

▼ sklearn Classification - 분류

```
import warnings
warnings.filterwarnings('ignore')
```

▼ 실습용 데이터 설정

- pandas DataFrame
 - iris.csv

```
import seaborn as sns

DF = sns.load_dataset('iris')

DF.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  -
 0   sepal_length    150 non-null    float64
 1   sepal_width     150 non-null    float64
 2   petal_length    150 non-null    float64
 3   petal_width     150 non-null    float64
 4   species         150 non-null    object
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

```
DF.head(3)
```

	sepal_length	sepal_width	petal_length	petal_width	species
0	5.1	3.5	1.4	0.2	setosa
1	4.9	3.0	1.4	0.2	setosa
2	4.7	3.2	1.3	0.2	setosa

▼ 1) 분석 변수 선택

- X : 'sepal_length', 'sepal_width', 'petal_length', 'petal_width'
- y : 'species'

```
X = DF[['sepal_length', 'sepal_width', 'petal_length', 'petal_width']]
y = DF['species']
```

▼ 2) Train & Test Split(with stratify)

- 7:3

```
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
                                                    test_size = 0.3,
                                                    stratify = y,
                                                    random_state = 2045)

print('Train Data : ', X_train.shape, y_train.shape)
print('Test Data : ', X_test.shape, y_test.shape)
```

```
Train Data : (105, 4) (105,)
Test Data : (45, 4) (45,)
```

```
DF['species'].value_counts()
```

```
virginica    50
versicolor  50
setosa       50
Name: species, dtype: int64
```

```
print(y_train.value_counts(), 'WnWn', y_test.value_counts())
```

```
virginica    35
versicolor  35
setosa       35
Name: species, dtype: int64
```

```
setosa       15
virginica    15
versicolor  15
Name: species, dtype: int64
```

▼ I. Logistic Regression

▼ 1) 모델 생성

- C : Regularization strength

- default : 1.0
- 값이 작아지면 weight 값을 0에 가깝게 학습
 - 다수의 데이터포인트에 맞추려는 경향
- 값이 커지면 weight 값을 제한하지 않음
 - 각각의 데이터포인트에 맞추려는 경향

```
%%time
```

```
from sklearn.linear_model import LogisticRegression
```

```
LR = LogisticRegression(C = 0.3,
                        penalty = 'l2',
                        multi_class = 'multinomial',
                        n_jobs = -1)
```

```
LR.fit(X_train, y_train)
```

```
CPU times: user 55.9 ms, sys: 36.1 ms, total: 92 ms
Wall time: 1.03 s
```

▼ 2) 모델 평가

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

```
print(accuracy_score(y_test, LR.predict(X_test)), '\n')
print(confusion_matrix(y_test, LR.predict(X_test)))
```

```
0.9333333333333333
```

```
[[15  0  0]
 [ 0 14  1]
 [ 0  2 13]]
```

▼ II. Decision Tree Classifier

▼ 1) 모델 생성

```
%%time
```

```
from sklearn.tree import DecisionTreeClassifier
```

```
DT = DecisionTreeClassifier(criterion = 'entropy',
                           max_depth = 3,
                           random_state = 2045)
```

```
DT.fit(X_train, y_train)
```

```
CPU times: user 25 ms, sys: 9.7 ms, total: 34.7 ms
Wall time: 112 ms
```

▼ 2) 모델 평가

```
print(accuracy_score(y_test, DT.predict(X_test)), '\n')
print(confusion_matrix(y_test, DT.predict(X_test)))
```

```
0.8888888888888888
```

```
[[15  0  0]
 [ 0 13  2]
 [ 0  3 12]]
```

▼ 3) Feature Importance

```
DT.feature_importances_
```

```
array([0.          , 0.          , 0.64899406, 0.35100594])
```

```
import matplotlib.pyplot as plt

plt.figure(figsize = (9, 6))
sns.barplot(DT.feature_importances_,
            ['sepal_length', 'sepal_width', 'petal_length', 'petal_width'])
plt.show()
```



sepal_length

▼ III. Random Forest Classifier

▼ 1) 모델 생성

```
%%time

from sklearn.ensemble import RandomForestClassifier

RF = RandomForestClassifier(criterion = 'entropy',
                           n_estimators = 100,
                           max_features = 3,
                           max_depth = 2,
                           random_state = 2045,
                           n_jobs = -1)

