University of Basel

Monte Carlo Tree Search for Carcassonne

Bachelor's Thesis

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Outline

Why Monte Carlo Tree Search?

- Monte Carlo Tree Search (MCTS) has been successfully applied to:
  - Hex
  - Lines of Action
  - Settlers of Catan
  - Go
- Hayden (2009) and Ameneyro et al. (2020) have suggested that MCTS produces good results on Carcassonne.
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Research Objectives

- Evaluating different variants of Monte Carlo Tree Search in regard to their performance on Carcassonne.
- Evaluating if the most powerful variant is capable of beating a human player.

Carcassonne

- Carcassonne is a tile-based board game for between two and five players.
- The board is iteratively built by placing tiles over the course of 72 rounds.
- Points are made by placing *meeples* strategically.
- Large state space with at least $5 \cdot 10^{40}$ reachable positions and a game tree with around 10^{192} terminal nodes (Heyden, 2009).

Source: https://www.dadsgamingaddiction.com/carcassonne/ (23.06.2022)

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Monte Carlo Tree Search

- MCTS is a method for finding optimal decisions in a given domain.
- It "combines the precision of tree search with the generality of random sampling" (Browne et al., 2012, p. 1).
- This is achieved by taking random samples in the state space and building a search tree according to the results.

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Training

- During training, a game tree is iteratively built.
- Each node has a visit count N and an expected score Q, which get updated during training.
- Each training iteration consists of four steps.

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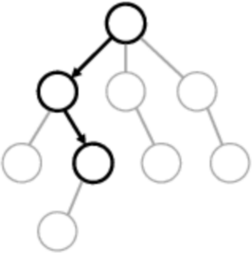
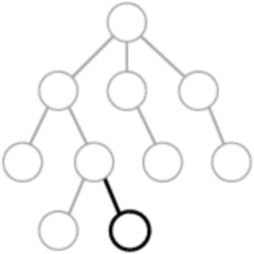
Step 1: Selection



- Traverse the game tree according to the *tree policy*, which maps each node to one of its children.
- Do this until an expandable node is reached.

Image Source: James et al. (2017), p. 2

Step 2: Expansion



- Add at least one child node and visit that child.

Image Source: James et al. (2017), p. 2

Step 3: Simulation

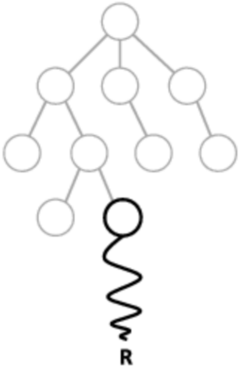
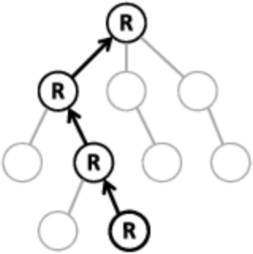


Image Source: James et al. (2017), p. 2

- Simulate the game until the end with moves decided by the *default policy*.
- Thereby sample a score R.
- The simulation can be replaced by a function with domain-specific knowledge.

Step 4: Backpropagation



The sampled score R is propagated back up the chosen path. For each node:

- $N \leftarrow N + 1$
- $Q \leftarrow Q + \frac{R - Q}{N}$

Image Source: James et al. (2017), p. 2

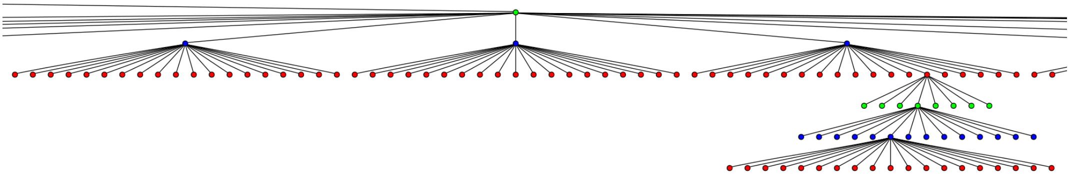
Practical Steps

1. Implementing Carcassonne.
2. Implementing the MCTS framework.
3. Testing and evaluating different MCTS configurations.

Implementation of Carcassonne

- Implemented in Java.
- Allows for MCTS variants and humans to play Carcassonne.
- The repository is publicly accessible under `https://github.com/maxjappert/mcts_carcassonne`

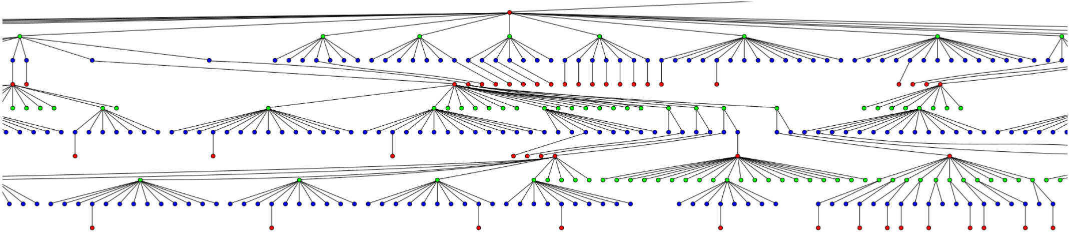
Implementation: Game Tree



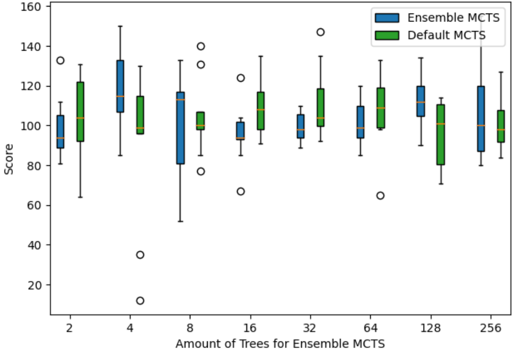
- Chance nodes: Randomly drawing a tile
- Placement nodes: Placing a tile
- Meeple nodes: Placing a meeple

