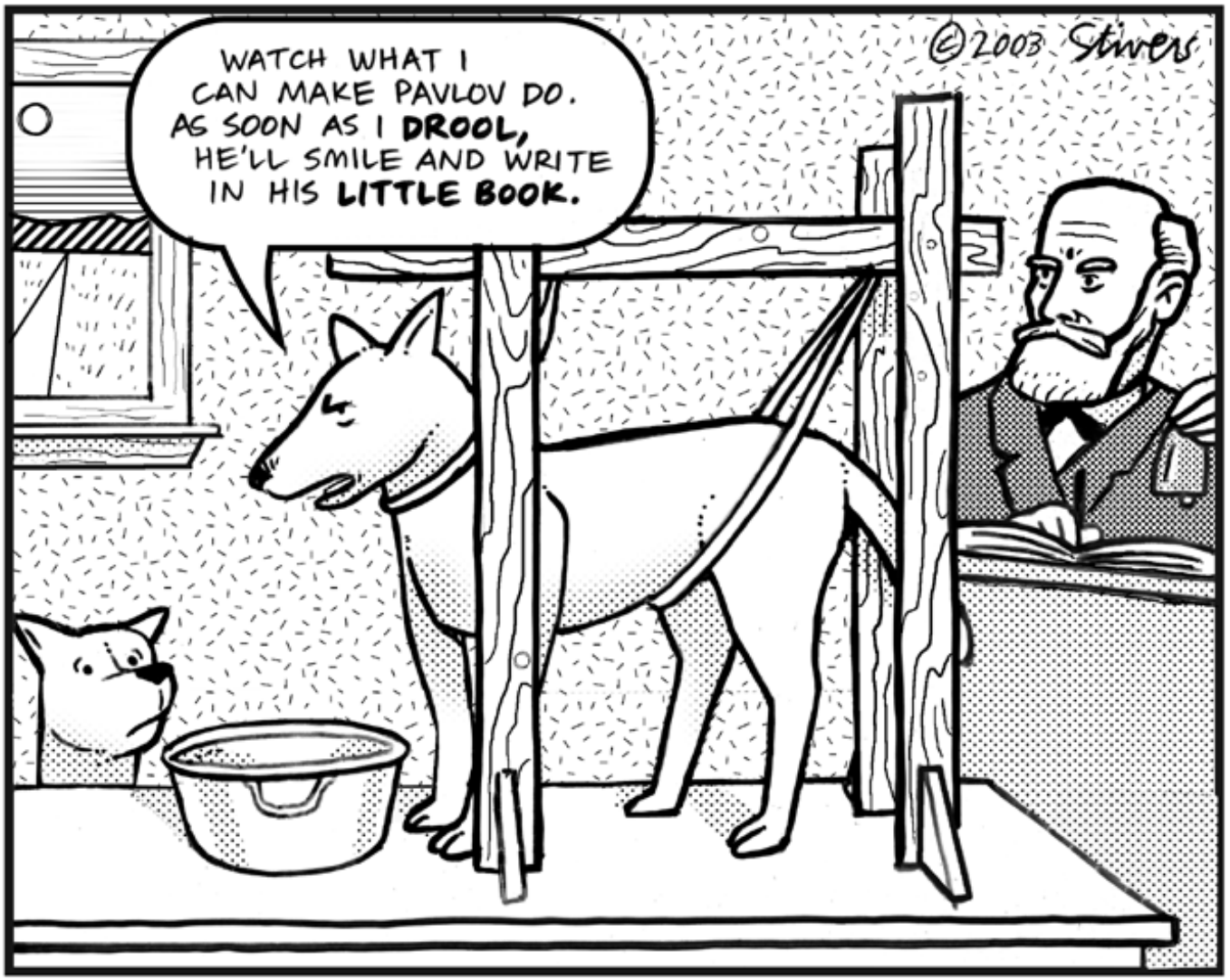
Reinforcement Learning
&
Monte Carlo Planning

(Slides by Alan Fern, Dan Klein, Subbarao Kambhampati, Raj Rao, Lisa Torrey, Dan Weld)


WATCH WHAT I CAN MAKE PAVLOV DO. AS SOON AS I DROOL, HE'LL SMILE AND WRITE IN HIS LITTLE BOOK.
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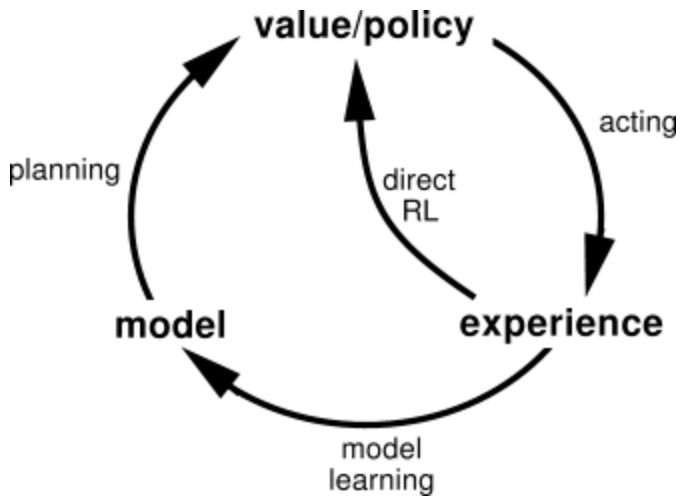
Learning/Planning/Acting



Reinforcement Learning

- Reinforcement learning:
  - Still have an MDP:
    - A set of states $s \in S$
    - A set of actions (per state) A
    - A model T(s,a,s')
    - A reward function R(s,a,s')
  - Still looking for a policy $\pi(s)$
  - New twist: don't know T or R
    - I.e. don't know which states are good or what the actions do
    - Must actually try actions and states out to learn

Main Dimensions

Model-based vs. Model-free

- Model-based vs. Model-free
  - Model-based → Have/learn action models (i.e. transition probabilities)
    - Eg. Approximate DP
  - Model-free → Skip them and directly learn what action to do when (without necessarily finding out the exact model of the action)
    - E.g. Q-learning

Passive vs. Active

- Passive vs. Active
  - Passive: Assume the agent is already following a policy (so there is no action choice to be made; you just need to learn the state values and may be action model)
  - Active: Need to learn both the optimal policy and the state values (and may be action model)

Main Dimensions (contd)

Extent of Backup

- Full DP
  - Adjust value based on values of *all* the neighbors (as predicted by the transition model)
  - Can only be done when transition model is present
- Temporal difference
  - Adjust value based only on the actual transitions observed

Strong or Weak Simulator

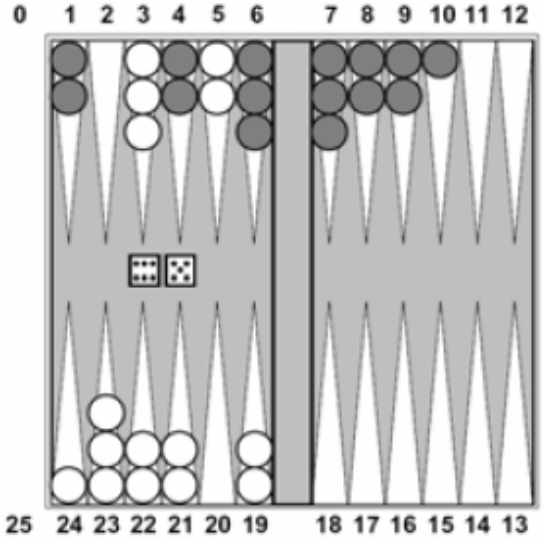
- Strong
  - I can jump to any part of the state space and start simulation there.
- Weak
  - Simulator is the real world and I can teleport to a new state.

Example: Animal Learning

- RL studied experimentally for more than 60 years in psychology
  - Rewards: food, pain, hunger, drugs, etc.
  - Mechanisms and sophistication debated
- Example: foraging
  - Bees learn near-optimal foraging plan in field of artificial flowers with controlled nectar supplies
  - Bees have a direct neural connection from nectar intake measurement to motor planning area

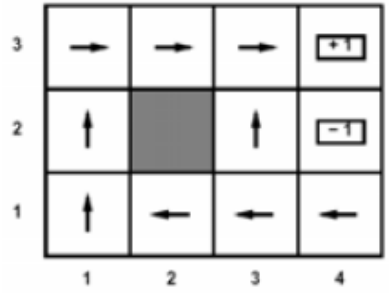
Example: Backgammon

- Reward only for win / loss in terminal states, zero otherwise
- TD-Gammon learns a function approximation to V(s) using a neural network
- Combined with depth 3 search, one of the top 3 players in the world



Does self learning through simulator.
[Infants don't get to "simulate" the world since they neither have T(.) nor R(.) of their world]

Passive Learning



- Simplified task
  - You don't know the transitions T(s,a,s')
  - You don't know the rewards R(s,a,s')
  - You are given a policy $\pi(s)$
  - Goal: learn the state values (and maybe the model)

- In this case:
  - No choice about what actions to take
  - Just execute the policy and learn from experience
  - We'll get to the general case soon

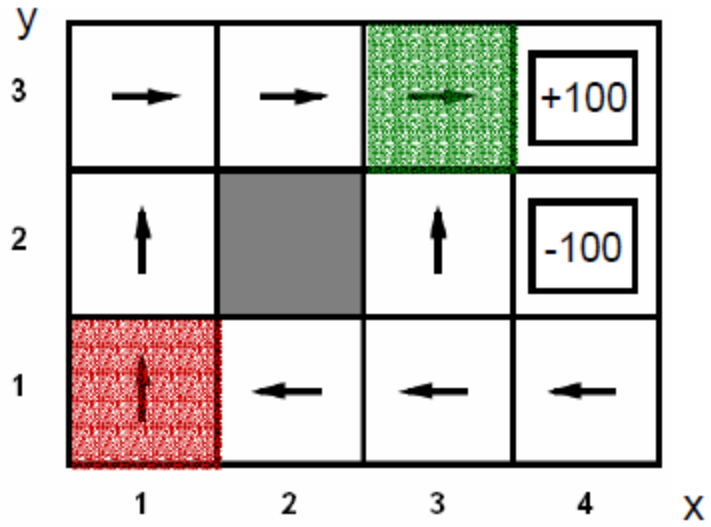
We are basically doing EMPIRICAL Policy Evaluation!

Example: Direct Estimation

- Episodes:

(1,1) up -1
(1,2) up -1
(1,2) up -1
(1,3) right -1
(2,3) right -1
(3,3) right -1
(3,2) up -1
(3,3) right -1
(4,3) exit +100
(done)

(1,1) up -1
(1,2) up -1
(1,3) right -1
(2,3) right -1
(3,3) right -1
(3,2) up -1
(4,2) exit -100
(done)



$\gamma = 1, R = -1$

U(1,1) ~ (92 + -106) / 2 = -7

U(3,3) ~ (99 + 97 + -102) / 3 = 31.3

But we *know* this will be wasteful
(since it misses the correlation between values of neibhoring states!)

Do DP-based policy evaluation!

Model-Based Learning

- Idea:
  - Learn the model empirically (rather than values)
  - Solve the MDP as if the learned model were correct
- Empirical model learning
  - Simplest case:
    - Count outcomes for each s,a
    - Normalize to give estimate of T(s,a,s')
    - Discover R(s,a,s') the first time we experience (s,a,s')
  - More complex learners are possible (e.g. if we know that all squares have related action outcomes, e.g. "stationary noise")

Example: Model-Based Learning

- Episodes:

(1,1) up -1
(1,2) up -1
(1,2) up -1
(1,3) right -1
(2,3) right -1
(3,3) right -1
(3,2) up -1
(3,3) right -1
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(1,1) up -1
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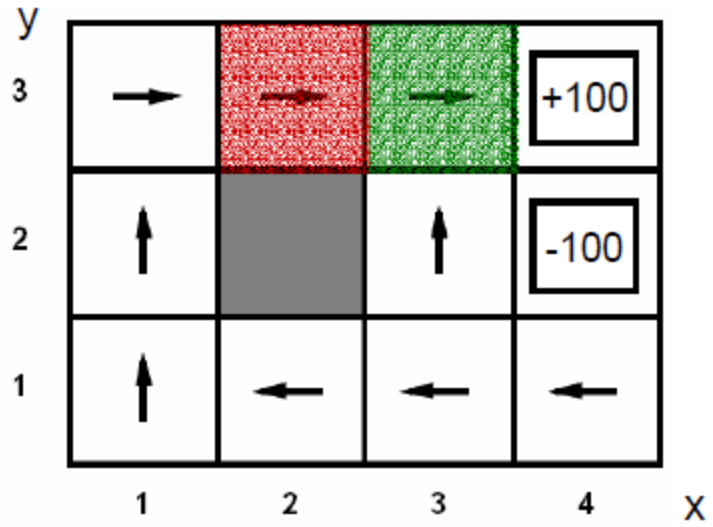


$\gamma = 1$

T(<3,3>, right, <4,3>) = 1 / 3

T(<2,3>, right, <3,3>) = 2 / 2

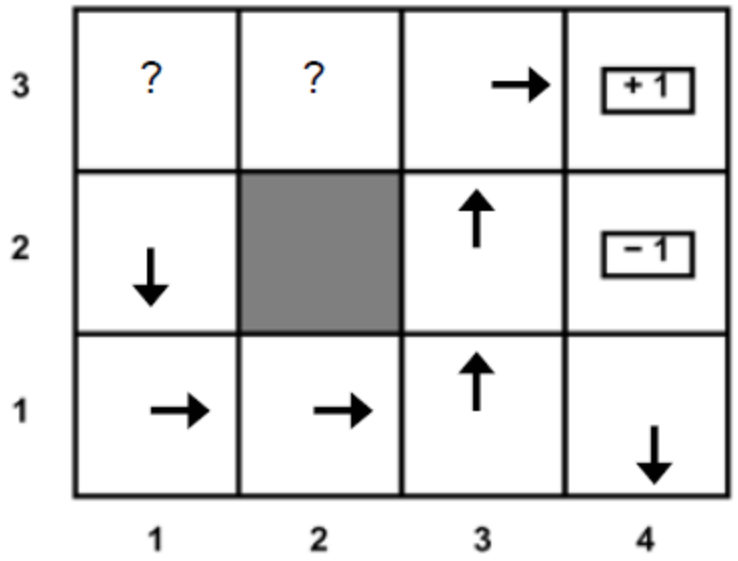
Model-Based Learning

- In general, want to learn the optimal policy, not evaluate a fixed policy

- Idea: adaptive dynamic programming
  - Learn an initial model of the environment:
  - Solve for the optimal policy for this model (value or policy iteration)
  - Refine model through experience and repeat
  - Crucial: we have to make sure we actually learn about all of the model

