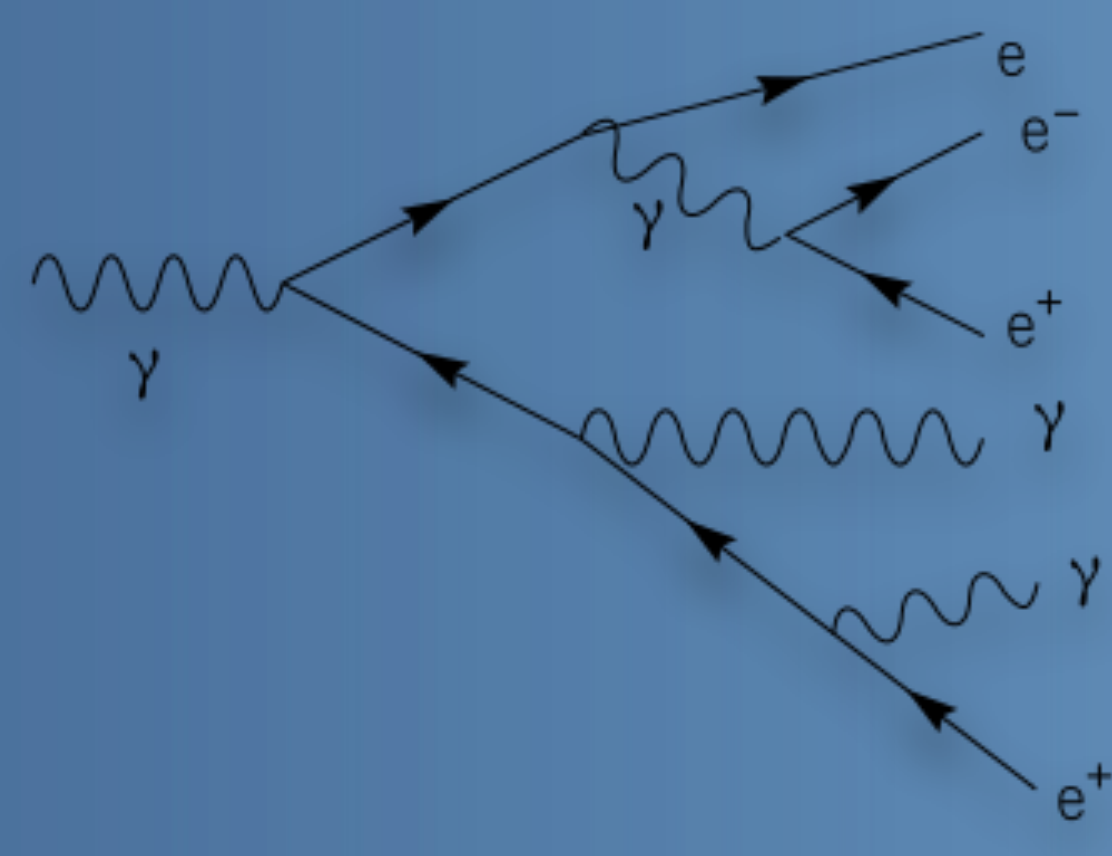


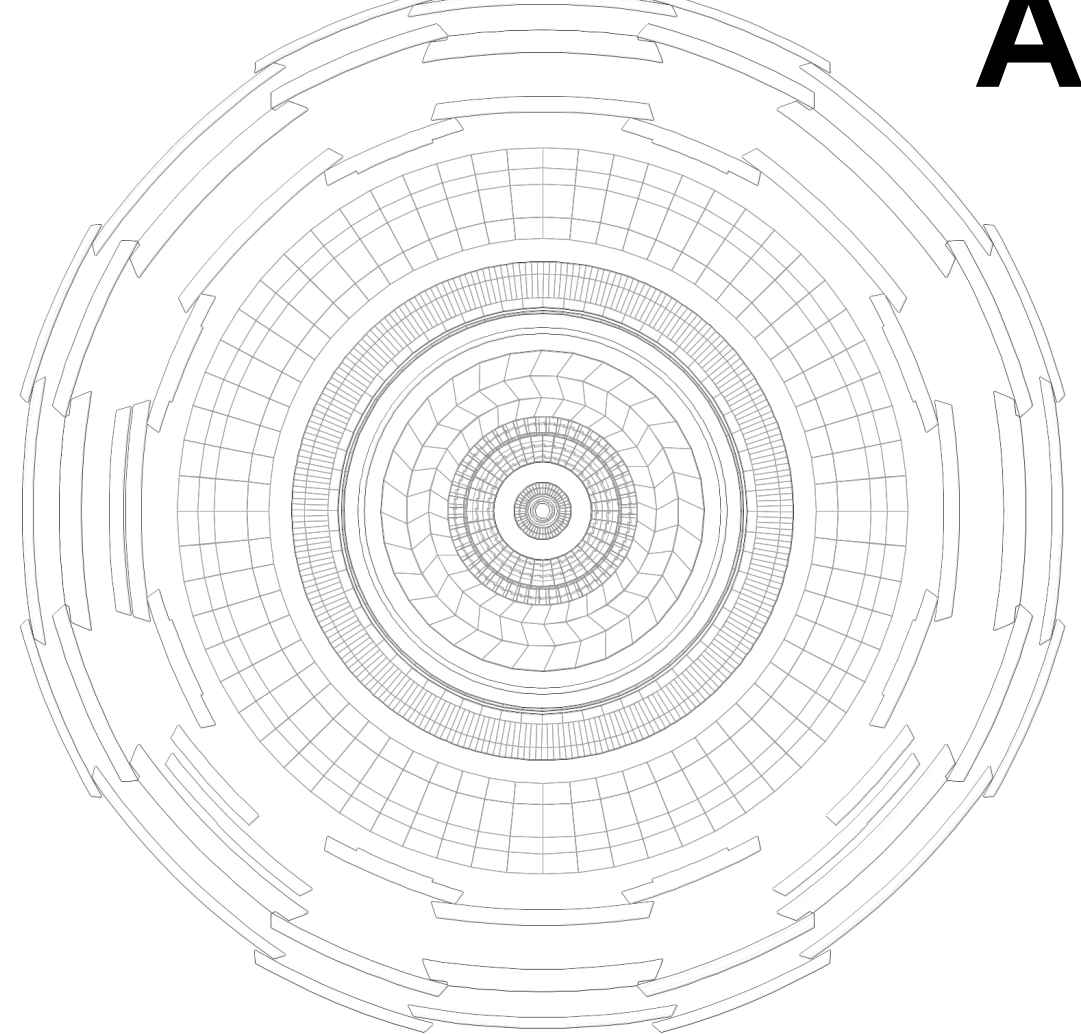
