

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

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Detailed Simulations is Crucial for Connecting Theory with Experimental Observations

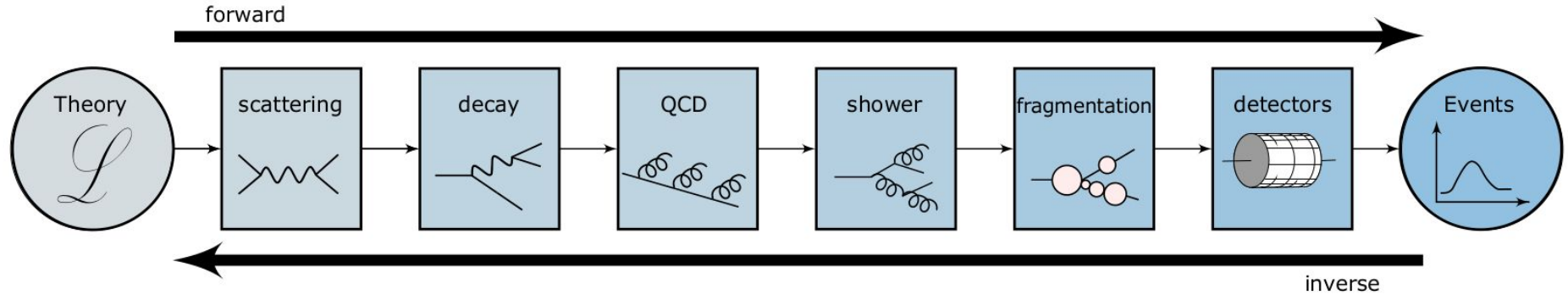


Figure from:
Machine learning and LHC event generation,
DOI: [10.21468/SciPostPhys.14.4.079](https://doi.org/10.21468/SciPostPhys.14.4.079)

Detailed Simulations is Resource Intensive Task

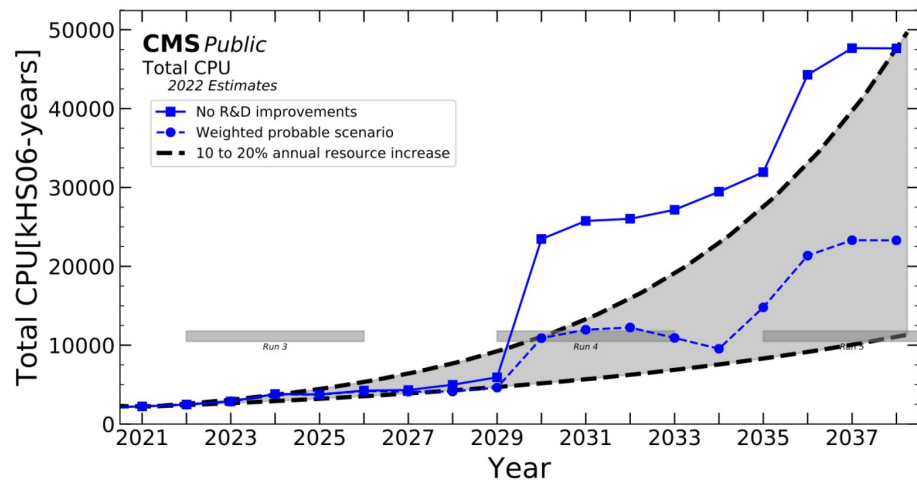


Figure from:

CMS Phase-2 Computing Model: Update Document,
http://cds.cern.ch/record/2815292/files/NOTE2022_008.pdf

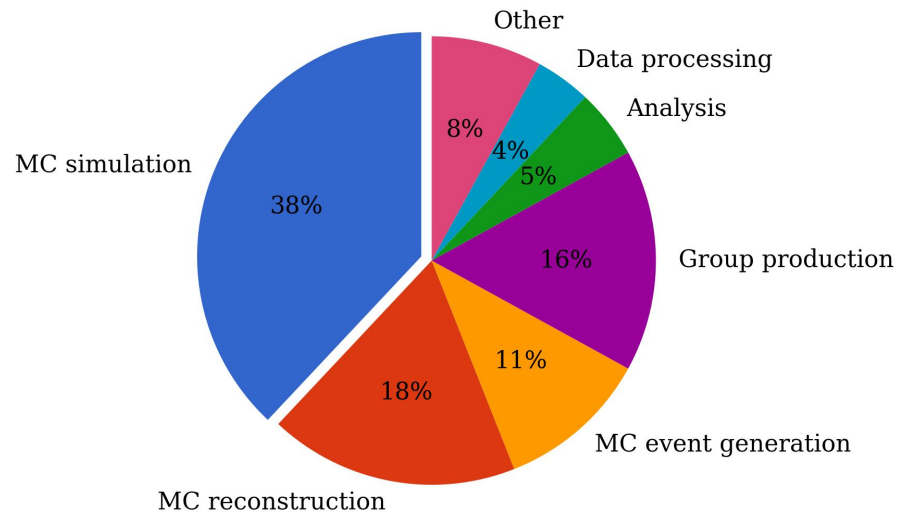
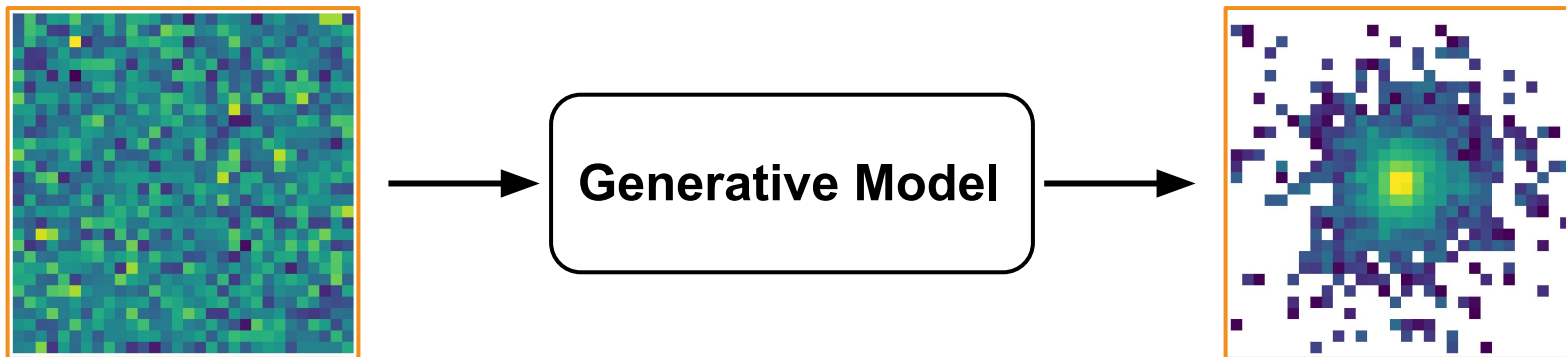


Figure adapted from:

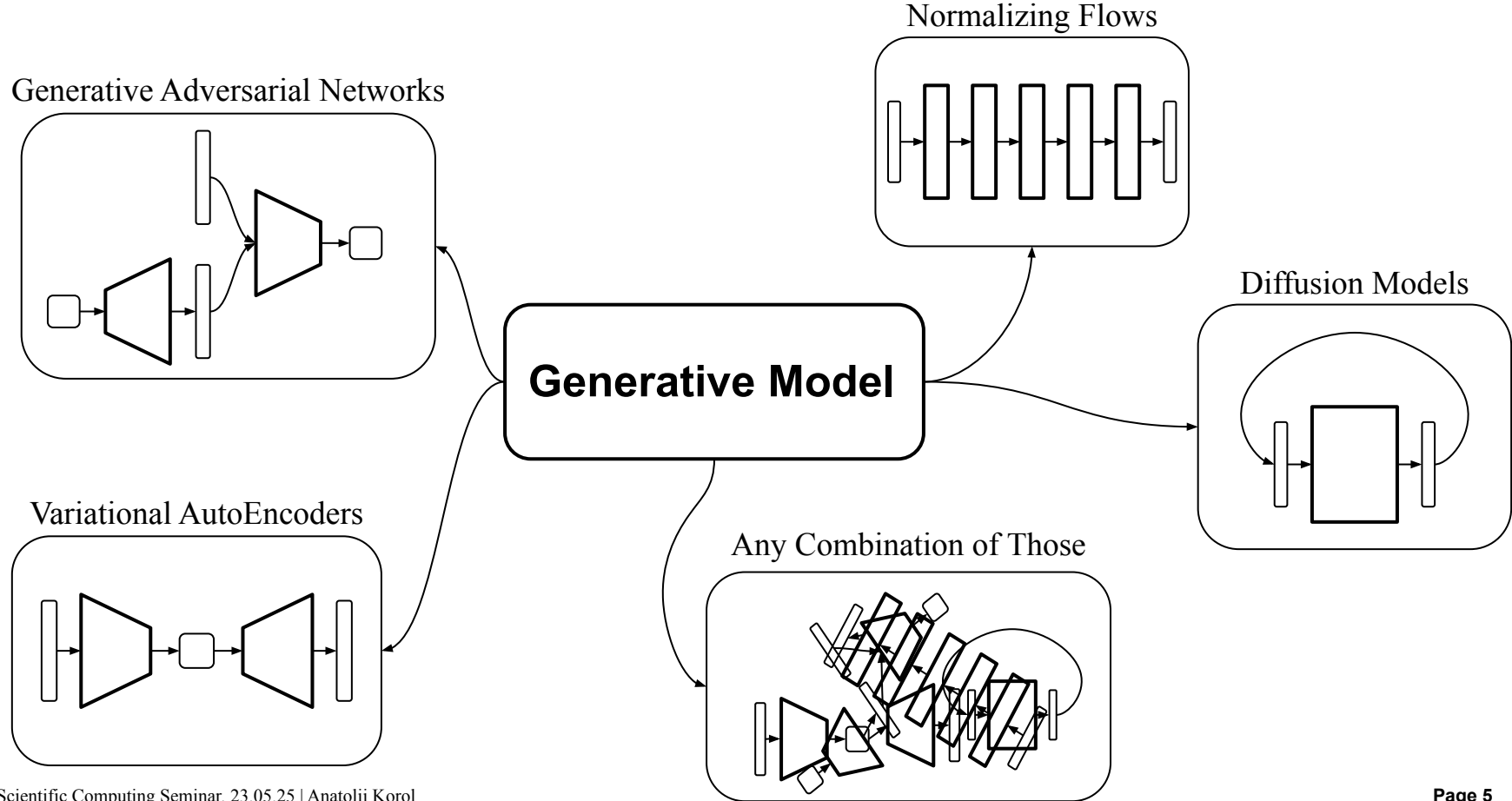
ATLAS HL-LHC Computing Conceptual Design Report,
<https://cds.cern.ch/record/2729668/files/LHCC-G-178.pdf>

Goal: replace (or augment) most intensive part of simulation with a faster generator based on **generative machine learning**

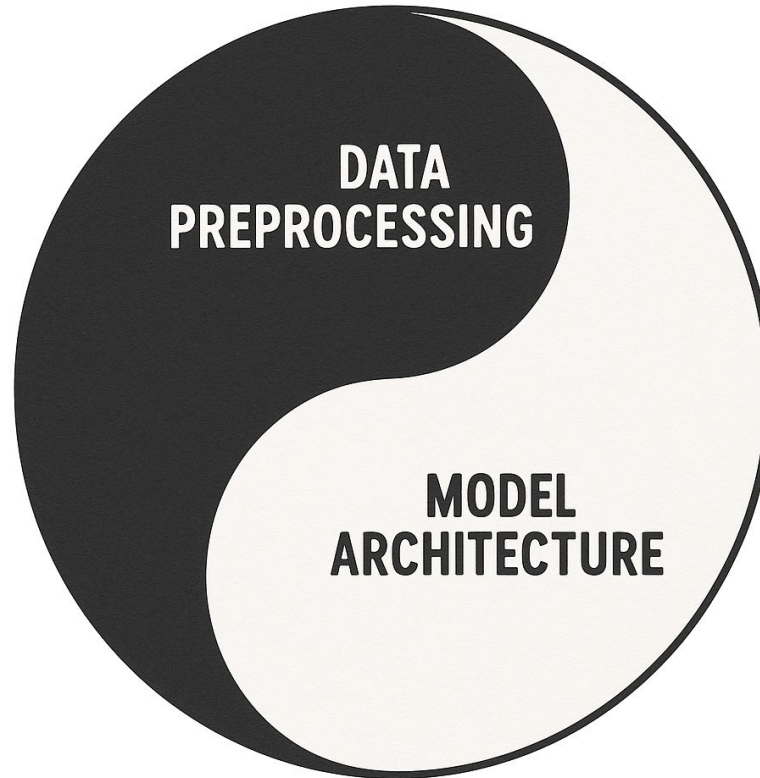
A Generative Model Is “Just a Function” That Maps Random Noise to Some Structure



Many Different Generative Models Exist Choose Any You Like

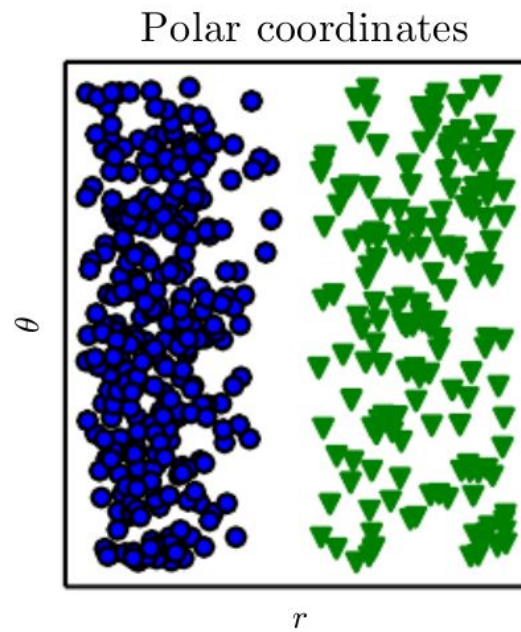
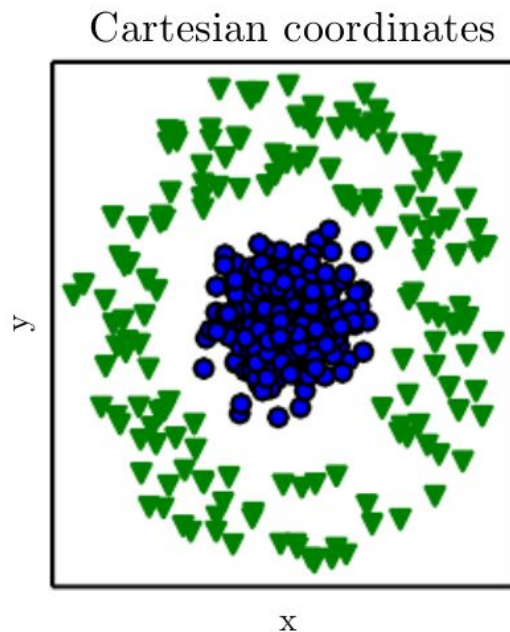


No Matter How Fancy Your Model Is the Performance Depends Heavily on the Representation of the Data It is Given



