StarHorse stellar parameters validated with open clusters

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Abstract: StarHorse and StarHorseNet are algorithms that compute stellar parameters from parallaxes and photometric or spectrometric information. The aim of this thesis is to verify the quality of the results of four different versions of these codes. We prove that estimating ages is complex and that distances and extinctions are generally reliable even if they present some systematic trends that must be taken into account.

I. INTRODUCTION

The characterisation of a star is achieved by knowing its mass, chemical composition, luminosity, age, etc. In addition, other properties like distance to the Sun or the suffered extinction are important too for determining the Galactic structure. But estimating them from observation is not trivial: it requires using stellar evolutionary models and dealing with parameters interdependence. Nowadays, there are several procedures to determine these astrophysical parameters from observational data, such as the codes called StarHorse and StarHorseNet. The results can be validated, for instance, by using field stars with well-known parameters, but also using stars belonging to open clusters (OCs).

OCs are groups of gravitationally tied stars that are born essentially at the same time from the same cloud of gas. Consequently, their members are expected to have nearly the same age and initial metallicity, to be approximately at the same distance and to be affected roughly by the same amount of interstellar extinction. This is why they constitute excellent samples to evaluate the precision and accuracy of astrophysical parameter calculations.

In the present analysis, we use OCs to validate the estimations of distances, extinctions and ages obtained from different versions of StarHorse employing the catalogues based on *Gaia* DR2 that were released by [1] (hereafter CG2020) and by [2] (hereafter D2021).

This work is structured as follows. The details of the studied data are explained in Section II. The comparison with the literature is treated in Section III and further analyses of the existence of some systematic trends are discussed in Section IV. Finally, Section V discusses conclusions and possible future projects.

II. DATA

Three different versions of the code StarHorse and one of StarHorseNet have been compared with CG2020 and D2021. The most important characteristics of the four algorithms and of both references are explained below.

A. StarHorse

StarHorse is a Bayesian tool that determines astrophysical parameters of individual stars from spectroscopic and photometric inputs [3]. It calculates the likelihood of a specific value of the estimated magnitude given a set of input data[1] and some astrophysical models –isochrones, the initial mass function (IMF), or density priors for different Galactic stellar populations. As output, it returns distance (d), extinction in the V band (A_V)[2], age (τ) and effective temperature (T_{eff}) as primary parameters and metallicity ([M/H]) and surface gravity (log[g]) as secondary parameters. All stars are considered to be single and hence, some bias for binaries may exist.

We consider three different versions of this code –each one having its own priors, origin of the input data and code upgrade.

In the first place, the 2019 algorithm incorporates both *Gaia* DR2 [4] photometry and parallaxes and Pan-STARRS1, 2MASS and AllWISE photometric catalogues. The extinction is limited into the range [-0.3, 4.0] mag and a grid of the log[τ] values is considered for the fitted isochrones. More information can be found in [5]. Only the highest quality[3] stars are used, which represents 1864[4] OCs in common with CG2020 and 1526 with D2021. From now, this sample will be referred to as SH2019.

Secondly, a calculation with cluster priors added, henceforward named SHprior. Along with the aforesaid evolutionary models, it includes the CG2020 distances, extinctions and ages as Gaussian priors for each star. When available, T_{eff} from SH2019 is used too. Consequently, a great agreement with the references –at least with CG2020– is expected in comparison with the other algorithms. It shares 1866 OCs with CG2020 and 1481 with D2021.

Thirdly, an algorithm similar to SH2019 which employs *Gaia* EDR3 [6] parallaxes and photometry instead of DR2 and which adds SkyMapper photometry for Southern hemisphere sources. Furthermore, the extinction limit is omitted and the 3D extinction map of [7] is utilized as informative prior. It will be referred as SH2021 and its total amount of common OCs is 1862 for CG2020 and 1529 for D2021. Further details will be available in Anders et al. 2021 [in prep.].

