Fuzzy Multiset Clustering for Metagame Analysis

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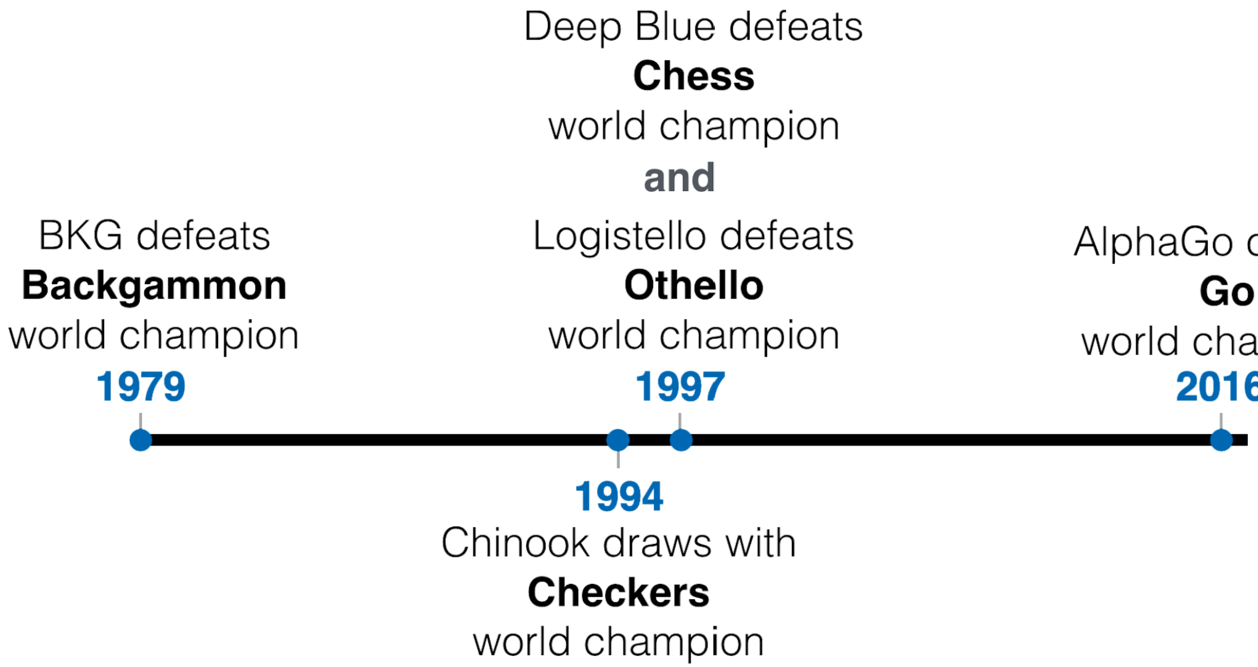
Why Game Research?

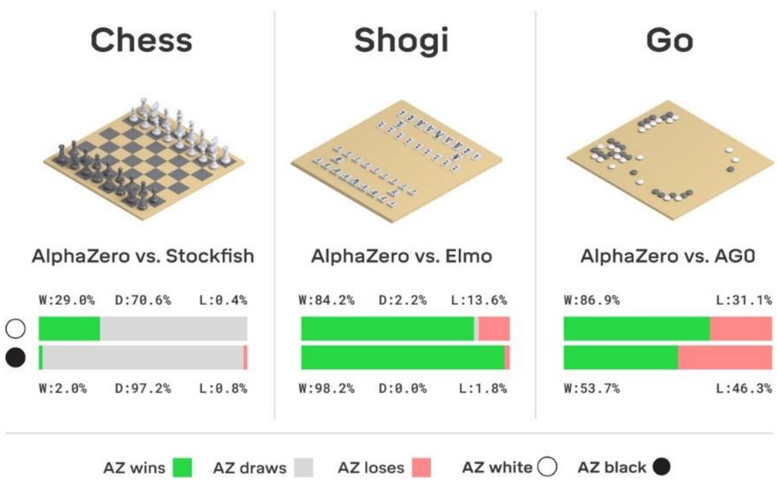
Games as “simulations” of real world tasks

- quantifiable goal, varying difficulty, large data sets
- digital games are fully accessible to computers

