Lab 8 : Decision Tree and Bagging

In this lab we will use Python to train decision tree classifiers.

I. Prerequisites

scikit-learn: Machine Learning package in Python

To install the scikit-learn in the VirtualMachine,

1). Open the terminal

2). Type the following command. And enter *cis4340* when password is asked.

```
sudo pip install scikit-learn
```

II. Data set and preprocessing

We will use the UCI car data set in this tutorial. We will make some modifications to the original file by removing several rows as well as 'car_name' and 'model' columns, thus leaving us with a table with 6 columns. Furthermore, we will transform the 'mpg' column into a binary variable (mpg <= 23 as class 0, mpg > 23 as class 1) and use it as the target variable to be predicted using the remaining 5 columns as attributes.

1). Import necessary toolboxes

```
import pandas as pd
import numpy as np
from sklearn.tree import DecisionTreeClassifier, export_graphviz
from sklearn.ensemble import BaggingClassifier
from sklearn import cross_validation
from sklearn.externals.six import StringIO
```

2). Load the car data and preprocessing

```
data = pd.read_csv("http://archive.ics.uci.edu/ml/machine-learning-databases/auto-mpg/auto-mpg.data-original",
delim_whitespace = True, header=None, names = ['mpg', 'cylinders', 'displacement', 'horsepower', 'weight', 'acceleration',
'model', 'origin', 'car_name'])

data = data.dropna()
data = data[~ data.cylinders.isin([3, 5, 7])]
data.cylinders = data.cylinders.astype(np.int)
```

3). Specify the samples matrix X with size [n_samples, n_features],
and array Y of integer values, size [n_samples], holding the class labels for the training samples.

```
X = data[['cylinders', 'displacement', 'horsepower', 'weight', 'acceleration']]
Y = data['mpg']
Y[Y <=23 ] = 0
Y[Y > 23 ] = 1
```

III. Building a Decision Tree Classifier

The following code can be used to build a decision tree classifier.

1). Split (X,Y) into train set (Xtrain, Ytrain), and test set (Xtest, Ytest).

```
Xtrain, Xtest, Ytrain, Ytest = cross_validation.train_test_split(X, Y, test_size=0.3, random_state=0)
```

Q. How many examples are in the train and test sets?

2). Grow a decision tree classifier using the train set (Xtrain, Ytrain).

```
clf = DecisionTreeClassifier(random_state = 0)
clf = clf.fit(Xtrain, Ytrain)
```

This process is growing a very large tree, where each leaf node is pure (contains training examples with the same class). Let us see how the tree looks like.

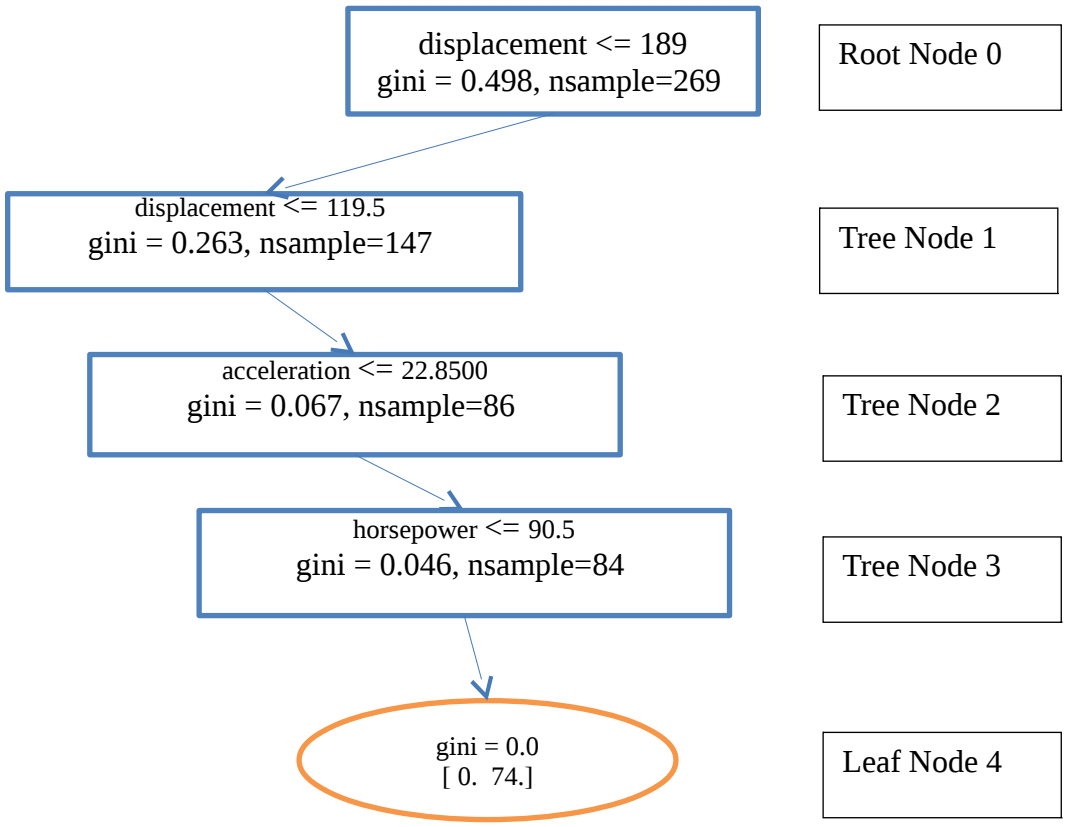
This is how we can visualize the resulting decision tree

```
dot_data = StringIO()
export_graphviz(clf, out_file=dot_data, feature_names = ['cylinders', 'displacement', 'horsepower', 'weight', 'acceleration'])
print(dot_data.getvalue())
```

