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Simulation-driven clustering analysis with an eye on future J-PAS data and large galaxy surveys

In the era of precision cosmology, large-scale structure analyses are essential for understanding the fundamental components that describe the distribution of galaxies. The J-PAS (Javalambre Physics of the Accelerating Universe Astrophysical Survey) is a promising galaxy survey designed to precisely measure photometric redshifts for galaxies up to z~1. Its redshift accuracy will not only allow for the identification of individual galaxies but also enable the mapping of large-scale cosmic structures. These accurate measurements of galaxy clustering will facilitate detailed comparisons with theoretical predictions and enable precise measurements of Baryon Acoustic Oscillations (BAOs). This, in turn, will allow for a more accurate description of the redshift power spectrum, which is crucial for constraining cosmological parameters like the growth factor and the background cosmology, both of which are fundamental for testing theories of gravity. Mock catalogues are indispensable in galaxy surveys as they provide realistic models of the universe, helping to interpret observational data, test methodologies, and evaluate uncertainties. Cosmological analysis of the large-scale structure demands exploiting the nonlinear information encoded in the cosmic web. Machine Learning techniques provide such tools, however, do not provide a priori assessment of uncertainties. This study aims at extracting cosmological parameters from modified gravity simulations through deep neural networks endowed with uncertainty estimations. We implement Bayesian neural networks (BNNs) with an enriched approximate posterior distribution considering two cases: one with a single Bayesian last layer, and another one with Bayesian layers at all levels. We train both BNNs with density fields and power-spectra from a suite of 2000 N-body simulations including modified gravity models. BNNs excel in accurately predicting parameters for Ωm and σ8 and their respective correlation with the MG parameter. We find out that BNNs yield well-calibrated uncertainty estimates overcoming the over- and under-estimation issues in traditional neural networks. We observe that the presence of MG parameter leads to a significant degeneracy with σ8 being one of the possible explanations of the poor MG predictions. Ignoring MG, we obtain a deviation of the relative errors in Ωm and σ8 by at least 30%.

Nivel de formación

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