



Deep Learning on SpiNNaker: Report

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Abstract

This paper reports on the preliminary research done for the dissertation project “Deep Learning on SpiNNaker” (formerly “A Tensorflow Backend to SpiNNaker”). SpiNNaker is a novel neuromorphic, massively parallel and energy efficient computer architecture designed for the task of modeling the human brain. The goal of “Deep Learning on SpiNNaker” is to find out, if SpiNNaker can be used to accelerate the training of deep neural networks (see e.g. Goodfellow et al., 2016). The preliminary research done for the dissertation phase in the summer of 2020 is described and all relevant findings are presented. Changes made to the initial project proposal are discussed. An outline in form of a work plan and relevant background information are presented as well. A literature review of Nita (2018) is given at the end of this report.

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1 Introduction

SpiNNaker is a digital neuromorphic computer architecture, designed to model the human brain. According to the SpiNNaker project's website:

SpiNNaker is a novel massively-parallel computer architecture, inspired by the fundamental structure and function of the human brain, which itself is composed of billions of simple computing elements, communicating using unreliable spikes (SpiNNaker Team, 2020).

This is rather a gross simplification of what SpiNNaker was designed for. Understanding the human brain is one of the biggest frontiers of science and there are many ideas on how one can model a complex and still mostly unknown structure such as the human brain. Therefore, there are many different proposed neuromorphic computer architectures and ideas on how to model the human brain, from early analogue approaches for vision systems like presented in Mead (1989) to large scale digital architectures like Blue Brain (Markram, 2006); all aiming to implement different types of neurons and models of the human brain efficiently (Furber and Temple, 2007).

SpiNNaker is an architecture for the large scale and real-time modeling of spiking neural networks (Furber et al., 2006a,b; Furber and Temple, 2007). Maass (1997) describes spiking neural networks as the third generation of neural networks. Unlike the second generation neural networks—which we will deal with in the dissertation project here reported on in the form of deep learning neural networks—spiking neural networks incorporate a concept of time in their action potentials (spikes). Neural networks of the second generation do not have a concept of time and fire every time they are activated. Spiking neural networks are derived from evidence collected from biological neural systems, which use the timing of spikes to encode information; they are therefore more closely representing neural systems of biological life than deep learning neural networks (Maass, 1997).

The SpiNNaker chip is a multiprocessor chip, which has 18 ARM cores, with a Network-on-Chip system for communication between cores (Furber and Temple, 2007; SpiNNaker Team, 2020). Each core can model up to 1000 spiking neurons. The spiking neurons in the neural network communicate with spike events (Furber and Temple, 2007). Spike events are—like their biological counterpart—inherently unstable and small. This is represented in the interconnection hardware. Small packets (40 or 72 bits) can be send, without guarantee of successful arrival. Even without this guarantee, one can still perform meaningful computations on SpiNNaker and fault detection and recovery mechanisms are implemented (SpiNNaker Team, 2020). 48 SpiNNaker chips are mounted on a SpiNNaker board. One can connect many SpiNNaker boards together, to build a massively parallel and energy efficient supercomputer that is able to run up to a billion spiking neurons in real time (Furber and Temple, 2007). Photos of the SpiNNaker hardware can be found in Appendix A.

SpiNNaker is targeted at three main areas of research: (i) neuroscience: understanding the human brain, (ii) robotics: low power hardware for implementing neural decision systems and (iii) computer science: new approach to supercomputing and massive parallelism (SpiNNaker Team, 2020). The dissertation project will concern itself with (iii) and one of the research areas of computer science, which has emerged as a driving force behind advancements in many fields and for many tasks like speech and image recognition, drug discovery and genomics: deep learning (LeCun et al., 2015).

While deep learning is a promising field and deep neural networks at the center of important advancements, like described above, they face a major problem: the sheer amount of computation needed for training them. Researchers at OpenAI have estimated, that the amount of computation needed for training state of the art

deep neural networks increases exponentially, doubling every 3.4 months (Amodei et al., 2019). In order to cope with such unprecedented amounts of computation and energy needed, the search for specialized hardware is well underway. Current state of the art hardware for accelerating the training of deep neural networks are ASICs like TPUs and general purpose GPUs (Jouppi et al., 2017; Mittal and Vaishay, 2019).

