Do Androids Dream of Explosive Sheep?

Building a Hearthstone AI

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Introduction

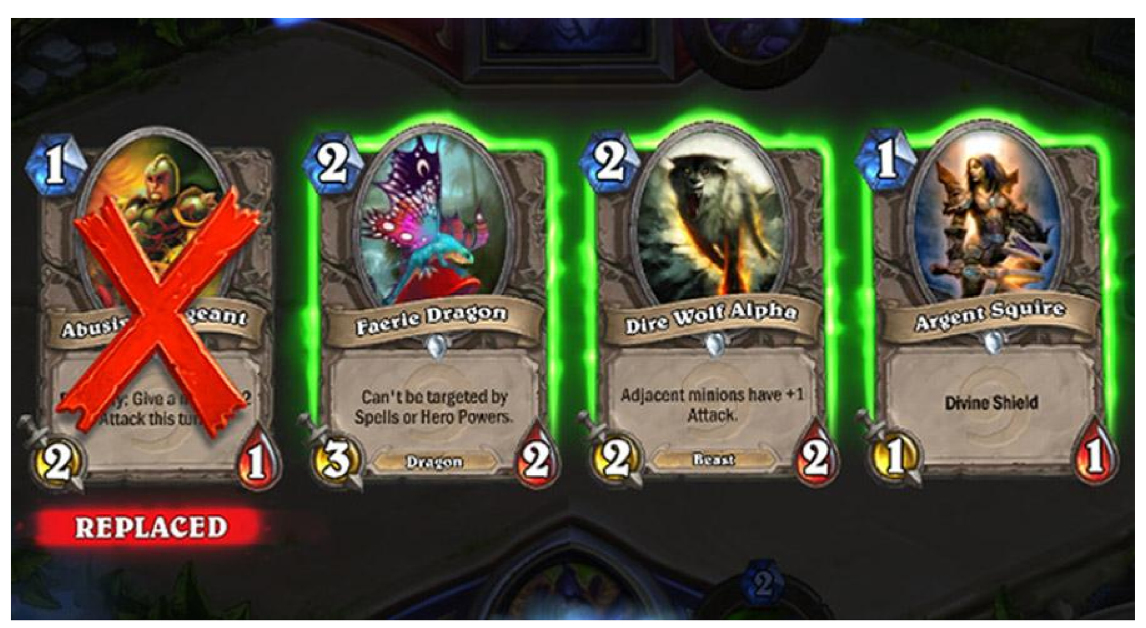
- **Hearthstone** is a popular turn based Trading Card Game produced by Blizzard Entertainment
- Hearthstone has a lot of factors at play in any given game, and we wished to find the most optimal **features** to capture game state
- Pro players will guess at what cards their opponent has
- **Our goal is to write a card predictor that will predict our opponent's deck based on what has been played so far, as well as a feature extractor that we can use to evaluate game states with our own minimax game player.**

Data Collection

- **Monte Carlo simulation** used to generate episodes, where each episode was a game
- **Rewards** given at end of game, either **win** or **loss**
- Generated games by simulating random agent playing against itself
- Data about popular decks scraped from hsreplays.com

Methods

Mulligan



- Used **mini-batch gradient descent** to determine which cards to replace and resample from the deck
- Trained by simulating games against itself repeatedly
- If won, the weights of the starting cards are increased by the learning rate
- If loss, the weights of the starting cards are decreased by the learning rate
- For faster convergence, simulated games against same deck, so that both players' starting cards used as data for gradient descent

Methods

Setup:

Used HearthSim/Fireplace framework to simulate the Hearthstone environment.

TD Learning

- Used **TD-learning** with Monte Carlo simulation to learn weights for our linear minimax evaluation function
- Used **Є-greedy** policy with Є = .75 to explore most of state space
- Update formula:

$$\mathbf{w} \leftarrow \mathbf{w} - \eta[\underbrace{\hat{V}_\pi(s;\mathbf{w})}_{\text{prediction}} - \underbrace{(r + \gamma \hat{V}_\pi(s';\mathbf{w}))}_{\text{target}}]\nabla_{\mathbf{w}} \hat{V}_\pi(s;\mathbf{w})$$

Parameters	η	γ	r if loss	r if won	r else
Values	0.001	0.9	-100	100	0

Card Prediction

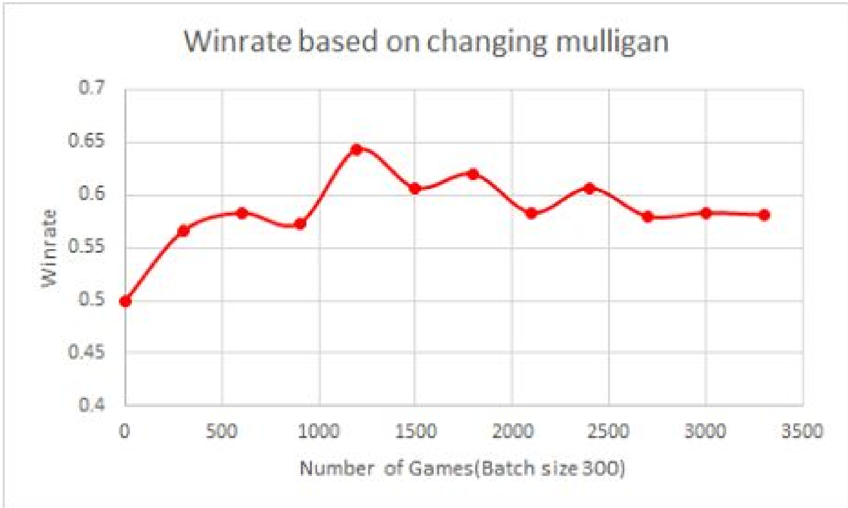
- Used card predictor to find the k-nearest decks given the cards played by the opponent throughout the course of the game
- As the game progresses, the predictor updates the prediction, learning which decks are the most probable
- When simulating opponent's turn for minimax, the card predictor was used to figure out all their possible sequences of actions from a given state, then utilized beam-search to limit branching factor

