# Adversarial Search 

## Chapter 5

". . . every game of skill is susceptible of being played by an automaton." from Charles Babbage, The Life of a Philosopher, 1832.

## Outline

$\diamond$ Games
$\diamond$ Perfect play

- minimax decisions
$-\alpha-\beta$ pruning
$\diamond$ Resource limits and approximate evaluation
$\diamond$ Games of chance
$\diamond$ Games of imperfect information


## Games vs. search problems

"Unpredictable" opponent $\Rightarrow$ solution is a strategy specifying a move for every possible opponent reply

Time limits $\Rightarrow$ unlikely to find goal, must approximate
Plan of attack:

- Computer considers possible lines of play (Babbage, 1846)
- Algorithm for perfect play (Zermelo, 1912; Von Neumann, 1944)
- Finite horizon, approximate evaluation (Zuse, 1945; Wiener, 1948; Shannon, 1950)
- First chess program (Turing, 1951)
- Machine learning to improve evaluation accuracy (Samuel, 1952-57)
- Pruning to allow deeper search (McCarthy, 1956)


## Types of games

|  | deterministic | chance |
| :---: | :---: | :---: |
| perfect information | chess, checkers, go, othello | backgammon monopoly |
| imperfect information | battleships, blind tictactoe | bridge, poker, scrabble nuclear war |

Game tree (2-player, deterministic, turns)


## Minimax

Perfect play for deterministic, perfect-information games
Idea: choose move to position with highest minimax value $=$ best achievable payoff against best play
E.g., 2-ply game:


## Minimax algorithm

```
function Minimax-Decision(state) returns an action
    inputs: state, current state in game
    return the \(a\) in Actions(state) maximizing Min-Value(Result( \(a\), state))
function MAX-VALUE(state) returns a utility value
    if Terminal-TESt(state) then return Utility(state)
    \(v \leftarrow-\infty\)
    for \(a\), \(s\) in \(\operatorname{Successors}(\) state \()\) do \(v \leftarrow \operatorname{Max}(v, \operatorname{Min}-\operatorname{Value}(s))\)
    return \(v\)
function Min-VALUE(state) returns a utility value
    if Terminal-Test(state) then return Utility(state)
    \(v \leftarrow \infty\)
    for \(a\), \(s\) in Successors \((\) state \()\) do \(v \leftarrow \operatorname{Min}(v, \operatorname{Max}-\operatorname{Value}(s))\)
    return \(v\)
```


## Properties of minimax

Complete?? Only if tree is finite (chess has specific rules for this). NB a finite strategy can exist even in an infinite tree!

Optimal??

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Time complexity?? $O\left(b^{m}\right)$
Space complexity?? $O(b m)$ (depth-first exploration)
For chess, $b \approx 35, m \approx 100$ for "reasonable" games
$\Rightarrow$ exact solution completely infeasible
But do we need to explore every path?



## $\alpha-\beta$ pruning example



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## $\alpha-\beta$ pruning example



## Why is it called $\alpha-\beta$ ?


$\alpha$ is the best value (to MAX) found so far off the current path
If $V$ is worse than $\alpha$, MAX will avoid it $\Rightarrow$ prune that branch
Define $\beta$ similarly for MIN

## Properties of $\alpha-\beta$

Pruning does not affect final result
Good move ordering improves effectiveness of pruning
With "perfect ordering," time complexity $=O\left(b^{m / 2}\right)$
$\Rightarrow$ doubles solvable depth
A simple example of the value of reasoning about which computations are relevant (a form of metareasoning)

Unfortunately, $35^{50}$ is still impossible!

## Resource limits

Standard approach:

- Use Cutoff-Test instead of Terminal-Test
e.g., depth limit (perhaps add quiescence search)
- Use Eval instead of Utility
i.e., evaluation function that estimates desirability of position

Suppose we have 100 seconds, explore $10^{4}$ nodes/second
$\Rightarrow 10^{6}$ nodes per move $\approx 35^{8 / 2}$
$\Rightarrow \alpha-\beta$ reaches depth $8 \Rightarrow$ pretty good chess program

## Evaluation functions



Black to move
White slightly better


White to move
Black winning

For chess, typically linear weighted sum of features

$$
\operatorname{Eval}(s)=w_{1} f_{1}(s)+w_{2} f_{2}(s)+\ldots+w_{n} f_{n}(s)
$$

e.g., $w_{1}=9$ with
$f_{1}(s)=$ (number of white queens) - (number of black queens), etc.

## Exercise - Tic-tac-toe

- Define $X_{n}$ as the number of rows, columns, or diagonals with exactly $n X$ 's and no $O$ 's. Similarly, $O_{n}$ is the number of rows, columns, or diagonals with exactly $n O^{\prime} s$ and no $X$ 's.
- The utility function assigns +1 to any position with $X_{3}=1$ and 1 for any position with $\mathrm{O}_{3}=1$. All other terminal positions have utility 0 .
- For non-terminal positions, we use a linear evaluation function defined as Eval $(s)=3 X_{2}(s)+X_{1}(s)-\left(3 \mathrm{O}_{2}(s)+\mathrm{O}_{1}(s)\right)$
a) Approximately how many games of tic-tac-toe are there?


## Exercise - Tic-tac-toe

b) What does the game tree look like (taking symmetry into account)?

## Digression: Exact values don't matter

MAX

MIN


Behaviour is preserved under any monotonic transformation of EvaL
Only the order matters:
payoff in deterministic games acts as an ordinal utility function

## How to achieve a good game of chess?

- Extensively tuned evaluation function
- Cutoff test with quiescence search
- Large transposition table [i.e., hash of previously seen positions, saved for re-use]
- Use of alpha-beta, with extra pruning
- Large database of optimal opening and endgame moves
- Fast computer!


## Exercise - Prove correctness of $\alpha-\beta$

- Question is whether to prune $\mathrm{n}_{\mathrm{j}}$, which is a max-node and descendent of $n_{1}$
- Basic idea is to prune it iff the minimax value of $n_{1}$ can be shown to be independent of the value of $n_{j}$
- Node $n_{1}$ takes on the minimum value among its children $n_{1}=\min \left(n_{2}, n_{21}, \ldots, n_{2 \mathrm{~b} 2}\right)$. Find a similar expression for $n_{2}$ and hence an expression for $n_{1}$ in terms of $n_{j}$.


