Enhancing Hearthstone deck building with a Generative Adversarial Network (GAN)

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Abstract

Acknowledgements

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Contents

1. Introduction

1.1 Overview

Bringing Artificial Intelligence to Hearthstone: Heroes of Warcraft is not a new concept, it has been subject to many studies in the field, where it be playing the game, suggesting moves to the player or building decks. Focusing on the field of deck building, it is a concept that exists across multiple trading card games such as Magic: The Gathering, Pokemon, Yu-Gi-Oh! and of course Hearthstone. Papers have studied these games more or less, but all seem to gravitate around similar deck building techniques, details of which will be expanded later on. These techniques seemingly been saturated, newer studies apply small scale changes to already defined methods [1]. Exploration of different techniques has been touched on but they seem to be outliers and of limited number [2], experimenting with other algorithms could show better, more interesting results instead of assuming that one saturated method is the best because of its popular usage.

1.2 Motivation

Using a Artificial Intelligence algorithm that has not been utilised nor researched in the field of deck building could provide insight into the Generative Adversarial Network (GAN) applications in other fields of research, as it is mostly limited to image generation. Along with this discovering another method for deck building that could bear fruit to similar or improved results, opening the way for more techniques and deeper research into the use of recorded data for deck generation.

1.3 Aims and Objectives

The aim of this project is to create a deck building artificial intelligence using a Generative Adversarial Network (GAN) and testing the viability of it, this will be achieved by completing the following objectives:

- Collecting user deck data from reliable sources

- Cleansing of user deck data
- Converting user deck data to vectors and back to human readable after training
- Implement GAN for single dimensional vector generation
- GAN hyper-parameter and layer optimization
- Simulating results against user decks
- Performing evaluations on resulting decks

1.4 Key Findings

This project has exhibited that it is possible to use Generative Adversarial Networks to generate decks for Hearthstone, a technique that seemingly no one has attempted to use, the AI demonstrates similarities to user created decks such as card types, type percentage, card duplicates, synergies and card spread. The decks tested have an average of 55% win rate, varying from class to class, match ups against other classes greatly influenced the outcome of a match. Although the win rate is heavily influenced by the AI playing it, considering that the simulator game playing AI will not play as well as a human player. The training process is much faster than anticipated (around 10 minutes), however the testing was much longer at around 1 - 2 hours depending of the number of decks created.

1.5 Structure

The structure of the report is as follows, first a literature review which presents an overview of Hearthstone, some of the important game mechanics and existing AI that have been used. Then a discussion of the requirements of the project and the methodology to implement them. Following this is a discussion of the potential legal and ethical issues with the project and what has been done to overcome them. The implementation of the project, a deep dive into how the project was completed. A testing and evaluation section describing the strategy and the results of the generated decks. Finally, a conclusion which summarises the project is given.

2. Literature Review

The purpose of this literature review is to define the technologies used in the field of artificial intelligence for building a deck in Hearthstone. To introduce, and compare previous works to determine their strengths and weaknesses. A review of the literature is valuable in understanding important aspects of a research area [3]. The structure of this literature review is as follows: the initial section will detail the background of the project, explaining the fundamentals of Hearthstone and deck building. Following that will be an introduction to the project, motivations, and research questions. Finally, we will have the core technologies used for similar projects.

2.1 Background

For the benefit of the reader, this section will introduce the basics of Hearthstone. It will emphasize the deck building aspect of the game including practices used by players.

2.1.1 Collectible Card Games

Collectible Card Games (CCG)[1] are a sub-genre of card games introduced in 1993 by Magic: The Gathering [2]. They require players to make a custom decks to play, they mix trading cards with strategy and deck building features. CCGs are usually defined as a turn-based game, where each player acquires their own collection of cards through the purchasing of "starter decks" for beginners or "booster packs" containing a small number of random cards from a *pool* of cards usually referred to as an expansion. The aim is to build an efficient deck that can account for the inconsistency that comes from the nature of card games, to predict and play around your opponent's actions to ultimately beat them. Some CCGs can prove to be lucrative for players as cards have a value intrinsic to their rarity and demand [3], this makes building the perfect deck rather difficult and usually costly.

[1] `https://en.wikipedia.org/wiki/Collectible_card_game`
[2] `https://en.wikipedia.org/wiki/Magic:_The_Gathering`
[3] `https://www.cardmarket.com/en/Magic/`

2.1.2 Hearthstone

Hearthstone: Heroes of Warcraft is a CCG developed by Blizzard Entertainment in 2013 [4], but with the twist of it being entirely digital, there is no physical version of the game. This choice unlocks potential for gameplay features that could not be implemented, in exchange for the tradability of cards.

Figure 2.1: Example of a Legendary Hearthstone card[4]

Two players face off wielding each a deck of their own making. Decks consist of exactly 30 cards. Players then take it in turns to play their cards, the objective being to reduce the other player's health to zero. On each player's turns that player draws a card and gains a "Mana Crystal" up to a maximum of 10 (crystals are refreshed every turn), these crystals are expended to cast a card from the player's hand. Before a match each player chooses to embody a class (such as Mage, Warrior, Rogue, Druid, etc. . .), each class has specific cards only they can add into their deck, these are adequately named "Class Cards", these are accompanied by "Neutral Cards" that any class can use. Classes also have access to an ability unique to them called a "hero power".

Each card in the game has a "mana" cost which shows how many mana crystals are needed to cast that card. They also have a card type, rarity, and an effect. In a deck, players can put duplicates of the same card (up to 2) except for "Legendary Cards" (figure 2.1) that are limited to a single copy due to their powerful effects. Players have a "Collection", where the cards they own are stored, to get new cards players can buy card packs with gold, the in-game currency of Hearthstone. Gold is earned slowly through quests, winning, and events, however this process can be sped up through the purchase of gold with real-life currency. Players can also choose to "Disenchant" their duplicate cards to gain another in-game currency called "Dust" which can be used to create a

[4]https://www.pinterest.fr/pin/573716440004576557/

[5]https://bothgunsblazingblog.wordpress.com/2014/06/22/hearthstone-analysis-and-deconstruction/

Figure 2.2: Example of a Hearthstone board[5]

card of the players choosing[6].

2.1.3 Deck Building

In the world of CCGs, there is a long-standing debate on how to measure the skill of a player. Although card games involve luck and circumstance, it is believed that there is a degree of strategy in the building and execution of decks whether it is just a slight increase in win probability or a fundamental to winning [5]. However, the debate stems from which is the most important, the building aspect or the execution aspect of CCGs. [6]

2.1.3.1 Metagame

Hearthstone is a game with lots of complex systems that are influenced by many factors, mainly due to a large number of cards and different playable heroes. In a game where there are lots of variables, players try to rank cards, heroes, and combinations to increase their chances to win. This phenomenon creates decks from a "pool" of top-rated cards, leaving out the mediocre, forcing players to use these top-rated decks in order to have a better chance of winning or be put at a disadvantage. The result is what is called the "Metagame" or *meta* for short[7]. Blizzard release updates to the game frequently through "expansions"[8] which add a variety of new cards to keep the game fresh. Shifts in the meta occur when these expansions are added and players experiment to

[6] `https://hearthstone.gamepedia.com/Crafting`
[7] `https://www.hearthstonetopdecks.com/hearthstones-best-standard-ladder-decks/`
[8] `https://hearthstone.gamepedia.com/Expansion`

find better combinations over time. However better cards may not be added, and changes in the meta may not occur, this dissuades players from continuing or returning to play knowing that they have already experienced all that they can. To avoid that Hearthstone has implemented two-game modes[9], one in which only cards added over the past two years are available, and another mode that allows all cards. Whilst this method has helped, it still does not put a stop to the possibility of a stale meta. Researchers have done studies on how to evolve the meta through AI means, by *balancing* powerful cards (Fernando et al.) [7]. Balancing a card means to adjust the power of said card to make it more or less viable in the current game environment. Fernando et al. discussed the idea that around 50% of Hearthstone's meta is derived from match-ups which is the win probability two decks have against each other, a favorable match-up being the one with the highest win probability or known in the community as *win rate*.

2.1.3.2 Mana Curve

Theorycrafting is a term used widely in many video games, it designates a mathematical analysis of a game's core mechanics to attempt to discover new strategies or combinations that could rival the current ones. Hearthstone is one such game, a large portion of the player base enjoys theorycrafting new decks that may *break* the meta, as in cause a fundamental shift of the current metagame. These players rely on fundamentals or schematics that are used as a guideline in building a new deck. The *mana curve* [10] is one such fundamental, it exists in all decks built in the game. Every card in Hearthstone has a cost, this cost determines the power of the card, a low-cost card will be weaker than a higher cost card since it would cost fewer resources to cast. This *mana curve* is a histogram of each card plotted by cost, it allows players to visualize how expensive in resources their deck is and to determine the deck's archetype.

Figure 2.3: Example of a Mana Curve[11]

[9] https://hearthstone.gamepedia.com/Game_format
[10] http://hearthstone.gamepedia.com/Mana_curve
[11] https://hearthstone.judgehype.com/deck-mage-tempo-ladder-legendaire-tgt-gvg/

2.1.3.3 Archetype

The word archetype is derived from the Greek word *archétypon* which means "beginning, origin", applied in the psychology field to categorize complex human behaviour called "Jungian Archetypes" [8]. This term was transposed into the deck building field of CCGs, a deck's archetype is meant to categorize and describe the behaviour of the deck from a high-level perspective, forgoing the need to play the deck to learn its strategy. In Hearthstone, most decks can be categorized by three main archetypes [9]:

- *Aggro* decks are the aggressive decks meant to defeat an opponent as quickly as possible, as a consequence the mana curve of such decks is focused towards the cheaper side of the histogram. Their power comes in the early turns, but they quickly become weaker to the other archetypes as the turns go on.

