GeantV GANs

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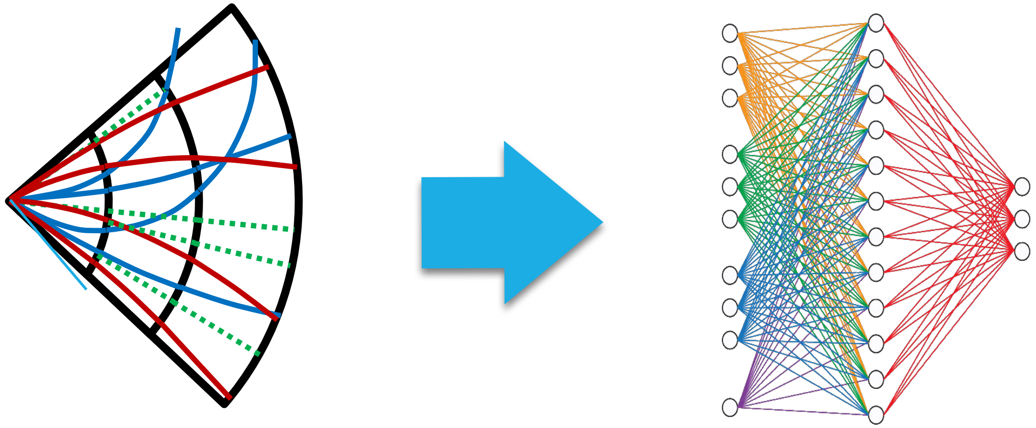
Outline

- Introduction: a general framework for fast simulation
- Simulation as an image reconstruction problem
- Generative Adversarial Networks (GAN)
- Summary & Outlook

Deep Learning for fast sim



Generic approach

Can encapsulate expensive computations

DNN inference step is faster than algorithmic approach

Already parallelized and optimized for GPUs/HPCs.

Industry building highly optimized software, hardware, and cloud services.

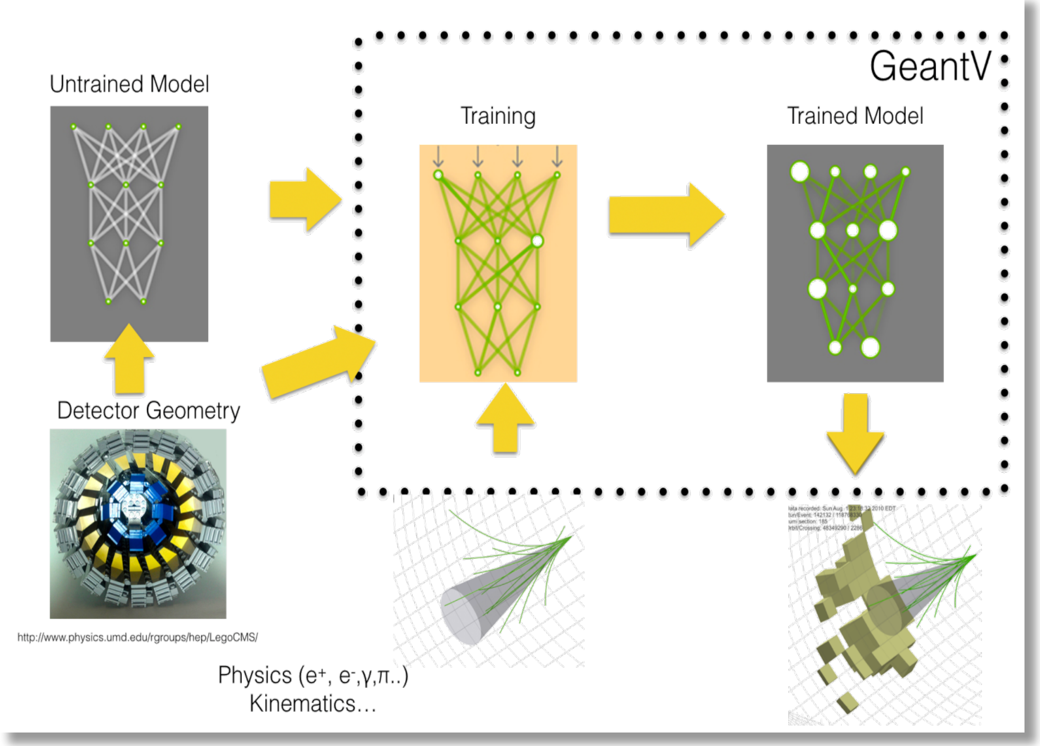
DL engine for fast simulation

A first proof of concept developed within GeantV for a generic, configurable tool

Embed the tool in the GeantV for testing

- Inference step
- Later: automated training

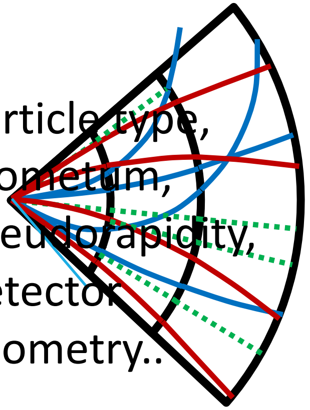
Make it available as standalone tool and in Geant fast simulation framework

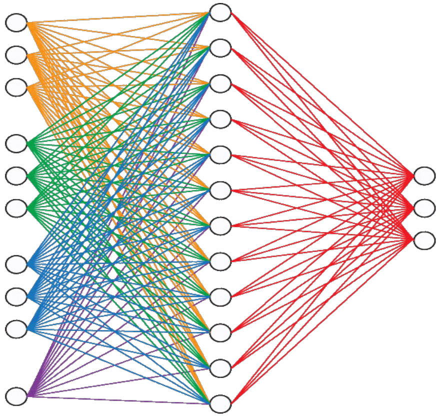


Simulation as “imaging"

EX. SIMULATION OF A CALORIMETER

Particle type,
momentum,
pseudorapidity,
detector
geometry..





Energy
depositions in
cells

Questions:

Can imaging approaches be useful?

Can we keep accuracy while doing things faster?

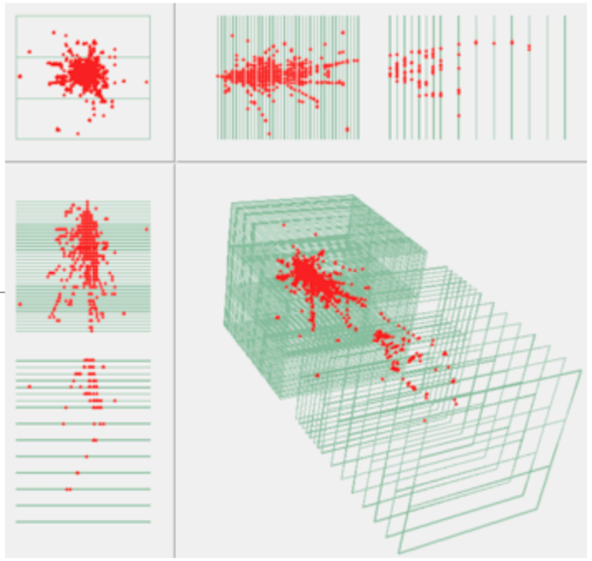
Can we sustain the increase in detector complexity (future highly-granular calorimeters are more demanding)?

