Lecture 13: Multi-Armed Bandits
CS486/686 Intro to Artificial Intelligence

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Outline

- Exploration/exploitation tradeoff
- Regret
- Multi-armed bandits
  - ϵ-greedy strategies
  - Upper confidence bounds
  - Thompson sampling

Exploration/Exploitation Tradeoff

- Fundamental problem of RL due to the active nature of the learning process

- Consider one-state RL problems known as bandits

Stochastic Bandits

- Formal definition:
  - Single state: $S = \{s\}$
  - A: set of actions (also known as arms)
  - Space of rewards (often re-scaled to be [0,1])
- No transition function to be learned since there is a single state
- We simply need to learn the **stochastic** reward function

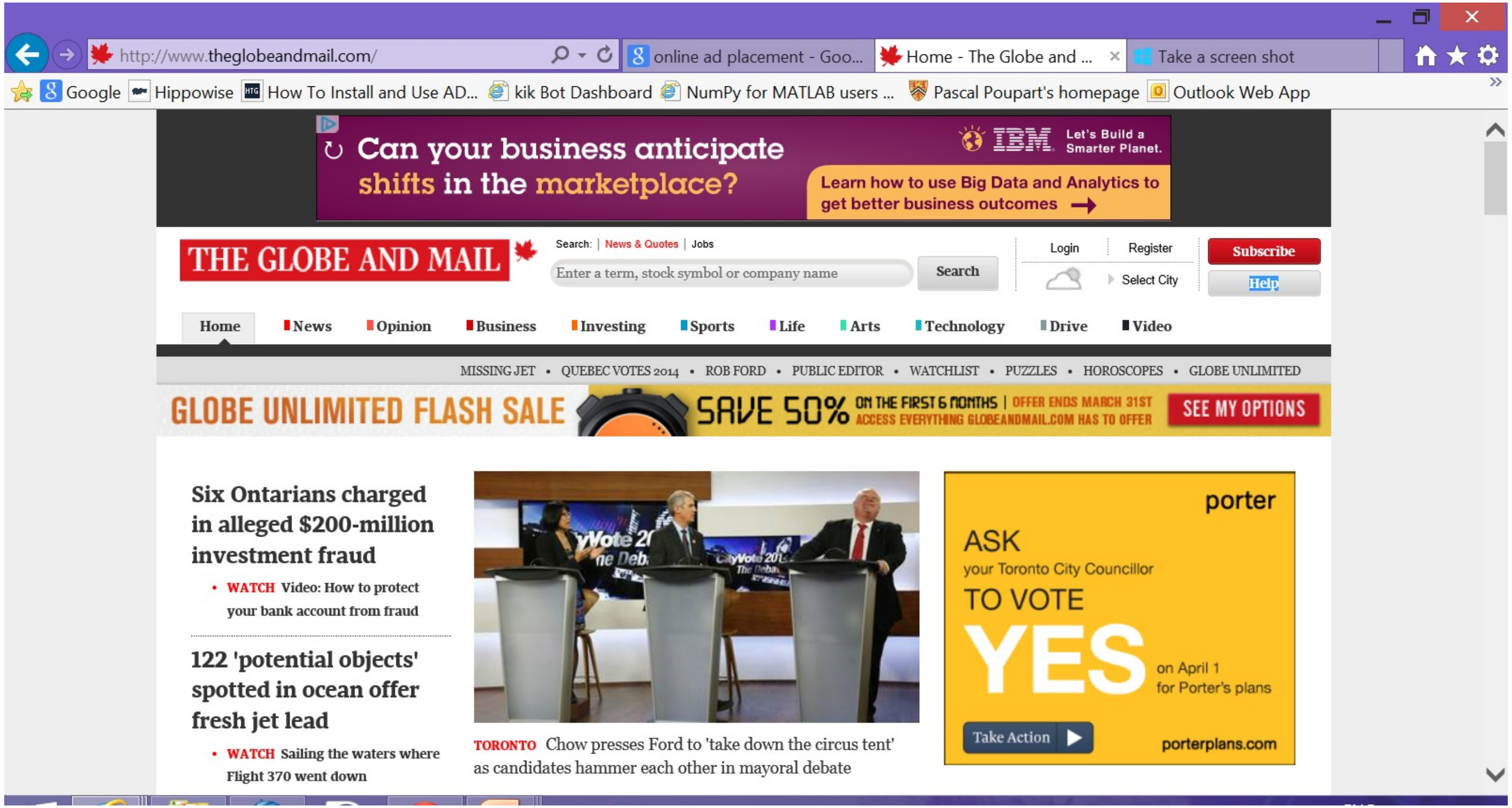
Origin and Applications

- "bandit" comes from gambling where slot machines can be thought as one-armed bandits.

