Machine Learning

Answer Sheet for Homework 7

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Problem 1

Set $\mu_- = 1 - \mu_+$, we have

$$1 - \mu_+^2 - \mu_-^2 = 1 - \mu_+^2 - \left(1 - \mu_+\right)^2 = \left(1 - \mu_+\right)\left(1 + \mu_+\right) - \left(1 - \mu_+\right)^2 \tag{1}$$

$$= 2\mu_+\left(1 - \mu_+\right) = -2\mu_+^2 + 2\mu_+ = -2\left(\mu_+ - \frac{1}{2}\right)^2 + \frac{1}{2} \tag{2}$$

$$\leq \frac{1}{2} \tag{3}$$

Hence, if $\mu_+ = 1/2 \in [0, 1]$, then the maximum value of Gini index is $1/2$.

$\square$

Problem 2

The normalized Gini index is

$$\frac{\left(1 - \mu_+^2 - \mu_-^2\right)}{\left(\frac{1}{2}\right)} = 2\left(1 - \mu_+^2 - \mu_-^2\right) \tag{4}$$

The squared error can be rewritten as

$$\mu_+\left(1 - \left(\mu_+ - \mu_-\right)\right)^2 + \mu_-\left(-1 - \left(\mu_+ - \mu_-\right)\right)^2 = 4\mu_+\left(1 - \mu_+\right)^2 + 4\mu_+^2\left(1 - \mu_+\right) \tag{5}$$

$$= 4\mu_+\left(1 - \mu_+\right) \leq 4 \times \frac{1}{4} = 1 \tag{6}$$

Hence the normalized squared error is

$$4\mu_+ (1-\mu_+) = 2(2\mu_+ (1-\mu_+)) = 2\left((1-\mu_+)(1+\mu_+) - (1-\mu_+)^2\right) \tag{7}$$

$$= 2\left(1-\mu_+^2-\mu_-^2\right) \tag{8}$$

which is equal to normalized Gini index.

$\square$

Problem 3

The probability of one example not sampled is

$$\left(1-\frac{1}{N}\right)^{pN} = \frac{1}{\left(\frac{N}{N-1}\right)^{pN}} = \frac{1}{\left(1+\frac{1}{N-1}\right)^{pN}} = \left(\frac{1}{\left(1+\frac{1}{N-1}\right)^{N}}\right)^{p} \tag{9}$$

As $N \to \infty$, we have

$$\lim_{N\to\infty}\left(\frac{1}{\left(1+\frac{1}{N-1}\right)^{N}}\right)^{p} = \left(\lim_{N\to\infty}\frac{1}{\left(1+\frac{1}{N-1}\right)^{N}}\right)^{p} = \left(\frac{1}{e}\right)^{p} = e^{-p} \tag{10}$$

So there approximately $e^{-p}\cdot N$ of the examples not sampled.

$\square$

Problem 4

Since $G = \text{Uniform}\left(\{g_k\}_{k=1}^{3}\right)$, so if at least two terms of $\{g_k\}_{k=1}^{3}$ ouput wrong result, then G outputs wrong result. Let $\{E_k\}_{k=1}^{3}$ be the set of examples that $\{g_k\}_{k=1}^{K}$ got wrong results. Apparently $|E_3| > |E_2| > |E_1|$ and $|E_1| + |E_2| > |E_3|$. So

1. Maximum of $E_{\text{out}}(G)$ happens at $E_3 \subset (E_1 \cup E_2)$. Then G outputs wrong result in the region of E_3 with $E_{\text{out}}(G) = 0.35$.

2. Minimum of $E_{\text{out}}(G)$ happens at $E_i \cap E_j = \phi$, $i \neq j$ and $1 \leq i, j \leq 3$ with $i, j \in \mathbb{N}$. Then G always ouputs the correct result since $(E_1 \cup E_2 \cup E_3) \subset \{\text{all examples}\}$.

Hence, $0 \leq E_{\text{out}}(G) \leq 0.35$.

