Artificial Intelligence

Games

Summary

Russell & Norvig: Chap 5, Sections 1 – 4

♢ Perfect decisions
- minimax search
- pruning α–β
- stochastic games

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

Games

chess, checkers, go, backgammon, bridge, poker
abstract, and **static**
chance e.g. dice, cards
complete information e.g. cards

◇ **real** soccer, exploration, search: environment partially observable, dynamic, incomplete information

In game theory chess is a two-player, deterministic, turn-taking, zero-sum game of perfect information (0+1,1+0,1/2+1/2)

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, we must approximate

An old challenge ...

- 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)

That is more and more central to the field

- ...
- Deep blue (IBM Watson, 1997)
- Alpha GO (Google Deep Mind, 2016)
- Deep stack (Bowling, 2017)

Types of games

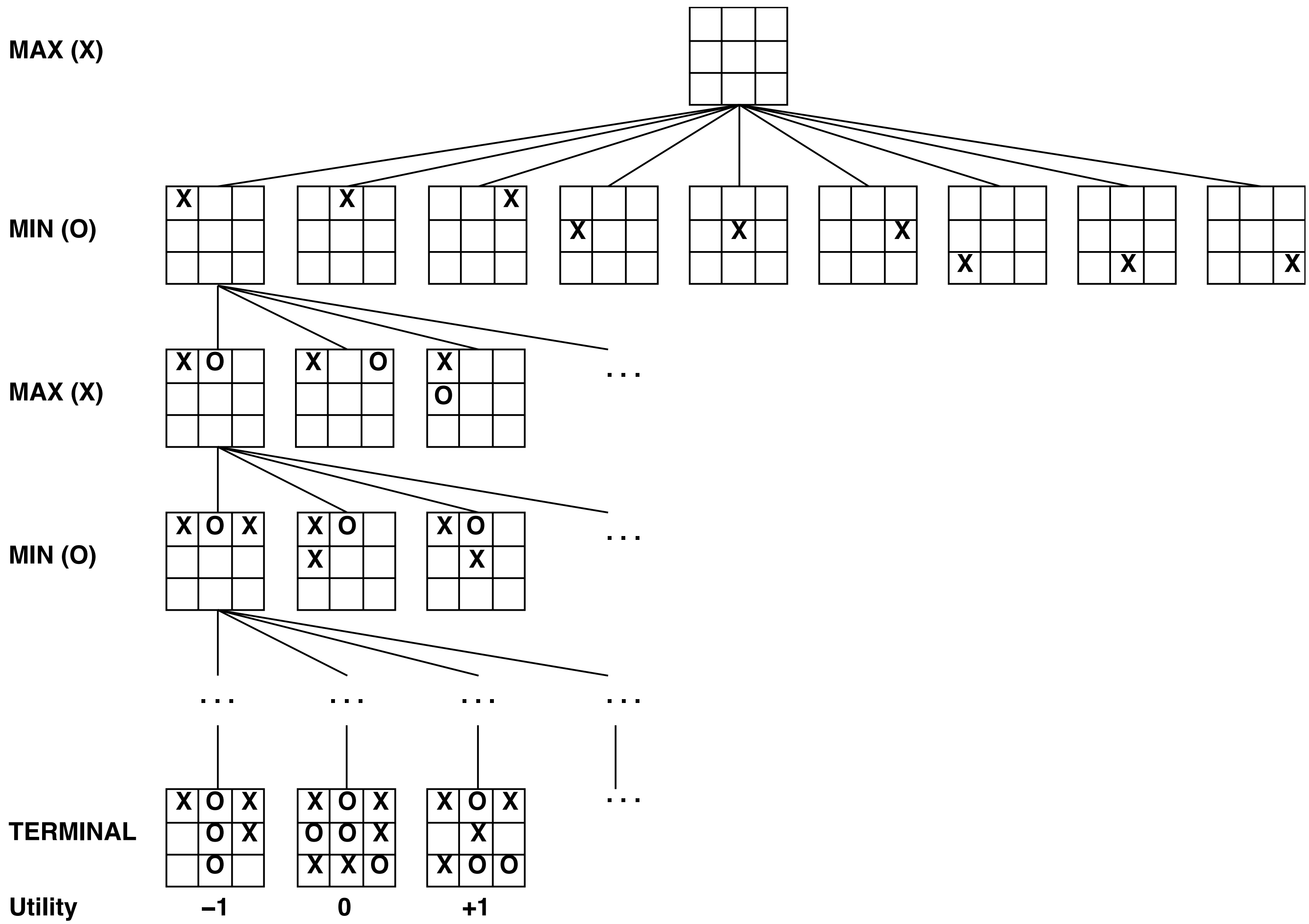
	deterministic	chance
perfect information	chess, checkers, go, othello	backgammon monopoly
imperfect information	battleships, blind tictactoe	bridge, poker, scrabble nuclear war

