A Model for Competitive Trading Card Game Metagame

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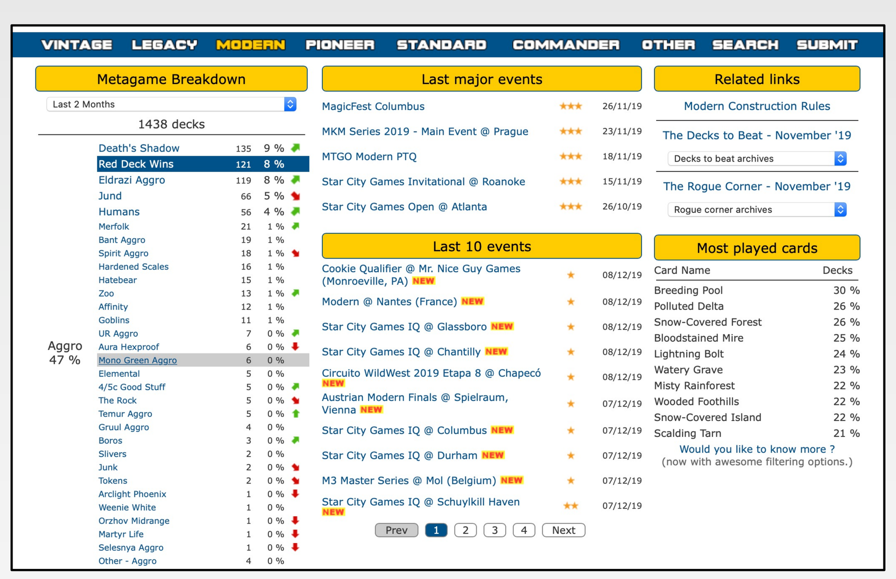
Introduction

Magic: The Gathering is a competitive trading card game in which players use decks of collectible cards to compete against other players. Originally released in 1993, MtG continues to release new sets of cards multiple times per year, making over $300M annually. Thanks to constant development and over 18,000 playable cards, many diverse strategies exist for deckbuilding.

One key aspect of MtG's development is the *metagame*, or what proportion of players choose to adopt which strategies. Even at the most competitive levels, there is no individual deck that consistently outperforms all others. Additionally, a deck can perform well against one type of strategy but poorly against another. These relative winrates can even be altered as new cards are printed and new innovations are made by players. Because of these complexities, the metagame is constantly shifting.



Screenshot of MtgTop8, a website used for MtG tournament reports

Objectives

This project attempts to use a mathematical model to make basic predictions about future metagame dynamics. The model is based on two input variables: the current metagame shares of all significant decks, and the relative winrates of those decks against each other. Several simplifying assumptions have been made, such as placing similar decks into a single category and assuming that players base their decisions exclusively on expected winrate.

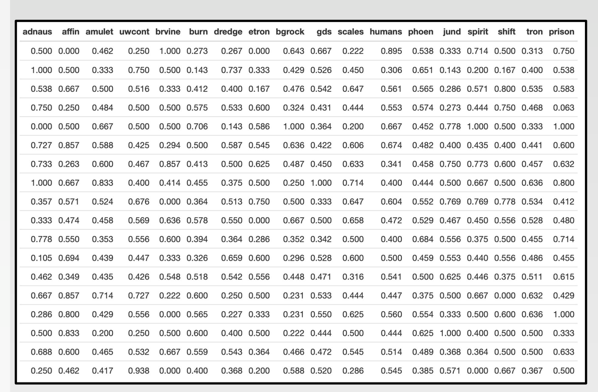
Methods

Data on the current metagame and winrates of decks are curated on many player-produced sites on the internet. This project used data from two sites:

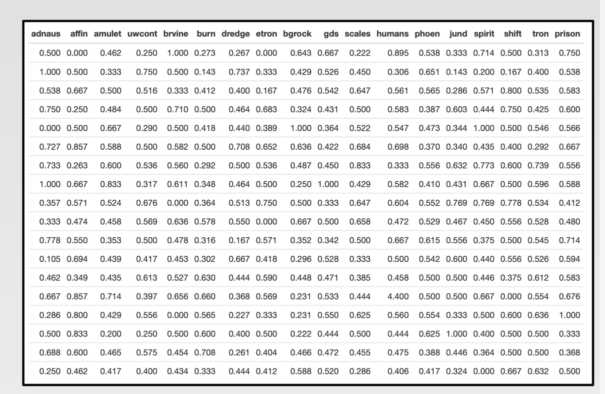
- mtgmeta.io for winrate data
- mtgtop8.com for metagame shares over time

Analysis was focused on data from competitive tournaments in the "Modern" format, from Jan. 2019 to Aug 2019. This range was selected for its quality and quantity of available data.