What resources are needed?

How generic the network can be?

Can we "adjust" architecture to fit a large class of detectors?

CLIC calorimeter

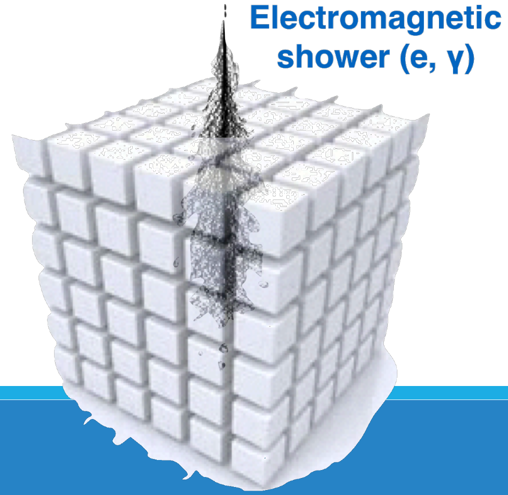


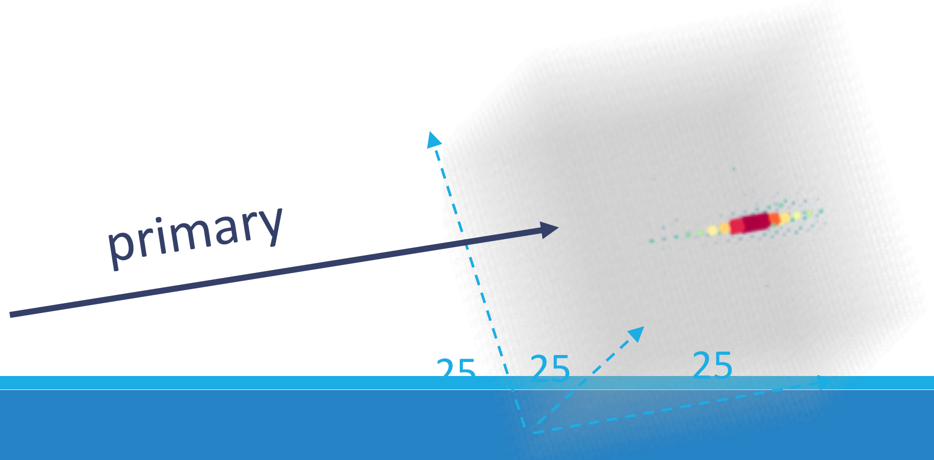
http://cds.cern.ch/record/2254048#

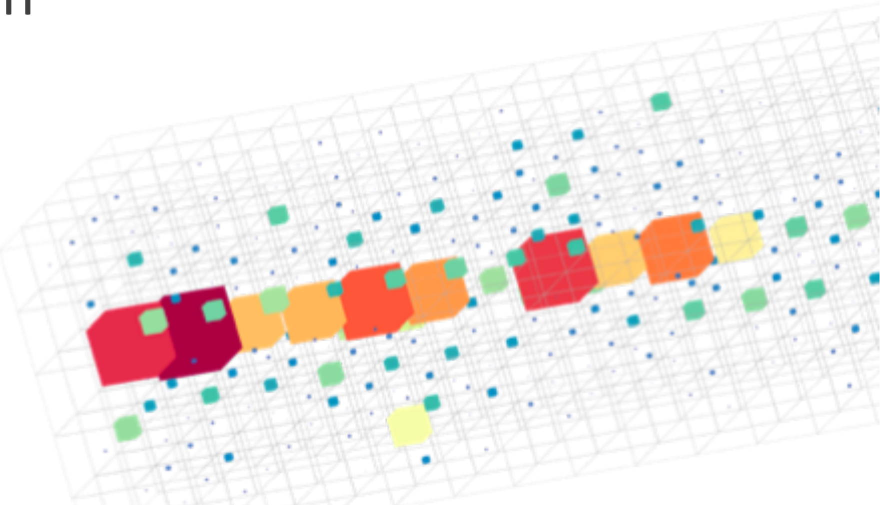
A electromagnetic calorimeter detector design associated to CLIC project

A highly segmented array of absorber material and silicon sensors

- 1.5 m inner radius, 5 mm×5 mm segmentation: 25 tungsten absorber layers + silicon sensors







