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Benchmarking Training of Neural Networks on Embedded Devices

Comparing Training of Neural Network Frameworks vs Systems

Programming Languages like C/C++



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Training on embedded devices is an area that still requires a lot of attention

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Part I: Introduction

An embedded system is a combination of hardware and software components put together to achieve a specific task. Often, embedded systems are built into a larger device or system and are used to collect, store, process, and analyse data, as well as to control the device's behaviour. Embedded devices are a category of tiny devices with physical, computational and memory constraints that are programmable to perform dedicated tasks.

Like most of the automotive industry, Scania employs embedded systems called Electronic Control Units (ECUs) in their trucks to supervise and regulate essential subsystems like the engine, transmission, braking, and electrical systems. Each of these subsystems has one or more ECUs to gather system data and transmit it to a central communicator where the data is processed and the systems operations are monitored.

Scania currently runs a massive fleet of around 600,000 connected heavy vehicles. The company's truck sales make up 62% of its global sales and Scania has been adding 60,000 trucks to its fleet annually [6]. This large fleet of **rolling vehicles** that are connected through the communicators opens up new possibilities. The different connected devices that monitor the health and state of the vehicle can be trained to predict system maintenance needs accurately and efficiently. For example, if the system can predict accurately that tire changes are required in 100kms then the driver can plan the route smartly to reach the workshop before the vehicle breakdown. This opportunity can be realised by running smart algorithms on the hardware that is currently available.

Machine learning (ML) on embedded devices is becoming increasingly popular due to its ability to provide real-time insight and intelligence to devices. This technology can be used to automate tasks, improve efficiency, and make better decisions. But this technology presents a unique set of challenges due to the limited resources available on these devices. Embedded devices are designed to be power efficient, have limited memory and processing power, and require closely tailored algorithms, making it difficult to use pre-existing machine learning models. Furthermore, embedded devices are often expected to produce real-time results, which further complicates the development process. Despite these challenges, machine learning on embedded devices has potential applications in a variety of areas, such as in the fields of robotics and autonomous vehicles.

One such ML application Scania has been developing in their LOBSTR [8] and FAMOUS [7] projects is the anomaly and fault detection models in a federated learning environment. Targeting to run the anomaly detection models on the existing ECUs with limited resources has many benefits and challenges.

Benefits to performing Anomaly Detection on ECUs

- Scania is committed to promote a shift towards autonomous and eco-friendly transport systems. The latest addition of Scania's connected trucks and buses will be embedded with upgraded ECUs and communication devices. However, this upgrade will make the stock of older hardware devices to become obsolete and regarded as e-waste, which could be prevented. Exploring the possibility of repurposing existing ECUs to run ML models aligns with Scania's vision of leading the way towards a sustainable future.
- Neural networks (NNs) are a type of machine learning that can detect intricate patterns not only across multiple data signals but also over time. *include benefits to NN approach to Anomaly Detection*
- Federated learning methods facilitate the training of pre-trained anomaly detection models on the ECUs installed in Scania's distributed fleet of connected trucks. Each ECU individually trains the model with its data and transmits the updated model parameters to a central server. This distributed learning approach enables early detection of faults or failures and ensures that critical data remains on the device. Also dependency on network bandwidth is reduced as only the aggregated model updates are communicated over the network, instead of transmitting the entire data sample.

Challenges to implementing Federated Models

- To reap the best benefits of these approaches, training of the model needs to be performed on board. However much of the potential of running machine learning applications on these devices remains unattained due to the difficulties in creating these applications and running training on-board. Approaches such as TensorFlow Lite (TFLite), Edge Impulse, and STM Cube AI implemented along the TinyML frameworks, enable running ML models targeted for small resource devices. **But these approaches are limited to inference and there is no open source support in the existing infrastructure for training ML models.**
- An Original Equipment Manufacturer (OEM) is responsible for the development and upkeep of the Scania ECU. However, the amount of information made available regarding the hardware design, memory layout, and operating system (OS) is restricted. To construct an embedded OS for a customized hardware, critical details such as the device tree, memory organisation, and boot flow are necessary. Obtaining this information from a functional board can be an enormous task requiring reverse engineering expertise.

