Astrostatistics Interest Group: Student Paper Award
Topic Contributed Papers Session (401) JSM 2020
August 5 2020

The Devil's in the Details: Photometric Biases in Modern Surveys

Stephen Portillo[1,2,*] and **Josh Speagle**[1,3,*] and Doug Finkbeiner[1]

[1]Harvard U., [2]DIRAC (U. of Washington), [3]U. of Toronto

[*]Equal contribution

Portillo, Speagle, & Finkbeiner (**PSF**) 2020, 1902.02374

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All data, code, and plots available online at https://github.com/joshspeagle/phot_bias

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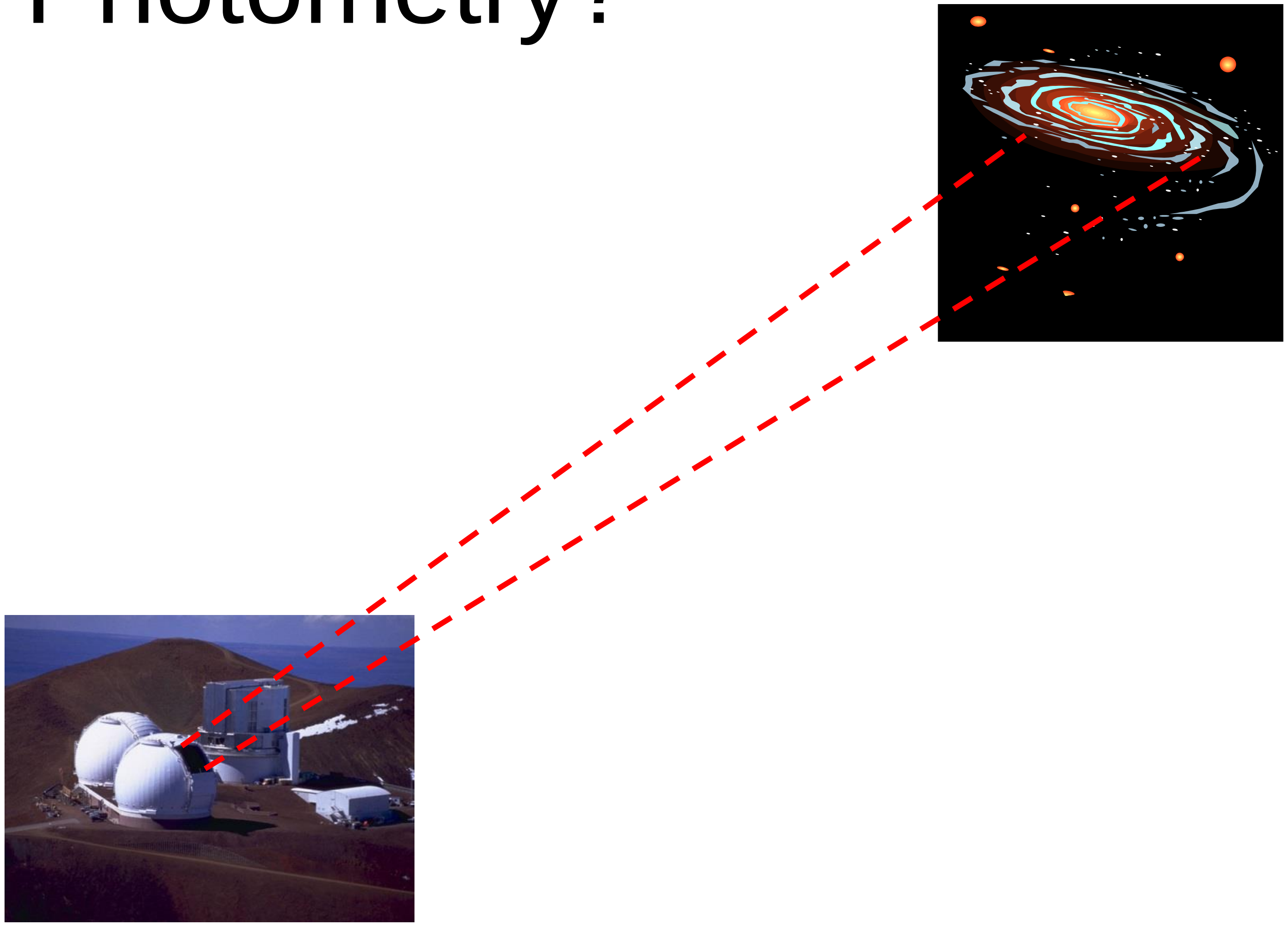
What is Photometry?



Keck Telecope (Hawaii)

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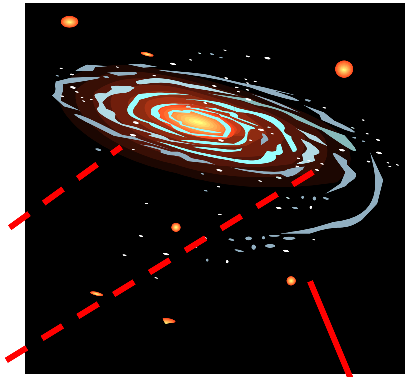

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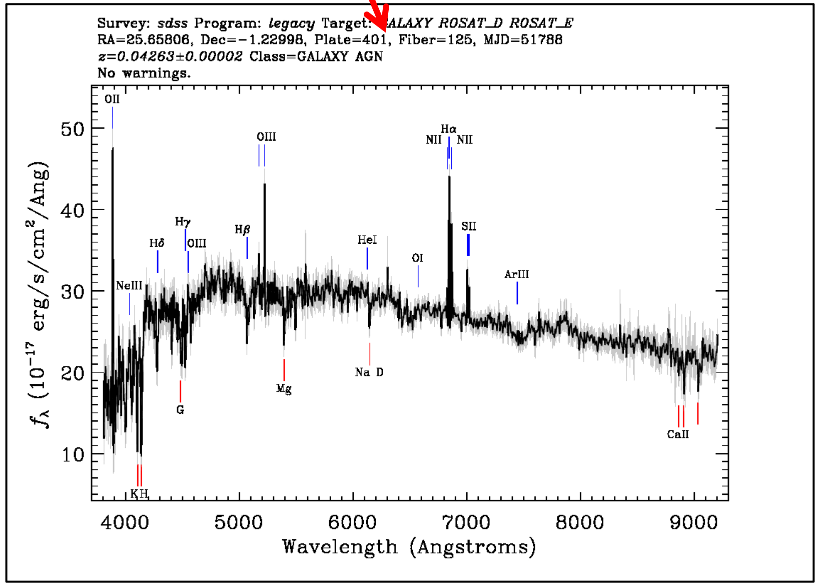

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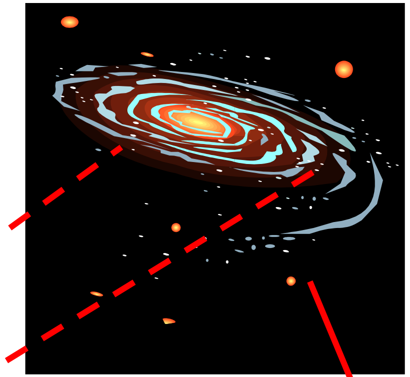

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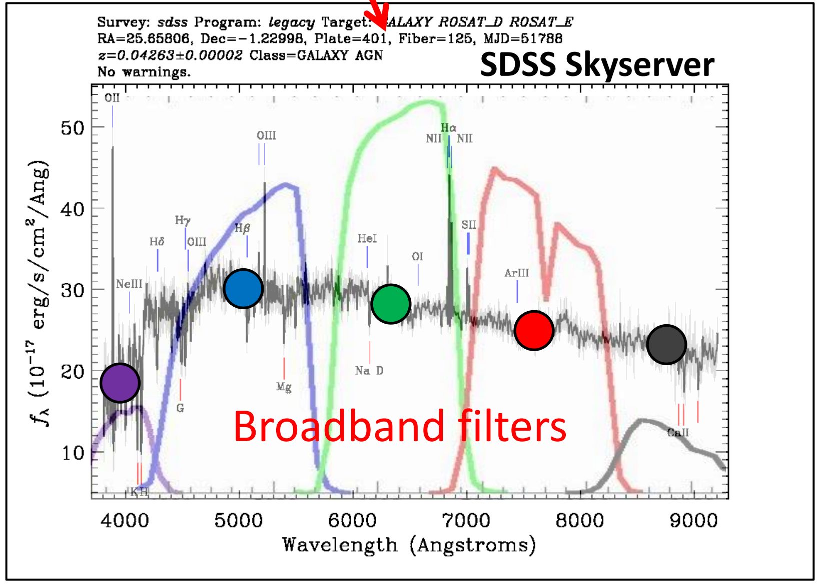

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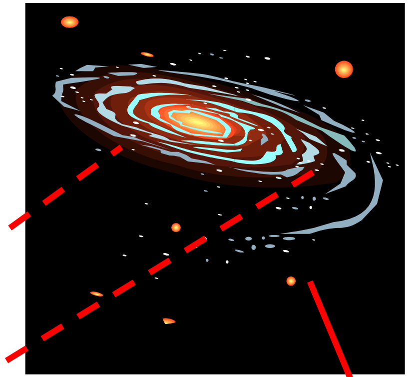
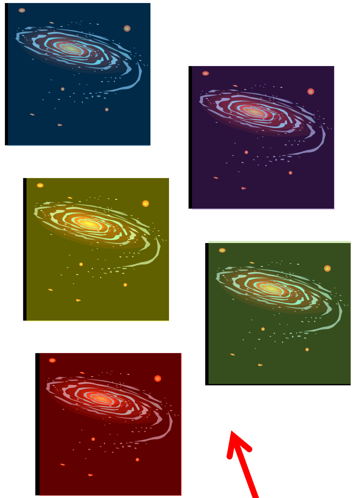
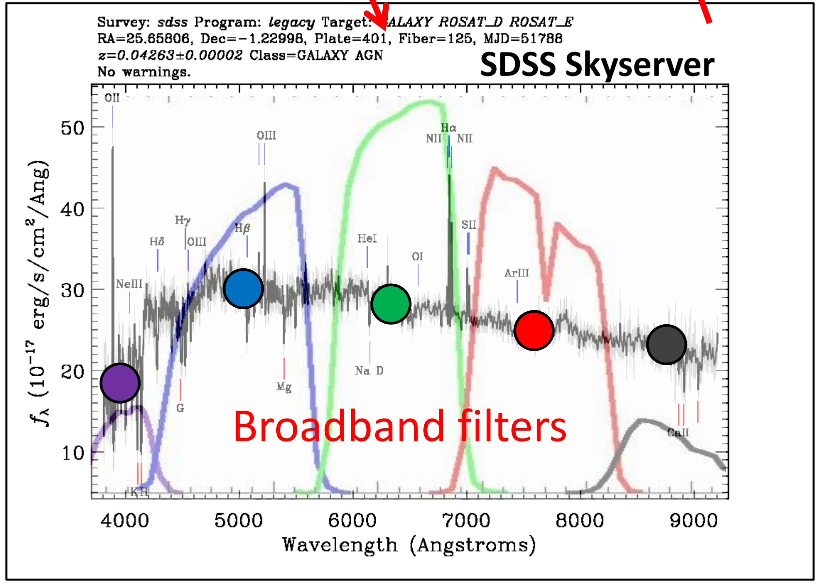
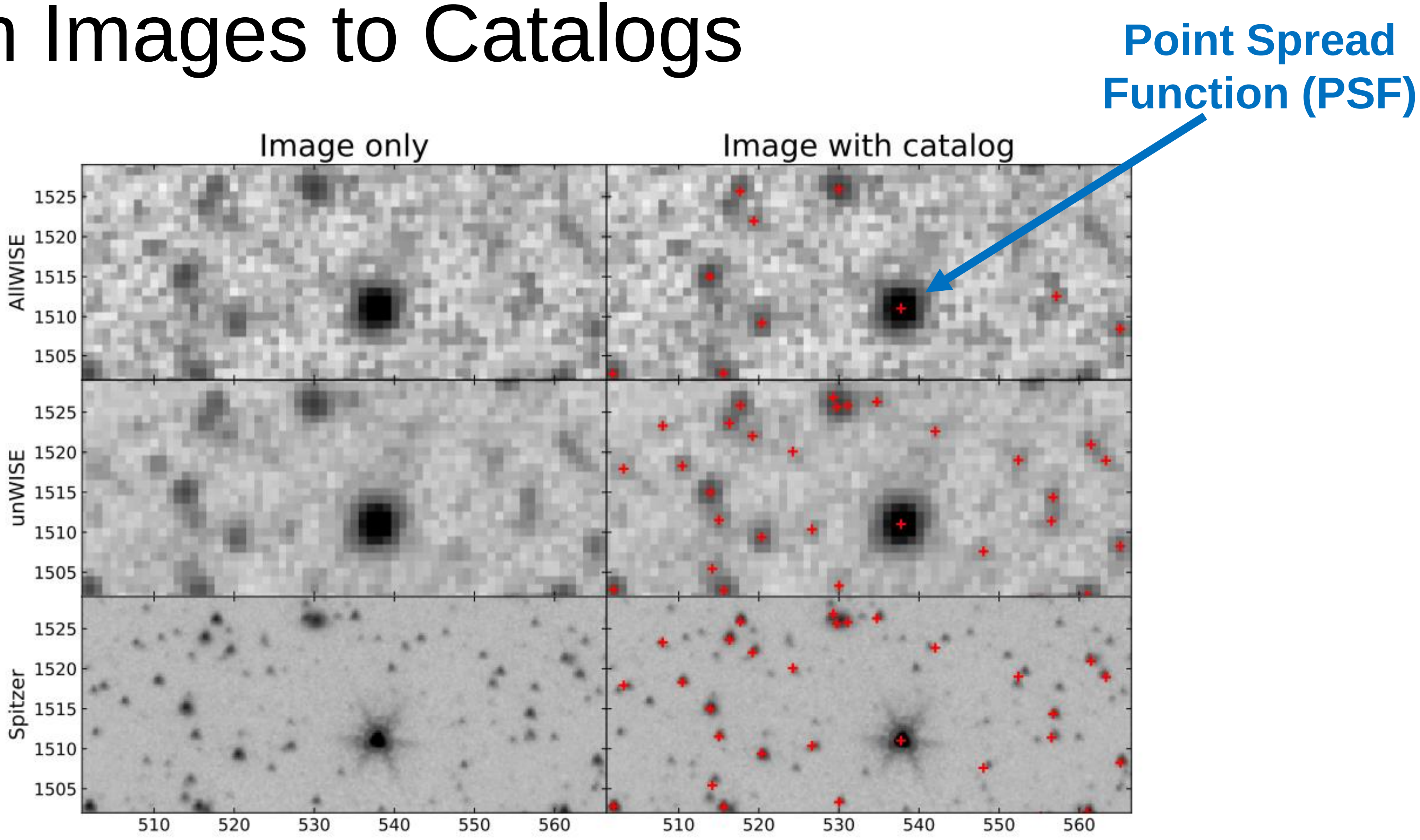


Spectral Energy Distribution (SED)





From Images to Catalogs



unWISE: Schlafly et al. (2019)

Motivation

“Big Data”-oriented work

- Most ~~of my work~~ focuses on using photometry from large surveys.
- Understanding the data is important.
- Small effects can add up over large populations.

Results

- Estimated fluxes are biased.
- Uncertainties are underestimated.