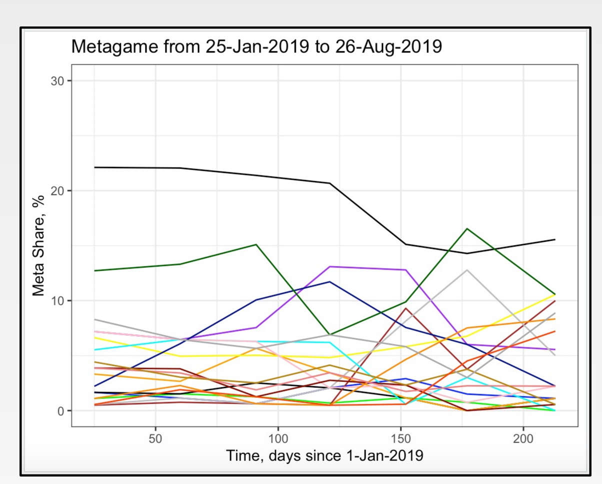
One winrate matrix was used for 25 Jan – 14 Jun, and another for 14 Jun – 26 Aug, corresponding to significant changes due to the introduction of new cards. Metagame percentages were sampled in one-month bins.



Winrates from 25 Jan – 14 Jun



Winrates from 14 Jun – 26 Aug



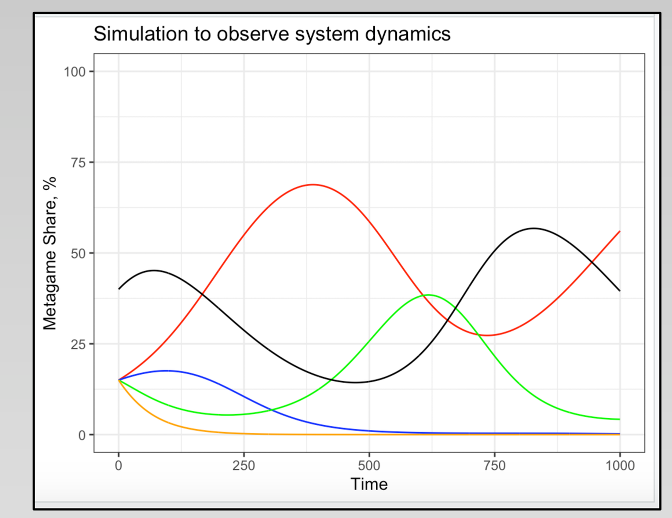
Metagame Shares of major archetypes from 25 Jan – 26 Aug

Player behavior was simulated with the assumption that competitive players will change their deck based on its expected winrate against the most recent field. For each deck archetype, a score is assigned proportional to its expected winrate against the field. In the next timestep, the metagame share of each deck is adjusted based on its score.

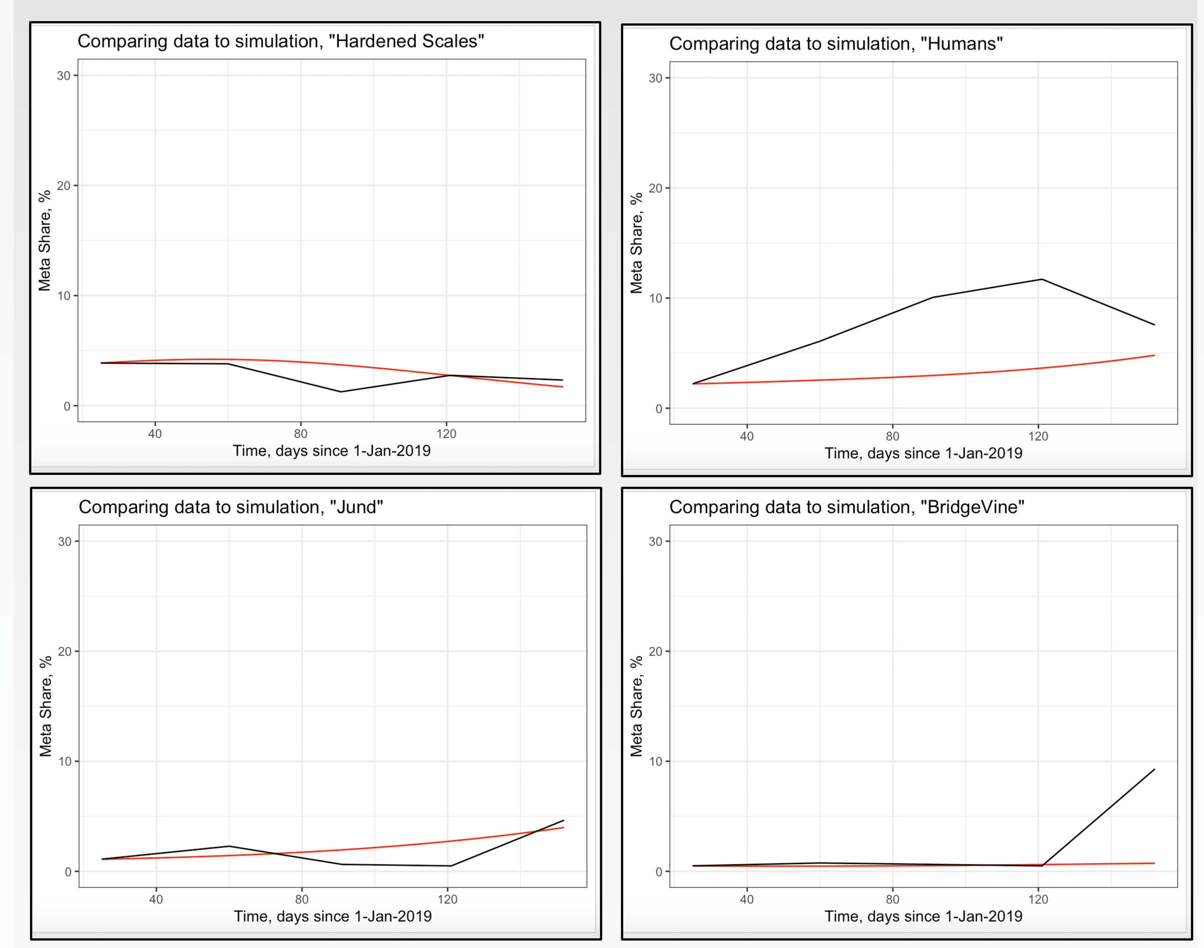
Players are assumed to have some amount of entrenchment in their current deck due to the monetary cost of switching. This is accounted for using a multiplicative factor, 'k', to adjust the magnitude of the changes at each time step. This parameter was selected by optimizing the median absolute deviation from actual data.

