Foundations of Artificial Intelligence

44. Monte-Carlo Tree Search: Introduction

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Board Games: Overview

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44.1 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 ⇝ this chapter
- 2002: Kearns et al. propose Sparse Sampling ⇝ this chapter
- 2002: Auer et al. present UCB1 action selection for multi-armed bandits ⇝ Chapter 45
- 2006: Coulom coins the term Monte-Carlo Tree Search (MCTS) ⇝ this chapter
- 2006: Kocsis and Szepesvári combine UCB1 and MCTS to the most famous MCTS variant, UCT ⇝ Chapter 45

Monte-Carlo Tree Search: Applications

Examples for successful applications of MCTS in games:

- board games (e.g., Go ⇝ Chapter 46)
- 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)

44.2 Monte-Carlo Methods

Monte-Carlo Methods: Idea

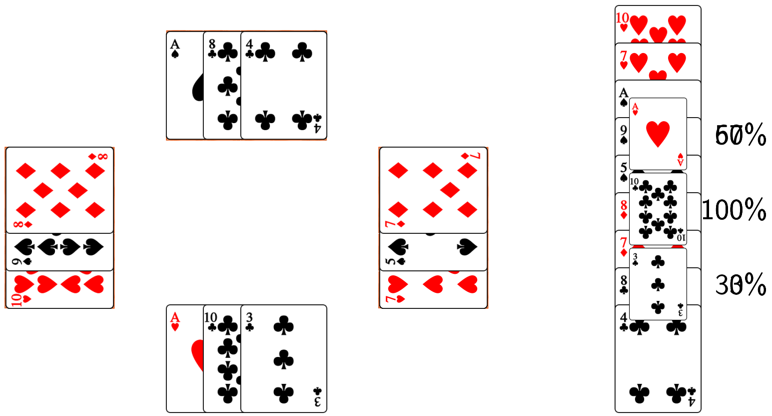
- summarize a broad family of algorithms
- decisions are based on random samples
- results of samples are aggregated by computing the average
- apart from that, algorithms can differ significantly

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

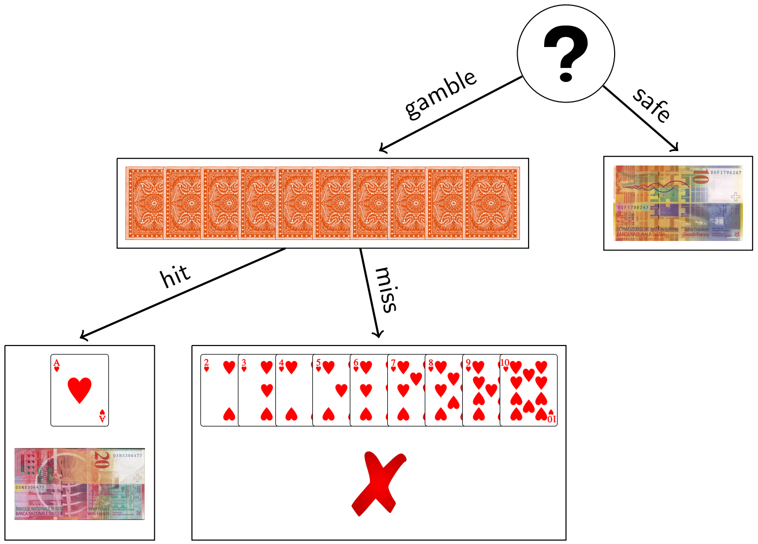
Hindsight Optimization: Example



Hindsight Optimization: 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

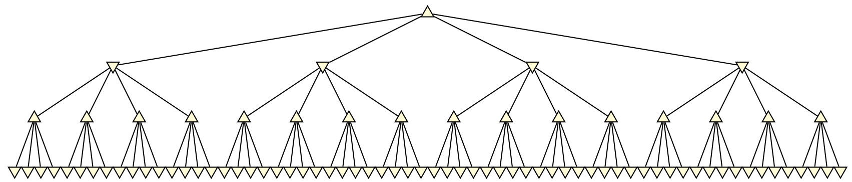
Hindsight Optimization: Suboptimality



44.3 Sparse Sampling

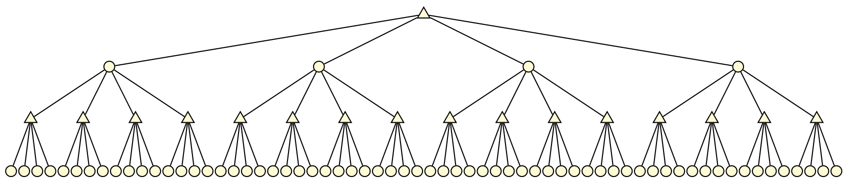
Reminder: Minimax for Games

Minimax: alternate maximization and minimization



Excursion: Expectimax for MDPs

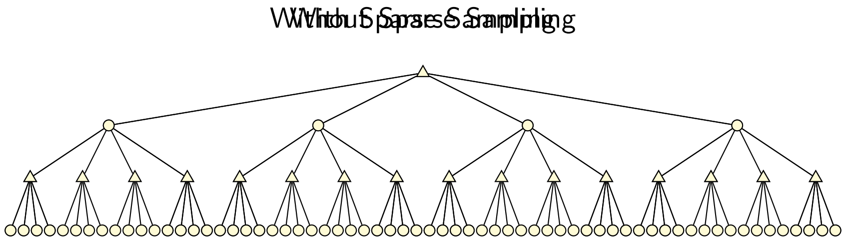
Expectimax: alternate maximization and expectation
(expectation = probability weighted sum)



