Lecture II:
Extended Source Photometry

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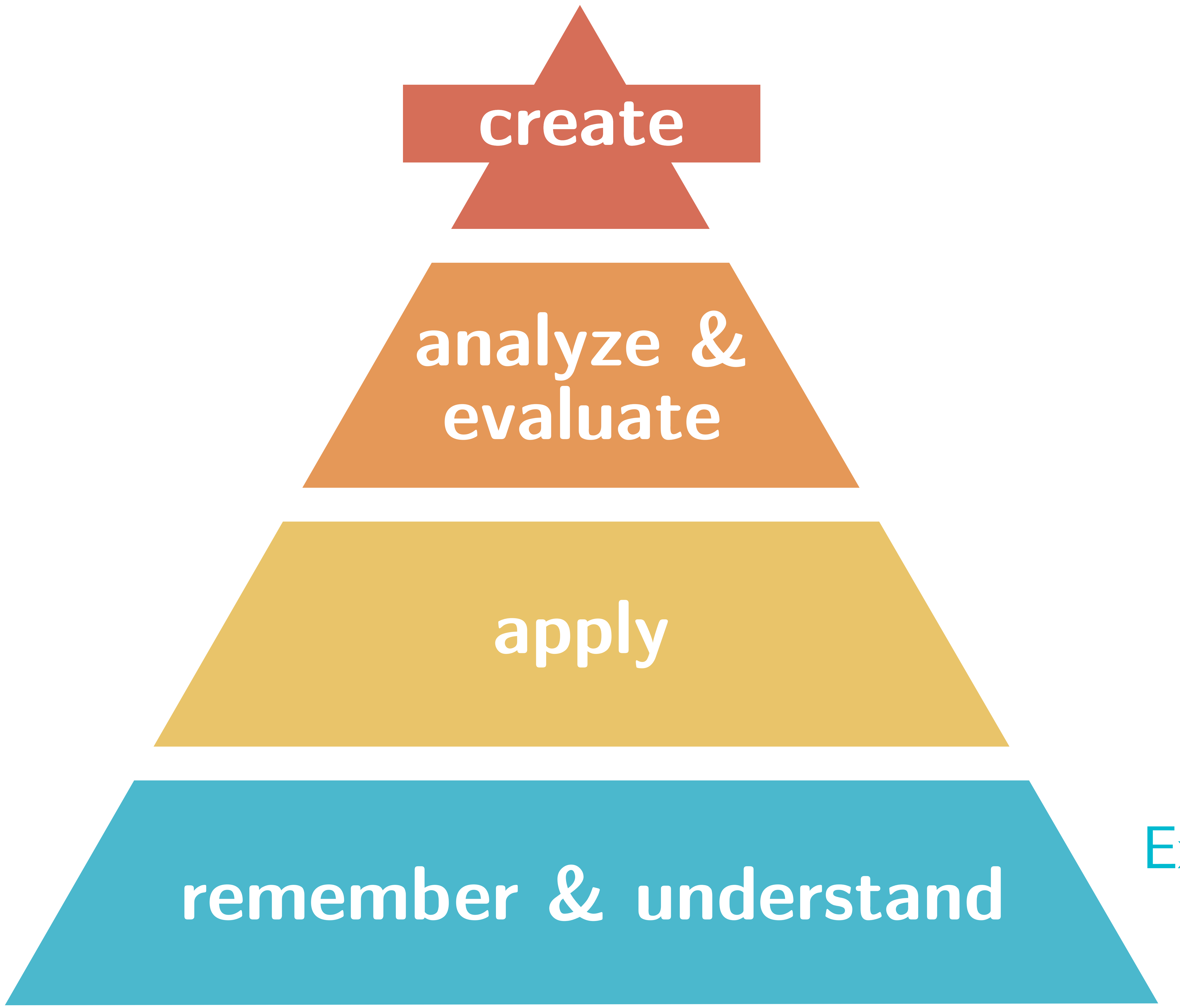
LSST Data Science Fellowship Lectures, 2025.09.17

Bloom's Taxonomy ... abbreviated



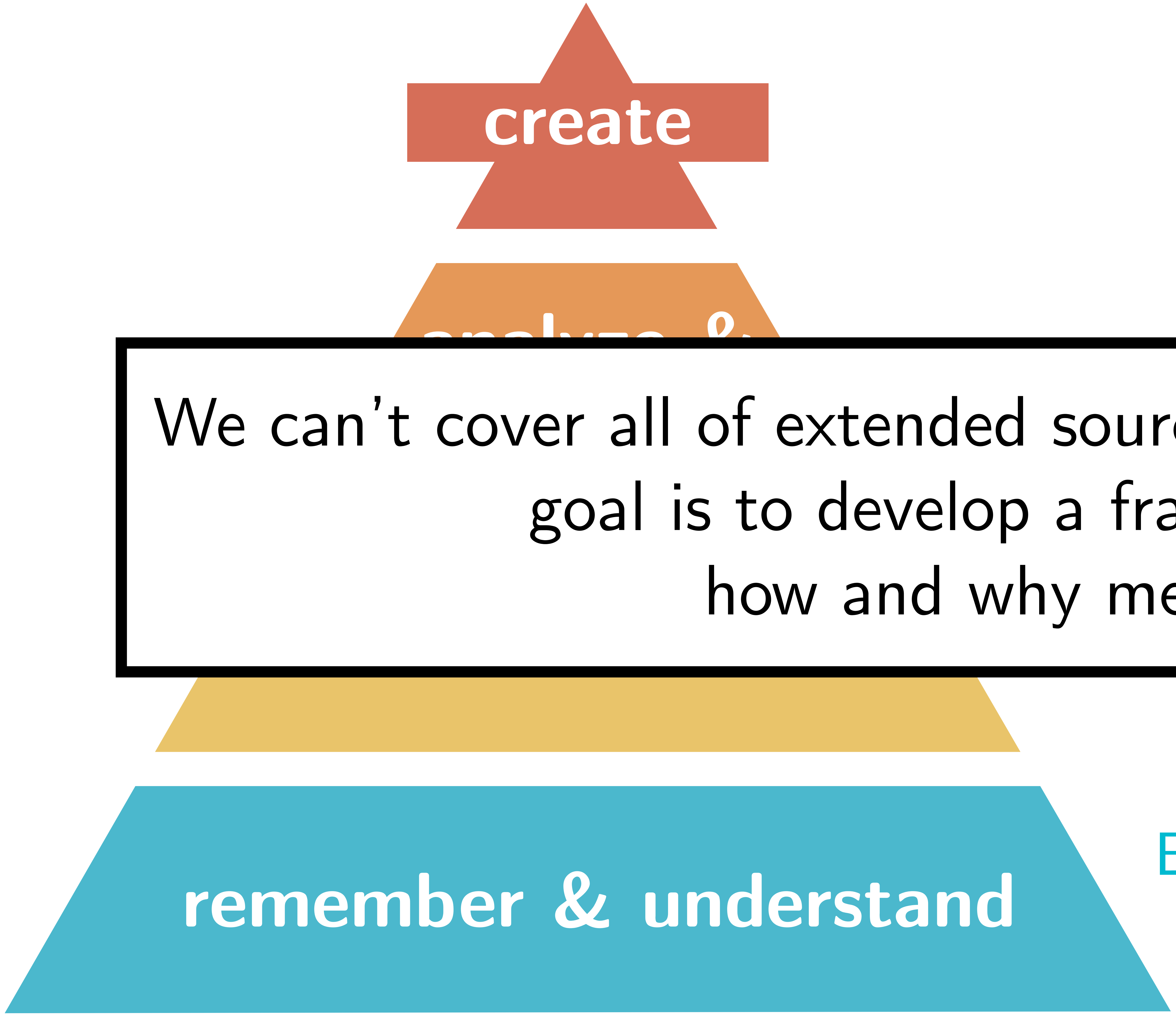
Problem set!

How are methods for extended source photometry developed?

Identify potential challenges of extended source photometry, & possible solutions

Explain how extended source photometry is different from point source photometry

Bloom's Taxonomy ... abbreviated



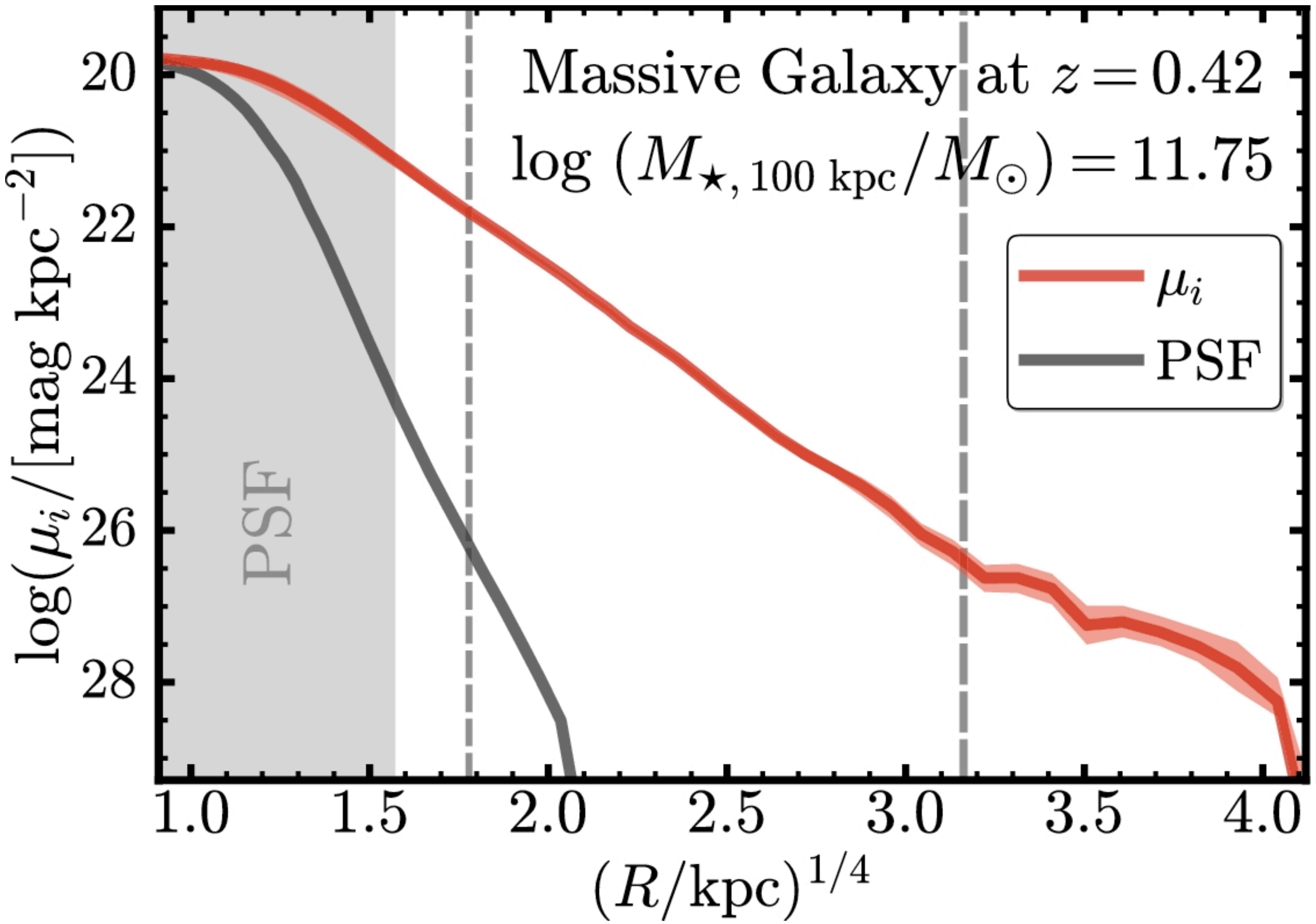
Problem set!

We can't cover all of extended source photometry in one lecture — the goal is to develop a framework to understand how and why methods are made.

source photometry, & possible solutions

Explain how extended source photometry is different from point source photometry

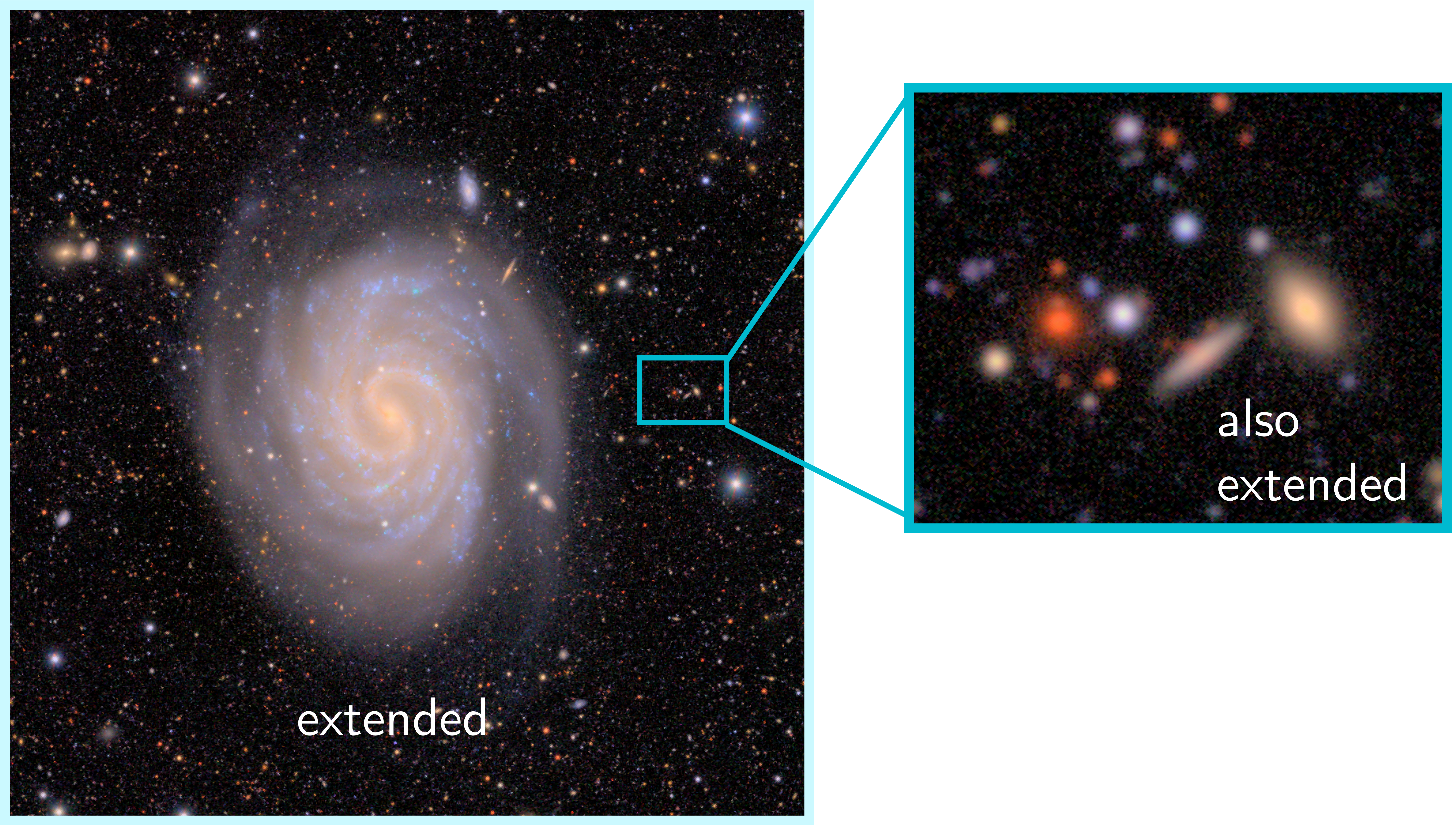
Point source vs. extended source



Extended sources are spatially resolved — profile extends beyond the **point spread function**

Huang+2018

Extended sources come in many flavors (scales)



https://skyviewer.app/

LSST!
Rubin Observatory (8.4m)

Extended photometry vs. point source photometry

Discuss with your partner:

You learned about point source photometry on Tuesday —
what additional information/complications might arise for extended sources?