Applications

- **Marketing** (ad placement, recommender systems)
- **Loyalty programs** (personalized offers)
- **Pricing** (airline seat pricing, cargo shipment pricing, food pricing)
- **Optimal design** (web design, interface personalization)
- **Networks** (routing)

Online Ad Placement



Online Ad Optimization

- Problem: which ad should be presented?

- Answer: present ad with highest payoff

$$payoff = clickThroughRate \times payment$$

  - Click through rate: probability that user clicks on ad
  - Payment: $$ paid by advertiser
    - Amount determined by an auction

Simplified Problem

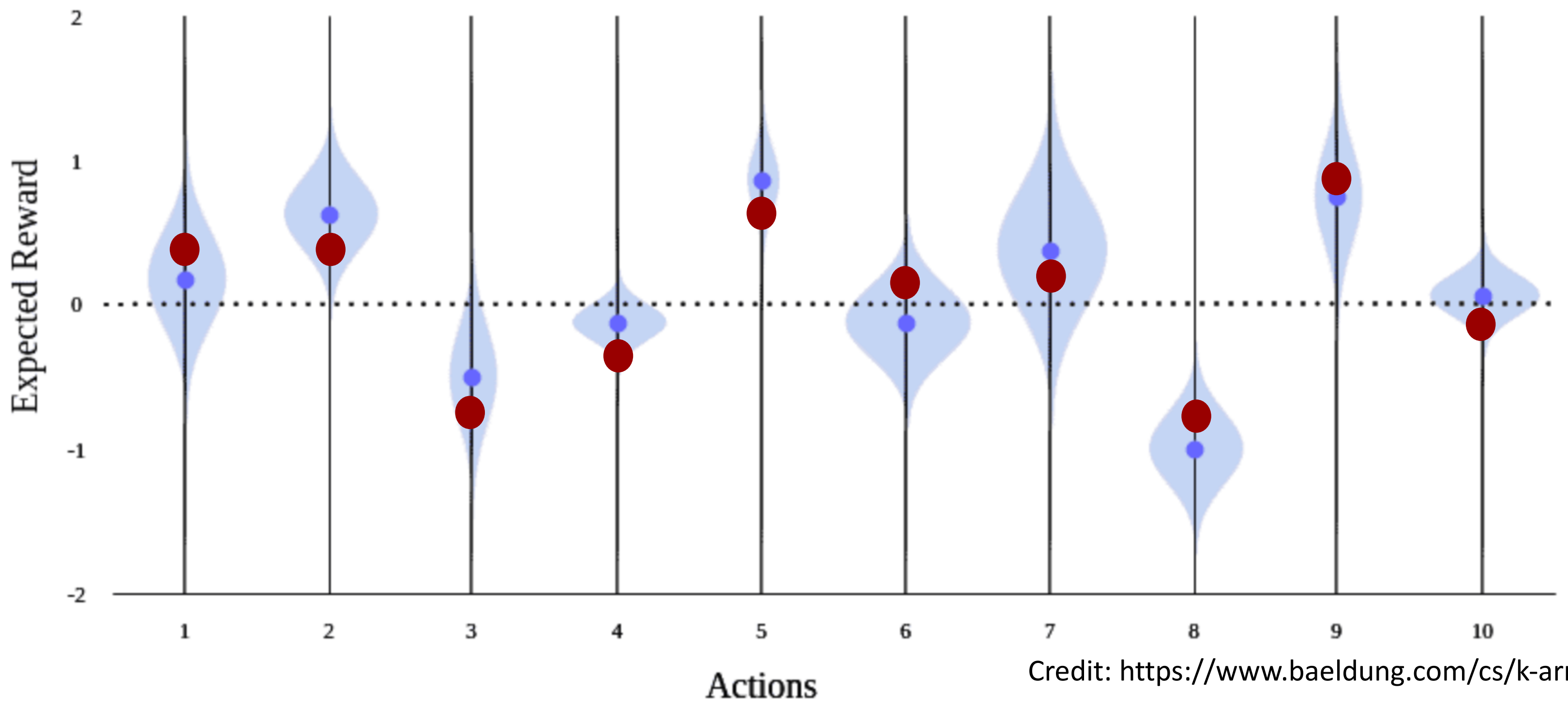
- Assume payment is 1 unit for all ads
- Need to estimate click through rate

- Formulate as a bandit problem:
  - Arms: the set of possible ads
  - Rewards: 0 (no click) or 1 (click)

- In what order should ads be presented to maximize revenue?
  - How should we balance exploitation and exploration?

