Games

CPS 270

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Why Study Games?

- Many human activities can be modeled as games
  - Negotiations
  - Bidding
  - TCP/IP
  - Military confrontations
  - Pursuit/Evasion
- Games are used to train the mind
  - Human game-playing, animal play-fighting

Why Are Games Good for AI?

- Games typically have concise rules
- Well-defined starting and end points
- Sensing and effecting are simplified
  - Not true for sports games
  - See robocup
- Games are fun!
- Downside: Getting taken seriously (not)
  - See robo search and rescue

History of Games in AI

- Computer games have been around almost as long as computers (perhaps longer)
  - Chess: Turing (and others) in the 1950s
  - Checkers: Samuel, 1950s learning program
- Usually start with naïve optimism
- Follow with naïve pessimism
- Simon: Computer chess champ by 1967
- Many, e.g., Kasparov, predicted that a computer would *never* be champion

Games Today

- Computers perform at champion level
  - Backgammon, Checkers, Chess, Othello
- Computers perform well
  - Bridge
- Computers still do badly
  - Go, Hex

Game Setup

- Most commonly, we study games that are:
  - 2 player
  - Alternating
  - Zero-sum
  - Perfect information
- Examples: Checkers, chess, backgammon
- Assumptions can be relaxed at some expense
- Economics studies case where number of agents is very large
  - Individual actions don't change the dynamics

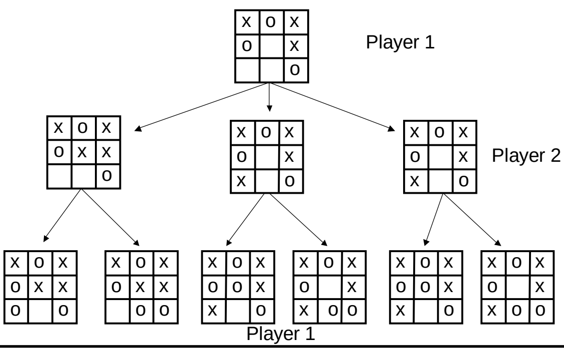
Zero Sum Games

- Assign values to different outcomes
- Win = 1, Loss = -1
- With zero sum games every gain comes at the other player's expense
- Sum of both player's scores must be 0
- Are any games truly zero sum?

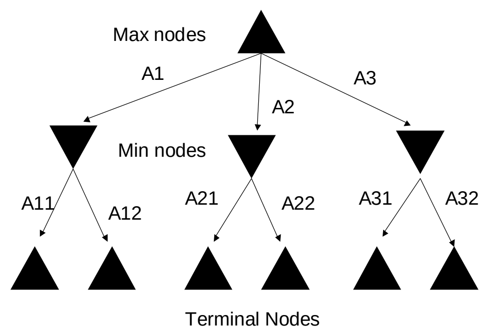
Characterizing Games

- Two-player games - very much like search
  - Initial state
  - Successor function
  - Terminal test
  - Objective function (heuristic function)
- Unlike search
  - Terminal states are often a large set
  - Full search to terminal states usually impossible

Game Trees



Game Trees



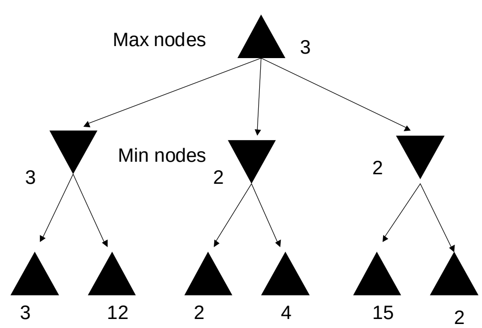
Minimax

- Max player tries to maximize his return
- Min player tries to minimize his return
- This is optimal for both (zero sum)

$$\text{minimax}(n_{\max}) = \max_{s \in \text{succesors}(n)} \text{minimax}(s)$$

$$\text{minimax}(n_{\min}) = \min_{s \in \text{succesors}(n)} \text{minimax}(s)$$

Minimax Values



Minimax Properties

- Minimax can be run depth first
  - Time $O(b^m)$
  - Space O(bm)
- Assumes that opponent plays optimally
- Based on a worst-case analysis
- What if this is incorrect?

