Міністерство освіти і науки України Національний технічний університет України «Київський політехнічний інститут імені Ігоря Сікорського» Факультет інформатики та обчислювальної техніки

Кафедра інформатики та програмної інженерії

Звіт

з лабораторної роботи № 4 з дисципліни «Програмування інтелектуальних інформаційних систем»

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Lab-4

```
import warnings
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn import metrics
from sklearn.model selection import train test split
from sklearn.model selection import GridSearchCV
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.preprocessing import StandardScaler
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC
from sklearn.linear model import LogisticRegression
from sklearn.ensemble import VotingClassifier
from sklearn.datasets import load wine
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.linear model import RidgeClassifier
from sklearn.ensemble import BaggingClassifier
from sklearn.model selection import cross val score
from sklearn.ensemble import AdaBoostClassifier,
GradientBoostingClassifier
from xgboost import XGBClassifier
from sklearn.linear model import Ridge, Lasso, LogisticRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.base import BaseEstimator, RegressorMixin, clone
warnings.filterwarnings(action='ignore')
seed = 42
```

Import data and data preprocessing

```
df = pd.read csv("resources/data.csv")
df.drop(['Unnamed: 32', 'id'], axis=1, inplace=True)
df['diagnosis']=df['diagnosis'].astype('category').cat.codes
X = df.drop(['diagnosis'], axis = 1)
y = df['diagnosis']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size =
0.3, random state = seed)
df.head()
   diagnosis
              radius_mean texture_mean
                                          perimeter_mean
                                                          area mean \
0
                    17.99
                                   10.38
                                                  122.80
                                                             1001.0
           1
                    20.57
                                   17.77
                                                  132.90
                                                             1326.0
1
           1
2
           1
                    19.69
                                   21.25
                                                  130.00
                                                             1203.0
```

```
3
                     11.42
                                     20.38
                                                      77.58
                                                                  386.1
4
            1
                     20.29
                                     14.34
                                                     135.10
                                                                 1297.0
   smoothness mean
                     compactness mean
                                       concavity mean
                                                         concave
points mean \
            0.11840
                               0.27760
                                                 0.3001
0.14710
                                                 0.0869
1
            0.08474
                               0.07864
0.07017
            0.10960
                               0.15990
                                                 0.1974
0.12790
                               0.28390
                                                 0.2414
3
            0.14250
0.10520
            0.10030
                               0.13280
                                                 0.1980
0.10430
                         radius worst
   symmetry mean
                                        texture worst
                                                        perimeter worst \
0
          0.2419
                                25.38
                                                 17.33
                                                                  184.60
1
                                24.99
                                                23.41
           0.1812
                                                                  158.80
2
                                                25.53
           0.2069
                                23.57
                                                                  152.50
3
           0.2597
                                14.91
                                                26.50
                                                                   98.87
4
          0.1809
                                22.54
                                                16.67
                                                                  152.20
                smoothness_worst
   area_worst
                                   compactness worst
                                                        concavity_worst \
0
       2019.0
                                               0.6656
                           0.1622
                                                                  0.7119
1
       1956.0
                           0.1238
                                               0.1866
                                                                  0.2416
2
       1709.0
                           0.1444
                                               0.4245
                                                                  0.4504
3
        567.7
                           0.2098
                                               0.8663
                                                                  0.6869
4
       1575.0
                           0.1374
                                               0.2050
                                                                  0.4000
                                            fractal dimension worst
   concave points worst
                           symmetry worst
0
                  0.2654
                                   0.4601
                                                             0.11890
1
                  0.1860
                                   0.2750
                                                             0.08902
2
                  0.2430
                                   0.3613
                                                             0.08758
3
                  0.2575
                                   0.6638
                                                             0.17300
4
                  0.1625
                                   0.2364
                                                             0.07678
[5 rows x 31 columns]
```

