Stellar Parameterization of LAMOST M Dwarf Stars

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Abstract

The M dwarf stars are the most common stars in the Galaxy, dominating the population of the Galaxy at faint magnitudes. Precise and accurate stellar parameters for M dwarfs are of crucial importance for many studies. However, the atmospheric parameters of M dwarf stars are difficult to determine. In this paper, we present a catalog of the spectroscopic stellar parameters ($T_{\text{eff}}$ and [M/H]) of $\sim$300,000 M dwarf stars observed by both LAMOST and Gaia using the Stellar Label Machine (SLAM). We train a SLAM model using APOGEE Data Release 16 labels with $2800 \leq T_{\text{eff}} \leq 4500K$ and $-2 < [M/H] < 0.5$ dex. The SLAM $T_{\text{eff}}$ is in agreement to within $50K$ compared to the previous study determined by APOGEE observations, and the SLAM [M/H] agrees within 0.12 dex compared to the APOGEE observation. We also set up a SLAM model trained by the BT-Settl atmospheric model with random uncertainties (in cross validation) to 60 K and agreeing within $\sim90 K$ compared to previous studies.

Unified Astronomy Thesaurus concepts: M dwarf stars (982); Astronomy data analysis (1858); Low mass stars (2050); Catalogs (205)

1. Introduction

In the Galaxy, M dwarfs are inherently faint objects but dominate the faint magnitudes of the Galaxy, and their number accounts for $\sim70\%$ of the total number of stars in the Milky Way (Bochanski et al. 2010). Kirkpatrick et al. (1999) discovered spectral classes L and T using the Two Micron All Sky Survey (Skrutskie et al. 2006). The T-type stars are completely comprised of brown dwarfs, while main-sequence (MS) stars earlier than M type are comprised of hydrogen-burning M dwarf stars, which are at the MS end of the Hertzsprung–Russell diagram (HRD); their features are in between the MS stars and T-type stars.

The M dwarf stars have lifetimes much longer than the Hubble time (Bochanski et al. 2010), which makes them valuable for tracing the chemical and dynamical history of the Galaxy. Previous studies also used M dwarf stars to determine the initial mass function (Covey et al. 2008; Bochanski et al. 2010) at the low-mass end. Furthermore, M dwarfs are primary candidates for exoplanet searching (Trifonov et al. 2018). Accurate and precise parameters including effective temperatures and chemical compositions of the planet-host stars play a key role in looking for habitable exoplanets.

The M dwarf stars are classified at wavelengths $6300$–$9000 \AA (Boeshaar 1976; Boeshaar & Tyson 1985; Kirkpatrick 1992). One of the main difficulties is that the prominent molecular absorption in the spectra of M dwarfs is hard to predict by atmospheric models (Mann et al. 2015). Moreover, obtaining spectra with high quality for these faint objects is challenging. Generally, the measurement of equivalent widths (EWs) and synthesis are the classical and most common methods to derive stellar parameters. However, synthesis is the favorable method to measure the stellar parameters for cool stars, since the EWs are difficult to measure for their crowded absorption lines (reviewed by Jofré et al. 2019).

With the development of new facilities, large surveys such as the Sloan Digital Sky Survey Apache Point Observatory Galactic Evolution Experiment (SDSS/APOGEE; Majewski et al. 2017) and Transiting Exoplanet Survey Satellite (TESS; Muirhead et al. 2018) missions and the Large Sky Area Multi-Object Fiber Spectroscopic Telescope (LAMOST; Cui et al. 2012; Deng et al. 2012 and Zhao et al. 2012) have collected incremental photometric and spectroscopic data of M dwarf stars. The LAMOST survey has provided nine million spectra in its Data Release 6 (DR6) at $R \sim 1800$, among which $\sim600,000$ spectra are M dwarf stars. However, these stars lack stellar parameters.

