

# Stat 548 HW4

Jiahao Yang

June 3, 2018

## Problem 0 Certify you read the HW Policies

### 0.1 List of Collaborators

None

### 0.2 List of Acknowledgements

None

### 0.3 Certify that you have read the instructions

I have read and understood these policies.

## Problem 1 Logarithmic Regret of UCB

### 1.1

By the Hoeffding's bound and the union bound, with probability greater than  $1 - \delta$ , we have that for all the arms and for all time steps  $K \leq t \leq T$ , the confidence bound(ConfBound) is  $c\sqrt{\frac{\log(t/\delta)}{N_{a,t}}}$ .

By the construction of the UCB algorithm, we know that

$$\hat{\mu}_{a,t} + \text{ConfBound} \geq \hat{\mu}_* + \text{ConfBound} \geq \mu_*$$

Thus,

$$\mu_a \geq \hat{\mu}_{a,t} - \text{ConfBound} \geq \mu_* - 2\text{ConfBound},$$

$$\mu_* - \mu_a \leq 2\text{ConfBound} = 2c\sqrt{\frac{\log(t/\delta)}{N_{a,t}}} \leq 2c\sqrt{\frac{\log(T/\delta)}{N_{a,t}}},$$

$$\Delta_a^2 \leq 4c^2 \frac{\log(T/\delta)}{N_{a,t}},$$

$$N_{a,t} \leq c_3 \frac{\log(T/\delta)}{\Delta_a^2}.$$

For each sub-optimal arm a, let t be the last time that arm a is been pulled up. Then we have  $N_{a,T} = N_{a,t} \leq c_3 \frac{\log(T/\delta)}{\Delta_a^2}$ .

## 1.2

The regret for arm  $a$  is  $\mu_\star - \mu_a = \Delta_a$ . And from section 1.1, we know that the total number of times that any sub-optimal arm  $a$  will be pulled up to time  $T$  will be bounded by  $c_3 \frac{\log(T/\delta)}{\Delta_a^2}$ .

Thus, with probability greater than  $1 - \delta$ , the total observed regret is bounded as following.

$$T\mu_\star - \sum_{t \leq T} \mu_{a_t} \leq c_3 \sum_{a \neq a_\star} \left( \frac{\log(T/\delta)}{\Delta_a^2} \Delta_a \right) = c_3 \sum_{a \neq a_\star} \frac{\log(T/\delta)}{\Delta_a}.$$

## 1.3

Choose  $\delta = \frac{1}{T^2}$ . Note that with probability greater than  $1 - \frac{1}{T^2}$ , our regret is bounded by  $c_3 \sum_{a \neq a_\star} \frac{\log(T/\delta)}{\Delta_a}$ . Also if we "fail", the largest regret we can pay is  $T$ , and this occurs with probability less than  $\frac{1}{T^2}$ . Thus the expected regret is,

$$\begin{aligned} T\mu_\star - E\left[\sum_{t \leq T} X_t\right] &\leq \left(1 - \frac{1}{T^2}\right) c_3 \sum_{a \neq a_\star} \frac{\log(T/(1/T^2))}{\Delta_a} + \frac{1}{T^2} T \\ &\leq c_3 \sum_{a \neq a_\star} \frac{3\log(T)}{\Delta_a} + \frac{1}{T} \frac{K-1}{\max(\Delta_a)} \\ &\leq \max(3c_3, 1) \sum_{a \neq a_\star} \frac{\log(T) + \frac{1}{T}}{\Delta_a} \\ &\leq \max(3c_3, 1) \sum_{a \neq a_\star} \frac{2\log(T)}{\Delta_a} \\ &\leq c_4 \sum_{a \neq a_\star} \frac{\log(T)}{\Delta_a} \end{aligned}$$

## 1.4

Since  $c_4 \sum_{a \neq a_\star} \frac{\log(T)}{\Delta_a} \leq c_4 \sum_{a \neq a_\star} \frac{\log(T)}{\Delta_{\min}} = c_4 \frac{(K-1)\log(T)}{\Delta_{\min}} \leq c \frac{K\log(T)}{\Delta_{\min}}$ , we have

$$T\mu_\star - E\left[\sum_{t \leq T} X_t\right] \leq c \frac{K\log(T)}{\Delta_{\min}}.$$

The UCB algorithm is shown below.

