Predicting the strength of Magic: The Gathering cards from card mechanics

Dustin Fink, Benjamin Pastel, Neil Sapra

I. Introduction

Magic: The Gathering is a trading card game, played by millions of players and with over 10,000 unique cards. In addition to products distributed by the game’s publisher, Wizards of the Coast, Magic also has a rich secondary market where individual cards are sold. The card values vary significantly, from a few cents to over $20,000. The price of a Magic card is dependent on its tournament playability, rarity, and collectability. However, the playability of a card is often misjudged when first released and so many cards are valued lower than their eventual worth. Here we develop a discriminative regression model to predict the market price of Magic cards. Our model assesses the value of a card by analyzing only features intrinsic to the card, such as its power, toughness, mana cost, and rules text (descriptions of these card fields can be found in the appendix). This provides a model which not only enables prediction of card value of products released in the future, but also provides insights, through the most relevant features, to what strategies and abilities in Magic are most effective.

II. Related Work

Previous applications of machine learning to Magic: The Gathering have worked on predicting the worth of cards in terms of price and tournament playability. Pawlicki et. al. used logistic regression and support vector machines to predict price based on price history and tournament playtime [1], while Hau et. al. looked at the synergy of a deck based on the performance of similar decks [2]. However, because both of these projects relied heavily on features that were not part of the cards themselves, they have limited application to new cards which do not yet have price history or tournament playtime. In order to predict the price of new cards, we restrict our feature set to features of the cards themselves.

III. Dataset and Features

We obtained data for 15,708 unique cards through the MTG JSON database [3]. We removed sets of cards known to have inflated price due to their collectability or scarcity, along with two joke sets. Price of the cards, as of 09 November 2015, was obtained through MTGStocks [4]. As the range of card prices spans several orders of magnitude, we considered the natural logarithm of the card price as our response variable, rather than the card price alone (Figure 1).

Features were extracted using an in-house feature extractor. We began with basic numerical card attributes such as the in-game resource cost, power, toughness, mana cost, and length of rules text, as well as crossings of these features determined by the domain expertise of one of the authors. However, we discovered that the predictive power of these attributes was surprisingly limited, yielding models with only 1-5% improvement on training set RMSE against randomly generated features.

As the strength of a card inherently lies in how it interacts with the gameplay, we eventually developed methods to extract features from the rules text. This part of the card is written in (mostly) natural language and may specify arbitrary effects on the gameplay.

After mixed results with several ad-hoc methods based on gameplay mechanics, we hit an order of magnitude improvement with n-grams. Specifically, we generated a feature for each consecutive sequences of words, numbers, or symbols...
that appeared anywhere on any card, and gave each card a value of “1” for all sequences present and “0” otherwise [5]. We found that n ≤ 3 was sufficient to capture most useful features, while still being computationally feasible.

N-grams provided over 400,000 features, and so a method of feature selection was required to make the model tractable as well as to prevent overfitting. We implemented and compared a variety of feature selection methods, including forward search, filtering features with low Mutual Information, and keeping a large number of features but regularizing them at the model level. Surprisingly, we found that two ad-hoc filtering methods outperformed all the other combinations we tried.

The first filter was to set a threshold r, and remove all features present on fewer than r cards. Low values of r performed well on training but overfit; empirically, we found r = 200 performed well. However, even with arbitrarily high r, the model continued to overfit on features which differed on only a few cards. For example, “search your library” and “your library for” are common phrases that are present on more than 700 cards; however, there are exactly 7 cards which contain the former but not the latter. So by assigning an extremely large positive theta to the former and a slightly larger negative theta to the latter, the model was able to fit an arbitrary value to those 7 cards, which generalized poorly to the test set. Accordingly, we set a second filter t, such that if two features were identical across all but t cards, one of the features was dropped. The value of t was similarly evaluated and set to t = 200.

IV. METHODS

After performing feature selection, all cards were converted into feature vectors x_1, ..., x_m, which formed the rows of the feature matrix X, with an additional intercept term. The log of the price of the cards formed the output vector y. We used the normal equations

$$\theta = (X^T X)^{-1} X^T \hat{y}$$

to obtain a feature vector θ that would reduce the root mean squared error (RMSE) between the predicted log-price of the cards Xθ and their actual log-price y. Thus our final model predicted the price of card i as h_θ(x_i) = θ^T x_i.

To evaluate our model, we calculated RMSE on an unseen test set. Additionally, to check that our results were not just predicting the average value, we compared our results to the training error of a linear model trained on a random feature matrix.

To investigate whether we should implement a more complex model such as support vector regression, we crudely approximated some of the benefits of support vector regression with a non-linear kernel by crossing all of our features together in several ways. We found no performance improvement or evidence of promising features in these cross features; therefore we decided to focus our resources on feature generation and selection.

V. OTHER ATTEMPTS

Two additional methods deserve mention that we implemented but ultimately abandoned.

A benefit of using a card-based method was the potential to uncover game mechanics from analysis of the magnitudes
of thetas associated with the features. Aside from the “rare” \( (\theta = 1.048) \) and “mythic rare” \( (\theta = 0.7753) \) rarities, the model learned which mechanics provide powerful effects in the game such as searching the library \( (\theta = 0.5005) \) and gaining additional effects from spells and abilities such as drawing additional cards per turn.

VII. CONCLUSION AND FUTURE WORK

While card prices for Magic: The Gathering are driven by other factors such as market supply and demand and tournament popularity, there is signal in the text of the card itself to help predict price. The usefulness of the n-gram features revealed the importance of card abilities such as searching your library and drawing cards over card power and cost, which are high for some good cards and low for others. It is surprising that numerical features such as power, toughness, and mana-cost were poor signals, even when crossed with each other. Locally-weighted linear regression and nearest neighbors were attempts to compare cards with many of the same features that differed along these lines, but neither of these methods proved very helpful. A more robust crossing of these features with the n-grams may have improved the results, but additional care would be needed to avoid overfitting. While n-grams worked as a proxy for card ability, a robust card parser that codified the rules of the game could drastically improve results. This may prove more feasible for online card games like Hearthstone, where card rules are already codified by the system. Additional avenues for research would include combining this project with previous projects, to determine how these features interact with price history and tournament play. However, the greatest use of this kind of prediction will be figuring out which of the hundreds of new cards may be worth something, and for that, focus on card-specific features is necessary.

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REFERENCES

[5] This outperformed variations such as using the number of times a particular sequence appeared as the feature value, disallowing numbers and symbols, etc.
[6] Finding the \( k \) nearest neighbors required significant optimization to be computationally tractable. We eventually found a matrix multiplication approach that was efficient to compute in Matlab.