Improving CNN Draughts Evaluators using Genetic Algorithms

Student Name: Thien P. Nguyen
Supervisor Name: Stefan Dantchev

Submitted as part of the degree of BSc Computer Science to the

Board of Examiners in the School of Engineering and Computing Sciences, Durham University
January 7, 2018

Abstract —

Background

Presently, competitive Draughts AI players are currently designed to play at a fixed ability. While it has produced very competitive and intelligent players, they require manual modifications in order to improve its performance. This is due to their dependency on pre-defined move databases, where optimal moves are pre-calculated, and recalled when necessary. By combining Neural Networks and Genetic Algorithms, this issue could possibly be solved by creating a player that can grow in ability over time, without the dependency on move-banks.

Aims

The purpose of this project is to explore approaches to tackle the game of English Draughts via the use of machine learning techniques. First, we study previous historical successes in the field, and look at the components that helped build their systems. Then, we look at contemporary methods of computer science that could be used to evolve the historical systems. The project will establish whether this approach provides an effective performance on the game.

Method

The initial population will consist of randomly generated AI players, which will play each other to determine the best player out of the population. The performance of championing AI players at every generation of the genetic algorithm are measured against previous champions. Appropiate algorithms are implemented to detect the overall development of the system's ability to play Checkers.

Proposed Solution.

The proposed solution starts with designing a neural network that evaluates the probability of a particular side winning, given a given state of a checkerboard. This is then used in a algorithm that evaluates future moves to predict the best move at a given position. This, alongside a set of weights for the neural network, creates a player that can evaluate potential moves. Finally, the player is then used on an existing Draughts framework that will provide the player with the ability to play Draughts.

Keywords — Artificial Intelligence, Neural Networks, Genetic Algorithms, MiniMax, Alpha Beta Pruning, Draughts

I INTRODUCTION

The intention of this project is to explore the effectiveness of genetic algorithms to improve the neurons of a neural network. Neural networks can be used to evaluate the performance of two players in a zero-sum game of checkers. We attempt to manipulate the neurons through various crossover and mutation strategies to increase the accuracy of the evaluation. This would allow us to create an effective Draughts playing agent that, when provided with the option to choose its own moves, would have the ability to learn without human input.

Draughts

English Draughts (or Checkers) is a popular 2-player boardgame played on an 8x8 chess board. Players choose a colour and begin with 12 pieces each of their respective colours, and they are placed on the dark-coloured squares of the board. Beginning with the black pieces, each player takes a turn to move a piece diagonally in one square. They also have the option to capture their opponments piece by moving two consecutive diagonal squares, where the opponments piece is placed immediately opposing the players piece. Pieces can be captured consecutively in a single turn if the moves afford the scenario. In the event that a piece reaches the opposite side of the board from where the piece originated, it is promoted to a king piece. King pieces have the ability to traverse backwards in the same diagonal motion as pawns. A player wins by capturing all of their opponments pieces. A player loses by having all of their pieces captured. A draw occurs when there is both players agree to draw after a three-fold repetition (where both players take three moves to simulate the same position), or a player has pieces on the board but cannot move any of them. A draw can be forced when both players fail to capture a piece after a set amount of moves.

Genetic Algorithms

Genetic algorithms (GAs) are a group of search techniques used to find exact or approximate solutions to optimisation and search problems. The methodology is inspired by Charles Darwin's evolutionism theory; individuals are created by the crossover of the genetic information of their parents. Genetic Algorithms consist of a population of agents, a tournament selection process, algorithmic crossover mechanisms against the genomes of the agents, and the introduction of probabilistic mutation on genomes. Genomes are metaphors of genetic information; it typically refers to a data structure, most commonly an 1D array.

Neural Networks

Neural Networks are non-linear statistical data-modelling tools, linking inputs and outputs adaptively in a learning process similar to how the human brain operates. Networks consist of units, described as neurons, and are joined by a set of rules and weights. The units are defined with characterisitics, and appear in layers. The first layer is defined as the input layer, and the last layer being the output. Layers between the two aforementioned are described as hidden layers. Data is analysed by processing them through the layers. Learning takes place in the form of the manipulation of the weights connecting the units in the layers. This allows it to model complex relationships between inputs and output, and it can also find patterns in the data.