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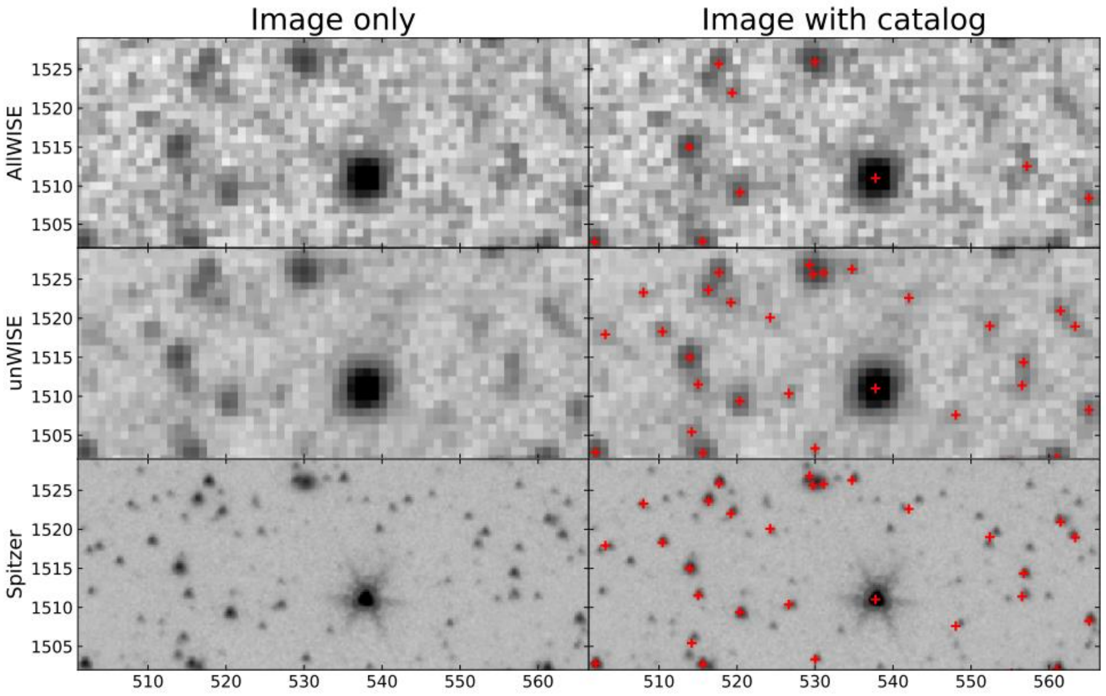
- Estimated fluxes are biased.
- Uncertainties are underestimated.

First reaction:

- No surprise: **photometry is hard**.
- Model mismatch (PSF, source)
- Blending issues
- Background estimation
- Unresolved sources
- Detection limits/selection effects
- Etc.



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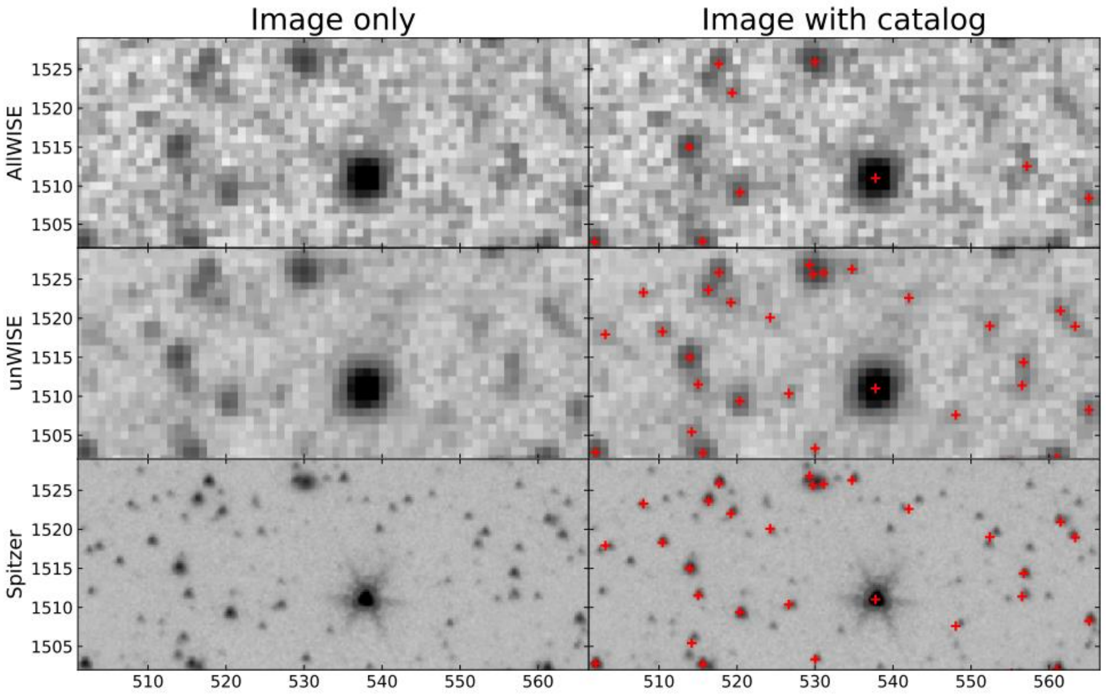

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Results

- Estimated fluxes are biased.
- Uncertainties are underestimated.

This is true even with perfect models and data!

First reaction:

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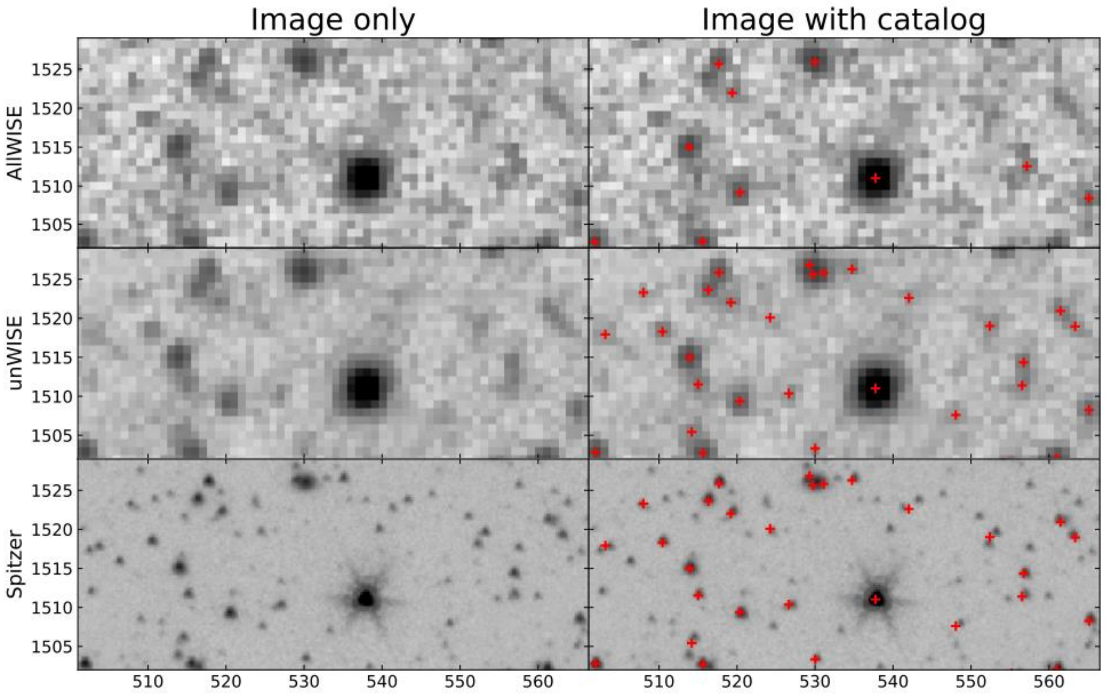

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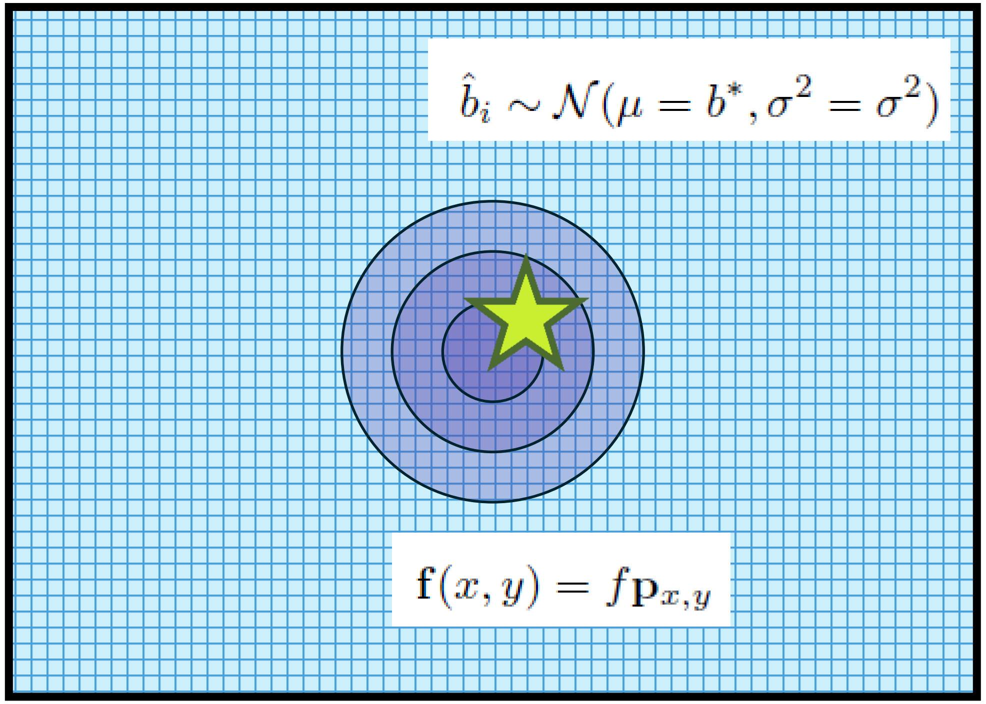
Starting Point

PSF = “point spread function”

- Single, isolated **point source** in **one band** with PSF known and Gaussian background noise.

$n \times m$ footprint



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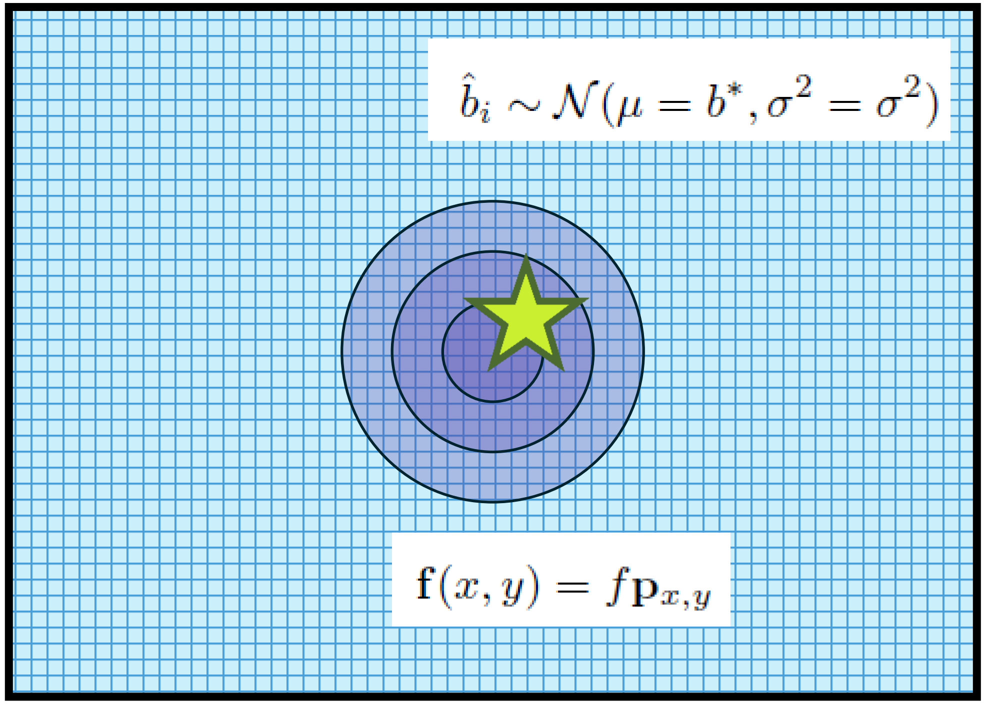

Likelihood

$\ln \mathcal{L}(x, y, f, b)$

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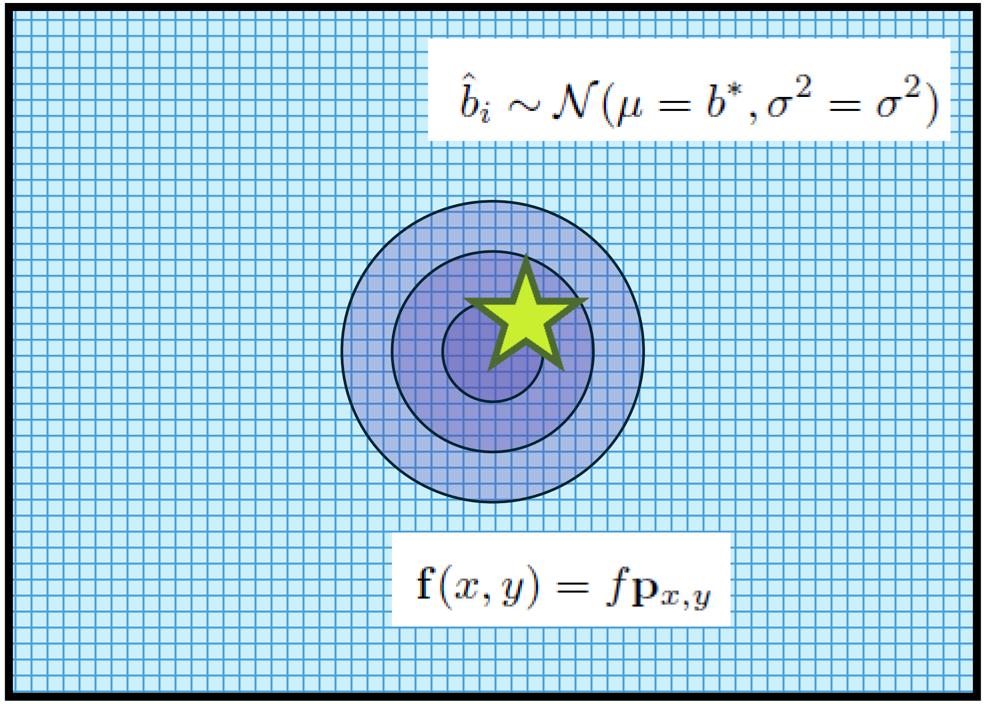


Likelihood

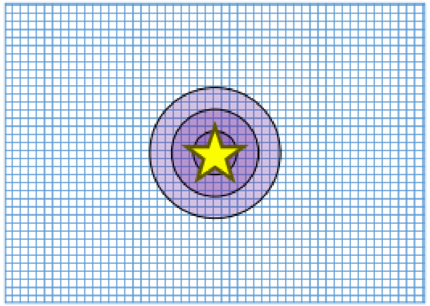
$$\ln \mathcal{L}(x, y, f, b)$$

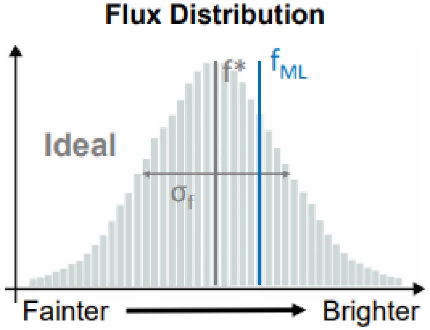
Maximum-Likelihood Solution

$$\partial_f \ln \mathcal{L}(x, y, f, b) = 0$$

Position Known

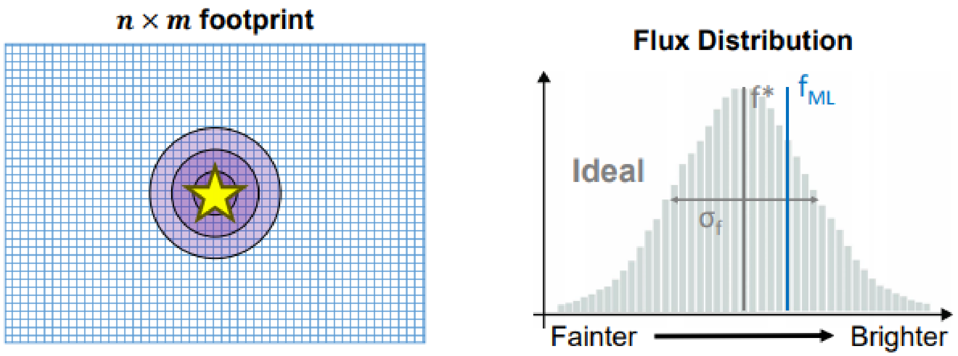
$n \times m$ footprint





Random noise sometimes leads to high fluctuations.