Implementation: Ensemble MCTS

- Alternative way of modelling randomness.
- k trees are built, whereby each assumes a fixed deck permutation.
- After training all trees "vote" on which move to pick.



Evaluation: Single Game Tree vs. Ensemble MCTS



$\rightsquigarrow$ Certain Ensemble MCTS configurations lead to performance increase.

Implementation: Degree of Exploration

- All "useful" tree policies are a function of the children's Q-value, because the game tree should be expanded in profitable directions.
- All "useful" tree policies must balance this exploitation with a degree of exploration.
- $\rightsquigarrow$ Most tree policies have an exploration parameter, which determines the degree of exploration.

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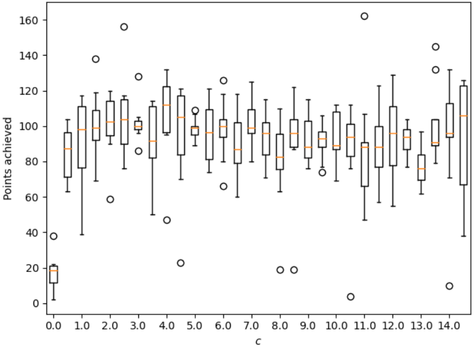
Evaluation: Degree of Exploration



$\rightsquigarrow$ Severe performance drop when exploration seizes.

Evaluation: Tree Policies

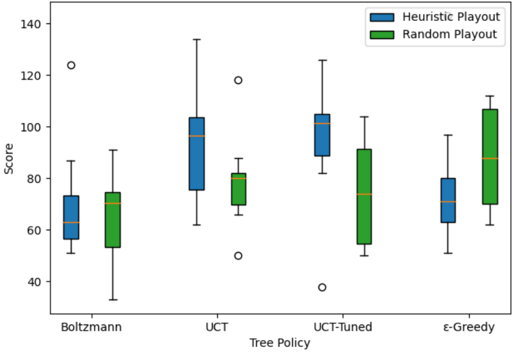
Measured \ Opponent	UCT	UCT-Tuned	Boltzmann	ε-Greedy	Dec. ε-G.	Heur. MCTS	Heuristic	Random
UCT	–	38.2%	**63.9%**	44.4%	**72.2%**	**83.3%**	**81.1%**	**100.0%**
UCT-Tuned	**61.8%**	–	**70.3%**	**51.4%**	**80.6%**	**86.1%**	**77.8%**	**100.0%**
Boltzmann	36.1%	29.7%	–	27.8%	**81.1%**	**63.9%**	**62.9%**	**100.0%**
ε-Greedy	**55.6%**	48.6%	**72.2%**	–	**86.5%**	**83.8%**	**78.4%**	**100.0%**
Decaying ε-Greedy	27.8%	19.4%	18.9%	13.5%	–	31.4%	**51.4%**	**89.2%**
Heuristic MCTS	16.7%	13.9%	36.1%	16.2%	**68.6%**	–	**59.5%**	**100.0%**
Heuristic	18.9%	22.2%	37.1%	21.6%	48.6%	40.5%	–	**100.0%**
Random	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	8.6%	–

$\rightsquigarrow$ UCT-Tuned performed best.

Implementation: Simulation Step

- Usually consists of randomly selecting moves.
- Adding domain-specific knowledge can potentially improve performance.
- We tested two alternatives:
  - Heuristic default policy
  - Direct heuristic evaluation

Evaluation: Heuristic Default Policy



⇝ A heuristic-guided playout increases performance slightly, but also increases the runtime by a factor of 30.

Evaluation: Direct-Heuristic Evaluation

- Decreases runtime per training iteration by a factor of 30 compared to using random sampling.
- Performed slightly worse than a random playout when considering a similar runtime.

Evaluation: Playing against MCTS

- We played six games against the strongest implementation.
- It won five of those games with an average score of 95.3 to 88.3.

Conclusion

- MCTS produces good results on the domain of Carcassonne.
- We found a variant which can outperform an average human player. This variant has the following properties:
  - UCT-Tuned as a tree policy.
  - Decaying exploration parameter of $c = 512/t$ for t training iterations.
  - Simulation with a random default policy.
  - Ensemble MCTS with four trees, 750 training iterations each.
- Interesting for further research:
  - Considering probability distribution over the deck in the game tree.
  - Optimising the heuristic functions.
  - Training a neural network to approximate the score given a state.
  - Bounding the simulation.

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Thank you
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