# 앙상블 실습

Majority Voting / Bagging / Boosting

### 데이터 설명

- 데이터셋: 유니버셜 은행
- 개인대출 제안에 대한 수락 여부
- 총 데이터: 5000개 (학습: 3000개, 테스트 2000개)
- 성공율: 9.6% (480명)

나이, 경력, 소득, 가족 수, 신용카드 월평균 사용 액, 교육, 담보 부채권, **개인대출**, 증권계좌, CD계좌, 온라인 뱅킹, 신용카드

| Age | Experience | Income | Fam | ily | CCAvg | Education | Mortgage | PersonalLoan | SecuritiesAccount | CDAccount | Online | CreditCard |
|-----|------------|--------|-----|-----|-------|-----------|----------|--------------|-------------------|-----------|--------|------------|
| 25  | 1          | 49     |     | 4   | 1.6   | 1         | 0        | 0            | 1                 | 0         | 0      | 0          |
| 45  | 19         | 34     |     | 3   | 1.5   | 1         | 0        | 0            | 1                 | 0         | 0      | 0          |
| 39  | 15         | 11     |     | 1   | 1.0   | 1         | 0        | 0            | 0                 | 0         | 0      | 0          |
| 35  | 9          | 100    |     | 1   | 2.7   | 2         | 0        | 0            | 0                 | 0         | 0      | 0          |
| 35  | 8          | 45     |     | 4   | 1.0   | 2         | 0        | 0            | 0                 | 0         | 0      | 1          |



위의 특성 변수를 이용하여 개인대출 가능 여부를 예측하는 분류기를 설계하는 문제

```
■ 데이터 로더
```

```
1 import pandas as pd
2 3 39 15 11 94720 1 1.0 1 0 0 0 0
3 4 35 9 100 94112 1 2.7 2 0 0 0 0
4 5 35 8 45 91330 4 1.0 2 0 0 0
3 bank_df = pd.read_csv('UniversalBank.csv')
4 bank_df.head()
```

#### ■ 특성 변수 선택

```
1 X = bank_df.drop (['ID','ZIPCode','PersonalLoan'], axis=1)
2 y = bank_df['PersonalLoan']
```

#### ■ 범주형 데이터 변환

```
1 from sklearn.preprocessing import LabelEncoder
2 classle = LabelEncoder()
3 y = classle.fit_transform(y)
4
```

#### ■ 데이터 분할

```
1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1, stratify=y)
```

■ 앙상블로 사용할 개별 모델 정의

```
1 from sklearn.tree import DecisionTreeClassifier # 결정 트리
2 from sklearn.neighbors import KNeighborsClassifier # K-최근접 이웃
3 from sklearn.linear model import LogisticRegression # 로지스틱 회귀 모델
6 logistic = LogisticRegression(solver='liblinear',
                                 penalty='12',
 8
                                 C=0.001,
 9
                                 random state=1)
10
11 tree = DecisionTreeClassifier(max depth=None,
                                 criterion='entropy',
12
13
                                 random state=1)
14
15 knn = KNeighborsClassifier(n neighbors=1,
16
                               p=2,
17
                               metric='minkowski')
```

#### ■ 앙상블-Voting 정의

```
1 from sklearn.ensemble import VotingClassifier # 과반수 투표(Majority Voting)
2 voting_estimators = [('logistic', logistic), ('tree', tree), ('knn', knn)]
3 voting = VotingClassifier(estimators = voting_estimators,
4 voting='soft')
```

#### ■ K-fold 교차 검증

ROC AUC: %0.3f (+/- %0.3f) [%s] (0.9724206139059355, 0.01593603549077189, 'Majority voting')

