COMP3130 – Group Project in Computer Science
10×10 Othello Learning Agent

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1. Abstract

An agent to play the board game *Othello* is created, with the ability to learn through reinforcement. The minimax algorithm is used for game playing, and a static evaluation function for the leaf nodes is learnt by self play. The agent learns the insignificance of the number of stones, and the significance of stone positioning. This agent is played against itself, and against other developed agents, and it's performance is analysed.

2. Problem overview

3. Solution overview

4. Optimisations

5. Static evaluation function

6.1. TD-λ

The TD-λ algorithm was used to learn the weighting of the static evaluation function's various features. The implementation of this algorithm is based on the one implemented by the Knightcap agent (http://citeseerx.ist.psu.edu/viewdoc/summary?doi=10.1.1.140.2003) At the end of each game played, the agent adjusts it's weights according to the following formula

$$w := w + \alpha \sum_{t=1}^{N-1} \Delta\tilde{J}(x_t, w) \times \left[\sum_{j=t}^{N-1} \lambda^{j-t} d_t \right]$$

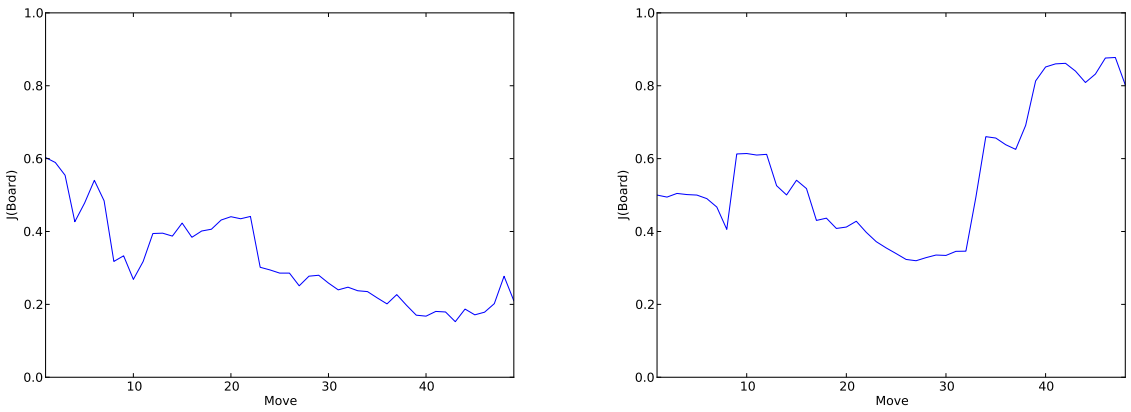
w	The vector of weights	x_t	The t^{th} board in the game
α	The learning rate	λ	The discount factor
N	The number of states in the game	d_t	$\tilde{J}(x_{t+1}, w) - \tilde{J}(x_t, w)$
$\Delta\tilde{J}$	The derivative of the $\tilde{J}$ function		

In the above formula, the $\tilde{J}$ function estimates the probability of winning from a given state, given a set of weights for features and our board. It approximates the J function,

$$J(x_t) = \begin{cases} 1, & \text{if } x_t \text{ is a winning state} \\ 0, & \text{if } x_t \text{ is a lost state} \end{cases}$$

For each game state x_t, we adjust the weights according to a factor d_t, which is the temporal difference. $d_t = \tilde{J}(x_{t+1}, w) - \tilde{J}(x_t, w)$, and the weight adjustment is scaled with this amount. The key observation is, for the true J function, $J(x_{t+1}) - J(x_t) = 0$, so we adjust our weights relative to this amount.

