

CaloClouds III: Ultra-Fast Geometry-Independent Highly-Granular Calorimeter Simulation

ML4Jets, Paris, France

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E. Buhmann², H. Day-Hall¹, T. Buss², F. Gaede¹, G. Kasieczka²,
W. Korcar², **A. Korol**^{1,*}, K. Krüger¹, P. McKeown^{1,3}

¹ Deutsches Elektronen-Synchrotron, DESY

² University of Hamburg, UHH

³ CERN

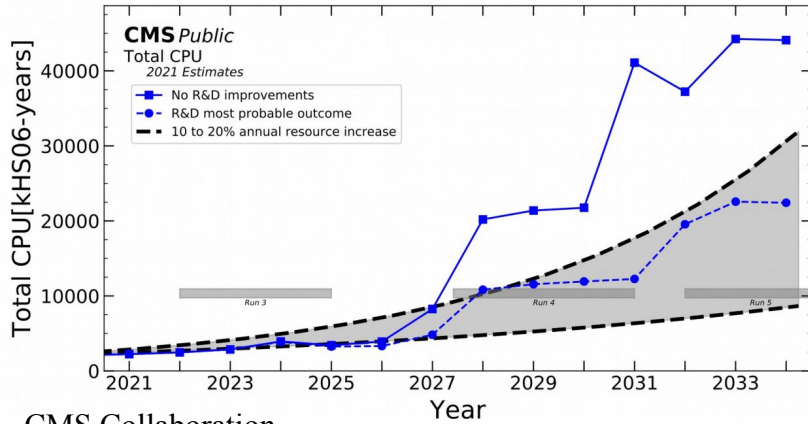
[*anatolii.korol@desy.de](mailto:anatolii.korol@desy.de)

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Introduction

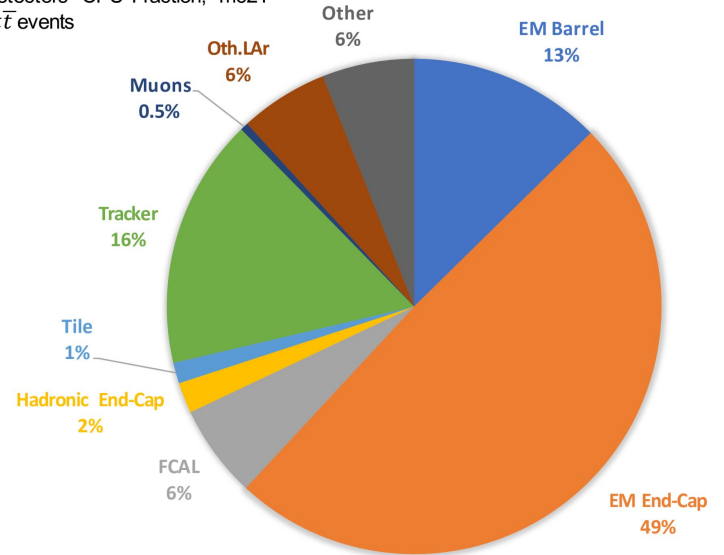
Time-consuming Simulations



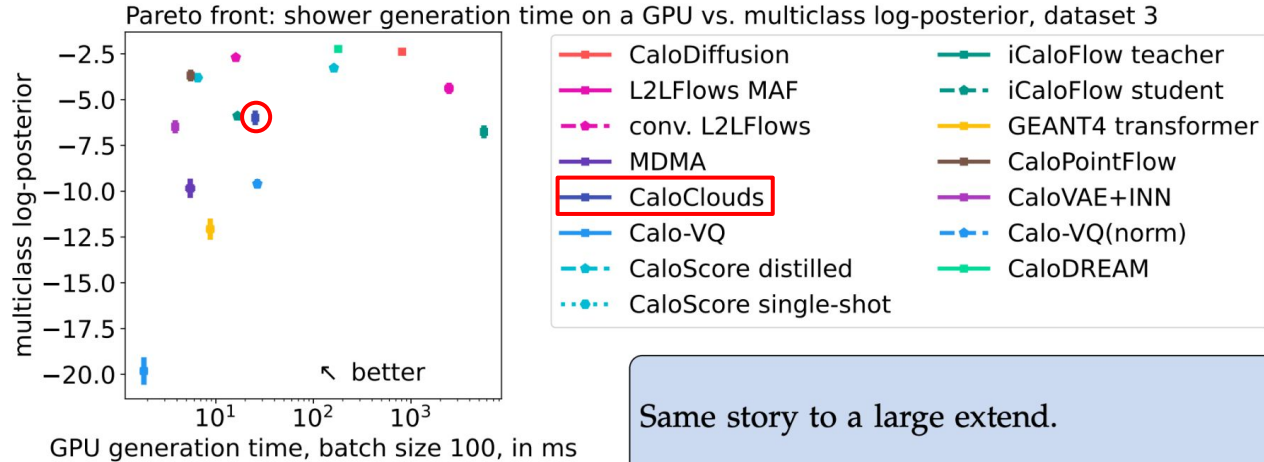
CMS Collaboration,
Offline and Computing Public Results (2021)
<https://twiki.cern.ch/twiki/bin/view/CMSPublic/CMSOfflineComputingResults>

Goal: replace (or augment) most intensive part of detector simulation (calorimeters simulation) with a faster generator, based on state-of-the-art machine learning techniques

ATLAS Simulation Preliminary
Subdetectors CPU Fraction, mc21
100 $t\bar{t}$ events



Pareto Fronts: Quality vs. Generation Time



Same story to a large extend.

Introduction

Almost Got an Invitation to Sweet Spot Club

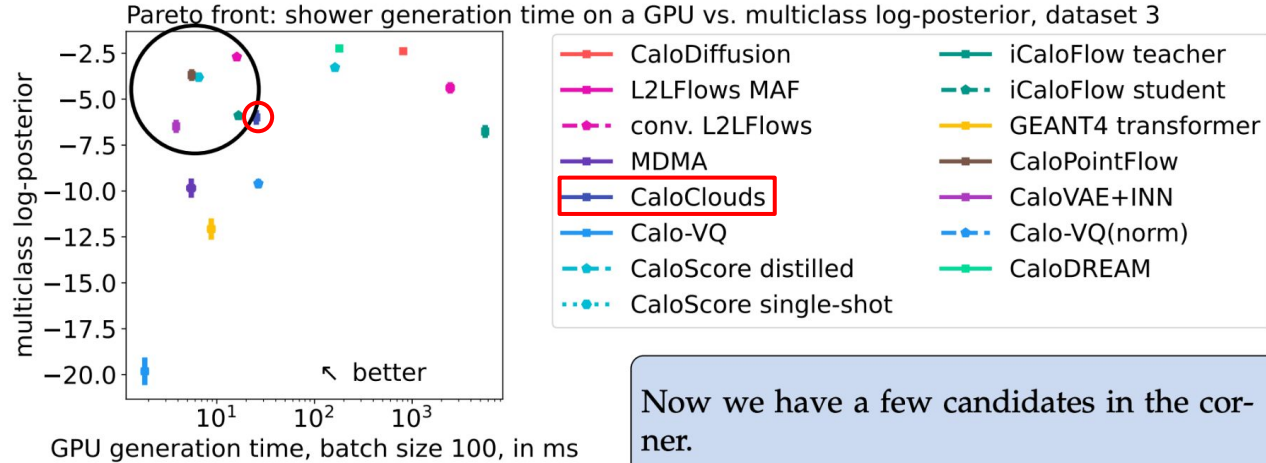
Courtesy C.Krause

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Pareto Fronts: Quality vs. Generation Time

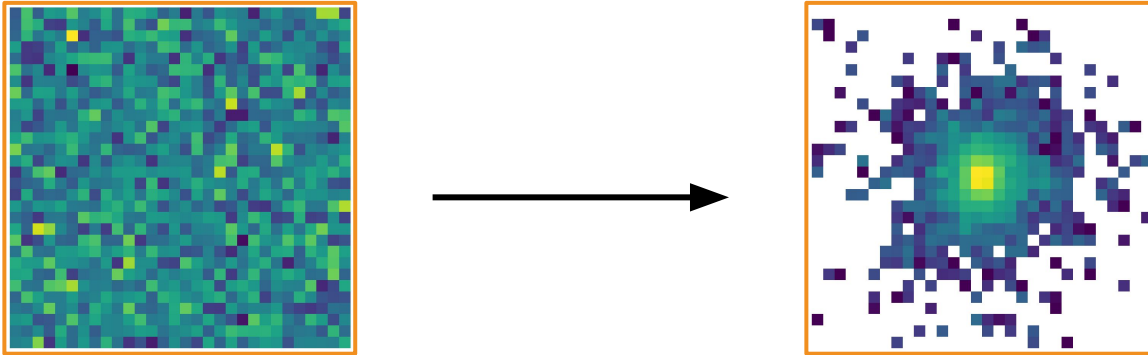


Now we have a few candidates in the corner.

