Adversarial search

Chapter 5

Artificial Intelligence

Slides from AIMA — `http://aima.cs.berkeley.edu`

Outline

- Games
- Perfect play
  - minimax decisions
  - α–β pruning
- Resource limits and approximate evaluation
- Games of chance
- Games of imperfect information

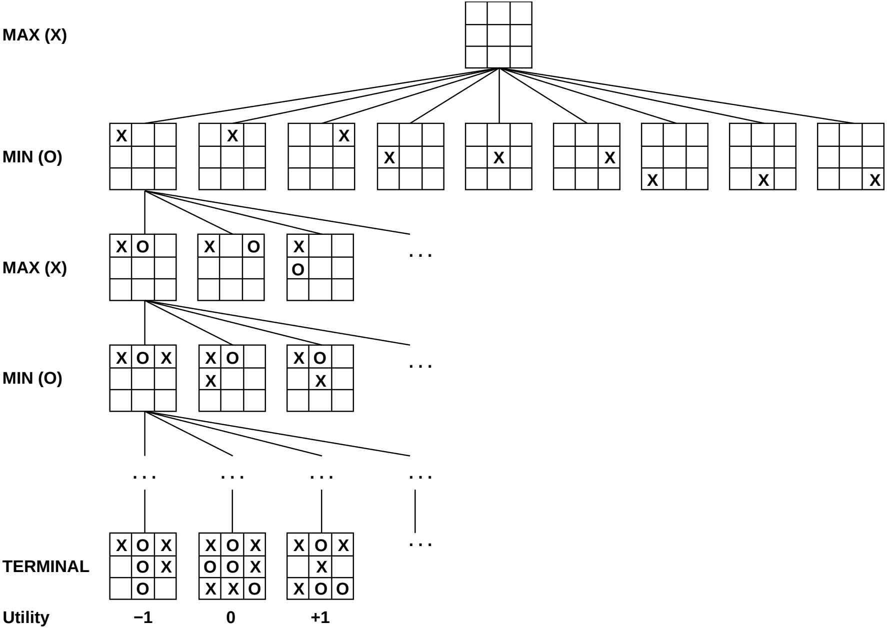
Games vs. search problems

- "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

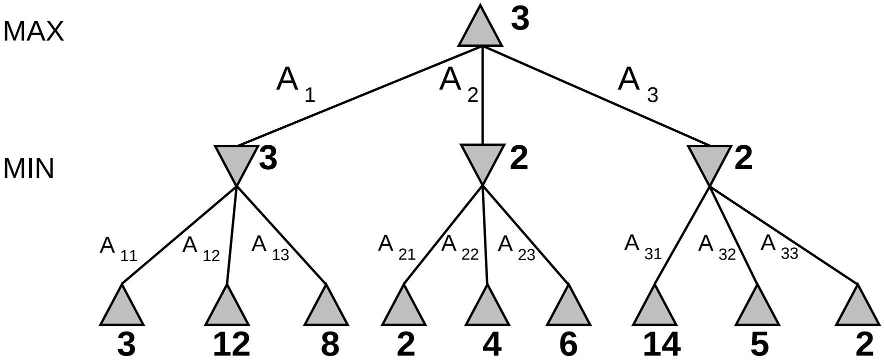
Game tree (2-player, deterministic, turns)



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 SUCCESSORS(*state*) **do** $v \leftarrow$ MAX(v, MIN-VALUE(s))
  return v

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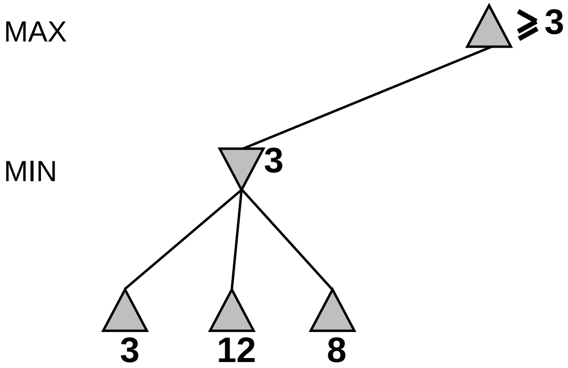
For chess, $b \approx 35$, $m \approx 100$ for “reasonable” games
$\Rightarrow$ exact solution completely infeasible

But do we need to explore every path?