Position Known



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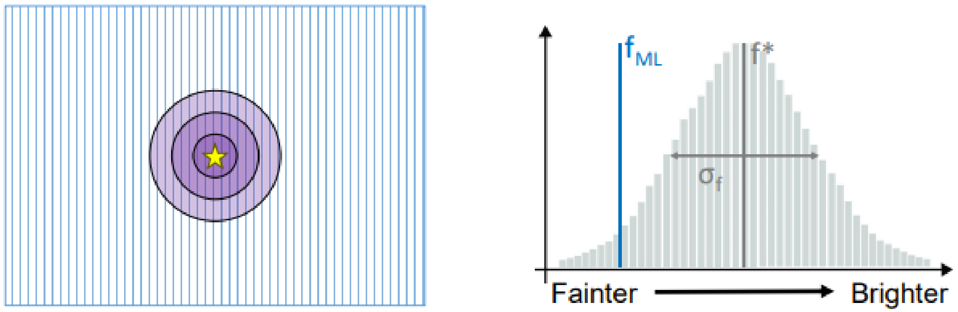
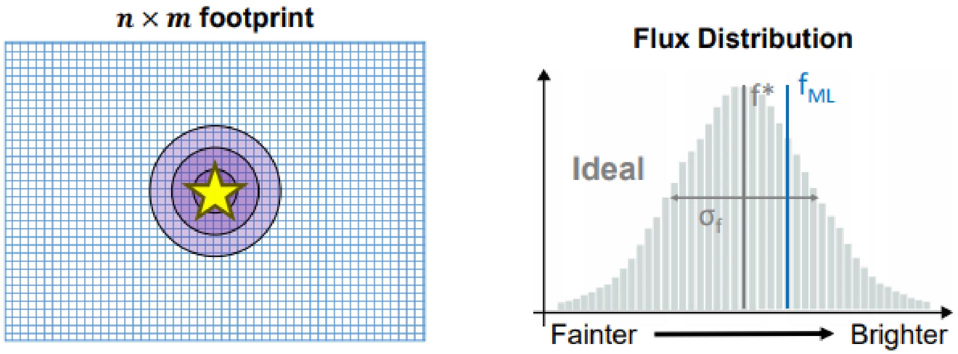


It also leads to low fluctuations with equal probability.

Position **Known**



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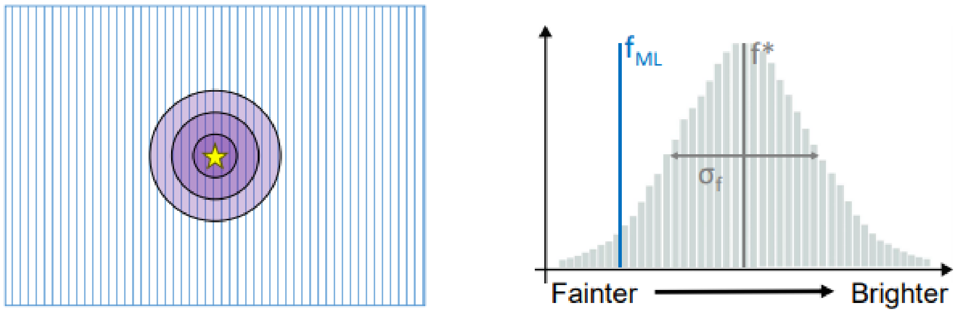

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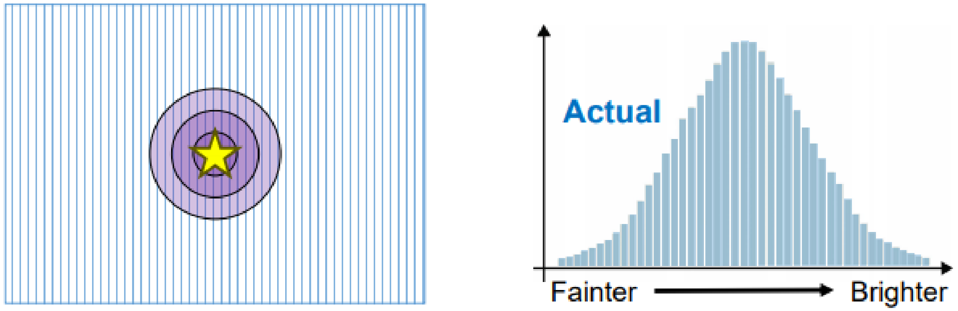
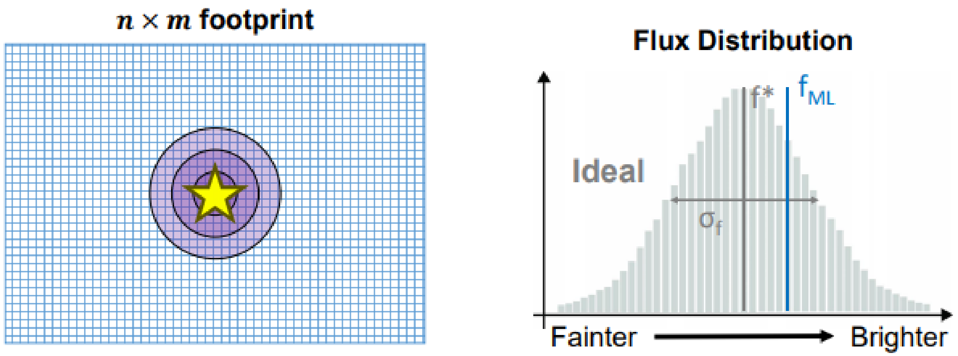


Because fluctuations are symmetric, the maximum-likelihood estimate is unbiased.

Position Known



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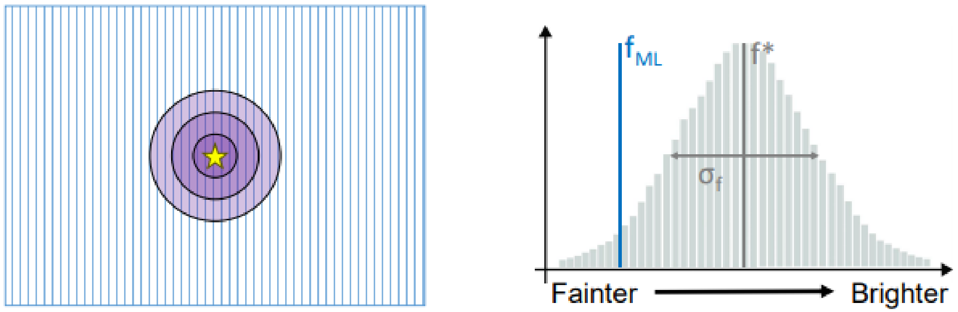

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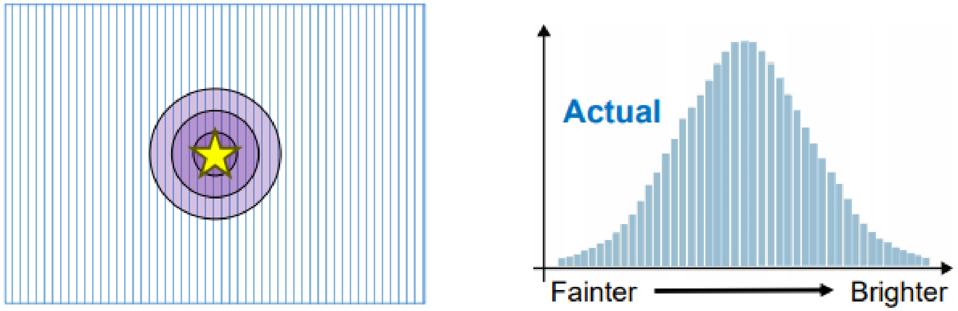

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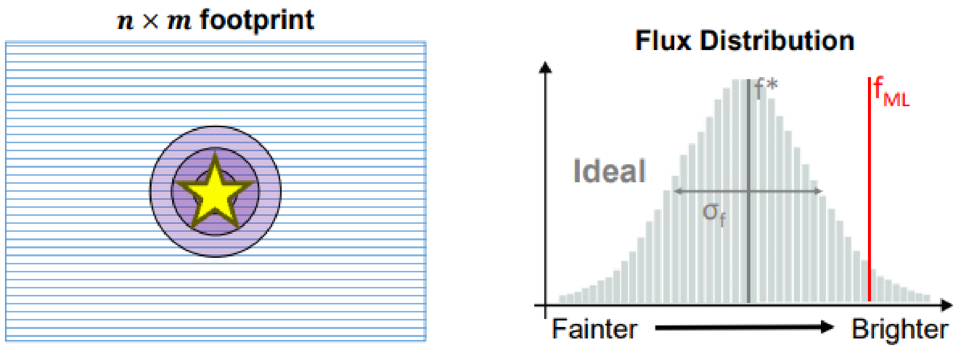
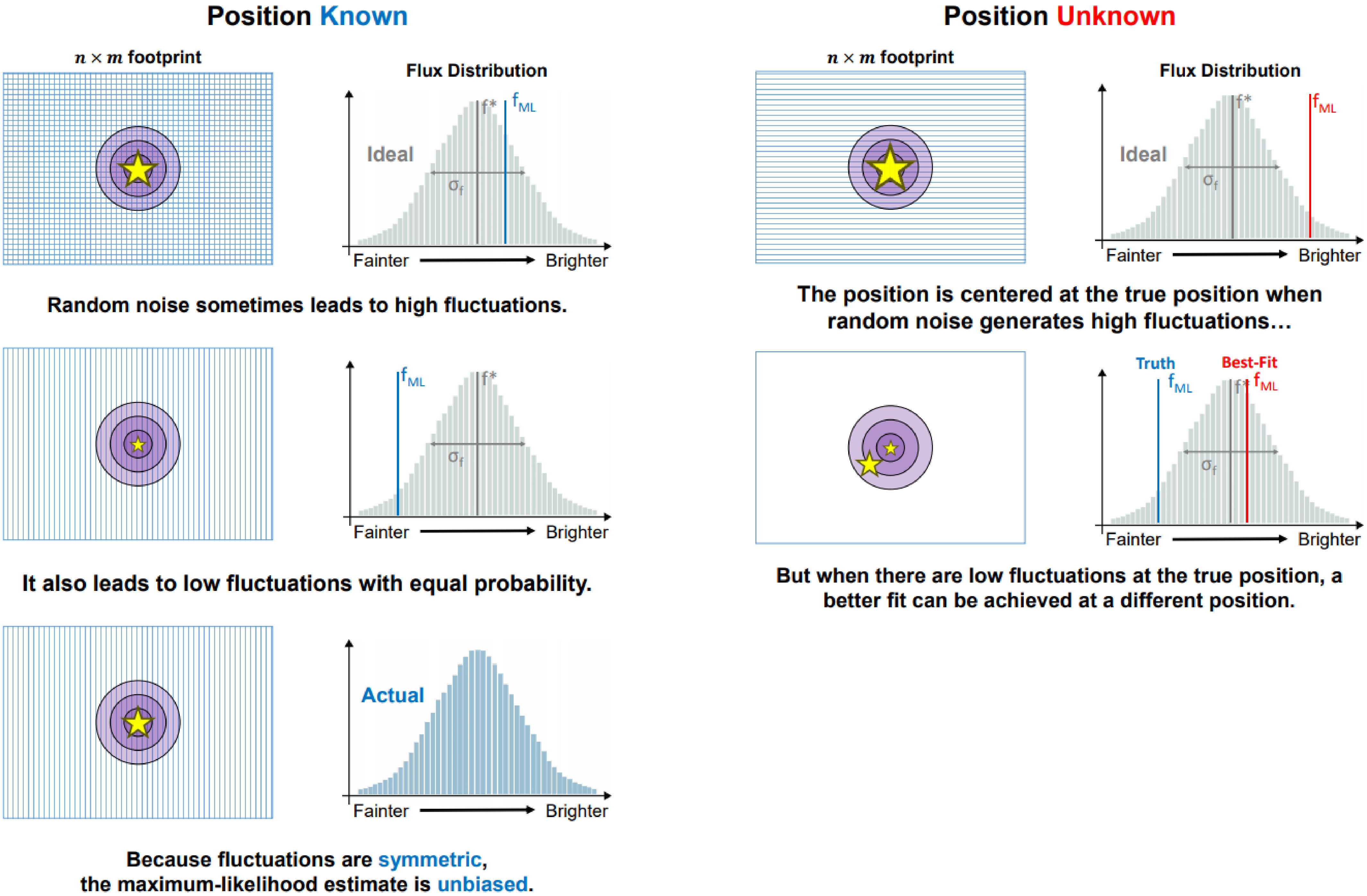


The position is centered at the true position when random noise generates high fluctuations…



Position Known
$n \times m$ footprint
Flux Distribution
Ideal
f^*
f_{ML}
σ_f
Fainter
Brighter
Random noise sometimes leads to high fluctuations.
f_{ML}
f^*
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$n \times m$ footprint
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Truth
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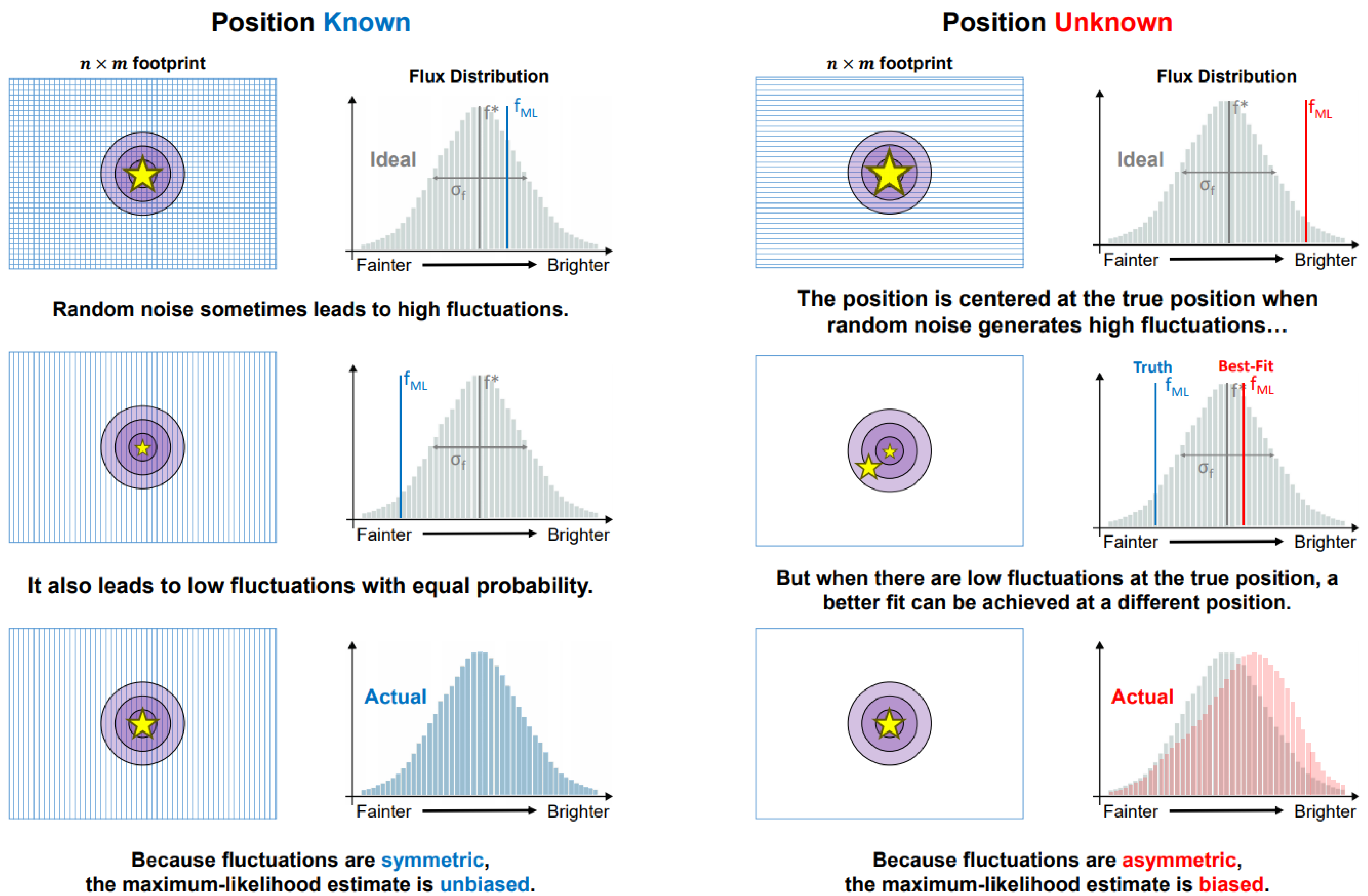
But when there are low fluctuations at the true position, a
better fit can be achieved at a different position.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Actual
Fainter
Brighter
Because fluctuations are asymmetric,
the maximum-likelihood estimate is biased.

