ENSEMBLE GENERATIVE MODELS FOR CALORIMETER SIMULATIONS

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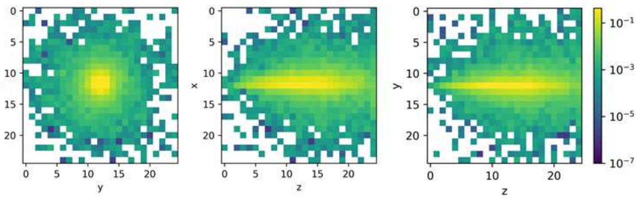
Introduction

- Monte Carlo simulations of calorimeter are time demanding.
- GANs offer a fast alternative.
- Previous 2DGAN model already has high fidelity.
- Can we get any improvement by building GAN ensemble on top of it?

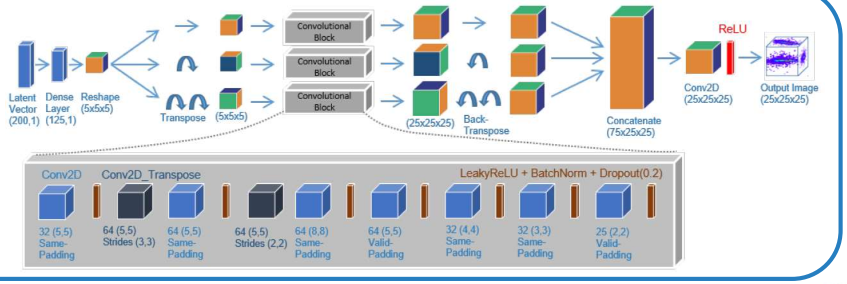
Training Data

- MC simulations of calorimeter.
- Images 25x25x25 pixels representing energy depositions.
- Primary particle energy E_p = 2-500 GeV
- Large dynamic range of pixel values
- Training set of 200 000 images.



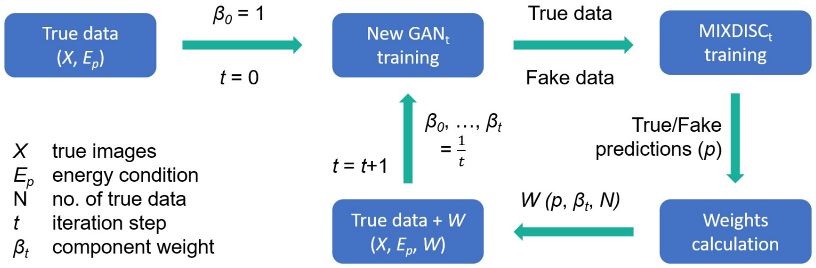
2DGAN Model[1]

- Conditional GAN architecture
  - E_p as an additional input
- 2Dconv layers applied to 3 rotations of the given sample
- Discriminator with auxiliary task
  - Estimation of primary energy E_p
- Training time ~ 4 h (GPU Tesla V100 32GB)



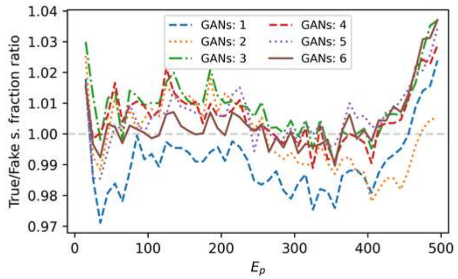
Ensemble structure

- Based on AdaGAN structure[2], training T GANs in a sequence.
- After each new GAN training, weighting training data based on discriminator True/Fake predictions trained on true data and images from previous generators.
- Uniform generator weights β_t
- Sampling from ensemble: 1) Randomly choose a generator based on generator weights $\beta_0, \beta_1, \ldots, \beta_T$. 2) Generate input E_p from U(2,500). 3) Sample an image from the chosen generator.



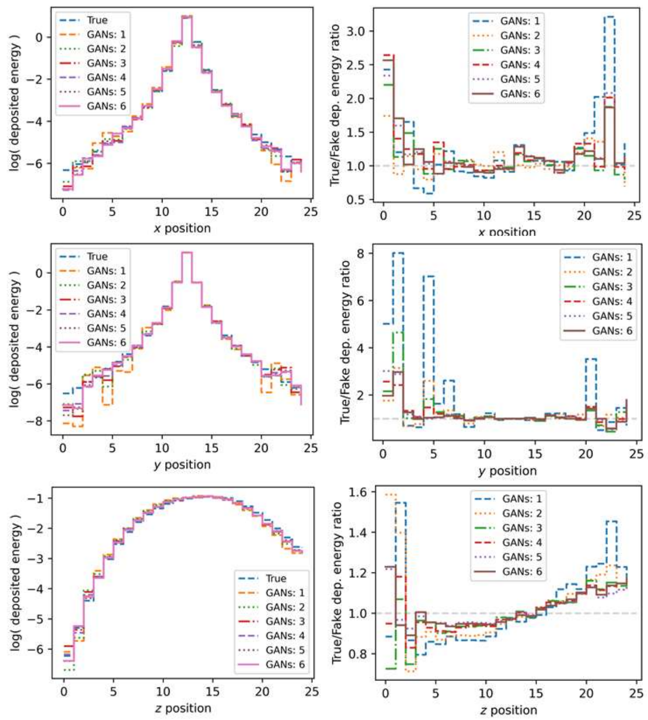
Sampling Fraction

- Sampling fraction = total deposited energy / E_p
- Adding generators → approaching true sampling fraction



Shower Shapes

- Relative energy profiles along axes
  - Log10 of average deposited energies
  - Ratio of Real/Fake average depositions



Conclusion

- Adding GANs – improvement in s. fraction.
- Significantly better simulation of depositions around the image edges.

References
[1] F. Rehm, S. Vallecorsa, et. al. Physics Validation of Novel Convolutional 2D Architectures for Speeding Up High Energy Physics Simulations. vCHEP 2021
[2] I. Tolstikhin, S. Gelly, et. al. AdaGAN: Boosting Generative Models. NIPS 2017