A Study on Parallel Machine Learning, Supervised Learning, and Reinforcement Learning

Christopher Arausa, Joe Anderson

Abstract

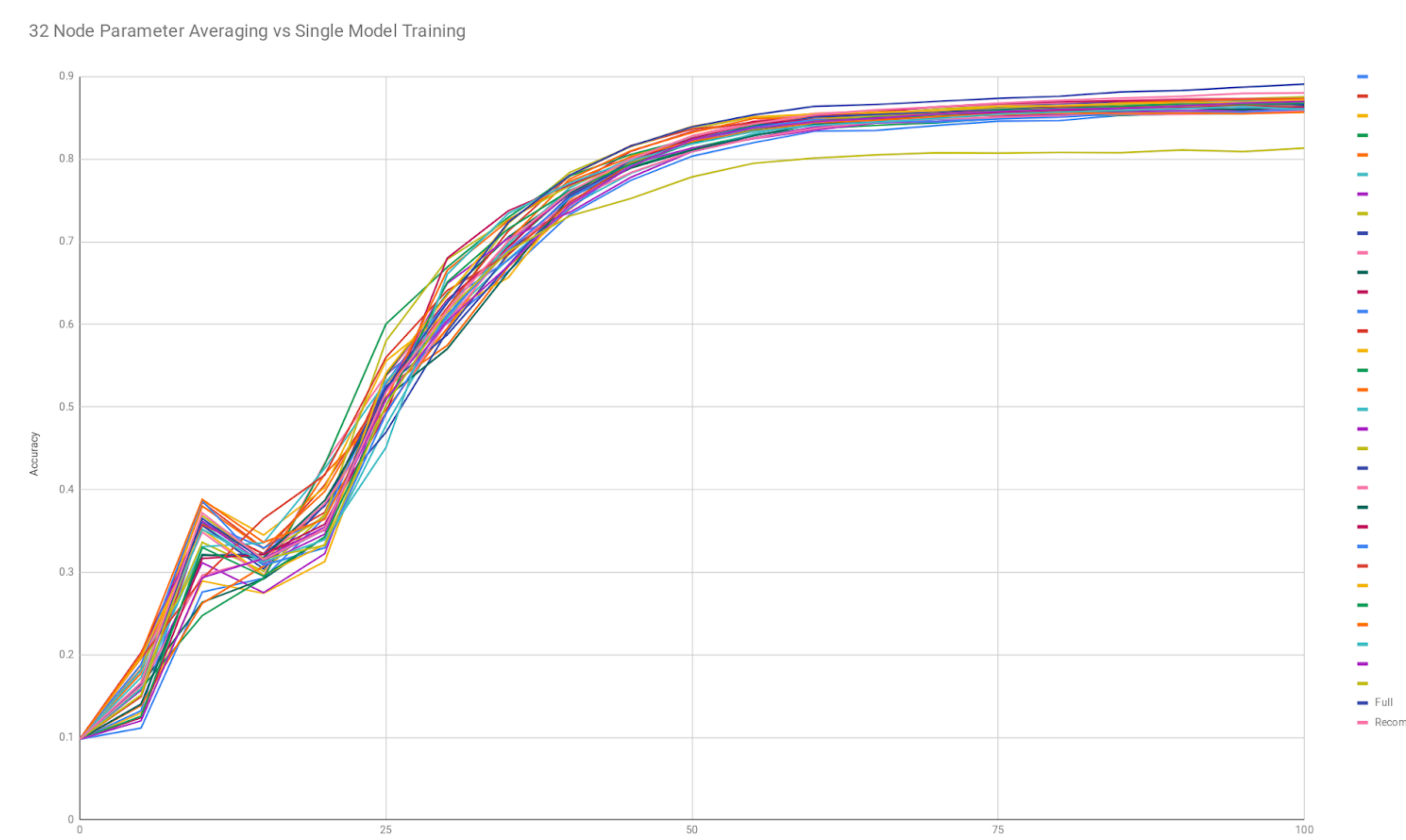
The goal of neural networks is typically to model some complex or unknown function. This is done by continuously reducing the error across a dataset, or sometimes by rewarding good behavior. However this is typically a very timely process when you begin to model very large datasets or complex functions. A common solution is to parallelize the training of the data across a cluster of networks. The big issue with most parallel learning techniques is the large communication bottleneck since most algorithms communicate after every batch. In this project I applied a naive parameter averaging approach at the end of training to see whether we can avoid communicating completely until the end.

