

CS 4375 Assignment 3Part 1

$$1) x \rightarrow y$$

Error:

$$\epsilon_i(x) = f(x) - h_i(x)$$

$$E(\epsilon_i(x)^2) = E[(f(x) - h_i(x))^2]$$

$$E_{avg} = \frac{1}{M} \sum_{i=1}^M E(\epsilon_i(x)^2)$$

Aggregate mode:

$$h_{agg}(x) = \frac{1}{M} \sum_{i=1}^M h_i(x)$$

$$E_{agg}(x) = E \left[\left\{ \frac{1}{M} \sum_{i=1}^M h_i(x) - f(x) \right\}^2 \right]$$

$$\text{To prove: } E_{agg} = \frac{1}{M} E_{avg}$$

Assumption: 0 mean errors $\Rightarrow E(\epsilon_i(x)) = 0$ for all i
 $E(\epsilon_i(x) \epsilon_j(x)) = 0$ for all $i \neq j$

$$\text{Ab: } E_{avg} = \frac{1}{M} \sum_{i=1}^M E(\epsilon_i(x)^2) = \frac{1}{M} \sum_{i=1}^M E((f(x) - h_i(x))^2)$$

$$= \frac{1}{M} \sum_{i=1}^M E(f(x)^2 + h_i(x)^2 - 2 f(x) h_i(x))$$

$$= \frac{1}{M} \sum_{i=1}^M (E(f(x)^2) + E(h_i(x)^2) - 2 E(f(x) h_i(x)))$$

$$= E(f(x)^2) + \frac{1}{M} \sum_{i=1}^M E(h_i(x)^2) - \frac{2}{M} \sum_{i=1}^M E(h_i(x))$$

~~Since, $E(\epsilon_i(x)) = 0, E(f(x)) = E(h_i(x))$~~

$$\therefore E_{avg} = E(f(x)^2) + \frac{1}{M} \sum_{i=1}^M (E(h_i(x)^2) - 2 E(h_i(x)))$$

Ans: $E_{avg} = E\left(\left(\frac{1}{M} \sum_{i=1}^M g_i(x)\right)^2\right)$

$$= E\left(\frac{1}{M^2} \left(\sum_{i=1}^M g_i(x)\right) \left(\sum_{j=1}^M g_j(x)\right)\right)$$

$$= E\left(\frac{1}{M^2} \sum_{i=1}^M \sum_{j=1}^M E(g_i(x) g_j(x))\right) \quad (\because \text{since } E(g_i(x) g_j(x)) = 0)$$

$$= \frac{1}{M} \left(\frac{1}{M} \sum_{i=1}^M E(g_i(x)^2) \right)$$

$$= \frac{1}{M} E_{avg}$$

$$2.) E_{avg}(x) = E\left[\left(\frac{1}{m} \sum_{i=1}^m \epsilon_i(x)\right)^2\right] \quad E_{avg} = \frac{1}{m} \sum_{i=1}^m E(\epsilon_i(x)^2)$$

$$\begin{aligned} E_{avg}(x) &= E\left(\frac{1}{m^2}\left(\epsilon_1(x) + \epsilon_2(x) + \dots + \epsilon_m(x)\right)^2\right) \\ &= \frac{1}{m} E\left(\frac{1}{m}\left(\epsilon_1(x) + \epsilon_2(x) + \dots + \epsilon_m(x)\right)^2\right) \\ &\leq \frac{1}{m} E\left(\epsilon_1^2(x) + \epsilon_2^2(x) + \dots + \epsilon_m^2(x)\right) \\ &= \frac{1}{m} \left(E\left(\sum_{i=1}^m \epsilon_i(x)^2\right)\right) \leq \frac{1}{m} \sum_{i=1}^m E(\epsilon_i(x)^2) \\ &\leq E_{avg} \leq E_{avg} \end{aligned}$$

Proof $2ab \leq a^2 + b^2$

$$a^2 - 2ab + b^2 \Rightarrow (a-b)^2 \geq 0 \quad \text{squares can't be negative}$$

$$\frac{1}{m} \left(\sum_{i=1}^m \epsilon_i(x) \right)^2 = \frac{1}{m} \left(\sum_{i=1}^m \epsilon_i(x) \right) \left(\sum_{i=1}^m \epsilon_i(x) \right) = \frac{1}{m} \sum_{i=1}^m \sum_{j=1}^m \epsilon_i(x) \epsilon_j(x)$$

$$\frac{1}{m} \sum_{i=1}^m \sum_{j=1}^m 2\epsilon_i(x) \epsilon_j(x) \leq \frac{1}{m} \sum_{i=1}^m \sum_{j=1}^m (\epsilon_i(x) + \epsilon_j(x))$$

$$\frac{2}{m} \sum_{i=1}^m \sum_{j=1}^m \epsilon_i(x) \epsilon_j(x) \leq \frac{2}{m} \sum_{i=1}^m \epsilon_i(x)$$

$$\frac{1}{m} \left(\sum_{i=1}^m \epsilon_i(x) \right)^2 \leq \sum_{i=1}^m \epsilon_i(x)$$

$$\begin{aligned} M \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_m \end{pmatrix} + m \begin{pmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_m \end{pmatrix} \\ = 2M(\epsilon_1 + \epsilon_2 + \dots + \epsilon_m) \end{aligned}$$