- *Control* decks are meant to control the state of the board through the use of expensive cards, they tend to generate a lot of cards and have a wide range of card choices. The mana curve of such an archetype is towards the expensive end of the histogram. They tend to have a few cards to play early in the game but have a multitude of win conditions in later turns.

- *Mid-range* decks are situated in the middle of the two other archetypes, focusing mainly on the mid-game, their win conditions are stronger than the aggro decks but weaker than the control decks. Their mana curve peaks in the middle of the histogram.

Hearthstone also has other archetypes that cover a shorter scale, they are usually introduced in the newer expansions and rotate out of the normal game after a couple of years [10]. For example, a highlander archetype is a deck with 30 unique cards. Archetypes are formed around specific cards with win conditions[12], meaning that they have the power to win the game. So in the example given in a highlander deck, there would be a card that has an effect that triggers from having only unique copies in the deck.

2.1.3.4 Resource Cost

In CCGs, cards have a certain cost to use, in Hearthstone that cost is mana which regenerates every turn. The cost of a card is determined by the power of said card, if it has a powerful effect, has decent attack and defence values, or even both. This cost will determine how late into the game a card can be played. However, a card that costs a lot can be considered weak and a low-cost card can be considered strong. The power of a card is determined through the resource cost, an invisible value that is hard to calculate and a subject of study [11]. Although the Zuin et al. study was used to predict the cost of a card in Magic: The Gathering, the resource calculation is still present in Hearthstone. It poses

[12] `https://playhearthstone.com/en-us/news/21363038`

a good solution to the balancing of the metagame and would be adaptable to Hearthstone. A card is considered efficient if the theoretical resource cost is higher than the current mana cost, and would be inefficient if the resource cost were to be lower than the mana cost. The resource cost of a card is something that may need to be considered when developing an AI for building decks. Stiegler et al. [12] applied a similar theory to design a deck-building AI based on a utility system that classified cards based on resource cost-effectiveness, mana curve, and synergies.

2.2 Project Introduction

The rising popularity of Hearthstone has attracted a lot of new players reaching over 100 million accounts in 2018 [13], however, due to the nature of collecting cards in the game some will not have the required cards to build the most popular decks. The game is free, anyone can download it, however, a lot of the content is locked behind a paywall[13]. Whilst it is possible to earn cards by earning "gold", it becomes a time-consuming ordeal that requires a lot of spare time to invest. With new expansions being added regularly, the game seems to become a never-ending grind, unless you decide to pay real money to acquire currency. This is where the term "pay-to-win" is used to describe Hearthstone [14], meaning that to get the most enjoyment and the highest chance to win, the player must spend money or be disadvantaged. The goal of this honours project is to create an AI that builds decks from a collection of cards, incomplete or otherwise in order to improve the game experience for players that are unable or not willing to pay. For players that do own a large collection of cards, it can also provide fresh new decks to play that differ from the more popular ones.

2.2.1 Related Works

Video games are the ideal tool for the training of Artificial Intelligence. The virtual space that a game provides is a realistic environment with a limited amount of information available [15] allowing control and knowledge over the behaviour of the AI. Hearthstone is a game that provides a platform for a wide variety of AI that differs from AI-benchmark games such as Chess or Go. Hoover et al. [16] classifies Hearthstone AI into specialized categories:

- Game Playing AI, rather self-explanatory, this form of AI is designed to play the game. Generally, tree search algorithms are used, Monte Carlo Tree Search (MTCS) in particular. However, this method is rather ineffective in Hearthstone due to the amount of hidden information and limited visibility of the AI. Developers of Hearthstone simulators, such as *MetaStone*[14] tend to use a greedy approach to compensate [17]. Some researchers attempt to use variations of MCTS and heuristics to work around the limited information [18][19][20].

[13] `https://en.wikipedia.org/wiki/Paywall`
[14] `http://www.demilich.net/`

- Developer Assisting AI, this AI help with certain issues that developers could have. Since Hearthstone has hundreds of cards, it is challenging to design cards with new flavour that are not identical to previously printed cards. Could there be a way to generate inspiration? Woolf "minimaxir" Max[15] created an API that generates Magic: The Gathering cards[16] using a transformer language model[17] for such a purpose. Another possible use is for balancing the game, since maintaining game balance when creating additional cards may create unfair combinations, or render some cards useless[7].

- Deck Building AI, these create decks for the player or another AI to use, most commonly created with Evolutionary Algorithms[1]. It has the inherent advantage of being usable in conjunction with other AI. Such combinations help ascertain potential balance issues without human bias involved. Since this is the main topic of this paper, a further in-depth explanation will be provided in the body.

Whilst all these AI are used in the context of Hearthstone, they are utilized for different aspects of the game, therefore, proving that Hearthstone is a platform with a constant influx of AI challenges to be met, a prime example is the additional *battlegrounds* gamemode[18], a variation of the game where the creatures attack on their own automatically, then completing your board as you progress between rounds. This alteration of the way the game is played will surely become the subject of a paper in the future.

2.2.2 Research Questions

Research Questions are essential to any methodical research, it is the first step in any project and fundamental to any successful project. Kowalczyk[21] described Research Questions as a metaphor for a house: "Your data collection forms the walls and your hypothesis that guides your data collection is the foundation. So, what is the research question? It is the ground beneath the foundation. It is what everything in a research project is built on. Without a question, you can't have a hypothesis. Without the hypothesis, you won't know how to study what you're interested in." The research questions in this literature review are defined as:

- **RQ1:** What are the current best deck-building techniques in Hearthstone?

- **RQ2:** What are the strengths and weaknesses of the different techniques?

- **RQ3:** With our findings, what techniques can be applied to optimize the deck-building problem in Hearthstone?

[15] `https://minimaxir.com/apps/gpt2-mtg/`
[16] For example cards: `https://github.com/minimaxir/mtg-gpt-2-cloud-run/tree/master/generated_card_dumps`
[17] `https://openai.com/blog/tags/gpt-2/`
[18] `https://hearthstone.gamepedia.com/Battlegrounds`

2.2.3 Assistance Systems

Despite AI being widely used in Hearthstone for research purposes, it is against Blizzard's Terms of Service (ToS) to use game-playing AI in Hearthstone (Section 1.C.II)[19]. However, a surge of Hearthstone deck tracking software [20] is being used by players without being banned. So how do players use this kind of software without violating ToS? It was revealed that turning on debug logs would provide enough information for these systems without breaking ToS [22] which birthed a whole sub-genre of AI coined as "Assistance Systems" designed to be used to assist the player without it being considered cheating. This brought on the creation of deck trackers, which mentioned above track which cards each player has used and tracks statistics. Whilst deck trackers are not AI since they just read logs, Bursztein [23] used this system to create an AI that predicted what cards the opponent would play in future turns, and used this predictor AI to climb to *legend* rank (the highest rank in competitive mode[21]). While it was not against ToS to use it, when they presented the tool, Blizzard reached out to them and asked them not to release the code as it was *game breaking*. The effectiveness of the tool was however limited to later turns, the accuracy is much lower (going as low as 50%) in first turns and becomes more accurate each turn. Some of the most crucial turns for some archetypes are in those early turns, so this AI would only maximise effectiveness for the *Control* Archetype (2.1.3.3).

Other assistance algorithms include Hearthstones Arena game mode[22], a mode in which the player drafts a deck one card at a time by selecting 1 of 3 possible choices from a pool of cards, using Apriori algorithms [24] such as HearthArena[23] to make suggestions based on data from a diverse range of high-quality decks created by player and/or deck building algorithms[25]. However, this sort of algorithm would only be useful in an environment where the player cannot select their cards.

The use of assistance systems is interesting but still requires the interactivity of a third party to function. The advantage to assistance systems is the ethical and legal implementation from it. The disadvantages such as the low accuracy rate of the prediction tool in earlier stages of the game, or the limited usability of the Apriori algorithm makes it difficult to be used in a standard deck-building format.

[19] `https://www.blizzard.com/en-us/legal/fba4d00f-c7e4-4883-b8b9-1b4500a402ea/blizzard-end-user-license-agreement`

[20] Some software examples: `https://hsreplay.net/downloads/?hl=en`
`https://go.overwolf.com/firestone-app/`
`http://hearthstonetracker.com/`
`https://trackobot.com/`

[21] `https://hearthstone.gamepedia.com/Ranked`

[22] `https://hearthstone.gamepedia.com/Arena`

[23] `https://www.heartharena.com/`

2.3 Genetic Algorithm

Developed AI algorithms often draw inspiration from biology[26], Genetic Algorithms (GA) is an example of this. GAs are a subset of Evolutionary Algorithms (EA) that base their training process the same way nature does, biological evolution through natural selection (Figure 2.5). A population of solutions each with a set of properties (chromosomes in nature) that are mutable is randomly generated. Each iteration or *generation* the algorithm selects the fittest individuals of the population using a fitness function, then the most fit are used to form the next generation. Some mutations of properties may occur in some of the population. The algorithm ends when either the correct fitness level is achieved or when the number of set generations is reached[27]. GAs are stochastic in nature, meaning that a single iteration would not be sufficient to provide significant statistical results [28]. The process is reminiscent of Charles Darwin's theory of evolution[24] and proves to be effective in optimization problems[26]. This algorithm is the most frequently used for deck building

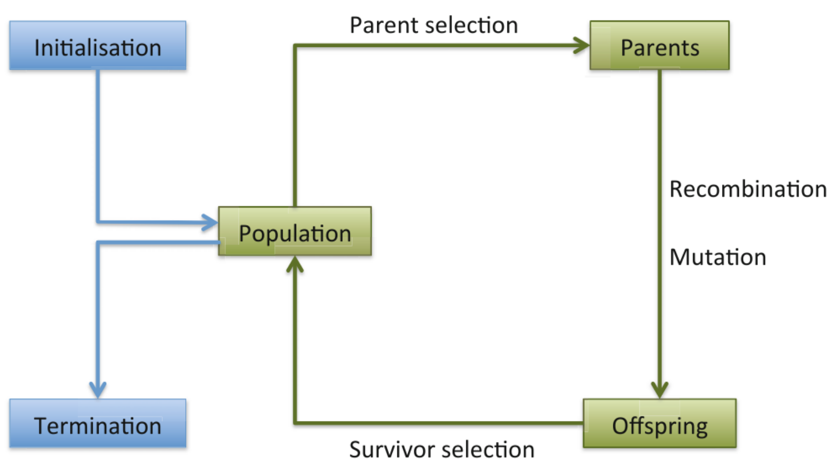

Figure 2.4: Evolutionary Algorithm Flowchart [26]

problems [29][30][31], although they are optimized in different ways. In GAs, there exists a fitness function that determines the fitness score of an individual that is used to create the next generation, and there is the mutation function which will randomly mutate some individuals (it may or may not improve the fitness of said individual).

