Reinforcement Learning in Board Games

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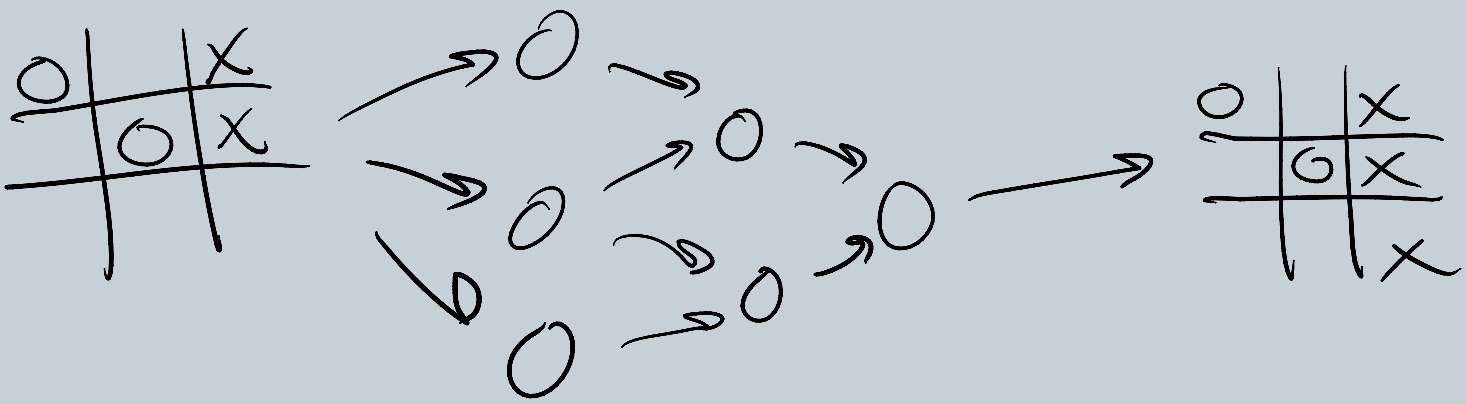


Paper Background

- Reinforcement learning in board games
  - Imran Ghory
  - 2004
- Surveys progress in last decade
- Suggests improvements
- Formalizes key game properties
- Develops a TD-learning game system

Why board games?

- Regarded as a sign of intelligence and learning
  - Chess
- Games as simplified models
  - Battleship
- Existing methods of comparison
  - Rating systems

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

History

- Basics developed by Arthur Samuel
  - Checkers
- Richard Sutton introduced TD-lambda
- Gerald Tesauro creates TD-Gammon
- Chess and Go
  - Worse then conventional AI

History

- Othello
  - Contradictory results
- Substantial growth since then
- TD-lambda has potential to learn game variants

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

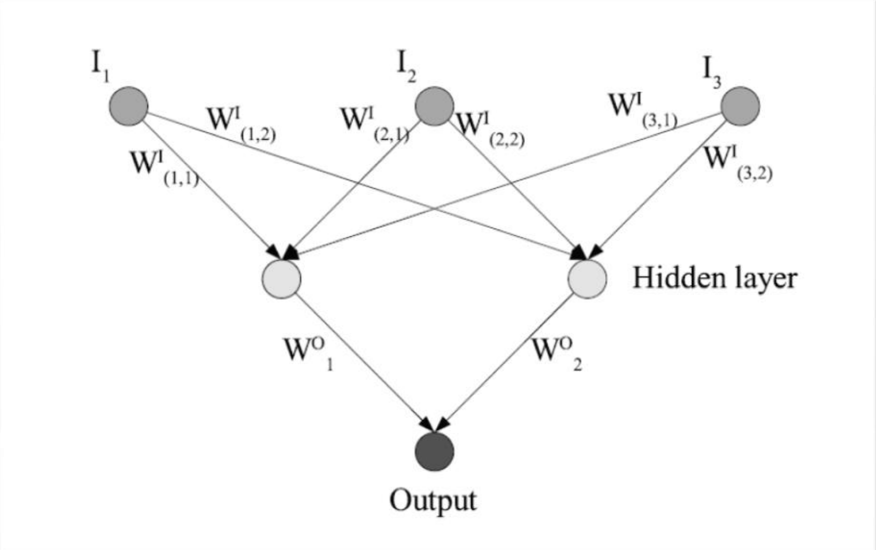
Temporal Difference Learning

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

N is the number of input nodes.

