Estimating Atmospheric Parameters of DA White Dwarf Stars with Deep Learning

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Abstract

The determination of atmospheric parameters of white dwarf stars (WDs) is crucial for researches on them. Traditional methodology is to fit the model spectra to observed absorption lines and report the parameters with the lowest $\chi^2$ error, which strongly relies on theoretical models that are not always publicly accessible. In this work, we construct a deep learning network to model-independently estimate $T_{\text{eff}}$ and log g of DA stars (DAs), corresponding to WDs with hydrogen-dominated atmospheres. The network is directly trained and tested on the normalized flux pixels of full optical wavelength range of DAs spectroscopically confirmed in the Sloan Digital Sky Survey. Experiments in test yield that the rms error for $T_{\text{eff}}$ and log g approaches 900 K and 0.1 dex, respectively. This technique is applicable for those DAs with $T_{\text{eff}}$ from 5000 to 40,000 K and log g from 7.0 to 9.0 dex. Furthermore, the applicability of this method is verified for the spectra with degraded resolution of ~200. So it is also practical for the analysis of DAs that will be detected by the Chinese Space Station Telescope.

Unified Astronomy Thesaurus concepts: DA stars (348); Spectroscopy (1558); Astronomy data analysis (1858)

1. Introduction

White dwarf stars (WDs) are the final stage of evolution of stars whose progenitor masses are below $8-10.5 M_\odot$, depending on metallicity (Doherty et al. 2014), which contain important information needed to comprehend stellar formation and evolution. Most of WDs, especially single ones (i.e., not in a binary system), will exist for a very long time due to their slow cooling processes, which means the cool ones may record information from extremely early times. Therefore, researches on those WDs are also helpful for understanding certain history of the Milky Way (e.g., Tremblay et al. 2014).

The number of spectroscopically identified WDs is increasing thanks to the Sloan Digital Sky Survey (SDSS; York et al. 2000; Eisenstein et al. 2011; Blanton et al. 2017) and most of them are actually DA types. Kleinman et al. (2004) reported 1888 DAs out of 2551 WDs based on the first data release (DR1; Abazajian et al. 2003). Using SDSS DR4 (Adelman-McCarthy et al. 2006), Eisenstein et al. (2006) presented 8000 DAs out of 9316 WDs. Based on SDSS DR7 (Abazajian et al. 2009), Kleinman et al. (2013) reported 19,713 WDs, 12,831 of which were DAs. Furthermore, 6887 DAs out of 8441 WDs were presented by Kepler et al. (2015) using SDSS DR10 (Ahn et al. 2014). Based on SDSS DR12 (Alam et al. 2015), Kepler et al. (2016) reported nearly 2883 WDs, 1964 out of which were DAs. Of the 20,088 WDs, 15,716 DAs were presented by Kepler et al. (2019) in SDSS DR14 (Abolfathi et al. 2018). The atmospheric parameters of these WDs were determined from theoretical spectral fitting. Stellar spectra contain much information about a star and it is exactly this point that allows us to explore the relation between the spectra and parameters of a star in different ways.

The artificial neural network (ANN) has long been applied to the determination of astrophysical parameters. Bailer-Jones et al. (1997) trained an ANN on a set of synthetic optical stellar spectra to get $T_{\text{eff}}$, log g, and [M/H]. Nowadays, due to the development of computing power and the availability of large data sets the ANN, especially with the deep learning method, has been widely used in astronomy to predict physical parameters of stars. Fabbro et al. (2018) applied the convolutional neural networks (CNN) to the data set from the Apache Point Observatory Galactic Evolution Experiment (APOGEE; Majewski et al. 2017). Liang et al. (2019) and Zhang et al. (2019) trained deep neural networks respectively to estimate parameters and abundances of main-sequence stars using spectra from APOGEE and the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST; Zhao et al. 2006, 2012), which both yielded excellent performances. Chandra et al. (2020) presented a generative fitting pipeline that interpolates theoretical spectra with ANN to determine atmospheric labels of WDs. However, there are still few works using ANN to estimate parameters of WDs so far.

In this work, a deep learning network is constructed based on an architecture called the residual network (ResNet; He et al. 2015) and is directly trained on the spectra of DAs identified in SDSS DR7, DR10, and DR12 to estimate atmospheric parameters. In Section 2, we introduce the reduction of data. In Section 3, our method and details of the training and test are described. Finally, the conclusion of this work is given in Section 4.

