Lecture 11: Fast Reinforcement Learning [1]

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CS234 Reinforcement Learning

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[1] With many slides from or derived from David Silver, Examples new

Refresh Your Understanding: Multi-armed Bandits

- Select all that are true:
  1. Up to slide variations in constants, UCB selects the arm with $\arg\max_a \hat{Q}_t(a) + \sqrt{\frac{1}{N_t(a)} \log(1/\delta)}$
  2. Over an infinite trajectory, UCB will sample all arms an infinite number of times
  3. UCB still would learn to pull the optimal arm more than other arms if we instead used $\arg\max_a \hat{Q}_t(a) + \sqrt{\frac{1}{\sqrt{N_t(a)}} \log(t/\delta)}$
  4. UCB uses $\arg\max_a \hat{Q}_t(a) + b$ where b is a bonus term. Consider $b = 5$. This will make the algorithm optimistic with respect to the empirical rewards but it may still cause such an algorithm to suffer linear regret.
  5. Algorithms that minimize regret also maximize reward
  6. Not Sure

Refresh Your Understanding: Multi-armed Bandits Solution

- Select all that are true:
  1. Up to slide variations in constants, UCB selects the arm with $\arg\max_a \hat{Q}_t(a) + \sqrt{\frac{1}{N_t(a)} \log(1/\delta)}$
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Where We are

- Last time: Bandits and regret and UCB (fast learning)
- This time: Bayesian bandits (fast learning)
- Next time: MDPs (fast learning)

Recall Motivation

- Fast learning is important when our decisions impact the world

Today

- Bandits and Probably Approximately Correct
- Bayesian bandits
- Thompson sampling
- Bayesian Regret

Settings, Frameworks & Approaches

- Over next couple lectures will consider 2 settings, multiple frameworks, and approaches
- Settings: Bandits (single decisions), MDPs
- Frameworks: evaluation criteria for formally assessing the quality of a RL algorithm
- Approaches: Classes of algorithms for achieving particular evaluation criteria in a certain set
- Note: We will see that some approaches can achieve multiple frameworks in multiple settings

Multiarmed Bandits Recap

- Multi-armed bandit is a tuple of $(\mathcal{A}, \mathcal{R})$
- $\mathcal{A}$: known set of m actions (arms)
- $\mathcal{R}^a(r) = \mathbb{P}[r \mid a]$ is an unknown probability distribution over rewards
- At each step t the agent selects an action $a_t \in \mathcal{A}$
- The environment generates a reward $r_t \sim \mathcal{R}^{a_t}$
- Goal: Maximize cumulative reward $\sum_{\tau=1}^{t} r_\tau$
- **Regret** is the opportunity loss for one step

$$l_t = \mathbb{E}[V^* - Q(a_t)]$$

- **Total Regret** is the total opportunity loss

$$L_t = \mathbb{E}[\sum_{\tau=1}^{t} V^* - Q(a_\tau)]$$

- Maximize cumulative reward $\iff$ minimize total regret

Simpler Optimism

- Last time saw UCB, an optimism under uncertainty approach, which has sublinear regret bounds
- Do we need to formally model uncertainty to get the right form of optimism?

Optimistic Initialization with Greedy Bandit Algorithms

- Simple and practical idea: initialize $\hat{Q}(s, a)$ to high value
- Update action value by incremental Monte-Carlo evaluation
- Starting with $N(a) > 0$

$$\hat{Q}_t(a_t) = \hat{Q}_{t-1} + \frac{1}{N_t(a_t)}(r_t - \hat{Q}_{t-1})$$

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- Encourages systematic exploration early on
- But can still lock onto suboptimal action
- Depends on how high initialize Q
- Check your understanding: What is the downside to initializing Q too high?
- Check your understanding: Is this trivial to do with function approximation? Why or why not?