H is the number of hidden nodes.

f() is our non-linear function.



Temporal Difference Learning

$$\Delta W_t = \alpha \sum_{k=1}^{t} \lambda^{t-k} \nabla_w Y_k d_t$$

$\mathbf{t}$ 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).

α 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*.

Disadvantage

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

TD Algorithm Variants

- TD-Leaf
  - Evaluation function search
- TD-Directed
  - Minimax search
- TD-Mu
  - Fixed opponent
  - Use evaluation function on opponent’s moves

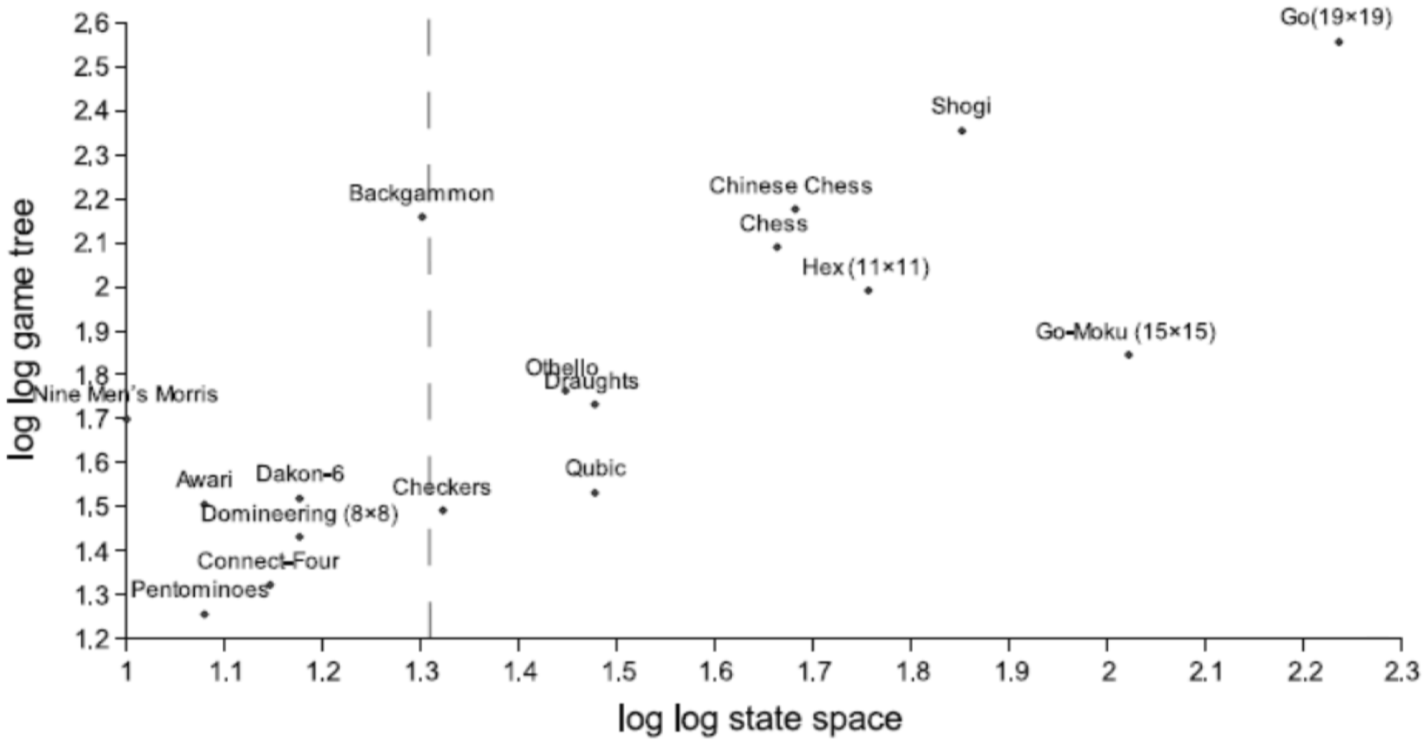
Current State

- Many improvements
  - Sparse and dubious validation
  - Hard to check
- Tuning weights
  - Nonlinear combinations
  - Differentiate between effective and ineffective
- Automated evolution method of feature generation
  - Turian

