New exoplanet candidates?

Deep learning exploration of the SHINE high-contrast imaging survey

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CONTEXT

Motivation: Our cutting-edge exoplanet imaging detection algorithm, **NA-SODINN** (Cantero et al., 2023), has achieved top rankings in the Exoplanet Imaging Data Challenge (Cantalloube et al., 2020) alongside the RSM* algorithm (Dahlqvist et al., 2020), outperforming most state-of-the-art post-processing techniques. We are now leveraging this advanced deep learning algorithm to reprocess the **F150 sample** from the *SpHere Infrared survey for Exoplanets* (SHINE, Desidera et al., 2021) with the goal of identifying new exoplanet candidates.

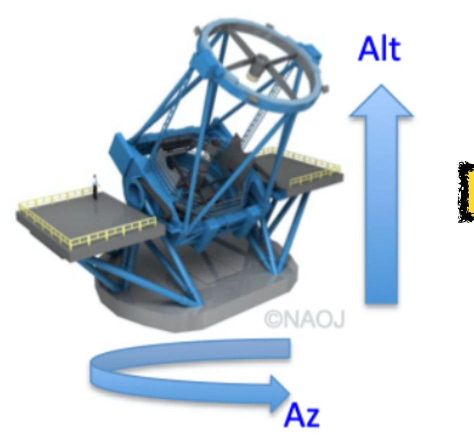
The poster **958 (Tuesday) is about the RSM algorithm. **Check it online or talk with Mariam Sabalbal!***

The F150 sample: 150 targets were observed with VLT/SPHERE between February 2015 and February 2017, consisting of 53 BA, 77 FGK, and 20 M stars, with ages ranging from 11 to 450 Myr, masses from 0.57 to 2.37 solar masses, and distances from 11 to 137 parsecs. The observations were conducted using H2-H3 narrowband filters with a 9" diameter FoV, employing *Angular Differential Imaging* (**ADI**, Marois et al., 2006) as observing strategy.

… but, how **ADI** works?

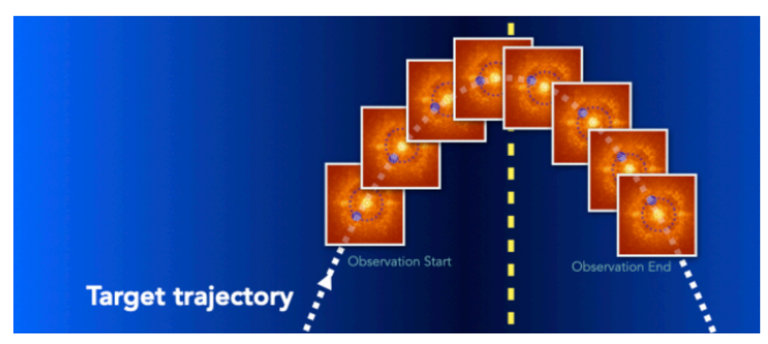
Images by Faustine Cantalloube

Use the Telescope + ExAO + Coronagraphy



with the **pupil-stabilized mode…**

… to take exposures at different parallactic angles (PAs).



Despite using a coronagraph to block out starlight, each coronagraphic frame is dominated by speckle noise (scattered starlight), which prevents the detection of potential planet signatures around the star.

However, speckles remain mostly fixed in the focal plane while the **exoplanet rotates** around the star with the PA.

