Fast Simulation at BESIII / ATLAS

Tong Liu[1], Qiaojia Ge[2], Yue Sun[1], Wenxing Fang[1], Weidong Li[1],

Rui Zhang[2], Ke Li[1]

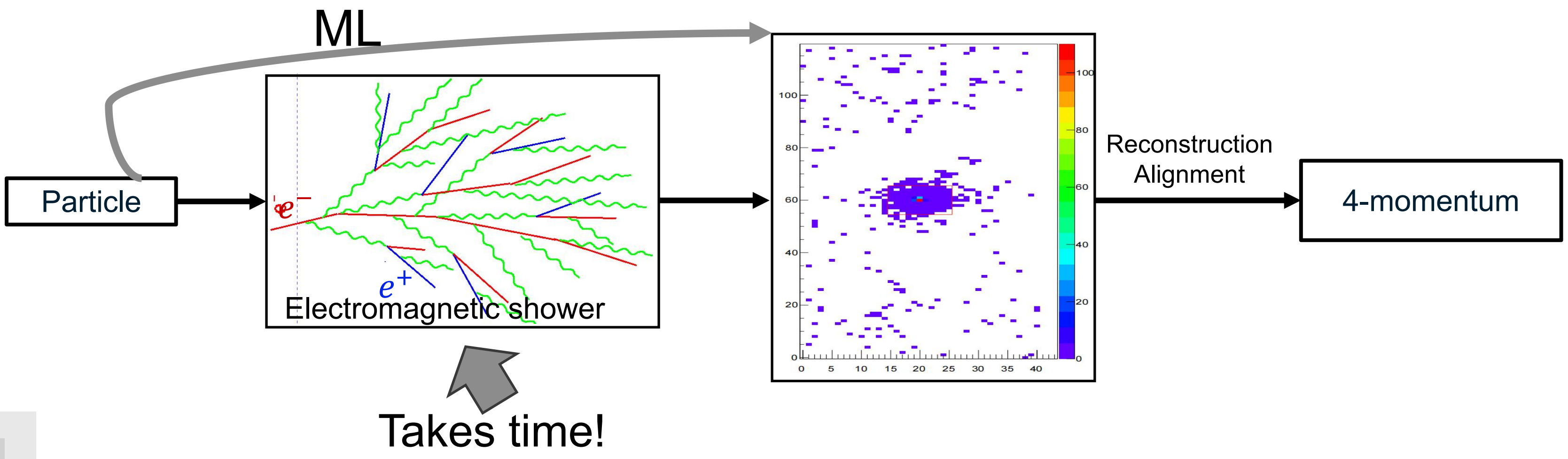
[1] Institute of High Energy Physics

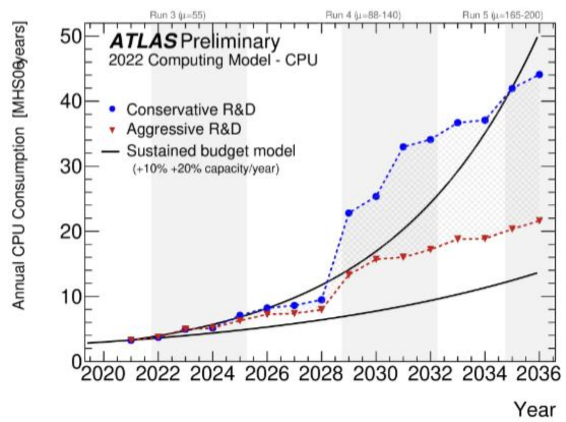
[2] Nanjing University

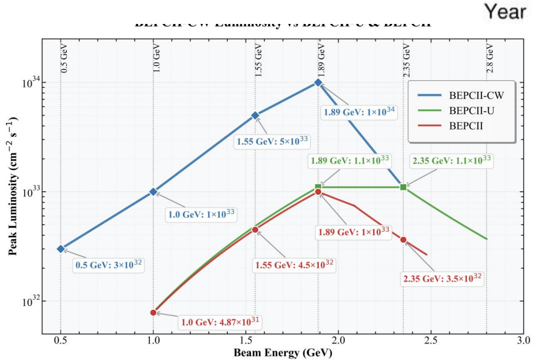
Outline

Introduction

- Machine learning (ML) has wide applications in HEP, especially detector simulation
- MC simulation with Geant4, especially for electromagnetic calorimeter (EMC), takes large CPU resources
  - Traditional: Geant4, gradually calculate the next state, complex due to secondary particles
  - ML: without Geant4, calculate hit map from input conditions
- In this talk: ML to acceleration simulation at ATLAS and BESIII

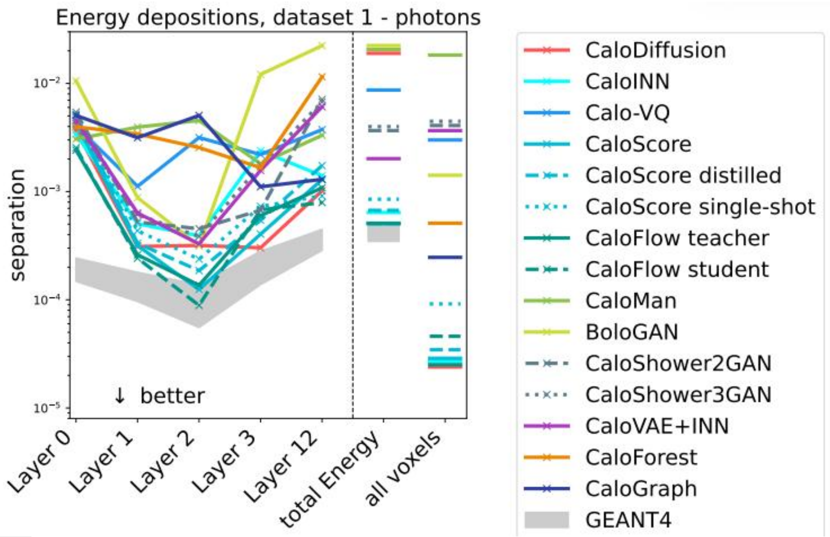




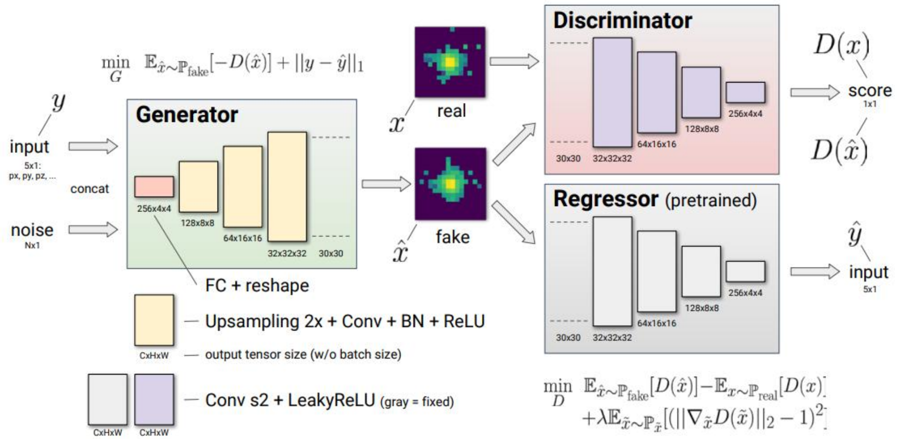


Introduction

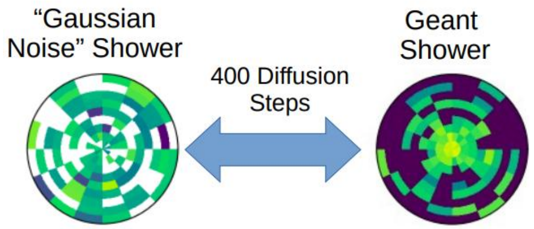
- Generative Adversarial Networks (GAN)
  - A discriminator (D) tries to discriminate the real and fake data; a generator (G) to produce fake data and tries to confuse discriminator, D/G trained alternately to improve performance
- Denoising Diffusion Probabilistic Models
  - Add noise steply, train to do denoising
- ML, like GAN and diffusion, is used for simulation at other experiments
- ML-simulation should also be tested at BESIII