Important Game Properties

- Board Smoothness
  - Capabilities tied to smoothness
  - Based on the board representation
- Divergence rate
  - Measure how a single move changes the board
  - Backgammon and Chess – low to medium
  - Othello – high
- Forced exploration
- State space complexity
  - Longer training
  - Possibly the most important factor

Importance of State space complexity



Training Data

- Random play
  - Limited use
- Fixed opponent
  - Game environment and opponent are one
- Database play
  - Speed
- Self-play
  - No outside sources for data
  - Slow
  - Learns what works
- Hybrid methods

Improvement: General

- Reward size
  - Fixed value
  - Based on end board
- Board encoding
- When to learn?
  - Every move?
  - Random moves?
- Repetitive learning
- Board inversion
- Batch learning

Improvement: Neural Network

- Functions in Neural Network
  - Radial Basis Functions
- Training algorithm
  - RPROP
- Random weight initialization
  - Significance

Improvement: Self-play

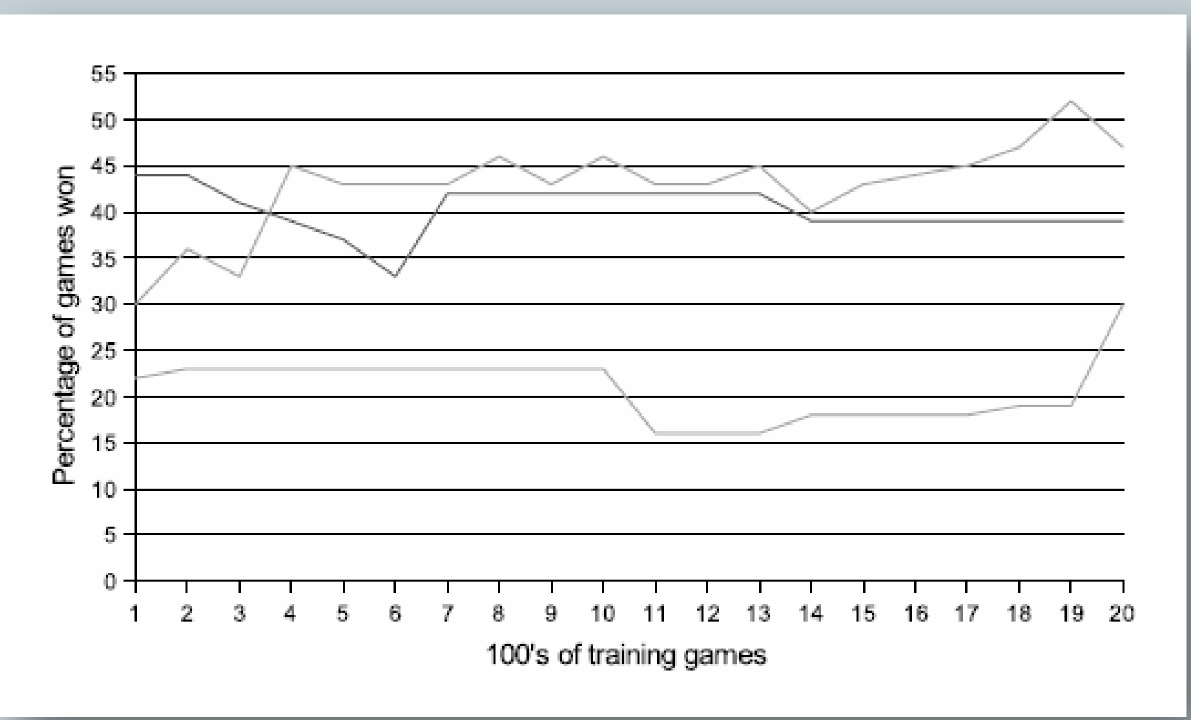
- Asymmetry
  - Game-tree + function approximator
- Player handling
  - Tesauro adds an extra unit
  - Negate score (zero-sum game)
  - Reverse colors
- Random moves
  - Algorithm
- Informed final board evaluation

Evaluation

- Tic-tac-toe and Connect 4
  - Amenable to TD-learning
  - Human board encoding is near optimal
- Networks across multiple games
  - A general game player
    - Plays perfectly near end game
    - Randomly otherwise
  - Random-decay handicap
    - % of moves are random
    - Common system

