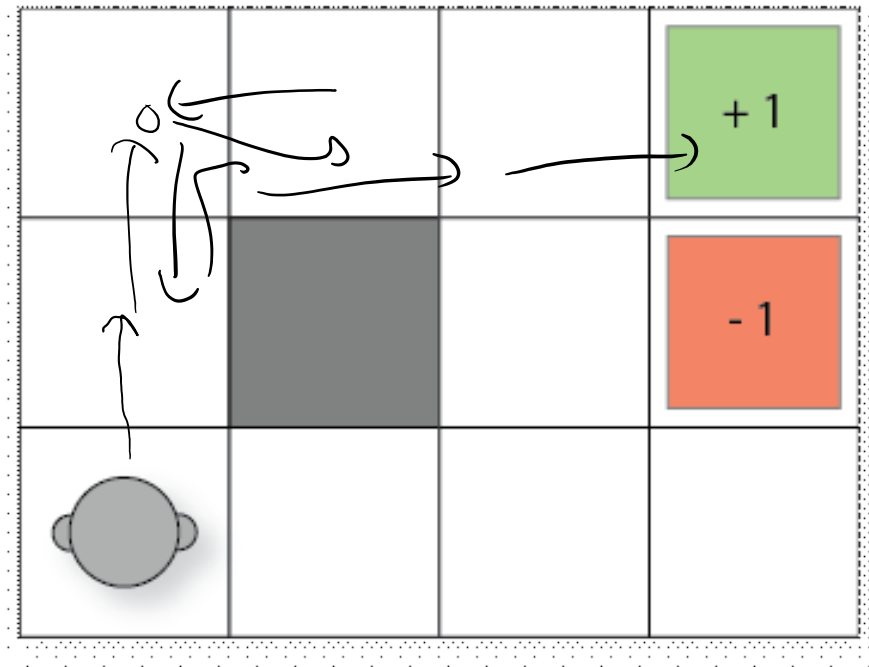


Monte-Carlo Tree Search

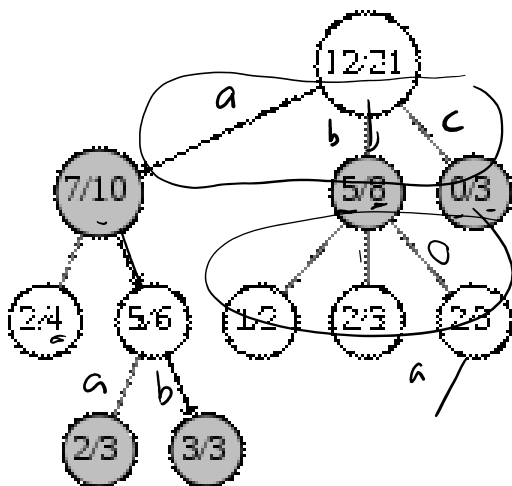
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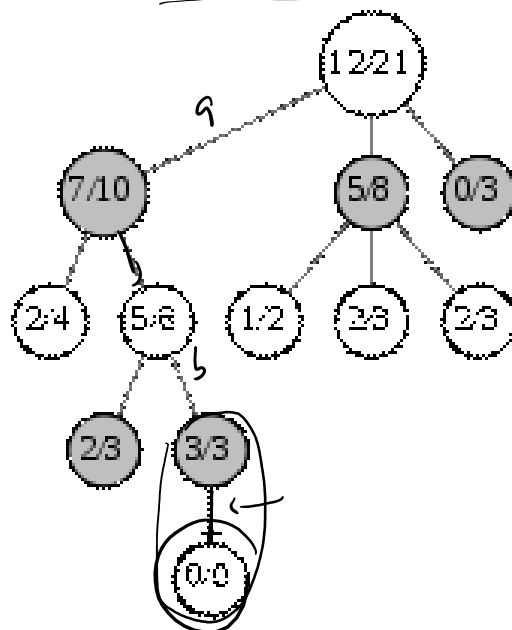
Monte-Carlo Tree Search (MCTS) overview