Hyperparameter tuning

Decision Tree

```
'max_depth': [2, 3, 5, 10, 50],
              'min samples split': [2, 3, 50, 100],
              'min samples leaf': [1, 5, 8, 10]
grid obj = GridSearchCV(base dt, parameters)
grid_obj = grid_obj.fit(X_train, y_train)
tuned dt = grid obj.best estimator
tuned dt.fit(X_train, y_train)
tuned dt y pred = tuned dt.predict(X test)
acc base dt = round(metrics.accuracy score(y test, base dt y pred) *
100, 2)
acc tuned dt = round(metrics.accuracy score(y test, tuned dt y pred) *
100, 2)
print('Accuracy of base Decision Tree model: ', acc base dt)
print('Accuracy of tuned Decision Tree model: ', acc tuned dt)
Accuracy of base Decision Tree model: 94.15
Accuracy of tuned Decision Tree model: 97.08
```

Random Forest

```
base rf = RandomForestClassifier()
base rf.fit(X train, y train)
base rf y pred = base rf.predict(X test)
parameters = \{'n_{estimators}': [4, 6, 9, 10, 15],
               'max_features': ['log2', 'sqrt', 'auto'],
'criterion': ['entropy', 'gini'],
               'max_depth': [2, 3, 5, 10],
               'min samples split': [2, 3, 5],
               'min samples leaf': [1, 5, 8]
grid obj = GridSearchCV(base rf, parameters)
grid_obj = grid_obj.fit(X_train, y_train)
tuned rf = grid obj.best estimator
tuned rf.fit(X train, y train)
tuned rf y pred = tuned rf.predict(X test)
acc base rf = round(metrics.accuracy score(y test, base rf y pred) *
100, 2)
acc tuned rf = round(metrics.accuracy score(y test, tuned rf y pred) *
100, 2)
```

```
print('Accuracy of base Random Forest model: ', acc_base_rf)
print('Accuracy of tuned Random Forest model: ', acc_tuned_rf)
Accuracy of base Random Forest model: 96.49
Accuracy of tuned Random Forest model: 97.08
```

Support Vector Machine

```
sc = StandardScaler()
X train = sc.fit transform(X train)
X test = sc.transform(X test)
base svc = SVC()
base_svc.fit(X_train, y_train)
base svc y pred = base svc.predict(X test)
parameters = [
  {'C': [1, 10, 100, 1000], 'kernel': ['linear']},
  {'C': [1, 10, 100, 1000], 'gamma': [0.001, 0.0001], 'kernel':
['rbf']},
grid obj = GridSearchCV(base svc, parameters)
grid obj = grid obj.fit(X train, y train)
tuned svc = grid obj.best estimator
tuned svc.fit(X train, y_train)
tuned svc y pred = tuned svc.predict(X test)
acc base svc = round(metrics.accuracy score(y test, base svc y pred) *
100, 2)
acc_tuned_svc = round(metrics.accuracy_score(y_test, tuned svc y pred)
* 100, 2)
print('Accuracy of base SVC model: ', acc base svc)
print('Accuracy of tuned SVC model: ', acc_tuned_svc)
Accuracy of base SVC model: 97.66
Accuracy of tuned SVC model: 97.66
```

K-Nearest Neighbors

```
grid_obj = GridSearchCV(base_knn, parameters)
grid_obj = grid_obj.fit(X_train, y_train)

tuned_knn = grid_obj.best_estimator_
tuned_knn.fit(X_train, y_train)
tuned_knn_y_pred = tuned_knn.predict(X_test)

acc_base_knn = round(metrics.accuracy_score(y_test, base_knn_y_pred) *
100, 2)
acc_tuned_knn = round(metrics.accuracy_score(y_test, tuned_knn_y_pred) *
100, 2)

print('Accuracy of base KNN model: ', acc_base_knn)
print('Accuracy of tuned KNN model: ', acc_tuned_knn)

Accuracy of base KNN model: 95.91
Accuracy of tuned KNN model: 95.91
```

