Estimação, Deteção e Análise II

04 – Técnicas de Melhoria

Bagging

Random Forests

Boosting

Bagging para classificação

1. Criar um *dataset* para classificação de forma aleatória

```
from sklearn.datasets import make_classification
X, y = make_classification(n_samples=1000, n_features=20, n_informative=15,
    n_redundant=5, random_state=5)
```

2. Definir o modelo

```
from sklearn.ensemble import BaggingClassifier
model = BaggingClassifier()
```

3. Avaliar o modelo e mostrar a performance

```
from sklearn.model_selection import RepeatedStratifiedKFold
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

from sklearn.model_selection import cross_val_score
n_scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1,
        error_score='raise')

from numpy import mean
from numpy import std
print('Accuracy: %.3f (%.3f)' % (mean(n_scores), std(n_scores)))
```

Resultado:

```
Accuracy: 0.866 (0.043)
```

Nota: Dada a aleatoriedade, o resultado pode variar

4. Fazer *fit* do modelo e aplicá-lo a uma nova instância

```
model.fit(X,y)
row = [[-4.7705504,-1.88685058,-0.96057964,2.53850317,-6.5843005,3.45711663,-
        7.46225013,2.01338213,-0.45086384,-1.89314931,-2.90675203,-0.21214568,-
        0.9623956,3.93862591,0.06276375,0.33964269,4.0835676,1.31423977,-
        2.17983117,3.1047287]]
yhat = model.predict(row)
print('Predicted Class: %d' % yhat[0])
```

Resultado:

```
Predicted Class: 1
```

Comparação de métodos Bagging em classificação

1. Importar o *dataset* iris e dividi-lo em variáveis independentes e dependente, treino e teste

```
from sklearn import datasets
iris = datasets.load_iris()

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target)
```

2. Definir os modelos a utilizar

```
from sklearn.dummy import DummyClassifier
from sklearn.linear_model import Perceptron
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
possible_base_estimators = [DummyClassifier(),
                            Perceptron(tol=1e-3),
                            DecisionTreeClassifier(),
                            KNeighborsClassifier()]
```

3. Definir a *grid* (*base model*, número de *base models*), correr o *bagging* e guardar o resultado

```
results = []
from sklearn.ensemble import BaggingClassifier
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import cross_val_score
from numpy import mean
for base_estimator in possible_base_estimators:
    for n_estimators in [1, 10, 20, 30, 40, 50, 60, 70, 80, 90, 100]:
        print(base_estimator, n_estimators)
        model = BaggingClassifier(n_estimators=n_estimators,
                 base_estimator=base_estimator, random_state=1)
        cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
        n_scores = cross_val_score(model, X_train, y_train, scoring='accuracy', cv=cv,
                 n_jobs=-1, error_score='raise')
        res = [base_estimator, n_estimators, mean(n_scores)]
        results.append(res)
```

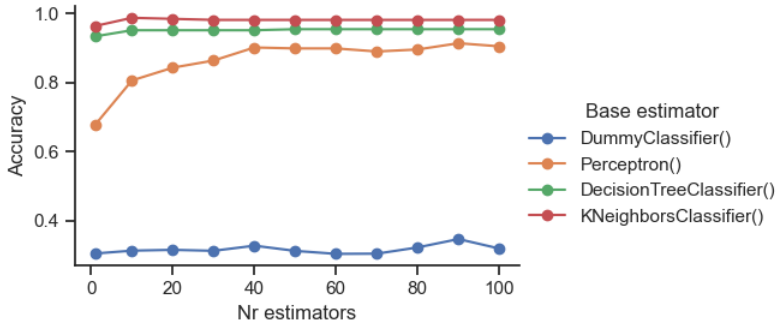
4. Converter os resultados num *dataframe* e atribuir nomes às colunas

```
from pandas import DataFrame
results = DataFrame(results)
results.columns =['Base estimator','Nr estimators','Accuracy']
```

5. Visualizar graficamente os resultados

```
from  matplotlib import pyplot
import seaborn
seaborn.set(style='ticks')
fg = seaborn.FacetGrid(data=results, hue='Base estimator', aspect=1.61)
fg.map(pyplot.plot, 'Nr estimators', 'Accuracy', marker='o').add_legend()
fg.savefig('bagging_comp.png')
```

Resultado:



Bagging para regressão

1. Criar um *dataset* para regressão de forma aleatória

```
from sklearn.datasets import make_regression
X, y = make_regression(n_samples=1000, n_features=20, n_informative=15, noise=0.1,
    random_state=5)
```

2. Definir o modelo

```
from sklearn.ensemble import BaggingRegressor
model = BaggingRegressor()
```

3. Avaliar o modelo e mostrar a performance

```
from sklearn.model_selection import RepeatedKFold
cv = RepeatedKFold (n_splits=10, n_repeats=3, random_state=1)

from sklearn.model_selection import cross_val_score
n_scores = cross_val_score(model, X, y, scoring='neg_mean_absolute_error', cv=cv,
        n_jobs=-1, error_score='raise')
from numpy import mean
from numpy import std
print('MAE: %.3f (%.3f)' % (mean(n_scores), std(n_scores)))
```