Problem Description

The scope of the thesis is to repurpose the existing Scania ECU and explore the challenges of building targeted NN models and training them on repurposed ECU using different approaches and evaluating their performances.

1. Background

Developing and maintaining applications that rely on neural network models on a fleet of embedded devices has several considerations. The application deployment process should allow for continuous updates to the neural network, transfer data or model updates from the embedded devices to off-board analytics or machine learning pipelines, and not interfere with the other applications on the embedded device, all the while maintaining correct representations in the neural network model. It is thus important to have an operating system that can support these applications with features such as process isolation, inter process communication mechanisms, multitasking etc.

The target embedded device to run these applications are the ECUs aboard a Scania vehicle. These ECUs have application processor cores that are capable of running rich operating systems such as linux distributions or real-time operating systems such as QNX, or VxWorks. All these operating systems also support hypervisors which allows for configurations where a host operating system runs standard automotive applications in addition to a guest operating system running the neural network application. This approach has the advantage of mitigating application crashes in the guest operating system and can provide a level of protection against software vulnerabilities [4]. Linux is the preferred choice for such a guest operating system due to its configurability and rich support for application development.

The next section looks at developing such an embedded linux environment and the process of developing neural network applications for that operating system.

1.1 Development For Embedded Linux

Building and maintaining embedded linux distributions with linux kernel and user made applications require tools that can provide build configuration support at multiple levels, interface or build a cross compiling toolchain, support for several c and also support for project management. There are several tools that provide this support such as OpenRT, but the primary candidates with the most generic applicability is Yocto and Buildroot. These systems have several advantages as can be understood from.

1.1.1 Toolchains & Cross compilers

Creating applications that are to be run on an embedded device requires a set of software components that are usually collectively referred to as Software Development Kits (SDK). This suite of programs usually contain a toolchain that is capable of converting application source code, such as those in C or C++, into executables that can be run on the target embedded device.

Such software development toolchains consists of a compiler, linker, libraries, debuggers etc to create executable programs for a target device.

Supporting embedded hardware requires a software stack that includes several components covered in the preceding section. The initial target machine was an ECU filling the role of a coordinator on the truck. However due to certain components missing from the stack layed out previously, namely board level support components such as Yocto meta layer, or the board level The details of the attempt at uncovering this information is layed out in [Appendix II](#). Ultimately a similar board, namely the iMX6SDB evaluation board, with the required information publicly provided by processor chip vendor NXP was chosen as the target platform.

1.1.2 Developing using QEMU

1.2 Training on Device

Mention traditional offboard training and onboard inference architecture vs approaches with training on board. Reference Tiny ML research

1.2.1 Federated Learning

link to federated learning, mention FAMOUS again

1.3 Neural Network Applications on Embedded Devices

Neural network applications are generally written using machine learning libraries such as TensorFlow or PyTorch

1.3.1 Different Programming Paradigms

Approaches to doing Machine Learning in Embedded Environments. Emphasis on how these applications are developed - e.g TFLite

1.4 General Distribution of Work

2. Theory

2.1 Neural Networks

2.2 Support for Neural Networks in Embedded Hardware

2.3 Embedded Linux Environment

Describe the process of boot flow introducing concepts such as Boot ROM, eMMC, IVT, boot-loader, kernel, file systems etc.

2.4 Performance Evaluation

Performance evaluation of programs

Part II: Implementation

Neural network inference has recieved a lot of attension in Tiny ML. The popular with efforts such as providing neural network application programmers a framework to port. Targetting even smaller devices with Tensorflow based neural network models is possible for inference only applications via Tensorflow Lite Micro [\[1\]](#).

