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Learning a Resource Scale for Collectible Card Games

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Introduction

Motivation

Collectible Card Games (CCG), also called a Trading Card Games (TCG), are games played with specially designed sets of cards.

- They've been around for over 20 years (since 1993 when *Magic: the Gathering* was introduced).
- The most popular games have millions of players across the globe, including its physical and digital versions.
- Recent trend in academic papers.

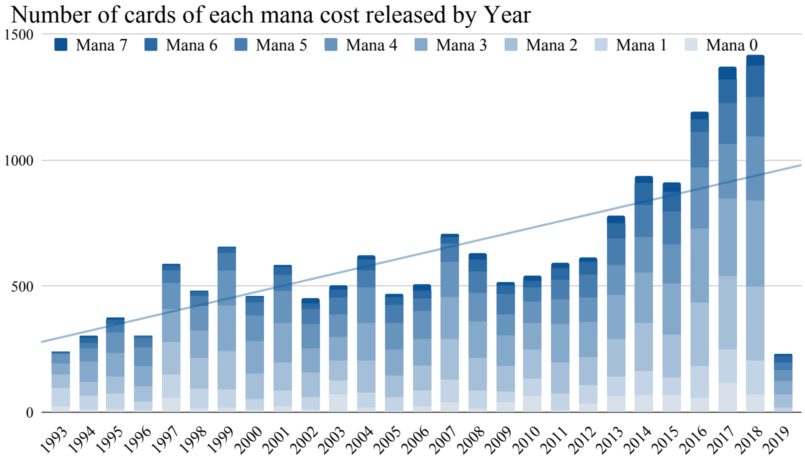
Motivation

Most CCG follow a similar design choice of integrating some source of resource to balance cards. Strong cards with powerful effects require more resource while weaker ones require less.

- *Hearthstone*: crystals.
- *Pokemon TCG*: energy.
- *Yu-Gi-Oh! TCG*: sacrificing monsters.
- *Magic: the Gathering*: mana.
- *Gwent*: provisions.
- etc...

The oldest title: Magic

In this work, we will mainly focus on *Magic: the Gathering*.



Anatomy of a Magic card

Mana cost

Mana is the main resource in the game, produced by *Land* cards. The symbols in the card's upper right corner indicate the cost to use this card. If the mana cost reads 3, you pay three mana of any kind plus one red mana to cast this card.

Card name

Card type

Tells you the card's type (*Land, Enchantment, Instant, Creature, Sorcery, Artifact or Planeswalker*). If it has a subtype, its also listed. For instance, *Paragon of Fierce Defiance* is a *Creature* card which also has *Human Warrior* as subtype.

Text box

Describe the card's abilities and special effects. Some abilities have italic reminder text to help explain what they do.

Expansion

Indicates which set the card is from as well as its rarity. Black symbols stand for common cards, silver for uncommons, gold for rares and orange from mythic rares. This version of *Paragon of Fierce Defiance* belongs to ***Magic** 2015* core set an is an uncommon card.

Power and Toughness

Creature cards have an extra special box describing its power and toughness. A creature's power indicate how much damage it deals in combat. Its toughness, on the other hand, indicates how much damage it can sustain in a single turn before being destroyed.

Overshadowed cards

Overshadowed cards

Overshadowed cards

Overshadowed cards

Similar yet different cards

Before starting to address what is **balanced** or **unbalanced**, we need to know what is **appropriate**.

There are dozens of different abilities which lead to exponential combinations of effects. **And** we still need to take into account different card types and colors. **And** there are nearly 20000 printed cards to take into consideration.

It becomes unfeasible to ask a human devise a set of rules to properly quantify the mana cost of a card. However, this can be solved though machine learning.