Fast Calorimeter Simulation Challenge 2022



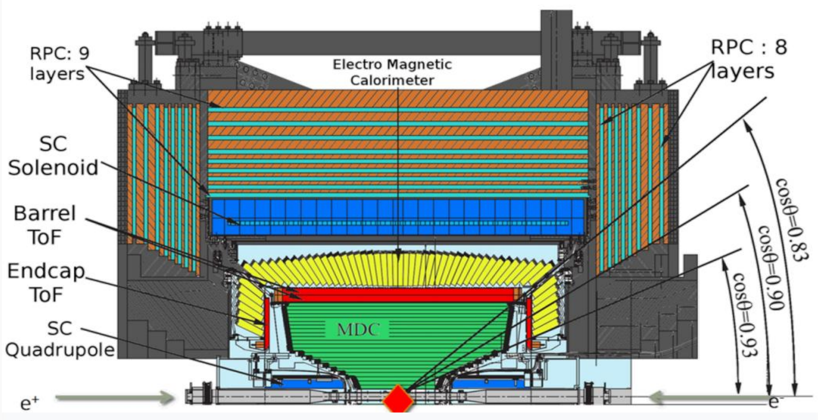
GAN @ LHCb



Diffusion @ ATLAS

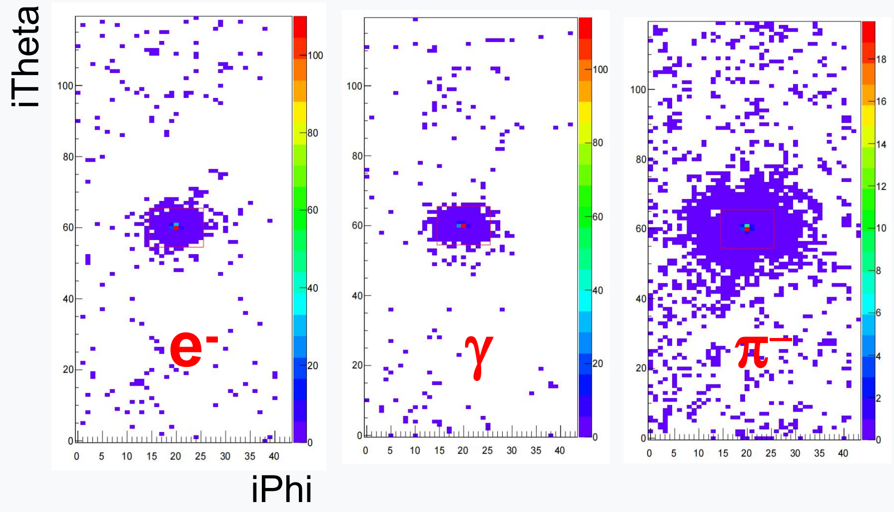
Fast Simulation at BESIII

- EMC: 44 layer*120 crystals in barrel, all pointing to IP.
- We simulate ~1M single-track events for $e/\gamma/\pi$ as training set
  - Full condition space sample: $0 < P < 3\ \mathrm{GeV}/c,\ 0 < \theta < 2\pi,\ 0 < \phi < 2\pi$
  - Single-momentum samples: $P = 0.5,\ 0.8,\ 1.2,\ \ldots 2.5\ \mathrm{GeV}/c$
  - Remove random trigger, randomness of IP, readout cutoff
- The 11x11 region contains nearly the entire detector response for e/γ



Energy Containment in 11×11 Region

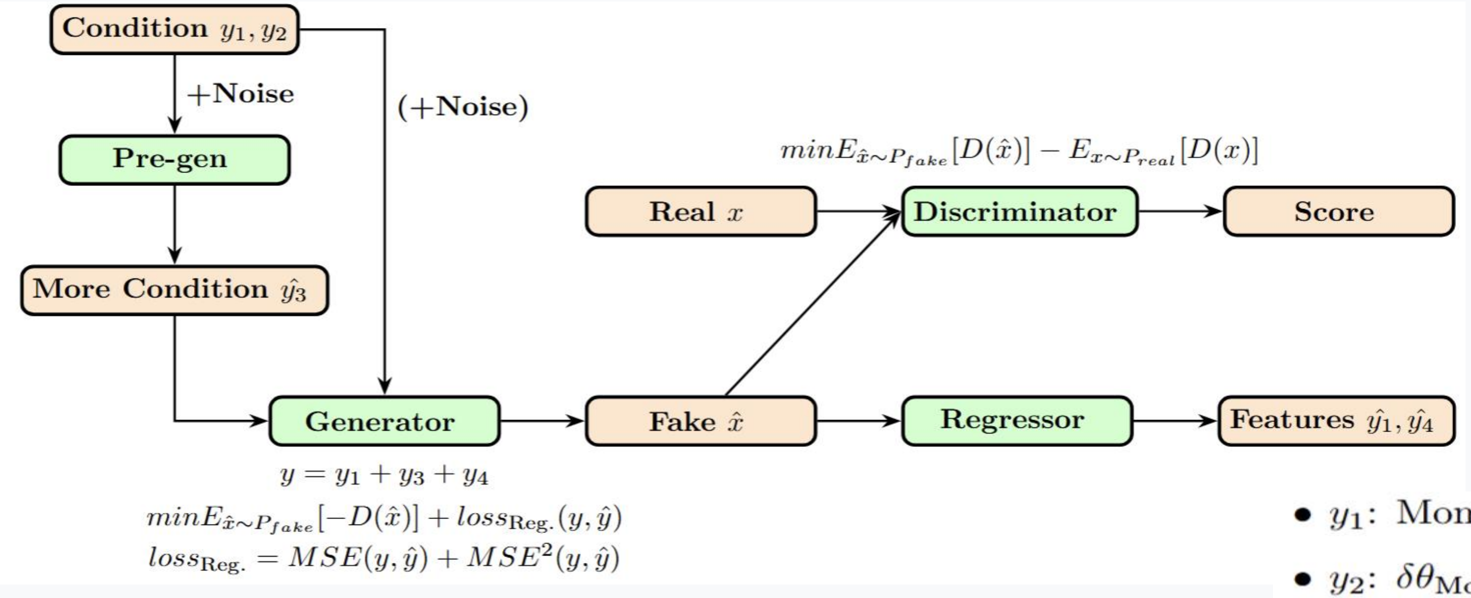
Particle	E_{11x11} / E_{tot} (%)
e^+	99.7
γ	99.8
π^+	87.7