Many efforts have attempted to decode the effective temperatures and chemical abundances of M dwarfs from high-resolution spectra in either the optical or the near-infrared (NIR) band (Woolf & Wallerstein 2005; Rajpurohit et al. 2014; Veyette et al. 2017; Rajpurohit et al. 2018; Mann et al. 2019). The APOGEE Stellar Parameter and Chemical Abundances Pipeline (ASPCAP) measurements of $T_{\text{eff}}$ and metallicity (García Pérez et al. 2016) for M dwarfs have been determined with precisions of $\sim100 K$ and 0.18 dex, respectively (Schmidt et al. 2016) by fitting with the atmospheric models. Furthermore, the APOGEE data of SDSS Data Release 16 (DR16; Jónsson et al. 2020) use new atmospheric grids that can estimate effective temperatures down to 3000 K. Birky et al. (2020, hereafter B20), using The Cannon (Ness et al. 2015; Ho et al. 2017), derived the effective temperatures and metallicities for 5875 APOGEE M dwarfs with 87 sources from Mann et al. (2015, hereafter M15) as a training data set. Effective temperatures were estimated by M15 by comparing spectra with the BT-Settl atmospheric models (Allard et al. 2013), and they calibrated their results using stars with determinations from interferometry (Boyajian et al. 2012; Mann et al. 2013).

Furthermore, Rajpurohit et al. (2018) determined the parameters of 45 M dwarfs using high-resolution $H$-band
spectra by fitting BT-Settl model grids. Dieterich et al. (2021) obtained stellar parameters of five M dwarf systems by fitting BT-Settl atmospheric and test current stellar models. Galgano et al. (2020) presented effective temperatures, radii, masses, and luminosities for 29,678 M dwarfs from LAMOST DR5 using The Cannon with a typical uncertainty of $T_{\text{eff}}$ of $\sim$110 K. They used stellar labels from the TESS Cool Dwarf Catalog (Muirhead et al. 2018), in which $T_{\text{eff}}$ was determined from the color–$T_{\text{eff}}$ relations in M15. In other words, the effective temperatures of all previous studies rely on the BT-Settl atmospheric model. It is noted that the parameters derived by the previous works display substantial systematic errors, since different works used the different spectral regions and lines with various methods (Jofré et al. 2019).

Recently, new techniques to derive stellar parameters with machine-learning algorithms (Ting et al. 2019; Xiang et al. 2019) have demonstrated high efficiency in processing large amounts of spectral data. Data-driven methods were illustrated as promising solutions in cool star parameterization (Jofré et al. 2019). These novel methods have performed well in transferring the known information from training data sets to entire data sets.

In this work, we build a data-driven model for LAMOST spectra based on the Stellar LAbel Machine (SLAM; Zhang et al. 2020) trained by APOGEE stellar labels and BT-Settl model atmospheres and synthetic spectra (Allard et al. 2013) to estimate the entire data set of LAMOST M dwarf stars.

This paper is organized as follows. In Section 2, we introduce how SLAM works. In Section 3, we describe M dwarf spectra selected from the LAMOST and Gaia surveys, as well as the training data set from the APOGEE survey and BT-Settl model. We then present the results in Section 4 and make a comparison with previous works. Section 5 raises discussions about the caveats of the results, and we assess the robustness and performance of the results and draw conclusions in Section 5.

Table 1

| Training Data Set | LAMOST Spectra with APOGEE Labels | BT-Settl Synthesis Spectra |
|-------------------|----------------------------------|---------------------------|
| Effective temperature | TEFF$_{\text{AP}}$ | TEFF$_{\text{BT}}$ |
| Metallicity | $M_{\text{H,AP}}$ | 

Note. The LAMOST spectra with APOGEE labels are used to estimate both the effective temperature and metallicities. The BT-Settl synthesis spectra are only used to determine $T_{\text{eff}}$.

2. Method

SLAM, developed by Zhang et al. (2020), has shown good performance in determining the stellar labels of LAMOST DR5. It is a data-driven model based on support vector regression (SVR; Vapnik 1997), which is a robust nonlinear regression model. The data-driven method has been demonstrated as one of the most practical ways to measure the stellar parameters of M dwarfs. Additionally, LAMOST data are suitable for data-driven methods because it is difficult to perform the standard methods of measuring EWs for parameter estimations of cool stars (Jofré et al. 2019) with low-resolution spectra. Meanwhile, the large quantity of LAMOST data demands the use of fast data-driven methods.

2.1. Support Vector Regression

The support vector machine (SVM; also support vector network; Cortes & Vapnik 1995) is one of the most important supervised machine-learning algorithms to be used for classification and regression. The regression algorithms of SVM, named SVR, have been used in many astronomical studies, particularly in spectral data analysis (Liu et al. 2012, 2014, 2015a, 2015b).

2.2. SLAM

SLAM has three hyperparameters, two of which are the penalty level ($C$) and tube radius ($\epsilon$) coming from the genetic SVR algorithm. The third one ($\gamma$) indicates the width of the radial basis function (RBF), which is the kernel adopted by SLAM.

