Game Playing

An AI Favorite

- structured task
- not initially thought to require large amounts of knowledge
- focus on games of perfect information

Game Playing

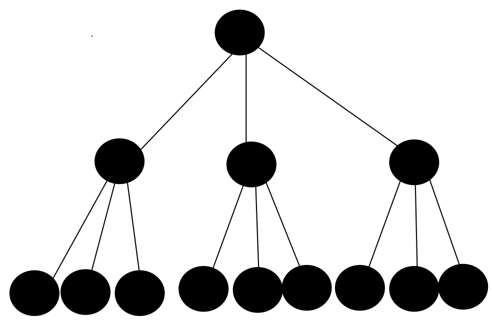
Initial State is the initial board/position

Operators define the set of legal moves from any position

Terminal Test determines when the game is over

Utility Function gives a numeric outcome for the game

Game Playing as Search



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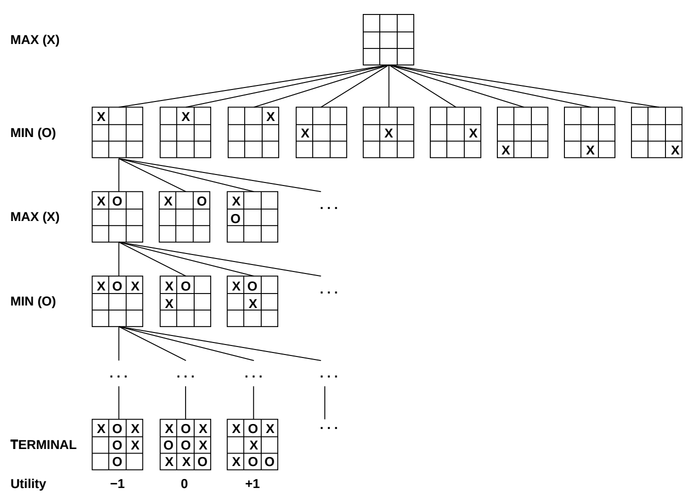
Partial Search Tree for Tic-Tac-Toe



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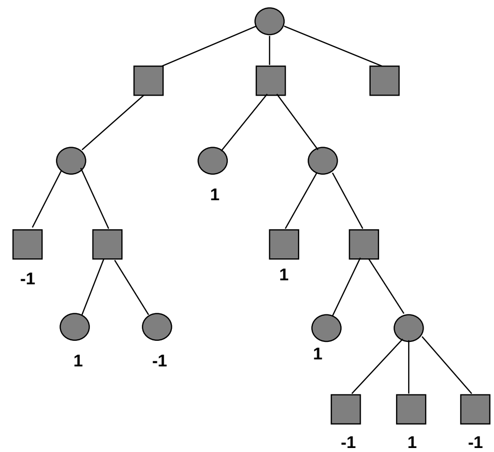
Simple Minimax



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Simplified Minimax Algorithm

1. Expand the entire tree below the root.
2. Evaluate the terminal nodes as wins for the minimizer or maximizer.
3. Select an unlabeled node, n, all of whose children have been assigned values. If there is no such node, we're done — return the value assigned to the root.
4. If n is a minimizer move, assign it a value that is the minimum of the values of its children. If n is a maximizer move, assign it a value that is the maximum of the values of its children. Return to Step 3.

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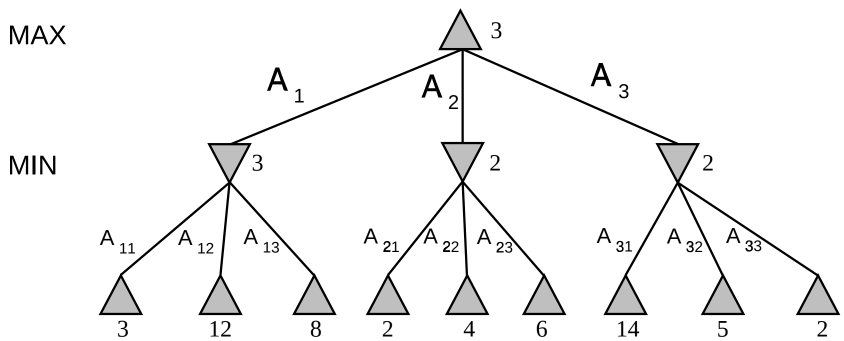
Another Example



