Finding Ultra-Faint Dwarf Galaxies in M81's Stellar Halo

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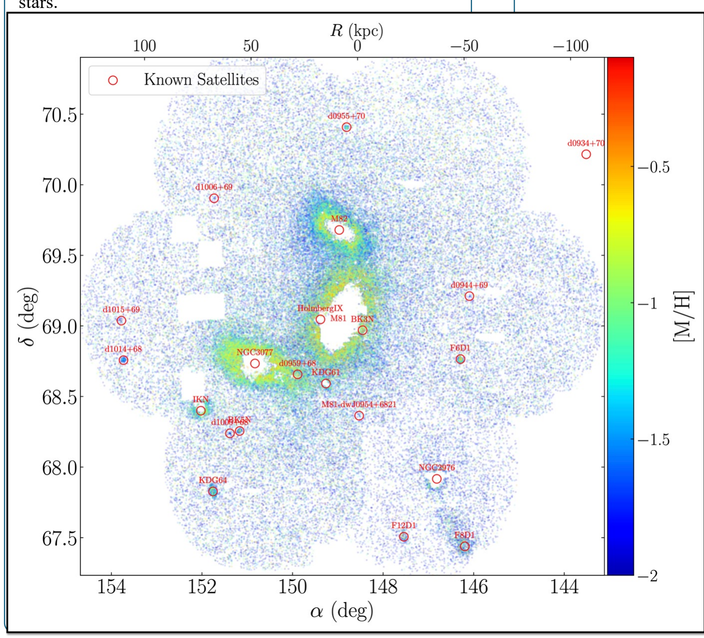
Context

M81 is a Milky Way mass galaxy in the Local Volume (D=3.6 Mpc) with a rich satellite population. It has two large satellite companions (M82 and NGC 3077) with which it is tidally interacting, and at least 17 other satellites with confirmed group membership. Here, we search for ultra-faint dwarfs (UFDs) in the M81 group using deep resolved star datasets from Subaru's Hyper Suprime Cam.

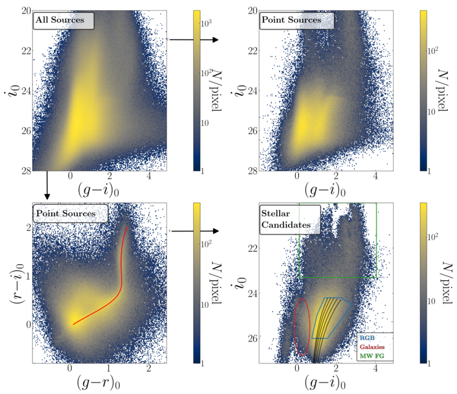
Since UFDs are old, intrinsically faint, and have extremely low surface brightnesses, the only way of discovering them is by looking for concentrations of individual, old RGB stars in survey datasets. Ground-based resolved-star datasets at these depths are plagued by background galaxy contaminants. Thus, we will discuss and compare the methods used for star-galaxy separation and the approaches used to find clustering of old, metal poor, RGB stars.



Star-Galaxy Separation

Morphology & Stellar Locus:

- Choose sources whose "spreads" are within 0.2" of local PSF
- Choose sources within photometric uncertainty of empirical stellar locus



Machine Learning based methods:

Parameters for classification:

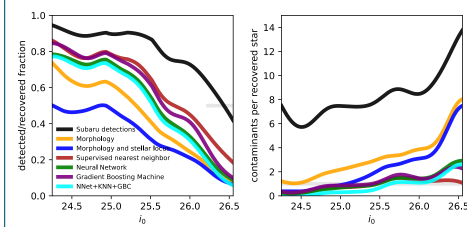
- Difference of $\sigma_{xx}, \sigma_{yy}, \sigma_{xy}$ with estimates of corresponding local PSF sizes for g, r bands (best seeing)
- i band magnitude, $g-r$, and $r-i$ colors

Models (optimized for recall):

- K- nearest neighbors (with ~10-25 neighbors)
- Gradient Boosting Machines
- Neural Network (20 neuron and 10 neuron hidden layers with 10% dropout)

Training set:

- True stars: 3002 Subaru stars crossmatched with HST fields
- Background objects: 6000 Subaru sources far from the halo likely to be background galaxies



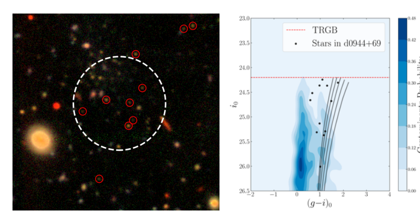
Results:

- Stellar locus+ morphology cuts reach a recall of 36% with 60% precision
- All three ML classifiers achieve a recall of ~60% with ~80% precision

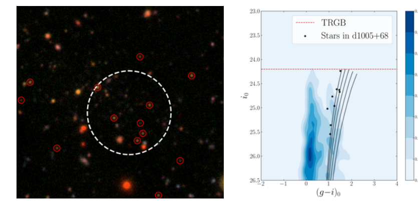
Search for UFDs

- Kernel Density Estimation with ~200pc foreground kernels and ~1kpc background kernels to count number of foreground and background stars.
- Establish significance through Poisson probability of obtaining foreground number of stars given expected number of stars (from background) at each location.
- Choose "clusterings" with chances less than 1 in a million and CMDs that resemble those of old, metal poor stellar populations

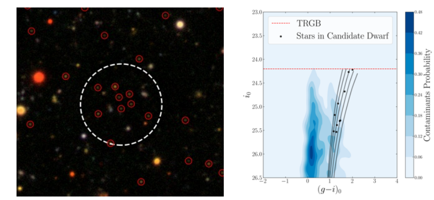
With this we recovered all but two known UFD satellites and then some…



A recovered UFD



Another recovered UFD



One of the candidates detected by our algorithm

Caveats:

- No obvious diffuse emission in any of the candidates (unlike d0944+69)
- Most candidates picked up due to artificial features in the data such as "data edges" caused by crowding deep in the halo or by bright foreground star with diffraction spikes
- Need HST follow-ups to establish candidates as UFDs

Conclusions

- Machine learning-based algorithms show promise for efficient star-galaxy separation, outperforming straightforward morphology and stellar locus cuts in large ground-based datasets.
- KDE-based UFD searches were reasonably successful in recovering the known satellites in the M81 halo. They are significantly limited by data quality issues
- We also pickup a few halo features within the footprint, which remain open to further analysis and interpretation.
- The methods discussed here (along with all their caveats) are relevant to upcoming Vera Rubin observatory datasets, which will spur rapid progress in the field with increased survey speeds

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