The architecture of SLAM consists of three steps.

1. **Preprocessing.** We normalize the spectra of the training data; in the mean time, we also standardize both stellar labels and spectral fluxes so that their mean is zero and variance is 1.
2. **Training.** We train the SVR model with stellar parameters as independent variables and flux at a given wavelength as dependent variables at each wavelength pixel using the training data set.
3. **Prediction.** We apply the optimized SVR model to predict the stellar labels for observed spectra.
To choose the best-fit hyperparameters at each wavelength, which is defined as the training procedure, SLAM minimizes the \( k \)-fold cross-validated mean squared error (CV-MSE), which is defined as

\[
\text{MSE}_j = \frac{1}{m} \sum_{i=1}^{m} [f_j(\theta) - f_{j,\text{obs}}]^2,
\]

where \( \theta = (T_{\text{eff}}, \log g, [M/H]) \) denotes the stellar label vector of the \( j \)th star in the training data, and \( f_j(\theta) \) is the \( j \)th pixel of the training spectra as a function of \( \theta \). In the prediction procedure, the posterior probability density function of \( \theta \) for an observed spectrum can be written as

\[
p(\theta|f_{\text{obs}}) \propto p(\theta) \prod_{j=1}^{n} p(f_{j,\text{obs}}|\theta),
\]

where \( p(f_{j,\text{obs}}|\theta) \) is the likelihood of the spectral flux \( f_{j,\text{obs}} \) varying with \( \theta \) based on the trained SVR model and \( p(\theta) \) is the prior of \( \theta \). The best estimate of the stellar labels can be found at the maximum of the posterior probability \( p(\theta|f_{\text{obs}}) \).

In practice, the logarithmic form of Equation (2) is used by adopting a Gaussian likelihood,

\[
\ln p(\theta|f_{\text{obs}}) = -\frac{1}{2} \sum_{j=1}^{n} \left[ \frac{f_{j,\text{obs}} - f_{j,\text{model}}(\theta)}{\sigma_{j,\text{obs}} + \sigma_{j,\text{model}}(\theta)} \right]^2 - \frac{1}{2} \sum_{j=1}^{n} \ln [2\pi (\sigma_{j,\text{obs}}^2 + \sigma_{j,\text{model}}(\theta)^2)],
\]

where \( f_{j,\text{obs}} \) is the \( j \)th pixel of the observed spectrum, \( f_{j,\text{model}}(\theta) \) is the SVR model-predicted spectral flux corresponding to the stellar label vector \( \theta \), \( \sigma_{j,\text{obs}} \) is the uncertainty of the \( j \)th pixel of the observed spectrum, and \( \sigma_{j,\text{model}}(\theta) \) is the uncertainty of the \( j \)th pixel of the model-predicted spectrum given the stellar labels \( \theta \). In practice, \( \sigma_{j,\text{model}}(\theta) \) is replaced with CV-MSE, which is independent of \( \theta \). SLAM adopts a maximum-likelihood estimation with a Levenberg–Marquardt (Moré 1978) least-squares optimizer as the optimization method to derive the most likely \( \theta \) for an observed spectrum.

3. Data

3.1. LAMOST Data

LAMOST (Guo Shou Jing Telescope) is one of the most efficient spectroscopic survey telescopes, providing 9,919,106 low-resolution (\( R \sim 1800 \)) optical spectra, among which 8,966,416 are stellar spectra, in its DR6 (Cui et al. 2012; Zhao et al. 2012; Deng et al. 2012). In LAMOST DR6, 607,142 spectra are published as the M dwarf catalog.

We first select stars from the LAMOST DR6\(^6\) M dwarf catalog (Yi et al. 2014; Guo et al. 2019) cross-matched with Gaia DR2 (Gaia Collaboration et al. 2018). Then, samples are selected using the following criteria to obtain reliable Gaia photometry (\( G_{BP} - G_{RP} \) color and \( G \)-band magnitude), astrometry (parallax), and LAMOST spectra.

1. parallax / parallax error > 5;
2. phot\_bp\_mean\_flux/phot\_bp\_mean\_flux\_error > 20, phot\_rp\_mean\_flux/phot\_rp\_mean\_flux\_error > 20, and phot\_g\_mean\_flux/phot\_g\_mean\_flux\_error > 20;
3. ruwe < 1.4
4. signal-to-noise ratio (S/N) at the \( i \) band of the LAMOST spectra is larger than 5.

