1. INTRODUCTION

Neural network models are typically trained using high-level scripting languages, such as Python, often using machine-learning packages including TensorFlow and PyTorch. Once training has completed, the neural network may be used for inference. While training utilises both forward propagation to generate outputs, and backwards propagation to update the network parameters, inference uses only forward propagation to compute outputs for a given set of inputs.

For many real-world applications, it can be useful to implement neural network inferencing in a more performant language such as C++. To serve that purpose, TensorFlow and PyTorch contain a C++ API, which is often used to perform inference for mobile and desktop applications that use neural network models. While these libraries are flexible and efficient, especially for larger networks, they are often inadequate for real-time systems.

The goal of RTNeural is to maintain a “real-time safe” alternative to the C++ API’s of TensorFlow and PyTorch. Since certain classes of neural network architectures are not practical for use in real-time systems, RTNeural only attempts to implement a small subset of neural network building blocks compared to other major libraries. While RTNeural is unable to match the run-time flexibility of these large libraries, it aims to be convenient for programmers by providing several choices for computational backends and options for defining the model architecture either at run-time or compile-time.

2. REAL-TIME SYSTEMS

For the purposes of this writing, consider a generic real-time system as a system which recieves blocks of input data at a given frequency, and has a set amount of time in which to process that data and compute any necessary outputs. A common example of this type of system is real-time audio processing, where a stream of audio samples at a given sample rate are fed to the processor in blocks. If the processor is unable to process the block fast enough to keep up with the system sample rate, the audio stream will contain a block of “incorrect” samples, often resulting in an audible “glitch”.

2.1. Constraints of Real-Time Systems

The fundamental reason why major neural network libraries including PyTorch and TensorFlow are not adequate for real-time use is that they do not strictly obey the rules of real-time programming. While the rules of real-time programming are not well-defined in scientific literature, a useful discussion is provided in [1]. The most generic rule of real-time programming is to avoid calling code (within the real-time processing code) that may take an “unbounded” amount of time, which includes operations such as thread locking, memory allocation, “garbage collection”, and interfacing with external hardware.

Unfortunately, most neural network libraries rely on dynamically resizable data structures, such as C++’s std::vector, which require memory allocation for most common operations. While this design choice allows for more convenient and flexible implementations, it slows down the real-time processing and leads to “spikes” in performance whenever the program needs to wait for the operating system to allocate additional memory. While the performance impact may be negligible for larger neural networks, it can be significant for small neural networks, which are often more practical for real-time applications.

Note that while many neural networks used in production run inference on a dedicated GPU to make better use of their highly parallelised architecture, this approach is poorly-suited for many real-time systems due to the overhead of interfacing with the external hardware, although recent progress has been made in this area [2]. However, due to the fact that smaller neural networks are typically better-suited for real-time inferencing, running inference on a CPU that supports SIMD instructions is often as fast if not faster than running on a GPU [3].

3. LIBRARY DESIGN

RTNeural is designed as a lightweight, real-time safe neural network inferencing library. To enable flexibility for programmers using the library, RTNeural supports three computational backends, as well as both run-time and compile-time APIs for loading trained neural networks and performing inference.

RTNeural currently supports the following neural network layers:
• Fully-Connected (Dense)
• 1-Dimensional Convolution (Conv1D)
• Long Short-Term Memory (LSTM) 4
• Gated Recurrent Unit (GRU) 5

As well as the following activation layers:
• tanh
• Rectified Linear Unit (ReLU)
• Sigmoid
• SoftMax

As mentioned above, not all layer types and layer sizes are suitable for real-time systems. For example, when analyzing the networks proposed for real-time use in [3, 6, 7, 8], the only layer types used are Dense, Conv1D, LSTM, and GRU, along with a handful of activation layers. Further, none of the layers in the networks proposed requires an input size larger than 100 channels; rather, the typical input size for the proposed real-time neural network layers is between 8-32 channels. With that in mind, RTNeural only implements a subset of the many neural network layers that may be used generally, and explicitly attempts to optimize performance for smaller layer sizes.