Tuning results

```
models = pd.DataFrame({
    'Model': ['Base Decision Tree', 'Tuned Decision Tree', 'Base
Random Forest', 'Tuned Random Forest',
              'Base Support Vector Machines', 'Tuned Support Vector
Machines', 'Base K-Nearest Neighbors', 'Tuned K-Nearest Neighbors'],
    'Accuracy': [acc_base_dt, acc_tuned_dt, acc_base_rf, acc_tuned_rf,
              acc base svc, acc tuned svc, acc base knn,
acc tuned knn]})
models.sort values(by='Accuracy', ascending=False)
                           Model Accuracy
4
    Base Support Vector Machines
                                     97.66
5
   Tuned Support Vector Machines
                                     97.66
1
             Tuned Decision Tree
                                     97.08
3
             Tuned Random Forest
                                     97.08
2
              Base Random Forest
                                     96.49
6
        Base K-Nearest Neighbors
                                     95.91
7
       Tuned K-Nearest Neighbors
                                     95.91
0
              Base Decision Tree
                                     94.15
```

Max Voting

```
estimators = []
estimators.append(('LR', LogisticRegression(solver='lbfgs',
multi_class='multinomial', max_iter=200)))
estimators.append(('SVC', SVC(gamma='auto', probability=True)))
```

```
estimators.append(('DTC', DecisionTreeClassifier()))
hard_voting = VotingClassifier(estimators=estimators, voting='hard')
hard_voting.fit(X_train, y_train)
y_pred = hard_voting.predict(X_test)

score = metrics.accuracy_score(y_test, y_pred)
print("Accuracy of Hard Voting model: %f" % score)

soft_voting = VotingClassifier(estimators=estimators, voting='soft')
soft_voting.fit(X_train, y_train)
y_pred = soft_voting.predict(X_test)

score = metrics.accuracy_score(y_test, y_pred)
print("Accuracy of Soft Voting model: %f" % score)

Accuracy of Hard Voting model: 0.988304
Accuracy of Soft Voting model: 0.988304
```

Weighted Averaging

```
class AverageWeight(BaseEstimator, RegressorMixin):
    def init (self, model, weight):
        self.model = model
        self.weight = weight
    def fit(self,X,y):
        self.models_ = [clone(x) for x in self.model]
        for model in self.models :
            model.fit(X,y)
        return self
    def predict(self,X):
        w = list()
        pred = np.array([model.predict(X) for model in self.models ])
        # for every data point, single model prediction times weight,
then add them together
        for data in range(pred.shape[1]):
            single = [pred[model,data]*weight for model,weight in
zip(range(pred.shape[0]), self.weight)]
            w.append(np.sum(single))
        return w
def rmse cv(model,X,y):
    rmse = np.sqrt(-
cross_val_score(model,X,y,scoring="neg mean squared error",cv=5))
    return rmse
estimators = []
estimators.append(LogisticRegression())
```

```
estimators.append(DecisionTreeRegressor())
estimators.append(Lasso())
estimators.append(Ridge())

w1 = 0.2
w2 = 0.3
w3 = 0.4
w4 = 0.1

weight_avg = AverageWeight(model=estimators, weight=[w1, w2, w3, w4])
score = rmse_cv(weight_avg, X, y)

print("Accuracy of Weighted Averaging model: %f" % score.mean())
Accuracy of Weighted Averaging model: 0.234249
```

Blending

```
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
test_size=0.25, random_state=seed)
x val = pd.DataFrame(X val)
x test = pd.DataFrame(X test)
model1 = DecisionTreeClassifier()
model1.fit(X train, y train)
val pred1=model1.predict(X val)
test pred1=model1.predict(X test)
val pred1=pd.DataFrame(val pred1)
test pred1=pd.DataFrame(test pred1)
model2 = KNeighborsClassifier()
model2.fit(X train,y train)
val pred2 = model2.predict(X val)
test pred2 = model2.predict(X test)
val pred2 = pd.DataFrame(val pred2)
test pred2 = pd.DataFrame(test pred2)
df val = pd.concat([x val, val pred1, val pred2], axis=1)
df_test = pd.concat([x_test, test_pred1, test_pred2], axis=1)
model = LogisticRegression()
model.fit(df val, y val)
print("Accuracy of Blending model: ", model.score(df_test, y_test))
Accuracy of Blending model: 0.9941520467836257
```