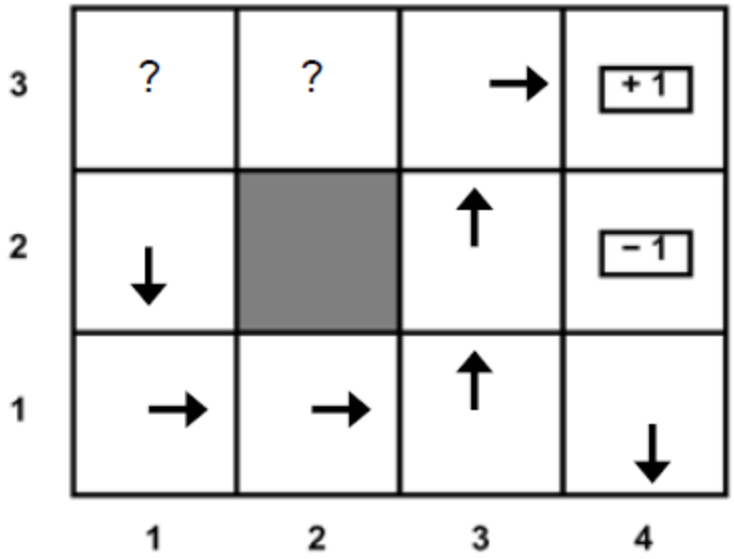
Example: Greedy ADP

- Imagine we find the lower path to the good exit first
- Some states will never be visited following this policy from (1,1)
- We'll keep re-using this policy because following it never collects the regions of the model we need to learn the optimal policy



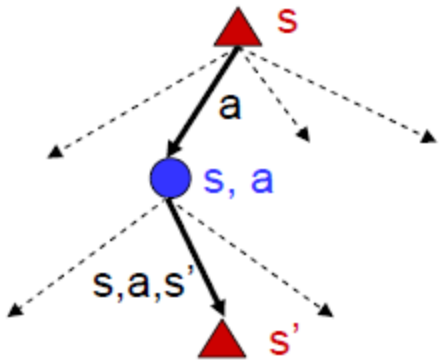
What Went Wrong?

- Problem with following optimal policy for current model:
  - Never learn about better regions of the space if current policy neglects them
- Fundamental tradeoff: exploration vs. exploitation
  - Exploration: must take actions with suboptimal estimates to discover new rewards and increase eventual utility
  - Exploitation: once the true optimal policy is learned, exploration reduces utility
  - Systems must explore in the beginning and exploit in the limit



Model-Free Learning

- Big idea: why bother learning T?
  - Update each time we experience a transition
  - Frequent outcomes will contribute more updates (over time)
- Temporal difference learning (TD)
  - Policy still fixed!
  - Move values toward value of whatever successor occurs



$$V^{\pi}(s) \leftarrow \sum_{s'} T(s, \pi(s), s')[R(s, a, s') + \gamma V^{\pi}(s')]$$

$$sample = R(s, a, s') + \gamma V^{\pi}(s')$$

$$V^{\pi}(s) \leftarrow V^{\pi}(s) + \alpha(sample - V^{\pi}(s))$$

updated estimate learning rate

Aside: Online Mean Estimation

- Suppose that we want to incrementally compute the mean of a sequence of numbers ($x_1, x_2, x_3, \ldots$)
  - E.g. to estimate the expected value of a random variable from a sequence of samples.

$$\hat{X}_{n+1} = \frac{1}{n+1}\sum_{i=1}^{n+1} x_i$$

average of n+1 samples

Aside: Online Mean Estimation

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$$\hat{X}_{n+1} = \frac{1}{n+1}\sum_{i=1}^{n+1} x_i = \frac{1}{n}\sum_{i=1}^{n} x_i + \frac{1}{n+1}\left(x_{n+1} - \frac{1}{n}\sum_{i=1}^{n} x_i\right)$$

average of n+1 samples

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$$= \hat{X}_n + \frac{1}{n+1}\left(x_{n+1} - \hat{X}_n\right)$$

average of n+1 samples

learning rate

sample n+1

- Given a new sample x_{n+1}, the new mean is the old estimate (for n samples) plus the weighted difference between the new sample and old estimate

Temporal Difference Learning

- TD update for transition from s to s':

$$V^{\pi}(s) \leftarrow V^{\pi}(s) + \alpha(R(s) + \gamma V^{\pi}(s') - V^{\pi}(s))$$

updated estimate

learning rate

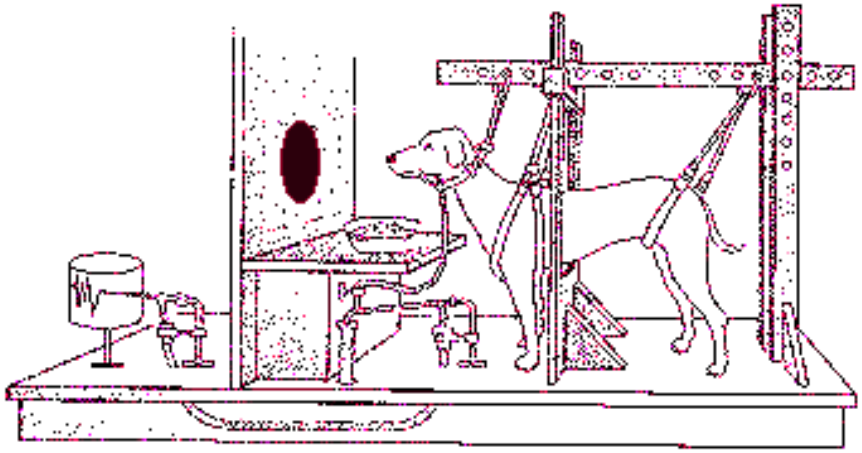
(noisy) sample of value at s based on next state s'

- So the update is maintaining a "mean" of the (noisy) value samples
- If the learning rate decreases appropriately with the number of samples (e.g. 1/n) then the value estimates will converge to true values! (non-trivial)

$$V^{\pi}(s) = R(s) + \gamma \sum_{s'} T(s, a, s') V^{\pi}(s')$$

Early Results: Pavlov and his Dog

- Classical (Pavlovian) conditioning experiments
- Training: Bell →Food
- After: Bell → Salivate
- Conditioned stimulus (bell) predicts future reward (food)



(http://employees.csbsju.edu/tcreed/pb/pdoganim.html)

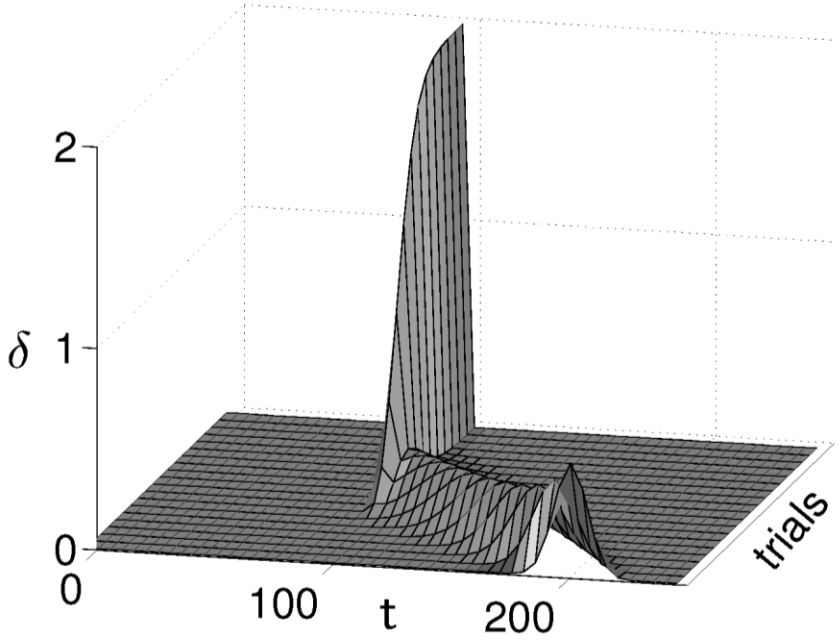
Predicting Delayed Rewards

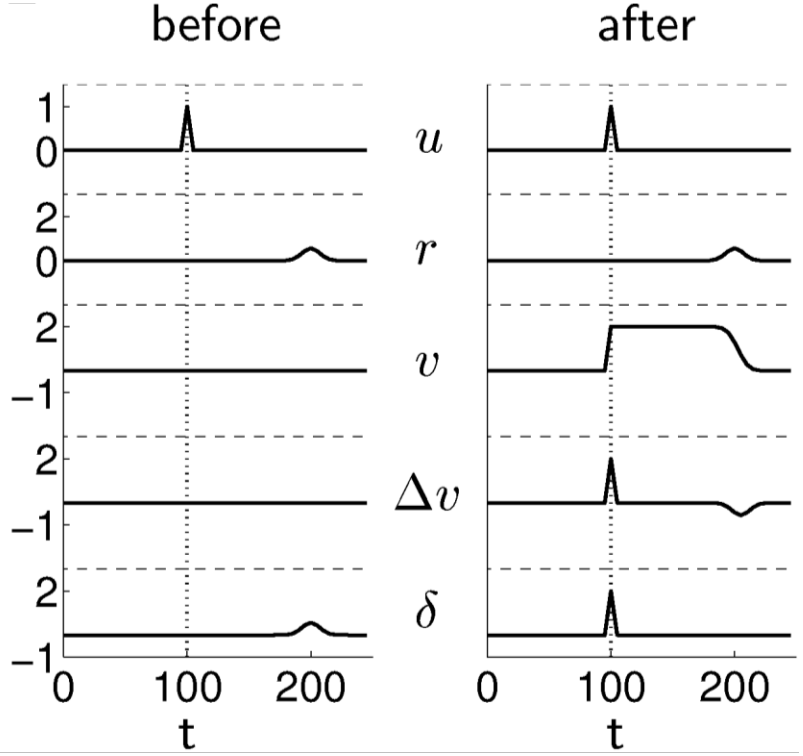
- Reward is typically delivered at the end (when you know whether you succeeded or not)
- Time: $0 \leq t \leq T$ with stimulus $u(t)$ and reward $r(t)$ at each time step t (Note: $r(t)$ can be zero at some time points)
- Key Idea: Make the output $v(t)$ predict *total expected future reward* starting from time t

$$v(t) \approx \left\langle \sum_{\tau=0}^{T-t} r(t+\tau) \right\rangle$$

Predicting Delayed Reward: TD Learning

Stimulus at t = 100 and reward at t = 200



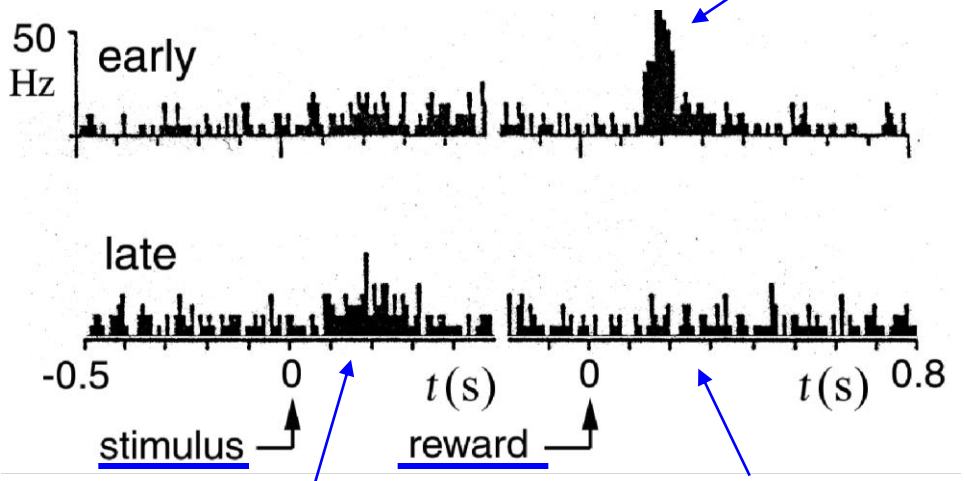


Prediction error δ for each time step
(over many trials)

Prediction Error in the Primate Brain?

Dopaminergic cells in Ventral Tegmental Area (VTA)

Reward Prediction error? $[r(t)+v(t+1)-v(t)]$



Before Training

After Training

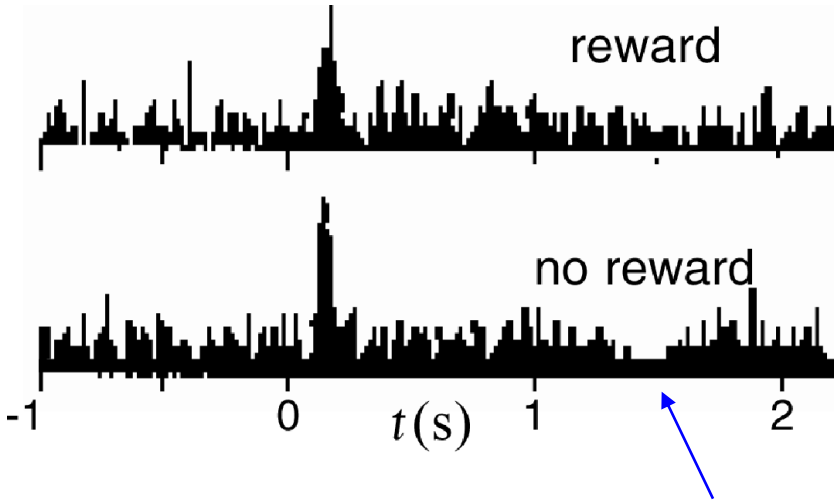
No error

$[0+v(t+1)-v(t)]$

$v(t) \approx r(t)+v(t+1)$

More Evidence for Prediction Error Signals

Dopaminergic cells in VTA



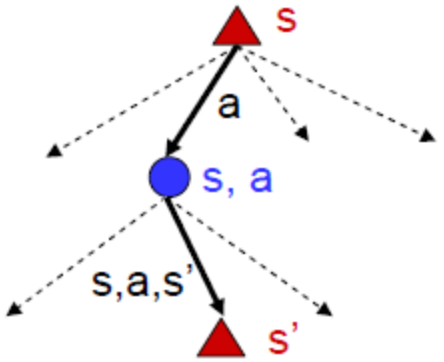
Negative error

$$r(t) = 0, v(t+1) = 0$$

$$[r(t) + v(t+1) - v(t)] = -v(t)$$

Problems with TD Value Learning

- TD value leaning is model-free for policy evaluation
- However, if we want to turn our value estimates into a policy, we're sunk:



$$\pi(s) = \arg\max_a Q^*(s,a)$$

$$Q^*(s,a) = \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s') \right]$$

- Idea: learn Q-values directly
- Makes action selection model-free too!

