# Term Project: Reinforcement learning applied to Othello

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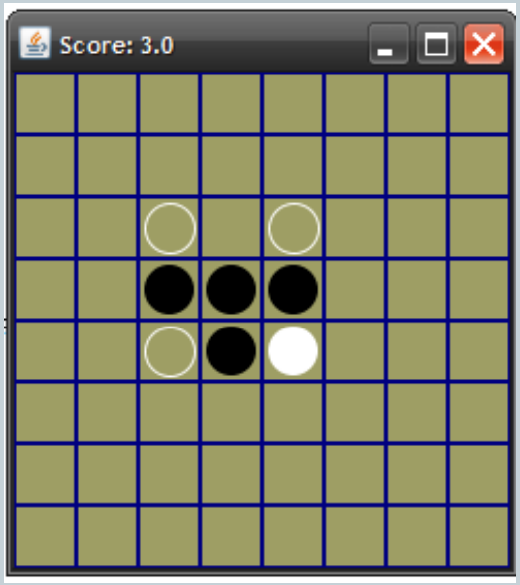
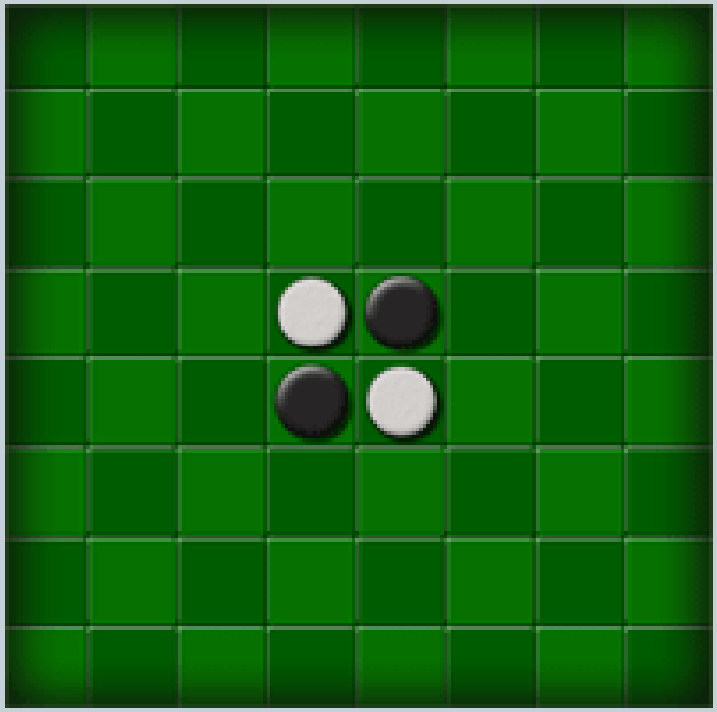


# Othello



# What is reinforcement learning?

- After a sequence of actions get a reward
  - Positive or negative
- Temporal credit assignment problem
  - Determine credit for the reward
  - Temporal Difference Methods
    - TD-lambda
    - Q-learning (TD(0))

# Contrast to Conventional Strategies

- Most methods use an evaluation function
- Use minimax/alpha-beta search
- Hand-designed feature detectors
  - Evaluation function is a weighted sum

- So why TD learning?
  - Does not need hand coded features
  - Generalization

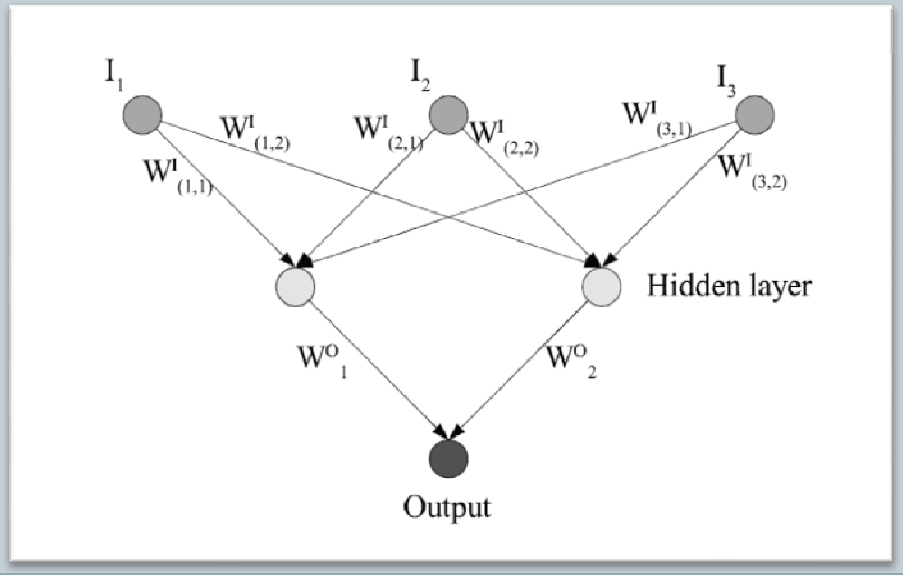
# Temporal Difference Learning

$$Output = \sum_{k=1}^{H} f(\sum_{j=1}^{N} I_{j,k} W_j^I) W_k^O$$

**N** is the number of input nodes.

**H** is the number of hidden nodes.

**f()** is our non-linear function.



# Temporal Difference Learning

$$\Delta W_t = \alpha(Y_{t+1} - Y_t) \sum_{k=1}^{t} \lambda^{t-k} \nabla_w Y_k$$

$\mathbf{t}$ is time (in our case move number).

