

CaloPointFlow

Generating Calorimeter Showers as Point Clouds

Simon Schnake^{1,2}, Dirk Krücker¹, Florian Rehm^{2,3}, Benno Käch^{1,4}
 Moritz Scham^{1,2}, Alexi Verney-Provatas^{1,2}, Sofia Vallecorsa³, Kerstin Borrás^{1,2}

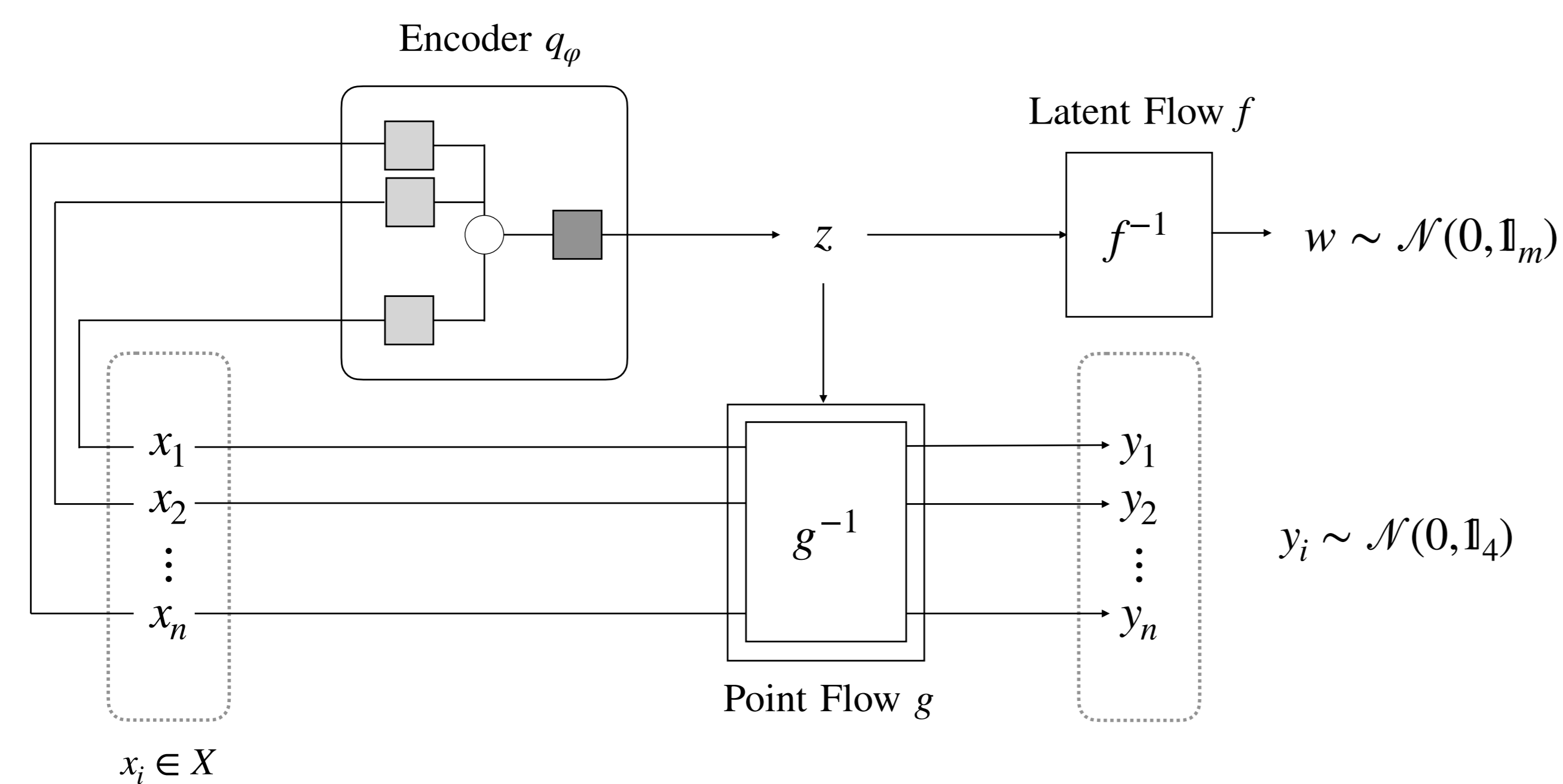


Abstract

In particle physics, precise simulations are necessary to enable scientific progress. However, accurate simulations of the interaction processes in calorimeters are complex and computationally very expensive, demanding a large fraction of the available computing resources in particle physics at present. Usually, generative models interpret calorimeter showers as 3D images. This approach becomes difficult for high-granularity calorimeters due to the larger sparsity of the data. In this study, we use this sparseness to our advantage and interpret the calorimeter showers as point clouds. A first model to learn calorimeter showers as point clouds is presented. The model is evaluated on a high granular calorimeter dataset.

Model

The model here described is based on *PointFlow* [4] and consists of three sub-models.

