

4.5 – 4.7

# GBM, XGBoost, LightGBM

CUAI 6조  
C6AI : 김소영 김유현 박민형 장재용

# Boosting

부스팅 알고리즘 : 여러 개의 약한 학습기(weak learner)를 순차적으로 학습-예측하면서 잘못 예측한 데이터에 가중치를 부여를 통해 오류를 개선해 나가면서 학습하는 방식

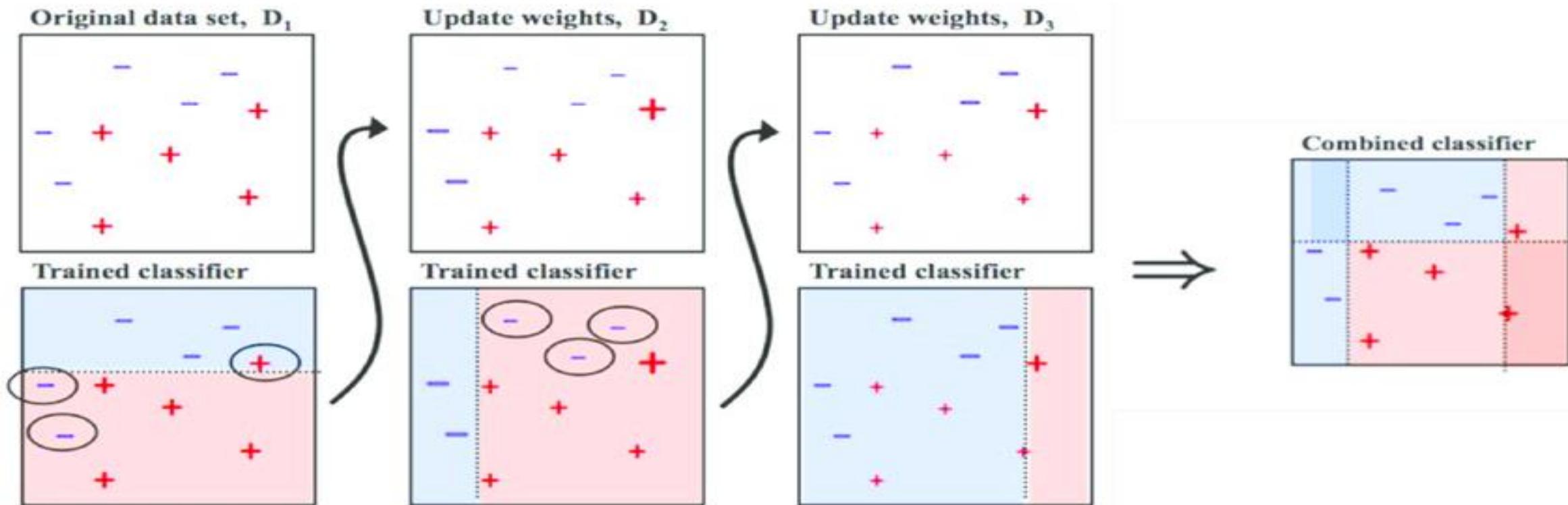
AdaBoost (Adaptive boosting)

Gradient Boosting Machine

# AdaBoost

AdaBoost(Adaptive boosting) :

오류 데이터에 가중치를 부여하면서 부스팅을 수행



# *1. GBM*

Gradient Boosting Machine

# GBM

Gradient Boost Machine(GBM) : AdaBoost와 유사하나 가중치 업데이트를 경사 하강법(Gradient Descent)를 이용

Input: training set  $\{(x_i, y_i)\}_{i=1}^n$ , a differentiable loss function  $L(y, F(x))$ , number of iterations  $M$ .

Algorithm:

1. Initialize model with a constant value:

$$F_0(x) = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, \gamma). \quad \text{Baseline model}$$

2. For  $m = 1$  to  $M$ :

1. Compute so-called pseudo-residuals:

$$r_{im} = -\left| \frac{\partial L(y_i, F(x_i))}{\partial F(x_i)} \right|_{F(x)=F_{m-1}(x)} \quad \text{for } i = 1, \dots, n.$$

2. Fit a base learner (e.g. tree)  $h_m(x)$  to pseudo-residuals, i.e. train it using the training set  $\{(x_i, r_{im})\}_{i=1}^n$ .

3. Compute multiplier  $\gamma_m$  by solving the following one-dimensional optimization problem:

$$\gamma_m = \arg \min_{\gamma} \sum_{i=1}^n L(y_i, F_{m-1}(x_i) + \gamma h_m(x_i)).$$

4. Update the model:

$$F_m(x) = F_{m-1}(x) + \gamma_m h_m(x).$$

3. Output  $F_M(x)$ .

이 과정은  
성수적이다  
라고

매우 빠르다

출처 : <https://3months.tistory.com/368>)

# GBM - Parameters

parameters	Detail
Loss	경사 하강법에서 사용할 비용 함수 지정 기본값 : deviance
Learning_rate	Weak learner가 순차적으로 오류 값을 보정해 나가는 데 적용하는 계수 기본값:0.1, 설정 가능 범위 : 0~1
n_estimators	Weak learner의 개수 기본값:100
subsample	Weak learner가 학습에 사용하는 데이터의 샘플링 비율 기본값:1(전체 데이터 사용을 의미)

# Parameters - Learning\_rate

## learning\_rate ▼

장점 : 업데이트되는 값이  
작아져서 최소 오류 값을  
찾아 예측 성능이 높아질  
가능성이 높음

단점 : 시간이 오래 걸리  
고 반복 횟수가 부족하면  
모든 weak learner의 반  
복이 완료돼도 최소 오류  
값을 찾지 못할 수 있음

## learning\_rate ▲

장점 : 빠른 수행이 가능

단점 : 최소 오류 값을 찾  
지 못하고 그냥 지나쳐 버  
려 예측 성능이 떨어질 가  
능성이 높음

# Parameters – n\_estimators

## - n\_estimators

weak learner 개수를 의미하며, 높을수록 성능  $\Delta$ , 수행시간  $\blacktriangleleft$

## - learning\_rate와 n\_estimator의 관계

learning rate이 작으면 성능은 일정 수준까지 향상될 확률은 높아지는데 이 때 n\_estimator을 줄여줌으로써 학습시간이 너무 길어지는 것을 방지 할 수 있다

