Final

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Predict the default of Credit Card holder

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1 Introduction

2 Context

Our study took payment data in October, 2005, from an important bank (a cash and credit card issuer) in Taiwan and the targets were credit card holders of the bank. Among the total 25,000 observations, 5529 observations (22.12%) are the cardholders with default payment. This research employed a binary variable – default payment (Yes = 1, No = 0), as the response variable.

3 Content

Following 23 variables as explanatory variables:

X1: Amount of the given credit (NT dollar): it includes both the individual consumer credit and his/her family (supplementary) credit.

X2: Gender (1 = male; 2 = female).

X3: Education (1 = graduate school; 2 = university; 3 = high school; 4 = others).

X4: Marital status (1 = married; 2 = single; 3 = others).

X5: Age (year).

X6–X11: History of past payment. We tracked the past monthly payment records (from April to September,2005) as follows: X6 = the repayment status in September, 2005; X7 = the repayment status in August,2005;…;X11 = the repayment status in April, 2005. The measurement scale for the repayment status is: 1 = pay duly; 1 = payment delay for one month;2 = payment delay for two months; …; 8 = payment delay for eight months; 9 = payment delay for nine months and above.

X12–X17: Amount of bill statement (NT dollar).(X12 = amount of bill statement in September,2005; X13 = amount of bill statement in August,2005 ;…; X17 = amount of bill statement in April,2005.)

X18–X23: Amount of previous payment (NT dollar).(X18 = amount paid in September, 2005; X19 = amount paid in August, 2005;…;X23 = amount paid in April,2005.)

4 Set up the environment

First, make sure you have python installed.

[ ]:
```
!python --version
```

If you don't have python installed - please follow this link for instructions.

Running the cell below will start the installation of required python libraries, assuming you have python already installed.

[ ]:
```
!pip install pandas
!pip install numpy
!pip install seaborn
!pip install matplotlib
!pip install plotly
!pip install iplot
!pip install seaborn
```

[1]:
```
#import the librarys
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import plotly as py
import plotly.graph_objs as go
from collections import Counter
from sklearn.model_selection import train_test_split
from plotly.offline import *
%matplotlib inline
np.random.seed(2021)
from imblearn.over_sampling import RandomOverSampler
from imblearn.combine import SMOTETomek
from imblearn.over_sampling import SMOTE
```

5 Load Default of Credit Card Clients data

The data was randomly divided into two groups, one for model training and the other to validate the model.

[10]:
```
#df_credit_raw = pd.read_excel ("../data/default of credit card clients.xls")
df_credit_raw = pd.read_excel ("/Users/yyyyushuqi/Downloads/default of credit␣
 ↪card clients.xls")
```

```
#df_credit_raw =  pd.read_excel('default_of_credit_card_clients.xls')
print (df_credit_raw.shape)
```

```
(30001, 25)
```

[11]:
```
df_credit = df_credit_raw.iloc[1:,1:]
print(df_credit.shape)
df_credit.head(10)
```

```
(30000, 24)
```

[11]:

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	…	X15	X16	X17	\
1	20000	2	2	1	24	2	2	-1	-1	-2	…	0	0	0	
2	120000	2	2	2	26	-1	2	0	0	0	…	3272	3455	3261	
3	90000	2	2	2	34	0	0	0	0	0	…	14331	14948	15549	
4	50000	2	2	1	37	0	0	0	0	0	…	28314	28959	29547	
5	50000	1	2	1	57	-1	0	-1	0	0	…	20940	19146	19131	
6	50000	1	1	2	37	0	0	0	0	0	…	19394	19619	20024	
7	500000	1	1	2	29	0	0	0	0	0	…	542653	483003	473944	
8	100000	2	2	2	23	0	-1	-1	0	0	…	221	-159	567	
9	140000	2	3	1	28	0	0	2	0	0	…	12211	11793	3719	
10	20000	1	3	2	35	-2	-2	-2	-2	-1	…	0	13007	13912	

