

Fast Inference of Machine Learning Models with SOFIE

Source Code

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root.cern

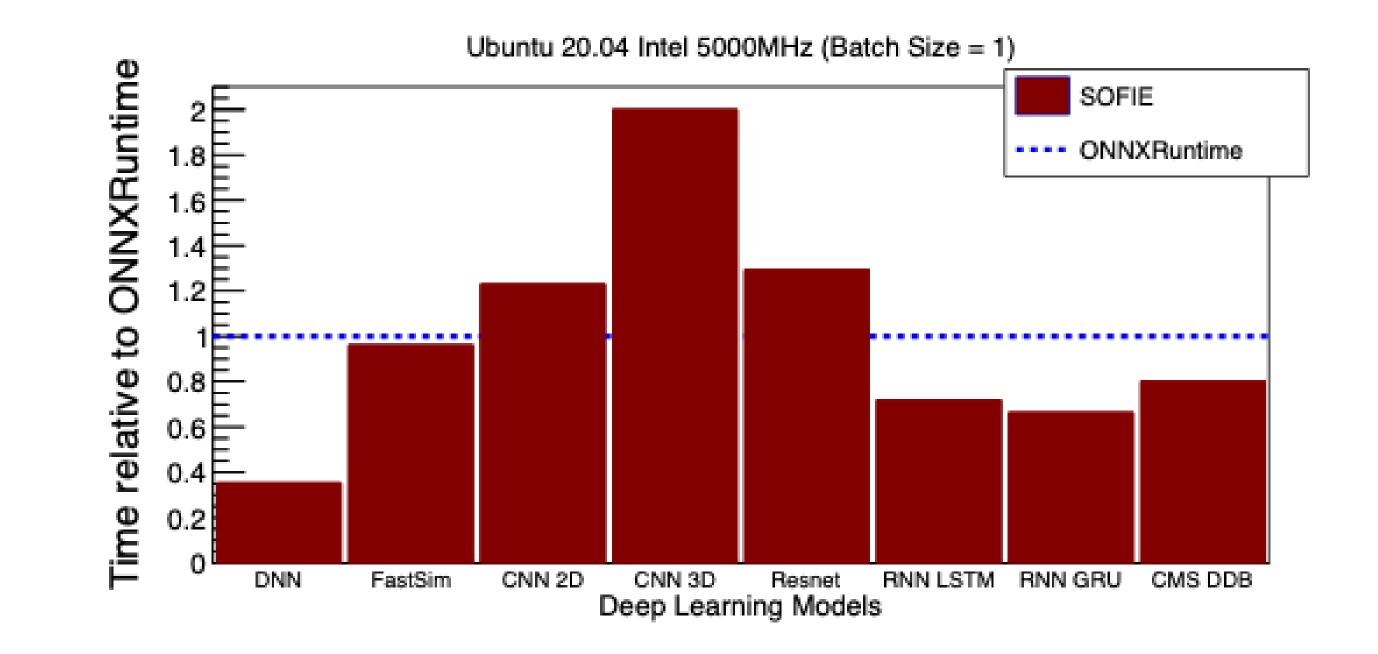
GNN size (nodes+edge

Motivation

- Popular machine learning libraries, such as Keras and PyTorch, provide functionality for inference, but support only their own models and are constrained by heavy dependencies
- SOFIE [2] creates standalone C++ inference code for a model with limited dependencies (only on BLAS libraries), which can be included in any other C++ project.
- SOFIE supports several types of deep learning models, including now message passing GNN.
- SOFIE can generate SYCL code that can run on various GPUs and is dependent only on Intel MKL BLAS and portBLAS libraries.