EMC hit map in barrel region from 100 events

Fast Simulation at BESIII - GAN

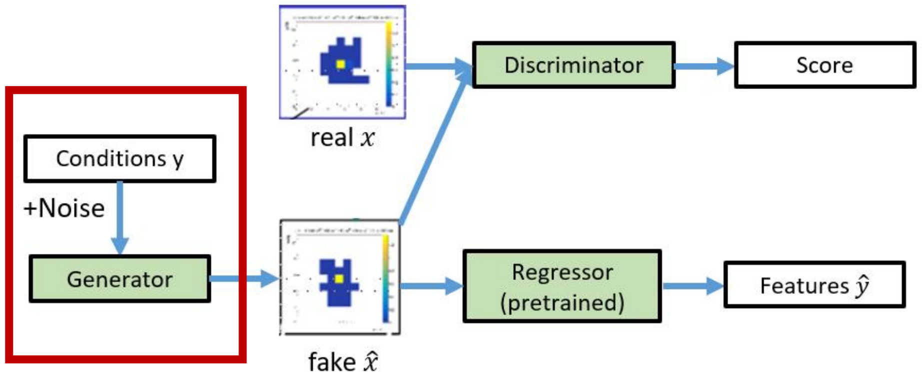
- Similar strategy as LHCb case: G + D + regressor (pretrained) + pre-gen (pretrained)
  - The pre-gen model: an advanced condition generator
- Decoupled Training: train with $y_{3,\,truth}$, generate with y_3, avoids error accumulation from pre-gen

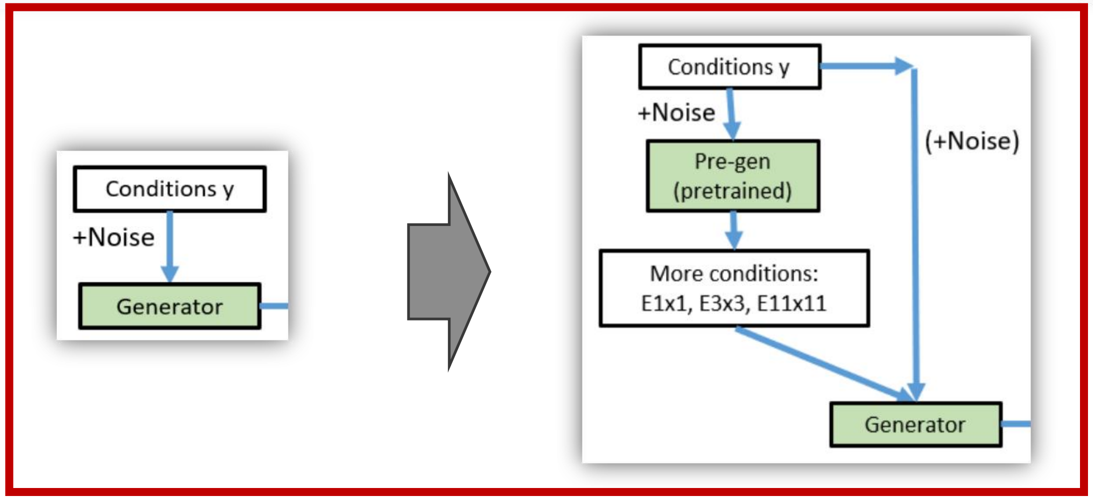


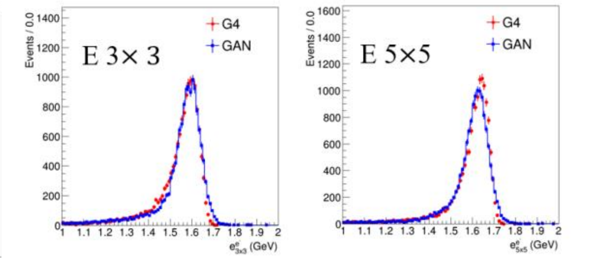
- y_1: $\mathrm{Mom}_{\mathrm{truth}}, \delta\phi_{\mathrm{Mom}}, \delta z_{\mathrm{pos.}}, \delta\phi_{\mathrm{Mom}}$
- y_2: $\delta\theta_{\mathrm{Mom}}, \theta$
- y_3: $E_{1\times1}, E_{3\times3}, E_{3\times3} - E_{1\times1}, \mathrm{Mom}_{\mathrm{truth}} - E_{3\times3}$
- y_4: a20Mom, a42Mom, secondMom, latMom

Fast Simulation at BESIII - GAN

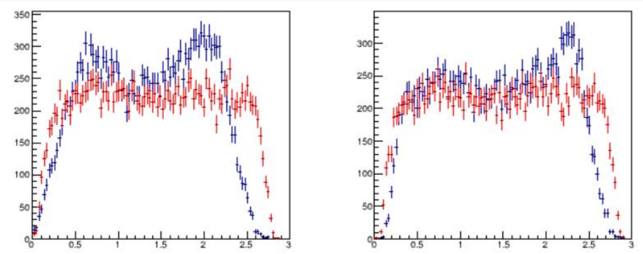
- BESIII tests the GAN simulation based on Bhabha ($e^+e^- \rightarrow e^+e^-$) events
- The model does not work well in a larger condition space
- To cover the full condition space, **a pretrained pre-gen model** is integrated



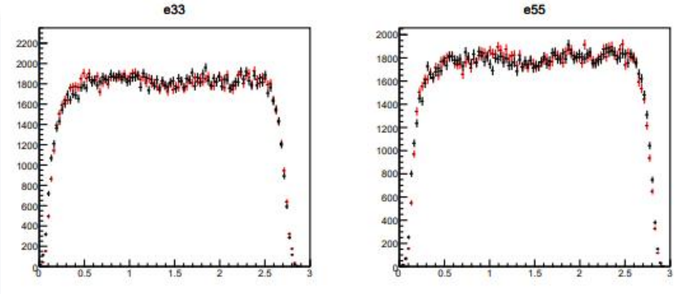




GAN for Bhabha events



GAN in large condition space



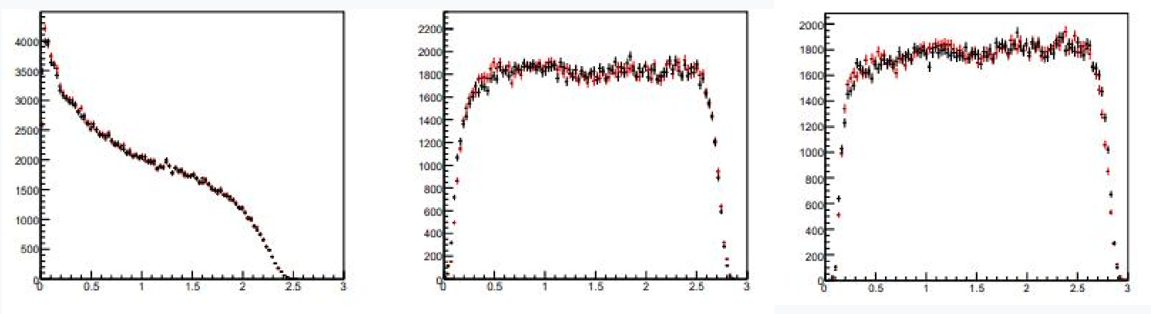
Pre-gen + GAN

Fast Simulation at BESIII - GAN

- ML reaches comparable accuracy to Geant4
  - In the full condition space, and for the single-momentum sample
- **~ 3 s for 90k particle**

