Realistic Calomplification

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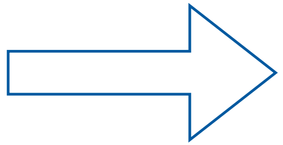
IDT-UM / ErUM-Data Meeting

Introduction

Need to speed up MC

- Event generation
- Calorimeter simulation



Use generative machine learning models

- Generative Adversarial Networks (GANs)
- Variational Autoencoders (VAEs)
- Normalizing Flows

$$\text{simulation speed} = \frac{\#\ \text{samples}}{\text{time}}$$

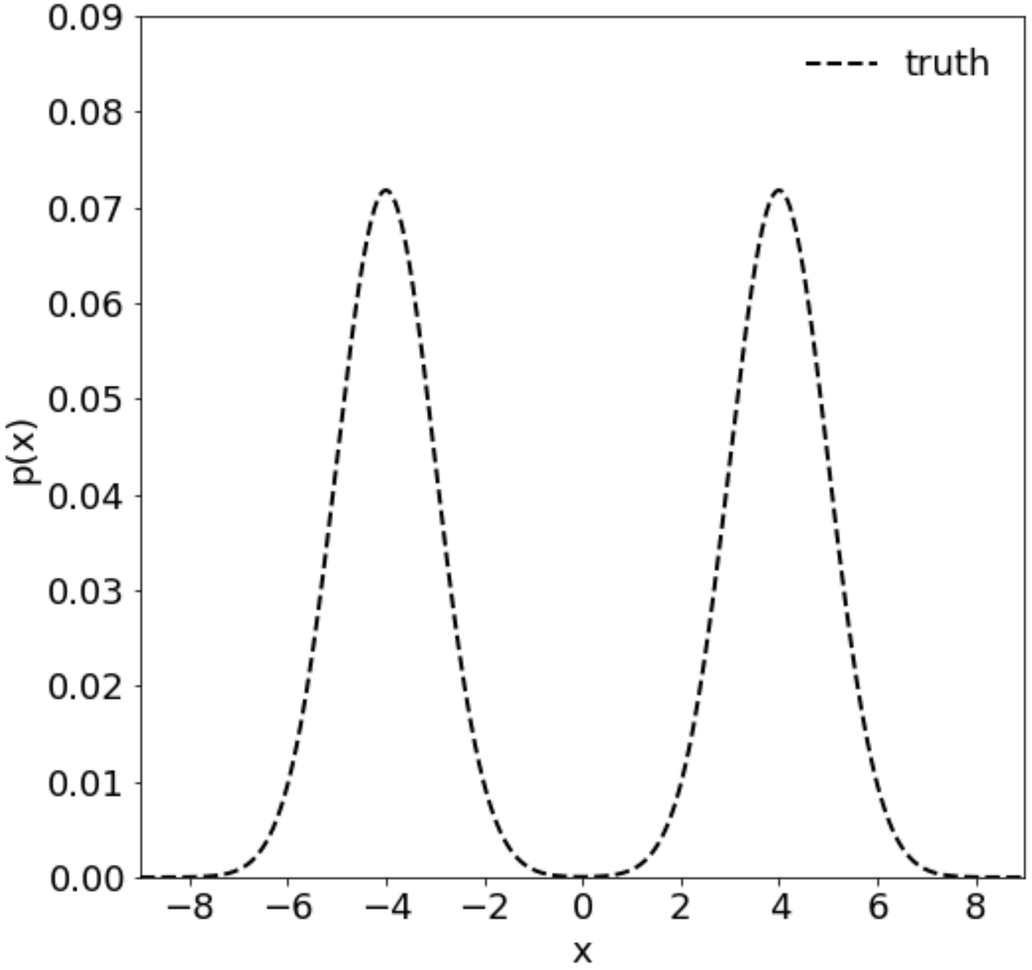
What about # samples? How many new points can a generative model generate?

Anja Butter et al. *GANplifying Event Samples*. 2021. arXiv: 2008.06545 [hep-ph]

Toy Model: Setup

- Camel back function:

$$P(x) = \frac{1}{2}\left(\mathcal{N}_{-4,1}(x) + \mathcal{N}_{4,1}(x)\right)$$



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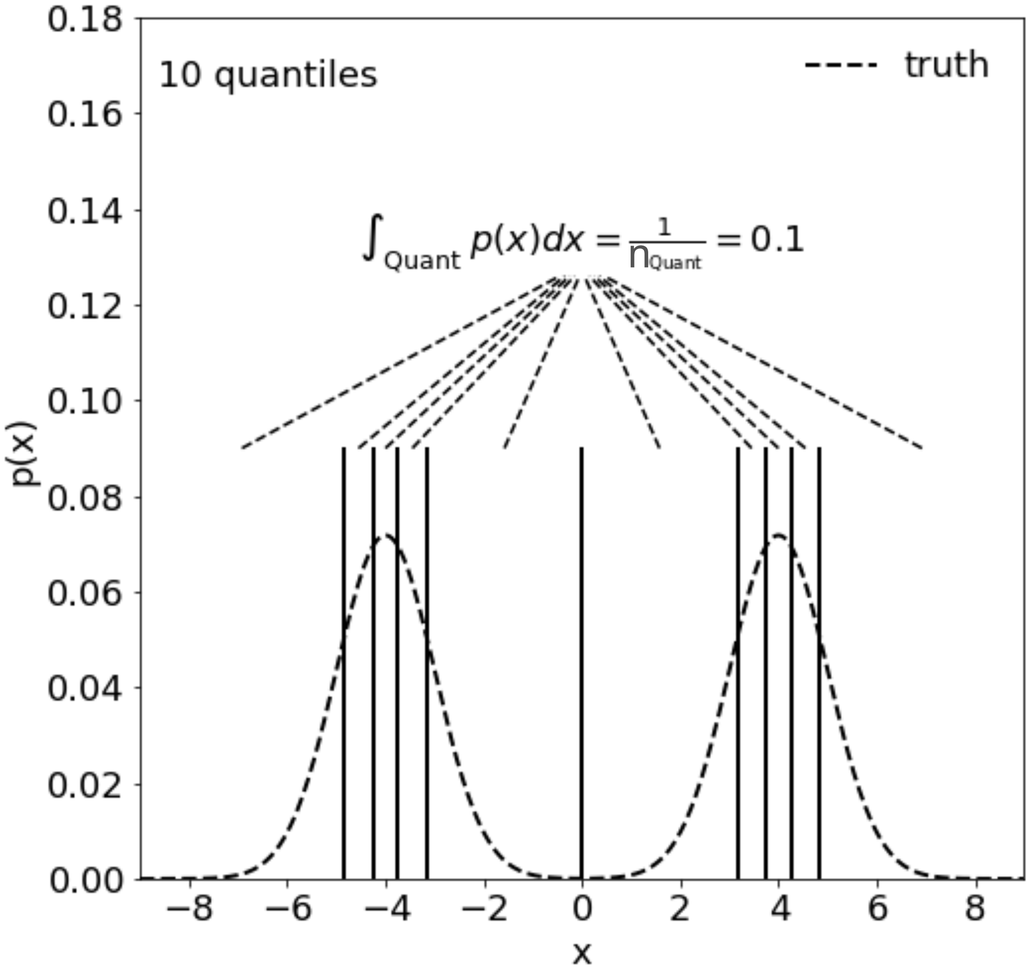
- *"Pearson χ^2-test"*:
  - Introduce equal probability quantiles



