Game playing

Chapter 5, Sections 1–5

Outline

♢ Perfect play

♢ Resource limits

♢ α–β pruning

♢ Games of chance

Games vs. search problems

"Unpredictable" opponent ⇒ solution is a contingency plan

Time limits ⇒ unlikely to find goal, must approximate

Plan of attack:

- algorithm for perfect play (Von Neumann, 1944)
- finite horizon, approximate evaluation (Zuse, 1945; Shannon, 1950; Samuel, 1952–57)
- pruning to reduce costs (McCarthy, 1956)

Types of games

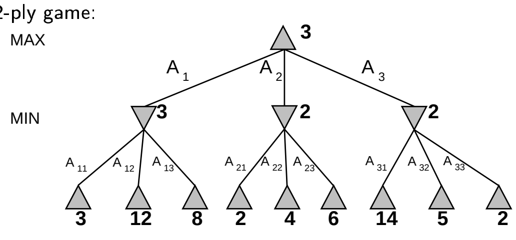
	deterministic	**chance**
perfect information	**chess, checkers, go, othello**	**backgammon monopoly**
imperfect information		**bridge, poker, scrabble nuclear war**

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(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)
```

Properties of minimax

Complete??

Optimal??

Time complexity??

Space complexity??

Properties of minimax

Complete?? Yes, if tree is finite (chess has specific rules for this)

Optimal?? Yes, against an optimal opponent. Otherwise??

Time complexity?? $O(b^m)$

Space complexity?? $O(bm)$ (depth-first exploration)

For chess, $b \approx 35$, $m \approx 100$ for "reasonable" games
⇒ exact solution completely infeasible

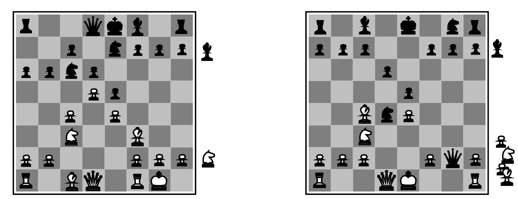
Resource limits

Suppose we have 100 seconds, explore 10^4 nodes/second
⇒ $\underline{10^6}$ nodes per move

Standard approach:

- *cutoff test*
  e.g., depth limit (perhaps add *quiescence search*)
- *evaluation function*
  = estimated desirability of position

Evaluation functions



Black to move
White slightly better

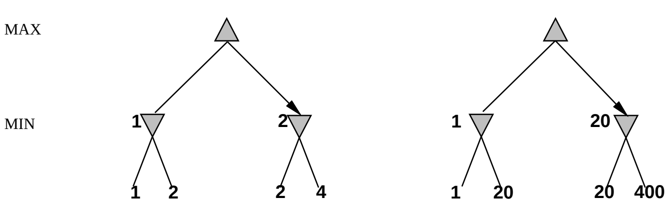
White to move
Black winning

For chess, typically *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
$f_1(s)$ = (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

Cutting off search

MINIMAXCUTOFF is identical to MINIMAXVALUE except
1. TERMINAL? is replaced by CUTOFF?
2. UTILITY is replaced by EVAL

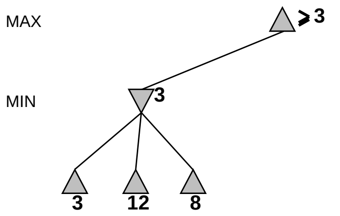
Does it work in practice?

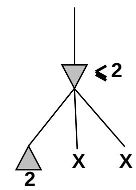
$$b^m = 10^6, \quad b = 35 \quad \Rightarrow \quad m = 4$$

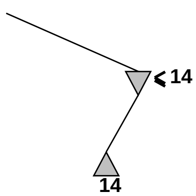
4-ply lookahead is a hopeless chess player!

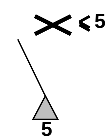
4-ply ≈ human novice
8-ply ≈ typical PC, human master
12-ply ≈ Deep Blue, Kasparov

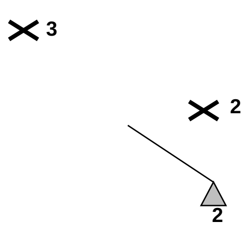
α–β pruning example











Properties of α–β

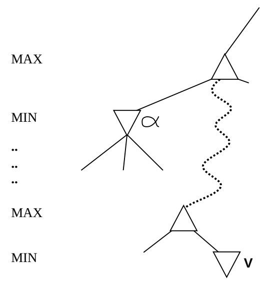
Pruning *does not* affect final result

Good move ordering improves effectiveness of pruning

With "perfect ordering," time complexity $= O(b^{m/2})$
$\Rightarrow$ *doubles* depth of search
$\Rightarrow$ can easily reach depth 8 and play good chess

A simple example of the value of reasoning about which computations are relevant (a form of *metareasoning*)

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

Basically MINIMAX + keep track of α, β + prune

```
function MAX-VALUE(state, game, α, β) returns the minimax value of state
   inputs: state, current state in game
           game, game description
           α, the best score for MAX along the path to state
           β, the best score for MIN along the path to state

   if CUTOFF-TEST(state) then return EVAL(state)
   for each s in SUCCESSORS(state) do
        α ← MAX(α, MIN-VALUE(s, game, α, β))
        if α ≥ β then return β
   end
   return α

function MIN-VALUE(state, game, α, β) returns the minimax value of state
   if CUTOFF-TEST(state) then return EVAL(state)
   for each s in SUCCESSORS(state) do
        β ← MIN(β, MAX-VALUE(s, game, α, β))
        if β ≤ α then return α
   end
   return β
```


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.

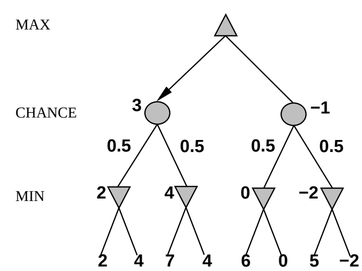
Othello: human champions refuse to compete against computers, who are too good.

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

E..g, in backgammon, the dice rolls determine the legal moves

Simplified example with coin-flipping instead of dice-rolling:



Algorithm for nondeterministic games

EXPECTIMINIMAX gives perfect play

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

. . .
if *state* is a chance node **then**
    return average of EXPECTIMINIMAX-VALUE of SUCCESSORS(*state*)
. . .

A version of α–β pruning is possible
but only if the leaf values are bounded. Why??

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)

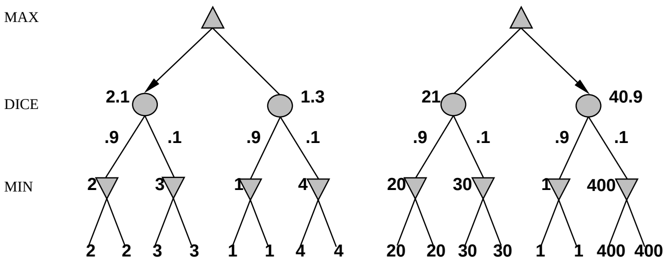
$$\text{depth } 4 = 20 \times (21 \times 20)^3 \approx 1.2 \times 10^9$$

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

Summary

Games are fun to work on! (and dangerous)

They illustrate several important points about AI

◇ perfection is unattainable ⇒ must approximate

◇ good idea to think about what to think about

◇ uncertainty constrains the assignment of values to states

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