The goal of the dissertation project introduced in this paper will be to analyze if SpiNNaker could be an energy efficient, scalable and fast alternative to the above mentioned hardware. Since deep neural networks are derived from the human brain and nerve system (Goodfellow et al., 2016) and SpiNNaker was designed to model the human brain, it seems rather plausible, that SpiNNaker will be a good target for accelerating the training of deep neural networks.

The findings of the preliminary work and the changes made to the original project scope are the focal point of this report. The original title of the dissertation project was “A Tensorflow Backend to SpiNNaker”. Tensorflow is a library for running fast linear algebra operations on distributed, heterogeneous systems, mainly designed for implementing computationally demanding machine learning algorithms like deep learning in a fast manner (Abadi et al., 2015). Because of SpiNNaker’s specialized design, which works rather contrary to that of Tensorflow and current hardware trends for building accelerators for deep learning and fast linear algebra operations, interfacing between SpiNNaker’s runtime and Tensorflow was deemed too difficult and not beneficial. Instead, this dissertation aims at implementing deep learning directly on SpiNNaker. Mario Antonioletti and Alan Stokes (2019) shows the original dissertation project’s scope.

This paper starts with presenting the final project proposal, in particular focusing on the benchmark to be conducted in Section 2. Afterwards related work is presented in Section 3. The main focus lies on presenting papers with benchmarks we can compare our implementation against. The paper continues by giving a work plan in Section 4, before presenting a risk analysis in Section 5. Afterwards the preliminary findings outlined above are discussed in more depth in Section 6. At last Section 7 will contain a review of a related dissertation project done in 2018: “Deep Learning Performance on Different Architectures” by Spyro Nita (Nita, 2018).

2 Final Project Proposal

This section will begin by giving an outline of the initial project proposal. The preliminary findings given in Section 6 led us to abandon it and the updated version is given below. The benchmark with which we will compare our deep learning implementation on SpiNNaker with other hardware platforms and deep learning libraries is presented.

The final project proposal will differ from the initial one in two meaningful ways: (i) we will implement deep learning algorithms and layers directly on SpiNNaker, instead of implementing a Tensorflow backend (see Section 6) and (ii) a different benchmark to measure the performance of SpiNNaker. At first glance, implementing a Tensorflow backend in order to enable deep learning on SpiNNaker seemed wise. Tensorflow already supports various hardware as its targets, like CPUs, GPUs or TPUs (Abadi et al., 2015; Jouppi, 2016). Without further knowledge at this point, adding a backend to SpiNNaker seemed the best way to get deep neural networks running on SpiNNaker, since we thought that this would be the road where the least work needs to be done. Simply implementing the low-level linear algebra operations that Tensorflow offers, was deemed less work than having to deal directly with deep learning and its complexity. As the preliminary research revealed, the discrepancy between Tensorflow’s architecture and SpiNNaker’s is too

big to overcome and to get a working deep learning neural network running in the limited amount of time for doing the dissertation was estimated to be impossible. This topic is further discussed in Section 6.

Concerning (ii), the benchmark proposed by the initial proposal was to benchmark our native deep learning implementation against the snn toolbox (Rueckauer et al., 2017). The snn toolbox allows taking pre-trained deep neural networks and convert them to spiking neural networks, which then can be deployed on SpiNNaker. The problem with this benchmark is the fact, that only pre-trained deep neural networks can be used and only inference would be possible on SpiNNaker. We do not aim at doing computationally inexpensive inference (at least compared to training). Rather we want to use SpiNNaker where it would be needed more: training a deep neural network—a computationally very costly operation (see Section 1).

Instead of benchmarking against the snn toolbox, we intend to go for a much more ambitious benchmark. We want to benchmark the performance of our implementation on SpiNNaker against other state of the art hardware and software libraries for deep learning based on a model for computer vision—a very popular problem domain for deep learning, providing many good benchmarks we can compare against (see Section 3).

