병원 개/폐업 분류 예측

수영이조

박정은 손다연 신선민 황수영

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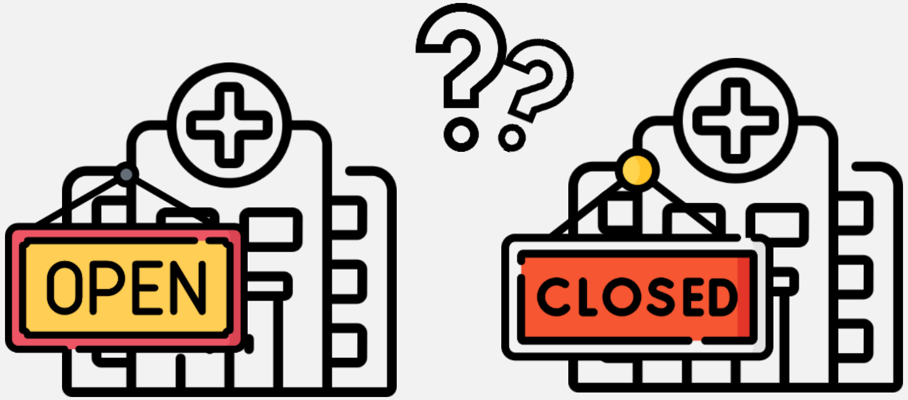
1. Introduction



1. 주제 및 목표

병원 폐업 여부를 예측하여 대출 승인여부 결정

2. 배경

한국 핀테크 기업 **모우다(MOUDA)**

: 상환기간 동안의 계속 경영 여부를 예측하여 병원들에게 금융 기회를 제공

- 일반적으로 병원 대출 시 **신용점수 또는 담보물**을 위주로 평가를 진행했던 기존 금융기관과의 차별점
- 신용 점수가 낮거나 담보를 가지지 못하는 우수 병원들에게도 **금융 기회를 제공**하자는 취지

3. 활용 데이터

- 의료기관의 폐업 여부가 포함된 최근 2개년의 재무정보와 병원 기본정보

(출처) Dacon 병원 개/폐업 분류 예측 경진대회 (https://dacon.io/competitions/official/9565/data/)

2. Data

[데이터 설명]

<병원 기본정보>

- inst_id: 병원 고유 번호
- OC: 영업/폐업 분류
- sido: 병원의 광역 지역 정보
- sgg: 병원의 시군구 자료
- openDate: 병원 설립일
- bedcount: 병원이 갖추고 있는 병상의 수
- instkind: 병원, 의원, 요양병원, 한의원, 종합병원 등 병원의 종류

<재무정보> 1: 2017 회계년도, 2: 2016 회계년도 >

- revenue1(2): 매출액
- salescost1(2): 매출원가
- sga1(2): 판매비와 관리비
- salary1(2): 급여
- noi1(2): 영업외수익
- noe1(2): 영업외비용
- Interest1(2): 이자비용
- ctax1(2): 법인세비용
- Profit1(2): 당기순이익
- liquidAsset1(2): 유동자산
- quickAsset1(2): 당좌자산
- receivableS1(2): 미수금(단기)
- inventoryAsset1(2): 재고자산
- nonCAsset1(2): 비유동자산
- tanAsset1(2): 유형자산
- OnonCAseet1(2): 기타 비유동자산
- receivableL1(2): 장기미수금
- debt1(2): 부채총계
- liquidLiabilities1(2): 유동부채
- shortLoan1(2): 단기차입금
- NCLiabilities1(2): 비유동부채
- longLoan1(2): 장기차입금
- netAsset1(2): 순자산총계
- surplus1(2): 이익잉여금

3. Analysis & Result

0. Import the necessary modules

```
import os
import numpy as np
import pandas as pd
import seaborn as sns
import shap
import xgboost as xgb
import lightgbm as lgb
import matplotlib.pyplot as plt

from sklearn.preprocessing import LabelEncoder
from sklearn.model_selection import train_test_split, StratifiedKFold, GridSearchCV
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier
from sklearn import svm
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score
from xgboost import XGBClassifier
from sklearn.metrics import confusion_matrix, accuracy_score, roc_auc_score
from sklearn.metrics import classification_report
from sklearn.model_selection import cross_val_score
```

3. Analysis & Result

1. Preprocess the data

```
#Reading the train and test files
train_prod_df = pd.read_csv('data\\train.csv') # 학습데이터
test_prod_df = pd.read_csv('data\\test_empty.csv') # 테스트데이터 (결과값 비어있음)
```

```
train_prod_df.head()
```

	inst_id	OC	sido	sgg	openDate	bedCount	instkind	revenue1	salescost1	sga1	...	debt2	liquidLiabilities2	shortl
0	1	open	choongnam	73	20071228	175.0	nursing_hospital	4.217530e+09	0.0	3.961135e+09	...	7.589937e+08	2.228769e+08	0.00000
1	3	open	gyeongnam	32	19970401	410.0	general_hospital	NaN	NaN	NaN	...	NaN	NaN	
2	4	open	gyeonggi	89	20161228	468.0	nursing_hospital	1.004522e+09	515483669.0	4.472197e+08	...	0.000000e+00	0.000000e+00	0.00000
3	7	open	incheon	141	20000814	353.0	general_hospital	7.250734e+10	0.0	7.067740e+10	...	3.775501e+10	1.701860e+10	9.21942
4	9	open	gyeongnam	32	20050901	196.0	general_hospital	4.904354e+10	0.0	4.765605e+10	...	5.143259e+10	3.007259e+10	1.75937

5 rows × 58 columns

```
test_prod_df.head()
```

	inst_id	OC	sido	sgg	openDate	bedCount	instkind	revenue1	salescost1	sga1	...	debt2	liquidLiabilities2	shortL
0	2	NaN	incheon	139	19981125.0	300.0	general_hospital	6.682486e+10	0.000000e+00	6.565709e+10	...	5.540643e+10	5.068443e+10	3.714334
1	5	NaN	jeju	149	20160309.0	44.0	hospital	3.495758e+10	0.000000e+00	3.259270e+10	...	6.730838e+10	4.209828e+10	2.420000
2	6	NaN	jeonnam	103	19890427.0	276.0	general_hospital	2.326031e+10	2.542571e+09	2.308749e+10	...	0.000000e+00	2.777589e+10	2.182278
3	8	NaN	busan	71	20100226.0	363.0	general_hospital	0.000000e+00	0.000000e+00	0.000000e+00	...	1.211517e+10	9.556237e+09	4.251867
4	10	NaN	jeonbuk	26	20040604.0	213.0	general_hospital	5.037025e+10	0.000000e+00	4.855803e+10	...	4.395973e+10	7.535567e+09	3.298427

5 rows × 58 columns

3. Analysis & Result

Fill the empty values

- Factor columns: Not_sure
- Numeric columns: -999

```
#Combining the train and test dataset
train_test_prod = train_prod_df.append(test_prod_df)
```

```
train_test_prod.shape
```

```
(428, 58)
```

```
#Get the object and numeric columns seperately
factor_columns = train_test_prod.select_dtypes(include = ['object']).columns
numeric_columns = train_test_prod.columns.difference(factor_columns)
```

```
factor_columns
```

```
Index(['OC', 'sido', 'instkind', 'ownerChange'], dtype='object')
```

```
numeric_columns
```

```
Index(['NCLiabilities1', 'NCLiabilities2', 'OnonCAsset1', 'OnonCAsset2',
       'bedCount', 'ctax1', 'ctax2', 'debt1', 'debt2', 'employee1',
       'employee2', 'inst_id', 'interest1', 'interest2', 'inventoryAsset1',
       'inventoryAsset2', 'liquidAsset1', 'liquidAsset2', 'liquidLiabilities1',
       'liquidLiabilities2', 'longLoan1', 'longLoan2', 'netAsset1',
       'netAsset2', 'noe1', 'noe2', 'noi1', 'noi2', 'nonCAsset1', 'nonCAsset2',
       'openDate', 'profit1', 'profit2', 'quickAsset1', 'quickAsset2',
       'receivableL1', 'receivableL2', 'receivableS1', 'receivableS2',
       'revenue1', 'revenue2', 'salary1', 'salary2', 'salescost1',
       'salescost2', 'sga1', 'sga2', 'sgg', 'shortLoan1', 'shortLoan2',
       'surplus1', 'surplus2', 'tanAsset1', 'tanAsset2'],
      dtype='object')
```

```
#After analysis realized that the bed counts of these two hospitals may have had wrong entries.
#Filling up the empty instkind and bedCount for hospital id 430 and 413
train_test_prod.loc[train_test_prod.inst_id == 430, ['instkind']] = 'dental_clinic'
train_test_prod.loc[train_test_prod.inst_id == 430, ['bedCount']] = 0
train_test_prod.loc[train_test_prod.inst_id == 413, ['bedCount']] = -999

#Fill the empty values in the object columns as "Not sure"
train_test_prod[factor_columns] = train_test_prod[factor_columns].fillna('Not_sure')
#Fill all the empty values in the numeric columns as -999
train_test_prod[numeric_columns] = train_test_prod[numeric_columns].fillna(-999)
```