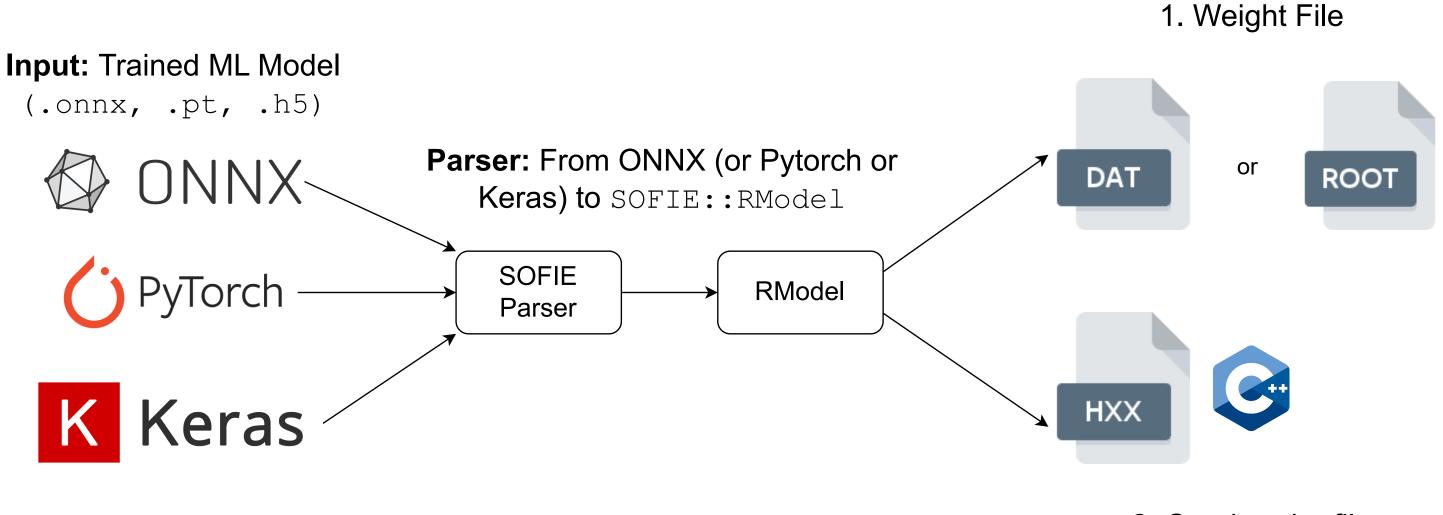
Benchmarks on CPU

We tested 8 different deep learning models with various complexity.
We compare the CPU time to evaluate the models using the C++ code generated by SOFIE or by using directly ONNXRuntime.

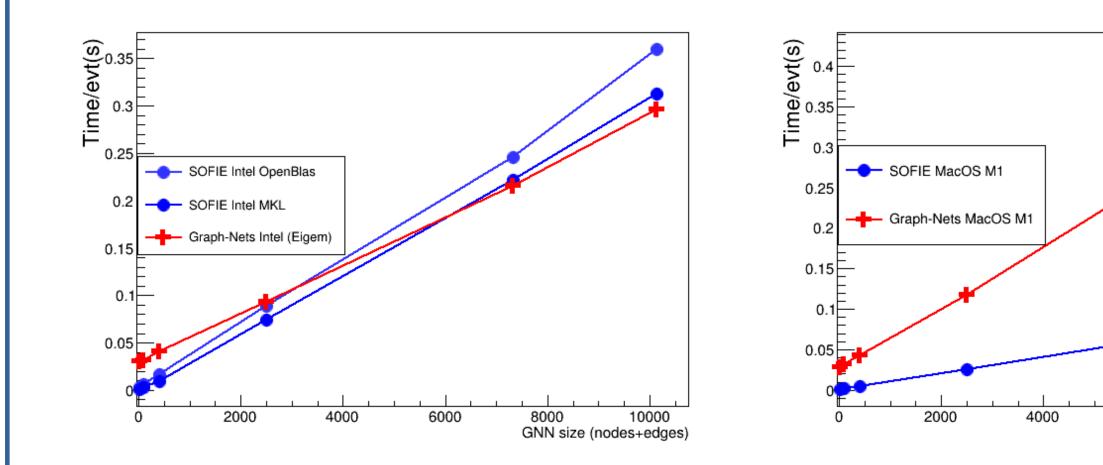


Description

- SOFIE accepts input in the form of a pre-trained machine learning model, presented in .onnx, .pt or .h5 format and transforms the input model into an equivalent graph of operators.
- The code generation step produces a C++ header file with the inference function in C++ and a weight file in .dat or .root format.



