What a Neural Network Can Learn about Othello

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Technical Report 96-10
January 20, 1996

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Keywords: Neural network, game-playing, temporal difference learning

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Abstract

Conventional Othello programs are based on a thorough analysis of the game, and typically employ sophisticated evaluation functions and supervised learning techniques that use large expert-labeled game databases. This paper presents an alternative method that trains a neural network to evaluate Othello positions via temporal difference (TD) learning. The approach is based on a network architecture that reflects the spatial and temporal organization of the problem domain. The network begins with random weights, and through self-play achieves an intermediate level of play. We also present a simple and effective method for analyzing what the network learned.

1 Introduction

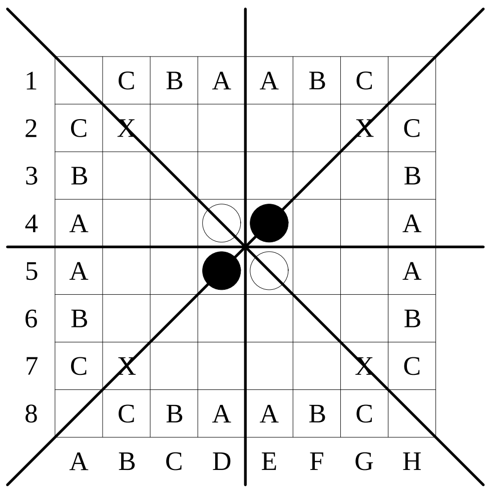
The game of Othello is a descendant of an old Japanese board game. Like chess, it is a deterministic, perfect information, zero-sum game of strategy between two players. The limited length of the game, typically sixty moves, and the small average branching factor, approximately seven, give Othello a complexity greater than checkers but less than chess. This complexity, which causes any attempt to find an exact solution on today's computers to fail miserably, and the alluring simplicity of the rules make the game an attractive domain for experimenting with automatic learning methods.

Various learning methods such as Bayesian learning (Lee & Mahajan, 1988; Lee & Mahajan, 1990) and genetic algorithms (Moriarty & Miikkulainen, 1993) have been applied previously to this domain with varying degrees of success. In this paper we present a different automatic technique for learning Othello strategy. Of interest are the extra steps in network engineering that were needed to improve the program's learning.

This method is based on training a neural network via Temporal Difference (TD) learning (Sutton, 1988). Tesauro demonstrated success with this approach with his TD-Gammon (Tesauro, 1992; Tesauro, 1994), which plays backgammon at a World-Championship level. That work has prompted many several researchers, including us, to apply this technique to other game domains (Walker, 1992; Brockington, 1995). The first report (Walker, 1992) of a straightforward application to Othello was discouraging. The neural network, whose input was a raw board configuration, was unable to advance beyond a novice level. Existing good Othello programs use a number of human-engineered high-level features, so one may surmise that the neural network was not able to find these.

In this paper we present three different neural network architectures for Othello, and compare them empirically. The simplest network achieves only a novice level of play, and the most complex network achieves an intermediate level. We show that incorporating spatial and temporal characteristics of the domain into the network structure results in creating a more accurate evaluation function. The overall training process becomes more effective and stable.

In addition to describing and comparing the three networks, we present a simple method for analyzing what the network learns. This analysis technique indicates that the most advanced network learned not only the weighted-squares strategy, but also certain patterns related to the concept of immediate mobility.



(a)

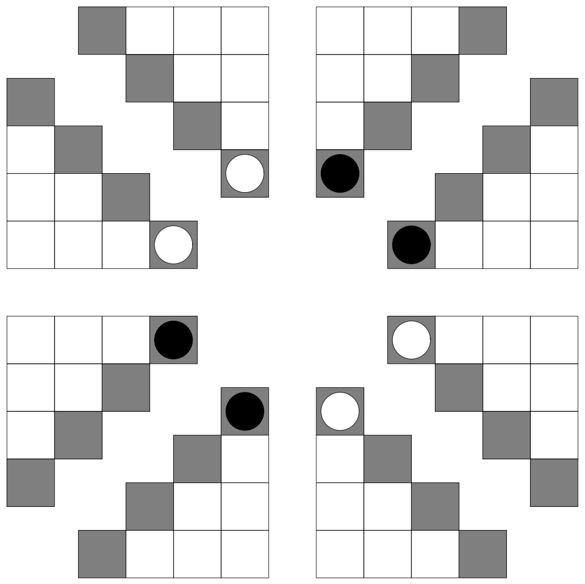

(b)

Figure 1: (a) shows the eight traingles of an Othello board; it also shows the initial board setup and standard Othello square notation; (b) shows the same eight triangles separately. The diagonal squares are shaded to emphasize that these squares are shared by two triangles.

