TECHNISCHE UNIVERSITÄT DRESDEN

Computational Logic ∴ Group

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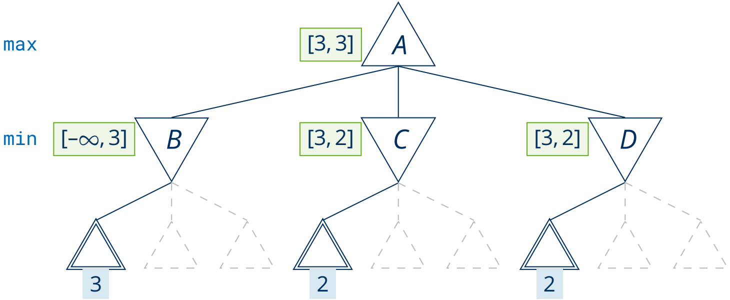
Playing Games: Monte Carlo Tree Search

Lecture 5, 13th May 2024 // Algorithmic Game Theory, SS 2024

Previously ...

- Game trees can be succinctly represented by **state-based game models**.
- **Minimax Tree Search** can be used to solve sequential (two-player zero-sum) games with perfect information.
- **Alpha-Beta Pruning** allows to reduce the search space without sacrificing solutions.
- **Heuristic Evaluation** of states can be used to reduce search depth.
- Further heuristics may reduce the search space (typically with sacrifices).



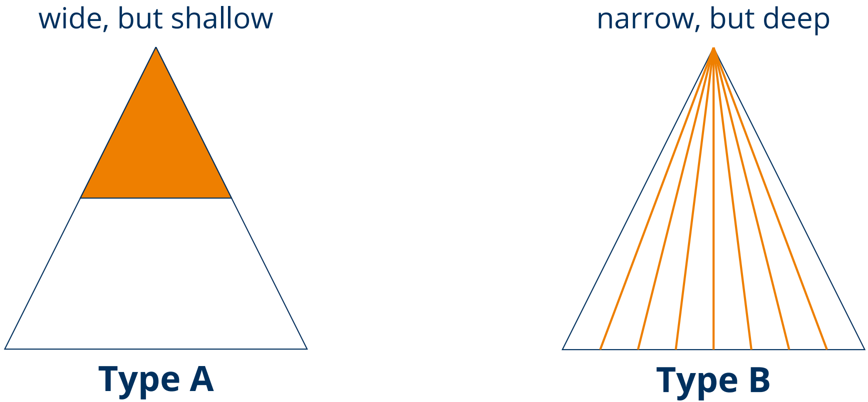
Overview

Monte Carlo Tree Search

Selection Policy: UCT

Tree Search: Shannon’s Type A and Type B

In Claude Shannon’s 1950 paper *Programming a Computer for Playing Chess*, he suggests two types of tree search strategies:



Tree Search: Shannon's Type A and Type B

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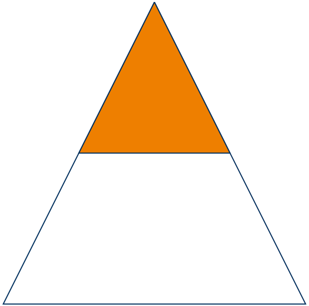
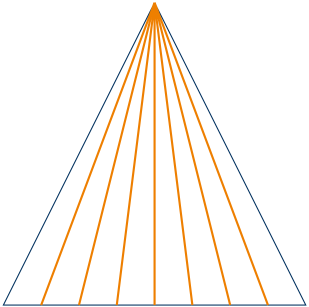
wide, but shallow



Type A

Alpha-Beta Tree Search

narrow, but deep



Type B

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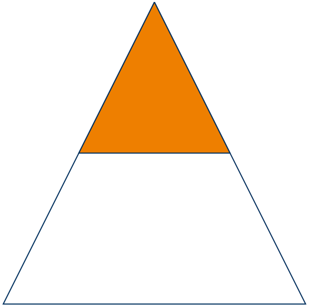

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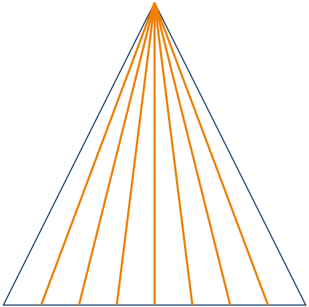

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- Random move sequences only inform about random play, so a playout policy is needed to bias simulation towards optimal play.
- In pure Monte Carlo search, we do N simulations starting in the current state and record average payoffs for all moves.
- Selection policy: Determines from which nodes to start simulations; faces the fundamental issue to balance exploitation and exploration.