Optimistic Initialization with Greedy Bandit Algorithms

- Simple and practical idea: initialize Q(a) to high value
- Update action value by incremental Monte-Carlo evaluation
- Starting with $N(a) > 0$

$$\hat{Q}_t(a_t) = \hat{Q}_{t-1} + \frac{1}{N_t(a_t)}(r_t - \hat{Q}_{t-1})$$

- Will turn out that if carefully choose the initialization value, can get good performance
- Under a new measure for evaluating algorithms

Framework: Probably Approximately Correct

- Theoretical regret bounds specify how regret grows with T

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- May care about bounding the number of non-small errors

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- Could be making lots of little mistakes or infrequent large ones
- May care about bounding the number of non-small errors
- More formally, probably approximately correct (PAC) results state that the algorithm will choose an action a whose value is ϵ-optimal ($Q(a) \geq Q(a^*) - \epsilon$) with probability at least $1 - \delta$ on all but a polynomial number of steps
- Polynomial in the problem parameters (#actions, ϵ, δ, etc)
- Most PAC algorithms based on optimism or Thompson sampling
- Some PAC algorithms using optimism simply initialize all values to a (specific to the problem) high value

Toy Example: Probably Approximately Correct and Regret

- Surgery: $\phi_1 = .95$ / Taping: $\phi_2 = .9$ / Nothing: $\phi_3 = .1$
- Let $\epsilon = 0.05$
- O = Optimism, TS = Thompson Sampling: W/in $\epsilon = \mathbb{I}(Q(a_t) \geq Q(a^*) - \epsilon)$

O	Optimal	O Regret	O W/in ϵ
a^1	a^1	0	
a^2	a^1	0.05	
a^3	a^1	0.85	
a^1	a^1	0	
a^2	a^1	0.05	

Framework: Probably Approximately Correct

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- May care about bounding the number of non-small errors
- More formally, probably approximately correct (PAC) results state that the algorithm will choose an action a whose value is ϵ-optimal ($Q(a) \geq Q(a^*) - \epsilon$) with probability at least $1 - \delta$ on all but a polynomial number of steps
- Polynomial in the problem parameters (#actions, ϵ, δ, etc)
- Most PAC algorithms based on optimism or Thompson sampling
- PAC approaches can be relevant to MDPs as well

Greedy Bandit Algorithms vs Optimistic Initialization

- **Greedy**: Linear total regret
- **Constant ϵ-greedy**: Linear total regret
- **Decaying ϵ-greedy**: Sublinear regret but schedule for decaying ϵ requires knowledge of gaps, which are unknown
- **Optimistic initialization**: Sublinear regret if initialize values sufficiently optimistically, else linear regret
- Check your understanding: why does fixed ϵ-greedy have linear regret? (Encourage you to do a proof sketch)

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Bayesian Bandits

- So far we have made no assumptions about the reward distribution $\mathcal{R}$
  - Except bounds on rewards
- **Bayesian bandits** exploit prior knowledge of rewards, $p[\mathcal{R}]$
- They compute posterior distribution of rewards $p[\mathcal{R} \mid h_t]$, where $h_t = (a_1, r_1, \ldots, a_{t-1}, r_{t-1})$
- Use posterior to guide exploration
  - Upper confidence bounds (Bayesian UCB)
  - Probability matching (Thompson Sampling)
- Better performance if prior knowledge is accurate

Short Refresher / Review on Bayesian Inference

- In Bayesian view, we start with a prior over the unknown parameters
  - Here the unknown distribution over the rewards for each arm
- Given observations / data about that parameter, update our uncertainty over the unknown parameters using Bayes Rule

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- For example, let the reward of arm i be a probability distribution that depends on parameter ϕ_i
- Initial prior over ϕ_i is $p(\phi_i)$
- Pull arm i and observe reward r_{i1}
- Use Bays rule to update estimate over ϕ_i:

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- Use Bays rule to update estimate over ϕ_i:

$$p(\phi_i|r_{i1}) = \frac{p(r_{i1}|\phi_i)p(\phi_i)}{p(r_{i1})} = \frac{p(r_{i1}|\phi_i)p(\phi_i)}{\int_{\phi_i} p(r_{i1}|\phi_i)p(\phi_i)d\phi_i}$$

Short Refresher / Review on Bayesian Inference II

- In Bayesian view, we start with a prior over the unknown parameters
- Give observations / data about that parameter, update our uncertainty over the unknown parameters using Bayes Rule

$$p(\phi_i|r_{i1}) = \frac{p(r_{i1}|\phi_i)p(\phi_i)}{\int_{\phi_i} p(r_{i1}|\phi_i)p(\phi_i)d\phi_i}$$

- In general computing this update may be tricky to do exactly with no additional structure on the form of the prior and data likelihood

Short Refresher / Review on Bayesian Inference: Conjugate

- In Bayesian view, we start with a prior over the unknown parameters
- Give observations / data about that parameter, update our uncertainty over the unknown parameters using Bayes Rule

$$p(\phi_i|r_{i1}) = \frac{p(r_{i1}|\phi_i)p(\phi_i)}{\int_{\phi_i} p(r_{i1}|\phi_i)p(\phi_i)d\phi_i}$$

- In general computing this update may be tricky
- But sometimes can b e done analytically
- If the parametric representation of the prior and posterior is the same, the prior and model are called **conjugate**
- For example, exponential families have conjugate priors

Short Refresher / Review on Bayesian Inference: Bernoulli

- Consider a bandit problem where the reward of an arm is a binary outcome 0, 1, sampled from a Bernoulli with parameter θ
  - E.g. Advertisement click through rate, patient treatment success/fails, ...
- The Beta distribution $Beta(\alpha, \beta)$ is conjugate for the Bernoulli distribution

$$p(\theta|\alpha,\beta) = \theta^{\alpha-1}(1-\theta)^{\beta-1}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}$$

where $\Gamma(x)$ is the Gamma family

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$$p(\theta|\alpha, \beta) = \theta^{\alpha-1}(1-\theta)^{\beta-1}\frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)}$$

  where $\Gamma(x)$ is the Gamma family
- Assume the prior over θ is $Beta(\alpha, \beta)$ as above
- Then after observed a reward $r \in \{0, 1\}$ then updated posterior over θ is $Beta(r+\alpha, 1-r+\beta)$

Bayesian Inference for Decision Making

- Maintain distribution over reward parameters
- Use this to inform action selection

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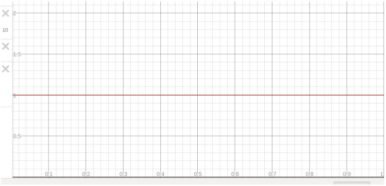
Thompson Sampling

Initialize prior over each arm a, $p(\mathcal{R}_a)$
for iteration$=1, 2, \ldots$ **do**
    For each arm a **sample** a reward distribution $\mathcal{R}_a$ from posterior
    Compute action-value function $Q(a) = \mathbb{E}[\mathcal{R}_a]$
    $a_t = \arg\max_{a \in \mathcal{A}} Q(a)$
    Observe reward r
    Update posterior $p(\mathcal{R}_a | r)$ using Bayes Rule
end for

Toy Example: Ways to Treat Broken Toes, Thompson Sampling

- True (unknown) Bernoulli parameters for each arm/action
- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Thompson sampling:
- Place a prior over each arm's parameter. Here choose Beta(1,1) (Uniform)
  1. Sample a Bernoulli parameter given current prior over each arm Beta(1,1), Beta(1,1), Beta(1,1):



Toy Example: Ways to Treat Broken Toes, Thompson Sampling[1]

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- Thompson sampling:
- Place a prior over each arm's parameter. Here choose Beta(1,1)
  1. Sample a Bernoulli parameter given current prior over each arm Beta(1,1), Beta(1,1), Beta(1,1): 0.3 0.5 0.6
  2. Select $a = \arg\max_{a \in A} Q(a) = \arg\max_{ainA} \theta(a) =$

