

Playing Draughts using Neural Networks and Genetic Algorithms

Thien Nguyen

Department of Computer Science
Durham University

January 27, 2018

Outline

Problem Description

Motivation

Related Work

Approach

Curent Progress

Conclusion

Why Draughts?



Figure: Schaeffer literally brute forced Checkers in 2007. [4]

Problem Description

A problem in Computer Science (..before AlphaZero existed)

Presently, A variety of Draughts AI players tend to be designed to play at a fixed ability.

While it has produced very competitive and intelligent players, they require human intervention in order to improve their performance.

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.

Motivation

Why have I chosen to tackle this?

- ▶ Enjoyed AI Search Submodule
- ▶ Interested in seeing whether genetic algorithms are still relevant
- ▶ Interested in machine learning
- ▶ ..I like board games

Related Work

Similar works of art but no cigar

Samuel (59')

Uses Genetic Algorithms to improve coefficients of a set of heuristics to evaluate Draughts games. [3]

Blondie24 (97')

Uses an Evolutionary Algorithm and Neural Networks to evaluate Draughts games. (Quite similar!) [1]

Giraffe (15')

Uses contemporary machine learning techniques to train a Neural Network to evaluate Chess games. [2]

Uber (Last month)

Uses genetic algorithms to train convolutional neural networks to play Atari Games. [5]

Current Approach

How will I tackle this; in a nutshell

- ▶ Evaluate a checkerboard state
- ▶ Choose the best move for a given state
- ▶ Make our checkerboard evaluator better

Evaluating Checkerboards

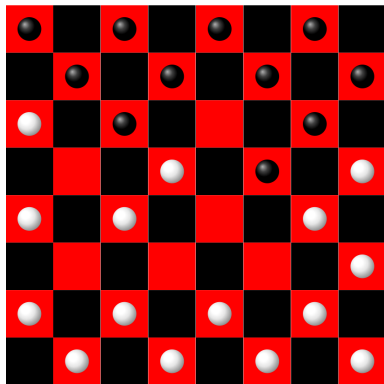
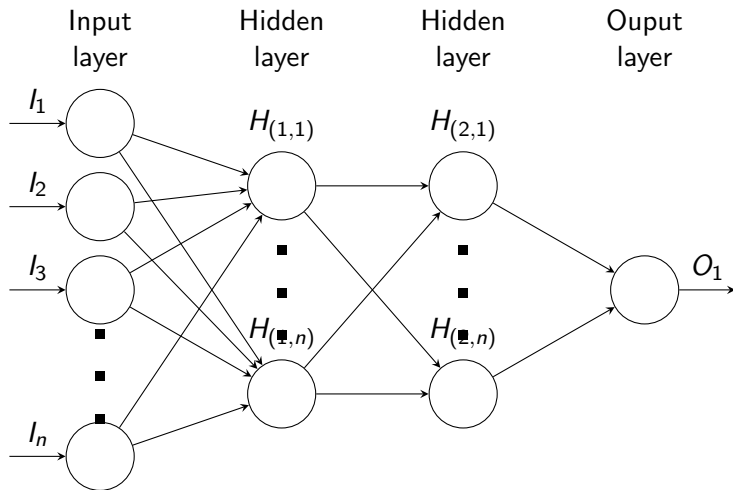
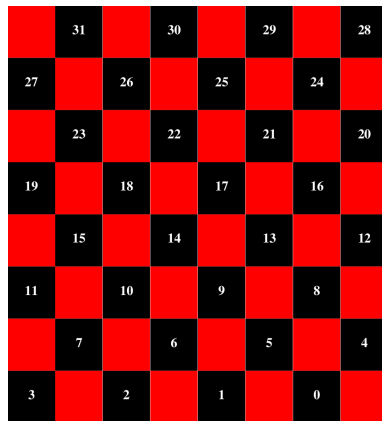


Figure: An example state of a checkerboard.