Q-Learning

- Learn Q*(s,a) values
  - Receive a sample (s,a,s',r)
  - Consider your old estimate: $Q(s,a)$
  - Consider your new sample estimate:

$$Q^*(s,a) = \sum_{s'} T(s,a,s') \left[R(s,a,s') + \gamma V^*(s') \right]$$

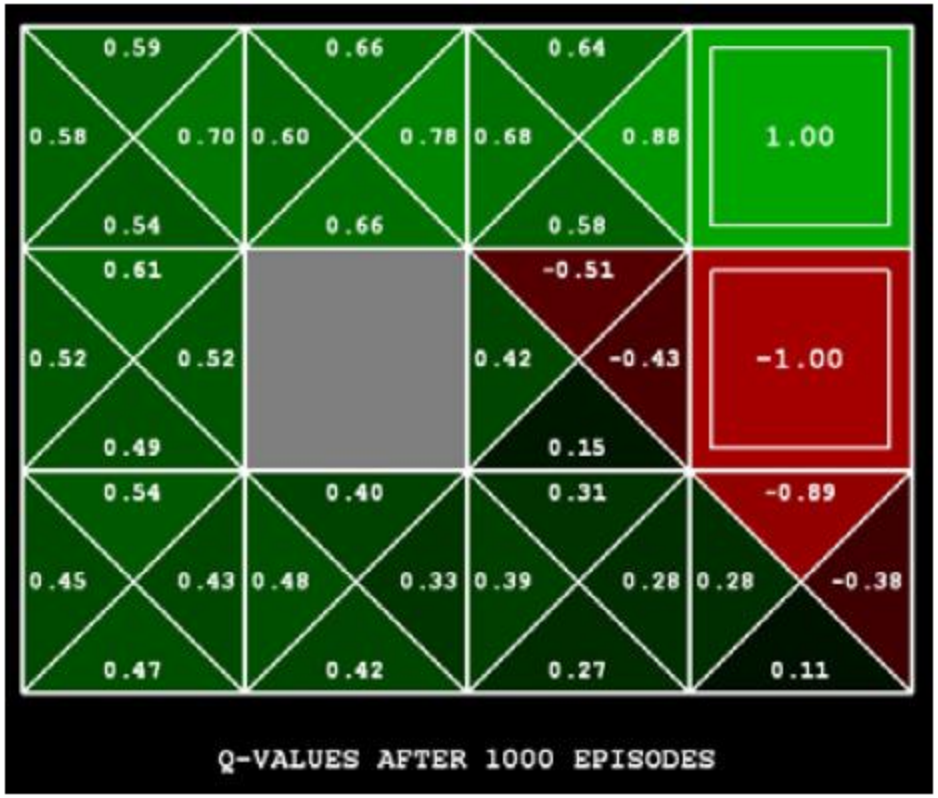
$$sample = R(s,a,s') + \gamma \max_{a'} Q(s',a')$$

  - Nudge the old estimate towards the new sample:

$$Q(s,a) \leftarrow Q(s,a) + \alpha \left[sample - Q(s,a) \right]$$

Q-Learning

- Q-learning produces tables of q-values:



Q-Learning Properties

- Will converge to optimal policy
  - If you explore enough
  - If you make the learning rate small enough
- Under certain conditions:
  - The environment model doesn't change
  - States and actions are finite
  - Rewards are bounded
  - Learning rate decays with visits to state-action pairs
    - but not too fast decay. ($\sum_i \alpha(s,a,i) = \infty$, $\sum_i \alpha^2(s,a,i) < \infty$)
  - Exploration method would guarantee infinite visits to every state-action pair over an infinite training period

Exploration / Exploitation

- Several schemes for forcing exploration
  - Simplest: random actions (ε-greedy)
    - Every time step, flip a coin
    - With probability ε, act randomly
    - With probability 1-ε, act according to current policy
  - Problems with random actions?
    - You do explore the space, but keep thrashing around once learning is done
    - One solution: lower ε over time
    - Another solution: exploration functions

Explore/Exploit Policies

- GLIE Policy 2: Boltzmann Exploration
  - Select action a with probability,

$$\Pr(a \mid s) = \frac{\exp\left(Q(s,a)/T\right)}{\sum_{a' \in A} \exp\left(Q(s,a')/T\right)}$$

  - T is the temperature. Large T means that each action has about the same probability. Small T leads to more greedy behavior.
  - Typically start with large T and decrease with time

Model based vs. Model Free RL

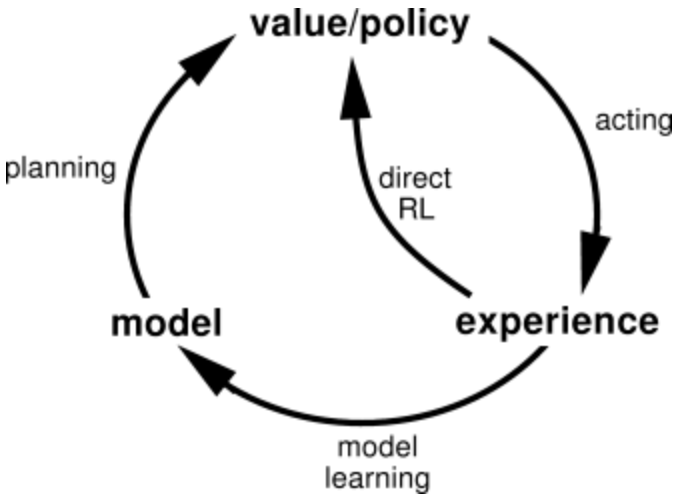
- Model based
  - estimate O($|\mathcal{S}|^2|\mathcal{A}|$) parameters
  - requires relatively larger data for learning
  - can make use of background knowledge easily

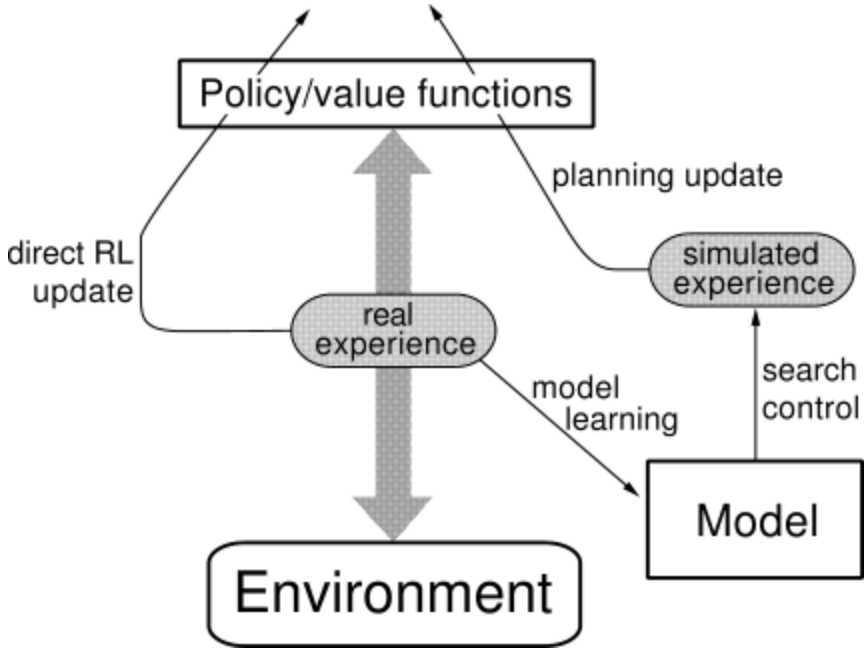
- Model free
  - estimate O($|\mathcal{S}||\mathcal{A}|$) parameters
  - requires relatively less data for learning

Applications of RL

- Games
  - Backgammon, Solitaire, Real-time strategy games
- Elevator Scheduling
- Stock investment decisions
- Chemotherapy treatment decisions
- Robotics
  - Navigation, Robocup
  - http://www.youtube.com/watch?v=CIF2SBVY-J0
  - http://www.youtube.com/watch?v=5FGVgMsiv1s
  - http://www.youtube.com/watch?v=W_gxLKSsSIE
- Helicopter maneuvering

Learning/Planning/Acting



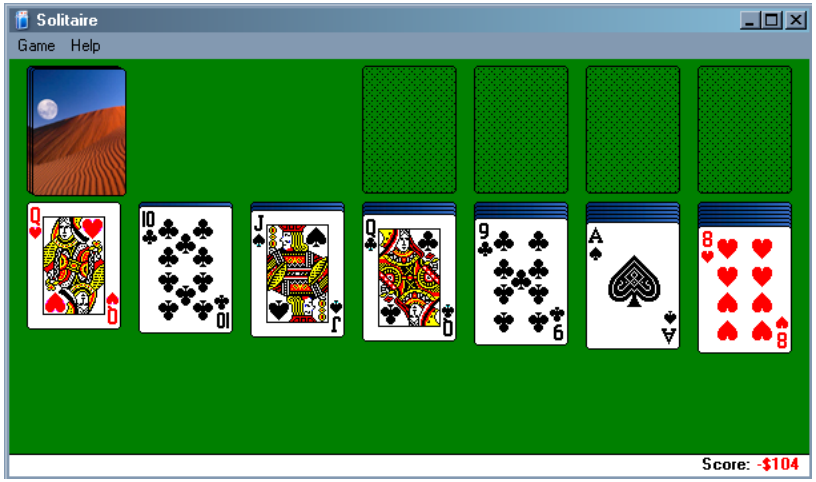


Planning **Monte-Carlo Planning** **Reinforcement Learning**

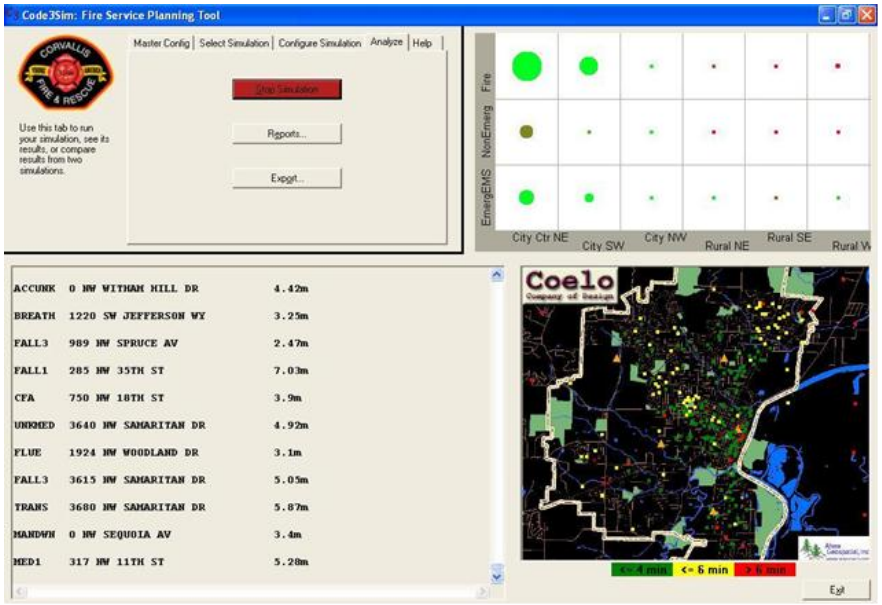
Monte-Carlo Planning

- Often a simulator of a planning domain is available or can be learned from data
  - Even when domain can't be expressed via MDP language

Klondike Solitaire



Fire & Emergency Response



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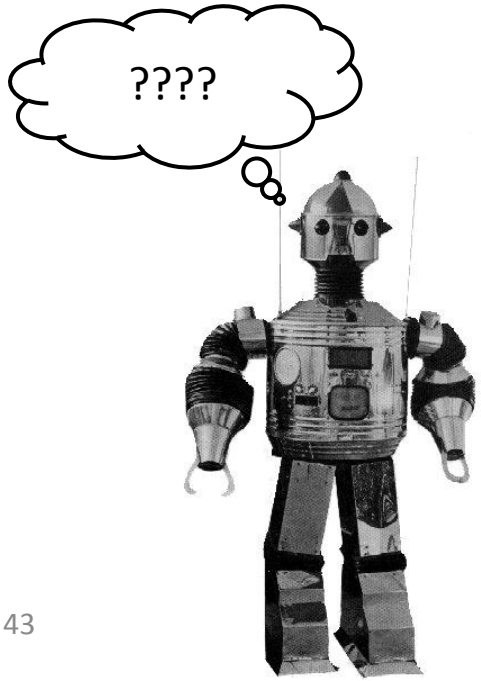
Example Domains with Simulators

- Traffic simulators
- Robotics simulators
- Military campaign simulators
- Computer network simulators
- Emergency planning simulators
  - large-scale disaster and municipal
- Sports domains (Madden Football)
- Board games / Video games
  - Go / RTS

In many cases Monte-Carlo techniques yield state-of-the-art performance. Even in domains where model-based planner is applicable.

