CSE 473: Artificial Intelligence
Spring 2017

Adversarial Search

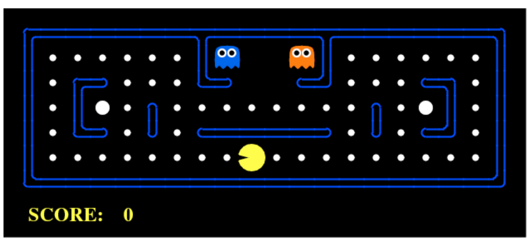
Dieter Fox

Based on slides adapted Luke Zettlemoyer, Dan Klein, Pieter Abbeel, Dan Weld, Stuart Russell or Andrew Moore

Game Playing State-of-the-Art 2017

- **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. Checkers is now solved!
- **Chess:** Deep Blue defeated human world champion Gary Kasparov in a six-game match in 1997. Deep Blue examined 200 million positions per second, used very sophisticated evaluation and undisclosed methods for extending some lines of search up to 40 ply. Current programs are even better, if less historic.
- **Othello:** Human champions refuse to compete against computers, which are too good.
- **Go:** In March 2016, AlphaGo beats 9-dan master Lee Sedol (3 wins, 1 loss, 1 win). Combines Monte-Carlo tree search with deep reinforcement learning.
- **Poker:** In December 2016, computer beats professional players at no-limit Texas hold 'em

Adversarial Search



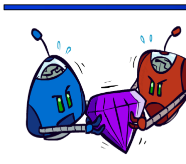
Game Playing

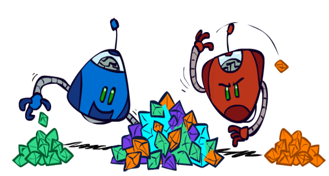
- Many different kinds of games!
- Choices:
  - Deterministic or stochastic?
  - One, two, or more players?
  - Perfect information (can you see the state)?
- Want algorithms for calculating a strategy (policy) which recommends a move in each state

Deterministic Games

- Many possible formalizations, one is:
  - States: S (start at s_0)
  - Players: P={1...N} (usually take turns)
  - Actions: A (may depend on player / state)
  - Transition Function: S x A → S
  - Terminal Test: S → {t,f}
  - Terminal Utilities: S x P → R
- Solution for a player is a policy: S → A

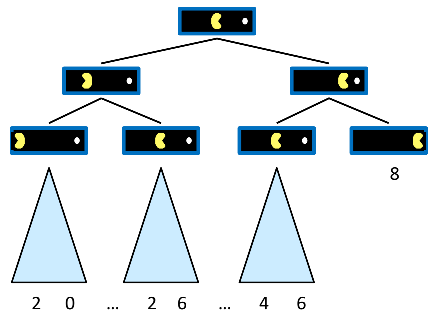
Zero-Sum Games





- Zero-Sum Games
  - Agents have opposite utilities (values on outcomes)
  - Lets us think of a single value that one maximizes and the other minimizes
  - Adversarial, pure competition
- General Games
  - Agents have independent utilities (values on outcomes)
  - Cooperation, indifference, competition, & more are possible

Single-Agent Trees



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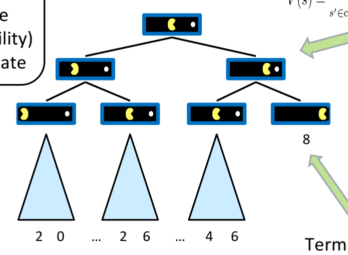
Value of a State

Value of a state: The best achievable outcome (utility) from that state

Non-Terminal States:

$$V(s) = \max_{s' \in \text{children}(s)} V(s')$$



Terminal States:

$$V(s) = \text{known}$$

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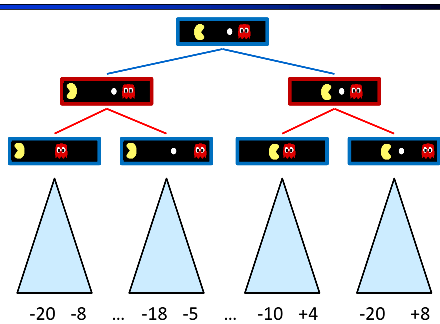
Adversarial Game Trees



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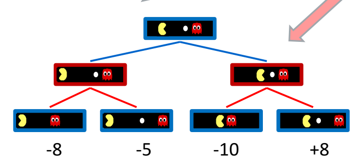
Minimax Values