Neural Networks



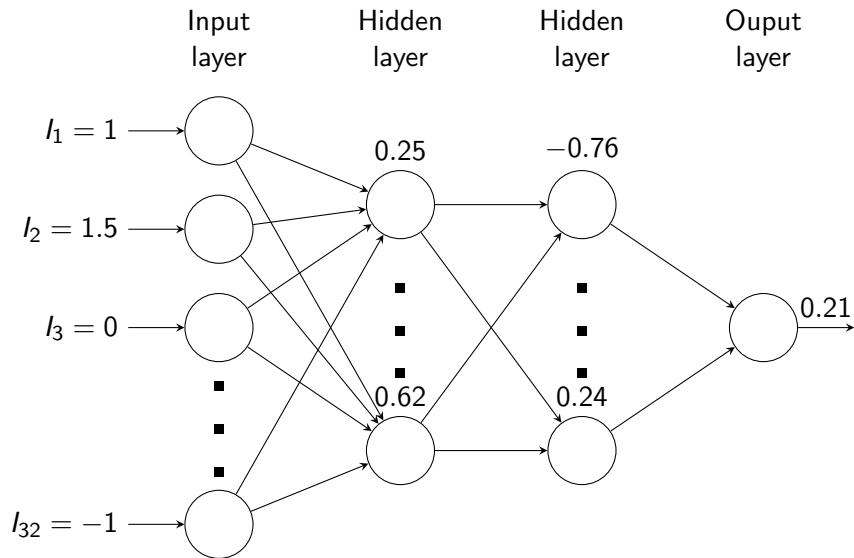
Checkerboard



	31		30		29		28
27		26		25		24	
	23		22		21		20
19		18		17		16	
	15		14		13		12
11		10		9		8	
	7		6		5		4
3		2		1		0	

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

Neural Networks



Activation Function

Neural networks use activation functions to simulate an output of a node given a set of input(s).

$$O = f((Input * weight) + Bias)$$

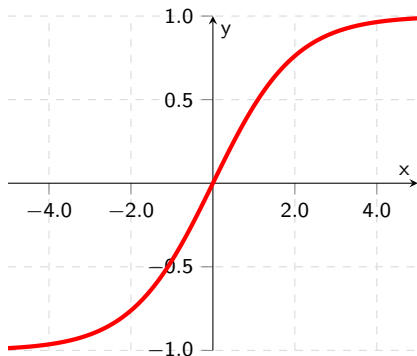
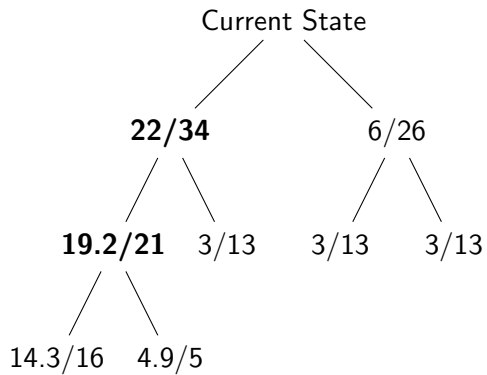


Figure: graph of tanh function

$$f(x) = \frac{2}{1+e^{-x}} - 1$$

Choosing moves



Monte Carlo Tree Search

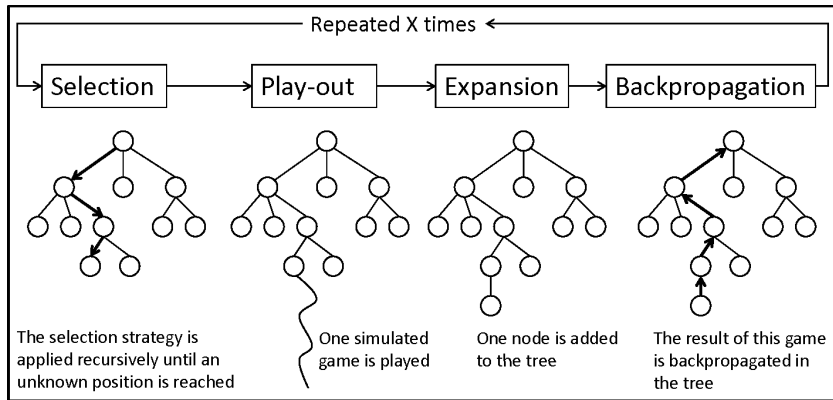


Figure: Diagram describing the MCTS process. Source: Winands et al. ([6])

Generating Agents

Agent

An agent is a generated set of weights and biases for a neural network.