This section contains the description of benchmark training applications created to test the performance of an ANN training cycle on an embedded board. The neural network structure, learning algorithm, and the dataset remain the same but the implementations are completed in traditional general purpose neural network frameworks as well as straightforward implementations in C and other languages

3. Design

The benchmark applications test the training phase of a Handwritten Digit Recognition Neural Network (HDR-NN) on the MNIST [3] dataset. MNIST is a popular dataset of handwritten digits commonly used for training image processing systems. It is a popular starting point for neural network implementations and has been used as the primary dataset in the benchmark experiments. The target embedded device is an Electronic Control Unit (ECU) board based on an iMX6 series processor

3.1 Neural Network Development Process

The target environment necessitates the use of cross compilers and as part of the development process multiple build environments and systems were examined. Ultimately, the primary platform that ended up being used was the Yocto Project extensible SDK (eSDK) based application development process running on a standard linux based build environment

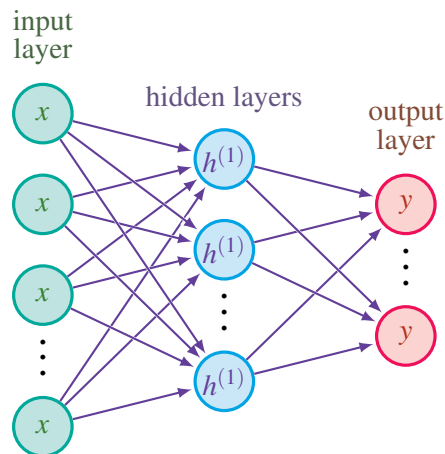
3.1.1 Compiler Toolchains & Yocto Recipes

The *meta-freescale* Yocto BSP layer by NXP supports the target processor and in combination with Poky can provide an eSDK that was primarily used to test and develop the benchmark applications.

GCC based cross compilers and debuggers were usefull for the C, C++ programs. The general portability of the benchmark applications and the Yocto project allows for further experiments to be conducted on different target architectures as well. For further optimisations that relies on hardware specific features such as ARM's CMSIS-NN cannot be so easily ported however

3.2 HDR-NN Benchmark Programs

The handwritten digit recognition neural network is a fully connected neural network and derives from the popular neural network textbook neuralnetworksanddeeplearning.com



The input layer has 784 neurons corresponding to 28 x 28 pixel images of the MNIST dataset and the output layer has 10 neurons corresponds to 10 different possible digits. The dimensions and depth of hidden layers of the network is configurable as well as other properties of the learning algorithm

3.2.1 The Learning Algorithm

The HDR-NN benchmark applications will all share the same standard training algorithm, namely Backpropagation with Stochastic Gradient Descent. Describing this algorithm in general purpose neural network frameworks is straight forward and plenty of general implementations of the algorithm exists in the wild, making the development process easier to target multiple programming paradigms. The configurable parameters of the learning algorithm in through out the implementations are the learning rate, the total number of epochs for training, and the batch size for gradient descent iterations

3.2.2 Verifying Correctness

The model structure can be configured in the same manner across the implementations, as well as the learning algorithm configuration. This means that the shape of the model, the input parameters, the connections between the neuron can be configured in the same manner across the implementations. Furthermore, the learning rate, the number of epochs, and the batch size are also configurable in the same manner. Once the different implementations are configured in a similar manner, the training of the model is completed and the resulting weights are compared.

4. Development

The HDR-NN benchmark application were completed in different programming languages and in neural network frameworks like Tensorflow. Details about the target environment and the benchmark implementations are layed out in this chapter

4.1 Target Hardware

Exploring the target ECU board involved several examinations of a known state of the board. The linux kernel binaries were made via the Yocto project however there was no access to source code such as the recipes or the meta-layers themselves

The i.MX SoCs have a special boot mode named Serial Download Mode (SDM) typically accessible through boot switches. When configured into this mode, the ROM code will poll for a connection on a USB OTG port

4.1.1 i.MX6 Overview

The iMX6 series is designed for high performance low power applications and target boards are configured with a single Cortex A9 core with the ARMv7 ISA. The processor supports NEON single-instruction multiple-data (SIMD) instructions, allowing for SIMD vector operations within the training program

