Deep Generative Models for Proton Zero Degree Calorimeter Simulations in ALICE, CERN

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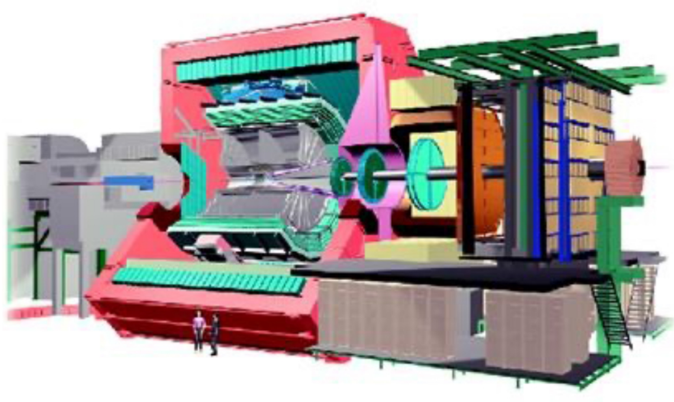
#TLDR

- CERN uses Large Hadron Collider (LHC) to study fundamental matter properties in High Energy Physics experiments.
- Understanding and analysing these experiments requires running complex **simulations** which are computationally very demanding.
- Leveraging **generative machine learning** provides an efficient alternative to existing approaches.
- We focus on simulating the **Proton Zero Degree Calorimeter** (ZDC) in the ALICE experiment, exploring modifications of **Generative Adversarial Networks**.

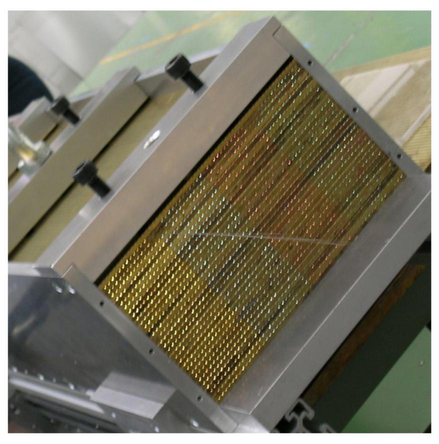
Simulation overview

ALICE TPC

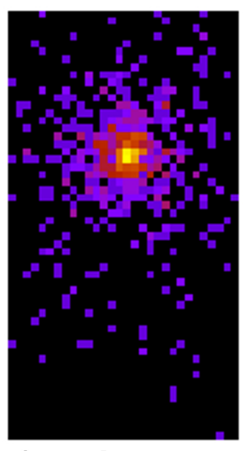


Simulation input: *Particle parameters*

Simulation output : *ZDC response*



Photons deposited in a fiber grid



1- channel pixel image

Zero Degree Calorimeter

Figure 1. Fast simulation overview

Take-aways

- Machine learning generative models provide **an efficient alternative to current simulation methods** used in High Energy Physics experiments at CERN.
- Adding **subsequent regularization** improves the fidelity of the generated images,
- SDI-GAN improves the diversity of generated samples,
- Intensity regularization helps to model wide range of distribution found in images from true dataset,
- Auxiliary regressor improves the geometric properties of generated data.

