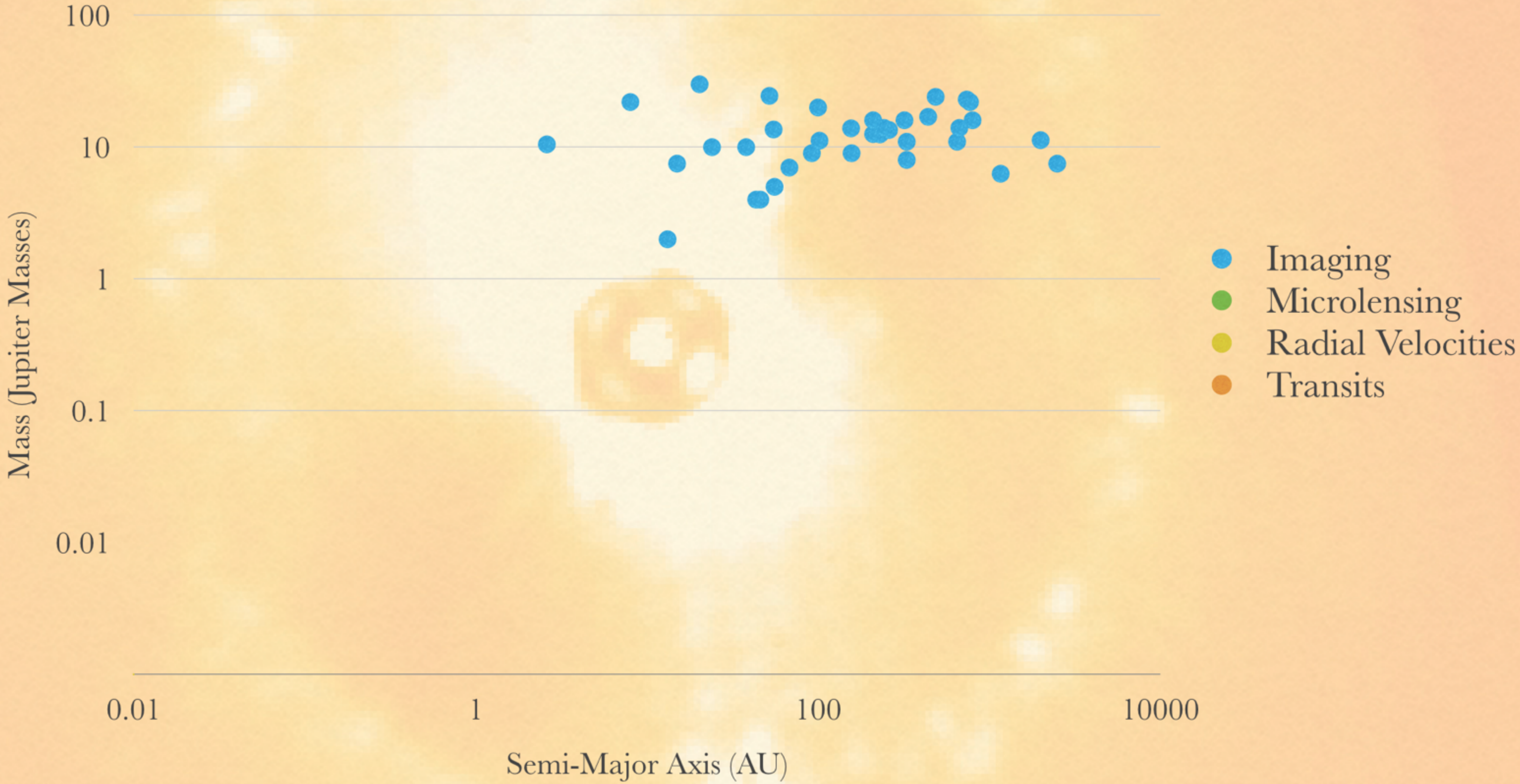
SYNERGIES BETWEEN POST–PROCESSING, WAVEFRONT SENSING AND CORONAGRAPH DESIGN

Marie Ygouf (Caltech/IPAC)
with inputs from Faustine Cantalloube, A.J. Riggs, Jeff Jewell, Graca Rocha, Mike Bottom, Vanessa Bailey, Julien Milli

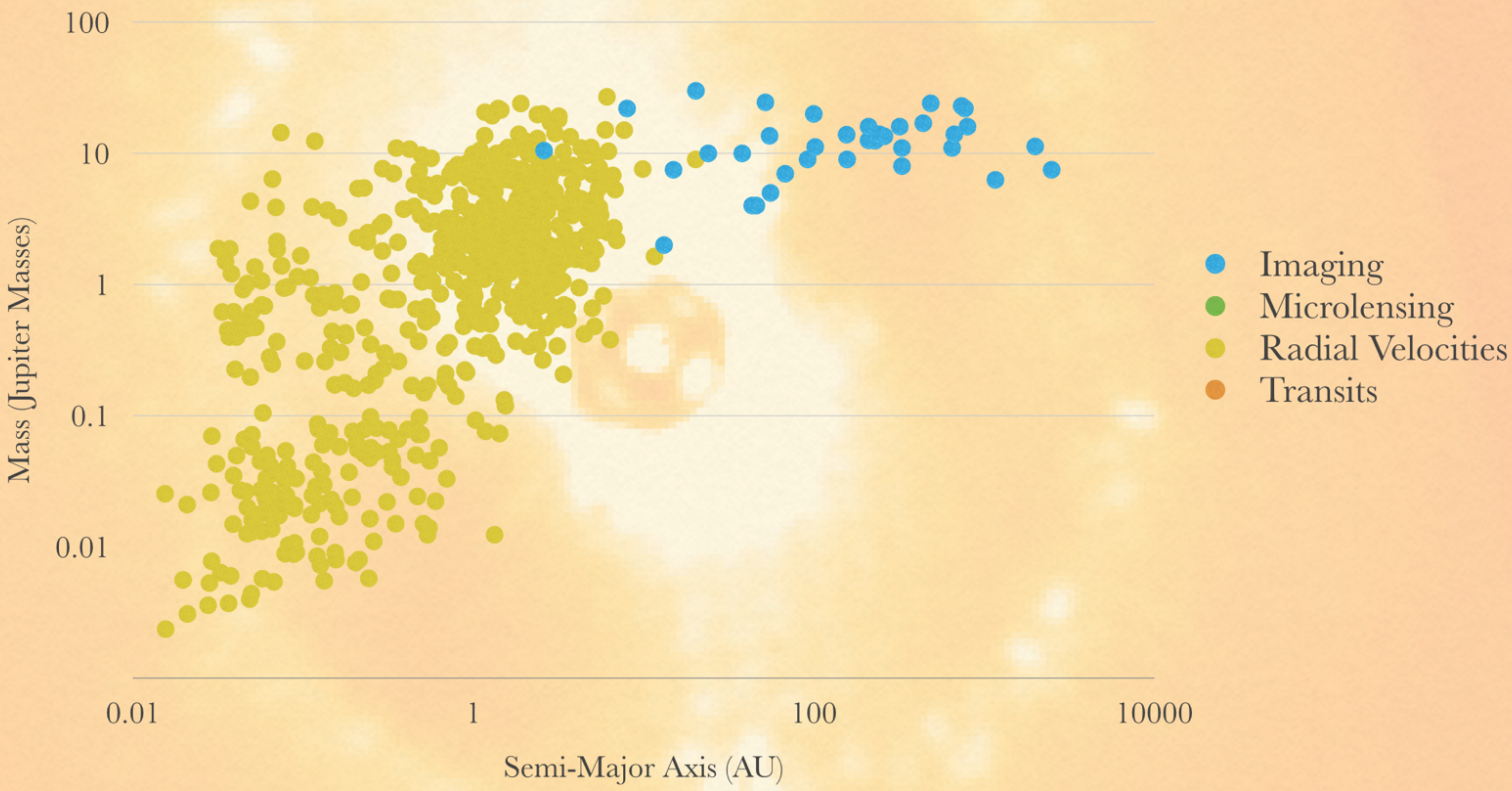
Workshop on Technology for Direct Detection and Characterization of Exoplanets
Keck Institute for Space Science (KISS)
April 10, 2018

Confirmed planets*



*As of April 10 2018 from exoplanetarchive.ipac.caltech.edu

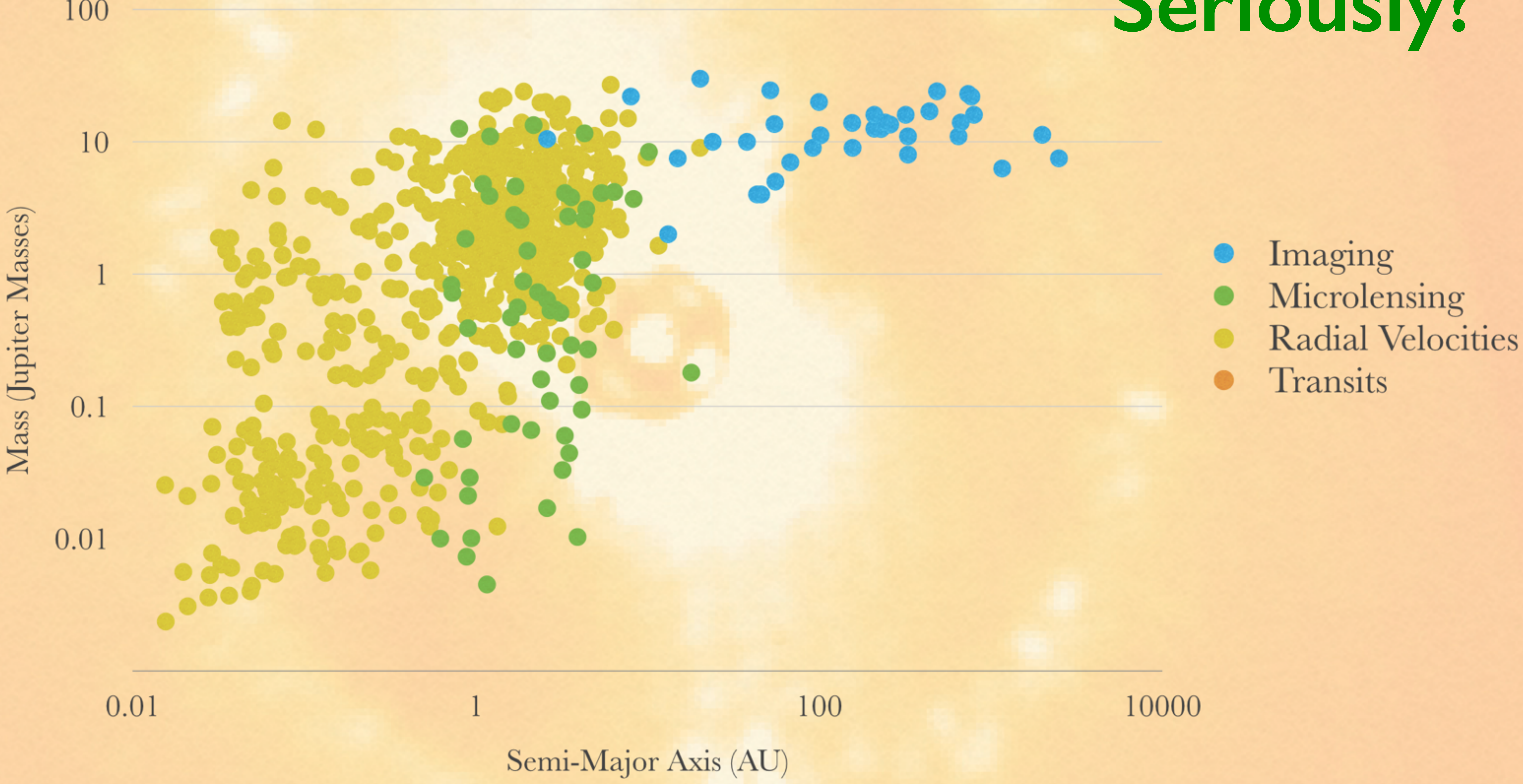
Confirmed planets*



*As of April 10 2018 from exoplanetarchive.ipac.caltech.edu

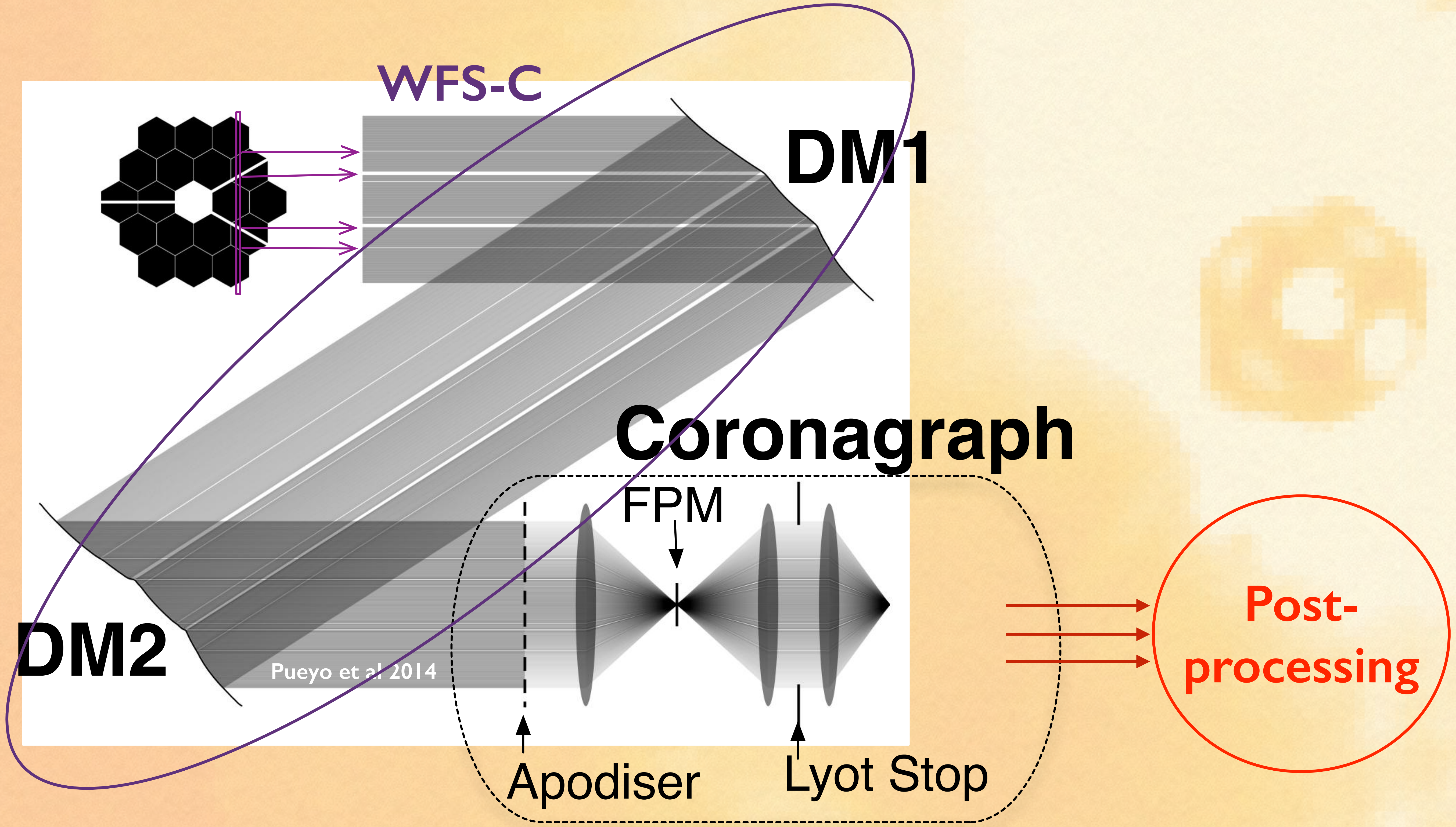
Confirmed planets*

Seriously?



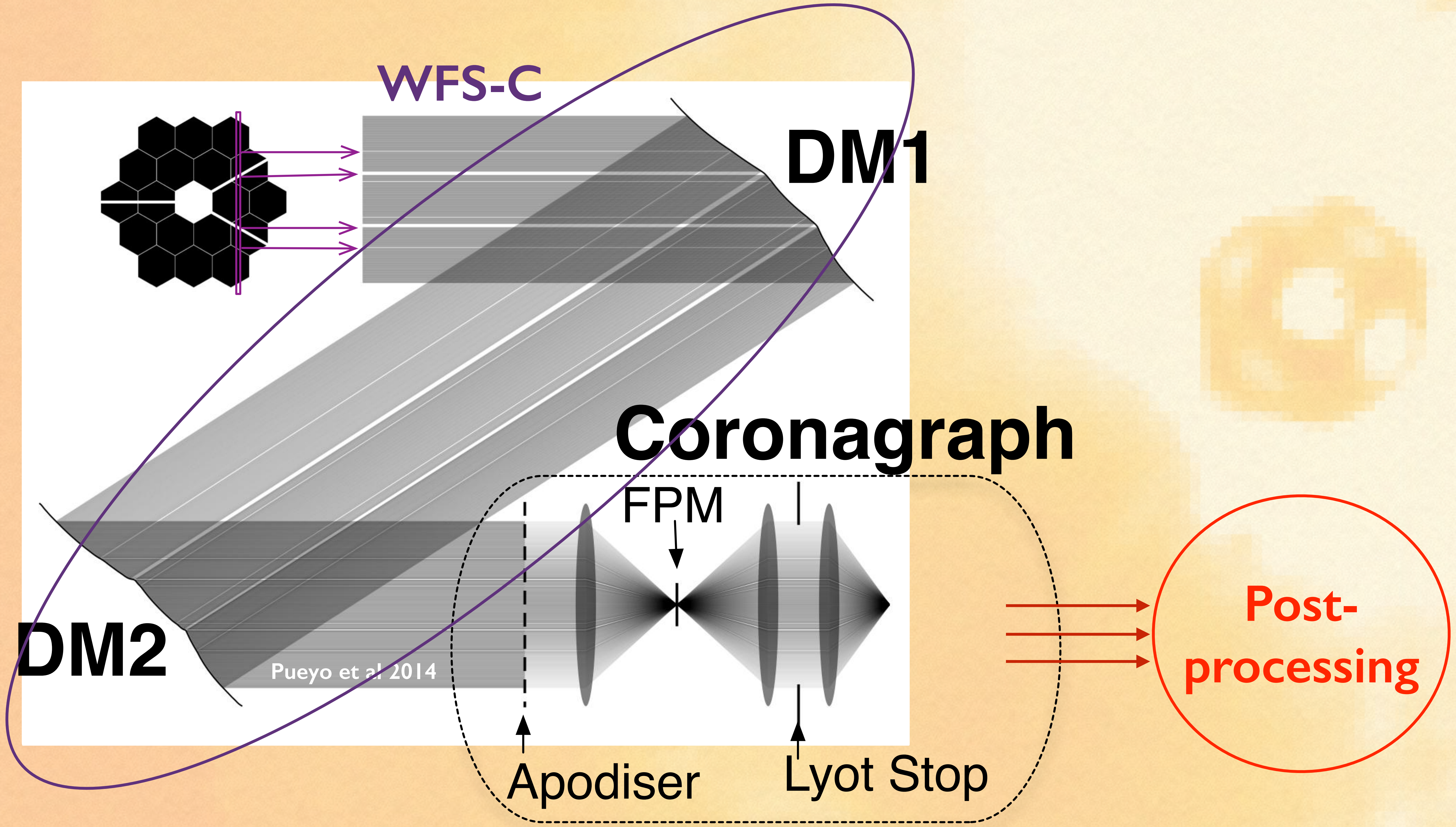
*As of April 10 2018 from exoplanetarchive.ipac.caltech.edu

THE PATH TOWARDS MORE DIRECT IMAGED PLANETS



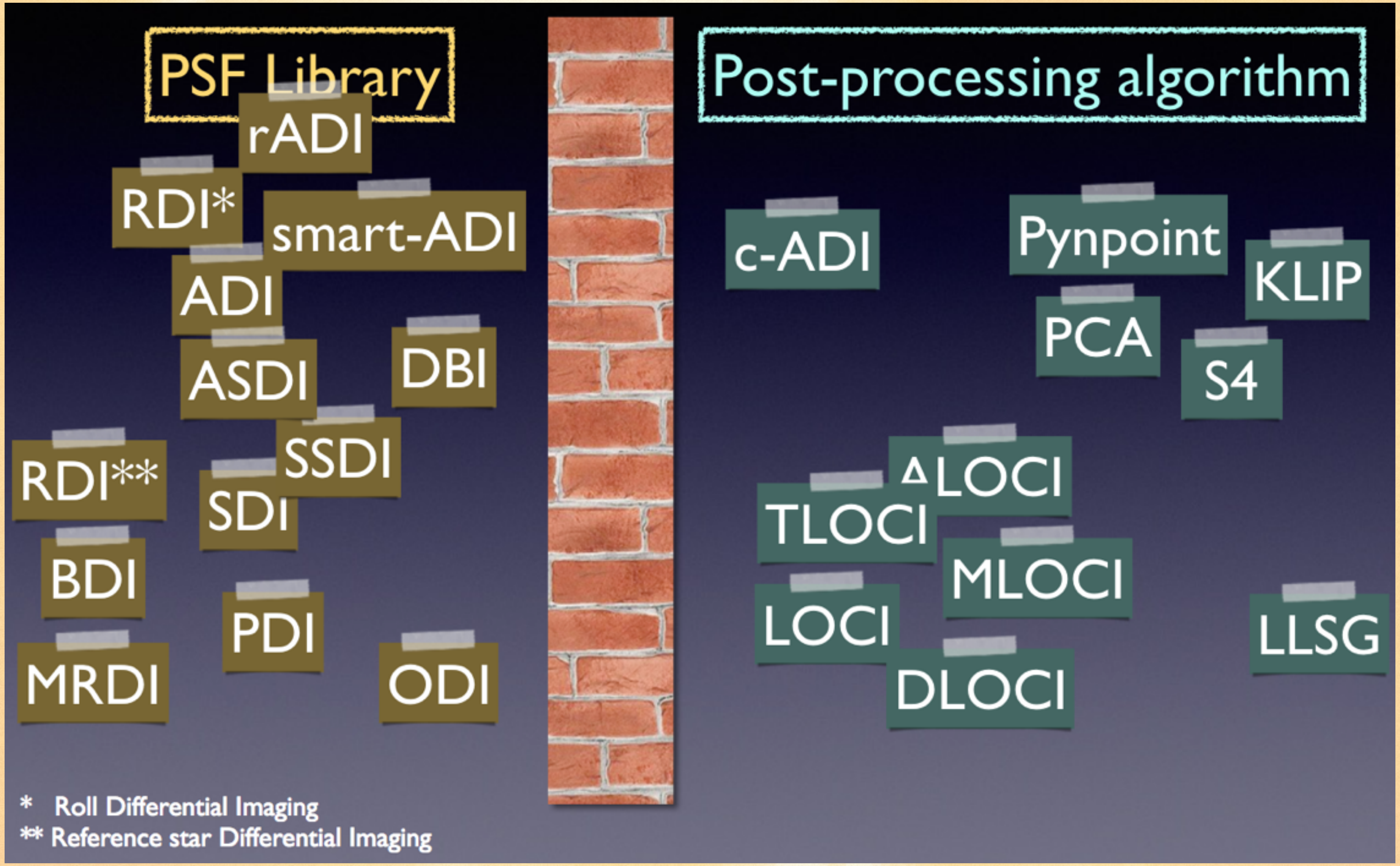
- Take a bigger telescope
- Build a better coronagraph
- Get a faster and better WFS/C
- Develop a better PP algorithm