	X18	X19	X20	X21	X22	X23	Y
1	0	689	0	0	0	0	1
2	0	1000	1000	1000	0	2000	1
3	1518	1500	1000	1000	1000	5000	0
4	2000	2019	1200	1100	1069	1000	0
5	2000	36681	10000	9000	689	679	0
6	2500	1815	657	1000	1000	800	0
7	55000	40000	38000	20239	13750	13770	0
8	380	601	0	581	1687	1542	0
9	3329	0	432	1000	1000	1000	0
10	0	0	0	13007	1122	0	0

```
[10 rows x 24 columns]
```

6 Split data to train and test

[50]:
```
# split the data for training purpose

from sklearn.model_selection import train_test_split

X = df_credit.loc[:, df_credit.columns != 'Y']
y = df_credit['Y'].values.astype('int')
```

```
X_train,X_test,y_train,y_test = train_test_split(X, y, stratify=y, test_size=0.
↪2, random_state=0)
X_train.columns.values
```

[50]:
```
array(['X1', 'X2', 'X3', 'X4', 'X5', 'X6', 'X7', 'X8', 'X9', 'X10', 'X11',
       'X12', 'X13', 'X14', 'X15', 'X16', 'X17', 'X18', 'X19', 'X20',
       'X21', 'X22', 'X23'], dtype=object)
```

[51]:
```
X_train.head(3)
```

[51]:

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	…	X14	X15	X16	\
6671	320000	1	1	2	26	-1	0	0	0	0	…	13917	12125	0	
12887	200000	1	1	1	40	-1	-1	-1	-1	-1	…	6360	2620	5900	
16219	120000	2	1	2	45	0	0	0	0	0	…	87941	89737	95451	

	X17	X18	X19	X20	X21	X22	X23
6671	0	1267	1700	243	0	0	220000
12887	37084	5007	7096	2620	6000	17703	4914
16219	97379	3079	3185	3251	7200	3600	3900

[3 rows x 23 columns]

[52]:
```
X_train1 = pd.DataFrame(X_train)
Data = X_train1
Data['Y']= y_train
```

[53]:
```
Data.head()
```

[53]:

	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	…	X15	X16	X17	\
6671	320000	1	1	2	26	-1	0	0	0	0	…	12125	0	0	
12887	200000	1	1	1	40	-1	-1	-1	-1	-1	…	2620	5900	37084	
16219	120000	2	1	2	45	0	0	0	0	0	…	89737	95451	97379	
5773	20000	2	1	2	22	-2	-2	-2	-2	-2	…	304	0	302	
22647	30000	2	3	1	42	0	0	0	0	0	…	2592	30094	29147	

	X18	X19	X20	X21	X22	X23	Y
6671	1267	1700	243	0	0	220000	0
12887	5007	7096	2620	6000	17703	4914	1
16219	3079	3185	3251	7200	3600	3900	0
5773	0	913	304	0	302	7676	0
22647	1371	1210	1000	30000	1046	1390	1

[5 rows x 24 columns]

7 deal with the imbalance data

7.0.1 Oversampling

[47]:
```
df_credit['Y'] = df_credit['Y'].astype('category')
ovs = RandomOverSampler(random_state = 42)
x1,y1 = ovs.fit_resample(Data.iloc[: , 0:-1],Data.Y)
df_credit_oversampling=x1
df_credit_oversampling["Y"]=y1
print("DATA_oversampling \ngood class:",␣
 ↪len(df_credit_oversampling[df_credit_oversampling.Y == 0]),
      "\nBad Class:", len(df_credit_oversampling[df_credit_oversampling.Y ==␣
 ↪1]))
```

```
DATA_oversampling
good class: 18691
Bad Class: 18691
```

7.0.2 Smote

[48]:
```
X_smote, y_smote = SMOTE().fit_resample(Data.iloc[:, 0:-1], Data.Y)
Counter(y_smote).items()
```