Currently, the most famous and probably biggest challenge for benchmarking computer vision models is the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), based on the ImageNet dataset. The ImageNet dataset consists of more than 14 million images, organized according to the WordNet hierarchy into over 21 thousand so called synsets (synonym sets) (Russakovsky et al., 2015; Miller, 1995). The ILSVRC is an annual competition running since 2010. It has produced many famous models, e.g. AlexNet, VGG16 or ResNet-50 (Krizhevsky et al., 2012; Simonyan and Zisserman, 2014; He et al., 2015). We intend to benchmark by training the most complex of these three models: ResNet-50. The benchmark will be to train ResNet-50 with 1000 categories (1.28 million images) of the ImageNet dataset (setting of the ILSVRC 2012) and measure the time it takes to finish the training. The top-1 accuracy of the model is evaluated on 50,000 test images and should be at least 74.9%, in order to compare it to the other benchmarks presented in Section 3.

In conclusion, our final project proposal will be implementing deep learning algorithms directly on SpiNNaker, instead of providing a backend to Tensorflow. We will benchmark this implementation and SpiNNaker against other benchmarks based on state of the art deep learning libraries and accelerators for fast training of neural networks, instead of benchmarking our implementation against the snn toolbox. For this benchmark we will train the famous ResNet-50 model based on the settings described above and compare our results against the results others generated with the same setting but with different libraries and hardware, presented below.

3 Related Work

This section will focus itself with related work important for the final project proposal. The main focus lies on benchmarks, with which we can compare our implementation on SpiNNaker with state of the art deep learning libraries and—more importantly—hardware. Further literature of importance for this project, e.g. He et al. (2015), Goodfellow et al. (2016) or Russakovsky et al. (2015), can be found in the References.

The benchmark settings described in the previous chapter are the image classification benchmark for training deep learning models of the recently launched MLPerf benchmark project. The MLPerf benchmark was proposed, to ensure fair performance comparisons between various hardware and software libraries for deep learning (Mattson et al., 2019). We intend to stick to the rules of the MLPerf benchmark. If the dissertation

paper	processor/accelerator	#	library	time
He et al. (2015)	Tesla P100	8	caffe	29 hours
Goyal et al. (2017)	Tesla P100	256	caffe2	1 hour
Smith et al. (2017)	TPU pod	1	Tensorflow	30 minutes
Akiba et al. (2017)	Tesla P100	1024	chainer	15 minutes
You et al. (2017)	Xeon Phi KNL	2048	caffe	14 minutes
Jia et al. (2018)	Tesla P40	2048	Tensorflow	6.6 minutes
Mikami et al. (2018)	Tesla V100	2176	NNL	3.7 minutes

Table 1: Selected timings from benchmarks other than MLPerf with a similar setting.

project will succeed as planned, we will submit our benchmark results to the MLPerf Training benchmark v0.7, which is due on the 21st of February 2021 (submitting the results to the MLPerf Training benchmark v0.7 is not part of the dissertation phase anymore—instead it is part of the follow up on the dissertation and is therefore not further regarded in this paper).

The results of MLPerf Training v0.6 can be found at <https://mlperf.org/training-results-0-6/>. Currently the fastest system for the image classification benchmark is based on Tensorflow and 1024 TPUs (one full TPUs pod) (Stone, 2019). It is able to finish in 1.28 minutes. Besides the MLPerf benchmark, which is quite new, there are a few older papers which use a similar setting for benchmarking their systems. These papers and their results are listed in Table 1. None can beat the fastest implementation on the TPUs pod. This is not surprising, given the fast pace of improvements in both hardware and software for deep learning and the fact, that the MLPerf benchmark results are the most recent.

4 Work Plan

This section will describe the time table for the actual dissertation period. The dissertation period starts on Monday the 25th of May 2020 and will end on Friday the 21st of August 2020. This covers 13 weeks, calendar week 22 to calendar week 34 inclusively.

There are three distinct main tasks to do for the dissertation project, which can be further broken down into more fine-grained subtasks:

- Implementing ResNet-50 on SpiNNaker
 1. Dense layer forward pass (Inference) (see Goodfellow et al., 2016)
 2. Stochastic gradient descent with dense layer backward pass (SGD) (see Goodfellow et al., 2016)
 3. Convolutional layer and ReLu layer (Conv) (see Goodfellow et al., 2016)
 4. Pooling layer (Pool) (see Goodfellow et al., 2016)
 5. Residual learning (RL) (see He et al., 2015)
 6. Optimize implementation (Optimize)
- Benchmarking

- Dissertation writing
 - Background
 - Log
 - Benchmark
 - Conclusion
 - Proof reading

There are a few dependencies between the subtasks. Benchmarking obviously depends on a finished implementation. Optimizing the implementation and benchmarking will depend on each other and will be done iteratively to the final benchmark. The background for the dissertation can be written independently from implementing and benchmarking. The log section and the benchmark section will depend on the implementation and benchmarking efforts. The conclusion section of the report depends on the log and the benchmark section of the dissertation. The subtasks of implementing ResNet-50 are enumerated, because they are done in succession, in the order they are presented. Only optimizing will depend on the benchmark, all else is independent from the rest.

