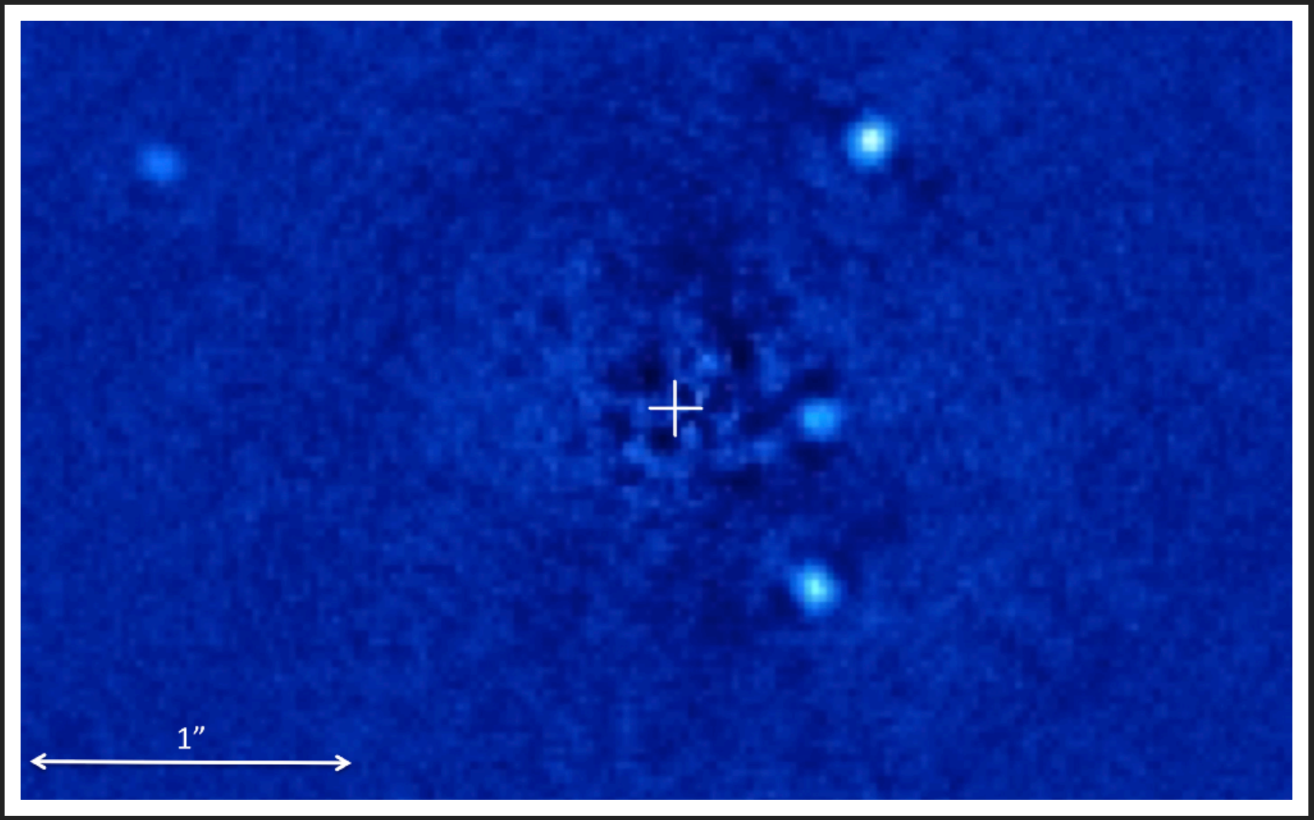


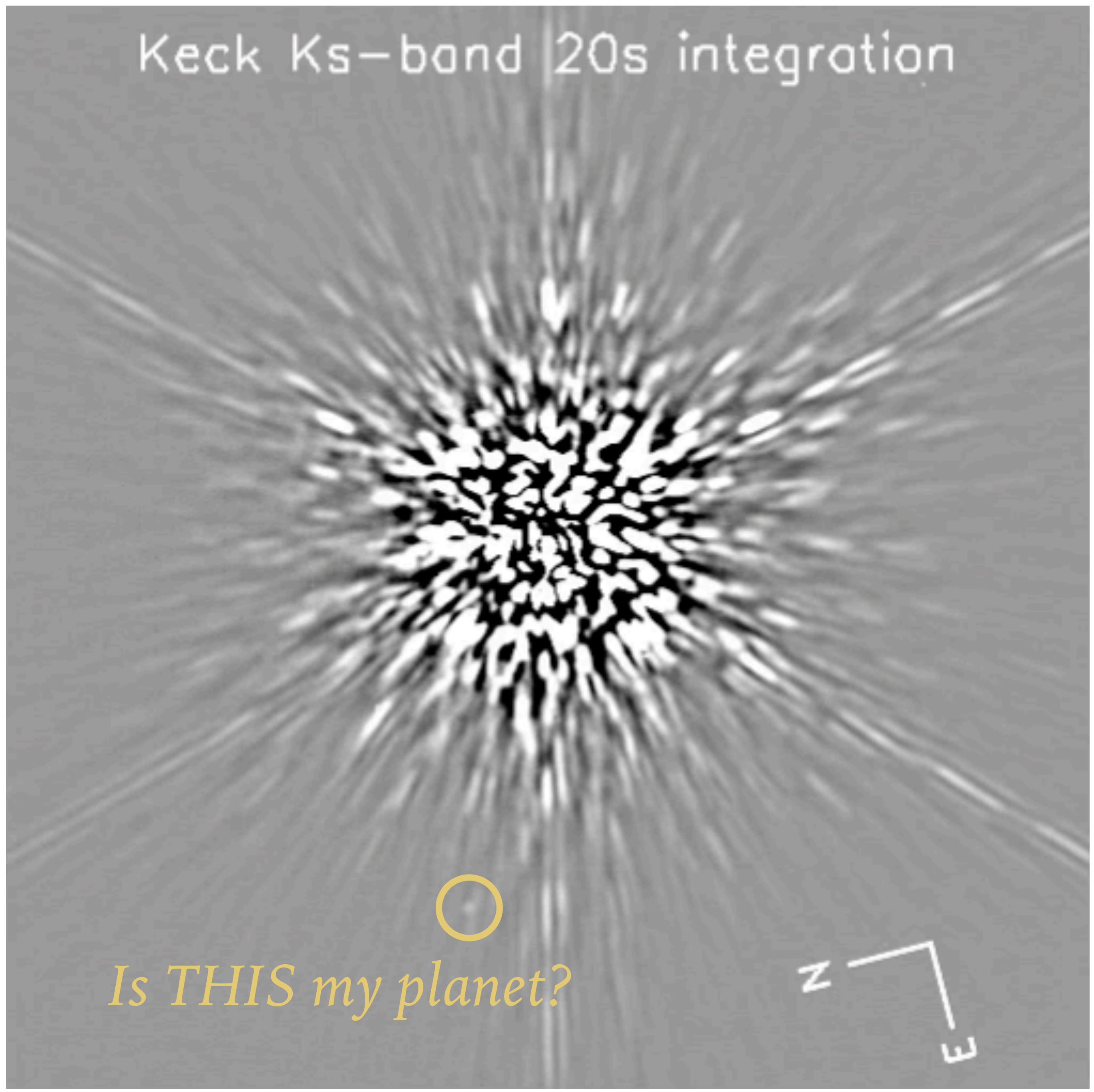
OLIVIER ABSIL - UNIVERSITY OF LIÈGE

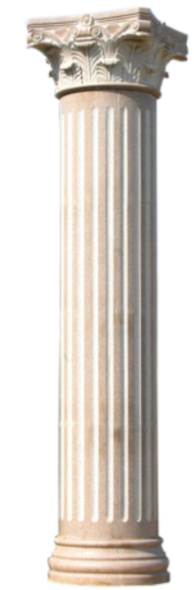
DEEP LEARNING FOR DIRECT EXOPLANET IMAGING

A NEEDLE IN A HAYSTACK

adaptive optics

coronagraphy





observing strategies

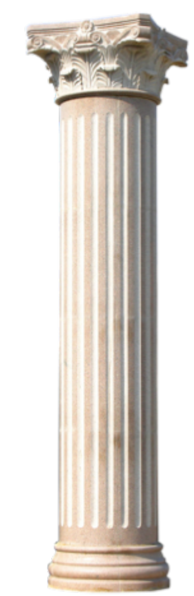
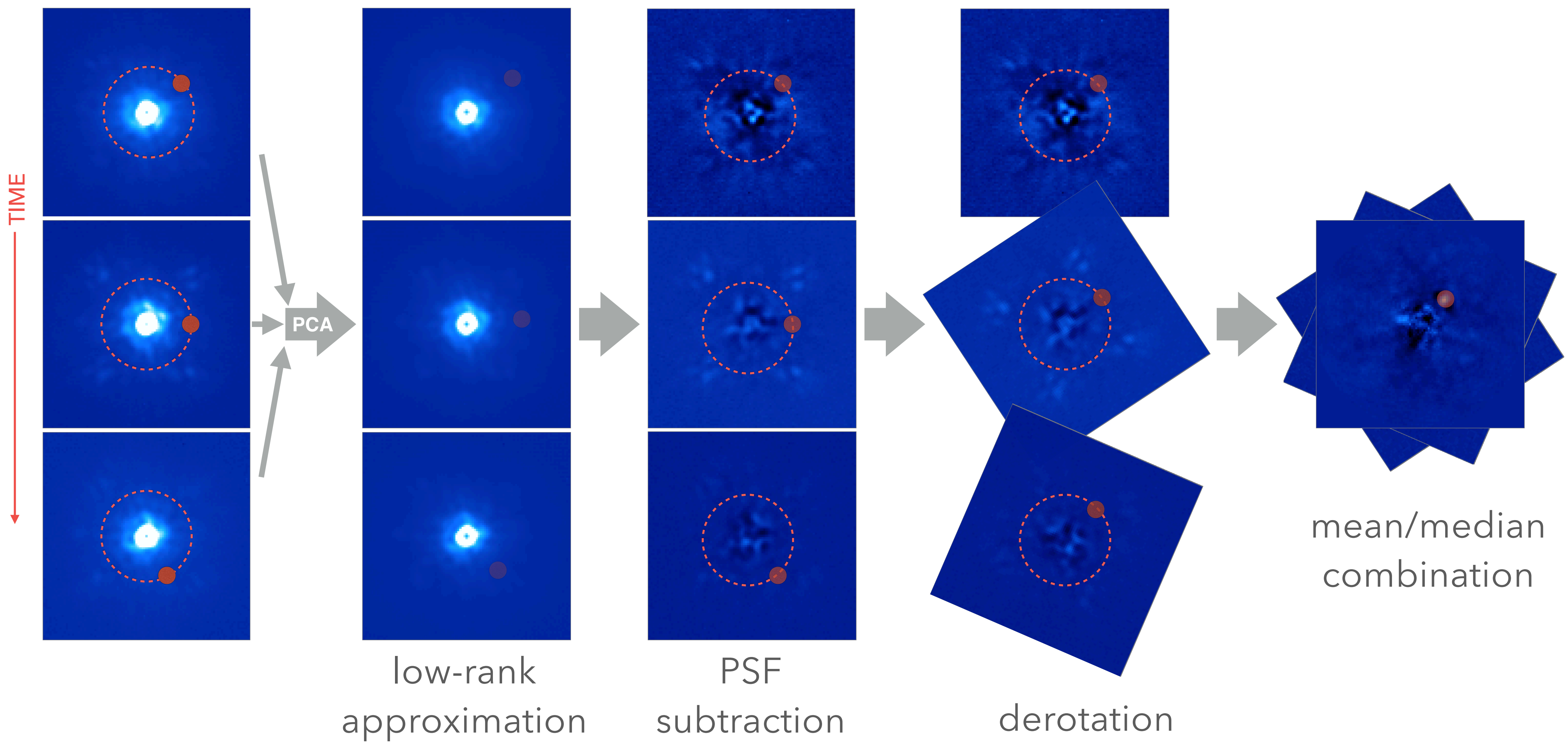


