Poster Wed 42

The Calorimeter Pyramid

Are you interested in a Pyramid Scheme?

Simon Schnake, Dirk Krücker, Kerstin Borras
29.04.24
EuCAIFCon24

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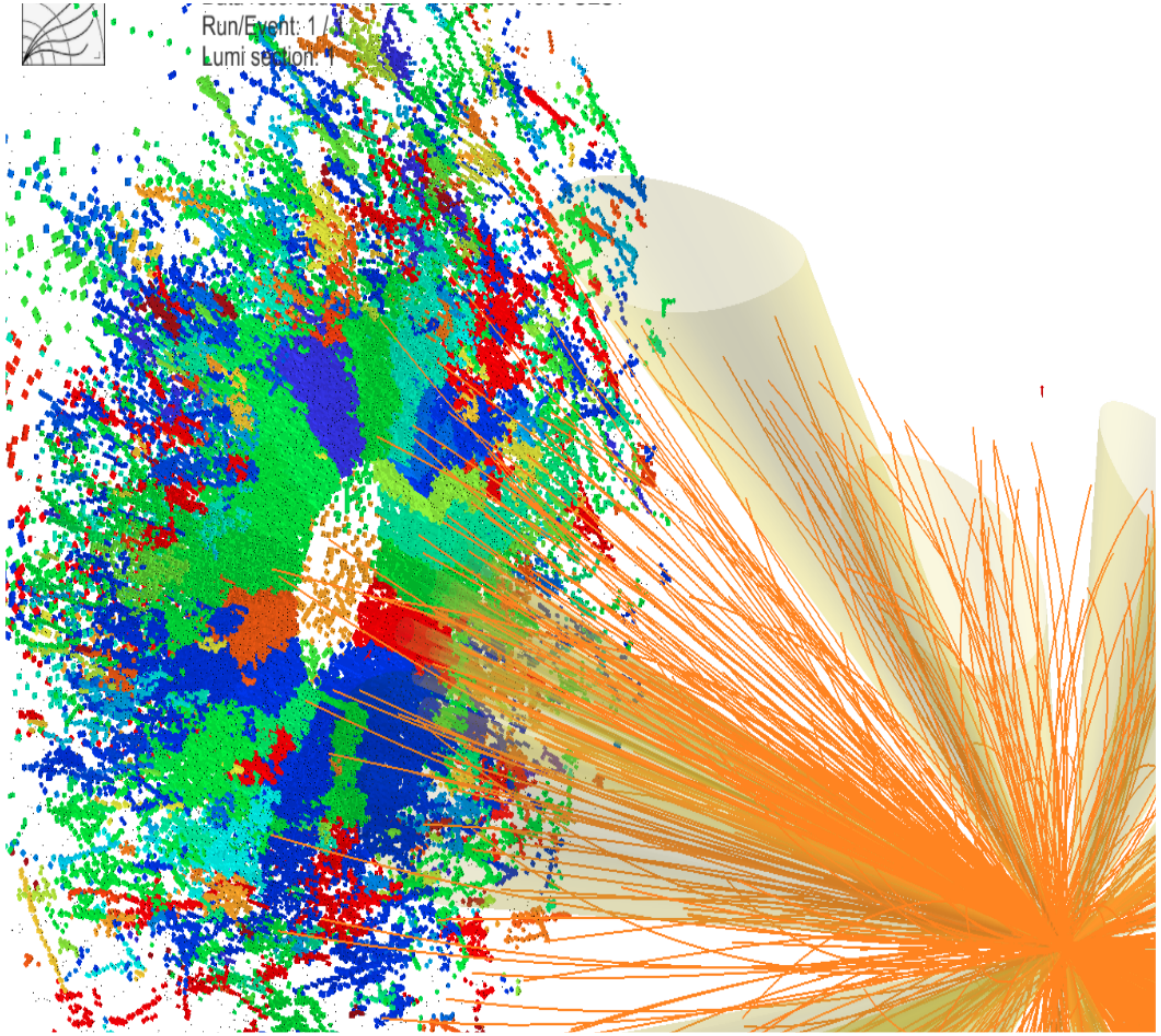
The Challenge

