Planning and Optimization

G8. Monte-Carlo Tree Search Algorithms (Part II)

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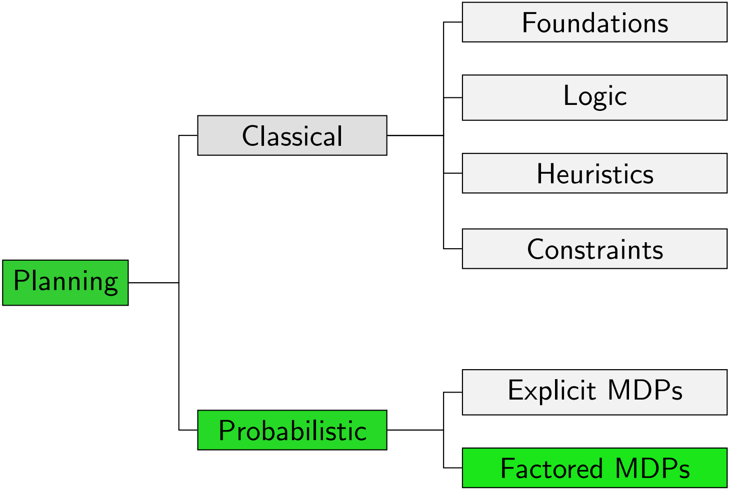
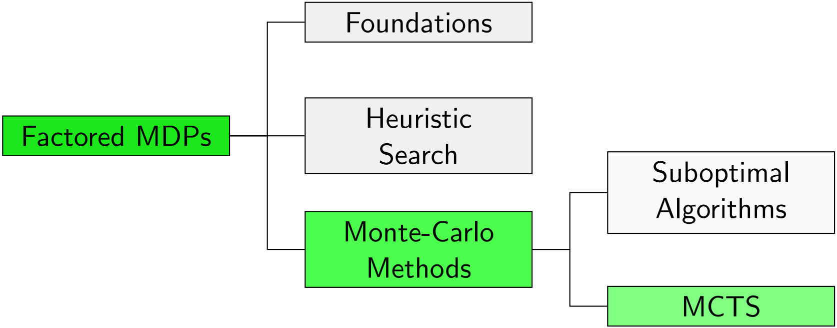
Content of this Course



Content of this Course: Factored MDPs



ε-greedy

ε-greedy: Idea

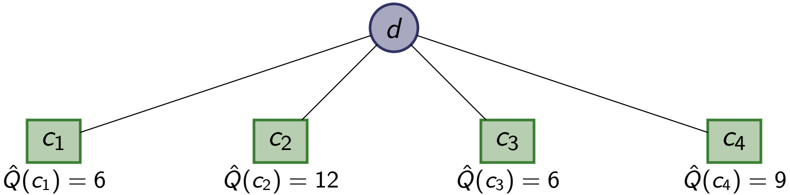
- tree policy parametrized with constant parameter ε
- with probability $1-\varepsilon$, pick one of the greedy actions uniformly at random
- otherwise, pick non-greedy successor uniformly at random

ε-greedy Tree Policy

$$\pi(a \mid d) = \begin{cases} \frac{1-\epsilon}{|L_\star^k(d)|} & \text{if } a \in L_\star^k(d) \\ \frac{\epsilon}{|L(d(s)) \setminus L_\star^k(d)|} & \text{otherwise,} \end{cases}$$

with $L_\star^k(d) = \{a(c) \in L(s(d)) \mid c \in \arg\min_{c' \in \text{children}(d)} \hat{Q}^k(c')\}$.

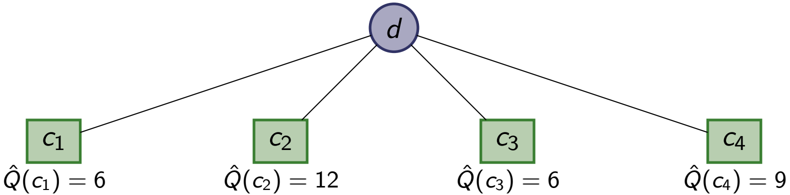
ε-greedy: Example



Assuming $a(c_i) = a_i$ and $\varepsilon = 0.2$, we get:

- $\pi(a_1 \mid d) =$
- $\pi(a_2 \mid d) =$
- $\pi(a_3 \mid d) =$
- $\pi(a_4 \mid d) =$

ε-greedy: Example



Assuming $a(c_i) = a_i$ and $\varepsilon = 0.2$, we get:

- $\pi(a_1 \mid d) = 0.4$
- $\pi(a_2 \mid d) = 0.1$
- $\pi(a_3 \mid d) = 0.4$
- $\pi(a_4 \mid d) = 0.1$

