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Chinese Astronomy and Astrophysics 41 (2017) 318–330

CHINESE
ASTRONOMY
AND ASTROPHYSICS

Stellar Atmospheric Parameterization Based on Deep Learning† ⋆

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Abstract Deep learning is a typical learning method widely studied in the fields of machine learning, pattern recognition, and artificial intelligence. This work investigates the problem of stellar atmospheric parameterization by constructing a deep neural network with five layers, and the node number in each layer of the network is respectively 3821-500-100-50-1. The proposed scheme is verified on both the real spectra measured by the Sloan Digital Sky Survey (SDSS) and the theoretic spectra computed with the Kurucz's New Opacity Distribution Function (NEWODF) model, to make an automatic estimation for three physical parameters: the effective temperature ($T_{\rm eff}$), surface gravitational acceleration (lg g), and metallic abundance (Fe/H). The results show that the stacked autoencoder deep neural network has a better accuracy for the estimation. On the SDSS spectra, the mean absolute errors (MAEs) are 79.95 for $T_{\rm eff}$/K, 0.0058 for (lg $T_{\rm eff}$/K), 0.1706 for lg $(g/({\rm cm \cdot s^{-2}}))$, and 0.1294 dex for the [Fe/H], respectively; On the theoretic spectra, the MAEs are 15.34 for $T_{\rm eff}$/K, 0.0011 for lg $(T_{\rm eff}/{\rm K})$, 0.0214 for lg$(g/({\rm cm \cdot s^{-2}}))$, and 0.0121 dex for [Fe/H], respectively.

Key words stars: fundamental parameters, stars: atmospheres, stars: abundances, methods: data analysis, methods: statistical

1. INTRODUCTION

To study the stellar properties of the Galaxy is an important problem of astrophysics[1], the large-scale LAMOST[2−4] and Sloan[5−7] sky surveys can obtain a huge number of spectral data of stars in the Galaxy, how to estimate automatically the physical parameters of stellar

† Supported by National Natural Science Foundation (61273248, 61075033), NNSF-CAS Joint Foundation (U1531242), Guangdong Natural Science Foundation (2014A030313425, S2011010003348)

Received 2015–11–10; revised version 2016–01–29

⋆ A translation of *Acta Astron. Sin.* Vol. 57, No.4, pp. 379–388, 2016

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0275-1062/17/$-see front matter
doi:10.1016/j.chinastron.2017.08.003

atmospheres from these huge number of spectra data has an important significance for the study of stellar properties.

Deep learning[8] is a hot point in the research fields of machine learning, pattern recognition, and artificial intelligence, especially in recent years under the promotion of information technical enterprises, such as Google, Baidu, Microsoft, Facebook, etc., the deep learning technique has made significant progresses, and successfully applied to image recognition, video analysis, natural language processing, electronic commerce, data analysis, pronunciation recognition, and other fields.

Deep learning has a distinct performance in the search and expression of non-linear relations, and suits the treatment of complex big data. Highly non-linear relations exist between the stellar spectra and the physical parameters of stellar atmospheres, and the actually measured spectra are high-dimensional data with noises. Hence, this paper has studied the application of deep learning technique in the estimation of physical parameters of stellar atmospheres.

2. DEEP LEARNING

The deep learning technique includes the following three basic types: stacked autoencoder, confidence network, and convolutional neural network. This paper studies the application of stacked autoencoder in the the estimation of physical parameters of stellar atmospheres, in the following we make a further introduction to this type of deep learning method.

The stacked autoencoder learning method is called also the stacked autoencoder neural network, actually it is a multi-layer feedforward neural network, the reason for the name of stacked autoencoder deep neural network is because that the training of this multi-layer feedforward neural network needs to make pre-training by using the stacked autoencoder algorithm, then to make a fine-tuning on it in combination with the linear regression network. In the following we introduce the multi-layer feedforward neural network, pre-learning, and fine-tuning, respectively.

2.1 Multi-layer Feedforward Neural Network

2.1.1 The structure of multi-layer feedforward neural network

The multi-layer feedforward neural network is characterized by its unidirectional data flow from the input layer to the output layer of the network, the structure of multi-layer feedforward neural network included totally p layers (one input layer, one output layer, and $p-2$ hidden layers) is shown in Fig.1.

In the figure, the superscripts of characters express the ordinal numbers of different layers in the network, n_k indicates the number of nodes of the k-th layer. $\boldsymbol{W}^{(k)}$ is a $n_k \times n_{k+1}$ matrix to be used for expressing the weights, $\boldsymbol{b}^{(k)}$ is a row vector of n_{k+1} dimensions to be used for expressing the biases. Generally, $\boldsymbol{W}^{(k)}$ and $\boldsymbol{b}^{(k)}$ are unified to be called as the connection parameters between the k-th layer and the $(k+1)$-th layer of the network. f_k is