Predicting Opponent Moves for Improving Hearthstone AI

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Contents

Hearthstone – an Online Card Game

- Hearthstone is an online collectible card game
- 2 players play a single game using a self-constructed deck of 30 out of more than 1000 cards
- Next to a small amount of standard-cards most cards have unique effects and

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Hearthstone – Game Components and States

Monte Carlo Tree Search (MCTS)

Monte Carlo Tree Search (MCTS): Adding Monte Carlo simulations (or rollouts) after adding a new node to the tree.

Two different policies are used on each episode:

- **Tree Policy:** Selecting a node for expansion in the search tree (e.g. Greedy, UCB).
- **Default Policy:** Control the simulations outside the tree (e.g. picking actions at random)

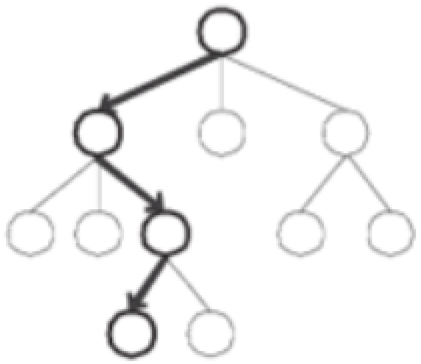
UCB1

$$a_t = \arg\max_{a \in A} \underbrace{Q_t(a)}_{\text{Exploitation}} + C \underbrace{\sqrt{\frac{\ln N(s)}{N(s,a)}}}_{\text{Exploration}}$$

Monte Carlo Tree Search - Tree Policy

1. Tree Selection:

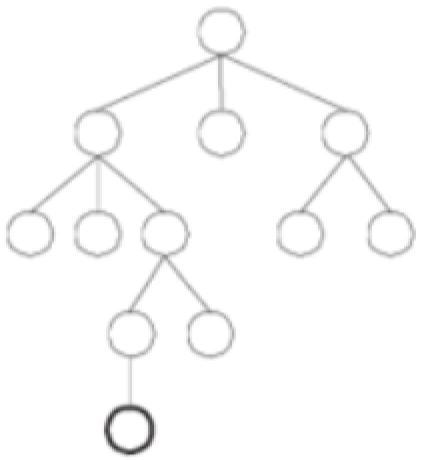
Following the **tree policy** (i.e. UCB1), navigate the tree until reaching a node with at least one child state that was not explored yet.



2. Expansion:

Add a new node in the tree, as a child of the node reached in the tree selection step.

- this node resembles an action

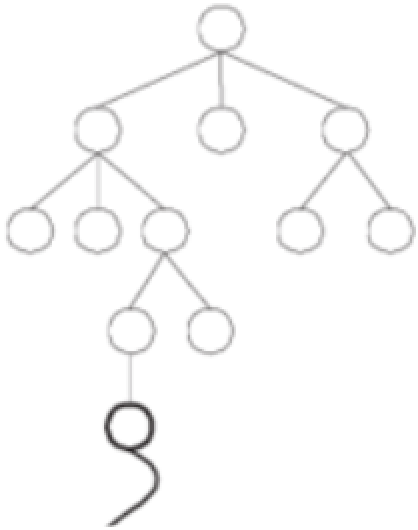


Monte Carlo Tree Search - Default Policy

3. Monte Carlo Simulation/Rollout:

Following the **default policy**, advance the state until a terminal state or a pre-defined maximum number of steps.

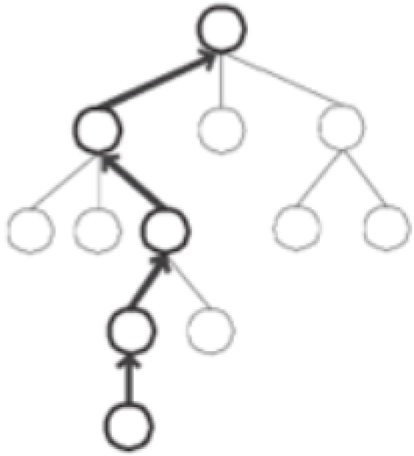
- calculate the return of this episode.