Modern calorimeters have millions of channels

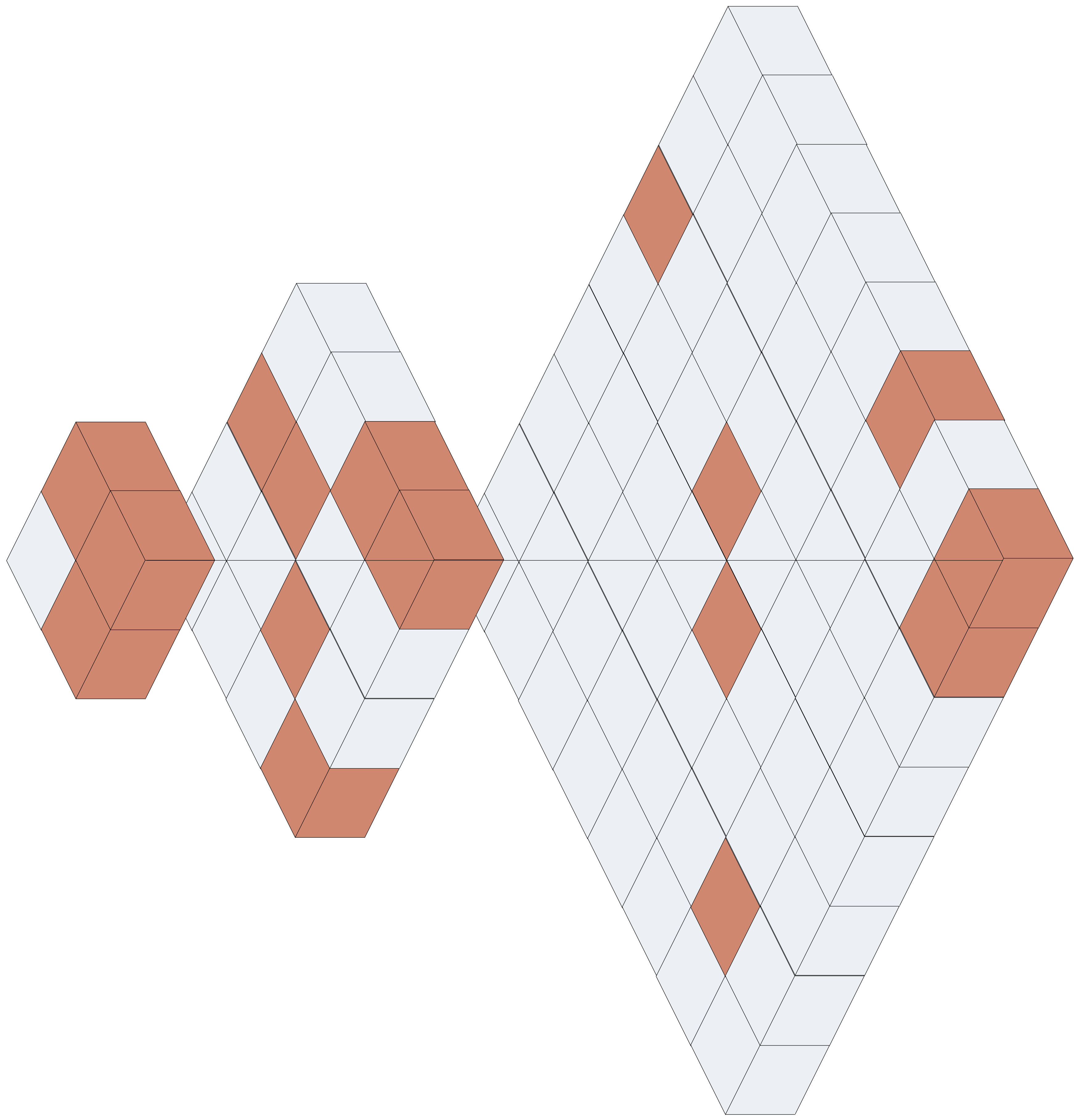


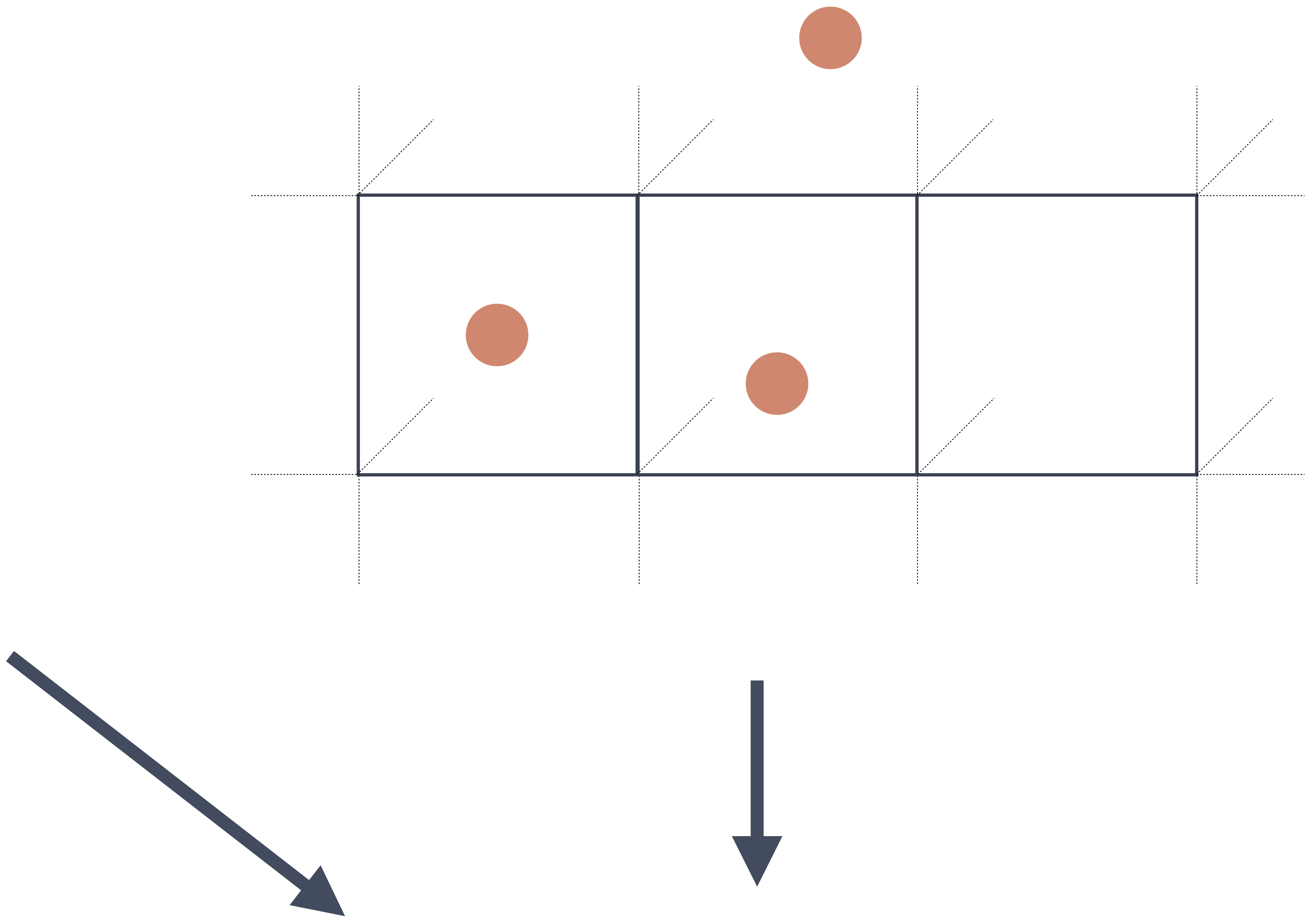
Simulated view of one HGCal endcap, containing particles from the nominal 140 pileup interaction expected at the HL-LHC
[D. Newbold - The High-Luminosity Upgrade of the CMS Detector]

How do you scale generative models to millions of cells?

