

Adaptive Neural Network Usage in Computer Go

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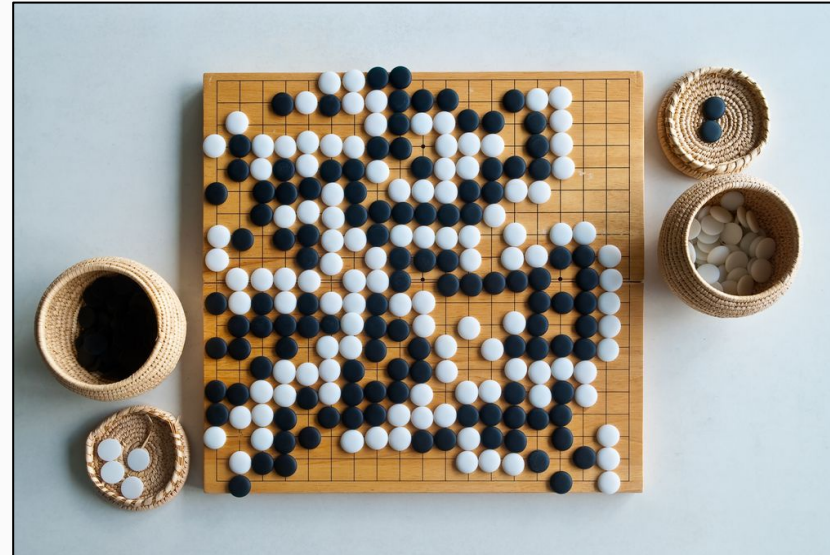


Outline

- The Game of Go
- Computer Go Techniques
- Our Project
- Conclusions
- Future Work

What is Go?

- Two-player alternating stone placing game
- 19x19 board
- **Group**: Connected pieces
- **Liberty**: Empty adjacent position to group
- **Captured**: When a group has no liberties
- **Territory**: Empty locations “controlled” by a player
- No stone sacrifice
- Winner determined by territory and stone captures



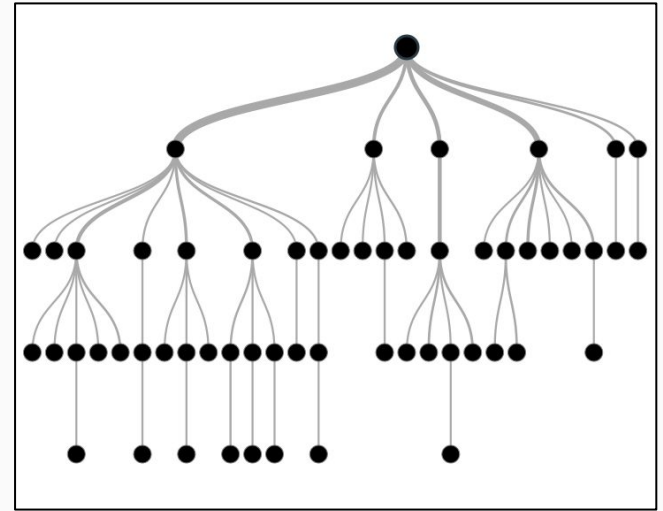
What Makes Go Interesting?

- Incredibly complex
- $\sim 10^{81}$ atoms in the known universe
- Orders of magnitude harder than chess
- Complexity closely resembles real world
- Can lead to advances in artificial intelligence

	Chess	Go
Possible board states	10^{47}	10^{170}
Possible legal move sequences	10^{123}	10^{360}

Why Study Go AI?

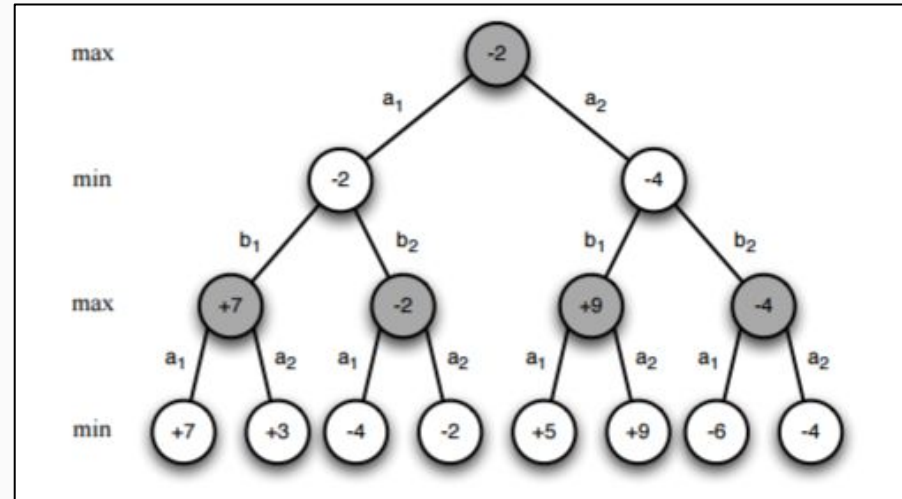
- Functionally infinite states and sequences
- Actions have long term influences
- States are not always as they appear
- In short, **very** hard
- Similar to sequential decision based problems