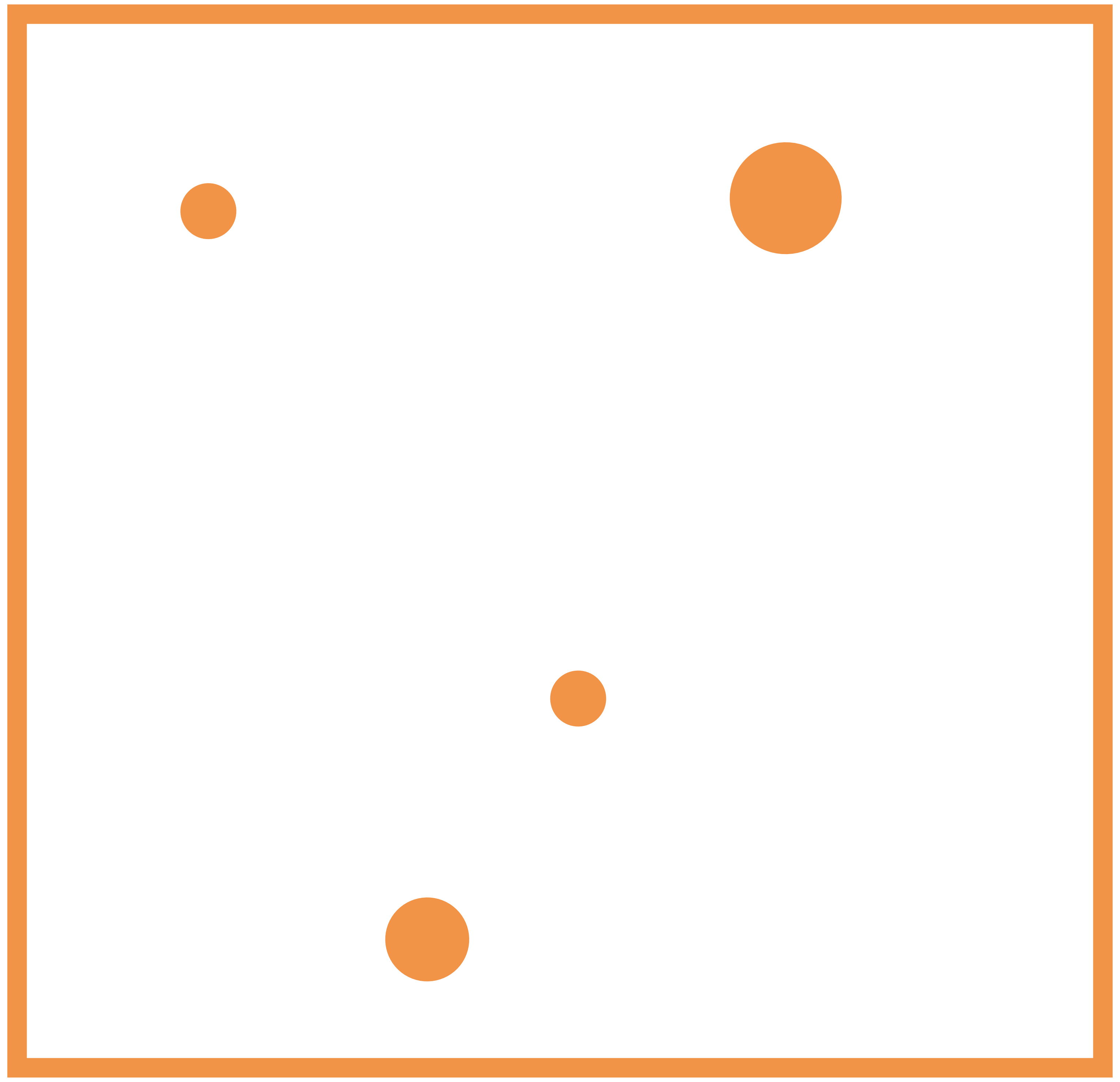
Extended photometry vs. point source photometry

Discuss with your partner:

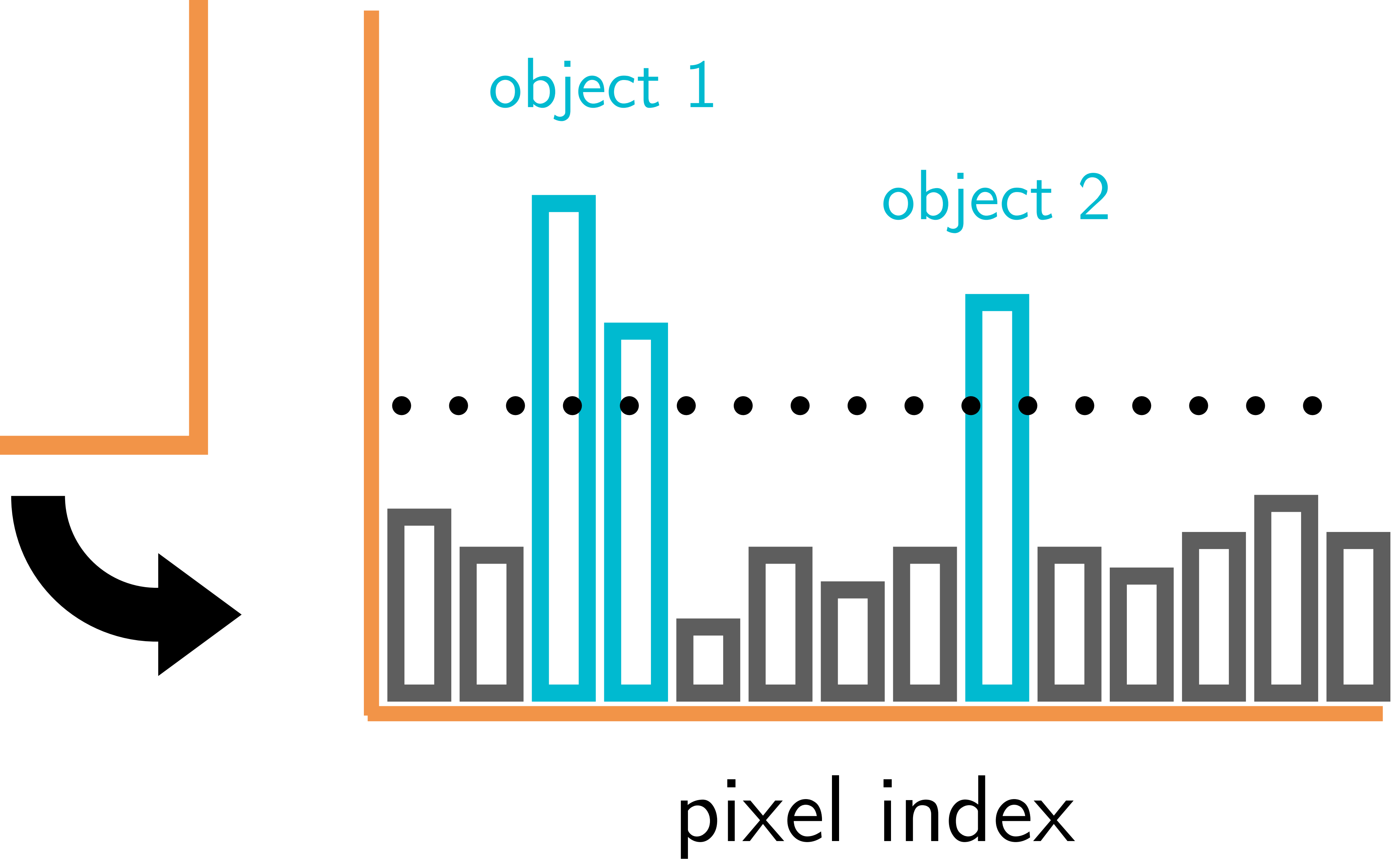
You learned about point source photometry on Tuesday —
what additional information/complications might arise for extended sources?

- Can measure sizes & shapes
- Don't know what the observed profile should be
- Sources blend together
  (but we don't know what their individual profiles are!)
- Ambiguity in what is one source versus 2+ sources

Image segmentation - a definition.



Segmentation is the process of identifying the locations and boundaries of extended sources from an image.