RF.fit(X_train, y_train)
```

CPU times: user 208 ms, sys: 35.2 ms, total: 243 ms
Wall time: 280 ms

▼ 2) 모델 평가

```
print(accuracy_score(y_test, RF.predict(X_test)), '\n')
print(confusion_matrix(y_test, RF.predict(X_test)))
```

0.9333333333333333

```
[[15  0  0]
 [ 0 15  0]
 [ 0  3 12]]
```

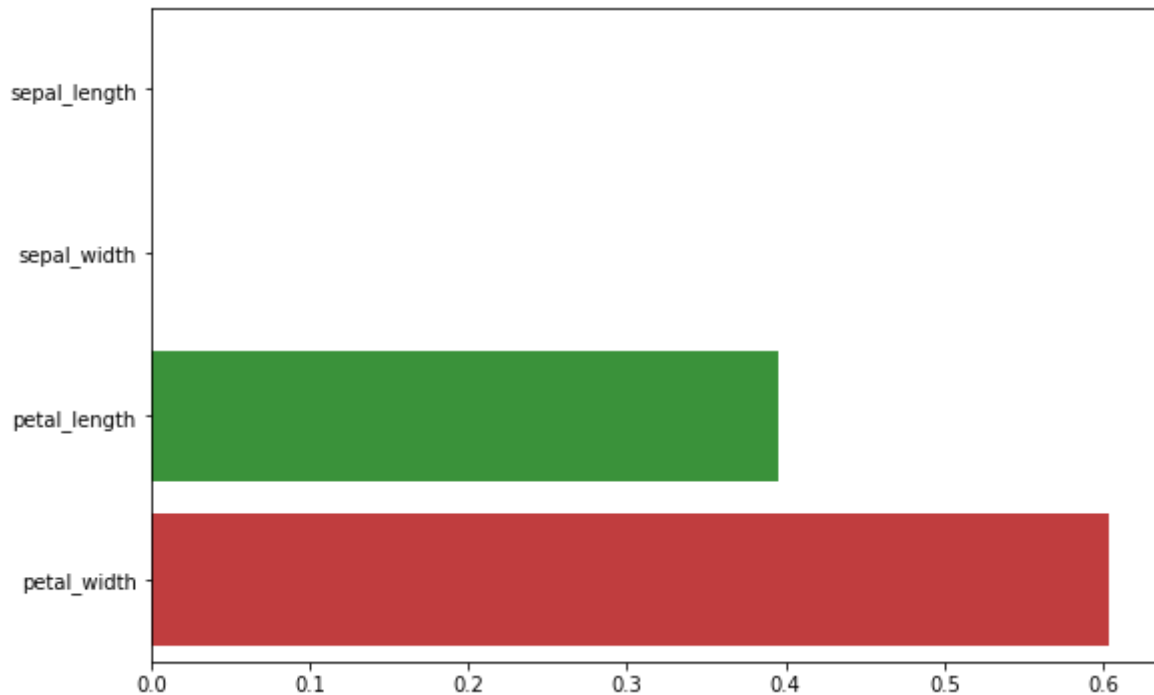
▼ 3) Feature Importance

```
RF.feature_importances_
```

```
array([2.17808494e-04, 0.00000000e+00, 3.95922779e-01, 6.03859413e-01])
```

```
import matplotlib.pyplot as plt

plt.figure(figsize = (9, 6))
sns.barplot(RF.feature_importances_,
            ['sepal_length', 'sepal_width', 'petal_length', 'petal_width'])
plt.show()
```



▼ IV. Gradient Boosting Machine(GBM) Classifier

▼ 1) 모델 생성

- loss : 경사하강법에 사용될 오차함수
- learning_rate : 반복 학습에 적용될 학습률
 - 너무 작으면 학습 시간이 오래 걸릴 수 있음
 - 너무 크면 학습 속도는 빠르지만 최적화 되지 못할 수 있음
 - n_estimators와 함께 상호보완적으로 사용
- n_estimators : weak learner 개수
 - 약한학습기들이 순차적으로 오차를 보정
 - 많을 수록 학습시간이 길어짐

```
%time
```

```
from sklearn.ensemble import GradientBoostingClassifier
```

```
GBC = GradientBoostingClassifier(loss = 'deviance',  
                                n_estimators = 500,  
                                learning_rate = 0.01,  
                                max_features = 3,  
                                max_depth = 3)
```

