Jafar — Intelligent Othello Agent

Joshua Nelson, Tim Cosgrove, Andrew Haigh

COMP3130 Research Project

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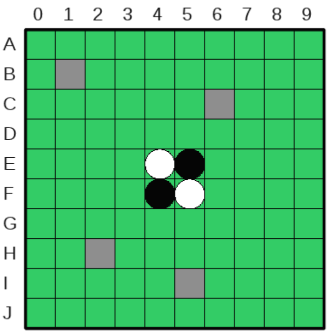
YEAH, I NAMED THE BIRD IAGO...
LIKE FROM "OTHELLO"...

Problem Overview

- The Game — 10x10 Modified Othello



(a) Initial Configuration

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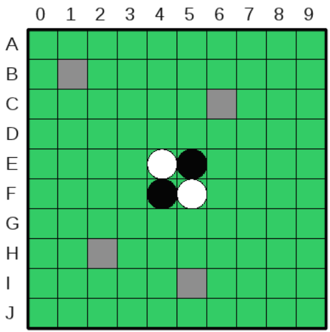
- The Problem — Intelligent AI player



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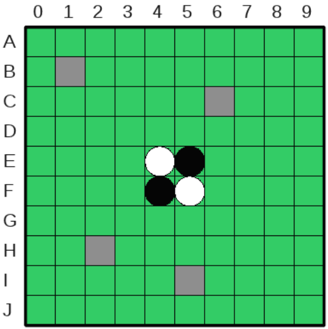
- The Problem — Intelligent AI player
- Solution basis



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Solution Structure

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- NegamaxPlayer (varying depth argument)
- OpeningPlayer
- GreedyPlayer

Static Evaluation

- The FeatureSet class — Maintains a list of *features*; functions which evaluate a game state based on some criteria of strength

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- LegalMoves
- Visibility
- StoneCount
- BlockedAdjacent, CornerPieces, SidePieces

TD-λ

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- Solution - use the TD λ formula to calculate the new weights
- $w := w + \alpha \sum_{T=1}^{N-1} \tilde{J}(x_t, w) * (\sum_{j=t}^{N-1} \lambda^{j-t} d_t)$

The J Function

$$w := w + \alpha \sum_{T=1}^{N-1} \Delta \tilde{J}(x_t, w) * (\textstyle\sum_{j=t}^{N-1} \lambda^{j-t} d_t)$$

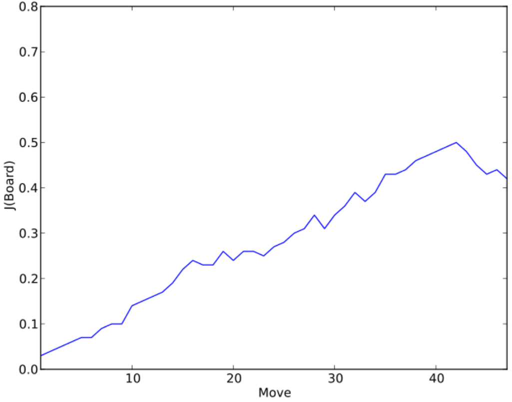
- The J function returns a probability of winning, given a set of weights and a board.
- The perfect J function would always return 0 or 1 precisely.
- We are trying to learn a good approximation to the J function

TD: Temporal difference

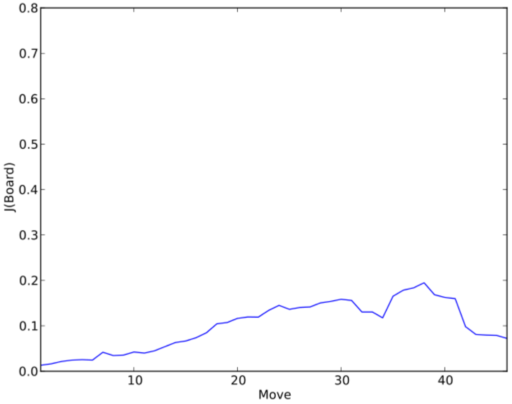
$$w := w + \alpha \sum_{T=1}^{N-1} \Delta\tilde{J}(x_t, w) * \left(\sum_{j=t}^{N-1} \lambda^{j-t} d_t\right)$$

- d_t is the *Temporal Difference* between successive game states.
- The key observation is that for an ideal J function this would always be zero.
- $\Delta\tilde{J}(x_t, w)$ corrects each weight according to whether it was pointing us in the right direction.