THE PATH TOWARDS MORE DIRECT IMAGED PLANETS



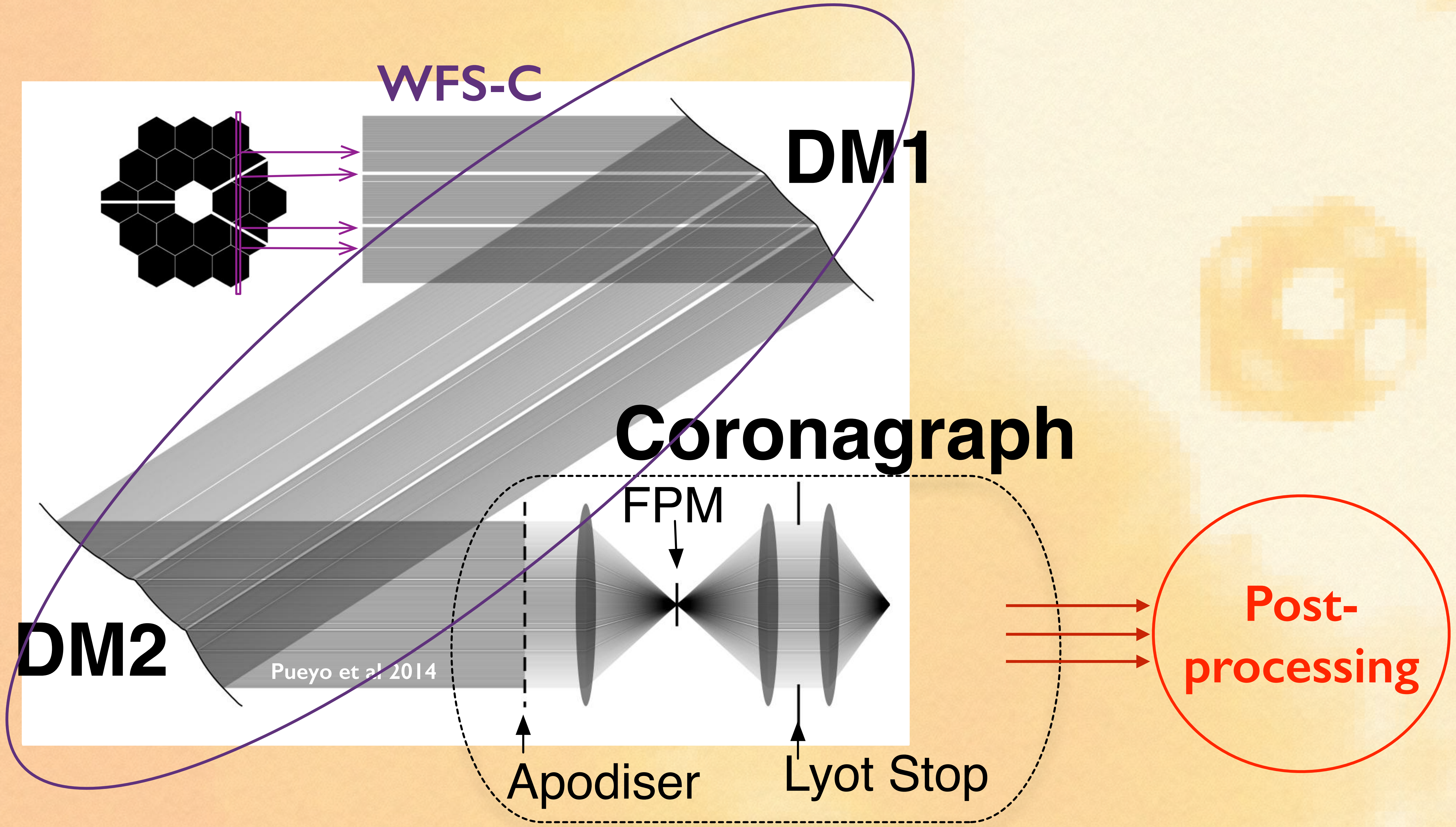
- Take a bigger telescope
- Build a better coronagraph
- Get a faster and better WFS/C
- Develop a better PP algorithm

CURRENT PP TECHNIQUES



From IPAC Science Talk Jan 18th, 2017 "Post-processing techniques for high-contrast imaging & overview of the ALICE program" by Elodie Choquet

THE PATH TOWARDS MORE DIRECT IMAGED PLANETS



- Take a bigger telescope
- Build a better coronagraph
- Get a faster and better WFS/C
- Develop a better PP algorithm

SYNERGIES BETWEEN PP AND WFS/C

- With the dedicated instruments and search for even better performance contrast, there is an increasing interest to exploit the information from WFS/C to inform post-processing
  - Instrument characterization from telemetry data
  - Vanessa Bailey (GPI) - Julien Milli (SPHERE) - Garima Singh (SCExAO)
- What can we do with current techniques?
  - Frame selection - and that's pretty it for now

SYNERGIES BETWEEN PP AND WFS/C

- With the dedicated instruments and search for even better performance contrast, there is an increasing interest to exploit the information from WFS/C to inform post-processing
  - Instrument characterization from telemetry data
  - Vanessa Bailey (GPI) - Julien Milli (SPHERE) - Garima Singh (SCExAO)
- What can we do with current techniques?
  - Frame selection - and that's pretty it for now

Question is:

How can we further improve from there?

BAYESIAN ANALYSIS PROVIDES THE FRAMEWORK FOR EXPLOITATION OF TELEMETRY TO INFER PP

- Assumptions
  - Data => $\mathbf{i}_\lambda$ Coronagraphic data cube
  - Unknowns => x Planets
- Maximization of posterior probability $\mathscr{L}(x|\mathbf{i}_\lambda)$ or probability of the **unknown** given the **data**
  - Stochastic framework
  - Noise statistic gives likelihood $\mathscr{L}(\mathbf{i}_\lambda|x)$ or probability of the **data** given the **unknown**
  - Use **Bayes' rule** to convert $\mathscr{L}(\mathbf{i}_\lambda|x)$ into $\mathscr{L}(x|\mathbf{i}_\lambda)$

BAYESIAN ANALYSIS PROVIDES THE FRAMEWORK FOR EXPLOITATION OF TELEMETRY TO INFER PP

- Assumptions
  - Data => $\mathbf{i}_\lambda$ Coronagraphic data cube
  - Unknowns => x Planets

Bayes' rule

$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\boxed{\mathscr{L}(x)}}{\mathscr{L}(\mathbf{i}_\lambda)}$$

Probability of the unknown
=
Knowledge about the instrument

- Maximization of posterior probability $\mathscr{L}(x|\mathbf{i}_\lambda)$ or probability of the **unknown** given the **data**
  - Stochastic framework
  - Noise statistic gives likelihood $\mathscr{L}(\mathbf{i}_\lambda|x)$ or probability of the **data** given the **unknown**
  - Use **Bayes' rule** to convert $\mathscr{L}(\mathbf{i}_\lambda|x)$ into $\mathscr{L}(x|\mathbf{i}_\lambda)$

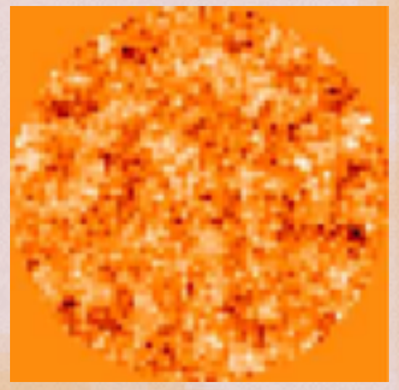
APPLICATION TO PP FOR DIRECT IMAGING

Ygouf et al. 2013, A&A

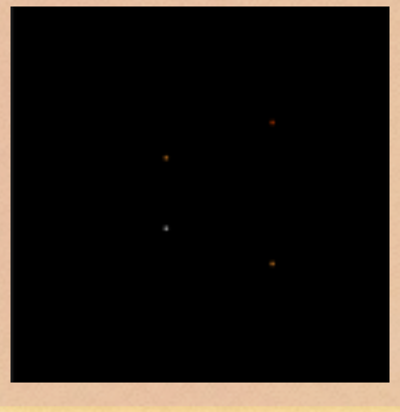
Input parameters = Unknowns

Star flux f_λ^*

Aberrations ϕ



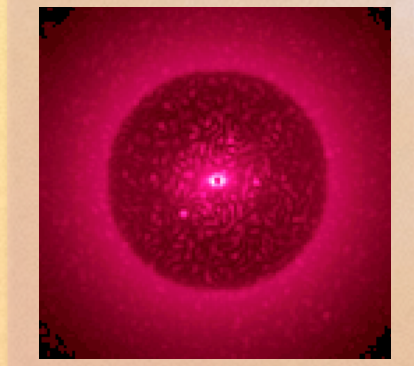
Object o_λ



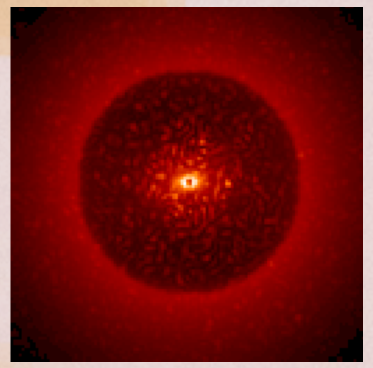
Inversion

$$i_\lambda = f_\lambda^* \cdot h_\lambda^c(\phi) + o_\lambda * h_\lambda^{nc}(\phi) + n$$

Data

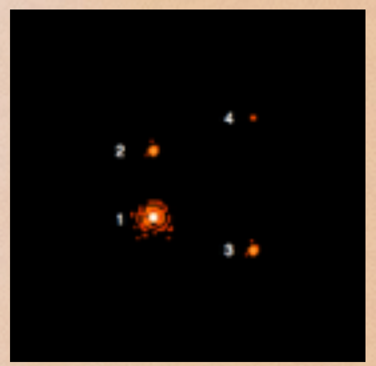


=



Speckle field

+



Planet image

$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\mathscr{L}(x)}{\mathscr{L}(\mathbf{i}_\lambda)}$$

Sum on wavelengths

Sum on pixels

Least square distance between the data and the model

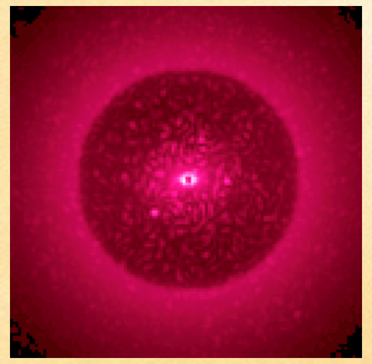
$$J\left(\{o_\lambda\},\{f_\lambda^*\},\delta_u\right) = \sum_\lambda \sum_{x,y} \frac{1}{2\sigma_n^2(x,y)} \left| i_\lambda - f_\lambda^* \cdot h_\lambda^c(\delta_u) - o_\lambda * h_\lambda^{nc} \right|^2 (x,y) + R_{x,y,\lambda}(o,\delta)$$

Weight

APPLICATION TO PP FOR DIRECT IMAGING

Ygouf et al. 2013, A&A

Data



$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\mathscr{L}(x)}{\mathscr{L}(\mathbf{i}_\lambda)}$$

Sum on wavelengths

Sum on pixels

Least square distance between the data and the model

+

Regularization terms

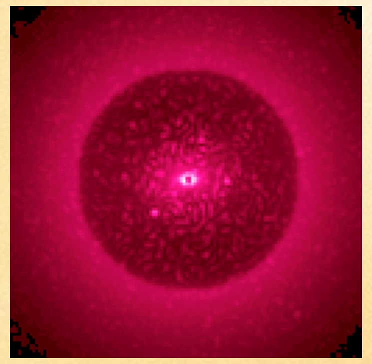
$$J(\{o_\lambda\},\{f^*_\lambda\},\delta_u) = \sum_\lambda \sum_{x,y} \underbrace{\frac{1}{2\sigma_n^2(x,y)}}_{\text{Weight}} \left|\underbrace{i_\lambda}_{\text{Data}} - f^*_\lambda \cdot h^c_\lambda(\delta_u) - o_\lambda * h^{nc}_\lambda\right|^2 (x,y) + R_{x,y,\lambda}(o,\delta)$$

Ygouf et al. 2013, A&A

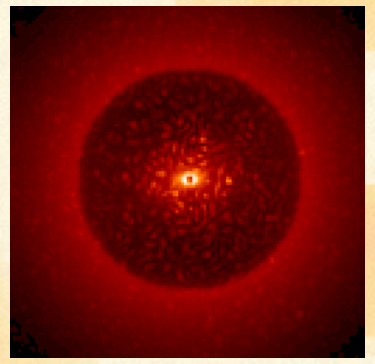
APPLICATION TO PP FOR DIRECT IMAGING

Ygouf et al. 2013, A&A

Data



=



Speckle field

$$\mathcal{L}(x|\mathbf{i}_\lambda) = \frac{\mathcal{L}(\mathbf{i}_\lambda|x)\,\mathcal{L}(x)}{\mathcal{L}(\mathbf{i}_\lambda)}$$

Sum on wavelengths

Sum on pixels

Least square distance between the data and the model

\+

Regularization terms

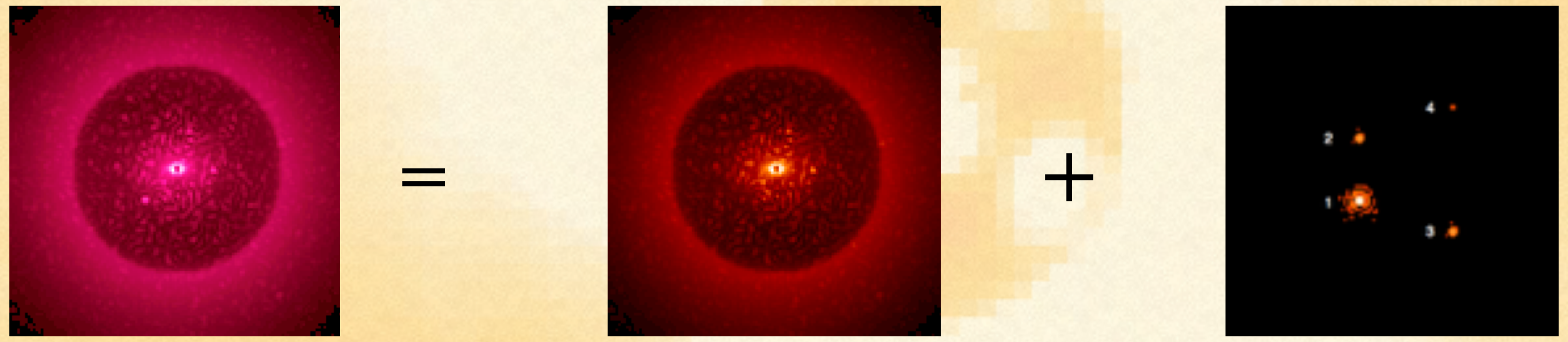
$$J\left(\{o_\lambda\},\{f^*_\lambda\},\delta_u\right) = \sum_\lambda \sum_{x,y} \frac{1}{2\sigma_n^2(x,y)} \left| i_\lambda - f^*_\lambda \cdot h^c_\lambda(\delta_u) - o_\lambda * h^{nc}_\lambda \right|^2 (x,y) + R_{x,y,\lambda}(o,\delta)$$

Weight Data Speckle Field

Ygouf et al. 2013, A&A

APPLICATION TO PP FOR DIRECT IMAGING

Ygouf et al. 2013, A&A



$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\mathscr{L}(x)}{\mathscr{L}(\mathbf{i}_\lambda)}$$

Sum on wavelengths — Sum on pixels — Least square distance between the data and the model + Regularization terms

$$J\left(\{o_\lambda\},\{f_\lambda^*\},\delta_u\right) = \sum_\lambda \sum_{x,y} \underbrace{\frac{1}{2\sigma_n^2(x,y)}}_{\text{Weight}} \left| \underbrace{i_\lambda}_{\text{Data}} - \underbrace{f_\lambda^* \cdot h_\lambda^c(\delta_u)}_{\text{Speckle Field}} - \underbrace{o_\lambda * h_\lambda^{nc}}_{\text{Planet image}} \right|^2 (x,y) + R_{x,y,\lambda}(o,\delta)$$

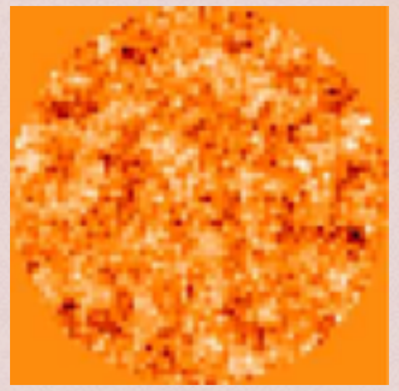
Ygouf et al. 2013, A&A

Ygouf et al. 2013, A&A

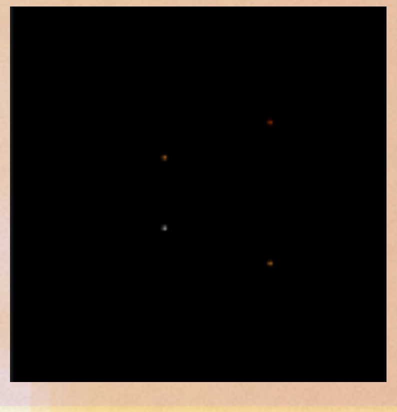
Input parameters = Unknowns

Star flux f_λ^*

Aberrations ϕ



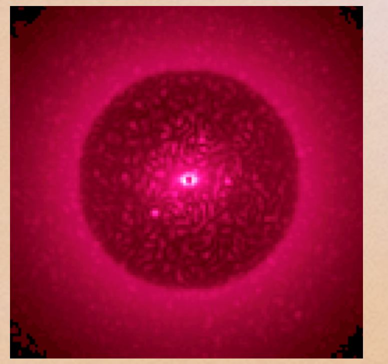
Object o_λ



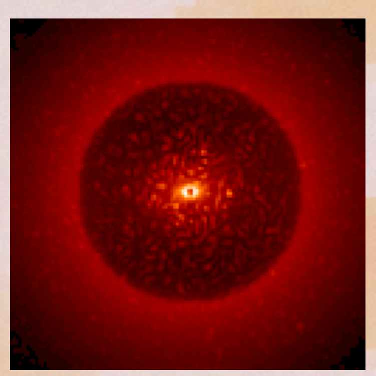
Inversion

$$i_\lambda = f_\lambda^* \cdot h_\lambda^c(\phi) + o_\lambda * h_\lambda^{nc}(\phi) + n$$

Data

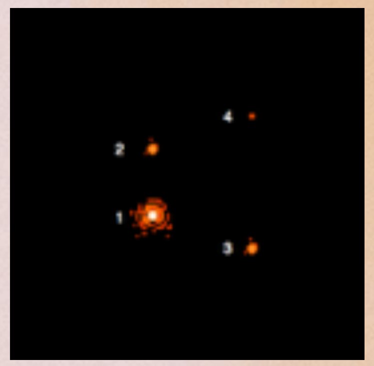


=



Speckle field

+



Planet image

$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\mathscr{L}(x)}{\mathscr{L}(\mathbf{i}_\lambda)}$$

Sum on wavelengths | Sum on pixels | Least square distance between the data and the model + Regularization terms

$$J(\{o_\lambda\},\{f_\lambda^*\},\delta_u) = \sum_\lambda \sum_{x,y} \frac{1}{2\sigma_n^2(x,y)} \left| i_\lambda - f_\lambda^* \cdot h_\lambda^c(\delta_u) - o_\lambda * h_\lambda^{nc} \right|^2 (x,y) + R_{x,y,\lambda}(o,\delta)$$

Weight Data Speckle Field Planet image

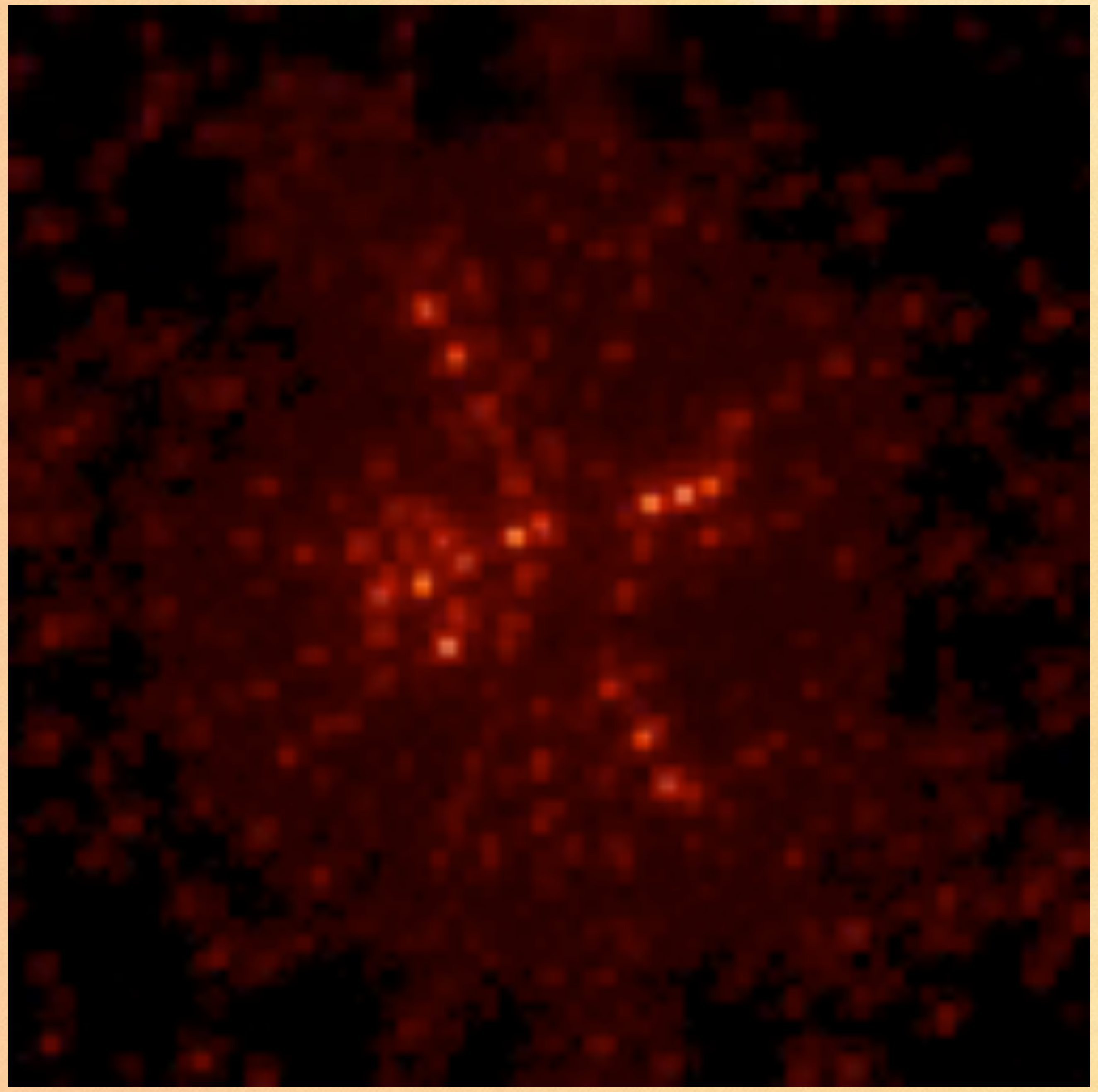
Ygouf et al. 2013, A&A

AND IT WORKS!