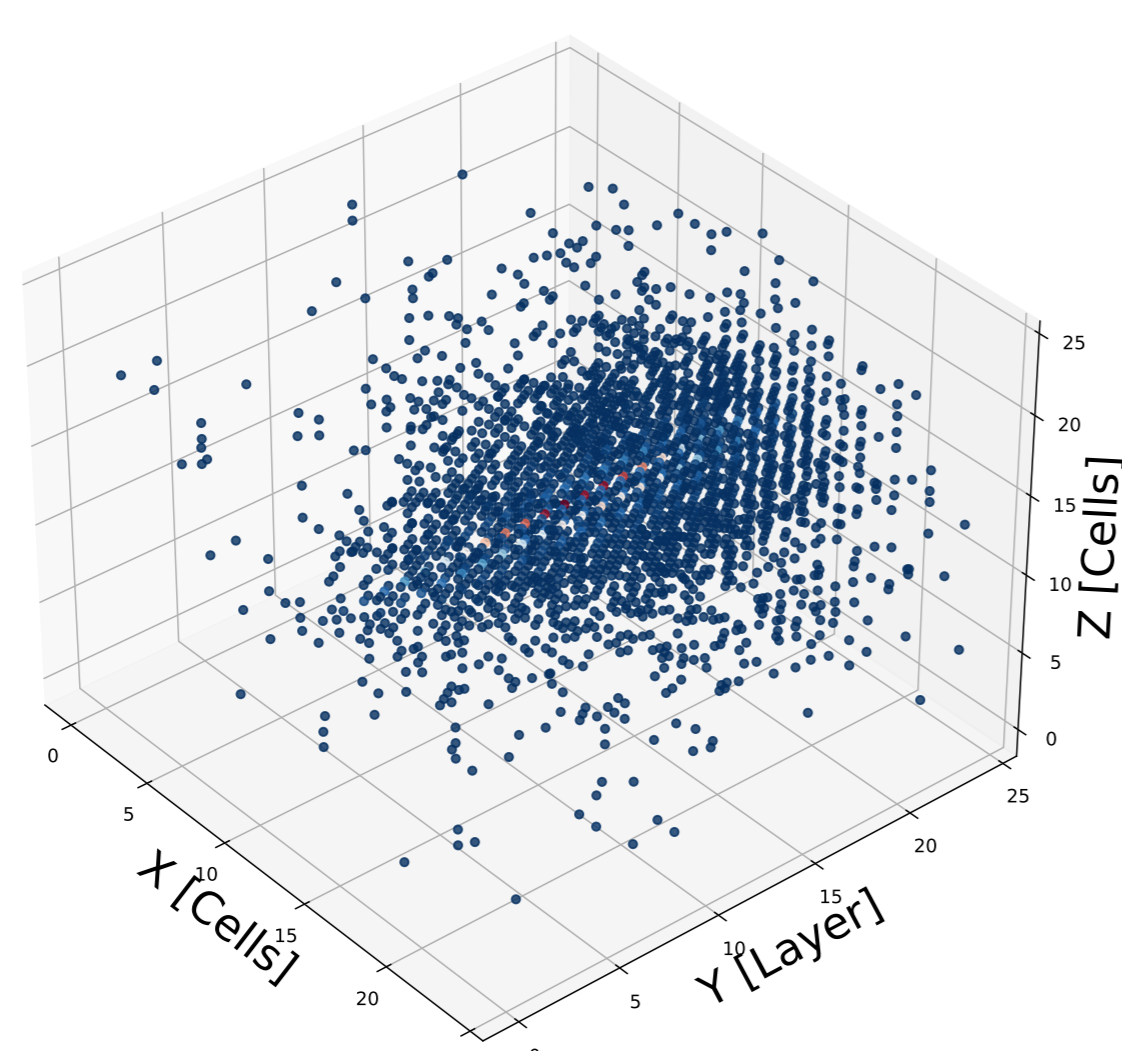


The z -representation is **enriched with the number of all hits** n_{hits} and the transformed *total energy of the hits* E_{sum} . Both flows are *conditional normalizing flows*, based on **rational quadratic spline** (RQS) coupling layers[1] and **ResNet[2] conditioners**. The *Point Flow* transforms each