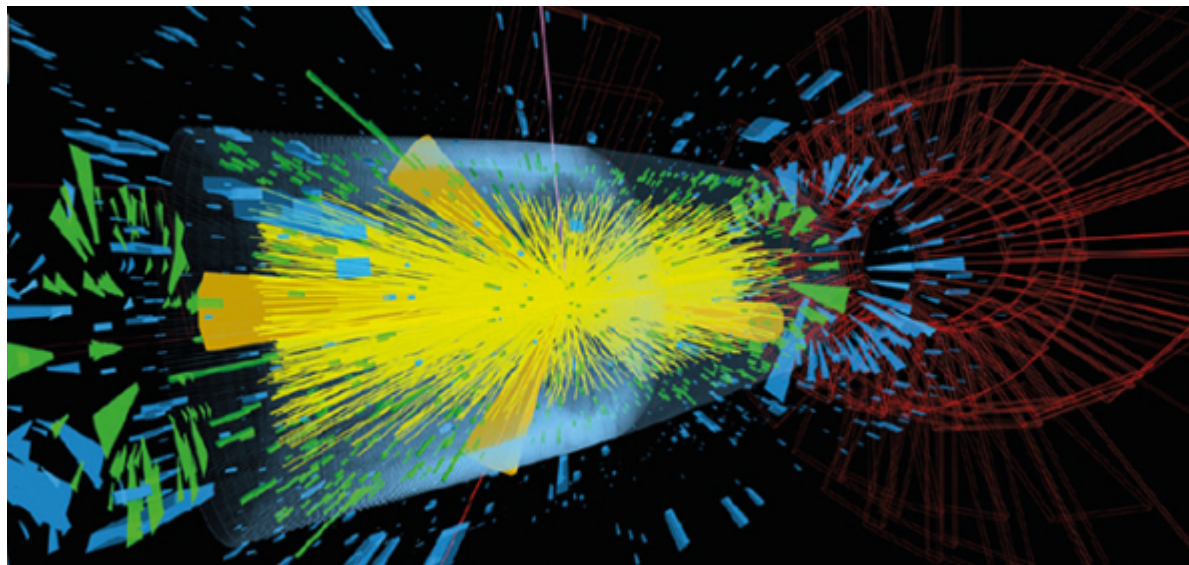


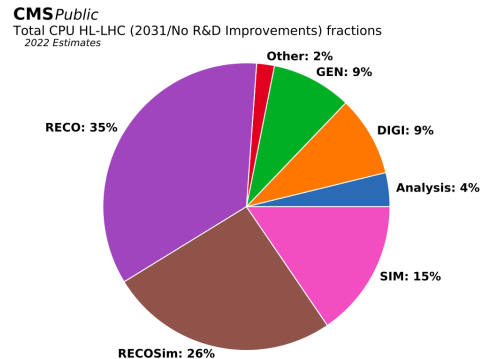
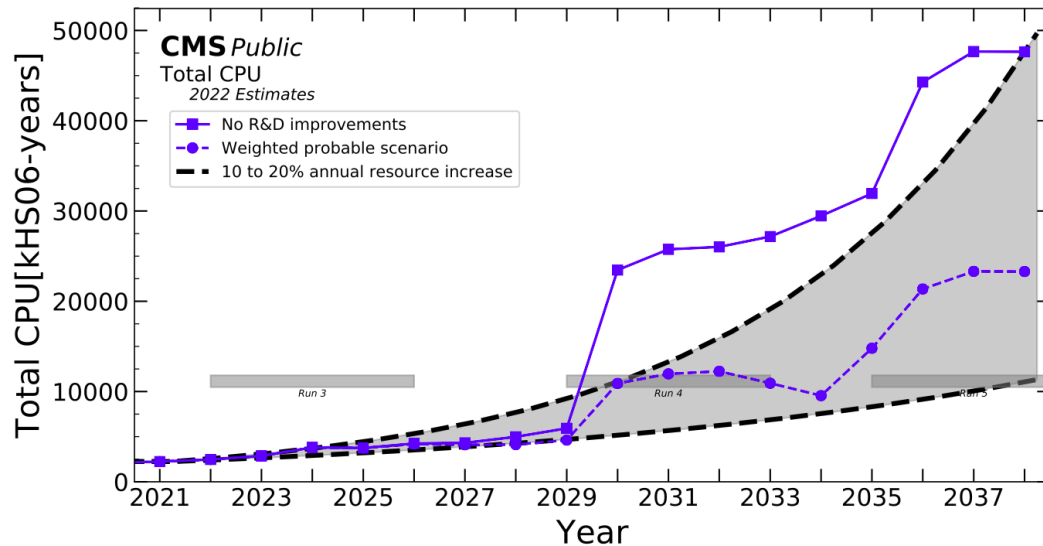
CaloDiffusion



Oz Amram

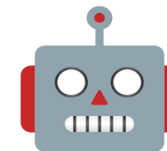
On behalf of CaloDiffusion Team
HSF Simulation / IML ML WG
Dec. 1st, 2025

Need for Fastsim



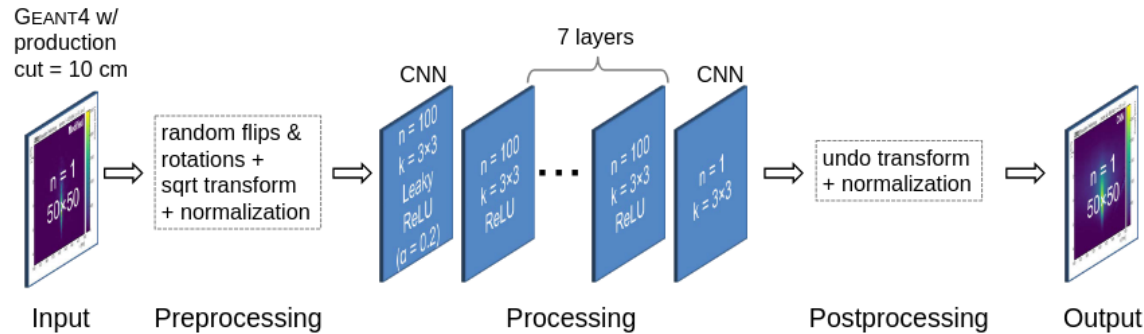
- Computing resources constrained in HL era
- Significant fraction of SIM will need to be FastSim!
 - Calo sim. bottleneck
- High quality fast simulation of calorimeters needed!