image processing

Soummer et al 2012; Amara & Quanz 2012

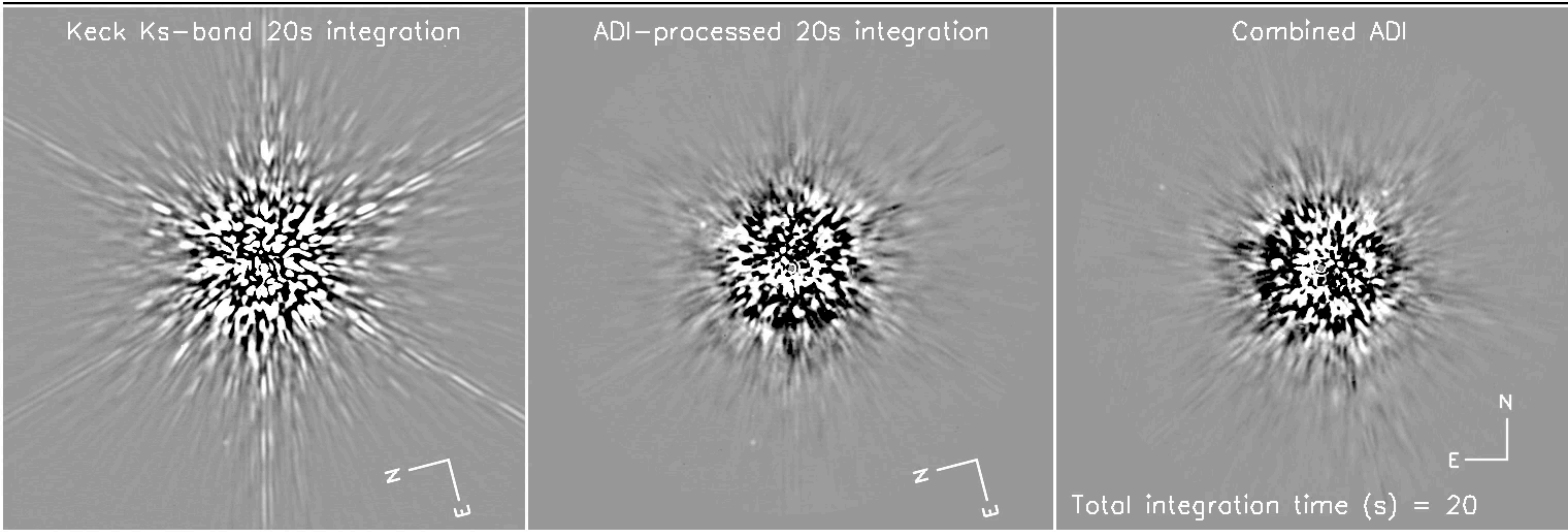
ANGULAR DIFFERENTIAL IMAGING (USING PCA)



Marois et al. 2006

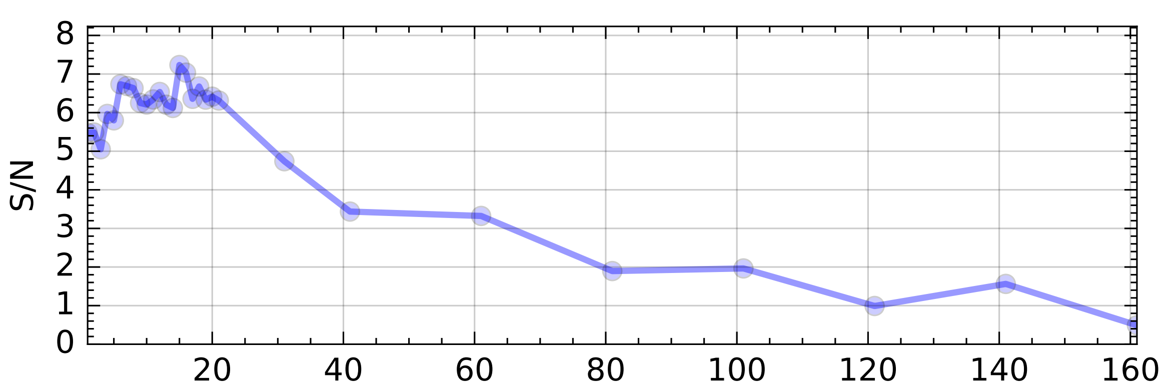
ANGULAR DIFFERENTIAL IMAGING AT WORK

Raw data → PSF subtraction → Derotation + combination



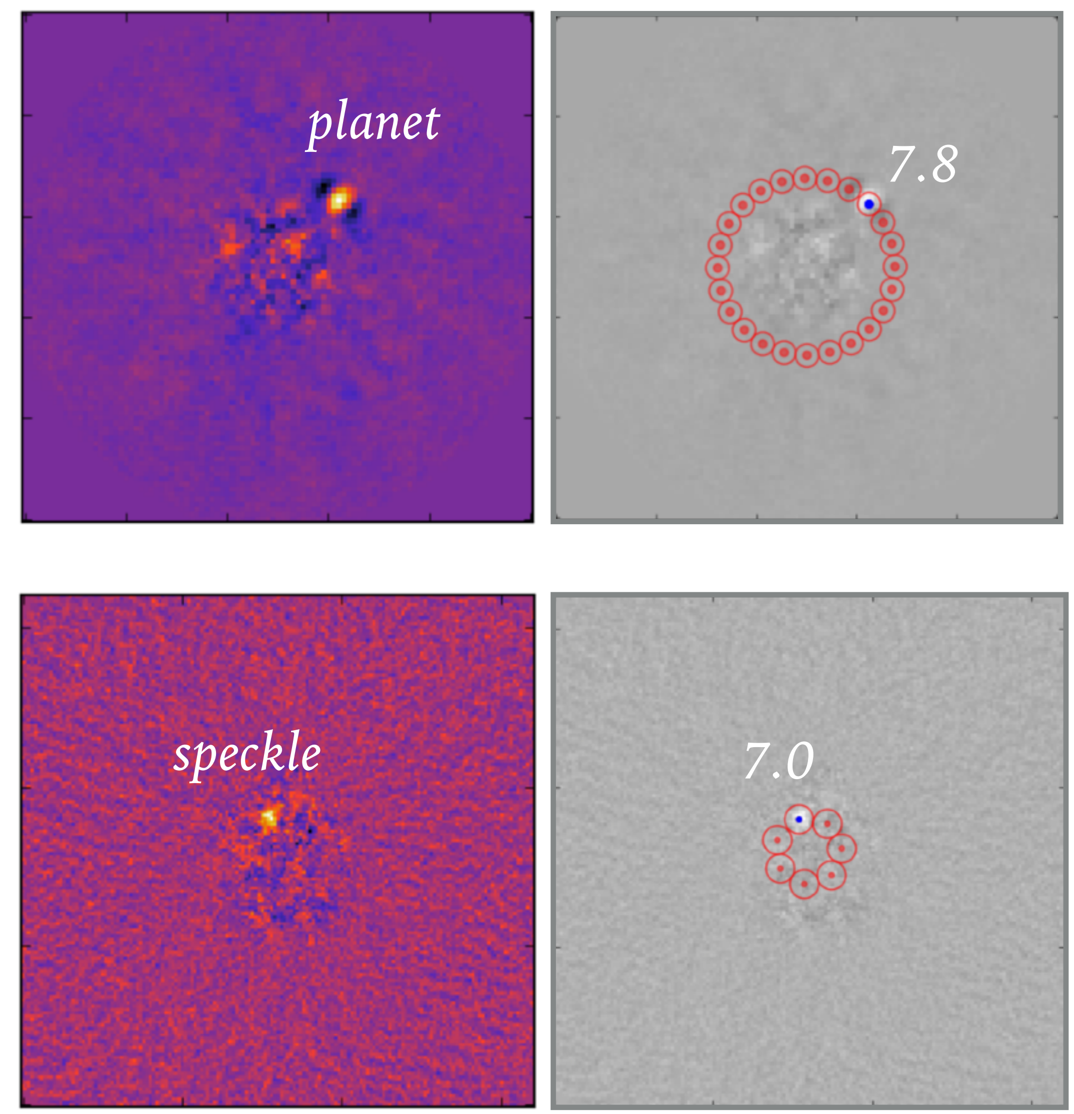
CLAIMING DETECTIONS IN THE FINAL IMAGE

- S/N computed in concentric annuli, for each resolution element (resel)
- Standard threshold = 5σ
- Major caveats
  - noise generally not Gaussian
  - small sample statistics
- Behavior of S/N vs PCA rank can help identifying true signal



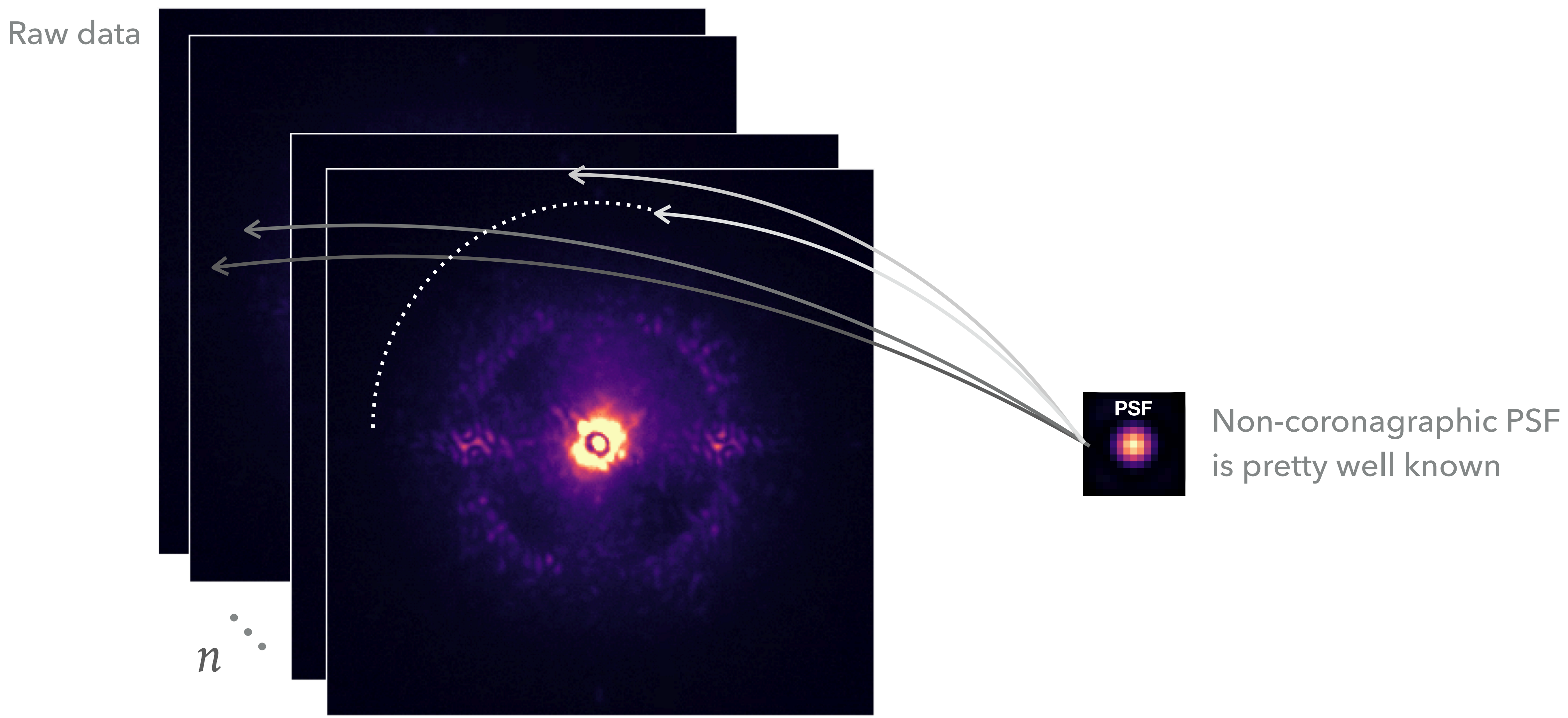
$$S/N = \frac{\overline{x}_1 - \overline{x}_2}{s_2\sqrt{1+\frac{1}{n_2}}}$$

(two-sample t-test)