2 The Game of Othello.

Othello (Brockington, 1995) is played on an 8-by-8 grid, using dual-colored black-and-white disks. Black commences play from the initial board configuration shown in Figure 1(a). A *legal move* for a player is the placement of a piece on the board resulting in the capture of one or more opponent's pieces. A *capture* occurs when a player places a piece of his color in a blank (empty) square adjacent to a line of one or more pieces of the opposing color followed by a piece of his own color. Captured disks are not removed from the board, but are instead flipped to the captor's color. Play continues until neither player has a legal move, which usually happens when the board is completely filled. At the end of the game, the pieces of each color are counted, and the player with the greater number of pieces is declared the winner.

3 Network architectures

Our investigation led us to try three different network architectures for Othello.

3.1 Network 1

We begin by considering a classical fully-interconnected neural network with one hidden layer, similar to the network created by Walker (1992). The network has 64 input units corresponding to the 64 squares of the Othello board. Each input unit outputs a value of +1, 0, or -1 according to whether the corresponding board square contains a black disc, no disc, or a white disk.

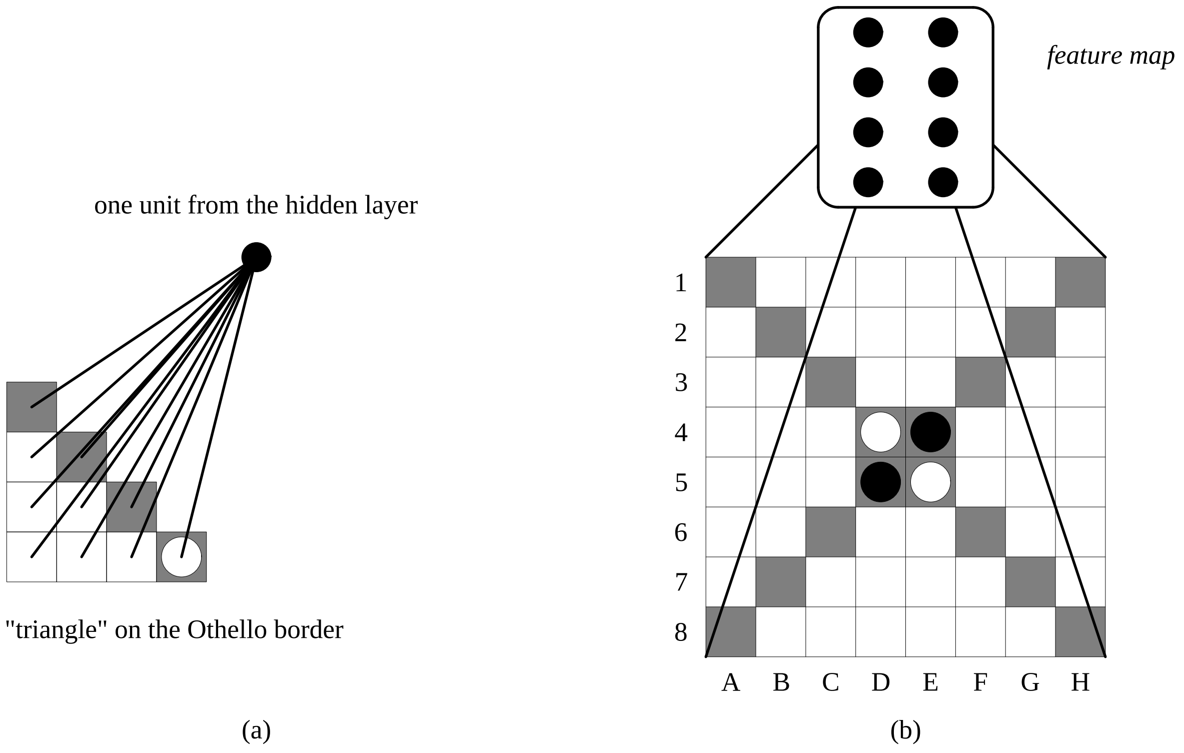

one unit from the hidden layer
"triangle" on the Othello border
(a)
feature map
1
2
3
4
5
6
7
8
A B C D E F G H
(b)

Figure 2: (a) ten input units of a board triangle form a hidden unit; (b) eight triangles form a feature map.

The network is fully-interconnected at each level. This means that the output of every input unit is an input to every hidden unit, and the output of every hidden unit is an input to the single output unit. In addition, every hidden unit has a connection from a bias unit that always assumes value +1. The output of each hidden unit is the linear combination of its inputs squashed by a sigmoid function. If x is the linear combination, then

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

is the output of the hidden unit. This is a standard method for constructing a non-linear activation function. The hidden layer has 55 units, which was determined by trial-and-error. The single output unit also has a bias connection and sigma activation function.

3.2 Network 2

The second network takes into account the symmetry of the board, which is a spatial property of the domain. Every position is invariant under rotation and reflection. The relative positions of the pieces and board edges are always preserved. This causes certain sets of squares to form equivalence classes. For example, the four corner squares form a class. So too do the eight squares that are vertically or horizontally adjacent to a corner square (called the ‘C’ squares). There are a total of ten such equivalence classes, indicating that there are ten distinct kinds of squares on the board.

