Data Mining of Deck Archetypes in Hearthstone*

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Abstract. Computer games have become a very interesting environment or testbed to develop new algorithms in many of the branches of Artificial Intelligence. In fact, collectible card games, such as Hearthstone, have recently attracted the attention of researchers because of their characteristics: uncertainty, randomness, or the infinite and unpredictable interactions that can occur in a game. In this game each player composes decks to face other players from a pool of more than 3,000 cards, each one with its own rules and statistics. This implies a great variability of decks and card combinations with rich effects. This paper proposes the use of clustering techniques to extract information from data provided by Hearthstone players, i.e. a Game Mining approach. To do so, more than 500,000 decks created by game players (both experts and just enthusiasts) have been downloaded from *Hearthpwn* website. Thus, a descriptive analysis of this dataset, along with Data Mining techniques, have been carried out in order to understand which archetypes (or deck types) are the favourites among the community of players, and what relationships can be identified between them. The results show that it is possible to use clustering algorithms such as K-Means to automatically detect the archetypes used by the players.

Keywords: Game Data Mining · Collectible Card Games · Hearthstone · Archetypes · Clustering Algorithms · K-Means · Agglomerative Hierarchical Clustering

1 Introduction

Although there is a large amount of work devoted to the use of AI in video games, most of it is focused on making agents that play, or allow to generate content.

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However, a very interesting area of application is the modeling of players. That is, starting from information related to how the human player interacts with the game to obtain useful knowledge. Furthermore, understanding and modelling the interaction between the player and the game can be considered a holy grail for game developers and designers [22].

The interaction between players and games is particularly challenging in the area of Collectible Card Games (CCGs), such as Magic The Gathering. This type of games involves a lot of human interaction not only during the game, but also during the creation of the decks to be used from a pool of thousands of cards. These decks are usually shared and commented on the internet, so many players use them as a basis to create their own versions. In addition, the appearance of new cards and expansions makes players have to adapt their decks to the current meta-game, that is, to the players' behavior at a given time.

One of the most popular Digital CCGs (DCCGs) nowadays is HearthStone, Heroes of Warcraft (HS), with over 40 million players. In addition, this game is becoming a *de facto* benchmark for researchers in artificial intelligence branches, due to the enormous amount of combinations when creating decks, along with the randomness of the effects of the cards, and the hidden information [9].

In HS, players build a deck of 30 cards from a card pool (that can be expanded buying random packs). To win, players must reduce the health of the opponent's Hero from 30 to 0, using the two types of cards available: *spells*, that affect the battleground and are then discarded, and *minions*, that stay in play and can attack the enemy's Hero or other minions. There are also, *weapons*, a sub-set of spells that allow the hero to attack other characters during several turns using special abilities. Each card has an associated cost (in number of mana *crystals*), that is reduced from the player's bunch after a card is played. This amount of crystals of each player is replenished at the beginning of the turn and increased in one up to a maximum of 10.

In HS, deckbuilding is limited to the neutral card pool and the cards that belong to the *class* of the Hero chosen for the game: Druid, Mage, Hunter, Paladin, Priest, Rogue, Shaman, Warlock, or Warrior. Every Hero class comes with a different Hero Power (costing 2 crystals to use), that in conjunction with their card set, matches every Hero to different deck archetypes. For example, Priest's healing abilities are a very powerful choice for decks that attempt to control the board, but not so convenient for aggressive ones, that aim to quickly end the game.

Due to its popularity, players share the list of cards they use in their decks publicly on websites such as Hearthpwn[4], where users and game enthusiasts vote for, copy and comment on the most popular decks. Currently, this website has a huge amount of data: over 600,000 decks in total for all Hero classes, and game modes. The data obtained by crowdsourcing, like those on this website, allows for a dynamic, extensive and organic study of user-generated data [16]. The created decks can be entered into archetypes: that is, decks with a specific behavior and use. For example, the *Jade Druid* archetype is one in which the

[4] https://www.hearthpwn.com/

Druid class uses Jade Idols and other cards with the *Jade* keyword to obtain stronger and stronger effects. Players are familiar with these archetypes and often create other archetypes to counteract them.