The Right Data Representation Can Turn an Impossible Problem into an Easy One

impossible task for
linear model



easy to solve with
vertical line

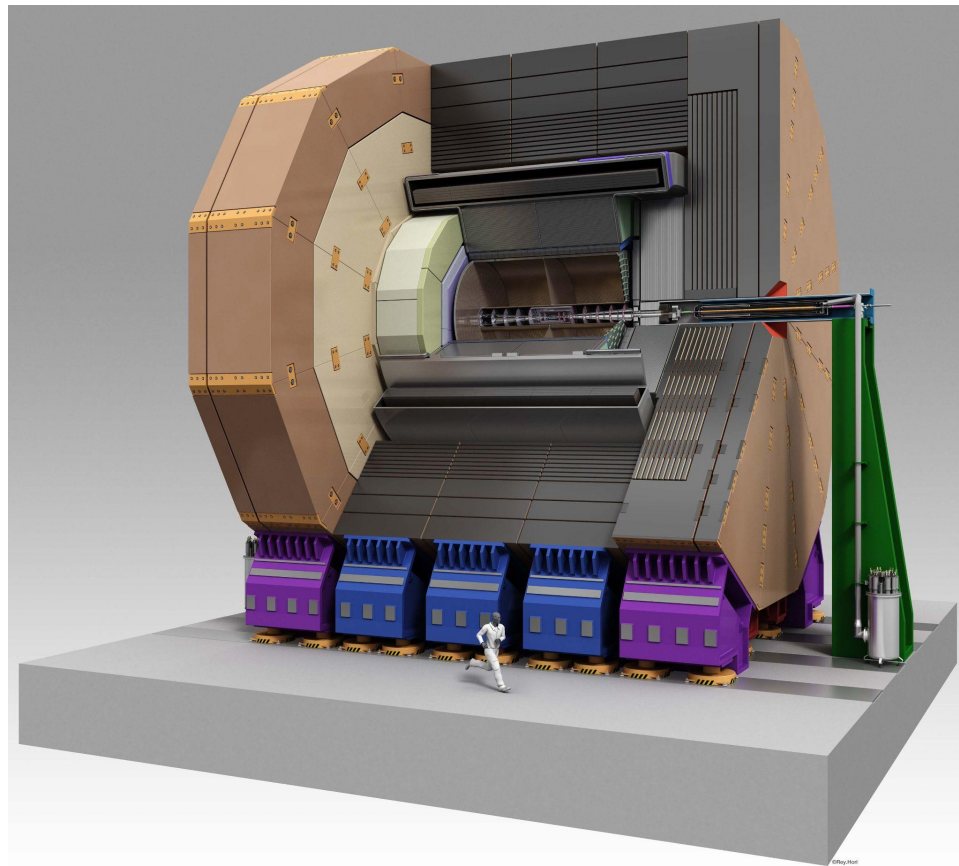
Figure from:

Deep Learning, Ian Goodfellow and Yoshua Bengio and Aaron Courville,
<https://www.deeplearningbook.org/>

Target: Generative Model for Electromagnetic Showers

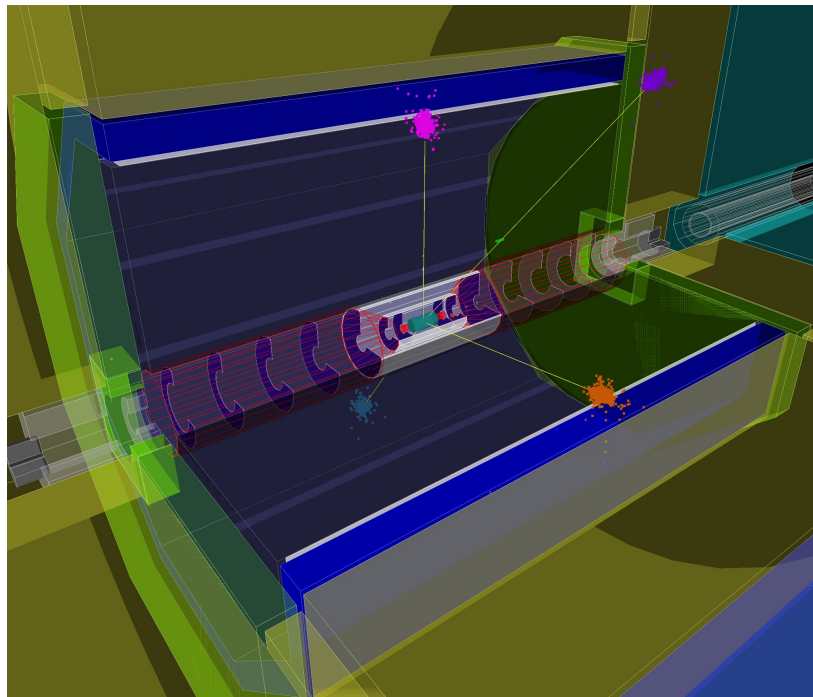
Case study: International Large Detector (ILD) concept

- Detailed and realistic simulation model
- Optimized for Particle Flow (PandoraPFA):
 - High granularity calorimeters
- Same technologies are widely planned for future experiments: e.g. HL-LHC, e^+e^- Higgs Factories
- Presents challenges for a realistic use case

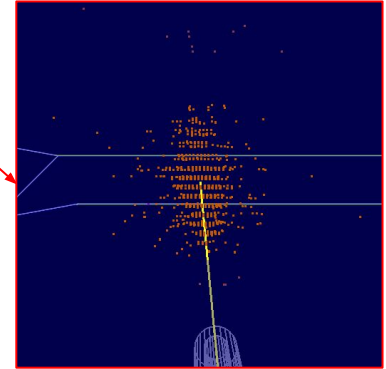
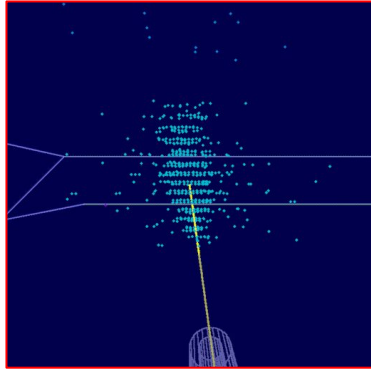
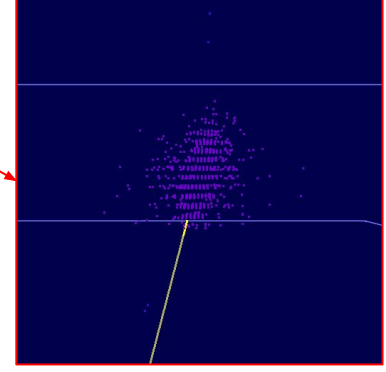
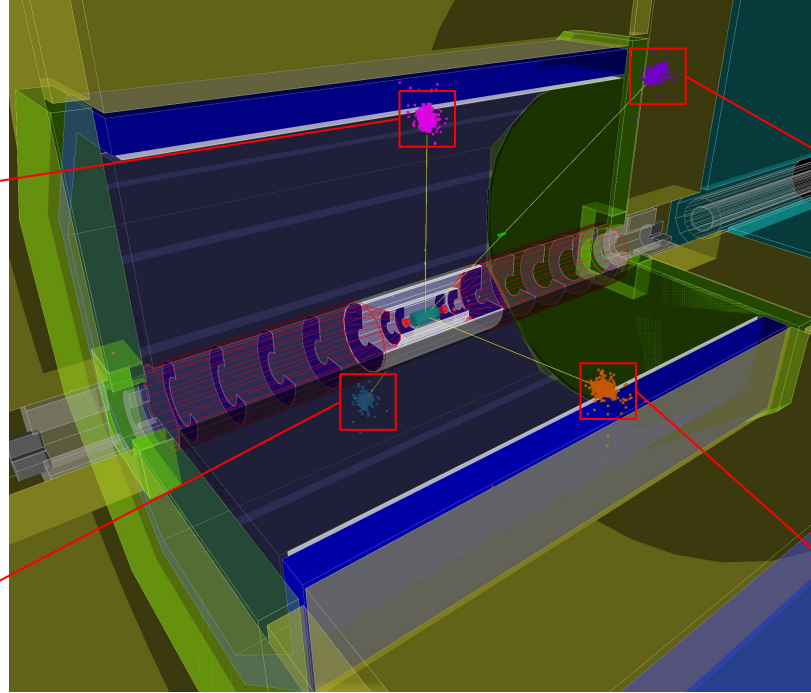
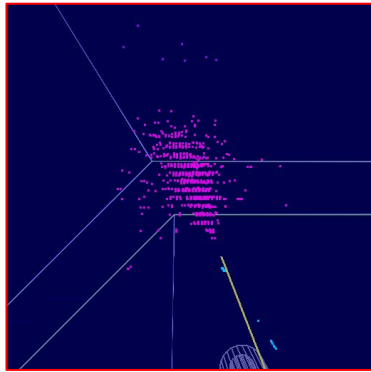


Dataset Preparation

Exploiting Geometrical Symmetries of the Detector



Shower Development is Consistent Across Regions with Identical Material Structure

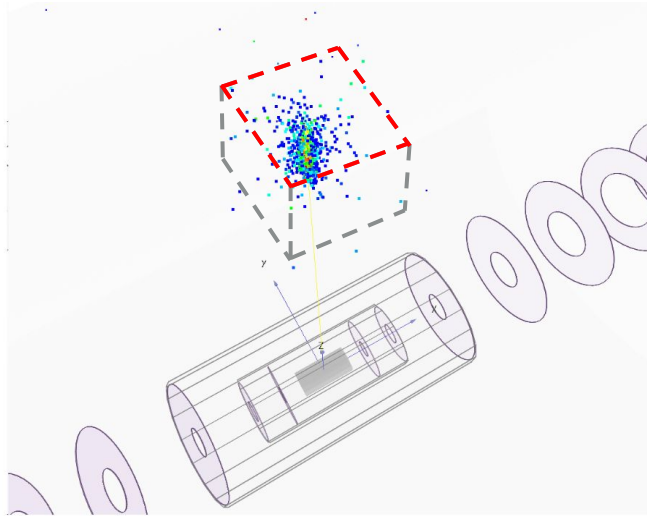


The only things that differ are the **energy** and **angle**

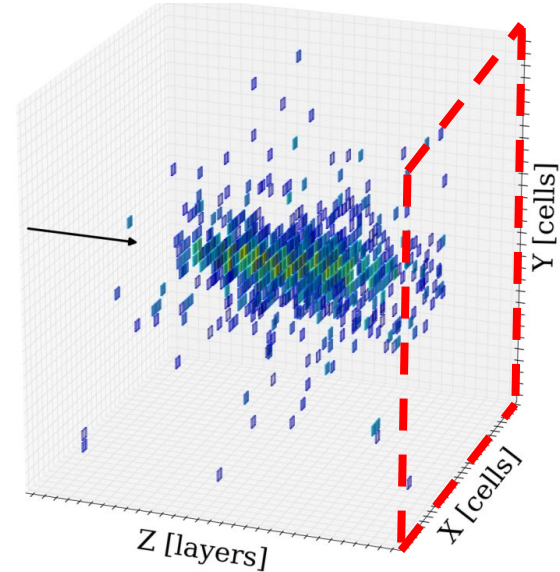
Image Representation

Previous Studies Rely on Fixed Grid Representation

60 GeV photon shower in the ILD ECAL



Regular grid 30x30x30

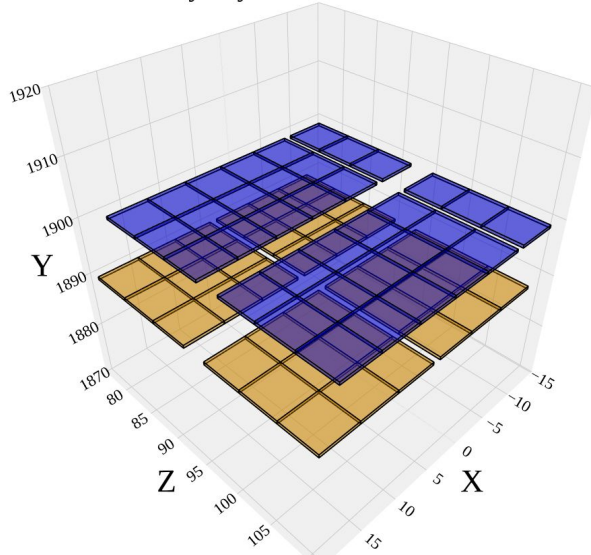


One to one mapping from detector cells to a regular grid

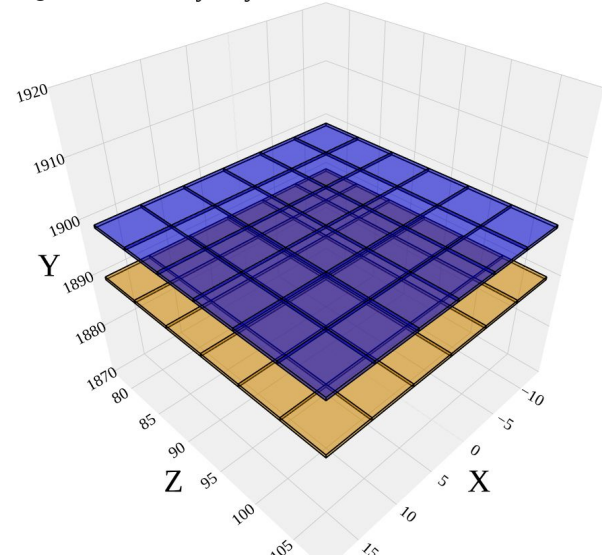
Problems with Image Representation of the EM Showers

ILD ECAL Layers Structure

Real Geometry Layout



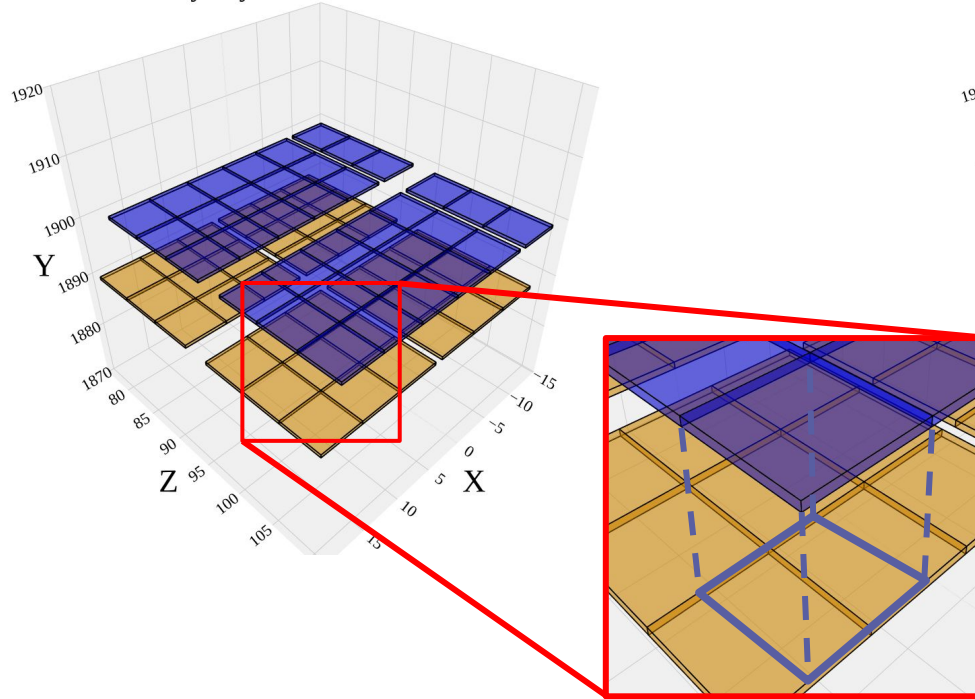
Regular Geometry Layout



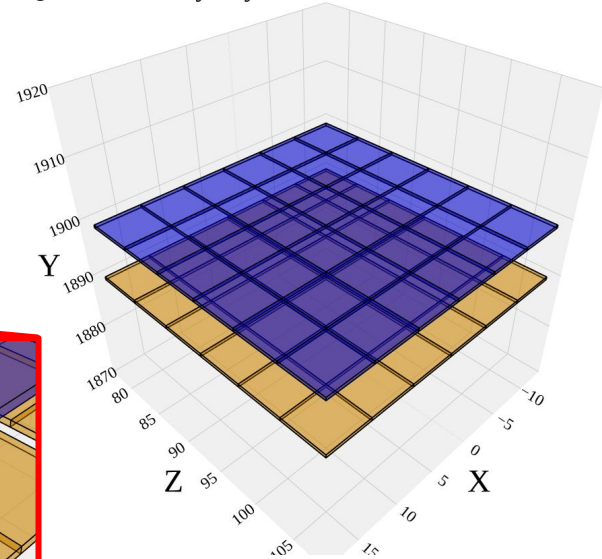
Problems with Image Representation of the EM Showers

