Combined APOGEE-GALAH stellar catalogues using the Cannon

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ABSTRACT

APOGEE and GALAH are two high resolution multi-object spectroscopic surveys that provide fundamental stellar parameters and multiple elemental abundance estimates for about half a million stars in the Milky Way. Both surveys observe in different wavelength regimes and use different data reduction pipelines leading to significant offsets and trends in stellar parameters and abundances for the common stars observed in both surveys. Such systematic differences/offsets in stellar parameters and abundances make it difficult to effectively utilize them to investigate Galactic abundance trends in spite of the unique advantage provided by their complementary sky coverage and different Milky Way components they observe. Hence, we use the Cannon data-driven method selecting a training set of 4418 common stars observed by both surveys. This enables the construction of two catalogues, one with the APOGEE-scaled and the other with the GALAH-scaled stellar parameters. Using repeat observations in APOGEE and GALAH, we find high precision in metallicity (~0.02–0.4 dex) and alpha abundances (~0.02–0.03 dex) for spectra with good signal-to-noise ratio (SNR > 80 for APOGEE and SNR > 40 for GALAH). We use open and globular clusters to validate our parameter estimates and find small scatter in metallicity (0.06 dex) and alpha abundances (0.03 dex) in APOGEE-scaled case. The final catalogues have been cross-matched with the Gaia EDR3 catalogue to enable their use to carry out detailed chemo-dynamic studies of the Milky Way from perspectives of APOGEE and GALAH.

Key words: surveys – stars: abundances – Galaxy: disc – Galaxy: evolution – Galaxy: formation – Galaxy: structure.

1 INTRODUCTION

The field of Galactic archaeology (Freeman & Bland-Hawthorn 2002) deals with dissecting the Milky Way into its various components with the aim to unravel the processes that contributed to the formation and evolution of our Galaxy. Stellar spectroscopy plays a crucial role in this field by enabling accurate measurement of stellar parameters and detailed chemical compositions of stars in the Galaxy. Such measurements are crucial in tracing these stars back to their birth sites providing clues to the physical processes that led them to their present position in the Galaxy.

There are a plethora of data available in the form of spectra, astrometric, and photometric information, as well as multiwavelength maps with the advent of large-scale spectroscopic (Apache Point Observatory Galactic Evolution Experiment/APOGEE: Eisenstein et al. 2011, RAidal Velocity Experiment/RAVE: Steinmetz et al. 2006, Gaia-ESO: Gilmore et al. 2012, Large Sky Area Multi-Object Fiber Spectroscopic Telescope/LAMOST: Cui et al. 2012, Galactic Archaeology with HERMES/GALAH: De Silva et al. 2015, Abundances and Radial velocity Galactic Origins Survey/ARGOS: Ness et al. 2012), astrometric (Hipparcos: Perryman et al. 1997, Gaia: Gaia Collaboration 2016), and photometric surveys (Two-Micron All Sky Survey/2MASS: Skrutskie et al. 2006, Sloan Digital

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Sky Survey/SDSS: Stoughton et al. 2002, Vista Variables in the Vía Láctea/VVV: Minniti et al. 2010, the SkyMapper Southern Survey: Wolf et al. 2018). These surveys have enabled the chemodynamic characterization of stellar populations in the Milky way that constitute different Milky Way components like thin disc, thick disc, halo, bulge, etc. For example, star count observations in the solar neighbourhood (Yoshii 1982; Gilmore & Reid 1983) led to the discovery of the thick disc, followed by its characterization as the old α-enhanced population in the double sequence exhibited by the solar neighbourhood stars in the [α/Fe] versus [Fe/H] plane (Fuhrmann 1998; Bensby, Feltzing & Lundström 2003; Reddy, Lambert & Allende Prieto 2006; Adibekyan et al. 2012; Haywood et al. 2013). At present, data from large-scale spectroscopic surveys (Anders et al. 2014; Hayden et al. 2015; Weinberg et al. 2019) have led to the discovery of this trend at different galactocentric radius, R, and average height, [Z], across the Galaxy shedding light on the disc formation and evolution scenarios. In addition, many age determination methods have been developed that uses these survey data to provide valuable information about the star formation histories and age metallicity relation of disc stellar populations (Casagrande et al. 2011; Bedell et al. 2018; Lin et al. 2020; Nissen et al. 2020). Secular processes such as radial migration (Sellwood & Binney 2002; Schönrich & Binney 2009; Minchev & Famaey 2010), which leads to the mixing of stars across the Galaxy, are also being explored using a combination of accurate phase space information from Gaia (Gaia Collaboration 2018) and chemistry and age information of stars from large-scale spectroscopic surveys (Buder et al. 2019). The discovery of streams and dynamically different stellar populations in the Milky Way halo, considered to be the result of past accretion/merger events (Belokurov et al. 2018; Helmi et al. 2018; Ibata, Malhan & Martin 2019; Myeong et al. 2019) using the Gaia data and their further exploration with chemistry from large-scale spectroscopic surveys (Buder et al. in preparation) is another example. Multiple components in the Bulge metallicity distribution function discovered by multiple individual and large-scale spectroscopic observations, are being studied in detail to understand the origin of the Bulge and its connection with the Milky Way bar and Galaxy evolution (Ness et al. 2013; Rojas-Arriagada et al. 2017, 2020). There are many upcoming surveys [4-metre Multi-Object Spectroscopic Telescope/4MOST: de Jong et al. (2019), Sloan Digital Sky Survey/SDSS-V: Kollmeier et al. (2017), WEAVE: Dalton et al. (2018)] that will further improve our understanding of the formation and evolution of the Milky Way and its components.

The above-mentioned large-scale spectroscopic surveys derive fundamental stellar parameters and elemental abundances from observed stellar spectra via dedicated pipelines using spectral fitting routines that fit observed spectra with synthetic spectra generated from stellar model atmospheres, model grids, and line lists, all of which are different-specific to the respective survey. Thus, even though there are overlaps in the observed stars between many spectroscopic surveys, there are significant systematic differences in their derived stellar parameters as well as abundances. This difference can also lead to misinterpretation of abundance trends estimated using the derived parameters from different surveys. Thus it is necessary to combine such complementary surveys with their parameters scaled with respect to either survey so that the resulting volume complete sample can be used to map and decipher the global chemodynamic trends of stellar populations in the Milky Way.

One step towards this direction of combining surveys (or scaling them with respect to each other) was made with the introduction of the data driven approach known as the Cannon (Ness et al. 2015). Ho et al. (2017) used the Cannon to derive the stellar parameters for around 450,000 giant stars in LAMOST (low spectral resolution survey) by bringing them to the scale of APOGEE (high spectral resolution) survey. Recently, Wheeler et al. (2020) used the Cannon to estimate abundances representing five different nucleosynthetic channels, for 3.9 million stars in LAMOST, by training LAMOST spectra with GALAH DR2 stellar parameters and abundances (also referred to as ‘labels’) for stars in common to both surveys. The Cannon has also been used to propagate information from one survey to another, and to derive higher precision stellar parameters, abundances, mass and age information using survey pipeline estimate as the training set labels (Ness et al. 2016; Casey et al. 2017; Buder et al. 2018; Zhang et al. 2019; Hasselquist et al. 2020, etc.). The StarNet (Fabbro et al. 2018), a convolutional neural network model, was able to predict stellar parameters by training on APOGEE spectra with APOGEE Stellar Parameter and Chemical Abundance Pipeline (ASPCAP) labels (T\text{eff}, \log\ g, and [Fe/H]). When compared with the Cannon results trained on the same data, the StarNet showed similar behaviour, though the StarNet performed poorly on small training sets compared to the Cannon. A deep neural network designed by Leung & Bovy (2019) was used to determine stellar parameters from APOGEE spectra using the full wavelength range, while censored portions of the spectrum were used to derive individual element abundances. The Payne (Ting et al. 2019) is another tool that explicitly models spectra as a function of stellar parameters. Xiang et al. (2019) used the data driven Payne to train a model that predicts stellar parameters and abundances for 16 elements from LAMOST DR5 spectra using stars in common with APOGEE DR14 and GALAH DR2 as the training set. Thus, there are many tools and methods available to put different surveys on the same scale.

In this work, we use the data-driven approach, the Cannon 2 (Ness et al. 2015; Casey et al. 2016), to put the stellar parameters (T\text{eff}, \log\ g, and [Fe/H]) and general [α/Fe] abundance on the same scale for the surveys, APOGEE and GALAH. For this, we have to select a training set composed of common stars observed in both the surveys, with high fidelity stellar labels, as well as high quality spectra. Since both the surveys yield stellar parameters and abundances with dedicated pipelines from high-resolution spectra (though in different wavelength ranges), we cannot choose either survey to be the best. Hence, we carry out the exercise in both ways, i.e. (i) train Cannon model on APOGEE spectra with GALAH labels and (ii) train Cannon model on GALAH spectra with APOGEE labels and derive stellar parameters and [α/Fe] values for both cases. We also (iii) train Cannon model on GALAH spectra with GALAH labels and (iv) Cannon model on APOGEE spectra with APOGEE labels, so that we can combine (i) and (iii) to provide the GALAH-scaled stellar parameter catalogue, and (ii) and (iv) to provide the APOGEE-scaled stellar parameter catalogue.

We describe the data used in this paper in Section 2. In Section 3, we give a brief description of the Cannon, followed by the training set selection, cross-validation of the Cannon estimates compared to the input labels from the training set, testing, flagging, and error estimation. We carry out astrophysical validation of our Cannon estimates using open and globular cluster members in Section 4. Finally, we discuss the limitations and caveats, as well as notable improvements in Cannon estimates with respect to survey pipeline estimates in Section 5.

### 2 DATA

We use the latest available data release of APOGEE (DR16) and GALAH (DR3). We make use of the fundamental stellar parameters:
Teff, log g, [Fe/H], and [α/Fe] from those catalogues, along with the stellar spectra for each star.