Slot Machines as MDP?

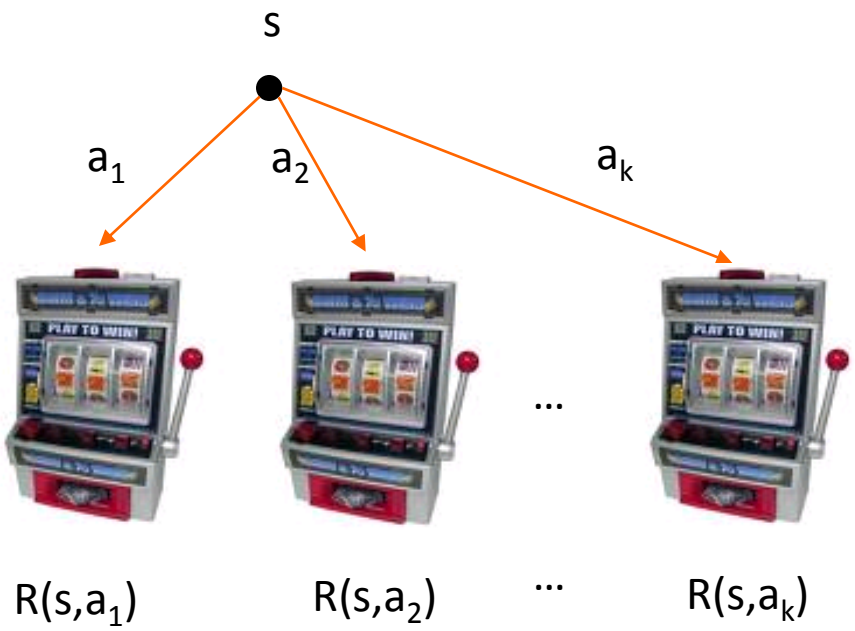


Outline

- Uniform Sampling
  - PAC Bound for Single State MDPs
  - Policy Rollouts for full MDPs
- Adaptive Sampling
  - UCB for Single State MDPs
  - UCT for full MDPs

Single State Monte-Carlo Planning

- Suppose MDP has a single state and k actions
  - Figure out which action has best expected reward
  - Can sample rewards of actions using calls to simulator
  - Sampling a is like pulling slot machine arm with random payoff function R(s,a)

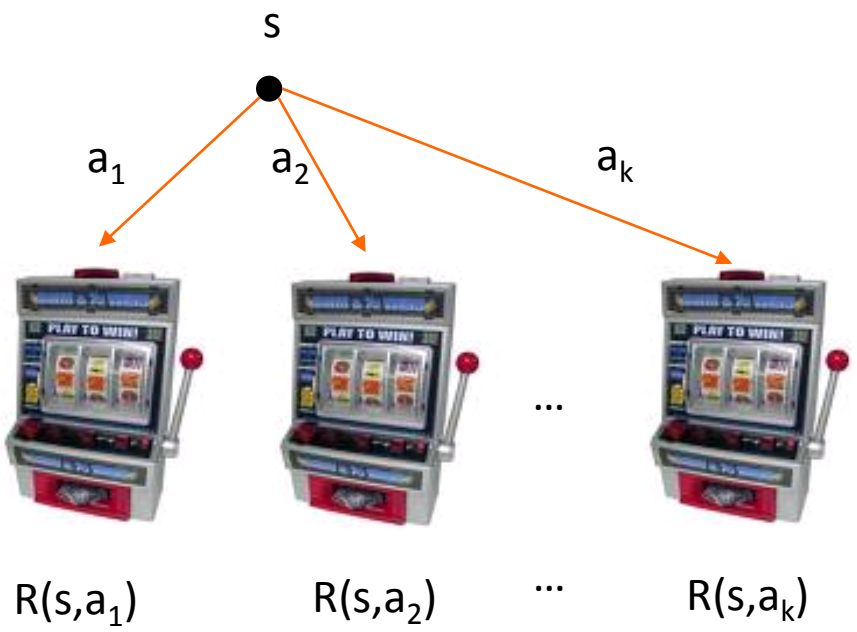


Multi-Armed Bandit Problem

PAC Bandit Objective

Probably Approximately Correct (PAC)

- Select an arm that probably (w/ high probability, 1-δ) has approximately (i.e., within ε) the best expected reward
- Use as few simulator calls (or pulls) as possible

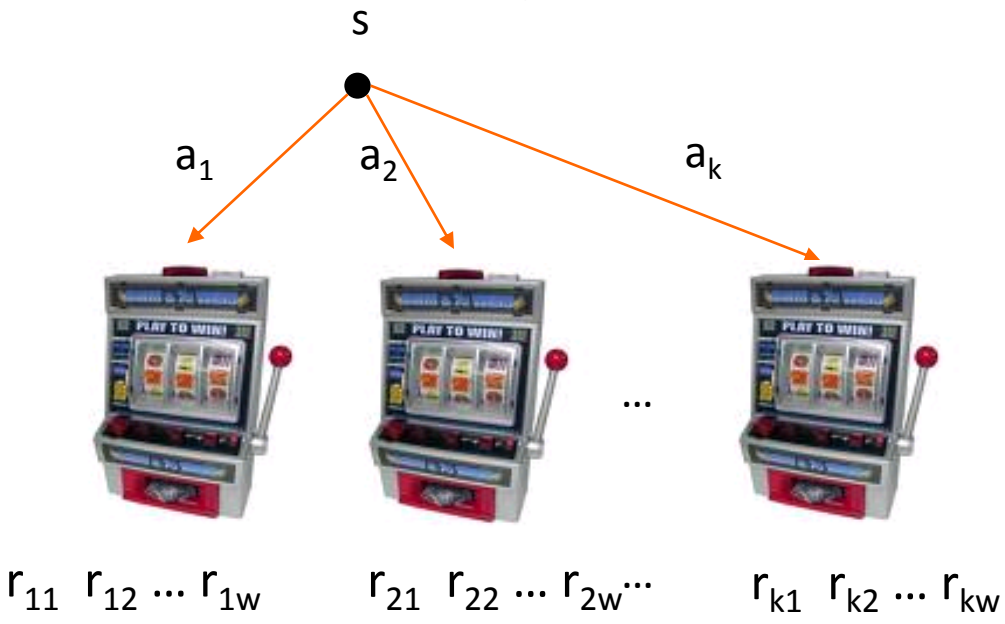


Multi-Armed Bandit Problem

UniformBandit Algorithm

NaiveBandit from [Even-Dar et. al., 2002]

1. Pull each arm **w** times (uniform pulling).
2. Return arm with best average reward.



How large must w be to provide a PAC guarantee?

Aside: Additive Chernoff Bound

- Let R be a random variable with maximum absolute value Z. An let r_i (for i=1,…,w) be i.i.d. samples of R
- The Chernoff bound gives a bound on the probability that the average of the r_i are far from E[R]

Chernoff Bound

$$\Pr\left(\left|E[R]-\frac{1}{w}\sum_{i=1}^{w} r_i\right| \geq \varepsilon\right) \leq \exp\left(-\left(\frac{\varepsilon}{Z}\right)^2 w\right)$$

Equivalently:

With probability at least $1-\delta$ we have that,

$$\left|E[R]-\frac{1}{w}\sum_{i=1}^{w} r_i\right| \leq Z\sqrt{\frac{1}{w}\ln\frac{1}{\delta}}$$

UniformBandit PAC Bound

With a bit of algebra and Chernoff bound we get:

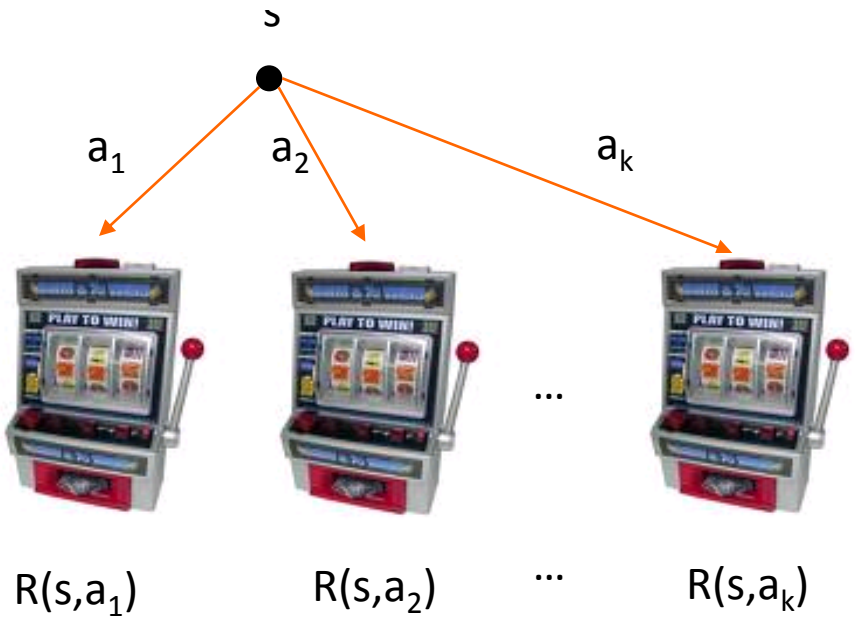
If $w \geq \left(\frac{R_{\max}}{\varepsilon} \right)^2 \ln \frac{k}{\delta}$ for all arms simultaneously

$$\left| E[R(s,a_i)] - \frac{1}{w} \sum_{j=1}^{w} r_{ij} \right| \leq \varepsilon$$

with probability at least $1-\delta$

- That is, estimates of all actions are **ε**–accurate with probability at least 1- δ
- Thus selecting estimate with highest value is approximately optimal with high probability, or PAC

Simulator Calls for UniformBandit



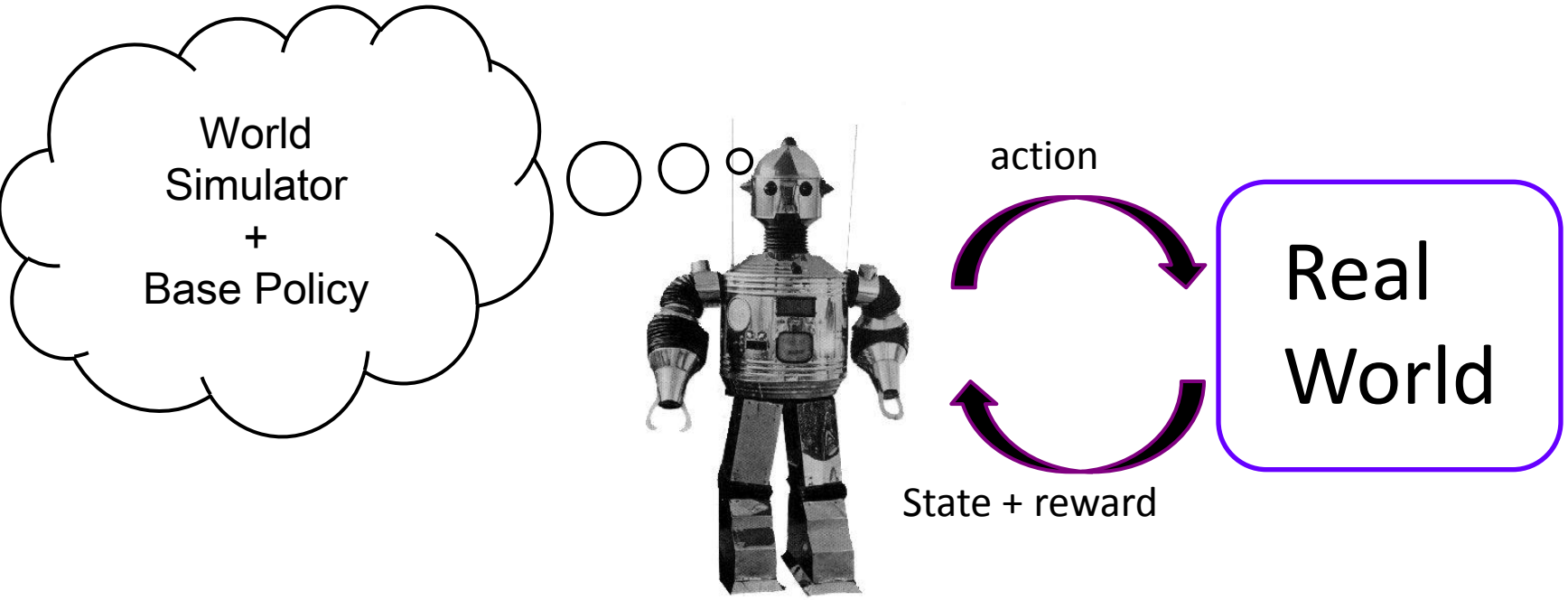
- Total simulator calls for PAC: $k \cdot w = O\left(\frac{k}{\varepsilon^2} \ln \frac{k}{\delta}\right)$
- Can get rid of ln(k) term with more complex algorithm [Even-Dar et. al., 2002].

