Deriving Spectral Abundances in DESI with Machine Learning

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Abstract

Chemo-dynamics is an integral component of stellar archeology, granting us the opportunity to trace the evolution of our home galaxy. While the Gaia mission supplies the radial velocities, parallaxes, proper motions, and positions of almost 2 billion stars[1], we still lack high-resolution abundances for large populations of stars. To remedy this, our project's goal is to derive stellar abundances from spectra collected by the Dark Energy Spectroscopic Instrument (DESI), which has mapped more than 6 million stars[2], using a neural network trained with Apache Point Observatory Galactic Evolution Experiment (APOGEE)[3,4] targets from a DESI and APOGEE cross match. **The predicted metallicities from our network were notably more accurate with respect to APOGEE than metallicities given by DESI's stellar parameters (SP) pipeline.**

Data

The data utilized in our neural network training was obtained by cross matching internal DESI data with APOGEE Data Release 17[5, 6]. We then removed targets with signal to noise ratios less than 50, masked abundance errors, etc. Note that not all data from DESI's most recent data release has been process by the SP pipeline. The fluxes were continuum normalized, with unphysically big fluxes masked out; the final data set size is 8384.

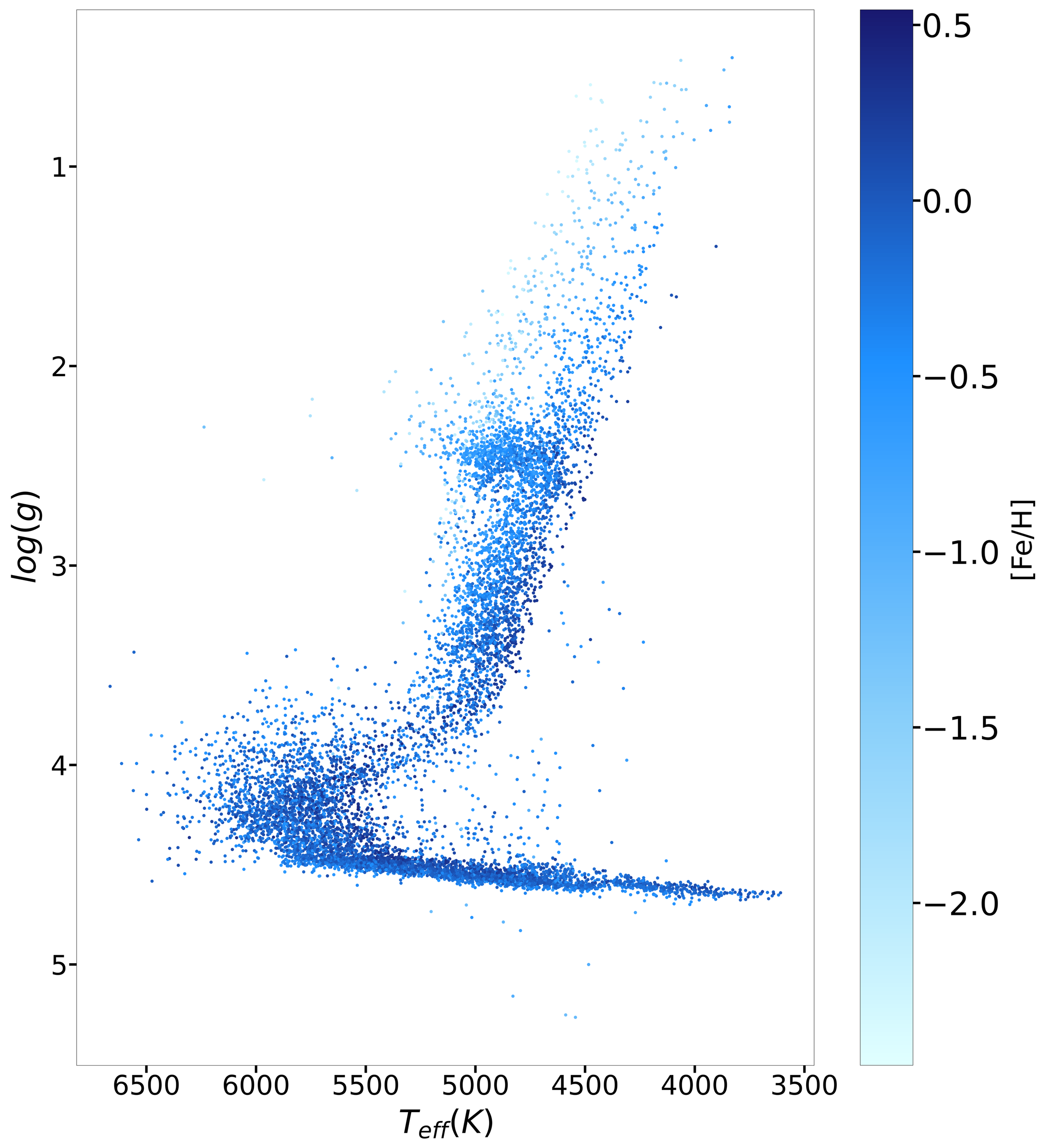

Fig. 1 log(g) vs T_{eff} of cross-matched targets colored by metallicity

Methods

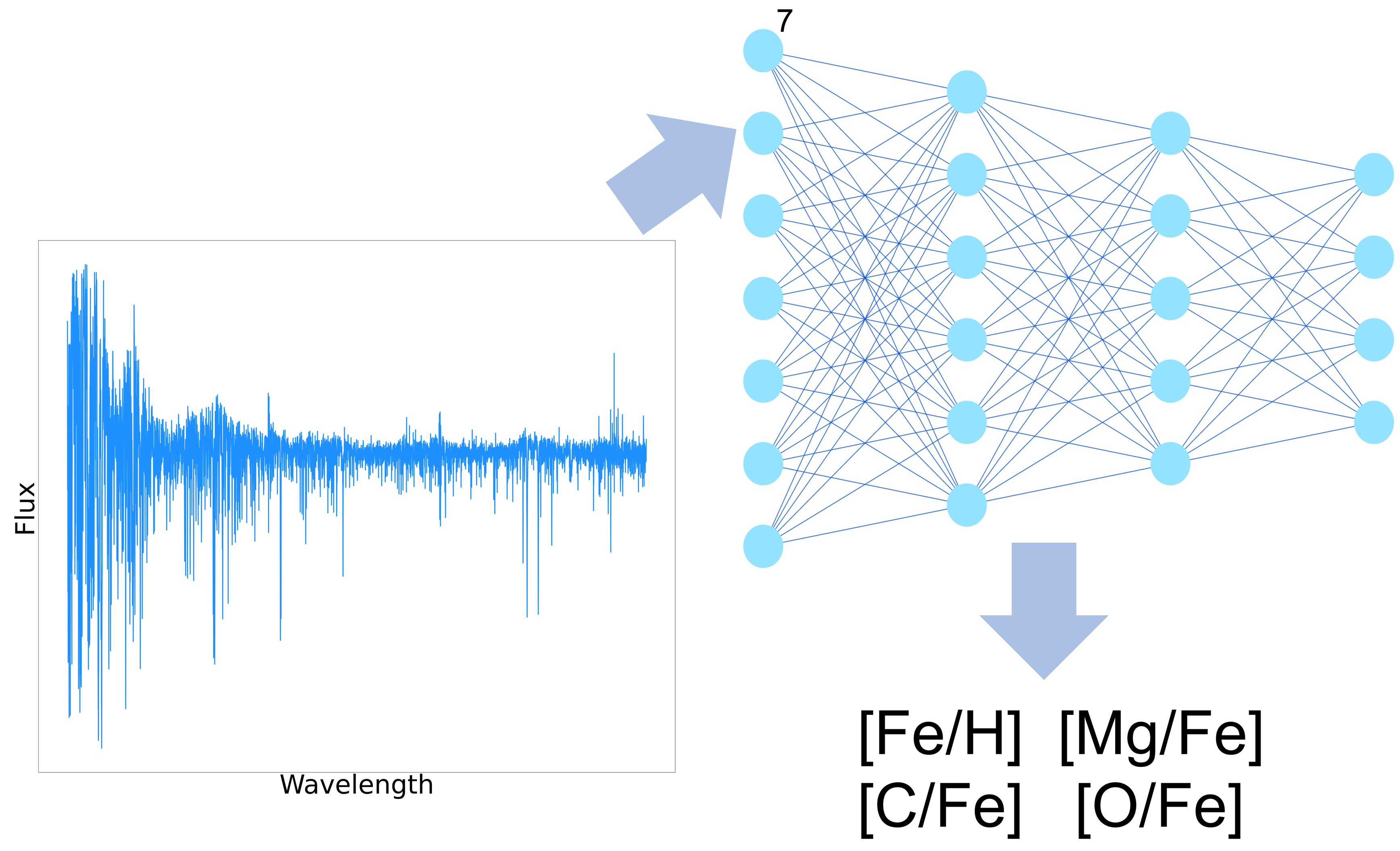

Fig. 2 Schematic of methods

We defined a fully connected neural network with 4 hidden layers and a custom χ^2 loss function (Eq. 1) using PyTorch[8].