Problem definition

Games as search problems

- The **initial state**, with the positions on the board.
- The next player.
- A set of **actions** defining admissible moves in a given state.
- A **transition model**, defining the state transitions determined by the moves.
- A **termination test**, determining when the game is over (**terminal states**).
- A **utility function**, to compute the numerical result of a game.

Game tree (2-player, deterministic, turns)



Minimax

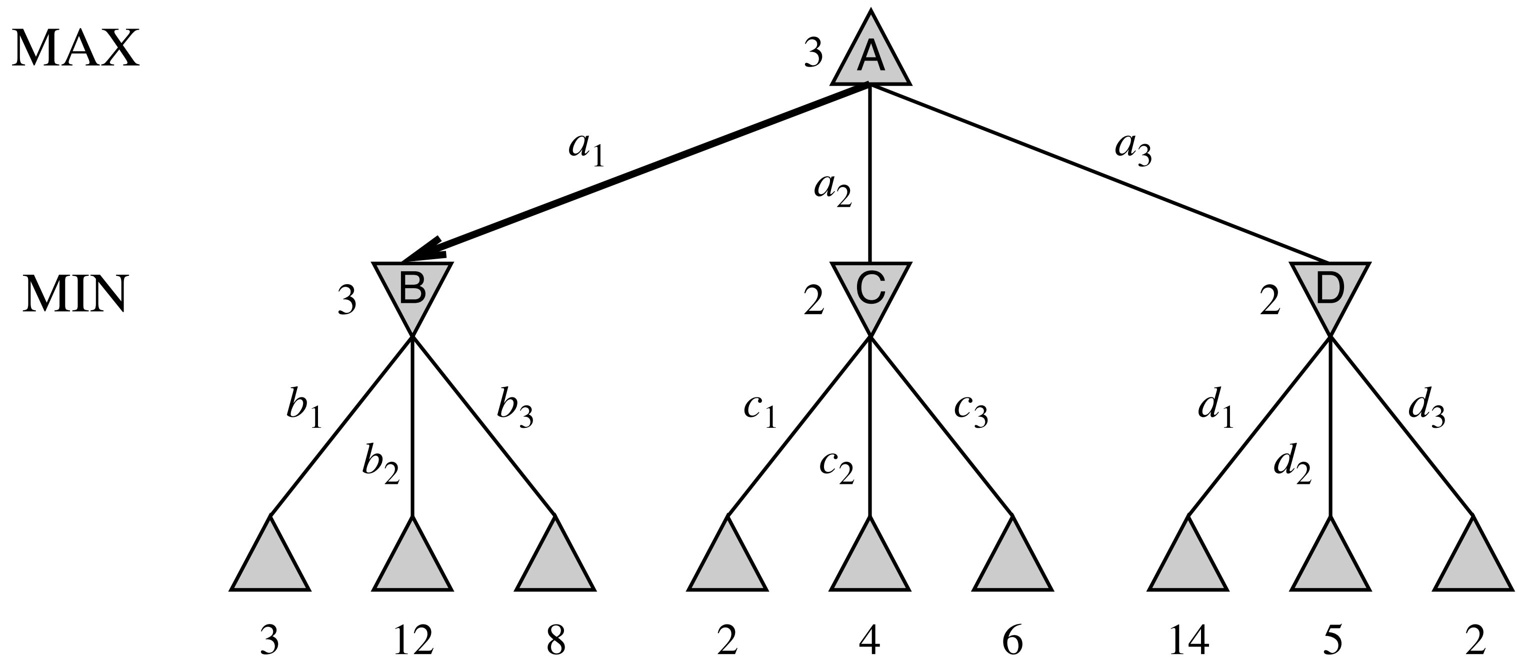
Perfect play for deterministic, perfect-information games

Idea: choose move to position with highest *minimax value*
= best achievable payoff against best play

1. generate the game tree
2. compute utility for each terminal state
3. use utility at level $N+1$ to compute it at level N, Choosing min for the opponent's moves and max for the own moves.