$\square$

Problem 5

Since $G = \text{Uniform}\left(\{g_k\}_{k=1}^K\right)$, so if at least $(K+1)/2$ terms of $\{g_k\}_{k=1}^K$ ouput wrong result, then G outputs wrong result. Let $\{E_k\}_{k=1}^K$ be the set of examples that $\{g_k\}_{k=1}^K$ got wrong results.

If G outputs wrong result on some example $\mathbf{x}$, then we have

$$\mathbf{x} \in \bigcap_{i=1}^{((K+1)/2)+m} E_{\alpha_i} \tag{11}$$

where α_i is some index satisfies $1 \leq \alpha_i \leq K$ and $m \in (\mathbb{N} \cup \{0\})$ with $0 \leq m < (K+1)/2$. And

$$\left| \bigcap_{i=1}^{((K+1)/2)+m} E_{\alpha_i} \right| \leq \frac{2}{K+1+2m} \sum_{k=1}^{K} e_k \leq \frac{2}{K+1} \sum_{k=1}^{K} e_k \tag{12}$$

(12) holds due to

$$\bigcap_{i=1}^{((K+1)/2)+m} E_{\alpha_i} \subseteq E_\beta \tag{13}$$

where β is some index such that $|E_\beta| = \min_{\alpha_i} |E_{\alpha_i}|$. So

$$\left(\frac{K+1}{2} + m\right) \left| \bigcap_{i=1}^{((K+1)/2)+m} E_{\alpha_i} \right| \leq \left(\frac{K+1}{2} + m\right) |E_\beta| \leq \sum_{k=1}^{K} |E_k| \tag{14}$$

(14) holds since size of E_β is the samllest among $(((K+1)/2)+m)$ terms and $\sum_{k=1}^K |E_k|$ must contains the $(((K+1)/2)+m)$ terms.

Hence, we have

$$E_{\text{out}}(G) \leq \frac{2}{K+1} \sum_{k=1}^{K} e_k \tag{15}$$

□

Problem 6

By the definition of U_t, we have

$$
\begin{aligned}
U_{t+1} &= \frac{1}{N}\sum_{n=1}^{N}\exp\left(-y_n\sum_{\tau=1}^{t}\alpha_\tau g_\tau\left(\mathbf{x}_n\right)\right) && (16)\\
&= \frac{1}{N}\sum_{n=1}^{N}\exp\left(-y_n\sum_{\tau=1}^{t-1}\alpha_\tau g_\tau\left(\mathbf{x}_n\right)-y_n\alpha_t g_t\left(\mathbf{x}_n\right)\right) && (17)\\
&= \frac{1}{N}\sum_{n=1}^{N}\exp\left(-y_n\sum_{\tau=1}^{t-1}\alpha_\tau g_\tau\left(\mathbf{x}_n\right)\right)\exp\left(-y_n\alpha_t g_t\left(\mathbf{x}_n\right)\right) && (18)\\
&= \sum_{n=1}^{N}u_n^{(t)}\exp\left(-y_n\alpha_t g_t\left(\mathbf{x}_n\right)\right) && (19)\\
&= \sum_{\substack{n\\ y_n\neq g_t(\mathbf{x}_n)}}u_n^{(t)}\exp\left(-y_n\alpha_t g_t\left(\mathbf{x}_n\right)\right)+\sum_{\substack{n\\ y_n= g_t(\mathbf{x}_n)}}u_n^{(t)}\exp\left(-y_n\alpha_t g_t\left(\mathbf{x}_n\right)\right) && (20)\\
&= \sum_{\substack{n\\ y_n\neq g_t(\mathbf{x}_n)}}u_n^{(t)}\exp\left(\alpha_t\right)+\sum_{\substack{n\\ y_n= g_t(\mathbf{x}_n)}}u_n^{(t)}\exp\left(-\alpha_t\right) && (21)\\
&= \exp\left(\alpha_t\right)\left(\epsilon_t\right)\sum_{n=1}^{N}u_n^{(t)}+\exp\left(-\alpha_t\right)\left(1-\epsilon_t\right)\sum_{n=1}^{N}u_n^{(t)} && (22)\\
&= U_t\left(\exp\left(\alpha_t\right)\left(\epsilon_t\right)+\exp\left(-\alpha_t\right)\left(1-\epsilon_t\right)\right)=U_t\cdot 2\sqrt{\epsilon_t\left(1-\epsilon_t\right)} && (23)
\end{aligned}
$$

