

CS3000: Algorithms & Data

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Lecture 22:

- Online Learning

~~UNPUBLISHED~~

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Picking Good Experts

- Suppose you have N “experts” making predictions
 - Weather forecasters
 - Financial advisors
 - Recommender systems
 - ...
- Most of them are bad, but one might be good!
- Who’s predictions should we trust?

Model



- There are T time periods, in each:

- experts make predictions $f_{t,1}, \dots, f_{t,N} \in \{0,1\}$
- you have to make a decision $p_t \in \{0,1\}$
- some outcome $q_t \in \{0,1\}$ is revealed
- a "mistake" is when $p_t \neq q_t$

binary outcomes
("rain"/"sun")

- Goal: minimize mistakes



- The # of mistakes we make is M
- The best expert in hindsight makes M^* mistakes
- Want to ensure that $M \approx M^*$

Level I: The Halving Algorithm (HA)

- Assumption: some expert makes 0 mistakes

Let $C_1 \leftarrow \{1, \dots, n\}$

For $t = 1, \dots, T$:

Let p_t be the majority vote of experts in C_t

Let C_{t+1} be the experts with no mistakes so far

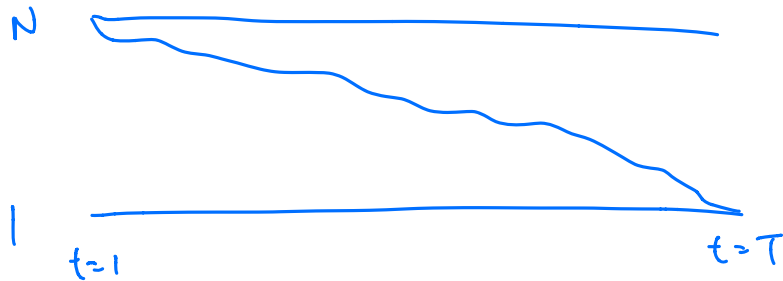
Level I: The Halving Algorithm

$$M^* = 0$$

- **Thm:** If some expert makes 0 mistakes then HA makes $\leq \log_2 N$ mistakes.

Measure of progress: $|C_t|$

Fact: $N = |C_1| \geq |C_2| \geq \dots \geq |C_T| \geq 1$



If we make a mistake on day t , then $|C_{t+1}| \leq \frac{|C_t|}{2}$

$$\therefore |C_T| \leq N \cdot 2^{-M}$$

Key Equation:

$$1 \leq |C_T| \leq N \cdot 2^{-M}$$

$$\Rightarrow 1 \leq N \cdot 2^{-M}$$

$$2^M \leq N$$

$$M \leq \log_2 N$$

□

Level II: Repeated Halving (RHA)

Let $C_1 \leftarrow \{1, \dots, n\}$

For $t = 1, \dots, T$:

Let p_t be the majority vote of experts in C_t

Let C_{t+1} be the experts with no mistakes so far

If $C_{t+1} = \emptyset$, let $C_{t+1} = \{1, \dots, n\}$

Diagram illustrating the progression of expert sets C_t over time $t=1$ to T . The sets are shown as intervals of size $\log_2 N$.

Best expert makes M^* mistakes \times $\log_2 N$ mistakes / interval

$$M \leq (M^* + 1) \log_2 N$$

Level II: Repeated Halving

- **Thm:** If some expert makes $\leq M$ mistakes then RHA makes $\leq (M + 1)(\log_2 N + 1)$ mistakes.
- Worse than the best expert by a factor of $\log_2 N$

Level III: Weighted Majority (WM)

Give each expert a weight $w_{t,i} \leftarrow 1$

$W_t = \sum_{i=1}^N w_{t,i}$ → measure of progress

$W_1 = N$

For $t = 1, \dots, T$:

Let p_t be the weighted majority vote of experts

For $i = 1, \dots, N$:

If (expert i made a mistake): $w_{t+1,i} \leftarrow \frac{w_{t,i}}{2}$

Else: $w_{t+1,i} \leftarrow w_{t,i}$

$\sum_{i: f_{t,i}=1} w_{t,i}$ vs. $\sum_{i: f_{t,i}=0} w_{t,i}$

Level III: Weighted Majority

- **Thm:** If some expert makes $\leq M^*$ mistakes then WM makes $\leq 2.4(M^* + \log_2 N)$ mistakes.

