ML Tutorial 5

June 25, 2018

0.1 models

Regression	Classification
LinearRegression	LogisticRegression (**penalty**: ‘l2’, **solver**: {‘liblinear’})
Lasso (L1 regularized) (**alpha**: 1)	LogisticRegression (**alpha**: 1, **penalty**: ‘l1’, **solver**: {‘liblinear’, ‘sag’})
Ridge (L2 regularized) (**alpha**: 1)	LogisticRegression (**alpha**:1, **penalty**: ‘l2’, **solver**: {‘liblinear’,‘newton-cg’, ‘lbfgs’, ‘sag’, ‘saga’})
ElasticNet (**alpha**: 1, **l1_ratio**: 0.5)	LogisticRegression (**alpha**:1, **l1_ratio**: 0.5, **multi_class**: ‘multinomial’, **solver**: {‘newton-cg’, ‘lbfgs’, ‘sag’, ‘saga’})
KNeighborsRegressor (**n_neighbors**: 5)	KNeighborsClassifier (**n_neighbors**: 5)
DecisionTreeRegressor (**max_depth**: 3, **min_samples_leaf**: 10)	DecisionTreeClassifier (**max_depth**: 3, **min_samples_leaf**: 10)
RandomForestRegressor (**n_estimators**: 10, **max_depth**: 3, **min_samples_leaf**: 10)	RandomForestClassifier (**n_estimators**: 10, **max_depth**: 3, **min_samples_leaf**: 10)
VotingClassifier (**voting**: {‘hard’, ‘soft’})	

0.2 metrics for n-fold cross-validation and test set performance

Regression	Classification
MSE (lower is better)	Classification Error (lower is better)
neg_mean_squared_error (higher is better)	accuracy (higher is better)
AUC	
f1	

0.3 Using GridSearchCV()

```
from sklearn import datasets
from sklearn.linear_models import LogisticRegression
from sklearn.model_selection import GridSearchCV

iris = datasets.load_iris()
```

```
parameters = {'alpha':[0.1, 1, 10], 'solver':['liblinear', 'lbfgs', 'sag']}
log_clf = LogisticRegression(penalty='l2')
clf = GridSearchCV(log_clf, parameters, scoring="accuracy")
clf.fit(iris.data, iris.target)

>> sorted(clf.cv_results_.keys())
...
['mean_fit_time', 'mean_score_time', 'mean_test_score',...
 'mean_train_score', 'param_C', 'param_kernel', 'params',...
 'rank_test_score', 'split0_test_score',...
 'split0_train_score', 'split1_test_score', 'split1_train_score',...
 'split2_test_score', 'split2_train_score',...
 'std_fit_time', 'std_score_time', 'std_test_score', 'std_train_score'...]

 # best parameter combination is the row which has the best score/rank of 1
>> pd.DataFrame(clf.cv_results_)
```

```
In [94]: %matplotlib inline

         import numpy as np
         import pandas as pd
         import matplotlib.pyplot as plt
         import sklearn
         import seaborn as sns
         sns.set()
```

```
In [95]: iris.head()
```

Out[95]:

	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
3	4.6	3.1	1.5	0.2	setosa
4	5.0	3.6	1.4	0.2	setosa

0.3.1 before starting on trees

```
# remember to run the following installs
> brew install graphviz
> pip3 install pydotplus
```

```
In [100]: from sklearn.tree import DecisionTreeClassifier

          iris = sns.load_dataset('iris')

          clf = DecisionTreeClassifier(max_depth=3)

          x = iris.drop("species", axis=1)
          y = iris["species"]
          clf.fit(x,y)
```

```
Out[100]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                      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 [101]: x.columns
```

```
Out[101]: Index(['sepal_length', 'sepal_width', 'petal_length', 'petal_width'], dtype='object'
```

