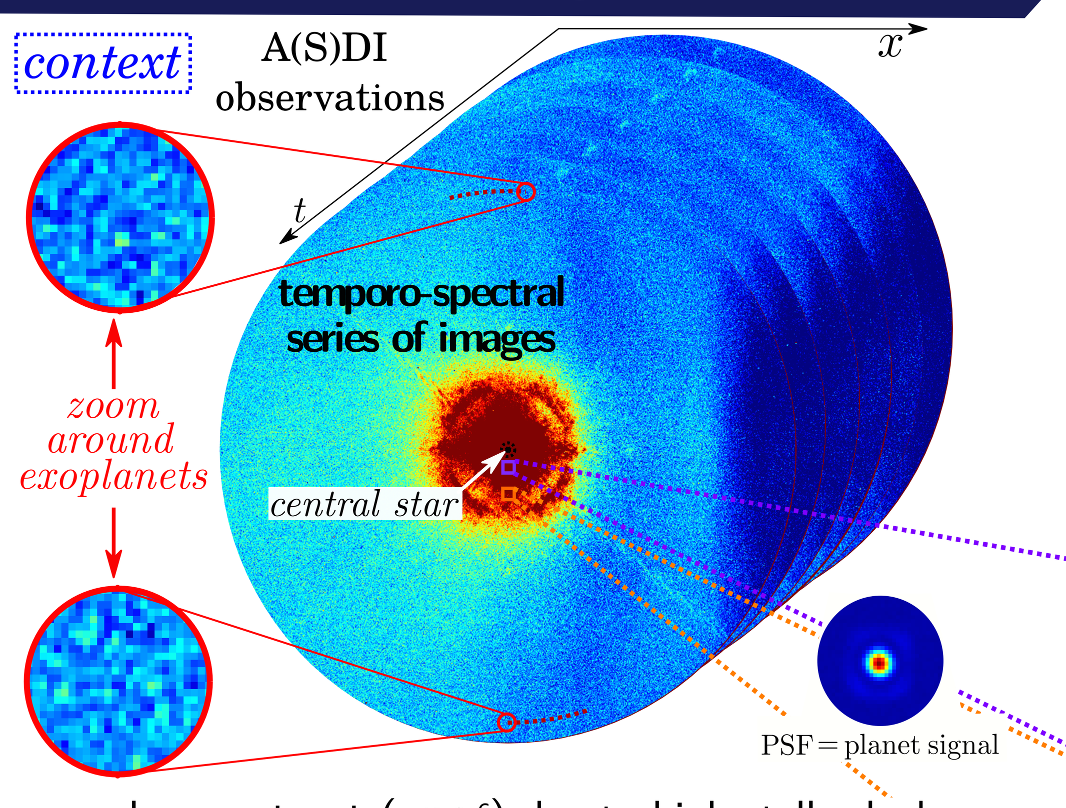
NEW POST-PROCESSING ALGORITHMS INTEGRATING A STATISTICAL MODELING FOR DISK RECONSTRUCTION AND EXOPLANET DETECTION

