

Exploration in Reinforcement Learning (theory)

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- The deadline is **January 20, 2023. 23h59**
- By doing this homework you agree to the *late day policy, collaboration and misconduct rules* reported on Piazza.
- **Mysterious or unsupported answers will not receive full credit.** A correct answer, unsupported by calculations, explanation, or algebraic work will receive no credit; an incorrect answer supported by substantially correct calculations and explanations might still receive partial credit.
- Answers should be provided in **English**.
- [My answers can be found after each exercise.](#)

1 Best Arm Identification

In best arm identification (BAI), the goal is to identify the best arm in as few samples as possible. We will focus on the fixed-confidence setting where the goal is to identify the best arm with high probability $1 - \delta$ in as few samples as possible. A player is given k arms with expected reward μ_i . At each timestep t , the player selects an arm to pull (I_t), and they observe some reward ($X_{I_t,t}$) for that sample. At any timestep, once the player is confident that they have identified the best arm, they may decide to stop.

δ -correctness and fixed-confidence objective. Denote by τ_δ the stopping time associated to the stopping rule, by i^* the best arm and by \hat{i} an estimate of the best arm. An algorithm is δ -correct if it predicts the correct answer with probability at least $1 - \delta$. Formally, if $\mathbb{P}_{\mu_1, \dots, \mu_k}(\hat{i} \neq i^*) \leq \delta$ and $\tau_\delta < \infty$ almost surely for any μ_1, \dots, μ_k . Our goal is to find a δ -correct algorithm that minimizes the sample complexity, that is, $\mathbb{E}[\tau_\delta]$ the expected number of sample needed to predict an answer. Assume that the best arm i^* is *unique* (i.e., there exists only one arm with maximum mean reward).

Notation

- I_t : the arm chosen at round t .
- $X_{i,t} \in [0, 1]$: reward observed for arm i at round t .
- μ_i : the expected reward of arm i .
- $\mu^* = \max_i \mu_i$.
- $\Delta_i = \mu^* - \mu_i$: suboptimality gap.

Consider the following algorithm

The algorithm maintains an active set S and an estimate of the empirical reward of each arm $\hat{\mu}_{i,t} = \frac{1}{t} \sum_{j=1}^t X_{i,j}$.

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Input:  $k$  arms, confidence  $\delta$ 
 $S = \{1, \dots, k\}$ 
for  $t = 1, \dots$  do
    Pull all arms in  $S$ 
     $S = S \setminus \left\{ i \in S : \exists j \in S, \hat{\mu}_{j,t} - U(t, \delta') \geq \hat{\mu}_{i,t} + U(t, \delta') \right\}$ 
    if  $|S| = 1$  then
        STOP
        return  $S$ 
    end
end

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- Compute the function $U(t, \delta)$ that satisfy the any-time confidence bound. Let

$$\mathcal{E} = \bigcup_{i=1}^k \bigcup_{t=1}^{\infty} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta')\}.$$

Using Hoeffding's inequality and union bounds, shows that $\mathbb{P}(\mathcal{E}) \leq \delta$ for a particular choice of δ' . This is called “bad event” since it means that the confidence intervals do not hold.

- Show that with probability at least $1 - \delta$, the optimal arm $i^* = \arg \max_i \{\mu_i\}$ remains in the active set S . Use your definition of δ' and start from the condition for arm elimination. From this, use the definition of $\neg \mathcal{E}$.
- Under event $\neg \mathcal{E}$, show that an arm $i \neq i^*$ will be removed from the active set when $\Delta_i \geq C_1 U(t, \delta')$ for some constant $C_1 \in \mathbb{N}$. Compute the time required to have such condition for each non-optimal arm. Use the condition of arm elimination applied to arm i^* .¹
- Compute a bound on the sample complexity (after how many *pulls* the algorithm stops) for identifying the optimal arm w.p. $1 - \delta$.
- We assumed that the optimal arm i^* is unique. Would the algorithm still work if there exist multiple best arms? Why?

Note that also a variations of UCB are effective in pure exploration.