Previous Techniques

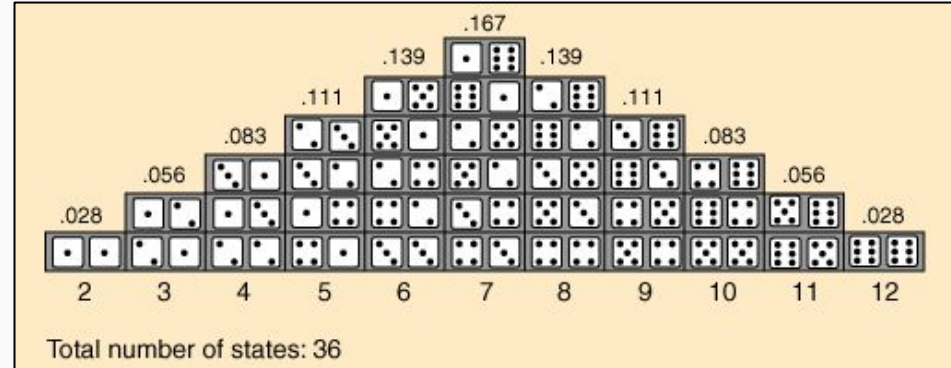
Minimax

- Tree of possible move sequences
- Assumes perfect play
- One player maximizes tree
- One player minimizes tree
- Best move chosen for root player
- Requires the entire tree mapped
- OR
- A heuristic function



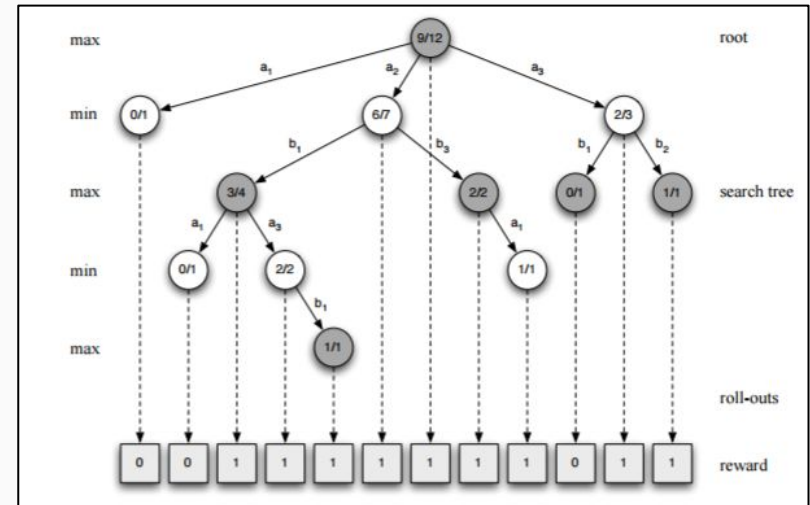
Monte Carlo Simulation

- Policy based
- Value estimation
- Simulate games based on policy
- Sensitive to policy choice
- Randomization of policy



