A Large and Pristine Sample of Standard Candles across the Milky Way: ~100,000 Red Clump Stars with 3% Contamination

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Received 2018 March 17; revised 2018 April 14; accepted 2018 April 17; published 2018 May 3

Abstract

Core helium-burning red clump (RC) stars are excellent standard candles in the Milky Way. These stars may have more precise distance estimates from spectrophotometry than from Gaia parallaxes beyond 3 kpc. However, RC stars have values of \(T_{\text{eff}}\) and \(\log g\) that are very similar to some red giant branch (RGB) stars. Especially for low-resolution spectroscopic studies where \(T_{\text{eff}}, \log g, \) and [Fe/H] can only be estimated with limited precision, separating RC stars from RGB through established methods can incur \(~20\%\) contamination. Recently, Hawkins et al. demonstrated that the additional information in single-epoch spectra, such as the C/N ratio, can be exploited to cleanly differentiate RC and RGB stars. In this second paper of the series, we establish a data-driven mapping from spectral flux space to independently determined asteroseismic parameters, the frequency and the period spacing. From this, we identify 210,371 RC stars from the publicly available LAMOST DR3 and APOGEE DR14 data, with \(~9\%\) contamination. We provide an RC sample of 92,249 stars with a contamination of only \(~3\%\), by restricting the combined analysis to LAMOST stars with \(S/N_{\text{pix}} \geq 75\). This demonstrates that high-signal-to-noise ratio (S/N), low-resolution spectra covering a broad wavelength range can identify RC samples at least as pristine as their high-resolution counterparts. As coming and ongoing surveys such as TESS, DESI, and LAMOST will continue to improve the overlapping training spectroscopic-asteroseismic sample, the method presented in this study provides an efficient and straightforward way to derive a vast yet pristine sample of RC stars to reveal the three-dimensional (3D) structure of the Milky Way.

Key words: methods: data analysis – stars: distances – techniques: spectroscopic

Supporting material: machine-readable tables

1. Introduction

Low-mass stars will evolve off the main sequence at the end of their core hydrogen burning phase: during the red giant branch (RGB) ascent, the star has an inert helium core surrounded by a hydrogen burning shell (Iben 1968). They will then go through the helium flash (for \(M \geq 0.8 M_{\odot}\)) and quickly descend in the \(T_{\text{eff}} – \log g\) diagram to reach the core helium-burning phase called the red clump (RC).

For mapping the Galaxy, RC stars are exciting and highly sought-after tracers, because their brightness and color are well-constrained given their metallicity and age (e.g., Stanek et al. 1998; Girardi 2016; Hawkins et al. 2017). Their tight, well-defined position in color–absolute magnitude space makes them exceptional standard candles, when combined with good photometry. This then enables precise three-dimensional (3D) mapping of stars and gas in the Milky Way. Gaia will, of course, provide parallax-based distance estimates for RC stars. For example, for unreddened stars, the expected distance precision will be \(\sim 10\%\) at \(~3\) kpc for Gaia DR2 data. But the distance precision based on parallaxes will rapidly deteriorate beyond \(~3\) kpc and for stars in the Galactic plane that are highly reddened. On the other hand, using RC stars, we can achieve high-precision distance estimates, with precise photometry, up to \(~10\) kpc, with a distance error of \(~6\%\) (Bovy et al. 2014; Hawkins et al. 2017). Therefore, “clean” and extensive samples of RC stars are key to unraveling the structure of the distant Milky Way beyond the Galactic neighborhood.

Asteroseismic parameters of a giant star—in particular, the large frequency separation between \(p\)-modes, \(\Delta \nu\), and the period spacing of the mixed \(g\)- and \(p\)-modes, \(\Delta P\)—provide a remarkably clean separation of RC and RGB stars (e.g., Bedding et al. 2011). Of course, asteroseismology probes the stellar interior and hence plausibly can diagnose core helium burning in a star, while spectroscopy at face value only probes surface properties. Therefore, clean spectroscopic classification of RC stars has proven to be challenging, because RC stars show similar values of \(T_{\text{eff}}, \log g\) to those of part of the RGB phase. The established spectroscopic classification approach is to classify a star as RC or RGB on the basis of \(T_{\text{eff}} – \log g – \text{[Fe/H]}\) and their color–magnitude, when compared to theoretical expectation from isochrones (e.g., Bovy et al. 2014). Precise classification with this approach requires a precision of \(T_{\text{eff}}\) and \(\log g\) to be much better than \(100\) K and 0.1 dex, respectively, a condition hard to meet especially for low-resolution spectroscopy. Consequently, this approach typically incurs a contamination rate of \(~20\%\) for low-resolution spectra (Wan et al. 2015).

