A Deep Learning Tool for Fast Simulation

Gulrukh Khattak, Sofia Vallecorsa, Federico Carminati

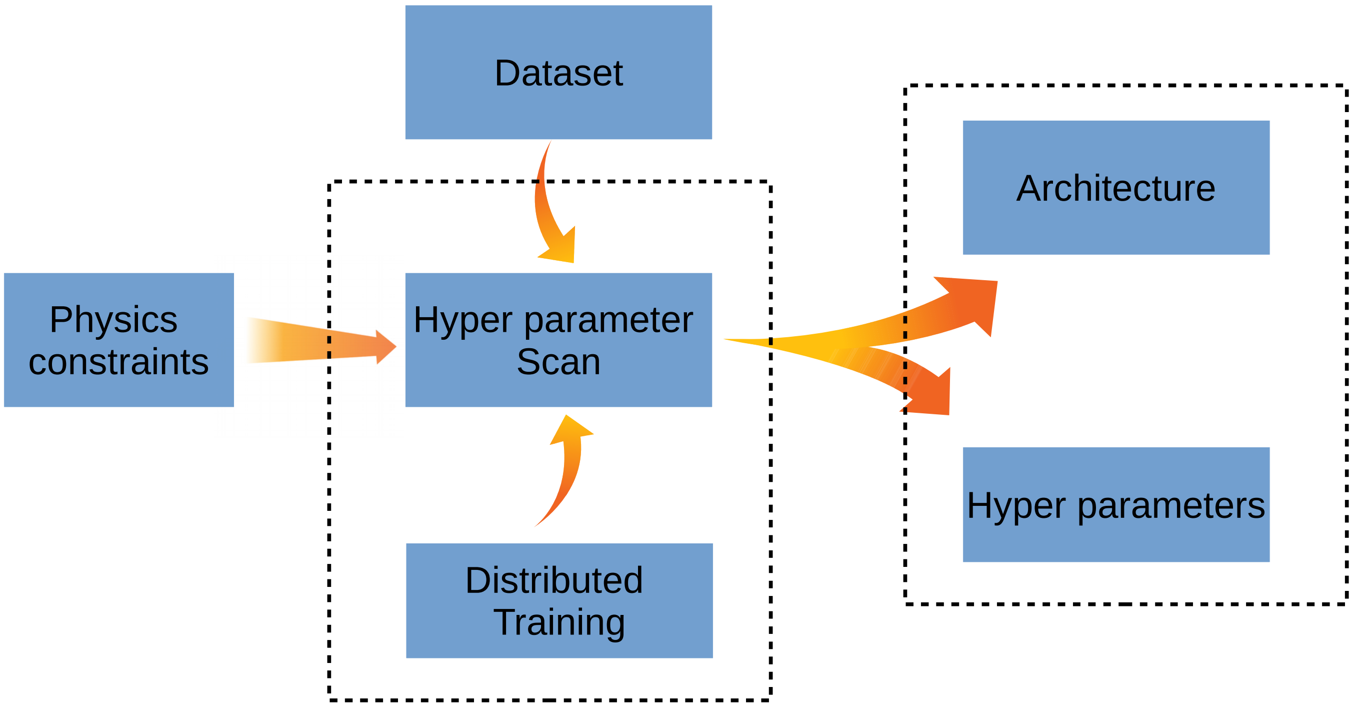
Overview

- Fast Simulation Framework
- Calorimeter Dataset
- 3D GAN
- Physics validation
- GAN optimization
- Future Plans

Generalized Simulation Framework

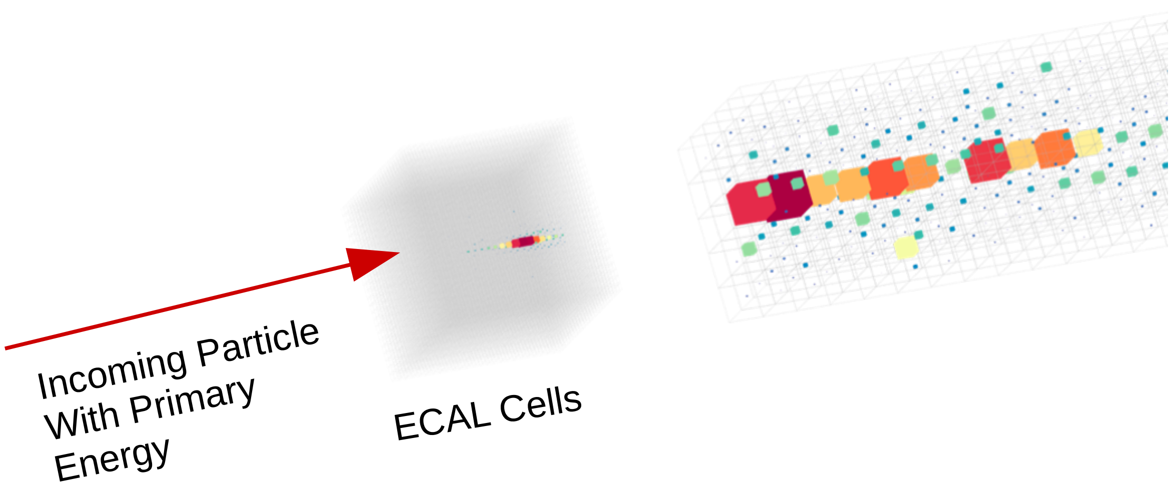
- Detector output treated as image:
  - Preserving Accuracy
  - Sustaining increase in detector complexity
- Generalizing the approach
  - Adjust Hyper parameters like architecture, loss function, etc.
  - Within available resources

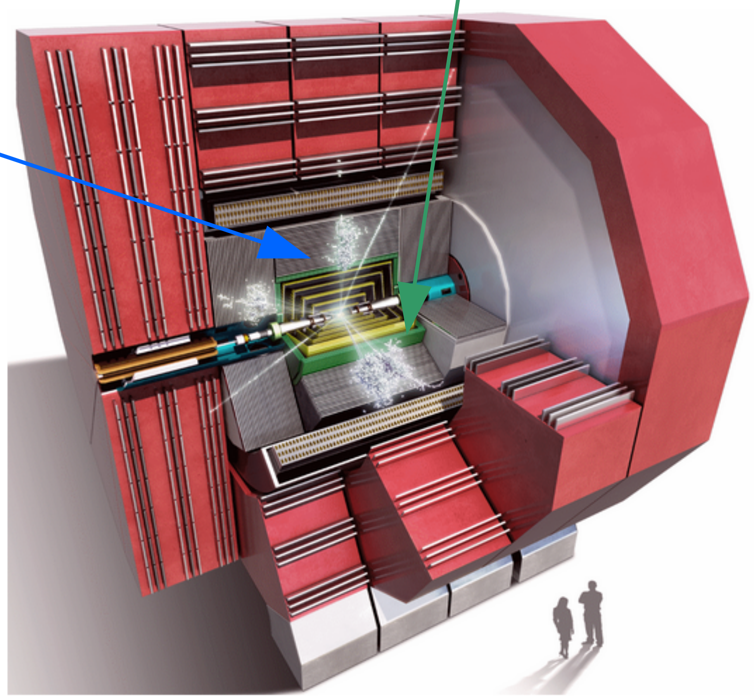
- Proof of concept
  - Understanding performance and validating accuracy
- Implementation
  - Understand and optimize computing resources