2. Data Set

We collect all spectra of DAs spectroscopically confirmed in SDSS DR7, DR10, and DR12. Corresponding atmospheric parameters are obtained from the catalogs published in Kleinman et al. (2013) and Kepler et al. (2015, 2016). To begin with, the data are filtered with the following criteria: (a) single DAs; (b) signal-to-noise ratio in the $g$ band, $S/N_g \geq 10$; and (c) relative errors of $T_{\text{eff}}$ and log g $\leq 10\%$, which yield 9159 objects. Then we apply a 3D correction ($\text{ML2}/\alpha=0.8$) to $T_{\text{eff}}$ and log g according to the calibration from Tremblay et al. (2013).

Figure 1 shows the distributions of $T_{\text{eff}}$ and log g of the filtered data. Based on this, we further select the objects that satisfy 5000 K $\leq T_{\text{eff}} \leq 40,000$ K and 7.0 dex $\leq$ log g $\leq$ 9.0 dex and finally get 8490 DAs. Next we preprocess them in two ways.

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2.1. Preprocessing on Original Spectra: Data Set 1

We normalize the original spectra of DAs with the script provided by Blanco-Cuaresma et al. (2014). First, a spectrum is resampled with an equivalent wavelength step. Next, a median and maximum filter with different window sizes are applied to find the continuum points. The median filter (here we set the wavelength step = 30 in the script) replaces the flux value of the central pixel with the median value in the running window and then the maximum filter (we set the wavelength step = 120) will replace it with the maximum value. The former smooths out noise and the later ignores deeper fluxes that belong to absorption lines (the continuum will be placed in slightly upper or lower locations depending on the values of those parameters). Once the spectrum is filtered, the continuum model will be fitted with a group of splines (we set the splines number = 8 and degree = 2) and finally the spectrum is normalized by dividing all the fluxes by the model. One example (object spSpec-54612-2922-626.fit in DR7) is as shown in Figure 2.

2.2. Preprocessing on Spectra with Degraded Resolution: Data Set 2

The Chinese Space Station Optical Survey (CSS-OS) is a planned full-sky survey operated by the Chinese Space Station Telescope (CSST; Gong et al. 2019). CSST is a 2 m space telescope in the same orbit of the China Manned Space Station.
which is planned to be launched at the end of 2022. There are three spectroscopic bands covering 255–1000 nm and the resolutions of these bands are all about 200 (Gong et al. 2019).

To figure out whether our deep learning method is practicable under this situation, we plan to test it with synthetical spectra. First, we interpolate the original spectra with an equal interval of wavelength ($\Delta \lambda = 1$ Å). Then we degrade the resolution of all interpolated spectra to 200 and Gaussian noise ($\sigma = \text{flux}/30$) is added to simulate real spectra observed by CSST. Finally, we normalize them in the same way as mentioned above. Figure 3 shows an example (object spSpec-52943-1584-513.fit in DR7) of the data reduction.

For all spectra, there are few characteristics of absorption lines and much noise after 7500 Å, so we ignore this portion. Considering the actual conditions of all samples, we decide to use fluxes between the wavelength range of 3834.4 Å to 7500.7 Å ($\log \lambda(\text{Å}) \in [3.5837, 3.8751]$), a common region for all spectra, as input of the network.

3. Method

3.1. Network

ANN has been widely applied to data analyses in many fields thanks to the vast development of computing power and the availability of large data sets. A neural network is a series of algorithms that aims to map the relationships between input data and output labels that we care about. The most important feature of neural networks is that they are adaptive, which means they can change or adapt the parameters like weights and biases (see below) within themselves as they learn from continuous training. A deep learning neural network is a stack of neural networks composed of many layers.

He et al. (2015) introduced ResNet to solve the problems caused by vanishing or exploding gradients when training very deep neural networks. The structure of the ResNet block is illustrated in Figure 4. Output of each block is related to the results of previous hidden layers, as well as the initial input. We adopt this as the basic structure of our network because of its good performance after experiments.

The frame of our network is displayed in Figure 5. First of all, each flux value of a continuum-normalized spectrum is allocated to a node (black point) of the input layer. All of nodes are fully connected to neurons (blue points) in the next dense layer, so a neuron will receive all of the fluxes delivered by the nodes. Output of the $n$th neuron $y^{(n)}$ is determined by
Equation (1) where \( x \) is the received fluxes, \( m \) is the number of flux pixels (nodes), whereas parameters \( w^{(n)} \) and \( b^{(n)} \) stand for weights and biases of this neuron that are going to be adjusted during training. These outputs are sequentially passed to ResNet blocks.

\[
y^{(n)} = \sum_{i=1}^{m} w_{i}^{(n)} x_{i} + b^{(n)}
\]

The batch normalization (BN) layer (Ioffe & Szegedy 2015) applies a transformation that maintains the mean close to zero and the standard deviation close to 1 for each neuron channel over a training mini-batch (the data are usually divided into several batches and the network is successively trained on the data of one batch size at a time rather than the whole data set due to limited computer memory). Use of a BN layer will dramatically accelerate the training process and improve performance (Ioffe & Szegedy 2015). The activation layer is used to impart nonlinearity to inputs from the last layer to improve the performance and stability of the network. The output of each node (gray point) in the activation layer will be passed to neurons in the next dense layer and then neurons will sequentially transmit their outputs calculated with the same mechanism as described in Equation (1) to the second sub-block. It is worth nothing that eventual outputs of one ResNet block are obtained by adding the outputs (F(X)) computed from the whole block and the initial inputs (X) as mentioned above.