B. StarHorseNet

StarHorseNet [8] (hereinafter denoted as SHNet) is a machine-learning version of the StarHorse code built as an Artificial Neural Network (ANN). Input data involve *Gaia* DR2 parallaxes and photometry as for SH2019, while the [9] survey is used as the training set. As SHNet is an ANN,

[1] Input options are photometric observations, parallaxes or parameters priors based on spectroscopic data.

[2] A_V refers to the extinction at λ=5420Å.

[3] Those sources with both SH_OUTFLAG = "00000" and SH_GAIAFLAG = "000".

[4] Every mentioned number of OCs refers just to clusters that have evaluated parameters.

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instead of including forced priors[5], it learns the relationships between the respective inputs and output parameters from the training set. Only the highest quality[6] stars are analysed, which represent each one of the 1867 OCs of CG2020 and 1529 clusters in common with D2021.

C. CG2020 and D2021

We selected the CG2020 catalogue of 1867 OCs as the first reference for this analysis. The main reason for this decision is its completeness and the homogeneity of its derived parameters. Distance, extinction and age of each cluster are estimated with an ANN trained on a set of high-quality measurements in order to apply a unique method for all the OCs as well as to diminish the impact of the noisier data (differential extinction, blue stragglers, changes in binary fractions on the main sequence…). The range of its astrophysical parameters is shown in Fig. 1. 90% of the clusters are nearer than 4.4 kpc and have less than 2.5 magnitudes of extinction. Moreover, the 10^{th}-90^{th} percentile of log(τ) covers the range from 7.2 to 9.1 dex.

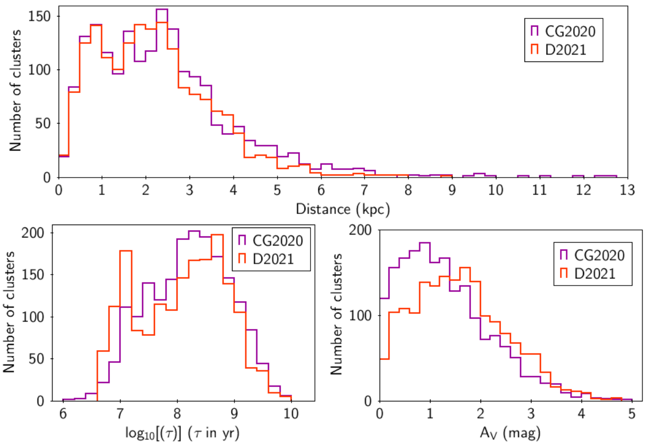

FIG. 1: Distribution of distance, log(age) and extinction of the studied clusters for both references.

We use the D2021 survey as reference as well in order to prove if discrepancies come mostly from the algorithms or if they are generated by the chosen reference as well. It contains parameters of 1743 OCs determined by isochrones fitting of *Gaia* DR2 photometry. Their ranges are shown in Fig. 1. 90% of the clusters are nearer than 3.9 kpc and have an extinction lower than 2.9 mag. Moreover, the 10^{th}-90^{th} percentile of log(τ) includes from 7.0 to 9.0 dex.

III. PARAMETER COMPARISON

An initial analysis for the datasets of the four algorithms has been done looking for deviations in distances, extinctions and ages.

A. Distances

Fig. 2 shows that the four algorithms have a reasonable accuracy since the majority of the stars present less than 20% of deviation. Moreover, the means of Gaussians adjusted to all the data of each series of the upper panel does not reach 4% in any case. Not only the mean of SH2019 is compatible with zero when one considers its standard error, but also the systematic trends exhibited by the other samples are smaller than the typical uncertainty of CG2020 distances (5-10%).

The distribution of the differences with D2021 are less accurate, but they have precisions with the same order of magnitude than with CG2020. Besides, the mean of the distances relative error provided by D2021 is 5.8%, so the algorithms means agree with it.