3. Analysis & Result

Split the whole data into train and test set

- dependent column: OC (0:close, 1:open)
- independent columns: others
- train_prod_X: train set with independent columns
- train_prod_Y: train set with dependent column
- test_prod_X: test set with independent columns
- test_prod_Y: the objective of prediction

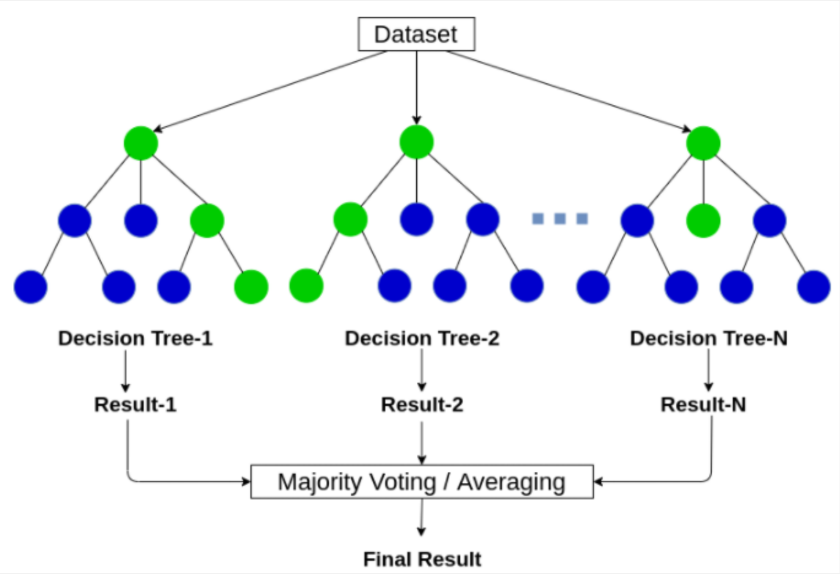
```
#Convert all the object columns to numeric since the ML algorithms don't accept object features directly
fac_le = LabelEncoder()
train_test_prod[factor_columns] = train_test_prod.loc[:,factor_columns].apply(lambda x : fac_le.fit_transform(x))

#Splitting back data to train prod and test prod
#값이 있으면 train 데이터셋 값이 비어있으면 test 데이터셋
train_prod = train_test_prod.loc[train_test_prod.OC != 0,]
test_prod = train_test_prod.loc[train_test_prod.OC == 0,]

# 1,2 를 0,1로 바꾸기 (0이 폐업(close) 1이 폐업X(open))
train_prod['OC'] = train_prod['OC'] - 1

#Obtain the submission ID to create the submission file later
sub_id = test_prod.inst_id

#Get the dependent and independent column
dep = 'OC'
indep = train_prod.columns.difference([dep])

train_prod_X = train_prod[indep]
train_prod_Y = train_prod[dep]
test_prod_X = test_prod[indep]
#test_prod_Y = test_prod[dep]
```

3. Analysis & Result

2. Classification Model(1) - Random Forest

Random Forest

- 분류/회귀예측에 이용되는 앙상블 기법 중 하나로, 대표적인 배깅 모형에 해당
- 다수의 결정 트리를 구성한 뒤 평균 또는 과반수 투표 등을 이용하여 하나의 랜덤 포레스트로 결합



A. Hyperparameter tuning of Random forest

B. Check the over-fitting of tuned model

C. Calculate the cut-off value for classification

D. Compare default model to tuned model

3. Analysis & Result

A. Hyperparameter tuning of Random forest (using 3-fold cross validation)

- n_estimators : The number of trees in the forest
- max_features : The number of features to consider when looking for the best split
- max_depth : The maximum depth of the tree

```
np.random.seed(100)
n_estimators = [int(x) for x in np.linspace(start = 10, stop = 300, num = 10)] # Number of trees in random forest
max_features = ['auto', 'sqrt'] # Number of features to consider at every split
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)] # Maximum number of levels in tree
max_depth.append(None)

random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth}
```

3. Analysis & Result

Check the best hyperparameter combination and train the Random forest model with it

```
rf_random.best_params_
```

```
{'max_depth': 100, 'max_features': 'sqrt', 'n_estimators': 74}
```

```
###########################################################################
############ Random Forest with hyper-parameter tuning
###########################################################################
estimators = rf_random.best_params_['n_estimators']
max_depth_tune = rf_random.best_params_['max_depth']
max_features_tune = rf_random.best_params_['max_features']

np.random.seed(100)

# 하이퍼파라미터 적용
RF_prod_tune = RandomForestClassifier(n_estimators = estimators,
                                      max_depth = max_depth_tune,
                                      max_features = max_features_tune)

# 훈련
RF_prod_tune.fit(train_prod_X, train_prod_Y)

# 결과: class가 0 or 1
RF_prod_predicted_tune = RF_prod_tune.predict(test_prod_X)

# 결과: class 1에 속할 확률
RF_prod_prediction_tune = RF_prod_tune.predict_proba(test_prod_X)[:,1]

# 튜닝 후 예측 결과 출력
sub_RF_tune = pd.DataFrame({'inst_id' : sub_id , 'OC' : RF_prod_prediction_tune })
sub_RF_tune = sub_RF_tune[['inst_id', 'OC']]
sub_RF_tune
```

	inst_id	OC
0	2	0.959459
1	5	0.783784
2	6	0.567568
3	8	0.824324
4	10	0.932432
...	...	...
122	424	0.378378
123	425	0.702703
124	429	0.581081
125	430	0.824324
126	431	0.567568

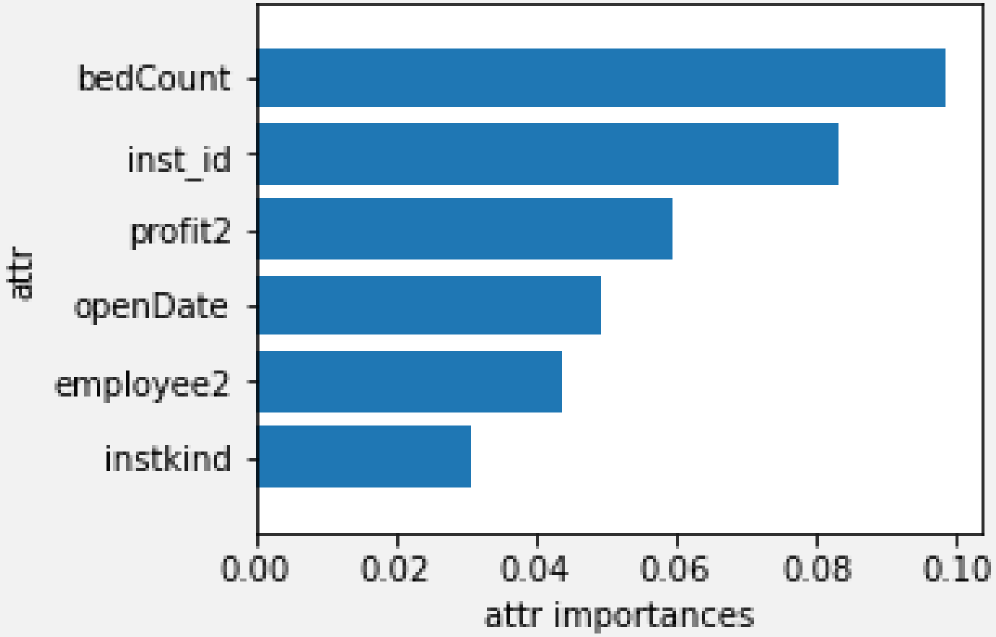
127 rows × 2 columns

3. Analysis & Result

Check the best hyperparameter combination and train the Random forest model with it

```
def setting(data):
    return data[0]

RF_fi_li = []# randomforest feature importance list
for i in range(RF_prod_tune.n_features_):
    RF_fi_li.append((RF_prod_tune.feature_importances_[i],train_prod_X.columns[i]))

RF_fi_li_sorted = sorted(RF_fi_li, key=setting)
```

```
plot_feature_importances_rf(RF_prod_tune)
plt.show()
```