# GBM – Code(1)

```
from sklearn.ensemble import GradientBoostingClassifier
import time
import warnings
warnings.filterwarnings('ignore')

X_train, X_test, y_train, y_test = get_human_dataset()

from sklearn.model_selection import GridSearchCV
gb_clf = GradientBoostingClassifier(random_state=0)
params={'n_estimators':[100,500],
        'learning_rate':[0.05,0.1]}
grid_cv=GridSearchCV(gb_clf, param_grid=params, cv=2, verbose=1)
start_time=time.time()
grid_cv.fit(X_train,y_train)

print("GridSearch 소요시간: {:.2f}".format(time.time()-start_time))
print('최적 하이퍼 파라미터:{\n',grid_cv.best_params_)
print('최고 예측 정확도: {:.4f}'.format(grid_cv.best_score_))
gb_pred = grid_cv.best_estimator_.predict(X_test)
gb_accuracy = accuracy_score(y_test, gb_pred)
print("GBM 정확도: {:.4f}".format(gb_accuracy))
```

GBM

GridSearchCV

# GBM – Code(2)

Fitting 2 folds for each of 4 candidates, totalling 8 fits

[Parallel(n\_jobs=1)]: Using backend SequentialBackend with 1 concurrent workers.  
[Parallel(n\_jobs=1)]: Done 8 out of 8 | elapsed: 14.4min finished

GridSearch 소요시간: 1314.77

최적 하이퍼 파라미터:

```
{'learning_rate': 0.1, 'n_estimators': 500}
```

최고 예측 정확도: 0.904108

GBM 정확도: 0.9454

Fitting 2 folds for each of 4 candidates, totalling 8 fits

[Parallel(n\_jobs=4)]: Using backend LokyBackend with 4 concurrent workers.  
[Parallel(n\_jobs=4)]: Done 8 out of 8 | elapsed: 6.6min finished

GridSearch 소요시간: 845.40

최적 하이퍼 파라미터:

```
{'learning_rate': 0.1, 'n_estimators': 500}
```

최고 예측 정확도: 0.904108

GBM 정확도: 0.9454

줄어든 수행시간

동일 성능

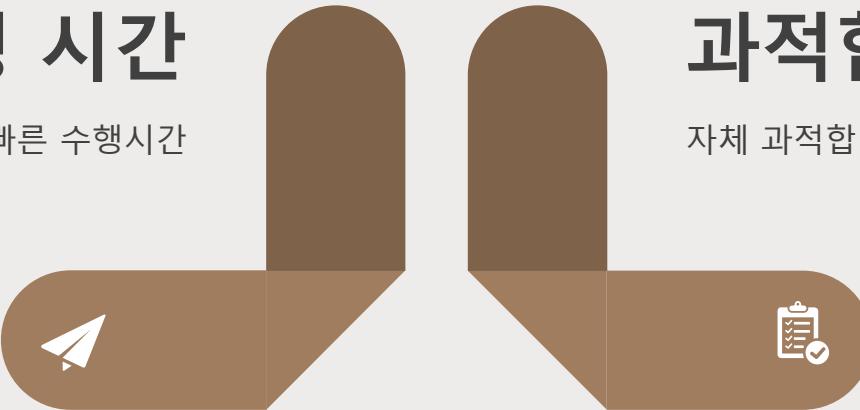
## *2. XGBoost*

eXtra Gradient Boost

# *eXtra Gradient Boost* 주요 장점

## 빠른 수행 시간

GBM 대비 빠른 수행시간



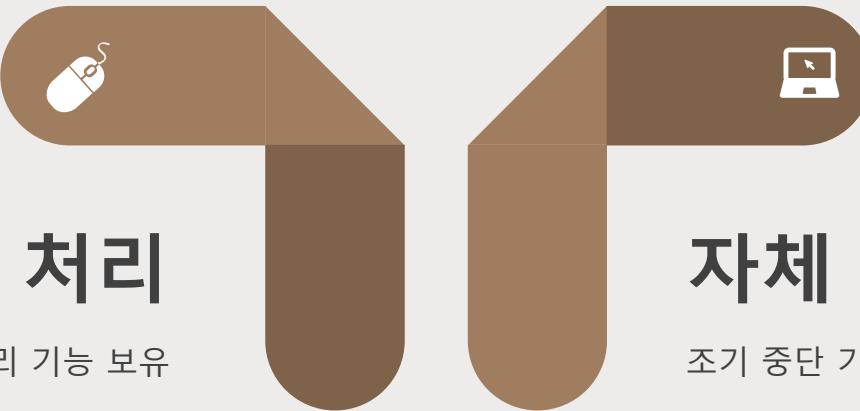
## 과적합 규제

자체 과적합 규제 기능 보유



## 결손값 자체 처리

결손값 자체 처리 기능 보유



## 자체 내장된 교차 검증

조기 중단 기능으로

# *eXtra Gredient Boost* 모듈 종류

파이썬 래퍼  
**XGBoost 모듈**

사이킷런 래퍼  
**XGBoost 모듈**

# *eXtra Gredient Boost 모듈 종류*

## 파이썬 래퍼 XGBoost 모듈

```
dtrain=xgb.DMatrix(data=X_train, label=y_train)
dtest=xgb.DMatrix(data=X_test, label=y_test)
params={ 'max_depth':3, 'eta':0.1, 'objective':'binary:logistic',
          'eval_metric':'logloss', 'early_stoppings':100}
• num_rounds=400
wlist=[(dtrain,'train'),(dtest,'eval')]
xgb_model=xgb.train(params=params, dtrain=dtrain, num_boost_round=num_rounds, evals=wlist)
pred_probs=xgb_model.predict(dtest)
```

## 사이킷런 래퍼 XGBoost 모듈

```
from xgboost import XGBClassifier
xgb_wrapper = XGBClassifier(n_estimators=400, learning_rate=0.1, max_depth=3)
evals=[(X_test, y_test)]
xgb_wrapper.fit(X_train, y_train, early_stopping_rounds=100, eval_metric='logloss', eval_set=evals, verbose=True)
w_preds=xgb_wrapper.predict(X_test)
```

# *eXtra Gredient Boost* 파라미터

```
xgb_wrapper = XGBClassifier(booster='gbtree',
                             nthread=4,
                             silent=1,
                             n_estimators=400,
                             learning_rate=0.1,
                             max_depth=3,
                             subsample=1,
                             min_child_weight=3,
                             gamma=0,
                             colsample_bytree=1,
                             colsample_bylevel=1,
                             reg_lambda=1,
                             reg_alpha=0,
                             objective='binary:logistic')

evals=[(X_test, y_test)]

xgb_wrapper.fit(X_train, y_train,
                 early_stopping_rounds=100,
                 eval_metric='logloss',
                 eval_set=evals)
```