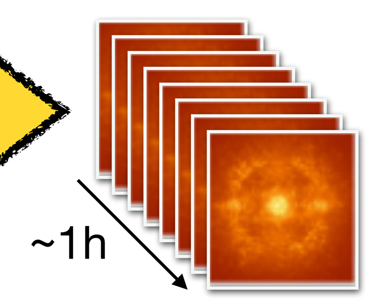
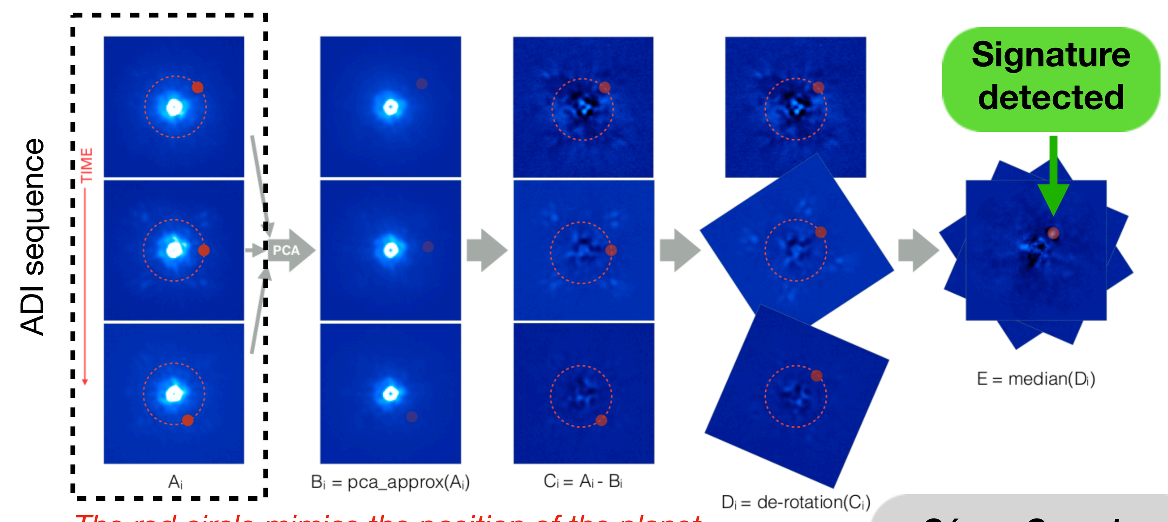


Image processing is thus needed to disentangle the planet signature from speckle residuals in the ADI sequence.

The most common image processing is **ADI-PCA:** (B) model the PSF of each frame with a number of principal components, (C) subtract the model image, (D) de-rotate the residuals according to the PA, and (E) collapse them into a **processed frame**.