α–β pruning example



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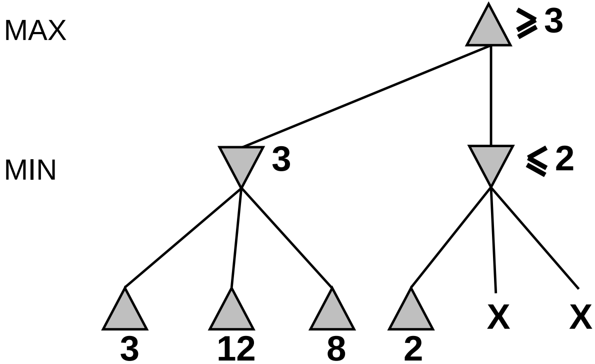

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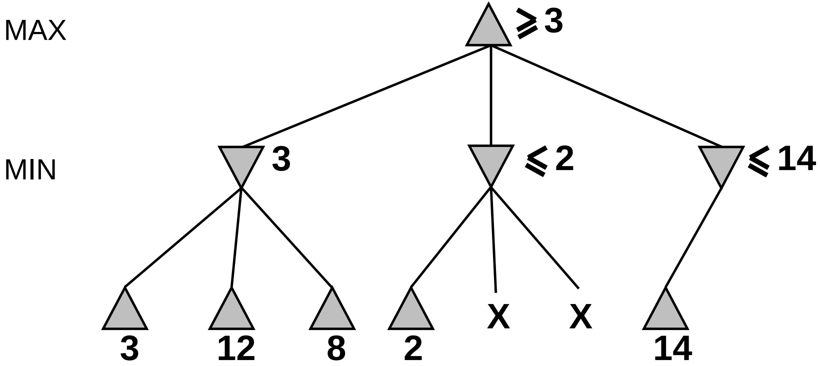

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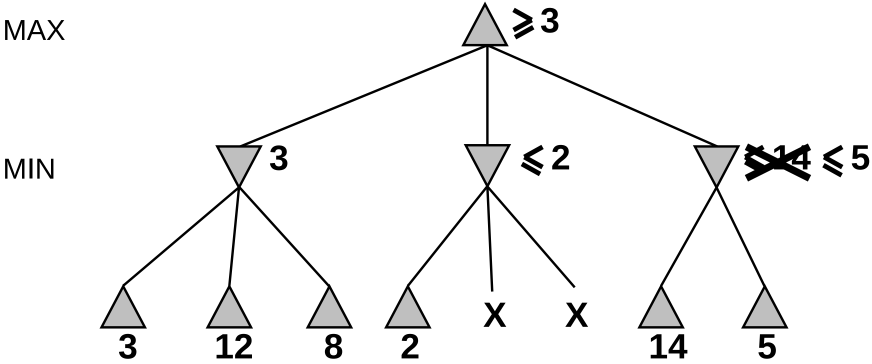

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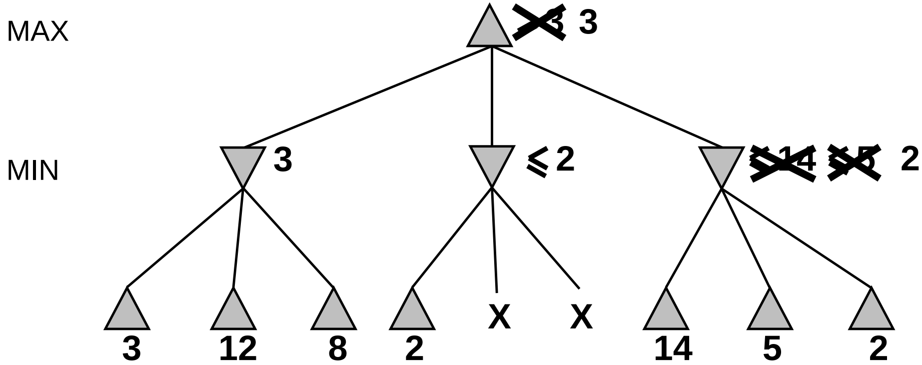
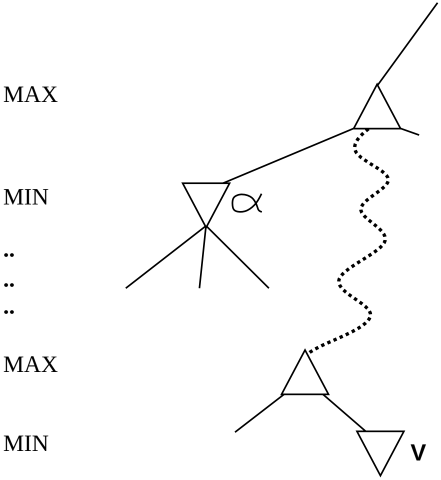


Why is it called α–β?