4. Back-propagation:

Update the values of $Q(s, a)$, $N(s)$ and $N(s, a)$ of the nodes visited in the tree during steps 1 and 2.

- Values of nodes visited during the simulation will not be updated.



Why we cannot use MCTS effectively?

- Monte Carlo Tree search needs a Forward Model for executing many simulations starting from the current state
  - We now the rules of the game, so the Forward Model is available
  - But we do not know the current state of the system!

- The player does not know the real state of the game, which consists of
  - The board state
  - The own and the opponent‘s cards
  - The cards in both decks
  - All previously played cards

Sources of Uncertainty

- Specifically the player does not know:
  - Which specific cards he will draw in the future
  - Which cards the opponent has on his hand or in the deck

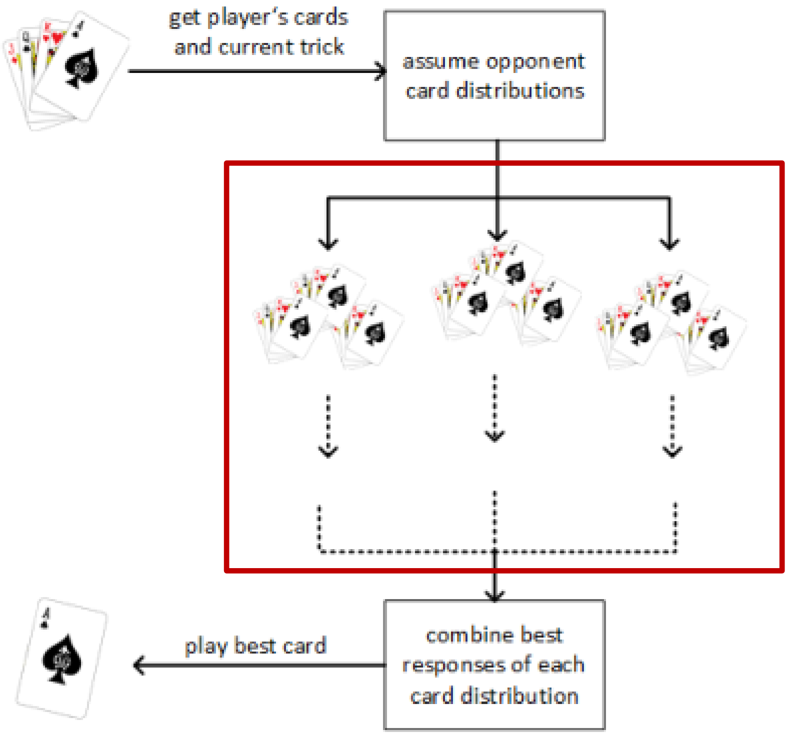
- We need to adapt Monte Carlo Tree Search as long as we do not know the current game state.

MCTS for an Unknown Card Distribution

- If the real gamestate is unknown we can still guess multiple times:
  - information about the opponent‘s hero and cards that were already played restrict the open card pool

- Use and ensemble of MCTS agents with majority vote

- **This does not suffice in Hearthstone!**
  - **Too many possible card distributions**



Method used for Doppelkopf

Dockhorn, A., Doell, C., Hewelt, M., & Kruse, R. (2017). A decision heuristic for Monte Carlo tree search doppelkopf agents. In *2017 IEEE Symposium Series on Computational Intelligence (SSCI)* (pp. 1–8). IEEE. http://doi.org/10.1109/SSCI.2017.8285181

