Neural Network Content Generation for Magic the Gathering

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Abstract

In this paper we will develop models which analyze cards from Magic the Gathering in order to enable the development of automated systems to assist game developers with the generation of new content.

Introduction

As of 2014, there were over 2.14 billion game players worldwide [2]. This incredible number of players is consuming game content at an average rate of seven hours a week [10]. In this paper we will focus specifically on the analyzing the game content for the collectable card game Magic the Gathering (Magic). In Magic, players collect cards that they use to form sixty card decks used to battle other players in the game, either online or in real life.

Since 1993, over twenty three thousand Magic cards have been designed. Today, Magic is owned and created by Wizards of the Coast, a Hasbro company. Magic accounts for about one quarter of Hasbro's annual revenue [3]. We estimate that the cost of product design for Magic, which includes the creation of new cards costs between 50 million and 125 million annually[3].

Four new Magic card sets are designed and released each year [5] and the cards for each set are distributed among six primary colors: Red, Green, Black, White, Blue and Colorless. These colors are the thematic foundation of the game and therefor influence impact card art, type, and effects. For example, the color "Red" is described as, "drawn from the mountains and embodies the principles of impulse and chaos. The mana symbol for red is represented by a fireball" [9]. Common red creatures are goblins and fire elementals. Conversely, green "draws power of forests and embodies the principles of instinct and interdependence. The mana symbol for green is represented by a tree." [9]. Common green creatures are elves and forest animals.

In this paper, we propose the development of models which can analyze Magic cards to help assist and reduce the overall cost of designing new Magic cards. Specifically, we will:

1. Collect and process the complete set of Magic cards.
2. Predict the color of a Magic the Gathering card.
3. Predict the creature type of a Magic the Gathering card.
4. Use Style Transfer to alter the appearance of a Magic the Gathering card.

Data Description

About the data. The data for this study was captured using the scryfall.com API. Scryfall provides Magic card meta-data and images. The use of this data for research is permissible based on the scryfall terms of service which state, "Scryfall provides our card data and image database free of charge for the primary purpose of creating additional Magic software, performing research, or creating community content (such as videos, set reviews, etc) about Magic and related products"[7].

Data Pre-Processing Steps.

1. Downloading the data and converting the semi-structured JSON data to structured data frames
2. Removing non-english cards
3. Dataset reduction to remove multicolored cards. We hope to included multicolored cards in future analysis.
4. Remove any "token" cards that are not actually played.
5. Cleanup and identify land cards
6. Download and crop image data
7. Cleanup the card-type taxonomy

Methods and Results

Predicting the color and card type

We developed two models. The first model predicts the color type and the second predicts the card type. In both cases we used the following methods to produce our models.

1. We ensured our data was evenly distributed.
2. We split our data into training and test data. We set aside 80% of the data for training. Of the training data, we used 5% for validation. The remaining 20% of the data we used for testing.
3. We initialized the model using the transfer learning VGG-19 weights and trained only the last 10 layers of our model.
4. Adjusted our taxonomy of color types and card types to minimize confusion.
5. We used validation accuracy for early stopping to choose the best model, preventing overfitting.

Color results. Our final model produced an overall accuracy score of 42.4%. The confusion matrix below shows where our model succeeded and where it struggled. For example, our model struggled to distinguish between black (B) and blue (U). This isn't surprising given that in the game, black and blue are often allies and share similar thematic elements. Regardless, we are satisfied with the results because the model performs significantly better than the baseline of random model (16%).

Let **SET** be **CONV** → **POOL** → **NORM** → **DROPOUT**

1. Simple CNN: **SET1** → **SET2** → **SET3** → **FULLY** → **SOFTMAX**
2. Simple CNN + channel averages: Injecting average channel value of input image as an auxiliary input to the fully connected part of the Simple CNN.
3. Color-net Model: We reviewed the work in color net which is used for vehicle color recognition [6] and experimented if detection of just overall main color improves our accuracy. But our data is more complex than just base colour. So, it did not help much.
4. VGG19 Transfer Learning: In this we have initialized our color classification model with weights of VGG19 [8] and trained last 10 layers.

In our final model, we merged multi-color cards to include a copy of each card in the data set to each of its respective colors and also included colourless cards as a class.