Similar yet different cards

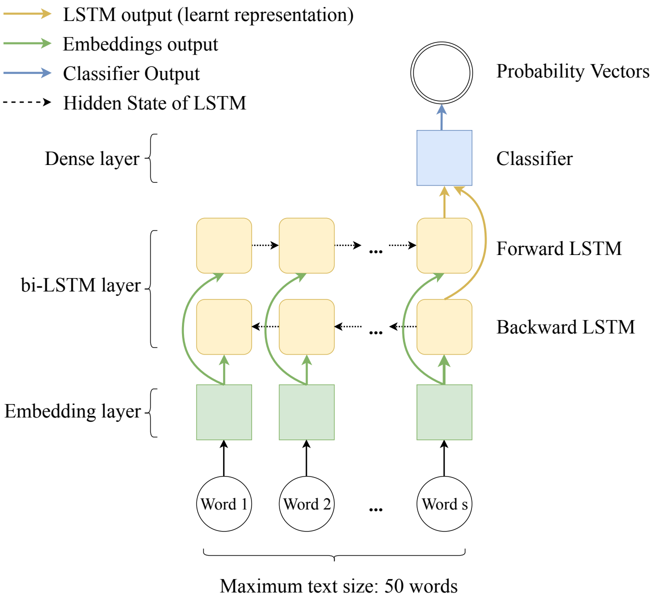
Proposed Approach

Task at hand

- We want to perform a classification task over Magic cards with its mana cost being the target class.o

- However, maybe the most important feature is not a numeric one: the card's effect.
  - **Solution**: learn a vector representation of each card's text.

Representation learning



Classification

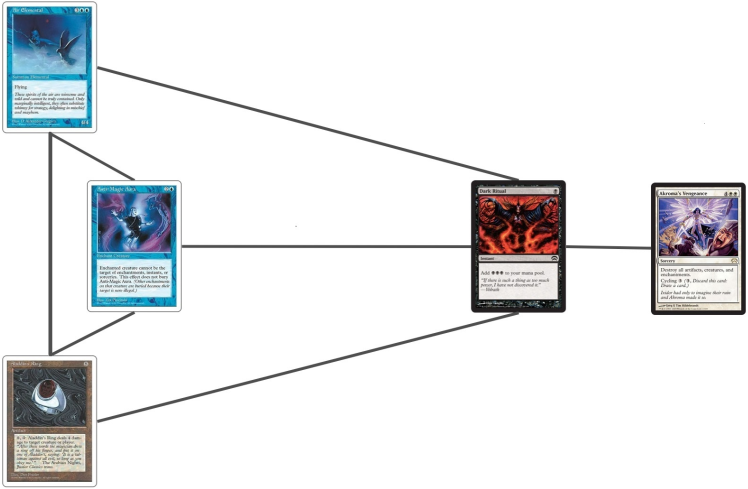
- Feed the LSTM intermediary output to another model alongside the remaining features.

- However, categorical features are too sparse and make any feasible learning a challenging task.
  - **Solution**: compress these features using node embeddings.

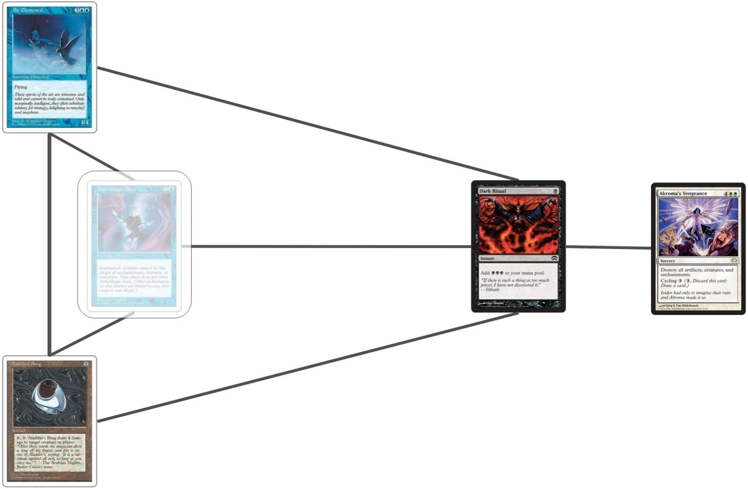
Node Embeddings

Node Embeddings

Node Embeddings



Node Embeddings



Experiments

Main questions to be answered

1. In collectable card games, how well can a card's resource cost be predicted from its features?
2. Does the usage of latent outputs as inputs to other models exceed a typical end-to-end network?
3. What is the impact of modeling sparse categorical features as node-embeddings?
4. Given collectable card games features, can we exploit some sort of inherent pattern?
5. What is the impact of allowing the model to abstain from giving a doubtful prediction?
6. What is the impact of specializing in the most difficult parts of the problem?

