EMC Fast Simulation

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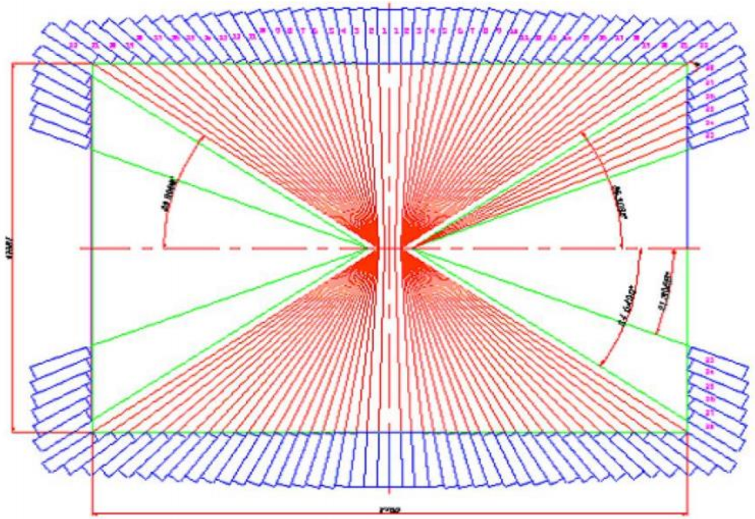
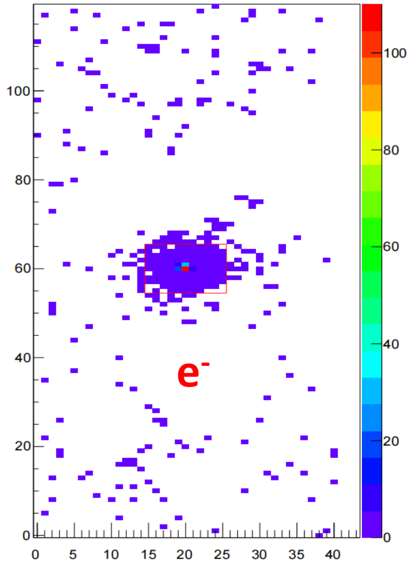
Outline

- Introduction
- Samples
- EMC simulation with ML
  - GAN
  - Diffusion
- Summary

Introduction

- With improved luminosity, MC with higher statistics is required
- MC simulation, 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
- EMC: 44 layer*120 crystals in barrel, we focus on barrel region firstly
  - To avoid energy leakage caused by the gap

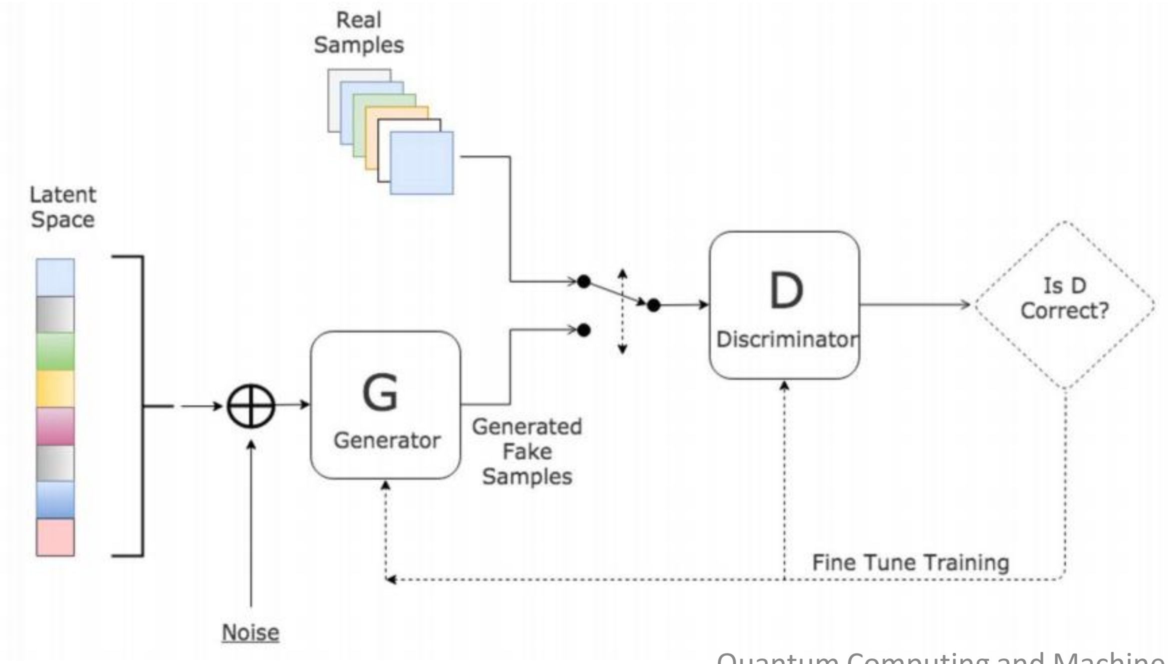


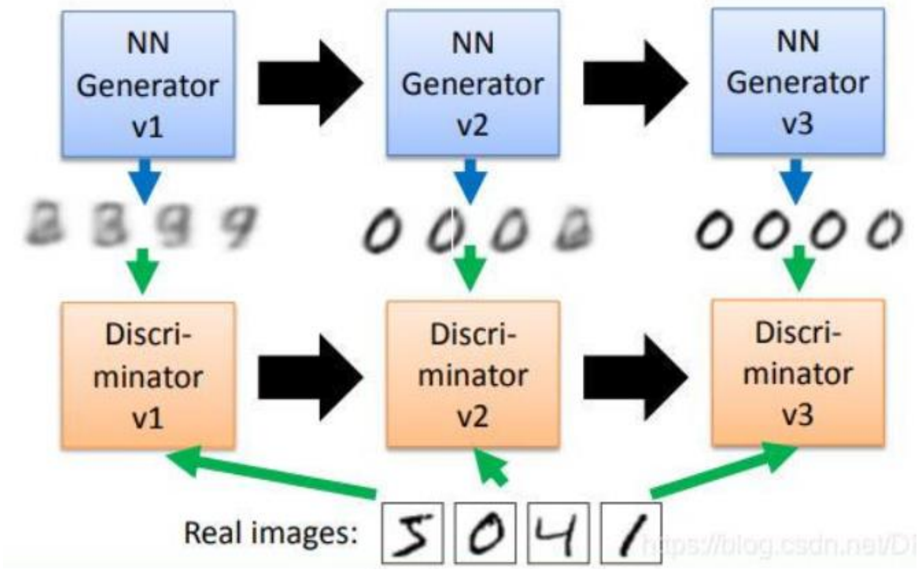


Introduction

arXiv:1406.2661

- Generative Adversarial Networks (GAN) is one of the most popular models
  - A discriminator tries to discriminate the real and fake data
  - A generator to produce fake data, tries to confuse discriminator
  - $\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$
  - Train D and G alternately





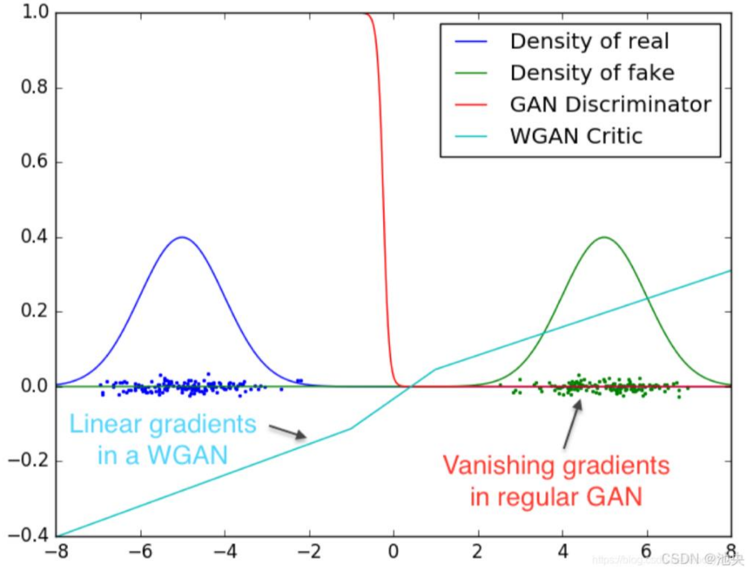
Introduction

arXiv:1701.07875

- Wasserstein GAN, an improved GAN
  - To solve instability and gradient vanishing
    - Especially if two distributions are non-overlapping.
  - Replace Discriminator with a Critic
    - Replace JS divergence with the Wasserstein distance, print scores instead of probabilities
    - Lipschitz Constraint: via weight clipping or gradient penalty (wGAN-GP)
  - Loss for D(C) and G:
    - $L_{\text{critic}} = \mathbb{E}_{x \sim P_r}[f_w(x)] - \mathbb{E}_{z \sim P_z}[f_w(G(z))]$
    - $L_G = -\mathbb{E}_{z \sim P_z}[f_w(G(z))]$

K-Lipschitz Constraint:

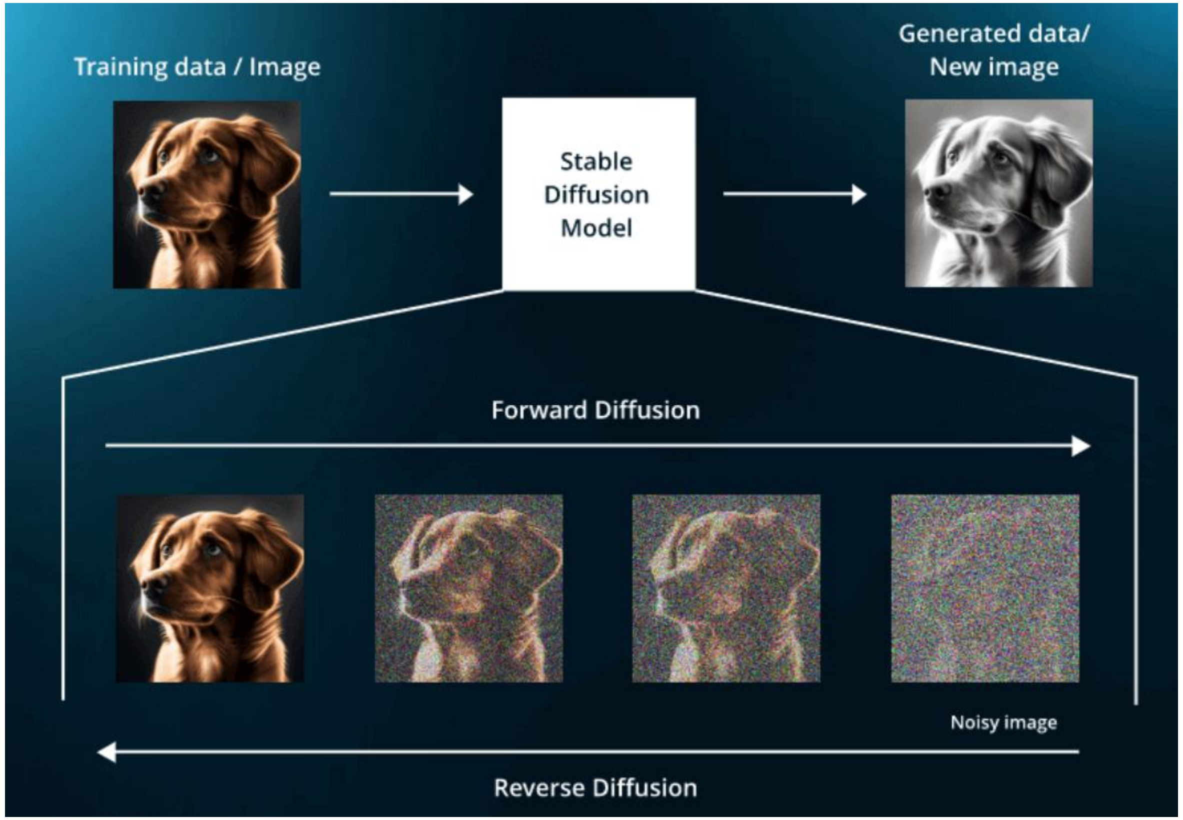
$$|f(x_1) - f(x_2)| \leq K|x_1 - x_2|$$



Introduction

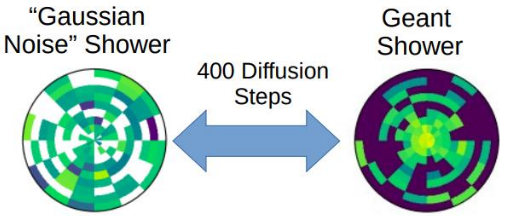
arxiv: 2006.11239

- Denoising Diffusion Probabilistic Models (DDPM)
  - Add noise steply
  - Train a model to do denoising



