Game Playing and AI

Game playing as a problem for AI research
– game playing is non-trivial
  • players need “human-like” intelligence
  • games can be very complex (e.g., Chess, Go)
  • requires decision making within limited time
– games usually are:
  • well-defined and repeatable
  • fully observable and limited environments
– can directly compare humans and computers

Definition:

- **Zero-sum**: one player’s gain is the other player’s loss. Does not mean fair.
- **Discrete**: states and decisions have discrete values
- **Finite**: finite number of states and decisions
- **Deterministic**: no coin flips, die rolls – no chance
- **Perfect information**: each player can see the complete game state. No simultaneous decisions.
### Game Playing and AI

<table>
<thead>
<tr>
<th>Fully Observable (perfect info)</th>
<th>Deterministic</th>
<th>Stochastic (chance)</th>
</tr>
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<tbody>
<tr>
<td>Checkers, Chess, Go, Othello</td>
<td>Backgammon, Monopoly</td>
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<td>Bridge, Poker, Scrabble</td>
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All are also multi-agent, adversarial, static tasks

### Game Playing as Search

- **Consider two-player, perfect information, deterministic, 0-sum board games:**
  - e.g., chess, checkers, tic-tac-toe
  - Board configuration: a specific arrangement of "pieces"
- **Representing board games as search problem:**
  - **states:** board configurations
  - **actions:** legal moves
  - **initial state:** starting board configuration
  - **goal state:** game over/terminal board configuration

### Game Tree Representation

- **What’s the new aspect to the search problem?**
- **There’s an opponent we cannot control!**

### Greedy Search using an Evaluation Function

- **A Utility function** is used to map each terminal state of the board (i.e., states where the game is over) to a score indicating the value of that outcome to the computer
  - **We’ll use:**
    - positive for winning; large + means better for computer
    - negative for losing; large − means better for opponent
    - 0 for a draw
    - typical values (loss to win): 
      - $-\infty$ to $+\infty$
      - -1.0 to +1.0
Greedy Search using an Evaluation Function

- Expand the search tree to the terminal states on each branch
- Evaluate the Utility of each terminal board configuration
- Make the initial move that results in the board configuration with the maximum value

Minimax Principle

Assume both players play optimally
- assuming there are two moves until the terminal states,
- high Utility values favor the computer
  - computer should choose maximizing moves
- low Utility values favor the opponent
  - smart opponent chooses minimizing moves

Greedy Search using an Evaluation Function

- Assuming a reasonable search space, what's the problem?
  - This ignores what the opponent might do!
  - Computer chooses C
  - Opponent chooses J and defeats computer

Minimax Principle

- The computer assumes after it moves the opponent will choose the minimizing move
- The computer chooses the best move considering both its move and the opponent’s optimal move
Propagating Minimax Values
Up the Game Tree

- Explore the tree to the terminal states
- Evaluate the Utility of the resulting board configurations
- The computer makes a move to put the board in the best configuration for it assuming the opponent makes her best moves on her turn(s):
  - start at the leaves
  - assign value to the parent node as follows
    - use *minimum* when node is the opponent’s move
    - use *maximum* when node is the computer's move

Deeper Game Trees

- Minimax can be generalized to more than 2 moves
- *Propagate* values up the tree

General Minimax Algorithm

For each move by the computer:
1. Perform depth-first search, stopping at terminal states
2. Evaluate each terminal state
3. Propagate upwards the minimax values
   - if opponent's move, propagate up minimum value of its children
   - if computer's move, propagate up maximum value of its children
4. Choose move at root with the maximum of the minimax values of its children

Search algorithm independently invented by Claude Shannon (1950) and Alan Turing (1951)

Complexity of Minimax Algorithm

Assume all terminal states are at depth \(d\) and there are \(b\) possible moves at each step

- Space complexity
  - Depth-first search, so \(O(bd)\)
- Time complexity
  - Branching factor \(b\), so \(O(b^d)\)