Initial J function
Lost game



J function after 6000 iterations
Lost game



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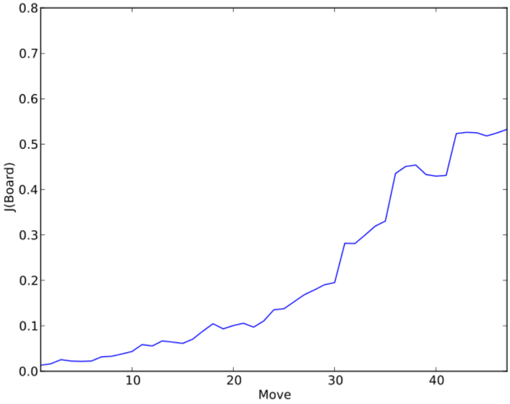
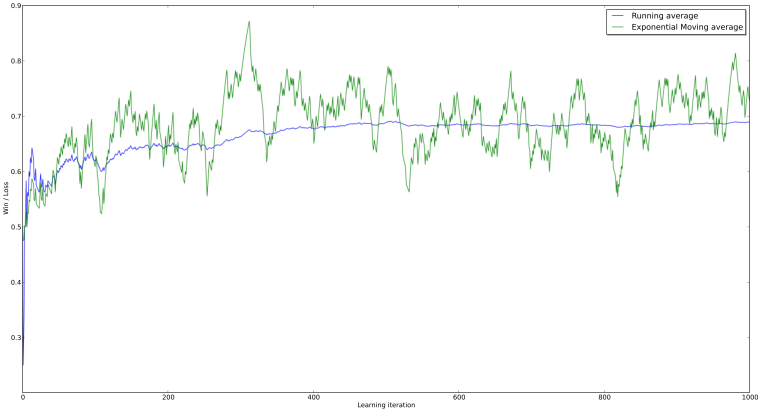
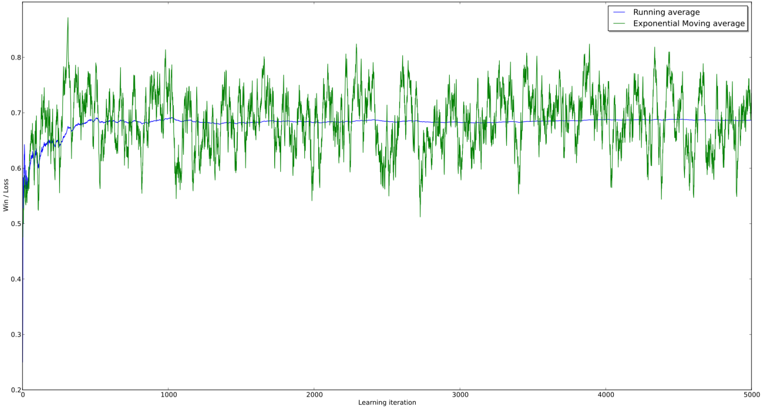


