Principled Inference from Images:

The PSF & Stellar Photometry

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postdoc

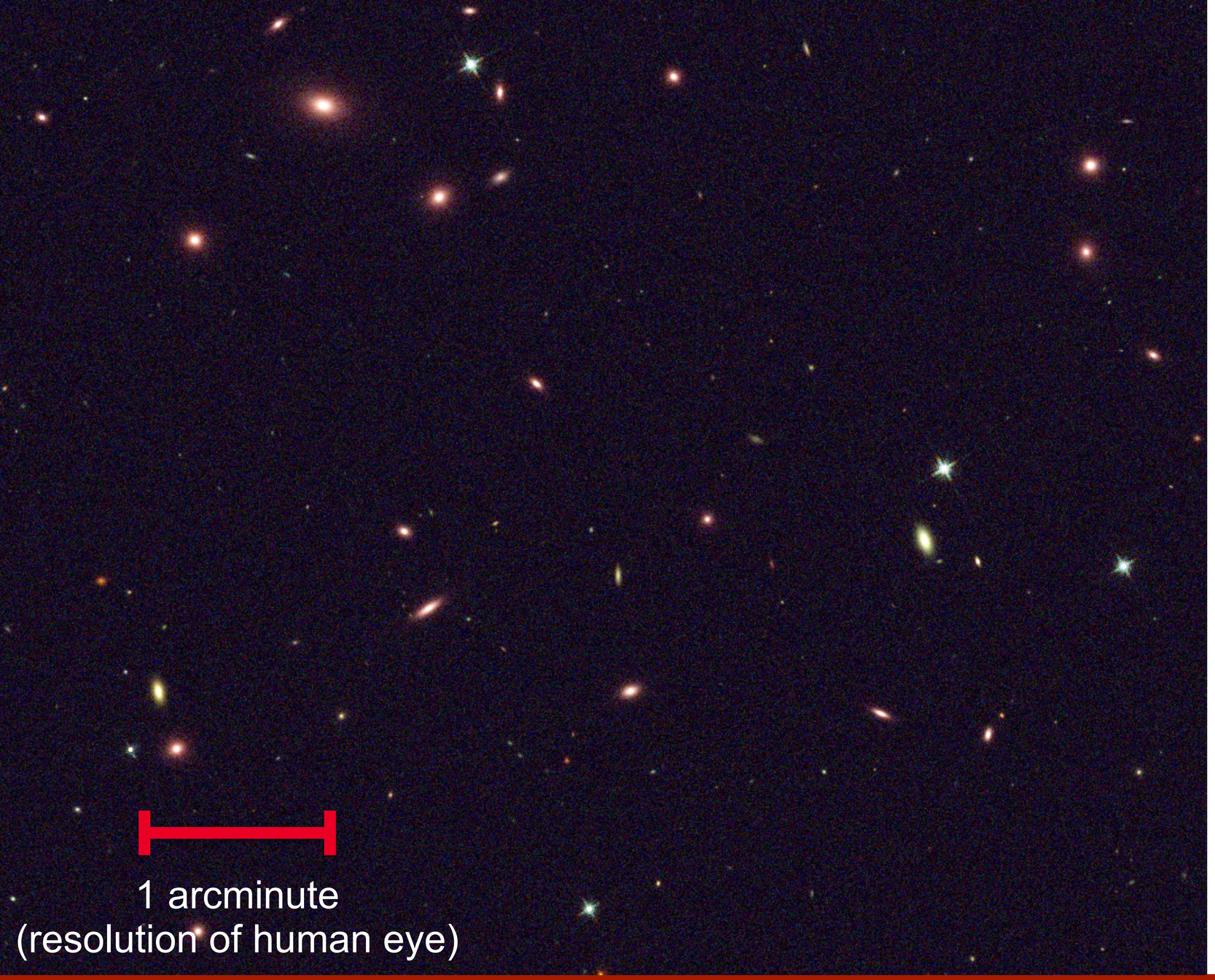
PhD

grew up

college

My Trajectory

https://www.legacysurvey.org/viewer

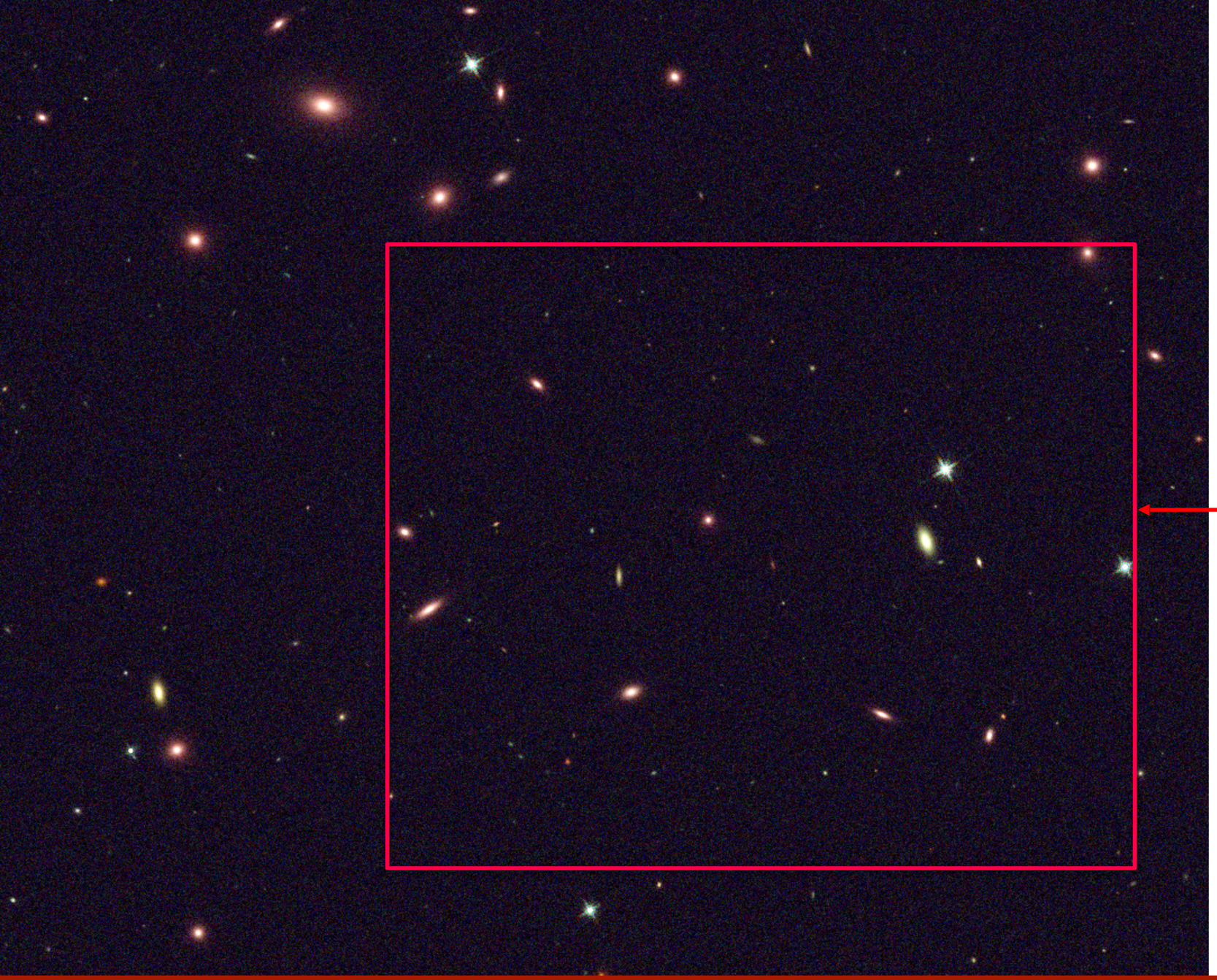


Start with a typical (simulated) scene…

Start with a typical (simulated) scene…

Then add some lensing.

Gravitational Lensing



Start with a typical (simulated) scene…

Then add some lensing.

This region is typical of the weak lensing…

Gravitational Lensing

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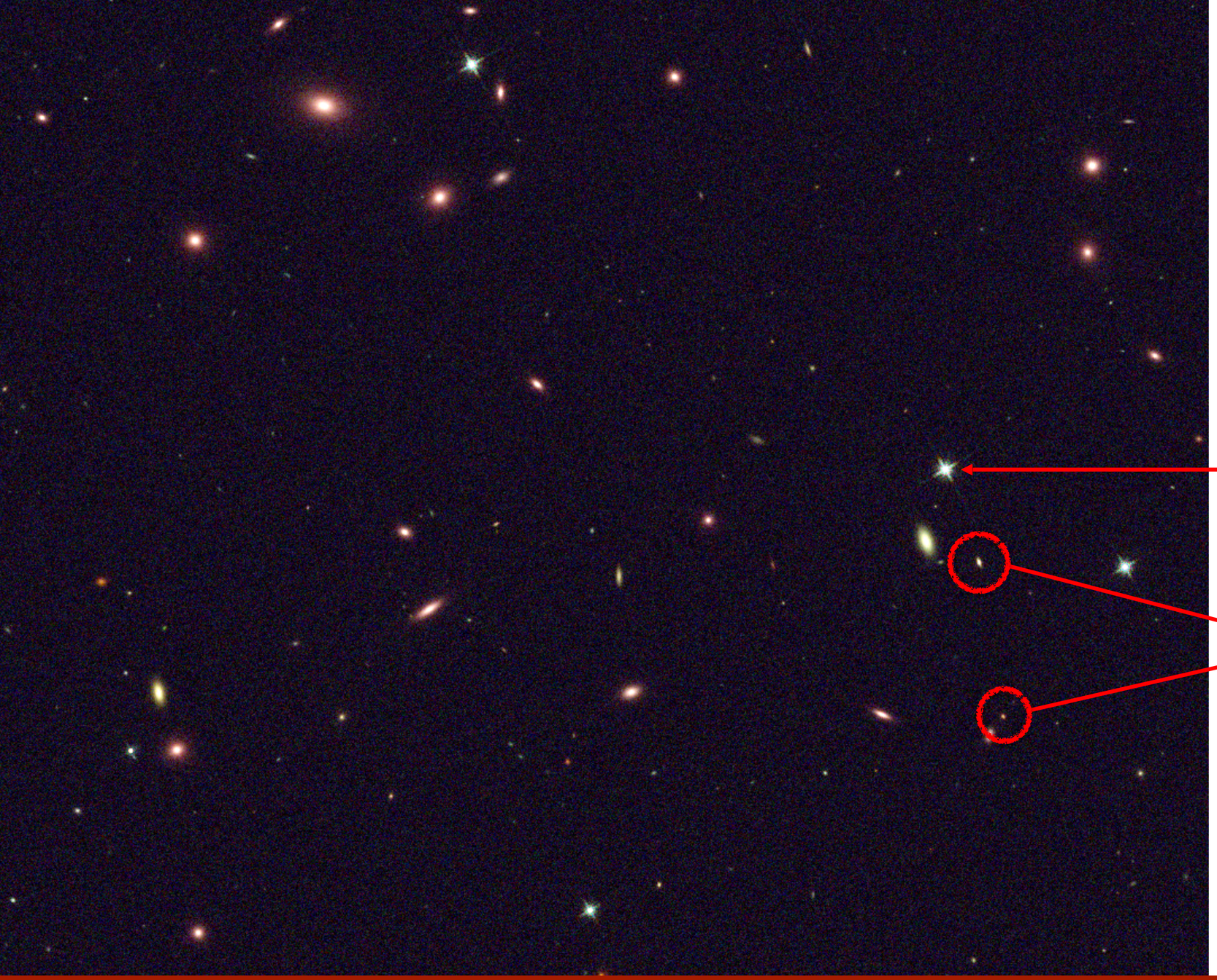
Gravitational Lensing