Monte Carlo Tree Search

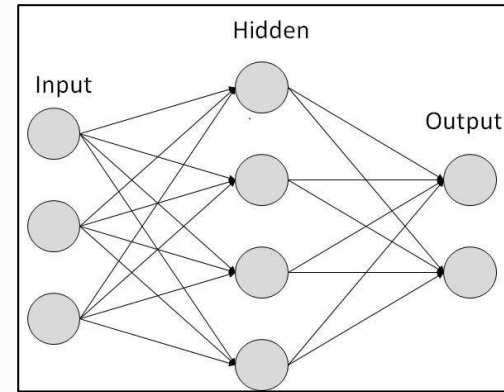
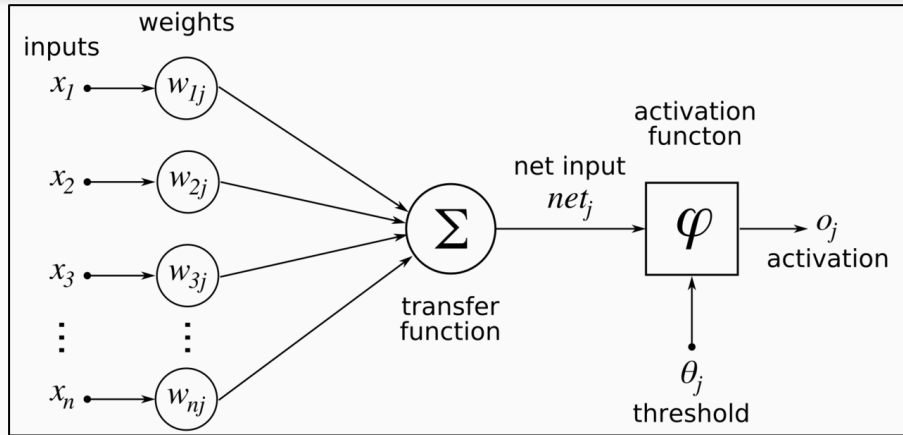
- A combination of game tree search and Monte Carlo simulation
- Limited minimax with heuristic
- Gradually adapt Monte Carlo policy
- Rely on fixed policy for “leaf” nodes
- Works well with Go



Upper Confidence on Trees

- Action selection is treated as separate problem for every node
- Select action a that maximizes following equation
 - (estimated value of action a) + (modified bias sequence)
- Bias sequence is higher for less explored states/actions
- More likely to choose unexplored nodes
- Handles exploration-exploitation dilemma

Convolutional Neural Networks



- Functions similarly to normal neural network
- Processes overlapping tiles from input
- Great at visual identification

AlphaGo

- Developed by Google
- Two neural networks and MCTS
- Massive computing resources
- Plays moves that humans would not
- Beat best human player, Lee Sedol, in 2016



Last Year's MQP

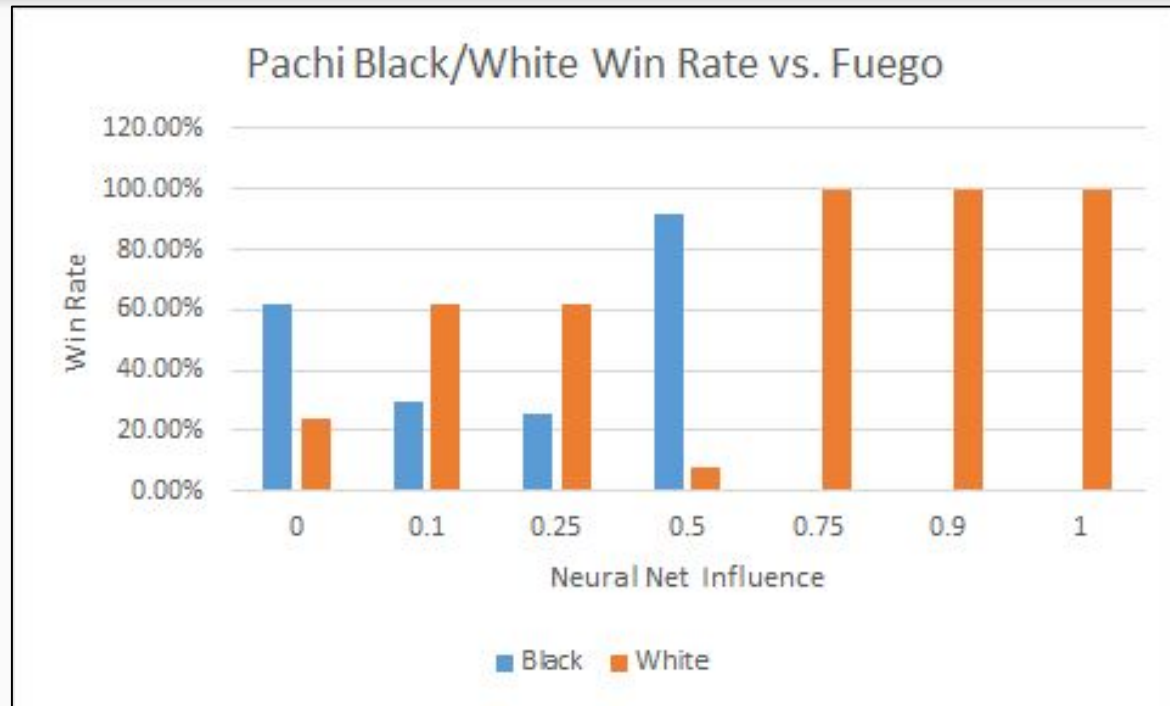
- 4 approaches to help move selection
 - Introduce a neural network to Pachi
 - Change the neural network used based on tree depth
 - Train a neural network to inform Pachi search
 - Teach a neural network to use Pachi's search
- Using a single neural network gave the best result
- Anomalous results