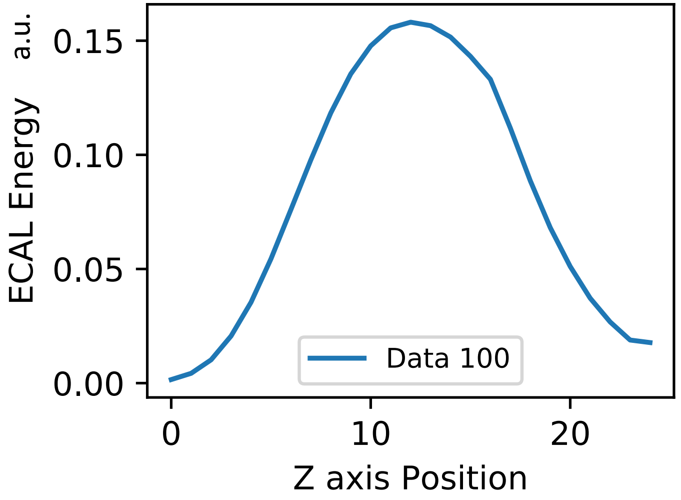
Data is essentially a 3D image

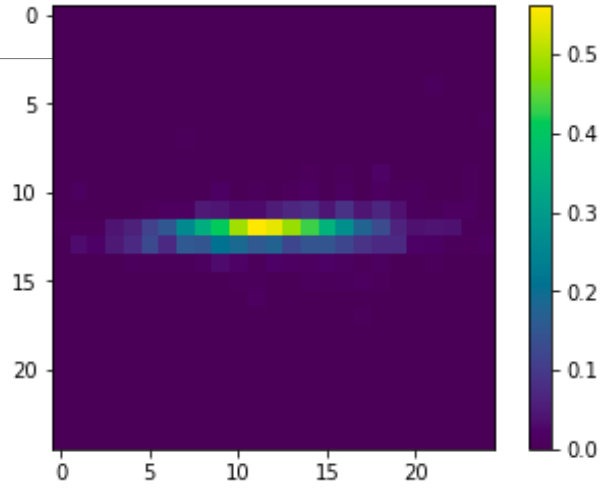
CLIC calorimeter data

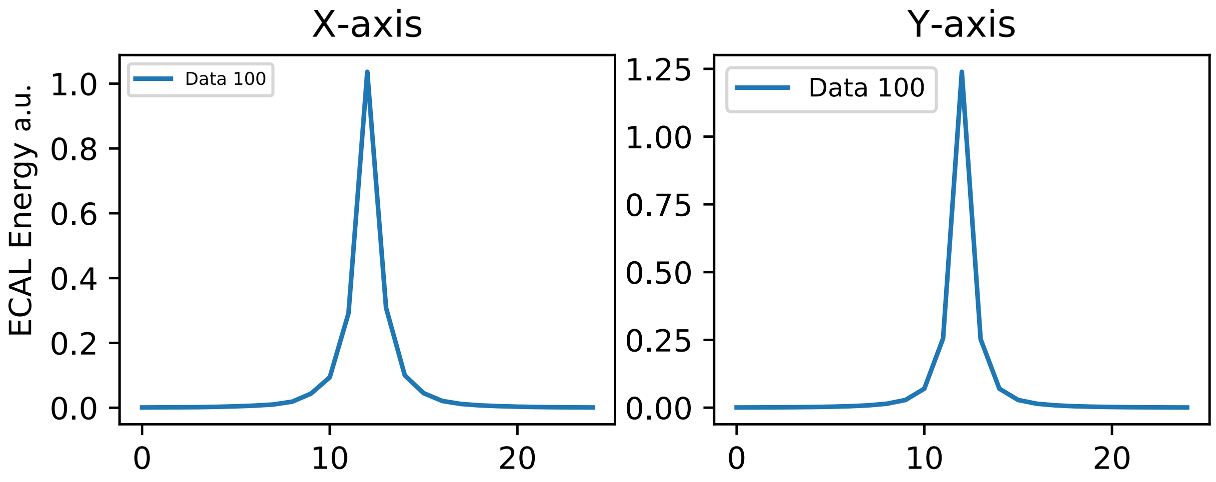
Pixelize detector response around shower barycentrum

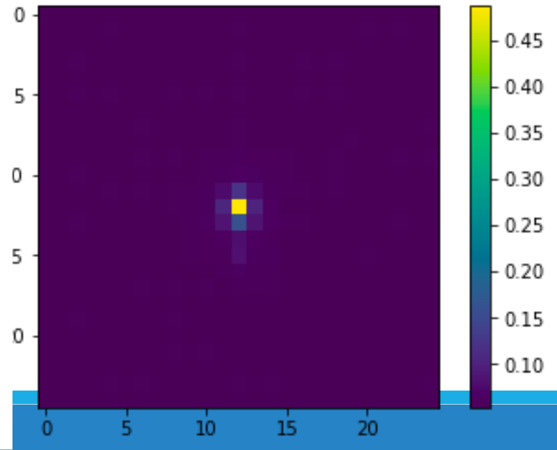
Sparse Images

Non-linear location-dependency features









GeantV GAN for calorimeter images

Generative Adversarial Networks

3D (de)convolutions to describe full shower development

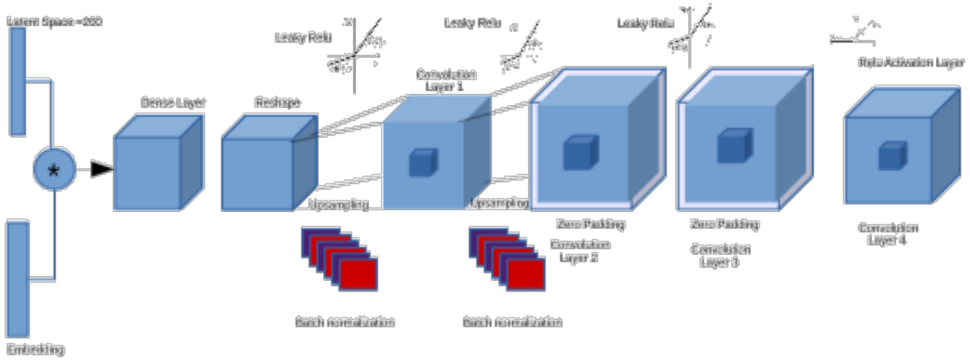
- Architecture similar to auxiliary classifier GANs

Implemented tips&tricks found in literature

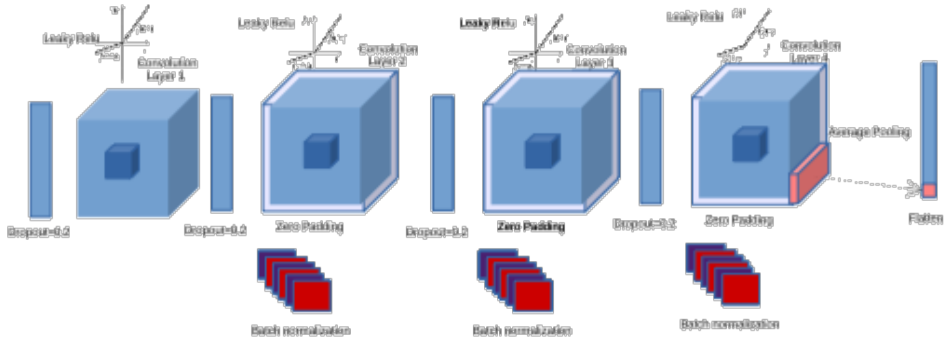
- Some helpful (no batch normalisation in the last step, LeakyRelu, no hidden dense layers, no pooling layers)
- Some not (Adam optimiser)