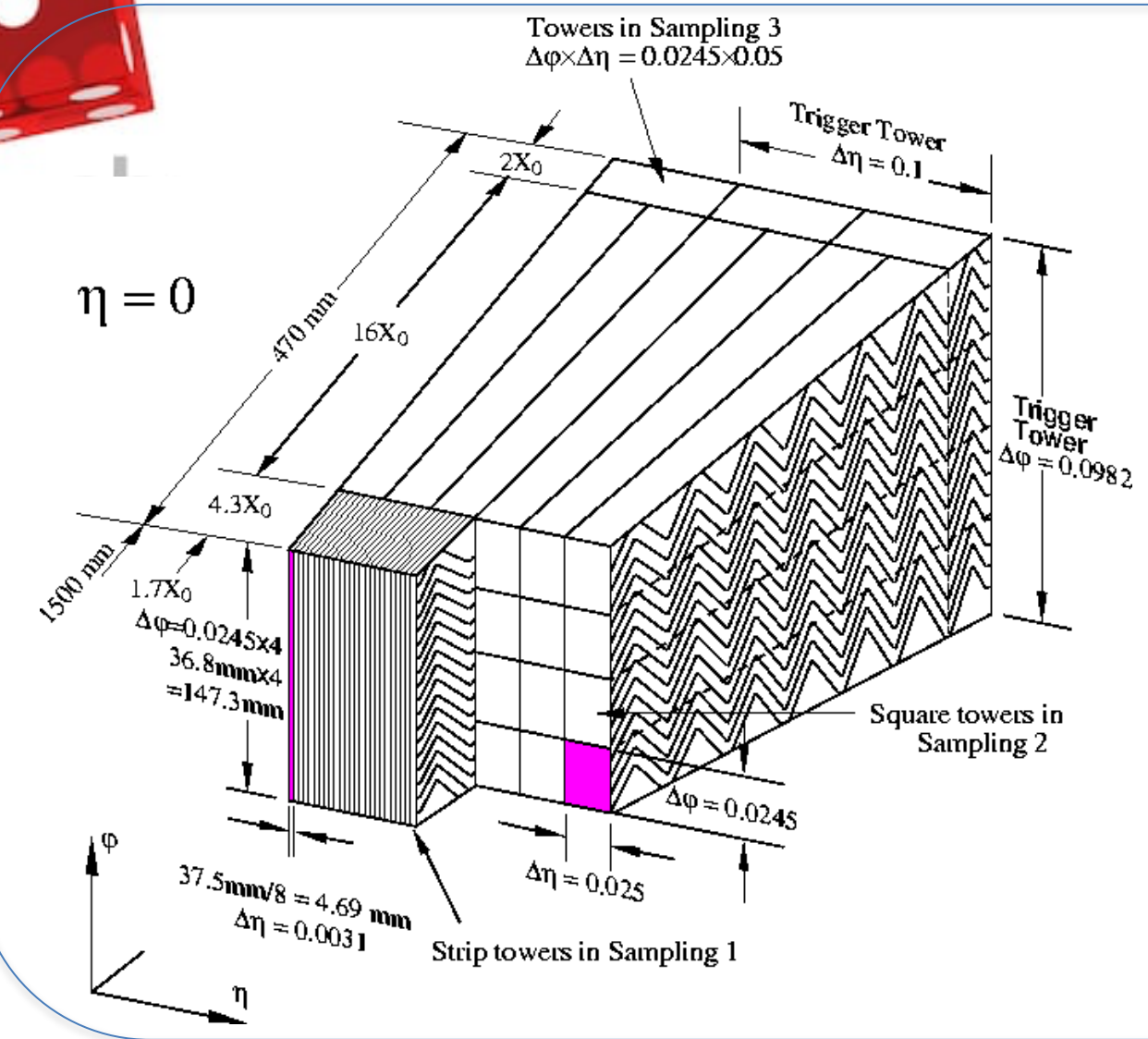
# Generative Adversarial Networks for fast shower simulation in ATLAS