Introduction

- GAN and Diffusion models are studied at LHCb and ATLAS
- BESIII is an ideal place to perform ML-simulation: simpler detector, smaller phase space



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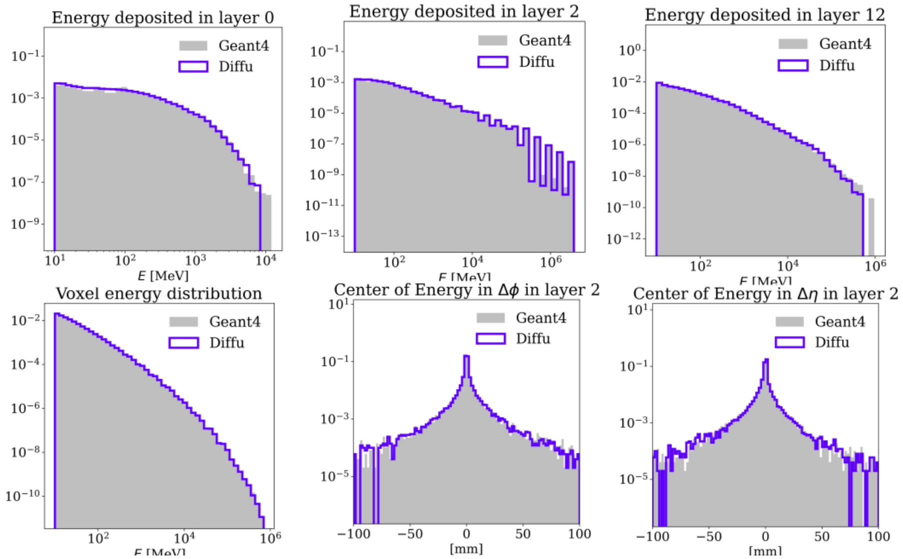
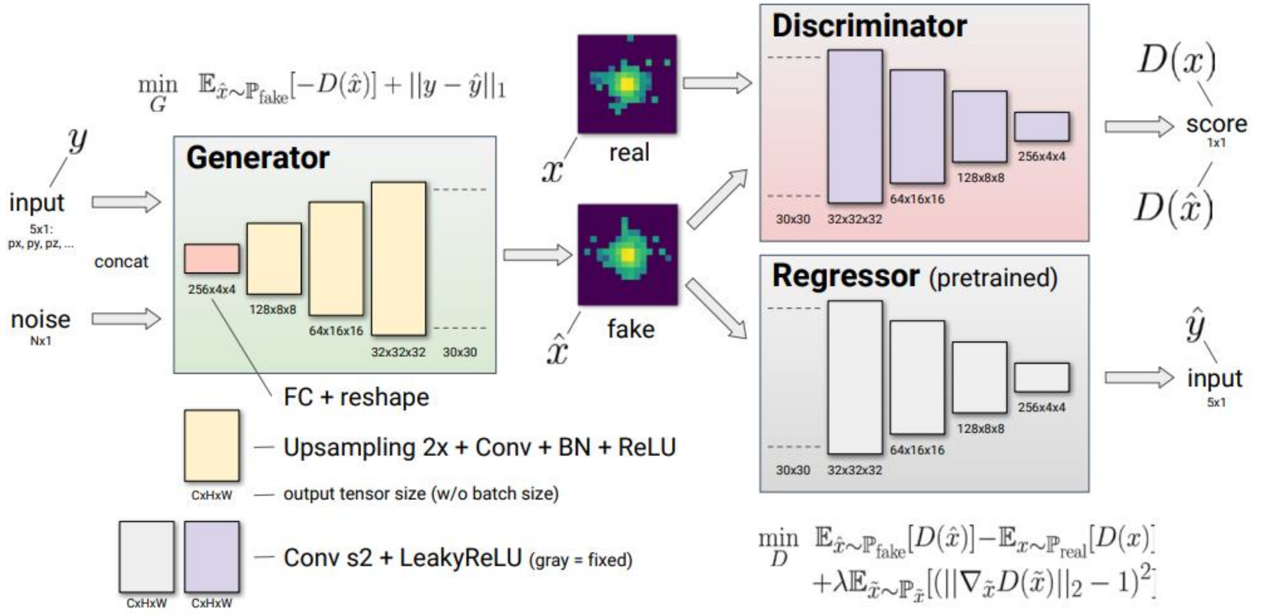
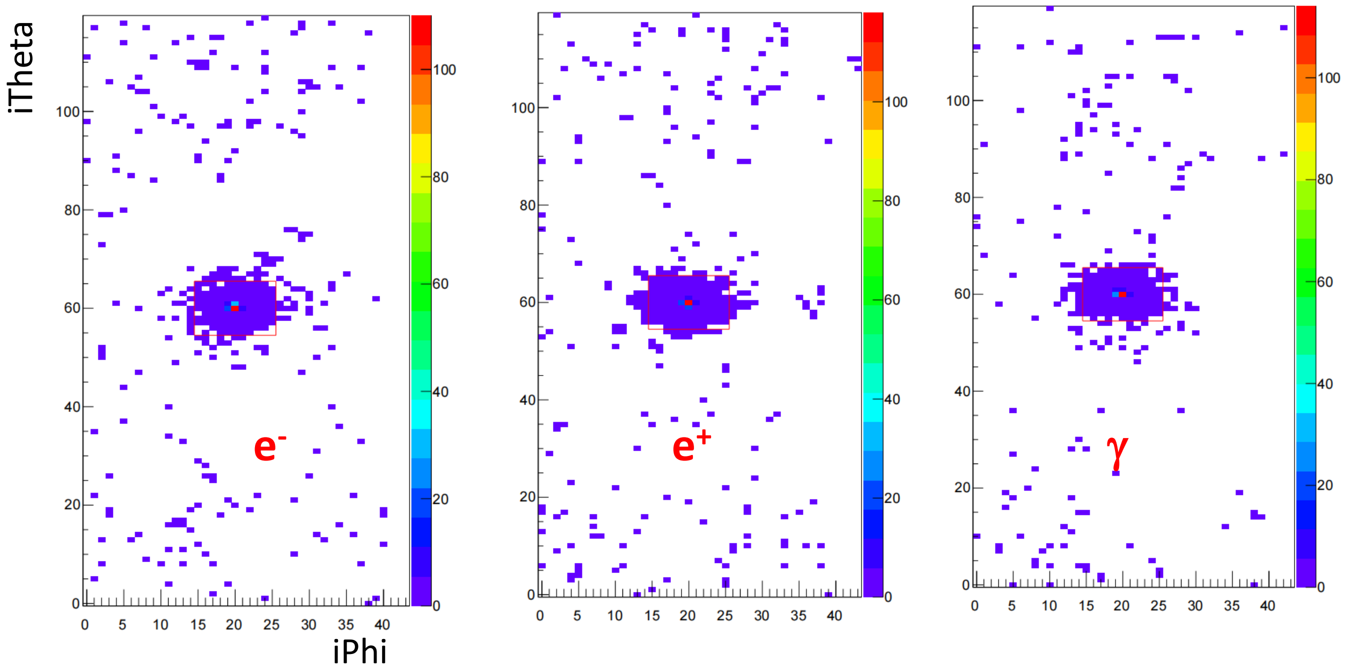


EPJ Web Conf. **214** 02034 (2019)



Samples

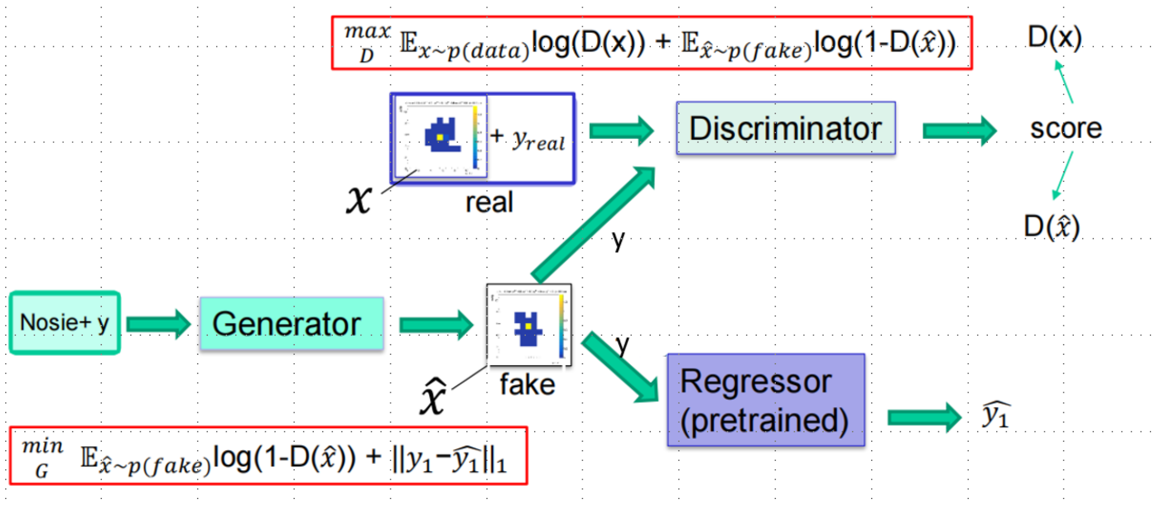
- We simulate ~1M single-track events for $e^+/e^-/\gamma$ as train set
  - With 0<Mom<3, 0<theta<2π, 0<phi<2π
  - And smaller samples as test set
  - Remove random trigger, remove randomness of IP
- Simulate 11x11 hit map
  - Below shows EMC hit map in barrel region from 100 events with P>1 GeV/c^2

