



Reduced Precision Strategies for Deep Learning: 3DGAN Use Case

4th IML Machine Learning Workshop

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Electromagnetic Calorimeters

- Calorimeter detectors create particle showers and measure the energy of particles produced in the collisions
- Their simulations are resource intensive
 → replace them by a faster approach











3D Training Data

3D shower image granularity: 25x25x25





Generative Adversarial Networks 3DGAN

• Train two networks (Generator & Discriminator) in a minmax game



- GANs reach a good level of accuracy*
 - → We want to further decrease the computational speed with low precision computing

*Particle Detector Simulation using Generative Adversarial Networks with Domain Related Constraints, Gul Rukh

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Old Conv3D Generator Network

• Until now: Representing 3D images \rightarrow Using 3D convolutional layers



- Conv3D layers are not supported in lower precision
 - → Creating neural network consisting only of Conv2D layers
 - First approach: Channel dimension as 3rd dimension
 - Bad accuracy

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New Conv2D Generator Network



- Solving a 3D problem with 2D layers
- 3x speedup on GPU

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Increasing the number of parameters → more powerful network → higher accuracy

Why Reduced Precision?

- If we change to a new simulation approach, we want to make sure to use the hardware as efficient as possible
- Deep Learning training and inference are computational resource intensive
 - Models need a large amount of memory
 - Moving data to and from the compute engines strains the bandwidth

→ Reduced-precision computation reduces memory and bandwidth occupation

Reduced Precision Computing

• Quantization: Converting a number from a higher to a lower format

• E.g. from float32 to int8



- Quantization Tool: Intel Low Precision Optimization Tool (iLoT) https://github.com/intel/lp-opt-tool
- Reference Tool: TensorFlow Lite





Quantization Problems

- TensorFlow supports no negative quantized values (signed int8)
- → All quantization tools do not support LeakyReLU function
- Implementation of those delayed our work

• TensorFlow Lite:

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- Does not support signed int8 \rightarrow no LeakyReLU
- Does not support transpose convolutional layers for up-sampling

Computational Evaluation

(of iLoT model)

• The quantized model reached a speedup of **1.8x**





- GAN simulation configuration: Oct, 2020: TensorFlow v2.3; Test by Intel; Test date: 11/10/2020; Platform: Intel(R) Xeon(R) Platinum 8280 CPU; Cascade Lake architecture; #Nodes: 1; #Sockets: 2; Cores/socket: 28; Threads/socket: 56; HT: On; Turbo: On; System DDR Mem Config: 12 slots / 16GB / 2933; OS: CentOS Linux 7; Kernel: 3.10.0-957.el7.x86_64
- Geant4 simulation time was taken from a previous measurement in 2018



Physics Evaluation

 Validation metrics: Mean squared error (MSE) of 2D projections of the showers between GAN and validation data

Model	MSE (Lower is better)
float32	0.061
iLoT int8	0.053
TFLite float16	0.253
TFLite int8	0.340

iLoT int8 shows a good accuracy
TensorFlow Lite int8 performs worse

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Physics Evaluation

- Ep: Incident energy of the particle into the calorimeter or generator network

The optimization of the quantization does not take this metrics into account

→ more detailed studies needed

CERN Openlab Ratio of Ecal and Ep for 2-500 GeV





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- **38000x** speedup of GAN to Geant4
- 2x speedup due to conversion from Conv3D to Conv2D on CPU
 - 3x speedup on GPU
- **1.8x** speedup due to quantization from float32 to int8
- **68000x** total speedup of quantized GAN versus Geant4 simulation

Good physics accuracy for optimization metrics



QUESTIONS?

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