► We tested also the CPU performance for **GNN models** varying the number of nodes and edges on Linux and MacOS architectures



2. C++ header file

Outputs

The generated code can be easily integrated in C++ applications or compiled on the flight using the ROOT JIT capabilities of CLING and used in Python code.

Benchmarks on GPU

We tested 6 different configurations for various platforms and execution backends using the SYCL code extension of SOFIE.

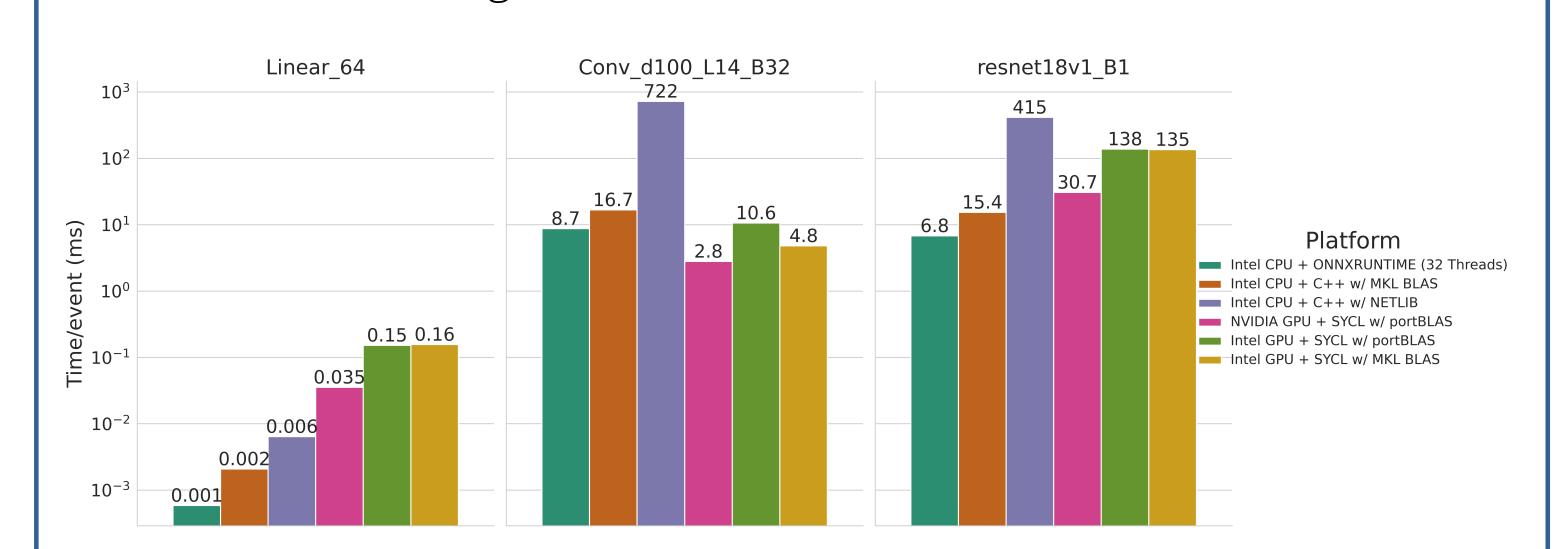
The model can also be evaluated within ROOT RDataFrame.

