Physics-Informed Deep Learning in Astrophysics

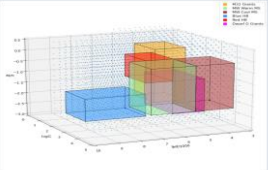
Viska Wei
Laszlo Dobos
Carrie Filion
Tamas Budavari
Rosemary Wyse
Alex Szalay

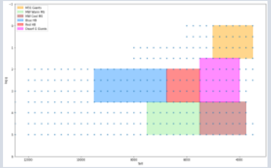
We developed a physics-informed hierarchical scheme to estimate astrophysical parameters from stellar spectra.

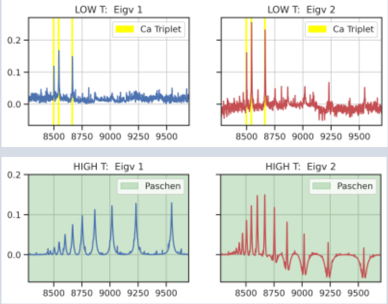
The PFS Project

The world-wide astronomical community is undertaking a series of comprehensive surveys using this new wide-field telescope, imaging cameras, and software pipelines, with scientific goals that include the structure of our Milky Way Galaxy; the evolution of galaxies; and the distribution and properties of dark matter. One of the great challenges of designing the survey to address these questions is determining exactly which astronomical objects should be observed in detail and how long each should be exposed. As the telescope costs $100k to operate per night, we must carefully select the 500k objects out of billions to target. Our research is to develop deep learning algorithms that optimize this target selection with insights from physics, statistics, data science and AI.

Partitioning Parameter Space:
We subdivide the grid of stellar models for our targets into 6 distinct boxes in Teff, log g and [M/H].

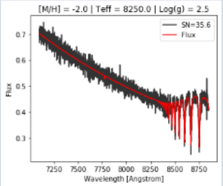


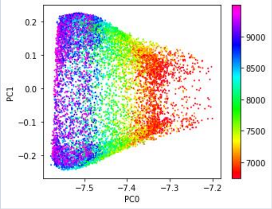




Interpolation of the Spectra:
In each box we build a separate PCA basis for the spectra. Use them to build get interpolated spectra at any parameter value.

Simulate Observations:
We create realistic simulated observations of our targets, including variable S/N. We generate a large training set from these.





Resampling the Spectra:
We resample the spectra to low resolutions (1pixel=300km/s) and build a lo-rez PCA basis for 3D parameter estimation.

INTRODUCTION

Modern machine learning is becoming increasingly important in science. Machine learning, in particular Deep Learning is emerging as a promising way to overcome this barrier. In science we need to understand and estimate the statistical significance of our derived results, and there is skepticism towards 'black-box' techniques. For data with large dimensions, the networks can get quite large, making training slow and cumbersome. As a result, serious attention is being given to Physics Informed Machine Learning – how we can use prior knowledge about underlying symmetries, geometric and physical properties of the data to simplify network design.

Box Definition → Box Spectra Generator → Downsample to ignore redshift → PCA → Noise Realization → DNN

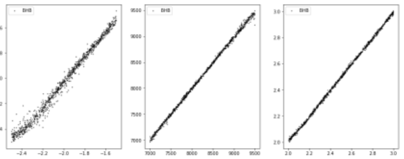
RESULTS

We have successfully demonstrated that we can clearly subdivide stellar spectra into distinct boxes based upon their physical parameters, using Deep Learning. Using a sparse embedding through Principal Component Pursuit as a preprocessor to DNNs, we can perform locally optimized analyses of the physical parameters of the stars, enabling smaller networks and higher accuracy. We have demonstrated that we can obtain satisfactory separations in parameter space for different types of stellar targets.

