EXOPLANET DETECTION IN ANGULAR DIFFERENTIAL IMAGING: COMBINING A STATISTICS-BASED LEARNING WITH A DEEP-BASED LEARNING FOR IMPROVED DETECTIONS

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1. Statistical modeling of the nuisance

context

ground-based direct imaging in pupil-tracking mode

VLT/SPHERE coronagraph + adaptive optics imager + IFS

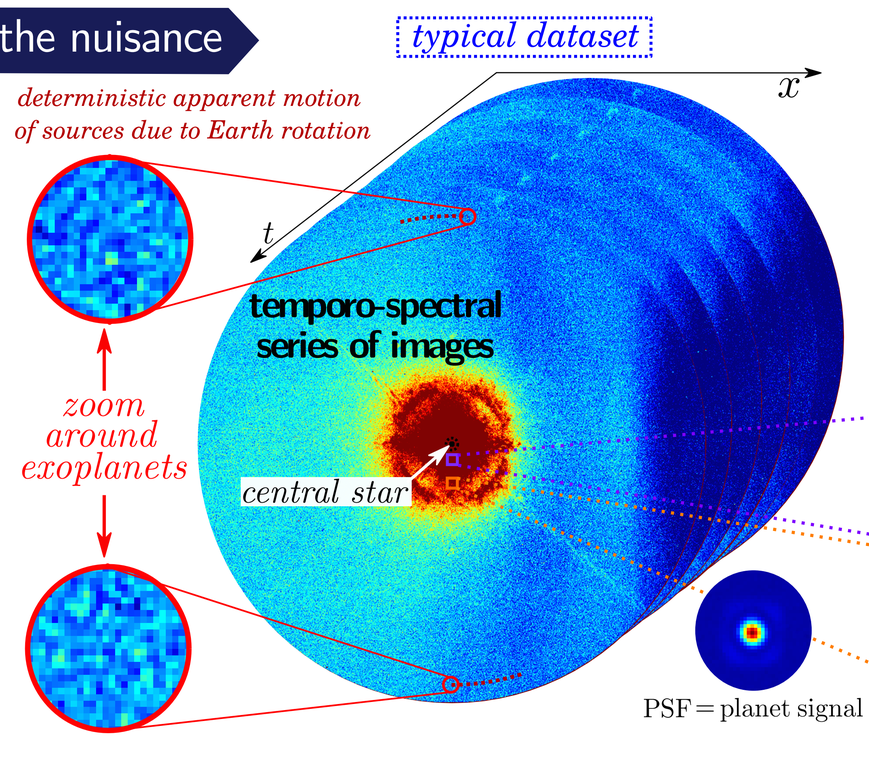
unmixing problem: exoplanets *vs* stellar leakages