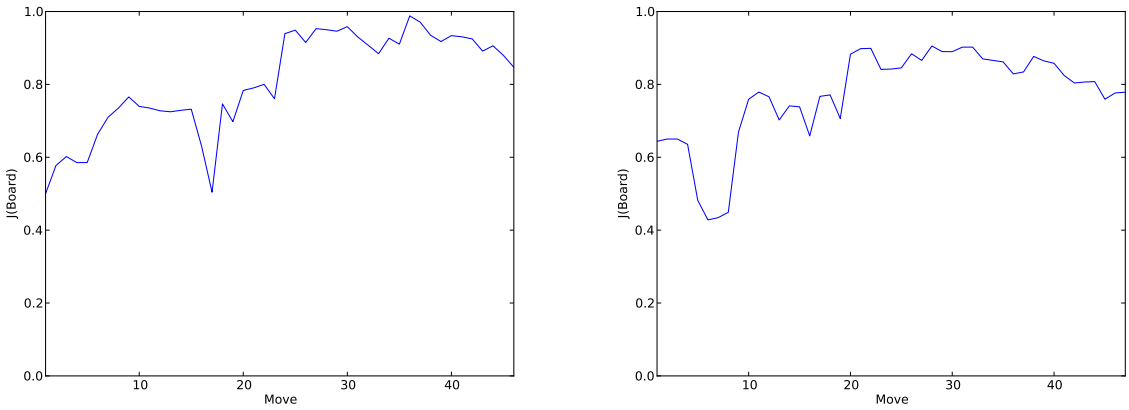
From Figure 1, we can see that the $\tilde{J}$ function, while not accurate for the entirety of the game, is able to predict the results within the last 20 moves. In comparison, Figure 2 indicates that the $\tilde{J}$ function initially is a bad approximation, as even after losing a game, the estimated probability of winning is high.



(a) Losing a game

(b) Winning a game

Figure 1: $\tilde{J}$ Function after 1000 learning iterations



(a) Losing a game

(b) Winning a game

Figure 2: $\tilde{J}$ Function initially

In Figure 3, we can see the progress of the learning agent as it plays against a fixed opponent. After about 1000 games, the agent settles on a win/loss ratio of approximately 0.7.

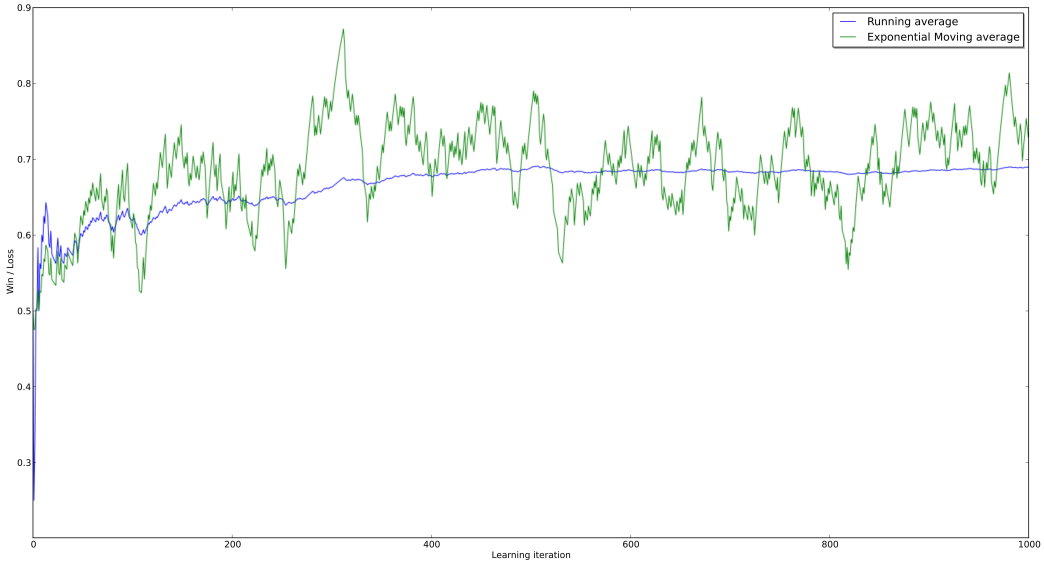


Figure 3: Learning Progress of a 4-ply Learning player vs. a 4-ply Minimax player

6.2. ELO arena

6.3. Comparison of TD-λ and ELO arena

7. Performance evaluation

8. Improvements