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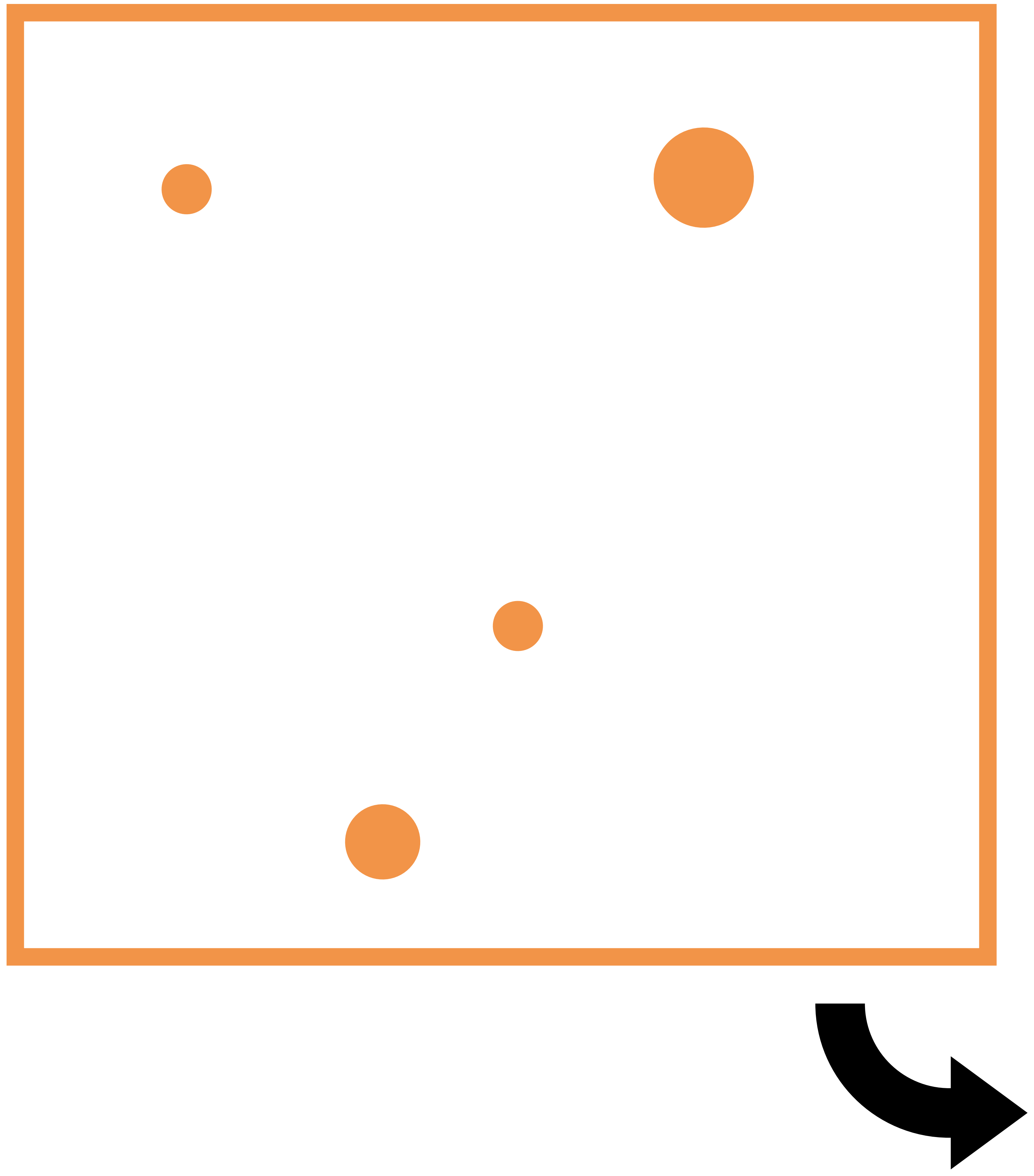
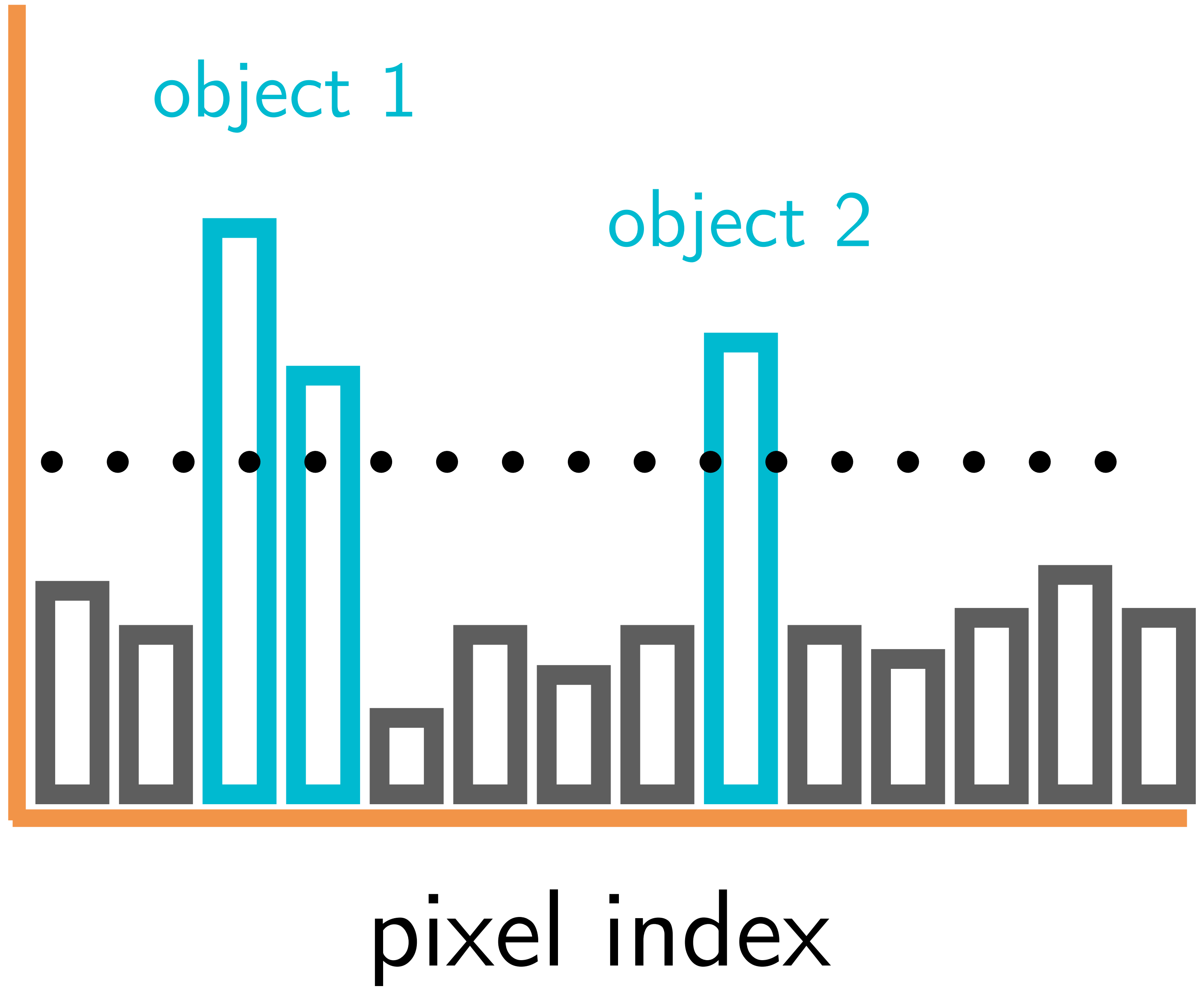
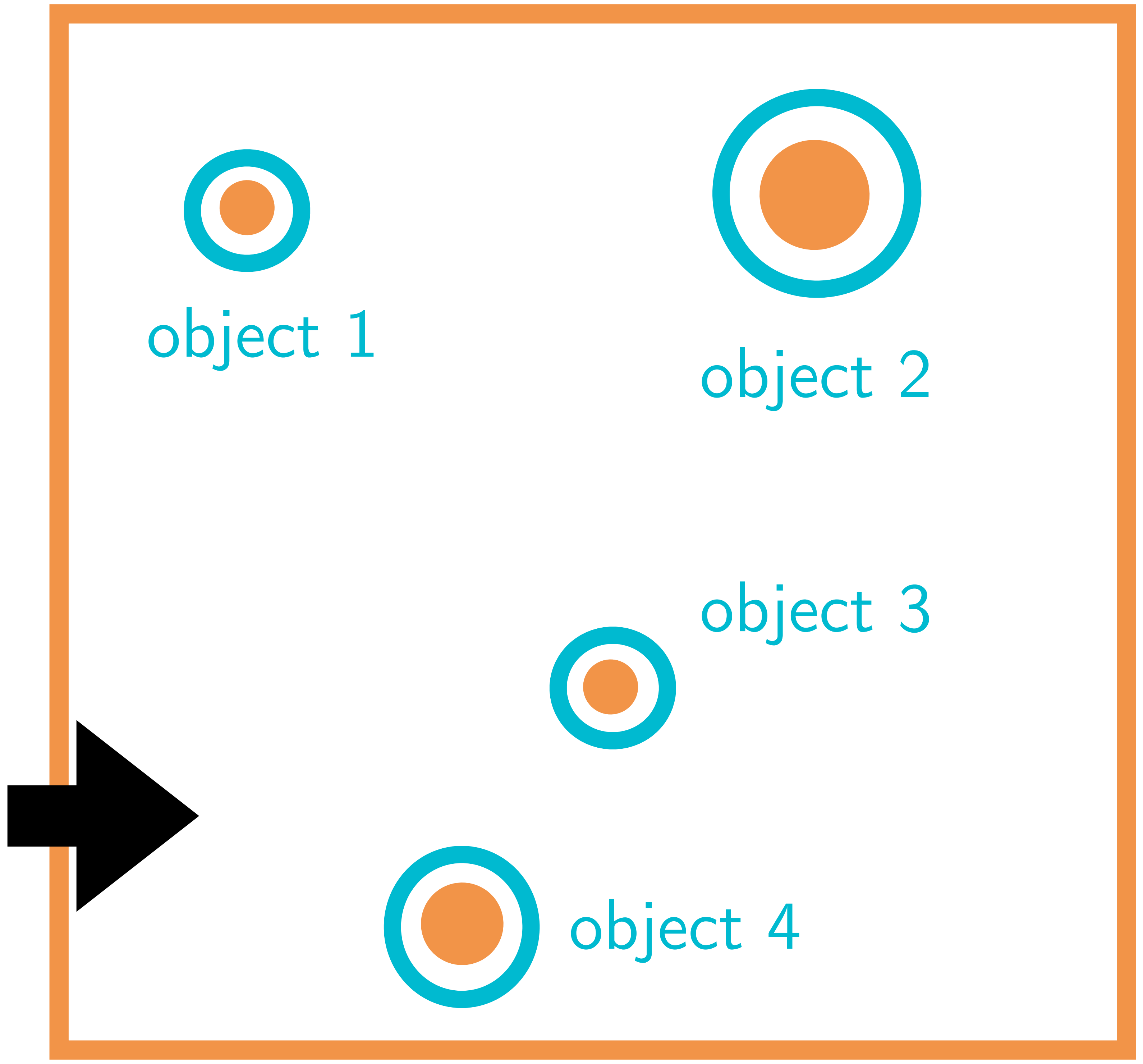
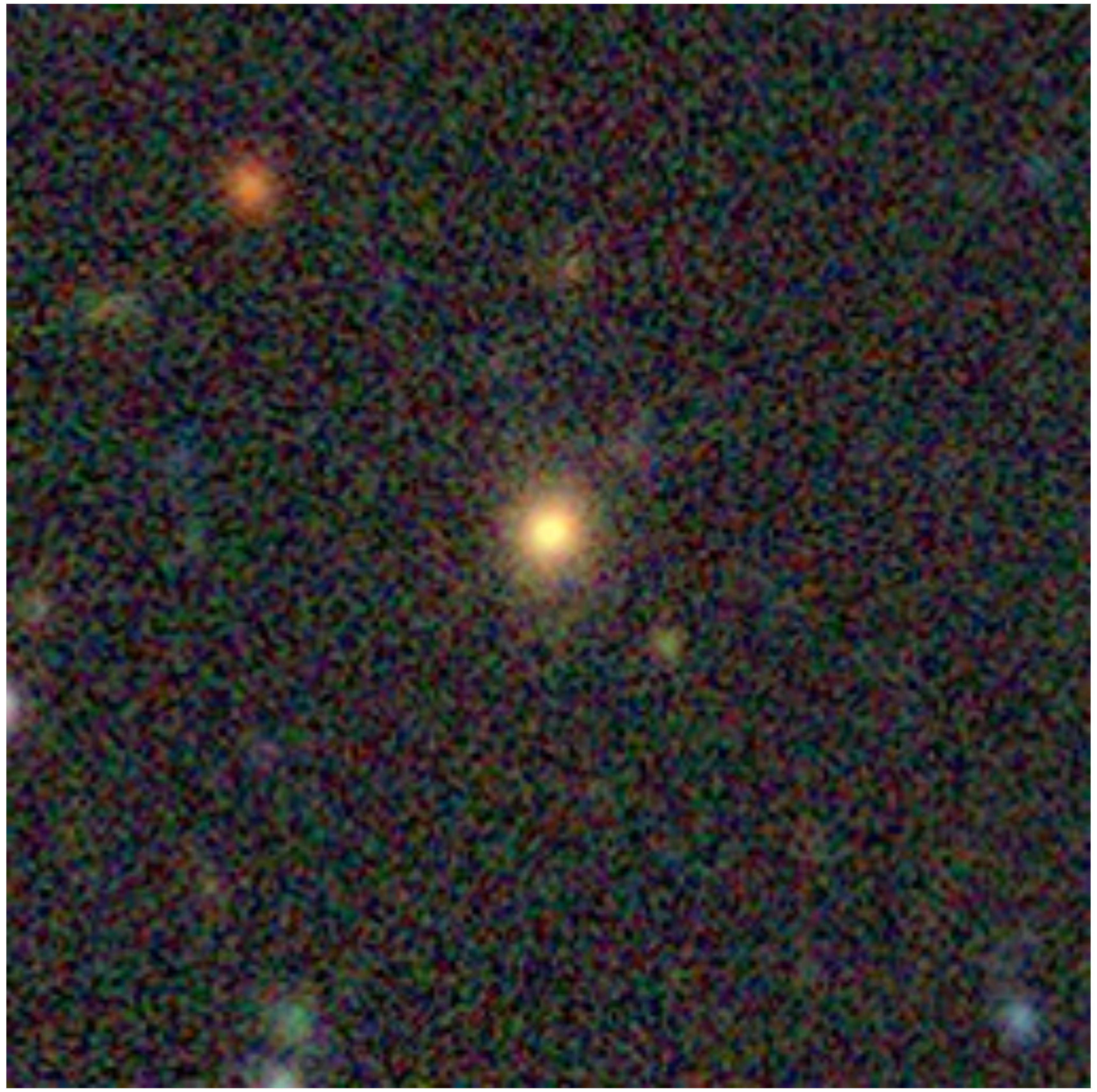