Deckbuilding

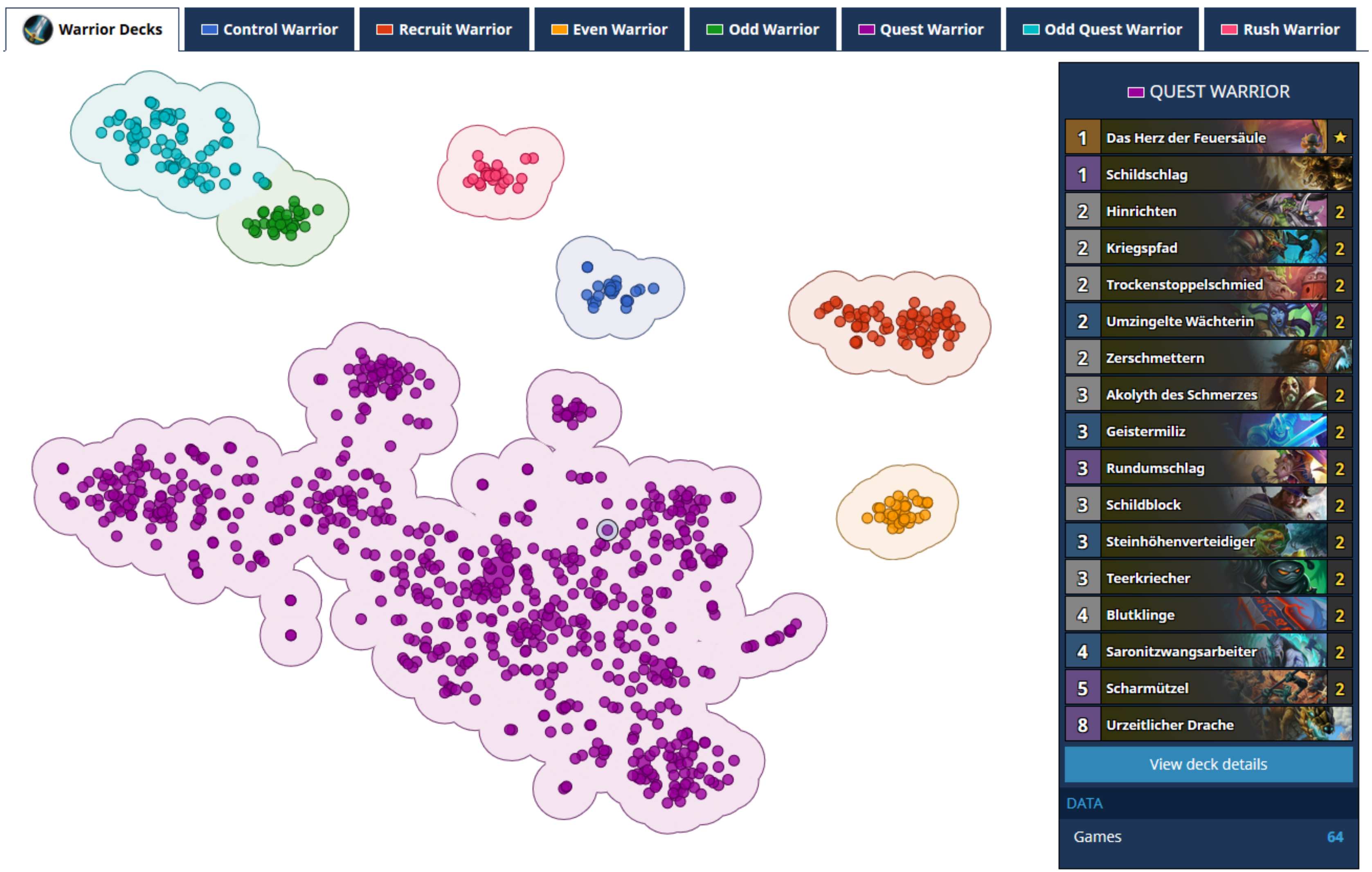
- By common knowledge popular decks often employ critical properties such as:
  - A stable mana curve
  - Strong synergies
  - A strategy to reach the win-condition
- Most decks can be categorized in deck types, which are common to the meta-game
  - Those decks often consist of similar cards, but do not necessarily contain the same 30 cards

