



• 18/4/20

$$\hat{X}_{t,i} = \left[ \frac{\mathbb{1}\{A_t=i\} X_t}{P_{t,i}} \right] \downarrow$$

$\downarrow$   
 $P_{t,i}$

Analysis of EXP-3:

Recall  $\hat{X}_{t,i} = 1 - \frac{\mathbb{1}\{A_t=i\} (1-X_t)}{P_{t,i}}$

• AIS:

- 1) Input  $n, k, \eta$
- 2)  $\hat{S}_{0,i} = 0 \forall i$
- 3) for  $t=1 \dots n$  do

$$E[\hat{X}_{t,i}] = P_{t,i} - (1-X_t) + (1-P_{t,i}) \cdot 1 = P_{t,i} - 1 + X_t + 1 - P_{t,i} = X_t$$

4 Calculate  $P_{t,i} = \frac{\exp(\eta \hat{S}_{t-1,i}^{\uparrow})}{\sum_{j=1}^k \exp(\eta \hat{S}_{t-1,j}^{\uparrow})}$

$\omega_{t-1}$

5) Sample  $A_t \sim P_t$  & observe  $X_t$

6)  $\hat{S}_{t,i} = \hat{S}_{t-1,i} + \frac{\mathbb{1}\{A_t=i\} (1-X_t)}{P_{t,i}}$

7) we find  $E(\hat{S}_{t,i}) = P_{t,i} \hat{S}_{t-1,i} + P_{t,i} (1-X_t) + (1-P_{t,i}) \hat{S}_{t-1,i} + 1 - P_{t,i} = \hat{S}_{t-1,i} + X_{t,i}$

• So, if arm  $j$  is pulled;

$$\hat{S}_{t,j} = \hat{S}_{t-1,j} + 1 - \frac{(1-x_t)}{P_{t,j}}$$

• if arm  $j$  is not pulled.

$$\hat{S}_{t,j} = \hat{S}_{t-1,j} + 1$$

$$\mathbb{E}[\hat{S}_{t,j}] = \hat{S}_{t-1,j} + x_{t,j}$$

Thm: Let  $x \in [0,1]^{n \times k}$  &  $\pi$  be the policy EXP-3

with  $\eta = \sqrt{\log(k)/nk}$ ; then

$$R_n(\pi, x) \leq 2 \sqrt{nk \log k}$$

Proof:

Define  $R_{n,i} = \sum_{t=1}^n x_{t,i} - \mathbb{E} \left[ \sum_{t=1}^n x_t \right]$

Using arm  $i$  always

• We will bound  $R_{ni}$  for all  $i$ .

Let  $i$  be fixed:

$$\mathbb{E} \left[ \hat{S}_{ni} \right] = \mathbb{E} \left[ \sum_{t=1}^n \hat{X}_{ti} \right]$$
$$\searrow = \sum_{t=1}^n \mathbb{E} \left[ \hat{X}_{ti} \right]$$

$$= \sum_{t=1}^n \left\{ (1-p_{ti}) \cdot 1 + p_{ti} \left[ 1 - \frac{(1-\pi_i)}{p_{ti}} \right] \right\}$$

$$= \sum_{t=1}^n 1 - p_{ti} + p_{ti} - (1-\pi_i)$$

$$\mathbb{E} \left[ \hat{S}_{ni} \right] = \sum_{t=1}^n \pi_i \quad (\text{unbiased estimator})$$

$$\mathbb{E}_t \left[ \hat{X}_{ti} \right] = \sum_{i=1}^k p_{ti} x_{ti} = \sum p_{ti} \mathbb{E}_t \left[ \hat{X}_{ti} \right]$$

Now  $\mathbb{E} \left[ \mathbb{E}_t \left[ \hat{X}_{ti} \right] \right] = \mathbb{E} \left[ \hat{X}_{ti} \right]$   $\mathbb{E} \left[ \mathbb{E} \left[ \hat{X}_{ti} \right] \right]$

$$\therefore R_{ni} = \mathbb{E} \left[ \hat{S}_{ni} \right] - \mathbb{E} \left[ \sum p_{ti} \mathbb{E}_t \left[ \hat{X}_{ti} \right] \right]$$

$$= E \left[ \hat{S}_{ni} - \sum_{t=1}^n \frac{h}{L} \sum_{i=1}^L P_{ti} X_{ti} \right]$$

