Strategy Acquisition for the Game Othello Based on Reinforcement Learning

Taku Yoshioka, Shin Ishii and Minoru Ito
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Speaker : Sameer Agarwal
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Task

To produce a computer program that plays the game of Othello

Why play games ?

- Rich problem domain
- There is money to be made
- Pit man against machine
- It is fun

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Classic Computer Game Playing

Basic Assumption

Rational opponent who will try to beat you

Classical Approach

- MinMax Search – extremely expensive O(b^d)
- Some improvement using alpha-beta pruning O($b^{d/2}$)
- Full MinMax even with alpha-beta is not feasible
- Use a **payoff function**

Problem

The payoff function is only a **heuristic**.
How to construct a good **payoff function** ?

Good Payoff Function = Good Player

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Payoff Function Construction

- First attempts at game playing used hand crafted payoff functions
- Typically linear

Research on Machine-learned payoff functions

- Arthur Samuel build a checkers program which learned its own payoff function.(1954)
- Gerry Tesauro built TD-Gammon based on TD-Reinforcement learning. Top ranked player in the world today. (1995)

Is it possible to construct an algorithm that can learn a good payoff function for Othello?

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Rules of Othello

- 2 player game
- Each player starts with 2 discs on the board and 30 discs in reserve
- Player with more disks on the board at the end of the game wins

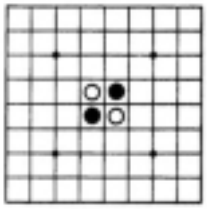

FIGURE 1

Start position

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Making a Move

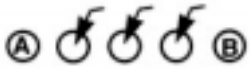
A move consists of "outflanking" your opponent's disc(s), then flipping the outflanked disc(s) to your color.

To **outflank** means to place a disc on the board so that your opponent's row (or rows) of disc(s) is bordered at each end by a disc of your color. (A "row" may be made up of one or more discs.)

Here's one example:

White disc **A** was already in place on the board.
The placement of white disc **B** outflanks the row of three black discs.

Before : 

After : 

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Another Example

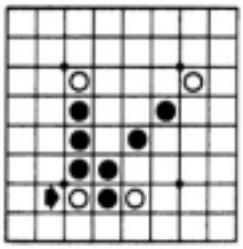

FIGURE 2

Before

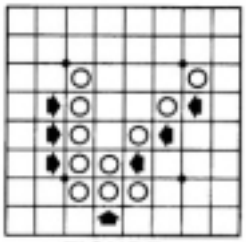

FIGURE 3

After

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Contributions of this Paper

- Radial Basis Function (called NGnets) based payoff function.
- MinMax Reinforcement Learning.
- Demonstration that it is possible to learn a payoff function autonomously using MinMax Learning.
- A comparison with an evaluation function based on a Multilayer Perceptron (MLP)
- A comparison with an evaluation function based on TD(0) Reinforcement Learning.

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Organization of the rest of the talk

- Algorithm Design
  - Strategy – How do we search for a good move ?
  - Payoff Function – How do we know what is a good move ?
  - Learning Method – How to construct a good payoff function ?
- Experimental Setup
- Experiment Results
- Conclusion

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Strategy

Optimal Evaluation Function

$$V_b^* = \begin{cases} B(s) - W(s) & (\text{if } s \text{ is the final state}) \\ \max_b \{\min_w \{V_b^*(S(S(s,b),a))\}\} & (\text{otherwise}) \end{cases}$$

Optimal Action

$$b^* = \arg\max_b \{\min_w \{V_b^*(S(S(s,b)w))\}\}$$

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Back in the real world (strategy)

Since we **do not** know the **optimal** V^* we make do with an estimate

$$\hat{b} = \arg\max_b \{\min_w \{\hat{V}_b(S(S(s,b)w))\}\}$$

Here $\hat{V}_b$ is the estimated payoff function that we construct.