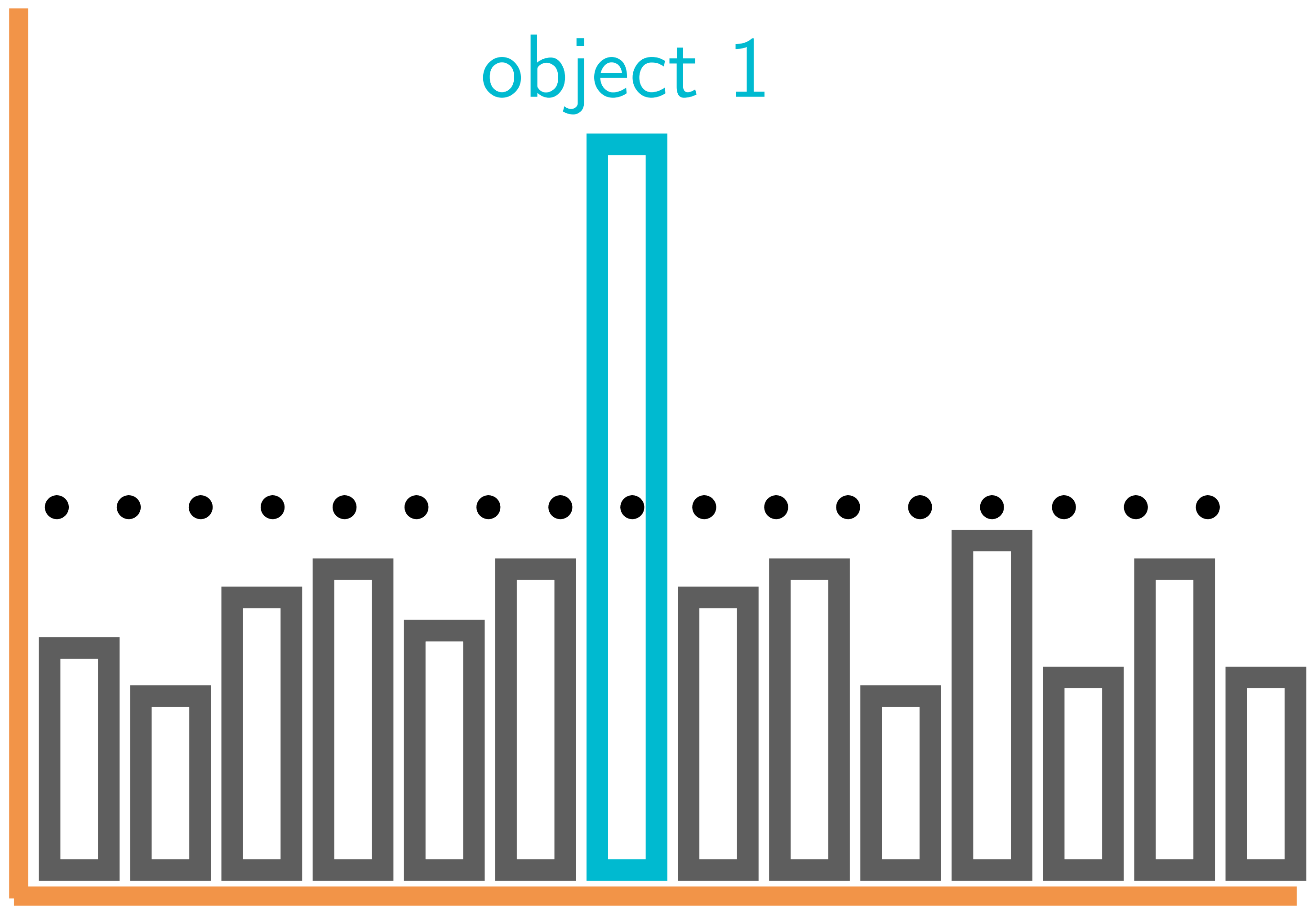
Segmentation challenges: Deblending



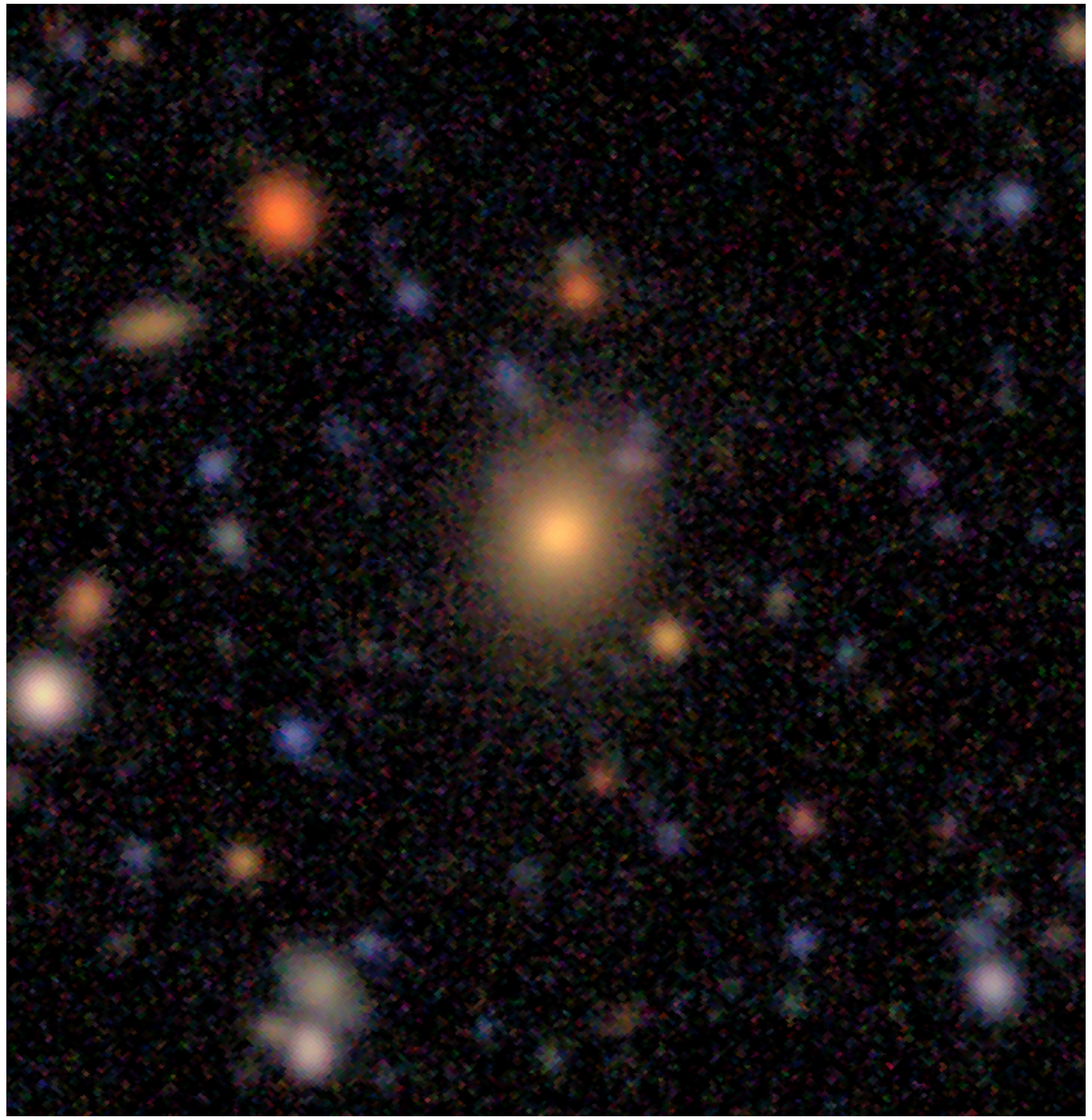
Legacy Imaging Survey

Deblending is the process of separating which pixels (or fractional pixels) belong to what source.

This problem gets harder with survey depth:



Segmentation challenges: Deblending



LSST First Light imaging

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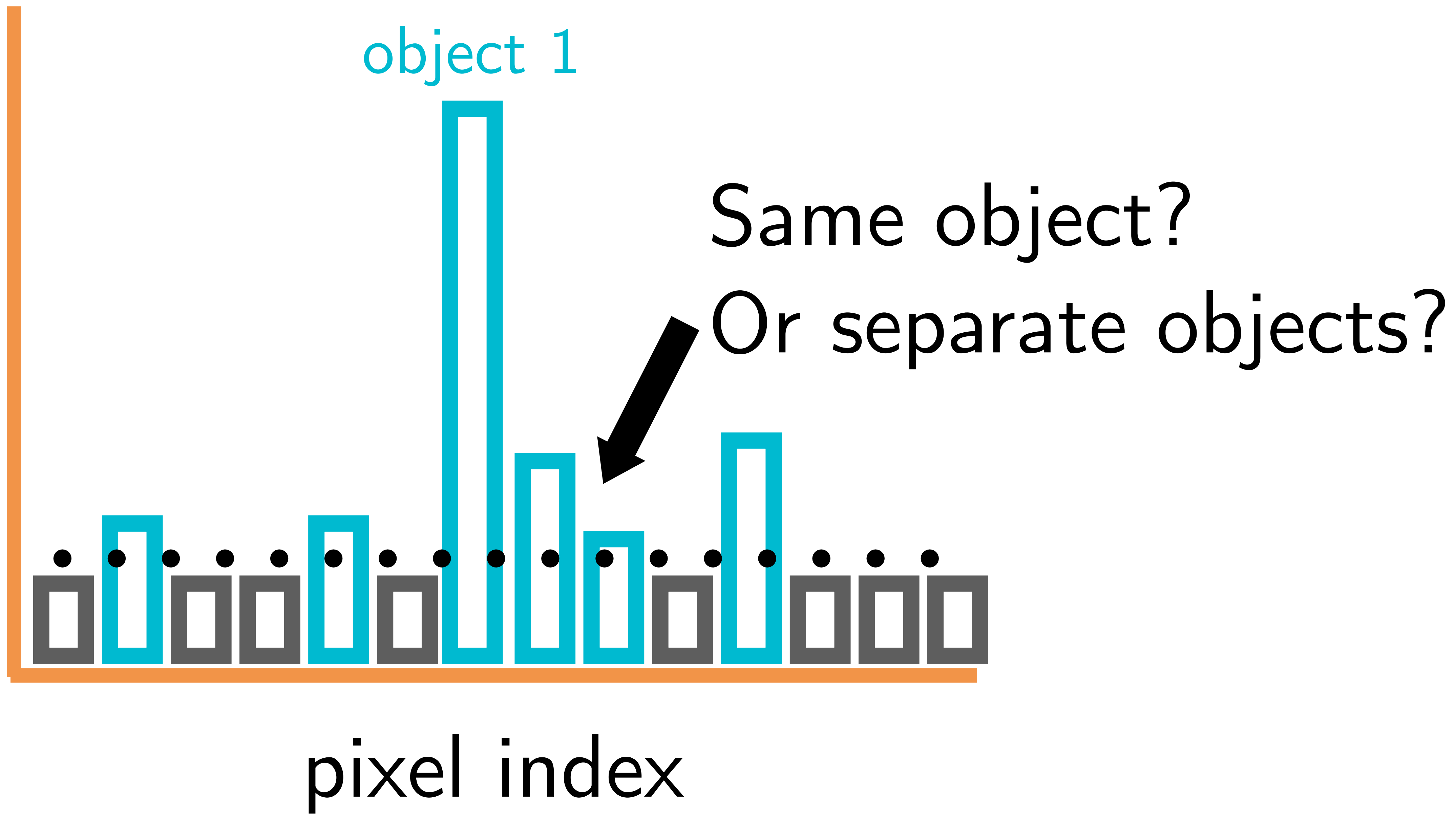
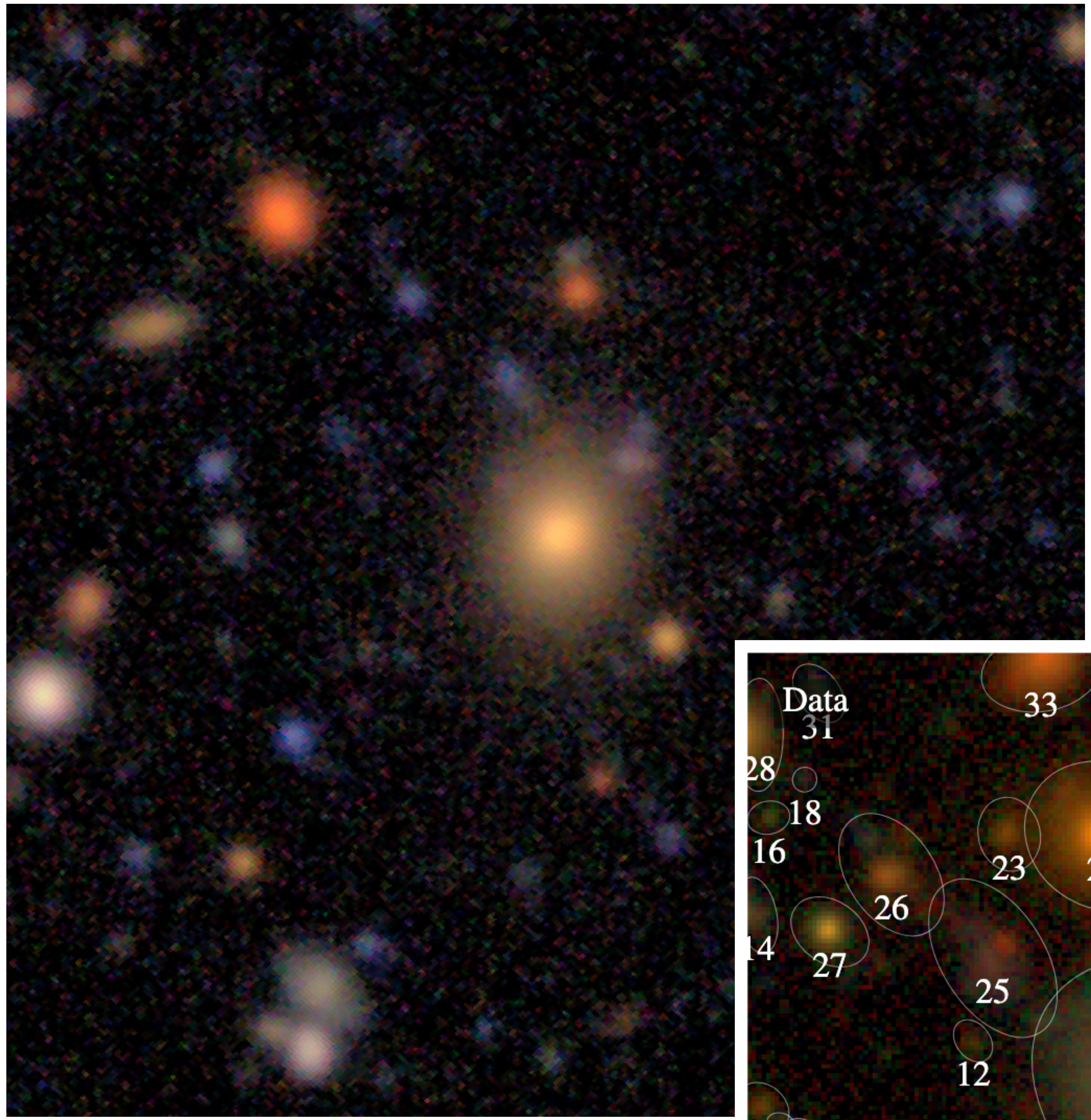
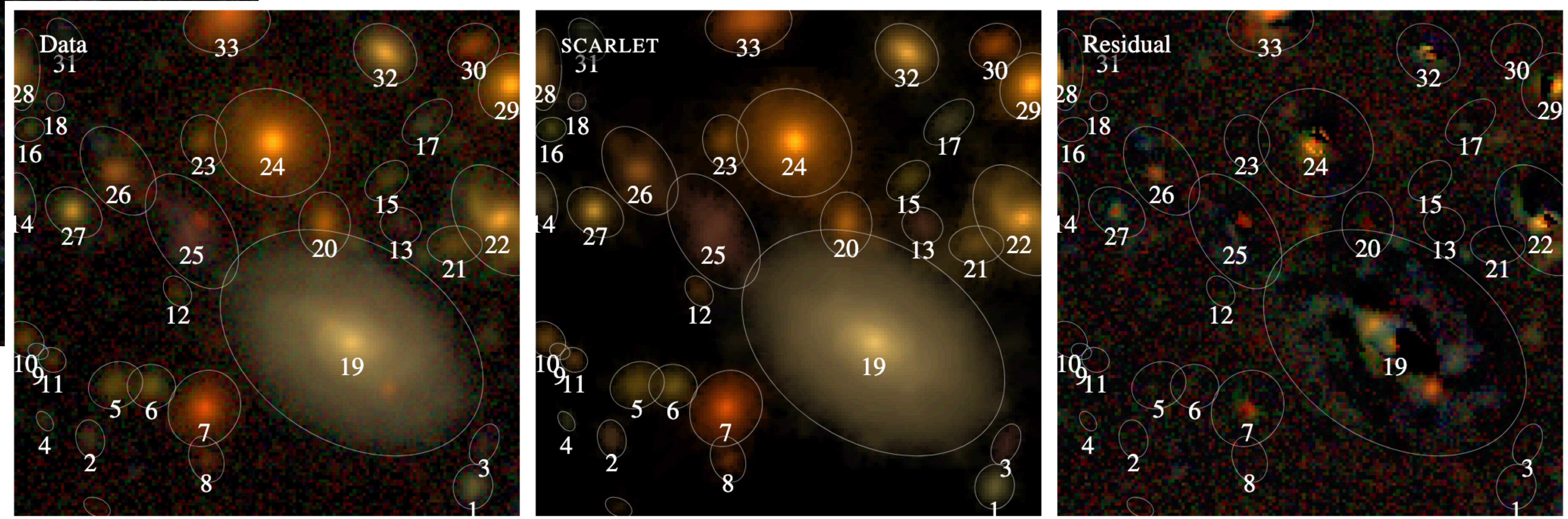


Segmentation challenges: Deblending



- Deblending is a problem that just keeps getting harder the deeper our surveys go!
- Because we don't know the light profile of extended sources, we need to make some assumptions:

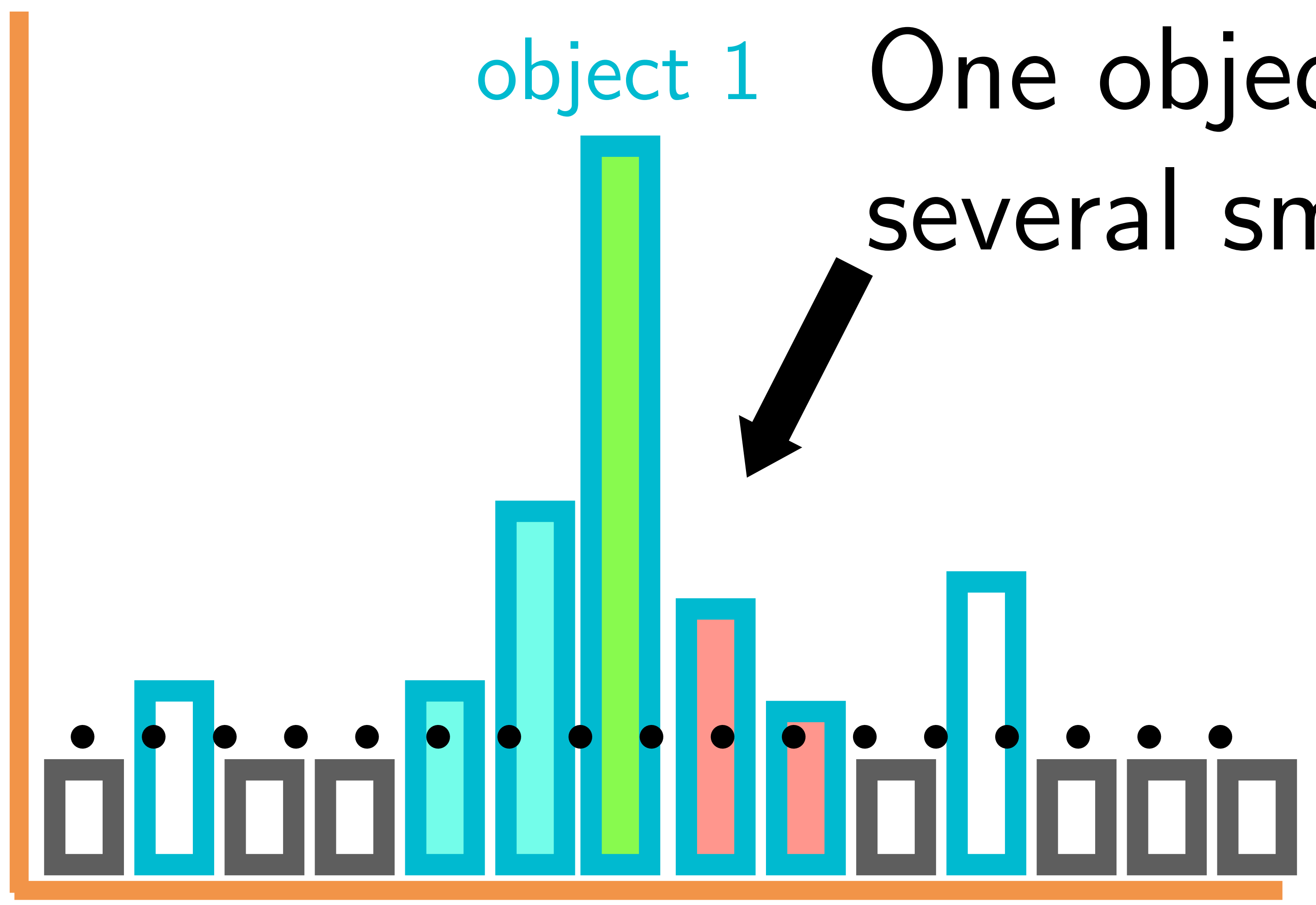


Melchior+2018

Segmentation challenges: Fragmentation

gri-composite

Fragmentation is when deblending goes “too far”, and single objects are fragmented into multiple sources:

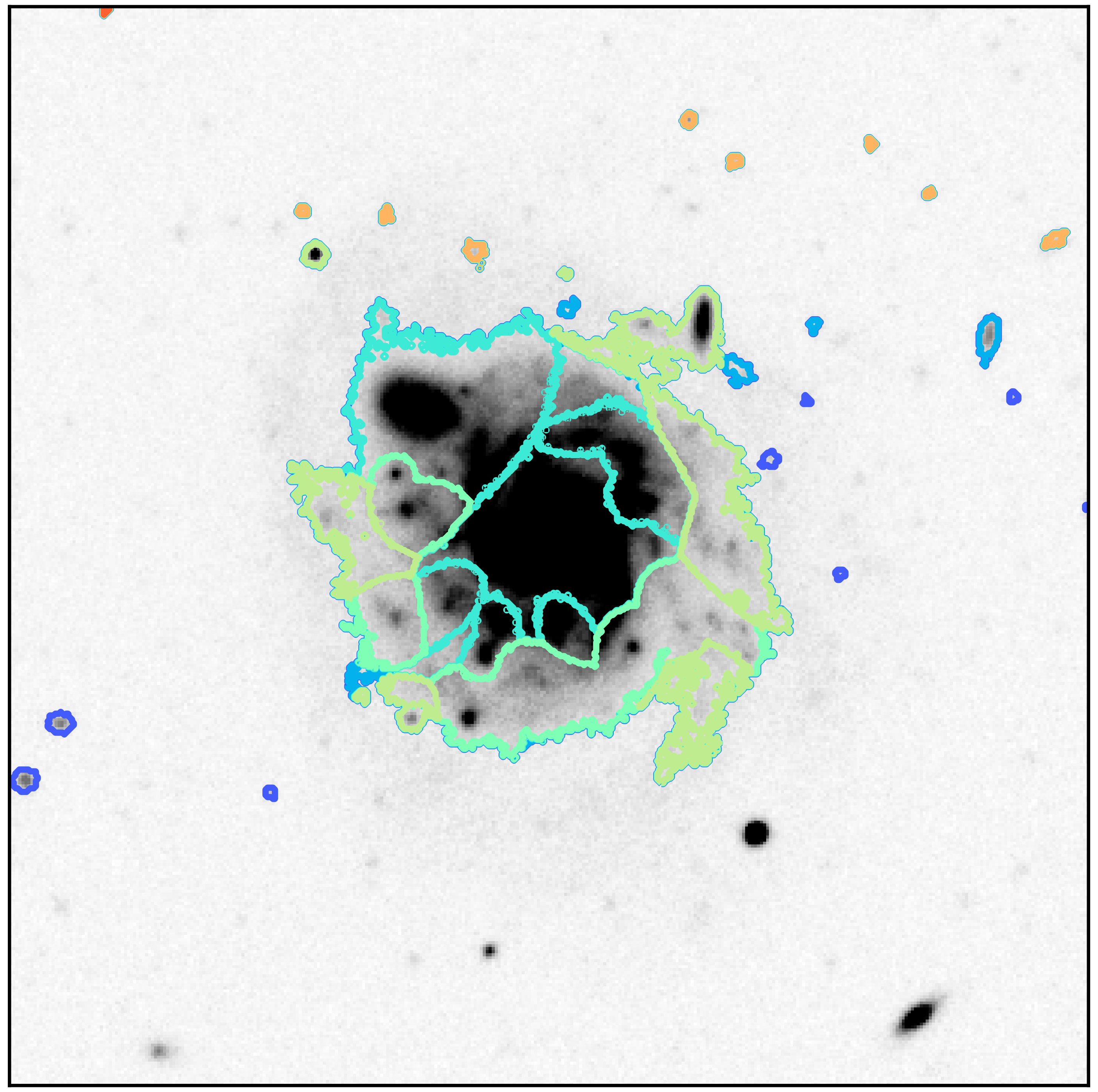


One object gets broken up into several smaller objects

pixel index

Segmentation challenges: Fragmentation

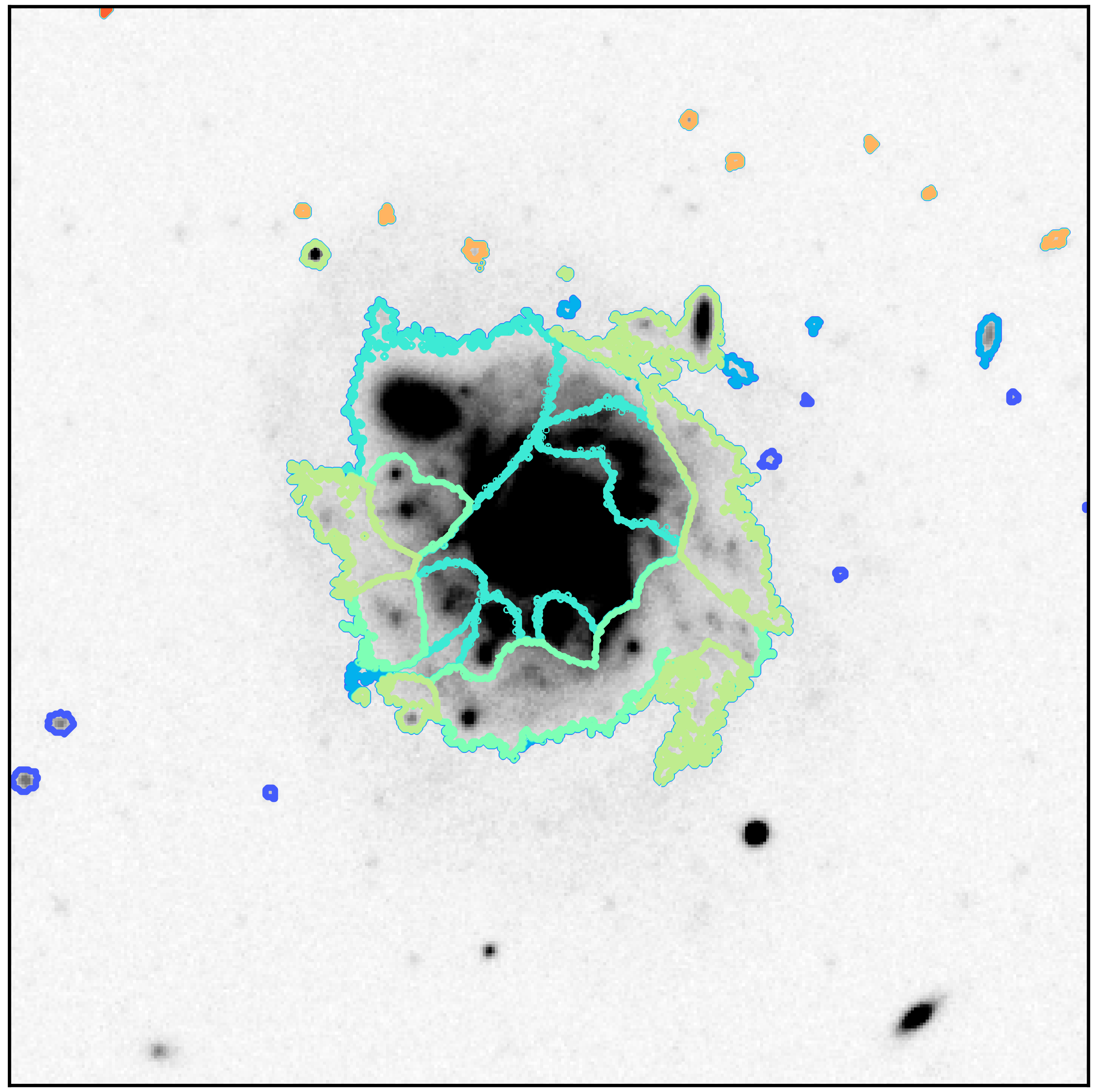
gri-composite



fragmented

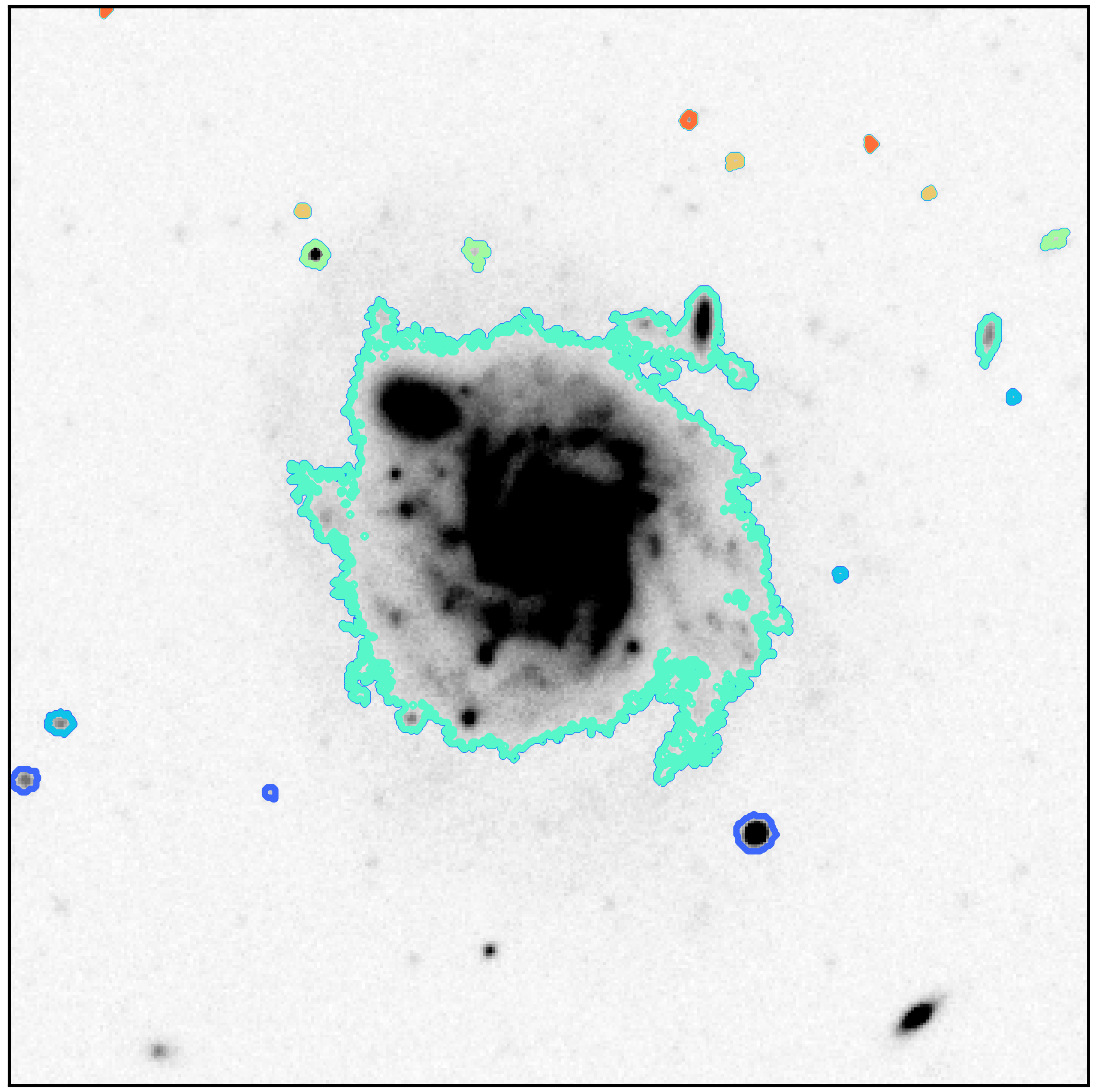
Segmentation challenges: Fragmentation

gri-composite



fragmented

galactic substructures
broken into separate objects



under-deblended

nearby galaxies
flagged as substructrue

Strategies to balance deblending and fragmentation

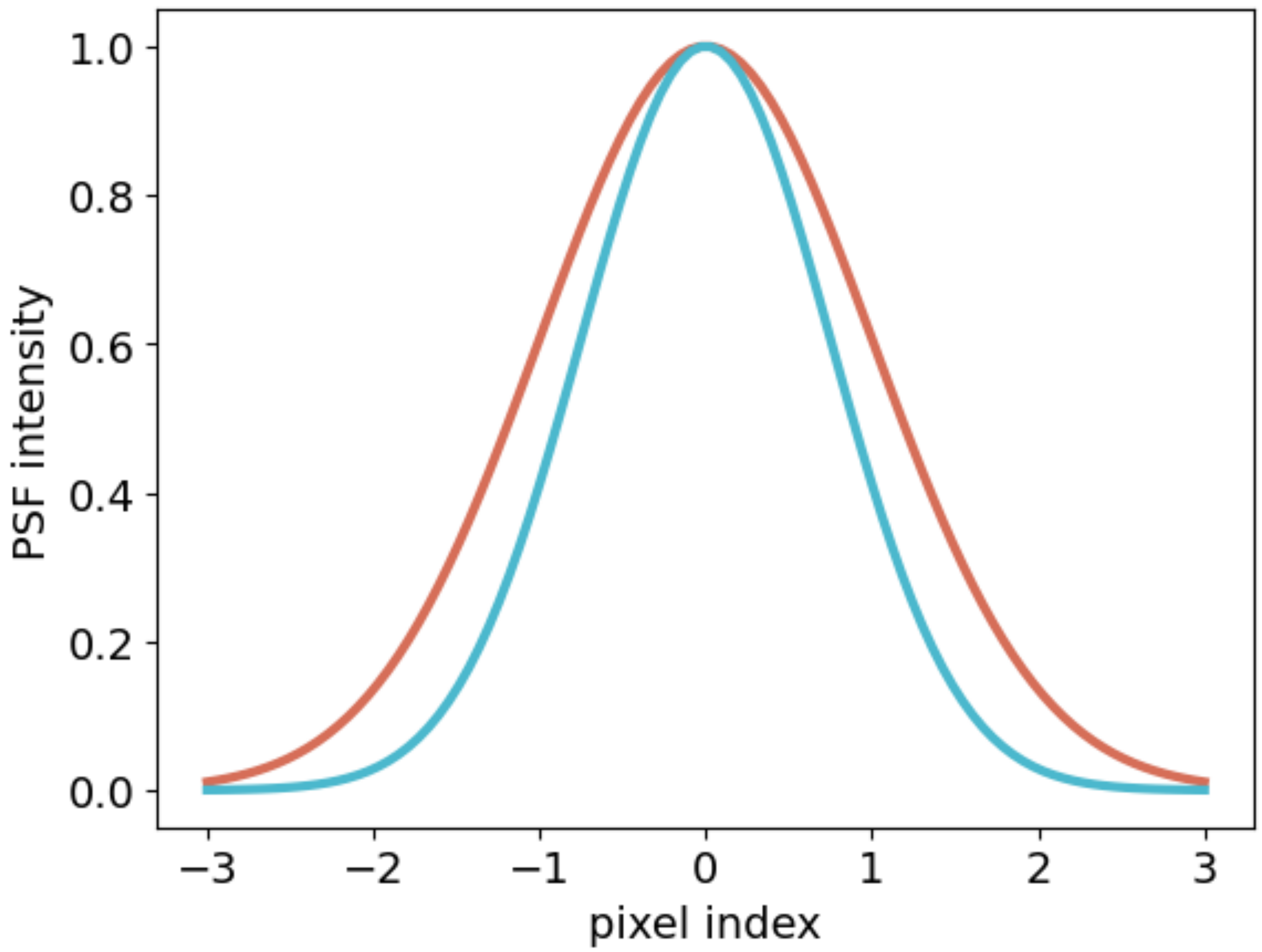
- In practice, not every catalog needs to serve every science case
- Often, science-specific catalogs are useful and/or necessary. For example:
  - Nearby/large galaxies
  - Very low surface brightness galaxies
  - Point source catalogs

Strategies to balance deblending and fragmentation

- In practice, not every catalog needs to serve every science case
- Often, science-specific catalogs are useful and/or necessary. For example:

	Catalogs optimized for this science would:
Nearby/large galaxies	tend to under-deblend small galaxies
Very low surface brightness galaxies	tend to under-deblend small galaxies
Point source catalogs	Fragment large galaxies

Photometric challenges: Multiband photometry

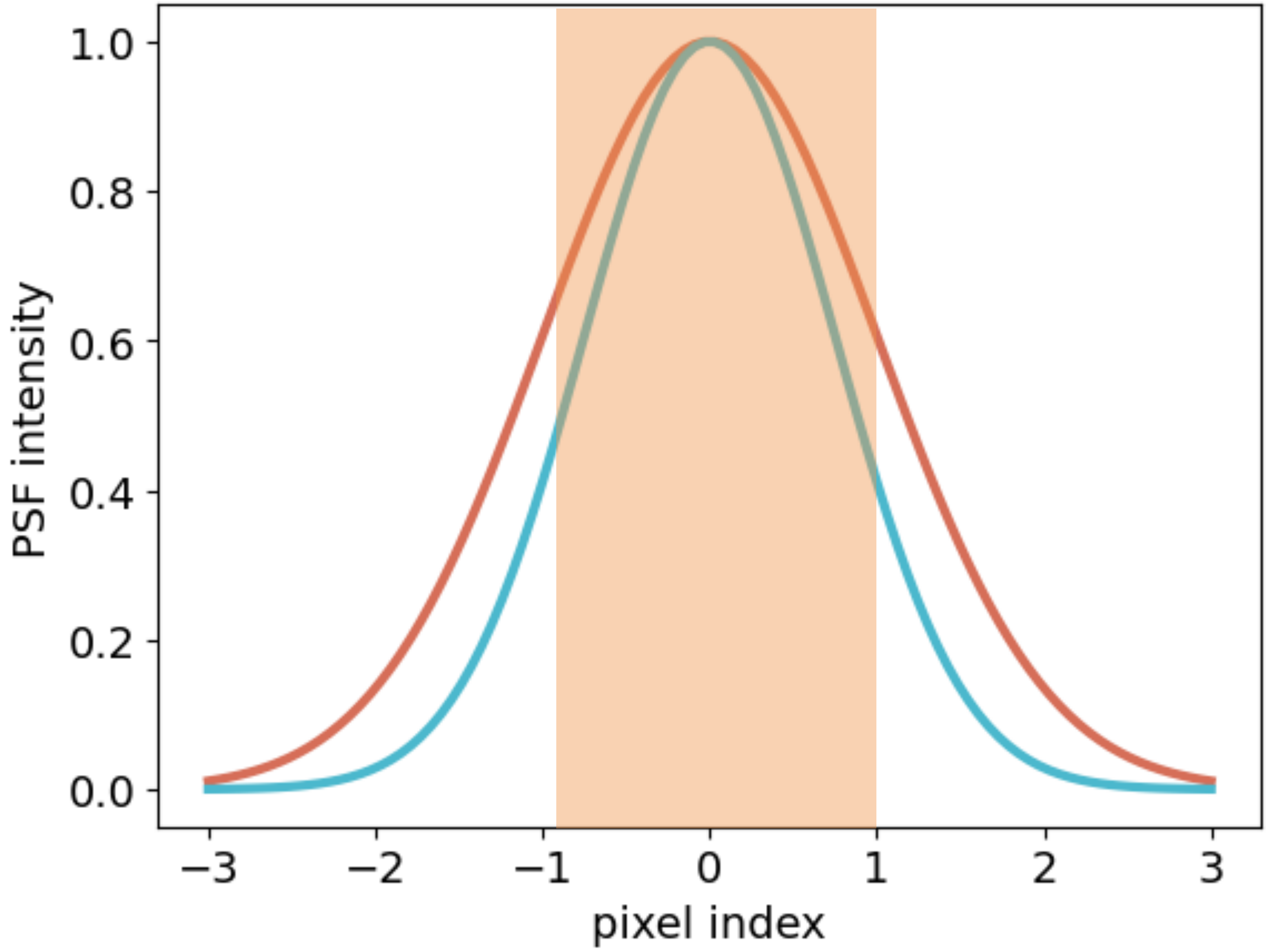


Say we have two bands, **g** and **i**.

We want to measure g-i color $[m_g - m_i = -2.5\log_{10}(F_g^\nu / F_i^\nu)]$,

but g and i have different PSFs.

Photometric challenges: Multiband photometry



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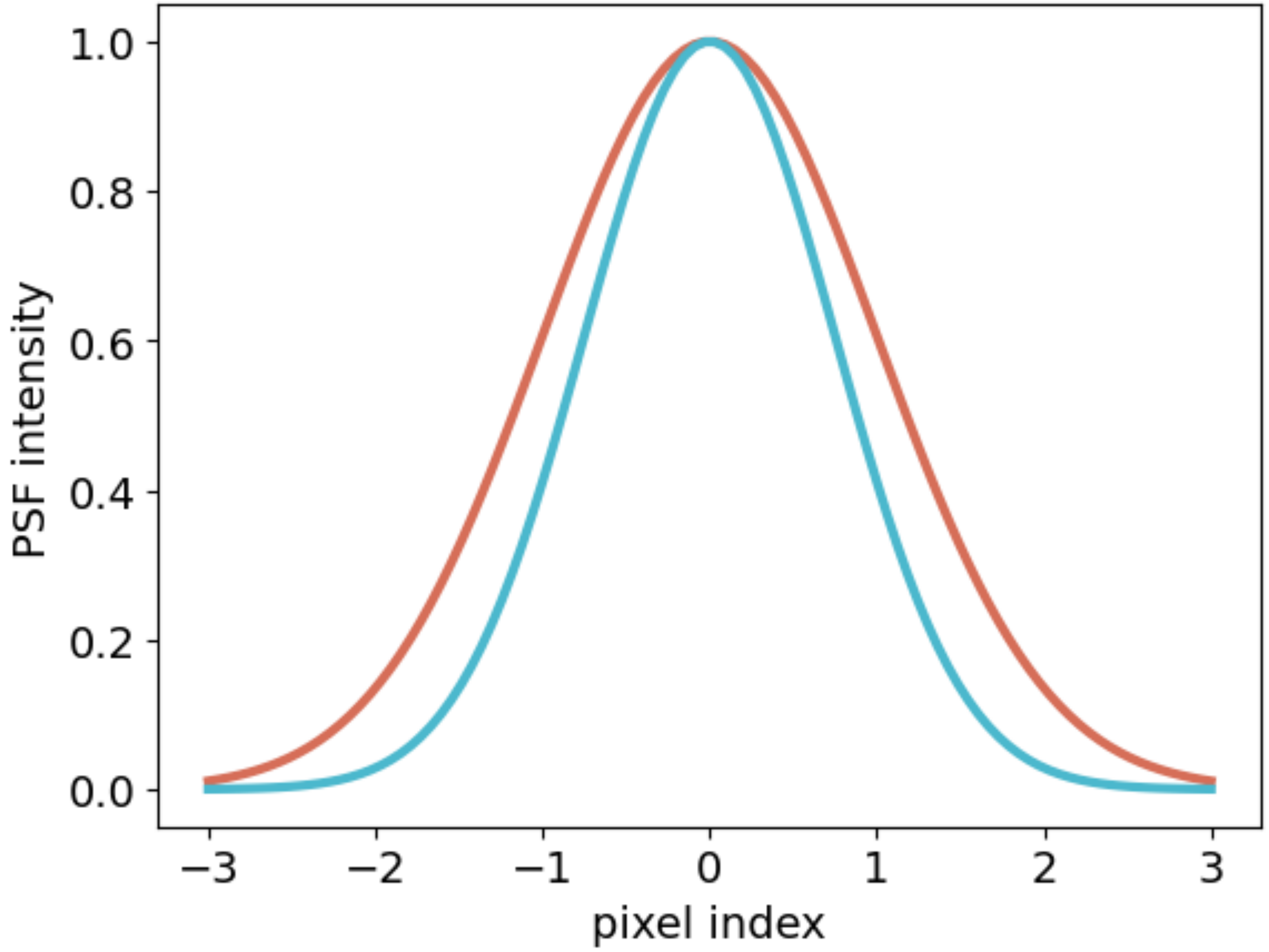
$[m_g - m_i = -2.5\log_{10}(F^{\nu}_g/F^{\nu}_i)]$,

but g and i have different PSFs.

Forced photometry at fixed aperture?

g-band will appear artificially brighter

Photometric challenges: Multiband photometry



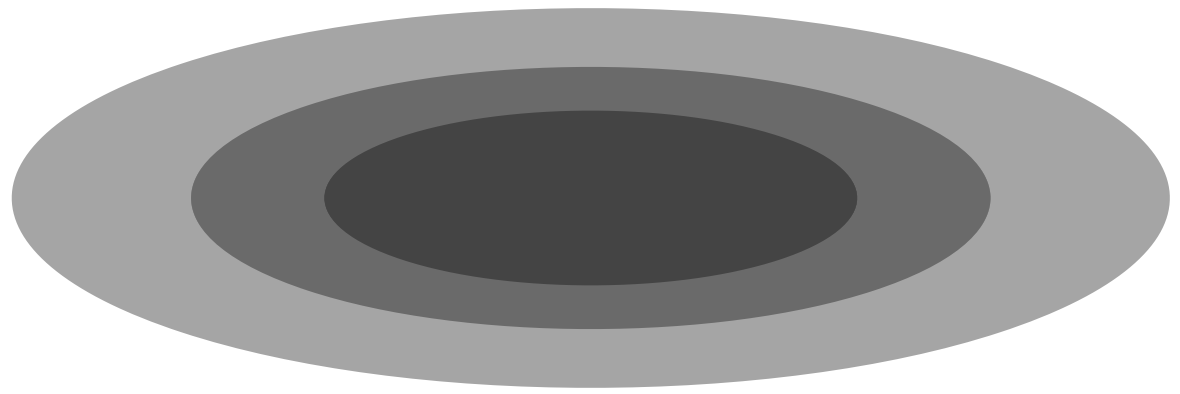
Solutions:

- Image pretreatment
  (e.g. PSF matching — convolve all images to worst seeing)

- PSF modeling
  (e.g. Gaussian Aperture and PSF, "GAaP" photometry)