Start with a typical (simulated) scene…

Then add some lensing.

Telescope optics (PSF) affects shapes

We must estimate *distances* from colors of galaxies to ~1%

And we must quantify the impact of lensing to 1% *of the effect size*

Gravitational Lensing

Principled inference from images: Day 1

Goal:

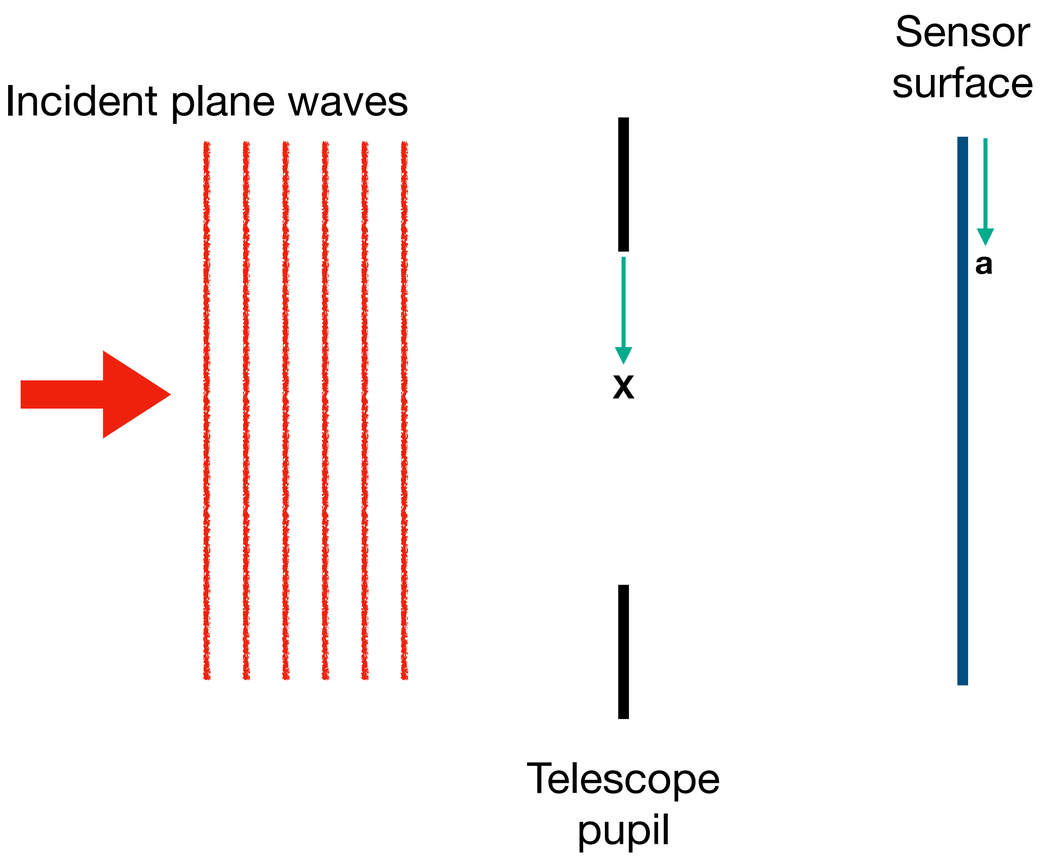
1. Understand some things about the PSF

- How it arises
- How to simulate it
- How it is related to the information available from an image

2. Understand how to design a measurement algorithm.

- Do some measurements on simulated stellar images
- Design and validate an algorithm for measuring the brightness of a star.
- Perform a simple science traceability exercise.

Fourier optics



For an incoherent, distant point source:

$$I(\boldsymbol{a}) = \left| \int d^2\boldsymbol{x}\, P(\boldsymbol{x})\, e^{-2\pi i\, x\, a/\lambda} \right|^2$$

P describes the shape of the pupil.
x is the coordinate in the pupil plane.
ϕ includes information about the shape of the wave at the pupil.

This lets us express the response to a *point source* in terms of the physical properties of the telescope.

Fourier optics

If the response to a point source is *p(**u**)*

we can write the image ***I*** as a convolution of what's on the sky (*g*) with p.

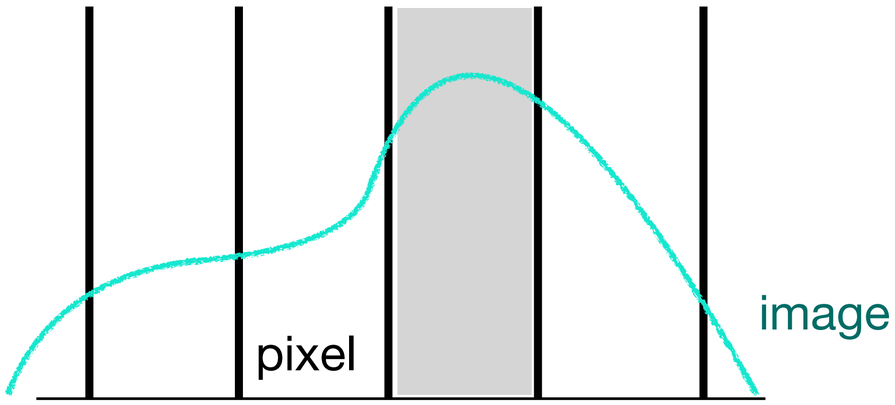
$$I(\boldsymbol{x}) = \int d^2\boldsymbol{u}\, g(\boldsymbol{u})\, p(\boldsymbol{x} - \boldsymbol{u})$$

Convolutions are hard.

We can make our lives a little easier by remembering the *convolution theorem*:

$$\hat{I} = \hat{g} \cdot \hat{p}$$

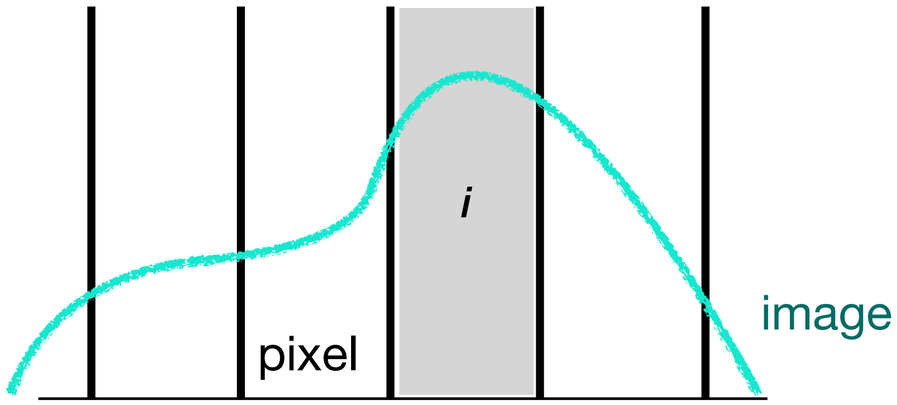
Pixelization



$$D_i = \int d\boldsymbol{x}^2 \, I(\boldsymbol{x}) \, \Pi_i(\boldsymbol{x})$$

The number of counts in one pixel is an integral of the intensity over the pixel shape.