Consider an Othello board, as shown in Figure 1(a). If we break the board into 8 pieces by straight lines, it will result in eight triangularly-shaped groups, as shown in Figure 1(b). Every triangle consists of the ten kinds of square. The triangle is an invariant for reflection or rotation of the board. The pieces inside one of the triangles would not be affected by either rotation or reflection. The relative positions of the triangles with respect to each other are also preserved. We want the network to reflect this symmetry. It should react the same way (output the same number) on two different boards produced by rotation and/or reflection. To achieve this we incorporate the technique of weight-sharing described by Rumelhart *et al.* (1986), and used successfully by Le Cun *et al.* (1989).

Every board square has a corresponding input unit in the neural network. Recall that the output value of each unit is 1, 0, or -1, depending on whether the square is occupied by black, is empty, or is occupied by white. You may imagine that the input units are also arranged in the 8-by-8 grid and that this grid could also be broken into eight triangles with ten units each. We connect all input units from one triangle to one unit in the hidden layer, as shown in Figure 2(a). Eight hidden units connected to the different triangles form a plane that Le Cun *et al.* (1989) call a *feature map*, as indicated in Figure 2(b).

We want the total output of a feature map to remain the same if we rotate the board. Therefore, every unit in the feature map must represent the same function of its input units. This is achieved by input weight sharing among units in the feature map. For example, there are eight input units corresponding to the different B-squares on the board. Each one is connected to a different hidden unit in a feature map. Weight sharing guarantees that all these connections have the same weight value.

Several feature maps define the hidden layer of the network. All units in the hidden layer are connected to one output unit. All hidden units and the single output unit have a bias connection and a sigma activation function. In our experiments the network has twelve feature maps. Thus, we have 64 input units, 96 hidden units, and one output unit.

3.3 Network 3

An analysis of the game of Othello (Rosenbloom, 1982) shows that it has at least three rather distinguishable stages: opening-, middle-, and end-game. Every game stage lasts approximately twenty moves and it is believed to have a unique strategy. For example, mobility (number of legal moves) plays an important role during the middle-game, whereas the number of discs owned becomes the main factor toward the end. Training one network to evaluate board states in different game phases is the same as training the network to perform different tasks at different times. The network can become a victim of the effect of temporal crosstalk (Jacobs, 1990). Thus, it seems reasonable to have a different network trained for every game phase.

The disk count provides a good approximation of the game state (Lee & Mahajan, 1990). We designed the third network as a supercomposition of three different networks from the previous section. In this composition the coefficients, which are also called application coefficients (Berliner, 1979), are functions of the disc count. To smooth the transition between