- Time complexity is a major problem since computer typically only has a limited amount of time to make a move
Complexity of Game Playing

• Assume the opponent’s moves can be predicted given the computer’s moves
• How complex would search be in this case?
  – worst case: $O(b^d)$ branching factor, depth
  – **Tic-Tac-Toe**: ~5 legal moves, 9 moves max game
    • $5^9 = 1,953,125$ states
  – **Chess**: ~35 legal moves, ~100 moves per game
    • $b^d \sim 35^{100} \sim 10^{354}$ states, only $\sim10^{90}$ legal states
  – **Go**: ~250 legal moves, ~150 moves per game
• Common games produce enormous search trees

Complexity of Minimax Algorithm

• Minimax algorithm applied to complete game trees is impractical in practice
  – instead do depth-limited search to **ply** (depth) $m$
  – but Utility function defined only for terminal states
  – we need to know a value for non-terminal states
• **Static Evaluation functions** use heuristics to estimate the value of non-terminal states

Static Board Evaluation

• A **Static Board Evaluation (SBE) function** is used to estimate how good the current board configuration is for the computer
  – it reflects the computer’s chances of winning from that node
  – it must be easy to calculate from a board configuration
• For example, for **Chess**:
  
  $SBE = \alpha \cdot \text{materialBalance} + \beta \cdot \text{centerControl} + \gamma \cdot \ldots$

  where material balance = Value of white pieces - Value of black pieces, pawn = 1, rook = 5, queen = 9, etc.
Minimax with Evaluation Functions

- The same as general Minimax, except
  - only go to depth $m$
  - estimates value at leaves using the SBE function
- How would this algorithm perform at Chess?
  - if could look ahead ~4 pairs of moves (i.e., 8 ply),
    would be consistently beaten by average players
  - if could look ahead ~8 pairs, is as good as human master
**Minimax Algorithm**

```plaintext
function Max-Value(s)
inputs: s: current state in game, Max about to play
output: best-score (for Max) available from s
    if (s is a terminal state or at depth limit)
        then return (SBE value of s)
    else
        v = -\infty  // v is current best minimax value at s
        foreach s’ in Successors(s)
            v = max(v, Min-Value(s’))
        return v

function Min-Value(s)
output: best-score (for Min) available from s
    if (s is a terminal state or at depth limit)
        then return (SBE value of s)
    else
        v = +\infty  // v is current best minimax value at s
        foreach s’ in Successors(s)
            v = min(v, Max-Value(s’))
        return v
```

**Minimax Example**

**Summary So Far**

- Can’t use Minimax search to end of the game
  -- if we could, then choosing optimal move is easy
- SBE isn’t perfect at estimating/scoring
  -- if it was, just choose best move without searching
- Since neither is feasible for interesting games, combine Minimax and SBE concepts:
  -- Use Minimax to cutoff search at depth \( m \)
  -- use SBE to estimate/score board configuration

**Alpha-Beta Idea**

- Some of the branches of the game tree won’t be taken if playing against an intelligent opponent
- “If you have an idea that is surely bad, don’t take the time to see how truly awful it is.”
  -- Pat Winston
- Pruning can be used to ignore some branches
- While doing DFS of game tree, keep track of:
  -- At maximizing levels:
    - highest SBE value, \( v \), seen so far in subtree below each node
    - lower bound on node’s final minimax value
  -- At minimizing levels:
    - lowest SBE value, \( v \), seen so far in subtree below each node
    - upper bound on node’s final minimax value
**Alpha-Beta Idea: Alpha Cutoff**

- **Depth-first traversal order**
- After returning from A, can get at least 100 at S
- After returning from F, can get at most 20 at B
- At this point no matter what minimax value is computed at G, S will prefer A over B. So, S loses interest in B
- There is no need to visit G. The subtree at G is pruned. Saves time. Called "Alpha cutoff" (at MIN node B)

