Machine Learning Inference: SOFIE

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Motivation



Fast Evaluation of Machine Learning models is more and more relevant

- ML tools like Tensorflow/PyTorch have functionality for inference
 - can run only for their models
 - usage in a C++ environment can be cumbersome
 - require heavy dependence
- A standard for describing deep learning models:
 - ONNX ("Open Neural Network Exchange")
 - cannot describe all possible deep learning models (e.g. GNN) fully
- ONNXRuntime: an efficient inference engine based on ONNX
 - can work in both C++ and Python
 - supporting both CPU and GPU
 - can be challenging to integrate in the HEP ecosystem
 - control of threads, dependencies, etc..
 - not optimised for single-event evaluation





Machine Learning Inference in ROOT



SOFIE : System for Optimised Fast Inference code Emit

Input: trained ML model file

- ONNX: Common standard for ML models
- Tensorflow/Keras and PyTorch models (with reduced support than ONNX)
- Since 6.32 support message passing GNNs from DeepMind's Graph Nets

• Output: generated C++ code

- Easily invokable directly from C++ (plug-and-use)
- Minimal dependency (on BLAS only)
- Can be compiled at run time using ROOT Cling JIT and can be used in Python.

Outputs



1. Weight File

GPU Extension of SOFIE



Extended SOFIE functionality to produce GPU code using SYCL

// generate SYCL code internally
model.GenerateGPU();
// write output header and data weight file
model.OutputGeneratedGPU();



namespace TMVA_SOFIE_Linear_event{

struct Session {

Session(std::string filename ="") {
 if (filename.empty()) filename =
 "Linear_event.dat";
 std::ifstream f;
 f.open(filename);
 // read weight data file

std::vector<float> infer(float*
tensor_input1){



- Minimise overhead of data transfers between host and device
- Manage buffers efficiently, declaring them at the beginning
- Use libraries for GPU Offloading: GPU BLAS from Intel one API and PortBLAS for other GPUs
- **Fuse operators** when possible in a single kernel
- Replace conditional check with relational functions

#include "Model.hxx" // create session class TMVA_SOPTE Model::Session ses("model_woights.dat"); //-- event loop for (ievt = 0; ievt < N; ievt++) { // evaluate model: input is a C float array float * input = event[ievt].GetData(); </pre>

auto result = ses.infer(input);

Inference code needs to be linked against oneAPI MKL libraries and compiled using SYCL compiler

SOFIE GNN Support



Since ROOT version 6.32 support inference of **GNN**s

- parsing available for GNNs built from DeepMind's Graph Net library
- supporting a LHCb model for full event interpretation (<u>arXiv:2304.08610</u>)
- Developed C++ classes for representing GNN structure.
 - based on SOFIE RModel and the ROperator classes which provide the functionality to generate C++ inference code
- **Python code** (based on PyROOT) for parsing from the Graph Nets models





ONNX Supported Operators

data

W (64×3×7×7) BatchNormalization scale (64) B (64) mean (64) var (64)

MaxPoo

W (64×64×3×3) BatchNormalization scale (64) B (64) mean (64) var (64)

BatchNormalizatio

scale (64) B (64)

mean (64) var (64)

Add

Relu

1×3×224×224



Operators implemented in ROOT	CPU	GPU
Perceptron: Gemm	✓	~
Activations: Relu, Selu, Sigmoid, Softmax, Tanh, LeakyRelu, Swish	✓	~
Convolution and Deconvolution (1D, 2D and 3D)	✓	✓
Pooling: MaxPool, AveragePool, GlobalAverage	√	~
Recurrent: RNN, GRU, LSTM	√	~
Layer Unary operators: Neg, Exp, Sqrt, Reciprocal, Identity	✓	~
Layer Binary operators: Add, Sum, Mul, Div	✓	✓
Other Layer operators: Reshape, Flatten, Transpose, Squeeze, Unsqueeze, Slice, Concat, Reduce, Gather	✓	~
BatchNormalization, LayerNormalization	✓	~
Custom operator	✓	

current CPU support available in **ROOT 6.30**

GPU/SYCL is implemented in a <u>ROOT PR</u>

Benchmarking Time of Inference

CPU event performance of SOFIE vs ONNXRuntime



GPU (SYCL) vs CPU performance

 using a Resnet model with varying batch size



CPU time for GNN inference

• varying GNN size (node + edges)

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Summary



SOFIE, fast and easy-to-use inference engine for Deep Learning models, is available in ROOT

- Can be easily integrated with other ROOT tools (*RDataFrame*) for ML inference in end-user analysis
- Supporting several **ONNX** operators and also **GNN**s
- A prototype implementation for **GPU** using **SYCL** has been developed
 - plan to extend to CUDA and/or ALPAKA following some interest by experiments to deploy in their GPU-based trigger system

Future developments according to user needs and received feedback

- aim to support the latest production model of experiments (GNN and transformers)
- models used for fast simulations (GAN and VAE)

Other ML Activities



RBatchGenerator: Batching ROOT files

Serving tensors to ML training pipelines (ongoing R&

- Generate batches directly from a ROOT file
- As fast as traditional ML software
- Scales to very large file sizes
- Easy to add to workflow

Marking on direct integration with DDateEroma





NGT Activities

- SFT is hosting common activities of Next Generation Trigger project
 - Support tools for fast ML in FPGA:
 - hls4ml (for DL) and Conifer (BDT)
 - develop new functionality to support experiment needs
 - Develop the software infrastructure for hardware-aware neural network training workflows.
 - enable the development and deployment of hardware-optimal Al-based real-time algorithms.





high level synthesis for machine learning





from V. Lonchar at 24th IEEE Real-Time Conference