- ▶ An initial agent would have a randomly generated set of weights and biases
- ▶ initial values range from -0.2 to 0.2.

Tournament

1. Generate a population of random agents (A population of 15 is used.)
2. Make agents play each other
3. Order agents by the amount of points scored
4. The best few agents are chosen to stay on for the next tournament
5. Make new agents from them
6. The losers are destroyed
7. Repeat step 2-6 with the new agents until satisfied

Crossover Mechanism

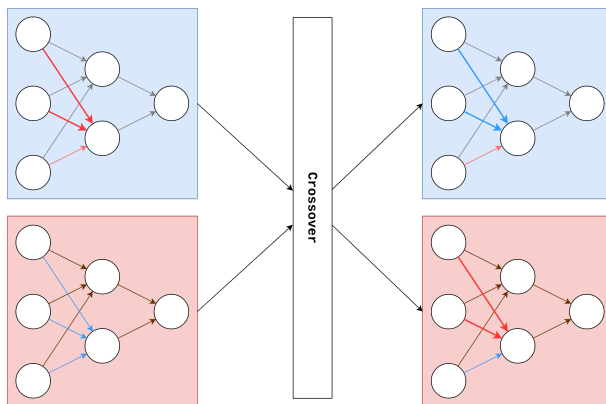


Figure: Offspring agents are created from a pair of parent agents. Each offspring is a reciprocal crossover of each other. A random hidden node is chosen, and influential inputs for that node are swapped between the two agents.

Mutation

$WeightP$ is the current weight, K represents the number of weights and biases in the neural network, and m represents a random floating point in the range of $[-1,1]$:

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

Mutation influence is dependent on the number of weights in the system; The more weights in the network implies a less significant mutation.

Evaluation

How will I judge my outcome?

- ▶ Measurements held to measure evolution progress
- ▶ Play final agent against agent from prior stages to indicate whether it has been learning
- ▶ Play against a randomly playing bot to see it is actually thinking
- ▶ Play against different move making algorithms (Vanilla MCTS, $\alpha\beta$ MiniMax)
- ▶ Also play against human players on popular checkers websites

Current Progress

What have I done already?

- ▶ The initial set up is ready*
- ▶ It has been trained*
- ▶ It plays relatively well (anecdotaly)
- ▶ Relatively ineffective at end game performances...

Remaining Work

What do I still need to do?

- ▶ * Squash potential bugs that could impede performance/provide false positives
- ▶ Experiment with different crossover and mutation mechanisms
- ▶ Optimise training (enforce threefold repetition)
- ▶ Train the system for a bit longer
- ▶ Measure the system's performance against other players

Fin.

Any Questions?

References

Nanos gigantum humeris insidentes



Kumar Chellapilla and David Fogel.

Evolving Neural Networks to Play Checkers without Expert Knowledge.
IEEE Transactions on Neural Networks, 10(6):1382–1391, 1999.



Matthew Lai.

Giraffe: Using Deep Reinforcement Learning to Play Chess.
(September), 2015.



A L Samuel.

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



Jonathan Schaeffer and Robert Lake.

Solving the Game of Checkers.
Games of No Chance, 29:119–133, 1996.



Felipe Petroski Such, Vashisht Madhavan, Edoardo Conti, Joel Lehman, Kenneth O. Stanley, and Jeff Clune.

Deep Neuroevolution: Genetic Algorithms Are a Competitive Alternative for Training Deep Neural Networks for Reinforcement Learning.
arXiv:1712.06567 [cs], December 2017.
arXiv: 1712.06567.



M. H. M. Winands, Y. Björnsson, and J. T. Saito.

Monte Carlo Tree Search in Lines of Action.
IEEE Transactions on Computational Intelligence and AI in Games, 2(4):239–250, December 2010.