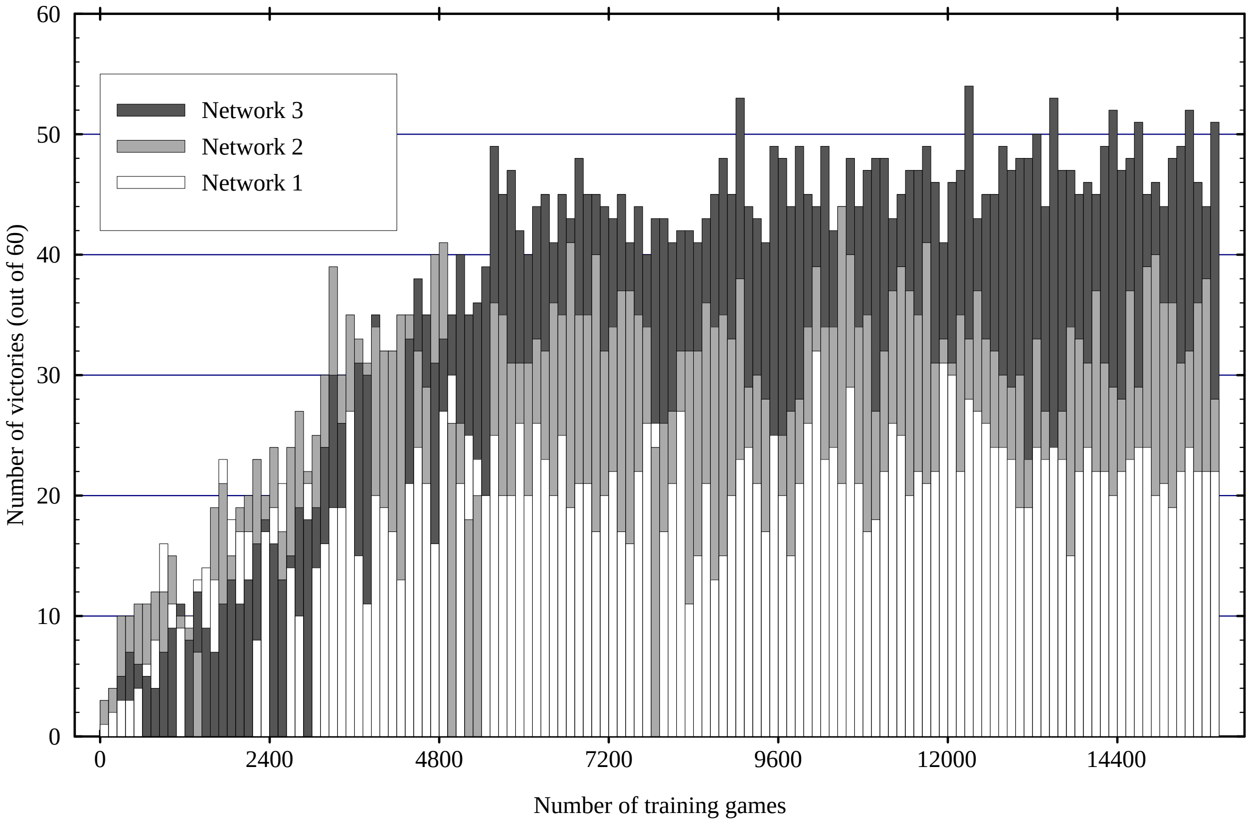


Figure 3. Learning curves for three networks over 15,000 training games

the game phases we choose a sufficiently smooth function:

$$AC_i(n) = Exp\left((-\frac{(n-\mu_i)^2}{\sigma^2}\right)$$

where σ=20, and μ assumes values 4, 34, and 64.

Therefore, Network 3 has 64 inputs, 96x3=288 hidden units, and three output units. Despite its complex architecture it has approximately the same number of connections as Network 1. Thus, all computations take the same time for both networks.

4 Training and Evaluation

4.1 Training

Every network was trained by playing against itself for over 15,000 games. The weights were initialized to uniform random numbers in the range [-1,+1]. The following formula was used to update the network weights:

$$\Delta w_t = \alpha(P_{t+1} - P_t)\nabla_w P_t$$

where α is the learning rate. A value close to 0.1 is generally used, since higher learning rates degrade performance, whereas lower rates reduce fluctuations in performance (Sutton,