Biases in PSF Photometry

- Under basic assumptions we can derive a 1st-order **bias**:

$$\mathbb{E}[f^*_{\mathrm{ML}}] \approx f_{\mathrm{ML}} \left[1 - \underbrace{\frac{\tilde{\sigma}^2_{f_{\mathrm{ML}}}}{f^2_{\mathrm{ML}}}}_{\mathrm{SNR}^{-2}} \right]$$

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SNR^{-2}

- Applying this correction increases the **variance**:

$$\tilde{\sigma}_{f^*_{\mathrm{ML}}} = \sqrt{\tilde{\sigma}^2_{f_{\mathrm{ML}}} + \mathbb{V}[f^*_{\mathrm{ML}}]} \approx \tilde{\sigma}_{f_{\mathrm{ML}}} \left(1 + \frac{1}{2} \frac{\mathbb{V}[f^*_{\mathrm{ML}}]}{\tilde{\sigma}^2_{f_{\mathrm{ML}}}} \right) = \tilde{\sigma}_{f_{\mathrm{ML}}} \left(1 + \frac{1}{2} \frac{\tilde{\sigma}^2_{f_{\mathrm{ML}}}}{f^2_{\mathrm{ML}}} \right)$$

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- This is an example of **bias-variance trade-off**.

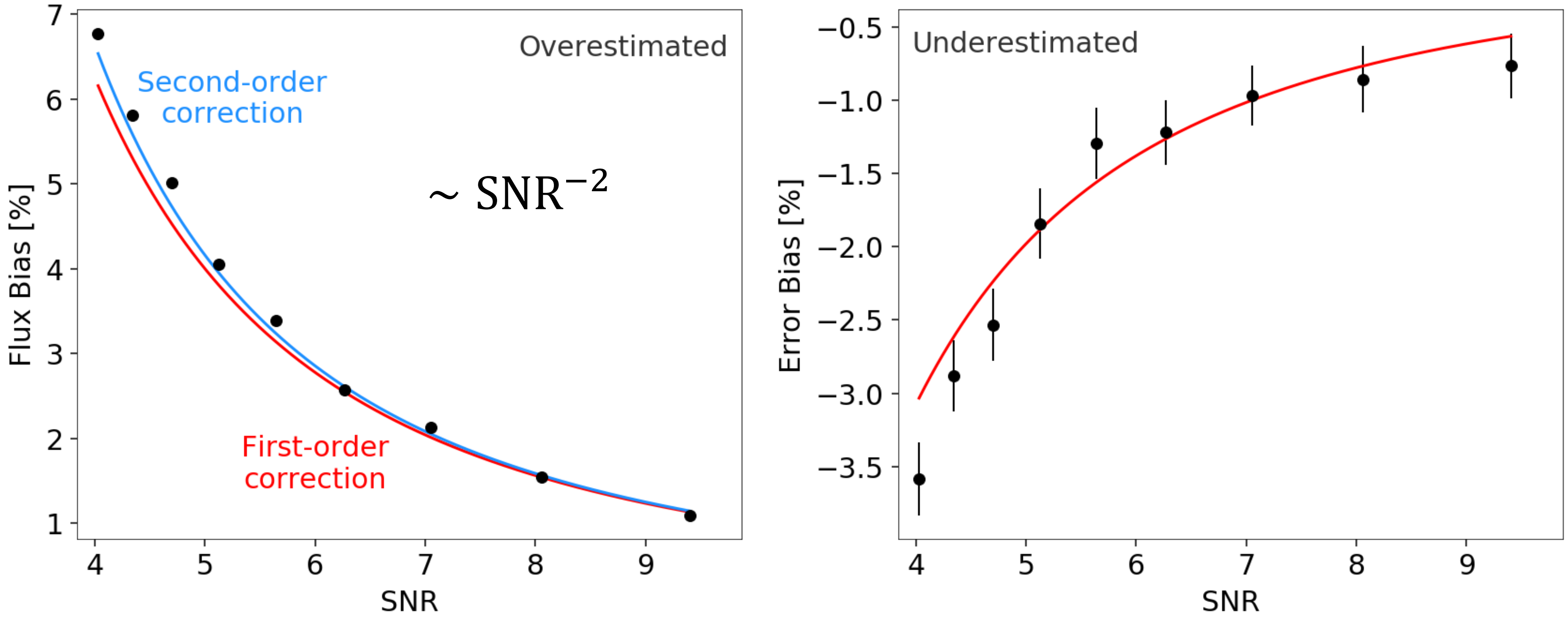
10-sigma source:

- Flux: +1% bias.

Biases in PSF Photometry

- Position **unknown**, background known

Background fixed



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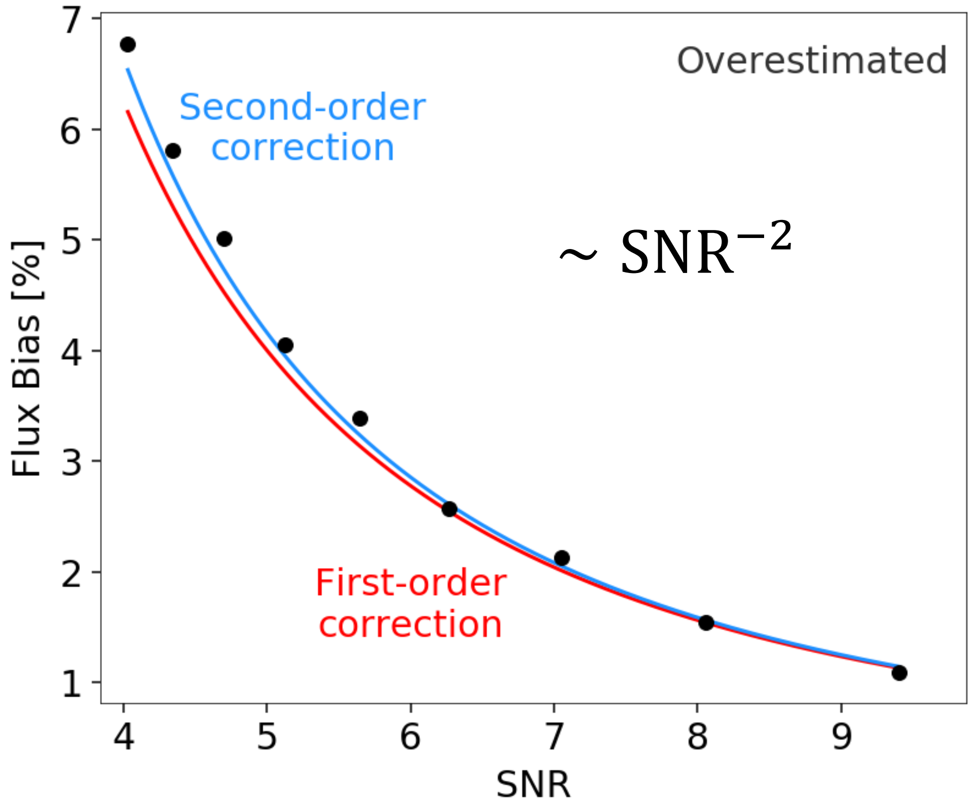
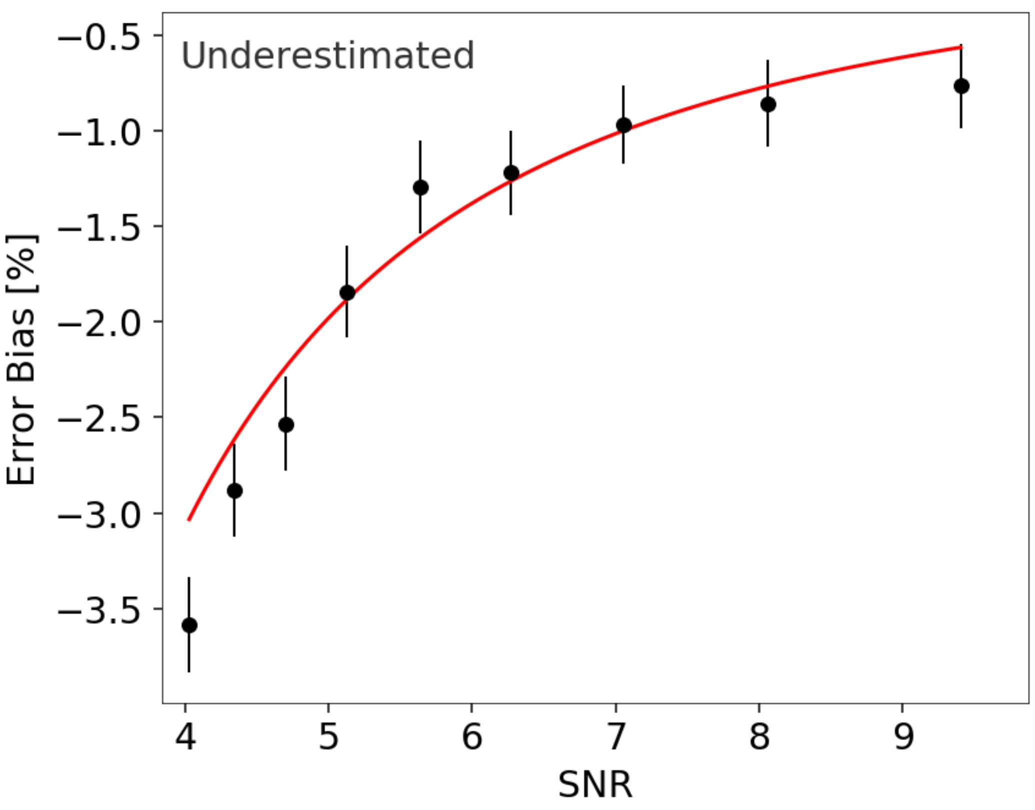
Background fixed





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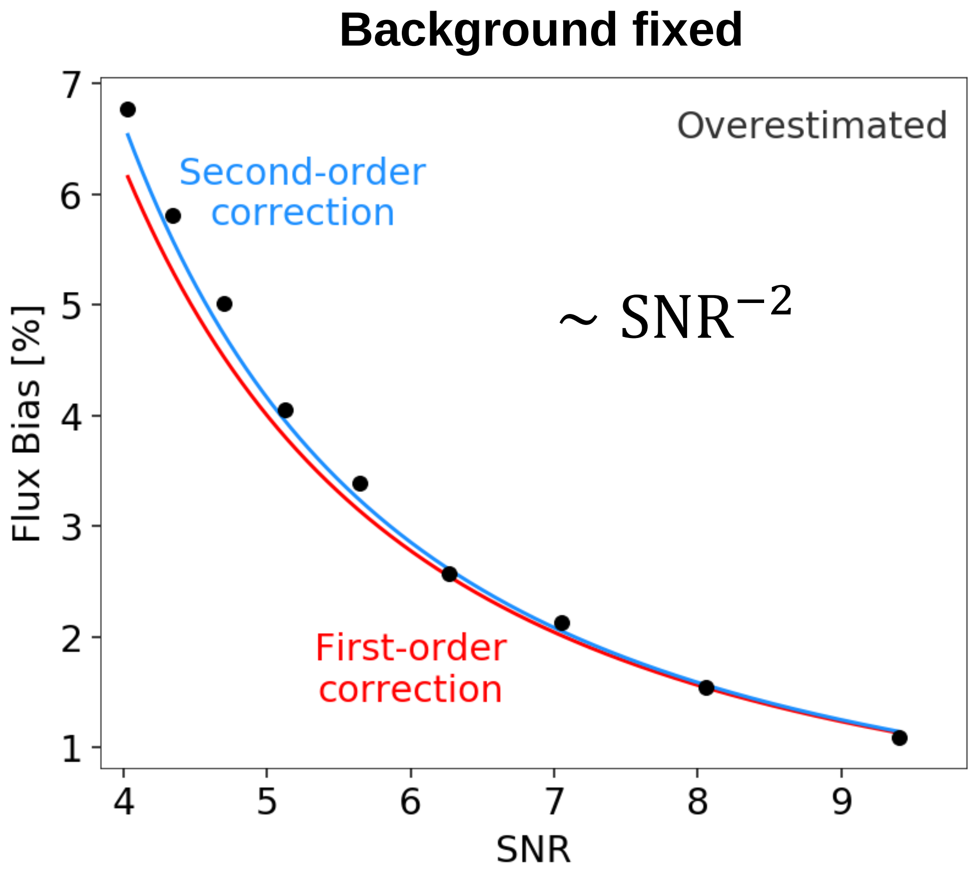
Biases in PSF Photometry

- Position **unknown**, background **unknown**



- Need to account for covariance between background and other parameters.

10-sigma source:
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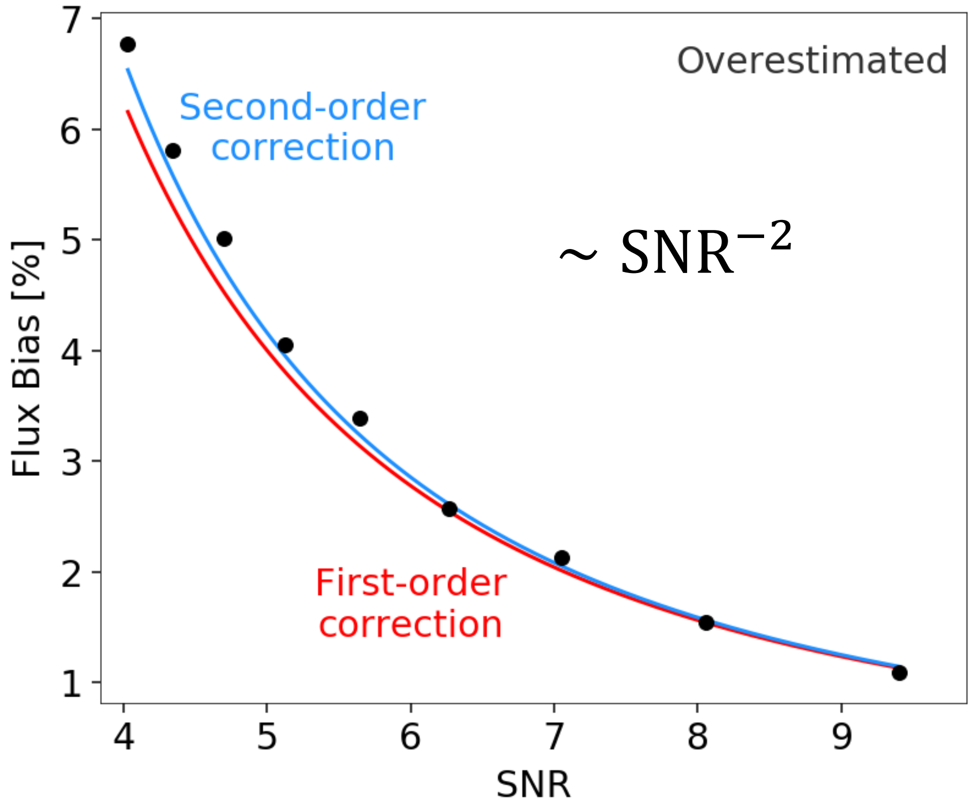


- Need to account for covariance between background and other parameters.