¹Note that $at \geq \log(bt)$ can be solved using Lambert W function. We thus have $t \geq \frac{-W_{-1}(-a/b)}{a}$ since, given $a = \Delta_i^2$ and $b = 2k/\delta$, $-a/b \in (-1/e, 0)$. We can make the bound more explicit by noticing that $-1 - \sqrt{2u} - u \leq W_{-1}(-e^{-u-1}) \leq -1 - \sqrt{2u} - 2u/3$ for $u > 0$ [Chatzigeorgiou, 2016]. Then $t \geq \frac{1+\sqrt{2u}+u}{a}$ with $u = \log(b/a) - 1$.

1.1 Answer - Best Arm Identification

- To start, let's define the any-time confidence bound such that:

$$\mathbb{P} \left(\bigcup_{t=1}^{\infty} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta)\} \right) \leq \delta$$

It comes that:

$$\mathbb{P} \left(\bigcup_{t=1}^{\infty} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta)\} \right) \leq \sum_{t=1}^{\infty} \mathbb{P} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta)\}$$

Therefore, it's to find $U(t, \delta)$ that satisfies:

$$\mathbb{P} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta)\} \leq \frac{\delta}{2t^2}$$

Using Hoeffding's inequality, it comes that:

$$\mathbb{P} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta)\} \leq 2\exp(-2t(U(t, \delta))^2)$$

Hence,

$$\frac{\delta}{2t^2} = 2\exp(-2t(U(t, \delta))^2) \iff U(t, \delta) = \sqrt{\frac{\log(\frac{4t^2}{\delta})}{2t}}$$

Now, let's find a particular δ' such that $\mathbb{P}(\mathcal{E}) \leq \delta$.

$$\begin{aligned} \mathbb{P}(\mathcal{E}) &= \mathbb{P} \left(\bigcup_{i=1}^k \bigcup_{t=1}^{\infty} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta')\} \right) \leq \sum_{i=1}^k \sum_{t=1}^{\infty} \mathbb{P} \{|\hat{\mu}_{i,t} - \mu_i| > U(t, \delta')\} \\ &\leq \sum_{i=1}^k \sum_{t=1}^{\infty} \frac{\delta'}{2t^2} = \sum_{i=1}^k \frac{\delta'}{2} \sum_{t=1}^{\infty} \frac{1}{t^2} = \frac{k\delta'\pi}{12} \leq k\delta' \implies \boxed{\delta' = \frac{\delta}{k}} \end{aligned}$$

- Now, let's find that with probability at least $1 - \delta$, the optimal arm $i^* = \arg \max_i \{\mu_i\}$ remains in the active set S .

Recall: the optimal arm i^* doesn't remain in S if $\exists j \in S, \hat{\mu}_{j,t} - U(t, \delta') \geq \hat{\mu}_{i^*,t} + U(t, \delta')$ (1)

We suppose that \mathcal{E} (resp. \mathcal{E}^c) holds with probability δ (resp. $1 - \delta$), where:

$$\mathcal{E}^c = \bigcap_{i=1}^k \bigcap_{t=1}^{\infty} \{|\hat{\mu}_{i,t} - \mu_i| \leq U(t, \delta')\}$$

It comes that:

$$\begin{aligned} -U(t, \delta') \leq \hat{\mu}_{i^*,t} - \mu_{i^*} \leq U(t, \delta') &\implies \hat{\mu}_{i^*,t} + U(t, \delta') \geq \mu_{i^*} \\ -U(t, \delta') \leq \hat{\mu}_{j,t} - \mu_j \leq U(t, \delta') &\implies \hat{\mu}_{j,t} - U(t, \delta') \leq \mu_j \end{aligned}$$

Hence, with (1) inequality:

$$\mu_j \geq \hat{\mu}_{j,t} - U(t, \delta') \geq \hat{\mu}_{i^*,t} + U(t, \delta') \geq \mu_{i^*}$$

Which cannot hold since i^* is the optimal arm.

Hence with probability $1 - \delta$, the optimal arm i^* remains in the active set S .

- Now, let's show that under \mathcal{E}^c , an arm $i \neq i^*$ will be removed from the active set when:

$$\Delta_i \geq C_1 U(t, \delta')$$

Recall: the arm i doesn't remain in S if $\hat{\mu}_t^* - U(t, \delta') \geq \hat{\mu}_{i,t} + U(t, \delta')$ (1). Where $\hat{\mu}_t^*$ is the estimated reward of the arm with the largest expected reward μ^* .

