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REVISITING THE AGE SCALE OF GALACTIC GLOBULAR CLUSTERS

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Abstract. Globular clusters (GCs) are among the oldest stellar populations in the Milky Way and provide key constraints on Galactic formation. We derive homogeneous absolute ages for 29 GCs using deep HST/HUGS photometry, APOGEE DR17 spectroscopy, and Gaia DR3 distances. Bayesian inference with the SPInS code and BaSTI stellar grids is complemented by a neural network (*NEST*) trained on synthetic isochrones. Ridge-line extraction of the CMD ensures robust sampling of the main-sequence turn-off. We obtain typical age uncertainties of $\lesssim 0.5$ Gyr, consistent with literature results. The neural network reproduces SPInS ages while reducing computation time by an order of magnitude. This hybrid SPInS+*NEST* framework enables precise and efficient age determinations, paving the way for a homogeneous dating of the full HUGS sample.

Keywords: Globular clusters, Stellar evolution, Age determination, Bayesian inference, Neural networks, Milky Way

1 Introduction

Accurate GC ages are essential to reconstruct the Galaxy's assembly history and set constraints on cosmological timescales. Classical isochrone fitting around the main-sequence turn-off (e.g. VandenBerg et al. 2013) is limited by uncertainties in distance, reddening, and chemical composition. Recent advances have transformed the field: Gaia DR3 provides precise cluster distances (Baumgardt & Vasiliev 2021), the HUGS survey delivers homogeneous deep photometry (Piotto et al. 2015; Nardiello et al. 2018), and APOGEE spectroscopy constrains [Fe/H] and [α/Fe] (Schiavon et al. 2024). Together with modern stellar grids such as BaSTI (Pietrinferni et al. 2013), these data enable statistically rigorous Bayesian analyses. At the same time, machine-learning emulators *NEST* (Boin et al. in prep. 2025) offer a promising way to accelerate stellar inference. In this work, we combine ridge-line CMD extraction, Bayesian inference with SPInS (Stellar Parameters INferred Systematically) (Lebreton & Reese 2020), and a neural network trained on synthetic isochrones (Boin et al. in prep. 2025) to derive homogeneous ages for 29 Galactic GCs.

2 Methodology

For each cluster, we extract a ridgeline from the CMD by performing magnitude binning in the F814W band and applying a bootstrap-based procedure to identify the median point in each bin. These ridgeline stars along with metallicity, representing the most probable evolutionary path (Fig. 1, left), are used as input to SPInS- for Bayesian analysis with BaSTI stellar grids and MCMC sampling. This yields posterior probability distributions for stellar parameters, including age, metallicity, and mass etc. The reliability of the results is verified by comparing SPInS-generated isochrones (Fig. 1, left) with the observed CMD data. To assess the potential of using alternative methods for stellar age estimation, we integrate a neural network (Boin et al. in prep. 2025) trained on SPInS-generated isochrones from BaSTI (solar + α-enhanced). The NN takes ($M_{F814W}, (F606W - F814W)$, [Fe/H], [$\alpha$/Fe]) as inputs and outputs the stellar age, enabling rapid age estimation. This approach was tested to evaluate if the neural network provides consistent age estimates compared to the full SPInS method, offering a faster alternative for future analyses. For each ridge-line star, the NN is queried multiple times to construct an age PDF via Monte Carlo sampling. Individual stellar PDFs are combined into a consensus cluster age (Fig. 1, middle) distribution using log-pooling (Koliander et al. 2022), which avoids singularities and preserves uncertainties.

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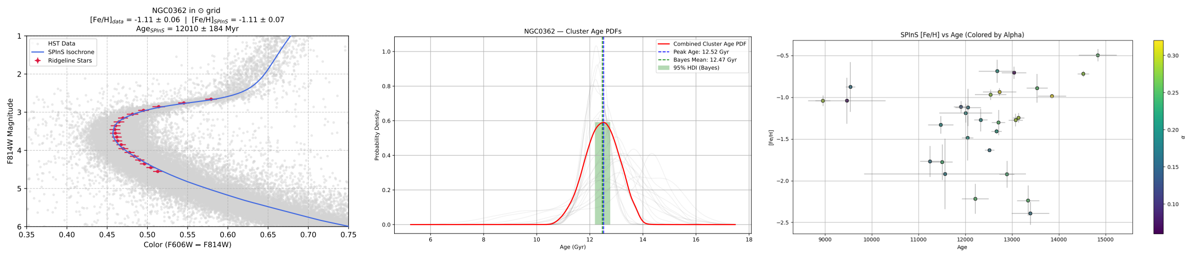

Fig. 1. Left: CMD fit for NGC 362. Middle: log-pooling of age PDFs. Right: comparison with literature.

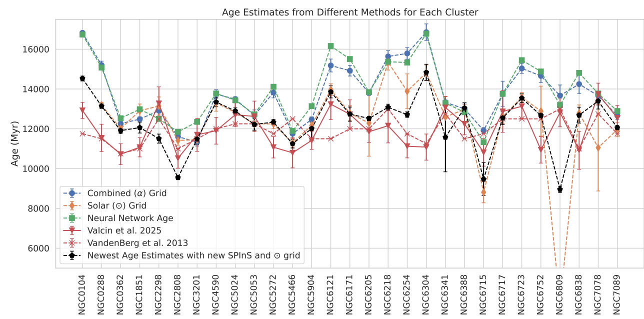

Fig. 2. Comparison of SPInS-derived ages (using different stellar grids) with literature values from (VandenBerg et al. 2013) and (Valcin et al. 2025), as well as neural network (NN) ages based on the solar BaSTI grid.

3 Results and Discussion

Using the solar-scaled BaSTI grid in SPInS, we obtain typical age uncertainties of $\lesssim 0.5$ Gyr across our sample. The recovered ages show good agreement with the literature, including the works of (VandenBerg et al. 2013) and (Valcin et al. 2025) (Fig. 2). The neural network ages are consistent with SPInS in the solar-α grid on which the network was trained (Fig. 2), while reducing computation time by an order of magnitude.

The age-metallicity relation we derive is broadly consistent with previous studies (Fig. 1, right), showing the expected bifurcation that points to the presence of ex-situ clusters. A few clusters appear older than in the literature, likely reflecting CMD morphology complexities that require manual treatment, which we are currently investigating.

4 Conclusions

We derived homogeneous ages for 29 Galactic GCs with $\lesssim 0.5$ Gyr uncertainties using a hybrid SPInS+NN framework. Results agree with the literature, with NN reducing computation time by $\sim$10×. This method is ready to be scaled to the full HUGS sample.

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