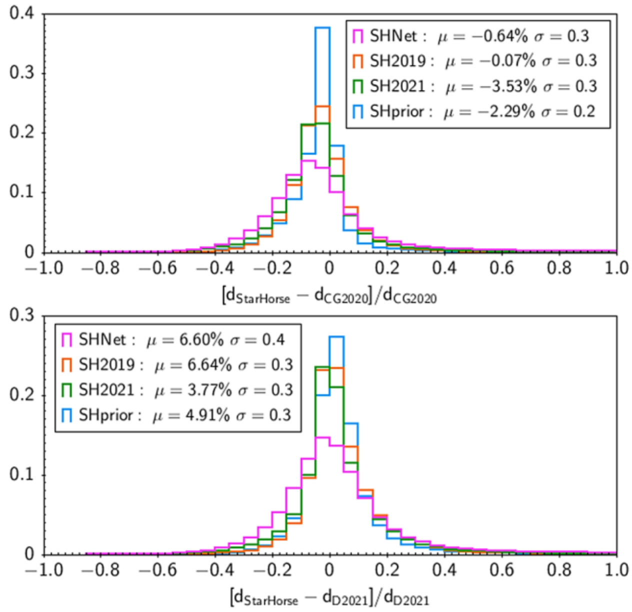

FIG. 2: Normalized histograms of the relative difference in distance in the sense StarHorse or StarHorseNet value minus the reference one: CG2020 above and D2021 below. The inserted values are the means (μ) and the standard deviations (σ) of adjusted Gaussians.

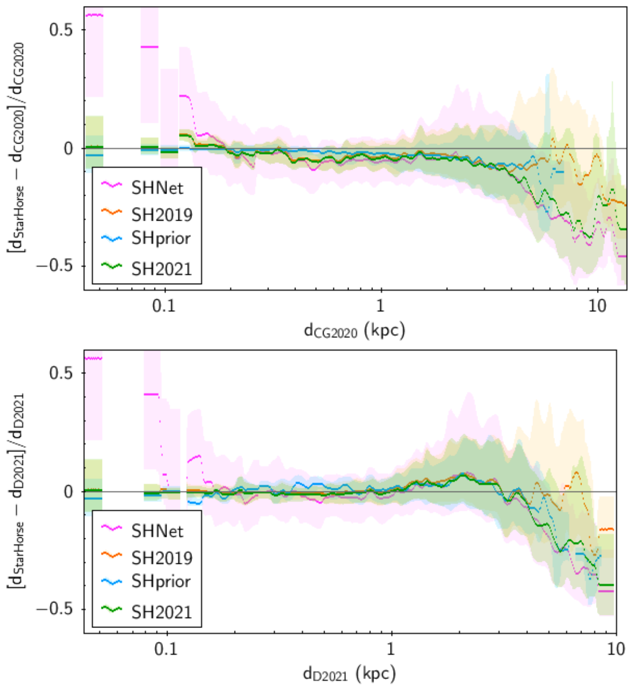

FIG. 3: Median and 1σ percentile of the relative difference in distance for each cluster. With CG2020 above and D2021 below.

In Fig. 3, the relative difference for each star is compared with its cluster distance in logarithmic scale, to keep in mind that most clusters are located closer than 4kpc. It proves that

[5] Apart from the same extinction upper boundary as for SH2019.
[6] Those sources with SHNet_OUTFLAG = "000000", which means they do not have too large 1σ associated uncertainties.

the four algorithms tend to underestimate the distance with respect to CG2020 and that they compare better with D2021 from 0.1 to 1 kpc. Despite that, the 1-4 kpc overestimation of the bottom panel is the responsible of the larger and positive means for D2021 in Fig. 2. In both cases, the deviation increases with the distance and it is also clear that SHNet greatly overestimates the distance to the nearest clusters.

