Robust Implicit Networks via Non-Euclidean Contractions

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Abstract

Implicit neural networks, a.k.a., deep equilibrium networks, are a class of implicit-depth learning models where function evaluation is performed by solving a fixed point equation. They generalize classic feedforward models and are equivalent to infinite-depth weight-tied feedforward networks. While implicit models show improved accuracy and significant reduction in memory consumption, they can suffer from ill-posedness and convergence instability.

This paper provides a new framework, which we call Non-Euclidean Monotone Operator Network (NEMON), to design well-posed and robust implicit neural networks based upon contraction theory for the non-Euclidean norm ℓ_∞. Our