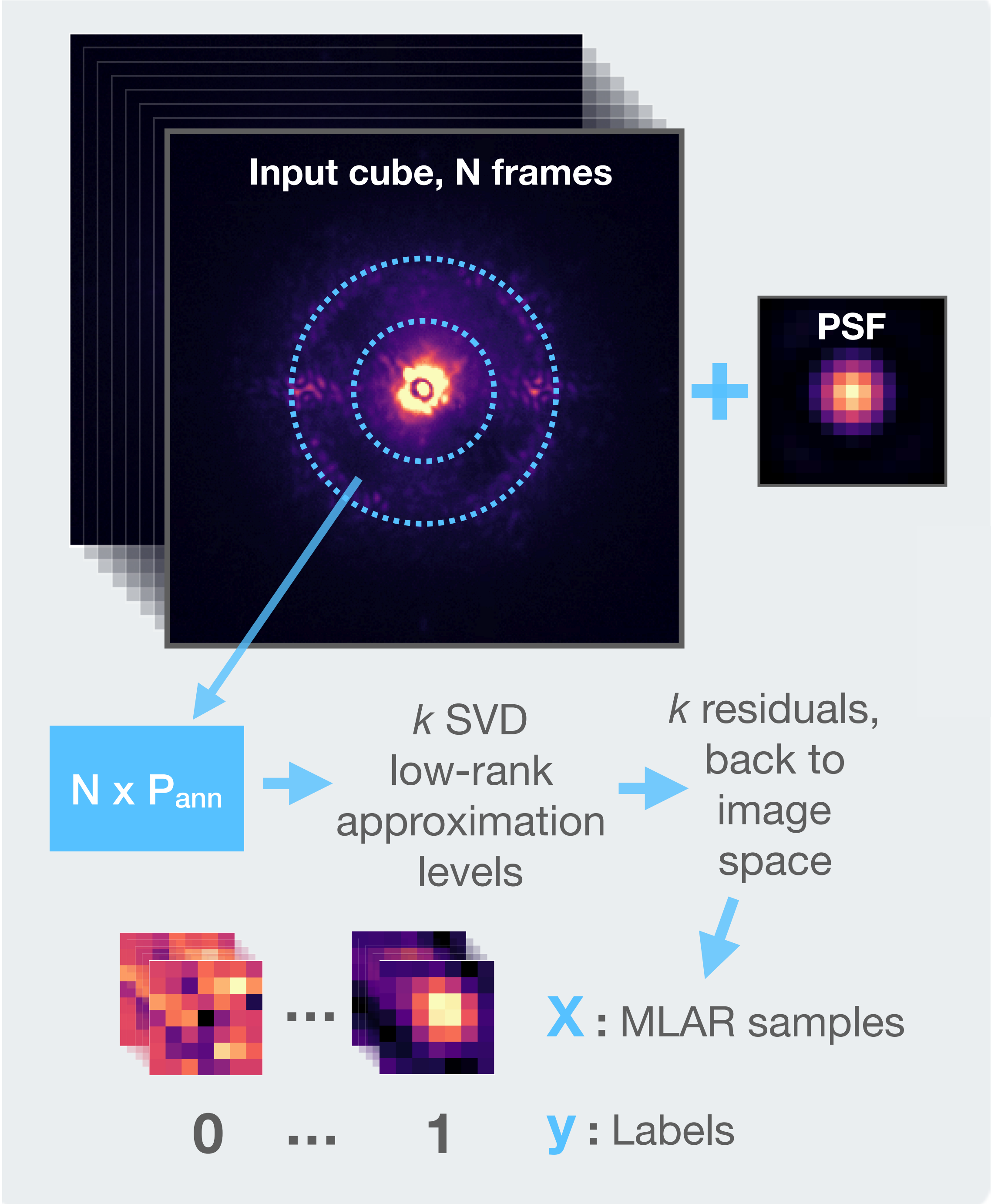
TOWARDS A SUPERVISED CLASSIFIER

- No labeled HCI data sets –> need to rely on fake planet injections (following ADI trajectories)



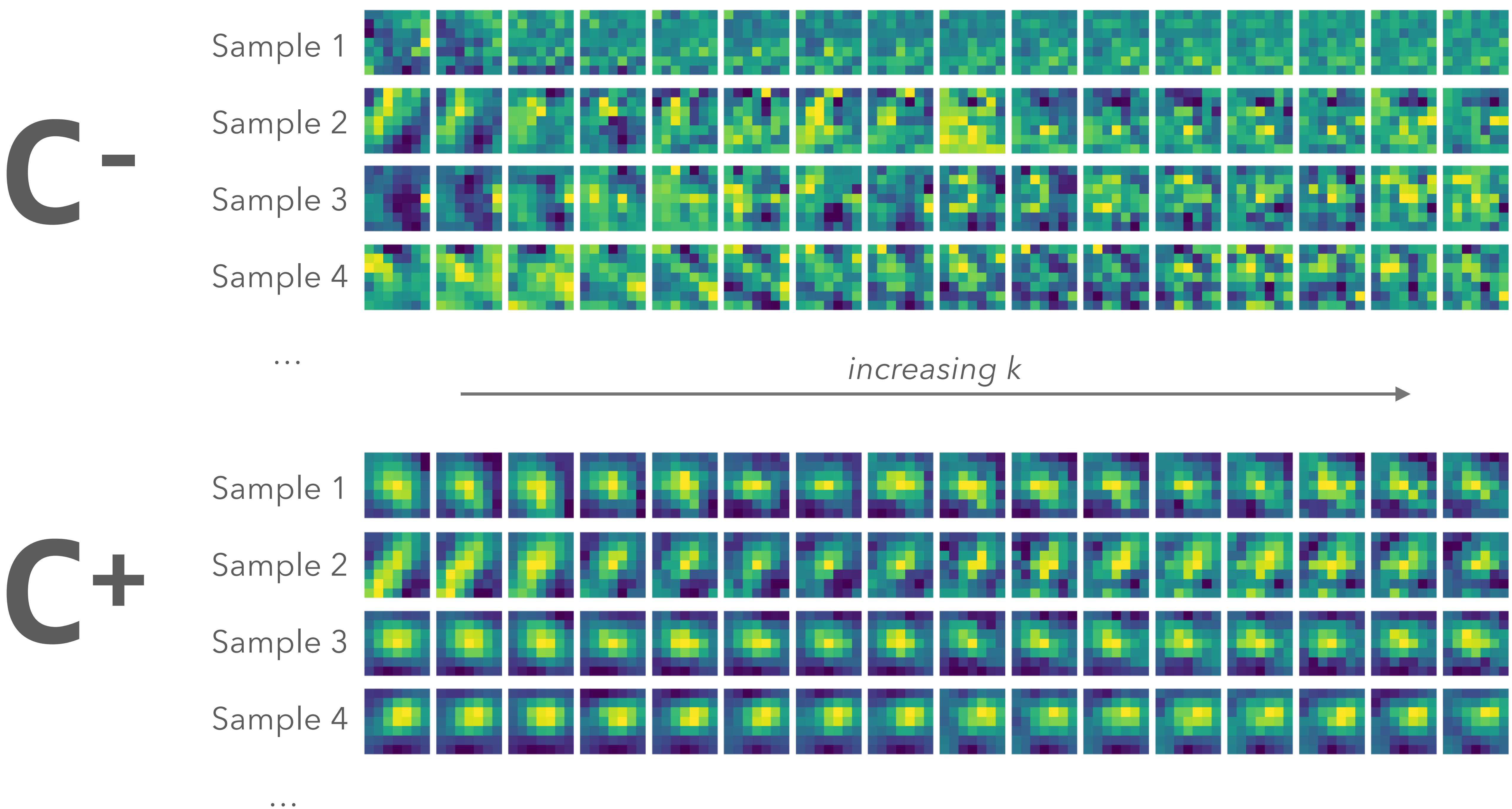
TOWARDS A SUPERVISED CLASSIFIER

- Raw data too noisy, but final image not enough for training
  - divide final image into small patches
  - data augmentation mandatory
- Planets and speckles look alike
  - use behavior vs PCA rank as discriminative feature
    –> Multi-level Low-rank Approximation Residual (MLAR)