The Gantt chart presented in Table 2 is derived from these dependencies and displays the work plan for the dissertation period. The most challenging week will be calendar week 32 with four tasks to do in parallel. It will be the week the final benchmark must be finished and the writing of the benchmark section will begin. For the background section of the dissertation is a lot of time allocated. Not all of the time will be necessary, or just a little time per week will be dedicated to the writing of this section. The last week before the deadline will solely be spent on proof reading. Calendar week 33 could be used as a buffer week, if the benchmark will not be finished after calendar week 32.

Implementation is broken down into many subtasks. One of the risks this project faces will be the author's inability to implement ResNet-50 (see Section 5). But even if that should be the case, one could theoretically run a simple neural network on SpiNNaker, after the SGD task is finished. This would be after the third week and it would allow us to benchmark our implementation on a far smaller scale than ResNet-50 would provide. So presentable results should be achieved early in the dissertation phase, even if after the Inference and SGD tasks problems are encountered. This ensures a successful completion of the dissertation, even if the implementation should not be completable in its full extend.

5 Risk Analysis

This section will look at risks for the successful completion of the dissertation and how they can be overcome. There are three main risks that will endanger the progress of the dissertation:

- Losing direct access to SpiNNaker knowledge
- Hardware destruction
- Failure to implement ResNet-50 on SpiNNaker
- University closes, because of Corvid-19

CW Task \	22	23	24	25	26	27	28	29	30	31	32	33	34
Implement													
Inference													
SGD													
Conv													
Pool													
RL													
Optimize													
Benchmark													
Writing													
Background													
Log													
Benchmark													
Conclusion													
Proof reading													

Table 2: Gantt chart displaying the work plan for the dissertation period.

Alan Stokes is one of the dissertation's supervisors and part of the core team of SpiNNaker developers. He is the main source of information concerning the SpiNNaker hardware and runtime. In the case he should not be able to participate and help during this project, the successful completion of the implementation and benchmarking phases would be in jeopardy. To cope with this case, a second source of SpiNNaker knowledge was already established. There exists a google group with most of the people using SpiNNaker in it, including the other members of the SpiNNaker core team. The SpiNNaker core team has the goal of answering any question asked in the group within 24 hours. Therefore, the risk of failure is reduced to the risk of having to adjust the benchmark, because the implementation phase will take longer.

There is a SpiNNaker board (see Appendix A for a picture of a SpiNNaker board) allocated for work on this dissertation. A SpiNNaker board is a costly piece of hardware. While the destruction of the board would put the author into financial problems, it is not endangering the successful completion of the dissertation, since there is the supercomputer in Manchester (see Appendix A for a picture of the supercomputer) where the work on the dissertation can be done on. The benchmarks will be run on the supercomputer anyways. Only the implementation phase could take longer, because rapid prototyping on a dedicated piece of hardware would not be possible, since the supercomputer must be shared with other researchers.

Writing scientific programs like deep neural networks is not a trivial task. So is writing software for a complex runtime such as the SpiNNaker runtime. Like stated above, the benchmark proposed is more ambitious than the original proposed benchmark. It could be, that as of right now unknown complications could make it impossible to implement ResNet-50 on SpiNNaker in the time span of the dissertation. But even if the final benchmark is impossible to achieve, due to an unfinished implementation, there is the log section of the dissertation (see Section 4). The log section will contain everything done during the implementation and benchmarking phase. Problems encountered will be documented and even if the final benchmark will not be achieved or the performance is off, the log section will show where the problems were, which is a result usable for future efforts of implementing deep learning on SpiNNaker. So, even if the final benchmark will not be a success, presentable results for the dissertation will still be available.

