Deep Learning on SpiNNaker

Master Thesis

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Declaration

I declare that this dissertation was composed by myself, that the work contained herein is my own except where explicitly stated otherwise in the text, and that this work has not been submitted for any other degree or professional qualification except as specified.

Jonas Fassbender
August 2020

Abstract

Contents

1. Introduction

Deep learning is revolutionizing the world. It has become part of our daily lives as consumers, powering major software products—from recommendation systems over translation tools to web search (LeCun et al., 2015). Major breakthroughs in fields like computer vision or natural language processing were achieved through the use of deep learning (Krizhevsky et al., 2012; Hinton et al., 2012). It has emerged as a driving force behind discoveries in numerous domains like particle physics, drug discovery, genomics or gaming (Ciodaro et al., 2012; Ma et al., 2015; Leung et al., 2014; Silver et al., 2016).

Deep learning has become so ubiquitous that we are changing the way we build modern hardware to account for its computational demands. From the way edge devices like mobile phones or embedded systems are build over modern CPUs to specialized hardware designed only for deep learning models (Deng, 2019; Boitano, 2020; Perez, 2017; Jouppi et al., 2017). Whole state-of-the-art supercomputers are build solely for deep learning (Langston, 2020). Hardware manifacturers are faced with a major challenge in meeting the computational demands arising from inference and more importantly training deep learning models. OpenAI researchers have estimated that the computational costs of training increases exponentially; approximately every 3.4 months the cost doubles (Amodei et al., 2019). With the end of Moore's Law chip makers have to get creative in scaling up computing the same way machine learning researchers are scaling up their models (Simonite, 2016). Production and research into new hardware designs for deep learning are well on the way.

Another field which has high computational demands for very specific tasks and algorithms is neuroscience. Neuroscience has long been linked to deep learning, which has its origin in reasearch done by neuroscientists (McCulloch and Pitts, 1943). While in the recent past deep learning research has been more focused on mathematical topics like statistcs and probability theory, optimization or linear algebra, researchers are again looking over to neuroscience in order to further improve the capabilities of deep learning models (Marblestone et al., 2016). But not only the algorithms used by neuroscientists are drawing interest from the deep learning community. Computational neuroscience has long been trying to develop hardware for the efficient modeling of the human brain. Neuromorphic computer architectures are being developed to meet the demands for efficient computing for the specific task of running large-scale spiking neural networks used for modeling brain functions.

2. Background

2.1 An Introduction to Deep Learning

2.2 Computer Vision: ImageNet and the ILSVRC

2.3 Benchmarking Deep Learning Systems: The MLPerf Benchmark

2.4 SpiNNaker as a Neuromorphic Computer Architecture

2.5 Related Work

3. Deep Learning on SpiNNaker

4. Benchmark

5. Discussion

6. Conclusion

7. Next Steps

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