# Foundations of Artificial Intelligence

## 43. Monte-Carlo Tree Search: Introduction

Malte Helmert and Gabriele Röger

University of Basel

May 17, 2017

# Board Games: Overview

chapter overview:

# Introduction

# Monte-Carlo Tree Search: Brief History

- Starting in the 1930s: first researchers experiment with Monte-Carlo methods
- 1998: Ginsberg's GIB player competes with expert Bridge players
- 2002: Kearns et al. propose Sparse Sampling
- 2002: Auer et al. present UCB1 action selection for multi-armed bandits
- 2006: Coulom coins the term Monte-Carlo Tree Search (MCTS)
- 2006: Kocsis and Szepesvári combine UCB1 and MCTS to the most famous MCTS variant, UCT

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# Monte-Carlo Tree Search: Applications

Examples for successful applications of MCTS in games:

- board games (e.g., Go $\rightsquigarrow$ Chapter 45)
- card games (e.g., Poker)
- AI for computer games
  (e.g., for Real-Time Strategy Games or Civilization)
- Story Generation
  (e.g., for dynamic dialogue generation in computer games)
- General Game Playing

Also many applications in other areas, e.g.,

- MDPs (planning with stochastic effects) or
- POMDPs (MDPs with partial observability)

# Monte-Carlo Methods

# Monte-Carlo Methods: Idea

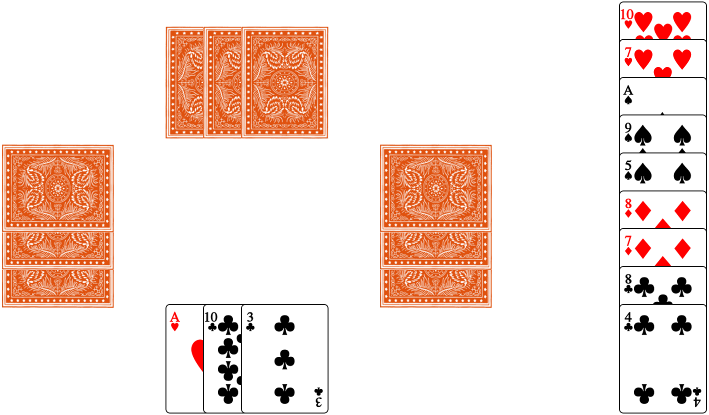
- summarize a broad family of algorithms
- decisions are based on random samples
- results of samples are aggregated by computing the average
- apart from that, algorithms can differ significantly

# Monte-Carlo Methods: Example

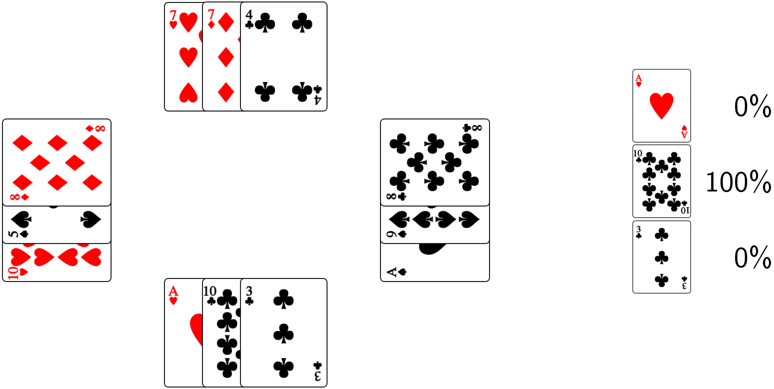
Bridge Player GIB, based on Hindsight Optimization (HOP)

- perform samples as long as resources (deliberation time, memory) allow:
- sample hand for all players that is consistent with current knowledge about the game state
- for each legal action, compute if perfect information game that starts with executing that action is won or lost
- compute win percentage for each action over all samples
- play the card with the highest win percentage

