PA_RandomForest

September 18, 2018

1 Programming assignment for random forest

```
In [84]: from sklearn import datasets, model_selection, ensemble, tree, metrics, learning_curv

         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
```

1.1 0 Import data

```
In [26]: X, y = datasets.load_digits(return_X_y=True)

In [27]: print(datasets.load_digits().DESCR)
```

```
Optical Recognition of Handwritten Digits Data Set
===================================================

Notes
-----
Data Set Characteristics:
    :Number of Instances: 5620
    :Number of Attributes: 64
    :Attribute Information: 8x8 image of integer pixels in the range 0..16.
    :Missing Attribute Values: None
    :Creator: E. Alpaydin (alpaydin '@' boun.edu.tr)
    :Date: July; 1998

This is a copy of the test set of the UCI ML hand-written digits datasets
http://archive.ics.uci.edu/ml/datasets/Optical+Recognition+of+Handwritten+Digits

The data set contains images of hand-written digits: 10 classes where
each class refers to a digit.

Preprocessing programs made available by NIST were used to extract
normalized bitmaps of handwritten digits from a preprinted form. From a
total of 43 people, 30 contributed to the training set and different 13
to the test set. 32x32 bitmaps are divided into nonoverlapping blocks of
4x4 and the number of on pixels are counted in each block. This generates
```

```
an input matrix of 8x8 where each element is an integer in the range
0..16. This reduces dimensionality and gives invariance to small
distortions.

For info on NIST preprocessing routines, see M. D. Garris, J. L. Blue, G.
T. Candela, D. L. Dimmick, J. Geist, P. J. Grother, S. A. Janet, and C.
L. Wilson, NIST Form-Based Handprint Recognition System, NISTIR 5469,
1994.

References
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  - C. Kaynak (1995) Methods of Combining Multiple Classifiers and Their
    Applications to Handwritten Digit Recognition, MSc Thesis, Institute of
    Graduate Studies in Science and Engineering, Bogazici University.
  - E. Alpaydin, C. Kaynak (1998) Cascading Classifiers, Kybernetika.
  - Ken Tang and Ponnuthurai N. Suganthan and Xi Yao and A. Kai Qin.
    Linear dimensionalityreduction using relevance weighted LDA. School of
    Electrical and Electronic Engineering Nanyang Technological University.
    2005.
  - Claudio Gentile. A New Approximate Maximal Margin Classification
    Algorithm. NIPS. 2000.
```

1.2 1 Preprocessing data

1.2.1 1.1 Missing values

In [29]:
```python
print(X.shape, y.shape)
```

```
(1797, 64) (1797,)
```

In [37]:
```python
X_df = pd.DataFrame(X)
y_df = pd.DataFrame(y)
```

In [44]:
```python
X_df.head(2)  # Number of attributes = 64: {0, ..., 63}
```

Out[44]:
```
     0    1    2     3     4    5    6    7    8    9  ...   54   55   56  \
0  0.0  0.0  5.0  13.0   9.0  1.0  0.0  0.0  0.0  0.0 ...  0.0  0.0  0.0
1  0.0  0.0  0.0  12.0  13.0  5.0  0.0  0.0  0.0  0.0 ...  0.0  0.0  0.0

    57   58    59    60    61   62   63
0  0.0  6.0  13.0  10.0   0.0  0.0  0.0
1  0.0  0.0  11.0  16.0  10.0  0.0  0.0

[2 rows x 64 columns]
```

In [43]:
```python
y_df.T.head(5)  # Number of classes = 5, number of instances = 1796.
```

```
Out[43]:    0     1     2     3     4     5     6     7     8     9     ...   1787  \
         0     0     1     2     3     4     5     6     7     8     9   ...      5

            1788  1789  1790  1791  1792  1793  1794  1795  1796
         0     4     8     8     4     9     0     8     9     8

         [1 rows x 1797 columns]
```

Check if the missing values present

```
In [49]: print('X missing vals: ', X_df.isna().any().any())  # First .any() for rows, second
         print('y missing vals: ', y_df.isna().any().any())  # Same
```

```
X missing vals:  False
y missing vals:  False
```

1.2.2 1.2 Categorical features

In this data there are no categorical and binary values, so we continue work with real values.

