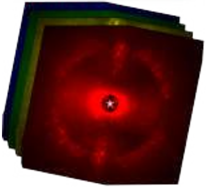
Approches *science des données* pour l'exploration des environnements circumstellaires en imagerie à haut contraste & haute résolution angulaire

Olivier Flasseur

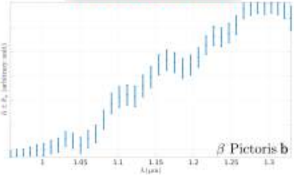
multi-variate data



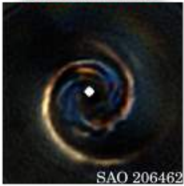
⇒

detection

characterization



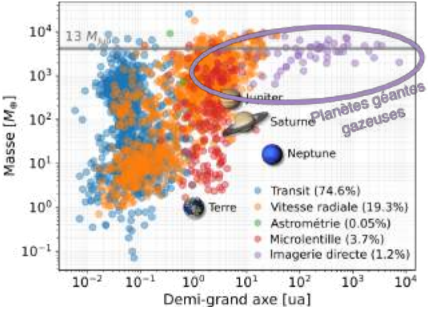
reconstruction

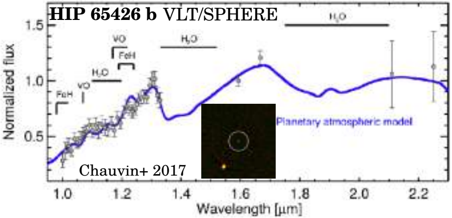


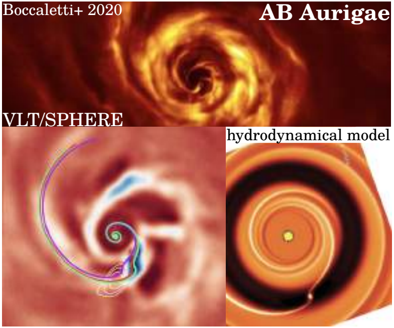
travaux conjoints avec de nombreux collègues et étudiants, notamment du :

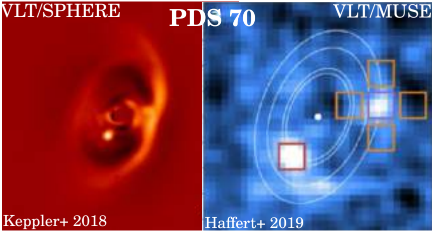
Journées SF2A - 04 au 07 juin 2024 - Marseille

Exoplanetary science – *some key scientific drivers*





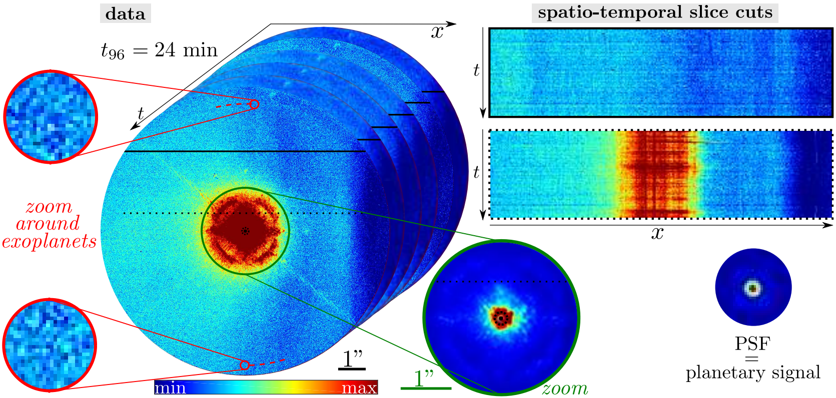




Frequency and diversity of planets? Architecture of systems?
How do planets form? How do planets interact with the disk?

Goal: modeling the nuisance component (speckles + noise)

angular differential imaging (ADI) = temporal diversity



Peculiarities

- **Faint signal** from the exoplanets
- **Non-stationary** and **spatially correlated** strong nuisance component
- **Strong fluctuations** (stellar leakages)
- **Multi-spectral** data available

$\Rightarrow$ **Signal unmixing is critical**

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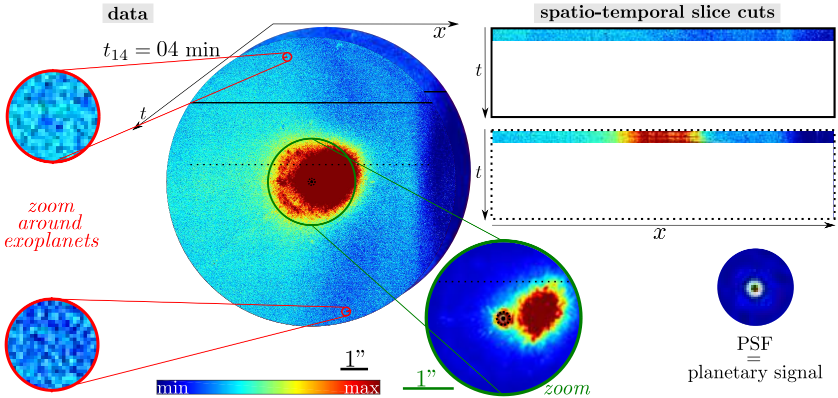

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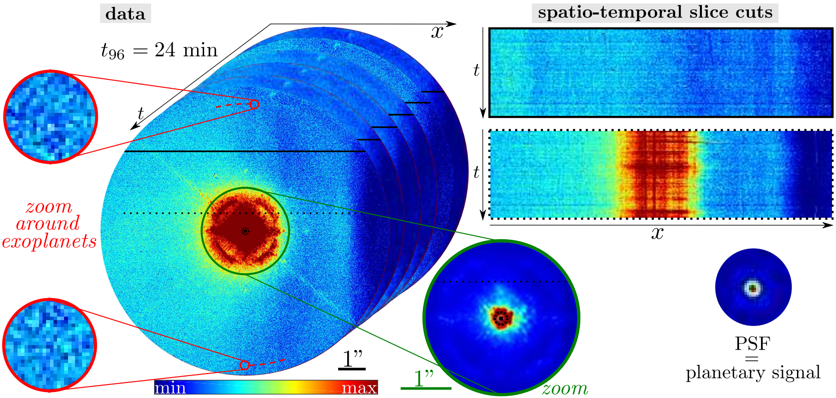

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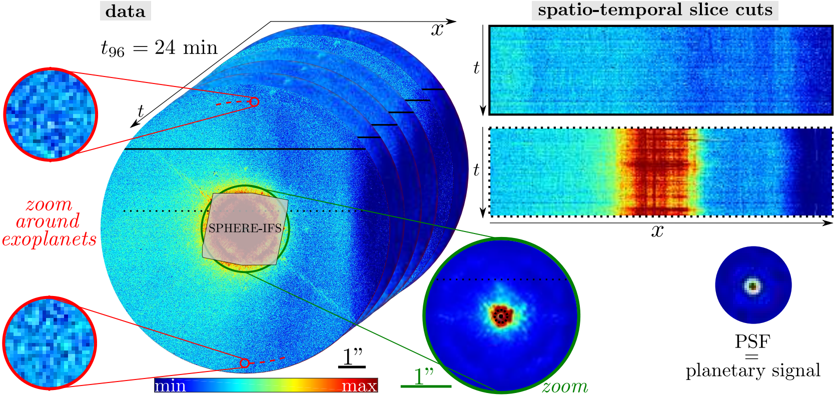

