

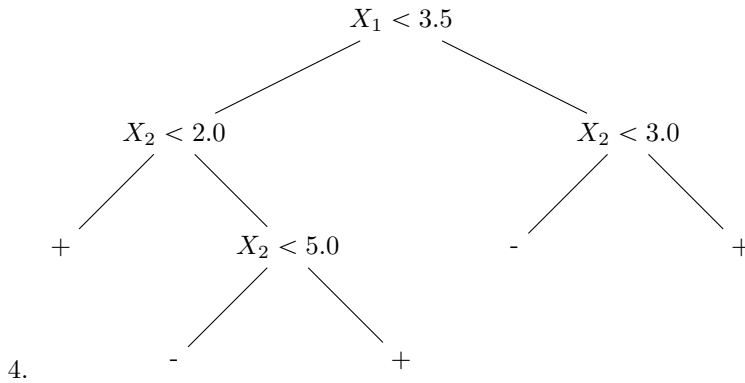
# CS680, Spring 2020, Assignment 6

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## Exercise 1

1. We should pick  $t = 2.0$ .
2. We should pick  $t = 5.0$ .
3. I will choose  $\mathbf{X}_2$  with  $t = 5.0$ . Because in this case, Gini Index is smaller.



- 4.
5. Yes. In the first level,  $X_1 < 3.5$  is true, will go to left subtree. In the second level,  $X_2 < 2.0$  is false, will go to right subtree. In the third level,  $X_2 < 5.0$  is false, will go to right child, which is label '+'.

## Exercise 2

1. *Proof.* By induction on  $t$ . When  $t = 1$ ,  $p_i^1 = \frac{w_i^1}{\sum_{j=1}^n w_j^1}$ ,  $\tilde{p}_i^1 = \frac{\tilde{w}_i^1}{\sum_{j=1}^n \tilde{w}_j^1}$ , where  $w^1$  and  $\tilde{w}^1$  are obviously same.

When  $t = m$ , assume  $p^m = \tilde{p}^m$ , then,  $\frac{w_i^m}{\sum_{j=1}^n w_j^m} = \frac{\tilde{w}_i^m}{\sum_{j=1}^n \tilde{w}_j^m}$ .

Now we prove it on  $t = m + 1$ .

$$\text{When } t = m + 1, p^{m+1} = \frac{w_i^{m+1}}{\sum_{j=1}^n w_j^{m+1}} = \frac{w_i^m \exp(-y_i \beta_m h_m(\mathbf{x}_i))}{\sum_{j=1}^n w_j^m \exp(-y_j \beta_m h_m(\mathbf{x}_j))} = \frac{w_i^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{\frac{1}{2} y_i h_m(\mathbf{x}_i)}}{\sum_{j=1}^n w_j^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{\frac{1}{2} y_j h_m(\mathbf{x}_j)}}.$$

$$\text{Now, } \tilde{p}^{m+1} = \frac{\tilde{w}_i^{m+1}}{\sum_{j=1}^n \tilde{w}_j^{m+1}} = \frac{\tilde{w}_i^m \tilde{\beta}_m^{1 - |\tilde{h}_m(\mathbf{x}_i) - \tilde{y}_i|}}{\sum_{j=1}^n \tilde{w}_j^m \tilde{\beta}_m^{1 - |\tilde{h}_m(\mathbf{x}_j) - \tilde{y}_j|}} = \frac{\tilde{w}_i^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{1 - |\tilde{h}_m(\mathbf{x}_i) - \tilde{y}_i|}}{\sum_{j=1}^n \tilde{w}_j^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{1 - |\tilde{h}_m(\mathbf{x}_j) - \tilde{y}_j|}}$$

$$\tilde{p}^{m+1} = \frac{\tilde{w}_i^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{|\tilde{h}_m(\mathbf{x}_i) - \tilde{y}_i| - 1}}{\sum_{j=1}^n \tilde{w}_j^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{|\tilde{h}_m(\mathbf{x}_j) - \tilde{y}_j| - 1}} = \frac{\tilde{w}_i^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{\left(\frac{1}{2} y_i h_m(\mathbf{x}_i) - \frac{1}{2}\right)}}{\sum_{j=1}^n \tilde{w}_j^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{\left(\frac{1}{2} y_j h_m(\mathbf{x}_j) - \frac{1}{2}\right)}} = \frac{\tilde{w}_i^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{\frac{1}{2} y_i h_m(\mathbf{x}_i)}}{\sum_{j=1}^n \tilde{w}_j^m \left(\frac{1 - \epsilon_m}{1 + \epsilon_m}\right)^{\frac{1}{2} y_j h_m(\mathbf{x}_j)}}$$

Therefore,  $\tilde{p}^{m+1}$  and  $p^{m+1}$  are indeed equal because  $\frac{w_i^{m+1}}{\sum_{j=1}^n w_j^{m+1}} = \frac{\tilde{w}_i^{m+1}}{\sum_{j=1}^n \tilde{w}_j^{m+1}}$ .

Thus, the updates are exactly are equivalent to what we learned in class.