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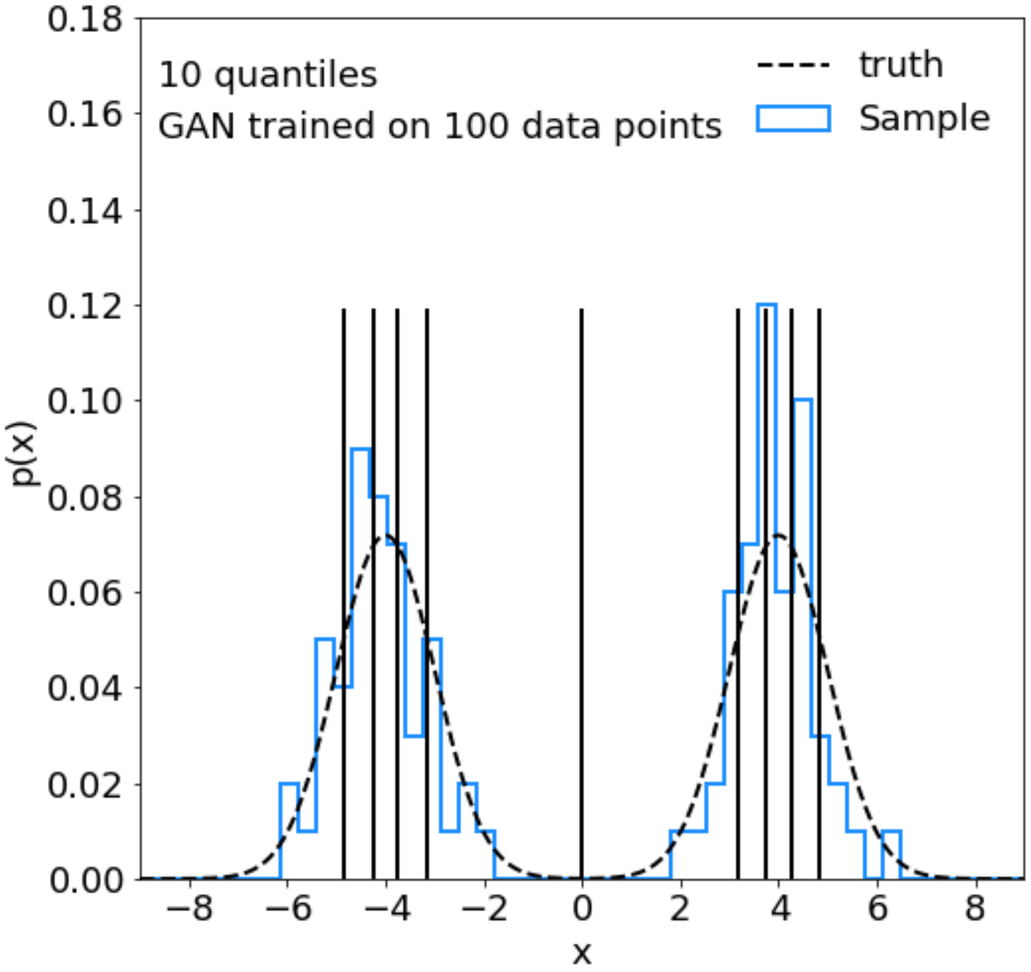
- Camel back function:

$$P(x) = \frac{1}{2}\left(\mathcal{N}_{-4,1}(x) + \mathcal{N}_{4,1}(x)\right)$$

- *"Pearson χ^2-test"*:
  - Introduce equal probability quantiles
  - Generate data and calculate

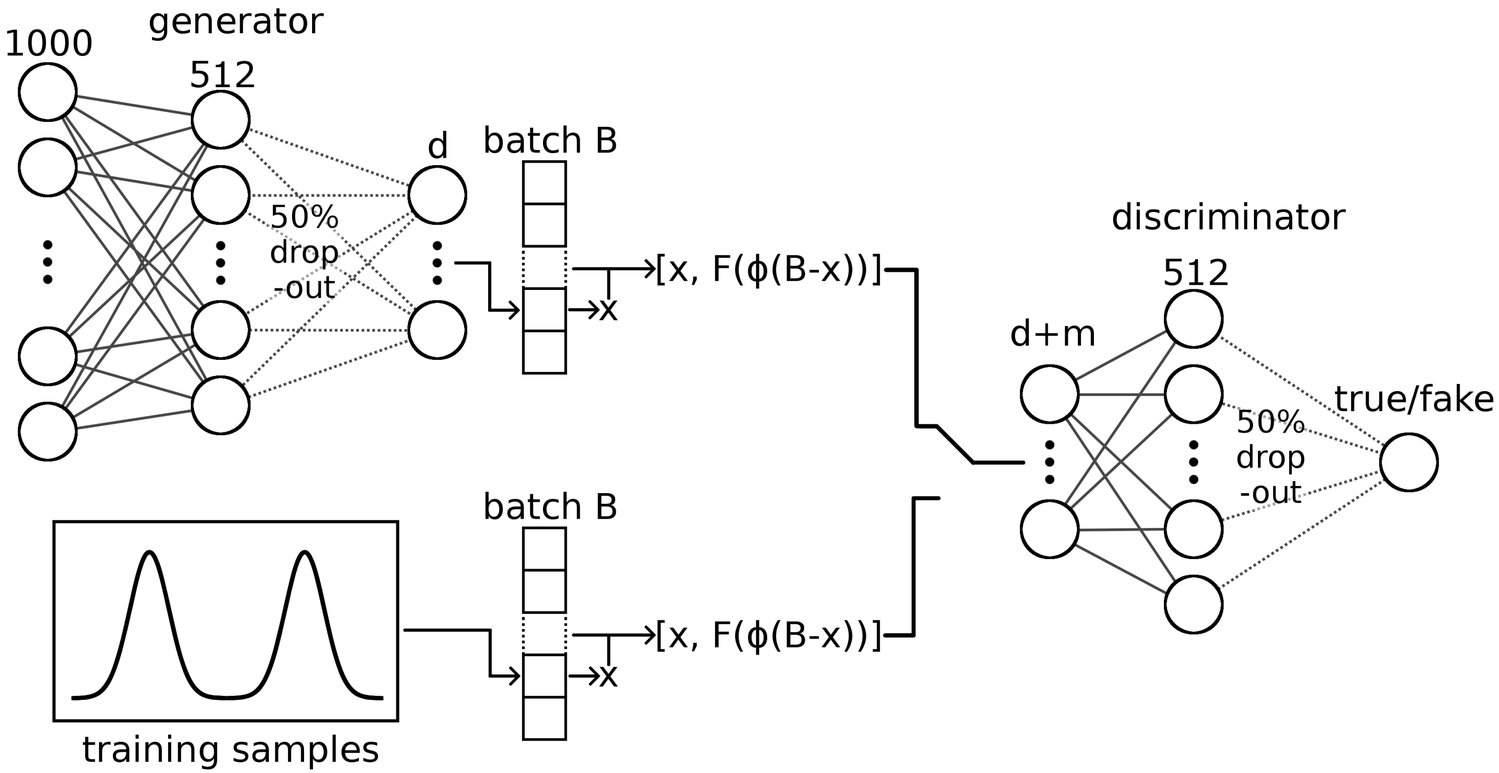
$$\hat{\chi}^2_{n_{\text{quant}}} = n_{\text{quant}} \sum_{j=0}^{n_{\text{quant}}} \left(x_j - \frac{1}{n_{\text{quant}}} \right)^2$$