The last risk would be the event of a quarantine in Edinburgh, where the university campus will be closed. Already events are canceled and regions in Europe are put under quarantine, because of the Corvid-19 virus (Borghese and John, 2020). In case of campus closure, direct contact to the supervisors would be lost. Meetings and discussions would have to be remotely over Skype or an other service. This is currently the main way of communication and would not impact the project. The dedicated SpiNNaker board is also stored on campus. Like stated above, remote access to the supercomputer in Manchester is possible. While taking the dedicated SpiNNaker board away from campus would be possible, it would increase the risk of hardware destruction.

6 Preliminary Findings

This section will present the preliminary findings. The research phase until now has been all about setting the right background for a successful dissertation phase. Like stated in Section 2, the final project proposal has changed quite a bit from the initial one, thanks to the preliminary findings. There are three main pieces of knowledge gained: (i) the main problem will be the author's ability to program ResNet-50 on SpiNNaker, which is not a trivial task, (ii) implementing a Tensorflow backend is not a feasible thing to do in the short time for the dissertation and (iii) the discovery of the MLPerf benchmark, which gives us a perfect setting for finding out, if SpiNNaker can compete with state of the art hardware for deep learning.

The first finding we had was that programming will be non-trivial. SpiNNaker has a complex runtime. The neuromorphic computer architecture is unlike any other and therefore the programming model differs drastically from more common ones. To overcome the difficulties of programming on SpiNNaker will be the major challenge of the dissertation. Every task not directly concerned with implementing and writing the report must be minimized or even removed completely.

This was accomplished by the preliminary research in two major ways. From the beginning it was clear, that the initially proposed benchmark against the ssn tool (see Section 2) is not the desired one and really only an afterthought. At the beginning Tensorflow was much more of a focal point. But because of the difficulties of implementing a backend for Tensorflow and the fact that it is yet unknown if SpiNNaker is even a good platform for deep learning, a benchmark for finding this out should be the first step, before one can worry about how to interface SpiNNaker with already established libraries for deep learning.

Another reason, why the initial benchmark was disregarded quite early in the research phase, is the fact that training deep learning neural networks is the really computationally expensive operation for which high performance solutions must be developed, not doing inference with them. Also, benchmarking SpiNNaker vs. SpiNNaker implementation does not even offer half the insights, because only the native deep neural network would be compared against the deep neural network transformed to a spiking neural network. Only the implementation would be benchmarked, not SpiNNaker, even though the much more interesting insight would be SpiNNaker's performance compared to other state of the art accelerators, like GPU or TPU clusters.

Because programming SpiNNaker is hard enough of a task, having to interface the complex SpiNNaker runtime with the complex Tensorflow runtime was simply deemed too difficult. At the beginning, implementing a Tensorflow backend seemed sensible. Tensorflow already offers interfaces to state of the art accelerators like GPUs and TPUs. Research on how to implement hardware backends to Tensorflow revealed, that the Tensorflow community recommends working with Tensorflow's extended linear algebra compiler (XLA). A description of XLA can be found at: <https://www.tensorflow.org/xla>. Instead of having to implement every Tensorflow core operation, one has only to implement a XLA backend, which is significantly

simpler and more scalable (Tensorflow Team, 2020). Tensorflow Team (2020) describes three types of XLA backend implementations:

1. CPUs without XLA support, either with LLVM backend or not
2. Non-CPUs with LLVM backend
3. Non-CPUs without LLVM backend

SpiNNaker would fall under category three, which is the category requiring the most effort (Tensorflow Team, 2020). Interfacing SpiNNaker with XLA in the time span of the dissertation is not deemed possible.

Another point not in favor of a Tensorflow backend would be the fact, that SpiNNaker’s neuromorphic architecture is quite different from the architecture of common deep learning accelerators and libraries. Tensorflow implements fast linear algebra operations on heterogeneous and distributed hardware (Abadi et al., 2015). Accelerators like GPUs and TPUs are designed for doing fast linear algebra operations using instruction level parallelism. For example, NVIDIA GPUs come with Tensor Cores. A Tensor Core is a specialized piece of hardware performing a 4×4 fused multiply-add-accumulate matrix operation (MAC) per clock cycle (Markidis et al., 2018). Google’s first version of the TPU comes with 256×256 MACs performing 8-bit integer operations (Jouppi et al., 2017). The ARM cores on SpiNNaker on the other hand do not have a fast MAC unit. It is designed to run small neurons communicating with each other over unstable spiking events (Furber and Temple, 2007).