4.2 HDR-NN Implementation

With the primary focus on training, MNIST dataset was primarily loaded in an easily readable format appropriate to the corresponding paradigms and the correctness verification routines and execution statistics measurement runs were seperated. The benchmark executions did not produce disk I/O after the dataset was read, unlike the correctness verification runs which produced the final weights from the execution runs that were subsequently compared with the other benchmark program execution output weights

4.2.1 The Reference HDR-NN in Python

This is the baseline implementation and follows close to the implementation exhibited on [neural-networksanddeeplearning.com](https://neuralnetworksanddeeplearning.com). The implementation uses the n-dimensional array data structure present in the popular Python programming language library Numpy

4.2.2 Tensorflow Lite based HDR-NN

Developing ANNs on tensorflow using Keras is straightforward with good support and well documented APIs. Building the same model for a Tensorflow Lite (TFLite) was more involved however still straightforward

4.2.3 C based HDR-NN

The C implementation had the least amount of external dependencies and contained the network in float arrays within structs.

4.2.4 CPP based HDR-NN

Part III: Analysis

A hand digit recognition neural network (HDR-NN) model is implemented in C, C++ Eigen, Python Numpy and Pytorch. The performance of HDR-NN training implementations was evaluated on the iMX6SDB evaluation board, which was programmed with an Embedded Linux built using The Yocto Project. To gauge the effectiveness of the models, we compared model accuracy, execution time, and peak memory usage while altering the number of layers and neurons in each layer. Furthermore, we address the obstacles encountered in developing the NN model and compiling it to operate on the target hardware.

5. Measurement

The benchmark applications were executed on an embedded linux operating system and the measurements were taken primarily based on the perf_events linux API

6. Results

A hand digit recognition application is implemented in different paradigms, specifically C, C++, Python, and Pytorch, which are the benchmark applications. Each this application is a fully connected feedforward neural network composed of multiple layers of neurons connected in a directed graph. The model has a constant input size of 784 and output size of 10. The hidden layer sizes vary depending on the implementation:

- C and C++ Eigen: 2, 4, 8, 32, 128, (32,16), and (128,16)
- Python-Numpy: 2, 8, 32, (32,16)
- Tensorflow/Pytorch:

The MNIST dataset is selected to train the model. This dataset contains 60,000 training images and 10,000 test images of hand-written digits. The model is trained using stochastic gradient descent, which is an optimization algorithm used to minimize a loss function. The backpropagation algorithm is used to calculate the gradients of the loss function with respect to the weights of the network. Finally, the mean square error loss function is used to measure the difference between the predicted output and the actual output of the network. The values of the biases and weights are initialized randomly with the PNGR random generator and a starting seed which are chosen to be identical for the different benchmark applications. The training hyperparameters are set to 30 epochs with a batch size of 10, a learning rate of 3 and sigmoid activation.

It is essential that the hardware utilised for benchmarking closely resembles the Scania ECU's IMX6 processor, as this will make it easier to replicate the experiment on a repurposed ECU and will also provide the most precise results. The IMX6Q-SABRE Smart Devices evaluation board, which is armed with four 32-bit Cortex A9 cores, is an ideal choice. The Cortex A9 core is equipped with ARM V7 instruction set architecture and a powerful VFPv3 floating point unit with NEON SIMD capabilities. The processor has 32 KB instruction and data L1 caches, 1 MB L2 cache and 1 GB DDR3 SDRAM memory. The benchmark applications are designed to be run on a single core of the IMX6 processor, although it supports quad-core, to ensure the experiment is straightforward and easier to manage. This will also guarantee that the results are precise and accurate.

The yocto project is used to create a custom embedded linux distribution for the imx6qsabresd machine. The NXP yocto project guide ([link](#)) provides the instructions for building the Linux image, and additional packages such as cmake, python3 are installed during the build. The resulting image file, which used to flash the hardware, has a size of 300Mb.

