IMPROVING INVERSE PROBLEM SOLVERS BASED ON GEOMETRIC UNDERSTANDING OF DIFFUSION GENERATIVE MODELS

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ABSTRACT

Recently, diffusion generative models (DGMs) show surprising results in generative models in terms of sample diversity and quality. In light of this, approaches for solving inverse problems using DGMs are suggested. The majority of current approaches, however, rely on naive projection onto convex set[1] and do not examine DGMs themselves and ignore the impact of projection method on diffusion sampling path. Our contribution is to propose a novel geometric viewpoint of DGMs that can derive a correction term improving conventional inverse problem solvers. In respect of inverse problems, we draw a new picture of DGM-solvers of inverse problems and propose a manifold constrained gradient (MCG) term that can mitigate previous methods, based on the understanding of the geometry of DGMs. Specifically, we argue that when the data lies in a low-dimensional structure, the set of data with intermediate noise is the interpolating manifold between the data manifold and the hypersphere of pure noise. Moreover, we reveal why conventional methods are prone to inference errors in the sense of manifolds and show how MCG term can reduce the inference errors. Our new method with MCG can respect the geometry of DGMs and can be used to solve diverse inverse problems.[2]

REFERENCES

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