Criteria 1–3 aim to select stars with both accurate photometry and astrometry. Here \( \text{ruwe} \) is the renormalized unit-weight error that measures astrometric goodness of fit, and criterion 3 is for selecting stars with small renormalized unit-weight error. Criterion 4 aims to select spectra with a clear stellar spectral signature. Similar to B20, criterion 5 aims to select the MS M dwarfs as shown in Figure 1.

We display the selected M dwarf samples in HRDs (Figure 1). The \( G \)-band absolute magnitude is estimated from the Bayesian distance from Bailer-Jones et al. (2018). To investigate the contamination of M giant stars, we draw 35,382 M giants on Figure 1 (Zhong et al. 2019). We select \( M_G + A_G \leq 5 \) to remove the contaminations. Some of the M dwarf stars are not located at the MS but rather below and above it. There are \( \sim 7000 \) stars on the top side of the quadrangle that are likely pre-MS stars or

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\(^6\) http://dr6.lamost.org
binaries. About 1000 stars on the bottom side might be white dwarf–MS binaries. We remove these stars and only select 379,258 M dwarf samples that fell into the quadrangle for the estimation of the stellar parameters. Most of the M dwarf stars are located within a few hundred parsecs. Therefore, the interstellar extinction of M dwarfs is mostly very low. There may be a few stars with large extinction and thus a location beyond the selection area. These stars may be removed mistakenly.

3.2. Training Data Set

Since SLAM is a data-driven model that assumes stellar labels as ground truth, reliable stellar parameters of training data sets are needed. To date, various methods and training data sets have been developed and introduced to measure labels (stellar parameters) for M dwarfs. In this work, we use APOGEE stellar parameters and BT-Settl synthetic spectra, respectively, as the training data sets separately described in Sections 3.2.1 and 3.2.2.

3.2.1. APOGEE Labels as Training Data

García Pérez et al. (2016) presented the ASPCAP, which fits observed NIR spectra to synthetic spectra made with the code FERRE (Allende Prieto et al. 2006). The measurement of $T_{\text{eff}}$ for M dwarfs reaches the precision of 100 K in the range 3550
K < $T_{\text{eff}}$ < 4200 K, and the mean precision of ASPCAP metallicities is 0.18 dex in the range $-1.0 < [\text{M/H}] < 0.2$ (Schmidt et al. 2016). For APOGEE DR16, Jönsson et al. (2020) used the new MARCS stellar atmospheric models, which are continuous from 3000 to 4000 K for $T_{\text{eff}}$. The stellar parameters of DR16 are enhanced significantly for cool stars with $T_{\text{eff}} < 3500$ K, avoiding discontinuities in ASPCAP at 3500 K. As for the metallicity of DR16, the comparison with six well-studied open clusters shows a faint difference of 3500 K. As for the metallicity of DR16, the comparison with six well-studied open clusters shows a faint difference of 0.004 dex (Donor et al. 2020; Jönsson et al. 2020).

We cross-match our selected M dwarf APOGEE DR16 catalog 7 and obtain about 4317 common stars with LAMOST spectra and APOGEE labels as training data. We further select 3785 samples using the following criteria:

1. $2800 \text{ K} < T_{\text{eff}} < 4500 \text{ K},$
2. $T_{\text{eff}}$ uncertainty smaller than 100 K,
3. $-2$ dex $< [\text{M/H}] < 0.5$ dex,
4. [M/H] uncertainty smaller than 0.1 dex, and
5. $\log g > 4$ dex.

3.2.2. BT-Settl as Training Data

Another independent training data set is the BT-Settl spectra. Unlike the empirical spectra with APOGEE stellar labels, the BT-Settl model atmospheres and synthetic spectra (Allard et al. 2013) are computed by solving the radiative transfer using the mixing-length theory (Böhm-Vitense 1958). The BT-Settl model can be used to determine the parameters from moderately active very low mass stars (VLMs), brown dwarfs, and planetary-mass objects. The BT-Settl model would be a useful supplement and extend the effective temperature lower than 3000 K. Since a data-driven method is more difficult to train at the edge of the training labels, we finally use the $T_{\text{eff}}$ range from 2200 to 7000 K as the training labels.

