Set 4: Game-Playing

ICS 271 Fall 2016
Kalev Kask
Overview

- **Computer programs that play 2-player games**
  - game-playing as search
  - with the complication of an opponent

- **General principles of game-playing and search**
  - game tree
  - minimax principle; impractical, but theoretical basis for analysis
  - evaluation functions; cutting off search; replace terminal leaf utility fn with eval fn
  - alpha-beta-pruning
  - heuristic techniques
  - games with chance

- **Status of Game-Playing Systems**
  - in chess, checkers, backgammon, Othello, etc, computers routinely defeat leading world players.

- **Motivation: multiagent competitive environments**
  - think of “nature” as an opponent
  - economics, war-gaming, medical drug treatment
### Types of games

<table>
<thead>
<tr>
<th>Deterministic</th>
<th>Chance</th>
</tr>
</thead>
<tbody>
<tr>
<td>perfect information</td>
<td>backgammon</td>
</tr>
<tr>
<td>chess, checkers, go, othello</td>
<td>monopoly</td>
</tr>
<tr>
<td>imperfect information</td>
<td>bridge, poker, scrabble, nuclear war</td>
</tr>
</tbody>
</table>

Not Considered: Physical games like tennis, croquet, ice hockey, etc.
(but see “robot soccer” http://www.robocup.org/)
Search versus Games

• Search – no adversary
  – Solution is a path from start to goal, or a series of actions from start to goal
  – Heuristics and search techniques can find *optimal* solution
  – Evaluation function: estimate of cost from start to goal through given node
  – Actions have cost
  – Examples: path planning, scheduling activities

• Games – adversary
  – Solution is strategy
    • strategy specifies move for every possible opponent reply.
  – Time limits force an *approximate* solution
  – Evaluation function: evaluate “goodness” of game position
  – Board configurations have utility
  – Examples: chess, checkers, Othello, backgammon
Solving 2-player Games

- Two players, fully observable environments, deterministic, turn-taking, zero-sum games of perfect information
- Examples: e.g., chess, checkers, tic-tac-toe
- Configuration of the board = unique arrangement of “pieces”
- Statement of Game as a Search Problem:
  - States = board configurations
  - Operators = legal moves. The transition model
  - Initial State = current configuration
  - Goal = winning configuration
  - payoff function (utility) = gives numerical value of outcome of the game
- Two players, MIN and MAX taking turns. MIN/MAX will use search tree to find next move
- A working example: Grundy's game
  - Given a set of coins, a player takes a set and divides it into two unequal sets. The player who cannot do uneven split, looses.
  - What is a state? Moves? Goal?
Grundy’s game - special case of nim

**Figure 4.14** Exhaustive minimax for the game of nim. Bold lines indicate forced win for MAX. Each node is marked with its derived value (0 or 1) under minimax.
Game Trees: Tic-tac-toe

Figure 5.1 A (partial) search tree for the game of Tic-Tac-Toe. The top node is the initial state, and MAX moves first, placing an X in some square. We show part of the search tree, giving alternating moves by MIN (O) and MAX, until we eventually reach terminal states, which can be assigned utilities according to the rules of the game.

How do we search this tree to find the optimal move?
The Minimax Algorithm

- Designed to find the optimal strategy or just best first move for MAX
  - Optimal strategy is a solution tree

**Brute-force:**
- 1. Generate the whole game tree to leaves
- 2. Apply utility (payoff) function to leaves
- 3. Back-up values from leaves toward the root:
  - a Max node computes the max of its child values
  - a Min node computes the min of its child values
- 4. When value reaches the root: choose max value and the corresponding move.

