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Next generation cosmological analysis with a re-usable library of machine learning emulators across a variety of cosmological models and datasets

In recent years, disparities have emerged within the context of the concordance model regarding the estimated value of the Hubble constant H_0 [1907.10625] using Cosmic Microwave Background (CMB) and Supernovae data (commonly referred to as the Hubble tension), the clustering σ_8 [1610.04606] using CMB and weak lensing, and the curvature Ω_K [1908.09139, 1911.02087] using CMB and lensing/BAO, and between CMB datasets. The study of these discrepancies between different observed datasets, which are predicted to be in agreement theoretically by a cosmological model, is called tension quantification.
We approach this problem by producing a re-usable library of machine learning emulators across a grid of cosmological models through detecting cosmological tensions between datasets from the DiRAC allocation (DP192). This library will be released at this conference as part of the pip-installable package unimpeded (https://github.com/handley-lab/unimpeded) and serve as an analogous grid to the Planck Legacy Archive (PLA), but machine learning enhanced and expanded to enable not only parameter estimation (currently available with the MCMC chains on PLA), but also allowing cosmological model comparison and tension quantification. These are implemented with piecewise normalising flows [2305.02930] as part of the package margarine [2205.12841], though alternative density estimation methods can be used. The combination of nested sampling and density estimation allows us to obtain the same posterior distributions as one would have found from a full nested sampling run over all nuisance parameters, but many orders of magnitude faster. This allows users to use the existing results of cosmological analyses without the need to re-run on supercomputers. Currently, a systematic coverage of nine cosmological models and 30 datasets (to be extended) are easily accessible via the unimpeded package using a few lines of code. Hyperparameter tuning for cosmological normalising flows are explored across a grid of datasets and models with different combinations of architecture (number of hidden layers), learning rate/scheduling and activation function (e.g. sigmoid, tanh and ReLU) for the best performance.

We believe this work represents a significant step forward in cosmological data analysis, providing a versatile, efficient, and user-friendly platform to address current observational tensions and advance our understanding of the Universe.

AI keywords

anomaly detection, emulators, neural network, normalising flow, machine learning enhanced bayesian statistics

Primary author: ONG, Dily Duan Yi (University of Cambridge)

Co-authors: BEVINS, Harry (University of Cambridge); HANDLEY, Will

Presenter: ONG, Dily Duan Yi (University of Cambridge)

Track Classification: Simulations & Generative Models