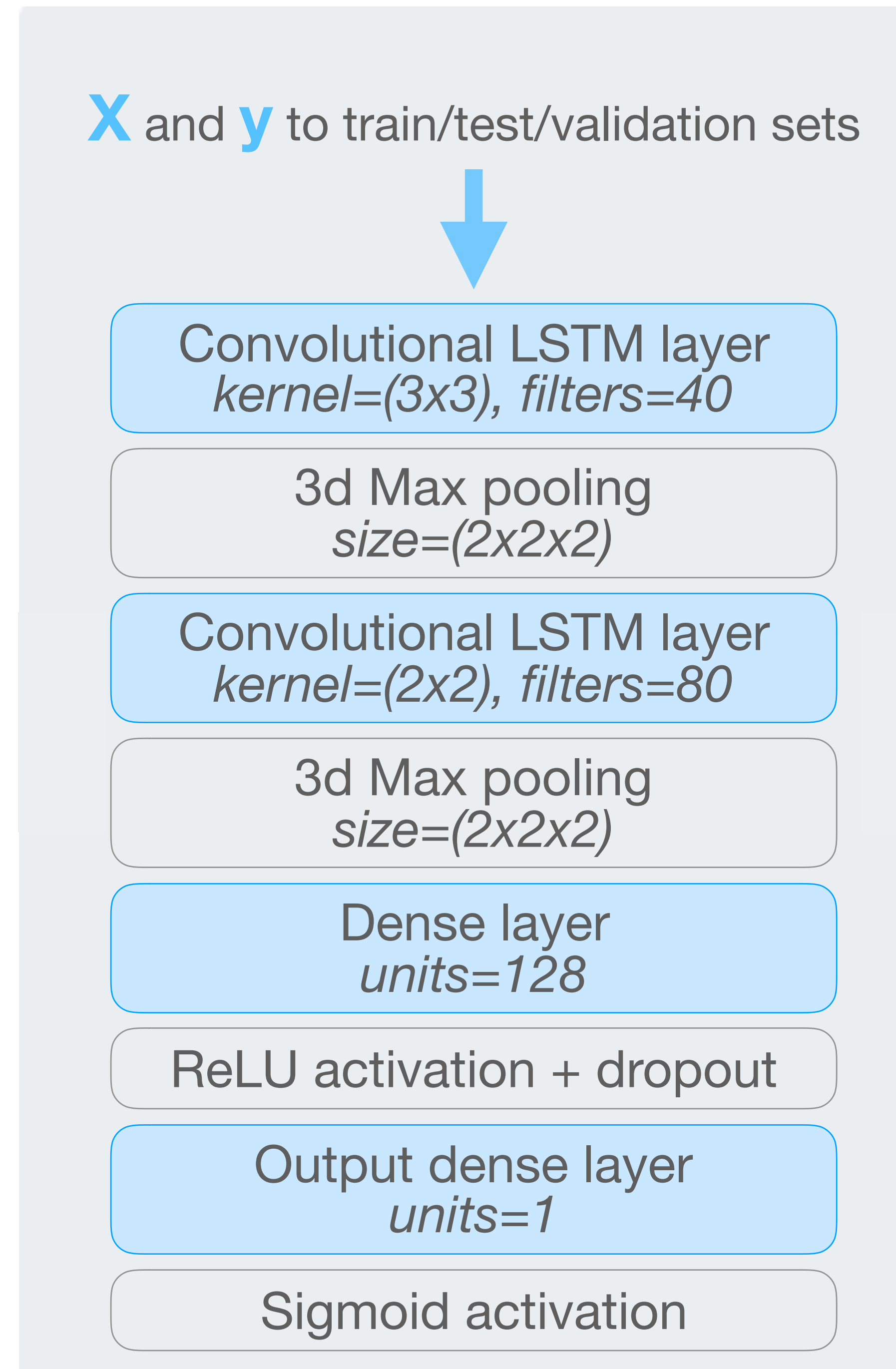
LABELED DATA SET

Labels: $\hat{\mathbf{y}} \in \{\mathbf{c}^-, \mathbf{c}^+\}$

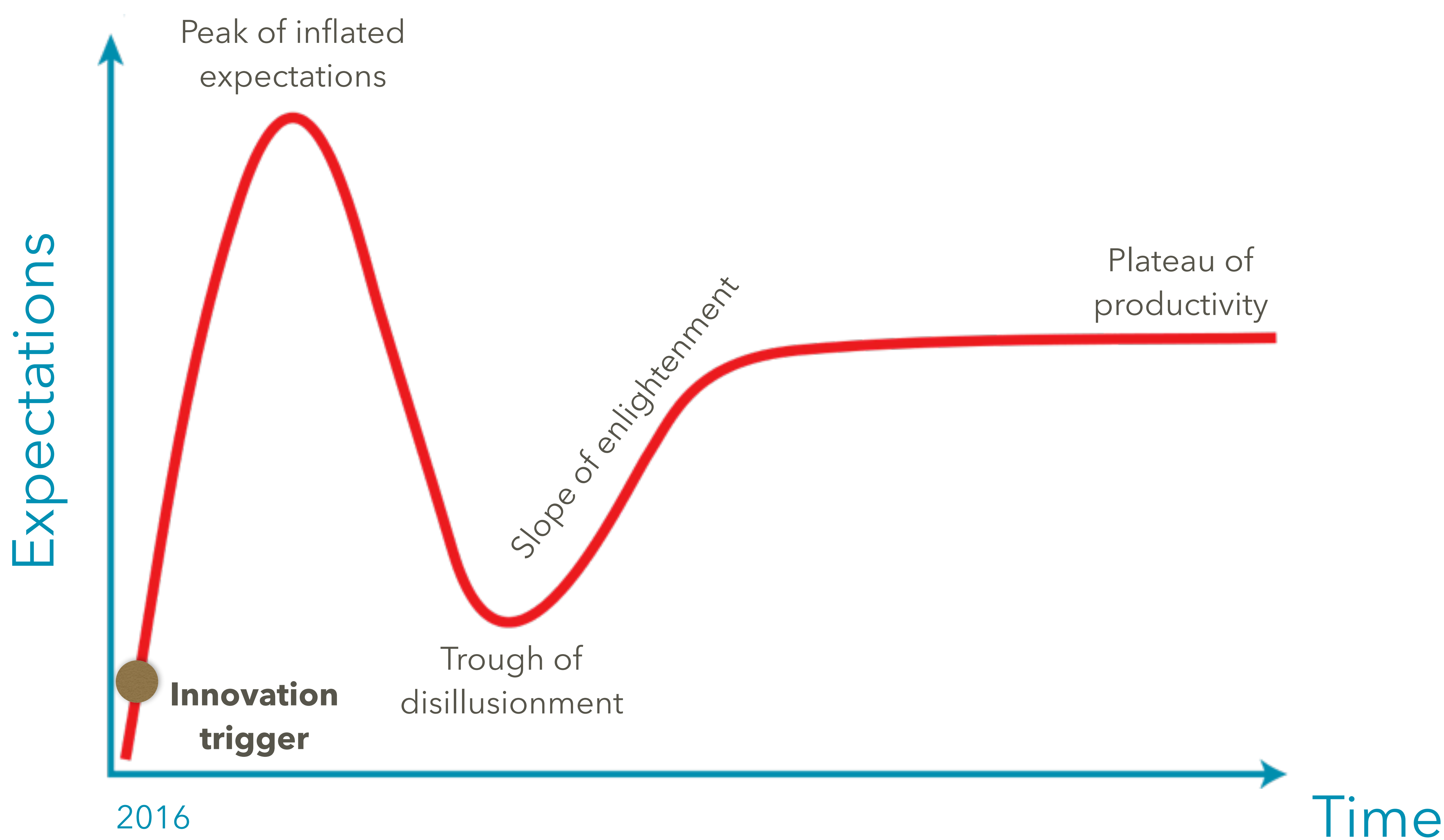


BUILDING A DISCRIMINATIVE MODEL: SODINN

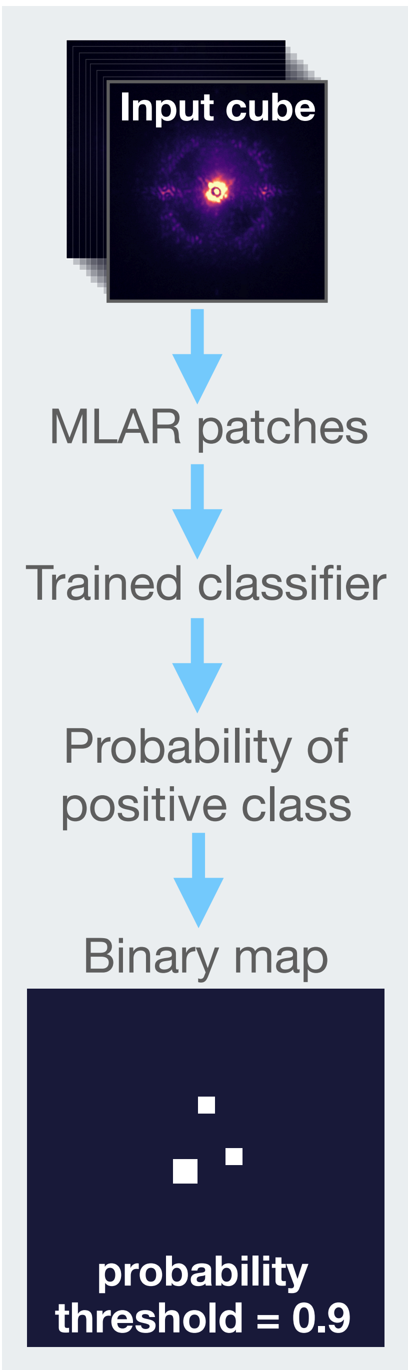
- Training a classifier $f : \mathcal{X} \to \mathcal{Y}$
- Goal: make predictions on unseen samples $\hat{y}_n = p(c^+ \mid \mathrm{MLAR\ sample})$
- SODINN network architecture based on:
  - convolutional neural network (CNN), leveraging image structure
  - long-short term memory (LSTM), leveraging behavior vs PCA rank



