

# Foundations of Machine Learning — Homework Assignment 3

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## A. Boosting-type Algorithm

### 1. Proof of convexity and differentiability

Given:  $\phi_p(u) = \max((1+u)^p, 0)$

To prove: 1. Function  $\phi_p(u)$  is convex and differentiable

And 2.  $\forall u \in \mathbb{R}$  and  $p > 1, 1_{u \leq 0} \leq \phi_p(-u)$

Proof of  $\forall u \in \mathbb{R}$  and  $p > 1, 1_{u \leq 0} \leq \phi_p(-u)$  There are three cases here:

When  $u = 0$

$$\begin{aligned} 1_{u \leq 0} &= 1 \\ \phi_p(u) &= \max((1-0)^p, 0) = 1 = 1_{u \leq 0} \end{aligned}$$

When  $u < 0$

$$\begin{aligned} 1_{u \leq 0} &= 1 \\ \phi_p(u) &= \max((1-u)^p, 0) = 1 = 1_{u \leq 0} \end{aligned}$$

Proof of Convexity and Differentiability: The function can be written as a piecewise function based on the value of p:

When p is even (2 and more)

$$\phi_p(x) = (1+u)^p$$

When p is odd (1 and more) the

$$\phi_p(x) = \begin{cases} 0, & \text{if } u \leq -1 \\ (1+u)^p, & \text{otherwise} \end{cases}$$

## C. Randomized Halving

### 1. Psuedo code

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**Algorithm 1** Randomized Halving

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1:  $H_1 \leftarrow H$ 
2: for  $t \leftarrow 1$  to  $T$  do
3:    $RECEIVE(x_t)$ 
4:    $r_t \leftarrow \frac{\sum_{i: y_{t,i}=1} 1}{|H_t|}$ 
5:    $p_t \leftarrow 1$ 
6:   if  $r_t \leq \frac{3}{4}$  then
7:      $p_t \leftarrow \lceil \frac{1}{2} \log_2 \frac{1}{1-r_t} \rceil$ 
8:    $\hat{y}_t \leftarrow GetRandomNumberWithProbability([1, 0], [p_t, 1 - p_t])$ 
9:    $RECEIVE(y_t)$ 
10:  if  $\hat{y}_t \neq y_t$  then
11:     $H_{t+1} \leftarrow \{c \in H_t : c(x_t) = y_t\}$ 
return  $H_{T+1}$ 

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### 2. Prove $\forall t \geq 1, E[\mu] \leq \frac{\phi_t - \phi_{t+1}}{2}$

Given: Potential function:  $\phi_t = \log_2 |H_t|$  and  $\mu_t = 1_{y_t \neq \hat{y}_t}$

Proof:

We are only considering the case when the predicted value  $\hat{y}_t$  is not equal to the received value  $y_t$ . The value of expectation can be written as

$$\begin{aligned} E[\mu_t] &= p_t * 1 + (1 - p_t) * 0 \\ &= p_t * 1 \end{aligned}$$

The probability of predicting 1 by the randomized algorithm is the probability of making a mistake since we are only considering the cases in which we make mistakes ( $\mu_t = 1_{y_t \neq \hat{y}_t}$ )

Therefore,

$$\begin{aligned} E[\mu_t] &= p_t \\ &= \lceil \frac{1}{2} \log_2 \frac{1}{1-r_t} \rceil 1_{r_t \leq \frac{3}{4}} + 1_{r_t > \frac{3}{4}} \\ &\leq \lceil \frac{1}{2} \log_2 \frac{1}{1-r_t} \rceil \end{aligned}$$

Since, the Expectation will be 1 when  $r_t > \frac{3}{4}$  which corresponds to the maximum expectation here, we can upper bound the expectation by using  $r_t \leq \frac{3}{4}$  as  $\lceil \frac{1}{2} \log_2 \frac{1}{1-r_t} \rceil$  equals 1 when  $r_t = \frac{3}{4}$

Let  $E_1, E_0, E_t$  denote the number of experts predicting 1, 0 and the total number of experts in a round  $t$ .

$$\begin{aligned}
 E[\mu_t] &\leq \left\lfloor \frac{1}{2} \log_2 \frac{1}{1-r_t} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 \frac{1}{1-r_t}}{2} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 \frac{1}{1-r_t}}{2} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 \frac{1}{1-\frac{|E_1|}{|H_t|}}}{2} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 \frac{|H_t|}{|H_t|-|E_1|}}{2} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 \frac{|H_t|}{|E_0|}}{2} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 |H_t| - \log_2 |E_0|}{2} \right\rfloor \\
 &= \left\lfloor \frac{\log_2 |H_t| - \log_2 |H_{t+1}|}{2} \right\rfloor \\
 &= \left\lfloor \frac{\phi_t - \phi_{t+1}}{2} \right\rfloor \\
 \therefore E[\mu_t] &\leq \frac{\phi_t - \phi_{t+1}}{2}
 \end{aligned}$$

### 3. Expected number of mistakes.

Given:  $N$  be the total number of experts at the beginnning of the iterations (denoted by  $H_1$ ). Since we are considering a relizable scenario at the end of the algorithm the number of experts should be atleast one. So  $H_T = 1$ .

To Prove: The expected number of mistakes made by Randomized Halving is at most  $\frac{1}{2} \log_2 N$

Proof:

Lets consider the total expectation of mistakes of the Randomized Halving

algorithm over  $T$  iterations.

$$\begin{aligned}
E[\mu_T] &\leq \sum_{t=1}^T \frac{\phi_t - \phi_{t+1}}{2} \\
&\leq \frac{(\phi_{H_1} - \phi_{H_2}) + (\phi_{H_2} - \phi_{H_3}) \cdots (\phi_{H_{T-2}} - \phi_{H_{T-1}}) + (\phi_{H_{T-1}} - \phi_{H_T})}{2} \\
&\leq \frac{\phi_{H_1} - \phi_{H_T}}{2} \\
&\leq \frac{\phi_N - \phi_T}{2} \\
&\leq \frac{\phi_N}{2} \\
&\leq \frac{1}{2} \log_2 N
\end{aligned}$$

Hence proved.

Here  $\phi_T = 0$  because the number of experts at line  $T$  is 1. Therefore, log of  $T$  will be zero.

#### 4. [Bonus Question]

As we have seen in the previous answer, the mistakes made by the randomized algorithm is bounded by  $\frac{1}{2} \log_2 N$ . This upper bound is dependent only on the number of initial experts,  $N$ . Therefore any randomized algorithm that is dependent on the opinion of the experts to generate its predictions will have similar upper bound of  $\lfloor \frac{1}{2} \log_2 N \rfloor$ . The floor function is used as mistakes are natural numbers.