But this limitation can be overcome when considering full spectral information, as illustrated by Hawkins et al. (2018). They showed that photospheric abundances in APOGEE spectra must reflect the interior structure of the stars via the efficacy of extra-mixing on the upper RGB (Martell et al. 2008; Masseron & Gilmore 2015; Masseron & Hawkins 2017; Masseron et al. 2017) and can therefore be used to infer asteroseismic parameters and discriminate RC from RGB stars.
Ting et al. (2017) demonstrated that even at low-resolution (R = 2000), spectra do contain spectral information of many abundances, going beyond the basic stellar parameters. Combining these studies implies that with suitable spectro-astroseismic training data, data-driven empirical mapping that relates low-resolution spectra to asteroseismic parameters can be established and provides a much cleaner separation of the RC and RGB stars, which is the focus of this study.

2. Method: Direct Spectral Separation of RC and RGB Stars

In this paper, we set out to establish data-driven mapping from spectra to asteroseismic parameters, using an extensive sample of stars with asteroseismology from Kepler and spectra from APOGEE (Majewski et al. 2017) and LAMOST (Xiang et al. 2017). The spectra serve as input to predict the asteroseismic parameters as output. Once such a mapping is optimized, it can then be applied to all spectra to predict their asteroseismic values from such spectra. We will apply this approach to two large-scale spectroscopic surveys that span different resolutions and wavelength coverage as a sample application of this method. We will adopt the high-resolution (R = 225000) infrared (λ = 1500–1700 nm) APOGEE survey and the low-resolution (R = 1800) optical (λ = 390–900 nm) LAMOST survey. We will cross-validate this method with the sample overlapping among these two surveys.

First, we need to construct a training set that has both spectra and asteroseismic values. Following Hawkins et al. (2018), we adopt the asteroseismic sample from Vrard et al. (2016), which provides estimates for both the frequency separation (Δν) between adjacent acoustic p-modes and the period spacing of the mixed gravity g- and acoustic p-modes. We restrict ourselves to objects from the Vrard catalog that have asteroseismic values consistent with the SSI catalog (ΔνSSI – ΔνVrard) < 2 μHz. Cross-matching this sample with the full APOGEE DR14 and LAMOST DR3 catalogs yield samples of 2853 and 1137 stars in common, respectively. Here, we only consider stars that have median spectroscopic S/N > 50 to avoid noisy training data. For each of the two spectroscopic-asteroseismic samples, we set aside 100 stars as a validation set for the training step; in particular, we terminate the iteration of the training step (below) when the models fail to improve the asteroseismic parameter prediction for this validation set.

We continuum-normalize all APOGEE spectra following Ness et al. (2015) in which a fourth-order polynomial is fitted to a subset of pixels that have the least data-driven gradients. As for LAMOST, we continuum-normalize the spectra following Ho et al. (2017) and Ting et al. (2017), where a smoothed version of the spectrum with a kernel size of 50 Å is adopted as the continuum.

As the empirical relation that we will establish below is trained on a defined training set that spans a specific stellar parameter regime, it is crucial to only apply this relation to stars with similar stellar parameters, not extrapolating too far from the training values. To ensure this, we follow the approach developed in Ting et al. (2016). We adopt the Teff, log g and [Fe/H] values of the APOGEE-asteroseismic and LAMOST-asteroseismic training sets from LAMOST DR3 and APOGEE DR14, and construct 3D convex hulls based on these stellar parameter values. We will only attempt to estimate asteroseismic parameters for stars in APOGEE DR14 and LAMOST DR3 that are within these restricted minimum convex polygons that encompass the training set. Imposing this selection criterion leaves us with a total of 413,472 stars from LAMOST DR3 and 80944 stars from APOGEE DR14.