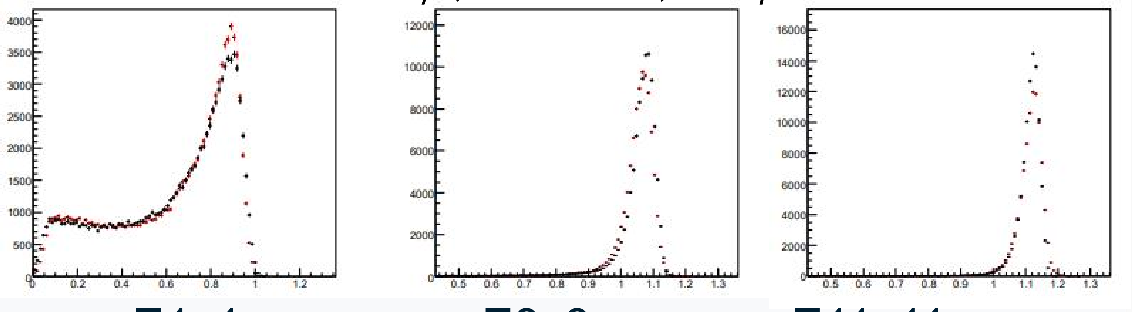
Geant4
GAN

$0 < P < 3\ \mathrm{GeV}/c,\ 0 < \theta < 2\pi,\ 0 < \phi < 2\pi$



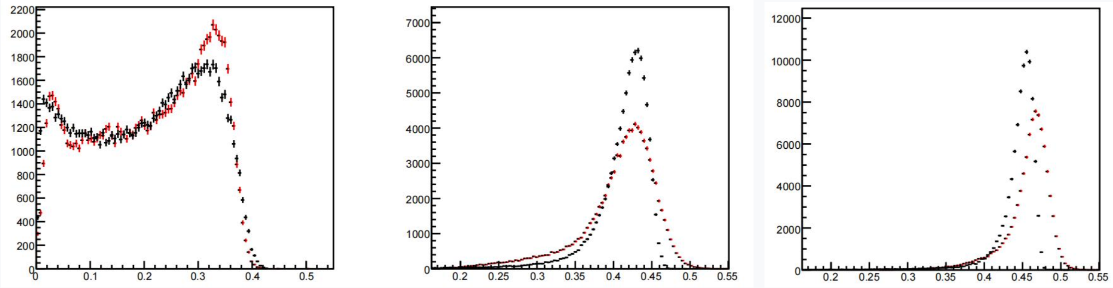
E1x1 E3x3 E11x11

$P = 1.2\ \mathrm{GeV}/c,\ 0 < \theta < 2\pi,\ 0 < \phi < 2\pi$



E1x1 E3x3 E11x11

$P = 0.5\ \mathrm{GeV}/c,\ 0 < \theta < 2\pi,\ 0 < \phi < 2\pi$



E1x1 E3x3 E11x11

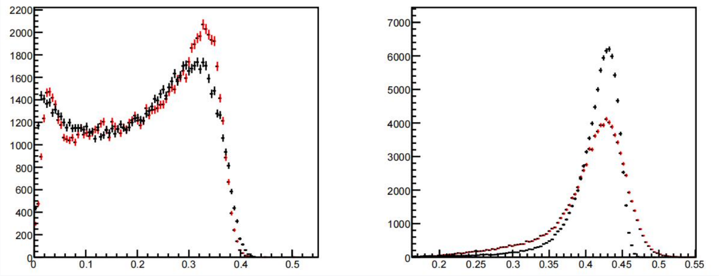
Fast Simulation at BESIII - GAN

- Mixture of Experts (MoE): use multiple specialized “expert”, with a gate that activates only a subset of experts.
- Use momentum as input of gate, calculate **weighted summary** of Gs
  - Lower speed, still acceptable
  - Improved quality for low-momentum particle
  - ~20k trainable parameters per G

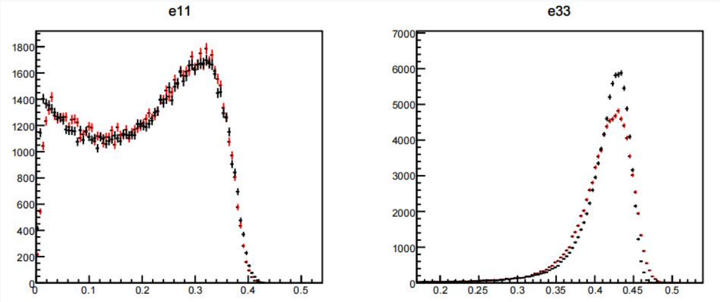
Time * 90k evts

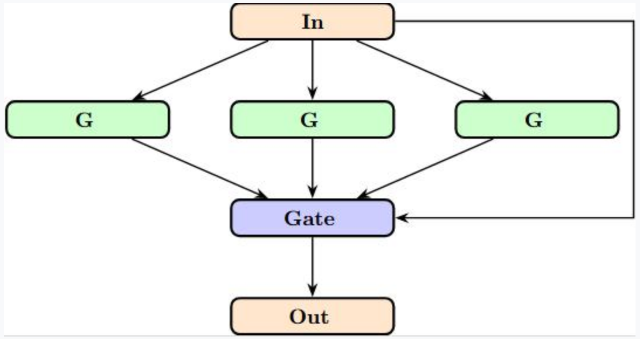
Configuration	Time
1 Generator	~3~4 s
MoE - 2 Generator	~5 s
MoE - 3 Generator	~7 s
MoE - 10 Generator	~11 s