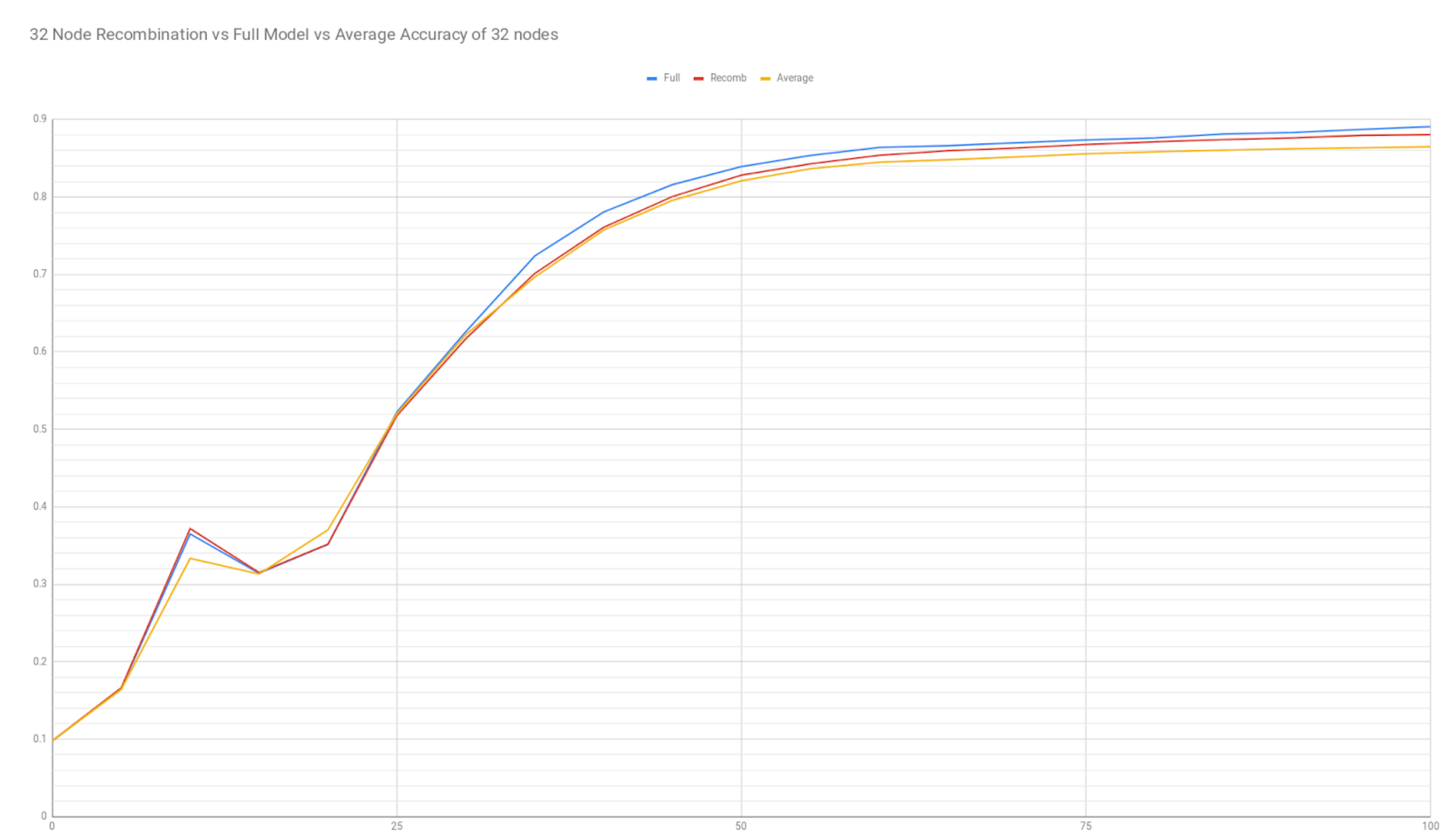
Method

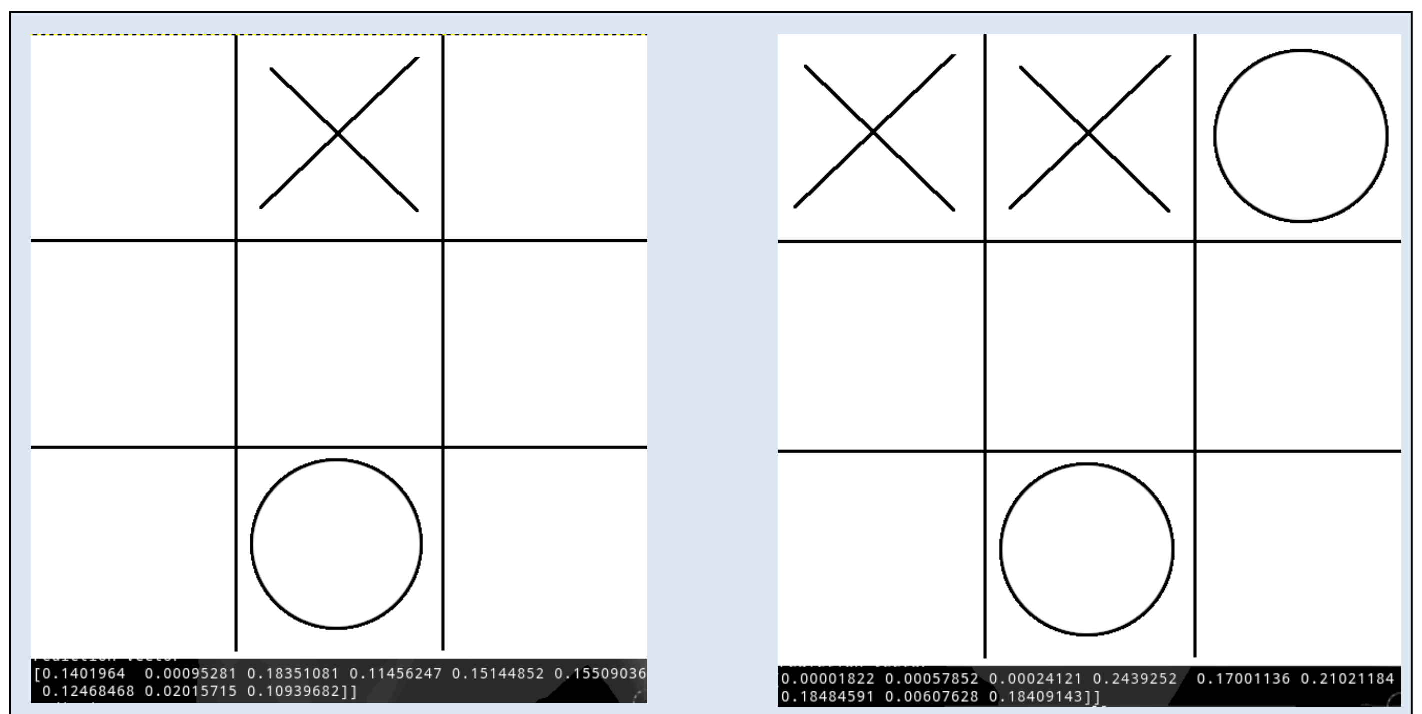
The neural networks were coded using tensorflow's graph. One single-model trained on all of the training data was maintained, and the rest of the sub-models had their training data partitioned. The partitioning of training data was done randomly in hopes to avoid any sort of over-specialization or falling too deep into a local minima. Validation data remained the same across all models.

Results

When networks of node count 4,10, and 32 were initialized on the same weights and biases and trained on randomly partitioned training data, the accuracy of the recombination model stayed within 2-3% of the single-model trained on all of the data.







Notice the prediction vectors are near 0 for invalid moves.

Abstract

The goal of this project was to train a neural network to play a game without explicitly coding the rules. Then to subsequently train the same model to improve using reinforcement learning to determine if there is a noticable difference in training time required between pure reinforcement learning and the combination of reinforcement learning and supervised learning.

Method

The neural network was coded using tensorflow's graph. The network was set up as a classification problem with a 1x18 input space for the locations of X&Os on the board and a 1x9 output space for the move it wants to make given the position. The move selected was the max value move in the output vector. The training data was collected from the full database of possible tic tac toe games.

Results

By training a neural network on the database of all possible tic tac toe games, there was a 45% win-rate achieved versus a randomized engine. However the move-vectors that are generated are always valid moves. So the network understands the rules, but isn't very good at using them.

Future Works

Apply reinforcement learning to a model already trained with supervised learning to see whether it's faster or worthwhile to teach a neural network the rules of the game first. Train a network off of solely the best moves, instead of the entire database.