Our Project

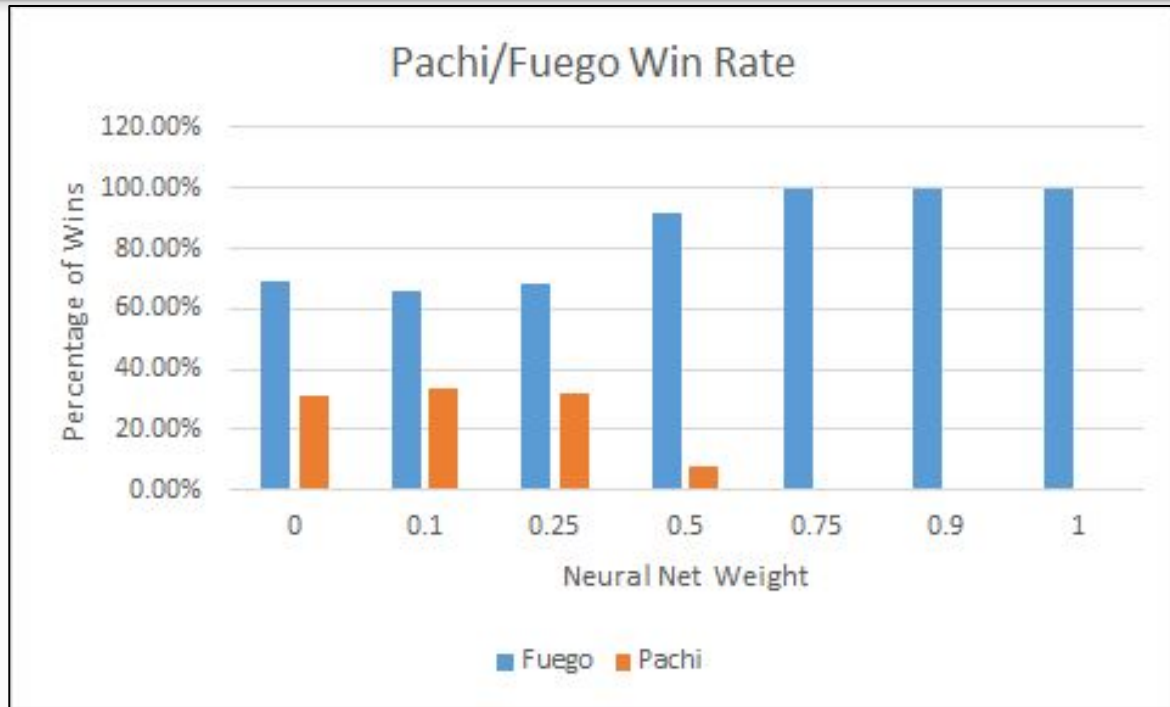
Overview

- Investigated anomalous data
- Reinterpreted last year's results
- Adaptive neural network weighting
- Compared optimized neural network Pachi to default Pachi

