

$$\text{policy} = \text{solve}(\underline{\text{solver}}, \underline{m})$$

offline
calculation

$$a = \text{action}(\text{policy}, s)$$

online
calculation

k-armed Bernoulli Bandits

$$\theta \quad p(w)$$

$$p(\theta_i | o_1, o_2, \dots, o_{t-1}) = \text{Beta}$$

loop

pull arm i based on policy \leftarrow
observe o_t , get r_t

$$p(\theta_i | o_1, o_2, \dots, o_{t-1}) = \text{Beta}(w+1, l+1)$$

$$\hat{Q}_i = \frac{w}{w+l} = \hat{\theta} \quad \text{argmax}_i \hat{Q}_i$$

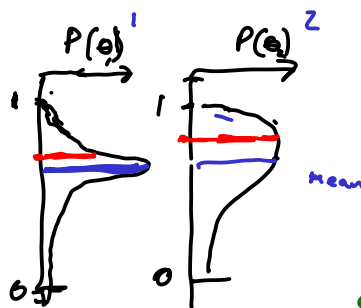
- ϵ -greedy: wp. $1-\epsilon$ choose $\text{argmax}_i \hat{Q}_i$
wp. ϵ choose random

- softmax

$$P(i) = \frac{e^{\alpha \hat{Q}_i}}{\sum_j e^{\alpha \hat{Q}_j}}$$

- Interval

- UCB



$\hat{\theta} + 1$ standard dev



(not expensive)

Bayesian
Expensive

$$\text{argmax}_i \hat{Q}_i + \sqrt{\frac{\ln \sum_j N_j}{N_i}}$$

- Thompson Sampling

sample θ_i from $P(\theta_i | o_1, \dots, o_t)$
choose $\text{argmax}_i \theta_i$

ad hoc

Optimal Policies for Bandits Finite Horizon h

MDP

$$P(\theta | \dots) = \text{Beta}(w+1, l+1)$$

$$S = \{ (w_1, l_1, \dots, w_n, l_n) \}_{w, l \in 1..h}$$

exponential in h

$$R(s, i, s') = \begin{cases} +1 & \text{if } w_i \text{ was incremented} \\ 0 & \text{o.w.} \end{cases}$$

$$A = \{ 1 \dots k \}$$

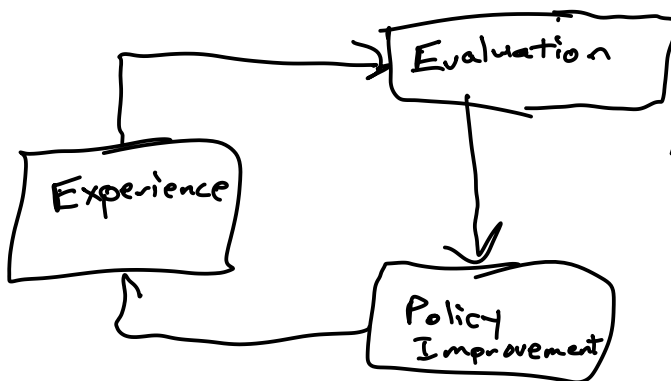
T = increment win or loss according to belief probabilities

$$P(o_t = 1 | s) = \int p_{\text{Beta}(\cdot)}(\theta) \theta d\theta$$

Gittins Index

Exploration + Exploitation \leftarrow Bandits
Credit Assignment
Generalization

RL



Offline or Online

often used in offline fashion with simulator

Model Based: 1. Learn MDP model from experience
2. Solve MDP

Model Free: Learn value or policy directly from experience

On-Policy

Off-Policy: Able to improve policy without new experience from that policy

Model - Based RL

Max Likelihood

$$N(s, a, s') , p(s, a)$$

$$N(s, a) = \sum_{s'} N(s, a, s')$$

$$T(s' | s, a) = \frac{N(s, a, s')}{N(s, a)}$$

$$R(s, a) = \frac{p(s, a)}{N(s, a)}$$

loop

Choose a based on exp. strat.

Observe s', r

$N(s, a, s') ++$

$p(s, a) += r$

update T, R

update $Q \leftarrow$ expensive . (Value Iteration)

$s \leftarrow s'$