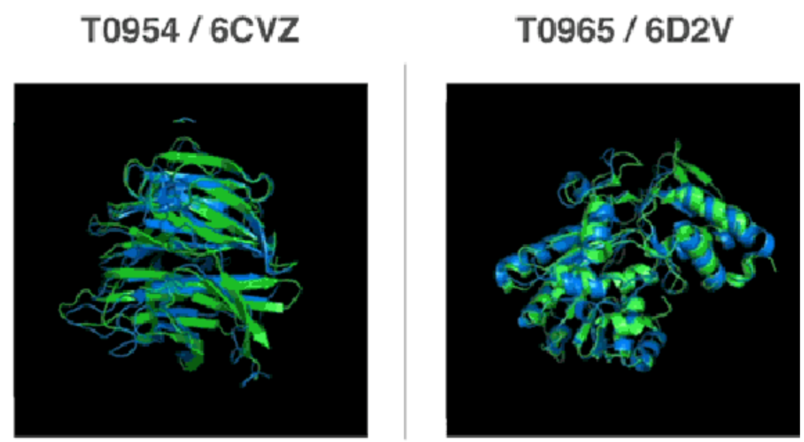


Research Beyond Games

- see for example AlphaGo to AlphaFold
  - Deep Learning + effective search schemes
  - same algorithms are successful in completely different applications



AlphaZero



AlphaFold

Hearthstone – A collectible card game

- online collectible card game
  - millions of players world wide
  - more than 1000 cards

- two games in one:

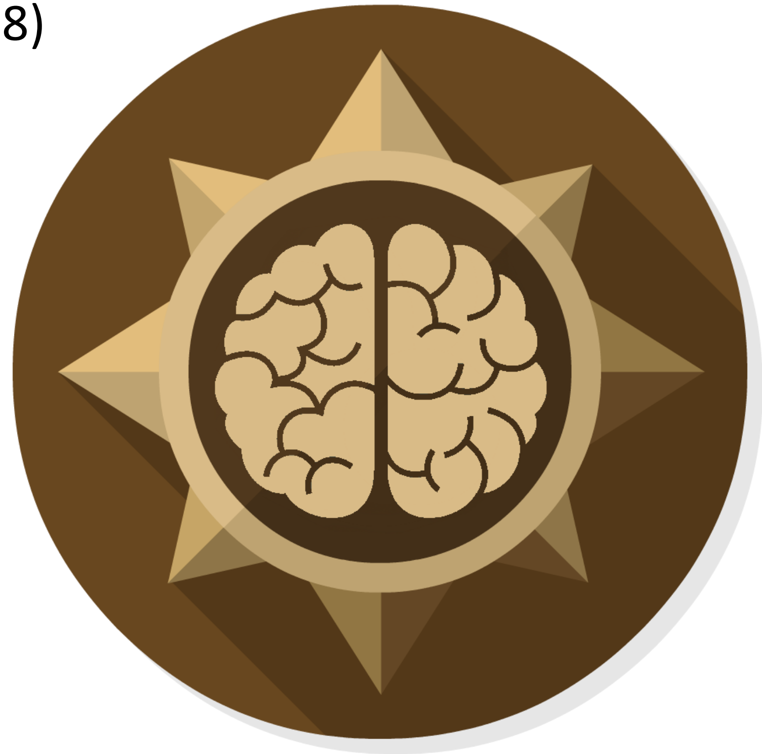
two players play a single game each using a self-constructed deck of 30 cards

whole community plays a meta-game about deck selection/construction

Hearthstone – Game Components and States

Hearthstone – The next challenge for AI

- Hearthstone AI competition (started in 2018)
  - More than 80 submissions by research teams from all over the world

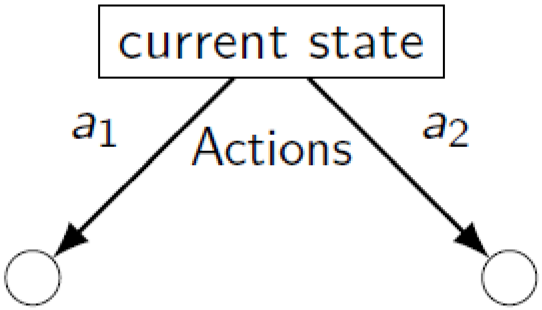


- **Challenges:**
  - partial observation
  - dynamic metagame
  - enormous deck space
  - important card synergies
  - new content every few months