2.1 APOGEE

The Apache Point Observatory Galaxy Evolution Experiment (APOGEE; Majewski et al. 2017) observes in the near-infrared H-band (15 000–17 000 Å), split into three bands at high spectral resolution (R ∼ 22 500) and high signal-to-noise ratios (SNR), in both the Northern and Southern hemispheres. As a part of SDSS-IV (Blanton et al. 2017), the APOGEE-2 survey makes use of the APOGEE instrument (Wilson et al. 2012) on the Sloan 2.5 m Telescope (Gunn et al. 2006) at the Apache Point Observatory (APO) for Northern hemisphere observations, and the 2.5m du Pont telescope at Las Campanas Observatory (LCO; Bowen & Vaughan 1973) with the twin near-infrared (NIR) spectrograph (Wilson et al. 2019) for Southern hemisphere observations.

We make use of the data products from DR16 (Ahumada et al. 2020), which contains a total of 473 307 sources with derived atmospheric parameters and elemental abundances of up to 26 species from the APOGEE Stellar Parameters and Chemical Abundances Pipeline (ASPCAP; García Pérez et al. 2016) using MARCS grid of atmospheric models (Jónsson et al. 2020). For our work, we use the calibrated ‘PARAM’ stellar parameters and abundances described in Jónsson et al. (2020) as they have shown that there are several systematic issues with the spectroscopic (FPARAM) measurements of stellar parameters [section 6.3 and fig. 10 in (Jónsson et al. 2020)]. In addition to the catalogue, we also make use of the ‘apStar’ and ‘asStar’ spectra, which are the combined spectra of multiple visits, all in a common rest frame and identical wavelength solution across all sources.

2.2 GALAH

GALactic Archaeology with HERMES (GALAH; De Silva et al. 2015) is a high-resolution spectroscopic survey of the Milky Way using the High Efficiency and Resolution Multi-Element Spectrograph (HERMES; Barden 2010; Sheinis et al. 2015) on the Anglo-Australian Telescope. The HERMES spectrograph provides high-resolution (R ∼ 28 000) spectra from 4700–7900 Å in four wavelength bands.

We make use of data from the latest GALAH data release (GALAH DR3; Buder et al. 2021), which includes the K2-HERMES survey (Wittenmyer et al. 2018; Sharma et al. 2019) and the TESS-HERMES survey (Sharma et al. 2018), and provides up to 30 element abundances from various nucleosynthesis channels for 678 423 spectra of 588 571 stars. Here, we will refer to this data set collectively as the GALAH survey. Observations are reduced through a standardized pipeline developed for the GALAH survey as described in Kos et al. (2017). In this data release, all stellar parameters and elemental abundances have been estimated via the spectrum synthesis code Spectroscopy Made Easy (SME; Valenti & Piskunov 1996; Piskunov & Valenti 2017) with 1D MARCS stellar atmosphere models (Gustafsson et al. 2008). In addition to the catalogue, we also make use of the GALAH spectra,2 all in a common rest frame. After removing 12 181 stars that are missing the spectra for some of their chips, we are left with 576 390 GALAH spectra.

3 METHOD

3.1 The Cannon

The Cannon (Ness et al. 2015), in simple terms, is a data-driven method that generates a model for stellar spectra based on a training set of spectra, for which the stellar parameters and abundances are known with high fidelity (i.e., high SNR and/or accurate estimates). This model can then be used to infer the same labels for any set of continuum normalized spectra that have been sampled on to a common wavelength grid with uniform start and end wavelengths as that of the training set. The Cannon relies on the following assumptions: similar labels imply similar spectra and each spectrum is a smooth function of its labels such that changes in labels result in a smooth variation of spectra.

In the training step, the spectral model coefficients are fit at each wavelength pixel while keeping the labels fixed for all training set star spectra. The spectral model thus generated characterizes the flux at each wavelength pixel as a function of the given labels, with label coefficient values describing the influence of the corresponding label at a certain wavelength pixel. In the label inference step, the label coefficients are fixed, while likelihood optimization is carried out to predict the labels from the flux values at each wavelength pixel of each test spectrum.

We use the Cannon 2 described in Casey et al. (2016)3 and use a quadratic model with Teff, log g, [Fe/H], [α/Fe], microturbulence (υmicro), and line broadening (υbroad) as the labels, resulting in a spectral model of the following form:

\[ F_\lambda = v(\lambda)_\alpha + \text{noise} \]  

where F_\lambda is the flux at each wavelength pixel, \(\lambda\), for each star, \(\alpha\) in the training set. \(\theta_\alpha\) is the set of spectral model coefficients for multiple label combinations at each \(\lambda\) pixel, \(l_\lambda\) represents the labels and \(v(\lambda)_\alpha\) is the ‘vectorizing function’, which is in the form of a 2 degree quadratic polynomial and the labels have been normalized or scaled in the following manner:

\[ l_\lambda = \frac{l_\lambda - l_{\lambda,50}}{l_{\lambda,97.5} - l_{\lambda,2.5}} \]  

where \(l_{\lambda,2.5}\), \(l_{\lambda,2.5}\) and \(l_{\lambda,2.5}\) are respectively the 2.5th, 50th, and 97.5th percentile values of the label, \(\lambda\), in the training set.

Finally, noise is drawn from a Gaussian distribution with zero mean and variance defined as the sum of the variance in flux, \(\sigma_\lambda^2\), and excess variance at each wavelength pixel, \(\chi_\lambda^2\). While variance in flux at each wavelength pixel is obtained from the observed spectra file of each star, excess variance is estimated along with \(\theta_\alpha\) in the training step by optimizing the likelihood function:

\[ \text{arg min}_{\theta_\alpha} \left[ \sum_{\alpha=0}^{N_{\text{spec}}-1} \frac{[F_\lambda - v(\lambda)_\alpha]^2}{\sigma_\lambda^2 + \chi_\lambda^2} + \sum_{n=0}^{N_{\text{spec}}-1} \ln \left( \frac{\sigma_\lambda^2 + \chi_\lambda^2}{\sigma_\lambda^2} \right) \right] \]  

In the test step, hereby called the label inference step, labels corresponding to each test spectrum, \(m\), are predicted by optimizing the likelihood function:

\[ \text{arg min}_{\theta_\alpha} \left[ \sum_{\alpha=0}^{N_{\text{spec}}-1} \frac{[F_{\lambda,\alpha} - v(\lambda)_\alpha]^2}{\sigma_\lambda^2 + \chi_\lambda^2} \right] \]  

In the following section, we explain the quality cuts used to choose a high-quality training set in order to generate the required Cannon spectral model as described above.

1https://data.sdss.org/sas/dr16/apogee/spectro/redux/r12/stars/
2https://docs.datacentral.org.au/galah/dr5/spectra-data-access/
3https://github.com/andycasey/AnniesLasso
3.2 Training set

We construct one training set that can be used to carry out four combinations of cross-survey Cannon training and modelling. Hence, we use the GALAH DR3 combined spectra catalogue with one entry per star for which spectra from multiple exposures have been stacked to estimate their stellar parameters and elemental abundances. In the case of APOGEE, we choose stars with stellar parameters derived from high SNR combined spectrum. Similarly, we choose combined spectra from both surveys for constructing the training set and later in testing stage where predictions are made.

We find 14,406 stars based on cross-match using the APOGEE ID and star_id columns in APOGEE DR16 and GALAH DR3 catalogues with Topcat (Taylor 2005, 2020). We remove stars with invalid GALAH and APOGEE stellar parameters and further select reliable and high-quality survey labels/stellar parameters by certain constraints for each survey.

For GALAH, we choose stars with SNR ratio of spectra in the green arm (snr_s2_sfrad) > 25, chi-square value of stellar parameter fitting the following constraints (chi2_sp < 4, and the flag that describes various GALAH reduction and analysis issues indicating the quality of spectra and estimated stellar parameters (flag_sp) is equal to zero.

For APOGEE, we choose stars with SNR > 80, in addition to removing stars for which selected bits (16: bad T eff, 17: bad log g, 18: bad v micro, 19: bad metals, 20: bad [α/Fe], and 23: bad overall for star) in the ASPCAPFLAG have been set.

As for selecting good quality spectra, we neglect spectra with STARFLAG bits set for selected few bits (0: bad pixels, 3: very bright neighbour, 4: low snr, 9: significant number of pixels in high persistence region, 10: significant number of pixels in medium persistence region, 11: significant number of pixels in low persistence region, 12: obvious positive jump in blue chip, 13: obvious negative jump in blue chip, and 17: broad lines).

Fig. 1 shows the Kiel diagrams for all stars in GALAH (left-hand panel) and APOGEE (right-hand panel) overlaid with the training set contours with respective pipeline estimates in black. In Fig. 2, we show the systematic difference trends in T eff, log g, [Fe/H], [α/Fe], v micro, and v broad for these stars, with T eff, GALAH on the x-axis and APOGEE-GALAH values on the y-axis. The two clumps, cool (4000 < T eff < 5200 K) and hot (5200 < T eff < 6200 K), seen for all parameters approximately represent difference trend for giants and dwarfs, respectively. Table 1 lists the mean and standard deviation (calculated as the mid-value of 84th–16th percentile to get rid of outliers) values for all stars, giants, and dwarfs. In this case, giants and dwarfs are selected based on log g cut of 3.5.

Among the six stellar parameters, we find significant differences/offsets in the case of [Fe/H], v micro, and v broad. The differences for all parameters have a non-zero mean value and exhibits various trends with T eff. APOGEE temperatures are higher and derive higher log g values for hot dwarfs compared to GALAH. Meanwhile, cool giants in APOGEE have lower [α/Fe] measurements compared to GALAH.