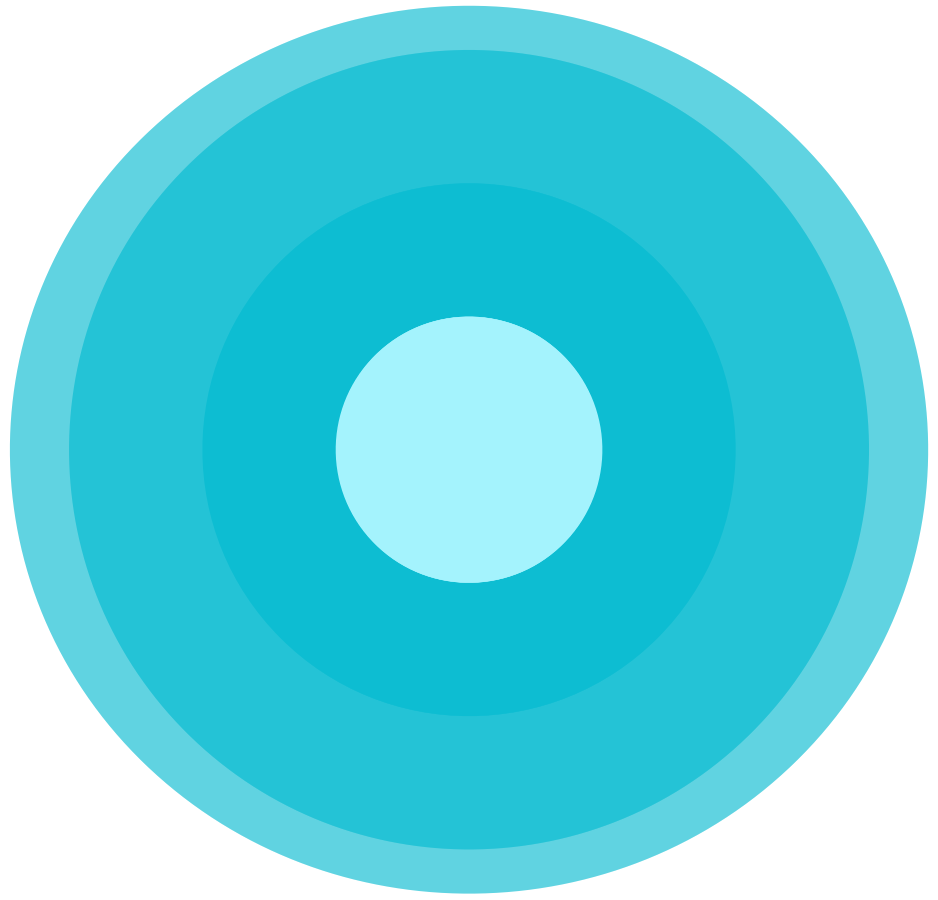
- Galaxy modeling
  (e.g. Sersic model convolved with PSF)

Test case: PSF matching

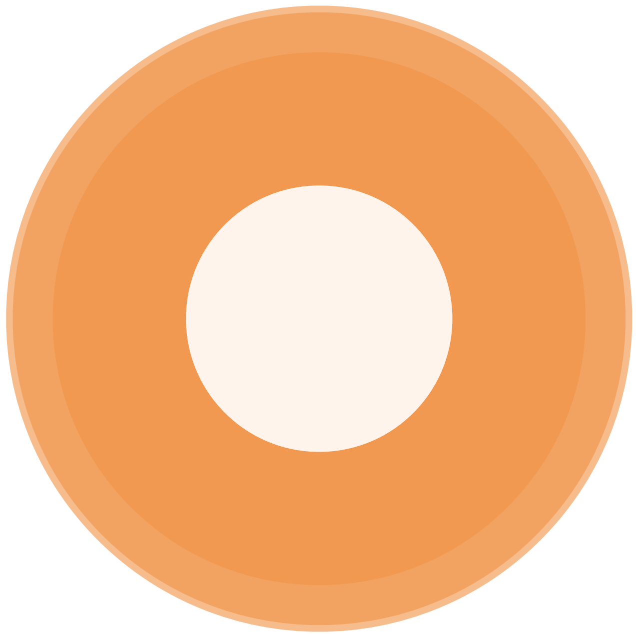


$S(x, y)$

Let's consider a source with the intrinsic surface brightness profile $S(x, y)$.



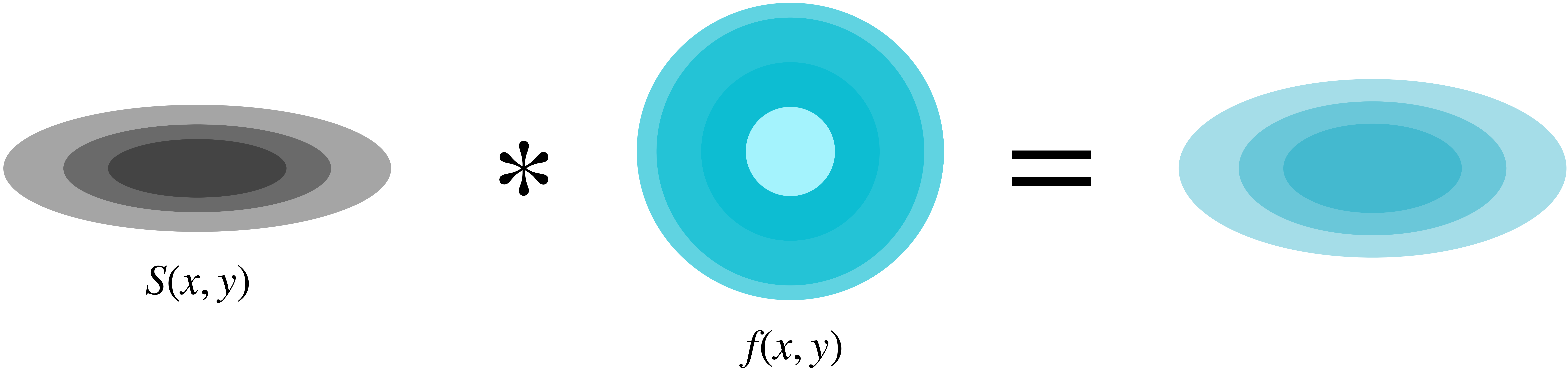
$f(x, y)$



$g(x, y)$

Now, let's observe what the source looks like in two images with different PSFs, $f(x, y)$ and $g(x, y)$

Test case: PSF matching

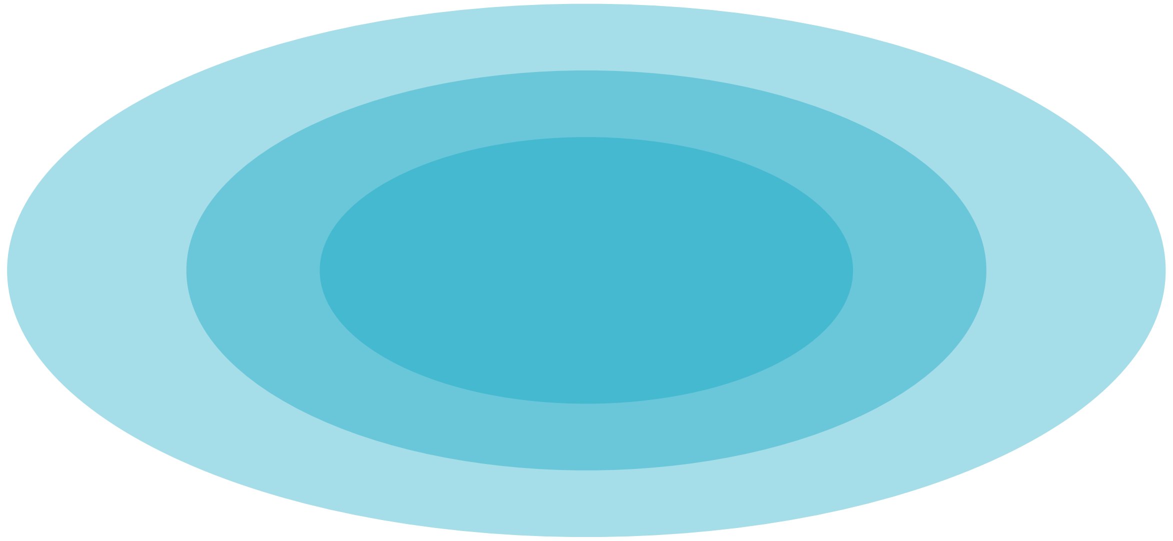


The resulting image is the **convolution** of the intrinsic source and the PSF

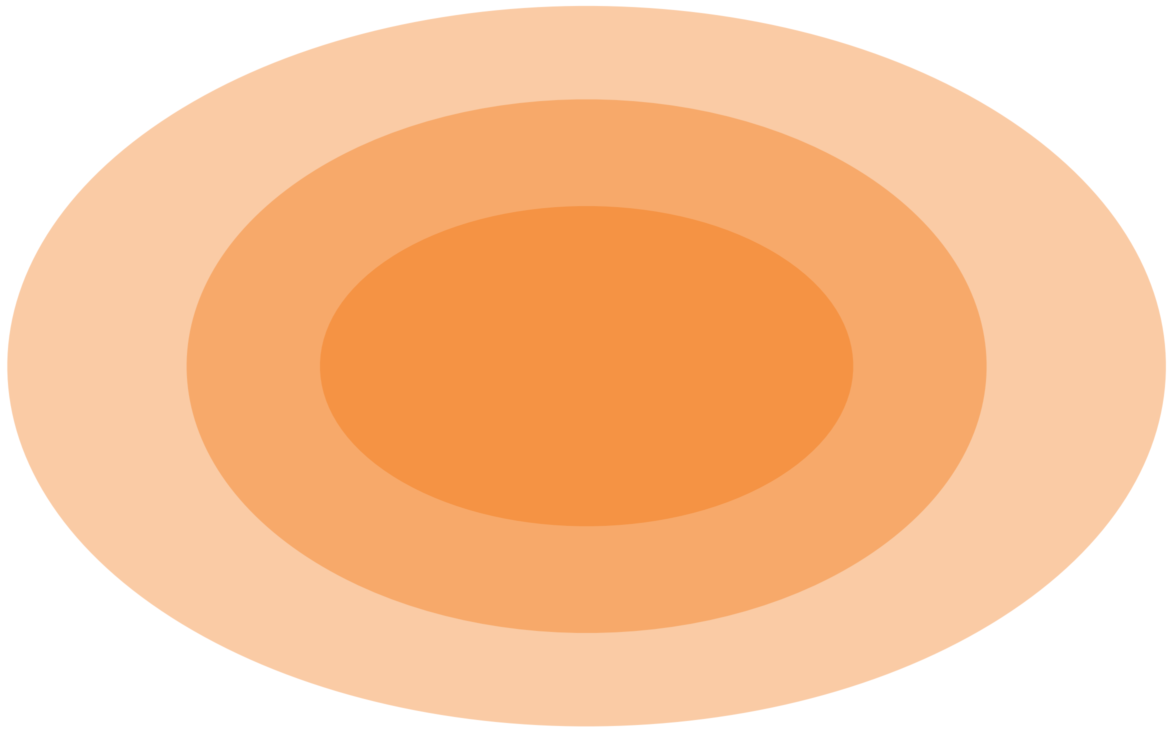
$$S_f(x, y) = \int\int S(x', y') f(x - x', y - y') dx' dy' = (S * f)(x, y)$$

Test case: PSF matching

This means that the apparent morphology of a source is linked to the image PSF:



$(S * f)(x, y)$



$(S * g)(x, y)$

Test case: PSF matching

One way to account for this is to **PSF match** all images to the *worst* (widest) PSF by computing the **matching kernel**

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This is the function $K\{f \to g\}$ such that

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Or: the function that, when convolved with the better-seeing PSF, produces the worse-seeing PSF.

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One theoretically nice (but often noisy in practice) way to do this is to note that:

$$\mathscr{F}[f * g] = \mathscr{F}[f]\mathscr{F}[g]$$

Fourier transform

Parametric and model photometry

PSF matching is great because it allows us to do matched aperture photometry without making assumptions about the intrinsic source profile $S(x, y)$.

But it also has drawbacks — for example, we're convolving to the worst seeing and therefore throwing some information away from higher quality data.

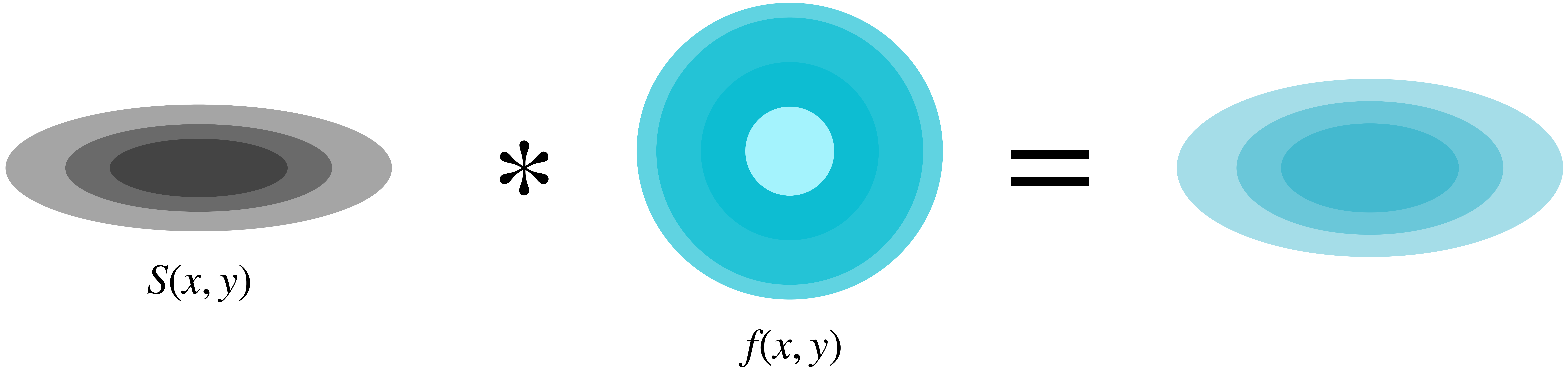
Parametric and model photometry

PSF matching is great because it allows us to do matched aperture photometry without making assumptions about the intrinsic source profile $S(x, y)$.

But it also has drawbacks — for example, we're convolving to the worst seeing and therefore throwing some information away from higher quality data.