NB Parallel 'FlashSim' effort is complementary

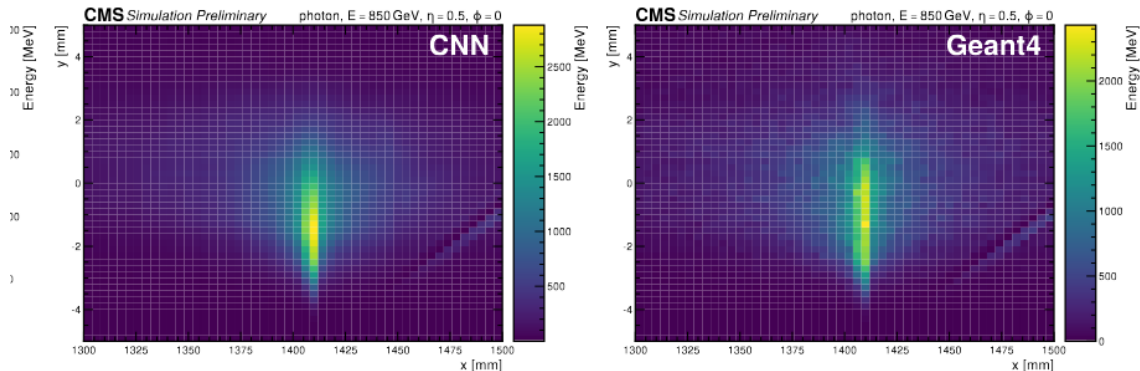


Early Work : Refining FastSim with CNN's

- Studied whether a faster simulation (modified Geant) could be upscaled to higher resolution



- Some success → output matched Geant qualitatively



- However scaling to better quality seemed difficult

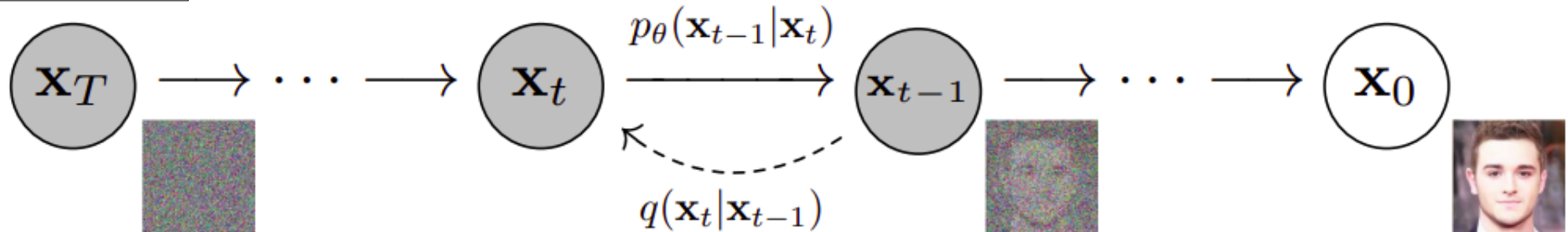
2202.05320

Enter CaloChallenge

- Grant received for further CMS R&D
- CaloChallenge announced just as I was starting my postdoc
 - Great opportunity to develop methods & compare with community
- Also diffusion models taking over gen AI world
 - Similar ‘denoising’ strategy to prev. approach

Diffusion Models

2006.11239

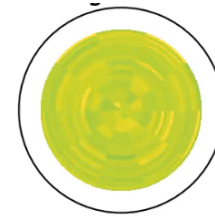


- Diffusion process: Starting with some image, **iteratively add Gaussian noise**, eventually reaching pure noise
- Train a model to **invert the diffusion process**
- Generate by starting from noise image, **iteratively denoise** using trained model
- Can condition on additional input information
 - Eg. text prompt or incident particle energy

'CaloDiffusion'

- Generative diffusion model for Calo simulation
- We use diffusion **400 steps for baseline model**
 - Quality first, speed later
- Denoising network is has 'U-net' architecture based on 3D convolutions
 - Primary input: Noisy shower
 - Conditioning inputs: incident particle energy & diffusion step
- Training objective normalized noise component of the shower
 - Denoising → subtracting noise off
- Several novel optimizations utilized

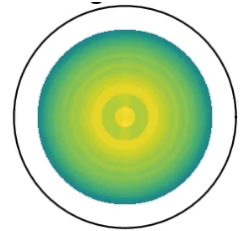
"Gaussian Noise"
Shower



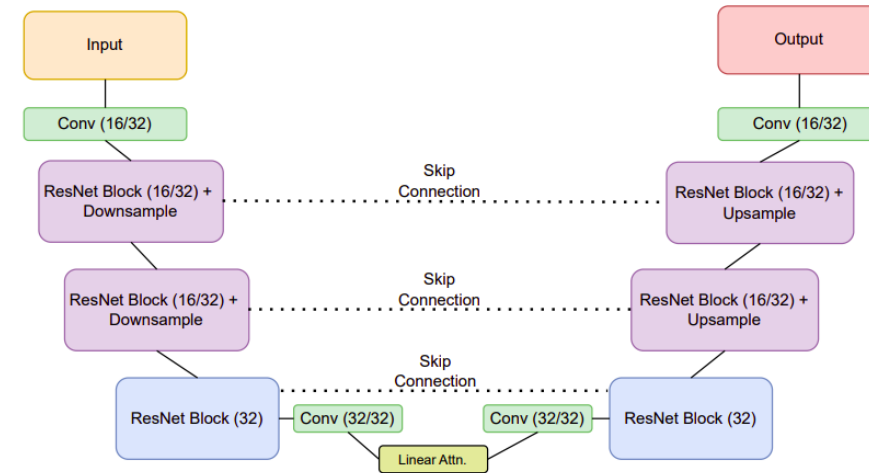
400 Diffusion
Steps



Geant
Shower



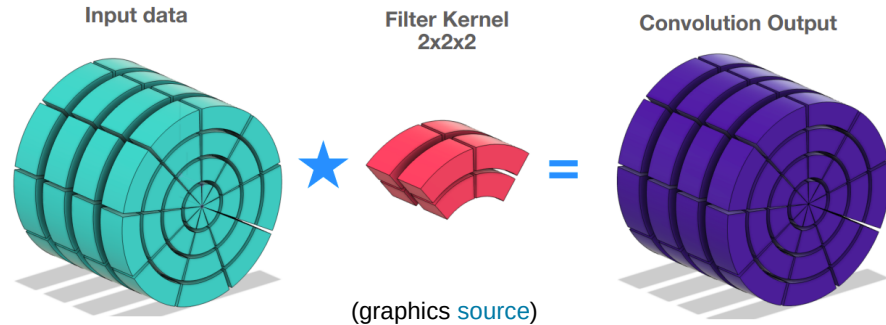
**Denoising
Model**



Optimizing for Cylindrical Data

- Regular convolutions assume pure translation symmetry
- Our data : phi is **periodic**, and R & Z **not translation invariant**

Implement **cylindrical convolutions** to respect periodic boundary of phi



‘Circularly’ pad phi dimension before 3D conv

Allow convolutions to be **conditional on R & Z** by using additional channels

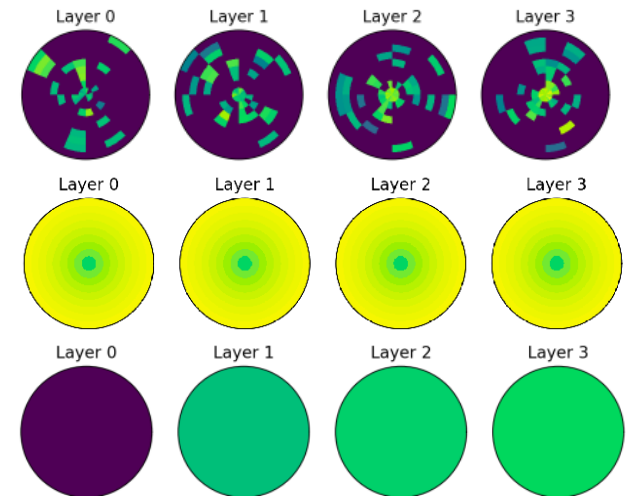
Shower input

+

‘Radius input’