We now construct a mapping from the normalized spectra, i.e., a vector with a dimensionality of the number of pixels, Npix, to the two asteroseismic values Δν and ΔP. This is a highly nonlinear mapping that we construct through standard “machine-learning” approaches. We adopt a simple neural network that consists of three fully connected layers, each of which with Nnodes = 300 hidden nodes, and the nodes are connected with a sigmoid activation function σ. We explored more elaborate networks, such as convolutional neural networks, but found them not to improve the classification, presumably because the mapping at hand is still relatively straightforward. Therefore, we keep the network simple for mathematical readability and the speed of training the network. Specifically, we presume that the asteroseismic Δν and ΔP can be written as a function of the normalized flux s, where

\[(Δν, ΔP) ≡ f(s)\] (1)

where \(i \in \{1, 2\}\), \(j, k, l \in \{1, ..., N_{\text{nodes}}\}\), and \(m \in \{1, ..., N_{\text{pix}}\}\). We consider an L1 loss function to optimize the hyperparameter \(p \equiv (w, b)\) to best describe the training set. In other words, we minimize \(\sum_{i=1}^{N_{\text{pix}}}(Δν, ΔP)_i - f(s_i[p])\), where \(s_i\) are the normalized fluxes of the \(i\)th training spectra and \((Δν, ΔP)_i\) are their corresponding asteroseismic values from Vrard et al. (2016). We adopt the python PYTORCH package for this optimization. We did not consider the observed flux and asteroseismic parameter uncertainties, and simply adopted the mean values for the flux and the asteroseismic parameters. We explored whether the inclusion of flux uncertainties and 2MASS photometry as extra input in training significantly improved the asteroseismic parameter prediction, but found this not to be the case.

3. Results and Discussion

We now show the results of predicting asteroseismic parameters directly from APOGEE and LAMOST spectra. The right panels of Figure 1 illustrate immediately that this works, as single-epoch spectra can predict Δν and ΔP well, echoing Hawkins et al. (2018). The left panels of Figure 1 show the “ground truth” for the LAMOST and APOGEE training samples, the distribution of asteroseismic Δν and ΔP with its RGB and RC dichotomy. The right panels show the predictions for the same parameters but now derived from the much larger test sample using our modeling of the LAMOST and APOGEE spectra. The distribution of these Δν and ΔP predictions show the exact same morphology as the training set, attesting at least qualitatively the fidelity of the spectroscopic Δν and ΔP estimates. Even though spectra probe only the photospheric properties of the stars, they “know” about the evolutionary states through subtle effects such as the [C/N] ratio. Classically, estimating Δν and ΔP requires multi-epoch light curves from dedicated surveys, such as Kepler, and a careful “boutique analysis” (e.g., Bedding et al. 2011). Providing estimates of asteroseismic parameters from vastly abundant spectroscopic data is therefore valuable by itself. We note

http://ceps.spacecience.org/asteroseismology.html
however that our “data-driven” predicted asteroseismic values are tied to the absolute scale outlined in Vrard et al. (2016) and inherit any biases that the catalog might have.

But most relevant for the paper at hand, Figure 1 illustrates that the spectroscopically estimated asteroseismic parameters, especially ΔP, should allow us to cleanly separate the RC stars from the RGB stars (Bedding et al. 2011). This is because RC stars have very different ΔP (~300 s) than their RGB cousins (~70 s), even though they might share the same $T_{\text{eff}}$ and $\log g$. The two modes in ΔP are clearly visible for both test samples in the right panels of Figure 1. We adopt a conservative approach for identifying RC stars by choosing ΔP > 250 s, which minimizes the (false positive) contamination in the intermediate ΔP region. With this criterion, our method yields 179,286 RC stars from LAMOST, 58343 of which are from LAMOST spectra with S/N$_{\text{pix}}$ > 75, and 36908 RC stars from APOGEE. The results of our modeling are summarized in Tables 1 and 2.

In this study, we consider both the primary RC stars (formed from lower-mass stars) and the secondary RC stars (from more massive stars) together. However, the bottom right panel of Figure 1 suggests that it is also possible to classify primary and secondary RC stars using this method. At least for APOGEE, there is a visible bifurcation in Δν for stars with ΔP ≥ 250 s. Stars with Δν ≥ 6μHz may be classified as secondary RC stars (Yang et al. 2012). However, due to the lack of secondary RC stars in the training sample, we do not attempt to separate the two groups. Nonetheless, using Δν ≥ 6μHz as a selection criterion, we found that the “contamination” from secondary RC samples is pretty negligible and only consists of ~2%–4% of our RC sample.