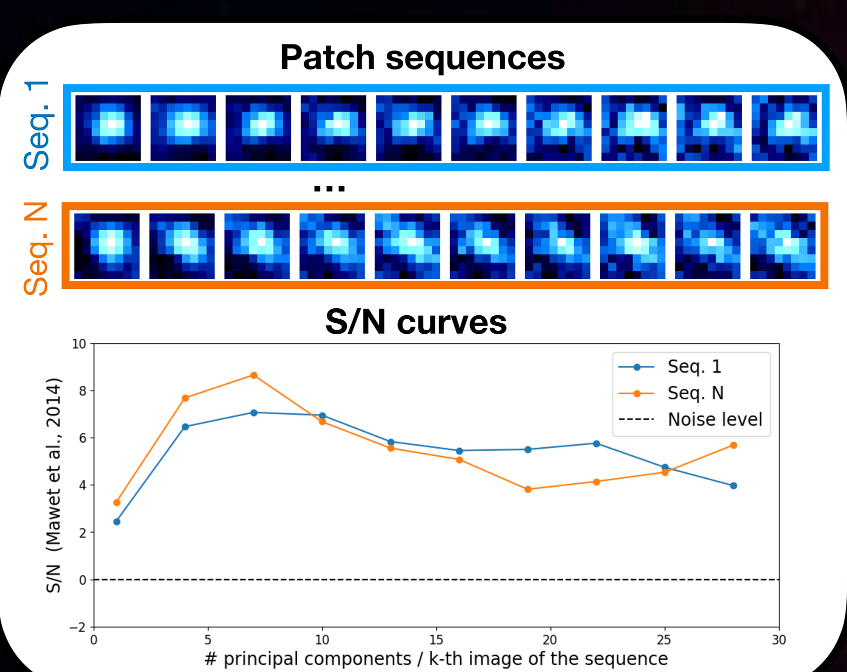


The red circle mimics the position of the planet

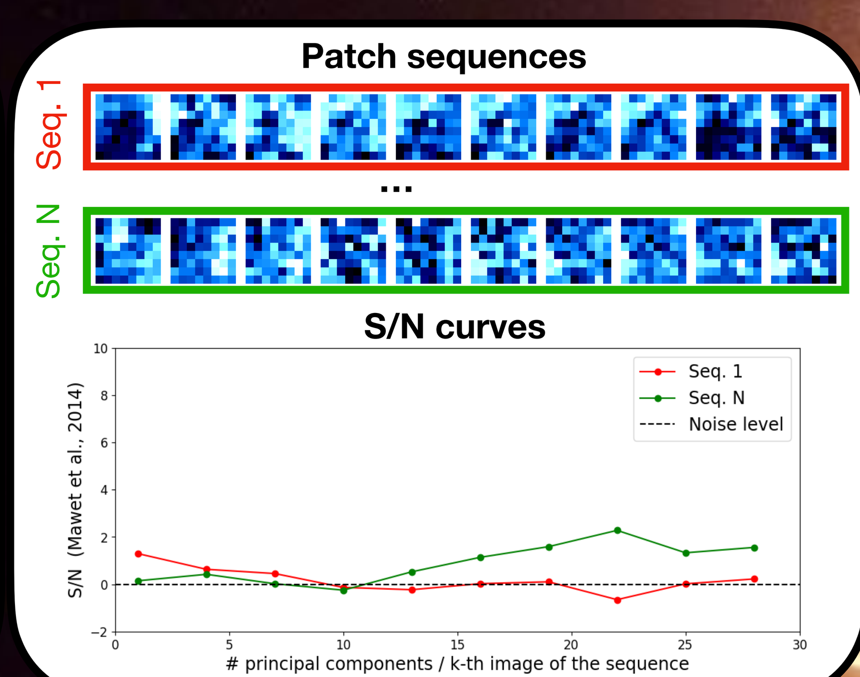
Gómez Gonzalez (September 2017)

THE METHOD

NA-SODINN: NA-SODINN addresses the detection task as a **supervised classification** problem. The input to NA-SODINN is an ADI sequence where we aim to identify new candidates. The training set is also derived from this input and consists of two classes of patch sequences, each with their S/N curves: one class includes planet signatures (we inject fake planets), and the other contains only image noise (no injection).



Planetary class



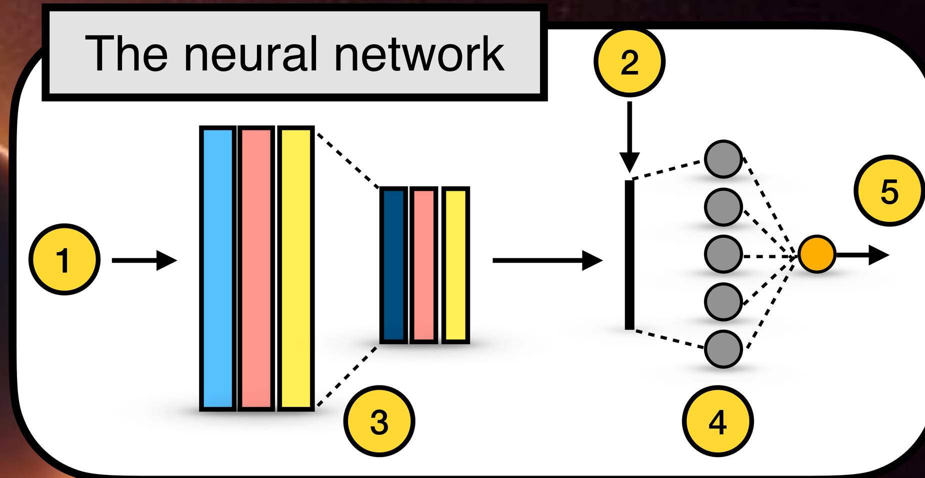
Noise class

Each patch in a sequence and its S/N in the corresponding curve are generated from the **ADI-PCA processed frame**. The difference between patches in a same sequence (and S/N values) is simply the number of principal components (PCs) used for PSF modeling in ADI-PCA.

SCAN ME

By training on thousands of these samples, the model learns to distinguish between the two classes. Once the model achieves a training accuracy of 99.99%, it is used to predict the class of new samples (never seen in the training), which are generated from each pixel in the FoV of the same ADI sequence. This inference process produces a detection map based on the model confidence.

The neural network



1. **Input:** patch sequence
2. **Input:** S/N curve
3. **Convolutional blocks:** capture spatio-temporal correlations
4. **Dense layer:** capture correlations from feature maps and S/N curves.
5. **Loss:** Binary cross-entropy

