Probabilistic Mapping of Dark Matter by Neural Score Matching

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Abstract

We present a novel methodology to address many ill-posed inverse problems, by providing a description of the posterior distribution, which enables us to get point estimate solutions and to quantify their associated uncertainties. Our approach combines Neural Score Matching for learning a prior distribution from physical simulations, and a novel posterior sampling method based on an Ordinary Differential Equation solver to sample the full high-dimensional posterior of our problem.
In the astrophysical problem we address, by measuring the lensing effect on a large number of galaxies, it is possible to reconstruct maps of the Dark Matter distribution on the sky. But because of missing data and noise dominated measurement, the recovery of dark matter maps constitutes a challenging ill-posed inverse problem.

We propose to reformulate the problem in a Bayesian framework, where the target becomes the posterior distribution of mass given the galaxies shape observations. The likelihood factor, describing how light-rays are bent by gravity, how measurements are affected by noise, and accounting for missing observational data, is fully described by a physical model. Besides, the prior factor is learned over cosmological simulations using a recent class of Deep Generative Models based on Neural Score Matching and takes into account theoretical knowledge. We are thus able to obtain samples from the full Bayesian posterior of the problem and can provide Dark Matter map reconstruction alongside uncertainty quantifications.

We present an application of this methodology to the reconstruction of the HST/ACS COSMOS field and yield the highest quality convergence map of this field to date. We find the proposed approach to be superior to previous algorithms, scalable, providing uncertainties, using a fully non-Gaussian prior and promising for future weak lensing surveys (Euclid,

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Slides: in PDF

Video: https://youtu.be/uiAHV1SxNLc