- Validation on simulated data

  Ygouf et al. 2013, A&A

SPHERE
Spectro-Polarimetric
High-contrast
Exoplanet REsearch



Movie:

Evolution of the planet image reconstruction as we minimize the criterion J

Sum on wavelengths

Sum on pixels

Least square distance between the data and the model

\+

Regularization terms

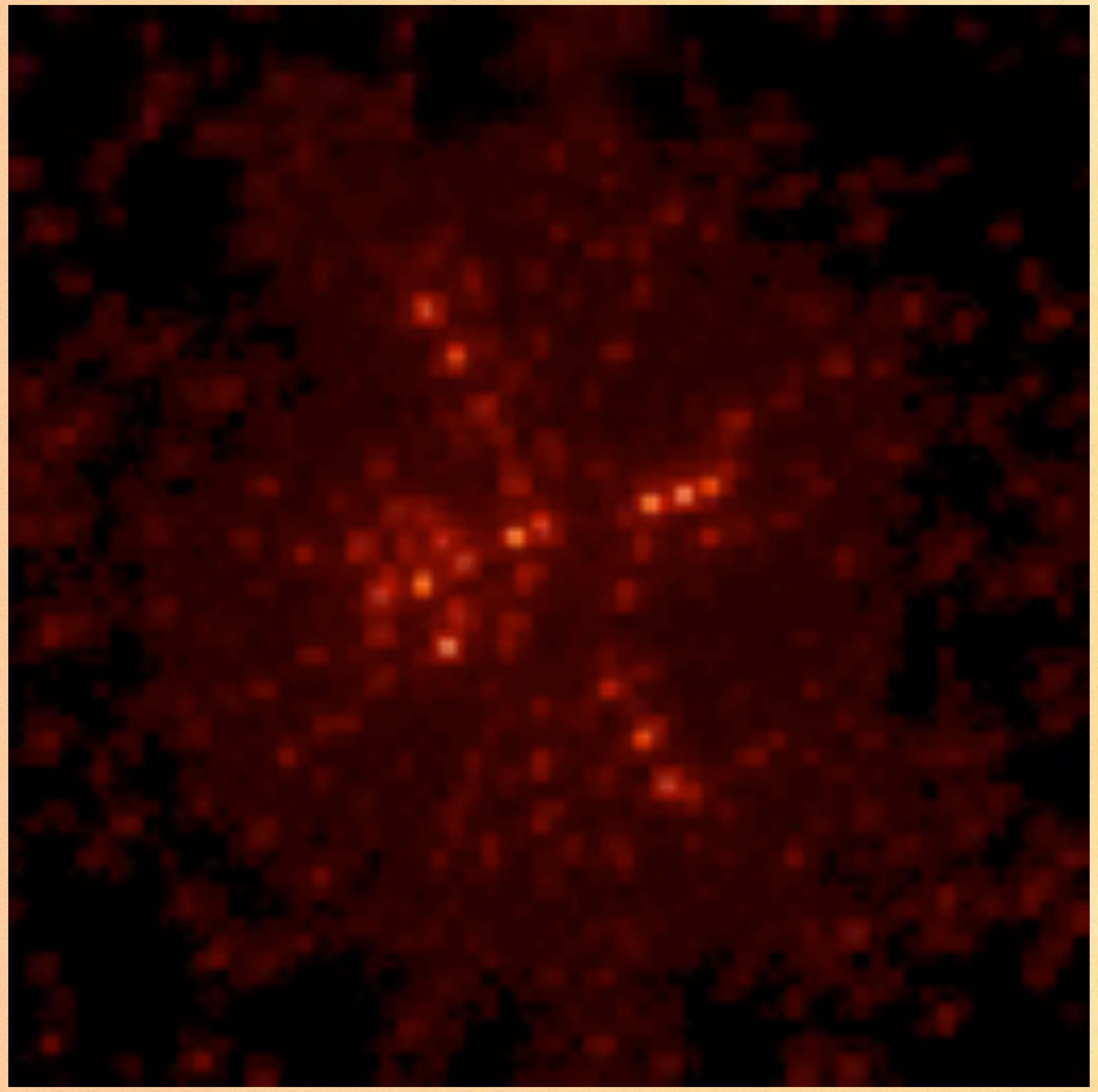
$$J\left(\{o_\lambda\},\{f_\lambda^*\},\delta_u\right) = \sum_\lambda \sum_{x,y} \underbrace{\frac{1}{2\sigma_n^2(x,y)}}_{\text{Weight}} \left| \underbrace{i_\lambda}_{\text{Data}} - \underbrace{f_\lambda^* \cdot h_\lambda^c(\delta_u)}_{\text{Speckle Field}} - \underbrace{o_\lambda * h_\lambda^{nc}}_{\text{Planet image}} \right|^2 (x,y) + R_{x,y,\lambda}(o,\delta)$$

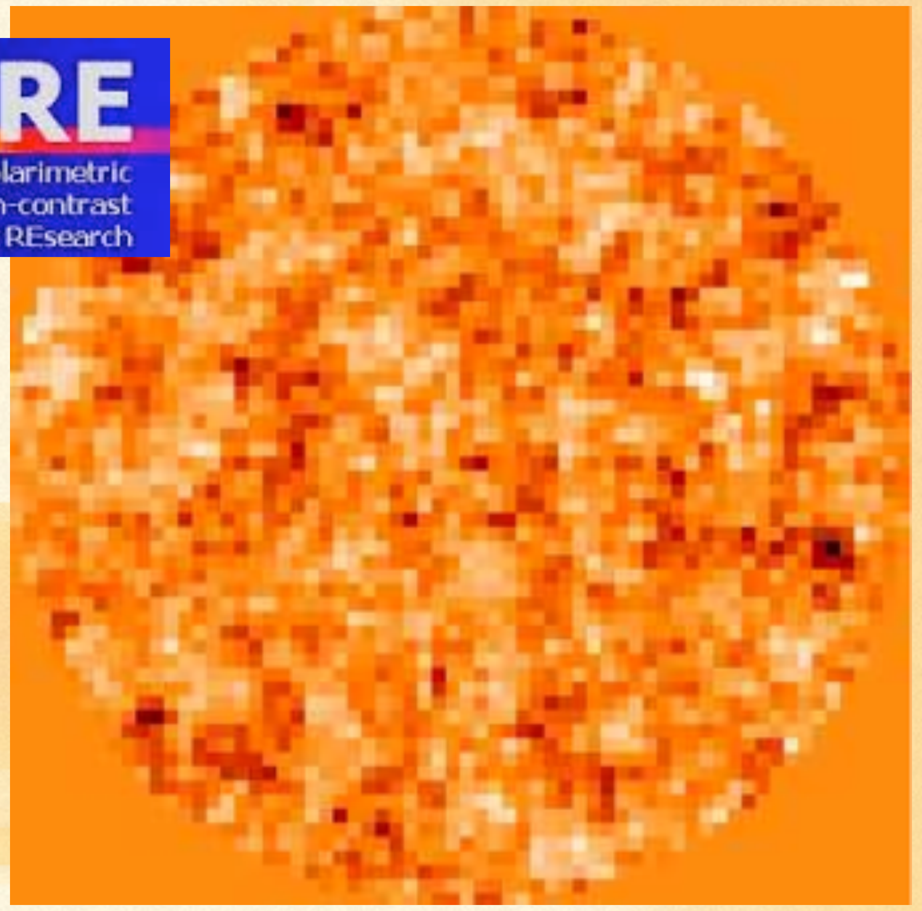
Ygouf et al. 2013, A&A

AND IT WORKS!

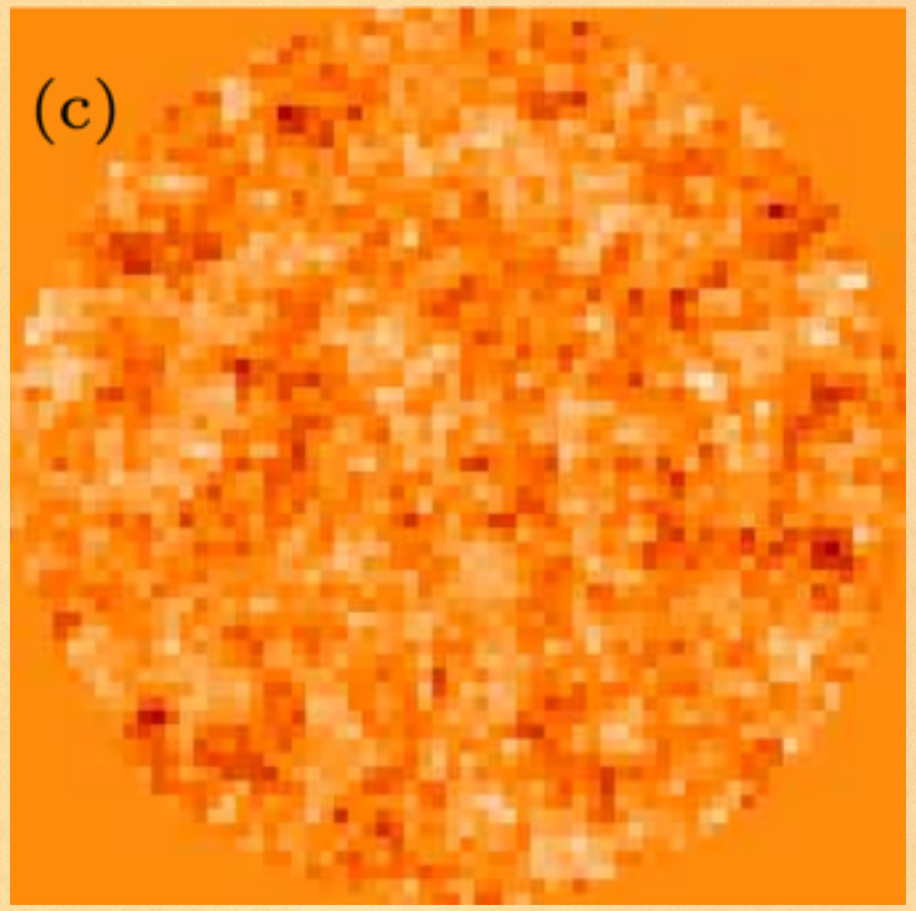
- Validation on simulated data

  Ygouf et al. 2013, A&A





Simulated phase

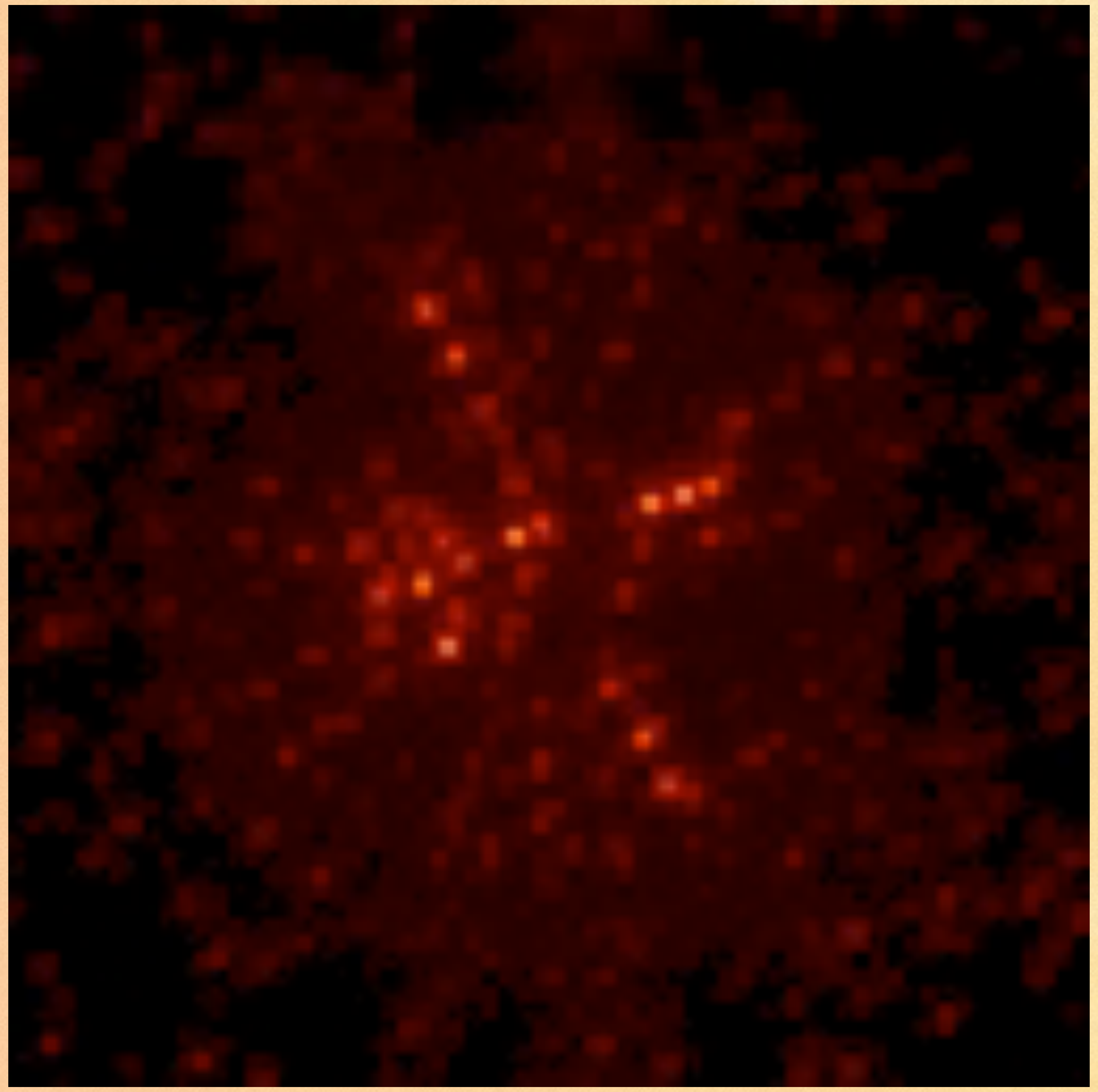


Estimated phase

AND IT WORKS!

- Validation on simulated data

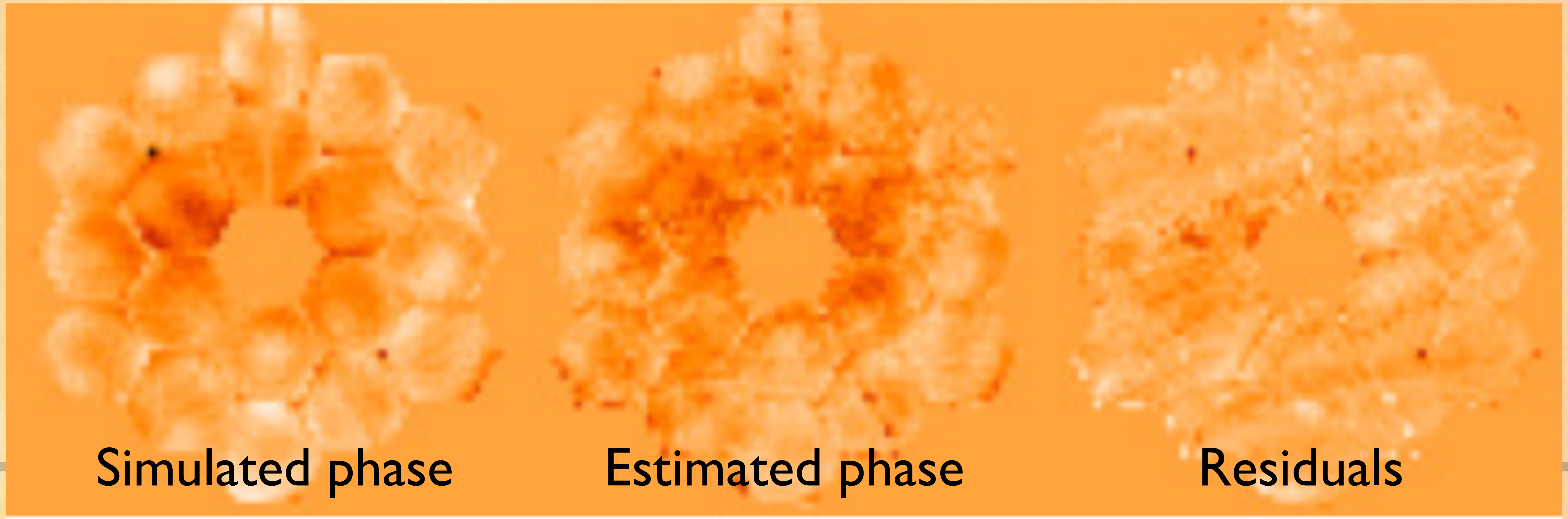
  Ygouf et al. 2013, A&A



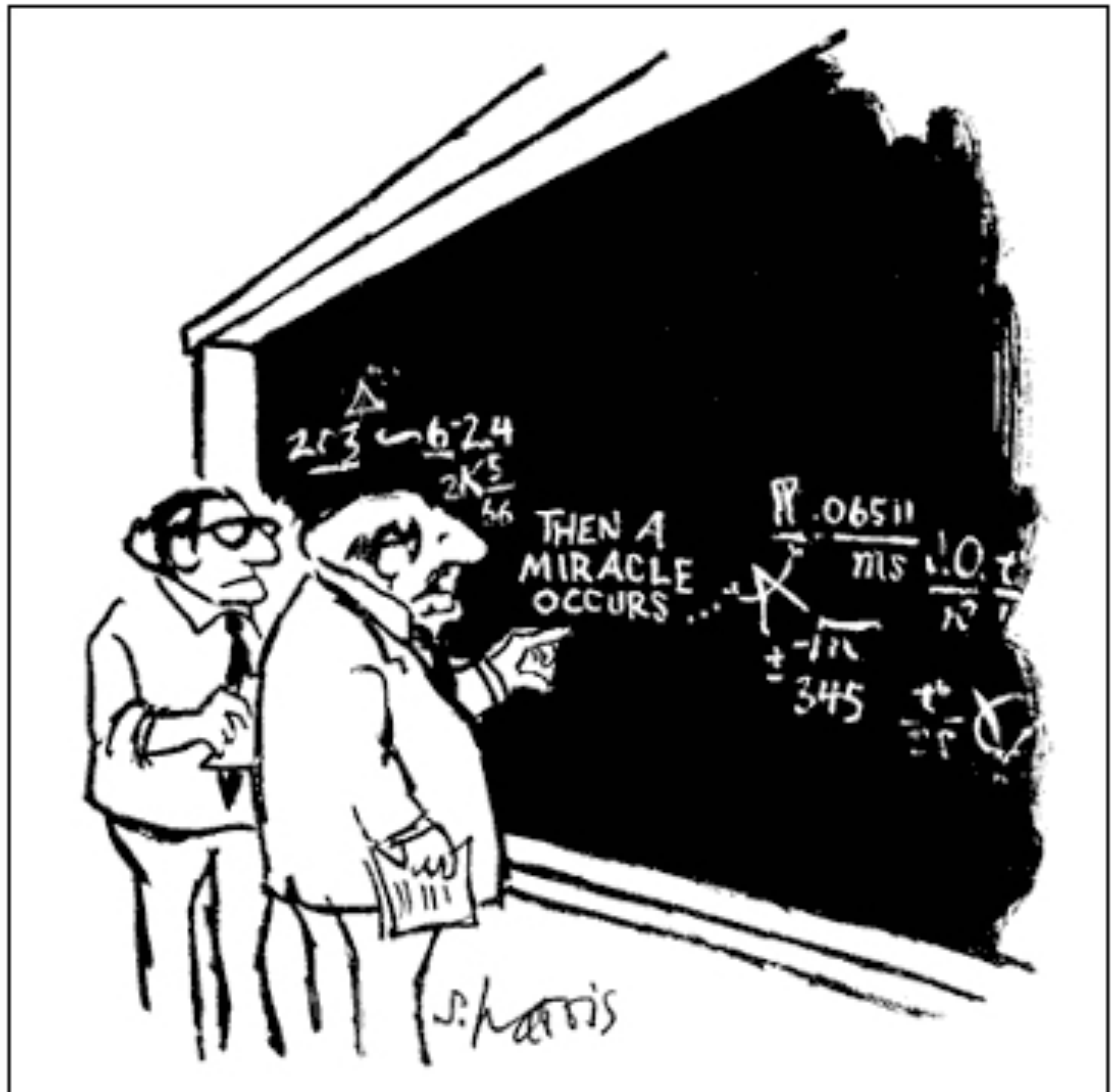
Potential for WFS&C

Simulated phase   Estimated phase

JWST



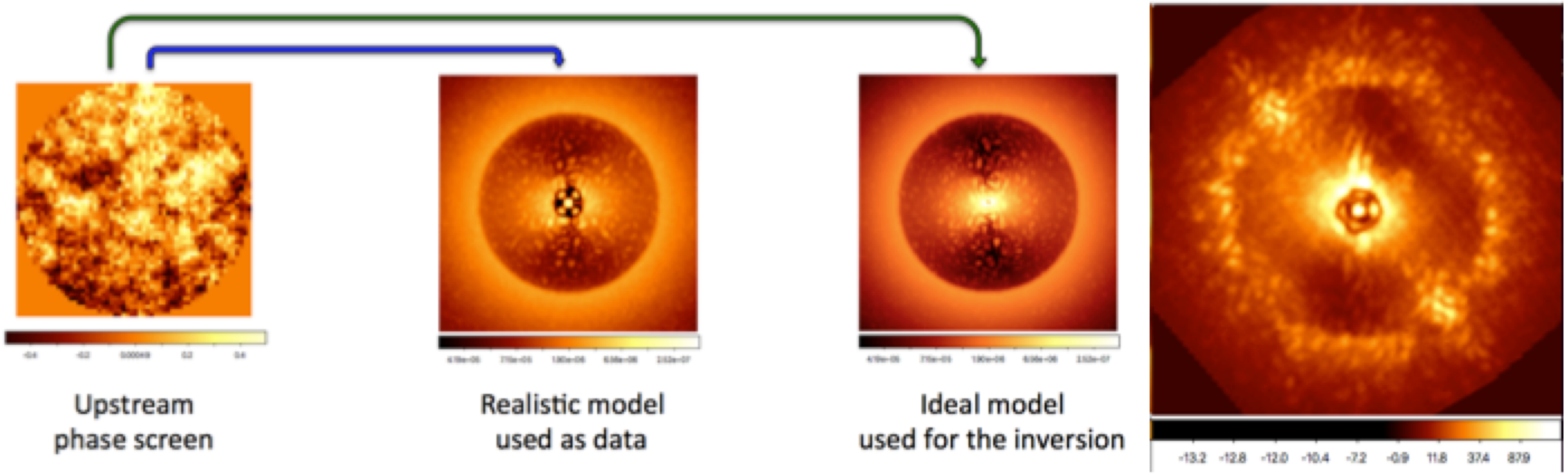
CHALLENGES



“I think you should be more explicit here in step two.”