+

‘Layer input’

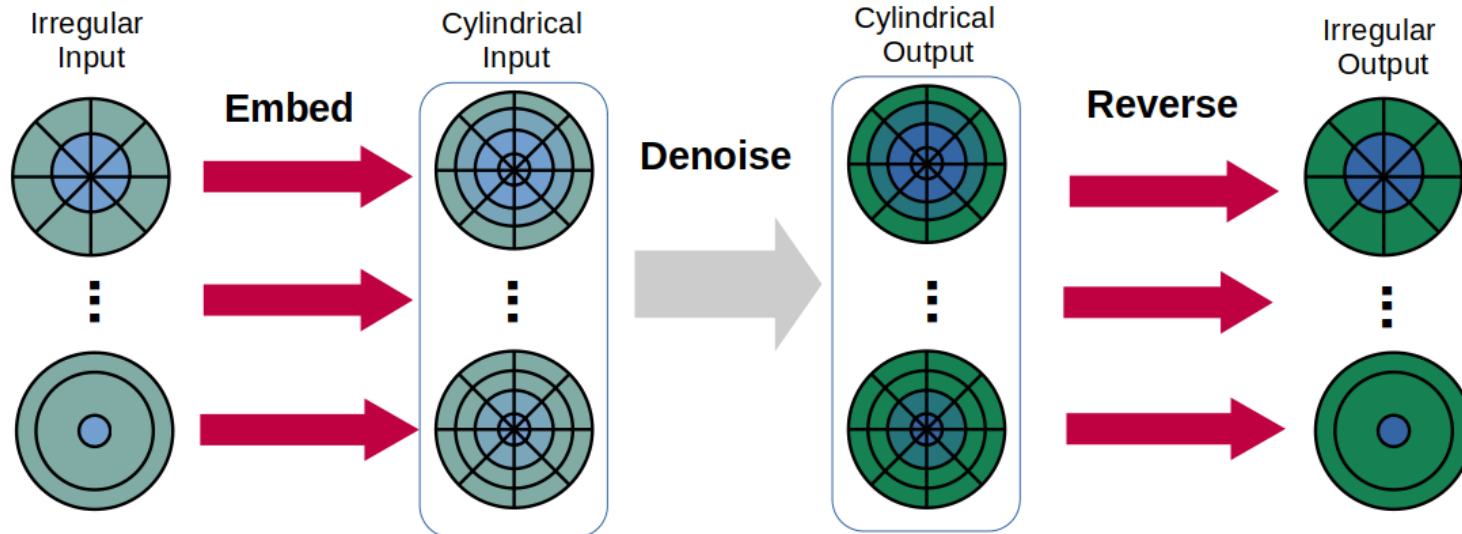


Additional input channels

One Innovation : Embedding Irregular Geometries

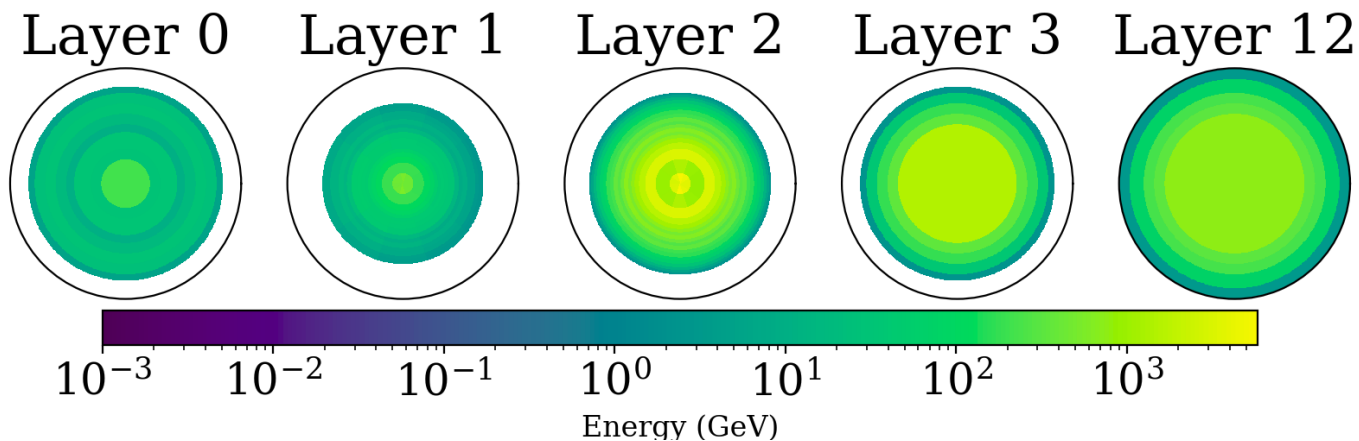
- Real detectors (ie HGCal) have **irregular structure** in different layers
 - Different radial / angular bins in each layer → can't apply your favorite ML tools (like convolutions)
- Learn an **GLaM-orous embedding** that maps input into **regular cylindrical structure**