Minimax

E.g., 2-ply game:



The best move for player 1 in A is a_1,
The best move for player 2 in B is b_1

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 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**

$v \leftarrow$ MIN(v, MAX-VALUE(s))

return v

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

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
$\Rightarrow$ exact solution completely infeasible

Extension to multiple players

The notion of minimax game trees extends to multiple players.

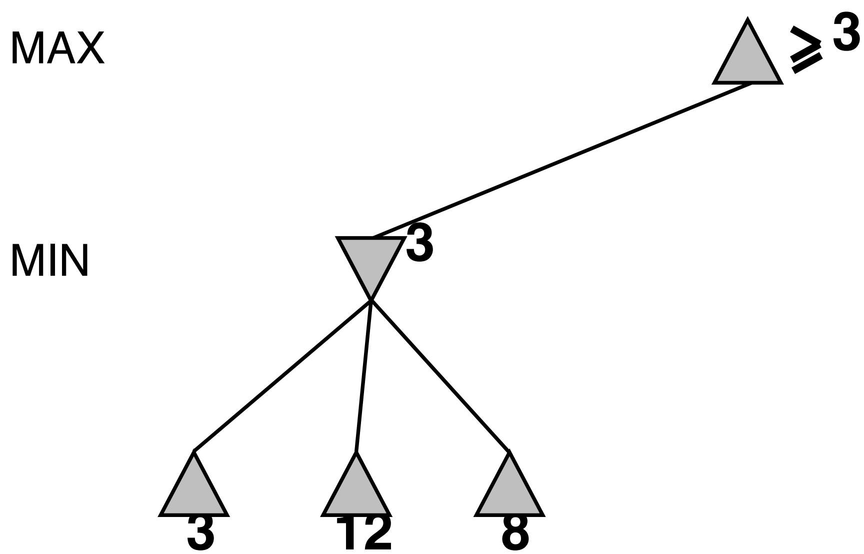
The value of the game becomes a vector with a value for each player.

At each step each player maximizes its own utility, but more complex strategies are needed:

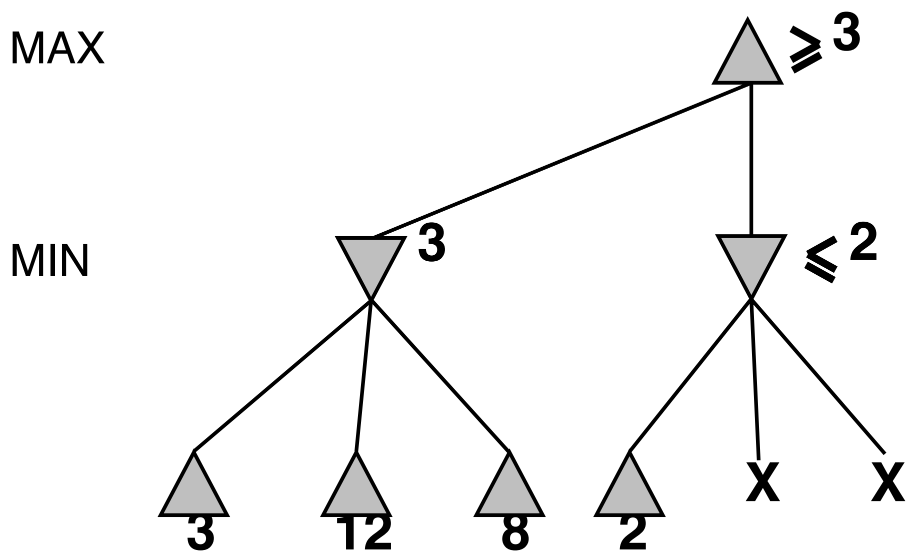
♢ alliances

♢ cooperation (non zero-sum games)