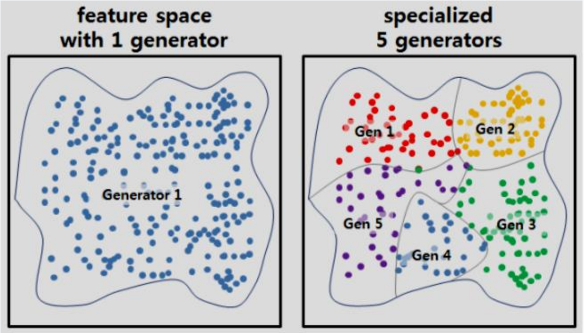
w/o MoE



MoE-3Gen

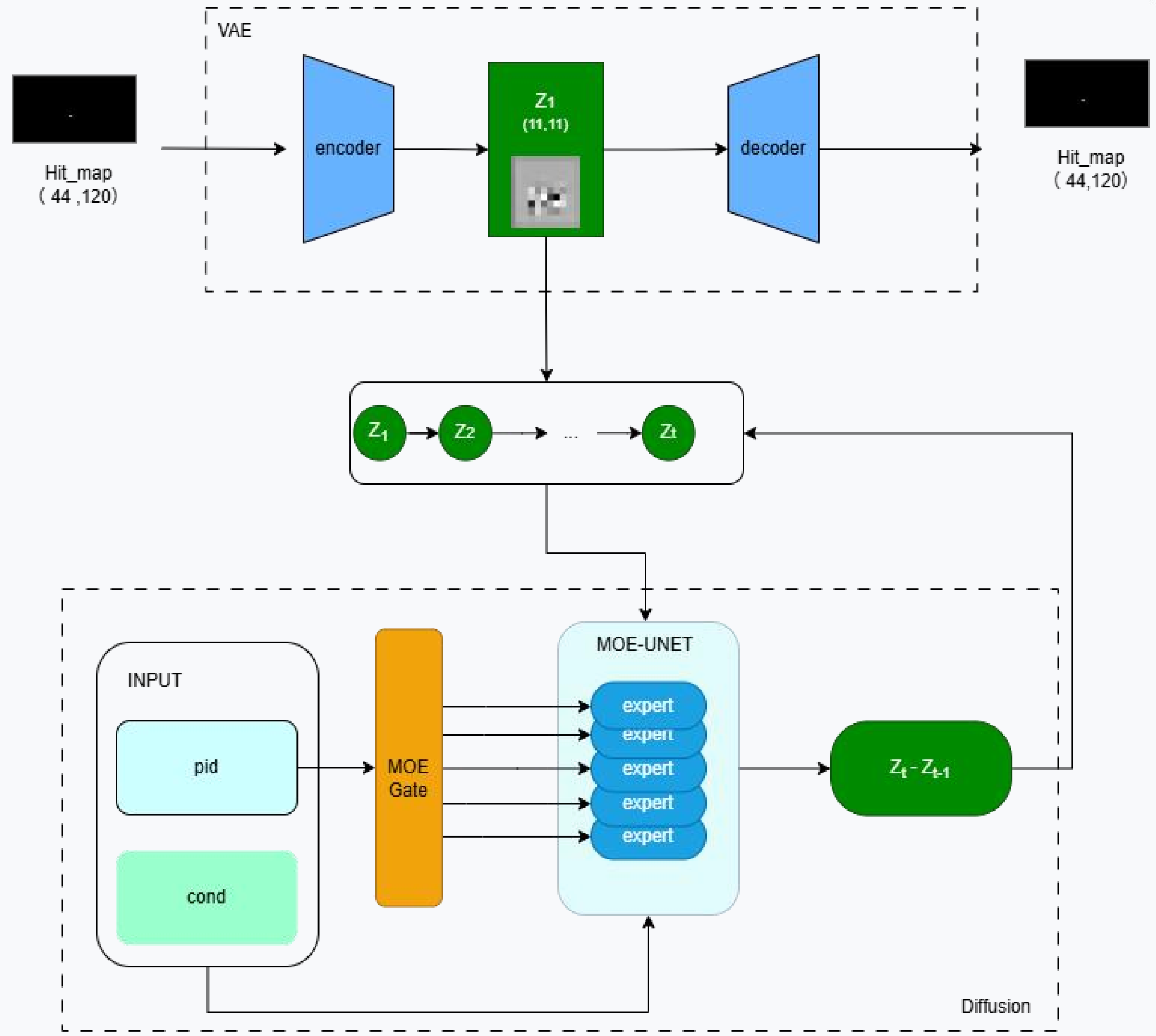






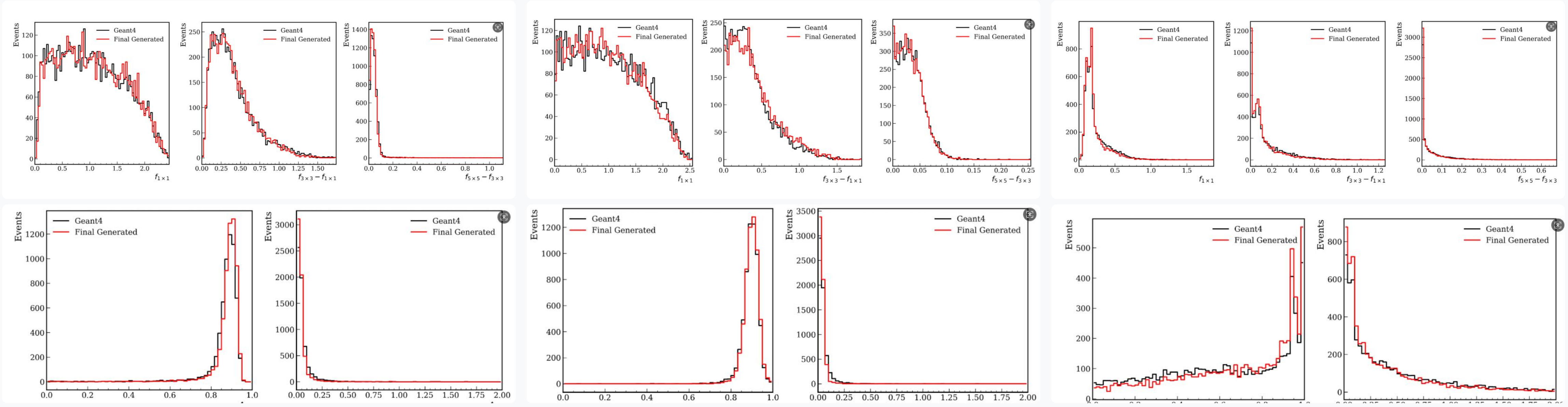
Fast Simulation at BESIII - diffusion

- A VAE to simulate hit map (44×120 for the full detector)
  - Share for different particles
- A diffusion to simulate the latent space (11×11) for VAE
  - A gate controls expert activation
  - Different expert handle different particle type
  - ~10 M trainable parameters per expert



Fast Simulation at BESIII - diffusion

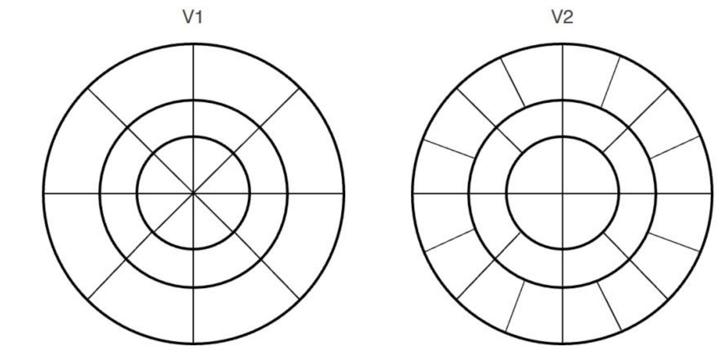
- Good performance for all particle's simulation
- Currently include $e^+/e^-/\gamma/\pi^+/\pi^-$