States Under Agent's Control:

$$V(s) = \max_{s' \in \text{successors}(s)} V(s')$$

States Under Opponent's Control:

$$V(s') = \min_{s \in \text{successors}(s')} V(s)$$



Terminal States:

$$V(s) = \text{known}$$

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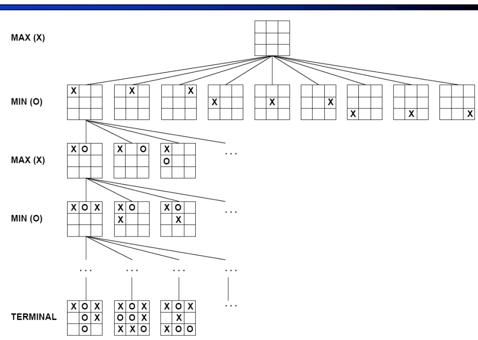
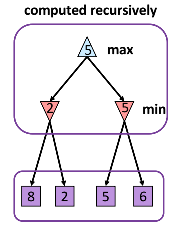
Tic-tac-toe Game Tree



Adversarial Search (Minimax)

- Deterministic, zero-sum games:
  - Tic-tac-toe, chess, checkers
  - One player maximizes result
  - The other minimizes result
- Minimax search:
  - A state-space search tree
  - Players alternate turns
  - Compute each node's minimax value: the best achievable utility against a rational (optimal) adversary

Minimax values: computed recursively



Terminal values: part of the game

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Minimax Implementation

def max-value(state):
  initialize v = -∞
  for each successor of state:
    v = max(v, min-value(successor))
  return v

def min-value(state):
  initialize v = +∞
  for each successor of state:
    v = min(v, max-value(successor))
  return v

$$V(s) = \max_{s' \in \text{successors}(s)} V(s')$$

$$V(s') = \min_{s \in \text{successors}(s')} V(s)$$

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Minimax Implementation (Dispatch)

def value(state):
  if the state is a terminal state: return the state's utility
  if the next agent is MAX: return max-value(state)
  if the next agent is MIN: return min-value(state)

def max-value(state):
  initialize v = -∞
  for each successor of state:
    v = max(v, min-value(successor))
  return v

def min-value(state):
  initialize v = +∞
  for each successor of state:
    v = min(v, max-value(successor))
  return v

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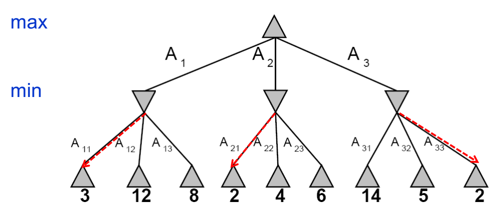
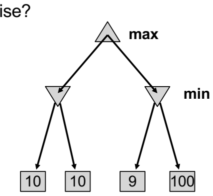
Concrete Minimax Example



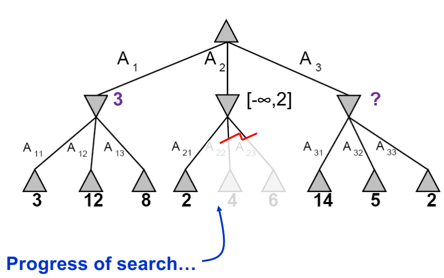
Minimax Properties

- Optimal?
  - Yes, against perfect player. Otherwise?
- Time complexity
  - $O(b^m)$
- Space complexity?
  - O(bm)



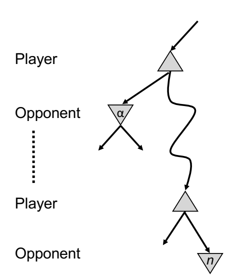
- For chess, b ≈ 35, m ≈ 100
  - Exact solution is completely infeasible
  - But, do we need to explore the whole tree?