# *eXtra Gredient Boost* 파라미터

## 일반 파라미터

NO	이름	내용	디폴트 값
01	<b>booster</b>	사용할 부스터의 종류를 선택하는 것. gbtree(tree based model) 또는 gbliner(linear model) 선택	gbtree
02	<b>silent</b>	실행 메시지를 출력하고 싶지 않은 경우 1로 설정.	0
03	<b>nthread</b>	CPU의 실행 스레드 개수를 조정.	CPU 전체 스레드 다 사용

# eXtra Gredient Boost 파라미터

## 부스터 파라미터

NO	이름	내용	디폴트 값
01	<b>learning rate</b>	부스팅을 반복적으로 수행할 때 업데이트 되는 학습률 값.	0.1
02	<b>n_estimators</b>	부스트 트리의 갯수	0
03	<b>max_depth</b>	트리의 최대 깊이	None
04	<b>subsample</b>	데이터를 샘플링하는 비율값.	1
05	<b>min_child_weight</b>	하위에 필요한 인스턴스 가중치의 최소 합.	1
06	<b>gamma</b>	트리의 리프노드의 추가분할을 결정할 최소 손실 감소값.	0

# *eXtra Gredient Boost* 파라미터

## 부스터 파라미터

NO	이름	내용	디폴트 값
01	<b>reg_lambda</b>	L2 regulation 적용값.	1
02	<b>reg_alpha</b>	L1 regulation 적용값.	0
03	<b>colsample_bytree</b>	트리 생성할 때 feature를 샘플링해주는 비율	1

# *eXtra Gredient Boost* 파라미터

## 과적합 해결

learning\_rate

gamma

min\_child\_weight

subsample,  
colsample\_bytree

# eXtra Gredient Boost 파라미터

## 학습 태스크 파라미터

NO	이름	내용	디폴트 값
01	<b>objective</b>	최솟값을 가져야할 손실함수를 정의.	reg:linear
02	<b>eval_metric</b>	검증에서 사용되는 함수를 정의	default according to objective
03	<b>early_stoppin g_rounds</b>	더 이상 개선이 없을 때 반복을 멈추고 조기 중단할 수 있는 최소 반복 횟수	None

# eXtra Gredient Boost 파라미터

## Early\_Stopping

```
xgb_wrapper = XGBClassifier()
evals=[(X_test, y_test)]
xgb_wrapper.fit(X_train, y_train, early_stopping_rounds=10,
                  eval_metric='logloss', eval_set=evals, verbose=True)
w_preds=xgb_wrapper.predict(X_test)
```

```
[...]
[50] validation_0-logloss:0.090051
[51] validation_0-logloss:0.089605
[52] validation_0-logloss:0.089577
[53] validation_0-logloss:0.090703
[54] validation_0-logloss:0.089579
[55] validation_0-logloss:0.090357
[56] validation_0-logloss:0.091587
[57] validation_0-logloss:0.091527
[58] validation_0-logloss:0.091986
[59] validation_0-logloss:0.091951
[60] validation_0-logloss:0.091939
[61] validation_0-logloss:0.091461
[62] validation_0-logloss:0.090311
Stopping. Best iteration:
[52] validation_0-logloss:0.089577
```

# XGBClassifier를 이용한 유방암 분석

## 1step

분석 전  
데이터  
엿보기

## 2step

XGBClassifier  
모델 구축

## 3step

구축한 모델의  
성능측정 및  
피처중요도  
알아보기

# 1step - 분석 전 데이터 엿보기 (Breast Cancer)

```
In [22]: #사이킷런 라이브 XGBoost 클래스의 XGBClassifier 임포트
from xgboost import XGBClassifier
import pandas as pd
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')

dataset=load_breast_cancer()
X_features=dataset.data
y_label=dataset.target
cancer_df=pd.DataFrame(data=X_features,columns=dataset.feature_names)
cancer_df['target']=y_label
cancer_df.head(3) #본격적인 데이터 분석 전 판다스 데이터 프레임 객체로 데이터 모양 확인
```

Out [22] :

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter	worst area	worst smoothness	worst con
0	17.99	10.38	122.8	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	17.33	184.6	2019.0	0.1622	
1	20.57	17.77	132.9	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	23.41	158.8	1956.0	0.1238	
2	19.69	21.25	130.0	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	25.53	152.5	1709.0	0.1444	

3 rows × 31 columns

#사이킷런 데잍 XGBoost를 래스와 XGBCClassifier의 포트

```
from xgboost import XGBClassifier
import pandas as pd
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split
import warnings
warnings.filterwarnings('ignore')
```

```
dataset=load_breast_cancer()
X_features=dataset.data
y_label=dataset.target
cancer_df=pd.DataFrame(data=X_features,columns=dataset.feature_names)
cancer_df['target']=y_label
cancer_df.head(3) #본격적인 데이터 분석은 판다스 데이터 프레임 자체로 데이터 모양 확인
```

# 30 Features (Breast Cancer Data)

	mean radius	mean texture	mean perimeter	mean area	mean smoothness	mean compactness	mean concavity	mean concave points	mean symmetry	mean fractal dimension	...	worst texture	worst perimeter	worst area	worst smoothness	worst compactness
0	17.99	10.38	122.8	1001.0	0.11840	0.27760	0.3001	0.14710	0.2419	0.07871	...	17.33	184.6	2019.0	0.1622	0.1622
1	20.57	17.77	132.9	1326.0	0.08474	0.07864	0.0869	0.07017	0.1812	0.05667	...	23.41	158.8	1956.0	0.1238	0.1238
2	19.69	21.25	130.0	1203.0	0.10960	0.15990	0.1974	0.12790	0.2069	0.05999	...	25.53	152.5	1709.0	0.1444	0.1444