The accuracy of the model is evaluated after each training epoch on the MNIST test set. After the training of the model for 30 epochs, the final weights and biases of the network and the accuracy on the test set are saved for analysis. This data is used to verify the correctness of the NN model in each benchmark application. The GNU time program is a great tool for monitoring the performance of applications. It allows us to measure the execution time and peak memory usage, which is used to compare the effectiveness of training the neural network model on the custom hardware implemented with different paradigms.

The python script created runs the experiment, executing each of the benchmark applications (C, C++, Python, Pytorch) one after the other. Every benchmark application is designed to be repeated 10 times, and all the measurements for each of the hidden layer configurations are saved for each of these iterations. The average values of the model accuracy, execution time and peak memory usage across all iterations are utilized for the analysis.

(we also reason the impact of execution time in the decision to skip some network configurations and add a table of the experiments conducted)

6.1 Evaluating Correctness

6.1.1 Accuracy

As the benchmark applications are developed to be identical by keeping the same structure and configurations, the model accuracy is expected to be similar. The (figure 6.1) showcases that the different implementations perform similarly irrespective of the number of parameters.

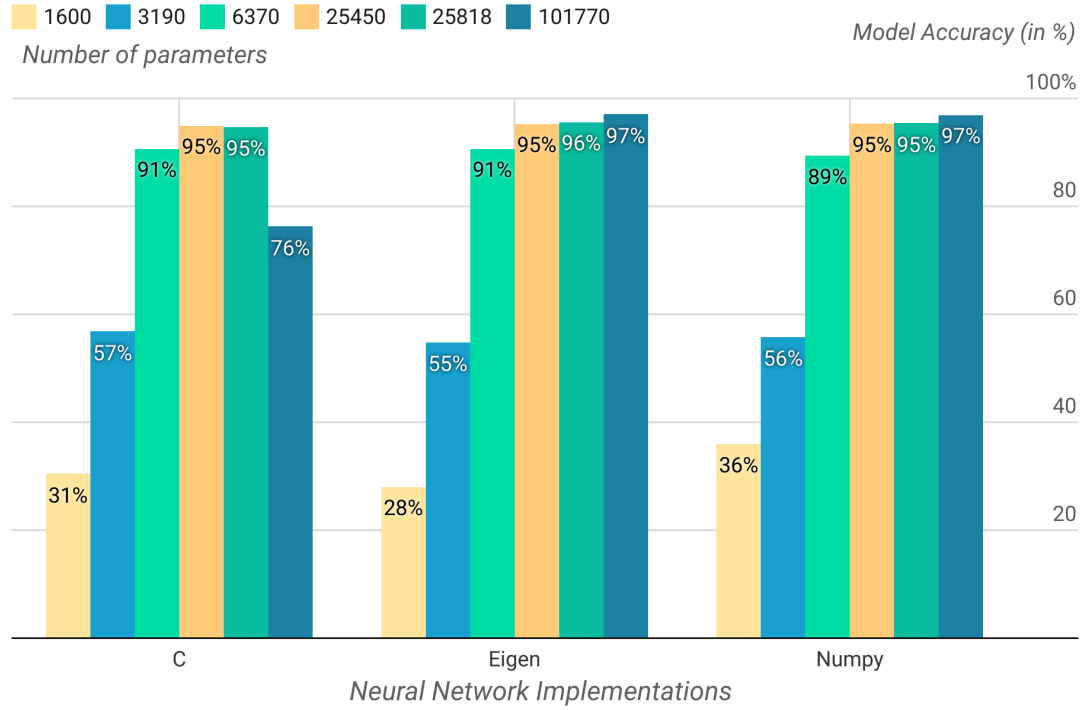


Figure 6.1. Comparing the accuracy of the different HDR-NN implementations.

Further, an abnormal behaviour can be observed when the number of parameters exceeds 101770. The accuracy of the C implementation decreases due to (an unknown bug).

(TODO: evaluate the mean squared error in accuracy between the benchmark applications)

6.1.2 Weights and Biases

(TODO: evaluate the mean squared error in the generated weights and biases between the different implementation. Also, reason how the data structure in each of the implementation influence the error.)

