Controlling Quality for a Physics-Driven Generative Models and Auxiliary Regression Approach

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Problem: high energy physics experiments heavily rely on the results of MC simulation of data used to extract physics results. However, *the detailed simulation often requires tremendous amount of computation resources.*

Solution: *Generative Adversarial Networks and other deep learning generative techniques can drastically speed up the computationally heavy simulations like a simulation of the calorimeter response.* The auxiliary regression extension to the GAN-based fast simulation demonstrated improvements of the physics quality for generated objects. This approach introduces physics metrics to a Discriminator path of the model thus allows direct discrimination of objects with poorly reproduced properties.

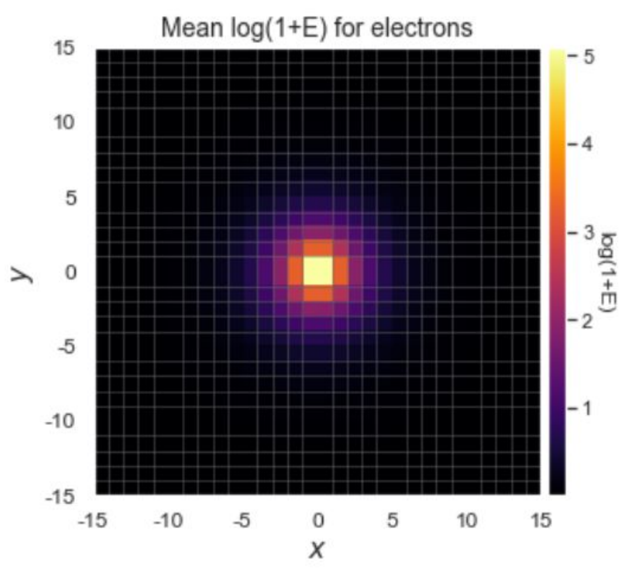
In this presentation we discuss the requirements to the quality of the auxiliary regressor to provide a necessary precision of the generative models built on top of this regressor.

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

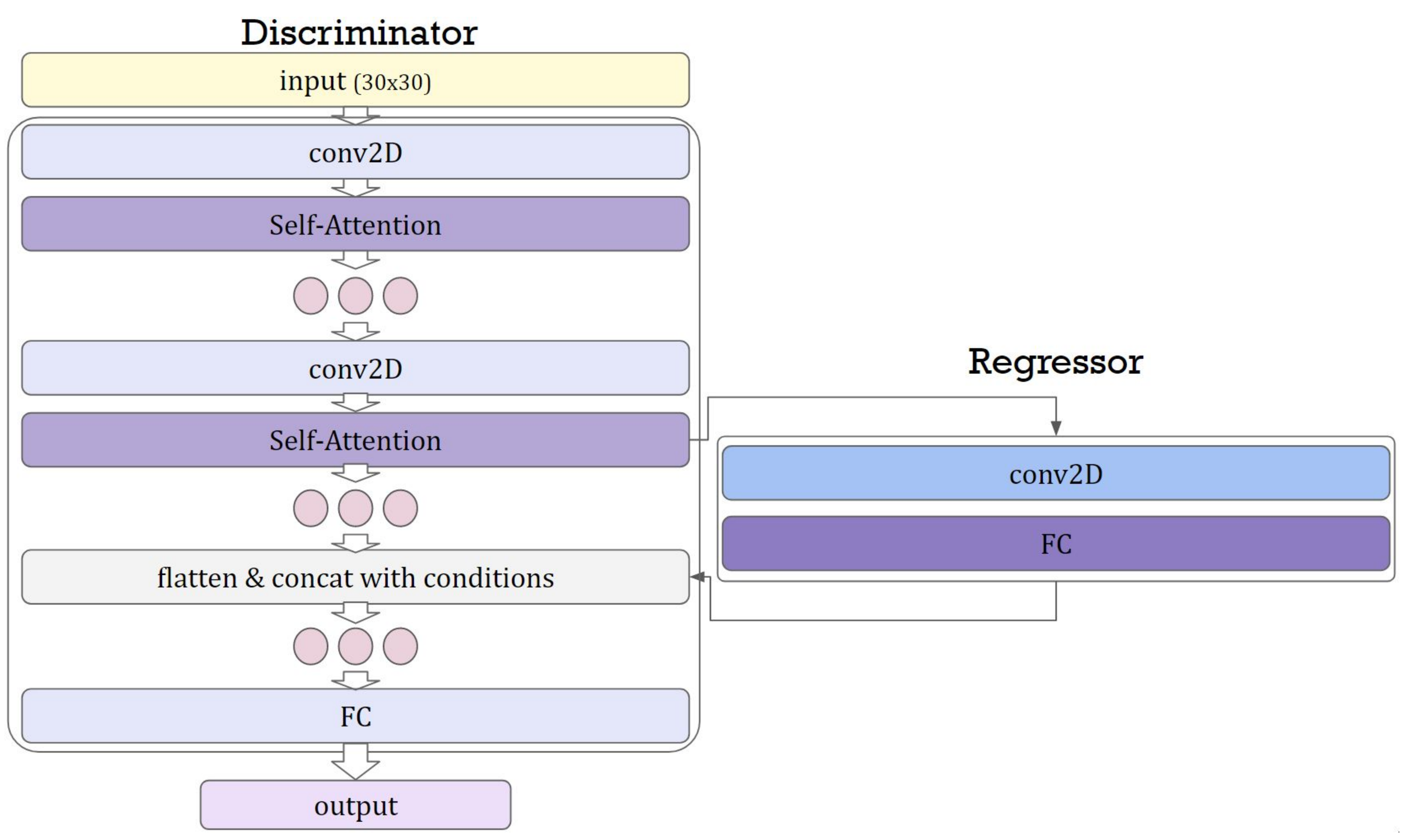
Input:
- ParticlePoint (x,y,z) – known starting point location
- ParticleMomentum (p_x, p_y, p_z) –known momentum