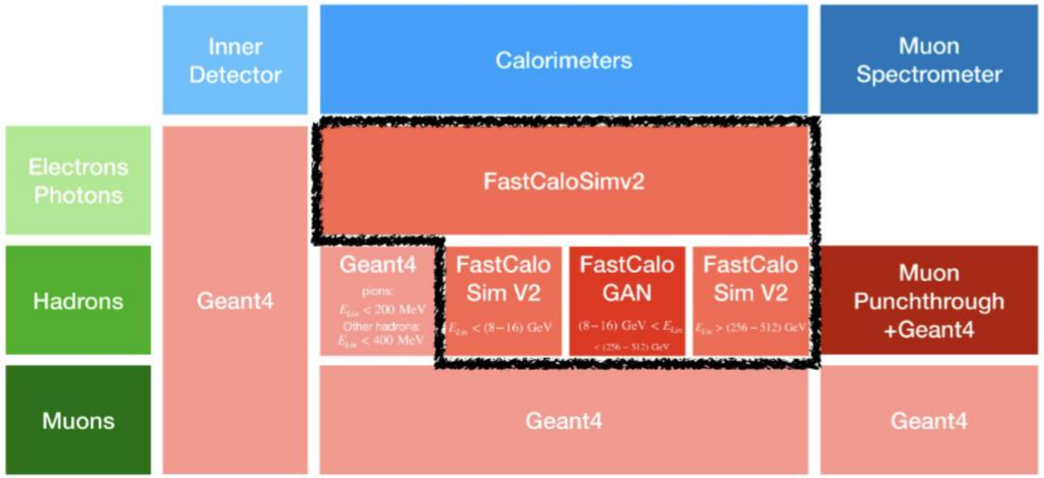


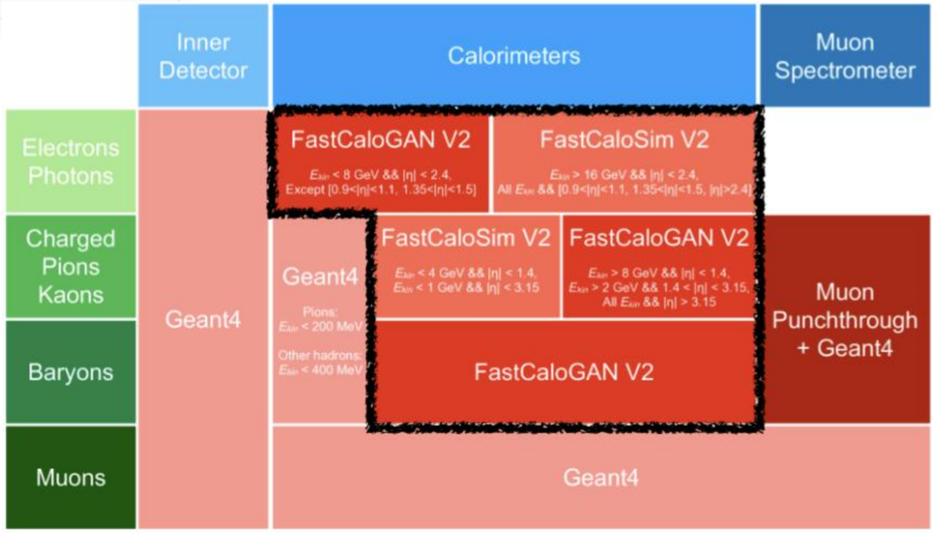
Fast Simulation at ATLAS

- AF3 Run3: Improved over AF3 Run2 version
- FastCaloGAN V2 is better in increased phase space
  - New voxelisation: more bins
  - Architecture and hyperparameters optimised for each particle, energy range, and |η|
  - Introduced proton for baryon simulations