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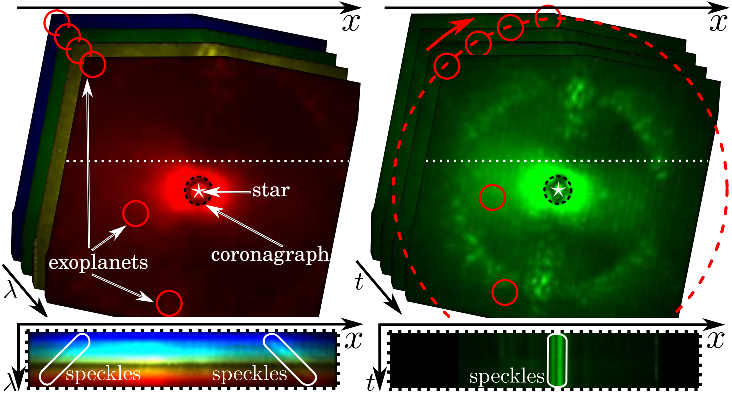
angular & spectral diff. im. (ASDI) = temporal & spectral diversity



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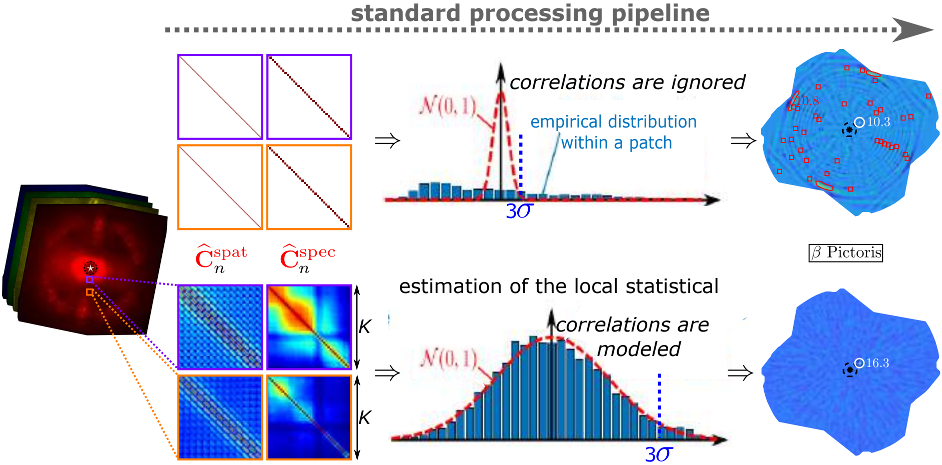
Accounting for the *correlations* of the nuisance component



$$\underbrace{f_{n,t,\lambda}}_{\text{pixel }(N)\ \text{time }(T)\ \text{channel }(L)} = m_{n,\lambda} + \sigma_{n,t}\, \boldsymbol{u}_{n,t,\lambda} \qquad \boldsymbol{u}_{n,t,\lambda} \sim \mathcal{N}\left(\mathbf{0}, \Phi(\mathbf{C}_n^{\mathrm{spat}}, \mathbf{C}_n^{\mathrm{spec}})\right)$$

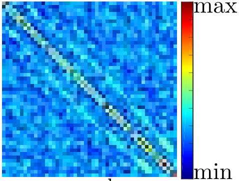
pixel (N) time (T) channel (L)

beyond white noise hypothesis

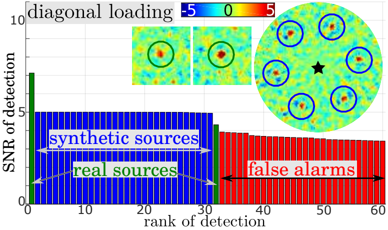
$\Rightarrow$ **unsupervised and regularized estimation from the data**

Accurate estimation in large dimension – *example*

- Low nb of samples ⇒ empirical covariances very noisy / rank deficient



sample covariance



Accurate estimation in large dimension – *example*

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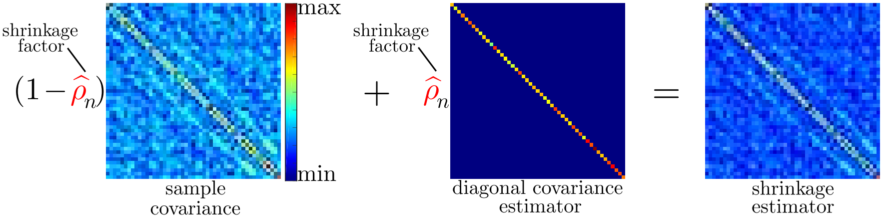
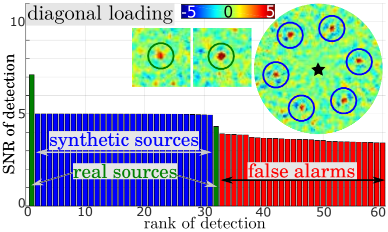
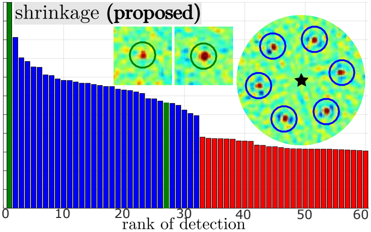
- Data-driven and spatially adaptive regularization by *shrinkage*:



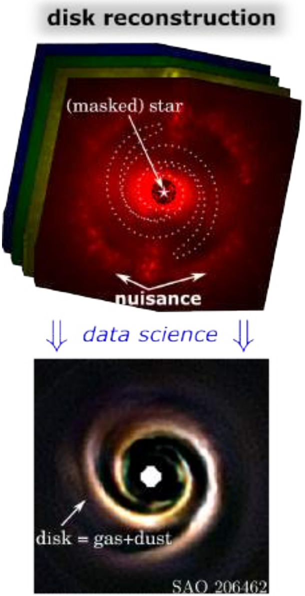
⇒ **optimal estimation by risk minimization for various structures**

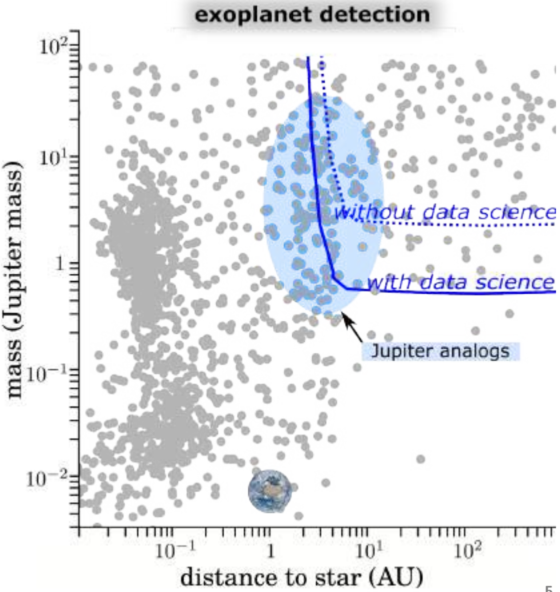


⇒



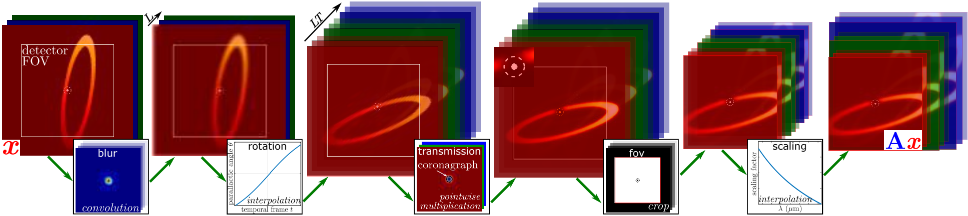
Data science: essential for high-contrast imaging





