Identification of ultracool dwarfs in J-PLUS DR2 using Virtual Observatory tools and Machine Learning techniques

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AGENCIA ESTATAL DE INVESTIGACIÓN

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EXCELENCIA MARÍA DE MAEZTU

1. Scientific context
2. VO methodology
3. Machine Learning methodology
4. Conclusiones and future work

Scientific context: Ultracool dwarfs

- UCDs comprise the lowest mass members of the stellar population and brown dwarfs
- From the M7 V to the extended L, T and Y spectral types
- Effective temperatures of $T_{eff} \lesssim 2900\ K$
- Relevant role in the search for Earth-like exoplanets, in the study of Galactic kinematics and in the understanding of the boundary between stellar and substellar objects

Scientific context: J-PLUS

- Javalambre Photometric Local Universe Survey, conducted from the Observatorio Astrofísico de Javalambre (OAJ)
- Multi-filter survey with 12 optical bands
- Large coverage of the electromagnetic spectrum, which allows a more accurate determination of physical parameter
- The J-PLUS Data Release 2 covers 2 176 deg^2

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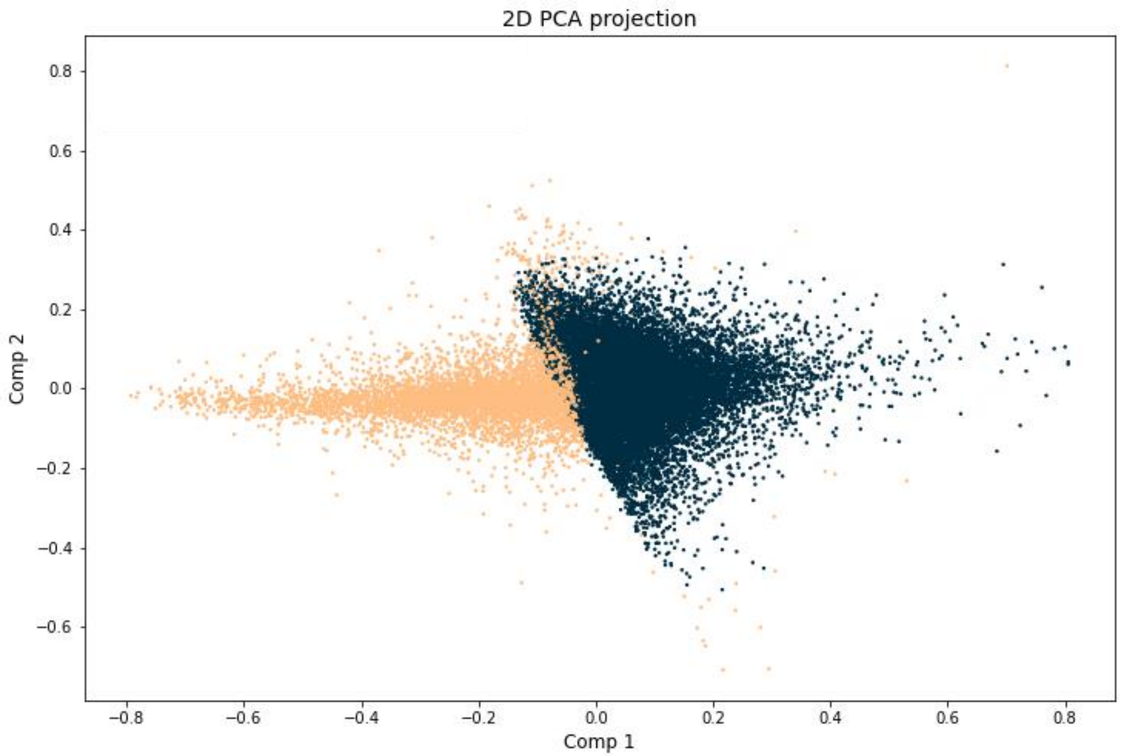
SDSS9
J-PLUS DR2

Scientific context: SVO

- The Virtual Observatory (IVOA) is an international initiative to provide seamless access to the data available from astronomical archives and services as well as state-of-the-art tools
- The vision that astronomical datasets and other resources should work as a whole
- This is made possible by standardization of data and metadata, by standardization of data exchange methods, and by the use of a registry, which lists available services and what can be done with them
- The Spanish Virtual Observatory is part of IVOA

Scientific context: PCA step

- Reduces a lower data set to a lower dimension by identifying the axes that account for the largest amount of variance
- The expectation behind is that the entire data set can be well characterized along a small number of dimensions
- Deterministic nature, i.e. different runs of PCA on a given dataset will always produce the same results