Pixelization



$$D_i = \int dx^2 \, I(\boldsymbol{x}) \, \Pi_i(\boldsymbol{x})$$

$$D_i = \int dx^2 \, I(\boldsymbol{x}) \, \Pi(\boldsymbol{x} - \boldsymbol{x}_i)$$

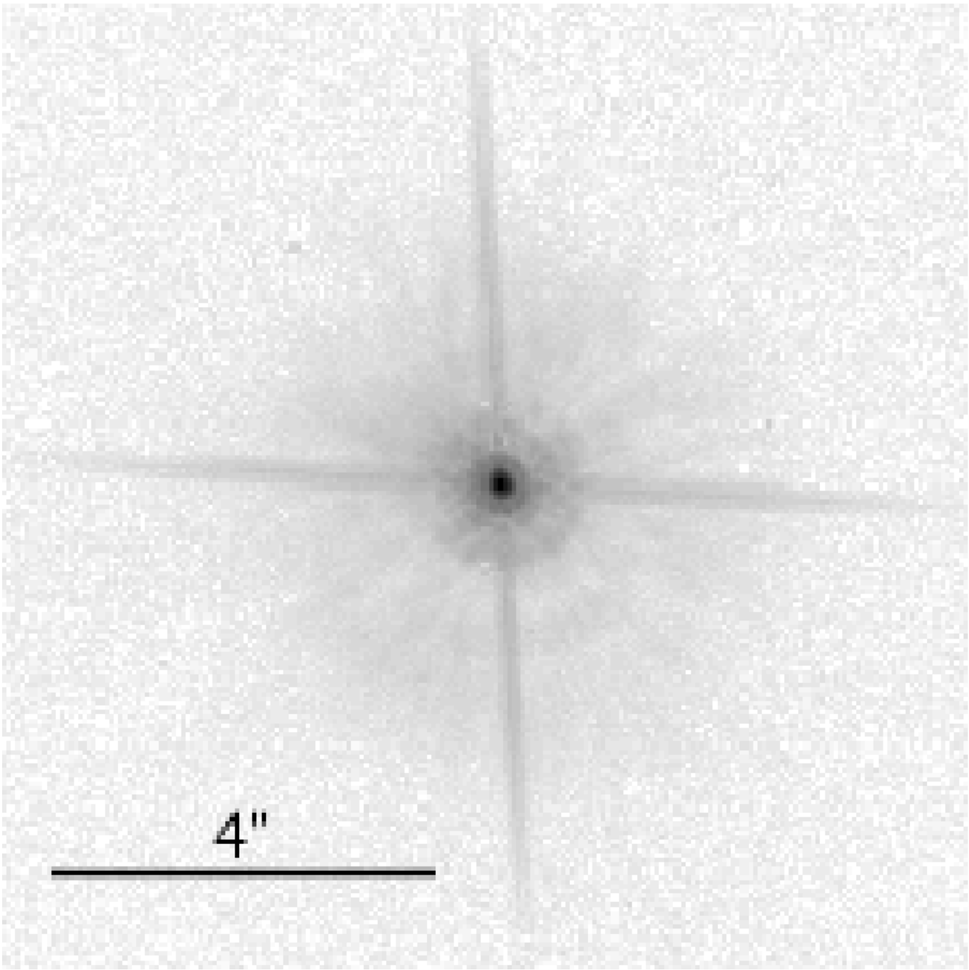
If all the pixels are the same, differing only by a shift…

…then this is just another convolution, so we **can** include the pixel shape in the PSF.

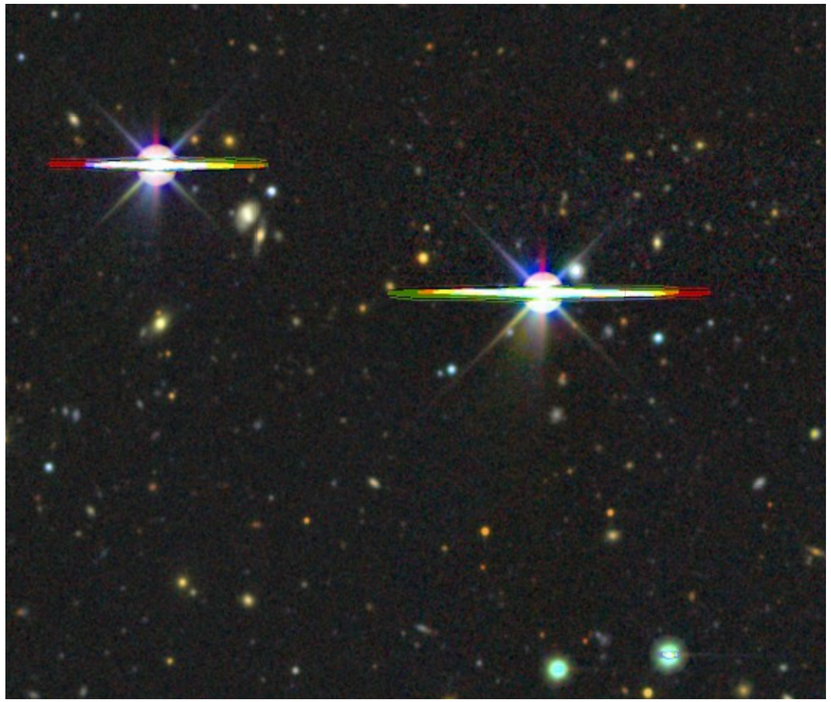
Anatomy of a PSF

HST ACS F625W

- Core
- Diffraction spikes
- Wings



Fourier optics



Exercise 1: Why do stars look like this?

Following the notebook you'll:

- Make PSFs using model telescope apertures.
- See how to synthesize images given a PSF.
- Understand how noise and the PSF interact to destroy information.

<u>Next:</u>

Create a simple conda environment for this exercise:

conda create env -n dsfp-psf numpy scipy astropy matplotlib galsim jupyter -c conda-forge

then open my "What's in a PSF?" notebook.

Fourier optics

Where does this break down?

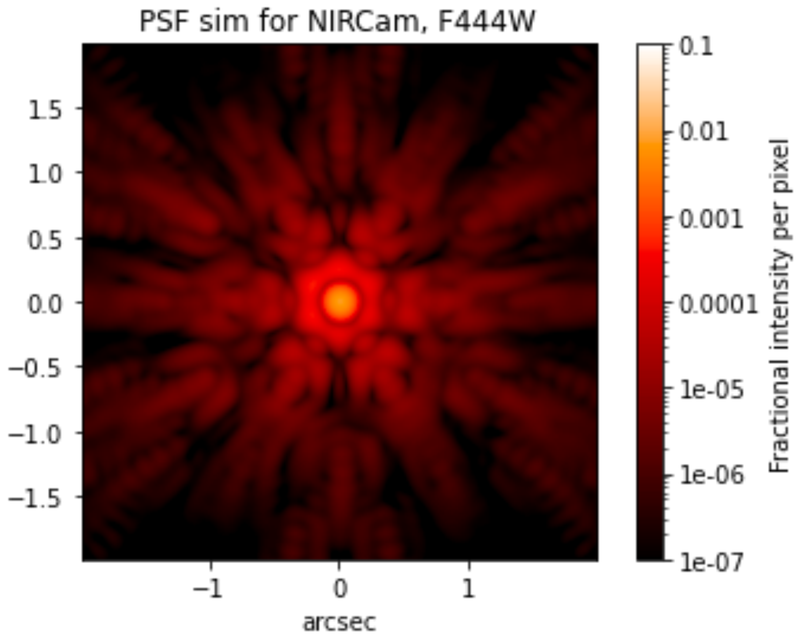
$$I(\boldsymbol{a}) = \left| \int d^2\boldsymbol{x}\, P(\boldsymbol{x})\, e^{i\phi(\boldsymbol{x}) - 2\pi i\, x\, a/\lambda} \right|^2$$

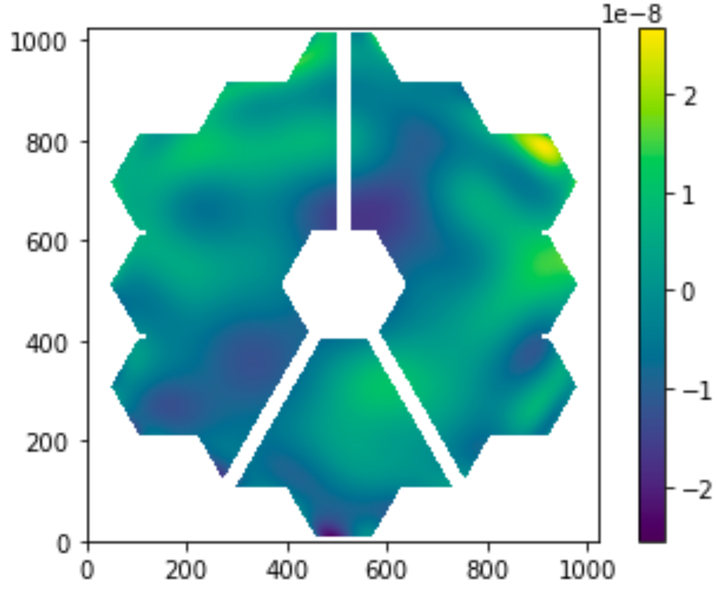
$$\phi(\boldsymbol{x}) = \frac{2\pi}{\lambda} W(\boldsymbol{x})$$

The field isn't generally a plane wave at the aperture!

Imperfections in the optics, or the presence of an atmosphere can introduce phase shifts.

Generally, we model this with *W(**x**)*.

