scores can be used for feature selection. We calculate the feature importance score using the Extreme Gradient Boosting Classifier, a new method to us. We try it because it can handle the NA values and we want the feature selection can be independent from missing values imputation. The plot shows that the fscores of the variables are relatively even. Based on the feature importance score and correlation matrix, we decide using all the features to train the model.

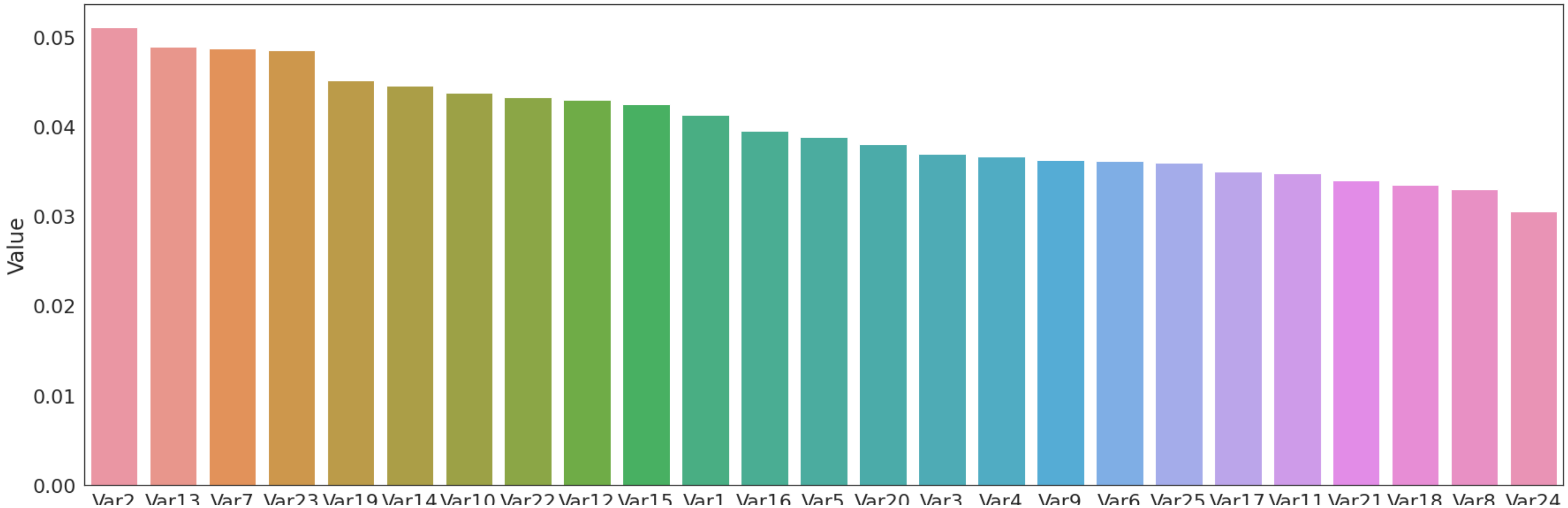
```
#Calculate F Score using XGBClassifier
xgb = XGBClassifier()
xgb.fit(X, y)

print(xgb.feature_importances_)
```

```
[0.04133776 0.05112833 0.03696365 0.0366514  0.03879234 0.03617461
 0.04874695 0.03297965 0.03630921 0.04380286 0.03478123 0.04296348
 0.04893994 0.04453174 0.04247182 0.03954437 0.03496708 0.03346421
 0.0451227  0.03806745 0.03399083 0.0432881  0.04849649 0.03049842
 0.03598537]
```

```
f_xgb = pd.DataFrame(data={'Feature':X.columns,'Value':xgb.feature_importances_})
f_xgb = f_xgb.sort_values(['Value'],ascending=False )
plt.figure(figsize=(15,8))
sns.barplot(f_xgb['Feature'],f_xgb['Value'])
plt.gcf().set_size_inches(30,10)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From v
  FutureWarning
```



Train-Test Split

```
X_train, X_test, y_train, y_test = train_test_split(X_num_transformed, labels,test_size=.1, random_state=0)
print(X_train.shape)
print(y_test.shape)
print(X_test.shape)
print(y_train.shape)
```

```
(9720, 25)
(1080,)
(1080, 25)
(9720,)
```

Baseline Models

This part examines five classification models including Logistic Regression, KNeighborsClassifier, Random Forest, GradientBoostingClassifier, and HistGradientBoostingClassifier with their default parameters. We chose HistGradientBoostingClassifier because there are NA values in the raw data, and the model can be trained with missing values, so we will train it with raw data. Next, we'll select one model to tune parameters. Accuracy is mainly measured by ROC-AUC, but accuracy score and classification report will also be considered.