3. Analysis & Result

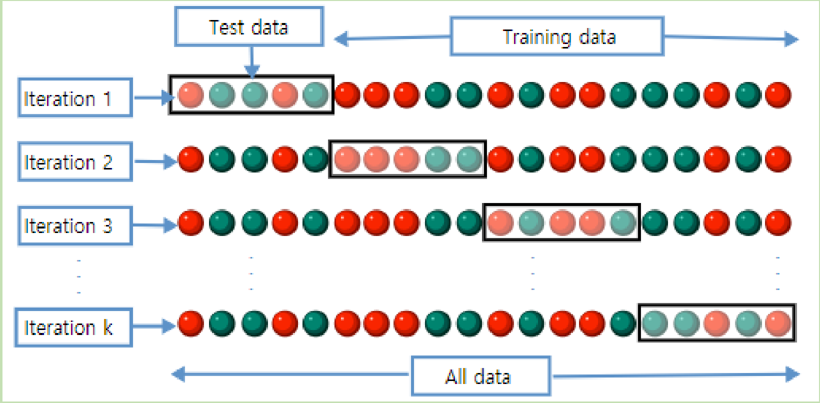
B. Check the over-fitting of tuned model (using 5-fold cross validation)

- 하이퍼파라미터 튜닝 범위가 무작위로 설정되었기 때문에 튜닝 결과가 훈련 데이터에 **과대적합** 되었을 가능성이 존재
- **교차 검증**을 통해 과대적합 여부를 확인한 결과, 모든 fold에서 적절한 분류 성능을 보임

```
# model, train, target, cross validation
np.random.seed(10)
scores = cross_val_score(RF_prod_tune, train_prod_X, train_prod_Y, cv=5)
print(scores)
print('mean : ',scores.mean())
```

```
[0.93442623 0.95       0.95       0.95       0.93333333]
mean :  0.9435519125683062
```

[K-fold cross validation]



3. Analysis & Result

C. Calculate the cut-off value for classification

```
# 예측결과 0(close) 라벨링
close_idx = [5, 6, 24, 30 ,64, 123, 229, 258, 293, 341, 425, 429, 431]
test_prod_labeled = test_prod[['inst_id', 'OC']] # 결과 라벨링 된 테스트 데이터프레임
test_prod_labeled['OC'] = [0 if id in close_idx else 1 for id in test_prod['inst_id']] # 라벨링
y_true = list(test_prod_labeled['OC'])
```

1) Construct the test set with real answer

```
start = 5
end = 9
```

```
max_accuracy = -1
coval_max = -1

for i in range(start,end):
    print('='*60)
    coval = i/10
    print(" cut-off value : " ,coval)
    print('-'*22)

    sub_RF_tune_ths = sub_RF_tune[['inst_id', 'OC']]
    sub_RF_tune_ths['OC'] = [1 if oc>=coval else 0 for oc in sub_RF_tune_ths['OC']] # 확률값을 1,0으로 변환
    y_prod = list(sub_RF_tune_ths['OC'])

    print(classification_report(y_true, y_prod, target_names=['open', 'close']))
    print(accuracy_score(y_true,y_prod))

    if max_accuracy < accuracy_score(y_true,y_prod):
        max_accuracy = accuracy_score(y_true,y_prod)
        coval_max = coval
```

2) Examine the optimal cut-off value (0.5~0.8 by 0.1)

3. Analysis & Result

C. Calculate the cut-off value for classification

cut-off value : 0.5

	precision	recall	f1-score	support
open	0.33	0.08	0.12	13
close	0.90	0.98	0.94	114
accuracy			0.89	127
macro avg	0.62	0.53	0.53	127
weighted avg	0.84	0.89	0.86	127

0.889763779527559

cut-off value : 0.7

	precision	recall	f1-score	support
open	0.77	0.77	0.77	13
close	0.97	0.97	0.97	114
accuracy			0.95	127
macro avg	0.87	0.87	0.87	127
weighted avg	0.95	0.95	0.95	127

0.952755905511811

cut-off value : 0.6

	precision	recall	f1-score	support
open	0.67	0.46	0.55	13
close	0.94	0.97	0.96	114
accuracy			0.92	127
macro avg	0.80	0.72	0.75	127
weighted avg	0.91	0.92	0.91	127

0.9212598425196851

cut-off value : 0.8

	precision	recall	f1-score	support
open	0.65	1.00	0.79	13
close	1.00	0.94	0.97	114
accuracy			0.94	127
macro avg	0.82	0.97	0.88	127
weighted avg	0.96	0.94	0.95	127

0.9448818897637795

3. Analysis & Result

C. Calculate the cut-off value for classification

```
cut-off value :  0.5

             precision    recall  f1-score   support

       open       [illegible]                       13
      close       0.91      0.98      0.95       114

avg / total       0.87      0.90      0.87       127
```

```
cut-off value :  0.7

              precision    recall  f1-score   support

        open       0.77      0.77      0.77        13
       close       0.97      0.97      0.97       114

    accuracy                           0.95       127
   macro avg       0.87      0.87      0.87       127
weighted avg       0.95      0.95      0.95       127

0.952755905511811
```

Optimal cut-off value
(according to 'accuracy')

```
cutoff_rf = coval_max
cutoff_rf
```

```
0.7
```

```
                                          13
                                          14

avg / total       0.87      0.90      0.87       127

0.8976377952755905
```

```
cut-off value :  0.8

             precision    recall  f1-score   support

       open       0.61      0.85      0.71        13
      close       0.98      0.94      0.96       114

avg / total       0.94      0.93      0.93       127

0.9291338582677166
```

D. Compare default model to tuned model

< Defalut model >

n_estimators : default / max_features : default / max_depth : defalut

```
np.random.seed(100)
RF_prod = RandomForestClassifier()
RF_prod_model = RF_prod.fit(train_prod_X, train_prod_Y)
RF_prod_prediction = RF_prod.predict_proba(test_prod_X)[:,1]
```

Compare 2 models with optimal cut-off value

```
sub_RF = pd.DataFrame({'inst_id' : sub_id , 'OC' : RF_prod_prediction })
sub_RF = sub_RF[['inst_id', 'OC']]
sub_RF['OC'] = [1 if oc>=cutoff_rf else 0 for oc in sub_RF['OC']]
y_prod = list(sub_RF['OC'])
```

```
sub_RF_customized = sub_RF_tune[['inst_id', 'OC']]
sub_RF_customized['OC'] = [1 if oc >= cutoff_rf else 0 for oc in sub_RF_customized['OC']] # 확률값을 1,0으로 변환
y_prod_customized = list(sub_RF_customized['OC'])
```

3. Analysis & Result

```python
# Before tuned
print('=========Before tuned=========')
print(classification_report(y_true, y_prod, target_names=['class 0', 'class 1']))
print(accuracy_score(y_true, y_prod))
# After tuned
print('=========After tuned=========')
print(classification_report(y_true, y_prod_customized, target_names=['class 0', 'class 1']))
print(accuracy_score(y_true, y_prod_customized))
```

```
============Before tuned============
              precision    recall  f1-score   support

     class 0       0.75      0.69      0.72        13
     class 1       0.97      0.97      0.97       114

    accuracy                           0.94       127
   macro avg       0.86      0.83      0.84       127
weighted avg       0.94      0.94      0.94       127

0.9448818897637795
```