The aim of this paper is to demonstrate whether it is possible to extract information from large user-created datasets within the scope of the DCCGs, i.e. conduct a Game Data Mining [5] study. Specifically, the application of clustering algorithms will allow us to detect groups of decks with common features, and check if they are included within known archetypes. This can be useful for researchers in Artificial Intelligence, for example, since by detecting certain cards in the opponent's deck, the corresponding archetype can be inferred, and thus the agent could adapt its actions accordingly in order to face the predicted behaviour. This can also be useful for game developers that want to study how the players are using the game resources and how they adapt to changes such as new expansions or card updates.

The process that we are going to follow in this work consists of downloading the dataset and pre-processing to remove unnecessary information. Next, a descriptive analysis of the dataset will be performed to obtain relevant information before applying clustering algorithms. An expert player will analyze the different clusters to confirm that they correspond to different decks archetypes.

The rest of the paper is structured as follows. After the state of the art in section 2, Section 3 describes the methodology used to obtain the dataset, preprocess and analyze it. In the following section a descriptive analysis of the dataset is made and the results of the clustering method are discussed. Finally, in Section 5 the conclusions and future lines of work are presented.

2 State of the art

Game Data Mining [5] is one of the multiple research lines that videogames have brought. This is understood as the application of Data Mining techniques to datasets related to any videogame, such as telemetry measures, user-monitoring data, player-generated information, play recordings, etc. Normally the aim is the extraction of knowledge, mainly focused on getting some conclusions about any of the game factors related with player experience [20], such as: enjoyment, playability, engagement or balance; which could help the designers to improve the game mechanics. Other approaches are centered on modelling the player's behaviour itself [3], which is very useful in the creation of non-player characters, for instance.

Obtaining the dataset is the main bottleneck, thus, even if this research line has been widely studied in several papers, the games analysed are just a few - those for which there are available data -.

For instance, Thurau and Bauckhage [18] analysed more than 190 million records (from 4 years) of *World of Warcraft* game and found different tendencies in the evolution of guilds. Weber and Mateas [19] applied classification techniques in order to forecast enemy behaviour in *StarCraft*. Also *Madden NFL* [21] and (Infinite) *Super Mario* [20] have been studied from this perspective.

However the most prolific game so far has been *Tomb Raider: Underworld*, which has been deeply analysed in many papers. Drachen et al. have several works applying different data mining and machine learning techniques to more than 1300 records of players that have finished the game, such as [3], where the authors applied Self-Organizing Maps to identify player models (archetypes), or [15] in which the researchers used classification methods in order to predict the players behaviour with respect to their game finishing time (or their potential withdraw).

The objective of the present paper is also to analyze data to find archetypes, but we are considering Hearthstone, which, to our knowledge, has not been analyzed with this purpose yet.

This DCCG, anyway, has been one of the most prolific games/environments for research in the last years. The studies have been mainly focused on the creation of competitive agents to play autonomously the game [2, 17, 9], but there are in addition other works centered on the design part, such as the game mechanics analysis or the game balance testing [8].

Data mining has also been applied to HS. Indeed there have been two Data Mining Challenges (AAIA'17[5] and AAIA'18[6]) using this game as a testbed. However, the 2017 Challenge and the derived papers [13, 10] was devoted to help AI to win the game, whereas the 2018 edition and related papers [14, 12] had as aim to predict win-rates for specific decks.

Thus, in this study we will apply clustering methods to a big dataset, but instead of trying to model player behaviour as in [4], we aim to discover key features (cards in this case) in predefined decks which could lead us to identify a cluster or set of decks as belonging to an archetype. This would help to (automatically) identify game 'profiles' in those decks belonging to the same cluster as an already known archetype, which could be useful for developers (to evaluate game mechanics or the impact of an expansion) and also for autonomous agents (to decide the best strategy to face an opponent), as already mentioned in the Introduction.