We emphasize that the training of the spectral model was done entirely independently for the APOGEE and the LAMOST data.

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**Figure 1.** Single-epoch spectra can infer precise asteroseismic parameters. The left panels illustrate the asteroseismic values Δν and ΔP from Vrard et al. (2016) for the training sample, used to construct the mapping from spectra to asteroseismic parameters. Plotted on the right panels are the results when applying this mapping to all APOGEE and LAMOST spectra that have similar spectroscopic stellar parameters as the training set. Inferring asteroseismic parameters from spectra yields a cleaner separation for RC and RGB stars—there is a distinct bimodal distribution in ΔP. The RC stars are centered at around ΔP = 300 s and the RGB stars around ΔP = 70 s.
sets. Therefore, stars that were observed by both APOGEE and LAMOST constitute an excellent cross-validation set to quantify the contaminant rate, which is the focus of Figure 2. The right panel of Figure 2 shows the $\Delta P$ spectroscopic estimates for all overlapping test stars (14442 stars), showing good agreement between the two surveys. The standard deviations of $\Delta P$ and $\Delta \nu$ between these two surveys are 50 s and 1 $\mu$Hz, indicating that APOGEE and LAMOST can estimate asteroseismic parameters to such precision. However, due to the current small overlapping sample size between the asteroseismic and spectroscopic data, it is hard to estimate the exact contamination rate directly from the asteroseismic “ground truth.” This situation will improve with surveys such as TESS, which will provide more stars with asteroseismic estimates in the very near future. Nonetheless, in this study, we attempt to quantify the contamination rate from the APOGEE-LAMOST overlapping sample. We note that because APOGEE has higher-resolution spectra and higher signal-to-noise ratio, typically $S/N \approx 200$, analyzing the LAMOST data with higher $S/N$, our approach does very well: at $S/N_{pix} = 50$, the contamination rate is about 5%–10%; and at $S/N_{pix} = 100$, the contamination is only $\lessapprox 3\%$. The low contamination rate is perhaps not surprising as we exploit the full spectral information, beyond the stellar parameters that were previously explored. As shown in the y-axis, the overall contamination rate is about 9% when integrating over the full range of $S/N$. This is two times lower than previous approaches for LAMOST, yielding 179,286 presumed RC stars. As the primary goal of this study is to present a pristine catalog, in the following, we only select stars with $S/N_{pix} > 75$. This criterion leaves 58343 LAMOST RC stars, with a contamination rate of only 3%. When combined with the APOGEE non-duplicating sample, we have a total 92249 “pristine” RC stars. Here, we publish both our classifications, as well as the spectroscopically inferred asteroseismic parameters that permit independent classifications.

While the $S/N$ cut severely impacts the completeness of our RC pristine catalog, as shown in the top x-axis, we emphasize that our approach is primarily limited only by the spectra quality, not the astrophysical degeneracy in stellar parameters between RC and RGB stars. We caution however that the completeness stated only aims to serve a rough guide. Due to the lack of spectroscopic-asteroseismic training “ground truth,” here we adopt a somewhat ad-hoc definition for completeness. We define the completeness to be the fraction of the number of stars with $\Delta P > 250$ s to the total number of stars with $\Delta P > 200$ s, assuming that the number of RC stars that get wrongly classified to have $\Delta P < 200$ s is compensated by the number RGB stars classified with $\Delta P > 200$ s.

Another advantage of this method is that it is incredibly efficient and does not require deriving stellar parameters beforehand. Training the empirical relation takes $<5$ GPU minutes, and inferring the asteroseismic catalog for all 413,472

### Table 1

| Designation | R.A. (deg) | Decl. (deg) | S/N | $\Delta P$ (s) | $\Delta \nu$ ($\mu$Hz) | Classification | $T_{eff}$ (K)$^a$ | $\log g$ | [Fe/H]$^a$ |
|-------------|------------|------------|-----|---------------|------------------------|----------------|----------------|----------|-----------|
| J20430.94-011616.7 | 331.12894 | $-1.27132$ | 18.6 | 236.87 | 3.48 | ... | 4940 | 2.04 | $-1.36$ |
| J20432.60+005112.5 | 331.13586 | 0.85349 | 199.5 | 76.99 | 5.02 | ... | 4725 | 2.69 | $-0.45$ |
| J03014.28+001548.8 | 45.42620 | 0.26358 | 9.9 | 354.40 | 5.55 | RC$^b$ | 4901 | 2.53 | $-0.57$ |
| J233420.50+332151.5 | 353.58542 | 33.36431 | 86.5 | 302.82 | 4.55 | RC_Pristine$^b$ | 4937 | 2.47 | $-0.46$ |