point x_i separately, it is conditioned on the latent variable z . The *Latent Flow* is conditioned on the energy E_{in} .

Shower generation:

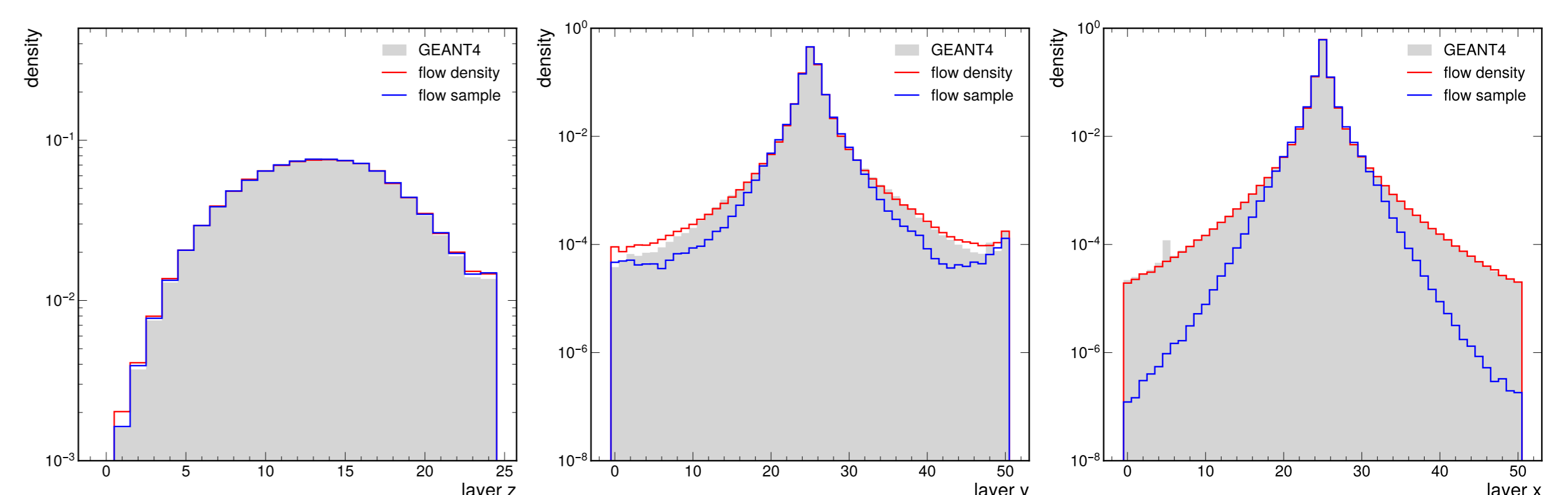
- sample large number of points (10k) + probabilities
- average probability in each cell
- sample n_{hits} cells without replacement
- sample energies for picked cells