Minimax

function MINIMAX-DECISION(*game*) **returns** *an operator*

for each *op* **in** OPERATORS[*game*] **do**
VALUE[*op*] ← MINIMAX-VALUE(APPLY(*op*, *game*), *game*)
end
return the *op* with the highest VALUE[*op*]

---

function MINIMAX-VALUE(*state*, *game*) **returns** *a utility value*

if TERMINAL-TEST[*game*](*state*) **then**
return UTILITY[*game*](*state*)
else if MAX is to move in *state* **then**
return the highest MINIMAX-VALUE of SUCCESSORS(*state*)
else
return the lowest MINIMAX-VALUE of SUCCESSORS(*state*)

The Need for Imperfect Decisions

Problem: Minimax assumes the program has time to search to the terminal nodes.

Solution: Cut off search earlier and apply a heuristic evaluation function to the leaves.

Static Evaluation Functions

Minimax depends on the translation of board quality into a single, summarizing number. Difficult. Expensive.

- Add up values of pieces each player has (weighted by importance of piece).
- Isolated pawns are bad.
- How well protected is your king?
- How much maneuverability to you have?
- Do you control the center of the board?

- Strategies change as the game proceeds.

Design Issues of Heuristic Minimax

Evaluation Function: What features should we evaluate and how should we use them? An evaluation function should:

1.
2.
3.

Linear Evaluation Functions

- $w_1 f_1 + w_2 f_2 + ... + w_n f_n$
- This is what most game playing programs use
- Steps in designing an evaluation function:
  1. Pick informative features
  2. Find the weights that make the program play well

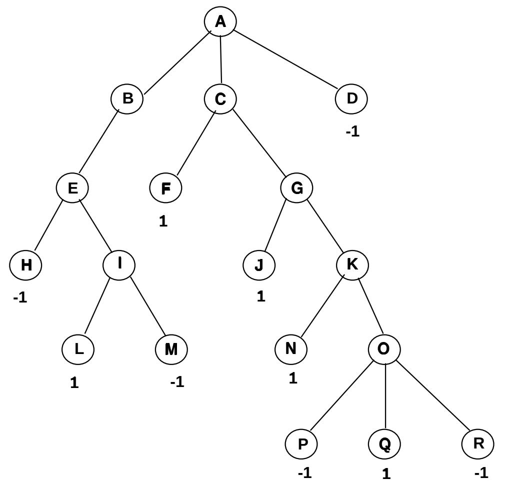
Design Issues of Heuristic Minimax

Search: search to a constant depth

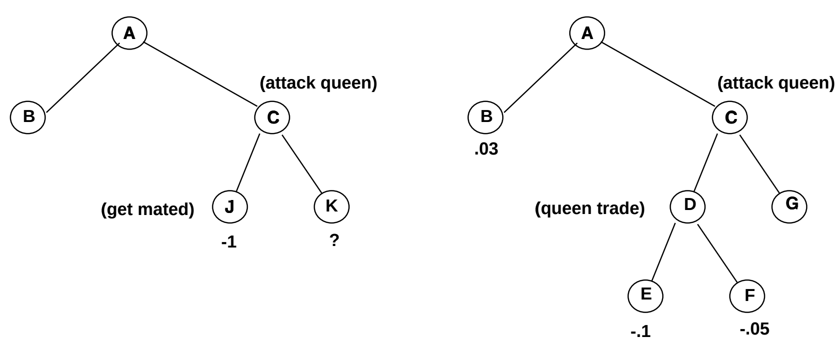
Problems:

- Some portions of the game tree may be "hotter" than others. Should search to *quiescence*. Continue along a path as long as one move's static value stands out (indicating a likely capture).
- *Horizon effect*
- Secondary search. (*singular extension heuristic)*

Improving Minimax — $\alpha - \beta$ pruning



Two More Examples



Algebraic Solution

Let $g' = e(g)$. Then $c' = \min(-.05, g')$.