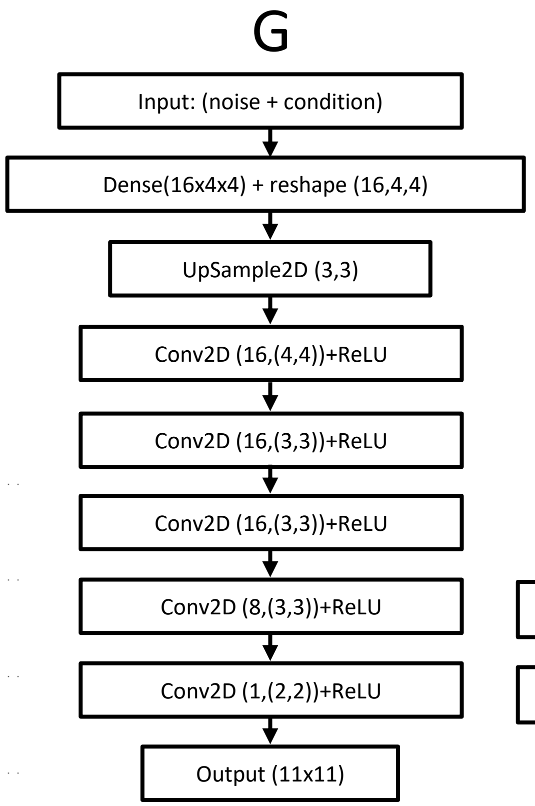


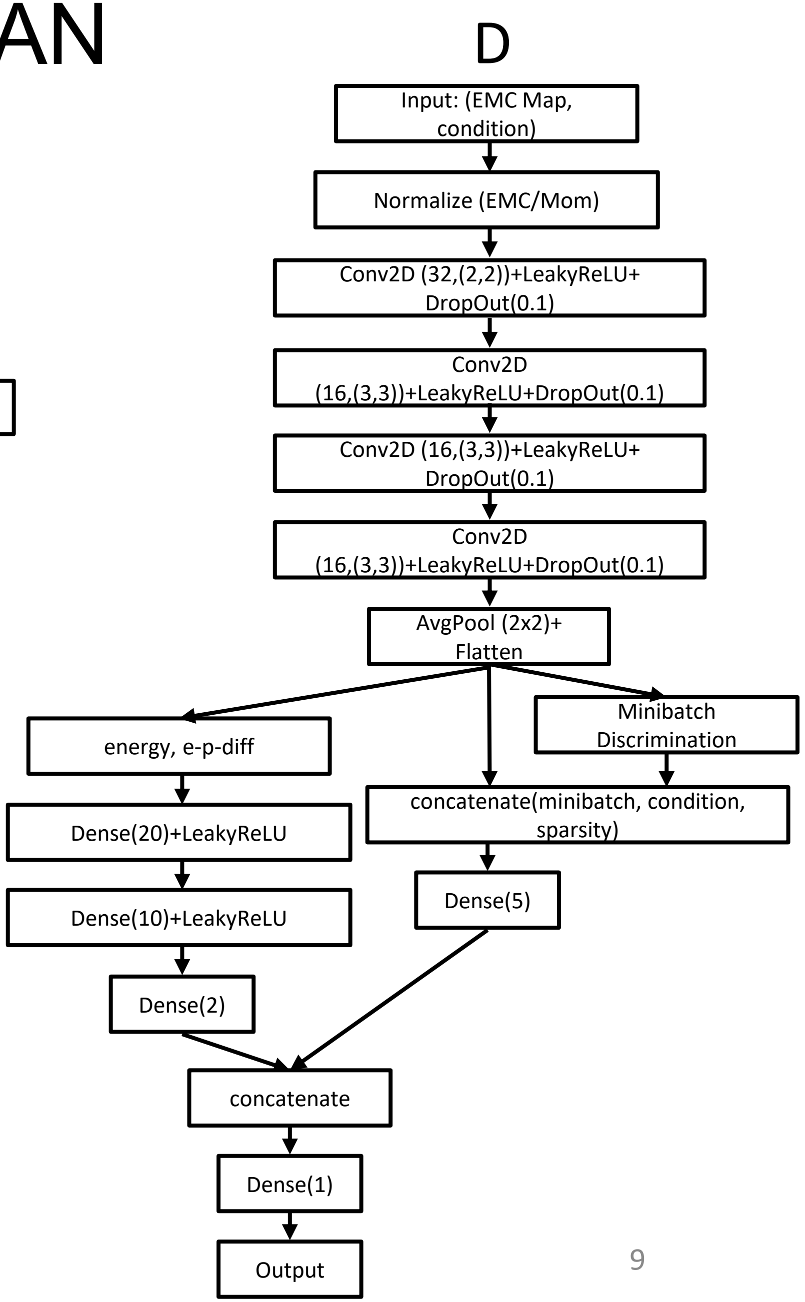
	E11x11 / Etot (%)
e^+	99.7
e^-	99.8
γ	99.8

EMC simulation with ML - GAN

- Similar strategy as LHCb case
- Use MC truth as input conditions
- Use regressor to reconstruct observables
- Use observables to constrain
- ~46k trainable parameters in generator