After processes operated by three ResNet blocks, data flow is continuously passed to the rest layers. The final layer is still a dense layer with only two neurons representing the outlets of \( T_{\text{eff}} \) and \( \log g \). We instantiate two networks based on two data sets with the frame as shown in Figure 5. For data set 1, the number of nodes in the input is 2915, which is determined by the number of flux pixels. We place 280 neurons in each dense layer except for the last dense layer for which we place two. For data set 2, there are 3666 nodes in the input since we interpolate observed spectra (the wavelength interval is 0.0001 in logarithmic form) with the wavelength step 1 Å and the number of neurons in the dense is 340. For both cases, we use the ReLU function that returns the maximum between the input and zero in the activation layer. Other configurations will be fixed automatically.

3.2. Training and Test

We obtain \( T_{\text{eff}} \) and \( \log g \) of DAs from the WDs catalogs reported by Kleinman et al. (2013) and Kepler et al. (2015, 2016) and match these parameters with corresponding spectra. The parameters were determined through theoretical fitting and are able to generally describe the actual states of the DAs. We adopt these parameters as reference values to construct and verify our networks. After 3D correction, we filter the data with certain criteria and get 8490 samples. Then we preprocess these spectra in two ways yielding two data sets: normalized observed spectra and synthetical spectra with \( R = 200 \). We split them randomly into two parts: 70% for training (5943) and 30% for test (2547). Finally, we use continuum-normalized fluxes as input and normalized \( T_{\text{eff}}, \log g \) (i.e., minimum is zero and maximum is 1) as the output of the networks. The results of each part of every data set are shown in Figures 6 and 7. We adopt rms error (RMSE) and mean absolute error (MAE) (see Equation (2), where \( z_{i} \) is the
reference value and \( \hat{z}_i \) is the parameter estimated by networks) as metrics of the performance of the networks.

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{i=1}^{N} (z_i - \hat{z}_i)^2}, \quad \text{MAE} = \frac{1}{N} \sum_{i=1}^{N} |z_i - \hat{z}_i| \tag{2}
\]

For the training part of data set 1, the RMSE and MAE of \( T_{\text{eff}} \) we get are 133.7 K and 100.9 K, respectively. As for log \( g \), they are 0.01 dex and 0.01 dex, which means that the network has fully learned properties of the training data.

The test part is used to provide an unbiased evaluation on the final model. The tendency of the result for \( T_{\text{eff}} \) generally seems to be fine although there is a little dispersion at \( T_{\text{eff}} \sim 11000 \) K owing to the spectral degeneracy of DAs (Eisenstein et al. 2006), leading to RMSE = 906.4 K and MAE = 508.8 K. The situation for log \( g \) is complicated. Since the distribution of log \( g \) of our samples is mainly located between 7.0 and 9.0 dex, especially \( \sim 8.0 \) dex (see Figure 1), the performance is better when log \( g \in [7.75, 8.25] \) dex where more data are concentrated. For the side with smaller log \( g \), predicted values are a little higher than the reference ones and for the region with higher log \( g \), the former is mostly smaller than the latter, which results in RMSE = 0.11 dex and MAE = 0.08 dex. The performance from the test part shows that there is no bad overfitting within the network.

In terms of data set 2, we instantiate the second network with the same frame but different configurations, also resulting in similar consequences (see Figure 7). The reason why performances of two networks trained on two data sets with different spectra resolutions are analogous may be because

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**Figure 6.** Results of data set 1. Red points: predicted parameters by the network versus reference parameters from WDs catalogs in published papers. Solid line means there is no error.
there are strong and wide hydrogen lines rather than very close absorption lines, making different resolutions lead to little effects.

For both data sets, we also calculate the residual ($\Delta = \hat{z} - z$) of the parameters for each part. Furthermore, we infer the mean and standard deviation (Std) of the residual for the test part, as shown in Figure 8.

