

Machine Learning Homework 5

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Problem 1. AdaBoost is a greedy exponential loss with the following two properties, prove them.

$$\alpha_t = \arg \min_{\alpha} \sum_{i=1}^n D_t(i) \exp\{-y_i \alpha_t h_t(x_i)\} \quad (1)$$

$$\prod_{t=1}^T z_t = \frac{1}{n} \sum_{i=1}^n \exp\left\{-y_i \sum_{t=1}^T \alpha_t h_t(x_i)\right\} = \frac{1}{n} \sum_i \exp\{-y_i f(x_i)\} \quad (2)$$

Proof. We first prove (1). Denote $F_t(\alpha) = \sum_{i=1}^n D_t(i) \exp\{-y_i \alpha_t h_t(x_i)\}$, when $F_t(\alpha)$ reaches its minimum,

$$\begin{aligned} \frac{\partial F_t(\alpha)}{\partial \alpha} &= \sum_{i=1}^n -y_i h_t(x_i) D_t(i) \exp\{-y_i \alpha_t h_t(x_i)\} = 0 \\ \Rightarrow \sum_{i=1}^n I[y_i \neq h_t(x_i)] D_t(i) \exp\{I[y_i \neq h_t(x_i)] \alpha_t\} &= \sum_{i=1}^n I[y_i = h_t(x_i)] D_t(i) \exp\{-I[y_i = h_t(x_i)] \alpha_t\} \end{aligned}$$

Given the fact that

$$\sum_{i=1}^n D_t(i) I[y_i \neq h_t(x_i)] + \sum_{i=1}^n D_t(i) I[y_i = h_t(x_i)] = \sum_{i=1}^n D_t(i) = 1$$

We have

$$\epsilon_t \exp\{\alpha_t\} = (1 - \epsilon_t) \exp\{-\alpha_t\}$$

Therefore,

$$\alpha_t = \frac{1}{2} \ln \frac{1 - \epsilon_t}{\epsilon_t} = \frac{1}{2} \ln \frac{1 + \gamma_t}{1 - \gamma_t}$$

We then prove (2). Given that

$$\begin{aligned} z_t &:= \sum_{i=1}^n D_t(i) \exp\{-y_i \alpha_t h_t(x_i)\} \\ D_t(i) &:= \frac{D_{t-1}(i) \exp\{-y_i \alpha_{t-1} h_{t-1}(x_i)\}}{z_{t-1}} \end{aligned}$$

Obviously,

$$\begin{aligned} z_T &= \sum_{i=1}^n D_T(i) \exp\{-y_i \alpha_T h_T(x_i)\} \\ &= \sum_{i=1}^n \frac{D_{T-1}(i) \exp\{-y_i \alpha_{T-1} h_{T-1}(x_i)\}}{z_{T-1}} \exp\{-y_i \alpha_T h_T(x_i)\} \\ &\dots\dots \\ &= \sum_{i=1}^n D_1(i) \frac{\exp\left\{-y_i \sum_{t=1}^T \alpha_t h_t(x_i)\right\}}{\prod_{t=1}^{T-1} z_t} \end{aligned}$$

Therefore, we have our conclusion.

$$\prod_{t=1}^T z_t = \frac{1}{n} \sum_{i=1}^n \exp \left\{ -y_i \sum_{t=1}^T \alpha_t h_t(x_i) \right\} = \frac{1}{n} \sum_{i=1}^n \exp \{ -y_i f(x_i) \}$$

□

Problem 2. Suppose $\gamma_t \geq \gamma \geq 0$ for $t \in [1, \dots, T]$. Then

$$\begin{aligned} P_s(yf(x) \leq 0) &= \frac{1}{n} I[y_i f(x_i) \leq 0] \\ &\leq \frac{1}{n} \sum_{i=1}^n \exp \{ -y_i f(x_i) \} \\ &\leq (1 - \gamma^2)^{\frac{T}{2}} \end{aligned} \tag{3}$$

Proof. We first prove that

$$\frac{1}{n} I[y_i f(x_i) \leq 0] \leq \frac{1}{n} \sum_{i=1}^n \exp \{ -y_i f(x_i) \}$$

However, this is quite obvious given the fact that $I[y_i f(x_i) \leq 0] \leq \exp \{ -y_i f(x_i) \}$ everywhere (surrogate loss of 0-1 loss).

We then prove that

$$\frac{1}{n} \sum_{i=1}^n \exp \{ -y_i f(x_i) \} \leq (1 - \gamma^2)^{\frac{T}{2}}$$

We already know that

$$\frac{1}{n} \sum_{i=1}^n \exp \{ -y_i f(x_i) \} = \prod_{t=1}^T z_t$$

Therefore,

$$\begin{aligned} \frac{1}{n} \sum_{i=1}^n \exp \{ -y_i f(x_i) \} &= \prod_{t=1}^T \left\{ \sum_{i=1}^n \exp \{ \alpha_t \} D_t(i) I[y_i \neq h_t(x_i)] + \exp \{ -\alpha_t \} D_t(i) I[y_i = h_t(x_i)] \right\} \\ &= \prod_{t=1}^T \{ \exp \{ \alpha_t \} \epsilon_t + \exp \{ -\alpha_t \} (1 - \epsilon_t) \} \\ &= \prod_{t=1}^T \left\{ \sqrt{\frac{1 + \gamma_t}{1 - \gamma_t}} \frac{1 - \gamma_t}{2} + \sqrt{\frac{1 - \gamma_t}{1 + \gamma_t}} \frac{1 + \gamma_t}{2} \right\} \\ &= \prod_{t=1}^T \sqrt{1 - \gamma_t^2} \\ &\leq (1 - \gamma^2)^{\frac{T}{2}} \end{aligned}$$

□

Problem 3. Calculate the following function

$$\sum_{i=1}^n D_{t+1}(i) I[y_i \neq h_t(x_i)] \tag{4}$$

Proof.

$$\begin{aligned}
\sum_{i=1}^n D_{t+1}(i) I[y_i \neq h_t(x_i)] &= \sum_{i=1}^n \frac{D_t(i) \exp\{-y_i \alpha_t h_t(x_i)\}}{\sum_i D_t(i) \exp\{-y_i \alpha_t h_t(x_i)\}} I[y_i \neq h_t(x_i)] \\
&= \frac{\sum_{i=1}^n \exp\{\alpha_t\} D_t(i) I[y_i \neq h_t(x_i)]}{\sum_{i=1}^n \exp\{\alpha_t\} D_t(i) I[y_i \neq h_t(x_i)] + \exp\{-\alpha_t\} D_t(i) I[y_i = h_t(x_i)]} \\
&= \frac{\exp\{\alpha_t\} \epsilon_t}{\exp\{\alpha_t\} \epsilon_t + \exp\{-\alpha_t\} (1 - \epsilon_t)}
\end{aligned}$$

Given that

$$\alpha_t = \frac{1}{2} \ln \frac{1 + \gamma_t}{1 - \gamma_t} = \frac{1}{2} \ln \frac{1 - \epsilon_t}{\epsilon_t}$$

We have

$$\begin{aligned}
\sum_{i=1}^n D_{t+1}(i) I[y_i \neq h_t(x_i)] &= \frac{\frac{1 - \epsilon_t}{\epsilon_t} \epsilon_t}{\frac{1 - \epsilon_t}{\epsilon_t} \epsilon_t + (1 - \epsilon_t)} \\
&= \frac{1}{2}
\end{aligned}$$

□