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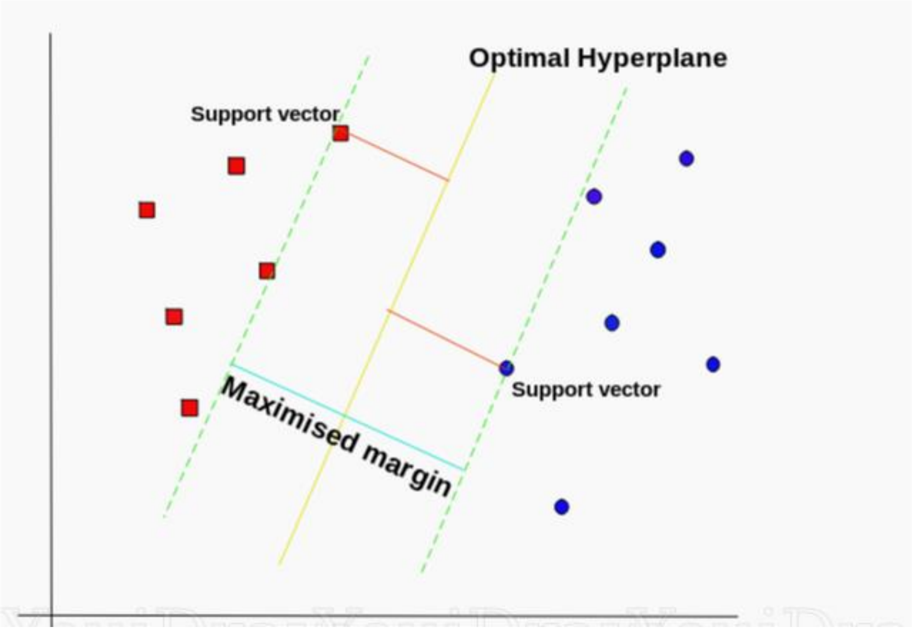
Scientific context: SVM algorithm

- Supervised ML algorithm
- The idea behind is to find a hyperplane that separates data into two classes while maximizing a marging
- Linear classifier: we can gain linear separation by mapping the data to a higher dimensional space with different kernels (polynomial, Radial Basis Function…)



https://gdcoder.com/support-vector-machine-vs-logistic-regression/

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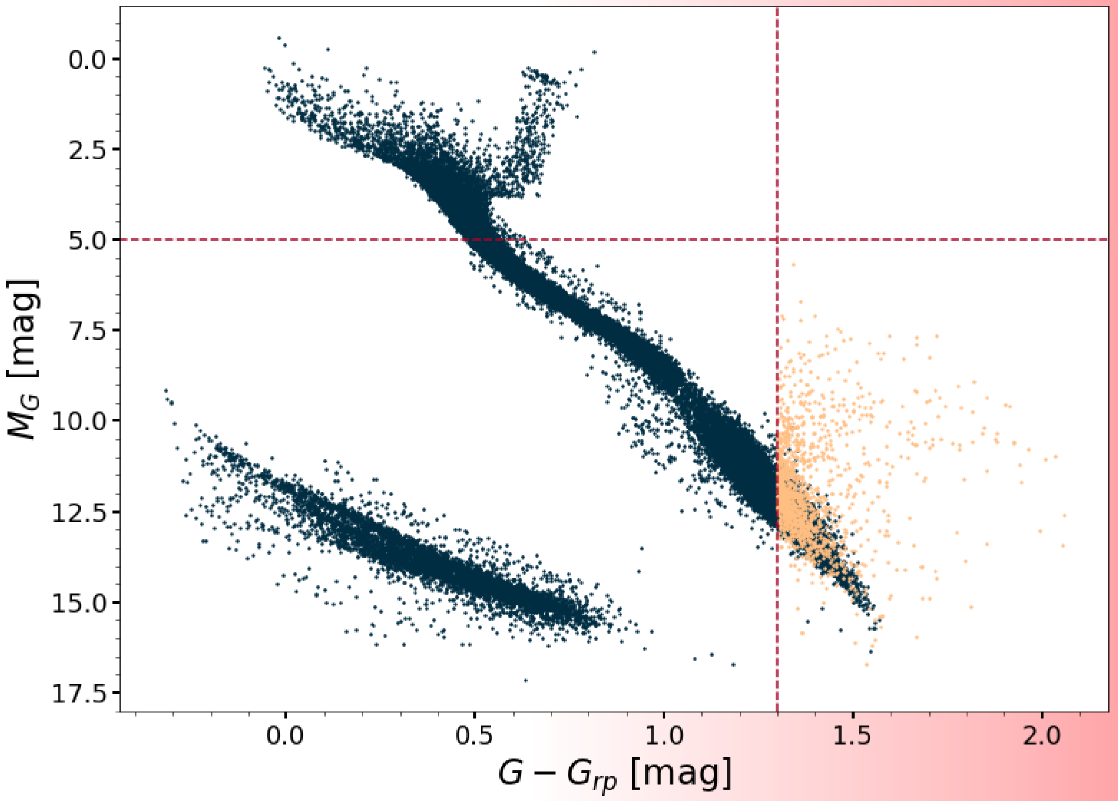
VO Methodology: Pre-screening process