$$\text{with } \hat{\chi}^2_{n_{\text{quant}}} \xrightarrow{n_{\text{quant}} \to \infty} \chi^2 \left(P(x), P_{\text{samples}} \right)$$



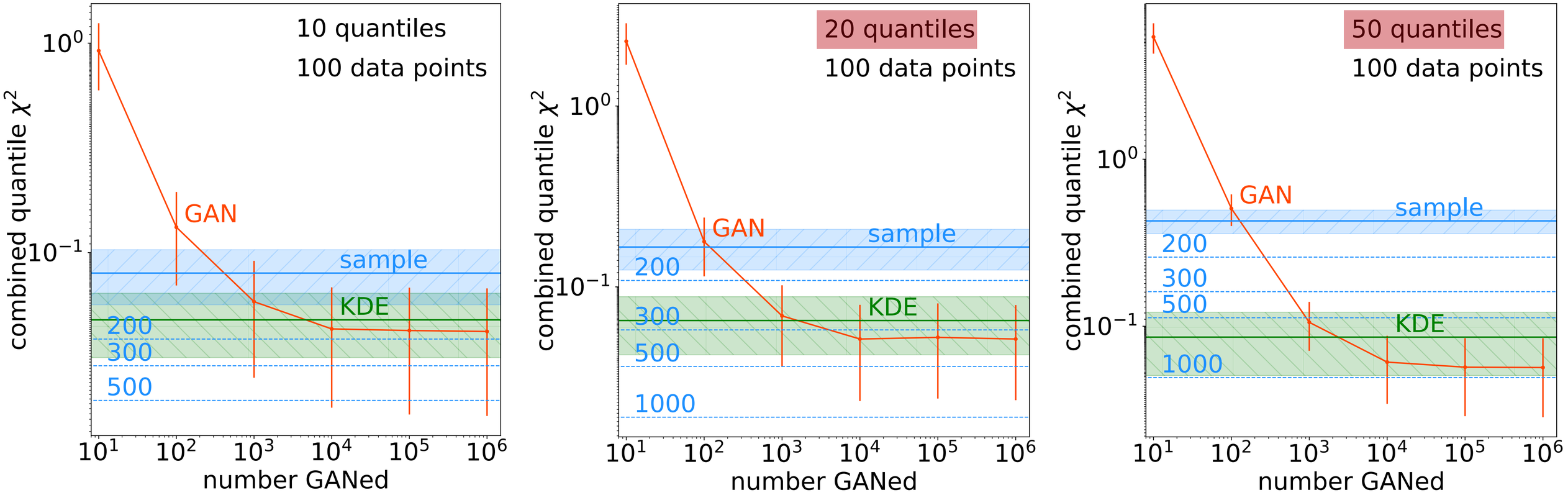
Toy Model: Generative Network

- Train on $n_{\text{data}} = 100$ data points generated from P(x)
- Prone to mode-collapse and overfitting:
  - Dropout
  - Noise augmentation
  - Batch-statistics
- Generate high amounts of data from Network