CLIC Calorimeter Dataset

- Compact Linear Collider CLIC: Proposed linear particle accelerator
- Electromagnetic calorimeter : Array of Tungsten absorber and silicon sensors
- Event as 3D images
- 200,000 Electron events from 10 to 500 GeV simulated with Geant 4
- ECAL 25 x 25 x 25 → 15, 625 cells



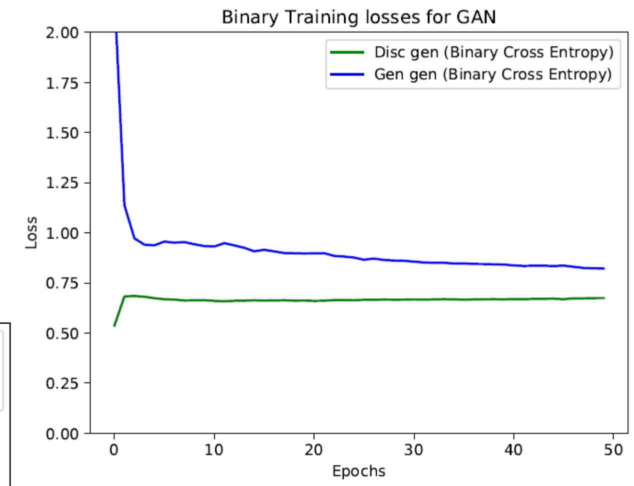


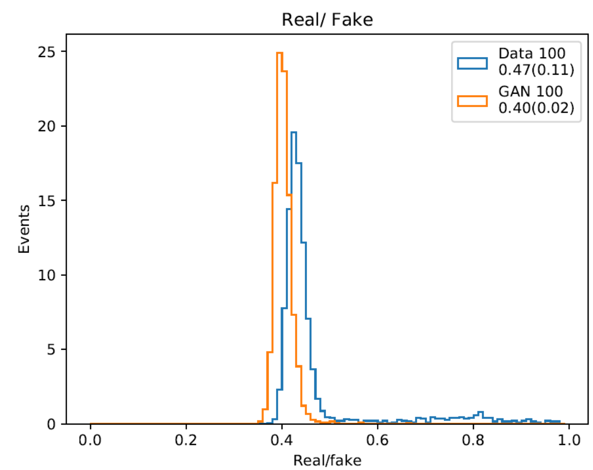
http://cds.cern.ch/record/2254048

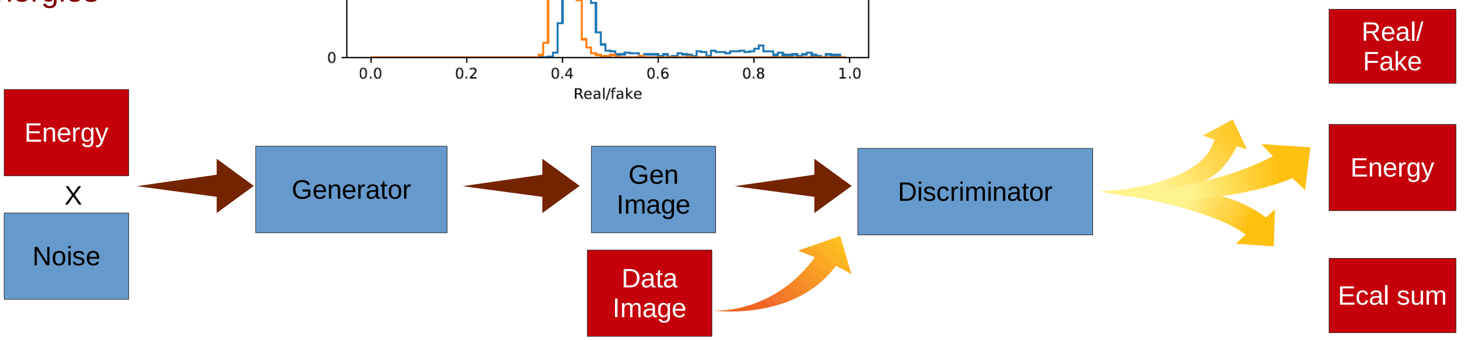
http://clicdp.web.cern.ch/

3DGAN

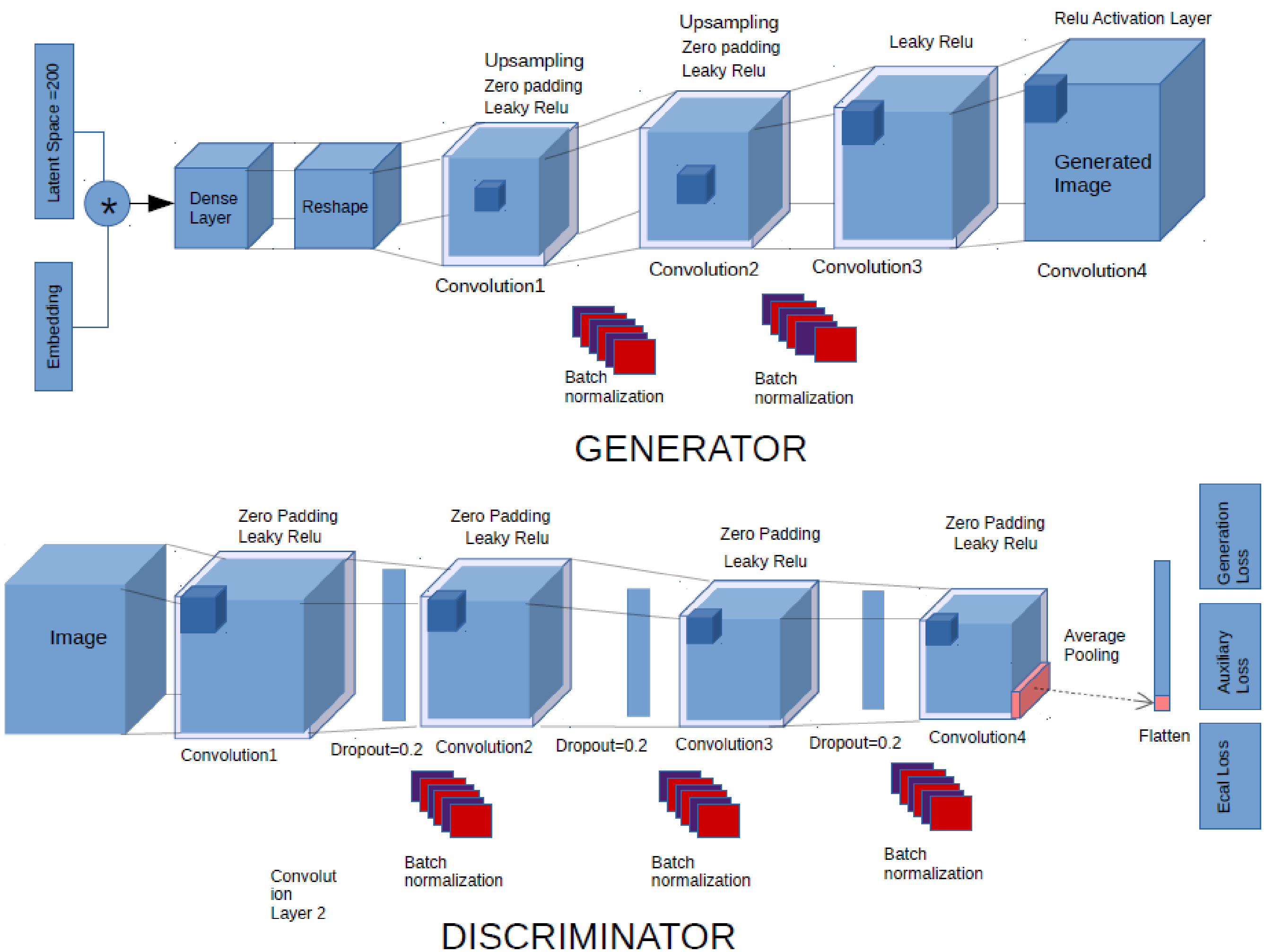
- Parametric, Physics consistency, similar Probability Distribution
- Conditioned on Particle Type as:
  - Embedding
- Conditioned on Energy as:
  - Super-imposed on latent noise vector:
    - Latent Space x Energy
  - Loss Function
    - Binary Cross Entropy
      - Generational Loss (Real ? Fake)
    - Mean Absolute Percentage Error
      - Auxiliary Regression Energy
      - ECAL Sum of cell energies
    - Loss Weights