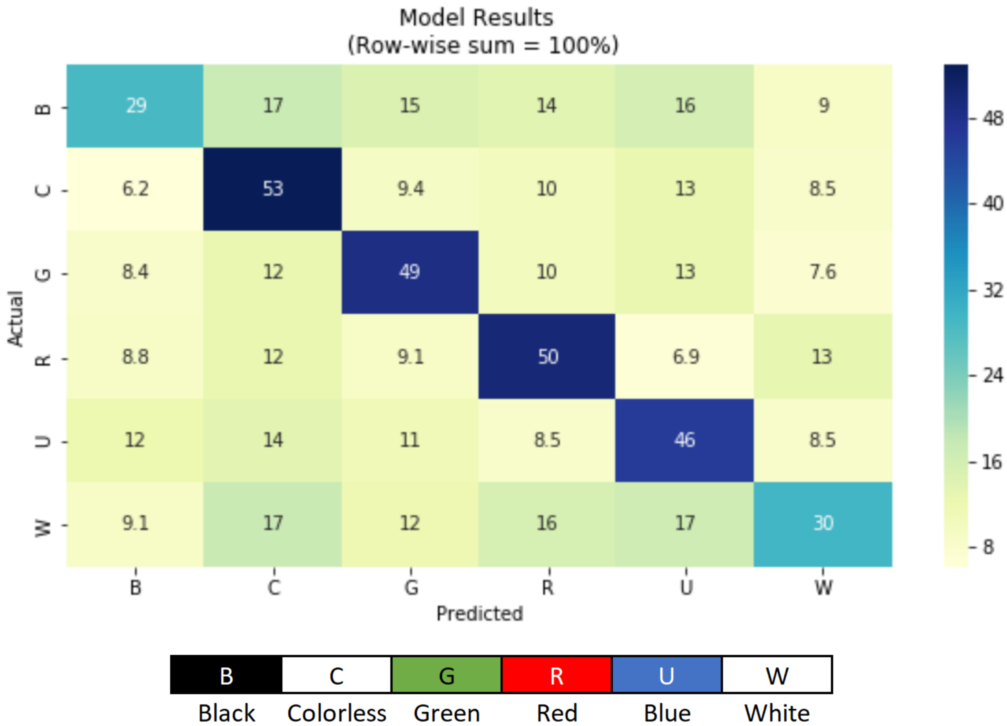

Figure 1. Confusion matrix for color model

The train & test accuracy of all color models tried can be seen in Table 1.

Table 1

Color Prediction Results

Model	Colors	Train Acc	Test Acc
Simple CNN	Single	92.75%	43.78%
Simple CNN + channel averages	Single	44.52%	42.15%
Color-net Model	Single	49.17%	44.47%
VGG19 Transfer Learning	Single	71.45%	48.80%
VGG19 Transfer Learning	Merged multi	53.36%	42.40%

Card type results. Our final card type model produced an overall accuracy score of 60.0%. This is substantially more accurate that the color results. The confusion matrix below shows where our model succeeded and where it struggled. You can see that our model most often confuses creatures and spells. We attribute this to the fact that many spells feature creatures being impacted by the spell. For example, an elf being struck by a lighting bolt spell. Hence, we

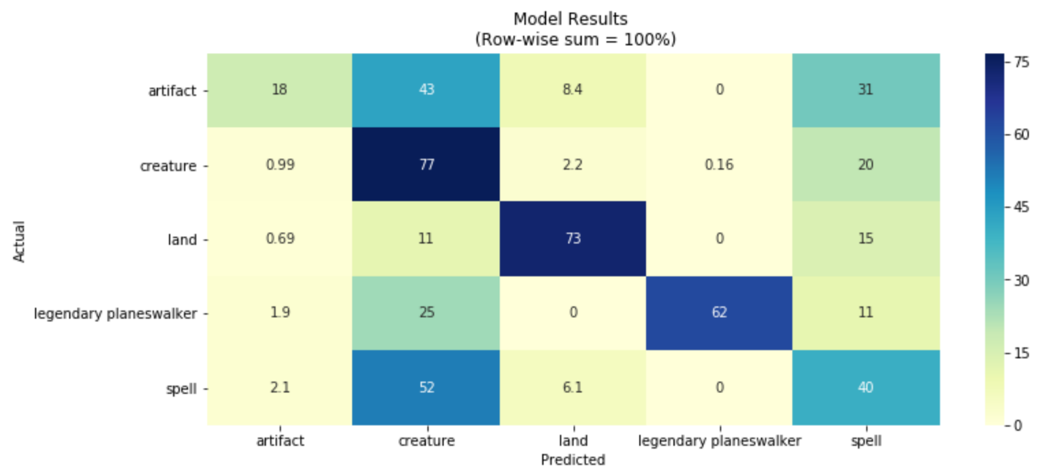

Figure 2. Confusion matrix for card type model

The train & test accuracy of all card type models tried can be seen in Table 2.