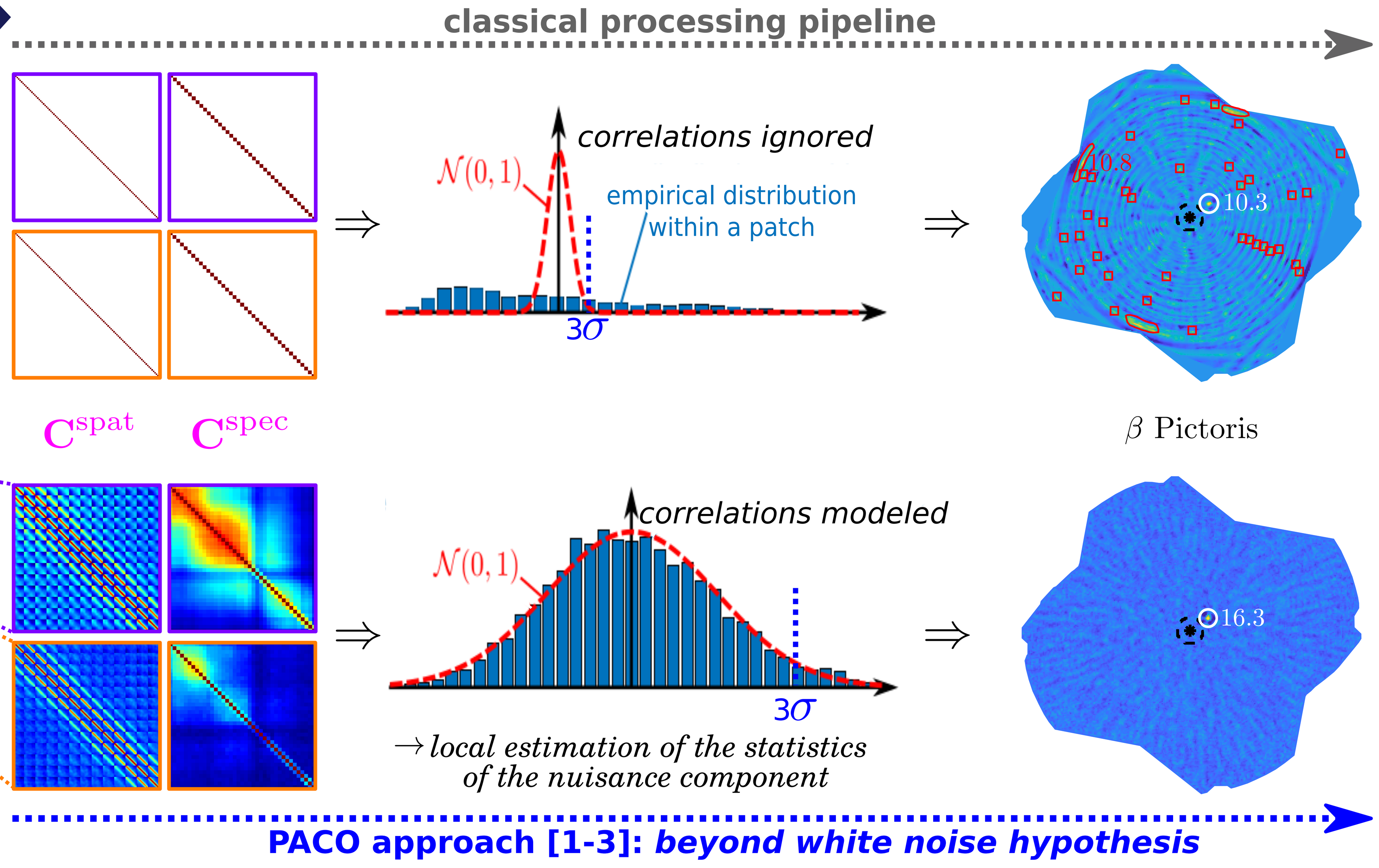
Olivier Flasseur[a,b], Théo Bodrito[b], Samuel Thé[c], Julien Mairal[b], Jean Ponce[b], Anne-Marie Lagrange[a,d] Maud Langlois[c], Eric Thiébaut[c], Loïc Denis[e]

1. Statistical modeling of the nuisance

context



very low contrast ($<10^{-6}$) due to high stellar leakages
correlated and nonstationary nuisance component
⇒ **unmixing problem** ⇐
lack of groundtruth, unbalanced classes



statistical model

→ GSM model:

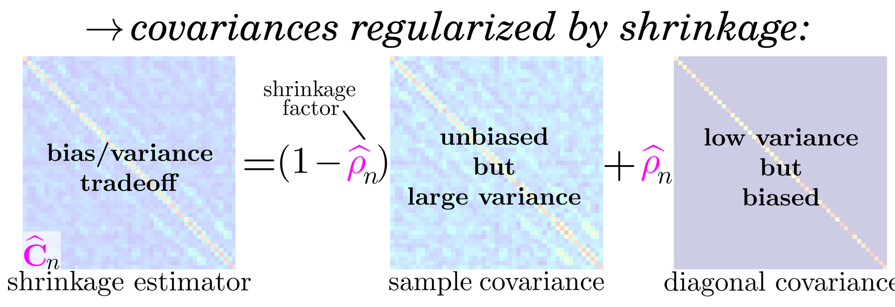
$$f_{n,t,\lambda} = m_{n,\lambda} + \kappa_{n,t}\, u_{n,t,\lambda}$$

pixel time channel

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

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

→ covariances regularized by shrinkage:



goals combining this statistical modeling...

...with a reconstruction framework
→ to improve circumstellar disk reconstruction

see Part 2.

...with a learning framework
→ to improve exoplanet detection sensitivity

see Part 3.

2. Circumstellar disk reconstruction

• ***Image formation model:***

$$\underbrace{r}_{\text{A(S)DI stack}} = \underbrace{\mathbf{A}}_{\text{direct model}}\, \underbrace{x}_{\text{sought object}} + \underbrace{f}_{\text{nuisance component}}$$

$\mathbf{A}$:= zoom ∘ crop ∘ convolution ∘ attenuation ∘ rotation

• ***Inverse problem:***

$$\widehat{x} = \arg\min_{x>0} \underbrace{\mathscr{D}(r, \mathbf{A}\,x, \Omega)}_{\text{data fidelity}} + \underbrace{\mathscr{R}(x, \mu)}_{\text{regularization}}$$