[1]Note:This is a made up example. This is not the actual expected efficacies of the various treatment options for a broken toe

Toy Example: Ways to Treat Broken Toes, Thompson Sampling

- True (unknown) Bernoulli parameters for each arm/action
- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Thompson sampling:
- Place a prior over each arm's parameter. Here choose $\theta_i \sim$Beta(1,1)
  1. Per arm, sample a Bernoulli θ given prior: 0.3 0.5 0.6
  2. Select $a_t = \arg\max_{a \in A} Q(a) = \arg\max_{ainA} \theta(a) = 3$
  3. Observe the patient outcome's outcome: 0
  4. Update the posterior over the $Q(a_t) = Q(a^3)$ value for the arm pulled

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- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
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  3. Observe the patient outcome's outcome: 0
  4. Update the posterior over the $Q(a_t) = Q(a^1)$ value for the arm pulled
     - Beta(c_1, c_2) is the conjugate distribution for Bernoulli
     - If observe 1, $c_1 + 1$ else if observe 0 $c_2 + 1$
  5. New posterior over Q value for arm pulled is:
  6. New posterior $p(Q(a^3)) = p(\theta(a_3) = Beta(1, 2)$

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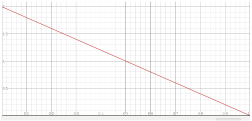
  1. Sample a Bernoulli parameter given current prior over each arm Beta(1,1), Beta(1,1), Beta(1,1): 0.3 0.5 0.6
  2. Select $a_t = \arg\max_{a \in A} Q(a) = \arg\max_{ainA} \theta(a) = 1$
  3. Observe the patient outcome's outcome: 0
  4. New posterior $p(Q(a^1)) = p(\theta(a_1) = Beta(1, 2)$



Toy Example: Ways to Treat Broken Toes, Thompson Sampling

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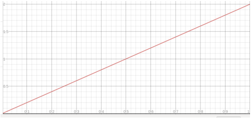
- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Thompson sampling:
- Place a prior over each arm's parameter. Here choose $\theta_i \sim$Beta(1,1)
    1. Sample a Bernoulli parameter given current prior over each arm Beta(1,1), Beta(1,1), Beta(1,2): 0.7, 0.5, 0.3

Toy Example: Ways to Treat Broken Toes, Thompson Sampling

- True (unknown) Bernoulli parameters for each arm/action
- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Thompson sampling:
- Place a prior over each arm's parameter. Here choose $\theta_i \sim$Beta(1,1)
  1. Sample a Bernoulli parameter given current prior over each arm Beta(1,1), Beta(1,1), Beta(1,2): 0.7, 0.5, 0.3
  2. Select $a_t = \arg\max_{a \in A} Q(a) = \arg\max_{ainA} \theta(a) = 1$
  3. Observe the patient outcome's outcome: 1
  4. New posterior $p(Q(a^1)) = p(\theta(a_1) = Beta(2, 1)$



Toy Example: Ways to Treat Broken Toes, Thompson Sampling

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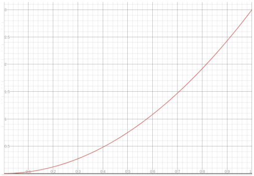
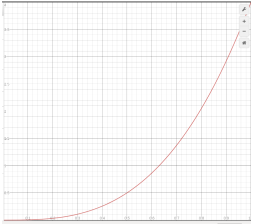
- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Thompson sampling:
- Place a prior over each arm's parameter. Here choose $\theta_i \sim$Beta(1,1)
  1. Sample a Bernoulli parameter given current prior over each arm Beta(2,1), Beta(1,1), Beta(1,2): 0.71, 0.65, 0.1
  2. Select $a_t = \arg\max_{a \in A} Q(a) = \arg\max_{ainA} \theta(a) = 1$
  3. Observe the patient outcome's outcome: 1
  4. New posterior $p(Q(a^1)) = p(\theta(a_1) = Beta(3, 1)$