Batch training

Loss is combined cross entropy

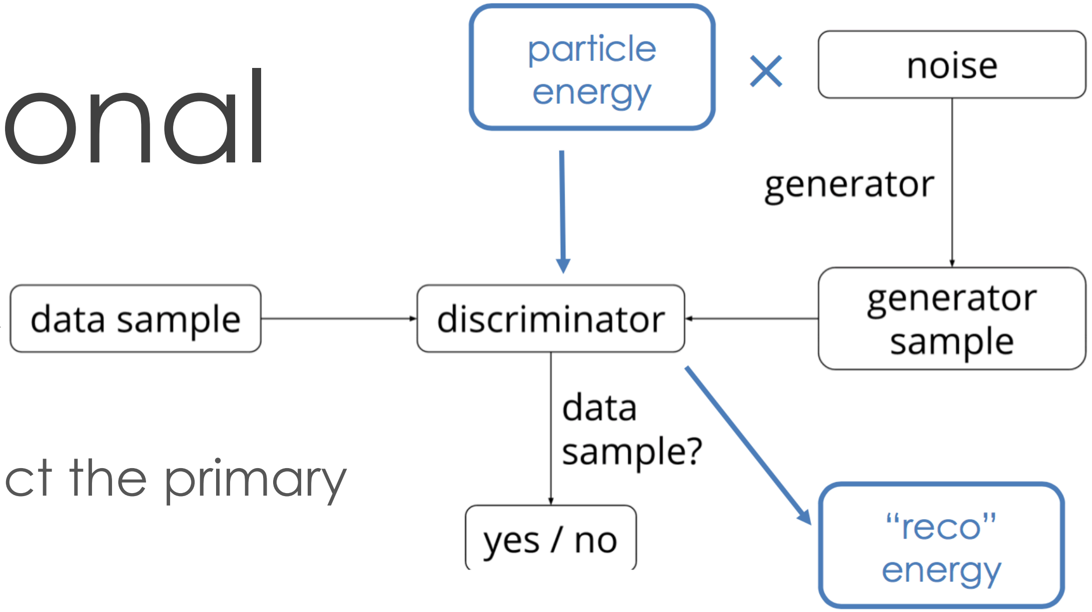


GENERATOR



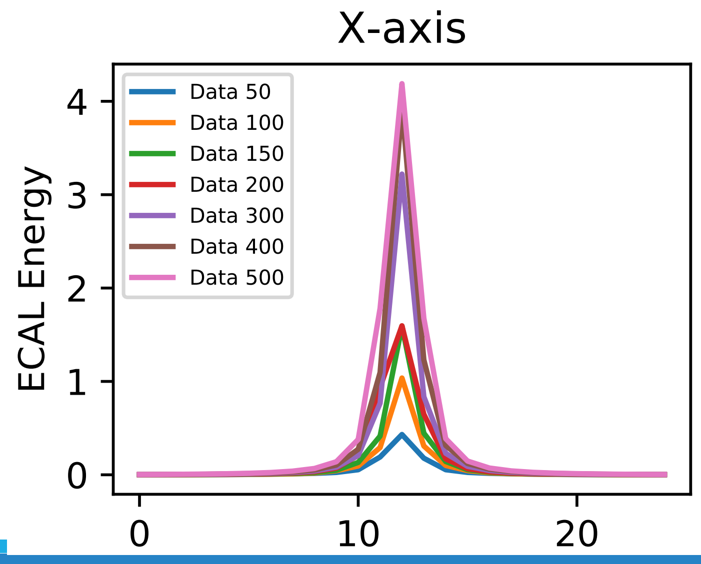
DISCRIMINATOR

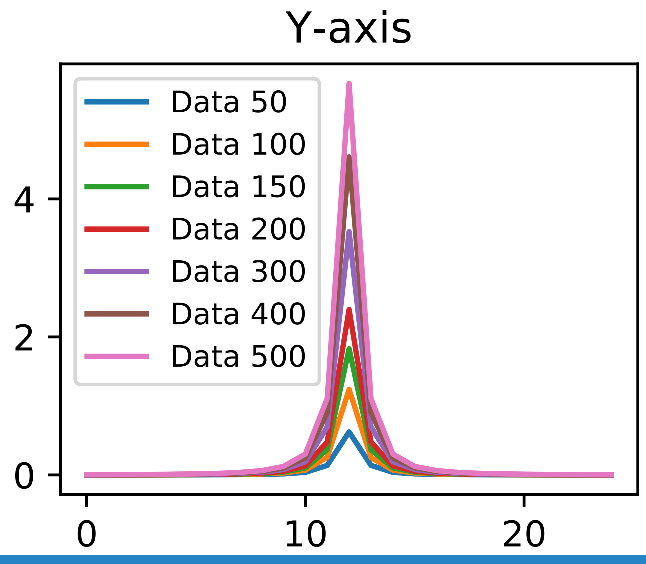
Conditioning on additional variables



Add a regression task to the discriminator to reconstruct the primary particle energy

Train the generator to reproduce correct shapes





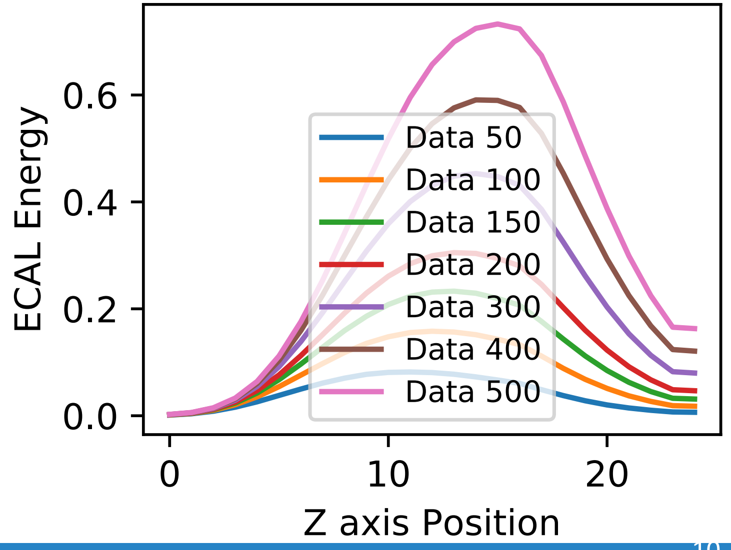


Image quality assessment and validation

- Detailed study of calorimeter response
  - Energy distribution in single cells
- Average shower shapes
- Primary particle energy estimation from discriminator
- High level variables (e.g. jet features)
- Does analysis tools performance change if we replace detailed simulation with GAN generated data? (e.g. particle identification algorithms)

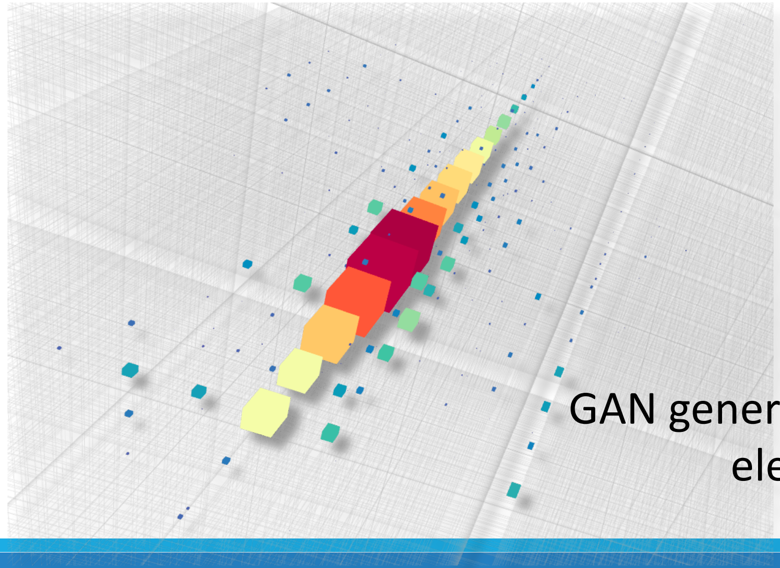
WORK iN PROGRESS

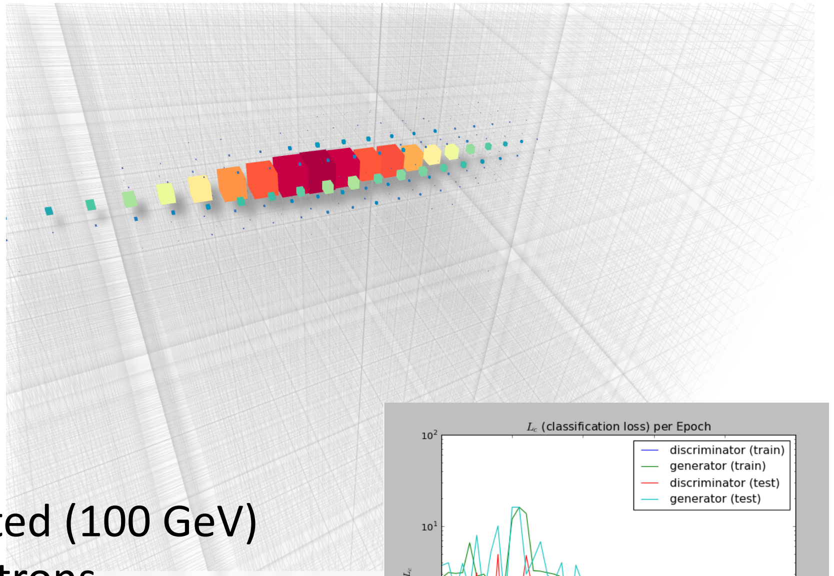
Comparison to full sim and different fast sim tools