Introduction

Generative Models

- A Generative Model is just a function that maps random noise to a some structure
- In most cases the structure is an **image representation** of the electromagnetic (EM) shower in the calorimeter

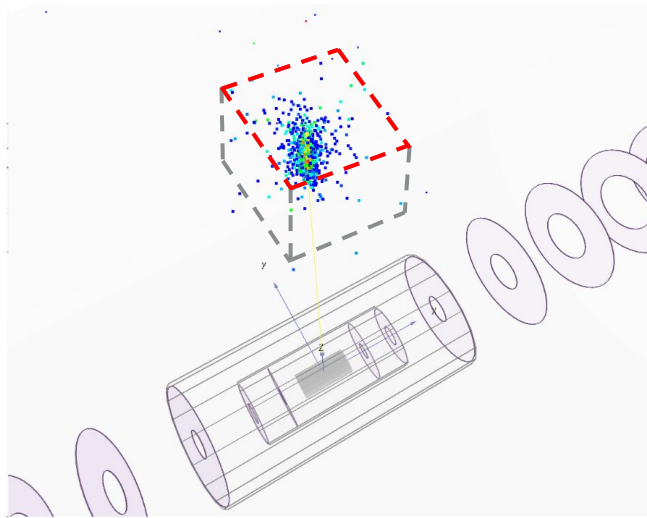


- There exist numerous generative models
 - Generative Adversarial Networks (GANs)
 - Autoencoders (AE), e.g. BiB-AE
 - Flow-based models
 - Diffusion Models (DMs)

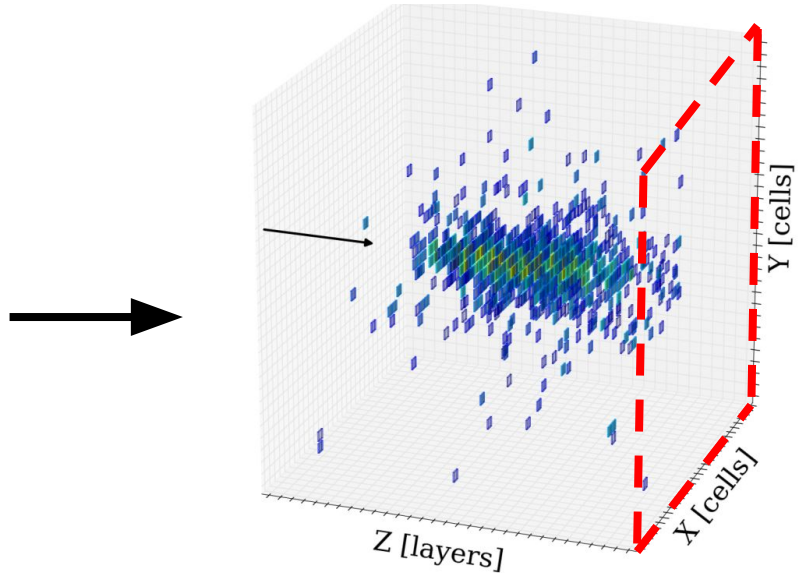
Image Representation of the EM Showers

ILD Detector

A simulated 60 GeV photon shower in the ILD detector



Regular grid 30x30x30

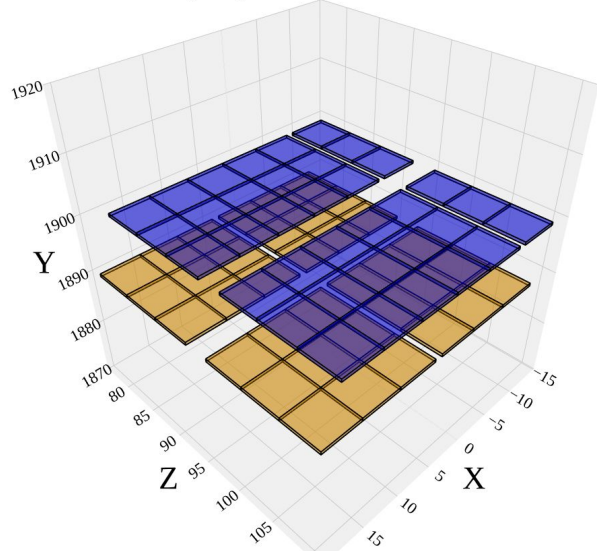


One to one mapping from detector geometry to a regular grid

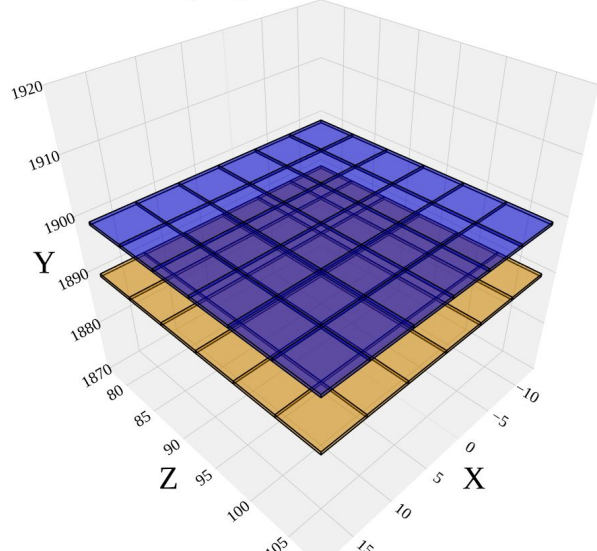
Problems with Image Representation of the EM Showers

ILD Detector, ECAL Layers Structure

Real Geometry Layout



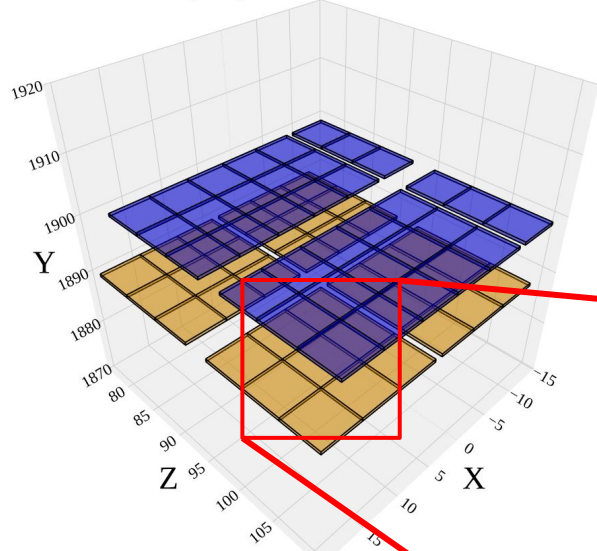
Regular Geometry Layout



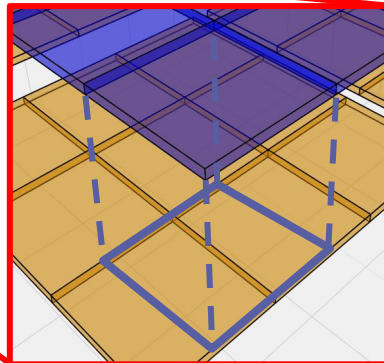
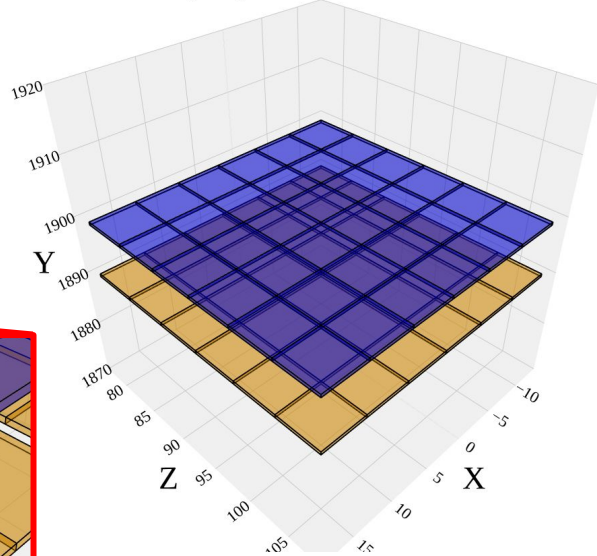
Problems with Image Representation of the EM Showers

ILD Detector, ECAL Layers Structure

Real Geometry Layout

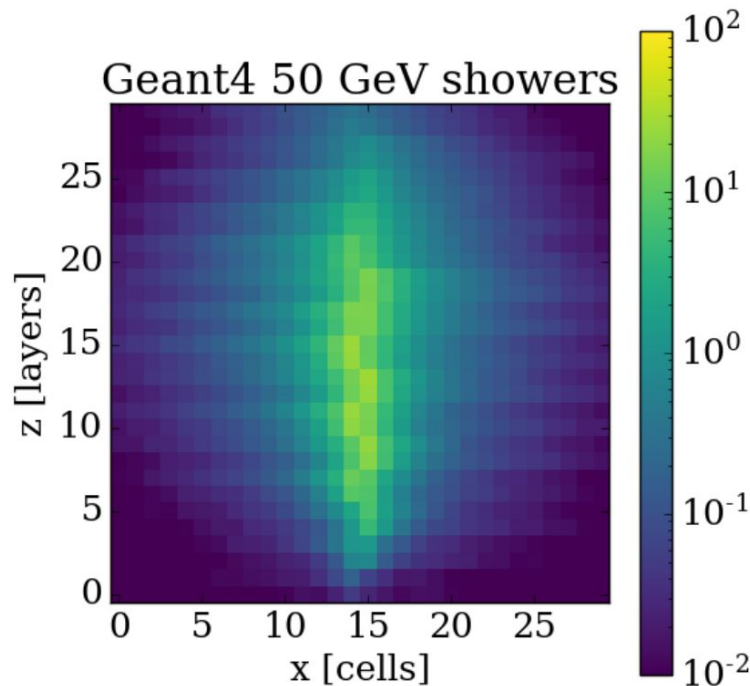
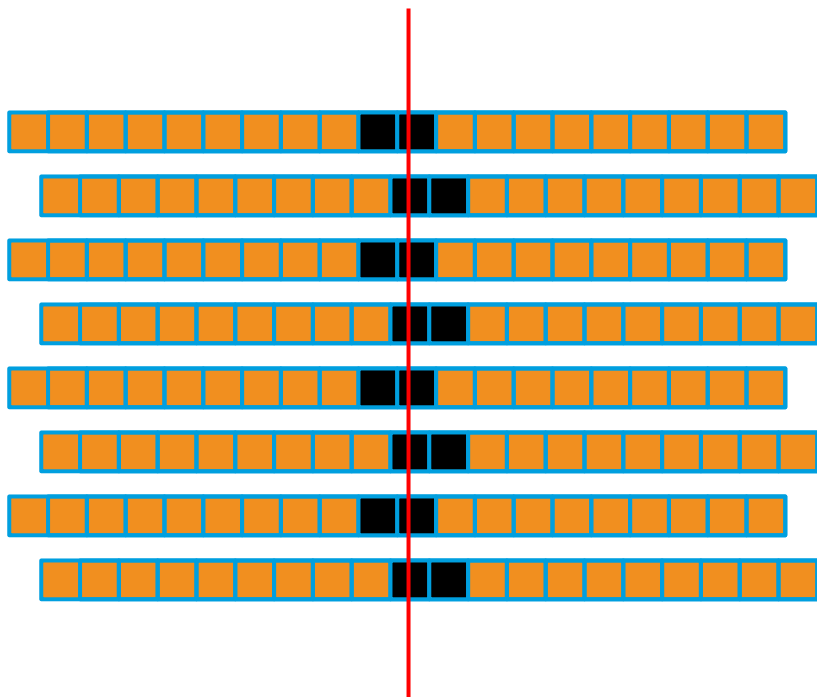