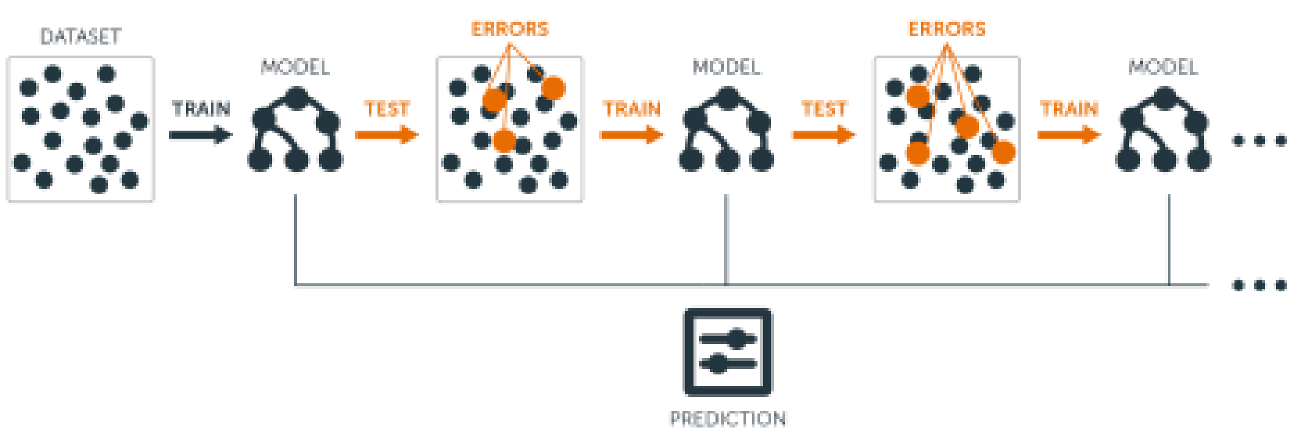
```
============After tuned============
              precision    recall  f1-score   support

     class 0       0.77      0.77      0.77        13
     class 1       0.97      0.97      0.97       114

    accuracy                           0.95       127
   macro avg       0.87      0.87      0.87       127
weighted avg       0.95      0.95      0.95       127

0.952755905511811
```

3. Analysis & Result

3. Classification Model(2) - GBM

GBM

- 분류/회귀예측에 이용되는 앙상블 기법 중 하나로, 대표적인 부스팅 모형에 해당
- 기존 타겟값과 그 residual을 예측하는 모형을 반복적으로 구성하고 결합함으로써 모형의 예측력을 높여가는 방법



A. Hyperparameter tuning of GBM

B. Check the over-fitting of tuned model

C. Calculate the cut-off value for classification

D. Compare default model to tuned model

3. Analysis & Result

A. Hyperparameter tuning of GBM (using 3-fold cross validation)

- n_estimators : The number of boosting stages to perform
- max_features : The number of features to consider when looking for the best split
- max_depth : The maximum depth of the individual estimators
- min_sample_split : The minimum number of samples required to split an internal node

```
import matplotlib.pylab as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 12, 4
```

```
target = 'OC'
IDcol = 'inst_id'

predictors = [x for x in train_prod_X.columns if x not in [target, IDcol]]
param_test1 = {'n_estimators':range(80,121,20),'max_depth':range(2,5),'max_features':['sqrt','auto',None]}

gsearch1 = GridSearchCV(estimator = GradientBoostingClassifier(learning_rate=0.1, subsample=1.0,random_state=10),
param_grid = param_test1, scoring='accuracy',n_jobs=-1, cv=5)

gsearch1.fit(train_prod_X[predictors],train_prod_Y)
```

3. Analysis & Result

A. Hyperparameter tuning of GBM (using 3-fold cross validation)

- n_estimators : The number of boosting stages to perform
- max_features : The number of features to consider when looking for the best split
- max_depth : The maximum depth of the individual estimators
- min_sample_split : The minimum number of samples required to split an internal node

```
import matplotlib.pylab as plt
%matplotlib inline
from matplotlib.pylab import rcParams
rcParams['figure.figsize'] = 12, 4
```

```
target = 'OC'
IDcol = 'inst_id'

predictors = [x for x i
param_test1 = {'n_estim

gsearch1 = GridSearchCV
param_grid = param_test

gsearch1.fit(train_prod
```

```
GridSearchCV(cv=5, estimator=GradientBoostingClassifier(random_state=10),
             n_jobs=-1,
             param_grid={'max_depth': range(2, 5),
                         'max_features': ['sqrt', 'auto', None],
                         'n_estimators': range(80, 121, 20)},
             scoring='accuracy')
```

3. Analysis & Result

Check the best hyperparameter combination and train the GBM model with it

```
gsearch1.best_params_
```

```
{'max_depth': 4, 'max_features': 'sqrt', 'n_estimators': 80}
```

값 적용

```
np.random.seed(100)
estimators = gsearch1.best_estimator_.n_estimators
max_depth=gsearch1.best_estimator_.max_depth
max_features=gsearch1.best_estimator_.max_features
random_state=gsearch1.best_estimator_.random_state

GBM_prod_tune = GradientBoostingClassifier(n_estimators = estimators ,max_depth=max_depth, max_features=max_features,random_state = random_state )
GBM_prod_model_tune = GBM_prod_tune.fit(train_prod_X, train_prod_Y)
GBM_prod_prediction_tune = GBM_prod_tune.predict_proba(test_prod_X)[:,1]

sub_GBM_tune = pd.DataFrame({'inst_id' : sub_id , 'OC' : GBM_prod_prediction_tune })
sub_GBM_tune = sub_GBM_tune[['inst_id', 'OC']]
sub_GBM_tune
```

3. Analysis & Result

Check the best hyperparameter combination and train the GBM

```
gsearch1.best_params_
```

```
{'max_depth': 4, 'max_features': 'sqrt', 'n_estimators': 80}
```

값 적용

```
np.random.seed(100)
estimators = gsearch1.best_estimator_.n_estimators
max_depth=gsearch1.best_estimator_.max_depth
max_features=gsearch1.best_estimator_.max_features
random_state=gsearch1.best_estimator_.random_state

GBM_prod_tune = GradientBoostingClassifier(n_estimators = estimators ,max_depth=max_depth, max_features=max_feat
GBM_prod_model_tune = GBM_prod_tune.fit(train_prod_X, train_prod_Y)
GBM_prod_prediction_tune = GBM_prod_tune.predict_proba(test_prod_X)[:,1]

sub_GBM_tune = pd.DataFrame({'inst_id' : sub_id , 'OC' : GBM_prod_prediction_tune })
sub_GBM_tune = sub_GBM_tune[['inst_id', 'OC']]
sub_GBM_tune
```

result

	inst_id	OC
0	2	0.999099
1	5	0.989135
2	6	0.867966
3	8	0.997392
4	10	0.999350
...	...	...
122	424	0.124770
123	425	0.362668
124	429	0.195613
125	430	0.987424
126	431	0.249631