The giant and dwarf clumps in the Fig. 2c hints at different systematic trends of [Fe/H] with respect to T eff for giants and dwarfs. There is a steep declining trend for giants, with higher metallicity values (~0.4 dex relative to GALAH abundances) measured by APOGEE for cool giants (T eff < 4500 K). This trend is similar to one of the possible caveats mentioned in GALAH DR3 (section 6.5 of Buder et al. 2021). They have noticed a significant trend of underestimated [Fe/H] with increasing metallicity, when comparing with GALAH DR2, for the metal-rich ([Fe/H] > 0) giants and red clump stars. As discussed in Buder et al. 2021, the reasons for this could be many fold, e.g., missing/unreliable molecular line data, the underestimation of blending and incorrect continuum normalization, over/under estimation of v micro etc. For dwarfs, there is better agreement between APOGEE and GALAH metallicities with a slight increase (upto ~0.15–0.2 dex) in APOGEE metallicity for hotter stars (T eff > 6000 K).
Table 1. Mean and scatter values of APOGEE-GALAH difference for six stellar labels in the training set.

| Parameter (unit) | APOGEE-GALAH | All | Giants | Dwarfs |
|------------------|---------------|-----|--------|--------|
|                  | μ  | σ  | μ  | σ  | μ  | σ  |
| $T_{\text{eff}}$ (K) | 14 | 84 | 35 | 68 | 0  | 94 |
| log $g$ (dex)     | 0.06 | 0.12 | 0.03 | 0.13 | 0.08 | 0.10 |
| [Fe/H] (dex)      | 0.02 | 0.08 | 0.05 | 0.10 | 0.00 | 0.06 |
| [$\alpha$/Fe] (dex) | −0.03 | 0.05 | −0.04 | 0.06 | −0.02 | 0.05 |
| $v_{\text{micro}}$ (km s$^{-1}$) | −0.05 | 0.37 | 0.07 | 0.30 | −0.14 | 0.40 |
| $v_{\text{broad}}$ (km s$^{-1}$) | −2.80 | 1.50 | −3.08 | −1.21 | −2.59 | 1.62 |

In Fig. 2c, we find significant scatter ($>\sim 0.30$ km s$^{-1}$) in the $v_{\text{micro}}$ difference between the two surveys, with mean differences of $-0.05$, 0.07, and $-0.14$ km s$^{-1}$ for the whole sample, giants, and dwarfs, respectively. The difference in trends for giants and dwarfs are also evident from the two clumps. Such a significant difference may be attributed to the way in which $v_{\text{micro}}$ is determined in GALAH and APOGEE. While empirical relations (equations 4 and 5 in Buder et al. 2021) are employed in the case of GALAH, APOGEE uses $v_{\text{micro}}$ as a free parameter while determining synthetic spectra that best fits the observed spectra.

In Fig. 2f, a systematic difference in $v_{\text{broad}}$ can be seen with the APOGEE values consistently lower than GALAH values. This may again be attributed to the difference in $v_{\text{broad}}$ determination in both surveys. In GALAH, $v_{\text{broad}}$ is determined using SME by setting $v_{\text{mac}}$ (macroturbulent velocity) to 0 and only fitting for $v_{\text{sin} i}$ (rotational velocity). In APOGEE, $v_{\text{broad}}$ for dwarfs are the $v_{\text{sin} i}$ values estimated in the same way as in the case of $v_{\text{micro}}$ using a grid with seven steps of $v_{\text{sin} i}$ (1.5, 3.0, 6.0, 12.0, 24.0, 48.0, and 96.0 km s$^{-1}$), while for giants an empirical relation is used to estimate $v_{\text{mac}}$ (Jönsson et al. 2020).

Even though there is reasonably a good agreement between the two surveys (especially for $T_{\text{eff}}$ and log $g$) in Fig. 2, there are systematic differences in [Fe/H], [$\alpha$/Fe], $v_{\text{micro}}$, and $v_{\text{broad}}$ for the same stars in both surveys. As mentioned in Section 2, both surveys observe stars in different wavelength regimes (optical for GALAH and NIR for APOGEE) and employ different methodology and pipelines to estimate these parameters which could result in such systematic differences. These systematic differences for same stars, as well as contrasting difference trends for giants and dwarfs, thus show the importance of placing these surveys on the same abundance scales if they are to be used in conjunction. This also emphasizes the need for observation of larger number of common stars between large-scale spectroscopic surveys, which will enable cross survey calibrations, as well as more consistent analysis pipelines in the future.

### 3.3 Training

Once the training set is finalized, we proceed to carry out the training and cross-validation. As mentioned in Section 1, the objective of this work is to provide two combined stellar parameter catalogues of APOGEE and GALAH, one scaled in terms of APOGEE and the other in terms of GALAH. Hence, we use spectra and labels from both surveys in four different combinations, starting from the training step. To avoid any confusion resulting from this, hereafter we introduce a naming convention to indicate each case in Table 2:

In the following section, we focus on APOGEE Cannon GALAH SME (ACGS) and GALAH Cannon APOGEE ASPCAP (GCAA), while similar exercises for APOGEE Cannon APOGEE ASPCAP (ACAA) and GALAH Cannon GALAH SME (GCGS) are explained in Appendix A.

We limit the labels that we train and infer to $T_{\text{eff}}$, log $g$, [Fe/H], [$\alpha$/Fe], $v_{\text{micro}}$, and $v_{\text{broad}}$ where [Fe/H] and [$\alpha$/Fe] refer to the general metallicity and alpha abundance labels in each survey. We do not go
beyond the general alpha abundance to include individual elements as in such cases, we need to know all abundances for each training set entry – which becomes an increasingly difficult task with an increasing number of elements. In particular, elements other than the alpha-elements, like Li or s- and r-process elements are impossible to measure always throughout the whole parameter space. Various challenges involved in determination of more elements using the Cannon model is discussed in detail in Buder et al. (2018).

While we use the whole spectral wavelength range for training and determining label coefficients for $T_{\text{eff}}, \log g$, [Fe/H], $v_{\text{micro}}$, and $v_{\text{broad}}$, we make use of censoring line masks in the case of [$\alpha$/Fe]. This is similar to the use of line masks in SME to estimate abundances for each element in a spectrum. [$\alpha$/Fe] for GALAH is determined from an error-weighted combination of selected lines of Si, Mg, Ti, and Ca, while APOGEE [$\alpha$/M] is determined from a combination of O, Mg, Si, S, Ca, and Ti lines. We decided to use line masks for the common elements in both surveys (Si, Mg, Ti, and Ca) to be used as censors in the training step. This ensures that Cannon does not incorporate incorrect correlations from other lines in the respective spectra while predicting [$\alpha$/Fe] values. In the case of GALAH, the line masks for Si, Mg, Ti, and Ca are available in the line list used to determine respective abundances with SME (table A2 in Buder et al. 2021). For APOGEE, Jónsson et al. (2020) provides the windows and weights used in the determination of stellar abundances in their table 3. We select the wavelength windows for Si, Mg, Ti, and Ca lines.

In the training step, four Cannon models corresponding to ACGS, GCGS, GCAA, and ACAA are created using spectra and labels of stars in the training set. Coefficient matrix, $\theta_1$, and scatter, $s_1$, are obtained by optimizing equation (3.1), given the labels in each case.

### 3.4 Cross-validation

In order to verify how well the Cannon model is able to recover the training set labels, we carry out a 12-fold cross-validation. For this, we create 12 random subgroups from the training set, then use them individually as a test set while the remaining 11 are treated as the training data. We show the resulting one-to-one relation, i.e. predicted label values versus input label values for ACGS and GCAA in Figs 3 and 4, respectively.

When we train the Cannon model on APOGEE spectra using GALAH SME labels (ACGS; Fig. 3), all labels, except $v_{\text{broad}}$ and [$\alpha$/Fe], follow a tight one-to-one relation. $T_{\text{eff}}$ relation is tight with mean difference of $\sim$5 K and scatter of $\sim$ 90 K. The Cannon estimates for $\log g$ and [Fe/H] values are similar to corresponding input GALAH labels, while larger dispersion in input GALAH [$\alpha$/Fe] values is reflected in the Cannon output as well. The tightest one-to-one relation is seen in the case of $v_{\text{micro}}$, for which the input GALAH labels are estimated using empirical relations. As this relation is a function of GALAH $T_{\text{eff}}$ and $\log g$, these values are well correlated with respective spectra in the training step and thus ensure that the Cannon model is able to reproduce them from APOGEE spectra in the label inference step. The largest scatter is seen in the case of $v_{\text{broad}}$, meaning that the Cannon model is not able to correlate the input GALAH $v_{\text{broad}}$ values with the features in APOGEE spectra. At the same time, we find that the Cannon model trained on GALAH spectra using GALAH labels (GCGS) are able to estimate similar $v_{\text{broad}}$ values from GALAH spectra in the label inference step with less scatter (see Appendix, Fig. A1). Thus the reason for the large dispersion seen here in the case of $v_{\text{broad}}$ is not clear.

When we train the Cannon model on GALAH spectra using APOGEE ACSAP labels (Fig. 4), the Cannon output values for $T_{\text{eff}}, \log g$, [Fe/H], and [$\alpha$/Fe] is as seen in ACGS, with tight one-to-one relations with the respective APOGEE ACSAP values. There are significant deviations in the case of $v_{\text{micro}}$ and $v_{\text{broad}}$. The Cannon outputs for input $v_{\text{micro}}$ APOGEE, $>1$ km s$^{-1}$ follow one-to-one relation, whereas the Cannon estimates are higher for lower $v_{\text{micro}}$ APOGEE values. This indicates that the Cannon model is unable to find significant correlation between $v_{\text{micro}}$ APOGEE values and corresponding GALAH spectra in this lower $v_{\text{micro}}$ APOGEE range. Much tighter one-to-one trend is seen in the case of $v_{\text{broad}}$, though there are significant deviations for lower $v_{\text{broad}}$ APOGEE values. When we use the Cannon model trained on APOGEE spectra using APOGEE labels (ACGA), the resulting Cannon $v_{\text{micro}}$ and $v_{\text{broad}}$ estimates also show significant deviations in similar $v_{\text{micro}}$ and $v_{\text{broad}}$ ranges (see Appendix A1). This may be because of the limited sensitivity at such low values of $v_{\text{micro}}$ and $v_{\text{broad}}$.

In all cases and for all labels, there are deviations from the one-to-one line close to the high and low values of the respective labels, i.e. the label space edges. This most likely shows the inability of the Cannon to interpolate at the training set edges.

Overall, the 12-fold cross-validation shows the capability of the Cannon models trained on APOGEE (GALAH) spectra with GALAH (APOGEE) labels (with training set comprising good quality stars commonly observed by both surveys) to infer GALAH (APOGEE) scaled values of $T_{\text{eff}}, \log g$, [Fe/H], and [$\alpha$/Fe] from APOGEE (GALAH) spectra.

### 3.5 Application to GALAH and APOGEE

We proceed to use the Cannon models after training and cross-validation to predict the GALAH-scaled labels for 437 445 APOGEE spectra and APOGEE-scaled labels for 576 390 GALAH spectra of unique stars. Using four Cannon spectral models corresponding to ACGS, GCGS, GCAA, and ACAA, all six labels are estimated for each case by optimizing the log likelihood function in equation (3.1), given the respective coefficient matrix, $\theta_1$, and scatter, $s_1$, from the training step.