Framework of simulations

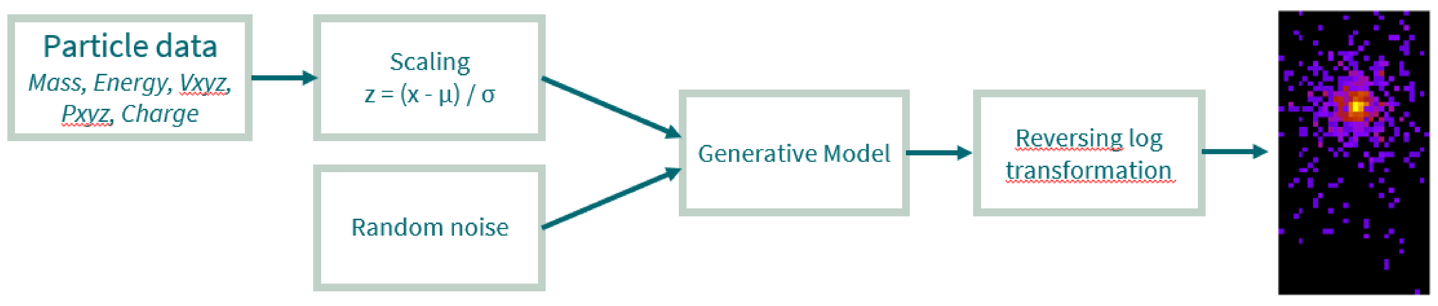


Figure 2. Simulation framework

