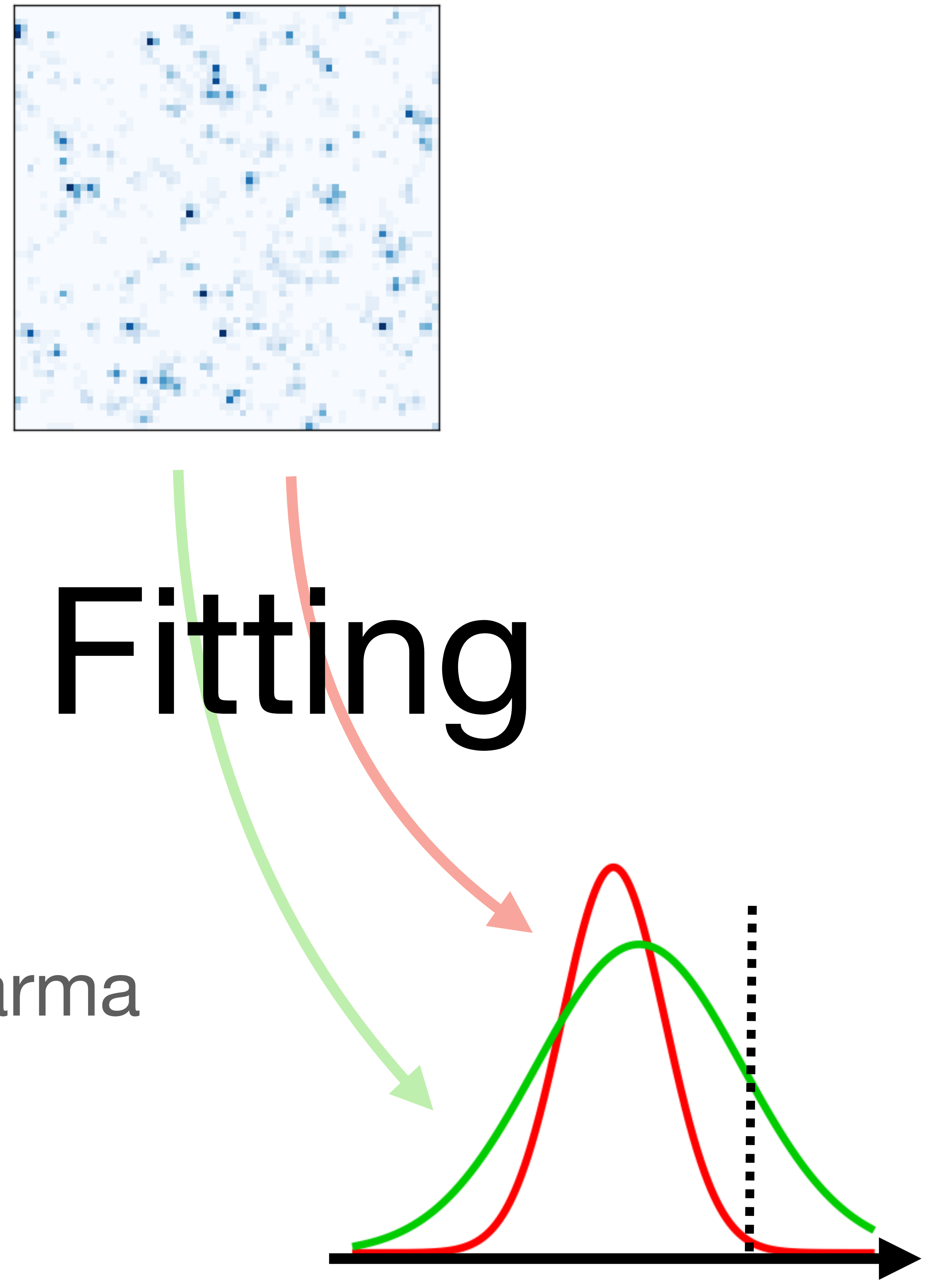
# Overconfidence in Non-Poissonian Template Fitting



Yitian Sun

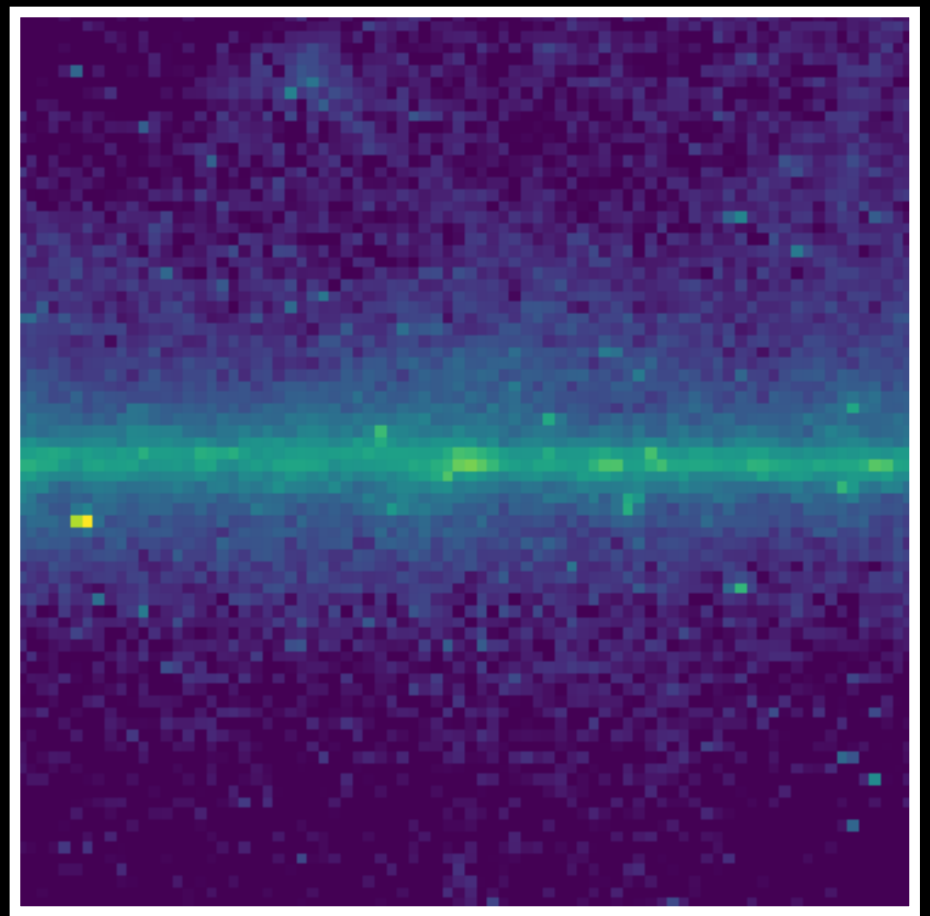
with Yuqing Wu, Tracy R. Slatyer, and Siddharth Mishra-Sharma

TeVPA 2024 | Aug 26th | KICP University of Chicago

The NSF Institute for Artificial Intelligence and Fundamental Interactions

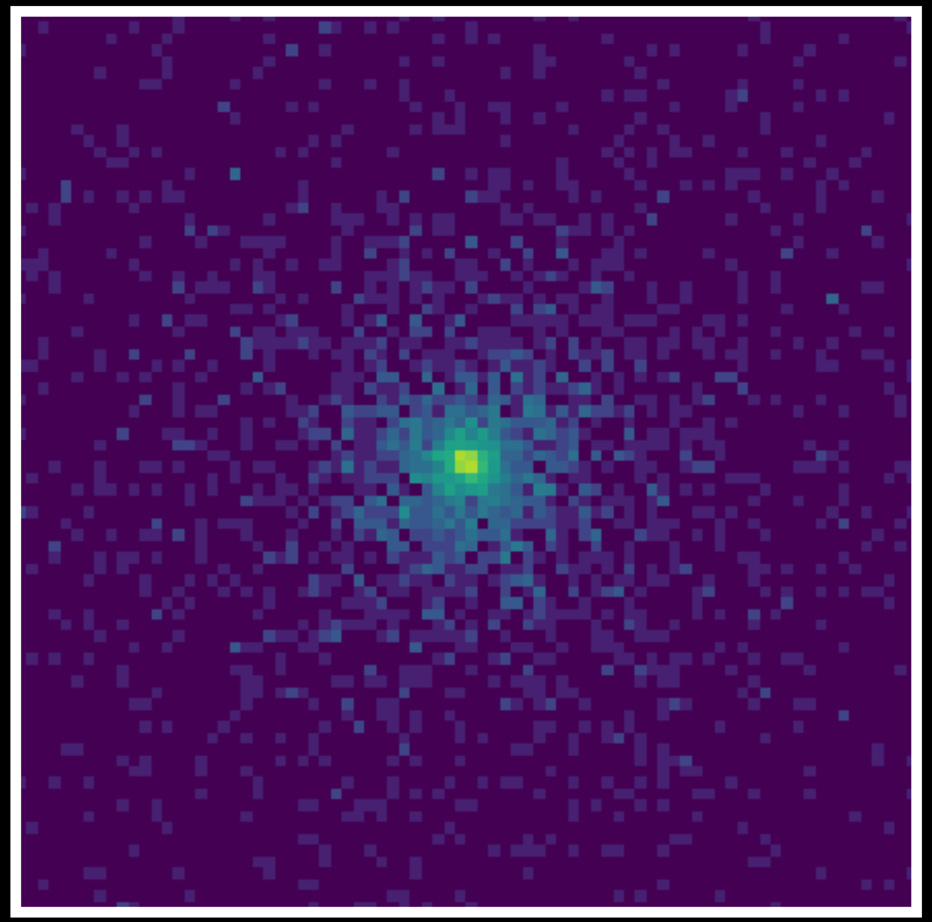
A long time ago in the galactic center far, far away…

# Galactic Center Excess of γ-ray (GCE)

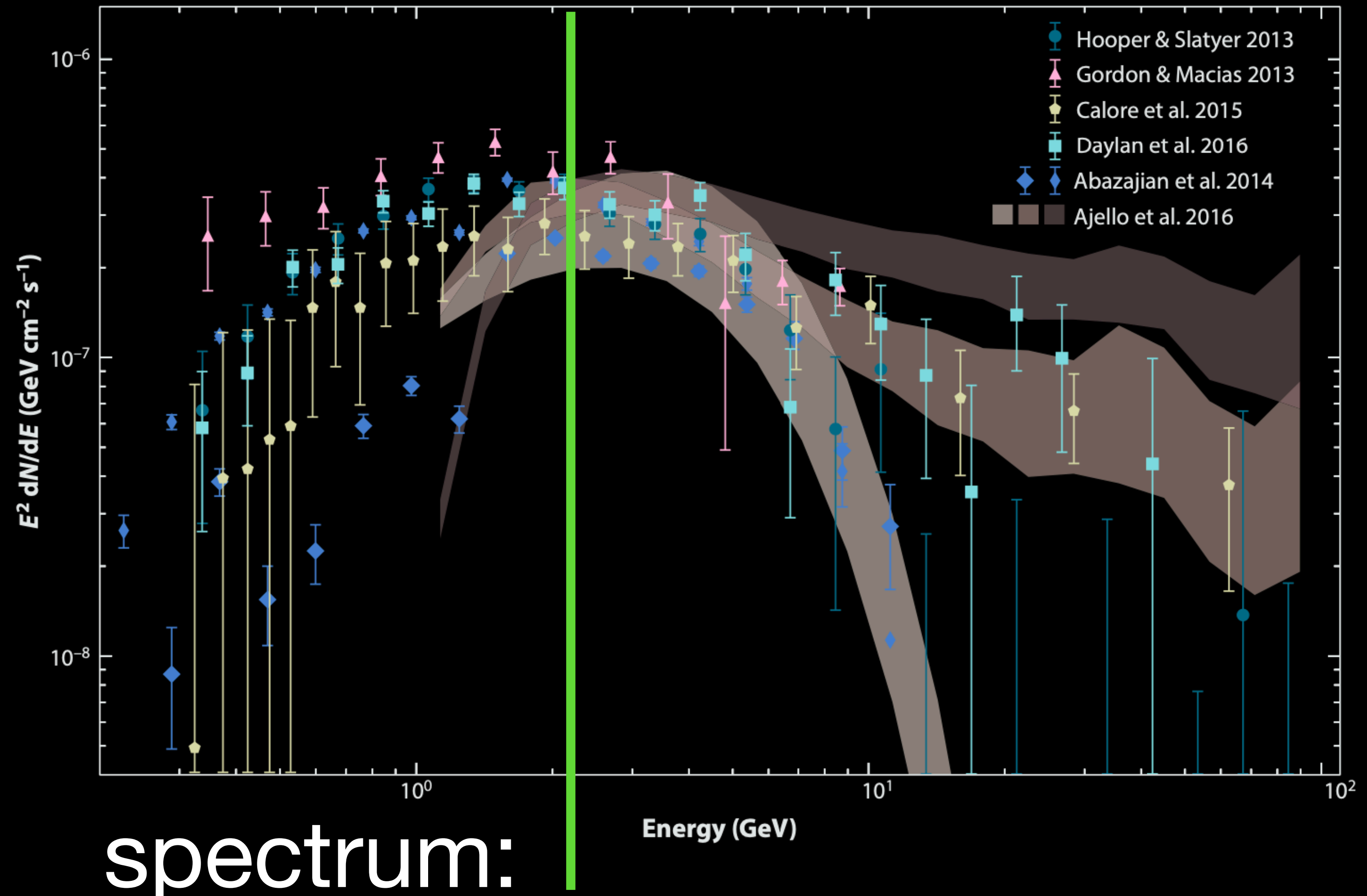


Fermi telescope image
|<—      40°      —>|
data: 2009 - now

⊃



morphology:
spherical-like,
extended up to 15°




spectrum:
peak at 2 GeV,
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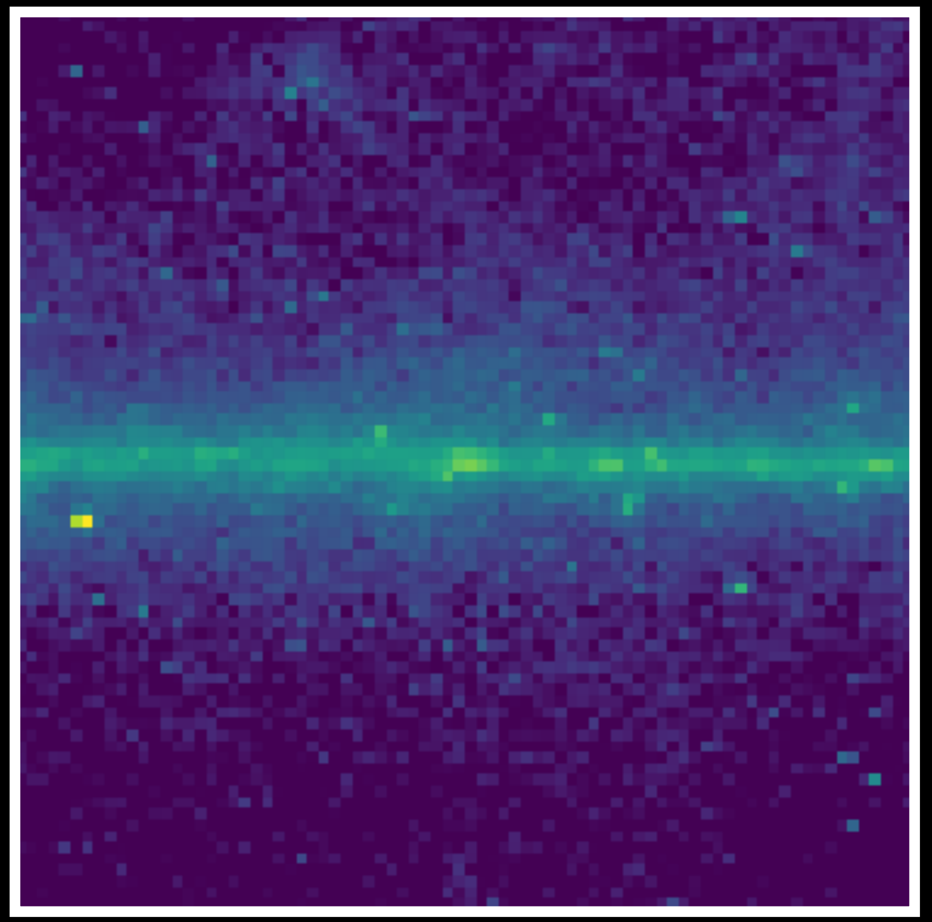