Deep learning operations in Tensorflow and on state of the are accelerators are implemented on a layer-level with matrix operations (Goodfellow et al., 2016). Deep learning offers an abstraction much more convenient and closer to SpiNNaker’s architecture than matrix operations over the layers of a deep neural network: the neurons inside each layer. For Tensorflow, we would have to implement fast and distributed linear algebra operations, without having the benefit of MAC units. This is not what SpiNNaker originally was designed for and would most certainly lead to an unoptimal implementation. Instead, implementing deep neural networks on the abstraction level of neurons instead of layers is a more natural fit.

With removing Tensorflow from the project proposal, we were able to reduce a fairly big chunk of work, which we probably would not have been able to fit into the time span of the dissertation. To fully reduce the tasks to do for the successful completion of the dissertation to implementing, benchmarking the implementation and writing the report (see Section 4), MLPerf offers the last bit (see Section 3). At the beginning—already after the ssn toolbox benchmark was disregarded—we were planning on comparing the SpiNNaker implementation against a deep neural network running on a different supercomputer, such as Cirrus (EPCC, 2020). That would have meant, that we would have to conduct two benchmarks, one on SpiNNaker, another one on Cirrus. Thanks to MLPerf and the other benchmarks presented in Section 3, we can remove the benchmark on a different architecture, which will save a lot of time needed for implementing ResNet-50 on SpiNNaker.

With removing Tensorflow from the project proposal and having the MLPerf benchmark for comparison, we are able to reduce the tasks to do for a successful dissertation to a minimum. This enables us to focus on the most important tasks, while still maintaining a reasonable level of impact in the case of success and even reducing the risk of failure.

7 Deep Learning Performance on Different Architectures: Review

This section will concern itself with a review of the dissertation of Spyro Nita, which he did for earning his Master of Science in High Performance Computing with Data Science at the University of Edinburgh: “Deep Learning Performance on Different Architectures” (Nita, 2018). First, a summary of his dissertation will be given, before the review of his work is presented. The review will start by looking at how well the context of the dissertation is explained and how well the scope of the dissertation’s problem is defined. The last part of the review will be the consideration of the dissertation’s layout and formatting. After the review, the importance of the dissertation for “Deep Learning on SpiNNaker” will be discussed and evaluated.

Nita (2018) concerns itself with measuring the computational performance of two different approaches for training deep neural networks: (i) distributed training using GPUs and (ii) distributed training using CPUs. The dissertation is a work derived of the efforts of Team EPCC at the Student Cluster Competition at the International Supercomputing Conference 2018, held in Frankfurt, where Team EPCC competed against other teams by building a small supercomputing cluster and running various benchmarks on it, to see which team built the best supercomputing cluster. One of these benchmarks concerned itself with measuring the performance of training a deep neural network on the clusters, which is picked up in Nita (2018) and represents the benchmark for approach (i).

The benchmark is based on the famous ImageNet dataset, like the ILSVRC (see Section 2). Contrary to the ILSVRC, the benchmark for the Student Cluster Competition only concerns itself with the throughput of images during training and not with the accuracy of the trained models. The throughput is measured in images per second. Only if two teams should have the same throughput during training is the training accuracy taken into account as the secondary criterion for tie-breaking. The teams participating in the Student Cluster Competition had to train the VGG16 deep neural network—a famous model architecture introduced in the ILSVRC 2014 by researchers from Oxford University (Simonyan and Zisserman, 2014). The main limitation for the clusters were their power budget of 3kW and—for the ImageNet benchmark—a maximum runtime of three hours (Nita, 2018).

Nita (2018) compares the throughput of the supercomputing cluster of Team EPCC for the performance of a distributed GPU system against Cirrus—a supercomputer hosted by the EPCC—for the performance of a distributed CPU system (EPCC, 2020).

