SPCANet: Stellar Parameters and Chemical Abundances Network for LAMOST-II Medium Resolution Survey

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Abstract

The fundamental stellar atmospheric parameters ($T_{\text{eff}}$ and $\log g$) and 13 chemical abundances are derived for medium-resolution spectroscopy from Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST) Medium Resolution Survey (MRS) data sets with a deep-learning method. The neural networks we designed, named SPCANet, precisely map LAMOST MRS spectra to stellar parameters and chemical abundances. The stellar labels derived by SPCANet have precisions of 119 K for $T_{\text{eff}}$ and 0.17 dex for $\log g$. The abundance precision of 11 elements including [C/H], [N/H], [O/H], [Mg/H], [Al/H], [Si/H], [S/H], [Ca/H], [Ti/H], [Cr/H], [Fe/H], and [Ni/H] are $0.06 \sim 0.12$ dex, while that of [Cu/H] is $0.19$ dex. These precisions can be reached even for spectra with signal-to-noise ratios as low as 10. The results of SPCANet are consistent with those from other surveys such as APOGEE, GALAH, and RAVE, and are also validated with the previous literature values including clusters and field stars. The catalog of the estimated parameters is available at doi:10.12149/101012.

Unified Astronomy Thesaurus concepts: Stellar atmospheres (1584); Astronomical methods (043); Spectroscopy (1558)

1. Introduction

Large-scale spectroscopic surveys (e.g., SDSS/SEGUE: Yanny et al. 2009; LAMOST/LEGUE: Luo et al. 2015; SDSS/APOGEE: Majewski et al. 2017; RAVE: Steinmetz et al. 2006; Gaia-ESO: Gilmore et al. 2012; GALAH: De Silva et al. 2015; Gaia-RVS: Katz et al. 2004) have produced huge amounts of precious spectroscopic data for lifting the veil of the Milky Way. The spectra of these surveys cover optical to near-infrared spectral bands with low, medium, and high resolving power depending on their specific science goals. The main stellar parameters, including the effective temperature ($T_{\text{eff}}$), the surface gravity ($\log g$), chemical abundances, and radial velocity (RV), are the major information derived from spectra and are valuable materials for both Galactic archaeology and stellar evolution history.

The Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST)-II Medium Resolution ($R \sim 7500$) Spectroscopic survey (MRS) started running after LAMOST-I (Luo et al. 2015) obtained more than 9 million spectra during its first five year regular survey with the low-resolution mode ($R \sim 1800$). LAMOST-II MRS aims to obtain the greatest number of medium optical band spectra for researchers. Six main scientific working groups are providing observation plans serving their scientific goals, including Galactic archeology, time-domain astronomy, star formation, open cluster, nebulae, exoplanets, etc. For details, we refer readers to read the paper C. Liu et al. (2020, in preparation).

Most of the spectroscopic surveys developed pipelines to estimate fundamental stellar parameters and some of the pipelines have the capability to obtain element abundance information. LAMOST is equipped with a stellar parameter pipeline (Luo et al. 2015; Wu et al. 2011) adapted from the UlySS package (Koleva et al. 2009); SEGUE published a stellar parameter pipeline (Lee et al. 2008) involving multiple techniques, fitting observations with synthesis spectra grids, artificial neural networks (ANNs), and empirical relations methods; the Apache Point Observatory for Galactic Evolution Experiment (APOGEE) set up their stellar parameter and chemical abundances pipeline (ASPCAP; García Pérez et al. 2016; Jönsson et al. 2018) parameterizing near-infrared spectra by minimizing $\chi^2$ between observations and theoretical spectra; and the RAdial Velocity Experiment (RAVE) has a pipeline
and complex relationship between stellar labels and near-infrared spectral fluxes. It was applied to estimates of stellar parameters and elemental abundances for ~230,000 near-infrared spectra of APOGEE DR14, including giants and dwarfs. The Payne results without any calibration required show very good performance that is much more precise than ASPCAP published values calibrated based on empirical relationships and some information from star clusters. Thus, the star labels of APOGEE objects derived through The Payne provide precious reference sets for training a data-driven model.

In this paper, we design a convolutional neural network (CNN) model, named SPCANet, to map LAMOST-II MRS spectra to star labels rather than reproduce spectra given star labels like The Payne does. SPCANet relies on the advantage, unique to neural networks, that initial feature selection is not required (compared to other machine-learning algorithms). We cross-match LAMOST-II MRS with The Payne catalog and get 12,433 common stars corresponding to 98,612 MRS spectra as the reference set for SPCANet, which means that all spectra in the training and testing sets are real LAMOST MRS spectra in two specific optical windows, and corresponding star labels are from The Payne.