4. Conlusion

In this work, we construct a deep learning network based on the ResNet structure. The network is directly trained and tested on the continuum-normalized spectral pixels of DAs spectroscopically confirmed in SDSS DR7, DR10, and DR12 to map the spectra onto atmospheric parameters. The RMSE related to the estimated and reference parameters reaches 900 K for $T_{\text{eff}}$ and 0.1 dex for $\log g$. Furthermore, we show that the method is also applicable for the spectra with a degraded resolution of $\sim$200.

Compared with the traditional methodology that achieves parameter determinations of DAs, our network does not depend on complex theoretical models because it directly uses observed normalized fluxes as input to find the matching parameters. The method is feasible for DAs with $T_{\text{eff}}$ from 5000 to 40,000 K and $\log g$ from 7.0 to 9.0 dex.

The existing limitation is that we do not infer the errors of each estimated parameter due to the running mode of the network. In addition, it only works for DA types currently since it is not easy to recognize and grasp common features from the spectra of other WD types by merely training neural networks.

In the future, we will continue to collect data of WDs and improve the ability of our method to determine physical parameters of the stars more accurately.
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References

Abazajian, K., Adelman-McCarthy, J. K., Agüeros, M. A., et al. 2003, AJ, 126, 2081
Abazajian, K. N., Adelman-McCarthy, J. K., Agüeros, M. A., et al. 2009, ApJS, 182, 543
Abolfathi, B., Aguado, D. S., Aguilar, G., et al. 2018, ApJS, 235, 42
Adelman-McCarthy, J. K., Agüeros, M. A., Allam, S. S., et al. 2006, ApJS, 162, 38
Ahn, C. P., Alexandroff, R., Allende Prieto, C., et al. 2014, ApJS, 211, 17
Alam, S., Albareti, F. D., Allende Prieto, C., et al. 2015, ApJS, 219, 12
Bailer-Jones, C. A. L., Irwin, M., Gillmore, G., & von Hippel, T. 1997, MNRAS, 292, 157
Blanco-Cuaresma, S., Soubiran, C., Heiter, U., & Jofré, P. 2014, A&A, 569, A111
Blanton, M. R., Bershady, M. A., Abolfathi, B., et al. 2017, AJ, 154, 28
Chandra, V., Hwang, H.-C., Zakamska, N. L., & Budavári, T. 2020, MNRAS, 497, 2688
Doherty, C. L., Gil-Pons, P., Siess, L., Lattanzio, J. C., & Lau, H. H. B. 2014, MNRAS, 446, 2599
Eisenstein, D. J., Liebert, J., Harris, H. C., et al. 2006, ApJS, 167, 40
Eisenstein, D. J., Weinberg, D. H., Agol, E., et al. 2011, AJ, 142, 72
Fabbro, S., Venn, K. A., O’Briain, T., et al. 2018, MNRAS, 475, 2978
Gong, Y., Liu, X. K., Cao, Y., et al. 2019, ApJ, 883, 203
He, K. M., Zhang, X. Y., Ren, S. Q., & Sun, J. 2015, arXiv:1512.03385
Ioffe, S., & Szegedy, C. 2015, arXiv:1502.03167
Kepler, S. O., Pelosi, I., Koester, D., et al. 2015, MNRAS, 446, 4078
Kepler, S. O., Pelosi, I., Koester, D., et al. 2016, MNRAS, 455, 3413
Kepler, S. O., Pelosi, I., Koester, D., et al. 2019, MNRAS, 486, 2169
Kleinman, S. J., Harris, H. C., Eisenstein, D. J., et al. 2004, ApJ, 607, 426
Kleinman, S. J., Kepler, S. O., Koester, D., et al. 2013, ApJS, 204, 5

Figure 8. Upper panel: residuals of parameters of each part for data set 1. Blue points represent the training part and the red points represent the test part. Lower panel: same as the upper, but for data set 2.
Liang, X. L., Zhao, J. K., Chen, Y. Q., et al. 2019, ApJ, 887, 193
Majewski, S. R., Schiavon, R. P., Frinchaboy, P. M., et al. 2017, AJ, 154, 94
Tremblay, P. E., Kalirai, J. S., Soderblom, D. R., Cignoni, M., & Cummings, J. 2014, ApJ, 791, 92
Tremblay, P. E., Ludwig, H. G., Steffen, M., & Freytag, B. 2013, A&A, 559, A104
York, D. G., Adelman, J., Anderson, J. E. J., et al. 2000, AJ, 120, 1579
Zhang, X., Zhao, G., Yang, C. Q., Wang, Q. X., & Zuo, W. B. 2019, PASP, 131, 094202
Zhao, G., Chen, Y. Q., Shi, J. R., et al. 2006, ChJAA, 6, 265
Zhao, G., Zhao, Y. H., Chu, Y. Q., Jing, Y. P., & Deng, L. C. 2012, RAA, 12, 723