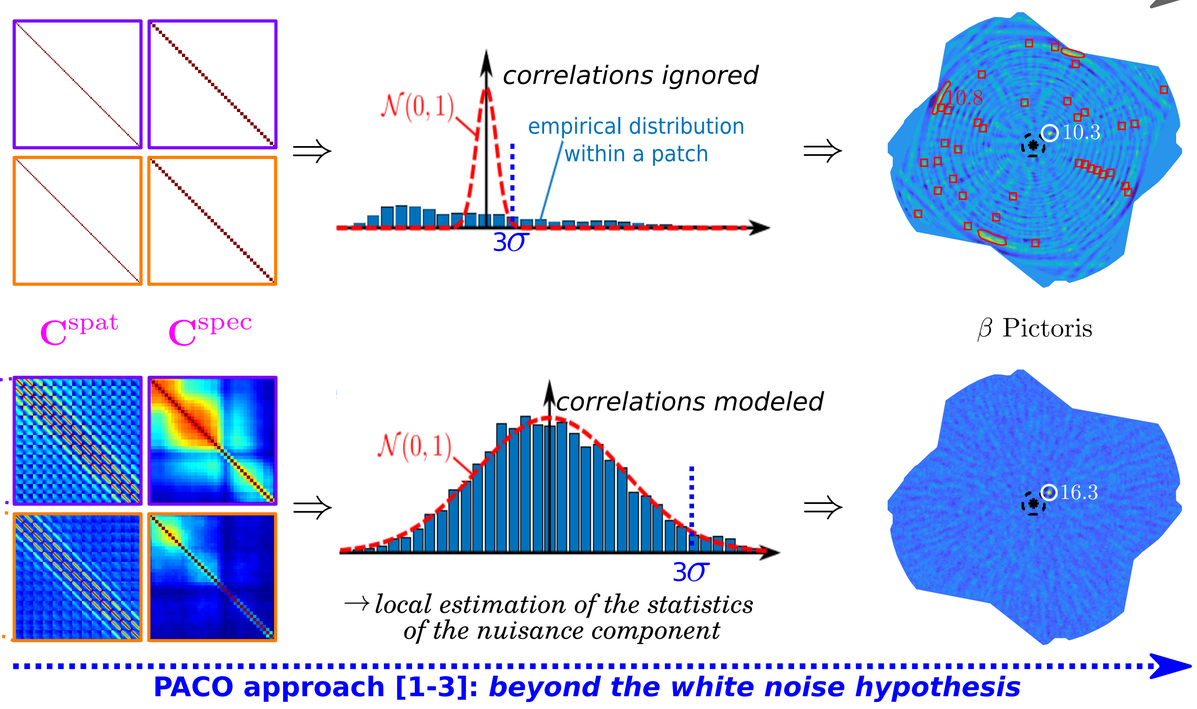
issues

very low contrast ($<10^{-6}$) due to high stellar leakages

correlated and nonstationary nuisance component

lack of groundtruth unbalanced classes





data model

$\rightarrow$*additive model:*

$$\underbrace{r_{t,\lambda}}_{\text{time}} = \underbrace{\alpha_\lambda}_{\text{channel}} \underbrace{h_{t,\lambda}}_{\text{unknown flux}} + \underbrace{f_{t,\lambda}}_{\text{nuisance}}$$

off-axis PSF

quasi-static + stochastic

nuisance model $\rightarrow$*GSM model:*

$$f_{n,t,\lambda} = m_{n,\lambda} + \kappa_{n,t}\, u_{n,t,\lambda}$$

n: patch around pixel

$$u_{n,t,\lambda} \sim \mathcal{N}\left(\mathbf{0}, \Phi(\mathbf{C}_n^{\text{spat}}, \mathbf{C}_n^{\text{spec}})\right)$$

$$\Omega = \{m, \kappa, \mathbf{C}^{\text{spat}}, \mathbf{C}^{\text{spec}}\}$$

$\rightarrow$*data-driven regularization of covariances by shrinkage:*

$$\underbrace{\text{bias/variance tradeoff}}_{\widehat{\mathbf{C}}_n \text{ shrinkage estimator}} = (1-\widehat{\rho}_n)\underbrace{\text{unbiased but large variance}}_{\text{sample covariance}} + \widehat{\rho}_n \underbrace{\text{low variance but biased}}_{\text{diagonal covariance}}$$

shrinkage factor

goal

combine this stastistical modeling with a learning framework

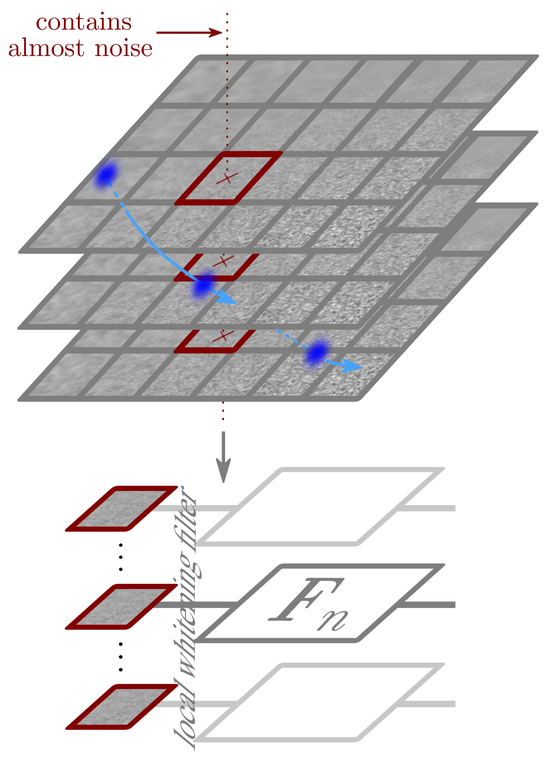
$\rightarrow$*to improve exoplanet detection sensitivity*

see Section 2.

2. Combination with a deep-based learning

• ***Preprocessing***: centering and local whitening with statistical model of the nuisance

$\rightarrow$ *to improve SNR and stationarity*



• ***Learning***: supervised training with simulated exoplanets $\rightarrow$*to correct small discrepancies between statistical model and observations*

samples:

