# Fast Simulation of High Granularity Calorimeters with Deep Generative Models

Peter McKeown Deutsches Elektronen-Synchrotron 16.03.2021



#### **Outline**

#### 1 The ILD detector

#### 2 Generative Models

- Conditioning Generative Models
- Generative Adversarial Networks
- **3** Overview of previous work
- 4 Angular conditioning efforts

#### **The ILD Concept**

- International Large Detector (ILD) concept for the International Linear Collider (ILC)
  - Higgs Factory
- Optimized for Particle Flow
  - Reconstruct each individual particle in subdetector
  - Obtain optimal detector resolution
- Key features:
  - Precise tracking and vertexing
  - Excellent hermeticity
  - High granularity calorimeters



## **The ILD Electromagnetic Calorimeter**

- Destructively measure particle's energy
  - Produce shower of secondary particles until totally absorbed
- Sampling calorimeter- measure fraction of energy
- ILD proposal: Si-W ECAL
  - 30 layers of alternating active and passive material
  - 20 layers: 2.1 mm thick
  - 10 layers 4.2 mm thick
  - 5x5 mm<sup>2</sup> silicon cells
  - ~ 80 million channels for barrel
- Geometry is not perfectly regular... → Project onto regular grid



## **The Strain on HEP Computing Resources**

- Ever increasing demand for computing resources
  - MC generation largest fraction
  - Calorimeters most intensive part of detector simulation



#### WALL CLOCK CONSUMPTION PER WORKFLOW



D. Costanzo, J. Catmore, ATLAS Computing update, LHCC meeting , 2019

#### **Generative Models**

- Approach to fast simulation- amplify statistics
- Promising solution: generative models
  - Generate new samples following the distribution of original data
  - Map random noise to data
  - Highly parallelizable
  - Conditioning

See preceding talk by Sascha outlining proof of principle: T 38.8- GANplifying Event Samples arXiv:2008.06545



## **Getting High: Simulating the ILD ECAL with Deep Learning**

- Previous work in our group: ILD ECAL simulation with 3 generative models
  - 30x30x30 regular grid of calorimeter cells
  - 950k photon showers
  - Continuous range of energies: 10-100 GeV
  - Fixed incident point
  - Perpendicular to the calorimeter face



Getting High: High Fidelity Simulation of High Granularity Calorimeters with High Speed

Erik Buhmann · Sascha Diefenbacher · Engin Eren · Frank Gaede · Gregor Kasieczka · Anatolii Korol · Katja Krüger

arXiv:2005.05334

#### **Getting High: Generative Adversarial Network**



\* For details on the other architectures see: T21.5 from Erik (Decoding Photons: Physics in the Latent Space of a BIB-AE Generative Network, arXiv:2102.12491) and T57.1 from Sascha

## **Getting High: High Fidelity Simulation**



 BIB-AE successfully reproduces MIP peak at 0.2 MeV (postprocessing)



• Mean and width well reproduced

## **Conditioning requirements for a general simulation**

- Conditioning for a general calorimeter simulation:
  - Energy
  - Particle type
  - Incidence point
  - Two angles
    - Polar angle: θ
    - Azimuthal angle: φ



#### **Angular conditioning- Training data**

In Progress: condition generative networks on particle's angle of incidence and energy .

25

20

10

5

0

0

5

10

15

z [layers] 15

- Start simple:
  - Fixed energy- 20 GeV •
  - Only vary polar angle in one direction- from 90°-30°
  - Fixed particle type- photons
- Problem: How to make sure the full shower is contained? .
  - Extend the grid in y: shape (30,30,40) (z,x,y)
  - Shift gun position •
- Currently have 132k showers for training ٠



#### **Angular conditioning- GAN network architecture**

- Begin with the simplest architecture
- Give  $tan(\theta_z)$  and E as separate network parameters
- Multiply both by noise before passing to network
- Generator learning rate 10<sup>2</sup> larger than discriminator





#### **Angular conditioning- Preliminary results**

DESY. | DPG Spring Meeting, Dortmund 21| Peter McKeown | 16.03.2021



## **Angular conditioning- Ongoing progress**

• Compare generated and GEANT4 distributions for a fixed angle of 60 degrees



#### **Angular conditioning- Preliminary results**





#### **Angular conditioning- Angular benchmark**

- Find principal axis of showers- benchmark for model
- Diagonalize analogue inertia tensor
- Principal axis is eigenvector with the smallest eigenvalue
- In order to reconstruct the true angle:
  - Layers in ILD ECAL are not regularly spaced in z
  - Take this into account in positions of hits used in the inertia tensor



#### **Angular conditioning- Angular benchmark**

- Find principal axis of showers- benchmark for model
- Diagonalize analogue inertia tensor
- Principal axis is eigenvector with the smallest eigenvalue
- In order to reconstruct the true angle:
  - Layers in ILD ECAL are not regularly spaced in z
  - Take this into account in positions of hits used in the inertia tensor



#### Conclusion

• Demonstrated angular and energy conditioning in a GAN architecture

#### **Next Steps**

- Train on more data
- Quantitative metric for epoch selection
- Study trade off in physics distributions when angular conditioning is introduced
- More sophisticated architectures e.g. BIB-AE
- Vary energy and study effect on performance



#### **Getting high: Generative models- Wasserstein GAN**



#### **Getting high: Generative models- BIB-AE**



#### **Getting high- other physics distributions**



#### **Getting high- other physics distributions**



#### **Angular conditioning- Preliminary results**



#### **Angular conditioning- Preliminary results**



# Angular conditioning- other physics distributions (preliminary)



#### **Angular conditioning- Checking full shower is contained**



#### Angular conditioning- GAN network architecture: more details

- Generator:
  - Noise vector of length 100, uniformly between -1 and 1
  - 4 transposed 3D convolutional layers
  - ReLU activation functions
  - Learning rate: 1x10<sup>-3</sup>
- Discriminator:
  - Five 3D convolutional layers- batch normalization except final layer
  - Two fully connected layers for readout
  - LeakyReLU; sigmoind in the final layer
  - Learning rate: 1x10<sup>-5</sup>
- Trained for 50 epochs
- Use Adam optimizer with a learning rate of 2x10<sup>-5</sup>