#### ■ GridSearch방식을 이용한 모델 최적화

```
1 from sklearn.model selection import GridSearchCV # 하이퍼파라미터 튜닝
2
3 params = {'logistic C': [0.001, 0.1, 100.0],
            'tree max depth': [1, 3, 5],
 5
            'knn n neighbors': [1, 3, 5]}
7 grid = GridSearchCV(estimator=voting,
 8
                      param grid=params,
 9
                       cv=10,
                      scoring='roc auc',
10
11
                       iid=False)
12 grid.fit(X train, y train)
13
14 for r, in enumerate(grid.cv results ['mean test score']):
      print("%0.3f +/- %0.3f %r"
15
16
            % (grid.cv results ['mean test score'][r],
               grid.cv results ['std test score'][r] / 2.0,
17
               grid.cv results ['params'][r]))
18
19
20 print('최적의 파타미터: %s' % grid.best params )
21 print('ACU: %.3f' % grid.best score )
```

```
Scoring
                              Function
Classification
'accuracy'
                              metrics.accuracy score
'balanced_accuracy'
                              metrics.balanced_accuracy_score
'average_precision'
                              metrics.average_precision_score
'neg_brier_score'
                              metrics.brier score loss
                              metrics.fl score
'f1 micro'
                              metrics.fl_score
'f1 macro'
                              metrics.fl_score
'f1_weighted'
                              metrics.fl_score
'f1_samples'
                              metrics.fl score
'neg_log_loss'
                              metrics.log loss
'precision' etc.
                              metrics.precision_score
'recall' etc.
                              metrics.recall_score
'jaccard' etc.
                              metrics.jaccard score
'roc auc'
                              metrics.roc auc score
'roc auc ovr'
                              metrics.roc_auc_score
'roc auc ovo'
                              metrics.roc_auc_score
'roc_auc_ovr_weighted'
                              metrics.roc auc score
'roc_auc_ovo_weighted'
                              metrics.roc_auc_score
Clustering
'adjusted mutual info score'
                              metrics.adjusted mutual info score
'adjusted_rand_score'
                              metrics.adjusted_rand_score
'completeness_score'
                              metrics.completeness_score
'fowlkes_mallows_score'
                              metrics.fowlkes_mallows_score
'homogeneity_score'
                              metrics.homogeneity score
'mutual info score'
                              metrics.mutual_info_score
'normalized_mutual_info_score'
                             metrics.normalized mutual info score
'v_measure_score'
                              metrics.v_measure_score
Regression
'explained_variance'
                              metrics.explained_variance_score
'max_error'
                              metrics.max_error
'neg mean absolute error'
                              metrics.mean absolute error
'neg_mean_squared_error'
                              metrics.mean_squared_error
'neg_root_mean_squared_error'
                             metrics.mean_squared_error
'neg_mean_squared_log_error'
                              metrics.mean squared log error
'neg median absolute error'
                              metrics.median absolute error
                              metrics.r2_score
'neg_mean_poisson_deviance'
                              metrics.mean_poisson_deviance
'neg_mean_gamma_deviance'
                              metrics.mean gamma deviance
```

```
최적의 파타미터: {'knn__n_neighbors': 3, 'logistic__C': 100.0, 'tree__max_depth': 5} ACU: 0.986
```

### 배깅 방식(Bagging) 실습 #2 (분류)

#### ■ 특성 변수 선택

```
1 X = bank_df.drop (['ID','ZIPCode','PersonalLoan'], axis=1)
2 y = bank_df['PersonalLoan']
```

#### ■ 범주형 데이터 변환

```
1 from sklearn.preprocessing import LabelEncoder
2 classle = LabelEncoder()
3 y = classle.fit_transform(y)
4
```

#### ■ 데이터 분할

```
1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1, stratify=y)
```

## 배깅 방식(Bagging) 실습 #2 (분류)

■ 앙상블로 사용할 개별 모델 정의

```
[ ] 1 from sklearn.tree import DecisionTreeClassifier # 결정 트리
2
3 tree = DecisionTreeClassifier(max_depth=None,
4 criterion='entropy',
5 random_state=1)
```

#### ■ 앙상블-Bagging 정의

### 배깅 방식(Bagging) 실습 #2 (분류)

#### ■ K-fold 교차 검증

## 부스팅 방식(Boosting) 실습 #3 (분류)

#### ■ 특성 변수 선택

```
1 X = bank_df.drop (['ID','ZIPCode','PersonalLoan'], axis=1)
2 y = bank_df['PersonalLoan']
```

#### ■ 범주형 데이터 변환

4 bank df.head()

```
1 from sklearn.preprocessing import LabelEncoder
2 classle = LabelEncoder()
3 y = classle.fit_transform(y)
4
```

#### ■ 데이터 분할

```
1 from sklearn.model_selection import train_test_split
2 X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3, random_state=1, stratify=y)
```

## 부스팅 방식(Boosting) 실습 #3 (분류)

■ 앙상블로 사용할 개별 모델 정의

```
1 from sklearn.tree import DecisionTreeClassifier # 결정 트리
2 3 # 배깅과 차이점: mex_depth =1 로 변경
4 tree = DecisionTreeClassifier(max_depth=1,
5 criterion='entropy',
6 random_state=1)
7
```

■ 앙상블-Boosting 정의

```
1 from sklearn.ensemble import AdaBoostClassifier # 부스팅(Boosting)
2 3 adaboost = AdaBoostClassifier(base_estimator=tree, # 수정
4 n_estimators=500,
5 learning_rate = 0.1, # 수정
6 random_state=1)
7
```

## 부스팅 방식(Boosting) 실습 #3 (분류)

#### ■ K-fold 교차 검증

```
1 from sklearn.model_selection import cross_val_score # 교차타당도 # 추가
2 3 clf_labels = ['Decision tree', 'Ada boost']
4 all_clf = [tree, adaboost]
5 for clf, label in zip(all_clf, clf_labels):
6     scores = cross_val_score(estimator=clf,X=X_train,y=y_train,cv=10,scoring='roc_auc')
7     print("ROC AUC: %0.3f (+/- %0.3f) [%s]", (scores.mean(), scores.std(), label))

ROC AUC: %0.3f (+/- %0.3f) [%s] (0.8829135713666967, 0.023406169666276122, 'Decision tree')
ROC AUC: %0.3f (+/- %0.3f) [%s] (0.9835566978095359, 0.010774714837632118, 'Ada boost')
```