The text output should look something like this:

```
0 [label="displacement <= 189.5000\ngini = 0.498832243888\nsamples = 269", shape="box"] ;
1 [label="displacement <= 119.5000\ngini = 0.263964089037\nsamples = 147", shape="box"] ;
0 -> 1 ;
2 [label="acceleration <= 22.8500\ngini = 0.0673336938886\nsamples = 86", shape="box"] ;
1 -> 2 ;
3 [label="horsepower <= 90.5000\ngini = 0.046485260771\nsamples = 84", shape="box"] ;
2 -> 3 ;
4 [label="gini = 0.0000\nsamples = 74\nvalue = [  0.  74.]", shape="box"] ;
3 -> 4 ;
```

This piece of text corresponds to the following part of the whole decision tree:



Q. What is the question at the root of the tree?

Q. How deep is the tree?

As we discussed in the class, the tree obtained in this way will be very accurate on the training data, but not very accurate on the test data. Let us calculate the accuracy of the tree on the train and test data.

3). Predict labels on train and test data using the decision tree.

```
predict_train = clf.predict(Xtrain)
predict_test = clf.predict(Xtest)
```

4). Calculate the accuracy on training and test data.

```
accuracy_train = sum(predict_train == Ytrain) / float(len(Ytrain))
print(accuracy_train)
accuracy_test = sum(predict_test == Ytest) / float(len(Ytest))
print(accuracy_test)
```

Q. Discuss the difference in accuracies. Is it consistent with what we discussed in the class?

IV. Build a Decision Tree with Early Stopping

1). One way to prevent overfitting is to stop growing the tree before it becomes too large. There is a parameter in the decision tree code that specifies the minimum size of leaf nodes (defined as the minimum number of training examples ending up in any leaf).

```
leaf = 5
clf = DecisionTreeClassifier(min_samples_leaf = leaf)
clf = clf.fit(Xtrain, Ytrain)
```

Note: if we do not specify min_samples_leaf, the default value is 1 (as was the case in Part III).

3). Predict labels on train and test data using the decision tree.

```
predict_train = clf.predict(Xtrain)
predict_test = clf.predict(Xtest)
```

4). Calculate the accuracy on training and test data.

```
accuracy_train = sum(predict_train == Ytrain) / float(len(Ytrain))
print(accuracy_train)
accuracy_test = sum(predict_test == Ytest) / float(len(Ytest))
print(accuracy_test)
```

Q. Discuss the difference in accuracies. How does it compare with the first decision tree you built?

V. A Bagging Classifier with DT as the base Classifier

As we discussed in class, training multiple decision trees on different random samples of training data and using their majority vote often results in superior accuracy. Let us train 100 decision trees and check their accuracy on test data.

1). Train 100 DTs by samplilng 0.8 from (Xtrain, Ytrain) each time.

```
n_estimators = 100
leaf = 1
bag_trees = []
for i in range(n_estimators):
    ratio = 0.8
    rs = np.random.choice(len(Ytrain), np.floor(len(Ytrain) * ratio))
```

```
    Xtrain_rs, Ytrain_rs = Xtrain[rs,:], Ytrain[rs]
    clf = DecisionTreeClassifier(min_samples_leaf = leaf)
    clf = clf.fit(Xtrain_rs, Ytrain_rs)
    bag_trees.append(clf)
```

2). Get the prediction for each example in (Xtest) with each of the 100 DTs.

```
predictions = np.zeros((len(Ytest), n_estimators))
for i in range(n_estimators):
    predictions[:, i] = bag_trees[i].predict(Xtest)
```

3). Select the final label for each example which is voted by the majority of the 100 DTs.

```
predict_bagging = np.zeros((len(Ytest), ))
for i in range(len(Ytest)):
    most_vote = 1 if sum(predictions[i, :]) >= n_estimators/2 else 0
    predict_bagging[i] =  most_vote
```

4). Report the accuracy.

```
accuracy = sum(predict_bagging == Ytest) / float(len(Ytest))
print('Test accuracy with bagging  = ' + str(accuracy))
```

Q. How does the accuracy of decision tree ensemble compare to accuracies observed in Parts III and IV.

VI. Tasks and Submission

Task 0. Answer all the questions appear in the tutorial

Task 1. For the early stopping parameter min_samples_leaf, set its values to 1, 5, 10. Report the training and testing accuracy for each value respectively.

Task 2. By default, DecisionTreeClassifer use *criterion = 'gini'*, which stands for Gini impurity to split a node in the tree. Repeat III with the *criterion = 'entropy'* . Report the train and test accuracy.

Task 3. Change the n_estimator in V and draw the trend of test accuracy when increasing the n_estimator.