Logistic Regression

```
lr = LogisticRegression()
lr.fit(X_train, y_train)
pred_lr = lr.predict(X_test)
```

```
pred_proba_lr = lr.predict_proba(X_test)[:,1]
pred_proba_lr
```

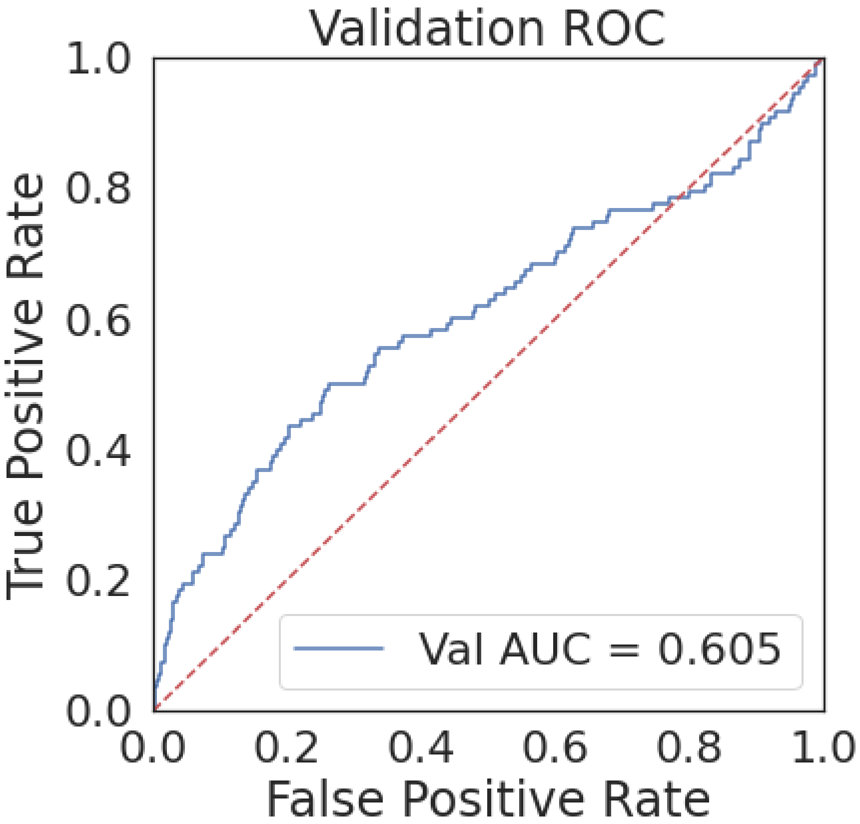
```
array([0.27977383, 0.10491382, 0.1340248 , ..., 0.09007307, 0.12578598,
       0.1390702 ])
```

```
print(accuracy_score(y_test, pred_lr))
roc_auc_score(y_test, lr.decision_function(X_test))
```

```
0.9
0.6054907788446883
```

```
fpr, tpr, threshold = metrics.roc_curve(y_test, pred_proba_lr)
roc_auc = metrics.auc(fpr, tpr)
plt.figure(figsize=(6,6))
plt.title('Validation ROC')
plt.plot(fpr, tpr, 'b', label = 'Val AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
```

```
plt.ylim([0,  1])
plt.ylabel('True  Positive  Rate')
plt.xlabel('False  Positive  Rate')
plt.show()
```




```
print(classification_report(y_test,  pred_lr))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95       972
           1       0.00      0.00      0.00       108

    accuracy                           0.90      1080
   macro avg       0.45      0.50      0.47      1080
```

```
weighted avg       0.81      0.90      0.85      1080

/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
  _warn_prf(average, modifier, msg_start, len(result))
/usr/local/lib/python3.7/dist-packages/sklearn/metrics/_classification.py:1318: UndefinedMetricWarning: Precision and F-score are ill-defin
  _warn_prf(average, modifier, msg_start, len(result))
```

