

GAN with an Auxiliary Regressor for the Fast simulation of the Electromagnetic Calorimeter Response

Problem: calorimeter response simulation procedure is one of the most computationally expensive parts of the LHCb experimental program. Historically it relies on the Monte Carlo methods which require a tremendous amount of computation resources. These methods may have difficulties with the expected High Luminosity Large Hadron Collider need, so the experiment is in urgent need of new fast simulation techniques.

Solution: use Generative Adversarial Networks as a possible solution to speed up the simulation, providing researchers with the necessary physics performance. In order to apply GANs practically, their performance should be properly evaluated using quality metrics and meet the physics requirements. In our previous study [1] we applied Self-Attentions and improved the performance of the model, however one of the quality metrics can be improved

In this presentation we propose adding Auxiliary Regressor into Discriminator to improve the quality of generated objects

Using Generative Model to Simulate Detector Response

Main goal is to **generate energy distribution in ECAL:**

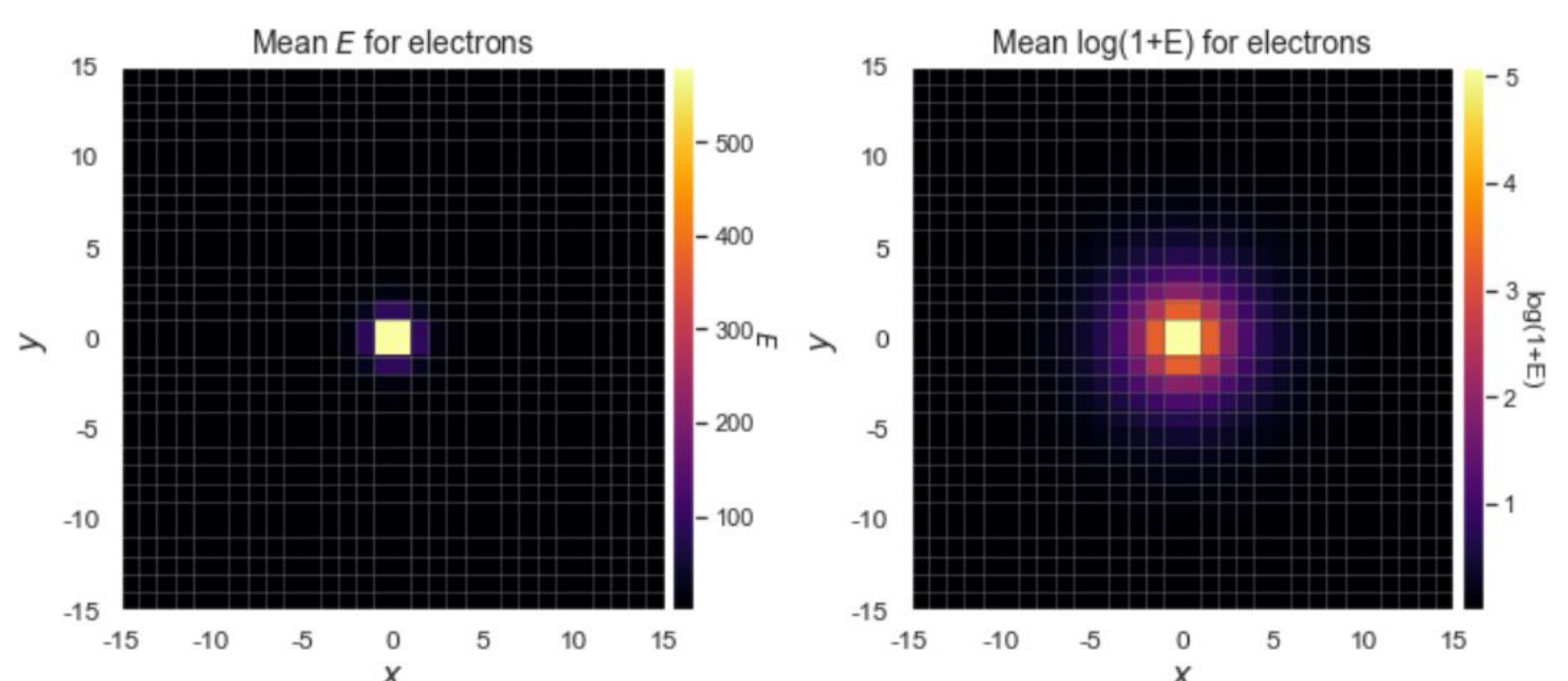
- Faster than Geant4
- Improve performance of the previously published models