Network Architecture

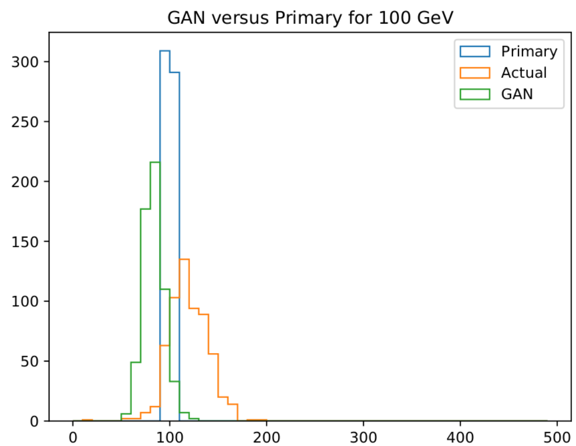


https://github.com/svalleco/3Dgan/tree/Energy-gan

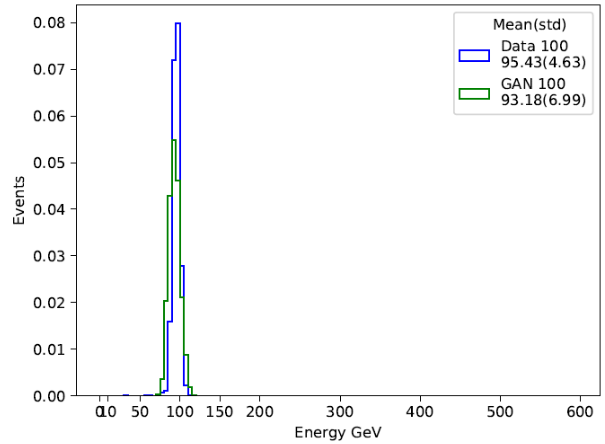
Validation and Optimization

- GAN vs GEANT Comparison for Physics Validation
  - More than 200 Plots :
    - Maximum Energy position, Energy deposited along different axis, Discriminator outputs, Total Energy Deposition, Shower moments, Hits above a threshold, etc.
- 3DGAN Optimization
  - Network Architecture:
    - Layers, filters, kernels
  - Loss:
    - Additional terms, Weights, Functions
    - Fit for Primary Energy vs. Sum of energies deposited in ECAL
  - Pre-processing:
    - Scaling of data
- Acceptable level of Physics accuracy achieved