3 rows × 31 columns

# 2step-XGBClassifier모델 구축

```
: #테스트셋 20% 분리  
X_train,X_test,y_train,y_test=train_test_split(X_features,y_label,test_size=0.2,random_state=156)
```

```
: evals=[(X_test,y_test)]  
xgb_wrapper=XGBClassifier(n_estimators=400,learning_rate=0.1,max_depth=3)  
xgb_wrapper.fit(X_train,y_train,  
                 early_stopping_rounds=100,eval_metric='logloss',eval_set=evals,  
                 verbose=True)|  
ws100_preds=xgb_wrapper.predict(X_test)
```

```
[0] validation_0-logloss:0.61352  
Will train until validation_0-logloss hasn't improved in 100 rounds.  
[1] validation_0-logloss:0.547842  
[2] validation_0-logloss:0.494247  
[3] validation_0-logloss:0.447986  
[4] validation_0-logloss:0.409109  
[5] validation_0-logloss:0.374977  
[6] validation_0-logloss:0.345714  
[7] validation_0-logloss:0.320529  
[8] validation_0-logloss:0.29721  
[9] validation_0-logloss:0.277991  
[10] validation_0-logloss:0.260302  
[11] validation_0-logloss:0.246037  
[12] validation_0-logloss:0.231556  
[13] validation_0-logloss:0.22005  
[14] validation_0-logloss:0.208572  
[15] validation_0-logloss:0.199993  
[16] validation_0-logloss:0.190118  
[17] validation_0-logloss:0.181818  
[18] validation_0-logloss:0.174729
```

#테스트셋 20% 분리

```
X_train,X_test,y_train,y_test=train_test_split(X_features,y_label,test_size=0.2,random_state=156)
```

테스트 셋 20%분리

Eval set을 테스트 셋으로 정의

```
evals=[(X_test,y_test)]  
xgb_wrapper=XGBClassifier(n_estimators=400,learning_rate=0.1,max_depth=3)  
xgb_wrapper.fit(X_train,y_train,  
                 early_stopping_rounds=100,eval_metric='logloss',eval_set=evals,  
                 verbose=True)|  
ws100_preds=xgb_wrapper.predict(X_test)
```

XGB분류기 모델 설정

학습시키기

테스트 셋으로 예측하기

# Finding Minimum ‘LogLoss’

```
[0]    validation_0-logloss:0.61352
[1] Will train until validation_0-logloss hasn't improved in 100 rounds.
[2]    validation_0-logloss:0.547842
[3]    validation_0-logloss:0.494247
[4]    validation_0-logloss:0.447986
[5]    validation_0-logloss:0.409109
[6]    validation_0-logloss:0.374977
[7]    validation_0-logloss:0.345714
[8]    validation_0-logloss:0.320529
[9]    validation_0-logloss:0.29721
[10]   validation_0-logloss:0.277991
[11]   validation_0-logloss:0.260302
[12]   validation_0-logloss:0.246037
[13]   validation_0-logloss:0.231556
[14]   validation_0-logloss:0.22005
[15]   validation_0-logloss:0.208572
[16]   validation_0-logloss:0.199993
[17]   validation_0-logloss:0.190118
[18]   validation_0-logloss:0.181818
[19]   validation_0-logloss:0.174729
```

오  
차  
감  
소

[311] validation\_0-logloss:0.085948

Stopping. Best iteration:

[211] validation\_0-logloss:0.085593

# 3step-구축한 모델의 성능측정 및 피처중요도 알아보기

```
from sklearn.metrics import accuracy_score,precision_score,recall_score,confusion_matrix
```

```
def get_clf_eval(y_test , pred):
    confusion = confusion_matrix( y_test, pred)
    accuracy = accuracy_score(y_test , pred)
    precision = precision_score(y_test , pred)
    recall = recall_score(y_test , pred)
    print('오차 행렬')
    print(confusion)
    print('정확도: {:.4f}, 정밀도: {:.4f}, 재현율: {:.4f}'.format(accuracy, precision, recall))
```

```
get_clf_eval(y_test,ws100_preds)
```

