BOSTON UNIVERSITY COLLEGE OF ARTS AND SCIENCES

Thesis

SIMULTANEOUS MULTI-PARTY LEARNING: HYPERGRAPH STOCHASTIC GRADIENT DESCENT

by

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To be a warrior is not a simple matter of wishing to be one. It is rather an endless struggle that will go on to the very last moment of our lives. No one is born a warrior, in exactly the same way that no one is born an average person. We make ourselves into one or the other.

Natsume Sōseki

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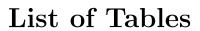
ABSTRACT

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List of Abbreviations

SSGD

ANN	 Artificial Neural Network
ASGD	 Asynchronous Stochastic Gradient Descent
BP	 Backpropagation
C-PSGD	 Centralized Parallel Stochastic Gradient Descent
D-PSGD	 Decentralized Parallel Stochastic Gradient Descent
DCG	 Dynamic Computation Graph
DNN	 Deep Neural Network
GD	 Gradient Descent
$_{\mathrm{HgSGD}}$	 Hypergraph Stochastic Gradient Descent
L-BFGS	 Limited-memory Broyden-Fletcher-Goldfarb-Shanno
ML	 Machine Learning
MPC	 Multi-Party Computation
NEAT	 Neuroevolution of Augmenting Topologies
NN	 Neural Network
P2P	 Peer-to-peer
SGD	 Stochastic Gradient Descent
SMPL	 Simultaneous Multi-Party Learning

Synchronous Stochastic Gradient Descent

Introduction

- 1.1 Evolutionary Algorithms
- 1.2 Democratizing Machine Intelligence

; Blurb on importance of democracy ξ

Background

- 2.1 Deep Learning
- 2.1.1 Supervised Learning
- 2.1.2 Unsupervised Learning

Generative Adversarial Networks

We digress to give a concise background on the seminal work by (Goodfellow et al., 2014) on Generative Adversarial Networks.

2.1.3 Semi-Supervised Learning

Semi-Supervised Learning with GANs

(Salimans et al., 2016)

- 2.2 Gradient-based Learning
- 2.2.1 Model Parallelism
- 2.2.2 Data Parallelism
- 2.2.3 Problems with Distributed Training

Stale Gradients

Parameter Synchronization

2.2.4 Distributed Training Optimizations

(Dean et al., 2012)

Quantization

Sparsification

(Lin et al., 2017)

2.3 Related Work

2.3.1 Centralized Parameter Server

Synchronous Data Parallelism

Asynchronous Data Parallelism

2.3.2 Decentralized Parameter Servers

P2P Distributed Training

3.1 Hypergraph Stochastic Gradient Descent

Decentralized Paradigm

Cliques and Hypergraphs

Experiments

- 4.1 Baseline
- 4.1.1 Wallclock Performance
- 4.1.2 Gradient Analysis
- 4.1.3 Convergence Analysis
- 4.2 Hypergraph Stochastic Gradient Descent
- 4.2.1 Wallclock Performance

Random Validation Accuracy

Best Validation Accuracy

Worst Validation Accuracy

Weighted Validation Accuracy

Weighted by Number of Peers

Weighted by Number of Cliques

4.2.2 Gradient Analysis

Random Validation Accuracy

Best Validation Accuracy

Worst Validation Accuracy

Weighted Validation Accuracy

Weighted by Number of Peers

Weighted by Number of Cliques

4.2.3 Convergence Analysis

Random Validation Accuracy

Best Validation Accuracy

Worst Validation Accuracy

Weighted Validation Accuracy

Weighted by Number of Peers

Weighted by Number of Cliques

Conclusions

5.1 Summary

Time to get philosophical and wordy.

IMPORTANT: In the references at the end of thesis, all journal names must be spelled out in full, except for standard abbreviations like IEEE, ACM, SPIE,https://preview.overleaf INFOCOM, ...

5.2 Future Work

5.2.1 Information Diffusion

Contagion Theory

Percolation Theory

5.2.2 Alternative Optimizations

Second-Order Methods

(Ba et al., 2016)

Deep Neuroevolution

Parameter synchronization Initializing with the same seed and passing seeds used for pseudonumber generators to derive parameter updates instead of passing entire set of parameter matrices as with distributed gradient optimization. (Such et al., 2017)

- 5.2.3 Anonymous P2P Communication
- 5.2.4 Optimizations

Max-Flow Algorithms

Routing for Optimal Clique Formation

Appendix A

Proof of Intractability of Model Inversion Against Generative Adversarial Nets

This is the appendix.

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CURRICULUM VITAE

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Basically, this needs to be worked out by each individual, however the same format, margins, typeface, and type size must be used as in the rest of the dissertation.