Area used to estimate background

$$\sigma_f^2(x,y) = \boxed{\frac{A}{A - A_{\mathrm{psf}}(x,y)}} \times \tilde{\sigma}_f^2$$

Effective PSF area

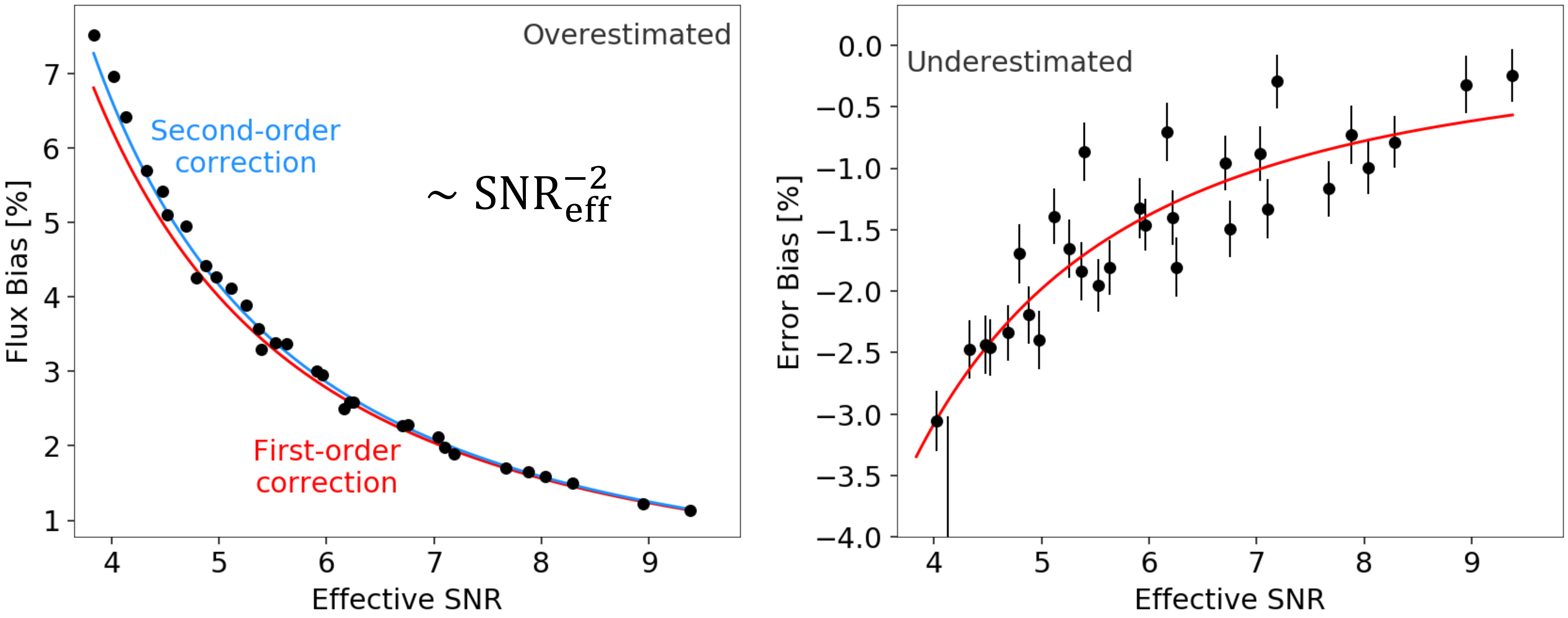
10-sigma source:

- **Flux: +1% bias.**
- **Variance: -0.1% bias.**

Biases in PSF Photometry

- Position **unknown**, background **unknown**

Background variable



Biases in PSF Photometry

- Position **unknown**, background **unknown**

Flux Bias

$$\frac{\delta_{f_{\mathrm{ML}}}}{f_{\mathrm{ML}}} \approx \frac{\sigma^2_{f_{\mathrm{ML}}}}{f^2_{\mathrm{ML}}}$$

Extra degrees of freedom allows fit to chase noise.

Error Bias

$$\frac{\delta_{\tilde{\sigma}^2_f}}{\sigma^2_f}(x,y) = -\frac{A_{\mathrm{psf}}(x,y)}{A}$$

Ignoring covariances underestimates errors.

Biases in Extended Source Photometry

Flux Bias

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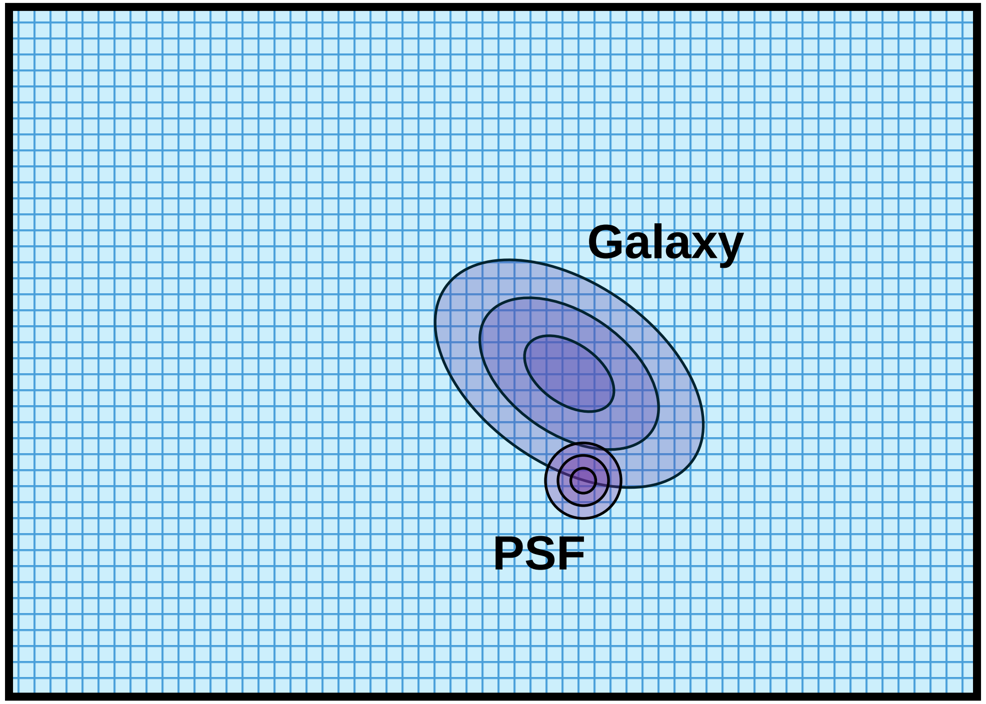
Biases in Extended Source Photometry

$n \times m$ footprint



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Biases in Extended Source Photometry

- More parameters

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Biases in Extended Source Photometry

- More parameters

Flux Bias

$$\frac{\delta_{f_{\mathrm{ML}}}}{f_{\mathrm{ML}}} \approx \boxed{\frac{p-1}{2}} \frac{\sigma^2_{f_{\mathrm{ML}}}}{f^2_{\mathrm{ML}}}$$

Extra degrees of freedom allows fit to chase noise.

$\boldsymbol{p = 3 \rightarrow 6 - 10}$

Shape parameters soak up noise.

Error Bias

$$\frac{\delta_{\tilde{\sigma}^2_f}}{\sigma^2_f}(x, y) = -\frac{A_{\mathrm{psf}}(x, y)}{A}$$

Ignoring covariances underestimates errors.

Biases in Extended Source Photometry

- More parameters, more covariances

Flux Bias

$$\frac{\delta_{f_{\rm ML}}}{f_{\rm ML}} \approx \boxed{\frac{p-1}{2}} \frac{\sigma^2_{f_{\rm ML}}}{f^2_{\rm ML}}$$

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$p = 3 \rightarrow 6 - 10$

Shape parameters soak up noise.

Error Bias

$$\boxed{\frac{\delta_{\tilde{\sigma}^2_f}}{\sigma^2_f}}(x, y) = -\frac{2A_{\mathrm{psf}}(x, y)}{A}$$

Ignoring covariances underestimates errors.

Shape parameters add covariances.

Biases in Extended Source Photometry

- More parameters, more covariances, larger effective area

Flux Bias

$$\frac{\delta_{f_{\mathrm{ML}}}}{f_{\mathrm{ML}}} \approx \frac{p-1}{2}\frac{\sigma^2_{f_{\mathrm{ML}}}}{f^2_{\mathrm{ML}}}$$

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$$\frac{\delta_{f_{\rm ML}}}{f_{\rm ML}} \approx \frac{p-1}{2}\frac{\sigma^2_{f_{\rm ML}}}{f^2_{\rm ML}}$$

Extra degrees of freedom allows fit to chase noise.

$p = 3 \rightarrow 6 - 10$

Shape parameters soak up noise.

Error Bias

$A_{\rm gal+psf}$

$$\frac{\delta_{\tilde{\sigma}^2_f}}{\sigma^2_f}(x,y) = -\frac{2\boxed{A_{\rm psf}(x,y)}}{A}$$

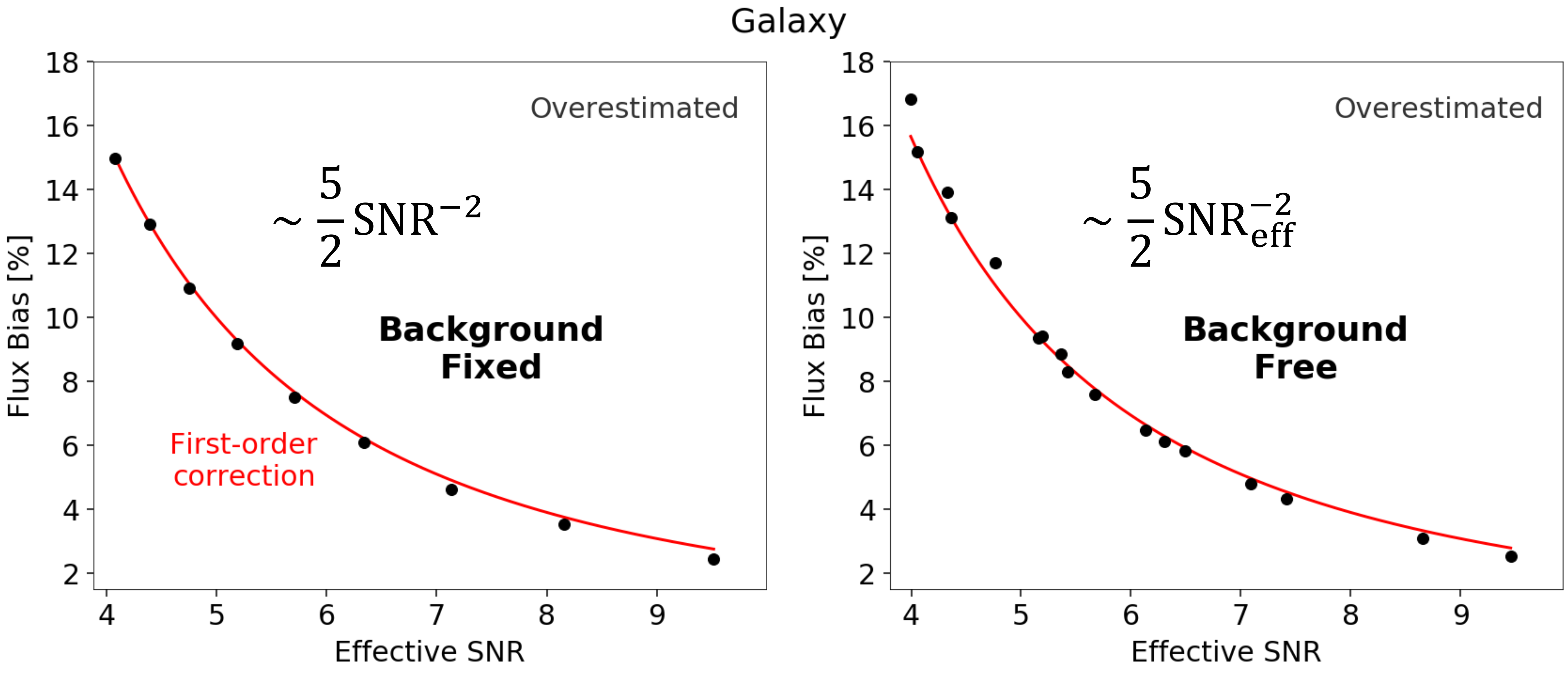
Ignoring covariances underestimates errors.

Shape parameters add covariances.

Extended shape impedes background estimation.

Biases in Extended Source Photometry

- More parameters, more covariances, larger effective area



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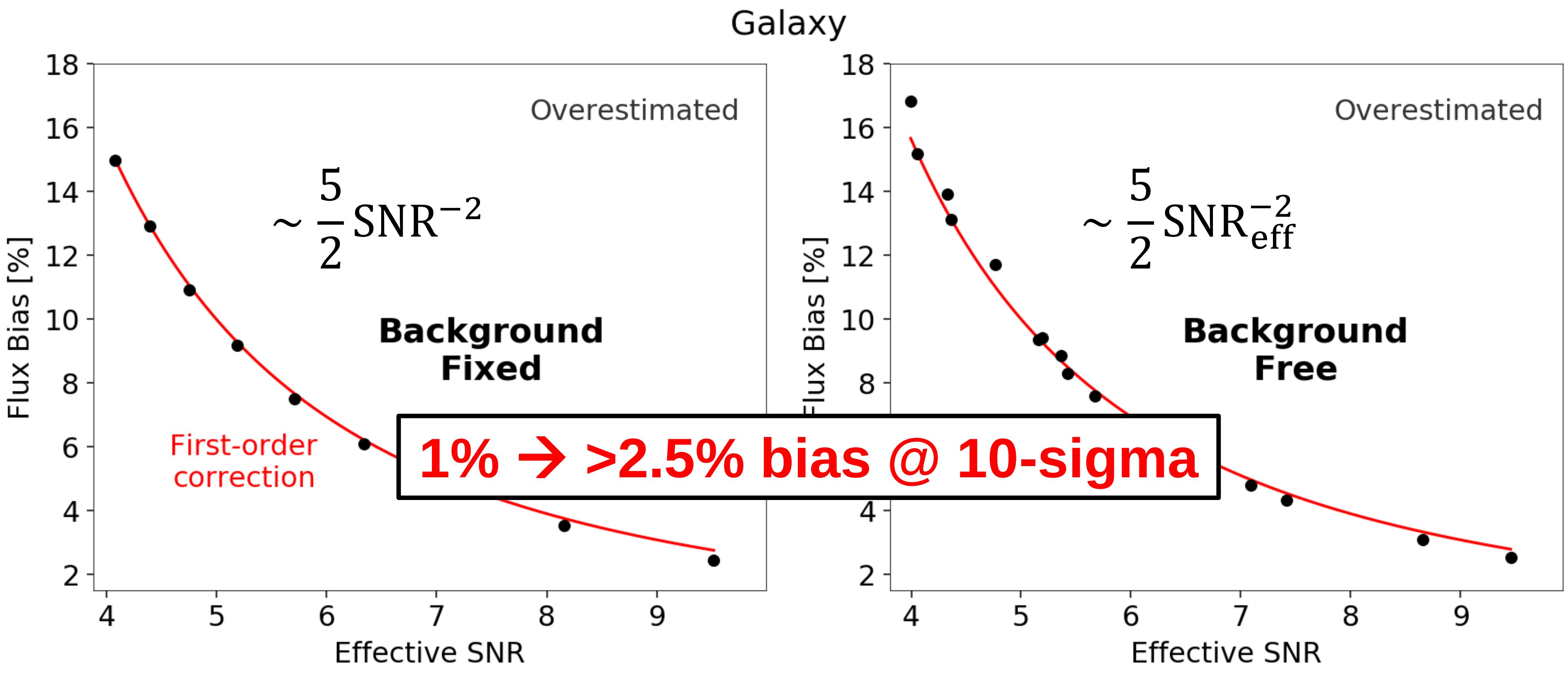
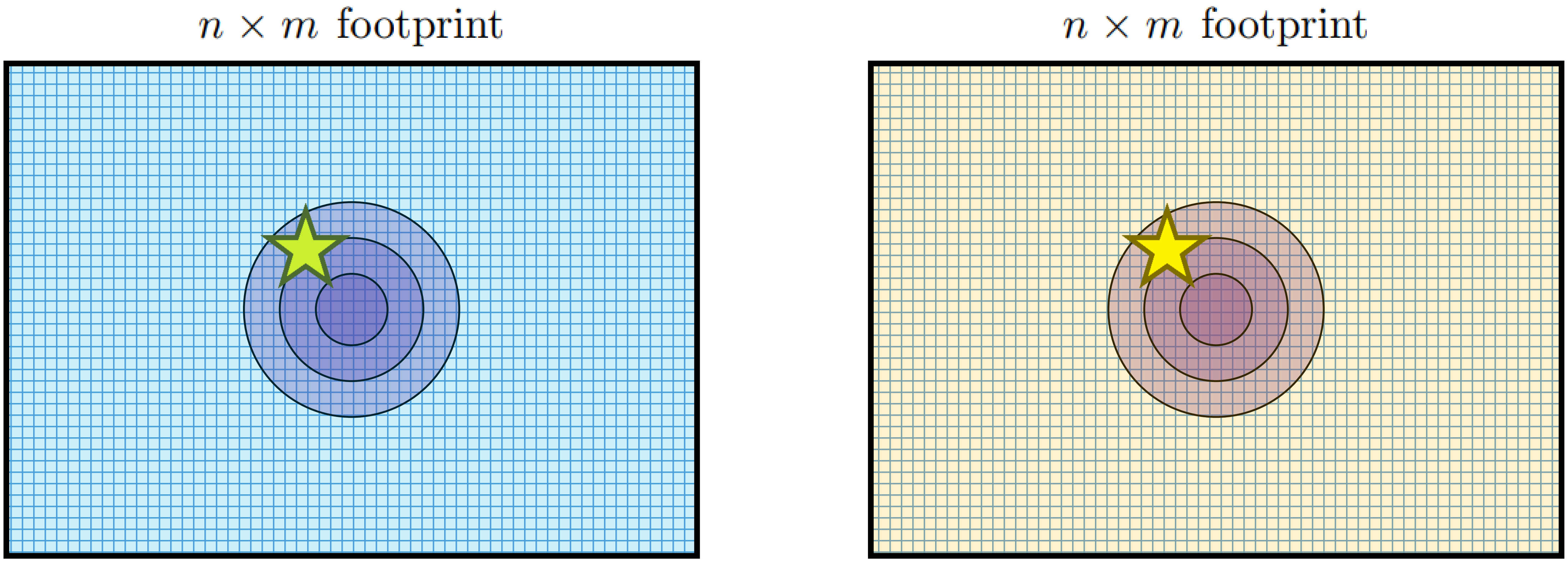