오차 행렬

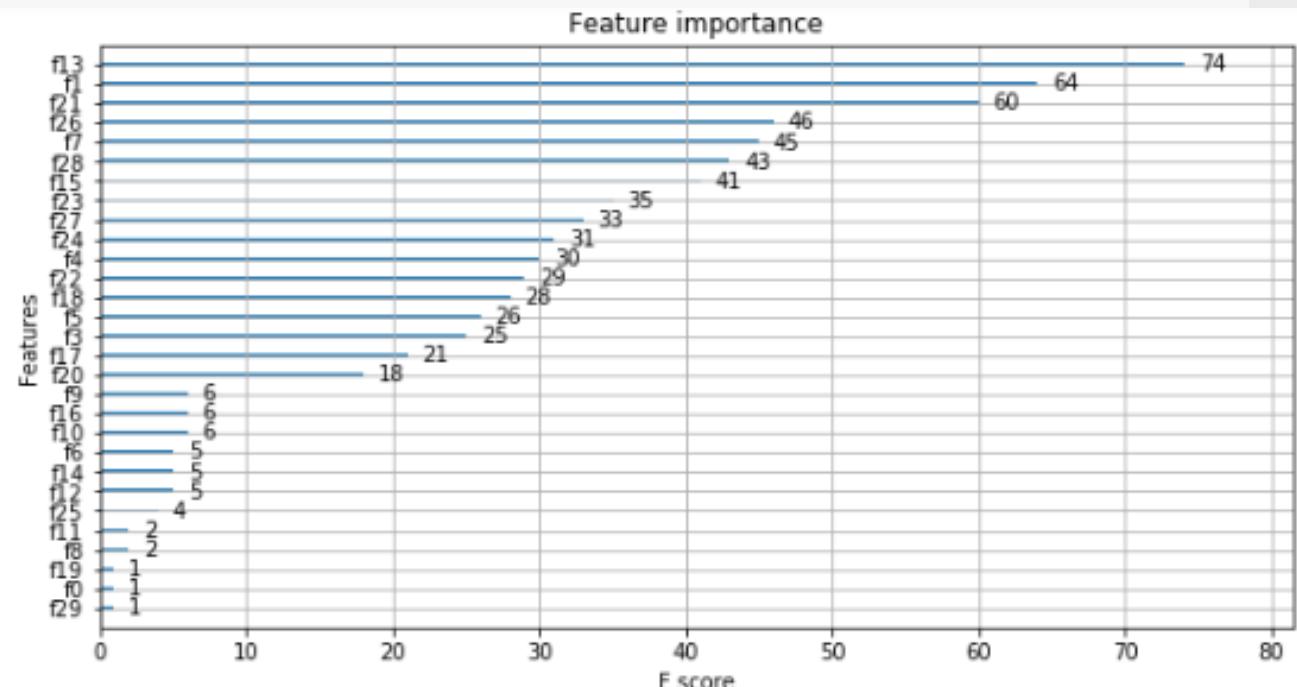
```
[[34  3]
 [ 1 76]]
```

정확도: 0.9649, 정밀도: 0.9620, 재현율: 0.9870

```
from xgboost import plot_importance
import matplotlib.pyplot as plt
%matplotlib inline

fix,ax=plt.subplots(figsize=(10,12))

plot_importance(xgb_wrapper,ax=ax)
```



```

from sklearn.metrics import accuracy_score,precision_score,recall_score,confusion_matrix

def get_clf_eval(y_test , pred):
    confusion = confusion_matrix( y_test, pred)
    accuracy = accuracy_score(y_test , pred)
    precision = precision_score(y_test , pred)
    recall = recall_score(y_test , pred)
    print('오차 행렬')
    print(confusion)
    print('정확도: {:.4f}, 정밀도: {:.4f}, 재현율: {:.4f}'.format(accuracy, precision, recall))

get_clf_eval(y_test,ws100_preds)

```

## 3장의 get\_clf\_eval 함수를 이용

오차 행렬

`[[34 3]  
 [ 1 76]]`

TP	FN
FP	TN

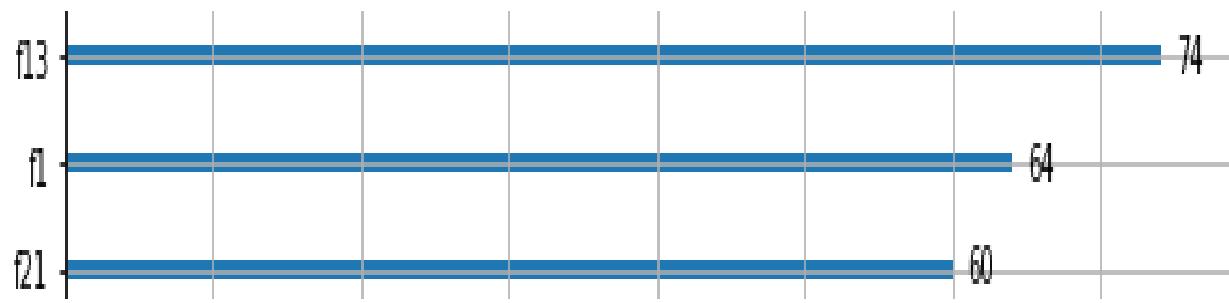
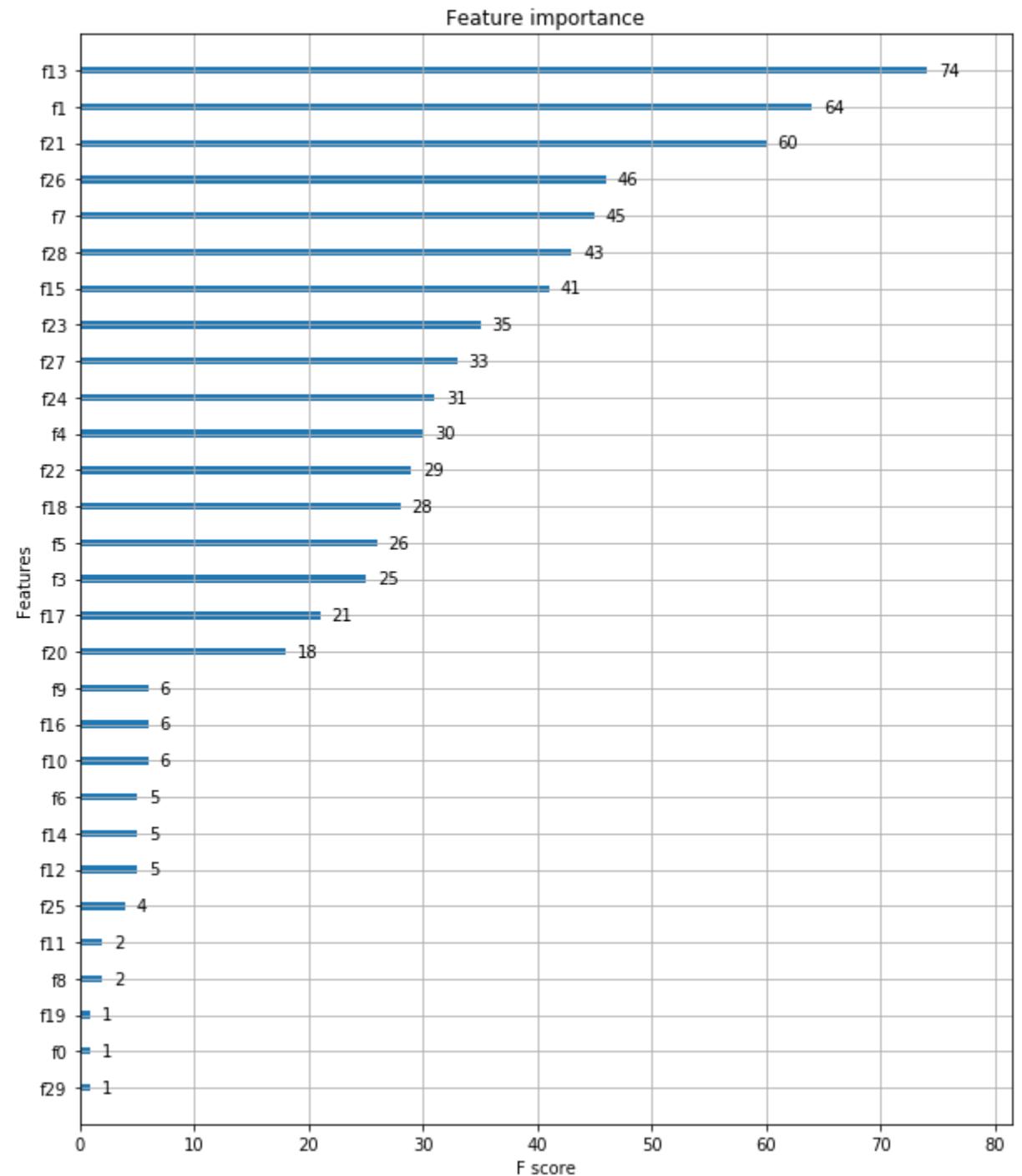
정확도: 0.9649, 정밀도: 0.9620, 재현율: 0.9870

```
from xgboost import plot_importance
import matplotlib.pyplot as plt
%matplotlib inline

fix,ax=plt.subplots(figsize=(10,12))

plot_importance(xgb_wrapper,ax=ax)
```