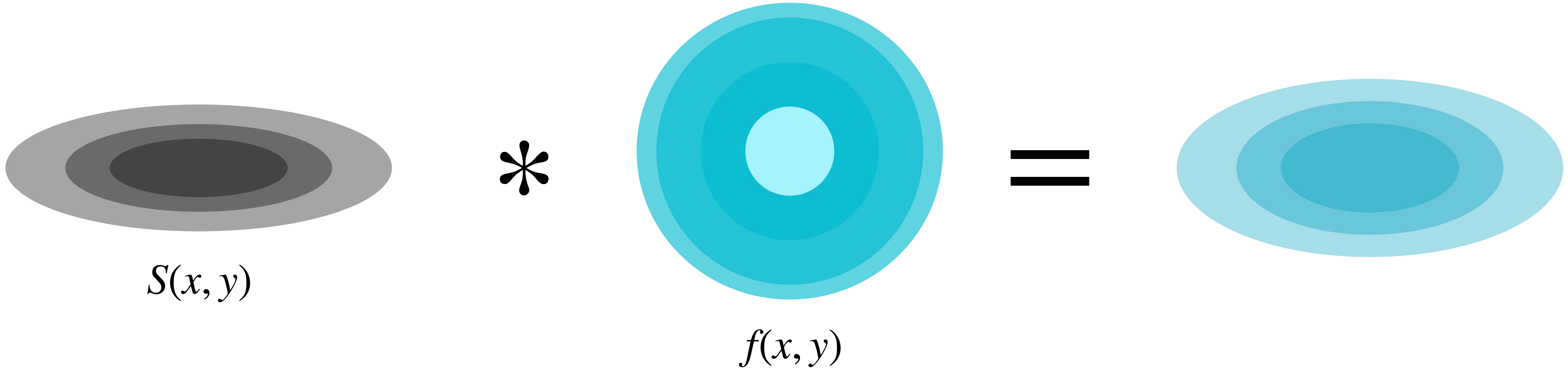
So now, let's explore what assuming a flexible function for $S(x, y)$ can do for extended source photometry.

Parametric and model photometry



If we make assumptions about the shape of $S(x, y \mid \vec{\phi})$ for some profile parameters $\vec{\phi}$, we can predict what $(S * f)(x, y)$ for a our choice of $\vec{\phi}$ and compare to images directly.

Parametric and model photometry



If we make assumptions about the shape of $S(x, y \mid \overrightarrow{\phi})$ for some profile parameters $\overrightarrow{\phi}$, we can predict what $(S * f)(x, y)$ for a our choice of $\overrightarrow{\phi}$ and compare to images directly.

This allows us to account for differences in PSF without convolving to worse seeing by predicting both $(S * f)(x, y \mid \overrightarrow{\phi})$ and $(S * g)(x, y \mid \overrightarrow{\phi})$.

A brief intro to galaxy models: the Sersic profile

$$I(x, y) = I_e \exp\left(-b_n\left[\left(\frac{r(x, y)}{R_{\mathrm{eff}}}\right)^{(1/n)} - 1\right]\right)$$

The **Sersíc profile** is a very commonly-used profile for smooth galaxy modeling:

A brief intro to galaxy models: the Sersic profile

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Advantages:

- Parametric form can easily be convolved with PSF
- Easily interpretable parameters
- Flexibility allows for fits to a broad variety of galaxies

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$$I(x,y) = I_e \exp\left(-b_n \boxed{\left[\left(\frac{r(x,y)}{R_{\mathrm{eff}}}\right)^{(1/n)} - 1\right]}\right)$$

$$r(x,y)^2 = (x - x_0)^2 + (y - y_0)^2(1 - \epsilon)^{-2}$$

$$\Gamma(2n) = 2\gamma(2n, b_n)$$

At $r(x,y) = R_{\mathrm{eff}}$ the exponentiated term drops to zero

Which means that I_e is defined as the surface brightness at R_{eff}

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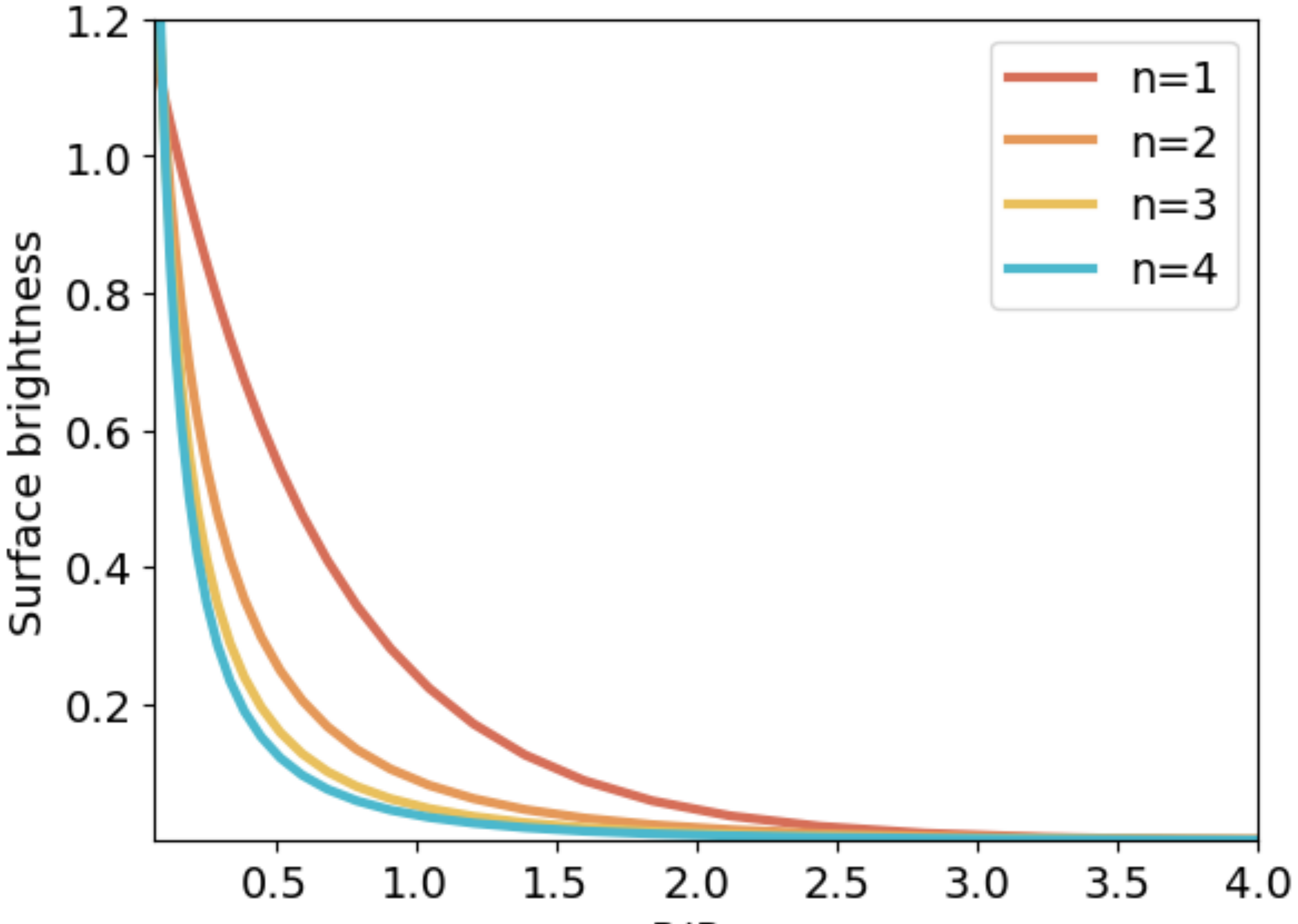

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The Sersic index n sets the profile concentration — higher n means more concentrated

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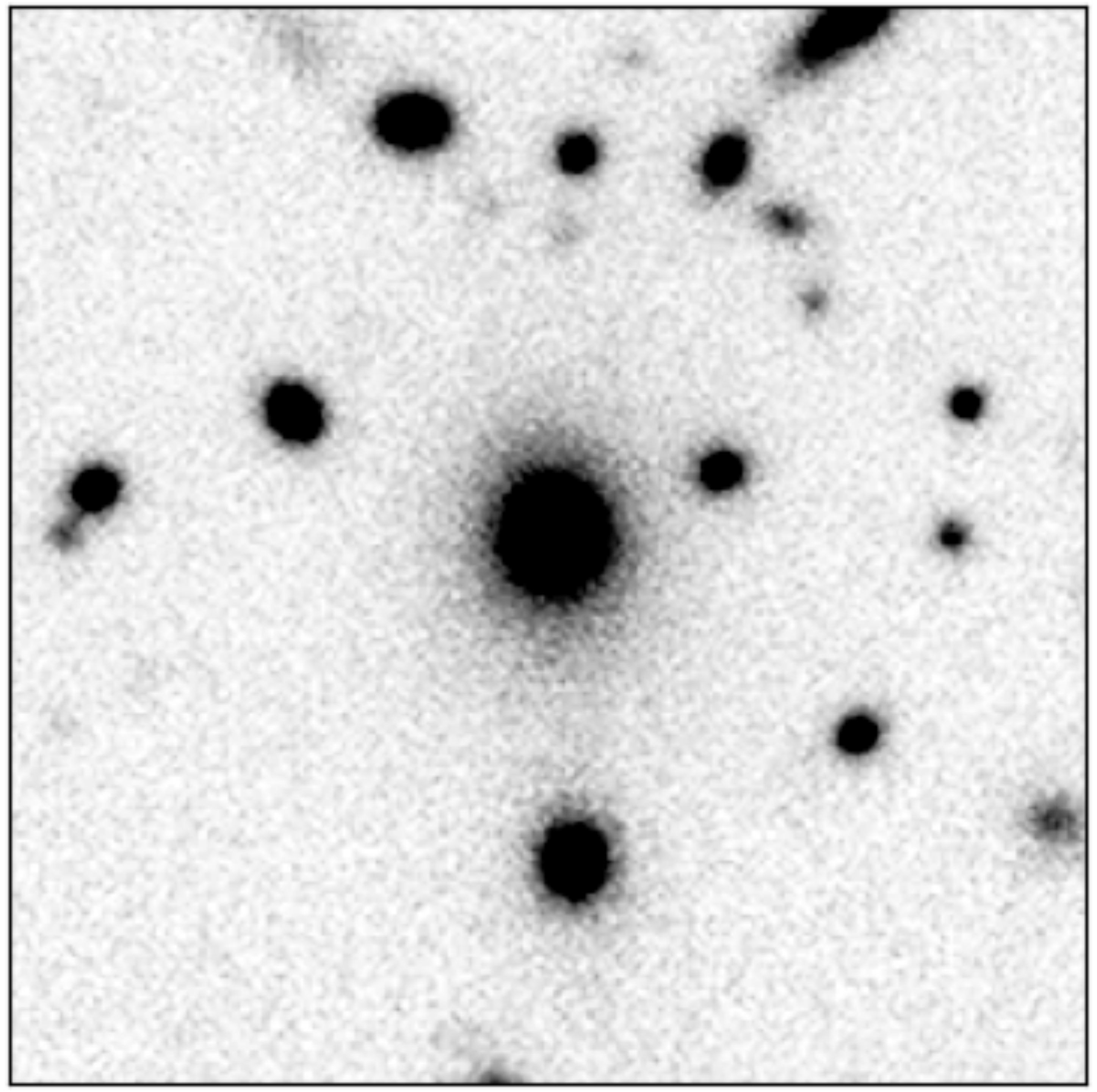
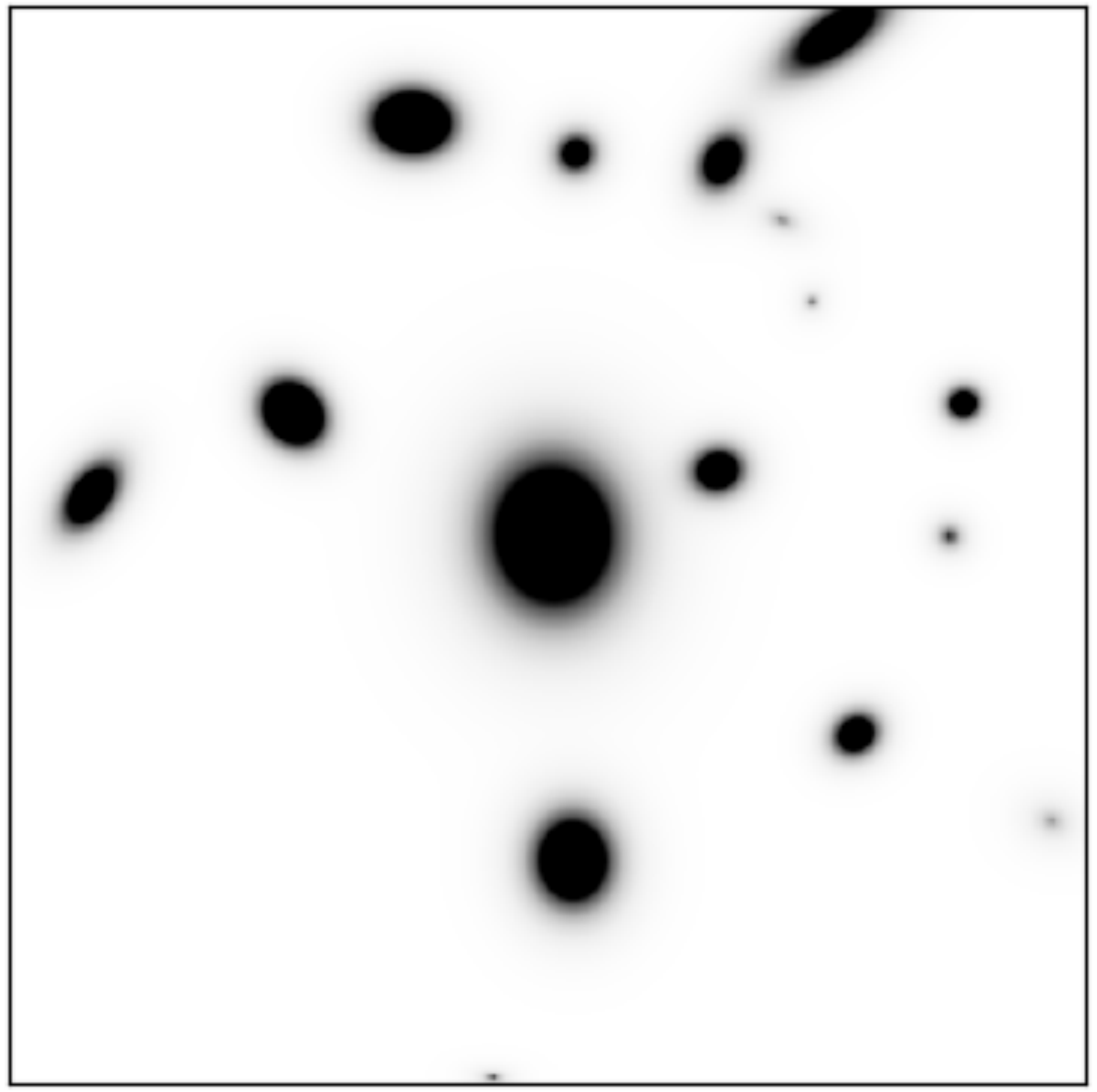


Legacy Survey



Sersic scene model

But as a reminder — galaxies are complicated!

Simple parametric models are a great tool in the toolbox.

But different science cases can different approaches:

- More complicated/flexible galaxy modeling
  Constrained matrix factorization
- Non-parametric detection and source photometry
  Stream detection/photometry
- Multiscale detection methods
  Wavelet decomposition