```
GBC.fit(X_train, y_train)
```

```
CPU times: user 1.03 s, sys: 1.52 ms, total: 1.03 s  
Wall time: 1.04 s
```

▼ 2) 모델 평가

```
print(accuracy_score(y_test, GBC.predict(X_test)), 'Wn')  
print(confusion_matrix(y_test, GBC.predict(X_test)))
```

```
0.9333333333333333
```

```
[[15  0  0]  
 [ 0 15  0]  
 [ 0  3 12]]
```

▼ 3) Feature Importance

```
GBC.feature_importances_
```

```
array([0.02798488, 0.08328638, 0.34126561, 0.54746313])
```

```
import matplotlib.pyplot as plt  
  
plt.figure(figsize = (9, 6))  
sns.barplot(GBC.feature_importances_,  
            ['sepal_length', 'sepal_width', 'petal_length', 'petal_width'])  
plt.show()
```



▼ V. Adaptive Boosting Classifier

▼ 1) 모델 생성

```
%%time

from sklearn.ensemble import AdaBoostClassifier

ABC = AdaBoostClassifier(n_estimators = 1000,
                        learning_rate = 0.001,
                        random_state = 2045)

ABC.fit(X_train, y_train)
```

CPU times: user 1.46 s, sys: 9.74 ms, total: 1.47 s
Wall time: 1.47 s

▼ 2) 모델 평가

```
print(accuracy_score(y_test, ABC.predict(X_test)), 'Wn')
print(confusion_matrix(y_test, ABC.predict(X_test)))
```

0.8888888888888888

```
[[15  0  0]
 [ 0 13  2]
 [ 0  3 12]]
```

▼ 3) Feature Importance

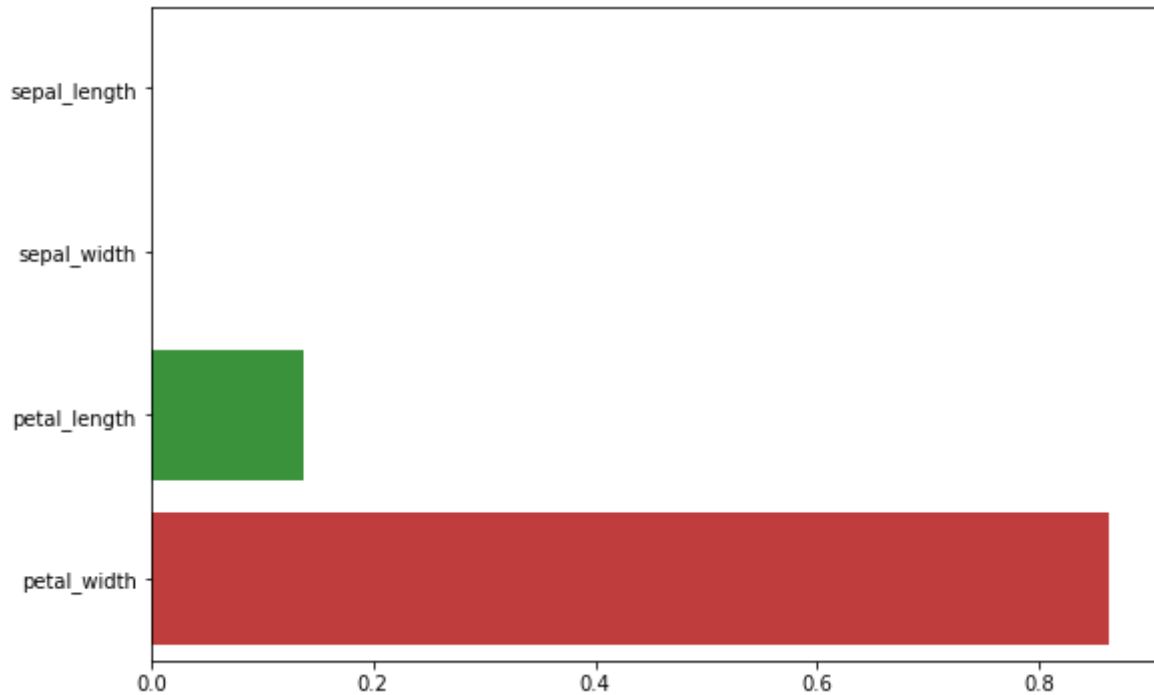
```
ABC.feature_importances_
```