KNN

```
knn=KNeighborsClassifier()
knn.fit(X_train, y_train)
pred_knn = knn.predict(X_test)
```

```
pred_proba_k = knn.predict_proba(X_test)[:,1]
pred_proba_k
```

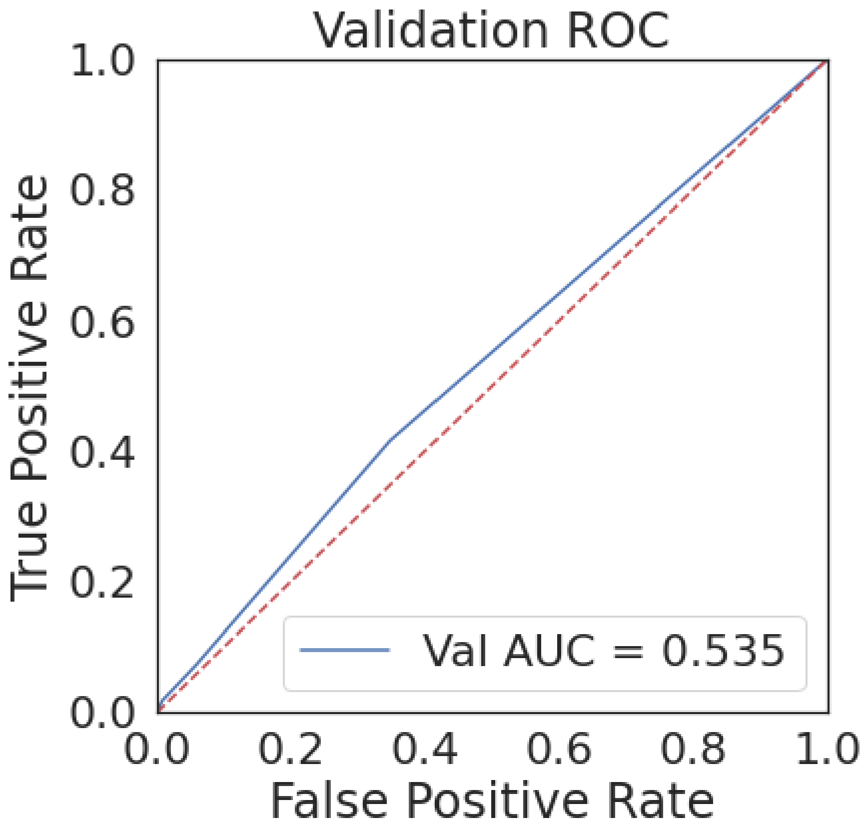
```
array([0.2, 0. , 0.2, ..., 0.2, 0. , 0. ])
```

```
print(accuracy_score(y_test, pred_knn))
roc_auc_score(y_test, pred_proba_k)
```

```
0.8944444444444445
0.5346841182746533
```

```
fpr, tpr, threshold = metrics.roc_curve(y_test, pred_proba_k)
roc_auc = metrics.auc(fpr, tpr)
plt.figure(figsize=(6,6))
plt.title('Validation ROC')
plt.plot(fpr, tpr, 'b', label = 'Val AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
```

```
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




```
print(classification_report(y_test, pred_knn))
```

```
              precision    recall  f1-score   support

           0       0.90      0.99      0.94       972
           1       0.20      0.02      0.03       108
```

```
    accuracy                           0.89      1080
   macro avg       0.55      0.51      0.49      1080
weighted avg       0.83      0.89      0.85      1080
```

Random Forest

```
rf = RandomForestClassifier()
rf.fit(X_train, y_train)
pred_rf = rf.predict(X_test)
```