Regularized reconstruction – *framework*

- Data model: $\boldsymbol{r} = \mathbf{A}\,\boldsymbol{x} + \boldsymbol{f} \in \mathbb{R}^{NLT}$ with $\boldsymbol{x} \in \mathbb{R}^{N'L}$, $\boldsymbol{f} \gg \mathbf{A}\,\boldsymbol{x}$.
- Direct operator: $\mathbf{A} \equiv$ scaling $\circ$ fov $\circ$ transmission $\circ$ rotation $\circ$ blur.



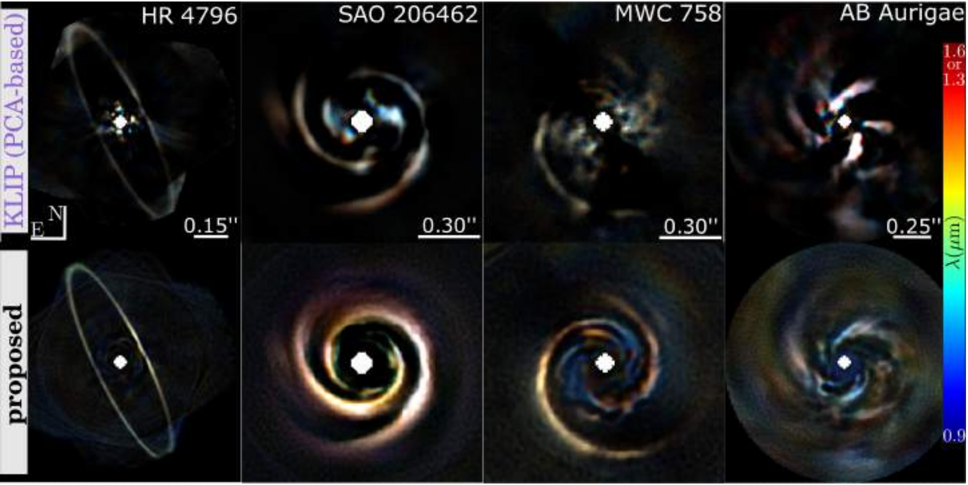
Regularized reconstruction of the spatio-spectral flux distribution $\boldsymbol{x}$

Solving an inverse-problem:

$$\widehat{\boldsymbol{x}} = \underset{\boldsymbol{x}>\mathbf{0}}{\arg\min}\{\mathscr{C}(\boldsymbol{r},\boldsymbol{x},\mathbf{A},\boldsymbol{\Omega},\boldsymbol{\mu}) = \mathscr{D}(\boldsymbol{r},\mathbf{A}\,\boldsymbol{x},\boldsymbol{\Omega}) + \mathscr{R}(\boldsymbol{x},\boldsymbol{\mu})\}\,,$$

- $\mathscr{D}(\boldsymbol{r},\mathbf{A}\,\boldsymbol{x},\boldsymbol{\Omega})$: data-fidelity term, depends on $\boldsymbol{\Omega}$ statistics of $\boldsymbol{f}$,
- $\mathscr{R}(\boldsymbol{x},\boldsymbol{\mu})$: regularization term, depends on hyperparameters $\boldsymbol{\mu}$.

Results: *disk reconstruction from SPHERE-IFS data*



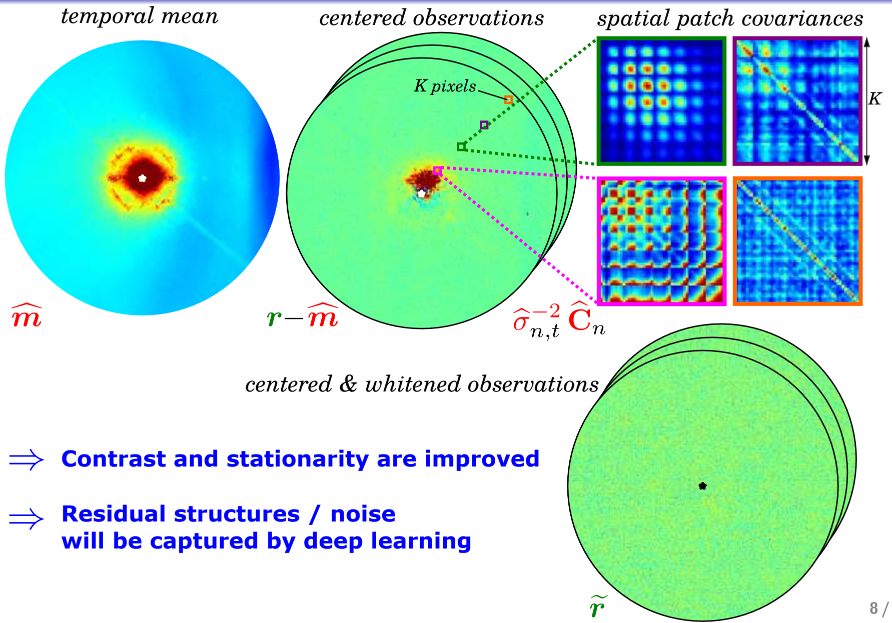
statistical model ⇒ reduced residual stellar leakages

image formation model ⇒ reduced artifacts & improved resolution

Joint spectral processing ⇒ critical for complex disk structures

Flasseur+, submitted to MNRAS, 05/2024 (https://arxiv.org/abs/2109.12644)

Statistical modeling: *removing (most of) the correlations*

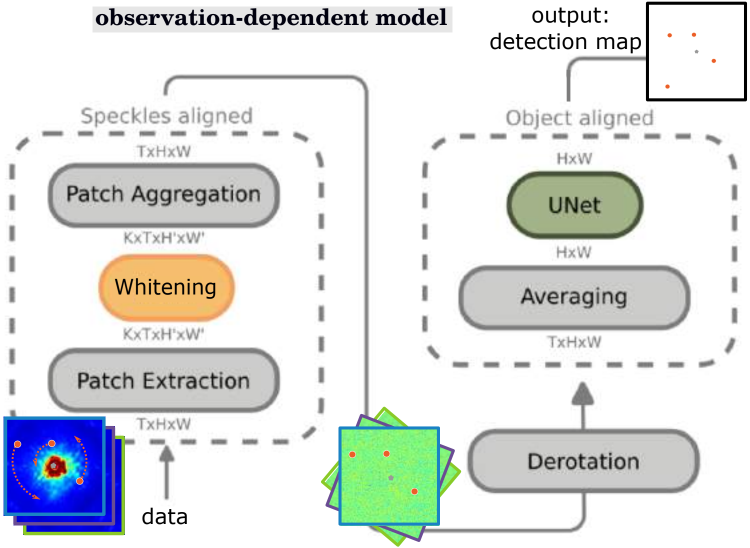


$\Longrightarrow$ **Contrast and stationarity are improved**

$\Longrightarrow$ **Residual structures / noise will be captured by deep learning**

