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Analysing exoplanetary data using unsupervised machine-learning

I. P. Waldmann
University College London, Physics & Astronomy, United Kingdom (ingo@star.ucl.ac.uk)

The field of transiting extrasolar planets and especially the study of their atmospheres is one of the youngest and most dynamic subjects in current astrophysics. Permanently at the edge of technical feasibility, we are successfully discovering and characterising smaller and smaller planets. To study exoplanetary atmospheres, we typically require a 10^{-4} to 10^{-5} level of accuracy in flux. Achieving such a precision has become the central challenge to exoplanetary research and is often impeded by systematic (nongaussian) noise from either the instrument, stellar activity or both. Dedicated missions, such as Kepler, feature an a priori instrument calibration plan to the required accuracy but nonetheless remain limited by stellar systematics. More generic instruments often lack a sufficiently defined instrument response function, making it very hard to calibrate. In these cases, it becomes interesting to know how well we can calibrate the data without any additional or prior knowledge of the instrument or star.

In this conference, we present a non-parametric machine-learning algorithm, based on the concept of independent component analysis, to de-convolve the systematic noise and all non-Gaussian signals from the desired astrophysical signal. Such a 'blind' signal de-mixing is commonly known as the 'Cocktail Party problem' in signal-processing. We showcase the importance and broad applicability of unsupervised machine learning in exoplanetary data analysis by discussing: 1) the removal of instrument systematics in a re-analysis of an HD189733b transmission spectrum obtained with Hubble/NICMOS; 2) the removal of time-correlated stellar noise in individual lightcurves observed by the Kepler mission.