Homework Assignment 6

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1 Offline Evaluation of Bandit Algorithms (60 points)

1.1

Algorithm UCB1 Initialization : Play each action once. for t=N+1,N+2,... do Play A_t =arg max $\hat{\mu}_{t-1}(a) + \sqrt{\frac{3 \ln t}{2N_{t-1}(a)}}$ Set $\hat{\mu}_t = \frac{\hat{L}_t(a)}{N_t(a)}$ $\hat{L}_t(a) = \hat{L}_{t-1}(a) + l_t^a * K$ end for

Algorithm EXP3

Input: Learning rate η $\forall a: \hat{L}_0(a) = 0$ for t=1,2,... do $\forall a: p_t(a) = \frac{e^{-\eta_t \hat{L}_{t-1}(a)}}{\sum_{a'} e^{-\eta_t \hat{L}_{t-1}(a')}}$ Sample A_t according to p_t and play it Observe and suffer $l_t^{A_t}$ $\operatorname{Set} \hat{l}_t^a = \frac{l_t^a \mathbb{I}(A_t = a) * K}{p_t(a)}$ $\forall a: \hat{L}_t(a) = \hat{L}_{t-1}(a) + \hat{l}_t^a \text{ end for }$

where K is the number of actions.

From question, we can bound the expected regret of EXP3 with $\eta = \sqrt{\frac{\ln K}{tK}}$

$$\mathbb{E}[R_T] \le 2\sqrt{tK \ln K}$$

The proof is based on lemma 5.2 on page 63 in notes.

Let X_1^a, X_2^a, \dots be K sequences of non-negative numbers. Let $L_t(a) = \sum_{s=1}^t X_s^a$. We define $W_t = \sum_a e^{-\eta L_t(a)}$. Start with an upper bound.

$$\frac{W_t}{W_{t-1}} = \frac{\sum_a e^{-\eta L_t(a)}}{\sum_a e^{-\eta L_{t-1}(a)}} \tag{1}$$

$$= \sum_{a} e^{-\eta X_t^a} \frac{e^{-\eta L_{t-1}(a)}}{\sum_{a'} e^{-\eta L_{t-1}(a')}}$$
 (2)

$$=\sum_{a}e^{-\eta X_{t}^{a}}p_{t}(a)\tag{3}$$

$$\leq \sum_{a} (1 - \eta X_t^a p_t(a) + \eta^2 (X_a^t)^2) p_t(a) \tag{4}$$

$$\leq e^{-\eta X_t^a p_t(a) + \eta^2 (X_a^t)^2 p_t(a)}$$
(5)

in (3), we used the inequality $e^x \le 1 + x + x^2$, in (4) we used the inequality $1 + x \le e^x$. Thus, we can get

$$\sum_{t=1}^{T} \sum_{a} p_t(a) \hat{l}_t^a - \min \hat{L}_T(a) \le \frac{\ln K}{\eta} + \eta \sum_{t=1}^{T} \sum_{a} p_t(a) (\hat{l}_t^a)^2$$

By taking expectation,

$$\mathbb{E}\left[\sum_{t=1}^{T} \sum_{a} p_t(a)\hat{l}_t^a\right] - \mathbb{E}\left[\min \hat{L}_T(a)\right] \le \frac{\ln K}{\eta} + \eta \mathbb{E}\left[\sum_{t=1}^{T} \sum_{a} p_t(a)(\hat{l}_t^a)^2\right]$$

$$\Longrightarrow \mathbb{E}\left[\sum_{t=1}^{T} \sum_{a} p_t(a)\hat{l}_t^a\right] - \min \mathbb{E}\left[\hat{L}_T(a)\right] \le \frac{\ln K}{\eta} + \eta \mathbb{E}\left[\sum_{t=1}^{T} \sum_{a} p_t(a)(\hat{l}_t^a)^2\right]$$

We consider the expectation terms,

$$\mathbb{E}[\sum_{t=1}^{T} \sum_{a} p_t(a) \hat{l}_t^a] = \mathbb{E}[\sum_{t=1}^{T} \sum_{a} \mathbb{E}[p_t(a) \hat{l}_t^a | A_1, A_2, ..., A_{t-1}]] = \mathbb{E}[\sum_{t=1}^{T} \sum_{a} p_t(a) l_t^a]$$

which is the expected loss of EXP3

$$\mathbb{E}[\hat{L}_T)(a)] = \mathbb{E}[\sum \hat{l}_t^a] = \sum l_t^a$$

which is the cumulative loss of time T.