Since Othello is completely deterministic we include a random term to increase exploration. Hence

$$\hat{b} = \arg\max_b \{\min_w \{\hat{V}_b(S(S(s,b)w)) + N(0,\sigma_L)\}\}$$

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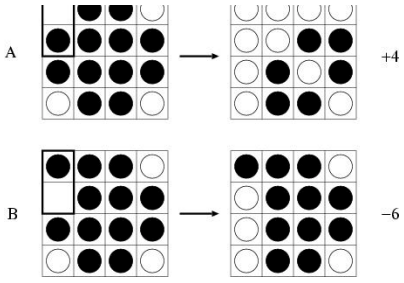
Payoff Function

Highly nonlinear game play

A single move can change the board drastically



MLP are useful for approximating “smooth” functions like Backgammon evaluation functions. Othello requires something different..

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Payoff Function : Algebraic Form

Normalized Gaussian Networks(NGNet)

$$V'(s) = \sum_{i=1}^{N} w_i N_i(s)$$ Weighted sum of normalized gaussians

$$N_i(s) = \frac{g_i(s)}{\sum_{j=1}^{N} g_j(s)}$$

$$g_i(s) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left(\frac{-|s-\mu_i|^2}{2\sigma^2}\right)$$

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Learning Method: MMRL

Goal : To minimize the prediction error over the length of the game

$$E = \frac{1}{2} \sum_{t=1}^{T} \{\hat{V}_b^*(s_t) - \hat{V}_b(s_t)\}^2$$

T is the length of the game
S_t is the state at the t-th black turn
V^* is the reinforcement signal

$$\hat{V}_b^* = \begin{cases} B(s) - W(s) & (\text{if } s \text{ is the final state}) \\ \max_b \left\{ \min_w \left\{ \hat{V}_b(S(S(s,b),a)) \right\} \right\} & (\text{otherwise}) \end{cases}$$

Perform Gradient Descent using the above error formula to get update rules for the parameters of the NGNet

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Putting it all Together

1. Initialize the parameters of the NGNet.
2. Start a game.
3. For each step t in the game:
   a. select a move based on the MinMax decision
   b. compute the weight corrections.
4. At the end of the game update the NGNet parameters.
5. Go to step 2.

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Experimental Setup

Heuristic Player 1 (non-adaptive)

If there are 10 or less positions left empty on the board,
then perform exhaustive search

else, choose the action a that maximizes the following function

$$V_w^1(s) = \frac{W(s') - B(s')}{W(s') + B(s')} + C(a) + N(0, \sigma_{HP1}) \quad \text{where } s' = S(s,a)$$

C(a) is 1 if a is a corner on the board 0 otherwise.

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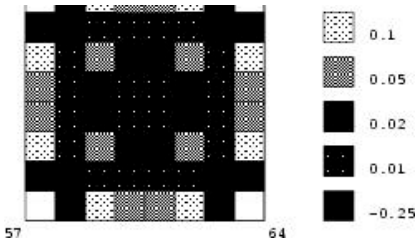
Heuristic Player 2(non-adaptive)

Chooses a move based on a 2-ply MinMax search using

$$V_w^2(s) = \sum_{i=1}^{64} f_i s_i + N(0, \sigma_{HP2})$$



The weights f_i are based on the above map

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Parameter settings for our player

1. No. of units in the NGNet = 100
2. Initially $w_i = 0$ and μ_i is set at random.
3. Each player plays 50,000 games for training against one opponents
4. Each training epoch is 500 games, with a 100 game test epoch
5. Testing is done by playing against one of the heuristic players

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Different Players Trained

Two Learning Players - Black and white sides **employ their own** NGNets
Train by playing against each other (RL1(B),RL1(W)

Training with HP1 - A black player is trained by playing **against a white** HP1 (RL2(B))

Self-Play - Black and white sides **share the same NGNet** SL(W), SL(B)

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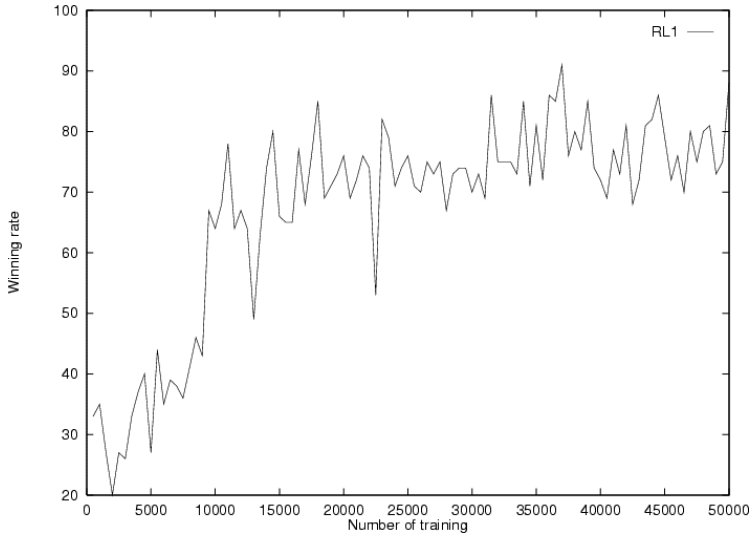
Experimental Results