3.2. Computational Backends

RTNeural supports three choices for the computational backend used by the library: Eigen 9, XSIMD 4 and the C++ Standard Template Library (STL). There is also experimental support for a fourth backend using Apple’s Accelerate framework 5; however this backend can only be used on Apple devices, and does not have complete support for all functionality provided by the other backends.

3.2.1. The Eigen Backend

Eigen is a highly-templated matrix computation library, with support for SIMD operations and vectorized maths functions. As well as being the cleanest and most readable implementation, the Eigen backend maintains good performance for networks of all sizes, performing particularly well as the network grows larger.

3.2.2. The XSIMD Backend

XSIMD is a C++ library which provides a common interface for SIMD instruction sets across different processor architectures. Therefore, the XSIMD backend implements the various neural network layers essentially using direct SIMD instructions. These implementations can avoid some of the overhead incurred by the Eigen implementations, leading to better performance for small neural networks.

3.2.3. The STL Backend

Since some compilers (particularly for embedded devices) may have difficulty compiling or linking with the Eigen or XSIMD libraries, the STL backend is provided as a fallback. Although the STL backend is typically the least performant, it can easily be compiled with any modern C++ compiler. Note that since the choice of backends is made at compile-time, the library will automatically exclude any unused libraries from the build process.

3.3. Loading Pre-Trained Models

Since RTNeural does not support training neural network models, the user must instead train the model themselves, and then load the model into RTNeural. To make this process more convenient, RTNeural provides Python scripts for saving sequential models trained using the TensorFlow Keras API to a JSON format, which can then be parsed by methods in RTNeural. For non-sequential model architectures, or models trained using a different framework, the user may export the model weights in whatever form they choose, and then load the weights into an RTNeural model, using the weight-setting functions provided with each layer.

3.4. Run-Time API

The RTNeural run-time API allows the user to load pre-trained models at run-time and perform inference on those models. Although the run-time API requires dynamic memory allocation since the number of input and output channels for each layer is not known at compile-time, RTNeural allocates all required memory while loading the model so that memory is never allocated as part of the real-time process. Note that while the run-time API is more flexible than the compile-time API, it has somewhat worse performance, since the compiler is unable to fully optimize certain parts of the inferencing process that are not known until the model is loaded at run-time. Listing 1 shows a simple example of running inference for a neural network with 3 input channels and 1 output channel, using the run-time API.

```c++
#include <RTNeural/RTNeural.h>

int main() {
    // load model from json
    std::ifstream jsonStream("model.json", std::ifstream::binary);
    auto model = RTNeural::json_parser::parseJson<
        double>(jsonStream);
    model->reset(); // reset model state
    // set up input vector
    double input[] = { 1.0, 0.5, -0.1 };
    // compute output
    double output = model->forward(input);
    return 0; // exit
}
```

Listing 1: Example of the RTNeural run-time API. Note that the type returned by parseJson is a std::unique_ptr<>.
3.5. Compile-Time API

It is typically preferable to use the RTNeural compile-time API in cases where the model architecture is known at compile-time. With the compile-time API, all required memory is allocated statically, and all functions needed for real-time inferencing are defined such that they can be inlined by the compiler [10]. Further, since the number of input and output channels needed for each layer is known at compile-time, the compiler can “unroll” loops as needed to optimize performance [11]. Listing 2 shows a simple example of running inference for a neural network with 3 input channels and 1 output channel, this time using the compile-time API.

```c
#include <RTNeural/RTNeural.h>

int main()
{
    // define model
    RTNeural::ModelT<double, 3, 1,
        RTNeural::DenseT<double, 3, 4>,
        RTNeural::TanhActivationT<double>,
        RTNeural::DenseT<double, 4, 1> > model;
    // load model from json
    std::ifstream jsonStream("model.json", std::ifstream::binary);
    model.parseJson(jsonStream);
    model.reset(); // reset model state
    // set up input vector
    double input[] = { 1.0, 0.5, -0.1 };
    // compute output
    double output = model.forward(input);
    return 0; // exit
}
```

Listing 2: Example of the RTNeural compile-time API

4. EXAMPLES

To date, RTNeural has mainly proven to be useful for real-time audio processing tasks. Two real-world applications where RTNeural is currently in use include guitar distortion effects, and analog tape emulation.