→ data fidelity with joint estimation x and Ω:

$$\mathscr{D}(r, \mathbf{A}\,x, \Omega) = \tfrac{1}{2}\sum_{n\in\mathbb{P}}\sum_t \log\det \widehat{\kappa}^2_{n,t}(x)\, \widehat{\mathbf{C}}_n(x) + \tfrac{1}{2}\sum_{n\in\mathbb{P}} \operatorname{tr}\left[\widehat{\mathbf{C}}_n^{-1}(x)\left(\widehat{\mathbf{W}}_n \odot \textstyle\sum_t \widehat{\kappa}^{-2}_{n,t}(x)\,\widehat{v}_{n,t}(x)\,\widehat{v}_{n,t}(x)^{\mathrm{t}}\right)\right]$$

$$\widehat{v}_{n,t}(x) = r_{n,t} - \widehat{m}_n(x) - [\mathbf{A}\,x]_{n,t} \quad \textit{(residuals)}$$

$$\widehat{\mathbf{W}}_n = (1-\widehat{\rho}_n) + \operatorname{diag}(\widehat{\rho}_n) \quad \textit{(shrinkage)}$$

proposed method

→ regularization with unsupervised setting of μ:

$$\mathscr{R}(x,\mu) = \underbrace{\mu_{\ell_1}\sum_{n=1}^{N}|x_n|}_{\text{sparsity}} + \underbrace{\mu_{\text{smooth}}\sum_{n=1}^{N}\sqrt{\|\boldsymbol{\Delta}_n x\|_2^2+\epsilon^2}}_{\text{edge-preserving}}$$

optimal μ minimizes SURE (MSE estimator [4]) adapted to account for Ω:

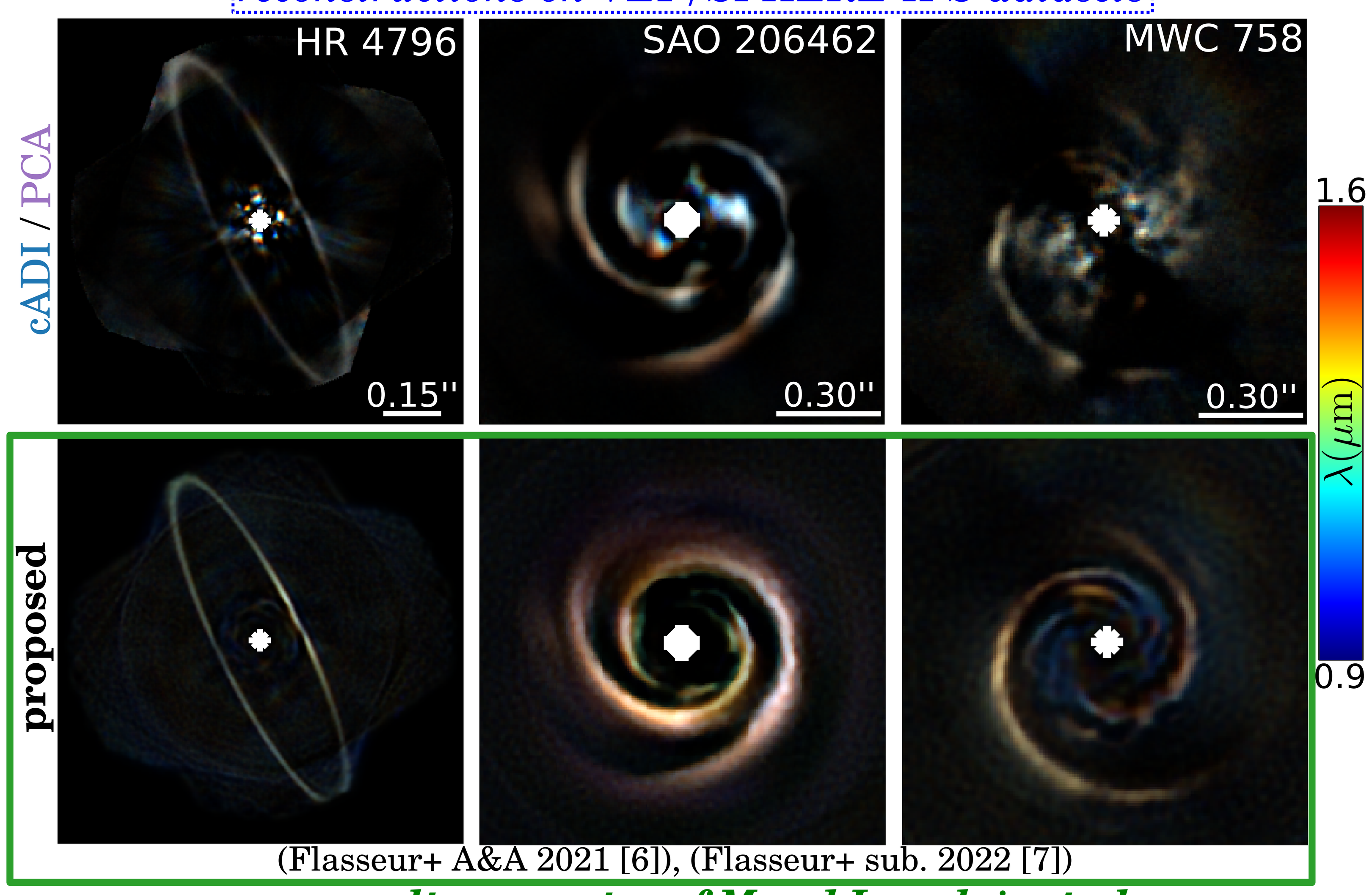
$$\text{SURE}(\mu) = \sum_{n\in\mathbb{P}}\sum_t \|r_{n,t} - \widehat{m}_n - [\mathbf{A}\,\widehat{x}_\mu(r)]_{n,t}\|^2_{\widehat{\kappa}^{-2}_{n,t}\widehat{\mathbf{C}}_n^{-1}} + 2\operatorname{tr}\left(\mathbf{A}\,\mathbf{J}_{\widehat{x}_\mu}(r)\right) - N$$