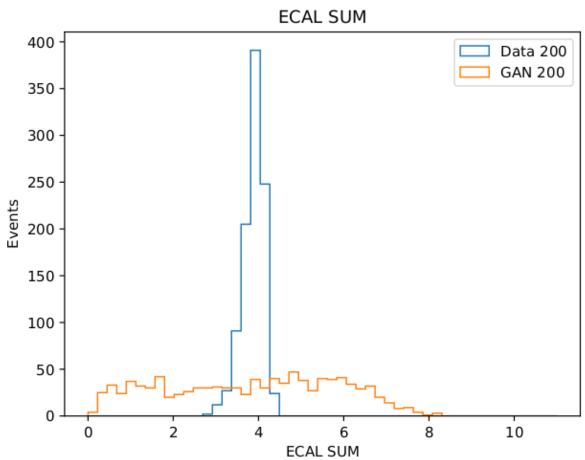
Loss Optimization



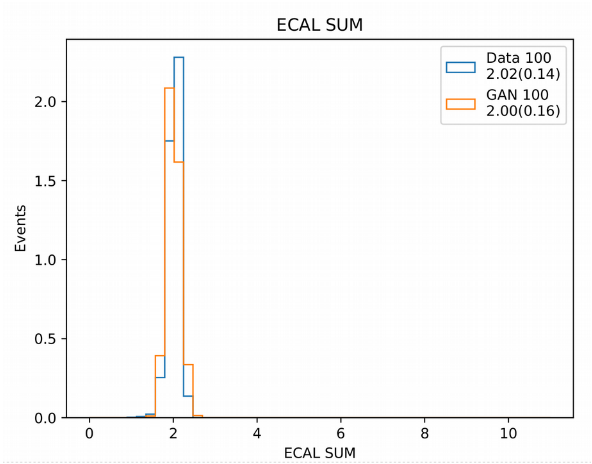
MAE



MAPE

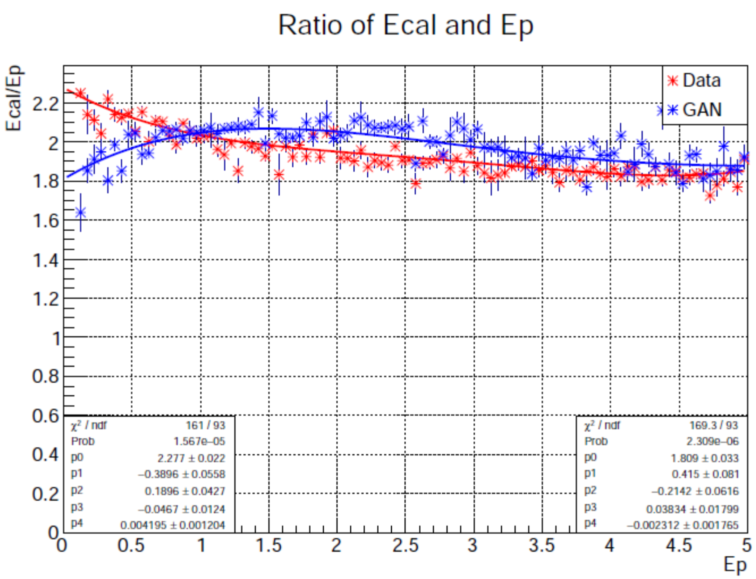


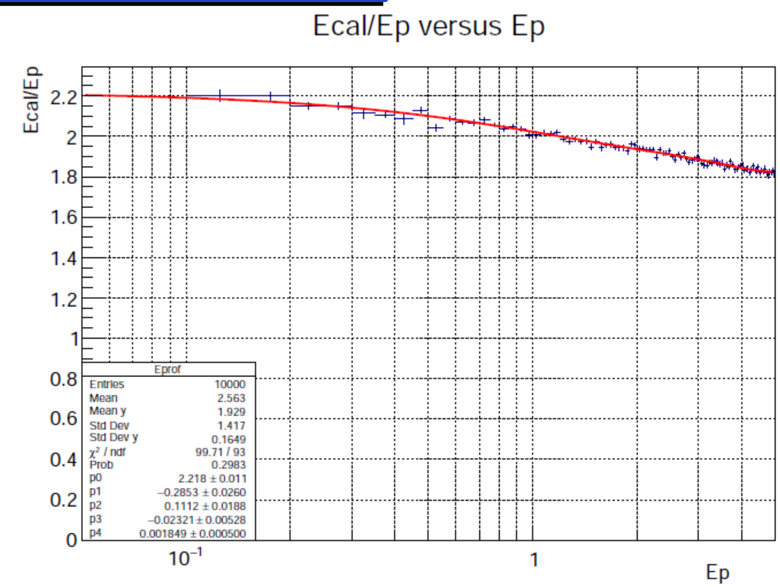
Before Ecal loss



After Ecal loss

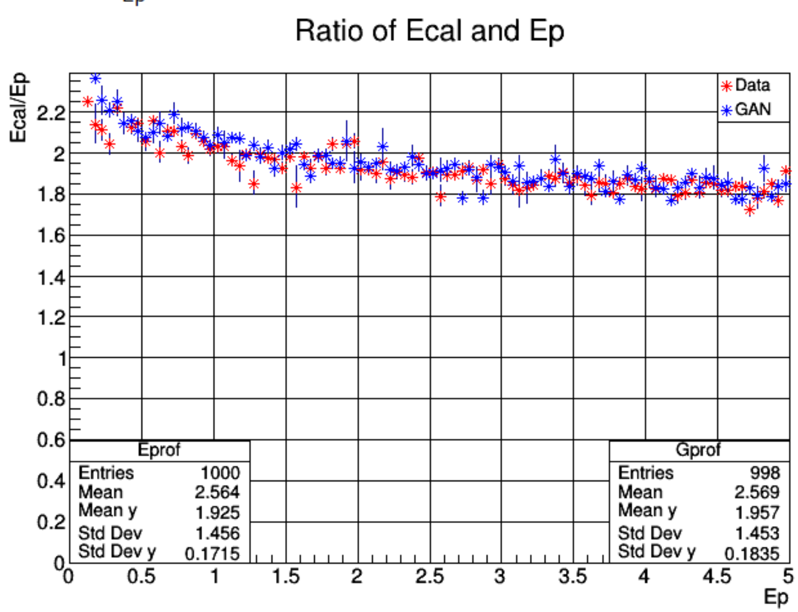
Sampling Fraction (Ep = GeV/100)