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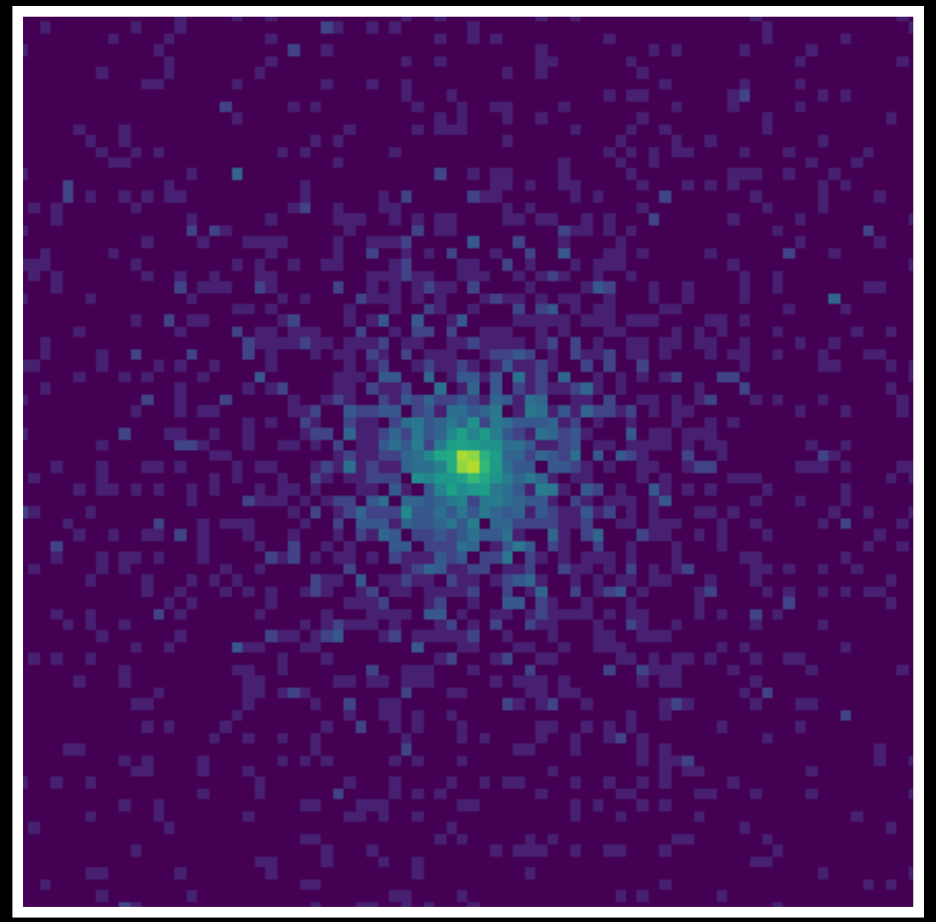

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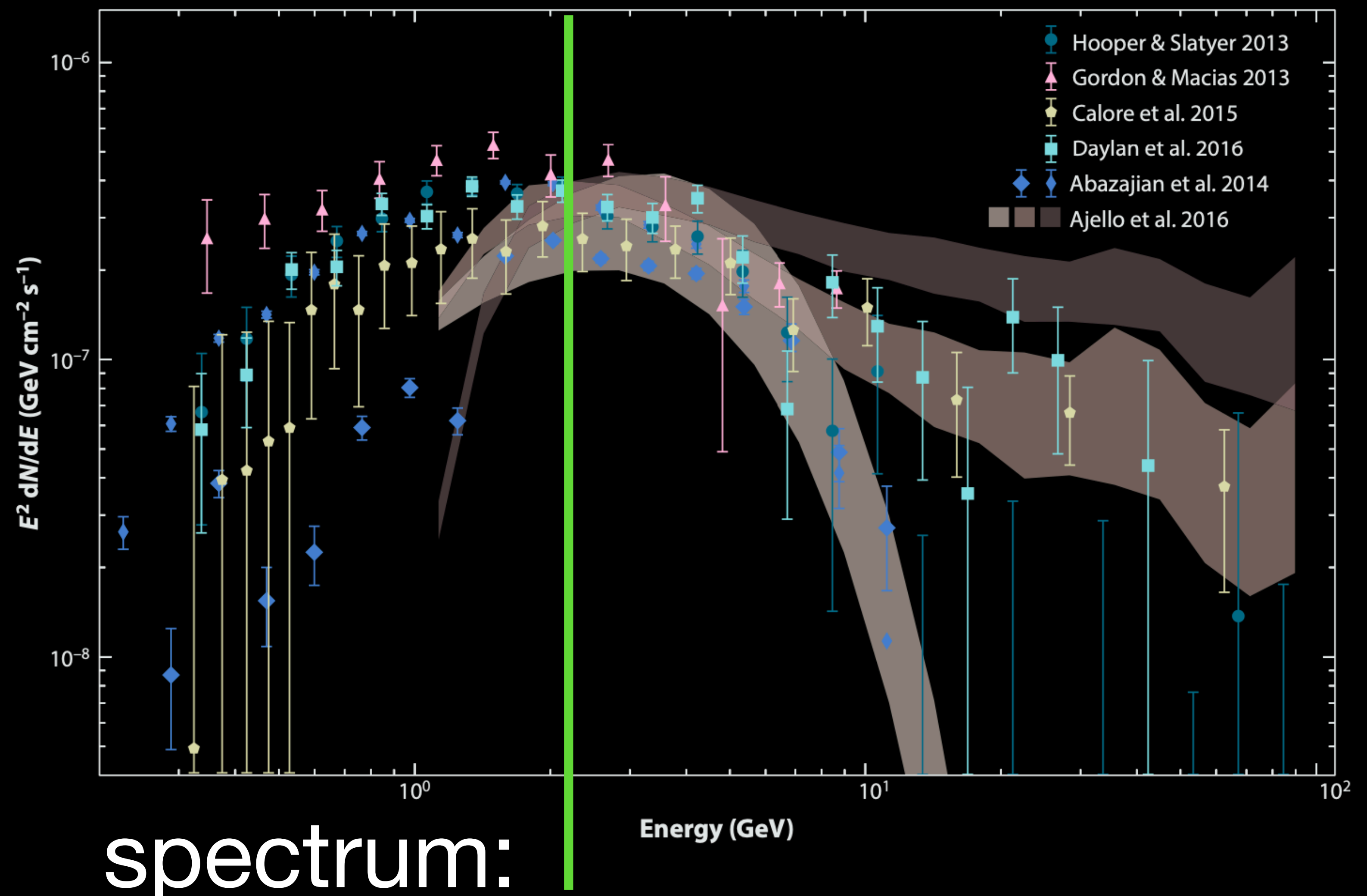


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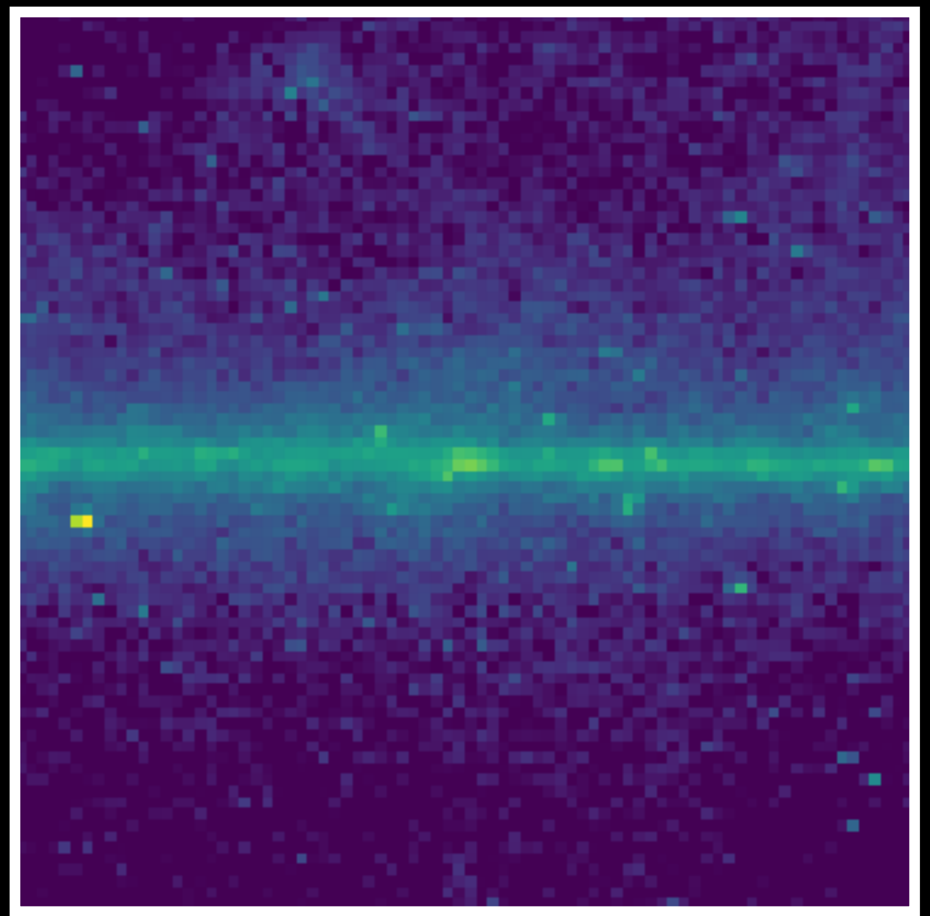

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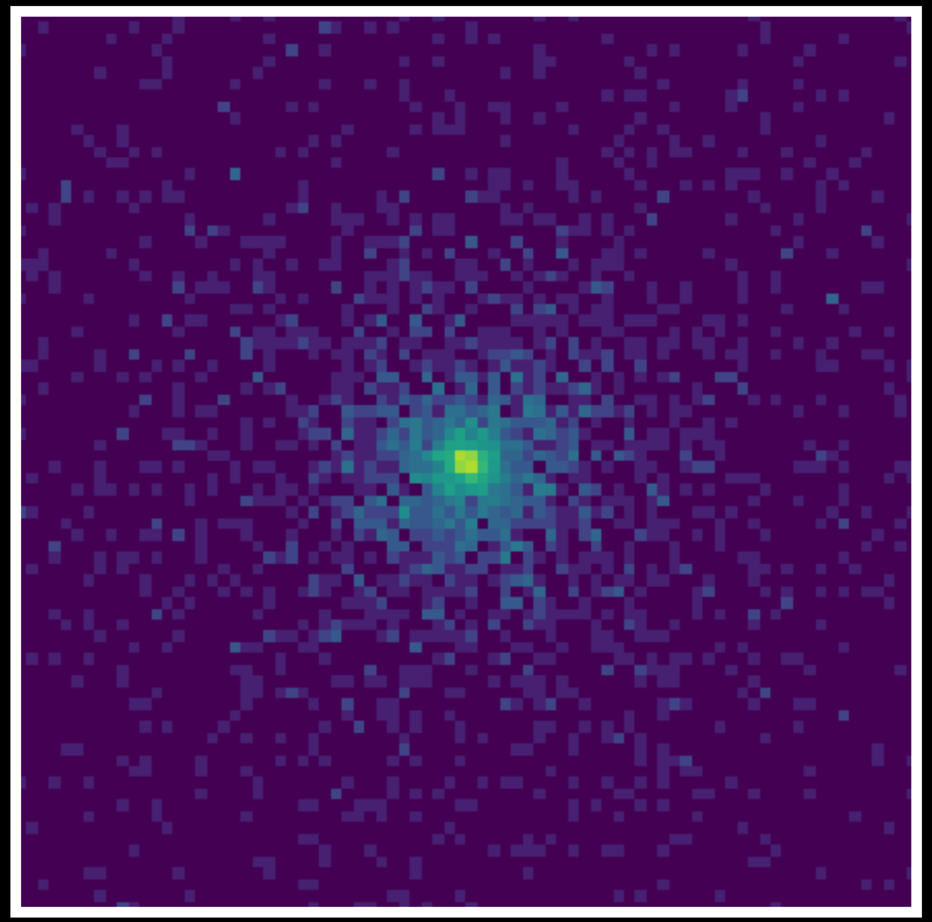

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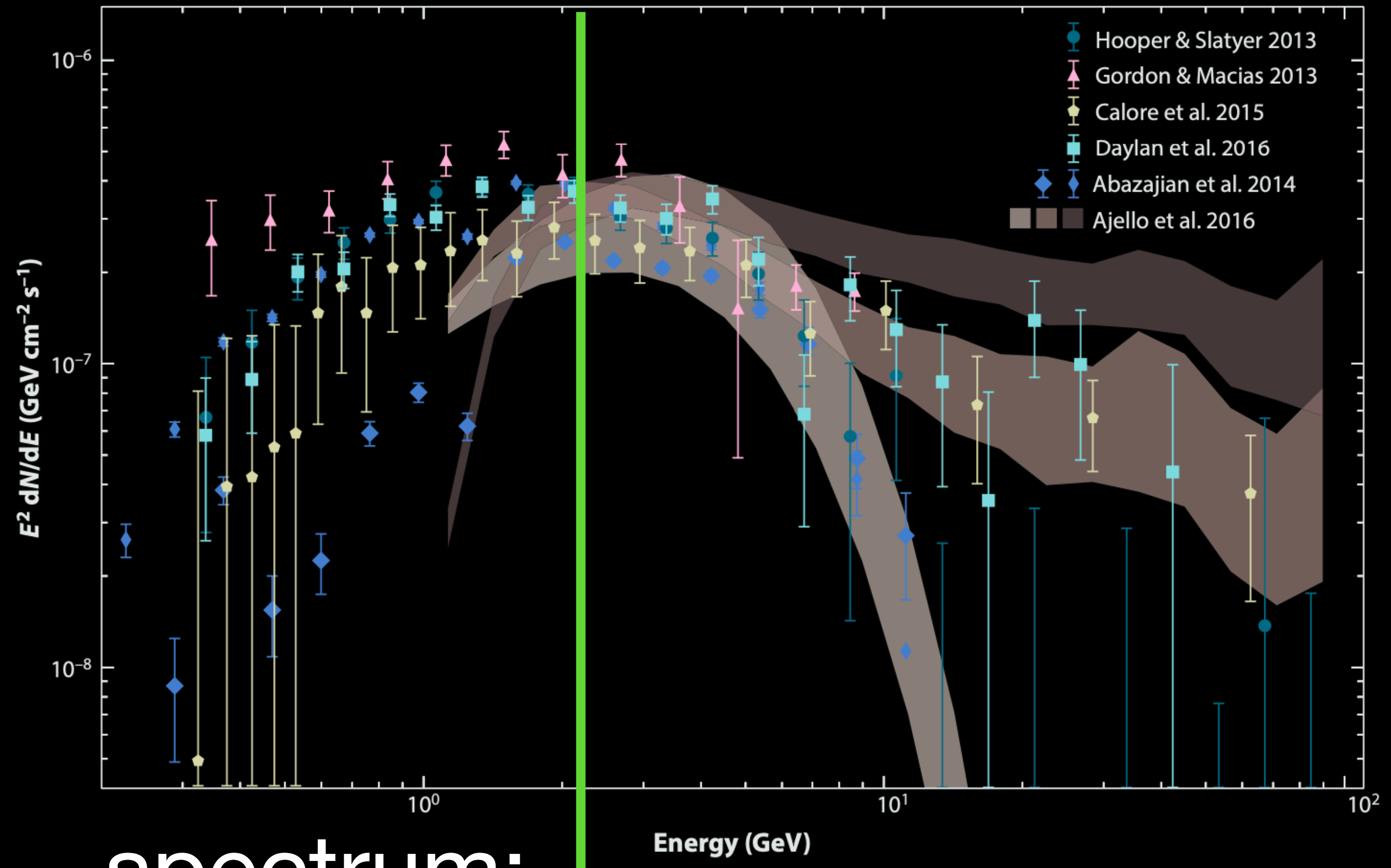


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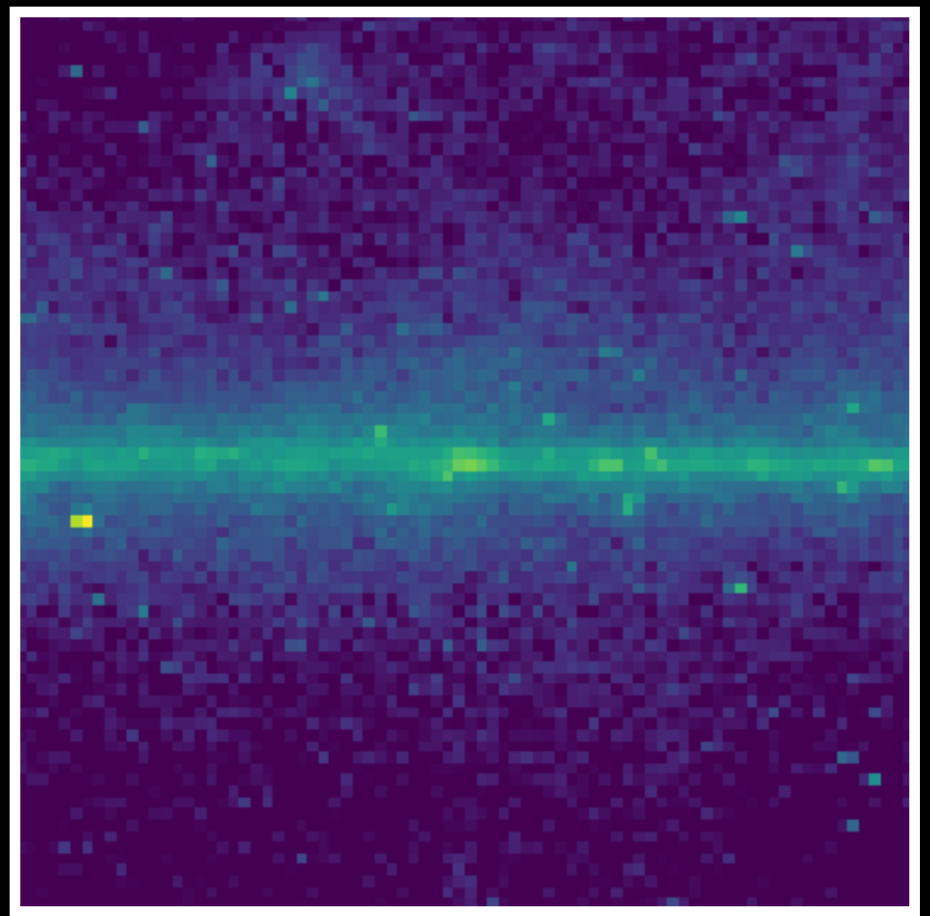

