



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.

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Abstract

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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 and 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 and 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 built and 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 built solely for deep learning (Langston, 2020). Hardware manufacturer 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 (Loeffler, 2018), 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 statistics and probability theory, optimization or linear algebra, researchers are again looking to neuroscience to further improve the capabilities of deep learning models (Marblestone et al., 2016).

But the algorithms developed by computational neuroscientists are not the only aspect drawing attention from the deep learning community. Computational neuroscience has long been trying to develop hardware for the efficient modeling of the human brain and neuromorphic computing—a computer architecture inspired by the biological nervous system—has been around since the 1980s (Mead, 1989). Today, neuromorphic computers are being developed to meet the demands for efficient computing needed to run large-scale spiking neural networks used for modeling brain functions (Furber, 2016). While being developed mainly for the task of modeling the human brain, deep learning has been linked to neuromorphic computing, especially in the context of commercial usability (Gomes, 2017). Both the low energy demands of neuromorphic computers—such as IBM’s True North (Cassidy et al., 2013) or The University of Manchester’s Spiking Neural Network Architecture (SpiNNaker) (Furber et al., 2006)—and their scalability and massive-parallelism are intriguing for two very important use cases of deep learning: (i) edge computing, for example robotics and mobile devices, (ii) supercomputers and the cloud-era (Gomes, 2017).

This thesis investigates the performance of SpiNNaker machines for deep learning by training the state-of-the-art computer vision model ResNet-50 under the closed division rules of the MLPerf benchmark (He et al., 2015; Mattson et al., 2019). In order to benchmark ResNet-50 on SpiNNaker a prototypical implementation was developed as part of this thesis.

- here a paragraph about the results

Section 2 presents the background of this thesis. An introduction to deep learning is given, as well as an overview of the benchmark presented in Section 4. The SpiNNaker architecture is also described and compared to current deep learning hardware. Related work can be found in Section 2.5. Section 3 presents the architecture of the prototype developed for benchmarking. In Section 5 the results of the benchmark are discussed, as well as the development process. Section 6 contains the conclusion, while Section 7 outlines the next steps for further increasing the performance of SpiNNaker by enhancing the prototype.

2. Background

2.1 An Introduction to Deep Learning

1. history of DL
2. clarify that DNNs are statistical methods (glorified non-linear classifiers) not biological like SNNs
3. concepts of the MLP:
 - layers
 - activations
 - forward- and backward-pass
 - SGD
 - ...
4. CNNs

2.2 Computer Vision: ImageNet and the ILSVRC

1. short section about imagenet and ilsvrc and their importance for computer vision
2. ResNet50 and residual stuff

2.3 Benchmarking Deep Learning Systems: The MLPerf Benchmark

1. short section about MLPerf (so short that I maybe add it to previous section. Could maybe be only a single paragraph.

2.4 SpiNNaker as a Neuromorphic Computer Architecture

1. describe spinnaker and the spinnaker architecture
2. compare to other DL accelerators (GPGPUs and TPUs)

2.5 Related Work

1. SNNToolbox for translating DNNs to SNNs (only inference)
2. TrueNorth has a paper about its DL implementation

3. Deep Learning on SpiNNaker

- concepts (layers, neurons, meta-neurons, ...)
- communication structure (partitions and global partition manager)
- ping-pong
- graph structure (especially focused on edge and host-SpiNN communication)
- interpreting neurons as domain decomposition over linear algebra compute graph
- backward pass: gradients computed two times so comm fabric is not overly used by unique partitions

4. Benchmark

5. Discussion

- space used inefficiently (cores and memory) → better domain decomposition

6. Conclusion

7. Next Steps

- multiple copies of the same network on the same machine → use all resources available
- better domain decomposition (SpiNNaker application graph or custom solution (application graph not helpful for neurons which become too big))
- smart algorithms vs. integrating with state-of-the-art libraries (investing time in stuff like SLIDE and the one paper by the Austrian guys about sparse connections explicitly mentioning SpiNNaker and neuromorphic chips or rather work on a trans-/compiler that efficiently translates linear algebra operations (like TF, PyTorch,...) onto SpiNNaker)
- integrate into compiler projects like Apache-TVM, XLA, Glow, nGraph, etc.
- implementing ONNX spec to make it easy for developers to use SpiNNaker (develop in PyTorch → run on SpiNNaker)

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