6.2 Evaluating effectiveness

6.2.1 Execution Time

The training time of the neural network applications increases exponentially as the network size increases by the power of 2 because the number of parameters in a fully connected network increases exponentially as the number of neurons increases. This leads to an increase in the amount of calculations needed for the network to learn, resulting in a longer run time for the training process. This behaviour can be observed in (figure 6.2) where the execution time increases drastically as number of parameters increases.

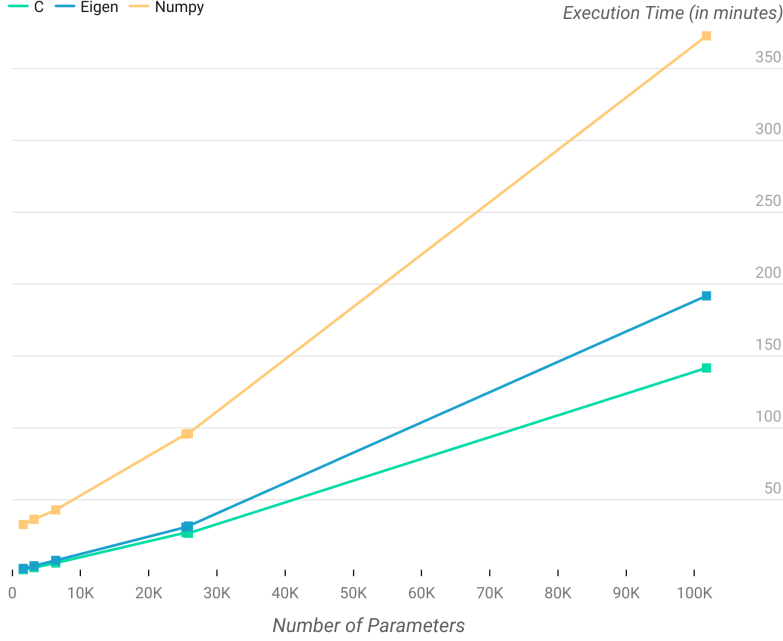


Figure 6.2. Comparing total run time for training the different HDR-NN programs

6.2.2 Peak Memory Usage

Regardless of the hidden layer sizes, the peak memory utilisation remains constant for the NN application across all implementations. The C++ Eigen implementation has the lowest run time memory footprint, while Python Numpy is the least efficient.

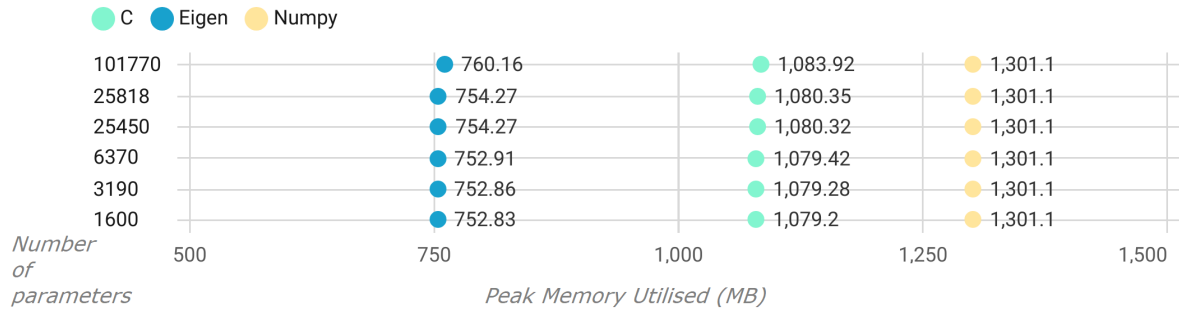


Figure 6.3. Peak Memory Utilized during training with different model sizes remain similar within the same implementation

(here we evaluate the percentage/ratio/cov between the applications.)