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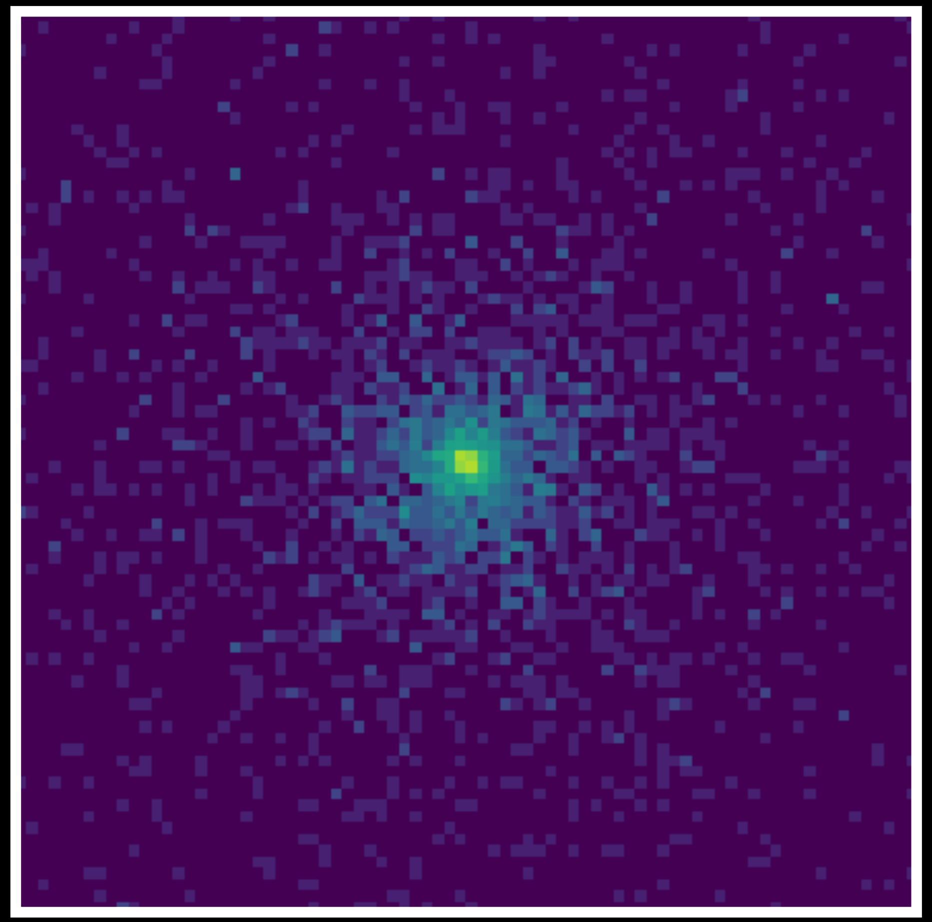

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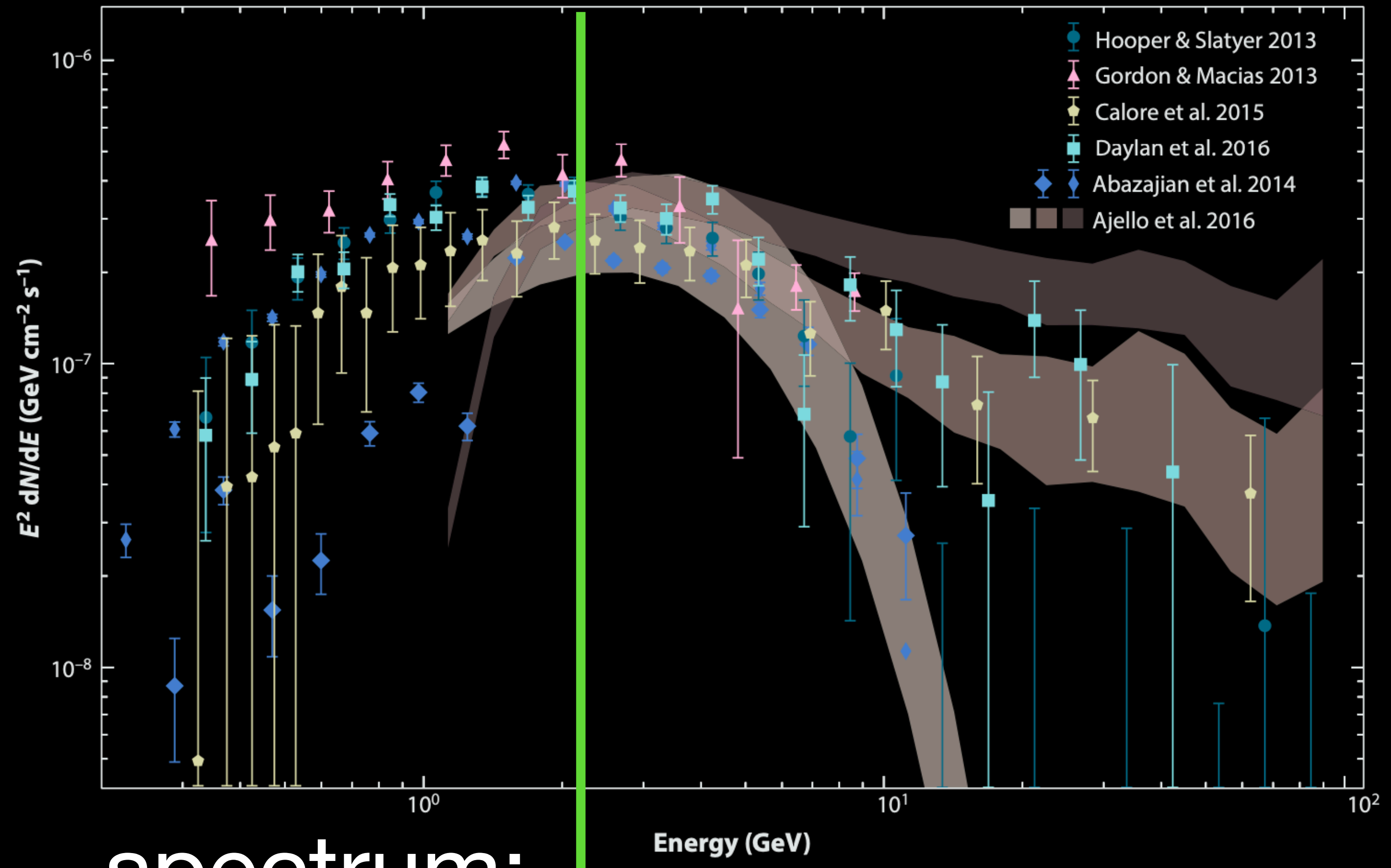


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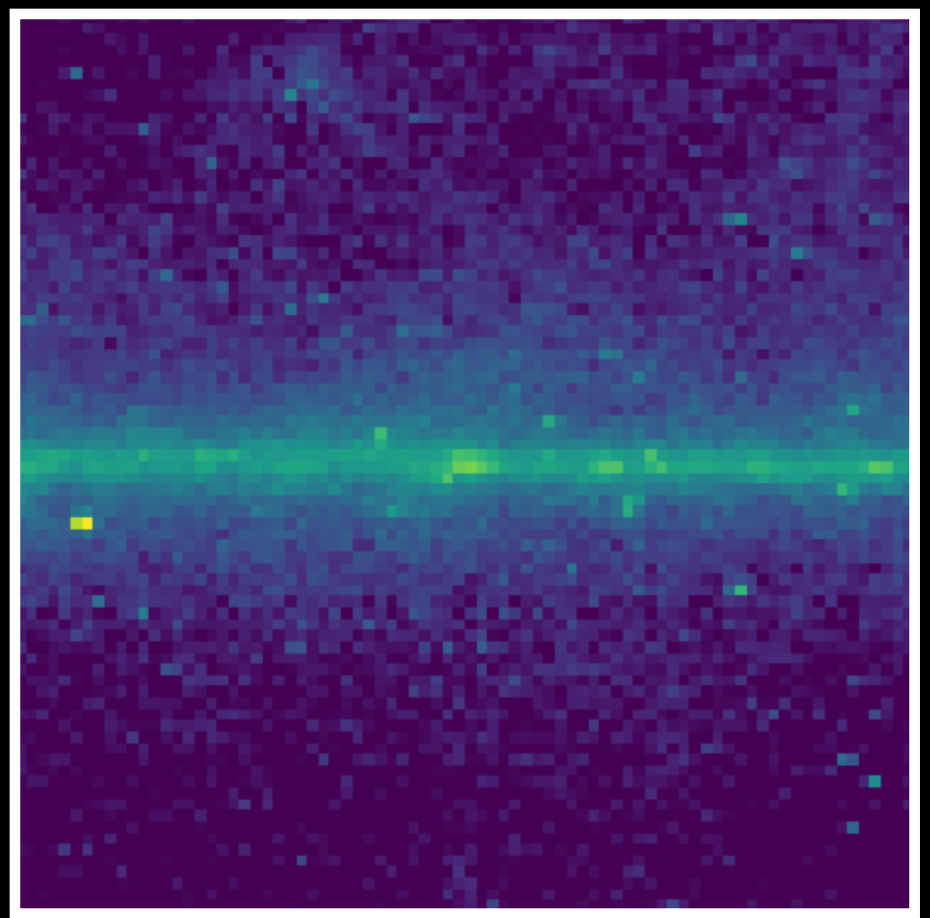

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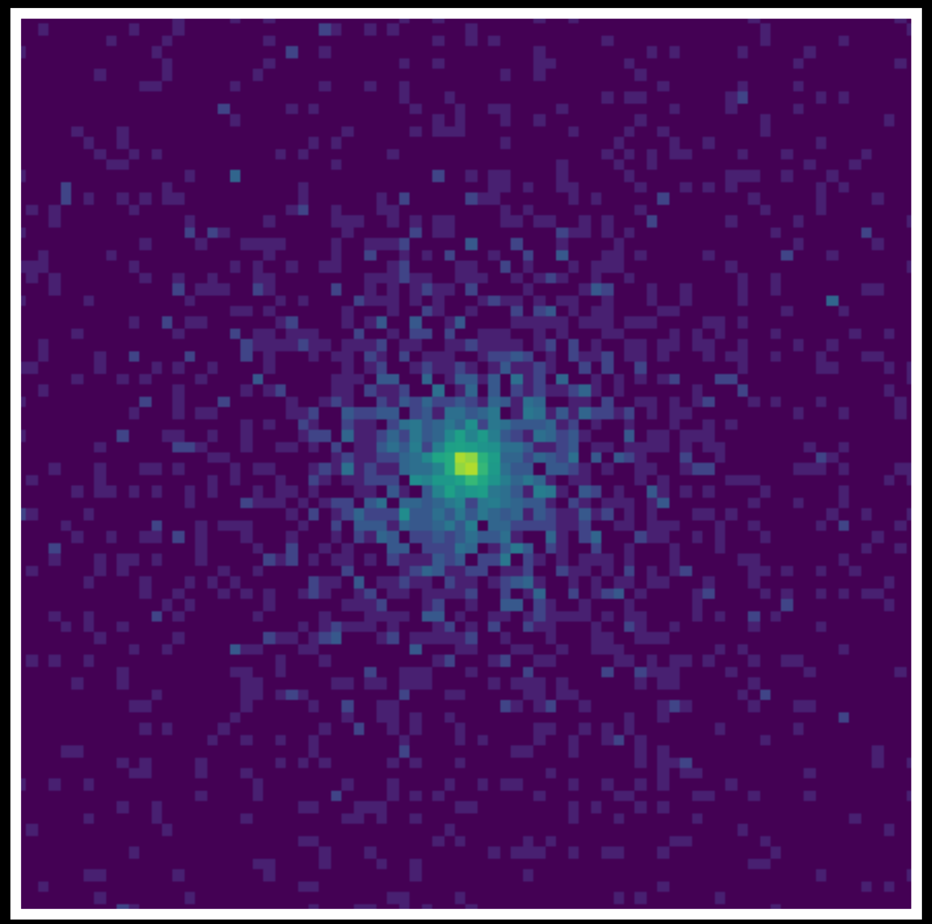

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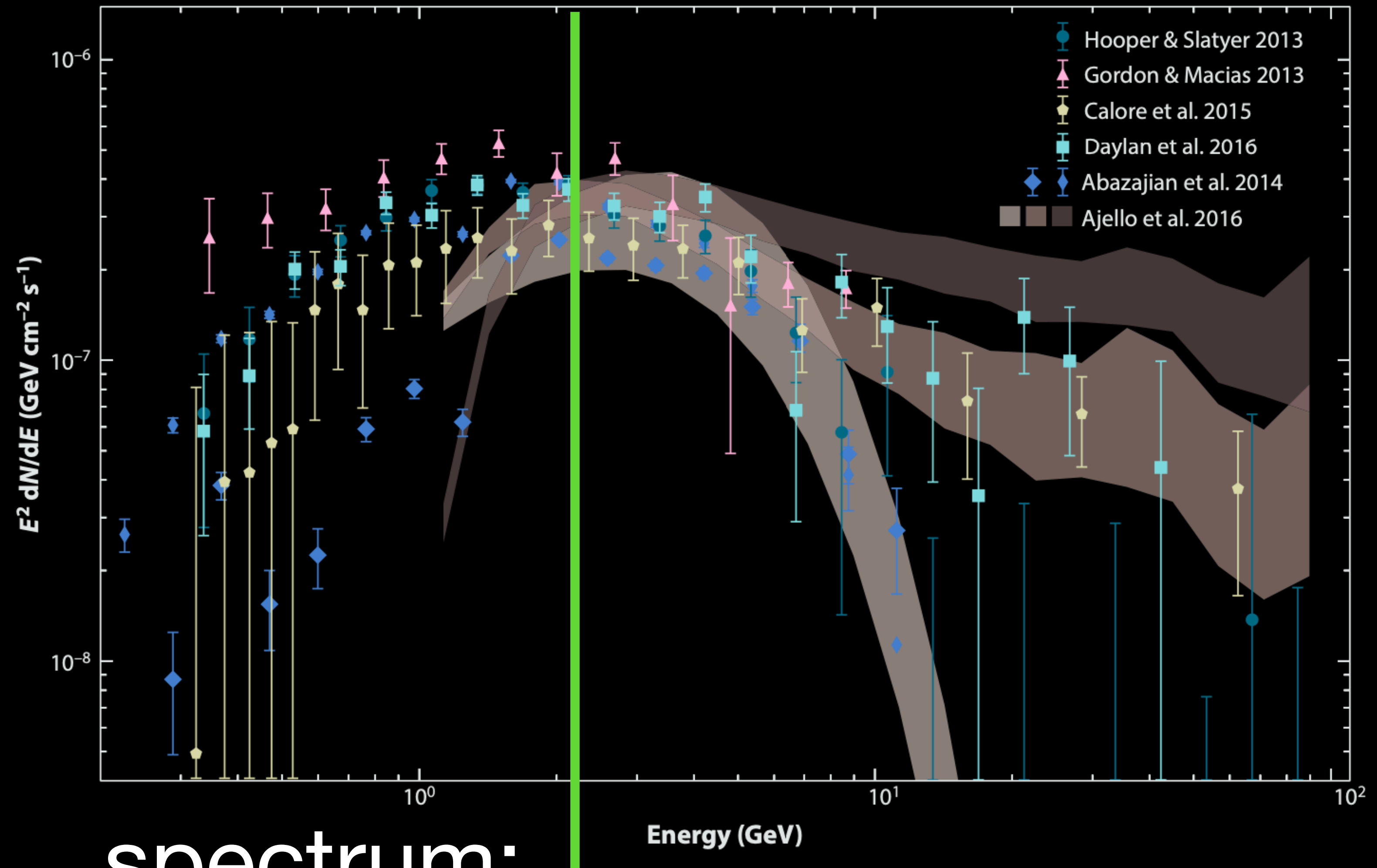


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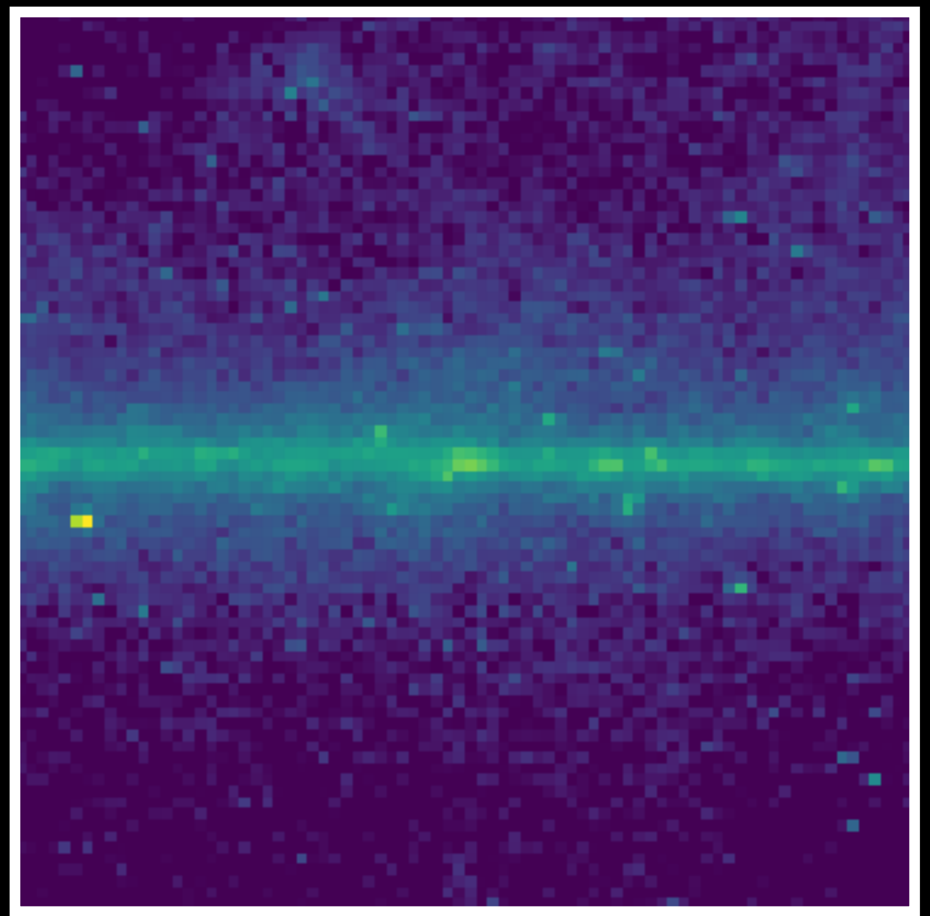

