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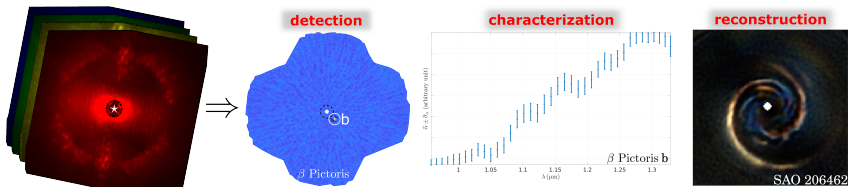


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From statistical learning to deep learning for improved modeling of the nuisance component in high-contrast imaging

Olivier Flasseur¹, Théo Bodrito²

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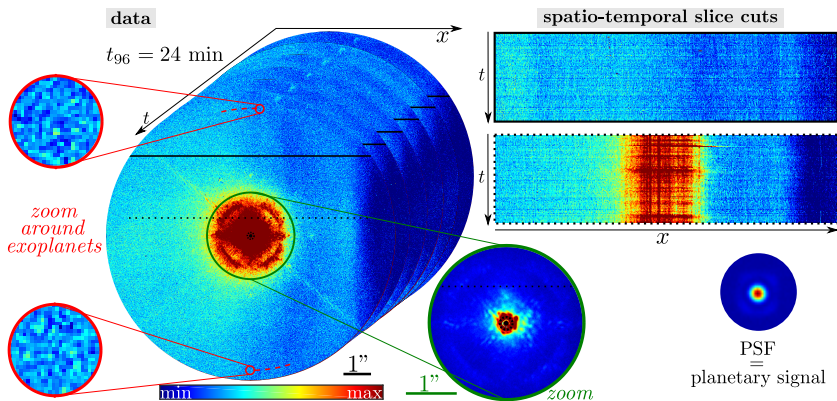
Théo B. (PhD student)



Exosystèmes IV - Jan. 30th - Feb. 1st 2024 - Lyon

Goal: modeling the nuisance component (speckles + noise)

angular differential imaging (ADI) = temporal diversity



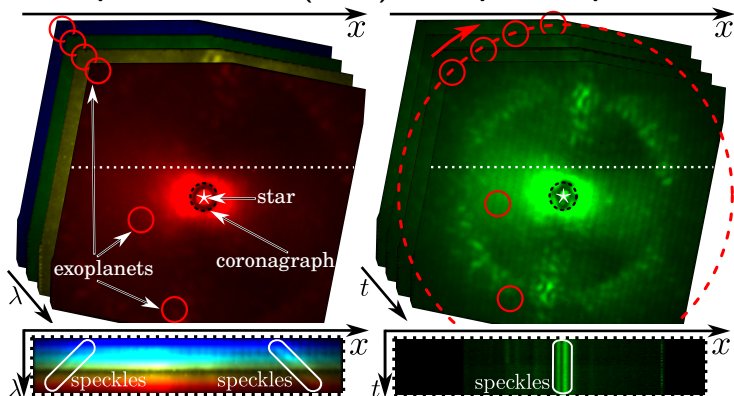
Peculiarities

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

⇒ **Signal unmixing is critical**

Goal: modeling the nuisance component (speckles + noise)

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



Peculiarities

- **Faint signal** from the exoplanets
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- **Multi-spectral** data available