Toy Model: 1D

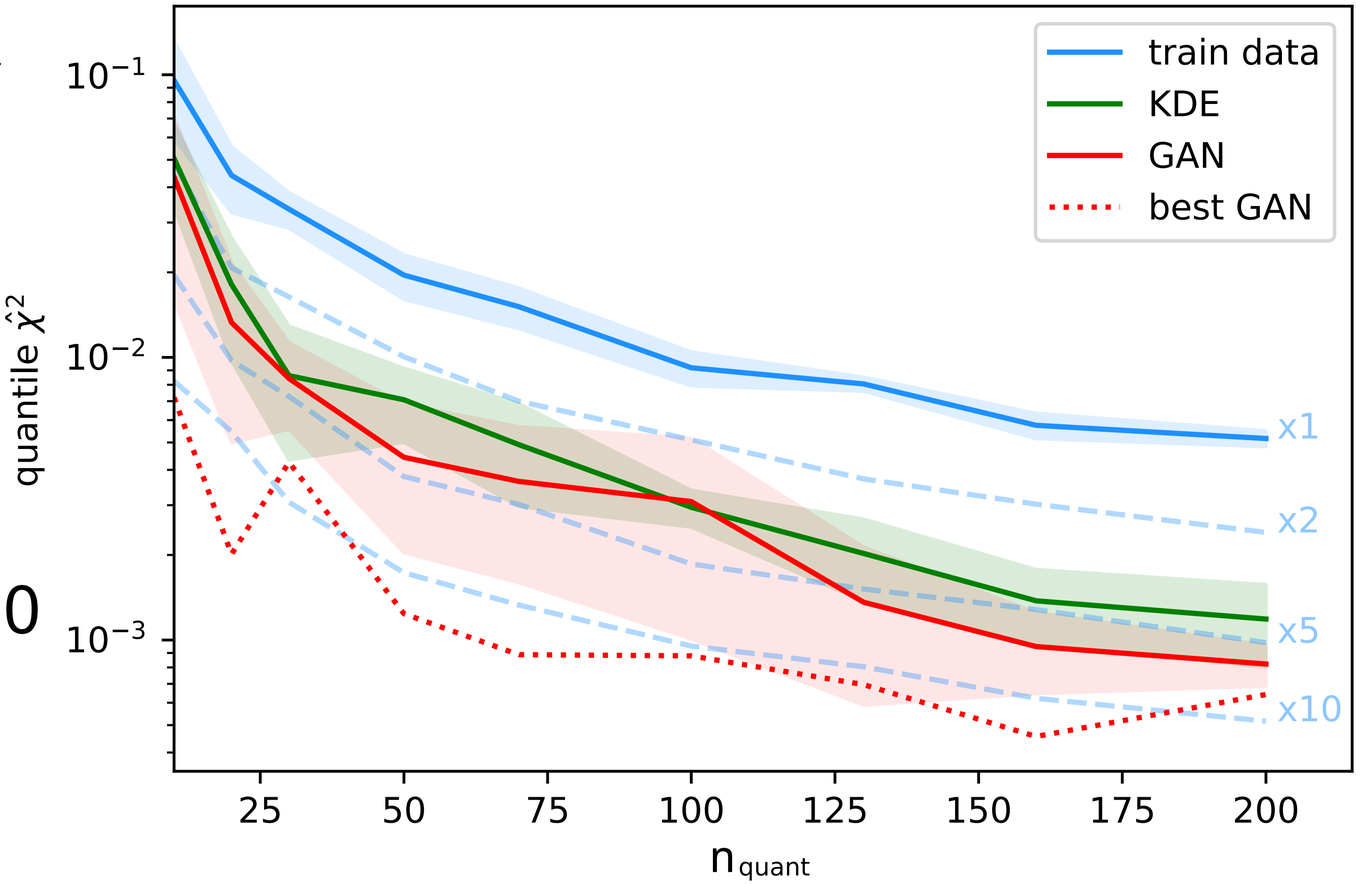
- Interpolation more noticeable for sparse data



- **However,** quantile measure breaks down for sparse data

Toy Model: 1D

- Examine high n_{quant} and high n_{data}
  - Train on $n_{\text{data}} = n_{\text{quant}}^2$
  - Generate $100 \cdot n_{\text{data}}$
- Examine which data converges to 0 (fastest)
- GAN amplifies data by a factor ~5



Calorimeter Simulations: Data

- 269k photon showers at 50 GeV in ILD detector [1]

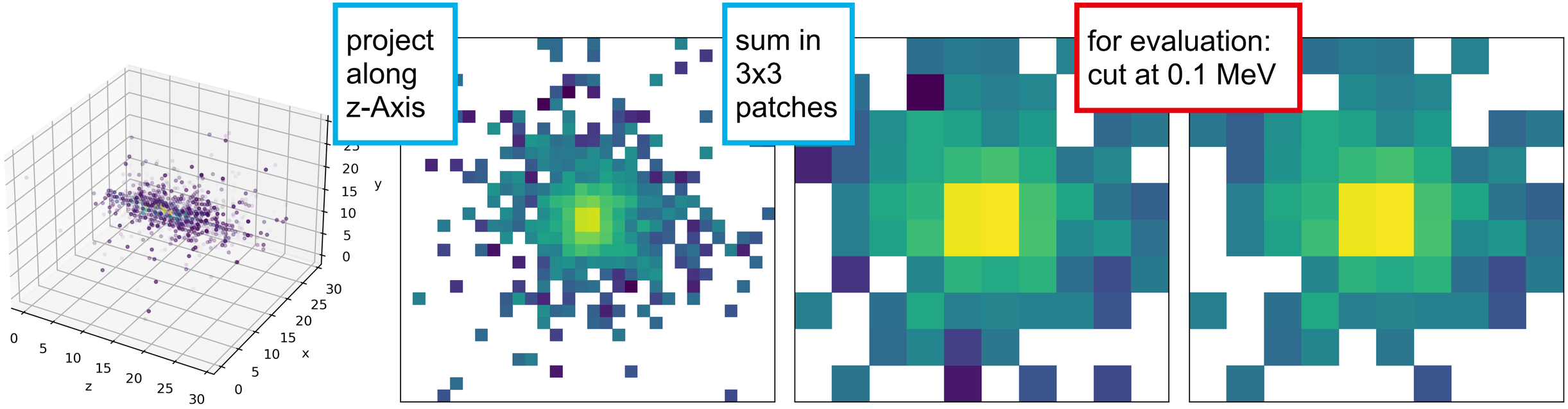


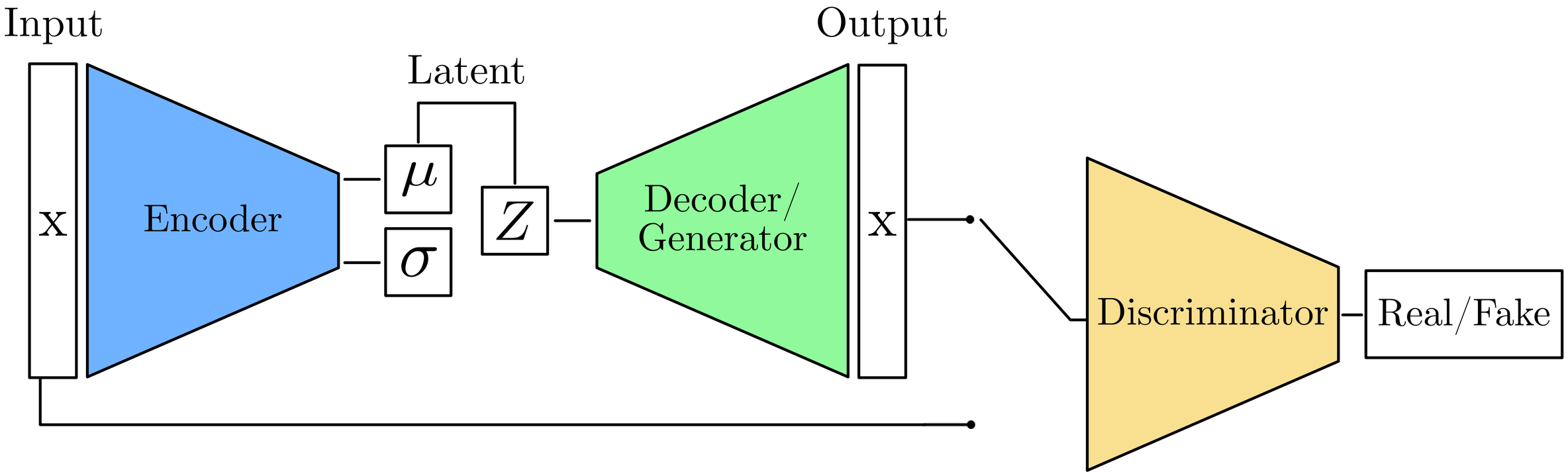
Image-shaped data

Unknown true distribution, limited data

Harder learning task → training on multiple training set sizes unfeasible

Calorimeter Simulations: Architecture

- Change to *location aware* VAE-GAN architecture [2,3,4]