Minimax in the Real World

- Search trees are too big
- Alternating turns double depth of the search
  - 2 ply = 1 full turn
- Branching factors are too high
  - Chess: 35
  - Go: 361
- Search from start never terminates in non-trivial games

Evaluation Functions

- Like heuristic functions
- Try to estimate value of a node without expanding all the way to termination
- Using evaluation functions
  - Do a depth-limited search
  - Treat evaluation function as if it were terminal
- What's wrong with this?
- How do you pick the depth?
- How do you manage your time?
  - Iterative deepening, quiescence

Desiderata for Evaluation Functions

- Would like to put the same ordering on nodes (even if values aren't totally right)
- Is this a reasonable thing to ask for?
- What if you have a perfect evaluation function?
- How are evaluation functions made in practice?
  - Buckets
  - Linear combinations
    - Chess pieces (material)
    - Board control (positional, strategic)

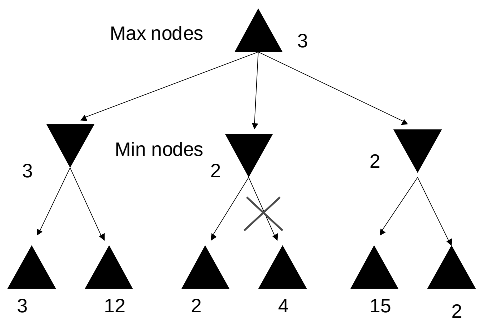
Search Control Issues

- Horizon effects
  - Sometimes something interesting is just beyond the horizon
  - How do you know?
- When to generate more nodes?
- If you selectively extend your frontier, how do you decide where?
- If you have a fixed amount of total game time, how do you allocate this?

Pruning

- The most important search control method is figuring out which nodes you don't need to expand
- Use the fact that we are doing a worst-case analysis to our advantage
  - Max player cuts off search when he knows min player can force a provably bad outcome
  - Min player cuts of search when he knows max can force a provably good (for max) outcome

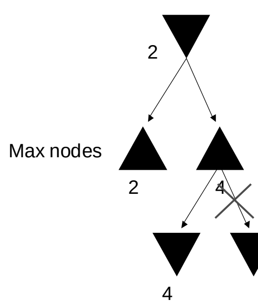
Alpha-beta pruning



How to prune

- We still do (bounded) DFS
- Expand at least one path to the "bottom"
- If current node is **max** node, and **min** can force a *lower* value, then prune siblings
- If current node is min node, and max can force a *higher* value, then prune siblings

Max node pruning



Implementing alpha-beta

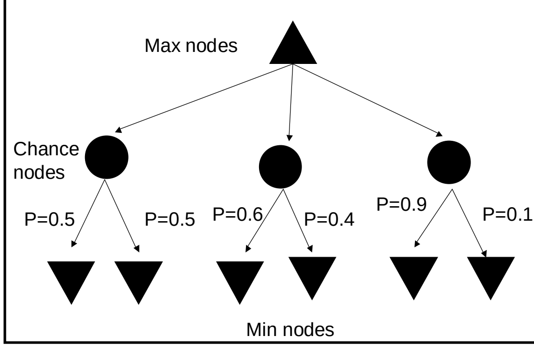
```
max_value(state, alpha, beta)
if cutoff(state) then return eval(state)
v ←-∞
for each s in successors(state) do
  v ← max(v, min_value(s, alpha, beta))
  if v >= beta the return v
  alpha ← max(alpha, v)
end
return v
```

```
min_value(state, alpha, beta)
if cutoff(state) then return eval(state)
v ←-∞
for each s in successors(state) do
 v ← min(v, max_value(s, alpha, beta))
  if v <= alpha the return v
 beta ← min(beta, v)
end
return v
```

Amazing facts about alpha-beta

- Empirically, alpha-beta has the effect of reducing the branching factor by half for many problems
- Effectively *doubles* horizon
- Alpha-beta makes the difference between novice and expert computer players

What About Probabilities?



Expectiminimax

- n random outcomes per chance node
- $O(b^m n^m)$ time

$$\text{eminimax}(n_{\max}) = \max_{s\in \text{succesors}(n)} \text{eminimax}(s)$$
$$\text{eminimax}(n_{\min}) = \min_{s\in \text{succesors}(n)} \text{eminimax}(s)$$
$$\text{eminimax}(n_{\text{chance}}) = \sum_{s\in \text{succesors}(n)} \text{eminimax}(s)p(s)$$

Expectiminimax is nasty

- High branching factor
- Randomness makes evaluation fns difficult
  - Hard to predict many steps into future
  - Values tend to smear together
  - Preserving order is not sufficient
- Pruning chances nodes is problematic
  - Prune based upon bound on an expectation
  - Need a priori bounds on the evaluation function

Multiplayer Games

- Things sort-of generalize
- We can maintain a vector of possible values for each player at each node
- Assume that each player acts greedily
- What’s wrong with this?

Conclusions

- Game tree search is a special kind of search
- Rely heavily on heuristic evaluation functions
- Alpha-beta is a big win
- Most successful players use alpha-beta
- Final thoughts:
  - Search effort vs. evaluation function effort
  - When to invest in your evaluation function?