DENSITY ESTIMATION ON LOW-DIMENSIONAL MANIFOLDS: AN INFLATION-DEFLATION APPROACH

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ABSTRACT

Normalizing Flows (NFs) are universal density estimators based on Neuronal Networks. However, this universality is limited: the density's support needs to be diffeomorphic to a Euclidean space. In this paper, we propose a novel method to overcome this limitation without sacrificing the universality. The proposed method inflates the data manifold by adding noise in the normal space, trains a NF on this inflated manifold and, finally, deflates the learned density. Our main result provides sufficient conditions on the manifold and the specific choice of noise under which the corresponding estimator is exact. Crucially, our method scales to high dimensions because it is based on one NF and does not require to compute its inverse. We also show that, if the embedding dimension is much larger than the manifold dimension, noise in the normal space can be well approximated by some Gaussian noise. This allows to use our method for approximating arbitrary densities on non-flat manifolds provided that the manifold dimension is known.