Uncertainty Quantification

- Distribution of rewards: $\Pr(r|a)$
- Expected reward: $R(a) = E(r|a)$
- Empirical average reward: $\tilde{R}(a) = \frac{1}{n}\sum_t^n r_t$



Credit: https://www.baeldung.com/cs/k-armed-bandit-problem

Simple Heuristics

- Greedy strategy: select the arm with the highest average so far
  - May get stuck due to lack of exploration

- ϵ-greedy: select an arm at random with probability ϵ and otherwise do a greedy selection
  - Convergence rate depends on choice of ϵ

Regret

- Let $R(a)$ be the unknown average reward of a
- Let $r^* = \max_a R(a)$ and $a^* = argmax_a R(a)$

- Denote by $loss(a)$ the expected regret of a

$$loss(a) = r^* - R(a)$$

- Denote by $Loss_n$ the expected cumulative regret for n time steps

$$Loss_n = \sum_{t=1}^{n} loss(a_t)$$

Theoretical Guarantees

- When ϵ is constant, then
  - For large enough t: $\Pr(a_t \neq a^*) \approx \epsilon$
  - Expected cumulative regret: $Loss_n \approx \sum_{t=1}^{n} \epsilon = O(n)$
    - Linear regret

- When $\epsilon_t \propto 1/t$
  - For large enough t: $\Pr(a_t \neq a^*) \approx \epsilon_t = O\left(\frac{1}{t}\right)$
  - Expected cumulative regret: $Loss_n \approx \sum_{t=1}^{n} \frac{1}{t} = O(\log n)$
    - Logarithmic regret

Empirical Mean

- Problem: how far is the empirical mean $\tilde{R}(a)$ from the true mean $R(a)$?

- If we knew that $\left|R(a) - \tilde{R}(a)\right| \leq bound$
  - Then we would know that $R(a) < \tilde{R}(a) + bound$
  - And we could select the arm with best $\tilde{R}(a) + bound$

- Overtime, additional data will allow us to refine $\tilde{R}(a)$ and compute a tighter $bound$.

Positivism in the Face of Uncertainty

- Suppose that we have an oracle that returns an upper bound $UB_n(a)$ on $R(a)$ for each arm based on n trials of arm a.

- Suppose the upper bound returned by this oracle converges to $R(a)$ in the limit:
  - i.e., $\lim_{n\to\infty} UB_n(a) = R(a)$

- Optimistic algorithm
  - At each step, select $argmax_a \ UB_n(a)$

Convergence

- Theorem: An optimistic strategy that always selects $\text{argmax}_a UB_n(a)$ will converge to a^*

- Proof by contradiction:
  - Suppose that we converge to suboptimal arm a after infinitely many trials.
  - Then $R(a) = UB_\infty(a) \geq UB_\infty(a') = R(a')\ \forall a'$
  - But $R(a) \geq R(a')\ \forall a'$ contradicts our assumption that a is suboptimal.

Probabilistic Upper Bound

- Problem: We can't compute an upper bound with certainty since we are sampling

- However, we can obtain measures f that are upper bounds most of the time
  - i.e., $\Pr\big(R(a) \leq f(a)\big) \geq 1 - \delta$
  - Example: Hoeffding's inequality

$$\Pr\left(R(a) \leq \tilde{R}(a) + \sqrt{\frac{\log\left(\frac{1}{\delta}\right)}{2n_a}} \right) \geq 1 - \delta$$

where n_a is the number of trials for arm a

Upper Confidence Bound (UCB)

- Set $\delta_n = 1/n^4$ in Hoeffding's bound
- Choose a with highest Hoeffding bound

UCB(h)