[1] Dockhorn, A., & Mostaghim, S. (2019). Introducing the Hearthstone-AI Competition, 1–4. Retrieved from http://arxiv.org/abs/1906.04238

Creating an AI for Hearthstone

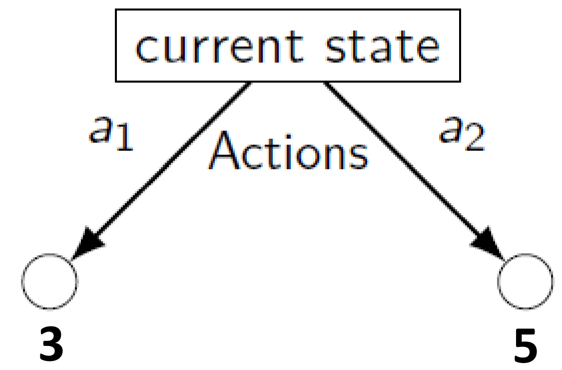
I. **Random:** play an action at random



Creating an AI for Hearthstone

I. **Random:** play an action at random

II. **Greedy:** rate each action or its outcome using a scoring function

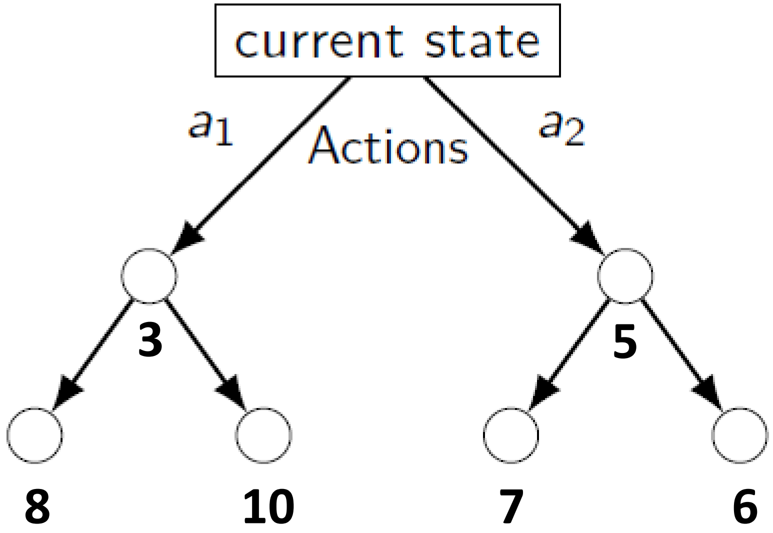


Creating an AI for Hearthstone

I. **Random:** play an action at random

II. **Greedy:** rate each action or its outcome using a scoring function

III. **Search:** optimize a sequence of actions instead



Creating an AI for Hearthstone

I. **Random:** play an action at random

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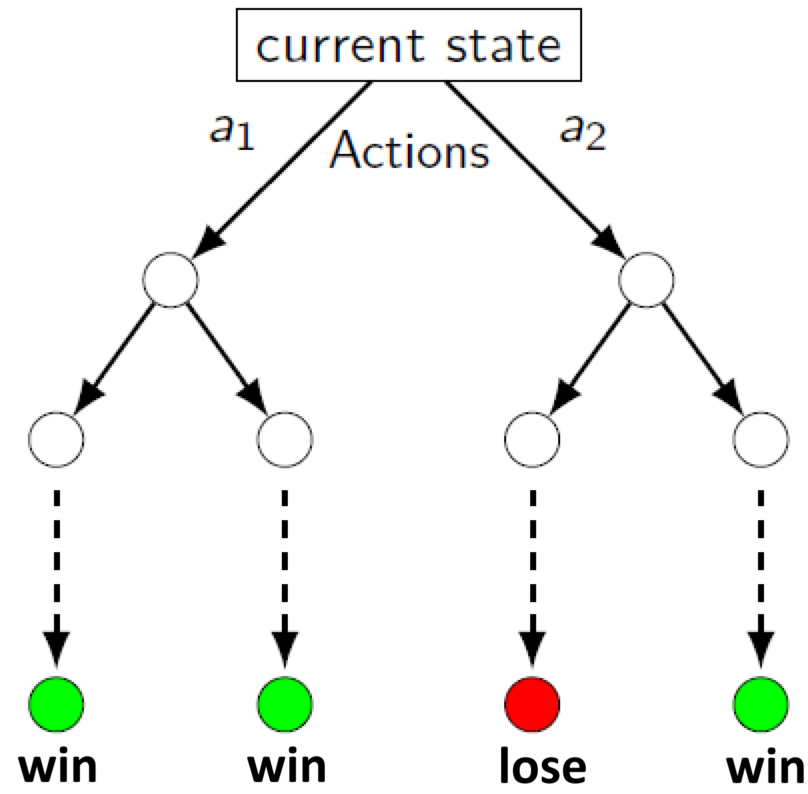
IV. **MCTS:** simulate the game till the end and use terminal states as scoring function