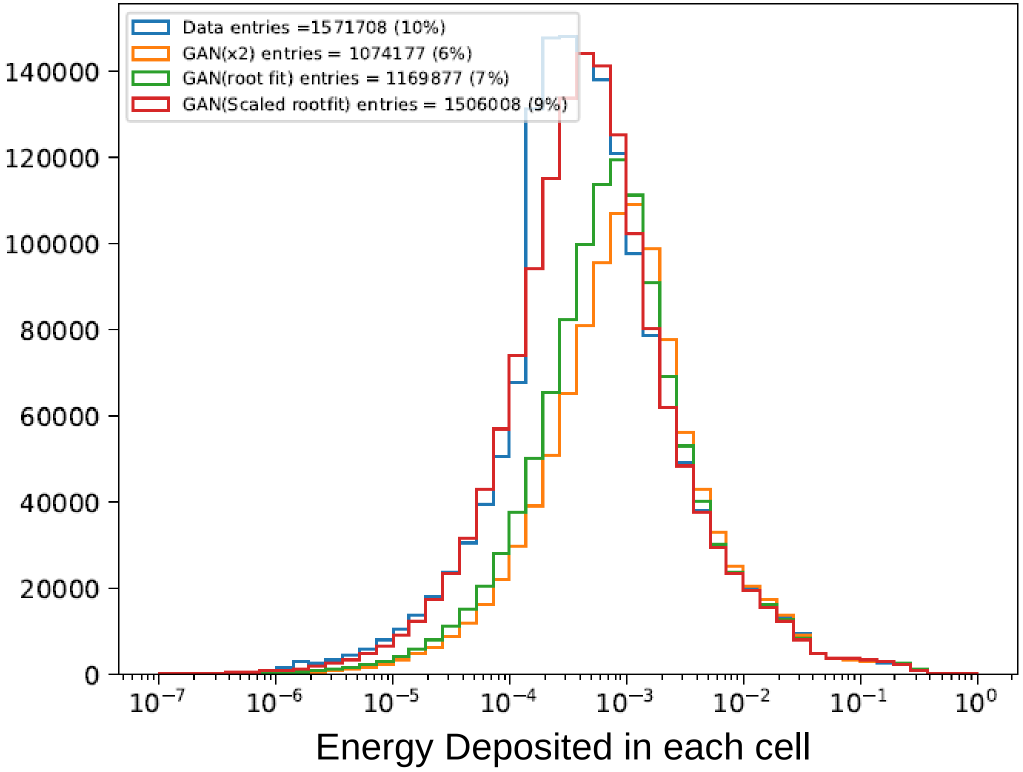
Constant Factor of 50

Fitting the Data to fourth order polynomial

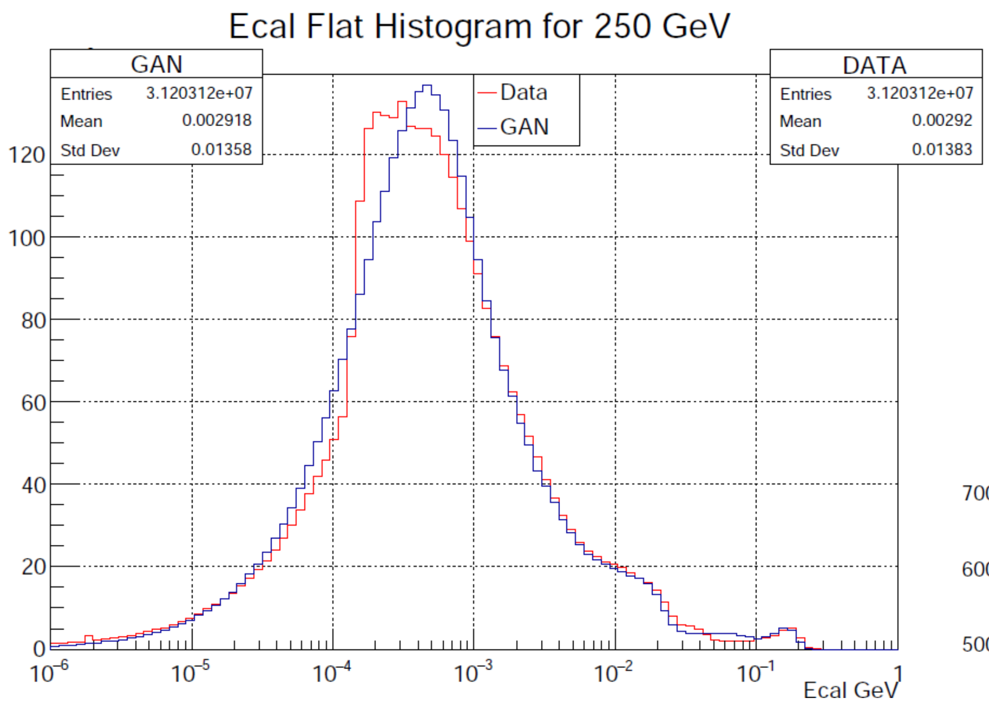


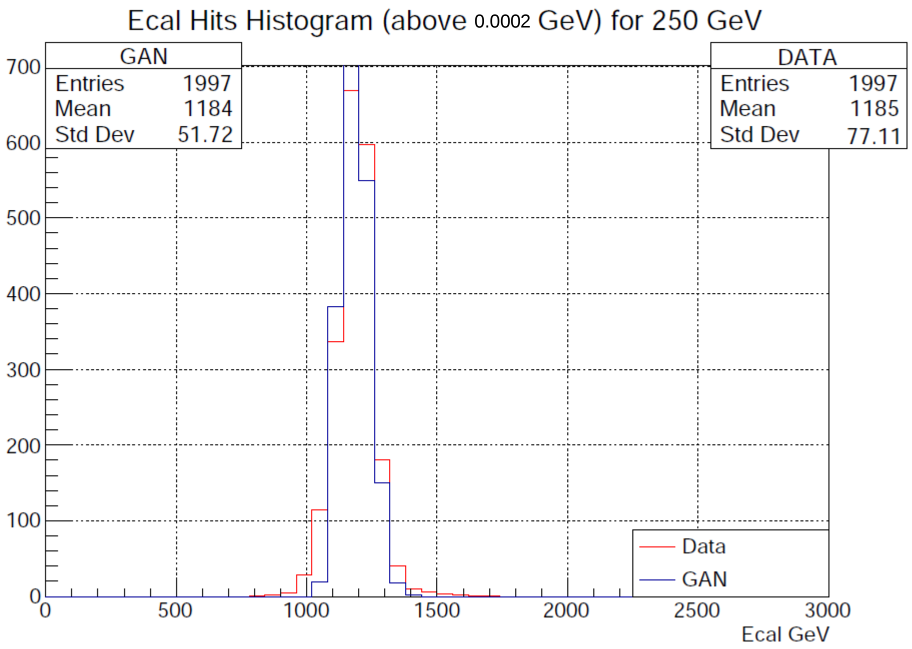
Histogram of energies deposited in cells for 10 to 500 GeV

- Geant4 Data
- GAN
  - ECAL sum = Fixed Factor x Ep
  - 4th order polynomial fit for ECAL sum
  - Cell energies scaled by 100