Mana Curves

- The players can play their cards using mana
- Each turn the pool of available mana increases by one
- The mana curve of a deck describes how much cards per cost are included in the deck

Card Synergies

Meta-Decks


Warrior Decks
Control Warrior
Recruit Warrior
Even Warrior
Odd Warrior
Quest Warrior
Odd Quest Warrior
Rush Warrior
QUEST WARRIOR
1 Das Herz der Feuersäule
1 Schildschlag
2 Hinrichten 2
2 Kriegspfad 2
2 Trockenstoppelschmied 2
2 Umzingelte Wächterin 2
2 Zerschmettern
3 Akolyth des Schmerzes 2
3 Geistermiliz 2
3 Rundumschlag 2
3 Schildblock 2
3 Steinhöhenverteidiger 2
3 Teerkriecher 2
4 Blutklinge 2
4 Saronitzwangsarbeiter 2
5 Scharmützel 2
8 Urzeitlicher Drache
View deck details
DATA
Games 64

Finding Probable Card-Combinations

- Meta-decks and card synergies tell us that we have strong dependencies between cards in a deck
- We want to predict likely cards by observing frequent card-combinations in a database of played games
- Counting bi-grams of co-occuring cards:
  - **isolated**: cards need to be played at the same turn
  - **successive**: cards need to be played in successive turns
  - **combined**: isolated and successive counts are added

