Generative Models for Fast Calorimeter Simulation: LHCb Case

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Simulation in LHC

- The significant part of the computing resources are used for MC simulation in High Energy Physics experiments in LHC
- About 53% of the simulations resources are spent to simulation processes in calorimeters
- In Run 3 a significant increase in luminosity is planned
- We need to speed up the simulation.

Simulating of the Calorimeter Responses

GEANT

- Simulation of the particle passing through the material now is provided by GEANT application.
- GEANT simulation is very detailed
- Calorimeter has less granularity, than GEANT simulation step
- We can simulate detector's response by using simpler model

Formulation of the Simulation Problem

- Input: particle parameters (i.e. 3D momentum + 2D coordinate)
- Output: calorimeter response

Shower Library

https://indico.cern.ch/event/740959/

- Store showers, simulated by GEANT
- For input parameters choose the the most suitable shower and, respectively, the detector's response

Generative Model: Variational Auto Encoders(VAE)

- Model samples the energy value in cells of response from the set of distributions
- Parameters of distributions is tuned by training neural network

Generative Model: Generative Adversarial Network(GAN)

- Model consists of two parts: generator tries to create objects similar to real, discriminator tries to distinguish real object from generated
- Training ends when the discriminator stops seeing the differences between real and generated

Classical GAN objective function

- P_{real} - the distribution over real data, P_{gen} - the distribution over generated data, x - real object, $\hat{x}$ - generated object, z - input noise
- $\max_D \mathbb{E}_{x \sim P_{real}} [\log D(x)] + \mathbb{E}_{\hat{x} \sim P_{gen}} [\log(1 - D(\hat{x})]$
- $\min_G \mathbb{E}_{z \sim P_z} [-\log(D(G(z)))]$

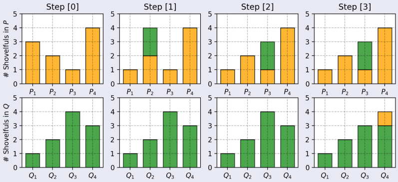
- We can choose the measure by which we want to match the distributions.
- The Wasserstein distance can provide a meaningful and smooth representation of the divergence between two distributions

Wasserstein GAN objective function

- $\max_D \mathbb{E}_{y \sim p(y)} D(y) + \mathbb{E}_{\tilde{y} \sim p(\tilde{y})} D(\tilde{y}) + \lambda \mathbb{E}_{\tilde{y} \sim p(\tilde{y})} (\|\nabla_{\tilde{y}} p_{\tilde{y}}\| - 1)^2$, $\tilde{y} = \alpha * y + (1 - \alpha)\hat{y}$
- $\min_G \mathbb{E}_{z \sim p_z(z)} [-D(G(z))]$
- Wasserstein GAN decreases Wasserstein measure between real and generated samples

Wasserstein distance

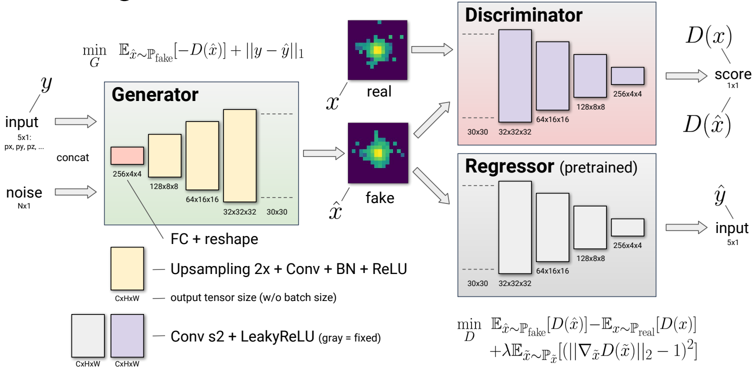
- $W(P_{real}, P_{gen})$ can be informally interpreted as a cheapest transportation plan to move sand from first pile(distribution) to second
- $\Pi(P_{real}, P_{gen})$ - is the set of all possible joint probability distributions ("all possible way to move sand") between P_{real} and P_{gen}
- $\gamma \in \Pi(P_{real}, P_{gen})$ - one joint distribution ("one possible transport act"), $\sum_{\hat{x}} \gamma(x, \hat{x}) = P_{real}(x)$, $\sum_{x} \gamma(x, \hat{x}) = P_{gen}(\hat{x})$
- $W(P_{real}, P_{gen}) = \inf_{\gamma \in \Pi(P_{real}, P_{gen})} \mathbb{E}_{(x,\hat{x})\sim\gamma}[\|x - \hat{x}\|]$
- $\sum_{x,\hat{x}} \gamma(x, \hat{x}) \|x - \hat{x}\| = \mathbb{E}_{(x,\hat{x})\sim\gamma} \|x - \hat{x}\|$