First 3D images

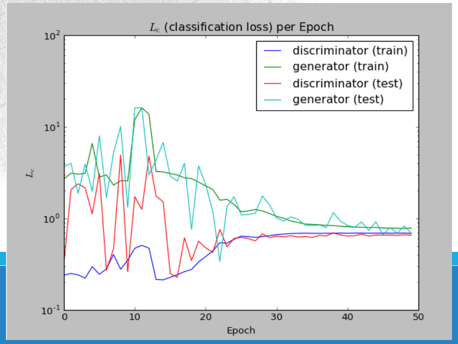
First generated results look promising!

Qualitative results show no collapse problem

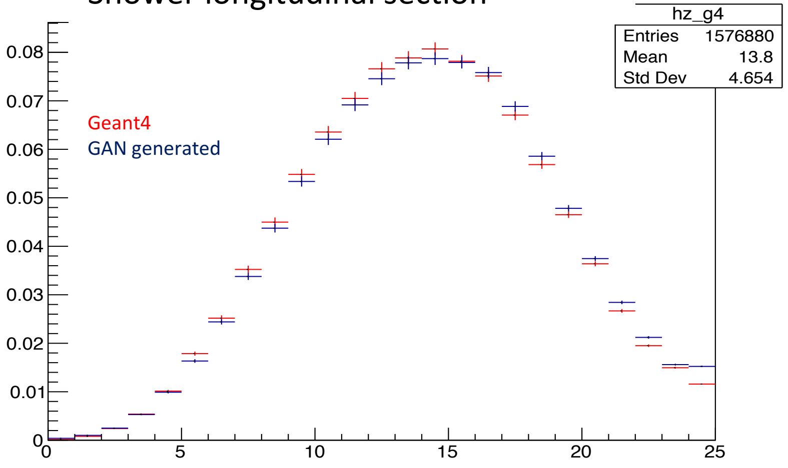




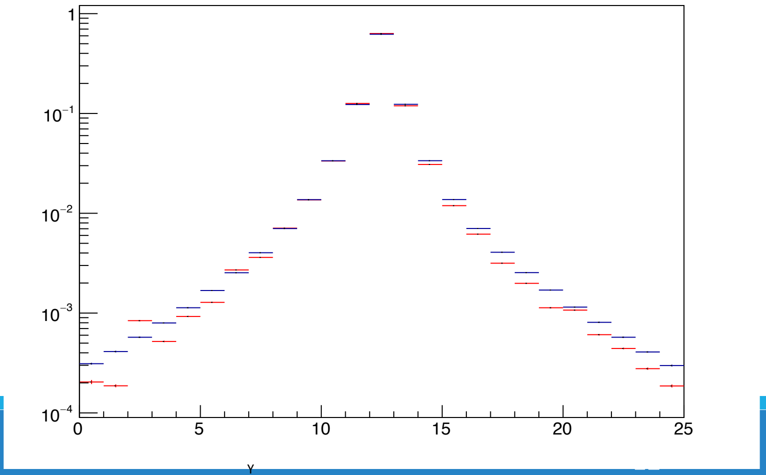
GAN generated (100 GeV) electrons



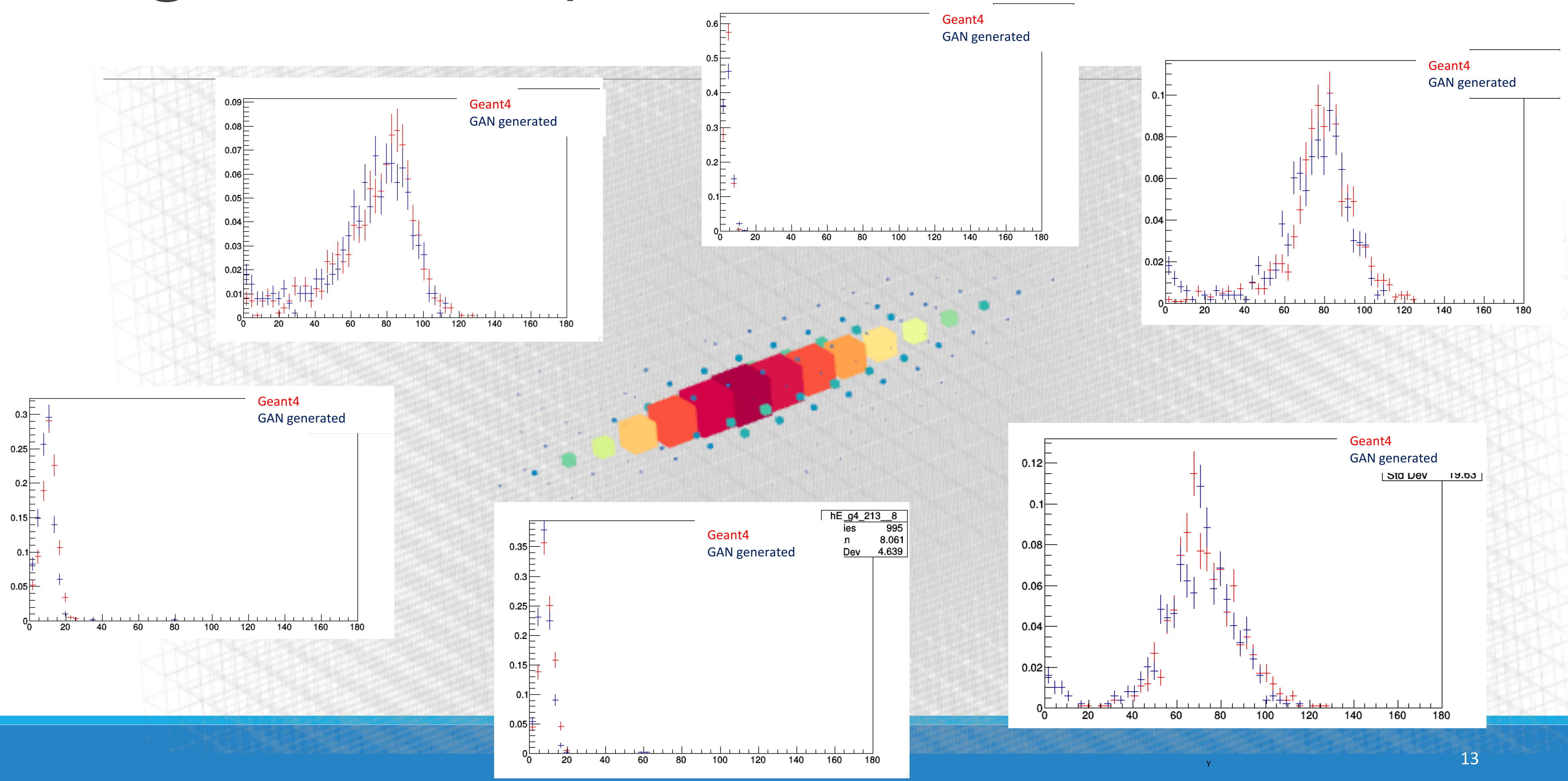
Shower longitudinal section



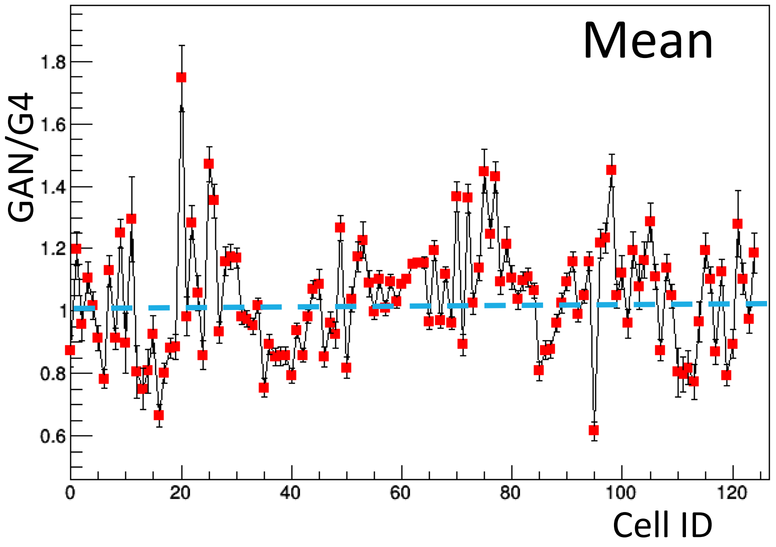
Shower transverse section

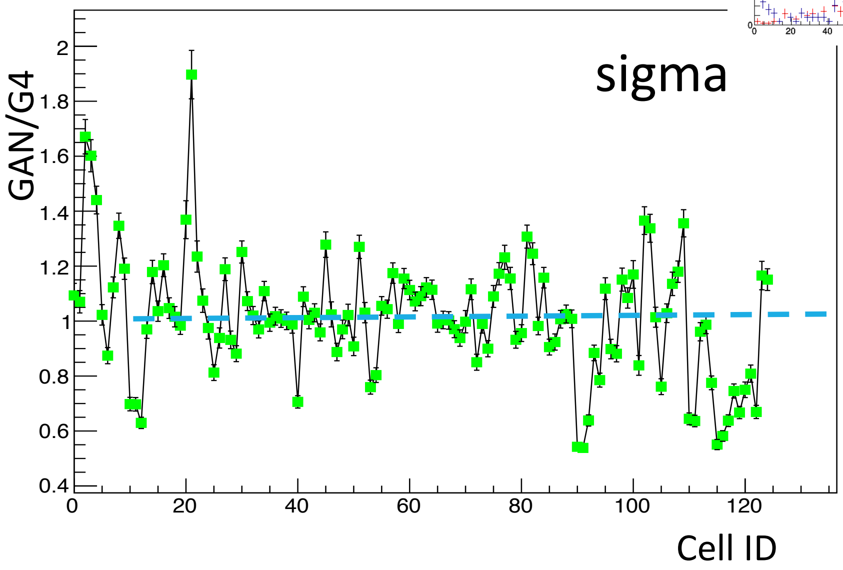


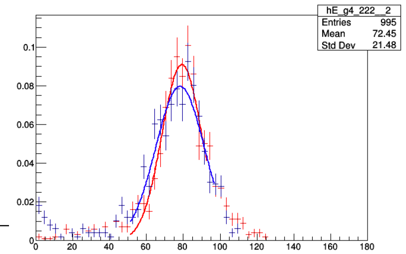