Outline

- Uniform Sampling
  - PAC Bound for Single State MDPs
  - Policy Rollouts for full MDPs
- Adaptive Sampling
  - UCB for Single State MDPs
  - UCT for full MDPs

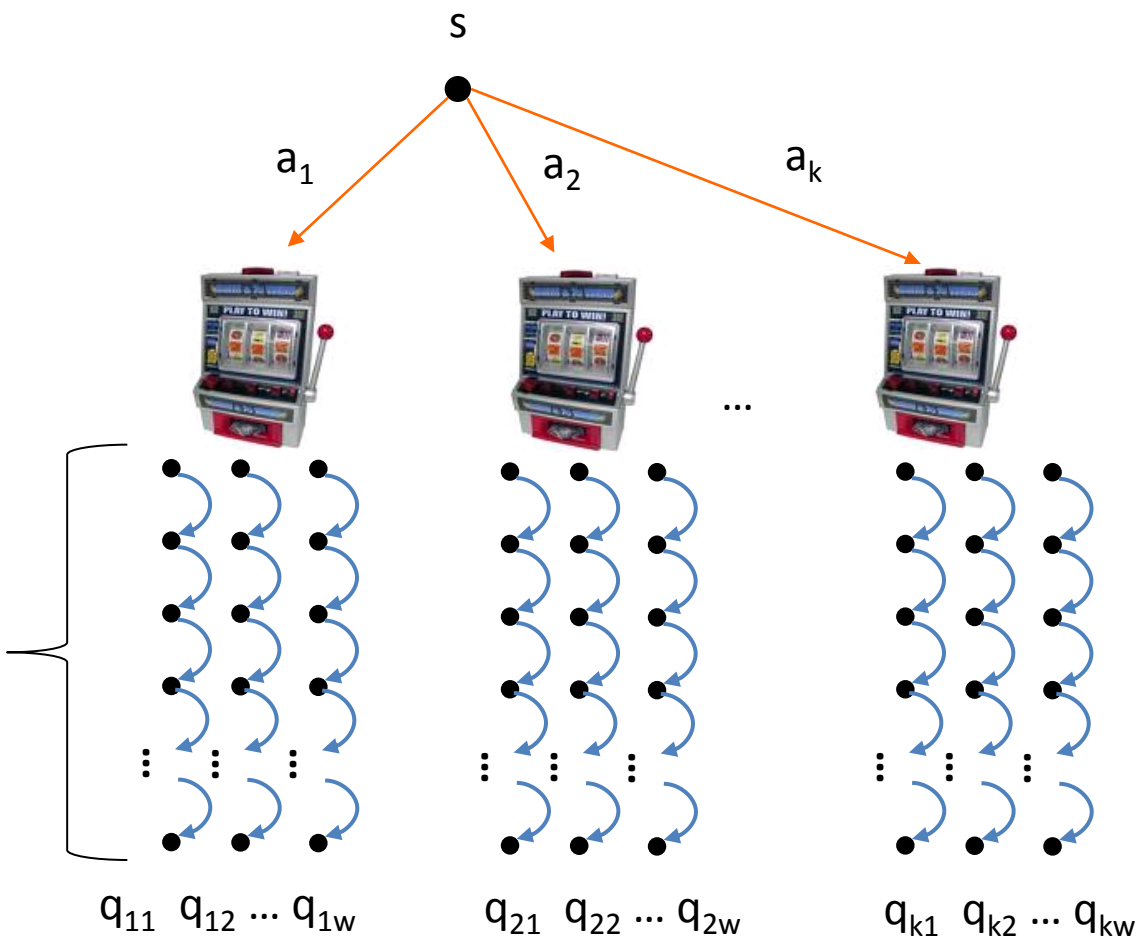
Policy Improvement via Monte-Carlo

- Now consider a multi-state MDP.
- Suppose we have a simulator and a non-optimal policy
  - E.g. policy could be a standard heuristic or based on intuition
- Can we somehow compute an improved policy?



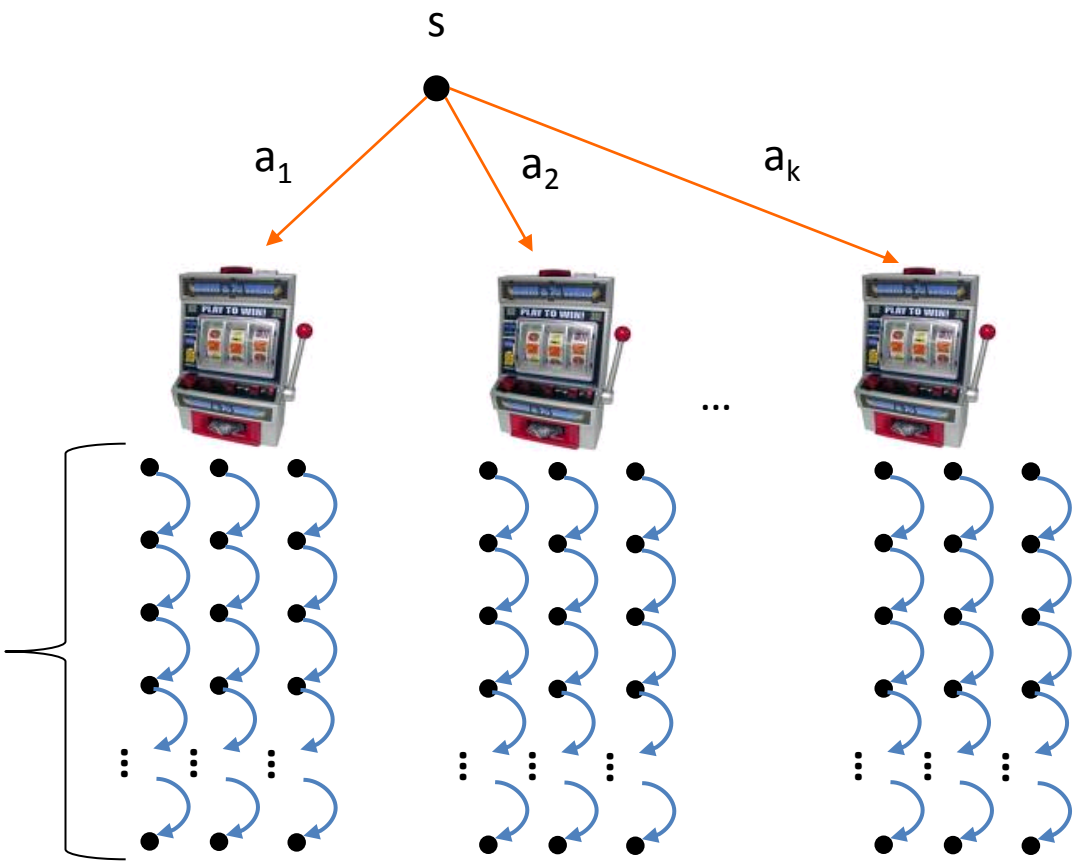
Policy Rollout Algorithm

1. For each a_i, run SimQ(s,a_i,π,h) **w** times
2. Return action with best average of SimQ results



Policy Rollout: # of Simulator Calls

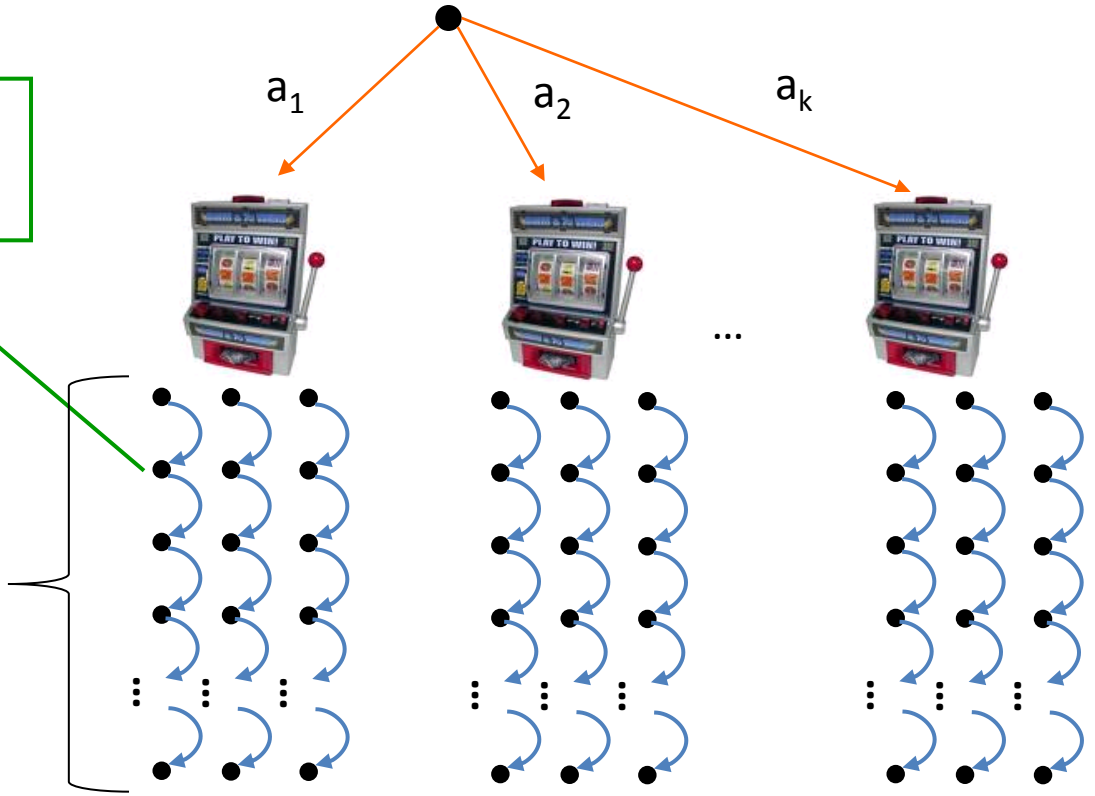
SimQ(s,a_i,π,h) trajectories
Each simulates taking action a_i then following π for h-1 steps.



- For each action, **w** calls to SimQ, each using h sim calls
- Total of khw calls to the simulator

Multi-Stage Rollout

Each step requires khw simulator calls



Trajectories of SimQ(s,a_i,Rollout(π),h)

- Two stage: compute **rollout policy** *of* **rollout policy** of π
- Requires $(khw)^2$ calls to the simulator for 2 stages
- In general exponential in the number of stages

Rollout Summary

- We often are able to write simple, mediocre policies
  - Network routing policy
  - Compiler instruction scheduling
  - Policy for card game of Hearts
  - Policy for game of Backgammon
  - Solitaire playing policy
  - Game of GO
  - Combinatorial optimization
- Policy rollout is a general and easy way to improve upon such policies
- Often observe substantial improvement!

Example: Rollout for Thoughtful Solitaire

[Yan et al. NIPS'04]

Player	Success Rate	Time/Game
Human Expert	36.6%	20 min
(naïve) Base Policy	13.05%	0.021 sec

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1 rollout	31.20%	0.67 sec

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(naïve) Base Policy	13.05%	0.021 sec
1 rollout	31.20%	0.67 sec
2 rollout	47.6%	7.13 sec
3 rollout	56.83%	1.5 min
4 rollout	60.51%	18 min
5 rollout	70.20%	1 hour 45 min

Deeper rollout can pay off, but is expensive

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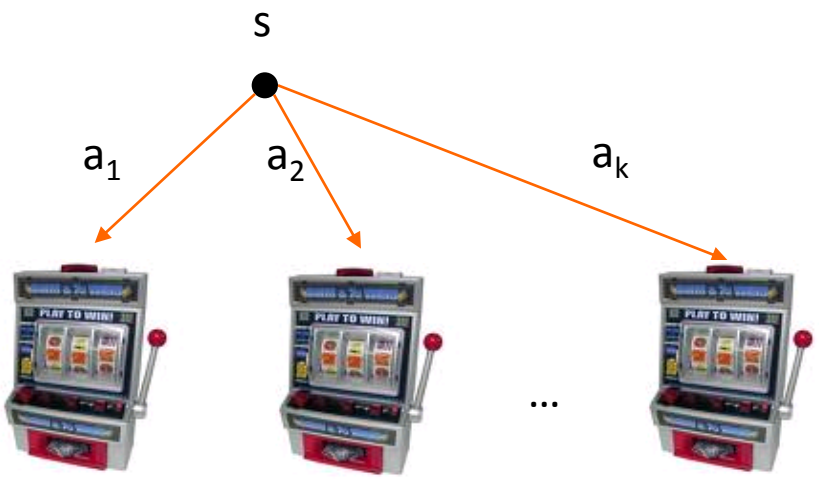
Non-Adaptive Monte-Carlo

- What is an issue with Uniform sampling?
  - time wasted equally on all actions!
  - no early learning about suboptimal actions
- Policy rollouts
  - Devotes equal resources to each state encountered in the tree
  - Would like to focus on most promising parts of tree

But how to control exploration of new parts of tree??

Regret Minimization Bandit Objective

- **Problem:** find arm-pulling strategy such that the expected total reward at time n is close to the best possible (i.e. pulling the best arm always)
  - UniformBandit is poor choice --- waste time on bad arms
  - Must balance **exploring** machines to find good payoffs and **exploiting** current knowledge



UCB Adaptive Bandit Algorithm

[Auer, Cesa-Bianchi, & Fischer, 2002]

- Q(a) : average payoff for action a based on current experience
- n(a) : number of pulls of arm a
- Action choice by UCB after n pulls:

Assumes payoffs in [0,1]

$$a^* = \arg\max_a Q(a) + \sqrt{\frac{2 \ln n}{n(a)}}$$

Value Term:
favors actions that looked good historically

Exploration Term:
actions get an exploration bonus that grows with ln(n)

Doesn't waste much time on sub-optimal arms unlike uniform!

UCB Algorithm [Auer, Cesa-Bianchi, & Fischer, 2002]

$$a^* = \arg\max_a Q(a) + \sqrt{\frac{2 \ln n}{n(a)}}$$

Theorem: expected number of pulls of sub-optimal arm **a** is bounded by:

$$\frac{8}{\Delta_a^2} \ln n$$

where Δ_a is regret of arm **a**

- Hence, the expected regret after *n* arm pulls compared to optimal behavior is bounded by O(log *n*)
- No algorithm can achieve a better loss rate

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UCB Based Policy Rollout

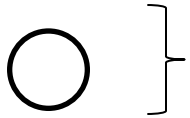
- Allocate samples non-uniformly
  - based on UCB action selection
  - More sample efficient than uniform policy rollout
  - Still suboptimal.