Regular Geometry Layout



Problems with Image Representation of the EM Showers

ILD Detector, ECAL Layers Structure, Staggering Effect



Models have to learn not only EM shower properties, but also geometry “artifacts”, like **staggering effect**

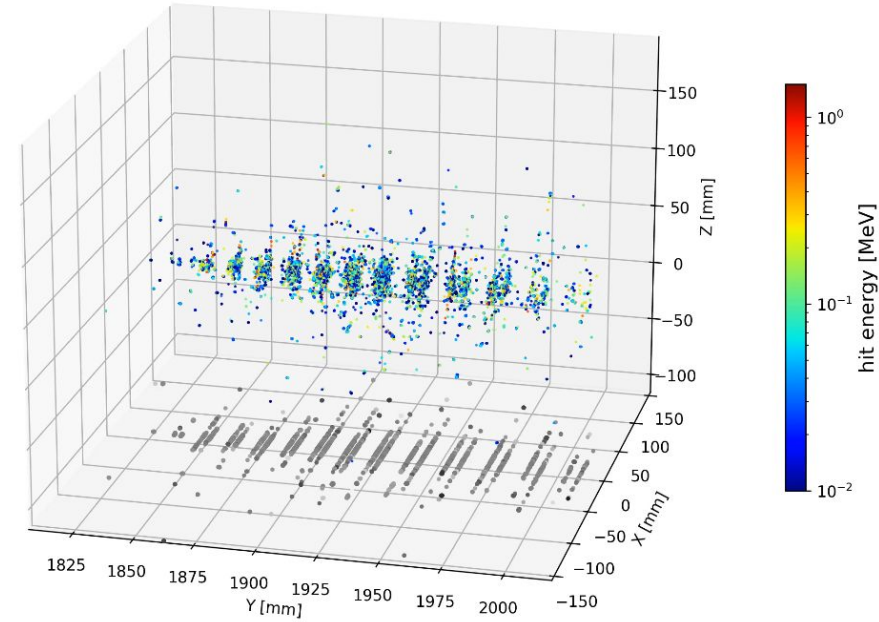
Point Cloud Representation of the EM Showers

GEANT4 Steps

A way to overcome potential issues from irregular (realistic) cell geometry would be to use much higher granularity/resolution

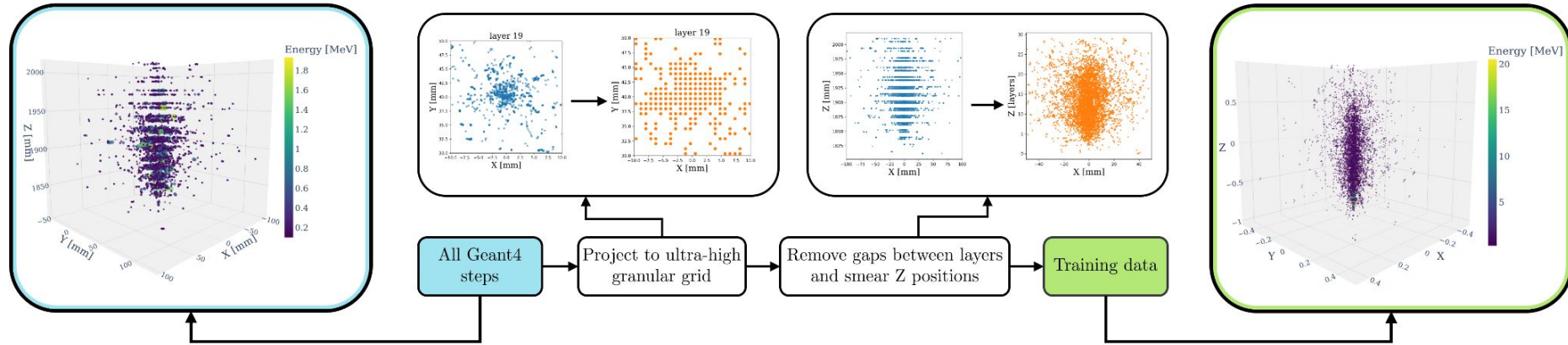
- All G4 interactions, ultimate resolution
- Detached from detector layer geometry
- Too many points to generate, $\sim 40k$ per shower (need pre-processing step to reduce number of spacepoints)

Photon
Energy: 90 [GeV]
Event: 4
Time step: 0.98246 [ns]



Point Cloud Representation of the EM Showers

Data Preprocessing

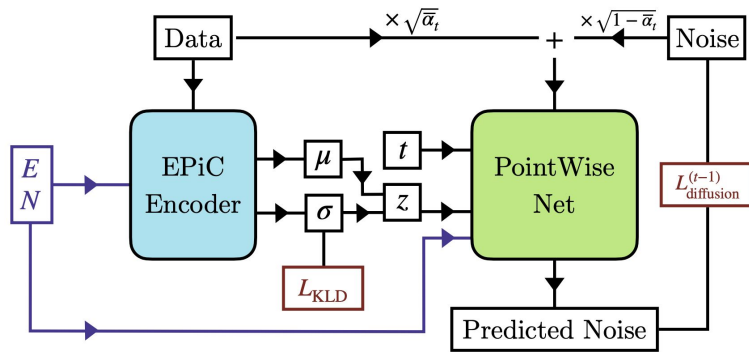


Number of points reduced to ~6k per shower, high enough resolution to move the shower in different place without harming physical properties of the shower

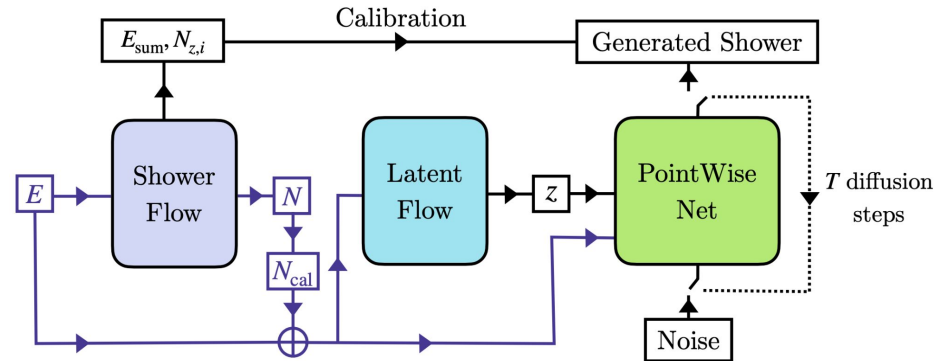
Point Cloud + Diffusion Model

CaloClouds, Model Overview

CaloClouds: Fast Geometry-Independent
Highly-Granular Calorimeter Simulation,
Buhmann, AK, et al. 2023, [arXiv:2305.04847](https://arxiv.org/abs/2305.04847)



(a) Training at random time step t

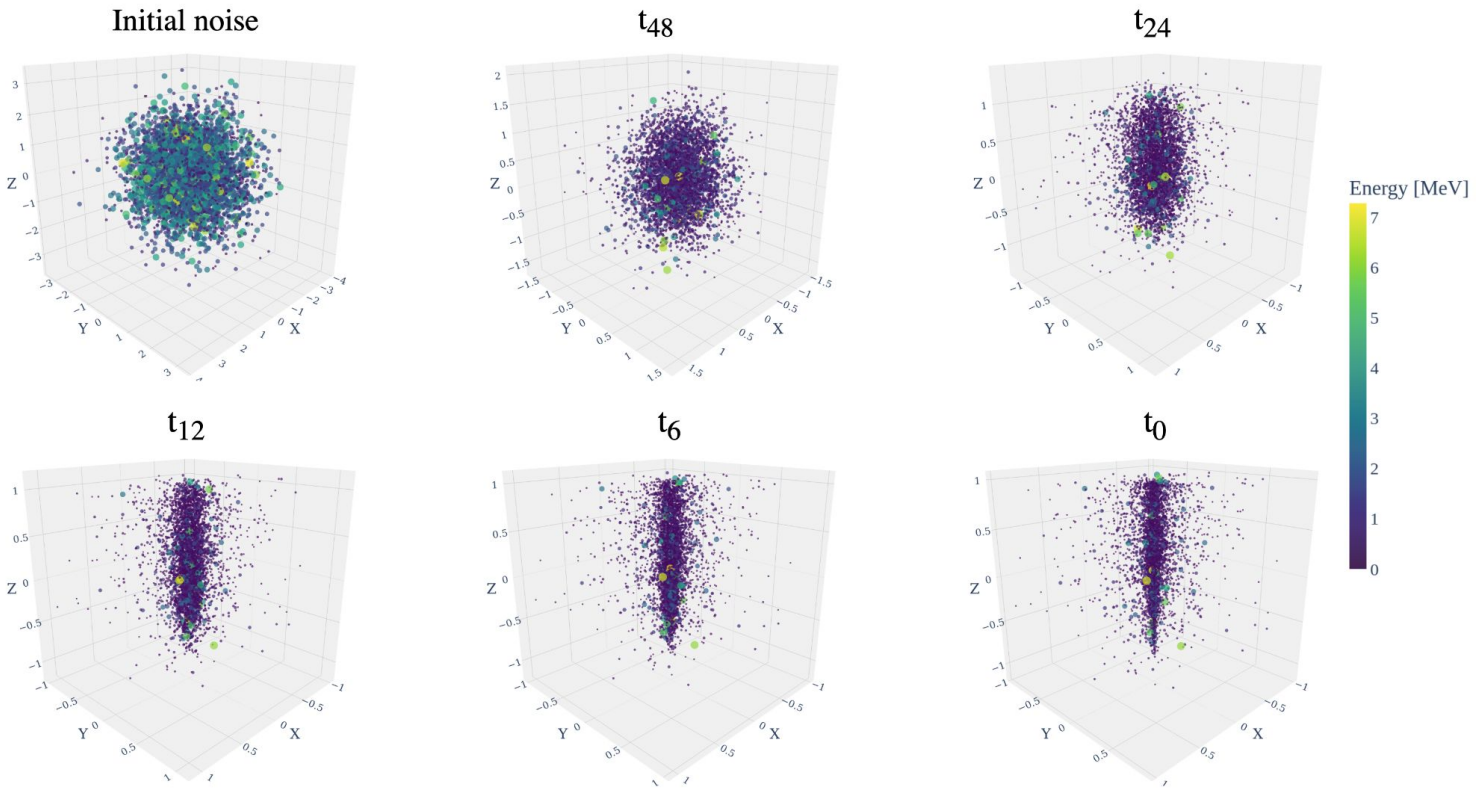


(b) Sampling with reverse diffusion through all time steps T

- GANs and VAEs convert noise from some simple distribution to a data sample
- **DMs learn to gradually denoise data starting from noise**