Deep learning: *capturing residual correlations*

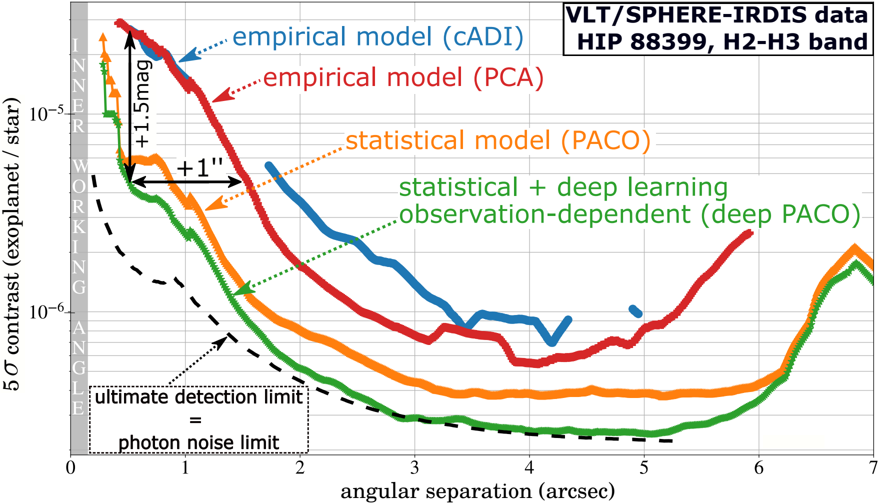
observation-dependent model



ADI: Flasseur+, MNRAS 2023 (https://arxiv.org/abs/2303.02461)
ASDI: Flasseur+, EUSIPCO, 2023 (https://arxiv.org/abs/2306.12266)

work funded by COBREX
(PI: A.-M. Lagrange)

Results: improved detection sensitivity



statistics + deep learning ⇒ gain & optimal far from the star

ADI: Flasseur+, MNRAS 2023 (https://arxiv.org/abs/2303.02461)
ASDI: Flasseur+, EUSIPCO, 2023 (https://arxiv.org/abs/2306.12266)

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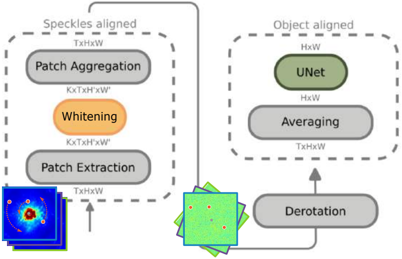
Deep learning: *capturing residual correlations*

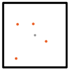
observation-dependent model (1)



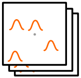
Common part: ***whitening***
via estimation of spatial covariances

Outputs

model (1): binary detection map



model (2): residual flux distribution cube

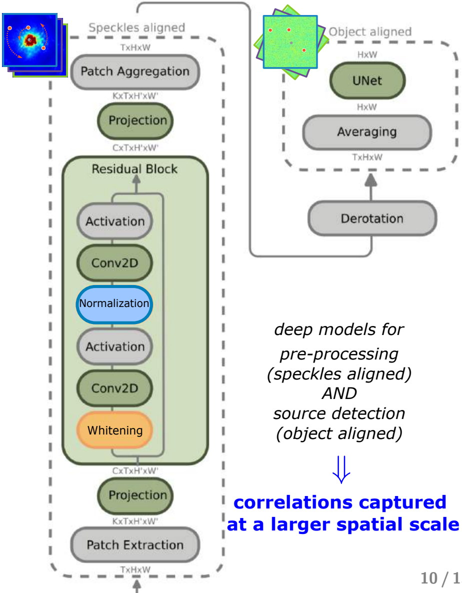


reconstruction loss (flux)
instead of detection loss

$\Downarrow$

improved robustness

observation-independent model (2)



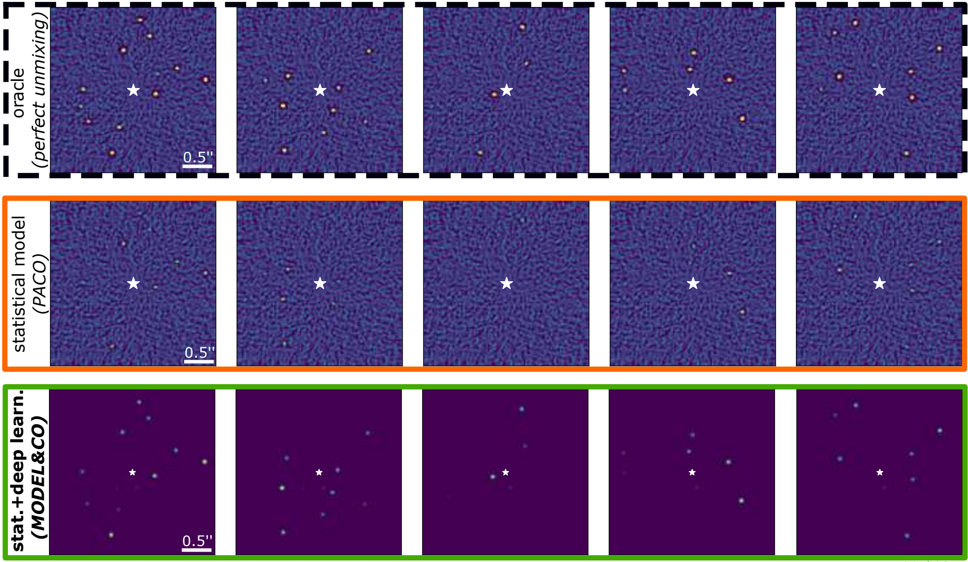
deep models for
pre-processing
(speckles aligned)
AND
source detection
(object aligned)

$\Downarrow$

correlations captured
at a larger spatial scale

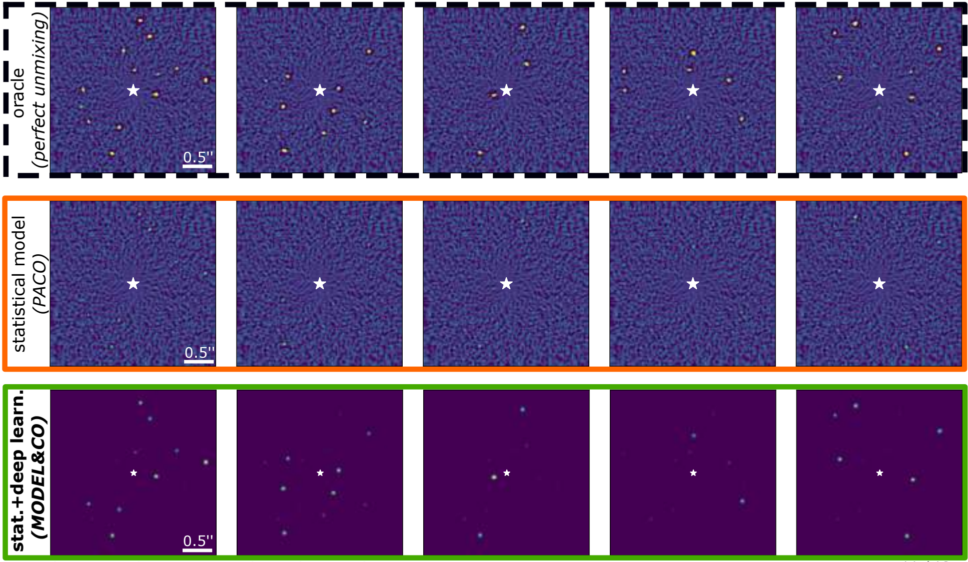
Results: deep learning by-passes the limits of ADI