GLaM : Geometry Latent Mapping

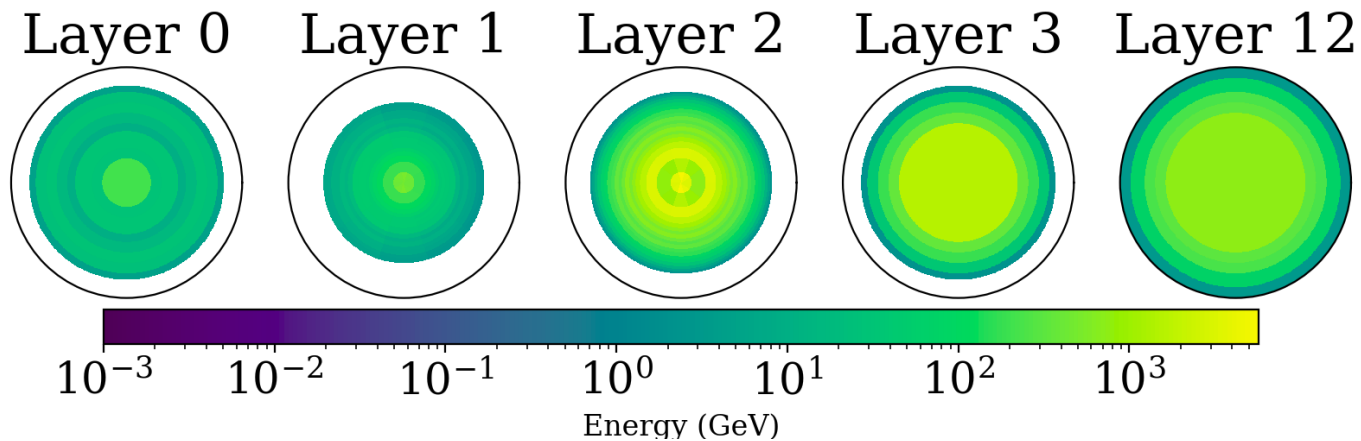


Average Showers

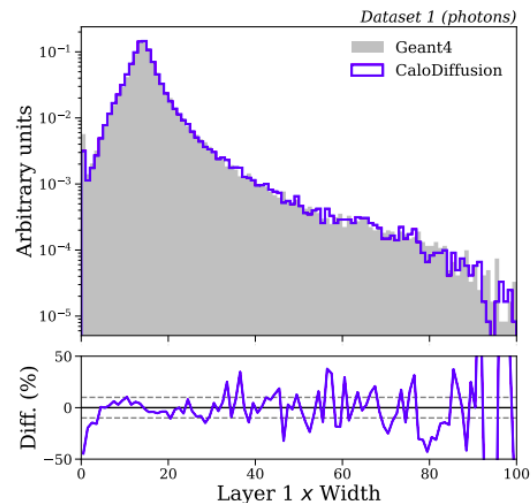
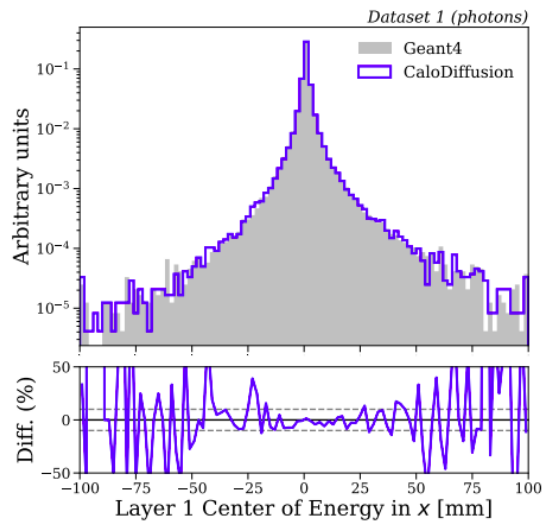
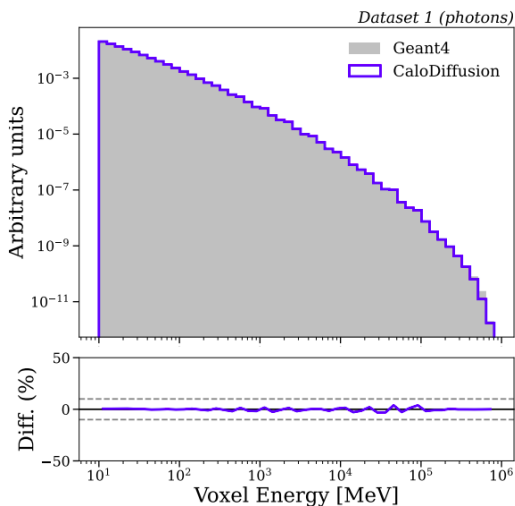
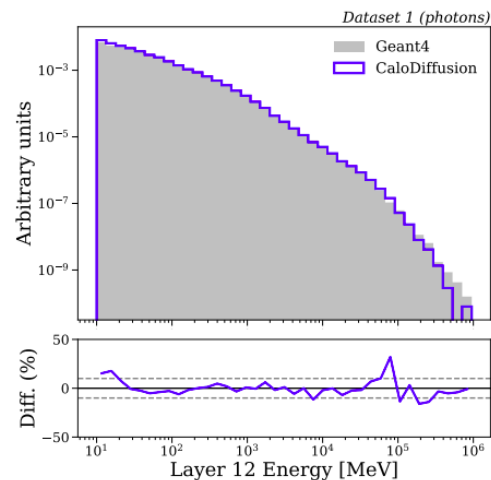
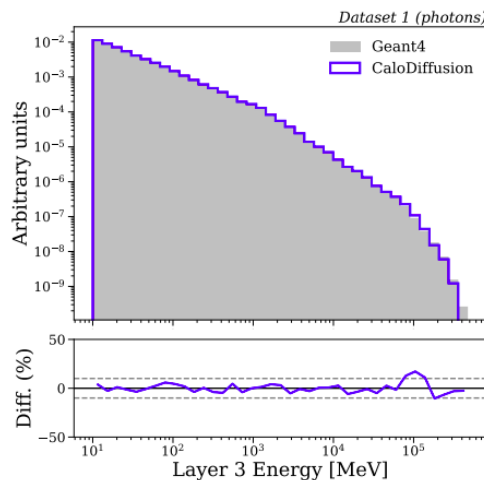
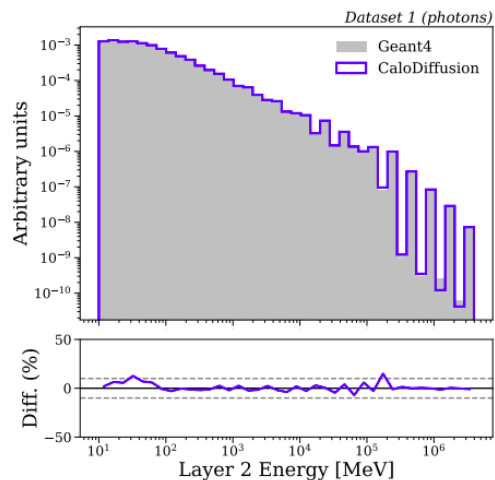
Geant