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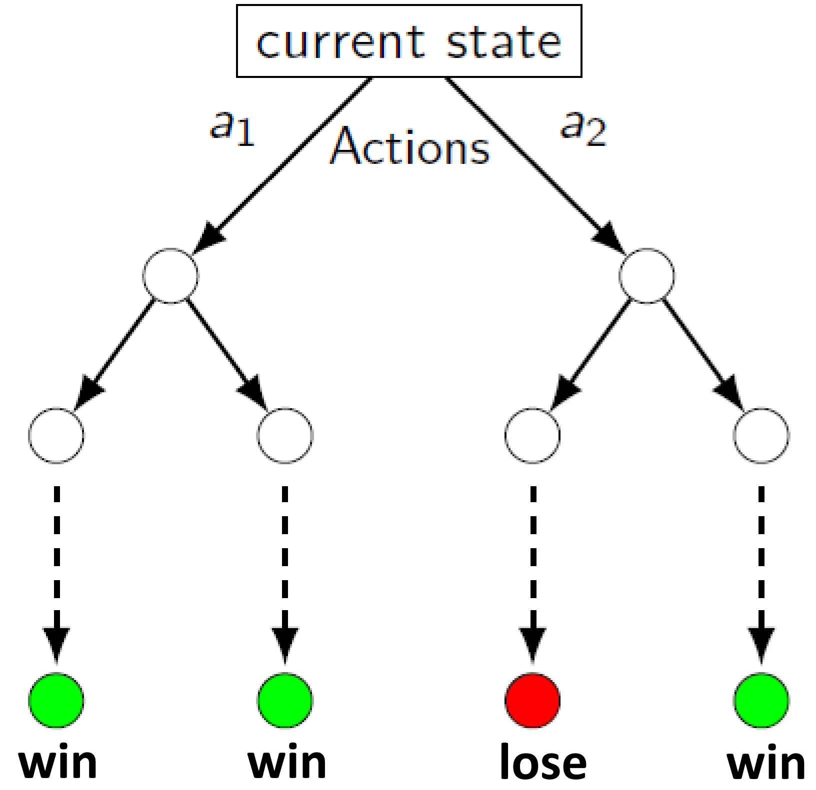
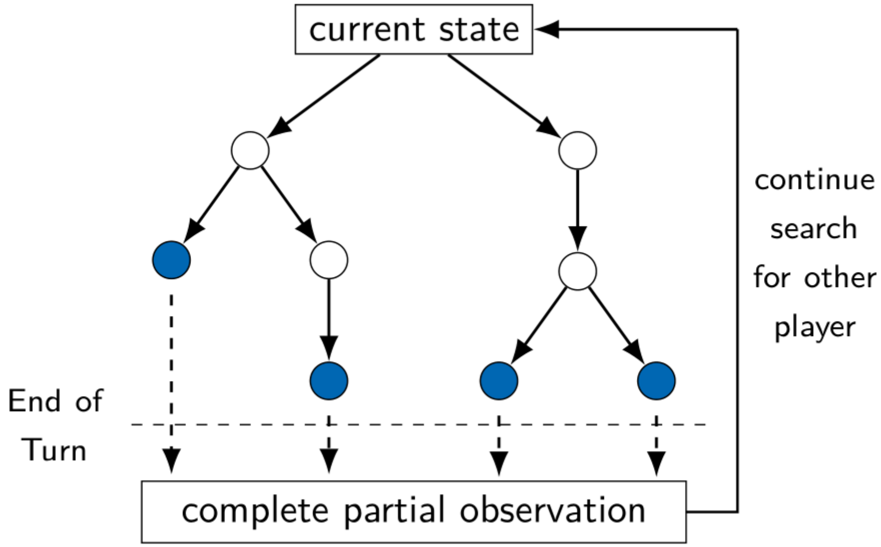


