

II. Prove that AdaBoost.M1 is equal to forward stagewise additive modeling using the loss function.  $L(y, f(x)) = \exp(-yf(x))$

Basis classifier :  $G_m(x) \in \{-1, 1\}$

For the  $G_m(x)$  and  $\beta_m$  to be added, one must solve

$$\begin{aligned}
 (\beta_m, G_m(x)) &= \underset{\beta, G}{\operatorname{argmin}} \sum_{i=1}^N \exp[-y_i (f_{m-1}(x_i) + \beta G(x_i))] \\
 &= \underset{\beta, G}{\operatorname{argmin}} \underbrace{\sum_{i=1}^N \exp[-y_i (f_{m-1}(x_i))]}_{\substack{\text{depend neither on } \beta \text{ nor } G}} \cdot \exp[-y_i \beta G(x_i)] \\
 \Rightarrow (\beta_m, G_m(x)) &= \underset{\beta, G}{\operatorname{argmin}} \sum_{i=1}^N \boxed{W_i^{(m)}} \exp[-y_i \beta G(x_i)] \quad (1.1) \\
 &= \underset{\beta, G}{\operatorname{argmin}} e^{-\beta \sum_{y_i=G(x_i)} W_i^{(m)}} + e^{\beta \sum_{y_i \neq G(x_i)} W_i^{(m)}} \quad I(y_i \neq G(x_i)) \\
 &= \underset{\beta, G}{\operatorname{argmin}} e^{\beta \sum_{i=1}^N W_i^{(m)} \cdot I(y_i \neq G(x_i))} + e^{-\beta \sum_{i=1}^N W_i^{(m)}} - e^{-\beta \sum_{i=1}^N W_i^{(m)}} \\
 &= \underset{\beta, G}{\operatorname{argmin}} (e^{\beta} - e^{-\beta}) \sum_{i=1}^N W_i^{(m)} \cdot I(y_i \neq G(x_i)) + e^{-\beta \sum_{i=1}^N W_i^{(m)}} \\
 &= \underset{\beta, G}{\operatorname{argmin}} \sum_{i=1}^N W_i^{(m)} \left[ \frac{(e^{\beta} - e^{-\beta}) \sum_{i=1}^N W_i^{(m)} I(y_i \neq G(x_i))}{\sum_{i=1}^N W_i^{(m)}} + e^{-\beta} \right]
 \end{aligned}$$

use  $\text{error}_m = \frac{\sum_{i=1}^N W_i^{(m)} I(y_i \neq G_m(x_i))}{\sum_{i=1}^N W_i^{(m)}} \quad (\text{mentioned in sec 1})$

assum  $f(\beta) = \sum_{i=1}^N W_i^{(m)} [(e^{\beta} - e^{-\beta}) \text{error}_m + e^{-\beta}]$

$f'(\beta) = \sum_{i=1}^N W_i^{(m)} \cdot [(e^{\beta} + e^{-\beta}) \text{error}_m + e^{-\beta}]$

$$\Rightarrow \sum_{i=1}^N w_i^{(m)} [(e^{\beta_m} + e^{-\beta_m}) \cdot \text{error}_m - e^{-\beta_m}] = 0$$

$$\Rightarrow (e^{\beta_m} + e^{-\beta_m}) \cdot \text{error}_m - e^{-\beta_m} = 0$$

$$\Rightarrow e^{2\beta_m} \cdot \text{error}_m + \text{error}_m - 1 = 0$$

$$\Rightarrow \beta_m = \frac{1}{2} \log \left( \frac{1 - \text{error}_m}{\text{error}_m} \right)$$

For each  $\beta > 0$ ,  $\underline{G_m} = \arg \min_G \sum_{i=1}^N w_i^{(m)} I(y_i \neq G(x_i))$

the classifier that minimizes the weighted error rate

The approximation is then updated

$$f_m(x) = f_{m-1}(x) + \beta_m G_m(x)$$

The weights for the next iteration to be

$$w_i^{(m+1)} = w_i^{(m)} \cdot \exp[-\beta_m y_i G_m(x_i)]$$

$$\text{use } -y_i G_m(x_i) = 2 I(y_i \neq G_m(x_i)) - 1$$

$$= w_i^{(m)} \cdot \exp[2\beta_m I(y_i \neq G_m(x_i))] \cdot \exp(-\beta_m)$$

$$= w_i^{(m)} \exp[\underline{d_m I(y_i \neq G_m(x_i))}] \cdot \exp(-\beta_m) \quad \text{where } \underline{d_m} = 2\beta_m$$

is equal to Algorithm 1. 2d no effect

AdaBoost.M1 minimizes the exponential loss criterion via a forward-stage-wise additive modeling approach

see Algorithm 1.