UCT Algorithm [Kocsis & Szepesvari, 2006]

- Instance of Monte-Carlo Tree Search
  - Applies principle of UCB
  - Some nice theoretical properties
  - Better than policy rollouts – asymptotically optimal
  - Major advance in computer Go
- Monte-Carlo Tree Search
  - Repeated Monte Carlo simulation of a rollout policy
  - Each rollout adds one or more nodes to search tree
- Rollout policy depends on nodes already in tree

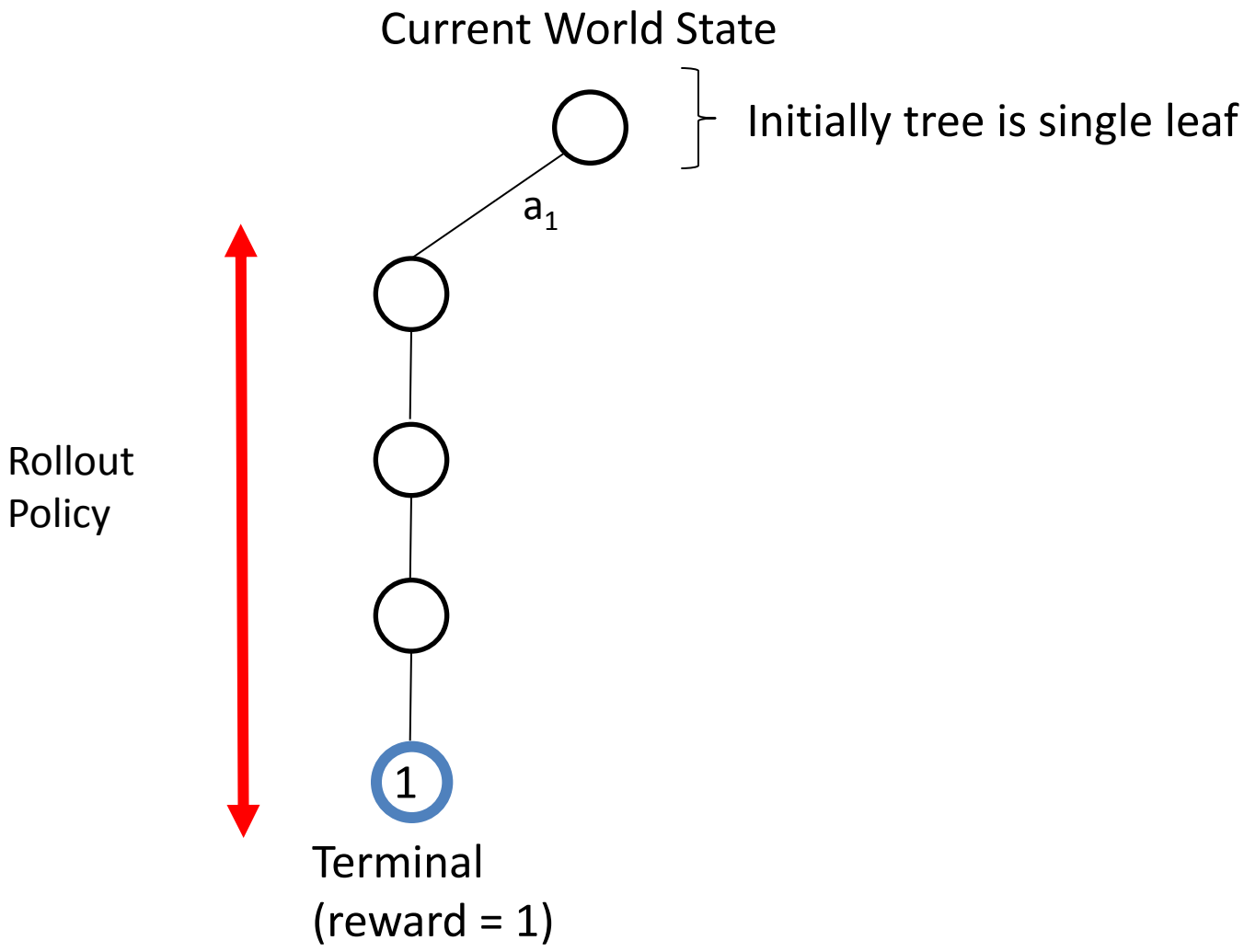
At a leaf node perform a random rollout

Current World State

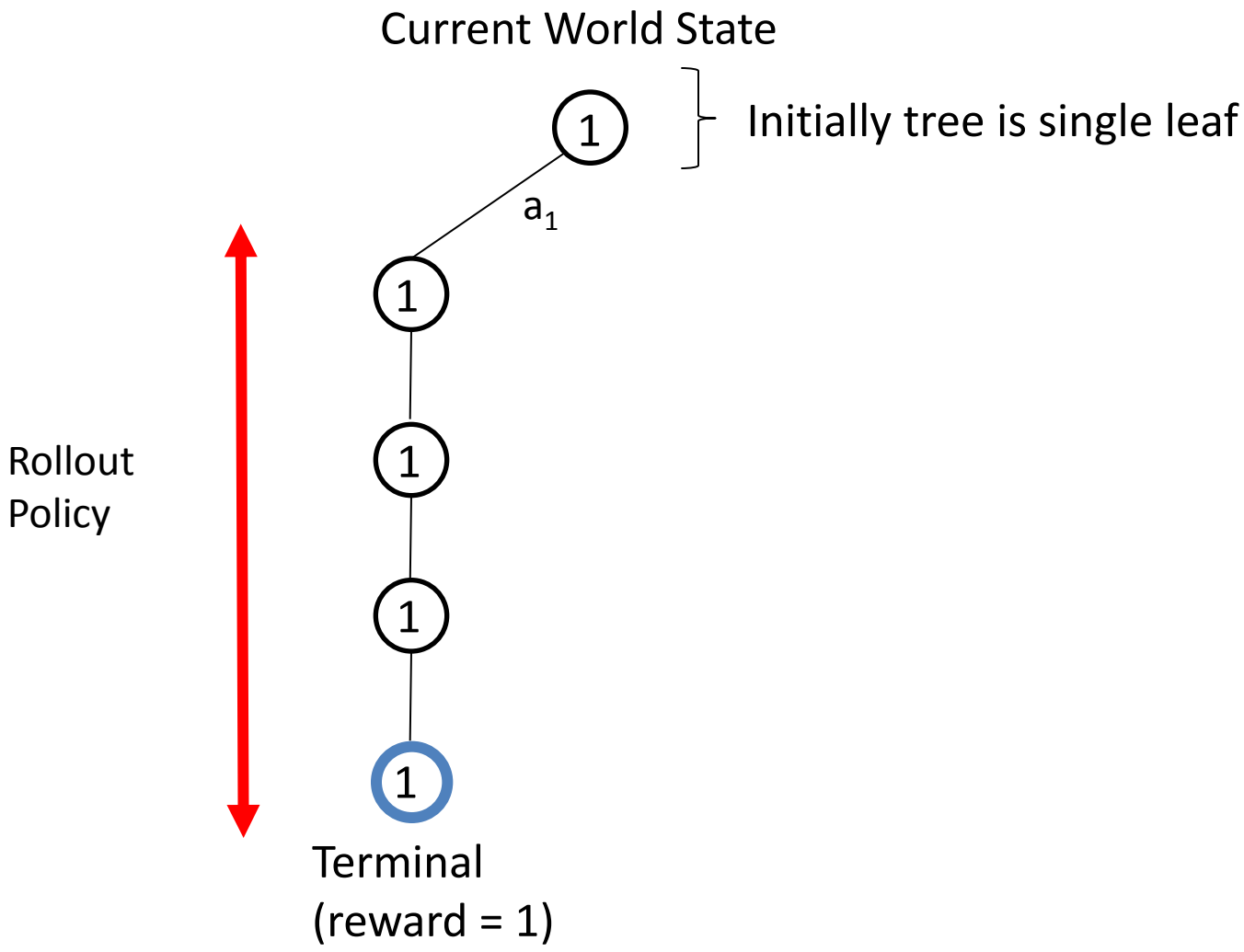


Initially tree is single leaf

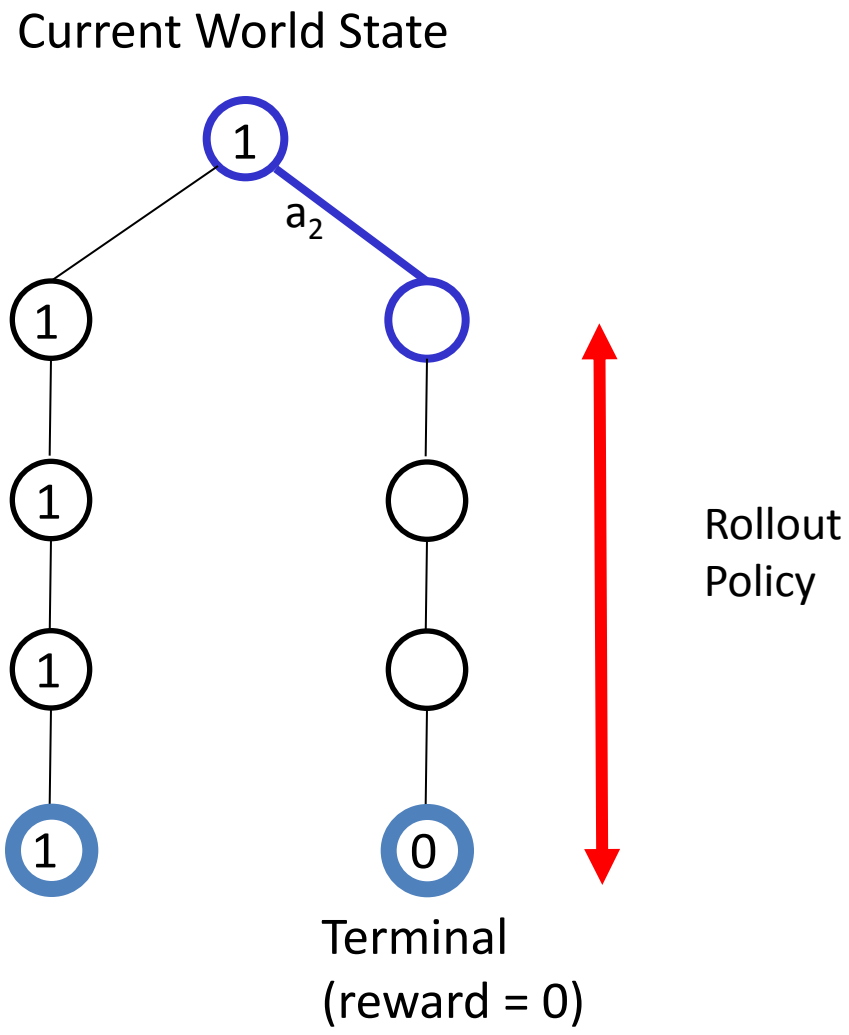
At a leaf node perform a random rollout



At a leaf node perform a random rollout



Must select each action at a node at least once



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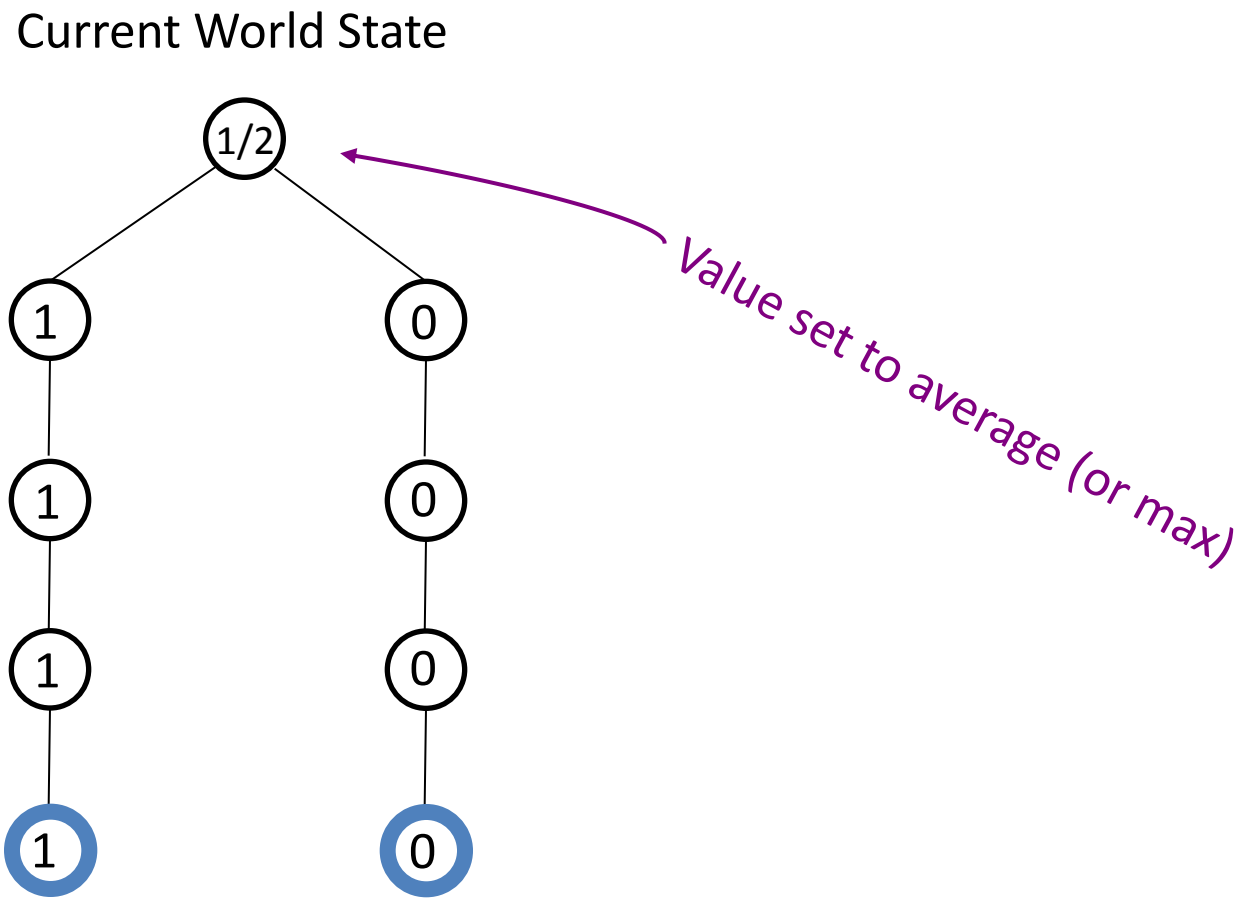
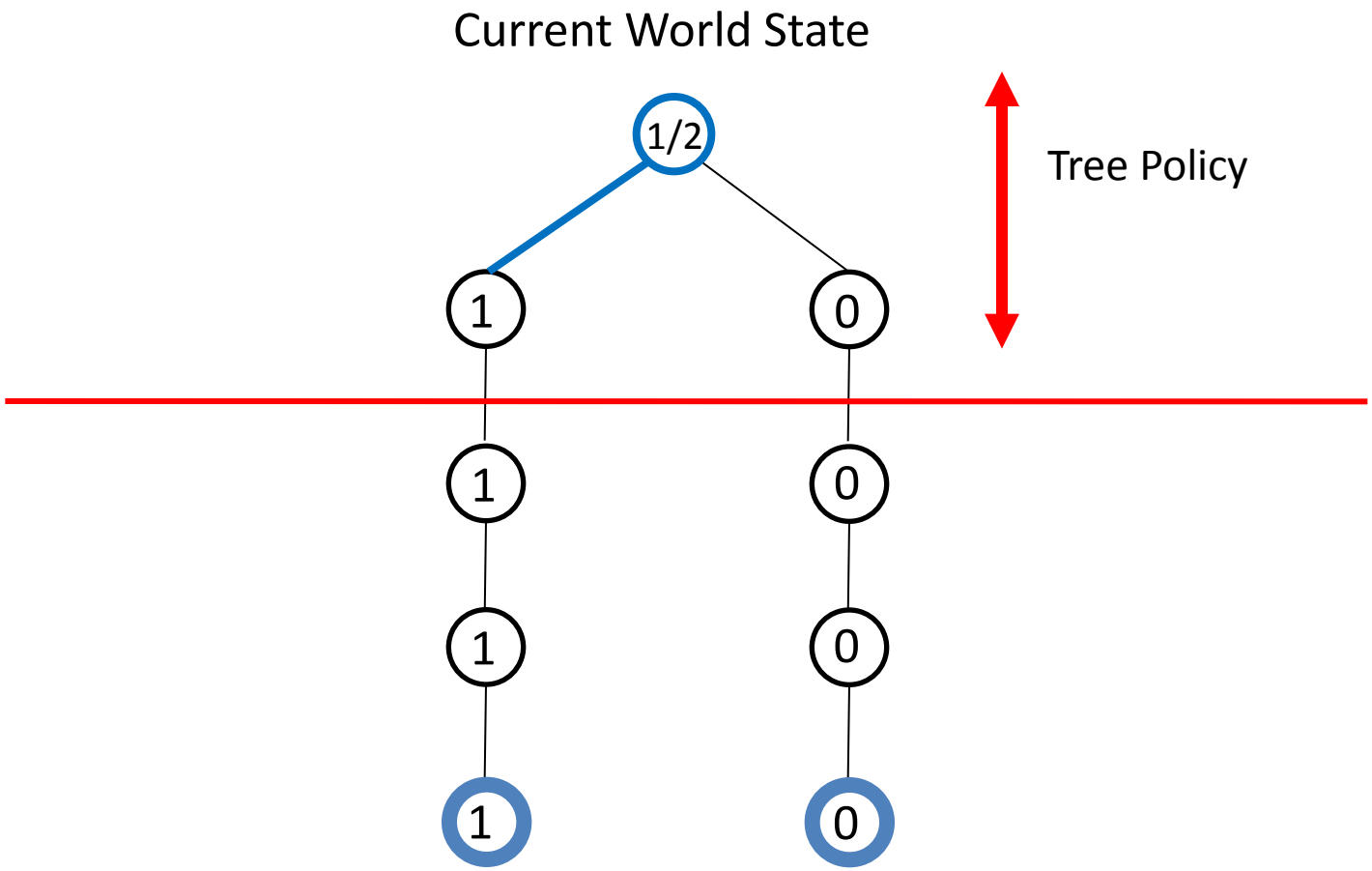