Problem: we cannot simulate beyond our own turn, since the cards of our opponent are unknown to us

InfoSet MCTS / Ensemble MCTS

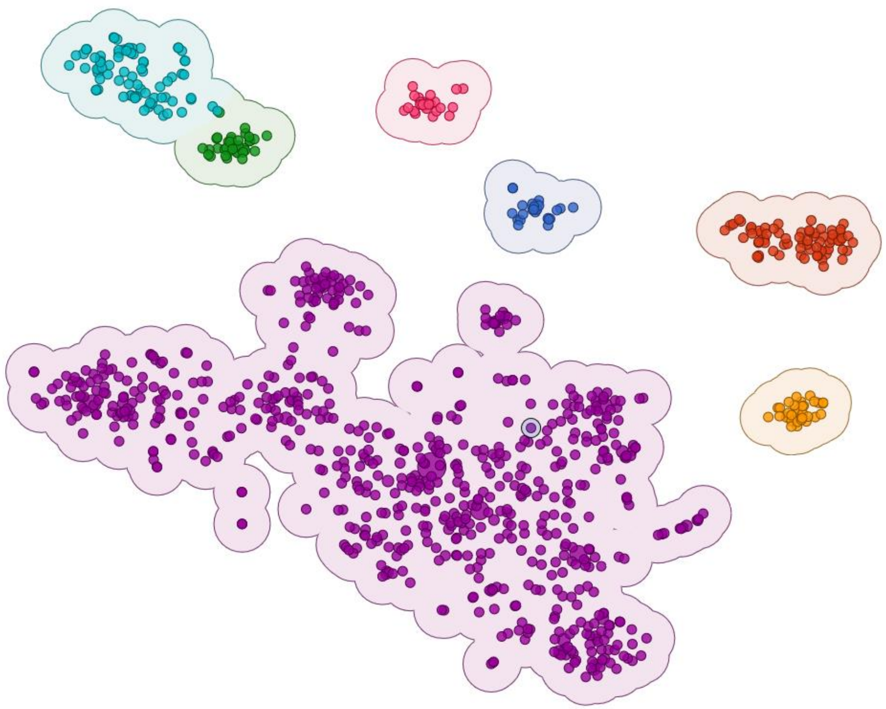
- **Predict Opponent‘s hand cards to simulate the opponent‘s turn**
- Repeat this process and aggregate the result to get a likely estimate



[2] 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
[3] Dockhorn, A., Frick, M., Akkaya, Ü., & Kruse, R. (2018). Predicting Opponent Moves for Improving Hearthstone AI. In J. Medina, M. Ojeda-Aciego, J. L. Verdegay, D. A. Pelta, I. P. Cabrera, B. Bouchon-Meunier, & R. R. Yager (Eds.), *17th International Conference on Information Processing and Management of Uncertainty in Knowledge-Based Systems, IPMU 2018* (pp. 621–632). Springer International Publishing.

The Metagame

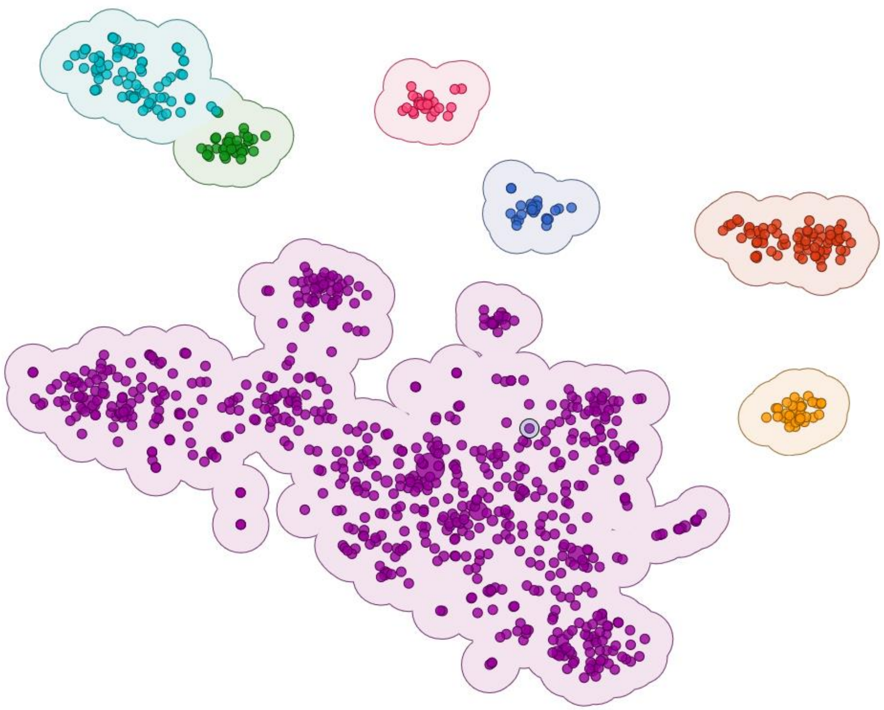
- The **metagame** is defined by the decks players usually play.
- Clustered deck space, but some cards can appear across multiple clusters
  - **Question:** How can we describe and find these clusters?