Point Cloud + Diffusion Model

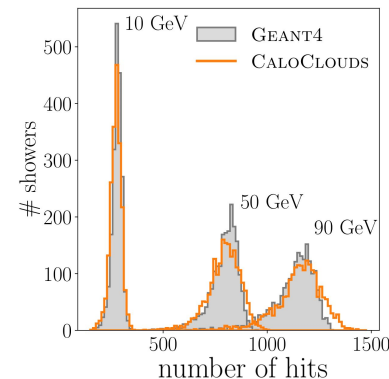
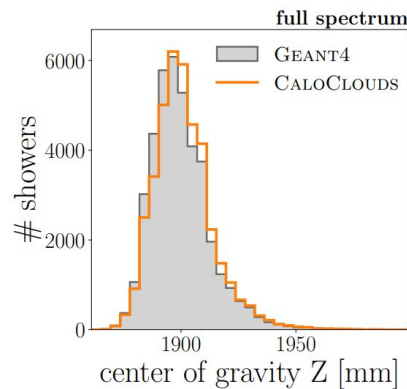
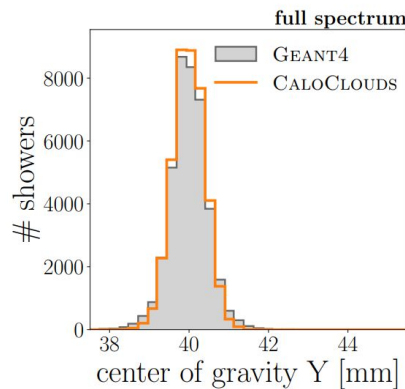
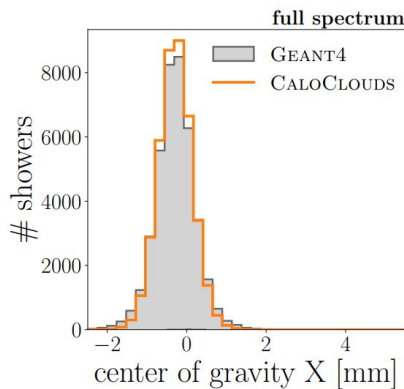
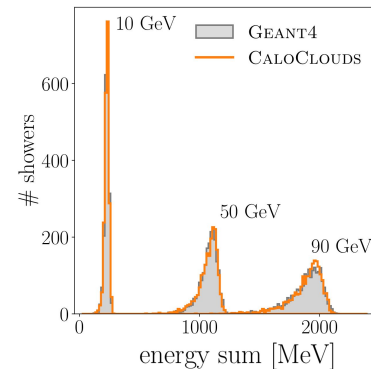
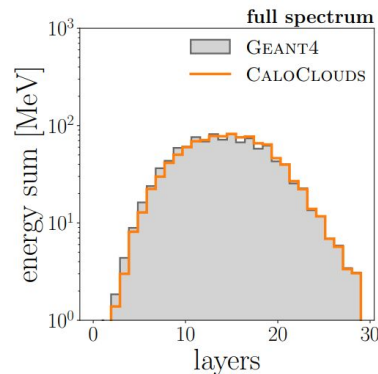
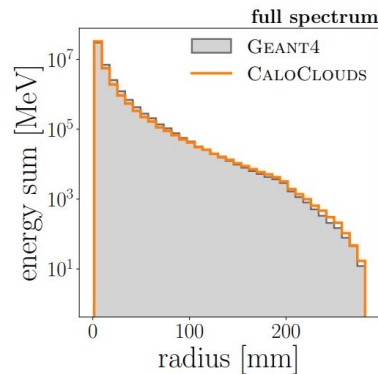
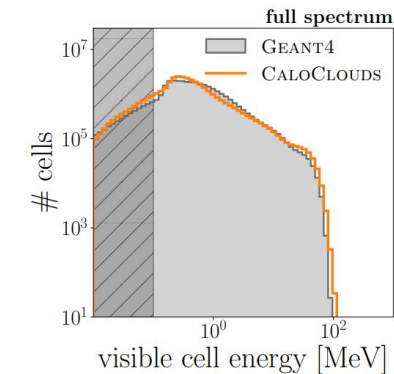
Reverse Diffusion Process



Point Cloud + Diffusion Model

Physics Observables

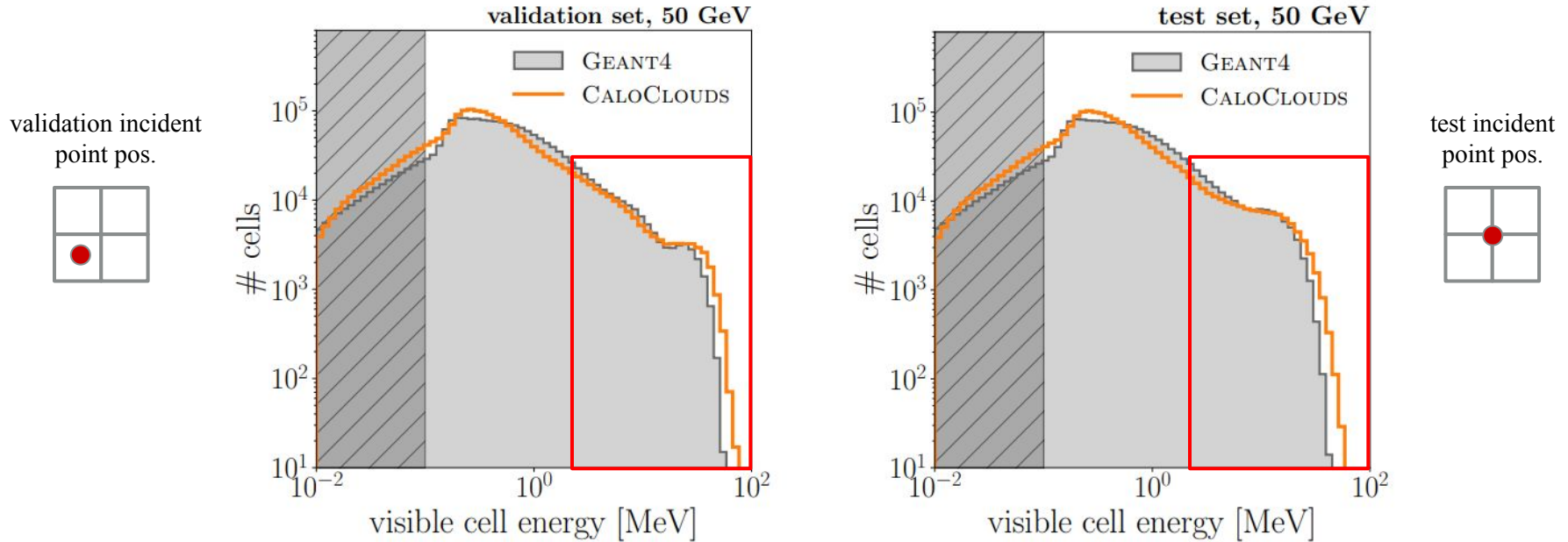
CaloClouds: Fast Geometry-Independent Highly-Granular Calorimeter Simulation,
Buhmann, AK, et al. 2023, [arXiv:2305.04847](https://arxiv.org/abs/2305.04847)



Point Cloud + Diffusion Model

Physics Observables For Different Positions

CaloClouds: Fast Geometry-Independent
Highly-Granular Calorimeter Simulation,
Buhmann, AK, et al. 2023, [arXiv:2305.04847](https://arxiv.org/abs/2305.04847)



Per-cell energy distribution for the 50 GeV validation (left) data set, created at the same position as the training data set and for a 50 GeV test (right) data set simulated at a different position with the generated point cloud translated to this position


Point Cloud + Diffusion Model

Speedup, CaloClouds I

CaloClouds: Fast Geometry-Independent
Highly-Granular Calorimeter Simulation,
Buhmann, AK, et al. 2023, [arXiv:2305.04847](https://arxiv.org/abs/2305.04847)

Hardware	Simulator	Time / Shower [ms]	Speed-up
CPU	GEANT4	4082 ± 170	$\times 1$
	CALOCLOUDS	3509 ± 220	$\times 1.2$
GPU	CALOCLOUDS	38 ± 3	$\times 107$

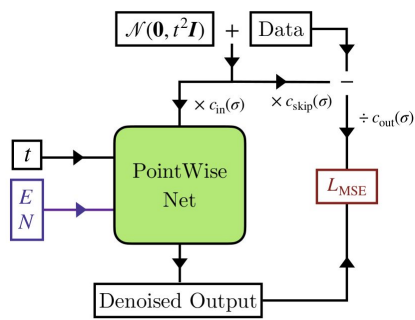
Not impressive
inference time



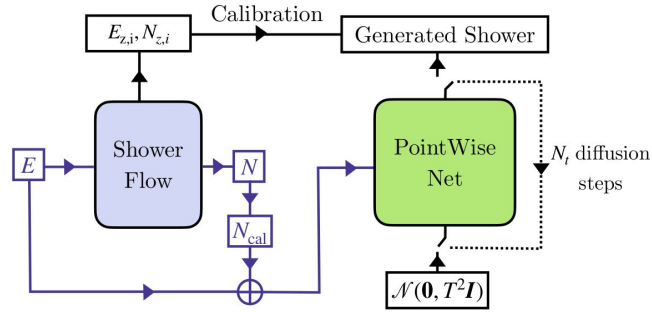
Point Cloud + Diffusion Model

CaloClouds II, Model Overview

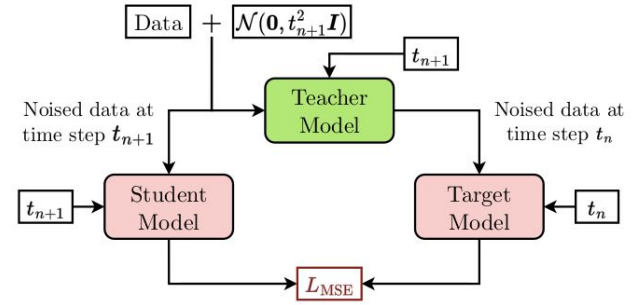
CaloClouds II: Ultra-Fast Geometry-Independent Highly-Granular Calorimeter Simulation,
Buhmann, AK, et al. 2023, [arXiv:2309.05704](https://arxiv.org/abs/2309.05704)