[48]:
```
dict_items([(0, 18691), (1, 18691)])
```

8 Feature Selection

[9]:
```
# with LASSO
from sklearn.linear_model import LogisticRegression

logr = LogisticRegression(C=0.1, penalty="l1", solver="liblinear",␣
 ↪random_state=0)
logr.fit(X_train, y_train)
sorted_tuples = sorted(list(zip(X_train.columns.values,logr.
 ↪coef_[0])),key=lambda x:x[1],reverse=True)
for feature,coef in sorted_tuples:
    print(f'{feature:30s} : {coef: 0.3f}')

print(f'\nColumns to remove: {X_train.columns[logr.coef_[0] == 0]}')
```

```
X6                             :  0.717
X13                            :  0.294
X14                            :  0.125
X7                             :  0.103
```

```
X17                             :  0.091
X8                              :  0.091
X5                              :  0.085
X9                              :  0.030
X10                             :  0.020
X16                             :  0.001
X15                             : -0.021
X11                             : -0.042
X23                             : -0.051
X20                             : -0.063
X2                              : -0.065
X4                              : -0.070
X1                              : -0.074
X21                             : -0.085
X22                             : -0.087
X3                              : -0.089
X19                             : -0.224
X18                             : -0.277
X12                             : -0.579

Columns to remove: Index([], dtype='object')
```

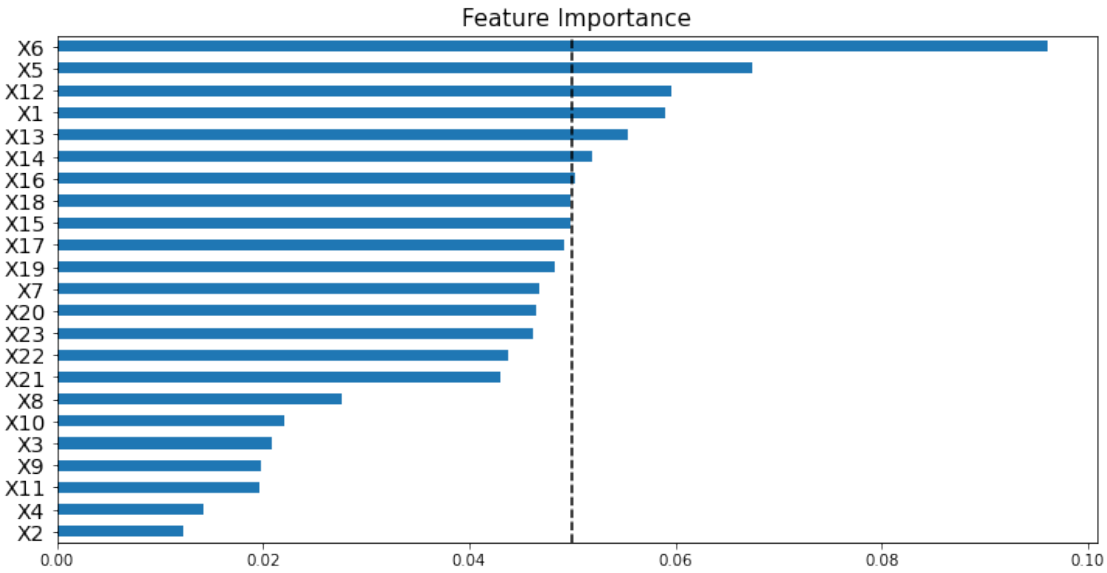
[10]:
```
# Tree based model feature importance
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(random_state=123).fit(X_train,y_train)
rf.feature_importances_ # (normalized) total reduction of function measuring␣
 ↪impurity
feature_importances = pd.Series(rf.feature_importances_,index=X_train.columns)
feature_importances.sort_values(ascending=False).round(3)
```

[10]:
```
X6     0.137
X7     0.078
X2     0.068
X4     0.057
X8     0.052
X12    0.044
X3     0.043
X1     0.042
X5     0.040
X18    0.038
X13    0.034
X9     0.034
X19    0.033
X20    0.033
X14    0.032
X15    0.031
```

```
X10    0.031
X16    0.030
X11    0.030
X17    0.030
X23    0.030
X21    0.029
X22    0.027
dtype: float64
```