- α is the best value (to max) found so far off the current path
- If V is worse than α, max will avoid it $\Rightarrow$ prune that branch
- Define β similarly for min

The α–β algorithm

function ALPHA-BETA-DECISION(*state*) **returns** an action
  return the *a* in ACTIONS(*state*) maximizing MIN-VALUE(RESULT(*a*, *state*))

---

function MAX-VALUE(*state*, α, β) **returns** *a utility value*
  inputs: *state*, current state in game
    α, the value of the best alternative for max along the path to *state*
    β, the value of the best alternative for min along the path to *state*

  if TERMINAL-TEST(*state*) **then return** UTILITY(*state*)
  $v \leftarrow -\infty$
  for *a*, *s* in SUCCESSORS(*state*) **do**
    $v \leftarrow$ MAX(v, MIN-VALUE(s, α, β))
    if $v \geq \beta$ **then return** v
    $\alpha \leftarrow$ MAX(α, v)
  return v

---

function MIN-VALUE(*state*, α, β) **returns** *a utility value*
  same as MAX-VALUE but with roles of α, β reversed

Properties of α–β

- Pruning **does not** affect final result
- Good move ordering improves effectiveness of pruning
- With "perfect ordering," time complexity = $O(b^{m/2})$
  $\Rightarrow$ **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:

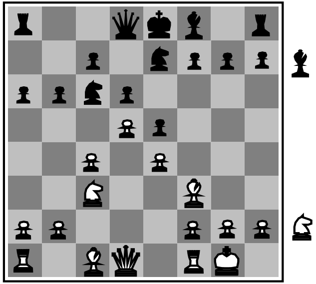
- Use Cutoff-Test instead of Terminal-Test
  e.g., depth limit (perhaps add quiescence search)
- Use Eval instead of Utility
  i.e., evaluation function that estimates desirability of position

Suppose we have 100 seconds, explore 10^4 nodes/second

$\Rightarrow$ 10^6 nodes per move $\approx 35^{8/2}$ $\Rightarrow$ α–β reaches depth 8

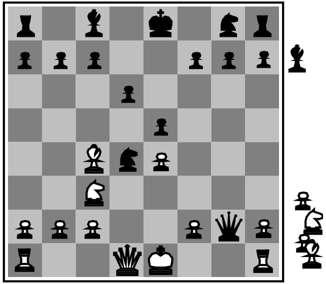
$\Rightarrow$ pretty good chess program

Evaluation functions



Black to move

White slightly better



White to move

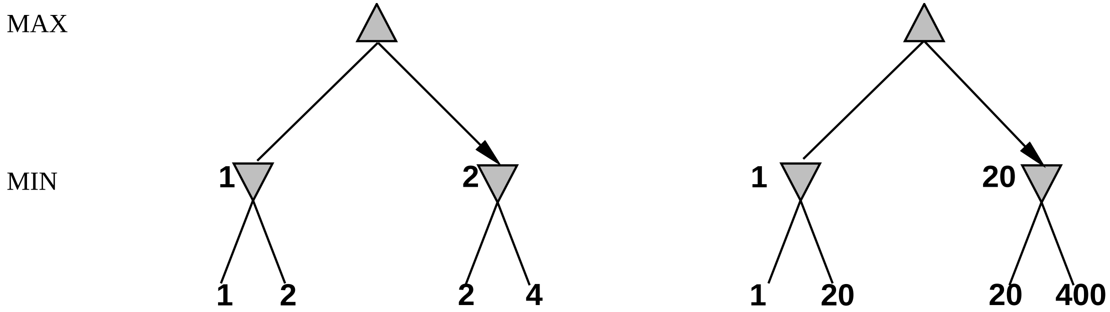
Black winning

For chess, typically linear weighted sum of features

$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s)$$

e.g., $w_1 = 9$ with
$f_1(s)$ = (number of white queens) – (number of black queens), etc.