At each time  $t$ :

1) Pull arm :

$$a_t = \operatorname{argmax}(\hat{\mu}_{a,t} + c\sqrt{\frac{\log(t/\delta)}{N_{a,t}}}) := \operatorname{argmax}(\hat{\mu}_{a,t} + \operatorname{ConfBound}_{a,t}),$$

where  $c \leq 10$  and  $\delta = \frac{1}{T^2}$ ,

2) Observe reward  $X_i$ ,

3) Update  $\mu_{a,t}, N_{a,t}, \operatorname{ConfBound}_{a,t}$

## Problem 2 Thompson Sampling

### 2.1

From the question, we know that

$$\mu_1 = 1/6, \mu_2 = 1/2, \mu_3 = 2/3, \mu_4 = 3/4, \mu_5 = 5/6.$$

And it is obvious that if we keep pull the arm with biggest expected reward, the maximum expected reward we can obtain in T steps is  $\frac{5T}{6}$ .

### 2.2

The quantities that the algorithm maintains in memory are shown below.

- 1) the parameters of distribution  $Beta(\alpha_{a,t}, \beta_{a,t})$ ,  $\alpha_{a,t}$  and  $\beta_{a,t}$ .
- 2) the sample from posterior distribution  $Beta(\alpha_{a,t}, \beta_{a,t})$ ,  $\hat{\mu}_{a,t}$ .
- 3) the observed reward,  $X_t$ .
- 4) the number of times we pulled arm a up to time t,  $N_{a,t}$ .

The updates for the posterior distributions is,

$$Beta(\alpha_{a,t+1}, \beta_{a,t+1}) = \begin{cases} Beta(\alpha_{a,t}, \beta_{a,t}), & a_t \neq a \\ Beta(\alpha_{a,t} + X_t, \beta_{a,t} + 1 - X_t), & a_t = a \end{cases} \quad (1)$$

### 2.3

The plot is shown below.

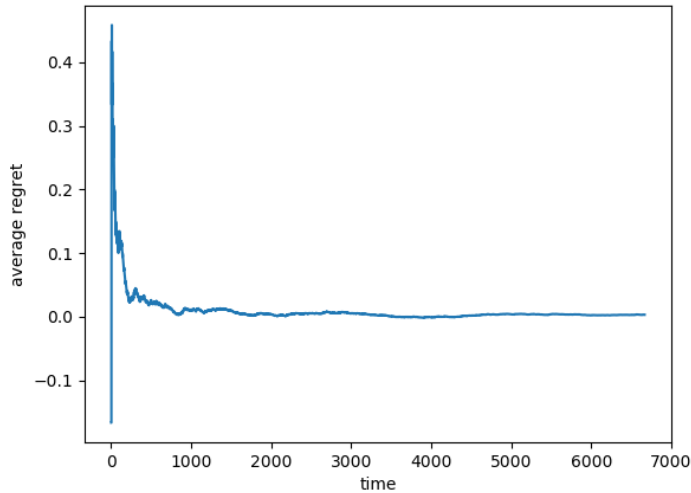


Figure 1: average regret vs time

### 2.4

The results are shown below.