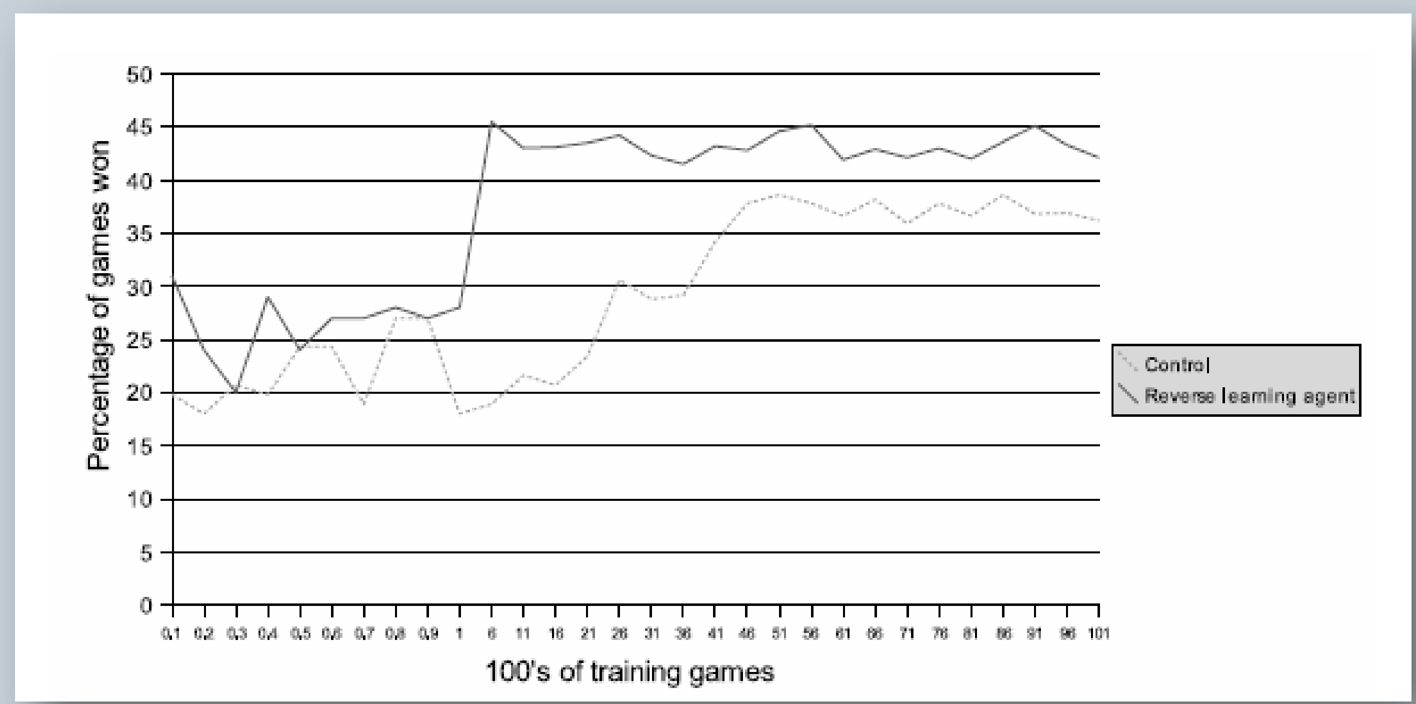
Random Initializations

- Significant impact on learning



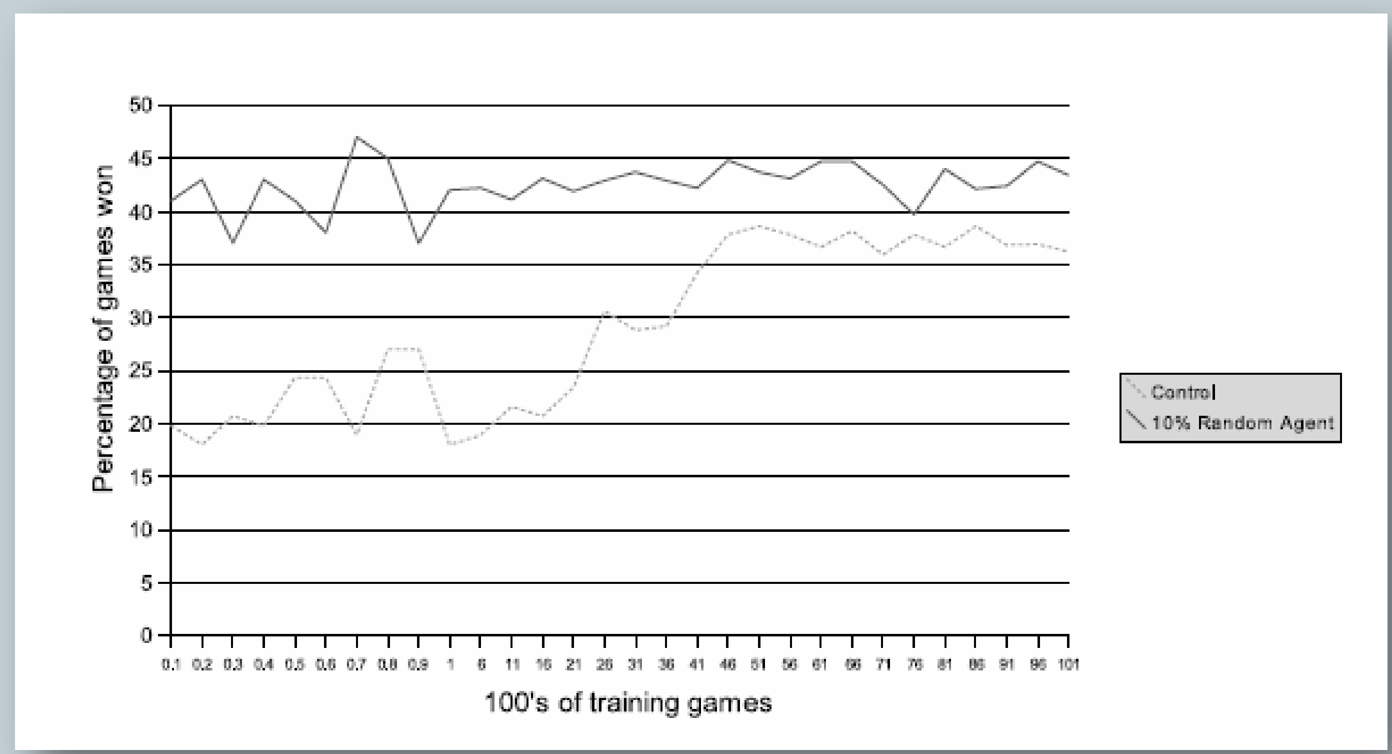
Inverted Board