In the following sections, we demonstrate the effectiveness of our Cannon models by comparing model spectra with observed spectra (both GALAH and APOGEE) and plotting the systematic differences of all labels for common stars in APOGEE and GALAH.
3.5.1 Cannon model spectra

Here, we compared observed survey spectra with the spectra generated by the Cannon models to demonstrate how well Cannon spectral models reproduce the observed spectra. For this, we first estimate the residual values (observed – model normalized flux) for all 4418 stars in the training set at each wavelength/pixel. We then plot the median residual value along with the respective 16th and 84th percentile values at each pixel as shown in Figs 5 and 6 for model spectra comparisons with GALAH spectra and APOGEE spectra, respectively. In both the figures, we show observed solar-type star spectrum from the respective survey in the top row to help the readers identify lines and the residual plots for APOGEE-scaled and GALAH-scaled cases, respectively, in the top and bottom rows with the full survey wavelength ranges plotted in the panels from left to right. The solid scatter points represent the median residual value estimated at each pixel and the band around each point/pixel denote the 16th and 84th percentile values of residuals at the respective pixel.

Median values for majority of pixels are very close to 0 with the 16th and 84th percentile values lying within 0.01, except in the case of GALAH chip 1 which is found to be inherently noisy. In the case of GALAH (Fig. 5), slightly higher residual values are seen at either bad/noisy pixels or pixels that correspond to lines of elements (e.g. Cr at ∼5700 Å, Cu at ∼5782 Å, and strong K line at ∼7700 Å) that have not been modelled in our Cannon models. Comparing the pixel positions of higher residual values with lines in APOGEE solar-type star spectrum, it is evident that the bad/noisy spike pixels are the dominant reason for higher residuals in the case of APOGEE (Fig. 6).
3.5.2 Systematic difference using common stars

In order to demonstrate the effectiveness of our method, we compare GALAH-scaled labels from APOGEE spectra (ACGS) and GALAH spectra (GCGS) for common stars which are in the training set. For the same stars, we compare APOGEE-scaled labels from APOGEE spectra (ACAA) and GALAH spectra (GCAA). This is shown in Figs 7 and 8 where we plot the differences in all six labels as a function of $T_{\text{eff}}$ for ACGS – GCGS and ACAA – GCAA, respectively. This is similar to Fig. 2 where we showed the differences between the pipeline values from APOGEE and GALAH. Table 3 lists the mean and scatter of the difference values for all labels in each case. On comparison with the mean and scatter values for APOGEE-GALAH listed in Table 1, we find reduced scatter and less trends for common stars in both surveys from GALAH-scaled and APOGEE-scaled catalogues. The improvement is especially evident in metallicity and alpha abundance with the
Figure 7. Same as Fig. 2 except for label differences between training set stars in ACGS and GCGS. Compared to differences seen in Fig. 2, metallicity and alpha abundance differences have decreased scatter and less trends, demonstrating the effectiveness of the Cannon models.

Figure 8. Same as Fig. 2 except for label differences between training set stars in ACAA and GCAA. Reduced scatter and not less trends are seen here, with the mean difference always lying close to 0. This demonstrates the effectiveness of our method and the Cannon models we used.

3.6 Flagging

As a first step, we need to flag Cannon estimates that lie outside the bounds of the training set labels since the Cannon cannot reliably extrapolate to different regimes outside of the training set. For each test set spectra, we estimate the distance, $D$, of the test set Cannon estimate, $l_{test}$, to the training set labels, $l_{nTs}$, in similar way as described in Buder et al. (2018) and Ho et al. (2017):

$$D = \sum \frac{\sum (l_{test} - l_{nTs})}{R_l^2} \ldots$$

(5)
where $K_i$ represents the uncertainties in each label for which we use RMS values obtained from cross-validation step in Section 3.4. Using $T_{\text{eff}}$, log g, [Fe/H], [$\alpha$/Fe] as the label space, $l_i$ we calculate the average distance to the closest 10 stars in the training set and flag those Cannon estimates that are farther than eight ($2\sigma$ for four labels). We indicate this in the final catalogue by setting the flag $\text{Cannon\_dist}$ to 1. In addition, we provide $\text{flag\_spectra}$ to indicate problematic spectra from APOGEE (STARFLAG bits as explained in Section 3.2) and GALAH, $\text{flag\_sp\_aspcap}$ to indicate stars that have been flagged by respective surveys (flag$_{sp}$ in GALAH and ASPCAP FLAG in APOGEE) and $\text{flag\_survey}$ to indicate the stars with invalid values (from ASPCAP and SME) for the labels we use. $\text{flag\_sp\_aspcap}$ follows the same format as in the respective survey. $\text{flag\_spectra}$ for APOGEE stars follow the format in APOGEE DR16 catalogue, while value of 1 is used to indicate bad GALAH spectra. With these flags, we indicate those stars/spectra that have corresponding issues and emphasize that it is better to avoid these stars for exploring the Milky Way chemo-dynamic trends. Table A1 lists and describe all the above mentioned flags.

3.7 Error and precision

The Cannon provides covariance errors that are very small and likely to be underestimated (Casey et al. 2017). In the following sections, we explain precision and precision estimation using repeat observations in each survey and from the label difference of stars in the training set as a function of SNR.

3.7.1 Error

We use the Cannon results for repeat observations in each survey to determine the factor by which covariance errors for each label have to be scaled in order to get a reasonable error estimate. In APOGEE, there are 28570 groups of repeated observations with the group size varying from 2 to 14. Meanwhile, there are 47189 groups of repeated observations of sizes 2–15.

We calculate the pair-wise differences between the labels we derived from multiple visits over the quadrature sum of their formal covariance errors. For each label, $l_i$, we introduce a scaling factor, $f$, as shown below:

$$\delta l = \frac{l_1 - l_2}{\sqrt{(\sigma_{l_1}^2 + \sigma_{l_2}^2) \cdot f}}$$

Under the ideal assumption that the derived labels are unbiased and the Cannon covariance errors are correct, we expect $\delta l$ (without scaling factor) to follow a normal distribution with zero mean and variance of unity. The resulting $\delta l$ distribution is found to be significantly different from the expected normal distribution for all labels except [$\alpha$/Fe] for Cannon estimates in ACGS, GCGS, GCAA, and ACAA. This indicates that covariance errors obtained from Cannon are not correct. Hence, we proceed to vary $f$ in equation (6) until variance of $\delta l$ distribution tend to reach unity.

In Table 4, we list the scaling factor for each label estimated from repeat observations for each catalogue. In all cases, scaling factor for [$\alpha$/Fe] are close to 1, which can be attributed to the fact that the Cannon covariance error for [$\alpha$/Fe] is indicative of the actual error.

### Table 3. Mean and scatter values in ACGS – GCGS and ACAA – GCAA difference of six stellar labels for common stars in APOGEE and GALAH.

| Parameter (unit) | ACGS – GCGS | ACAA – GCAA |
|------------------|-------------|-------------|
| $T_{\text{eff}}$ (K) | 2 | 66 | -4 | 73 |
| log g (dex) | 0.03 | 0.12 | -0.02 | 0.12 |
| [Fe/H] (dex) | 0.00 | 0.05 | 0.00 | 0.05 |
| [$\alpha$/Fe] (dex) | 0.01 | 0.04 | 0.00 | 0.02 |
| $v_{\text{micro}}$ (km s$^{-1}$) | 0.00 | 0.03 | -0.06 | 0.34 |
| $v_{\text{radial}}$ (km s$^{-1}$) | -0.01 | 1.78 | -0.06 | 1.07 |

### Table 4. Scaling factor for each label covariance error estimated from repeat observations using equation (6) for each catalogue.

| Parameter (unit) | ACGS | GCGS | GCAA | ACAA |
|------------------|------|------|------|------|
| $T_{\text{eff}}$ (K) | 12200 | 7200 | 6925 | 11352 |
| log g (dex) | 18 | 8.6 | 8.5 | 19 |
| [Fe/H] (dex) | 8.9 | 6.4 | 7.7 | 9 |
| [$\alpha$/Fe] (dex) | 1.2 | 0.5 | 0.4 | 1.2 |
| $v_{\text{micro}}$ (km s$^{-1}$) | 3.8 | 2.1 | 5.3 | 12 |
| $v_{\text{radial}}$ (km s$^{-1}$) | 52.1 | 31.5 | 29 | 56 |
4 VALIDATION

We combine APOGEE Cannon GALAH SME (ACGS) and GALAH Cannon GALAH SME (GCGS) to construct the GALAH-scaled catalogue. Similarly, we combine GALAH Cannon APOGEE ASPCAP (GCAA) and APOGEE Cannon APOGEE ASPCAP (ACAA) to construct the APOGEE-scaled catalogue. Both the catalogues provide stellar parameters, metallicity, and global alpha abundances for 1013835 stars corresponding to the sum of number of unique stellar spectra in each survey (437445 in APOGEE and 576390 in GALAH). After applying the flags as mentioned in the Section 3.6, we are left with slightly less than 50 per cent of the total number of stars in the catalogues, but with good quality spectra and the survey parameters on a common scale in each catalogue.

In this section, we carry out external astrophysical validation of the Cannon estimates to investigate how well the Cannon is able to learn from GALAH and APOGEE labels, along with their respective spectra, to produce the GALAH- and APOGEE-scaled catalogues. To do this though, we have only a limited number of stars from other high-resolution spectroscopic studies that have been observed by APOGEE and/or GALAH (e.g. Reddy et al. 2003, 2006; Bensby, Feltzing & Oey 2014 etc). So we rely on open and globular clusters, which contain stars that are born from the same parental molecular cloud and are expected to have similar ages. Hence, we expect the stars in open and globular clusters to follow the same theoretical isochrone track in the Kiel diagram and to have similar metallicities and abundances.

4.1 Astrophysical validation

In this section, we investigate the astrophysical validity of the stellar parameters in our catalogues. We start by searching for members of previously observed, well studied open and globular clusters in our combined GALAH-scaled and APOGEE-scaled catalogues. We then check the consistency of our Cannon estimated metallicities of these member stars with that in APOGEE and/or GALAH, as well as with that in the literature.