**Minimax:**
Search the game-tree in a DFS manner to find the value of the root.
Figure 5.2  A two-ply game tree as generated by the minimax algorithm. The △ nodes are moves by MAX and the ◇ nodes are moves by MIN. The terminal nodes show the utility value for MAX computed by the utility function (i.e., by the rules of the game), whereas the utilities of the other nodes are computed by the minimax algorithm from the utilities of their successors. MAX’s best move is $A_1$, and MIN’s best reply is $A_{11}$. 
Two-Ply Game Tree

MAX

MIN

3  12  8  2  4  6  14  5  2
Two-Ply Game Tree
Two-Ply Game Tree

Minimax maximizes the utility for the worst-case outcome for max

A solution tree is highlighted
Properties of minimax

• **Complete?**
  – Yes (if tree is finite).

• **Optimal?**
  – Yes (against an optimal opponent).
  – Can it be beaten by an opponent playing sub-optimally?
    • No. (Why not?)

• **Time complexity?**
  – $O(b^m)$

• **Space complexity?**
  – $O(bm)$ (depth-first search, generate all actions at once)
  – $O(m)$ (backtracking search, generate actions one at a time)
Game Tree Size

- **Tic-Tac-Toe**
  - $b \approx 5$ legal actions per state on average, total of 9 plies in game.
    - “ply” = one action by one player, “move” = two plies.
  - $5^9 = 1,953,125$
  - $9! = 362,880$ (Computer goes first)
  - $8! = 40,320$ (Computer goes second)
  → **exact solution quite reasonable**

- **Chess**
  - $b \approx 35$ (approximate average branching factor)
  - $d \approx 100$ (depth of game tree for “typical” game)
  - $b^d \approx 35^{100} \approx 10^{154}$ nodes!!
  → **exact solution completely infeasible**

- It is usually impossible to develop the whole search tree. Instead develop part of the tree up to some depth and evaluate leaves using an evaluation fn
- **Optimal strategy (solution tree) too large to store.**
Static (Heuristic) Evaluation Functions

• **An Evaluation Function:**
  – Estimates how good the current board configuration is for a player
  – Typically, one figures how good it is for the player, and how good it is for the opponent, and subtracts the opponent's score from the player
  – Othello: Number of white pieces - Number of black pieces
  – Chess: Value of all white pieces - Value of all black pieces

• **Typical values from -infinity (loss) to +infinity (win) or [-1, +1].**
• **If the board evaluation is X for a player, it’s -X for the opponent**
• **Example:**
  – Evaluating chess boards
  – Checkers
  – Tic-tac-toe
Applying MiniMax to tic-tac-toe

- The static evaluation function heuristic

\[
\begin{align*}
\text{X has 6 possible win paths:} & \quad E(n) = 6 - 5 = 1 \\
\text{O has 5 possible wins:} & \\
\text{X has 4 possible win paths; O has 6 possible wins} & \quad E(n) = 4 - 6 = -2 \\
\text{X has 5 possible win paths; O has 4 possible wins} & \quad E(n) = 5 - 4 = 1
\end{align*}
\]

Heuristic is \( E(n) = M(n) - O(n) \)
where \( M(n) \) is the total of My possible winning lines
\( O(n) \) is total of Opponent's possible winning lines
\( E(n) \) is the total Evaluation for state \( n \)

Figure 4.16 Heuristic measuring conflict applied to states of tic-tac-toe.
Backup Values

Figure 4.17  Two-ply minimax applied to the opening move of tic-tac-toe.
Figure 4.18  Two-ply minimax applied to X's second move of tic-tac-toe.
Figure 4.19  Two-ply minimax applied to X's move near end game.
Feature-based evaluation functions

• Features of the state
• Features taken together define categories (equivalence) classes
• Expected value for each equivalence class
  – Too hard to compute
• Instead
  – Evaluation function = weighted linear combination of feature values
Figure 5.8 Two chess positions that differ only in the position of the rook at lower right. In (a), Black has an advantage of a knight and two pawns, which should be enough to win the game. In (b), White will capture the queen, giving it an advantage that should be strong enough to win.