ONNX Supported Operators

Operators implemented in ROOT	CPU	GPU
Perceptron (GEMM)	\checkmark	\checkmark
Convolution (1D, 2D, 3D)	\checkmark	\checkmark
DeConvolution (1D, 2D, 3D)	\checkmark	\checkmark
Recurrent (RNN, GRU, LSTM)	\checkmark	
Activations (Relu, Selu, Swish, LeakyRelu, Tanh,)	\checkmark	\checkmark
Pooling (MaxPool, AveragePool,)	\checkmark	\checkmark
BatchNorm, LayerNorm	\checkmark	\checkmark
Binary Op (Add, Sum, Mul, Div,)	\checkmark	\checkmark
Unary Op (Neg,Sqrt,Exp,)	\checkmark	\checkmark
Reshape, Flatten, Concat, Reduce, Gather	\checkmark	\checkmark
Transpose, Slice, Squeeze, Unsqueeze	\checkmark	\checkmark
Custom operator	\checkmark	

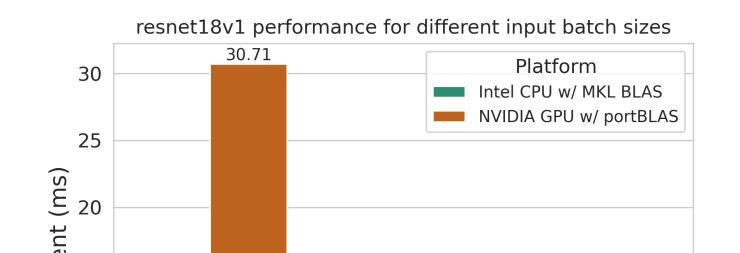
Support for Missing operators can be added on user requests

GNN Support

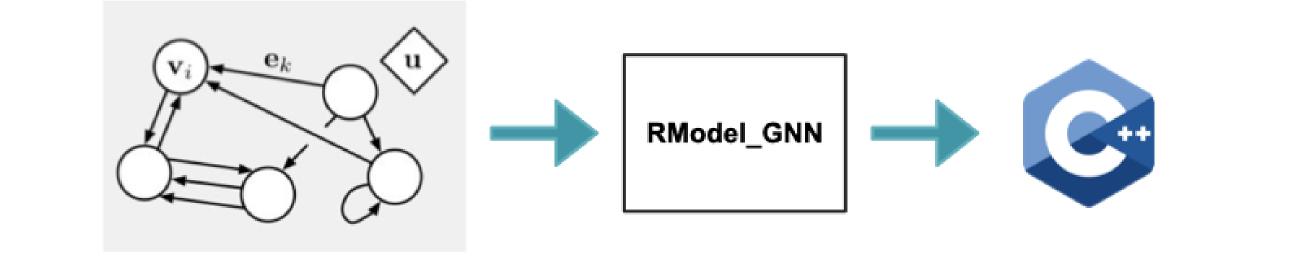


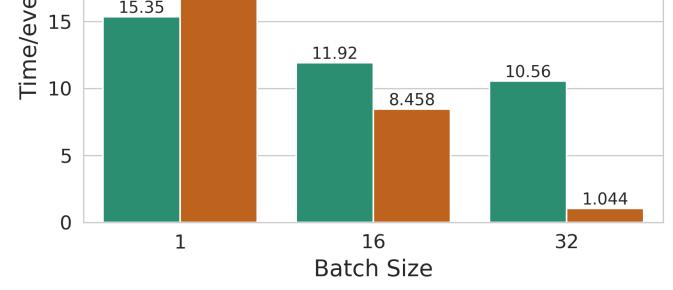
There is significant correlation between performance improvement and model size.

Models with fewer layers and lower computational complexity, such as Linear_64 exhibit inferior performance on GPU compared to models with more extensive layer counts, such as Convolutional or resnet models.



 SOFIE can generate C++ code from GNN models based on the Graph Nets library [1]





The performance for the same model (resnet18v1_81) varies considerably with the input **batch size**.

KEY REFERENCES

- [1] DeepMind. Graph Nets Library. URL: https://github.com/google-deepmind/graph_nets.
- [2] Lorenzo Moneta Sitong An et al. "SOFIE: C++ Code Generation for Fast Inference of Deep Learning Models in ROOT/TMVA". In: Journal of Physics: Conference Series 2438.1 (Feb. 2023), p. 012013. DOI: 10.1088/1742-6596/2438/1/012013. URL: https://dx.doi.org/10.1088/1742-6596/2438/1/012013.

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MORE INFORMATION





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