2. *Proof.*

$$\mathbb{E}[\exp(-yH)|\mathbf{X} = \mathbf{x}] = \exp(H) \cdot P(y = -1|\mathbf{X} = \mathbf{x}) + \exp(-H) \cdot P(y = 1|\mathbf{X} = \mathbf{x}) \quad (1)$$

To minimize (1), let  $\frac{\partial \mathbb{E}}{\partial H} = 0$ .

$$\begin{aligned} \frac{\partial \mathbb{E}[\exp(-yH)|\mathbf{X} = \mathbf{x}]}{\partial H} &= \exp(H) \cdot P(y = -1|\mathbf{X} = \mathbf{x}) - \exp(-H) \cdot P(y = 1|\mathbf{X} = \mathbf{x}) = 0 \\ H &= \frac{1}{2} \log \frac{P(y = 1|\mathbf{X} = \mathbf{x})}{P(y = -1|\mathbf{X} = \mathbf{x})} \end{aligned} \quad (2)$$

Therefore, the exponential loss is proportional to the log odds ratio.

$$3. \text{ When } \bar{h}_t(\mathbf{x}) = -h_t(\mathbf{x}), \bar{\epsilon}_t = \sum_{i=1}^n p_i^t \cdot [[\bar{h}_t(\mathbf{x}_i) \neq y_i]] = 1 - \epsilon_t, \bar{\beta}_t = \frac{\bar{\epsilon}_t}{1 - \bar{\epsilon}_t} = -\beta_t.$$

Since  $\exp(-y_i \bar{\beta}_t \cdot -h_t(\mathbf{x}_i)) = \exp(-y_i \beta_t h_t(\mathbf{x}_i))$ , therefore the update in  $w$  is the same.

4. *Proof.*

$$\begin{aligned} \hat{\mathbb{E}}_t \exp[-y\beta h_t(\mathbf{x})] &= P(h_t(\mathbf{x}) = y) \exp[-y\beta h_t(\mathbf{x})] + P(h_t(\mathbf{x}) \neq y) \exp[-y\beta h_t(\mathbf{x})] \\ &= (1 - \epsilon) \exp(-\beta) + \epsilon \exp(\beta) \end{aligned} \quad (3)$$

To minimize (3), let let  $\frac{\partial \hat{\mathbb{E}}_t \exp[-y\beta h_t(\mathbf{x})]}{\partial \beta} = 0$ .

$$\begin{aligned} \frac{\partial \hat{\mathbb{E}}_t \exp[-y\beta h_t(\mathbf{x})]}{\partial \beta} &= \epsilon_t \exp(\beta) - (1 - \epsilon_t) \exp(-\beta) = 0 \\ \beta &= \frac{1}{2} \log \frac{1 - \epsilon_t}{\epsilon_t} \end{aligned} \quad (4)$$

5.

$$\begin{aligned} \epsilon_{t+1}(h_t) &= \sum_{i=1}^n p_i^{t+1} \cdot [[h_t(\mathbf{x}_i) \neq y_i]] = \sum_{i=1}^n \frac{w_i^{t+1}}{\sum_{j=1}^n w_j^{t+1}} \cdot [[h_t(\mathbf{x}_i) \neq y_i]] \\ &= \sum_{i=1}^n \frac{w_i^t \exp(-y_i \beta_t h_t(\mathbf{x}_i))}{\sum_{j=1}^n w_j^t \exp(-y_j \beta_t h_t(\mathbf{x}_j))} \cdot [[h_t(\mathbf{x}_i) \neq y_i]] \\ &= \sum_{y_i \neq h_t(\mathbf{x}_i)} \frac{w_i^t \exp(\beta_t)}{\sum_{y_i \neq h_t(\mathbf{x}_j)} w_j^t \exp(\beta_t) + \sum_{y_i = h_t(\mathbf{x}_j)} w_j^t \exp(-\beta_t)} \end{aligned}$$

now we multiply a  $\frac{1}{\sum_{k=1}^n w_k^t}$  on both numerator and denominator

$$\begin{aligned} &= \sum_{y_i \neq h_t(\mathbf{x}_i)} \frac{\frac{w_i^t}{\sum_{k=1}^n w_k^t} \exp(\beta_t)}{\sum_{y_i \neq h_t(\mathbf{x}_j)} \frac{w_j^t}{\sum_{k=1}^n w_k^t} \exp(\beta_t) + \sum_{y_i = h_t(\mathbf{x}_j)} \frac{w_j^t}{\sum_{k=1}^n w_k^t} \exp(-\beta_t)} \\ &= \sum_{y_i \neq h_t(\mathbf{x}_i)} \frac{p_i^t \exp(\beta_t)}{P(y \neq h_t(\mathbf{x})) \cdot \exp(\beta_t) + P(y = h_t(\mathbf{x})) \cdot \exp(-\beta_t)} \\ &= \frac{P(y \neq h_t(\mathbf{x})) \cdot \exp(\beta_t)}{P(y \neq h_t(\mathbf{x})) \cdot \exp(\beta_t) + P(y = h_t(\mathbf{x})) \cdot \exp(-\beta_t)} \\ &= \frac{\epsilon_t \exp(\beta_t)}{\epsilon_t \exp(\beta_t) + (1 - \epsilon_t) \exp(-\beta_t)} \\ &= \frac{\epsilon_t}{\epsilon_t + (1 - \epsilon_t) \exp(-2 \cdot \frac{1}{2} \log \frac{1 - \epsilon_t}{\epsilon_t})} \\ &= \frac{\epsilon_t}{\epsilon_t + (1 - \epsilon_t) \frac{\epsilon_t}{1 - \epsilon_t}} \\ &= \frac{1}{2} \end{aligned} \quad (5)$$