127 rows × 2 columns

3. Analysis & Result

B. Check the over-fitting of tuned model (using 5-fold cross validation)

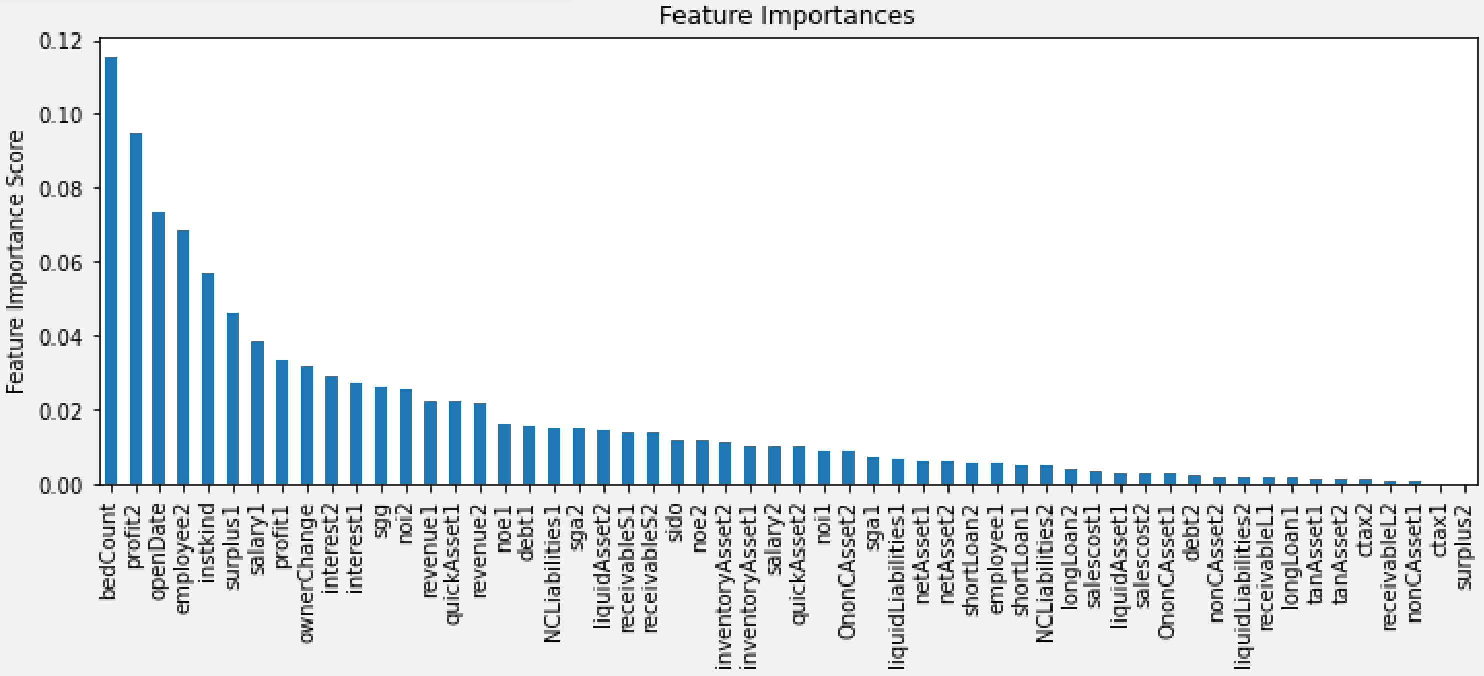
```
# GBM 함수를 만들고 교차 검증을 수행하는데 도움을 주는 함수
def modelfit(alg, dtrain, predictors, performCV=True, printFeatureImportance=True, cv_folds=5):
    global train_prod_Y
    #Fit the algorithm on the data
    alg.fit(dtrain[predictors],train_prod_Y)

    #Predict training set:
    dtrain_predictions = alg.predict(dtrain[predictors])
    dtrain_predprob = alg.predict_proba(dtrain[predictors])[:,1]

    #Perform cross-validation:
    if performCV:
        cv_score = cross_val_score(alg, dtrain[predictors], train_prod_Y, cv=cv_folds, scoring='roc_auc')

    #Print model report:
    print ("\nModel Report")
    print ("Accuracy : %.4g" % accuracy_score(train_prod_Y.values, dtrain_predictions))
    print ("AUC Score (Train): %f" % roc_auc_score(train_prod_Y, dtrain_predprob))

    if performCV:
        print ("CV Score : Mean - %.7g | Std - %.7g | Min - %.7g | Max - %.7g" % (np.mean(cv_score),np.std(cv_score),
                                                                                 np.min(cv_score),np.max(cv_score)))

    #Print Feature Importance:
    if printFeatureImportance:
        feat_imp = pd.Series(alg.feature_importances_, predictors).sort_values(ascending=False)
        feat_imp.plot(kind='bar', title='Feature Importances')
        plt.ylabel('Feature Importance Score')
```

3. Analysis & Result

B. Check the over-fitting of tuned model (using 5-fold cross validation)

```
#Choose all predictors except target & IDcols
predictors = [x for x in train_prod.columns if x not in [target,IDcol]]
modelfit(GBM_prod_tune, train_prod_X, predictors)
```

```
Model Report
Accuracy : 1
AUC Score (Train): 1.000000
CV Score : Mean - 0.8006251 | Std - 0.1054412 | Min - 0.6551724 | Max - 0.9766082
```



C. Calculate the cut-off value for classification

Examine the optimal cut-off value (0.5~0.8 by 0.1)

```
max_accuracy = -1
coval_max = -1

for i in range(start,end):
    print('='*60)
    coval = i/10
    print(" cut-off value : " ,coval)
    print('-'*22)

    sub_GBM_tune_ths = sub_GBM_tune[['inst_id', 'OC']]
    sub_GBM_tune_ths['OC'] = [1 if oc>=coval else 0 for oc in sub_GBM_tune_ths['OC']]
    y_prod = list(sub_GBM_tune_ths['OC'])
    print(classification_report(y_true, y_prod, target_names=['open', 'close']))
    print(accuracy_score(y_true,y_prod))

    if max_accuracy < accuracy_score(y_true,y_prod):
        max_accuracy = accuracy_score(y_true,y_prod)
        coval_max = coval
```

3. Analysis & Result

C. Calculate the cut-off value for classification

```
================================================================
 cut-off value :  0.5
-----------------------
              precision    recall  f1-score   support

        open       0.57      0.31      0.40        13
       close       0.93      0.97      0.95       114

    accuracy                           0.91       127
   macro avg       0.75      0.64      0.67       127
weighted avg       0.89      0.91      0.89       127

0.905511811023622
```

```
================================================================
 cut-off value :  0.7
-----------------------
              precision    recall  f1-score   support

        open       0.75      0.69      0.72        13
       close       0.97      0.97      0.97       114

    accuracy                           0.94       127
   macro avg       0.86      0.83      0.84       127
weighted avg       0.94      0.94      0.94       127

0.9448818897637795
```

```
================================================================
 cut-off value :  0.6
-----------------------
              precision    recall  f1-score   support

        open       0.62      0.38      0.48        13
       close       0.93      0.97      0.95       114

    accuracy                           0.91       127
   macro avg       0.78      0.68      0.71       127
weighted avg       0.90      0.91      0.90       127

0.9133858267716536
```

```
================================================================
 cut-off value :  0.8
-----------------------
              precision    recall  f1-score   support

        open       0.77      0.77      0.77        13
       close       0.97      0.97      0.97       114

    accuracy                           0.95       127
   macro avg       0.87      0.87      0.87       127
weighted avg       0.95      0.95      0.95       127

0.952755905511811
```

3. Analysis & Result

C. Calculate the cut-off value for classification

```
cut-off value :  0.5
```

	precision	recall	f1-score	support
open	0.57	0.31	0.40	13

Optimal cut-off value
(according to 'accuracy')

```
cutoff_GBM = coval_max
cutoff_GBM
```

```
0.8
```

```
cut-off value :  0.7
```

	precision	recall	f1-score	support
open	0.75	0.69	0.72	13
close	0.97	0.97	0.97	114
accuracy			0.94	127
macro avg	0.86	0.83	0.84	127
weighted avg	0.94	0.94	0.94	127

0.9448818897637795

	precision	recall	f1-score	support
open	0.62	0.38	0.48	13
close	0.93	0.97	0.95	114
accuracy			0.91	127
macro avg	0.78	0.68	0.71	127
weighted avg	0.90	0.91	0.90	127

0.9133858267716536

```
cut-off value :  0.8
```

	precision	recall	f1-score	support
open	0.77	0.77	0.77	13
close	0.97	0.97	0.97	114
accuracy			0.95	127
macro avg	0.87	0.87	0.87	127
weighted avg	0.95	0.95	0.95	127

0.952755905511811

3. Analysis & Result

D. Compare default model to tuned model

< Defalut model >

n_estimators : default / max_features : default / max_depth : default / min_sample_split : default

```
np.random.seed(100)
GBM_prod = GradientBoostingClassifier()
GBM_prod_model = GBM_prod.fit(train_prod_X, train_prod_Y)
GBM_prod_prediction = GBM_prod.predict_proba(test_prod_X)[:,1]
```

Compare 2 models with optimal cut-off value

```
sub_GBM = pd.DataFrame({'inst_id' : sub_id , 'OC' : GBM_prod_prediction })
sub_GBM = sub_GBM[['inst_id', 'OC']]
sub_GBM['OC'] = [1 if oc>=cutoff_GBM else 0 for oc in sub_GBM['OC']]
y_prod = list(sub_GBM['OC'])

sub_GBM_customized = sub_GBM_tune[['inst_id', 'OC']]
sub_GBM_customized['OC'] = [1 if oc >= cutoff_GBM else 0 for oc in sub_GBM_customized['OC']] # 확률값을 1,0으로 변환
y_prod_customized = list(sub_GBM_customized['OC'])
```