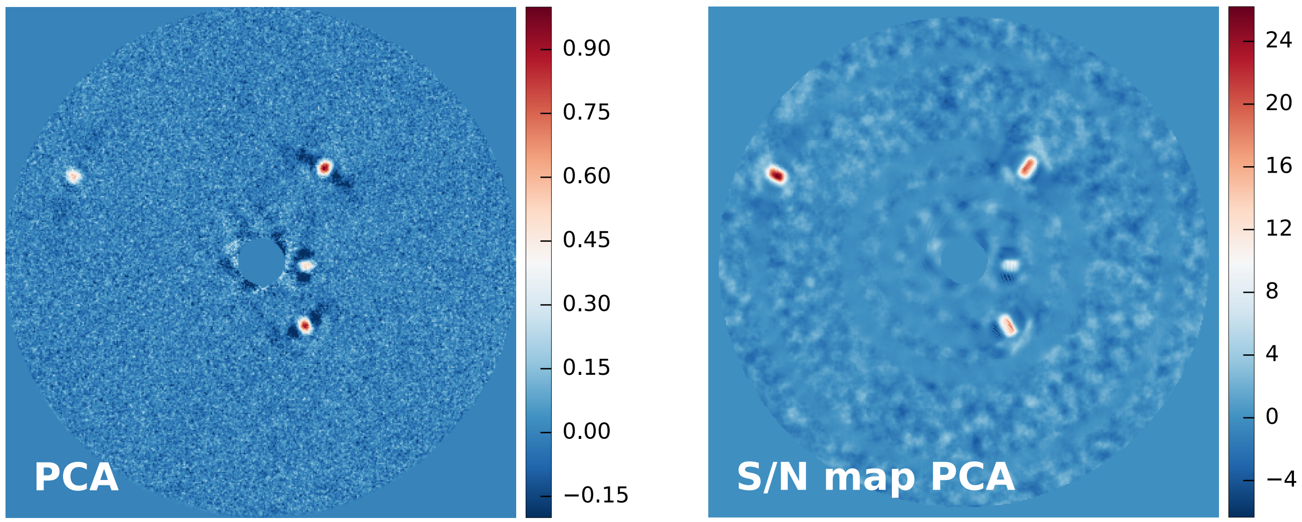
INTERLUDE #1: THE HYPE CURVE

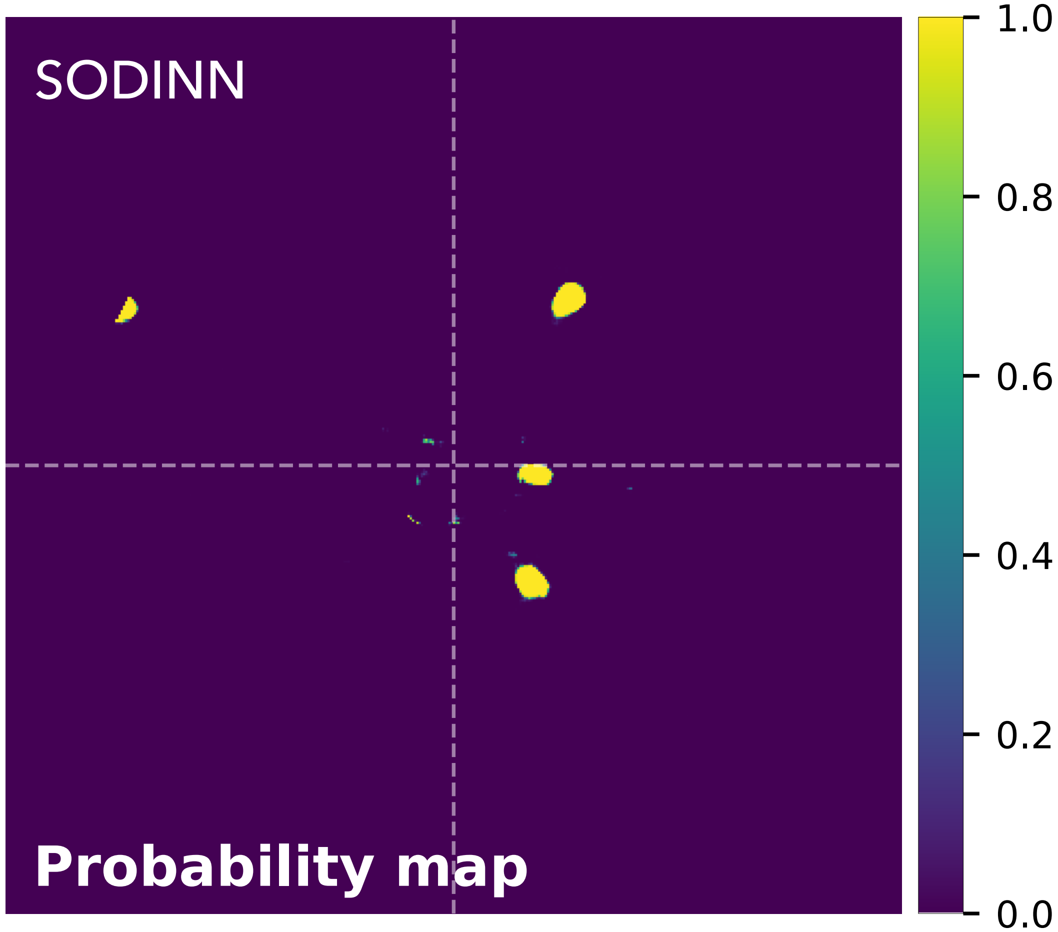


SODINN AT WORK

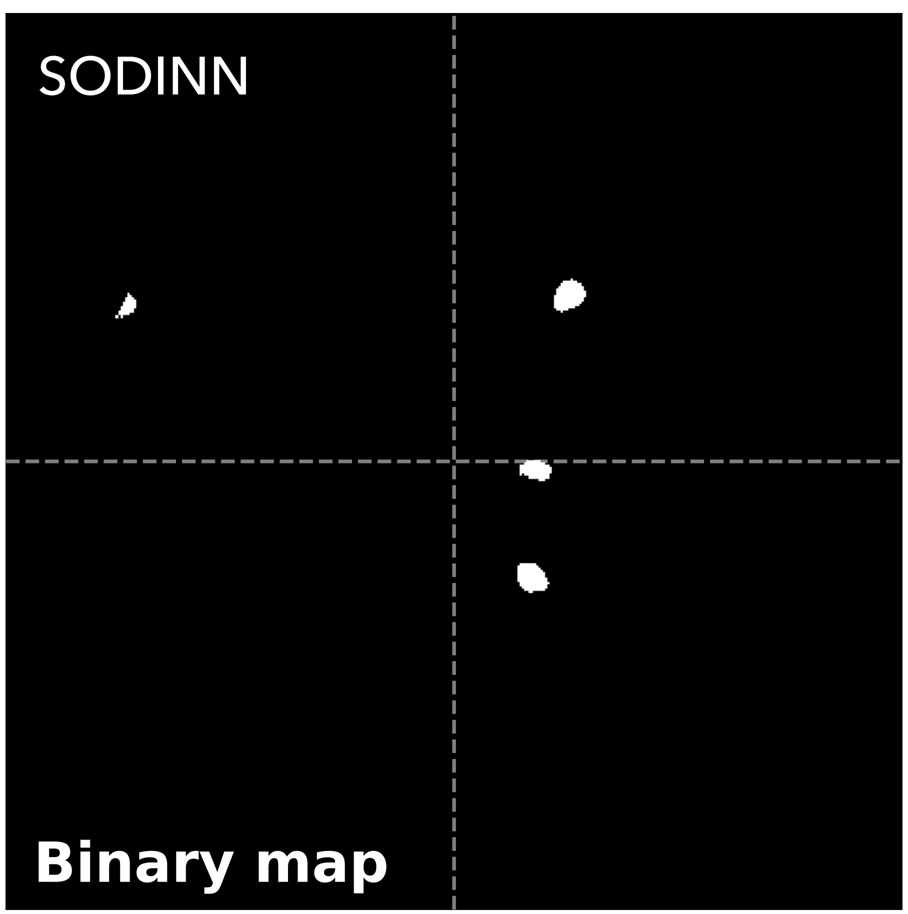


LBTI/LMIRCam data on well-known HR8799 system





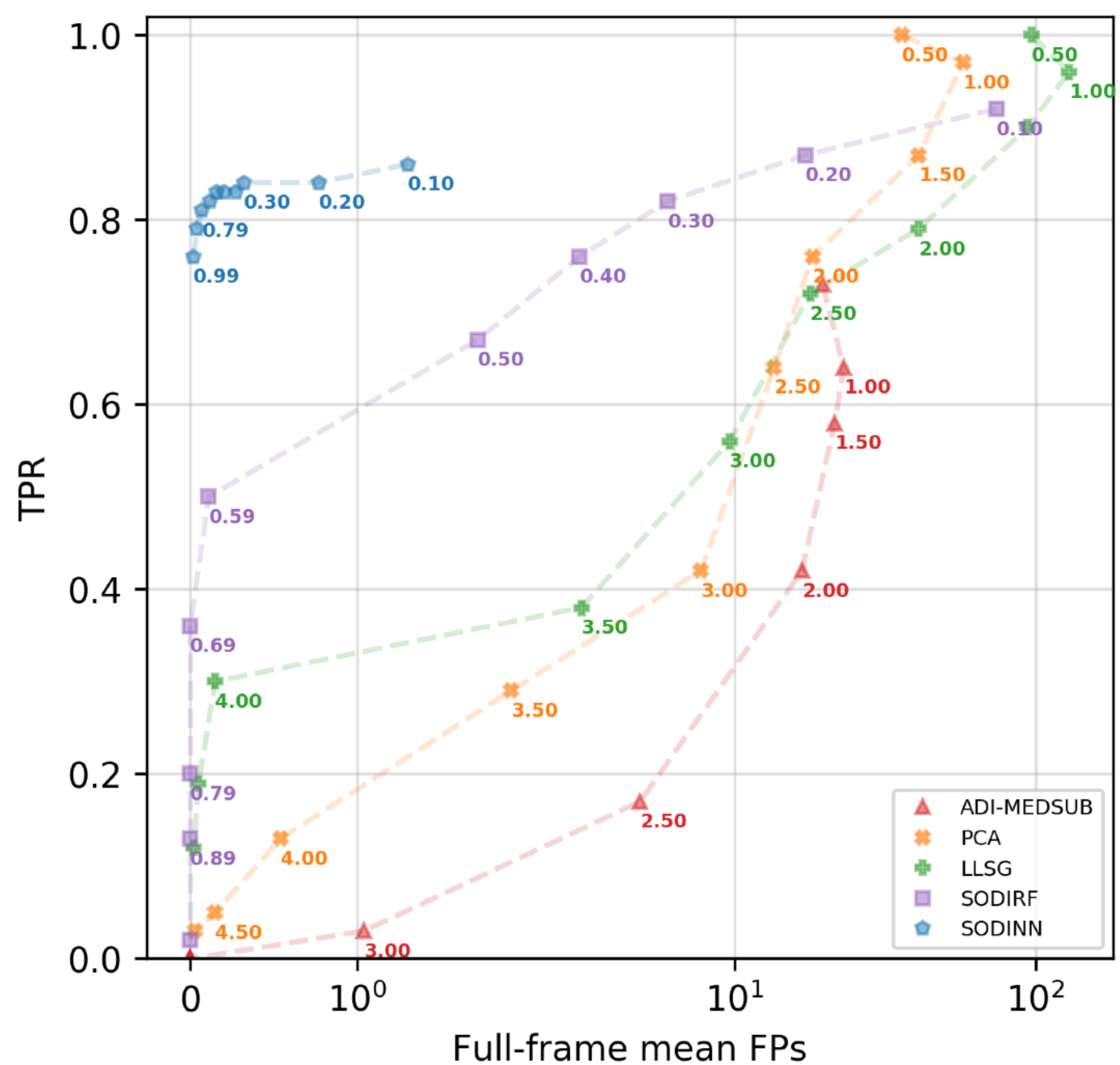
$$\hat{y}_n = p(c^+ \mid \text{MLAR sample})$$



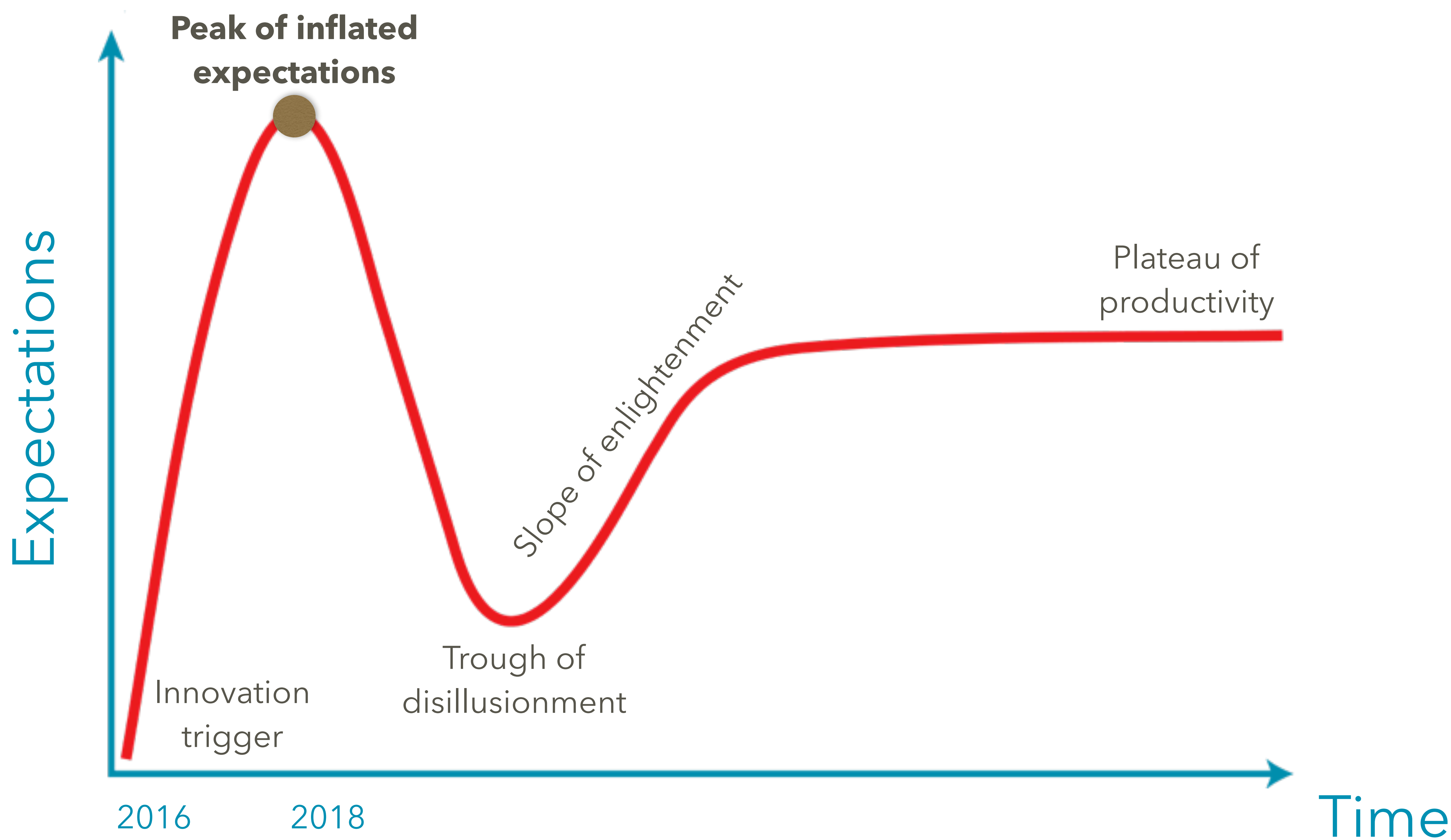
(after thresholding)

EVALUATION IN RECEIVER-OPERATING CHARACTERISTIC SPACE

- Not your standard ROC space
  - need to work at low FPR, don't want to see whole ROC space!
  - interested in total number of FPs inside whole field of view
- SODINN seems to be playing in a different league