3 Methodology

3.1 Obtaining the dataset

As the objective of this work is to analyze the decks that players create, it is necessary to obtain a large amount of data. In our case we have used the data available on a repository: the HearthPwn website (`https://www.hearthpwn.com/`). This database contains information about all the cards available in the game, and offers to its users the possibility to create and share decks built from those cards. Currently there are more than 600,000 decks created, allowing filtering by expansion, hero class, or type of game, among others. Users can view other users' decks and copy them into the game to use against other players.

[5] https://knowledgepit.ml/aaia17-data-mining-challenge/
[6] https://knowledgepit.ml/aaia18-data-mining-challenge/

Typically, the most popular and proven powerful decks are copied, or variations are created from them.

To download the data we have made a script in Python that allows to iterate by `deck id` to get the URL of that deck and download the specific deck webpage. That web in HTML format is parsed using the *BeautifulSoup* [7] library to obtain the list of cards, the date, the class and the game type of deck (Game types in Hearthstone are: Ranked, Tavern Brawl, Arena and Adventures). With the name of the cards it would also be possible to access to more information, such as the cost of making the complete deck with Arcane Dust (the virtual currency of the game), the *mana* cost of each card, or the card type: Spell, Minion or Weapon. Other information such as the Rarity of cards, can als be extracted.

We have limited the decks to those belonging to the "Ranked" category. This game mode is the one where players prepare their decks in order to compete against other players, because it is the most popular game mode. It also is the most common in the whole dataset, with a proportion of 62%.

Each sample (row) will be a deck identifier, and each feature (columns) will be a card from the entire collection. A 1 in a position indicates that the deck has that card, a 2 indicates that it has 2 copies (the maximum for non legendary cards) and a 0 indicates that it is not included in the deck.

3.2 Method of analysis

Initially we will perform a descriptive analysis of the dataset, to see the number of decks per Hero Class, the date of creation, or the most common cards of each class. This can be useful as an initial overview of the whole dataset, and will help to understand further analyses.

Then, a clustering analysis have been conducted using two techniques:

– **K-Means** [11], a classic method which starts from a set of patterns and tries to separate them into k different groups, according to their features.
– **Agglomerative Hierarchical Clustering (AHC)** analysis [7], an algorithm which, starting from samples, pairs two by two similar clusters and builds a binary tree, called *dendrogram*, representing their similarity.

The first technique has been applied because it is very fast but also very effective, as it has been proved in hundreds of studies with all kinds of data. On the other side, Hierarchical clustering offers a very simple visual output, that could be interpreted easily by a human expert, as this is the case in this work.

The input of both algorithms is the dataset. While in K-Means we want to detect if we can extract archetypes (clustering decks), in the AHC we want to extract information about how cards are related (clustering cards). That is the reason in the AHC the input is the transpose of the array: now each card is a row, and each feature (column name) is the ID of the deck the card belongs.

Since each hero has a subset of specific cards that only that class can use, it does not make sense to do the clustering analysis with all the cards/decks,

[7] `https://pypi.org/project/beautifulsoup4/`

as the clusters obtained would be the classes themselves, considering they have disjoint features - their exclusive cards -.

In the case of K-Means we have focused on three classes: Druid, Mage and Warrior, as they have a very wide range of archetypes to play.

The obtained results of the analysis are presented and discussed in the following section.

4 Results

4.1 Descriptive Analysis of the Dataset

Figure 1 shows the distribution of dataset decks by hero class. Although they have a similar number, there is a 32% difference between the class with the highest number of decks (Priest) and the one with the least (Warrior). The most common classes (Priest, Mage and Druid) are also more oriented to control and long-term strategy, so it can explain the variability of user-created decks.