$$\frac{1}{m}\frac{1}{n}\Sigma_{i=1}^{n}\Sigma_{j=1}^{m}\frac{\left([X/H]_{target\ i,\ j}-[X/H]_{pred\ i,\ j}\right)^2}{\sigma^2_{[X/H]\ i,\ j}}$$

Eq. 1

The purpose of a χ^2 loss function is to allow our network to favor targets with smaller uncertainties during training.

Results

After 200 epochs of training, we obtained a best χ^2 loss of 12.40 on the test set, which implies our residuals are around 3.5 times the measurement error from APOGEE. This demonstrates the intrinsic precision limitations of DESI, something our network cannot overcome.

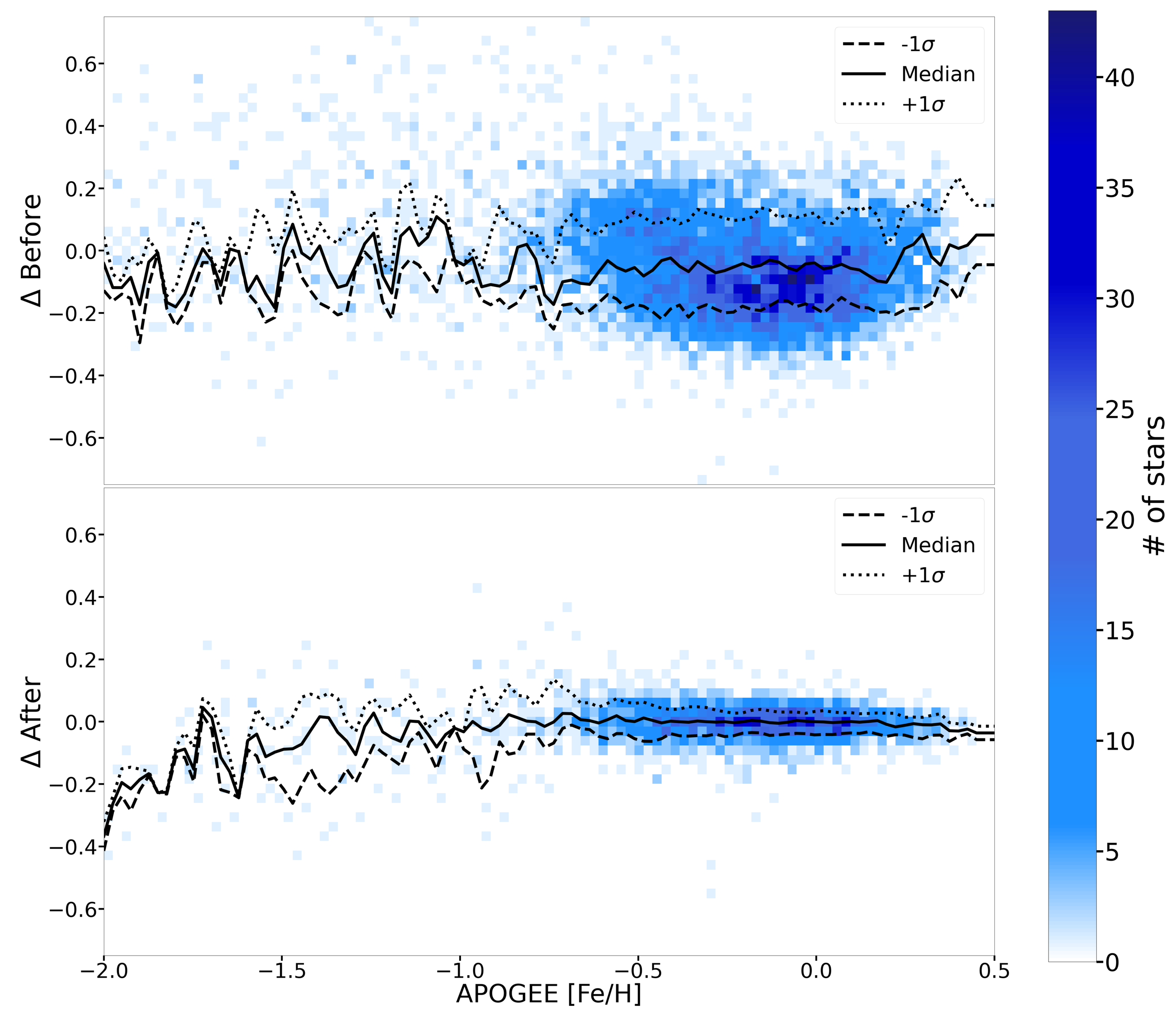

Fig. 3 2D residuals histograms of DESI radial velocity pipeline (top) and neural network predictions (bottom)

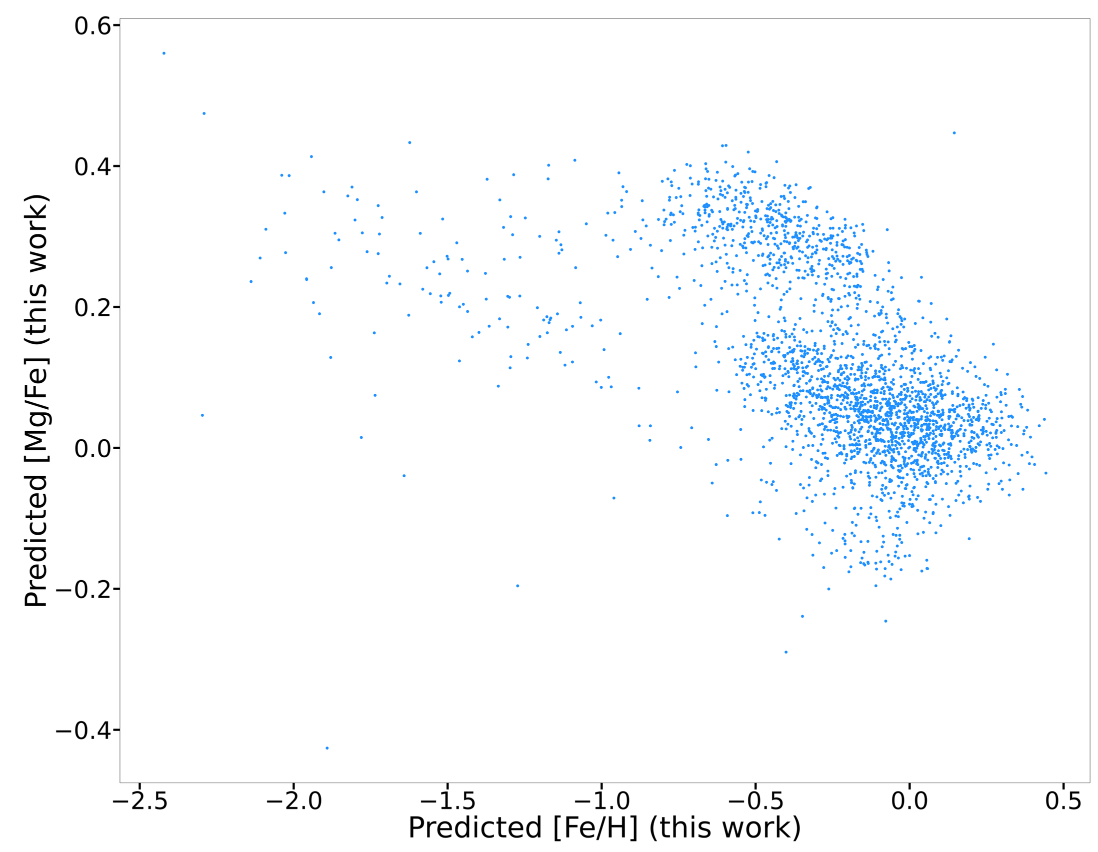

Fig. 4 [Mg/Fe] vs [Fe/H] scatter of neural network predictions

Future Work

- Expand network to predict more stellar abundances
- Run network over all available DESI spectra
- Generate errors with abundance predictions
- Generate baseline predictions using APOGEE abundances

References

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