$$\mathbb{E}\left[\sum_{t=1}^{T} \sum_{a} p_t(a) (\hat{l}_t^a)^2\right] = \mathbb{E}\left[\sum_{t=1}^{T} (\hat{l}_t^a)^2\right] \le KT$$

Hence, we can get

$$\mathbb{E}[R_T] \le 2\sqrt{tK\ln K}$$

with
$$\eta = \sqrt{\frac{\ln K}{tK}}$$
, $\mathbb{E}[R_T] \leq 2\sqrt{tK\ln(K)}$

1.2

- (a) The best arm is 14 and the worst is 16.
- (b) The best and two worst arms is 14, 2, 16.
- (c) The best and three worst arms is 14, 13, 2, 16.
- (d) The best, the median, and the worst arm is 14, 1, 16.

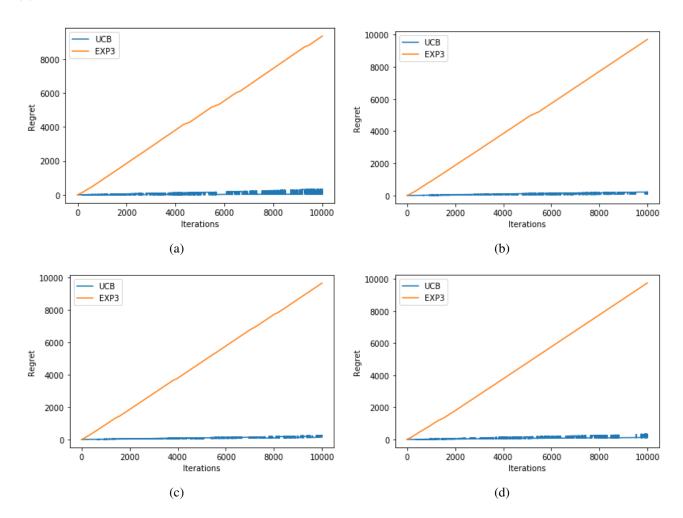


Figure 1: Regret with different arms

(But I think the plots are not correct, the line shouldn't be linear.)

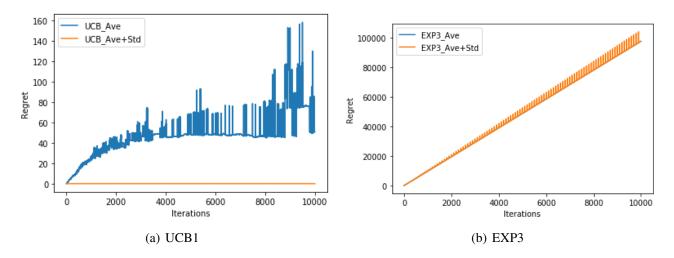


Figure 2: Regret of two algorithms

2 Empirical Evaluation of UCRL2 (25 points)

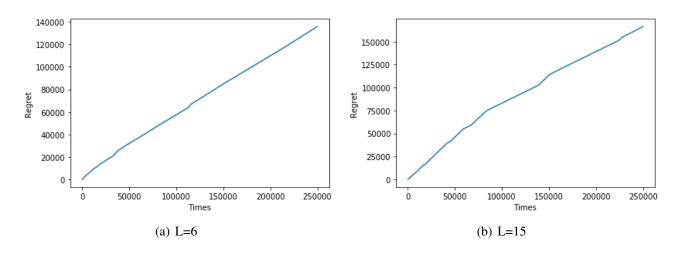


Figure 3: Regret with different states' numbers

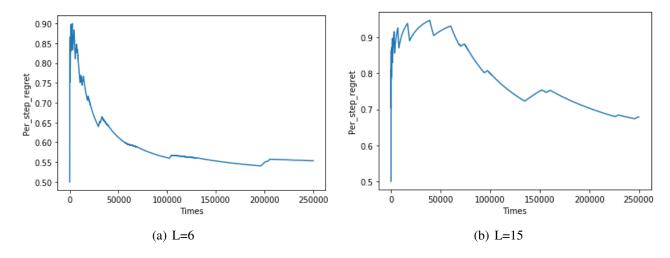


Figure 4: Pre_step_Regret with different states' numbers

With more states, the accumulated regret become more. Also each step's regret become bigger. L=15 take much more times to decrease the average regrets.

3 Computing Diameter (15 points)

3.1

For all optimal action a^* , let $p(s|s_0,a)=\delta$, whereas $p(s|s_0,a^*)=\delta+\epsilon$ for $\epsilon\in(0,\delta)$. Further, let $p(s_0|s,a)=\delta$ for all a. The diameter is $\frac{1}{\delta}$.