```
array([0.    , 0.    , 0.137, 0.863])
```

```
import matplotlib.pyplot as plt

plt.figure(figsize = (9, 6))
sns.barplot(ABC.feature_importances_,
            ['sepal_length', 'sepal_width', 'petal_length', 'petal_width'])
plt.show()
```



▼ VI. eXtra Gradient Boost(XGBoost) Classifier

▼ 1) 모델 생성

- booster : 'gbtree' or 'gblinear'
- reg_lambda : L2 Regularization

```
%time

from xgboost import XGBClassifier

XGB = XGBClassifier(booster = 'gbtree',
                    n_estimators = 500,
                    learning_rate = 0.5,
                    reg_lambda = 0.05,
                    n_jobs = -1)

XGB.fit(X_train, y_train)
```

```
CPU times: user 145 ms, sys: 31.1 ms, total: 176 ms  
Wall time: 259 ms
```

2) 모델 평가

```
print(accuracy_score(y_test, XGB.predict(X_test)), 'Wn')  
print(confusion_matrix(y_test, XGB.predict(X_test)))
```

```
0.9111111111111111
```

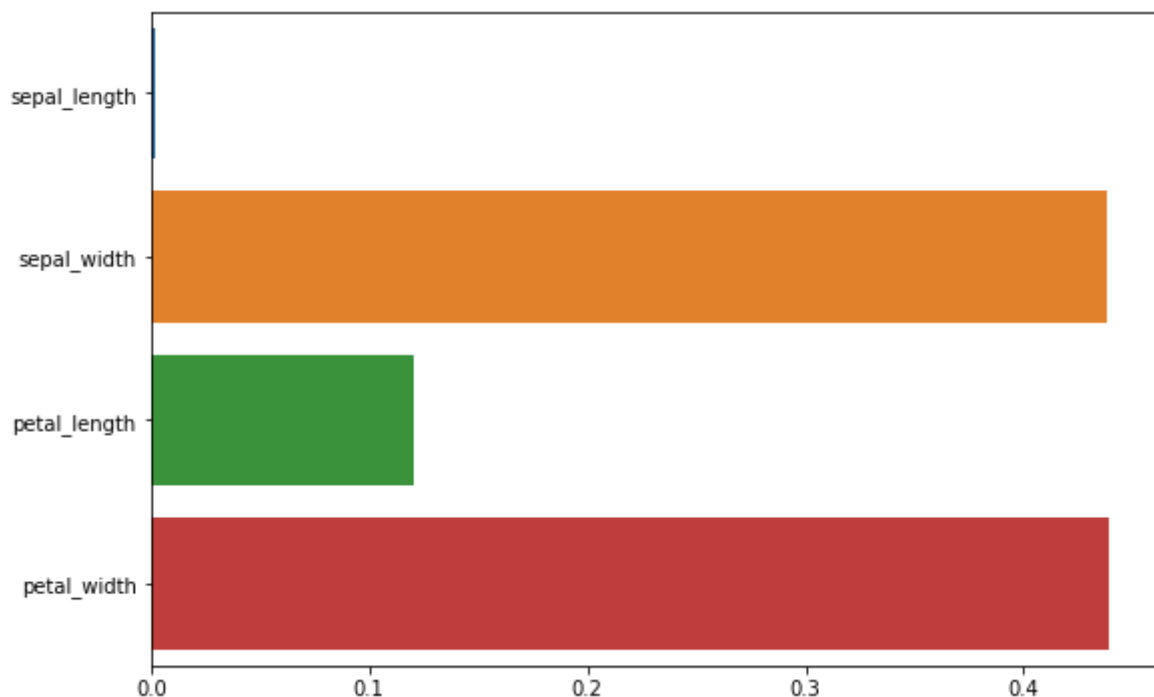
```
[[15  0  0]  
 [ 0 15  0]  
 [ 0  4 11]]
```

3) Feature Importance

```
XGB.feature_importances_
```

```
array([0.00226077, 0.43800136, 0.12052245, 0.4392154 ], dtype=float32)
```

```
import matplotlib.pyplot as plt  
  
plt.figure(figsize = (9, 6))  
sns.barplot(XGB.feature_importances_,  
            ['sepal_length', 'sepal_width', 'petal_length', 'petal_width'])  
plt.show()
```



▼ VII. LightGBM Classifier

▼ 1) 모델 생성

```
%%time

from lightgbm import LGBMClassifier

LGB = LGBMClassifier(n_estimators = 500,
                     max_depth = 3,
                     learning_rate = 0.5,
                     reg_lambda = 0.2,
                     n_jobs = -1)