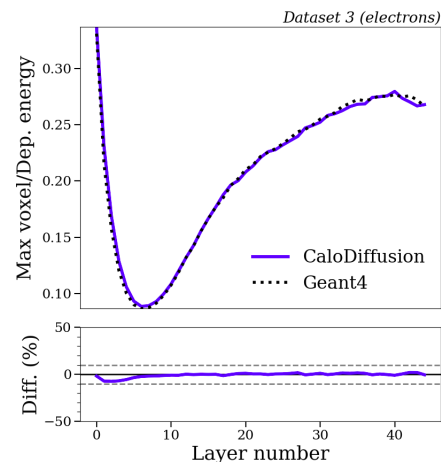
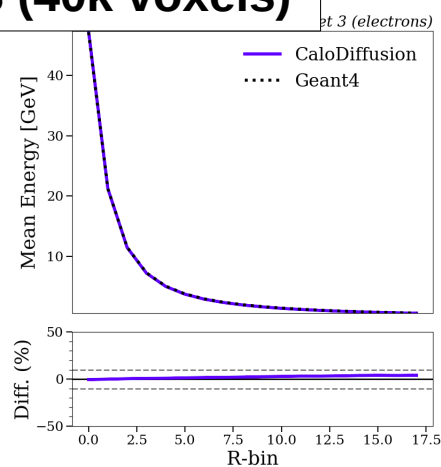
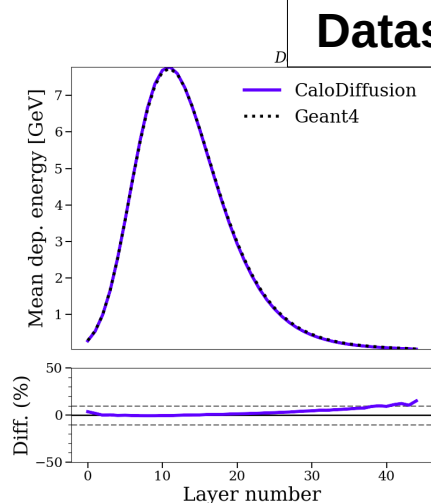
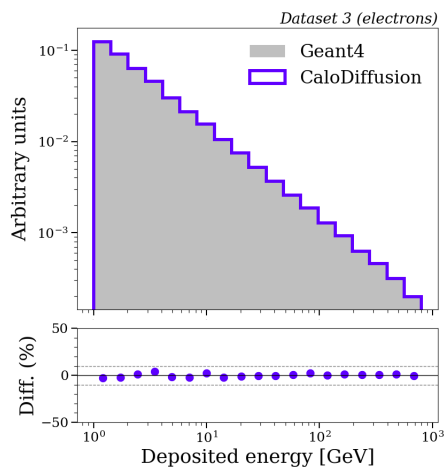
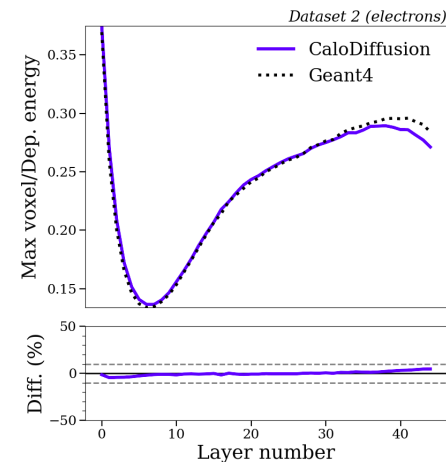
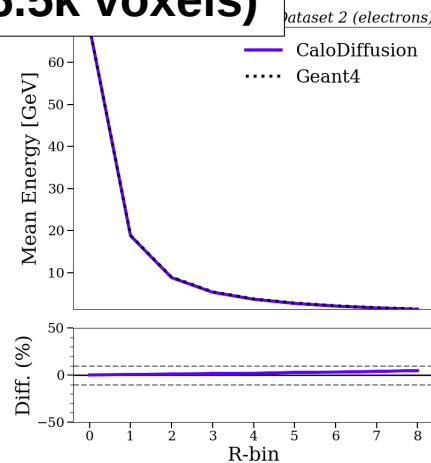
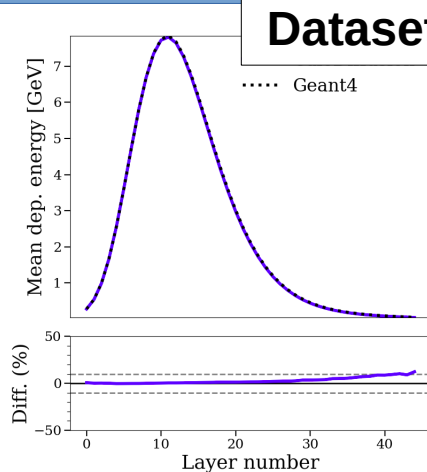
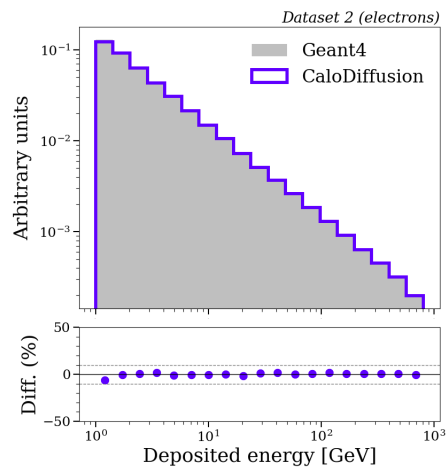
CaloDiffusion



CaloChallenge Dataset 1 Results



Results: Datasets 2 & 3



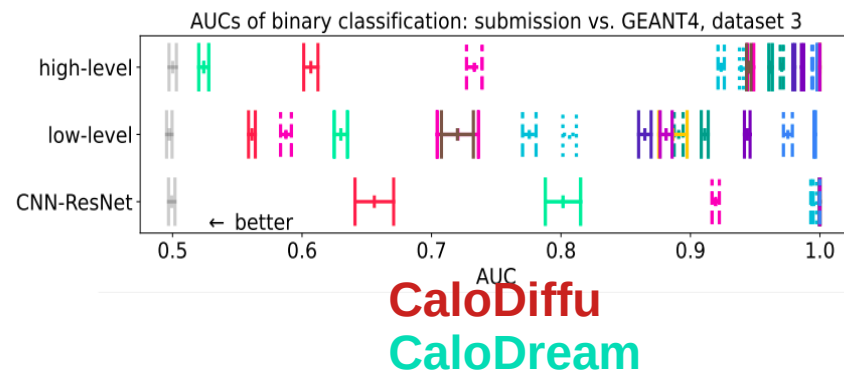
Performance Comparison

- Calodiffusion performed very well in CaloChallenge
- New benchmark in quality at time of publication
- Top-2 in quality on all datasets in final evaluation

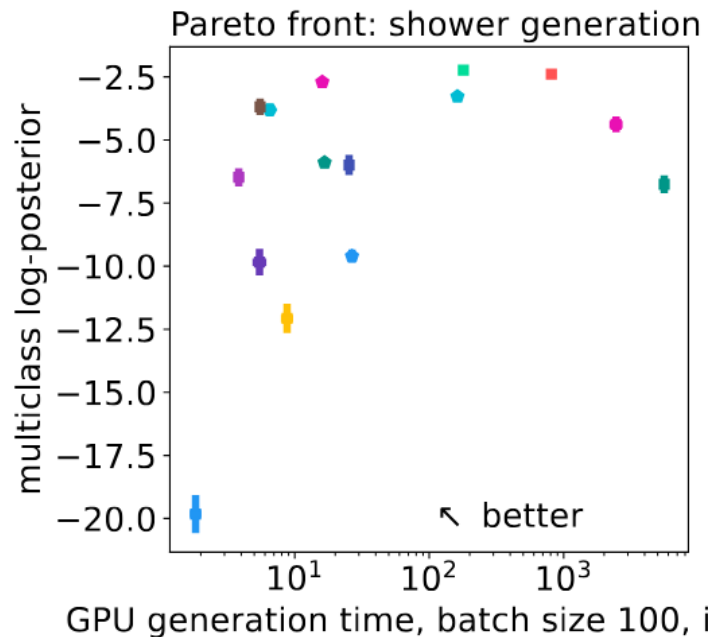
Comparisons at time of publication

Dataset	Classifier AUC (low / high)		
	CaloDiffusion	CaloFlow	CaloScore v2
1 (photons)	0.62 / 0.62	0.70 / 0.55	0.76 / 0.59
1 (pions)	0.65 / 0.65	0.78 / 0.70	- / -
2 (electrons)	0.56 / 0.56	0.80 / 0.80	0.60 / 0.62
3 (electrons)	0.56 / 0.57	0.91 / 0.95	0.67 / 0.85

