

## Week 3 - Lecture 16

Revisiting Exp3 Algo:

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

Initialization:  $\hat{L}_{0i} = 0 \forall i$

for  $t = 1, 2, \dots$

$$P_{ti} = \frac{\exp(-\eta_t \hat{L}_{(t-1)i})}{\sum_{j=1}^K \exp(-\eta_t \hat{L}_{(t-1)j})}$$

← note

$$P_{0i} = \frac{1}{K}$$

hence uniform  
distr.

Pick  $I_t \sim P_t$  observe  $l_{tI_t}$

$\forall i \in [K]$  update  $\hat{l}_{ti} = \frac{l_{ti} \mathbb{1}\{I_t = i\}}{P_{ti}}$

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

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### Regret Analysis

$$\bar{R}(n, \text{Exp3}) \leq \frac{K}{2} \sum_{t=1}^n \eta_t + \frac{\ln K}{\eta_n} \quad \text{--- (1)}$$

$$= \sqrt{2nK \ln K} \quad \text{with } \eta_t = \sqrt{\frac{2 \ln K}{t}}$$

$$= 2\sqrt{nk \log K} \quad \text{with } \eta_t = \sqrt{\frac{\log K}{tK}}$$

The whole idea is to show eq ①

$$\sum_{t=1}^n l_{tI_t} - \sum_{t=1}^n l_{tK} = \sum_{t=1}^n \mathbb{E}_{i \sim P_t} \hat{l}_{ti} - \sum_{t=1}^n \mathbb{E} \hat{l}_{tK} \quad \text{--- ②}$$

$$\mathbb{E}_{i \sim P_t} \hat{l}_{ti} \leq \frac{\eta_t^2}{2P_{I_t}} + \phi_{t-1}(\eta_t) - \phi_t(\eta_t) \quad \text{--- ③}$$

where  $\phi_t(\eta) =$

$$\frac{1}{n} \log \frac{1}{K} \sum_i \exp(-\eta_t \hat{l}_{ti})$$

Substituting eq 3 in eq 2, we have

$$\sum_{t=1}^n l_{tI_t} - \sum_{t=1}^n l_{tK} \leq \frac{\eta_t^2}{2P_{I_t}} + \phi_{t-1}(\eta_t) - \phi_t(\eta_t) - \sum_{t=1}^n \mathbb{E}_{I_t \sim P_t} \hat{l}_{tK} \quad \text{--- ④}$$

We are interested in the expectation of

$$\sum_{t=1}^n l_{tI_t} - \sum_{t=1}^n l_{tK}, \text{ hence:}$$

$$\mathbb{E} \left[ \sum_{t=1}^n l_{tI_t} - \sum_{t=1}^n l_{tK} \right] \leq \sum_{t=1}^n \left\{ \mathbb{E} \left[ \frac{\eta_t^2}{2P_{I_t}} \right] + \mathbb{E} \left[ \phi_{t-1}(\eta_t) - \phi_t(\eta_t) \right] \right\}$$

$$- \mathbb{E} \left[ \sum_{t=1}^n \mathbb{E}_{I_t \sim P_t} l_{t, I_t} \right] \quad (5)$$

Now we will bound the Expectation of each term in R.H.S.

$$\mathbb{E} \left[ \sum_{t=1}^n \frac{\eta_t^2}{2 P_{t, I_t}} \right] = \mathbb{E} \left[ \sum_{t=1}^n \underset{\substack{\uparrow \\ \text{w.r.t the} \\ \text{adversary}}}{\mathbb{E}_t} \left[ \underset{\substack{\uparrow \\ \text{w.r.t the probability dist} \\ \text{of the learner, } P_t}}{\frac{\eta_t}{2 P_{t, I_t}}} \right] \right]$$

$$= \mathbb{E} \left[ \sum_{t=1}^n \sum_{j=1}^K \frac{\eta_t}{2 P_{t, j}} \times P_{t, j} \right]$$