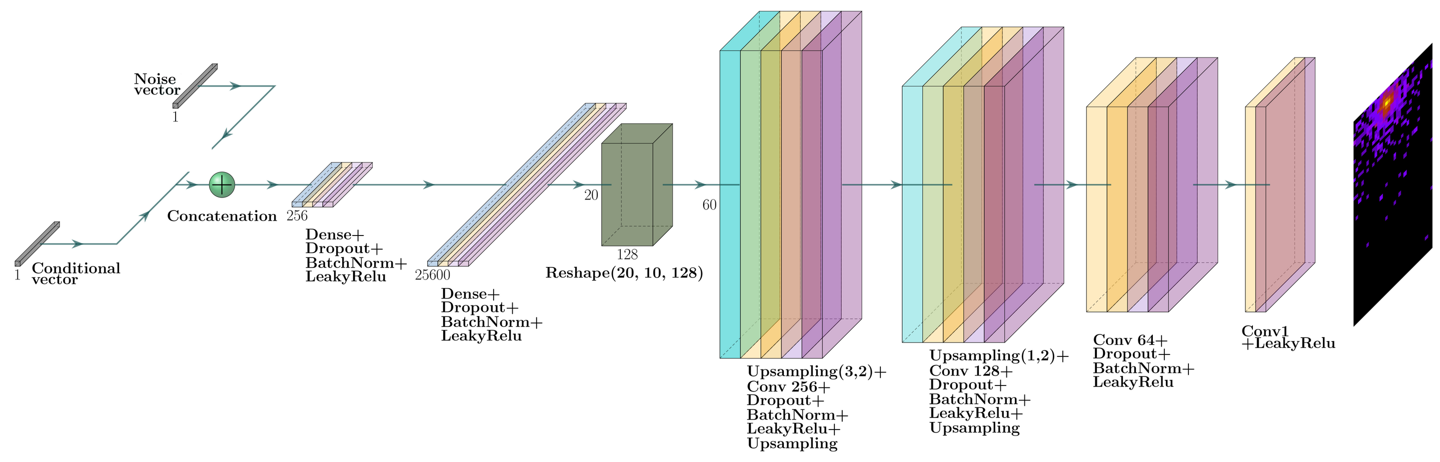
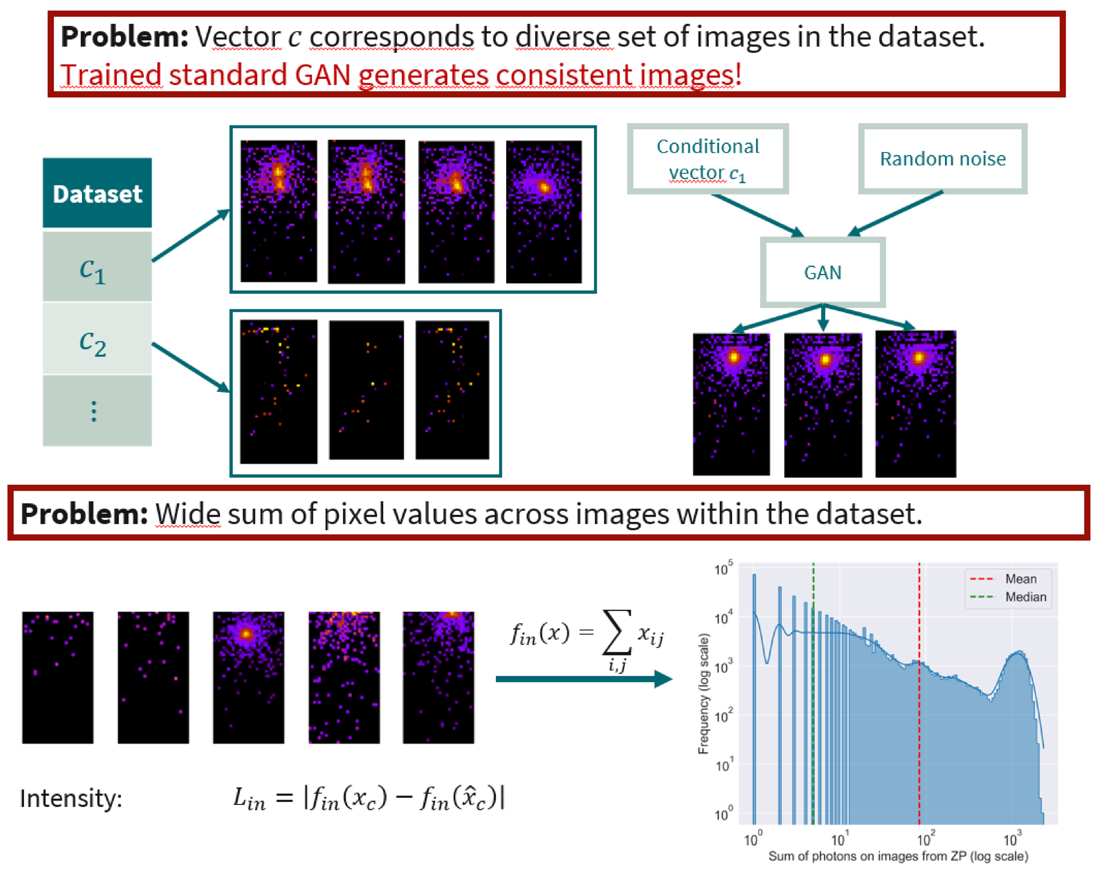