Toy Example: Ways to Treat Broken Toes, Thompson Sampling

- True (unknown) Bernoulli parameters for each arm/action
- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Thompson sampling:
- Place a prior over each arm's parameter. Here choose $\theta_i \sim$Beta(1,1)
  1. Sample a Bernoulli parameter given current prior over each arm Beta(2,1), Beta(1,1), Beta(1,2): 0.75, 0.45, 0.4
  2. Select $a_t = \arg\max_{a \in A} Q(a) = \arg\max_{a in A} \theta(a) = 1$
  3. Observe the patient outcome's outcome: 1
  4. New posterior $p(Q(a^1)) = p(\theta(a_1) = Beta(4, 1)$



Toy Example: Ways to Treat Broken Toes, Thompson Sampling vs Optimism

- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- How does the sequence of arm pulls compare in this example so far?

Optimism	TS	Optimal	Regret Optimism	Regret TS
a^1	a^3			
a^2	a^1			
a^3	a^1			
a^1	a^1			
a^2	a^1			

Toy Example: Ways to Treat Broken Toes, Thompson Sampling vs Optimism

- Surgery: $\theta_1 = .95$ / Taping: $\theta_2 = .9$ / Nothing: $\theta_3 = .1$
- Incurred regret?

Optimism	TS	Optimal	Regret Optimism	Regret TS
a^1	a^3	a^1	0	0
a^2	a^1	a^1	0.05	
a^3	a^1	a^1	0.85	
a^1	a^1	a^1	0	
a^2	a^1	a^1	0.05	

On to General Setting for Thompson Sampling

- Now we will see how Thompson sampling works in general, and what it is doing

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Probability Matching

- Assume have a parametric distribution over rewards for each arm
- **Probability matching** selects action a according to probability that a is the optimal action

$$\pi(a \mid h_t) = \mathbb{P}[Q(a) > Q(a'), \forall a' \neq a \mid h_t]$$

- Probability matching is often optimistic in the face of uncertainty
  - Uncertain actions have higher probability of being max
- Can be difficult to compute probability that an action is optimal analytically from posterior
- Somewhat incredibly, a simple approach implements probability matching

Thompson Sampling

Initialize prior over each arm a, $p(\mathcal{R}_a)$
for iteration$=1, 2, \ldots$ **do**
    For each arm a **sample** a reward distribution $\mathcal{R}_a$ from posterior
    Compute action-value function $Q(a) = \mathbb{E}[\mathcal{R}_a]$
    $a_t = \arg\max_{a \in \mathcal{A}} Q(a)$
    Observe reward r
    Update posterior $p(\mathcal{R}_a | r)$ using Bayes Rule
end for

Thompson sampling implements probability matching

- Thompson sampling:

$$\pi(a \mid h_t) = \mathbb{P}[Q(a) > Q(a'), \forall a' \neq a \mid h_t]$$
$$= \mathbb{E}_{\mathcal{R}|h_t}\left[\mathbb{1}(a = \arg\max_{a \in \mathcal{A}} Q(a))\right]$$

Framework: Regret and Bayesian Regret

- How do we evaluate performance in the Bayesian setting?
- Frequentist regret assumes a true (unknown) set of parameters

$$Regret(\mathcal{A}, T; \theta) = \mathbb{E}_\tau \left[\sum_{t=1}^{T} Q(a^*) - Q(a_t) | \theta \right] \leq \mathbb{E}_\tau \left[\sum_{t=1}^{T} U_t(a_t) - Q(a_t) | \theta \right]$$

where $\mathbb{E}_\tau$ denotes an expectation with respect to the history of actions taken and rewards observed given an algorithm $\mathcal{A}$.

