

## Week 3 — Lecture 17

In each round

learner picks  $P_t$

Adversary picks  $l_t$

Types of Adversary :

— Oblivious : Before game begins Adversary chooses the losses for all rounds

$$\{l_1, l_2, \dots, l_n\}$$

— Non-Oblivious : losses can be assigned to each action based on the past observations

Exp3 holds for both kinds of adversary.

Two kinds of  $\mathbb{E}$  were taken, one for learner & one for adversary, holds for non-oblivious case, which is the worse of the two.

$$R(n, \pi) = \sum_{t=1}^n l_t I_t - \min_i \sum_{t=1}^n l_{ti} \quad \begin{array}{l} \text{true loss} \\ \text{incurred} \end{array} \quad \textcircled{1}$$

$$\mathbb{E}[R(n, \pi)] = \mathbb{E}\left[\sum_{t=1}^n l_t I_t\right] - \min_i \mathbb{E}\left[\sum_{t=1}^n l_{ti}\right] \quad \textcircled{2}$$

The bound on  $\textcircled{2}$  (already derived) will be very

...

different, may be higher, than that for ①

We want to bound  $R(n, \pi)$ . For a good algorithm we would want to know

$$\Pr \{ R(n, \pi) \leq \mathbb{E}[R(n, \pi)] \} \leftarrow \text{should be high}$$

While finding the bound for ① we will only consider the oblivious adversary.

For the bound on a quantity, single value, to be low we would want the estimates to have low variance.

### Estimates of Exp 3

$$\hat{l}_{ti} = \frac{l_{ti}}{p_{ti}} \mathbb{1}\{I_t = i\}$$

$$\mathbb{E}[\hat{l}_{ti}] = l_{ti}$$

$$\text{Var}(\hat{l}_{ti}) = \frac{1}{p_{ti}}$$

If  $p_{ti}$  is small then variance will be very high.

### Exp 3.P Algorithm

Input:  $\{r_t\}$ ,  $K$ ,  $\gamma$   $[\gamma \in (0, 1)]$ ,  $\beta$ ,  $\delta$

Initialize:  $\hat{L}_{oi} = 0$

for  $t = 1, 2, \dots$

$$\forall i \quad P_{ti} = \frac{(1-\gamma) \exp(-\eta_t \hat{L}_{ti})}{\sum_j \exp(-\eta_t \hat{L}_{tj})} + \frac{\gamma}{K}$$

Draw  $I_t \sim P_t$

$$\forall i \quad \hat{l}_{ti} = \frac{l_{ti} \mathbb{1}\{I_t = i\} + \beta}{P_{ti}}$$

$$\text{and } \hat{L}_{ti} = \hat{L}_{(t-1)i} + \hat{l}_{ti}$$

High probability bound for Exp3.P

for  $\gamma = 1$   
only uniform  
distr. applies

if  $\gamma = 0$   
is back to  
Exp3

Also ensures  
that  $P_{ti}$  is not  
arbitrarily close to  
zero, it is bound  
by  $\gamma/K$ , thus  
ensuring low  
variance

For any  $\delta \in (0, 1)$  if Exp3.P is run  
with

$$\beta = \sqrt{\frac{\log K / \delta}{nK}}, \quad \eta = 0.95 \sqrt{\log K}, \quad \gamma = \sqrt{\frac{K \log K}{n}}$$

Then,

$$R(n, \text{Exp3.P}) \leq 5.15 \sqrt{nK \log(K/\delta)} \quad \text{with probability } (1-\delta)$$

$$\text{Further if } \beta = \sqrt{\frac{\log K}{nK}} \quad *$$

$$R(n, \text{Exp3.P}) \leq \sqrt{\frac{nK}{\log K}} \log(1/\delta)$$

(stop after  
n rounds)

$$+ 5.15 \sqrt{nK \log K}$$

with probability  $(1-\delta)$

↑  
because we are  
considering  
individual regret  
& not  $\mathbb{E}$

\* This situation is when we don't specify  $\delta$  a-priori  
 High Probability bounds are more desired than  
 expected bounds, as it bounds the actual regret we  
 face at every round. But these bounds are difficult  
 to maintain because they are guaranteed by  $\Pr(1-\delta)$

High Probability bounds can be converted  
 to expected bound by considering:

$$\mathbb{E}[X] \leq \int_0^1 \frac{1}{\delta} \Pr\{X \geq \ln \frac{1}{\delta}\} d\delta$$

$$\left[ R(n, \text{Exp3P}) - 5.15 \sqrt{nK \log K} \right] \sqrt{\frac{\log K}{nK}} > \log(1/\delta)$$

holds ~~with~~ w.p.  $\delta$

$$\text{Let } \left[ R(n, \text{Exp3P}) - 5.15 \sqrt{nK \log K} \right] \sqrt{\frac{\log K}{nK}} = X$$

Then

$$\mathbb{E} \left[ R(n, \text{Exp3P}) - 5.15 \sqrt{nK \log K} \right] \sqrt{\frac{\log K}{nK}} \leq 1$$

$$\mathbb{E} [R(n, \text{Exp3P})] \leq \sqrt{\frac{nK}{\log K}} + 5.15 \sqrt{nK \log K}$$

Exp3IX Algorithm

Forces implicit exploration

Input:  $\{\eta_t\}, K, \gamma, \beta$

Initialize:  $\hat{L}_{0i} = 0$

for  $t = 1, 2, \dots$

$$\forall i \quad P_{ti} = \frac{\exp(-\eta_t \hat{L}_{ti})}{\sum_j \exp(-\eta_t \hat{L}_{tj})}$$

Draw  $I_t \sim P_t$ , incur loss  $l_{ti}$

$$\forall i \quad \hat{l}_{ti} = \frac{l_{ti} \mathbb{1}\{I_t = i\}}{P_{ti} + \gamma}$$

$$\text{and } \hat{L}_{ti} = \hat{L}_{(t-1)i} + \hat{l}_{ti}$$