⇒ **Signal unmixing is critical**

Positioning within the post-processing landscape

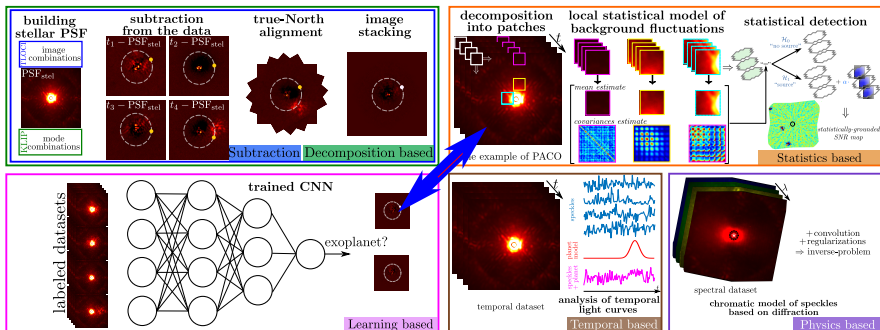
Subtraction - Decomposition: cADI(Marois+ 2006); LOCI(Lafrénière+ 2007); ALOCI(Currie+ 2012); KLIP/PCA(Soumer+ 2012),(Amara+ 2012); TLOCI(Lafrénière+ 2014); LLSG(Gonzalez+ 16); NMF(Ren+ 18)

Statistics: MOODS(Smith+2009); ANDROMEDA(Cantalloube+ 2016); FMMF(Ruffio+ 2017); PACO(Flasseur+ 2020), etc.

(Deep) Learning: S4(Fergus+ 2014); (NA)SODINN(Gonzalez+ 2017),(Cantero+ 2023); CNN(Yip+ 2020)

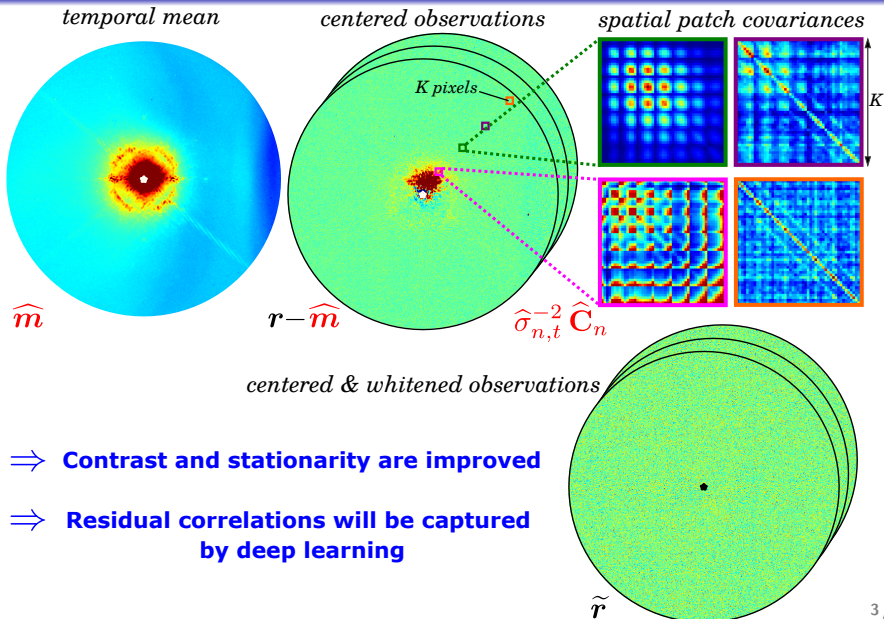
Temporal: STIM(Pairet+ 2019); RSM(Dahlqvist+ 2020); TRAP(Samlund+ 2021); HSR(Gebhard+ 2022)

Physics: PeX(Devanay+ 2017), MEDUSAE(Cantalloube+ 2018), etc.



