Monte Carlo Tree Search

Tackleing high branching factors

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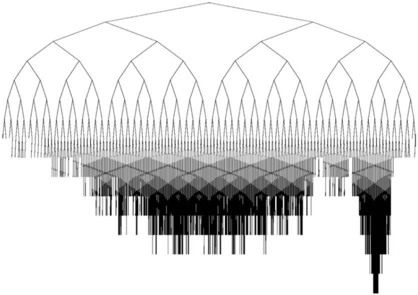

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What are we going to learn?

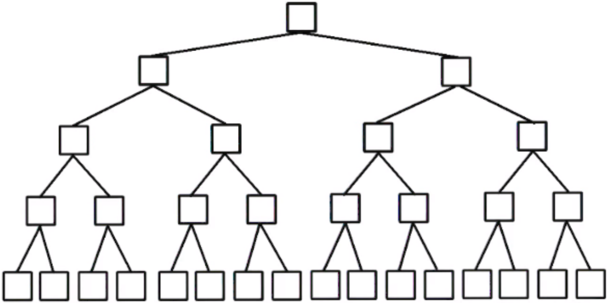
1. Introduction
   - Recap: Game tree search
   - Motivation: Why use MCTS?
2. Step back: Decision Theory
   - Markov Decision Processes
   - Application to combinatorial games
3. Vanilla MCTS
   - Dynamic tree building
   - Rollout and backpropagation
   - Policies
4. Exploration & Exploitation
   - Multi-armed bandits
   - Upper confidence bound action selection
   - The UCT algorithm
   - Enhancements
5. How well does it do? - Examples
6. Conclusion

Recap: Game tree search

- Game tree: depth d, branching factor b
- minimax: b^d (leave nodes grow exponentially)
- $\alpha - \beta$ speed up: $b^{d/2}$
- Domain dependent heuristics: e.g. quiescence search, null-move pruning

$\rightarrow$ success depends on evaluation function

$\rightarrow$ very limited search depth for large b (Chess $\bar{b} \approx 35$, Go $\bar{b} \approx 250$)



Motivation: Why use MCTS?

- No evaluation function needed! (domain independent)
- Grows a tree instead of pruning it $\rightarrow$ high branching factors not so bad
- Built-in "iterative deepening" and asymmetric tree growth
- Used by *Alpha Zero*, *Leela Chess Zero* and even *Total War: Rome II*

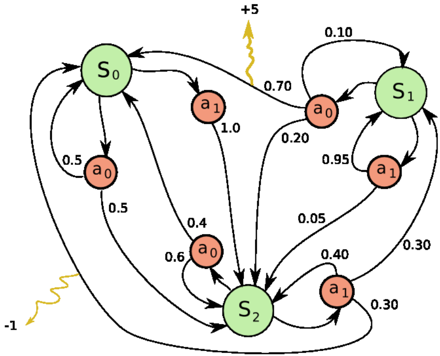
Takeaways

- Generality of MCTS
- Be able to implement MCTS by your own

Model for a sequential decision problem:

- Set of states S
- Set of actions A
- transition model $T(s, a, s')$
  $\rightarrow$ Markov property
- reward $R(s, a, s')$

Objective:
Find function $\pi : S \rightarrow A$ that maximizes expected reward $\bar{R}$