CHALLENGE 1: APPLICATION TO REAL DATA IS HARD => WORK IN PROGRESS

Test on realistic simulations: *Cantalloube et al. 2017 (AO4ELT)*
Implementation of a realistic coronagraph model: *Cantalloube et al. 2018 (SPIE)*



Simulated images at 967nm

SPHERE-IFS image

From Faustine Cantalloube's presentation

CHALLENGE 2: CRITERION MINIMIZATION

$$h_\lambda^c = TF\left\{\left[p_d e^{j(\phi_u+\phi_d)} \otimes p_d e^{j(\phi_u+\phi_d)}\right] \times e^{-\frac{1}{2}D_{\phi_r}}\right\}$$
$$+\left[\frac{1}{S_u^{\,2}}\iint\left(e^{-\frac{1}{2}D_{\phi_r}} * p_u e^{j\phi_u}\right)\times\left(p_u e^{j\phi_u}\right)^* d\rho^2\right]\times\left[TF^{-1}\left(p_d e^{j\phi_d}\right)\right]^*$$
$$-\frac{2}{S_u}\Re\left\{TF^{-1}\left[p_d e^{j(\phi_u+\phi_d)}\times\left(e^{-\frac{1}{2}D_{\phi_r}} * \left(p_u e^{j\phi_u}\right)^*\right)\right]\times\left(p_d e^{j\phi_d}\right)^*\right\}$$

Sum on wavelengths

Sum on pixels

Least square distance between the data and the model

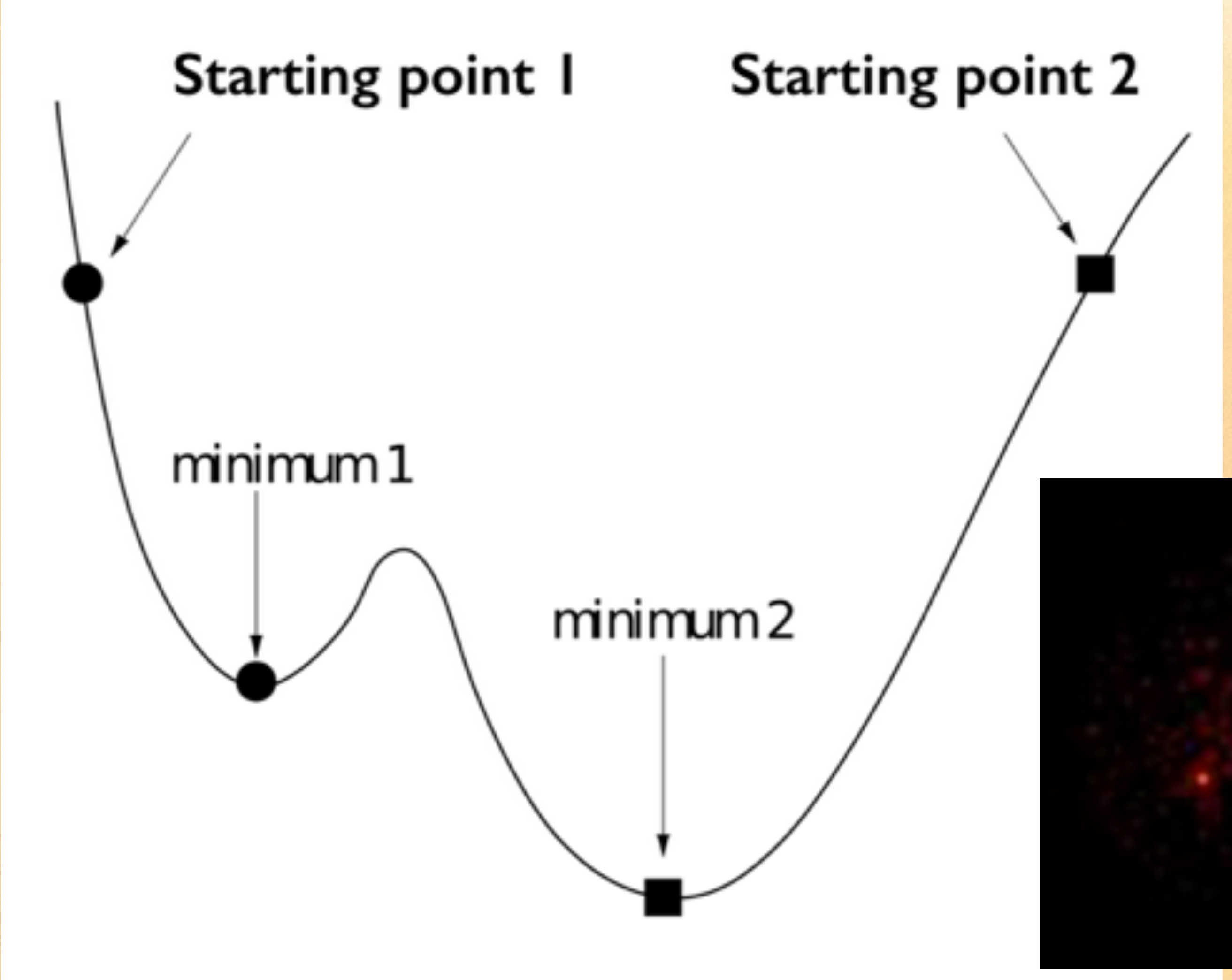
+

Regularization terms

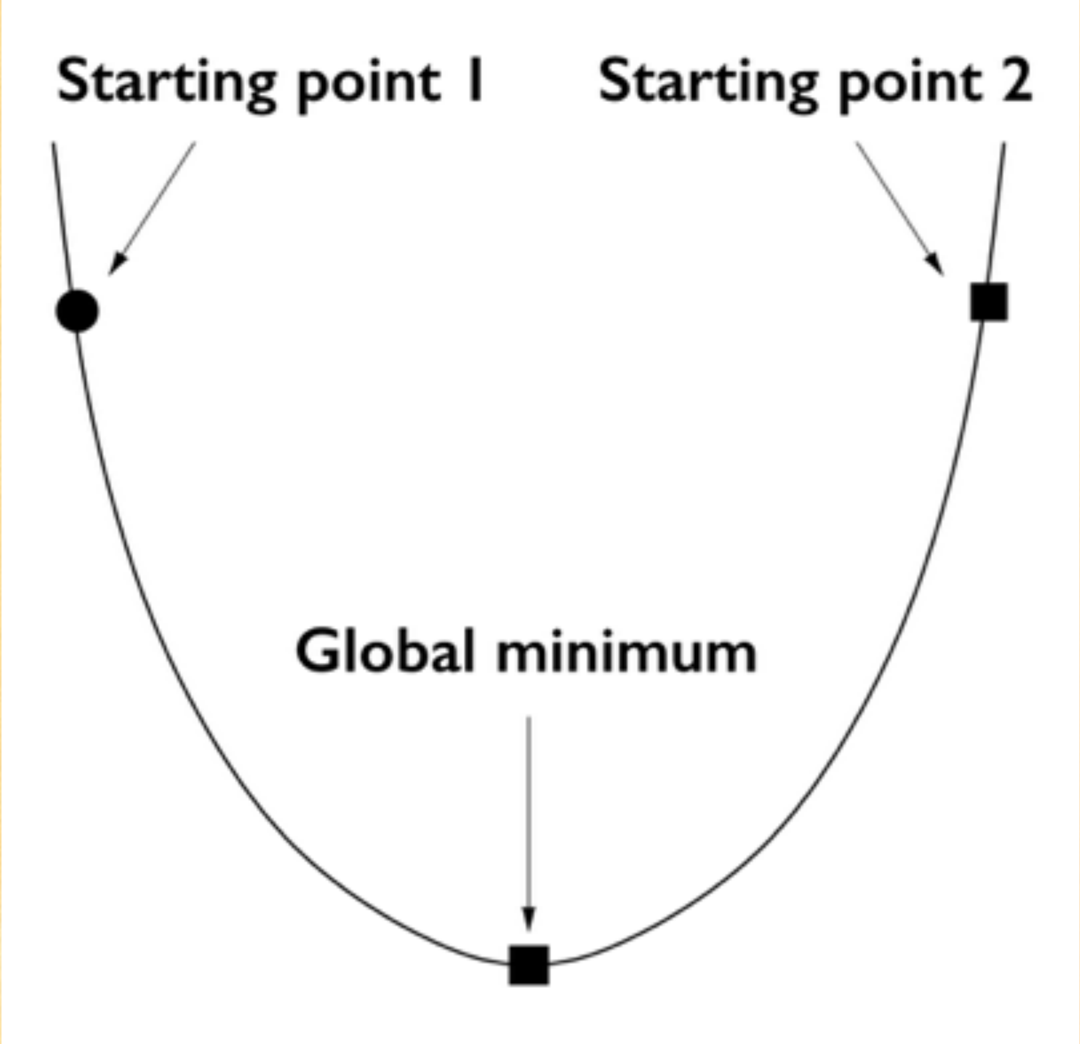
$$J\left(\left\{\underline{o_\lambda}\right\},\left\{\underline{f_\lambda^*}\right\},\underline{\delta_u}\right) = \sum_\lambda \sum_{x,y} \frac{1}{2\sigma_n^2(x,y)}\left|i_\lambda - \underline{f_\lambda^*}\cdot h_\lambda^c\left(\underline{\delta_u}\right) - \underline{o_\lambda} * h_\lambda^{nc}\right|^2(x,y) + \boxed{R_{x,y,\lambda}(o,\delta)}$$

Regularization term(s)

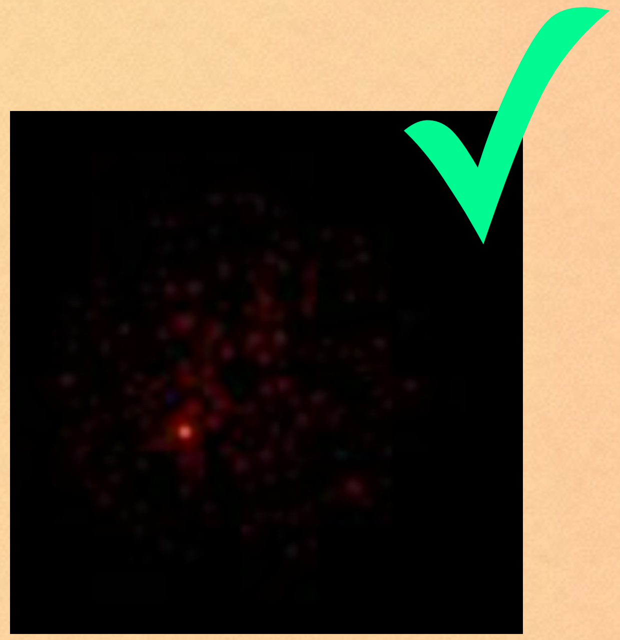
Ygouf et al. 2013, A&A



Non-convex criterion



Convex criterion



CHALLENGE 2: CRITERION MINIMIZATION

Bayes' rule

$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\boxed{\mathscr{L}(x)}}{\mathscr{L}(\mathbf{i}_\lambda)}$$

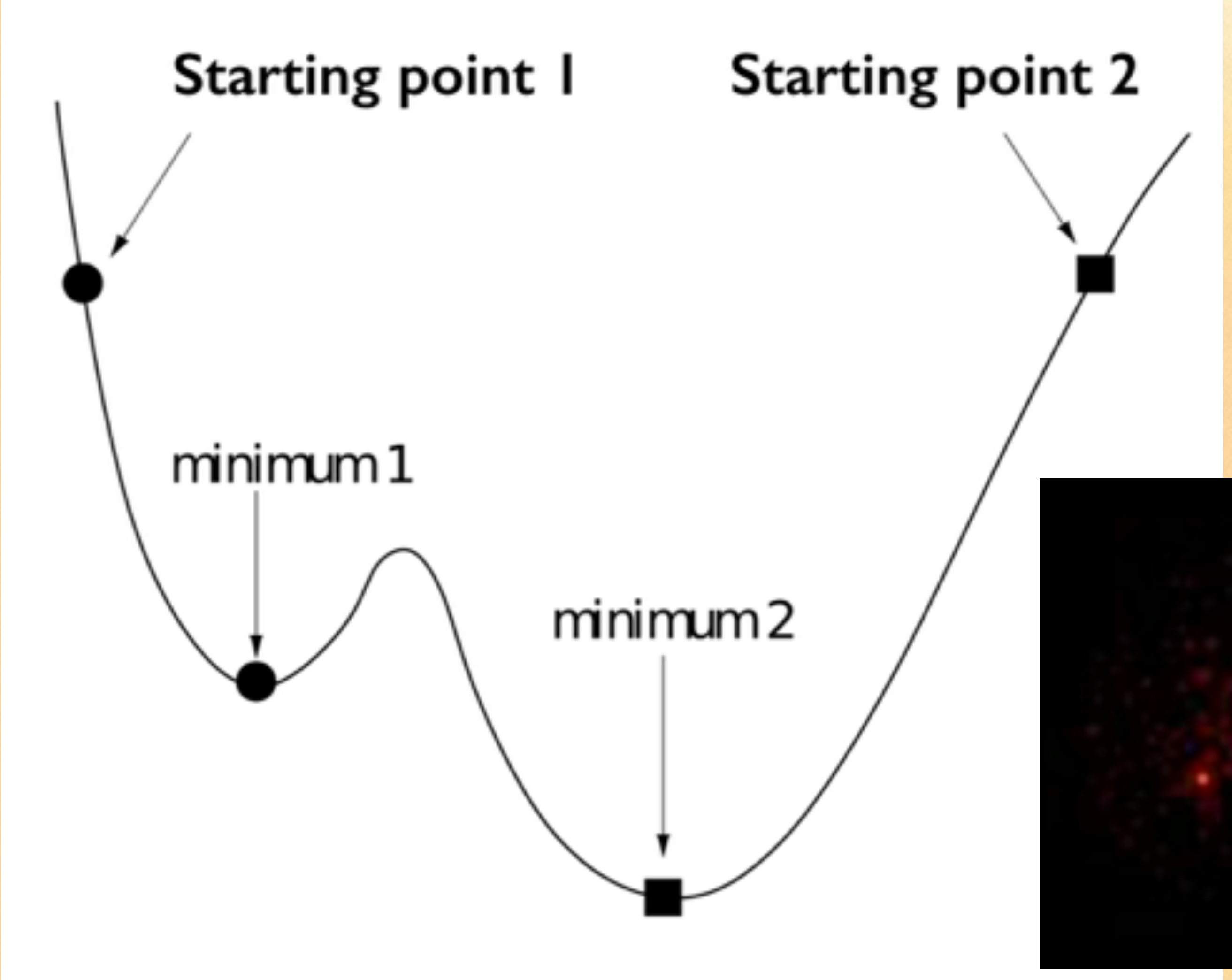
Probability of the unknown
=
Knowledge about the instrument

Sum on wavelengths — Sum on pixels — Least square distance between the data and the model + Regularization terms

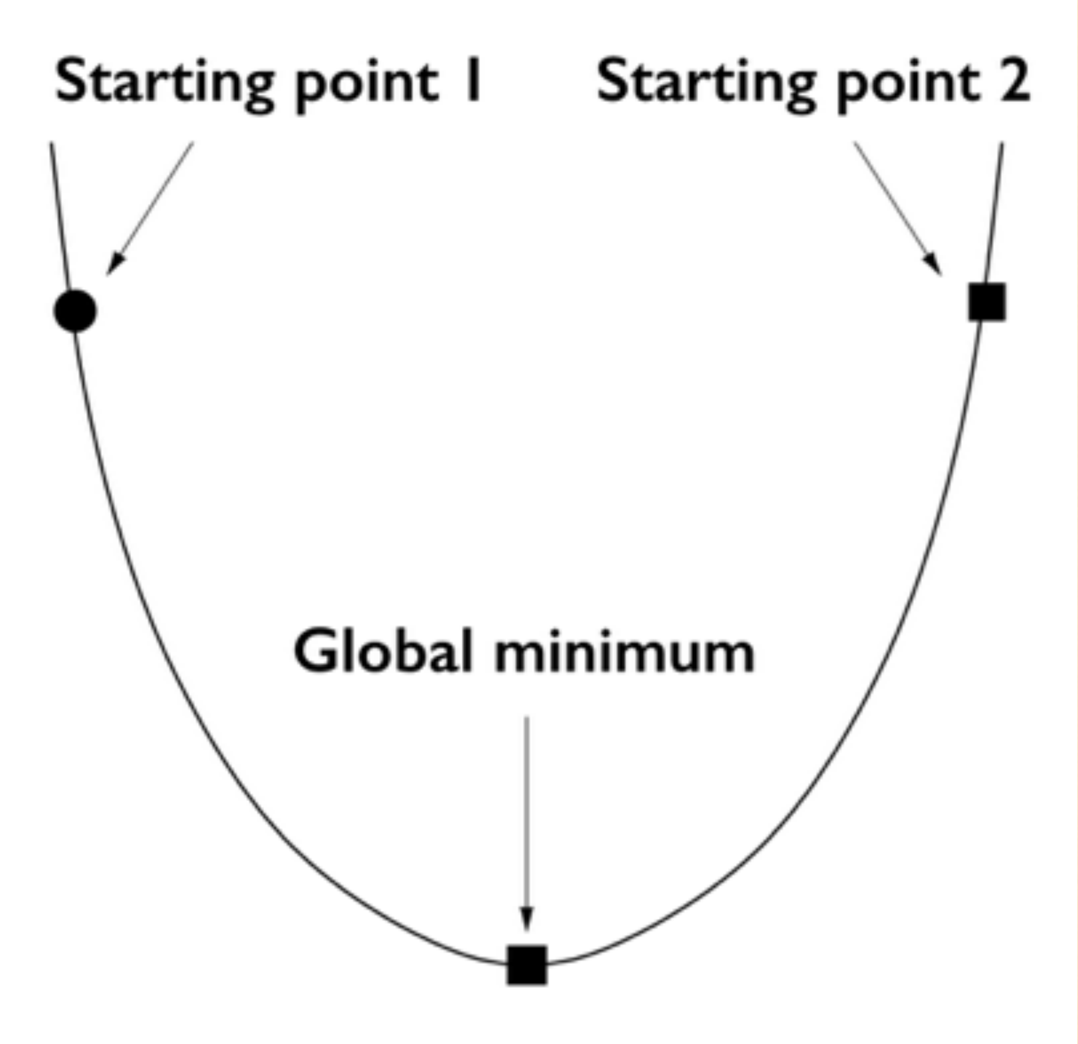
$$J\left(\{\underline{o_\lambda}\},\{\underline{f^*_\lambda}\},\underline{\delta_u}\right) = \sum_\lambda \sum_{x,y} \frac{1}{2\sigma_n^2(x,y)} \left|i_\lambda - \underline{f^*_\lambda}\cdot h^c_\lambda(\underline{\delta_u}) - \underline{o_\lambda} * h^{nc}_\lambda\right|^2(x,y) + \boxed{R_{x,y,\lambda}(o,\delta)}$$

Regularization term(s)

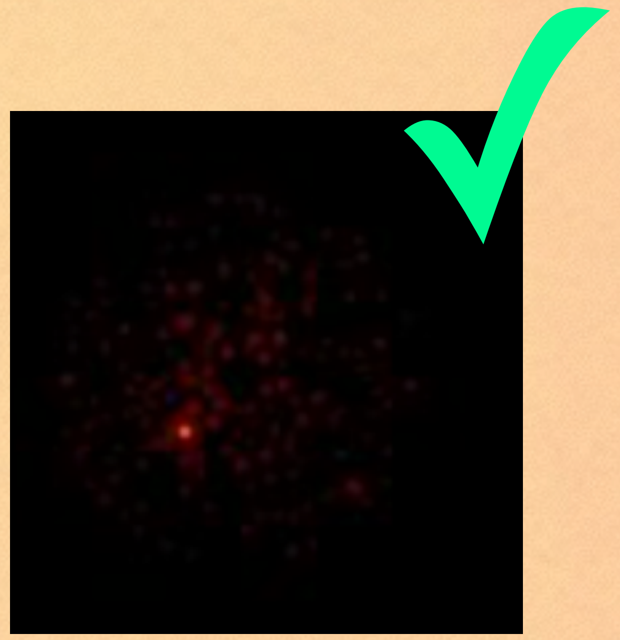
Ygouf et al. 2013, A&A



Non-convex criterion



Convex criterion



CHALLENGE 2: CRITERION MINIMIZATION

Bayes' rule

$$\mathscr{L}(x|\mathbf{i}_\lambda) = \frac{\mathscr{L}(\mathbf{i}_\lambda|x)\,\boxed{\mathscr{L}(x)}}{\mathscr{L}(\mathbf{i}_\lambda)}$$