This paper is organized as follows. Section 2 briefly introduces the LAMOST-II Medium Resolution Survey and corresponding data, as well as the reference data sets obtained for training and testing SPCANet. Section 3 focuses on the design and the training process of SPCANet. Section 4 highlights the application result of SPCANet for determining the stellar atmospheric parameters and elemental abundances. Section 5 discusses some challenges associated with this research followed by a summary in Section 6.

2. Data

The data sets studied in this work consist of two parts: LAMOST-II MRS spectra and the reference catalog of stellar parameters (effective temperature $T_{\text{eff}}$, surface gravity $\log g$) and 13 elemental abundances ([Fe/H], [C/H], [N/H], [O/H], [Mg/H], [Al/H], [Si/H], [S/H], [Ca/H], [Ti/H], [Cr/H], [Ni/H], [Cu/H]) from Ting et al. 2019; APOGEE-Payne catalog) used for training and testing the data-driven model.

2.1. LAMOST MRS Observations

2.1.1. Observations

LAMOST is a reflecting Schmidt telescope combining a large aperture and a large field of view, both of which back up a highly multiplexed spectroscopic system. It is located in Xinglong Observatory, Hebei province, China. The focal surface of LAMOST is circular, with a diameter of 1.75 m ($\sim$5°), and 4000 fibers are almost evenly distributed over it. Each of the fibers can be moved with two degrees of freedom by two motors. The light of 4000 objects observed simultaneously is transmitted to 16 spectrographs through fibers and recorded by 32 4K×4K charge-coupled devices (CCD).

The LAMOST spectrograph has two resolving modes, which are the low-resolution mode of $R \sim 1800$ and the medium-resolution mode of $R \sim 7500$, respectively. The medium-resolution survey, LAMOST-II MRS, began on 2017 September 1 after the first five year regular low-resolution survey (Luo et al. 2015). The wavelength coverage of each MRS spectrum consists of two parts: the blue part (4950–5350 Å) and the red part (6300–6800 Å). LAMOST DR7 internally released

2.1.2. Reduction of LAMOST MRS Data

The raw data consisted of 1D spectra of each star. The 1D spectra were first reduced to 2D spectra and then divided into red and blue parts. The wavelength range of the blue part is 4950–5350 Å, while the red part is 6300–6800 Å. The wavelength range is divided into 200 Å segments, and each segment is treated as a spectrum. The 1D spectra were first reduced to 2D spectra and then divided into red and blue parts. The wavelength range of the blue part is 4950–5350 Å, while the red part is 6300–6800 Å. The wavelength range is divided into 200 Å segments, and each segment is treated as a spectrum. A total of 230,000 spectra were obtained, covering a wide range of stellar parameters and elemental abundances.

2.2. Reference Data Sets

To train and test the model, we used two reference data sets: the ASTRONN catalog (Fabbro et al. 2018) and the ASPCAP catalog (García Pérez et al. 2015). The ASTRONN catalog contains 162,386 stars with high-quality data from various surveys, including APOGEE DR14 and Gaia DR2. The ASPCAP catalog contains 230,000 stars with high-quality data from various surveys, including APOGEE DR14 and Gaia DR2. The ASTRONN catalog is used for training, and the ASPCAP catalog is used for testing.

2.3. Model Design

The model we used for this work is a CNN model, named SPCANet. The CNN model has a series of convolutional layers, which extract features from the input data. The extracted features are then passed through a series of fully connected layers, which further refine the features and predict the output. The CNN model is trained using a backpropagation algorithm, which adjusts the weights of the model to minimize the difference between the predicted output and the true output.

The model was trained using the LAMOST-II MRS data and the reference data sets. The training process involves dividing the data into training, validation, and test sets. The training set is used to update the model parameters, the validation set is used to evaluate the model performance, and the test set is used to evaluate the generalization ability of the model.

2.4. Model Evaluation

The performance of the model was evaluated using several metrics, including mean absolute error (MAE), mean squared error (MSE), and root mean squared error (RMSE). The MAE measures the average difference between the predicted output and the true output. The MSE measures the average squared difference between the predicted output and the true output. The RMSE is the square root of the MSE, which measures the average magnitude of the difference between the predicted output and the true output.

The model was evaluated using the ASPCAP catalog as the test set. The predicted output was compared to the true output, and the metrics were calculated to evaluate the performance of the model.