Two Strategies

Super Resolution or **Point Clouds**





Sparse Super Resolution

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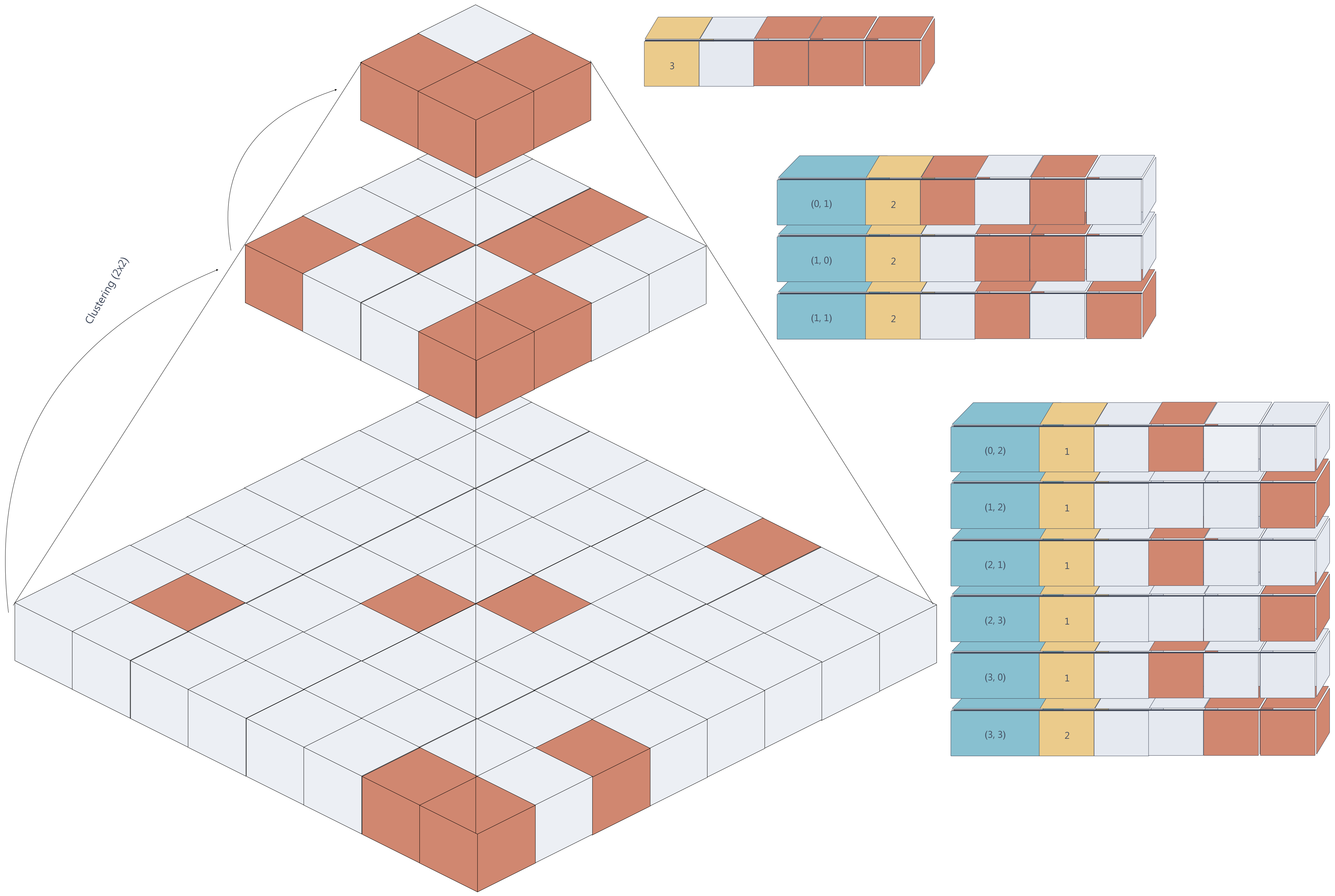
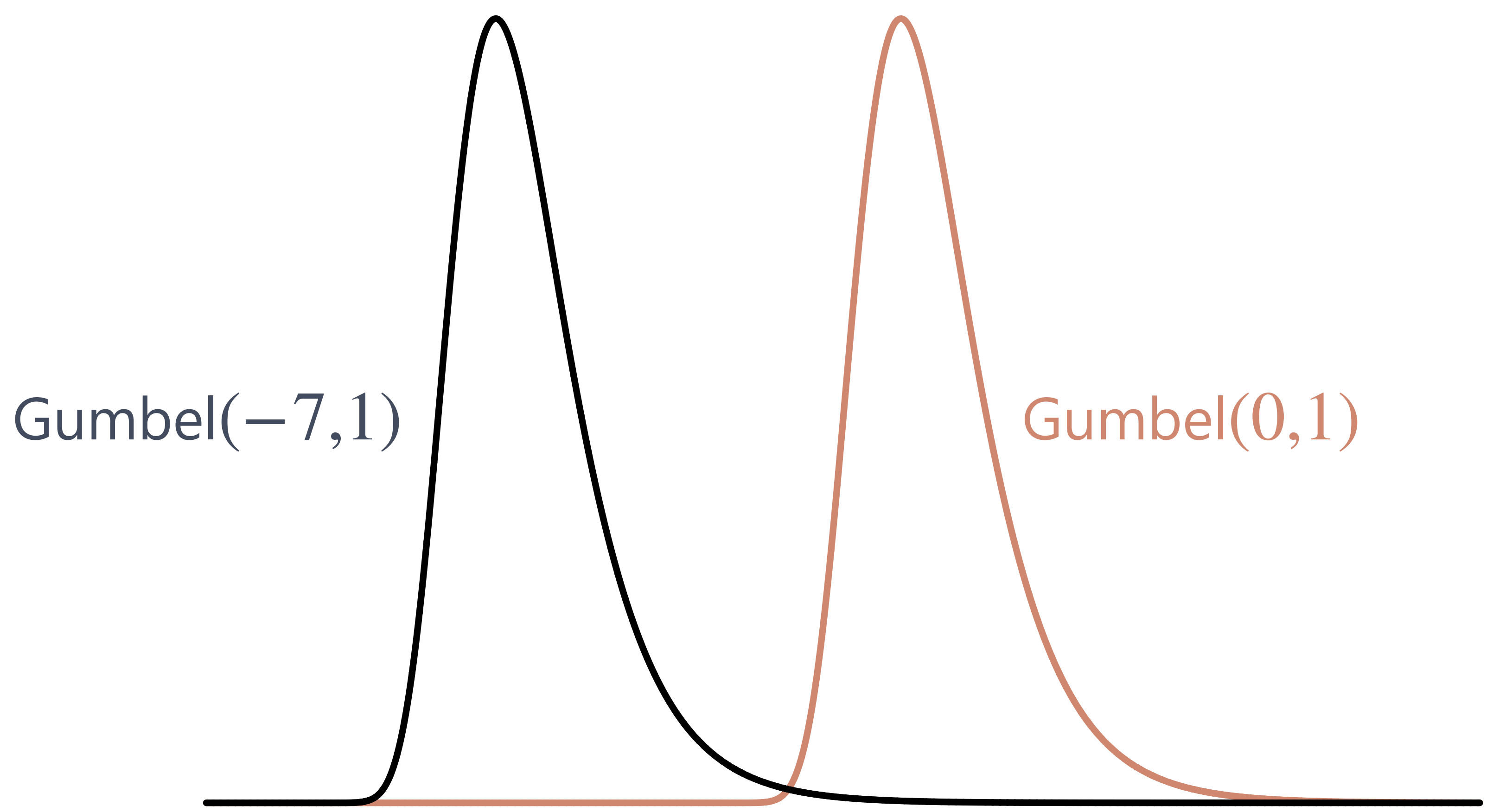
The Calorimeter Pyramid

