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Neural Embedding: Learning the Embedding of the Manifold of Physics Data

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There is a growing recent interest in endowing the space of collider events with a metric structure calculated directly in the space of its inputs. For quarks and gluons, the recently developed energy mover's distance has allowed for a quantification of what is different between physical events. However, the large number of particles within jets makes using metrics and interpreting these metrics particularly difficult. In this work, we introduce a flexible framework based on neural embedding to embed a manifold from a jet to lower-dimensional spaces using a defined metric. We demonstrate a low distortion and robust embedding can be achieved with Energy movers distance in two dimensions. Furthermore, we show that we can construct a self-organized space that captures the core physical features of a jet, including the splitting angularity and the number of prongs. Using the notion of volume in the embedded space, we propose the volume-adjusted roc-curve to measure the energy mover's volume that a dedicated jet selection has on the total phase space of jets. Finally, we equate the volume to the inclusivity of a jet kinematic selection and show how this approach can quantify the effectiveness of anomaly searches and measurements in performing unbiased, inclusive measurements.

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