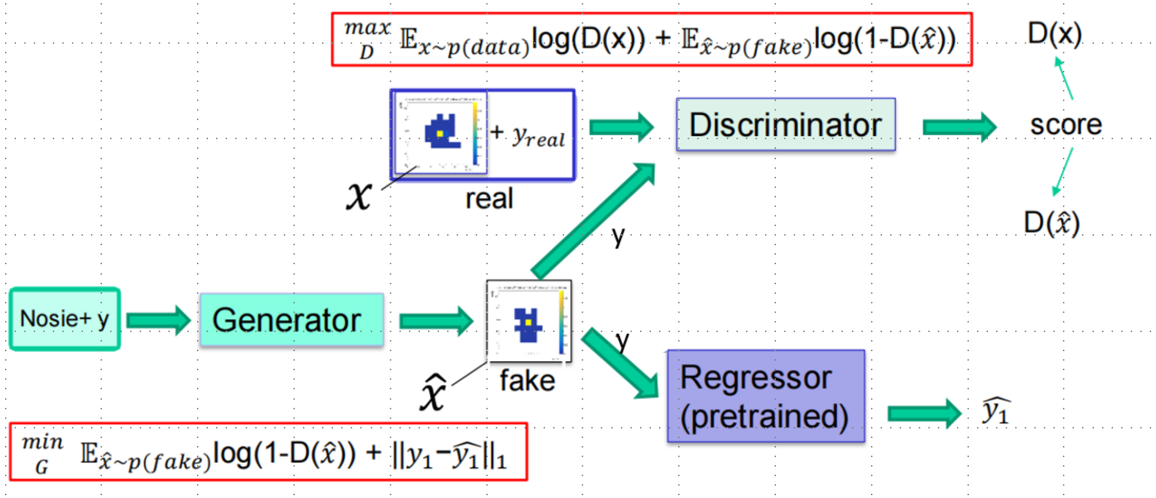


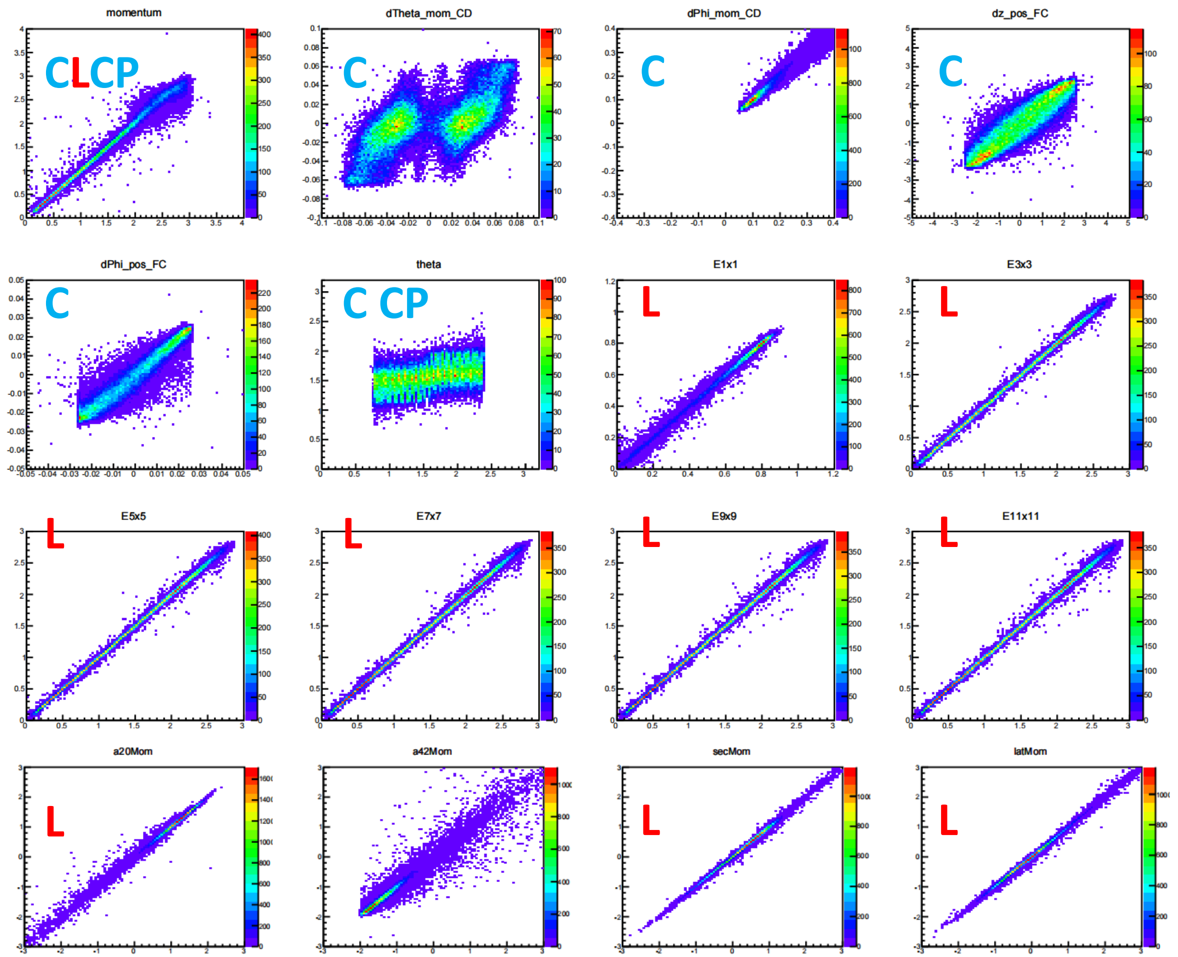


EMC simulation with ML - GAN

C: condition
L: for loss
CP: condition for γ

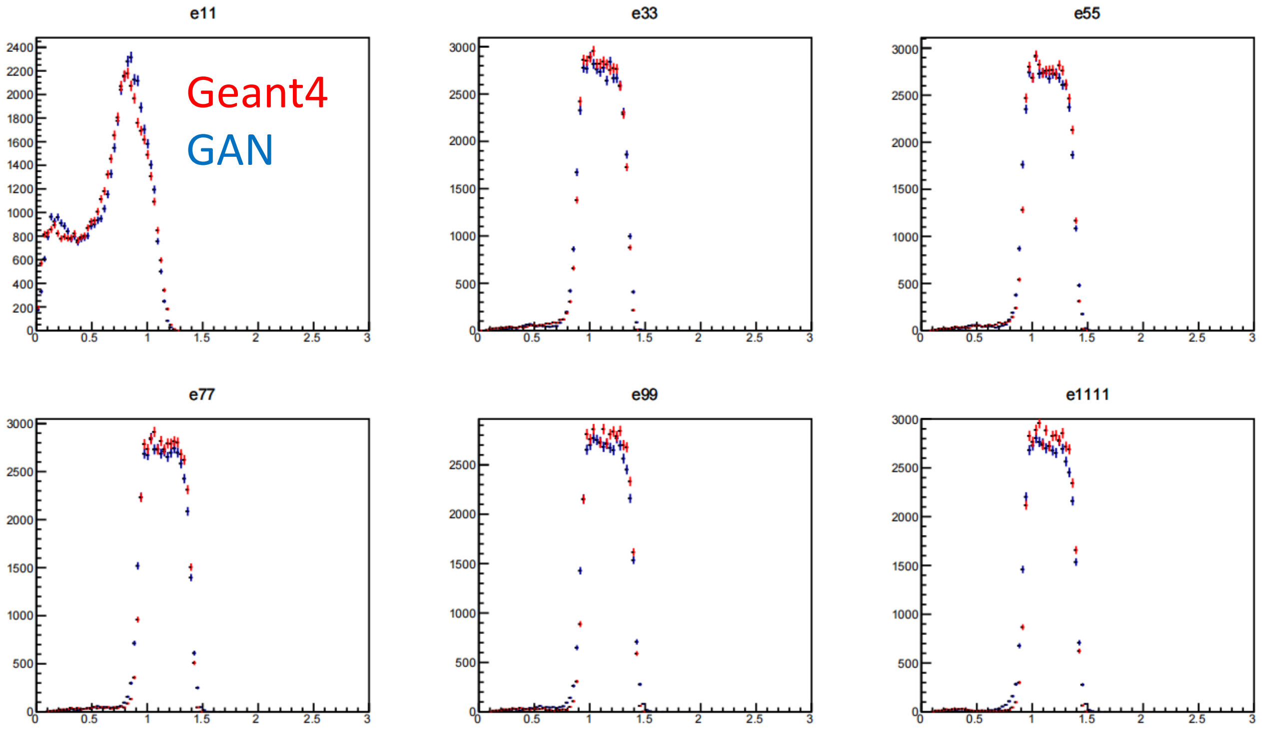
- Similar strategy as LHCb case
- Use MC truth as input conditions
- Use regressor to reconstruct observables
- Use observables to constrain
- ~46k trainable parameters in generator



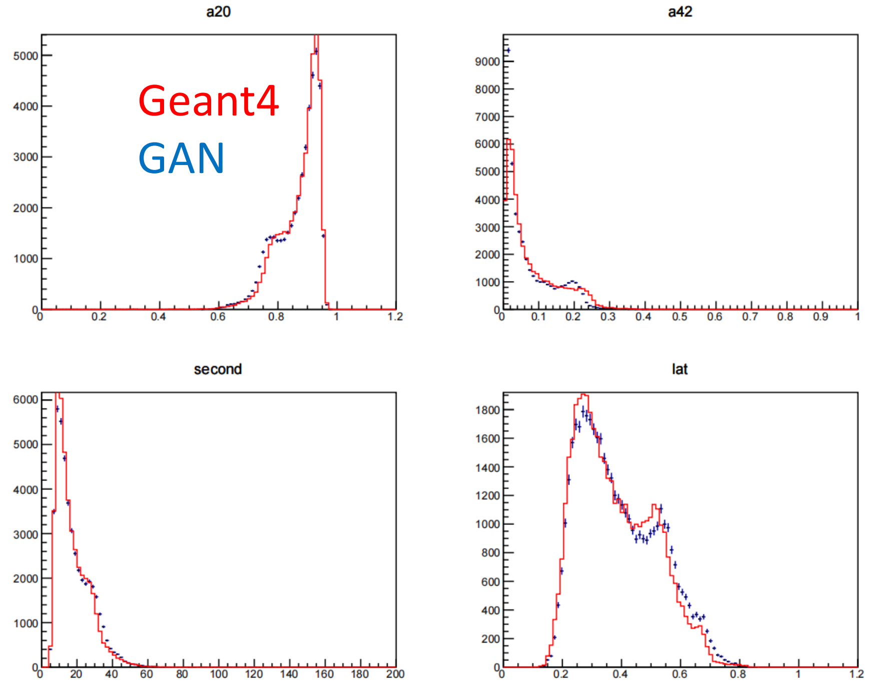


EMC simulation with ML – GAN for e^+

- With $1<\mathrm{Mom}<1.5$, $0<\theta<2\pi$, $0<\phi<2\pi$
- 50k tracks ~ **2s**



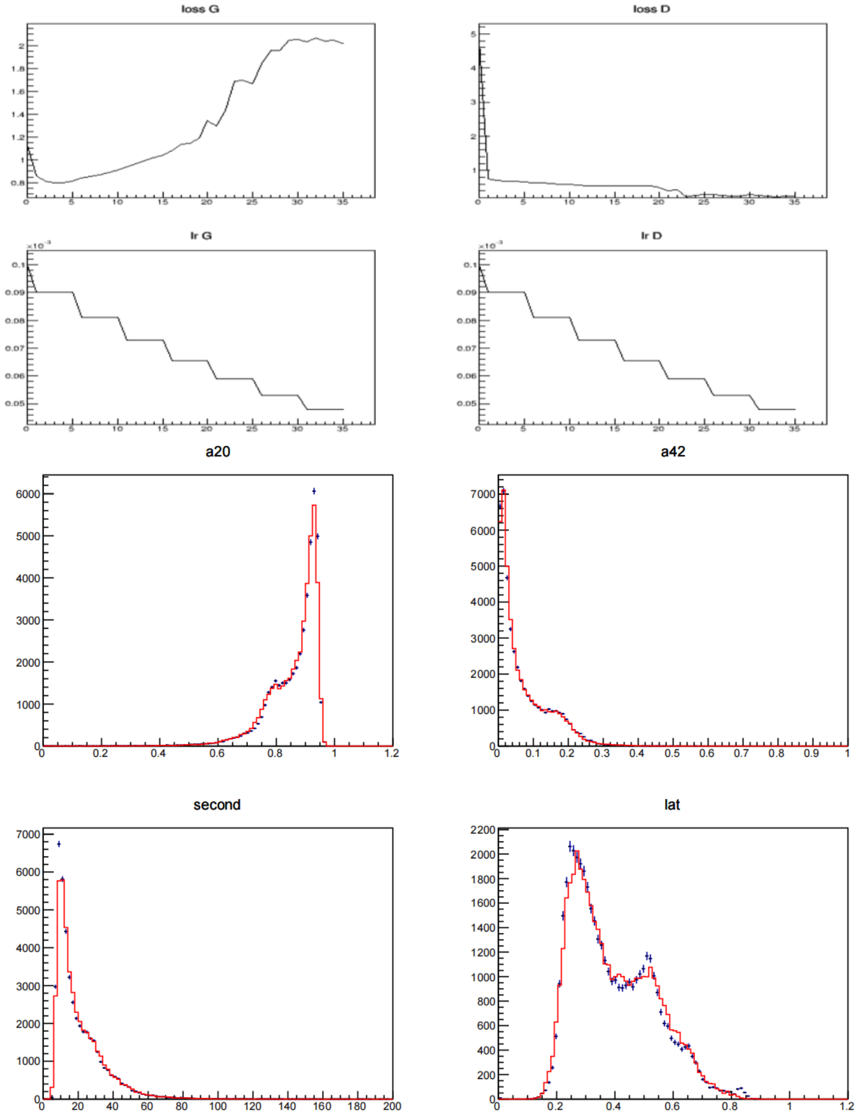
E1x1, E3x3 … E11x11



a20Mom, a42Mom, secondMom, latMom

EMC simulation with ML – GAN for e$^+$

- With 0<Mom<3, 0<theta<2π, 0<phi<2π
- 50k tracks ~ **2s**



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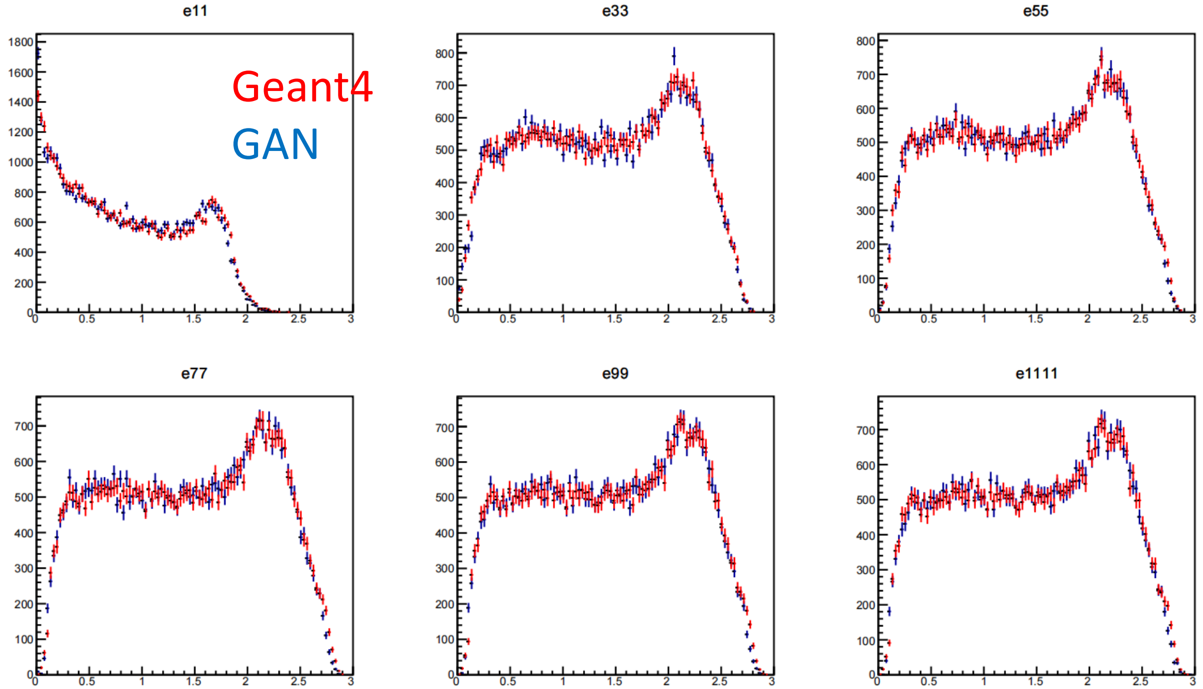
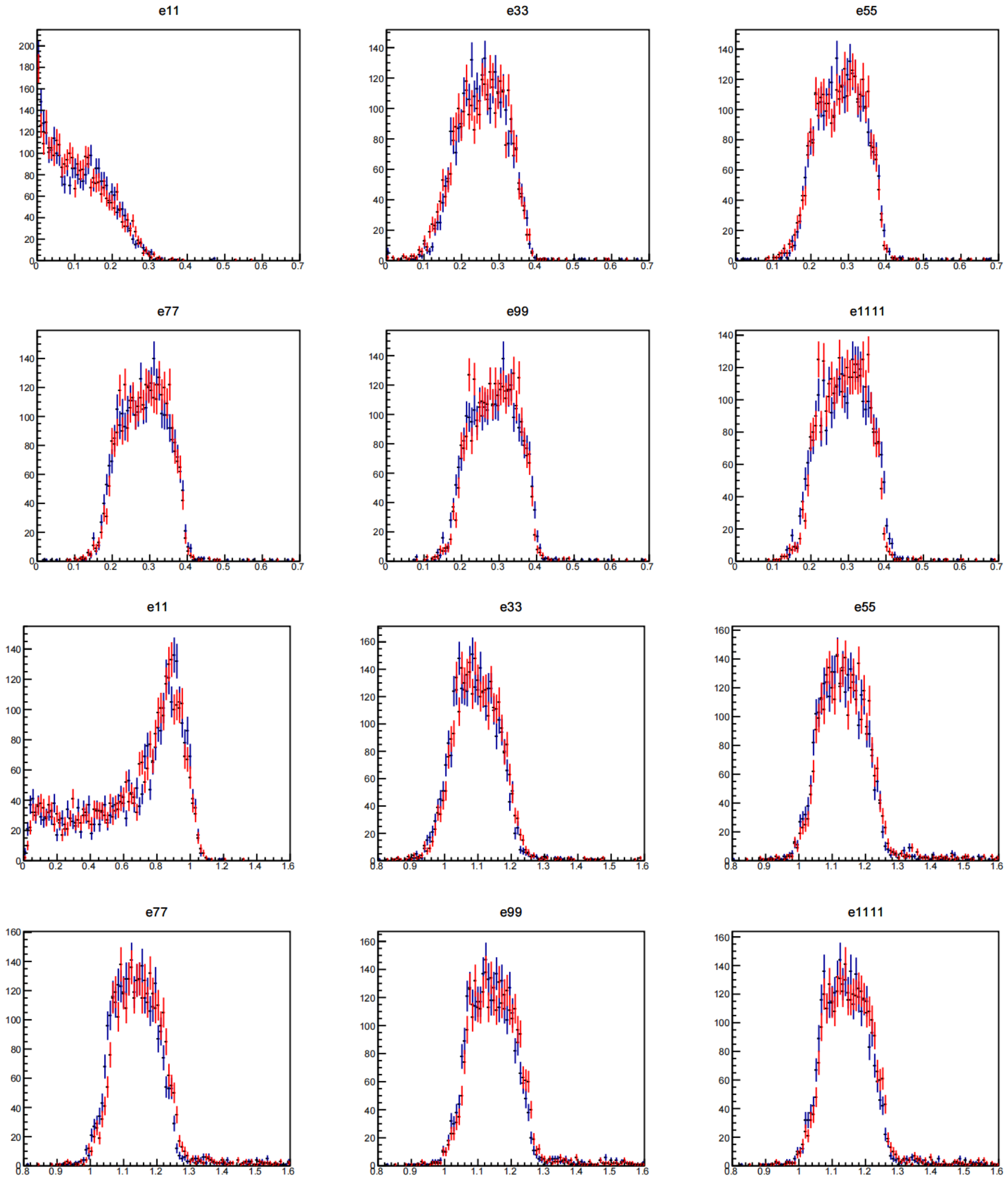