B. Extinction A_V

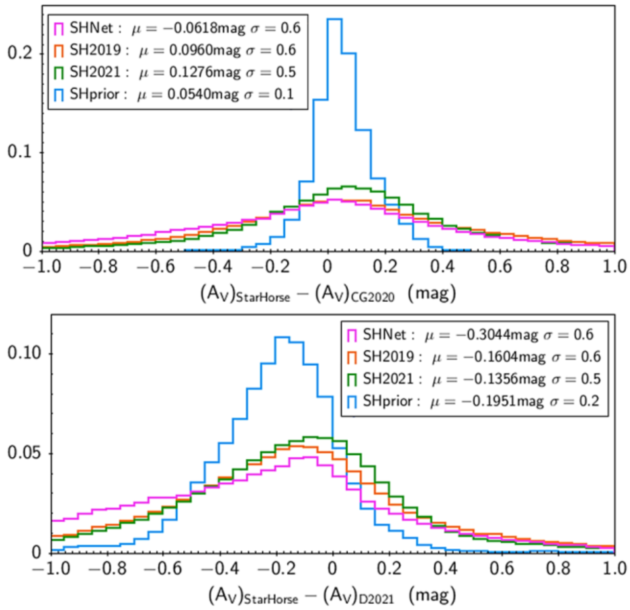

FIG. 4: Normalized histograms of the difference in extinction with the same characteristics as Fig. 2.

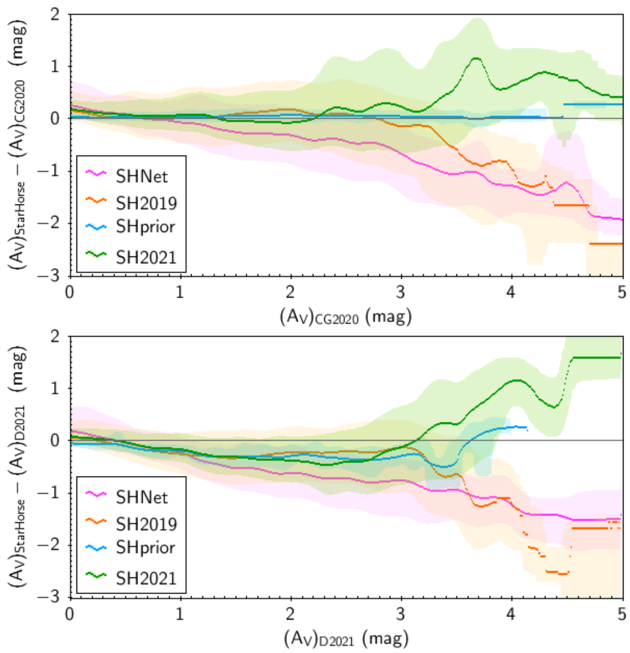

FIG. 5: The same as in Fig. 3 but comparing extinction differences.

Fig. 4 shows the histogram of the extinction differences. With both references, SHprior presents the narrowest distribution so it is the most precise, and at the same time, it is the most accurate only in relation to CG2020 because of its priors. The other three algorithms have broader distributions, although all the means of the upper panel are compatible with the CG2020 extinction uncertainty –which is estimated within 0.1 and 0.2 magnitudes. In the lower panel, all the means are larger than D2021 mean error in extinction (0.12 mag) and the distributions become asymmetric. Thus, extinctions compare better with GC2020.

Fig. 5 confirms that SHprior extinctions fit almost exactly with CG2020 along all the range, while SH2019 and specially SHNet tend to underestimate them due to their $A_V \leq 4.0$ mag boundary. Instead, as SH2021 does not include any range restriction, its extinctions are in better agreement although it tends to overestimate them at large extinctions. The D2021 panel of this figure reveals similar trends apart from a global underestimation caused by D2021 systematic trends with respect to CG2020 (figure 15 of [2]).

C. Ages

Fig. 6 shows the histogram of age differences with respect to CG2020 for the three StarHorse algorithms and also with respect to D2021 for SHprior. SHNet is not shown because it does not provide any calculation of stellar ages.

