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# Fast collider simulations with graph neural networks.

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There has been significant development recently in generative models for accelerating collider simulations. Work on simulating jets, extremely prevalent at hadron colliders such as the LHC and potentially FCC-hh, has primarily used image-based representations, which tend to be sparse and of limited resolution. We advocate for the more natural 'particle cloud' representation of jets, i.e. as a set of particles in momentum space, and discuss four physics- and computer-vision-inspired metrics: (1) the 1-Wasserstein distance between high- and low-level feature distributions; (2) a new Fréchet ParticleNet Distance; (3) the coverage; and (4) the minimum matching distance as means of quantitatively and holistically evaluating generated particle clouds. We then present our new graph message-passing generative adversarial network (MPGAN), which has excellent performance on gluon, top quark, and lighter quark jets on all metrics, validated against real samples via bootstrapping as well as existing point cloud generative models. We measure a three-orders-of-magnitude improvement in latency as compared to traditional simple Monte Carlo simulations, and anticipate up to five-orders-of-magnitude improvements compared to full detector simulations at current and future colliders. This technique thus shows significant promise for addressing the computational needs of High-Luminosity-LHC and future colliders.

## In-person or Virtual?

In-person

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