ILD ECAL Layers Structure

Real Geometry Layout

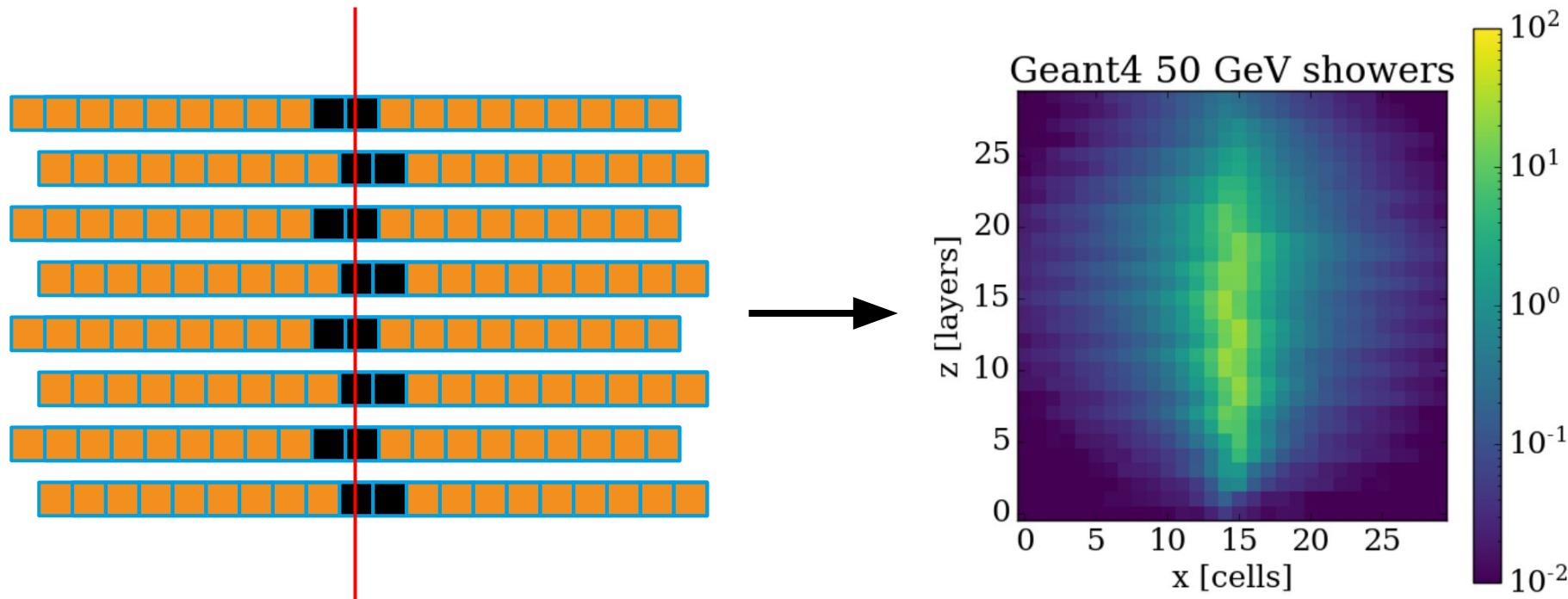


Regular Geometry Layout



Problems with Image Representation of the EM Showers

Staggering Effect



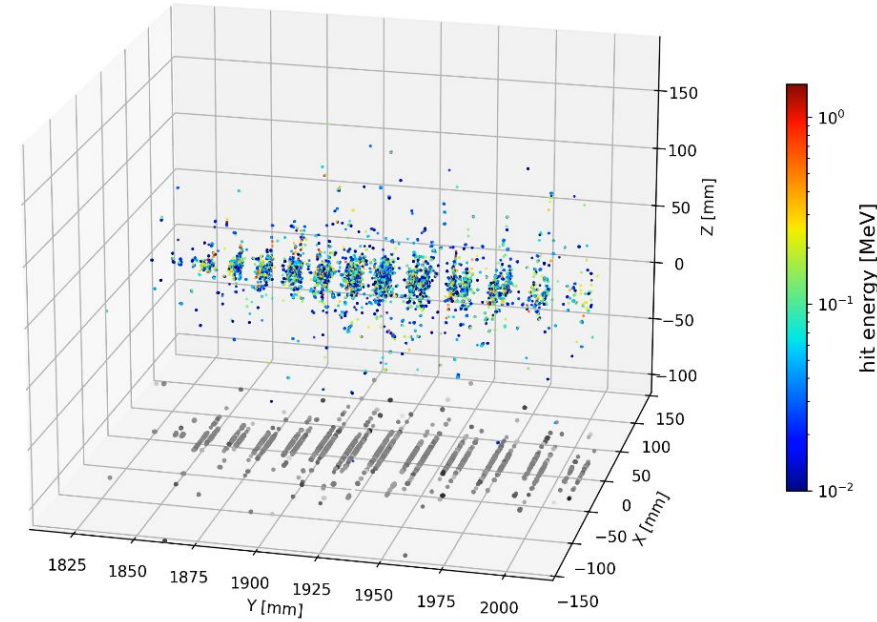
Models have to learn not only EM shower properties, but also geometry “artifacts”, like **staggering effect**

Point Cloud Representation of the EM Showers

To address potential issues from irregular (realistic) cell geometry, one could use much higher resolution

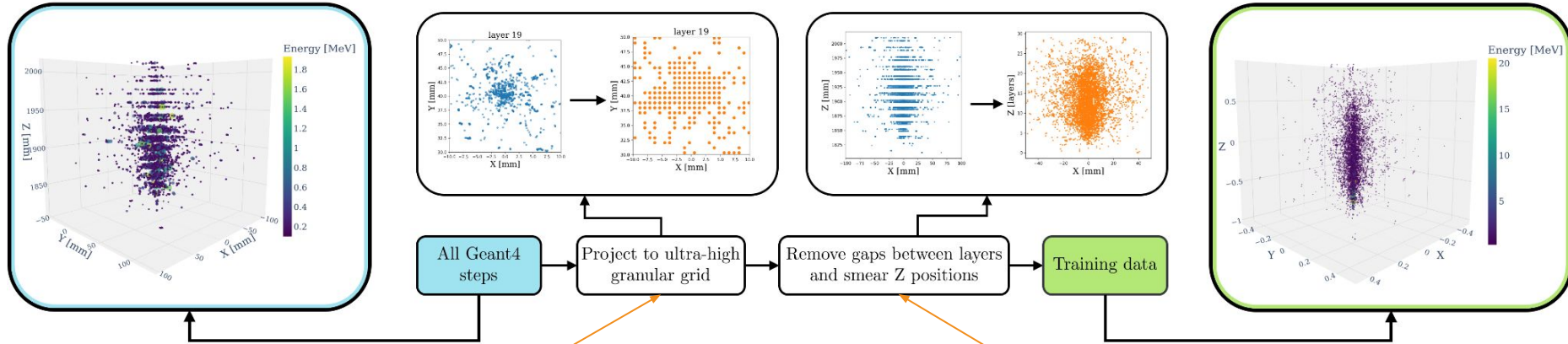
- GEANT4 Steps, ultimate resolution
- Detached from detector layer geometry
- **Require preprocessing step to reduce number of spacepoints**

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



Point Cloud Representation of the EM Showers

Data Preprocessing

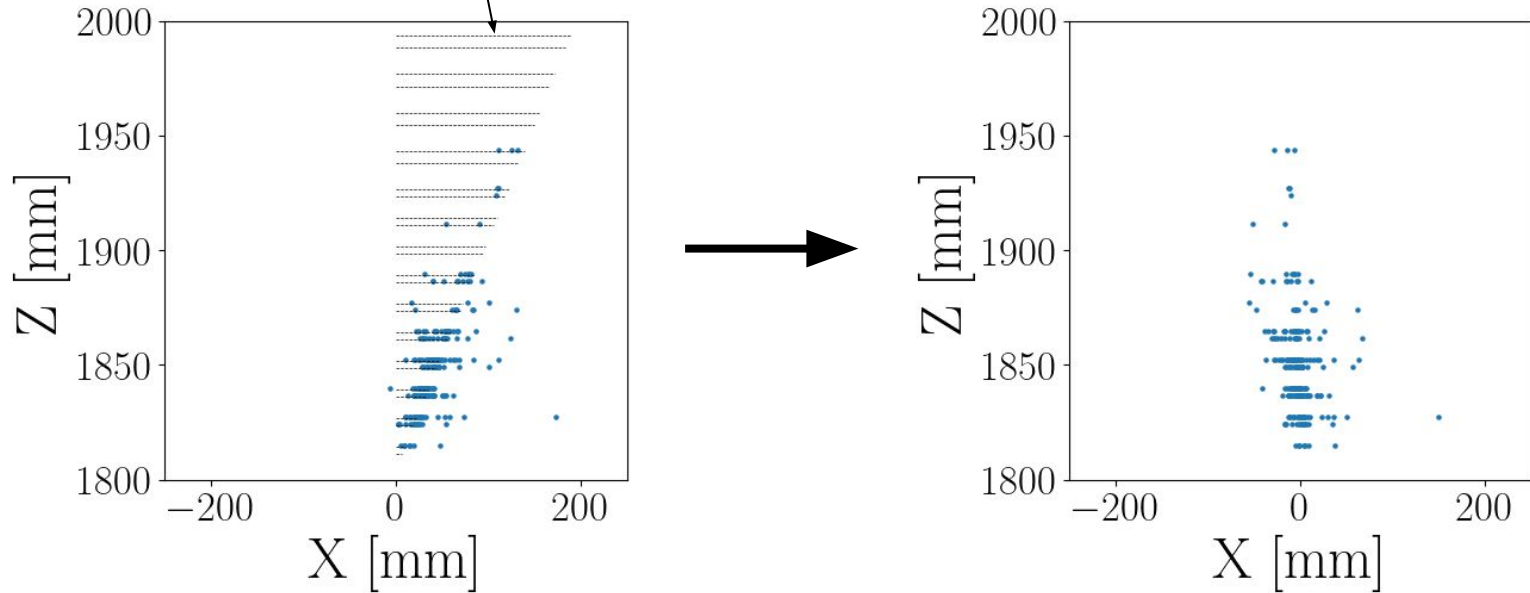


Reduces number of points per shower while maintaining sufficient resolution for translation invariance

For a better training objective, continuous space is easier to learn than quantized one

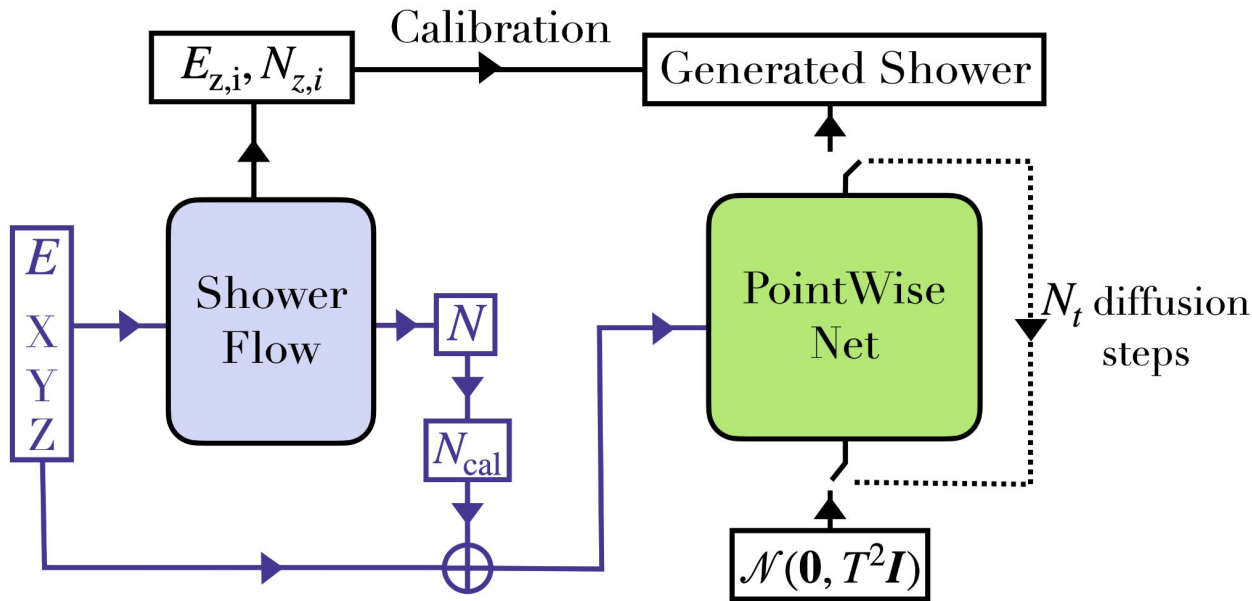
Simple Trick to Simplify the Objective

- Applying a layer-wise **geometrical offset** to showers entering at an angle, aligning them as if they had an orthogonal impact