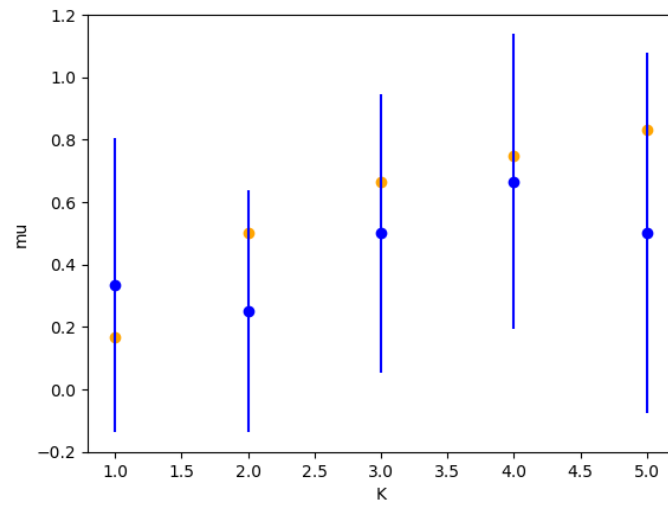


Figure 2: mu vs arm when  $T = 6$

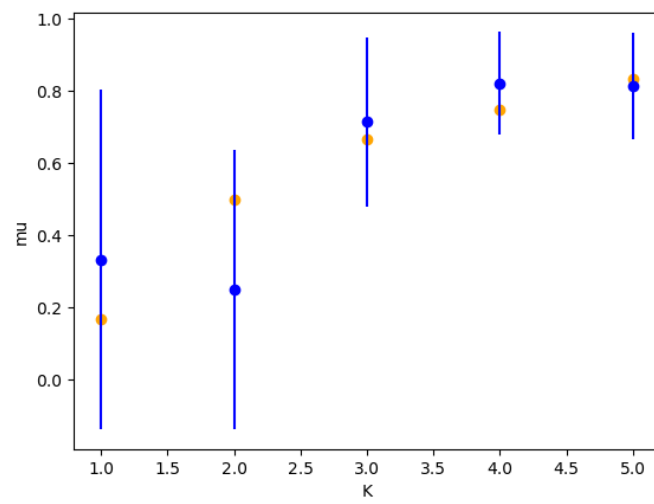


Figure 3: mu vs arm when  $T = 66$

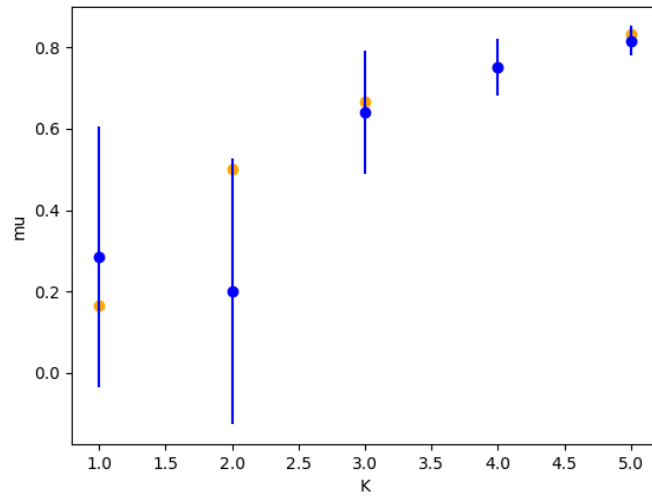


Figure 4: mu vs arm when  $T = 666$

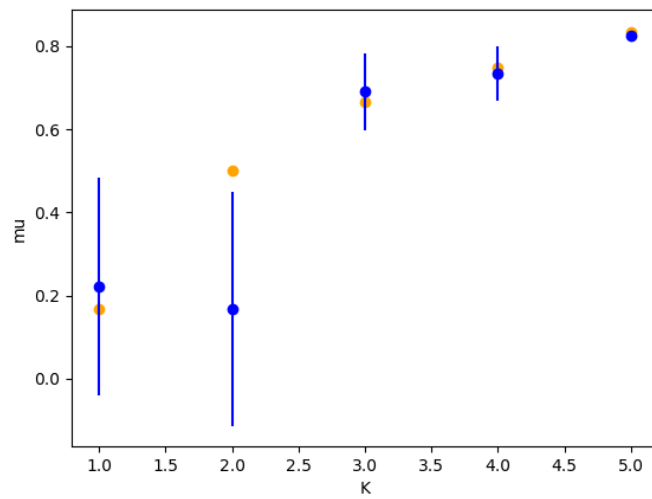


Figure 5: mu vs arm when  $T = 6666$

## 2.5

The result is shown below.

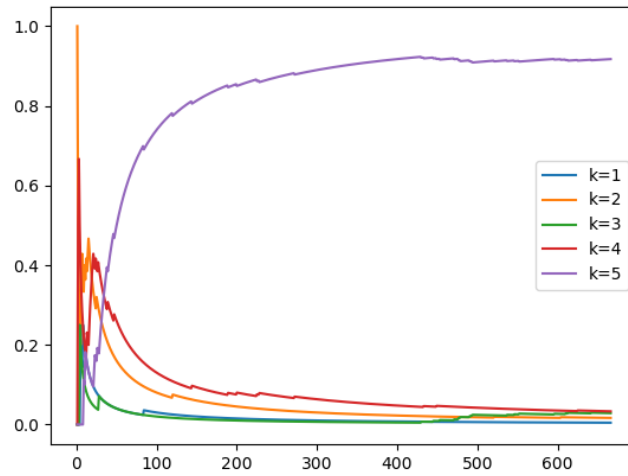


Figure 6: mu vs arm when  $T = 6666$

## 2.6

From screen print of my code when I choose  $T = 6666$  is

```
the first time achieve 0.95 and stays 10 steps: 3529
```

Figure 7: screen print when  $T = 6666$

The first time achieve 0.95 and stays 10 steps is 3529.