How Machine Learning can improve AI in Hearthstone: Heroes of Warcraft

Abstract

This paper reviews different applications of machine learning techniques in a development of AI player for a collectible card video game Hearthstone: Heroes of Warcraft. Its main objective is to present selected aspects of the game, in which machine learning can help an artificial player to make better decisions and increase its winning chances. Moreover, the paper describes some of experiments conducted by our research team at Silver Bullet Solutions, as a part of the research on GRAIL - a general framework for designing AI players in video games.

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1. Introduction

Hearthstone: Heroes of Warcraft is a free-to-play online video game developed and published by Blizzard Entertainment [1]. Simple general rules and appealing design made this game successful among casual players (according to Blizzard’s data, in the first quarter of 2017, the player-base of the game was about 70 million and it grows with each of the released expansions), as well as within the eSport community, with cash-prize tournaments and many international events every year.

Hearthstone is an example of a turn-based collectible card game between two opponents. During a game, players use their custom decks of thirty cards, along with a selected hero with a unique power. They use mana points to cast spells or summon minions to attack the opponent, with the goal to reduce the opponent’s health to zero. Building efficient decks is an essential skill and many archetypes of decks exists. These archetypes are characterized by different distributions of the card’s mana cost and thus are meant for players with different play styles. There are also sets of cards which synergize well due to their unique properties and can be used in many different decks.

In recent years, Hearthstone has become a testbed for AI research. A community of passionate players and developers has started the HearthSim project (https://hearthsim.info/) [2] and created many tools that allow simulating the game for the purpose of AI and machine learning experiments. Several researchers have already used this game in their studies – one objective of this paper is to review their work. Moreover, our research team at Silver Bullet Solutions decided to use Hearthstone as one of case-studies which aim to demonstrate capabilities of our video game’s AI designing framework, called GRAIL [4]. For this reason, the second objective of this article is to explain how some powerful heuristic search
algorithms can be combined with prediction models that derive from the machine learning domain, in order to construct a smart and cunning artificial Hearthstone player.

Machine learning (ML) is commonly described as a science of getting computers to act without being explicitly programmed [5]. One of its most prominent sub-fields is the supervised learning, which deals with problems related to a construction of mathematical models for making predictions about investigated phenomena. For instance, we may want to construct a model which automatically detects patients of a pediatric clinic who suffer from influenza.

To ‘teach’ a computer how to make accurate predictions, we show him examples of medical records (symptoms observed by a doctor, e.g. body temperature, headache, and so on) obtained from patients who visited the clinic in the past. For each example, we also tell him what is the correct prediction value (whether the patient was diagnosed with influenza or not). For this to work, it is necessary to represent the medical records in a way that can be understood by a machine, for example, by attribute-value vectors. In this way, we may create a table in which rows correspond to different patients and columns store values of different attributes. Based on data from such a table, a computer can derive a function discriminating the symptoms of influenza from other conditions.

Properties of this function largely depend on an algorithm that is used in the learning process. Some algorithms, such as those which construct decision trees, will generate a set of decision rules, e.g. ‘IF body_temperature > 38.5 AND headache = true AND muscle_ache = true THEN diagnose = influenza’. Other algorithms, e.g. support vector machines or multi-layer perceptrons, will generate a mathematical formula that describe different decisions [6].

2. Machine Learning on Hearthstone data

In the following sections, I am discussing a few tasks related to designing a challenging AI player for Hearthstone, focusing on possible applications of machine learning techniques. I will briefly explain how ML algorithms can be used and what data they need in order to boost performance of game’s AI.

2.1. Predicting a composition of opponent’s deck

In Hearthstone, knowing which cards are likely to appear in the opponent’s deck can greatly boost your chances of winning the game. If a player could accurately predict which cards will his opponent play, he would be able to adjust his own strategy and effectively counter opponent’s moves.