4. Results

Note that the APOGEE stellar parameters and BT-Settl depend on different atmospheric models and are not necessarily consistent with each other. Therefore, we use them as the training data independently and predict two sets of stellar labels based on the two data sets.

We used observed (LAMOST spectra with APOGEE labels) and synthetic (BT-Settl) spectra, respectively, as the training data set. The notation of the stellar parameters ($T_{\text{eff}}, [\text{M/H}]$) of the LAMOST M dwarfs is named by the different training data sets, as shown in Table 1.

First, we estimate the $T_{\text{eff}}$ and [M/H] using the APOGEE labels as the training set described in Sections 4.1.1 ($T_{\text{eff}}$) and 4.2 ([M/H]). We further use the synthetic spectra from BT-Settl models and obtain $T_{\text{eff}}$. More details are discussed in Section 4.1.2.

4.1. Effective Temperature

4.1.1. APOGEE Temperature

First of all, we combine the LAMOST spectra with the corresponding APOGEE labels as the training data set to train the SLAM model. Effective temperature ($T_{\text{eff}}$) and metallicity ($M_{\text{H\_AP}}$) are determined for the test data set by applying this SLAM model. In this section, we discuss $T_{\text{eff}}$ and leave $M_{\text{H\_AP}}$ to Section 4.2.

A tenfold cross validation is taken to estimate the precision and accuracy of the APOGEE-trained SLAM labels. The CV scatter and bias denote the standard and mean deviation, respectively, and can be written as

$$CV - \text{bias} = \frac{1}{n} \sum_{i=1}^{n} (\hat{\theta}_{i,\text{SLAM}} - \theta_i) \quad (4)$$

and

$$CV - \text{scatter} = \frac{1}{n} \sqrt{\sum_{i=1}^{n} (\hat{\theta}_{i,\text{SLAM}} - \theta_i)^2}, \quad (5)$$

where $\hat{\theta}_{i,\text{SLAM}}$ is the stellar label of the $i$th star predicted by SLAM, and $\theta_i$ denotes the stellar label of the $i$th star as ground truth. Theoretically, a robust data-driven algorithm has a small CV bias and scatter. The CV results displayed in Figure 2 indicate that the $T_{\text{eff}}$ reaches a precision of 50 K with no bias when $S/N_i > 100$.

Spectroscopic temperatures and metallicities were derived by B20 for 5875 M dwarfs from the APOGEE survey. We cross-match the LAMOST data with their results and obtain 1913 common stars. Among them, B20, LAMOST, and APOGEE DR16 together have 1286 common stars.

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7 https://www.sdss.org/dr16/irspec/aspcap/
compare the stellar parameters in the two catalogs separately with those we obtained using SLAM. As illustrated in the top panels of Figure 3, the $T_{\text{eff}}$ of APOGEE DR16 and TEFF_AP are in good agreement, which is not surprising because TEFF_AP is estimated by the stellar labels of APOGEE. The $\sim 50$ K scatter and 3 K bias are identical to the test results of cross validation, which are reasonable. The middle panels of Figure 3 show the comparison between TEFF_AP and B20; the residuals between the two have a dispersion of $\sim 60$ K and an offset of 185 K. This bias is mainly due to the 182 K difference between the temperature of APOGEE and B20. This is the result of the different stellar atmospheric models used in the stellar parameterization.

4.1.2. BT-Settl Temperature

We then set up the alternative training data set using BT-Settl synthetic spectra so that the lower $T_{\text{eff}}$ can go down beyond 3000 K. We follow the preprocessing procedure developed by Zhang et al. (2020)\(^8\) to adjust the resolution and wavelength to be the same as the LAMOST low-resolution spectra. The

\(^8\) https://github.com/hypergravity/astroslam
training labels of the model grids\textsuperscript{9} are 2200 K < \(T_{\text{eff}}\) < 7000 K, 
\(-1.0 \text{ dex} < [M/H] < 0.0 \text{ dex}, 2.5 < \log g < 5.5 \text{ dex} \) with steps of 100 K, 0.5 dex, and 0.5 dex, respectively.