Final CaloChallenge Results



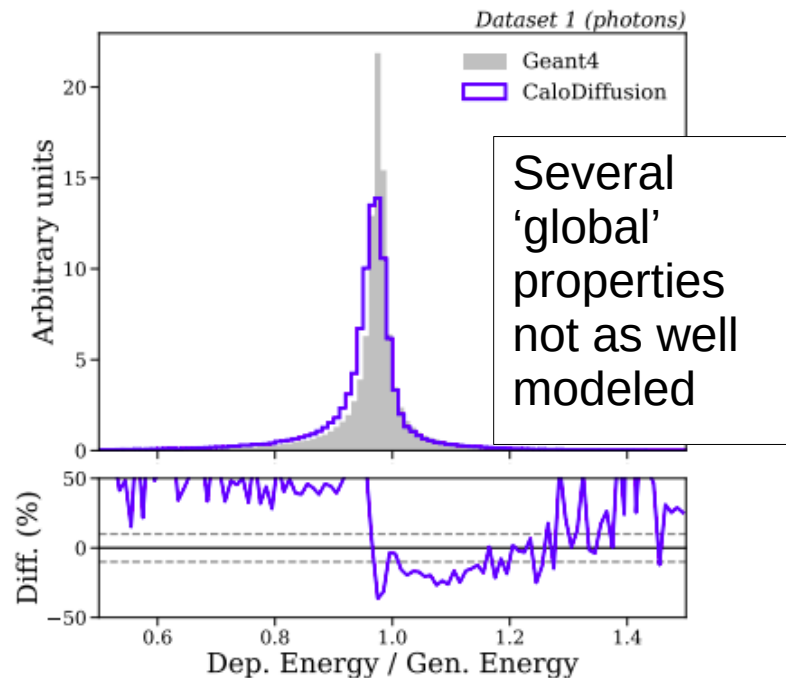
Areas for Improvement



Generation speed

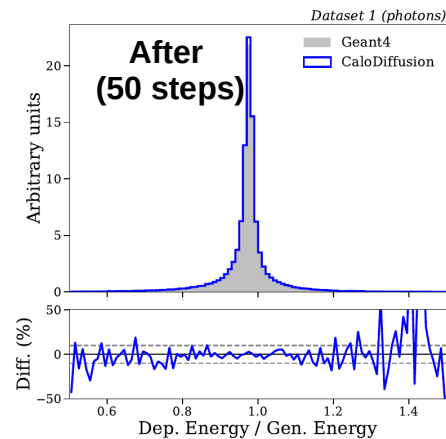
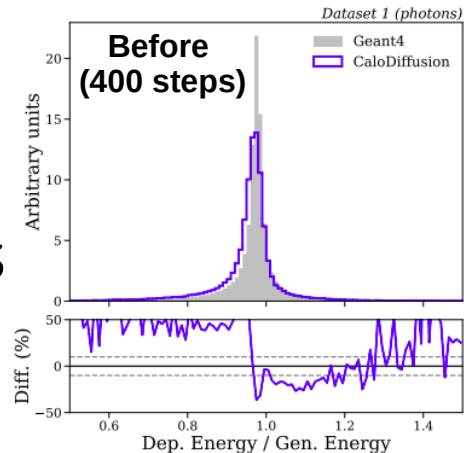
CaloDiffusion slower than other models

→ 400 diffusion iters is a lot



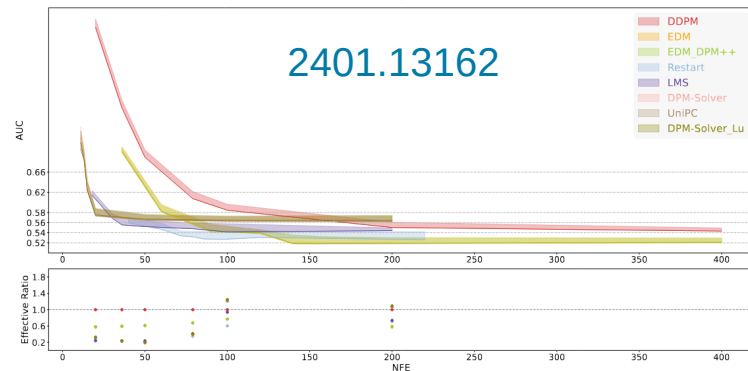
Post-Challenge Improvements

- Learn from other methods!
- Factorize model: separate network for 'global' properties (energy per layer), and 'shape'
- Speedups from better sampling algo's
 - Distillation techniques
 - Ongoing R&D
- Time to move to CMS datasets !

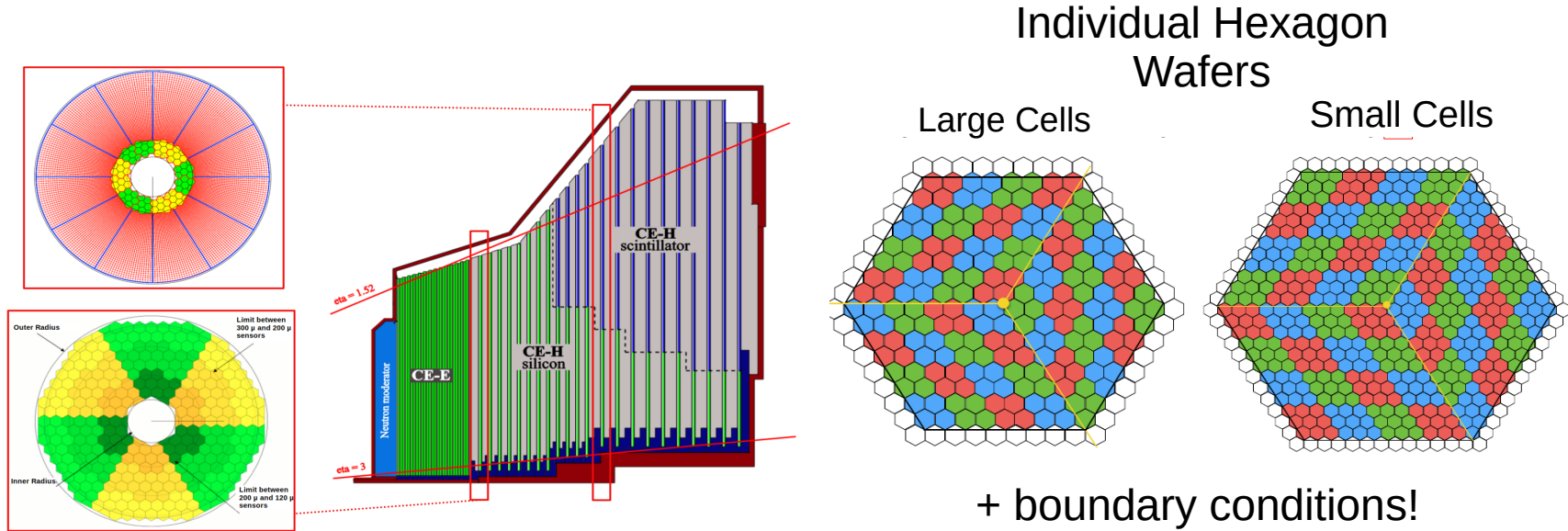


Choose Your Diffusion: Efficient and flexible ways to accelerate the diffusion model in fast high energy physics simulation

