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Generative Networks for Simulation and Statistic for Generative Networks

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The rapidly increasing demands of LHC physics pose a major challenge for Monte Carlo simulation. With the High-Luminosity LHC expected to deliver an order of magnitude more data, generating sufficiently large and high-fidelity simulated datasets will become increasingly computationally demanding. Recent developments demonstrate that generative machine learning can provide substantial computational speed-ups while retaining the accuracy required for physics analyses.

However, the potential of generative simulation goes beyond simply replacing an expensive simulation step. Once a generative model is trained on a finite Monte Carlo dataset, it can be sampled arbitrarily many times, raising a fundamental question: how many of these generated events are statistically useful? The concept of generative amplification addresses precisely this question by comparing the statistical power of generated samples with that of the original training data.

I present a framework for quantifying generative amplification without requiring access to large independent holdout samples. Two complementary approaches are introduced: an averaging measure based on phase-space integrals and a differential measure based on hypothesis testing. Applied to generative models for LHC event generation, these methods allow us to identify regions of phase space in which generated samples can provide genuine statistical amplification, as well as regions where model uncertainties limit the effective sample size.

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