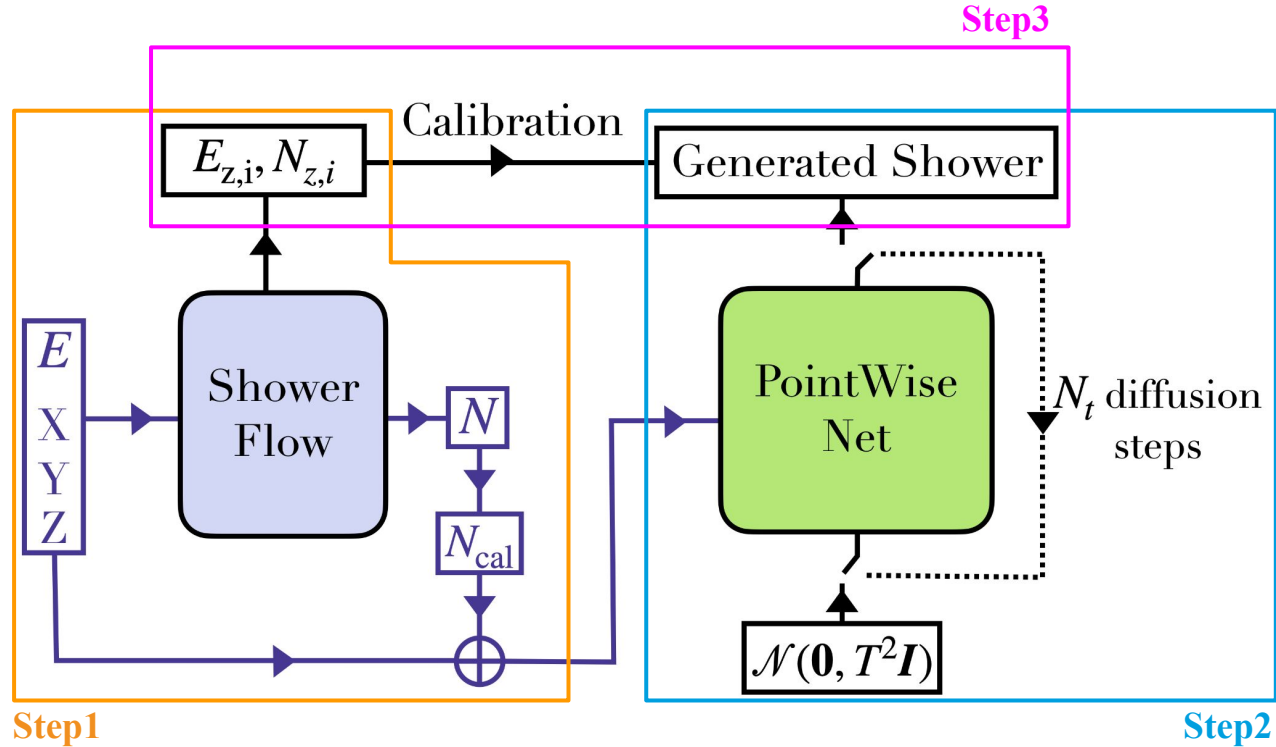
Advantages: smaller box and a simplified training objective

