Literature Survey

Durham University

26th October 2017

1 Introduction

1.1 Problem Background

The purpose of this project is to explore alternative approaches to tackle the game of english Draughts via the use of contemporary machine learning approaches. We will be measuring

1.2 Terms

- **Genetic Algorithm** An evolutionary method that solves optimisation problems. This is based on Darwin's theorem of perpetually evolving populations of solutions.
- **Neural Network** A computational model based on the operations of "interconnected processing elements, which process information by their dynamic state response to external inputs." [1]
- **Draughts** In this project we will be using the British Draughts (American Checkers) rules. For the sake of clarity these rules will be enforced:
    1. The game is played on an 8x8 checkerboard.
    2. Jumps are enforced in the event that it is possible for a player to make one.
    3. Multiple jumps are enforced.
    4. In the event that a piece performs a multiple jump, if it lands on a promotion row (where a piece is promoted into a king), then its move is terminated.
- **Ply**: a ply refers to one turn taken by one of the players.
- **ELO:** A rating system that measures the relative performance between players in a given game.

2 Themes

Historically, Draughts has been used as a testing ground for artificial intelligence since the concept. In 1959, Arthur Samuel devised an evaluator for Draughts, and created an early concept of what is now described as Alpha Beta Pruning.

Since the advent of machine learning, academic involvement within the machine learning spectrum has greatly expanded, with the introduction of modern techniques such as the use of Deep Learning strategies, Support Vector Machines and K-Means Clustering.

In 2001, B. Fogel and Cheliapelia took a different approach towards playing draughts using feed-forward convolutional neural networks and genetic algorithms. Their resulting player, Blondie24[Fogel(2001)] reached an average ELO rating of 1901

To date, the game of draughts has been described to be weakly solved by Schaeffer. As the game has been deemed 'solved' by many, the use of machine learning has leaned towards applications in more difficult zero-sum games such as Chess, and, more recently, Go.

The use of genetic algorithms has been commonly overshadowed by other contemporary methods in Machine Learning. It has been shown by

that the use of genetic algorithms can be greater than what backpropagation can afford.

3 Proposed Direction

The approach taken would follow the a similar framework as described for Blondie24.contemporary

The neural networks would take as input a board, and outputs a value that determines the effectiveness of that board. The number of hidden layers are dependent on the heuristics, proposed by M. Kusiak and K. Waledzik. This is left for experimentation during the implementation of the project.

The genetic algorithm would be used to improve the quality of the weights of the neural networks. We will need a population of neural networks (which have varying weights), with a round-robin style tournament as the evaluation function. Finalists are chosen as the basis for the next generation.

Experimentation of techniques would be conducted in these areas, and I could imagine that they would be tested independently of each other.

- Effectiveness of the min-max algorithm - Genetic Crossover Algorithm - Genetic Mutation Algorithm - Effectiveness of the Neural Network - When/where to perform the genetic algorithm

An interface is also needed in order to test the AI. There are multiple options for this; It could be built for the web, with a 'node.js' backend, which would interact with the AI, or we can simply use a program built locally for it.

In order to test it's performance, we could, like _Chellapilla_ and _Fogel's_ paper, make an account for the AI at a popular gaming site and act as the intermediary for it. This would provide a lot of benefits, such as a relative ELO amongst other players on the site.

4 Conclusion

5 References

5

D. B. Fogel, *Blondie24: Playing at the Edge of AI*, 2001. [Online]. Available: http://www.sciencedirect.com/science/article/pii/B9781558607835500167 ;

M. Lai, "Giraffe: Using Deep Reinforcement Learning to Play Chess," no. September, 2015. [Online]. Available: http://arxiv.org/abs/1509.01549 ;

D. B. Fogel, "Evolving a Checkers Player," 2000; .

M. Kusiak, K. Walezedik, and M. Jacek, "Evolutionary approach to the game of checkers," vol. 1, no. 48 22, pp. 600–661, 2007; .

J. Schaeffer and R. Lake, "Solving the Game of Checkers," *Games of No Chance*, vol. 29, pp. 119–133, 1996. [Online]. Available: http://books.google.com/books?hl=en&lr=&id=cYB-ra2T8i4C&oi=fnd&pg=PA119&dq=Solving+the+G