Sparse Super Resolution

First, learn all hit cells → Second, learn the energies of the hits





Choose your Diffusion

Efficient and flexible ways to accelerate ~~diffusion~~ (DM/CFM) in HEP

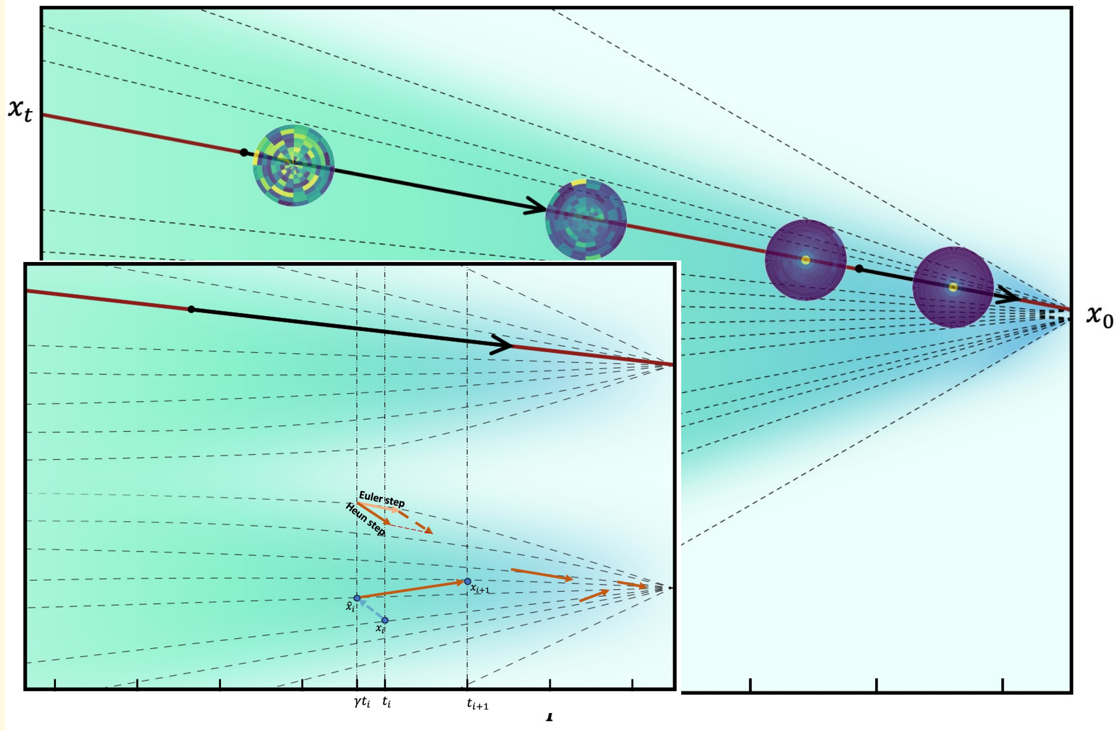
Cheng Jiang, Sitian Qian, Huilin Qu

2401.13162

CERN
Peking University 1898
The University of Edinburgh

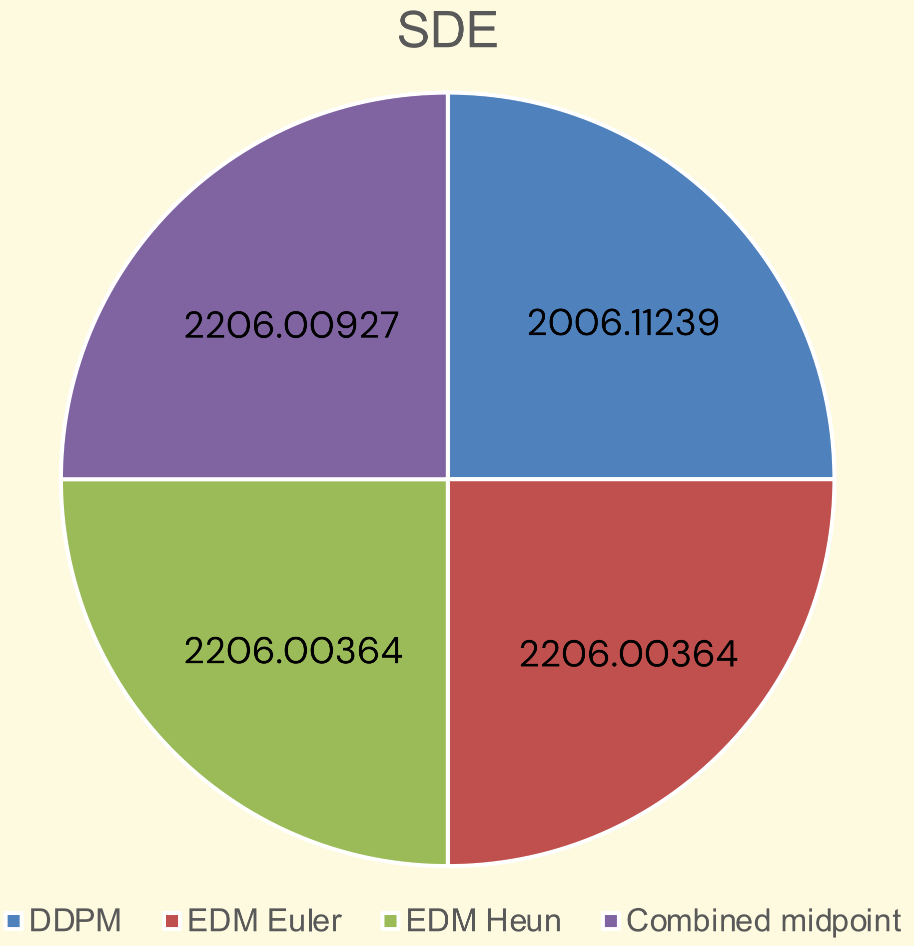
Motivation

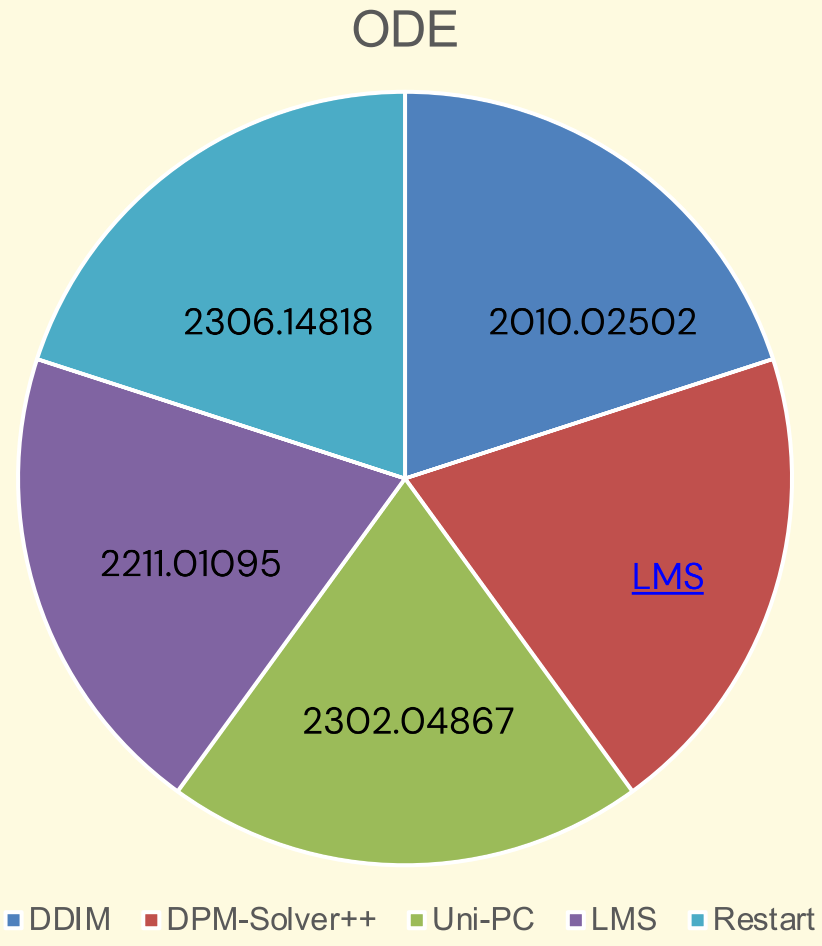
- The study focuses mostly on Score Matching, in which the score function is solved by different choices of SDE/ODE. How we could effectively accelerate the generative model, by replacing only parts of that.



- Backward process (training-free):