Dataset

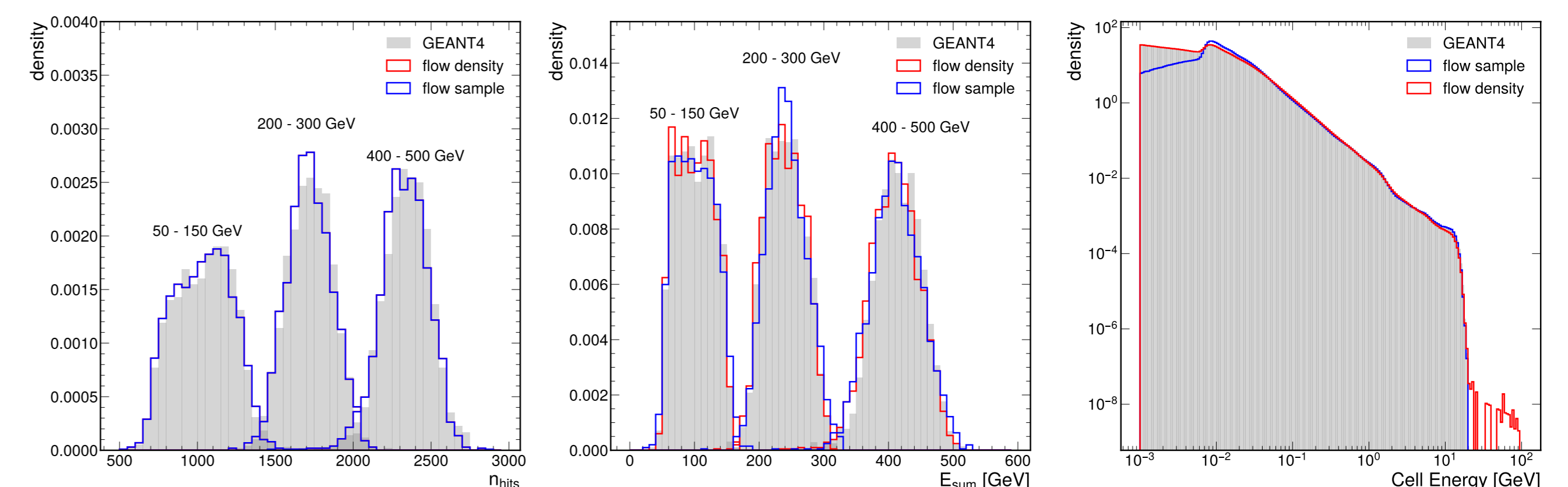


The CLIC Calorimeter Dataset [3] was used. The dataset consists out of **800k events**. Each event contains the simulated energies measured by the **(51 × 51 × 25)** scintillator cells. This energy is the result of the electromagnetic shower coming from a single **electron** traveling at a fixed angle through the calorimeter. The **initial energy** of this electron is uniformly distributed **between 10 – 510 GeV**. The voxel dataset is transformed into a point cloud dataset.

Results and Discussion



The **average shower profile** in all directions are shown. The results of the direct density of the model and the results after sampling from the model are compared with the simulation data. It can be seen that the model produces matching results, but the tails of the distributions are not well represented by the sampling.



Three statistics of the showers are compared. The first two show that both **the number of cells hit** and the **sum of the energy in the cells** agree well with the results of GEANT4 - both for the direct density of the model and for the sampled results. The right graph shows the individual **cell energy distribution**. There are significantly fewer low-energy hits after sampling. This is consistent with the decrease in the tails.

Conclusion and Outlook

The results of the model appear promising. Except for the tails, the model generates showers of a high quality. A possible further development to get the problems of the model at the tails under control would be the use of a post-processing network. We are currently investigating the model's performance on other datasets. This will be part of another publication.

Overall, the model shows good results and can overcome the problems of voxel based models.

References

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- [3] Maurizio Pierini and Matt Zhang. CLIC Calorimeter 3D images: Electron showers at Fixed Angle, January 2020.
- [4] Guandao Yang, Xun Huang, Zekun Hao, Ming-Yu Liu, Serge Belongie, and Bharath Hariharan. Pointflow: 3d point cloud generation with continuous normalizing flows, 2019.