The possibility to utilize machine learning for predicting opponent’s cards was in the scope of research conducted by Elie Bursztein from Google [3]. He noticed that even though the number of possible deck compositions is large, experienced players will tend to use a limited number of decks which correspond to different archetypes and are considered ‘optimal’ by the Hearthstone community. In general, two different decks of the same archetype (and for the same type of a hero) will often have a common ‘core’ and differ only on a small subset of less important cards (or cards which have a similar role in a deck). Moreover, some cards are restricted to a specific hero class and other cards are simply underpowered, and thus rarely used in games. As a consequence, the composition of players’ decks becomes more predictable.
For the purpose of his work, Burszttein obtained a data set describing 50,000 replays of Hearthstone games. He analyzed each replay and counted for every pair of cards how many times it cooccurred in the same playout. Based on those counts, he was able to estimate the conditional probability that a card will be played given the knowledge about previously played cards. These probabilities allowed him to accurately predict which cards will occur during completely new Hearthstone matchups. His results varied depending on a turn in which the predictions were made [3]. They are presented in Figure 2.

![Figure 2: Results for the problem of predicting which cards will be played during a Hearthstone matchup (according to [3]).](image)

### 2.2. Supporting players in building their decks

Another example of a task where machine learning can improve winning chances of a player (AI as well as human) is the assessment of Hearthstone cards and decks. As I mentioned before, in Hearthstone there are cards which synergize well, even though the same cards may be not very useful by themselves or in a combination with the most of other available cards. Finding out which sets of cards are efficient is not an easy task. For this reason, less experienced players may find it hard to decide which cards they should include in their decks.

Hearthstone community developed several tools which aim at facilitating the construction of powerful decks. Moreover, many players exchange their ideas and experience on several web portals, such as the HearthPWN [7]. This abundance of data on the composition of real players’ decks, coupled with additional information about results of games in which they were used, can be utilized by ML algorithms to create an automatic card assessment and recommendation system.
One way of doing this can be based on the analysis of associations between cards found in decks of winning players. For instance, algorithms for finding frequent item sets from a domain of market basket analysis could be used to mine sets of cards that often appear in ‘winning decks’. Their counts can be compared with the corresponding counts obtained from ‘loosing decks’ and the difference (perhaps normalized by the total number of occurrences) can be used to quantify their strength. Of course, this simple approach can be complicated by taking into account different archetypes and heroes, and by introducing constraints resulting from the limited access of beginning players to more powerful cards.

2.3. Helping AI to choose reasonable moves

Machine learning techniques can also be directly applied to support decision making of artificial players. One may imagine a Hearthstone matchup as a sequence of game states, i.e. snapshots of the situation during the game (played and available cards, hp status of the heroes, and so on) after every action of the players. Having a sufficiently large collection of game replays, it is possible to create a data set whose records correspond to different states of a game with additional information regarding how a given game ended (i.e. who won). This set can be then used to train a prediction model using one of the supervised learning algorithms. As a result, we would get a tool for scoring player’s moves.
In the simplest scenario, when a player needs to make an in-game decision, we could show all the possible consequences (i.e. game states resulting from our possible decisions) to the prediction model. The model would score them and we could simply choose the move which generates the highest chance of winning the game. Of course, we could significantly improve performance of our player by combining this approach with some heuristic search algorithms that perform a deeper exploration of possible move sequences. One example of such an algorithm if Monte Carlo Tree Search (MCTS) [8].

One of fundamental problems related to the design of a prediction model for scoring possible moves is related to the appropriate representation of game states. On the one hand, this representation should convey as much information about the situation during the game as possible to facilitate learning of complex patterns. On the other hand, if the representation is too large and contains many unnecessary details, then the learning becomes less efficient and the resulting model may not generalize well (i.e. it can be over-fitted to the known examples of data and yield poor performance for new, previously unseen cases).

For this reason, one way to construct a good representation of Hearthstone game states is to combine, so called, feature engineering and dimensionality reduction methods. The feature engineering is a methodology of constructing attributes that can be used to represent complex objects (such as the game states) in decision tables [9]. If the feature engineering is done manually (e.g. by a domain expert), then the attribute construction process depends on domain knowledge of an expert and it can be regarded as a way of transferring this knowledge into a prediction model.

Typically, a set of attributes defined based on expert’s knowledge needs to be reduced before it can be used for constructing a prediction model. There are many algorithms described in the machine learning literature, which can be employed for this particular purpose [10]. In a different approach, the task of transforming features from the set defined by an expert into a representation that facilitates learning is transferred to the prediction model construction algorithms. A prominent example of such a prediction method is the family of artificial neural networks.

