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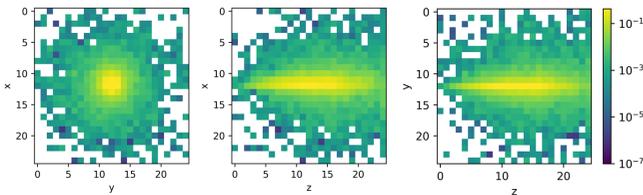
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## Introduction

- 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.

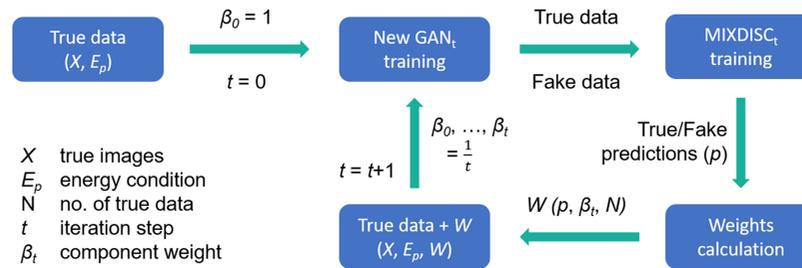


## 2DGAN Model<sup>[1]</sup>

- 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)

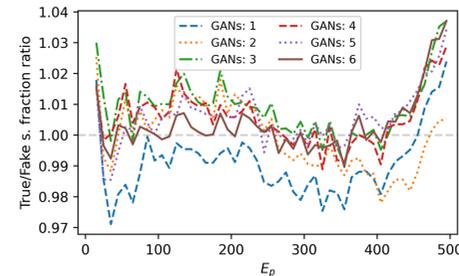
## Ensemble structure

- Based on AdaGAN structure<sup>[2]</sup>, 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  $\beta_t$
- Sampling from ensemble: 1) Randomly choose a generator based on generator weights  $\beta_0, \beta_1, \dots, \beta_T$ . 2) Generate input  $E_p$  from  $U(2,500)$ . 3) Sample an image from the chosen generator.



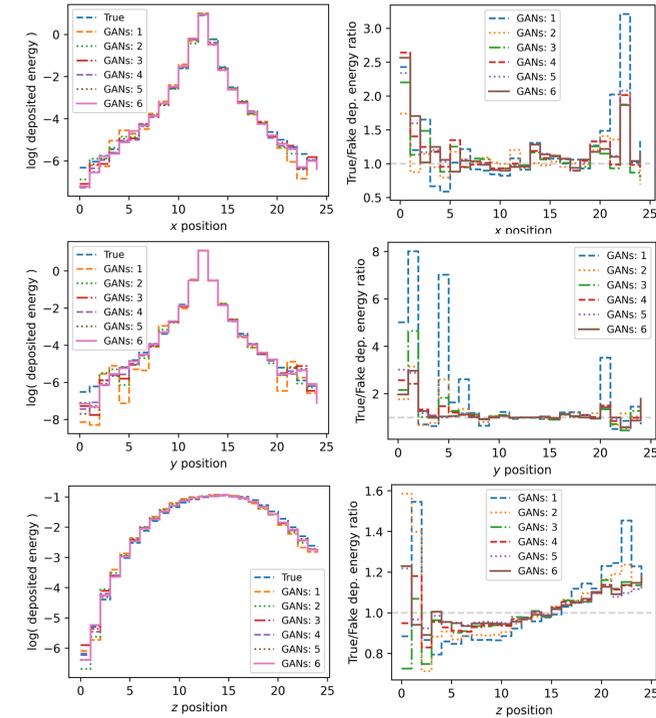
## Sampling Fraction

- 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