

Approximation and Online Algorithms
with Applications

8

Multi-Armed Bandit Weight Majority Algorithm

- o We are focusing on 1 stock, and thinking if we should buy this stock at time t, \dots, T .
- o For each time t , we are going to hear opinion from n experts.
 $x_1^{(t)}, x_2^{(t)}, \dots, x_n^{(t)}$, and make a decision.
 $\in \{\text{buy, not-buy}\}$

o We will immediately know the result of the decision immediately.
[Stock get up (should buy) or Stock get down (should not buy)]

Input : $x_1^{(t)}, x_2^{(t)}, \dots, x_n^{(t)} \in \{\text{buy, not-buy}\}$ for all t

Output : $y^{(t)} \in \{\text{buy, not-buy}\}$ for all t .

Objective Function : $p^{(t)} = \begin{cases} 1 & \text{if } y^{(t)} \text{ is the right decision} \\ 0 & \text{otherwise} \end{cases}$

Maximize. $\sum_{t=1}^T p^{(t)}$.

Key Idea : We should believe in experts who give us a good recommendation in previous step.

Algorithm

1: Weight for all experts: $w_1, \dots, w_n = 1$

2: For $t=1$ to T :

If $\sum_{i: x_i^{(t)} = \text{buy}} w_i \geq \sum_{i: x_i^{(t)} = \text{not-buy}} w_i$ \rightarrow Sum of weight of experts who suggest buy
 $y^{(t)} = \text{buy}$ \rightarrow Sum of weight of experts who suggest not buy

else

$y^{(t)} = \text{not-buy}$

For all expert i that makes a wrong suggestion, $w_i \leftarrow w_i / 2$

\downarrow
we believe them less and put a smaller to them.

<u>Example</u>	Time	Expert 1	Expert 2	Experts	
	1	Buy 1	Not-Buy 1	Not-Buy 1	\rightarrow Not-Buy (Wrong)
	2	Not-Buy 1	Buy 1/2	Not-Buy 1/2	\rightarrow Not-Buy (right)
	3	Buy 1	Not-Buy 1/2	Not-Buy 1/4	\rightarrow Buy (right)

2 right decisions

Score = 2

Theorem : # mistake decisions $\leq 2.42(m + \lg_2 n)$

where m is #mistake of best expert.

Weight of the best expert after the T^{th} iteration.

$$= \frac{1}{2^m} \quad (\text{The weight is initialized to 1, and is divided by 2 for } m \text{ times})$$

The sum of all weights after the T^{th} iteration. $= W_T$

$$\geq \frac{1}{2^m}$$

The sum of all weight after the t^{th} iteration W_t

= Sum of weight with correct suggest

C_t

+ Sum of weight with incorrect suggest

I_t

$$W_{t+1} = C_t + I_t / 2$$

$$= W_t - I_t / 2$$

$$\leq W_t - W_t / 4$$

$$= 3/4 W_t$$

larger when we make a mistake decision.

$$I_t \geq C_t$$

$$I_t \geq \frac{1}{2} W_t \quad \Rightarrow \quad \begin{array}{|c|c|} \hline C_t & I_t \geq W_t/2 \\ \hline \end{array} \quad W_t$$

$$\begin{array}{|c|c|c|} \hline C_t & I_t/2 & I_t/2 \\ \hline \end{array} \quad \begin{array}{l} - \\ W_t/4 \end{array}$$

$$W_{t+2} \leq 3/4 W_t$$

(when we make a mistake decision)

$$I_t/2 \geq W_t/4$$

$$W_1 = n \quad [\text{The weights of all } n \text{ experts are } 1]$$

$$W_{P_1} \leq \frac{3}{4}n \quad [\text{After we made } 1 \text{ mistake}]$$

$$W_{P_2} \leq \left(\frac{3}{4}\right)^2 n \quad [\text{After we made } 2 \text{ mistakes}]$$

$$W_{P_3} \leq \left(\frac{3}{4}\right)^3 n \quad [\text{After we made } 3 \text{ mistakes}]$$

$$\vdots$$
$$W_T \leq \left(\frac{3}{4}\right)^M n \quad [\text{After } M \text{ mistakes}]$$

