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New Physics with Neural Networks

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Introduction

In this project, I developed upon *BaCoN* [1, 3], a Bayesian, convolutional neural network which classifies observations of the density distribution of the Universe into which cosmological theory they most closely align with.

The standard model of modern cosmology is ΛCDM, which posits complete agreement with General Relativity through the introduction of dark matter and dark energy. BaCoN was designed to estimate the confidence that observations resulted from ΛCDM or the competing DGP, $f(R)$ or wCDM theories. It is designed to be used on vast, high resolution datasets expected from Stage-IV cosmological studies.

My work on BaCoN focused on making it more scalable, so it can leverage Stage–IV data; including the dark matter – dark energy scattering mechanism in its data and making it better at detecting unseen physics.

Background

ΛCDM demonstrates excellent agreement with most, but not all cosmological observations. Furthermore, dark energy and dark matter elude direct observation. The competing theories originally included in BaCoN are DGP, which introduces additional spatial dimensions; $f(R)$, which modifies GR formalism and wCDM, which models evolving dark energy. Each leaves a distinct fingerprint on the *power spectrum*, which measures the Universe's density distribution statistically.

The power spectrum is given by

$$P(k, z) = \left\langle \left|\delta_{\vec{k}}(z)\right|^2 \right\rangle ,$$

where $\delta_{\vec{k}}$ are the modes of the Fourier transform of the *density perturbation field* – the fractional deviation over position and time of Universe's density from its mean. Here, we are averaging over all spatial orientations of $\vec{k}$, and z is the redshift.

Objectives & Methods

Reduce Training Times: BaCoN models previously took days to train. I improved upon this by redeveloping their data pipeline to use native data handling for Tensorflow, the Python library in which BaCoN is built. This offers various computational optimisations, including *mapping*, *caching* and *prefetching*.

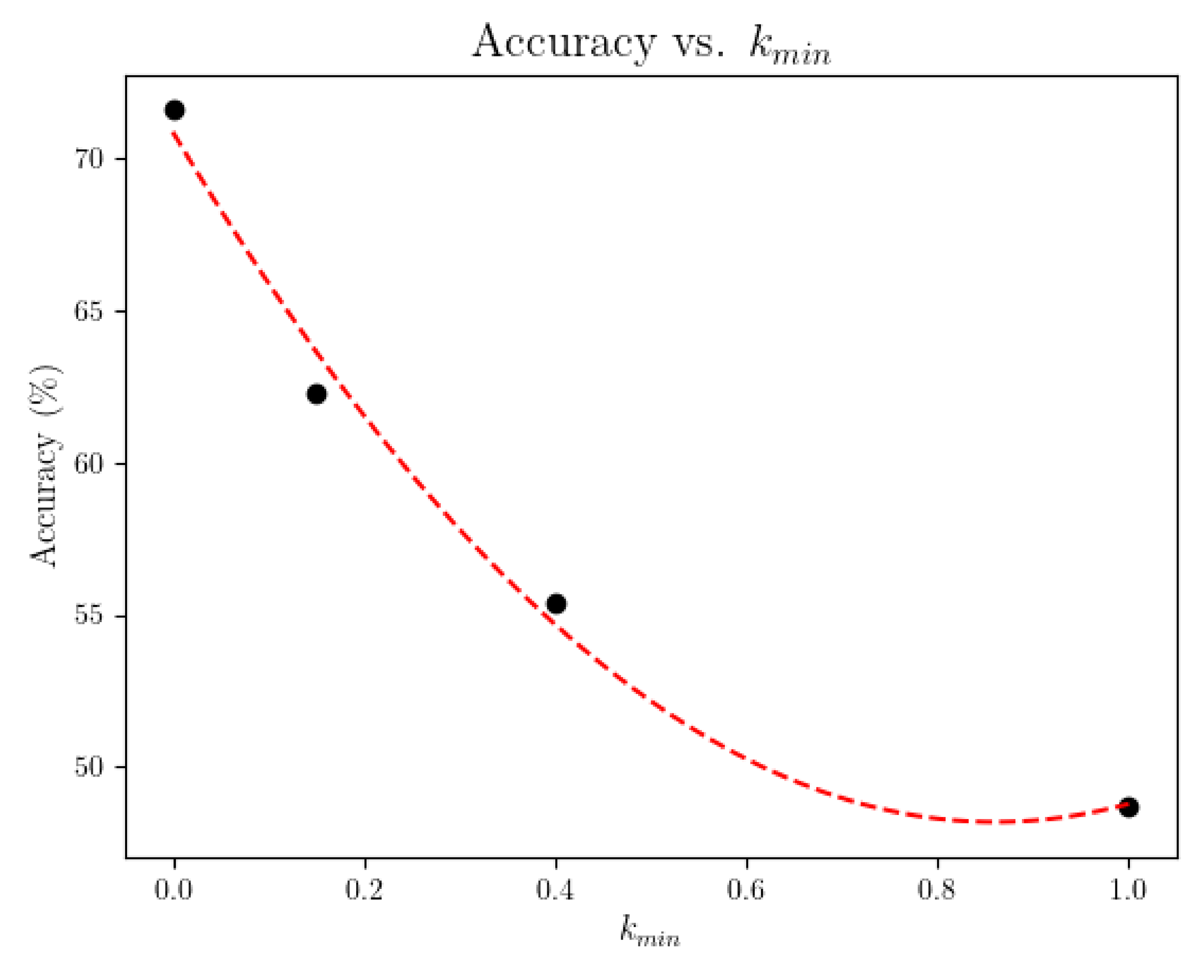
Incorporate Dark Scattering: Simpson [2] presented a mechanism for dark matter – dark energy scattering as an extension to the wCDM model. After including this theory, I investigated the accuracy impact of varying the included length scales k and dark scattering strengths ξ in the data.