Bagging

```
rf = RandomForestClassifier()
et = ExtraTreesClassifier()
knn = KNeighborsClassifier()
svc = SVC()
rg = RidgeClassifier()
clf array = [rf, et, knn, svc, rg]
for clf in clf array:
    vanilla scores = cross val score(clf, X, y, cv=10, n jobs=-1)
    bagging clf = BaggingClassifier(clf,max samples=0.4,
max features=10, random state=seed)
    bagging scores = cross val score(bagging clf, X, y, cv=10,n jobs=-
1)
    print ("Mean of: {1:.3f}, std: (+/-) {2:.3f}
[{0}]".format(clf. class . name ,vanilla scores.mean(),
vanilla scores.std()))
    print ("Mean of: \{1:.3f\}, std: (+/-) \{2:.3f\} [Bagging \{0\}]\
n".format(clf.__class__.__name__,bagging_scores.mean(),
bagging scores.std()))
Mean of: 0.961, std: (+/-) 0.030 [RandomForestClassifier]
Mean of: 0.954, std: (+/-) 0.037 [Bagging RandomForestClassifier]
Mean of: 0.967, std: (+/-) 0.028 [ExtraTreesClassifier]
Mean of: 0.953, std: (+/-) 0.032 [Bagging ExtraTreesClassifier]
Mean of: 0.930, std: (+/-) 0.029 [KNeighborsClassifier]
Mean of: 0.931, std: (+/-) 0.029 [Bagging KNeighborsClassifier]
Mean of: 0.914, std: (+/-) 0.029 [SVC]
Mean of: 0.910, std: (+/-) 0.042 [Bagging SVC]
Mean of: 0.954, std: (+/-) 0.025 [RidgeClassifier]
Mean of: 0.935, std: (+/-) 0.024 [Bagging RidgeClassifier]
clf = [rf, et, knn, svc, rg]
eclf = VotingClassifier(estimators=[('Random Forests', rf), ('Extra
Trees', et), ('KNeighbors', knn), ('SVC', svc), ('Ridge Classifier',
rg)], voting='hard')
for clf, label in zip([rf, et, knn, svc, rg, eclf], ['Random Forest',
'Extra Trees', 'KNeighbors', 'SVC', 'Ridge Classifier', 'Ensemble']):
    scores = cross_val_score(clf, X, y, cv=10, scoring='accuracy')
    print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (scores.mean(),
scores.std(), label))
Accuracy: 0.96 (+/- 0.03) [Random Forest]
Accuracy: 0.96 (+/- 0.02) [Extra Trees]
```

```
Accuracy: 0.93 (+/- 0.03) [KNeighbors]
Accuracy: 0.91 (+/- 0.03) [SVC]
Accuracy: 0.95 (+/- 0.03) [Ridge Classifier]
Accuracy: 0.96 (+/- 0.02) [Ensemble]
```

Boosting

```
ada boost = AdaBoostClassifier(random state=seed)
ada boost.fit(X train, y train)
ada boost.score(X test,y test)
grad boost=
GradientBoostingClassifier(learning rate=0.01, random state=seed)
grad boost.fit(X train, y train)
grad boost.score(X test,y test)
xgb boost=XGBClassifier(random state=1,learning rate=0.01)
xqb boost.fit(X train, y_train)
xgb boost.score(X test,y test)
eclf = VotingClassifier(estimators=[('Ada Boost', ada_boost), ('Grad
Boost', grad boost), ('XG Boost', xgb boost)], voting='hard')
clf = [rf, et, knn, svc, rg]
for clf, label in zip([ada_boost, grad_boost, xgb_boost,eclf], ['Ada
Boost','Grad Boost','XG Boost','Ensemble']):
    scores = cross_val_score(clf, X, y, cv=10, scoring='accuracy')
    print("Accuracy: %0.2f (+/- %0.2f) [%s]" % (scores.mean(),
scores.std(), label))
Accuracy: 0.96 (+/- 0.03) [Ada Boost]
Accuracy: 0.95 (+/- 0.02) [Grad Boost]
Accuracy: 0.95 (+/- 0.02) [XG Boost]
Accuracy: 0.96 (+/- 0.02) [Ensemble]
```