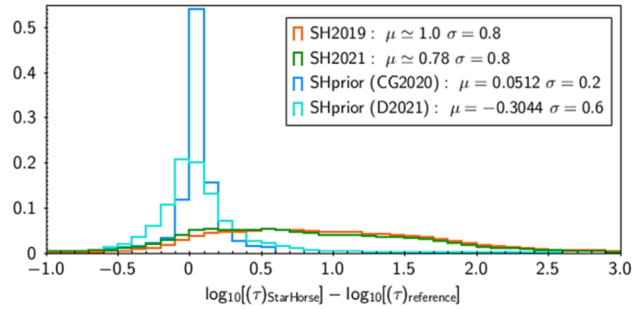

FIG. 6: Normalized histograms of the difference in the log(τ) in the same sense hitherto referred. The reader might be aware of the wide range and the asymmetry of the horizontal axis.

SH2019 and SH2021 are rather unsuccessful in estimating the stellar ages: their distributions are very broad and peak considerably far from zero (near 1.0 with both references), having deviations up to two orders of magnitude from both catalogues. Furthermore, the results mostly imitate the pattern of the initial grid of isochrones instead of extending over all the possible continuous values.

By construction, SHprior is able to reproduce the values provided by CG2020 with a considerable accuracy even though it overestimates them a little bit. Its mean difference agrees with the uncertainty between 0.1 dex and 0.25 dex specified in CG2020. In respect of D2021, the distribution becomes broader and less accurate as expected.

IV. SYSTEMATIC DIFFERENCES

The existence of possible systematic biases depending on sky direction or on the stellar spectral type of cluster members (that is, T_{eff} and log[g]) is analysed via sky plots and Kiel diagrams. We only compare with CG2020 in order to use the greatest number of OCs as possible and given that the two references lead to the same general conclusions. Furthermore, while we analysed more than 30 plots, we only reproduce in the following sections the most relevant ones.

A. Sky distribution

On the one hand, it is remarkable that both the *Gaia* EDR3 improvement with respect to *Gaia* DR2 and the inclusion of a dust map in SH2021 priors allow a slightly smoother distribution of extinction differences than SH2019, as seen in Fig. 7. However, SH2021 underestimates the extinction at the anticenter with respect to CG2020. This bias is also derived with D2021 and thus, it can be a consequence of the dust map used as a prior.

Consistently with Fig. 2, both algorithms have uniform maps of distance differences which tend to a barely underestimation.

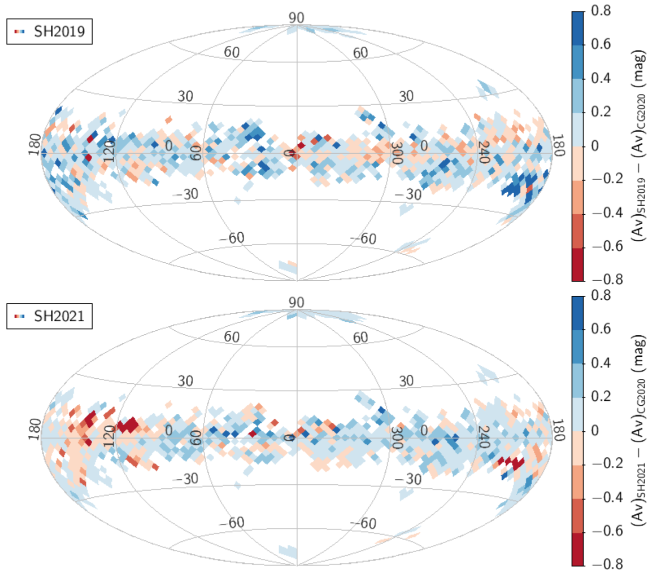

FIG. 7: Sky distribution in Galactic coordinates of the Fig. 4 differences for SH2019 (above) and for SH2021 (below). The colour coding shows the median of each HEALPix.

On the other hand, as we have already mentioned, the nearest clusters –as the Hyades and Melotte 111– have a very overestimated SHNet distance. In addition, as proven in Fig. 8, this algorithm underestimates the extinction at the lower Galactic latitudes except at the anticenter direction, where dust quantity diminishes. Contrarily as expected from the relation between distance and extinction via magnitudes, i.e. $m - M = 5 \cdot \log_{10}(d_{[pc]}) - 5 + A$, corresponding distances are not generally overestimated, even if some outlying values increase these means with respect to the medians.