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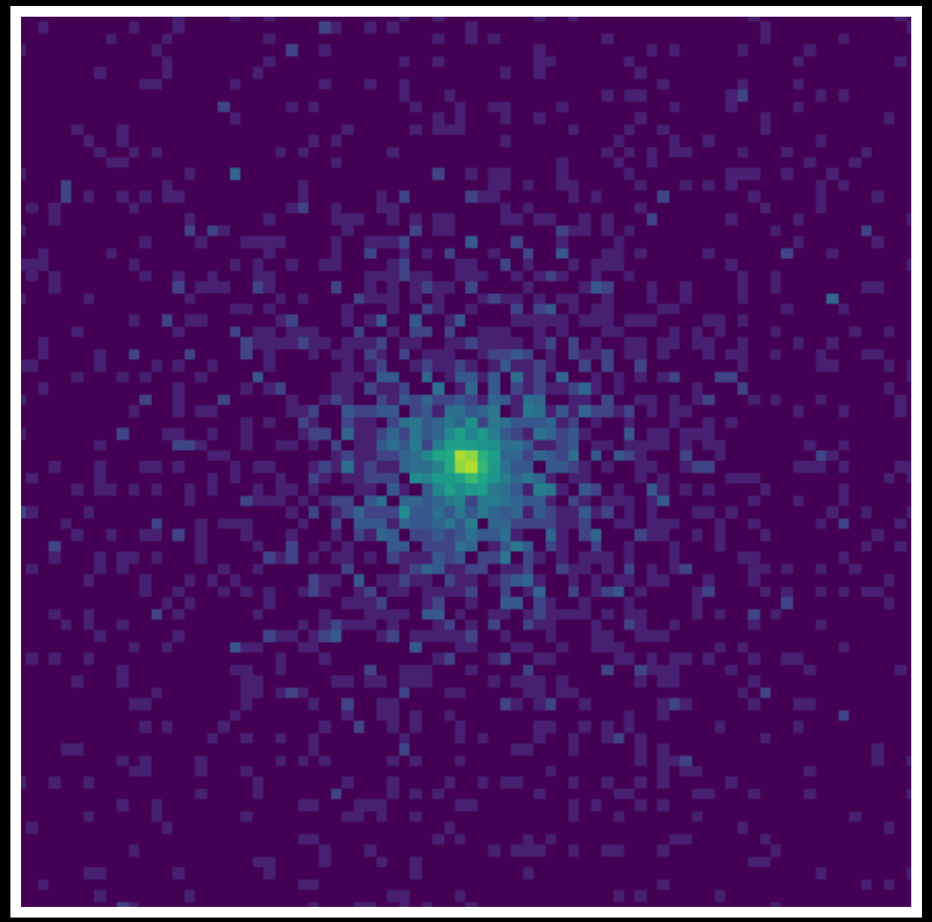

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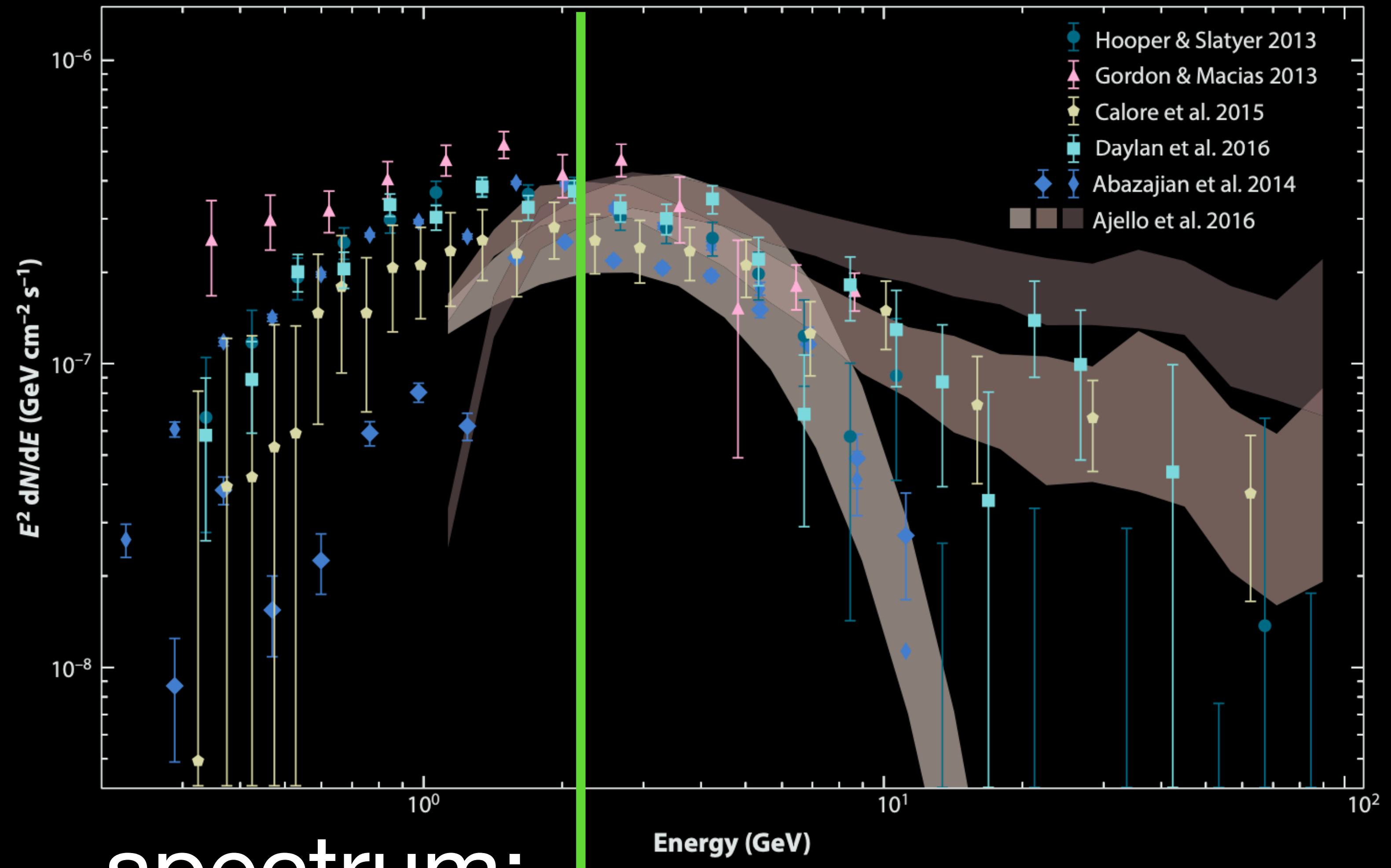


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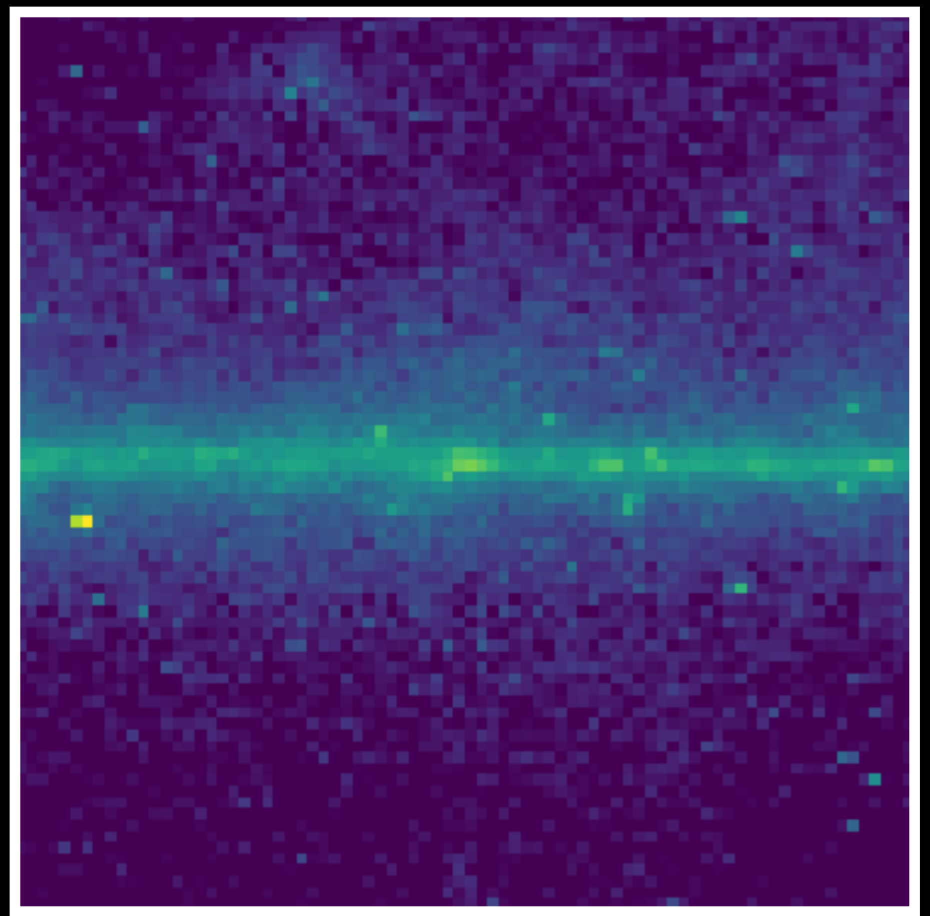

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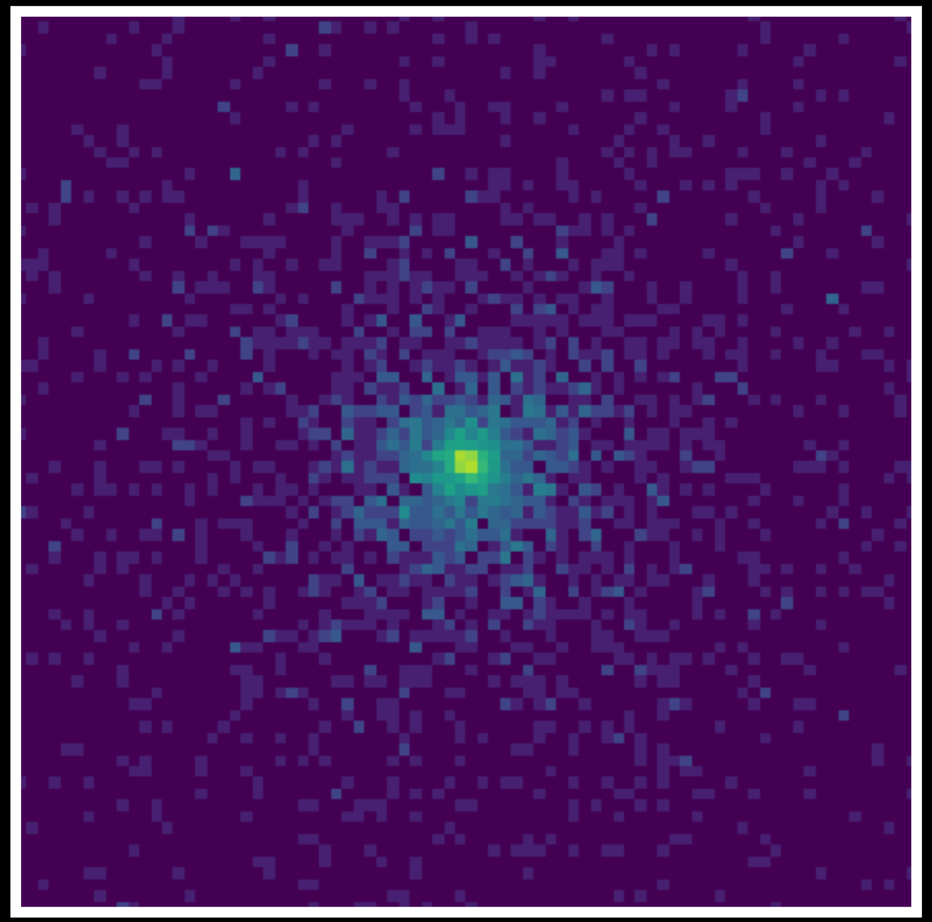

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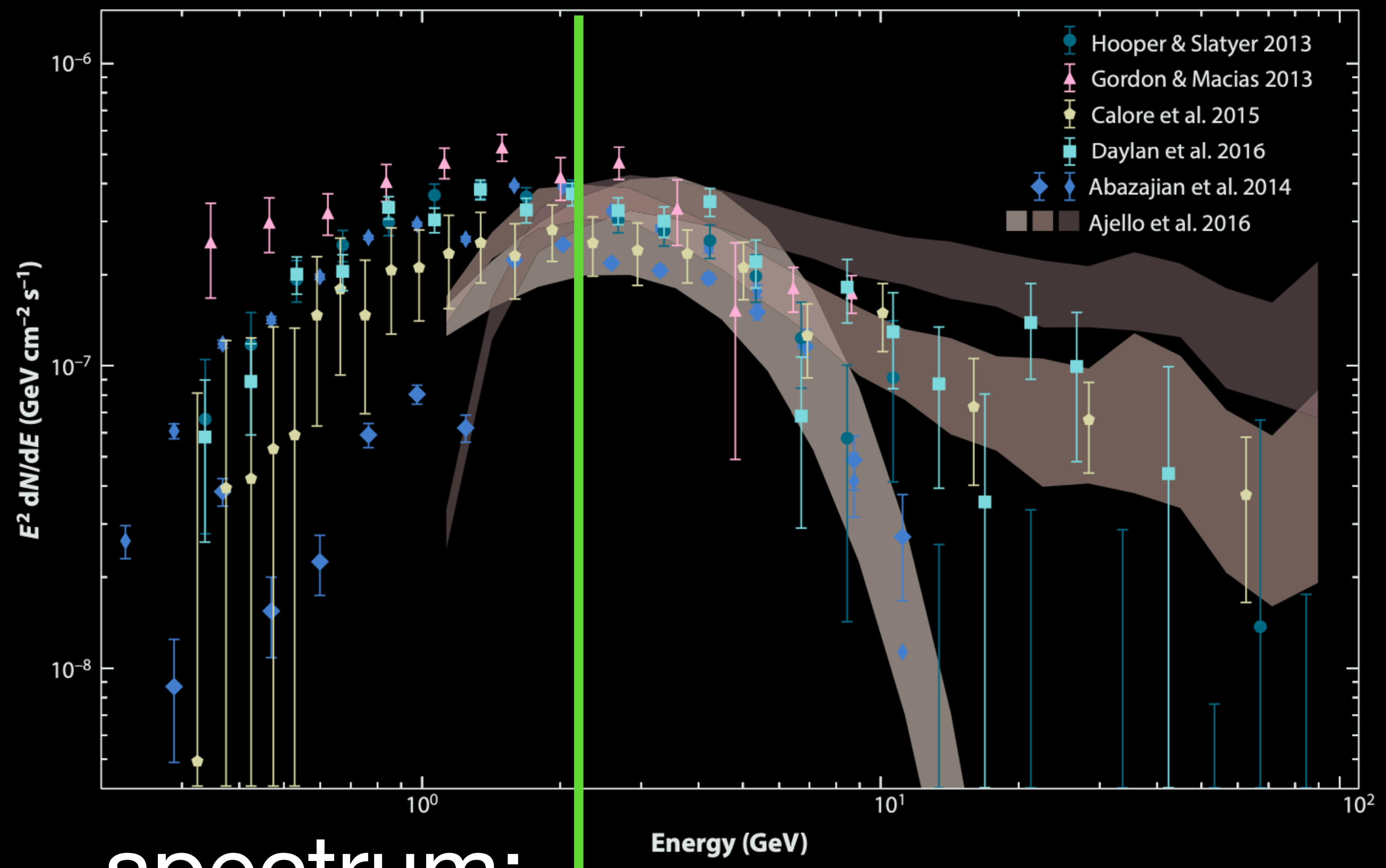


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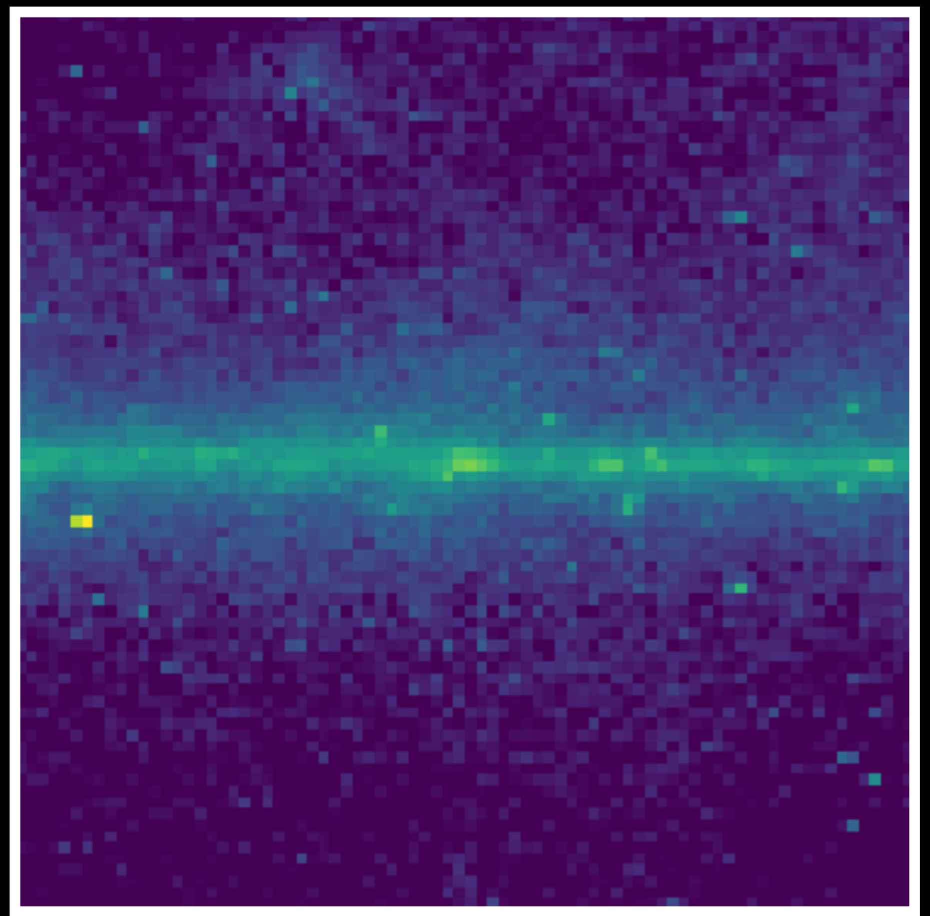