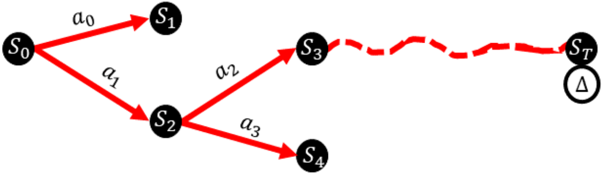
towardsdatascience.com

Application to combinatorial games

Combinatorial games

Two player, zero-sum, perfect information, deterministic, sequential

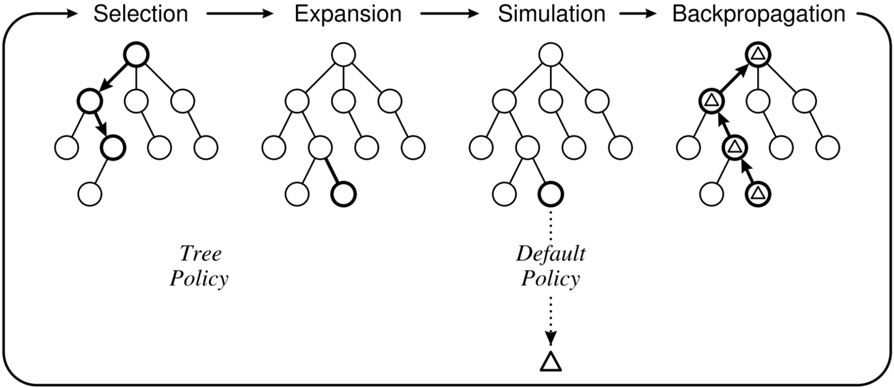
- $S \triangleq$ all possible board positions
- $A \triangleq$ all possible moves
- transition model $T(s,a,s') = \begin{cases} 0 \text{ if } a \text{ is illegal} \\ 1 \text{ if } a \text{ is legal} \end{cases}$
- reward $R(s,a,s') = \begin{cases} 0 \text{ if } s' \text{ is non} - \text{terminal} \\ \Delta \text{ if } s' \text{ is terminal} \end{cases}$



Step 1 Start MCTS in root (current) node

Step 2 Run until a computational/time constraint is met

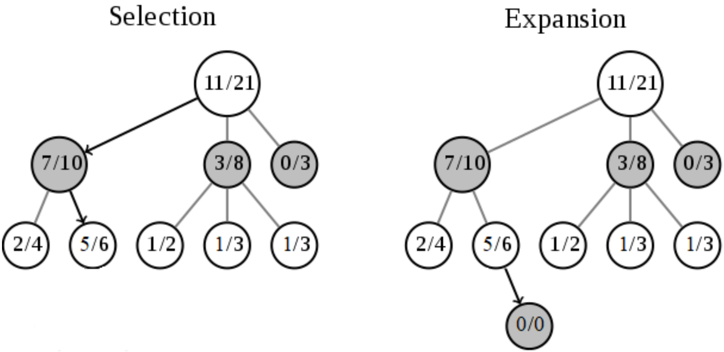
Step 3 Take action to the "best" child node → Step 1



Browne et al. [2]

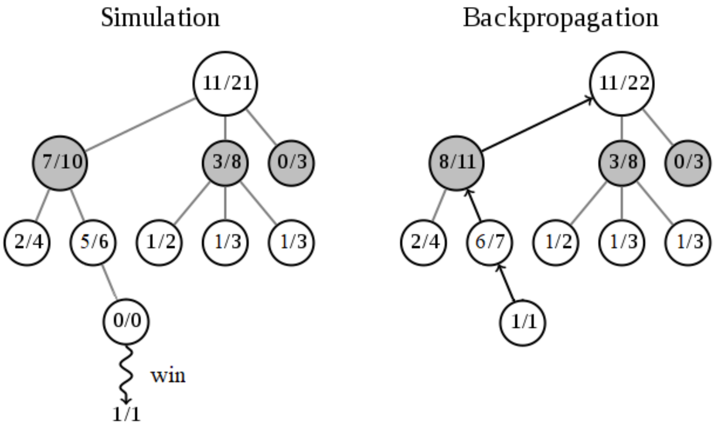
Dynamic tree building

- Selection of child nodes based on node statistics (here: wins/visits $\approx Q$-value)
- Expansion of the tree when reaching a leave node



Rollout and backpropagation

- Simulation until reaching sufficient depth (here: terminal state)
- Update of node statistics based on the simulation outcome



Policies

Rollout/default policy

- responsible for simulation $\rightarrow$ value estimation
- usually: select random action at every node (*flat* Monte-Carlo)
- *AlphaGo*: rollout replaced by NN value estimation

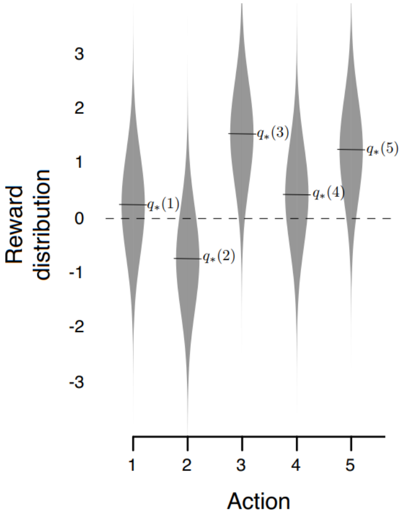
Tree policy

- responsible for selection and expansion $\rightarrow$ building a useful tree
- for example: $\hat{a}(s) = \mathrm{argmax}_a(Q(s'))$ $\rightarrow$ this is too greedy!
- Ideally: *always* select action close to, and ultimately converge to the optimal action $\rightarrow$ UCT algorithm (Kocsis and Szepesvari [5])

- Slot-machine with k arms and random payoffs X_j
- Task: maximize payoff over a period of time
- But: the reward distributions are unknown