Monte Carlo Tree Search: Example (1)

1. Selection

`max`'s choice

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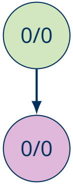
2. Expansion



max's choice

max's statistics

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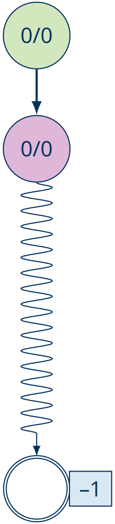
2. Expansion
3. **Simulation**



Monte Carlo Tree Search: Example (1)

1. Selection
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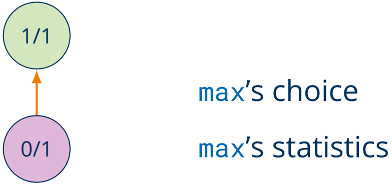
4. **Backpropagation**



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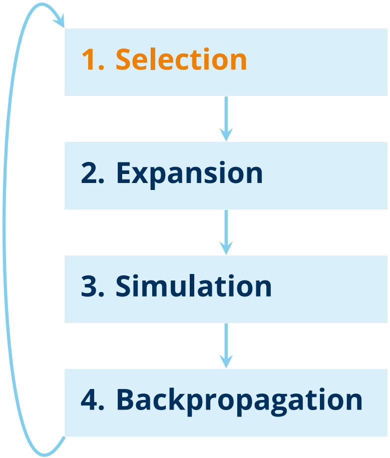

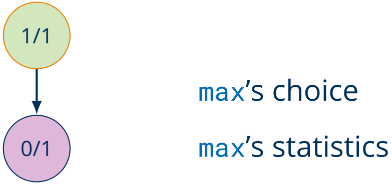

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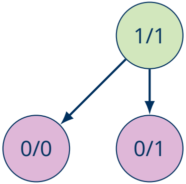

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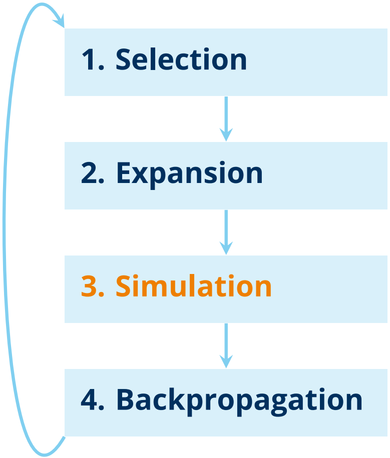

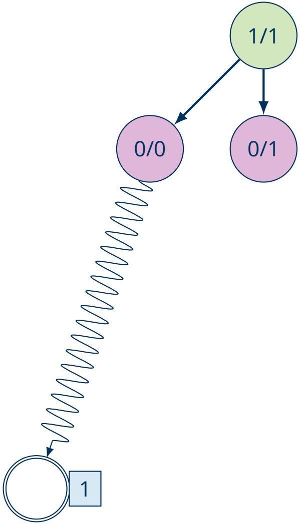

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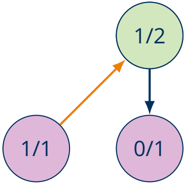

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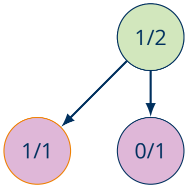