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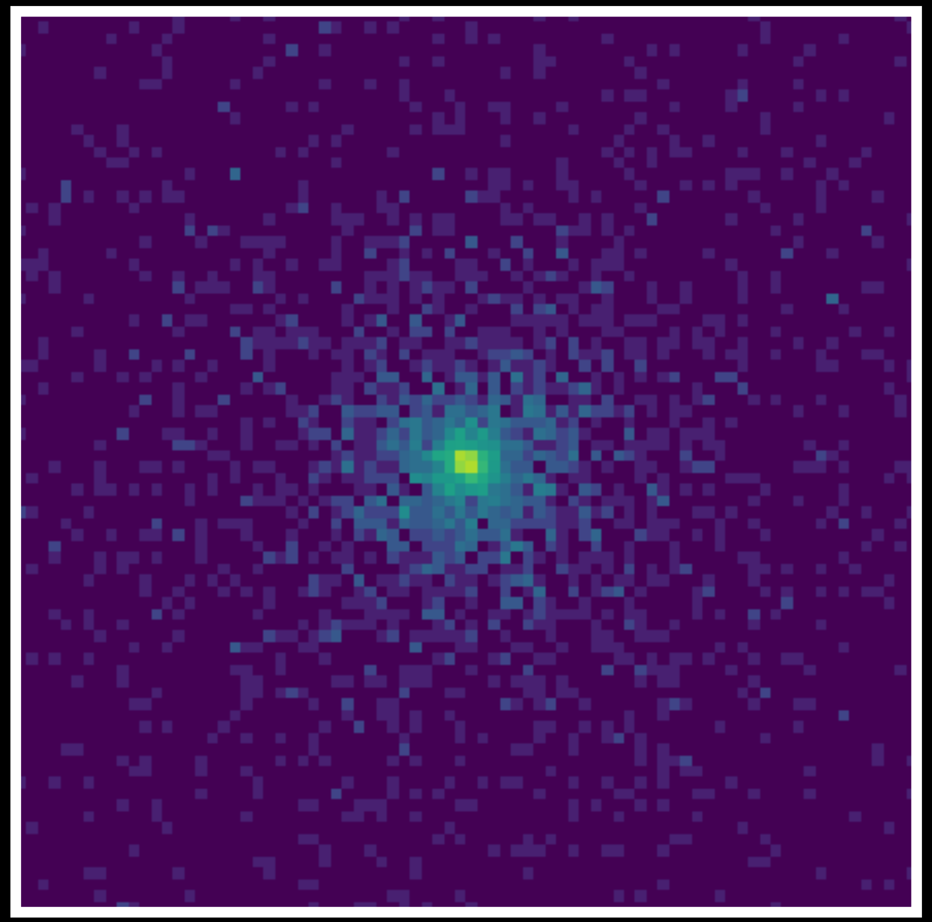

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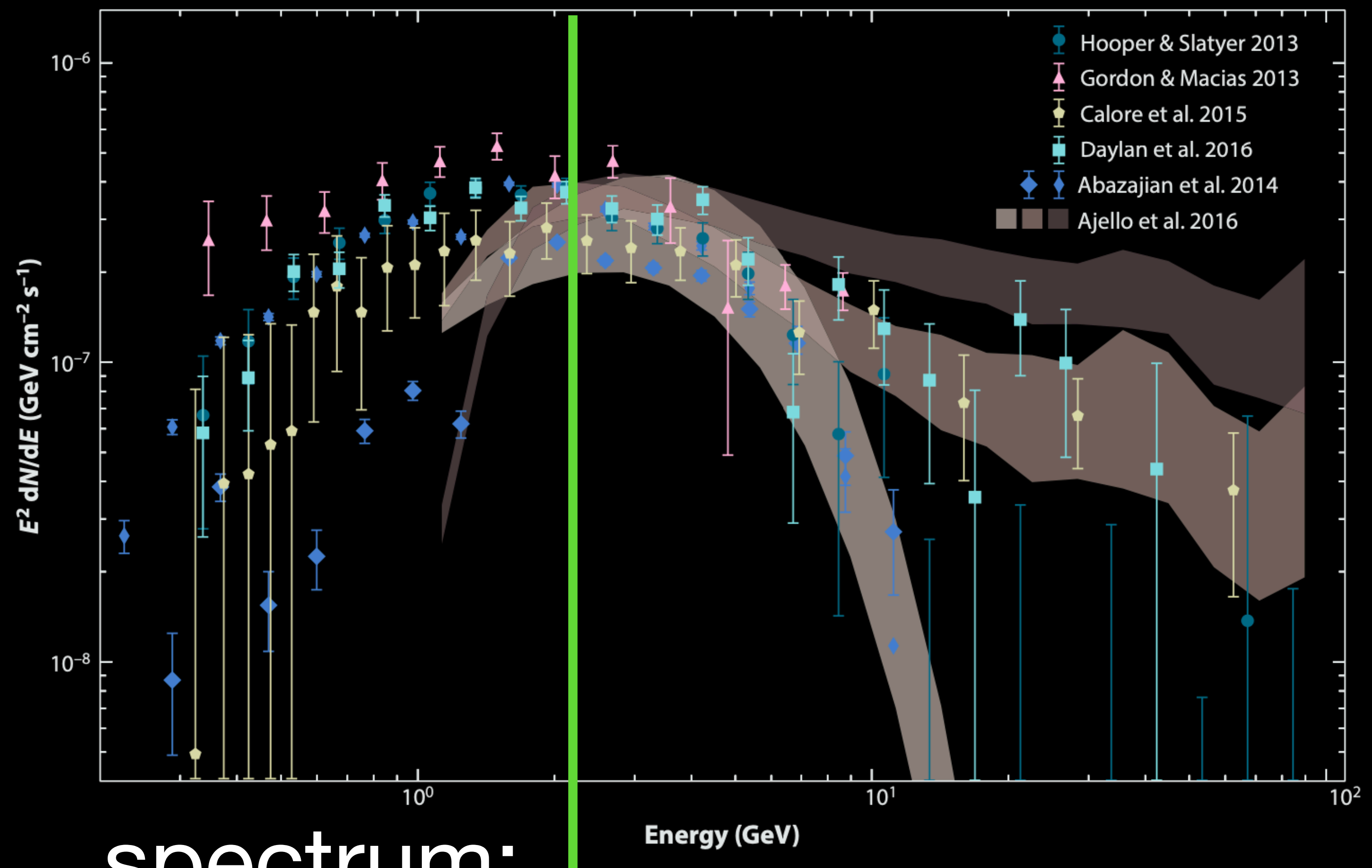


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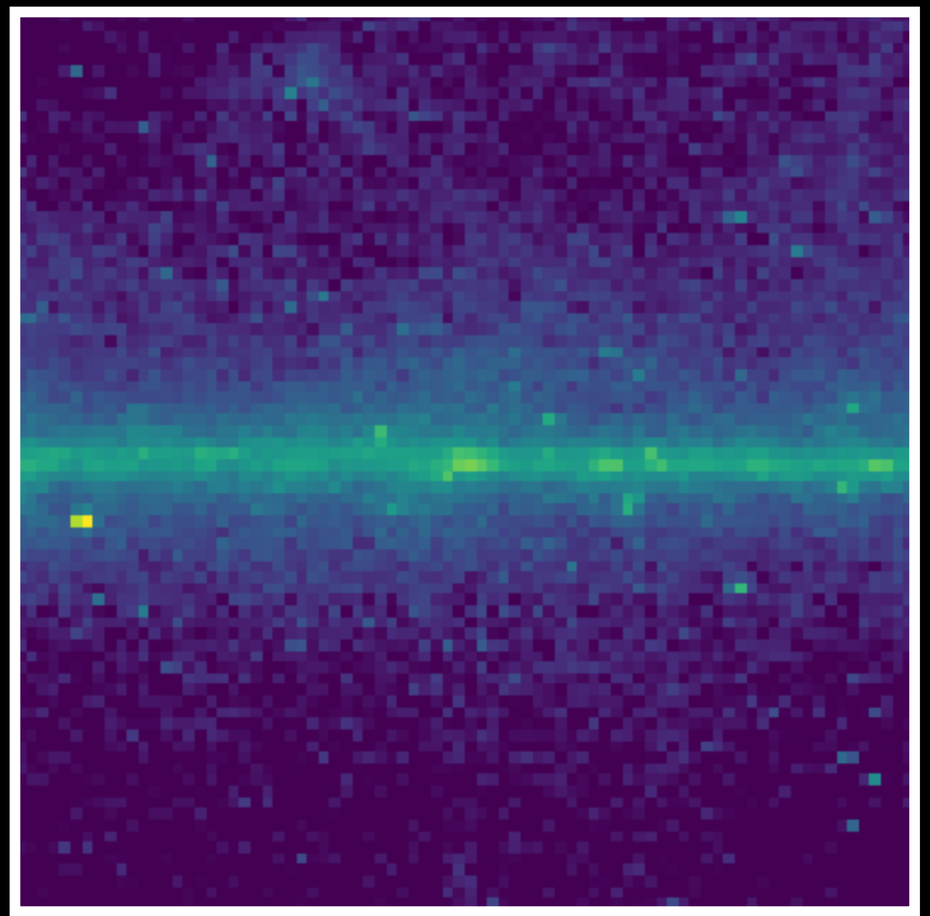

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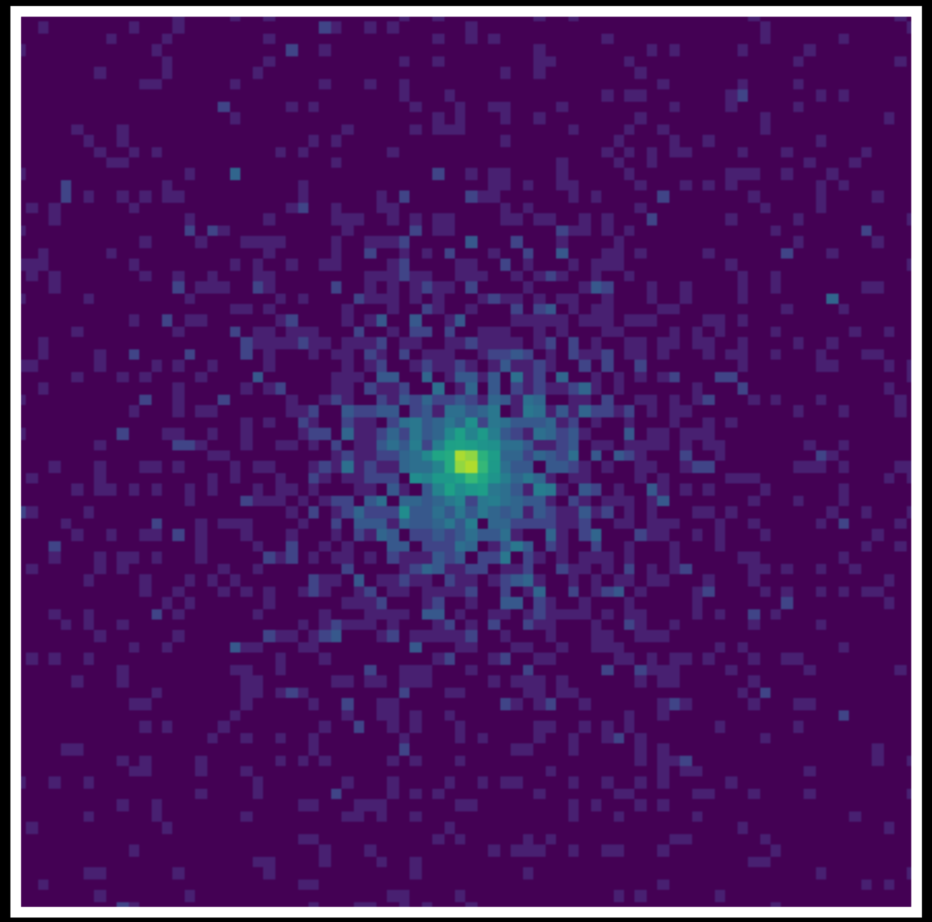