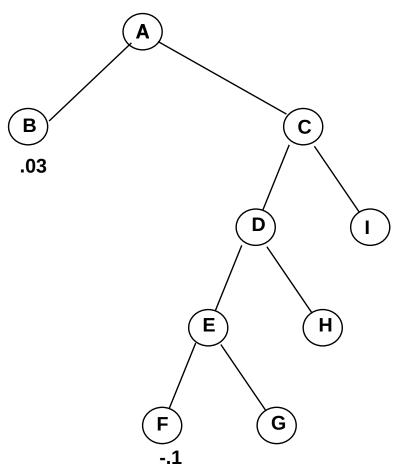
The value assigned to the root node a is

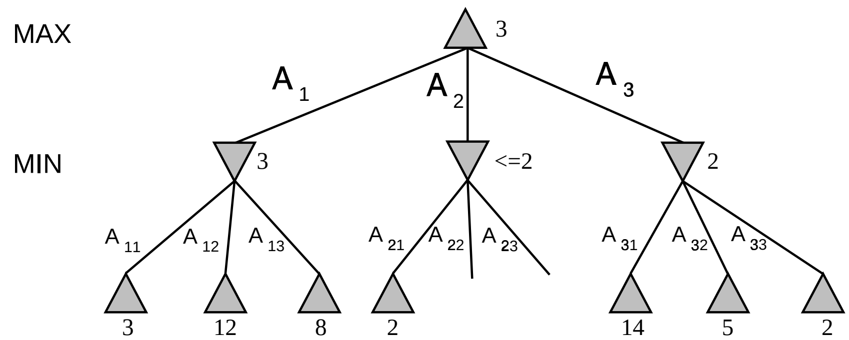
$$a' = \max(.03, \min(-.05, g')) = .03$$

because $\min(-.05, g') \leq -.05 < .03$.

The value assigned to a is independent of the value assigned to g.

A deep $\alpha - \beta$ cutoff





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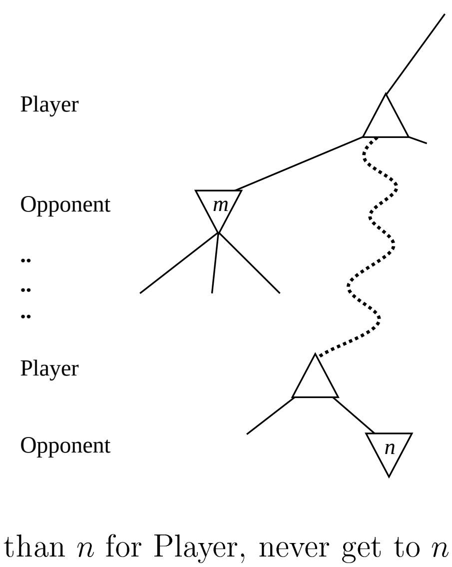

If m is better than n for Player, never get to n in play.

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$\alpha - \beta$ **Search**

c = search cutoff
α = lower bound on Max's outcome; initially set to $-\infty$
β = upper bound on Min's outcome ; initially set to $+\infty$

We'll call $\alpha - \beta$ procedure recursively with a narrowing range between α and β.

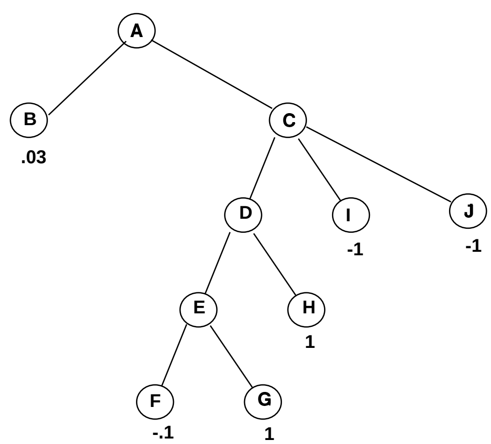
Maximizing levels may reset α to a higher value; Minimizing levels may reset β to a lower value.