4.1.1 Open clusters

We cross-match our catalogues with the open cluster member catalogue provided by Spina et al. (2021) for 205 clusters observed by at least one of the survey, APOGEE (DR16) or GALAH (DR3). From our GALAH-scaled and APOGEE-scaled catalogues, we choose stars with flag Cannon dist, flag survey, flag spectra set to 0, SNR cuts as in the training set and remove stars flagged by both surveys (flag_sp_aspcap). From the open cluster catalogue, we choose member stars with membership probability, P_mem, > 0.5. We identify 113 open clusters with at least one member in our catalogues that satisfy these conditions. For our investigation, we choose 5 open clusters: Blanco 1, IC 4665, Melotte 22, NGC 2682, and Ruprecht 147.

We show Kiel diagrams for members of the above mentioned clusters colour coded by their metallicities in Fig. 10. The plots for clusters are arranged from left to right in increasing order of their ages from literature (Cantat-Gaudin et al. 2020), with the top row showing survey pipeline (SME/ASPCAP) estimates, middle and bottom row showing GALAH-scaled and APOGEE-scaled values, respectively, for same stars. We also overplot PARSEC isochrones (Bressan et al. 2012) in each panel, where the isochrone ages are from Cantat-Gaudin et al. (2020) and metallicities are adopted from Heiter et al. (2014). For each cluster, we separate out the spectra of stars from each survey (indicated by different symbols in the Fig. 10) and list median metallicities and standard deviations of GALAH-scaled and APOGEE-scaled cases for their respective spectra in Table 5. In addition, we also list the median and standard deviation values of the pipeline metallicity estimates, enabling us to compare and quantify
the similarity of Cannon estimates to the respective survey pipeline estimates.

For Blanco 1 and IC 4665, there are no APOGEE stars in our catalogues after quality cuts. Except for IC 4665, member stars from rest of the clusters consistently lie on the theoretical isochrone track defined by respective age and metallicity from literature, for both Cannon estimates, as well as individual survey pipeline estimates. In IC 4665, GALAH SME log g estimates also show deviation from the track at higher $T_{\text{eff}}$ for a few stars in the GALAH-scaled case, which is more pronounced in GALAH-scaled case at $T_{\text{eff}} > 6000$ K. This is not unexpected since there are fewer lines in the GALAH wavelength windows for these hotter stars. Similar deviations from tracks or scatter in log g are evident in the case of other two young clusters, Melotte 22 and Blanco 1, pointing out the problems in the GALAH SME estimates and spectra of hot dwarf stars.

Within the standard deviations, GALAH-scaled and APOGEE-scaled median metallicity values are consistent with that from the median survey pipeline estimates of stars in GALAH and APOGEE surveys, and with the literature values (see Table 5). At the same time, we see higher values of the standard deviations in GALAH-scaled metallicities compared to APOGEE-scaled cases. This is expected since GALAH SME estimates also show higher values of standard deviation compared to APOGEE ASPCAP values for all clusters. In the case of Ruprecht 147, GALAH-scaled median metallicities from APOGEE spectra (ACGS) are consistent with GALAH SME median metallicity. Similarly, APOGEE-scaled median metallicities estimated from GALAH spectra (GCAA) are consistent with the more metal rich APOGEE ASPCAP median metallicity estimate. These are clear indications of the ability of the Cannon to carry out cross survey scaling.

### 4.1.2 Globular clusters

Unlike in the case of open clusters, there are no combined catalogues of globular clusters in APOGEE and GALAH. So we cross-match our catalogues with the latest Gaia EDR3 globular cluster catalogue (Vasiliev & Baumgardt 2021). As in the case of open clusters, we choose stars from our catalogues with flag Cannon-dist, flag_spectra set to 0, SNR cuts as in the training set, globular cluster member stars with membership probability >0.5 and remove stars flagged by both surveys (flag_sp_aspcap). This results in nearly 28 globular cluster populations with only two of them having spectra in both APOGEE and GALAH. For our investigation, we choose five globular clusters: NGC 104 (47 Tuc), NGC 2808, NGC 288, NGC 6121, and NGC 6809. We show Kiel diagrams for members of the above mentioned clusters colour coded by their metallicities in Fig. 11. The plots for clusters are arranged from left to right in decreasing order of their metallicities from literature (VandenBerg et al. 2013), with the top row showing survey pipeline (SME/ASPCAP) estimates, middle and bottom row showing GALAH-scaled and APOGEE-scaled values respectively for same stars. We also overplot PARSEC isochrones (Bressan et al. 2012) in all panels where the isochrone ages and metallicities of these clusters are from VandenBerg et al. (2013). In Table 6, we list the median metallicities and standard deviations.
Table 5. Median metallicity and standard deviation estimated for members of five open clusters from the catalogue of Spina et al. (2021) cross-matched with the catalogues in this work. The names of clusters are listed in the first column, metallicity of the cluster from high resolution study (Heiter et al. 2014) in the second column, the abbreviations for the catalogues (see Section 3.5) with the number of stars from each catalogue in brackets in the third column, Cannon metallicity estimates from each catalogue in the fourth column, and survey pipeline metallicity estimates corresponding to the spectra mentioned (in the catalogue name) in the same row in the last column.

| Cluster   | [Fe/H]_{literature} (median, std dev) | Catalogue (No.) | [Fe/H]_{Cannon} (median, std dev) | [Fe/H]_{Survey} (median, std dev) |
|-----------|----------------------------------------|-----------------|----------------------------------|----------------------------------|
| IC 4665   | -0.03, 0.04                            | GCGS (13)       | -0.05, 0.13                      | -0.03, 0.10                      |
|           |                                        | ACGS (0)        |                                  |                                  |
|           |                                        | GCAA (13)       | 0.03, 0.10                       | -0.03, 0.10                      |
|           |                                        | ACAA (0)        |                                  |                                  |
| Melotte 22| -0.01, 0.05                            | GCGS (36)       | -0.05, 0.15                      | -0.03, 0.09                      |
|           |                                        | ACGS (62)       | 0.00, 0.10                       | -0.01, 0.04                      |
|           |                                        | GCAA (36)       | 0.00, 0.05                       | -0.03, 0.09                      |
|           |                                        | ACAA (62)       | 0.00, 0.04                       | -0.01, 0.04                      |
|           |                                        | GCGS (35)       | 0.0, 0.09                        | -0.05, 0.07                      |
|           |                                        | ACGS (0)        |                                  |                                  |
|           |                                        | GCAA (35)       | -0.01, 0.06                      | -0.05, 0.07                      |
|           |                                        | ACAA (0)        |                                  |                                  |
| Blanco 1  | 0.03, 0.07                             | GCGS (16)       | 0.05, 0.06                       | 0.03, 0.06                       |
|           |                                        | ACGS (29)       | 0.07, 0.08                       | 0.12, 0.03                       |
|           |                                        | GCAA (16)       | 0.11, 0.07                       | 0.03, 0.06                       |
|           |                                        | ACAA (29)       | 0.10, 0.05                       | 0.12, 0.03                       |
| Ruprecht 147 | 0.16, 0.08                              | GCGS (85)       | -0.05, 0.09                      | -0.06, 0.07                      |
|           |                                        | ACGS (109)      | -0.06, 0.07                      | 0.00, 0.03                       |
|           |                                        | GCAA (85)       | -0.02, 0.07                      | -0.06, 0.07                      |
|           |                                        | ACAA (109)      | 0.00, 0.05                       | 0.00, 0.03                       |
| NGC 2682  | 0.0, 0.06                              | GCGS (13)       | -0.05, 0.13                      | -0.03, 0.10                      |
|           |                                        | ACGS (0)        |                                  |                                  |
|           |                                        | GCAA (13)       | 0.03, 0.10                       | -0.03, 0.10                      |
|           |                                        | ACAA (0)        |                                  |                                  |

of GALAH-scaled and APOGEE-scaled cases for their respective spectra, as well as from survey pipelines (SME/ASPCAP), in addition to respective cluster metallicities from VandenBerg et al. (2013). From the plots, we find Cannon and survey pipeline estimates to follow theoretical isochrone tracks in the case of NGC 104. For NGC 2808, NGC 6121, and NGC 288, survey pipeline estimates are systematically offset (lower T_eff) from the respective theoretical isochrone tracks while the Cannon estimates are closer to them. This is a clear indication of the quality of Cannon estimates compared to the survey pipeline estimates and shows the ability of the Cannon models to correct the shift in pipeline estimates by learning it from field stars that are dominant in the training set. For the most metal poor cluster in our sample, NGC 6809, both the Cannon and survey pipeline estimates are offset from the stellar track. For this cluster, the median metallicity from the literature is ~0.25 dex more metal poor than those from the Cannon, as well as survey pipeline estimates. This is most likely the reason for the shift in Cannon and pipeline estimates compared to the theoretical isochrone track. On the other hand, during the cross-validation of the training set, we have seen that the Cannon estimates for stars with metallicities lower than ~1.5 dex may be wrong due to being scarcely represented in the training set and values close to the training set boundary. But consistency of Cannon estimates with the survey pipeline estimates gives strength to the validity of the Cannon estimates in this case.

For all clusters except NGC 288 and NGC 104, median metallicities from the Cannon are consistent with the median metallicity values from survey pipelines. In NGC 288, median metallicity from GALAH SME (~1.07 dex) is more metal rich than GALAH-scaled (~1.12 dex) and APOGEE-scaled (~1.26 dex) values from GALAH spectra for the same set of stars, while we find consistent median metallicities from APOGEE ASPCAP and Cannon estimates from APOGEE spectra. This means that for NGC 288 members, metallicity information estimated from GALAH spectra with the Cannon model trained on GALAH spectra using APOGEE ASPCAP labels (GCAA) results in more accurate (and closer to literature estimate) metallicity values compared to GALAH SME values. Similarly, the Cannon model trained on APOGEE spectra using GALAH SME labels (ACGS) is able to derive consistent metallicity information from APOGEE spectra, while slight decrease in median metallicity compared to GALAH SME estimate is seen in the case of GCGS. This points out that the GALAH SME metallicity estimates could be wrong, which is confirmed in the next section where we find significant systematic differences in stellar parameters for these stars between APOGEE and GALAH.