Probability of the unknown

=

Knowled

the inst

Sum on wavelengths

Sum on pixels

Least square distance between the data and the model

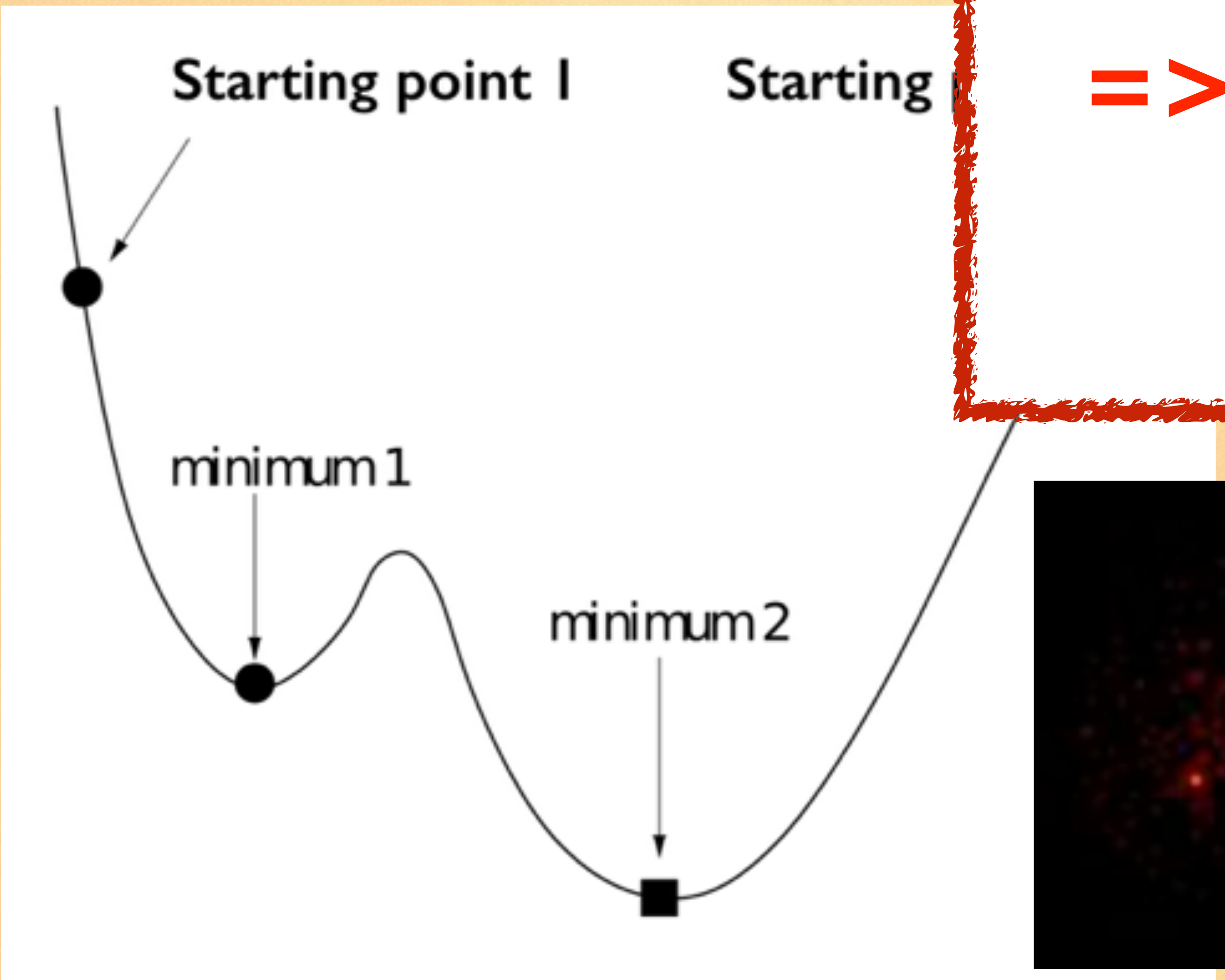
\+

Regularization terms

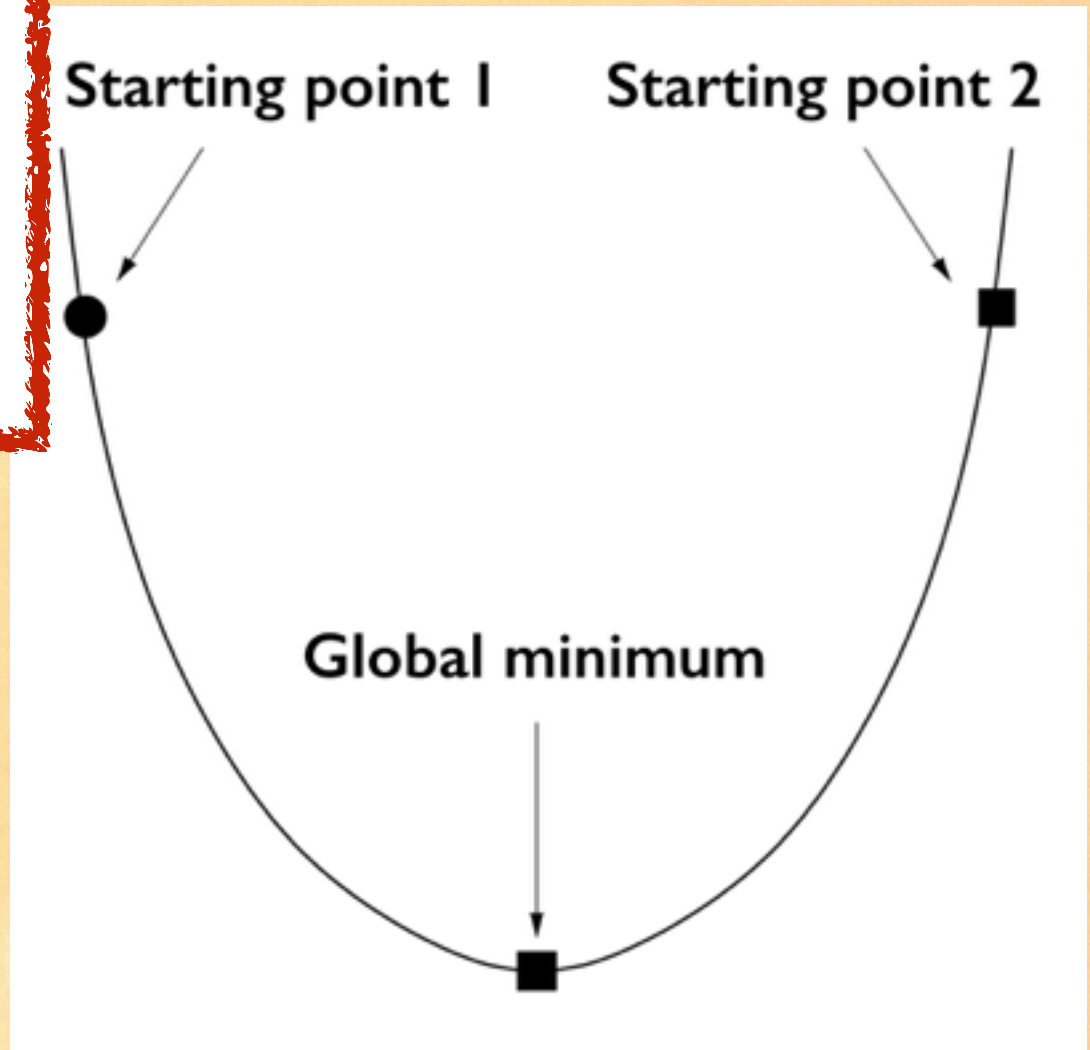
$$J(\{o_\lambda\},\{f_\lambda^*\},\delta_u) = \sum\sum \frac{1}{\sigma^2_\lambda(x,y)}\left|i_\lambda - \underline{f_\lambda^*}\cdot h_\lambda^c(\underline{\delta_u}) - \underline{o_\lambda} * h_\lambda^{nc}\right|^2(x,y) + \boxed{R_{x,y,\lambda}(o,\delta)}$$

Regularization term(s)

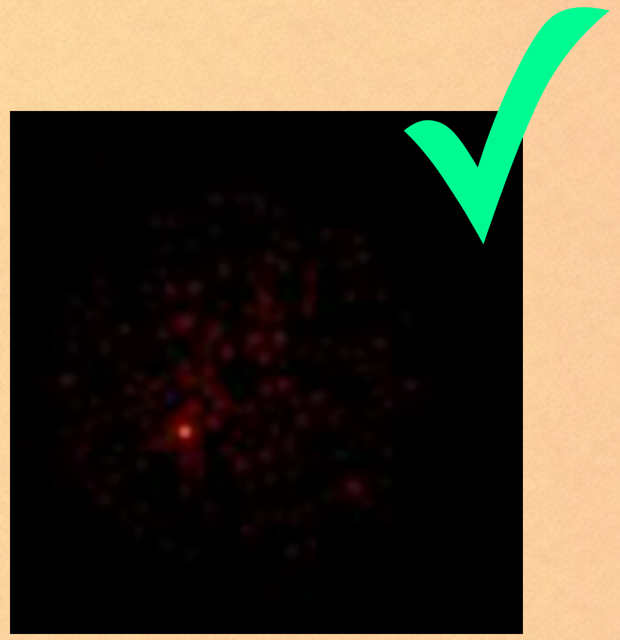
This is how we can make use of the telemetry data => SYNERGIES BETWEEN PP and WFS&C



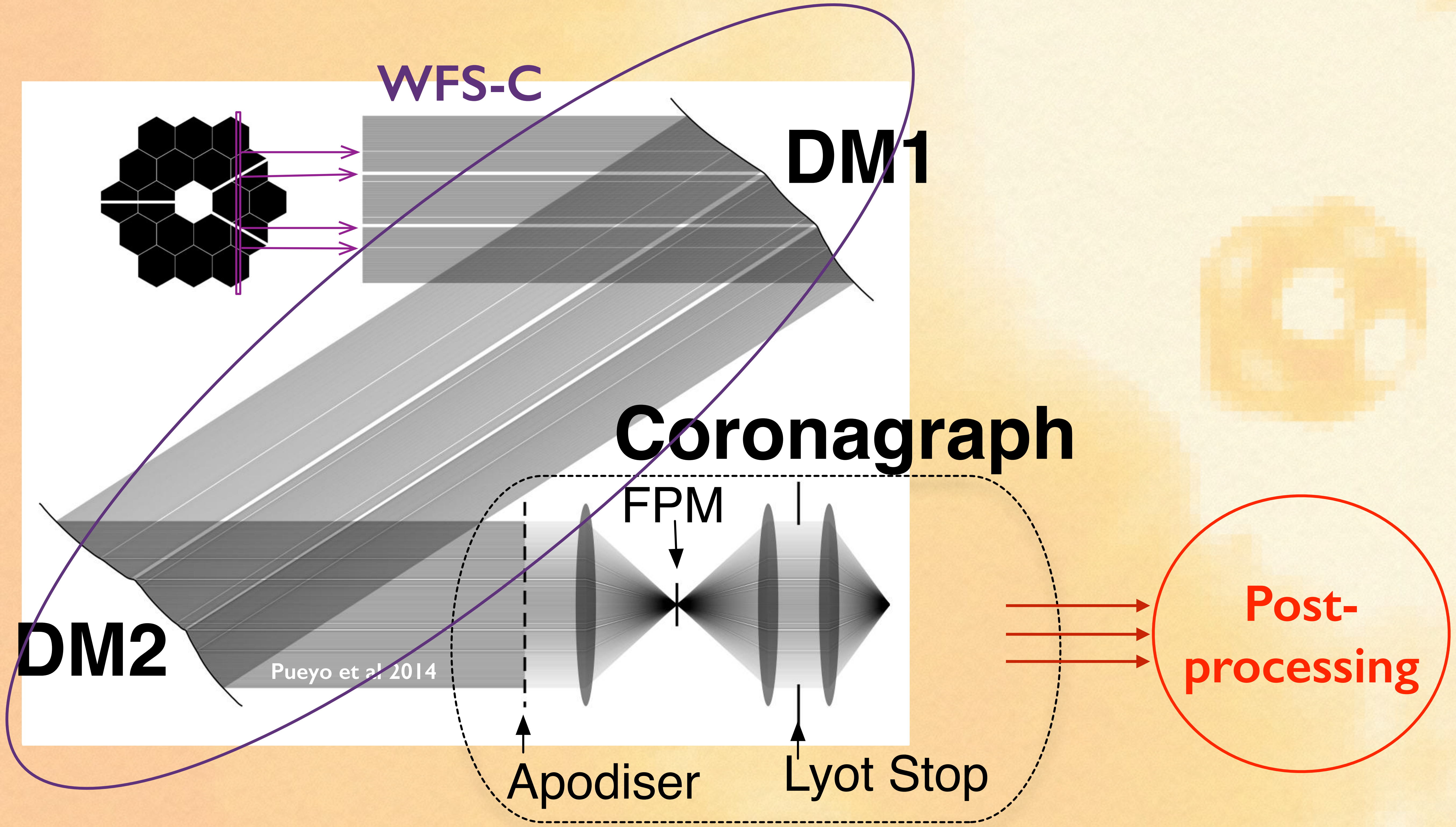
Non-convex criterion



Convex criterion



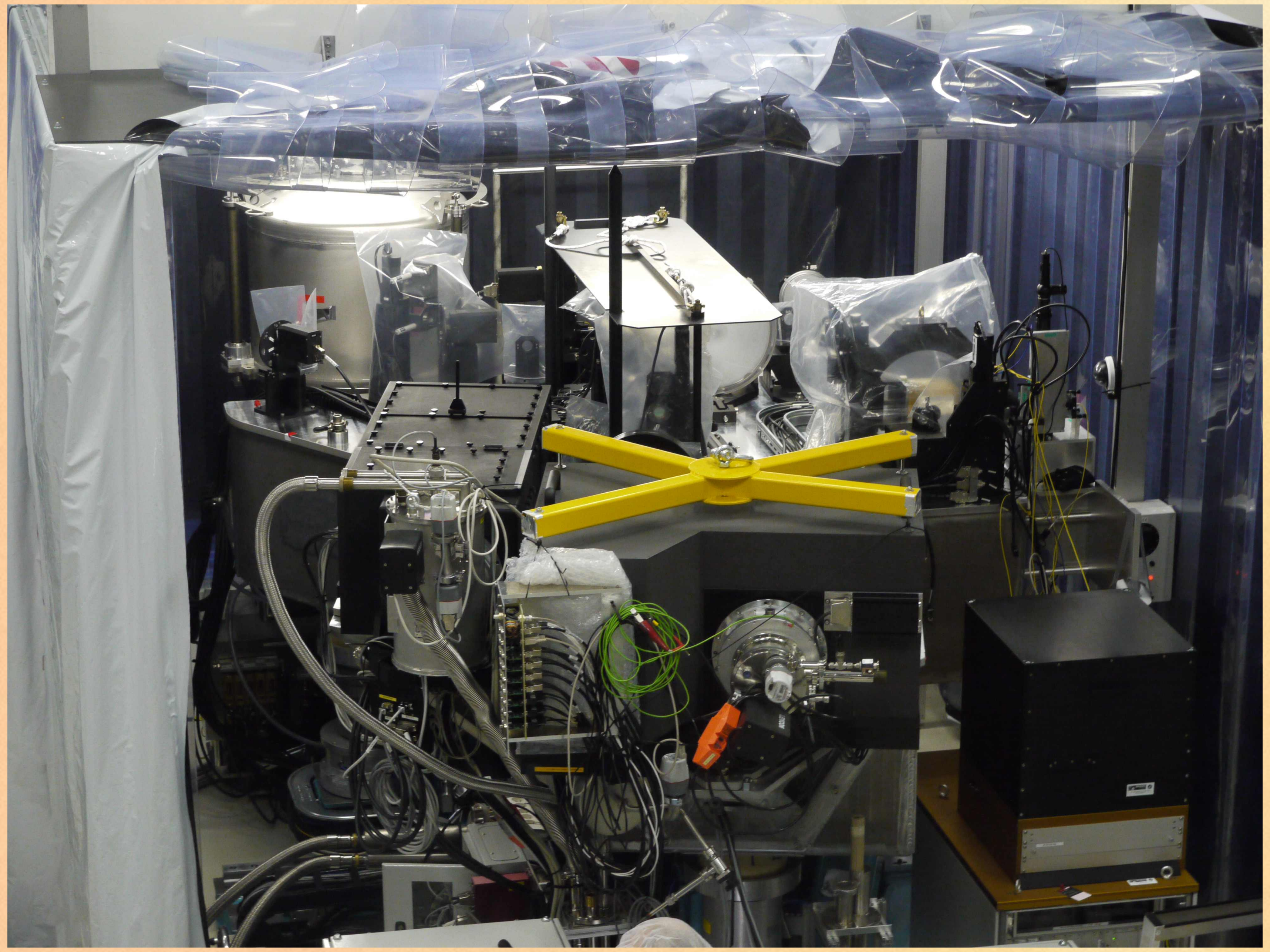
CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

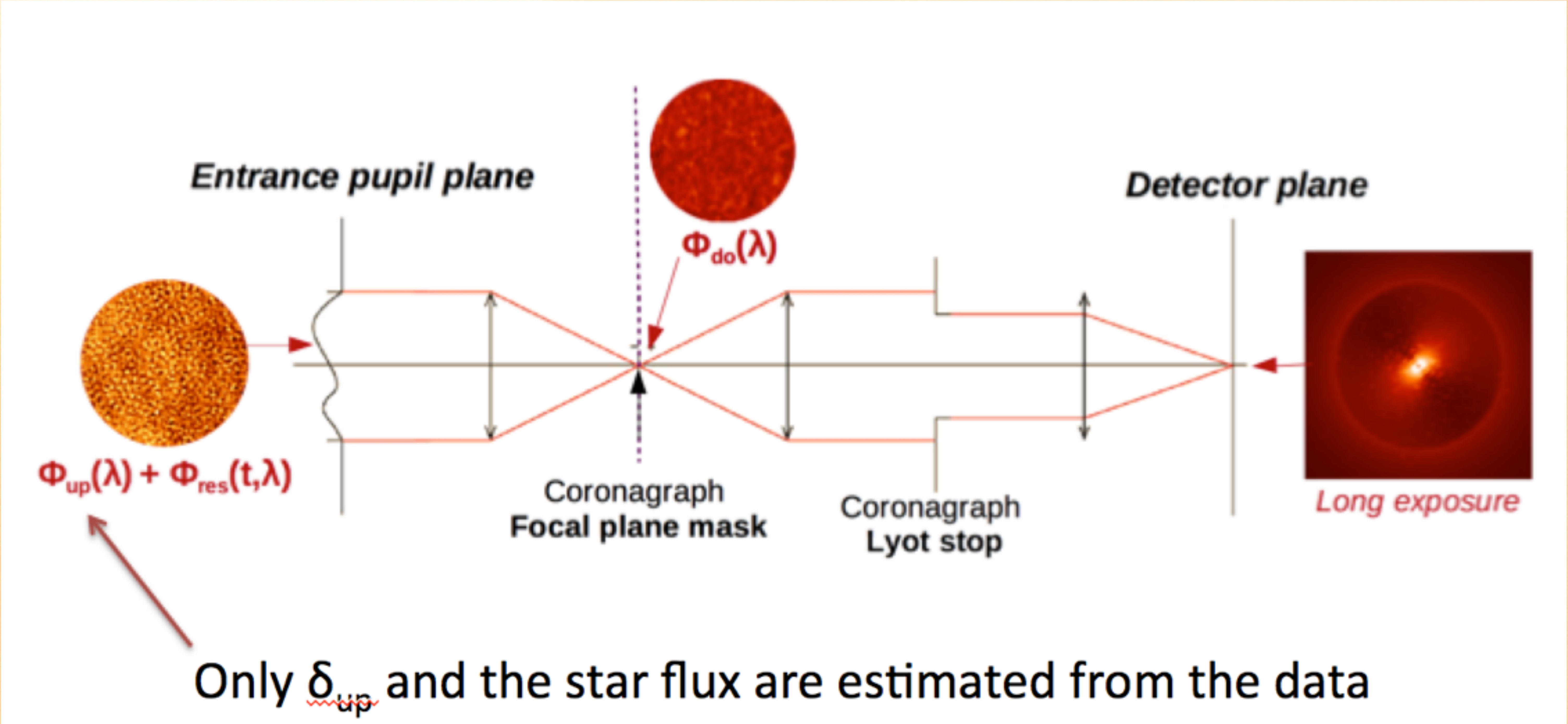


- Take a bigger telescope
- Build a better coronagraph
- Get a faster and better WFS/C
- Develop a better PP algorithm

CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

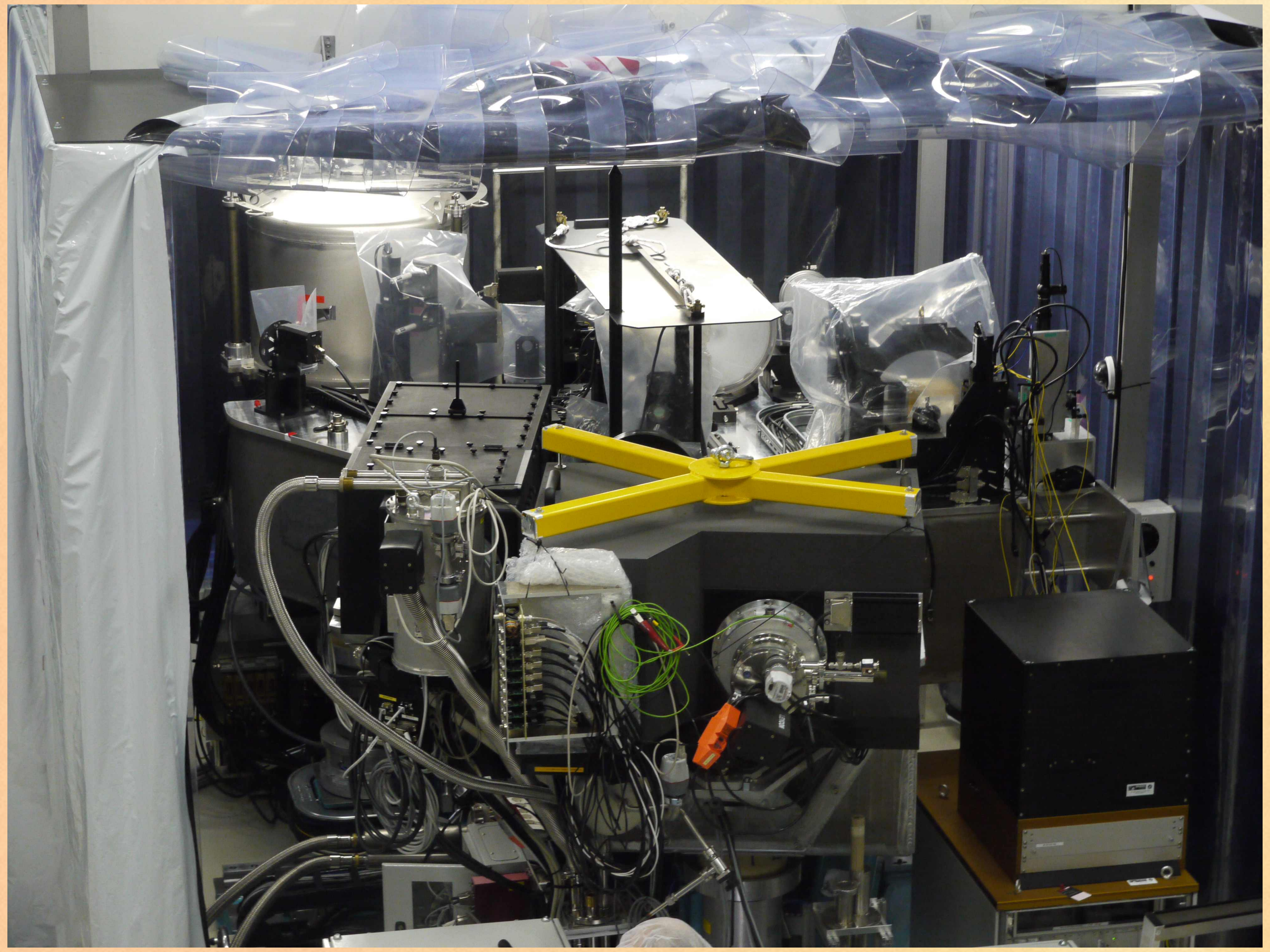
SPHERE
Spectro-Polarimetric
High-contrast
Exoplanet REsearch