Since

$$
U_1=\sum_{n=1}^{N}u_n^{(1)}=\sum_{n=1}^{N}\frac{1}{N}=1 \tag{24}
$$

we have

$$
\begin{aligned}
U_3 &= U_2\cdot 2\sqrt{\epsilon_2\left(1-\epsilon_2\right)}=\left(U_1\cdot 2\sqrt{\epsilon_1\left(1-\epsilon_1\right)}\right)\cdot 2\sqrt{\epsilon_2\left(1-\epsilon_2\right)} && (25)\\
&= 4\sqrt{\epsilon_1\epsilon_2\left(1-\epsilon_1\right)\left(1-\epsilon_2\right)} && (26)
\end{aligned}
$$

which can be generalized as

$$
U_{T+1}=\prod_{t=1}^{T}\left(2\sqrt{\epsilon_t\left(1-\epsilon_t\right)}\right) \tag{27}
$$

□

Problem 7

To compute s_n, we need to find the optimal η of

$$\min_{\eta} \frac{1}{N} \sum_{n=1}^{N} \left((y_n - s_n) - \eta g_t(\mathbf{x}_n) \right)^2 := A \tag{28}$$

From $\partial A / \partial \eta = 0$, we have

$$\eta = \frac{\sum_{n=1}^{N} g_t(\mathbf{x}_n)(y_n - s_n)}{\sum_{n=1}^{N} g_t^2(\mathbf{x}_n)} \tag{29}$$

Now $s_n = 0$ and $g_1(\mathbf{x}) = 2$, so

$$\eta = \frac{2\sum_{n=1}^{N} y_n}{4\sum_{n=1}^{N}} = \frac{1}{2N} \sum_{n=1}^{N} y_n \tag{30}$$

Since $\eta = \alpha_1$, so

$$\alpha_1 g_1(\mathbf{x}_n) = \frac{2}{2N} \sum_{n=1}^{N} y_n = \frac{1}{N} \sum_{n=1}^{N} y_n = s_n \tag{31}$$

□

Problem 8

From the equatio of optimal η, we have

$$\eta = \frac{\sum_{n=1}^{N} g_t(\mathbf{x}_n)(y_n - s'_n)}{\sum_{n=1}^{N} g_t^2(\mathbf{x}_n)} = \frac{\sum_{n=1}^{N} y_n g_t(\mathbf{x}_n) - \sum_{n=1}^{N} s'_n g_t(\mathbf{x}_n)}{\sum_{n=1}^{N} g_t^2(\mathbf{x}_n)} = \alpha_t \tag{32}$$

so

$$\sum_{n=1}^{N} y_n g_t(\mathbf{x}_n) - \sum_{n=1}^{N} s'_n g_t(\mathbf{x}_n) = \alpha_t \sum_{n=1}^{N} g_t^2(\mathbf{x}_n) = \sum_{n=1}^{N} \alpha_t g_t^2(\mathbf{x}_n) = \sum_{n=1}^{N} (s_n - s'_n) g_t(\mathbf{x}_n) \tag{33}$$

where s'_n is defined as the s_n in iteration $(t-1)$ and $s_n = s'_n + \alpha_t g_t(\mathbf{x}_n)$, so

$$\sum_{n=1}^{N} s_n g_t(\mathbf{x}_n) = \sum_{n=1}^{N} y_n g_t(\mathbf{x}_n) \tag{34}$$

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Problem 9

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Problem 10

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Problem 11

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Problem 12

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Problem 13

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Problem 14

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Problem 15

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Problem 16

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Problem 17

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Problem 18

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Problem 19

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Problem 20

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Reference

[1] Lecture Notes by Hsuan-Tien LIN, Department of Computer Science and Information Engineering, National Taiwan University, Taipei 106, Taiwan.