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



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 ⇒ resources are wasted in non-promising parts of the tree

44.4 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

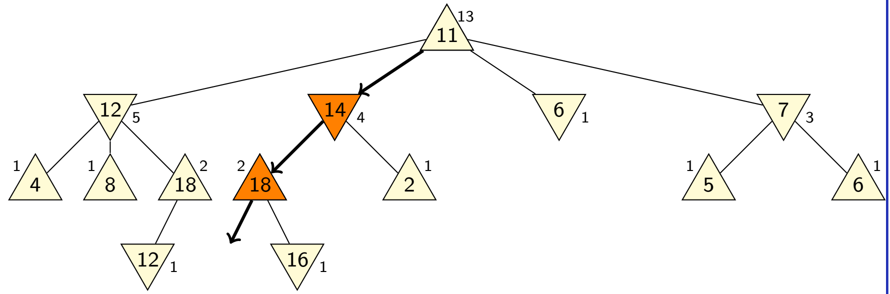
Monte-Carlo Tree Search: Iterations

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

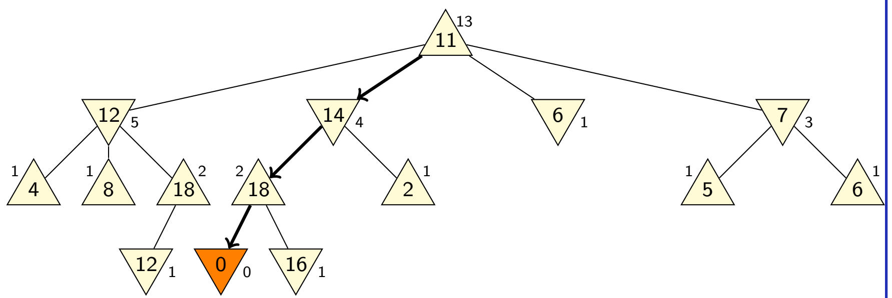
Monte-Carlo Tree Search

Selection: apply tree policy to traverse tree



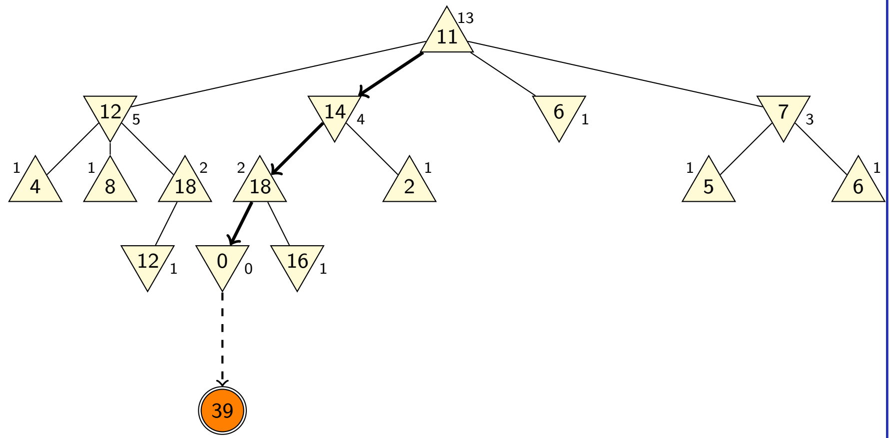
Monte-Carlo Tree Search

Expansion: create a node for first state beyond the tree



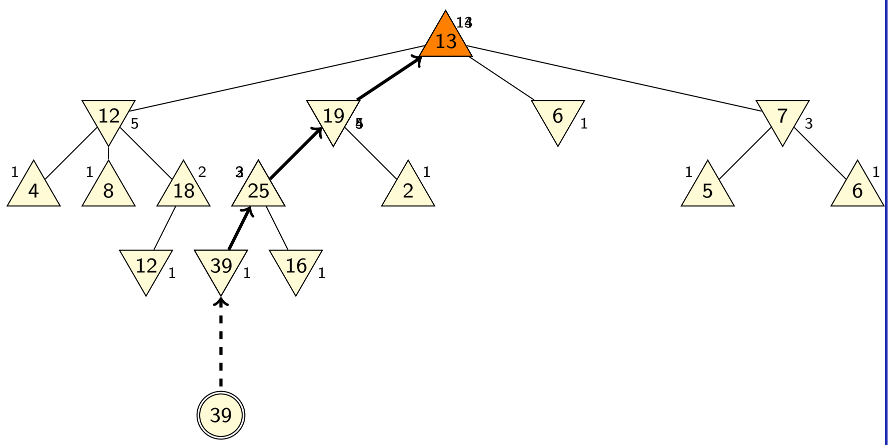
Monte-Carlo Tree Search

Simulation: apply default policy until terminal state is reached



Monte-Carlo Tree Search

Backpropagation: update utility estimates of visited nodes



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 $u(n.\text{state})$
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*

44.5 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.
  (We analyze its theoretical properties in the next chapter)