Two astrometric approaches

- Parallax-based:
  - Relative error of less than 20% in parallax
  - $G - G_{RP} > 1.3$ - Pecaut & Mamajek (2013)
- Proper motion-based:
  - Relative error of less than 20% in both pm components
  - Only sources with non-zero pm
  - $G - G_{RP} > 1.3$ - Pecaut & Mamajek (2013)

One photometric approach

- Colour cut of $r - z > 2.2$ using J-PLUS photometry



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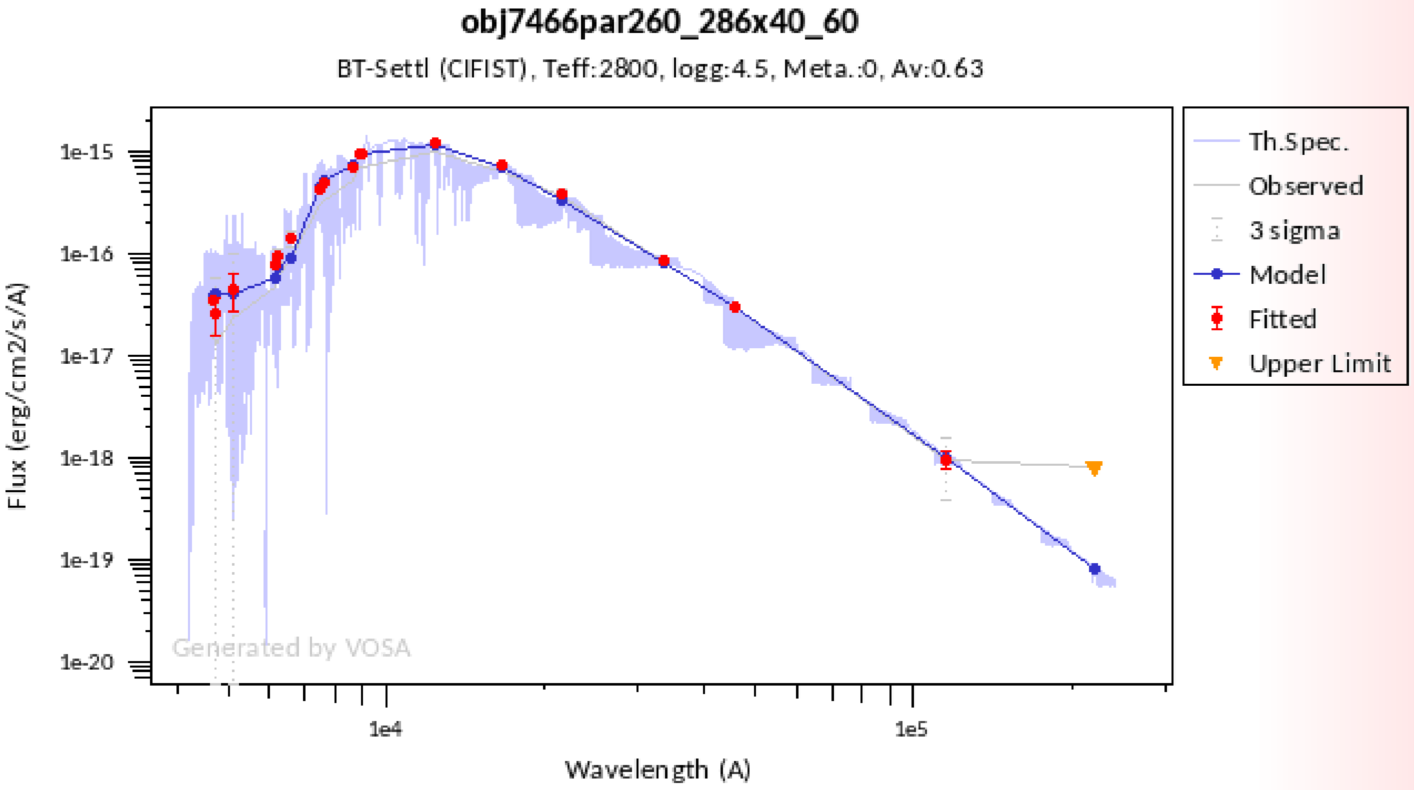
VO Methodology: Final candidate UCDs

- We used VOSA to complement J-PLUS photometry with optical and infrared VO catalogues
- VOSA fit: effective temperature cut of $T_{eff} \leq 2900\ K$