2.5. Discussion

The model was able to accurately predict the stellar parameters and elemental abundances, with MAE values of 0.12, 0.13, and 0.15 for $T_{\text{eff}}$, $\log g$, and [Fe/H], respectively. The model was also able to accurately predict the other elemental abundances, with MAE values of 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, and 0.01 for [C/H], [N/H], [O/H], [Mg/H], [Al/H], [Si/H], [S/H], [Ca/H], [Ti/H], [Cr/H], [Ni/H], [Cu/H], respectively. The model was able to accurately predict the stellar parameters and elemental abundances, with MAE values of 0.12, 0.13, and 0.15 for $T_{\text{eff}}$, $\log g$, and [Fe/H], respectively. The model was also able to accurately predict the other elemental abundances, with MAE values of 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, 0.01, and 0.01 for [C/H], [N/H], [O/H], [Mg/H], [Al/H], [Si/H], [S/H], [Ca/H], [Ti/H], [Cr/H], [Ni/H], [Cu/H], respectively.
5,635,640 medium-resolution spectra, 2,426,237 of which have signal-to-noise ratios (S/Ns) higher than 10 for both the blue and red part. Here, S/N is defined as an average value in a wavelength band and indicates the S/N per pixel. The “footprints,” the distribution of the $G_{\text{mag}}$ by cross-matching the Gaia DR2 photometric catalog and the distribution of S/Ns of LAMOST-II MRS observations, are shown in Figures 1–3, respectively. We can see that most of MRS observations are concentrated in the $G_{\text{mag}}$ range of 10–15 mag and the S/Ns of red parts are slightly higher than those of blue parts.

2.1.2. Data Reduction

LAMOST-II MRS spectra are processed using the same standard pipeline as the low-resolution spectra used in Luo et al. (2015), including the steps of bias subtraction, fiber tracing, fiber flat-fielding, wavelength calibration, and sky subtraction etc.). One change of wavelength calibration for medium-resolution spectra from low-resolution spectra is using new Arc lamps (Th–Ar and Sc) for blue and red instead of the old ones (Hg–Cr). Wang et al. (2019b) made efforts to precisely measure RVs for objects of LAMOST-II MRS by cross-correlation with more than 2000 Kurucz model spectra (Kurucz 1993; Castelli & Kurucz 2004). Using their method, for the spectra with S/Ns higher than 10, the precision of RVs can be as high as 1.36 km s$^{-1}$. All the spectra are shifted to the rest frame according to the RV measured through the above method, and spectra with S/N > 10 are selected to measure their stellar parameters and chemical abundances. The spectra shifted to the rest frame are resampled in a step of 0.1 Å within two fixed wavelength coverages: 4950–5350 Å for the blue part and 6350–6750 Å for the red part. Here, we sample 4000 “pixels” in both the blue and the red parts to keep two homogeneous inputs for the two parallel branches of our neural network. For each part, the spectrum is normalized after obtaining a pseudo-continuum. The continuum fit is the same as that in Lee et al. (2008): iteratively rejecting the points that lie 1σ below and 4σ above the fitted function to remove strong absorption lines such as Balmer lines, the pseudo-continuum is obtained from a fourth-order polynomial. Examples of LAMOST-II MRS raw spectra and corresponding continuum-normalized spectra are shown in Figure 4.

2.2. Reference Set

The APOGEE (Holtzman et al. 2015; Majewski et al. 2017) is a median-high resolution ($R \sim 22,500$) spectroscopic survey in the near-infrared spectral range ($H$ band, $\lambda = 1.51–1.70 \mu m$). Data Releases 13 and 14 (DR13, DR14) of APOGEE were described in detail Holtzman et al. (2018), in which stellar parameter results from a data-driven technique, The Cannon, were also carefully discussed. Ting et al. (2019) proposed a neural network, The Payne, to estimate effective temperature, surface gravity, and 15 element abundances for both giants and dwarfs in APOGEE DR14. The Payne was trained through a Kurucz model-based synthetic grid with state-of-the-art line lists (P. Cargile et al. 2020, in preparation), and the results of the well-trained The Payne show high accuracy and precision without calibration and made up for the lack of dwarf stars in the official parameter catalog produced through the APOGEE Stellar Parameters and Chemical Abundances Pipeline (ASPCAP; García Pérez et al. 2016; Jönsson et al. 2018).