The original grid from BT-Settl is too sparse. So we first interpolate the grid to obtain a new training data set with denser grids. Because SLAM is a forward model, it can be used to do the interpolation. We randomly draw 15,000 points in the parameter space with 2800 K < \(T_{\text{eff}}\) < 4500 K, 
\(-1.0 \text{ dex} < [M/H] < 0.0 \text{ dex}, \) and 4.5 < \(\log g\) < 5.5 \text{ dex} following the uniform distributions. The corresponding synthetic spectra are obtained from the SLAM model \textit{SLAM}_0, which is trained by the sparse original grid of BT-Settl. We then train model \textit{SLAM}_1 with the 15,000 synthetic spectra interpolated from model \textit{SLAM}_0 as the training data set. Finally, we predict \(TEFF_{\text{BT}}\) for the LAMOST spectra using \textit{SLAM}_1.

Similar to Section 4.1.1, tenfold cross-validation is used to test the performance and robustness of our model. Random Gaussian noise is added to the test spectra. The left panel of Figure 2 shows that CV errors change with a given \(S/N\). We obtain a random error of 40 K with a CV bias of 5 K at \(S/N > 100\). The results of the CV errors indicate that our method works effectively. Figure 2 also shows that CV scatter varies with \(S/N\). Note that the \(S/N\) is

\textsuperscript{9} https://phoenix.ens-lyon.fr/Grids/BT-Settl/CIFIST2011b

Figure 6. The top left panel displays the HRD of \(\sim 9000\) M dwarf stars with \(S/N_i > 50\), a subsample of our catalog in the SLAM \(T_{\text{eff}}\) (\textit{TEFF\_AP}) vs. Gaia \(M_\odot\) plane, and is colored by \(M_{\text{H\_AP}}\). The top right panel shows the same HRD as the top left panel, but the x-axis is the \(G_{\text{BP}} - G_{\text{RP}}\) colors. The bottom panel displays the contours drawn with the same stars as the top left panel, while the temperatures are \(TEFF_{\text{BT}}\). The solid lines indicate the the Padova and Trieste Stellar Evolutionary Code (PARSEC) isochrones from [M/H] = −1.0 to 0.6 dex. The gray dashed curves represent the locations of 0.3, 0.5, and 0.7 \(M_\odot\).
Figure 7. Metallicity distribution in Hyades. The vertical line indicates the metallicity [Fe/H] = 0.13 given by previous studies.

Table 2
The Field Definition of the Stellar Parameter Catalog of LAMOST M Dwarf Stars

| Column       | Unit   | Description                             |
|--------------|--------|-----------------------------------------|
| source_id    |        | Gaia identification ID                  |
| obsid        |        | LAMOST unique spectra ID                |
| ra_obs       | deg    | LAMOST fiber pointing R.A.              |
| dec_obs      | deg    | LAMOST fiber pointing decl.             |
| snru         |        | LAMOST signal noise at SDSS u band      |
| srgg         |        | LAMOST signal noise at SDSS g band      |
| snmr         |        | LAMOST signal noise at SDSS r band      |
| snni         |        | LAMOST signal noise at SDSS i band      |
| snrz         |        | LAMOST signal noise at SDSS z band      |
| z            |        | LAMOST redshift uncertainty             |
| type         |        | Magnetic activity                       |
| T\(\text{EFF\_BT}\) | K    | Effective temperature from BT-Settl-trained SLAM |
| T\(\text{EFF\_BT\_ERR}\) | K   | Uncertainty of effective temperature from BT-Settl-trained SLAM |
| T\(\text{EFF\_AP}\) | K    | Effective temperature from APOGEE-trained SLAM |
| T\(\text{EFF\_AP\_ERR}\) | K   | Uncertainty of effective temperature from APOGEE-trained SLAM |
| M\(\text{\_H\_AP}\) | dex   | [M/H] from APOGEE-trained SLAM          |
| M\(\text{\_H\_AP\_ERR}\) | dex  | Uncertainty of [M/H] from APOGEE-trained SLAM |

Metallicities could also be estimated by the BT-Settl models together with \(T_{\text{eff}}\). However, the derived BT-Settl [M/H] (hereafter M\(\text{\_H\_BT}\)) shows no clear correlation with observed data published in previous studies (see the bottom panels of Figure 5). In the metal-poor regime ([M/H] < −0.25 dex), though it has a larger scatter, the correlation between the M\(\text{\_H\_BT}\) and APOGEE metallicities is obvious. But for [M/H] > −0.25 dex, M\(\text{\_H\_BT}\) cannot distinguish well the metallicities of stars. This is probably due to the lack of model grids with [M/H] > 0. Therefore, the BT-Settl-trained [M/H] is not adopted in our catalog (Table 4).