Single cell response



Single cell response



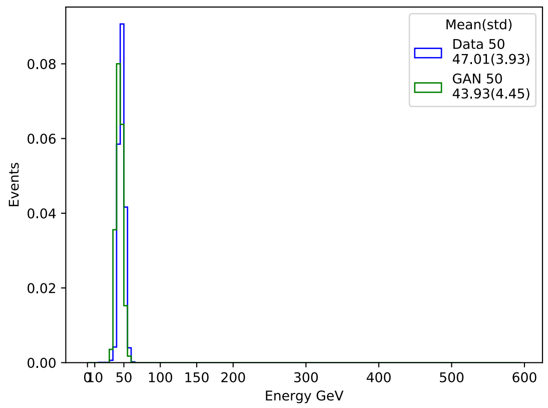




Single cell response is not perfect

- Set up higher level criteria for image validation (reconstructed variables)

Energy regression test



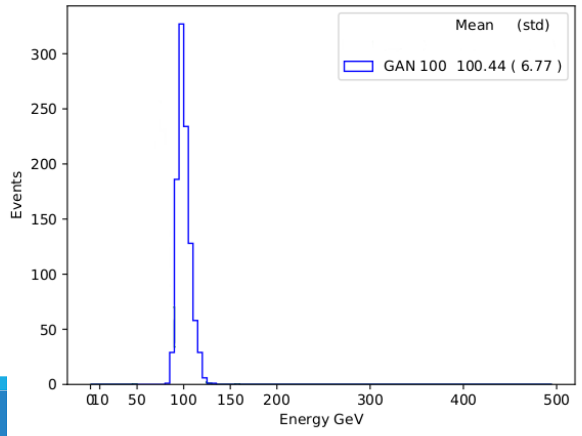
Train the network on a uniform energy spectrum (100-500) GeV

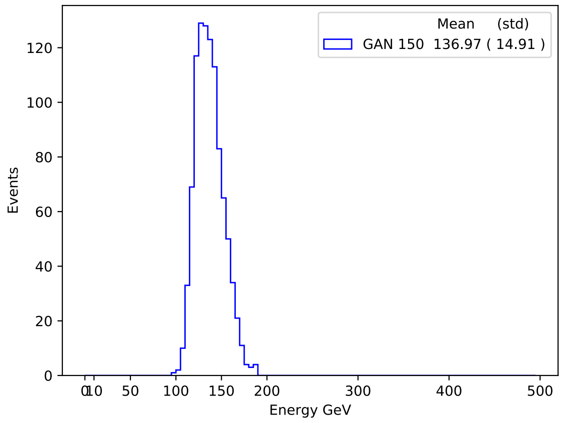
Test the capability of the discriminator to correctly predict the primary particle energy.