VLT/SPHERE-IRDIS data *parallactic rotation* $\simeq$ *23°*



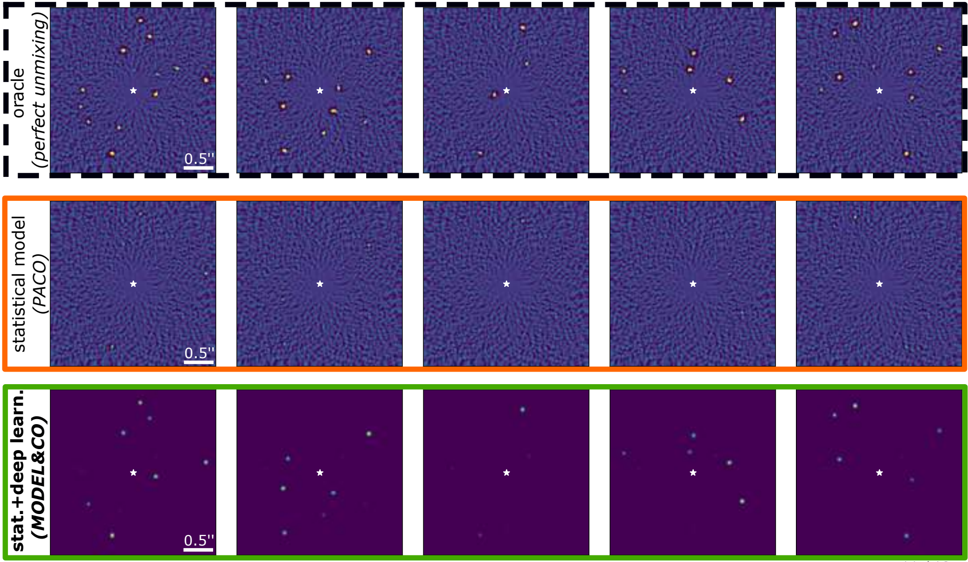
Results: deep learning by-passes the limits of ADI

VLT/SPHERE-IRDIS data *parallactic rotation* $\simeq$ *10°*



Results: deep learning by-passes the limits of ADI

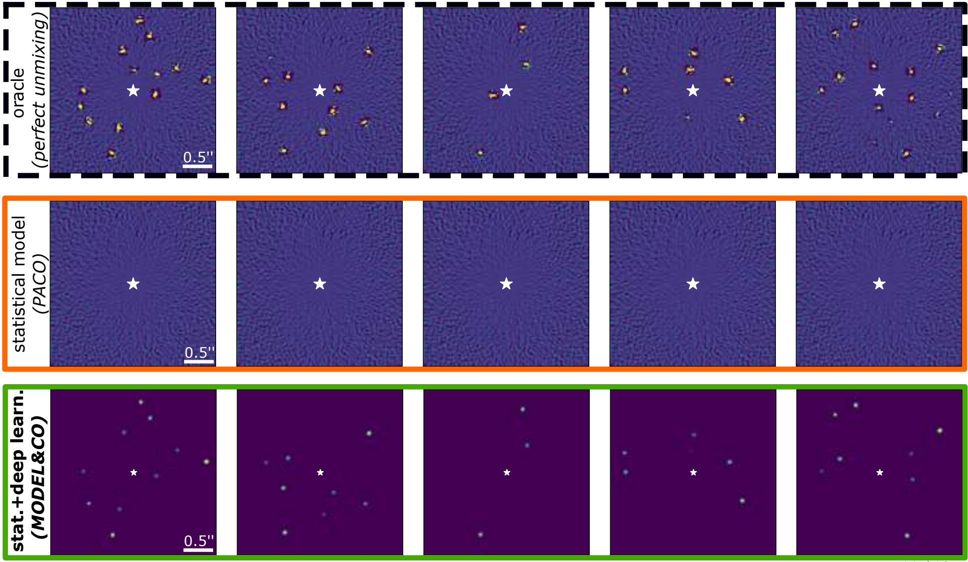
VLT/SPHERE-IRDIS data *parallactic rotation* $\simeq$ $6°$



T. Bodrito, O. Flasseur+, to be submitted

Results: deep learning by-passes the limits of ADI

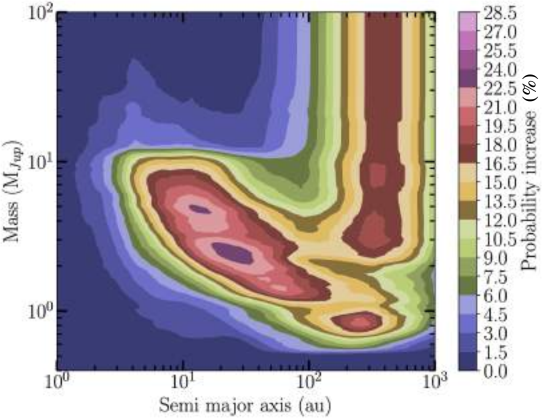
VLT/SPHERE-IRDIS data *parallactic rotation $\simeq 2°$!*



T. Bodrito, O. Flasseur+, to be submitted

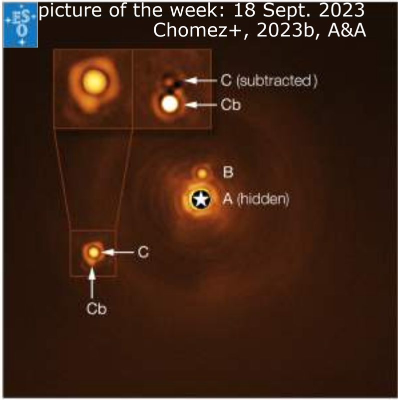
Progresses in data science ⇒ promising results

Some examples:



Chomez+, to be submitted, 2024

New planetary-mass object found in quadruple system



⇒ improved completeness on VLT/SPHERE

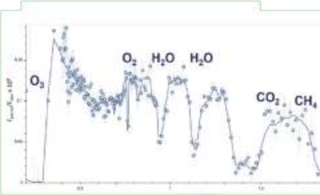
$>$ 20 candidates to be confirmed with second epoch analysis

a work funded by COBREX *(PI: A.-M. Lagrange)*

What's next?

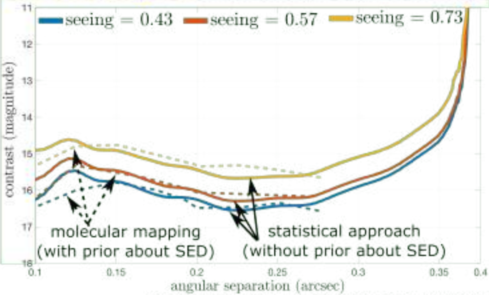
Goals:

imaging in reflected light, Neptune analogs, access to telluric...Earth's twins...prebiotic signs...

