



Cosmological **Reconstruction from** LSS Observables: Neural Network based Light-Matter Connection

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arXiv: **1805.02247** With Uros Seljak, Yu Feng Sexten, July 3, 2018 Theoretical challenges for precision galaxy clustering

Motivation

Aim:

Reconstruct initial, Gaussian matter field (**s**) given the nonlinear observed field (**d** = proxy: halo mass field)

Power spectrum is the summary statistic for Gaussian fields

Multiple statistics to extract information from observed nonlinear field, that are suboptimal and hard to combine



Forward Modeling & Bayesian Reconstruction

$$\mathcal{L}(s) = [d - \mathcal{F}(s)]^\dagger N^{-1} [d - \mathcal{F}(s)] + s^\dagger S^{-1} s$$

Residual Term

Prior Term

3

High dimensional optimization (simulation size > 2 million) Need **Gradients** of forward models



Neural Network Model for Observables

Aim: Given final matter density field, generate a field of the discrete observables (proxy: dark matter halos)

2 step procedure:

- 1. We need position of halos-*Classification network* ~6000 weights
- 2. We need value of observable -Regression network ~500 weights

Train to match the halo mass field upto a predefined number density



Fully connected neural networks

Model overview

Features:

- Smoothed densities at different scales & their difference
- Non-local: densities from neighbouring points



Take product of both the predicted fields (i.e. outputs of the network)

Position Prediction







Mass Prediction







Model = NNp x NNm



Empty points are either zero or exponentially suppressed, thus maintaining discreteness along with differentiability

Neural Network Performance

Final Matter Field



True Data Field



Neural Network Prediction



Modeling Error & Loss Function

Estimated for log of smoothed mass fields

Functional Form :

$$ln(M^m_R+M_0)-ln(M^d_R+M_0)$$

Displaced **log-normal pdf** is a good fit for the noise-model



$$\mathcal{L}(s) = \frac{1}{2}sS^{-1}s^{\dagger} + \sum_{i} \left(\frac{\mu_{\mathrm{N}} + \log(\mathrm{M}_{\mathrm{R},i}^{\mathrm{NN}} + \mathrm{M}_{0}) - \log(\mathrm{M}_{\mathrm{R},i}^{\mathrm{FOF}} + \mathrm{M}_{0})}{2\sigma_{\mathrm{N}}}\right)^{2} \times \mathrm{f}_{\mathrm{eff}}.$$

Initialize

Data



Initial Matter Field



Final Matter Field

Halo Mass Field





Data



Initial Matter Field



Final Matter Field

Halo Mass Field





Standard Reconstruction

1.0





Gain in Fisher information content for BAO over standard reconstruction - ~15-20% (in real space, at z=0, unweighted standard reconstruction)

Model in Redshift Space

Reconstructed dark matter velocity field at halo position is quite close to the true center-of-mass halo velocity



Approach:

Use the dark-matter velocity field to move the predicted real-space mass grid along the line of sight

Reconstruction with halos in redshift space



Significant improvement along the line of sight

Standard BAO reconstruction



~30-60% improvement perpendicular to LOS, ~factor of 2-3 along the LOS

Summary & Prospects

- A novel approach using neural networks to model observables (proxy: halo mass field) from final matter density field
- Bayesian reconstruction of initial matter field from halo mass field using neural network model
- Reconstruction of dark matter velocity field at halo positions to model redshift space
- ~15-30% improvement over standard reconstruction (without any weighting) at z=0 in real space
- From redshift space, ~30-60% improvement perpendicular to LOS, ~factor of 2-3 along the LOS
- Take into account galaxies (centrals & satellites), scatter in halo mass & stellar mass, survey geometry and other systematics

Thank You