Predicting cards in a game using AI training

Introduction

Machine learning is everywhere nowadays. From driving cars, to predicting diseases, computers are slowly getting better at doing everything. Slowly, but surely, humans are being overtaken. The common theme with many of these tasks though is that they are classification problems where the computer has perfect information. For our Extended Experimental Investigation, we decided to take this one step further; we wanted to try and train an AI to guess hidden information better than a human.

Hearthstone is an online card collecting and battling game. The aim of the game is to build a "deck" out of 30 cards which the player has purchased, and use them to beat opponents. There are over 2,000 cards in the game. Players do not know the content of each other's hands. Our goal was to predict what card an opponent would play before they played it using machine learning. If we succeed, we will have shown that computers can deal with hidden data better than humans can. This has been attempted before, but in a different way (Bursztein, E. 2016).

Figure 1: A typical Hearthstone card

We chose this game as our field of study for one main reason. In Hearthstone, decks tend to fall into a number of popular "archetypes". People often copy their decks from online deck sharing websites, so experts can often predict decks from just a few cards. This gives our network a better chance than in a game like UNO, where it is nearly impossible to guess what cards the opponent may be holding.

Method

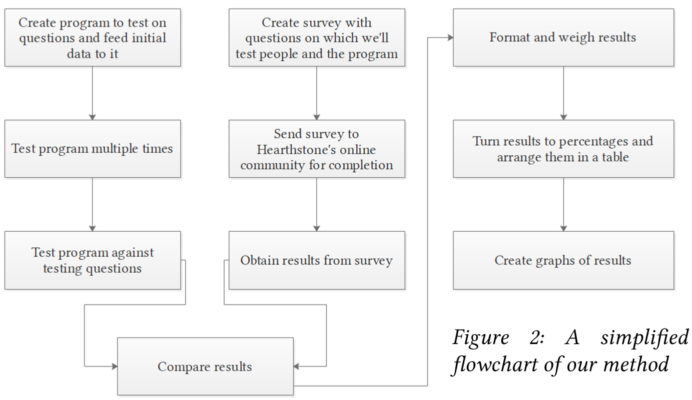

Figure 2: A simplified flowchart of our method

We decided to go with two approaches to the problem: statistical analysis and neural networks. In order to do any machine learning we needed a dataset. We got this in the form of around two thousand recordings of Hearthstone games, courtesy of hearthscy.com. This data was then used not only to train the various AI, but also for the actual benchmarking.

The statistical method looks at the statistical relationship between cards that are often played together. First it would look through all the recorded games and analyse the amount of times any two cards were played together in the same turn. Then given the last three cards played it would look at the cards played often alongside them and find the card that best fit the overlap. Then it would rank its guesses by confidence. A full explanation as well as the code is available online with the code itself (Petschack, M. 2019 https://github.com /Midataur/hearth-logger).

The other method we decided to try was making a neural network. A neural network is essentially a very simplified version of how our brains work. As a result they are very good for finding patterns and relationships between data. Unfortunately we could not end up getting ours to work, so we did not include it in the final results. Regardless we still believe that this approach would be effective.

To test out our AI's results of answering the questions we posed it with, we needed a baseline to compare it to.

We got this in the form of a human trial. We created a survey using Google Forms and posted it to the website reddit.com to obtain the human results. The survey provided the participants with six games from our dataset and asked them to predict what the next card played would be. We gave both the humans and the AI five guesses as even the very best human players can't guess correctly in one prediction every time. And after wieghing and comparing the valid results of the survey and the program's answers to the same question, this is what we ended up with.

Results

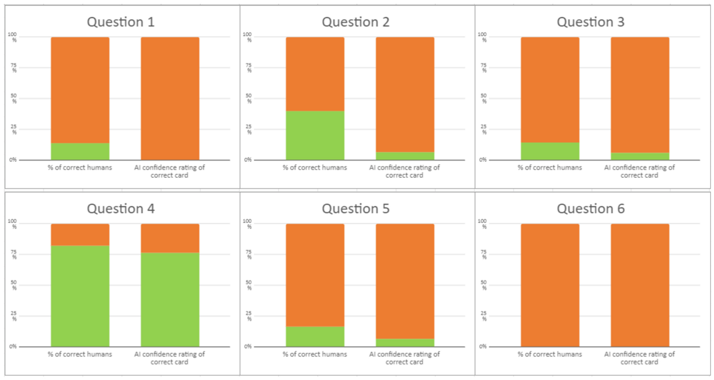

Figure 3: Our results, where red represents incorrect and green correct confidence/amount of answers

Discussion

In almost every game we tested the computer put the card in its top 5 with the exceptions being the first and last question. This is likely because the cards played are uncommon. Due to this the AI may have never encountered them. This issue also reflected in the human answers as for example Question 6 was the only one that no human answered correctly. An important thing to note is that while the percentage of humans that guessed any given card correctly was always higher than the AI's confidence rating, the AI did better than 70% of the human players and was as good as a further 17%, although our sample size was not very large at only 17 human respondents so the results may not represent all players well.

While better than the average human, the AI was still beaten by the best. A bigger training dataset may improve accuracy but the pure statistical method probably won't ever beat the best players due to limited pattern recognition. This is where a neural network would be best as it would have a chance of finding these patterns. In the future we will try to build the network again when we have more experience.

Conclusion

In the end our AI was able to reliably put the correct card in its top 5 better than most humans tested. The next step for us would be to build a tool allowing the AI to automatically pick up data from the game so we can test it live. Another path is to redo the experiment with a larger number of participants to get more representative data. Overall, despite setbacks, the experiment can be considered a success. We thouroughly enjoyed it.

Bibliography

Bursztein, E. (2016). I am a legend: hacking Hearthstone using statistical learning methods. Paper presented at Computational Intelligence and Games conference 2016, Santorini, Greece. Abstract retrieved fromhttps://elie.net/static/files/i-am-a-legend-hacking-hearthstone-using-statistical-learning-methods/i-am-a-legend-hacking-hearthstone-using-statistical-learning-methods-paper.pdf

Grad, L. (2017, September). Helping AI to Play Hearthstone using Neural Networks. Paper presented at the Federated Conference on Computer Science and Information Systems, Prague, Czech Republic. Abstract retrieved from https://ieeexplore.ieee.org/document/8104525

Silver, D., Huang, A., Maddison, C. J., Guez, A., Sifre, L., van den Driessche, G., … Hassabis, D. (2016). Mastering the game of Go with deep neural networks and tree search. Nature, 529(7587), 484–489. https://doi.org/10.1038/nature16961

Karen Hao. (2019). DeepMind wants to teach AI to play a card game that's harder than Go. Artificial intelligence/Machine learning. Retrieved from https://www.technologyreview.com/s/612886/deepmind-wants-to-teach-ai-how-to-play-a-card-game-thats-harder-than-go/

Brian Merchant (2015). The AI That Learned Magic (the Gathering). Tech by Vice. Retrieved from https://www.vice.com/en_us/article/bmjke3/the-ai-that-learned-magic-the-gathering