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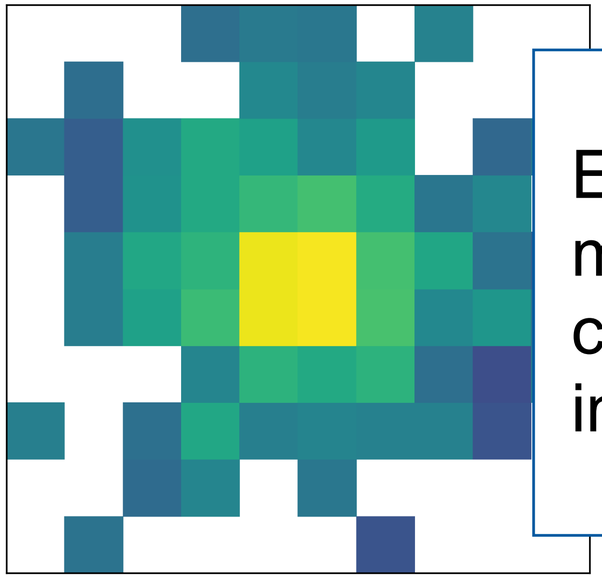
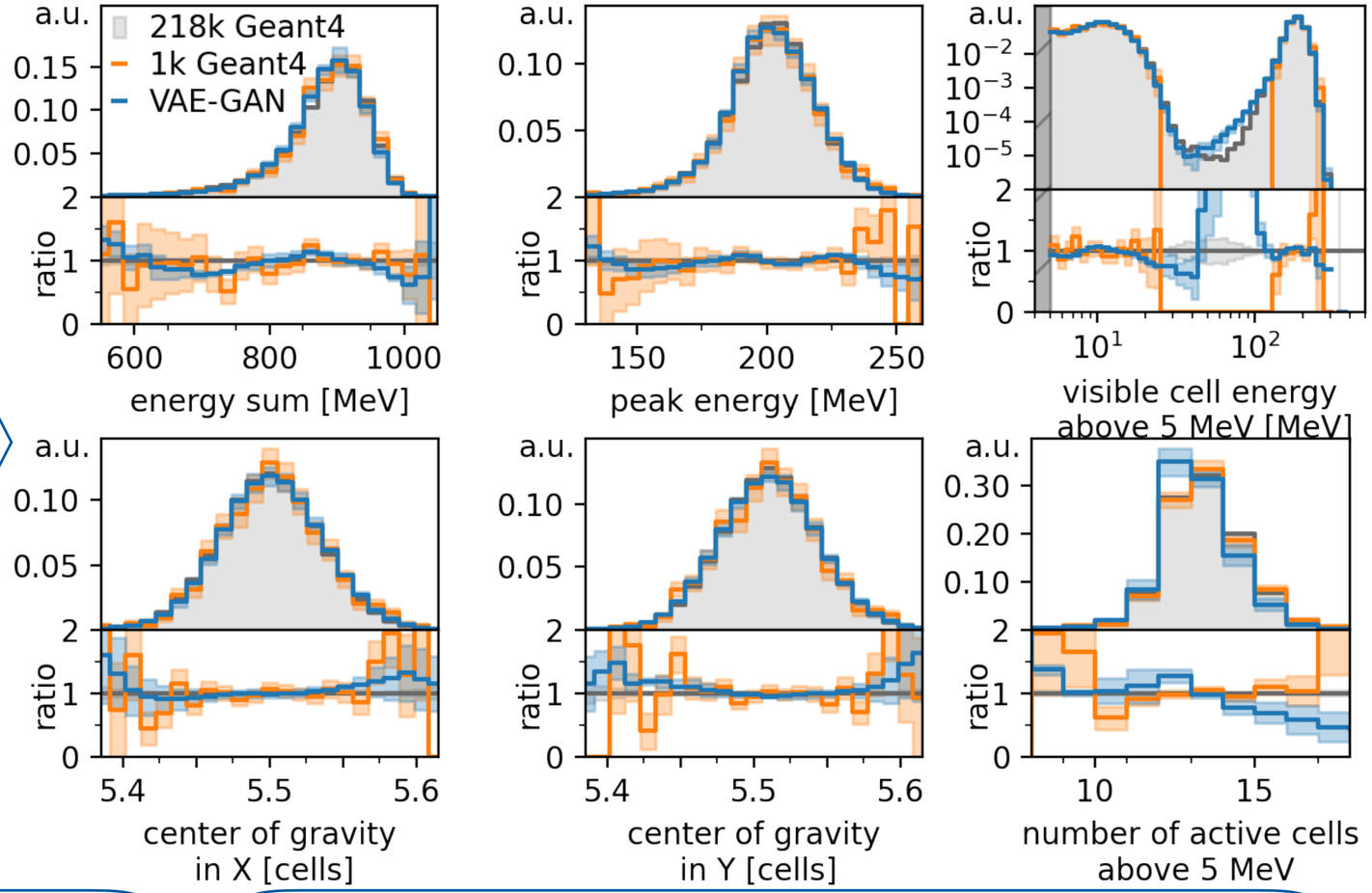
Calorimeter Simulations: Setup