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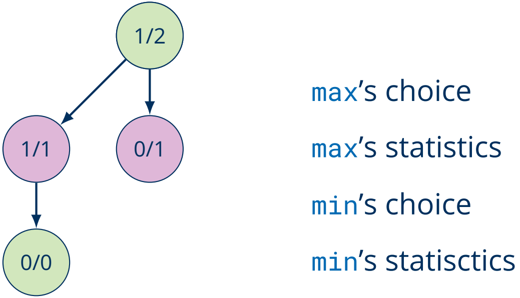

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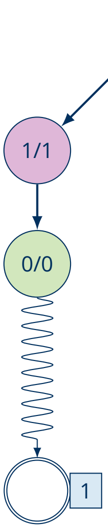

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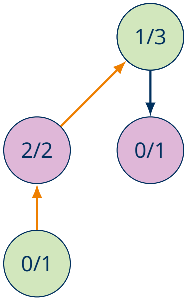

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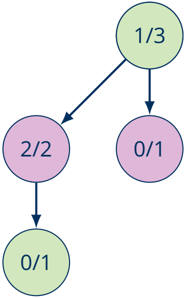

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Monte Carlo Tree Search: Example (2)

1. Selection

2. Expansion

3. Simulation

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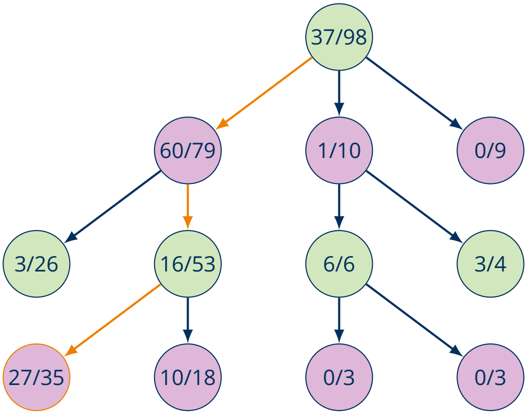

Monte Carlo Tree Search: Example (2)

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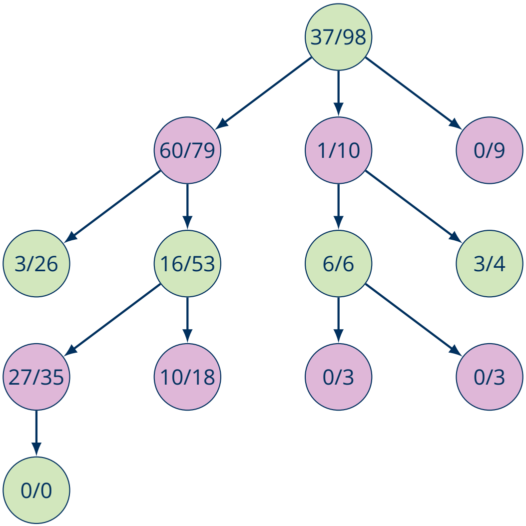

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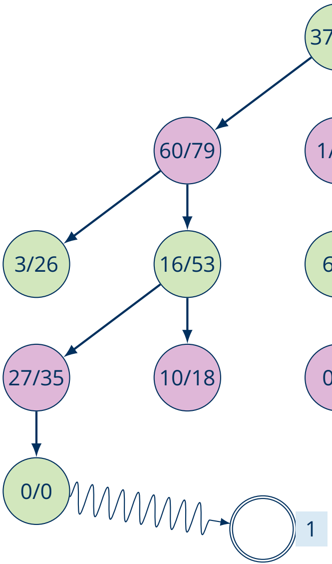

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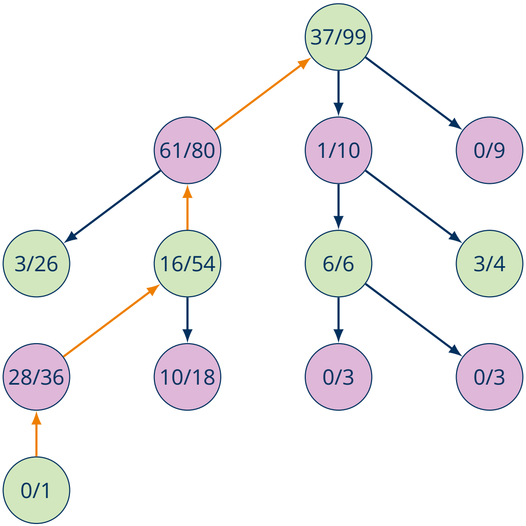