```
pred_proba_rf = rf.predict_proba(X_test)[:,1]
pred_proba_rf
```

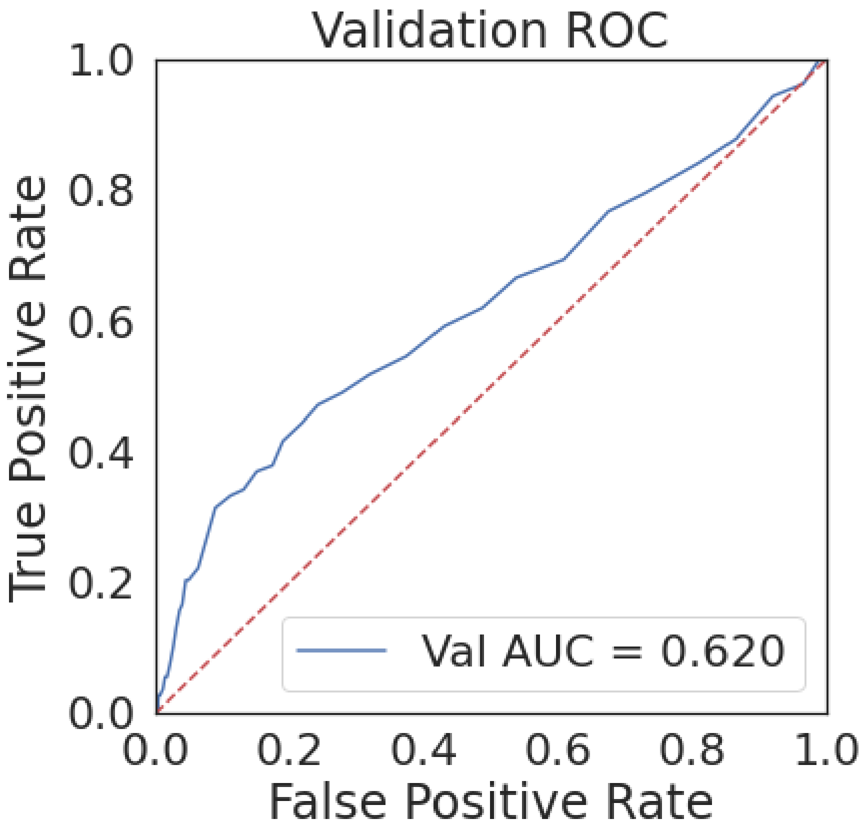
```
array([0.23, 0.1 , 0.11, ..., 0.08, 0.07, 0.07])
```

```
print(accuracy_score(y_test, pred_rf))
roc_auc_score(y_test, pred_proba_rf)
```

```
0.899074074074074
0.6200988797439414
```

```
fpr, tpr, threshold = metrics.roc_curve(y_test, pred_proba_rf)
roc_auc = metrics.auc(fpr, tpr)
plt.figure(figsize=(6,6))
plt.title('Validation ROC')
plt.plot(fpr, tpr, 'b', label = 'Val AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

```
plt.show()
```




```
print(classification_report(y_test,  pred_rf))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95       972
           1       0.00      0.00      0.00       108

    accuracy                           0.90      1080
   macro avg       0.45      0.50      0.47      1080
weighted avg       0.81      0.90      0.85      1080
```

Gradient Boosting Classifier

```
GBC = GradientBoostingClassifier()
GBC.fit(X_train, y_train)
pred_GBC = GBC.predict(X_test)
```

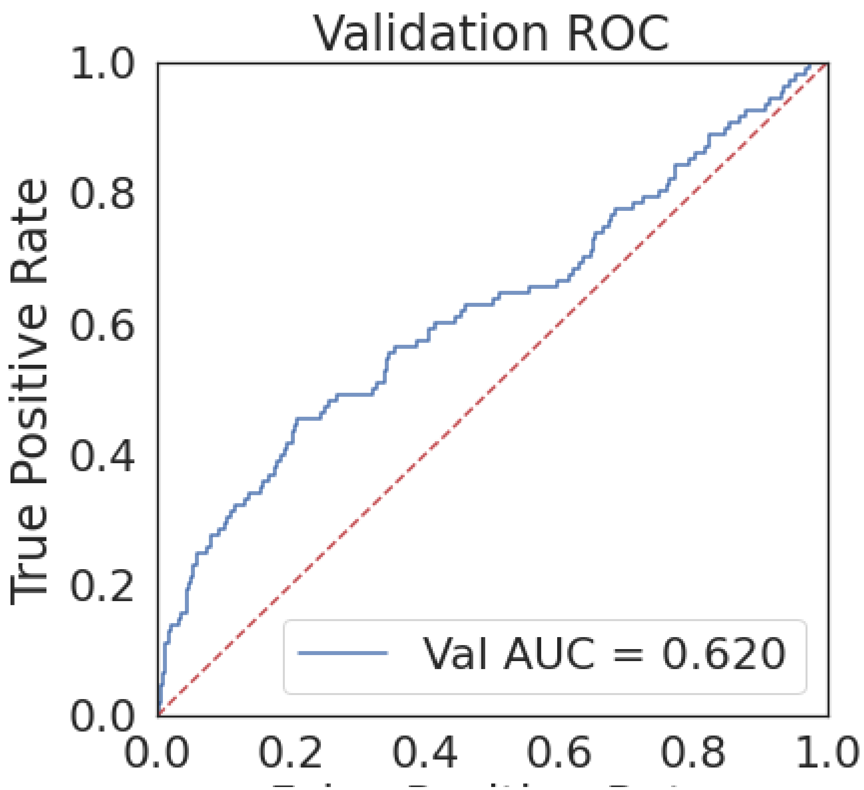
```
pred_proba_GBC = GBC.predict_proba(X_test)[:,1]
pred_proba_GBC
```

```
array([0.26328101, 0.07258158, 0.09365214, ..., 0.08291227, 0.10063384,
       0.09623653])
```

```
print(accuracy_score(y_test, pred_GBC))
roc_auc_score(y_test, pred_proba_GBC)
```

```
0.8981481481481481
0.6203894223441548
```

```
fpr, tpr, threshold = metrics.roc_curve(y_test, pred_proba_GBC)
roc_auc = metrics.auc(fpr, tpr)
plt.figure(figsize=(6,6))
plt.title('Validation ROC')
plt.plot(fpr, tpr, 'b', label = 'Val AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