We have adopted **almost all mainstream samplers/schedulers** to do comprehensive comparisons **on both shower cells** (*CaloChallenge*) **and jet constituents** (*JetNet*)



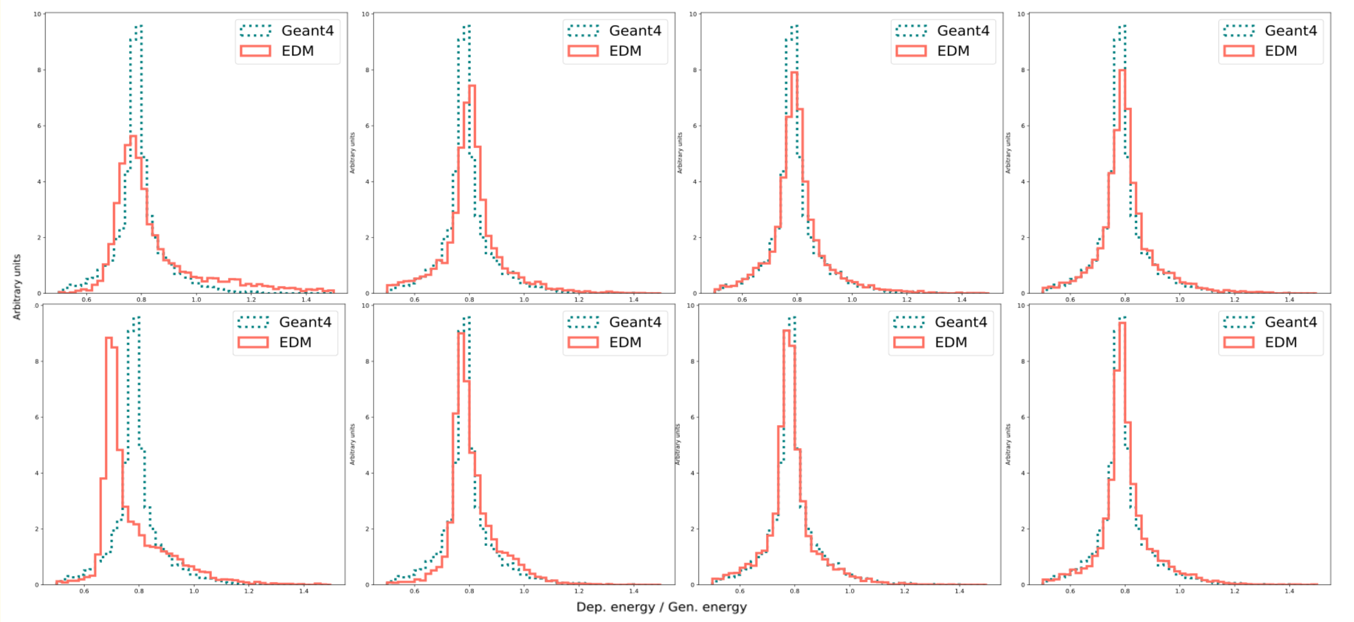


- Forward process (faster divergence):

Effective way to mitigate the challenging optimization: **Denoiser function with preconditioning parameters, weighted by min-Signal-to-Noise ratio (min-SNR)**

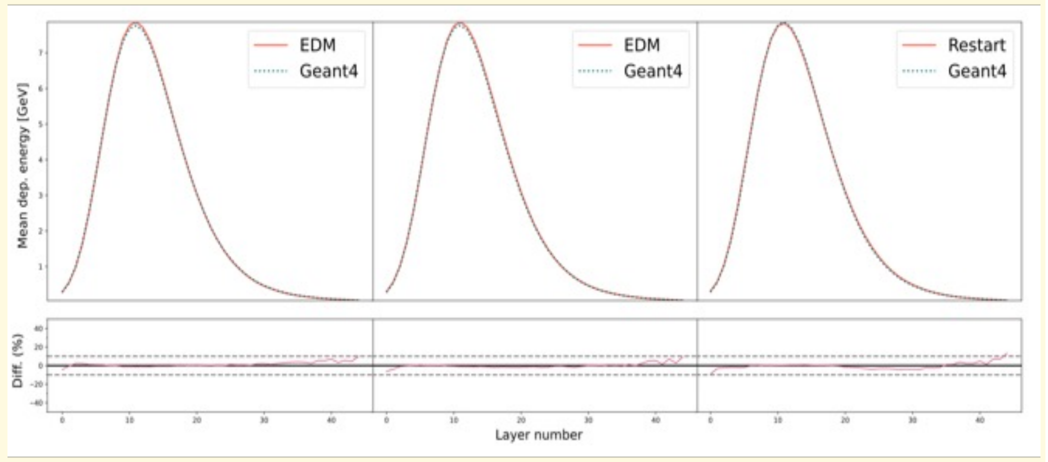
$$\mathcal{L} = \mathbb{E}_{t,\varepsilon}[\boldsymbol{w(t)}||\boldsymbol{F(c_{in}x_t, t)} - \frac{\mathbf{1}}{\boldsymbol{c_{out}}}(\boldsymbol{x_0} - \boldsymbol{c_{skip}x_t})||_2^2]$$

