

We progress in rounds and @ time s , an adversary picks $l_s \in \mathbb{R}^k$, learner pick $I_s \in [k]$, learner observes l_{s, I_s} .

$$R_t = \sum_{s=1}^t l_{s, I_s} - \min_{i \in [k]} \sum_{s=1}^t l_{s, i}$$

Two types of adversaries

- adaptive adversary: loss @ time t is dependent on the players actions up to time t
- oblivious adversary: fixes all of it's losses ahead of time.

Goal $\mathbb{E} R_t \rightarrow$ expectation being taken over the randomness in learner and adversary.

Pseudo-Regret:

$$\begin{aligned} PR_t &= \mathbb{E} \left[\sum_{s=1}^t l_{s, I_s} - \min_{i \in [k]} \mathbb{E} \left[\sum_{s=1}^t l_{s, i} \right] \right] \\ &= \max_{i \in [k]} \mathbb{E} \left[\sum_{s=1}^t l_{s, I_s} - l_{s, i} \right] \end{aligned}$$

In general: $PR_t \leq \mathbb{E} R_t$

Stochastic Setting $\rightarrow PR_t$

For oblivious adversaries: $\min_{i \in [k]} \mathbb{E} \left[\sum_{s=1}^t l_{s, i} \right] = \min_{i \in [k]} \sum_{s=1}^t l_{s, i}$

$$\rightarrow PR_t = \mathbb{E} R_t$$

Remark Any deterministic learner will incur linear regret against some adversary.

\rightarrow at time t the learner has to choose a distribution $q_t \in \Delta_K = \{ (x_1, \dots, x_K) : \sum_{i=1}^K x_i = 1, x_i \geq 0 \}$ and then play $I_t \sim q_t$.

@ time s you see loss l_{s, I_s}

$$\forall j \in [K] \quad \hat{l}_{s,j} = \frac{\mathbb{1}\{I_t = j\} l_{s, I_s}}{q_{s,j}}, \quad q_{s,j} \neq 0$$

$$\mathbb{E} [\hat{l}_{s,j}] = \mathbb{E} \left[\mathbb{E} \left[\hat{l}_{s,j} \mid I_1, l_{1, I_1}, \dots, I_{s-1}, l_{s-1, I_{s-1}} \right] \right]$$

$$= \mathbb{E} \left[q_{s,j} \cdot \frac{l_{s,j}}{q_{s,j}} + (1 - q_{s,j}) \cdot 0 \right]$$

$$= \mathbb{E} [l_{s,j}] \rightarrow \text{IPS estimator}$$

\rightarrow Estimator for the reward of total reward for each arm

$$\hat{S}_{t,j} = \sum_{s=1}^t \hat{l}_{s,j}$$

Algorithm 7 EXP3**Input:** $\gamma \in [0, 1], \eta > 0, k$

- 1: Initialize $\lambda = (\frac{1}{k}, \dots, \frac{1}{k}), p_0 = \lambda$
- 2: for $s = 1, \dots, t$ do
- 3: Let $q_s = (1 - \gamma)p_s + \gamma\lambda$
- 4: Draw $I_s \sim q_s$ and observe loss ℓ_{s, I_s}
- 5: Calculate the estimated total rewards for each $i \in [k]$

$$\hat{S}_{si} = \sum_{r=1}^s \frac{\mathbf{1}(I_r = i) \ell_{r, I_r}}{q_{ri}}$$

- 6: Calculate the sampling distribution

$$p_{s+1, i} = \frac{\exp(-\eta \hat{S}_{si})}{\sum_{j=1}^k \exp(-\eta \hat{S}_{sj})} \text{ for } i \in [k].$$

7: end for

Theorem 6. Assume $\gamma \in [0, 1], \eta > 0$ and for all $i \in [k]$ and $s \leq t$, we have $|\ell_{si}| \leq 1$. Then for all $i \in [k]$

$$\mathbb{E} \left[\sum_{s=1}^t \ell_{s, I_s} - \ell_{s, i} \right] \leq \frac{\log(k)}{\eta} + 2\gamma t + \frac{1}{\eta} \mathbb{E} \left[\sum_{s=1}^t \sum_{j=1}^k q_{s, j} \psi(-\eta \hat{\ell}_{s, j}) \right]$$

where $\psi(x) = e^x - 1 - x \leq x^2, x \leq 1$

$$q_{s, j} \cdot \eta^2 \hat{\ell}_{s, j}^2$$

Example $\gamma = \eta k, \eta = \sqrt{\frac{3k \log(k)}{t}} \mid q_s = (1 - \gamma)p_s + \gamma\lambda$

$$|\eta \hat{\ell}_{s, j}| \leq \left| \eta \frac{\ell_{s, j}}{q_{s, j}} \right| \leq \eta \frac{k}{\gamma} \leq 1$$