but no closed-form expression for Jacobian $\mathbf{J}$

⇒ perturbation approach [5]:

$$\operatorname{tr}\left(\mathbf{A}\,\mathbf{J}_{\widehat{x}_\mu}(r)\right) \approx \xi^{-1}\boldsymbol{b}^{\mathrm{t}}\,\mathbf{A}\,[\widehat{x}_\mu(r+\xi\boldsymbol{b}) - \widehat{x}_\mu(r)]$$

reconstructions on VLT/SPHERE-IFS datasets



(Flasseur+ A&A 2021 [6]), (Flasseur+ sub. 2022 [7])

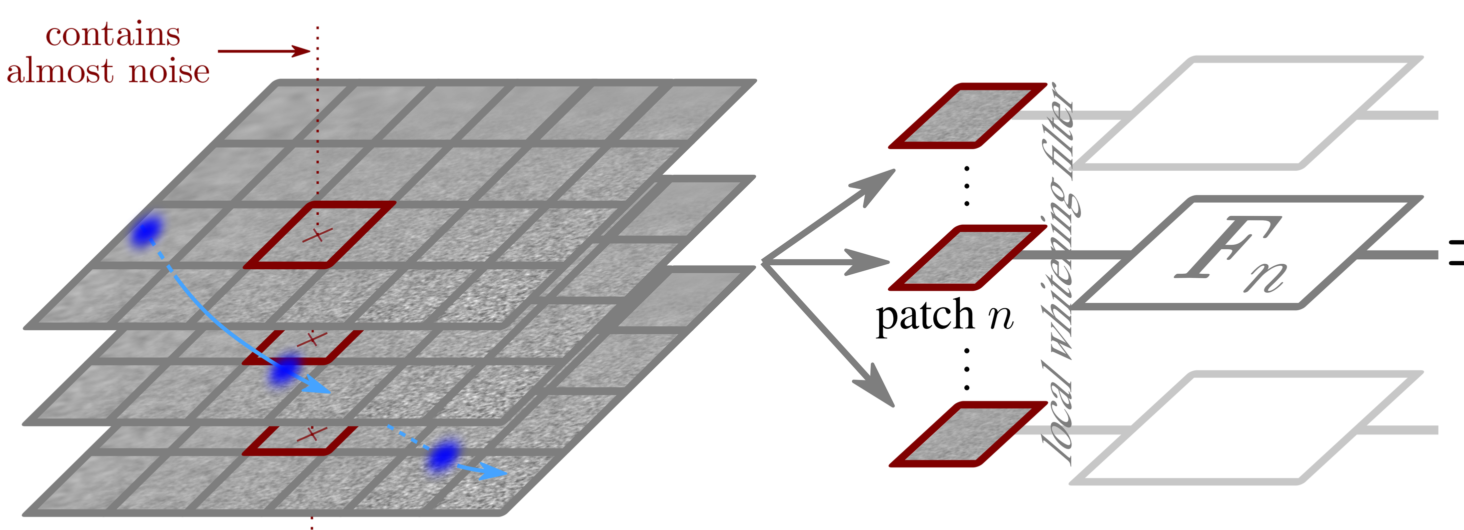
more results on poster of Maud Langlois et al.