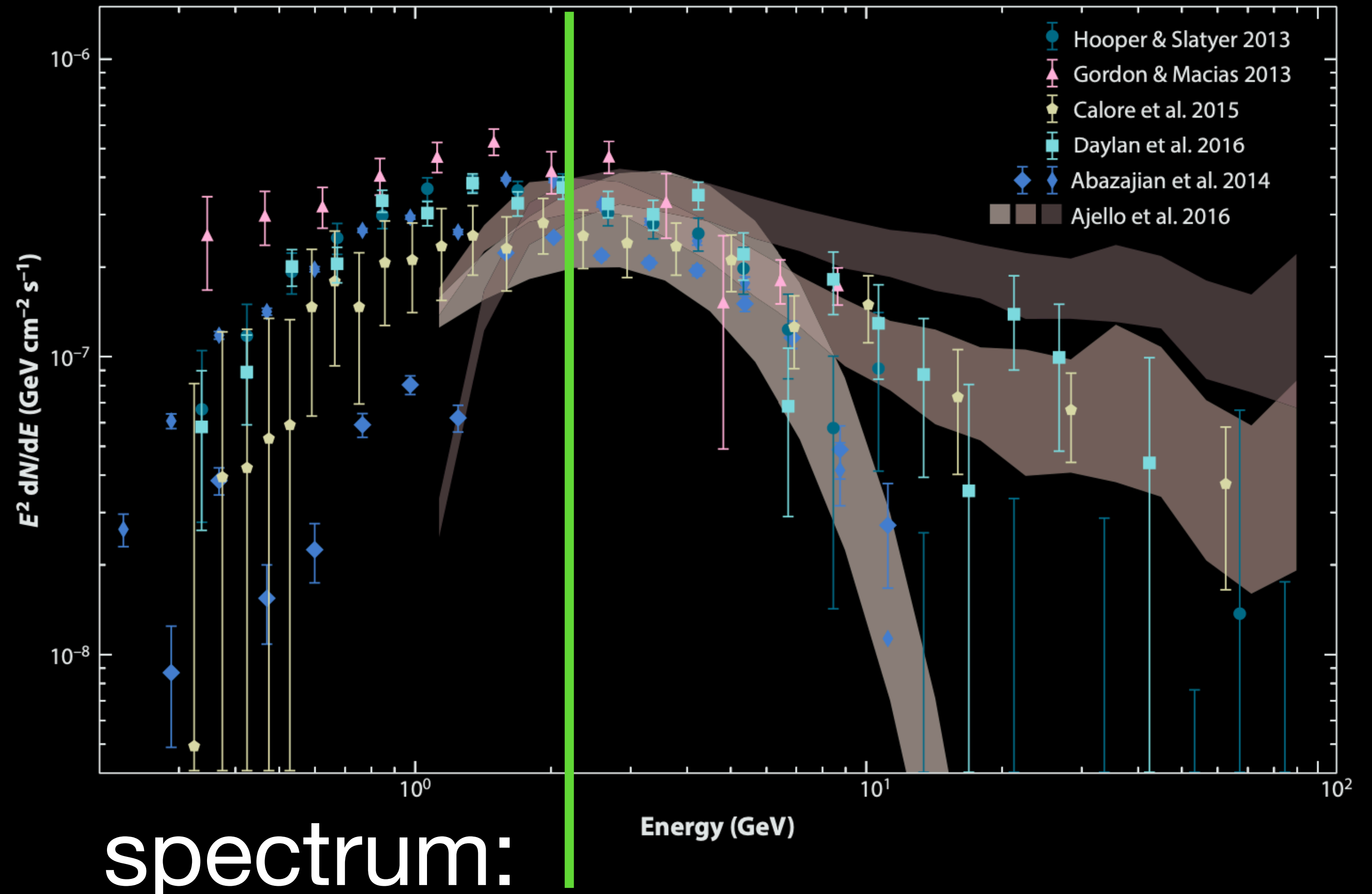


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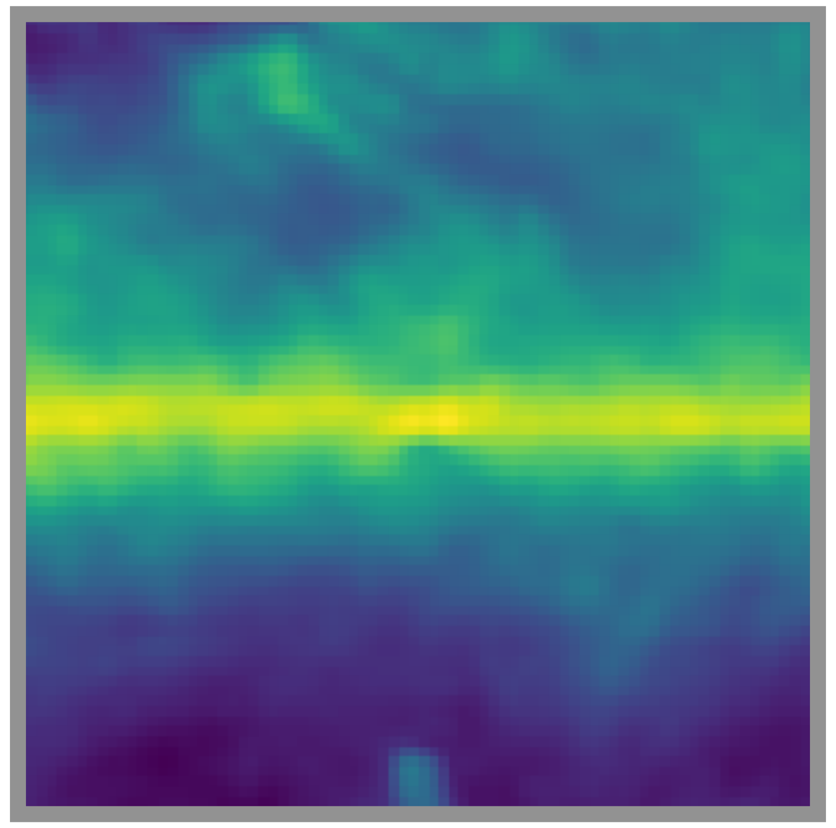
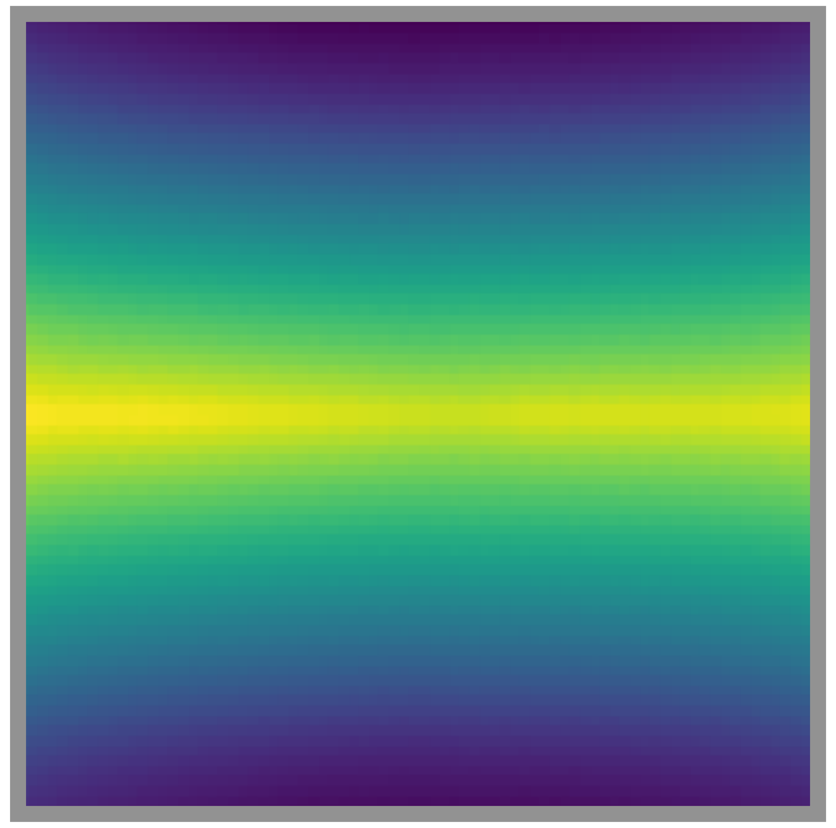
$\pi^0$ + bremsstrahlung



inverse Compton scattering



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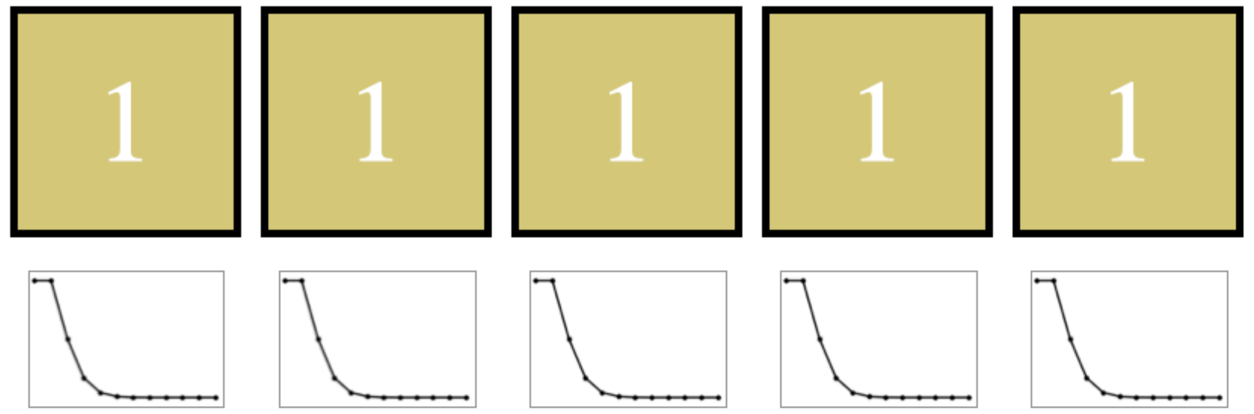

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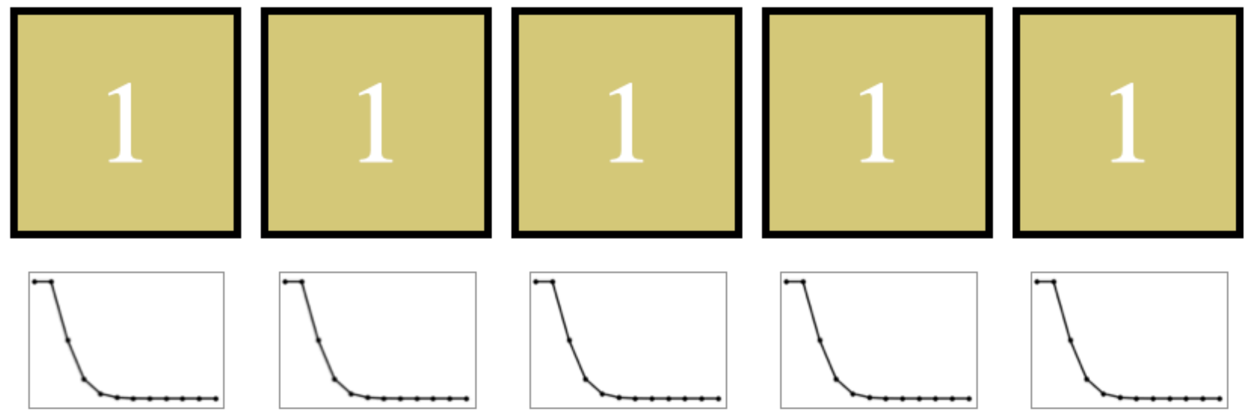
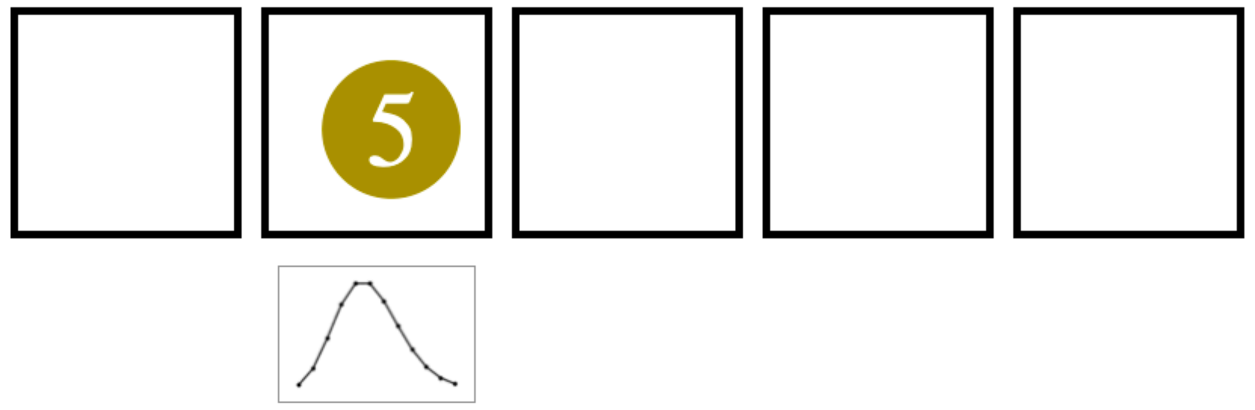



Unresolved point sources:



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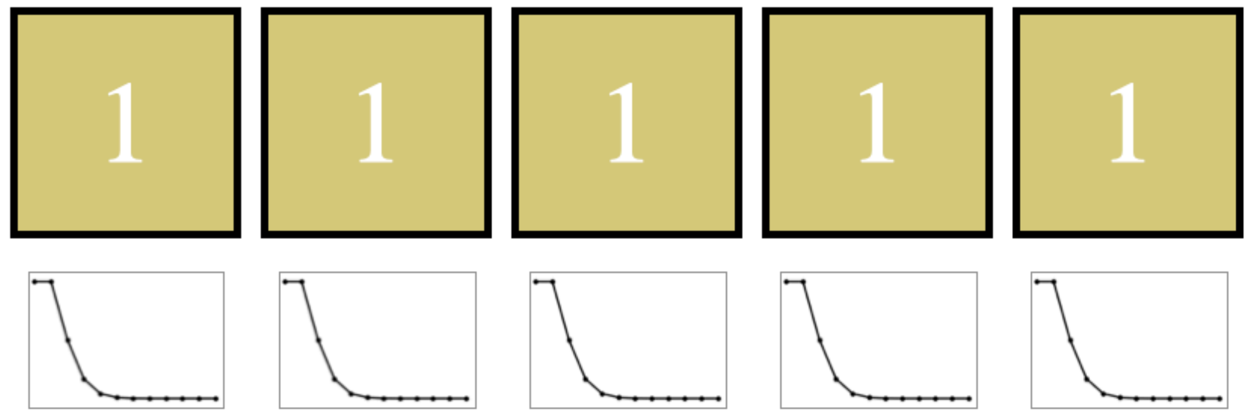


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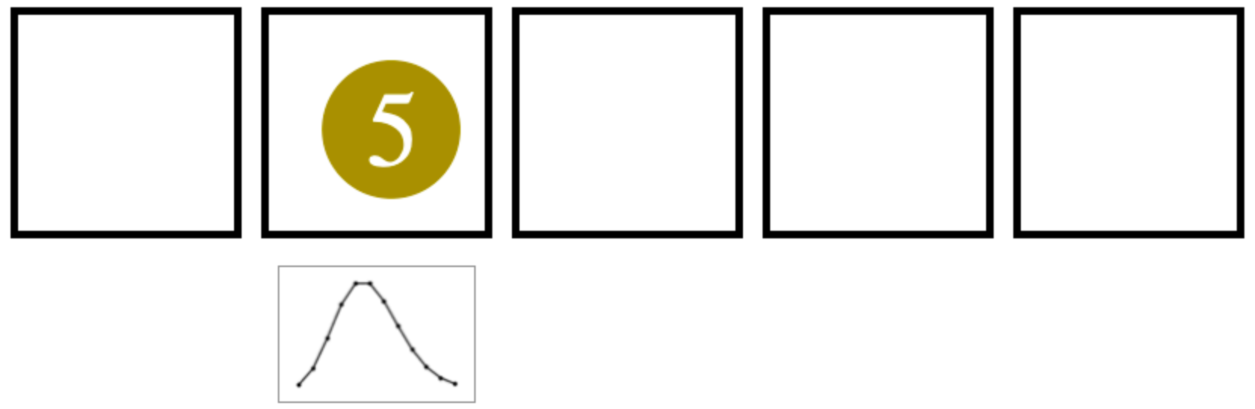


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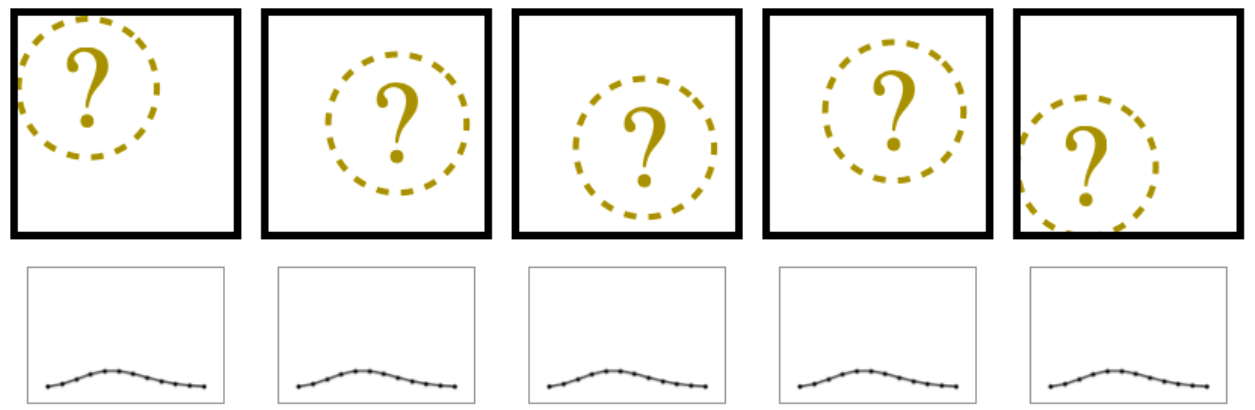

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Non-Poissonian Template Fitting is a likelihood (-based fitting method) that include unresolved point sources.

It achieves this by (implicitly) accounting for all the ways in which an observed count in a pixel is made up.

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diffuse #1 #2
point source

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$1 + 1 + 1$: diffuse, #1, #2 point source

$1 + 2$: diffuse, #1 point source

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- $1 + 1 + 1$: diffuse, #1 and #2 point source
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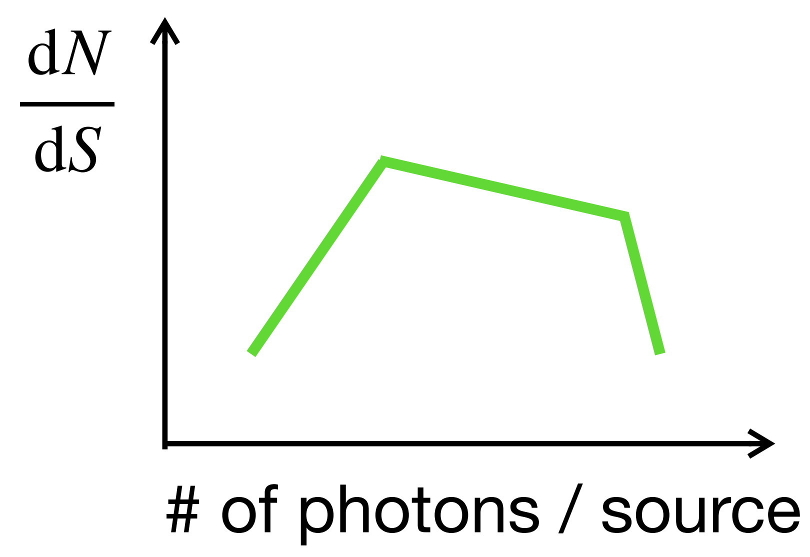
marginalized over all the ways this photon count can be obtained, e.g. the source count distribution:



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Likelihood from different pixels are still independent.