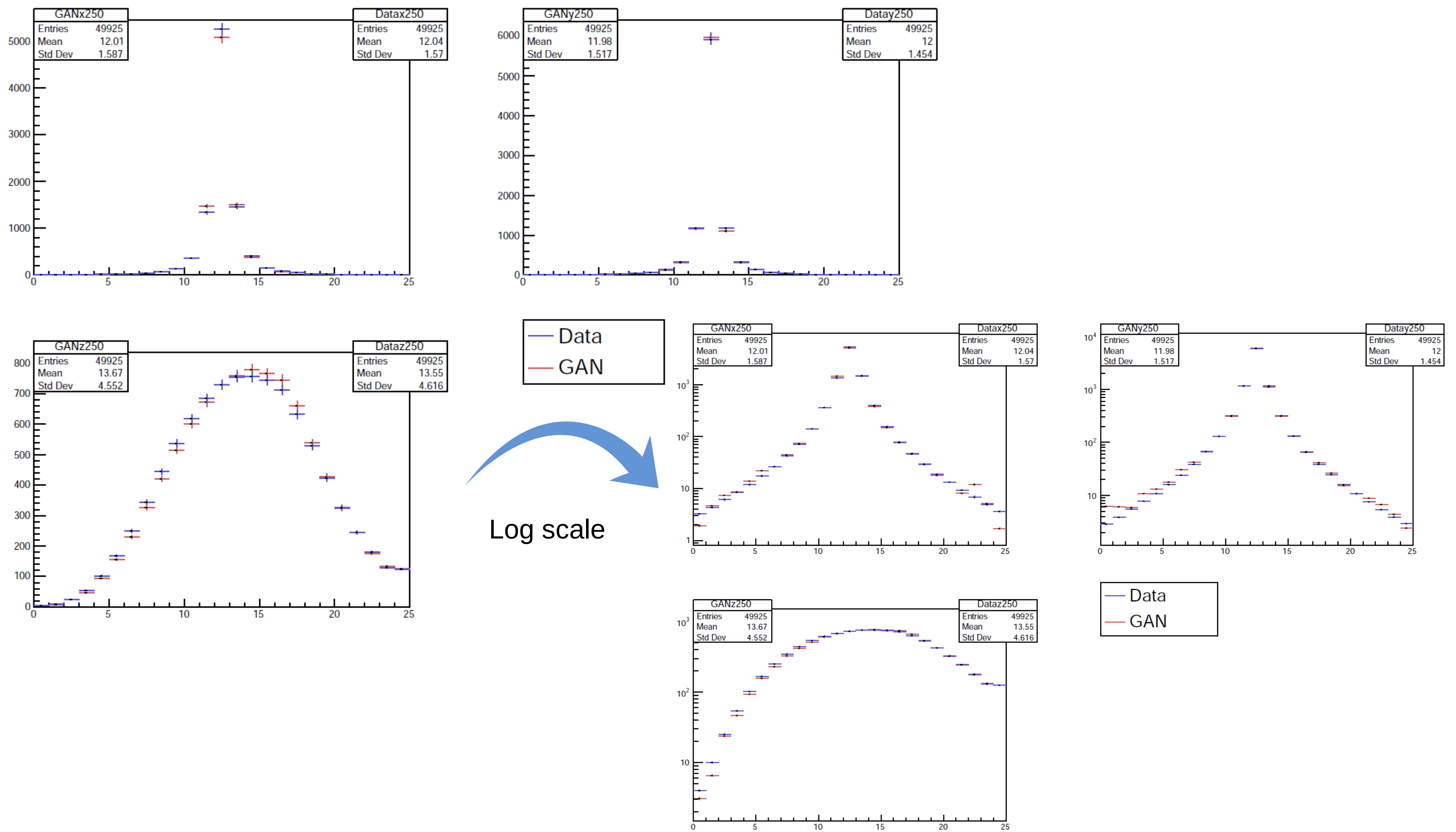


Cell Energy deposition

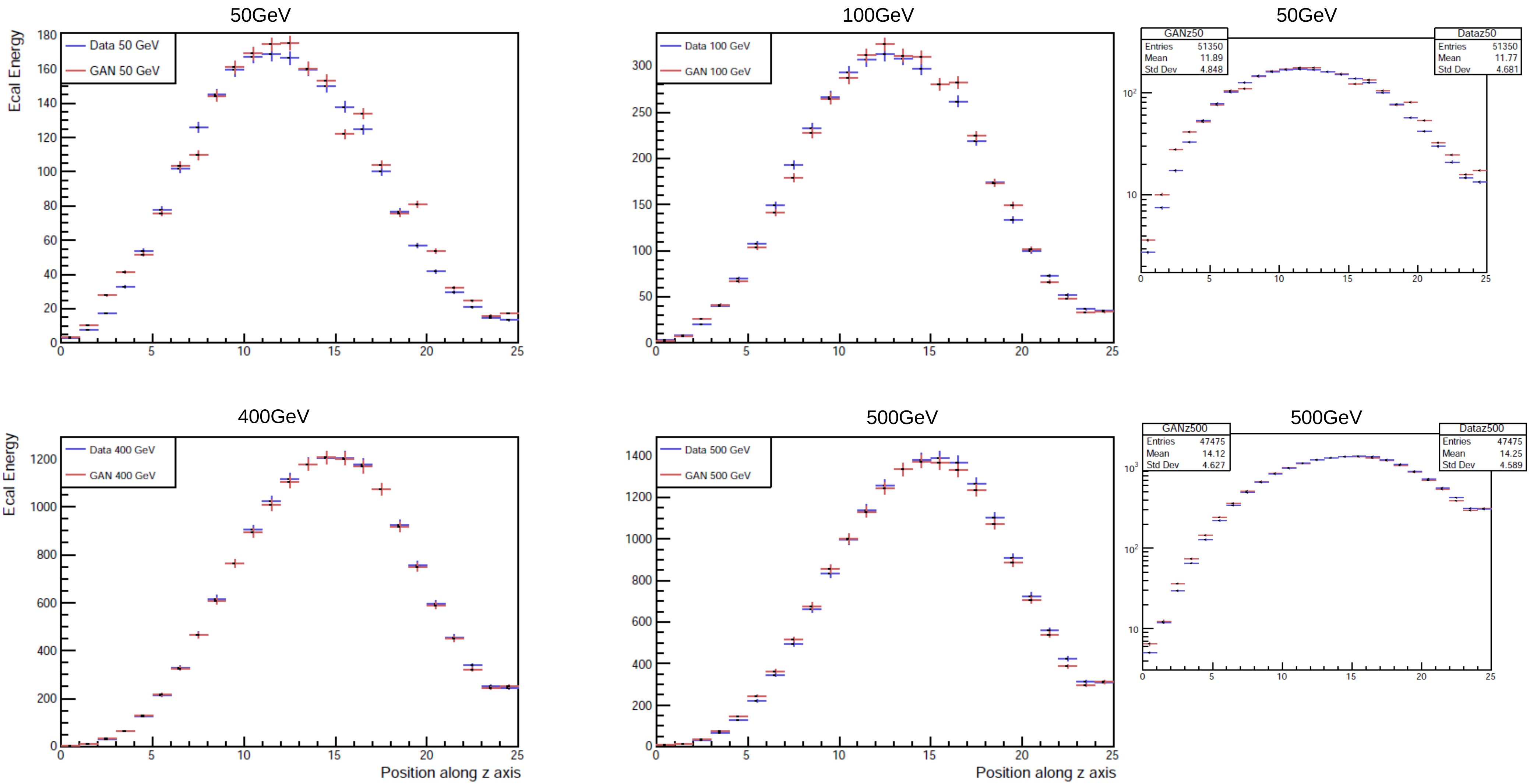




Shower Energy Deposition going along x, y and z axis for 250 GeV

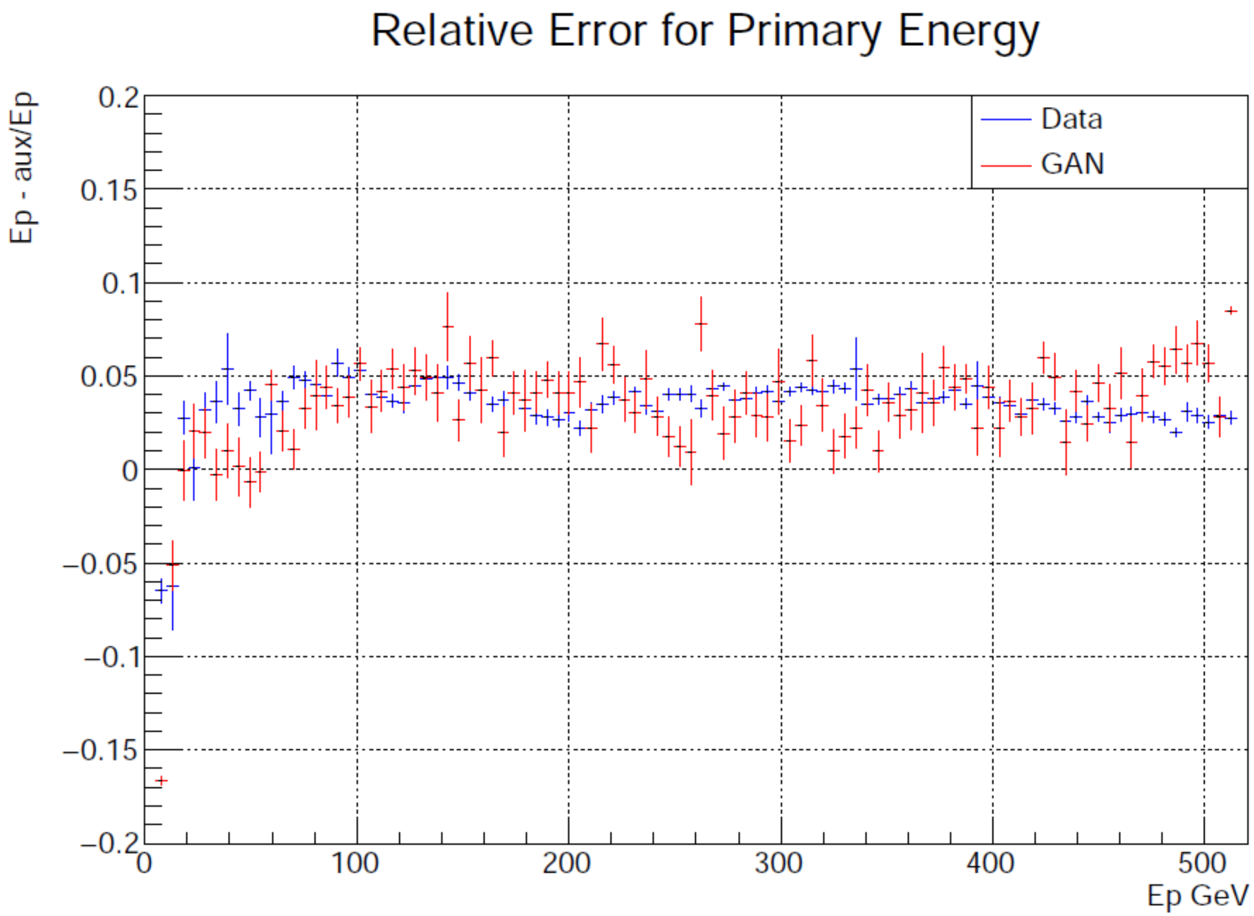


Longitudinal Energy profiles along z axis with electron energies of 50, 100, 400 and 500 GeV