Feature Extraction

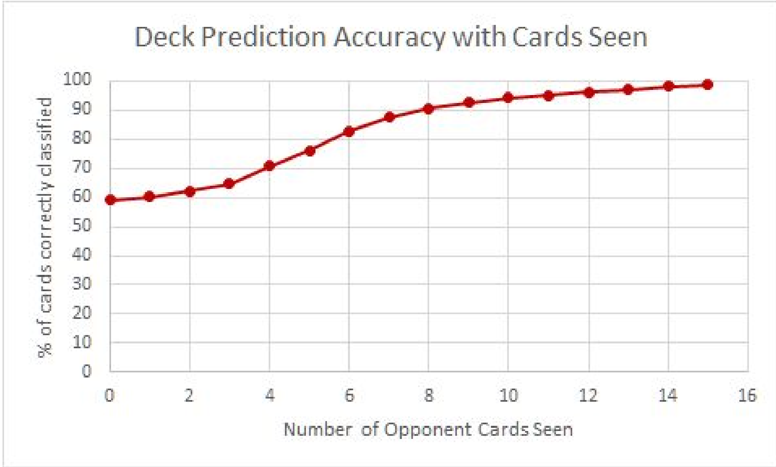
- Started with sets of high level features to capture overall state
- Ignored details such as interactions between cards
- Found the optimal set of features by utilizing **backward search** starting with set of features that were initialized from existing domain knowledge
- Trained and tested by running 200 simulated games(each game is around 10 turns) against an aggressive agent

Evaluation

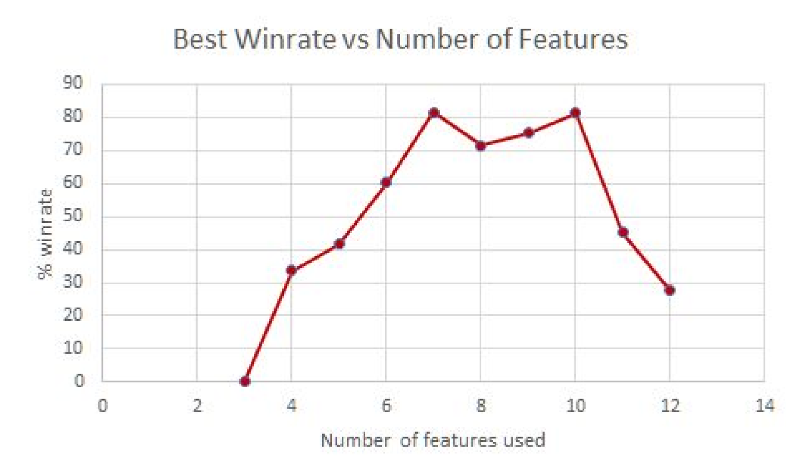
Mulligan



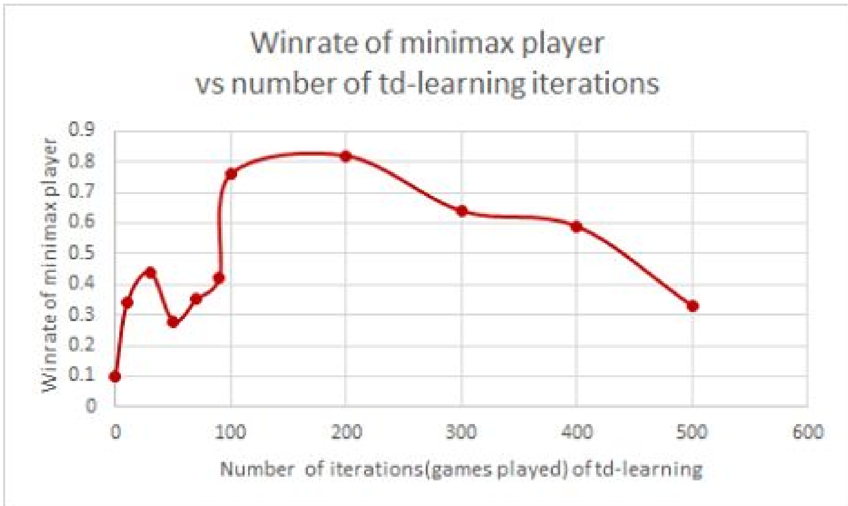
Deck Predictions



Feature Extraction



Minimax Agent



- The best set of features we found was a set of 7 features, each of which is highly valued during human play
- Calculated deck prediction percentages by averaging over 80% of most frequently played decks, repeated 100 times for all decks and averaged the classification accuracy
- With the most relevant features, our minimax player achieved a peak win rate of 81.5% against an aggressive agent
- To test our mulligan, we kept all other factors equal, and one agent chose to mulligan random cards, while the other used the mulligan weights learned
- The agent we played against is a close approximation of real world play, as aggressive decks are the most common that people play

Conclusion and Future Work

- Our AI performed better than we expected. We suspect that this may be due to feature extraction pruning all the unnecessary features. That set up td-learning to learn more accurate weights for the relevant features, resulting in enhanced performance.
- Our card predictor accurately predicted the cards the opponent would play, leading to more accurate evaluation of game states and making overall better decisions.

For future work, we'd like to focus on:

- Try a neural network for TD-Learning
- Try a neural network for Softmax Card Prediction
- Interact with live game to test against real players