Cheng Jiang^{1*}, Sitian Qian^{2†} and Huilin Qu^{3‡}

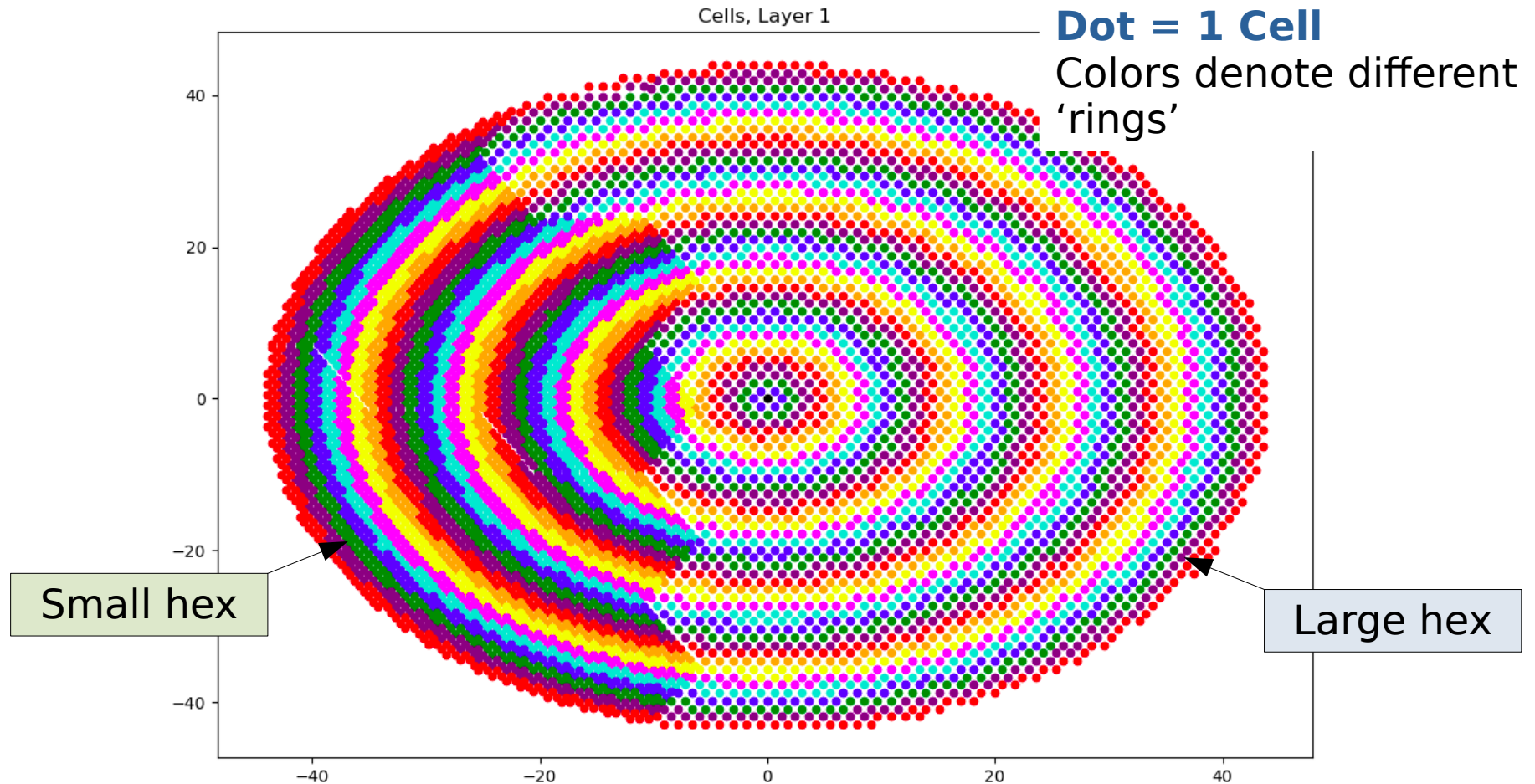


CMS HGCal

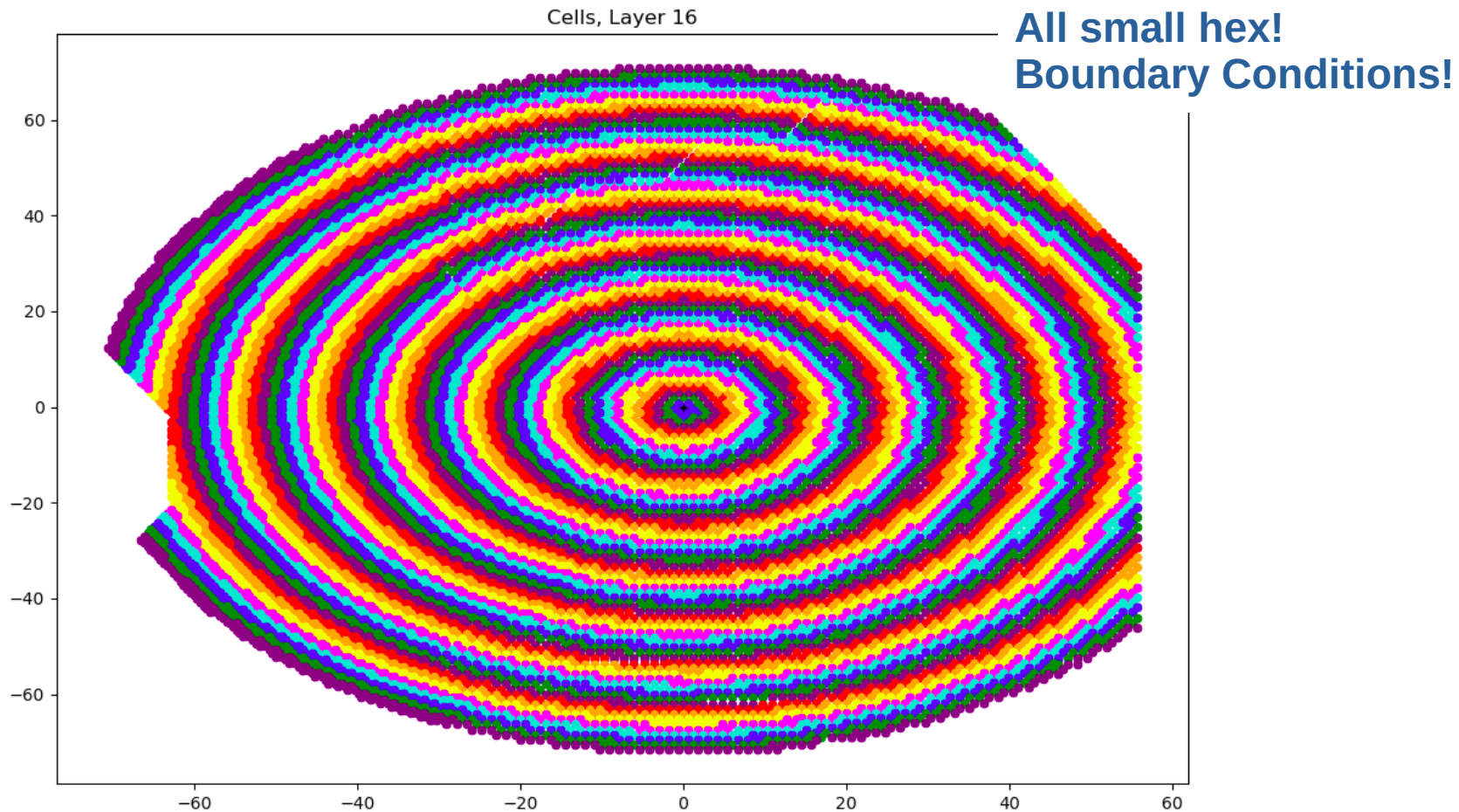


- Simulating HGCal significantly more difficult than CaloChallenge
 - Significantly higher granularity (10x or more)
 - Very complicated geometry!