3. Exoplanet detection

proposed method

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

→ to improve SNR and stationarity



👍 parameter-free 👍 local adaptivity

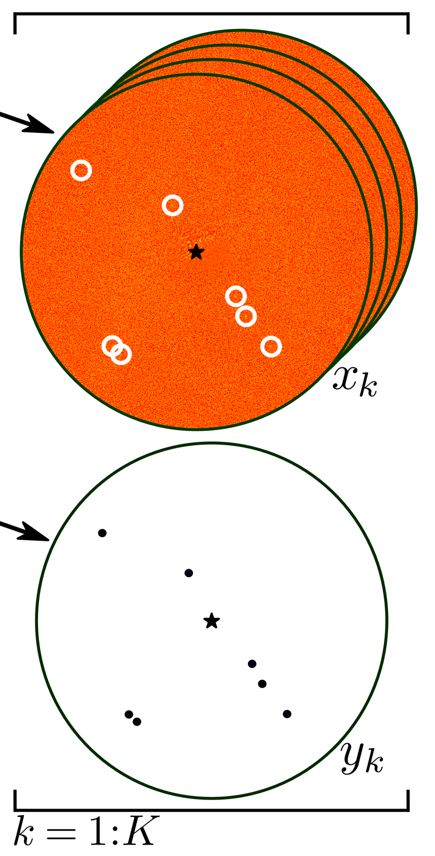
• ***Learning:*** supervised training with simulated exoplanets

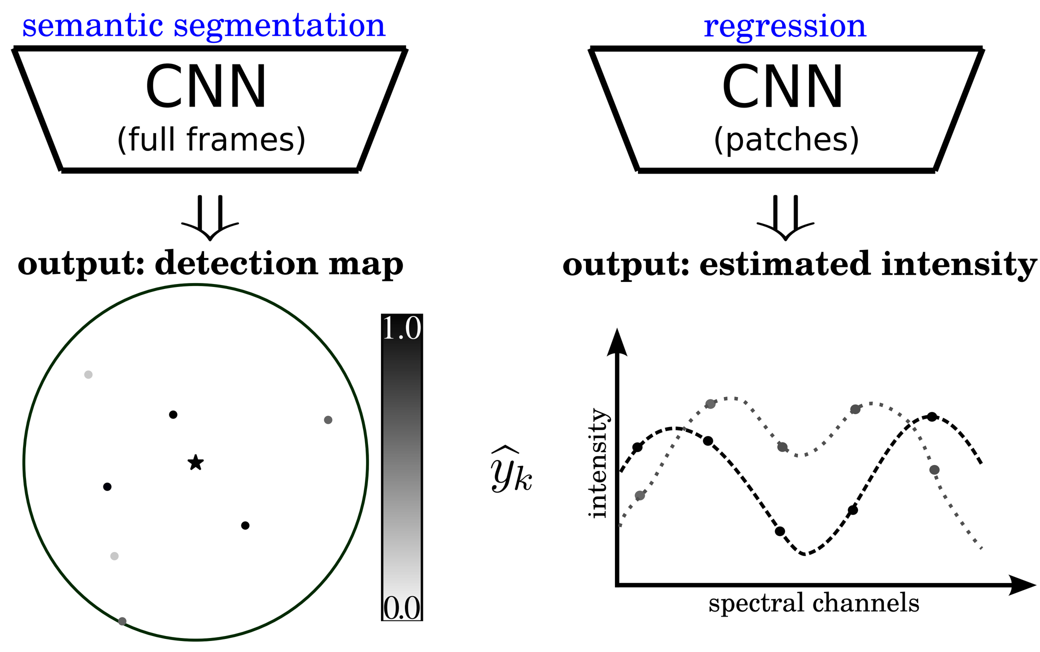
→ to correct small discrepancies statistical model/observations