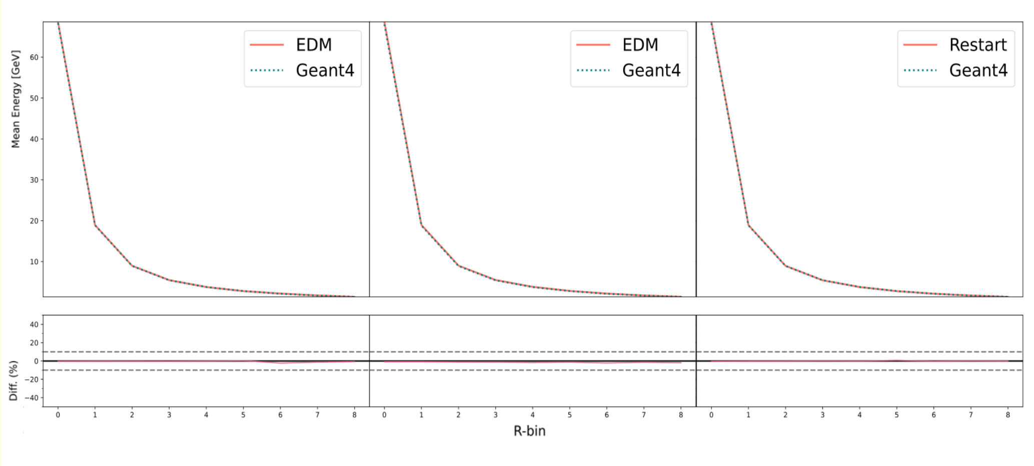
$$\boldsymbol{w(t)} = {(\boldsymbol{t} * \boldsymbol{\sigma_c})}/{(\boldsymbol{t^2} + \boldsymbol{\sigma_c^k})^2}$$



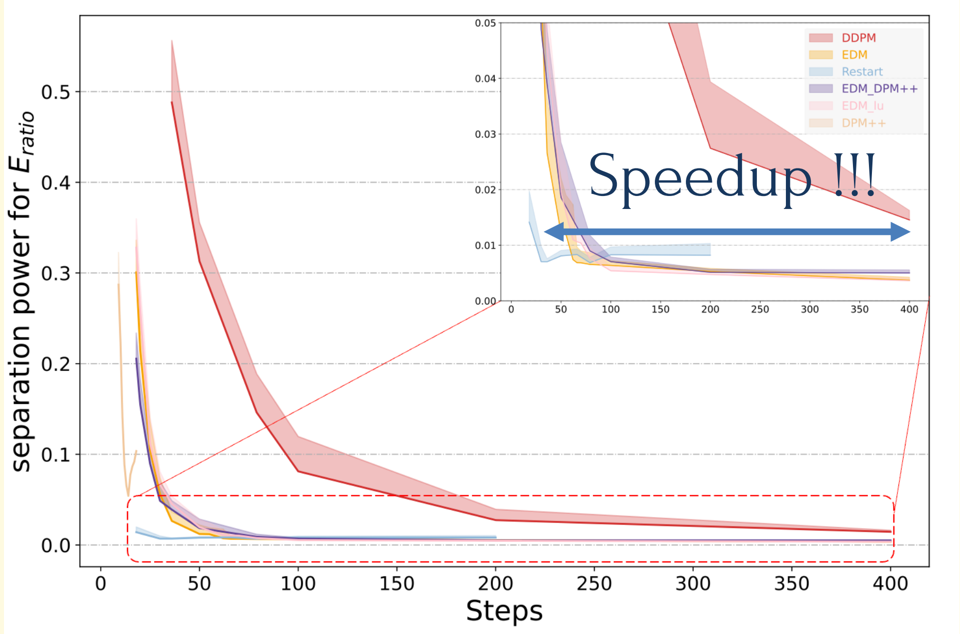
Results & More (Wed Loc #45)

