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End-To-End Latent Variational Diffusion Models for Unfolding LHC Events.

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High-energy collisions at the Large Hadron Collider (LHC) provide valuable insights into open questions in particle physics. However, detector effects must be corrected before measurements can be compared to certain theoretical predictions or measurements from other detectors. Methods to solve this inverse problem of mapping detector observations to theoretical quantities of the underlying collision, referred to as unfolding, are essential parts of many physics analyses at the LHC. We investigate and compare various generative deep learning methods for unfolding at parton level. We introduce a novel unified architecture, termed latent variation diffusion models, which combines the latent learning of cutting-edge generative art approaches with an end-to-end variational framework. We demonstrate the effectiveness of this approach for reconstructing global distributions of theoretical kinematic quantities, as well as for ensuring the adherence of the learned posterior distributions to known physics constraints. Our unified approach improves the reconstruction of parton-level kinematics as measured by several distribution-free metrics.

Brainstorming idea [title]

Diffusion Models for Particle-Level Constituent Unfolding

Brainstorming idea [abstract]

Machine-learning powered unfolding has proven effective in estimating low-dimensional quantities like parton-level and particle-level jet kinematics, primarily because the detector-level data offer ample information for approximating these distributions. However, a significant challenge remains in unfolding the jet constituents, largely due to the high-dimensional nature of this problem. We propose exploring transformer architectures to model the variable-length, complex distribution of jet constituents estimated from detector observations. We wish to augment our existing latent variation diffusion model by incorporating attention mechanisms within the diffusion steps, offering a novel approach for high-dimensional variational distribution learning. Despite the promise, several theoretical and practical hurdles must be overcome, including defining how diffusion will operate in a variable-dimensional context and optimizing the learning dynamics for such a high-dimensional problem space.

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