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



Auxiliary Regressor for GANs

- In order to improve the quality of produced distributions, especially of those statistics that we use during quality evaluation, we propose **Auxiliary Regressor**
- Its goal is to evaluate some particular metrics that we want to reproduce
- It **shares the first layers** with the regular Discriminator
- We try to provide the NN with the information about the desired metrics, expecting it to learn it as now **discriminators can detect generated objects with badly reproduces metrics values**
- It even becomes possible to **optimize a quality metric that was not differentiable before**, as now we can use backpropagation to train a network that approximates it
- The training procedure is either **multi-task**:
  - Both networks are trained simultaneously with two losses: regression (MSE) and adversarial (Hinge)
- … or **two-step**:
  - Models are trained for the regression task only
  - All obtained weights of the regressor are frozen and pluged it into the Discriminator
  - Finally, the model is fit in an adversarial setting with hinge loss only
- By introducing an additional task into the training procedure we let our model catch some general information that can be useful for both objectives
- An example of AUX-Regressor extension architecture looks as follows:



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

Comparing regressors

- To study the relationship between regression and generation qualities we compare different architectures for the regression part:
  - CNN-based model from scratch (CNN)
  - CNN-based model with Self-Attentions from scratch (CNN SA)
  - Discriminator-like architecture from scratch (DiscArch)
  - Pretrained Discriminator-like architecture tuned with high learning rate (DiscArch HLR)
  - Pretrained Discriminator-like architecture tuned with low learning rate (DiscArch LLR)