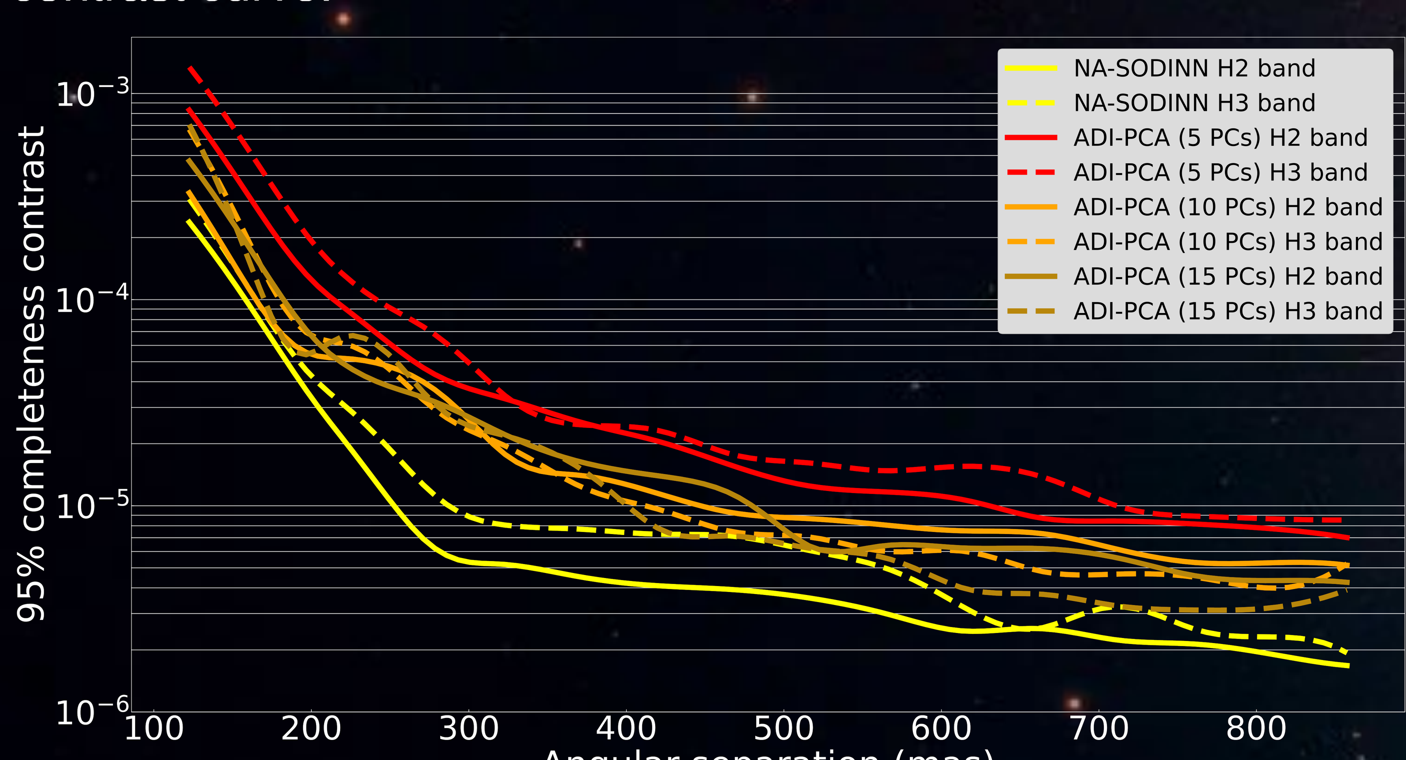
Legend

- Conv-LSTM + Tanh
- Conv-LSTM + Tanh
- Spatial dropout 3D
- Maxpooling 3D
- Dense units + ReLU + Dropout
- Output (exoplanet confidence)
- Flatten