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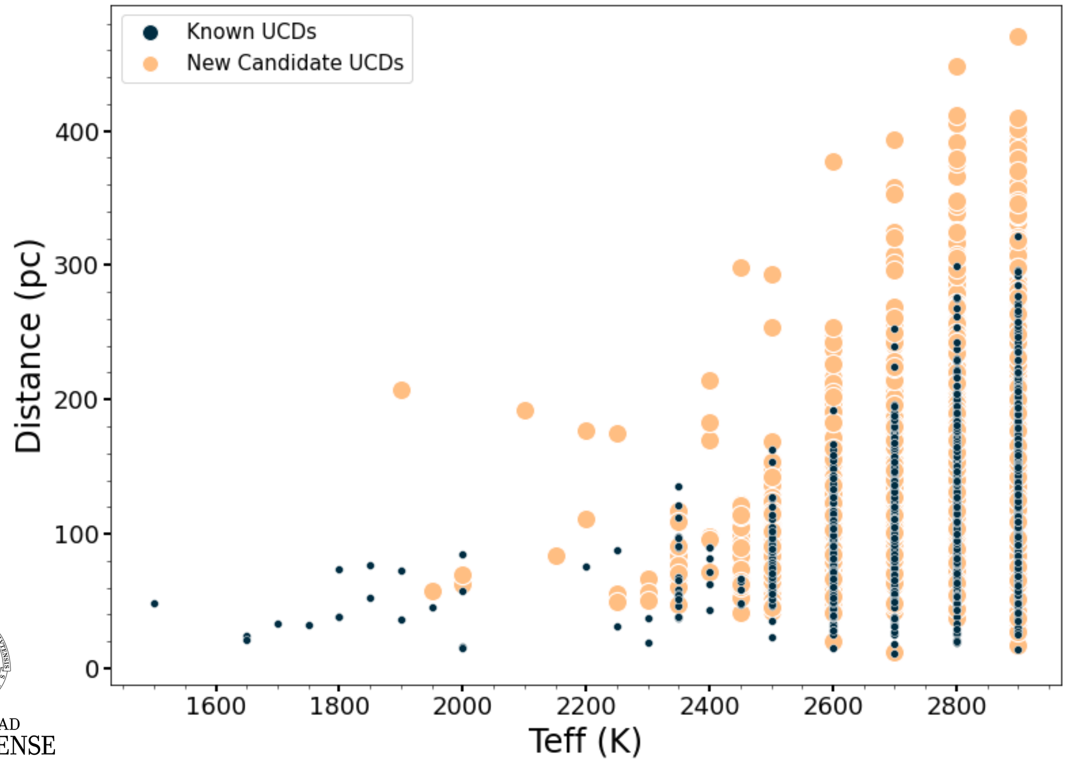
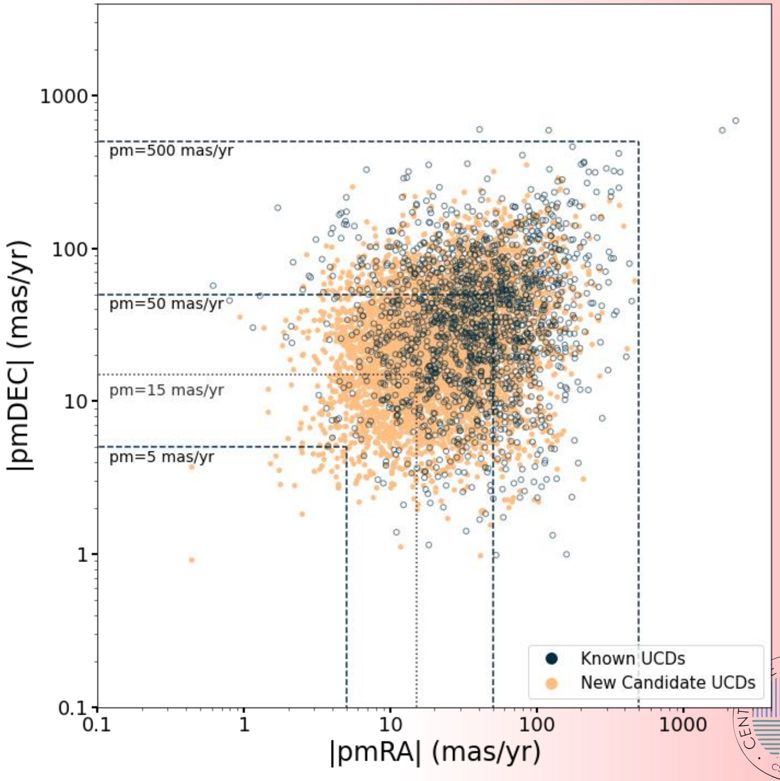
VO Methodology: Results