Motivation

Whilst the use of evolutionary algorithms and neural networks have been explored to create draughts players, my intention is to explore the effectiveness of genetic algorithms and neural networks. The intention is to determine the possibility of developing a performant draughts playing agent by the use of GANNs (Genetic Algorithms and Neural Networks).

Deliverables

Minimum

- Implement a feed-forward neural network
- Implement a checkers game interface
- Implement a decision making process that chooses a move from a given position of a checkers board.
- Implement a genetic algorithm that uses a population of agents that have their own independently functioning neural network.

Intermediate

- An interface to play against an agent.
- A monte-carlo search of the move space.
- Multi-processing of the tournament selection process for the genetic algorithm.

Advanced

- An agent produced by this process can play to an ELO of at least 1200.
- Agents can be played against human input through a simple user interface.

Related Work

Arthur Samuel pioneered the concept of an self learning program that can play Checkers, through the use of using evolutionary algorithms (Samuel 2000). However, the work described did not consider the use of neural networks (as it was not conceived at the time). It was also dependent on a set of heuristics that Samuel devised, which could handicap the agent's ability to play, as they are dependent on the effectiveness of Samuel's heuristics.

The idea of evolving neural networks to play Draughts is based on the success Chellapilla and Fogel had in evolving their own Checkers neural networks using far less sophisticated hardware (Chellapilla & Fogel 1999). Their work, Blondie24, used a neural network as the evaluator function, and used an evolutionary algorithm to evolve the agents. However, crossover mechanisms were not considered in the creation of new agents. Blondie24's neural network structure consists of a $\{32, 40, 10, 1\}$ set. Spatial awareness as it takes an immediate input of the positions on the board. This makes it inherently more difficult for the neural network to generate heuristics based on spatial awareness as it is not immediately considered.

II DESIGN

Requirements

Functional Requirements

Code	Description	Priority
F1	A checkers gameboard is created.	High
F2	Agents are able to harness neural networks to assist in their move decision.	High
F3	Offspring agents can be created using parents.	High
F4	The weights and biases of the Agent's neural network are saved to storage.	High
F5	Humans are able to play against the Agents.	High

Non-Functional Requirements

Code	Description
N1	Agents only choose valid, legal moves.
N2	Agents always return a valid, legal move.
N3	Agents are able to play against other agents.

Algorithms and Data Structures

.1 MiniMax Decision Making

In order to choose the best move given a current position, the decision making process for an agent could revolve around the use of minimax algorithm. This algorithm would expand the tree of potential moves until some depth is reached. From here, an evaluation function is used to calculate the value of the nodes at this depth. The best potential position for a given player can be deduced from the nodes at this stage, which is quantified with a value.

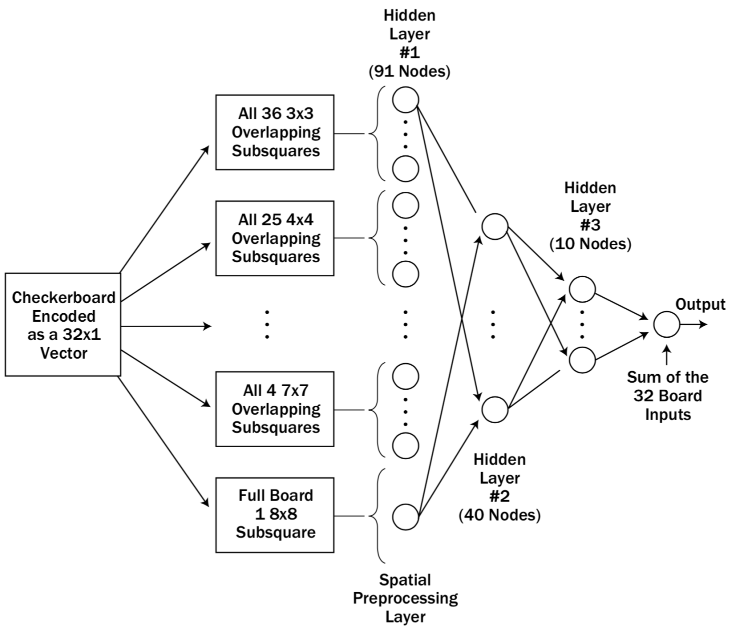
The best value propagates upwards until it reaches to a child of the root node. The use of alpha-beta pruning will help to prune unnecessary moves, reducing the number of calculations. Once the possible moves have been considered, the best child node is chosen, representing the best move given the players position.

