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CRV: A Framework for Visualizing Card Relationships in Digital Collectible Card Games

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1. Introduction

Digital collectible card games (DCCGs) form a popular genre of video games characterized by the necessity for players to build a deck to engage in turn-based one-versus-one matches. Generally, deck construction and match gameplay are two key components, constituting the core experience of DCCGs.

DCCGs often boast extensive libraries of available cards, numbering in the thousands, which could be overwhelming and confusing for beginners not yet familiar with the intricacies of the games. A case in point is the well-known title "Yu-Gi-Oh! Master Duel", which has a vast card pool exceeding 10,000 unique cards [1]. Even though many card databases are equipped with powerful search functionalities, inexperienced players may encounter difficulties in detecting potential combinations of cards because of the huge volume of information. In addition, from a game developer's perspective, the issue of imbalanced card designs frequently becomes clear in real-world scenarios. Although designers could address this concern by implementing a ban list or making direct modifications to card effects, their evaluations tend to be inadequate during the design phase.

In this research, we introduce a novel approach to visualizing card relationships within DCCGs, serving as a valuable tool for both players and designers to overcome information overload. Our method involves conceptualizing cards as nodes and their relationships as edges, thereby facilitating the construction of a dynamic 3D or 2D graph with an interactive user interface. Through the provision of clear visualizations, we aim to help users in the realms of deck construction and card design, facilitating a more profound comprehension of the intricacies of DCCGs.

2. Related Work

Since words in context and cards in DCCGs possess similar properties, we could conceptualize cards and decks in DCCGs as analogous to words and sentences in linguistic structures respectively. As a result, the study of natural language processing may offer valuable insights for our research. The co-occurrence network is a method to analyze text that calculates the co-occurrence of entities and then use a graphic visualization to discover potential relationships between entities represented within written material. Puerta et al. [2] analyzed Twitter information by constructing co-occurrence networks from a selected subset of 3,000 tweets. The findings from this analysis indicate that co-occurrence networks derived from pre-cleaned text provides meaningful information showing structure and relevance for terms, which could be an effective support for analysts in general text analytic tasks. We apply the technique of co-occurrence network analysis to construct a comprehensive relationship map for cards in DCCGs.

3. Method

In this research, we employ the concept of "Co-occurrence Rate" as a metric to evaluate the relationships existing among individual cards. Specifically, we define "co-occurrence" as the concurrent presence of two cards within the same deck. Formally, given cards $c_1, c_2, \dots, c_n$ and decks $D_1, D_2, \dots, D_m$, where each deck is a multiset $D_j = \left\{c_{i_{j,1}}, c_{i_{j,2}}, \dots, c_{i_{j,k_j}}\right\}$ of k_j cards, the co-occurrence rate $\mathrm{cor}(c_s, c_t)$ of two cards c_s and c_t is defined as the ratio of the two cards co-occurring in a deck to the number of the decks that have at least one of the cards:

$$\mathrm{cor}(c_s, c_t) = \frac{\left|\left\{D_j \mid c_s \in D_j \wedge c_t \in D_j\right\}\right|}{\left|\left\{D_j \mid c_s \in D_j \vee c_t \in D_j\right\}\right|}$$

We define a threshold denoted as α to evaluate the co-occurrence rate between two cards. If the calculated co-occurrence rate is higher than this threshold, it is inferred that a meaningful relationship exists between the two cards, allowing them to be incorporated into our visualization. Furthermore, we use the co-occurrence rate as a pivotal factor in determining the length of an edge connecting the respective cards c_s and c_t, which is calculated by $\delta/\mathrm{cor}(c_s, c_t)$, where δ is a coefficient for the adjustment of visualization.

However, it is worth noting that some powerful cards in a DCCG are able to boost almost any decks in which they are placed, and they are often involved in the decks of a majority of players. Given the challenges posed by establishing relationships between these highly versatile cards and a vast array of other cards, we propose a filtering mechanism designed to exclude such influential cards from our visualization. This filter is activated when the co-occurrence rate exceeds a predefined threshold, denoted as β, ensuring that only

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significant relationships are emphasized in our visual representation.