As it has been seen previously, if \mathcal{E}^c holds, it comes that:

$$-U(t, \delta') \leq \hat{\mu}_t^* - \mu^* \leq U(t, \delta') \implies \hat{\mu}_t^* \geq \mu^* - U(t, \delta')$$

$$-U(t, \delta') \leq \hat{\mu}_{i,t} - \mu_i \leq U(t, \delta') \implies \hat{\mu}_{i,t} \leq \mu_i + U(t, \delta')$$

Hence, with inequality (1):

$$\mu^* - 2U(t, \delta') \geq \mu_i + 2U(t, \delta') \iff \mu^* - \mu_i = \Delta_i \geq 4U(t, \delta')$$

Now, let's compute the time required to have such condition for each non-optimal arm.

Since $U(t, \delta') = \sqrt{\frac{\log(\frac{4kt^2}{\delta})}{2t}}$, the condition comes that:

$$\Delta_i \geq 4\sqrt{\frac{\log(\frac{4kt^2}{\delta})}{2t}}$$

Then, it's needed to find the minimum value of t which holds this inequality, for each arm (T_i).

$$\Delta_i \geq 4\sqrt{\frac{\log(\frac{4kt^2}{\delta})}{2t}} \iff \frac{\Delta_i t}{8} \geq \log(\frac{4t^2}{\delta})$$

$$\implies \forall i (\neq i^*) \in S, T_i \leq C \frac{\log(\frac{k \log(\Delta_i^{-2})}{\delta})}{\Delta_i^2}$$

- Now, let's compute a bound on the sample complexity. As it has been seen previously, each arm $i \neq i^*$ will be removed from the active set S after it has been sampled at most T_i times. Therefore to find upper bound on the sample complexity, it's need to sum the upper bounds on the sample on each non-optimal arm. The bound is:

$$\mathcal{O} \left(\sum_{i=1, i \neq i^*}^k \frac{\log(k \log(\Delta_i^{-2}))}{\Delta_i^2} \right)$$

- Since the optimal arm i^* doesn't remain in S if $\exists j \in S, \hat{\mu}_{j,t} - U(t, \delta') \geq \hat{\mu}_{i,t} + U(t, \delta')$, it should not work since it won't converge. Indeed, once all non-optimal arms will be removed, the algorithm will iterate to infinity.

End of Answer - Best Arm Identification.

Let's move on - 2 Regret Minimization in RL

2 Regret Minimization in RL

Consider a finite-horizon MDP $M^* = (S, A, p_h, r_h)$ with stage-dependent transitions and rewards. Assume rewards are bounded in $[0, 1]$. We want to prove a regret upper-bound for UCBVI. We will aim for the suboptimal regret bound ($T = KH$)

$$R(T) = \sum_{k=1}^K V_1^*(s_{1,k}) - V_1^{\pi_k}(s_{1,k}) = \tilde{O}(H^2 S \sqrt{AK})$$

Define the set of plausible MDPs as

$$\mathcal{M}_k = \{M = (S, A, p_{h,k}, r_{h,k}) : r_{h,k}(s, a) \in \beta_{h,k}^r(s, a), p_{h,k}(\cdot|s, a) \in \beta_{h,k}^p(s, a)\}$$

Confidence intervals can be anytime or not.

- Define the event $\mathcal{E} = \{\forall k, M^* \in \mathcal{M}_k\}$. Prove that $\mathbb{P}(\neg \mathcal{E}) \leq \delta/2$. First step, construct a confidence interval for rewards and transitions for each (s, a) using Hoeffding and Weissmain inequality (see appendix), respectively. So, we want that

$$\mathbb{P}\left(\forall k, h, s, a : \hat{r}_{h,k}(s, a) - r_h(s, a) \leq \beta_{h,k}^r(s, a) \wedge \|\hat{p}_{h,k}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 \leq \beta_{h,k}^p(s, a)\right) \geq 1 - \delta/2$$

- Define the bonus function and consider the Q-function computed at episode k

$$Q_{h,k}(s, a) = \hat{r}_{h,k}(s, a) + b_{h,k}(s, a) + \sum_{s'} \hat{p}_{h,k}(s'|s, a) V_{h+1,k}(s')$$

with $V_{h,k}(s) = \min\{H, \max_a Q_{h,k}(s, a)\}$. Recall that $V_{H+1,k}(s) = V_{H+1}^*(s) = 0$. Prove that under event \mathcal{E} , Q_k is optimistic, i.e.,

$$Q_{h,k}(s, a) \geq Q_h^*(s, a), \forall s, a$$

where Q^* is the optimal Q-function of the unknown MDP M^* . Note that $\hat{r}_{H,k}(s, a) + b_{H,k}(s, a) \geq r_{H,k}(s, a)$ and thus $Q_{H,k}(s, a) \geq Q_H^*(s, a)$ (for a properly defined bonus). Then use induction to prove that this holds for all the stages h .

- In class we have seen that

$$\delta_{1k}(s_{1,k}) \leq \sum_{h=1}^H Q_{h,k}(s_{hk}, a_{hk}) - r(s_{hk}, a_{hk}) - \mathbb{E}_{Y \sim p(\cdot|s_{hk}, a_{hk})}[V_{h+1,k}(Y)] + m_{hk} \quad (1)$$

where $\delta_{hk}(s) = V_{hk}(s) - V_h^{\pi_k}(s)$ and $m_{hk} = \mathbb{E}_{Y \sim p(\cdot|s_{hk}, a_{hk})}[\delta_{h+1,k}(Y)] - \delta_{h+1,k}(s_{h+1,k})$. We now want to prove this result. Denote by a_{hk} the action played by the algorithm (you will have to use the greedy property).

1. Show that $V_h^{\pi_k}(s_{hk}) = r(s_{hk}, a_{hk}) + \mathbb{E}_p[V_{h+1,k}(s')] - \delta_{h+1,k}(s_{h+1,k}) - m_{h,k}$
2. Show that $V_{h,k}(s_{hk}) \leq Q_{h,k}(s_{hk}, a_{hk})$.
3. Putting everything together prove Eq. 1.

- Since $(m_{hk})_{hk}$ is an MDS, using Azuma-Hoeffding we show that with probability at least $1 - \delta/2$

$$\sum_{k,h} m_{hk} \leq 2H \sqrt{KH \log(2/\delta)}$$

Show that the regret is upper bounded with probability $1 - \delta$ by

$$R(T) \leq 2 \sum_{kh} b_{hk}(s_{hk}, a_{hk}) + 2H \sqrt{KH \log(2/\delta)}$$

- Finally, we have that [Domingues et al., 2021]

$$\sum_{h,k} \frac{1}{\sqrt{N_{hk}(s_{hk}, a_{hk})}} \lesssim H^2 S^2 A + 2 \sum_{h=1}^H \sum_{s,a} \sqrt{N_{hK}(s, a)}$$

Complete this by showing an upper-bound of $H \sqrt{SAK}$, which leads to $R(T) \lesssim H^2 S \sqrt{AK}$

2.1 Answer - Regret Minimization in RL

- As explained in the question, it's needed to show that:

$$\mathbb{P}\left(\forall k, h, s, a : |\hat{r}_{hk}(s, a) - r_h(s, a)| \leq \beta_{hk}^r(s, a) \wedge \|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 \leq \beta_{hk}^p(s, a)\right) \geq 1 - \delta/2$$

$$\mathbb{P}\left(\exists k, h, s, a : |\hat{r}_{hk}(s, a) - r_h(s, a)| > \beta_{hk}^r(s, a) \vee \|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 > \beta_{hk}^p(s, a)\right) \leq \delta/2$$

$$\mathbb{P}\left(|\hat{r}_{hk}(s, a) - r_h(s, a)| > \beta_{hk}^r(s, a)\right) + \mathbb{P}\left(\|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 > \beta_{hk}^p(s, a)\right) \leq \delta/2$$

For rewards Using Hoeffding's inequality, it comes that:

$$\mathbb{P}\left(|\hat{r}_{hk}(s, a) - r_h(s, a)| > \beta_{hk}^r(s, a)\right) \leq 2\exp(-2N_{h,k}(\beta_{hk}^r(s, a))^2)$$

We want that :

$$2\exp(-2N_{h,k}(\beta_{hk}^r(s, a))^2) = \frac{\delta}{4|S||A|HK} \iff \beta_{hk}^r(s, a) = \sqrt{\frac{\log(\frac{8|S||A|HK}{\delta})}{2N_{h,k}}}$$

It comes that:

$$\mathbb{P}\left(|\hat{r}_{hk}(s, a) - r_h(s, a)| > \beta_{hk}^r(s, a)\right) \leq 2\exp\left(\frac{-2N_{h,k}\log(\frac{\delta}{8|S||A|HK})}{-2N_{h,k}}\right) = \frac{\delta}{4|S||A|HK} \leq \frac{\delta}{4}$$

For transitions Using Weissmain inequality, it comes that:

$$\mathbb{P}\left(\|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 > \beta_{hk}^p(s, a)\right) \leq (2^{|S|} - 2)\exp\left(-\frac{N_{h,k}(\beta_{hk}^p(s, a))^2}{2}\right)$$

We want that:

$$(2^{|S|} - 2)\exp\left(-\frac{N_{h,k}(\beta_{hk}^p(s, a))^2}{2}\right) = \frac{\delta}{4|S||A|HK} \iff \beta_{hk}^p(s, a) = \sqrt{\frac{2\log((2^{|S|}-2)4|S||A|HK)}{N_{h,k}}}$$

It comes that:

$$\mathbb{P}\left(\|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 > \beta_{hk}^p(s, a)\right) \leq (2^{|S|} - 2)\exp\left(-\frac{N_{h,k}\left(\sqrt{\frac{2\log((2^{|S|}-2)4|S||A|HK)}{N_{h,k}}}\right)^2}{2}\right) = \frac{\delta}{4|S||A|HK} \leq \frac{\delta}{4}$$

So finally, it comes that:

$$\mathbb{P}\left(\exists k, h, s, a : |\hat{r}_{hk}(s, a) - r_h(s, a)| > \beta_{hk}^r(s, a) \vee \|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 > \beta_{hk}^p(s, a)\right) \leq \frac{\delta}{4} + \frac{\delta}{4} = \frac{\delta}{2}$$

Hence,

$$\boxed{\mathbb{P}\left(\forall k, h, s, a : |\hat{r}_{hk}(s, a) - r_h(s, a)| \leq \beta_{hk}^r(s, a) \wedge \|\hat{p}_{hk}(\cdot|s, a) - p_h(\cdot|s, a)\|_1 \leq \beta_{hk}^p(s, a)\right) \geq 1 - \frac{\delta}{2}}$$

- The bonus function is defined as:

$$b_{h,k}(s, a) = H\sqrt{\frac{2\log((2^{|S|}-2)4|S||A|HK)}{N_{h,k}}}$$

Induction will be used to prove that for all the stages:

$$Q_{h,k}(s, a) \geq Q_h^*(s, a), \forall s, a$$

For $h = H$: Note that $\hat{r}_{H,k}(s, a) + b_{H,k}(s, a) \geq r_{H,k}(s, a)$ and thus $Q_{H,k}(s, a) \geq Q_H^*(s, a)$.

For $h < H$: We suppose that $Q_{h,k}(s, a) \geq Q_h^*(s, a), \forall s, a$. It's known that $V_{h,k}(s) = \min\{H, \max_a Q_{h,k}(s, a)\}$, $Q_{h,k}(s, a) \geq Q_h^*(s, a)$ and then $V_{h,k}(s) \geq V_h^*(s)$.

It comes that:

$$Q_{h-1,k}(s, a) = \hat{r}_{h-1,k}(s, a) + b_{h-1,k}(s, a) + \sum_{s'} \hat{p}_{h-1,k}(s'|s, a) V_{h,k}(s')$$

$$Q_{h-1,k}(s, a) \geq \hat{r}_{h-1,k}(s, a) + b_{h-1,k}(s, a) + \sum_{s'} \hat{p}_{h-1,k}(s'|s, a) V_h^*(s')$$

$$Q_{h-1,k}(s, a) \geq r_{h-1,k}(s, a) + \sum_{s'} p_{h-1,k}(s'|s, a) V_h^*(s') \quad \text{under } \mathcal{E}$$

Hence,

$$Q_{h-1,k}(s, a) \geq Q_{h-1}^*(s, a) \quad \forall (s, a)$$

So finally, $Q_{h,k}(s, a) \geq Q_h^*(s, a) \quad \forall (s, a)$

- 1. Let's show that $V_h^{\pi_k}(s_{hk}) = r(s_{hk}, a_{hk}) + \mathbb{E}_p[V_{h+1,k}(s')] - \delta_{h+1,k}(s_{h+1,k}) - m_{h,k}$.

$$\begin{aligned} m_{h,k} &= \mathbb{E}_{Y \sim p(\cdot | s_{hk}, a_{hk})} [\delta_{h+1,k}(Y)] - \delta_{h+1,k}(s_{h+1,k}) \\ &\implies \delta_{h+1,k}(s_{h+1,k}) = \mathbb{E}_{Y \sim p(\cdot | s_{hk}, a_{hk})} [\delta_{h+1,k}(Y)] - m_{h,k} \\ &\implies \delta_{h+1,k}(s_{h+1,k}) = \mathbb{E}_p[V_{h+1,k}(s') - V_h^{\pi}(s')] - m_{h,k} \\ &\implies \delta_{h+1,k}(s_{h+1,k}) = \mathbb{E}_p[V_{h+1,k}(s')] - V_h^{\pi}(s_{h+1,k}) + r(s_{h,k}, a_{h,k}) - m_{h,k} \\ &\implies \boxed{V_h^{\pi}(s_{h,k}) = \mathbb{E}_p[V_{h+1,k}(s')] + r(s_{h,k}, a_{h,k}) - m_{h,k} - \delta_{h+1,k}(s_{h+1,k})} \end{aligned}$$

- 2. Then, let's show that $V_{h,k}(s_{hk}) \leq Q_{h,k}(s_{hk}, a_{hk})$.

It's known $V_{h,k}(s) = \min\{H, \max_a Q_{h,k}(s, a)\}$ and $\max_a Q_{h,k}(s_{hk}, a) = Q_{h,k}(s_{hk}, a_{hk})$.

Hence,

$$V_{h,k}(s_{hk}) = \min\{H, \max_a Q_{h,k}(s_{hk}, a)\} \leq Q_{h,k}(s_{hk}, a_{hk})$$

- 3. Finally, let's show that

$$\delta_{1k}(s_{1,k}) \leq \sum_{h=1}^H Q_{h,k}(s_{hk}, a_{hk}) - r(s_{hk}, a_{hk}) - \mathbb{E}_{Y \sim p(\cdot | s_{hk}, a_{hk})} [V_{h+1,k}(Y)] + m_{hk}$$

Induction will be used to prove that.

For $h=H$:

$$\begin{aligned} \delta_{Hk}(s_{H,k}) &= V_{H,k}(s_{Hk}) - V_H^{\pi_k}(s_{Hk}) \\ &\leq Q_{H,k}(s_{Hk}, a_{Hk}) - V_H^{\pi_k}(s_{Hk}) \\ &= Q_{H,k}(s_{Hk}, a_{Hk}) - \mathbb{E}_p[V_{H+1,k}(s')] - r(s_{H,k}, a_{H,k}) + m_{H,k} + \delta_{H+1,k}(s_{H+1,k}) \\ &= \sum_{h=H}^H Q_{h,k}(s_{hk}, a_{hk}) - \mathbb{E}_p[V_{h+1,k}(s')] - r(s_{h,k}, a_{h,k}) + m_{h,k} \end{aligned}$$

For $h < H$: We suppose that:

$$\delta_{1k}(s_{1,k}) \leq \sum_{h=1}^H Q_{h,k}(s_{hk}, a_{hk}) - r(s_{hk}, a_{hk}) - \mathbb{E}_{Y \sim p(\cdot | s_{hk}, a_{hk})} [V_{h+1,k}(Y)] + m_{hk}$$