Bjørke and Fludal [29] used a genetic algorithm to construct decks for Magic: The Gathering based on a certain pool of cards. Instead of using a fitness function that would calculate the score of a deck, they pitted each deck in that gener-

[24] https://en.wikipedia.org/wiki/Natural_selection

ation against each other in a tournament format using a Magic: The Gathering game simulator, each deck had the same number of games to play and they would select the fittest decks based of their win rate in the tournament. While theoretically, the idea is sound, the time that it took was substantial for an unremarkable win rate (less than 60%). With 50 matches per deck over 350 generations, it took 43 hours to execute. Due to the time it takes, it would be unusable for players as it would simply take too long.

Garcia-Sanchez et al. had a similar approach using lexicographical fitness with a Hearthstone game simulator called *MetaStone*[25], separating the fitness evaluation into three parts: one part counted the number of victories of in 16 games, another part which determined the deck correctness (no more than 2 duplicates, only 1 legendary, etc...), and the last part was applying standard deviation to the number of victories, it being optimal if the deck won against every opponent [30]. The results were achieved faster much faster and were of a better standard than Bjørke and Fludal's work[29], however, the results were not as high as they could have been, mainly due to the fitness function using *MetaStone's* greedy AI to play. The decisions made by the AI would be greedy and different from that of a human player. The mutation function could also have been touched on, allowing the mutation to make smarter decisions about which cards to mutate.

Garcia-Sanchez et al. tackled the problem once again and touched on the mutation function [31], they developed a *smart mutation* function that would replace a card in a deck with another of a similar cost (roughly $\pm$ 1). The results with the smart mutation were overall better than without it. This may solve one of the weaknesses of their previous work[30] but still uses the same greedy simulator heuristic.

2.4 Machine Learning

Machine Learning is a subset of Artificial Intelligence that constructs systems that can learn and improve without the need to be explicitly programmed. Burkov described it as "a subfield of computer science that is concerned with building algorithms which, to be useful, rely on a collection of examples of some phenomenon." [32]

This section of the review will present Machine Learning techniques that have been used or could possibly be used for deck building.

2.4.1 Artificial Neural Network

Artificial Neural Networks (ANN) also known as Neural Networks (NN) for short is an algorithm that was inspired by the biological neural networks seen in brains. They are a group of interconnected nodes or *neurons* typically organised into multiple layers, an input layer, an output and n amount of hidden layers. Through many loops known as *epochs*, the NN trains itself using data

[25] `https://github.com/demilich1/metastone`

from datasets to ultimately make a prediction based on given data as an input. Each node is weighted, and these weights are updated throughout the training process increasing the weight of positive output and decreasing on a negative one, allowing the system to make more accurate predictions [33]

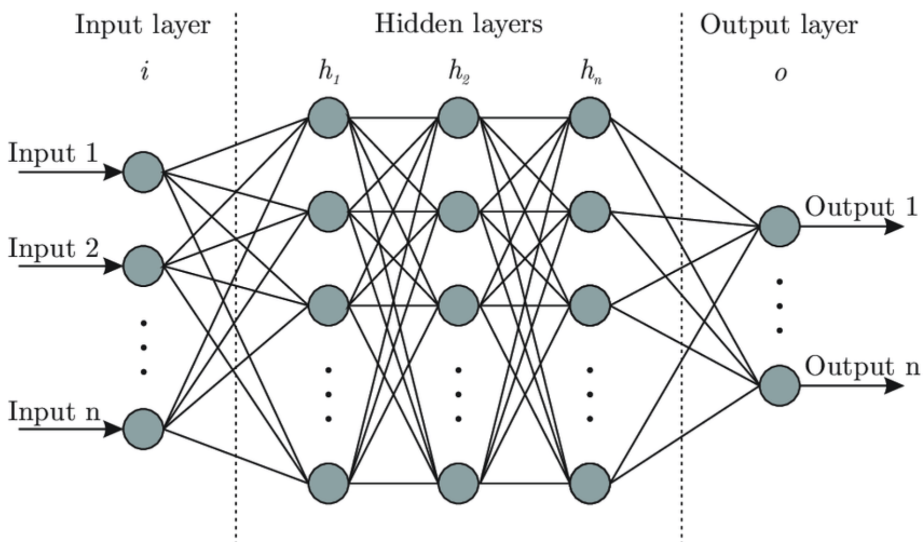

Figure 2.5: Artificial Neural Network architecture [34]

The approach to developing a deck-building AI is done differently than a GA. Ward et al. created a NN that emulated the choices a human would make when drafting a deck from a pool of cards for Magic: The Gathering [2]. The idea was to select the cards that were chosen by a human in the dataset (target variable). The resulting accuracy on the test set was 65.7%. The main drawback to this technique is that it requires the data to be clean, since the dataset used was a lot of decks drafted by human players, the data within may be suboptimal or purposefully tampered with, which would cause the AI to build weaker decks.

Jakubik attempted a different method by using a NN to predict the win rate of a Hearthstone deck learned by using the results of observed matches [35]. This was a proposed solution to the AAIA'18 data mining challenge and came second. However, Jakubik's solution was subject to over-fitting, which Hieu Vu et al. tackled during the same challenge, which brought them the winning solution to the AAIA'18 data mining challenge[36]. They tackled over-fitting by doubling the number of input features (or nodes) to account for the opposing player, they added an extra hidden layer and more test cases to compensate. Jakubik [35] and Hieu Vu [36] rely on data of games that have already been played meaning that this method is not suitable for the construction of the decks rather the prediction of the win rate based on games that have been played. Ward et al. paper is the better technique of the three papers to build good decks, however, it requires clean and uncorrupted data.

2.4.2 Generative Adversarial Networks

Generative Adversarial Networks (GAN) is an application of generative modeling originally described in 2014 by Goodfellow[37], which is an unsupervised learning task that automatically discovers patterns in the input data that the model can then use to output new examples that could have been drawn from the original data. A GAN uses a generative model to generate a similar output and a discriminator model uses supervised learning techniques to determine the probability of the generative output to be part of the training data[37]. The goal of the generative model or *generator* is to create an output that can trick the discriminator into thinking it was part of the dataset. Goodfellow et al. use a fake money analogy: "We can think of the generator as being like a counterfeiter, trying to make fake money, and the discriminator as being like police, trying to allow legitimate money and catch counterfeit money"[38]. The GAN trains itself like this until the generator can create something that tricks the discriminator. Figure 1.6 shows the architecture of a GAN

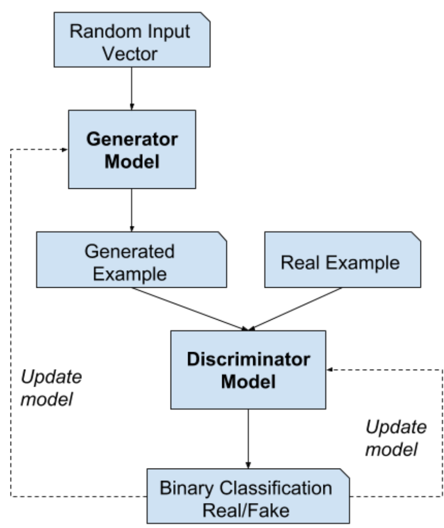

Figure 2.6: Generative Adversarial Network architecture[26]

As of writing this, there have not been any applications of a GAN for building decks. However, Rodriguez Torrado et al. combined a GAN with a procedural content generator to create different playable levels that were randomly generated from the generative model[39]. The GAN struggled to make playable and unique levels when provided a small amount of data. With this paper, it

[26] `https://machinelearningmastery.com/what-are-generative-adversarial-networks-gans/`

is theoretically possible to apply a GAN in a deck-building context but it will require a large amount of data to provide malleable results.