• Proof:

• measure of progress is $W_t = \sum_{i=1}^N w_{t,i}$

• if we make M mistakes, then $W_T \leq N \cdot \left(\frac{3}{4}\right)^M$

• if the best expert i^* makes M^* mistakes, then

$$W_T = \sum_{i=1}^N w_{T,i} \geq w_{T,i^*} = \left(\frac{1}{2}\right)^{M^*}$$

$$\Rightarrow \left(\frac{1}{2}\right)^{M^*} \leq W_T \leq N \cdot \left(\frac{3}{4}\right)^M$$

$$\left(\frac{1}{2}\right)^{M^*} \leq N \cdot \left(\frac{3}{4}\right)^M \quad (\text{take } \log_2 \text{ of both sides})$$

$$M^* \log_2 \left(\frac{1}{2}\right) \leq M \log_2 \left(\frac{3}{4}\right) + \log_2 N$$

$$-M^* \log_2 2 \leq -M \log_2 \left(\frac{4}{3}\right) + \log_2 N$$

$$M \leq \frac{M^* \log_2 2 + \log_2 N}{\log_2 \left(\frac{4}{3}\right)}$$

$$M \leq 2.4 (M^* + \log_2 N) \quad \square$$

Level III: Weighted Majority

- **Thm:** If some expert makes $\leq M^*$ mistakes then WM makes $\leq 2.4(M^* + \log_2 N)$ mistakes.

Some expert has wt $\geq 2^{-M^*}$

Every mistake decreases total wt by a factor of $(\frac{3}{4})$

$$2^{-M^*} \leq W_T \leq N \cdot \left(\frac{3}{4}\right)^M$$

$$-M^* \leq \log_2 N + M \log_2 \left(\frac{3}{4}\right)$$

$$M \leq (M^* + \log_2 N) \frac{-1}{\log_2(3/4)}$$

$$= \frac{1}{\log_2(4/3)} \approx 2.4$$

Level III: Weighted Majority

- **Thm:** If some expert makes $\leq M^*$ mistakes then WM makes $\leq 2.4(M + \log_2 N)$ mistakes.

Some expert has wt $\geq (1-\epsilon)^{M^*}$

Every mistake decreases total wt by a factor of $(1-\frac{\epsilon}{2})$

$$(1-\epsilon)^{M^*} \leq N \cdot (1-\frac{\epsilon}{2})^M$$

$$M^* \cdot \ln(1-\epsilon) \leq \ln N + M \cdot \ln(1-\frac{\epsilon}{2})$$

$$-M^* \cdot \ln\left(\frac{1}{1-\epsilon}\right) \leq \ln N - M \cdot \ln\left(\frac{1}{1-\frac{\epsilon}{2}}\right)$$

$$M \leq M^* \cdot \left(\frac{\ln\left(\frac{1}{1-\epsilon}\right)}{\ln\left(\frac{1}{1-\frac{\epsilon}{2}}\right)} \right) + \frac{\ln N}{\ln\left(\frac{1}{1-\epsilon}\right)}$$

Level III: Weighted Majority

- **Thm:** If some expert makes $\leq M^*$ mistakes then WM makes $\leq 2.4(M^* + \log_2 N)$ mistakes.
- **Thm:** Any **deterministic** strategy can be forced to make at least $2M^*$ mistakes

Level IV: Randomized Weighted Majority

Give each expert a weight $w_{t,i} \leftarrow 1$, $W_t \leftarrow \sum_i w_{t,i}$

For $t = 1, \dots, T$:

Choose i with probability $w_{t,i}/W_t$ (Splitting a dollar across the experts)

For $i = 1, \dots, N$:

If (expert i made a mistake): $w_{t+1,i} \leftarrow (1 - \epsilon) \cdot w_{t,i}$

Else: $w_{t+1,i} \leftarrow w_{t,i}$, $W_{t+1} \leftarrow \sum_i w_{t+1,i}$

Level IV: Randomized Weighted Majority

- **Thm:** If some expert makes $\leq M^*$ mistakes then RWM makes $\leq (1 + \varepsilon) \cdot M^* + \frac{\log_2 N}{\varepsilon}$ mistakes