New voxelisation: more bins



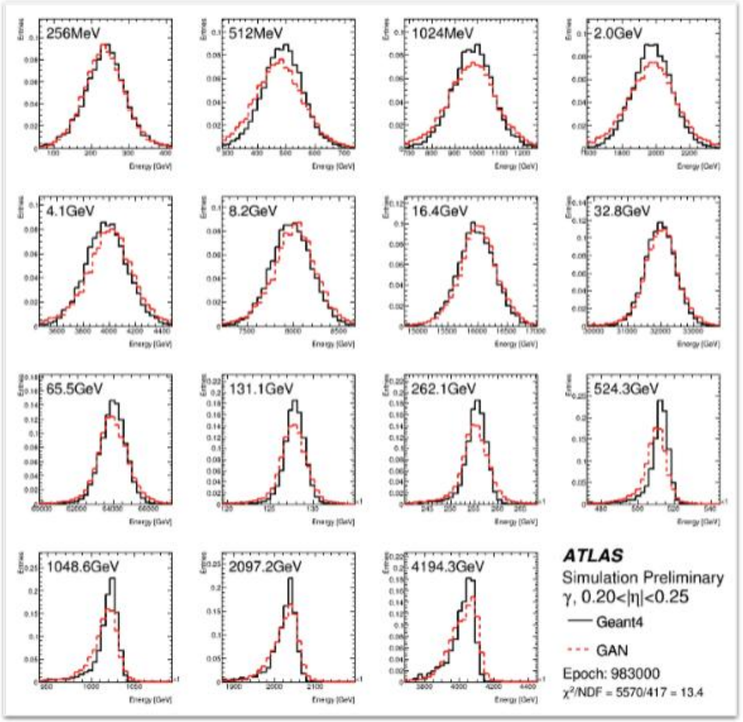




Fast Simulation at ATLAS

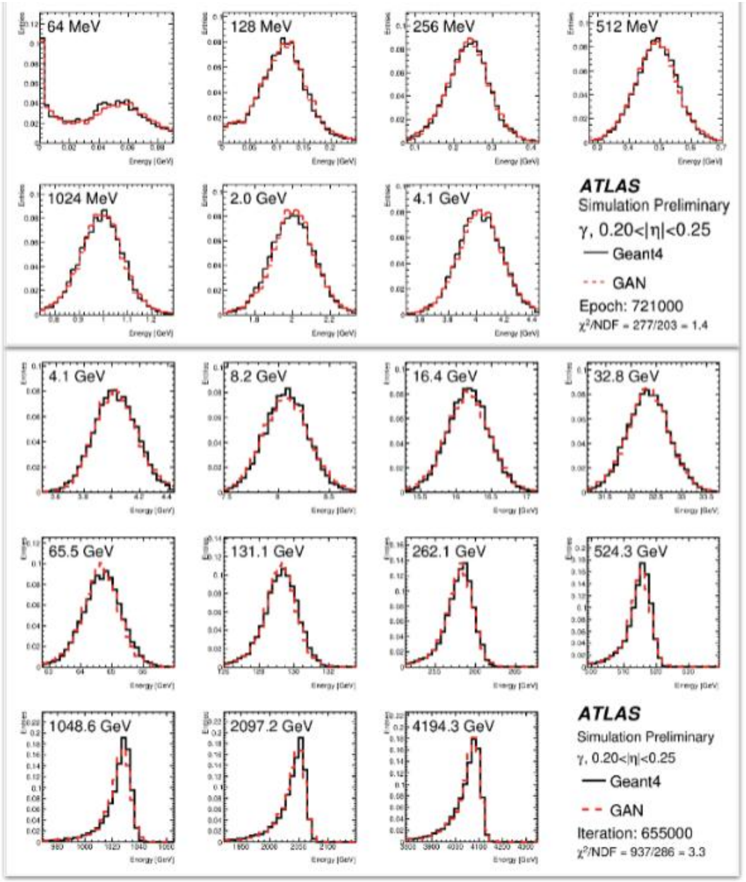
- Significant improvement for photon

V1



χ^2/NDF = 12.3

V2

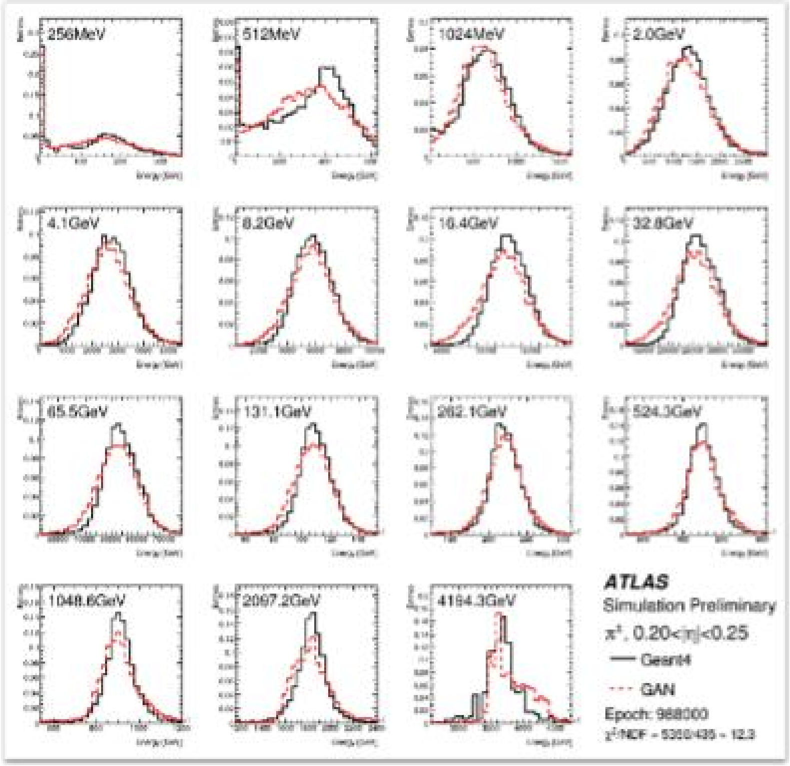


χ^2/NDF = 2.5

Fast Simulation at ATLAS

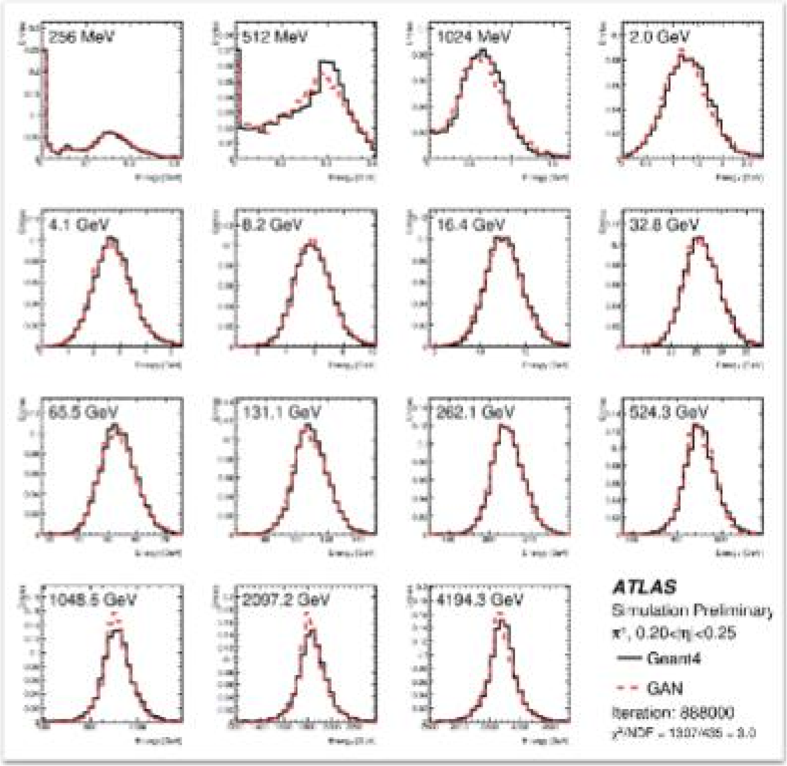
- Significant improvement for charged pions