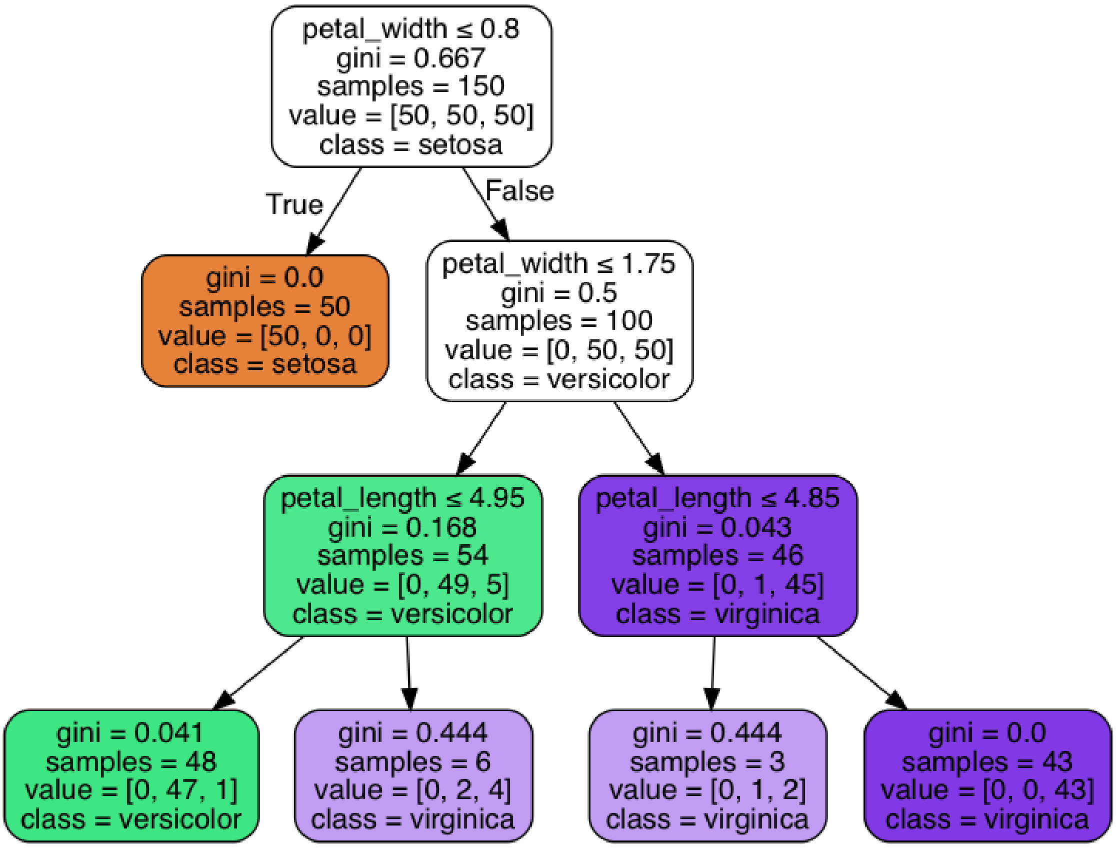
```
In [102]: y.unique()
```

```
Out[102]: array(['setosa', 'versicolor', 'virginica'], dtype=object)
```

```
In [103]: from sklearn.tree import export_graphviz
          from sklearn.externals.six import StringIO
          from IPython.display import Image
          import pydotplus

          dot_data = StringIO()
          export_graphviz(clf, out_file=dot_data,
                          filled=True,
                          rounded=True,
                          class_names=y.unique(),
                          feature_names=x.columns,
                          special_characters=True)
          graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
          Image(graph.create_png())
```

```
Out[103]:
```