Concerning the results of Nita (2018), two major problems were encountered: (i) cluster damage and failure of the Team EPCC cluster shortly before the competition and (ii) the fact that the CPU benchmark on Cirrus could not be distributed over multiple backend nodes. Fortunately benchmarks were done on the Team EPCC cluster, before its failure and Nita (2018) presents the results of using the first node of the cluster with six NVIDIA V100 GPUs. Concerning (ii), Nita (2018) presents the results for a single backend node and assumes that Cirrus would be able to linearly scale to multiple backend nodes, when comparing the two clusters. The single node of the Team EPCC cluster with its six NVIDIA V100 GPUs generates a throughput of 2,052 images per second, while a single backend node of Cirrus (two Intel Xeon E5-2695 processors, each with 18 physical cores) can generate a throughput of just 18 images per second. Assuming linear scaling over multiple backend nodes of Cirrus, 21 nodes would be needed for the throughput of a single NVIDIA V100 GPU. Nita (2018) concludes that GPUs offer a significant advantage compared to CPUs, when it comes to training deep neural networks.

The dissertation starts with an introduction, which includes a description of the dissertation’s layout. The second chapter concerns itself with a description of convolutional neural networks for image classification,

describing ImageNet and VGG16 as a special convolutional neural network. Chapter three describes everything concerning the Student Cluster Competition, including the benchmarks, rules and various features of the Team EPCC cluster, including the used hardware, operating system and other important software libraries. It also describes the difficulties and hardware damage to the cluster and—concerning the ImageNet benchmark—how the images were preprocessed and reformatted to the TFRecord format (Abadi et al., 2015). Chapter four concerns itself with the optimization of the VGG16 neural network, mainly through different parameters which are passed to Tensorflow, which is used for implementing VGG16. It thoroughly describes how one can distribute training across multiple GPUs. The benchmark for the Student Cluster Competition is described and analyzed, as is the benchmark for Cirrus. The chapter ends by comparing both. Nita (2018) concludes by summarizing the results presented in chapter four and gives an outline for future work, which could shed more light on the performance of GPU and CPU clusters for training deep neural networks. The two main points of emphasis for future work presented are: (i) scaling training to hundreds of CPU nodes (see e.g. You et al., 2017, for distributing training onto multiple CPUs) and (ii) comparing power consumption of CPU nodes against GPU nodes.

The best thing to say about Nita (2018) is how well the whole experience of the Student Cluster Competition is communicated by the author. Nita (2018) does not simply give a description of everything that is important for the benchmark, but gives a very conclusive and elaborate review of the whole competition. It serves as a red line throughout the whole dissertation.

Chapter four contains the benchmark and its results. It is a conclusive chapter and well annotated with useful references. The difficulties of the environment are clearly described and while there were failures and the benchmarks on both the cluster of Team EPCC and Cirrus are not optimal, these difficulties are discussed openly and the presented results are sensible.

Overall, Nita (2018) describes the context and problem scope well. Its only problem is, it does not make it easy for the reader to see that. The layout can only be described as cluttered and a few passages and paragraphs are simply unnecessary. For example, Chapter 3.4 does not belong in the chapter that concerns itself with the Student Cluster Competition, if it belongs into the dissertation at all. While the chosen data format could be seen as an optimization and therefore should be described in chapter four, problems during the download before the competition are irrelevant to the benchmark. Also chapter three and two could be swapped, which would have made for an easier introduction to the dissertation, where one is first confronted by the whole context and rather gentle chapter about the Student Cluster Competition, instead of by a description of convolutional neural networks and ImageNet. The first paragraph of the introduction to the dissertation is just weird and seems to pay homage to Goodfellow et al. (2016), which also starts with a similarly weird introduction about Greek mythology and the craving of humankind for thinking machines; absolutely irrelevant for both: benchmarking deep neural networks and deep learning in general.

A second point of critique could be the absence of a chapter on related work, which gives a rough overview of other, comparable benchmarks. Some other benchmarks, like You et al. (2017), are referenced in the dissertation, but the reader does not get a general overview over what else is out there.

Nita (2018) and “Deep Learning on SpiNNaker” overlap in their problem scope, in the sense that both concern itself with benchmarking the training speed of deep neural networks. Both focusing on image recognition based on the ImageNet dataset. While probably not directly important for the benchmark conducted as part of “Deep Learning on SpiNNaker”, since Nita (2018) benchmarks the VGG16 model and “Deep Learning on SpiNNaker” will focus on ResNet-50 (see Section 2), Nita (2018) still provided a great first point of reference for the literature review done so far.