- We identified a total of 9 810 candidate UCDs, of which only 1 981 were previously reported (increase of ~135% in J-PLUS DR2 sky coverage)
- In-Depth kinematic and binarity analysis of the candidate UCDs
- Our methodology allows us to go to further distances and smaller proper motions in the search for UCDs





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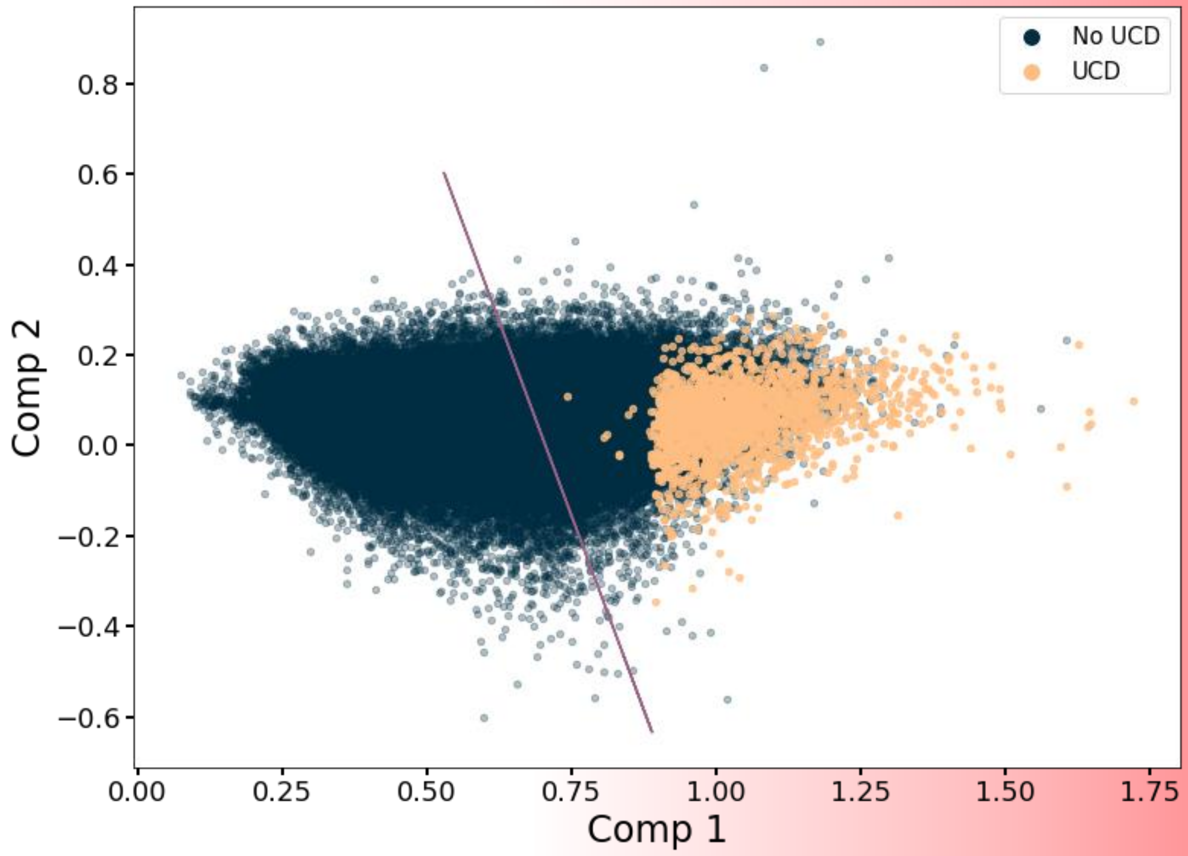
ML Methodology: PCA step

1. We relied only J-PLUS photometry, using as features eight different colours ($i-z, r-i, J0861-i$ ...)
2. We labeled the instances as positive or negative class using the candidate UCDs obtained with the VO methodology
3. Stratified sampling for training and test sets
4. PCA model: 94% of the variance along the two first Principal components
5. First cut in the identification of UCDs to reduce the imbalance of the data



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ML Methodology: SVM step

1. The SVM model is developed using the reduced sample obtained with the PCA filtering
2. Exhaustive search for the optimal SVM hyperparameters using *GridSearchCV* class from the Python package SCIKIT-LEARN
3. Best recall score with an RBF kernel and hyperparameters $C = 1000, \gamma = 0.001$
4. Recall of 98% and 96% in the test set and in the blind test, respectively

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ML Methodology: Results

- The PCA filter is able to remove the hottest objects ($T_{eff} \geq 4\ 100\ K$)
- We recover nearly all the UCD objects, but we still need to apply VOSA to a significant number of objects
- Restrictive methodology in terms of photometric quality