$V \leftarrow 0,\ \ n \leftarrow 0,\ \ n_a \leftarrow 0 \quad \forall a$

Repeat until $n = h$

Execute $\text{argmax}_a\ \tilde{R}(a) + \sqrt{\frac{2 \log n}{n_a}}$

Receive r

$V \leftarrow V + r$

$\tilde{R}(a) \leftarrow \frac{n_a \tilde{R}(a) + r}{n_a + 1}$

$n \leftarrow n + 1, \quad n_a \leftarrow n_a + 1$

Return V

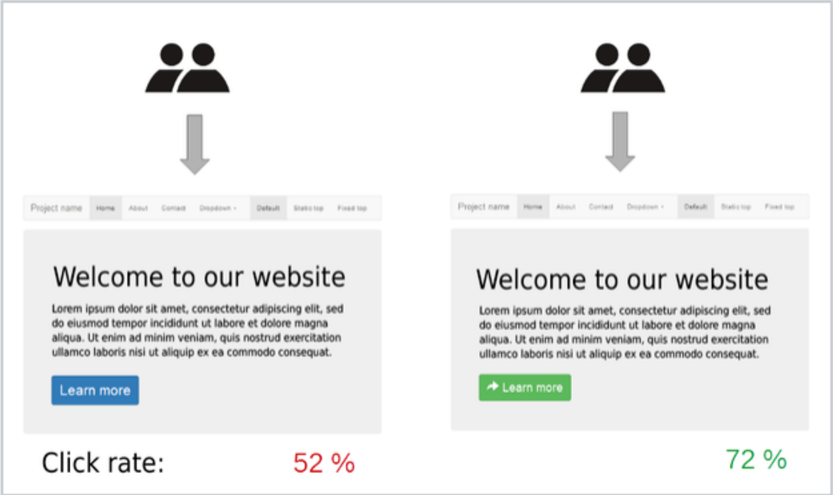
UCB Convergence

- **Theorem:** Although Hoeffding's bound is probabilistic, UCB converges.
- **Idea:** As n increases, the term $\sqrt{\frac{2\log n}{n_a}}$ increases, ensuring that all arms are tried infinitely often
- Expected cumulative regret: $Loss_n = O(\log n)$
  - Logarithmic regret

Extension of A/B Testing

- **A/B Testing:** randomized experiment with 2 variants
  - Select best variant after completion of experiment

Example: email marketing
- "Offer ends this Saturday! Use code A” (response rate: 5%)
- "Offer ends soon! Use code B" (response rate: 3%)



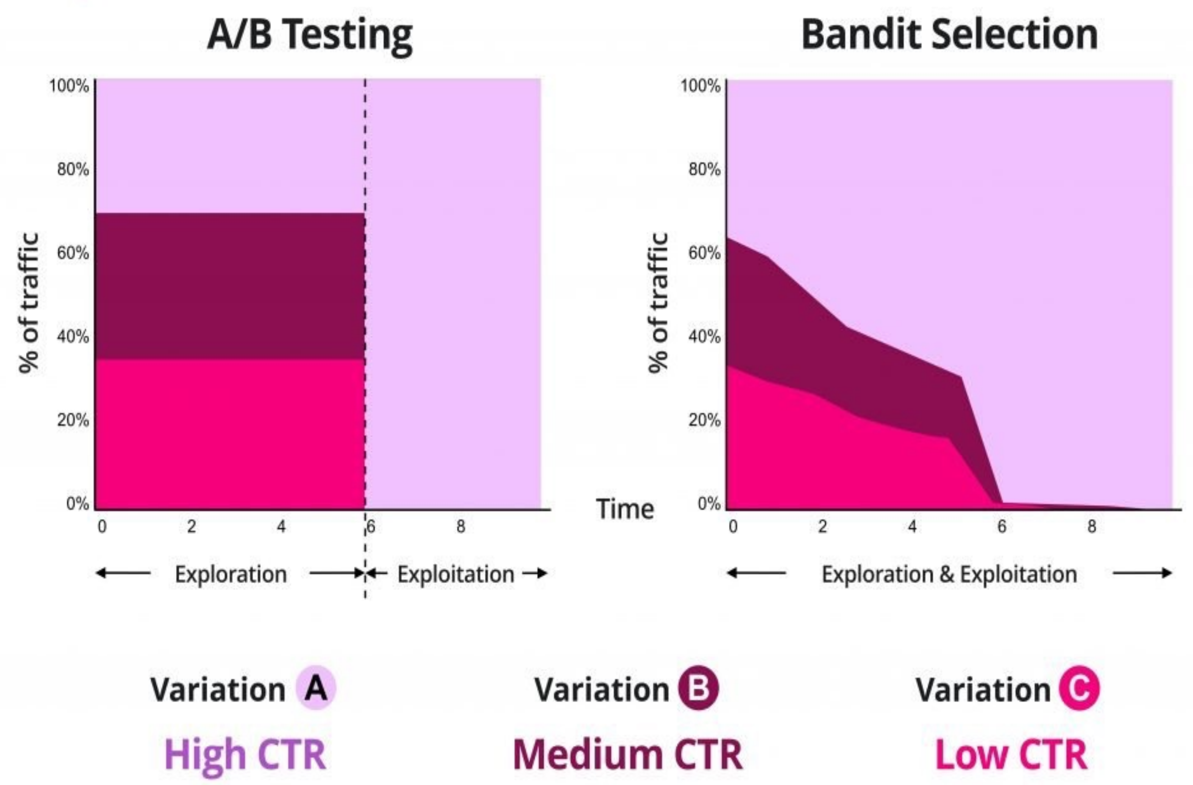
Example of A/B testing on a website. By randomly serving visitors two versions of a website that differ only in the design of a single button element, the relative efficacy of the two designs can be measured.