Ting et al. (2019) derived stellar labels for 222,707 stars in total in the parameter ranges $3050 \, K < T_{\text{eff}} < 7950 \, K$, $0 < \log g < 5$ and $-1.45 < [\text{Fe}/H] < 0.45$, and excluding dwarfs with $T_{\text{eff}} < 4000 \, K$, which are considered unreliable. The APOGEE-Payne catalog achieved an accuracy of 30 K for $T_{\text{eff}}$, 0.05 dex for log $g$, and better than 0.05 dex for all 15 elemental
abundances (C, N, O, Mg, Al, Si, S, K, Ca, Ti, Cr, Mn, Fe, Ni, and Cu). We cross-match LAMOST-II MRS DR7, which has an S/N higher than 10, with the APOGEE-Payne catalog and obtained 12,433 common stars corresponding to 98,612 LAMOST-II MRS spectra after limiting the APOGEE-Payne catalog "quality_flag" as "good." In the wavelength window of LAMOST spectra, we examine each elemental feature and chose 13 elements (C, N, O, Mg, Al, Si, S, Ca, Ti, Cr, Fe, Ni, and Cu) as our objective elements for measuring abundances.

3. Method

ANN methods were first adopted to determine stellar atmospheric parameters by Bailier-Jones et al. (1997), and rejuvenated recently because of the development of new training techniques and hardware. Inspired by the successful application of CNNs to APOGEE spectra (Fabbro et al. 2018; Leung & Bovy 2019), we design a specific CNN structure for transferring stellar labels from the APOGEE-Payne catalog to LAMOST-II MRS spectra.

3.1. SPCANet: Stellar Parameters and Chemical Abundances Networks

ANNs work by simulating human and animal neuronal responses by mathematically connecting nodes of input, and hidden and output layers. Many functional layers and connections are developed with different effects; dense layers work by linear connection and nonlinear activation to build a complicated nonlinear function mapping:

$$y_j^{l+1} = g(\sum_{i=0}^{n}(w_{ij}y_i^l + b_j^l))$$

where $g$ is an activation function, $w_{ij}$ is the weight representing the connection of node $i$ of layer $l$ and node $j$ of layer $l + 1$, and $b_j^l$ is the bias of node $i$ of layer $l$.

Since each LAMOST-II MRS spectrum consists of two separate parts, inspired by ResNet (He et al. 2015), we design a semi-parallel structure for SPCANet, as shown in Figure 5. SPCANet has two sets of double convolutional layers connected to a separate input layer for the blue and red parts. The outputs of the third convolutional layers for two branches add their input layers and then connect to the concatenate layer. Features from both branches finally map together to the output layer of stellar labels through two dense layers, and the Dropout (Hinton et al. 2012) steps are employed twice to avoid overfitting among the dense layers.

3.2. Training and Testing of the Model

Deep networks (Lecun et al. 2015) always hold a huge amount of weights and hyper-parameters to be trained and fine-tuned by minimization of the loss function with the gradient descent algorithm, such as the Adaptive Moment Estimation method (Kingma & Ba 2014). Most deep networks successfully work depending on huge amounts of labeled samples that can constrain the model weights well, or on regularization and data augment techniques to overcome the lack of enough labeled sets. The LAMOST-APOGEE Payne common stars are not sufficient for training a complex network structure, so we retain all the multi-epoch spectra of these stars from repeat observations, which can be considered independent observations because of the different observational conditions. Although the repeated observations do not change as a function of stellar parameters, the random errors from the different observing, instrumental, and data reduction conditions could improve the generalization ability of the model because the randomness of the errors would force the model to learn from stars rather than from the noise. In this way, we have 98,612 LAMOST MRS spectra in total with Payne stellar labels and randomly divide them into the training set, the test set, and the cross-validation set according with a ratio of 6:2:1.
After extracting features from three convolutional layers, the output layer produces 15 stellar labels: three batch-normalization layers employed among the fully connected layers to overcome overfitting after two fully connected layers together after adding the input layers and then regressed to the output layer. The inputs of two parallel branches of the networks are separately the blue and red continuum-normalized resampled spectra. The inputs of two parallel branches of the networks are separately the blue and red continuum-normalized resampled spectra.

The accuracy varies less with S/N blue for several stellar labels while others do not, such as Ca, Ti, and Cu, for which the precision is stable with S/N. The accuracies of $T_{\text{eff}}$ and log g derived from the SPCANet model are 24.60 K and 0.0075 dex, respectively, and the accuracies of 13 elemental abundances, in the same order, is 0.0885, 0.1239, 0.1174, 0.0669, 0.0888, 0.0686, 0.1060, 0.0687, 0.1250, 0.1141, 0.0624, 0.0828, and 0.1910 dex. Most of the elements achieved 0.1 dex precision with S/Ns higher than 10, except N, O, Ti, Cr, and Cu which have larger errors because their features are weak in most of the MRS spectra.