Conclusions and future work

- Paper under review by the J-PLUS consortium
- We consolidated and further developed a search methodology, introduced in Solano et al. (2019), to be used for deeper and larger surveys like J-PAS and Euclid
- The ML methodology is more efficient in the sense that it allows a greater number of non-UCD objects to be discarded prior to analysis with VOSA
- Real turning point: ML methodology that more significantly filters the number of objects we need to analyze with VOSA
    - Independent Component Analysis (ICA)
    - Ensemble learning

Thanks for your attention

SVO
Spanish Virtual Observatory

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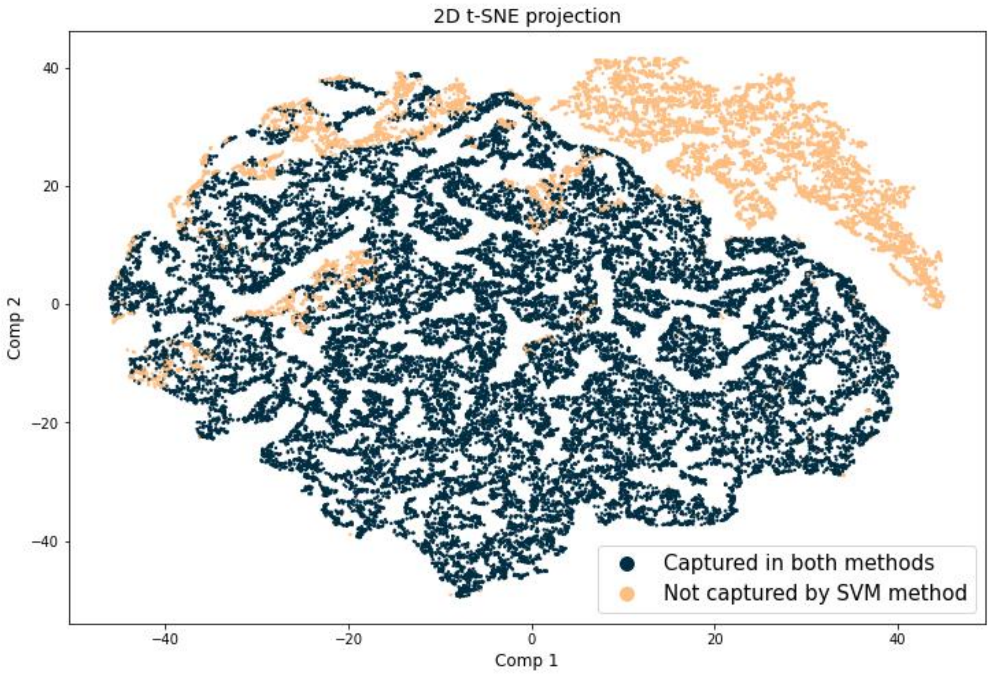