# Hindsight Optimization: Example



# Hindsight Optimization: Example



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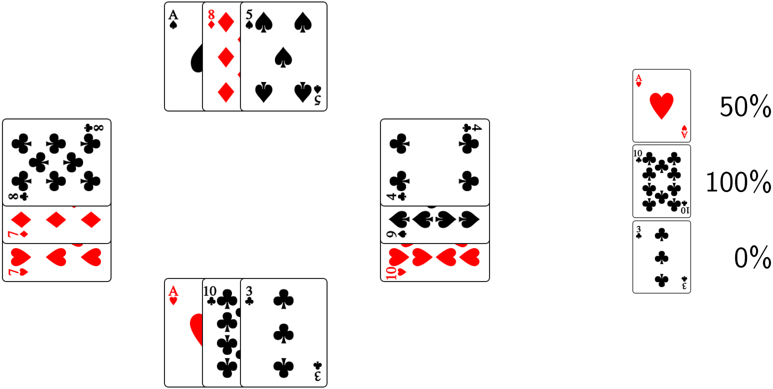
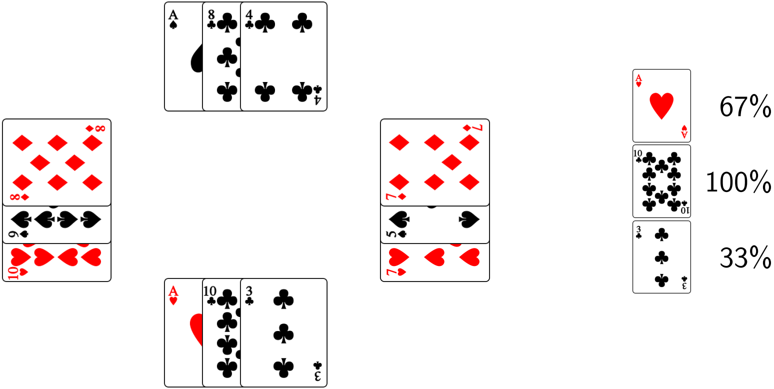


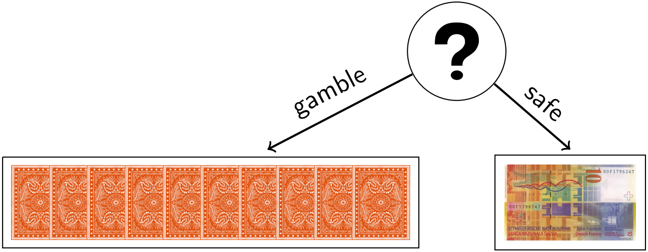
# Hindsight Optimization: Example



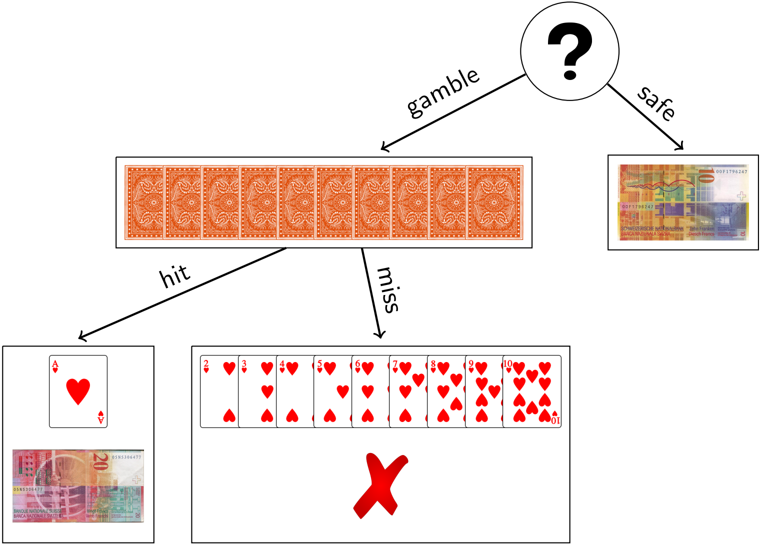
# Hindsight Optimization: Restrictions

- HOP well-suited for imperfect information games like most card games (Bridge, Skat, Klondike Solitaire)
- must be possible to solve or approximate sampled game efficiently
- often not optimal even if provided with infinite resources