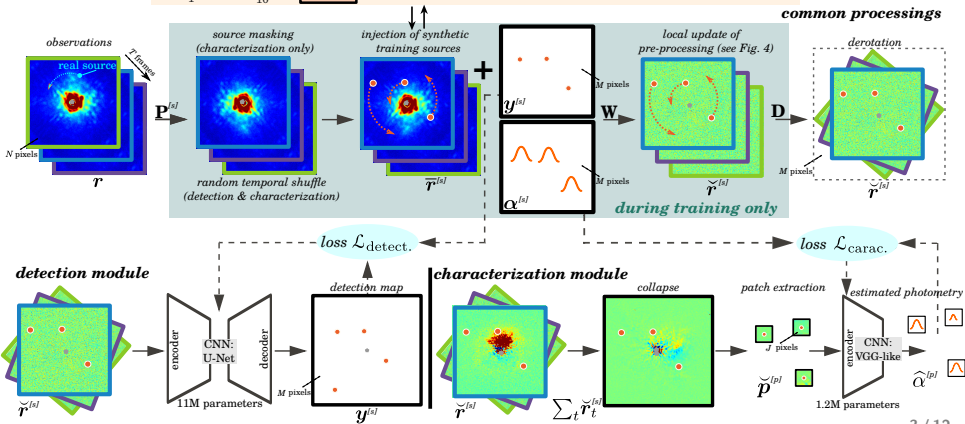
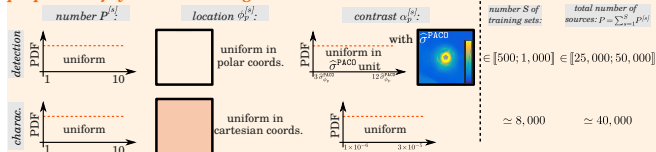
⇒ **Motivation: combining advantages of two approaches**

Pre-processing: *removing (most of) the correlations*



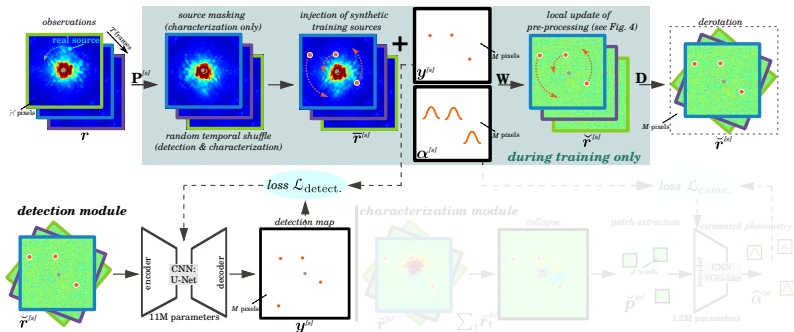
Deep learning: capturing residual correlations

properties of synthetic training sources



Detection pipeline

Task: supervised pixel-wise classification



Loss function: custom similarity metric for very unbalanced classes

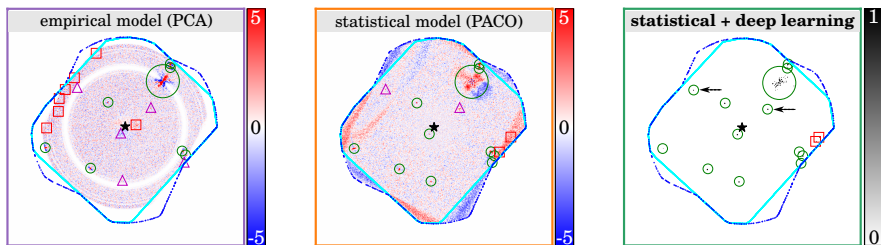
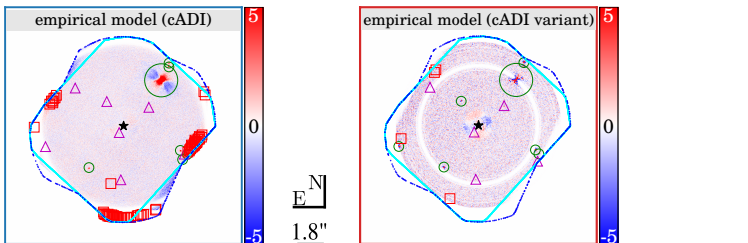
$$\mathcal{L}(\mathbf{y}^{[s]}, \hat{\mathbf{y}}^{[s]}) = 1 - \underbrace{\frac{\sum_{m=1}^M \mathbf{y}_m^{[s]} \hat{\mathbf{y}}_m^{[s]} + \epsilon}{\sum_{m=1}^M \mathbf{y}_m^{[s]} + \hat{\mathbf{y}}_m^{[s]} + \epsilon}}_{\text{source error}} - \underbrace{\frac{\sum_{m=1}^M (1 - \mathbf{y}_m^{[s]}) (1 - \hat{\mathbf{y}}_m^{[s]}) + \epsilon}{\sum_{m=1}^M 2 - \mathbf{y}_m^{[s]} - \hat{\mathbf{y}}_m^{[s]} + \epsilon}}_{\text{background error}}$$