**Alpha Cutoff**

- At each MIN node, keep track of the minimum value returned so far from its visited children
- Store this value as \( v \)
- Each time \( v \) is updated (at a MIN node), check its value against the \( \alpha \) value of all its MAX node ancestors
- If \( \alpha \geq v \) for some MAX node ancestor, don’t visit any more of the current MIN node’s children; i.e., prune (cutoff) all subtrees rooted at remaining children of MIN

**Beta Cutoff Example**

- After returning from B, can get at most 20 at MIN node A
- After returning from G, can get at least 25 at MAX node C
- No matter what minimax value is found at H, A will NEVER choose C over B, so don’t visit node H
- Called "Beta Cutoff" (at MAX node C)

**Beta Cutoff**

- At each MAX node, keep track of the maximum value returned so far from its visited children
- Store this value as \( v \)
- Each time \( v \) is updated (at a MAX node), check its value against the \( \beta \) value of all its MIN node ancestors
- If \( v \geq \beta \) for some MIN node ancestor, don’t visit any more of the current MAX node’s children; i.e., prune (cutoff) all subtrees rooted at remaining children of MAX
Implementation of Cutoffs
At each node, keep both $\alpha$ and $\beta$ values, where $\alpha =$ largest (i.e., best) value from its MAX node ancestors in search tree, and $\beta =$ smallest (i.e., best) value from its MIN node ancestors in search tree. Pass these down the tree during traversal.
- At MAX node, $v =$ largest value from its children visited so far; cutoff if $v \geq \beta$
  * $v$ value at MAX comes from its descendants
  * $\beta$ value at MAX comes from its MIN node ancestors
- At MIN node, $v =$ smallest value from its children visited so far; cutoff if $\alpha \geq v$
  * $\alpha$ value at MIN comes from its MAX node ancestors
  * $v$ value at MIN comes from its descendants

Implementation of Alpha Cutoff
\[
\begin{align*}
\text{max} & \quad \alpha = \infty \\
\text{min} & \quad \beta = \infty \\
\end{align*}
\]
Initialize root’s values

\[
\begin{align*}
\text{max} & \quad \alpha = -\infty \\
\text{min} & \quad \beta = 200 \\
\end{align*}
\]
\[
\begin{align*}
v & = 200
\end{align*}
\]

Alpha Cutoff Example
Notes:
• Alpha cutoff means not visiting some of a MIN node’s children
• v values at MIN come from descendants
• Alpha value at MIN come from MAX node ancestors
**Alpha-Beta Algorithm**

function Max-Value (s, α, β)  
inputs:
    s: current state in game, Max about to play
    α: best score (highest) for Max along path from s to root
    β: best score (lowest) for Min along path from s to root

if (s is a terminal state or at depth limit)
then return (SBE value of s)  

v = -∞  // v = best minimax value found so far at s

for each s' in Successors(s)
    v = max( v, Min-Value(s', α, β))
    if (v ≥ β) then return v  // prune remaining children
    α = max(α, v)

return v  // return value of best child

---

**Alpha-Beta Example**

function Min-Value(s, α, β)

if (s is a terminal state or at depth limit)
then return (SBE value of s)

v = +∞  // v = best minimax value found so far at s

for each s' in Successors(s)
    v = min( v, Max-Value(s', α, β))
    if (α ≥ v ) then return v  // prune remaining children
    β = min(β, v)

return v  // return value of best child
Alpha-Beta Example

Call Stack

brown: terminal state

v(F) = alpha(F) = 4, maximum seen so far
Why? Smart opponent will choose W or worse, thus O's upper bound is –3. So, at F computer shouldn’t choose O:-3 since N:4 is better.
v(B) = beta(B) = 4, minimum seen so far

v(B) = beta(B) = -5, updated to minimum seen so far
\[ v(A) = \text{alpha}(A) = -5, \] maximum seen so far