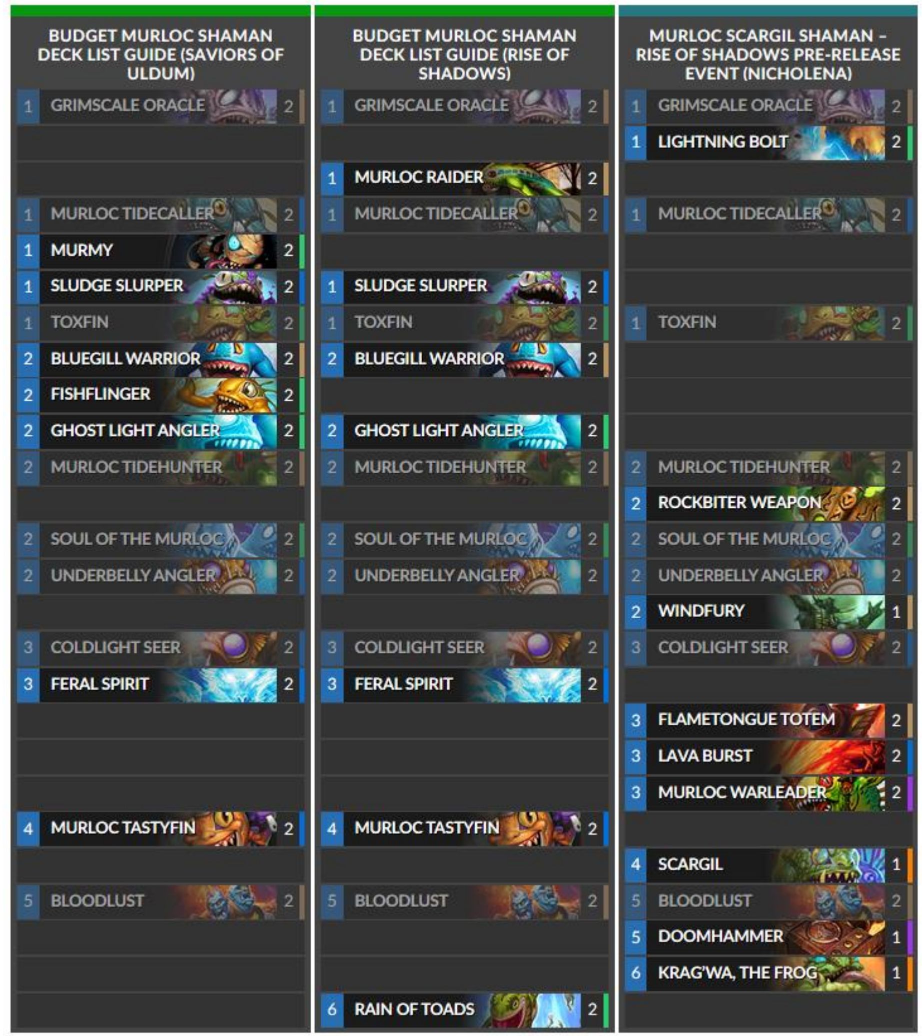


The Meta-Game

Decks can be organized hierarchically

- low levels share a lot of cards
- higher levels share concepts
  - called “deck archetypes“





Decks Analysis – Multiset of Cards

- Attributes of a deck:
  - contains 30 cards
  - can contain the same card multiple times (except legendaries)