  → Trade-off needed between exploration of the reward distribution and its exploitation

  → Policy must consider mean μ_j and variance σ_j of the sample distribution



Sutton et al. [6]

Upper confidence bound (UCB) action selection

- Basic idea: Select arm that maximizes an UCB, e.g. $\hat{a} = \mathrm{argmax}_a(\mu_j + \sigma_j)$
- Problem: some trade-off, but no game-theoretic guarantees
- Solution: use an UCB that minimizes the *regret* $R_N = \mu^* N - \sum_j \mu_j \mathbf{E}[N_j]$

$$UCB1 = \mu_j + \sqrt{2 \ln N / N_j} \text{ (Auer et al. [1])}$$

$\rightarrow$ Growth of R_N within a factor of an optimal policy

$\rightarrow$ Also applicable to non-stationary distributions! [5]

The UCT algorithm (Upper Confidence bounds for Trees)

Back to MCTS: Model node selection as multi-armed bandit problem

- Arms correspond to actions
- Payoffs correspond to expected reward Q_j/N_j

UCT policy

$\hat{a} = \mathrm{argmax}_a(Q_j/N_j + C \cdot \sqrt{2 \ln N/N_j})$

- large first term: exploitation
- large second term: exploration, C domain-dependent parameter
- For $N \to \infty$, game-theoretic minimax tree is built!

Enhancements

Tree-policy:

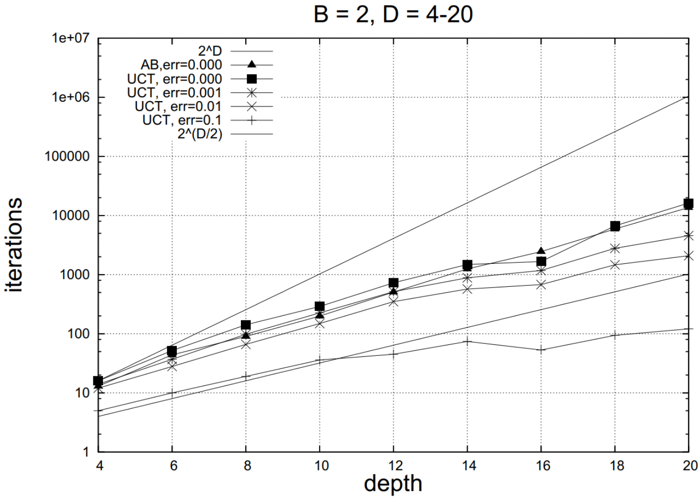
- First Play Urgency → encourage early exploitation
- Progressive bias → blend in heuristic value for low visit count
- Search seeding → keep value estimates of previous MCTS runs

Rollout policy: e.g. use (learned) evaluation function
Update step: e.g. All Moves As First (AMAF)
General enhancements:

- Parallelization → run MCTS multiple times
- Pruning

Overview: Browne et al., *A Survey of Monte Carlo Tree Search Methods*, 2012 [2]

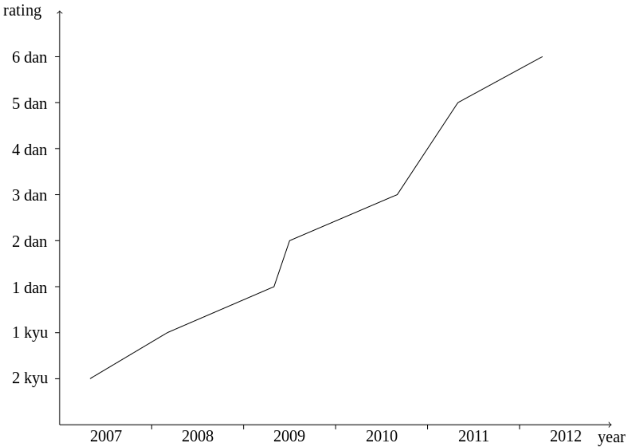
Example: random game trees (P-games)