2.5 Hybrids

In AI, aspects of a problem to be solved can be optimised through the use of multiple AI. This section of the review discusses papers that have used a combination of machine learning and evolutionary algorithms. The reason why GAs are combined with Machine Learning techniques is that GAs do not require lots of data to function, this allows for uses such as parameter optimization, Sehgal et al.[40] uses GAs to speed up the learning process of their Deep Reinforcement Learning (RL) agent and provided the maximum success rate faster. Such et al. [41] used it for similar work, and stated that is was a competitive alternative to popular RL training techniques. It has also been observed that in the chemical field that the GA could outperform generative models in a discriminator neural network [42], exploring the possibility of an application in GANs. The use of genetic algorithms in hybrid neural networks is mainly for achieving results faster [40][41], however in highly parametrized systems the GA tends to struggle to find the optimal combination. [43]

2.6 Conclusion & Final Thoughts

This literature review has covered existing deck building solutions from Hearthstone and Magic: The Gathering, including evolutionary algorithms, neural networks, and various assistance systems. Potential solutions such as hybrid algorithms and Generative Adversarial Algorithms have also been discussed. Based on this literature review, it has been determined that evolutionary algorithms are the most popular method of tackling the problem therefore the most saturated of new solutions to explore. Machine Learning is a more obscure usage, focusing mainly on win rate prediction and card ranking. Hybrid algorithms and GANs have not yet been used in a deck-building context. In the context of GAs and NNs, they attempt to solve the deck building problem from different perspectives, the GA attempt to build a deck directly and test it in a simulated environment to determine the power of the deck in real-time, whereas the NN focuses on previous data that it uses to predict the power of the deck. They achieve the same goal, however, GAs are more direct and provided concrete results whereas the NN focuses on an indirect prediction from previous use cases. Moving forward this paper will explore solutions within those methods.

3. Methodology

3.1 Overview

The project implemented will be written in Python, in the form of three python notebooks, each with a specific task. The first notebook collects card data from an API and creates a card dataset, the second notebook scrapes deck data to create datasets for each class, and finally the last notebook will house the AI and the simulator testing. A user simply needs to run the notebooks to get their results, an input is required when deciding what class the user wants the deck to be. With the second notebook, additional datasets can be created and used in the place of the old ones for training the AI.

This project outputs JSON files for the card and deck data, one file for the card data and ten files for the deck data (one for each class). When executing the AI, the user is presented with a certain number of decks, the number varies on how well the GAN trained, these decks are tested and the user is shown graphs and charts of deck composition, overall winrate and winrate per class. They can see the cards within the deck to use at their own leisure.

3.2 Functional Requirements

a. AI **MUST** output a legal deck following the rules of Hearthstone. Meaning that a deck should be composed of 30 cards, with no more than 2 duplicates of any card (excluding legendaries, which can only have a single copy).

b. AI **MUST** output a deck following the rules of the "Standard" game mode. Meaning that the AI can only use the classic card set and the latest expansions from the past 2 years.

c. AI **MUST** use a generative adversarial network in order to generate a deck. The network will include a generator to create a similar and a discriminator to determine if the deck is part of the dataset.

d. AI **MUST** use a dataset of user created decks from the latest expansions in standard format (Rise of Shadows, Saviors of Uldum, Descent of Dragons, Ashes of Outland, Scholomance Academy, Madness at the Darkmoon Faire) collected from Hearthpwn.

e. AI created decks **MUST** be tested in a simulator to output a predicted win-rate and determine the playability of the deck versus user created decks. A total of 16 games should be played for optimal results. This will allow for the completion of requirement "f".

f. The generated deck **SHOULD** have a calculated win-rate of over 50%. Ideally around 60%, so that the AI can make worthwhile decks. Meaning that the created decks should win at least half of the time, and in an ideal scenario they would win more often than lose.

g. AI **SHOULD** output a dataset of decks it generated following the same format as the training data, as to log the output and determine a possible bias.

h. AI **SHOULD** be able to generate a deck from a limited collection of cards, so it can be useful to players without access to all cards in Hearthstone.

i. AI **COULD** be used in the wild format, making use of all expansions to create competitive decks from a larger pool of cards.

j. An interface **COULD** be created to accommodate the AI and assist in feature implementation and accessibility of users.

3.3 Non-Functional

a. **MUST** have written consent from Hearthpwn to scrape data for dataset

b. Data collected **MUST** conform to GDPR regulations and be anonymous, since the identities of decks created by users is not needed.

c. **MUST** use Python as the programming languages of choice for the access to expansive libraries for data manipulation and AI creation.

d. **MUST** use Jupyter notebook as the software for coding the AI. It provides a platform for Python, and the cells are useful for making small changes without having to re-execute the whole program.

e. Dataset size **MUST** not be more than 100,000 rows as to decrease time to train and prevent overfitting.

f. The training process of the AI **SHOULD** take less than 3 hours, to allow a faster uptime if the AI needs to retrain after an update.

g. AI **SHOULD** use card data from the The Hearthstone API on RapidAPI if needed, to collected data such as card effects, images and tribal tags based of the name of the cards.

h. AI **SHOULD** use deck data scraped from Hearthpwn to train from using a coded web scraper.

i. Creation of a deck after training **SHOULD** not take more than 10 minutes. As to allow the to be quick to use by others whilst allowing for testing time with the simulator and the generation of graphs

j. **COULD** generate graphs of performance of decks outputted by the AI and simulators to visualise the training and testing process including the results of the created decks.

3.4 Approach

The project was designed using a agile methodology, equipped with logging, initially from a Trello board for the literature review and then migrated to github commit logs for the implementation of the project. The aim was to implement a requirement, testing it, fixing bugs and integration issues and adding additional features, this process was then repeated for each requirement until completion.

Testing was done on a per feature basis, once a feature was implemented, a series of tests examples were created to ensure the functionality of it, if any errors or problems arose the focus would be shifted to fixing that issue. Evaluation was done after testing, once deemed ready, the AI was executed 10 times to create decks for each class which were evaluated over 100 games across all 10 classes, graphs then display these results.

3.5 Libraries

This section describes what libraries have been used in this project, the aim is to show transparency and understand some more ambiguous parts of the implementation. Note that all of these libraries are Python libraries.

3.5.1 Web Scaper and API

3.5.1.1 Requests

The requests library is a simple HTTP library that allows the user to send HTTP requests, whether it be GET or POST. This library was selected above others because over 500,000 others use this library aswell meaning that the library is stable and enables long term projects to stay active. This is used for both web scraping and api calls as both require to get a uri to get the information needed for the datasets.

3.5.1.2 Json

The json library allows for the encoding and decoding of json data, this is used for creating the outputs of the API calls and Web scraping, it is also used as an input for loading these data files and processing the data.

3.5.1.3 Beautiful Soup

Beautiful Soup is a library for web scraping, it pulls out data from HTML and XML files. There are three main libraries for web scraping, Selenium, Scrapy and Beautiful Soup. Selenium is mainly used for AJAX requests and Web Application testing, so it is not ideal for this project as the request library is being used to make http calls. Scrapy whilst having more features, and being faster than Beautiful Soup, it is meant for complex web systems with middleware which are not needed in the scope of my project. Beautiful Soup was chosen for its simplicity and flexibility on small scale projects, since this will mainly be used for scraping data to create datasets. Originally Beautiful Soup was used for the collection of card data, it is no longer used for that as the resulting output was missing crucial data such as class, cost and image links, so an API for collecting the card data was used instead, which allowed the data to be stored in JSON format.

3.5.2 GAN

3.5.2.1 Keras

Keras is a deep learning API that runs using Tensorflow, a machine learning platform which focuses on enabling speedy experimenting, it is simple to use and very well documented making it easy to implement models. This is what was used for the creation of the Generative Adversarial Network, specifically the implementation of the generator and the discriminator.

3.5.2.2 Numpy

Numpy is a python library designed for working with arrays, it aims to provide array objects that are 50x faster than standard python lists, since the GAN will be using a lot of arrays this is ideal for achieving faster training times. This library was used throughout the training process of the GAN, from sample generation to final deck results.

3.5.3 Evaluation

3.5.3.1 Matplotlib

Matplotlib is a data visualization library which allows data to be displayed through graphs and charts, this is used throughout the evaluation process of the project.

3.5.3.2 Time

Time is a python library that is used to measure execution time of functions, in this project it is used to calculate execution time of the GAN training and testing process.

3.5.3.3 Fireplace

Fireplace is the python library for the Hearthstone simulator, this is used for testing the generated decks against ones from the dataset. There are two other simulators worth considering, Sabberstone and Hearthbreaker. Hearthbreaker was used by the Google Deep Mind team for card generation however the project is no longer maintained, it has been for many years so that one cannot be used to fulfil our requirements. Sabberstone is written has a full interface but for testing that creates unnecessary bloat, so Fireplace is the better choice, it is maintained, and plays games in seconds, the main downside however is that only about half of the cards in the game are implemented. This is because some cards have tricky mechanics that are hard to implement and that the developers are to write interactions manually.

4. Legal and Ethical Considerations

Since data is a fundamental aspect to the success of the project, it is subject to certain legal and ethical implications that need to be addressed whether it be with the handling of the data or the collection of the data.

4.1 Legal

There are two main legal consideration for this project, the protection of data through GDPR and obtaining data through web scraping.

4.1.1 Data Protection

When dealing with personal data, developers are bound by laws to keep that data safe, the first most obvious law that needs to abided by is GDPR, which applies to the project since we are using EU data (among other countries aswell), certain protections must guaranteed. Some ways of protecting personal data are, pseudonymisation and anonymisation, in essence the user's identity is protected by a pseudonym or with nothing at all which means that there will be no trace back to them, this could be represented as an ID or a username. If the data can be reversed back to personal data then data protection obligations will still apply, however if it is not possible then that data is no longer personal [44]. Data minimisation should also be practised when dealing with personal data, this means that data should be lawful, fair, transparent and it should only involve data that is necessary for the task at hand, no more. So in the case only the essential information has been collected (deck data) to train the AI, it is completely anonymous. Data minimisation also extends to how the data is used, it should only be used for its intended purpose only and not to be shared to others. One final important legal implication I need to consider is usage of childrens data, since anyone can use my website I also need to consider the possibility of minors using the web system. GDPR covers specific safeguards for children, which include parental/guardian consent to children under the age of 16.