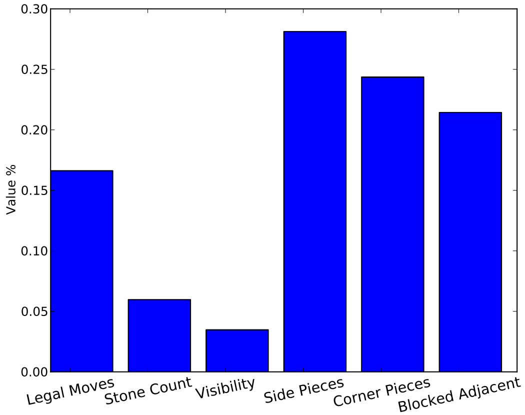
The first 1000 learning iterations



The first 5000 learning iterations

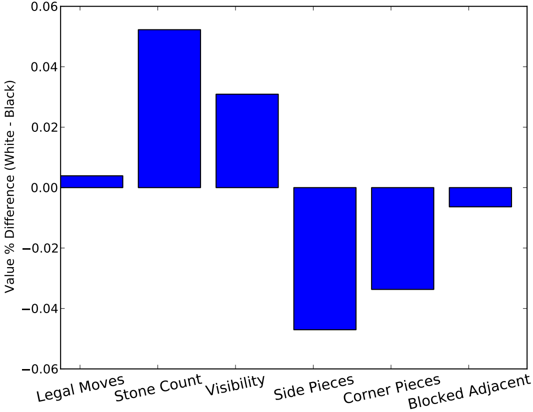


Self play - learnt weights

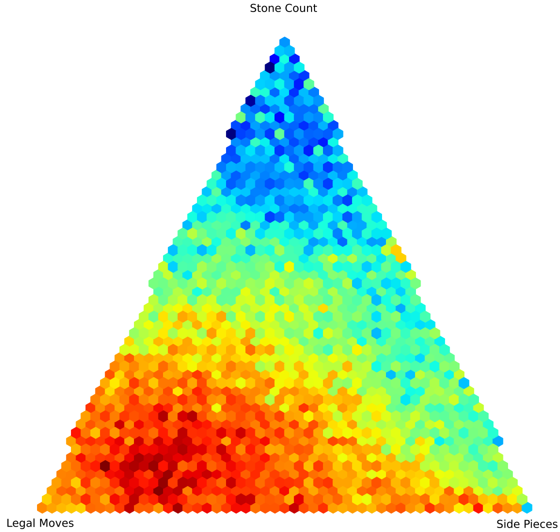


Self play - learnt weights

White - Black



Feature weight space visualisation



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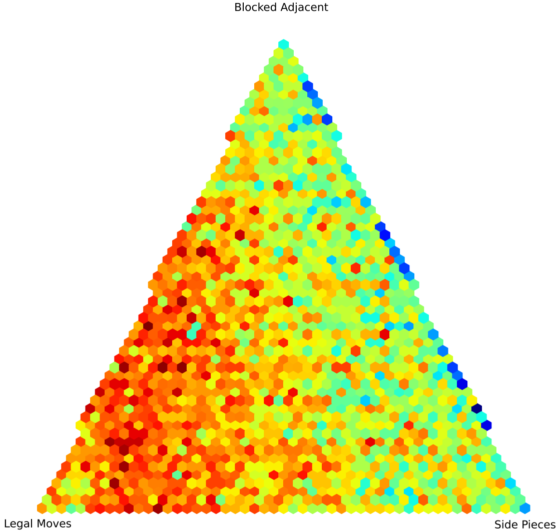

The Elo Rankings Arena

- Custom made genetic algorithm
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- Custom made genetic algorithm
- Pits a group of randomly generated agents against each other for Elo style ranking points
- Creates new agents from those who perform best
- Used more as a demonstration of the learning process
- Interesting to see it come to the same conclusions as TD-λ

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- Negamax optimisations (better transposition tables, prob-cuts, etc.)
- Better use of pre-computed data
- More board features (locked squares, open squares, etc.)
- More exploration in learning - randomise the initial board and play from that to explore more options

Design Methodology

- C with a python interface
  - Used this for tic-tac-toe warm up problem, decided against due to development overhead

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  Java
  - Sacrifice low level speed improvements for high level language features and built in data structures.

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