Input:

- ParticlePoint (x,y,z) – known starting point location
- ParticleMomentum (p_x, p_y, p_z) – known momentum

Output:

- Consider 20 mm cell to fit both 40 mm and 60 mm cells
- EnergyDeposit – 30×30 energy distribution matrix, shower width < 600 mm



Previous best-performing architecture is based on

Convolutional and Self-Attention layers

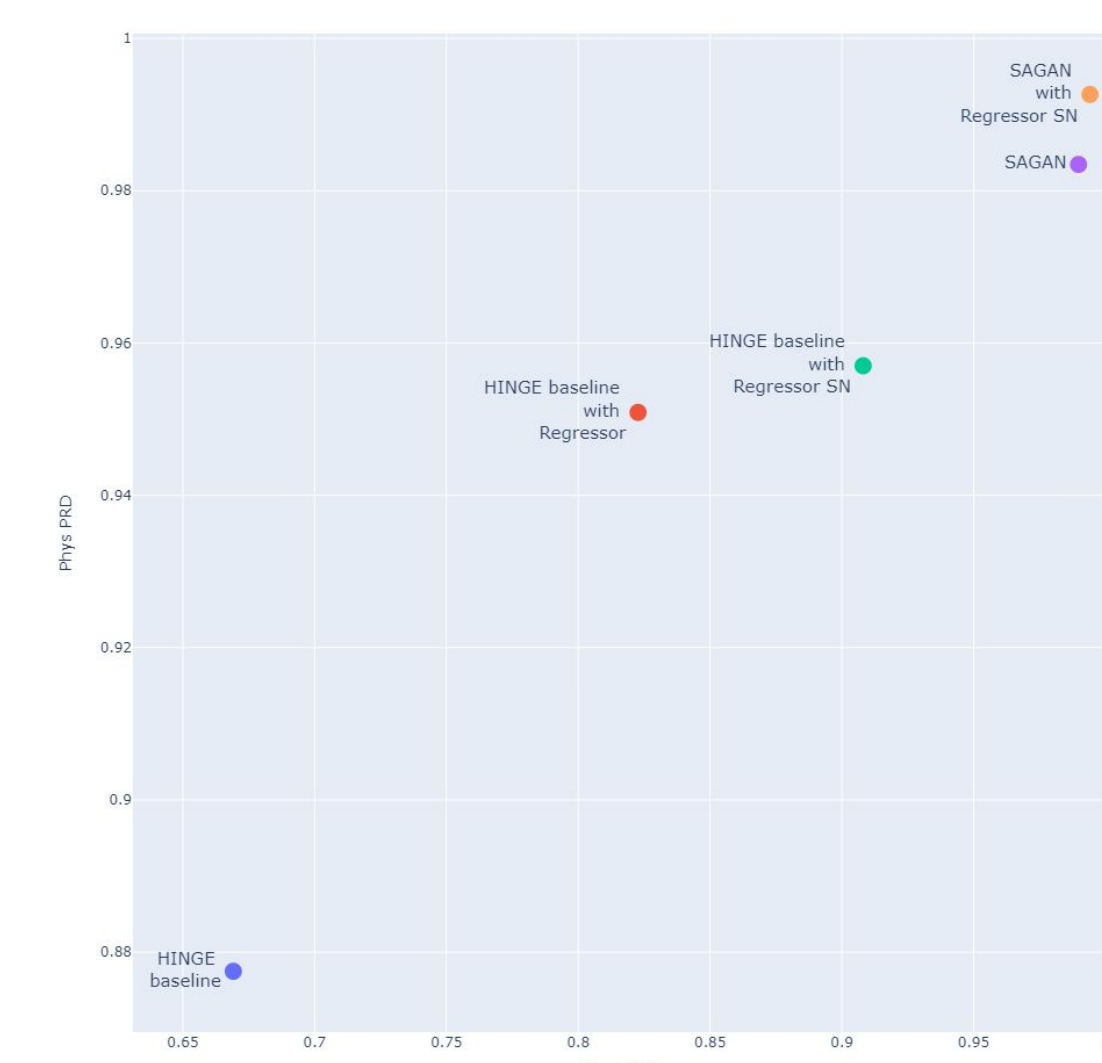
Performance evaluation

- To evaluate the quality of generated samples and the performance of the models PRD-AUC is used:

$$PRD(Q, P) = \{(\theta\alpha(\lambda), \theta\beta(\lambda)) | \lambda \in (0, \infty), \theta \in [0, 1]\},$$