An artificial neural network is a computational model inspired by the way in which biological neurons process signals in living organisms [11]. Individual neurons, represented by simple input signal aggregating functions, are connected into complex structures. Connections between neurons are able to convey an activation signal of varying strength. If the incoming signals are strong enough, the neuron becomes activated and the activation signal travels to other neurons connected to it. Such a network of connected neurons can be trained from examples to recognize complex patterns. Moreover, if the neurons are arranged into layers, the signals coming out of each layer can be interpreted as values of more general attributes that describe the training cases on a higher abstraction level [12]. This ability to automatically learn a more informative representation of data makes the artificial neural networks a powerful tool for making predictions about winning chances of players during a Hearthstone matchup.

3. Our experiments

Encouraged by the unquestionable successes of artificial neural networks (and particularly those having a multilayer structure, which are also called deep neural networks) in areas such as the speech recognition,
image classification, automatic translations, and e-mail spam detection, we decided to conduct a series of experiments related to the assessment of Hearthstone game states.

Our team created a simulator of the Hearthstone game, which allowed us to efficiently conduct thousands of Hearthstone games between AI bots. During each game, every action from the players was reported in a log file along with a detailed description of a current game state. At the end, every log had information regarding the result of the game, i.e. which player won. Using those logs, we were able to create a data set containing 4,000,000 records. Each record, described a single game state and had an additional attribute indicating the final result of the game, therefore, we could use this set to teach neural networks how to foresee winners of Hearthstone games. For this purpose we divided this set into two smaller ones – called training and test sets – which consisted of records obtained from a disjunctive collection of simulations. Our models learned from the examples included in the training set and that made predictions for the test records. In this way, we were able to estimate real predictive performance of tested models. We were also able to experiment with the feature engineering and measure impact of different features on the quality of predictions.
In our experiments we tested models with different structures – from very complex multilayer networks, to simple networks containing not more than a dozen of neurons. Surprisingly, the relatively simpler networks turned out to be more reliable than the ones with a complicated structure. In the case of a network with only two hidden layers (64 and 8 neurons, respectively), the quality of the predicted scores quantified using the popular AUC measure [13] exceeded 0.79. Moreover, such a network has an additional practical advantage – much less computations are needed to get its predictions. In our experiments we were also interested how well our models perform in different stages of a typical Hearthstone game, i.e. how accurate are their predictions at the beginning of a matchup, in the middle and in the final turns. Figure 5 shows average results obtained using our prediction models in consecutive turns. As expected, in the beginning of a game it is very difficult to predict the outcome, however, starting from turn 5 the average AUC of scores is higher than 0.70 and in turn 12 it reaches almost 0.85.

**Figure 4: Visualization of our data set computed using a deep autoencoder (the middle layer).**
In order to gather results from a broader range of prediction models on our data set, we decided to release it to the machine learning community [14]. We organized an international data mining competition within the framework of International Symposium Advances in Artificial Intelligence and Applications [15], called AAIA’17 Data Mining Challenge: Helping AI to Play Hearthstone [16]. The task in our competition was the same as in our experiments – to construct a prediction model which would be able to accurately predict a winner of a Hearthstone matchup based on a description of a single game state. The competition attracted nearly 300 participants from 28 countries and the submitted solutions provided us with a great reference point for our future research as well as invaluable insights regarding the data. The most successful solutions from the competition will be published in the conference’s proceedings and presented at the conference (Sep. 3-6, 2017).
4. Conclusions

The scope of this paper was on applications of machine learning methods in the task of designing AI for the game Hearthstone: Heroes of Warcraft. Results obtained by other researchers, as well as our own experience, show that ML can aid both human and AI players. In particular, examples provided in the paper show how various machine learning algorithms can facilitate the prediction of cards which will be played during the matchup, improve a composition of players’ decks, and enable automatic assessment of game states. Our experiments showed that learning from game logs is feasible and this observation has been confirmed by the results of AAIA’17 Data Mining Challenge.

References:

AAIA’17 Data Mining Challenge: Helping AI to Play Hearthstone page: https://knowledgepit.fedcsis.org/contest/view.php?id=120