# Hindsight Optimization: Suboptimality



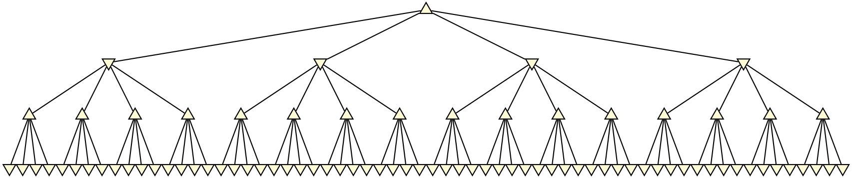
# Hindsight Optimization: Suboptimality



# Sparse Sampling

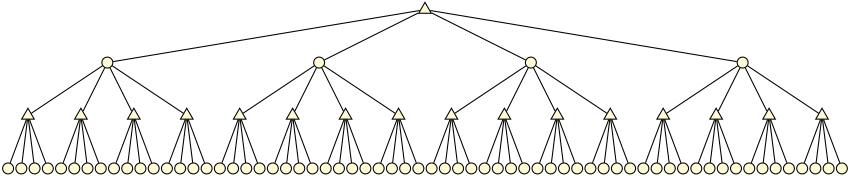
# Reminder: Minimax for Games

Minimax: alternate maximization and minimization



# Excursion: Expectimax for MDPs

Expectimax: alternate maximization and expectation
(expectation = probability weighted sum)

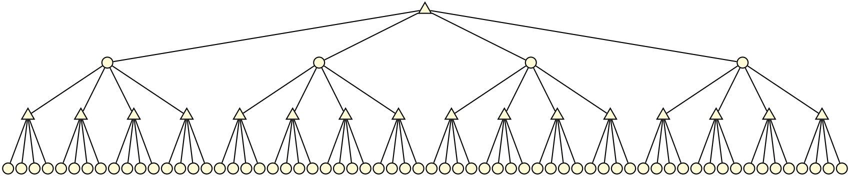


# Sparse Sampling: Idea

- search tree creation: sample a constant number of outcomes according to their probability in each state and ignore the rest
- update values by replacing probability weighted updates with average
- near-optimal: utility of resulting policy close to utility of optimal policy
- runtime independent from the number of states

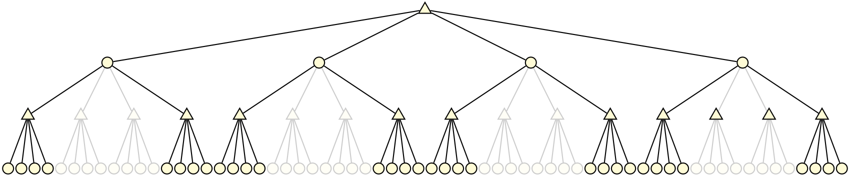
# Sparse Sampling: Search Tree

Without Sparse Sampling



# Sparse Sampling: Search Tree

With Sparse Sampling



# Sparse Sampling: Problems

- independent from number of states, but still exponential in lookahead horizon
- constant that gives the number of outcomes large for good bounds on near-optimality
- search time difficult to predict
- tree is symmetric $\Rightarrow$ resources are wasted in non-promising parts of the tree

# MCTS

# Monte-Carlo Tree Search: Idea

- perform iterations as long as resources (deliberation time, memory) allow:
- builds a search tree of nodes $n$ with annotated
  - utility estimate $\hat{Q}(n)$
  - visit counter $N(n)$
- initially, the tree contains only the root node
- execute the action that leads to the node with the highest utility estimate

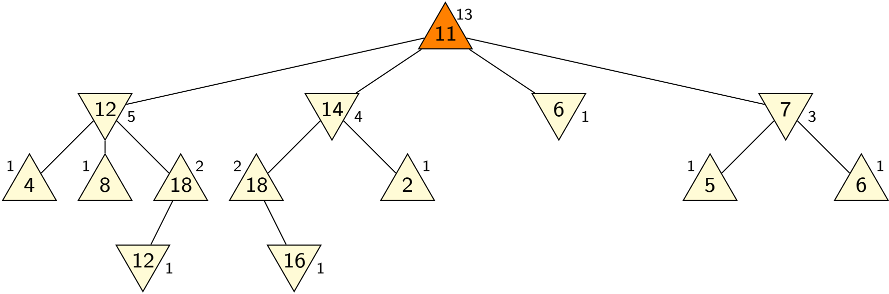
# Monte-Carlo Tree Search: Iterations

Each iteration consist of four phases:

- selection: traverse the tree by applying tree policy
- expansion: add to the tree the first visited state that is not in the tree
- simulation: continue by applying default policy until terminal state is reached (which yields utility of current iteration)
- backpropagation: for all visited nodes $n$,
  - increase $N(n)$
  - extend the current average $\hat{Q}(n)$ with yielded utility

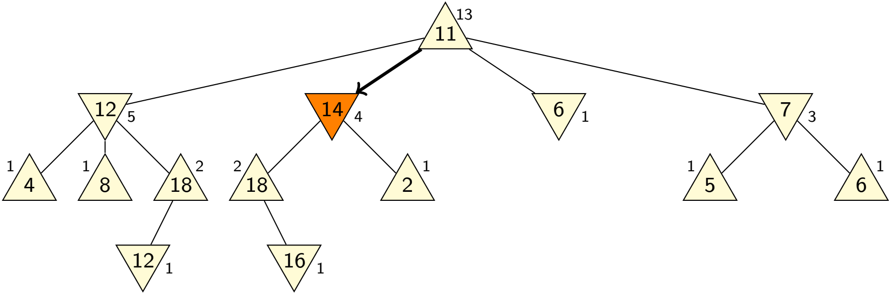
# Monte-Carlo Tree Search

Selection: apply tree policy to traverse tree



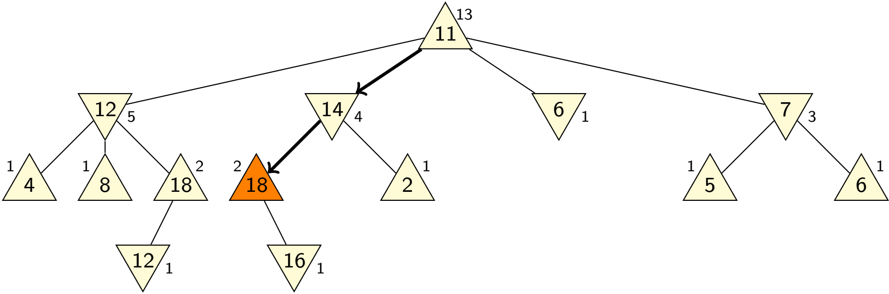
# Monte-Carlo Tree Search

Selection: apply tree policy to traverse tree



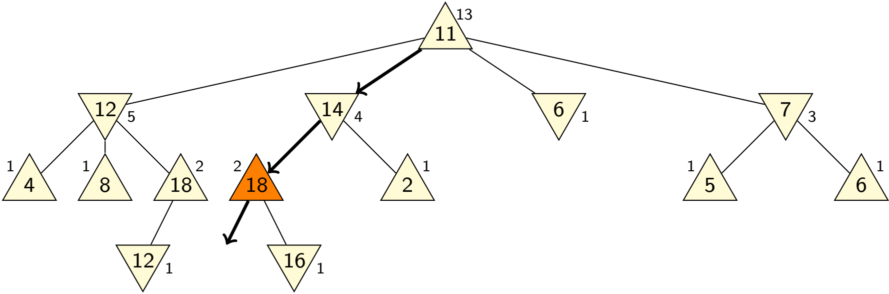
