

# NYCU Pattern Recognition, HW3

310551079 梁友誠

## Part. 1, Coding:

### 1. Entropy and Gini Index of the array

```
print("Gini of data is ", gini(data))  
✓ 0.4s  
Gini of data is 0.4628099173553719  
  
print("Entropy of data is ", entropy(data))  
✓ 0.3s  
Entropy of data is 0.9456603046006401
```

### 2. Decision Tree:

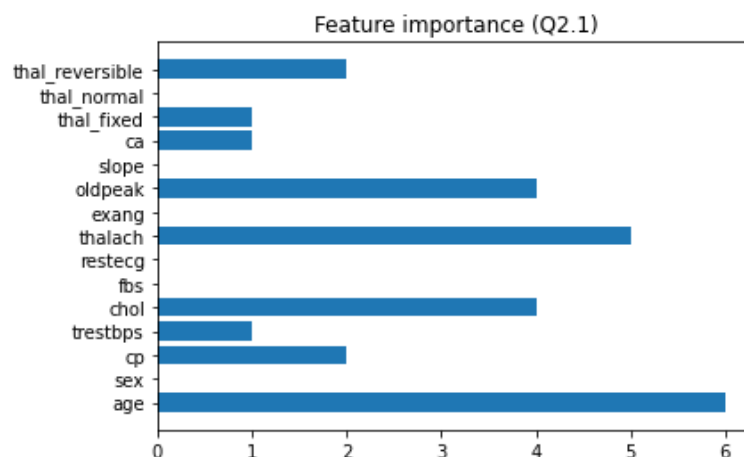
2.1: Criterion = 'gini', Max\_depth=3 and Max\_depth=10:

```
criterion=gini, max_depth=3, accuracy: 0.78  
criterion=gini, max_depth=10, accuracy: 0.69
```

2.2 Max\_depth=3, Criterion='gini' and Criterion='entropy':

```
criterion=gini, max_depth=3, accuracy: 0.78  
criterion=entropy, max_depth=3, accuracy: 0.75
```

### 3. Feature importance of my decision tree (max\_depth = 10):



4. AdaBoost ( $n\_estimators=10$  and  $n\_estimators=100$ ):

```
n_estimators = 10, criterion=entropy, max_depth=1, accuracy: 0.81
```

```
n_estimators = 100, criterion=entropy, max_depth=1, accuracy: 0.81
```

5. Random Forest:

5.1: Criterion='gini', Max\_depth = None, Max\_features =  $\sqrt{n\_features}$ , Bootstrap=True,  $n\_estimators=10$  and  $n\_estimators=100$ :

```
n_estimators=10, max_features=sqrt(n_features), accuracy: 0.78  
n_estimators=100, max_features=sqrt(n_features), accuracy: 0.84
```

5.2: Criterion = 'gini', Max\_depth = None,  $N\_estimators = 10$ , Bootstrap = True, Max\_features= $\sqrt{n\_features}$  and Max\_features= $n\_features$

```
n_estimators=10, max_features=sqrt(n_features), accuracy: 0.84  
n_estimators=10, max_features=n_features, accuracy: 0.79
```

6. I used the **upsampling** of class0 as the new training dataset to increase the accuracy of the model. The ratio of class0 and class1 is 63:135 at first, after upsampling twice of class0, the ratio of class0 and class1 will become 126:135. And then I use this new dataset to train Random Forest. The hyperparameter of the model is  $n\_estimators = 10\sim 20$ ,  $max\_features = \sqrt{n\_features} * 2$ ,  $decision\ tree\ depth = 2$ ,  $criterion = "entropy"$ . Due to the randomness of Random Forest, we will not get the same accuracy score on the testing dataset after each training. Therefore, I need to train the model several times and then choose the best model with the best accuracy  $> 0.85$ . The best accuracy I can get at last is **0.86**.

```
Test-set accuracy score: 0.86
```

## Part. 2, Questions:

Q1.