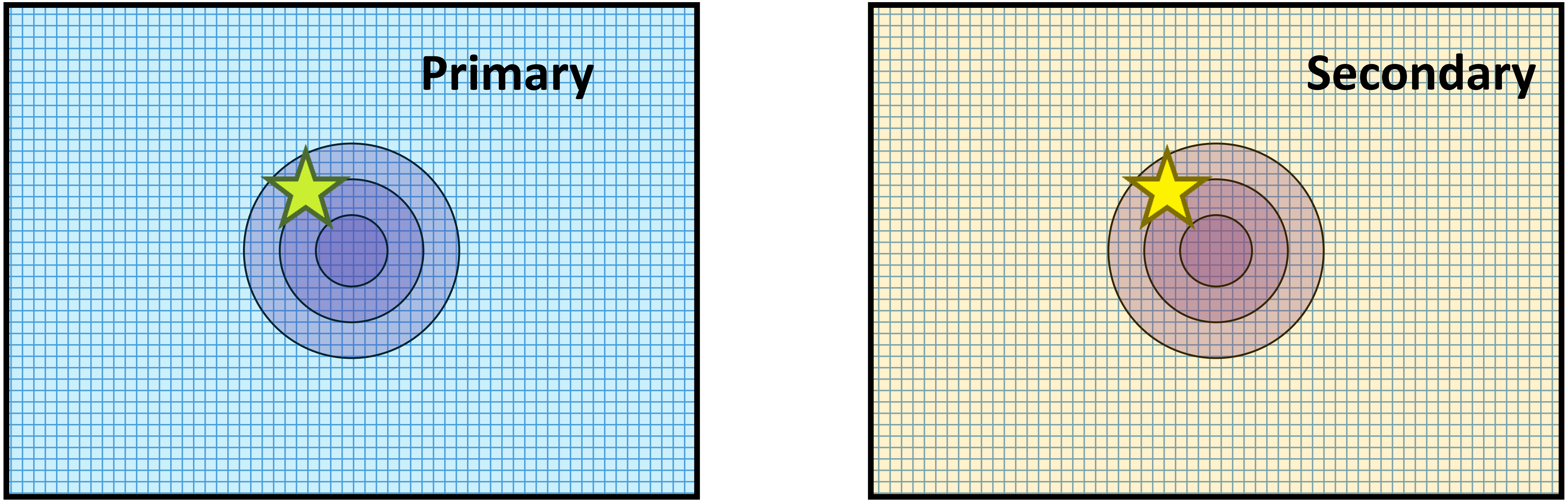
Biases in Multi-band Photometry



Biases in Forced Multi-band Photometry

- Detect in one band, fix position, force photometry in others

$n \times m$ footprint $\qquad$ $n \times m$ footprint



Biases in Forced Multi-band Photometry

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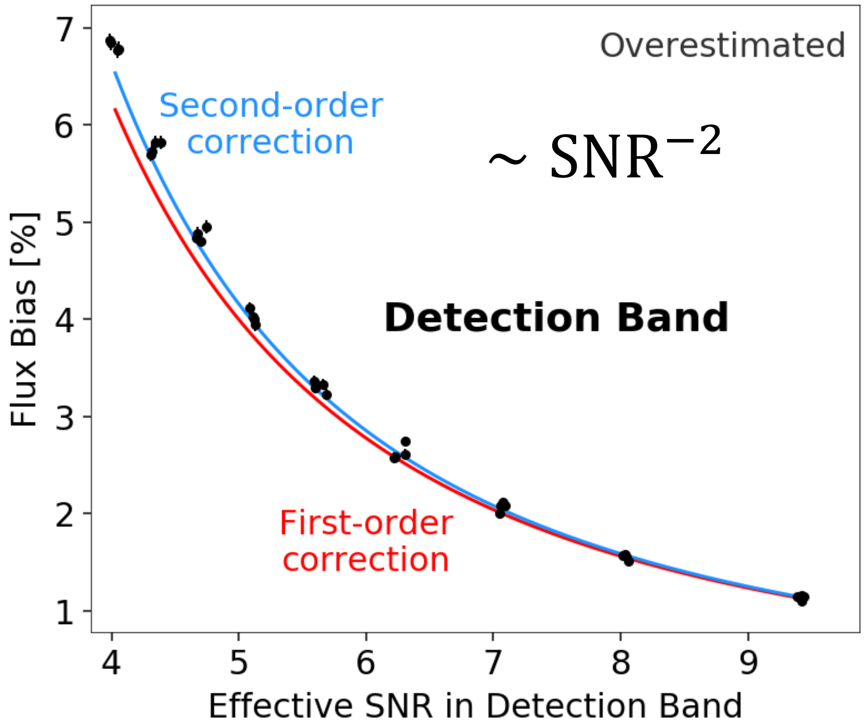

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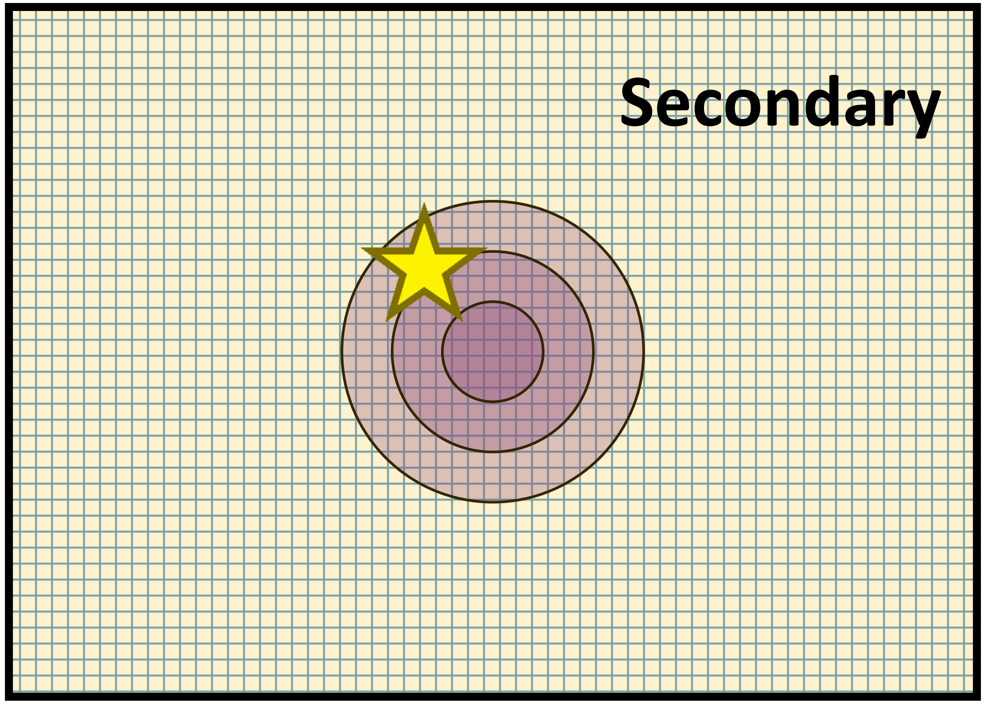

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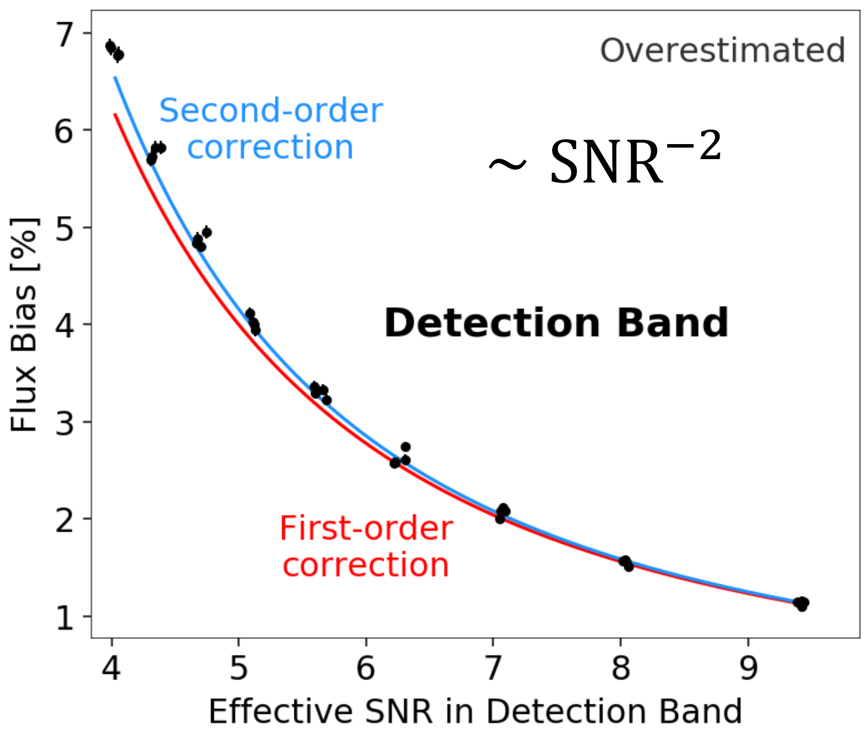

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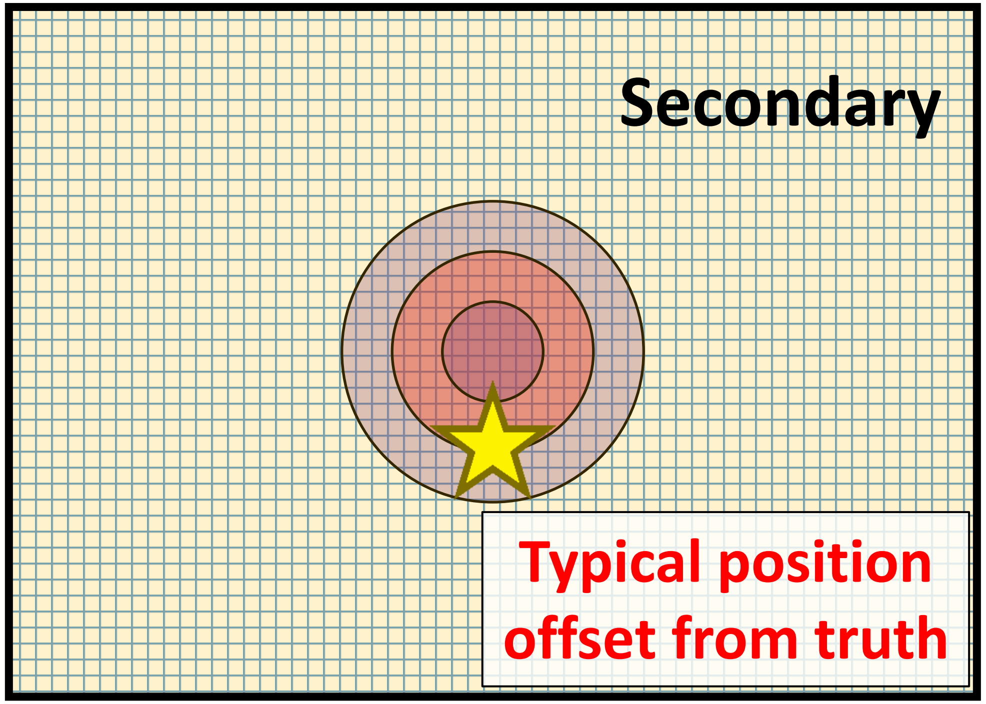

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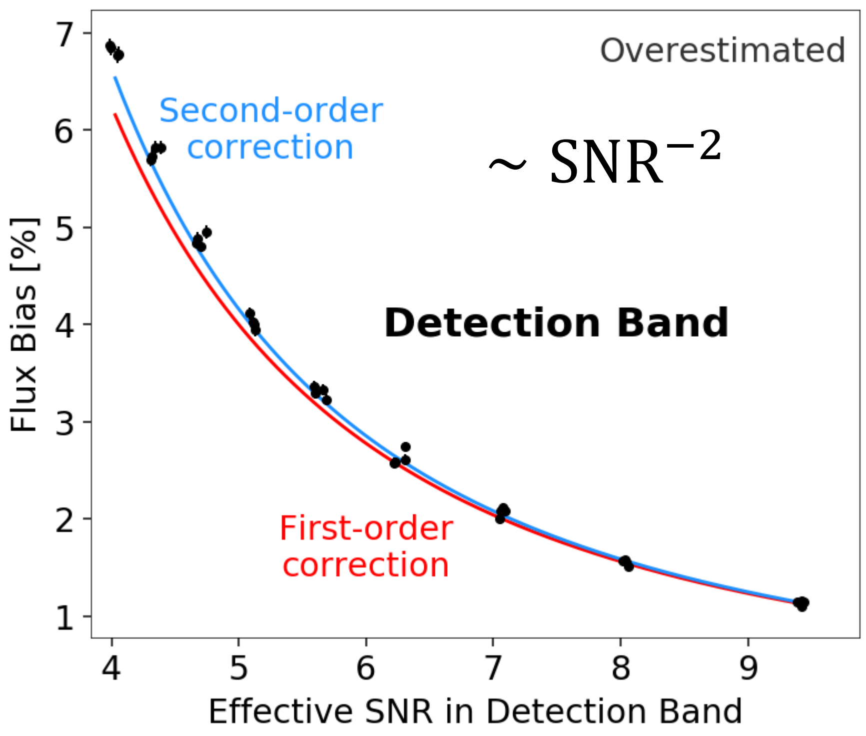

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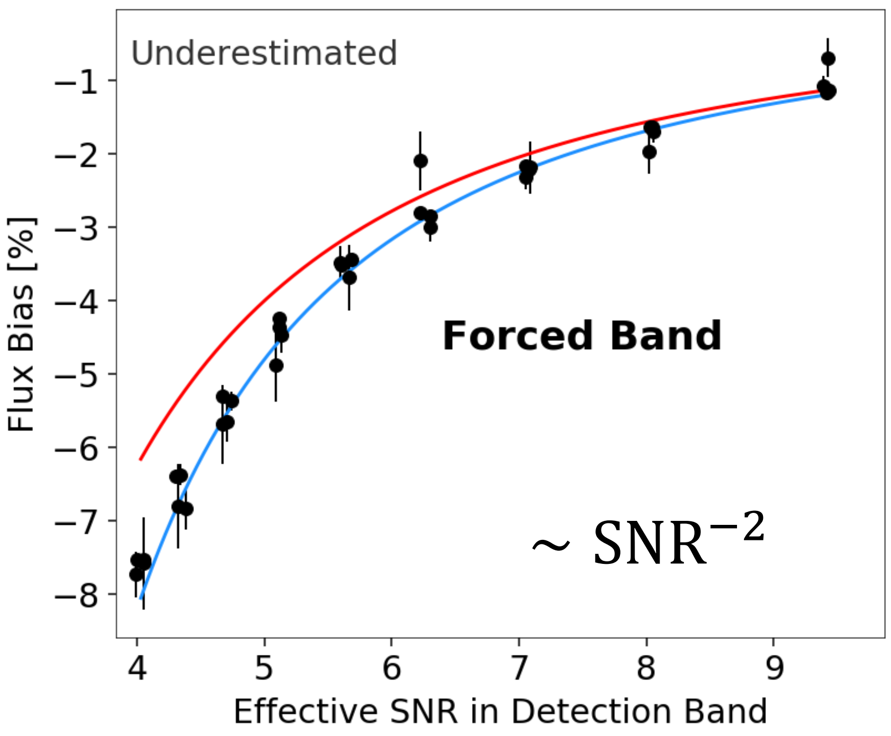