Learning Behavior [RL1(B) / HP1(W)]

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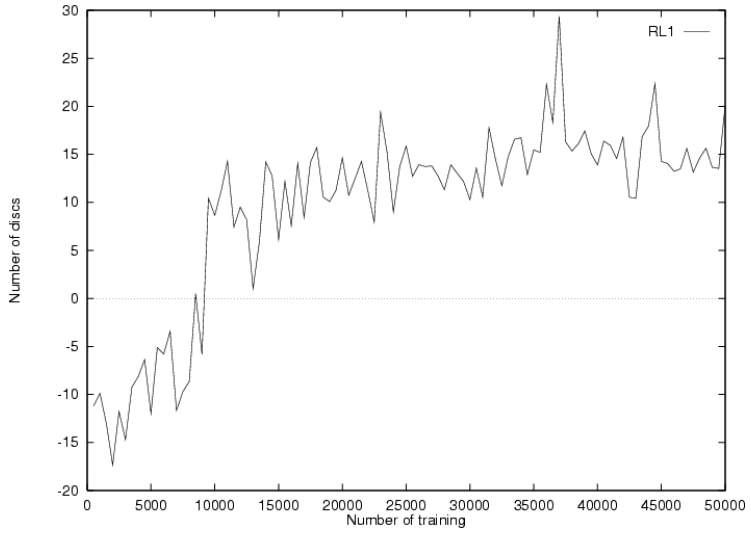
Experimental Results



Average number of discs won [RL1(B)]

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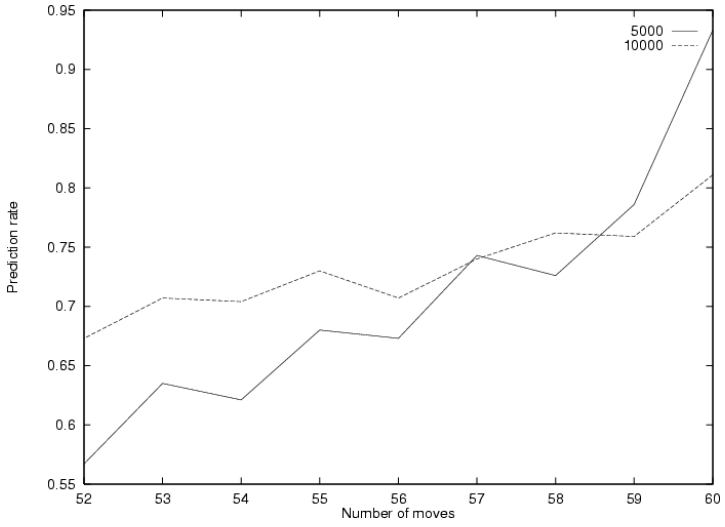
Experimental Results



Predictive Behavior RL1(B)

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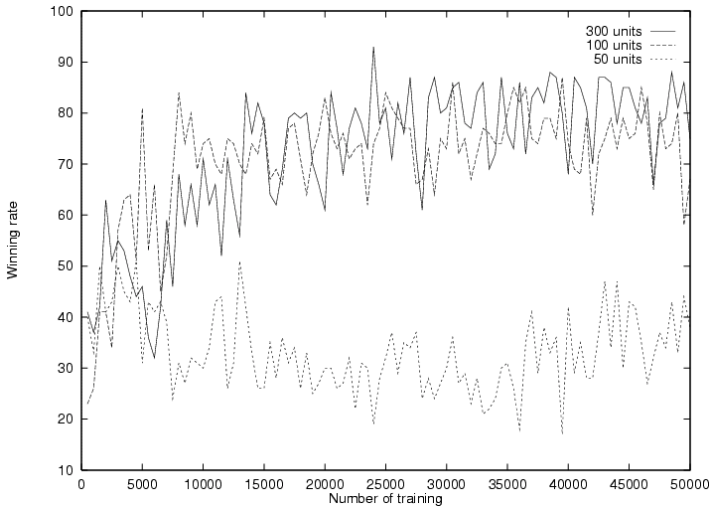
Experimental Results