- Speeds up initial training

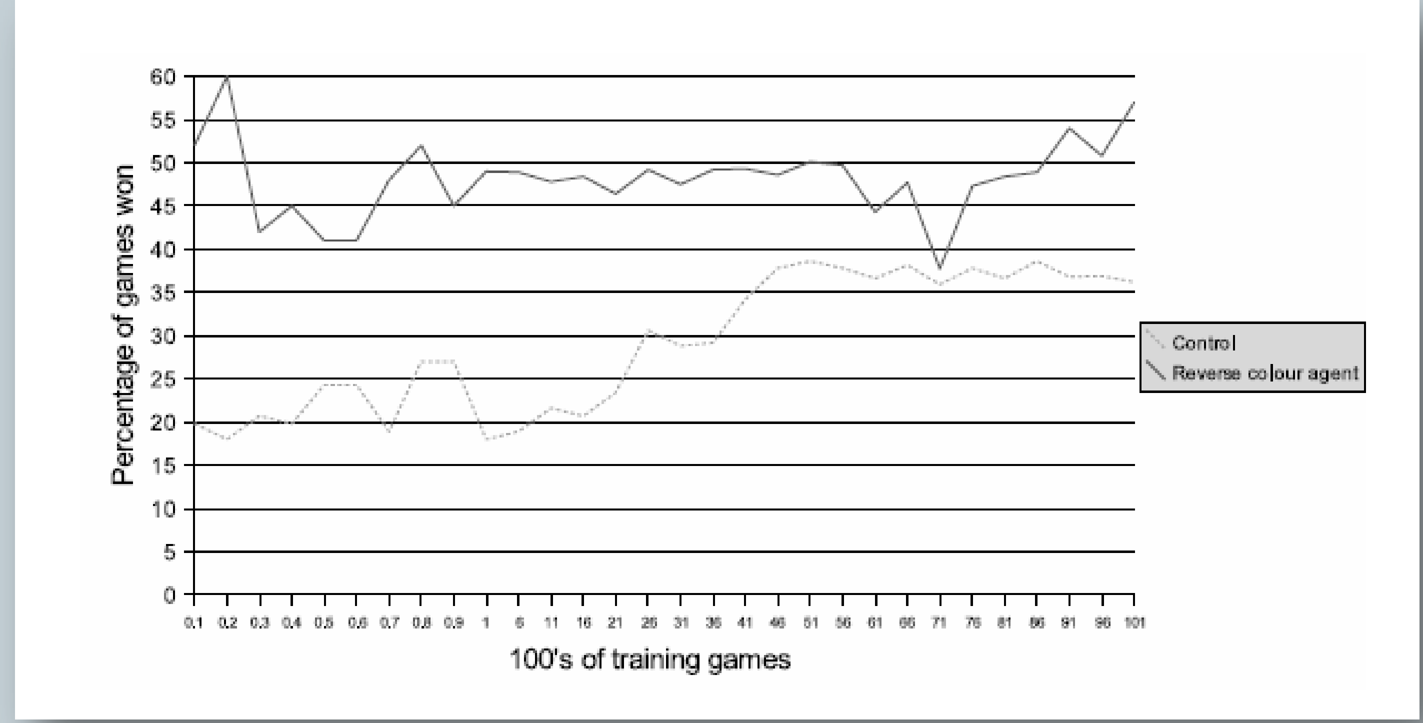


Random Move Selection

- More sophisticated techniques are required