Pruning Example

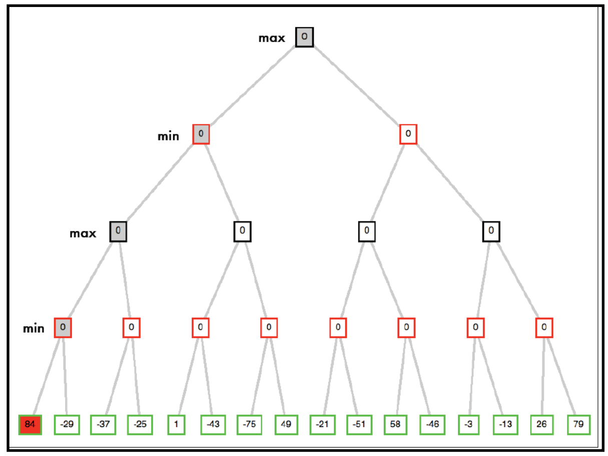


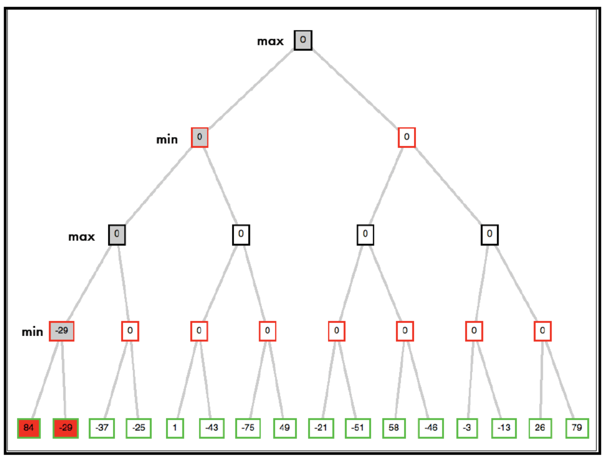
α-β Pruning

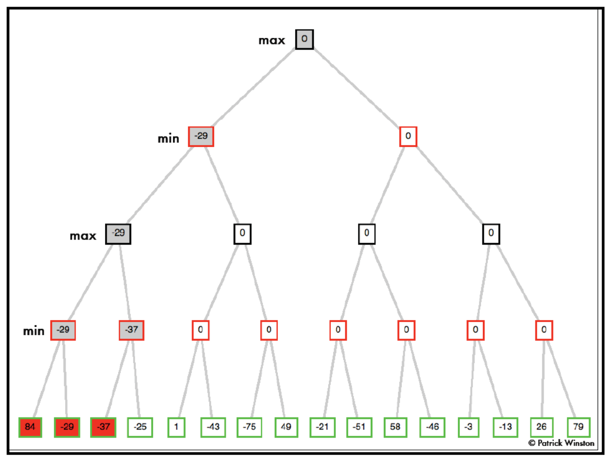
- General configuration
  - α is the best value that MAX can get at any choice point along the current path
  - If *n* becomes worse than α, MAX will avoid it, so can stop considering *n*'s other children
  - Define β similarly for MIN

