**Previous Works**

The complexity of Reversi is higher than checkers, but lower than chess. Due to this fact, Reversi is the topic of many research endeavors. Chong et. al. used a very similar approach in most respects. The most interesting variation was the addition of a spatial preprocessing layer. They were only able to achieve master level play using a spatial preprocessing layer. The agents lacking this aspect were much more difficult to train and did not achieve levels of play comparable to the spatial neural networks.[] Our approach choses to exclude this type of layer, in order to determine how much spatial information can be learned by a basic neural network. Festa and Davino proved fairly strong play can be achieved by using a minimax algorithm with a strong heuristic function.[] STATE WHETHER MINIMAX WAS INCLUDED OR NOT. Boris and Goran applied a similar strategy to the popular puzzle game 2048. The primary difference in their approach was the evolution style. These networks were also allowed to change in shape during the evolutive process.[] This approach would be an interesting technique to explore in future work. Shahzad et. al. compared the level of play achieved by different evaluation functions. They included a standard Weight Piece Counter (WPC), Multilayer Perceptron Networks (MLP), Temporal Difference Learning (TDL), and a Monte Carlo algorithm using Tournament Play Technique. Of the evaluation functions examined, MLP, the strategy used in this paper, was found to achieve the highest level of play. []

**Reversi Introduction**

The game Reversi, also commonly known as Othello, is two-player, zero-sum game. It is played on an 8x8 board with 64 identical game pieces. The pieces are double sided with a white side and black side. The game begins with the center four positions filled with white and black tiles in a diagonal fashion. The black player moves first. A game piece placed on the board will flip enemy tiles if there is an unbroken sequence of enemy tiles between the newly placed piece and an existing friendly piece. Tiles may be flipped in any of eight directions; up, down, left, right and diagonals. Tiles may also flip in more than one direction if there are unbroken chains in both directions. At any point in the game, a move is only valid if it flips enemy tiles. This means that turns may be passed back to the opposing player if no moves are available. However, voluntary passing of turns is not allowed. The game ends when either the board is full or both players have no more legal moves to make. The final score is calculated by counting the number of tiles controlled for each player. The player with the most tiles wins the game. Ties are a possibility if the game ends with both players controlling the same number of game pieces.

**Evaluation Function using a Neural Network**

The goal of experimentation is to create a strong reversi player who utilizes a neural network to make its decisions throughout the game. The player will analyze each available move according to a heuristic value calculated by its neural network. The highest heuristic value corresponds to the best move to chose. Neural networks differ by their assigned or evolved weights. In order to increase the skill of our players, we utilize a genetic algorithm to generate a population of organisms to evolve these weights. Organisms are assigned a fitness score based on the outcomes of games played against their neighbors. Parents are selected from these organisms to crossover their genes and create a new generation of players. Every 1,000 generations, our generated players’ skill level is analyzed by playing every organism against every organism from another population. The opposing population is either the first generation or a subsequent increment of 1,000 generations.

In these experiments, the initial generation is produced with no prior knowledge of the game. Established human strategies will not be given to the organisms in any way. Any appearance of intelligence they display is exclusively from the results of the genetic algorithm. A popular approach to increase skill level is to include a spatial preprocessing layer to provide organisms with more knowledge of the spatial relations of the board.[CITE THAT] However, our experiments will exclude this layer to see if our agents can learn spatial information on their own.

**Vanilla configuration**

To begin our project, we settled on a basic set of parameters which came to be known as the vanilla configuration. Features of the vanilla configuration include gameplay on a reversi board with size 8x8. Weights are generated at the start of an evolution by using a uniform distribution between - and . The activation function utilized by the neural network will be softplus. To generate the inputs given to neural networks, an array was created with each entry corresponding to a piece on the board. If the space is occupied by a friendly tile, the value of the entry is 1. For enemy tiles, we use -1 and empty tiles are assigned 0. The size of the population is 10x10 arranged in a hexagonal pattern.