Xgboost의 plot\_importance함수의 기능은?  
=>데이터의 피처 중요도를 그래프로 보여준다.  
피처 중요도란?  
=> label의 결정에 각 피처가 얼마나 영향을 주는 지에 대한 척도



피처 중요도가 높은 성분들



피처 중요도가 낮은 성분들

### *3. Light GBM*

Light Gradient Boosting Machine

# XGBoost VS Light GBM

## XGBoost

과적합이 일어날 확률이 적다

- 1. 메모리 사용량이 많다
- 2. 수행시간이 길다
- 3. 파라미터 튜닝 <- (GPU, 병렬처리)



## Light GBM

- 1. 학습과 예측수행에 걸리는 시간이 짧다
- 2. XGBoost와 성능 동일
- 3. 메모리 사용량이 비교적 적다
- 4. 명목형 변수의 자동변환과 최적분할

과적합이 발생하기 쉽다

# Light GBM - Parameters

Parameters	Detail
Num_iterations[n_estimators](100)	반복 수행하려는 트리의 개수 (많을수록 성능 △, 과적합확률 ▲)
learning_rate(0.1)	(작을수록 성능△, 과적합확률▲, 수행시간 ▲)
Max_depth(-1)	0이하일 때는 깊이 제한 X (과적합확률 ▲)
Boosting(gbdt)	부스팅의 트리로 사용할 모델
Min_data_in_leaf(20)	최종 결정클래스가 되기 위한 최소 데이터의 양 (낮을수록 과적합확률 ▲)
feature_fraction(1)	개별 트리를 학습할 때마다 무작위로 선택하는 피처 비율. (낮을수록 과적합확률 ▲)
bagging_fraction(1) [sub_sample]	데이터를 랜덤 샘플링하는 비율 (낮을수록 과적합확률▲)
Lambda(0)	정규화(Regularization) 정도 조절 (낮을수록 과적합확률▲)

# Light GBM – Hyper Parameter Tuning, HOW ???

## 1. 성능 향상

**Max\_depth** △

N\_estimators △

Num\_leaves △

**Learning\_rate** ▽

Min\_data\_in\_leaf ▽

## 2. 과적합 감소

**Max\_depth** ▽

N\_estimators ▽

Num\_leaves ▽

**LambdaL2, L1** △

Min\_data\_in\_leaf △

# Light GBM – Practice

## (Breast Cancer Detection)

```
from lightgbm import LGBMClassifier

import pandas as pd
import numpy as np
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_test_split

dataset=load_breast_cancer()
ftr=dataset.data
target=dataset.target

X_train, X_test, y_train, y_test = train_test_split(ftr,target,test_size=0.2, random_state=156)

lgbm_wrapper=LGBMClassifier(n_estimators=400)

evals=[(X_test,y_test)]
lgbm_wrapper.fit(X_train, y_train, early_stopping_rounds=100, eval_metric='logloss', # earlystopping 지정(100)
                  eval_set=evals, verbose=True)
preds=lgbm_wrapper.predict(X_test)
```

LOSS 감소

```
[114] valid_0's binary_logloss: 0.166509
[115] valid_0's binary_logloss: 0.165823
[116] valid_0's binary_logloss: 0.167059
[117] valid_0's binary_logloss: 0.169086
[118] valid_0's binary_logloss: 0.170012
[119] valid_0's binary_logloss: 0.168639
[120] valid_0's binary_logloss: 0.16907
[121] valid_0's binary_logloss: 0.16918
[122] valid_0's binary_logloss: 0.170233
[123] valid_0's binary_logloss: 0.165655
[124] valid_0's binary_logloss: 0.16695
[125] valid_0's binary_logloss: 0.170955
[126] valid_0's binary_logloss: 0.168916
[127] valid_0's binary_logloss: 0.172315
[128] valid_0's binary_logloss: 0.173734
[129] valid_0's binary_logloss: 0.174309
[130] valid_0's binary_logloss: 0.176719
[131] valid_0's binary_logloss: 0.176591
[132] valid_0's binary_logloss: 0.180168
[133] valid_0's binary_logloss: 0.179856
[134] valid_0's binary_logloss: 0.179251
[135] valid_0's binary_logloss: 0.18315
[136] valid_0's binary_logloss: 0.184656
[137] valid_0's binary_logloss: 0.187475
[138] valid_0's binary_logloss: 0.188721
[139] valid_0's binary_logloss: 0.188542
[140] valid_0's binary_logloss: 0.18817
[141] valid_0's binary_logloss: 0.185899
[142] valid_0's binary_logloss: 0.185452
[143] valid_0's binary_logloss: 0.186084
[144] valid_0's binary_logloss: 0.185302
[145] valid_0's binary_logloss: 0.187856
[146] valid_0's binary_logloss: 0.190334
[147] valid_0's binary_logloss: 0.192769
Early stopping, best iteration is:
[47]   valid_0's binary_logloss: 0.126108
valid_0's binary_logloss: 0.126108
```