ε-greedy: Asymptotic Optimality

Asymptotic Optimality of ε-greedy

- explores forever
- not greedy in the limit

$\rightsquigarrow$ not asymptotically optimal

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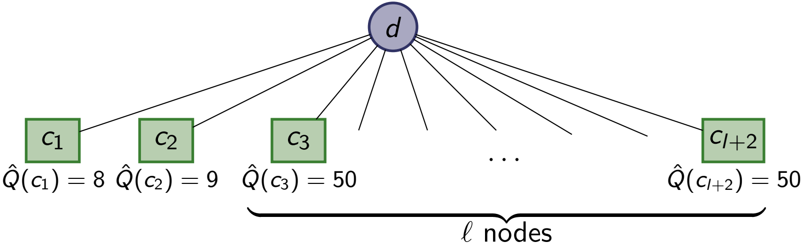
asymptotically optimal variant uses decaying ε, e.g. $\varepsilon = \frac{1}{k}$

ε-greedy: Weakness

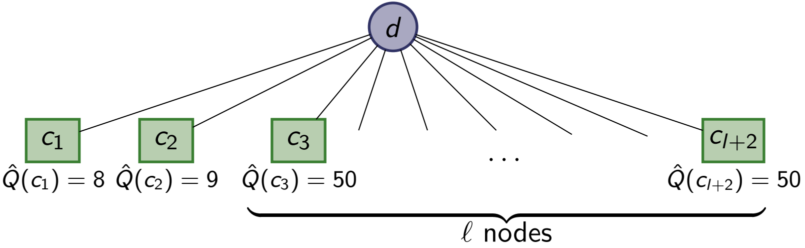
Problem:
when ε-greedy explores, all non-greedy actions are treated equally



Assuming $a(c_i) = a_i$, $\varepsilon = 0.2$ and $\ell = 9$, we get:

ε-greedy: Weakness

Problem:
when ε-greedy explores, all non-greedy actions are treated equally



Assuming $a(c_i) = a_i$, $\varepsilon = 0.2$ and $\ell = 9$, we get:

- $\pi(a_1 \mid d) = 0.8$
- $\pi(a_2 \mid d) = \pi(a_3 \mid d) = \cdots = \pi(a_{11} \mid d) = 0.02$

Softmax

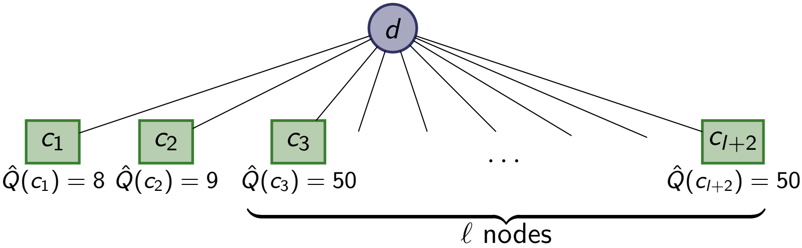
Softmax: Idea

- tree policy with constant parameter τ
- select actions proportionally to their action-value estimate
- most popular softmax tree policy uses Boltzmann exploration
- $\Rightarrow$ selects actions proportionally to $e^{\frac{-\hat{Q}_k(c)}{\tau}}$

Tree Policy based on Boltzmann Exploration

$$\pi(a(c) \mid d) = \frac{e^{\frac{-\hat{Q}_k(c)}{\tau}}}{\sum_{c' \in \text{children}(d)} e^{\frac{-\hat{Q}_k(c')}{\tau}}}$$

Softmax: Example



Assuming $a(c_i) = a_i$, $\tau = 10$ and $\ell = 9$, we get:

- $\pi(a_1 \mid d) = 0.49$
- $\pi(a_2 \mid d) = 0.45$
- $\pi(a_3 \mid d) = \ldots = \pi(a_{11} \mid d) = 0.007$

Boltzmann Exploration: Asymptotic Optimality

Asymptotic Optimality of Boltzmann Exploration

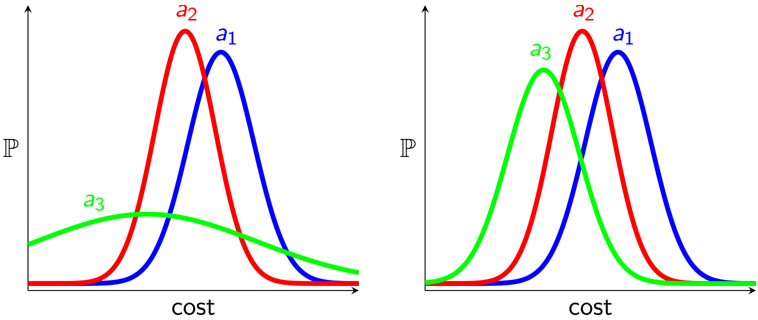
- explores forever
- not greedy in the limit:
  - state- and action-value estimates converge to finite values
  - therefore, probabilities also converge to positive, finite values

$\rightsquigarrow$ not asymptotically optimal

asymptotically optimal variant uses decaying τ, e.g. $\tau = \frac{1}{\log k}$

careful: τ must not decay faster than logarithmically
(i.e., must have $\tau \geq \frac{\text{const}}{\log k}$) to explore infinitely