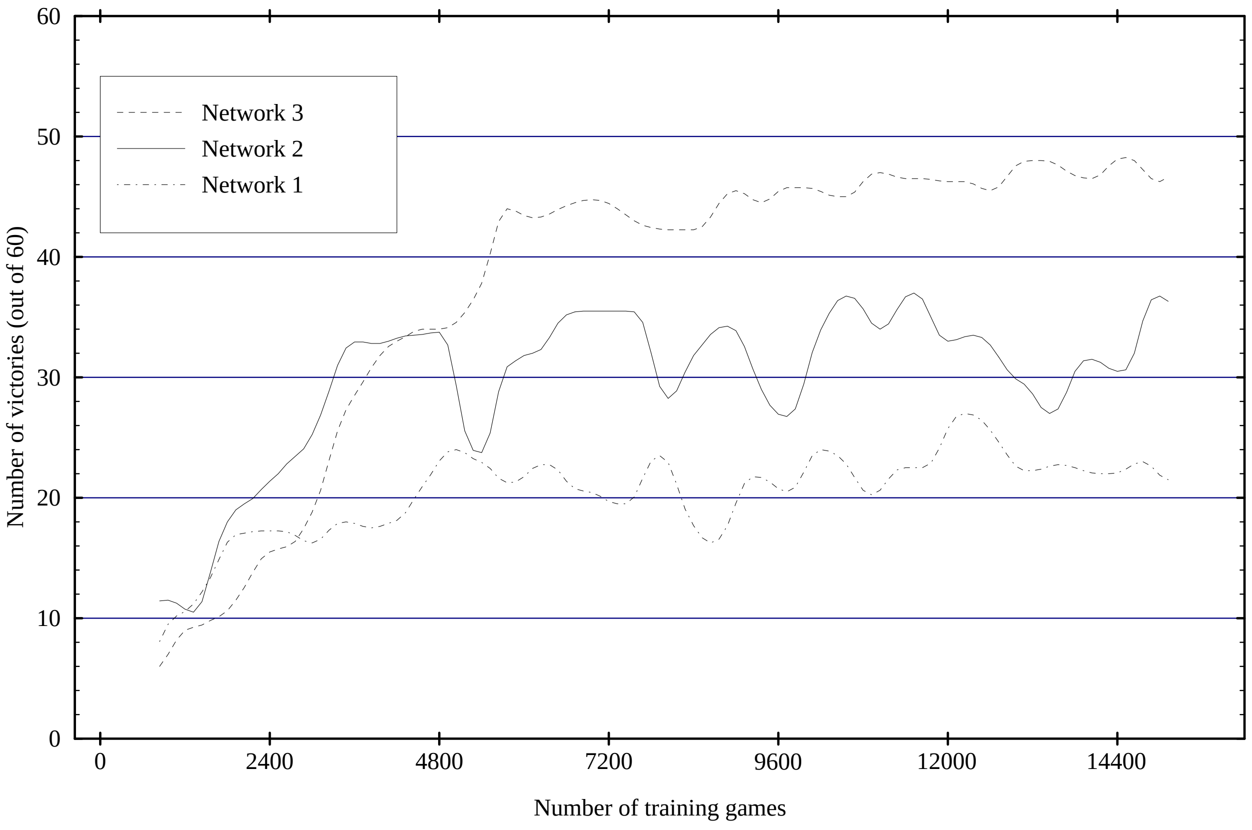


Figure 4: Smoothed learning curves for same three networks over same 15,000 training games

1988; Tesauro, 1992). We set α to 0.05. We also chose to set λ to 0, implementing TD(0). was The P_t is the current prediction, the output of the network given the current board state. The next prediction, the P_{t+1} is the result of the minimax search performed to the depth of two. At the end of the game, when there are fewer than eleven empty squares left, an exhaustive minimax search is performed and the P_{t+1} is the difference in disc counts for both opponents divided by ten and squashed with the same nonlinear function used in the network:

$$P_t = Sigma\left(\frac{\#ofNetDiscs - \#ofOppDiscs}{10}\right)$$

The weight changes are accumulated as the game progresses and the actual update is performed after the game is over.

The sigma function scales the final reward to the same range of values as the intermediate prediction values. Also, the particular shape of the function enforces the condition that the more discs the program wins/loses at the end of the game, the less important it is to predict the exact disc count.

Unlike backgammon, Othello is a deterministic game, so to ensure sufficient exploration of the state space, a stochastic factor was added to the learning process. Consider a game state encountered during the search. Suppose, it has n children and v_i is the evaluation for the ith child. Suppose also that we have evaluated $m < n$ children so far, with *best* being the child with the highest value encountered so far ($v_{best} = max(v_1, ..., v_m)$), and suppose that the next child is better ($v_{m+1} > v_{best}$). Then, we keep this next child as the new best ($best \leftarrow m + 1$) with probability 0.9.

4.2 Empirical Evaluation

The performance of the networks was measured by running them against another Othello playing program named Wystan[1], which uses an evaluation function that incorporates several high-level features such as mobility and stability. The games were started from several different positions generated as follows: start with the initial board setup. All combinations of the four first legal moves from this position will result in 244 different board states. Discarding the boards that are equivalent with respect to rotation and reflection we are left with sixty unique positions. Both programs played sixty games starting from these positions. The number of games won by the network was recorded as the performance measure.

Every network was trained for approximately 15,000 games. At intervals of 120 training games the learning was switched off and the network competed against Wystan. Figure 3 shows the learning curves for all three networks. Figure 4 shows the same learning curves smoothed. Network 1 loses to Wystan more than 60% of the time. Network 2 shows approximately the same degree of performance as Wystan. Network 3 defeats Wystan more than 75% of the time, with a best recorded result of 54 out of 60 victories. Network 3 shows markedly improved performance over Network 1.

Analysis of Network 3's play reveals that it appears to know to avoid an X-square when necessary and yet take an X-square when it is advantageous. It also behaves as though it has the concepts of mobility and stability along the edges. However, we were not able to discern such a concept by inspecting the weights. An alternative explanation is that by owning certain discs, say near the center, and not owning other discs, say further away from the center, the side effect is to attain better mobility than the opponent.

We have also done an informal comparison of Network 3 against LOGISTELLO [2] – the current World Champion among computer Othello players. The program that used 2-ply search achieved an easy victory against 1-ply LOGISTELLO though it was defeated by 2-ply version of the Champion.

5 Analysis

A neural network with one output unit represents a non-linear multivariable function $f(x_1, ..., x_n)$, where the arguments $(x_1, ..., x_n) = \mathbf{x}$ are the outputs of the input units. In our case x_i is the value for i-th square on an Othello board. It assumes values +1, 0, or -1, depending upon whether the square is occupied by a network's disc, is empty, or is occupied by an opponent's disc. The immediate analysis of such a function is usually difficult due to the complex nature of the neural network. We approximate $f(\mathbf{x})$ with a polynomial, for

[1]Author Jeff Clouse. Personal communication.