# Light GBM – Practice

## (Breast Cancer Detection)

```
from lightgbm import LGBMClassifier

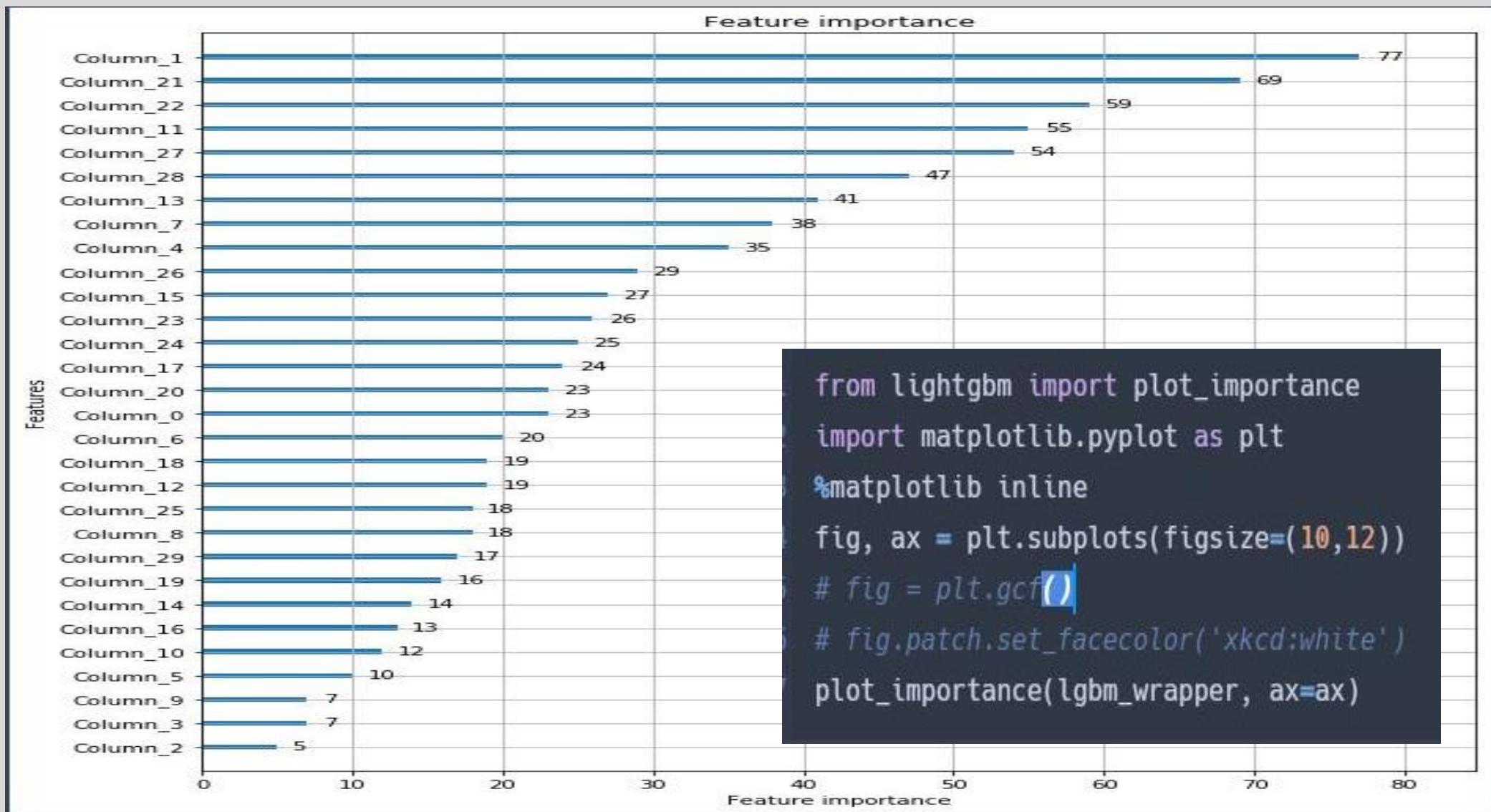
import pandas as pd
import numpy as np
from sklearn.datasets import load_breast_cancer
from sklearn.model_selection import train_t
    1 get_clf_eval(y_test,preds)

dataset=load_breast_cancer()
ftr=dataset.data
target=dataset.target

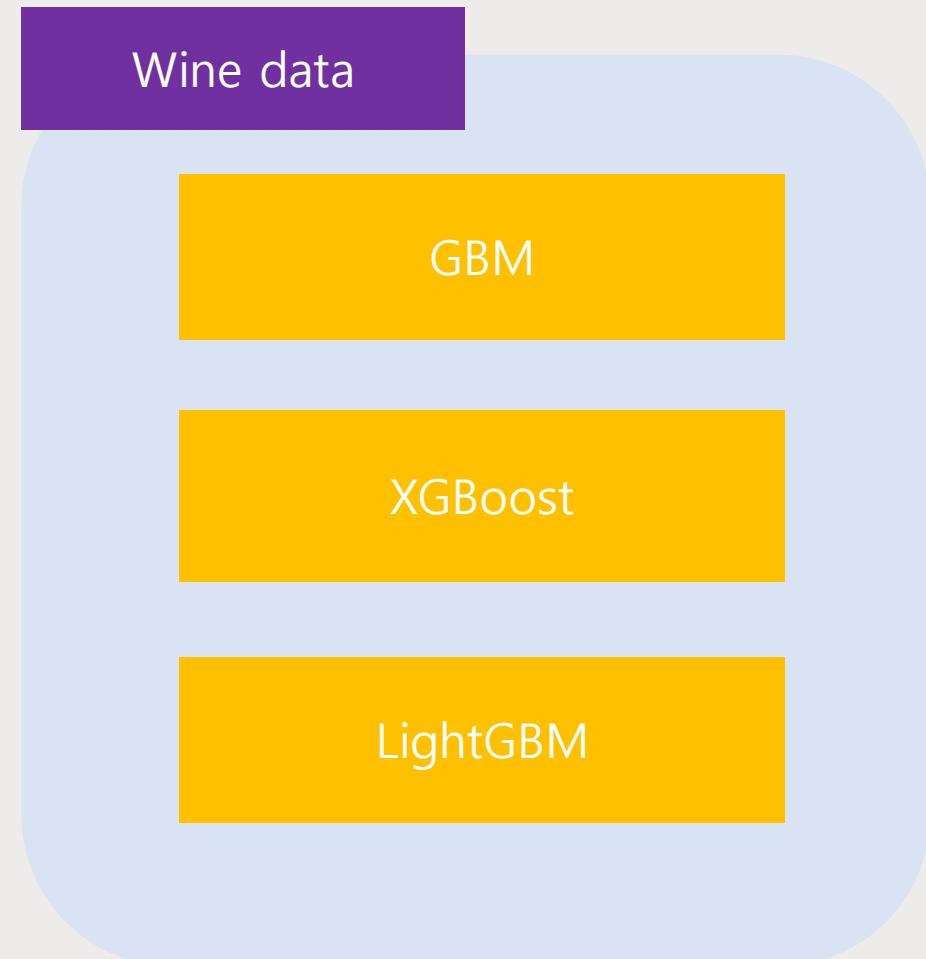
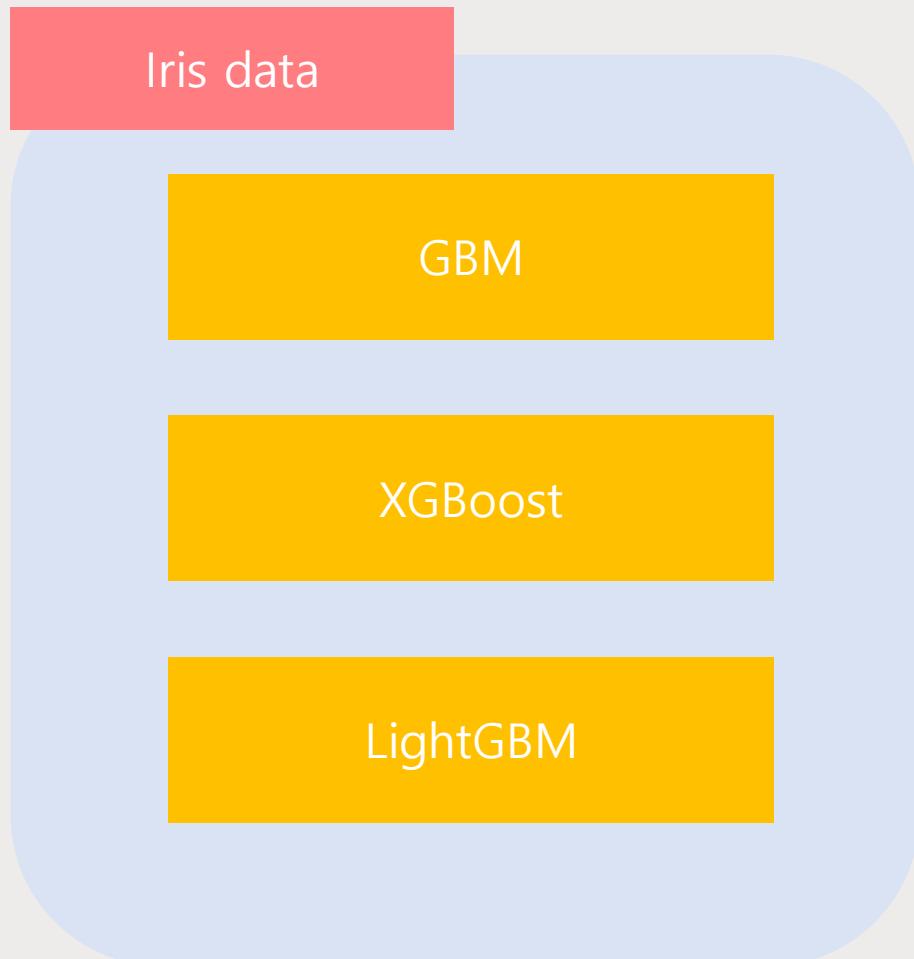
X_train, X_test, y_train, y_test = train_te
    오차 행렬
[[33  4]
 [ 2 75]]
    정확도: 0.9474, 정밀도: 0.9494, 재현율: 0.9740,      F1: 0.9615, AUC:0.9330
[114] valid_0's binary_logloss: 0.166509  valid_0's binary_logloss: 0.166509
[115] valid_0's binary_logloss: 0.165823  valid_0's binary_logloss: 0.165823
[116] valid_0's binary_logloss: 0.167059  valid_0's binary_logloss: 0.167059
[117] valid_0's binary_logloss: 0.169086  valid_0's binary_logloss: 0.169086
[118] valid_0's binary_logloss: 0.170012  valid_0's binary_logloss: 0.170012
[119] valid_0's binary_logloss: 0.168639  valid_0's binary_logloss: 0.168639
[120] valid_0's binary_logloss: 0.16907   valid_0's binary_logloss: 0.16907
[121] valid_0's binary_logloss: 0.16918   valid_0's binary_logloss: 0.16918
[122] valid_0's binary_logloss: 0.170233  valid_0's binary_logloss: 0.170233
[123] valid_0's binary_logloss: 0.165655  valid_0's binary_logloss: 0.165655
[124] valid_0's binary_logloss: 0.166509  valid_0's binary_logloss: 0.166509
[125] valid_0's binary_logloss: 0.170955  valid_0's binary_logloss: 0.170955
[126] valid_0's binary_logloss: 0.168916  valid_0's binary_logloss: 0.168916
[127] valid_0's binary_logloss: 0.172316  valid_0's binary_logloss: 0.172316