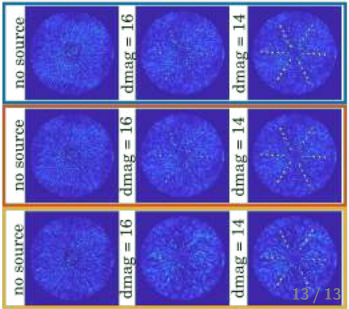


Data peculiarities: high spectral diversity, instabilities, highly structured PSF, massive

Some strategies: statistical /deep learning, data-driven approaches, data fusion



Courtesy simulations + photometry code: HARMONI simulation team.



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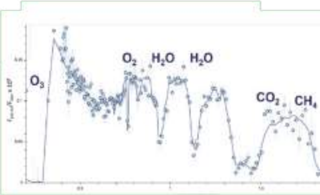

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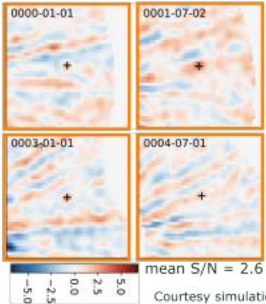
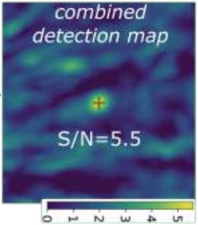
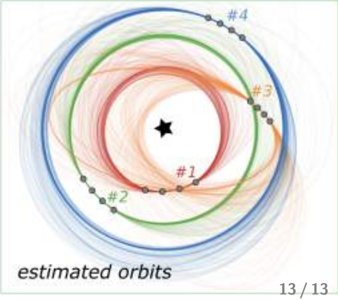


4x30 min exp., H-High band

⇒ data fusion algo. (Dallant+ 2023 A&A) ⇒



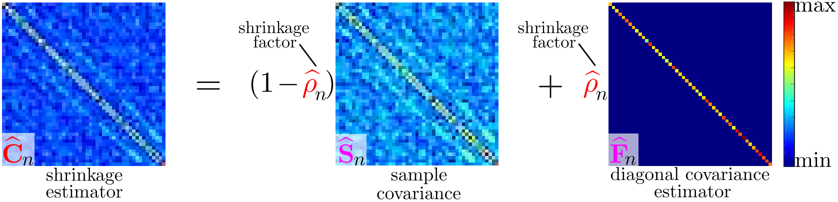


Courtesy simulations + photometry code: HARMONI simulation team.

Thank you

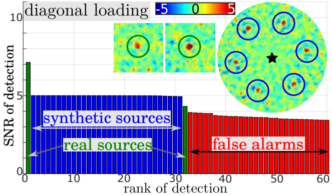
Accurate estimation in large dimension – *example*

- Low nb of samples ($T \simeq L \simeq K$) $\Rightarrow$ $\widehat{\mathbf{S}}_n^{\text{spat}}$ and $\widehat{\mathbf{S}}_n^{\text{spec}}$ noisy/rank-deficient
- Data-driven and spatially adaptive regularization by *shrinkage*:

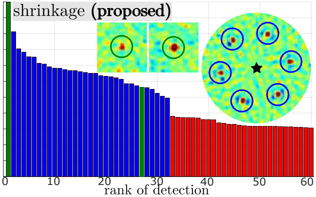


$\Rightarrow$ **optimal estimation by risk minimization for various structures**

$$\widehat{\rho}_n = \underset{\rho\in[0,1]}{\arg\min}\ \mathbb{E}(\|\widehat{\mathbf{C}} - \mathbf{C}\|_{\mathsf{F}}^2) = \frac{\mathbb{E}(\operatorname{tr}((\mathbf{C} - \gamma\widehat{\mathbf{S}})(\widehat{\mathbf{F}} - \widehat{\mathbf{S}}))}{\gamma\mathbb{E}(\operatorname{tr}((\widehat{\mathbf{F}} - \widehat{\mathbf{S}})^2))}, \text{ with } \mathbb{E}(\widehat{\mathbf{S}}) = \gamma^{-1}\mathbf{C}\,.$$

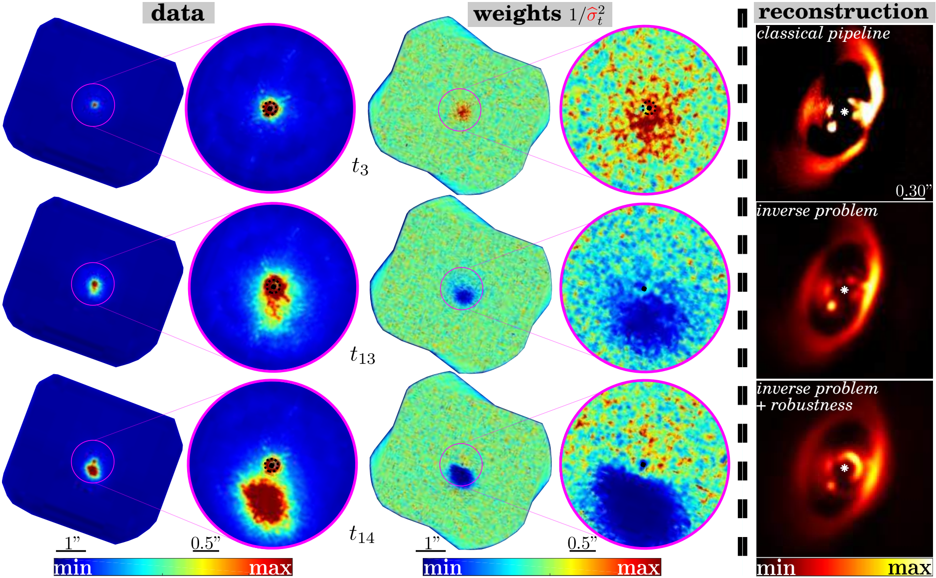


$\Rightarrow$



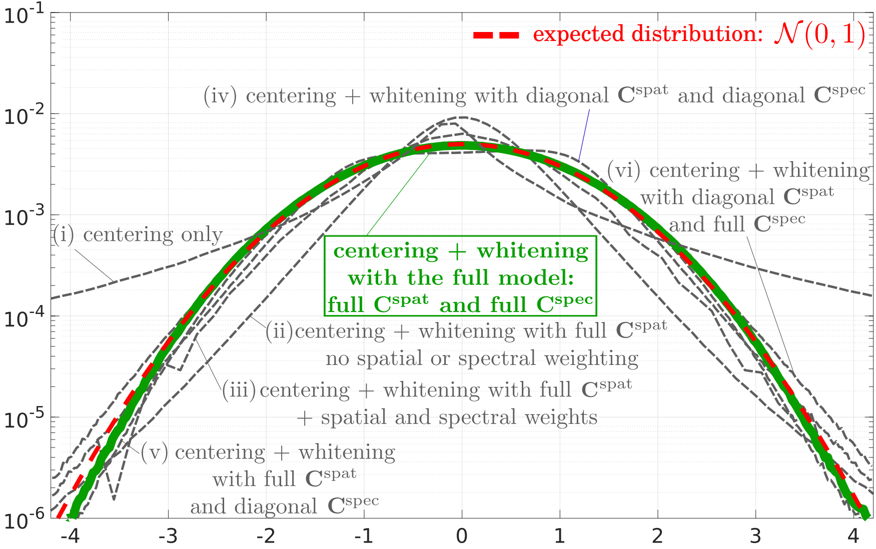
Flasseur, Thiébaut+, accepted, 2024 (https://arxiv.org/abs/2403.07104)