Results

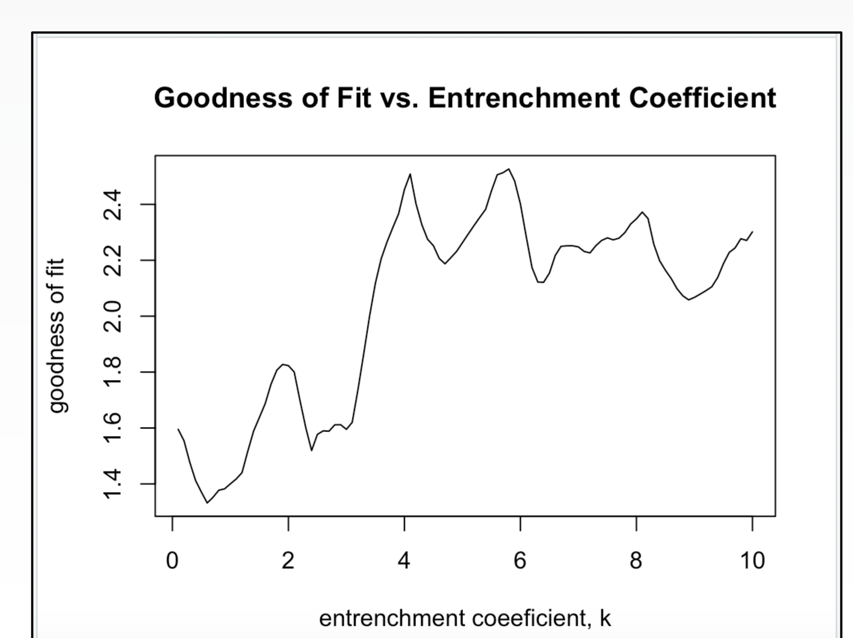
An example of a test simulation with five fabricated decks is shown below. It can be seen that certain decks tend to outperform the metagame, but once a deck gains too large of a share it will be vulnerable to targeting by its competitors.



Below are the results of a simulation starting from the metagame at the beginning of the observed data. The trajectories of several archetypes are shown alongside their simulated counterparts.



Comparing observed data to simulation. Left: good fit. Right: poor fit



Optimizing k for median absolute deviation from observed data

Conclusions

Although it produced good fits for certain decks, the model does not seem accurate enough to be of use to individual competitive players. However, it was more consistently accurate in predicting the general trend of a deck, which could be useful for assessing the impact of new cards given a prediction of their affect on the relative winrates of archetypes.

Limitations and Further Work

This project is limited by the complexity of the model and the quantity of the data.

The model could be improved by using a more nuanced approach to how players choose to update their strategies. For example, players will be more likely to change to a deck that has some overlap in terms of the cards of their current deck. Additionally, players do not necessarily base their decisions exclusively on the current metagame, but may use past data or even attempt to preemptively guess the future to stay ahead.

The data could be improved by gathering data from a larger timespan and by sampling the metagame and updating winrates at a higher frequency. With a fuller dataset, deck archetypes could be more finely broken down without compromising the statistical significance of the winrates.

Finally, the fit of the model to the data could be improved by applying a correction to the predicted metagame if it deviates too far from the observed data. This could mitigate the propagation of errors from initial conditions.

References

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