Copy alpha and beta values from A to C

\[ v(C) = \text{beta}(C) = 3, \] minimum seen so far
\[ v(C) (= 3) > \alpha(C) (= -5), \] so no cutoff
Alpha-Beta Example

Beta(C) not changed (minimizing)

Alpha-Beta Example

Call Stack

Alpha-Beta Example

Call Stack

Alpha-Beta Example

Call Stack

Alpha-Beta Example

Call Stack
**Alpha-Beta Example**

\[ v(J) = 9 \]

**Why?** Computer should choose P or better at J, so J’s lower bound is 9. But, smart opponent at C won’t take J:9 since H:3 is better for opponent.

**Alpha-Beta Example**

\[ v(J) \geq \beta(J) \text{ so stop expanding J (beta cutoff)} \]

**Alpha-Beta Example**

\[ v(C) \text{ and } \beta(C) \text{ not changed (minimizing)} \]
\[ v(A) = \alpha(A) = 3, \text{ updated to maximum seen so far} \]

\[ \alpha(A) = 3, \beta = +\infty \]

\[ \alpha(A) \text{ and } v(A) \text{ not updated after returning from D (because A is a maximizing node)} \]

How does the algorithm finish the search tree?
After visiting K, S, T, L and returning to E, alpha(E) (=3) ≥ v(E) (=2) so stop expanding E and don’t visit M (alpha cutoff).

Why? Smart opponent will choose L or worse, thus E’s upper bound is 2. So computer at A shouldn’t choose E:2 since C:3 is a better move.

Final result: Computer chooses move C

Another step-by-step example (from AI course at UC Berkeley) given at

https://www.youtube.com/watch?v=x8XHz4Gbdo
Effectiveness of Alpha-Beta Search

- Effectiveness depends on the order in which successors are examined; more effective (i.e., more cutoffs) if best successors are examined first.
- Worst Case:
  - ordered so that no pruning takes place
  - no improvement over exhaustive search
- Best Case:
  - each player's best move is visited first
- In practice, performance is closer to best, rather than worst, case

Effectiveness of Alpha-Beta Search

- In practice often get $O(b^{d/2})$ rather than $O(b^d)$
  - same as having a branching factor of $\sqrt{b}$
  - since $(\sqrt{b})^d = b^{d/2}$
- Example: Chess
  - Deep Blue went from $b \approx 35$ to $b \approx 6$, visiting 1 billionth the number of nodes visited by Minimax algorithm
  - permits much deeper search for the same time
  - makes computer chess competitive with humans

Dealing with Limited Time

- In real games, there is usually a time limit, $T$, on making a move
- How do we take this into account?
  - cannot stop alpha-beta algorithm midway and expect to use results with any confidence
  - so, we could set a conservative depth-limit that guarantees we will find a move in time < $T$
  - but then, the search may finish early and the opportunity is wasted to do more search

Dealing with Limited Time

In practice, use iterative deepening search (IDS)
- run alpha-beta search with depth-first search and an increasing depth limit
- when the clock runs out, use the solution found for the last completed alpha-beta search (i.e., the deepest search that was completed)
- “anytime algorithm”
**The Horizon Effect**

- Sometimes disaster lurks just beyond the search depth
  - computer captures queen, but a few moves later the opponent checkmates (i.e., wins)
- The computer has a limited horizon, it cannot see that this significant event could happen
- How do you avoid catastrophic losses due to “short-sightedness”?  
  - quiescence search  
  - secondary search

**Quiescence Search**
- when SBE value is frequently changing, look deeper than the depth limit
- look for point when game “quiets down”
- E.g., always expand any forced sequences

**Secondary Search**
1. find best move looking to depth $d$
2. look $k$ steps beyond to verify that it still looks good
3. if it doesn’t, repeat step 2 for next best move

**Book Moves**

- Build a database of opening moves, end games, and studied configurations
- If the current state is in the database, use database:
  - to determine the next move
  - to evaluate the board
- Otherwise, do Alpha-Beta search

