Monte Carlo Tree Search

CompSci 590.2
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A different view of how to plan

- So far, we have (mostly) assumed that we can compute a value function or policy in one big computation and use them for execution
- Exception: TD Gammon
  - Computes value function
  - Combines value function with search before each move
- What if we emphasized search more?

Searching before acting – “on line planning”

- Requires an accurate simulator
  - True for TD Gammon
  - Sensible assumption for most games
- Requires time to plan/search before each action - may not be practical for control problems
- Does not necessarily require planning for the entire state space, but
- Potentially wastes resources by continually replanning

Straw man

- Build a complete search tree out to depth d
- Alternate between action nodes and chance nodes
- Choose d so that $\gamma^d R_{max}$ is small
- Solve for policy in this tree recursive from leaves to root

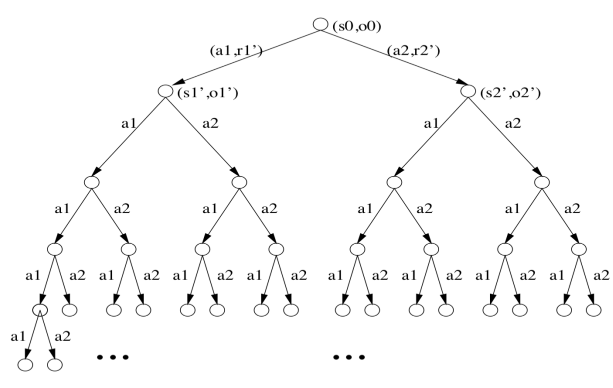
- Problem:
  - b = branching factor = (#of actions x #possible next states)
  - b^d nodes

Remove dependence on #next states

- Kearns et al. introduced trajectory trees
- Instead of considering all next states, sample next states
- Still branch on all actions
- Generate multiple trees instead one fat tree
- Evaluate potential policies against trees – value of policy is average value across trees

- Replaces dependence on #of next states with:
  - Dependence on VC dimension of policy space (linear), $1/\varepsilon^2$, $\log(1/\delta)$
  - # of trees needed to get good average evaluation of policies

Trajectory tree example



Kearns et al.

Trajectory tree limitations

- Main problem remains exponential dependence on d
- Each tree can still be very big
- Even if the number of trees isn't as bad as you might expect, still very expensive to do in practice

A different approach: Bandits

- Bandit problem:
  - Multiple slot machines with unknown expected payoffs
  - Need strategy for playing arms so that learn which slot machine is best without too much opportunity cost of learning
- Regret: Difference between what you got and what you could have gotten if you played optimally
- Goal: Algorithms with bounded regret

UCB1

Deterministic policy: UCB1.
Initialization: Play each machine once.
Loop:

Exploration bonus

– Play machine j that maximizes $\bar{x}_j + \boxed{\sqrt{\frac{2\ln n}{n_j}}}$, where $\bar{x}_j$ is the average reward obtained from machine j, n_j is the number of times machine j has been played so far, and n is the overall number of plays done so far.

From Auer et al., who show that UCB1 has regret **logarithmic in n**

Application to online planning

- Since we are using a simulator, we don't care so much about regret
- BUT: Don't still don't want to waste time
- Idea: What if we view each state as a sort of bandit problem when we explore a tree of possible outcomes from our current state?

Generic Monte Carlo Tree Search

```
function MonteCarloPlanning(state)
repeat
    search(state, 0)
until Timeout
return bestAction(state,0)

function search(state, depth)
if Terminal(state) then return 0
if Leaf(state, d) then return Evaluate(state)
action := selectAction(state, depth)
(nextstate, reward) := simulateAction(state, action)
q := reward + γ search(nextstate, depth + 1)
UpdateValue(state, action, q, depth)
return q
```