[9]:
```
fig,ax = plt.subplots(1,1,figsize=(12,6))
feature_importances.sort_values().plot.barh(ax=ax);
ax.set_yticklabels(ax.get_yticklabels(),fontsize=14);
ax.set_title('Feature Importance', fontsize=15);
plt.axvline(x=0.05, color='k', linestyle='--');
```



[10]:
```
# SelectFromModel
from sklearn.feature_selection import SelectFromModel

sfm = SelectFromModel(logr,threshold=None, prefit=True)
sfm.get_support() # boolean mask of features selected
X_train.columns[sfm.get_support()]
X_train_subset = sfm.transform(X_train)

sfm_rf = SelectFromModel(RandomForestClassifier(),␣
 ↪threshold='mean',prefit=False).fit(X_train,y_train)
print(f'select features: {X_train.columns[sfm_rf.get_support()]}')
```

```
select features: Index(['X1', 'X5', 'X6', 'X12', 'X13', 'X14', 'X15', 'X16',
```

```
'X17', 'X18',
       'X19', 'X20', 'X21', 'X23'],
      dtype='object')
```

[11]:
```
# Univariate tests
from sklearn.feature_selection import SelectKBest, f_classif

# select 3 best features
kbest = SelectKBest(score_func=f_classif, k=3).fit(X_train, y_train)
list(X.columns[kbest.get_support()])
```

[11]:
```
['X6', 'X7', 'X8']
```

[12]:
```
# Recursive Feature Elimination
from sklearn.feature_selection import RFE

rfe = RFE(LogisticRegression(penalty='none'), n_features_to_select=3, step=1).
 ↪fit(X_train,y_train)
X_train.columns[rfe.get_support()]
```

[12]:
```
Index(['X6', 'X12', 'X13'], dtype='object')
```

9 Build and Evaluate Advanced Model:

9.1 Gradient Boosting

[9]:
```
from sklearn.ensemble import GradientBoostingClassifier

#params = {'learning_rate':[0.1,0.05,0.01],
#          'n_estimators':[10,50,100],
#          'max_depth':[1,2,5,7],
#          'min_samples_split': [2,3,4],
#          'min_samples_leaf':[1,3,5]}
#gscv = GridSearchCV(GradientBoostingClassifier(), params, n_jobs=-1)
#gscv.fit(X_train,y_train)
#print(gscv.best_params_)
```

[10]:
```
# best params output{'learning_rate': 0.1, 'max_depth': 7, 'min_samples_leaf':␣
 ↪3, 'min_samples_split': 4, 'n_estimators': 100}
```

[11]:
```
start = timeit.default_timer()

gbc = GradientBoostingClassifier(learning_rate=0.1,
                                 max_depth=7,
                                 min_samples_leaf=3,
```

```
                                   min_samples_split=4,
                                   n_estimators=100,
                                   )
gbc.fit(X_train,y_train)

stop = timeit.default_timer()

print(f'training accuracy: {gbc.score(X_smote,y_smote):0.4f}')
print(f'test accuracy: {gbc.score(X_test,y_test):0.4f}')
print(f'AUC: {roc_auc_score(y_test, gbc.predict(X_test)):0.4f}')
print('Time: ', round(stop - start, 4), 's')
```

```
training accuracy: 0.9050
test accuracy: 0.8183
AUC: 0.6620
Time:  29.3384 s
```