4.1.2 Data Scraping

The laws surrounding data scraping is a grey area, whilst not technically illegal, there can be issues around collecting personal data from open tabs or sites that require a log in. To stay on the right side of the law, best practise is to check their Terms of Service or equivalent, worst case of a breach could be a court case so it is in the best interests of every party to verify before scraping. The site that needed to be scraped for this project was Hearthpwn[1], the data that needed to be scraped was public and pseudonymisation, since it was not behind a login page or any hidden pages it was not considered illegal. Before even writing the script, checking the Terms of Service of their site it said that data scraping was prohibited (Appendix A), this means that despite the data being public they do not want anyone using their data freely without permission. To get around this I sent an email to a representative of the site requesting permission to collect data for research purposes, after detailing the concept of the project and describing how the data would be used, the team at Hearthpwn granted me permission to scrape their site for data (Appendix B).

4.2 Ethical

This project raises certain ethical issues, raised from the collection of the user data, these issues are discussed below:

- Users may not know that their data is being used: Users may not be informed about their data being used to train the AI for this project.
- Users may not realise the scale of which their data is being collected: Users may not know that a web scraping script was used to mass collect deck data to create a training dataset.
- Users may not know how much information can be gained from analysing the data they have made available: Users may not realise that their data can be used to generate decks and data visualizations.
- Users may not realise the rights a company has regarding their public data: Users may not be informed about the amount of control the company has on their data.

These ethical issues concern mostly the users of the Hearthpwn platform, other data used in this project is not user related therefore are not concerned by these problems. The terms and conditions of the Hearthpwn site state that any User Generated Content can be used, reproduced, modified, adapted, published, translated, transmitted, create derivative works from, distributed, performed and displayed by the Company or third parties in any way that they choose so long as the data is not deleted.

[1] `https://www.hearthpwn.com/`

9. User Generated Content

Any materials, images, information, guides, builds, or other content that you post to or via the Services will be known as "User Generated Content." To the extent that any User Generated Content appears on the Services, you hereby grant Company to the furthest extent and for the maximum duration permitted by applicable law an unrestricted, worldwide, fully sub-licenseable, nonexclusive, and royalty-free right to use, reproduce, modify, adapt, publish, translate, transmit, create derivative works from, distribute, perform and display such User Generated Content in any form, format, or media, now known or hereafter devised, for the purpose of operating the Services, including any promotional or marketing services used by Company, which may include transmission of the same to a third party website. Such license will be immediately revoked in the event you delete such User Generated Content from the Services, except to the extent that such User Generated Content has been shared with or by a third party.other User or incorporated into any of Company's promotional or marketing materials. Nothing contained herein may be construed as to grant Company any ownership over, or liability for, your User Generated Content and nothing in these Terms will restrict any rights that you may have to use and exploit User Generated Content outside of the Services. You hereby represent and warrant that any User Generated Content that you post or otherwise upload via the Services is wholly original and/or you have the authorization to reproduce, adapt, modify, and/or display such Content.

Figure 4.1: User Generated Content section of Hearthpwn Terms of Service[2]

The users of the platform need to be made aware of this, some of the issues listed above can be addressed but not all issues have a full solution. The ethical issues mentioned above depends on the user awareness to the extend of which their data is being used and the impact it may have, however, it would prove difficult to communicated to the whole user base of Hearthpwn that their data is being used. The best course of action would be to either used an official training dataset that is not considered personal data to allow for more public use or limit the extent of this AI to research and academic purposes, the latter being the best solution at this current time as an updated public dataset does not exist as of the creation of this project.

[2] `https://www.magicfind.us/terms/`

5. Implementation

This section showcases the implementation steps of the project in three distinct sections: Card Data, Deck Data and Generative Adversarial Network. Each section will chronicle their respective development process, whilst discussing potential alternatives and limitations.

5.1 Card Data

5.1.1 Introduction

Before the development of the GAN can begin, data needs to be collected and formatted so that the GAN can be trained. The GAN can only take dimensional arrays as input, in the case of this project a vector, a single dimension array of numbers that identify specific cards to form a deck. From those deck vectors the GAN can learn, refine and generate new deck vectors that can be converted back into human readable form, resulting in a GAN created deck. In order to correctly identify the cards inside the deck vectors, going in and coming out of the GAN, a list of cards need to be compiled, each assigned with a unique numerical id that represents them.

5.1.2 Initial Method

5.1.2.1 Text File

The initial method was to start of by creating a text file, this text file would contain a list of each cards that exists in the standard game mode of Hearthstone, each card would be separated by a line break within the text file. The aim is to make the file readable by a Python method, so that a dictionary can be created to identify the card by a integer key.

On the official Hearthstone website they have an online collection of every card in the game, these cards can be filtered and sorted by class, game mode, cost etc... This is a good source of information to gather the card data as it is official, reliable and up-to-date, this seemed useful as a list of card names could be compiled from scraping the site which could then be used to vectorize the cards for the GAN. The requirement for this project is that the GAN must create standard decks from the past 2 years, so filtering to standard is necessary.

Figure 5.1: Hearthstone Collection Page[1]

Collecting the card data using the Beautiful Soup library proven futile, the site has a maximum card display setting meaning that only a small portion of the cards are displayed at one time, the rest are loaded by continuously scrolling to the bottom of the page. Due to the simple nature of the web scraper, it could not load the rest of the cards by scrolling (if the page was using different pages instead then it would have been possible to collect them), resulting in it only collecting a tiny portion of the standard cards. A solution was found by using a firefox web extension called "Open Web Scraper"[2].

Open Web Scraper is a scraper add-on that appends onto the web developer tools of a web browser. The user can then create a sitemap by entering a URL, then from this sitemap, the user can query information from the entered URL. After looking at the source code of the Hearthstone page, a query was written to get the name of every card on the page that was loaded beforehand with all the standard cards loaded. The query was `tr:nth-of-type(n)div.CardTableLayout__CardCropCell-sc-1jy3g9y-`, in short the query gets all names from the CardTableLayout table. The results are then highlighted in red on the page. These highlighted areas were then saved to a text file called cards-standard.txt (which can be view in Appendix C).

[1] `https://playhearthstone.com/en-us/cards`
[2] `https://webscraper.io/`

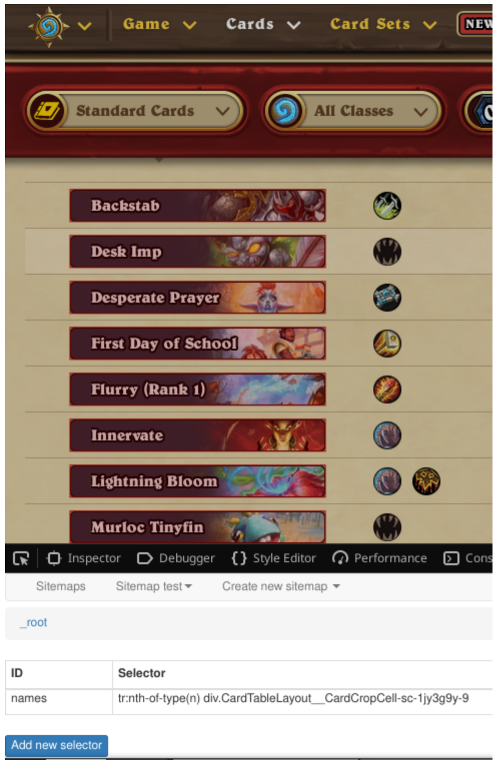

Figure 5.2: Open Web Scraper Results

5.1.2.2 Implementation of Initial Method

5.1.2.3 Limitations

5.1.3 Improved Method

5.1.3.1 BlizzardAPI

5.1.3.2 HSJSON

5.1.3.3 RapidAPI

5.1.3.4 Choice

5.1.3.5 Implementation of Improved Method

5.2 Deck Data

5.3 Generative Adversarial Network

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Appendix

Appendix A

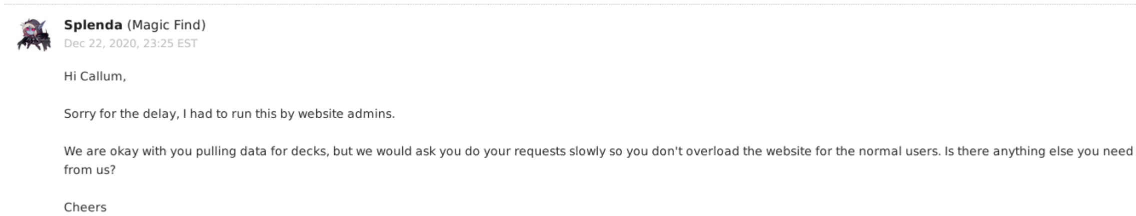
12. Prohibited Conduct

You are granted a non-exclusive, non-transferable, revocable license to access and use the Services, strictly in accordance with these Terms. As a condition of your use of the Services, you represent and warrant to Company that you will not use the Services for any purpose that is unlawful or prohibited by these Terms. Further, you agree that you will comply with these Terms and will not:

- Use the Services in any manner which could damage, disable, overburden, or impair the Services or interfere with any other party's use and enjoyment of the Services;
- Obtain or attempt to obtain any materials or information through any means not intentionally made available or provided for through the Services;
- Impersonate any person or entity, falsely claim an affiliation with any person or entity, or access the Services accounts of others without permission, forge another person's digital signature, misrepresent the source, identity, or content of information transmitted via the Services, or perform any other similar fraudulent activity;
- Harvest or collect the email addresses or other contact information of other users from the Services;
- Defame, harass, abuse, threaten or defraud users of the Services, or collect, or attempt to collect, personal information about users or third parties without their consent;
- Remove, circumvent, disable, damage or otherwise interfere with security-related features of the Services;
- Reverse engineer, decompile, disassemble or otherwise attempt to discover the source code of the Services or any part thereof, except and only to the extent that this activity is expressly permitted by the applicable law of your country of residence;
- Modify, adapt, translate or create derivative works based upon the Services or any part thereof, except and only to the extent that such activity is expressly permitted by applicable law notwithstanding this limitation;
- Access any website, server, software application, or other computer resource owned, used and/or licensed by Company including but not limited to the Services, by means of any robot, spider, scraper, crawler or other automated means for any purpose, or bypass any measures Company may use to prevent or restrict access to any website, server, software application, or other computer resource owned, used and/or licensed to Company, including but not limited to the Services;
- Interfere with or disrupt the Services or servers or networks connected to the Services, or disobey any requirements, procedures, policies or regulations of networks connected to the Services;
- Attempt to indicate in any manner that you have a relationship with Company or that Company has endorsed you or any products or services for any purpose; and
- Use the Services for any illegal purpose, or in violation of any local, state, national, or international law or regulation, including, without limitation, laws governing intellectual property and other proprietary rights, data protection and privacy.