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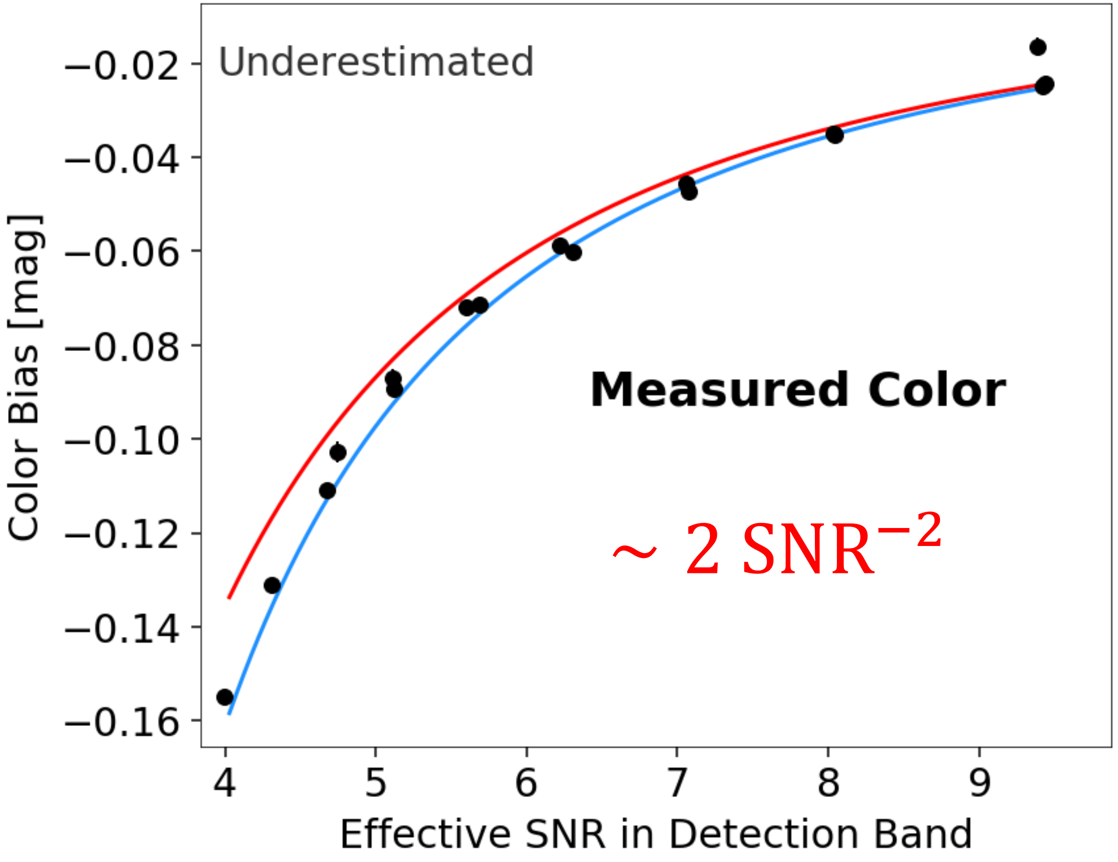

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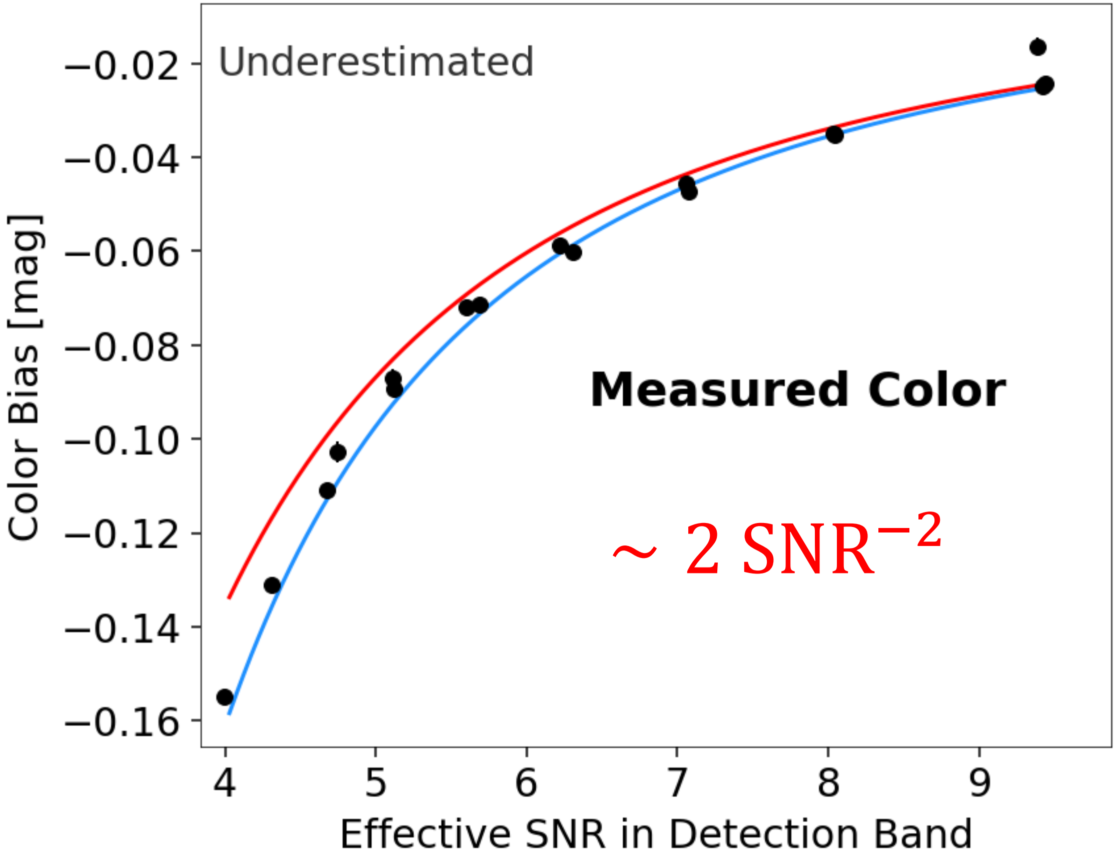


Star @ 10-sigma:

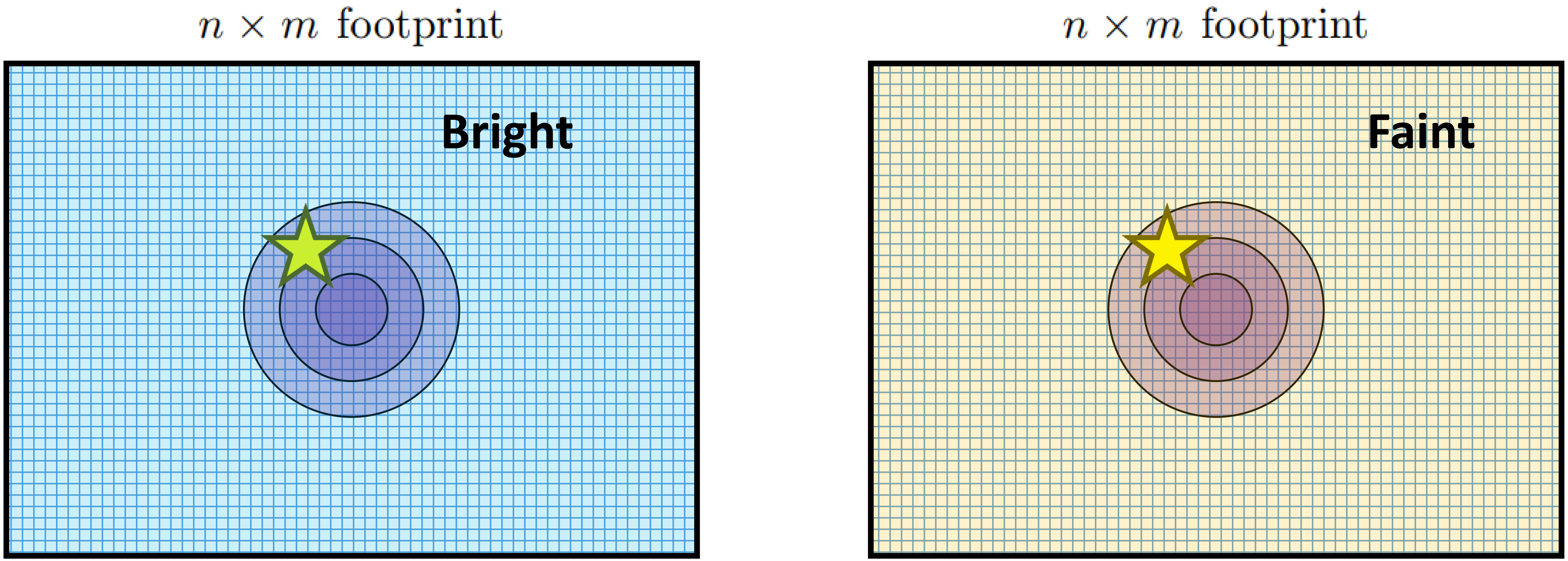
- 1% flux bias
- 0.02 mag color bias.

Galaxy @ 10-sigma:

- 2.5% flux bias
- **0.05 mag color bias.**

Biases in Joint Multi-band Photometry

- Fit all bands simultaneously (~ detect on stack, force in bands)



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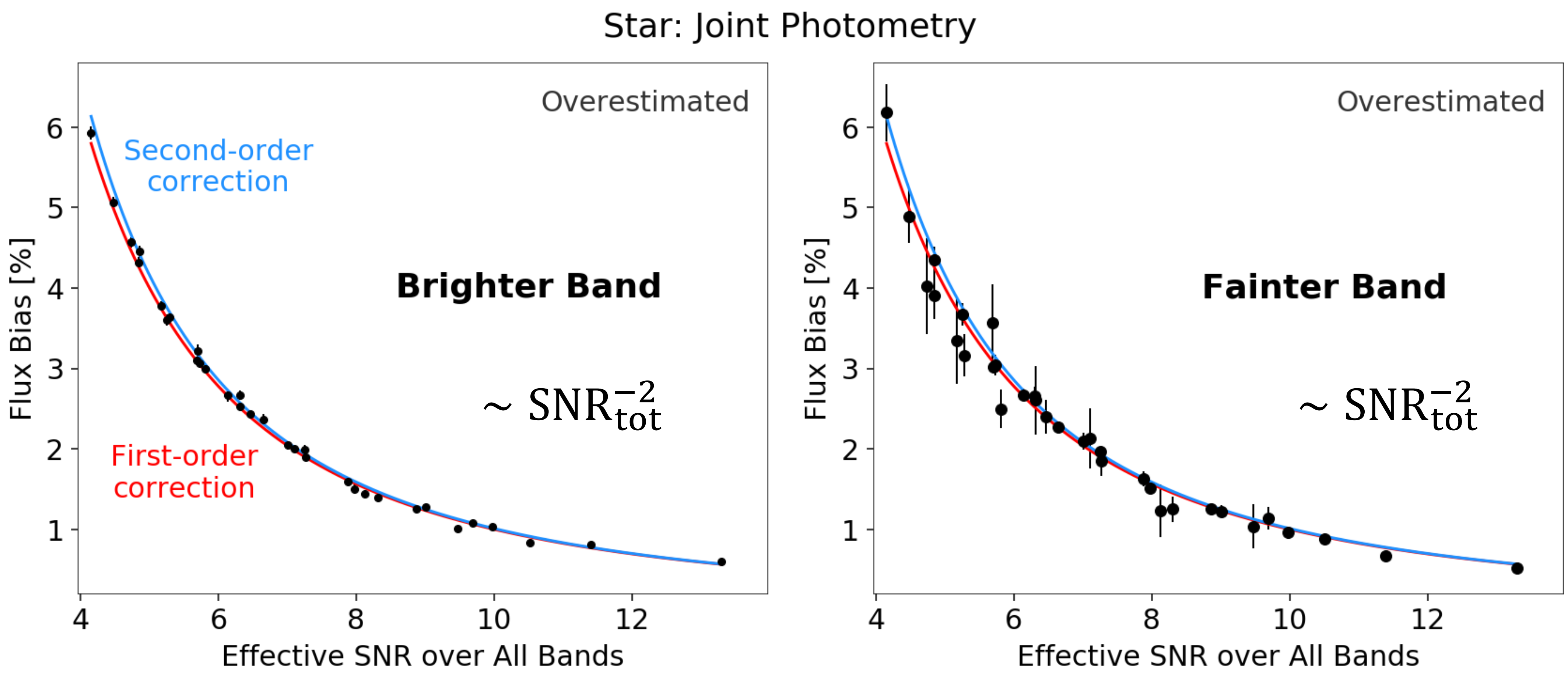

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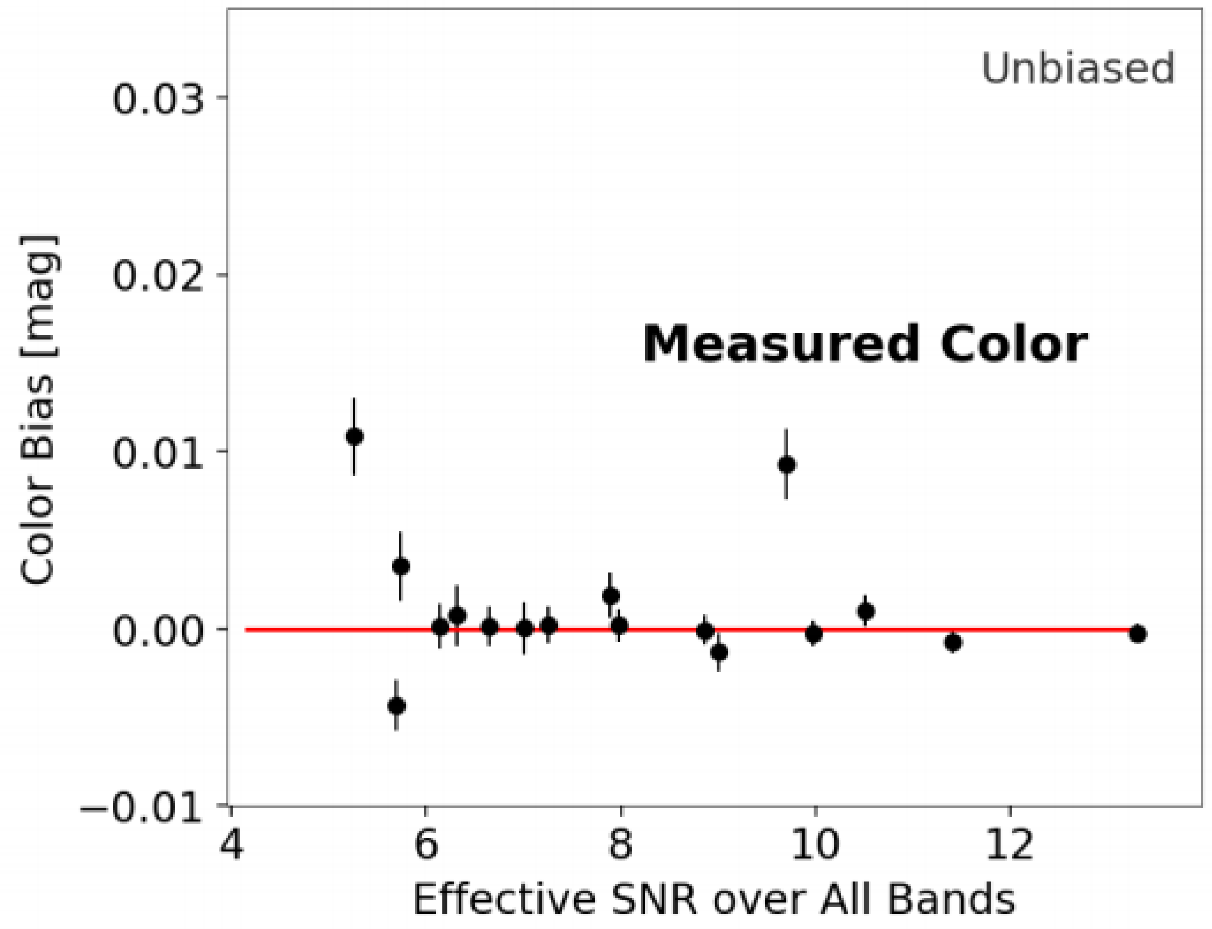


Biases in Multi-band Photometry

Forced Photometry

Positive bias in detection band.
Negative bias in forced bands.
Doubly-biased colors.

Joint Photometry

Positive bias evenly spread across all bands.
Unbiased colors.

Proof?