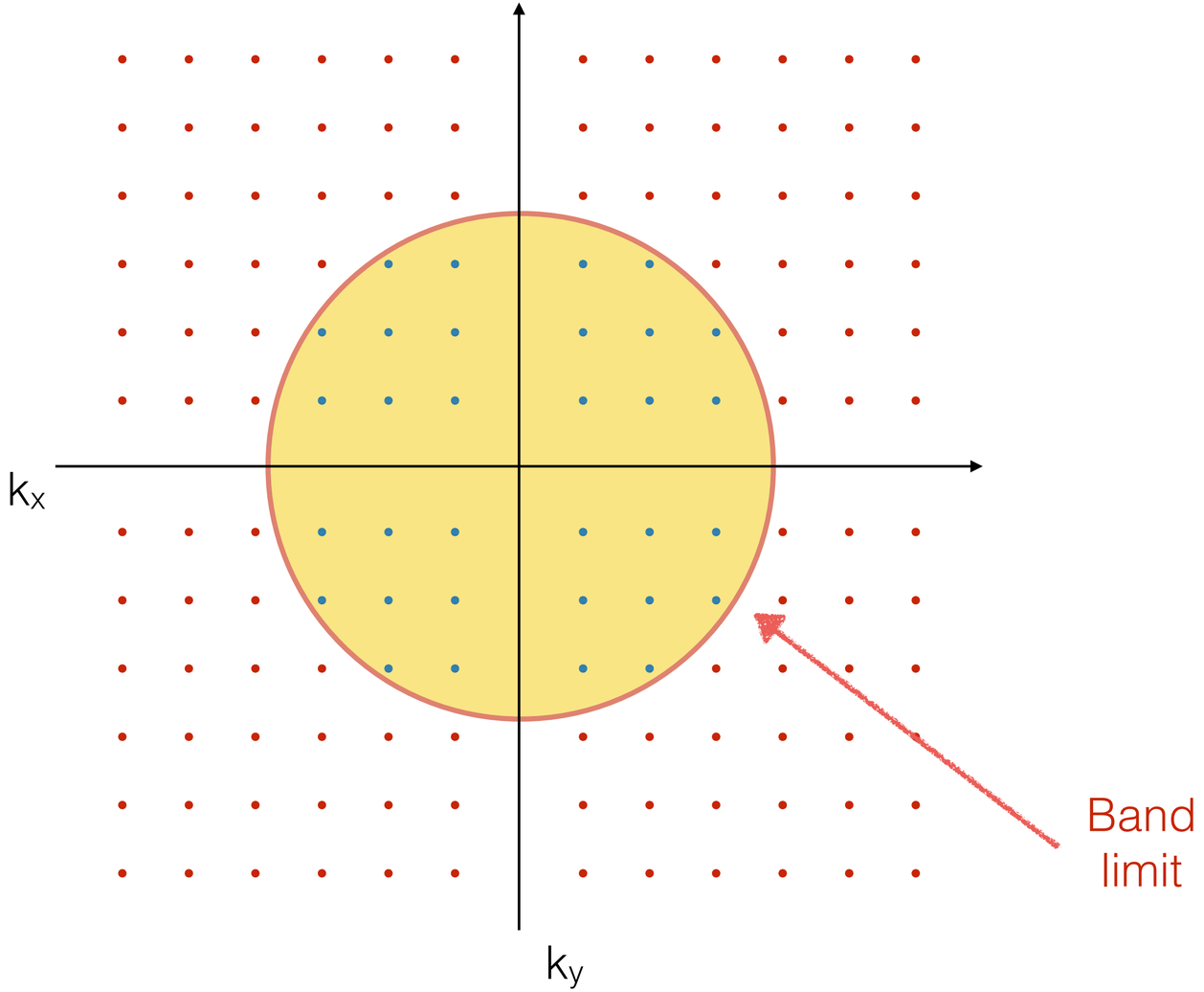


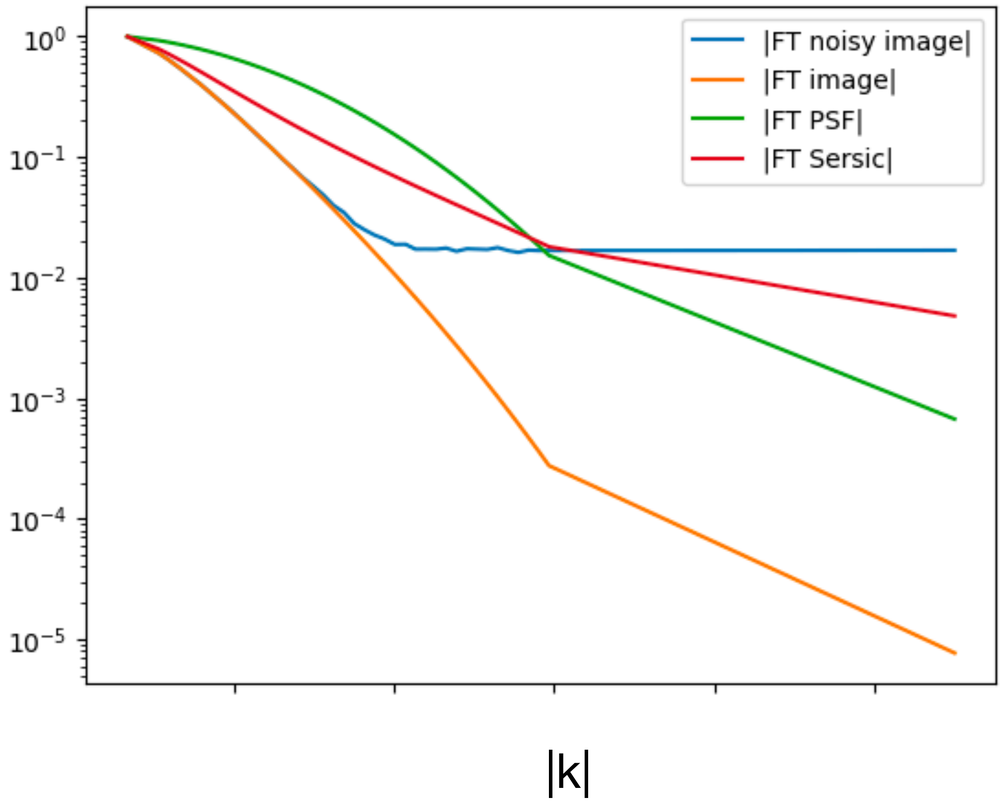


https://webbpsf.readthedocs.io/en/stable/index.html

Thinking in Fourier space

the information content of psf-convolved images





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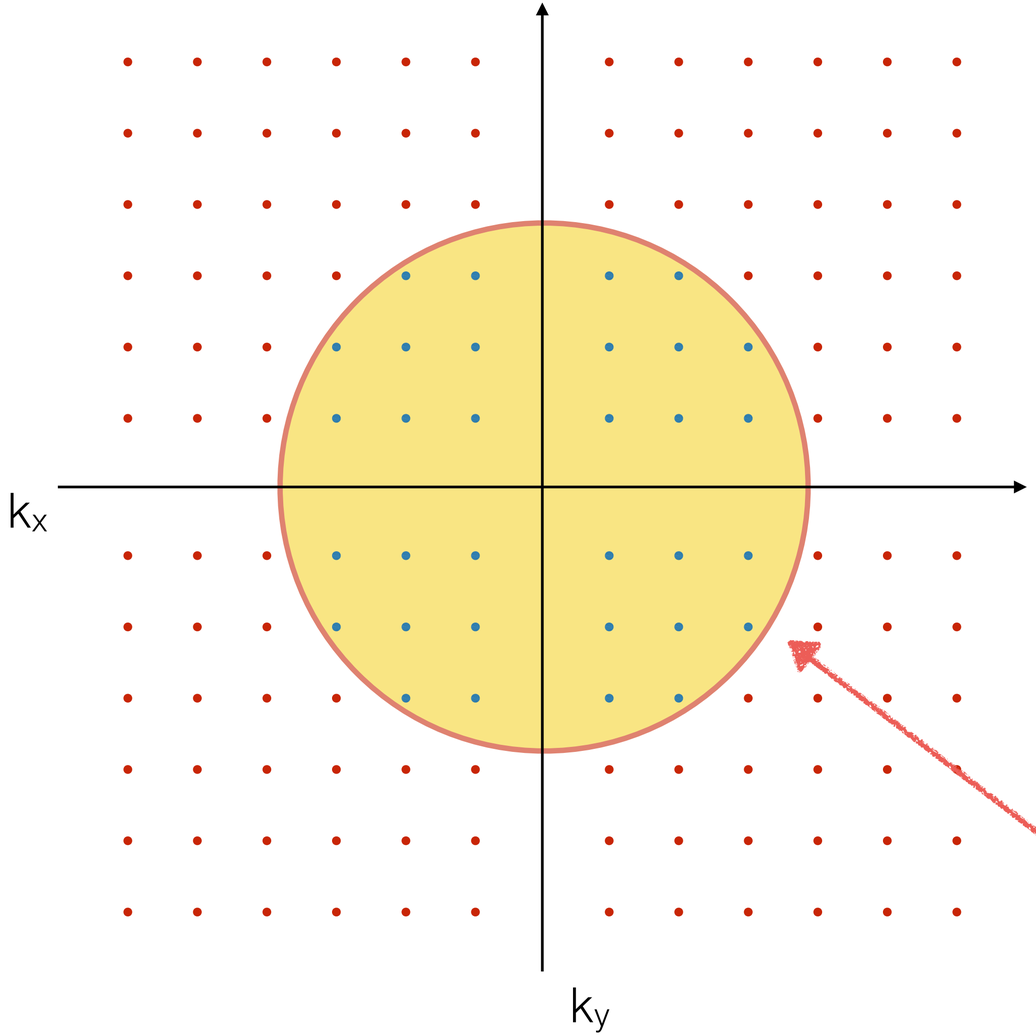
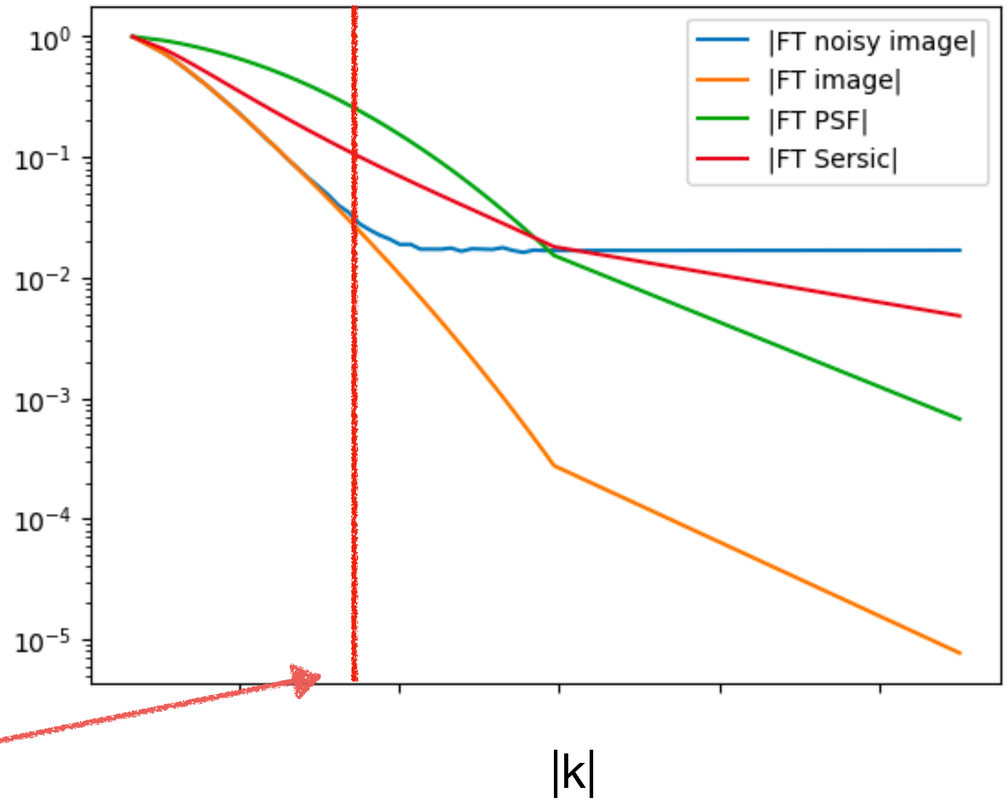


Band limit



Inferring the PSF from images.