Resultado:

```
MAE: -101.255 (9.184)
```

Nota: Dada a aleatoriedade, o resultado pode variar

4. Fazer *fit* do modelo e aplicá-lo a uma nova instância

```
model.fit(X,y)
row = [[0.88950817,-0.93540416,0.08392824,0.26438806,-0.52828711,-1.21102238,-
        0.4499934,1.47392391,-0.19737726,-0.22252503,0.02307668,0.26953276,0.03572757,-
        0.51606983,-0.39937452,1.8121736,-0.00775917,-0.02514283,-0.76089365,1.58692212]]
yhat = model.predict(row)
print('Prediction: %d' % yhat[0])
```

Resultado:

```
Prediction: -187
```

Random Forests

1. Importar o *dataset* iris e dividi-lo em variáveis independentes e dependente, treino e teste

```
from sklearn import datasets
iris = datasets.load_iris()

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target)
```

2. Definir a *grid* (número de *base models* e número de *features* a escolher em cada *split*), correr o *random forests* e guardar o resultado

```
results = []
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import cross_val_score
from numpy import mean
for n_estimator in [1, 50, 100, 250, 500, 750, 1000, 2500, 5000]:
    for features in ['auto', 'sqrt', 'log2']:
        print(n_estimator, features)
        model = RandomForestClassifier(n_estimators=100, max_features="auto")
        cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
        n_scores = cross_val_score(model, X_train, y_train, scoring='accuracy', cv=cv,
n_jobs=-1, error_score='raise')
        res = [n_estimator, features, mean(n_scores)]
        results.append(res)
```

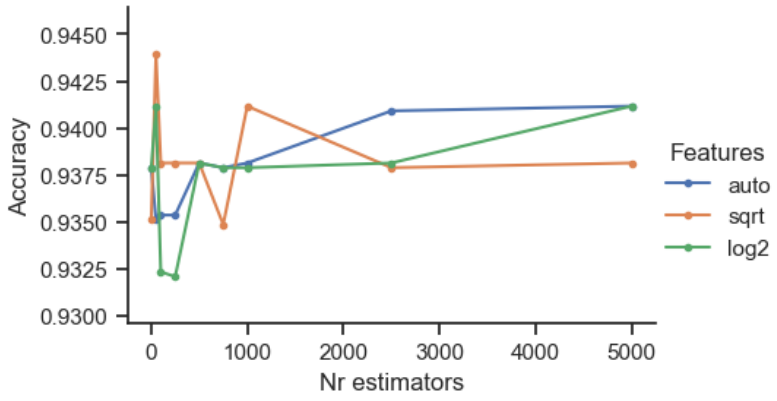
3. Converter os resultados num *dataframe* e atribuir nomes às colunas

```
from pandas import DataFrame
results = DataFrame(results)
results.columns =['Nr estimators', 'Features', 'Accuracy']
```

4. Visualizar graficamente os resultados

```
from matplotlib import pyplot
import seaborn
seaborn.set(style='ticks')
fg = seaborn.FacetGrid(data=results, hue='Features', aspect=1.61)
fg.set(ylim=(results['Accuracy'].min()-0.0025, results['Accuracy'].max()+0.0025))
fg.map(pyplot.plot, 'Nr estimators', 'Accuracy', marker='.').add_legend()
fg.savefig('randomForests.png')
```

Resultado:



Nota: Dada a aleatoriedade, o resultado pode variar

Boosting (*AdaBoost*)

1. Importar o *dataset* iris e dividi-lo em variáveis independentes e dependente, treino e teste

```
from sklearn import datasets
iris = datasets.load_iris()

from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(iris.data, iris.target)
```

2. Definir a *grid* (número de iterações), correr o *AdaBoost* (*default base learner*: *decision trees*) e guardar o resultado

```
results = []
from sklearn.ensemble import AdaBoostClassifier
from sklearn.model_selection import RepeatedStratifiedKFold
from sklearn.model_selection import cross_val_score
from numpy import mean
for n_estimator in [1, 10, 20, 30, 40, 50 , 60, 70, 80, 90, 100]:
    print(n_estimator)
    model = AdaBoostClassifier(n_estimators=n_estimator)
    cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
    n_scores = cross_val_score(model, X_train, y_train, scoring='accuracy', cv=cv,
n_jobs=-1, error_score='raise')
    res = [n_estimator, mean(n_scores)]
    results.append(res)
```

3. Converter os resultados num *dataframe* e atribuir nomes às colunas

```
from pandas import DataFrame
results = DataFrame(results)
results.columns =['Nr estimators', 'Accuracy']
```

4. Visualizar graficamente os resultados

```
from matplotlib import pyplot
import seaborn
seaborn.set(style='ticks')
fg = seaborn.FacetGrid(data=results, aspect=1.61)
fg.set(ylim=(results['Accuracy'].min()-0.0025, results['Accuracy'].max()+0.0025))
fg.map(pyplot.plot, 'Nr estimators', 'Accuracy', marker='.').add_legend()
fg.savefig('adaboost.png')
```

Resultado: