

UCB bandits w/independent arms

a^* = optimal action

a_t = action selected at time step t

$f^*(a)$ = mean reward of a under true reward

$$\text{regret}(\text{UCB}, T) = \sum_{t=1}^T \underbrace{f^*(a^*) - f^*(a_t)}_{\substack{\text{difference in} \\ \text{expected best reward} \\ \text{\& expected reward of action selected}}}$$

time
steps

difference in
expected best reward
& expected reward of action selected

$$= \sum_{t=1}^T [U_t(a_t) - f^*(a_t)] + [f^*(a^*) - U_t(a_t)]$$

where $U_t(a_t)$ is an upper confidence bound on the expected reward of action a_t at time t

can use Hoeffding or Azuma's inequalities to compute an upper bound on expected reward of each action at each time step

e.g. $U_t(a_t) = \underbrace{\hat{f}_t(a_t)}_{\substack{\text{empirical} \\ \text{avg reward} \\ \text{for action} \\ a_t}} + \sqrt{\frac{4 \log(t\delta)}{n_t(i)}} \leftarrow \# \text{ times tried action } a_t$ holds w/prob $\geq 1 - \delta t^{-2}$

what is the prob that on some step (in T steps) one of these upper confidence bounds will fail to hold?

$$\prod_{t=1}^T P(f^*(a^*) > U_t(a_t)) \leq \prod_{t=1}^T \underbrace{P(|f^*(a_i) - \hat{f}(a_i)| > \sqrt{\frac{4 \log(t\delta)}{n_t(i)}})}_{\text{arms}}$$

$$\leq \prod_{t=1}^T \prod_{i=1}^m \delta t^{-2}$$

$$\leq 2m\delta$$

aside: $\sum_{i=1}^{\infty} t^{-2} = \frac{\pi^2}{6} < 2$

\Rightarrow w/prob at least $1 - 2m\delta$ UCB will overestimate the true rewards on all T timesteps

$$\Rightarrow f^*(a^*) - U_t(a_t) \leq 0$$

$$\Rightarrow \text{regret}(\text{UCB}, T) \leq \sum_{t=1}^T U_t(a_t) - f^*(a_t) \quad (\text{dropped 2nd term})$$

* This is important because now can compare our bounds U_t (which are calculated) to observed reward $f^*(a_t)$ instead of unobserved $f^*(a^*)$

therefore with prob $\geq 1 - 2m\delta$

$$\text{regret}(\text{UCB}, T) \leq \sum_{t=1}^T U_t(a_t) - f^*(a_t)$$

$$\leq \sum_{t=1}^T \sqrt{\frac{4 \log(4\delta)}{n_t(a_t)}}$$

$$\leq \sqrt{4 \log(4\delta)} \sum_{t=1}^T \sqrt{\frac{1}{n_t(a_t)}}$$

$$(*) \quad = \sqrt{4 \log(4\delta)} \sum_{i=1}^m \sum_{n=1}^{n_t(i)} \sqrt{1/n} \quad \text{split by each of } m \text{ actions}$$

note $\sum_{n=1}^T \sqrt{1/n} \leq 2\sqrt{T}$ by an integral comparison, then

$\sum_{i=1}^m \sum_{n=1}^{n_t(i)} 1/\sqrt{n}$ is maximized if all arms pulled equally

$$\text{so } \sum_{i=1}^m \sum_{n=1}^{n_t(i)} \frac{1}{\sqrt{n}} \leq \sum_{i=1}^m \sum_{n=1}^{T/m} \frac{1}{\sqrt{n}}$$

$$\leq \sum_{i=1}^m 2\sqrt{T/m}$$

$$= 2m\sqrt{T/m}$$

$$= 2\sqrt{Tm}$$

substitute this back into (*)

$$\text{regret}(\text{UCB}, T) \leq 4\sqrt{mT \log(4\delta)} \quad \text{with prob at least } 1 - 2m\delta$$

can be made tighter in terms of log & constants

• Regret vs Bayesian regret

$$\text{regret}(\pi, T, \theta) = \sum_{t=1}^T E[f^*(a^*) - f^*(a_t) | \theta]$$

← parameters

$$\text{Bayes regret}(\pi, T) = \sum_{t=1}^T E[f^*(a^*) - f^*(a_t)] \quad \text{with respect to prior } \mu \text{ over } \theta$$

can be related

$$\text{let } \text{Bayes regret}(\pi, T) = O(g(T)) \text{ for some non-neg func } g$$

then $\forall \epsilon > 0$

$$P(\text{Regret}(\pi, T, \theta) \geq g(T)/\epsilon) \leq \epsilon \quad \forall T \text{ by Markov's inequality}$$

can also use to help bound impact of using wrong prior

• Lemma 2 (Posterior sampling). Let ϕ be the distrib of f^* & consider a function g (must satisfy a few properties - see references)

$$E[g(f^*) | H_t] = E[g(f_t) | H_t] \quad \text{when } H_t \text{ is the history of observed actions \& rewards}$$

$$\begin{aligned} \text{regret}(\text{Posterior Sampling}, T) &= \sum_{t=1}^T f^*(a^*) - f^*(a_t) \\ &= \sum_{t=1}^T |f_t(a_t) - f^*(a_t)| + \underbrace{|f^*(a^*) - f_t(a_t)|}_{= 0 \text{ in expec due to lemma}} \end{aligned}$$

expec. wrt prior

= 0 in expec due to lemma

Posterior sampling bound cont.

$$\begin{aligned} E \left[\sum_{t=1}^T |f_t(x_t) - f^*(x_t)| \right] &= E \left[\sum_{t=1}^T [f_t(x_t) - U_t(x_t)] + \sum_{t=1}^T [U_t(x_t) - f^*(x_t)] \right] \\ &\leq E \left[\sum_{t=1}^T |f_t(x_t) - U_t(x_t)| + \sum_{t=1}^T |U_t(x_t) - f^*(x_t)| \right] \\ &\leq 2 E \left[\sum_{t=1}^T |U_t(x_t) - \mathcal{L}_t(x_t)| \right] \end{aligned}$$

so now related to
upper & lower confidence bounds

$$\begin{aligned} \text{regret}(\text{posterior sampling}, T) &\leq 2 E \left[\sum_{t=1}^T |U_t(x_t) - \mathcal{L}_t(x_t)| \right] \\ &\leq 2 E \left[\sum_{t=1}^T 2 \sqrt{\frac{4 \log(T\delta)}{n_t(x_t)}} \right] \leftarrow \text{using same bounds as UCB} \\ &\leq 16 \sqrt{m T \log(T\delta)} \quad \text{w/prob} \geq 1 - 2m\delta \end{aligned}$$

so posterior sampling has same (ignoring constants, logs)
regret bounds!