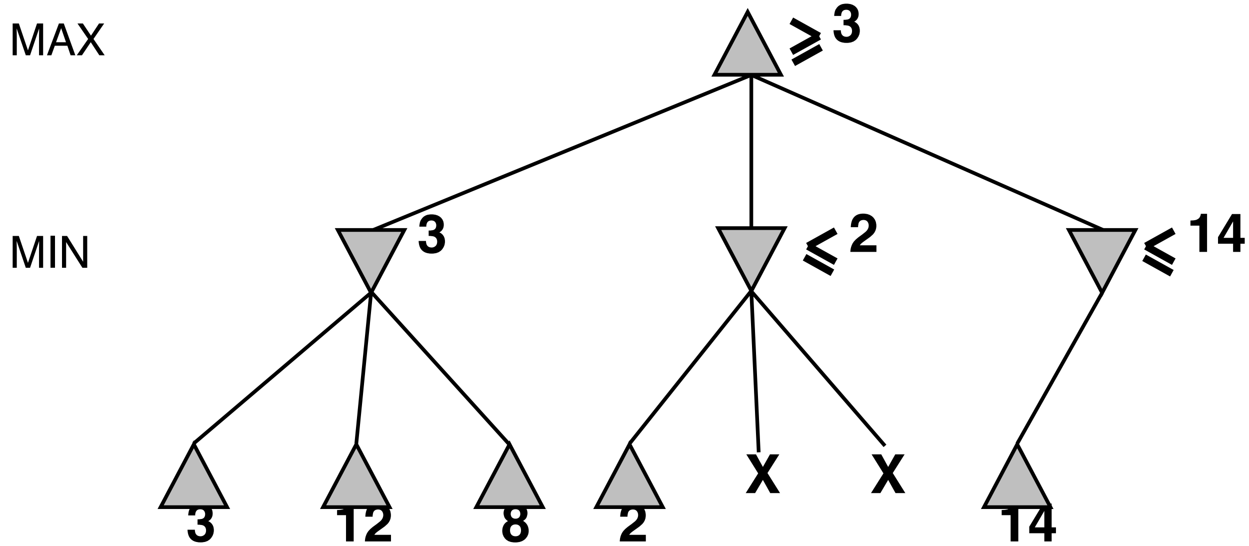
α–β pruning example



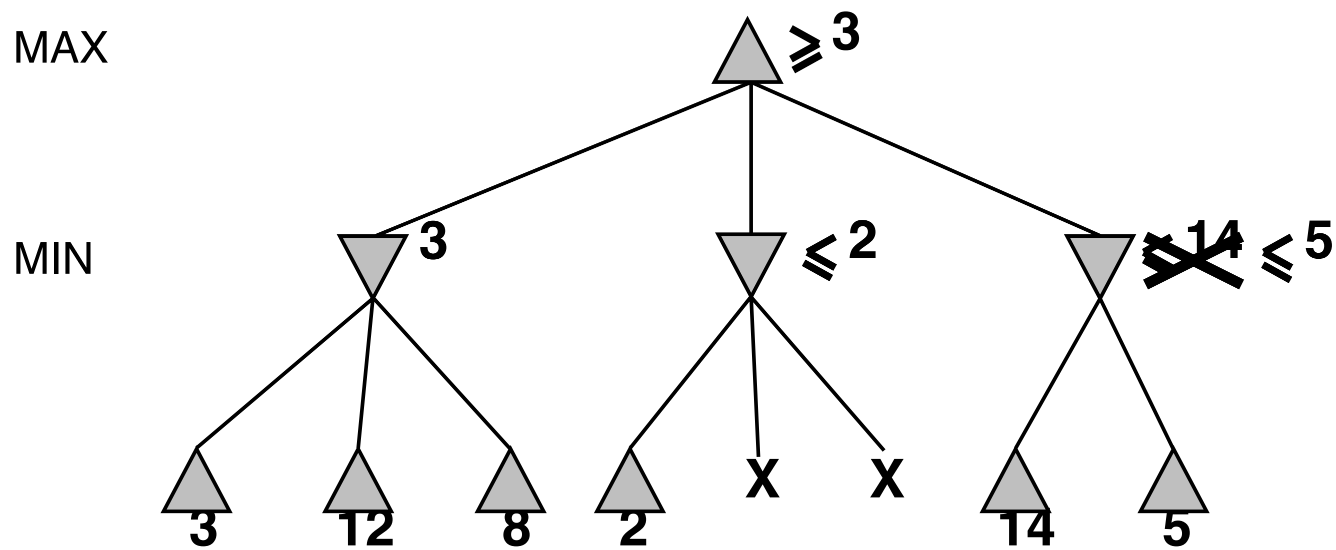
α–β pruning example



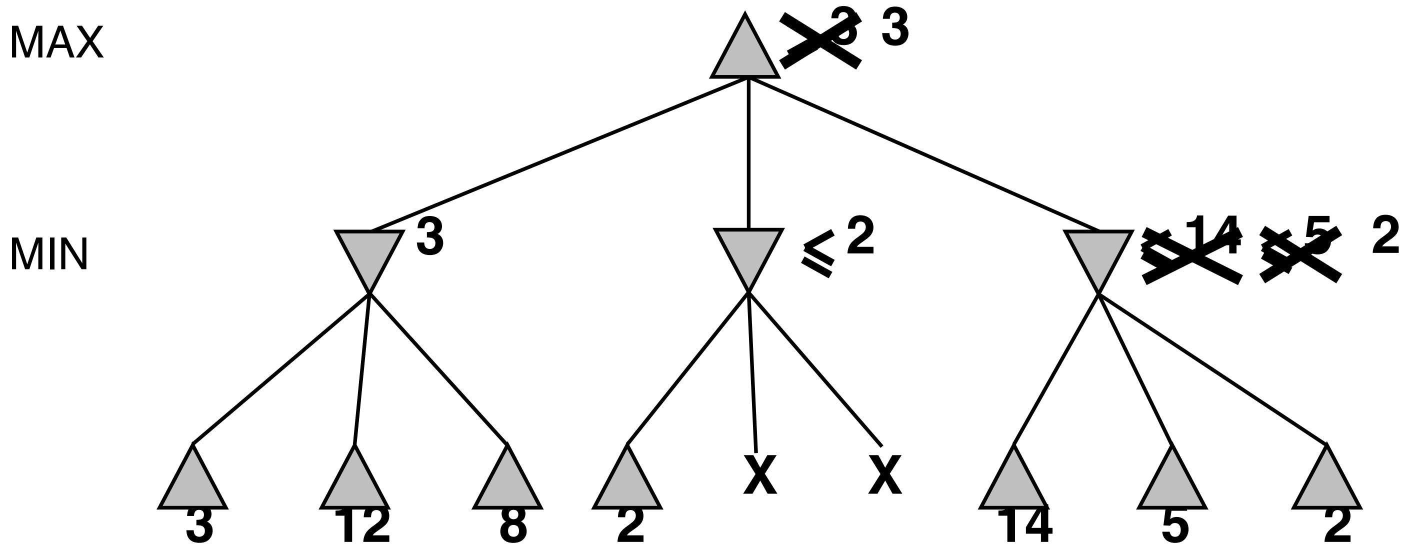
α–β pruning example



α–β pruning example



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

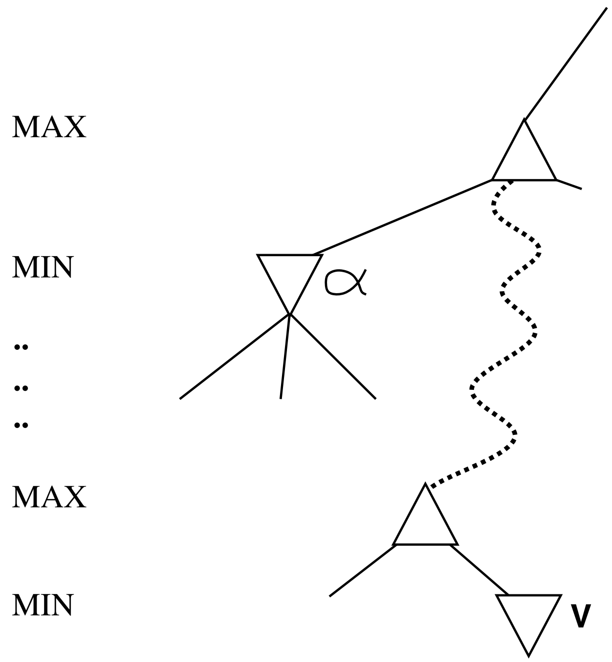
$\Rightarrow$ can easily reach depth 8 and play good chess

$+$ killer moves $+$ transposition table

Is perfect ordering achievable?

Metareasoning: reasoning about which computations are relevant

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

function ALPHA-BETA-DECISION($state$) **returns** an action

return the a in ACTIONS($state$) maximizing MIN-VALUE(RESULT($a, state$))

---

function $\textsc{Max-Value}(state, \alpha, \beta)$ **returns** *a utility value*

inputs: *state*, current state in game

α, best alt for MAX in the path to *state*

β, best alt for MIN in the path to *state*

if $\textsc{Terminal-Test}(state)$

then return $\textsc{Utility}(state)$

$v \leftarrow -\infty$

for a, s in $\textsc{Successors}(state)$ **do**

$v \leftarrow \textsc{Max}(v, \textsc{Min-Value}(s, \alpha, \beta))$

if $v \geq \beta$ **then return** v

$\alpha \leftarrow \textsc{Max}(\alpha, v)$

return v

Resource limits

Suppose we have 100 seconds, explore 10^4 nodes/second
$\Rightarrow$ 10^6 nodes per move