Varying Number of Centers [RL1(B) / HP1(W)]

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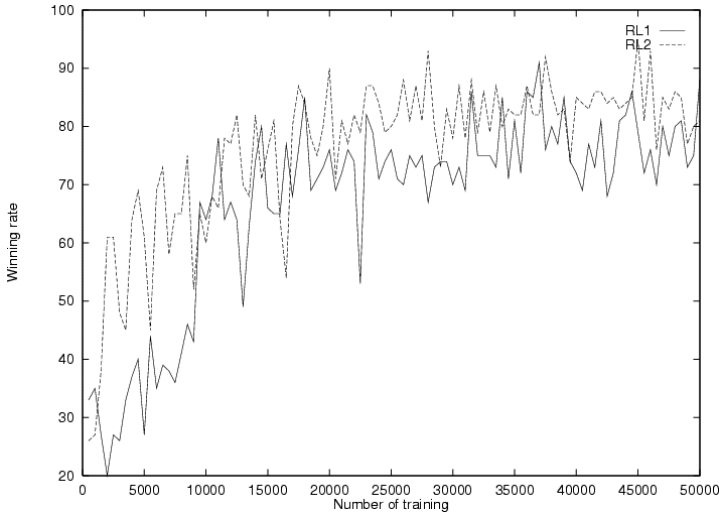
Experimental Results



Winning Rate
RL1(W) and RL2(W) against HP1(B)

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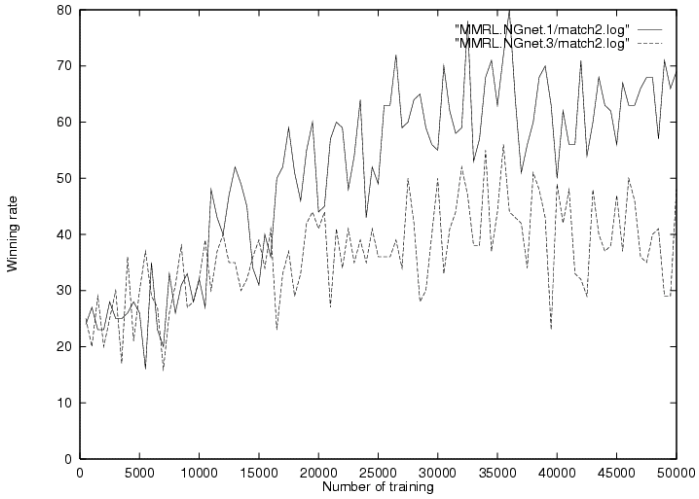
Experimental Results



Winning Rate
RL1(W) and RL2(W) against HP2(B)

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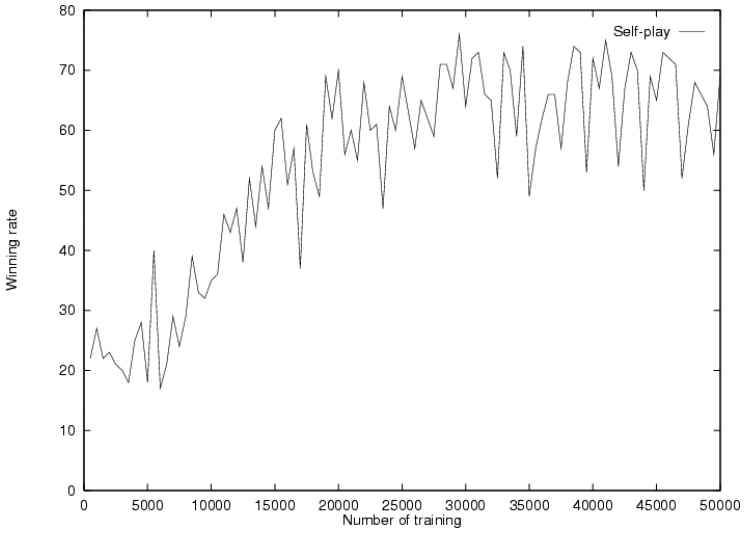
Experimental Results