Notes. Stars that have $\Delta P > 250$ s are classified as RC stars. This table is available in its entirety (with 413,472 rows) in machine-readable form.

$^a$ The stellar parameters values are adopted from LAMOST DR3.

$^b$ For LAMOST, we further distinguish RC stars with $S/N_{pix} > 75$ to be "RC_Pristine," and RC stars with $S/N_{pix} < 75$ to be "RC." (This table is available in its entirety in machine-readable form.)

### Table 2

| Designation | R.A. (deg) | Decl. (deg) | S/N | $\Delta P$ (s) | $\Delta \nu$ ($\mu$Hz) | Classification | $T_{eff}$ (K)$^a$ | $\log g$ | [Fe/H]$^a$ |
|-------------|------------|------------|-----|---------------|------------------------|----------------|----------------|----------|-----------|
| 2M00000211+6327470 | 0.00880 | 63.46308 | 122.9 | 233.62 | 3.33 | ... | 4694 | 2.42 | 0.02 |
| 2M00000446+5854329 | 0.01860 | 58.90915 | 148.5 | 313.75 | 3.82 | RC_Pristine$^b$ | 4756 | 2.37 | $-0.02$ |
| 2M00000555+1504343 | 0.02231 | 15.07621 | 184.9 | 84.17 | 14.81 | ... | 4914 | 3.22 | $-0.05$ |
| 2M00000866+7122144 | 0.03610 | 71.37069 | 495.8 | 82.83 | 4.34 | ... | 4685 | 2.55 | $-0.04$ |

Notes. Stars that have $\Delta P > 250$ s are classified as RC Stars. This table is available in its entirety (with 80,944 rows) in machine-readable form.

$^a$ The stellar parameters values are adopted from APOGEE DR14.

$^b$ For APOGEE, since most stars have $S/N_{pix} > 75$, we assume all RC stars to be “RC_Pristine.” (This table is available in its entirety in machine-readable form.)
LAMOST stars only takes \( \sim \)1 CPU minute. Therefore, one can imagine an efficient survey strategy would be collecting low S/N data in the first pass, and stars with high estimated \( \Delta P \) will then be followed up to improve the S/N and provide a more accurate classification.

Figure 3 shows that our determined RC stars agree well with stellar evolution models. The left and middle panels of Figure 3 show the \( T_{\text{eff}} \) and \( \log g \) of the RC stars (without S/N cut). The black lines indicate the stellar evolution models from the MIST isochrones (Choi et al. 2016) at 4 Gyr. The gray background illustrates the number density of all test stars and the blue symbols the training sample. These panels also demonstrate that, for the high-resolution APOGEE sample, as the \( T_{\text{eff}}-\log g \) estimates are sufficiently accurate, the classical \( T_{\text{eff}}-\log g \) method (e.g., Bovy et al. 2014) can do relatively well. On the other hand, the overlap in \( T_{\text{eff}} \) and \( \log g \) is not trivial for the low-resolution LAMOST sample, and the method presented in this study excels by exploring spectral information beyond the stellar parameters to achieve a low contamination rate. To further illustrate this point, the right panel shows the average contamination rate for different \( T_{\text{eff}} \) and \( \log g \). The background shows the number density of the APOGEE-LAMOST overlapping sample. We only show bins in which the overlapping sample has more than five RC stars. As shown, for LAMOST data with \( S/N_{\text{pix}} > 75 \), the contamination rate is \(< 5\% \) even for regions where RC stellar parameters directly overlap with the RGB stars. Nonetheless, the panel also shows that in the part where there is a lack of training data, the contamination can still be high and can only improve with a more extensive training sample collected in the near future.