- Set $\varepsilon = \sqrt{\frac{\log_2 N}{T}}$

$$M \leq M^* + M^* \sqrt{\frac{\log_2 N}{T}} + \sqrt{T \log_2 N}$$

$$\leq M^* + 2\sqrt{T \log_2 N}$$

$$\frac{M^*}{T} + 2\sqrt{\frac{\log_2 N}{T}}$$

Level IV: Randomized Weighted Majority

- **Thm:** If some expert makes $\leq M$ mistakes then RWM makes $\leq (1 + \varepsilon) \cdot M + \frac{\log_2 N}{\varepsilon}$ mistakes

Proof :

- Measure of progress: W_t
- $(1 - \varepsilon)^{M^*} \leq W_T$
- Every day we lose $F_t = \sum_{i: f_{t,i} \neq q_t} w_{t,i}$
- $W_{t+1} = W_t (1 - \varepsilon F_t) \quad \therefore W_T \leq N \cdot \prod_{t=1}^T (1 - \varepsilon F_t)$

$$(1-\varepsilon)^{M^*} \leq W_T \leq N \cdot \prod_{t=1}^T (1-\varepsilon F_t)$$

$$M^* \cdot \ln(1-\varepsilon) \leq \ln N + \sum_{t=1}^T \ln(1-\varepsilon F_t)$$

$$\leq \ln N - \varepsilon \sum_{t=1}^T F_t$$

what we want
to bound

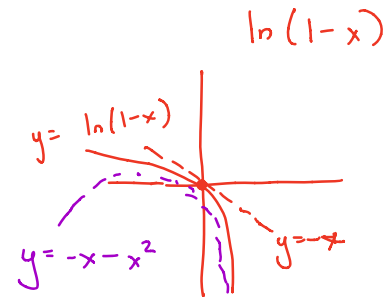
$$\varepsilon \sum_{t=1}^T F_t \leq \frac{-M^* \ln(1-\varepsilon) + \ln N}{\varepsilon}$$

$$= \frac{M^* \ln\left(\frac{1}{1-\varepsilon}\right) + \ln N}{\varepsilon}$$

$$\approx \frac{M^* \ln(1+\varepsilon) + \ln N}{\varepsilon}$$

$$\approx \frac{M^* (\varepsilon + \varepsilon^2) + \ln N}{\varepsilon}$$

$$= (1+\varepsilon) M^* + \frac{\ln N}{\varepsilon}$$



for small x
 $\ln(1-x) \approx -x$

Level IV: Randomized Weighted Majority

- **Thm:** If some expert makes $\leq M^*$ mistakes then RWM makes $\leq (1 + \varepsilon) \cdot M^* + \frac{\log_2 N}{\varepsilon}$ mistakes

Let F_t be the fraction of mistakes we made on day t

Want to bound $\sum_t F_t \approx F_t \propto \sum_i w_t m_{t,i}$

$$(1 - \varepsilon)^{M^*} \leq W_T \leq N \cdot \prod_{t=1}^T (1 - \varepsilon F_t)$$

$$M^* \cdot \ln(1 - \varepsilon) \leq \ln N + \sum_{t=1}^T \ln(1 - \varepsilon F_t)$$

$$\leq \ln N - \sum_{t=1}^T \varepsilon F_t$$

$$\sum_{t=1}^T F_t \leq \frac{\ln N}{\varepsilon} + \frac{M^*}{\varepsilon \ln(1/\varepsilon)}$$

Why I love this algorithm

- **Endless applications:**

- continuous optimization / linear programming
 - including maximum flow!
- machine learning
 - training machine learning models
 - combining weak models into strong models
 - online learning: updating models with more data
- probability theory
- game theory
 - how to play zero-sum games
- theory of computation

Why I care so much about this

- We often teach algorithms as a set of *ad hoc* tricks
 - These algorithms are easier to deploy
 - These algorithms are used often
 - These algorithms came first historically
 - These algorithms require less mathematical background
- Algorithms research today is much more systematic
 - More powerful and unified techniques
 - But requires more mathematical sophistication
 - Randomization / Probability / Statistics
 - Continuous Mathematics / Linear Algebra
 - **But beautiful and worth studying!**