# Monte-Carlo Tree Search

Selection: apply tree policy to traverse tree



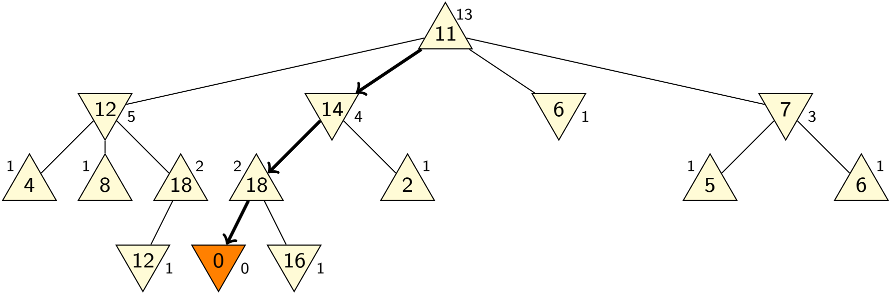
## Monte-Carlo Tree Search

Selection: apply tree policy to traverse tree



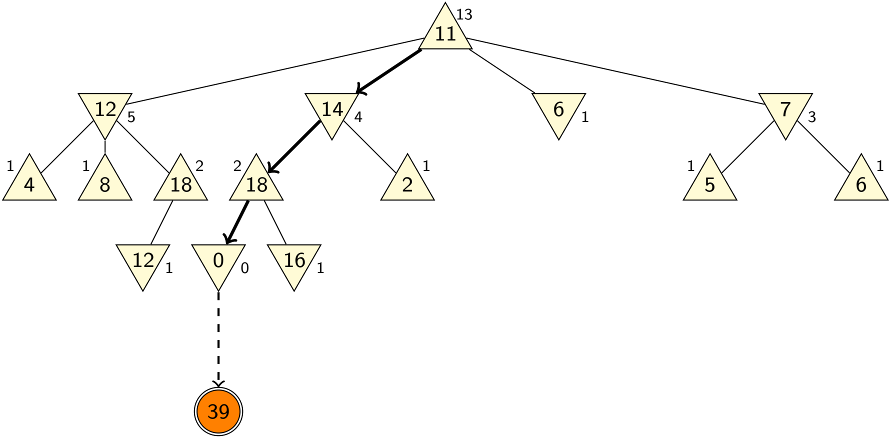
# Monte-Carlo Tree Search

Expansion: create a node for first state beyond the tree



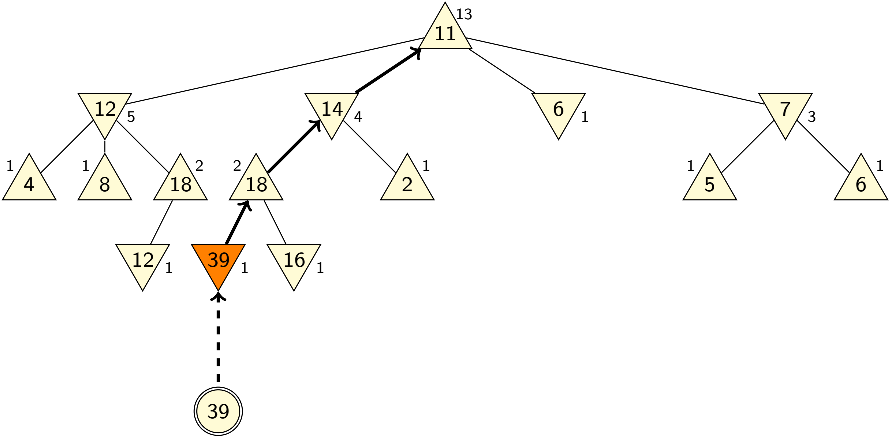
# Monte-Carlo Tree Search

Simulation: apply default policy until terminal state is reached



# Monte-Carlo Tree Search

Backpropagation: update utility estimates of visited nodes



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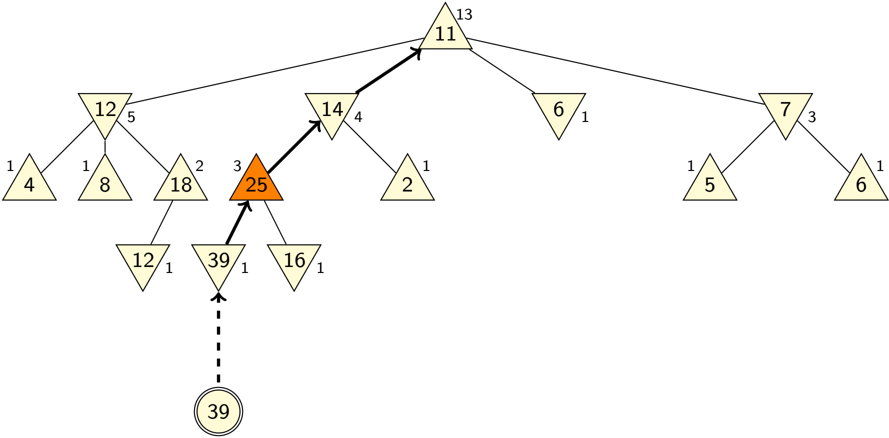