Anomalous Data



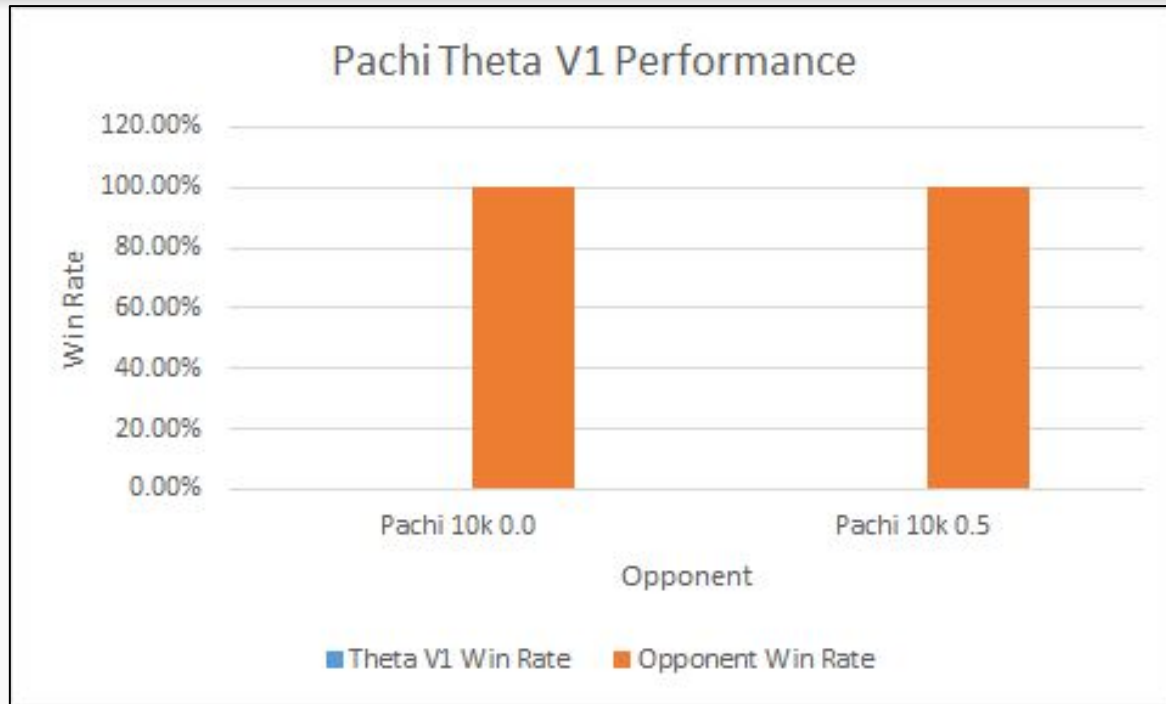
Reinterpreted Results



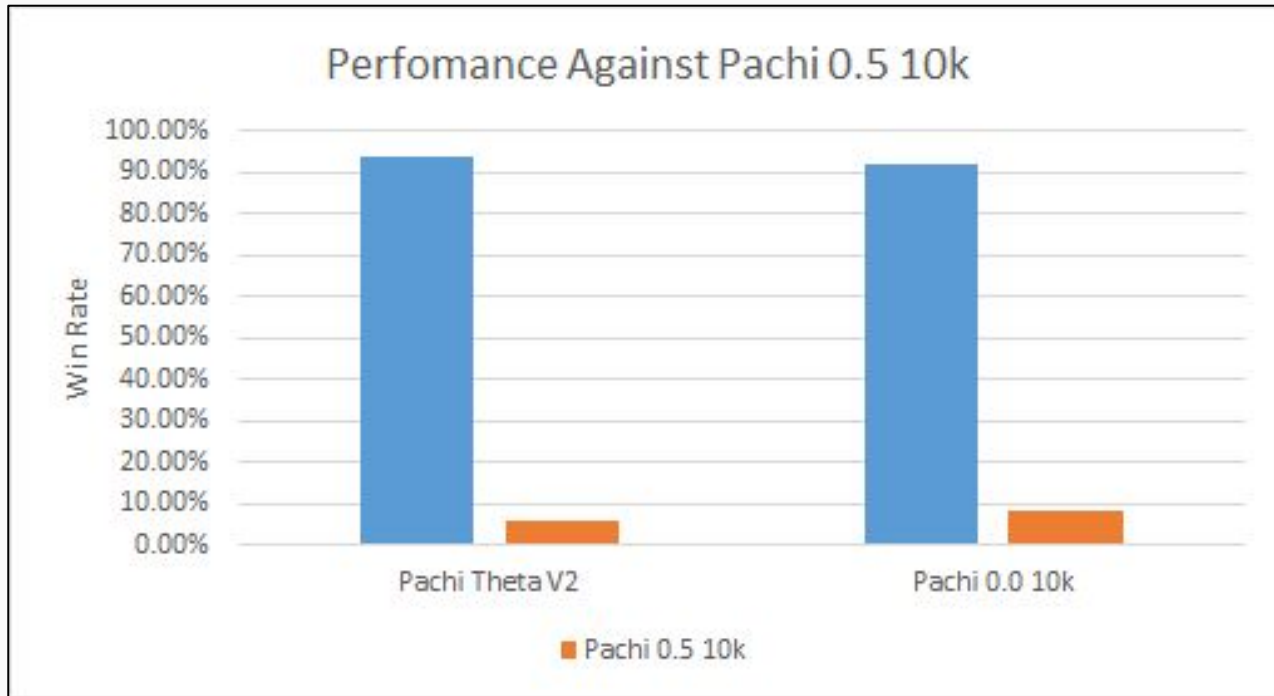
Adaptive Neural Network Weighting

- Determine the optimal weighting
- Go is complex, static weighting won't work
- Based on
 - Board state
 - Game turn
- Trained using Fuego
- Trained two different functions