Current human designed fast simulation methods fulfil need for large scale simulations at the cost of accuracy. Lightning fast neural nets could learn to generate the physics instead. A 2-vs-1 competition between neural networks is studied for EM shower simulation.

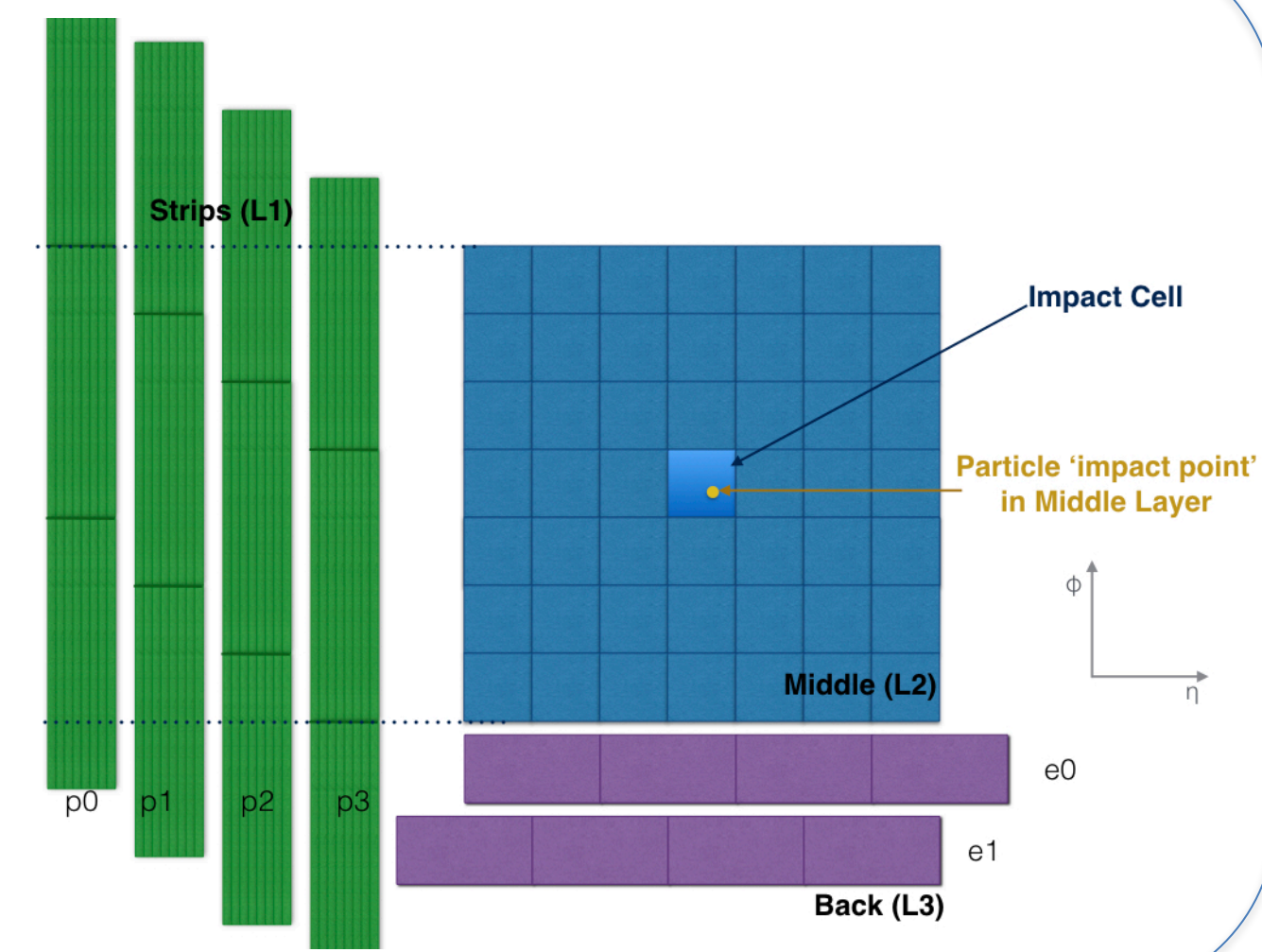


## Atlas EM Calorimeter

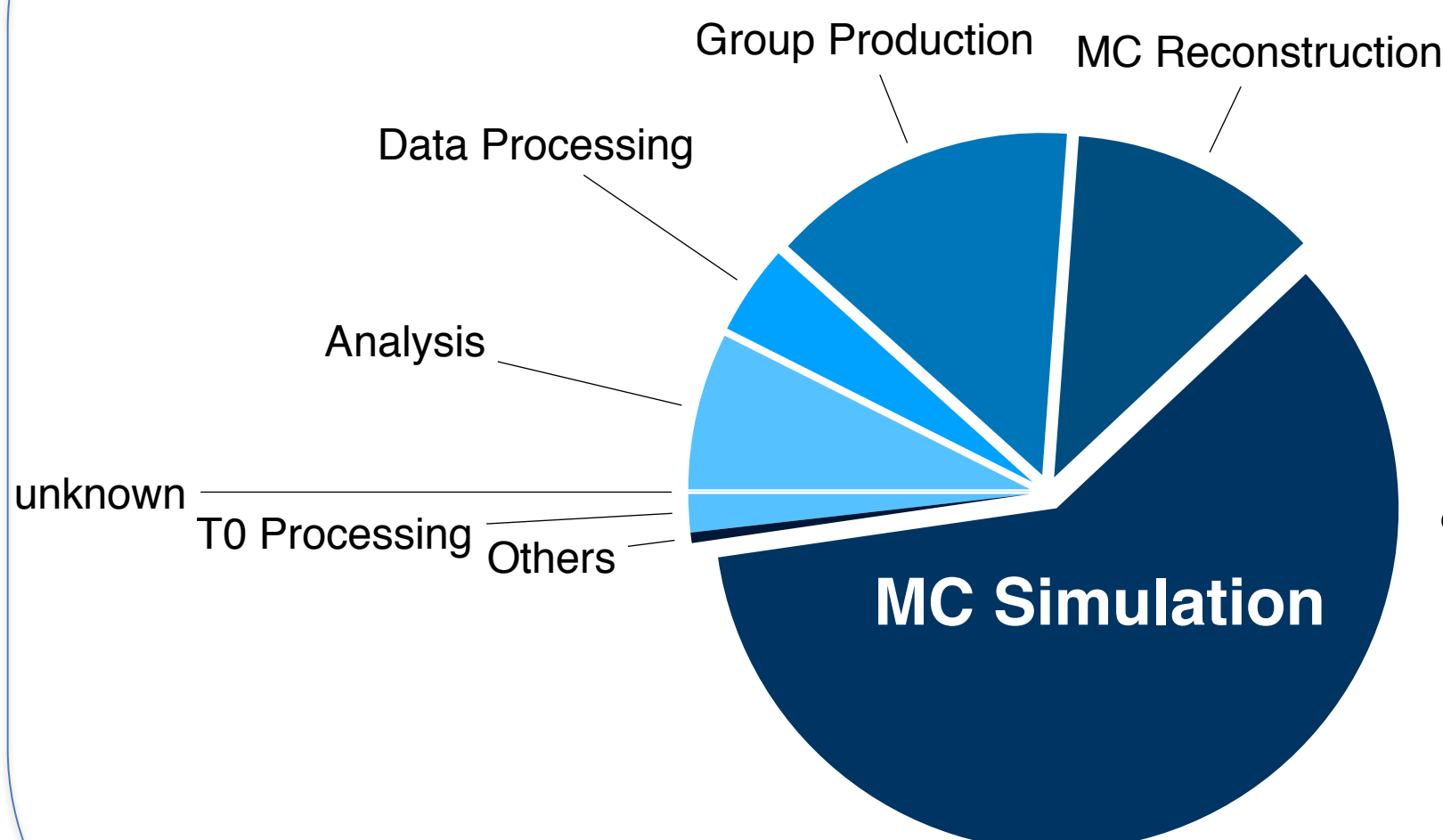


Alignment Configurations :

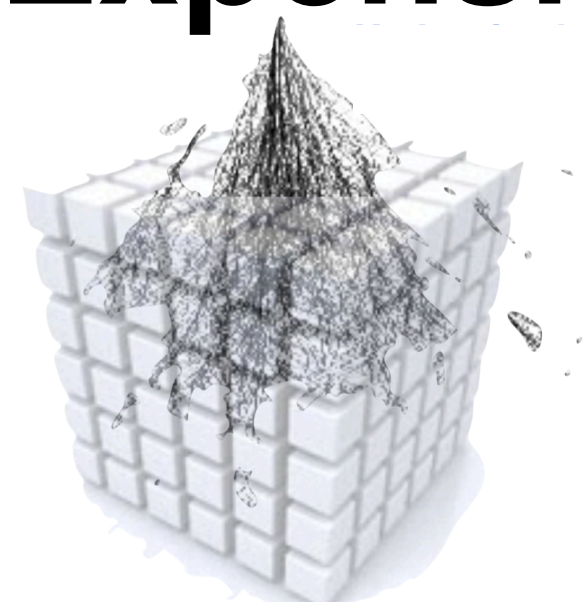
- 2- periodic in  $\eta$
- 4-periodic in  $\phi$