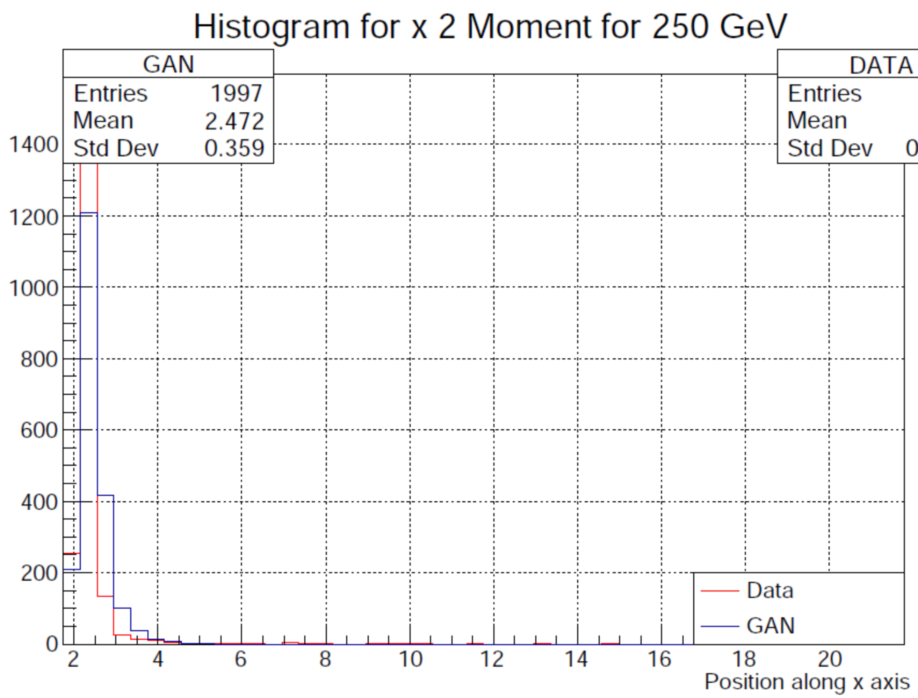


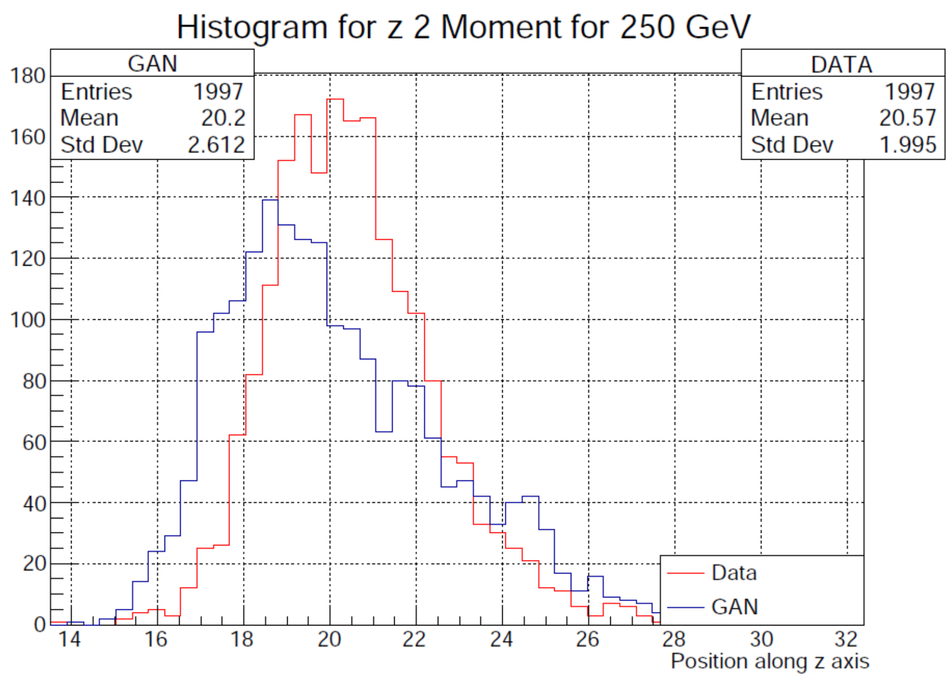
Auxiliary Energy Regression Error

- Reconstructed Primary Energy of incoming particle.
- Around 5 % error



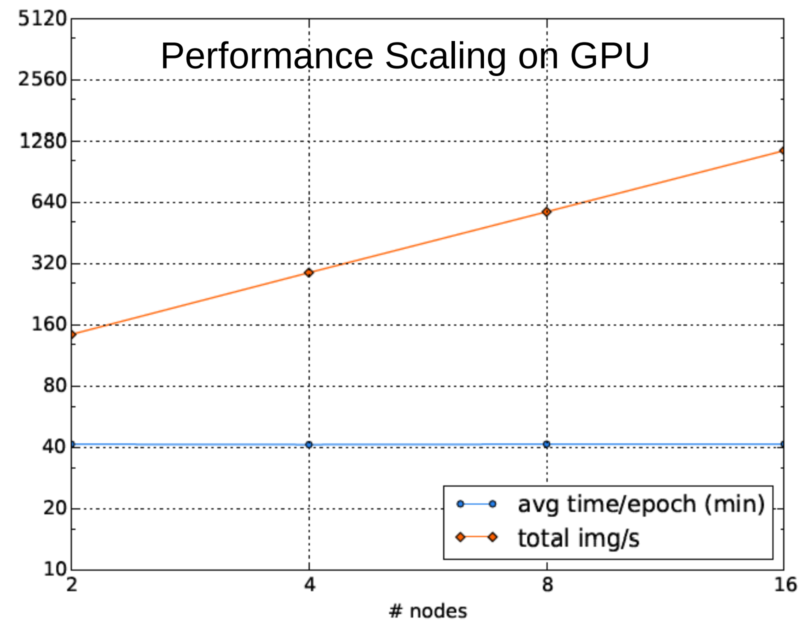
Shower Moments: 2^{nd} Moment = Shower widths

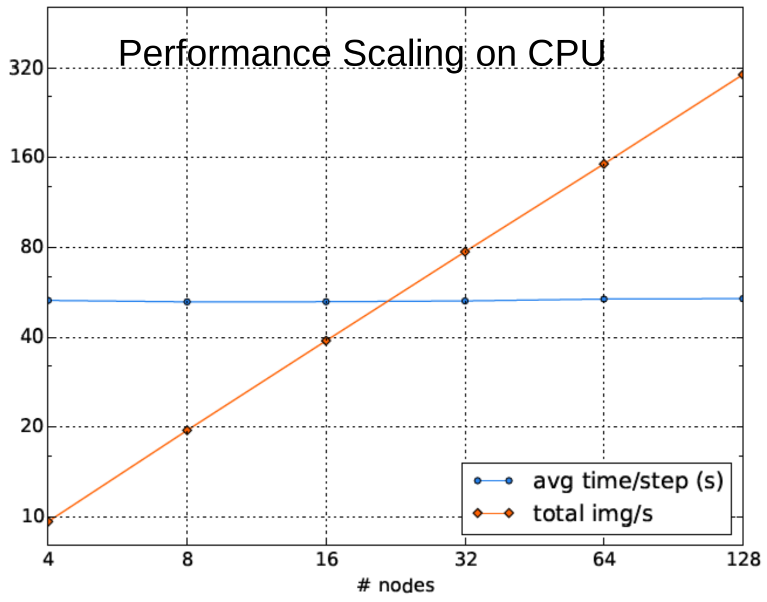




Distributed Training with Cray ML plugin

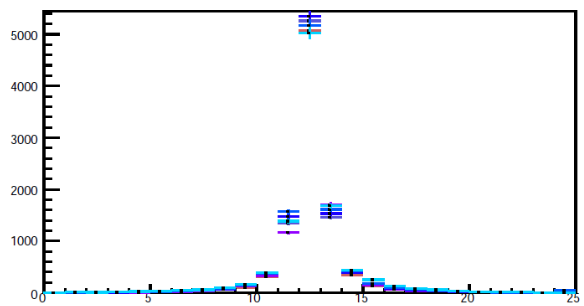
- Synchronous Stochastic Gradient Descent
  - Collaboration with D. Moise (Cray Inc.)