$$= \mathbb{E} \left[ \sum_{t=1}^n K \frac{\eta_t}{2} \right]$$

$$= \frac{K}{2} \sum_{t=1}^n \eta_t \quad \text{--- (6)}$$

$$\sum_{t=1}^n \left[ \phi_{t-1}(\eta_t) - \phi_t(\eta_t) \right]$$

$$\begin{aligned} &= \phi_0(\eta_1) - \phi_1(\eta_1) + \phi_1(\eta_2) - \phi_2(\eta_2) \\ &\quad + \phi_2(\eta_3) - \phi_3(\eta_3) + \phi_3(\eta_4) - \phi_4(\eta_4) \\ &\quad \dots \phi_{n-1}(\eta_n) - \phi_n(\eta_n) \end{aligned}$$

$$[\text{Clubbing all } \phi_1, \phi_2, \dots, \phi_{n-1}]$$

$$= \sum_{t=1}^{n-1} [\phi(\eta_{t+1}) - \phi(\eta_t)] + \phi(\eta_1) - \phi(\eta_n)$$

$$- \sum_{t=1}^n [\eta_t (\eta_{t+1}) - (\eta_t - \eta_{t+1})] \quad \text{---}$$

$$[\text{Abel Transformation}] \left[ \begin{array}{l} \phi_0(\eta_1) = 0 \\ (\log 1 = 0) \end{array} \right]$$

Therefore :

$$\begin{aligned} \sum_{t=1}^n [\phi_{t-1}(\eta_t) - \phi_t(\eta_t)] \\ = \sum_{t=1}^n [\phi_t(\eta_{t+1}) - \phi_t(\eta_t)] - \phi_n(\eta_n) \end{aligned}$$

--- (7)

Also, continuing this :

$$\begin{aligned} -\phi_n(\eta_n) &= + \frac{1}{\eta_n} \log K - \frac{1}{\eta_n} \log \sum_{i=1}^K \exp(-\eta_n \hat{L}_{ni}) \\ &\leq \frac{\log K}{\eta_n} - \frac{1}{\eta_n} \log \exp(-\eta_n \hat{L}_{nK}) \\ &= \frac{\log K}{\eta_n} + \sum_{t=1}^n \hat{L}_{tK} \end{aligned}$$

$\uparrow$   
 cumulative loss of  $K$ th action

From the summation only consider the  $K$ th-compo the summation will only become smaller

Taking expectation of  $-\phi_t(\eta_t)$

$$\mathbb{E}[-\phi_t(\eta_t)] \leq \frac{\log K}{\eta_n} + \mathbb{E} \left[ \sum_{t=1}^n \mathbb{E}_{I_t \sim P_t} \hat{L}_{tK} \right]$$

--- (7a)

Substituting (6) & (7a) into (5)

$$\mathbb{E} \left[ \sum_{t=1}^n L_{tT} - \sum_{t=1}^n L_{tK} \right] \leq \frac{K}{\eta_n} \sum_{t=1}^n \eta_t$$

$\uparrow$   
 $\mathbb{E}$  is w.r random

$$- \sum_{t=1}^n \eta_t \quad t=1 \quad \sum_{t=1}^n$$

$$+ \mathbb{E} \left[ \sum_{t=1}^n \phi_t(\eta_{t-1}) - \phi_t(\eta_t) \right]$$

$$+ \frac{\log K}{\eta_n} + \mathbb{E} \left[ \sum_{t=1}^n \mathbb{E} \hat{l}_{tK} \right]$$

$$- \mathbb{E} \sum_{t=1}^n \mathbb{E} [l_{tK}^*]$$

of learner  
(inside) &  
adversary  
(outside)

$$\text{If } \mathbb{E} \left[ \sum_{t=1}^n \phi_t(\eta_{t-1}) - \phi_t(\eta_t) \right] \leq 0 \quad \text{--- (8)}$$

Then we have shown (i)

$$= \frac{K}{2} \sum_{t=1}^n \eta_t + \frac{\log K}{\eta_n}$$

For proving (8), realize that  $\eta$  is chosen  
s.t., it is either a constant or is decreasing with  $t$

$$\eta_t = \sqrt{\frac{\log K}{tK}}$$

$$\text{Hence } \eta_t < \eta_{t-1}$$

To prove eq (8) need to show that

$$\phi_t(\eta) \text{ is increasing in } \eta$$

That can be shown by taking the derivative of

$$\phi_t, \text{ such that } \phi_t'(\eta) \geq 0$$

This last step  $\nearrow$  is left for us to do, need to

was  $\frac{1}{2} \log \frac{1}{2}$   
knew KL Divergence or simply take derivative