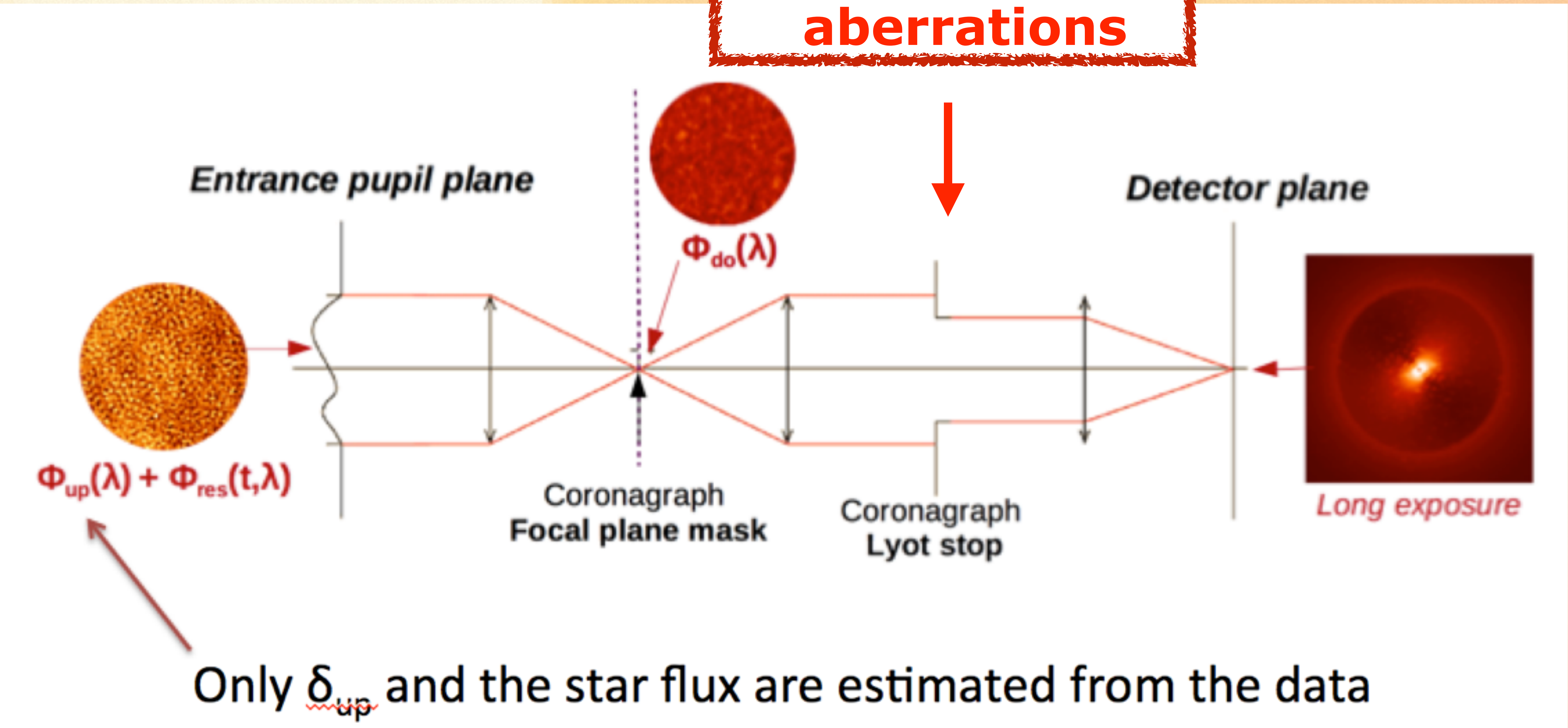


CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

SPHERE
Spectro-Polarimetric
High-contrast
Exoplanet REsearch

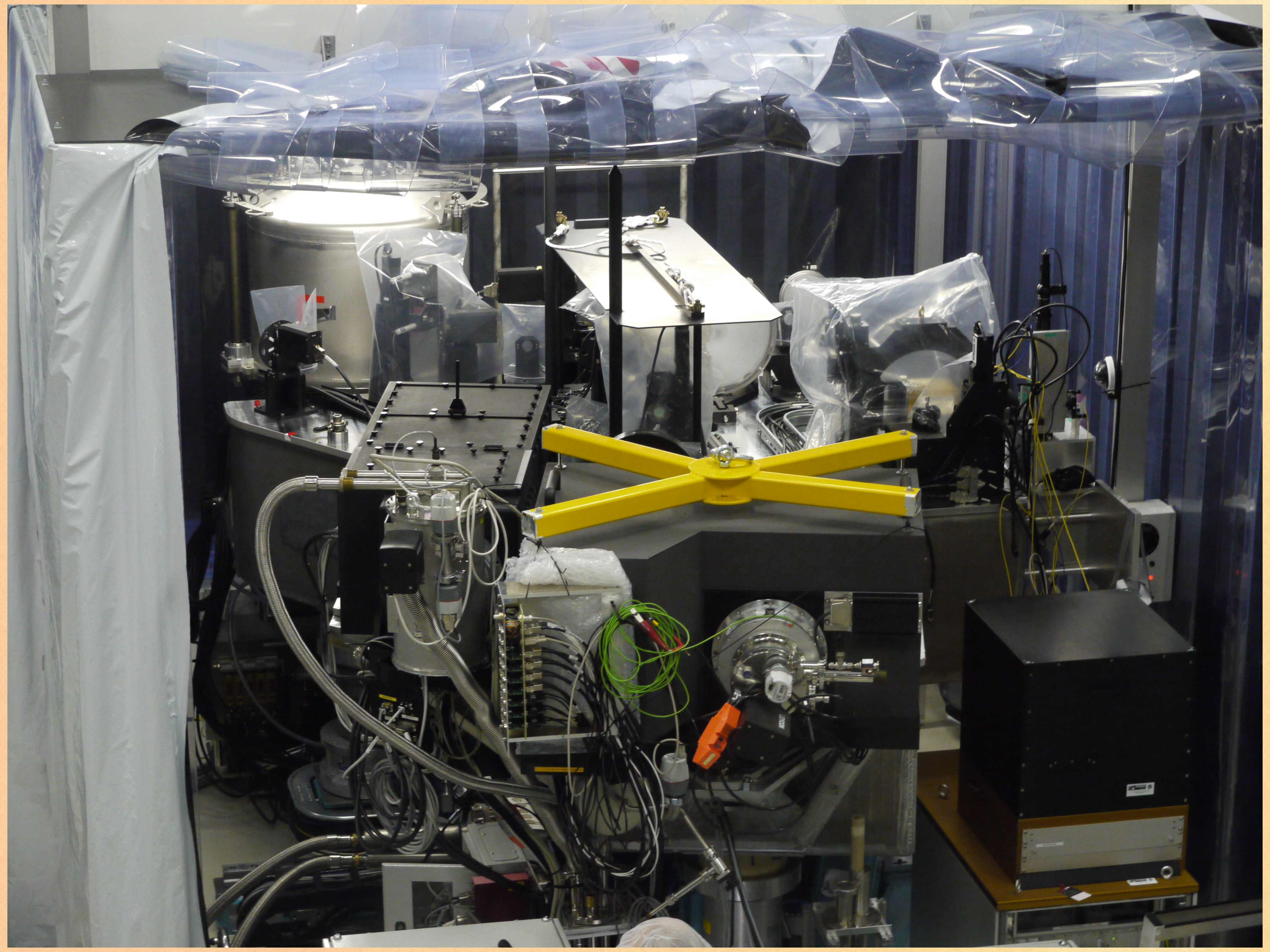


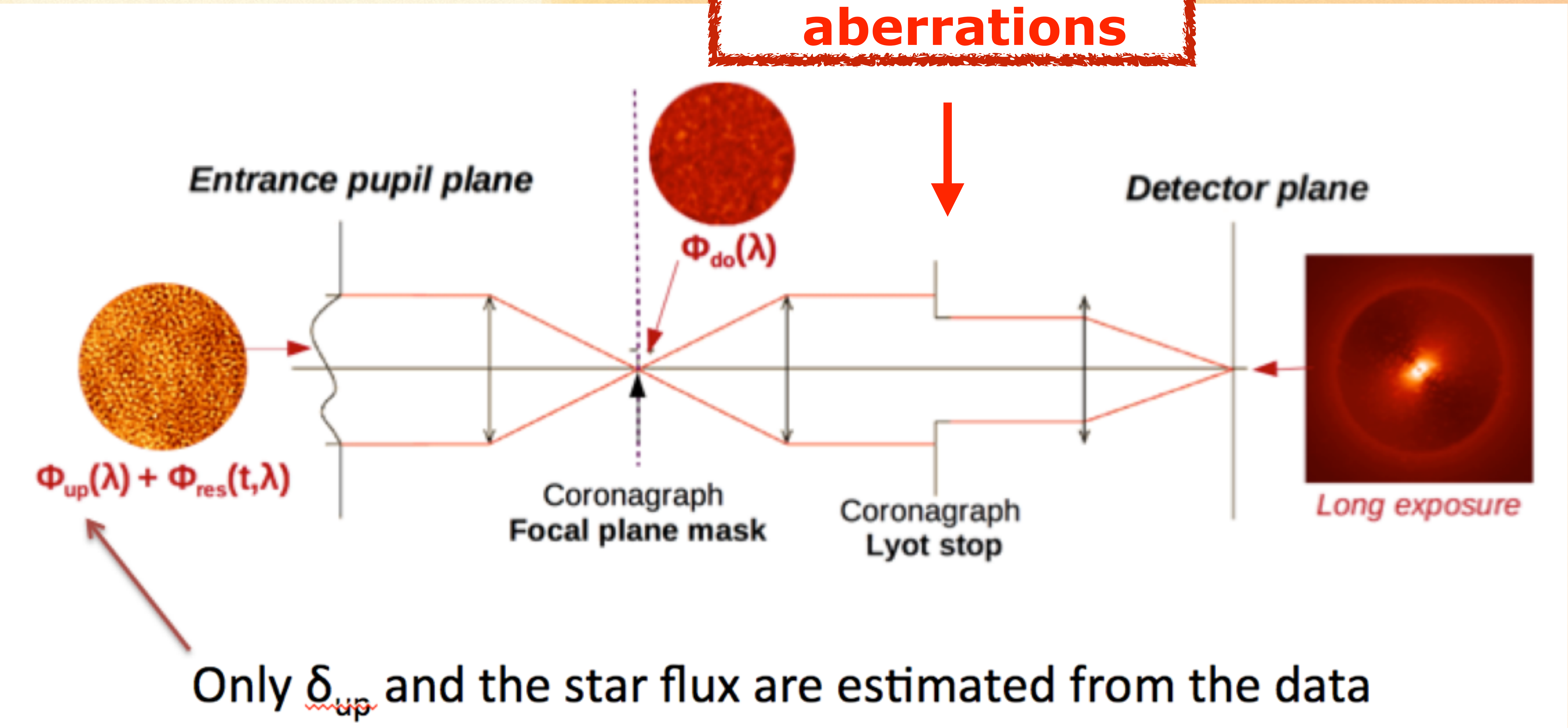
100 nm downstream aberrations



CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

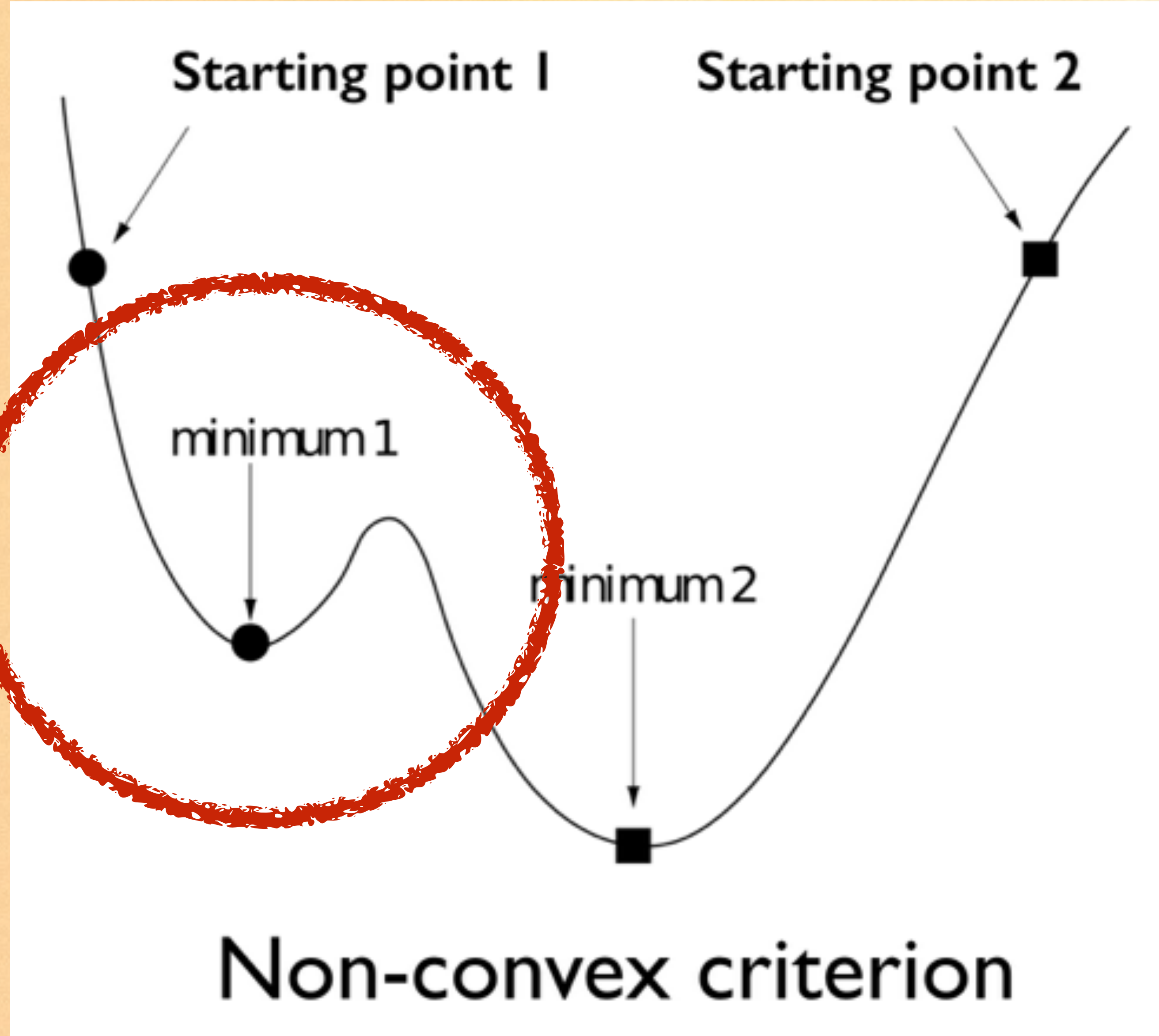
~~100 nm~~ 30 nm
downstream aberrations

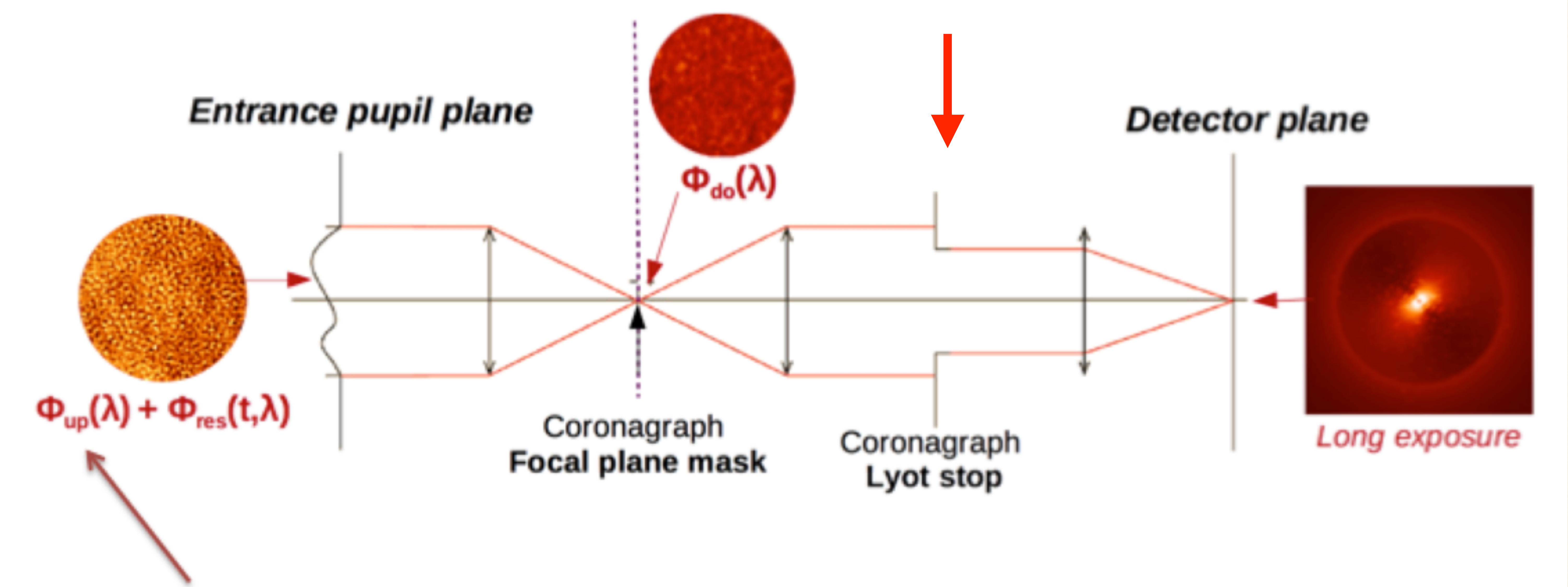




CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

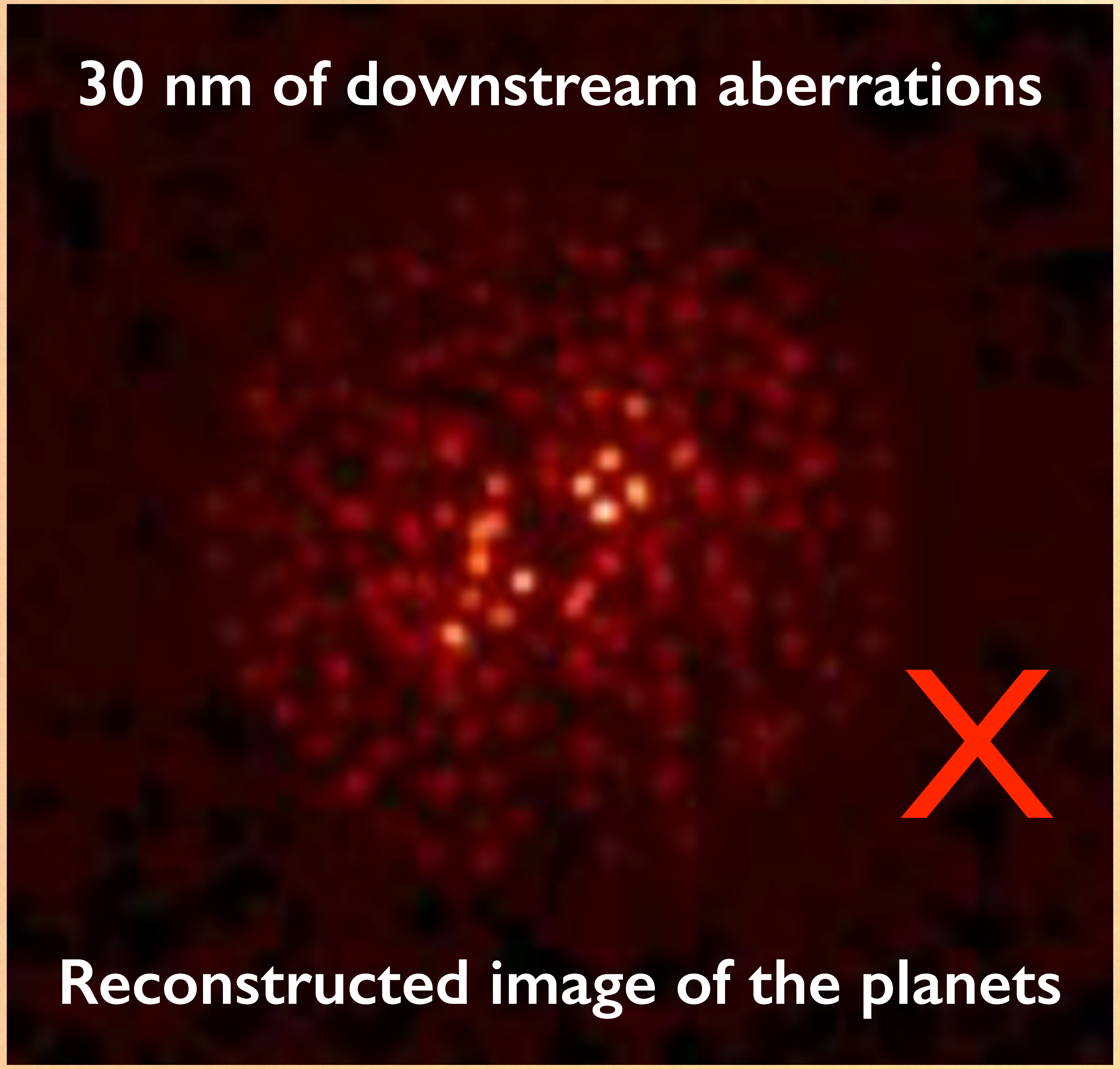
~~100 nm~~ 30 nm downstream aberrations

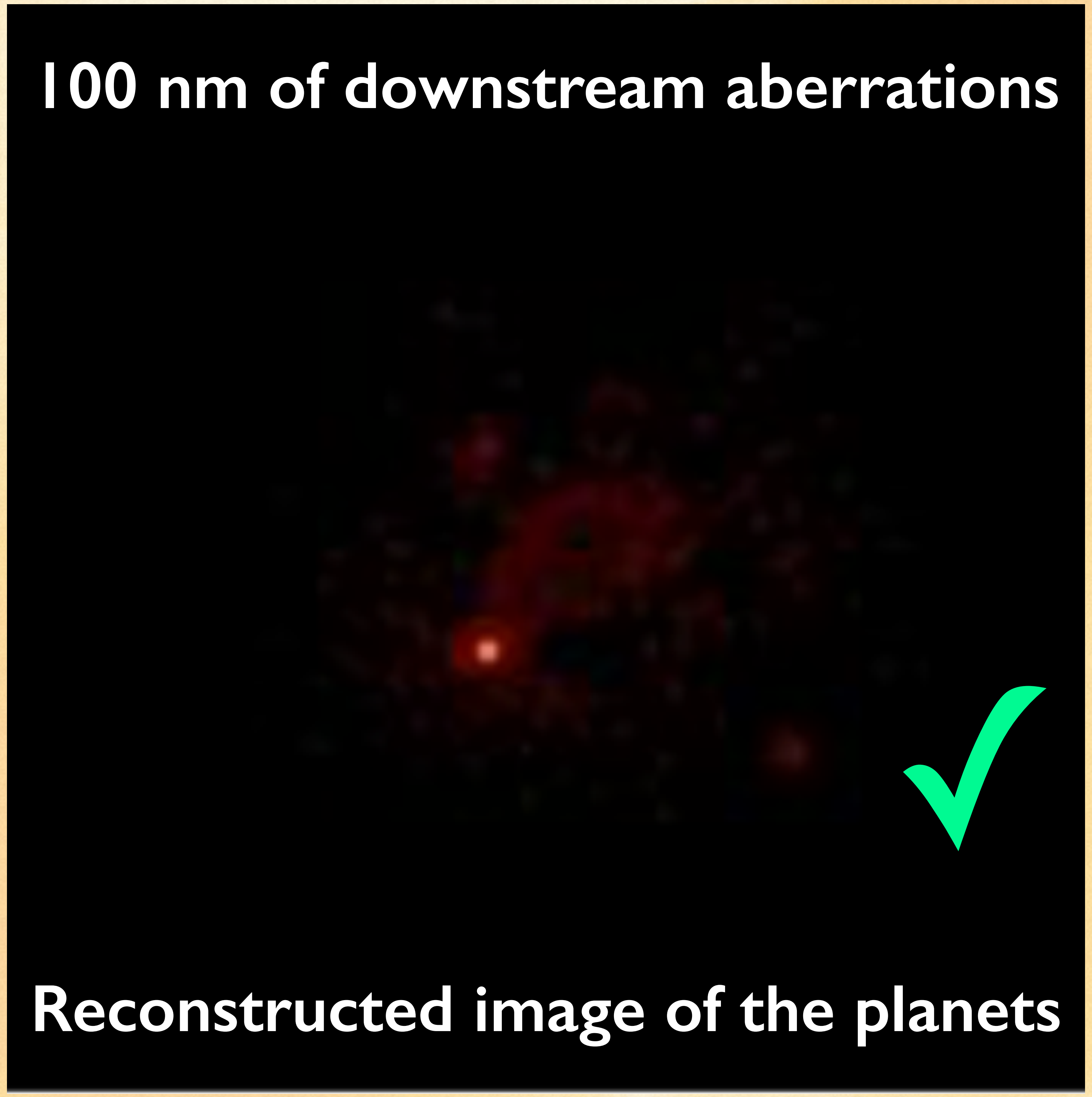


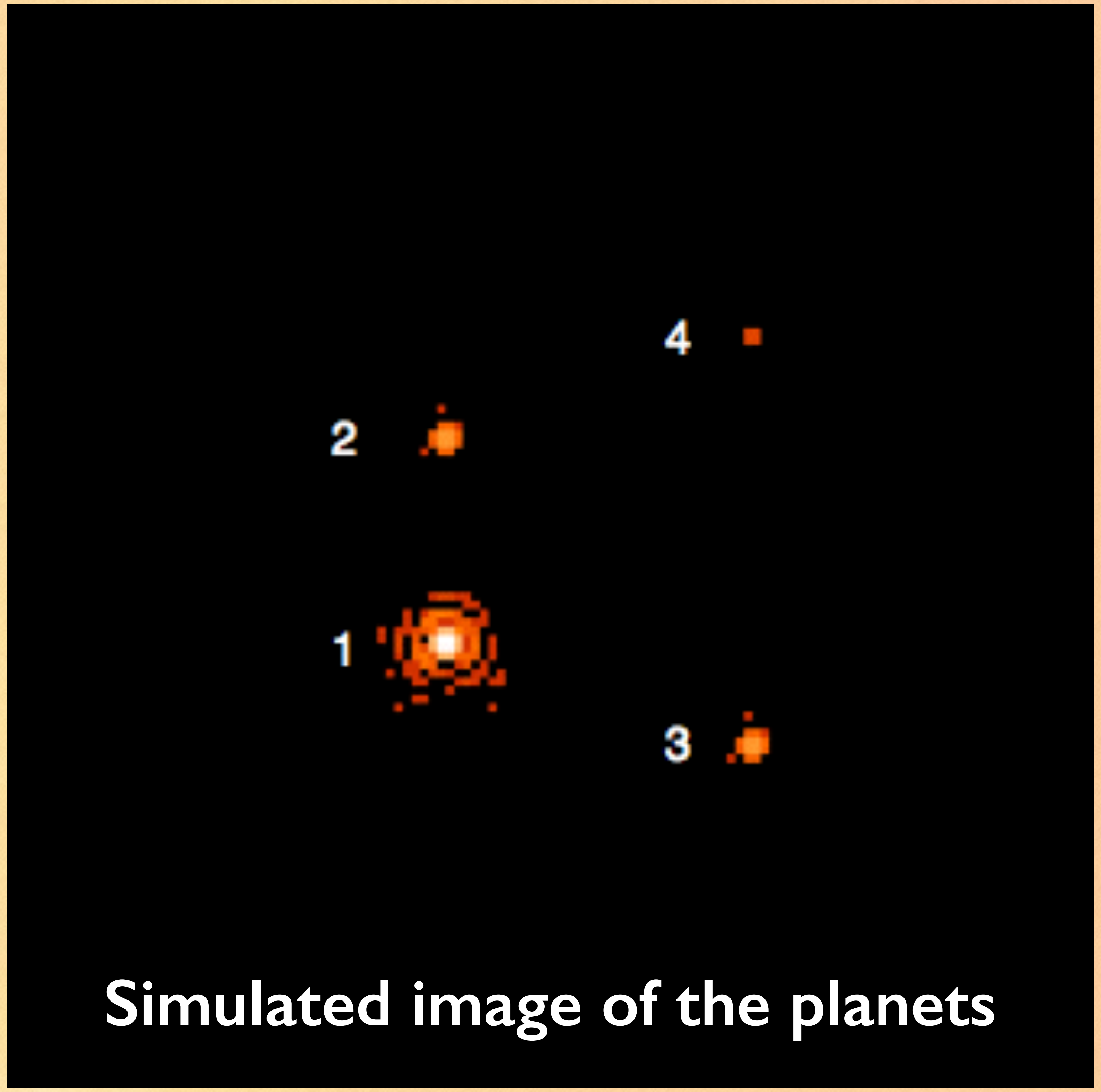


Only δ_{up} and the star flux are estimated from the data

LESSONS LEARNED

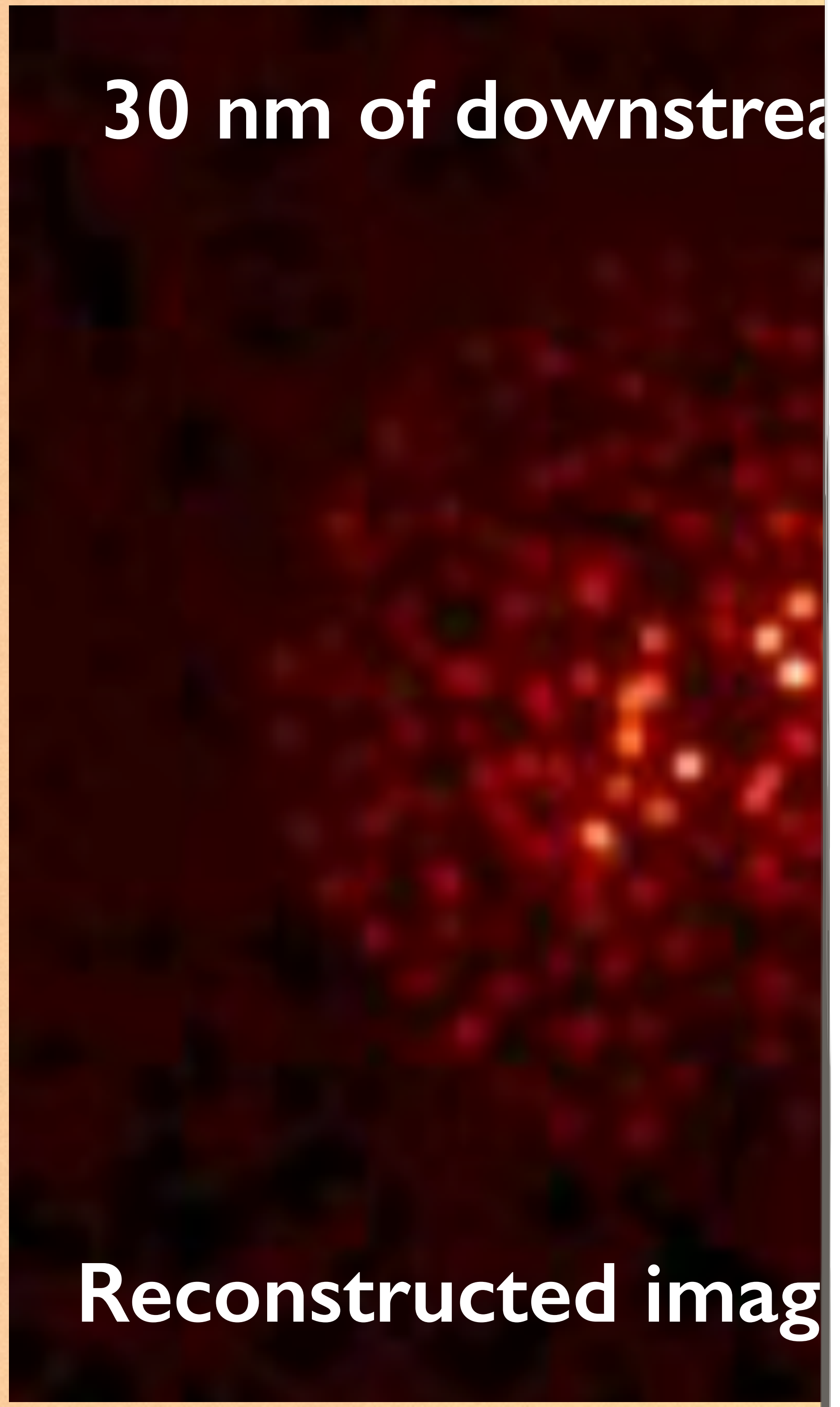






Ygouf 2013, PhD dissertation

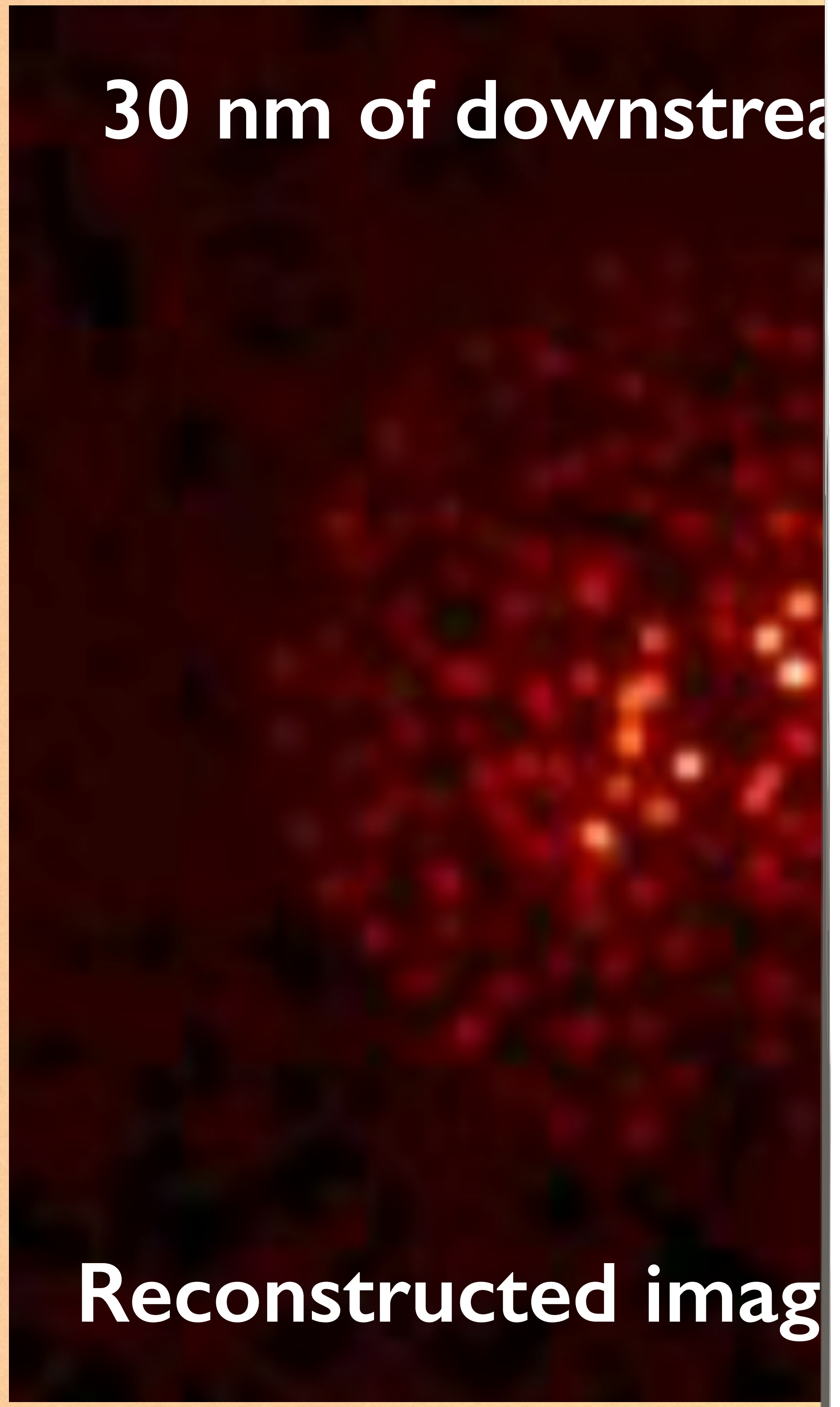
LESSONS LEARNED



- Never change two things at the same time

PhD dissertation

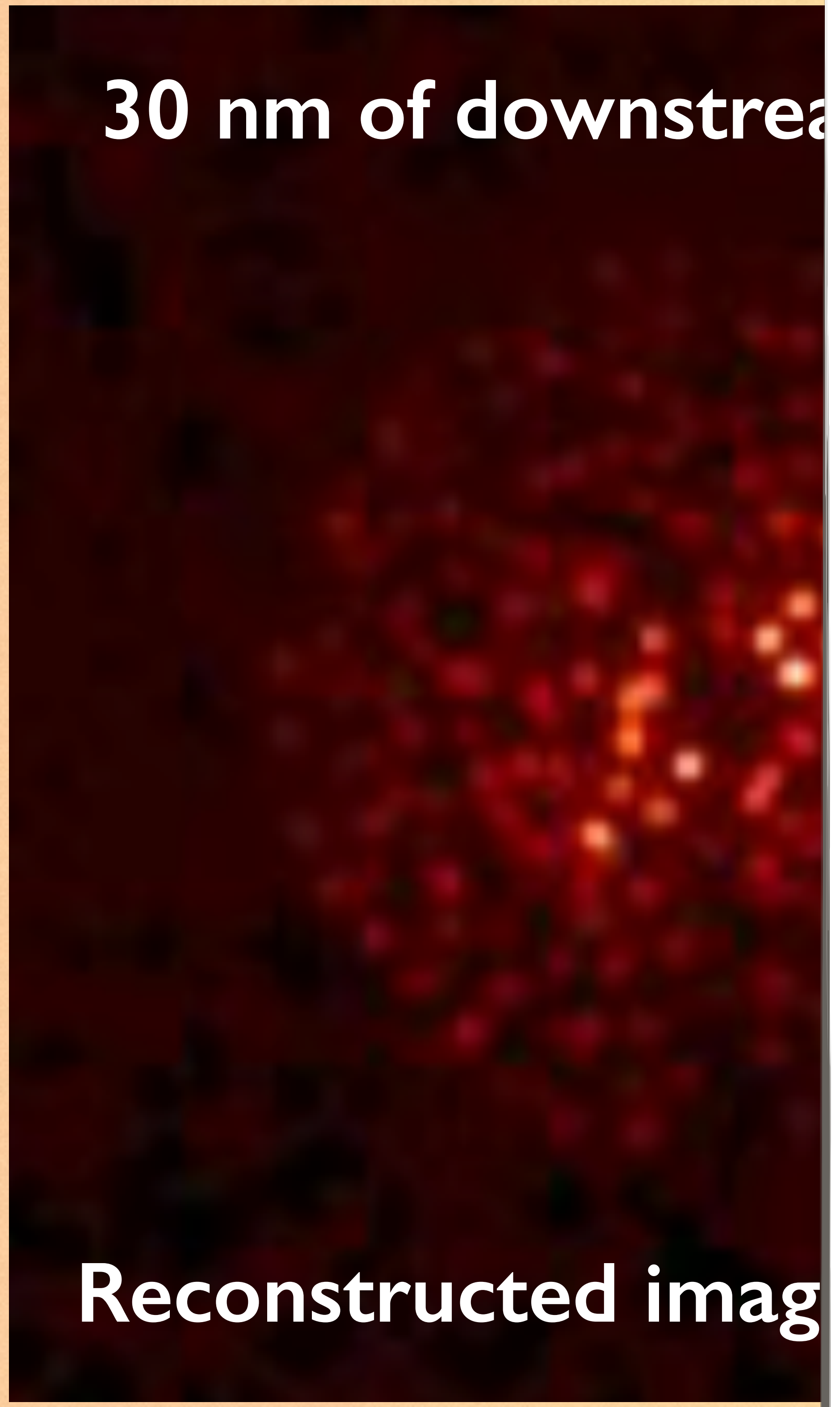
LESSONS LEARNED



- 0) Never change two things at the same time
- 1) Changing something on the model changes the shape of the criterion