In [ ]:
```
from sklearn.datasets import load_iris
from sklearn.tree import DecisionTreeClassifier

# Parameters
n_classes = 3
plot_colors = "ryb"
plot_step = 0.02

# Load data
iris = load_iris()

for pairidx, pair in enumerate([[0, 1], [0, 2], [0, 3],
                                [1, 2], [1, 3], [2, 3]]):
    # We only take the two corresponding features
    X = iris.data[:, pair]
    y = iris.target

    # Train
    clf = DecisionTreeClassifier().fit(X, y)

    # Plot the decision boundary
```

```python
            plt.subplot(2, 3, pairidx + 1)

            x_min, x_max = X[:, 0].min() - 1, X[:, 0].max() + 1
            y_min, y_max = X[:, 1].min() - 1, X[:, 1].max() + 1
            xx, yy = np.meshgrid(np.arange(x_min, x_max, plot_step),
                                 np.arange(y_min, y_max, plot_step))
            plt.tight_layout(h_pad=0.5, w_pad=0.5, pad=2.5)

            Z = clf.predict(np.c_[xx.ravel(), yy.ravel()])
            Z = Z.reshape(xx.shape)
            cs = plt.contourf(xx, yy, Z, cmap=plt.cm.RdYlBu)

            plt.xlabel(iris.feature_names[pair[0]])
            plt.ylabel(iris.feature_names[pair[1]])

            # Plot the training points
            for i, color in zip(range(n_classes), plot_colors):
                idx = np.where(y == i)
                plt.scatter(X[idx, 0], X[idx, 1], c=color, label=iris.target_names[i],
                            cmap=plt.cm.RdYlBu, edgecolor='black', s=15)

        plt.suptitle("Decision surface of a decision tree using paired features")
        plt.legend(loc='lower right', borderpad=0, handletextpad=0)
        plt.axis("tight")
        plt.show()
```

```python
In [109]: from scipy.special import comb

          def prob_majority_is_right(N, p):
              start = N//2 + 1
              total=0
              for k in range(start, N+1):
                  total += comb(N,k) * p**k * (1-p)**(N-k)
              return total

          for N in range(1,1001,10):
              print("P(majority is right for size {0}):\n {1:.2f}".format(N, prob_majority_is_r
```

```
P(majority is right for size 1):
 0.51
P(majority is right for size 11):
 0.53
P(majority is right for size 21):
 0.54
P(majority is right for size 31):
 0.54
P(majority is right for size 41):
 0.55
```

```
P(majority is right for size 51):
 0.56
P(majority is right for size 61):
 0.56
P(majority is right for size 71):
 0.57
P(majority is right for size 81):
 0.57
P(majority is right for size 91):
 0.58
P(majority is right for size 101):
 0.58
P(majority is right for size 111):
 0.58
P(majority is right for size 121):
 0.59
P(majority is right for size 131):
 0.59
P(majority is right for size 141):
 0.59
P(majority is right for size 151):
 0.60
P(majority is right for size 161):
 0.60
P(majority is right for size 171):
 0.60
P(majority is right for size 181):
 0.61
P(majority is right for size 191):
 0.61
P(majority is right for size 201):
 0.61
P(majority is right for size 211):
 0.61
P(majority is right for size 221):
 0.62
P(majority is right for size 231):
 0.62
P(majority is right for size 241):
 0.62
P(majority is right for size 251):
 0.62
P(majority is right for size 261):
 0.63
P(majority is right for size 271):
 0.63
P(majority is right for size 281):
 0.63
```

```
P(majority is right for size 291):
 0.63
P(majority is right for size 301):
 0.64
P(majority is right for size 311):
 0.64
P(majority is right for size 321):
 0.64
P(majority is right for size 331):
 0.64
P(majority is right for size 341):
 0.64
P(majority is right for size 351):
 0.65
P(majority is right for size 361):
 0.65
P(majority is right for size 371):
 0.65
P(majority is right for size 381):
 0.65
P(majority is right for size 391):
 0.65
P(majority is right for size 401):
 0.66
P(majority is right for size 411):
 0.66
P(majority is right for size 421):
 0.66
P(majority is right for size 431):
 0.66
P(majority is right for size 441):
 0.66
P(majority is right for size 451):
 0.66
P(majority is right for size 461):
 0.67
P(majority is right for size 471):
 0.67
P(majority is right for size 481):
 0.67
P(majority is right for size 491):
 0.67
P(majority is right for size 501):
 0.67
P(majority is right for size 511):
 0.67
P(majority is right for size 521):
 0.68
```

```
P(majority is right for size 531):
 0.68
P(majority is right for size 541):
 0.68
P(majority is right for size 551):
 0.68
P(majority is right for size 561):
 0.68
P(majority is right for size 571):
 0.68
P(majority is right for size 581):
 0.69
P(majority is right for size 591):
 0.69
P(majority is right for size 601):
 0.69
P(majority is right for size 611):
 0.69
P(majority is right for size 621):
 0.69
P(majority is right for size 631):
 0.69
P(majority is right for size 641):
 0.69
P(majority is right for size 651):
 0.70
P(majority is right for size 661):
 0.70
P(majority is right for size 671):
 0.70
P(majority is right for size 681):
 0.70
P(majority is right for size 691):
 0.70
P(majority is right for size 701):
 0.70
P(majority is right for size 711):
 0.70
P(majority is right for size 721):
 0.70
P(majority is right for size 731):
 0.71
P(majority is right for size 741):
 0.71
P(majority is right for size 751):
 0.71
P(majority is right for size 761):
 0.71
```

```
P(majority is right for size 771):
 0.71
P(majority is right for size 781):
 0.71
P(majority is right for size 791):
 0.71
P(majority is right for size 801):
 0.71
P(majority is right for size 811):
 0.72
P(majority is right for size 821):
 0.72
P(majority is right for size 831):
 0.72
P(majority is right for size 841):
 0.72
P(majority is right for size 851):
 0.72
P(majority is right for size 861):
 0.72
P(majority is right for size 871):
 0.72
P(majority is right for size 881):
 0.72
P(majority is right for size 891):
 0.72
P(majority is right for size 901):
 0.73
P(majority is right for size 911):
 0.73
P(majority is right for size 921):
 0.73
P(majority is right for size 931):
 0.73
P(majority is right for size 941):
 0.73
P(majority is right for size 951):
 0.73
P(majority is right for size 961):
 0.73
P(majority is right for size 971):
 0.73
P(majority is right for size 981):
 0.73
P(majority is right for size 991):
 0.74
```

In [ ]:

```python
# VotingClassifier

from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import VotingClassifier

log_clf = LogisticRegression()
rnd_clf = RandomForestClassifier()
knn_clf = KNeighborsClassifier()

voting_clf = VotingClassifier(voting =' hard',
    estimators =[(' lr', log_clf), (' rf', rnd_clf), (' knn', knn_clf)])
```