OR

use Cauchy-Schwarz $|\langle u, v \rangle|^2 \leq \langle u, u \rangle \cdot \langle v, v \rangle$

$$|\langle \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_m \end{bmatrix}, \begin{bmatrix} 1 \\ 1 \\ \vdots \\ 1 \end{bmatrix} \rangle|^2 \leq (\underbrace{(1+1+\dots+1)}_{m}) (\epsilon_1^2 + \epsilon_2^2 + \dots + \epsilon_m^2)$$

$$u = \langle \epsilon_1, \epsilon_2, \dots, \epsilon_m \rangle$$

$$v = \langle 1, 1, \dots, 1 \rangle$$

$$(\epsilon_1 + \epsilon_2 + \dots + \epsilon_m)^2 \leq m(\epsilon_1^2 + \epsilon_2^2 + \dots + \epsilon_m^2)$$

$$\frac{1}{m} \left(\sum_{i=1}^m \epsilon_i(x) \right)^2 \leq \sum_{i=1}^m \epsilon_i(x)$$

(3)

$$D_{t+1}(i) = \frac{D_t(i)}{Z_t} e^{-\alpha_t h_t(i) y(i)}$$

Reference: Princeton Cos 402
Fall '08 readings
boosting.pdf

$$D_1 = \frac{1}{N}$$

$$D_2 = \frac{1}{N Z_1} e^{-\alpha_1 h_1(i) y(i)}$$

$$D_3 = \frac{1}{N Z_1 Z_2} e^{-\alpha_1 h_1(i) y(i)}$$

$$D_{t+1}(i) = \frac{1}{N(z_1 z_2 \dots z_t)} e^{-y(i) \sum_{j=1}^t \alpha_j h_j(i)}$$

$$D_{t+1}(i) = \frac{1}{N(z_1 z_2 \dots z_t)} e^{-y(i) \sum_{j=1}^t \alpha_j h_j(i)}$$

$$\begin{aligned} \text{Error}_r &= \frac{1}{N} \left(\sum_i^t h_t(x_i) \neq y_i \right) \\ &= \frac{1}{N} \left(\sum_i^t I(y(i) \neq \sum_{j=1}^t \alpha_j h_j(i)) \right) \leq \frac{1}{N} \sum_i^t \exp(-y(i) (\sum_{j=1}^t \alpha_j h_j(i))) \\ &= (z_1 z_2 \dots z_t) \left(\sum_i^t D_{t+1}(i) \right) \quad \{e^x > 1 \Leftrightarrow x > 0\} \end{aligned}$$

$$= z_1 z_2 \dots z_t$$

$D_{t+1}(i)$'s are normalized
and add to be 1

$$H(x) \text{ Error} \leq \prod_{j=1}^t z_j$$

$$= \prod_{j=1}^t z_j = \prod_{j=1}^t \left(\sum_i^t D_j(i) \exp(-\alpha_j I(h_j(x_i) = y_i)) \right)$$

$$= \prod_{j=1}^t \left(\sum_{\text{correct}} D_j(i) e^{-\alpha_j} + \sum_{\text{incorrect}} D_j(i) e^{\alpha_j} \right)$$

$$= \prod_{j=1}^t \left(e^{\alpha_j} (1 - \epsilon_j) + e^{y_j \alpha_j} \epsilon_j \right) = \prod_{j=1}^t \left(e^{-\frac{1}{2} \ln \left(\frac{1-\epsilon_j}{\epsilon_j} \right)} (1 - \epsilon_j) + e^{\frac{1}{2} \ln \left(\frac{1-\epsilon_j}{\epsilon_j} \right)} \epsilon_j \right)$$

$$= \prod_{j=1}^t \left(\sqrt{\frac{\epsilon_j}{1-\epsilon_j}} (1 - \epsilon_j) + \sqrt{\frac{1-\epsilon_j}{\epsilon_j}} \epsilon_j \right) = \prod_{j=1}^t \left(\frac{1-\epsilon_j}{\sqrt{1-\epsilon_j}} + \sqrt{\frac{1-\epsilon_j}{\epsilon_j}} \epsilon_j \right) = \prod_{j=1}^t \sqrt{\epsilon_j (1-\epsilon_j)}$$

$$= \prod_{j=1}^t \sqrt{\sqrt{\frac{1}{2} - \gamma_j} \left(\frac{1}{2} + \gamma_j \right)} = \prod_{j=1}^t \sqrt{1 - 4\gamma_j^2} \leq \prod_{j=1}^t \exp(-2\gamma_j^2) = \exp\left(-2 \sum_{j=1}^t \gamma_j^2\right)$$

$$1 + x \approx e^{x^2}$$

$$\text{Error} \leq \exp\left(-2 \sum_{j=1}^t \gamma_j^2\right)$$