In NGC 104, median metallicity estimated from Cannon models trained on GALAH spectra using GALAH SME (GCGS) and APOGEE ASPCAP (GCAA) labels are more metal rich compared to the pipeline estimates, as well as literature value. On further investigation by comparing GALAH spectra of NGC 104 members with similar T_eff, log g, and [Fe/H] from GALAH SME, we found differences in spectra of stars with more metal rich Cannon estimates. This difference is found to be due to enhanced N abundance in stars with more metal-rich Cannon estimates resulting in strong CN bands as shown in Figs A4 and A5. Thus, these pervasive CN lines may blend with atomic features, resulting in higher [Fe/H] estimates by the Cannon models for these stars. These stars are also found to belong to the second-generation population in NGC 104 based on their enhanced N, Na, Al, and low O, Mg abundances from GALAH SME. At the same time, majority of NGC 104 members in our APOGEE sample (ACGS and ACAA) belongs to the first-generation population.
based on their ASPCAP light element abundances. Hence, we do not see similar difference in [Fe/H] Cannon estimates compared to the pipeline estimates using APOGEE spectra (ACGS and ACA). For all clusters excluding young open clusters, we find a mean scatter of 0.06 dex in APOGEE-scaled metallicity estimates and slightly higher scatter of 0.065 dex in GALAH-scaled metallicity estimates. We find a smaller mean scatter of 0.03 dex in both APOGEE and GALAH-scaled alpha abundance estimates. Overall, we find the Cannon metallicity estimates to be consistent with that in literature and follow expected theoretical isochrone tracks in the Kiel diagram, showing the quality of our GALAH- and APOGEE-scaled catalogues.

4.1.3 Chemical trends in clusters

Though the median metallicities from the Cannon estimates show good consistency with that from respective survey pipelines, as well as those from the literature, it is important to check for any significant trends in chemistry (metallicity and alpha abundance) with temperature. For cluster members (both open and globular clusters), we expect such trends to be non-existent owing to the chemical homogeneity of their birth cloud. At the same time, atomic diffusion can lead to differences in surface abundance values for different evolutionary phases (i.e. main sequence turn-off stars and giants) of cluster members as well (Dotter et al. 2017). In addition to atomic diffusion, Spina et al. (2020) have shown that stellar parameters and abundances vary as a function of the stellar activity in young stars. Hence, we also have to take this into account while investigating chemical trends in clusters.

In this work, where we have used the Cannon to estimate GALAH-scaled labels from APOGEE spectra (and GALAH spectra) and APOGEE-scaled labels from GALAH (and APOGEE spectra), we expect the Cannon estimates to follow the trends we see in the case of survey labels that have been used to train the model with. Thus, we expect GALAH-scaled cases (ACGS and GCGS) to exhibit similar trends as seen with GALAH SME values and APOGEE-scaled cases (GCAA and ACA) that of APOGEE ASPCAP. All figures discussed below are in the same format as in previous sections (Figs 10 and 11), with the top row showing the survey pipeline (SME/ASPCAP) estimates, middle and bottom rows showing the GALAH-scaled and APOGEE-scaled values, respectively, for the same stars. Estimates from GALAH spectra are indicated in blue circles and from APOGEE spectra in red triangles, with the median metallicity values in each case indicated with respectively colour-dashed lines.

In Fig. 12, first five columns show metallicity trends of five open clusters with respect to $T_{\text{eff}}$ and the next five columns show [$\alpha$/Fe] trends of the same clusters with respect to $T_{\text{eff}}$. We have arranged them from left to right in increasing order of their ages, from which it is clear that chemical trends with $T_{\text{eff}}$ are prominent for youngest clusters (IC 4665, Blanco 1, and Melotte 22). From GALAH SME estimates (first three columns in top row, blue circles), we see a slight negative trend for metallicity and positive trend for [$\alpha$/Fe] with increase in $T_{\text{eff}}$. As mentioned above, this could be the effect of stellar activity in young cluster members that is...
Table 6. Median metallicity and standard deviation estimated for members of five globular clusters from the latest Gaia EDR3 globular cluster catalogue (Vasiliev & Baumgardt 2021) cross-matched with the catalogues in this work. The names of clusters are listed in the first column, metallicity of the cluster from literature (VandenBerg et al. 2013) in the second column, the abbreviations for the catalogues (see Section 3.5) with the number of stars from each catalogue in brackets in the third column, Cannon metallicity estimates from each catalogue in the fourth column, and survey pipeline metallicity estimates corresponding to the spectra mentioned (in the catalogue name) in the same row in the last column.

| Cluster   | [Fe/H]_{literature} | Catalogue (No.) | [Fe/H]_{Cannon} (median, std dev) | [Fe/H]_{Survey} (median, std dev) |
|-----------|---------------------|----------------|-----------------------------------|-----------------------------------|
| NGC 104   | −0.76               | GCQS (181)     | −0.66, 0.08                       | −0.73, 0.07                       |
|           |                     | AGCS (90)      | −0.73, 0.09                       | −0.71, 0.04                       |
|           |                     | GCQA (181)     | −0.67, 0.07                       | −0.73, 0.07                       |
|           |                     | ACQA (90)      | −0.76, 0.04                       | −0.71, 0.04                       |
| NGC 2808  | −1.18               | GCQS (0)       | −                  | −                                   |
|           |                     | AGCS (31)      | −1.10, 0.06                     | −1.10, 0.05                       |
|           |                     | GCQA (0)       | −                  | −                                   |
|           |                     | ACQA (31)      | −1.12, 0.05                     | −1.10, 0.05                       |
| NGC 6121  | −1.18               | GCQS (0)       | −                  | −                                   |
|           |                     | AGCS (72)      | −1.03, 0.04                     | −1.01, 0.04                       |
|           |                     | GCQA (0)       | −                  | −                                   |
|           |                     | ACQA (72)      | −1.07, 0.03                     | −1.01, 0.04                       |
| NGC 288   | −1.32               | GCQS (19)      | −1.12, 0.05                     | −1.07, 0.04                       |
|           |                     | AGCS (33)      | −1.24, 0.06                     | −1.24, 0.04                       |
|           |                     | GCQA (19)      | −1.26, 0.09                     | −1.07, 0.04                       |
|           |                     | ACQA (33)      | −1.26, 0.07                     | −1.24, 0.04                       |
| NGC 6809  | −1.93               | GCQS (0)       | −                  | −                                   |
|           |                     | AGCS (31)      | −1.67, 0.04                     | −1.67, 0.07                       |
|           |                     | GCQA (0)       | −                  | −                                   |
|           |                     | ACQA (31)      | −1.71, 0.06                     | −1.67, 0.07                       |

Figure 12. [Fe/H] versus T_{eff} (left five columns) and [α/Fe] versus T_{eff} (right five columns) plots for five open clusters. We show survey pipeline (GALAH SME and APOGEE ASPCAP) estimates in the top row, GALAH-scaled values (AGCS and GCQS) in the middle row and APOGEE-scaled values (GCAA and ACQA) in the bottom row. Estimates from GALAH spectra are indicated in blue circles and from APOGEE spectra in red triangles, with the median metallicity and [α/Fe] values in each case indicated with respectively coloured dashed lines.
expected to strengthen saturated lines, resulting in a complicated interplay between effects on $T_{\text{eff}}$, log $g$ and chemical abundances (Spina et al. 2020). Among young clusters, only Melotte 22 has stars from both APOGEE and GALAH. For this cluster, GALAH-scaled metallicities and alpha abundances enhance the trends imprinted from the SME pipeline compared to APOGEE-scaled estimates. APOGEE ASPCAP [$\alpha$/Fe] values in Melotte 22 shows a wave-like trend with $T_{\text{eff}}$, which completely disappears in the APOGEE-scaled values from APOGEE spectra. Meanwhile, GALAH-scaled [$\alpha$/Fe] values are higher for the same stars, a trend that is seen in GALAH SME estimates for cool stars in Blanco 1. Meanwhile, this trend is removed in the case of APOGEE- and GALAH-scaled [$\alpha$/Fe] values for Blanco 1. For older open clusters, Ruprecht 147 and NGC 2682, there are no significant trends seen in survey pipeline estimates and correspondingly in the Cannon estimates, with respect to $T_{\text{eff}}$. We also note that for NGC 2682, the median metallicity for the GALAH-scaled case and APOGEE-scaled case align with the respective survey pipeline estimates.

In Fig. 13, first five columns show metallicity trends of five globular clusters with respect to $T_{\text{eff}}$ and the next five columns show [$\alpha$/Fe] trends of the same clusters with respect to $T_{\text{eff}}$. We have arranged them from left to right in decreasing order of their metallicities. Unlike in open clusters, there are no obvious trends with $T_{\text{eff}}$ for survey pipeline estimates and Cannon estimates. In all clusters, GALAH-scaled estimates have larger standard deviations or scatter as listed in the Table 6. As mentioned in the previous section, for NGC 104, differences in spectra due to strong CN bands in second-generation stars result in higher metallicity values estimated from GALAH spectra in both GALAH-scaled and APOGEE-scaled cases (see Figs A4 and A5). In addition to this, there are few GALAH stars for which APOGEE-scaled $T_{\text{eff}}$ is higher (by ~100–150 K) than GALAH SME estimates. On further investigation, these are found to be red clump stars. In the training set, we find similar difference in $T_{\text{eff}}$ between APOGEE ASPCAP and GALAH SME estimates for red clump stars in the same GALAH $T_{\text{eff}}$ and log $g$ ranges. Thus, this offset is likely real that is propagated from the systematic differences in training set.

In the case of NGC 288, GALAH SME and APOGEE ASPCAP metallicity values are different (~0.2 dex as shown in Table 6). GALAH-scaled metallicity estimates for GALAH and APOGEE stars also show difference which is smaller than that between survey pipeline estimates. Meanwhile, APOGEE-scaled metallicity estimates from both set of stars are consistent with the APOGEE ASPCAP estimate. At the same time, GALAH-scaled and APOGEE-scaled [$\alpha$/Fe] estimates are consistent for both APOGEE and GALAH stars and with respective survey pipeline estimates. In Fig. 14, we show metallicity trends with log $g$ for survey pipeline estimates (top panel), GALAH-scaled estimates (middle panel) and APOGEE-scaled estimates (bottom panel). There is a clear offset between the log $g$ values of GALAH and APOGEE pipeline estimates (see Fig. 14), which resulted in the shift from theoretical isochrone tracks seen in Fig. 11. This offset is found to be the result of bad parallax measurements for NGC 288 members (located at a distance of ~9 kpc) leading to wrong GALAH SME log $g$ estimates (equation 1 in Buder et al. 2021). Interestingly, GALAH-scaled and APOGEE-scaled log $g$ for GALAH stars are shifted to correct log $g$ values (blue circles in middle and bottom panels in Fig. 14). This could also explain the improvement in APOGEE-scaled and GALAH-scaled metallicity estimates for GALAH stars. Thus, our Cannon models are able to improve incorrect pipeline estimates.