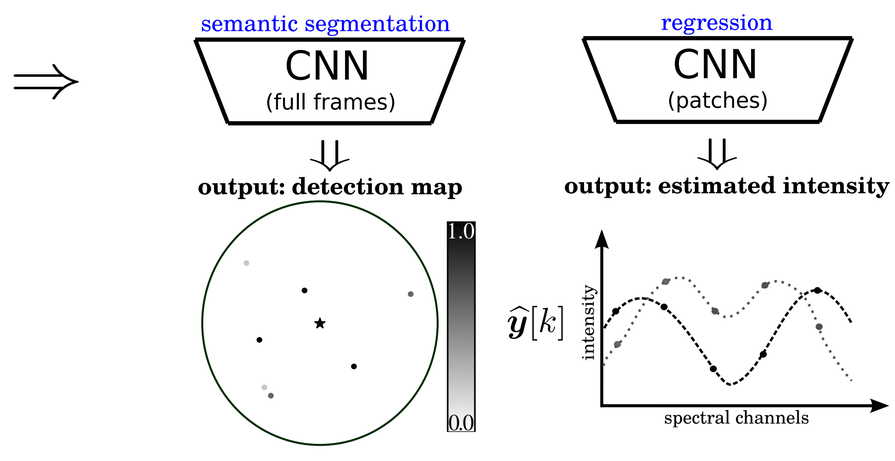
preprocessed images + shuffling + injected fake exoplanets

data augmentation to deal with absence of groundtruth

$$\left[\widetilde{\boldsymbol{r}}[k] \,;\, \boldsymbol{y}[k]\right]_{k=1:K}$$

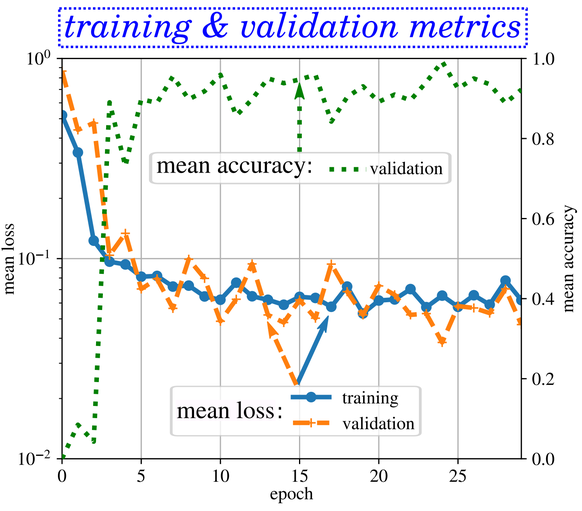
groundtruths:

location + intensity

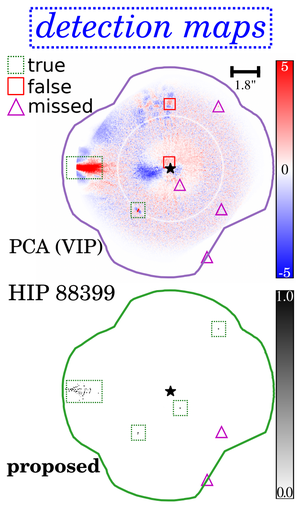


loss:	Dice score (overlap measure)	MSE
validation metric:	F1R score (tradeoff precision/recall)	MSE
architecture:	U-Net (backbone Res-Net18)	VGG-like
	trained from scratch	