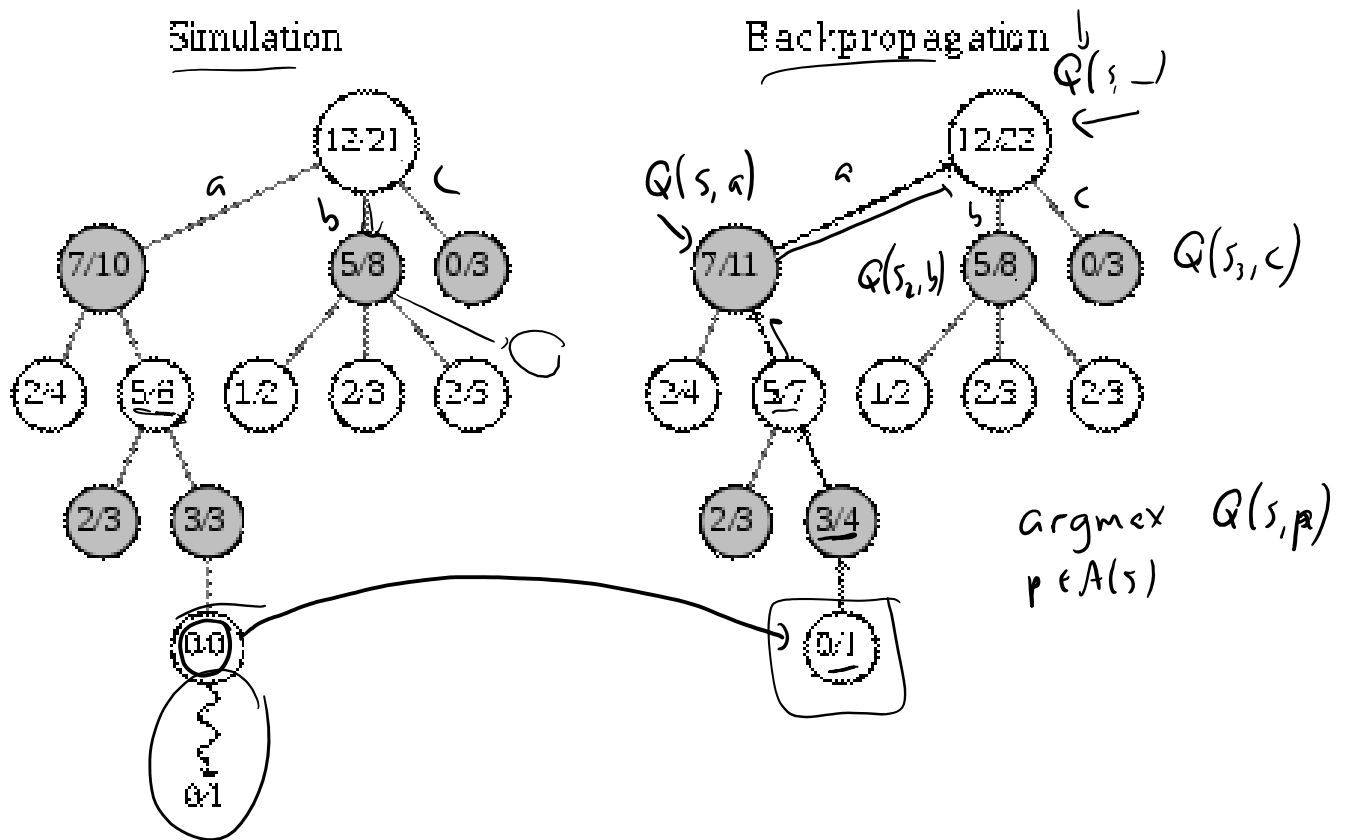
1. $Q(s,a)$ is the Q-function: an estimate of the value of applying a in state s .
2. $Q(s,a)$ is both the estimate but we will also use it as an heuristic.
3. The search tree is incrementally built.
4. MCTS is an *anytime* algorithm: we terminate whenever and give the best answer so far.

Selection



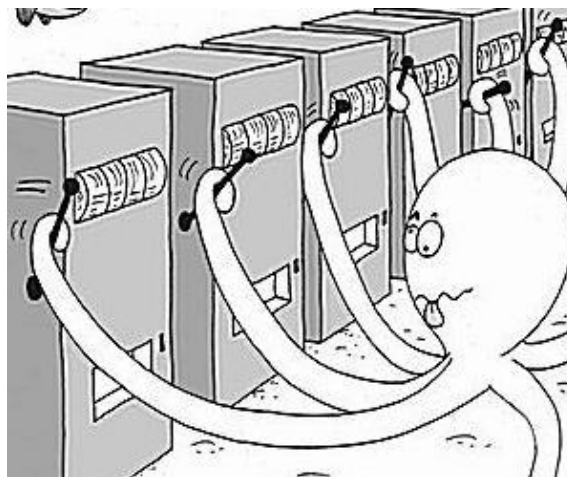
Expansion





Multi-armed bandits

Imagine that you have N number of slot machines (or poker machines in Australia), which are sometimes called one-armed bandits. Over time, each bandit pays a random reward from an unknown probability distribution. Some bandits pay higher rewards than others. The goal is to maximize the sum of the rewards of a sequence of lever pulls of the machine.



$$\epsilon = 0.1$$

Exploration vs exploitation

1. ϵ -greedy: exploit best action with probability $(1-\epsilon)$ and random action with probability ϵ
2. ϵ -decreasing: ϵ -greedy, but decrease ϵ over time
3. Softmax: select action with probability proportional to $Q(s, a)$ so far

Upper confidence bounds (UCB)

$$\arg \max a \in A \left[\underbrace{Q(s, a)}_{\text{exploit}} + \underbrace{\sqrt{\frac{2 \ln N(S)}{N(a, s)}}}_{\text{exploit}} \right]$$

Upper confidence tree (UCT)

UCT = UCB + MCTS (almost!)

$$\arg \max a \in A \left[Q(s, a) + 2C_p \sqrt{\frac{2 \ln N(S)}{N(a, s)}} \right]$$

C_p is an exploration constant > 0

$$C_p < \frac{1}{2} \Rightarrow \text{exploit}$$

$$C_p = \frac{1}{2} \Rightarrow \text{UCT}$$

$$C_p > \frac{1}{2} \Rightarrow \text{explore}$$

UCT playing Mario Brothers: [A MCTS-based Mario-playing controller](#)



UCT playing Freeway: [UCT Freeway - atari 2600](#)



Value/policy iteration vs. MCTS

Value/policy it => full policy
Computational