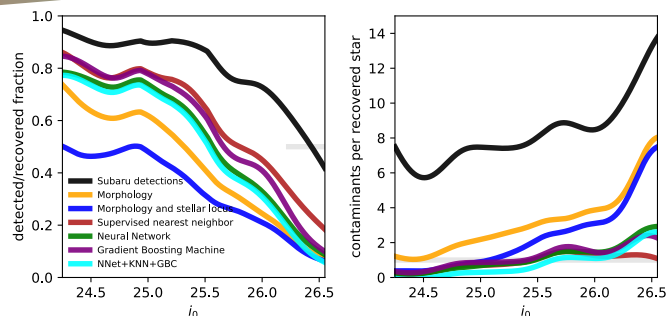




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M81, a Milky Way mass galaxy in the Local Volume ( $D=3.6$  Mpc), has a rich satellite population, including M82 and NGC 3077, and 17 other confirmed satellites. We search for ultra-faint dwarfs (UFDs) in the M81 group using deep datasets from Subaru's Hyper Suprime Cam. Due to their age, faintness, and low surface brightness, UFDs are discovered by identifying concentrations of old RGB stars in survey datasets. Ground-based datasets at these depths face background galaxy contamination, so we will discuss and compare star-galaxy separation methods and approaches to finding clusters of old, metal-poor RGB stars.

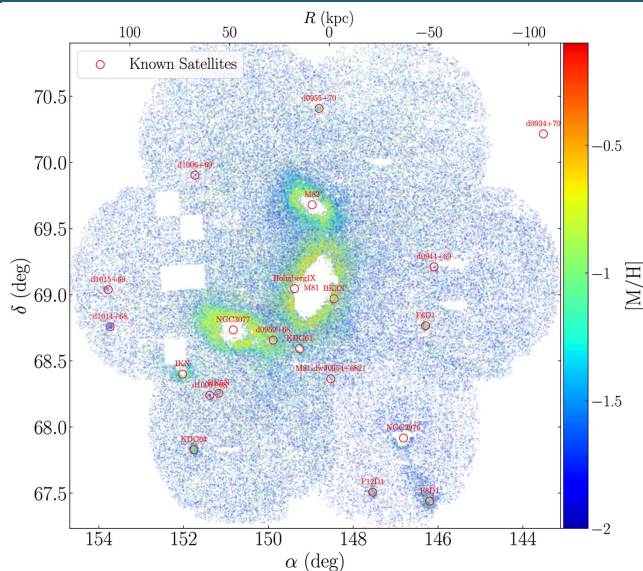


## Search for UFDs

- Kernel Density Estimators used to find '1 in a million' clustering of stars over their background random noise
- Clusters chosen whose CMDs resemble those of old, metal poor stellar populations

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

## 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: K Nearest Neighbors, Gradient Boosting Machine, Neural Network

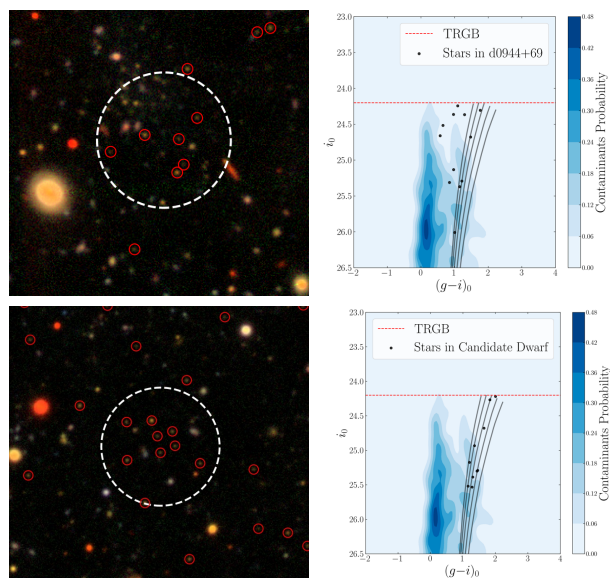
Training set:

- 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

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### 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