## Showers Computationally Expensive

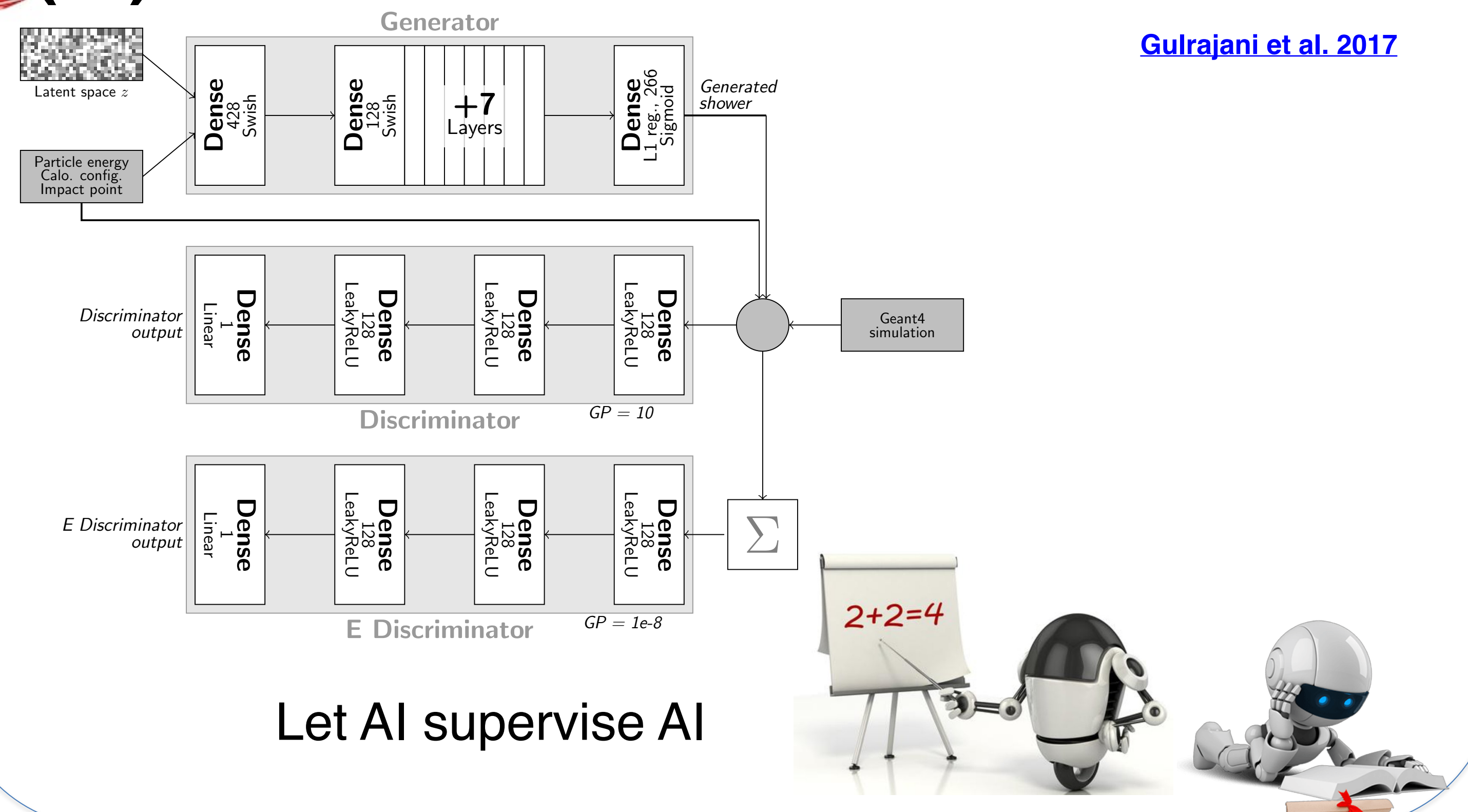


- Cascade quantum simulations are expensive for Geant4
- Only final shower image is recorded