```
print(classification_report(y_test, pred_GBC))
```

```
              precision    recall  f1-score   support

           0       0.90      1.00      0.95       972
           1       0.33      0.02      0.04       108

    accuracy                           0.90      1080
   macro avg       0.62      0.51      0.49      1080
weighted avg       0.84      0.90      0.86      1080
```

HistGradientBoostingClassifier

```
X_train1, X_test1, y_train1, y_test1 = train_test_split(X, y,test_size=.1)
```

```
pd.DataFrame(X_train1)
```

	Var1	Var2	Var3	Var4	Var5	Var6	Var7	Var8	Var9	Var10	...	Var16	Var17	Var18	
7404	6.3020	-6.2594	9.8574	6.9316	8.6801	0.5442	6.2204	NaN	-1.0223	6.9150	...	13.7930	11.5912	-0.3673	
7823	16.2131	NaN	14.6117	5.1260	NaN	NaN	5.7025	NaN	-1.4550	8.1899	...	14.4793	4.0788	-13.4581	1
504	10.8382	0.4223	7.7905	8.4910	9.1841	-7.2718	NaN	15.2296	5.2442	9.8734	...	NaN	9.8767	NaN	
9512	12.3717	-0.7374	8.9582	4.9482	10.3156	-6.4860	NaN	20.2737	NaN	8.8533	...	14.7275	NaN	-12.4020	
7421	15.1114	0.9359	15.4063	5.8997	11.0361	-17.9907	NaN	14.0604	-3.0555	6.1340	...	14.0641	6.6566	-10.8661	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
368	6.0463	NaN	12.6329	6.6294	9.2953	4.0116	5.4612	12.5536	NaN	8.2288	...	NaN	7.3113	NaN	2
1183	12.7043	NaN	10.8366	12.1264	8.8449	3.7087	5.3716	21.5695	NaN	NaN	...	NaN	5.8715	-8.6373	1
10512	9.0427	NaN	9.5443	NaN	NaN	-0.7791	NaN	17.5419	-3.9030	7.8986	...	13.6471	6.9440	-6.5668	3
4117	14.8195	5.8222	10.5616	NaN	9.7147	NaN	5.3787	22.2014	6.3506	7.8949	...	13.9347	14.1338	NaN	1
8004	NaN	-3.3968	6.8010	NaN	13.5134	11.9066	4.5143	NaN	4.7773	8.5789	...	14.2688	11.2083	-16.1990	3

9720 rows × 25 columns