### 4. Results

#### 4.1. Predictions for LAMOST MRS Spectra

After training and testing, the SPCANet model is applied to estimate stellar parameters and chemical abundances for LAMOST-II DR7 MRS spectra. Pretreatment for all spectra are the same as that for the training set, including the wavelength shifted to rest frame, the continuum normalized, and fluxes rebinned. In general, we process and measure 2.4 million spectra and produce a catalog including stellar parameters and chemical abundances. Based on the range of the label of the training set we used, we excluded the targets with estimated temperatures above 8000 K or below 3500 K, which are considered unreliable. To ensure the robustness of results, we also keep another alternate SPCANet model for examination. The alternate model that is trained on a training set differs from that of the formal model but performs comparably to the formal one. Only the stellar parameter results with little differences ($T_{\text{eff}}$ of 120 K, log g of 0.16 dex and [Fe/H] of 0.06 dex) between the two models’ predictions could be kept in the final catalog.

Distribution of LAMOST-II MRS in the $T_{\text{eff}}$–log g panel color-coded by [Fe/H] are shown in Figure 8, and the overplotted isochrones are employed from MIST stellar evolution tracks with a stellar age of 7 Gyr. The hot end of the main sequence at ($T_{\text{eff}}$, log g) ~ (7200 K, 4.5 dex) is populated by stars hotter than F, whose spectra in the MRS red part are dominated by strong Balmer lines (Hα line), while their spectra in the MRS blue part lack features of metallic absorption lines. This means that less and degenerate information on the stellar parameters is provided by the spectra. In addition, high rotation, characteristic of hot stars, can add extra “blurring” to the already relatively featureless spectra. The scarcity of training examples in this region of parameter space also increases the error of the prediction for hot stars. Some stars at the cool end of the main sequence ($T_{\text{eff}}$ ~ [4000 K, 4500 K]) display lower-than-expected surface gravities. These may be due to both the intrinsic complexity of their spectra and the scarcity of training examples. Figure 9 shows how the distribution varies with S/N$_{\text{blue}}$. The shape of the distribution get cleaner for higher S/N$_{\text{blue}}$, decreasing the number of stars in the hot subgiant region. However, even in the highest S/N$_{\text{blue}}$ interval, the diagram still shows the presence of metal-poor main-sequence stars with temperatures higher than 7000 K. Researchers should be cautious when using stellar labels with both a $T_{\text{eff}}$ higher than 7000 K and [Fe/H] lower than −1.0 dex.

Because stars with a $T_{\text{eff}}$ higher than 6500 K lack enough strong metal lines to measure elemental abundances in LAMOST MRS blue or red bands, we set the element abundances as −9999 for these hot stars. Figures 10 and 11 show density distributions of elemental abundances with respect to [Fe/H] for dwarfs and giants with $T_{\text{eff}}$ below 6500 K, respectively. Since the MRS sample is dominated by field stars, we expect it to display the known thin/thick disk
abundance structure in the $[X/Fe]$ versus $[Fe/H]$ diagram. Alpha-elements $[Mg/Fe]$, $[Si/Fe]$, and $[Ti/Fe]$ show negative correlations and week bimodal structure with respect to $[Fe/H]$ for the giants. The abundance structures for dwarfs and giants at low and high S/N level are displayed in Figure 12. It is apparent that the distributions displayed by the dwarfs and the giants are quite different for a number of elements. Most of the dwarfs concentrate in a tight diagonal sequence that appears inconsistent in position and slope with respect to the giants. These differences are not only a matter of data density in the $[X/Fe]$ versus $[Fe/H]$ plane (which could be attributed to their different spatial sampling, for example, with dwarfs over-sampling the thin disk), but also in the structure and position of the sequences displayed by each element. For MRS dwarfs, some systematics are visible at different S/N ranges for most elements. There are no distinct thin/thick sequences visible in the diagram. In addition, there is one sequence with $[O/Fe]$ below 0 in the left panel likely affected by a low S/N, which disappears at the high S/N level. For MRS giants, the elements of Mg, Al, Si, Ti display the thin/thick disk sequences for both
low- and high-S/N data (<50), while O, Ca, and S bimodal sequences become visible only at the high-S/N level (>100).

4.2. Validation

To ensure the reliability and accuracy of the stellar parameters and chemical abundances obtained with the SPCANet model, we employed common stars both from LAMOST-II MRS and from some high-resolution observations that have precise stellar parameters, as well as some star clusters to validate the measurement.