**More on Evaluation Functions**

The board evaluation function estimates how good the current board configuration is for the computer
- it is a heuristic function of the board’s features  
  - i.e., $\text{function}(f_1, f_2, f_3, \ldots, f_n)$
- the features are numeric characteristics
  - feature 1, $f_1$, is number of white pieces
  - feature 2, $f_2$, is number of black pieces
  - feature 3, $f_3$, is $f_1/f_2$
  - feature 4, $f_4$, is estimate of “threat” to white king
  - etc.
Linear Evaluation Functions

- A **linear evaluation function** of the features is a weighted sum of $f_1, f_2, f_3, \ldots$
  
  \[ w_1 f_1 + w_2 f_2 + w_3 f_3 + \ldots + w_n f_n \]
  
  - where $f_1, f_2, \ldots, f_n$ are the features
  - and $w_1, w_2, \ldots, w_n$ are the weights

- More important features get more weight

Linear Evaluation Functions

- The quality of play depends directly on the quality of the evaluation function

- To build an evaluation function we have to:
  1. construct good features using expert domain knowledge
  2. pick or learn good weights

Examples of Algorithms that Learn to Play Well

**Checkers**


- Learned by playing thousands of times against a copy of itself
- Used an IBM 704 with 10,000 words of RAM, magnetic tape, and a clock speed of 1 kHz
- Successful enough to compete well at human tournaments

**Backgammon**

G. Tesauro and T. J. Sejnowski, “A Parallel Network that Learns to Play Backgammon,” *Artificial Intelligence, 39*(3), 357-390, **1989**

- Also learned by playing against itself
- Used a non-linear evaluation function - a neural network
- Rated one of the top three players in the world
Non-Deterministic Games

Some games involve chance, for example:
- roll of dice
- spin of game wheel
- deal of cards from shuffled deck

How can we handle games with random elements?

The game tree representation is extended to include “chance nodes.”
1. computer moves
2. chance nodes (representing random events)
3. opponent moves

Non-Deterministic Games

Weight score by the probability that move occurs
Use expected value for move: instead of using max or min, compute the average, weighted by the probabilities of each child
Non-Deterministic Games

Choose move with the \textit{highest expected value}

\begin{align*}
\alpha & = 2 \quad 7 \\
\beta & = 6 \quad 9 \\
\gamma & = 0 \quad 5 \\
\delta & = 4 \quad 8 \\
\epsilon & = 50/50 \quad 4 \\
\end{align*}

Expectimimimax

\begin{align*}
\text{Expectimimimax}(n) &= \text{SBE}(n) \quad \text{for } n, \text{ a Terminal state or state at cutoff depth} \\
&= \max_{s \in \text{Succ}(n)} \text{expectimimimax}(s) \quad \text{for } n, \text{ a Max node} \\
&= \min_{s \in \text{Succ}(n)} \text{expectimimimax}(s) \quad \text{for } n, \text{ a Min node} \\
&= \sum_{s \in \text{Succ}(n)} P(s) \times \text{expectimimimax}(s) \quad \text{for } n, \text{ a Chance node}
\end{align*}

Non-Deterministic Games

- Non-determinism increases branching factor
  – 21 possible distinct rolls with 2 dice (since 6-5 is same as 5-6)
- Value of lookahead diminishes: as depth increases, probability of reaching a given node decreases
- Alpha-Beta pruning less effective

History of Search Innovations

- Shannon, Turing: Minimax search \quad 1950
- Kotok/McCarthy: Alpha-Beta pruning \quad 1966
- MacHack: Transposition tables \quad 1967
- Chess 3.0+: Iterative-deepening \quad 1975
- Belle: Special hardware \quad 1978
- Cray Blitz: Parallel search \quad 1983
- Hitech: Parallel evaluation \quad 1985
- Deep Blue: ALL OF THE ABOVE \quad 1997
Computers Play GrandMaster Chess