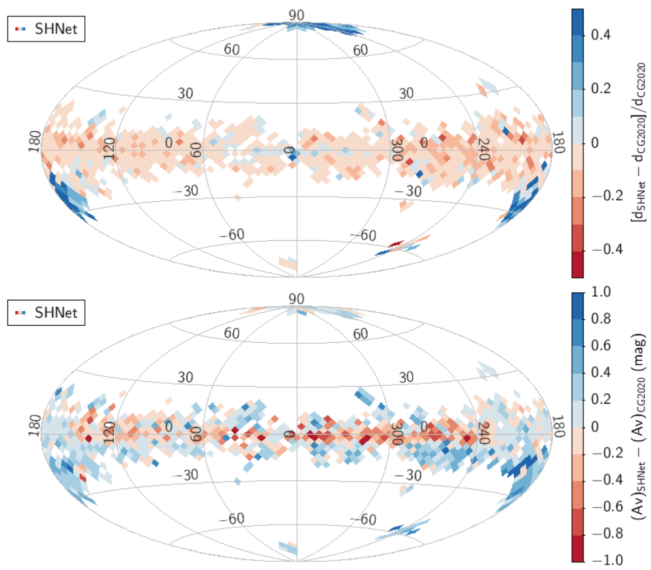

FIG. 8: Sky distribution in Galactic coordinates of the differences of distances (above) and extinctions (below) for SHNet. The colour coding shows the median of each HEALPix.

As predicted, the sky distribution of the three parameters differences for SHprior are very uniform and they correspond with results in Section III without noticeable substructure.

B. Kiel diagram

A spectroscopic Hertzsprung-Russell diagram, also called Kiel diagram, is a log[g]-T_{eff} graph. Its advantage is that these two values do not depend on distance nor extinction (at least in the case of spectroscopic observations). In this work, it is used to detect the existence of biases as a function of log[g] or T_{eff}.

It is obvious from Fig. 9 that even if the four algorithms exhibit a clear main sequence and red giant branch, they distribute the stars in different ways. On the one hand, SH2019, SHprior and SH2021 present a pre-main-sequence and an unrealistic termination near log[g] = 3.5 dex that might be created by the algorithm itself. On the other hand, SHNet shows a reduced temperature range, having a colder bluish edge of the main sequence. Finally, when plotting densities, all but SHprior[7] exhibit a prominent red clump around the coordinates (T_{eff}, log[g]) = (4800 K, 2.5 dex).

The distance to giant stars is mainly overestimated by all the algorithms excluding SH2021 as seen in Fig. 9. It is also shown that SHprior has a strong dichotomy: for surface gravity higher than 3.4 dex, a slight underestimation prevails, while for lower gravities, the overestimation dominates. Additionally, SH2021 is the most homogeneous through all the corresponding diagram.

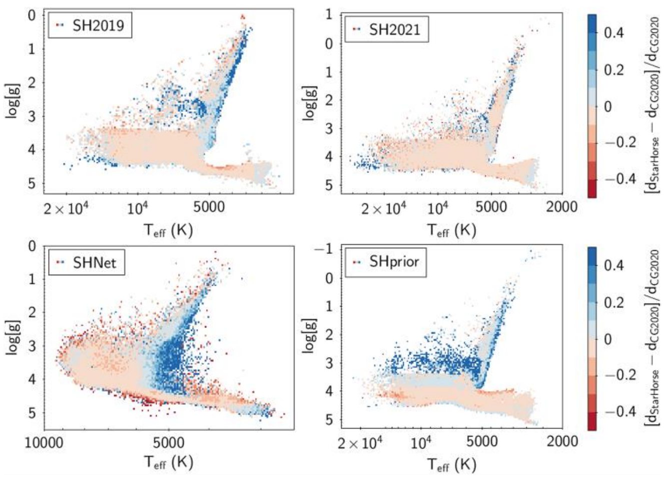

FIG. 9: Kiel diagrams for the results of the four algorithms with the same distances differences as in Fig. 2 at the auxiliar axis. Colour range is the same for all the figures.