$\mathbf{T}$ is the final time (total number of moves).

$Y_t$ is the evaluation of the board at time $t$ when $t \neq T$.

$Y_T$ is the true reward (i.e. win, loss or draw).

$\alpha$ is the learning rate.

$\nabla_w Y_k$ is the partial derivative of the weights with respect to the output.

$d_T$ is the *temporal difference*.

# Key Observation

- If we let

$$e_{ijk}^{t} = \sum_{n=1}^{t} \lambda^{t-n} \frac{\partial P_k^n}{\partial w_{ij}^n}.$$

at time step t. Then at time step t+1,

$$e_{ijk}^{t+1} = \lambda e_{ijk}^{t} + \frac{\partial P_k^{t+1}}{\partial w_{ij}^{t+1}}$$

# Temporal Difference Learning

- If we let $\lambda = 0$, then, we get

$$\Delta W_t = \alpha(Y_{t+1} - Y_t)\nabla_w Y_k$$

- Widrow-Hoff rule
- Makes $Y_t$ closer to $Y_{t+1}$

# Disadvantage

- Requires lots of training
- Self-play
  - Short-term pathologies
  - Randomization

# Setup

- Board: 64 element vector
  - +1 = black
  - 0 = empty
  - -1 = white
  - Corresponds to human representation
- Network
  - 64 inputs
  - 30 hidden nodes – Sigmoid activation
  - Single output
    - Goal: predict final game score

# Setup

- TD lambda learning
  - Lambda = 0.3
  - Learning rate = 0.005
  - Reward is endgame score
- Move selection
  - Evaluate every legal 1 ply move
  - Choose randomly with exponential weight

# Player Handling

- Two Neural Networks
- Board inversion
  - On white's move, invert board and score
  - Faster and superior learning

# Training Data

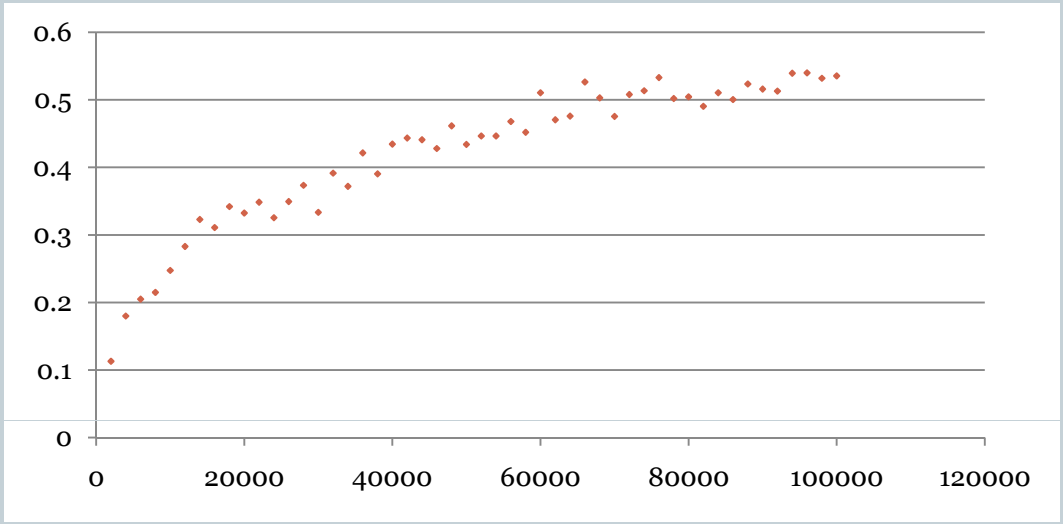
- Recall:
  - Random play
  - Fixed opponent
  - Database play
  - Self-play
- I focused on:
  - Database play
  - Self-play

# Opponent

- Java Othello
  - www.luthman.nu/Othello/Othello.html
  - Variable levels corresponding to ply depth
- Used as benchmark
- Trained against

