Analysis of Stellar Spectra from LAMOST DR5 with Generative Spectrum Networks

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Abstract.
We derived the fundamental stellar atmospheric parameters (Teff, log g, [Fe/H] and [Îś/Fe]) of low-resolution spectroscopy from LAMOST DR5 with Generative Spectrum Networks(GSN), which follows the same scheme as a normal ANN with stellar parameters as the inputs and spectrum as outputs. After training on PHOENIX theoretical spectra, the GSN model performed effectively on producing synthetic spectra. Combining with Bayes framework, application in analysis of LAMOST observed spectra become efficient on the Spark platform. Also, we examined and validated the results by comparing with reference parameters of high-resolution surveys and asteroseismic results. Our method is credible with a precision of 130K for Teff, 0.15 dex for log g, 0.13 dex for [Fe/H] and 0.10 dex for [α/Fe].

1. Introduction

Most sky surveys result in extensive databases of stellar spectra for dissecting and understanding the Milky Way. The fundamental information derived from such spectra includes the effective temperature (T_{eff}), logarithm of surface gravity (log g), abundance of metal elements with respect to hydrogen ([Fe/H]), and the abundance of alpha elements with respect to iron ([α/Fe]), are valuable for Galactic archaeology and stellar evolution history. Many projects have been carried out to detect specific objects at high/low resolution covering a range of wavelengths.

In this report, we designed a new structure of artificial neural networks, Generative Spectrum Networks(GSN), a similar neural network proposed by Dafonte et al. (2016), which follows the same scheme as a typical ANN, except that the inputs and outputs are inverted. This approach was proposed and applied to simulations of prospective Gaia RVS (Cropper et al. 2018) spectra based on the Kurucz model (Kurucz 1993). However, real observed spectra were not tested. It should be noted that there is a sign discrepancy between the synthetic and observed spectra for errors from extinction, redden, seeing, contamination of stray light, instruments and post data processing. We improve the generative artificial neural network training on Phoenix (Husser et al. 2013) spectra for estimation of the parameters of LAMOST (Luo et al. 2015) observations. In combination with a Bayesian framework and Monte Carlo(MC) method, the networks can be used to derive not only stellar atmospheric parameters, but also their posterior distribution. The computing cost is always an insurmountable obstacle during the application of the MC method for a large number of data-sets. However, the distributed computing platform SPARK improves the viability of employing MC sampling methods based on Bayes theory. To the best of our knowledge, we are the first group to utilize SPARK estimating stellar parameters in this way. Moreover, our method adds an abundance of alpha elements ([α/Fe]) with respect to the existing catalog provided by LASP (Luo et al. 2015; Wu et al. 2011).

2. Data

The spectra employed in this report consist of two parts: synthetic spectra calculated from PHOENIX mode (Husser et al. 2013) and LAMOST spectra from the internal fifth data release(LAMOST DR5; Luo et al. in preparation). The synthetic spectra with reference parameters(T_{eff}, log g, [Fe/H] and [α/Fe]) are used for training and testing the GSN model. Then, the stellar parameters of the LAMOST spectra were estimated using the achieved GSN model.

3. Methods

In this report, we designed a new structure of artificial neural networks which consists of a fully-connected network with an input layer, three hidden layers, and an output layer, to generate spectra by training PHOENIX model spectra. Generative Spectrum Networks can produce model spectra when a team of parameters is given. Using chi-square distance as a proxy to match the spectrum to be measured with model grids is common and most methods use this approach. However, the uncertainty estimation would be difficult for template matching. Combined with Bayes rule, Monte-Carlo sampling is an effective way to obtain the posterior distribution over the parameters given the observed spectrum.

4. Results

To ensure the reliability and accuracy of the stellar parameters obtained with GSN, we employed the parameter catalogs of some sub-sample catalogs of LAMOST DR5 common stars, with external precise stellar parameters derived from high-resolution observations, or by other methods used for comparing and validation. To obtain reliable results, we only selected spectra with SNRg >30 for comparison purposes.

The comparison of LAMOST DR5 with APOGEE DR14 (Holtzman et al. 2018) and PASTEL catalogue (Soubiran et al. 2016) are provided in the Fig 1 and Fig 2. As shown in the figures, our results of stellar parameters show great agreement with the results derived from the high-resolution APOGEE spectra and the results from other literatures.

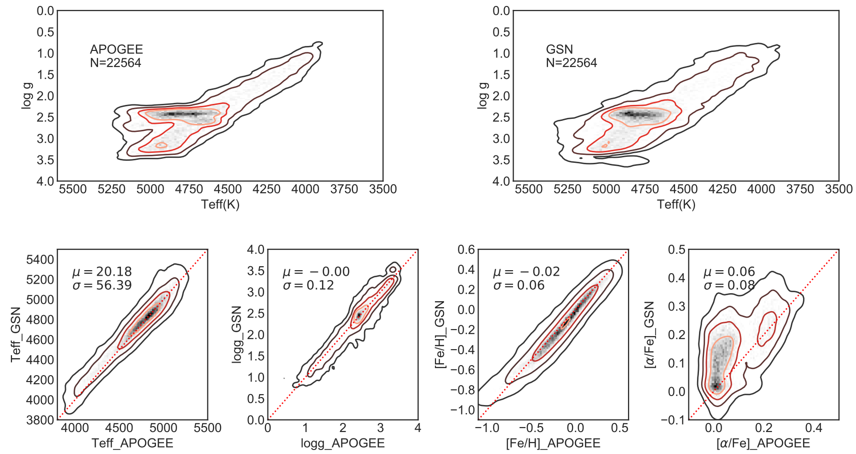

Figure 1. The density distribution of APOGEE parameters (top left panel) and GSN results (top right panel) for LAMOST 23,315 stars with SNR_g greater than 30. Also, the comparison between GSN stellar parameters and the APOGEE parameters are showed in the four bottom panels. The red dash lines in the bottom panels are one-to-one lines.

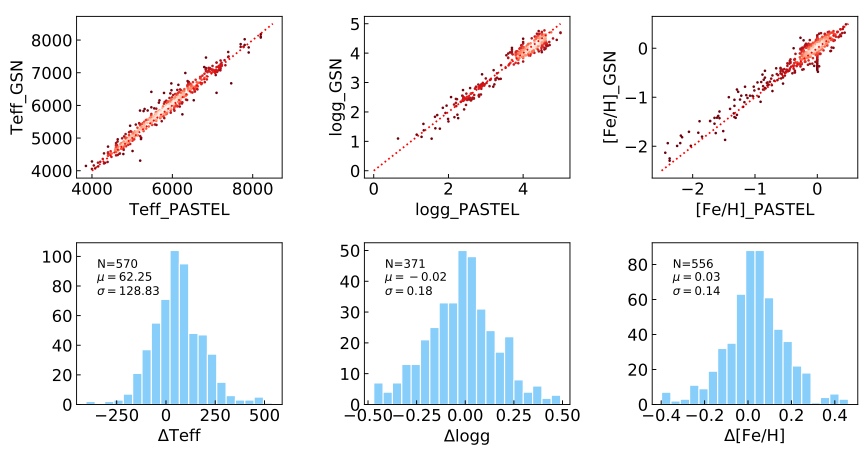

Figure 2. The color-coded scatter of GSN stellar parameters compared with the PASTEL catalogue for LAMOST DR5 spectra with $\mathrm{SNR}_g \geq 30$ are showed in the three top panels. The red dash lines in the top panels are one-to-one lines. The distributions of the discrepancies for T_{eff}, log g and [Fe/H] are shown in the three bottom panels.

5. References

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