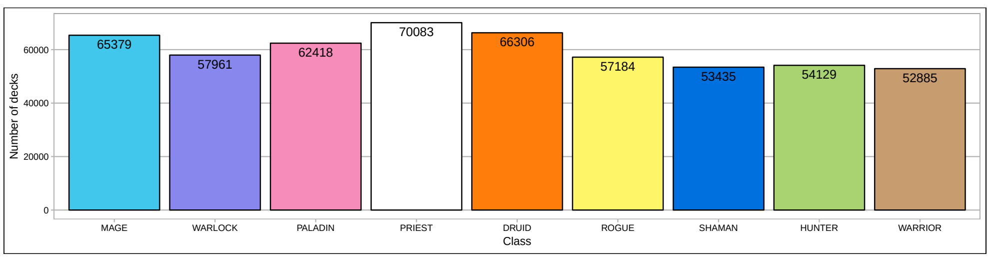


Fig. 1: Number of decks by hero class.

Figure 2 shows the creation of decks over time. The spikes that occur immediately after a new expansion emerges can be seen clearly. Therefore, many of these new decks may not adapt to the meta-game during the season of that expansion, but are the basis for more refined decks.

Figure 3 is particularly interesting, as it shows that, despite having more than 3000 cards available in the pool, all classes have one particular card with more than 50% chance. Even, the probability of some classes is extremely high, like *Backstab* in Rogue decks (with 80% chance of appearing). Classes like Mage or Priest have up to 3 cards with a percentage of appearance of more than 70%. The Warlock class is perhaps the least predictable with respect to its top ten, however, there is a minimum of a 30% chance of getting one of the 10 cards right.

4.2 Clustering Analysis

K-Means algorithm has been applied to the decks in order to see how they are related. We have set to 10 the number of clusters for each class, a value expected

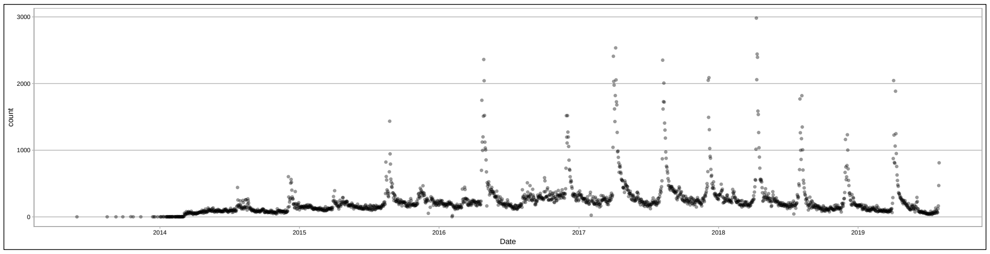


Fig. 2: Number of decks introduced in the data bases analyzed, over time. It is interesting to observe how the spikes in the number of decks are in correspondence to the release of a new expansion, that added more cards to the available pool while at the same time often removing some of the previously popular cards.

to produce enough variety of archetypes, while delivering a reasonable amount of data to be analyzed.

After applying K-Means, we extracted the 15 most common cards from the decks of each cluster. Figure 4 show the percentage of each one for each cluster.

One of the authors, a HearthStone player that reached the highest rank (Legend) in the competitive ladder, manually inspected the clusters and provided an expert analysis for three classes, selected because of an anticipated larger variety of deck archetypes: Druid, Mage, and Warrior. In the following, the notation used for clusters is the initial of the hero class, plus the cluster id (e.g. M2 indicates the second cluster for the Mage class). Also, Figure 4 shows the ten most common cards in each cluster.