3. Analysis & Result

```
# Before tuned
print('=========Before tuned=========')
print(classification_report(y_true, y_prod, target_names=['class 0', 'class 1']))
print(accuracy_score(y_true, y_prod))
# After tuned
print('=========After tuned=========')
print(classification_report(y_true, y_prod_customized, target_names=['class 0', 'class 1']))
print(accuracy_score(y_true, y_prod_customized))
```

```
============Before tuned============
              precision    recall  f1-score   support

     class 0       0.80      0.92      0.86        13
     class 1       0.99      0.97      0.98       114

    accuracy                           0.97       127
   macro avg       0.90      0.95      0.92       127
weighted avg       0.97      0.97      0.97       127

0.968503937007874
```

```
============After tuned============
              precision    recall  f1-score   support

     class 0       0.77      0.77      0.77        13
     class 1       0.97      0.97      0.97       114

    accuracy                           0.95       127
   macro avg       0.87      0.87      0.87       127
weighted avg       0.95      0.95      0.95       127

0.952755905511811
```

3. Analysis & Result

4. Classification Model(3) -XGBOOST

XGBOOST

GBM보다 속도와 성능이 향상된 라이브러리

A. Hyperparameter tuning of XGBOOST

B. Check the over-fitting of tuned model

C. Calculate the cut-off value for classification

D. Compare default model to tuned model

3. Analysis & Result

A. Hyperparameter tuning of XGBOOST (using 3-fold cross validation)

- eta : The learning rate
- num_boost_round : The number of boosting rounds

```
dtrain_prod = xgb.DMatrix(data = train_prod_X, label = train_prod_Y)
dtest_prod = xgb.DMatrix(data = test_prod_X)

#Custom error function for the XGB model
threshold = 0.5
def eval_error(preds, dtrain):
    labels = dtrain.get_label()
    preds = (preds > threshold ).astype('float')
    return "accuracy", accuracy_score(labels, preds)


param_tmp = {'eta': [0.1, 0.2, 0.3, 0.4]}
nrounds = 2
```

```
xgb_classifier = XGBClassifier(objective='binary:logistic',nthread=1)
skf = StratifiedKFold(n_splits=3, shuffle = True, random_state = 42)

grid_search_XGB = GridSearchCV(xgb_classifier, param_grid = param_tmp, scoring='accuracy',
                               n_jobs=4, cv=skf.split(train_prod_X, train_prod_Y), verbose=2)
grid_search_XGB.fit(train_prod_X, train_prod_Y)
```

```
Fitting 3 folds for each of 4 candidates, totalling 12 fits
```

```
[Parallel(n_jobs=4)]: Done  12 out of  12 | elapsed:   59.2s remaining:    0.0s
[Parallel(n_jobs=4)]: Done  12 out of  12 | elapsed:   59.2s finished
```

```
GridSearchCV(cv=<generator object _BaseKFold.split at 0x00000207F813C620>,
       error_score='raise',
       estimator=XGBClassifier(base_score=None, booster=None, colsample_bylevel=None,
       colsample_bynode=None, colsample_bytree=None, gamma=None,
       gpu_id=None, importance_type='gain', interaction_constraints=None,
       learning_rate=None, max_delta_step=None, max_depth=None,
       min_child_w..._pos_weight=None, subsample=None,
       tree_method=None, validate_parameters=None, verbosity=None),
       fit_params=None, iid=True, n_jobs=4,
       param_grid={'eta': [0.1, 0.2, 0.3, 0.4]}, pre_dispatch='2*n_jobs',
       refit=True, return_train_score='warn', scoring='accuracy',
       verbose=2)
```

3. Analysis & Result

Check the best hyperparameter combination and train the XGB model with it

```
grid_search_XGB.best_params_
```

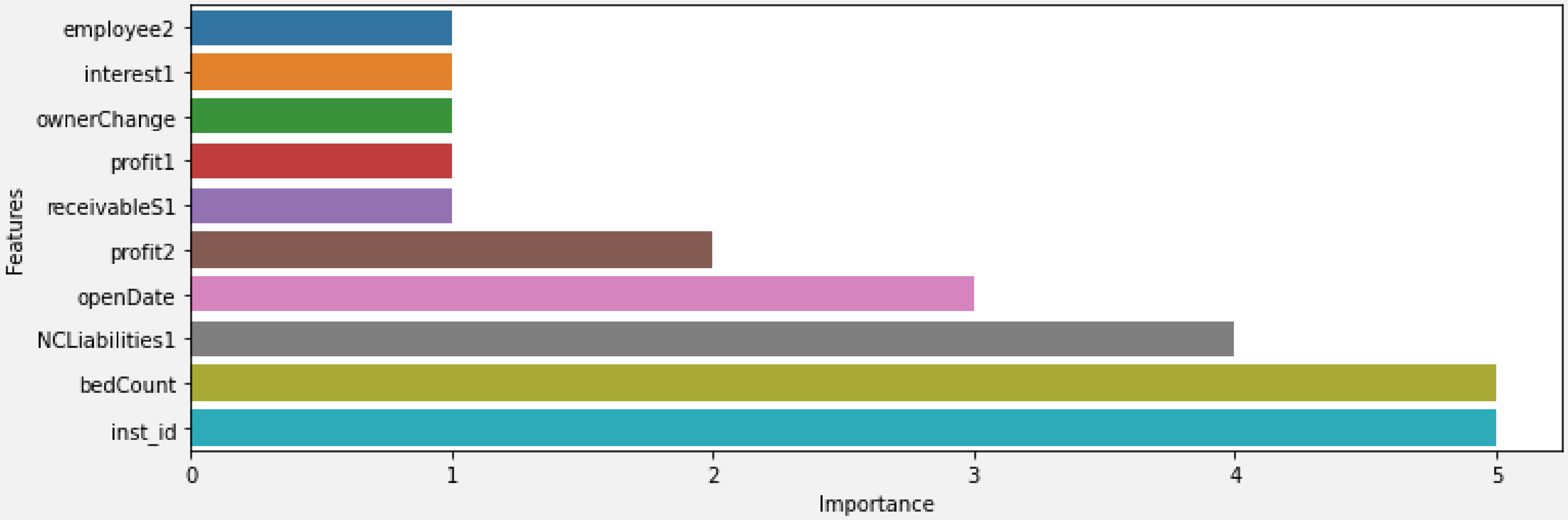
```
{'eta': 0.3}
```

```
#############################################################################
############ XGBOOST - tuning
#############################################################################
np.random.seed(100)
best_param = {'eta': grid_search_XGB.best_params_['eta']}

xgb_model_tune = xgb.train(best_param,
                      dtrain_prod,
                      num_boost_round = nrounds ,
                      feval = eval_error,
                      #maximize = True,
                      #early_stopping_rounds = 10,
                      )

XGB_prediction = xgb_model_tune.predict(dtest_prod)
sub_XGB_tune= pd.DataFrame({'inst_id' : sub_id , 'OC' : XGB_prediction })
sub_XGB_tune= sub_XGB_tune[['inst_id', 'OC']]
```

3. Analysis & Result

Check the best hyperparameter combination and train the XGB model with it

```
#PLotting the feature importance
xgb_Imp_tune = pd.DataFrame({'Features' : list(xgb_model_tune.get_score().keys()),
                             'Importance' : list(xgb_model_tune.get_score().values())}).sort_values(['Importance'])
plt.figure()
sns.barplot(xgb_Imp_tune.Importance, xgb_Imp_tune.Features)
plt.show()
```



3. Analysis & Result

B. Check the over-fitting of tuned model (using 5-fold cross validation)

```
# model, train, target, cross validation
np.random.seed(10)
xgb_model_tune_clf = XGBClassifier(objective='binary:logistic',
                                   learning_rate=grid_search_XGB.best_params_['eta'] )

scores = cross_val_score(xgb_model_tune_clf, train_prod_X, train_prod_Y, cv=5)
print(scores)
print('mean : ',scores.mean())
```

```
[0.95081967 0.95       0.95       0.95       0.95      ]
mean :  0.9501639344262296
```

3. Analysis & Result

C. Calculate the cut-off value for classification

Examine the optimal cut-off value (0.5~0.8 by 0.1)

```
max_accuracy = -1
coval_max = -1
for i in range(start,end):
    print('='*60)
    coval = i/10
    print(" cut-off value : " ,coval)
    print('-'*22)

    sub_XGB_tune_ths = sub_XGB_tune[['inst_id', 'OC']]
    sub_XGB_tune_ths['OC'] = [1 if oc>=coval else 0 for oc in sub_XGB_tune_ths['OC']]
    y_prod = list(sub_XGB_tune_ths['OC'])
    print(classification_report(y_true, y_prod, target_names=['open', 'close']))
    acc= accuracy_score(y_true,y_prod)
    print(acc)
    if max_accuracy < acc:
        max_accuracy = acc
        coval_max = coval
```

