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Unveiling the stellar halo with TGAS

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Abstract. The detailed study of the Galactic stellar halo may hold the key to unlocking the assembly history of the Milky Way. Here, we present a machine learning model for selecting metal poor stars from the TGAS catalogue using 5 dimensional phase-space information, coupled with optical and near-IR photometry. We characterise the degree of substructure in our halo sample in the Solar neighbourhood by measuring the velocity correlation function.

Keywords. Galaxy: halo, Galaxy: structure, Galaxy: kinematics and dynamics

1. Introduction

Selecting a reliable halo sample of stars is a challenging task. Helmi *et al.* (2017) used mostly a spectroscopic metallicity criterion to select halo stars from the cross-match between the TGAS and RAVE catalogues (Gaia Collaboration *et al.* 2016; Kunder *et al.* 2017). However, this limited that study to a sample covering only one hemisphere.

Here, we present the first attempt at creating a method based on a Support Vector Classifier (SVC) to select metal poor halo star candidates relying on the synergy between TGAS and ALLWISE, both all-sky surveys (Wright *et al.* 2010). This powerful technique can deal with large amounts of data, is not memory intensive, and performs classifications quickly. Most importantly, the SVC can handle the extreme imbalance driven by the fact that halo stars are expected to be $< 1\%$ of the total sample.

2. Training the SVC

To train the SVC, we label stars as halo by using the full phase-space and metallicity information available via TGAS and RAVE. We tag stars as halo if they have [m/H] $\leqslant -1.5$ dex, $\Delta\pi/\pi \leqslant 0.3$, distance > 100 pc, $\Delta v_{\rm los} \leqslant 10$ km/s and for which the astrophysical parameters have been reliably determined (S/N $\geqslant 20$, AlgoConv $\neq$ -1, and CorrCoeff $\geqslant 10$ in RAVE). The tagged stars also need to have a probability of $\geqslant 90\%$ of being halo according to a dynamical model fitted to the RAVE data (Piffl *et al.* 2014).

To train the SVC we use 10 features: 5D phase-space information (x, y, z, v_l, v_b) from TGAS, the values of the distribution functions for the thin disk and halo, marginalized over the $v_{\rm los}$ for each star from the dynamical model by Piffl *et al.* (2014), and the Gaia G together with the ALLWISE WISE1 and WISE2 magnitudes, whose colours are proxy for metallicity. Here we focus on the RGB stars (G-WISE1 $\geqslant 1.7$ and absolute G $\leqslant 4$).

After careful tuning, our model recovers at least 75% of the tagged halo stars, with a maximum contamination level of $\sim 65\%$. The two panels in Fig. 1 show the performance of the model on TGAS $\times$ RAVE data unused during the fitting process.

When appling our model to all RGB stars in the TGAS $\times$ ALLWISE data with $\Delta\pi/\pi \leqslant 0.3$, we classify 1036 stars as halo candidates. The left and middle panels in Fig. 2 show colour magnitude diagrams on which the halo star candidates are marked with open circles.

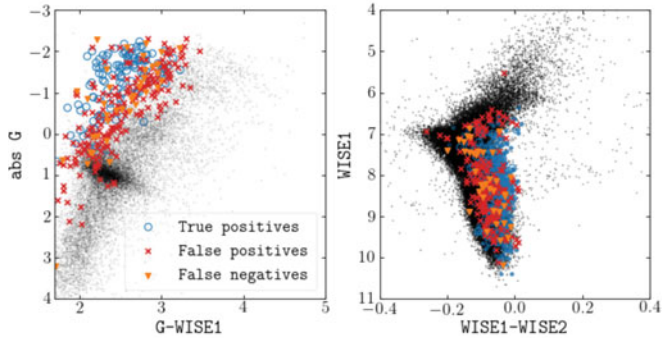

Figure 1. Evaluating the SVC on TGAS × RAVE data, unused during the model fitting and optimizing process. The open circles are the correctly predicted halo stars, the crosses are the false positives, and the solid triangles are the false negatives.

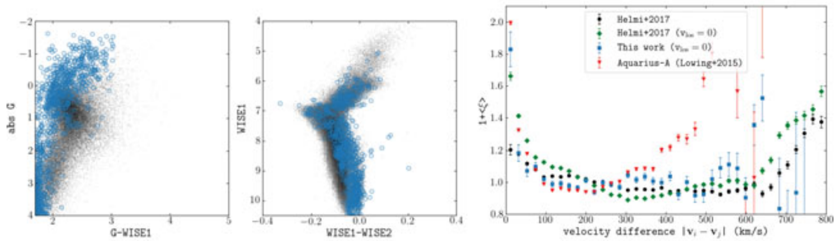

Figure 2. Left and middle panels: halo star candidates in TGAS (open circles). Right: velocity correlation function for the halo sample by Helmi *et al.* (2017), simulations, and this work which uses 5 of the 6 phase-space coordinates to compute the velocities. All samples are in qualitative agreement with each other, and exhibit significant clustering on small scales.

3. Velocity correlation function

To estimate the degree of substructure in our halo sample, we calculate the velocity correlation function using 5D phase-space information. On the third panel in Fig. 2 we compare it to the 6D phase-space sample from Helmi *et al.* (2017), together with the case obtained by assuming $v_{\rm los} = 0$. We also show the correlation function for an "equivalent" sample of stars from one of the Aquarius haloes (Lowing *et al.* 2015). We find significant clustering on small scales, in qualitative agreement with the metallicity selected halo sample from Helmi *et al.* (2017) and the simulations (Lowing *et al.* 2015).

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