Druid Clusters D1, D5, D7 all present cards that provide advantages in the late game (such as *Wild Growth* and *Nourish*); but while D1 and D7 have control cards (such as *Starfall*), D5 exploits the late-game advantage to close combos, using potentially one-turn-kills like *Malygos* or *Aviana*. Clusters D2 and D6, on the contrary, have none of these cards, but feature weak, cheap creatures such as *Arcane Raven* and *Fire Fly*, plus cards that enhance all friendly creatures on the board, such as *Savage Roar*, thus grouping decisively Aggressive archetypes. D3 and D9 show a preponderance of *Jade* cards (*Jade Idol*, *Jade Spirit*, *Jade Behemoth*), thus placing these decks in the category of *Jade Druid*, a specialized midrange archetype. Cluster D10 presents mostly cards with the *C'Thun* keyword, identifying the decks belonging to this cluster as variants of the combo *C'Thun Druid* archetype. Clusters D4 and D8 are harder to categorize, as they seem to either be mid-range variations of aggressive decks, or present poor cohesion, possibly representing outliers.

Mage Clusters M3, M4, M6, and M9 all represent aggressive archetypes, featuring cards such as *Fireball* and *Frostbolt*. M3 exploits synergies with secrets (*Arcanologist*, *Counterspell*, *Medivh's Vallet*), M4 relies upon *Flamewaker* and cheap spells to damage to opponent, M6 shows a strong presence of *Mech* minions

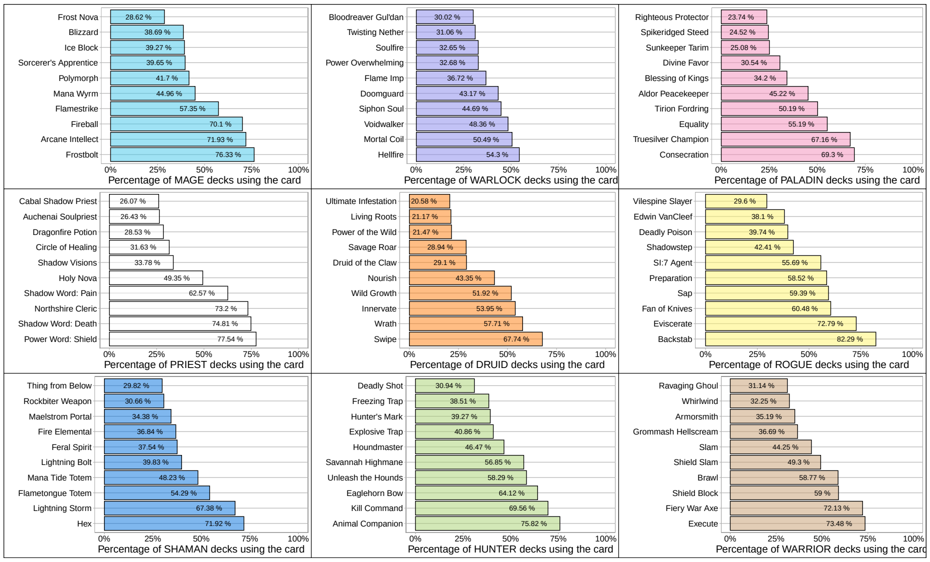


Fig. 3: Most commons cards in decks, by hero class. Interestingly, some of the cards that appear most frequently has been banned or 'nerfed' (cost increased and/or effectiveness reduced) over time. Notable examples are *Power word: Shield* for Priest, *Innervate* for Druid, *Hex* for Shaman, and *Fiery War Axe* for Warrior.

(*Mechwarper*, *Snowchugger*), and M9 is based around cheap spells (*Ice Lance*, *Magic Trick*) plus the minion *Mana Cyclone* to generate new damaging spells. Clusters M2, M5, M7, and M8 all fall under different control archetypes, using either secrets in the case of M2, a large number of board resets (*Doomsayer*, *Flamestrike*) for M5, or a unique late-game finisher (*Dragoncaller Alanna*, *C'Thun*) for clusters M7 and M8, respectively. Notably, cluster M7 also includes decks built using only odd-cost cards, exploiting the synergy with *Baku, the Mooneater*, that provides a powerful effect in exchange for limiting the possibilities of deck construction. Cluster M1 encompasses decks using the synergy between *Elemental* minions and *Jaina, Frost Lich*, thus positioning these archetypes in a mid-range position. Finally, cluster M10 includes combo decks, based on the quest *Open the Waygate*, *Archimage Antonidas*, and *Sorcerer's Apprentice*.