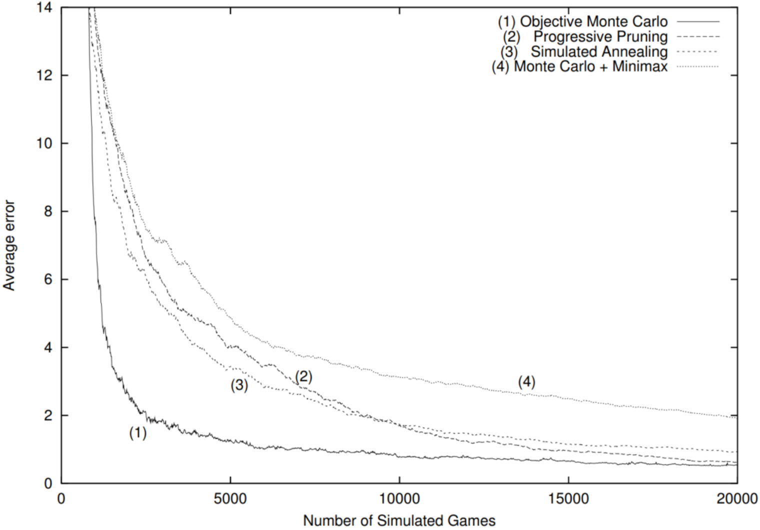
Koscsis and Sepesvari [5]

Example: Go

Improvements in computer Go since onset of MCTS



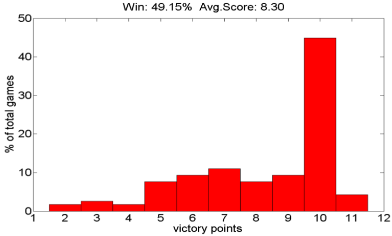
Example: Go



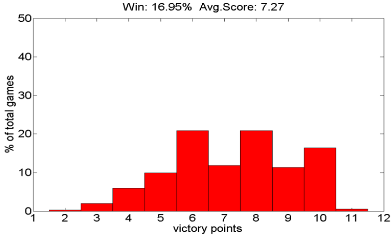
Chaslot et al. 2006 [4]

Example: Settlers of Catan

- JSettlers is a handcrafted agent
- 1 MCTS player (with some domain knowledge) vs 3 JSettlers



MCTS-10000 player



JSettlers player

Szita et al. [7]

Conclusion

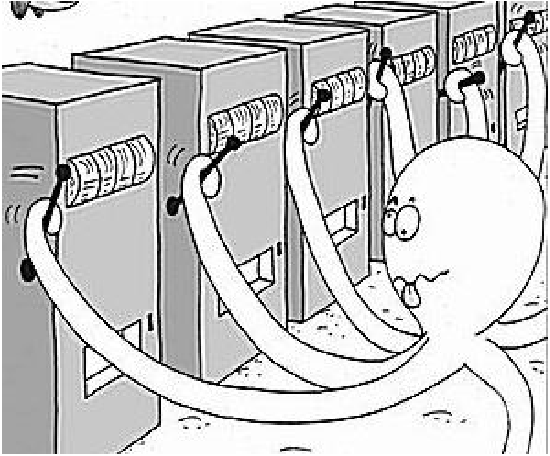
MCTS is ...

- ... a way to iteratively approximate decision trees
- ... employing random simulations to deal with delayed rewards
- ... aheuristic while converging to an optimal strategy
- ... more similar to how humans play games
- ... an important part of modern RL systems

However, ...

- ... still needs domain knowledge to produce human-like performance
- ... runs/games are independent $\rightarrow$ there is no learning, intelligence?

Thank you for your attention!
Questions? Ideas? Comments?



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References I

P. Auer, N. Cesa-Bianchi, and P. Fischer.
Finite-time analysis of the multiarmed bandit problem.
Machine Learning, 47(2):235–256, May 2002.

C. B. Browne, E. Powley, D. Whitehouse, S. M. Lucas, P. I. Cowling, P. Rohlfshagen, S. Tavener, D. Perez, S. Samothrakis, and S. Colton.
A Survey of Monte Carlo Tree Search Methods.
IEEE Transactions on Computational Intelligence and AI in Games, 4(1):1–43, 2012.

G. Chaslot, S. Bakkes, I. Szita, and P. Spronck.
Monte-Carlo Tree Search: A New Framework for Game AI.
In *AIIDE*, 2008.

G. Chaslot, J. takeshi Saito, J. W. H. M. Uiterwijk, B. Bouzy, and H. J. Herik.
Monte-Carlo Strategies for Computer Go.

References II

L. Kocsis and C. Szepesvári.
Bandit based Monte-Carlo Planning.
In *In: ECML-06. Number 4212 in LNCS*, pages 282–293. Springer, 2006.

R. S. Sutton, A. Barto, and A. G. Barto.
Reinforcement Learning.
Adaptive computation and machine learning. MIT Press, Cambridge, Mass. [u.a.], 3. printing edition, 2000.

I. Szita, G. Chaslot, and P. Spronck.
Monte-Carlo Tree Search in Settlers of Catan.
volume 6048, pages 21–32, 05 2009.