3. Analysis & Result

C. Calculate the cut-off value for classification

```
=============================================================
 cut-off value :  0.5
----------------------
              precision    recall  f1-score   support

        open       0.75      0.92      0.83        13
       close       0.99      0.96      0.98       114

    accuracy                           0.96       127
   macro avg       0.87      0.94      0.90       127
weighted avg       0.97      0.96      0.96       127

0.9606299212598425
```

```
=============================================================
 cut-off value :  0.7
----------------------
              precision    recall  f1-score   support

        open       0.57      1.00      0.72        13
       close       1.00      0.91      0.95       114

    accuracy                           0.92       127
   macro avg       0.78      0.96      0.84       127
weighted avg       0.96      0.92      0.93       127

0.9212598425196851
=============================================================
```

```
=============================================================
 cut-off value :  0.6
----------------------
              precision    recall  f1-score   support

        open       0.67      0.92      0.77        13
       close       0.99      0.95      0.97       114

    accuracy                           0.94       127
   macro avg       0.83      0.94      0.87       127
weighted avg       0.96      0.94      0.95       127

0.9448818897637795
```

```
=============================================================
 cut-off value :  0.8
----------------------
              precision    recall  f1-score   support

        open       0.10      1.00      0.19        13
       close       0.00      0.00      0.00       114

    accuracy                           0.10       127
   macro avg       0.05      0.50      0.09       127
weighted avg       0.01      0.10      0.02       127

0.10236220472440945
```

3. Analysis & Result

C. Calculate the cut-off value for classification

```
==============================================================
 cut-off value :  0.5
----------------------
               precision    recall  f1-score   support

        open       0.75      0.92      0.83        13
       close       0.99      0.96      0.98       114

    accuracy                           0.96       127
   macro avg       0.87      0.94      0.90       127
weighted avg       0.97      0.96      0.96       127

0.9606299212598425
```

```
==============================================================
 cut-off value :  0.7
----------------------
               precision    recall  f1-score   support

        open       0.10      1.00      0.19        13
       close

 avg / total

0.10
```

Optimal cut-off value
(according to 'accuracy')

```
cutoff_XGB = coval_max
cutoff_XGB
```

```
0.5
```

```
==============================================================
 cut-off value :  0.6
----------------------
               precision    recall  f1-score   support

        open       0.10      1.00      0.19        13
       close       0.00      0.00      0.00       114

 avg / total       0.01      0.10      0.02       127

0.10236220472440945
```

```
==============================================================
 cut-off val

        open       0.10      1.00      0.19        13
       close       0.00      0.00      0.00       114

 avg / total       0.01      0.10      0.02       127

0.10236220472440945
```

3. Analysis & Result

D. Compare default model to tuned model

< Defalut model >
eta : default

```
XGB_prod = XGBClassifier()
XGB_prod.fit(train_prod_X, train_prod_Y)
XGB_prod_prediction = XGB_prod.predict_proba(test_prod_X)[:,1]
```

Compare 2 models with optimal cut-off value

```
sub_XGB= pd.DataFrame({'inst_id' : sub_id , 'OC' : XGB_prediction })
sub_XGB= sub_XGB[['inst_id', 'OC']]
sub_XGB['OC'] = [1 if oc>=cutoff_XGB else 0 for oc in sub_XGB['OC']]
y_prod = list(sub_XGB['OC'])
```

```
sub_XGB_customized = sub_XGB_tune[['inst_id', 'OC']]
sub_XGB_customized['OC'] = [1 if oc >= cutoff_XGB else 0 for oc in sub_XGB_customized['OC']] # 확률값을 1,0으로 변환
y_prod_customized = list(sub_XGB_customized['OC'])
```

3. Analysis & Result

```python
# Before tuned
print('==========Before tuned==========')
print(classification_report(y_true, y_prod, target_names=['class 0', 'class 1']))
print(accuracy_score(y_true, y_prod))
# After tuned
print('==========After tuned==========')
print(classification_report(y_true, y_prod_customized, target_names=['class 0', 'class 1']))
print(accuracy_score(y_true, y_prod_customized))
```

```
============Before tuned============
              precision    recall  f1-score   support

     class 0       0.75      0.92      0.83        13
     class 1       0.99      0.96      0.98       114

    accuracy                           0.96       127
   macro avg       0.87      0.94      0.90       127
weighted avg       0.97      0.96      0.96       127

0.9606299212598425
```

```
============After tuned============
              precision    recall  f1-score   support

     class 0       0.75      0.92      0.83        13
     class 1       0.99      0.96      0.98       114

    accuracy                           0.96       127
   macro avg       0.87      0.94      0.90       127
weighted avg       0.97      0.96      0.96       127

0.9606299212598425
```

4. Conclusion

GBM

============Before tuned============

	precision	recall	f1-score	support
class 0	0.80	0.92	0.86	13
class 1	0.99	0.97	0.98	114
accuracy			0.97	127
macro avg	0.90	0.95	0.92	127
weighted avg	0.97	0.97	0.97	127

0.9685039370078740

Random Forest

============After tuned============

	precision	recall	f1-score	support
class 0	0.77	0.77	0.77	13
class 1	0.97	0.97	0.97	114
accuracy			0.95	127
macro avg	0.87	0.87	0.87	127
weighted avg	0.95	0.95	0.95	127

0.952755905511811

XGB

===

cut-off value : 0.5

----

	precision	recall	f1-score	support
open	0.75	0.92	0.83	13
close	0.99	0.96	0.98	114
accuracy			0.96	127
macro avg	0.87	0.94	0.90	127
weighted avg	0.97	0.96	0.96	127

0.9606299212598425

4. Conclusion

Final model → GBM

GBM

============Before tuned============

	precision	recall	f1-score	support
class 0	0.80	0.92	0.86	13
class 1	0.99	0.97	0.98	114
accuracy			0.97	127
macro avg	0.90	0.95	0.92	127
weighted avg	0.97	0.97	0.97	127

0.9685039370078740

Random Forest

============After tuned============

	precision	recall	f1-score	support
class 0	0.77	0.77	0.77	13
class 1	0.97	0.97	0.97	114
accuracy			0.95	127
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weighted avg	0.95	0.95	0.95	127

0.952755905511811

XGB

===

cut-off value : 0.5

----

	precision	recall	f1-score	support
open	0.75	0.92	0.83	13
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macro avg	0.87	0.94	0.90	127
weighted avg	0.97	0.96	0.96	127

0.9606299212598425

4. Conclusion

Final Model Review

```
#Examine the optimal hyperparameter.
opt_depth = GBM_prod_model.max_depth
opt_features = GBM_prod_model.max_features
opt_estimators = GBM_prod_model.n_estimators

print('best max_depth:',opt_depth)
print('best max_features:',opt_features)
print('best n_estimators:',opt_estimators)
```

```
best max_depth: 3
best max_features: None
best n_estimators: 100
```