SDSS Stripe 82

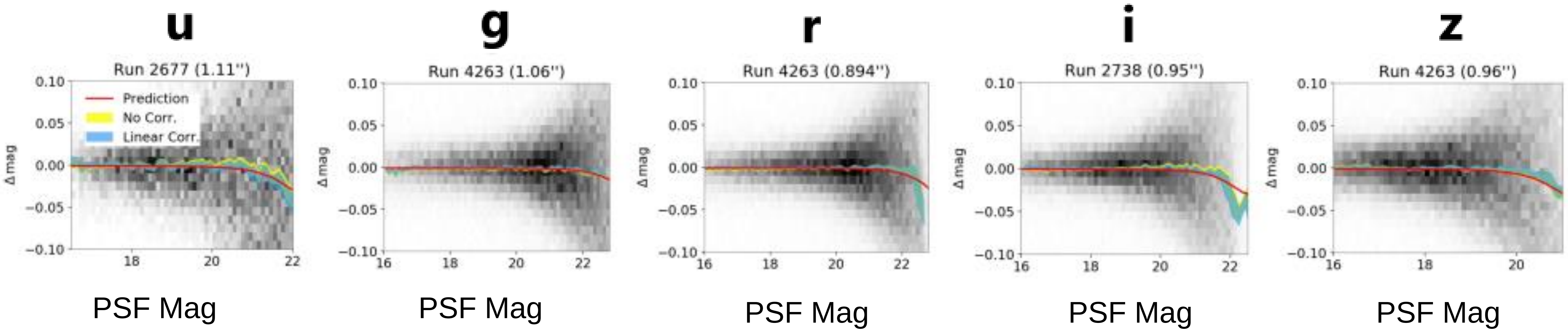
- **Repeated imaging**: compare catalog computed from a **“deep stack”** of all images (“truth”) vs **individual runs** (“realization”)

- **“Forced” photometry**: detect in r-band, force in others

- **PSF magnitudes**

Stripe 82

See all the data (and hundreds of similar plots) at https://github.com/joshspeagle/phot_bias



Identical bias across all bands!

Biases in Forced Multi-band Photometry

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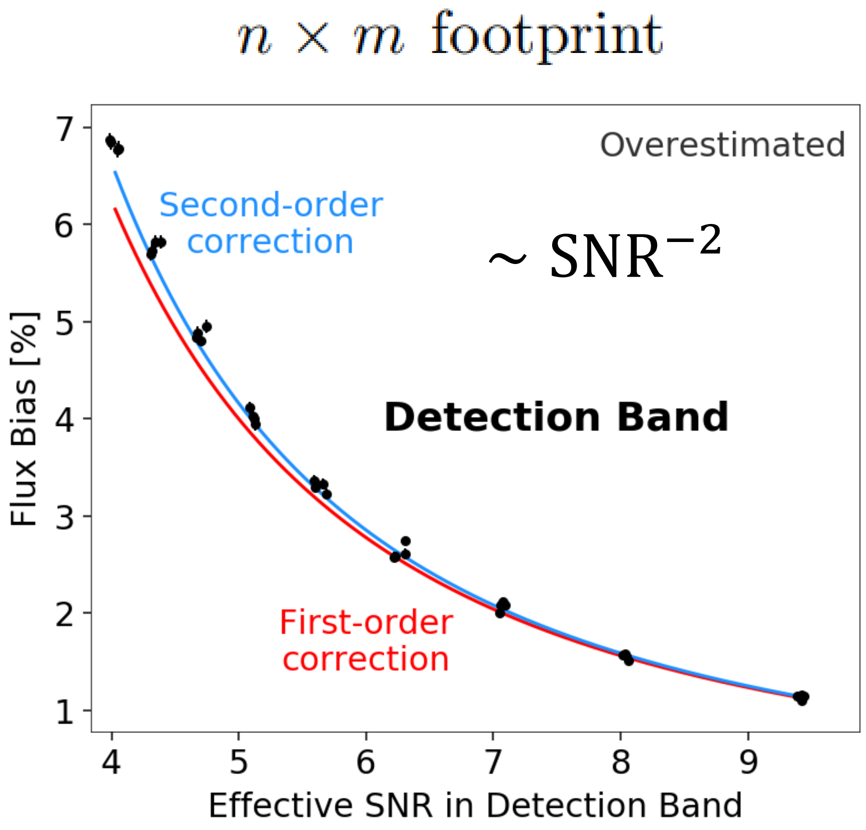

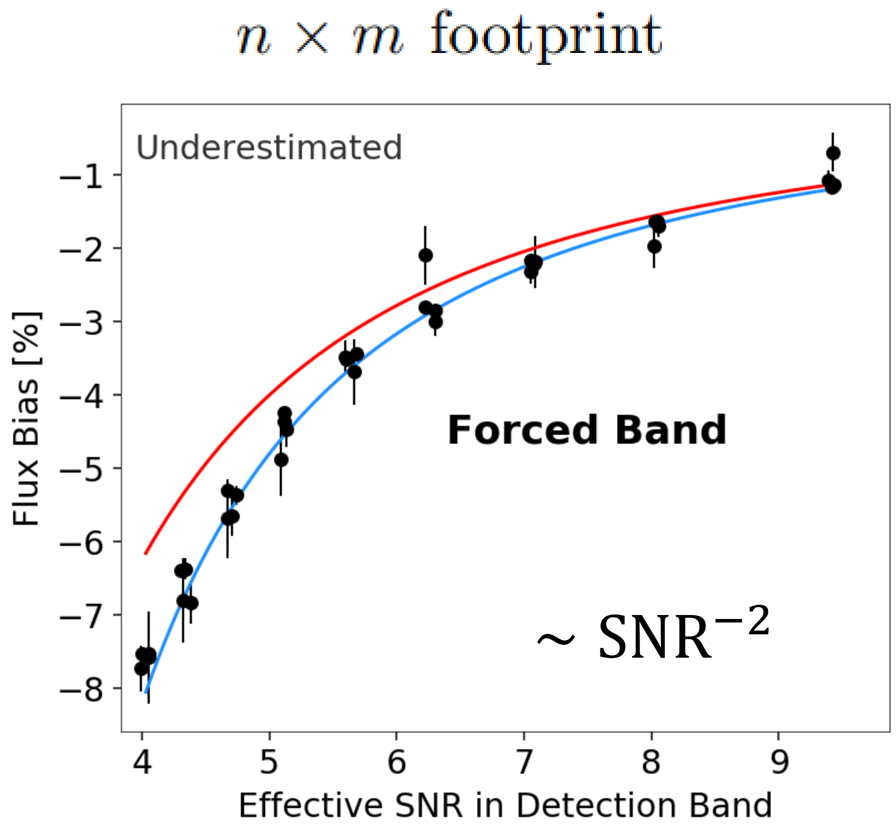

Astrostatistics Interest Group: Student Paper Award
Topic Contributed Papers Session (401) JSM 2020
August 5 2020

The Devil's in the Details: Photometric Biases in Modern Surveys

Stephen Portillo[1,2,*] and **Josh Speagle**[1,3,*] and Doug Finkbeiner[1]

[1]Harvard U., [2]DIRAC (U. of Washington), [3]U. of Toronto

[*]Equal contribution



Portillo, Speagle, & Finkbeiner (**PSF**) 2020, [1902.02374](1902.02374)

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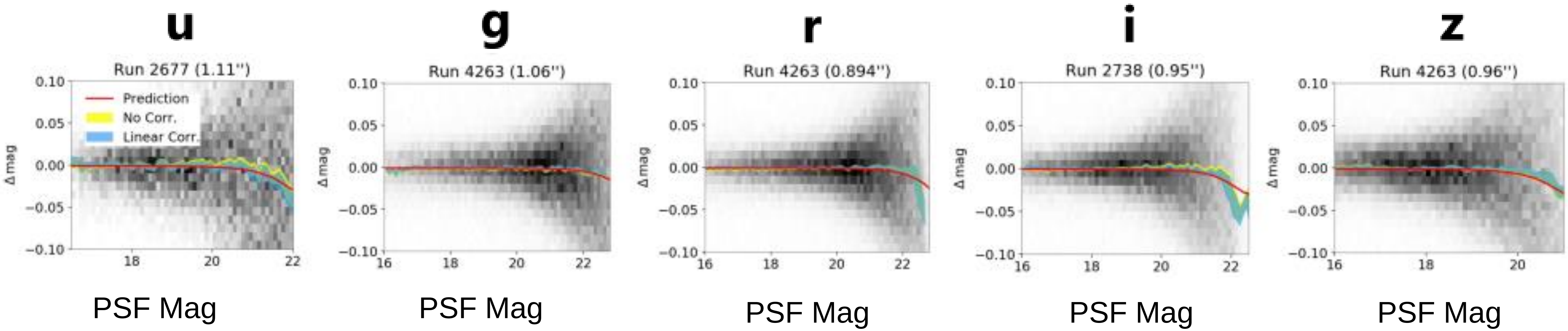

Implementation-specific effect:

- SDSS pipeline allows for **"local re-centering"** of forced position.
- Enough to undo forcing effect!

Why use models at all?

- If we know that the MLE is biased and our models may be wrong, why not do something simple like **aperture photometry**?

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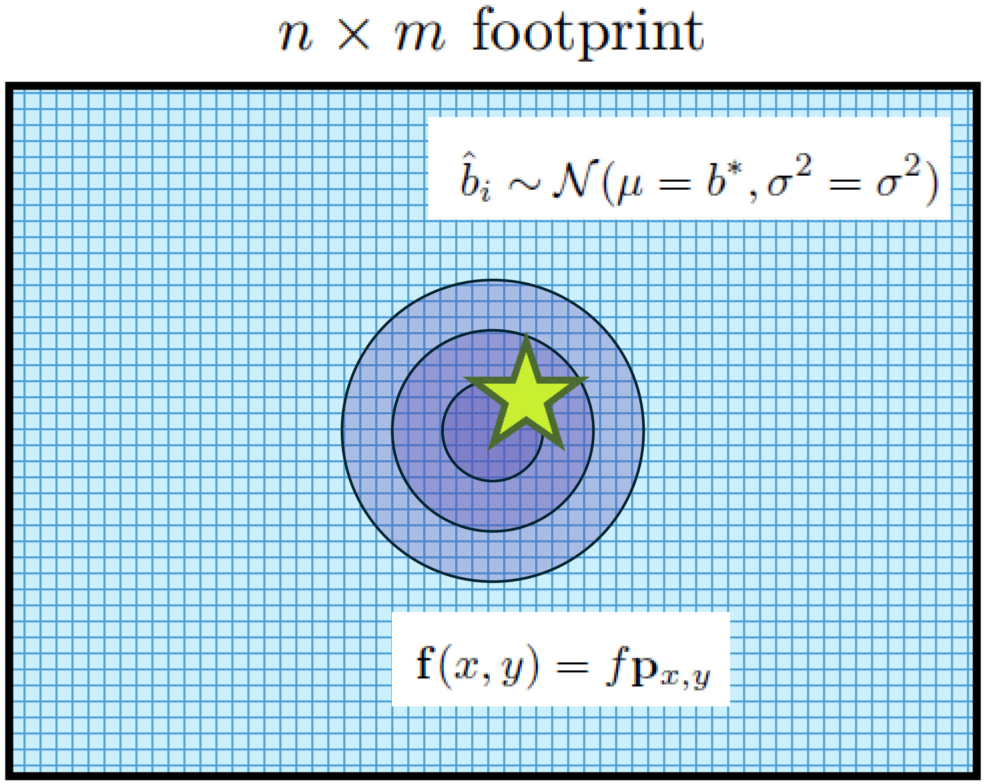

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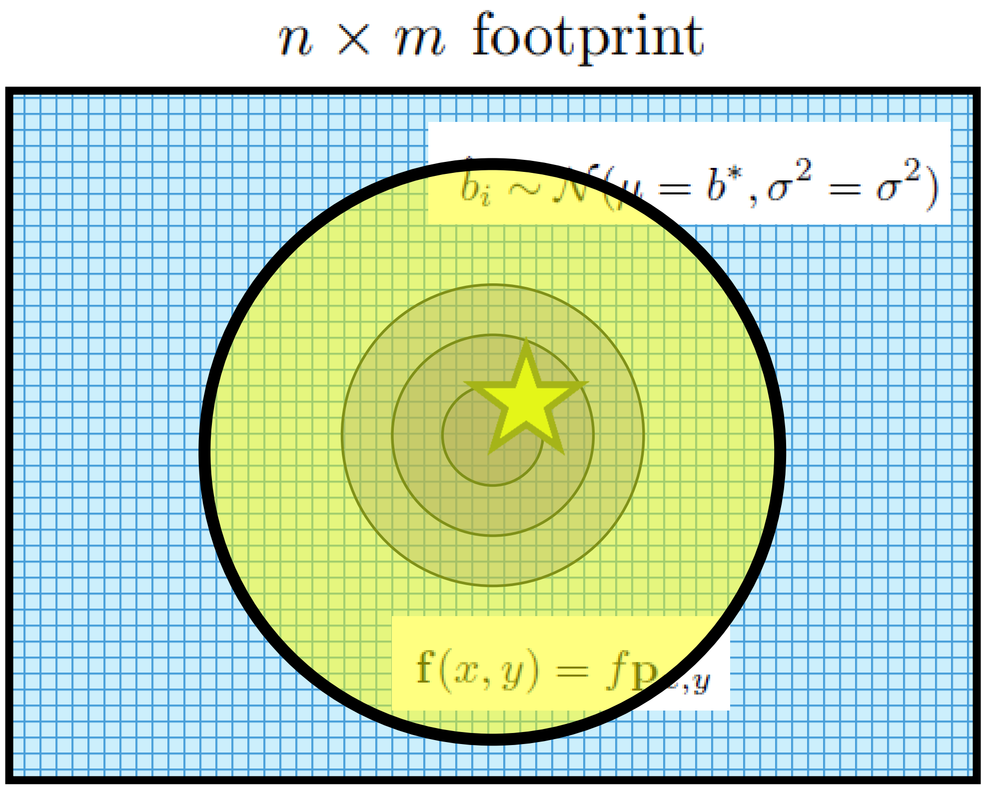

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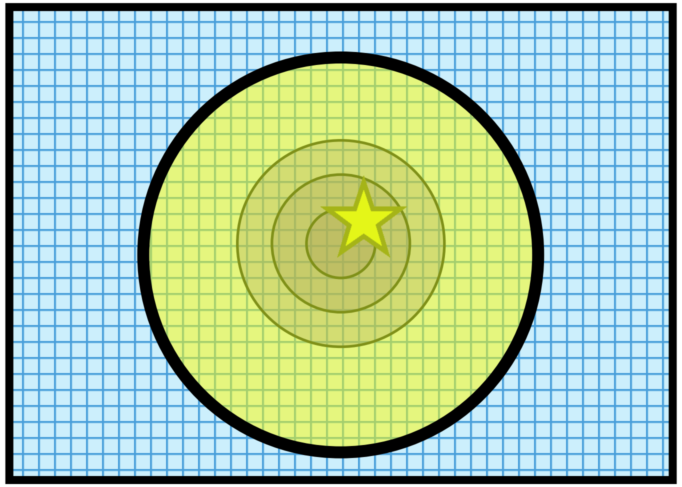
  - (we confirm this with SDSS S82 data)



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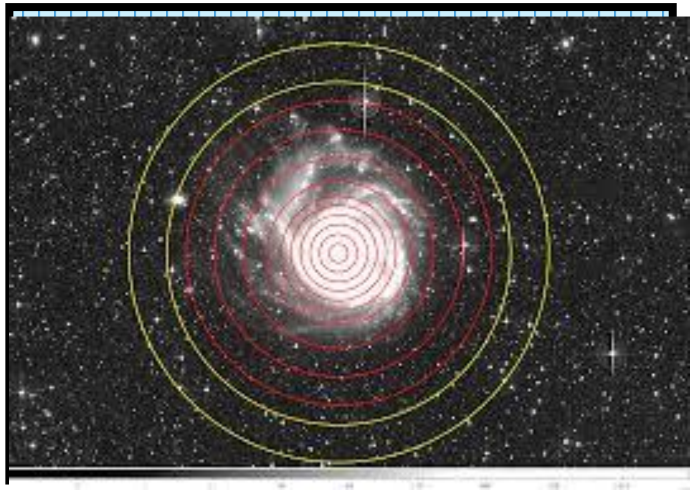

Has a purpose, but should be used judiciously!

Summary

- MLE photometry has a bias that goes as **SNR^-2**.
- Proportional to number of parameters of fit: **(p-1)/2**
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- **Forced photometry is dangerous.** Joint is better.

- Behavior is sensitive to implementation – **talk to pipeline teams**!
- These biases likely present in many modern photometry catalogs.