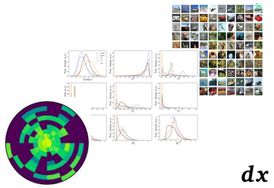
Acceleration of the ML based fast simulation in high energy physics

Cheng Jiang[1] Sitian Qian[2] Huilin Qu[3]

[1]University of Edinburgh [2]Peking University [3]CERN

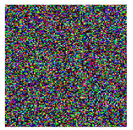
0. Score Matching Generative Models

Sketch line of Score Matching Generative Models: Matching two distributions via score matching



Forward process (sample to noise):

$$dx = f(x,t)dt + g(t)w_t$$

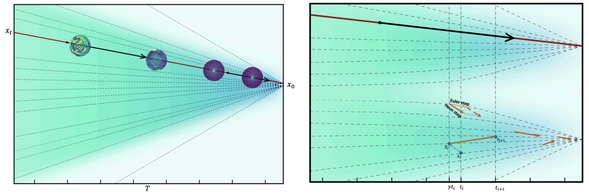


Backward process (noise to sample):

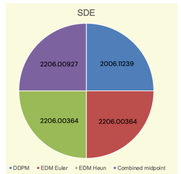
$$dx = [f(x,t) - g(t)^2 \nabla_x \log p_t(x)]dt + g(t)d\tilde{w}$$

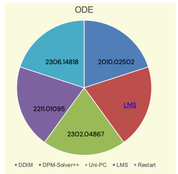
Score Matching Generative Model (CMFs… DMs…) = score estimator (done with NN) && dynamics (sampler and scheduler for ODE/SDE)

Replace the dynamics

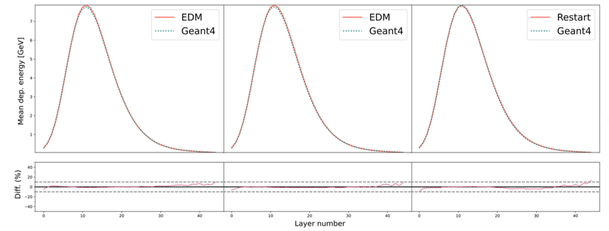


Different ways of modeling dynamics lead to different performance





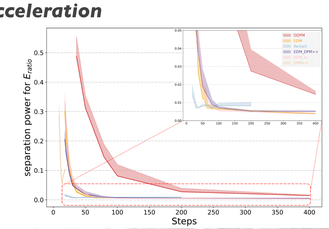
Replace the dynamics, on calorimeter simulation

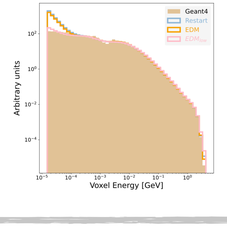


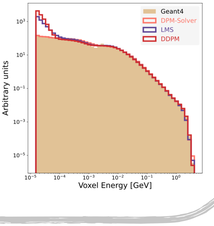
Architect following CaloDiffusion, with listed samplers and schedulers

CaloChallenge Dataset 2

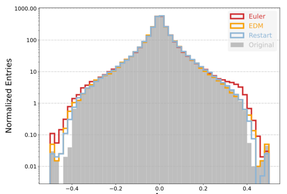
O(10) acceleration

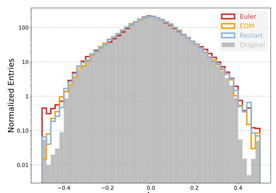






Replace the dynamics, on high level kinematics

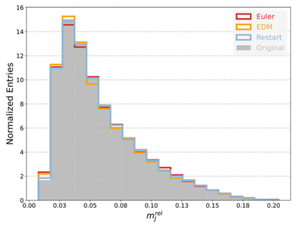


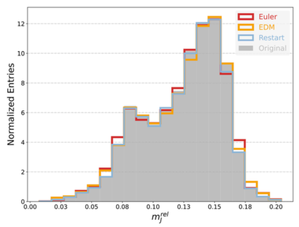


Jedi-net dataset

Left: gluon initiated jet, Right: top initiated jet

Top/Gluon	AUC	FPD
Euler 200	52.6/53.5	0.15/0.19
EDM 50	51.7/51.9	0.05/0.07
Restart 18	51.6	0.04/0.05
Restart_multi 18	51.2	**0.02/0.02**



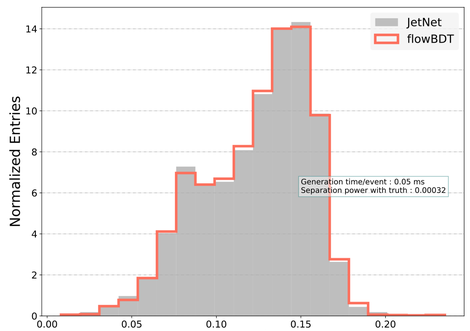


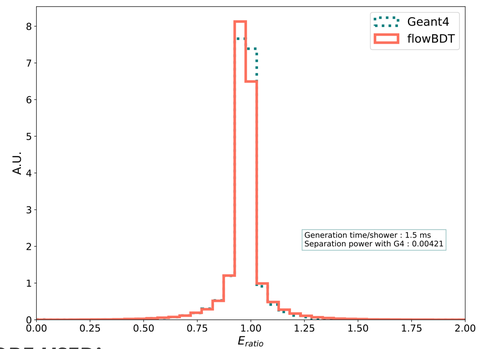
Replace the score estimator, preliminary results

Instant generate for high level kinematics

*Using Boosted Decision Tree (BDT) as the score function estimator for **tabular** data!*

O(ms) generation with calorimeter showers





Time with 1 CPU CORE USED!

5. Information

Sampler & Scheduler

ArXiv: 2401.13162

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‡]

1 School of Physics and Astronomy, University of Edinburgh, EH9 3FD, Edinburgh, United Kingdom
2 School of Physics, Peking University, 100871, Beijing, China
3 CERN, EP Department, CH-1121 Geneva 23, Switzerland

* C.Jiang-19@sms.ed.ac.uk, † sqian@pku.edu.cn, ‡ huilin.qu@cern.ch

Abstract

The diffusion model has demonstrated promising results in image generation, recently becoming mainstream and representing a notable advancement for many generative modeling tasks. Prior applications of the diffusion model for both fast event and detector simulation in high energy physics have shown exceptional performance, providing a viable solution to generate sufficient statistics within a constrained computational budget in preparation for the High Luminosity LHC. However, many of these applications suffer from slow generation with large sampling steps and face challenges in finding the optimal balance between sample quality and speed. The study focuses on the latest benchmark developments in efficient ODE/SDE-based samplers, schedulers, and fast convergence training techniques. We test on the public CaloChallenge and JetNet datasets with the designs implemented on the existing architecture, the performance of the generated classes surpass previous models, achieving significant speedup via various

FlowBDT study: public soon! (2403.xxxxx)