For chess, typically \textit{linear} weighted sum of features

\[ \text{Eval}(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s) \]

e.g., \( w_1 = 9 \) with
\[ f_1(s) = (\text{number of white queens}) - (\text{number of black queens}), \] etc.
Digression: Exact values don’t matter

MAX

MIN

Behaviour is preserved under any *monotonic* transformation of $\text{EVAL}$

Only the order matters:
- payoff in deterministic games acts as an *ordinal utility* function
Summary so far

• Deterministic game tree: alternating levels of MAX/MIN
• minimax algorithm
  – DFS on the game tree
  – Leaf nodes values defined by the (terminal) utility function
  – Compute node values when backtracking
  – Impractical – game tree size huge
• Cutoff depth
  – Heuristic evaluation fn providing relative value of each configuration
  – Typically (linear) function on the features of the state
Alpha-Beta Pruning
Exploiting the Fact of an Adversary

• If a position is provably bad:
  – It is NO USE expending search time to find out exactly how bad, if you have a better alternative

• If the adversary can force a bad position:
  – It is NO USE expending search time to find out the good positions that the adversary won’t let you achieve anyway

• Bad = not better than we already know we can achieve elsewhere.

• Contrast normal search:
  – ANY node might be a winner.
  – ALL nodes must be considered.
  – (A* avoids this through knowledge, i.e., heuristics)
Alpha Beta Procedure

• **Idea:**
  – Do depth first search to generate partial game tree,
  – Give static evaluation function to leaves,
  – Compute bound on internal nodes.

• **α, β bounds:**
  – α value for max node means that max real value is at least α.
  – β for min node means that min can guarantee a value no more than β.

• **Computation:**
  – Pass current α/β down to children when expanding a node
  – Update α(Max)/β(Min) when node values are updated
    • α of MAX node is the max of children seen.
    • β of MIN node is the min of children seen.
Alpha-Beta Example

Do DF-search until first leaf

Range of possible values

Figure 5.2 A two-ply game tree as generated by the minimax algorithm. The $\Delta$ nodes are moves by MAX and the $\nabla$ nodes are moves by MIN. The terminal nodes show the utility value for MAX computed by the utility function (i.e., by the rules of the game), whereas the utilities of the other nodes are computed by the minimax algorithm from the utilities of their successors. MAX's best move is $A_1$, and MIN's best reply is $A_{11}$. 
Alpha-Beta Example (continued)
Alpha-Beta Example (continued)
Alpha-Beta Example (continued)

MAX

MIN

[3, 3]

[3, +\infty]

3

12

8
Alpha-Beta Example (continued)

This node is worse for MAX
Alpha-Beta Example (continued)

```
[3,3]  3  12  8  2  14
```

```
MAX

MIN
```

```
[3,14] ≥ 3 ≤ 2 ≤ 14
```

```
[3,3]  12  8  2  14
```

```
[∞,2] ≤ 2 ≤ 14
```

```
[∞,14]
```

```
X  X
```

```
[∞,14]
```
Alpha-Beta Example (continued)

The Alpha-Beta pruning algorithm is demonstrated with a decision tree. The tree has a MAX at the root with a value of $[3,5]$. Below are the MIN values at each leaf node:

- MIN at leaf node $3$: $[3,3]$
- MIN at leaf node $12$: $[-\infty, 2]$
- MIN at leaf node $8$: $[3,5]$ (pruned)
- MIN at leaf node $2$: $[3,5]$ (pruned)
- MIN at leaf node $14$: $[-\infty, 5]$
- MIN at leaf node $5$: $[-\infty, 5]$

The algorithm prunes the branches where the MIN values indicate that the path is not optimal, improving efficiency.
Alpha-Beta Example (continued)
Alpha-Beta Example (continued)
Tic-Tac-Toe Example with Alpha-Beta Pruning

Figure 4.17 Two-ply minimax applied to the opening move of tic-tac-toe.
Alpha-beta Algorithm

- Depth first search  
  - only considers nodes along a single path from root at any time

\[ \alpha = \text{highest-value choice found at any choice point of path for MAX} \]
  (initially, \( \alpha = -\infty \))

\[ \beta = \text{lowest-value choice found at any choice point of path for MIN} \]
  (initially, \( \beta = +\infty \))

