# NYCU Introduction to Machine Learning, Homework 3

**Deadline: Nov. 28, 23:59** 

### Part. 1, Coding (50%):

For this coding assignment, you are required to implement the <u>Decision Tree</u> and <u>Adaboost</u> algorithms using only NumPy. After that, train your model on the provided dataset and evaluate the performance on the testing data.

### (30%) Decision Tree

### **Requirements:**

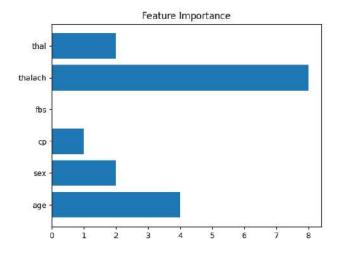
- Implement gini index and entropy for measuring the best split of the data.
- Implement the decision tree classifier (CART, Classification and Regression Trees) with the following two arguments:
- **criterion**: The function to measure the quality of a split of the data. Your model should support "gini" and "entropy".
- max\_depth: The maximum depth of the tree. If max\_depth=None, then nodes are expanded until all leaves are pure. max\_depth=1 equals to splitting data once.

#### Tips:

- Your model should produce the same results when rebuilt with the same arguments, and there is no need to prune the trees.
- You can use the recursive method to build the nodes.

#### Criteria:

- 1. (5%) Compute the gini index and the entropy of the array [0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1].
- 2. (10%) Show the accuracy score of the testing data using criterion="gini" and max\_depth=7. Your accuracy score should be higher than 0.7.
- 3. (10%) Show the accuracy score of the testing data using criterion="entropy" and max\_depth=7. Your accuracy score should be higher than 0.7.
- 4. (5%) Train your model using criterion="gini", max\_depth=15. Plot the <u>feature</u> <u>importance</u> of your decision tree model by simply counting the number of times each feature is used to split the data. Your answer should look like the plot below:



(This is not the answer, it's just an example plot.)

## (20%) Adaboost

#### **Requirements:**

- Implement the Adaboost algorithm by using the decision tree classifier (max depth=1) you just implemented as the weak classifier.
- The Adaboost model should include the following two arguments:
- **criterion**: The function to measure the quality of a split of the data. Your model should support "gini" and "entropy".
- n\_estimators: The total number of weak classifiers.

### Tips:

• You can set any random seed to make your result reproducible.

#### Criteria:

5. (20%) Tune the arguments of AdaBoost to achieve higher accuracy than your Decision Trees.

Points	Testing Accuracy
20 points	0.8 <= acc
15 points	0.78 <= acc < 0.8
10 points	$0.76 \le acc \le 0.78$
5 points	0.74 <= acc < 0.76
0 points	acc < 0.74

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# **Part. 2, Questions (50%):**

- 1. (10%) True or False. If your answer is false, please explain.
  - a. (5%) In an iteration of AdaBoost, the weights of misclassified examples are increased by adding the same additive factor to emphasize their importance in subsequent iterations.
  - b. (5%) AdaBoost can use various classification methods as its weak classifiers, such as linear classifiers, decision trees, etc.

2. (10%) How does the number of weak classifiers in AdaBoost influence the model's performance? Please discuss the potential impact on overfitting, underfitting, computational cost, memory for saving the model, and other relevant factors when the number of weak classifiers is too small or too large.

3. (15%) A student claims to have a brilliant idea to make random forests more powerful: since random forests prefer trees which are diverse, i.e., not strongly correlated, the student proposes setting m = 1, where m is the number of random features used in each node of each decision tree. The student claims that this will improve accuracy while reducing variance. Do you agree with the student's claims? Clearly explain your answer.

- 4. (15%) The formula on the left is the forward process of a standard neural network while the formula on the right is the forward process of a modified model with a specific technique.
  - a. (5%) According to the two formulas, describe what is the main difference between the two models and what is the technique applied to the model on the right side.
  - b. (10%) This technique was used to deal with overfitting and has many different explanations; according to what you learned from the lecture, try to explain it with respect to the ensemble method.

$$z^{(l+1)} = w^{(l+1)}y^l + b^{(l+1)}$$
  $egin{aligned} oldsymbol{r}^l &= Bernoulli(p) \ oldsymbol{ ilde{y}}^l &= oldsymbol{r}^l y^l \ z^{(l+1)} &= w^{(l+1)} oldsymbol{ ilde{y}}^l + b^{(l+1)} \ y^{(l+1)} &= f(z^{(l+1)}) \end{aligned}$