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

Results: an example of inferred detection maps

VLT/SPHERE-IRDIS data

star: HD 95086



○ true detection

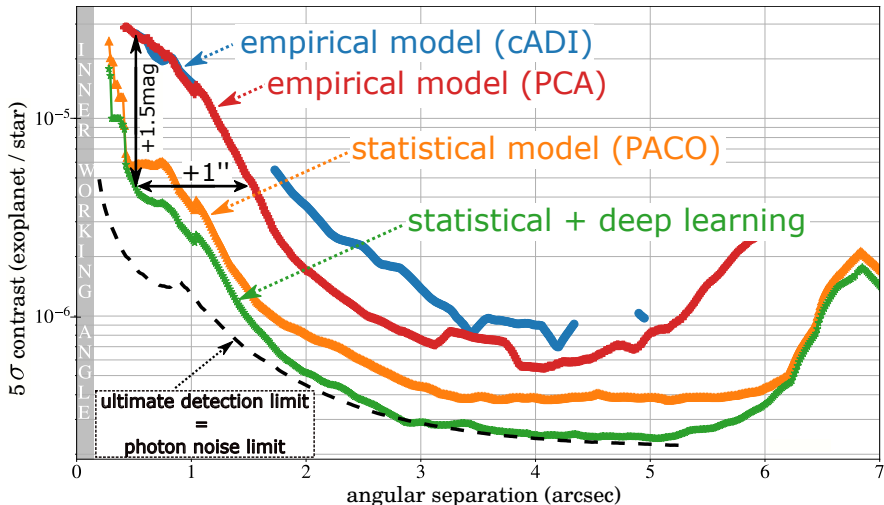
△ missed detection

□ false detection

Results: improved detection sensitivity

VLT/SPHERE-IRDIS data

star: HIP 88399



⇒ additional gain up to 0.5 mag + \simeq optimal far from the star

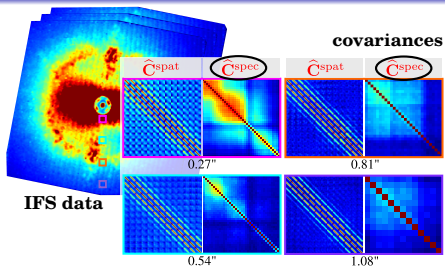
Results: joint multi-spectral processing

Method

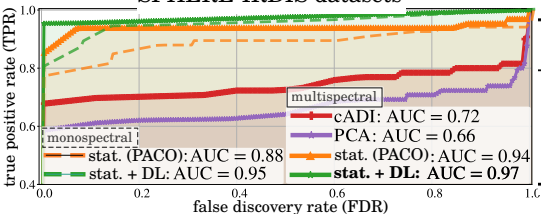
Statistical learning:

joint modeling of spatial and spectral covariances.