We also have $\psi(x) \leq x^2, x \leq 1$

$$\frac{\log k}{\eta} + 2\eta k t + \frac{1}{\eta} \mathbb{E} \left[\sum_{s=1}^t \sum_{j=1}^k q_{s, j} \eta^2 \hat{\ell}_{s, j}^2 \right]$$

$$\leq \frac{\log k}{\eta} + 2\eta kt + \frac{1}{\eta} \mathbb{E} \left[\sum_{s=1}^t \sum_{j=1}^k \eta^2 l_{s,j}^2 \right]$$

$$\leq \frac{\log k}{\eta} + 3\eta kt$$

$$\leq \sqrt{3kt \log k} \rightarrow \text{even against oblivious adversary!}$$

$$\begin{aligned} \mathbb{E} \hat{l}_{s,j}^2 &= \mathbb{E} \frac{\mathbb{1}\{I_t = j\} l_{s,j}^2}{q_{s,j}^2} \\ &= \frac{l_{s,j}^2}{q_{s,j}^2} \leq \frac{1}{q_{s,j}} \end{aligned}$$

Proof $\hat{S}_t := \sum_{s=1}^t \sum_{j=1}^k q_{s,j} \hat{l}_{s,j}, \quad W_t = \sum_{j=1}^k \exp(-\eta \hat{S}_{t,j})$

$$\rightarrow \hat{S}_t = \sum_{s=1}^t l_{s, I_s}$$

$$\textcircled{1} \exp(-\eta \hat{S}_{t,i}) \leq \sum_{j=1}^k \exp(-\eta \hat{S}_{t,j})$$

$$\begin{aligned}
 & \prod_{j=1}^t \frac{W_j}{W_{j-1}} \\
 &= W_t \\
 &= W_0 \cdot \frac{W_1}{W_0} \cdot \frac{W_2}{W_1} \cdots \frac{W_t}{W_{t-1}} \\
 &= K \prod_{s=1}^t \frac{W_s}{W_{s-1}}
 \end{aligned}$$

$$\frac{W_s}{W_{s-1}} = \sum_{j=1}^K \frac{\exp(-\eta \hat{S}_{s,j})}{W_{s-1}}$$

$$= \sum_{j=1}^K \frac{\exp(-\eta \hat{S}_{s-1,j})}{W_{s-1}} \cdot \exp(-\eta \hat{l}_{s,j})$$

$$\psi(x) = e^x - 1 - x$$

$$= \sum_{j=1}^K P_{s,j} \exp(-\eta \hat{l}_{s,j})$$

$$= \sum_{j=1}^K P_{s,j} (\psi(-\eta \hat{l}_{s,j}) + 1 - \eta \hat{l}_{s,j})$$

$$\text{If } x \leq e^x \quad = 1 - \eta \sum_{j=1}^K P_{s,j} \hat{l}_{s,j} + \sum_{j=1}^K P_{s,j} \psi(-\eta \hat{l}_{s,j})$$

$$\leq \exp(-\eta \sum_{j=1}^K P_{s,j} \hat{l}_{s,j}) + \sum_{j=1}^K P_{s,j} (1 - \eta \hat{l}_{s,j})$$

→ plug into telescoping product

$$\exp(-\eta \hat{S}_{ti}) \leq k \exp\left(-\eta \sum_{s=1}^t \sum_{j=1}^k P_{s,j} \hat{l}_{s,j} + \sum_{s=1}^t \sum_{j=1}^k P_{s,j} \psi(-\eta \hat{l}_{s,j})\right)$$

$$\sum_{s=1}^t \sum_{j=1}^k P_{s,j} \hat{l}_{s,j} \leq \hat{S}_{ti} + \frac{\log k}{\eta} + \frac{1}{\eta} \sum_{s=1}^t \sum_{j=1}^k P_{s,j} \psi(-\eta \hat{l}_{s,j})$$

$$q_s = (1-\gamma) p_s + \gamma \lambda \rightarrow P_{s,j} = \frac{q_{s,j} - \gamma \lambda_j}{1-\gamma} \leq \frac{q_{s,j}}{1-\gamma}$$

Multiply both sides by $1-\gamma$, add

$$\gamma \sum_{s=1}^t \sum_{j=1}^k \frac{1}{k} \hat{l}_{s,j} - \sum_{s=1}^t \sum_{j=1}^k q_{s,j} \hat{l}_{s,j} \leq -\gamma \hat{S}_{ti} + \gamma \sum_{s=1}^t \sum_{j=1}^k \lambda_j \hat{l}_{s,j} + \frac{\log(k)}{\eta} + \frac{1}{\eta} \sum_{s=1}^t \sum_{j=1}^k q_{s,j} \psi(-\eta \hat{l}_{s,j})$$

$$\text{IT } \dots \hat{1} \dots \frac{t}{k} \dots 1 \dots 7$$

$$|E[-\gamma \mathcal{L}_{t,i} + \gamma \mathcal{L} \sum_{s=1}^b \frac{1}{K} \mathcal{L}_{t,rj}]|$$

$$|\mathcal{L}_{s,rj}| \leq \gamma \mathbb{E} \left[\sum_{s=1}^b \sum_{j=1}^K \frac{1}{K} \hat{\mathcal{L}}_{s,rj} - \frac{1}{K} \hat{\mathcal{L}}_{s,i} \right]$$

$$\leq 2\gamma t$$