```
HGB = HistGradientBoostingClassifier()
HGB.fit(X_train1, y_train1)
pred_HGB = HGB.predict(X_test1)
```

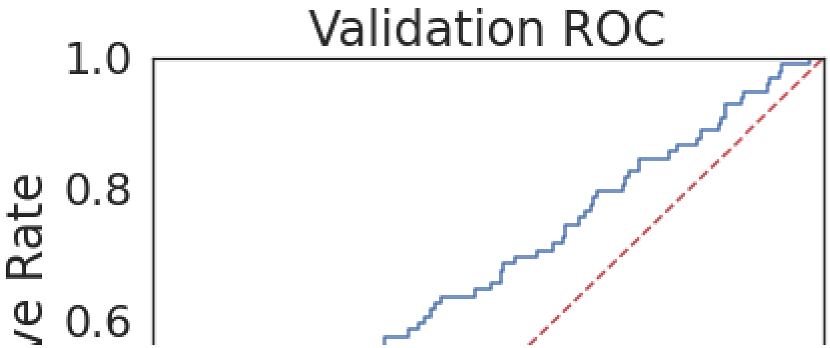
```
pred_proba_HGB = HGB.predict_proba(X_test1)[:,1]
pred_proba_HGB
```

```
array([0.05571966, 0.12678995, 0.08010094, ..., 0.07326192, 0.0717292 ,
       0.14123194])
```

```
print(accuracy_score(y_test1, pred_HGB))
roc_auc_score(y_test1, pred_proba_HGB)
```

```
0.9064814814814814
0.6294545866411311
```

```
fpr, tpr, threshold = metrics.roc_curve(y_test1, pred_proba_HGB)
roc_auc = metrics.auc(fpr, tpr)
plt.figure(figsize=(6,6))
plt.title('Validation ROC')
plt.plot(fpr, tpr, 'b', label = 'Val AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
plt.show()
```




```
print(classification_report(y_test1,  pred_HGB))

              precision    recall  f1-score   support

           0       0.91      1.00      0.95       981
           1       0.00      0.00      0.00        99

    accuracy                           0.91      1080
   macro avg       0.45      0.50      0.48      1080
weighted avg       0.82      0.91      0.86      1080
```

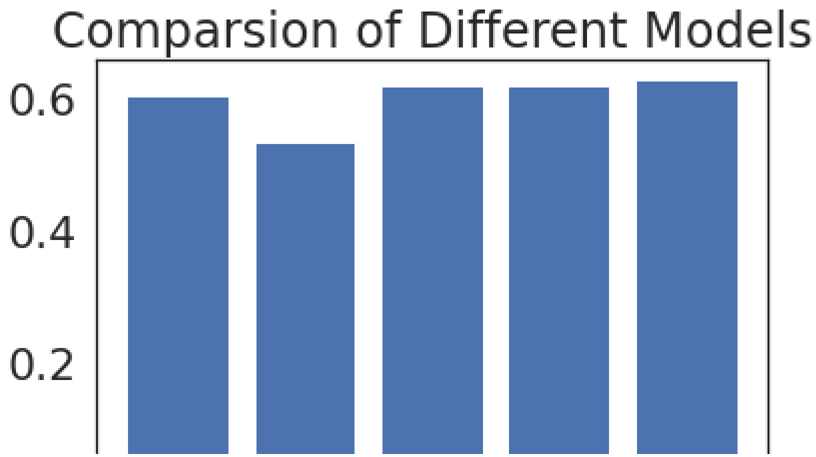
False Positive Rate

Model Selection

Based on the many experiments we tried, we chose Logistic Regression for further training, which is our best performing model in the competition.

```
keys  =  ['LR','KNN','RF','GBC','HGB']
values=[roc_auc_score(y_test,  pred_proba_lr),roc_auc_score(y_test,  pred_proba_k),roc_auc_score(y_test,  pred_proba_rf),roc_auc_score(y_test,  pı
plt.bar(keys,values)
plt.title('Comparsion  of  Different  Models')
```

```
Text(0.5, 1.0, 'Comparsion of Different Models')
```



Further Training of Selected Model

Balancing Data with SMOTE

```
oversample = SMOTE(random_state=0)
X_train_s, y_train_s = oversample.fit_resample(X_train, y_train)
# Prepare for hyperparamater tuning
X_s, y_s = oversample.fit_resample(X_num_transformed, labels)
```