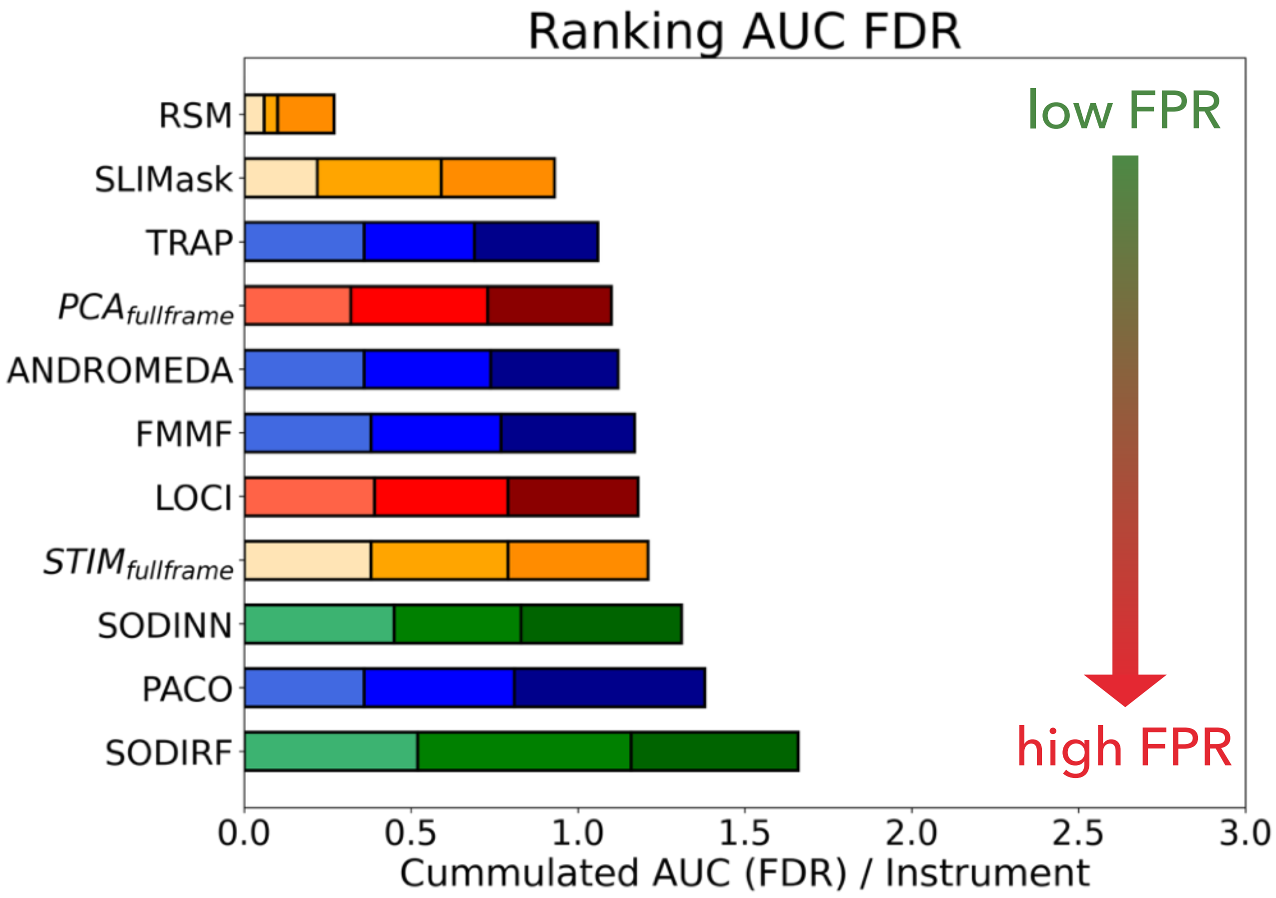


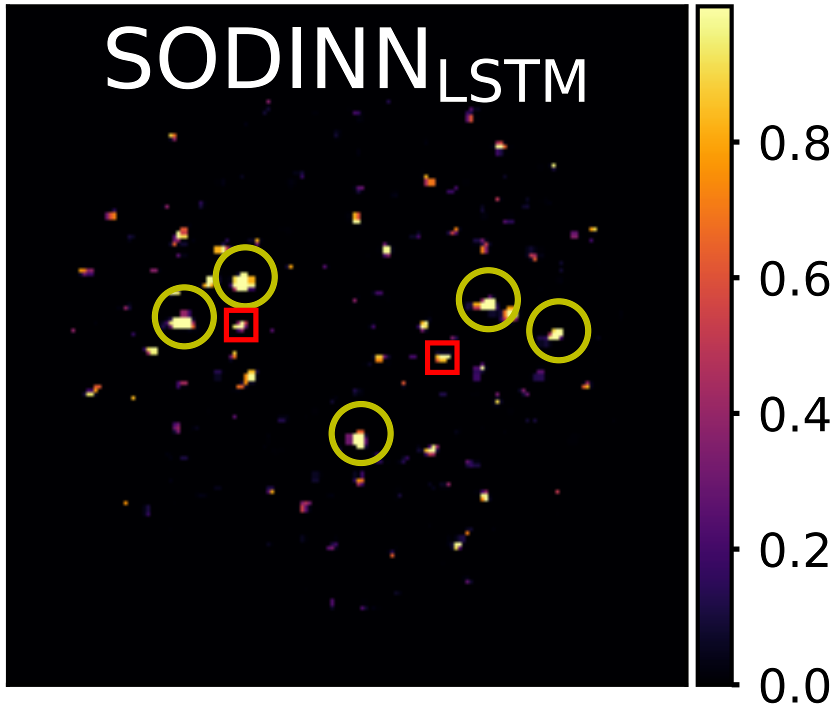
INTERLUDE #2: THE HYPE CURVE



THE EXOPLANET IMAGING DATA CHALLENGE

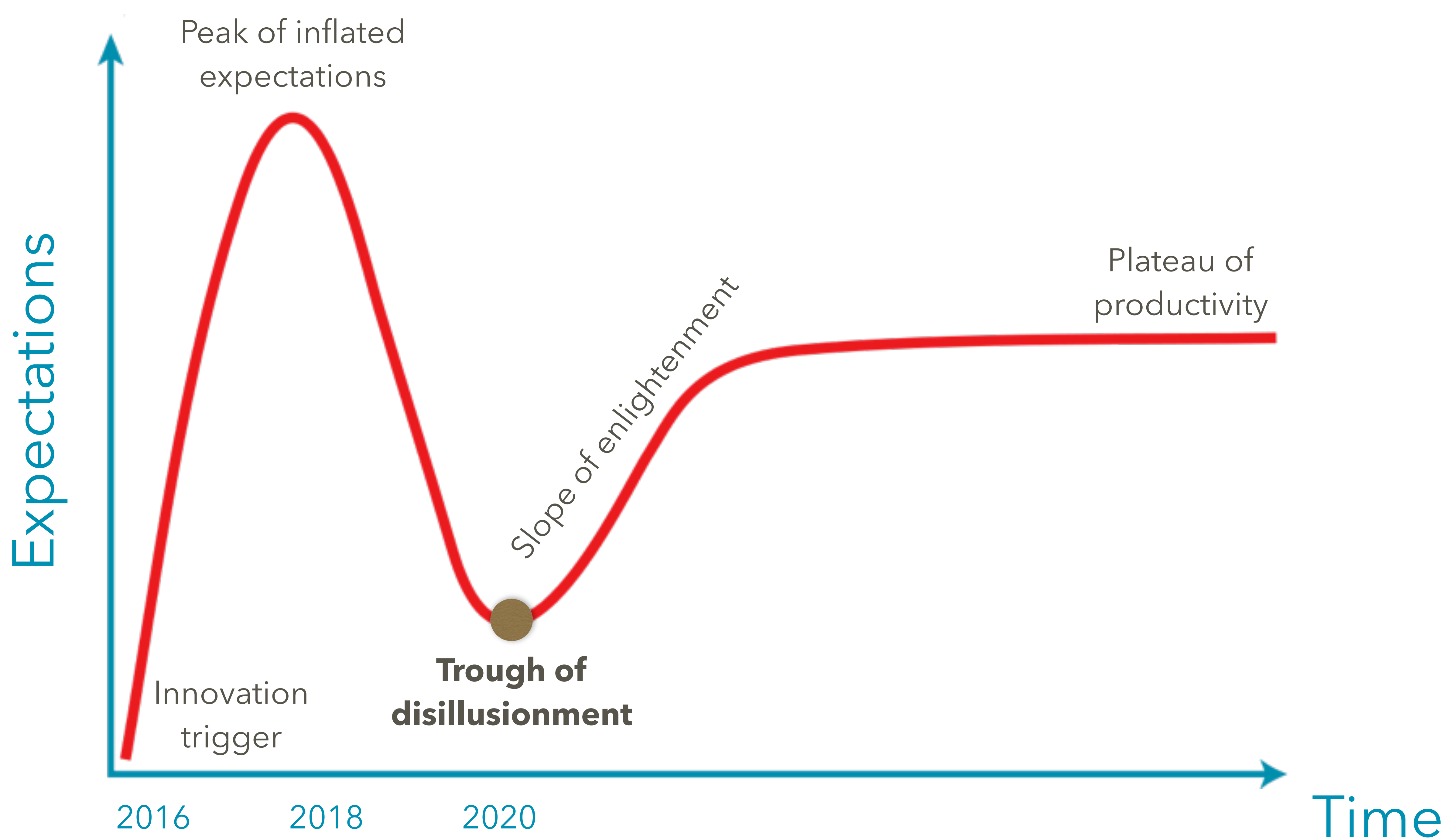
- Community effort to evaluate / compare HCI algorithms
  - challenge: exoplanet detection in various HCI data sets
- SODINN ranks poorly due to high FPR in some data sets





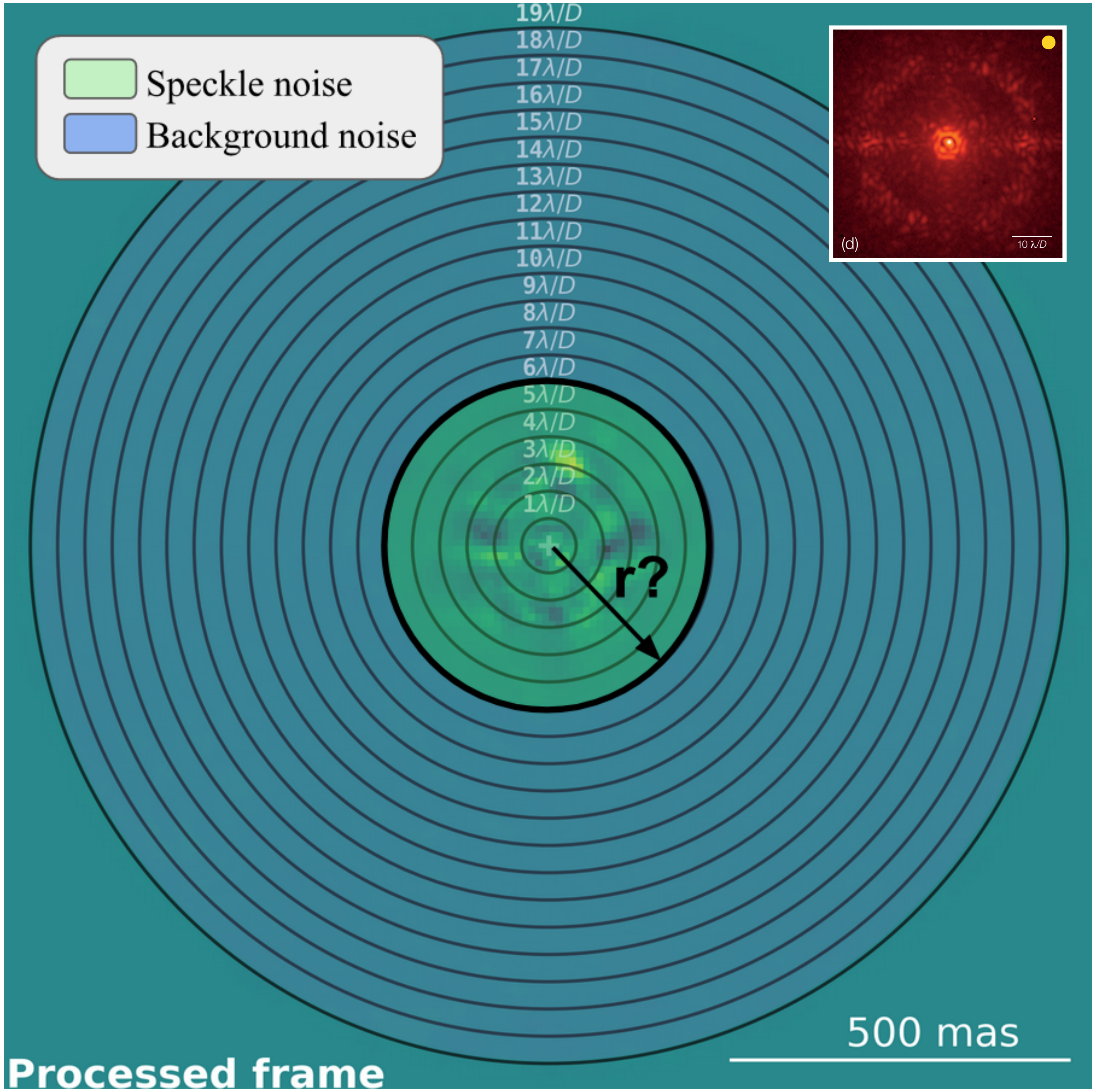
One example where SODINN « failed »

INTERLUDE #3: THE HYPE CURVE



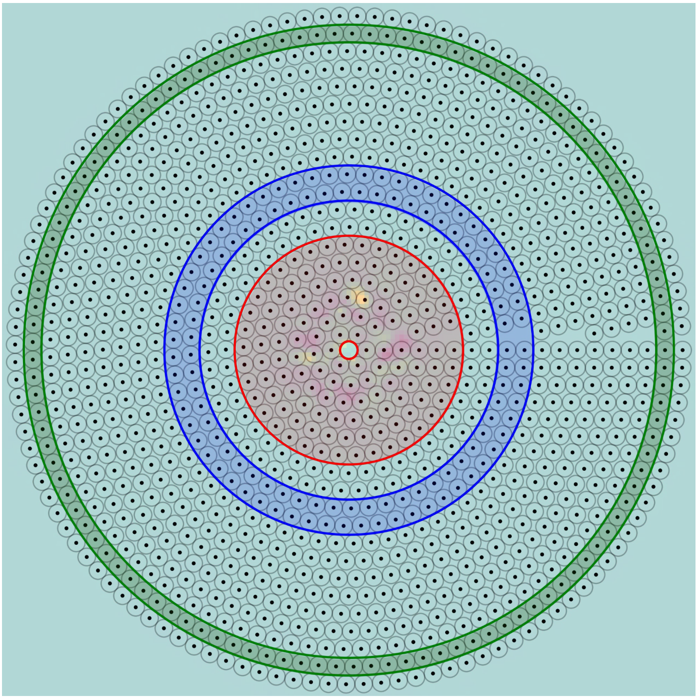
USING LESSONS LEARNED FROM DATA CHALLENGE