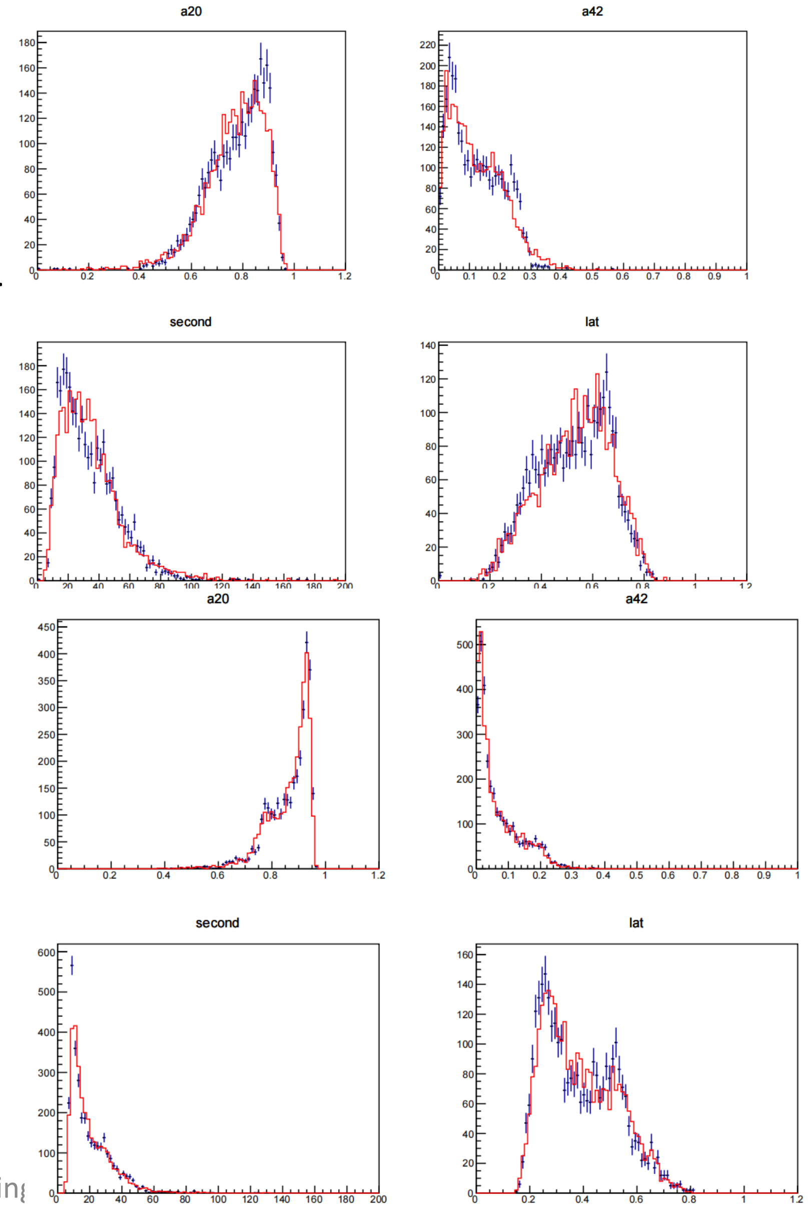
E1x1, E3x3 … E11x11

EMC simulation with ML – GAN for e^+



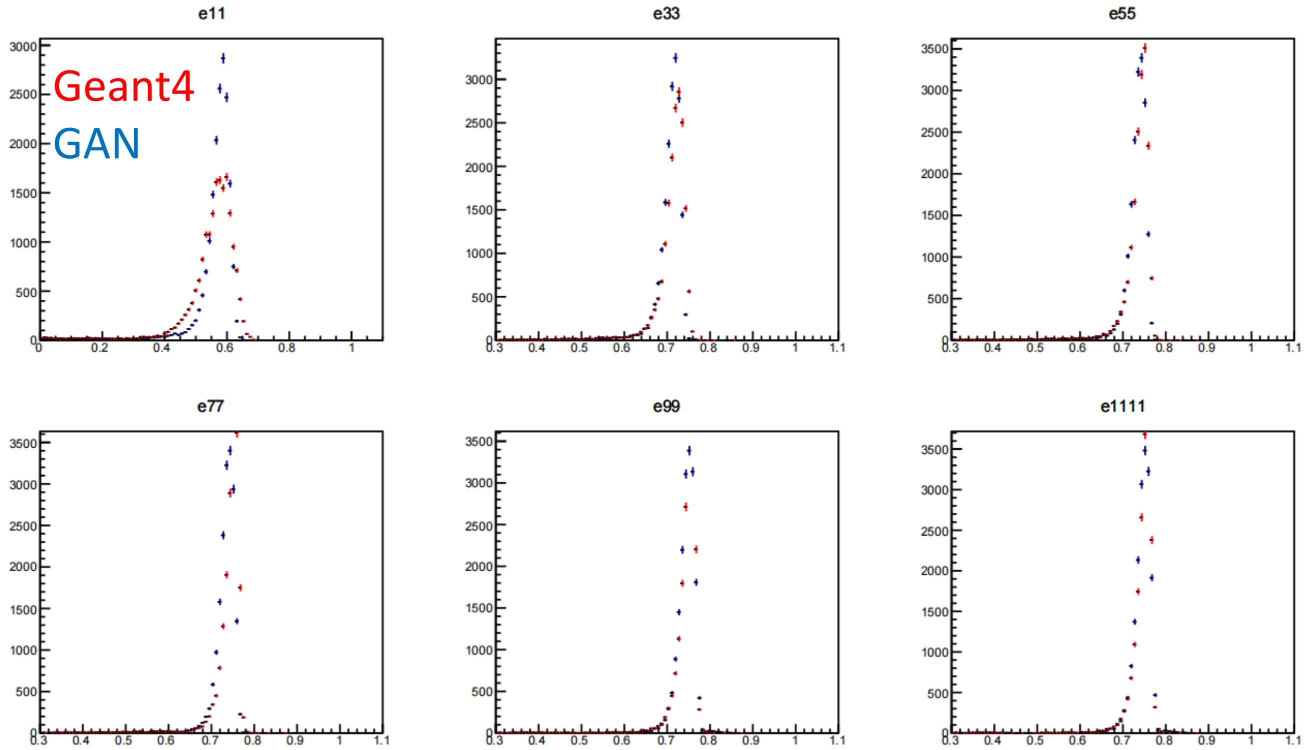
0.2<P<0.4

1.1<P<1.3

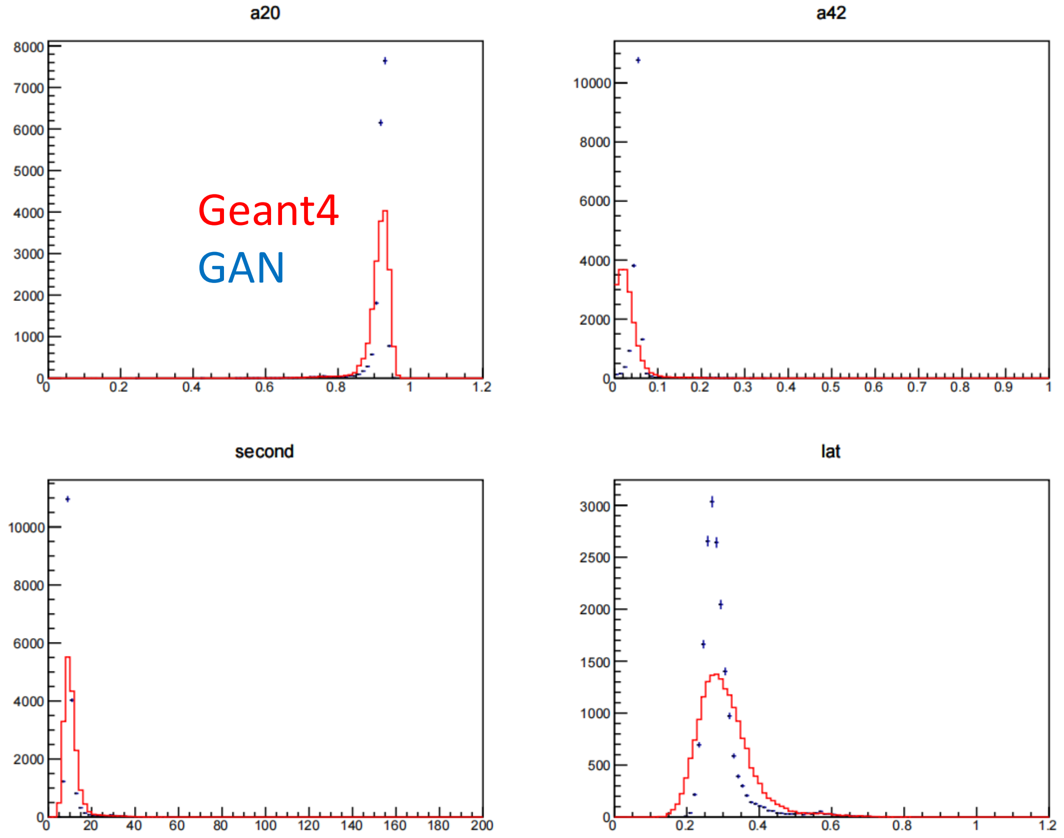


EMC simulation with ML – GAN for e^+

- Repeat the simulation for a single track to study the **resolution from simulation**
  - (Px,Py,Pz,E)= (0.32 0.73 0.01 0.80)