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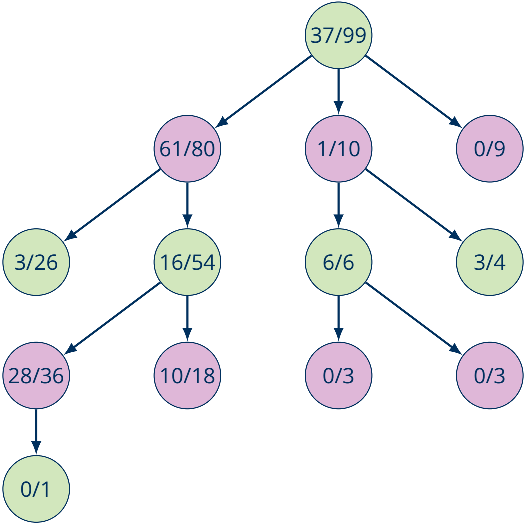

Monte Carlo Tree Search: Algorithm

function **monte-carlo-tree-search**(s: *state*) {
  tree := **get-tree-below**(s)
  while **is-time-remaining**() **do** {
    leaf := **select**(*tree*)
    child := **expand**(*leaf*)
    result := **simulate**(*child*)
    back-propagate(*tree*, *child*, *result*) }
  return **move-to-node-with-most-playouts**(*tree*) }

- **get-tree-below** returns the search tree below the node for the state
- **is-time-remaining** checks whether we are still within the time limit
- **select** uses the selection policy to find a node to expand next
- **expand** adds a new child to the given node (makes a move)
- **simulate** does a full playout, returning only the result (utility value)
- **back-propagate** propagates the result value up the search tree

Selection Policy: UCT

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An effective policy: UCT – "upper confidence bounds applied to trees".

UCT ranks moves according to their "upper confidence bound" value.

Definition

The **upper confidence bound** value for a node n is obtained thus:

$$\mathrm{UCB1}(n) := \frac{U(n)}{N(n)} + c \cdot \sqrt{\frac{\ln N(n')}{N(n)}}$$

where

- n' is the unique parent of n in the search tree,
- $U(n)$ is the total utility of node n (summed up over all playouts),
- $N(m)$ is the total number of playouts through node m,
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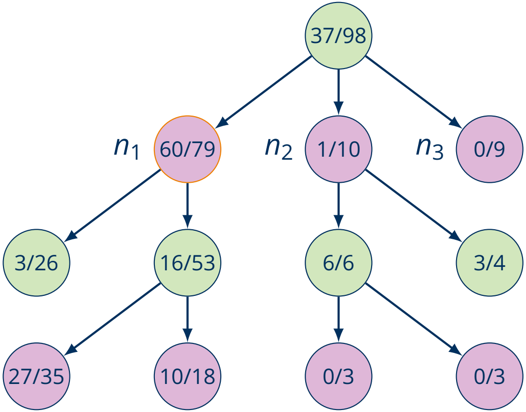
Constant c balances exploitation (first fraction) and exploration (square root).

UCT: Example

$$\text{UCB1}(n_1) = \frac{60}{79} + \sqrt{\frac{2 \cdot \ln 98}{79}}$$
$$\approx 0.76 + 0.34 = 1.1$$



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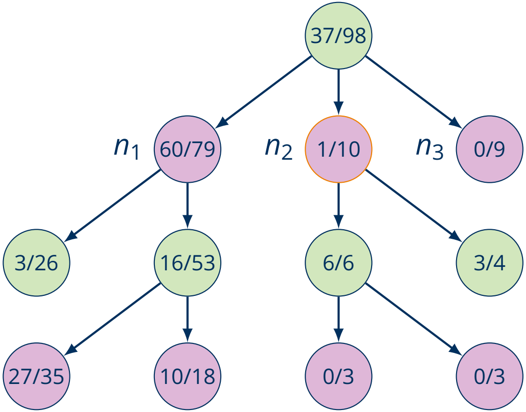