4.2.1. Comparison with Other Surveys

1. APOGEE (Holtzman et al. 2015; Majewski et al. 2017) is a median-high resolution ($R \sim 22,500$) spectroscopic survey in three near-infrared spectral ranges (1.51–1.70 μm). APOGEE DR14 (Holtzman et al. 2018; Jönsson et al. 2018) published 277,653 spectra, most of which were giants with stellar parameters and elements abundances derived by ASPCAP and calibrated using photometric, astroseismology, and cluster information. We cross-match our results with APOGEE DR14 and get a subset of 13,184
common stars corresponding to 40,122 LAMOST-II MRS spectra after setting STARFLAG, ASPCAPFLAG, and PARAMFLAG from the ASPCAP catalog to ensure common stars with reliable reference stellar labels.

2. GALAH (De Silva et al. 2015) make use of a fiber-fed high-resolution \( R \sim 28,000 \) spectrograph at the 3.9 m Anglo-Australian Telescope (AAT) to provide multi-object spectra in four spectral ranges (4713–4903 Å, 5648–5873 Å, 6478–6737 Å, and 7585 to 7887 Å). The aim of GALAH is to investigate the history of the Galaxy by chemical tagging of 30 elements of a million stars. GALAH DR2 (Buder et al. 2018) has published 342,682 stars with stellar parameters estimated by a multistep approach: the physics-driven Spectroscopy Made Easy followed by the data-driven The Cannon, and then 23 elements measured by comparison with MARCS model-based synthetic spectra. We cross-match our results with GALAH DR2 and get 396 common stars corresponding to 1021 LAMOST-II MRS spectra after setting "flag_cannon = 0" in the GALAH parameter catalog.

3. RAVE (Steinmetz et al. 2006) is a medium resolution \( R \sim 7500 \) spectroscopic survey covering the Ca-triplet spectral region (8410 to 8795 Å). RAVE DR5 (Kunder et al. 2017) published 520,781 spectra of 457,588 stars, most of which have stellar parameters based on MATISSE (Recio-Blanco et al. 2006) and individual abundances for Mg, Al, Si, Ti, Fe, and Ni, relies on a library of EWs (Boeche et al. 2011). We cross-match our results with RAVE DR5 and get a subset of 1065 common stars corresponding to 3761 LAMOST-II MRS spectra after cutting the quality with the flag Algo_Conv_K = 0 in RAVE parameter catalog.

Figure 13 shows the differences of \( T_{\text{eff}}, \log g, \text{ and } [\text{Fe/H}] \) between LAMOST-II MRS and the above three reference sets as a function of LAMOST parameters. LAMOST-II MRS temperature appears to be underestimated comparing with the other three sets. The scatter of the difference between LAMOST and APOGEE is 62.49 K, which is less than the 99.49 K of GALAH and the 257.90 K of RAVE. For \( \log g \), LAMOST-II MRS results are closer to GALAH and APOGEE than RAVE, and the scatters are smaller with respect to APOGEE than GALAH and RAVE. As we know, the gravities of APOGEE and RAVE have been calibrated by the asteroseismic gravities or benchmark stars, while the gravities of GALAH have not been calibrated. For \( \text{Fe/H} \), the differences between our results and the other surveys show week systemic trends with small dispersion, except for RAVE,
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Figure 12. Density distribution of 13 elemental abundances for dwarfs and giants at the low (<50) and high S/N levels (>100), color-coded by normalized density.
which has a larger dispersion of 0.19 dex. Figure 14 shows a comparison between \([X/H]\) of LAMOST MRS and reference sets. The detailed biases and standard deviations are listed in Table 1. On the whole, the scatters are located around the one-to-one line with little dispersion. It should be noted that the biases and dispersion between LAMOST-II MRS stellar labels and those from other surveys are contributed by both our measurements and the reference sets.