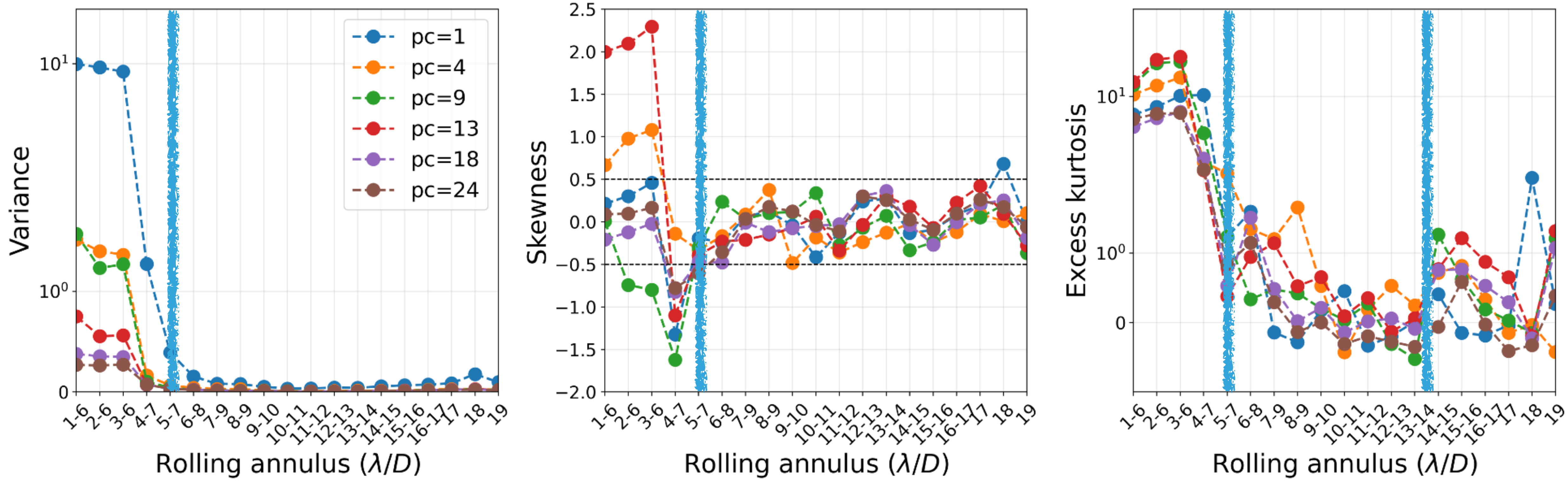
- Working locally seems useful
- New concept: noise-adapted SODINN
  - split the field of view to produce more uniform noise regimes
  - train SODINN separately on each noise regime



HOW TO DEFINE NOISE REGIMES?

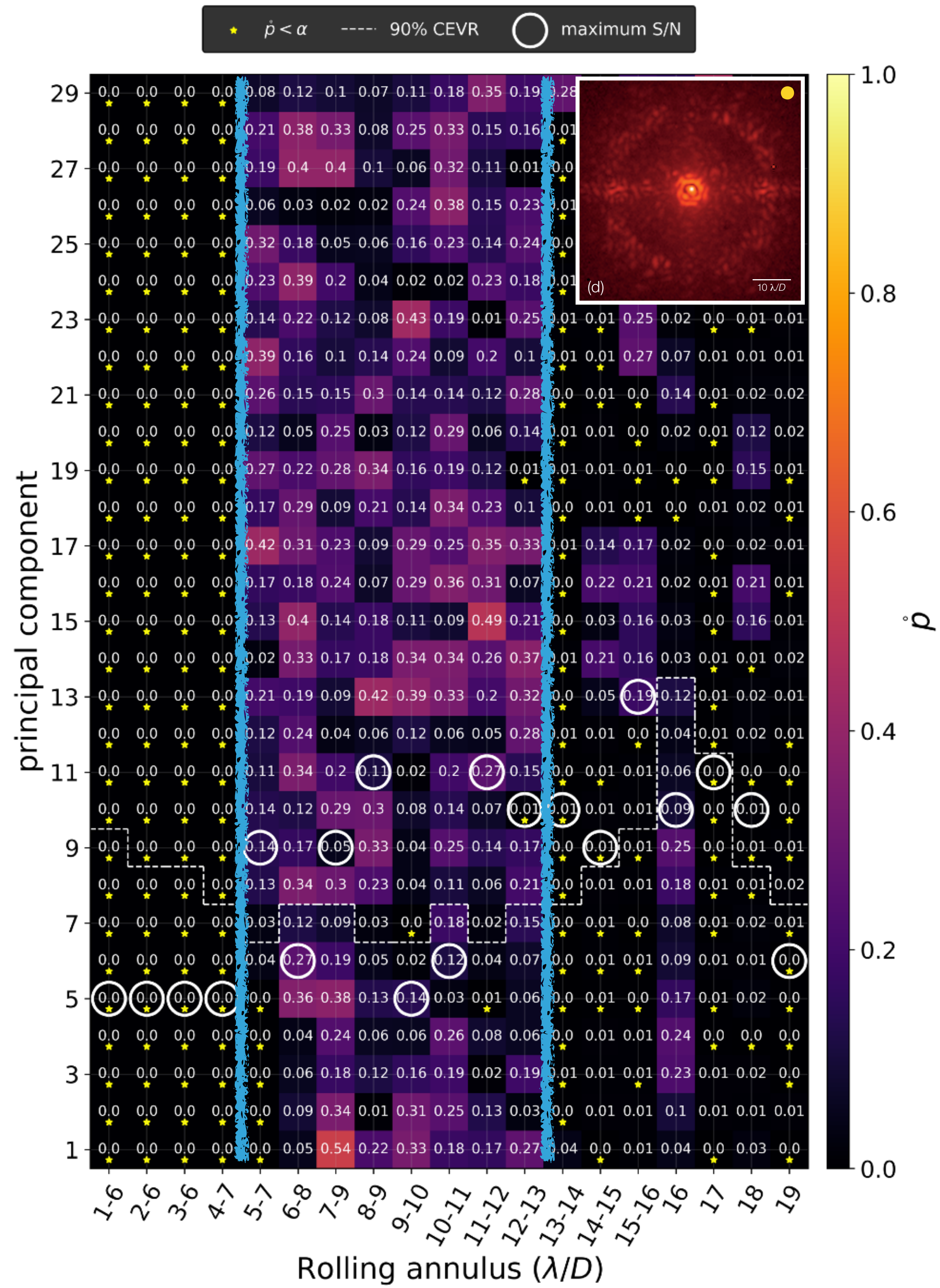
- Statistical moments give a first hint
  - define rolling annuli to have enough samples
  - exploration of moments vs PCA rank gives more robust results





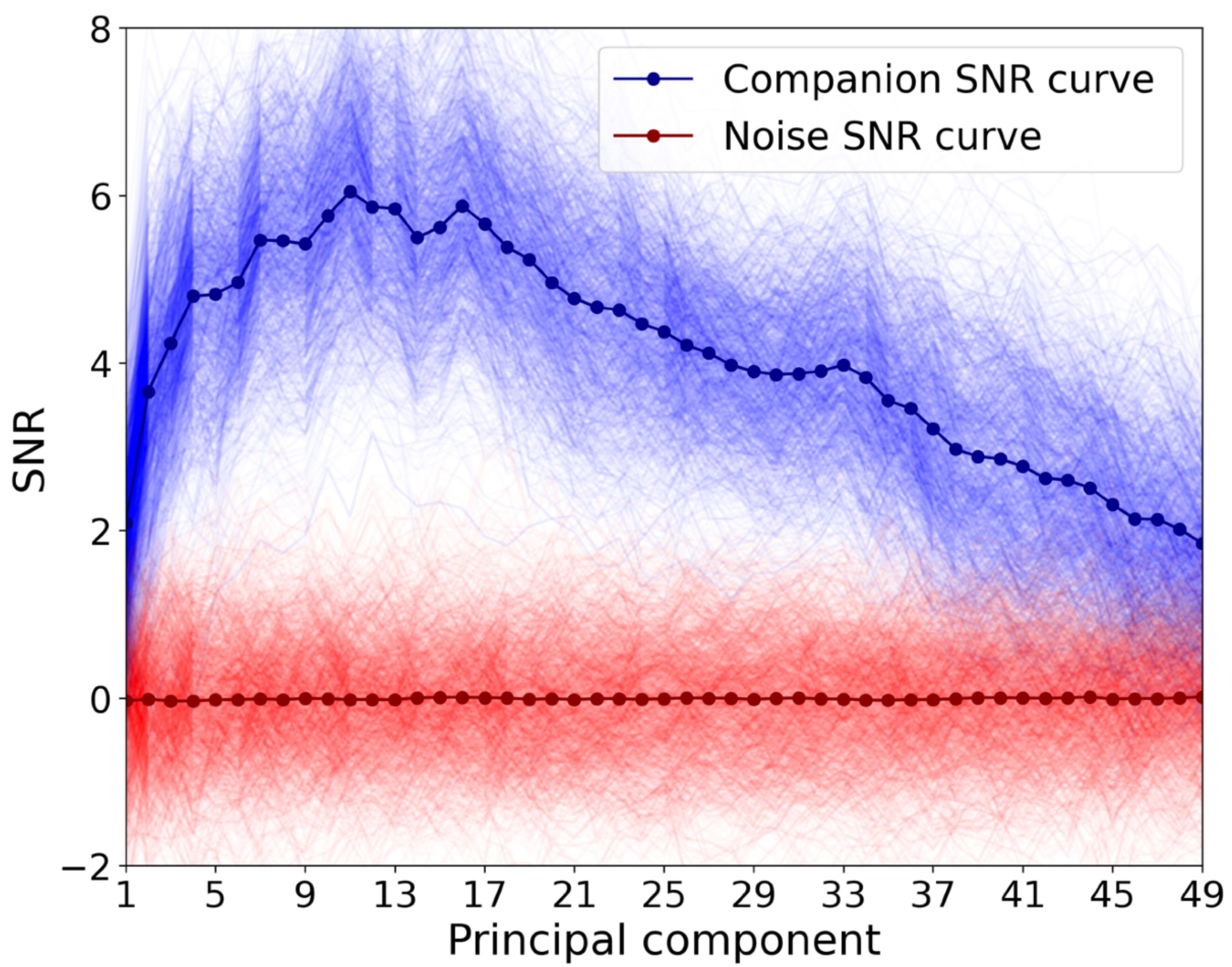
HOW TO DEFINE NOISE REGIMES?