Warrior Clusters W1, W2, W3, and W4 all represent variations of Warrior Control archetypes. Decks in W1 rely upon *Dead Man's Hand* to try and finish the game through fatigue damage, W2 groups both Mech synergy (*Dr. Boom, Mad Genius*, *Zilliax*) and Odd Warrior (*Baku, the Mooneater*), W3 decks seem to exploit older cards (*Sylvanas*, *Justicar Trueheart*) possibly representing Wild decks, W3 is a Control version of *C'Thun Warrior*, with the *C'Thun* cards and several other synergies. W8 is a set of decisively aggressive decks, with cards such as *Leeroy Jenkins*, *Patches the Pirate*, *Southsea Deckhand*. W6, W7, and W10 all represent combo decks: W6 includes cards that can damage all minions on the board (*Whirlwind*, *Death's Bite*) plus minions that benefit from being damaged (*Grim Patron*, *Frothing Berserker*); W7 and W10 are variations of *C'Thun Warrior*, with less control elements with respect to W3, and cards such as *Brann Bronzebeard* to try and finish the game using a colossal amount of damage from *C'Thun*. Cluster W5 groups together Quest Warrior archetypes based on *Fire Plume's Heart*, and more generic mid-range decks still based on Taunt minions (*Stonehill Defender*, *Direhorn Hatchling*). Finally, cluster W9 shows relatively few points in common between its decks, with the most common card being *Fiery War Axe* appearing in only 68% of cases, and might thus represent a collection of outliers, or very different mid-range decks.

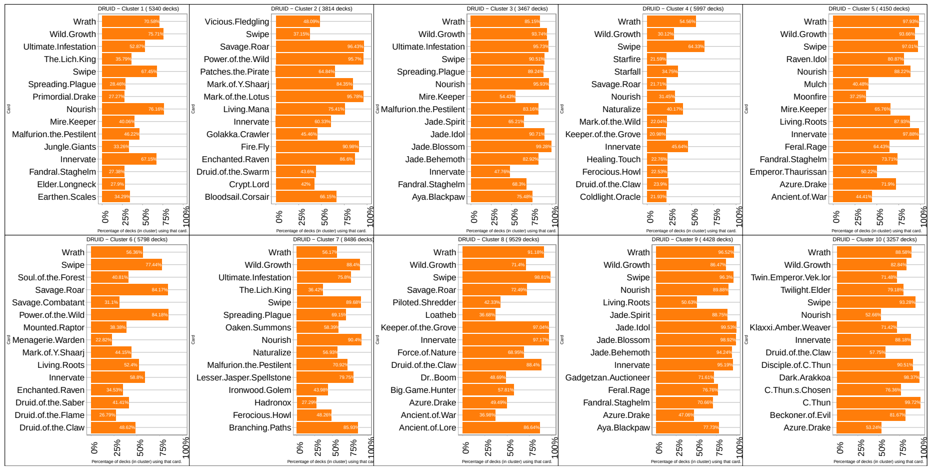
Once the clusters generated by K-Means have been analyzed, Agglomerative Hierarhical Clustering has been applied. AHC can show also interesting information about the influence of the cards. We have run the method for the three heroes, but due to space limitations we are showing and analyzing here only the results of the Warrior class, as they are somehow representative and interesting.