E1x1, E3x3 … E11x11



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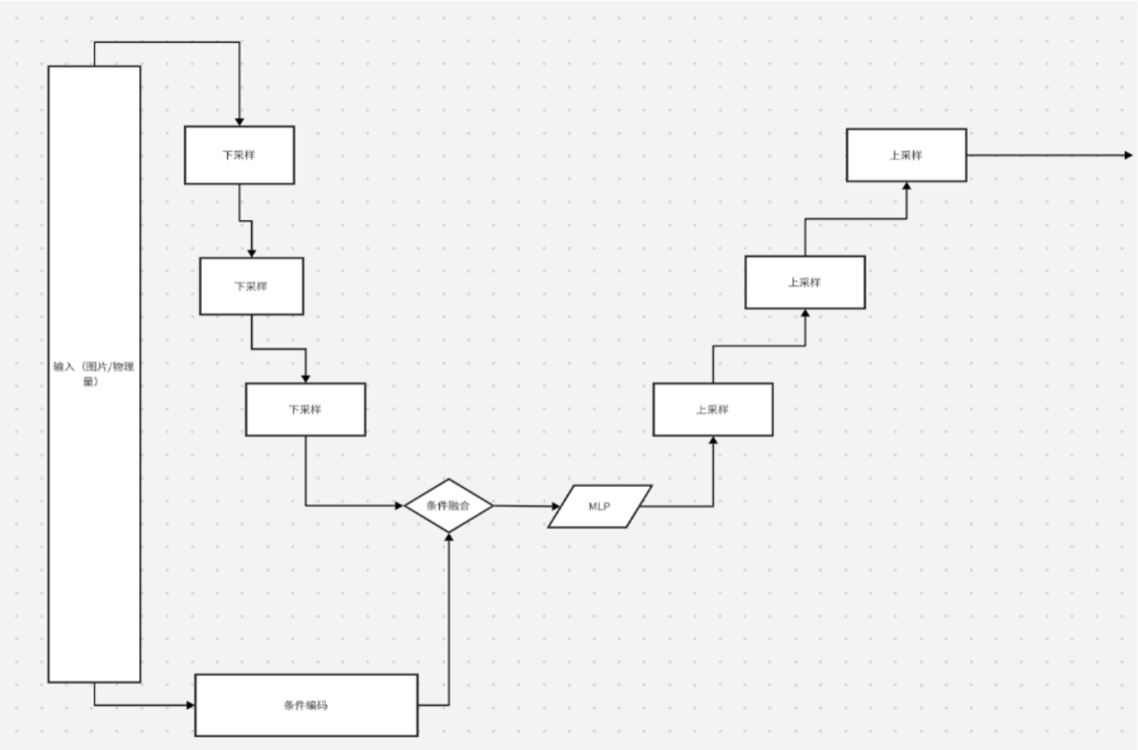
EMC simulation with ML – diffusion for γ

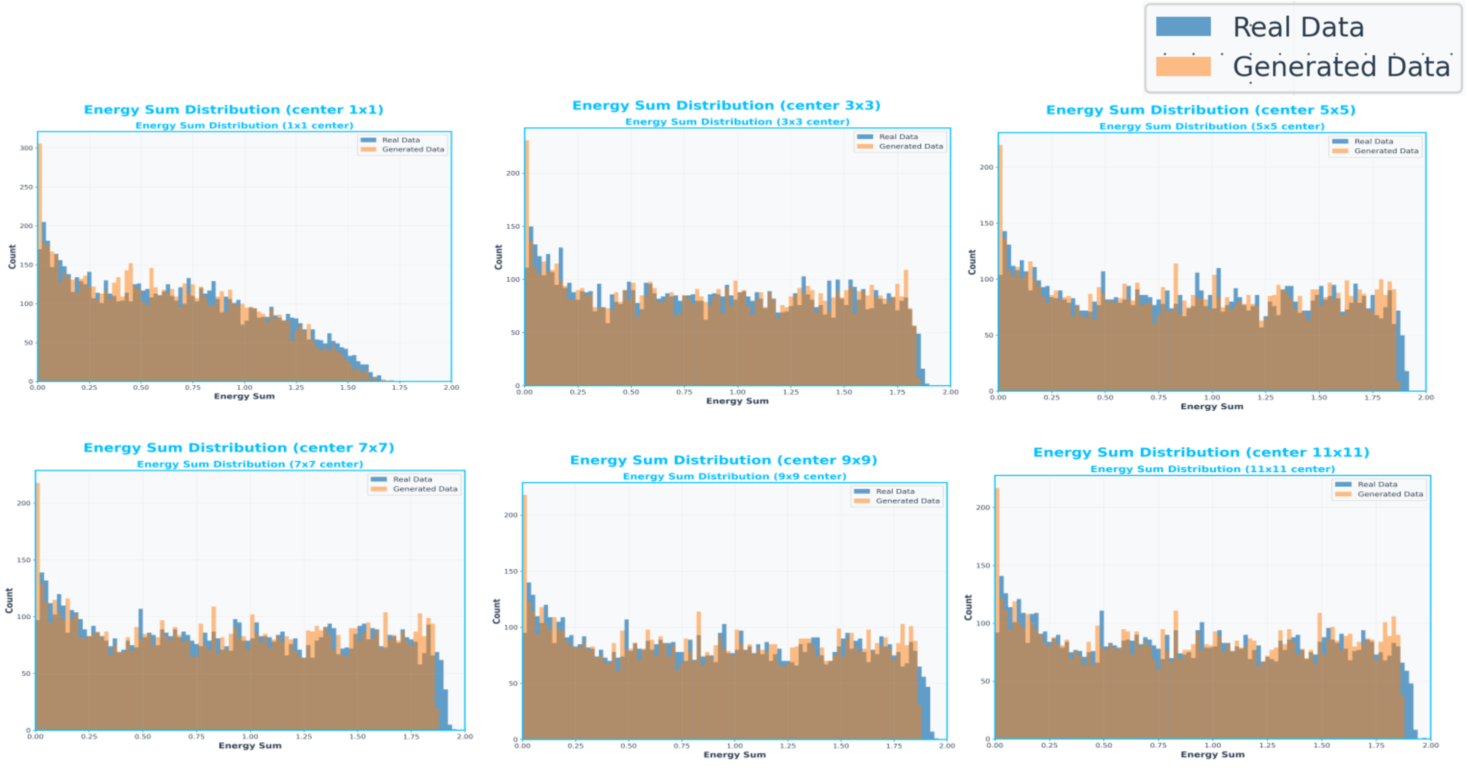
- Use a diffusion model to generate the shape of hit map
    - U-net architecture
    - 8.5 M trainable parameters



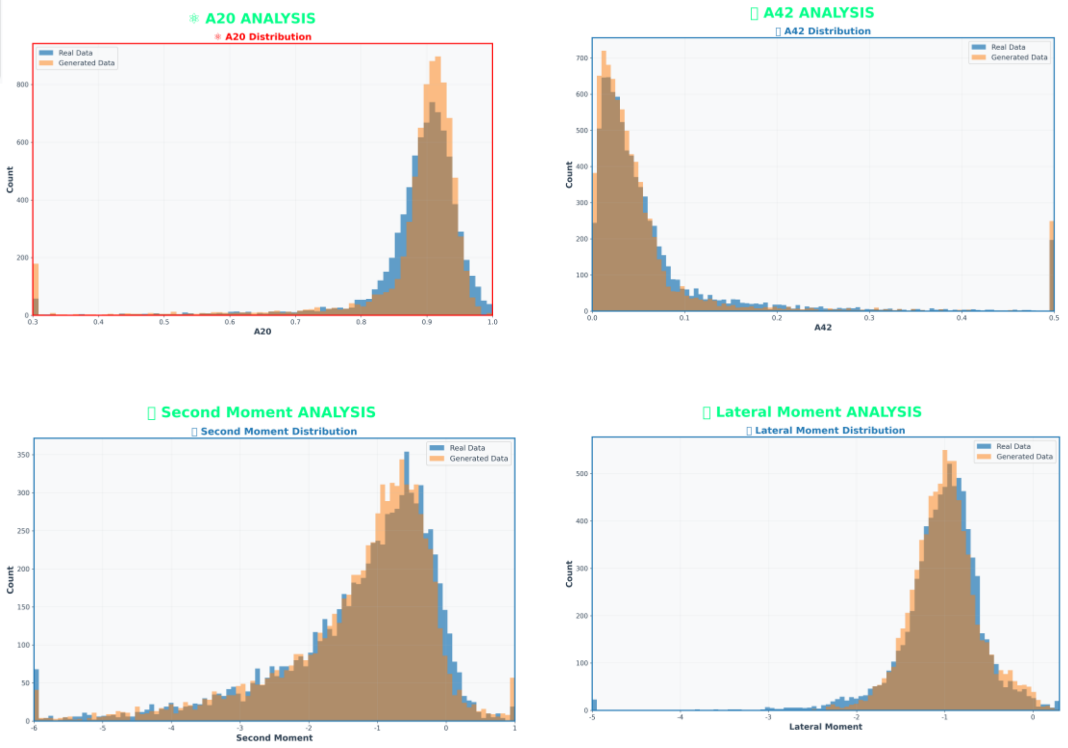
Diffusion Model Architecture Analysis
Convolutional Layers: 18
Fully Connected (Dense) Layers: 9
Normalization Layers: 17
Activation Layers: 19
Conditional Encoding Layers: 21

EMC simulation with ML – diffusion for γ

- Use a diffusion model to generate the shape of hit map (E/Etot)
    - 8.5 M trainable parameters