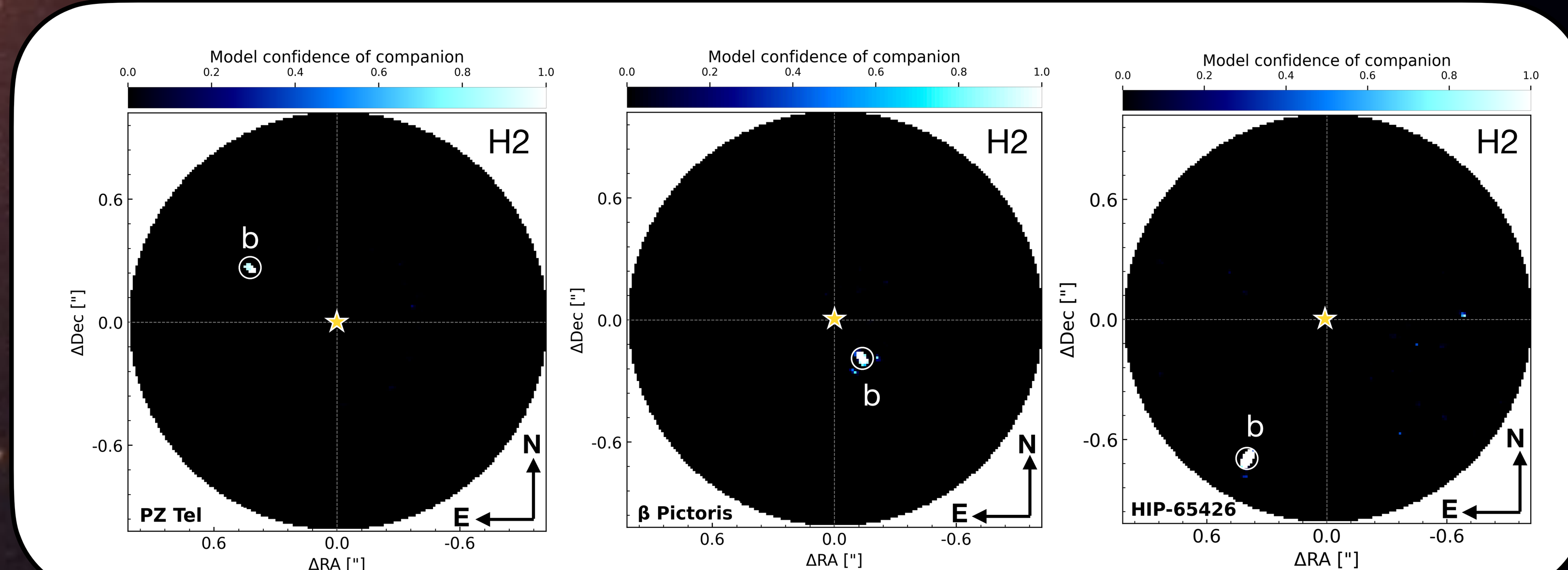
This long process (generate training set + training + inference) is repeated for each noise regime (annular region dominated by speckle or background noise) in the ADI-PCA processed frame. This stratification strategy helps the model better capture correlations during training (Cantero et al., 2023).

PRELIMINARY RESULTS & PERSPECTIVES

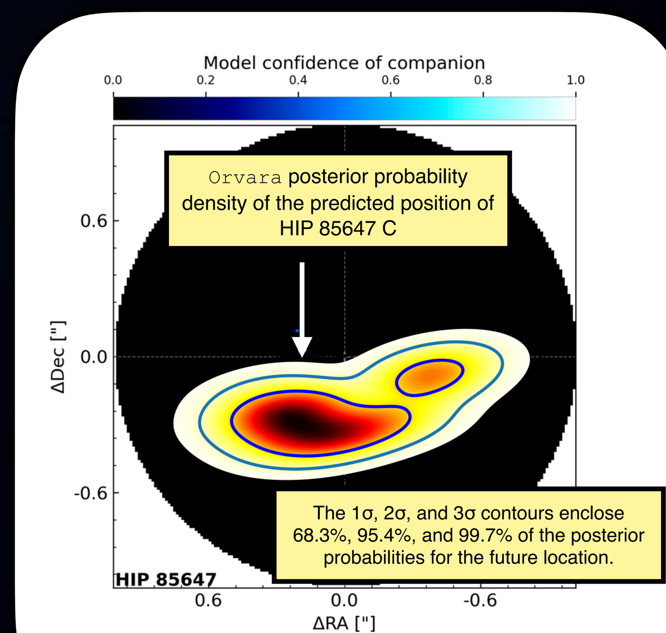
Contrast curves: The flux ratio (or contrast) between the exoplanet and its parent star is used as a metric to evaluate the detection limits. Typical contrasts range from 10^{-3} – 10^{-4} for hot Jupiters and can be as low as 10^{-10} for Earth-like planets in the habitable zone. To assess the sensitivity of NA-SODINN on the F150 sample, we calculate a contrast curve (CC) for each target. This involves computing the minimum flux of injections required to achieve a 95% completeness (the algorithm successfully recovers 95% of all injections at each angular separation). Once all CCs are computed, we derive the mean contrast curve.



Example of NA-SODINN detections on SHINE of confirmed targets



Future avenues: The *`Orvara` Python package (Brandt et al., 2021) can simultaneously fit orbits to RVs, absolute astrometry (Hipparcos & Gaia), and relative astrometry from direct imaging. By combining NA-SODINN with `Orvara`, we aim to achieve better detection constraints, enhancing the discovery of new companions in surveys.



See poster **1253 (William Ceva)*

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