The mini-max method will have a search depth of 4ply (where the agent will search four moves ahead.) This should allow the agents to form a basic stategy where they can plan their moves in advance. There are inherent tradeoffs with having a higher ply count; asymptopic complexity of mini-max is expoential; it being $O(x^y)$ for x being the branching factor, and y being depth. Branching factor will consist of the moves from each agent in a given game. This expotential growth is the achillies heel to the mini-max approach.

Once initial development on the mini-max algorithm is complete, it is possible to use the framework as a base to migrate to a hybrid technique that combines mini-max and a more contemporary algorithmic paradigm, Monte-Carlo Tree Search (MCTS). MCTS differs from mini-max where future moves are randomly played to the end of the game. It acts as a sampling of possible outcomes, and does not depend on an evaluation function at all. The random simulation of games are skewed such that more reasonable moves are chosen. A survey by Browne et al. found that MCTS can dramatically outperform mini-max based search engines in games where evaluation functions are otherwise difficult to obtain (Browne et al. 2012).

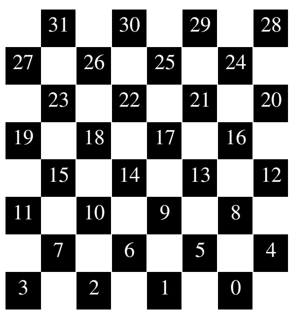
MCTS-EPT (or MCTS with early playout termination) is introduced by Lorentz (Lorentz 2016). MCTS-EPT modifies the MCTS random playout approach; Instead of allowing the random moves play to the end of the game, the number of moves traversed are capped and an evaluation function can be used from that caped position instead. The termination ply would be capped at 6ply. This could potentially improve the amount of foresight for a given set of moves, without the need to depend on random generations of moves to the end, and the need to evaluate more moves (as typically needed even with alpha-beta pruning on a mini-max algorithm).

Figure 1: The chosen neural network model. Note that the checkboard is preprocessed.



.2 Neural Network

Figure 2: The indexes of the 32 pieces of the input layer are the immediate values of the positions on the board.



In order to evaluate the board, we will use a feed-forward multilayer perceptron style neural network. The network would contain 4 layers; the input layer consists of 91 nodes, with the output node having 1. Hidden layers will have 40 and 10 nodes respectively.

It is common knowledge that a King piece is worth more than a pawn, but it is disputed about its precise value advantage. For the sake of completeness, a King's piece value is to be weighted at 1.5x the regular pawn value.

The input array takes in the form of the grid array of the board. The intention is to weigh the Black pawns with a value of 1, and white pawns as -1. To create the input layer, we treat the checkboard into a 1D array, with the indexes displayed in figure 2. The array is used to calculate all possible subsquares of the checkerboard, ranging from a 3x3 kernel to a 8x8. Each subsquare is summed up to create an input node. There are consequently 91 combinations of the subsquares, thus forming the input layer.

Weights of a neuron are summed with their bias, and are passed through an activation function (or transfer function) to become an input for another neuron. Activation functions usuall have a sigmoid shape, but may also take the form of other shapes. Common characterisitics of these functions include values to be monotonically increasing, continuous, differentiable and bounded.

Our initial choice for the activation function will be the sigmoid function, shown in figure 3. There exists inherent issues related to the properties of their derivatives, discussed by Hinton. However, since this issue is related to the properties of a gradient based learning method and not through a stochastic learning method (which genetic algorithms are), this is not a concern for the project. Other functions will be explored, inclduing ReLU (Rectified Linear Units), Noisy ReLU, and linear.

.3 Genetic Algorithms

The genetic algorithm is the premise of the system's learning strategy. We discuss the various algorithms that form the collection of GA stategies below. For the system we choose a population size of 15.

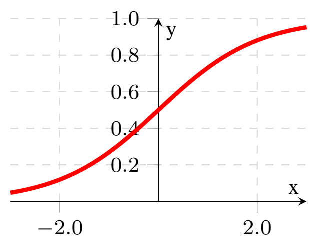


Figure 3: graph of sigmoidal function $f(x) = \frac{1}{1+e^{-x}}$

.4 Population Generation

The initial population will consist of randomly generated weights and biases of the neural network, with values from [-1,1]. For a population size of 15, the next generation is created using the best five agents from the current generation. They will continue to play in the next generation. The agents are also chosen as a base to create 10 new agents from.