Figure 5 show the complete generated dendrogram of the Warrior cards, and more detail of the subtrees with height=4 is shown in Figure 6. The height of the fusion, provided on the vertical axis, indicates the similarity/distance between two cards. The higher the height of the fusion, the less similar the cards are. This height is known as the cophenetic distance between the two cards. Most of the cards are in a big cluster (subtree 4), but there exist several relevant cards (single cards) that have enough weight to appear in their own subtree, even at level 1. Several pair of cards shown are usually used in combos, have some kind of synergies or belong to the same expansion. For example: *N'Zoth* and *Bloodsail Cultist*.

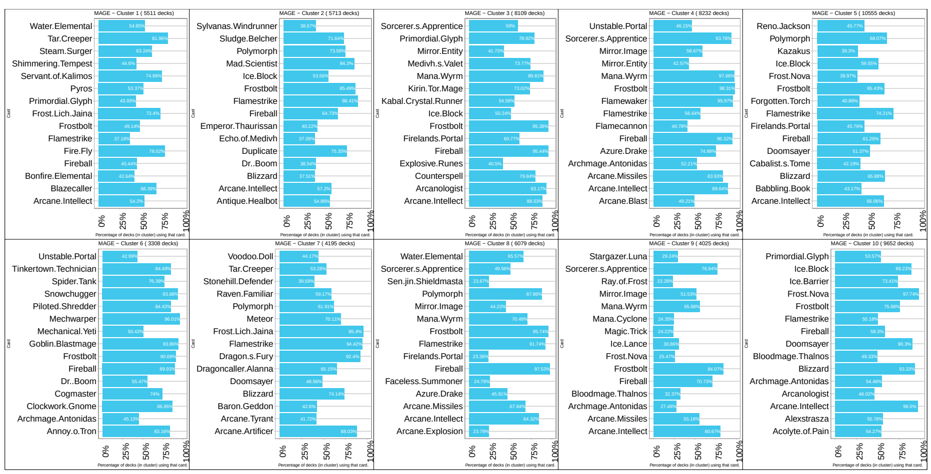
5 Conclusions

Understanding how players play a game is a major concern for developers, as they can adapt elements of the game, such as the rules and content, to facilitate the balance or fun it can provide. In this paper we propose to use Game Data Mining [5], to obtain information about how players create *Hearthstone* decks. The goal is to demonstrate if using a large set of user-created card lists it is possible to extract deck archetypes automatically. To do this we have extracted a dataset from the *HearthPwn* website and performed a descriptive analysis plus applied clustering algorithms.

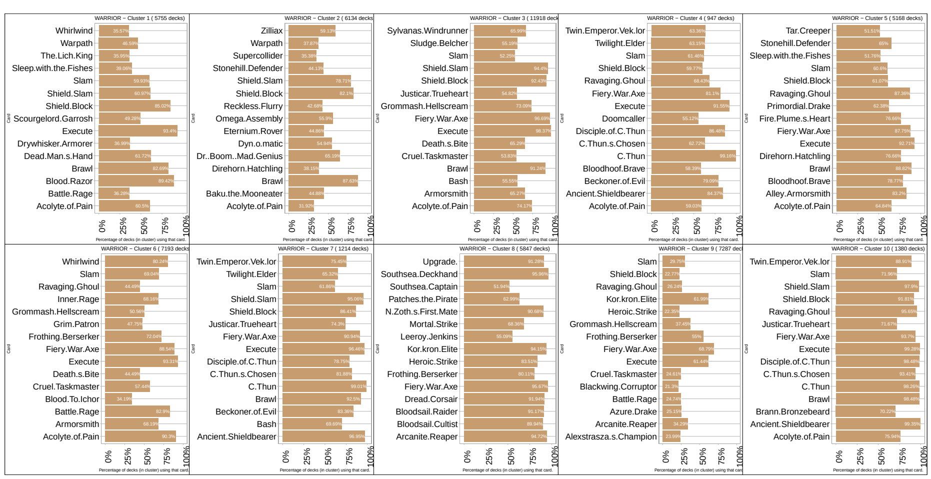
After expert analysis of the results, we have provided information on how the cards are related to each other, and how it is possible to detect different archetypes from the data created by the users. However, the proposed automatic clustering approach also showed a few limitations: 3 out of the 30 clusters analyzed seems to be composed of mostly outlier decks, identifying no clear archetype (D4, D8, W9); moreover, distinct clusters in the same hero class seem to present very similar archetypes (W7, W10); and finally, it is sometimes pos-



(a) Druid



(b) Mage



(c) Warrior

Fig. 4: Ten most common cards of each cluster for Druid (a), Mage (b) and Warrior (c).