(a) Training



(b) Sampling



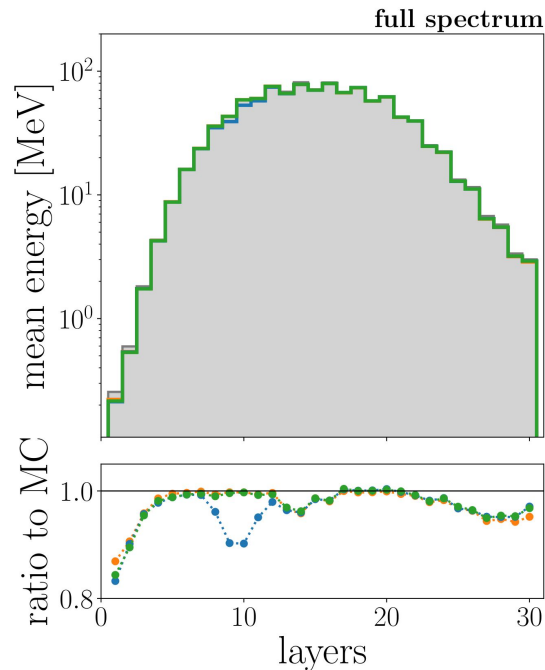
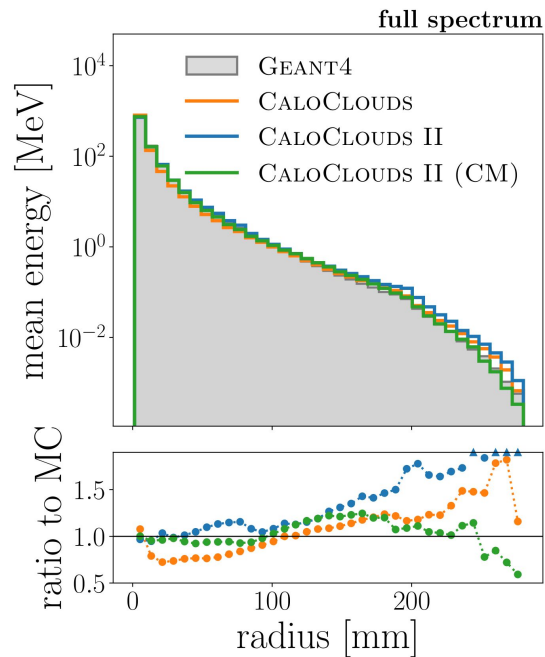
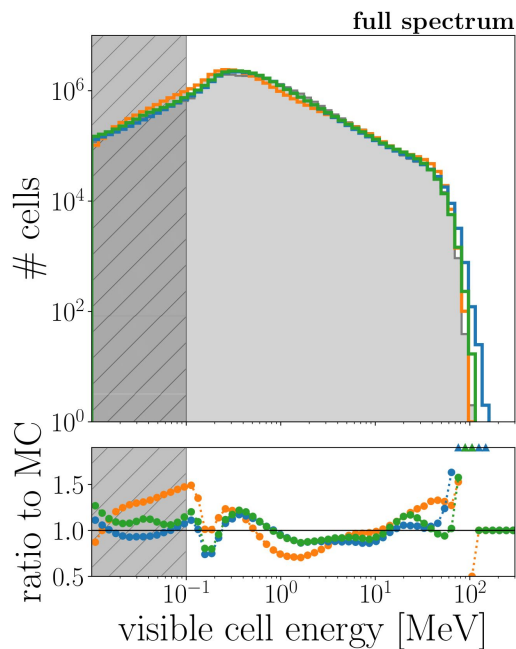
Consistency Distillation

Modified version of CaloClouds + Consistency Distillation → significantly reduced inference time

Point Cloud + Diffusion Model

Physics Observables

CaloClouds II: Ultra-Fast Geometry-Independent
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Point Cloud + Diffusion Model

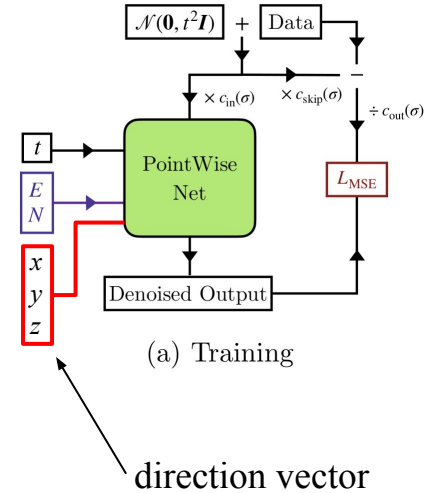
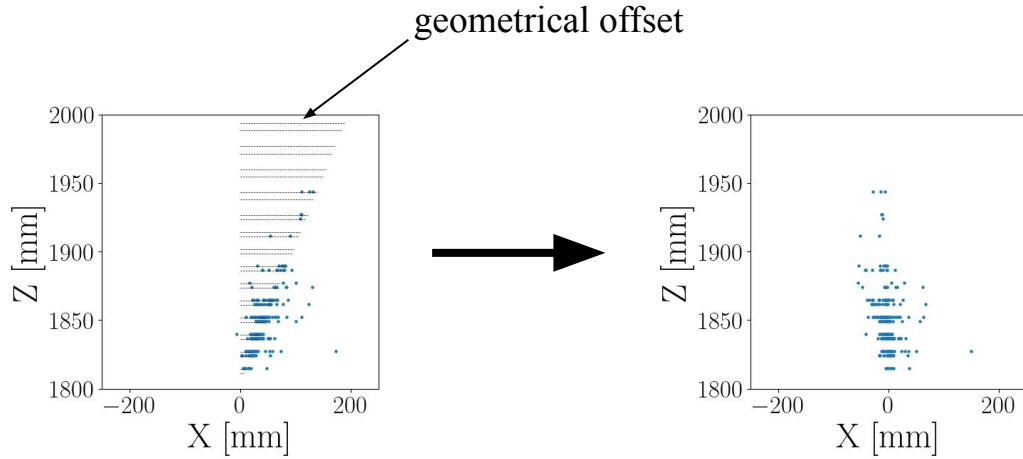
Speedup, CaloClouds II

CaloClouds II: Ultra-Fast Geometry-Independent
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Buhmann, AK, et al. 2023, [arXiv:2309.05704](https://arxiv.org/abs/2309.05704)

Hardware	Simulator	NFE	Batch Size	Time / Shower [ms]	Speed-up
CPU	GEANT4			3914.80 ± 74.09	$\times 1$
	CALOCLOUDS	100	1	3146.71 ± 31.66	$\times 1.2$
	CALOCLOUDS II	25	1	651.68 ± 4.21	$\times 6.0$
	CALOCLOUDS II (CM)	1	1	84.35 ± 0.22	$\times 46$
GPU	CALOCLOUDS	100	64	24.91 ± 0.72	$\times 157$
	CALOCLOUDS II	25	64	6.12 ± 0.13	$\times 640$
	CALOCLOUDS II (CM)	1	64	2.09 ± 0.13	$\times 1873$

Point Cloud + Diffusion Model

CaloClouds III, Adding Angular Conditioning



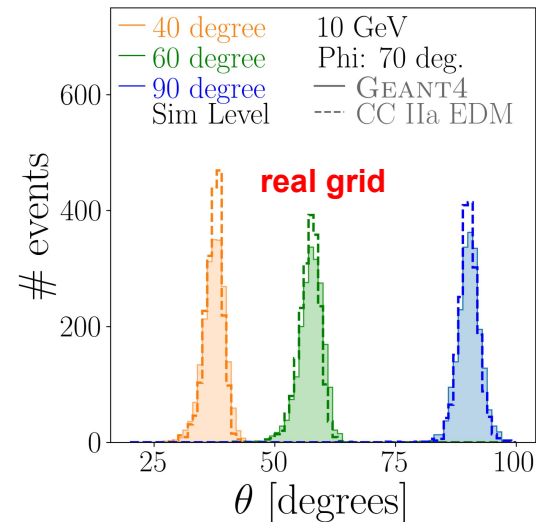
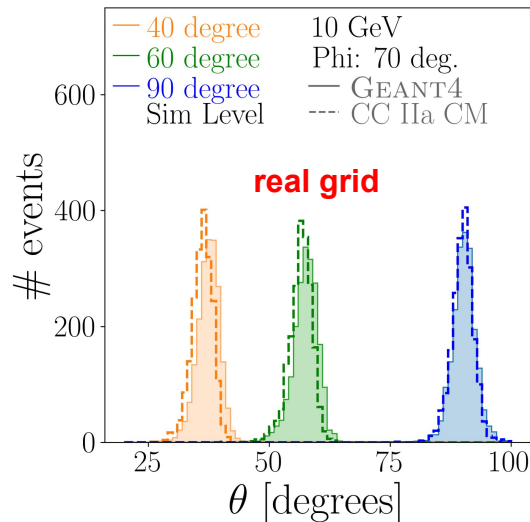
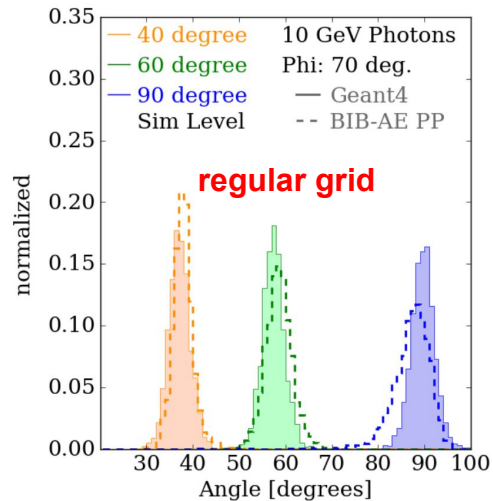
Additional data preprocessing step, another conditioning vector