LGB.fit(X_train, y_train)
```

CPU times: user 195 ms, sys: 17.1 ms, total: 213 ms
Wall time: 154 ms

▼ 2) 모델 평가

```
print(accuracy_score(y_test, LGB.predict(X_test)), 'Wn')
print(confusion_matrix(y_test, LGB.predict(X_test)))
```

0.9555555555555556

```
[[15  0  0]
 [ 0 15  0]
 [ 0  2 13]]
```

▼ 3) Feature Importance

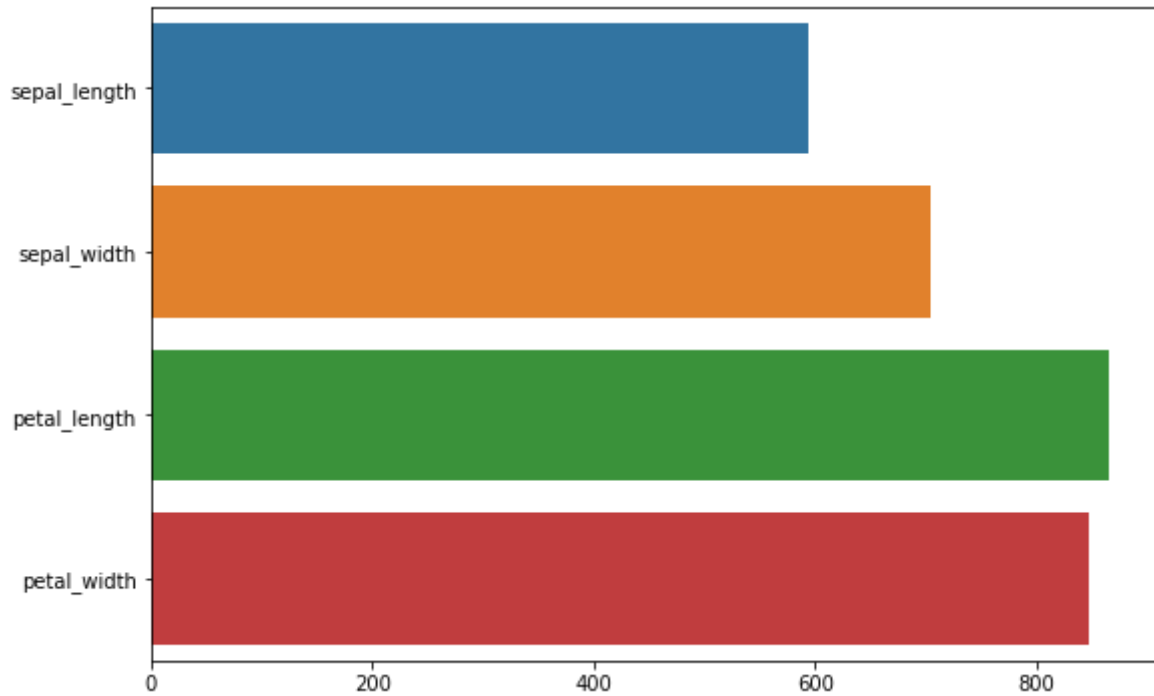
```
LGB.feature_importances_
```

array([594, 704, 866, 847])

```
import matplotlib.pyplot as plt

plt.figure(figsize = (9, 6))
sns.barplot(LGB.feature_importances_,
            ['feature_length', 'feature_width', 'total_length', 'total_width'])
```

```
[ sepal_length, sepal_width, petal_length, petal_width ]
plt.show()
```



▼ VIII. K-Nearest Neighbors Classifier

▼ 1) 모델 생성

```
%%time

from sklearn.neighbors import KNeighborsClassifier

KNN = KNeighborsClassifier(n_neighbors = 5,
                           n_jobs = -1)

KNN.fit(X_train, y_train)
```

CPU times: user 2.44 ms, sys: 47 µs, total: 2.49 ms
Wall time: 4.94 ms

▼ 2) 모델 평가

```
print(accuracy_score(y_test, KNN.predict(X_test)), 'Wn')
print(confusion_matrix(y_test, KNN.predict(X_test)))
```

0.9777777777777777

```
[[15  0  0]  
 [ 0 15  0]  
 [ 0  1 14]]
```

#

#

#

The End

#

#

#

✓ 0초 오전 8:45에 완료됨