“Deep Blue” (IBM)

- Parallel processor, 32 “nodes”
- Each node had 8 dedicated VLSI “chess chips”
- Searched 200 million configurations/second
- Used minimax, alpha-beta, sophisticated heuristics
- Average branching factor ~6 instead of ~40
- In 2001 searched to 14 ply (i.e., 7 pairs of moves)
- Avoided horizon effect by searching as deep as 40 ply
- Used book moves

Computers can Play GrandMaster Chess

Kasparov vs. Deep Blue, May 1997

- 6 game full-regulation chess match sponsored by ACM
- Kasparov lost the match 2 wins to 3 wins and 1 tie
- Historic achievement for computer chess; the first time a computer became the best chess player on the planet
- Deep Blue played by “brute force” (i.e., raw power from computer speed and memory); it used relatively little that is similar to human intuition and cleverness


Status of Computers in Other Deterministic Games

- Checkers
  - First computer world champion: Chinook
  - Beat all humans (beat Marion Tinsley in 1994)
  - Used Alpha-Beta search and book moves
- Othello
  - Computers easily beat world experts
- Go
  - Branching factor $b \approx 360$, very large!
  - Beat Lee Sedol, one of the top players in the world, in 2016, 4 games to 1
Game Playing: Go
Google’s AlphaGo beat Korean grandmaster Lee Sedol 4 games to 1 in 2016

Quiz: Name These Robots

How to Improve Performance?
• Reduce depth of search
  — Better SBEs
    • Use deep learning to learn good features rather than use “manually-defined” features
• Reduce breadth of search
  — Explore a subset of the possible moves instead of exploring all
    • Use randomized exploration of the search space

Monte Carlo Tree Search (MCTS)
• Concentrate search on most promising moves
• Best-first search based on random sampling of search space

• Monte Carlo methods are a broad class of algorithms that rely on repeated random sampling to obtain numerical results. They can be used to solve problems having a probabilistic interpretation.
**Pure Monte Carlo Tree Search**

- For each possible legal move of current player, simulate *k* random games by selecting moves at random for both players until game over (called *playouts*); count how many were wins out of each *k* playouts; move with most wins is selected
- **Stochastic simulation** of game
- Game must have finite number of possible moves, and game length is finite

**Exploitation vs. Exploration**

- Rather than selecting a child at random, how to select best child node during tree descent?
  - **Exploitation**: Keep track of average win rate for each child from previous searches; prefer child that has previously lead to more wins
  - **Exploration**: Allow for exploration of relatively unvisited children (moves) too
- Combine these factors to compute a “score” for each child; pick child with highest score at each successive node in search

**MCTS Algorithm**

Recursively build search tree, where each round consists of:
1. Starting at root, successively select best child nodes using scoring method until leaf node *L* reached
2. Create and add best new child node, *C*, of *L*
3. Perform a random playout from *C*
4. Update score at *C* and all of *C*’s ancestors in search tree

**Monte Carlo Tree Search (MCTS)**

Key: number games won / number played playouts

[Diagram showing the MCTS algorithm with a tree structure, selection, expansion, and key notation.]
### State-of-the Art Go Programs

- Google’s AlphaGo
- Facebook’s Darkforest
- MCTS implemented using multiple threads and GPUs, and up to 110K playouts
- Also used a deep neural network to compute SBE

### Summary

- Game playing is modeled as a search problem
- Search trees for games represent both computer and opponent moves
- Evaluation functions estimate the quality of a given board configuration for each player
  - good for opponent
  - neutral
  - + good for computer

- Minimax algorithm determines the “optimal” moves by assuming that both players always chooses their best move
- Alpha-beta algorithm can avoid large parts of the search tree, thus enabling the search to go deeper
- For many well-known games, computer algorithms using heuristic search can match or out-perform human experts