Indistinguishable high-level features for shower from cell-level generations



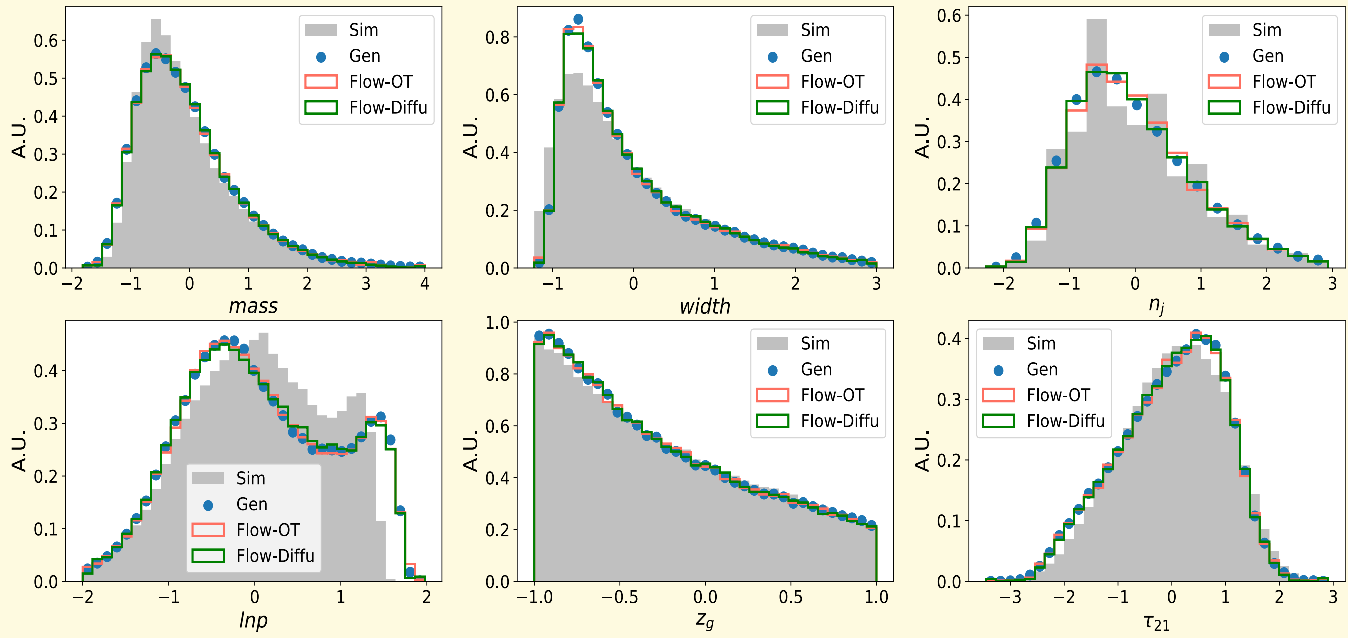


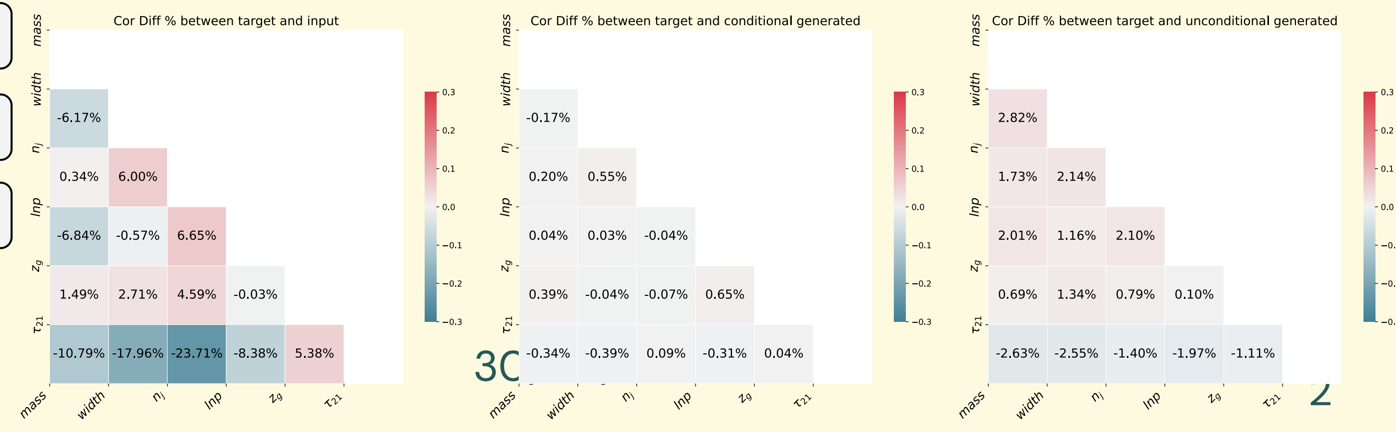
Achieve O(10) acceleration with comparable performance for current benchmark models



	AUC	Separation	FPD
DDPM 79/200/400	55.3/53.2/*52.6*	0.0810/0.0344/*0.0155*	0.074/0.046/*0.043*
EDM 39/79/200	54.1/**52.0**/51.5	0.0256/0.0076/**0.0055**	0.035/**0.027**/0.023
EDM_DPM++ 79	52.3	0.0103	0.026
EDM_Lu 79	52.2	0.0086	0.026
Restart 18/36/79	55.2/**52.0**/51.8	0.0169/0.073/0.0057	0.059/**0.025**/0.022
LMS 36	53.8	0.0305	0.095
DPM++ 20	59.8	0.0534	0.146
Uni-PC 20	60.3	0.1304	0.152

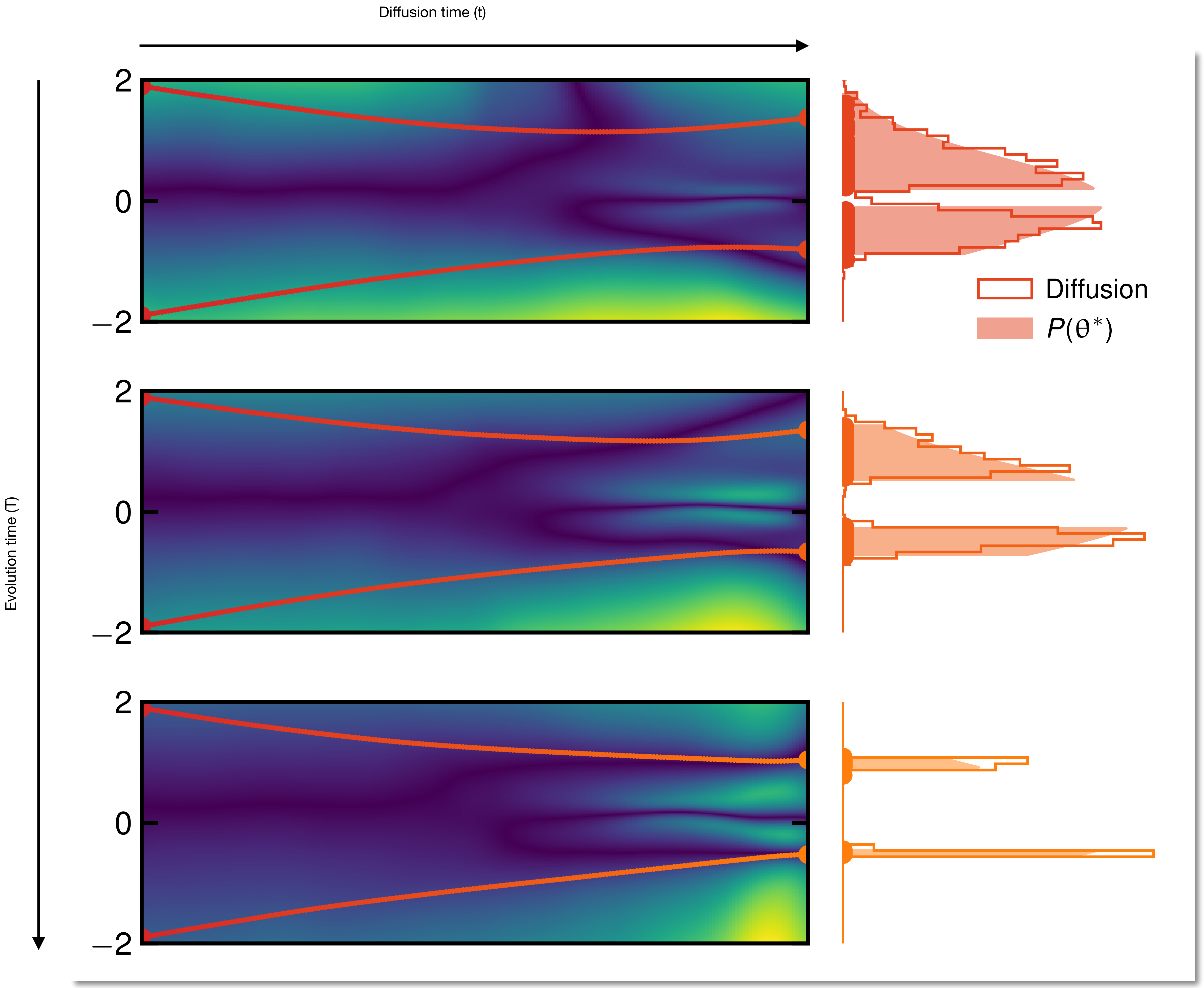
How about replacing the backbone for the model? **Changing flow matching with Unet/Transformer backbone to GBDT, which latter has much faster training and inference time.** Is this even possible?? YES! (BUFF: BDT based-ultra-fast flow matching.) Few mins training, below millisecond generation time, could replace most flow-based model. E.g. Unfolding, huge improvement on correlation difference