- Pass current values of \( \alpha \) and \( \beta \) down to child nodes during search.
- Update values of \( \alpha \) and \( \beta \) during search:
  - MAX updates \( \alpha \) at MAX nodes
  - MIN updates \( \beta \) at MIN nodes
When to Prune

- Prune whenever $\alpha \geq \beta$.
  - Prune below a Max node whose alpha value becomes greater than or equal to the beta value of its ancestors.
    - **Max nodes update alpha** based on children’s returned values.
  - Prune below a Min node whose beta value becomes less than or equal to the alpha value of its ancestors.
    - **Min nodes update beta** based on children’s returned values.
Alpha-Beta Example Revisited

Do DF-search until first leaf

\[
\alpha = -\infty, \quad \beta = +\infty
\]

\(\alpha, \beta, \text{initial values}\)

\(\alpha, \beta, \text{passed to children}\)
MIN updates $\beta$, based on children
MIN updates $\beta$, based on children.
No change.
MAX updates $\alpha$, based on children.

$\alpha = 3$

$\beta = +\infty$

3 is returned as node value.
Alpha-Beta Example (continued)

\[ \alpha = 3 \]
\[ \beta = +\infty \]

\( \alpha, \beta, \text{ passed to children} \)

\[ \alpha = 3 \]
\[ \beta = +\infty \]
Alpha-Beta Example (continued)

MIN updates $\beta$, based on children.

$\alpha = 3$

$\beta = +\infty$

$\alpha = 3$

$\beta = 2$
Alpha-Beta Example (continued)

\[ \alpha = 3 \]
\[ \beta = +\infty \]

\[ \alpha \geq \beta, \text{ so prune.} \]
Alpha-Beta Example (continued)

MAX updates $\alpha$, based on children.
No change.

$\alpha = 3$

$\beta = +\infty$

2 is returned as node value.
Alpha-Beta Example (continued)

\[ \alpha = 3 \]
\[ \beta = +\infty \]

\( \alpha, \beta, \text{passed to children} \)
Alpha-Beta Example (continued)

MIN updates $\beta$, based on children.

$\alpha = 3$

$\beta = +\infty$

MIN

MAX

$\alpha = 3$

$\beta = 14$
Alpha-Beta Example (continued)

MIN updates $\beta$, based on children.

$\alpha = 3$
$\beta = +\infty$

MIN

3

MAX

3
12
8

$\leq 2$

X
X

14
5
Alpha-Beta Example (continued)

\[ \alpha = 3 \]
\[ \beta = +\infty \]

2 is returned as node value.
Max calculates the same node value, and makes the same move!
Alpha Beta Practical Implementation

- **Idea:**
  - Do depth first search to generate partial game tree
  - Cutoff test:
    - Depth limit
    - Iterative deepening
    - Cutoff when no big changes (quiescent search)
  - When cutoff, apply static evaluation function to leaves
  - Compute bound on internal nodes
  - Run $\alpha$-$\beta$ pruning using estimated values
  - **IMPORTANT**: use node values of previous iteration to order children during next iteration
Example

-which nodes can be pruned?
Answer to Example

-which nodes can be pruned?

Answer: NONE! Because the most favorable nodes for both are explored last (i.e., in the diagram, are on the right-hand side).
Second Example
(the exact mirror image of the first example)

-which nodes can be pruned?
Answer to Second Example
(the exact mirror image of the first example)

which nodes can be pruned?

Answer: LOTS! Because the most favorable nodes for both are explored first (i.e., in the diagram, are on the left-hand side).
Effectiveness of Alpha-Beta Search

- **Worst-Case**
  - Branches are ordered so that no pruning takes place. In this case alpha-beta gives no improvement over exhaustive search

- **Best-Case**
  - Each player’s best move is the left-most alternative (i.e., evaluated first)
  - In practice, performance is closer to best rather than worst-case
    - E.g., sort moves by the remembered move values found last time.
    - E.g., expand captures first, then threats, then forward moves, etc.
    - E.g., run Iterative Deepening search, sort by value last iteration.