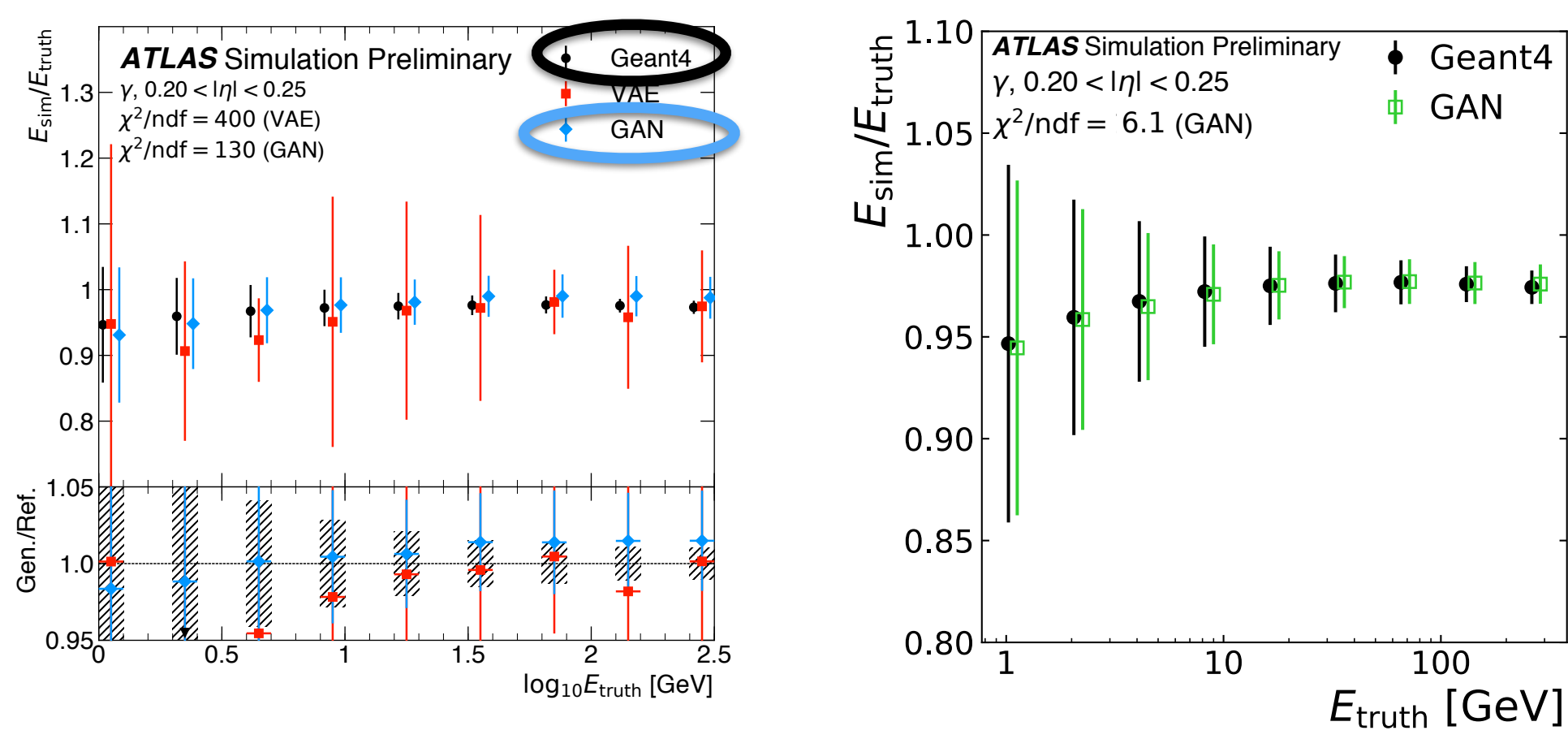
## (W) Generative Adversarial Networks

Gulrajani et al. 2017



Let AI supervise AI

## Why we need the third network



Bars = standard deviation not error

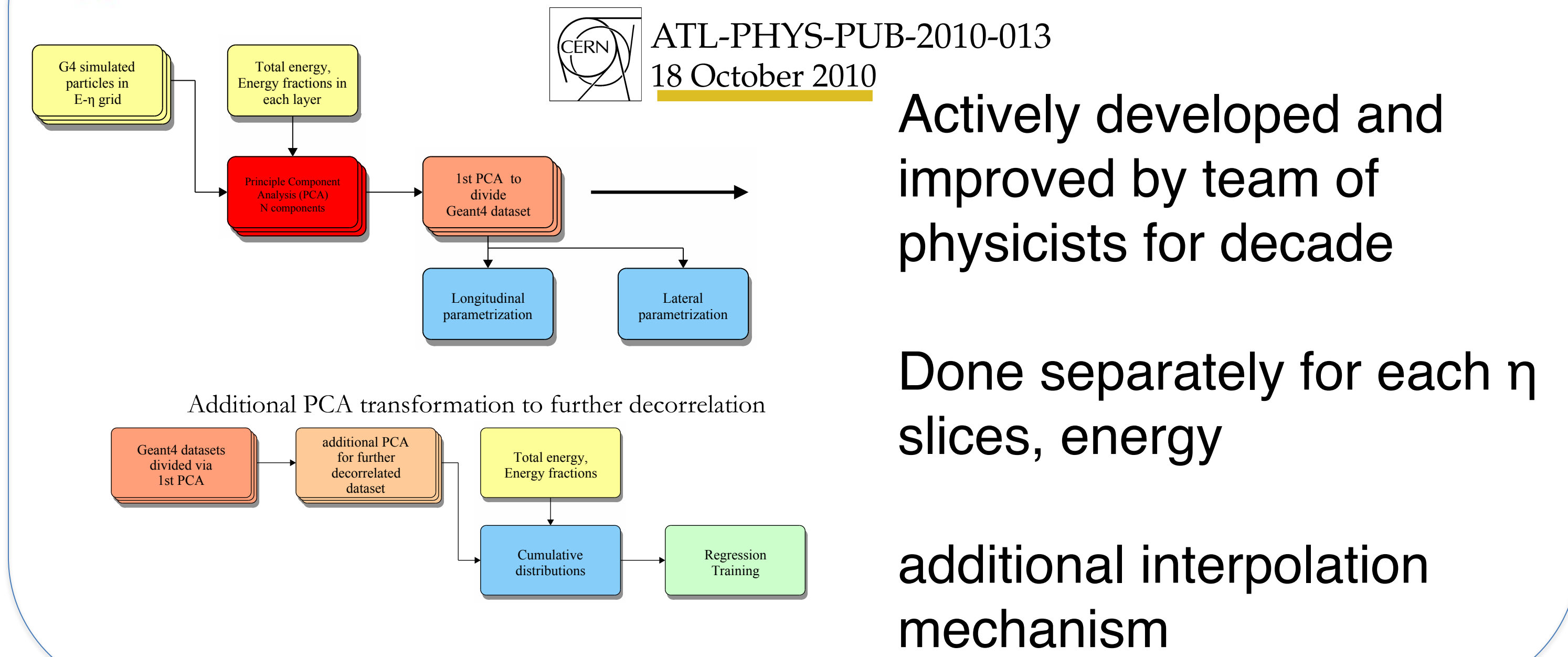
Look at single photon showers at {1,2,4,8,16, 32, 65, 131, 262} GeV