[2]Available on the Internet Othello Server (IOS) at telnet://faust.uni-paderborn.de:5000

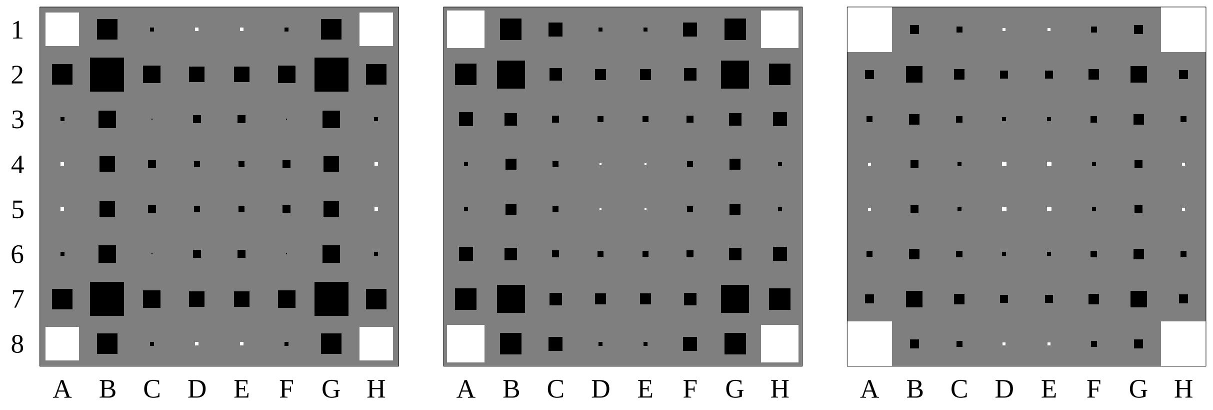


Figure 5. Depiction of first-order coefficients for Network 3

example, by using a Taylor decomposition:

$$f(\mathbf{x}) = f(\mathbf{0}) + \sum_i C_i^1 x_i + \frac{1}{2!}\sum_{ij} C_{ij}^2 x_i x_j + R^3(\mathbf{x}),$$

where an n-th order coefficient is defined as [3]

$$C^n_{i_1\ldots i_n} = \frac{1}{n!}\frac{\partial^n f}{\partial x_{i_1}\ldots\partial x_{i_n}}\bigg|_{\mathbf{0}}.$$

The advantage of this approach is that $C^n_{i_1\ldots i_n}$ could be easily interpreted in a conditional form "if the i_1 square is occupied by ... and i_2 square is occupied by, and ..., then add this amount to the final board evaluation." For example, C_i^1 defines the independent contribution of x_i to $f(\mathbf{x})$.

These coefficients define the **relative** importance of the interactions among squares. The values should be interpreted as 'better' or 'worse', not 'good' or 'bad'. The remainder ($R^n(\mathbf{n})$) is important. For every coefficient $C^n_{i_1\ldots i_n}$ there always will be a coefficient of a higher order $C^{m>n}_{j_1\ldots j_m}$ that will modify the original one if and only if $x_{i_1}\ldots x_{i_n} = x_{j_1}\ldots x_{j_m}$. However, for our purposes it is sufficient that this modification be much smaller than the coefficient itself. Our estimations show that $R^n(\mathbf{n})$ decreases as n increases.

The first-order coefficients can be visualized as an 8-by-8 grid of black and white squares, as shown in Figure 5, where every square corresponds to a location on an Othello board. The area of the square is proportional to the absolute value of the coefficient. The white and black squares represent positive and negative values respectively.

Figure 5 shows the first-order coefficients computed for the three networks that form Network 3. The leftmost picture defines the network that is most responsible for an opening game stage, the second one – for a middle-game, and the third one – for an end-game. Each one of these pictures roughly represents the weighted square strategy (Rosenbloom, 1982),

[3]We decompose the function about $\mathbf{0}$.

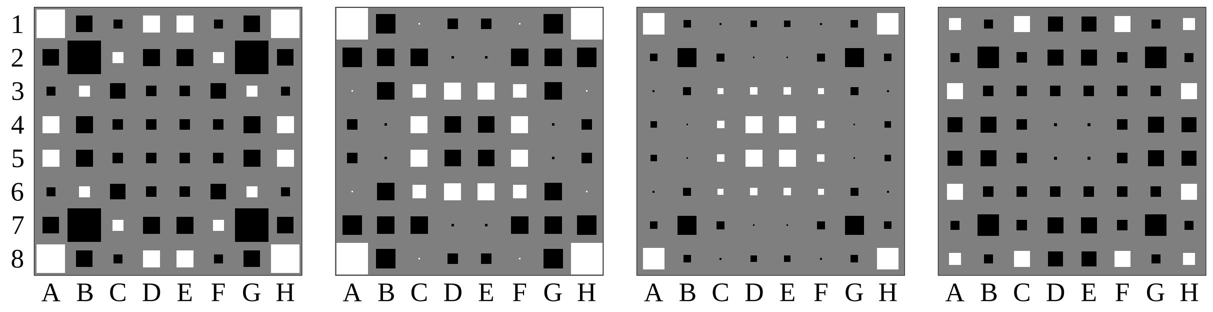


Figure 6: Depiction of first-order coefficients for four most important feature maps in the first network of Network 3