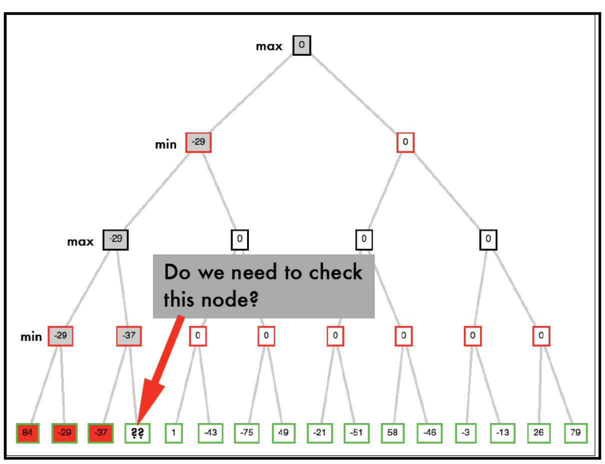


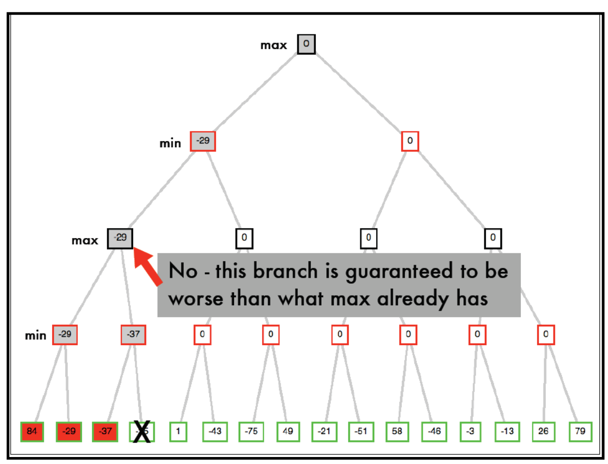
Alpha-Beta Pruning

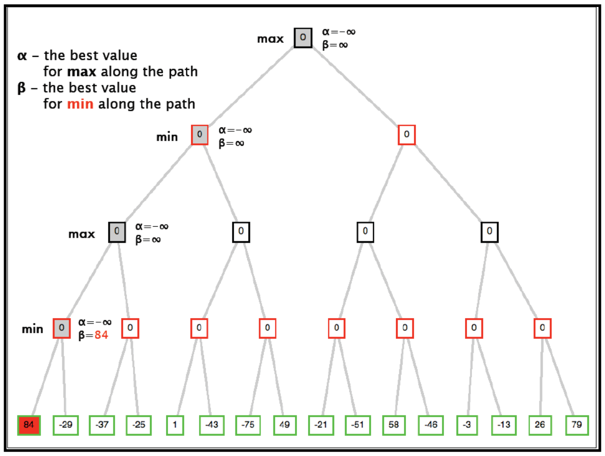


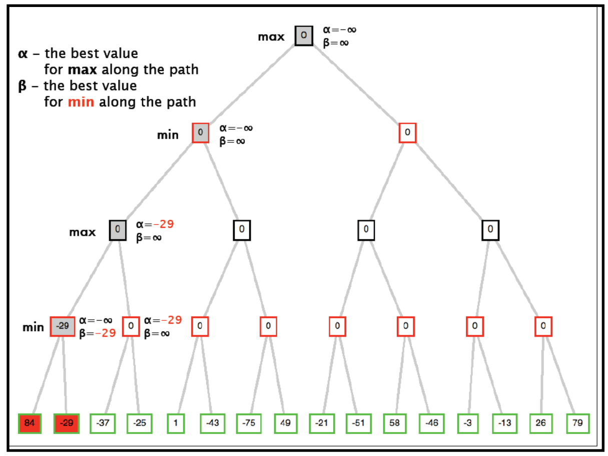









max
α=−∞ β=∞
α – the best value for max along the path
β – the best value for min along the path
min
α=−∞ β=∞
max
α=−∞ β=∞
min
α=−∞ β=84
84 -29 -37 -25 1 -43 -75 49 -21 -51 58 -46 -3 -13 26 79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α=−29 β=∞
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α=−∞ β=−29
α=−29 β=∞
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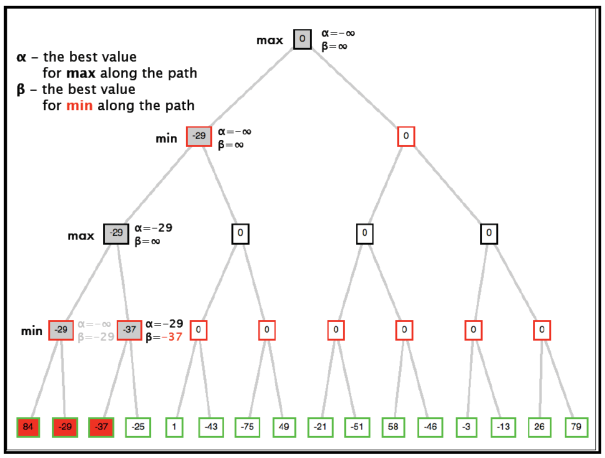
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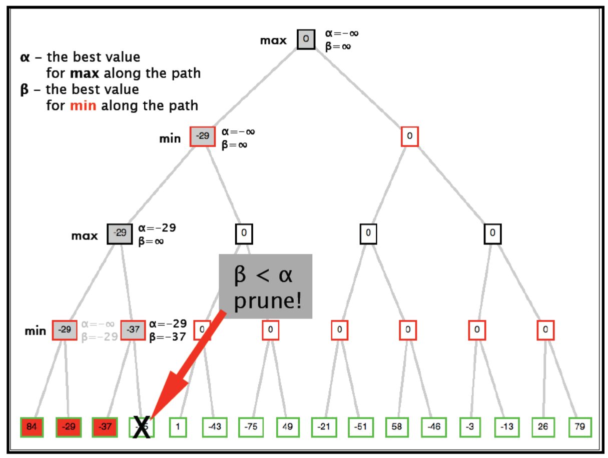