Performance evaluation

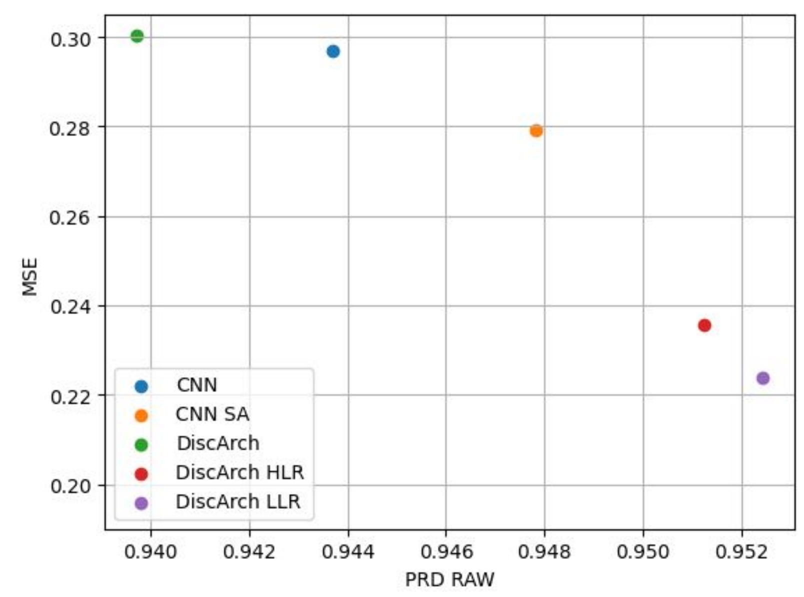
- To evaluate the quality of generated samples and the performance of the models PRD-AUC is used:

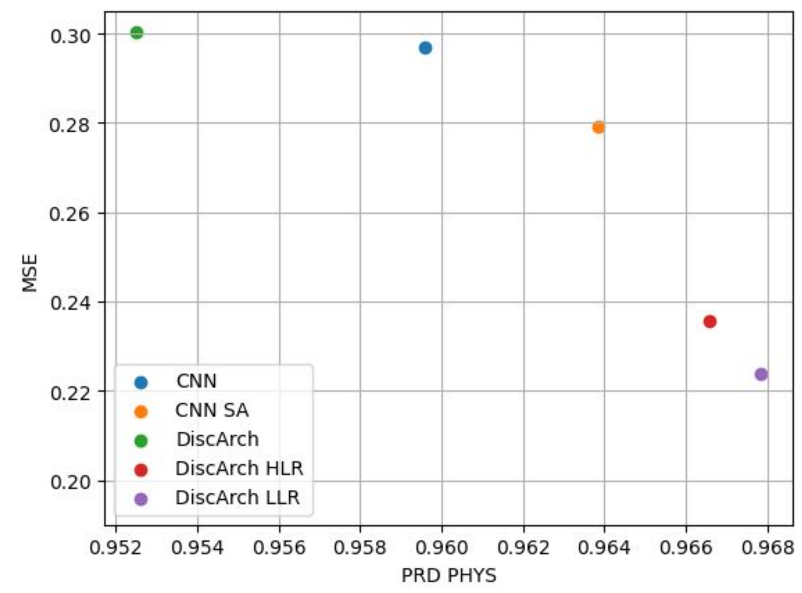
  PRD(Q, P) = {(θα(λ), θβ(λ))|λ ∈ (0, ∞), θ ∈ [0, 1]},

  where P and Q are distributions, defined on a finite state space,

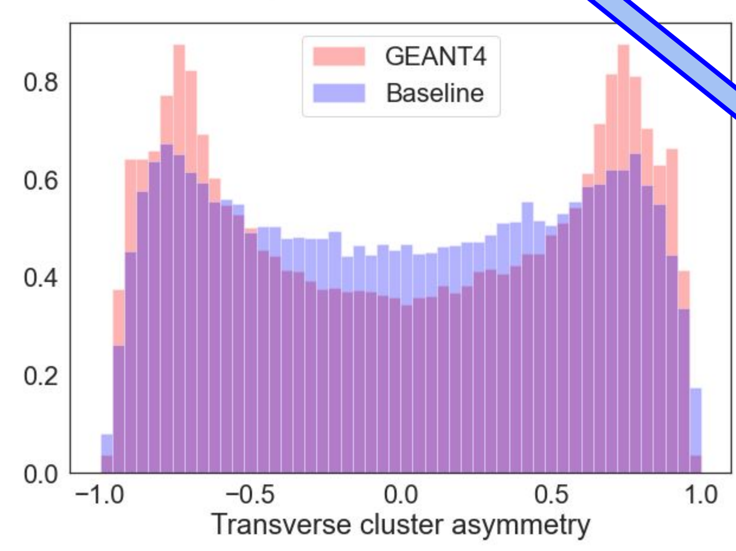
  α(λ) = ∑ min(λP(ω), Q(ω)), ω∈Ω, β(λ) = ∑ min(P(ω), Q(ω) / λ), ω∈Ω
- Use the minimum of two PRD-AUC scores, evaluated over raw images and over a set of physical metrics (shower asymmetry, shower width, the number of cells with energies above a certain threshold)