Digression: Exact values don't matter



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

Deterministic games in practice

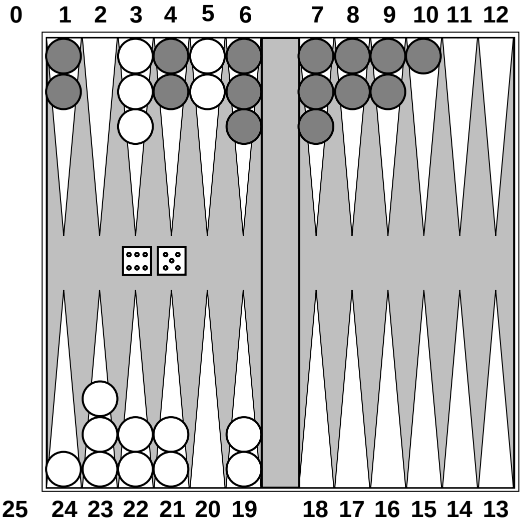
Checkers: Chinook ended 40-year-reign of human world champion Marion Tinsley in 1994. Used an endgame database defining perfect play for all positions involving 8 or fewer pieces on the board, a total of 443,748,401,247 positions.

Chess: Deep Blue defeated human world champion Gary Kasparov in a six-game match in 1997. Deep Blue searches 200 million positions per second, uses very sophisticated evaluation, and undisclosed methods for extending some lines of search up to 40 ply.

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.

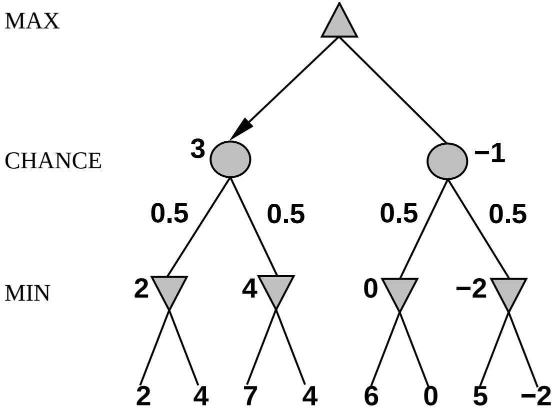
Nondeterministic games: backgammon



Nondeterministic games in general

In nondeterministic games, chance introduced by dice, card-shuffling

Simplified example with coin-flipping:



Algorithm for nondeterministic games

EXPECTIMINIMAX gives perfect play

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

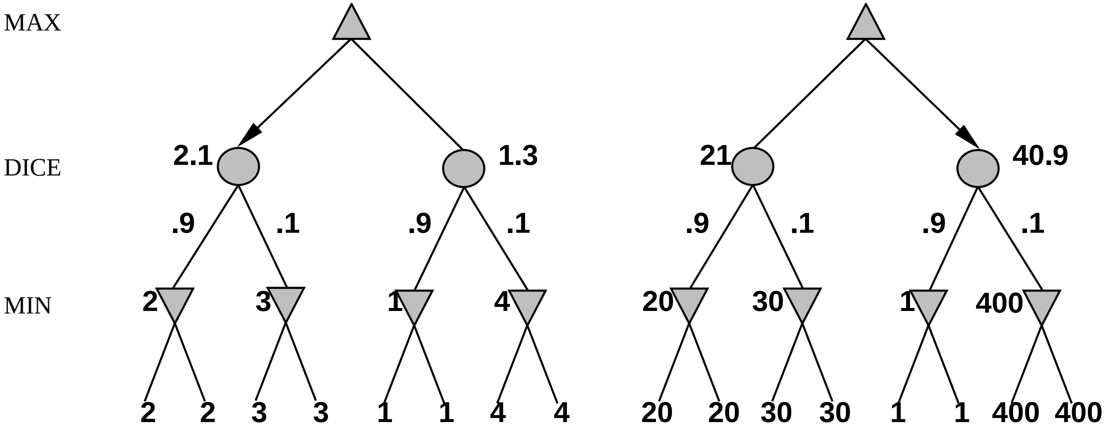
...
if *state* is a MAX node **then**
return the highest EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)
if *state* is a MIN node **then**
return the lowest EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)
if *state* is a chance node **then**
return average of EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)
...

Nondeterministic games in practice

- Dice rolls increase b: 21 possible rolls with 2 dice
  Backgammon $\approx$ 20 legal moves (can be 6,000 with 1-1 roll)

  $$\text{depth } 4 = 20 \times (21 \times 20)^3 \approx 1.2 \times 10^9$$
- As depth increases, probability of reaching a given node shrinks
  $\Rightarrow$ value of lookahead is diminished
- α–β pruning is much less effective
- TDGAMMON uses depth-2 search + very good EVAL
  $\approx$ world-champion level

Digression: Exact values DO matter



- Behaviour is preserved only by positive linear transformation of EVAL
- Hence EVAL should be proportional to the expected payoff