Then, it comes that:

$$\delta_{h-1,k}(s_{h-1,k}) = V_{h-1,k}(s_{h-1,k}) - V_{h-1}^{\pi_k}(s_{h-1,k})$$

$$\begin{aligned}
&\leq Q_{h-1,k}(s_{h-1,k}, a_{h-1,k}) - V_{h-1}^{\pi_k}(s_{h-1,k}) \\
&= Q_{h-1,k}(s_{h-1,k}, a_{h-1,k}) - \mathbb{E}_p[V_{h,k}(s')] - r(s_{h-1,k}, a_{h-1,k}) + m_{h-1,k} + \delta_{h,k}(s_{h,k}) \\
&= Q_{h-1,k}(s_{h-1,k}, a_{h-1,k}) - \mathbb{E}_p[V_{h,k}(s')] - r(s_{h-1,k}, a_{h-1,k}) + m_{h-1,k} + \delta_{h,k}(s_{h,k}) \\
&\leq Q_{h-1,k}(s_{h-1,k}, a_{h-1,k}) - \mathbb{E}_p[V_{h,k}(s')] - r(s_{h-1,k}, a_{h-1,k}) + m_{h-1,k} \\
&\quad + Q_{h,k}(s_{h,k}, a_{h,k}) - \mathbb{E}_p[V_{h+1,k}(s')] - r(s_{h,k}, a_{h,k}) + m_{h,k} \\
&= \sum_{j=h-1}^H Q_{j,k}(s_{j,k}, a_{j,k}) - \mathbb{E}_p[V_{j+1,k}(s')] - r(s_{j,k}, a_{j,k}) + m_{j,k}
\end{aligned}$$

Hence:

$$\delta_{h,k}(s_{h,k}) \leq \sum_{j=h}^H Q_{j,k}(s_{j,k}, a_{j,k}) - \mathbb{E}_p[V_{j+1,k}(s')] - r(s_{j,k}, a_{j,k}) + m_{j,k}$$

So finally:

$$\boxed{\delta_{1,k}(s_{1,k}) \leq \sum_{h=1}^H Q_{h,k}(s_{h,k}, a_{h,k}) - \mathbb{E}_p[V_{h+1,k}(s')] - r(s_{h,k}, a_{h,k}) + m_{h,k}}$$

- Now, let's show that the regret is upper bounded with probability $1 - \delta$ by

$$R(T) \leq 2 \sum_{kh} b_{hk}(s_{hk}, a_{hk}) + 2H \sqrt{KH \log(2/\delta)}$$

To start with the definition of $R(T)$:

$$\begin{aligned}
R(T) &= \sum_{k=1}^K V_1^*(s_1, k) - V_1^{\pi_k}(s_1, k) \leq \sum_{k=1}^K V_{1,k}(s_1, k) - V_1^{\pi_k}(s_1, k) \text{ when } \mathcal{E} \text{ holds} \\
&\implies R(T) \leq \sum_{k=1}^K \delta_{1,k}(s_1, k) \\
&\leq \sum_{k=1}^K \sum_{h=1}^H Q_{h,k}(s_{h,k}, a_{h,k}) - \mathbb{E}_p[V_{h+1,k}(s')] - r(s_{h,k}, a_{h,k}) + m_{h,k} \\
&\leq \sum_{k=1}^K \sum_{h=1}^H Q_{h,k}(s_{h,k}, a_{h,k}) - \mathbb{E}_p[V_{h+1,k}(s')] - r(s_{h,k}, a_{h,k}) + 2H \sqrt{KH \log\left(\frac{2}{\delta}\right)} \\
&= \sum_{k=1}^K \sum_{h=1}^H \hat{r}_{h,k}(s, a) + b_{h,k}(s, a) + \mathbb{E}_{\hat{p}}[V_{h+1,k}(s')] - \mathbb{E}_p[V_{h+1,k}(s')] - r(s_{h,k}, a_{h,k}) + 2H \sqrt{KH \log\left(\frac{2}{\delta}\right)} \\
&\leq \sum_{k=1}^K \sum_{h=1}^H 2b_{h,k}(s, a) + 2H \sqrt{KH \log\left(\frac{2}{\delta}\right)}
\end{aligned}$$

So finally:

$$\boxed{R(T) \leq 2 \sum_{kh} b_{hk}(s_{hk}, a_{hk}) + 2H \sqrt{KH \log(2/\delta)}}$$