Constructing this pristine catalog of RC stars as standard candles across the Milky Way begs the question of whether it will retain value in light of \( \text{Gaia} \) data, which provide parallaxes for a billion stars. Figure 4 illustrates that knowing that a star is an RC stars provides better distance estimates for the majority of the Milky Way. Plotted in Figure 4 is the cumulative distribution of the number of pristine RC stars determined in this study as a function of heliocentric distances. We estimate the heliocentric distances by extrapolating the linear relation between \( \log(d) \) and 2MASS \( K \) band magnitude determined in Hawkins et al. (2017), where \( d \) is the heliocentric distance. We emphasize that the distances are only rough estimates, as we do not attempt to correct for color, stellar age, and extinction. The full distances and extinctions will be carried out in a future study following the hierarchical Bayesian method developed in Hawkins et al. (2017). We crossmatch our sample with \( \text{Gaia} \) DR1 to obtain the \( \text{Gaia} \) \( G \) band magnitude and calculate the end-of-mission \( \text{Gaia} \) parallax uncertainties following the estimates from de Bruijne et al. (2014). This is a conservative limit, as the coming \( \text{Gaia} \) DR2 parallax is about two times worse than the final catalog.\(^8\) As for the RC stars, we assume that the distances uncertainties are about 6% (e.g., Bovy et al. 2014; Hawkins et al. 2017). The fact that RC stars are better distance indicators for distant stars is expected: RC stars are brighter than \( G < 15 \) within 10 kpc from the Sun and are therefore not severely limited by the photometric uncertainties, unlike astrometric measurements, which quickly degrade with distance. We also note that while the distances in Figure 4

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\(^8\) https://www.cosmos.esa.int/web/gaia/dr2
truncate at 20 kpc, this is due to the S/N cut, which biases against distant stars. The full catalog in this study with no S/N cut has a sample size that is five times larger and reaches \(\sim 30\) kpc. Furthermore, the current LAMOST iDR5 (not publicly available) catalog is two times larger. Revisiting some of the low LAMOST S/N RC candidates can readily provide an RC sample catalog that is about \(\sim 500,000\) RC stars with 3% contamination and \(\sim 3\%\) distances out to \(\sim 30\) kpc.

4. Summary and Future Outlook

In this study, we present a catalog of 210,371 RC stars with contamination of 9%, derived from the APOGEE and LAMOST surveys. Among this sample, if we only consider spectra with S/Npix > 75, we have a pristine subsample of 92,249 RC clumps stars with 3% contamination, which is among the largest RC catalogs but with the least contamination.

We show that while single-epoch spectra only probe the photospheric properties of stars, a data-driven model can be established to predict asteroseismic parameters, in particular the frequency separation of stellar interior \(p\)-modes \(\Delta \nu\) and the mixed mode period spacing \(\Delta P\) consistent with Hawkins et al. (2018); here we present the spectral inferred \(\Delta \nu\) and \(\Delta P\) for about 500,000 stars. More importantly, such a data-driven model exploits additional spectral information beyond the stellar parameters \(T_{\text{eff}}, \log g, [M/H]\). As a result, the method yields a more pristine RC catalog through its inferred
asteroseismic parameters, especially low-resolution LAMOST spectra, because low-resolution spectra are more limited in the precision of $T_{\text{eff}}$ – $\log g$, which hamper the ability to separate out RC and RGB stars using traditional methods.

The RC catalog presented in this work provides an excellent opportunity to map the Galaxy in a complimentary way to Gaia particularly for distant stars. But more importantly, with surveys such as LAMOST, DESI, and TESS, which will provide many more spectroscopic-asteroseismic samples and low-resolution spectra from a significant fraction of stars in the Milky Way, the method presented in this study provides a straightforward way to select a pristine catalog of RC stars without the need of inferring stellar parameters. With low-resolution surveys such as LAMOST and DESI, we should be able to find an extensive and pristine sample of RC stars of about 500,000 RC stars out to 30 kpc. A dedicated effort can then be planned to follow up these RC stars to perform the ultimate Galactic cryptography of the Milky Way.