- Therefore, we define a deck to be a multiset of cards:

$$M = \{C_M(x)/x \ : \ x \in X\}$$

$$C_M : X \to \mathbb{N} \qquad C_M(x_i) = n_i$$

M	the deck multiset
X	the set of cards
x	a card
C_M	the number of inclusions

Decks Analysis – Multiset of Cards

- Based on this we define union and intersection

$$C_{L \cup M}(x) = C_L(x) \vee C_M(x) \qquad C_{L \cap M}(x) = C_L(x) \wedge C_M(x)$$

- Lets test this with a simple example:

$$D_1 = \{1/a,\ 1/b,\ 2/c,\ 1/d,\ 0/e,\ 2/f\}$$
$$D_2 = \{1/a,\ 1/b,\ 2/c,\ 0/d,\ 2/e,\ 1/f\}$$

$$D'_{D_1 \cup D_2} = \{1/a,\ 1/b,\ 2/c,\ \underline{1/d,\ 2/e,\ 2/f}\}$$

$$D''_{D_1 \cap D_2} = \{1/a,\ 1/b,\ 2/c,\ \underline{0/d,\ 0/e,\ 1/f}\}$$

Decks Analysis – Fuzzy Multiset of Cards

- We redefine the deck to be a fuzzy multiset of cards
  - C_A becomes a multiset of membership degrees $\mu_A(x)$

$$A = \{(x, 0.5),\ (x, 0.3),\ (y, 1),\ (y, 0.5),\ (y, 0.2)\}$$

  - we sort and group the membership degrees according to

$$(\mu_A^1(x), \ldots, \mu_A^p(x)), \qquad \mu_A^1(x) \geq \cdots \geq \mu_A^p(x)$$

$$A = \{\underbrace{(0.5, 0.3)}_{C_A(x)}/x,\ \underbrace{(1, 0.5, 0.2)}_{C_A(y)}/y\}$$

Decks Analysis – Fuzzy Multiset of Cards

- Based on this we define union and intersection

$$\mu^j_{A\cup B} = \mu^j_A(x) \vee \mu^j_B(x)$$
$$j = 1, 2, \ldots, L(x; A, B)$$

$$\mu^j_{A\cap B} = \mu^j_A(x) \wedge \mu^j_B(x)$$
$$j = 1, 2, \ldots, L(x; A, B)$$

- Lets test this with a simple example:

$$A = \{(0.5,\ 0.2)/x,\ (1.0,\ 0.5,\ 0.2)/y,\ (0.0, 0.0)/z\}$$
$$B = \{(1.0,\ 0.0)/x,\ (0.7,\ 0.6,\ 0.0)/y,\ (0.9, 0.5)/z\}$$

$$A \cup B = \{(1.0,\ 0.2)/x,\ (1.0,\ 0.6,\ 0.2)/y,\ (0.9, 0.5)/z\}$$
$$A \cap B = \{(0.5)/x,\ (0.7,\ 0.5)/y\}$$

Fuzzy Multiset Clustering

- We apply hierarchical clustering using the following distance functions

  - Euclidean distance for fuzzy multisets

$$d_{euclid}(A,B) = \left(\sum_{x \in X} \sum_{i}^{L(x;A,B)} \left(\mu_A^i(x) - \mu_B^i(x) \right)^2 \right)^{\frac{1}{2}}$$

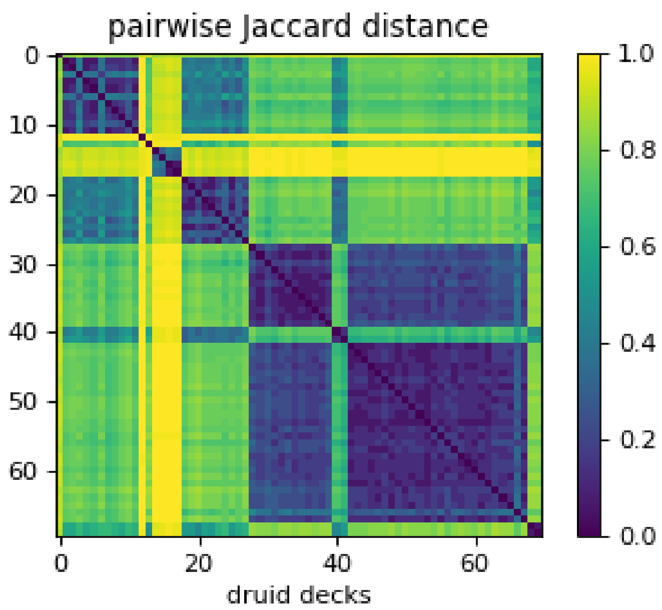
  - Jaccard distance for fuzzy multisets

