Deep learning for exoplanet detection and characterization by direct imaging at high contrast

The detection of exoplanets, the characterization of their atmospheres, and the study of exoplanet formation mechanisms are major current challenges in astrophysics. High-contrast direct imaging (HCI) is one of the observational techniques of choice to address these questions. However, such observations are particularly demanding due to the extreme contrast levels and angular resolution required. In addition to the use of extreme adaptive optics and coronagraphs, advances in data science have become critical for analyzing these observations and disentangling the signals of interest (exoplanets and circumstellar disks) from the strong nuisance component (speckles and noise) that corrupts the data.

In this context, we will present our recent developments [1, 2, 3] in deep learning applied to HCI, aimed at the optimal and reliable extraction of astrophysical information from multivariate observations (including spatial, temporal, spectral, and multi-epoch diversity). These approaches are based on a fine modeling of the different components contributing to the total signal and incorporate physical domain knowledge as prior information. Emphasis will be placed on (i) combining deep learning models with statistical modeling of the nuisance, (ii) leveraging large archival datasets as a valuable source of diversity for tackling the unmixing task, and (iii) jointly exploiting the spectral diversity of observations.

Our methods are tailored to the specific challenges of high-contrast imaging: (i) very low signal-to-noise ratios and non-stationary noise, (ii) detection of rare events, and (iii) absence of ground truth. Using real data from the VLT/SPHERE instrument, we will show that these approaches enable fine modeling and effective subtraction of the nuisance component, leading to reliable and nearly optimal estimates of the astrophysical quantities of interest. This results in significantly improved detection sensitivity and more accurate astro-photometric characterization. The proposed approaches are also scalable and readily applicable to large-scale surveys.

Looking ahead, instruments on the next generation of thirty-meter-class telescopes will enable the exploration of the innermost environments of Sun-like stars at unprecedented contrast levels. Achieving the associated scientific goals will require addressing several data science challenges: (i) approaching the ultimate performance limits of the instruments through optimal signal extraction, (ii) capturing complex, spatially structured nuisance exhibiting strong variability, and (iii) building robust nuisance models that go beyond the limitations of angular differential imaging, particularly in the vicinity of the host star. We will discuss these challenges in light of the methodological developments presented.

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[1] Flasseur, Bodrito, Mairal, Ponce, Langlois, Lagrange, « deep PACO: Combining statistical models with deep learning for exoplanet detection and characterization in direct imaging at high contrast », MNRAS, 527 (1), 2024.

[2] Bodrito, Flasseur, Mairal, Ponce, Langlois, Lagrange, « MODEL&CO: Exoplanet detection in angular differential imaging by learning across multiple Observations », MNRAS, 534 (2), 2024.

[3] Bodrito, Flasseur, Mairal, Ponce, Langlois, Lagrange, « A new statistical model of star speckles for learning to detect and characterize exoplanets in direct imaging observations », CVPR, 2025.