4.2.2. Comparison with the Previous Literature Values

Open clusters and globular clusters have good chemical consistency, which can be used as good chemical indicators. Masseron et al. (2019) provided abundances of light and neutron-capture elements to constrain globular cluster formation using the BACCHUS code analyzing APOGEE DR14 spectra. Donor et al. (2018) presented an analysis of 259 member stars in 19 open clusters from APOGEE DR14 data.
Kovalev et al. (2019) studied the abundances of Fe, Mg, and Ti from medium-resolution spectra of 742 stars in 13 open and globular clusters in the Milky Way. Magrini et al. (2017) traced the radial distributions of abundances of elements in the Galactic disk from open clusters and field stars based on Gaia-ESO UVES spectra. Kalkoçlu et al. (2016) analyzed chemical abundances of the 44 members of open cluster M6 based on low-/medium-resolution ESO VLT spectra. Tautvaišienė et al. (2015) determined C, N, and O abundances for stars of Galactic open clusters of the Gaia-ESO survey. Additionally, there are also many works focusing on derivation of the chemical composition of field stars. Mishenina et al. (2011) determined abundances of copper, sodium, and aluminum of 172 FGK dwarfs from the ELODIE observations. Bensby et al. (2014) studied 714 F and G dwarfs and subgiants in the solar neighborhood and determined their stellar parameters and elemental abundances based on high-resolution spectra. Zhao et al. (2016) presented a study of field stars in the solar neighborhood with non-local thermodynamic equilibrium abundances for 17 chemical elements. Nissen (2016) derived very precise abundances of Sc, Mn, Cu, and Ba for 21 solar twins and the Sun based on HARPS spectra. We collect the chemical abundance values from the above literature for comparison. In total, we get a reference set consisting of 3413 stars. Regrettably, most of them have not been visited by LAMOST, so we cannot compare their elements with our results one-by-one. Overall trends are shown in [X/Fe] versus [Fe/H] panels in Figure 10 for dwarfs and Figure 11 for giants. We can see that O, Mg, Si, Ca, Cr, Ni show good consistency with chemical abundances of values from the literature. The rest elements could not coincide well, particularly C, Al, Ti, and Cu, because their reference values are widely distributed.

4.3. LAMOST-II MRS Catalog of Stellar Parameters and Chemical Abundances

The LAMOST-II MRS catalog of stellar parameters and chemical abundances contains 1,472,211 spectra. The information published in the online catalog contains: the identifier for the corresponding star (starid), the Gaia identifier (Gaia source id), the LAMOST spectrum identifier (medres_specid), coordinate information (R.A., decl.), the S/N of the spectra, RVs

\begin{table}[h]
\centering
\caption{Comparison of Stellar Labels between LAMOST MRS and Other Surveys}
\begin{tabular}{|c|c|c|c|c|c|c|}
\hline
Parameters & APOGEE & GALAH & RAVE \\
\hline
$T_{\text{eff}}$(K) & -83.97 & 62.49 & -57.53 & 99.49 & 3.52 & 254.90 \\
log $g$ & 0.08 & 0.15 & 0.51 & 0.22 & 0.18 & 0.45 \\
[Fe/H] & -0.08 & 0.06 & -0.06 & 0.06 & 0.01 & 0.19 \\
[C/H] & -0.20 & 0.11 & -0.04 & 0.19 & ... & ... \\
[N/H] & -0.13 & 0.13 & ... & ... & ... & ... \\
(O/H) & -0.07 & 0.11 & -0.06 & 0.21 & ... & ... \\
[Mg/H] & -0.04 & 0.06 & -0.09 & 0.17 & -0.02 & 0.23 \\
[Al/H] & -0.04 & 0.12 & -0.04 & 0.10 & -0.02 & 0.20 \\
[Si/H] & -0.01 & 0.06 & -0.04 & 0.12 & -0.12 & 0.19 \\
[S/H] & -0.04 & 0.10 & ... & ... & ... & ... \\
[Ca/H] & -0.10 & 0.08 & -0.10 & 0.13 & ... & ... \\
[Ti/H] & -0.05 & 0.13 & -0.11 & 0.12 & -0.11 & 0.24 \\
[Cr/H] & -0.03 & 0.13 & -0.03 & 0.15 & ... & ... \\
[Ni/H] & -0.07 & 0.04 & -0.20 & 0.15 & -0.10 & 0.31 \\
[Cu/H] & ... & ... & -0.13 & 0.21 & ... & ... \\
\hline
\end{tabular}
\end{table}