Model Architecture



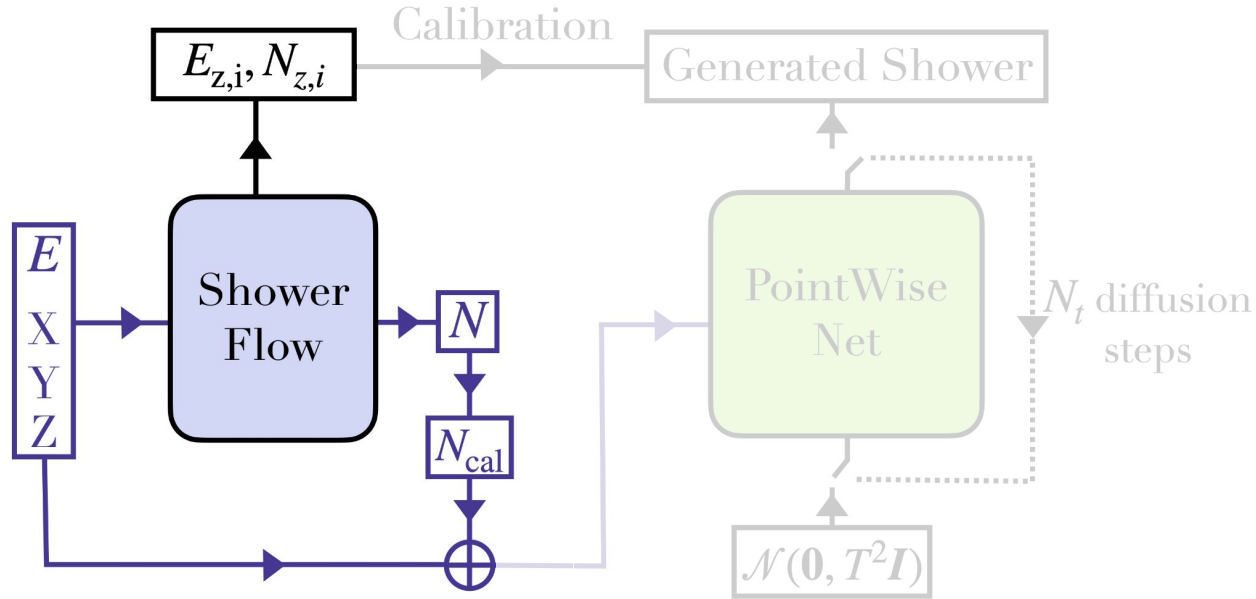
CaloClouds3

3 Steps Pipeline



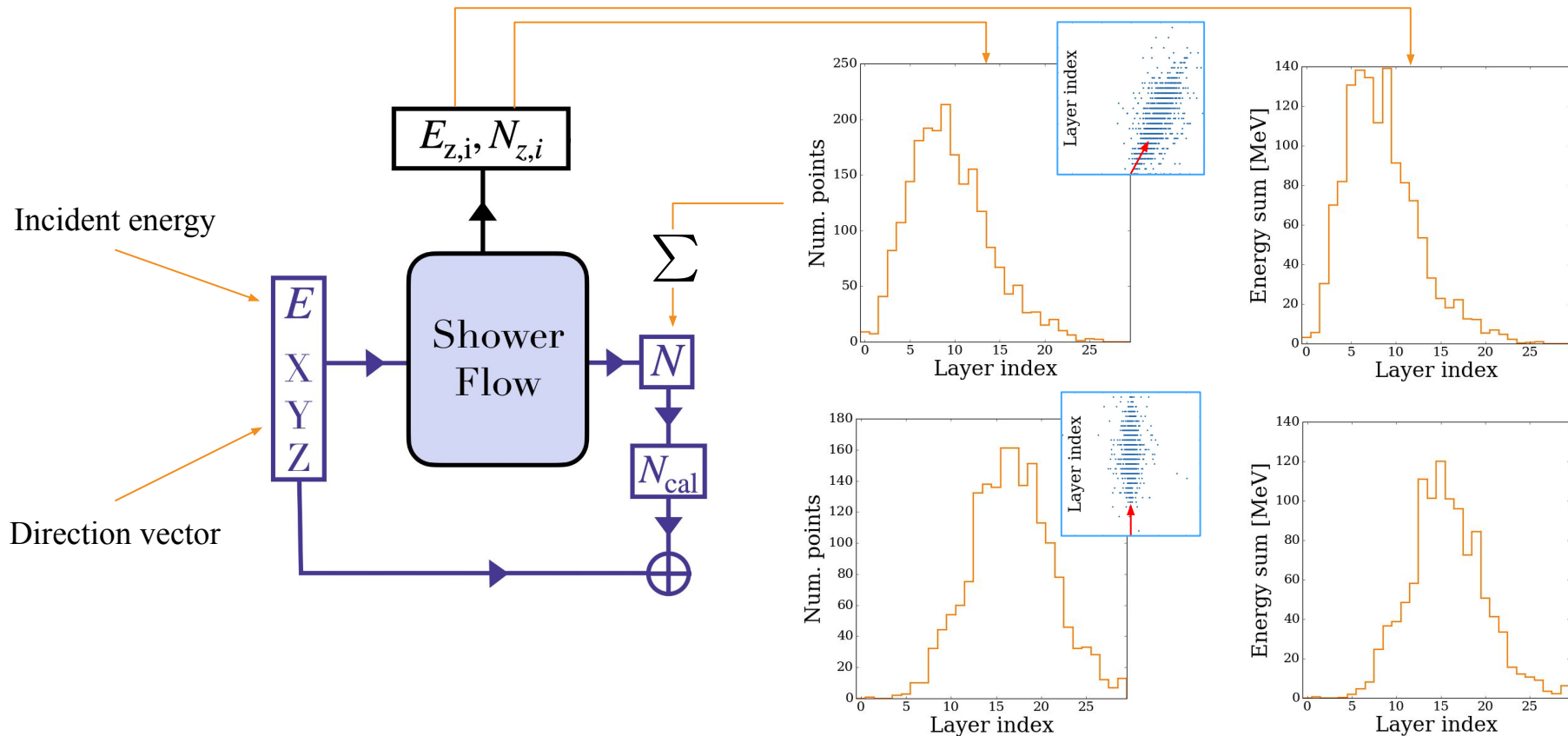
CaloClouds3

Step1: Normalizing Flow Model



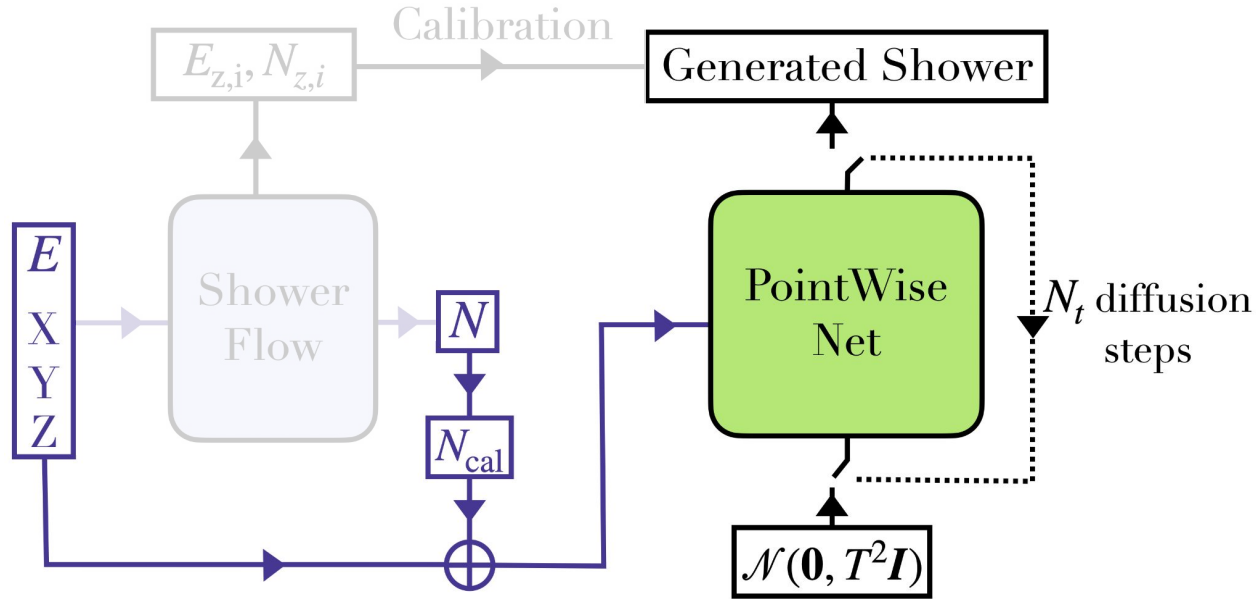
CaloClouds3

Normalizing Flow Model Generates Low Level Shower Observables



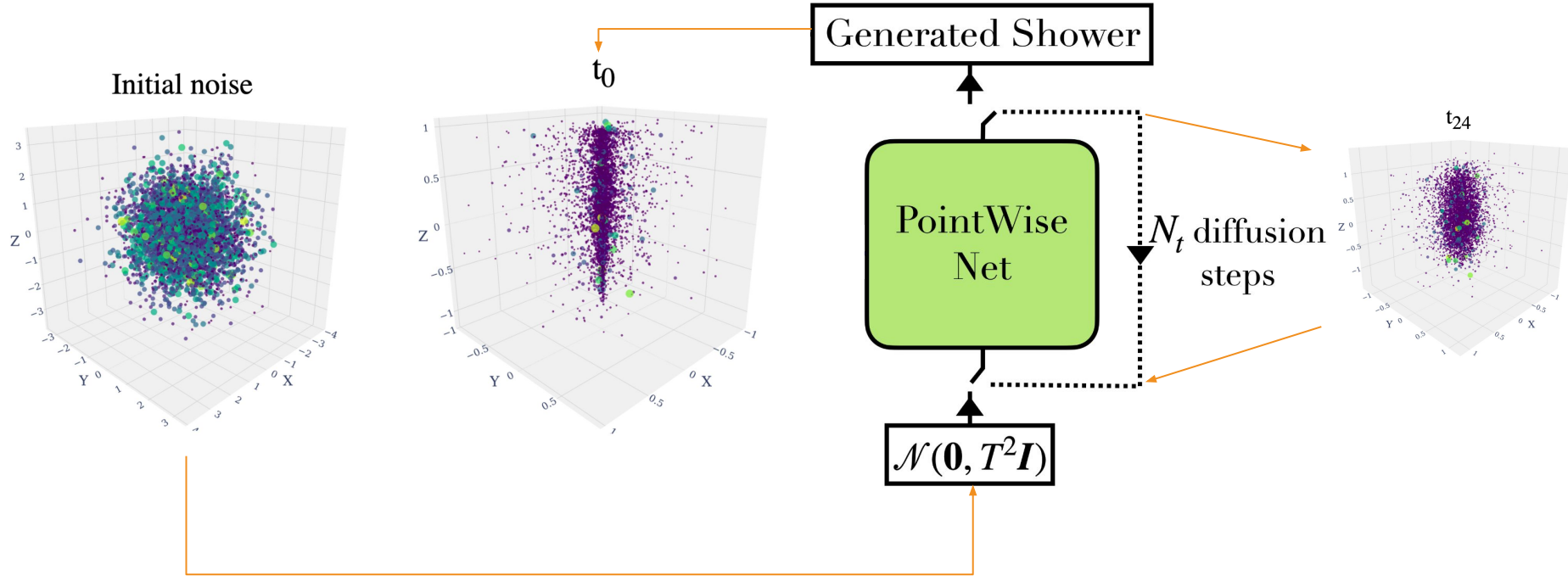
CaloClouds3

Step2: Diffusion Model



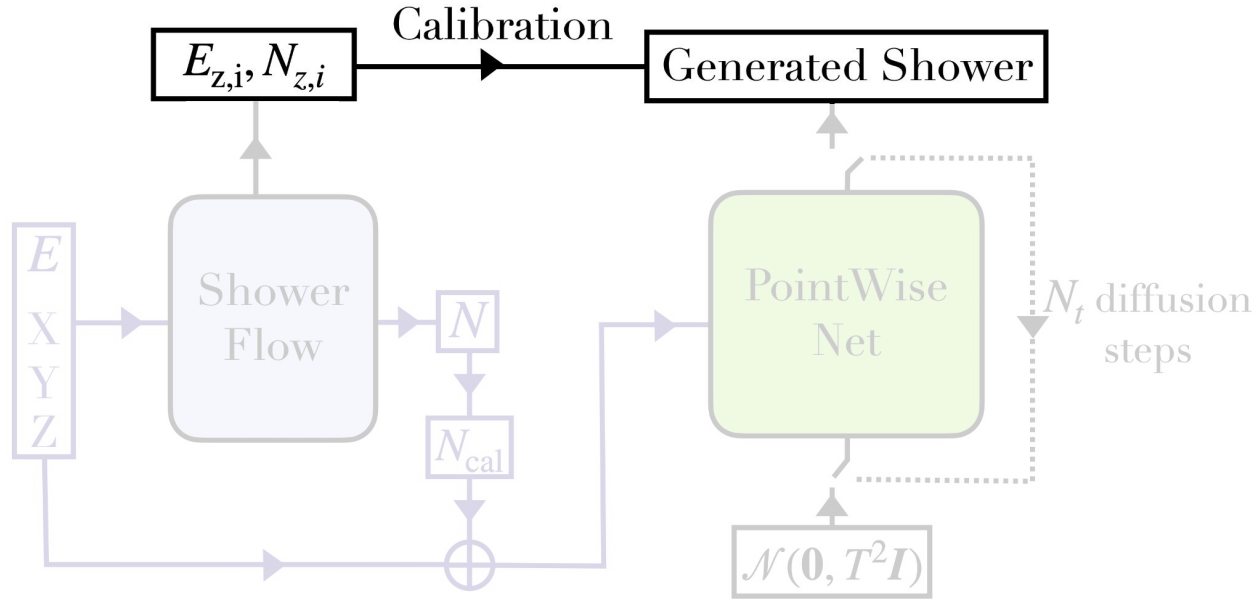
CaloClouds3

Step2: Diffusion Model



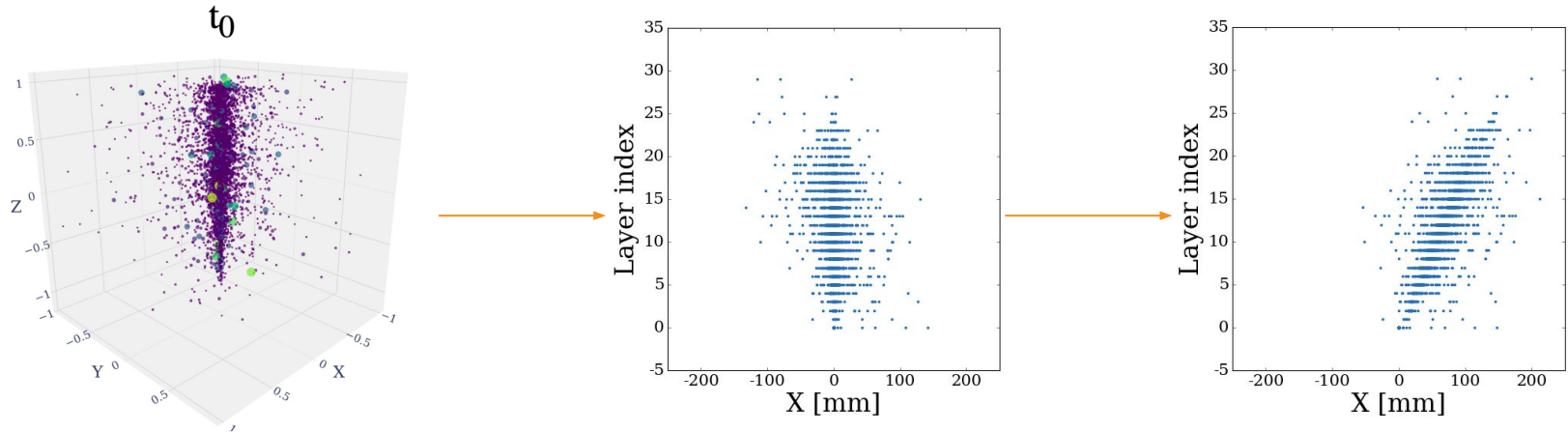
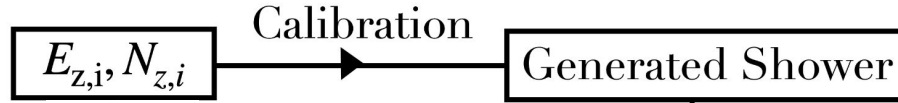
CaloClouds3

Step3: Calibration and Postprocessing



CaloClouds3

Step3: Calibration and Postprocessing



Integration into Simulation Chain

DDFastShowerML

Generic library for running ML-based fast sim models in DD4hep

Algorithm 1 Pseudocode illustrating the order of operations for the core components of the *DDFastShowerML* library.

```
1: if Trigger.checkTrigger(track) == True then
2:   Kill full simulation of particle
3:   localDir = Geometry.getLocalDir(track)
4:   inputs = Model.prepareInputs(track, localDir)
5:   outputs = Inference.runInference(inputs)
6:   localSPs = Model.convertOutput(track, localDir, outputs)
7:   globalSPs = Geometry.localToGlobal(track, localSP)
8:   for (sp in globalSPs) do
9:     HitMaker.makeHit(sp, track)
10:  end for
11: else
12:   Full simulation of particle with GEANT4
13: end if
```

Algorithm from:

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

Peter McKeown,

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

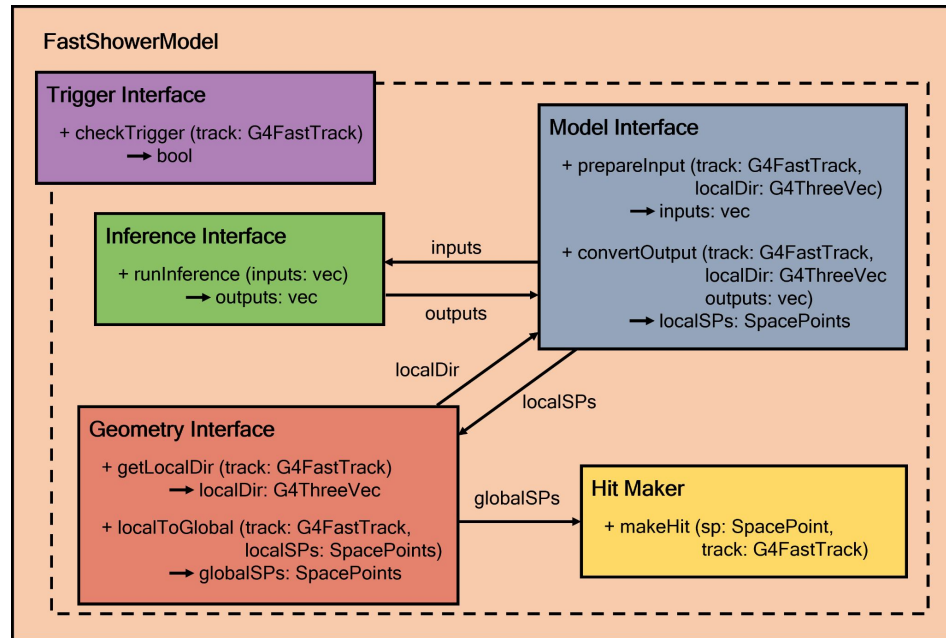


Figure from:

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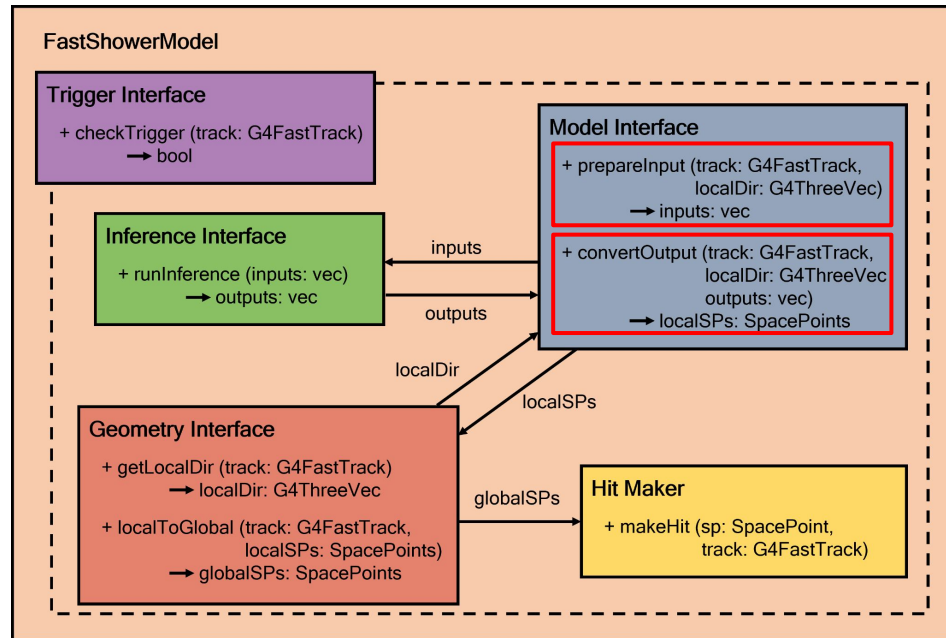


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DDFastShowerML

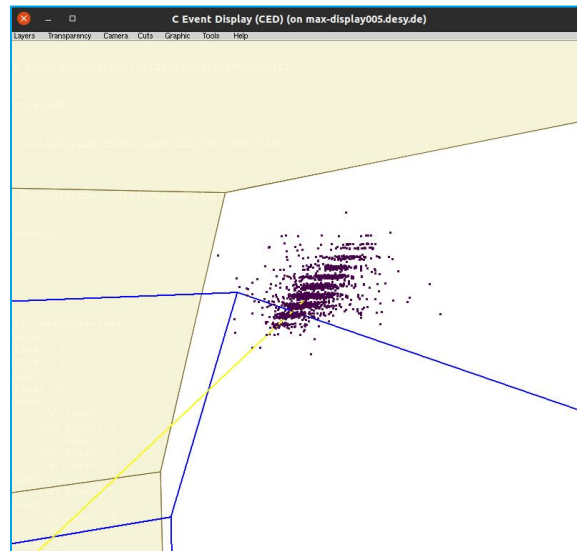
Generic library for running ML-based fast sim models in DD4hep

PyTorch

Scripted fast sim model

DDFastShowerML

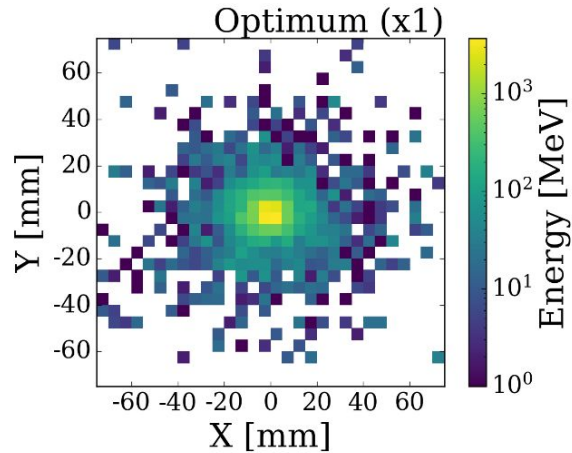
<https://gitlab.desy.de/ilcsoft/ddfastshowerml>



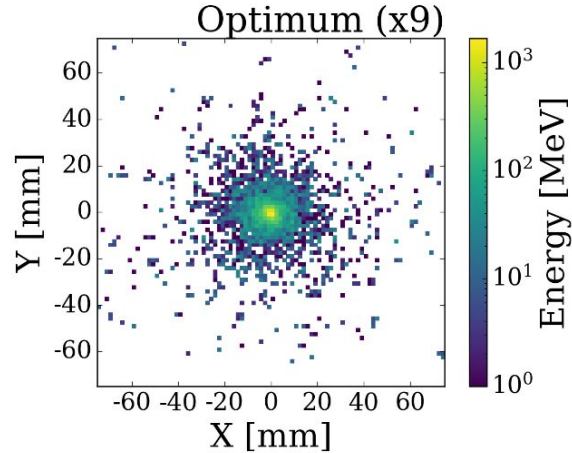
50 GeV photon shower generated
with CaloClouds3 in the ILD ECAL

Benchmarks

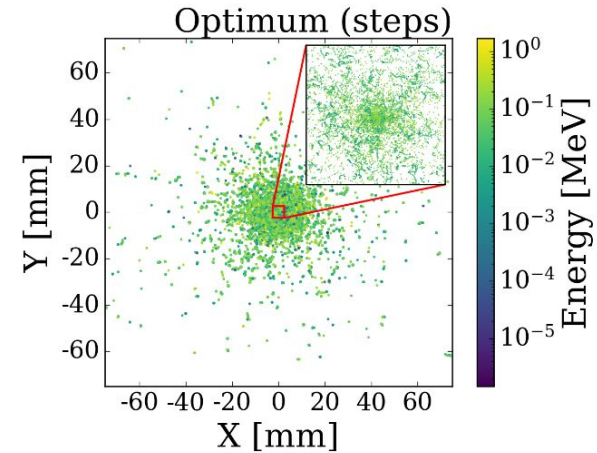
Optimal Generators Reference



- Cell-level readout
- Common approach, used by e.g. BIB-AE
- Regular grid



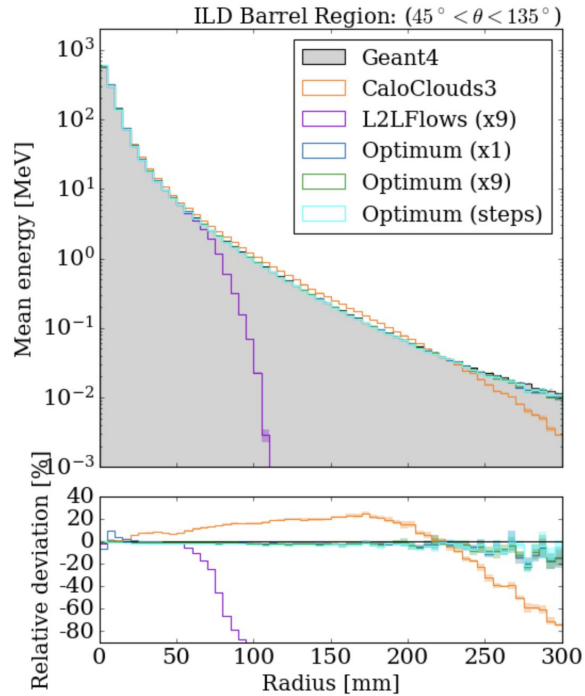
- x3 lateral resolution, x9 cells
- Used by L2LFlows model
- Regular grid



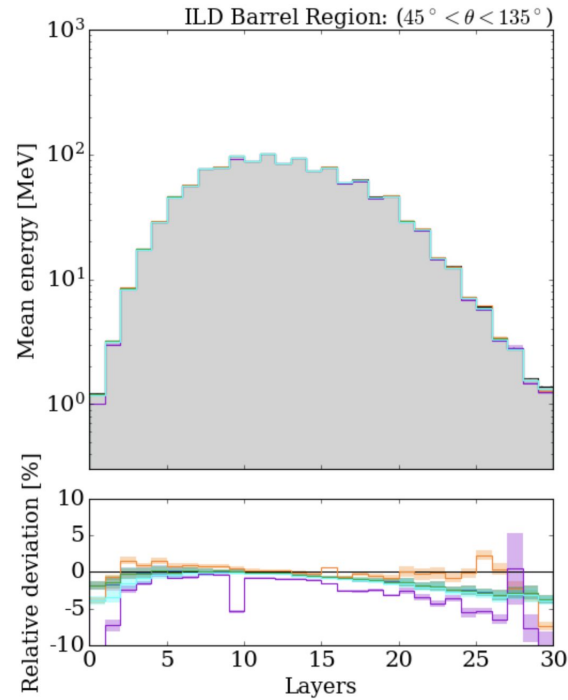
- Geant4 steps, highest resolution
- Used by CaloClouds model (with additional clustering)
- Point cloud representation