Model A misclassification rate:  $\frac{100+100}{800} = 25\%$

Model B misclassification rate:  $\frac{200}{800} = 25\%$

$\therefore$  misclassification rate is same in Model A and B.

Model A cross entropy:

$$\text{first node: } -\left(\frac{3}{4} \cdot \log_2\left(\frac{3}{4}\right) + \frac{1}{4} \cdot \log_2\left(\frac{1}{4}\right)\right) \doteq 0.81$$

$\quad \quad \quad -0.31 \quad \quad \quad -0.5$

$$\text{second node: } -\left(\frac{3}{4} \cdot \log_2\left(\frac{3}{4}\right) + \frac{1}{4} \cdot \log_2\left(\frac{1}{4}\right)\right) \doteq 0.81$$

$$\therefore \text{total entropy} = \frac{1}{2} \cdot 0.81 + \frac{1}{2} \cdot 0.81 = 0.81$$

Model A gini index:

$$\text{first node: } 1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2 = 0.375$$

$$\text{second node: } 1 - \left(\frac{3}{4}\right)^2 - \left(\frac{1}{4}\right)^2 = 0.375$$

$$\therefore \text{total gini} = \frac{1}{2} \times 0.375 + \frac{1}{2} \times 0.375 = 0.375$$

Model B cross entropy:

$$\text{first node: } -\left(\frac{1}{3} \cdot \log_2\left(\frac{1}{3}\right) + \frac{2}{3} \cdot \log_2\left(\frac{2}{3}\right)\right) \doteq 0.918$$

$\quad \quad \quad -0.518 \quad \quad \quad -0.389$

$$\text{second node: } 0$$

$$\text{total entropy: } \frac{3}{4} \cdot 0.918 \doteq 0.688$$

Model B gini index:

$$\text{first node: } 1 - \left(\frac{1}{3}\right)^2 - \left(\frac{2}{3}\right)^2 = \frac{4}{9}$$

$$\text{second node: } 0$$

$$\text{total gini: } \frac{3}{4} \cdot \frac{4}{9} = \frac{1}{3} \doteq 0.33$$

$$\therefore 0.688 < 0.81$$

$$0.33 < 0.375$$

both entropy and gini index in tree B are lower than tree A

Q2:

$$E_{x,t} [e^{-t g(x)}] = \sum_t \int e^{-t g(x)} p(t|x) p(x) dx$$

we know that  $t$  is defined as target value  $-1$  or  $1$

so we can rewrite  $E_{x,t} [e^{-t g(x)}]$  to

$$\int [e^{-g(x)} p(t=1|x) + e^{g(x)} p(t=-1|x)] p(x) dx$$

To minimize the error function, we set the derivative of the error function  $E$  w.r.t  $g(x)$  to 0.

$$\therefore \frac{dE}{dg(x)} = \frac{d}{dg(x)} \int [e^{-g(x)} p(t=1|x) + e^{g(x)} p(t=-1|x)] p(x) dx = 0$$

$$\Rightarrow y'(x) e^{g(x)} p(t=-1|x) - y'(x) e^{-g(x)} p(t=1|x) = 0$$

$$\Rightarrow y'(x) e^{g(x)} p(t=-1|x) = y'(x) e^{-g(x)} p(t=1|x)$$

$$\Rightarrow e^{g(x)} p(t=-1|x) = e^{-g(x)} p(t=1|x)$$

$$\Rightarrow \frac{e^{g(x)}}{e^{-g(x)}} = \frac{p(t=1|x)}{p(t=-1|x)}$$

$$\Rightarrow e^{2g(x)} = \frac{p(t=1|x)}{p(t=-1|x)}$$

$$\Rightarrow 2g(x) = \ln\left(\frac{p(t=1|x)}{p(t=-1|x)}\right)$$

$$\Rightarrow g(x) = \frac{1}{2} \ln\left(\frac{p(t=1|x)}{p(t=-1|x)}\right)$$

$\therefore g(x) = \frac{1}{2} \ln\left(\frac{p(t=1|x)}{p(t=-1|x)}\right)$  is the minimizing function