White Dwarfs as Probes of Fundamental Physics: Tracers of Planetary, Stellar and Galactic Evolution
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A catalog of 159,238 white dwarf ages

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Abstract. We employ Pan-STARRS photometry, Gaia trigonometric parallaxes, modern stellar evolution and atmosphere models, and our Bayesian fitting approach to determine cooling and total ages for 159,238 white dwarfs. In many cases we are able to derive precise ages (better than 5%) for individual white dwarfs. These results are meant for broad use within the white dwarf and stellar astrophysics communities and we plan to make available on-line the posterior distributions for cooling age, total age, initial stellar mass, and other parameters.

Keywords. Galaxy: stellar content, stars: evolution, stars: white dwarfs

1. Introduction

Many areas of astrophysics benefit from quality stellar ages. Gas giant exoplanets and brown dwarfs cool as they age, so if the age of a companion star can be determined, then such an object's temperature or luminosity can constrain its mass. Chemical-tagging–the determination of multiple quality elemental abundances to identify stars with a common origin–may allow a new approach to substructure analysis of our Galaxy. Adding age information for just a few stars in any such group would connect that stellar population to the assembly history of the Milky Way. Ultimately, with a large enough sample of precision stellar ages, one may assemble the star forming history of the Milky Way itself.

In this contribution, we aim to present initial results for a sample of ∼150,000 white dwarfs (WDs) for which we have derived ages. The age derivation is based on Pan-STARRS (Hodapp *et al.* 2004) photometry, Gaia (Cacciari, Pancino & Bellazzini 2016) trigonometric parallaxes, up-to-date models (Bergeron, Wesemael & Beauchamp 1995; Bressan *et al.* 2012; Bischoff-Kim & Montgomery 2018) and BASE-9, a statistical technique to fit the data with these models (von Hippel *et al.* 2006; van Dyk *et al.* 2009; Stein *et al.* 2013; Stenning *et al.* 2016). Conceptually, photometry constrains the spectral energy distribution (SED) of each star, which in turn constrains its effective temperature. Parallax constrains stellar distance and thereby absolute luminosity, and for a WD with its electron degenerate mass-radius relation, this also constrains its mass. For a WD of a given effective temperature and mass, assuming we know whether its surface is hydrogen or helium-dominated and assuming single star evolution, we can precisely determine its cooling age. If we further assume an initial final mass relation (IFMR; Williams, Bolte & Koester 2009), we can derive its precursor age and thus the total age of the star.

2. Data

We started with objects identified by Gentile Fusillo *et al.* (2019) using Gaia Data Release 2 (DR2) photometry and astrometry and chose those they identified with probabilities $\geqslant 75\%$ of being WDs. We merged these data with Pan-STARRS Data Release 1 (PS1) *grizy* photometry. We further require that PS1 g and r photometry have listed errors $\leqslant 0.1$ mag. While the ground-based PS1 photometry is not as accurate as Gaia photometry, the broad Gaia filters are less constraining of the stellar SEDs. PS1 is internally consistent, well-calibrated, and covers ~75% of the sky. The result of the above merging and pruning is a catalog of 160,705 WD candidates.

3. Methodology

We have developed a Bayesian statistical method for fitting stellar evolution models to photometry, which is further aided by priors on distance, metallicity, or other parameters. Our method has been successfully applied to single stellar populations in open clusters (DeGennaro *et al.* 2009; Jeffery *et al.* 2011; Hills *et al.* 2015; Jeffery *et al.* 2016; Bossini *et al.* 2019), multiple populations in globular clusters (Wagner-Kaiser *et al.* 2016a,b), binary field stars (Fouesneau *et al.* 2019), and single WD field stars (O'Malley, von Hippel & van Dyk 2013). We refer to our code suite as BASE-9, for Bayesian Analysis of Stellar Evolution with nine parameters.

BASE-9 relies on a combination of numerical integration and an adaptive Markov-chain Monte Carlo (Stenning *et al.* 2016) to derive the posterior distribution for a range of parameters. Of particular relevance for this study, BASE-9 reports stellar $T_{\rm eff}$, $log(g)$, zero age main sequence (ZAMS) mass, cooling age, precursor age, total age, parallax, and metallicity. Each star is run individually through BASE-9 based solely on its photometry and parallax information. Absorption along the line-of-sight to these nearby stars is assumed to be zero. A metallicity prior of $[\mathrm{Fe/H}] = 0.0 \pm 0.5$ is used, which is consistent with assuming that all of these WDs are Galactic disk objects. This will be true for the majority of these objects. WDs that show thick disk or halo kinematics will be rerun with more appropriate metallicity priors in the future. For this subset of metal-poor stars our metallicity prior will not affect their cooling ages but could affect their total ages, particularly if these stars evolved from low mass precursors.

We do not yet possess spectroscopy of these 160,705 WDs nor in many cases is the photometry sufficiently constraining to determine whether the atmospheres are H- or He-dominated. We thus assumed that all of these WDs have H-dominated atmospheres, which should be true for the majority (likely $\geqslant 70\%$) based on population statistics.