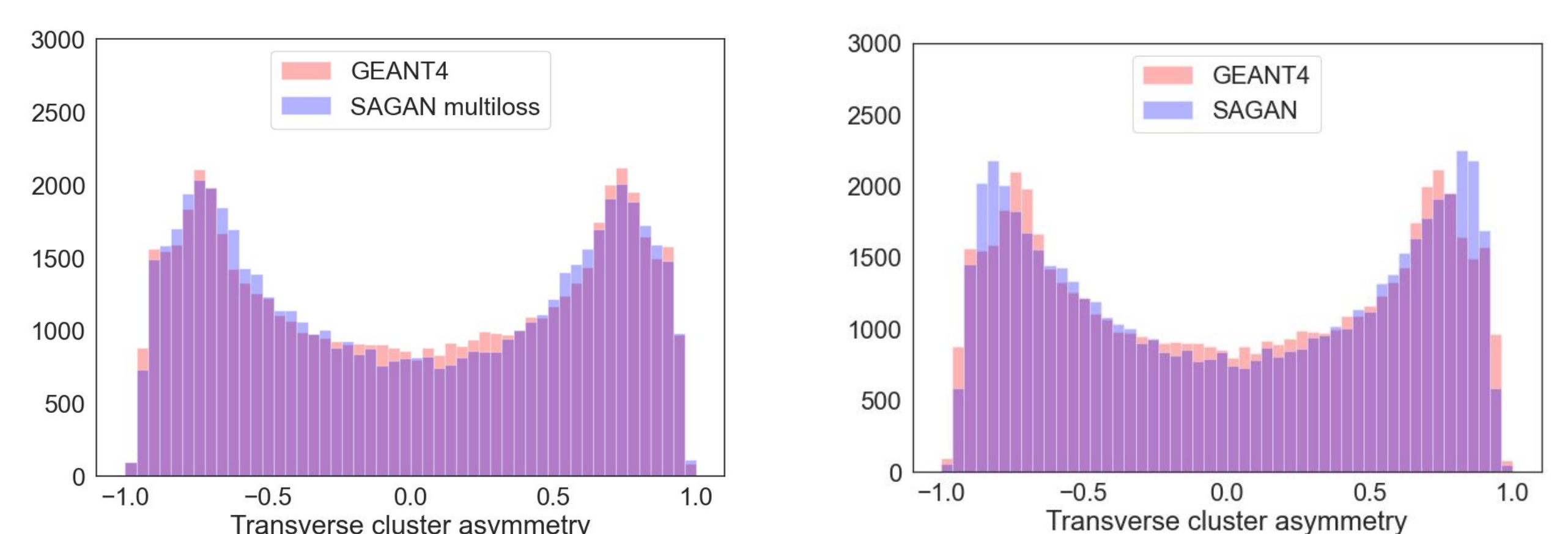
where P and Q are distributions, defined on a finite state space, $\alpha(\lambda) = \sum \min(\lambda P(\omega), Q(\omega)), \omega \in \Omega, \beta(\lambda) = \sum \min(P(\omega), \lambda Q(\omega)), \omega \in \Omega$

- Use the minimum of two PRD-AUC scores, evaluated over raw images and over a set of physical metrics (shower asymmetry, shower width, the number of cells with energies above a certain threshold)
- For every single architecture model performed better in case of using the Auxiliary regressor that evaluated asymmetry



Comparing distributions

- As we added a regressor that evaluates asymmetry, the distribution of asymmetry calculated over generated samples improved
- In our experiments, the regressor and GAN are fitted simultaneously, loss consists of weighted Adversarial Hinge loss and MSE, respectively.



Using Auxiliary Regressor to Evaluate Asymmetry

- Asymmetry is used in order to evaluate the performance of the model
- Asymmetry of generated objects should be improved to become closer to original one
- We added an auxiliary regressor to evaluate asymmetry of a given energy sample
- Use the output of the regressor as a condition inside Discriminator

Relationship between aux-regressor quality and results

- As we increase the weight of auxiliary loss, the quality of a regressor increases
- Thus the distribution of asymmetry that we evaluate using regressors improves