Standard approach:

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

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 $\approx$ human novice
8-ply $\approx$ typical PC, human master
12-14-ply $\approx$ Deep Blue, Kasparov

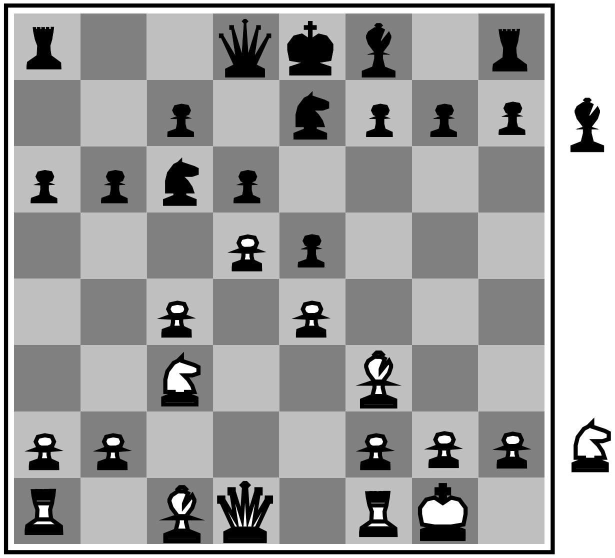
Evaluation functions

- order terminal states as true utility
- fast computation
- good correlation with actual chances of winning

Behaviour is preserved under any *monotonic* transformation of EVAL

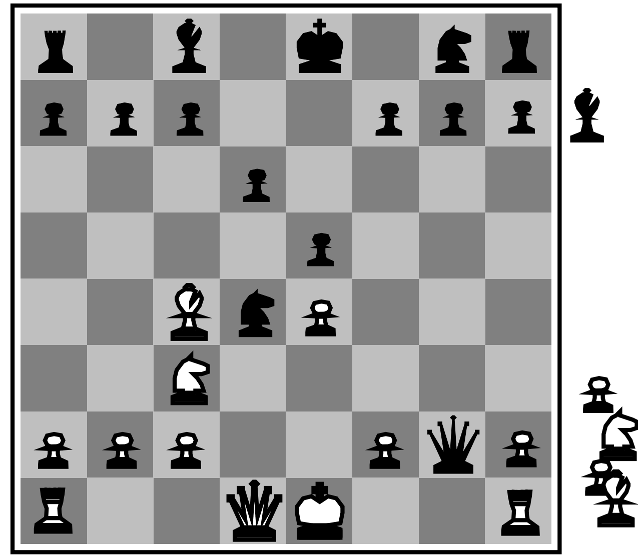
Exact values don't matter, only the order matters:
payoff in deterministic games acts as an *ordinal utility* function

Heuristic evaluation functions



Black to move

White slightly better



White to move

Black winning

For chess, typically *linear* weighted sum of features

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

Cut-off search

Replace $TERMINAL - TEST$ with:

if $CUTOFF - TEST(state, depth)$ **then return** $EVAL(state)$

Iterative deepening can be used when time is limited.