Boltzmann Exploration: Weakness



- Boltzmann exploration and ε-greedy only consider mean of sampled action-values
- as we sample the same node many times, we can also gather information about variance (how reliable the information is)
- Boltzmann exploration ignores the variance, treating the two scenarios equally

UCB1

Upper Confidence Bounds: Idea

Balance exploration and exploitation by preferring actions that

- have been successful in earlier iterations (exploit)
- have been selected rarely (explore)

Upper Confidence Bounds: Idea

- select successor c of d that minimizes $\hat{Q}^k(c) - E^k(d) \cdot B^k(c)$
  - based on action-value estimate $\hat{Q}^k(c)$,
  - exploration factor $E^k(d)$ and
  - bonus term $B^k(c)$.
- select $B^k(c)$ such that
  $Q_\star(s(c), a(c)) \leq \hat{Q}^k(c) - E^k(d) \cdot B^k(c)$
  with high probability
- Idea: $\hat{Q}^k(c) - E^k(d) \cdot B^k(c)$ is a lower confidence bound on $Q_\star(s(c), a(c))$ under the collected information

Bonus Term of UCB1

- use $B^k(c) = \sqrt{\frac{2 \cdot \ln N^k(d)}{N^k(c)}}$ as bonus term
- bonus term is derived from Chernoff-Hoeffding bound:
  - gives the probability that a sampled value (here: $\hat{Q}^k(c)$)
  - is far from its true expected value (here: $Q_\star(s(c), a(c))$)
  - in dependence of the number of samples (here: $N^k(c)$)
- picks the optimal action exponentially more often
- concrete MCTS algorithm that uses UCB1 is called UCT

Exploration Factor (1)

Exploration factor $E^k(d)$ serves two roles in SSPs:

- UCB1 designed for MAB with reward in $[0, 1]$
  $\Rightarrow \hat{Q}^k(c) \in [0; 1]$ for all k and c
- bonus term $B^k(c) = \sqrt{\frac{2 \cdot \ln N^k(d)}{N^k(c)}}$ always ≥ 0
- when d is visited,
  - $B^{k+1}(c) > B^k(c)$ if $a(c)$ is not selected
  - $B^{k+1}(c) < B^k(c)$ if $a(c)$ is selected
- if $B^k(c) \geq 2$ for some c, UCB1 must explore
- hence, $\hat{Q}^k(c)$ and $B^k(c)$ are always of similar size

$\Rightarrow$ set $E^k(d)$ to a value that depends on $\hat{V}^k(d)$

Exploration Factor (2)

Exploration factor $E^k(d)$ serves two roles in SSPs:

- $E^k(d)$ allows to adjust balance
  between exploration and exploitation
- search with $E^k(d) = \hat{V}^k(d)$ very greedy
- in practice, $E^k(d)$ is often multiplied with constant > 1
- UCB1 often requires hand-tailored $E^k(d)$ to work well

Asymptotic Optimality

Asymptotic Optimality of UCB1

- explores forever
- greedy in the limit

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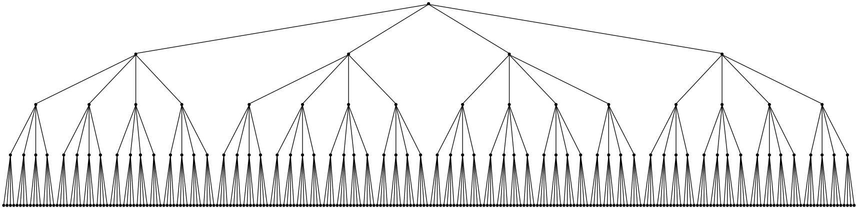
However:

- no theoretical justification to use UCB1 for SSPs/MDPs (MAB proof requires stationary rewards)
- development of tree policies active research topic

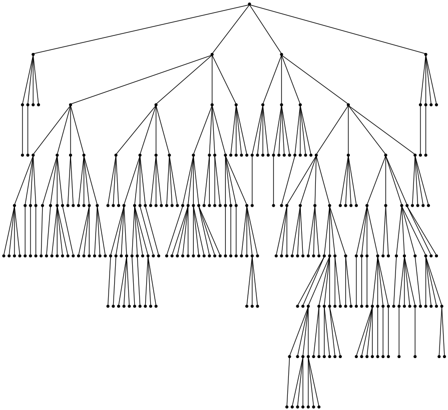
Symmetric Search Tree up to depth 4

full tree up to depth 4



Asymmetric Search Tree of UCB1

(equal number of search nodes)



Summary

Summary

- ε-greedy, Boltzmann exploration and UCB1 balance exploration and exploitation
- ε-greedy selects greedy action with probability $1 - \varepsilon$ and another action uniformly at random otherwise
- ε-greedy selects non-greedy actions with same probability
- Boltzmann exploration selects each action proportional to its action-value estimate
- Boltzmann exploration does not take confidence of estimate into account
- UCB1 selects actions greedily w.r.t. upper confidence bound on action-value estimate