4.3. Hertzsprung–Russell Diagram

Figure 6 displays the HRD of the LAMOST M dwarfs in the Gaia \(M_G\) versus logarithmic \(T_{\text{eff}}\) (TEFF\_AP) plane. Note that the \(M_G\) is estimated from the Bayesian distance from Bailey-Jones et al. (2018) with extinction removed. The 3D dust-reddening maps from Bayestar (Green et al. 2019) are used to estimate the visual extinction \(A_V\) for each star, and \(A_G\) is further estimated from \(A_V\) using the extinction factor from Wang & Chen (2019). Figure 6 is the dereddened HRD for a subsample of ~9000 M dwarf stars in our catalog. As illustrated in the top left panel, the metallicity (M\(\text{\_H\_AP}\)) can be clearly distinguished in the HRD. Moreover, the top right panel shows the color–magnitude diagram in the \(G_{\text{BP}} − G_{\text{RP}}\) versus \(M_G\) plane; the gradient of metallicity is still very clear and shows a similar trend as in the top left panel.

We further overlap the PARSEC (Bressan et al. 2012) theoretical tracks with the age of 1 Gyr and find that they are...
well fit with each other, as shown in the bottom panel of Figure 6. PARSEC version 1.2 S\(^{10}\) (Chen et al. 2014) provides revisions on VLMs from the BT-Settl model with a wide range of metallicities from −2.19 to +0.70 dex. As displayed in Figure 6, we found that (a) the HRD given by the PARSEC stellar model shows good agreement with our observed HRD for TEFF\(_{\text{AP}}\) and TEFF\(_{\text{BT}}\) and (b) stars above the isochrone of [M/H] = 0.6 are likely to be in binary systems.

### 4.4. Chromospheric Activity

Active M dwarf stars are the only class of stars whose stellar parameters are systematically affected by magnetic activity (Kochukhov 2021). The H\(_{\alpha}\) emission, which can be an indicator of chromospheric activity, might alter the reliability of the stellar parameterization. Guo et al. (2015) found that the fraction of active stars increases as the spectral subtype becomes later. In our work, \(~8\%\) of M dwarf stars have active magnetic fields. So, during the procedure of data preprocessing, the pixels at the wavelength of H\(_{\alpha}\) emission are masked to improve the precision of stellar parameter estimation.

### 5. Discussion and Conclusions

#### 5.1. The Accuracy of Metallicity Assessed from Open Clusters

To assess the accuracy of the metallicities estimated in our work, we select 23 Hyades member stars from our catalog. Hyades is the nearest open cluster, as far as we know (van Leeuwen 2009), with a metallicity of about +0.13 dex (Schuler et al. 2006). We select all stars in a circle with a radius of 5°, centered on R.A. of 66°725 and decl. of 15°867 from Gaia DR2. Then, we adopt that stars located within \(4 < \text{pmra/parallax} < 6, -2.5 < \text{pmdec/parallax} < 0\), and 0.04 < parallax < 0.05 are the member stars of Hyades, where pmra and pmdec are Gaia proper motions. We cross-match our catalog with this sample and obtain 23 M dwarf member stars. We find that the distribution of M\(_{\text{H}}\)\(_{\text{AP}}\) of the members has a mean of 0.0 dex and a standard deviation of 0.1 dex, as shown in Figure 7. This result tentatively verifies that the accuracy of M\(_{\text{H}}\)\(_{\text{AP}}\) is around 0.1 dex.

Furthermore, we cross-match our catalog with the Open Cluster Chemical Analysis and Mapping (OCCAM) survey (Donor et al. 2020) and obtain 138 member stars belonging to 15 open clusters. Figure 8 compares the [Fe/H] given by Donor et al. (2020) with M\(_{\text{H}}\)\(_{\text{AP}}\). The left panel shows that M\(_{\text{H}}\)\(_{\text{AP}}\) matches very well with the metallicity of the corresponding clusters in the range from −0.7 to 0.4 dex. A

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\(^{10}\) http://stev.oapd.inaf.it/cgi-bin/cmd
few stars with higher metallicity in the literature are estimated as lower metallicity using our method. This may imply some limit of the estimation in the metal-poor regime. The right panel of Figure 8 displays the distribution of residuals between the M_H_APs and [Fe/H] of OCCAM. The mean value is 0.01 dex, and the standard deviation is 0.1 dex. This illustrates that the uncertainty of the metallicity derived in this work is around 0.1 dex. Detailed information on the comparison of metallicities of cluster members is shown in Table 3.

