



Contribution ID: 23

Type: **not specified**

Chained Quantile Morphing with Normalizing Flows

Discrepancies between real and simulated collider events are a significant source of uncertainty in LHC physics, especially in the context of training machine learning models, where even small differences in input variable distributions can degrade the performance of a simulation-trained model. In this work we present a deep learning implementation of “chained quantile morphing”: a technique to correct Monte Carlo (MC) mis-modeling of data using normalizing flows. A collection of variables is corrected from MC to data using an iterative procedure, which ensures that their single-variable conditional densities match at each step. This approach is able to account for and preserve inter-variable correlations, and minimally shifts values in each sample. While originally conceived to correct MC to match data, the technique can be applied to map between any two distributions. We demonstrate the method using pairs of 2D toy datasets, jet substructure observables from different BSM signals, and events simulated by different MC generators. We also apply it to correct physically meaningful embeddings of collider events in a contrastive space.

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