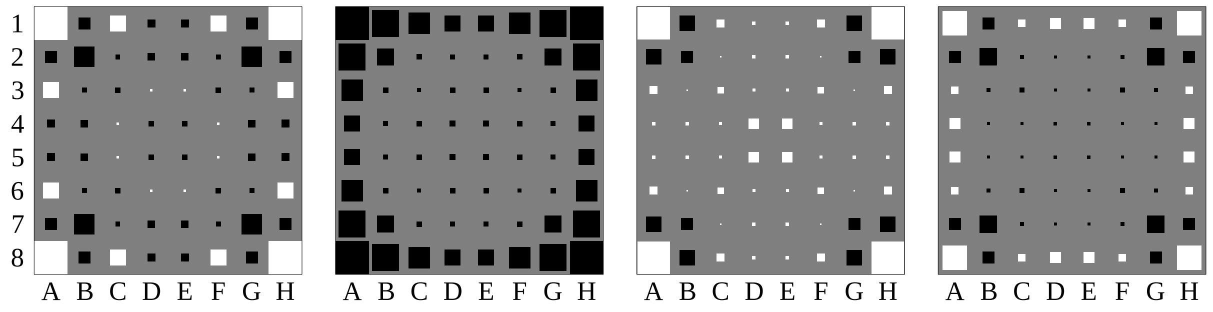


Figure 7: Depiction of first-order coefficients for four most important feature maps in the second network of Network 3

with a high positive value assigned to the corner squares and high negative value assigned to the X-squares. One should notice that taking an X-square becomes less unfavorable as the game progresses, which is due to the fact that the more discs that are on the board the less chance there is that taking an X-square will lead to the loss of a corner.

To see what features the feature maps have discovered we performed the same analysis on each feature map separately. Figures 6 and 7 show the most valuable four feature maps (the feature maps with the highest absolute values) from the first and the second networks. Some of these features are rather easy to interpret. For example, the second and the third maps in Figure 6 suggest one stay inside the central 16 squares during an opening. The third and fourth maps in Figure 7 suggest one capture the edges, however avoiding C-squares.

Next we describe some observations made for the second-order coefficients. Figure 8 shows the interactions of squares A8, B8, C8, and D8 with the rest of the board computed for the third network. For example, consider the interaction between A8 and B8:

$$C^2_{A8B8}x_{A8}x_{B8} = \frac{1}{2}\frac{\partial^n f}{\partial x_{A8}\partial x_{B8}}\bigg|_{\mathbf{0}} x_{A8}x_{B8}, x_{A8}x_{B8} = \begin{cases} -1, & x_{A8} \neq x_{B8} \\ 1, & x_{A8} = x_{B8} \end{cases},$$

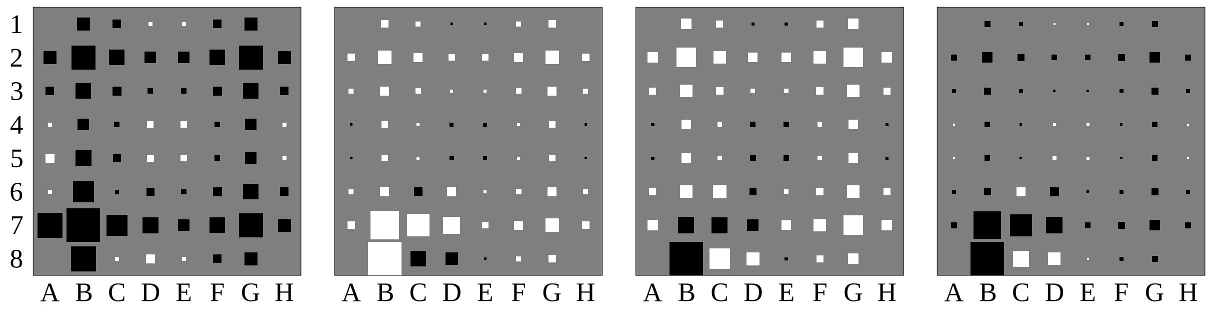


Figure 8: Depiction of second-order coefficients for squares A8, B8, C8, and D8 in the third network of Network 3

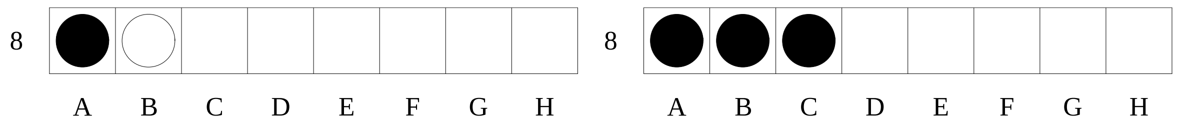


Figure 9. Left: black has a move at C1; Right: square C1 already taken.

where C^2_{A8B8} could be found in the first picture as the second square from the left in the bottom row. It is relatively big and black. We can interpret this result as "it is relatively unprofitable to have two discs of the same color on both A8 and B8." If this rule sounds counterintuitive, consider the interpretation "it is much worse to have two of your opponent's discs on both A8 and B8, than to have the opponent's disc on A8 and your disc on B8."