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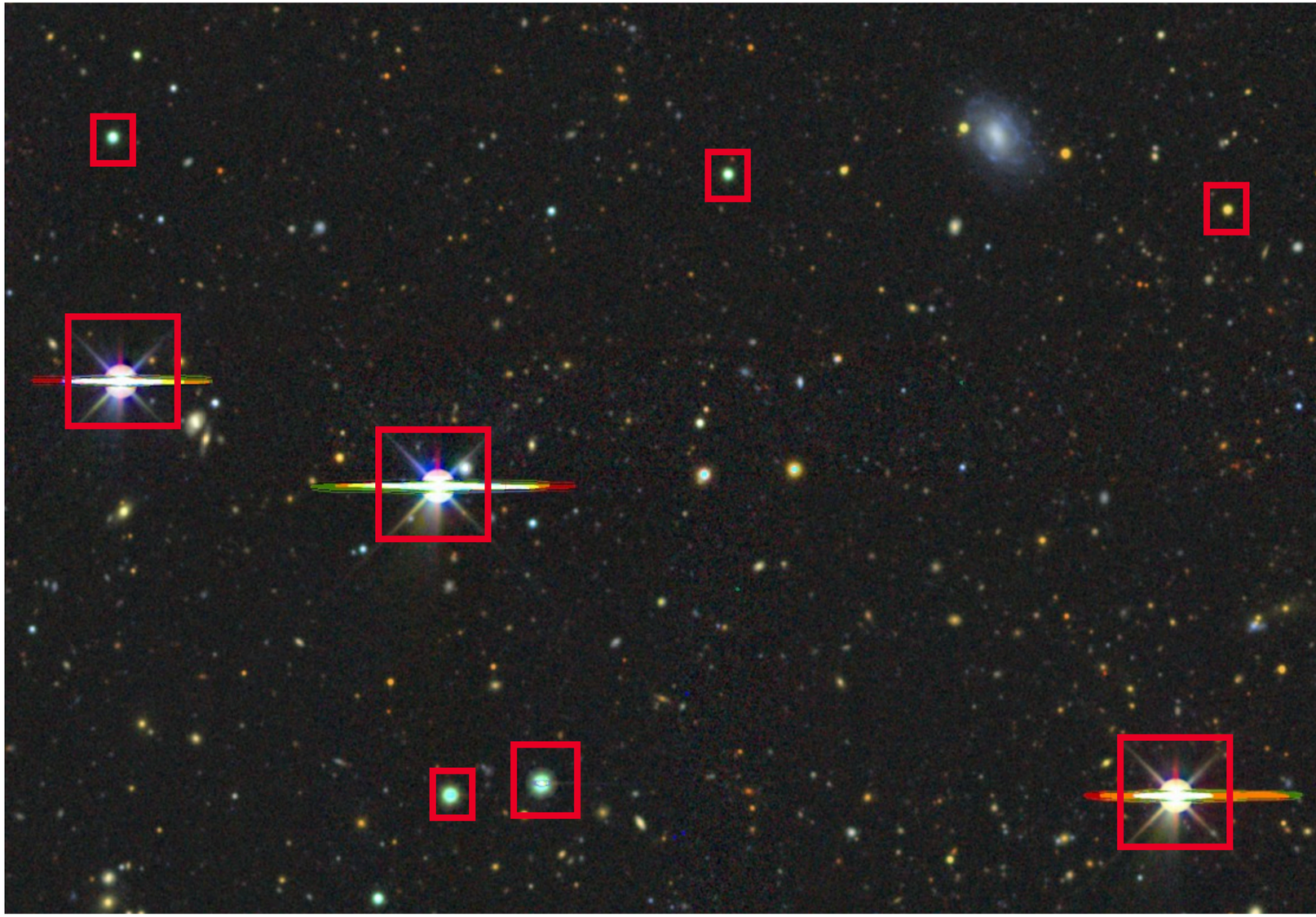
- Find the stars.



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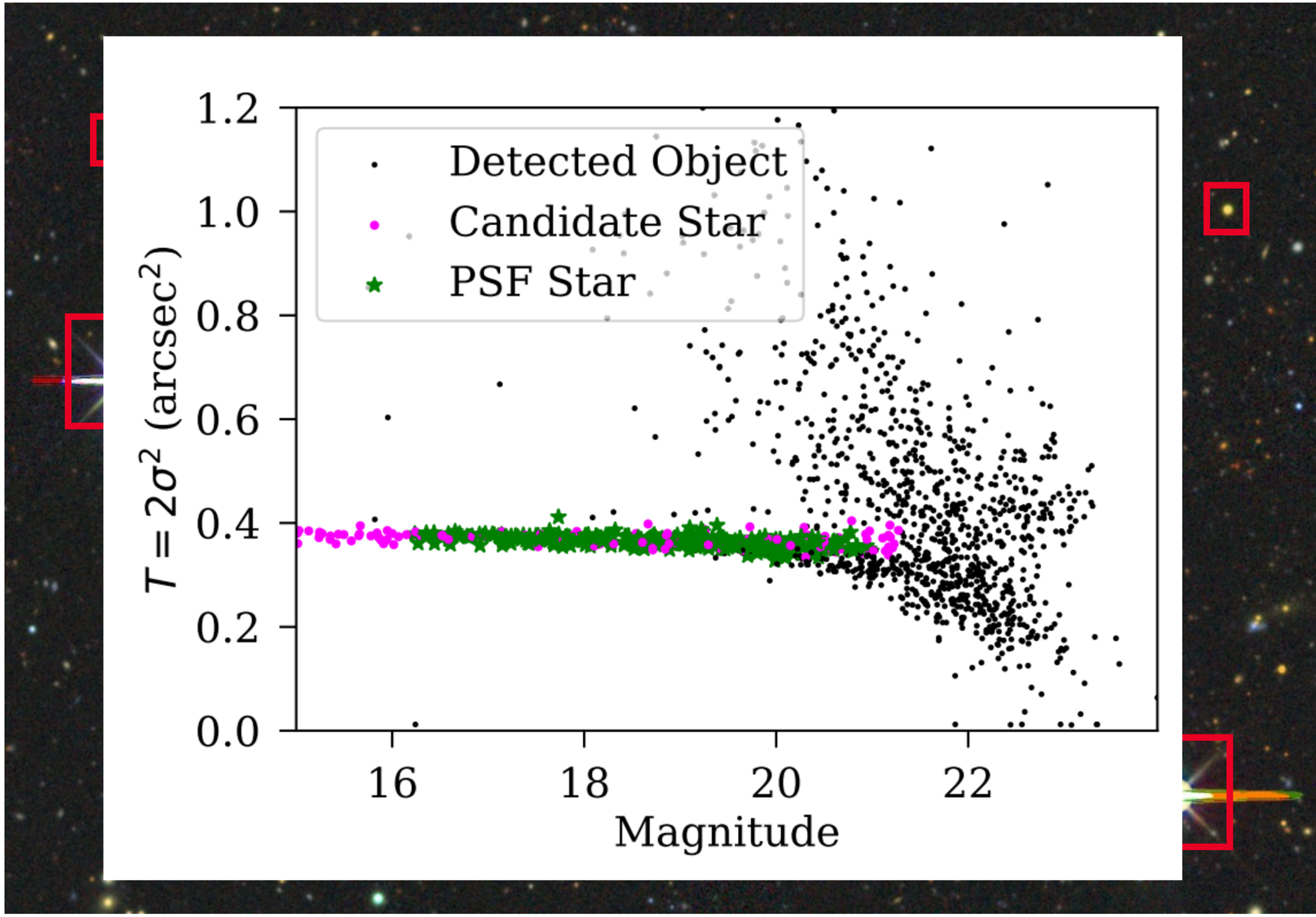
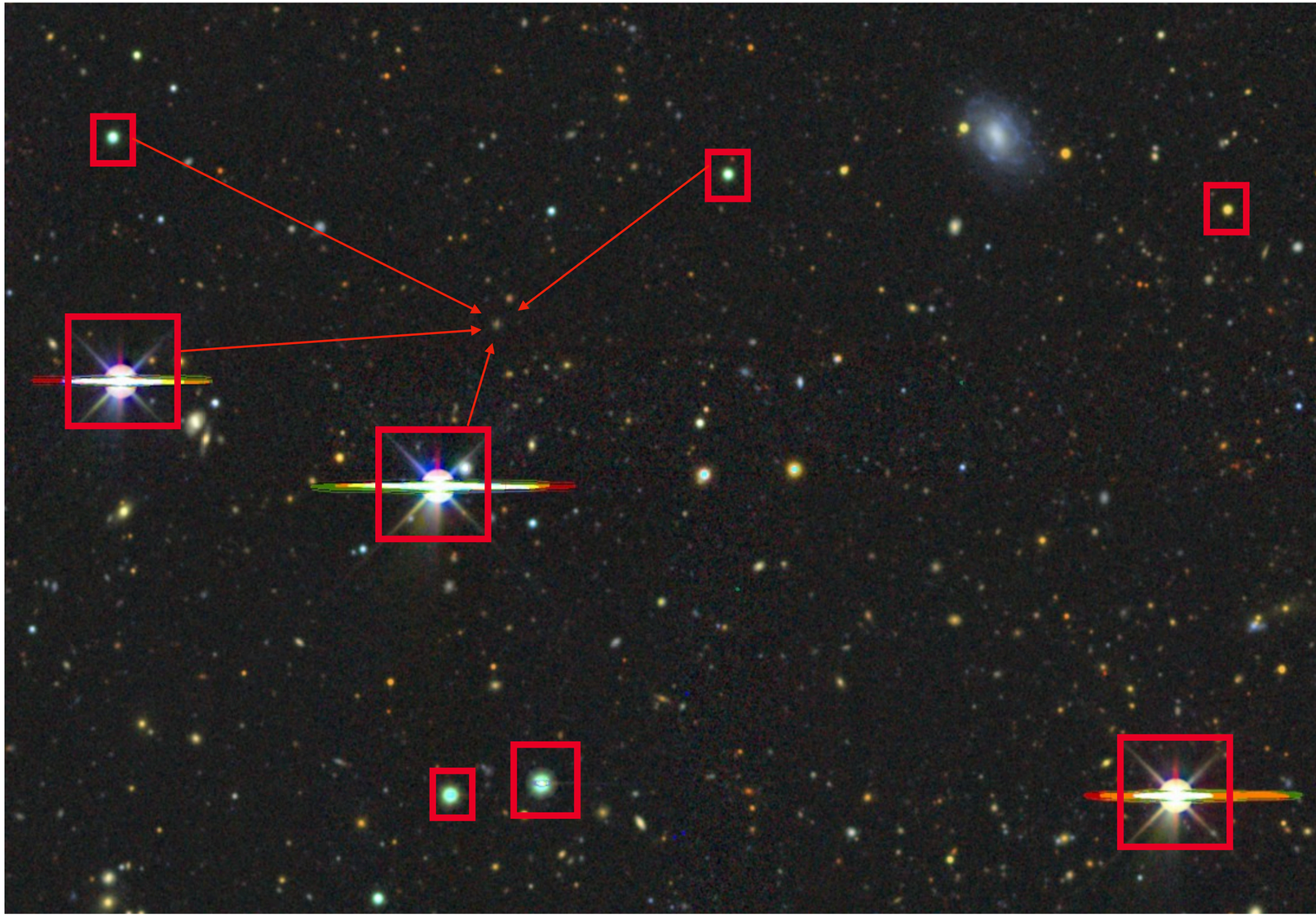