1.2.3 1.3 Stratification

```
In [54]: X_train, X_test, y_train, y_test = model_selection.train_test_split(
             X, y, test_size=0.3, stratify=y)
```

```
In [55]: print(X_train.shape, y_train.shape)
         print(X_test.shape, y_test.shape)
```

```
(1257, 64) (1257,)
(540, 64) (540,)
```

1.2.4 1.4 Balancing classes

Check if classes are disbalanced.

```
In [65]: val_set = set(y)
         print('Number of objects of...')
         for val in val_set:
             print(f'class {val}:', np.sum(y_train==val))
```

```
Number of objects of...
class 0: 124
class 1: 127
class 2: 124
class 3: 128
class 4: 127
class 5: 127
class 6: 127
```

```
class 7: 125
class 8: 122
class 9: 126
```

1.2.5 1.5 Scaling

In [83]:
```
X_train.mean(axis=0)
```

Out[83]:
```
array([0.00000000e+00, 2.90373906e-01, 5.11774065e+00, 1.18210024e+01,
       1.19037391e+01, 5.77167860e+00, 1.40015911e+00, 1.36833731e-01,
       4.77326969e-03, 1.96340493e+00, 1.03221957e+01, 1.20334129e+01,
       1.02601432e+01, 8.00875099e+00, 1.86316627e+00, 1.33651551e-01,
       3.18217979e-03, 2.65712013e+00, 9.92521877e+00, 6.99363564e+00,
       7.11694511e+00, 7.64916468e+00, 1.83134447e+00, 5.88703262e-02,
       1.59108990e-03, 2.56085919e+00, 9.10262530e+00, 8.76213206e+00,
       9.93874304e+00, 7.49005569e+00, 2.29355609e+00, 2.38663484e-03,
       0.00000000e+00, 2.36833731e+00, 7.68257757e+00, 9.12887828e+00,
       1.03603819e+01, 8.62688942e+00, 2.89737470e+00, 0.00000000e+00,
       9.54653938e-03, 1.63007160e+00, 6.89180589e+00, 7.26014320e+00,
       7.76292761e+00, 8.12251392e+00, 3.44391408e+00, 2.78440732e-02,
       1.03420843e-02, 7.42243437e-01, 7.50596659e+00, 9.57995227e+00,
       9.45107399e+00, 8.61256961e+00, 3.70883055e+00, 2.04455052e-01,
       7.95544948e-04, 2.77645187e-01, 5.46459825e+00, 1.20763723e+01,
       1.17732697e+01, 6.70485282e+00, 2.02307080e+00, 3.38106603e-01])
```

It will be better to scale the data, but it is not mentioned in the task, so we pass this step. In most cases scaling is performed as following:

1.3 2 Models training

1.3.1 2.1 Decision Tree Classifier

In [85]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [120]:
```
"""Definition and training step"""
tree_clf = DecisionTreeClassifier()
# tree_clf.fit(X, y)
```

Out[120]:
```
DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')
```

In [123]:
```
"""Validation step"""
score = model_selection.cross_val_score(tree_clf, X, y, cv=10, n_jobs=-1)
print('Answer:', score.mean())
```

```
Answer: 0.8236604157933186
```

1.3.2 2.2 Bagging Classifier

2.2.1 Bagging Classifier with default parameters

```
In [96]: from sklearn.ensemble import BaggingClassifier
```

```
In [124]: """Definition and #training step"""
          bagg_clf = BaggingClassifier(n_estimators=100)
          # bagg_clf.fit(X, y)
```

```
Out[124]: BaggingClassifier(base_estimator=None, bootstrap=True,
                   bootstrap_features=False, max_features=1.0, max_samples=1.0,
                   n_estimators=100, n_jobs=1, oob_score=False, random_state=None,
                   verbose=0, warm_start=False)
```

```
In [125]: """Cross-validation step"""
          score = model_selection.cross_val_score(bagg_clf, X, y, cv=10, n_jobs=-1)
          print('Answer:', score.mean())
```

```
Answer: 0.9221054937586872
```