PhD dissertation

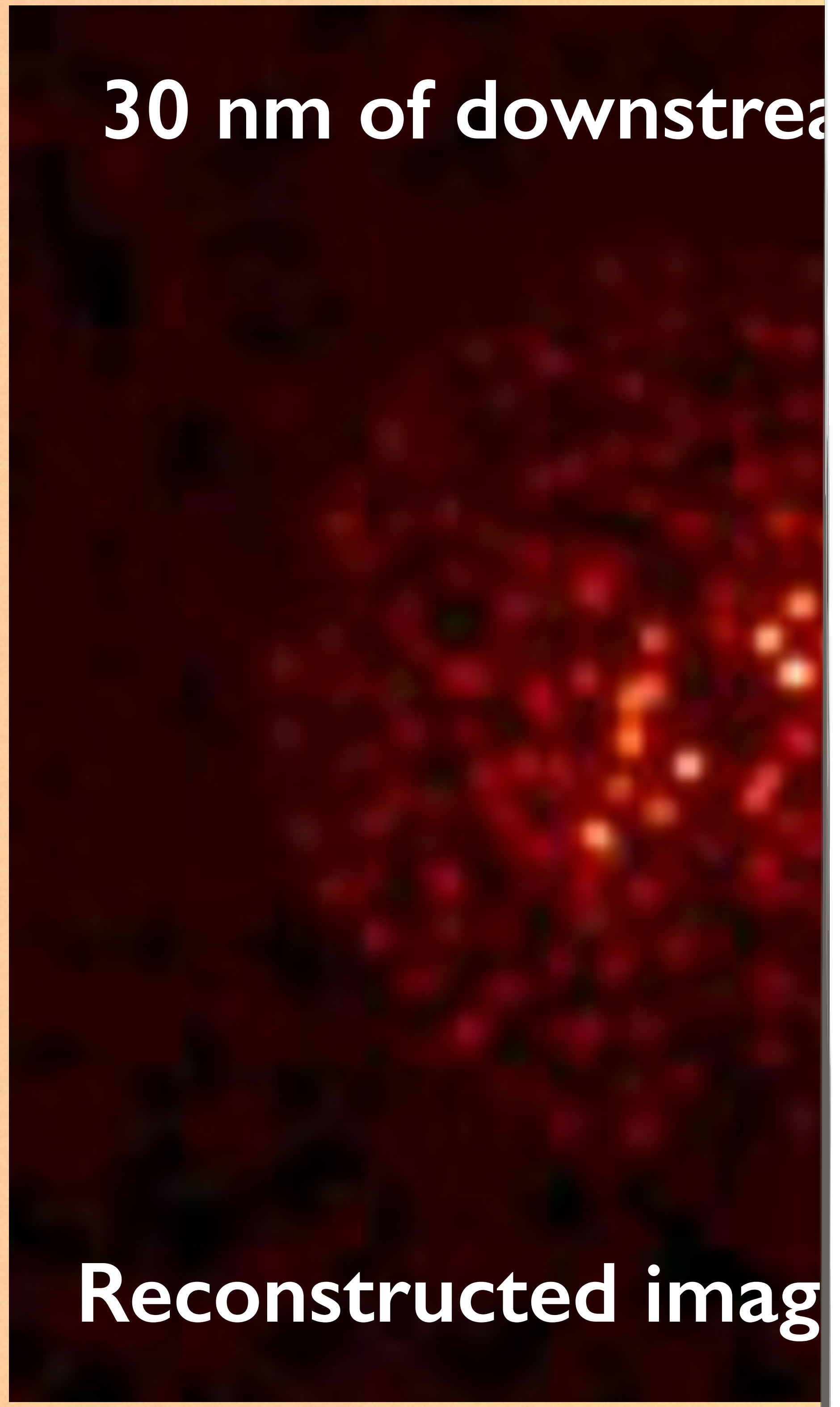
LESSONS LEARNED



- 0) Never change two things at the same time
- 1) Changing something on the model changes the shape of the criterion
- 2) Requirements on the design have an impact on post-processing strategy

PhD dissertation

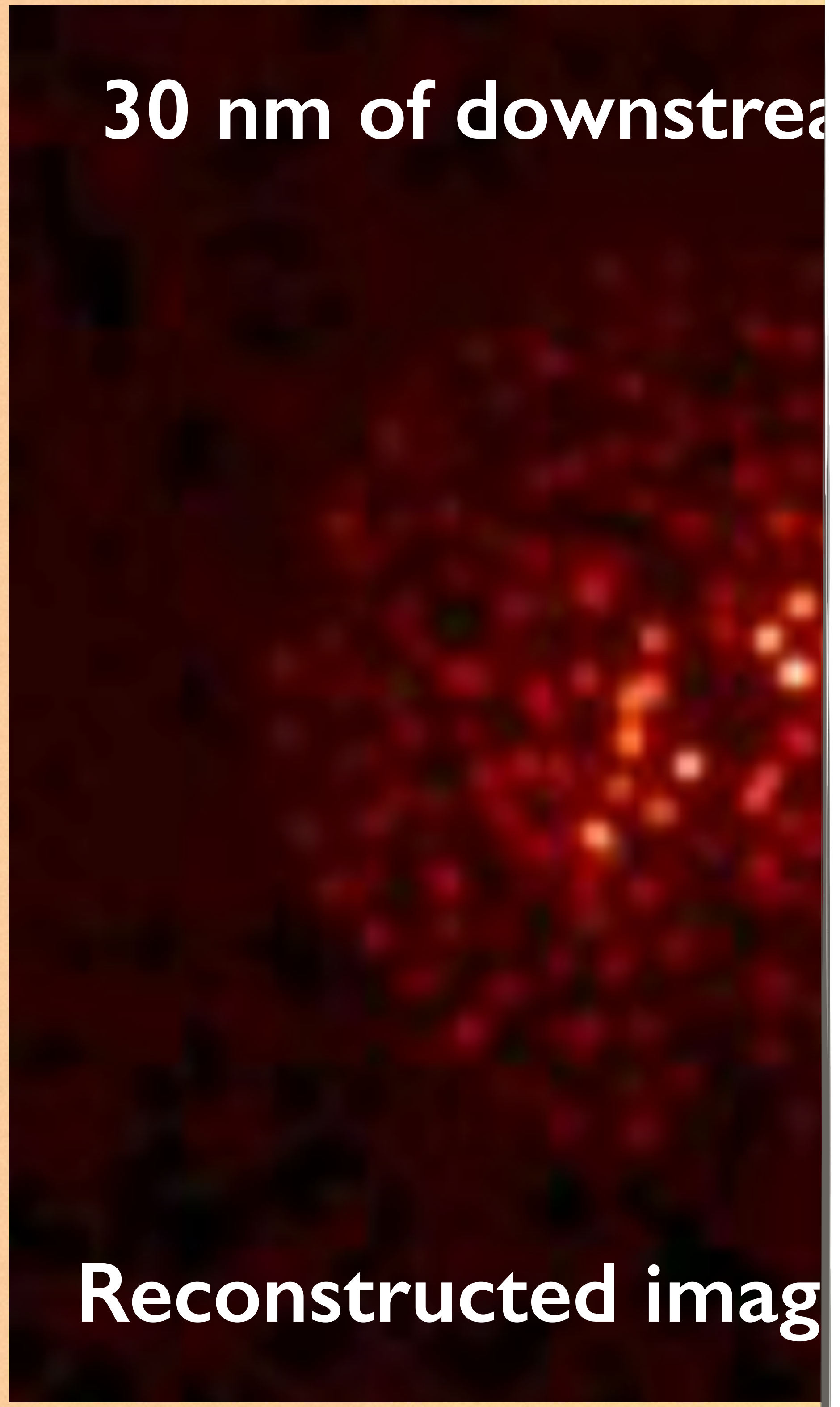
LESSONS LEARNED



- 0) Never change two things at the same time
- 1) Changing something on the model changes the shape of the criterion
- 2) Requirements on the design have an impact on post-processing strategy
- 3) Need to include post-processing as part of the coronagraph design => DESIGN DIVERSITY

PhD dissertation

LESSONS LEARNED

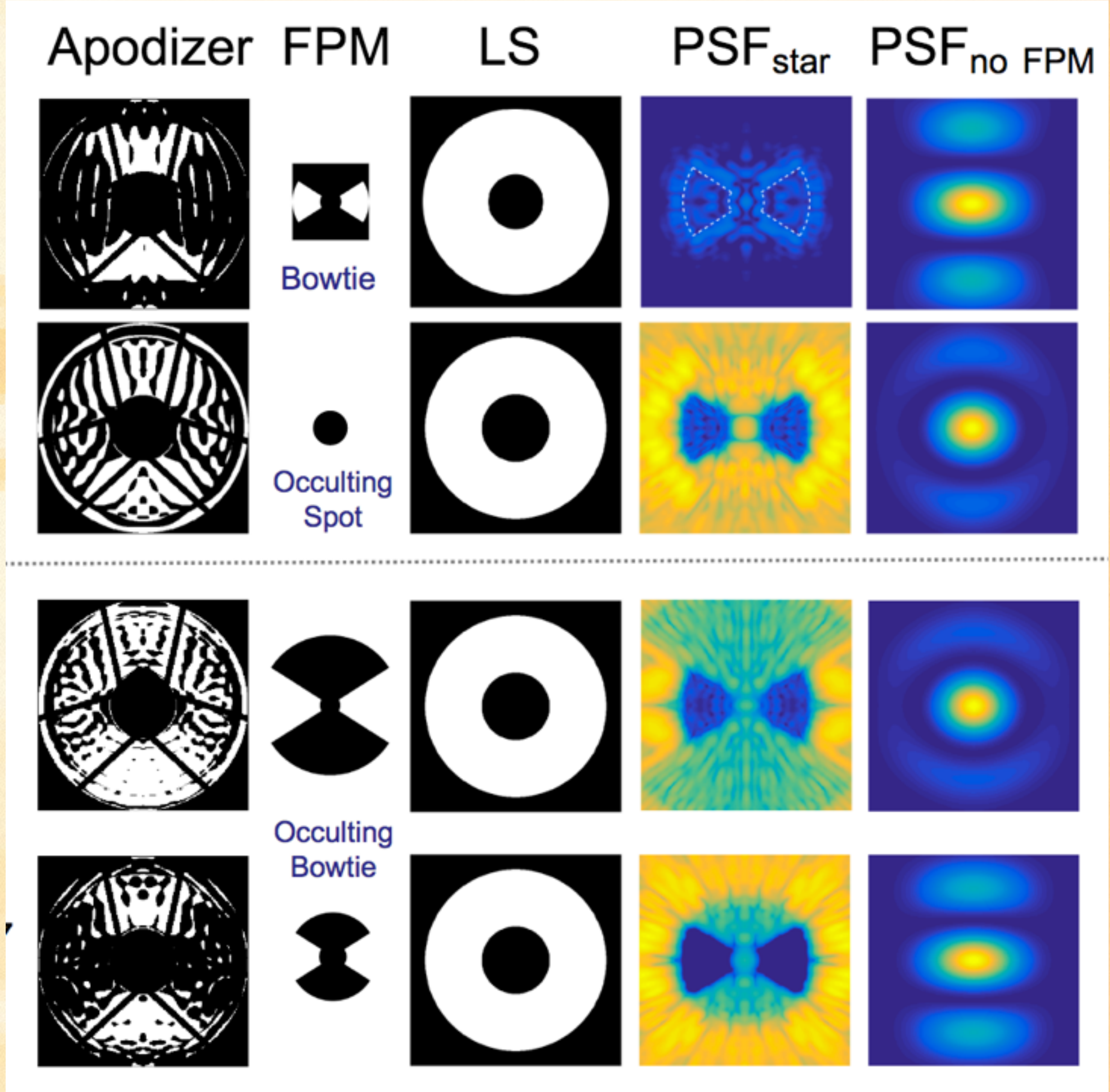


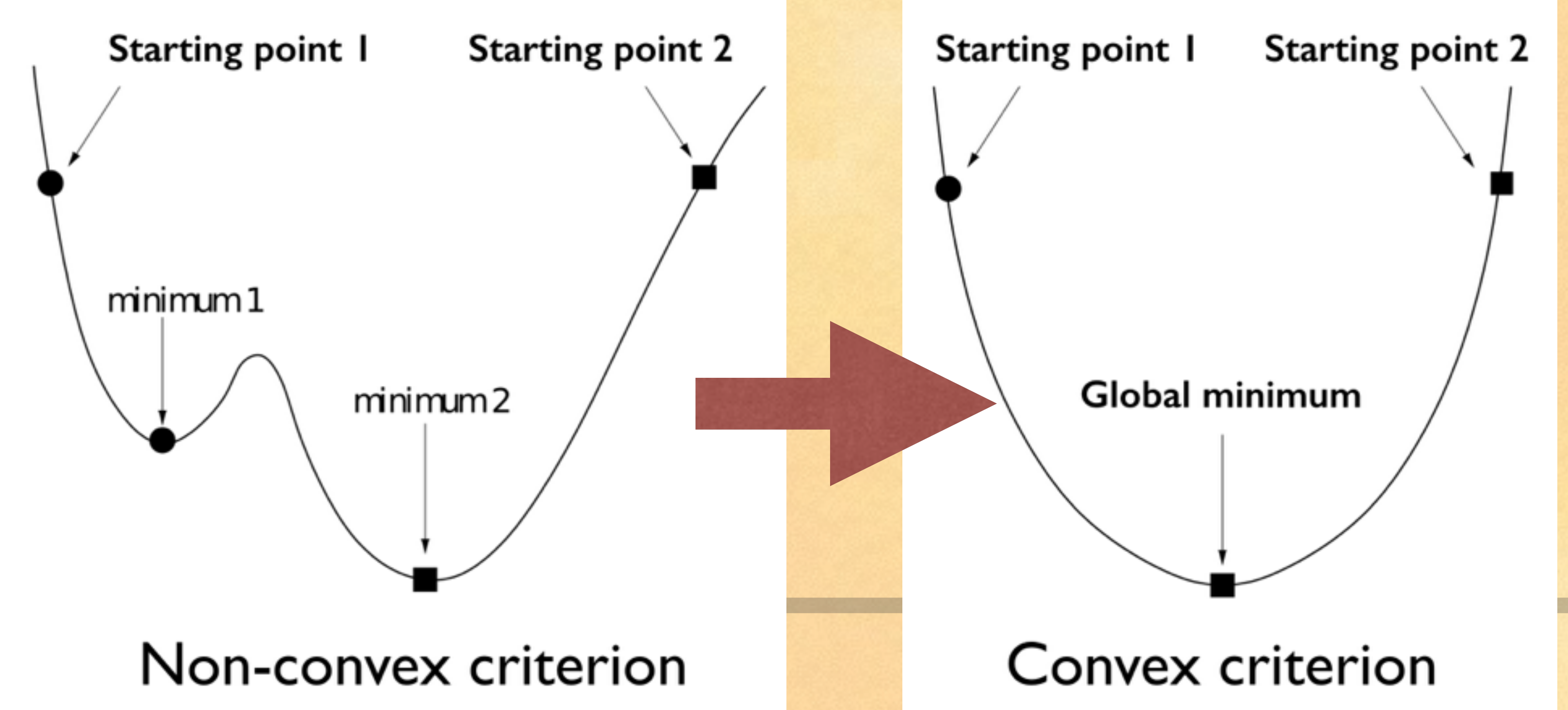
- 0) Never change two things at the same time
- 1) Changing something on the model changes the shape of the criterion
- 2) Requirements on the design have an impact on post-processing strategy
- 3) Need to include post-processing as part of the coronagraph design => DESIGN DIVERSITY
- 4) By doing so it may be possible to relax some of the design requirements

PhD dissertation

CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

- Example from WFIRST SPC
  - PSF is now field-dependent





Courtesy of A.J. Riggs

CLOSING THE LOOP: SYNERGY BETWEEN PP AND CORONAGRAPH DESIGN

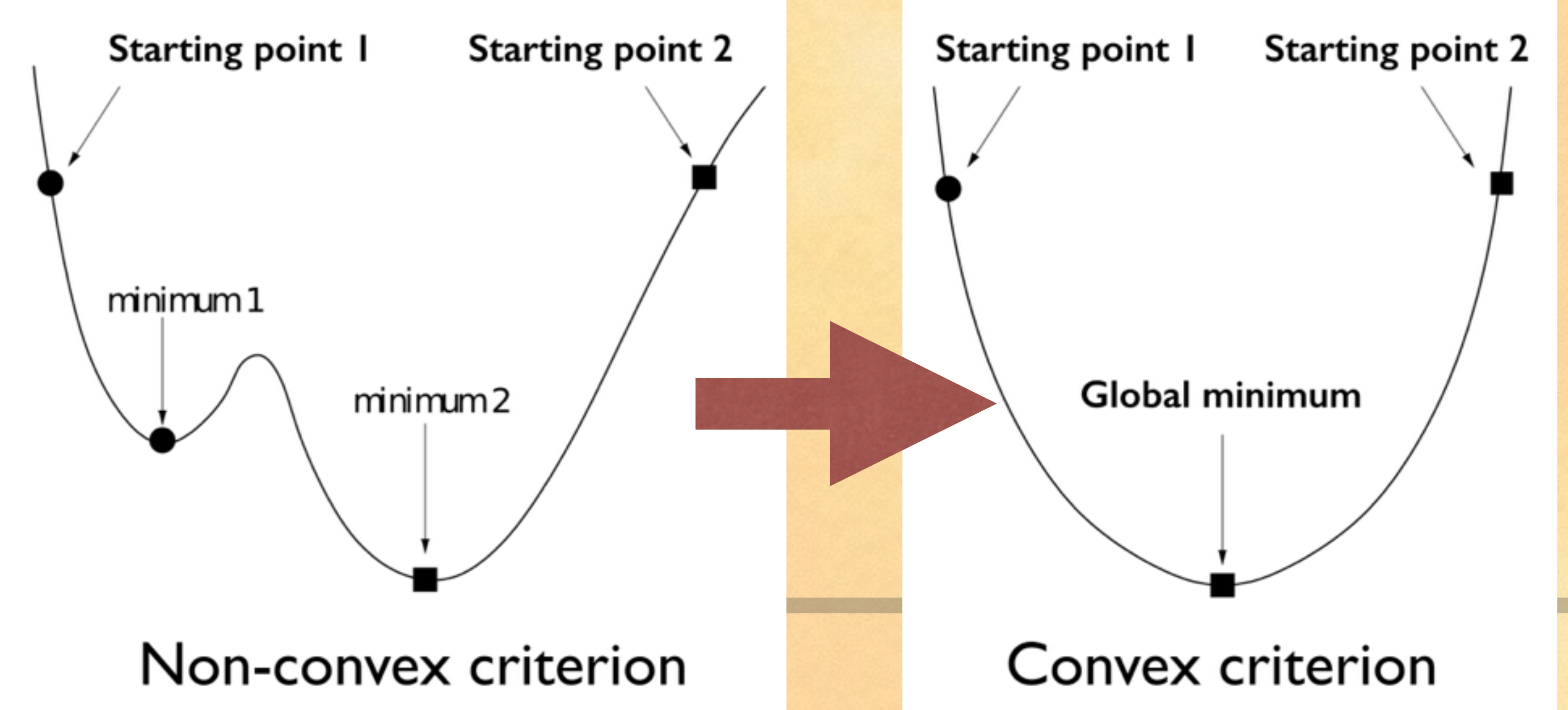
- Example from WFIRST
  - PSF is now field-dep

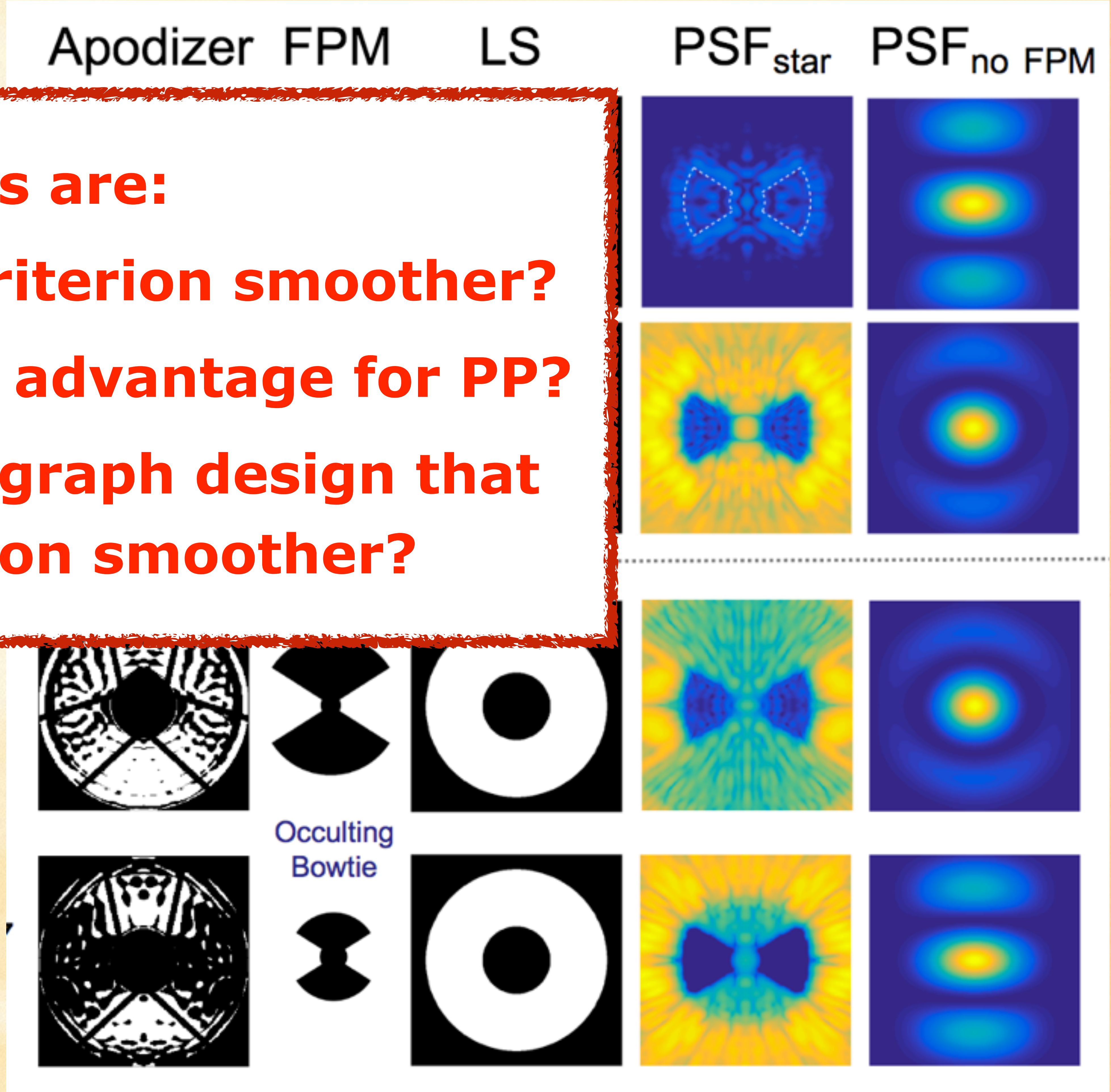
Questions are:

Does that make the criterion smoother?

Can we use that as an advantage for PP?

Can we find a coronagraph design that makes the criterion smoother?





Courtesy of A.J. Riggs

KEY MESSAGES

- PP is an essential component of a coronagraphic instrument and improving PP also mean using info from the instrument
- Bayesian formalism provides a way to include information about WFSC and the instrument
- Challenges of this kind of techniques lie in application to real data (how well we know the instrument model and systematics) and in optimization (criterion minimization => shape of the criterion)
- Direct imaging of exoplanet may benefit from synergies between PP, WFSC & coronagraph design

Recommendation:

When designing future high contrast imaging instruments, think about how the design and WFC&S may impact PP

"We choose to go to the Moon in this decade and do the other things, not because they are easy, but because they are hard."

–John F. Kennedy

"We went to the Moon, so we should be able to make that Bayesian stuff work."