```
print(X_train_s.shape)
print(y_train_s.shape)
```

```
(17532, 25)
(17532,)
```

Hyperparameters tuning with GridSearchCV

```python
C_vals = [1e-05,1e-06, 0.00001 ,0.0001, 0.001, 0.01, 0.1, 1, 10, 100]
class_weight = ['balanced',{0: 0.6, 1: 0.4},'None']
cv = StratifiedShuffleSplit(n_splits=10, test_size= .25, random_state=0)
param = {'C':C_vals, 'class_weight':class_weight}

lr=LogisticRegression()

grid = GridSearchCV(
        estimator=LogisticRegression(),
        param_grid = param,
        scoring = 'roc_auc',
        n_jobs= -1,
        cv=cv,
        error_score='raise'
)

grid.fit(X_train_s, y_train_s)
```

```
GridSearchCV(cv=StratifiedShuffleSplit(n_splits=10, random_state=0, test_size=0.25,
            train_size=None),
             error_score='raise', estimator=LogisticRegression(), n_jobs=-1,
             param_grid={'C': [1e-05, 1e-06, 1e-05, 0.0001, 0.001, 0.01, 0.1, 1,
                               10, 100],
                         'class_weight': ['balanced', {0: 0.6, 1: 0.4},
                                          'None']},
             scoring='roc_auc')
```

```python
print(grid.best_score_)
print(grid.best_params_)
print(grid.best_estimator_)
```

```
0.6627872359386608
{'C': 0.001, 'class_weight': {0: 0.6, 1: 0.4}}
LogisticRegression(C=0.001, class_weight={0: 0.6, 1: 0.4})
```

To get a better model, we must deal with the unbalance of data. Due to the size of our dataset, we chose oversampling rather than undersampling since undersampling could result in the loss of important information.

Model Performance with Balanced Data and Best Hyperparameters

```
lr = LogisticRegression(C=0.001, class_weight={0: 0.6, 1: 0.4})
lr.fit(X_train_s, y_train_s)
pred_lr = lr.predict(X_test)


pred_proba_lr = lr.predict_proba(X_test)[:,1]
pred_proba_lr
```

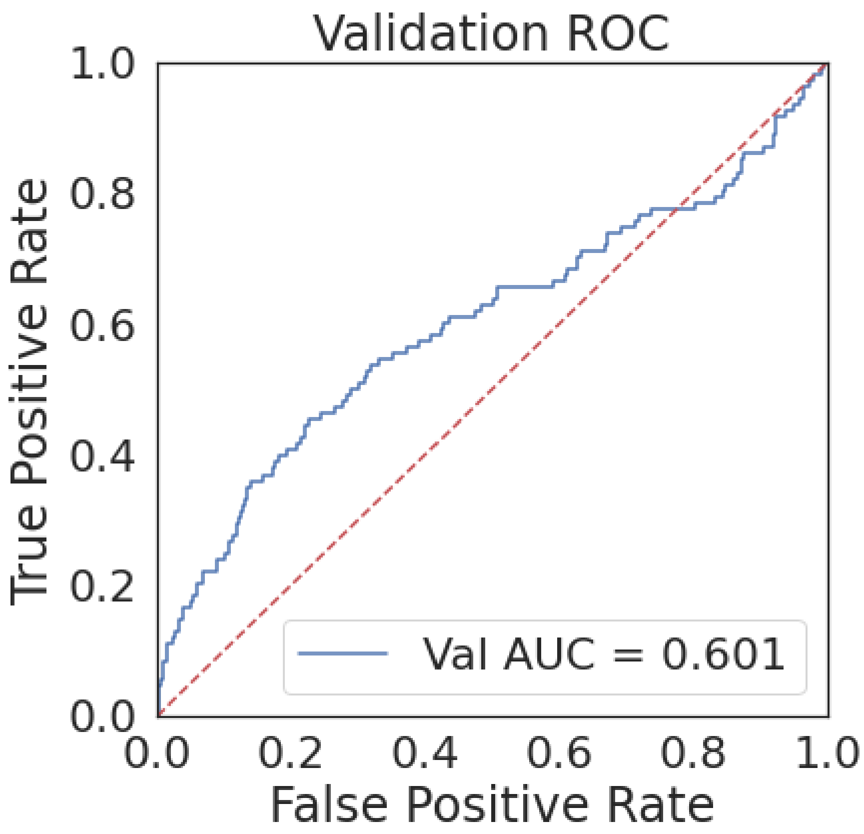
```
array([0.6028086 , 0.41010858, 0.44072951, ..., 0.39691499, 0.45397674,
       0.46611845])
```