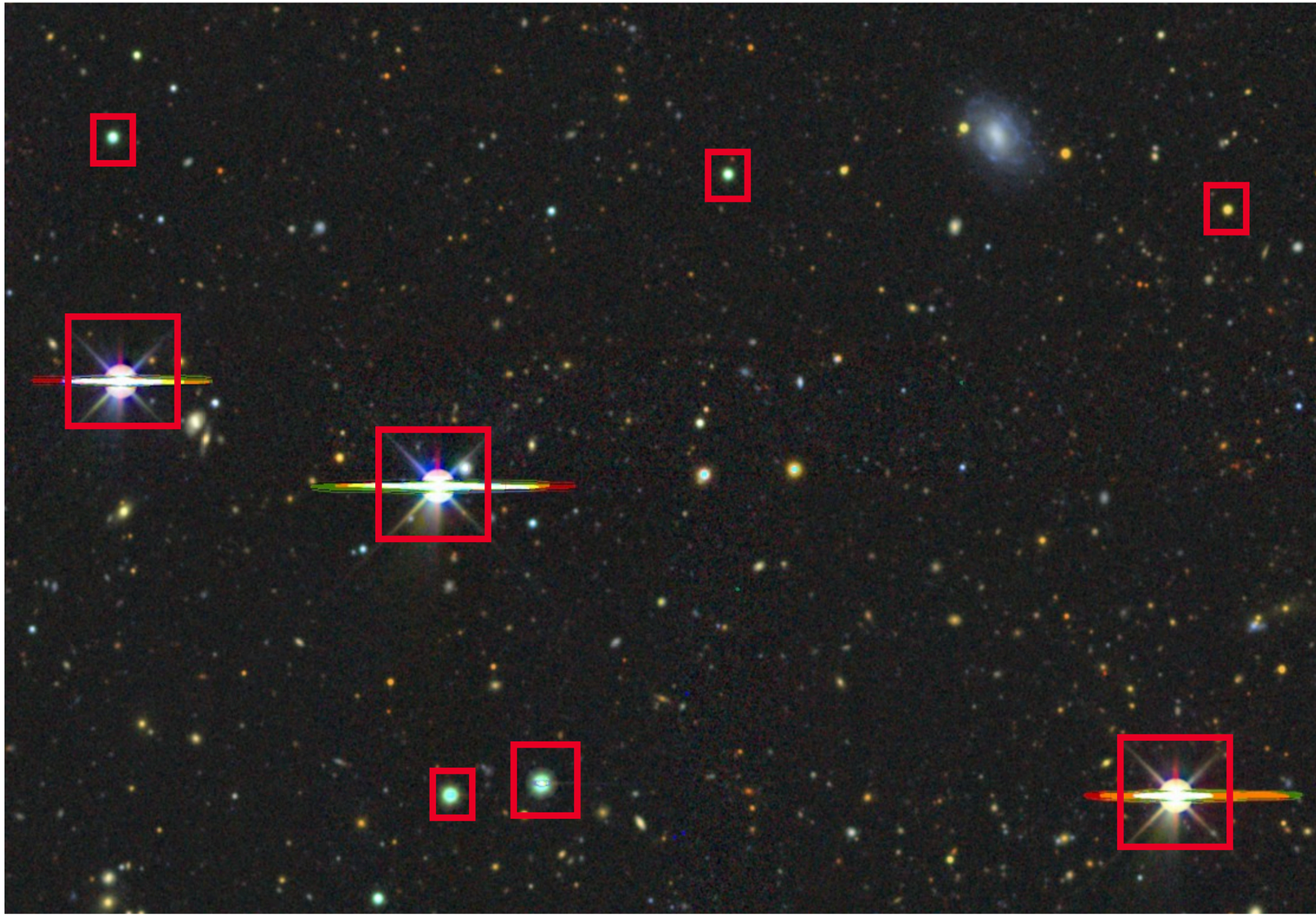
Inferring the PSF from images.

- Find the stars.
- Fit a parameterized model to each star
- Interpolate to locations of galaxies to predict PSF for model fitting.



Inferring the PSF from images.

- Find the stars.
- Fit a parameterized model to each star
- Interpolate to locations of galaxies to predict PSF for model fitting.
- Try really hard to validate where you can.



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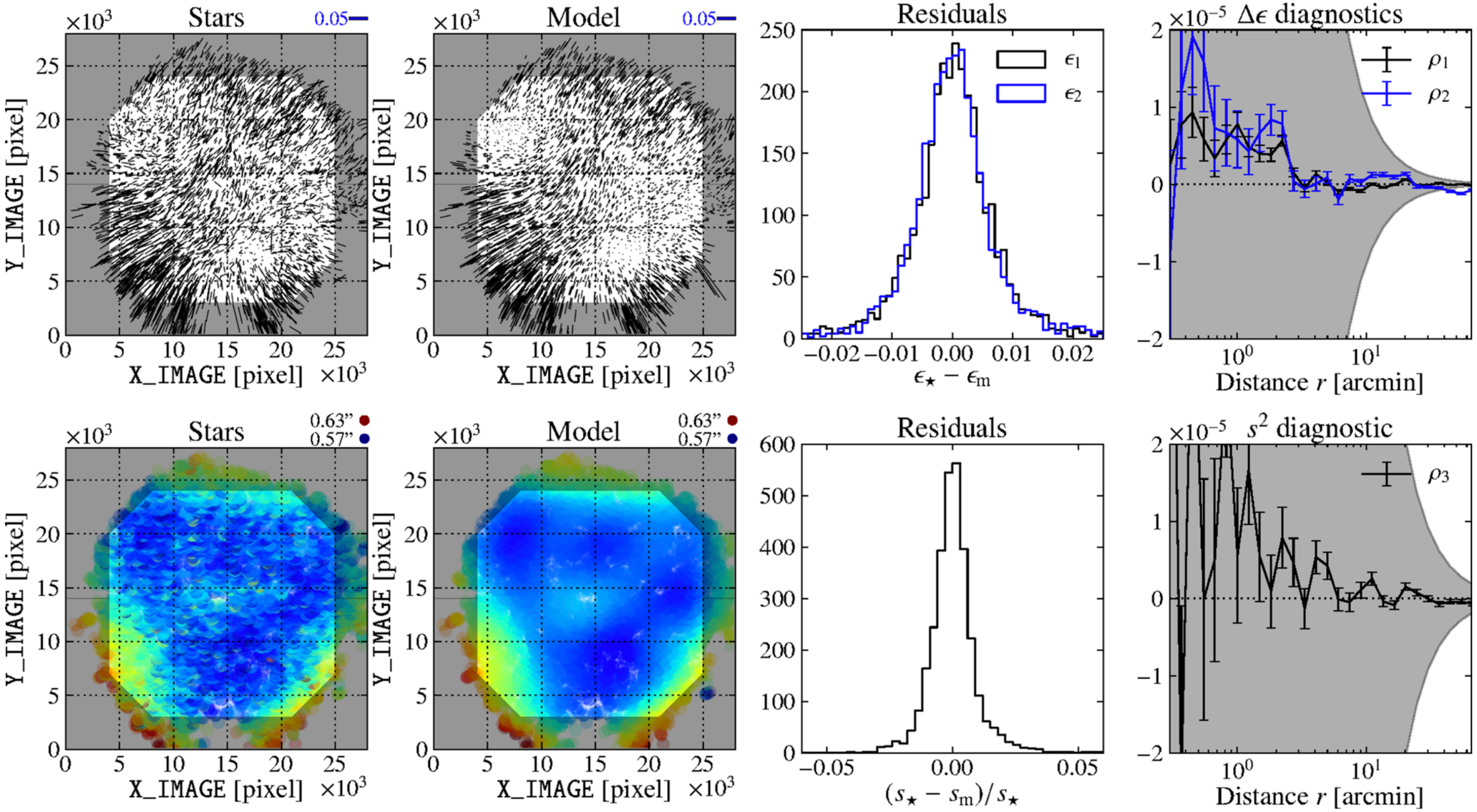
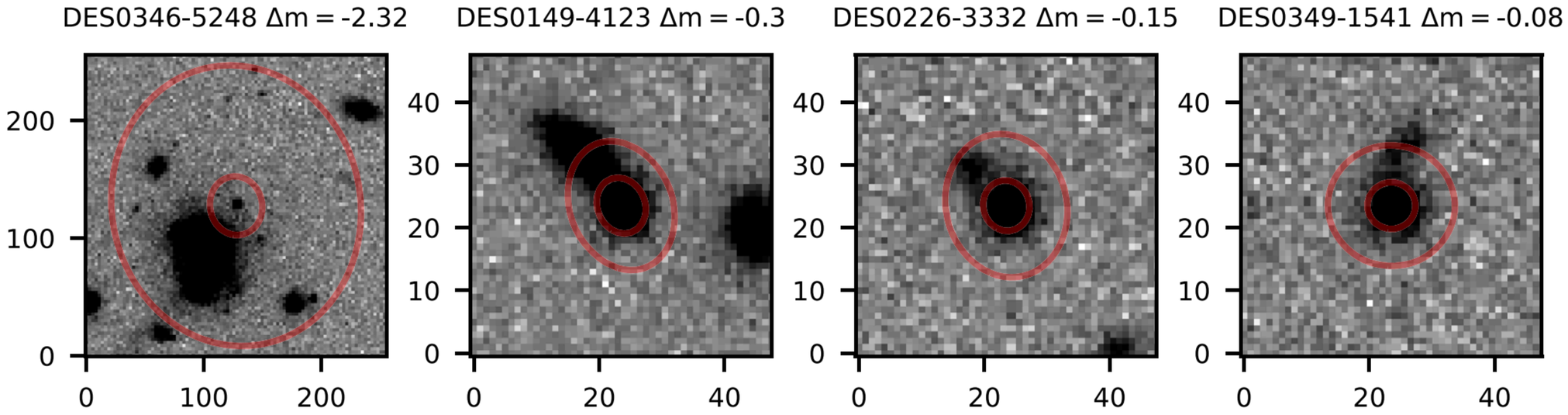