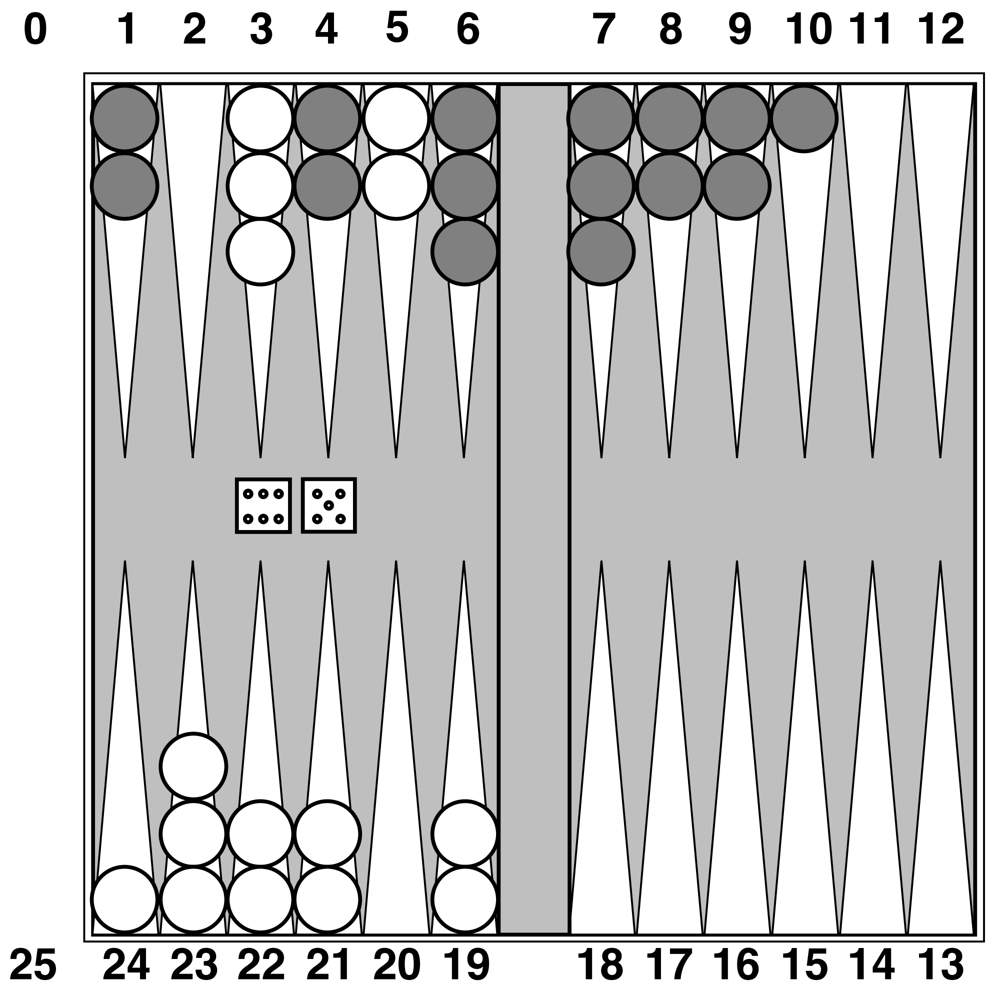
Quiescience search: to check whether the move that is cut off does not lead to a dramatic change in the evaluation function.

Further improvements

◇ **Forward pruning**: evaluating which moves are unlikely to win (estimate which moves are likely to be outside the $\alpha - \beta$ range, using ML to find the estimates)

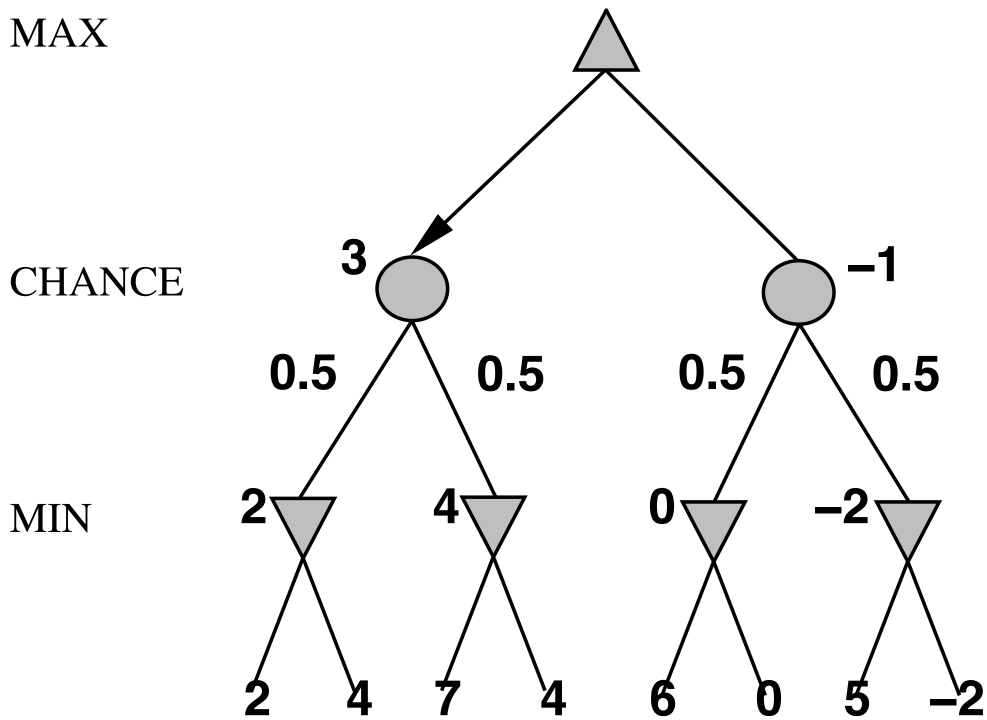
◇ **Lookup tables**: For openings and the terminal part of the games with few remaining pieces (games with more than 6 pieces have been fully analyzed – in checkers the whole game)

Nondeterministic games: backgammon



Nondeterministic games in general

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



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*)
. . .

