3D convolutional GAN for fast simulation

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F. Carminati, G. Khattak, S. Vallecorsa

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A DL engine for fast simulation

Provide a tool that can be configured and trained for different detectors

Start with time consuming detectors
  Next generation highly granular calorimeters

Train on detailed simulation
  Test training on real data

Test different models
  GAN, RNN

[Diagram showing untrained and trained models with arrows indicating process]

Physics (e^+, e^-, \pi, ..)
Kinematics...
A plan in two steps

Is generative models output accurate enough?
Can we sustain the increase in detector complexity?

How generic is this approach?
Can we “adjust” architecture to fit a larger class of detectors?
What resources are needed?

• A first proof of concept
• Understand performance and validate accuracy

• Prove generalisation is possible
• Understand and optimise computing resources
Proof of concept, benchmarking and validation
**CLIC calorimeter simulation**

*Data is essentially a 3D image*

Electromagnetic calorimeter detector design (*)
(Linear Collider Detector studies)

- 1.5 m inner radius, 5 mm×5 mm segmentation: 25 tungsten absorber layers + silicon sensors
- 1M single particle samples (e,γ,π)
  - Flat energy spectrum (10-500) GeV
  - Orthogonal to detector surface
  - +/- 10° random incident angle

Highly segmented
Sparse.

(*) [http://cds.cern.ch/record/2254048#](http://cds.cern.ch/record/2254048#)
3D convolutional GAN

Similar discriminator and generator models

3d convolutions (keep X,Y symmetry)

Condition training on several input variables

Auxiliary regression tasks assigned to the discriminator: cross check

Easily generalisable to multi-class approach (or multi-discriminator approach)
Validation and optimisation

Detailed GAN vs GEANT4 comparison (More than 200 Plots!)
  High level quantities (shower shapes)
  Calorimeter response (single cell response)
  Particle properties (primary particle energy)

Optimisation on
  Network Architecture (Layers, filters, kernels, initialisation)
  Losses definition
  Data pre-processing
  Rely on GAN losses only!! No physics variable explicitly constrained!

Results agree within a few % to Geant4 (labelled “DATA” in next slides 😊)

We run on Caltech ibanks GPU cluster thanks to Prof M. Spiropulu
Electrons shower shapes

50 GeV

100 GeV

500 GeV

400 GeV

50 GeV

100 GeV

500 GeV

500 GeV
Neutral Pions

GANx0
Entries: 50000
Mean: 12.06
Std Dev: 1.628

Datax0
Entries: 50000
Mean: 12.04
Std Dev: 1.563

GANy0
Entries: 50000
Mean: 11.99
Std Dev: 1.538

Datay0
Entries: 50000
Mean: 12
Std Dev: 1.462

GANz0
Entries: 50000
Mean: 13.96
Std Dev: 4.716

Dataz0
Entries: 50000
Mean: 13.98
Std Dev: 4.658

Log scale

X shape

Y shape

10-500 GeV

Z shape

Data

GAN

Log scale

X shape

Y shape

Z shape
Calorimeter sampling fraction

GAN seems to slightly overestimate slightly neutral pions energy deposits.
Generalisation & Computing resources

Distributed training
Hyper-parameter scans
Generalisation

Charged Pions

Charged pions have small energy deposits

Energy showers are delayed along Z

Preliminary

Ep GeV

Ecal/Ep

Data
GAN

X shape

Y shape

Z shape

Data
GAN

Ratio of Ecal and Ep

CERN openlab
Generalisation

Variable angle sample

Electrons enter the calorimeter with a 60°-120° angle range

Wider/asymmetric image size (51x51x25):

Adjust convolution parameters to improve energy description vs angle

Minimal architecture changes

Energy inclusive shower shapes (60° angle)
Computing performance

Distributed training is needed

Inference:
Geant4: 17 s/particle vs 3DGAN: 7 ms/particle
→ speedup factor > 2500!!

Training:
45 min /epoch on Tesla P100
Introduce data parallel training based on MPI
Test several libraries
Run on HPC clusters and Cloud (HNSciCloud providers)

More info in track T6

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Time to create an electron shower

<table>
<thead>
<tr>
<th>Method</th>
<th>Machine</th>
<th>Time/Shower (msec)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Full Simulation (geant4)</td>
<td>Intel Xeon Platinum 8180</td>
<td>17000</td>
</tr>
<tr>
<td>3d GAN (batch size 128)</td>
<td>Intel Xeon Platinum 8180</td>
<td>7</td>
</tr>
<tr>
<td>3d GAN (batch size 128)</td>
<td>GeForce GTX 1080</td>
<td>0.04</td>
</tr>
</tbody>
</table>
Summary & Plans

3D GAN: first step towards customizable simulation tool

- Initial results are very promising
- Agreement to Monte Carlo within few percent

Meta-optimization and hyper-parameters scans are key

- Tested several distributed training approaches on different platforms (GPUs/CPUs)
- Understand / optimize physics performance at scale

More on optimization and distributed training in J. Vlimant talk on Thursday (Track 6)

Questions?

Sofia.Vallecorsa@cern.ch

Thanks!
Discriminator regression on input energy

5% error on auxiliary energy regression
Conditioning and auxiliary tasks

Loss is linear combination of 3 terms:

- Combined cross entropy (real/fake)
- Mean absolute percentage error for regression tasks