Point Cloud + Diffusion Model

Angle Reconstruction

1 step

90 steps



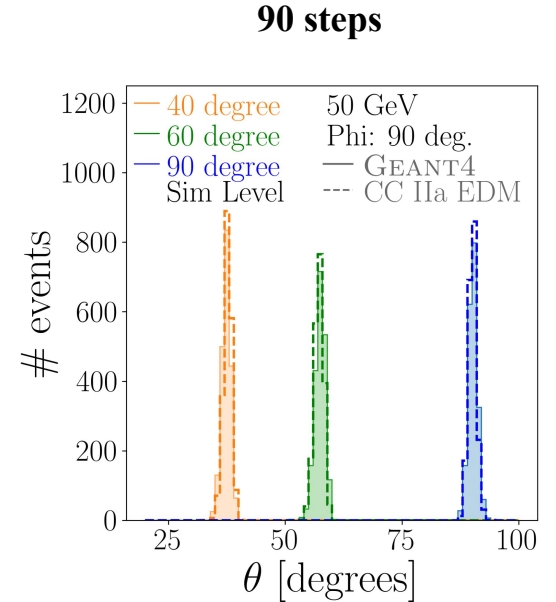
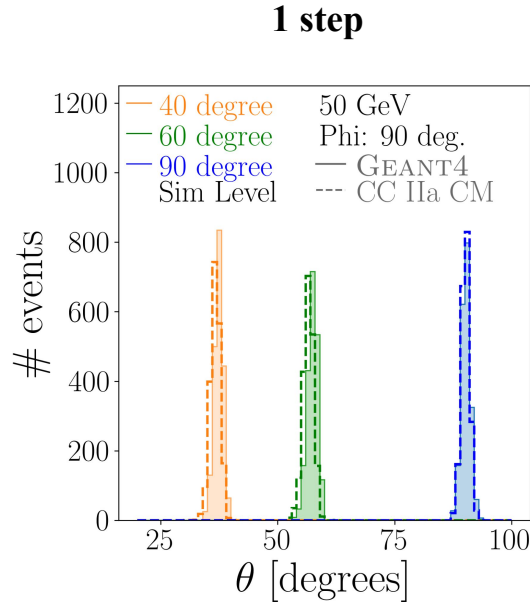
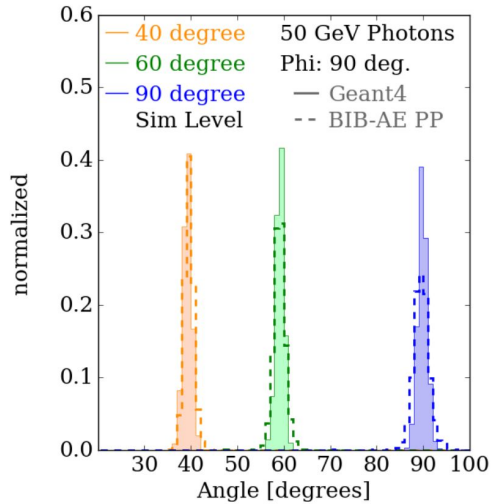
Development and Performance of a Fast Simulation Tool for Showers in High Granularity Calorimeters based on Deep Generative Models

Peter McKeown (Hamburg U.), 2024

DOI: [10.3204/PUBDB-2024-01825](https://doi.org/10.3204/PUBDB-2024-01825)

Point Cloud + Diffusion Model

Angle Reconstruction



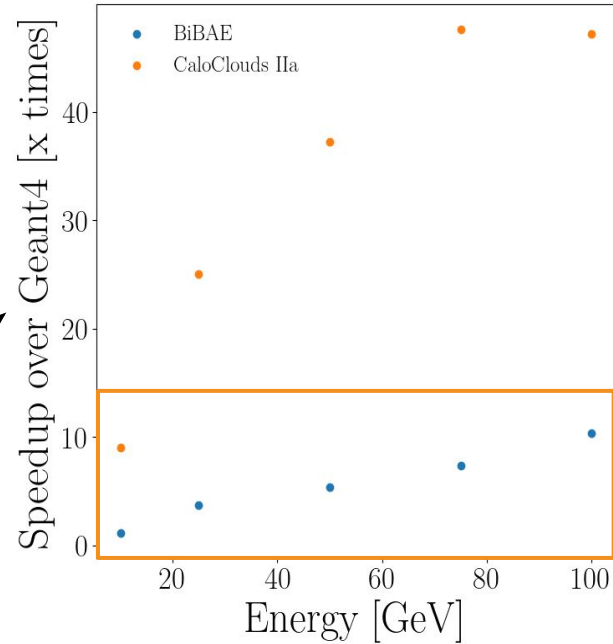
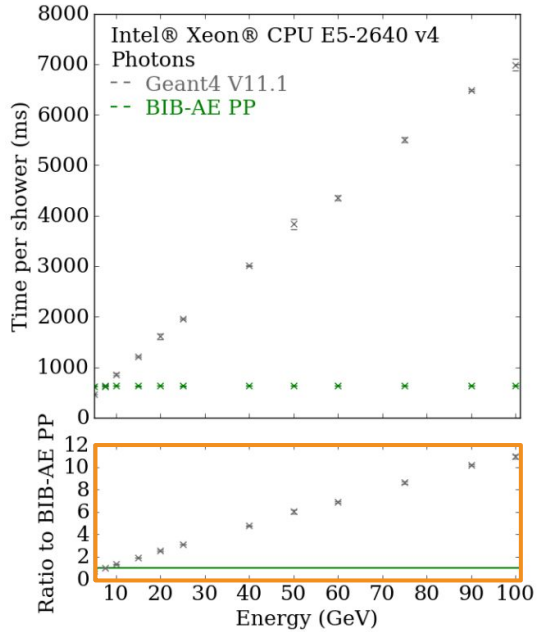
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Point Cloud + Diffusion Model

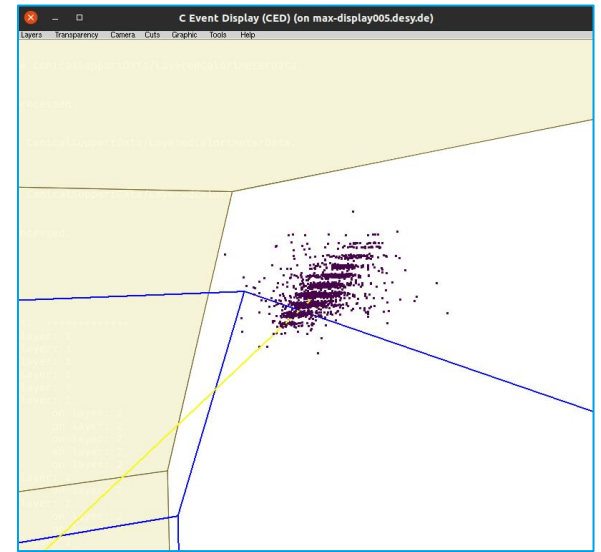
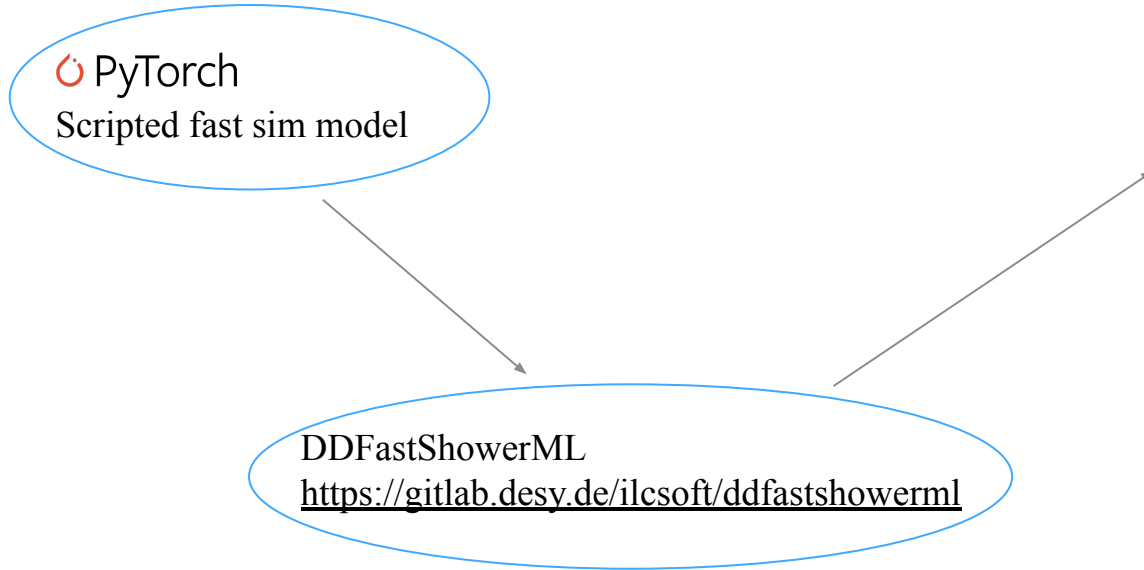
Speedup, CaloClouds III vs BiBAE



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Integration into Simulation Chain

DDFastShowerML



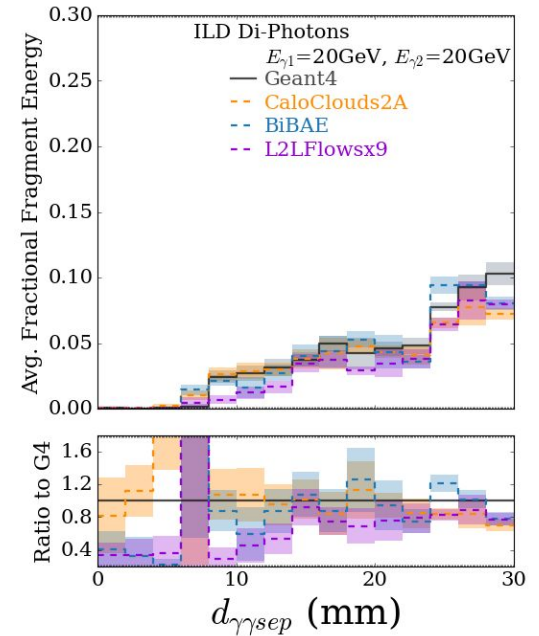
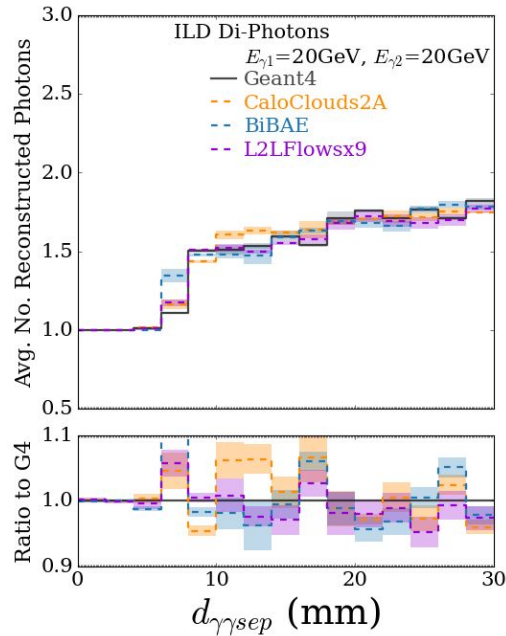
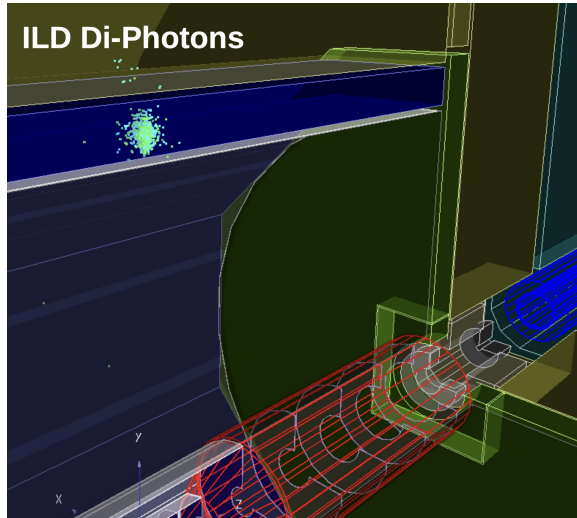
50 GeV photon shower generated with CaloClouds in the ILD ECAL