Single Particle Performance

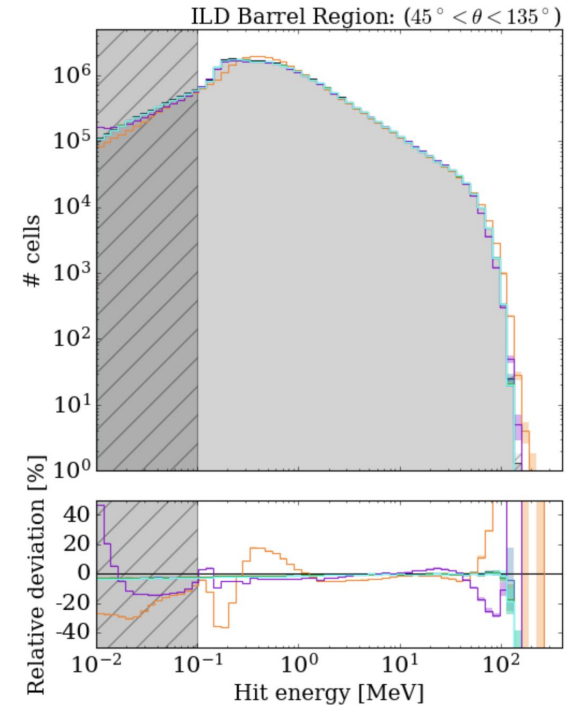
Radial Profile



Longitudinal Profile



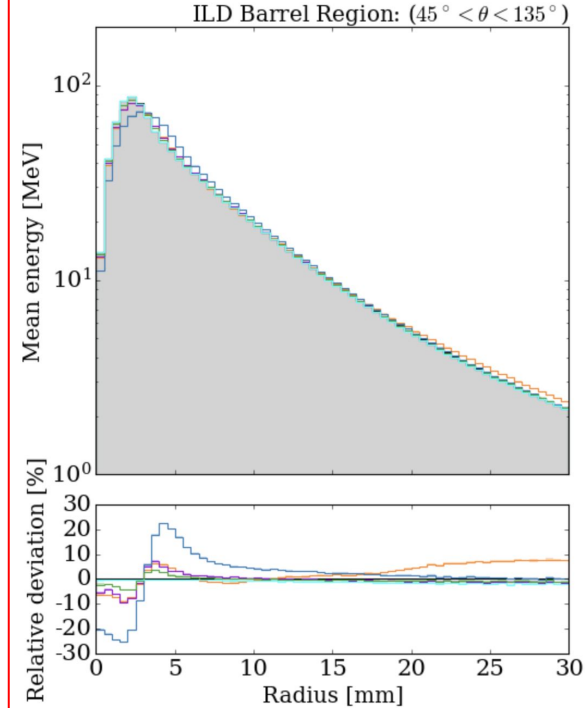
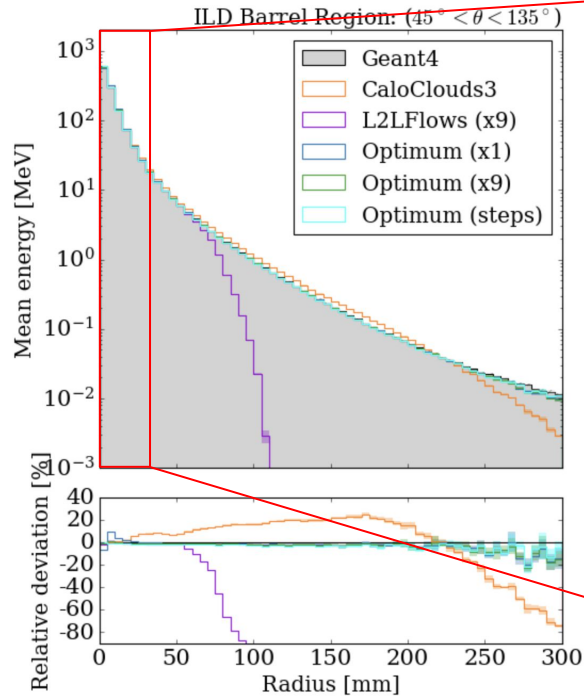
Hit Energy Spectrum



Single Particle Performance

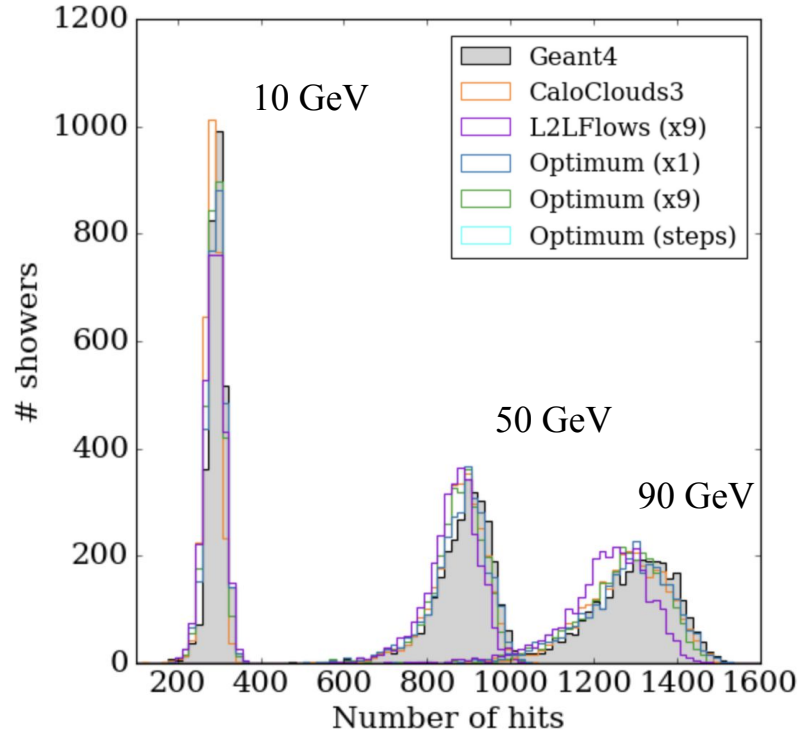
Radial Profile

> 90% of the shower content

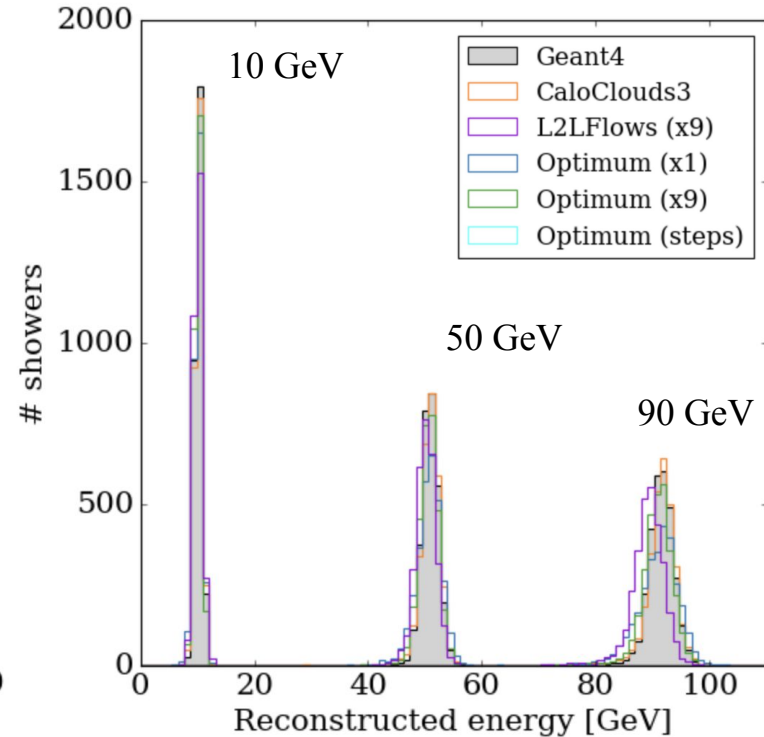


Single Particle Performance

Occupancy

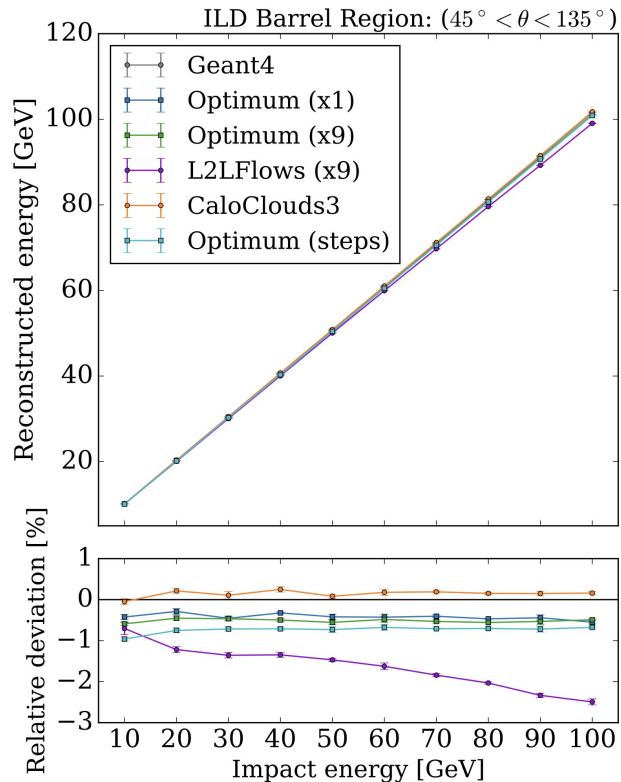


Energy Distribution

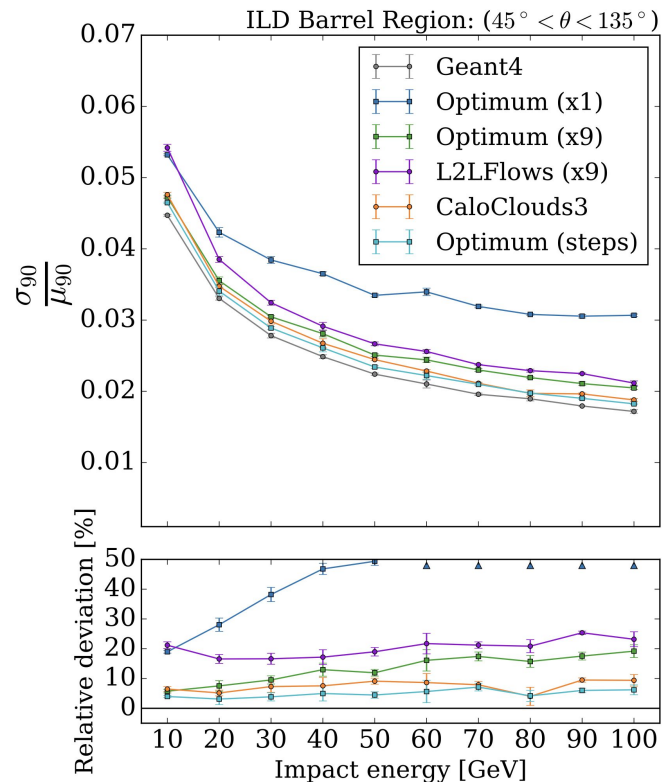


Single Particle Performance

Linearity

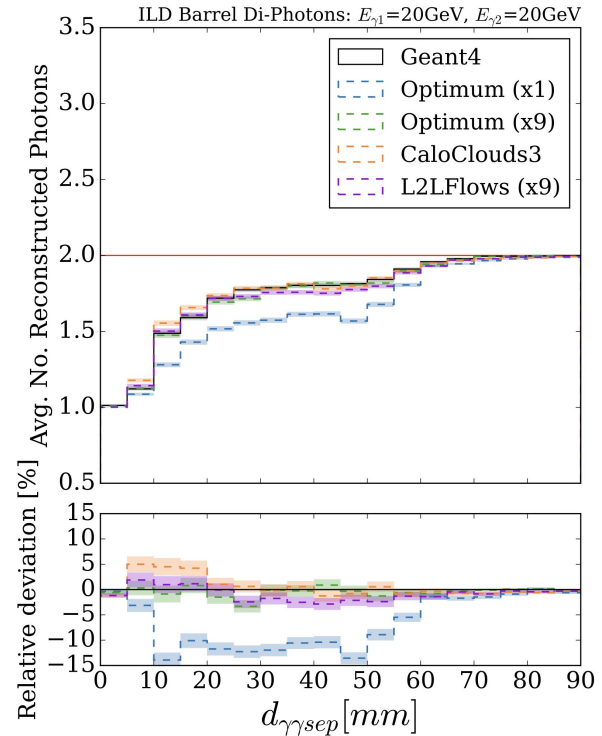
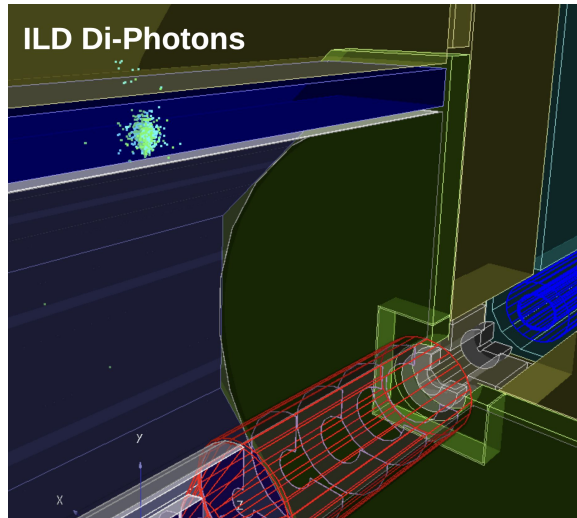