- Previously, it has been shown that:

$$R(T) \leq 2 \sum_{kh} b_{hk}(s_{hk}, a_{hk}) + 2H \sqrt{KH \log(2/\delta)}$$

Then, using bonus function previously defined, it comes that:

$$R(T) \leq 2H \sqrt{2 \log\left(\frac{(2^{|S|} - 2)4|S||A|HK}{\delta}\right)} \sum_{kh} \frac{1}{\sqrt{N_{h,k}(s_{hk}, a_{hk})}} + 2H \sqrt{KH \log(2/\delta)}$$

$$R(T) \leq 2H \sqrt{2 \log\left(\frac{(2^{|S|} - 2)4|S||A|HK}{\delta}\right)} \sum_{kh} \frac{1}{\sqrt{N_{h,k}(s_{hk}, a_{hk})}} + 2H \sqrt{KH \log(2/\delta)}$$

It's also known that:

$$\sum_{h,k} \frac{1}{\sqrt{N_{h,k}(s_{hk}, a_{hk})}} \lesssim H^2 S^2 A + 2 \sum_{h=1}^H \sum_{s,a} \sqrt{N_{hK}(s, a)}$$

Hence,

$$R(T) \leq 2H \sqrt{2 \log\left(\frac{(2^{|S|} - 2)4|S||A|HK}{\delta}\right)} (H^2 S^2 A + 2 \sum_{h=1}^H \sum_{s,a} \sqrt{N_{hK}(s, a)}) + 2H \sqrt{KH \log(2/\delta)}$$

$$R(T) \leq 2H \sqrt{2|S| \log\left(\frac{(8|S||A|HK)}{\delta}\right)} (H^2 S^2 A + 2 \sum_{h=1}^H \sum_{s,a} \sqrt{N_{hK}(s, a)}) + 2H \sqrt{KH \log(2/\delta)}$$

Finally,

$$\boxed{R(T) \leq H^2 |S| \sqrt{AK}}$$

End of Answer - Regret Minimization in RL.

End of HW3 RL - Thank you for reading!

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```

Initialize  $Q_{h1}(s, a) = 0$  for all  $(s, a) \in S \times A$  and  $h = 1, \dots, H$ 

for  $k = 1, \dots, K$  do
  Observe initial state  $s_{1k}$  (arbitrary)
  Estimate empirical MDP  $\widehat{M}_k = (S, A, \widehat{p}_{hk}, \widehat{r}_{hk}, H)$  from  $\mathcal{D}_k$ 


$$\widehat{p}_{hk}(s'|s, a) = \frac{\sum_{i=1}^{k-1} \mathbb{1}\{(s_{hi}, a_{hi}, s_{h+1,i}) = (s, a, s')\}}{N_{hk}(s, a)}, \quad \widehat{r}_{hk}(s, a) = \frac{\sum_{i=1}^{k-1} r_{hi} \cdot \mathbb{1}\{(s_{hi}, a_{hi}) = (s, a)\}}{N_{hk}(s, a)}$$


  Planning (by backward induction) for  $\pi_{hk}$  using  $\widehat{M}_k$ 
  for  $h = H, \dots, 1$  do
     $Q_{h,k}(s, a) = \widehat{r}_{h,k}(s, a) + b_{h,k}(s, a) + \sum_{s'} \widehat{p}_{h,k}(s'|s, a) V_{h+1,k}(s')$ 
     $V_{h,k}(s) = \min\{H, \max_a Q_{h,k}(s, a)\}$ 
  end
  Define  $\pi_{h,k}(s) = \arg \max_a Q_{h,k}(s, a), \forall s, h$ 
  for  $h = 1, \dots, H$  do
    Execute  $a_{hk} = \pi_{hk}(s_{hk})$ 
    Observe  $r_{hk}$  and  $s_{h+1,k}$ 
     $N_{h,k+1}(s_{hk}, a_{hk}) = N_{h,k}(s_{hk}, a_{hk}) + 1$ 
  end
end

```

Algorithm 1: UCBVI

A Weissmain inequality

Denote by $\widehat{p}(\cdot|s, a)$ the estimated transition probability build using n samples drawn from $p(\cdot|s, a)$. Then we have that

$$\mathbb{P}(\|\widehat{p}_h(\cdot|s, a) - p_h(\cdot|s, a)\|_1 \geq \epsilon) \leq (2^S - 2) \exp\left(-\frac{n\epsilon^2}{2}\right)$$

References

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