Games of imperfect information

E.g., card games, where opponent's initial cards are unknown

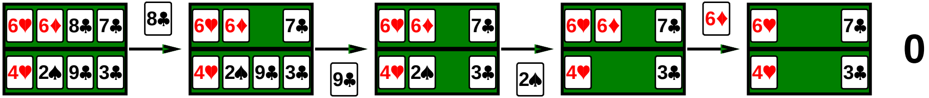
- Typically we can calculate a probability for each possible deal
- Seems just like having one big dice roll at the beginning of the game*

Idea: compute the minimax value of each action in each deal,
then choose the action with highest expected value over all deals*

- Special case: if an action is optimal for all deals, it's optimal.*
- GIB, current best bridge program, approximates this idea by
  1. generating 100 deals consistent with bidding information
  2. picking the action that wins most tricks on average

Example

Four-card bridge/whist/hearts hand, MAX to play first



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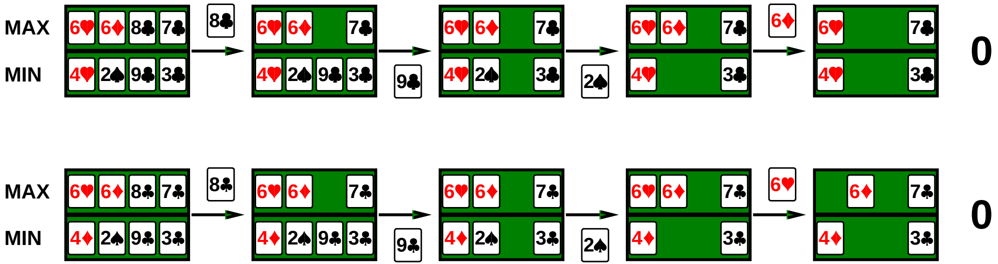

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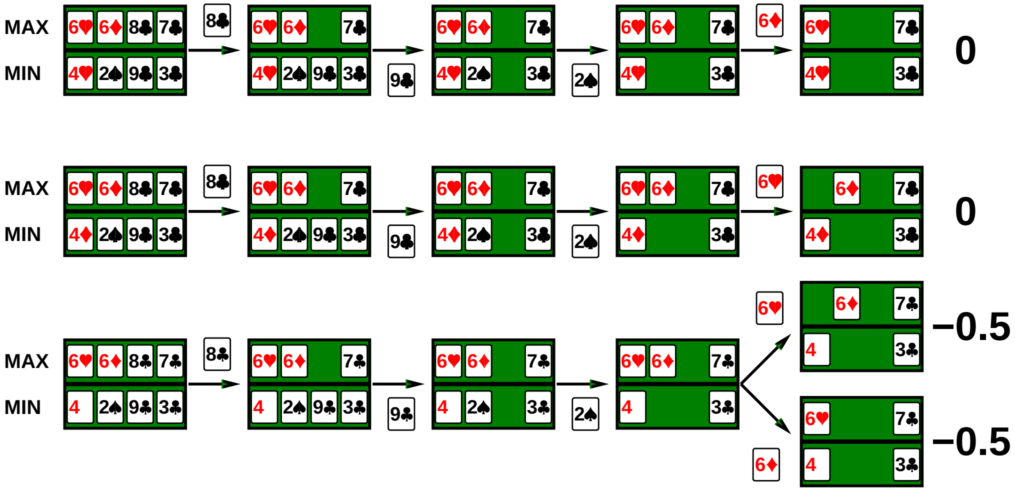

Commonsense example

Road A leads to a small heap of gold pieces
Road B leads to a fork:
take the left fork and you'll find a mound of jewels;
take the right fork and you'll be run over by a bus.

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take the left fork and you'll be run over by a bus;
take the right fork and you'll find a mound of jewels.

Road A leads to a small heap of gold pieces
Road B leads to a fork:
guess correctly and you'll find a mound of jewels;
guess incorrectly and you'll be run over by a bus.

Proper analysis

* Intuition that the value of an action is the average of its values in all actual states is **WRONG**

- With partial observability, value of an action depends on the information state or belief state the agent is in
- Can generate and search a tree of information states
- Leads to rational behaviors such as
  - Acting to obtain information
  - Signalling to one's partner
  - Acting randomly to minimize information disclosure

Summary

Games are fun to work on! (and dangerous)

They illustrate several important points about AI

- perfection is unattainable $\Rightarrow$ must approximate
- good idea to think about what to think about
- uncertainty constrains the assignment of values to states
- optimal decisions depend on information state, not real state

Games are to AI as grand prix racing is to automobile design