- **Alpha/beta best case is $O(b^{d/2})$ rather than $O(b^d)$**
  - This is the same as having a branching factor of $\sqrt{b}$,
    - $(\sqrt{b})^d = b^{(d/2)}$ (i.e., we have effectively gone from $b$ to square root of $b$)
  - In chess go from $b \sim 35$ to $b \sim 6$
    - permitting much deeper search in the same amount of time
  - In practice it is often $b^{(2d/3)}$
Final Comments about Alpha-Beta Pruning

• Pruning does not affect final results!!! Alpha-beta pruning returns the MiniMax value!!!

• Entire subtrees can be pruned.

• Good move *ordering* improves effectiveness of pruning

• Repeated states are again possible.
  – Store them in memory = transposition table
  – Even in depth-first search we can store the result of an evaluation in a hash table of previously seen positions. Like the notion of “explored” list in graph-search
Heuristics and Game Tree Search: limited horizon

• The Horizon Effect
  – sometimes there’s a major “effect” (such as a piece being captured) which is just “below” the depth to which the tree has been expanded.
  – the computer cannot see that this major event could happen because it has a “limited horizon”.
  – there are heuristics to try to follow certain branches more deeply to detect such important events
  – this helps to avoid catastrophic losses due to “short-sightedness”
  – push unavoidable large neg events “over” the horizon at additional cost

• Heuristics for Tree Exploration
  – it may be better to explore some branches more deeply in the allotted time
  – various heuristics exist to identify “promising” branches

• Search versus lookup tables
  – (e.g., chess endgames)
Iterative (Progressive) Deepening

• In real games, there is usually a time limit $T$ on making a move

• How do we take this into account?
• Using alpha-beta we cannot use “partial” results with any confidence unless the full breadth of the tree has been searched
  – So, we could be conservative and set a conservative depth-limit which guarantees that we will find a move in time $< T$
    • disadvantage is that we may finish early, could do more search

• In practice, iterative deepening search (IDS) is used
  – IDS runs depth-first search with an increasing depth-limit
  – when the clock runs out we use the solution found at the previous depth limit
Multiplayer Games

- Multiplayer games often involve alliances: If A and B are in a weak position they can collaborate and act against C.

- If games are not zero-sum, collaboration can also occur in two-game plays: if \((1000,1000)\) is a best payoff for both, then they will cooperate towards getting there and not towards minimax value.
In real life there are many unpredictable external events.

A game tree in Backgammon must include chance nodes.
Schematic Game Tree for Backgammon Position

- How do we evaluate a good move?
- By expected utility leading to expected minimax
  - Utility for MAX is the highest expected value of child nodes
  - Utility for MIN is the lowest expected value of child nodes
- Chance node take the EXPECTED value of their child nodes.
Algorithm for nondeterministic games

`EXPECTIMINIMAX` gives perfect play

Just like `MINIMAX`, except we must also handle chance nodes:

\[
\begin{align*}
\text{...} \\
\text{if } state \text{ is a } \text{Max} \text{ node then} \\
\quad \text{return the highest } & \text{EXPECTIMINIMAX-Value of Successors}(state) \\
\text{if } state \text{ is a } \text{Min} \text{ node then} \\
\quad \text{return the lowest } & \text{EXPECTIMINIMAX-Value of Successors}(state) \\
\text{if } state \text{ is a chance node then} \\
\quad \text{return average of } & \text{EXPECTIMINIMAX-Value of Successors}(state) \\
\text{...}
\end{align*}
\]
Evaluation functions for stochastic games

- Sensitivity to the absolute values
- The evaluation function should be related to the probability of winning from a position, or to the expected utility from the position
- Complexity: $O((bn)^m)$ where $m$ is the depth and $n$ is branching of chance nodes;
  - deterministic games – $O(b^m)$
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:

![Game Tree Diagram]
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:

\[ \begin{array}{c}
\text{[ } -\infty, +\infty \text{]} \\
0.5 \\
\text{[ } -\infty, 2 \text{]} \\
2 \\
\end{array} \quad \begin{array}{c}
\text{[ } -\infty, +\infty \text{]} \\
0.5 \\
\text{[ } -\infty, +\infty \text{]} \\
\end{array} \quad \begin{array}{c}
\text{[ } -\infty, +\infty \text{]} \\
0.5 \\
\text{[ } -\infty, +\infty \text{]} \\
\end{array} \quad \begin{array}{c}
\text{[ } -\infty, +\infty \text{]} \\
0.5 \\
\text{[ } -\infty, +\infty \text{]} \\
\end{array} \]
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:

```
      0.5
    /   \
 0.5   0.5
     /     /
 2   [2, 2] [2, 2] 2
     /     /
 [2, 2] [2, 2] [2, 2] [2, 2]
```

A node with a value of $[\infty, \infty]$ can be pruned.
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:

\[
\begin{array}{cccc}
& & & 2 \\
& & 2 & 2 \\
& 2 & 2 & 2 \\
\end{array}
\]
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:

```
          [ 1.5, 1.5 ]
         /   \
0.5     0.5
[ 2, 2 ]  [ 1, 1 ]
         /
2      2
```

```
          [ -\infty, +\infty ]
         /   \
0.5     0.5
[ -\infty, +\infty ]  [ -\infty, +\infty ]
         /
2      1
```
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:
Pruning in nondeterministic game trees

A version of $\alpha$-$\beta$ pruning is possible:

```
       [ 1.5 , 1.5 ]
      /       \
 0.5       0.5
  [ 2 , 2 ]  [ 1 , 1 ]
  /       \
2       2

  [ -\infty , +\infty ]
      /       \
 0.5       0.5
  [ 0 , 0 ]  [ -\infty , +\infty ]
      /       \
0       1
```
A version of $\alpha$-$\beta$ pruning is possible:

- An alternative: Monte Carlo simulations:
  - Play thousands of games of the program against itself using random dice rolls. Record the percentage of wins from a position.
Monte Carlo Tree Search (MCTS)

- Game tree very large, accurate eval fn not available. Example GO
- MC simulation/sampling
  - Many thousands of random self-play games
  - At the end of each simulation, update node/edge values
- Build a tree
  - incrementally: each simulation add highest non-tree node to tree
  - asymmetrically: pursue promising moves

- At each node, solve n-armed bandit problem
  - exploitation vs exploration
  - minimize regret
- Tree policy: select child/action using edge values $X_i + C*\sqrt{\ln(N)/N_i}$
  - $X_i$ = exploitation term, $C*\sqrt{\ln(N)/N_i}$ = exploration term
- Default policy: MC simulation
- winrate values of nodes will converge to minmax values, as $N \to \infty$
- When time is up, use a move with highest winrate
- Advantage – don’t need any heuristic fn; will converge faster if decent eval fn
AlphaGo

- MCTS simulation
- Policy/value estimation computed by (deep – 13 layers) neural network
  - Learned from 30 million human game samples
- Policy/value estimation alone (without MCTS) plays on avg level
- MCTS and policy/value eval fn equally important
Summary

- Game playing is best modeled as a search problem
- Game trees represent alternate computer/opponent moves
- Evaluation functions estimate the quality of a given board configuration for the Max player.
- Minimax is a procedure which chooses moves by assuming that the opponent will always choose the move which is best for them.
- Alpha-Beta is a procedure which can prune large parts of the search tree and allow search to go deeper.
- Human and computer (board) game playing moving in different separate directions: computer beat humans in most games and are getting better.
Deterministic games in practice

Checkers: Chinook ended 40-year-reign of human world champion Marion Tinsley in 1994. Used an endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 443,748,401,247 positions.


Othello: human champions refuse to compete against computers, who are too good.

Go: human champions refuse to compete against computers, who are too bad. In go, $b > 300$, so most programs use pattern knowledge bases to suggest plausible moves.