Better 'Random' Spectra: BaCoN is trained on a set of 'random' spectra to detect physics beyond the set of included theories. These should represent all sources of unseen physics. In [3], these are generated by filtering ΛCDM spectra, and in [1] by filtering random spectra from all theories. I argue that filtering an equal number from all theories could be more physically representative.

References

1. Mancarella, M., Kennedy, J., Bose, B. & Lombriser, L. Seeking new physics in cosmology with Bayesian neural networks. *Physical Review D.* **105.** 2. 2022. doi:10.1103/PhysRevD.105.023531.
2. Simpson, F. Scattering of dark matter and dark energy. *Physical Review D.* **82.** 8. 2010. doi:10.1103/physrevd.82.083505.
3. Thummel, L., Bose, B., Pourtsidou, A. & Lombriser, L. Beyond-ΛCDM Cosmologies with Bayesian Neural Networks II. *ArXiv.* 2024. doi:10.48550/arXiv.2403.16949.

Results



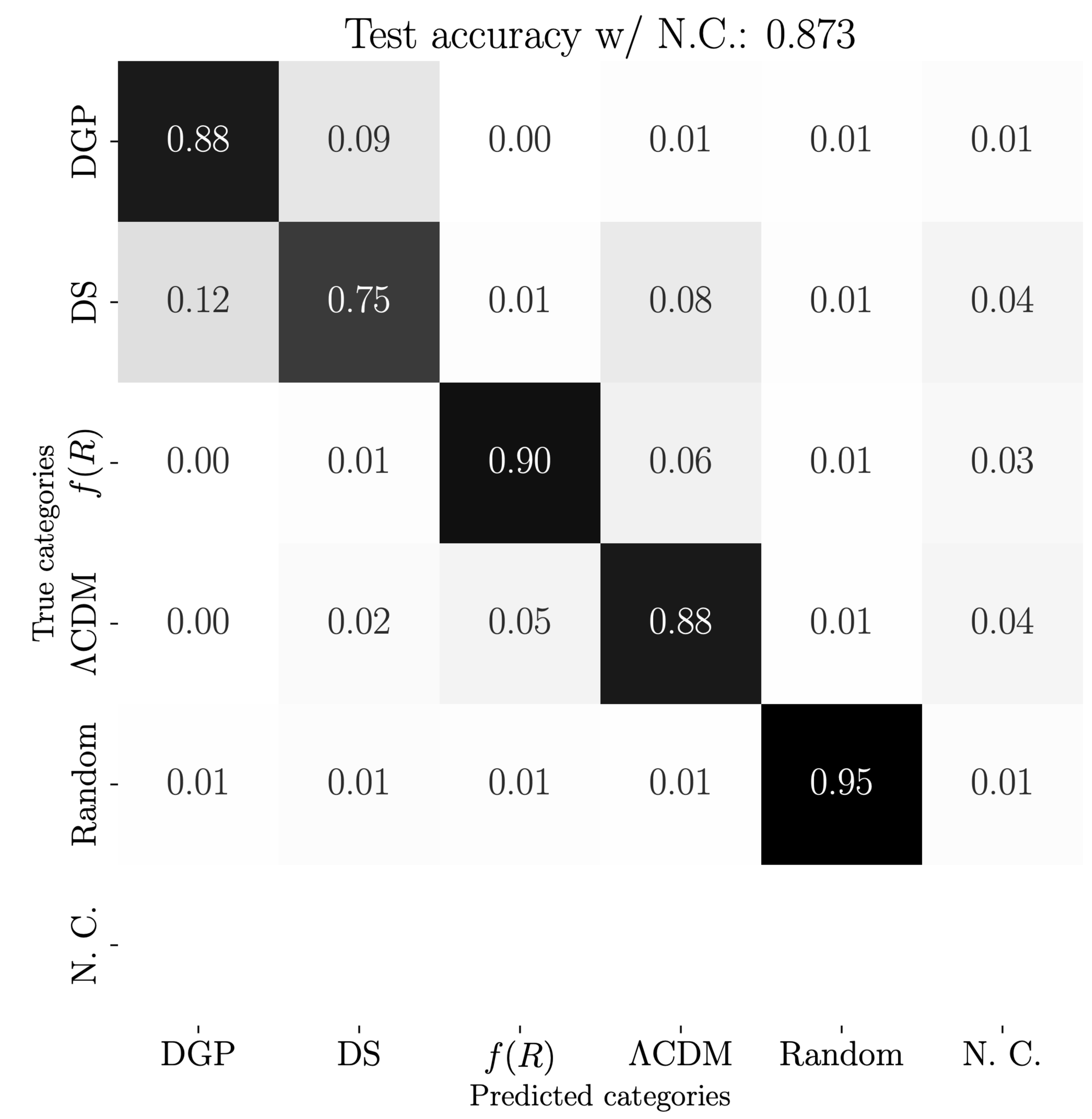
Dark Scattering as a Separate Theory: Including DS as a sixth theory resulted in poor accuracy – only 74.2%, with 41% of Dark Scattering and 52% of wCDM examples classified correctly.

Varying Physical Parameters: The top left figure demonstrates a steep accuracy loss when the longest (lowest k) scales are cut. Binning the ξ values included in the data had little effect; the bin with the highest values resulted in an accuracy of only 71.5%.

New Five-Class Model: Noting the degeneracy between DS and wCDM, I trained a model without wCDM. The *confusion matrix* for this model is shown in the bottom right, with 87.3% accuracy. Like wCDM spectra were, DS spectra were often confused for DGP or ΛCDM spectra, and vice-versa.

New Data Pipeline: Training time of the BaCoN models reduced ~30x, from a matter of days to a matter of hours, when trained using the same data and settings as in [3]. I was able to train models with a resolution 4× higher without a significant increase in training time. However, I noted a ~6% drop in accuracy. I decided to continue using this pipeline in my models.

New Random Class: The modified 'random' spectra prescription resulted in a insignificant 1% drop in accuracy. Given its potential for better representing unseen physics, I continued using my updated method in my models.



Conclusions and Future Work

New Data Pipeline: The dramatic reduction in training time will be particularly beneficial considering that BaCoN was designed for use on vast, high resolution datasets of upcoming Stage–IV survey data. The drop in accuracy is unusual, especially given that I confirmed that the spectra generated by the new pipeline match the form found in [3]. It is likely that this would be resolved by optimising the models' *hyperparameters*.

Model Performance: The new 'random' spectra are viable as they sustained accuracy. The accuracy drop when low-k modes are cut implies the models extract the most relevant information from these scales, despite being where wCDM and DS overlap most [2]. This could imply issues in BaCoN's noise model at shorter scales. Given the lack of improvement when using the highest ξ bin, combining wCDM and DS may be worthwhile, as a model with only DS gave moderate accuracy.