2.2.2 Bagging Classifier with contraint of features In this case we define number of features for training trees as $\sqrt{d}$, where d is the total number of features.

```
In [391]: """Definition and #training step"""
          bagg_clf = BaggingClassifier(n_estimators=100,
                                       max_features=int(np.sqrt(X.shape[1])))
          # bagg_clf.fit(X, y)

          """Cross-validation step"""
          score = model_selection.cross_val_score(bagg_clf, X, y, cv=10, n_jobs=-1)
          print('Answer:', score.mean())
```

```
Answer: 0.9271813255256948
```

2.2.3 Bagging Classifier with randomized trees In this case we will define number of features for every base tree.

```
In [392]: """Definition and #training step"""
          bagg_clf = BaggingClassifier(DecisionTreeClassifier(max_features='sqrt'),
                                       n_estimators=100)
          # bagg_clf.fit(X, y)

          """Cross-validation step"""
          score = model_selection.cross_val_score(bagg_clf, X, y, cv=10, n_jobs=-1)
          print('Answer:', score.mean())
```

```
Answer: 0.9555858540647373
```

1.3.3 2.3 Random Forest Classifier

Previous Bagging Classifier with randomized trees from (2.2.3) exactly is the Random Forset Classifier. In this section we will compare RFC from the `sklearn.ensemble` module with the previous one.

```
In [146]: from sklearn.ensemble import RandomForestClassifier
```

```
In [389]: """Definition and #training step"""
          rf_clf = RandomForestClassifier(n_estimators=100)
          # rf_clf.fit(X, y)
```

```
In [390]: """Cross-validation step"""
          score = model_selection.cross_val_score(rf_clf, X, y, cv=10, n_jobs=-1)
          print('Answer:', score.mean())
```

```
Answer: 0.9571978276974782
```

Close enough.

2.3.1 Estimating the impact of parameters of the Random Forest Classifier We will compare the following parameters:

```
In [260]: """Auxiliary function to return arrays of RFC quality values
          according to arrays of different params.
          """
          def score_arrays(train_data, train_labels, test_data=None, test_labels=None,
                           n_estimators=10,
                           max_features='auto',
                           max_depth=None,
                           test=False):
              """Fuction to return the array of score values according to parameters
              given in arguments.

              Returns
              -------
              n_estimators_q_range : ndarray

              max_features_q_range : ndarray

              max_depth_q_range : ndarray
              """

              from sklearn import model_selection, ensemble
```

```
        n_estimators_q_range = []
        n_estimators_test_q_range = []
        for num_ests in n_estimators:
            estimator = ensemble.RandomForestClassifier(n_estimators=num_ests)
            estimator.fit(train_data, train_labels)

            n_estimators_q_range.append(model_selection.cross_val_score(estimator,
                                        train_data, train_labels, cv=10, n_jobs=-1).mean
            if test:
                n_estimators_test_q_range.append(model_selection.cross_val_score(estimat
                                        test_data, test_labels, cv=10, n_jobs=-1).mean()

        max_features_q_range = []
        max_features_test_q_range = []
        for n_features in max_features:
            estimator = ensemble.RandomForestClassifier(max_features=n_features)
            estimator.fit(train_data, train_labels)

            max_features_q_range.append(model_selection.cross_val_score(estimator,
                                        train_data, train_labels, cv=10, n_jobs=-1).mean
            if test:
                max_features_test_q_range.append(model_selection.cross_val_score(estimat
                                        test_data, test_labels, cv=10, n_jobs=-1).mean()

        max_depth_q_range = []
        max_depth_test_q_range = []
        for depth in max_depth:
            estimator = ensemble.RandomForestClassifier(max_depth=depth)
            estimator.fit(train_data, train_labels)

            max_depth_q_range.append(model_selection.cross_val_score(estimator,
                                        train_data, train_labels, cv=10, n_jobs=-1).mean
            if test:
                max_depth_test_q_range.append(model_selection.cross_val_score(estimator,
                                        test_data, test_labels, cv=10, n_jobs=-1).mean()

        return ([np.array(n_estimators_q_range),
                np.array(max_features_q_range),
                np.array(max_depth_q_range)],
                [np.array(n_estimators_test_q_range),
                np.array(max_features_test_q_range),
                np.array(max_depth_test_q_range)])
```