Accounting for the *variability* of the nuisance component



⇒ large stellar leakages + outliers are identified & neutralized locally

Model relevance – *empirical distribution of residuals*



⇒ **modeling correlations of the nuisance is critical!**

Unsupervised & optimal setting of the algorithm

Optimizing a quantitative criterion

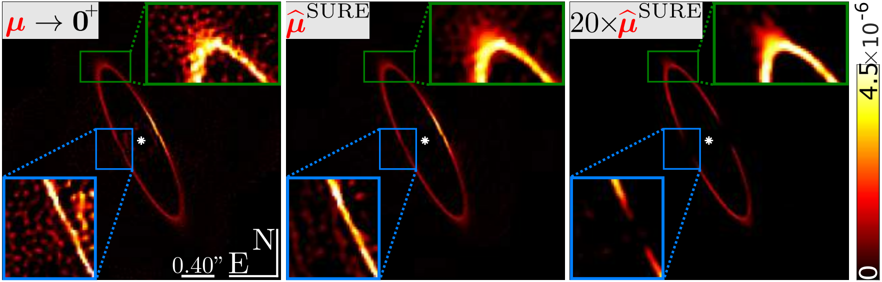
$$\mathscr{R}(\boldsymbol{x}, \boxed{\boldsymbol{\mu}}) = \boxed{\mu_{\ell_1}} \sum_{n=1}^{N'} \sum_{\ell=1}^{L} |x_{n,\ell}| + \boxed{\mu_{\text{smooth}}} \sqrt{\frac{1}{L} \sum_{\ell=1}^{L} \|\nabla_n \boldsymbol{x}_{\cdot,\ell}\|_2^2 + \tau^2}$$

$\Rightarrow$ Minimizing e.g. SURE (unbiased MSE estimator):

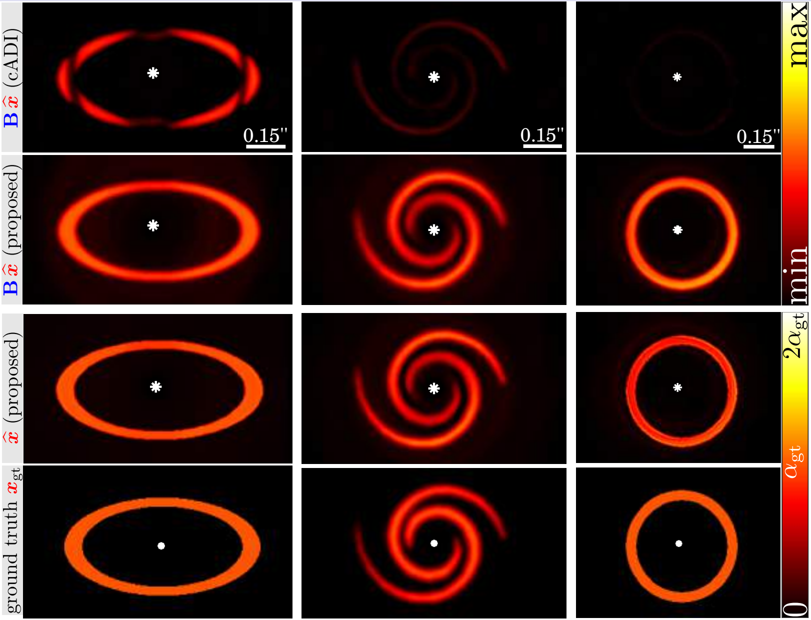
$$\text{SURE}(\boldsymbol{\mu}) = \sum_{n,\,t} \|\boldsymbol{r}_{n,t} - \widehat{\boldsymbol{m}}_n - [\mathbf{A}\,\boldsymbol{x}_{\boldsymbol{\mu}}(\boldsymbol{r})]_{n,t}\|^2_{\widehat{\boldsymbol{\sigma}}^{-2}_{n,t}\,\widehat{\mathbf{C}}^{-1}_n} + 2\,\mathrm{tr}\left(\mathbf{A}\,\mathbf{J}_{\mathbf{v}_{\boldsymbol{\mu}}}(\boldsymbol{r})\right) - NL$$

by accounting for the local statistics $\boldsymbol{\Omega}$ of $\boldsymbol{f}$.

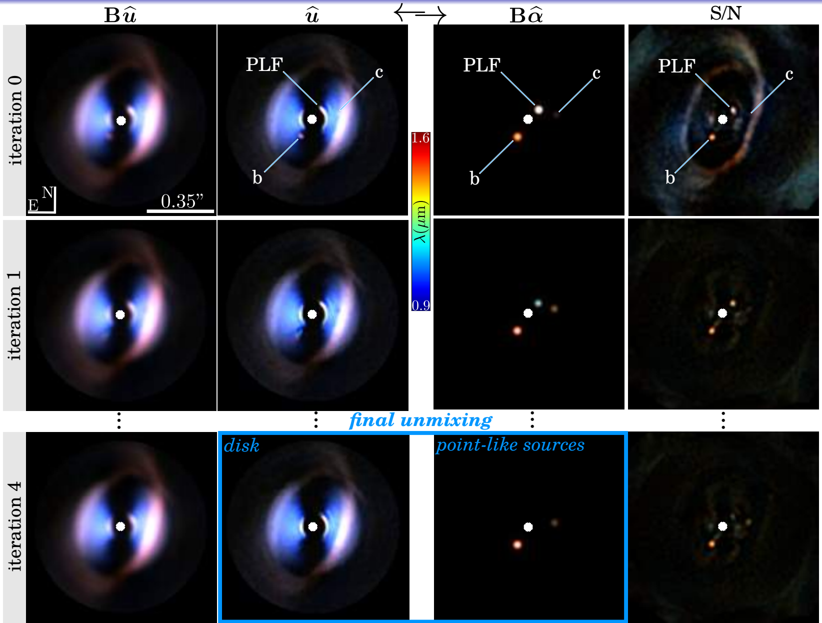
Example on VLT/SPHERE-IRDIS data (star HR 4786):