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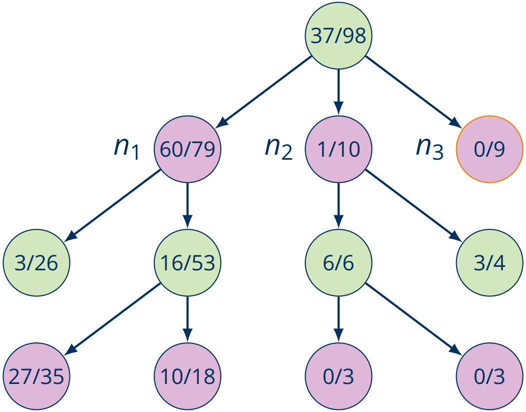

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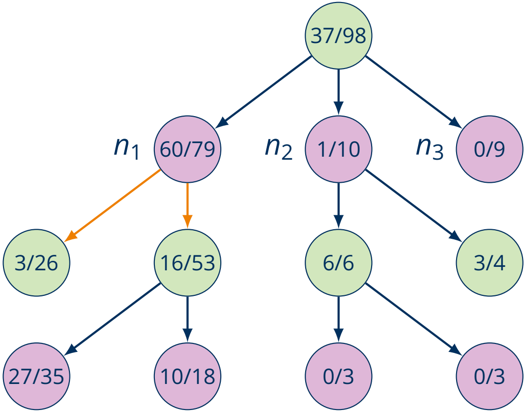

We thus continue with n_1 and apply UCB1 to its children.

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- A K-**armed bandit problem** is given by random variables $X_{i,n}$ for $1 \leq i \leq K$ and $n \geq 1$, where each i is the index of a gambling machine (the “arm” of a bandit).

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- A **policy** is a function mapping past plays and rewards to the next arm to play.
- The **regret** of a policy is the difference between the maximally possible payoff and the actually obtained payoff.

Digression: Multi-Armed Bandits (2)

- UCB1 is a specific policy of "playing" multi-armed bandits that achieves logarithmic regret (in the number *n* of plays; known to be optimal):

deterministic policy ucb1:

---

initialisation: play each machine once

loop:

play machine *j* that maximises $\bar{x}_j + \sqrt{\frac{2 \ln n}{n_j}}$ where

- $\bar{x}_j$ is the average reward obtained from machine *j*,
- n_j is the number of times machine *j* has been played so far,
- *n* is the overall number of plays done so far.

UCB1 for Multi-Armed Bandits: Example

Consider the following multi-armed bandit with arms 1, 2, and 3. After playing each arm once ($n = 1, 2, 3$), UCB1 determines the next arm to play.

n	u_1	n_1	u_2	n_2	u_3	n_3
$1, 2, 3$	0.3	1	0.0	1	1.0	1
UCB1	1.78		1.48		2.48	

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6			0.0 + 0.5	2		
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$1, 2, 3$	0.3	1	0.0	1	1.0	1
UCB1	1.78		1.48		2.48	
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- Computing the result of a playout takes linear time in the height of the game tree.
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- AlphaZero [Silver et al., 2018] learns a playout policy from self-play using neural networks (interleaving learning and MCTS).

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- Computer victory (AlphaGo) over human champions (2015 Fan Hui, 2016 Lee Sedol, 2017 Ke Jie)

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$\rightsquigarrow$ If there are single moves that can turn the game, MCTS might fail to consider those moves due to its stochastic mode of operation.

Conclusion

Summary

- **Monte Carlo Tree Search** uses random playouts to evaluate moves and keeps statistics on which moves led to which payoffs how many times.
- A **selection policy** balances exploitation and exploration.
- **UCT** is an effective selection policy that applies UCB1 to trees.
- A **playout policy** steers playout simulations towards realistic play.
- MCTS and deep reinforcement learning led to expert-level Go programs.

Action Points

- Implement a MCTS-based program for playing Tic-Tac-Toe.