```
print(accuracy_score(y_test, pred_lr))
roc_auc_score(y_test, lr.decision_function(X_test))
```

```
0.8305555555555556
0.6006992074378905
```

```
fpr, tpr, threshold = metrics.roc_curve(y_test, pred_proba_lr)
roc_auc = metrics.auc(fpr, tpr)
plt.figure(figsize=(6,6))
plt.title('Validation ROC')
plt.plot(fpr, tpr, 'b', label = 'Val AUC = %0.3f' % roc_auc)
plt.legend(loc = 'lower right')
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0, 1])
plt.ylim([0, 1])
plt.ylabel('True Positive Rate')
plt.xlabel('False Positive Rate')
```

```
plt.show()
```




```
print(classification_report(y_test,  pred_lr))
cm=confusion_matrix(y_test,  pred_lr)
```

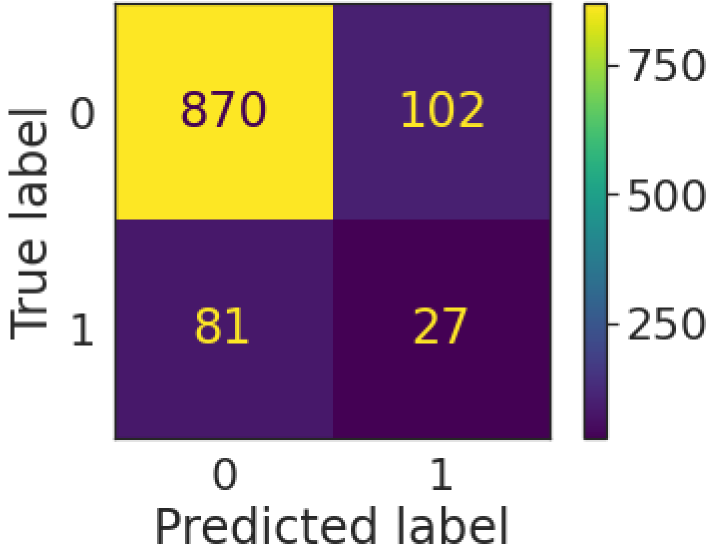
```
              precision    recall  f1-score   support

           0       0.91      0.90      0.90       972
           1       0.21      0.25      0.23       108

    accuracy                           0.83      1080
   macro avg       0.56      0.57      0.57      1080
weighted avg       0.84      0.83      0.84      1080
```

```
plot_confusion_matrix(lr , X_test , y_test)
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/utils/deprecation.py:87: FutureWarning: Function plot_confusion_matrix is deprecated; Functi
  warnings.warn(msg, category=FutureWarning)
<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at 0x7fee2dabb350>
```



Conclusion

Findings

- The good and stable perfermance of Logsitic Regression can be the reason why it is one of the most popular methods to classification cases in the real world.
- Algorithms could be fancy and powerful, but making the dataset informative and clean is essential to feed into our models and get a better performance. In this project, we did't show all the experiments we tried, but changing the way how we fill in NA value or the

methods we balance the data lead a bigger change than tuning the parameters. Both Gradient Boosting Classifier and Hist Gradient Boosting Classifer get a much better performance after we balanced the data with SMOTE.

- In the process of this project, we became more familiar with data pre-processing and the training of different models. Also, in order to improve the performance of our models and get better results in the competition, we learned a lot of models and data pre-processing methods that we did not know before, which was very exciting and greatly stimulated our interest in machine learning.

Output Prediction of Test Data

Although we tuning the best hyperparameters, but the best performance of our all the submissions is the one with default hyperparameters. It does not mean what we done before is not useful, but the model with default parameters perform better in this test dataset.

```
# use whole train data after transformation and balancing to fit the model

lr = LogisticRegression()
lr.fit(X_s, y_s)

x_pre = ct.fit_transform(test)
x_pre.shape

predict_lr2 = lr.predict_proba(x_pre)[:,1]
predict_lr2
```

```
    array([0.47527007, 0.68707136, 0.43246044, ..., 0.30978369, 0.48622168,
           0.51958333])
```

```
ID = np.arange(1,x_pre.shape[0]+1)
d = {'ID': ID, 'Y': predict_lr2}
out = pd.DataFrame(d)
out.to_csv('/content/pred_ready_0.65980.csv',
        index = False)
```

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