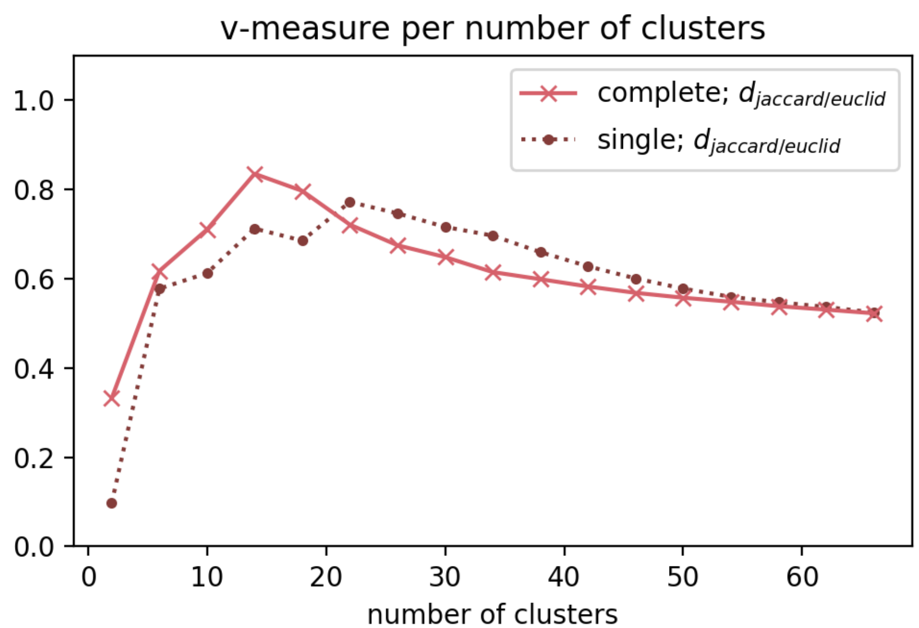
$$d_{jaccard}(x,y) = 1 - \frac{|x \cap y|}{|x \cup y|} = 1 - \frac{\sum_i \min(x_i, y_i)}{\sum_i \max(x_i, y_i)}$$

$$d_{jaccard}(A,B) = 1 - \frac{\sum_{x \in X} \sum_{j=1}^{L(x;A,B)} \mu_{A \cap B}^j}{\sum_{x \in X} \sum_{j=1}^{L(x;A,B)} \mu_{A \cup B}^j}$$

Result of the Clustering Process

- We evaluated our clustering based on labeled player data
  - Clusters match the expert descriptions to a large degree…
  - … and some may indicate labeling errors.
  - ➢ **remaining question**: what makes up a deck archetype?





Decks Analysis – Modelling Player Concepts

Core cards:

- cards that should be included in a certain deck type

Variant cards:

- optional or replacement cards

Deck archetype:

- representation of decks with a common theme
- Here, a centroid of decks in the same cluster:

$$\mu^k_{\langle \mathcal{C} \rangle}(x) = \frac{\sum_{M_i \in \mathcal{C}} \mu^k_{M_i}(x) \cdot C_{\mathcal{C}}(M_i)}{\sum_j C_{\mathcal{C}}(M_j)},$$

$$k = 1, \ldots, p, \quad \forall x \in X$$

Conclusion

- Fuzzy clustering matches human labelling
- Allows us to model natural language concepts
- Sampling based on the fuzzy centroid yields higher accuracy than probabilistic approaches
  - Related agent will participate in the 2020 Hearthstone AI competition

Next challenges:

- detect the deck archetype in play and predict the opponent's deck
- apply stream-mining to document changes in the metagame
- automatic documentation on the effectiveness of balance changes

Thank you for your attention!

Interested in trying it yourself? Download the Code to this paper on Github
https://github.com/ADockhorn/FuzzyDeckClustering

or check out our Hearthstone AI Competition at:
http://www.is.ovgu.de/Research/HearthstoneAI.html

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