Deep learning: *training with physical SED models (ExoREM).*



SPHERE-IRDIS datasets

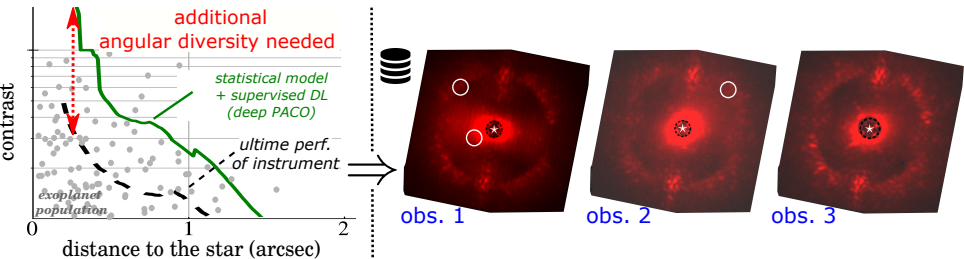


SPHERE-IFS datasets

PCA	stat. (PACO)	stat. + DL
0.65	0.80	0.96
0.36	0.68	0.76
0.52	0.79	0.85

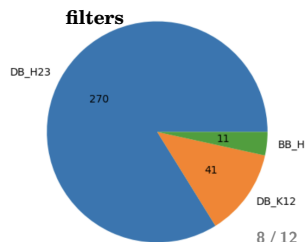
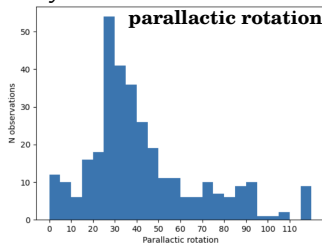
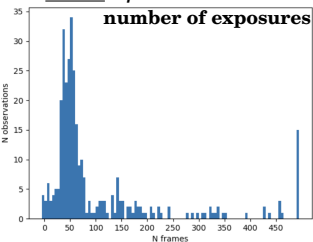
⇒ **Better precision/recall trade-off than a posteriori combination**

Learning the nuisance from multiple observations



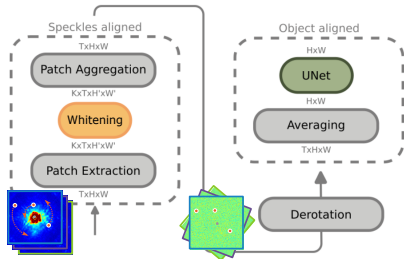
⇒ Leveraging database diversity to build highly non-linear models

Data: part of SHINE survey



Comparison between model architectures

observation-dependent model



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

Outputs

model (1): binary detection map



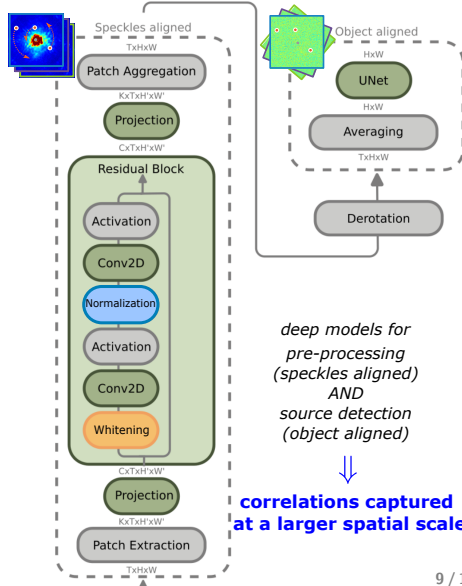
model (2): residual flux distribution cube



reconstruction loss (flux)
instead of detection loss

↓
improved robustness

observation-independent model



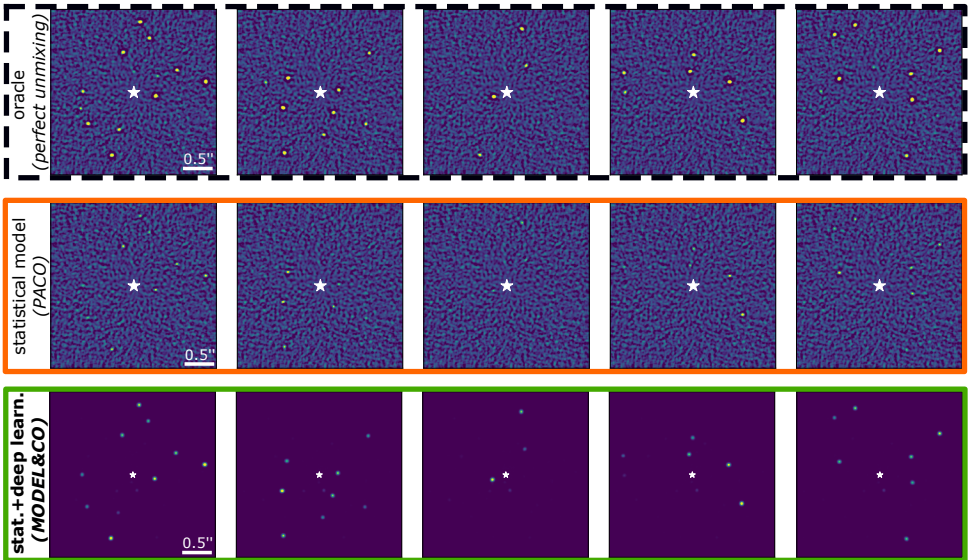
deep models for
pre-processing
(speckles aligned)
AND
source detection
(object aligned)