Easy to use library which can be adapted for all types of ML architectures in DD4hep

Di-Photons Reconstruction Benchmark

Two Photons Orthogonal to the Face of ILD ECAL

Courtesy P.McKeown



Di-Photon Reconstruction Benchmark provides a direct **physically relevant** quantification of model performance

Summary

**CaloClouds: Fast Geometry-Independent
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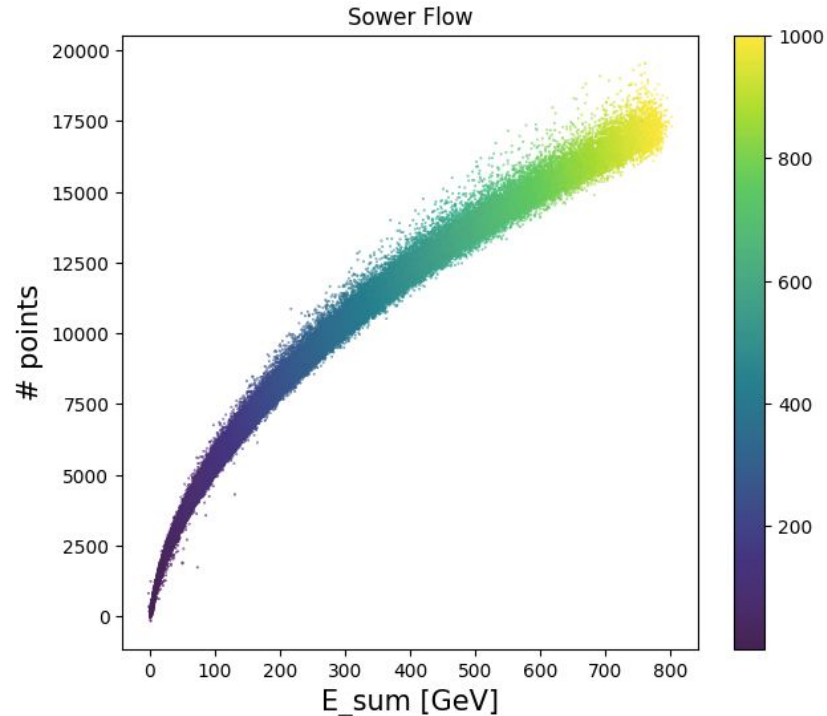
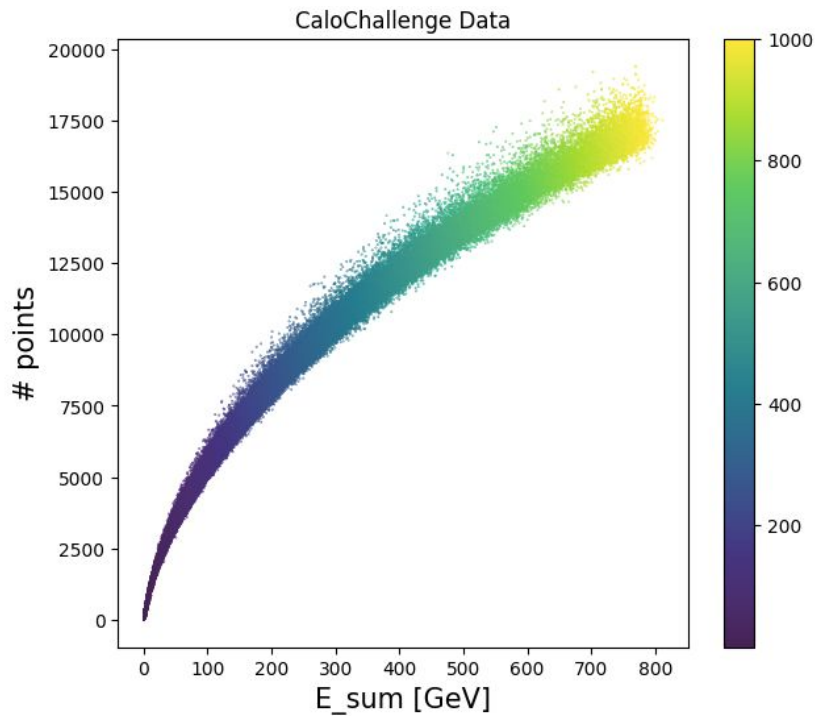
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- Investigated new generative model architecture for generating EM showers in highly-granular calorimeters
- The fidelity of CaloClouds' physical properties is competitive with SOTA models (BiBAE, L2LFlows), while offering $\sim x6$ faster inference
- Model integrated into existing software ecosystem
- Next steps: more in depth study of physics benchmarks

BACKUP SLIDES

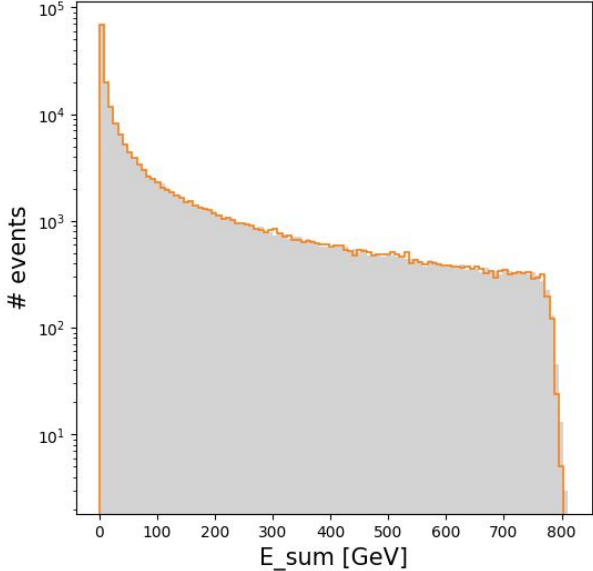
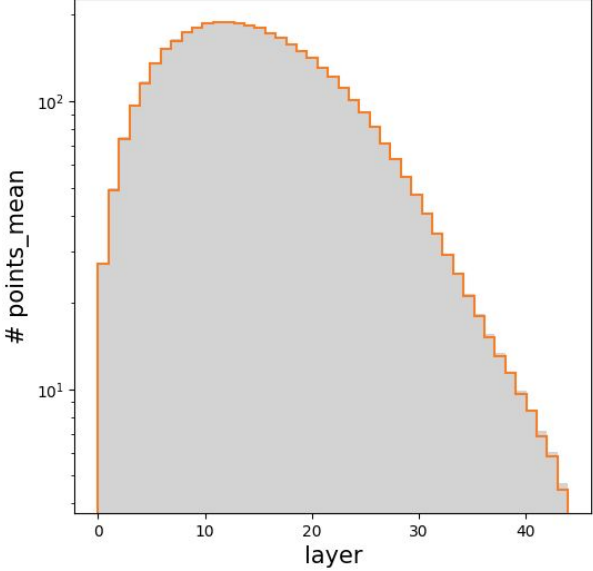
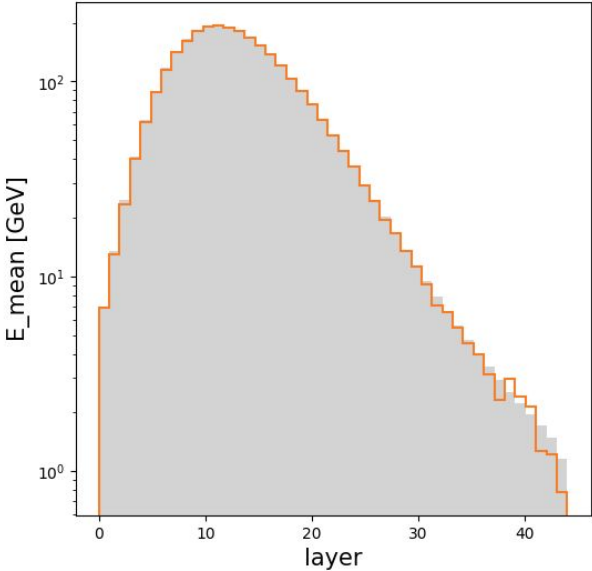
Shower Flow