At the end, we employ an open-source framework for “3D Force-Directed Graph” [3] to visualize a graph data structure in a three-dimensional space through a force-directed iterative layout. Furthermore, we plan to use “Cosmograph” as a complementary tool for two-dimensional visualizations [4].

4. Experiment

To empirically validate the efficacy of our approach, we have selected “Yu-Gi-Oh! Master Duel” as the primary subject of our case study. To prepare a necessary dataset for our analysis, we have collected approximately 5,000 decks belonging to elite players from the “Master Duel Meta” website, employing a Python-based web scraper.

In this experiment, we tentatively set $\alpha = 0.5$, $\delta = 10000$, and $\beta = 0.6$. Then we employ both “3D Force-Directed Graph” and “Cosmosgraph” to visualize the co-occurrence network. The results are shown in Figure 1.

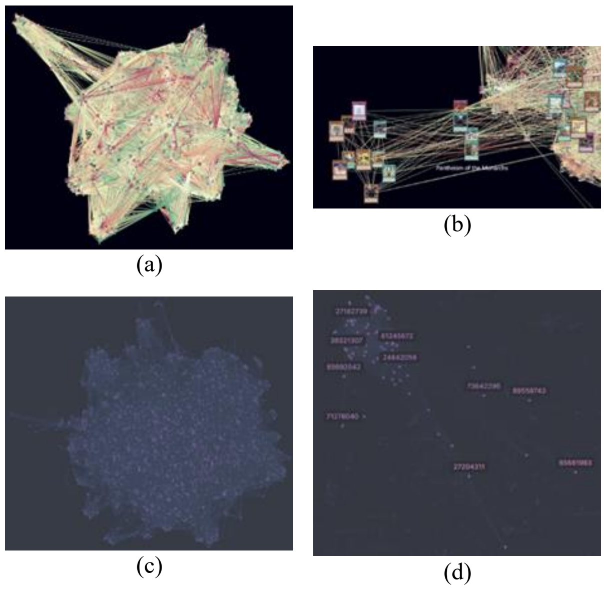

Figure 1: (a) “3D Force-Directed Graph”—Overall View (1000 decks, 2069 nodes, 60968 edges); (b) “3D Force-Directed Graph”—Partial View ; (c) “Cosmograph”—Overall View (5000 decks, 3427 nodes, 98718 edges); (d) “Cosmograph”—Click on a Single Card.

Although we did not employ a specific clustering method, we observed that cards belonged to the same “archetype” (characterized by a common string across all members of the group) naturally formed small clusters (Figure 1(a)). Commonly used “engines” (combinations of cards that synergize well) were readily identifiable and users can understand the compatibility of different engines, as those that work well together are positioned adjacently within our network (Figure 1(b)). Additionally, with the support of the built-in physical engine of “3D Force-Directed Graph, users could interact with the 3D graph including rotating, zooming and concentrating on individual nodes.

Nevertheless, it is evident that the 3D graph appears cluttered with an excessive number of nodes and links. Furthermore, without customizing the source code of “3D Force-Directed Graph”, the performance of interacting with a large 3D graph is poor, with the 1000-node threshold already presenting limitations. Therefore, the integration of a 2D graph, featuring interactive functionalities that enable the selective presentation of concise information, could assist users in exploring the combinations and relationships among cards. (Figures 1(c) and 1(d)).

5. Conclusion

In this paper, we introduced a graph visualization-based framework to visualize card relationships in DCCGs. Our methodology centers on the utilization of the metric of co-occurrence rates to infer relationships between pairs of cards.

For the future work, in addition to optimize parameters and programs, we would like to expand the scope of our analysis by incorporating text mining techniques to explore an additional dimension of relationships among cards, inferred from their in-game effects. For instance, if card A has an effect to add card B into a player’s hand, we categorize this association as a “direct” relationship. Our plan is to represent such distinct relationships within our graphical model in a manner that sets them apart from the co-occurrence-based relationships, thereby enhancing the efficacy of our visualization.

Our ultimate goal is to evolve this framework into a user-friendly software, ensuring accessibility and usability for end-users. As part of future work, we would also gather feedback from both players and game designers through survey methodologies and usability tests to assess our research.

References

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