Evaluate 1D metrics, calculated on images



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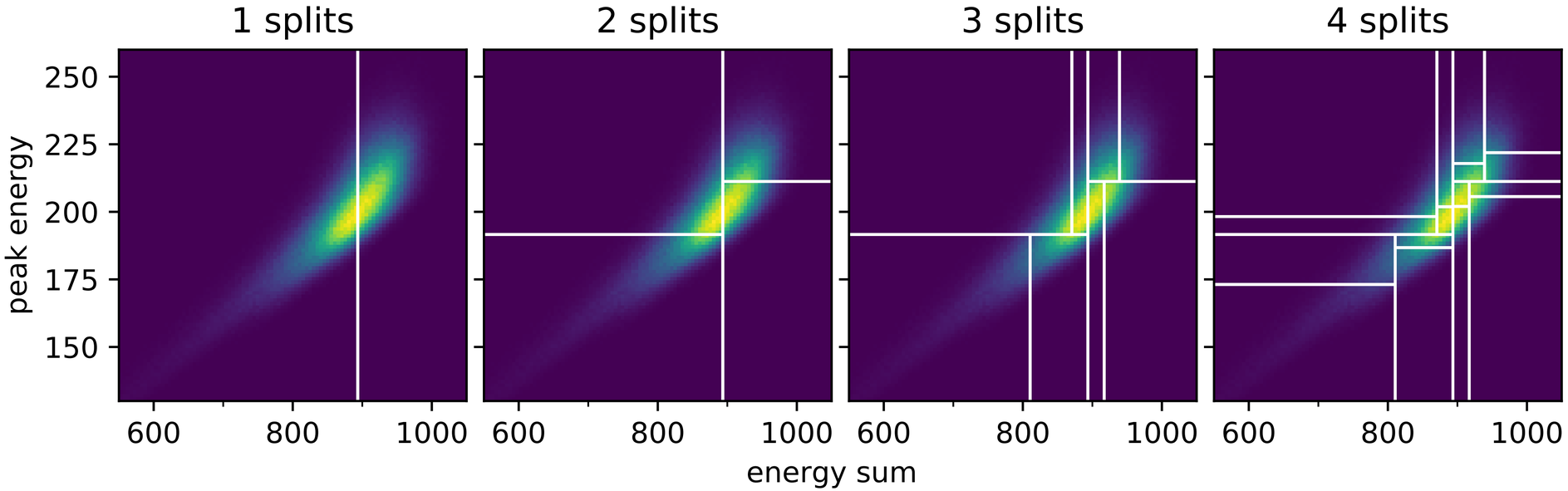
Calorimeter Simulations: Setup

- Split into **218k validation data points** and **50k evaluation data points**
- Generate quantiles by dividing the validation set into equal-sized parts



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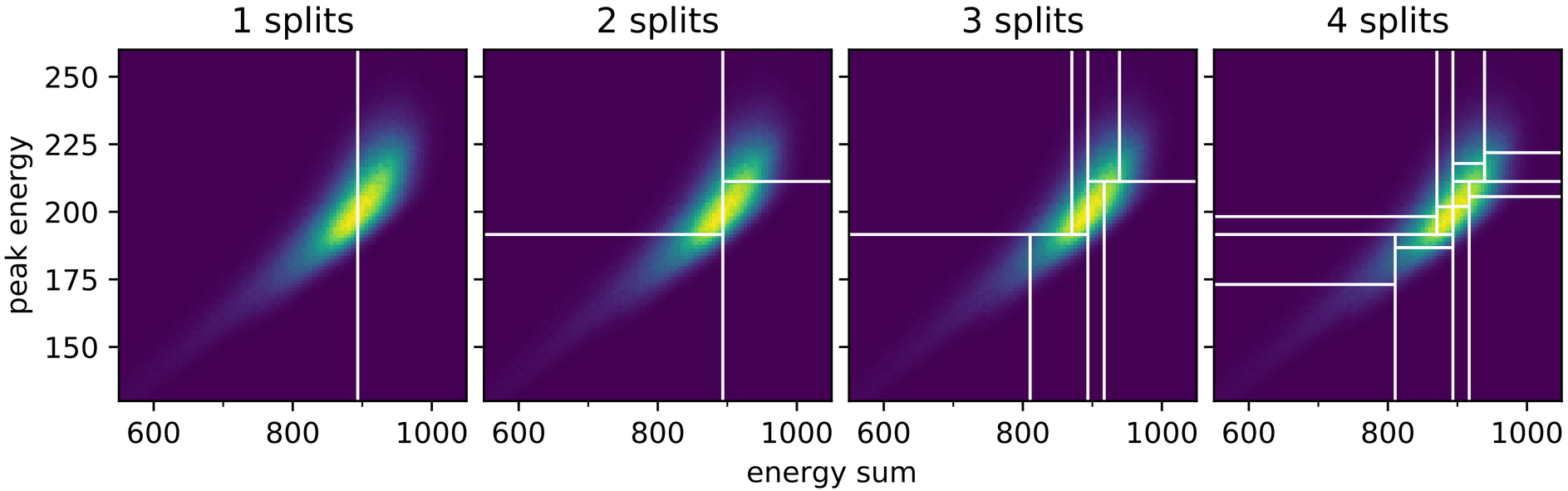
Calorimeter Simulations: Setup

Calculate $\overline{\mathrm{JSD}}(g\,||\,p) = \frac{1}{2}\sum_{Q_i \in \mathbf{Q}} \left(g_i \log \frac{g_i}{\frac{1}{2}(g_i + p_i)} + p_i \log \frac{p_i}{\frac{1}{2}(g_i + p_i)} \right).$