5.2. Precision of Metallicity from Wide Binary

We further assess the precision of the metallicity using M dwarf—M dwarf wide binaries (D. Qiu et al. 2021, in preparation). We start with the catalog of initial wide binary candidates released by Tian et al. (2020), which contains 807,611 candidates selected from Gaia DR2 within a distance of 4.0 kpc and a maximum projected separation $s = 1.0$ pc. This catalog contains many types of wide binaries (e.g., MS—MS, MS—white dwarf, white dwarf—white dwarf, etc.), and these wide binary stars may be polluted by visual binaries (chance alignments) at large separations, as described in Section 3.5 in Tian et al. (2020). We finally choose 92 pairs of binary stars with separations less than 3000 au to assess the precision of [M/H].

Figure 9 compares the differences of the metallicities (M_H_APs) of the companions of these binaries. The M_H_APs are expected to be consistent with each other if the companions are physically associated. The left panel shows that the pairs have similar [M/H], and only two of the 92 systems fall outside of the 3σ range. These outliers are most likely not physical binary stars. The mean difference of metallicity of the primary and secondary companions is 0.01 dex with a scatter of 0.23 dex. The right panel is the uncertainty-normalized metallicity difference; i.e., $\Delta[M/H]/\sigma_{\Delta[M/H]} = ([M/H]_1 - [M/H]_2)/\sqrt{\sigma_{[M/H]_1}^2 + \sigma_{[M/H]_2}^2}$. If the derived $\sigma_{[M/H]}$ values are accurate, the uncertainty-normalized metallicity difference should be distributed as a Gaussian distribution with $\sigma = 1$. As shown in the right panel, the distribution matches better with $\sigma \sim 0.8$, which suggests that the M_H_AP uncertainties may be overestimated by ~20%.

5.3. Summary

In this work, we have derived a spectroscopic catalog of stellar parameters for $\sim$300,000 M dwarf stars. Precise effective temperatures and metallicities of M dwarf stars from LAMOST DR6 and Gaia DR2 are given in this catalog. Stars located within the range of $2800 \lesssim T_{\text{eff}} < 4500 K$ of both TEFF_AP and TEFF_BT are finally adopted in our catalog. Two versions of effective temperatures are obtained with precisions of 40 K for TEFF_BT and 50 K for TEFF_AP at $S/N > 50$. In particular, TEFF_AP agrees with B20 with a 60 K scatter and a 185 K offset. The systematic errors come from different stellar atmospheric models, in this case, BT-Settl model and MARCS, respectively.

This study provides a method for using the BT-Settl model to obtain the parameters of LAMOST M dwarf stars. We also publish the code and stellar parameterization pipeline on the website.11 Note that the data-driven method to derive stellar labels strongly relies on training data sets, for the estimation in this work is on the BT-Settl model and stellar parameters of APOGEE. We address that SLAM can be used as the industrial framework against which to decode the stellar parameters of the cool atmosphere of M dwarf stars in upcoming surveys such as SDSS-V (Kollmeier et al. 2017).

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Facilities: LAMOST, Gaia.

Software: astropy (Astropy Collaboration et al. 2018), scipy (Virtanen et al. 2020), scikit-learn (Pedregosa et al. 2011), TOPCAT (Taylor 2005).

11 https://github.com/jiadonglee/MDwarfMachine
Appendix A

Catalog

Table 4 presents the final results of this work, the stellar parameters of the M dwarf stars of LAMOST and Gaia.

### Table 4

The Stellar Parameters ($T_{\text{eff}}$, $[\text{M}/\text{H}]$) of the LAMOST M Dwarf Catalog

| ObsID       | $T_{\text{eff}}$ |
|-------------|------------------|
| 300208242  | 3599             |
| 33171572   | 3676             |
| 438102143  | 3587             |
| 285016161  | 3628             |
| 185605033  | 3680             |
| 400180239  | 3681             |
| 8003208    | 3584             |
| 364813026  | 3645             |
| 387207221  | 3522             |
| 574612100  | 3451             |
| 218031212  | 3602             |
| 196704044  | 3606             |
| 212806086  | 3545             |
| 593209154  | 3635             |
| 600415191  | 3645             |
| 333012162  | 3280             |
| 287010071  | 3380             |
| 334502112  | 3643             |
| 35612149    | 3384             |
| 33107013    | 3507             |
| 557905051   | 3618             |

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