Figure 3. Architecture of the generator used across all tests

- The framework presents the simulation of Proton ZDC device,
- Given 9 conditional variables describing particle, we generate responses of the experiment,
- Conditional data include: mass, energy, charge, 3 position components and 3 momentum components of the particle during the collision,
- We test the effect of multiple regularization on the base GAN model,
- Architecture of generator is constant across all tests to ensure fair results.

Regularizations included in the simulation

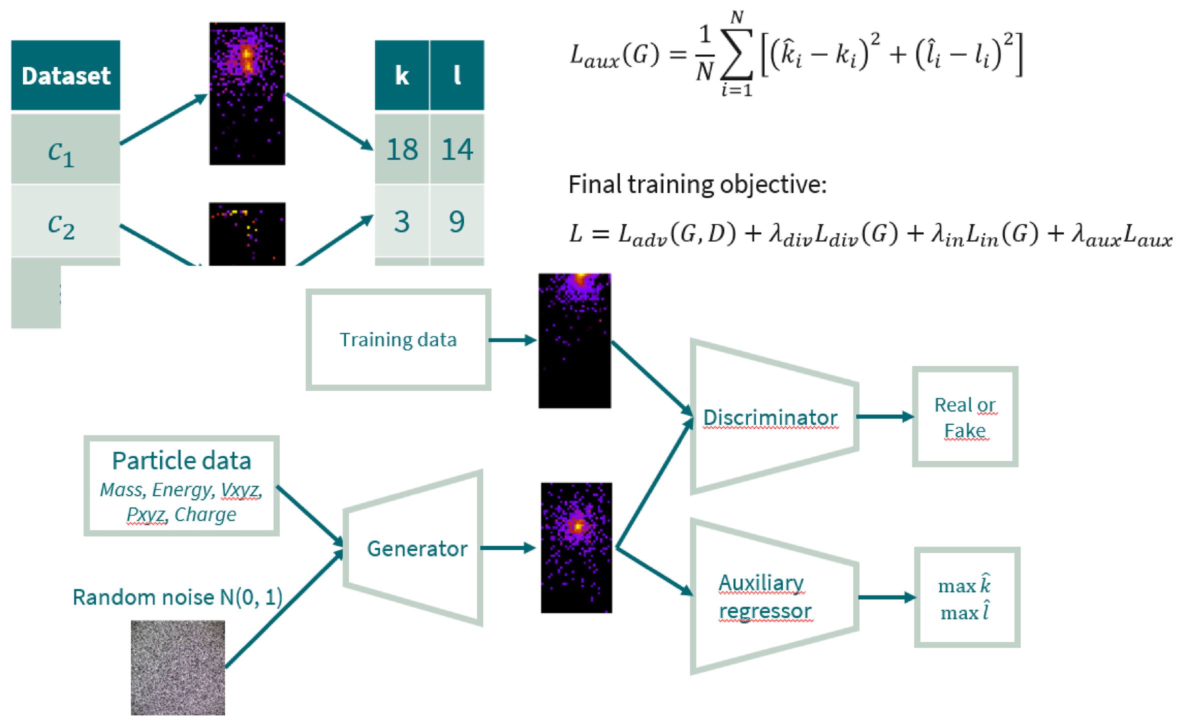


- Standard GAN produces indistinguishable predictions which lack diversity,
- We implement SDI-GAN model which introduced diversity to the predictions,
- During training of the generator should learn to match the diversity of each conditional vector c,
- During training we incorporate additional diversity measure L_{div} to the generator's loss objective where for each conditional vector we generate two images and calculate the $L1$ distance between them,
- We introduce intensity regularization with an objective to produce images with the same intensity (sum of pixels) as in the original data.

- It is hard to model the entire distribution of the sum of pixel values,
- Inclusion of **auxiliary regressor** positively influences the geometric properties of the generated images,
- As preprocessing step, we calculate coordinates of the maximum pixel value for each image in the dataset,
- Auxiliary regressor integrate additional network that learns to predict the coordinates of the maximum pixel value from the generated image,
- Auxiliary regressor is trained in pararell to the GAN.

Auxiliary regressor

Idea: We can control geometric properties of the generated image.