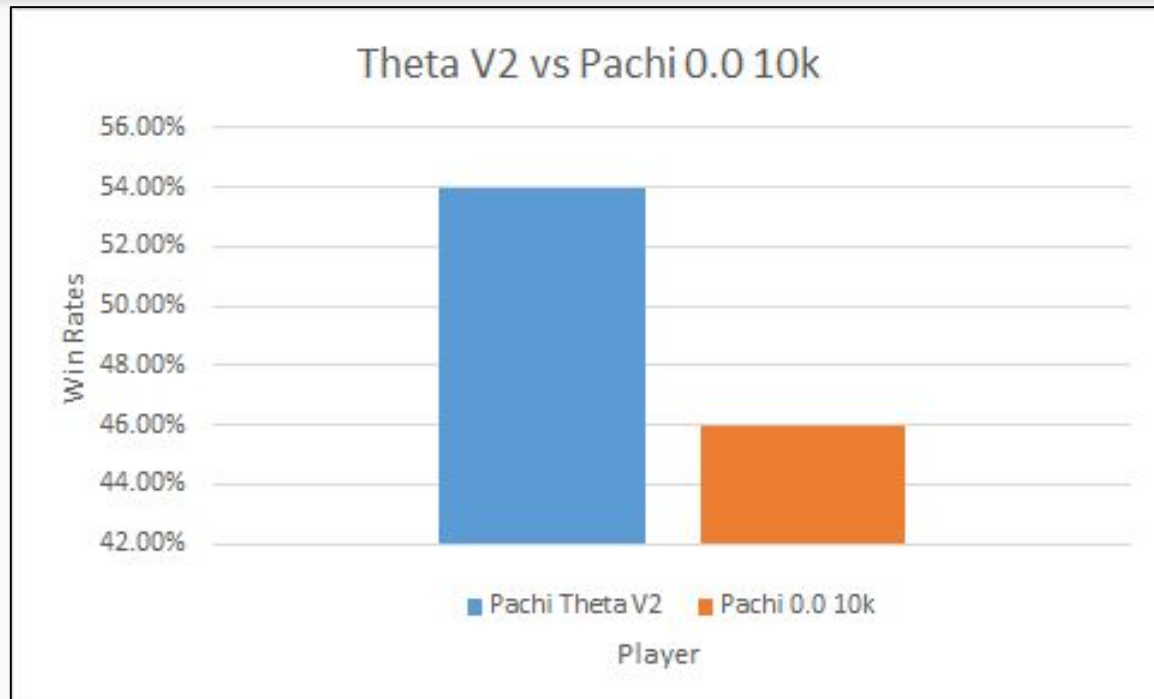
First Round Performance



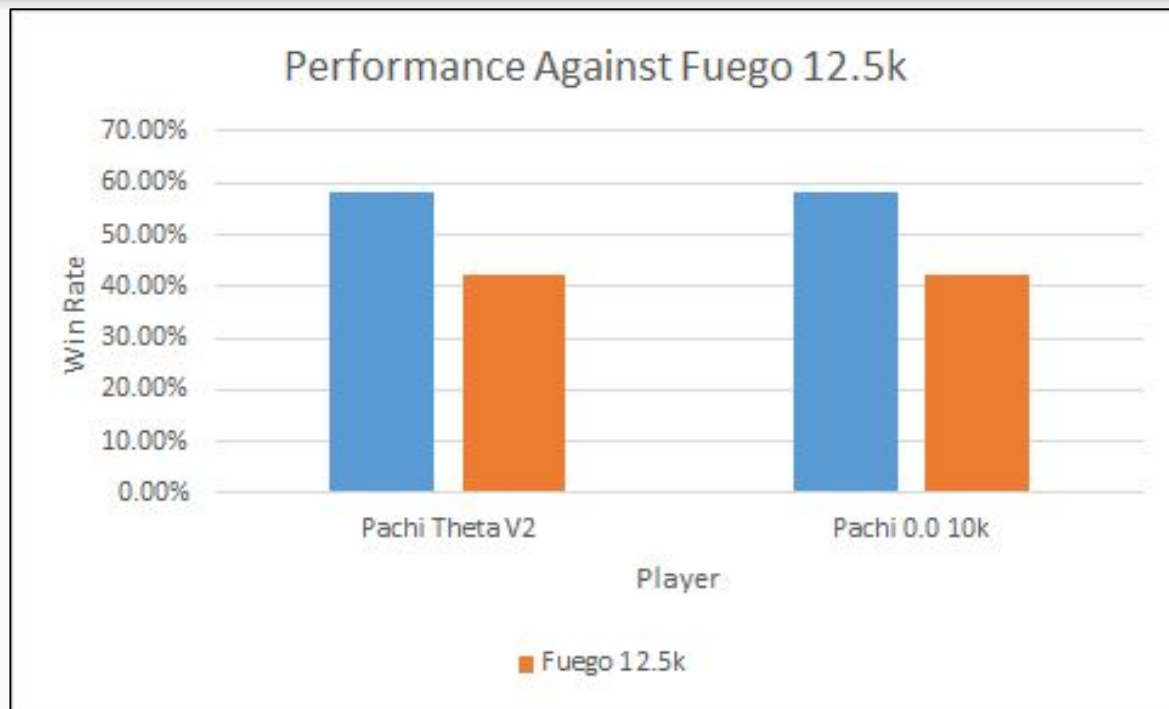
Second Round Performance



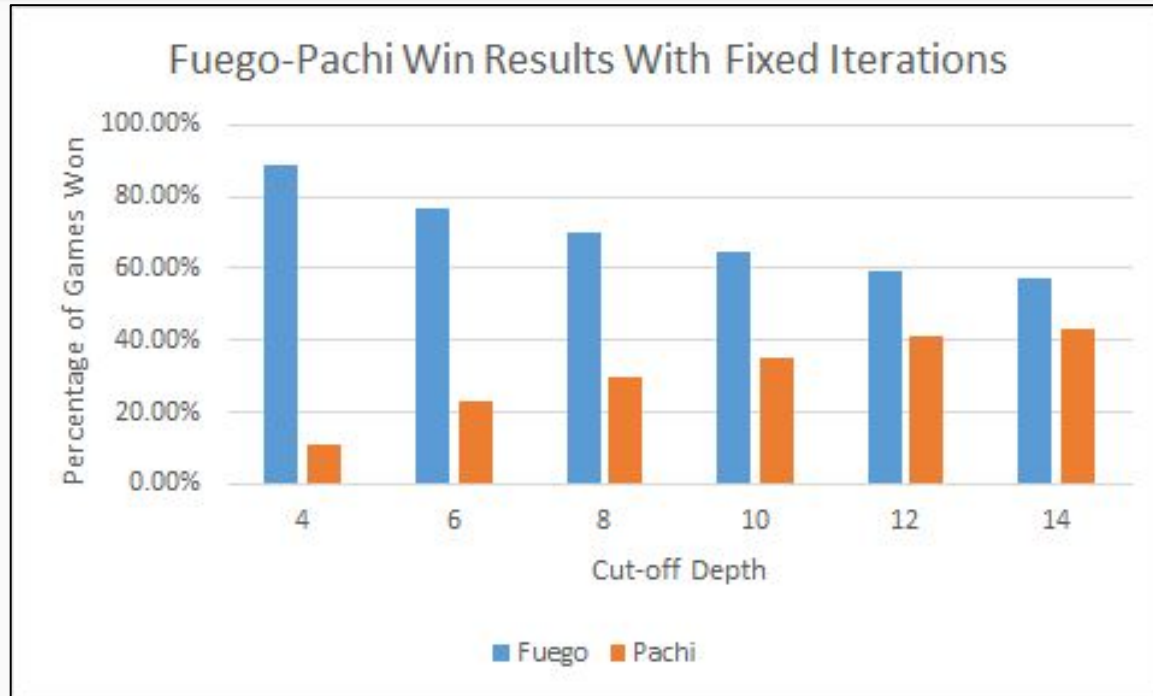
V2 vs. Default Pachi



V2 vs. Fuego

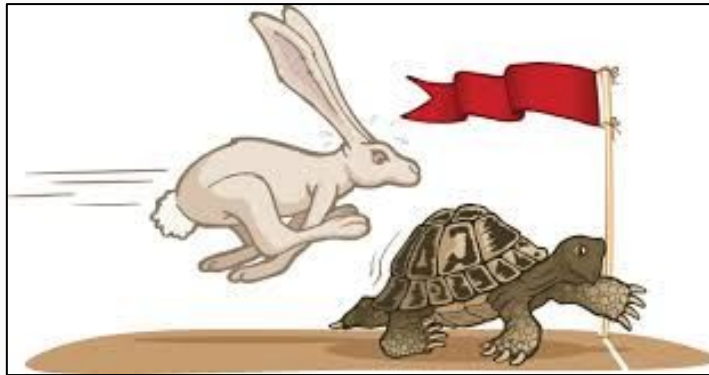


Depth Based Neural Network



Conclusions

- Adaptive weighting is powerful
- The faster neural network is not very good
- The slower neural network is strong