The next eight players are generated through the use of crossover strategies. The weights of the 1st and 2nd place agents are used as input to the crossover strategy and will generate 4 offsprings. Two are reciprocal crossover representations from the crossover, and the other two being directly mutated from the parents themselves. Another four children will be created using the same strategy, with the 2nd and 3rd agent's weights. The remaining two will be direct mutations of the 4th and 5th place agents.

.5 Tournament Selection

The tournament selection process revolves around each agent in the population playing 5 games as Black, against randomly selected opponments. Each game lasts a maximum of 100 moves from both players. If a winner is not deduced at this stage, a draw is called. Draws are also called when there is a three-fold move repetition from both players. A win is worth 2 points, a draw being none and a loss being -1 points. Both the agent and its opponment receives a score from the game. Scores are tallied up at the end of the tournament. Players are sorted by the number of points they scored. The best players would have the highest number of points.

.6 Coefficent Mutation

Weight and biases of an agent's neural network will increment by a random value that is created using the following formula, where $WeightP$ is the current weight, K represents the number of weights and biases in the neural network, and m representing a random floating point in the range of [-1,1]:

$$WeightN = WeightP + \frac{m}{\sqrt{2 * \sqrt{K}}}$$

The weights, as explained earlier will have a soft maximum of [-1, 1]. This would consequently mean that the mutation is not controlled, and dependent on the number of weights in the system; The more weights in the network implies a less significant mutation.

.7 Crossover Strategy

Two offsprings would be created from a pair of parents, with each offspring being the reciprocal crossover of each other. The weights of both parents (now each treated as a 1D array of coefficents), are divided contingent on the number of weights and biases for a given layer. Each layer should be treated separately to reduce the potential dependency on a purely randomly generated neural network. For each set of weights in a given layer, the following algorithm represents the crossover process:

Algorithm 1 Crossover Strategy

procedure CROSSOVER($parent_1$, $parent_2$)
loop for weights w in layers:
    $n \leftarrow$ length of w
    $i_1 \leftarrow$ *random integer*$(0, n-1)$
    $i_2 \leftarrow$ *random integer*$(0, n-1)$
    if $i_1 > i_2$ **then**
        swap i_1 and i_2
    $weights_{w,child1} = parent_1[0 \ldots i_1] + parent_2[i_1 + 1 \ldots i_2] + parent_1[i_2 + 1 \ldots n]$
    $weights_{w,child2} = parent_2[0 \ldots i_1] + parent_1[i_1 + 1 \ldots i_2] + parent_2[i_2 + 1 \ldots n]$
Return *child1,child2*

Choice of Programming Language

Several contenders exist with each having their inherent benefits. C++ is considered due to it's support for popular machine learning packages (most notably Google's TensorFlow.) In terns of performance, C++ trumps most languages due to its lower level characterisitics. C++ has notable parallelised packages (A popular library is OpenMP), which can assist in the overall throughput of the system. However, it would be difficult to write, due to my unfimiliarity with the language. Also, programs written in this language are less portable. It is not suitable for running on university machines without the use of a sandbox.

Javascript is a contender; Node.JS is a very powerful and popular package manager, npm. It is difficult to write multi-processed programs as Node.JS runs on a single thread by nature. It also lacks the support of popular machine learning libraries and performs relatively slower in some programming operations.

I have chosen Python 3.6 due to my familiarity, and the support of popular scientific packages, most notably NumPy. Python is also portable with a very wide compatability; for instance it is pre-installed on all popular UNIX machines and also has support from the university machines. Python development will be on Visual Studio Code, which again is a familiar tool and is also suited to the project.

When writing the system, there will be a heavy dependency on NumPy due to its C++ bindings. This increases the overall speed of the program relative to the performance of standalone python, especially in the case of numerical operations. The neural network would be written using this language, as opposed to the use of machine learning libaries to understand the inner workings of neural networks.

Object Oriented approaches are taken for the majority of the components that constitute the system, ranging from the neural network to the tournament system. Data structures are implemented using their own classes and methods where applicable. The modularity of object oriented programming provides the afforance of easier debugging and testing.

Players weights (for their neural networks) are stored in two forms, one of which is to be stored on an MongoDB NoSQL instance, and another local copy in JSON. This allows the individual agents to be played against humans.