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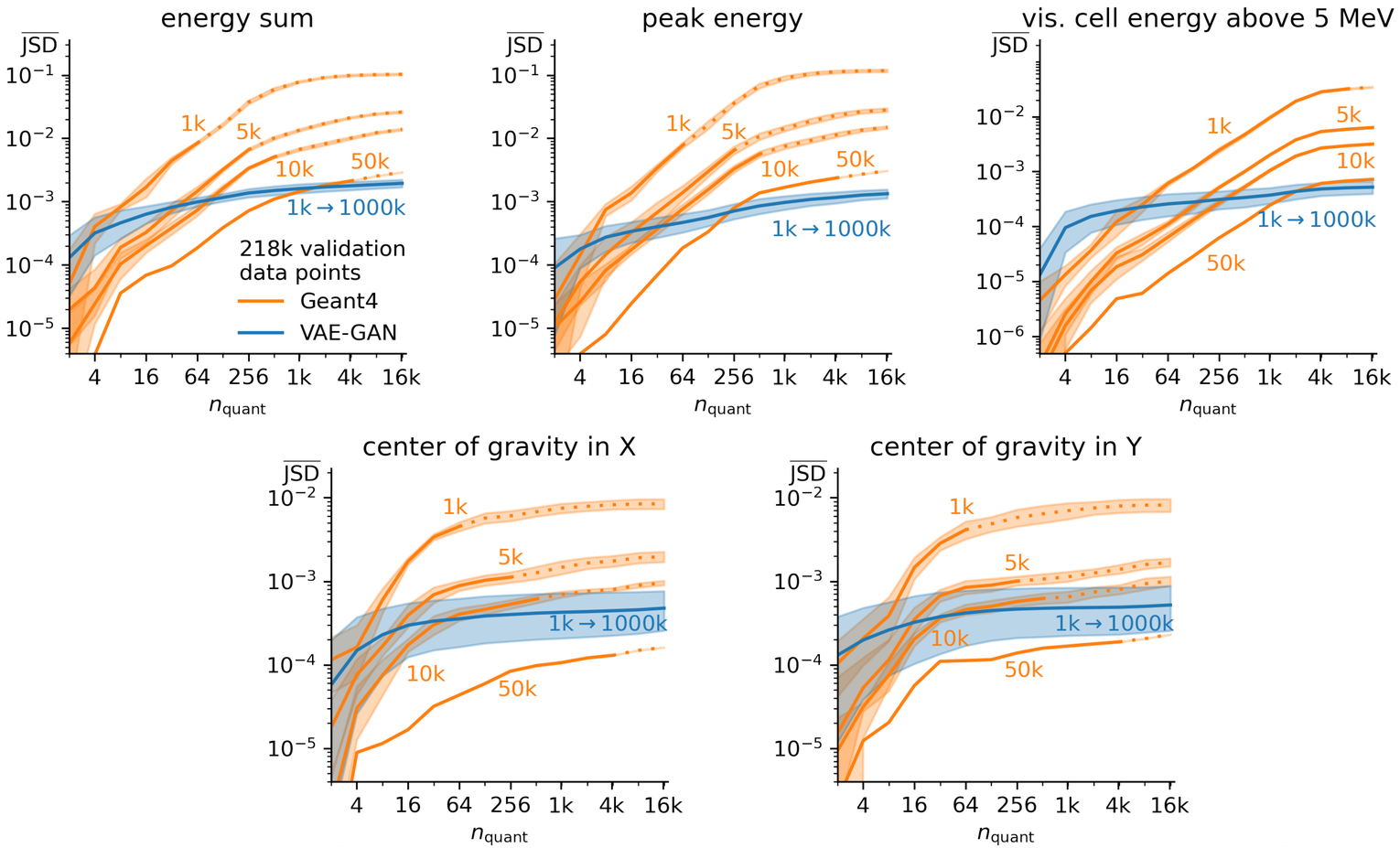
Calorimeter Simulations: Results

- Evaluate for fixed training set size
- Add multiples of the training set size
- Use less than $n_{\text{data}}/10$ bins



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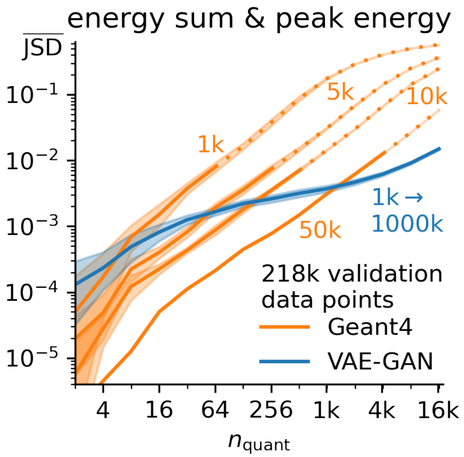

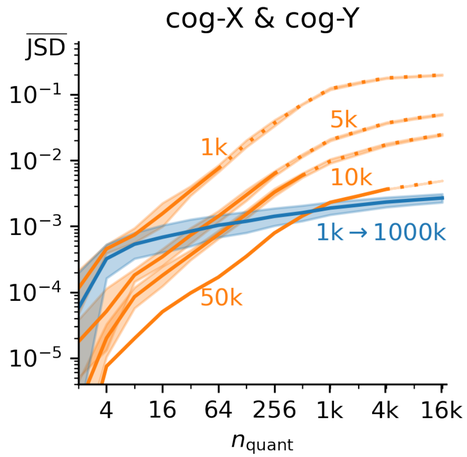

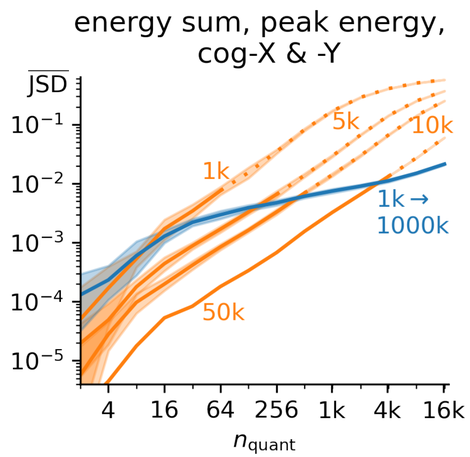

- High scale features: limited by amount of training data
- Low scale features: GAN estimation can not be matched by adding more data

Image-shaped data

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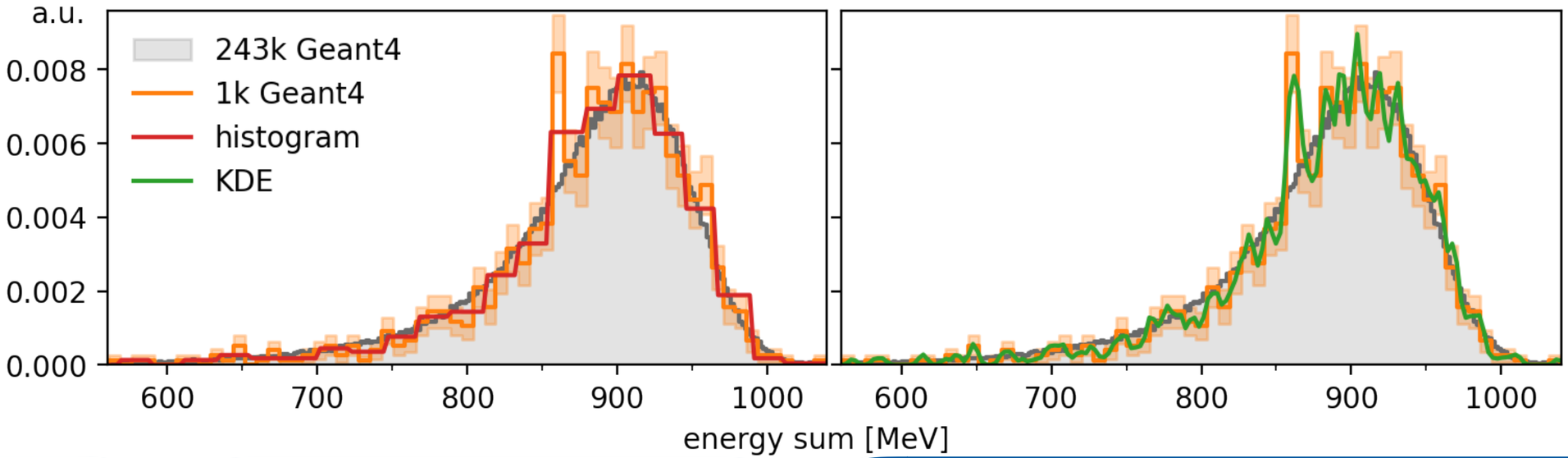
Calorimeter Simulations: Results

How good is the density estimation actually?