As shown in Fig. 10, SHprior provides the most uniform extinction deviations through the Kiel diagram. That said, each panel in Fig. 10 shows more pronounced substructure than its equivalent in Fig. 9.

Firstly, SH2019 and also SH2021 although less prominently, underestimate the giant stars extinctions as is expected due to their distance overestimation and the fact that the position over the diagram fixes the left-hand side value of the $m - M = 5 \cdot \log_{10}(d_{[pc]}) - 5 + A$ relation. On the other hand, SHNet reproduces the extinctions of CG2020 reasonably well for giant stars.

[7] The red clump is less evident in the Kiel diagram of SHprior.

Secondly, SH2021 tends to overestimate the extinction of the stars hotter than 10^4 K, while SH2019 overestimates the values only in some regions of the main sequence.

Finally, the deviations of the three StarHorse algorithms abruptly change their behaviour at $T_{eff} \sim 10^4$K and present a high overestimation. It can be caused by the IMF prior, which assumes that stars have a very small likelihood of being of type O and B. Despite of that, further analysis beyond the scope of this work is recommended to fully understand this feature, which is also seen with D2021. SHNet does not have such a structure, by contrast, its extinctions are underestimated for gravities between 2.8 and 4 dex and overestimated at greater values.

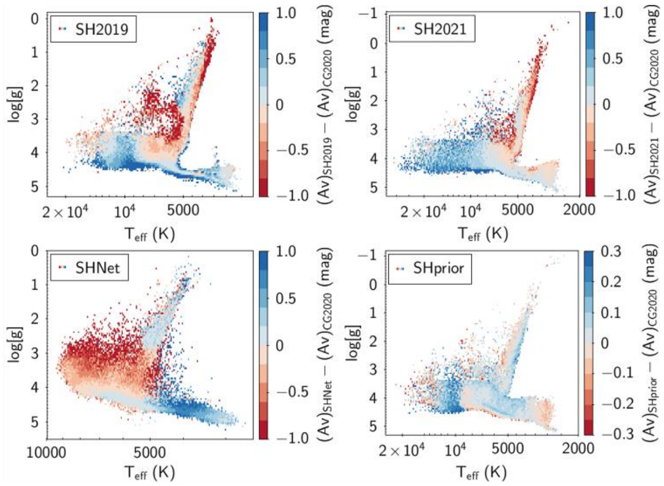

FIG. 10: Kiel diagrams for the results of the four algorithms with the same extinction differences as in Fig. 4 at the auxiliar axis.

The analysis for age deviations reveals that SHprior underestimates the ages of pre-main-sequence reddest stars and that it overestimates a little those of bluer and bigger stars. The giants and the rest of the main sequence agree considerably well with respect to CG2020.

V. CONCLUSIONS

- We compare datasets obtained from four different versions of the code StarHorse with two different references in order to verify the quality of the derived stellar parameters.
- In general, all algorithms compare better with CG2020 than with D2021, but discrepancies are almost always consistent with both references internal uncertainties.
- By construction, a better agreement of SHprior with CG2020 was expected and it has been proven. Further, the cluster priors of this algorithm allow it to be the most precise even if this advantage is not profitable when studying field stars.
- The other algorithms do not treat stars as members of clusters. As a result, SH2019 and SH2021 ages are not reliable and the extinctions of SHNet are questionable. Besides, they provide satisfactory results for distances up to 3 kpc and for extinctions smaller than 3 mag. Both the SHNet distances for very near stars and the extinction boundary prior should be avoided.
- We found some biases that could be corrected with further work. For instance, those in the extinction sky distribution of SHNet and the SH2021 overestimation at the Galactic anticenter or all the T_{eff} and log[g] dependences of the distances and extinctions.
- Other future research might be focused on analysing the coherence within each cluster of the metallicities of the algorithms. Furthermore, the studied parameters can be used to characterize some Galactic structures with the OCs.

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