

Week 3

Lecture 13

The expected regret can also be :

$$\mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \underbrace{\mathbb{E} \left[\sum_{t=1}^n \min_i x_{ti} \right]}_{\text{benchmark}} \quad (2a)$$

Here the benchmark is that we choose the best action in each round

$$\mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \underbrace{\min_i \mathbb{E} \left[\sum_{t=1}^n x_{ti} \right]}_{\text{benchmark}} \quad (2)$$

Here the benchmark is the one arm which if played for all rounds will give min loss

Though eq 2a is a better criterion, ^{but} it is harder to achieve and hence expected regret is defined by eq 2

As long as x_t are generated randomly the regret generated by eq 2a \geq regret by eq 2

This is because :

$$\mathbb{E} \left[\sum_{t=1}^n \min_i x_{ti} \right] \leq \min_i \mathbb{E} \left[\sum_{t=1}^n x_{ti} \right]$$

If x_t are generated according to some sequence then eq 2 becomes :

$$R(n, \pi) = \mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \min_i \left[\sum_{t=1}^n x_{ti} \right] \quad \text{--- (2b)}$$

In eq 2, the first term has 2 levels of randomness:
 \rightarrow randomness of loss by the adversary
 \rightarrow ~~do~~ arm selection by learner

$$\mathbb{E} [R(n, \pi)] = \mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \min_i \mathbb{E} \left[\sum_{t=1}^n x_{ti} \right] \quad \text{--- (2)}$$

\uparrow
 Pseudo regret, also known as

The learner chooses the next action based on history, hence the expected regret should ideally be over a particular sequence.

$$\therefore \mathbb{E} [R(n, \pi, \{x_t\})] = \mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \min_i \left[\sum_{t=1}^n x_{ti} \right] \quad \text{--- (2c)}$$

Assuming $\{X_t\}$ to be stochastic, \mathbb{E} have to be on both the terms on the R.H.S. of eq 2...

Hence revisiting the definitions again:

$$\begin{aligned} \text{Expected Regret:} \\ \mathbb{E} [R(n, \pi)] &= \mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \mathbb{E} \left[\sum_{t=1}^n \min_i x_{ti} \right] \\ &\geq \mathbb{E} \left[\sum_{t=1}^n x_{tI_t} \right] - \min_i \mathbb{E} \left[\sum_{t=1}^n x_{ti} \right] \end{aligned}$$

\uparrow

Pseudo regret

Whatever has been discussed till now about bandits is the Adversarial Bandit setting [starting from Lec 12]

Importance Sampling

At round t

$$P_t = (P_{t1}, P_{t2}, \dots, P_{tk})$$

Learner chooses $I_t \sim P_t$

Let $I_t = i$,

Learner suffers loss x_{ti}

At round t we can define an estimator for all $\{x_t\}$

Importance weighted estimator:

$$\forall j \in [K] \quad \hat{X}_{tj} = \frac{x_{tj}}{P_{tj}} \mathbb{1}\{I_t = j\} = \begin{cases} \frac{x_{ti}}{P_{ti}} & \text{for } j = i \\ 0 & \text{for } j \neq i \end{cases}$$

$$\mathbb{E}[\hat{X}_{tj}] = \sum_{i=1}^K \frac{x_{tj}}{P_{tj}} \mathbb{1}\{i=j\} \times P_{ti}$$

$$= \frac{x_{tj}}{P_{tj}} \times P_{tj}$$

$$= x_{tj}$$

Hence the importance weighted estimator is an unbiased estimator of the losses.

Hence though we don't have information for all the arms/actions, but we have unbiased estimators for all losses, which we can use to update the weights.