- Compare to KDE and histogram estimators (maximizing log-likelihood of cross-validation sets)



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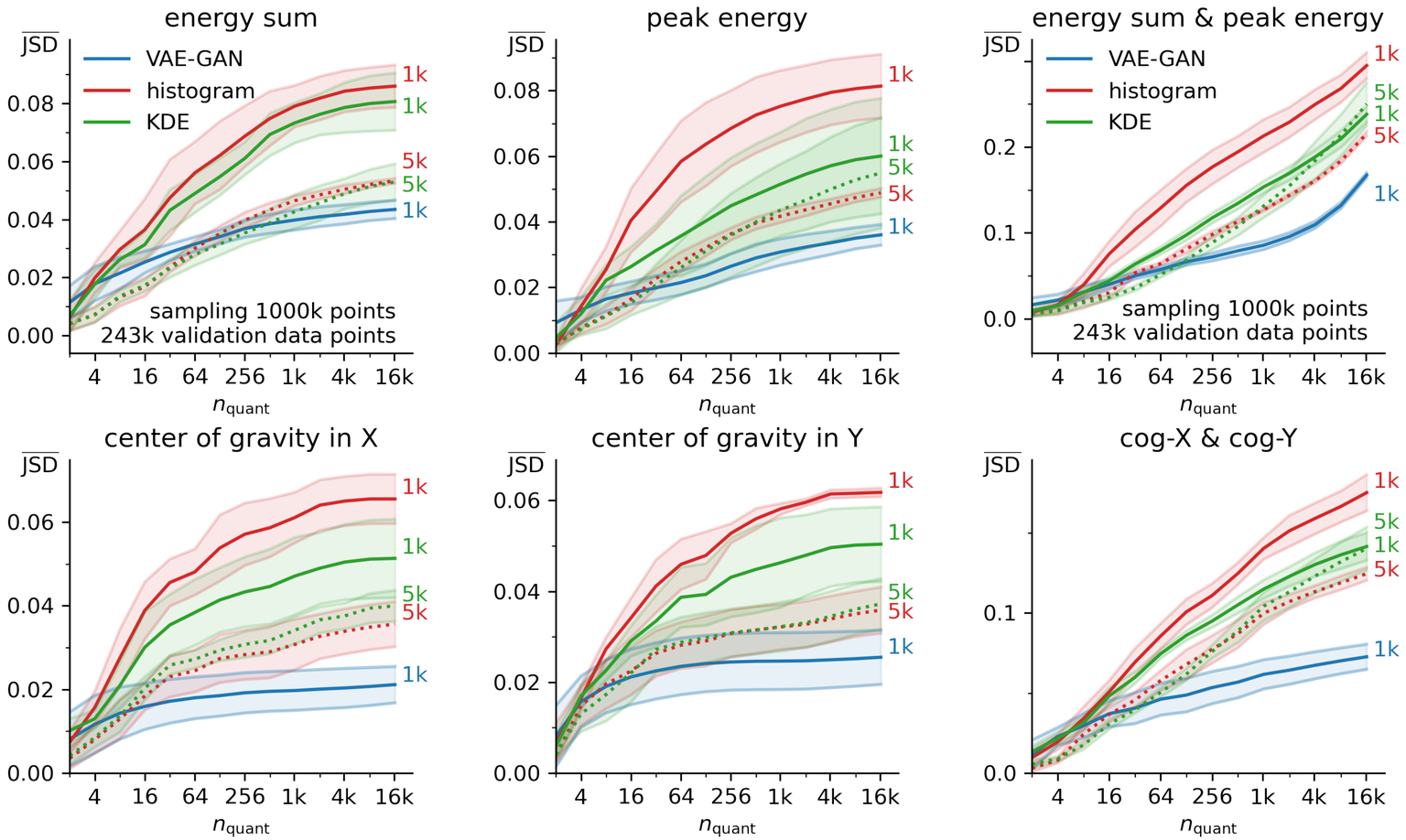
Calorimeter Simulations: Results

- Generate 10^6 samples from every density estimator



- GAN outperforms standard density estimators

Image-shaped data

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Conclusion

- What about # samples? How many new points should we generate from a generative model?
  - Depends on GAN setup and problem

  - For high-scale observables (e.g. *mean, standard deviation, low moments*) generative network limited to the amount of training data
  - For a smooth interpolation (e.g. *segments of the distribution, integrated quantities*) a generative networks outperform even higher numbers of data

References

[0]: P. Calafiura, J. Catmore, D. Costanzo, and A. Di Girolamo, “ATLAS HLLHC Computing Conceptual Design Report,” CERN, Geneva, Tech. Rep., Sep 2020. [Online]. Available: https://cds.cern.ch/record/2729668

[1]: ILD Concept Group, H. Abramowicz et al., *International Large Detector: Interim Design Report*, 3, 2020.

[2]: L. de Oliveira, M. Paganini, and B. Nachman, “Learning particle physics by example: Location-aware generative adversarial networks for physics synthesis,” *Computing and Software for Big Science*, vol. 1, no. 1, Sep 2017. [Online]. Available: http://dx.doi.org/10.1007/s41781017000046

[3]: M. Paganini, L. de Oliveira, and B. Nachman, “Calogan: Simulating 3d high energy particle showers in multilayer electromagnetic calorimeters with generative adversarial networks,” *Physical Review D*, vol. 97, no. 1, Jan 2018. [Online]. Available: http://dx.doi.org/10.1103/PhysRevD.97.014021

[4]: A. B. L. Larsen, S. K. Sønderby, H. Larochelle, and O. Winther, “Autoencoding beyond pixels using a learned similarity metric,” in *Proceedings of the 33rd International Conference on International Conference on Machine Learning Volume 48*. JMLR.org, 2016, p. 1558–1566.