Y.S.T. is grateful to be supported by the Martin A. and Helen Chooljian Membership from the Institute for Advanced Study in Princeton, the joint Carnegie-Princeton Fellowship from Princeton University and Carnegie Observatories and the Australian Research Council Discovery Program DP160103747. K.H. is funded by the Simons Foundation Society of Fellows and the Flatiron Institute Center for Computational Astrophysics in New York City. H.W.R.’s research contribution is supported by the European Research Council under the European Union’s Seventh Framework Programme (FP 7) ERC Grant Agreement no., [321035] and by the DFG’s SFB-881 (A3) Program. This project was developed in part at the 2017 Heidelberg Gaia Sprint, hosted by the Max-Planck-Institut for Astronomie, Heidelberg. This study makes use of the publicly released data from LAMOST DR3 and APOGEE DR14. The Guoshoujing Telescope (the Large Sky Area Multi-Object Fiber Spectroscopic Telescope LAMOST) is a National Major Scientific Project built by the Chinese Academy of Sciences. Funding for the project has been provided by the National Development and Reform Commission. LAMOST is operated and managed by the National Astronomical Observatories, Chinese Academy of Sciences. The Sloan Digital Sky Survey IV is funded by the Alfred P. Sloan Foundation, the U.S. Department of Energy Office of Science, and the Participating Institutions and acknowledges support and resources from the Center for High-Performance Computing at the University of Utah.

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Erratum: “A Large and Pristine Sample of Standard Candles across the Milky Way: ∼100,000 Red Clump Stars with 3% Contamination” (2018, ApJL, 858, L7)

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Received 2018 August 26; published 2018 September 12

Supporting material: machine-readable table

LAMOST provides separate individual spectra for stars that were visited more than once. We have now culled all duplicates in the original LAMOST red clump sample with the same LAMOST designation by including in the catalog only the visit with the highest signal-to-noise ratio (S/N) for each star. We have confirmed that this does not affect the APOGEE red clump catalog in the original article, as we have already taken into account the APOGEE duplicates. We have also verified that this modification does not alter the results in the Letter; if anything, excluding the lower S/N LAMOST spectra reduces the contamination rate slightly. After culling the duplicates, there are a total of 347,727 stars in our LAMOST catalog, of which we inferred their asteroseismic parameters from the LAMOST spectra. Among these stars, we determine that 149,732 stars are red clump stars (defined through ΔP > 250 s), 51,612 of which are from LAMOST spectra with $S/N_{\text{pix}} > 75$. These 51,612 stars are identified as “RC Pristine” because their classifications are more reliable (see Figure 2 in the original Letter), and we define the other red clump (RC) stars as “RC” in the catalog. When combining with the APOGEE catalog, there are a total of 180,897 unique red clump stars with a contamination rate of ∼9%. Most of the contamination comes from the low S/N LAMOST sample. If we restrict ourselves to LAMOST stars with $S/N_{\text{pix}} > 75$, there are a total of 85,539 stars with a contamination of only ∼3%. The updated Table 1 below is included in this erratum, along with its machine-readable counterpart.

Table 1

| Designation  | R.A. (deg) | DECL. (deg) | S/N | ΔP (s) | $\Delta\nu$ (μHz) | Classification | $T_{\text{eff}}$ (K)$^a$ | log $g$$^a$ | [Fe/H]$^a$ |
|--------------|------------|-------------|-----|--------|------------------|-----------------|-------------------|------|-------|
| J220430.94-011616.7 | 331.12894 | −1.27132 | 18.6 | 236.87 | 3.48 | … | 4940 | 2.04 | −1.36 |
| J220432.60+005112.5 | 331.13586 | 0.85349 | 199.5 | 76.99 | 5.02 | … | 4725 | 2.69 | −0.45 |
| J030142.28+001548.8 | 45.42620 | 0.26358 | 9.9 | 354.40 | 5.55 | RC$^b$ | 4901 | 2.53 | −0.57 |
| J233420.50+332151.5 | 353.58542 | 33.36431 | 86.5 | 302.82 | 4.55 | RC_Pristine$^b$ | 4937 | 2.47 | −0.46 |
| … | … | … | … | … | … | … | … | … | … |

Notes. Stars that have $\Delta P > 250$ s are classified as RC stars. This table is available in its entirety (with 347,727 rows) in machine-readable form.

$^a$ The stellar parameters values are adopted from LAMOST DR3.

$^b$ For LAMOST, we further distinguish RC stars with $S/N_{\text{pix}} > 75$ to be “RC_Pristine,” and RC stars with $S/N_{\text{pix}} < 75$ to be “RC.”

(This table is available in its entirety in machine-readable form.)

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