V1



χ^2/NDF = 12.3

V2



χ^2/NDF = 3.0

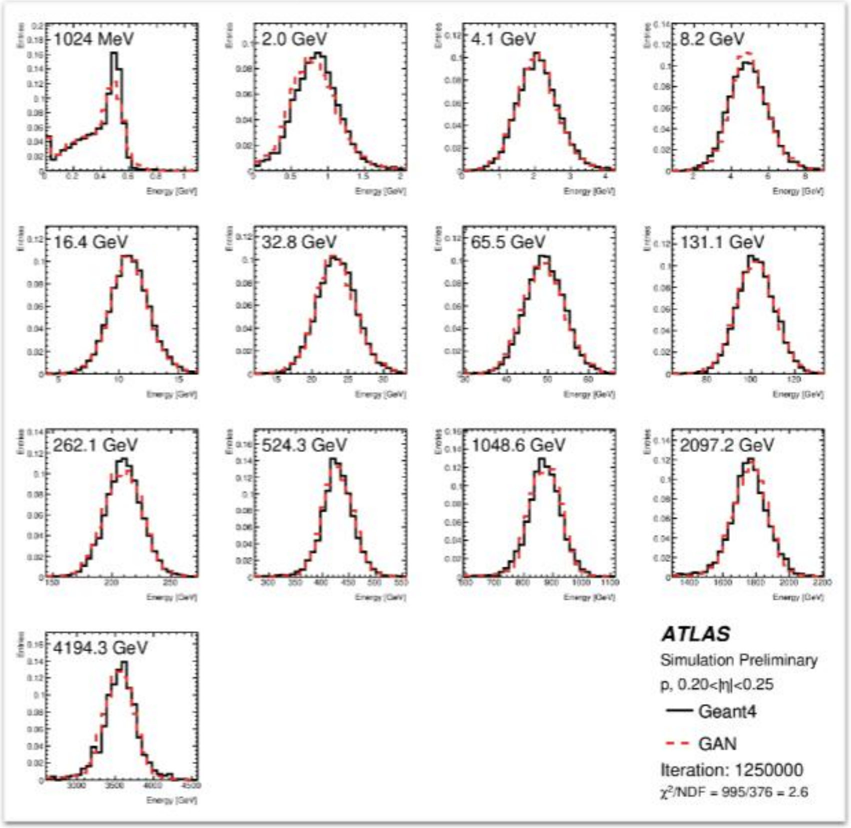
Fast Simulation at ATLAS

- Introduced proton for baryon simulations

V1

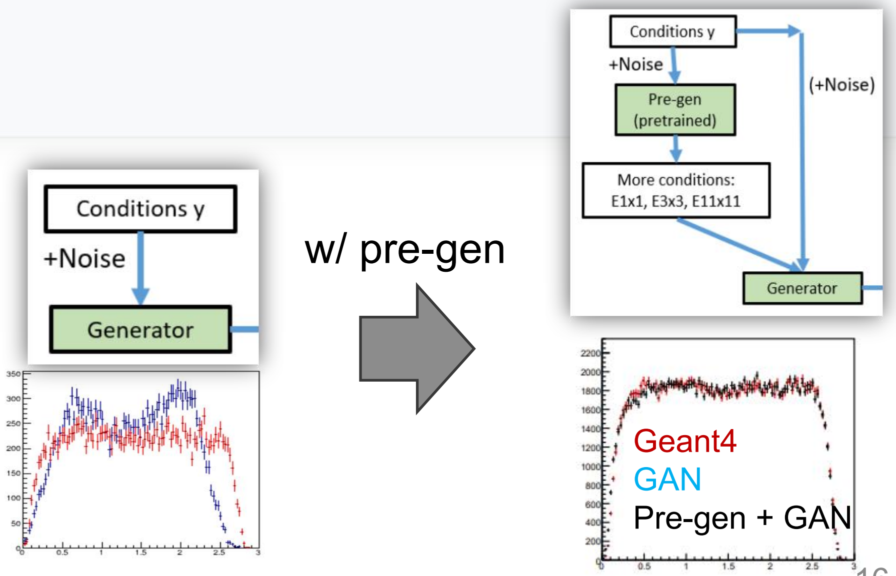
∅

V2



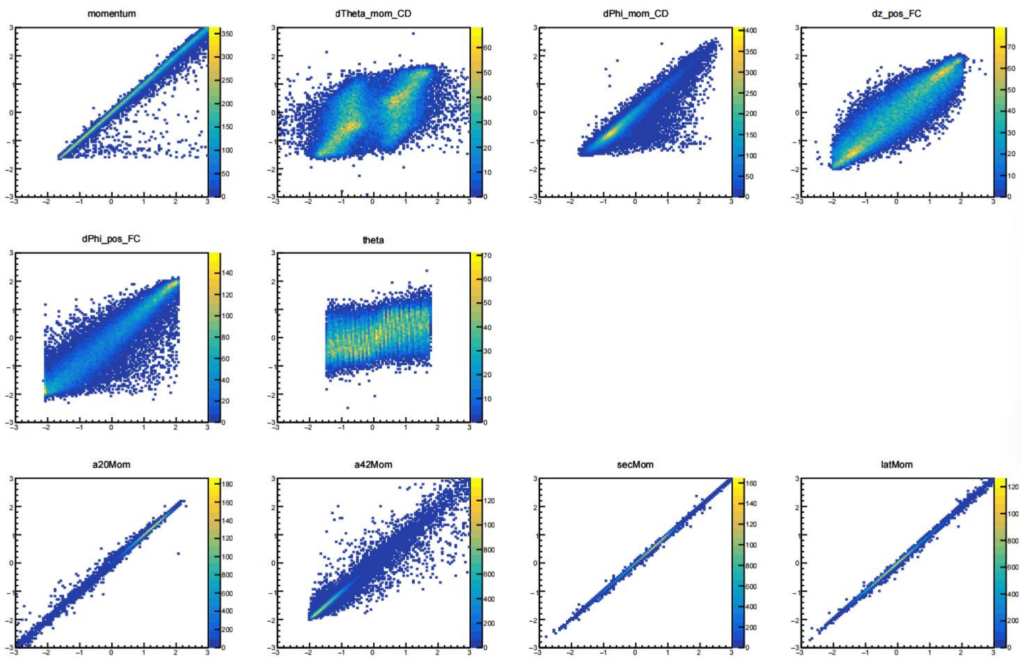
Summary

- Simulation for EMC@BESIII with ML reaches comparable accuracy to Geant4
  - For the full EMC detector, within full condition space
  - Performance in the full condition space is improved with pre-gen, further improved with MoE
  - GAN: 2-3 orders of magnitude faster; diffusion is slower, but still faster than Geant4
  - With diffusion, simulations of different particle are realized
- Similar model is applied to other experiment such as Super Tau-Charm Factory
- Fast simulation at ATLAS: FastCaloGAN V2, preparing AF4 and Run4

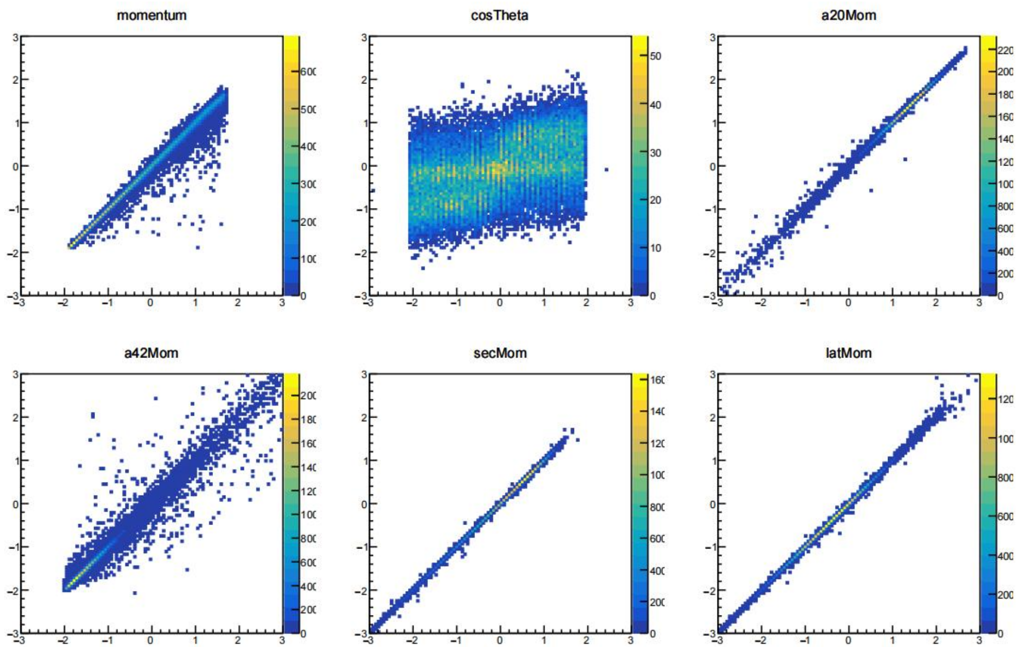


Regressor in GAN @BESIII

e^+

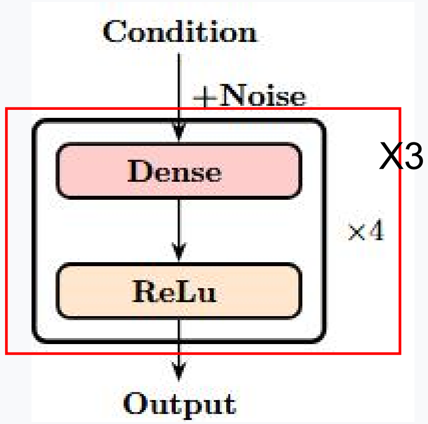


γ



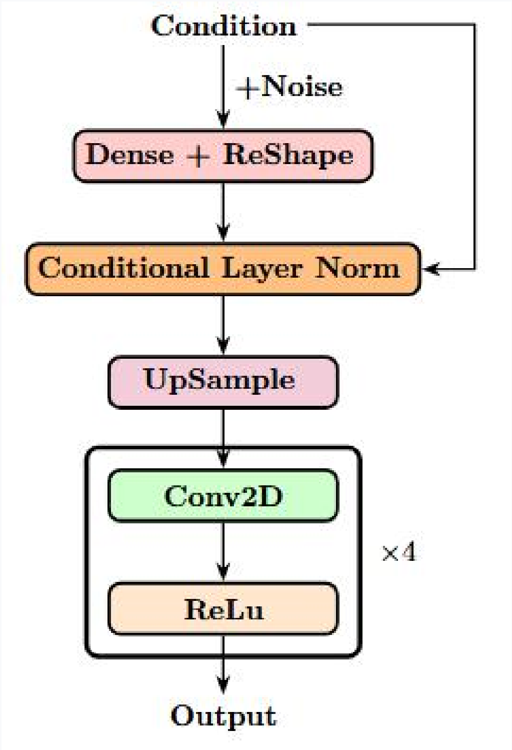
Current GAN Models @BESIII

Pre-gen



X3 expert

Generator



Discriminator