samples:
preprocessed images
+
shuffling
+
injected fake exoplanets

data augmentation to deal with lack of groundtruth

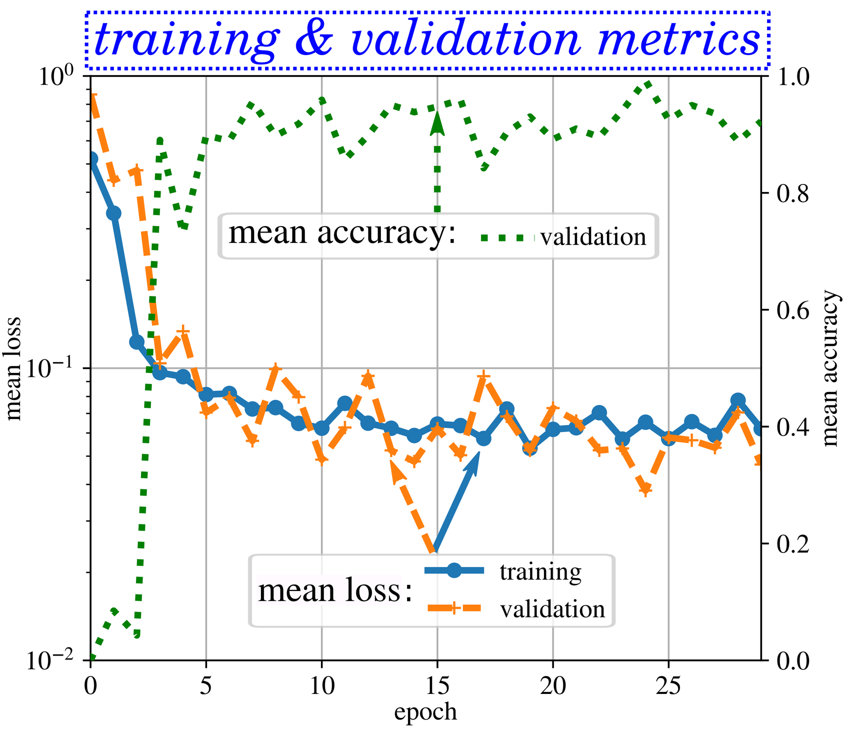
groundtruths:
location
+
intensity



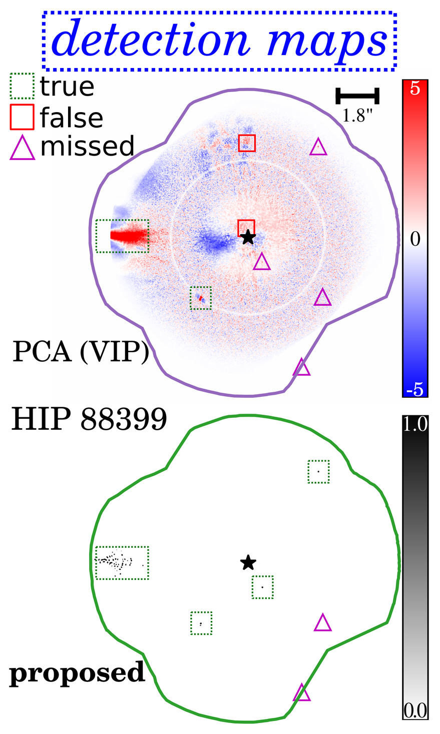


	semantic segmentation		regression
loss:	Dice score (overlap measure)		MSE
validation metric:	F1R score (tradeoff precision/recall)		MSE
architecture:	U-Net (backbone Res-Net18)	*trained from scratch*	VGG-like

