

## Lecture 21: UCB

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## 21.1 Introduction:

In previous class, we discussed about stochastic MAB setting. In this setting, each arm  $i \in [K]$  is associated with an (unknown) probability distribution  $\nu_i$  and reward of each arm is i.i.d from  $\nu_i$ . we stated some methods for stochastic MAB setting such as e-greedy, softmax, Bayesian exploration, optimistic exploration. we also stated the regret bound for UCB(1) algorithm i.e.  $O(\frac{K \log T}{\Delta})$ .

$$\tilde{R}_T = \sum_{i=1}^K \mathbb{E} [N_{i,(T)}] \Delta_i$$

In this lecture we consistance with previous lecture notation. In this lecture will discuss about the arm pulling policy of the UCB(1) algorithm. In the calculation of pseudo regret we need  $\mathbb{E} [N_{i,(T)}]$  where  $i \neq i^*$ , so we will find out the expected number of times sub-optimal arm pulled by the algorithm.

## 21.2 UCB

$I_t$  = arm pulled by the UCB algorithm at round  $t$

$$I_t = \arg \max_i \left\{ \hat{u}_{i, N_{i,(t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i,(t-1)}}} \right\} \quad (21.1)$$

$N_{i,(t-1)}$  = random variable that count how many times arm  $i$  pulled in  $(t-1)$  round

**Theorem:** *The expected number of pull of sub-optimal arm  $i$  after  $T$  round,  $\Delta_i = \mu^* - \mu_i$*

$$\begin{aligned} \mathbb{E} [N_{i,(T)}] &\leq \frac{4\alpha \log T}{\Delta_i^2} + \frac{\pi^2}{3} + 1 \\ \tilde{R}_T &= \sum_{k=1}^K \mathbb{E} [N_{i,(T)}] \Delta_i \\ &\leq \sum_{i \neq i^*} \frac{4\alpha \log T}{\Delta_i} + K \left( \frac{\pi^2}{3} + 1 \right) \end{aligned}$$

$$\leq \sum_{i \neq i^*} \frac{4\alpha \log T}{\Delta_i} + C \quad (21.2)$$

From (21.2), We can say that, in total round  $T$ , Number of times optimal arm pull(  $i^*$  )

$$T - (k - 1) \left( \frac{4\alpha \log T}{\Delta_i^2} + \left( \frac{\pi^2}{3} + 1 \right) \right)$$

**Proof :** In round  $t$ ,  $i \neq i^*$  ( define  $I_t = i$  ) is played ( $t > k$ ) if arm  $i$  ( sub-optimal arm) chosen then equation (21.3) hold

$$\hat{u}_{i, N_{i, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i, (t-1)}}} \geq \hat{u}_{i^*, N_{i^*, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i^*, (t-1)}}} \quad (21.3)$$

and also if arm  $i$  (i.e. sub-optimal) pulled then at least one of the following inequality hold.

$$\hat{u}_{i^*, N_{i^*, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i^*, (t-1)}}} < \mu^* \quad (21.4)$$

$$\hat{u}_{i, N_{i, (t-1)}} - \sqrt{\frac{\alpha \log t}{N_{i, (t-1)}}} > \mu_i \quad (21.5)$$

$$N_{i, (t-1)} \leq \frac{4\alpha \log T}{\Delta_i^2} \quad (21.6)$$

if equation (21.4), (21.5) and (21.6) does not hold, then

$$\hat{u}_{i^*, N_{i^*, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i^*, (t-1)}}} \geq \mu^*$$

$$\hat{u}_{i, N_{i, (t-1)}} - \sqrt{\frac{\alpha \log t}{N_{i, (t-1)}}} \leq \mu_i$$

$$N_{i, (t-1)} > \frac{4\alpha \log T}{\Delta_i^2}$$

Let arm  $i$  (sub-optimal one) pulled and given above inequality (21.4),(21.5) and (21.6) not hold then, we get,

$$\begin{aligned} \hat{u}_{i, N_{i, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i, (t-1)}}} &\leq \mu_i + 2\sqrt{\frac{\alpha \log t}{N_{i, (t-1)}}} && \text{since (21.5) false} \\ &\left\{ 2\sqrt{\frac{\alpha \log t}{N_{i, (t-1)}}} < \Delta_i, \text{ since (21.6) is false and } \mu_i = \mu_i^* - \Delta_i \right\} \\ &\leq \mu_i^* - \Delta_i + \Delta_i \\ &\leq \hat{u}_{i^*, N_{i^*, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i^*, (t-1)}}} && \text{From 21.4} \end{aligned}$$

Which is contradicting (21.3), hence if sub-optimal  $i$  pulled then atleast one of (21.4),(21.5) and (21.6) hold.