Overall, we find that in most cases, GALAH-scaled and APOGEE-scaled metallicities and [$\alpha$/Fe] values are following the trends exhibited by the respective survey pipeline estimates. We also find GALAH-scaled estimates to have comparatively higher scatter compared to APOGEE-scaled values, which is expected from their respective survey pipeline values. The plots discussed above thus
clearly display both qualities, as well as limitations, of our catalogues and show the ability of the Cannon to carry out cross survey scaling of large data sets from high-resolution spectroscopic surveys.

5 DISCUSSION AND CONCLUSIONS

We used the data-driven approach, the Cannon, to produce two catalogues of stellar parameters and general alpha abundances, one scaled in terms of the APOGEE survey and the other in terms of the GALAH survey. We chose the training set from among ~20,000 stars commonly observed in both the surveys, which after quality cuts (removing stars with low SNR, bad spectra, bad pipeline estimates, etc) resulted in a final training set sample of 418 stars. We have shown the importance of cross survey scaling with plots showing the systematic differences in stellar parameters, metallicities and alpha abundances using common observed stars in the training set. While there is reasonably good agreement between the two surveys (especially for T eff and log g), there are systematic differences in [Fe/H], [α/Fe], v_{micro} and v_{turb} for the same stars in both surveys (Fig. 2).

Most notably, [Fe/H] for giants and hot dwarfs are underestimated by GALAH when compared to APOGEE, while GALAH [α/Fe] measurements are overestimated for giants. Most of these offsets could be attributed to differences in the parameter estimation methods implemented in the APOGEE and GALAH surveys. We used our final training set to train four Cannon models in four combinations of spectra and labels, i.e. two models with spectra and labels from the different surveys respectively, and two models with spectra and labels from the same survey.

With the 12-fold cross-validation of stars in the training set (see Sections 3.4 and A1), we have shown that the Cannon models predict labels/parameters that are consistent with the input labels. We further demonstrate in Figs 5 and 6 that the model generated spectra with the Cannon estimates are very similar (16th and 84th percentile values of residuals at majority of pixels within −0.01 and 0.01) to the respective observed survey spectra. We have also shown that pixels with higher residuals are either bad/noisy pixels or lines of elements that have not been modelled by our Cannon models. We also demonstrate the effectiveness of our method in Figs 7 and 8, where we remade the Fig. 2 for common stars in APOGEE and GALAH but with Cannon estimates from GALAH-scaled and APOGEE scaled catalogues. We show that the mean systematic difference for metallicity and alpha abundance is very close to zero with lesser scatter and no significant trends in comparison with survey pipeline estimates in Fig. 2.

These models are then used to estimate labels from 437,445 APOGEE and 576,390 GALAH spectra, thus providing two combined catalogues with stellar parameters scaled to both the APOGEE and GALAH surveys. We carried out the validation of these catalogues with selected open and globular cluster members by comparing survey pipeline estimates and Cannon estimates in kiel diagrams and chemical trend plots as shown in Figs 10–13. In kiel diagrams, both GALAH-scaled and APOGEE-scaled Cannon estimates follow respective theoretical isochrone tracks (based on literature ages and metallicities) even when survey pipeline estimates do not (NGC 2808, NGC 6121, and NGC 288). In addition, median metallicity estimates within standard deviations are consistent with literature values thus validating our Cannon estimates. In the case of T eff trends for metallicities and alpha abundance in clusters, as expected, Cannon estimates follow spurious trends exhibited by respective pipeline estimates to which they are scaled. Meanwhile, there are a few cases where GALAH-scaled metallicities and alpha abundances enhance the trends imprinted from the SME pipeline, particularly for the very young clusters.

Significant offsets of ~0.5–1 dex between GALAH SME and APOGEE ASPCAP log g estimates for NGC 288 members (located at a distance of ~9 kpc) in Fig. 14 showed that incorrect parallaxes can have an effect on log g determination in GALAH. Interestingly, log g values of GALAH stars in both GALAH-scaled and APOGEE-scaled cases have been shifted to the correct range. This has also led to the correction of the overestimated GALAH SME metallicities in the APOGEE-scaled case and significant improvement in the GALAH-scaled case. This shows the ability of the Cannon models to correct survey pipeline estimates and illustrates the quality of our Cannon estimates.

We have thus demonstrated the effectiveness of our method to carry out cross survey scaling and showed the quality of the resulting Cannon estimates in both catalogues. However, there are some limitations and caveats in the method that we briefly discuss below.

5.1 Limitations in the training set

The training set is the starting point and one of the major factors that can affect parameter estimation using data-driven approaches like the Cannon. While the training set should be a representative of different
populations of stars that the survey (from which the input labels are taken) observed, the labels and spectra should also be reliable and of high quality. Since we are restricted to choosing the common stars observed in both the surveys for the training set in this work, we have limited options regarding the former criterion. We have carried out quality cuts as recommended by each survey for both the labels, as well as spectra, ensuring a good-quality training set. Ideally, in cases where the spectra and label are from the same survey (ACAA and GCGS), one can use a larger training set. Since our goal is to put the surveys on the same scale, we choose a single training set that passes all quality criteria and have sufficient number statistics. Thus our training set is limited by the fact that not all the best quality spectra or labels in the respective catalogue are included in it, rather we select the best labels from among the common stars observed in both the surveys. Still our final training set sample has reasonably broad coverage of the parameter space of both surveys (see Fig. 1), but one should exercise caution at the edges of the training set, in particular for metal-poor ([Fe/H] < -0.8) stars and for M-dwarfs, for which the Cannon labels deviate from the one-to-one relation. We have assigned dedicated flags that will help the user to identify such stars (see Section 3.6).

5.2 Propagation of parameter trends

By reproducing APOGEE-scaled labels from GALAH spectra and GALAH-scaled labels from APOGEE spectra, we are propagating the trends/issues in these parameters that arise from the input survey pipeline/analysis method. Such issues are evident in the labels when we compare them in Fig. 2. These include the lower metallicities determined for metal rich giants in GALAH and large differences in microturbulence and broadening values for stars in GALAH as well as APOGEE (see Section 3.2). We show the inability of the Cannon models to reproduce APOGEE microturbulence values in Figs 4 and A2. We also see the effect of this on Cannon temperature and surface gravity estimates in the case of ACAA (see Fig. A2). When we adopted the empirical relations used in GALAH to redefine microturbulence values for APOGEE, these trends are corrected (see Fig. A3). Thus, it is important to have accurate and reliable input labels in order to get better results from data-driven methods and machine learning tools and future surveys should aim to achieve this.

5.3 Limitations in the error determination

With repeat observations, we have been able to show that the errors for the labels from the Cannon are either incorrect or underestimated. We then estimate a scaling factor for each label and rescale their Cannon covariance errors. Using repeat observations, we also estimated precision for all labels as a function of SNR in the range of 36–50 K ($T_{\text{eff}}$), 0.06–0.1 dex (log g), 0.02–0.04 dex ([Fe/H]), and 0.02–0.03 dex ([α/Fe]) for SNR > 40 in GALAH and SNR > 80 in APOGEE. We choose the maximum value among rescaled covariance uncertainty and precision estimate at respective SNR to be the final error for each label. Thus, our errors are determined without taking into account any possible additional dependence on temperature and surface gravity as it is done in APOGEE (Jónsson
et al. 2020). Thus, there is a possibility that our errors are still underestimated.

Finally, we have ∼1 million stars with APOGEE-scaled and GALAH-scaled parameters in both catalogues, with a spatial coverage that spans inner and outer parts of the Milky Way, including thin disc, thick disc, and halo components. The mean metallicity and alpha abundance errors are 0.07 and 0.06 dex in the GALAH-scaled case, and 0.06 and 0.03 dex in the APOGEE-scaled cases. Once we implement flags in both catalogues to remove stars outside the training set boundary (flag_Cannon_dist), stars with bad spectra (flag_spectra), bad SME and ASPCAP labels (flag_sp_aspcap and flag_survey), and good snr (flag_snr), we have ∼280 000 GALAH stars and ∼170 000 stars from APOGEE, with a spatial coverage that spans the mid-plane, as well as halo regions of the Milky Way as shown in Fig. 15. Thus, we end up with less than 50 per cent of the total number of stars in the catalogues, but with good quality spectra and the parameters on a common scale in each catalogue. This is still an impressive number of stars with good spatial coverage to study the metallicity and alpha abundance trends of the Milky Way components.

Combining these catalogues with the latest Gaia EDR3 catalogue enables a comprehensive chemo-dynamic study of these different components that constitutes the Milky Way from the perspective of APOGEE and GALAH, separately. We have cross matched with Gaia EDR3 and included source ids from both DR2 and DR3, along with distances estimated by Bailier-Jones et al. (2021) in the final catalogues as listed in the table schema, Table A1.

5.4 Final conclusions

With this work, we have demonstrated the ability of the data-driven method, Cannon, to reliably estimate respective survey-scaled stellar parameters, metallicity, and alpha abundance. While having a few caveats, we find that the Cannon estimates are as good as or showed improvement over the respective survey pipeline estimates. These are encouraging signs to use currently available data-driven and machine learning tools to do cross-survey scaling with many more ongoing and upcoming spectroscopic surveys.

Among the limitations and caveats discussed above, the limited size and coverage of parameter space by the common stars observed in both surveys for the training set is foremost. This will hopefully improve in coming years, as both GALAH and APOGEE South continue to observe larger samples of stars going forward. Improvements in stellar model atmospheres and incorporation of 3D NLTE models in spectroscopic analysis will enable ongoing, as well as upcoming ground-based surveys, like SDSS-V (Kollmeier et al. 2017), 4MOST (de Jong et al. 2019), WEAVE (Dalton et al. 2018) etc., to achieve better accuracy and precision in stellar parameter and elemental abundances. Thus, we will have all the necessary ingredients to construct training sets that can be used to carry out cross-survey scaling, which will provide catalogues of stars with consistent stellar parameters and elemental abundances with a significant coverage of all components of the Galaxy.