Assume Geant4 is ideal

Additional Critic helps reproduce resolution of the detector  $\sigma E/E \sim 10\% \sqrt{E}$  very well

Graeme Stewart (CERN), Aishik Ghosh, David Rousseau (LAL, Orsay), Kyle Cranmer (NYU), Stefan Gadatsch, Tobias Golling, Dalila Salamani (UniGe), Gilles Louppe (ULiège)  
**PUB Note: ATL-SOFT-PUB-2018-001** SIM-2019-004

## Baseline: FastCaloSim

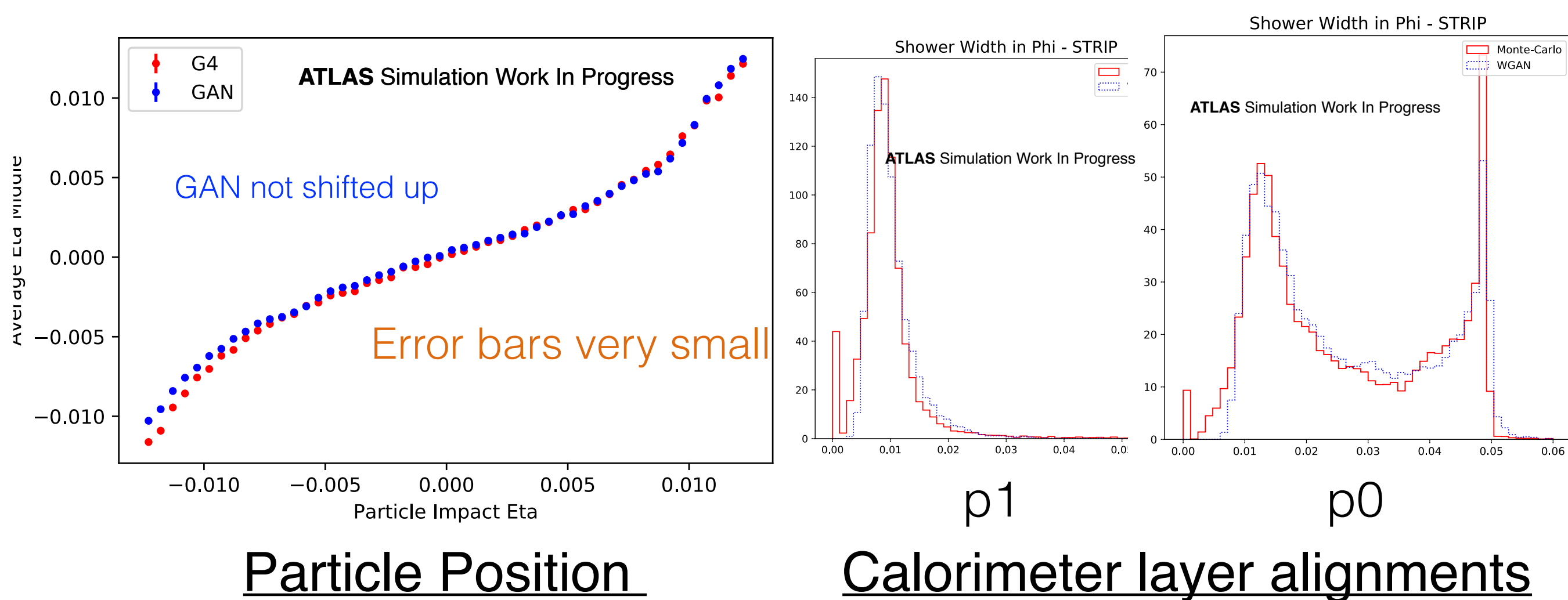


Actively developed and improved by team of physicists for decade

Done separately for each  $\eta$  slices, energy