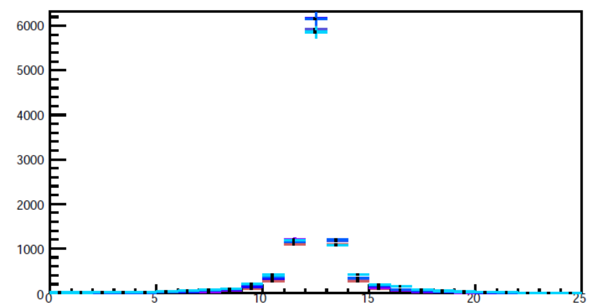


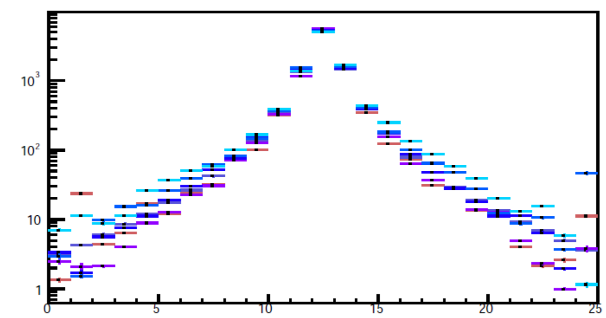


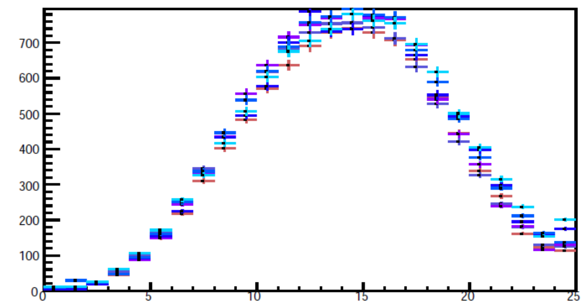
	GPU System	CPU System
Model	XC40/XC50	XC50
Computer nodes	Intel Xeon E5-2697 v4 @ 2.3GHz (18 cores, 64GB RAM) and NVIDIA Tesla P100 16GB	Two Intel Xeon Platinum 8160 @ 2.1GHz (2 x 24 cores, 192GB RAM)
Interconnect	Aries, Dragonfly network topology	Aries, Dragonfly network topology
Step	Epoch	Batch

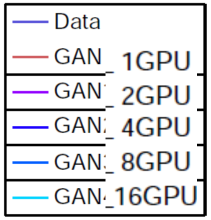
Validation of Distributed Training

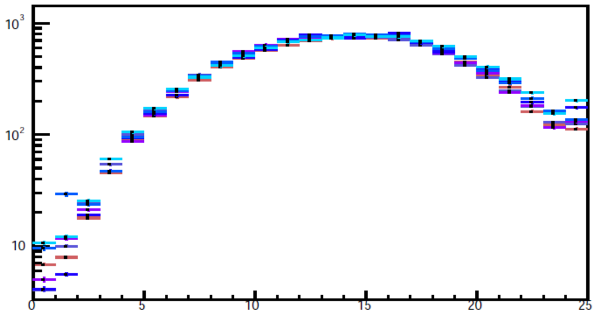






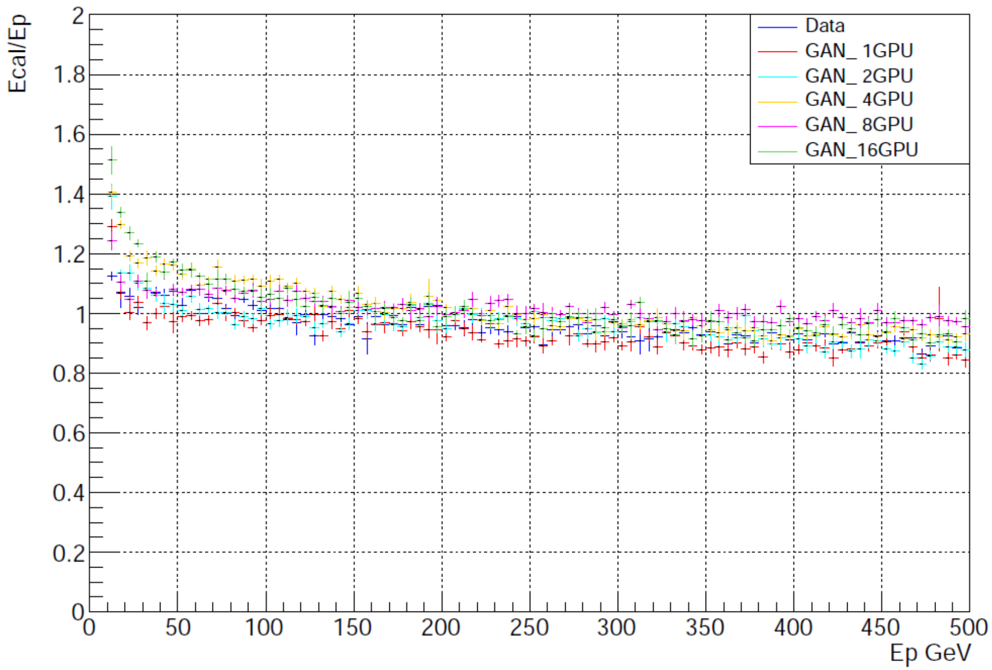






Shower Energy Profiles along x, y and z axis

Ratio of Ecal and Ep



Summary & Future Plans

- Hyper parameter scan
  - Optimization criterion
    - Generation loss for generator:
      - May not correspond to image quality
    - Sum of absolute relative error for histograms
      - Not stable
    - Likelihood function
  - Optimization function
    - Skopt Gaussian process minimization
    - Multi threaded version
      - Collaboration with Jean Roch Vlimant
  - A 2D version for developmental phase
- Distributed training
  - Asynchronous SGD
    - Collaboration with Jean Roch Vlimant
- Digitization and Reconstruction → Greater Speedup
- Other detectors……….

"Caltech ibanks GPU cluster thanks to Prof M. Spiropulu"

Bonus Slides

Publications

- NIPS 2017

  https://dl4physicalsciences.github.io/files/nips_dlps_2017_15.pdf

- ACAT 2017

  https://indico.cern.ch/event/567550/contributions/2627179/

- Super Computing SC2017

  http://sc17.supercomputing.org/SC17%20Archive/tech_poster/tech_poster_pages/post159.html

Some numbers

No.	Quantity	Discription	Size
1.	Memory	Data size	25 G bytes
2.		Discriminator Weights	300 k bytes
3.		Generator Weights	3.5 M bytes
4.		Architecture	2.5 k bytes
5.	Time	Geant4 Intel Xeon Platinum 8180	17000 ms/shower
6.		GAN (batch size = 128) Intel i7 @2.8GHz	66 ms/shower
7.		GAN (batche size =) Intel Xeon Platinum 8180	7 ms/shower
8.		GAN (batch size = 128) GeForce GTX 1080	0.04 ms/shower
8.	Parameters	Discriminator	73,450
9.		Generator	3,457,012