$$W_T \geq \frac{1}{2^m}$$

$$\frac{1}{2^m} \leq \left(\frac{3}{4}\right)^M n$$

$$-m = \lg 2^{-m} = \lg \frac{1}{2^m} \leq \lg \left[\left(\frac{3}{4}\right)^M n \right]$$

$$= \lg \left(\frac{3}{4}\right)^M + \lg n$$

$$= M \lg \frac{3}{4} + \lg n.$$

$$-m \leq (-0.415)M + \lg n$$

$$0.415M \leq m + \lg n$$

$$M \leq 2.42 [m + \lg n]$$

□

Use randomness

1: Weight for all expert: $w_1, \dots, w_n = 1$

2: For $t=1$ to T :

$$W_{\text{buy}} = \sum_{i: X_i^{(t)} = \text{buy}} w_i$$

$$W_{\text{no-buy}} = \sum_{i: X_i^{(t)} = \text{not-buy}} w_i$$

$$P_{\text{buy}} = W_{\text{buy}} / (W_{\text{buy}} + W_{\text{no-buy}})$$

$$P_{\text{not-buy}} = 1 - P_{\text{buy}}$$

Select $y^{(t)}$ according to that probability

For all expert i that makes a wrong suggestion, $v_i \leq w_i/2$

Theorem ^{Expected} [# mistake decisions] $\leq 1.39 n + 2 \ln n$
 ↗ decrease from $2.42 n + 2.42 \ln n$.

Proof

$F^{(t)}$:= Weight for the wrong decision

→ Prob. that we make a mistake decision.

$$\text{Expected [# mistake decision]} = \sum_{t=1}^T F^{(t)}$$

$$W^{(t)} := \sum_{i=1}^n w_i \text{ (at time } t \text{)}$$

$$W^{(1)} = \sum_{i=1}^n 1 = n.$$

$$W^{(2)} = n \cdot (1 - F^{(1)}) + n \cdot \frac{F^{(1)}}{2}$$

→ Correct decision
→ Wrong decision

$$= n \left(1 - \frac{F^{(1)}}{2} \right)$$

in correct prediction
divide by 2

$$\leq n \left(1 - \frac{F^{(1)}}{2} \right) \cdot F^{(2)}$$

$$\leq n \left(1 - \frac{F^{(1)}}{2} \right) \cdot (1 - F^{(2)})$$

↘ incorrect prediction
divide by 2.

$$W^{(1)} = n(1 - F^{(1)}/2)(1 - F^{(2)}) + n(1 - F^{(1)}/2)F^{(2)}/2$$

$$= n(1 - F^{(1)}/2)(1 - F^{(2)}/2)$$

⋮

$$W^{(m)} = n(1 - F^{(1)}/2)(1 - F^{(2)}/2) \dots (1 - F^{(m)}/2)$$

$$= n \prod_{t=1}^m (1 - F^{(t)}/2)$$

Weight of the best expert
 $= (\frac{1}{2})^m$

$$n \prod_{t=1}^m (1 - F^{(t)}/2) \geq (\frac{1}{2})^m$$

$$1+x \leq e^x$$

$$1-x \leq e^{-x}$$

$$\ln(1-x) \leq -x$$

$$\ln n + \sum_{t=1}^m \ln(1 - F^{(t)}/2) \geq \ln(\frac{1}{2})^m$$

$$\ln n + \sum_{t=1}^m (-F^{(t)}/2) \geq m \ln(\frac{1}{2})$$

$$-\ln n + -\sum_{t=1}^m (-F^{(t)}/2) \leq -m \ln(\frac{1}{2}) = m \ln 2$$

$$\sum_{t=1}^m F^{(t)}/2 \leq \ln n + 0.7m$$

$$\sum_{t=1}^m F^{(t)} \leq 2 \ln n + 1.4m$$

□

$$W_{(3)} = n(1 - E_{(1)}^{(1)}) \cdot E_{(1)}^{(2)} + n(1 - E_{(1)}^{(1)}) (1 - E_{(1)}^{(2)})/2$$