↓
**correlations captured
at a larger spatial scale**

Results: inferred detection maps

VLT/SPHERE-IRDIS data

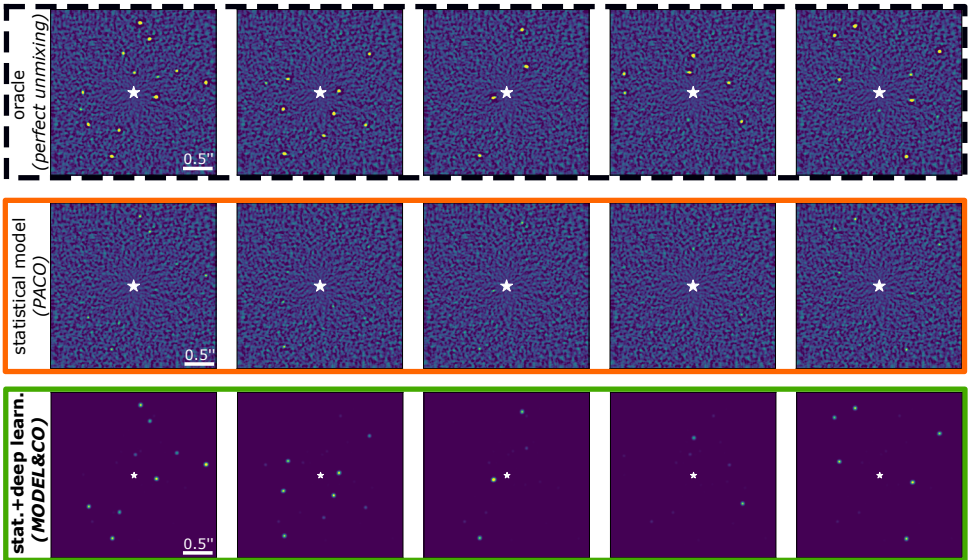
parallactic rotation $\approx 23^\circ$



Results: inferred detection maps

VLT/SPHERE-IRDIS data

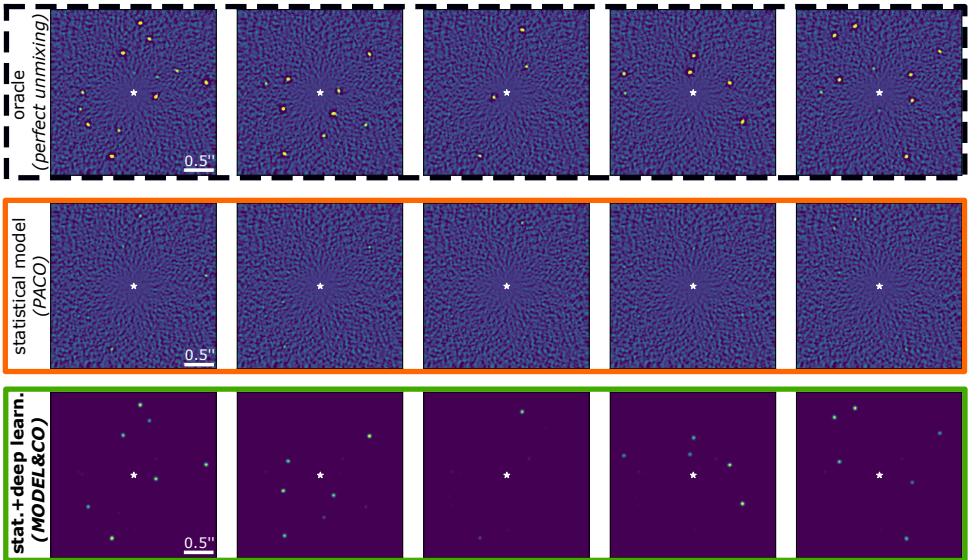