Winning Rate [SL(B) / HP(W)]

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Experimental Results

MinMax Learning tries to predict the end result of the game
TD Learning tries to predict the board state on the immediate future

$$z - P_t = \sum_{k=t}^{m} (P_{k+1} - P_k) \quad \text{where } P_{m+1} = z$$

Revised Payoff functions

$$\hat{V}_b^* = \begin{cases} B(s) - W(s) & (\text{if s is the final state}) \\ \hat{V}_b(S(S(s,b),w)) & (\text{otherwise}) \end{cases}$$

Revised Action

$$\hat{b} = \hat{V}_b(S(S(s,b)w)) + N(0,\sigma_T)$$

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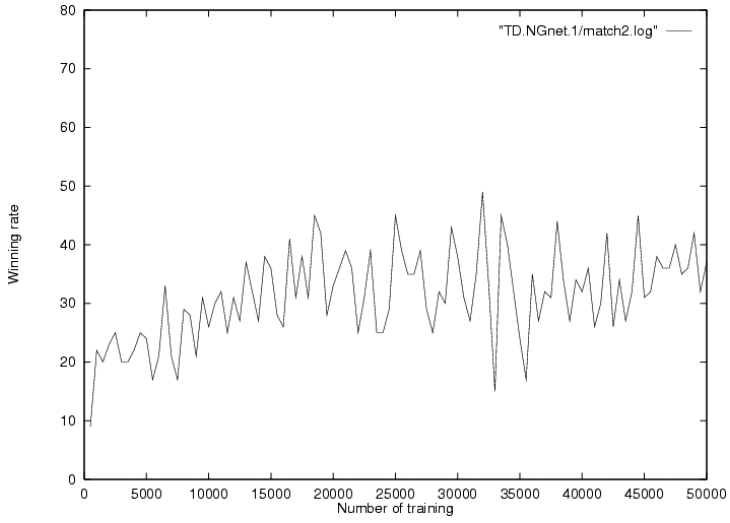
Experimental Results



Winning Rate [TD(B) / HP2(W)]

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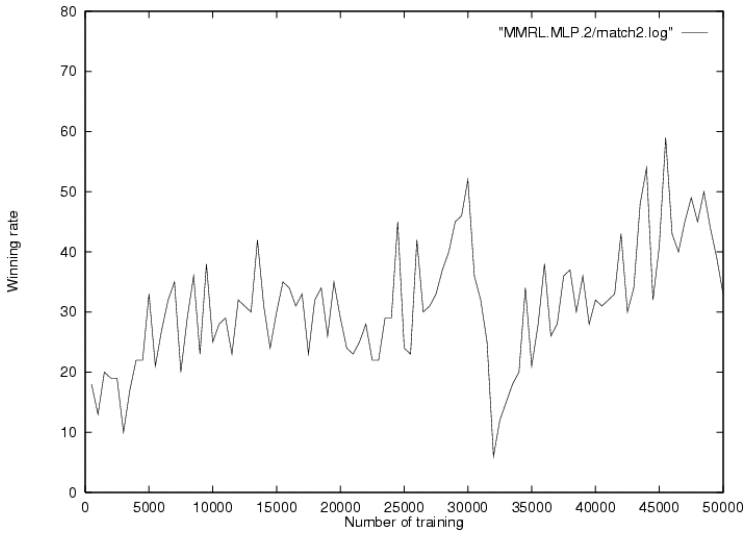
Experimental Results



Winning Rate
MLP(100 hidden units)(B) / HP2(B)

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Conclusions

1. A general purpose new game playing algorithm (MinMax RL) is proposed. It is shown to be successful against heuristic players.
2. A Radial Basis Function/NGNet based payoff function is shown to be effective for evaluating Othello board configurations.
3. RBFs are shown to be better than MLP based payoff functions.
4. MinMax-RL is shown to be better than TD(0).

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