4.1. Guitar Distortion

[12] describes a real-time “virtual analog” model of the famed Klon Centaur guitar distortion circuit. While the effect was originally implemented using a custom neural inferencing engine, more recent versions of the effect use RTNeural instead. Switching from the custom inferencing engine to RTNeural has resulted in a performance improvement of nearly 3x. Further, the neural network processing with RTNeural is approximately twice as fast as an alternative model of the circuit, developed using more traditional circuit modelling techniques.

4.2. Analog Tape Emulation

[13] derives a method for creating a real-time digital emulation of a magnetic tape recorder using physical modelling. In particular, the hysteresis process that describes the magnetisation of the tape is emulated using a discretized version of the Jiles-Atherton equation [14]. While the method described in the paper uses the 4th-order Runge-Kutta method to evaluate the equation in real-time, more recent implementations use the 2nd-order Runge-Kutta method, or a Newton-Raphson solver with either 4 or 8 maximum iterations.

Recently, the developer has introduced an alternative solver based on a “State Transition Network” (STN) [3], using RTNeural for real-time inferencing. The trained STN achieves similar accuracy to the 4-iteration Newton-Raphson solver while performing nearly 2x faster. The process of training and implementing the STN solver is described in [13].

5. PERFORMANCE COMPARISON

In order to better understand the performance benefits of RTNeural relative to other neural network inferencing libraries, a performance benchmark has been developed comparing the speed of each RTNeural backend against the PyTorch C++ API. The benchmark constructs a single layer with a given number of input and output channels (referred to as the “Layer Size”) and processes a random signal at 48 kHz sample rate. The speed of the layer is then measured as a “real-time factor” $v_{RT}$, defined as,

$$v_{RT} = \frac{t_{signal}}{t_{process}}$$

where $t_{signal}$ is the duration of the input signal, and $t_{process}$ is the amount of time taken by the layer to process the input. Note that for $v_{RT} < 1$ the layer processing is too slow to perform inferencing in real-time.

Figure 1 shows the performance results for a selection of layers using the RTNeural run-time API. As a reference, the results are compared to the performance of the PyTorch C++ API, using the same layers and layer sizes. Note that the dashed red line in the plots marks the “real-time” threshold $v_{RT} = 1$. Figure 2 shows a similar set of results for the RTNeural compile-time API. For the performance benchmarks shown here, all measurements were made using a 2019 MacBook Pro with an Intel® Core™ i7-9750H CPU, running at 2.6 GHz.

The results of the performance benchmarks show that RTNeural out-performs PyTorch for the smaller layer sizes, although PyTorch shows less change in performance as the layer size grows, implying that it will be better able to “scale up” for larger layer sizes. This performance trade-off between larger and smaller layer sizes is to be expected, since RTNeural is intentionally optimised to perform better for smaller layer sizes. Comparing the performance between the RTNeural backends shows that different backends perform best for different layer types and sizes. In general, it is recommended that users profile the performance of the network they are implementing on their target hardware to determine which backend is the best choice for their use-case.

The source code for the performance benchmarks can be found on GitHub[6] along with a full set of plots displaying performance results for all the neural layers supported by RTNeural.

[6] https://github.com/jatinchowdhury18/RTNeural-compare
6. CONCLUSION

RTNeural is a neural network inferencing library written in C++, and is optimised for use in systems with hard real-time constraints. The library is designed to be lightweight, by supporting only the most relevant subset of neural network layers; flexible, by supporting several computational backends and both run-time and compile-time API’s; and, most importantly, highly performant.

The library has already proven to be useful for real-time audio processing tasks, including guitar distortion and analog tape emulation. Further, performance benchmarks show that RTNeural can achieve superior performance compared to the PyTorch C++ API for smaller network sizes.

Future work will involve implementing more commonly used neural network layers, such as max-pooling [16] and batch normalization [17]. Additionally, new use-cases will be explored, including more audio-related tasks such as randomised overdrive [18] and wake-word detection [19], as well as real-time tasks in other domains.

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