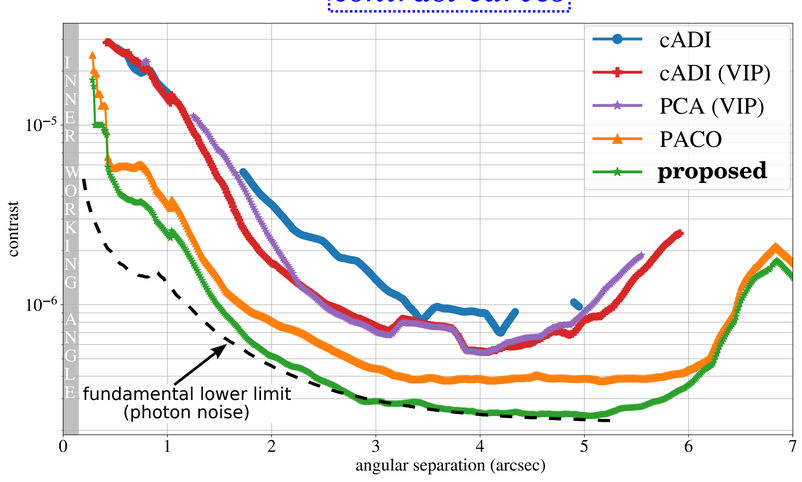
training & validation metrics



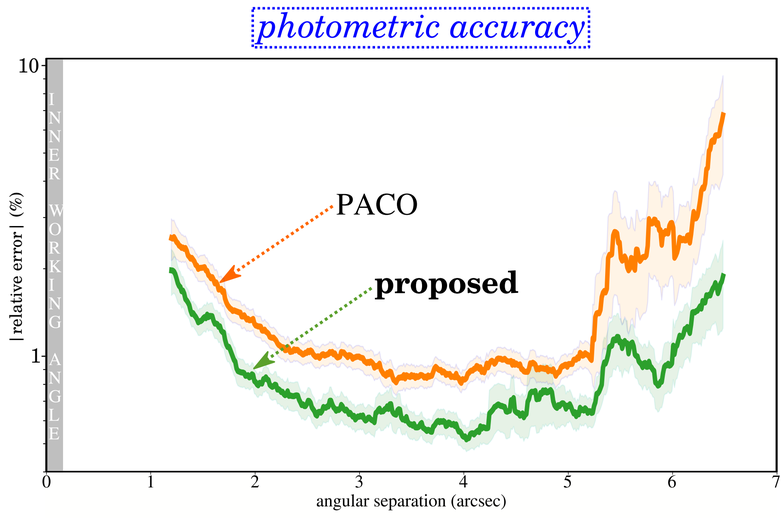
detection maps



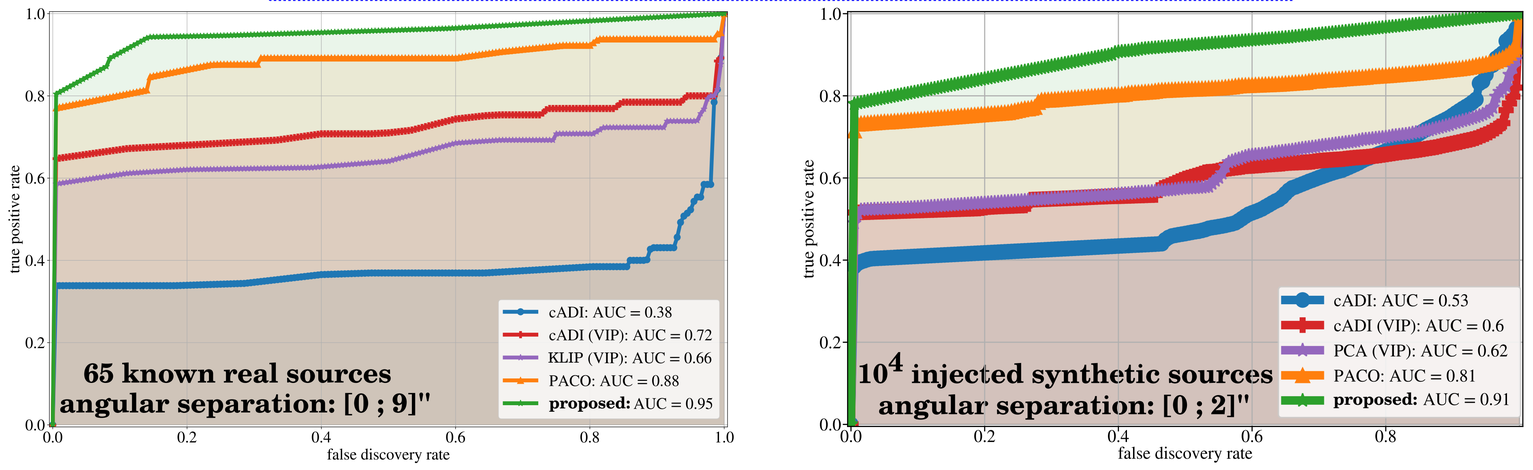
contrast curves



photometric accuracy



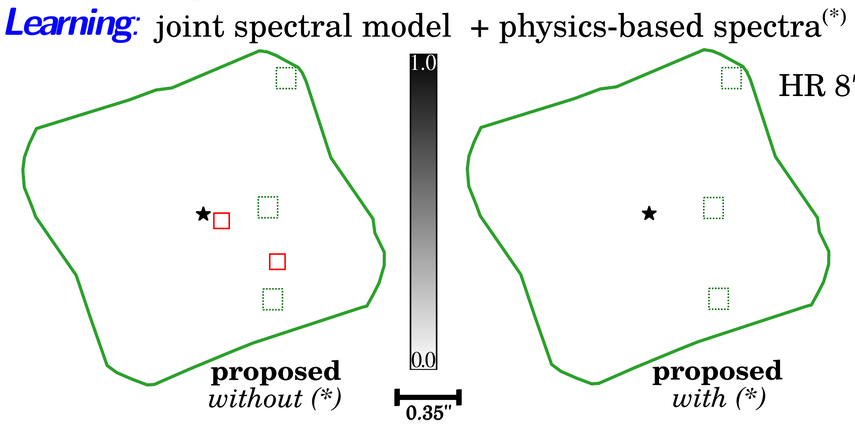
mean detection results on 11 datasets from VLT/SPHERE-IRDIS



extension for ASDI data

• ***Preprocessing***: spectral correlations accounted for

• ***Learning***: joint spectral model + physics-based spectra(*)



on-going & future works

control the uncertainties *(statistically interpretable detection confidence)*

include physics-based priors *(hybrid approaches)*

consider other tasks *(reconstruction of disks)*

[1] Flasseur+, A&A, 618, A138, 2018 [2] Flasseur+, A&A, 634, A2, 2020 [3] Flasseur+, A&A, 637, A9, 2020

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