- **Multi-armed bandits:** form of continual A/B testing

Multi-Armed Bandit

Components	Formal Def	Marketing
Actions (arms)	$a \in A$	{A, B, C}
Rewards	$r \in \mathbb{R}$	{0, 1}
Reward model	$\Pr(r\|a)$	unknown
Horizon	$h \in \mathbb{N}$ or ∞	$h = \infty$

Credit: Shubhankar Gupta (vwo.com)



Bayesian Learning

- Notation:
  - r^a: random variable for a's rewards
  - $\Pr(r^a; \theta)$: unknown distribution (parameterized by θ)
  - $R(a) = E[r^a]$: unknown average reward
- Idea:
  - Express uncertainty about θ by a prior $\Pr(\theta)$
  - Compute posterior $\Pr(\theta | r_1^a, r_2^a, \ldots, r_n^a)$ based on samples $r_1^a, r_2^a, \ldots, r_n^a$ observed for a so far.

- Bayes theorem:

$$\Pr(\theta | r_1^a, r_2^a, \ldots, r_n^a) \propto \Pr(\theta) \Pr(r_1^a, r_2^a, \ldots, r_n^a | \theta)$$

Distributional Information

- Posterior over θ allows us to estimate
  - Distribution over next reward r^a

$$\Pr(r^a|r_1^a, r_2^a, \dots, r_n^a) = \int_\theta \Pr(r^a; \theta) \Pr(\theta|r_1^a, r_2^a, \dots, r_n^a)\, d\theta$$

  - Distribution over $R(a)$ when θ includes the mean

$$\Pr(R(a)|r_1^a, r_2^a, \dots, r_n^a) = \Pr(\theta|r_1^a, r_2^a, \dots, r_n^a) \text{ if } \theta = R(a)$$

- To guide exploration:
  - UCB: $\Pr(R(a) \leq bound(r_1^a, r_2^a, \dots, r_n^a)) \geq 1 - \delta$
  - Bayesian techniques: $\Pr(R(a)|r_1^a, r_2^a, \dots, r_n^a)$

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Coin Example

- Consider two biased coins C_1 and C_2

$$R(C_1) = \Pr(C_1 = head)$$
$$R(C_2) = \Pr(C_2 = head)$$

- Problem:
  - Maximize # of heads in k flips
  - Which coin should we choose for each flip?

Bernoulli Variables

- r^{C_1}, r^{C_2} are Bernoulli variables with domain $\{0,1\}$

- Bernoulli distributions are parameterized by their mean
  - i.e., $\Pr(r^{C_1}; \theta_1) = \theta_1 = R(C_1)$