When all node actions tried once, select action according to tree policy



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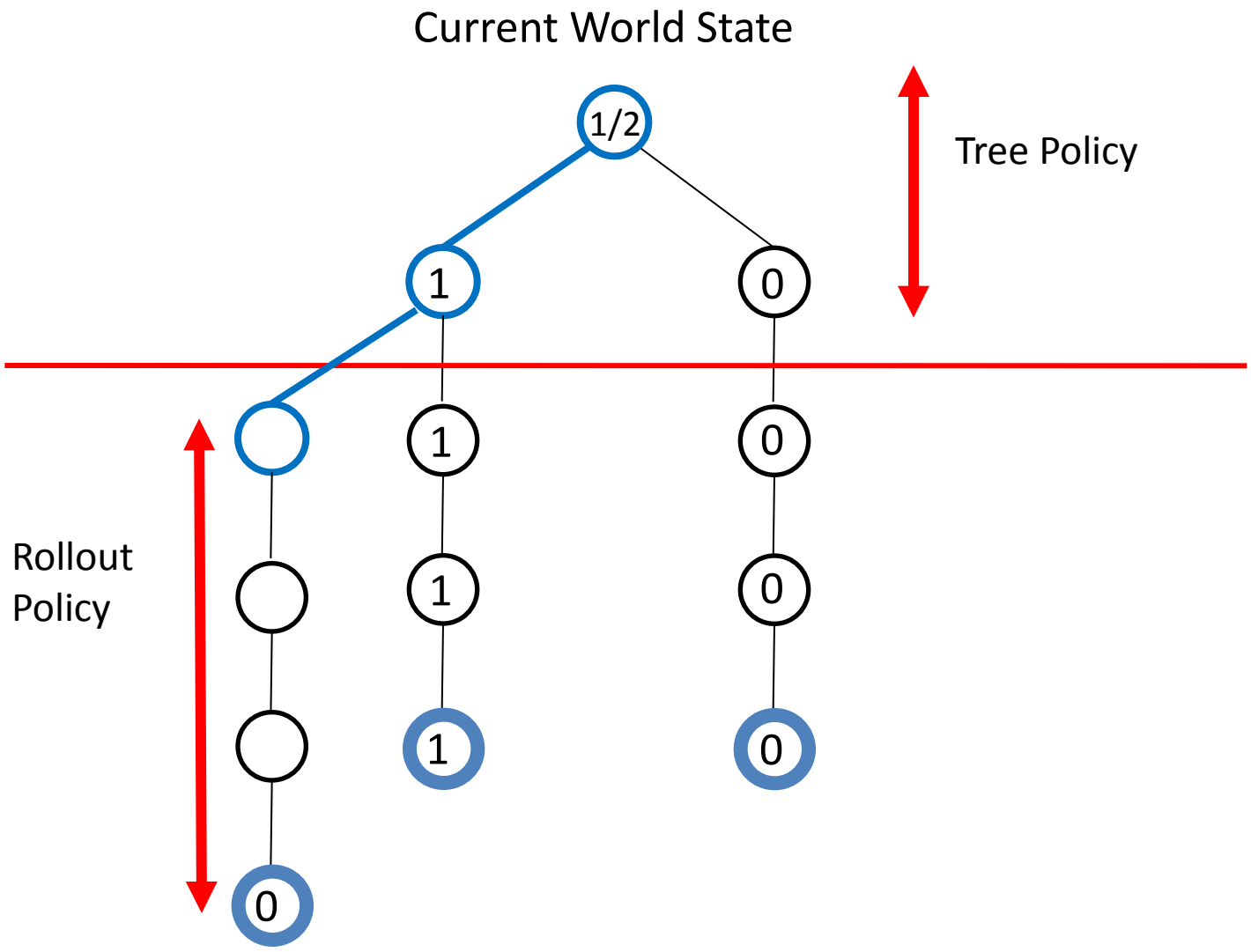

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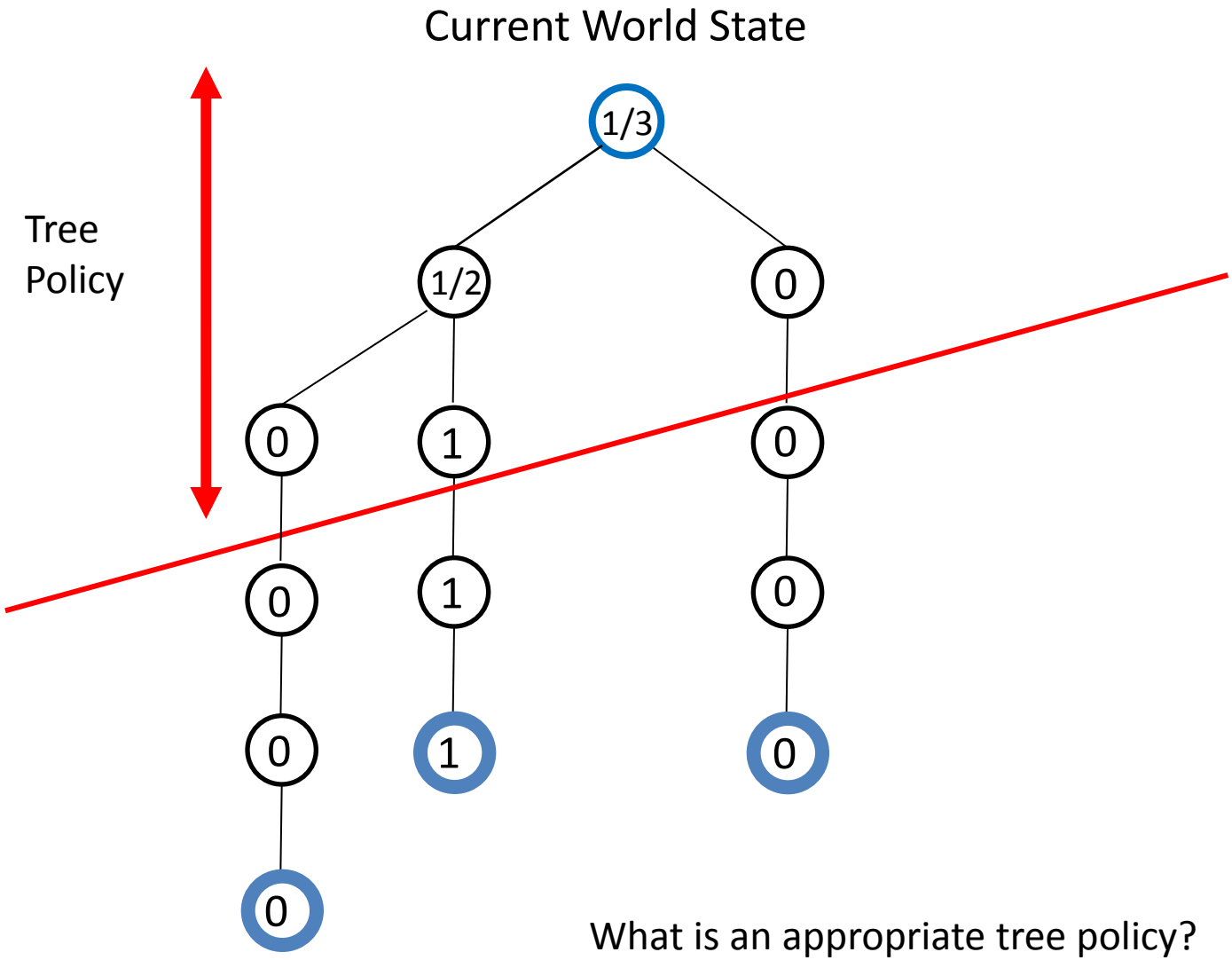


What is an appropriate tree policy?
Rollout policy?

UCT Algorithm [Kocsis & Szepesvari, 2006]

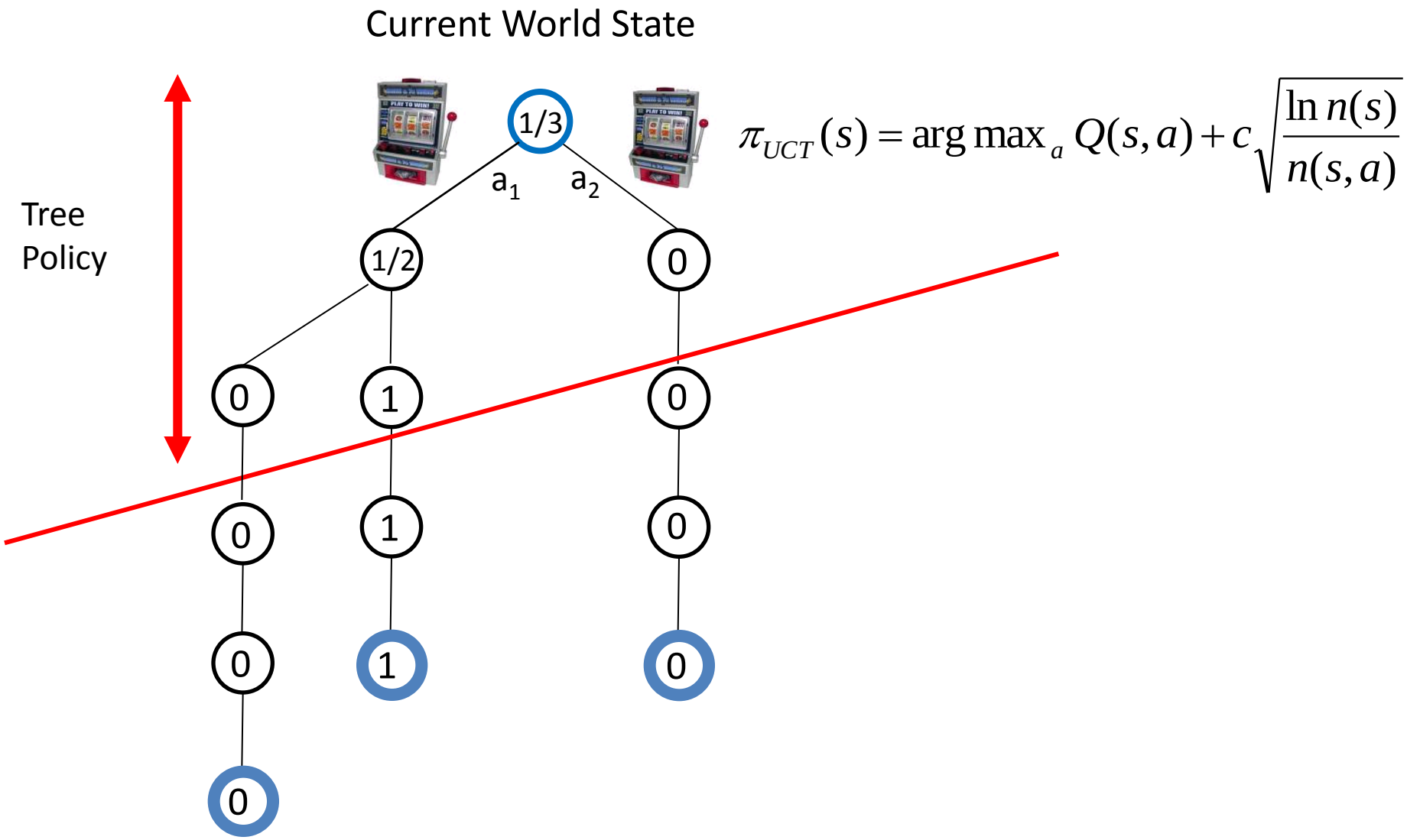
- Basic UCT uses random rollout policy

- Tree policy is based on UCB:
  - Q(s,a) : average reward received in current trajectories after taking action a in state s
  - n(s,a) : number of times action a taken in s
  - n(s) : number of times state s encountered