From Kocsis & Szepsesvari

Understanding UpdateValue

- Update value computes average value of descendants in the tree
- UCT includes an exploration bonus:
  - $C\sqrt{\frac{logN(s)}{N(s,a)}}$
  - C = sqrt(2) for bandits
- Issues:
  - Unlike bandits, some updates can include “stale” values from children, i.e., value of a node should reflect value of acting optimally for node’s children, but we update as we learn, so child values may not be right
  - How do you pick C?
  - Memory

Staleness

- K&S show that for sufficiently large C, we will converge to the correct values and and action at the root
- Intuition:
  - Eventually, the leaf values will start converging to the correct values
  - If C is big enough, then we'll get enough samples for parents of these nodes to converge, overwhelming errors from earlier iterations
  - Apply this idea inductively

How to pick C

- Not much practical guidance here
- In practice, this will need to be very large
- Why?
  - Leaf values still matter
  - May need exponential number of steps to find leaf values with high rewards
  - No inherent way around this
- In practice:
  - Make C big enough so that you burn all the time you have
  - Works better than it should in many cases

Memory

- What if you can’t afford to maintain value estimates for every node you encounter?
- Note: On modern computers, you can run out of memory very quickly!
- When you hit a node you don’t want to store the value for:
  - “Rollout”
  - Forward simulate to the end of the horizon using the current or random policy, and use this value
  - Does this make sense?

Go

- Ancient game that involves placing black/white stones on a lattice
- 9x9, 13x13, 19x19 (standard) versions
- Surround other players stones to capture and remove from board
- Objective: Maximize number of stones of your color on the board

Why Go is hard

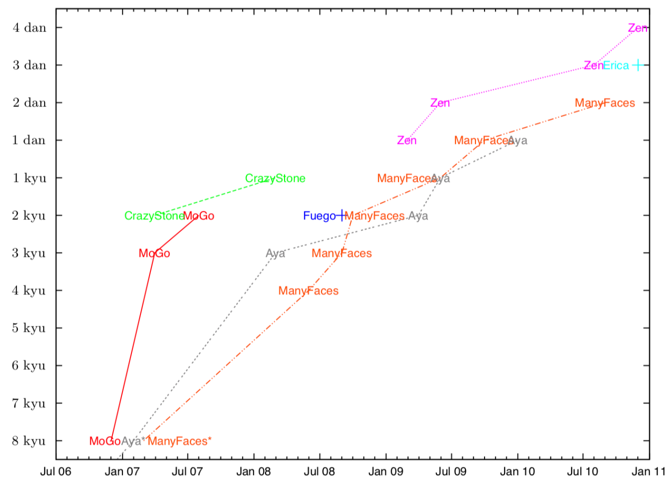
- ~200 moves per turn vs. ~37 in chess
- ~300 turns per game vs. ~57 in chess
- 10^{170} possible positions vs. 10^{47} in chess

- Evaluation is subtle – number of pieces on the board at any time is not in itself very predictive of outcome
- Very difficult to learn/invent a good evaluation function

MCTS for Go

- Classical approaches to Go did not do very well – nowhere close to master level play
- MCTS was a big improvement
- Tricks:
  - Parallelization
  - When/how to do rollouts
  - What policy to use for rollouts
  - Sharing information across subtrees
  - Using databases of expert moves when possible

Go Player ranking vs. time



From Gelly et al.

Does this work for other games?

- Kind of, but not all
- Not a big win for chess
- What's happening?
  - No practical way to pick D big enough to satisfy conditions for theoretical convergence to optimal behavior
  - Can't explore the entire (remaining) tree except very close to end of game
  - Rollouts are very important for estimating the value of the truncated tree

Rollouts: Chess vs. Go speculation

- Go positions are hard to evaluate, but perhaps at a certain point, the good ones and bad ones have **wide paths** towards certain outcomes that are hard to miss with sampling

- Chess tends to have very narrow paths, so that even towards the end of the game, getting towards a particular outcome can be like threading a needle – hard to find with sampling