$\alpha - \beta$ **Search Algorithm**

1. If the limit of search has been reached, compute $e(n)$ and report the result.
2. Otherwise, if the level is a **minimizing** level,
   - Until no more children or $\alpha \geq \beta$,
     - Use $\alpha - \beta$ search on child with current values of α and β; note the value, v, returned.
     - If $v < \beta$, reset β to v.
   - Report β.

3. Otherwise, the level is a **maximizing** level:
    - Until no more children or $\alpha \geq \beta$,
        - Use $\alpha - \beta$ search on child with current values of α and β; note the value, v, returned.
        - If $v > \alpha$, reset α to v.
    - Report α.

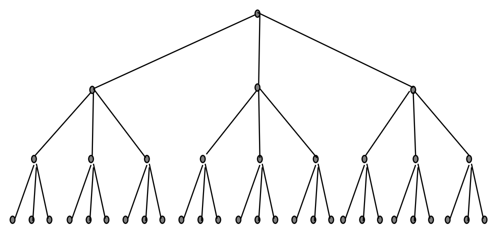
Example



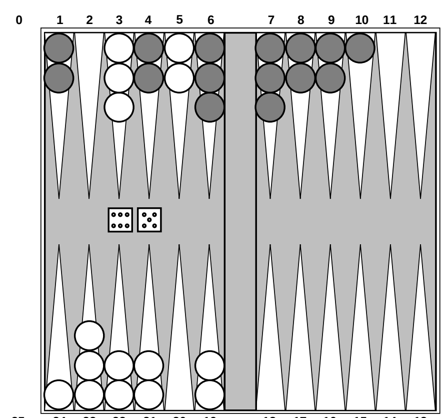
Search Space Size Reductions

Worst Case: In an ordering where worst options evaluated first, all nodes must be examined.

Best Case: If nodes ordered so that the best options are evaluated first, then what?



Backgammon – Board

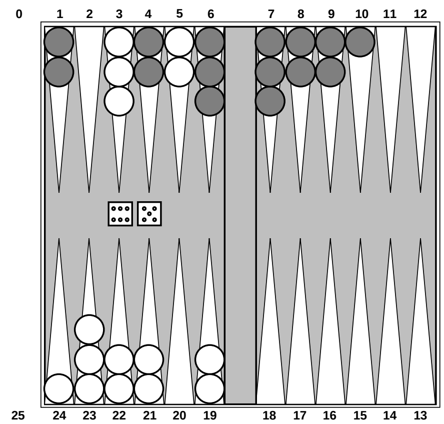


Backgammon – Rules

- Goal: move all of your pieces off the board before your opponent does.
- White moves counterclockwise toward 0.
- Black moves clockwise toward 25.
- A piece can move to any position except one where there are two or more of the opponent's pieces.
- If it moves to a position with one opponent piece, that piece is captured and has to start it's journey from the beginning.

Backgammon – Rules

- If you roll doubles you take 4 moves (example: roll 5,5, make moves 5,5,5,5).
- Moves can be made by one or two pieces (in the case of doubles by 1, 2, 3 or 4 pieces)
- And a few other rules that concern *bearing off* and *forced moves*.



White has rolled 6-5 and has 4 legal moves: (5-10,5-11), (5-11,19-24), (5-10,10-16) and (5-11,11-16).