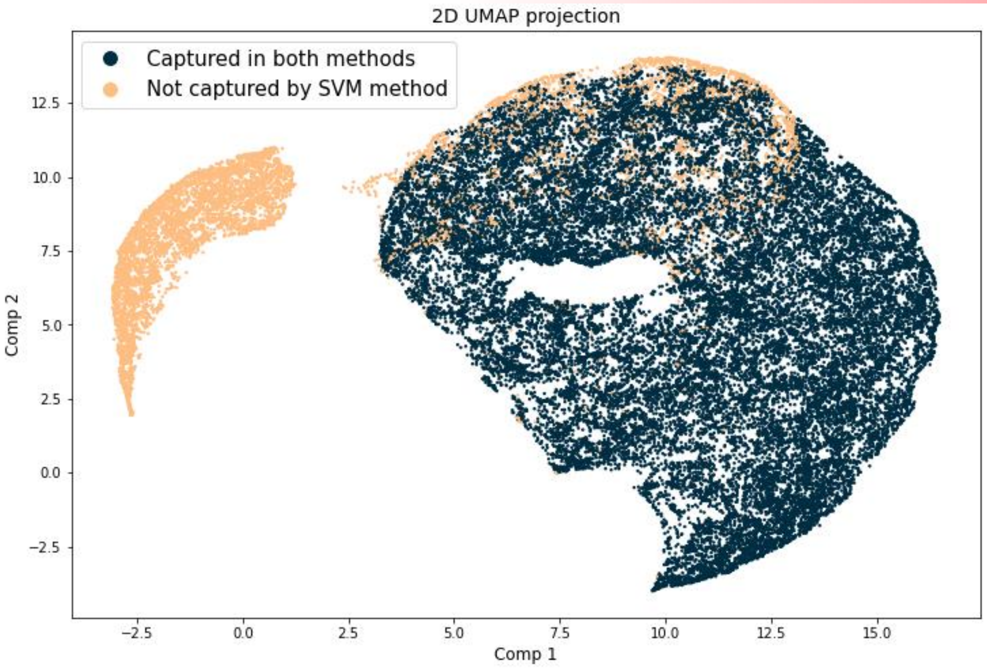

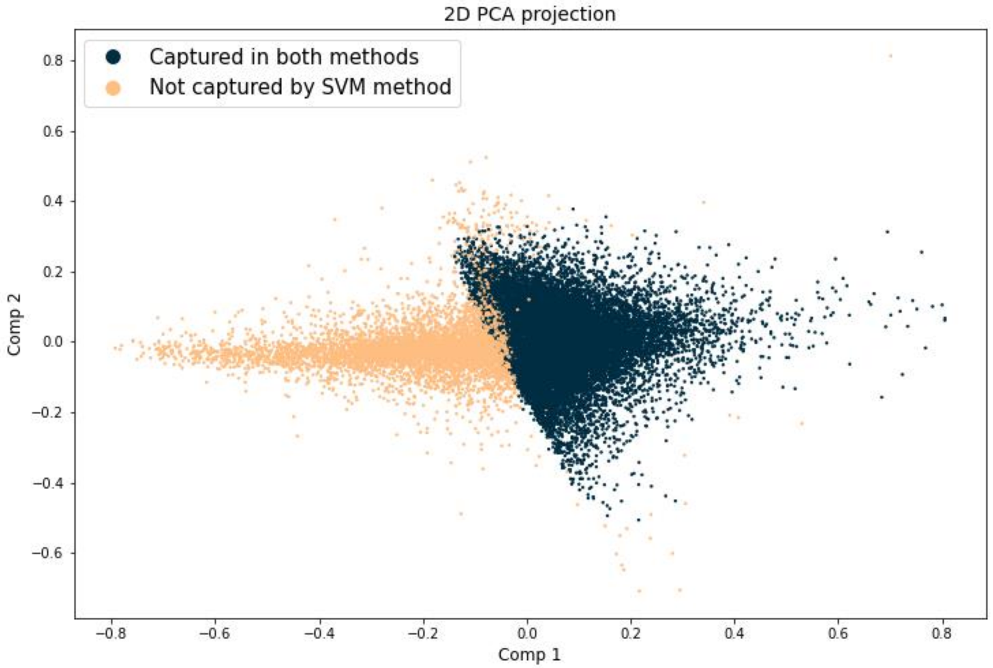

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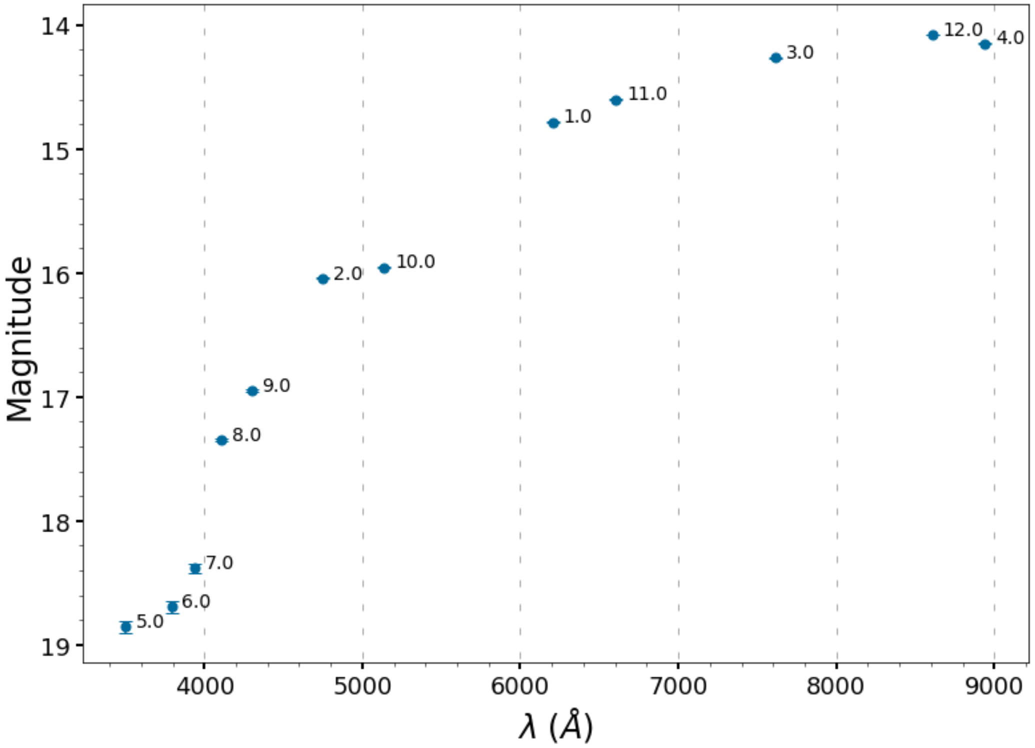
Tools