4. Conclusion

Final Model Review

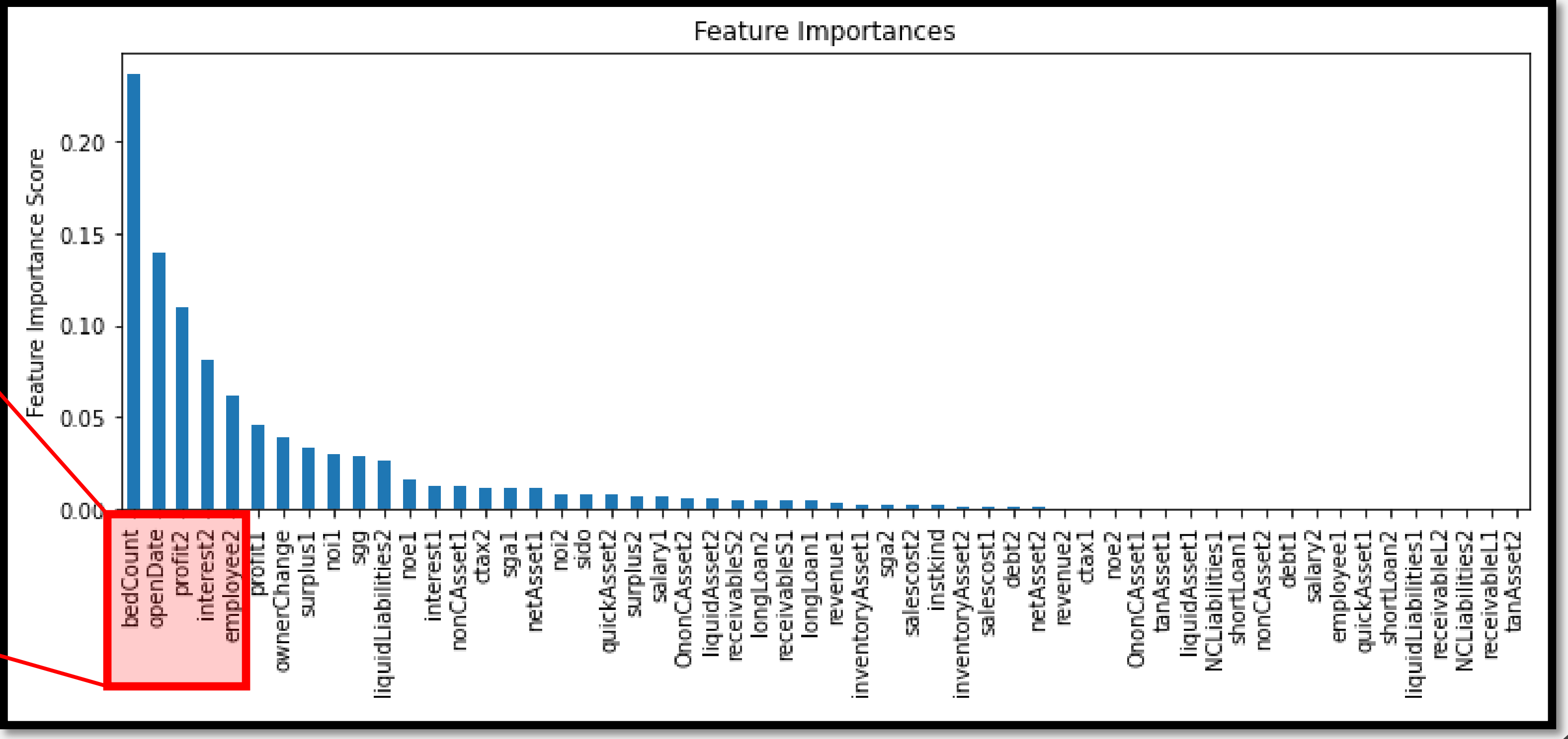
```
#Examine the optimal hyperparameter.
opt_depth = GBM_prod_model.max_depth
opt_features = GBM_prod_model.max_features
opt_estimators = GBM_prod_model.n_estimators

print('best max_depth:',opt_depth)
print('best max_features:',opt_featu
print('best n_estimators:',opt_estim
```

```
best max_depth: 3
best max_features: None
best n_estimators: 100
```

```
#Review the optimal model (GBM)
modelfit(GBM_prod_model, train_prod_X, predictors)
```

```
Model Report
Accuracy : 1
AUC Score (Train): 1.000000
CV Score : Mean - 0.8133091 | Std - 0.1082766 | Min - 0.7068966 | Max - 0.994152
```

bedcount
opendate
profit2
interest2
employee2



4. Conclusion

Find the missing answer

```
#Find the missing anwser.
answer_lst = list(test_prod_labeled.loc[test_prod_labeled['OC']==0]['inst_id'])
pred_lst = list(sub_GBM.loc[sub_GBM['OC']==0]['inst_id'])

print('answer:',answer_lst)
print('prediction:',pred_lst,'\n')

print('complement: ', list(set(answer_lst) - set(pred_lst)))
```

```
answer: [5, 6, 24, 30, 64, 123, 229, 258, 293, 341, 425, 429, 431]
prediction: [5, 6, 30, 64, 123, 165, 229, 258, 293, 341, 413, 424, 425, 429, 431]

complement:  [24]
```

Confusion matrix

```
print(classification_report(y_true, y_prod_final, target_names=['close', 'open']))
print(accuracy_score(y_true, y_prod_final))
```

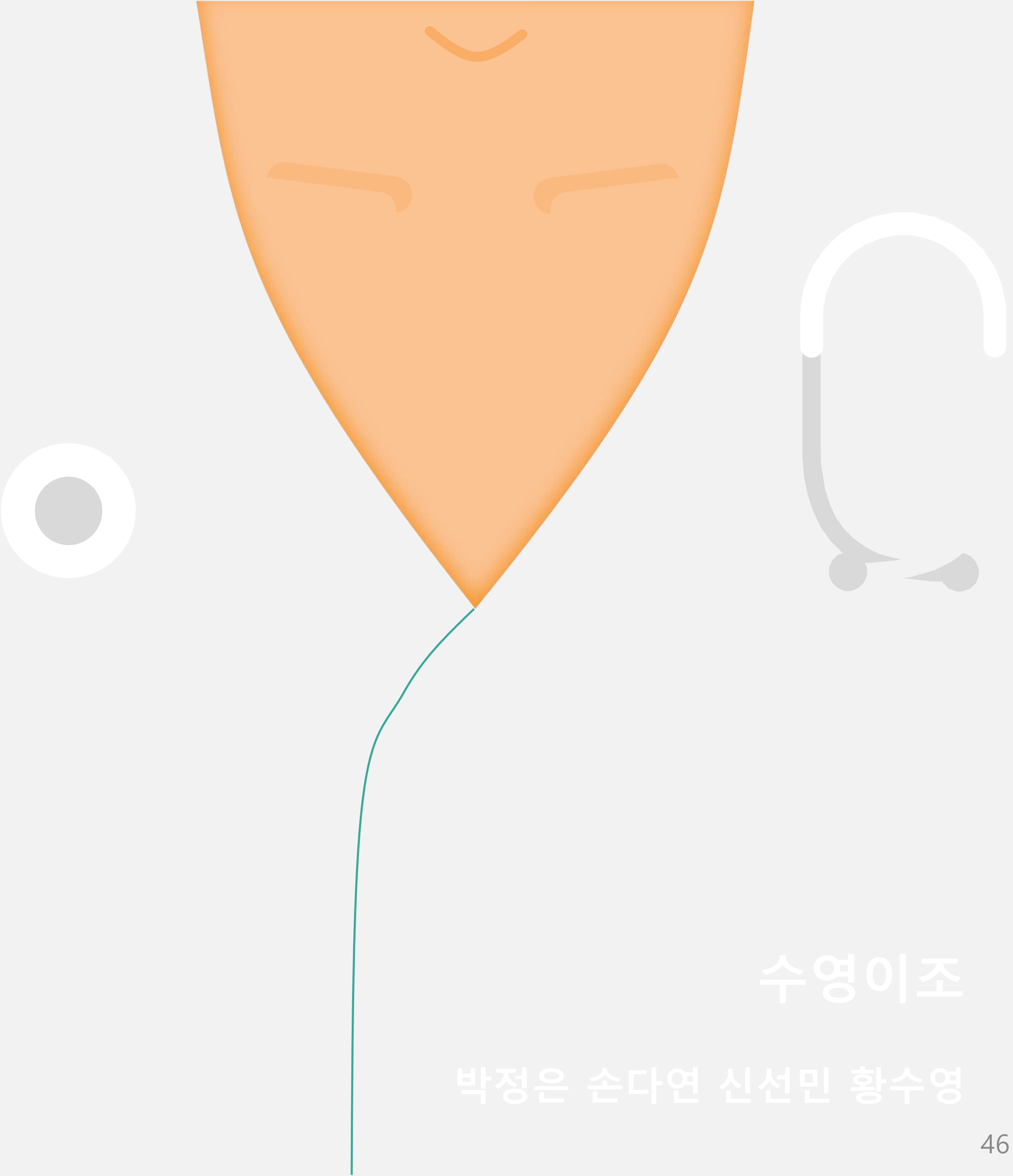
	precision	recall	f1-score	support
close	0.80	0.92	0.86	13
open	0.99	0.97	0.98	114
accuracy			0.97	127
macro avg	0.90	0.95	0.92	127
weighted avg	0.97	0.97	0.97	127

0.968503937007874

```
confusion_matrix(y_true, y_prod_final)
```

```
array([[ 12,   1],
       [  3, 111]], dtype=int64)
```

Thank you



수영이조

박정은 손다연 신선민 황수영