parallactic rotation $\simeq 10^\circ$



Results: inferred detection maps

VLT/SPHERE-IRDIS data

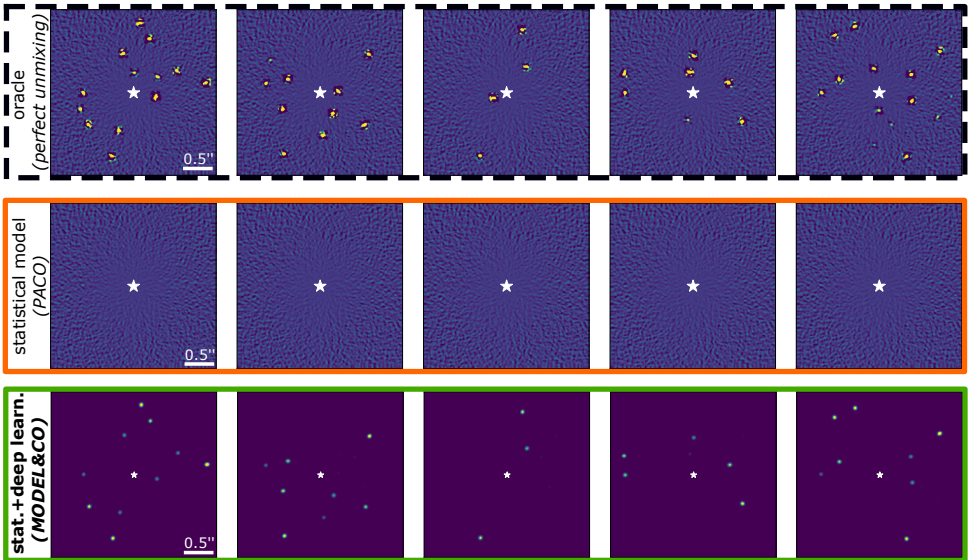
parallactic rotation $\simeq 6^\circ$



Results: inferred detection maps

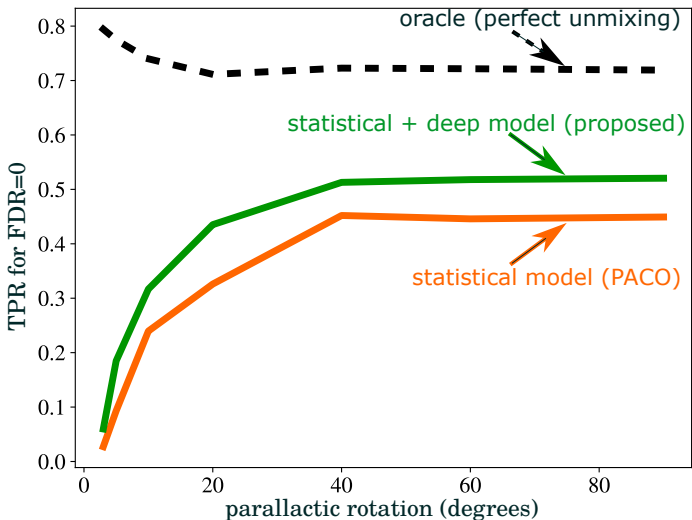
VLT/SPHERE-IRDIS data

parallactic rotation $\simeq 2^\circ$!