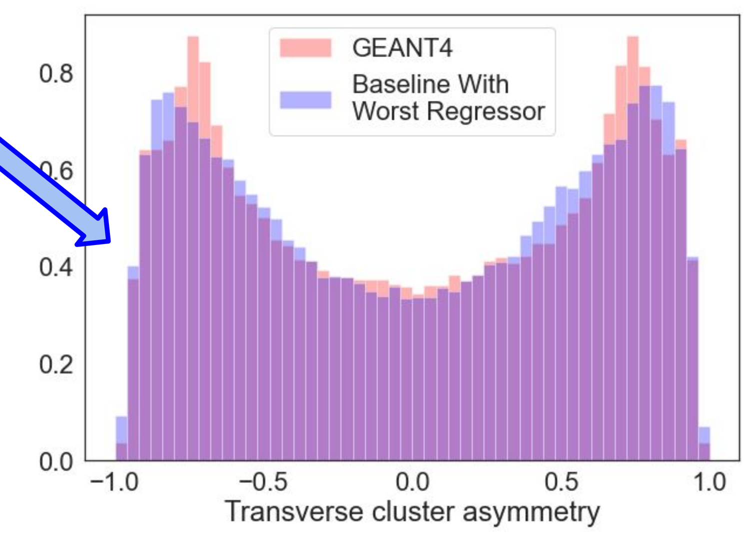
Model Name	Raw PRD	Phys PRD	MSE
Baseline	0.669	0.877	-
CNN	0.943	0.959	0.297
CNN SA	0.947	0.963	0.279
DiscArc	0.939	0.952	0.300
DiscArch HLR	0.951	0.966	0.235
DiscArch LLR	**0.952**	**0.967**	**0.223**





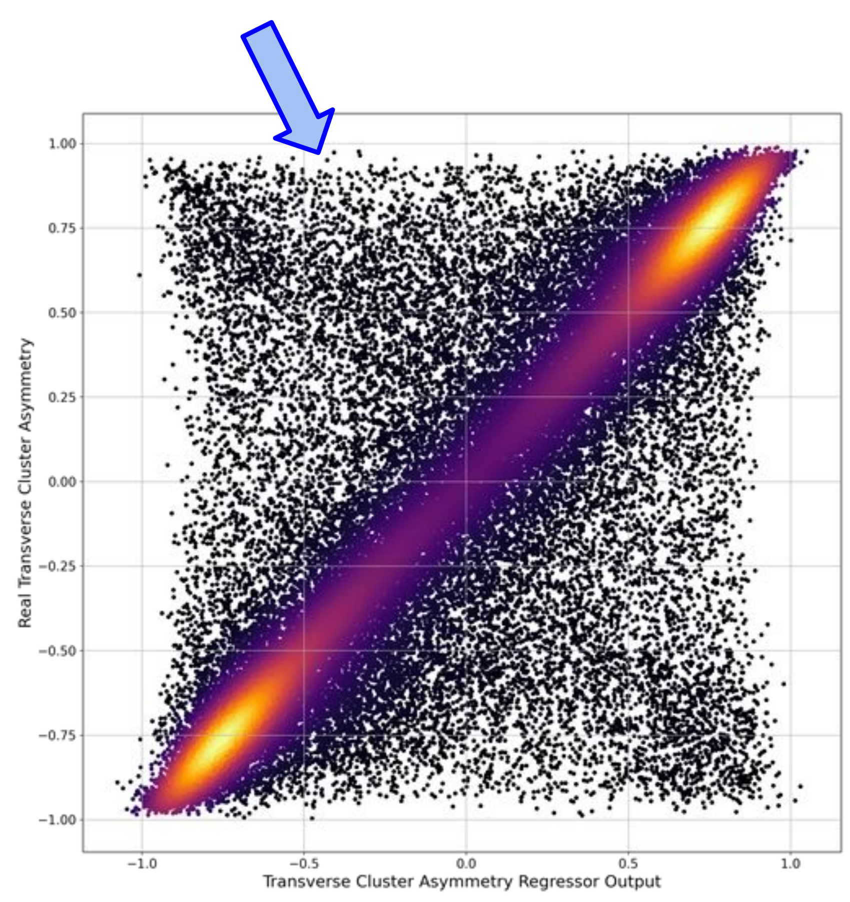
- Even the **worst regressor** highly improves the quality of generated objects in terms of objective metric