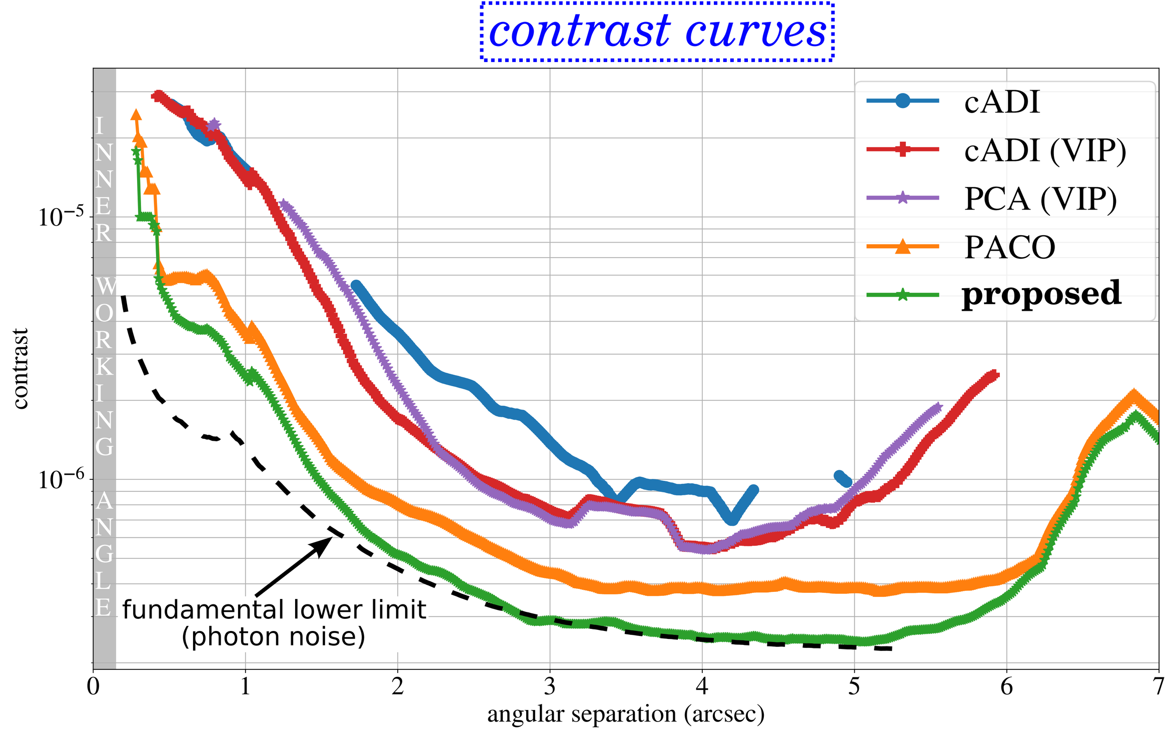
training & validation metrics



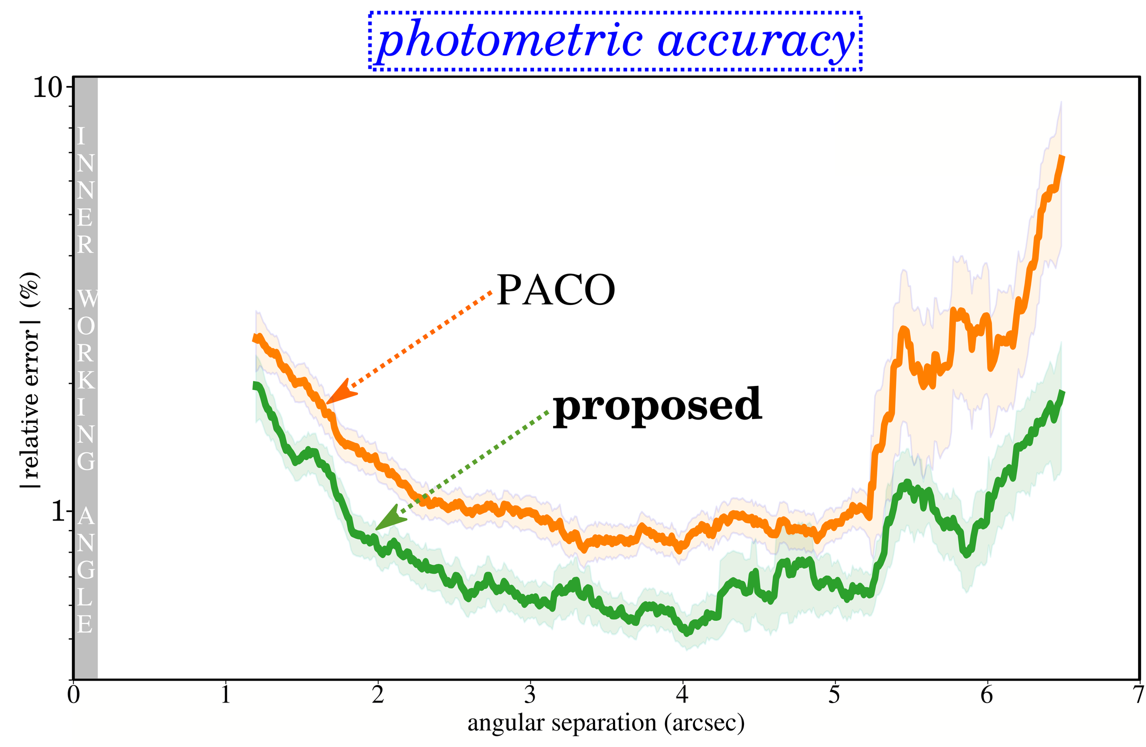
detection maps



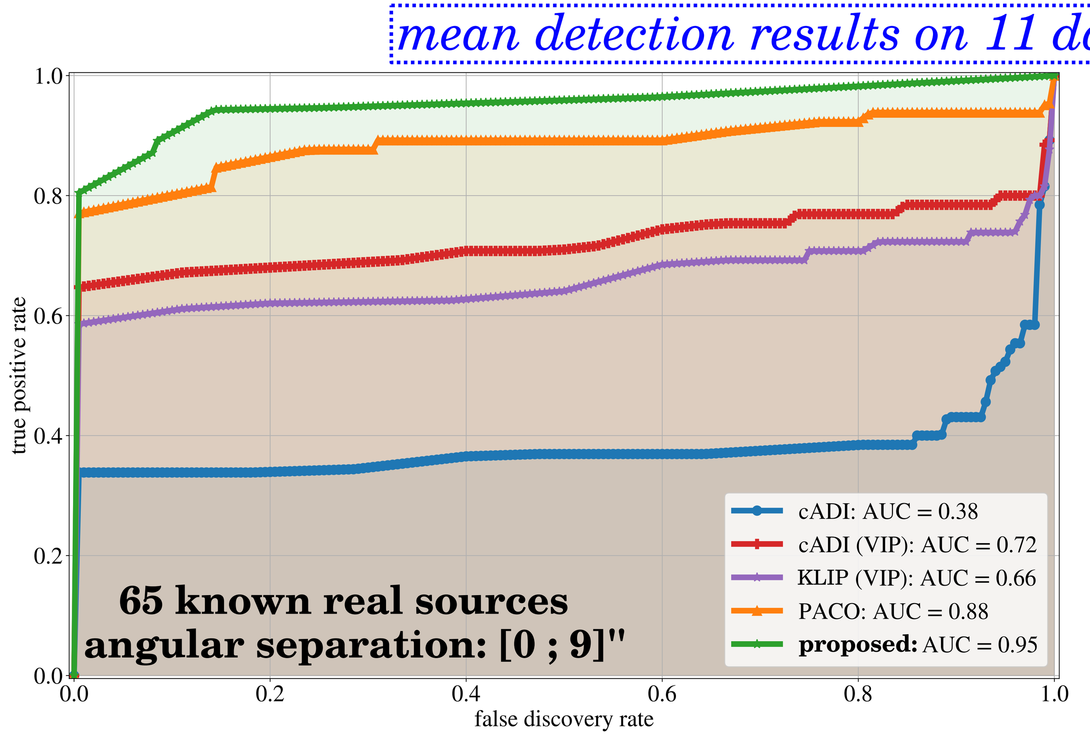
contrast curves

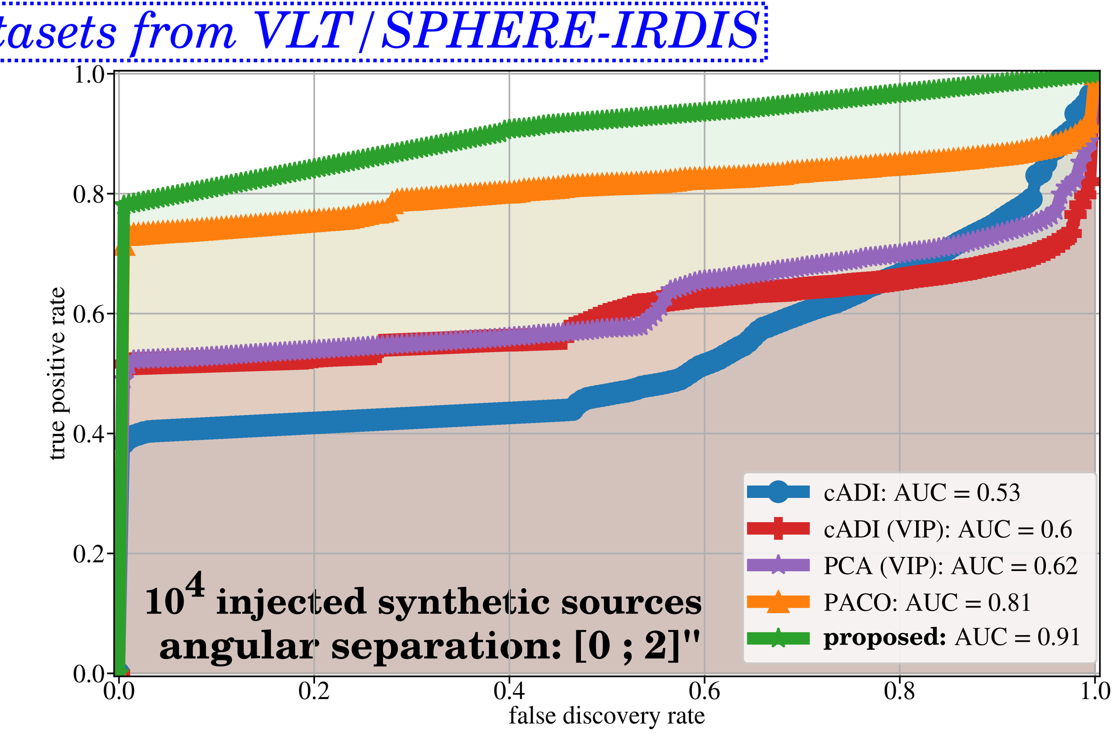


photometric accuracy



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

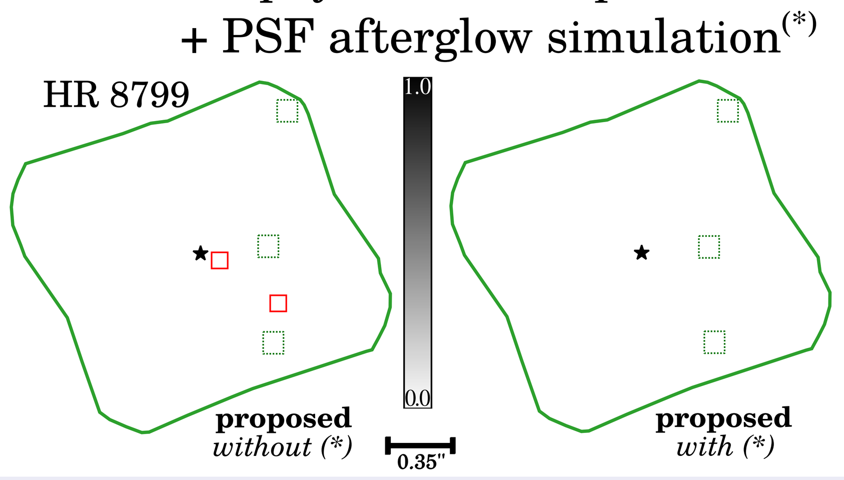




extension for ASDI data

• ***Preprocessing:*** spectral correlations

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



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 [4] Stein, JSTOR, 1981
[5] Ramani+, IEEE TIP, 21, 8, 2012 [6] Flasseur+, A&A, 651, A62, 2021 [7] Flasseur+, sub. 2022

This project has received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (COBREX; grant agreement n° 885593)