E1x1, E3x3 … E11x11



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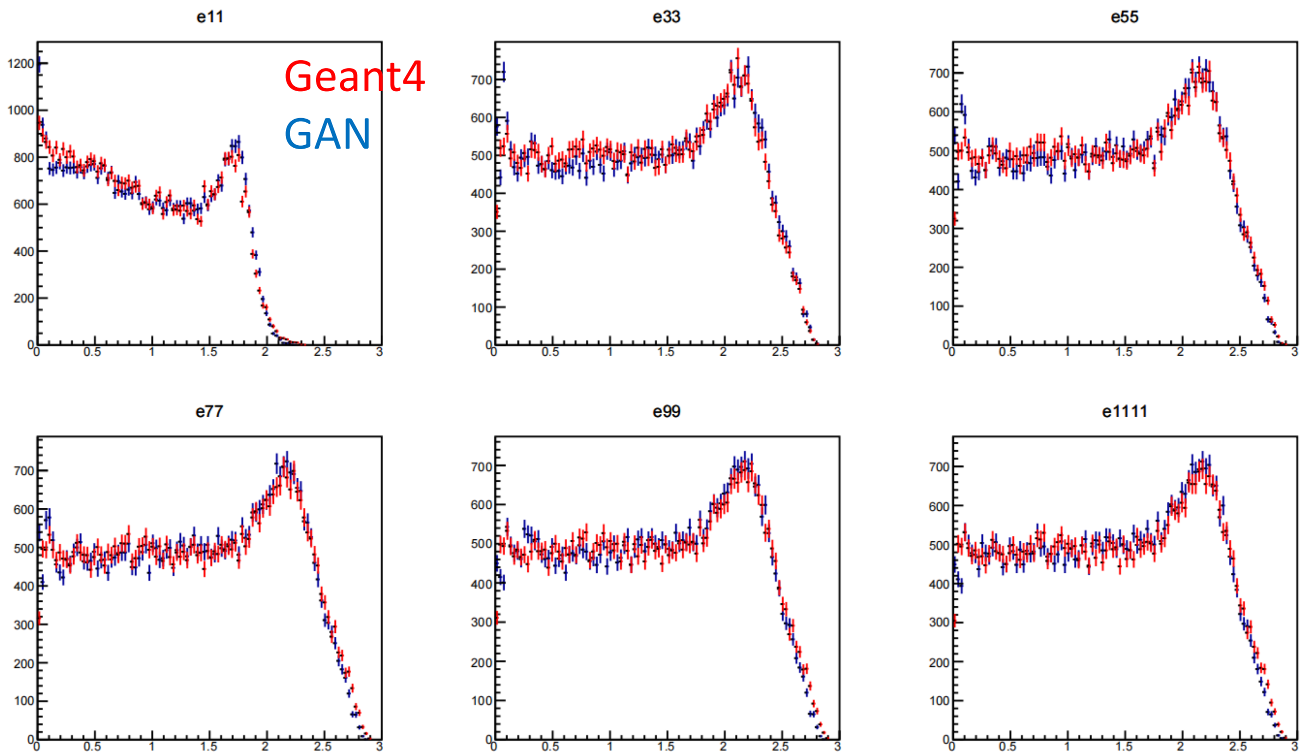
Summary & Next

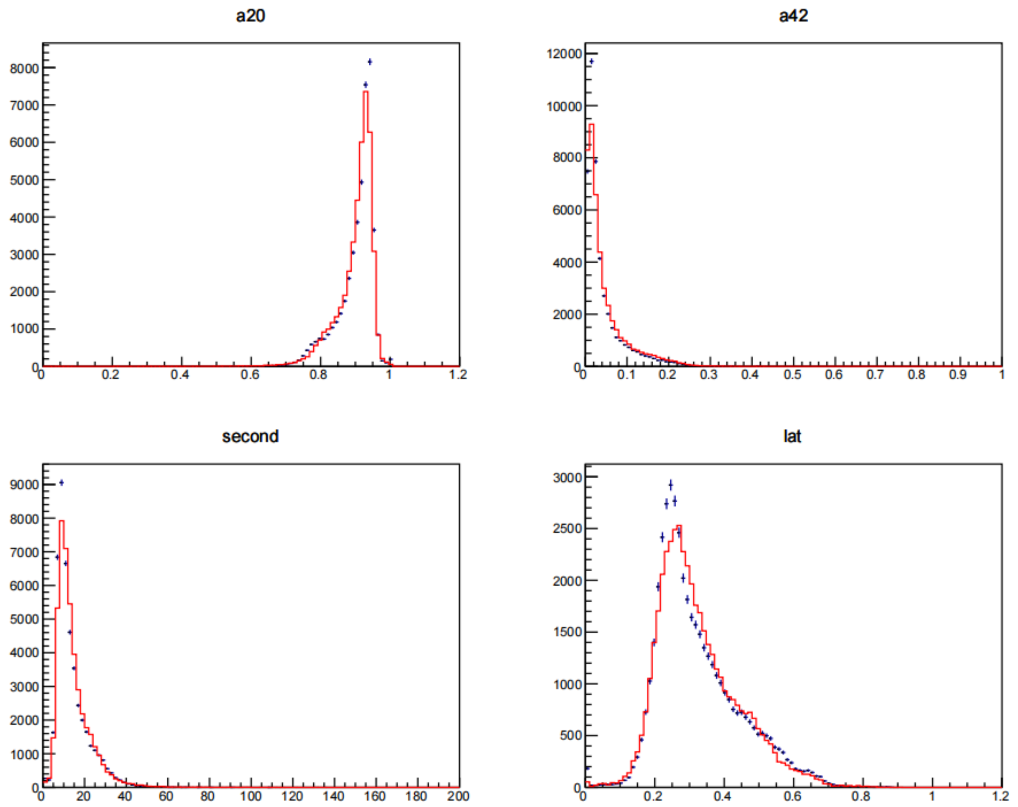
- We use ML to speed up the simulation
- The preliminary results are close to Geant4
  - GAN@CPU : 50k tracks ~ **2s**
- Further improvement are needed

GAN - gam

- 0<P<3, 0<theta<2pi, 0<phi<2pi



E1x1, E3x3 … E11x11



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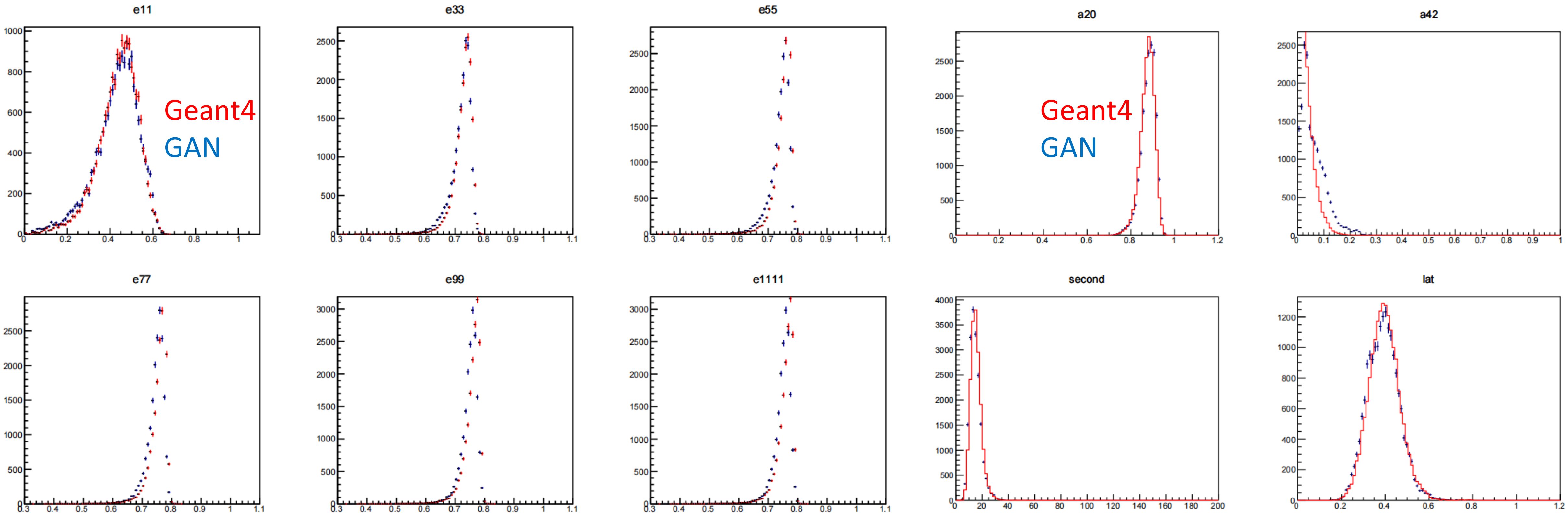
GAN - gam

- (Px,Py,Pz,E)= (0.32 0.73 0.01 0.80)