Define:  $\hat{S}_n = \sum_{t=1}^n \sum_{i=1}^L P_{ti} X_{ti}$

$$R_{ni} = E \left[ \hat{S}_{ni} - \hat{S}_n \right]$$

we want: to bound:  $\exp(\eta \hat{S}_{ni})$

$$\exp(\eta \hat{S}_{ni}) \leq \prod_{j=1}^L \exp(\eta \hat{S}_{nj})$$

set  $w_{tj} = \frac{h}{L} \exp(\eta \hat{S}_{tj})$

$$P_{tj} = \frac{\exp(\eta \hat{S}_{tj})}{w_{tj}}$$

$$\begin{aligned} \Rightarrow \exp(\eta \hat{S}_{ni}) &\leq w_n = w_0 \cdot \frac{w_1}{w_0} \cdot \frac{w_2}{w_1} \cdots \frac{w_n}{w_{n-1}} \\ &= \prod_{t=1}^n \left( \frac{w_t}{w_{t-1}} \right) \\ &= \exp(\eta) \exp(\eta) \cdots \exp(\eta) \\ &= \exp(\eta n) \end{aligned}$$

$$\begin{aligned} \frac{W_t}{W_{t-1}} &= \frac{\sum_j \exp(\eta \hat{s}_{tj})}{W_{t-1}} = \frac{\sum_j \exp(\eta (\hat{s}_{tj} + x_{tj}))}{W_{t-1}} \\ &= \sum_{j=1}^L \frac{\exp(\eta \hat{s}_{t-1j})}{W_{t-1}} \exp(\eta x_{tj}) \\ &= \sum_{j=1}^L p_{tj} \exp(\eta x_{tj}) \leftarrow e^{\eta x_{tj}} \end{aligned}$$

$e \in [0, 1]$

Now  $x_{tj} \leq 1 \quad \forall t, j$       $1 - \frac{\mathbb{1}\{A_t=j\}(1-x_t)}{p_{tj}}$

\* [This would not be true if we used

$$\hat{x}_{tj} = \frac{\mathbb{1}\{A_t=j\} x_t}{p_{tj}} \quad *$$

$$\exp(x) = 1 + x + \frac{x^2}{2!} + \frac{x^3}{3!} + \dots$$

$$\exp(x) \leq 1 + x + x^2 \quad \forall x \leq 1.$$

$$\exp(x) \leq 1 + x + \frac{x^2}{2} \quad \forall x \leq 0$$

$$\begin{aligned} \therefore \frac{W_t}{W_{t-1}} &\leq \sum P_{tj} (1 + \eta X_{tj}^1 + \eta^2 X_{tj}^2) \\ &\leq 1 + \sum \eta P_{tj} X_{tj}^1 + \eta^2 X_{tj}^2 P_{tj} \end{aligned}$$

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

$$\begin{aligned} \therefore \exp(\eta S_{n_i}^A) &\leq \prod_{t=1}^n \exp\left(\sum_{j=1}^k \eta P_{tj} \hat{X}_{tj}^1 + \eta^2 \sum_{j=1}^k \hat{X}_{tj}^2 P_{tj}\right) \\ &\leq k \exp\left(\eta \sum_{t=1}^n \sum_{j=1}^k P_{tj} X_{tj}^1 + \eta^2 \sum_{j=1}^k \sum_{t=1}^n \hat{X}_{tj}^2 P_{tj}\right) \end{aligned}$$

$$\leq k \exp\left(\eta S_n^A + \eta^2 \sum_{j=1}^k \sum_{t=1}^n X_{tj}^2 P_{tj}\right)$$

$$\therefore \eta \hat{S}_{n_i} \leq \log k + \eta S_n^A + \eta^2 \sum_{t=1}^n \sum_{j=1}^k X_{tj}^2 P_{tj}$$

$$\therefore \hat{S}_{n_i} - S_n^A \leq \frac{\log k}{\eta} + \eta \sum_{t=1}^n \sum_{j=1}^k X_{tj}^2 P_{tj}$$

Now  $\mathbb{E} [S_{hi}^{\wedge} - S_n^{\wedge}] = R_{hi}$ .

$$\mathbb{E} [S_{hi}^{\wedge} - S_n^{\wedge}] \leq \frac{10k}{2} + \mathbb{E} \left( \sum_{t=1}^n \sum_{j=1}^k P_{tj} x_{tj}^2 \right)$$

$$\mathbb{E} \left[ \sum_{t=1}^n \sum_{j=1}^k P_{tj} \left( 1 - \frac{\mathbb{1}(A_t=j) y_{tj}}{P_{tj}} \right) \right]$$