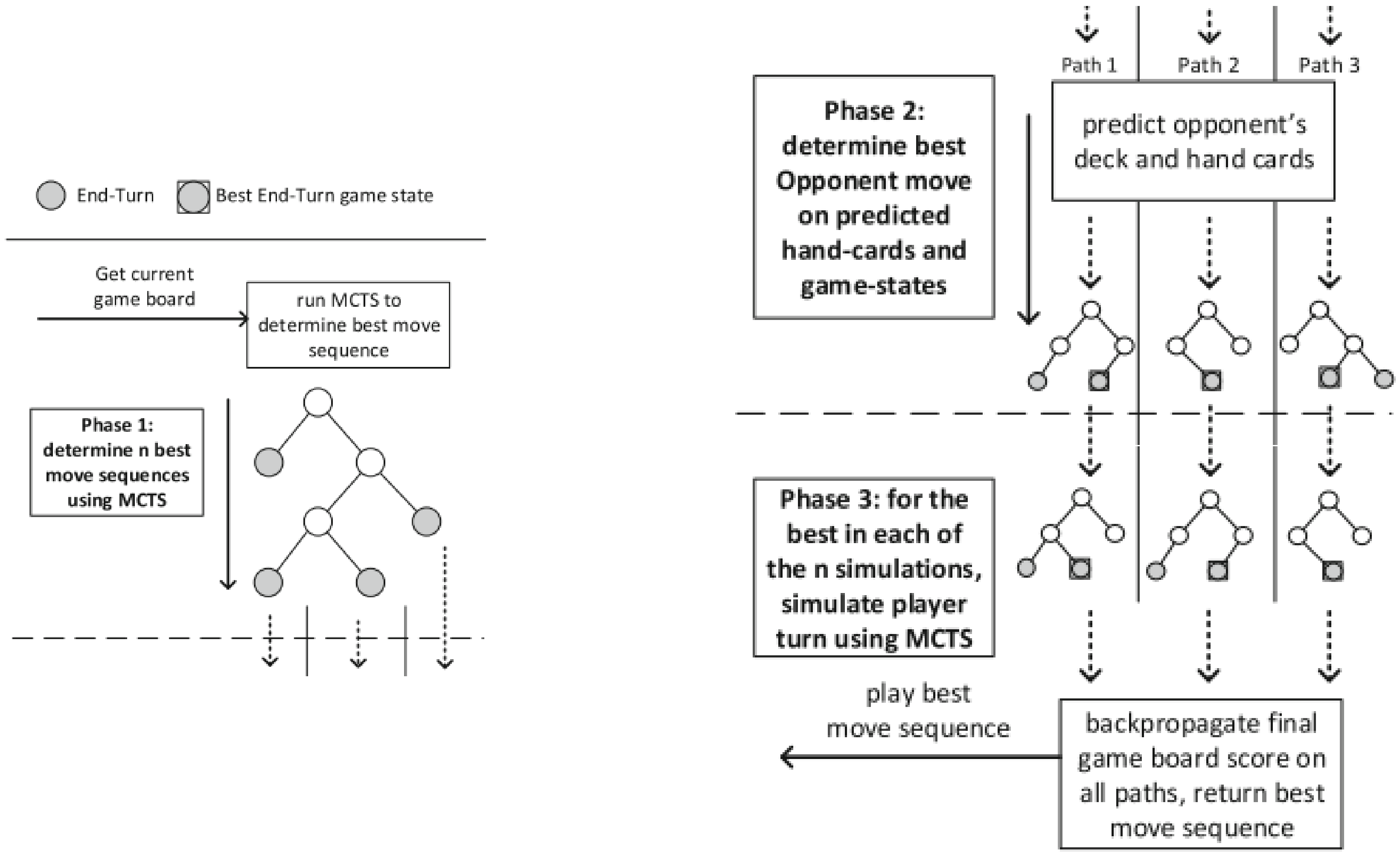
Adapting MCTS Gamestate Sampling

- A set of hand-cards is determined using the bi-gram database and all previously seen cards
    1. determine the number of co-occurences of each card
    2. filter possible cards by the rules of the deckbuilding process
    3. sample the opponent‘s hand cards based on the normalized co-occurence values

- Generate multiple set of opponent‘s hand cards and run MCTS on each of them

- Use (weighted) majority vote to determine the best card to be played

The overall Process



Evaluation

- We tested our agent against multiple other agents playing multiple decks
  - Random = randomly choose the next action
  - flatMC = flat Monte Carlo algorithm, simulate n times for each action
  - plainMCTS = MCTS using a randomly guessed game states
  - foMCTS = MCTS using the true game state (cheating)
  - Exh.s. = exhaustive search for best action, does not consider the opponent

Wins in %	Aggro	Mid	Control
Random	95	100	100
flatMC	81	73	94
plainMCTS	59	47	58
foMCTS	46	36	60
exh.s.	65	47	70

(a) predMCTS Aggro Deck

Wins in %	Aggro	Mid	Control
Random	99	98	100
flatMC	88	85	99
plainMCTS	71	55	76
foMCTS	59	50	76
exh.s.	62	70	85

(b) predMCTS Mid-Range Deck

Wins in %	Aggro	Mid	Control
Random	97	97	100
flatMC	73	54	89
plainMCTS	36	31	68
foMCTS	41	16	51
exh.s.	45	20	61

(c) predMCTS Control Deck

Conclusions

- Applying MCTS to Hearthstone is very limited due to missing information
  - Guessing a gamestate lets us apply MCTS with weak play strength

- Combining multiple of such guesses by creating an ensemble of MCTS helps but does not solve the problem efficient enough

- In this work we proposed a card-prediction to enhance the accuracy of sampling possible card distributions
  - An ensemble using such predicted gamestates is nearly as powerful as knowing the real gamestate

Limitations and Open Research Questions

- Our tests using an MCTS agent with full information on the current game-state show that a perfect prediction would yield slightly better results
  - Further improving the prediction accuracy promises to yield a stronger agent

➢ Explore the tradeoff between a complex prediction or more simulations/predicted card sets

➢ Can fuzzy sets and dempster-shafer theory help us to solve this problem more efficiently?

- We want to further explore meta-decks
  - How do they develop over time?
  - Can we detect changes in the meta and react accordingly?

➢ Important for deck-building and balancing!

Thank you for your attention!

Interested in trying it yourself? Check out our Hearthstone Competition at:
http://www.is.ovgu.de/Research/HearthstoneAI.html

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