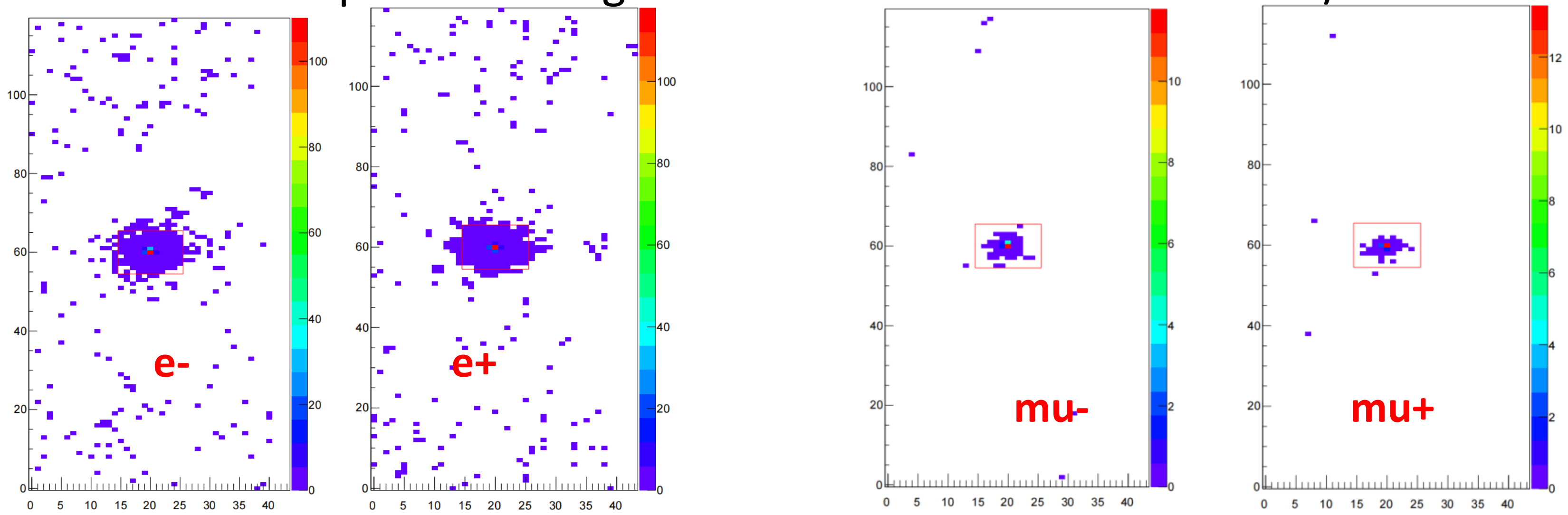


E1x1, E3x3 … E11x11

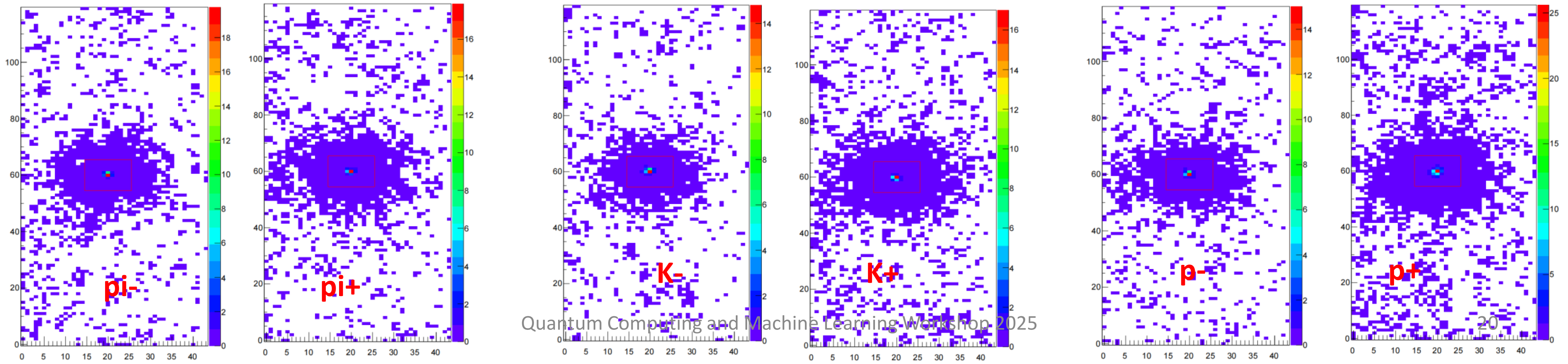
a20Mom, a42Mom, secondMom, latMom

Readout region

- EMC hit map in barrel region from 100 events with $P>1$ GeV/c^2



	E11x11 / Etot (%)
ep/em	99.7/99.8
mup/mum	99.9/99.9
pip/pim	89.7/85.5
Kp/Km	89.1/86.0
Pp/pm	88.7/84.8

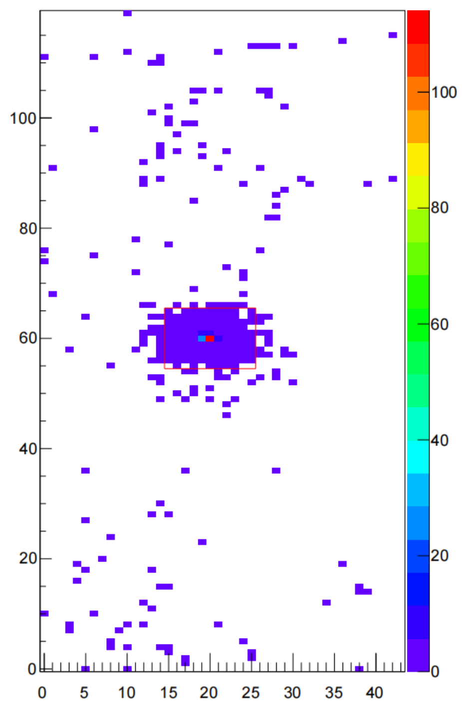


Readout region

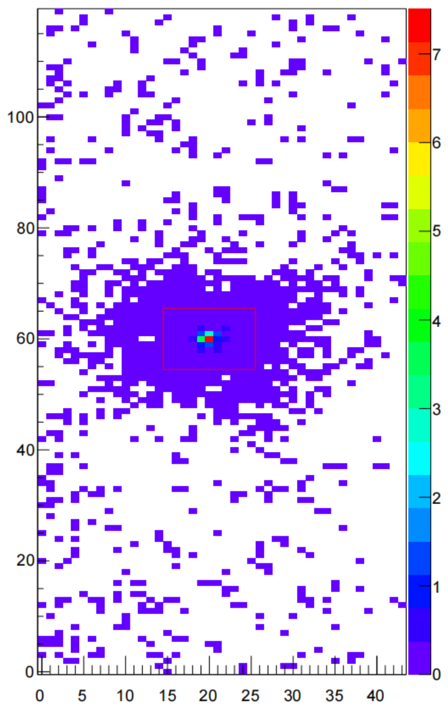
	E11x11 / Etot (%)
Gamma	99.8
n	87.7
nbar	91.6

- EMC hit map in barrel region from 100 events with P>1 GeV/c^2

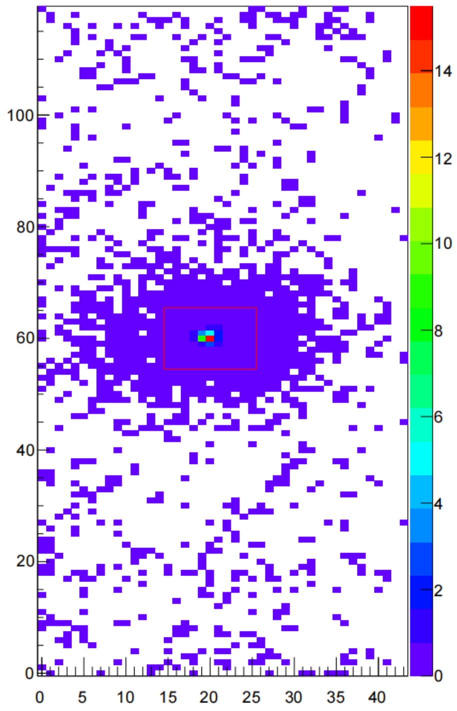
gamma



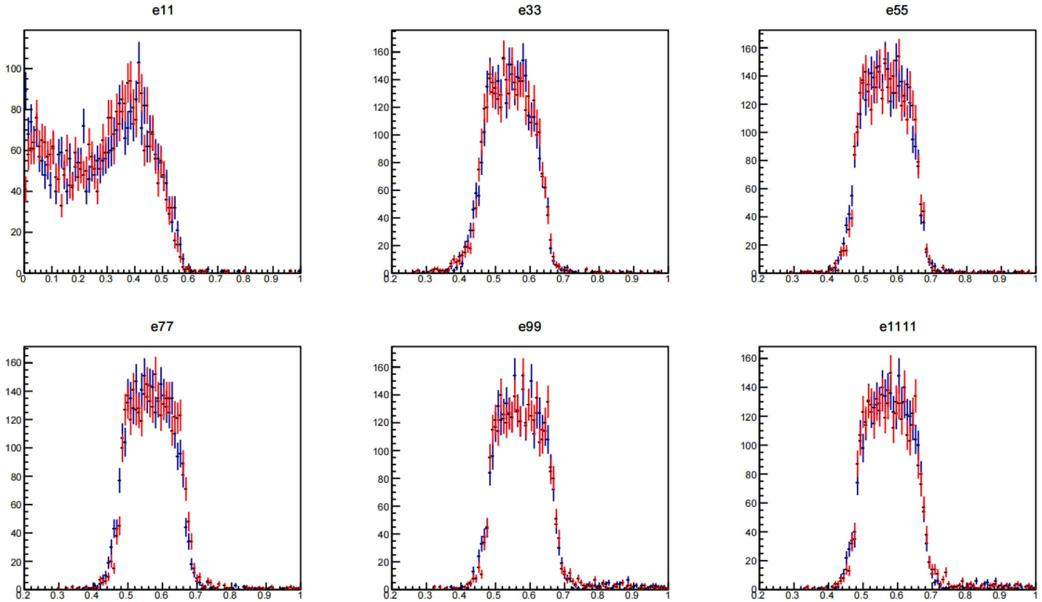
n

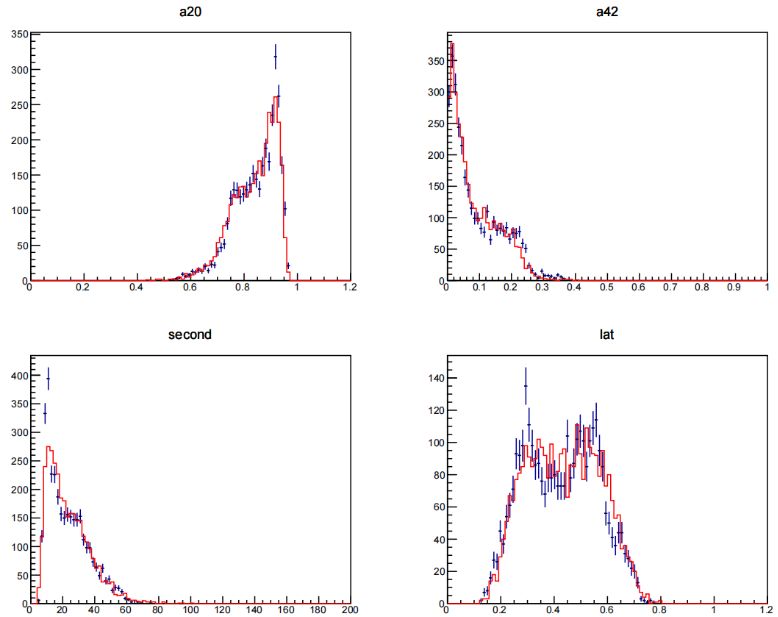


nbar

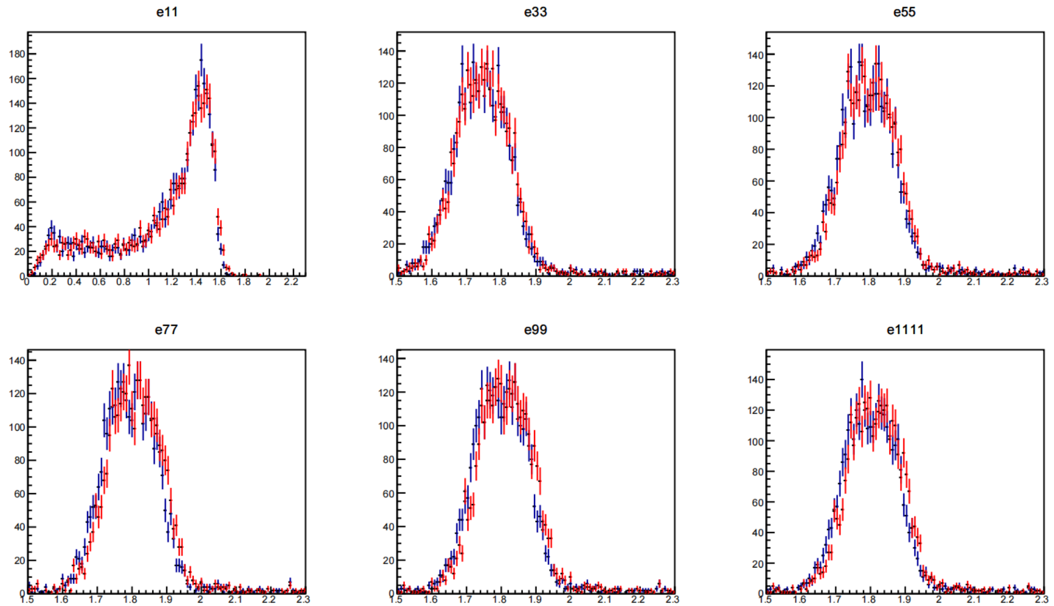


EMC simulation with ML – GAN for e^+





0.5<P<0.7



1.8<P<2