max
α=−29 β=∞
min
α=−∞ β=−29
α=−29 β=−37
84 -29 -37 -25 1 -43 -75 49 -21 -51 58 -46 -3 -13 26 79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α – the best value for max along the path
β – the best value for min along the path
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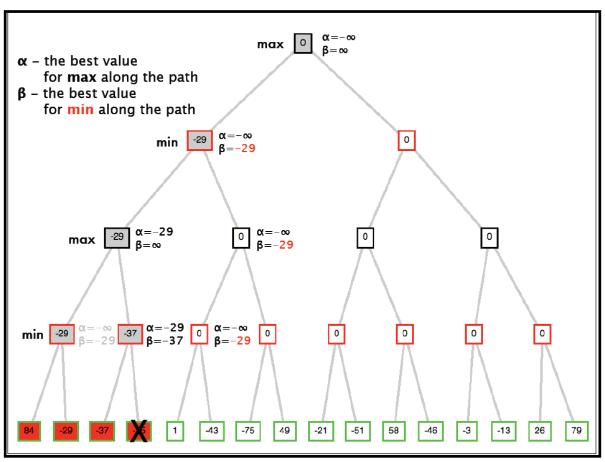
α=−∞ β=∞
max
α=−29 β=∞
β < α prune!
min
α=−∞ β=−29
α=−29 β=−37
84 -29 -37 X 1 -43 -75 49 -21 -51 58 -46 -3 -13 26 79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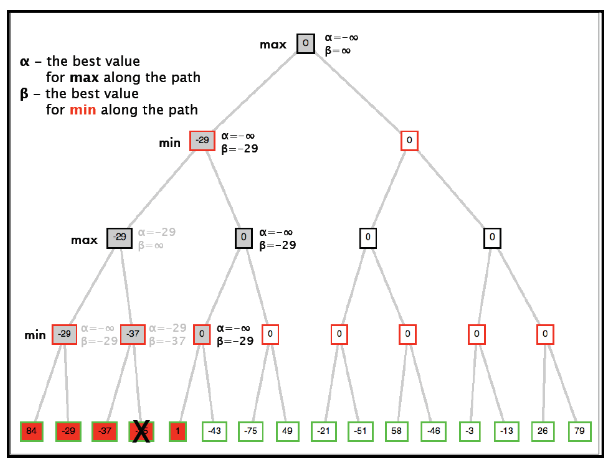
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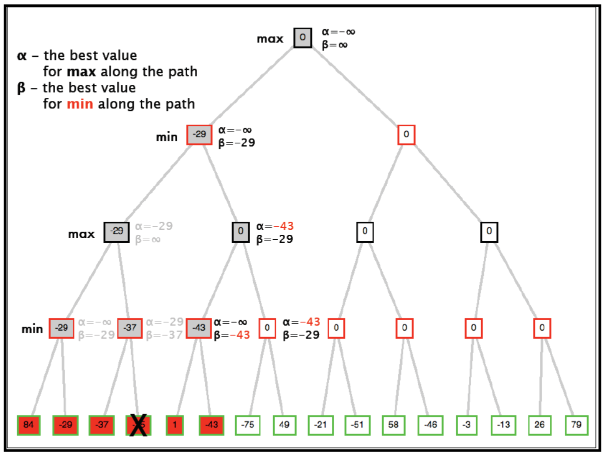