additional interpolation mechanism

## Detector Geometry Features



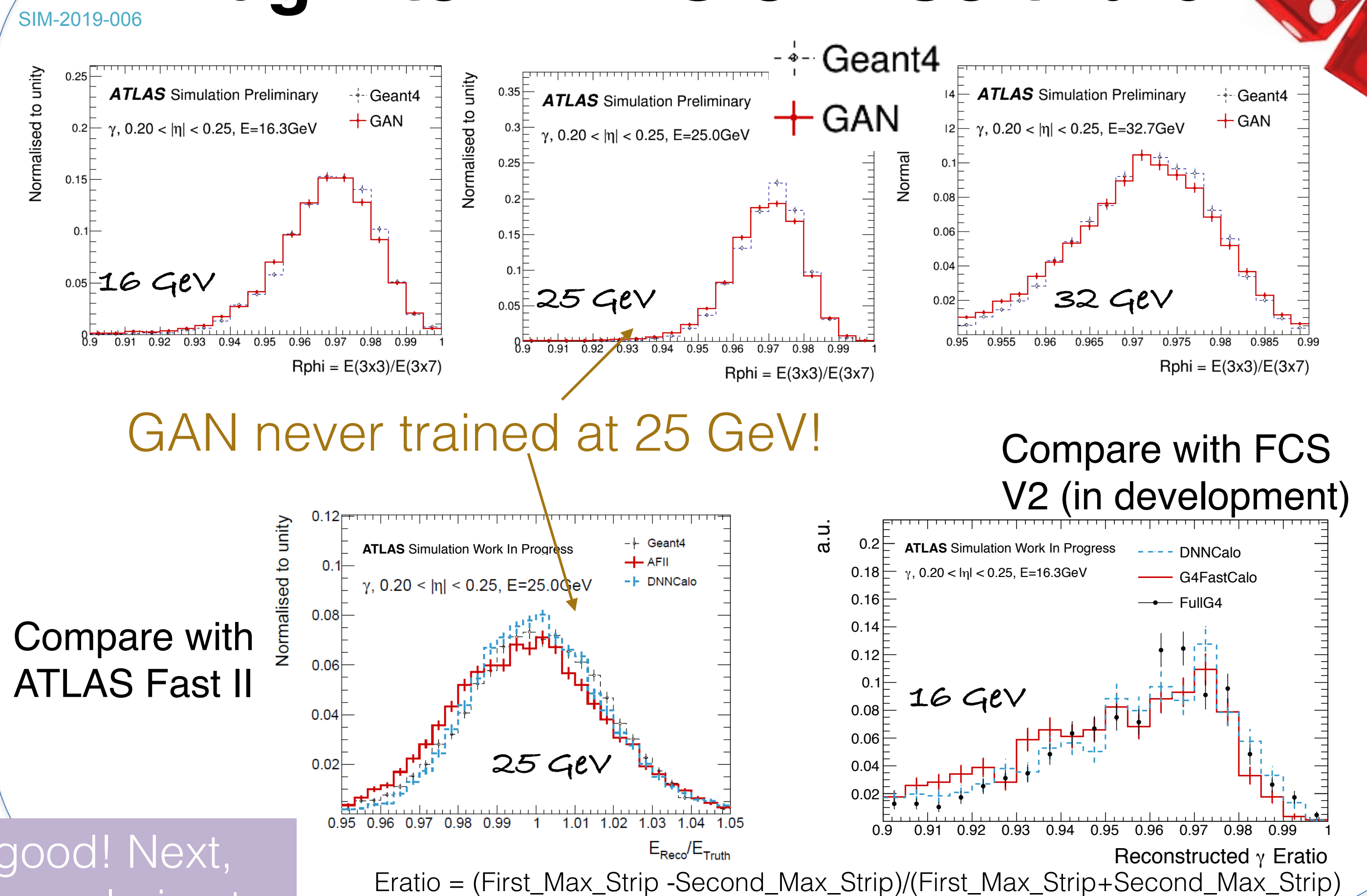
Particle Position

Calorimeter layer alignments

Conditional GAN:  
 2 continuous conditions,  
 72 discrete conditional combinations at training

GAN looks good! Next, expand to entire calorimeter

## Plug into ATLAS C++ Software



GAN never trained at 25 GeV!

Compare with FCS V2 (in development)

Compare with ATLAS Fast II

25 GeV

a.u.

Eratio = (First\_Max\_Strip - Second\_Max\_Strip) / (First\_Max\_Strip + Second\_Max\_Strip)