Properties of Expectiminimax

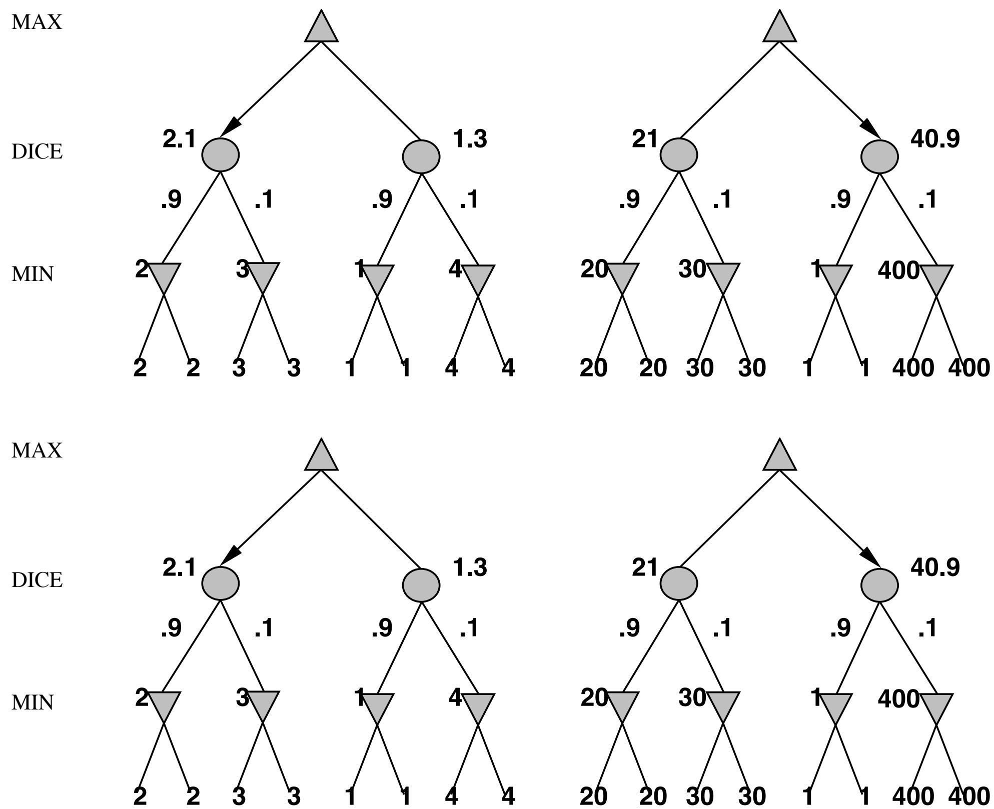
Completeness and **Optimality** can not be achieved because of the random steps, where the expected value is computed

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

Space complexity $O(bmnm)$ (depth-first exploration)

In backgammon $n = 21$, $b > 20$, $m = 3$

Digression: Exact values DO matter



Behaviour is preserved only by **positive linear** transformation of EVAL, which should be proportional to the expected payoff

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

Montecarlo search

Underlying principle:

- Use a game search and take random dice rolls (rollout).
- Keep playing against itself and compute the win percentage.

This gives a good estimate of the value of the position.

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, which are too good.

Go

Chess: b=35, d=80
Go: b=250, d=150

Before **AlphaGo** best programs used Montecarlo Tree Search, but reach only amateur level.

AlphaGo (Google DeepMind, 2016) wins against world champion after combining MC search and learning with Neural Networks

Position evaluation, which reduces the depth
Policy to select the best move, which limits breadth

Poker

Card games include an additional issue **Partial osservability**.

DeepStack (M. Bowling et al. 2017) wins against best poker players.

Learning:

- Policies for forward pruning
- To guess the cards of the other player through counterfactual regret minimization

Concluding

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