Results – *SPHERE-IFS data with synthetic disks*

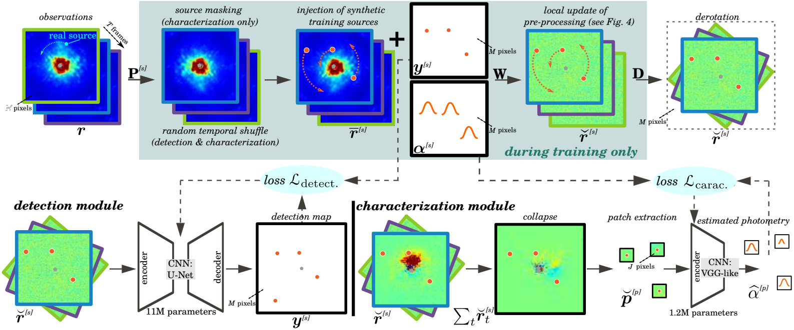


Unmixing point-like sources and extended features



Learning pipeline

Tasks: *supervised pixel-wise classification, supervised regression.*



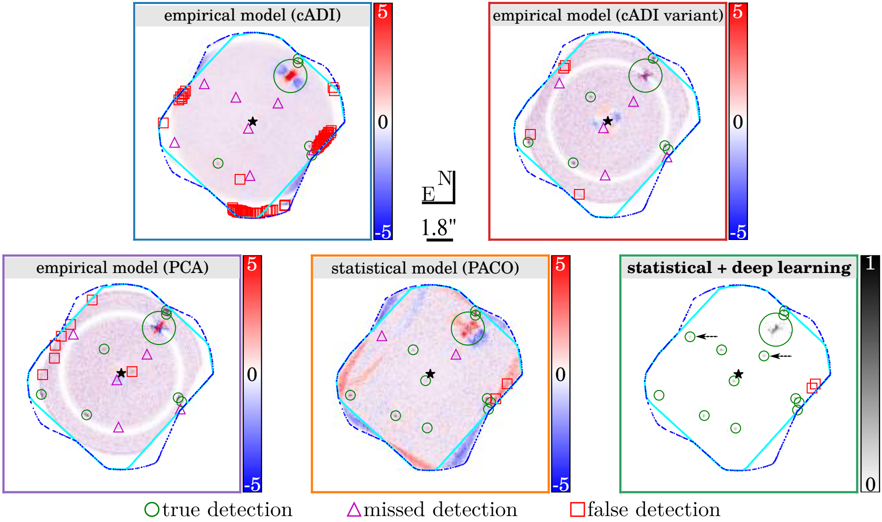
Detection loss: *similarity metric for very unbalanced classes.*

$$\mathscr{L}\left(\boldsymbol{y}^{[s]}, \widehat{\boldsymbol{y}}^{[s]}\right) = 1 - \underbrace{\frac{\sum_{m=1}^{M} \boldsymbol{y}_m^{[s]}\, \widehat{\boldsymbol{y}}_m^{[s]} + \epsilon}{\sum_{m=1}^{M} \boldsymbol{y}_m^{[s]} + \widehat{\boldsymbol{y}}_m^{[s]} + \epsilon}}_{\text{source error}} - \underbrace{\frac{\sum_{m=1}^{M} (1 - \boldsymbol{y}_m^{[s]})(1 - \widehat{\boldsymbol{y}}_m^{[s]} + \epsilon)}{\sum_{m=1}^{M} 2 - \boldsymbol{y}_m^{[s]} - \widehat{\boldsymbol{y}}_m^{[s]} + \epsilon}}_{\text{background error}}$$

⇒ Dedicated data-augmentation + whitening + loss: deep model specialized for each datacube without overfitting

Results: an example of detection maps

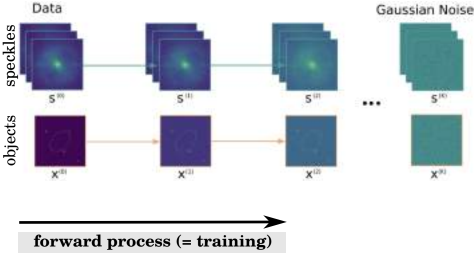
VLT/SPHERE-IRDIS data (HD 95086)

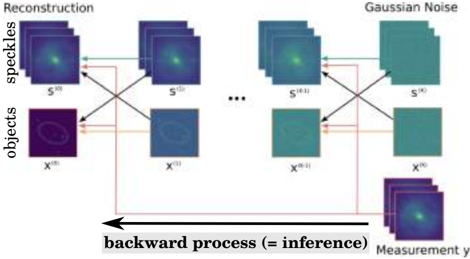


(Flasseur+ 2023, MNRAS, https://arxiv.org/abs/2303.02461)

Generative approach via diffusion model

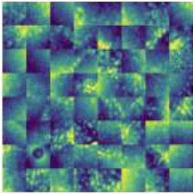
Principle:



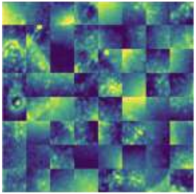


Results:

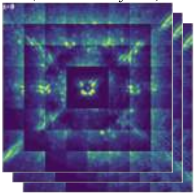
examples of training speckles



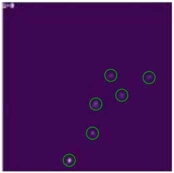
examples of generated speckles



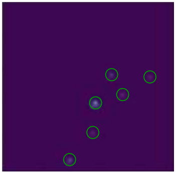
reconstructed speckles
(normalized by tiles)



reconstructed object



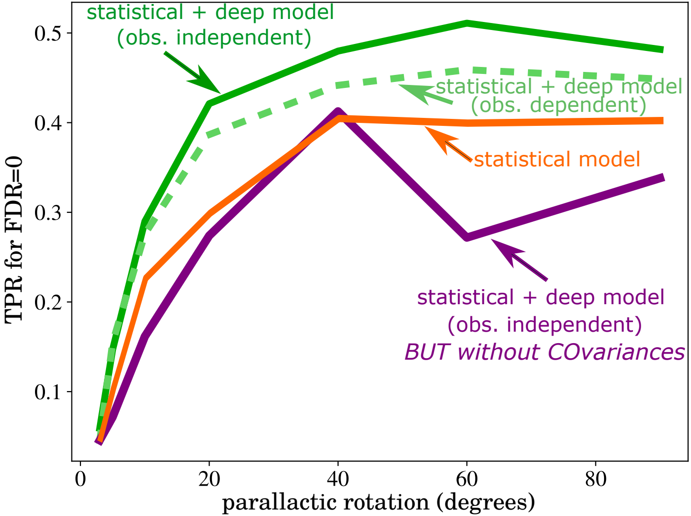
groundtruth object



$\Rightarrow$ **Realistic generated speckles but limited detection sensitivity**

Model ablation: importance of statistical model

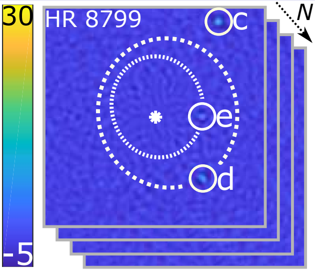
ROCs: mean results on VLT/SPHERE-IRDIS data



⇒ Modeling statistically the covariances is critical!

T. Bodrito, O. Flasseur+, to be submitted

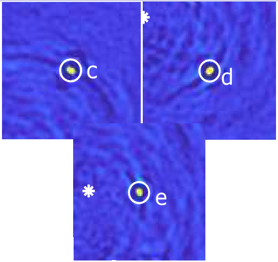
Fusing multiple observations

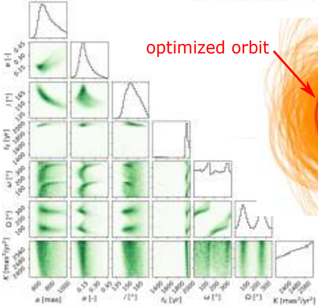


$\Longrightarrow$

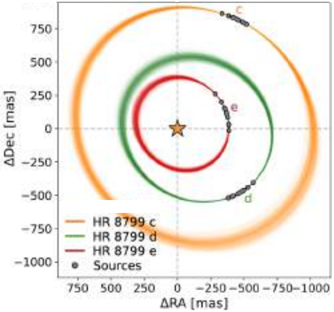
multi-epoch combination

$\Longrightarrow$





optimized orbit



Dallant+ 2023 A&A

gain in sensitivity $= \sqrt{N_{\textbf{observations}}}$