Title: Adverserial Search
AIMA: Chapter 6 (Sections 6.1, 6.2 and 6.3)

Introduction to Artificial Intelligence
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Berthe Y. Choueiry (Shu-we-ri)
choueiry@cse.unl.edu, (402)472-5444

Outline

- Introduction
- Minimax algorithm
- Alpha-beta pruning
Context

- In an MAS, agents affect each other's welfare
- Environment can be cooperative or competitive
- Competitive environments yield adversarial search problems (games)
- Approaches: mathematical game theory and AI games

Game theory vs. AI

- AI games: fully observable, deterministic environments, players alternate, utility values are equal (draw) or opposite (winner/loser)
  
In vocabulary of game theory: deterministic, turn-taking, two-player, zero-sum games of perfect information

- Games are attractive to AI: states simple to represent, agents restricted to a small number of actions, outcome defined by simple rules

Not croquet or ice hockey, but typically board games

Exception: Soccer (Robocup [www.robocup.org/])
Board game playing: an appealing target of AI research

Board game: Chess (since early AI), Othello, Go, Backgammon, etc.

- Easy to represent
- Fairly small numbers of well-defined actions
- Environment fairly accessible
- Good abstraction of an enemy, w/o real-life (or war) risks : —

But also: Bridge, ping-pong, etc.

Characteristics

- ‘Unpredictable’ opponent: contingency problem
  (interleaves search and execution)

- Not the usual type of ‘uncertainty’:
  no randomness/no missing information (such as in traffic)
  but, the moves of the opponent expectedly non benign

- Challenges:
  - huge branching factor
  - large solution space
  - Computing optimal solution is infeasible
  - Yet, decisions must be made. Forget A*...
Discussion

- What are the theoretically best moves?
- Techniques for choosing a good move when time is tight
  √ Pruning: ignore irrelevant portions of the search space
  × Evaluation function: approximate the true utility of a state without doing search

Two-person Games

- 2 player: Min and Max
- Max moves first
- Players alternate until end of game
- Gain awarded to player/penalty given to loser

Game as a search problem:

- Initial state: board position & indication whose turn it is
- Successor function: defining legal moves a player can take
  Returns {(move, state)*}
- Terminal test: determining when game is over
  states satisfy the test: terminal states
- Utility function (a.k.a. payoff function): numerical value for outcome e.g., Chess: win=1, loss=-1, draw=0
Usual search
Max finds a sequence of operators yielding a terminal goal scoring winner according to the utility function

Game search
• Min actions are significant
  Max must find a strategy to win regardless of what Min does:
  → correct action for Max for each action of Min
• Need to approximate (no time to envisage all possibilities difficulty): a huge state space, an even more huge search space
  e.g., chess: \[10^{40}\] different legal positions
  Average branching factor=35, 50 moves/player= 35^{100}
• Performance in terms of time is very important

Example: Tic-Tac-Toe
Max has 9 alternative moves
Terminal states’ utility: Max wins=1, Max loses = -1, Draw = 0
**Example:** 2-ply game tree

Max’s actions: $a_1, a_2, a_3$
Min’s actions: $b_1, b_2, b_3$

Minimax algorithm determines the optimal strategy for Max → decides which is the best move

**Minimax algorithm**

- Generate the whole tree, down to the leaves
- Compute utility of each terminal state
- Iteratively, from the leaves up to the root, use utility of nodes at depth $d$ to compute utility of nodes at depth $(d - 1)$:
  
  MIN ‘row’: minimum of children
  MAX ‘row’: maximum of children

**MINMAX-VALUE** ($n$)

\[
\begin{align*}
\text{Utility}(n) & \quad \text{if } n \text{ is a terminal node} \\
\max_{s \in \text{Succ}(n)} \text{MINMAX-VALUE}(s) & \quad \text{if } n \text{ is a Max node} \\
\min_{s \in \text{Succ}(n)} \text{MINMAX-VALUE}(s) & \quad \text{if } n \text{ is a Min node}
\end{align*}
\]
Minimax decision

- MAX’s decision: minimax decision maximizes utility under the assumption that the opponent will play perfectly to his/her own advantage
- Minimax decision maximes the worst-case outcome for Max (which otherwise is guaranteed to do better)
- If opponent is sub-optimal, other strategies may reach better outcome better than the minimax decision

Minimax algorithm: Properties

- $m$ maximum depth
  $b$ legal moves
- Using Depth-first search, space requirement is:
  $O(bm)$: if generating all successors at once
  $O(m)$: if considering successors one at a time
- Time complexity $O(b^m)$
  Real games: time cost totally unacceptable
Multiple players games

UTILITY($n$) becomes a vector of the size of the number of players

For each node, the vector gives the utility of the state for each player
to move

A

B

(1, 2, 6)

(1, 2, 6)

(1, 5, 2)

C

(1, 2, 6)

(6, 1, 2)

(1, 5, 2)

(5, 4, 5)

A

(1, 2, 6)

(4, 2, 3)

(6, 1, 2)

(7, 4, 1)

(5, 1, 1)

(1, 5, 2)

(7, 7, 1)

(5, 4, 5)

Alliance formation in multiple players games

How about alliances?

- A and B in weak positions, but C in strong position
  A and B make an alliance to attack C (rather than each other
  → Collaboration emerges from purely selfish behavior!
- Alliances can be done and undone (careful for social stigma!)
- When a two-player game is not zero-sum, players may end up
  automatically making alliances (for example when the terminal
  state maximizes utility of both players)
Alpha-beta pruning

- Minimax requires computing all terminal nodes: unacceptable

- Do we really need to do compute utility of all terminal nodes? ... No, says John McCarthy in 1956:

  It is possible to compute the correct minimax decision without looking at every node in the tree, and yet get the correct decision

- Use pruning (eliminating useless branches in a tree)

Example of alpha-beta pruning

Try 14, 5, 2, 6 below D
**General principal** of Alpha-beta pruning

If Player has a better choice $m$ at any choice point further up a parent node of $n$, $n$ will never be reached in actual play.

Once we have found enough about $n$ (*e.g.*, through one of its descendants), we can prune it (*i.e.*, discard all its remaining descendants).

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**Mechanism** of Alpha-beta pruning

$\alpha$: value of best choice so far for MAX, (maximum)

$\beta$: value of best choice so far for MIN, (minimum)

Alpha-beta search:

- updates the value of $\alpha$, $\beta$ as it goes along
- prunes a subtree as soon as its worse then current $\alpha$ or $\beta$
Effectiveness of pruning

Effectiveness of pruning depends on the order of new nodes examined

Savings in terms of cost

- Ideal case:
  Alpha-beta examines $O(b^{d/2})$ nodes (vs. Minimax: $O(b^d)$)
  $\rightarrow$ Effective branching factor $\sqrt{b}$ (vs. Minimax: $b$)

- Successors ordered randomly:
  $b > 1000$, asymptotic complexity is $O((b/\log b)^d)$
  $b$ reasonable, asymptotic complexity is $O(b^{3d/4})$

- Practically: Fairly simple heuristics work (fairly) well