Prohibited Conduct section of Hearthpwn Terms of Service[3]

Appendix B


Splenda (Magic Find)
Dec 22, 2020, 23:25 EST

Hi Callum,

Sorry for the delay, I had to run this by website admins.

We are okay with you pulling data for decks, but we would ask you do your requests slowly so you don't overload the website for the normal users. Is there anything else you need from us?

Cheers

Permission email from Hearthpwn team[4]

Appendix C

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Ancestral Healing
Backstab
Blur
Circle of Healing
Desk Imp
Embiggen
First Day of School
Forbidden Words
Inner Rage
Innervate
Lazul's Scheme
Lightning Bloom
Moonfire
Mutate
Power Word: Shield
Preparation
Raise Dead
Sacrificial Pact
Shadowstep
Silence
Totemic Might
Totemic Surge
Whispers of EVIL
Wisp
Abusive Sergeant
Acornbearer
Activate the Obelisk
Adorable Infestation
```

[3] https://www.magicfind.us/terms/

Aldor Attendant
Angry Chicken
Animated Broomstick
Arcane Breath
Arcane Missiles
Arcane Shot
Argent Squire
Athletic Studies
Battlefiend
Bazaar Burglary
Beaming Sidekick
Bestial Wrath
Blackjack Stunner
Blazing Battlemage
Blessing of Might
Blessing of Wisdom
Blood Imp
Bloodsail Corsair
Bloodsail Flybooter
Boom Squad
Brain Freeze
Brazen Zealot
Call of the Void
Carrion Studies
Charge
Claw
Clear the Way
Cleric of Scales
Consume Magic
Corrupt the Waters
Corruption
Crimson Sigil Runner
Crystal Power
Daring Escape
Deadly Poison
Demon Companion
Demonic Studies
Depth Charge
Desperate Measures
Devolving Missiles
Disciple of Galakrond
Double Jump
Draconic Studies
Dragon's Hoard
Dust Devil
Dwarven Sharpshooter

Earth Shock
Elemental Allies
Elven Archer
Embalming Ritual
Ethereal Augmerchant
Eye for an Eye
Felosophy
Felscream Blast
Fiendish Servant
Flame Imp
Font of Power
Forked Lightning
Frazzled Freshman
Frost Shock
Gibberling
Goldshire Footman
Grimscale Oracle
Guardian Augmerchant
Hack the System
Hand of Protection
Helboar
Holy Smite
Hot Air Balloon
Humility
Hungry Crab
Imprisoned Gan'arg
Imprisoned Homunculus
Imprisoned Sungill
Improve Morale
Infectious Sporeling
Inner Fire
Into the Fray
Intrepid Initiate
Jar Dealer
Lab Partner
Learn Draconic
Leper Gnome
Light's Justice
Lightning Bolt
Lightwarden
Magic Trick
Making Mummies
Mana Burn
Mind Vision
Mirror Image
Mogu Cultist

Mortal Coil
Murloc Raider
Murloc Tidecaller
Murmy
Mystery Winner
Nature Studies
Never Surrender!
Noble Sacrifice
Oh My Yogg!
Overwhelm
Partner Assignment
Pen Flinger
Pharaoh Cat
Pilfer
Plague of Flames
Plague of Madness
Potion Vendor
Praise Galakrond!
Primordial Studies
Prize Plunderer
Psychic Conjurer
Radiance
Raid the Sky Temple
Rain of Fire
Rapid Fire
Ray of Frost
Redemption
Reliquary of Souls
Renew
Repentance
Revolve
Righteous Cause
Risky Skipper
Rocket Augmerchant
Safety Inspector
Sand Breath
Savagery
Scarlet Subjugator
Secret Passage
Secretkeeper
Secure the Deck
Shadow Council
Shadowhoof Slayer
Shield Slam
Shield of Honor
Shieldbearer

Shimmerfly
Sinister Deal
Sinister Strike
Sky Raider
Sludge Slurper
Soulbound Ashtongue
Soulfire
Southsea Deckhand
Sphere of Sapience
Spirit Jailer
Spymistress
Stage Dive
Stonetusk Boar
Storm's Wrath
Strength in Numbers
Supreme Archaeology
Surging Tempest
Sword and Board
Throw Glaive
Timber Wolf
Togwaggle's Scheme
Tome of Intellect
Tour Guide
Toxfin
Toxic Reinforcements
Tracking
Treenforcements
Trueaim Crescent
Twin Slice
Unseal the Vault
Unstable Felbolt
Untapped Potential
Upgrade!
Ur'zul Horror
Violet Spellwing
Voidwalker
Voodoo Doctor
Wand Thief
Wave of Apathy
Whirlwind
Wicked Whispers
Wolpertinger
Worgen Infiltrator
Worthy Expedition
Young Dragonhawk
Young Priestess

Acidic Swamp Ooze
Air Raid
Amani Berserker
Ambush
Ancestral Spirit
Ancient Mysteries
Ancient Watcher
Apexis Smuggler
Arcane Explosion
Arcane Flakmage
Arcane Servant
Argent Braggart
Argent Protector
Armorsmith
Ashtongue Slayer
Astromancer Solarian
Bamboozle
Battle Rage
Betrayal
Blade Dance
Bloodfen Raptor
Bloodmage Thalnos
Bloodsail Raider
Bluegill Warrior
Bonechewer Brawler
Boneweb Egg
Breath of Dreams
Bug Collector
Bumper Car
Cagematch Custodian
Chaos Strike
Cleave
Clever Disguise
Cold Blood
Commanding Shout
Confection Cyclone
Corrosive Breath
Corsair Cache
Costumed Entertainer
Cram Session
Crazed Alchemist
Cruel Taskmaster
Crystal Merchant
Crystalsong Portal
Cult Neophyte
Dalaran Librarian

Dancing Cobra
Darkglare
Deathmatch Pavilion
Deck of Lunacy
Defias Ringleader
Demonfire
Diligent Notetaker
Dire Wolf Alpha
Dirty Tricks
Don't Feed the Animals
Doomsayer
Dragon Breeder
Dragonmaw Sentinel
Dreamway Guardians
Dwarven Archaeologist
E.T.C., God of Metal
EVIL Cable Rat
EVIL Conscripter
EVIL Genius
EVIL Totem
Envoy of Lazul
Evasive Chimaera
Eviscerate
Evocation
Execute
Expired Merchant
Explosive Evolution
Explosive Trap
Faerie Dragon
Feast of Souls
Felstalker
Fishflinger
Flare
Foxy Fraud
Freezing Trap
Fresh Scent
Frightened Flunky
Frostbolt
Frostwolf Grunt
Furious Felfin
Game Master
Grandmummy
Grizzled Wizard
Guess the Weight
Hand of A'dal
Hench-Clan Hogsteed

Heroic Strike
Holy Light
Holy Ripple
Horrendous Growth
Hunter’s Mark
Icicle
Immolation Aura
Imprisoned Felmaw
Imprisoned Scrap Imp
Imprisoned Vilefiend
In Formation!
Incanter’s Flow
Injured Tol’vir
Insight
Invocation of Frost
Ironbark
Kanrethad Ebonlocke
Keeper Stalladris
Khadgar
Knife Juggler
Kobold Geomancer
Kobold Sandtrooper
Kul Tiran Chaplain
Libram of Wisdom
Licensed Adventurer
Lightforged Blessing
Lightwell
Loot Hoarder
Lorewalker Cho
Lunar Eclipse
Mad Bomber
Magic Dart Frog
Mana Addict
Mana Cyclone
Mana Reservoir
Mana Wraith
Mana Wyrm
Manafeeder Panthara
Mark of the Wild
Master Swordsmith
Micro Mummy
Midway Maniac
Millhouse Manastorm
Minefield
Misdirection
Mo’arg Artificer

Murgur Murgurgle
Murloc Tidehunter
Mysterious Blade
Nat Pagle
Neferset Ritualist
Nether Breath
Netherwalker
Novice Engineer
Open the Cages
Pack Tactics
Parachute Brigand
Parade Leader
Patient Assassin
Penance
Phase Stalker
Pint-Sized Summoner
Plagiarize
Plot Twist
Power Word: Feast
Power of the Wild
Pressure Plate
Prize Vendor
Questing Explorer
Quicksand Elemental
Rampage
Redeemed Pariah
Redscale Dragontamer
Ringmaster's Baton
Rising Winds
Ritual Chopper
River Crocolisk
Rock Rager
Rockbiter Weapon
Rune Dagger
Rustsworn Initiate
Sanctuary
Sandstorm Elemental
Sandwasp Queen
Sap
Scavenger's Ingenuity
Scavenging Hyena
Serpent Egg
Sethekk Veilweaver
Shadow Clone
Shadow Word: Death
Shadow Word: Pain

Shadowjeweler Hanar
Shadowy Figure
Shiv
Shotbot
Showstopper
Shrubadier
Sightless Watcher
Sir Finley of the Sands
Skyvateer
Slam
Snack Run