Results: a better precision / recall trade-off

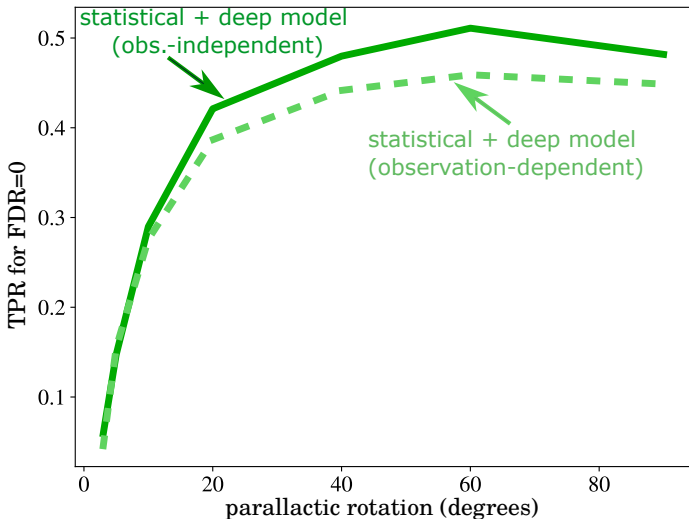
ROCs: mean results on VLT/SPHERE-IRDIS data



⇒ **Combined model (stat. + DL) leads to better fidelity**

Results: a better precision / recall trade-off

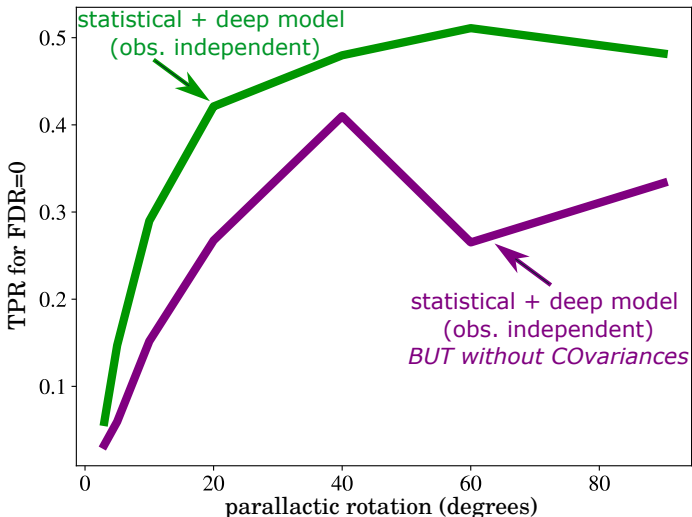
ROCs: mean results on VLT/SPHERE-IRDIS data



⇒ Capturing speckle diversity and large scale correlation is helpful

Model ablation: importance of statistical model

ROCs: mean results on VLT/SPHERE-IRDIS data



⇒ **Modeling statistically the covariances is critical!**

Take-home messages:

- *Combining stat. & deep models improves precision-recall,*
- *Modeling the covariances is critical,*
- *Leveraging from observations archive bypasses the limit of ADI,*
- *A single model: once trained, inference is super fast.*

⇒ **Could be useful for ELT's observations**
 (highly structured nuisance, massive data, limited ADI)

What's next?

- *Nuisance's model is flexible → disk reconstruction.*
- *Integrating more explicitly direct image formation model \mathbf{M} ,*
 - joint estimation nuisance s and objects x with **obs** = $s + \mathbf{M}x$
 - solving an inverse problem with neural network as proximal operator

$$\arg \max_{\mathbf{x}, \{\mu_{ij}, C_{ij}\}_{(i,j) \in \mathcal{S}}} \mathbb{P}_x(\mathbf{x}) \prod_{(i,j) \in \mathcal{S}} \prod_t \mathbb{P}_s(\mathbf{P}_{ij}(\mathbf{Y} - R_\phi(\mathbf{x}))_t | \mu_{ij}, C_{ij}) \mathbb{P}_C(C_{ij})$$

flux distrib. *nuisance parameters*