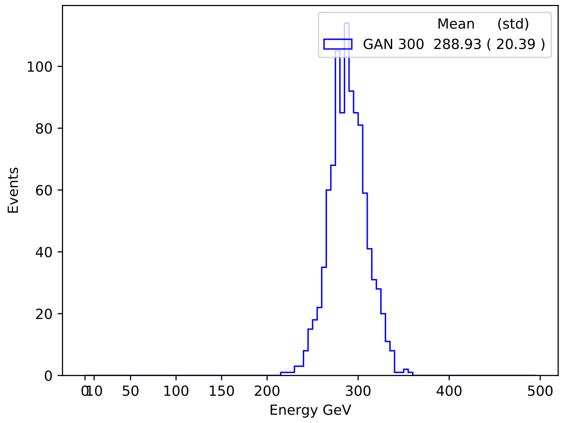
This is an additional regression task.

Not the typical simulation use case

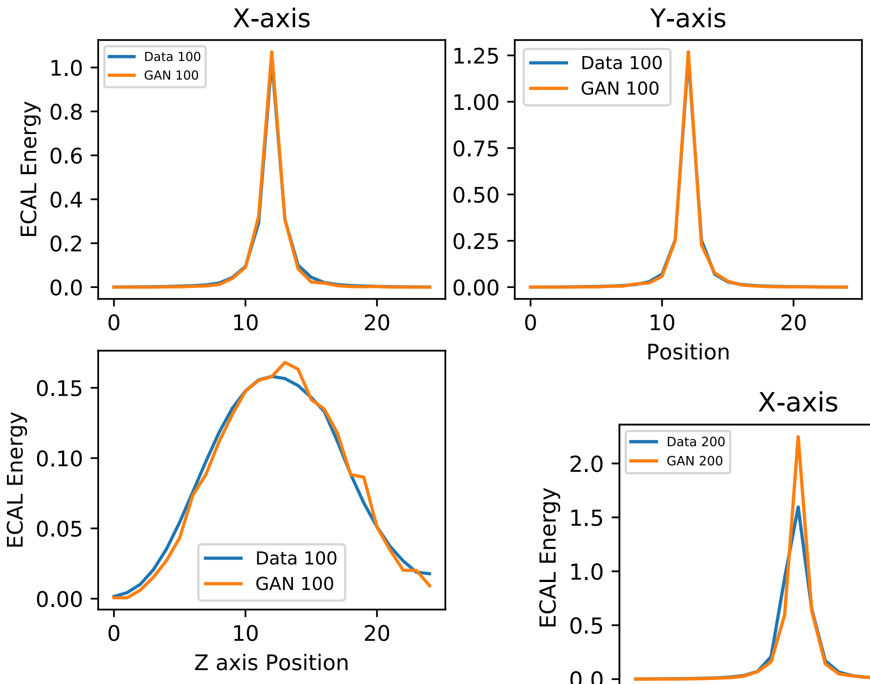
Energy (GeV)	Error (%)
100	5
150	13
200	10
300	6
400	10
500	15



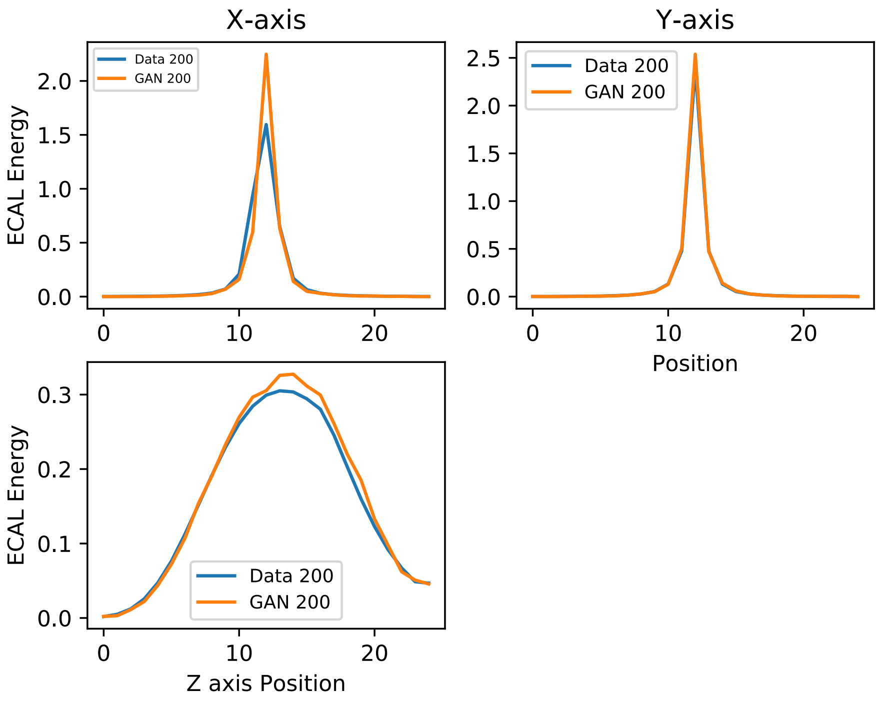


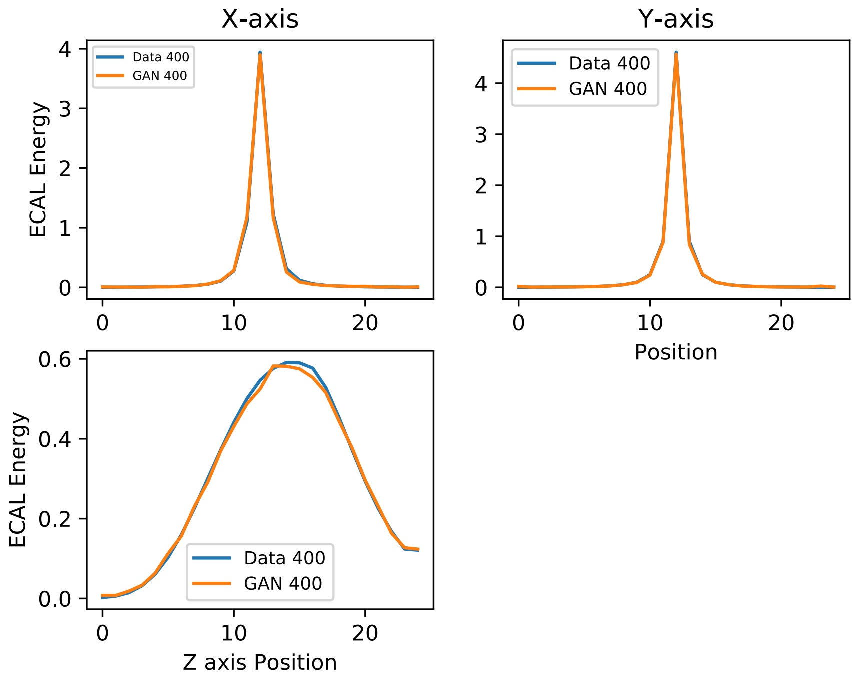


Shower shapes vs energy



Check that the networks correctly describes the energy shapes for different input energies (generator output)



