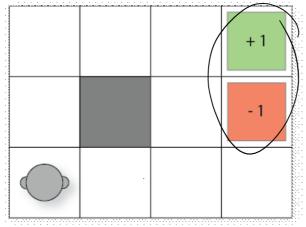
# Monte-Carlo Tree Search

Tuesday, 11 September 2018

13:58 PM



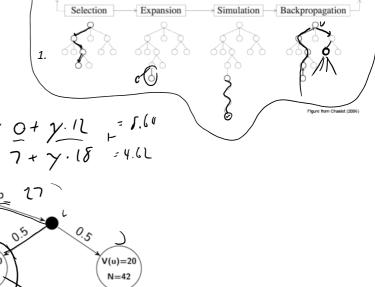
### Monte-Carlo Tree Search (MCTS) overview

- 1. V(s) is the estimate of the real value of a state.
- 2. But we will also use it as an heuristic.
- 3. The search tree is incrementally built.

1. Select

4. MCTS is an <u>anytime</u> algorithm: we terminate whenever and give the best answer so far.

4. Dackprox



# 2. $E \times p \times d$ 3. Simulade V(t)=12 V(t)=12 V(t)=12 V(t)=12 V(u)=40 N=38 V(u)=40 N=42 V(u)=20 N=42 V=2S V=2S

# Exercise

Your phone-stealing habits continue, but you are doing well and opening up to a new market of people. Each day, you can sell a bag of 20 iPhones, Samsung, Huawei, or Pixel phones, but the price varies with each buyer, and you don't know the probability that people will buy them. You decide to alternate: iPhones one day, Samsung the next, then Huawei, then Pixel. After 100 days, you notice the following average return per day:

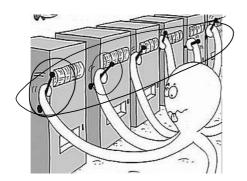
Samsung: \$400iPhone: \$250Pixel: \$200Huawei: \$150

To help with your supply, you need to decide what you want to do for the next 100 days. Assuming the next 100 days will look similar to the previous 100 days, what should you do?

https://pollev.com/timothymille936

### 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.



## Exploration vs exploitation

 $\textbf{1.} \quad \textbf{ $\in$-$greedy:} \in \text{in } [0,1] \text{ (typically around } 0.1) \text{ , choose the best with probability } 1-\textbf{$\in$}, \text{ and other choose randomly } 1-\textbf{$\in$}, \text{ and other choose } 1-\textbf{$\in$}, \text{ and other choose } 1-\textbf{$o$}, \text{ and other choose }$ 

2.  $\in$ -decreasing: as above but  $\in$  decreases over time

3. Softmax: choose proportionally

Upper confidence bounds (UCB)
$$R(b) = \underset{s}{\operatorname{argmex}} Q(s,c) + \underbrace{\frac{2 \ln(N(s))}{N(s,c)}}_{\underset{s}{\operatorname{himber of}}}$$

$$\underset{s}{\operatorname{chosen in } s}$$

Upper confidence tree (UCT)
UCT = UCB + MCTS (almost!)

UCT playing Mario Brothers: A MCTS-based Mario-playing controller



UCT playing Freeway: <u>UCT Freeway - atari 2600</u>



Value/policy iteration vs. MCTS