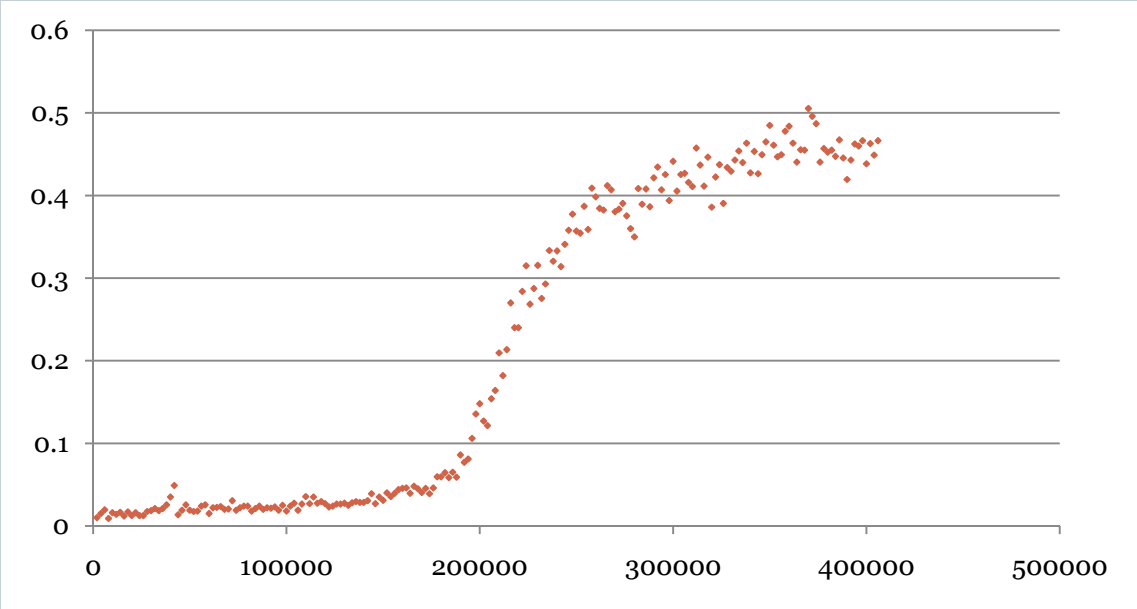
# Database Training

- Logistello database
  - 120,000 games
- Fast
  - less than 30 minutes to train on the full set
- Wins 10% games against a 1 ply opponent



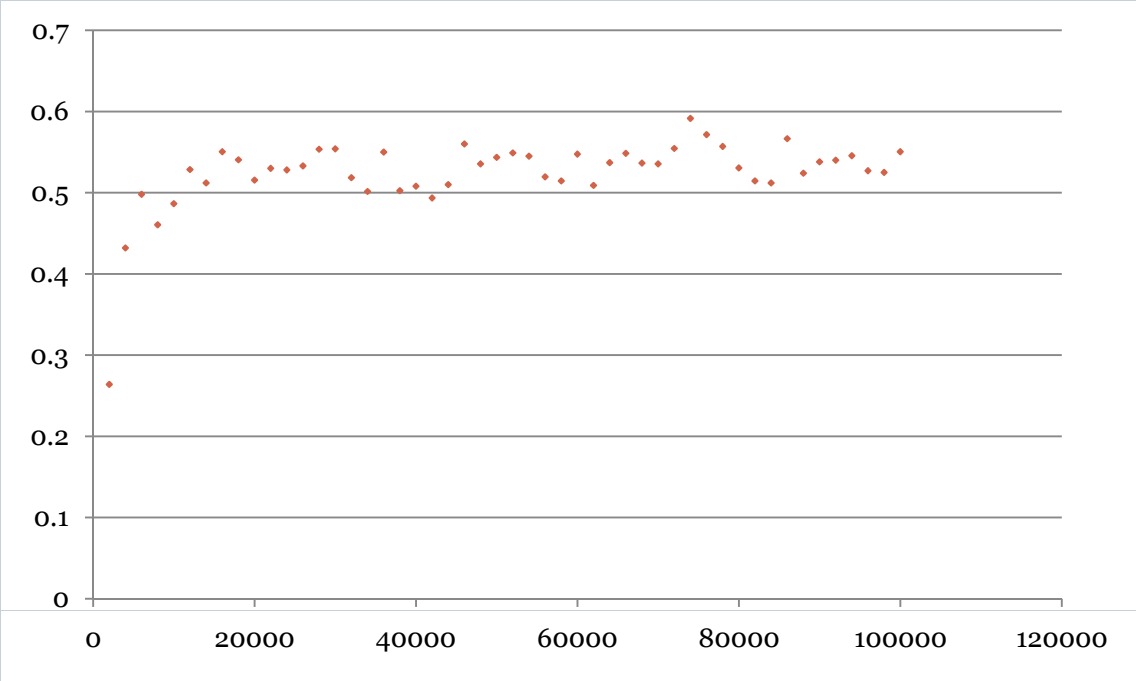
# Self-play

- Extremely slow improvement
  - Even after nearly 2,000,000 iterations almost no improvement
- Only wins 1% of games against 1 ply opponent



# Two Ply Opponent

- Opponent looks ahead one ply and chooses the best move
  - Much slower by a factor of 6 or more



# Website

- For source code and reference material
  - www.cs.hmc.edu/~gtucker/othello.html

# Conclusions

- Board inversion should definitely be used
- Initially, at least self-play is poor
- Database play significantly improves network
- Asymmetric self-play is far superior to standard self-play
- Playing a fixed opponent may be best

- Future Work
  - Add in additional feature detectors
  - Investigate more advanced depth play