6.3 Comparing the implementations

The tables in (figure 6.4 and figure 6.5) shows the comparison between C-Eigen, Eigen-Numpy and C-Numpy. It is calculated as the percentage of $1 - (x/y)$ where x is performance value of the application which has lower value and y is performance value of the application that has higher number.

| Network | C - Eigen | Eigen - Numpy | C - Numpy |
|---------|-----------|---------------|-----------|
| 1600 | 38% | 93% | 96% |
| 3190 | 31% | 89% | 92% |
| 6370 | 23% | 82% | 86% |
| 25450 | 12% | 68% | 72% |
| 25818 | 16% | 71% | 76% |
| 101770 | 26% | 49% | 62% |

Figure 6.4. Percentage difference between the implementations. Example: C is 38% faster than Eigen for the network size of 1600.

| Network | C - Eigen | Eigen - Numpy | C - Numpy |
|---------|-----------|---------------|-----------|
| 1600 | 30% | 42% | 17% |
| 3190 | 30% | 42% | 17% |
| 6370 | 30% | 42% | 17% |
| 25450 | 30% | 42% | 17% |
| 25818 | 30% | 42% | 17% |
| 101770 | 30% | 42% | 17% |

Created with Datawrapper

Figure 6.5. Percentage difference between the implementations

6.3.1 C vs Eigen

For smaller models, it can be observed that C is faster than Eigen (for the network size of 1600, C is 38 percent faster than Eigen). But as model becomes complex, Eigen perform better and the difference is execution time is less than 15 percent. Again the abnormal behaviour can be observed in case of network size 101770 where C is 26 percent faster than Eigen. More test on the C implementation needs to be conducted to identify the bug causing this behaviour.

With regards to memory utilisation Eigen perform better than C by 30%.

6.3.2 C vs Numpy

C constantly performs much better than Numpy. For the network size 101770, C is 62% faster. Numpy utilises 17% more runtime memory than C.

6.3.3 Eigen vs Numpy

Similar to C, irrespective of network size, Eigen is faster than Numpy by similar margins.

Eigen is efficient in memory utilisation and 42% better than Numpy.

6.3.4 Profiling

(TODO: perform profiling of the benchmark applications and note the results)

6.3.5 Failure/Fault testing

(TODO: perform the failure tests such as increases the network size until the application fails or system hangs.)

6.4 Repurposing Scania ECU

Scania ECU is like a black box with no information. A custom encased hardware that supports ethernet over modem and an UART interface along with hardware circuit schematic document was the only information available regarding the ECU. There is no information regarding the processor, memory support, bootloader. As the ECU is a production unit, there is no development tools on device and no support to port packages and application to the ECU. Many features on the bootloader, kernel were disabled making it futile to execute the common commands that provide system information.

The task of repurposing the Scania ECU comprised of reverse engineering and obtaining the required hardware/software information and flashing a custom operating system to benchmark the neural network applications. The first task was partially successfully as hardware information such as processor, architecture, I/O interfaces, device tree and software information such as kernel, compiler, glibc and versions was obtained. But information regarding the memory layout and boot flow could not be concretely reverse engineered. The second task was not achieved as flashing custom embedded linux always resulted in the ECU being bricked. Experiments conducted from booting the normal operation and from serial download mode had different issues and failed. While flashing from the normal boot, only the bootloader is replaced in the mtd partition. This could have failed because of incorrect u-boot image with wrong device trees or loading kernel failed as version mismatch between bootloader and kernel or checksum failure or size of the file is big overwriting a different region with crucial data. Serial download mode flashing required some crucial information regarding the memory load address and entry point for bootloader, kernel, root file system which is configured in the custom device tree. This information could be obtained from reverse engineering.

7. Discussion

7.1 Developer Experience

7.2 Early stopping

The training for all the implementations were executed by configuring the number of epochs as 30. This leads to the accuracy of model dropping significantly due to overfitting, which could be avoided if early stopping was implemented. But, early stopping is not implemented as the performance would be completely different and there wouldn't be a standard setting to compare the implementations.

8. Conclusion and Future Work

What does it all mean? Where do we go from here?

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Appendixes

Scania C300 Communicator