Choose your Diffusion

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

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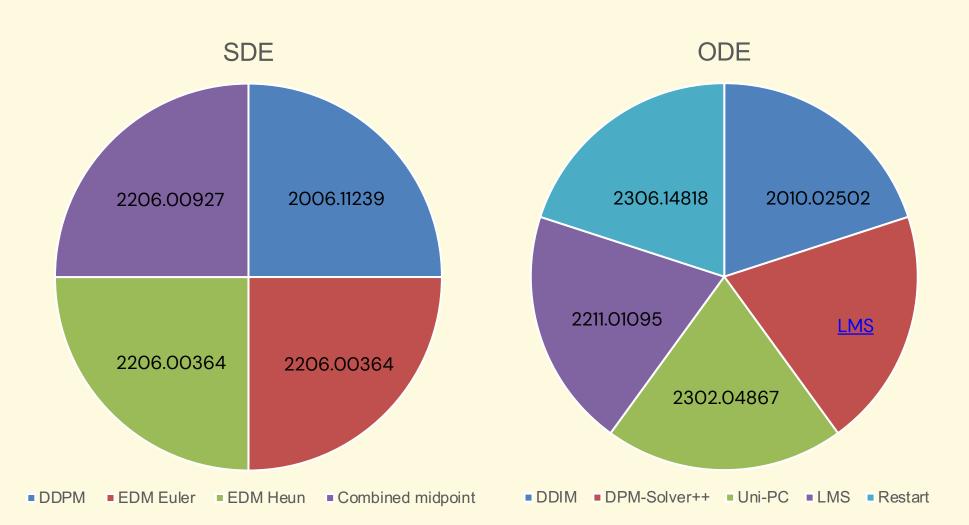


Motivation

- 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)

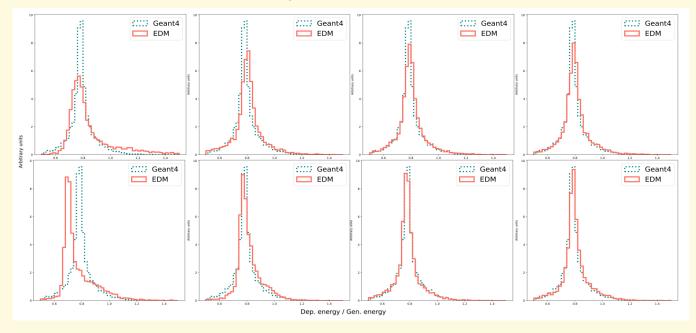


Forward process (faster divergence):

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

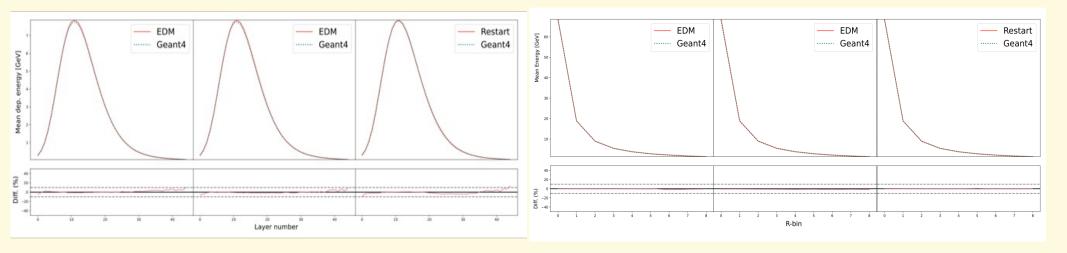
$$\mathcal{L} = \mathbb{E}_{t,\varepsilon}[w(t)||F(c_{in}x_t,t) - \frac{1}{c_{out}}(x_0 - c_{skip}x_t)||_{2}^{2}]$$

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



Results & More (Wed Loc #45)

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



Achieve O(10) acceleration with comparable performance for current

0.5

0.5

0.00

Speedup

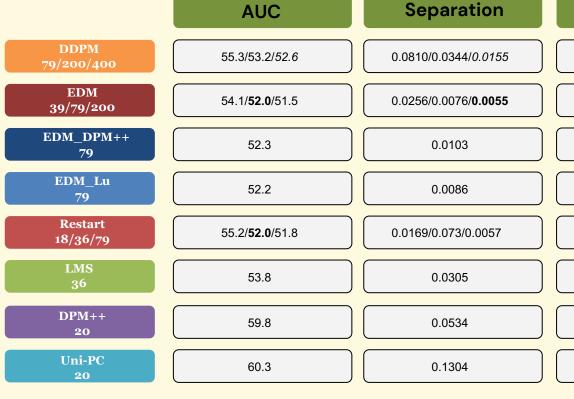
O.00

Speedup

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benchmark models



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