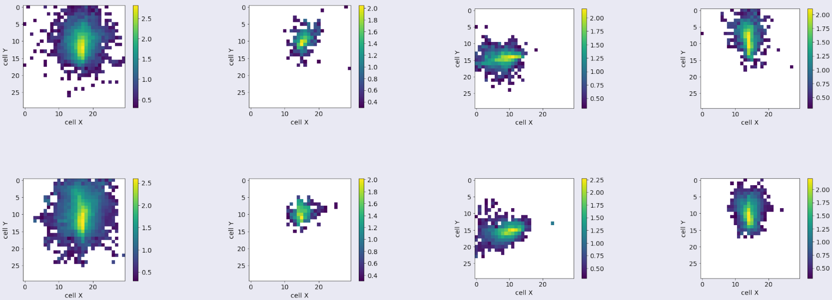
One of the possible transport plans

- Use stand-alone LHCb-like calorimeter GEANT4 setup to produce reference train and test samples
- Consider calorimeter response as a figure of 30*30 calorimeter cells to fit any possible granularity in LHCb calorimeter
- Deep Convolutional Neural Network (DCNN) as a generator and a discriminator
- Generator converts 5 initial particle parameters($3D$ momentum $+$ $2D$ coordinate) and the Gaussian noise to response
- We reconstruct 5 initial parameters on every generated images and try to minimize divergence between predicted and input particle parameters (add this term to generator loss)

Training scheme



5D: real and generated responses



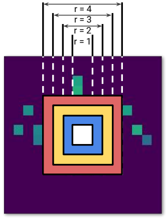
- E 63.7 GeV
- px/pz 0.005
- py/pz 0.154

- E 6.5 GeV
- px/pz 0.046
- py/pz 0.108

- E 15.6 Gev
- px/pz -0.196
- py/pz -0.036

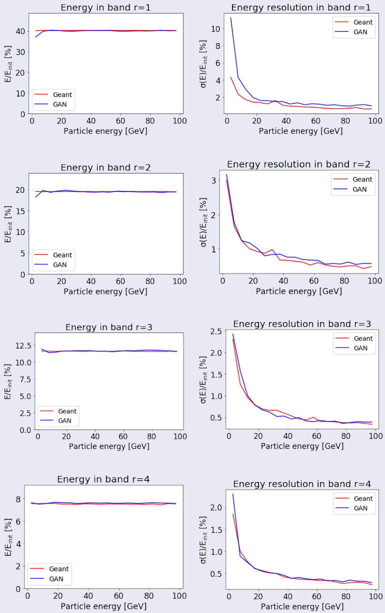
- E 15.6 GeV
- px/pz -0.019
- py/pz 0.181

1D case

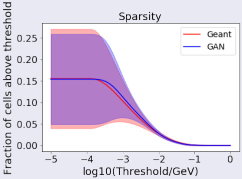


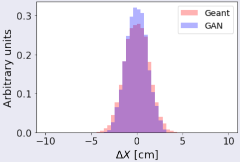
Energy fraction

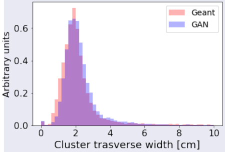
- E_{init} - the energy of particle
- $E_1 = \sum_{i=1}^{2} \sum_{j=1}^{2} E_{14+i,14+j}$
- $E_2 = \sum_{i=1}^{4} \sum_{j=1}^{4} E_{13+i,13+j} - E_1$
- $E_3 = \sum_{i=1}^{6} \sum_{j=1}^{6} E_{12+i,12+j} - E_2$
- $E_4 = \sum_{i=1}^{8} \sum_{j=1}^{8} E_{11+i,11+j} - E_3$

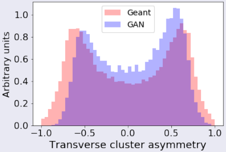


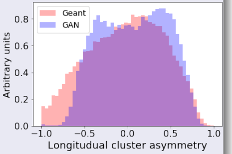
5D case











- Some chosen distributions are reproduced pretty well, some - not quite. The definition of quality metric is an issue. We can't observe all possible distributions

Time of generation

- 0.04 ms per sample on GPU
- 4.7 ms per sample on CPU

Conclusion

- We developed generative models to generate calorimeter responses.
- Generated responses look similar to real hits
- Described shape's property of response and statistical property of samples' set distributions matches in real and generated data.