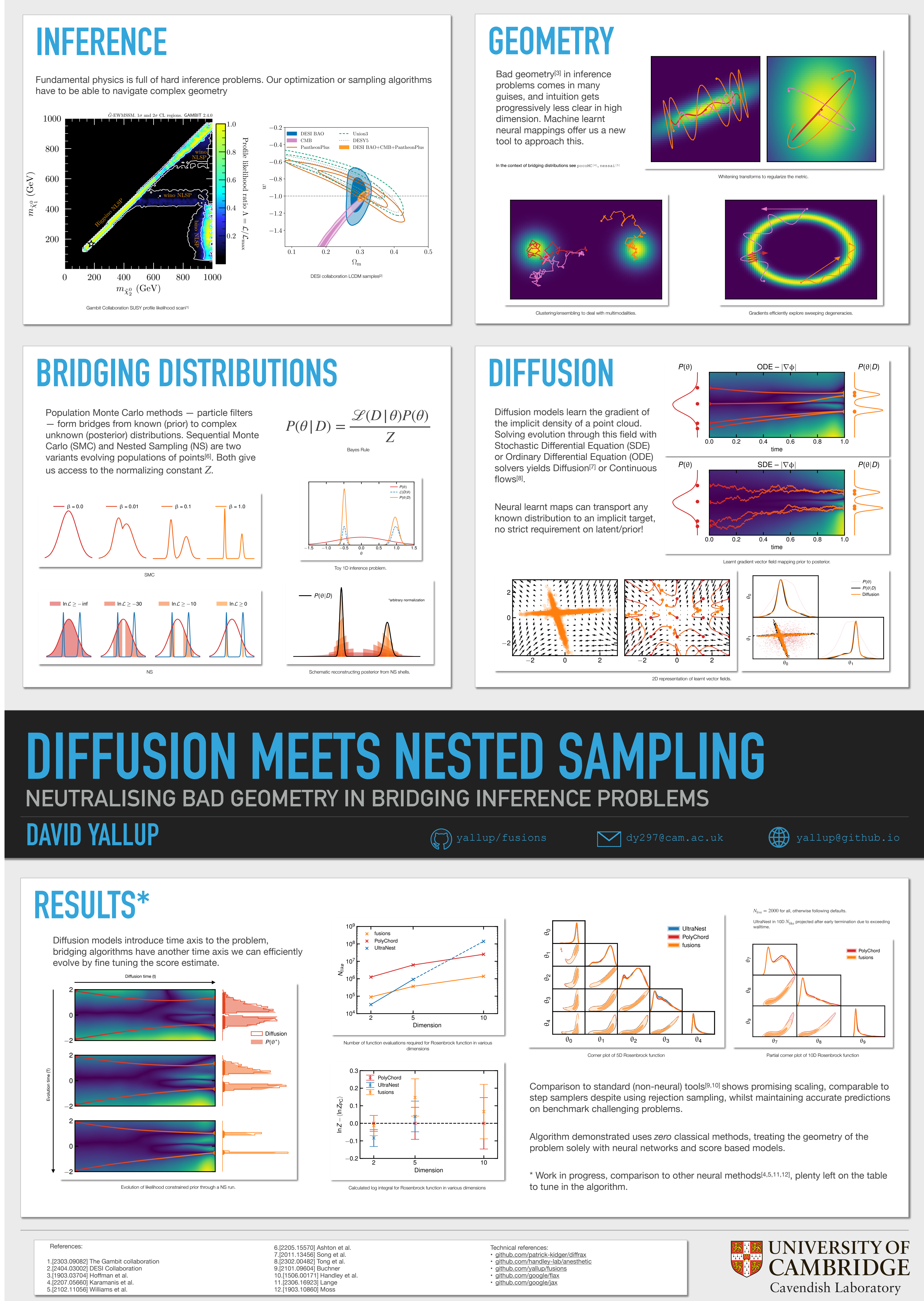


fusions

Can we bring the latest developments in score based generative modelling to a nested sampling paradigm?



Evolution of likelihood constrained prior through a NS run.



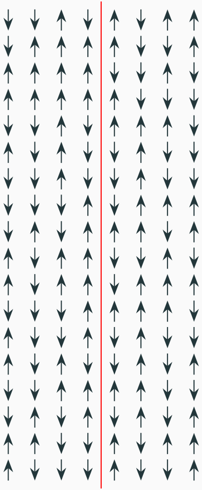
Calculating entanglement entropy with generative neural networks

Dawid Zapolski, Piotr Białas, Piotr Korcyl,
Tomasz Stebel, Mateusz Winiarski
Jagiellonian University in Kraków

Calculating entanglement entropy with generative neural networks

Quantum 1D Ising

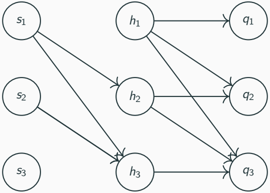
$S_n(A) = \frac{1}{1-n} \log \mathrm{Tr}\, \rho_A^n$



Classical 2D Ising

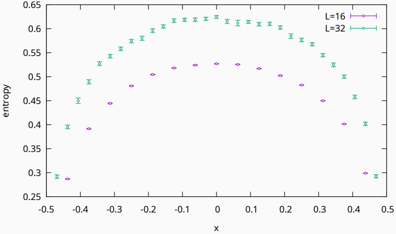
Calculating entanglement entropy with generative neural networks

Autoregressive neural network



$$q_\theta(\mathbf{s}) = \prod_{i=1}^{N} q_\theta\left(s_i | s_1, \ldots, s_{i-1}\right)$$

Entropy as a function of the subsystem size



National Science Centre Poland