- Bayesian regret assumes there is a prior over parameters

$$BayesRegret(\mathcal{A}, T; \theta) =$$

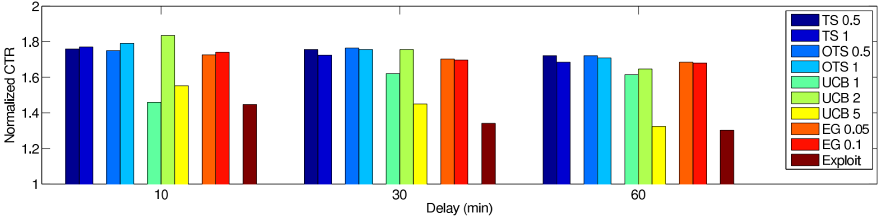
$$\mathbb{E}_{\theta \sim p_\theta, \tau} \left[\sum_{t=1}^{T} Q(a^*) - Q(a_t) | \theta \right] \leq \mathbb{E}_{\theta \sim p_\theta, \tau} \left[\sum_{t=1}^{T} U_t(a_t) - Q(a_t) | \theta \right]$$

Thompson sampling implements probability matching

- Thompson sampling(1929) achieves Lai and Robbins lower bound
- Frequentist bounds for Thompson sampling do not* (last checked) match best bounds for frequentist algorithms
- Empirically Thompson sampling can be effective, especially in contextual multi-armed bandits

Thompson Sampling for News Article Recommendation (Chapelle and Li, 2010)

- Contextual bandit: input context which impacts reward of each arm, context sampled iid each step
- Arms = articles
- Reward = click (+1) on article ($Q(a)$=click through rate)



Check Your Understanding: Thompson Sampling and Optimism

- Consider an online news website with thousands of people logging on each second. Frequently a new person will come online before we see whether the last person has clicked (or not). Select all that are true:
  1. Thompson sampling would be better than optimism here, because optimism algorithms are deterministic and would select the same action until we get feedback (click or not)
  2. Optimism algorithms would be better than TS here, because they have stronger regret bounds
  3. Thompson sampling could cause much worse performance than optimism if the initial prior is very misleading.
  4. Not sure

Check Your Understanding: Thompson Sampling and Optimism **Solutions**

- Consider an online news website with thousands of people logging on each second. Frequently a new person will come online before we see whether the last person has clicked (or not). Select all that are true:
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What You Should Understand

- Understand how multi-armed bandits relate to MDPs
- Be able to define regret and PAC
- Be able to prove why UCB bandit algorithm has sublinear regret
- Understand (be able to give an example) why e-greedy and greedy and pessimism can result in linear regret
- Be able to implement Thompson Sampling for bernoulli or Gaussian rewards
- Be able to implement UCB bandit algorithm

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Bayesian Regret Bounds for Thompson Sampling

- Regret(UCB,T)

$$BayesRegret(TS, T) = E_{\theta \sim p_\theta}\left[\sum_{t=1}^{T} f^*(a^*) - f^*(a_t)\right]$$

- Posterior sampling has the same (ignoring constants) regret bounds as UCB

Toy Example: Probably Approximately Correct and Regret

- Surgery: $\phi_1 = .95$ / Taping: $\phi_2 = .9$ / Nothing: $\phi_3 = .1$
- Let $\epsilon = 0.05$
- O = Optimism, TS = Thompson Sampling: W/in $\epsilon = \mathbb{I}(Q(a_t) \geq Q(a^*) - \epsilon)$

O	TS	Optimal	O Regret	O W/in ϵ	TS Regret	TS W/in ϵ
a^1	a^3	a^1	0	Y	0.85	N
a^2	a^1	a^1	0.05	Y	0	Y
a^3	a^1	a^1	0.85	N	0	Y
a^1	a^1	a^1	0	Y	0	Y
a^2	a^1	a^1	0.05	Y	0	Y