Energy Resolution



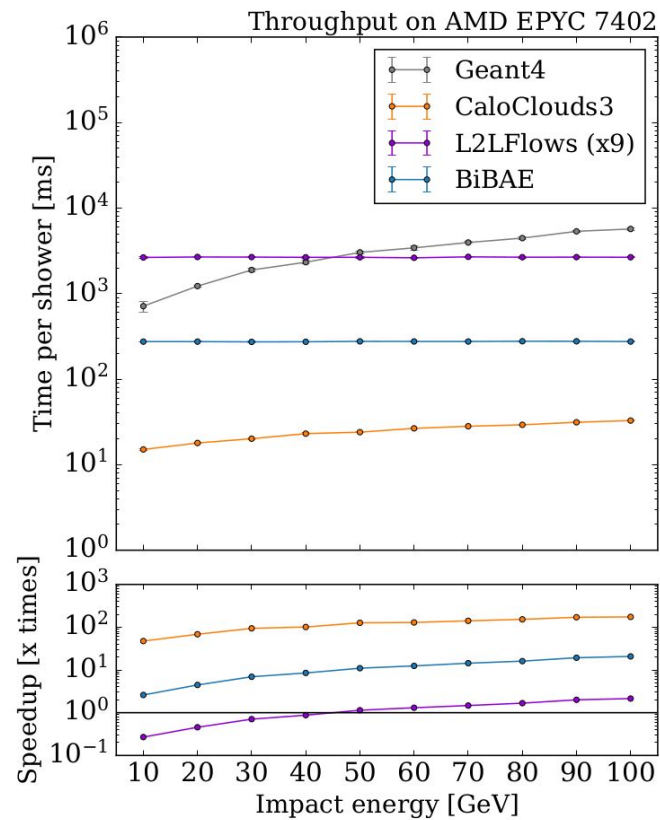
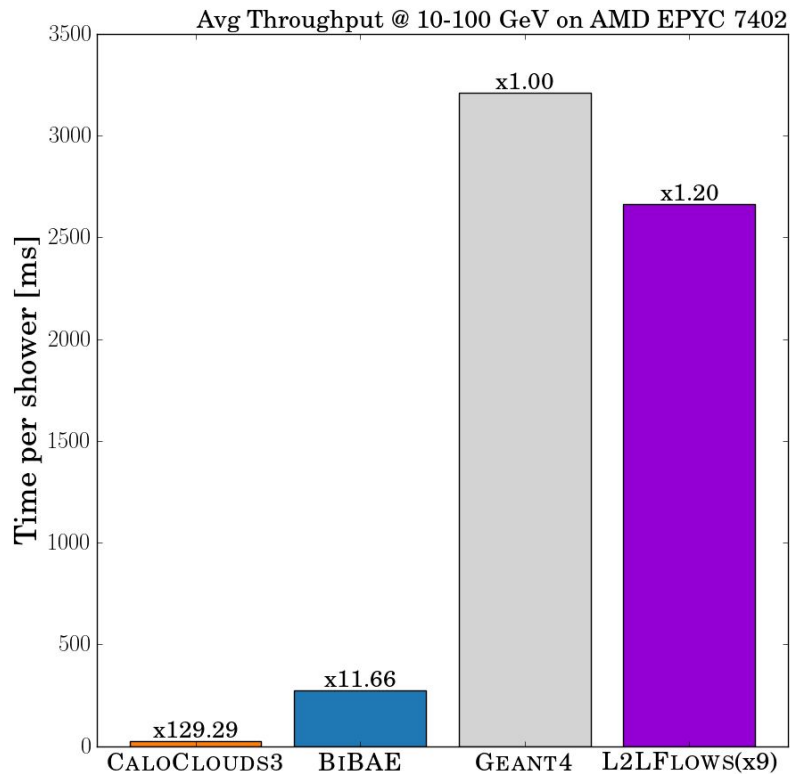
Di-Photons Reconstruction Benchmark

Courtesy P.McKeown



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

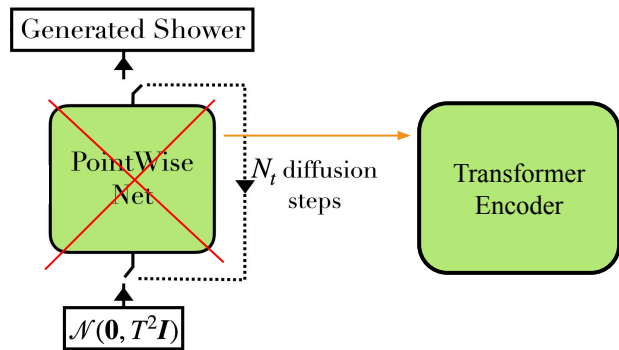
Timing



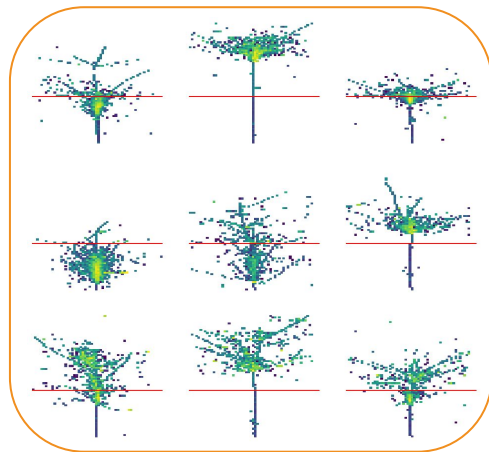
Possible Extensions

Hadron Showers

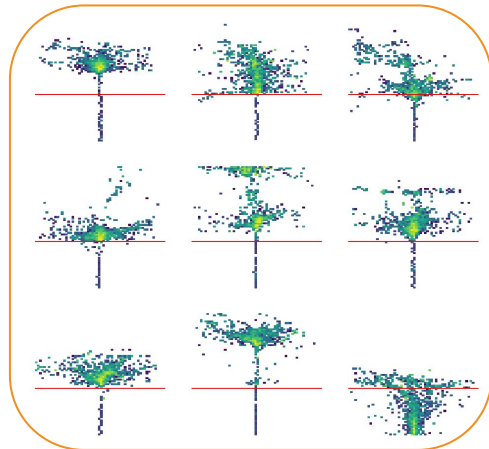
POC for Pion Showers in Combined ECAL + HCAL



Geant4



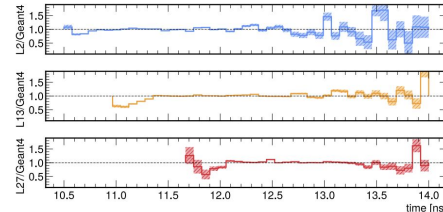
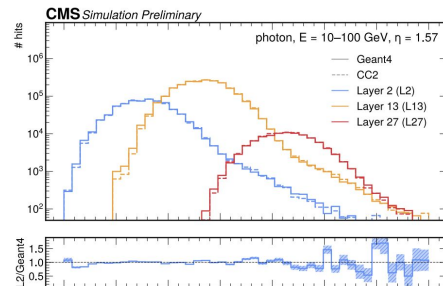
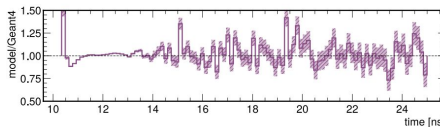
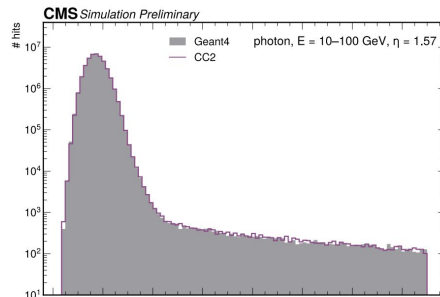
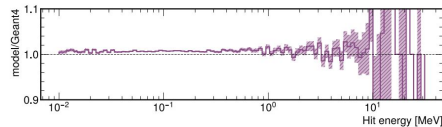
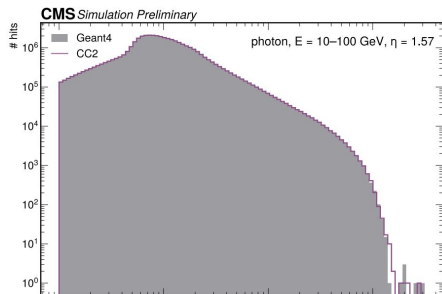
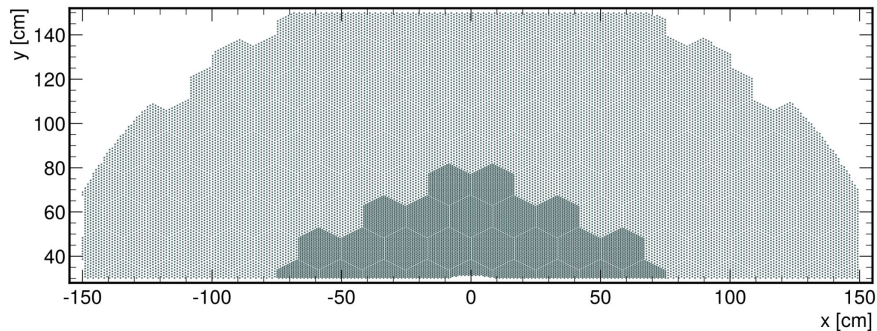
PionClouds



Different Detectors

Adopted for CMS-HGCAL by W. Korcari

It's about time: a Point Cloud Generative Model
for the CMS High Granularity Calorimeter, CMS
Collaboration. 2025, CMS-DP-2025-016,
CERN-CMS-DP-2025-016, [CDS:2932517](#)



Summary

**CaloClouds: Fast Geometry-Independent
Highly-Granular Calorimeter Simulation,**
Buhmann, AK, et al. 2023, [arXiv:2305.04847](#)

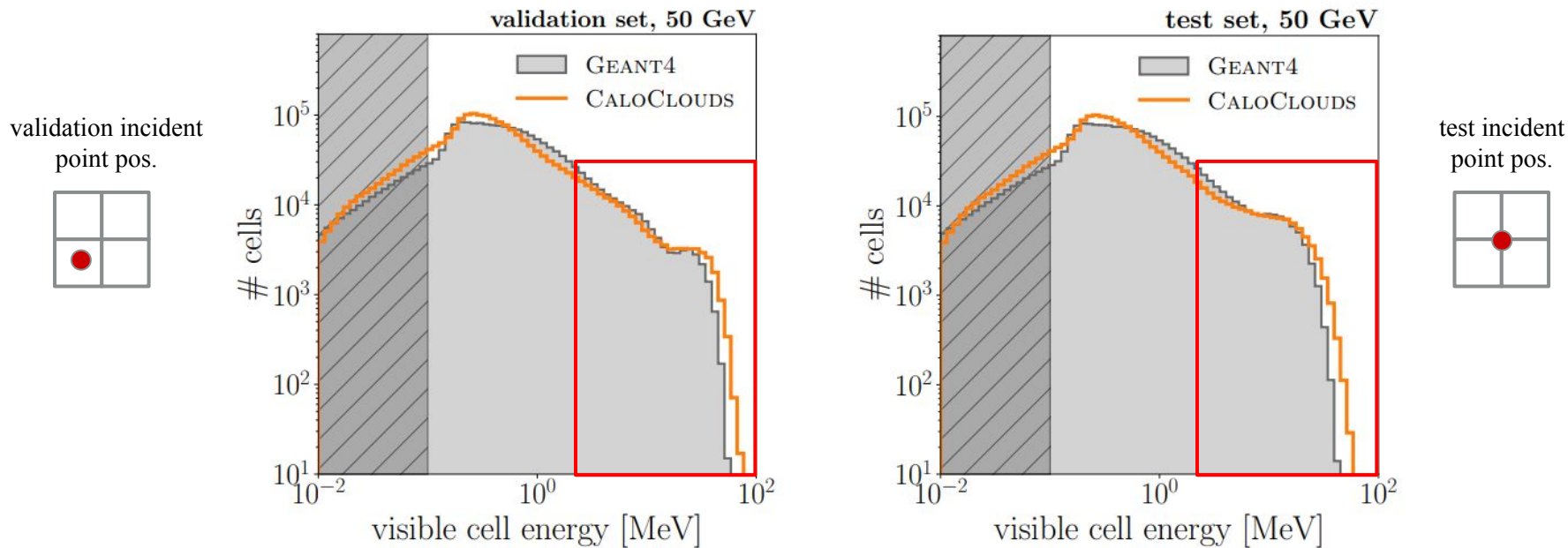
**CaloClouds II: Ultra-Fast Geometry-Independent
Highly-Granular Calorimeter Simulation,**
Buhmann, AK, et al. 2023, [arXiv:2309.05704](#)

- Traditional fixed grid representations suffer from geometry artifacts, limiting model generalization
- CaloClouds introduces a data representation paradigm that addresses this challenge
- CaloClouds offers a general solution that is easily adaptable to different detector geometries, e.g. CMS-HGCAL
- CaloClouds3 outperforms previous state-of-the-art models while being approximately $\sim 10\times$ faster, and $\sim 100\times$ faster than GEANT4 @ 10-100 GeV range on the same hardware

BACKUP SLIDES

Physics Observables at Different Positions

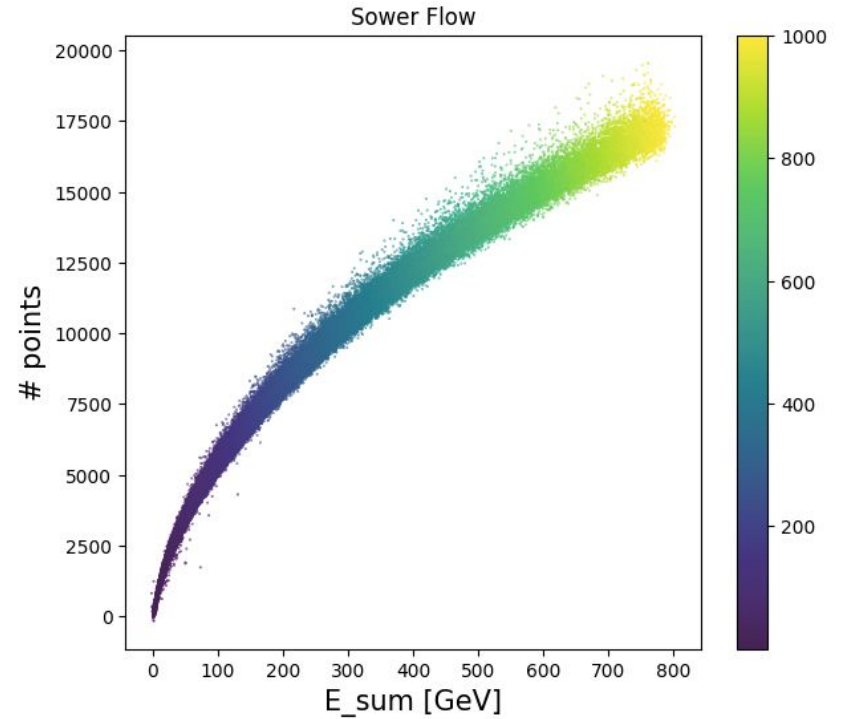
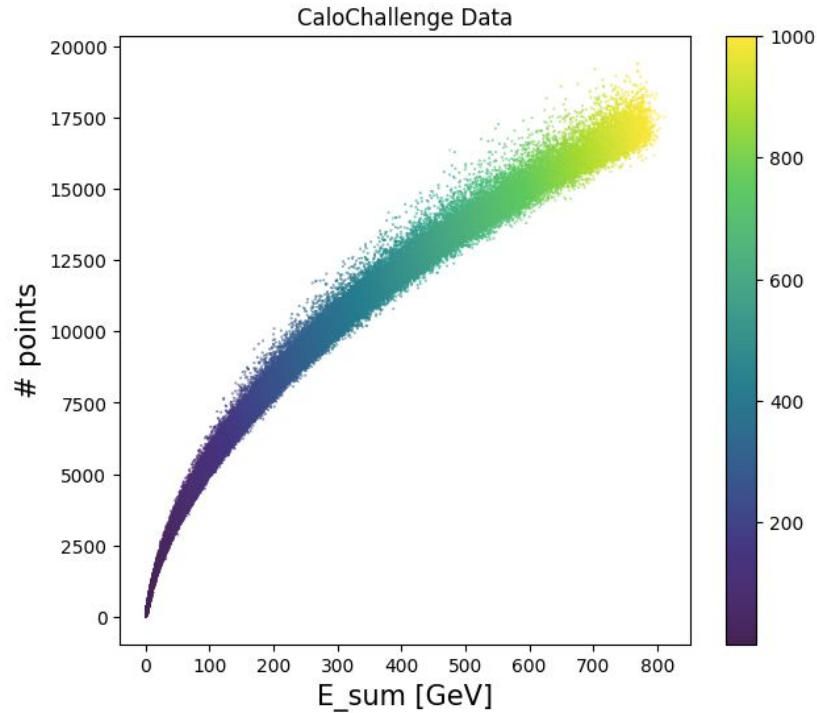
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Highly-Granular Calorimeter Simulation,**
Buhmann, AK, et al. 2023, [arXiv:2305.04847](https://arxiv.org/abs/2305.04847)