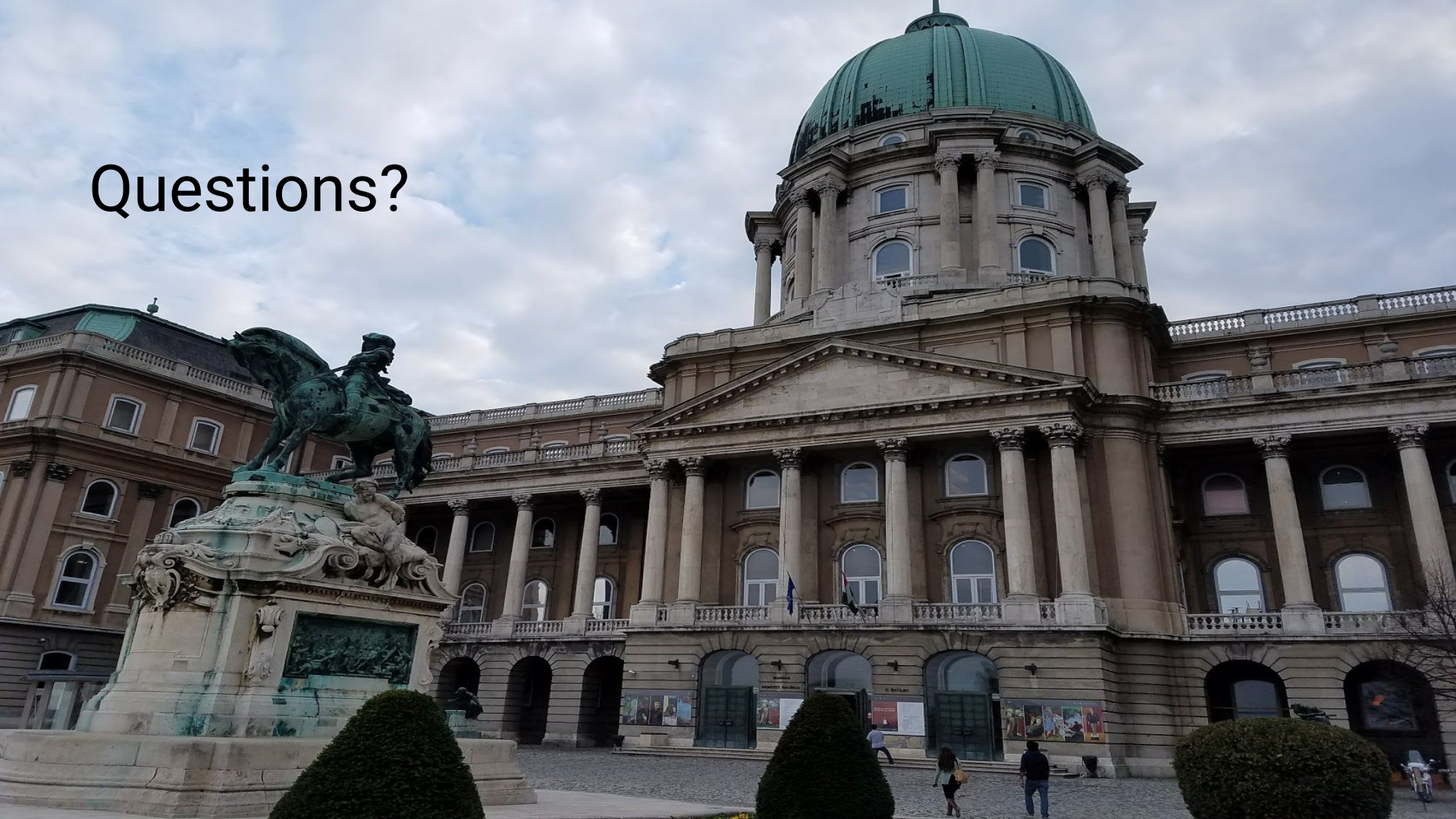
Future Work

- Use the slower, more accurate neural network
- Train function longer
- Experiment with more parameters
- Revisit the two other approaches from last year

Acknowledgements

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Questions?



Köszönöm!