[128] valid_0's binary_logloss: 0.173734  valid_0's binary_logloss: 0.173734
[129] valid_0's binary_logloss: 0.174309  valid_0's binary_logloss: 0.174309
[130] valid_0's binary_logloss: 0.176719  valid_0's binary_logloss: 0.176719
[131] valid_0's binary_logloss: 0.176591  valid_0's binary_logloss: 0.176591
[132] valid_0's binary_logloss: 0.180168  valid_0's binary_logloss: 0.180168
[133] valid_0's binary_logloss: 0.179856  valid_0's binary_logloss: 0.179856
[134] valid_0's binary_logloss: 0.179251  valid_0's binary_logloss: 0.179251
[135] valid_0's binary_logloss: 0.18315   valid_0's binary_logloss: 0.18315
[136] valid_0's binary_logloss: 0.184656  valid_0's binary_logloss: 0.184656
[137] valid_0's binary_logloss: 0.187475  valid_0's binary_logloss: 0.187475
[138] valid_0's binary_logloss: 0.188721  valid_0's binary_logloss: 0.188721
[139] valid_0's binary_logloss: 0.188542  valid_0's binary_logloss: 0.188542
[140] valid_0's binary_logloss: 0.18817   valid_0's binary_logloss: 0.18817
[141] valid_0's binary_logloss: 0.185899  valid_0's binary_logloss: 0.185899
[142] valid_0's binary_logloss: 0.185452  valid_0's binary_logloss: 0.185452
[143] valid_0's binary_logloss: 0.186084  valid_0's binary_logloss: 0.186084
[144] valid_0's binary_logloss: 0.185302  valid_0's binary_logloss: 0.185302
[145] valid_0's binary_logloss: 0.187856  valid_0's binary_logloss: 0.187856
[146] valid_0's binary_logloss: 0.190334  valid_0's binary_logloss: 0.190334
[147] valid_0's binary_logloss: 0.192769  valid_0's binary_logloss: 0.192769
Early stopping, best iteration is:
[47]    valid_0's binary_logloss: 0.126108  valid_0's binary_logloss: 0.126108
```

# Light GBM – Practice

(Breast Cancer Detection)



# 과제??



# Q&A

**THANK YOU**