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

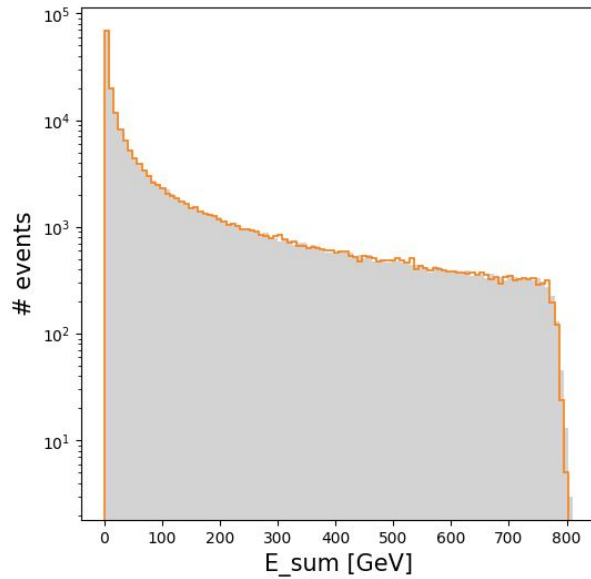
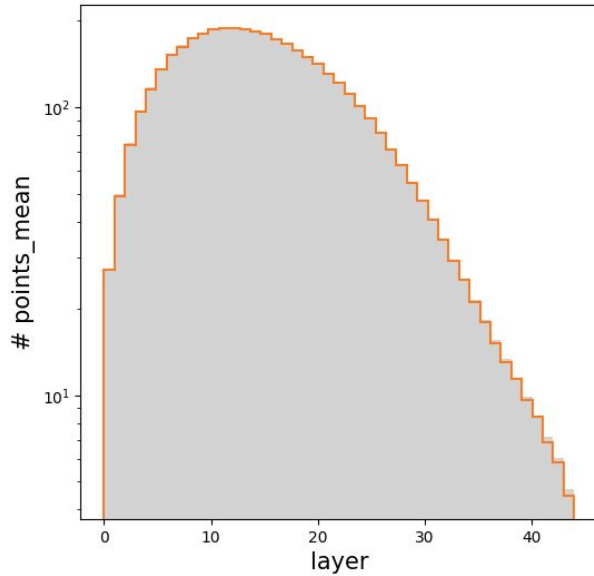
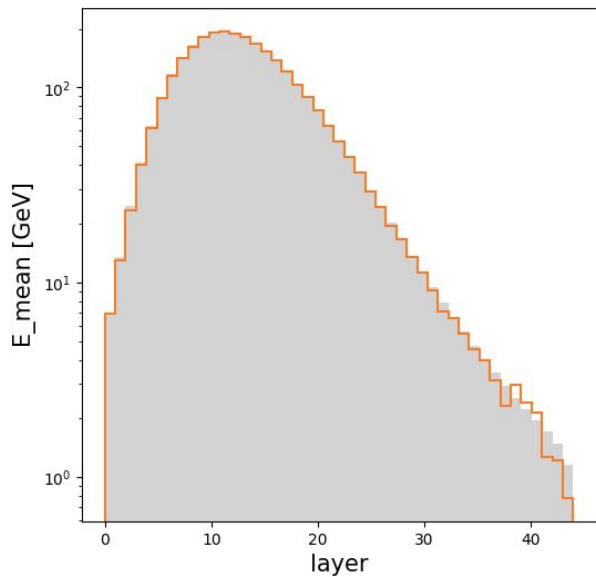
Shower Flow

Results

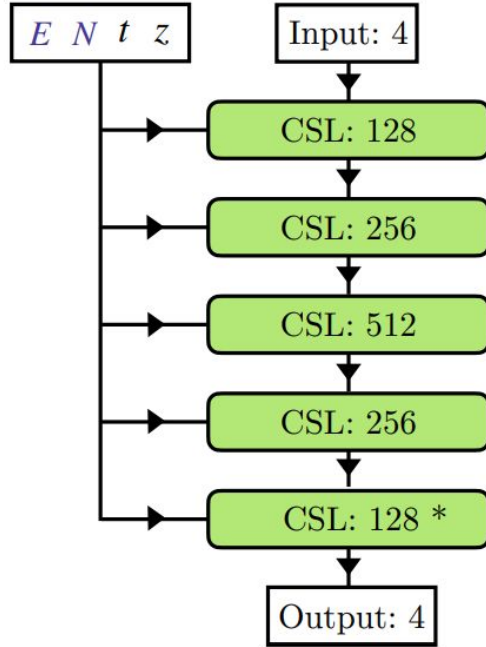


Shower Flow

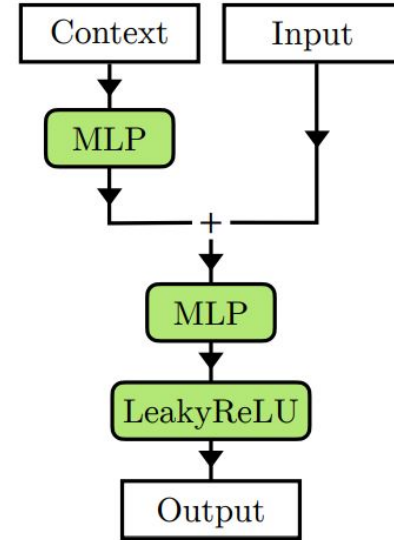
Results



PointWise Net



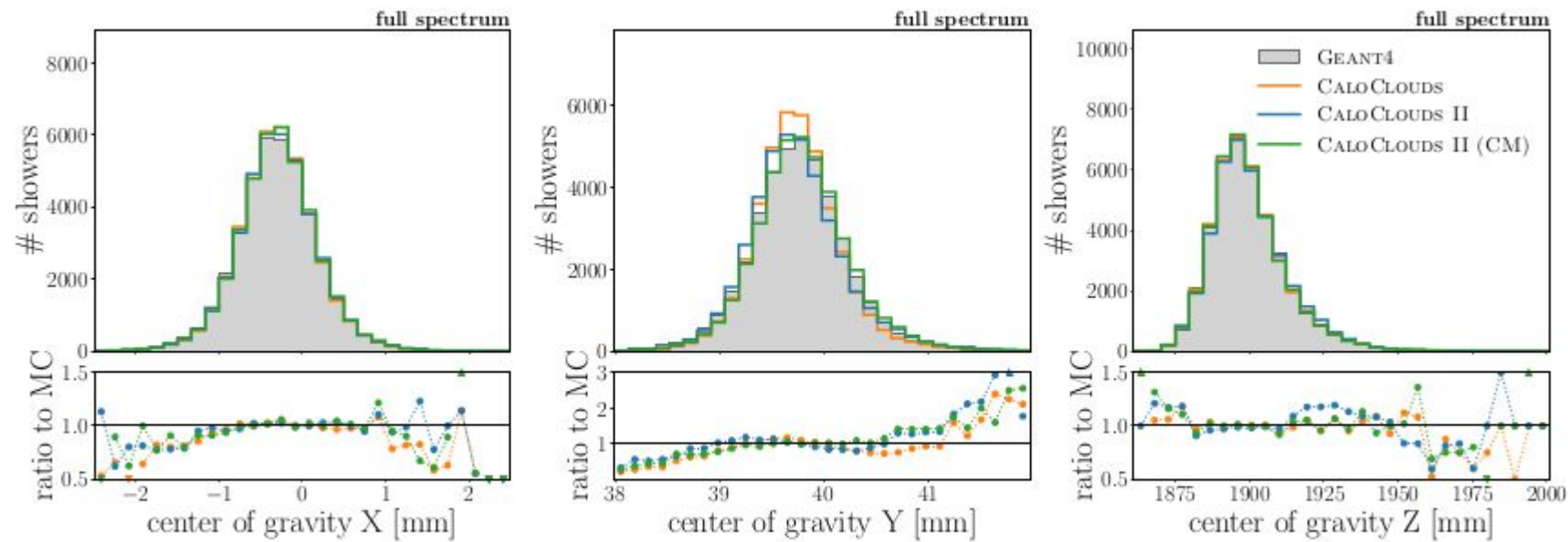
(a) PointWise Net



(b) ConcatSquash Layer (CSL)

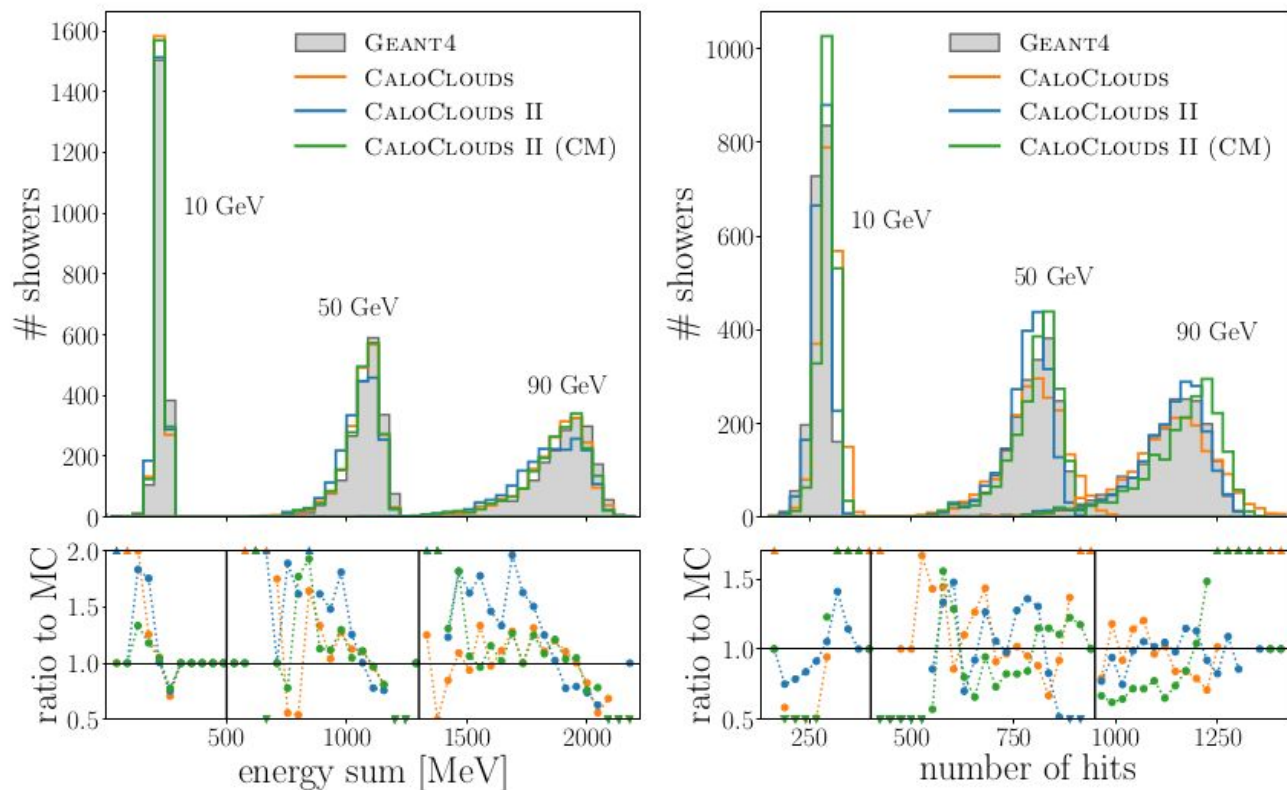
Center of Gravity

CaloClouds2



Visible Energy and Occupancy

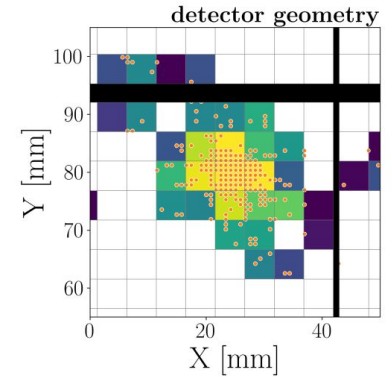
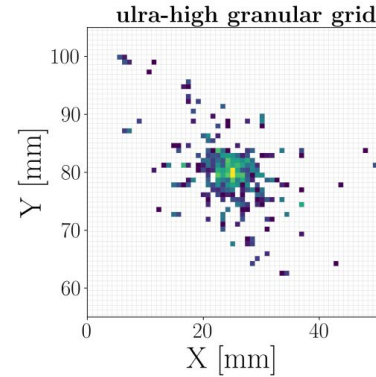
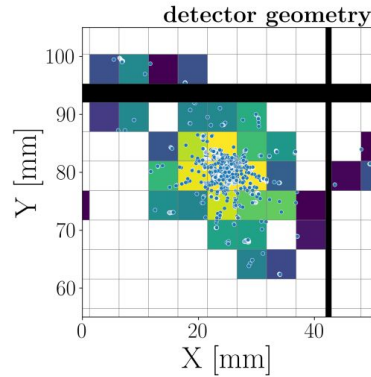
CaloClouds2



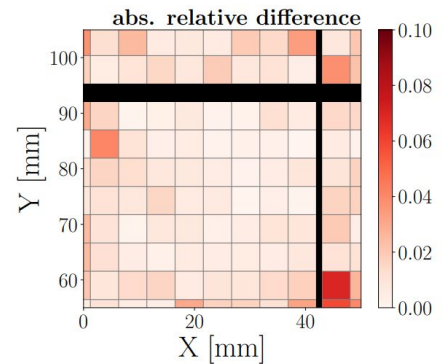
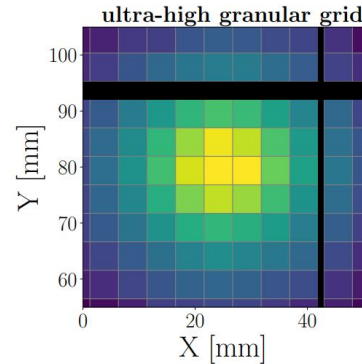
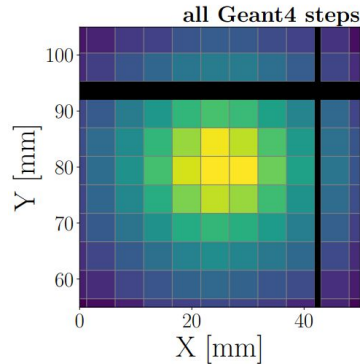
Point Cloud Representation of the EM Showers

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