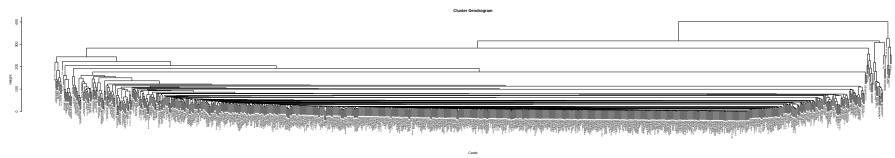


Fig. 5: Global AHC for all cards used by Warrior class.

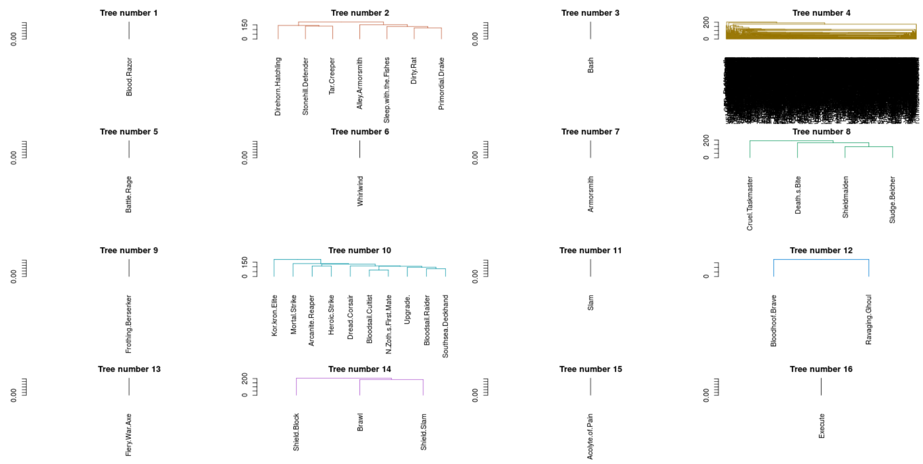


Fig. 6: Subtrees of the AHC cluster. Each id correspond to a leaf (from left to right) of a binary tree of 4 levels. So 1 is more related to 2, and 3 to 4, and therefore 1-2 and 3-4 are also related.

sible to detect two distinct archetypes inside the same cluster (M7, W2). These issues are typical of clustering, an unsupervised learning problem for which there is no ground truth, and parameters such as an arbitrary number of clusters have to be defined *a priori* by the user. Also, relationships between cards can be seen visually using the dendrogram generated by the AHC algorithm

As future work, a card co-appearance matrix can be made, in which each cell is the number of decks that share that particular pair of cards. Using other clustering algorithms, such as the Leiden Algorithm, card communities can be detected [1], and from using their centrality and density measures, these communities can be plotted in a strategic diagram to see what decks belong to motor, transversal, specialized or emerging/disappearing categories. Other visualization techniques, such as visualizing the cards networks, or studying the changes in decks along the time and expansion releases may help to understand how users play the game.

A feature extraction method could be also applied, in order to 'generate' features related to the decks, such as summarizing of the number of minions in the set, or the amount of beast cards, weapon cards, or combo cards, to cite some examples. This information could better describe the decks for their analysis.

Moreover, other clustering algorithms such as *Density-Based Spatial Clustering of Applications with Noise* [6] can partially solve the issue of deciding *a priori* the number of clusters; nevertheless, they feature different parameters to be tuned.

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