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Overall performance

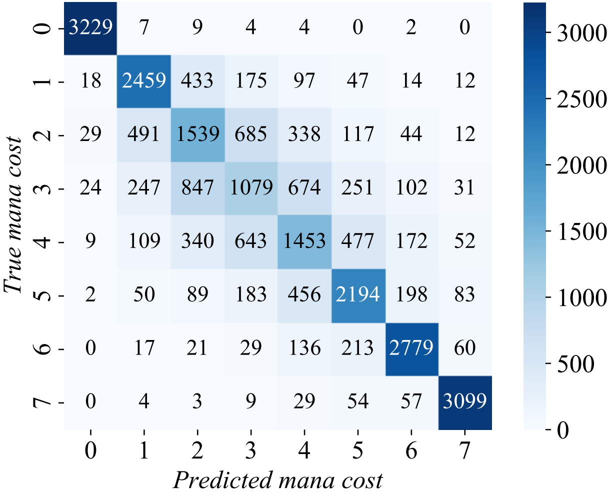
	Node-embeddings		*Many-hot encoded*	
	ACC	*MRR*	*ACC*	*MRR*
MLP (numeric)	.2031	.5012	*.0941*	.2634
XGBoost (numeric)	.5955	.6921	.5599	.6587
LSTM (text)	-	-	.6404	.7655
LSTM-XGBoost (text)	-	-	.6102	.7112
LSTM+MLP	.5954	.7344	.5913	.7342
LSTM-MLP	.5898	.7314	.5891	.7299
LSTM-XGBoost	**.6841**	**.8064**	**.6582**	**.7766**

Random	*.1250*	*.3398*

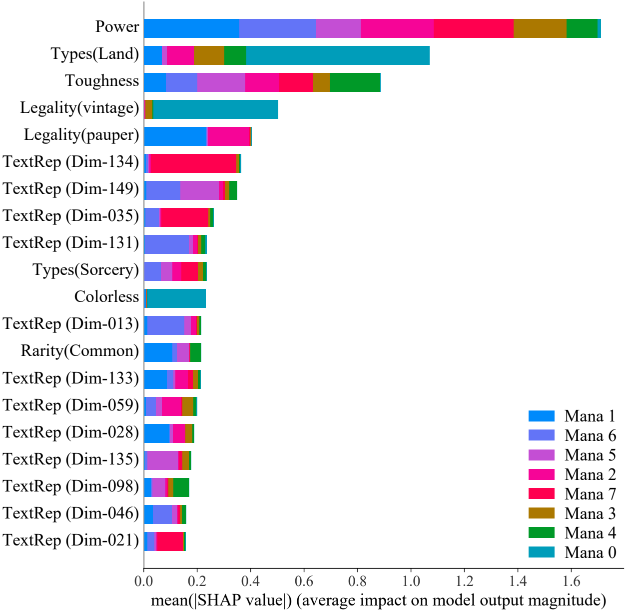
LSTM-XGboost confusion matrix

Confusion Matrix for LSTM-XGBoost

ACC : 0.6841 MRR : 0.8064



SHAPley values

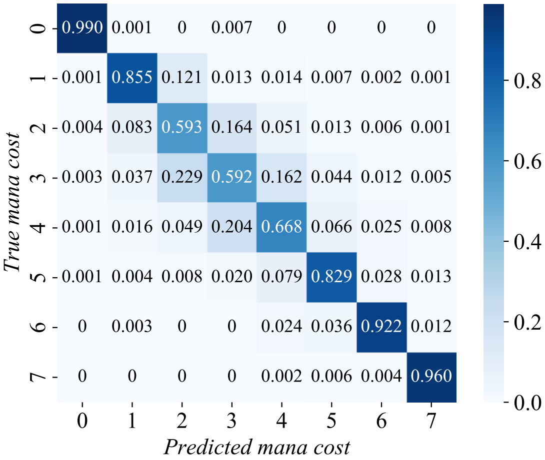


Performance while abstaining

Confusion Matrix for LSTM-XGBoost (0.5 certainty)

Macro-ACC : 0.8011 *Micro-ACC* : 0.9012

Macro-MRR : 0.8692 *Micro-MRR* : 0.9385



Conclusions

Closing Thoughts

- We proposed a novel approach to dealing with the task of recommending mana costs for “Magic: The Gathering” cards.
- This has never been done before.
- We present several arguments that corroborate with the hypothesis that it is possible to learn useful general features that explain a card’s mana cost.
- MRR of 0.8064 in regular circumstances, can go higher under some constraints.
  - The instances that the model miss classify the inputs might not be “true errors”

Thank you!

Predicted mana cost: 1

Predicted mana cost: 1

Predicted mana cost: 2

Predicted mana cost: 2

Predicted mana cost: 1

Predicted mana cost: 5

Predicted mana cost: 4