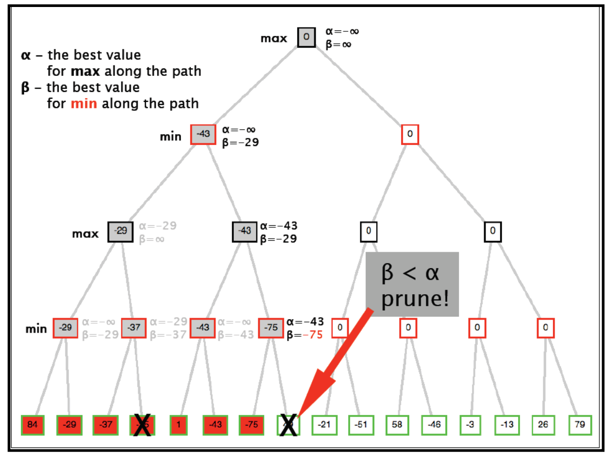

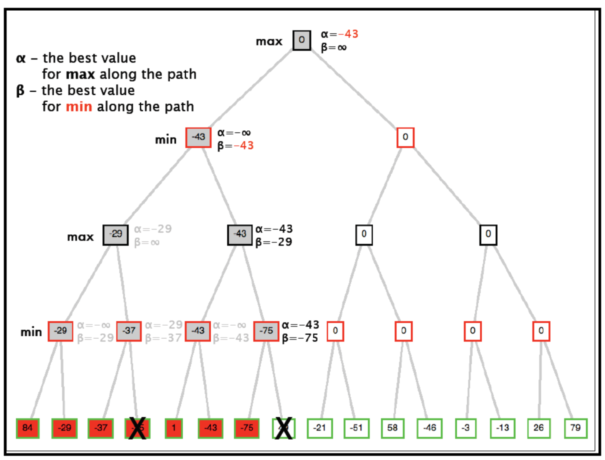

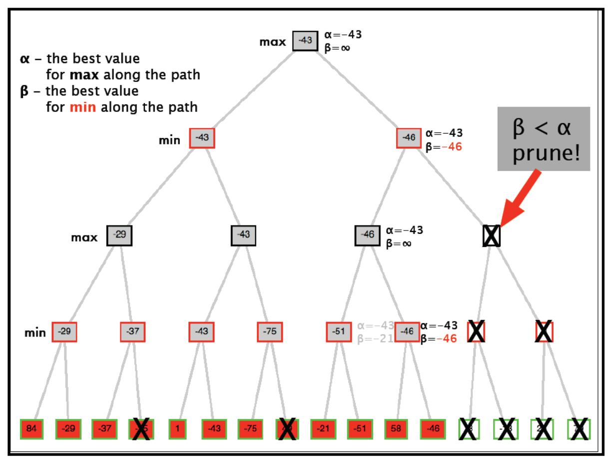

Alpha-Beta Pruning Properties

- This pruning has no effect on final result at the root
- Values of intermediate nodes might be wrong!
  - but, they are bounds
- Good child ordering improves effectiveness of pruning
- With “perfect ordering”:
  - Time complexity drops to $O(b^{m/2})$
  - Doubles solvable depth!
  - Full search of, e.g. chess, is still hopeless…

Alpha-Beta Implementation

α: MAX’s best option on path to root
β: MIN’s best option on path to root

```
def max-value(state, α, β):
    initialize v = -∞
    for each successor of state:
        v = max(v, value(successor, α, β))
        if v ≥ β return v
        α = max(α, v)
    return v
```

```
def min-value(state , α, β):
    initialize v = +∞
    for each successor of state:
        v = min(v, value(successor, α, β))
        if v ≤ α return v
        β = min(β, v)
    return v
```

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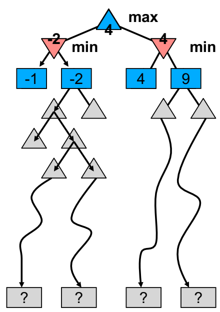
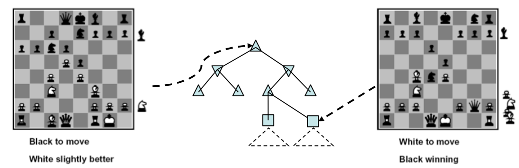
Resource Limits

- Cannot search to leaves
- Depth-limited search
  - Instead, search a limited depth of tree
  - Replace terminal utilities with an eval function for non-terminal positions
- Guarantee of optimal play is gone
- Example:
  - Suppose we have 100 seconds, can explore 10K nodes / sec
  - So can check 1M nodes per move
  - α-β reaches about depth 8 – decent chess program



Evaluation Functions

- Function which scores non-terminals

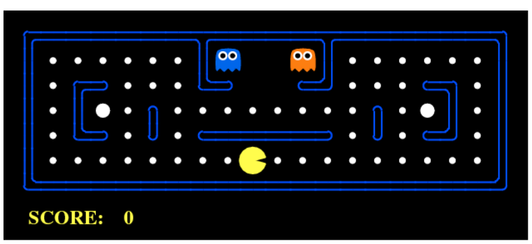


$$Eval(s) = w_1 f_1(s) + w_2 f_2(s) + \ldots + w_n f_n(s)$$

- Ideal function: returns the utility of the position
- In practice: typically weighted linear sum of features:
  - e.g. $f_1(s)$ = (num white queens – num black queens), etc.

Which algorithm?

α-β, depth 4, simple eval fun



Which algorithm?

α-β, depth 4, better eval fun