9.2 Gradient Boosting with Feature Selection

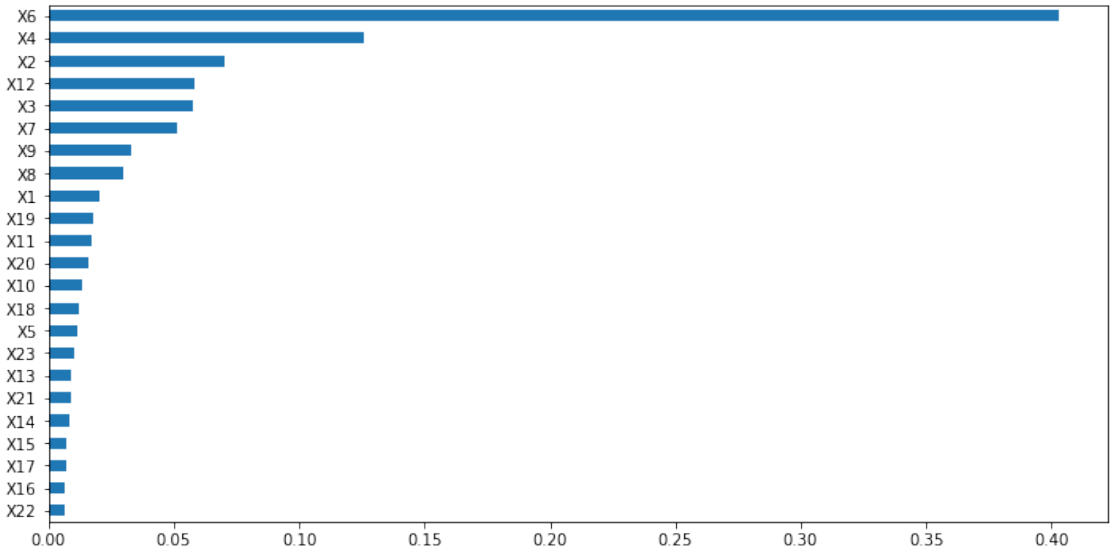
[12]:
```
feature_importances = pd.Series(gbc.feature_importances_,index=X_smote.columns)
display(feature_importances.sort_values(ascending=False).round(4))

fig,ax = plt.subplots(1,1,figsize=(12,6))
feature_importances.sort_values().plot.barh(ax=ax)
```

```
X6     0.4027
X4     0.1260
X2     0.0705
X12    0.0584
X3     0.0578
X7     0.0513
X9     0.0329
X8     0.0296
X1     0.0201
X19    0.0176
X11    0.0170
X20    0.0156
X10    0.0134
X18    0.0118
X5     0.0115
X23    0.0103
X13    0.0090
X21    0.0087
X14    0.0085
X15    0.0072
X17    0.0069
```

```
X16    0.0067
X22    0.0062
dtype: float64
```

[12]: <AxesSubplot:>



[13]:
```
from sklearn.feature_selection import SelectFromModel

sfm = SelectFromModel(gbc,
                      threshold='mean',
                      prefit=True)

X_train.columns[sfm.get_support()]
```

[13]: Index(['X2', 'X3', 'X4', 'X6', 'X7', 'X12'], dtype='object')

[14]:
```
X_train_fs = sfm.transform(X_smote)
X_test_fs = sfm.transform(X_smote)
```

[15]:
```
#params = {'learning_rate':[0.1,0.05,0.01],
#          'n_estimators':[10,50,100],
#          'max_depth':[1,2,5,7],
#          'min_samples_split': [2,3,4],
#          'min_samples_leaf':[1,3,5]}
#gscv = GridSearchCV(GradientBoostingClassifier(), params, n_jobs=-1)
#gscv.fit(X_train_fs,y_train)
#print(gscv.best_params_)
```

[16]:
```
#best params output:{'learning_rate': 0.05, 'max_depth': 5, 'min_samples_leaf':␣
↪3, 'min_samples_split': 2, 'n_estimators': 100}
```

[17]:
```
start = timeit.default_timer()

gbc_fs = GradientBoostingClassifier(learning_rate=0.05,
                                    max_depth=5,
                                    min_samples_leaf=3,
                                    min_samples_split=2,
                                    n_estimators=100,
                                    )
gbc_fs.fit(X_train_fs,y_train)

stop = timeit.default_timer()

print(f'training accuracy: {gbc_fs.score(X_train_fs,y_train):0.4f}')
print(f'test accuracy: {gbc_fs.score(X_test_fs,y_test):0.4f}')
print(f'AUC: {roc_auc_score(y_test, gbc_fs.predict(X_test_fs)):0.4f}')
print('Time: ', round(stop - start, 4), 's')
```

```
training accuracy: 0.8733
test accuracy: 0.8168
AUC: 0.6453
Time:  4.2256 s
```

[ ]:
```

```