

Assignment 7

Q.1 : The ε -Greedy Algorithm

$\forall t = 1, 2, \dots$

a) with probability $(1 - \varepsilon)$ choose arm with highest estimate, $A_t = \arg \max_i \hat{\mu}_i(t-1)$

b) with probability ε , select arm at random with uniform probability, i.e. $1/K$
where $K = \text{no. of arms}$

We know for Stochastic bandits :

$$\bar{R}(\pi, n) = \sum_{i=1}^K \mathbb{E}[T_i(n)] \Delta_i \quad \text{--- (1)}$$

where $\Delta_i = \max_a \mu_a - \mu_i$

and $T_i(n) = \text{no. of arm pulls}$

$$= \sum_{t=1}^n 1 \{I_t = i\}$$

Now for ε -greedy

$$T_i(n) = \frac{\varepsilon}{K} + (1 - \varepsilon) \Pr \left\{ \hat{\mu}_i \geq \arg \max_j \hat{\mu}_j^{(n-1)} \mid j \neq i \right\}$$

$$\begin{aligned}\mathbb{E}[T_i(n)] &= \mathbb{E}\left[\frac{\varepsilon}{K} + (1-\varepsilon) \Pr\left\{\hat{\mu}_i \geq \arg\max_{j \neq i} \hat{\mu}_j^{(n-1)}\right\}\right] \\ &= \frac{\varepsilon n}{K} + \mathbb{E}\left[(1-\varepsilon) \Pr\left\{\hat{\mu}_i \geq \arg\max_{j \neq i} \hat{\mu}_j^{(n-1)}\right\}\right]\end{aligned}$$

Substituting this in eq. (i)

$$\begin{aligned}\bar{R}(\varepsilon\text{-greedy}, n) &= \sum_{i=1}^K \left[\frac{\varepsilon n}{K} \Delta_i \overset{\text{Term (i)}}{\quad} \right. \\ &\quad \left. + \mathbb{E}\left[(1-\varepsilon) \Pr\left\{\hat{\mu}_i \geq \arg\max_{j \neq i} \hat{\mu}_j^{(n-1)}\right\}\right] \Delta_i \right] \\ &\quad \quad \quad \uparrow \\ &\quad \quad \quad \text{Term (ii)}\end{aligned}$$

Now if for any i $\hat{\mu}_i \geq \arg\max_{j \neq i} \hat{\mu}_j^{(n-1)}$, then the $\Delta_i = 0$, as per definition of Δ_i

Thus term ii would be equal to zero.

The regret thus simplifies to:

$$\bar{R}(\varepsilon\text{-greedy}, n) = \frac{\varepsilon n}{K} \sum_{i=1}^K \Delta_i$$

$$\Rightarrow \frac{\bar{R}_n}{n} = \frac{\varepsilon}{K} \sum_{i=1}^K \Delta_i$$

$$\forall \varepsilon > 0$$

Q.2: $\hat{\mu} = \sum_{t=1}^T \frac{X_t}{T}$, $T: \Omega \rightarrow \{1, 2, 3, \dots\}$

T is independent from X_T for all T

To prove: $P\left(\hat{\mu} - \mu \geq \sqrt{\frac{2 \log(1/\delta)}{T}}\right) \leq \delta$

Proof: Let $T = n$

$$P(\hat{\mu} - \mu \geq t) \leq \exp\left(\frac{-nt^2}{2\sigma^2}\right) \quad \text{--- (1)}$$

Let $\exp\left(\frac{-nt^2}{2\sigma^2}\right) = \delta$

Solving for t

$$\frac{-nt^2}{2\sigma^2} = \log \delta$$

$$\Rightarrow t^2 = \frac{-2\sigma^2 \log \delta}{n}$$

$$\Rightarrow t^2 = \frac{2\sigma^2 \log(1/\delta)}{n}$$

$$\Rightarrow t = \sqrt{\frac{2\sigma^2 \log(1/\delta)}{n}}$$

Since X_t 's are standard Gaussian random variables

$$\therefore \sigma^2 = 1$$

$$\therefore t = \sqrt{\frac{2 \log(1/\delta)}{n}}$$

Substituting in eq (1)

$$P\left(\hat{\mu} - \mu \geq \sqrt{\frac{2 \log(1/\delta)}{n}}\right) \leq \delta$$

Hence Proved