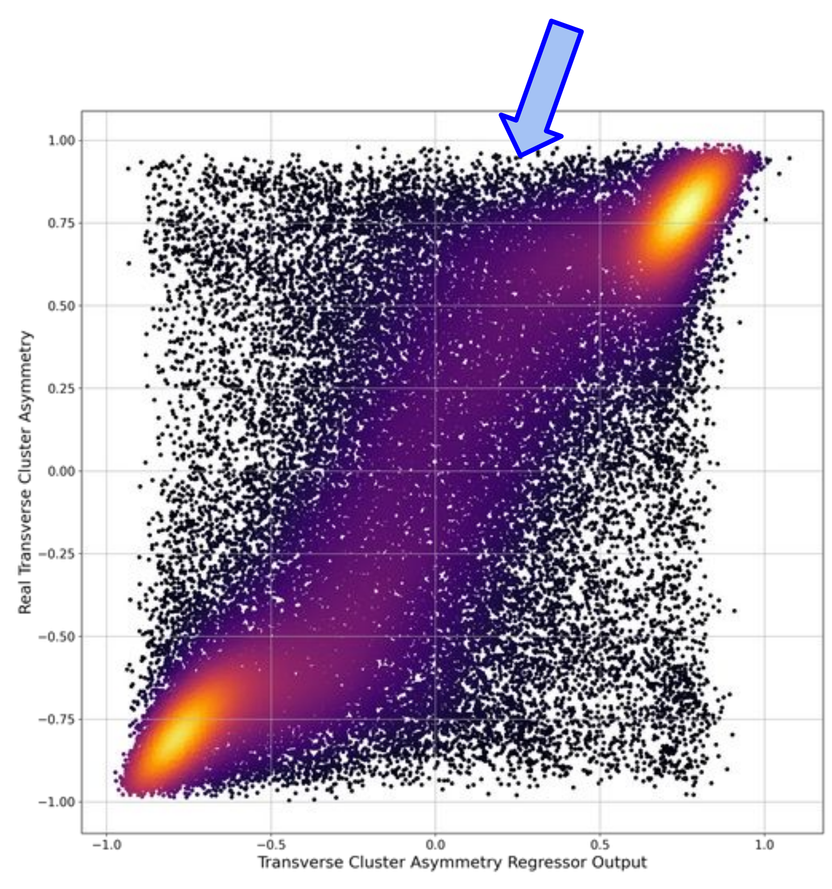




Two-Step vs Multi-Task

- Regressor with the lowest MSE was pretrained in multi-task manner
- Regressor with the highest MSE was trained only using Regression Loss
- They both have the same architecture
- **Multi-task** approach provides significantly better regressor quality than **two-step** approach





Summary

★ Incorporating extra surrogate regressor does improve quality of the generative model
★ The better quality of the regressors' predictions provides the better quality for the chosen metrics of the generative model (tested for **two-step** fitting procedure)
★ Even regressor with poor quality improves the quality of generated objects significantly
★ **Multi-Task** approach provided us with better quality