Table 2

Card type results

Model	Classes	Train accuracy	Test accuracy
Simple CNN	9	88.94%	37.97%
VGG19 Transfer Learning	9	68.21%	49.74%
VGG19 Transfer Learning	6	81.31%	59.00%
VGG19 Transfer Learning	5	75.65%	59.97%

Using Style Transfer to alter the appearance of a Magic card. Our style transfer model was based on the article, "Neural Algorithm of Artistic Style"[1]. We start with two images, a base image and a style image and we use these and a deep neural network to predict a third combined image. At each iteration our model attempts to minimize the the "content loss" in the combined image while working to minimize the "style loss". In addition, we measure the "total loss" to ensure that we maintain spatial continuity between the pixels in our combined image to ensure that it is still recognizable [1].

In particular, we initialize our weights using the deep convolutional neural network, vgg19 [8]. From there, we measured the style loss as defined as a sum of L2 distances between the Gram matrices of the representations of the base image and the style reference image, extracted from different layers of a convnet.

Figure 3 show that style transfer can be helpful in extracting color and texture information at different scales.

"setA" shows a successful transfer of the style from a "green" bear card to a "red" fire card. Visually, we feel that the new "red" bear can now be accurately describe as a "fire bear" and that it thematically fits into the "red" color type.

However, we found style transfer to be a blunt tool as it impacts the entire image. For example, in "setB" we attempted to convert a blue card to a red card. The red card prominently featured fire, which was detected as a "style" by our model. That style was then applied to our entire image. Additionally, notice that the checkered pattern in the base image was lost in the combined image. This was an an unsuccessful color conversion.

Finally, you can see the more traditional application of style transfer in "setC" and "setD" as we attempt to convert from a painted style to a realistic style and vice versa.

Overall, we feel the limitations in our current style transfer model reduce it's utility for content designers. While it can help in the thematic transmogrification from one color to another, further research is necessary to improve the quality of the style transfer. Specifically, we are interested in the potential that Generative Adversarial Networks (GAN) might play in allowing us to detect and generate new features on our base images.

Conclusion

In conclusion we feel these models show that it is possible to use deep networks to assist in the development of thematically appropriate game content. We were able to show that we could reliably predict the card color and card type. In situations where we could not accurately predict the color or type it is possible that more than one type is appropriate. We felt that style transfer showed promise in thematically changing the nature of a card, however, the current implementation has several weaknesses that need to be address. Specifically, we want to incorporate advances in generative adversarial networks which can help to create separation of high-level attributes (such the pose and type of creature) and stochastic variation in the generated images (e.g., building new fantasy creatures with different hair, scars, colors, eyes)[4]. While we do not think that deep networks can fully replace the artistic nature of the content used in games, we can envision a future where artists and content creators use deep learning tools to accelerate their work. For example, a magic card content development team can give an existing card to this system and ask it to generate a new card which falls into the similar category. In this case, this system finds the colour, card type and transfers the style based on the inputs to it.

Figure 3. Style transfer

References

[1] Leon A. et al. "A Neural Algorithm of Artistic Style". In: *arXiv.org* (Sept. 2015). URL: https://arxiv.org/abs/1508.06576.

[2] Christina Gough. *Number of gamers worldwide*. 2019. URL: https://www.statista.com/statistics/748044/number-video-gamers-world/.

[3] *Hasbro Reports Full-Year and Fourth Quarter 2018 Financial Results*. 2019. URL: https://cutt.ly/JrwxjZo.

[4] Tero Karras, Samuli Laine, and Timo Aila. "A Style-Based Generator Architecture for Generative Adversarial Networks". In: *CoRR* abs/1812.04948 (2018). arXiv: 1812.04948. URL: http://arxiv.org/abs/1812.04948.

[5] *Magic Standard Formats*. 2019. URL: https://magic.wizards.com/en/content/standard-formats-magic-gathering.

[6] Reza Fuad Rachmadi and I. Ketut Eddy Purnama. "Vehicle Color Recognition using Convolutional Neural Network". In: *CoRR* abs/1510.07391 (2015). arXiv: 1510.07391. URL: http://arxiv.org/abs/1510.07391.

[7] *Scryfall API Documentation*. 2019. URL: https://scryfall.com/docs/api.

[8] Karen Simonyan and Andrew Zisserman. *Very Deep Convolutional Networks for Large-Scale Image Recognition*. 2014. arXiv: 1409.1556 [cs.CV].

[9] *The color red*. 2019. URL: https://mtg.gamepedia.com/Red.

[10] *The State of Online Gaming*. 2018. URL: https://www.limelight.com/resources/white-paper/state-of-online-gaming-2018/.