    $\Pr(r^{C_2}; \theta_2) = \theta_2 = R(C_2)$

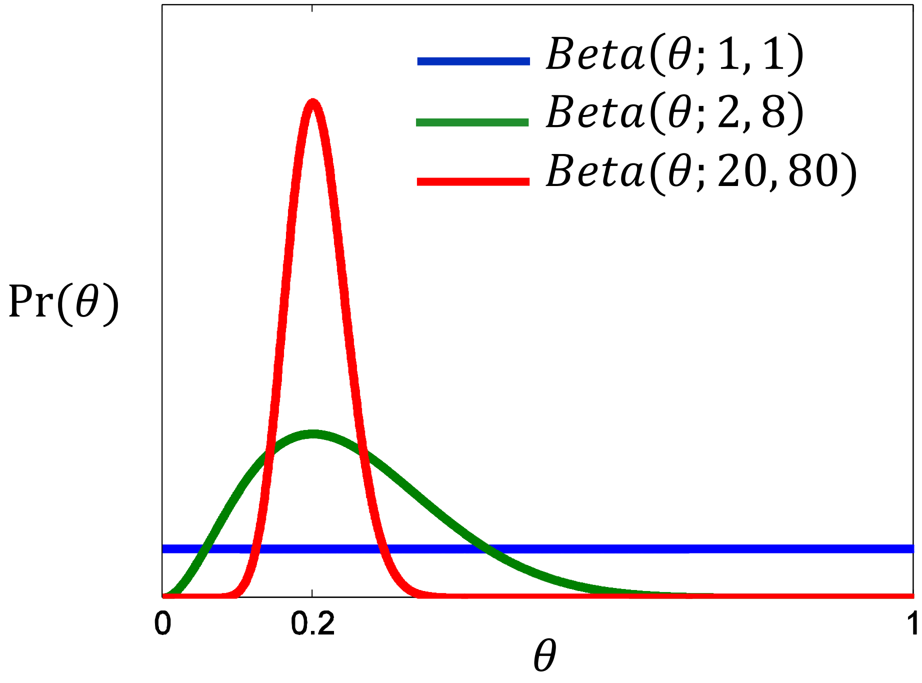
Beta Distribution

- Let the prior $\Pr(\theta)$ be a Beta distribution

$$Beta(\theta; \alpha, \beta) \propto \theta^{\alpha-1}(1-\theta)^{\beta-1}$$

- $\alpha - 1$: # of heads
- $\beta - 1$: # of tails

- $E[\theta] = \alpha/(\alpha + \beta)$



Belief Update

- Prior: $\Pr(\theta) = Beta(\theta; \alpha, \beta) \propto \theta^{\alpha-1}(1-\theta)^{\beta-1}$
- Posterior after coin flip:

$$\Pr(\theta|head) \propto \Pr(\theta) \quad \Pr(head|\theta)$$
$$\propto \theta^{\alpha-1}(1-\theta)^{\beta-1} \quad \theta$$
$$= \theta^{(\alpha+1)-1}(1-\theta)^{\beta-1} \propto Beta(\theta; \alpha+1, \beta)$$

$$\Pr(\theta|tail) \propto \Pr(\theta) \quad \Pr(tail|\theta)$$
$$\propto \theta^{\alpha-1}(1-\theta)^{\beta-1} \quad (1-\theta)$$
$$= \theta^{\alpha-1}(1-\theta)^{(\beta+1)-1} \propto Beta(\theta; \alpha, \beta+1)$$

Thompson Sampling

- Idea:
  - Sample several potential average rewards:

    $\hat{R}(a) \sim \Pr(R(a)|r_1^a, \dots, r_n^a)$ for each a
  - Execute $argmax_a \hat{R}(a)$

- Coin example
  - $\Pr(R(a)|r_1^a, \dots, r_n^a) = \text{Beta}(\theta_a; \alpha_a, \beta_a)$
    where $\alpha_a - 1 = \#heads$ and $\beta_a - 1 = \#tails$

Thompson Sampling (Bernoulli rewards)

ThompsonSampling(h)
Initialize $\alpha_a \leftarrow 1, \beta_a \leftarrow 1\ \forall a$
Repeat h times
Sample $\hat{R}(a) \sim Beta(R(a)|\alpha_a, \beta_a)\ \forall a$
$a^* \leftarrow \mathrm{argmax}_a\ \hat{R}(a)$
Execute a^* and receive r
if $r = 1$ then $\alpha_{a^*} \leftarrow \alpha_{a^*} + 1$
else $\beta_{a^*} \leftarrow \beta_{a^*} + 1$

Analysis

- Thompson sampling converges to best arm

- Theory:
  - Expected cumulative regret: $O(\log\ n)$
  - On par with UCB and ϵ-greedy

- Practice:
  - Thompson Sampling often outperforms UCB and ϵ-greedy