- Normality tests
    - various tests can be combined to provide more robust p-value
    - high p-value does not mean that the distribution is normal
- Also highlights how the optimal PCA rank changes as a function of distance

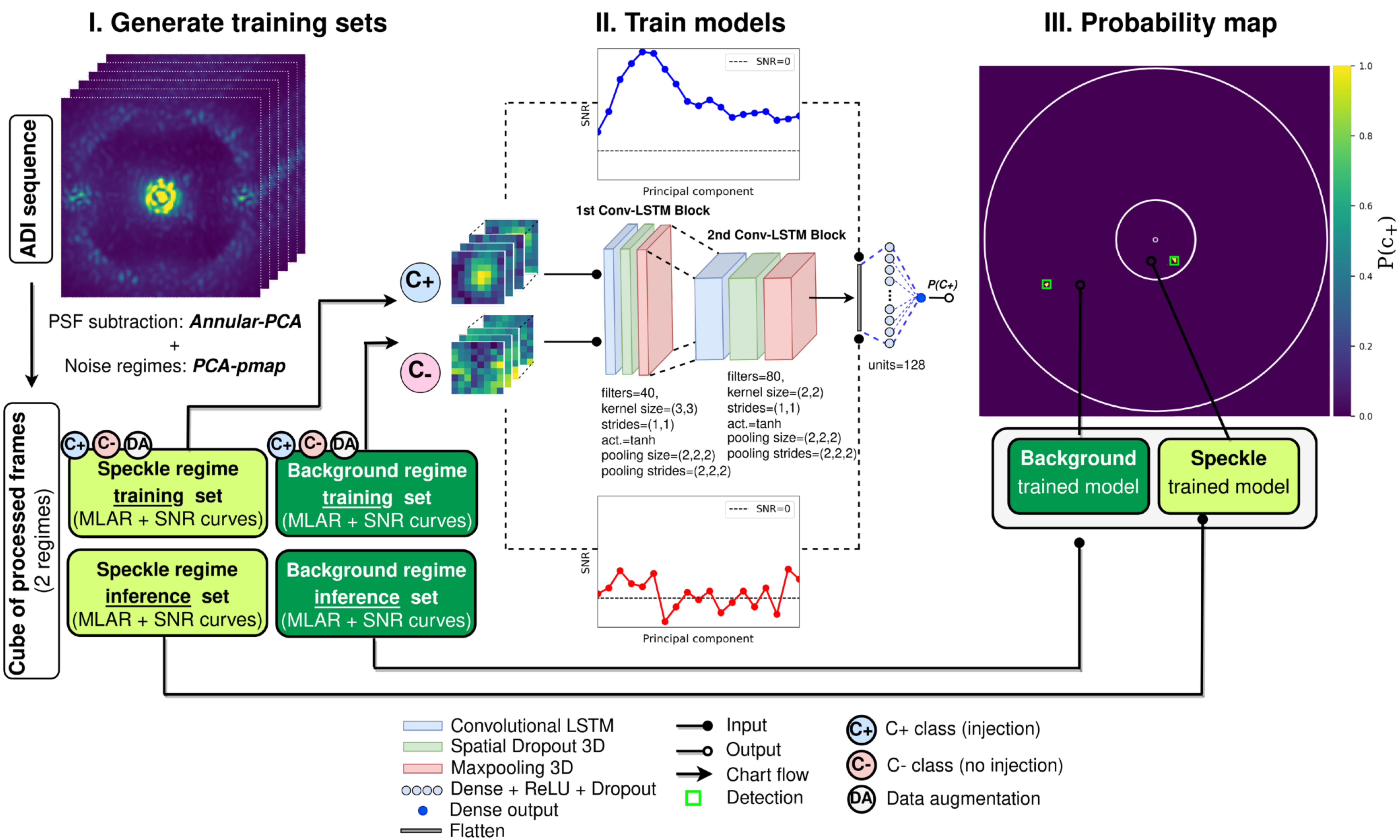


ADDING MORE NOISE-RELATED HANDCRAFTED FEATURES

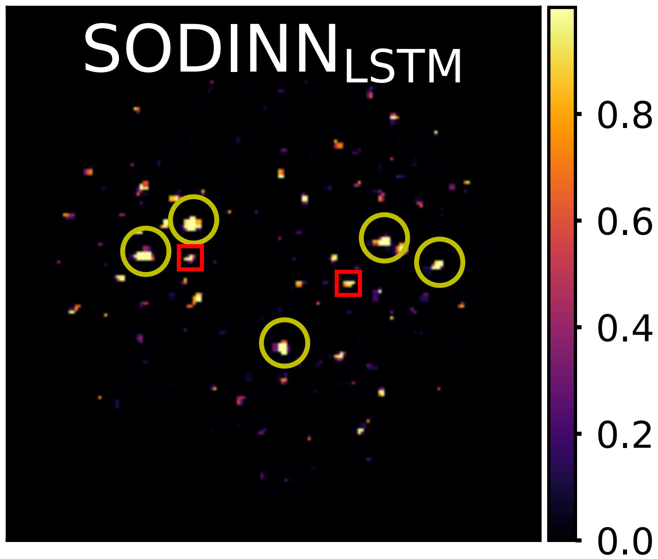
- MLAR patches catch signal evolution wrt PCA rank, but not S/N evolution
- S/N curve vs PCA rank can be used as additional feature in training

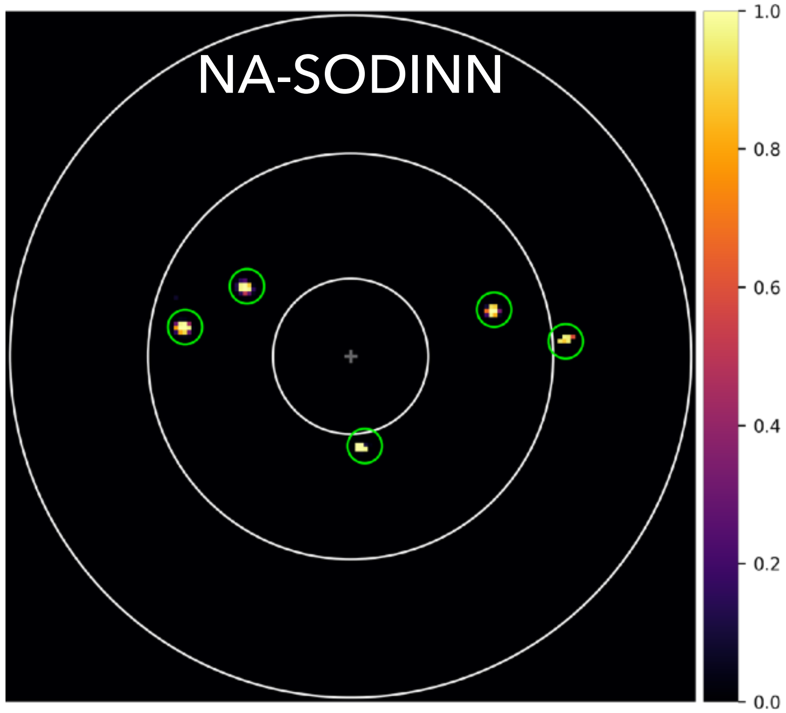


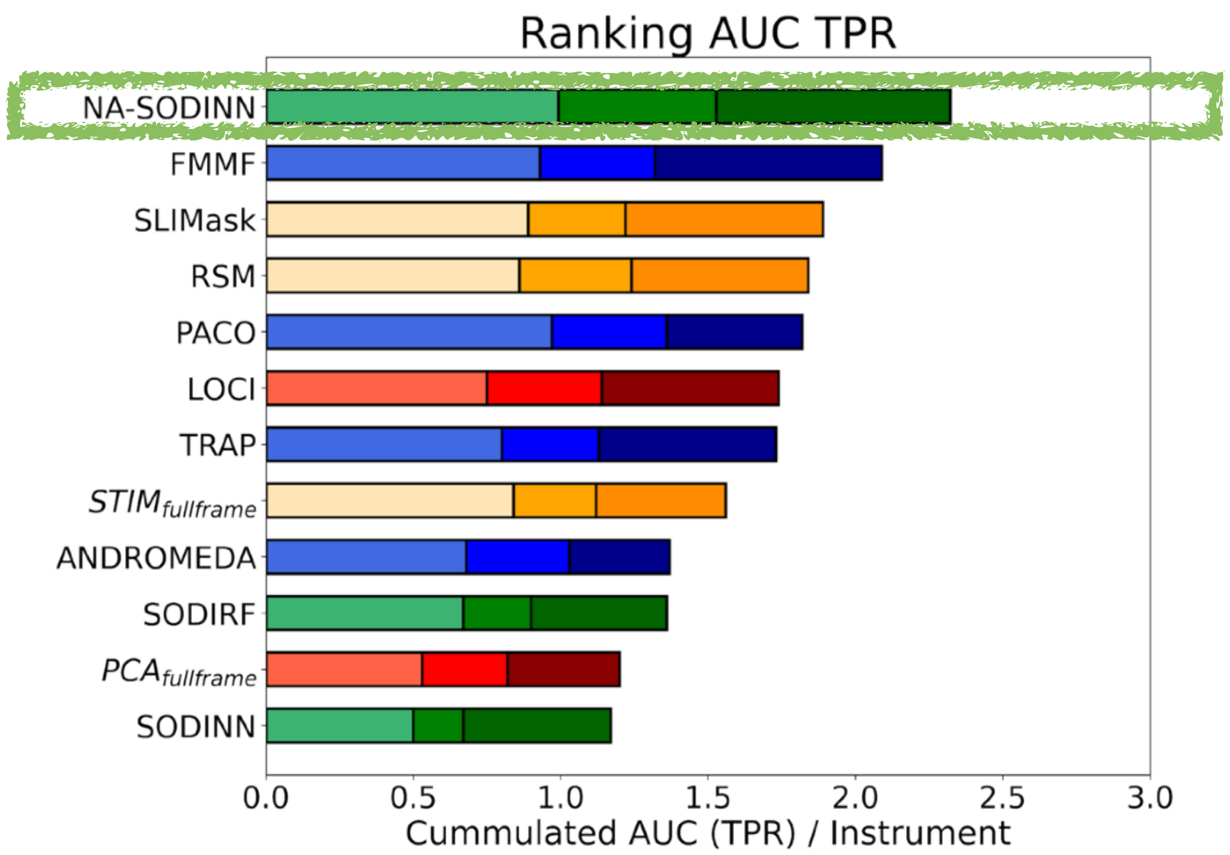
NA-SODINN MODEL

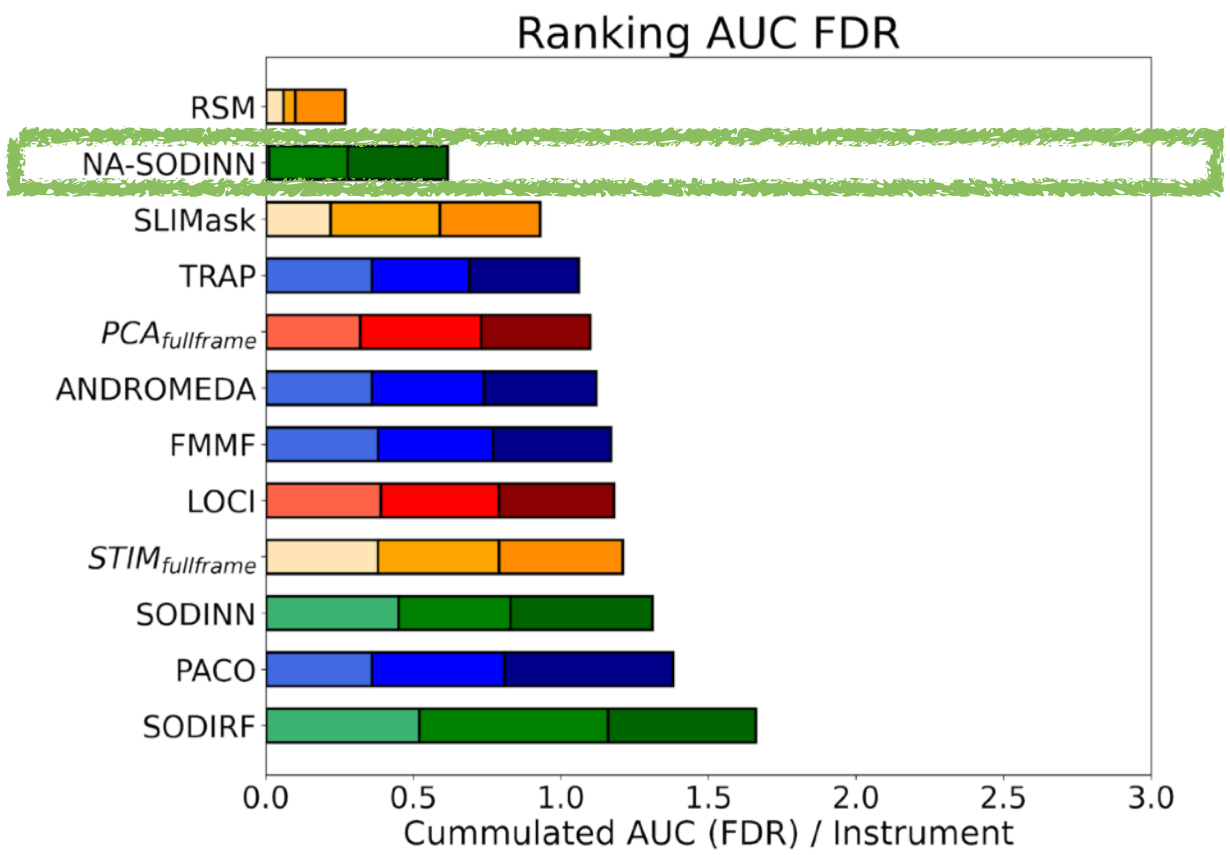


NEW ENTRY TO DATA CHALLENGE









CONCLUSION: THE HYPE CURVE

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