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Appendices

A Photos of SpiNNaker

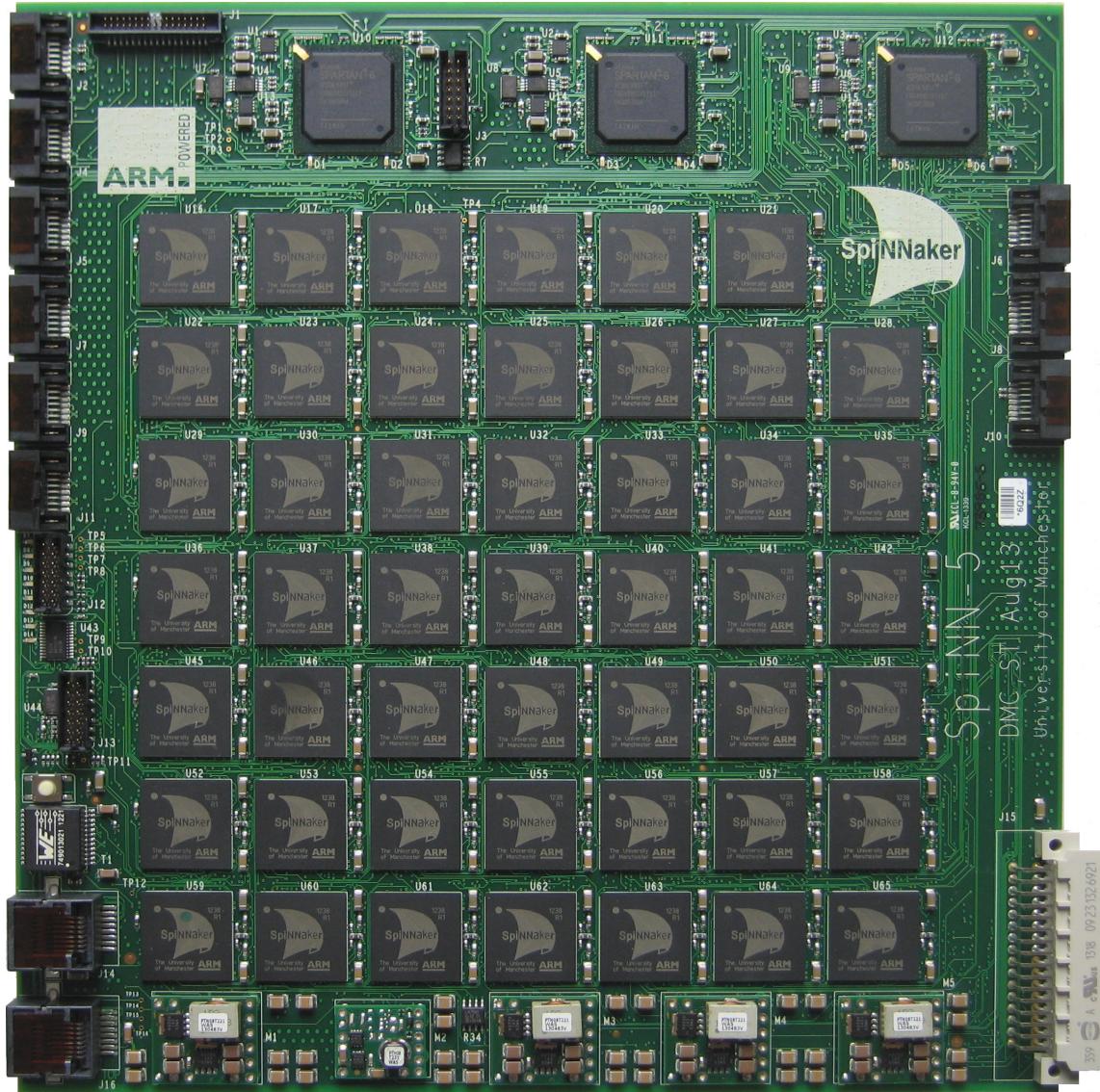


Figure 1: A single SpiNNaker board with 48 SpiNNaker chips. Each chip has 18 cores.



Figure 2: The one million core machine in Manchester. It is capable of running up to one billion spiking neurons in real-time.