$$\pi_{UCT}(s) = \arg\max_a Q(s,a) + c\sqrt{\frac{\ln n(s)}{n(s,a)}}$$

Theoretical constant that must be selected empirically in practice

When all node actions tried once, select action according to tree policy



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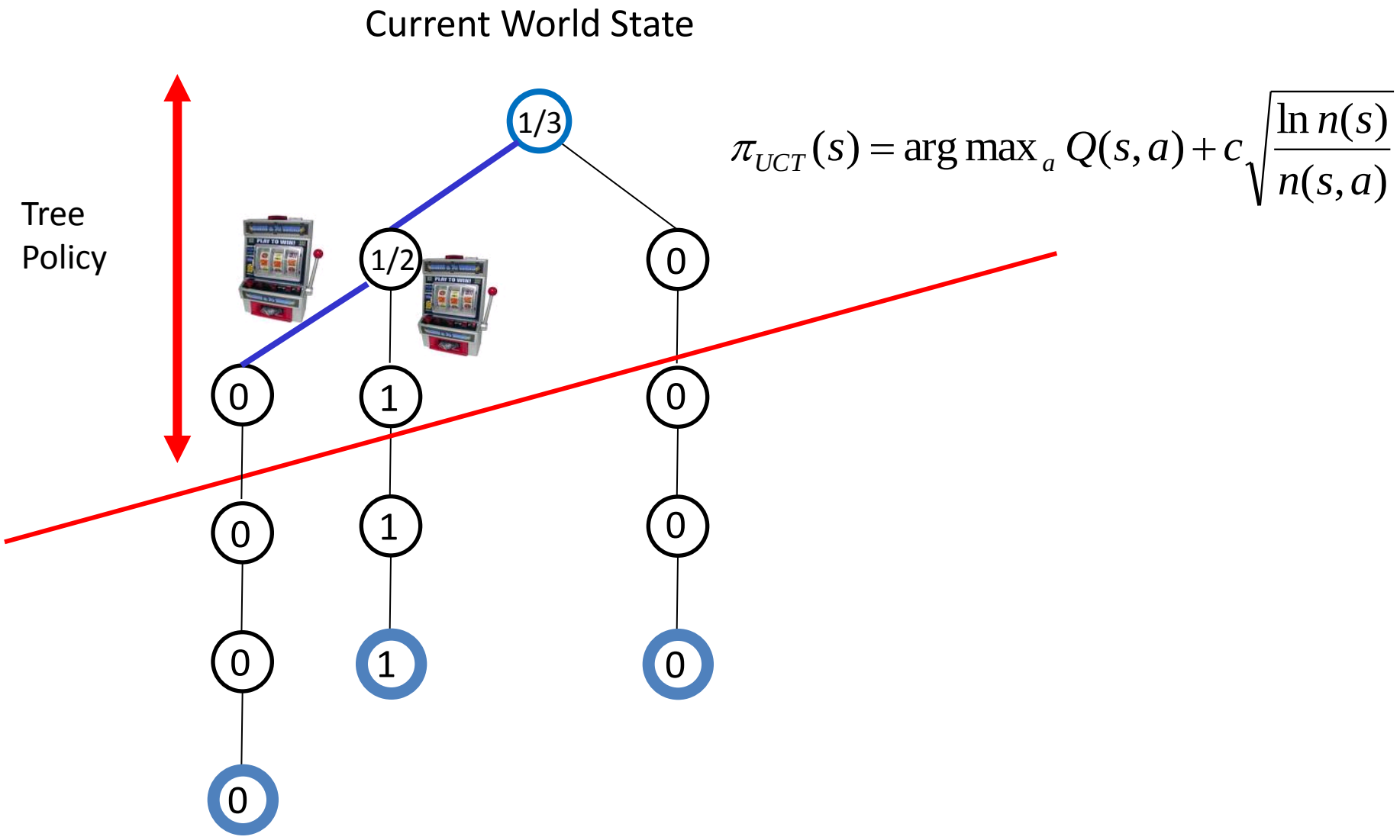
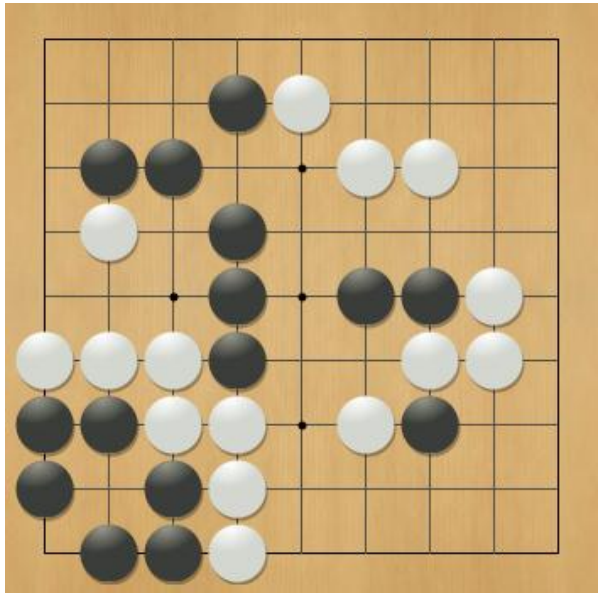


UCT Recap

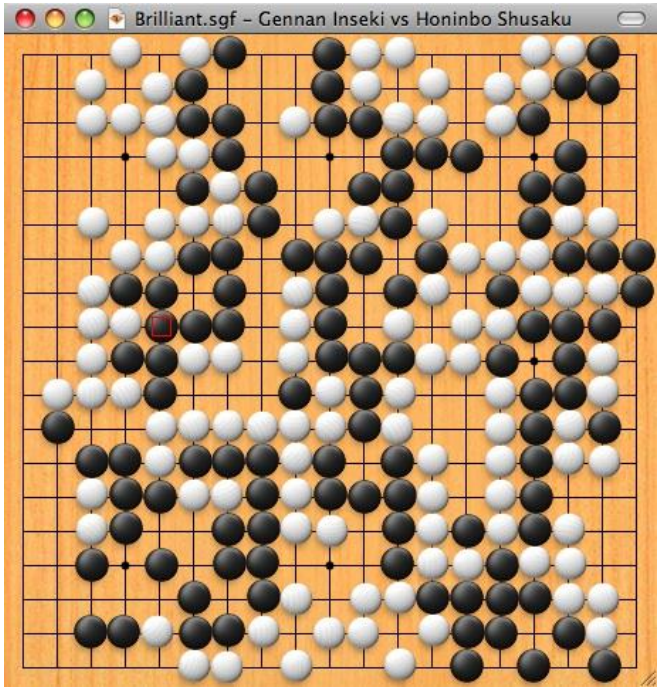
- To select an action at a state s
  - Build a tree using N iterations of monte-carlo tree search
    - Default policy is uniform random
    - Tree policy is based on UCB rule
  - Select action that maximizes Q(s,a)
    (note that this final action selection does not take the exploration term into account, just the Q-value estimate)

- The more simulations the more accurate

Computer Go



9x9 (smallest board)



19x19 (largest board)

- “Task Par Excellence for AI” (Hans Berliner)
- “New Drosophila of AI” (John McCarthy)
- “Grand Challenge Task” (David Mechner)

Game of Go

human champions refuse to compete against computers, because software is too bad.

	Chess	Go
Size of board	8 x 8	19 x 19
Average no. of moves per game	100	300
Avg branching factor per turn	35	235
Additional complexity		Players can pass

A Brief History of Computer Go

- *2005*: Computer Go is impossible!
- *2006*: UCT invented and applied to 9x9 Go *(Kocsis, Szepesvari; Gelly et al.)*
- *2007*: Human master level achieved at 9x9 Go *(Gelly, Silver; Coulom)*
- *2008*: Human grandmaster level achieved at 9x9 Go *(Teytaud et al.)*

- *ELO rating 1800 → 2600*

Other Successes

- Klondike Solitaire (wins 40% of games)
- General Game Playing Competition
- Real-Time Strategy Games
- Combinatorial Optimization

- Probabilistic Planning (MDPs)

- Usually extend UCT is some ways

Improvements/Issues

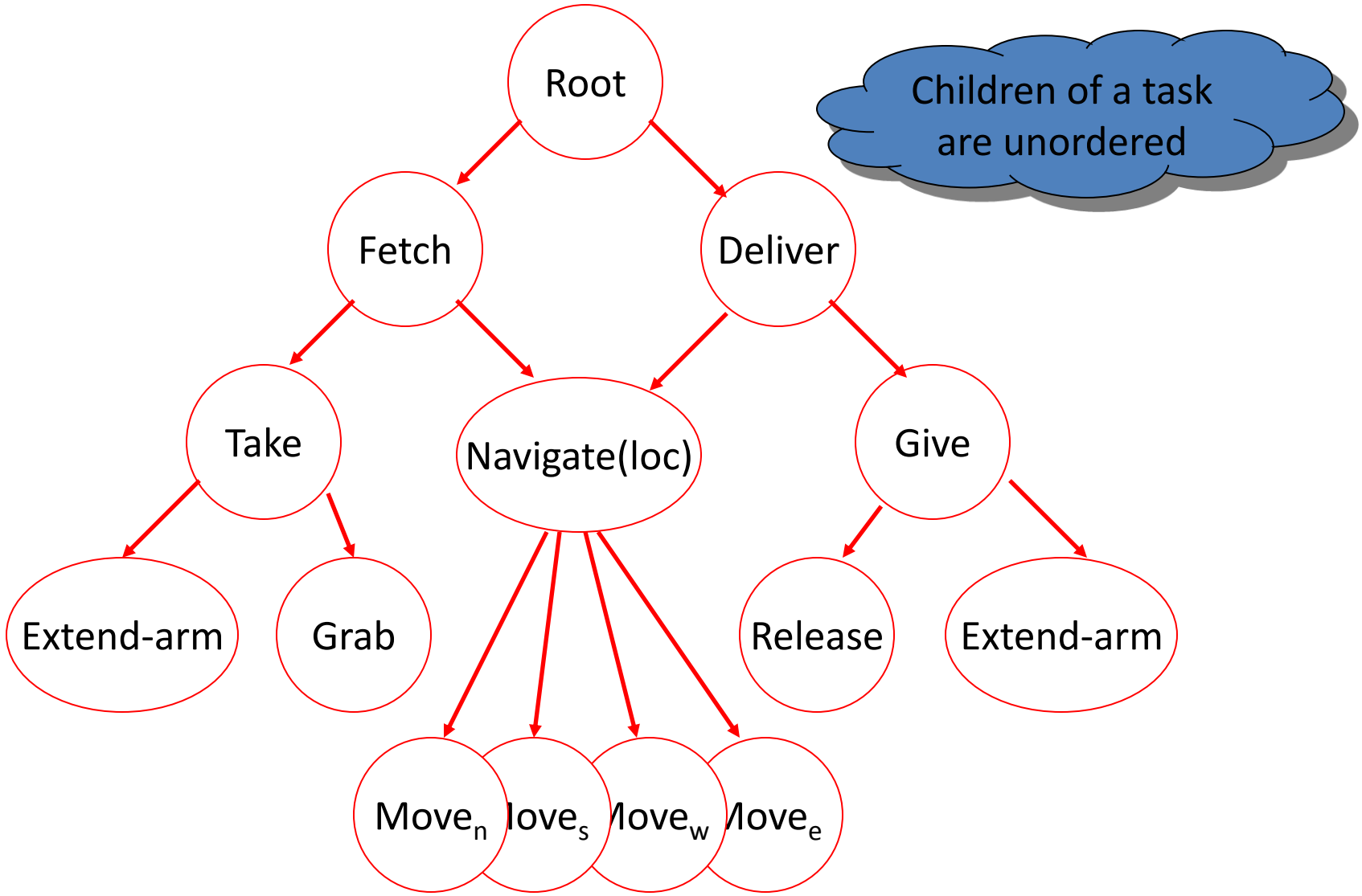
- Use domain knowledge to improve the base policies
  - E.g.: don't choose obvious stupid actions
  - better policy does not imply better UCT performance
- Learn a heuristic function to evaluate positions
  - Use heuristic to initialize leaves
- *Interesting question: UCT versus minimax*

Generalization in Learning

- In realistic situations, we cannot possibly learn about every single state!
  - Too many states to visit them all in training
  - Too many states to even hold the q-tables in memory

- Instead, we want to generalize:
  - Learn about some small number of training states from experience
  - Generalize that experience to new, similar states
  - This is a fundamental idea in machine learning, and we'll see it over and over again

Task Hierarchy: MAXQ Decomposition [Dietterich'00]



Summary

- Multi-armed Bandits
  - Principles of both RL and Monte-Carlo
- Reinforcement Learning
  - Exploration/Exploitation tradeoff
  - Passive/Active RL
  - Model free/Model based
- Monte-Carlo Planning
  - Exploration/Exploitation tradeoff
  - Uniform/Adaptive Sampling