Each organism plays 6 neighbors, and organisms on the edge play organisms along the opposite edge. This creates a torus shaped population. Organisms will only be allowed to search one move ahead of the current board state, thus no minimax algorithm is implemented within their gameplay. In order to rate our organisms, each is assigned a fitness function during this stage. To calculate the value, we use a combination of wins, losses, ties, and the number of pieces controlled by a player at the end of a match. Wins are awarded 64 points, losses earn 0 points, ties are awarded 32 points, and the number of pieces controlled is added to this sum.

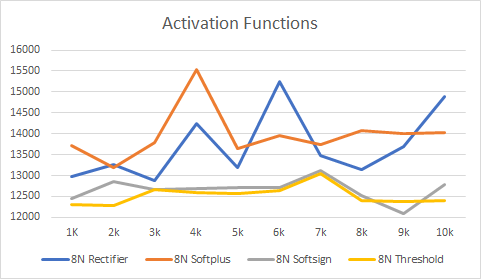
Each organism must choose another organism to crossover and produce a child organism. In the vanilla configuration, parents are selected from 6 surrounding neighbors using assigned probabilities based on their fitness scores. The lowest scoring neighbor is thrown out and his fitness score is subtracted from the remaining neighbors scores. This new value is directly proportional to the probability it will be selected as a parent. During crossover, each new gene within the child organism is assigned to either the mother or father’s corresponding gene with equal probability. [Mutation occurs with a 1% chance, and will generate a brand new weight, using the same uniform distribution, and reassign the old weight to the new weight.]

// finish this piece out

Of these properties, several settings will be varied for each future configuration. Basic variations include using rectifier, softsign, sigmoid, or threshold for the activation function.

**Activation Functions**

Populations using softplus, softsign, sigmoid, rectifier, and threshold were evolved for 10,000 generations using an 8 neuron network. Games were played between each agent in every 1,000th generation and the initial generation. Threshold appears to be the least successful as most of its generations had the lowest number of games won. Softsign’s trajectory was quite similar to threshold. The results of rectifier seem to be quite volatile, and fluctuate by large margins. If the activation functions were ranked by wins for each generation, softplus was consistently either first or second. IIt also had the highest number of total wins with 139,723 wins. Due to these properties, softplus was chosen as our vanilla configuration activation function.



**Neural Network Shapes**

Single Neuron

8 Neurons

8 - 3 Neurons

16 - 4 Neurons

**Mutation Types**

Uniform

Uniform Shake

Cauchy Shake

**Parent Selection**

>Mother 6 Fitness Probability

Mother 7 Fitness Probability

Both 7 fitness probability

Best mother 6

Best mother 7

Best both 7

Variations on vanilla

Activation functions

Mutations

Parent selection

Introduction

Gameplay

<http://ceur-ws.org/Vol-1107/paper2.pdf>

Minimax only, no neuralnet or evolution

Festa and Davino proved fairly strong play can be achieved by using a minimax algorithm with a strong heuristic function.[]

<https://ieeexplore-ieee-org.easydb.angelo.edu/stamp/stamp.jsp?tp=&arnumber=1438400>

Observing the Evolution of Neural Networks Learning to Play the Game of Othello

Minimax, neuralnet, even cites blondie24, **spatial preprocessing layer,** self adaptive gaussian mutation

Even got their players to master level

Chong et al used a very similar approach in most respects. The most interesting variation was the addition of a spatial preprocessing layer. They were only able to achieve master level play using a spatial preprocessing layer. The agents lacking this aspect were much more difficult to train and did not achieve levels of play comparable to the spatial neural networks. []

“Evolving multilayer neural networks for othello”

<https://ieeexplore-ieee-org.easydb.angelo.edu/stamp/stamp.jsp?tp=&arnumber=7818911>

Neuroevolution

Applied a similar strategy to the popular puzzle game 2048. The primary difference in their approach was the evolution style. These networks were also allowed to change in shape during the evolutive process. []This approach would be an interesting technique to explore in future work.

<https://ieeexplore-ieee-org.easydb.angelo.edu/stamp/stamp.jsp?tp=&arnumber=6209067>

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Just first name last name. Not reverse

Maybe use acm on citation machine