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DATA AVAILABILITY

The data underlying this article are available in the Data Central at https://cloud.datacentral.org.au/teamdata/GALAH/public/GALAH_DR3/

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APPENDIX A: GALAH CANNON GALAH SME (GCGS) & APOGEE Cannon APOGEE ASPCAP (ACAA)

We use the training set to generate Cannon model trained on GALAH (APOGEE) spectra using GALAH SME (APOGEE ASPCAP) labels, which is then used to predict stellar parameters for rest of GALAH (APOGEE) spectra. We carry out 12-fold cross-validation, error estimation from repeat observations and internal validation for both cases as shown below.

A1 Cross-validation

We follow the method described in Section 3.4 to carry out 12-fold cross-validation of the Cannon estimates for six labels using the training set. In the case of GALAH CANNON GALAH SME, we compare the Cannon outputs with input GALAH SME labels, while we compare the Cannon outputs with input APOGEE ASPCAP labels for APOGEE Cannon APOGEE ASPCAP. Figs A1 and A2 show the cross-validation results for GALAH CANNON GALAH SME and APOGEE Cannon APOGEE ASPCAP, respectively.

In the case of GALAH CANNON GALAH SME, all labels follow a tight one-to-one relation as indicated by the mean and scatter values as well. Largest scatter (0.48 km s\(^{-1}\)) is seen in the case of \(v_{\text{broad}}\) which is still much lower than in the case of APOGEE Cannon GALAH SME.

In the case of APOGEE Cannon APOGEE ASPCAP, all labels except \(v_{\text{micro}}\) and \(v_{\text{broad}}\) follow a tight one-to-one relation. Still, we find the Cannon to under estimate \(T_{\text{eff}}\) for cool stars (\(T_{\text{eff, APOGEE}} < 4500\) K) and stars with \(T_{\text{eff, APOGEE}} > 5000–5400\) K, while slightly over estimate \(T_{\text{eff}}\) for stars with \(T_{\text{eff, APOGEE}}\) in between these two limits. Similarly, we find the Cannon to slightly over predict log \(g\) for stars with log \(g_{\text{APOGEE}} > 4\) dex.

There are significant deviations in the case of \(v_{\text{micro}}\) and \(v_{\text{broad}}\) similar to that seen in the case of GALAH CANNON APOGEE ASPCAP (see Fig. 4). We find the Cannon outputs for input \(v_{\text{micro, APOGEE}} > 1\) km s\(^{-1}\) follow one-to-one relation, whereas the Cannon estimates have higher dispersion for lower \(v_{\text{micro, APOGEE}}\) values. This indicates that the Cannon model is unable to find significant correlation between \(v_{\text{micro, APOGEE}}\) values and corresponding APOGEE spectra. Much tighter one-to-one trend is seen in the case of \(v_{\text{broad}}\), though there are significant deviations for lower \(v_{\text{broad, APOGEE}}\) values. As mentioned in Section 3.4, this again possibly indicates the inefficiency/problems associated with the way \(v_{\text{micro}}\) and \(v_{\text{broad}}\) have been determined for APOGEE stars.
Table A1. Table schema of APOGEE-scaled and GALAH-scaled stellar parameter catalogues.

| Column name          | Unit          | Description                                      |
|---------------------|---------------|--------------------------------------------------|
| Unique ID           |               | Unique survey star id                           |
| dr2_source_id       |               | Gaia dr2 ID                                     |
| dr3_source_id       |               | Gaia dr3 ID                                     |
| ra                  | deg           | Right ascension                                 |
| dec                 | deg           | Declination                                     |
| teffCann            | K             | Cannon estimate of effective temperature       |
| e_teffCann          |               | error for teffCann                             |
| loggCann            | log(cm s⁻¹)   | Cannon estimate of surface gravity              |
| e_loggCann          |               | error for loggCann                             |
| fehCann             | dex           | Cannon estimate of metallicity                 |
| e_fehCann           |               | error for fehCann                              |
| alphafeCann         | dex           | Cannon estimate of [α/Fe]                       |
| e_alphafeCann       |               | error for alphafeCann                          |
| vmicroCann          | km s⁻¹        | Cannon estimate of microturbulence              |
| e_vmicroCann        |               | error for vmicroCann                           |
| vbroadvCann         | km s⁻¹        | Cannon estimate of broadening velocity          |
| e_vbroadvCann       |               | error for vbroadvCann                          |
| r_chi_sq            |               | reduced chi-square from Cannon                 |
| snrCann             |               | Signal-to-noise ratio from Cannon              |
| Cannon_distance     |               | Distance to the training set labels            |
| flag_id             |               | 0 – GALAH spectra, 1 – APOGEE spectra           |
| flag_Cannon_dist    |               | flag for quality of Cannon estimates (0/1)      |
| flag_spectra        |               | flag for problematic spectra                    |
| flag_sp_aspcap      |               | survey pipeline flag                            |
| flag_survey         |               | invalid survey pipeline estimates (1)           |
| flag_training       |               | star belonging to the training set (0)         |
| teff                | K             | Survey effective temperature                   |
| e_teff              |               | Survey effective temperature error              |
| logg                | log(cm s⁻¹)   | Survey surface gravity                         |
| e_logg              |               | Survey surface gravity error                    |
| feh                 | dex           | Survey metallicity                              |
| e_feh               |               | Survey metallicity error                        |
| alphafe             | dex           | Survey [α/Fe]                                   |
| e_alphafe           |               | Survey [α/Fe] error                             |
| vmicro              | km s⁻¹        | Survey microturbulence                          |
| e_vmicro            |               | Survey microturbulence error                    |
| vbroadv             | km s⁻¹        | Survey broadening velocity                      |
| e_vbroadv           |               | Survey broadening velocity error                |
| snr                 |               | Survey signal-to-noise ratio                   |
| r_ext               | pc            | Estimated distance from Bailer-Jones+21        |
| r_10                 | pc            | Lower bound from Bailer-Jones+21               |
| r_1H                 | pc            | Higher bound from Bailer-Jones+21              |
| parallax            | mas           | Gaia EDR3 parallax                              |
| e_parallax          | mas           | Gaia EDR3 parallax error                        |

To investigate this further, we carry out an exercise in which instead of the APOGEE $v_{\text{micro}}$, we make use of the empirical relation adopted in GALAH (equations 4 and 5 in Buder et al. 2021) to determine $v_{\text{micro}}$ for APOGEE as well. We do this since the Cannon could correlate the $v_{\text{micro}}$ from GALAH SME with APOGEE spectra in APOGEE Cannon GALAH SME (see Fig. 3). Including this new $v_{\text{micro}}$, we train Cannon model on APOGEE spectra using APOGEE labels. The cross-validation results from this exercise are shown in the Fig. A3. First of all, there is a tight one-to-one relation for $v_{\text{micro}}$. This is no surprise since the new empirical $v_{\text{micro}}$ is a function of $T_{\text{eff}}$ and log g, and thus the Cannon could identify tight correlation with corresponding spectra as well. This is again reflected in the $T_{\text{eff}}$ and log g estimated by the Cannon, which no longer show the issues that we found when APOGEE $v_{\text{micro}}$ is used to train the Cannon model. This can be considered as an evidence of the inefficiency/problems associated with the way $v_{\text{micro}}$ have been determined for APOGEE stars.
Figure A1. One-to-one relation of GALAH SME stellar labels (x-axis) in the training set versus corresponding values estimated by the Cannon from GALAH spectra (y-axis) after carrying out a 12-fold cross-validation test. The mean and scatter (calculated as the mid-value of 84th–16th percentile) in each label difference is indicated on the bottom right-hand side of each plot.

Figure A2. One-to-one relation of APOGEE ASPCAP stellar labels (x-axis) in the training set versus corresponding values estimated by the Cannon from APOGEE spectra (y-axis) after carrying out a 12-fold cross-validation test. The mean and scatter (calculated as the mid-value of 84th–16th percentile) in each label is indicated on the bottom right-hand side of each plot.
**Figure A3.** One-to-one relation of APOGEE ASPCAP stellar labels (x-axis) in the training set versus corresponding values estimated by the Cannon from APOGEE spectra (y-axis) after carrying out a 12-fold cross-validation test. The mean and scatter (calculated as the mid-value of 84th−16th percentile) in each label difference is indicated on the bottom right-hand side of each plot.

**Figure A4.** GALAH spectra for two NGC 104 members with similar stellar parameters from GALAH. In blue, we show star spectrum for which GALAH- and APOGEE-scaled stellar parameters from GALAH spectra (GCGC and GCAA) are consistent with GALAH SME. Star spectrum in red is an example where GCGS and GCAA metallicity estimates are more metal rich than GALAH SME value. This inconsistency can be attributed to the difference between the two spectra (red-blue), shown in green in the bottom panels (mean flux difference is indicated in these panels), arising due to pervasive CN lines that blend with atomic features in the red spectrum resulting in more metal-rich Cannon estimates.

**Figure A5.** Same as Fig. A4 but for another pair of stars with similar stellar parameters in NGC 104.

**APPENDIX B: METALLICITY DIFFERENCE IN NGC 104**

As mentioned in Section 4.1.2, GCGS and GCAA metallicity estimates are found to be more metal-rich than both survey pipeline estimates, as well as Cannon estimates from APOGEE spectra. To understand the reason for this, we compare GALAH spectra of two stars in NGC 104 with similar stellar parameters, out of which GCGS and GCAA metallicity is the same as GALAH SME estimate for one star and not for the other. Two such examples in the red and infrared wavelength ranges are shown in Figs A4 and A5, where spectra in blue are stars with consistent Cannon estimate and red spectra represent the inconsistent case. Residuals resulting from difference between red and blue spectra is shown in green in...
the bottom panels. We have computed illustrative synthetic spectra following Buder et al. (2021) for the relevant stellar parameters with a solar chemical composition, as well as with an enhancement in N of 0.8 dex, the difference between which is plotted in black in the same panel. The residual from observed spectra clearly follows that from the synthetic spectra, especially evident from the CN bands at $\sim 7870\,\text{Å}$, suggesting that the stars with more metal-rich Cannon estimates (red spectra) have enhanced N abundances and thus stronger CN bands.

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