- VO tools: Aladin, Topcat, VOSA, STILTS…
- Astronomical Data Query Language (ADQL) and VO TAP protocol
- Several Python packages (Pandas, Seaborn, Scikit-Learn, MocPy…)
- Machine Learning algorithms:
    - Principal Component Analysis (PCA)
    - Support Vector Machine (SVM)

Data sources

- J-PLUS DR2 photometry
- Parallaxes and proper motions from Gaia EDR3
- Complementary optical and infrared photometry from different VO catalogues available in VOSA



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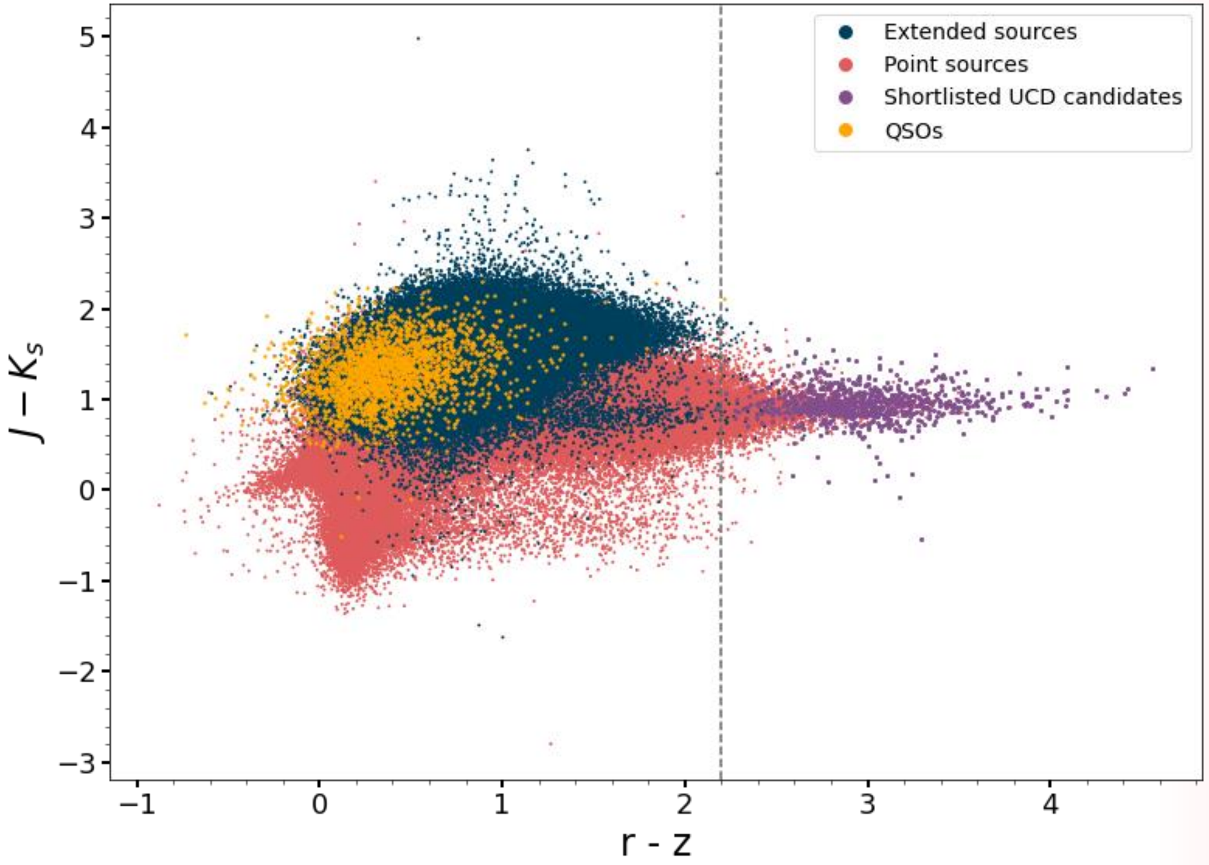

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VO Methodology: Obtaining the data

1. We divided the sky coverage of J-PLUS DR2 in 37 regions of 20x20 deg^2
2. We tessellated each region into smaller circular sub-regions of 1 deg radius
3. We built a Python code that to query the J-PLUS database over all the 20x20 deg^2 regions iteratively
4. We cross-matched the queried sources with *Gaia* EDR3 to obtain the astrometric information

```
SELECT filter_id, alpha_j2000, delta_j2000,
    mag_aper_6_0, mag_err_aper_6_0
FROM jplus.MagABSingleObj
WHERE alpha_j2000 between 2 and 5
AND delta_j2000 between 2 and 3
AND flags=0
AND filter_id between 1 and 4
AND class_star>0.1
```