Photometry.

Just count the photons from this star or galaxy. How hard can it be?



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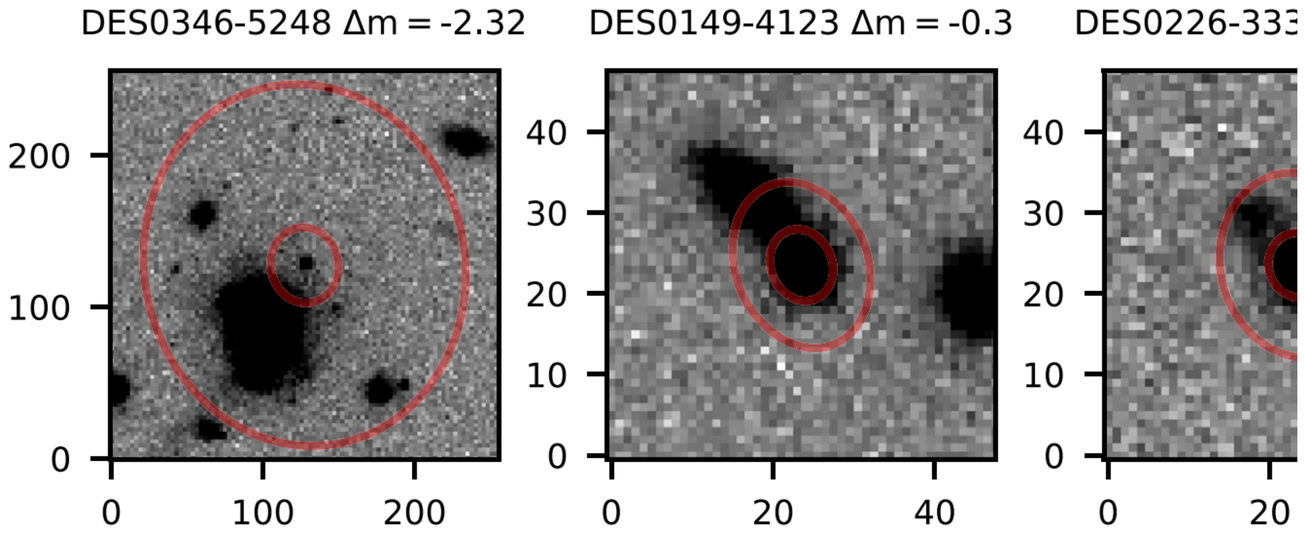
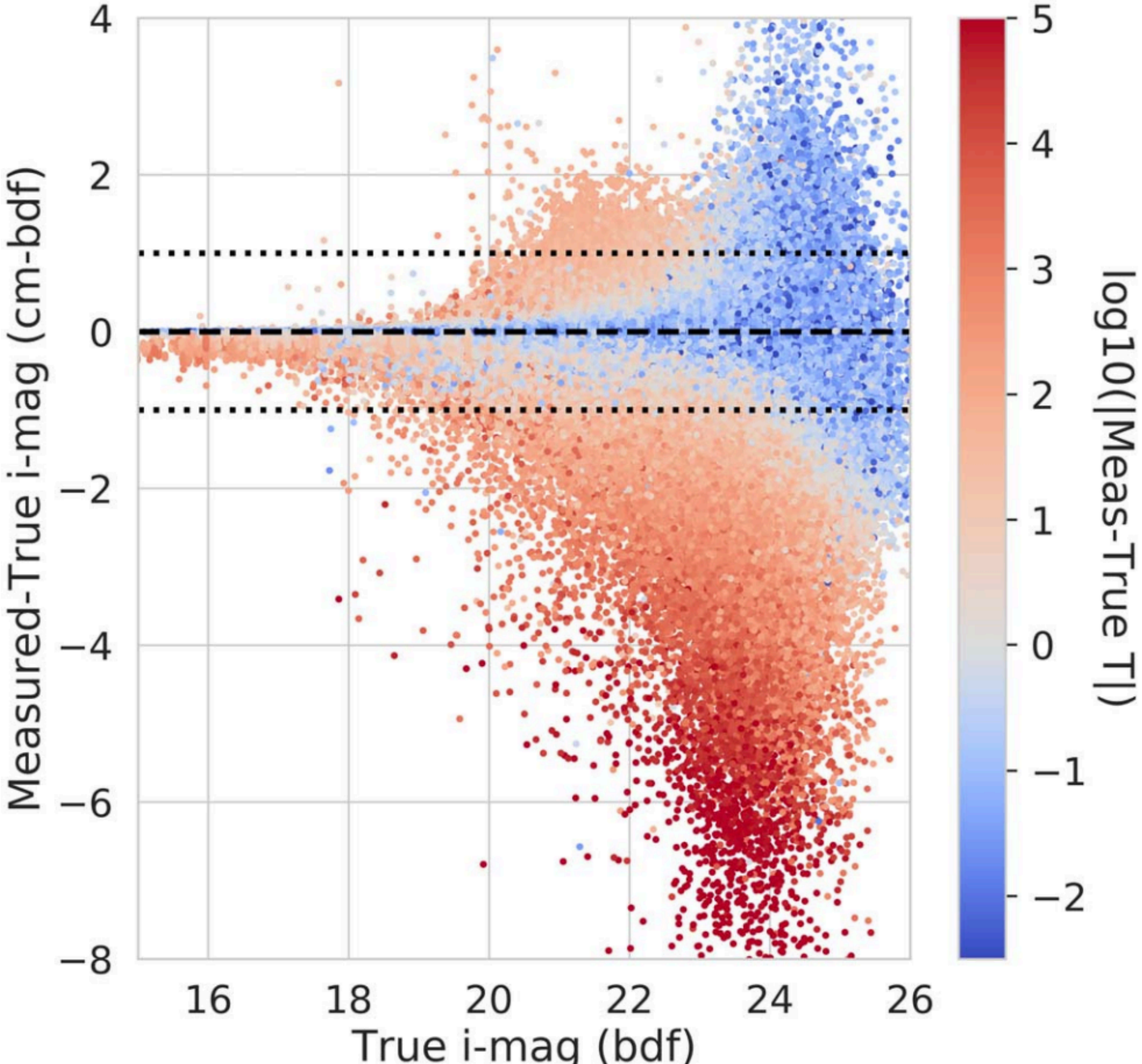
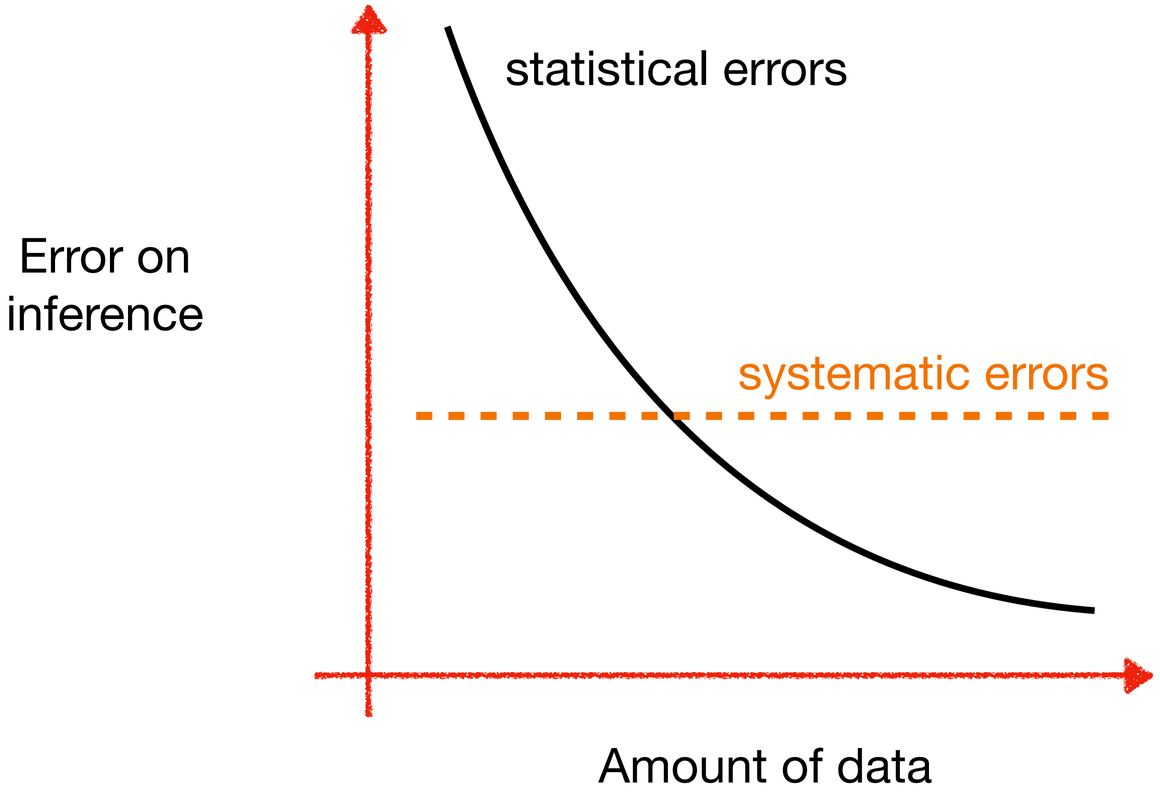




Photometry: statistical and systematic errors

Just count the photons from this star or galaxy. How hard can it be?