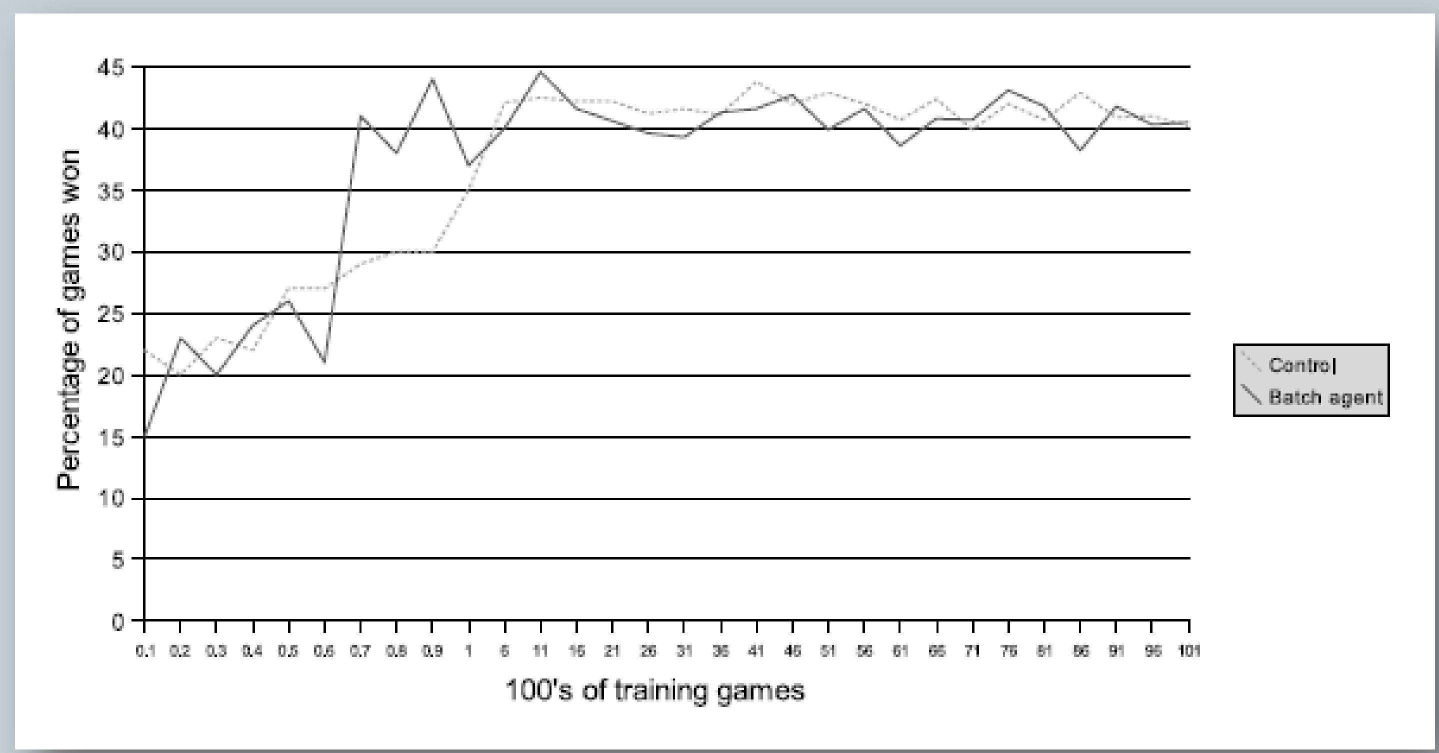


Reversed Color Evaluation



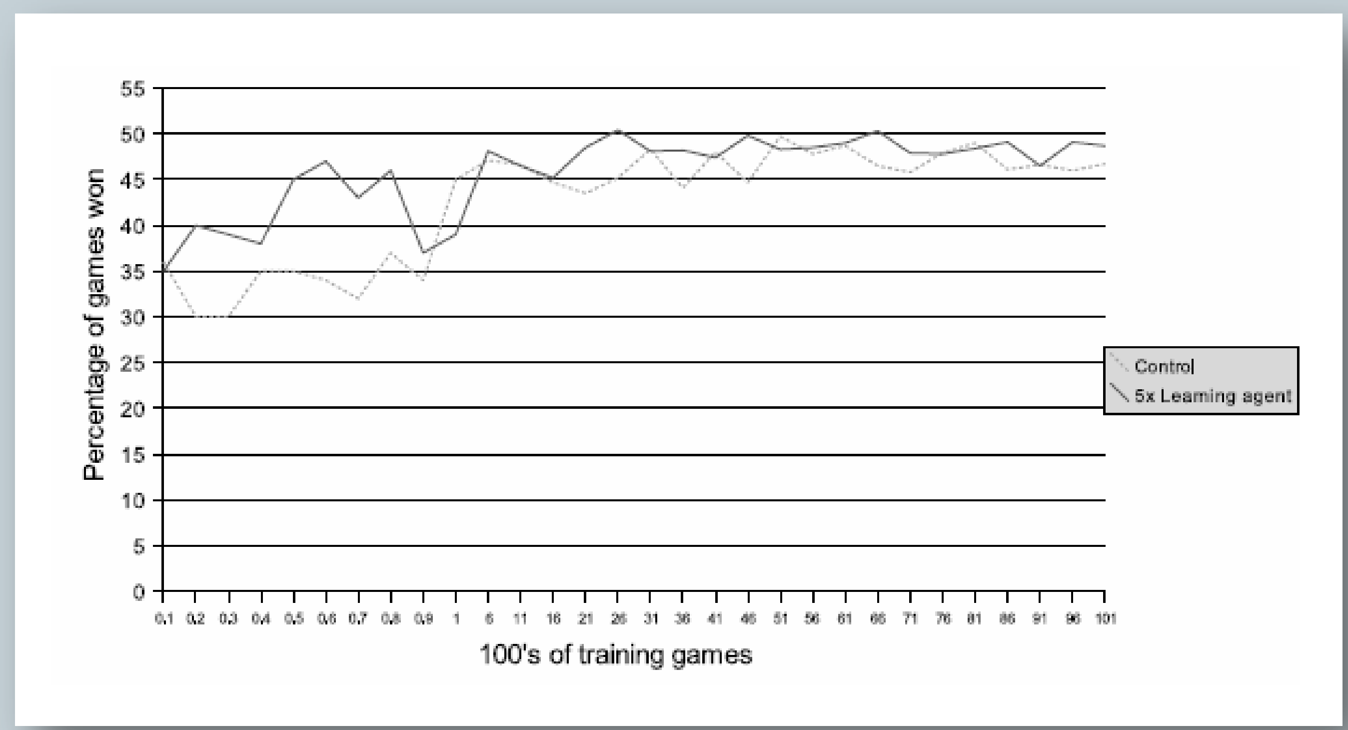
Batch Learning

- Similar to control



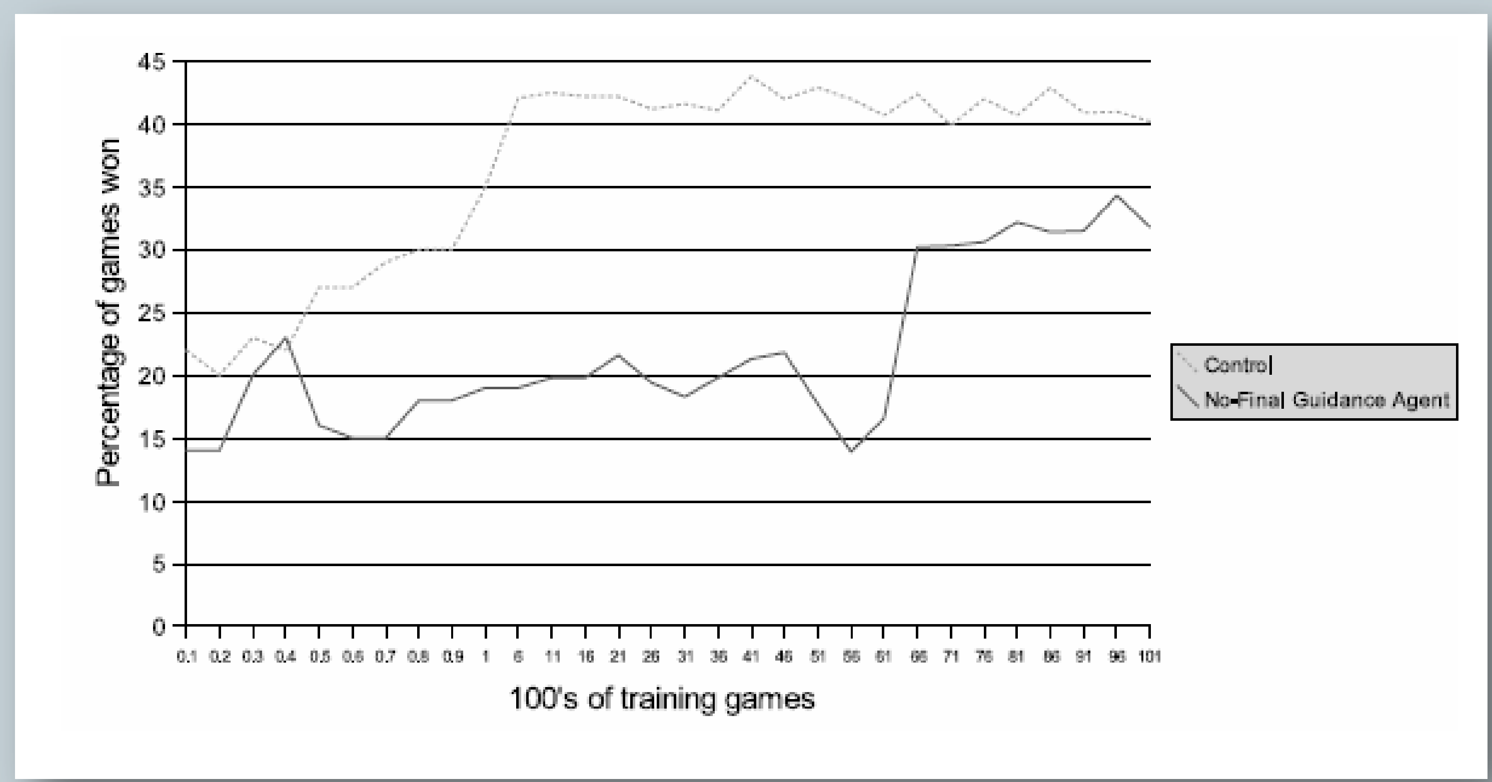
Repetitive learning

- No advantage



Informed Final Board Evaluation

- Extremely significant



Conclusion

- Inverted boards and reverse color evaluation
- Initialization is important
- Biased randomization techniques
- Batch learning has promise
- Informed final board evaluation is important