Tools

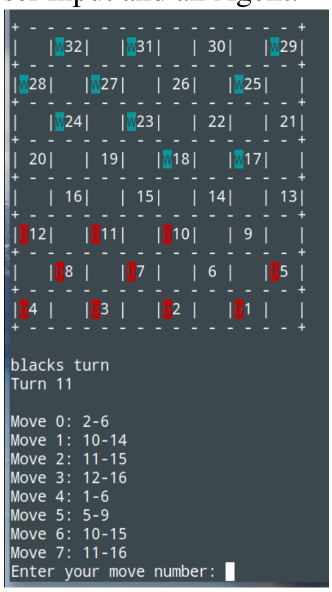
Initial runs will operate on a 1-ply load in order to determine the stability of the system on a 4-core Intel i5 6200u with 12GB's of memory. Development and debugging will also occcur on this machine. Once testing has proven to be stable, the system would run on Durham's MIRA (128-core Intel) distributed system with a 6-ply heavy load. In order to keep simulations running on MIRA, MOSH is used to maintain a consistent connection to MIRA. The end champion is then transferred to the initial machine in order to be played against by human input.

Interface

As our primary intention is to find an agent that learns to play, having a relatively friendly user interface is not necessarily important, i.e. a simple text-based interface would suffice. Due to the inherent computational strain the project requires, an interface based around having a command-line interface (CLI) the system is used. This allows the system to be initiated relatively faster as opposed to loading GUIs (Graphical User Interfaces). It also reduces the need for package dependencies, configurations and set-ups. The simulation would show statistics such as estimated finishing times, current generation count, scores of players in a given generation and the cummulative score of progress of the system.

When it comes to humans playing against the agent, the checkerboard can also be rendered using ASCII plaintext, users can make inputs through text (in the console or terminal); where the game will show human users the possible moves that a person can take. This system will be used to play against the agent, where the human will take inputs the moves on behalf of the agent's online opponment. A possible rendition is shown in figure 4.

Figure 4: An example CLI interface demonstrating a game of draughts between user input and an Agent.



Testing and Evaluation

The combined GANN (Genetic Algorithm/Neural Networks) are evaluated under competition style conditions. At each generation, each agent plays 5 games, with their opponment being from randomly chosen from the generation pool. Point scores are measured by 2,0,-1 where 2 is a win, 0 is a draw, and -1 is a loss. There is a hard cap of 100 moves, where the game is considered a draw if after the game hasn't ended after 100 moves from each player.

At the end of a given generation, we measure growth of performance by using the generation's champion. Presently we will use the mean of means approach. When a new chapmion is generated, it is played against the previous 5 champions from earlier generations. 6 games are played for each previous champion, with 3 being as Black, and 3 being White. A mean score is calculated from those 6 games. The overall performance of the current chapmion is the mean of the 5 sets of games. A positive improvement is when the mean of means are greater than 0.

Point Score for the champion games are measured by 1,0,-1 where a Win counts as 1 point and -1 for a loss. The weights are scaled differently to the regular tournament in order to accurately portray the difference between previous champions.

At the end of the generation run, the end player will be used to compete against human players on various online multiplayers checkers websites in order to determine an accurate ELO rating of the system.

References

Browne, C. B., Powley, E., Whitehouse, D., Lucas, S. M., Cowling, P. I., Rohlfshagen, P., Tavener, S., Perez, D., Samothrakis, S. & Colton, S. (2012), 'A Survey of Monte Carlo Tree Search Methods', *IEEE Transactions on Computational Intelligence and AI in Games* **4**(1), 1–43.

Chellapilla, K. & Fogel, D. (1999), 'Evolving Neural Networks to Play Checkers without Expert Knowledge', *IEEE Transactions on Neural Networks* **10**(6), 1382–1391.
URL: *http://ieeexplore.ieee.org/abstract/document/809083*

Lorentz, R. (2016), 'Using evaluation functions in Monte-Carlo Tree Search', *Theoretical Computer Science* **644**, 106–113.
URL: *http://linkinghub.elsevier.com/retrieve/pii/S0304397516302717*

Samuel, A. L. (2000), 'Some studies in machine learning using the game of checkers', *IBM Journal of Research and Development* **44**(1.2), 206–226.