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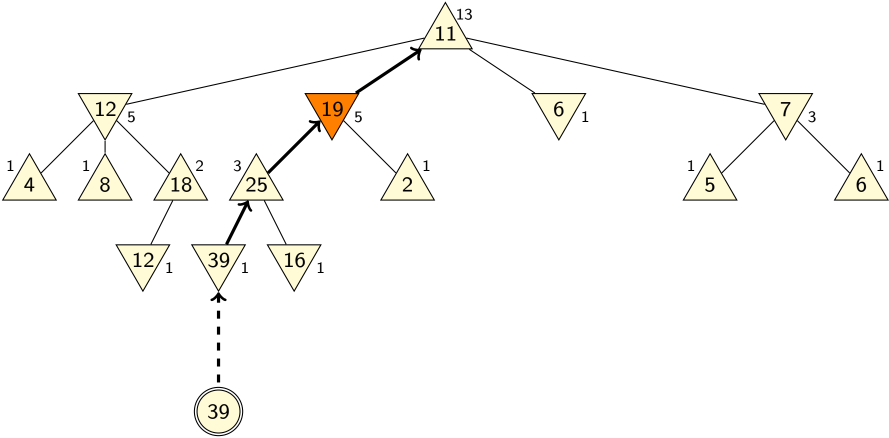
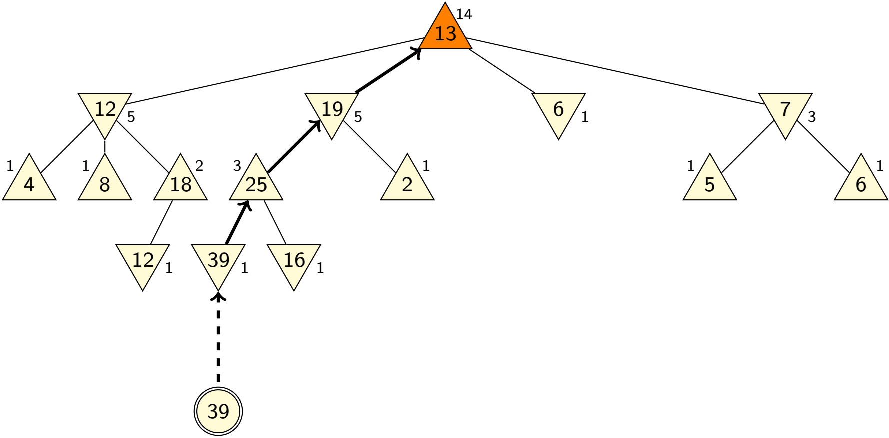


# Monte-Carlo Tree Search

Backpropagation: update utility estimates of visited nodes



# Monte-Carlo Tree Search: Pseudo-Code

## Monte-Carlo Tree Search

*tree* := **new** SearchTree
$n_0 = tree$.add_root_node()
**while** time_allows():
    visit_node($tree$, $n_0$)
$n^\star = \arg\max_{n \in \text{succ}(n_0)} \hat{Q}(n)$
**return** $n^\star$.get_action()

# Monte-Carlo Tree Search: Pseudo-Code

**function** visit_node($tree$, $n$)

**if** is_final($n$.state):
    **return** $u$($n$.state)
$s$ = $tree$.get_unvisited_successor($n$)
**if** $s \neq$ **none**:
    $n'$ = $tree$.add_child_node($n$, $s$)
    $utility$ = apply_default_policy()
    backup($n'$, $utility$)
**else**:
    $n'$ = apply_tree_policy($n$)
    $utility$ = visit_node($tree$, $n'$)
backup($n$, $utility$)
**return** $utility$

# Summary

# Summary

- Simple Monte-Carlo methods like Hindsight Optimization perform well in some games, but are suboptimal even with unbound resources
- Sparse Sampling allows near-optimal solutions independent of the state size, but it wastes time in non-promising parts of the tree
- Monte-Carlo Tree Search algorithms iteratively build a search tree. Algorithms are specified in terms of a tree policy and a default policy.