Snake Trap
Sneaky Delinquent
Snipe
Solar Eclipse
Sorcerer's Apprentice
Soul Shear
Soul of the Murloc
Spectral Sight
Spellbook Binder
Spitting Camel
Stage Hand
Starscryer
Steel Beetle
Stormforged Axe
Subdue
Sunfury Protector
Sunreaver Spy
Sweeping Strikes
Sweet Tooth
Swindle
Tasty Flyfish
Temple Berserker
Tenwu of the Red Smoke
Thoughtsteal
Transfer Student
Transmogrifier
Trick Totem
Twisted Knowledge
Umberwing
Underbelly Angler
Underbelly Fence
Vicious Scraphound
Vilefiend
Voracious Reader
Wandmaker

Waxmancy
Whirlkick Master
Wild Pyromancer
Windfury
Witch's Brew
Wrath
Wriggling Horror
Wyrmrest Purifier
Youthful Brewmaster
Zayle, Shadow Cloak
Zephrys the Great
Ace Hunter Kreen
Acrobatics
Akama
Alarm-o-Bot
Aldor Peacekeeper
Aldrachi Warblades
Ancharrr
Animal Companion
Apotheosis
Arcane Amplifier
Arcane Golem
Arcane Intellect
Arcane Watcher
Archspore Msshi'fn
Augmented Porcupine
Awaken!
BEEEES!!!
Banana Vendor
Bladestorm
Blessing of the Ancients
Blistering Rot
Bloated Python
Blood Knight
Bloodsworn Mercenary
Blowtorch Saboteur
Bogbeam
Bogstrok Clacker
Bomb Wrangler
Bonechewer Raider
Breath of the Infinite
Brightwing
Bronze Explorer
Bronze Herald
Bulwark of Azzinoth
Call to Adventure

Candletaker
Carnival Barker
Ceremonial Maul
Chaos Gazer
Chenvaala
Chopshop Copter
Cloak of Shadows
Clockwork Goblin
Coerce
Coldlight Seer
Combustion
Commander Rhyssa
Coordinated Strike
Counterspell
Dalaran Mage
Dark Prophecy
Dark Skies
Darkmoon Dirigible
Darkmoon Statue
Day at the Faire
Deadly Shot
Demolisher
Desert Hare
Desert Spear
Diving Gryphon
Dragonblight Cultist
Dragonmaw Overseer
Dragonrider Talritha
Drain Life
Dread Raven
Dreadlord's Bite
Dune Sculptor
EVIL Miscreant
EVIL Quartermaster
EVIL Recruiter
Eaglehorn Bow
Earthen Ring Farseer
Educated Elekk
Edwin VanCleef
Emperor Cobra
Enchanted Cauldron
Eye Beam
Faceless Rager
Faire Arborist
Fairground Fool
Fan of Knives

Far Sight
Feat of Strength
Felguard
Felsteel Executioner
Feral Spirit
Fiery War Axe
Fire Hawk
Firebrand
Flame Ward
Flametongue Totem
Flesheating Ghoul
Flight Master
Free Admission
Frost Nova
Frothing Berserker
Frozen Shadoweaver
Fungal Fortunes
Generous Mummy
Gift of Luminance
Goboglide Tech
Golden Scarab
Goody Two-Shields
Grand Totem Eys'or
Greyheart Sage
Gyreworm
Harvest Golem
Headcrack
Healing Touch
Hench-Clan Sneak
History Buff
Hooked Scimitar
Hunter's Pack
Ice Barrier
Imp Master
Impferno
Imprisoned Observer
Imprisoned Satyr
Inconspicuous Rider
Infested Goblin
Injured Blademaster
Insatiable Felhound
Instructor Fireheart
Ironbeak Owl
Ironforge Rifleman
Ironfur Grizzly
Jungle Panther

K'thir Ritualist
Kill Command
King Mukla
Kirin Tor Mage
Lady Vashj
Lava Burst
Lifeweaver
Lightning Breath
Lightning Storm
Line Hopper
Livewire Lance
Living Dragonbreath
Lord Barov
Madame Lazul
Magehunter
Magic Carpet
Magicfin
Magma Rager
Man'ari Mosher
Mana Tide Totem
Mark of Nature
Marshspawn
Messenger Raven
Mindflayer Kaahrj
Mindrender Illucia
Mirror Entity
Mischief Maker
Molten Blast
Moontouched Amulet
Murloc Warleader
Nazmani Bloodweaver
Neferset Thrasher
Netherwind Portal
Nine Lives
Overconfident Orc
Palm Reading
Perdition's Blade
Petting Zoo
Pit Master
Plague of Murlocs
Playmaker
Primordial Explorer
Professor Slate
Questing Adventurer
Rafaam's Scheme
Raging Worgen

Raid Leader
Ramkahen Wildtamer
Ramming Speed
Razorfen Hunter
Relentless Pursuit
Revenant Rascal
Rigged Faire Game
Robes of Protection
SI:7 Agent
Salhet's Pride
Satyr Overseer
Savage Roar
Scalerider
Scarlet Crusader
School Spirits
Seal Fate
Self-Sharpening Sword
Sense Demons
Serpentshrine Portal
Shadow Bolt
Shadow Madness
Shadowlight Scholar
Shan'do Wildclaw
Shardshatter Mystic
Shattered Sun Cleric
Shield Block
Silverback Patriarch
Sky Claw
Skybarge
Skydiving Instructor
Soul Cleave
Southsea Captain
Speaker Gidra
Spellbender
Spellward Jeweler
Stiltstepper
Stormhammer
Stormstrike
Sword of Justice
Tauren Warrior
Teron Gorefiend
Terrorguard Escapee
Thrallmar Farseer
Ticket Master
Tinkmaster Overspark
Totemic Reflection

Unbound Elemental
Underlight Angling Rod
Unleash the Hounds
Ursatron
Vaporize
Void Terror
Vulpera Scoundrel
Vulpera Toxinblade
Warmaul Challenger
Warsong Commander
Weaponized Wasp
Whack-A-Gnoll Hammer
Wild Growth
Wolfrider
Wrathscale Naga
Wretched Reclaimer
Zixor, Apex Predator
Altruis the Outcast
Ancestral Guardian
Ancient Brewmaster
Ancient Mage
Arathi Weaponsmith
Arcane Fletcher
Archmage Vargoth
Ashtongue Battlelord
Auspicious Spirits
Azure Explorer
Bad Luck Albatross
Balloon Merchant
Bite
Blade Flurry
Blessing of Kings
Body Wrapper
Bone Wraith
Brittlebone Destroyer
Burrowing Scorpid
Cabal Acolyte
Cascading Disaster
Chillwind Yeti
Circus Amalgam
Circus Medic
Cone of Cold
Conjured Mirage
Conjurer's Calling
Consecration
Crimson Hothead

Cult Master
Dark Iron Dwarf
Defender of Argus
Devoted Maniac
Disciplinarian Gandling
Diseased Vulture
Disguised Wanderer
Divine Rager
Dr. Boom's Scheme
Dragonbane
Dragonling Mechanic
Dragonmaw Poacher
Dread Corsair
Dunk Tank
Eager Underling
Equality
Escaped Manasaber
Ethereal Arcanist
Evasive Feywing
Fantastic Firebird
Fate Weaver
Felfin Navigator
Fiendish Rites
Fire Breather
Fireball
Fishy Flyer
Frenzied Felwing
Frizz Kindleroost
Garden Gnome
Germination
Glide
Gnomish Inventor
Grand Lackey Erkh
Grave Rune
Groundskeeper
Hammer of Wrath
Hecklebot
Hellfire
Hench-Clan Burglar
Hench-Clan Hag
Hench-Clan Shadequill
Hex
High Abbess Alura
High Priest Amet
Hippogryph
Hoard Pillager

Holy Nova
Houndmaster
Hyena Alpha
Il'gynoth
Illidari Felblade
Impbalming
Infiltrator Lilian
Kargath Bladefist
Kayn Sunfury
Keeper of the Grove
Kiri, Chosen of Elune
Kirin Tor Tricaster
Knife Vendor
Kor'kron Elite
Krolusk Barkstripper
Lightforged Zealot
Lightspawn
Lorekeeper Polkelt
Magtheridon
Maiev Shadowsong
Marked Shot
Marrowslicer
Mass Dispel
Master of Disguise
Mindgames
Mogu'shan Warden
Mok'Nathal Lion
Molten Breath
Mortal Strike
Multi-Shot
Nightshade Matron
Nozdormu the Timeless
Oasis Snapjaw
Occult Conjurer
Ogre Magi
Omega Devastator
Overgrowth
Pit Lord
Plaguebringer
Polymorph
Portal Keeper
Potion of Illusion
Power Infusion
Proud Defender
Psychopomp
Raging Felscreamer

Reaper's Scythe
Renowned Performer
Replicat-o-tron
Restless Mummy
Ring Toss
Rinling's Rifle
Rustsworn Cultist
SI:7 Infiltrator
Sahket Sapper
Scargil
Scion of Ruin
Scrap Shot
Sen'jin Shieldmasta
Shadow Word: Ruin
Shadow of Death
Shadowflame
Shifty Sophomore
Silvermoon Guardian
Sky Gen'ral Kragg
Soldier of Fortune
Soul Split
Soul of the Forest
Splitting Axe
Squallhunter
Star Student Stelina
Steeldancer
Stormwind Knight