Estimating scores with auxiliary function

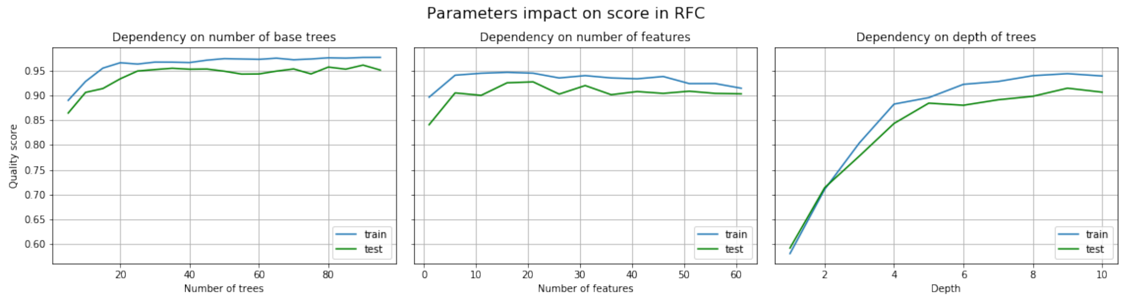
```
In [281]: %%time
          estimators_range = np.arange(5,100, step=5)
          max_features_range = np.arange(1, X.shape[1], step=5)
```

```
max_depth_range = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, None]

# rf_train_score = score_arrays(X_train, y_train, estimators_range,
#                               max_features_range,
#                               max_depth_range)

rf_train_test_score = score_arrays(X_train, y_train, X_test, y_test, estimators_range
                           max_features_range,
                           max_depth_range, test=True)
```

```
CPU times: user 12.3 s, sys: 3.72 s, total: 16.1 s
Wall time: 33.6 s
```

To see the dependence of the estimate on the parameters plot several we will draw several plots in parameter/quality coordinates

In [283]:
```
"""Plot dependencies"""
fig, ax = plt.subplots(1,3, sharey=True, figsize=(16,4))

fig.suptitle('Parameters impact on score in RFC', fontsize=16, y=1.05)

ax[0].plot(estimators_range, rf_train_test_score[0][0], label='train')
ax[0].plot(estimators_range, rf_train_test_score[1][0], label='test', c='g')
ax[0].set(xlabel='Number of trees',
          ylabel='Quality score',
         title='Dependency on number of base trees')
ax[0].legend(loc='lower right')

ax[1].plot(max_features_range, rf_train_test_score[0][1], label='train')
ax[1].plot(max_features_range, rf_train_test_score[1][1], label='test', c='g')
ax[1].set(xlabel='Number of features',
         title='Dependency on number of features')
ax[1].legend(loc='lower right')

ax[2].plot(max_depth_range, rf_train_test_score[0][2], label='train')
ax[2].plot(max_depth_range, rf_train_test_score[1][2], label='test', c='g')
ax[2].set(xlabel='Depth',
         title='Dependency on depth of trees')
ax[2].legend(loc='lower right')

for ax in ax:
    ax.grid(True)

fig.tight_layout();
```



Answers according to the task:

(2, 3, 4, 7)