Each picture on Figure 8 is drawn in its own scale and has corner coefficients removes due to their high values. Notice that the corner square affects, for example, all X-squares almost the same way, and C- and A-squares affect mostly only the closest X-square. We say that a corner is important for the whole board position and C- and A-squares are just locally important.

There is some evidence that the network may have acquired some notion of immediate mobility. For example, suppose the network plays black. The lefthand position of Figure 9, where black has a move at C1, will generate a significantly larger value than the righthand position of Figure 9, where C1 is already taken.

6 Conclusions

Our results show that incorporating spatial and temporal properties of the domain into the network architecture improves its performance. However, this is achieved with some loss of sensitivity in the network. For instance, Figure 10 shows two very different boards that would generate the same response from the network. This problem could probably be solved by considering pattern types other than the triangles we used (Buro, 1994).

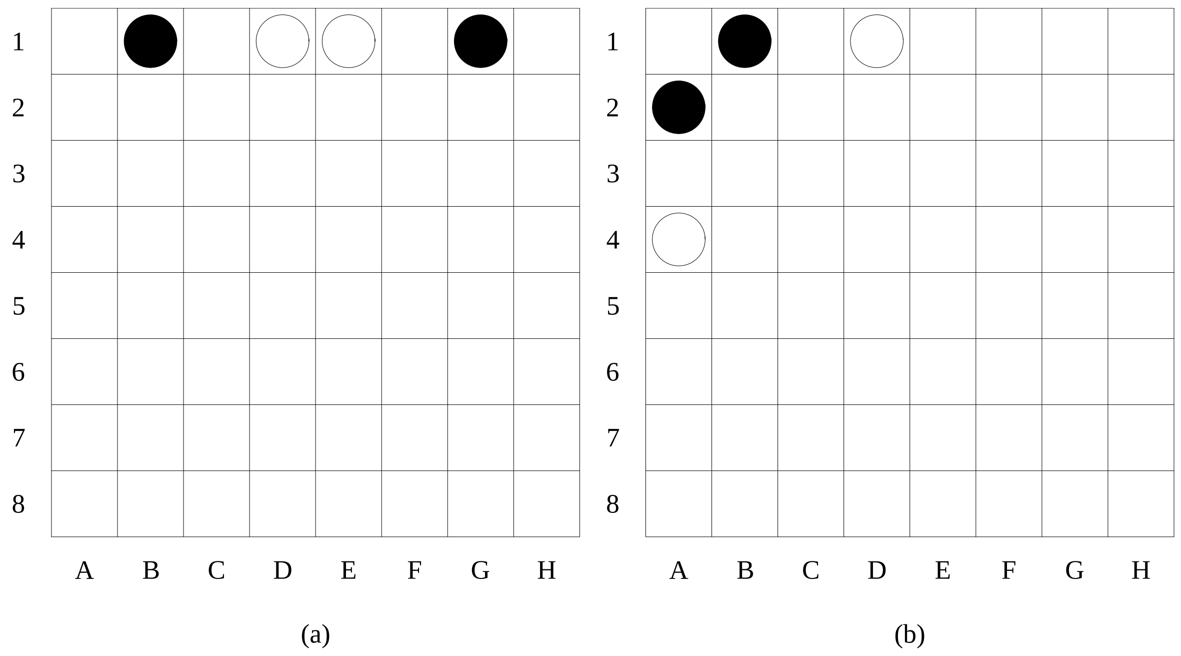


Figure 10. Two different boards that generate the same response from Network 3.

The second observation we make is that the game is not as symmetric as we have assumed. The fixed initial setup (Figure 1(a)) suggests that Othello positions are symmetric only to rotation by 180 degrees and/or reflection relative to a diagonal.

The third observation is that we defined a game stage by the total number of pieces on the board. This assumption is valid while the game is progressing evenly from the center to the edges. However, as this progression breaks down and the game begins to concentrate on one side of the board, this heuristic fails. For example, consider a game where all moves were made on the left side of the board. After roughly 30 moves the left side will be almost filled with discs, when the right side will be almost empty. The game on the left side is almost over, when on the right side it is just beginning. The network must be totally confused by such setup. A possible solution is to consider gating networks (Jacobs, Jordan, Nowlan & Hinton, 1991) as the mechanism for setting the values of the weights on the connections between the input and hidden layers.

We conclude that:

- Incorporating spatial and temporal properties of the domain in the network architecture leads to a significant improvement in performance.
- A neural network using only raw board configuration as input and trained against itself is able to achieve a reasonable level of performance.
- Approximating the network with a polynomial using a Taylor decomposition is a very fast and sufficiently accurate method for analyzing a network.

- The best network learned the weighted square strategy together with a weak notion of immediate mobility within a triangle.

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