Total run-time on Embry Riddle's Cray supercomputer was equivalent to ~3.5 cpu years on a single core and created ~300 GB of output for the posterior parameters. Over 99% of these WD candidates ran successfully through BASE-9, which indicates that these stars can plausibly be modeled as single WDs with the above-listed priors. This yielded posterior distributions for the above-listed parameters for 159,238 WDs. In most cases the parallax information was minimally informative (low precision). From among this sample, 23,244 WD candidates have relative parallax errors $\sigma_{\varpi}/\varpi \leqslant 10\%$ and 2,640 have relative parallax errors $\leqslant 2\%$.

4. Results

Figure 1 presents the distribution of ZAMS masses versus cooling ages for the full sample and the sample subsets limited by 10% and 2% parallax precision. Uncertainties are not plotted in this diagram to avoid burying many of the points, yet the age precision is typically high. The three samples differ somewhat in their age distribution, yet are broadly similar and can be characterized by the mean cooling age of each sample, which

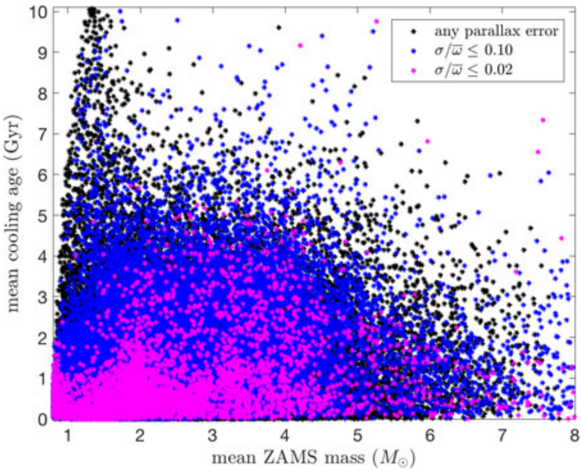

Figure 1. ZAMS mass versus cooling ages for 159,238 white dwarfs. The color version of this figure shows the full sample of stars in black, the 23,244 WDs with parallax precisions of 10% or better in blue, and the 2,640 WDs with parallax precisions of 2% or better in magenta.

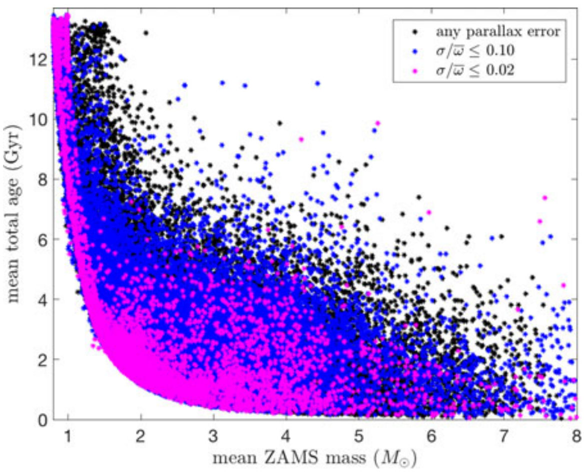

Figure 2. Same as Fig. 1, but for total stellar ages rather than cooling ages.

is 0.94, 1.04, and 0.76 Gyr, respectively. The average cooling age uncertainties for these three samples are 0.22, 0.15, and 0.03 Gyr, respectively. WDs from a very wide range of cooling ages, from significantly less than 1 Gyr up to 10 Gyr, are present in the sample over the entire precursor mass range. Even for the more limited subset of stars with reliable parallaxes (e.g., precisions at 10% or better), there are stars in the database that have been cooling for up to 10 Gyr throughout much of the precursor mass range. The deficit of higher mass and older stars is a selection effect based on their fainter apparent magnitude, which causes them to drop out of the Gaia sample (limited to G = 21).

Figure 2 presents the distribution of ZAMS masses versus total ages for these same stars. The mean total lifetimes of the stars of these three samples are 3.04, 3.63, and 3.24 Gyr. The total age uncertainties for a typical WD are now substantially larger, at 1.27, 1.06, and 0.53 Gyr, respectively. The total age depends, of course, on the precursor masses, and for low mass stars a very small uncertainty in mass can propagate to a relatively large uncertainty in precursor age. For this reason, if the sample is limited to only those WDs with precursor masses $\geqslant 2M_{\odot}$, then the uncertainty in total stellar age for the average star improves substantially to 0.71, 0.34, and 0.14 Gyr, respectively.

5. Future Work

Our goal is to make the posterior parameter distributions available via the world-wide web. It is challenging to make circa one million plots and summary statistics available, and we would be happy for ideas on how to accomplish this. We also plan to work out the selection effects that went into the input catalogs and the quality cuts and invert these to work out the star formation history for those Galactic stellar populations seen in the Solar Neighborhood.

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