Summoning Portal
Sunstruck Henchman
Swipe
Sword Eater
The Dark Portal
The Fist of Ra-den
The Nameless One
Torrent
Traveling Healer
Troll Batrider
Truesilver Champion
Twilight Drake
Umbral Skulker
Unsleeping Soul
Veiled Worshipper
Vendetta
Vessina
Vilefiend Trainer
Violet Spellsword

Violet Teacher
Vivid Spores
Waggle Pick
Water Elemental
Windspeaker
Wing Commander
Wrenchcalibur
Wretched Tutor
Zul'Drak Ritualist
Abomination
Aeroponics
Al'ar
Aldor Truthseeker
Amber Watcher
Anka, the Buried
Anubisath Defender
Apexis Blast
Arcanite Reaper
Assassin's Blade
Assassinate
Azerite Elemental
Bandersmosh
Bane of Doom
Barista Lynchen
Bazaar Mugger
Big Game Hunter
Big Ol' Whelp
Blessed Champion
Blessing of Authority
Blood Herald
Bloodlust
Boggspine Knuckles
Boompistol Bully
Booty Bay Bodyguard
Brawl
Captain Greenskin
Carousel Gryphon
Chaos Nova
Chromatic Egg
Chronobreaker
Cloud Prince
Cobalt Spellkin
Command the Illidari
Convincing Infiltrator
Crazed Netherwing
Crystal Stag

Cumulo-Maximus
Cutting Class
Dalaran Crusader
Dark Pharaoh Tekahn
Darkscale Healer
Derailed Coaster
Desert Obelisk
Doctor Krastinov
Doomhammer
Dragon Speaker
Dragon’s Pack
Druid of the Claw
Duel!
Earth Elemental
Elise the Enlightened
Explosive Shot
Faceless Corruptor
Faceless Lurker
Faceless Manipulator
Fen Creeper
Firework Elemental
Fleethoof Pearltusk
Force of Nature
Fortune Teller
Frostwolf Warlord
Glaivebound Adept
Glowfly Swarm
Greybough
Gurubashi Berserker
Hagatha’s Scheme
Hailbringer
Harrison Jones
Headmaster Kel’Thuzad
Holy Wrath
Hunting Party
Inara Stormcrash
Jandice Barov
Kobold Stickyfinger
Lake Thresher
Libram of Justice
Lothraxion the Redeemed
Malevolent Strike
Malygos, Aspect of Magic
Metamorphosis
Mortuary Machine
Mozaki, Master Duelist

Muckmorpher
Naga Sand Witch
Necrium Apothecary
Nightblade
Oasis Surger
Ogremancer
Optimistic Ogre
Phalanx Commander
Plague of Wrath
Platebreaker
Psyche Split
Ras Frostwhisper
Recurring Villain
Righteousness
Ringmaster Whatley
Rolling Fireball
Rotnest Drake
Ruststeed Raider
Sandhoof Waterbearer
Scalelord
Scrap Golem
Shadow Sculptor
Shattered Rumbler
Shield of Galakrond
Silver Hand Knight
Skyfin
Soulshard Lapidary
Spiteful Smith
Stampeding Kodo
Starfall
Starving Buzzard
Steward of Scrolls
Stormpike Commando
Stowaway
Stranglethorn Tiger
Sunreaver Warmage
Teacher's Pet
Temple Enforcer
Tent Trasher
Tentacled Menace
Time Rip
Totem Goliath
Trampling Rhino
Tundra Rhino
Twilight Runner
Vectus

Venture Co. Mercenary
Void Drinker
Waste Warden
Wasteland Assassin
Waxadred
Wrathspike Brute
Wyrm Weaver
Zai, the Incredible
Abyssal Summoner
Aeon Reaver
Aranasi Broodmother
Archmage
Argent Commander
Armagedillo
Armored Goon
Avenging Wrath
Bladed Lady
Blatant Decoy
Blizzard
Boulderfist Ogre
Cabal Shadow Priest
Cairne Bloodhoof
Camouflaged Dirigible
Candle Breath
Claw Machine
Corrupt Elementalist
Darkest Hour
Deck of Chaos
Devout Pupil
Dragonmaw Sky Stalker
Dread Infernal
Eccentric Scribe
Emerald Explorer
Evasive Wyrm
Fel Summoner
Fire Elemental
Flik Skyshiv
Forest Warden Omu
Frost Elemental
Gadgetzan Auctioneer
Grand Empress Shek'zara
Gyrocopter
Hammer of the Naaru
Hand of Gul'dan
Heistbaron Togwaggle
Hidden Oasis

Hogger
Imprisoned Antaen
Initiation
Judicious Junior
Keli'dan the Breaker
Khartut Defender
Kidnapper
Kronx Dragonhoof
Lord of the Arena
Mad Summoner
Maxima Blastenheimer
Nithogg
Nourish
Oblivitron
Onyx Magescribe
Pharaoh's Blessing
Portal Overfiend
Priestess of Elune
Reckless Rocketeer
Reno the Relicologist
Riftcleaver
Ring Matron
Runic Carvings
Safeguard
Savannah Highmane
Sayge, Seer of Darkmoon
Scarlet Webweaver
Scavenging Shivarra
Siphon Soul
Skull of Gul'dan
Smug Senior
Sorcerous Substitute
Starfire
Sunwalker
Swarm of Locusts
The Beast
The Black Knight
The Lurker Below
Tickatus
Unidentified Contract
Unleash the Beast
Unseen Saboteur
Utgarde Grapplesniper
Veranus
Violet Warden
Warglaives of Azzinoth

Wild Bloodstinger
Windfury Harpy
Xavius
Ancient of Lore
Ancient of War
Animated Avalanche
Arch-Villain Rafaam
Archmage Antonidas
Baron Geddon
Barrens Stablehand
Blastmaster Boom
Bloodboil Brute
Bonechewer Vanguard
Chef Nomi
Commencement
Core Hound
Cursed Vagrant
Cycle of Hatred
Darkmoon Tonk
Dinotamer Brann
Dragoncaster
Earthquake
Evasive Drakonid
Exotic Mountseller
Expendable Performers
Fel Guardians
Flamereaper
Flamestrike
Galakrond, the Nightmare
Galakrond, the Tempest
Galakrond, the Unbreakable
Galakrond, the Unspeakable
Galakrond, the Wretched
Gladiator's Longbow
Gorehowl
Goru the Mightree
Guardian of Kings
High Inquisitor Whitemane
Kael'thas Sunstrider
Keymaster Alabaster
Lady Liadrin
Lightforged Crusader
Marsh Hydra
Mask of C'Thun
Overflow
Priestess of Fury

Ravenholdt Assassin
Shu'ma
Siamat
Siegebreaker
Silas Darkmoon
Skeletal Dragon
Soul Mirror
Soulciologist Malicia
Sprint
Stormwind Champion
Strongman
Swampqueen Hagatha
Tak Nozwhisker
Tunnel Blaster
Umbral Owl
Underbelly Ooze
Valdris Felgorge
Vereesa Windrunner
War Golem
Wasteland Scorpid
Winged Guardian
Wrapped Golem
Al'Akir the Windlord
Arcane Devourer
Archwitch Willow
Batterhead
Beastmaster Leoroxx
Catrina Muerte
Cenarion Ward
Coilfang Warlord
Deathwing, Mad Aspect
Deep Freeze
Enhanced Dreadlord
Fel Lord Betrug
Flesh Giant
G'huun the Blood God
Gift of the Wild
Grand Finale
Grommash Hellscream
Gruul
Guardian Animals
Heroic Innkeeper
High Exarch Yrel
Hulking Overfiend
Idol of Y'Shaarj
Inner Demon

Ironbark Protector
Jepetto Joybuzz
Jewel of N'Zoth
Lay on Hands
Lucentbark
Mana Giant
Murozond the Infinite
Natalie Seline
Octosari
Pit Crocolisk
Plagued Protodrake
Power of Creation
Supreme Abyssal
The Forest's Aid
Tidal Wave
Tip the Scales
Tirion Fordring
Tomb Warden
Tortollan Pilgrim
Troublemaker
Turalyon, the Tenured
Twin Tyrant
Twisting Nether
Walking Fountain
Whirlwind Tempest
Zzeraku the Warped
Alexstrasza
Ancient Void Hound
Anubisath Warbringer
Archivist Elysiana
Blood of G'huun
Burly Shovelfist
Carnival Clown
Cenarius
Dragonqueen Alexstrasza
Fizzy Elemental
King Krush
Libram of Hope
Lord Jaraxxus
Malygos
Mass Resurrection
Mogu Fleshshaper
Nethrandamus
Nozdormu
Onyxia
Pit Commander

Plague of Death
Rattlegore
Sathrovarr
Ysera
Ysera, Unleashed
Ysiel Windsinger
Big Bad Archmage
C'Thun, the Shattered
Colossus of the Moon
Darkmoon Rabbit
Deathwing
Dimensional Ripper
Eye of the Storm
Jumbo Imp
Kalecgos
King Phaoris
Living Monument
Mind Control
N'Zoth, God of the Deep
Nagrand Slam
Nozari
Puzzle Box of Yogg-Saron
Pyroblast
Scrapyard Colossus
Sea Giant
Survival of the Fittest
The Amazing Reno
The Boom Reaver
Y'Shaarj, the Defiler
Yogg-Saron, Master of Fate