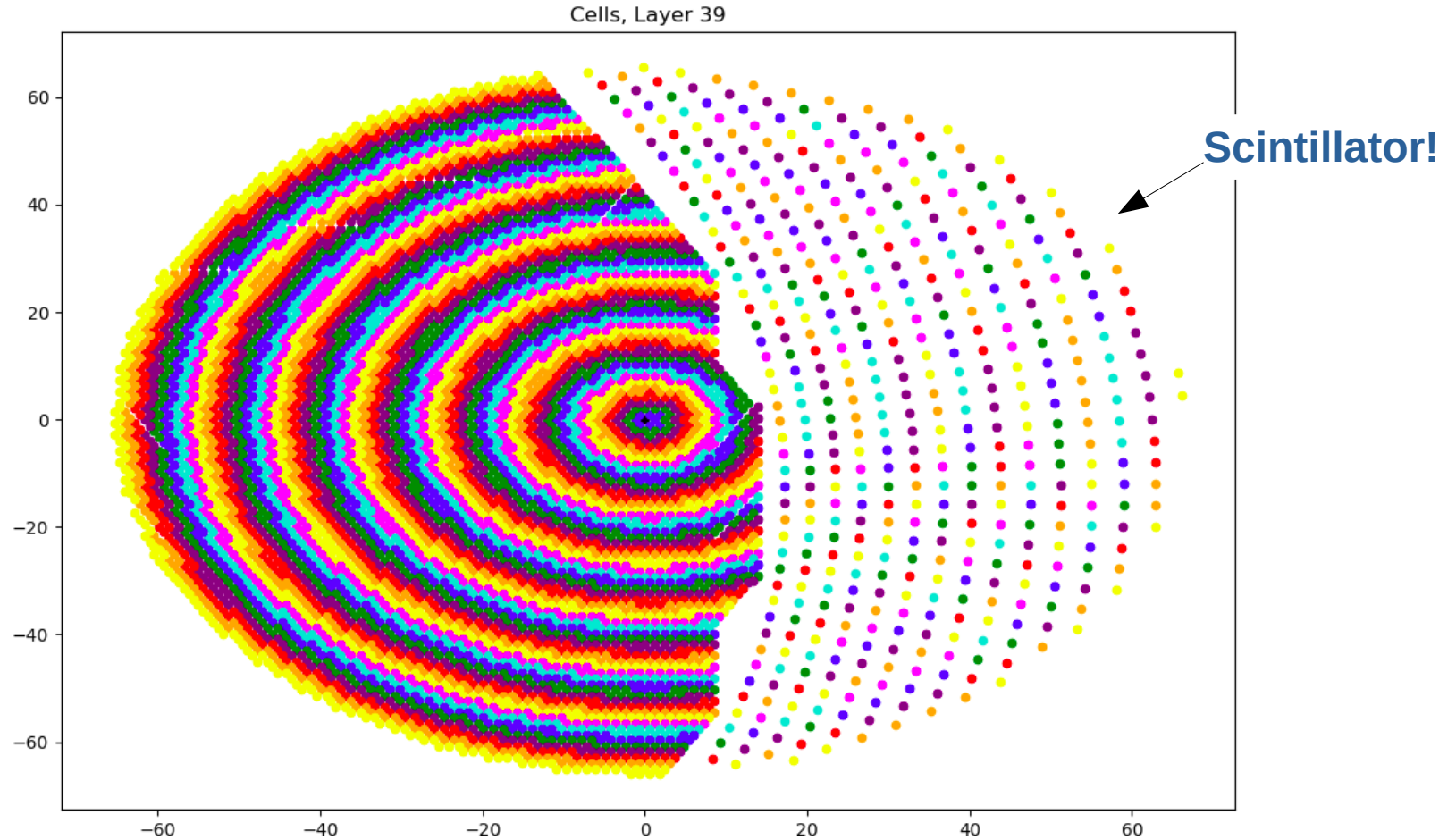
Example HGCal Region : Layer 1



Example HGCal Region : Layer 16

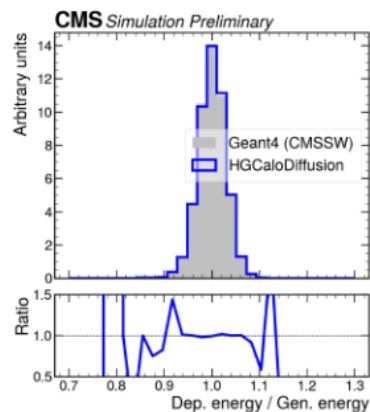
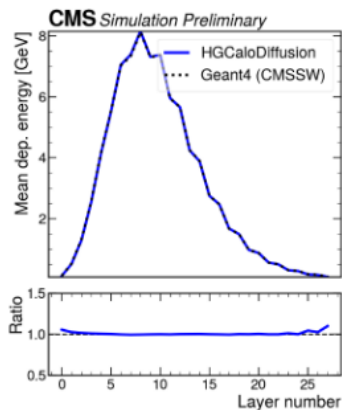


Example HGCal Region : Layer 39

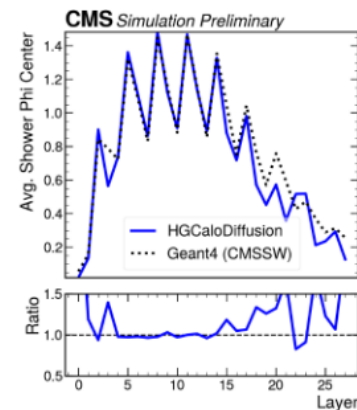


Performance (CHEP '24)

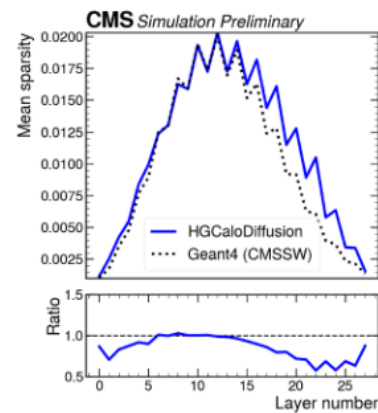
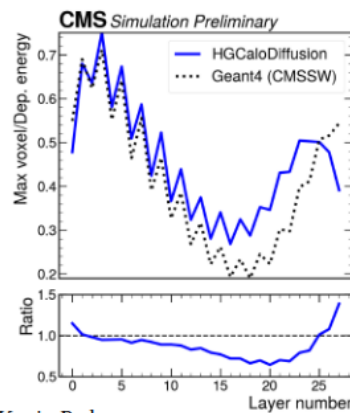
Global quantities well-modeled (thanks to LayerDiffusion)



GLaM allows reproduction of “sharp” features in original geometric space



Reasonable agreement in maximum voxel per layer and average sparsity ($n_E > 1 \text{ MeV}/n_{\text{hits}}$)



CHEP 2024

Kevin Pedro

10

Outlook

- CaloChallenge was very helpful for initial development of **CaloDiffusion**
- Now focus is on CMS application : **HGCal**
 - Significant step up in granularity & complexity
- Continue to improve **CaloDiffusion** to handle these challenges
 - Promising results so far
- Will employ SONIC ([link](#)) to enable GPU + multi-event batching
- Other models in CMS also being developed
- Look out for public results soon!