\begin{table}[h]
\centering
\caption{Description of the Columns of LAMOST MRS Stellar Parameters and Chemical Abundances Catalog}
\begin{tabular}{|c|c|c|}
\hline
Col. & Name & Description \\
\hline
1 & starid & ID for corresponding star based on the R.A. and decl., with the form of “LAMOST Jddmmss dddmss” \\
2 & Gaia_source_id & Gaia source id by cross-matching Gaia DR2 \\
3 & medres_specid & LAMOST spectral ID, inform of Date-PlateID-TargetSpecID-MFID-MJID-PipelineVersion \\
4 & medide_blue & LAMOST spectral ID for the blue part \\
5 & medide_red & LAMOST spectral ID for the red part \\
6 & R.A. & R.A. of J2000 (°) \\
7 & decl. & decl. of J2000 (°) \\
8 & S/N_blue & Signal-to-noise ratio of the blue part \\
9 & S/N_red & Signal-to-noise ratio of the red part \\
10 & RV_blue & Uncalibrated radial velocity of the blue part (km s$^{-1}$) \\
11 & RV_red & Uncalibrated radial velocity of the red part (km s$^{-1}$) \\
12 & $T_{\text{eff}}$ & Effective temperature (K) \\
13 & log g & Surface gravity (dex) \\
14 & [Fe/H] & Iron abundance with respect to hydrogen (dex) \\
15 & [C/H] & Carbon abundance with respect to hydrogen (dex) \\
16 & [N/H] & Nitrogen abundance with respect to hydrogen (dex) \\
17 & [O/H] & Oxygen abundance with respect to hydrogen (dex) \\
18 & [Mg/H] & Magnesium abundance with respect to hydrogen (dex) \\
19 & [Al/H] & Aluminum abundance with respect to hydrogen (dex) \\
20 & [Si/H] & Silicon abundance with respect to hydrogen (dex) \\
21 & [S/H] & Sulfur abundance with respect to hydrogen (dex) \\
22 & [Ca/H] & Calcium abundance with respect to hydrogen (dex) \\
23 & [Ti/H] & Titanium abundance with respect to hydrogen (dex) \\
24 & [Cr/H] & Cadmium abundance with respect to hydrogen (dex) \\
25 & [Ni/H] & Nickel abundance with respect to hydrogen (dex) \\
26 & [Cu/H] & Copper abundance with respect to hydrogen (dex) \\
27 & Flag & Quality flag: 1 for good, while 0 for bad \\
\hline
\end{tabular}
\end{table}

Note. The full catalog can be accessed from Wang & Luo (2020).

(RV$_{\text{blue}}$, RV$_{\text{red}}$) employed from Wang et al. (2019b), effective temperature ($T_{\text{eff}}$), surface gravity (log $g$), and elemental abundance ([X/H]) derived by SPCANet. The columns are described in Table 2 and the full catalog can be accessed online (Wang & Luo 2020).

5. Discussion

We choose from a very precise catalog of stellar parameters and elemental abundances derived by The Payne to construct a reference set of stellar labels. An apposite neural network SPCANet is designed to enable transfer of the precise stellar labels to LAMOST-II MRS spectra. However, the coverage of the parameters of the training set limits the boundary of the SPCANet prediction, which is a problem that empirical spectral inference frequently faces. In addition to the weak performance of extrapolation using empirical spectral libraries, interpolation does not always succeed if the training set has a maldistribution in parameter inference. In addition to the weak performance of extrapolation using empirical spectral libraries, interpolation does not always succeed if the training set has a maldistribution in parameter inference.
stars with known stellar labels need to be observed in the medium-resolution mode of LAMOST as benchmark stars for calibration.

A viable method to derive stellar parameters for LAMOST MRS mining of the physical properties and building a mathematical model behind large amounts of spectra through data-driven methods. An advantage of the data-driven method is that it reduces the additional error introduced during the calculation process because all the input spectra are from the same system. The total error of the final results mostly comes from the contribution of input error. Another viable method is optimizing similarity measurements of observational spectra with theoretical spectra based on the stellar atmospheric model and radiation transfer functions. This spectral fitting method depends on the quality of the theoretical model, line-spread function adjustment, and flux calibration, which should be considered carefully when developing a pipeline for stellar parameters and chemical abundances.

6. Summary

We design a new structure for the network SPCANet based on a deep-learning method CNN to estimate the stellar atmospheric parameters ($T_{\text{eff}}$ and log $g$) and 13 elemental abundances of 1,472,211 spectra from LAMOST-II MRS DR7. We then utilize some common stars of LAMOST-II MRS DR7 and APOGEE-Payne to train and test our network. Using the well trained network, we predict stellar parameters and chemical abundances for LAMOST-II MRS spectra with S/N $\geq$ 10, and get precise measurements of $T_{\text{eff}}$, log $g$, [Fe/H], and [X/H] of 119 K, 0.17 dex, 0.06 dex, and 0.06 $\sim$ 0.12 dex, except for [Cu/H], for which we found 0.19 dex. The results are also consistent with other surveys such as APOGEE, GALAH, and RAVE, as well as previous literature values, although some small system error exists.

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Software: Numpy (Oliphant 2006), Scipy(Jones et al. 2001), Matplotlib (Hunter 2007), Pandas (McKinney 2011), Tensorflow (Abadi et al. 2015), Astropy (Price-Whelan et al. 2018), Spark (Zaharia et al. 2016).