- Fitting the wrong model
- A bug in your code
- Your measurement

For some kinds of measurements, this is 90% of the conversation.

Simulating images
(the easy way)

- We now rely heavily on simulations to plan, forecast, and calibrate survey measurements.
- There are now battle-tested tools for doing this in Python.
- In the next section, we'll introduce GalSim, the modular image simulation toolkit.

Photometry.

Exercise 2: Simulate, then measure, some stars.

- Pose the question as a parameter estimation problem.

$$G(\boldsymbol{x}) = A\, T(\boldsymbol{x})$$

- Start by writing a likelihood for the data, ***D***, given the model parameter ***A***.

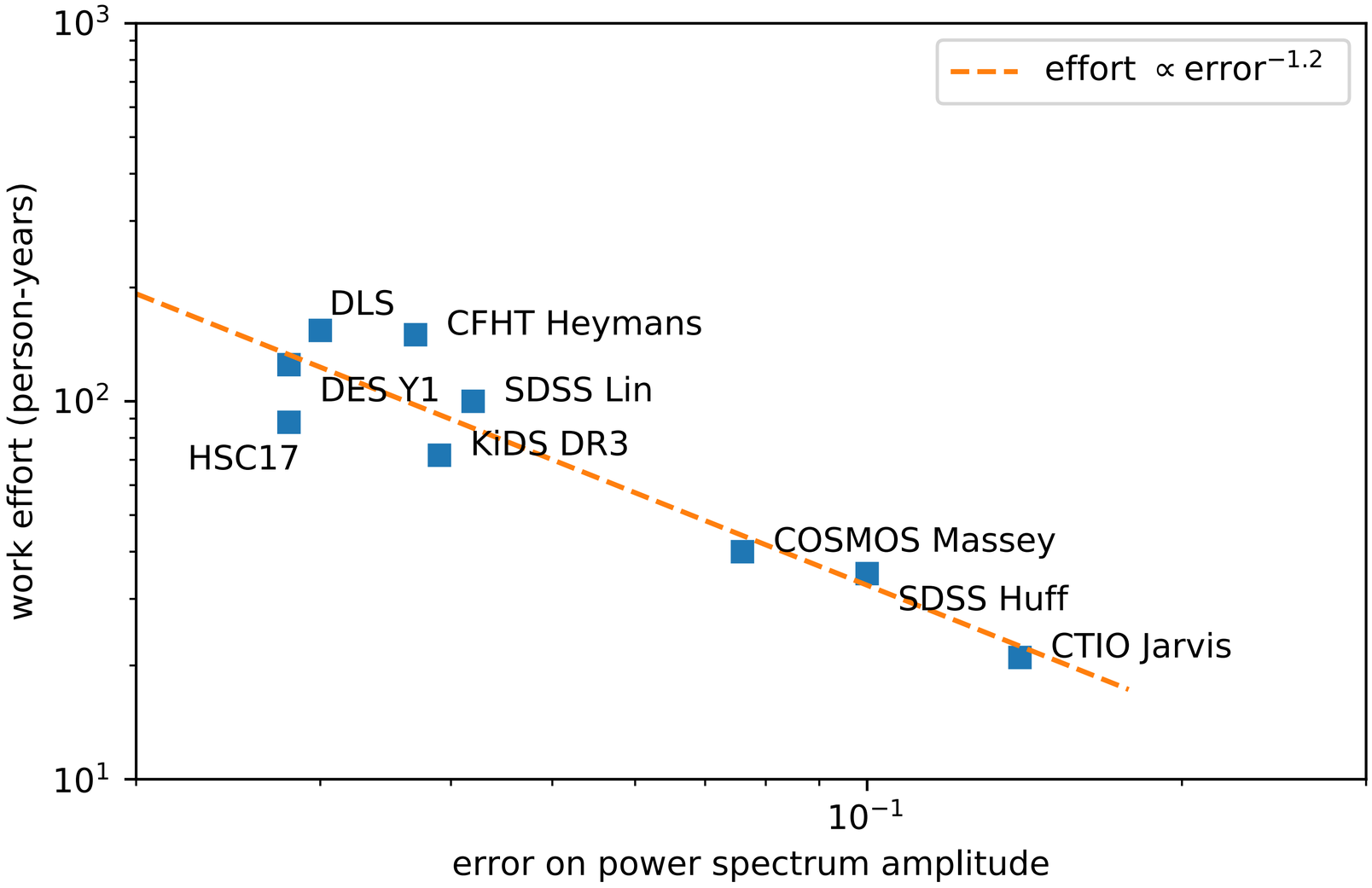
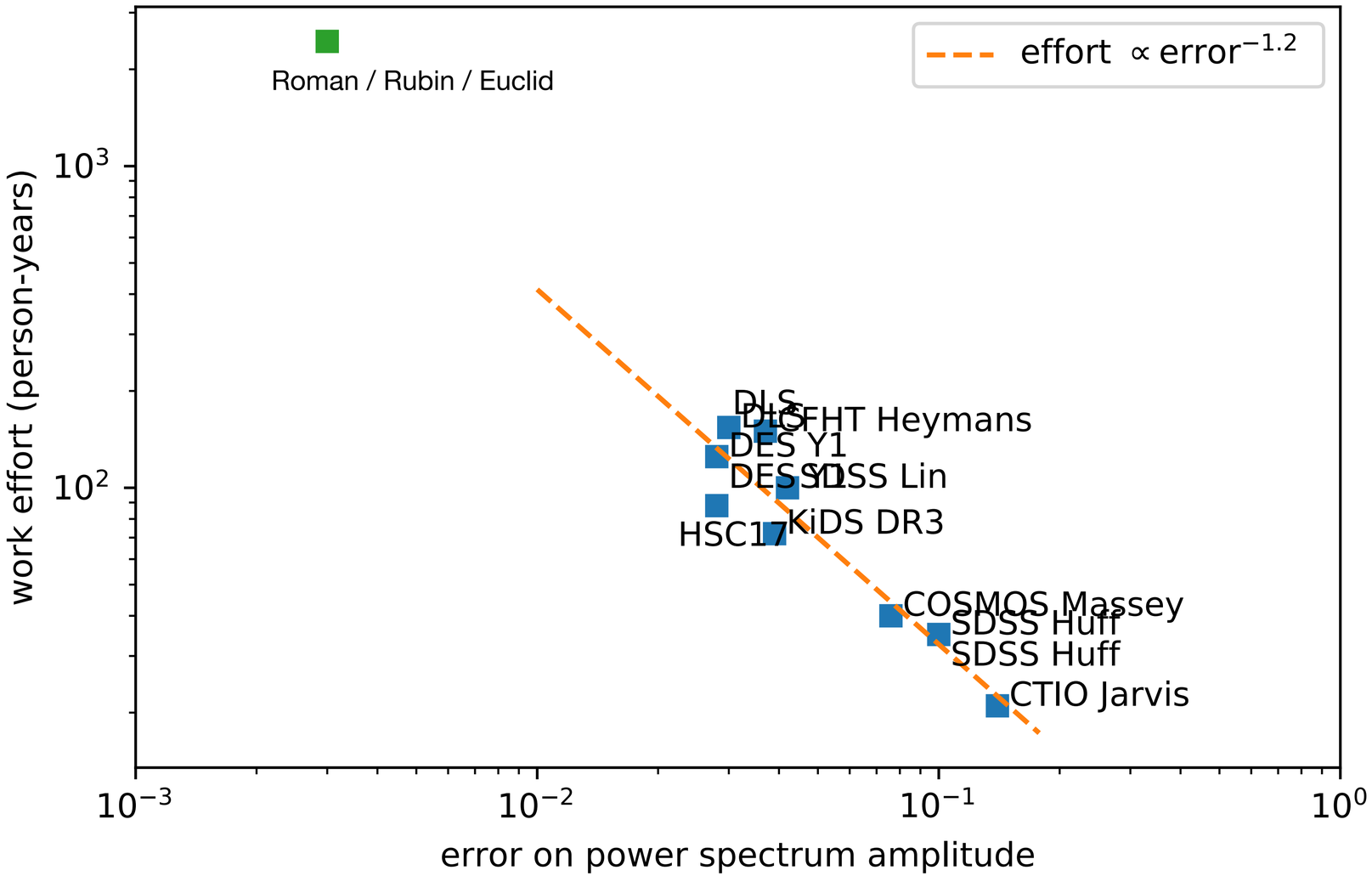
$$p(\, D \,|\, A)$$

- Derive an estimator if you can, optimize or sample if you cannot.

What did we just do:

- Origins and meaning of the PSF
- Tricks for simulating it.
- Implications for what you’re allowed to infer.
- Overview of how we infer it.

Larger context: precision science is hard!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