Results



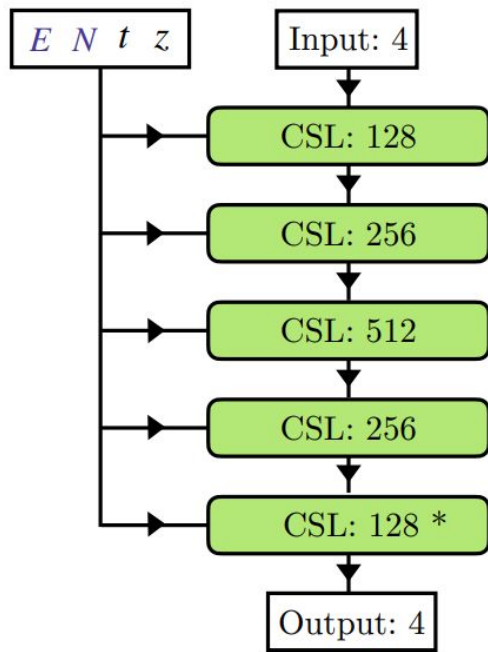
Shower Flow

Results

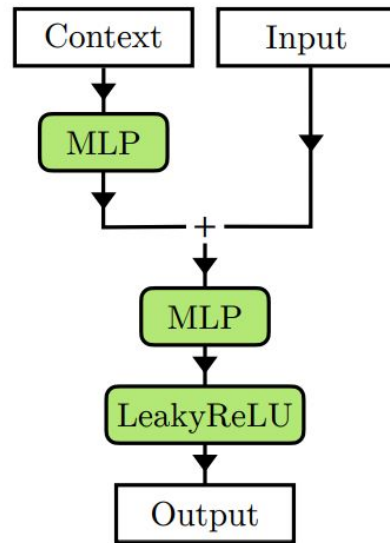


Point Cloud + Diffusion Model

PointWise Net



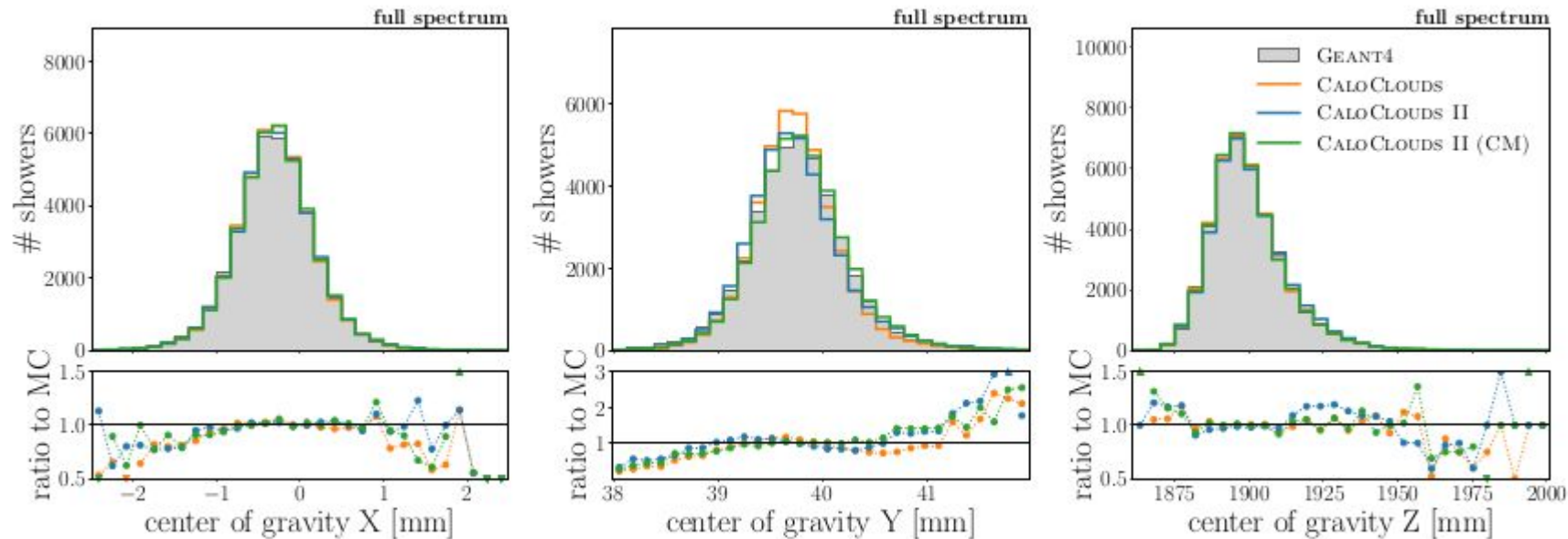
(a) PointWise Net



(b) ConcatSquash Layer (CSL)

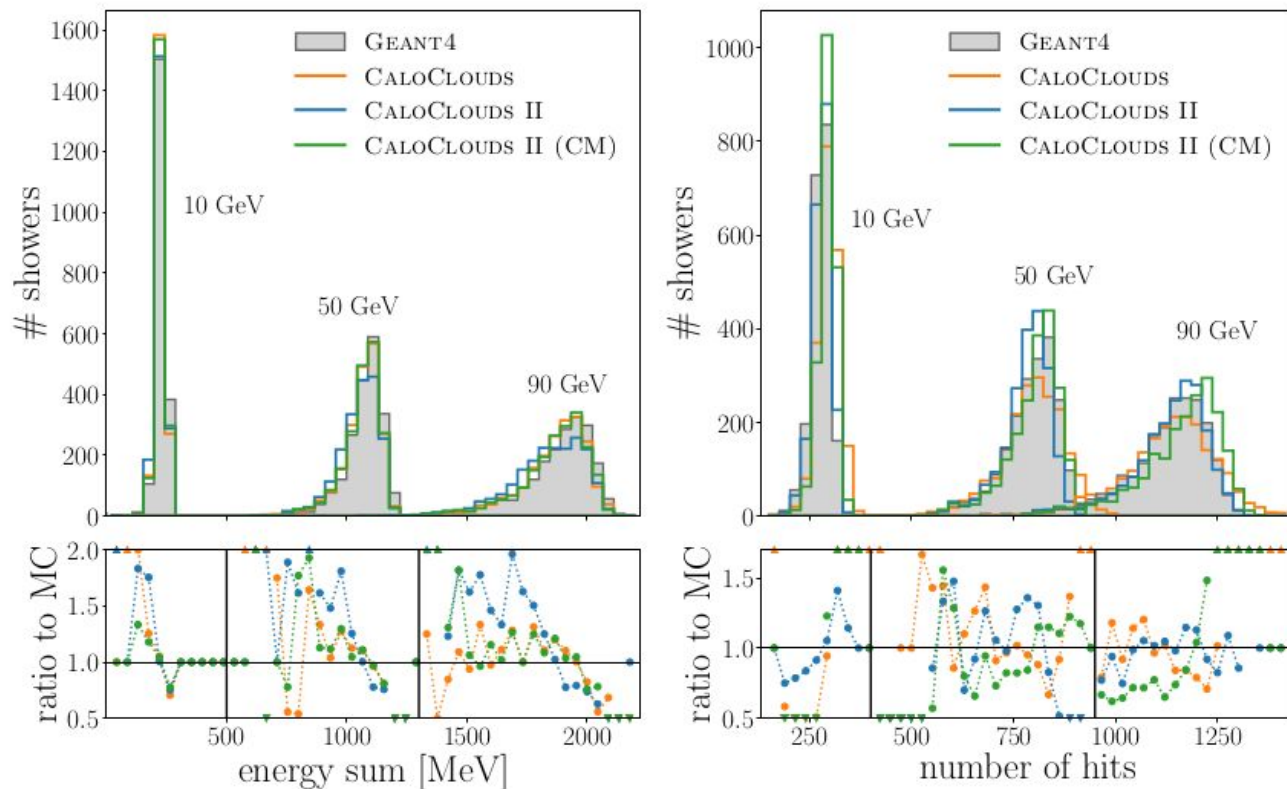
Point Cloud + Diffusion Model

Results, Position of the Center of Gravity



Point Cloud + Diffusion Model

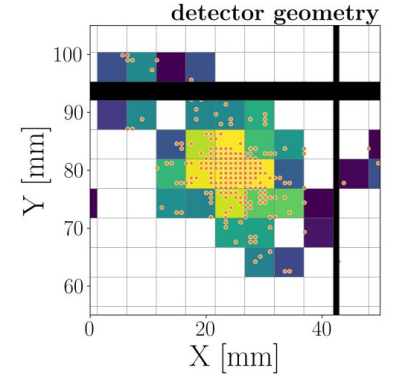
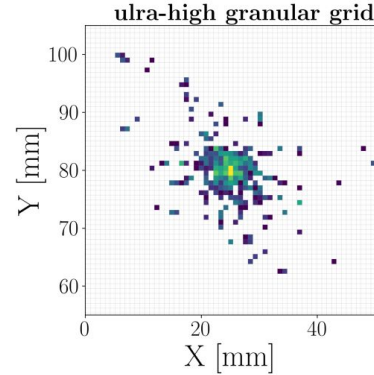
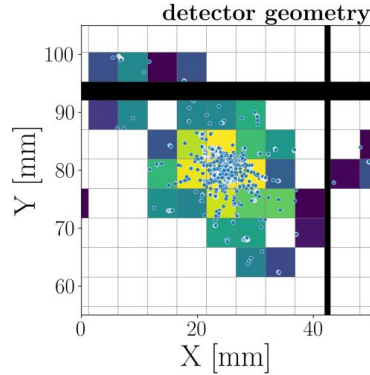
Results, Visible Energy and the Number of Hits



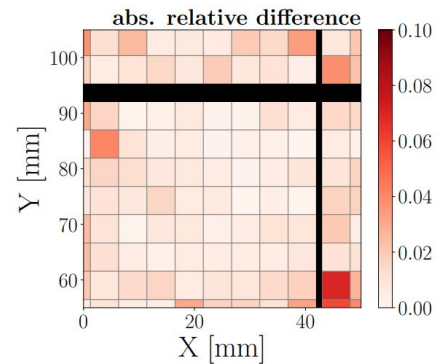
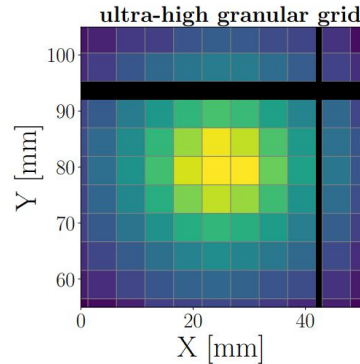
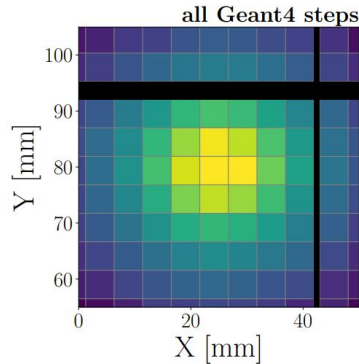
Point Cloud Representation of the EM Showers

Effects of the Pre-Clustering

Single event of 90 GeV shower in 21th layer



2k events of 90 GeV showers in 21th layer, overlay



Point Cloud Representation of the EM Showers

Effects of the Pre-Clustering