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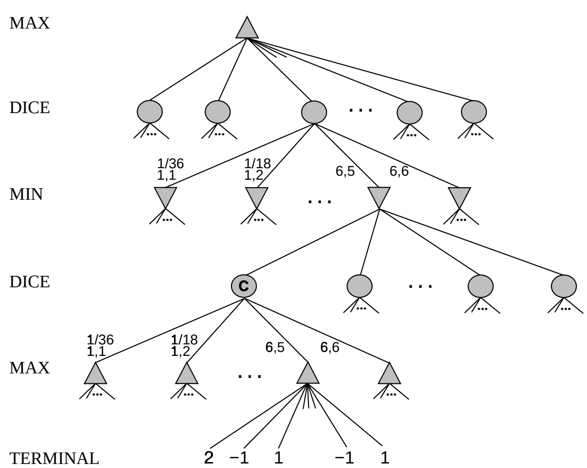
Game Tree for Backgammon



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State of the Art in Checkers

- 1952: Samuel developed a checkers program that learned its own evaluation function through self play.
- 1992: *Chinook* (J. Schaeffer) wins the U.S. Open. At the world championship, Marion Tinsley beat *Chinook*.

State of the Art in Backgammon

- 1980: *BKG* using one-ply search and lots of luck defeated the human world champion.
- 1992: Tesauro combines Samuel's learning method with neural networks to develop a new evaluation function, resulting in a program ranked among the top 3 players in the world.

State of the Art in Go

$2,000,000 prize available for first computer program to defeat a top level player.

History of Chess in AI

500	legal chess
1200	occasional player
2000	world-ranked
2900	Gary Kasparov

Early 1950's Shannon and Turing both had programs that (barely) played legal chess (500 rank).

1950's Alex Bernstein's system, ($500+\epsilon$).

1957 Herb Simon claims that a computer chess program would be world chess champion in 10 years...yeah, right.

1966 McCarthy arranges chess match, Stanford vs. Russia. Long, drawn-out match. Russia wins.

1967 Richard Greenblatt, MIT. First of the modern chess programs, *MacHack* (1100 ranking).

1968 McCarthy, Michie, Papert bet Levy (rated 2325) that a computer program would beat him within 10 years.

1970 ACM started running chess tournaments. Chess 3.0-6 (rated 1400).

1973 By 1973...Slate: "It had become too painful even to look at Chess 3.6 any more, let alone work on it."

1973 Chess 4.0: smart plausible-move generator rather than speeding up the search. Improved rapidly when put on faster machines.

1976 Chess 4.5: ranking of 2070.

1977 Chess 4.5 vs. Levy. Levy wins.

1980's Programs depend on search speed rather than knowledge (2300 range).

1993 DEEP THOUGHT: Sophisticated special-purpose computer; $\alpha - \beta$ search; searches 10 ply; singular extensions; rated about 2600.

1995 DEEP BLUE: searches 14-ply; considers 100–200 billion positions per move.

1997 DEEP BLUE: first match won against world-champion (Kasparov).

Concludes "Search"

- **Problem Solving as Search**
- **Uninformed search:** DFS / BFS / Uniform cost search
  time / space complexity
  size search space: up to approx. 10^{11} nodes
  special case: **Constraint Satisfaction / CSPs**
    generic framework: variables & constraints
    backtrack search (DFS); propagation (forward-checking / arc-consistency, variable / value ordering (but **incomplete**)

- **Informed Search:** use heuristic function guide to goal

  Greedy search

  A search / provably optimal*

  Search space up to approximately 10^{25}

  Local search (incomplete)

  Greedy / Hillclimbing

  Simulated annealing

  Tabu search

  Genetic Algorithms / Genetic Programming

  search space 10^{100} to 10^{1000}

- **Aversary Search / Game Playing**

  minimax

  Up to around 10^{10} nodes, 6 — 7 ply in chess.

  alpha-beta pruning

  Up to around 10^{20} nodes, 14 ply in chess.

  provably optimal

Search and AI

Why such a central role?

A. Basically, because lots of tasks in AI are **intractable**.
Search is "only" way to handle them.

Many applications of search, in e.g.,
Learning / Reasoning / Planning / NLU / Vision

Good thing: much recent progress (10^{30} quite feasible; sometimes up to 10^{1000}). **Qualitative difference from only a few years ago!**