Comparison of models trained with different regularization

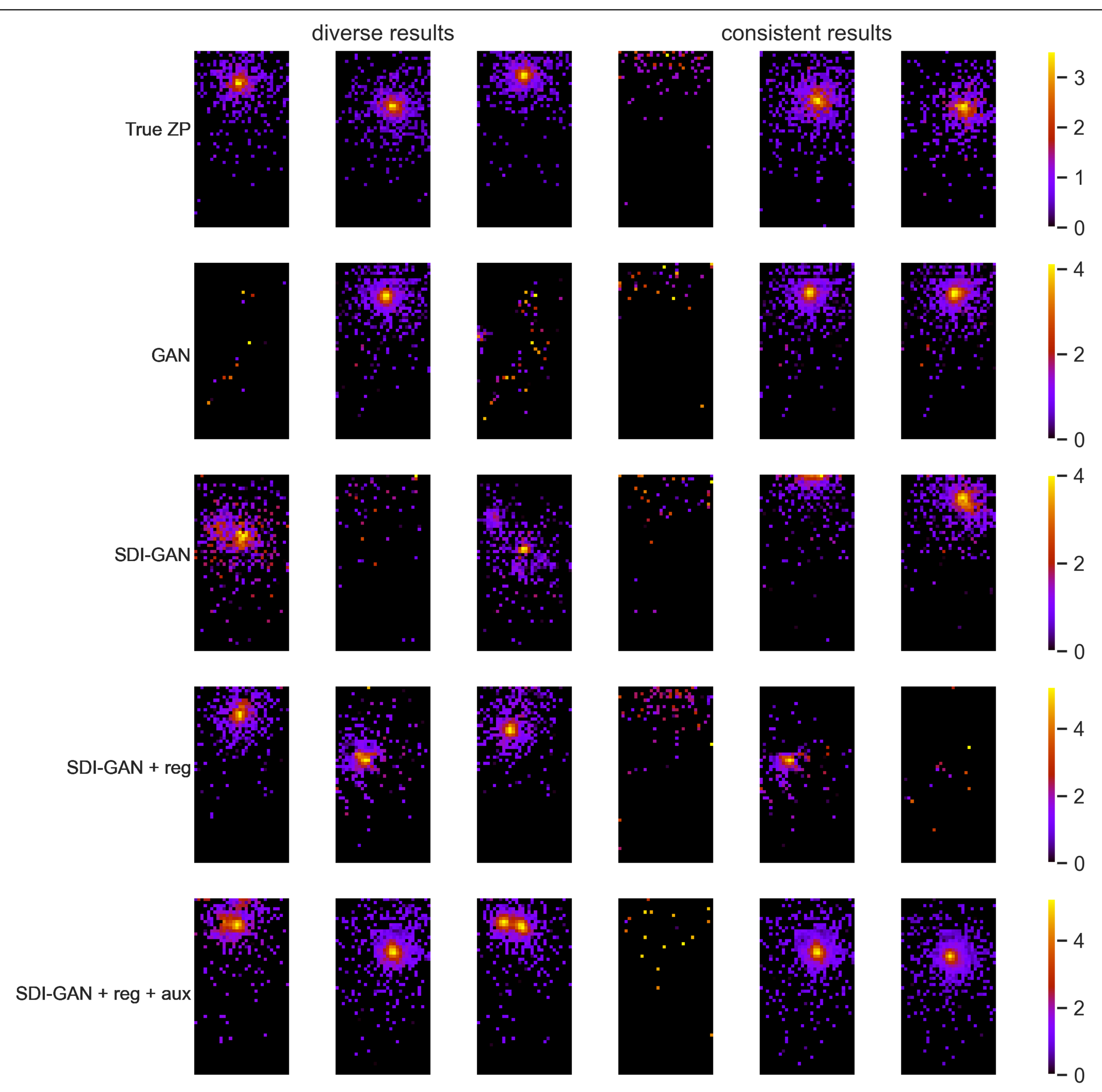


Figure 4. Results of particle generation

Model	MEAN WS	Std dev.
GAN	2.4752	1.6843
SDI-GAN	2.3571	1.6000
SDI-GAN + reg.	2.2916	1.8210
SDI-GAN + reg. + aux. reg.	**2.0777**	**1.6381**

Table 1. Wasserstein distance metric between original data distribution and models' predictions

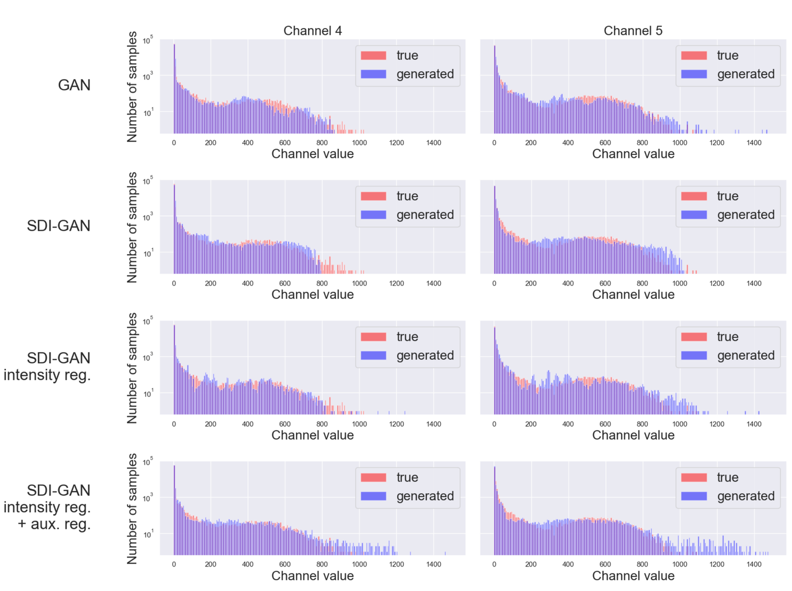


Figure 5. Histograms of true and generated distributions of channel values.

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