Define:  $u = \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil$  and  $u < T$

Now, We calculate Expected number of time sub-optimal arm pulled i.e.

$$\begin{aligned}\mathbb{E}[N_{i,(T)}] &= \mathbb{E}\left[\sum_{t=1}^T \mathbb{1}_{(I_t=i)}\right] \\ &= \mathbb{E}[N_{i,(u)}] + \mathbb{E}\left[\sum_{t=u+1}^T \mathbb{1}_{(I_t=i)}\right]\end{aligned}$$

Put the value of  $u$

$$\begin{aligned}&= \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil + \mathbb{E}\left[\sum_{t=u+1}^T \mathbb{1}_{(I_t=i \text{ and (21.6) is false})}\right] \\ &= \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil + \mathbb{E}\left[\sum_{t=u+1}^T \mathbb{1}_{(I_t=i \text{ and (21.4) or 21.5 hold})}\right] \\ &= \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil + \mathbb{E}\left[\sum_{t=u+1}^T \mathbb{1}_{(I_t=i \text{ and (21.4) hold})}\right] + \mathbb{E}\left[\sum_{t=u+1}^T \mathbb{1}_{(I_t=i \text{ and (21.5) hold})}\right] \\ &= \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil + \sum_{t=u+1}^T P\{I_t = i \text{ and (21.4) hold}\} + \sum_{t=u+1}^T P\{I_t = i \text{ and (21.5) hold}\}\end{aligned}\tag{21.7}$$

here,

$$\begin{aligned}P\{I_t = i \text{ and (21.4) hold}\} &\leq P\left\{\hat{u}_{i^*, N_{i^*, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i^*, (t-1)}}} < \mu^*\right\} \\ &\quad [we \text{ know that } P\{\hat{\mu} - \mu > \epsilon\} \leq \exp(-2n\epsilon^2)] \\ &\leq P\left\{\exists s \in \{1, 2, \dots, t\} \quad \hat{\mu}_{i^*, s} + \sqrt{\frac{\alpha \log t}{s}} < \mu^*\right\} \\ &\leq P\left\{\hat{\mu}_{i^*, s} + \sqrt{\frac{\alpha \log t}{s}} < \mu^*\right\} \\ &\leq \sum_{s=1}^t P\left\{\hat{\mu}_{i^*, s} + \sqrt{\frac{\alpha \log t}{s}} < \mu^*\right\} \\ &\leq \sum_{s=1}^t P\left\{\hat{\mu}_{i^*, s} - \mu^* < \sqrt{\frac{\alpha \log t}{s}}\right\}\end{aligned}$$

using Hoeffding's Inequality

$$\leq \sum_{s=1}^t \exp(-2s(\frac{\alpha \log t}{s}))$$

$$\begin{aligned}
&= \sum_{s=1}^t t^{-2\alpha} \\
&\leq \frac{1}{t^{2\alpha-1}}
\end{aligned}$$

similarly we can show,

$$\begin{aligned}
P\{I_t = i \text{ and (21.5) hold}\} &\leq P\left\{\hat{u}_{i^*, N_{i^*, (t-1)}} + \sqrt{\frac{\alpha \log t}{N_{i^*, (t-1)}}} < \mu^*\right\} \\
&\leq \frac{1}{t^{2\alpha-1}}
\end{aligned}$$

Back to equation (21.7)

$$\begin{aligned}
\mathbb{E}[N_{i, (T)}] &= \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil + 2 \sum_{t=u+1}^T \frac{1}{t^{2\alpha-1}} \\
&\left[ 2\alpha - 1 > 2, \text{ since } \alpha > \frac{3}{2} \right] \\
&\leq \lceil \frac{4\alpha \log T}{\Delta_i^2} \rceil + 2 \sum_{t=u+1}^T \frac{1}{t^2} \\
&\leq \frac{4\alpha \log T}{\Delta_i^2} + \frac{\pi^2}{3} + 1 \qquad \left\{ \sum_{t=u+1}^T \frac{1}{t^2} \rightarrow \frac{\pi^2}{6} \right\}
\end{aligned}$$

Hence Proved.

## Case Analysis :

Case-1: let  $\mu_1, \mu_2, \mu_3$  mean of 1,2,3 arm respectively and  $\Delta = \arg \min_i \Delta_i$

Case-2: and  $\bar{\mu}_1, \bar{\mu}_2, \bar{\mu}_3$  mean of three different arm and  $\bar{\Delta} = \arg \min_i \Delta_i$

Qus. : if  $\bar{\Delta} < \Delta$  then, in which case regret will be more ?

We know that,

$$\begin{aligned}
\tilde{R}_T &= \sum_{i=1}^K \mathbb{E}[N_i(T)] \Delta_i \\
&\leq \min \left\{ T\Delta, O\left(\frac{K \log T}{\Delta}\right) \right\}
\end{aligned}$$

Regret depend upon value of T, if T is small ,then  $T\Delta$  dominate.

if  $T \gg \frac{1}{\Delta}$ , than  $O(\frac{K \log T}{\Delta})$  dominate.

## 21.3 References:

[1] P. Auer, N. Cesa-Bianchi, and P. Fischer. Finite-time analysis of the multiarmed bandit problem. *Machine Learning*, 47(2):235256, 2002.