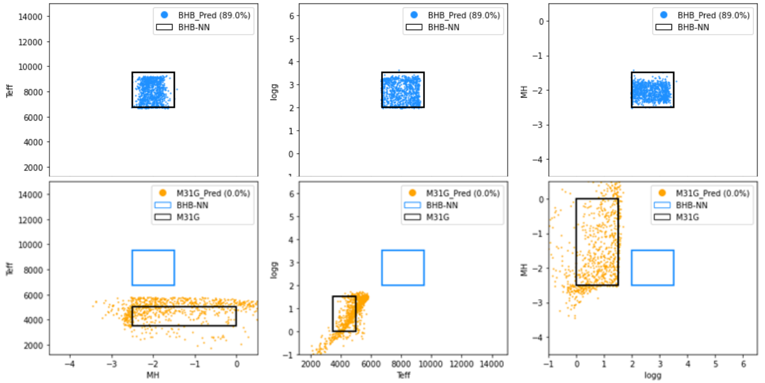
CONCLUSION

The hierarchical scheme not only reduces the complexity of recovering the embedded structure but also reduces computational cost and hardware requirements for the training. More importantly, the optimal sparsification scheme will increase the signal to noise in the data and improve the performance of inference and learning. We will also be able to estimate the uncertainties of the NN predictions with a confirmatory likelihood analysis.

Training Neural Nets:
Expand the training spectra on the PCA basis and use this to train a Deep Learning network to estimate all 3 main parameters.

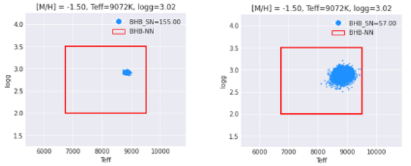


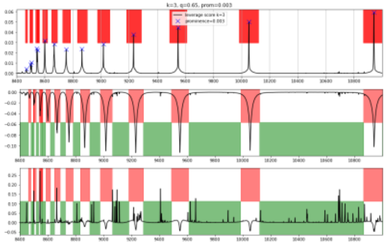
Use the NN as Discriminator:
The DNN trained on one box not only predicts membership correctly, but also provides a clean separation of spectra in distinct boxes as shown below. The top row shows the parameter predictions of randomly sampled noisy spectra within the same box (Blue horizontal Branch) while the bottom shows the predictions of different box spectra (M31 Giants).

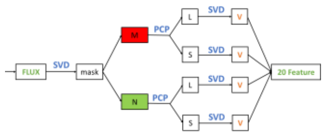


Estimating errors:

The estimation error grows with lower S/N, but the localization is still excellent.

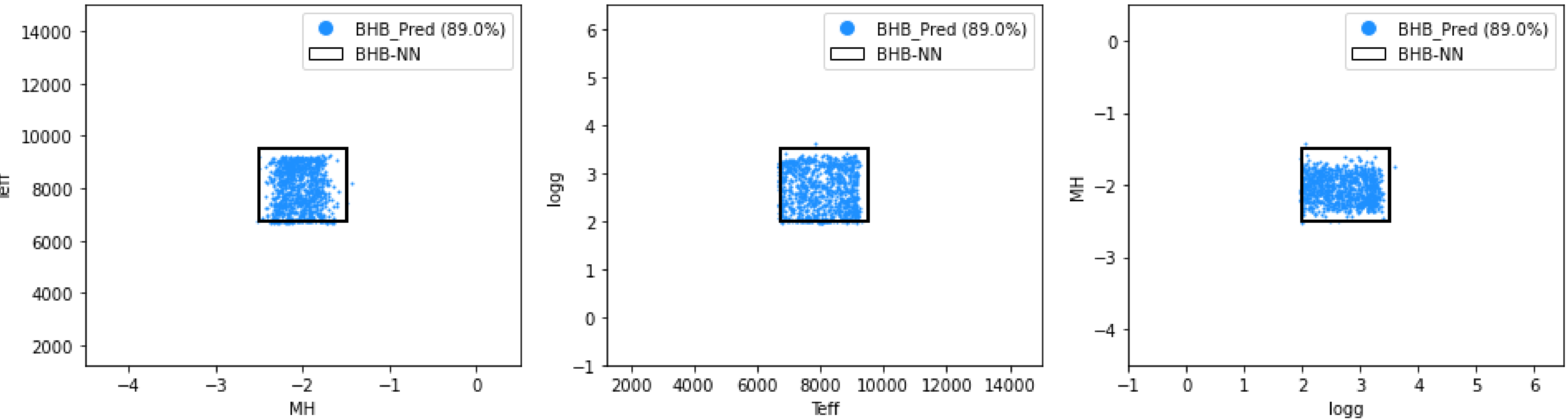






Next:
Using instrumental resolution models, in each box we will

- Use Principal Component Pursuit to build masked, sparse PCA templates
- Use log likelihood, measure the precise radial velocity
- Extract PCA coefficients in the rest frame
- Use a neural net to estimate precise physical parameters



BHB_Pred (89.0%)
BHB-NN
Teff
MH
logg
Teff
MH
logg