$y_{tj} = (1-x_{tj})$

$$= \sum_{t=1}^n \mathbb{E} \left( \sum_{j=1}^k P_{tj} \left( 1 - \frac{\mathbb{1}(A_t=j) y_{tj}}{P_{tj}} \right) \right)$$

$$\frac{\mathbb{1}(A_t=j) y_{tj}}{P_{tj}}$$

$$= \sum_{t=1}^n \mathbb{E} \left( 1 - 2 \frac{y_{tj}}{P_{tj}} + \frac{\mathbb{1}(A_t=j) y_{tj}}{P_{tj}} \right)$$



$$= \sum_{t=1}^n \mathbb{E} \left[ 1 - 2\gamma_t + \sum_{j=1}^k y_{tj}^2 \right]$$

$$= \sum_{t=1}^n \mathbb{E} \left[ (1 - \gamma_t)^2 + \sum_{j \neq A_t} y_{tj}^2 \right]$$

$$\leq \sum_{t=1}^n \mathbb{E} (1 + (k-1))$$

$$\leq \underline{nk}$$

$$\therefore R_{ni} \leq \frac{\log(k)}{\eta} + \eta nk$$

Setting  $\eta = \sqrt{\frac{\log(k)}{nk}}$

$$\leq 2\sqrt{nk \log k}$$

$$(1 - \hat{x}_{ti}) = \frac{\mathbb{1}\{A_t = i\} (1 - x_t)}{P_{ti}}$$

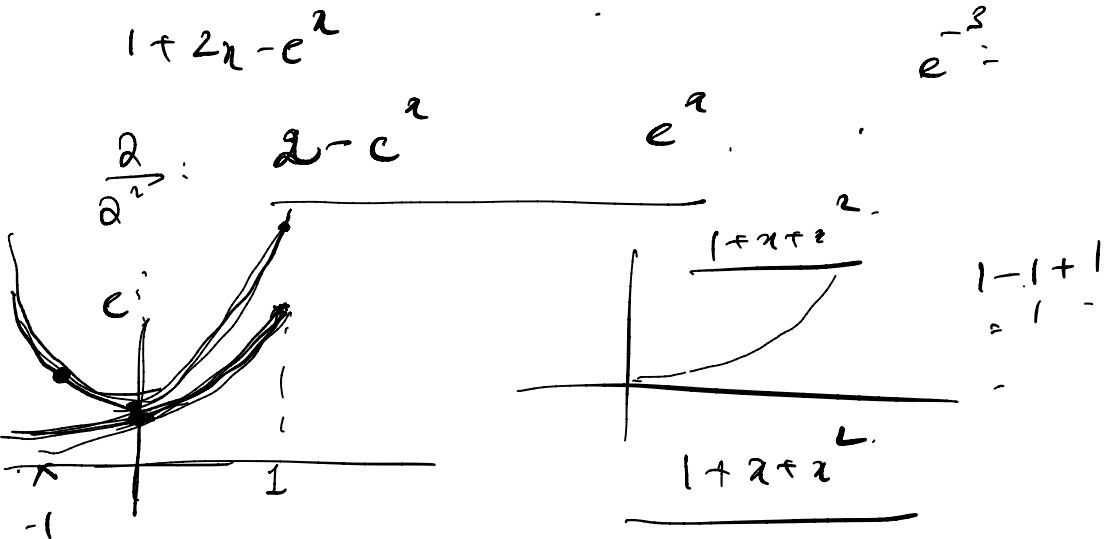
$$P_{ti} (1 - \hat{x}_{ti}) = \mathbb{1}\{A_t = i\} (1 - x_t)$$

$$\therefore \sum P_{ti} (1 - \hat{x}_{ti}) = \sum_i \mathbb{1}\{A_t = i\} (1 - x_t)$$

$$\therefore 1 - \sum P_{ti} \hat{x}_{ti} = (1 - x_t)$$

$$\therefore \underline{x_t = \sum P_{ti} \hat{x}_{ti}}$$

$$\underline{1 + 2x + x^2 - e^x \geq 0 \quad \forall x \leq 1}$$



Next:

Want regret to be small on expectation  
but with high probability!

will show:  $\forall \delta \in (0, 1)$ , w.p.  $(1 - \delta)$ ,

$$\hat{R}_n = O\left(\sqrt{nk \log\left(\frac{k}{\delta}\right)}\right)$$

Modification: 
$$\hat{Y}_{t,i} = \frac{\mathbb{1}\{A_t = i\} Y_t}{P_{t,i} + \sigma}$$

Called EXP-3-IX, implicit exploration