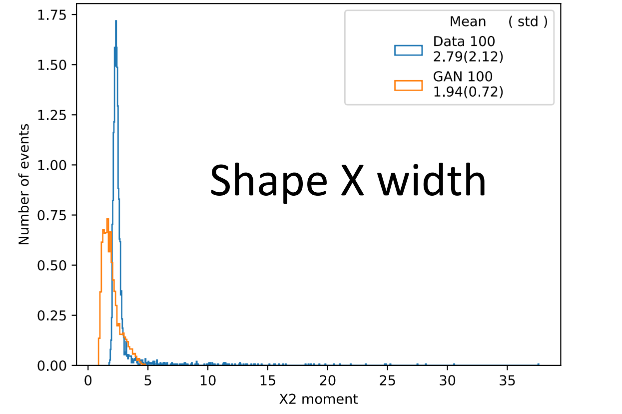


Further optimization

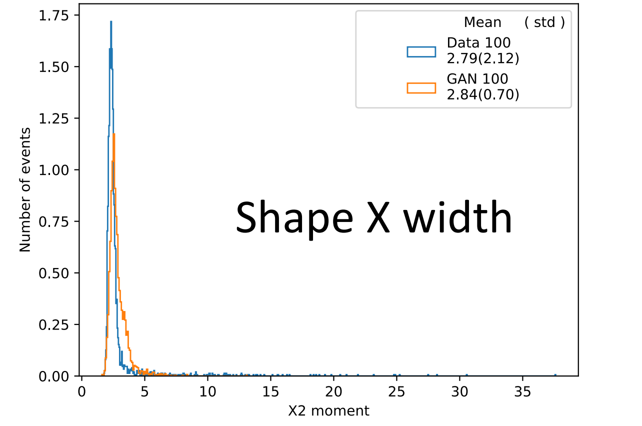
More detailed validation running several analyses tools on generated images (work done with M.Pierini (CMS), A. Farbin, B. Hooberman (ATLAS))

To improve GAN performance we need large hyper-parameter scans:

- Currently testing sklearn/skopt framework --> rather slow
- Scan cost function based on total energy deposited along each axis + position of shower max



Additional layer in discriminator:
Small filter size



From the computing resources perspective…

Inference

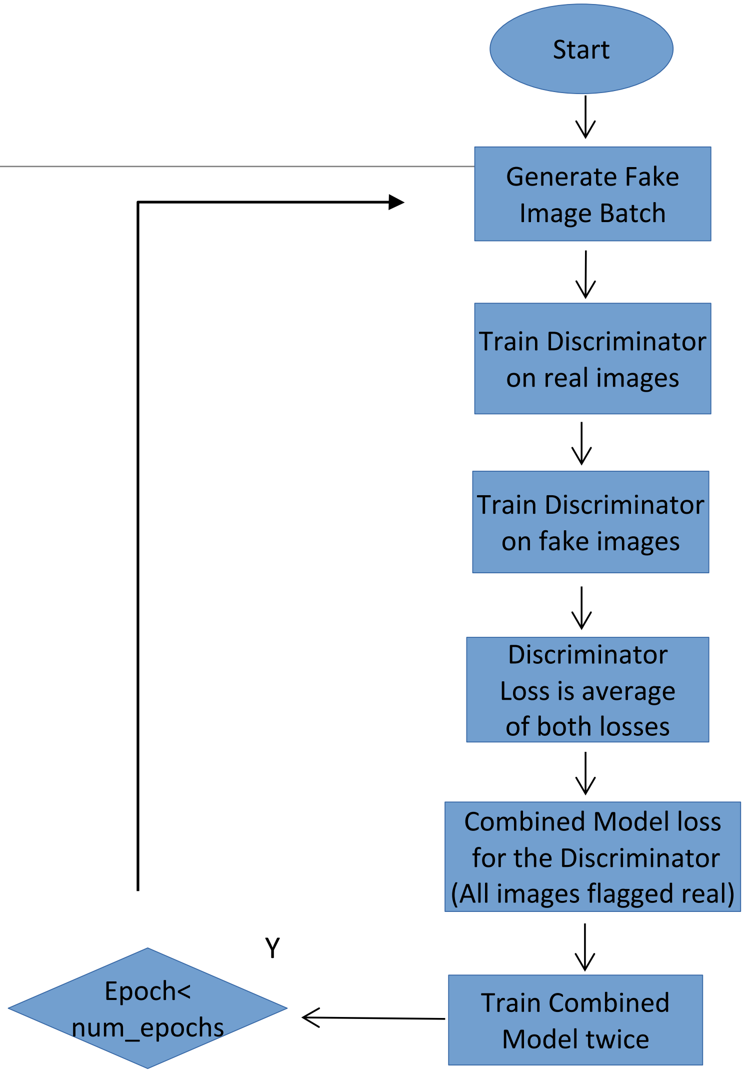
		Time/Shower (msec)
Full Simulation (G4)	Intel Xeon E5	56000
3d GAN (batchsize 128)	Intel i7 (laptop)	66
	GeForce GTX 1080	0.04

- Using a trained model is very fast
  - Orders of magnitude faster than detailed simulation
  - Even on a simple laptop!

Testing performance on FPGA and new integrated accelerator technologies (with HTC group)

Training

- Training on NVIDIA GTX-1080 (30 epochs, 180k particles): ~24h
- Test different hardware/environment
  - Intel® Xeon Phi™
  - Cloud
- We want to provide a generic, fully configurable tool
- Optimal network design depends on the problem to solve
  - Hyper-parameters tuning and meta-optimization
- Parallelization on distributed systems



Summary

A generic framework with common fast sim algorithm and strategies for mixing full and fast sim

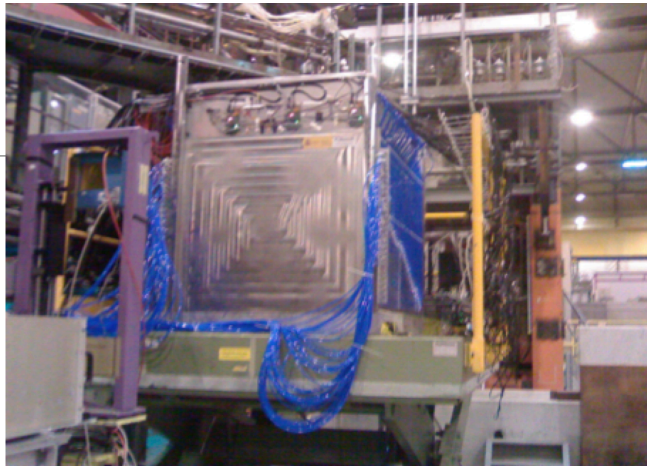
- Could bring great benefit to the HEP community
- Serve small experiments/collaborations as well

Generative Models seem good candidates to speedup simulation

- Rely on the possibility to interpret “events” as “images”
- First GANs applications to calorimeter simulations look very promising
- Many studies ongoing in the different experiments

Plans

SDHCAL prototype during SPS test beam



3d GAN is the initial step of a wider plan towards a generic fully configurable tool

- Refining validation
- Implement parallel training (probably start with data parallel approach) and study scaling on clusters
- Studying how generic our network can be:
  - Test on highly granular calorimeters (FCC LAr calorimeter, CALICE SDHCAL)
- Integrated example in GeantV
  - First inference tool in GeantV beta