# Non-Poissonian Template Fitting with PSF

with point spread function (PSF)

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$D \sim \mathrm{Pois}\left( \mathrm{PSF}\left[ \sum S_i \Phi_i(x) \right] \right)$

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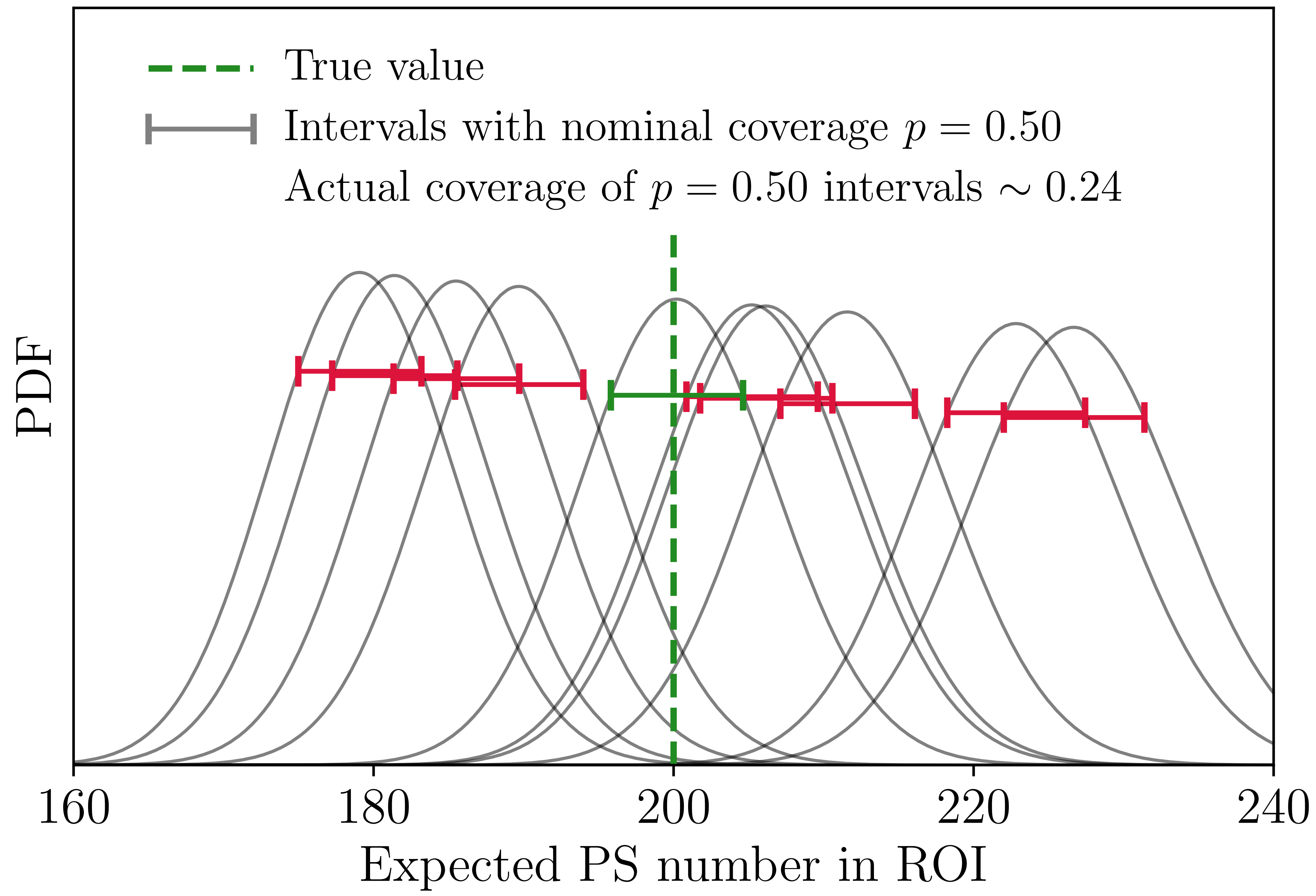
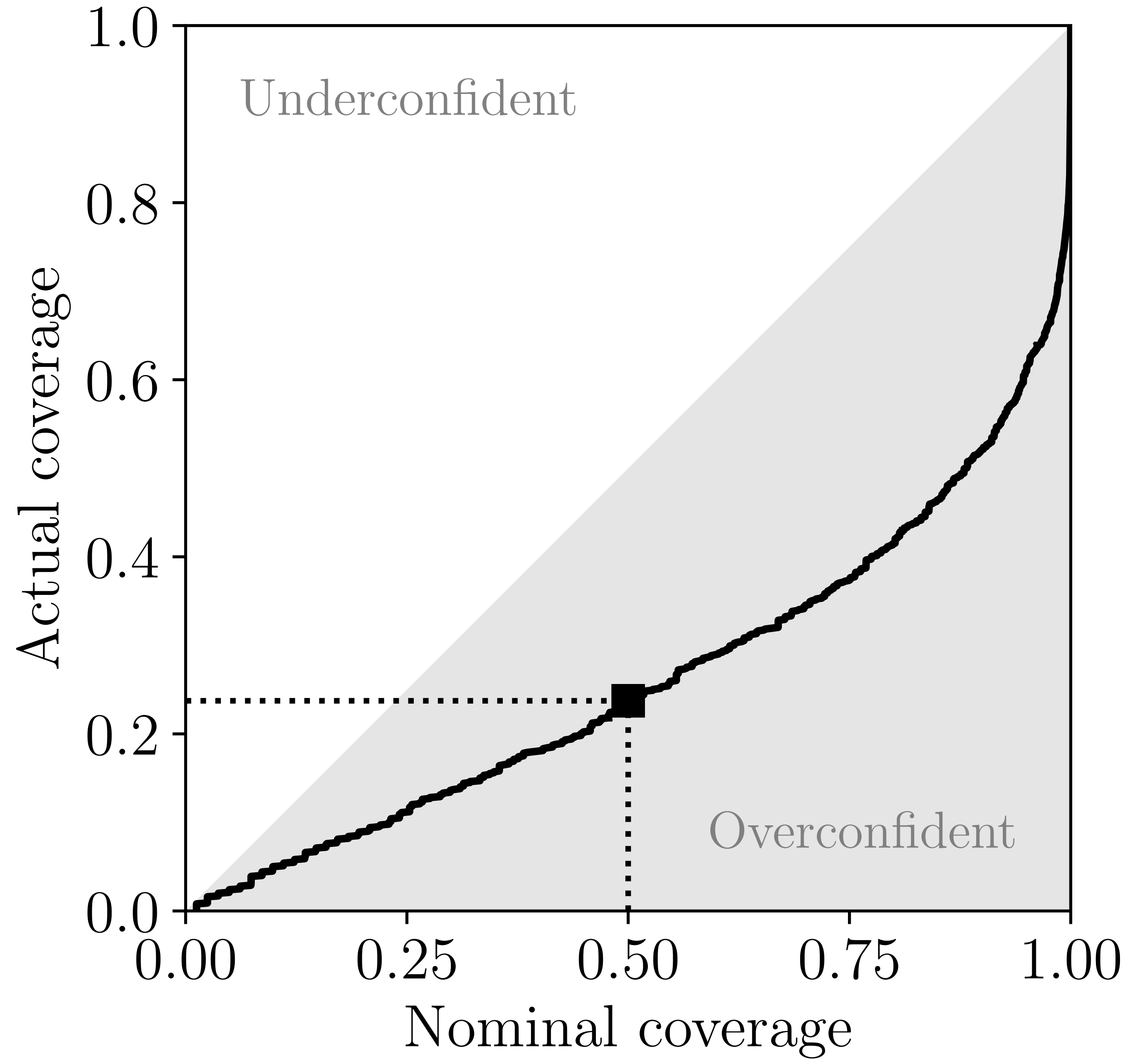
How reliable are the posteriors produced from this likelihood?

# An overconfident fit under the coverage test

Example: fits to many simulations



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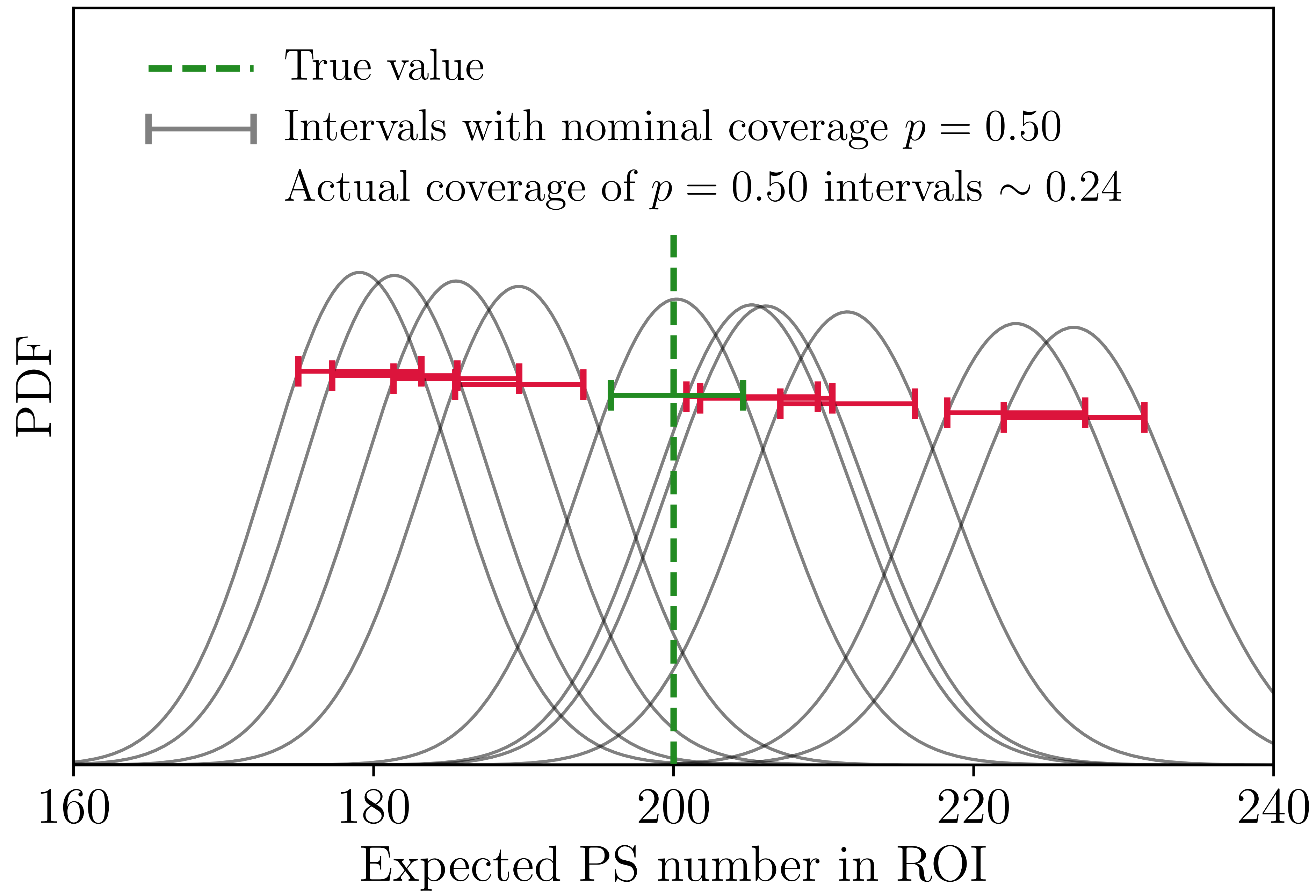
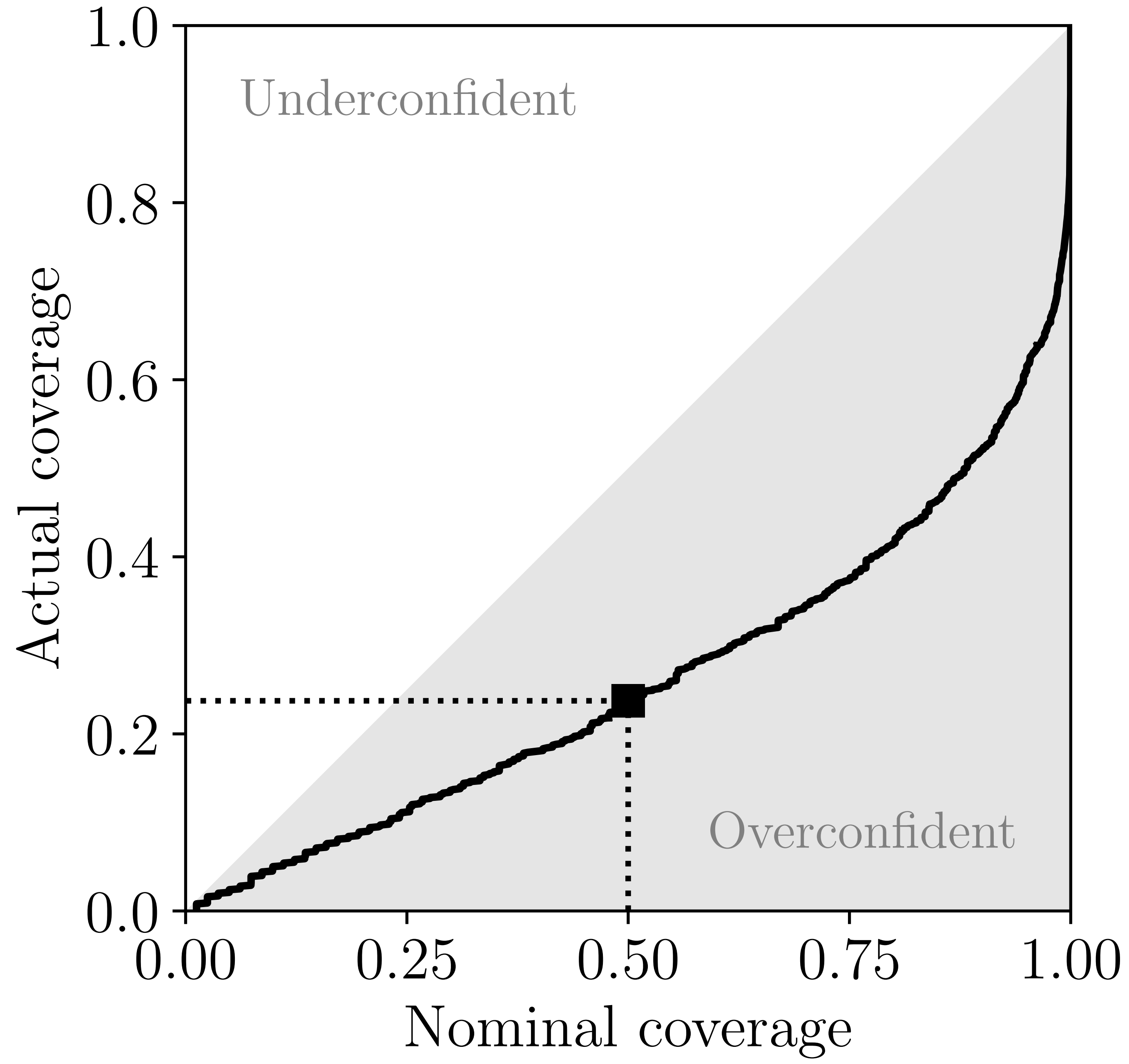
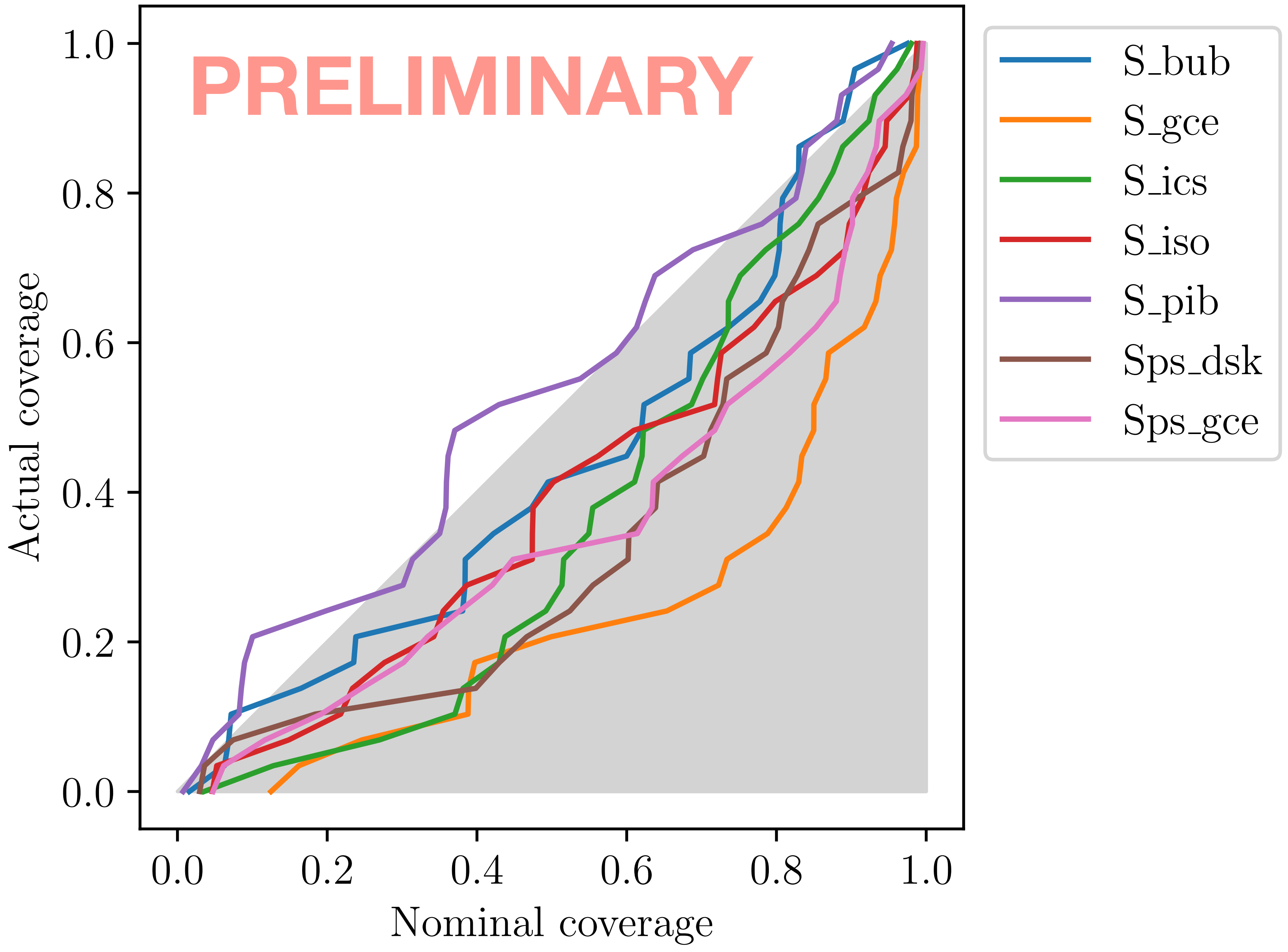



An example fit of the galactic center:



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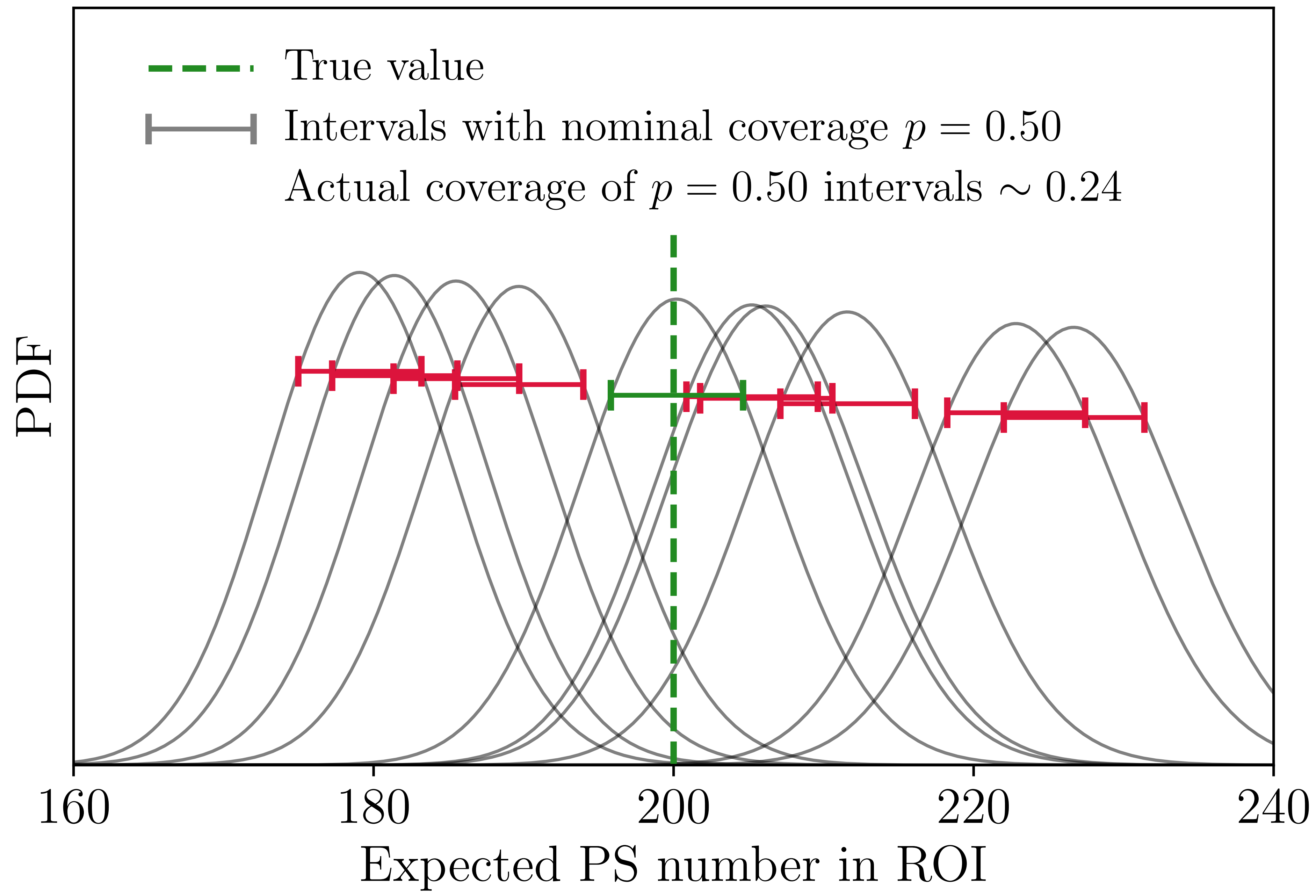


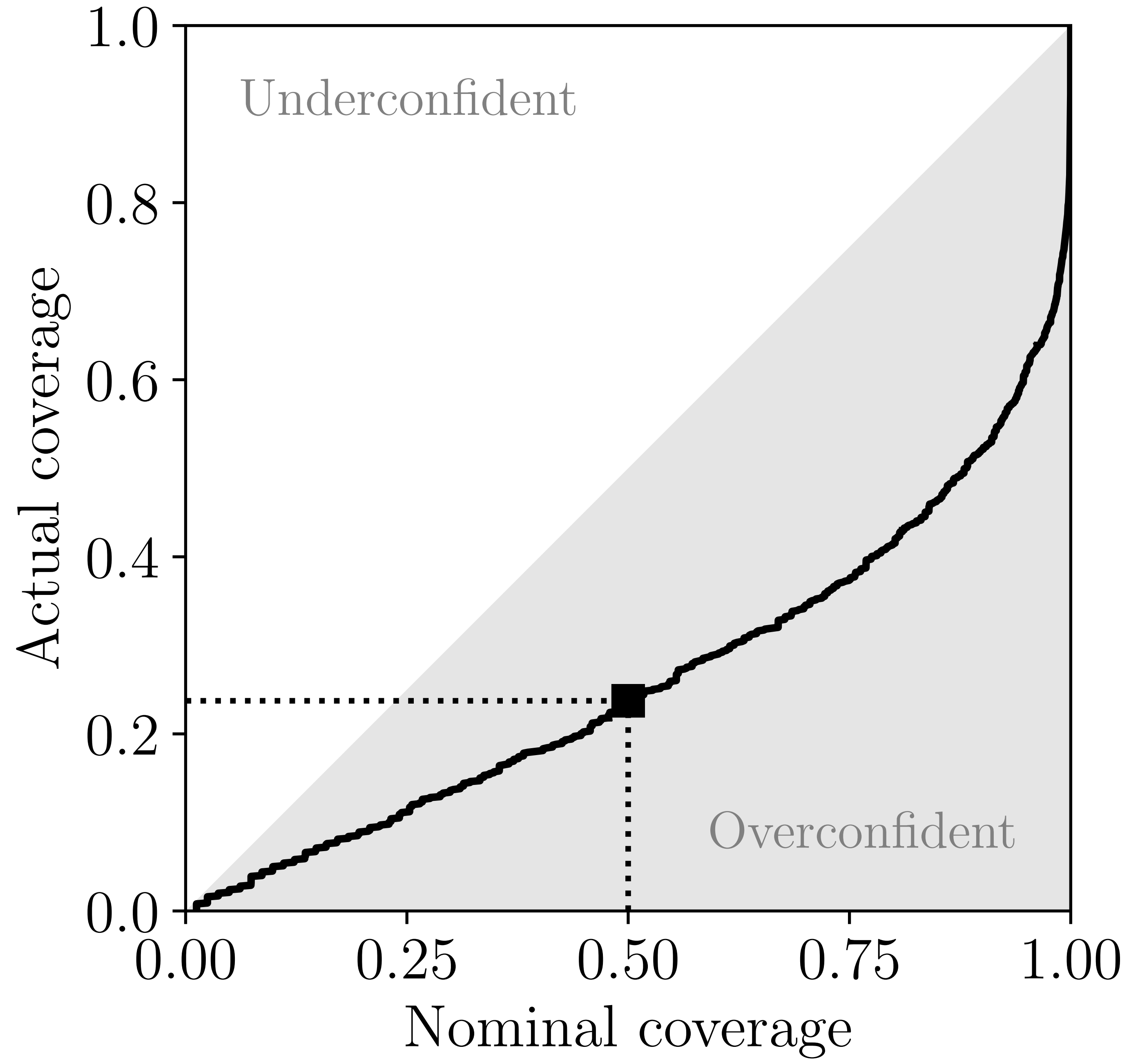


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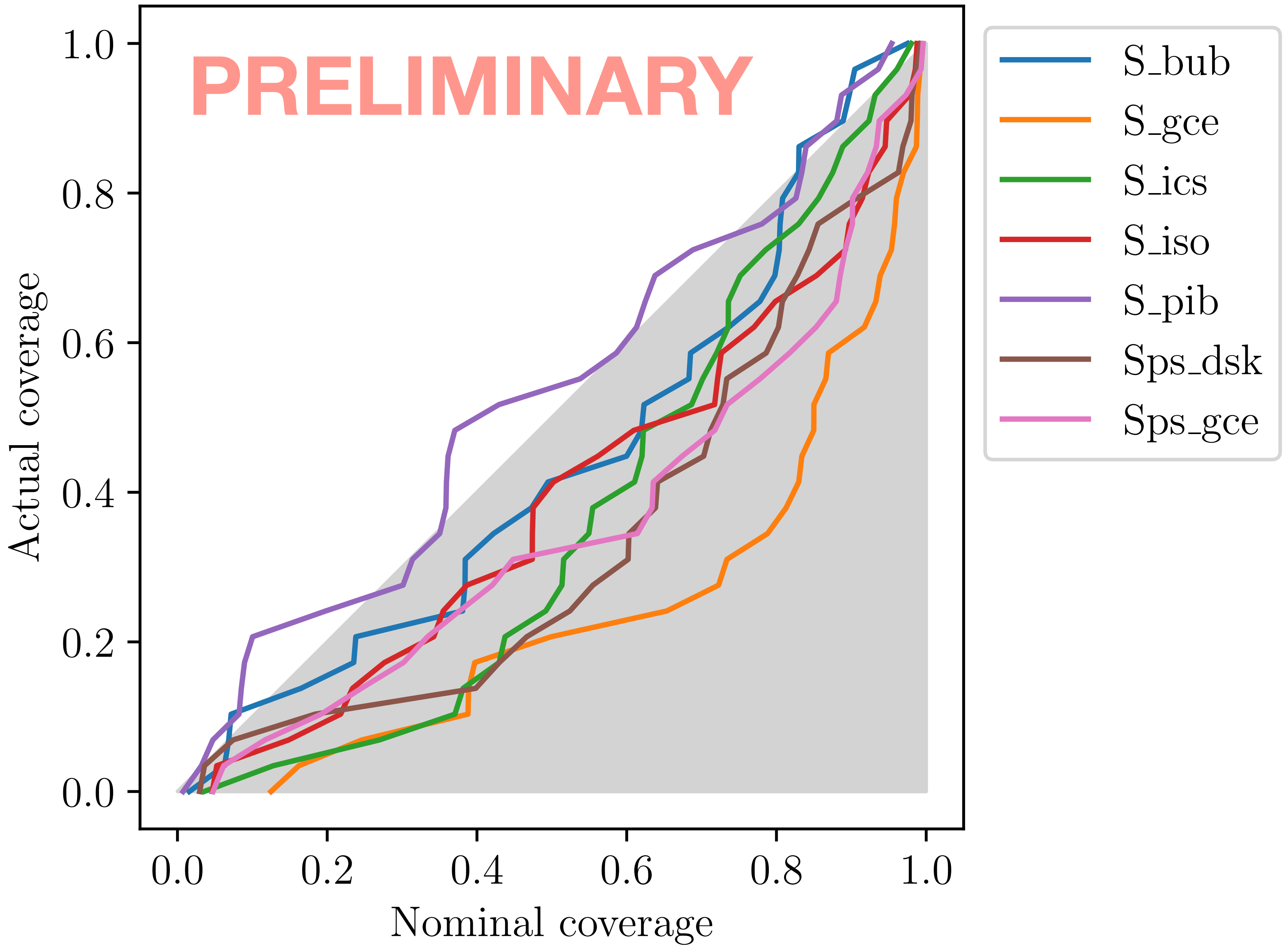


Pointed out in Collin et al 2018

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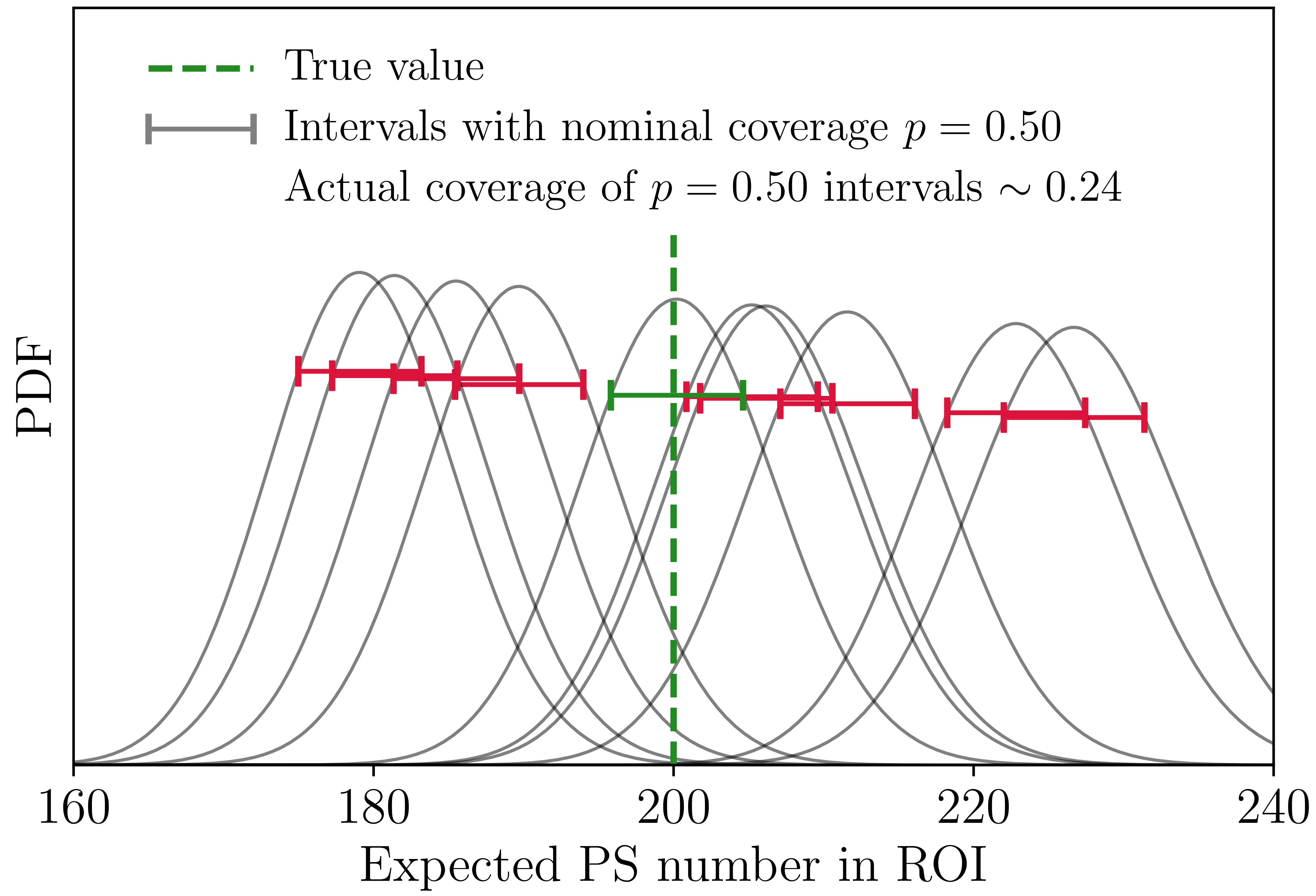


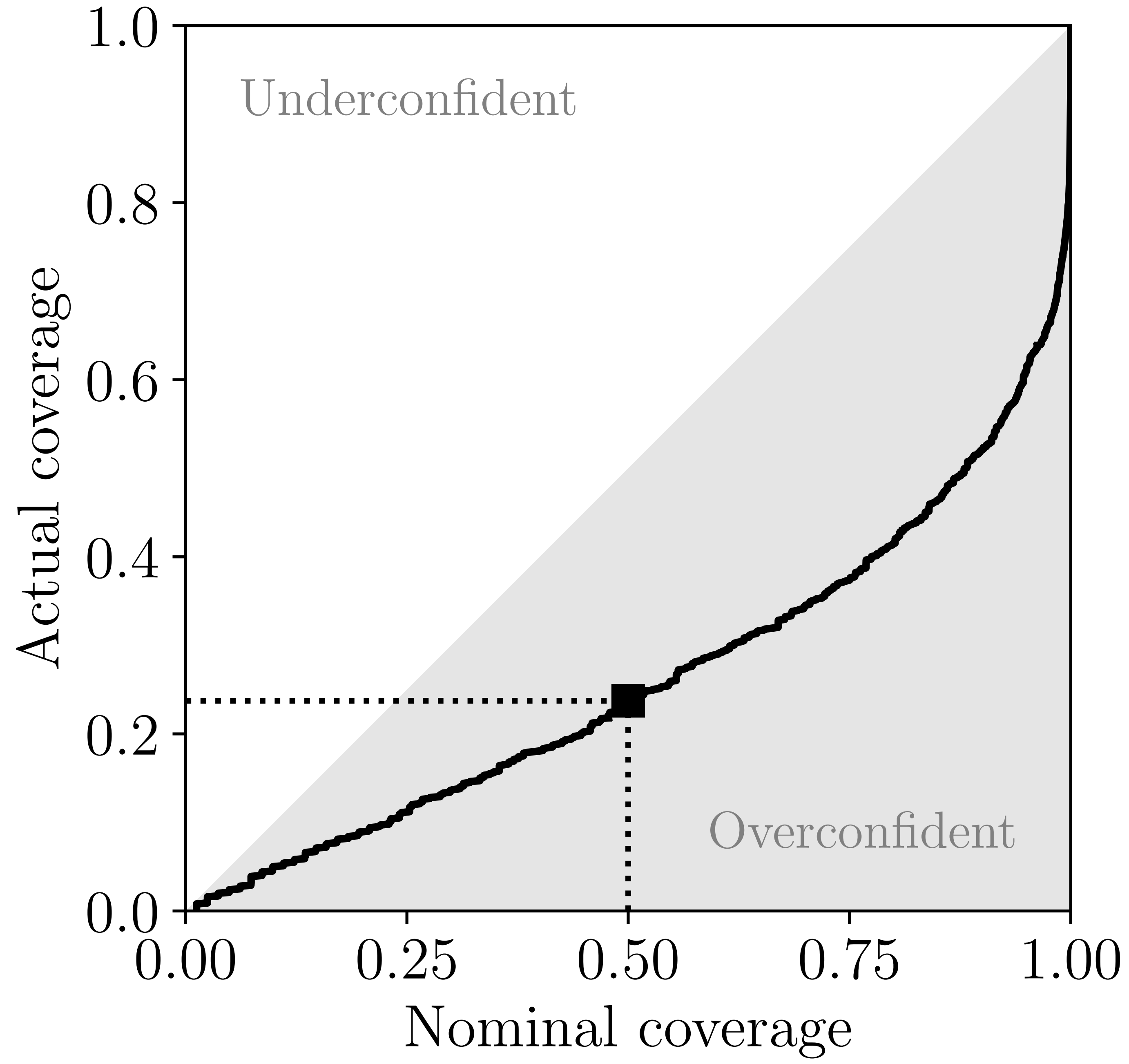


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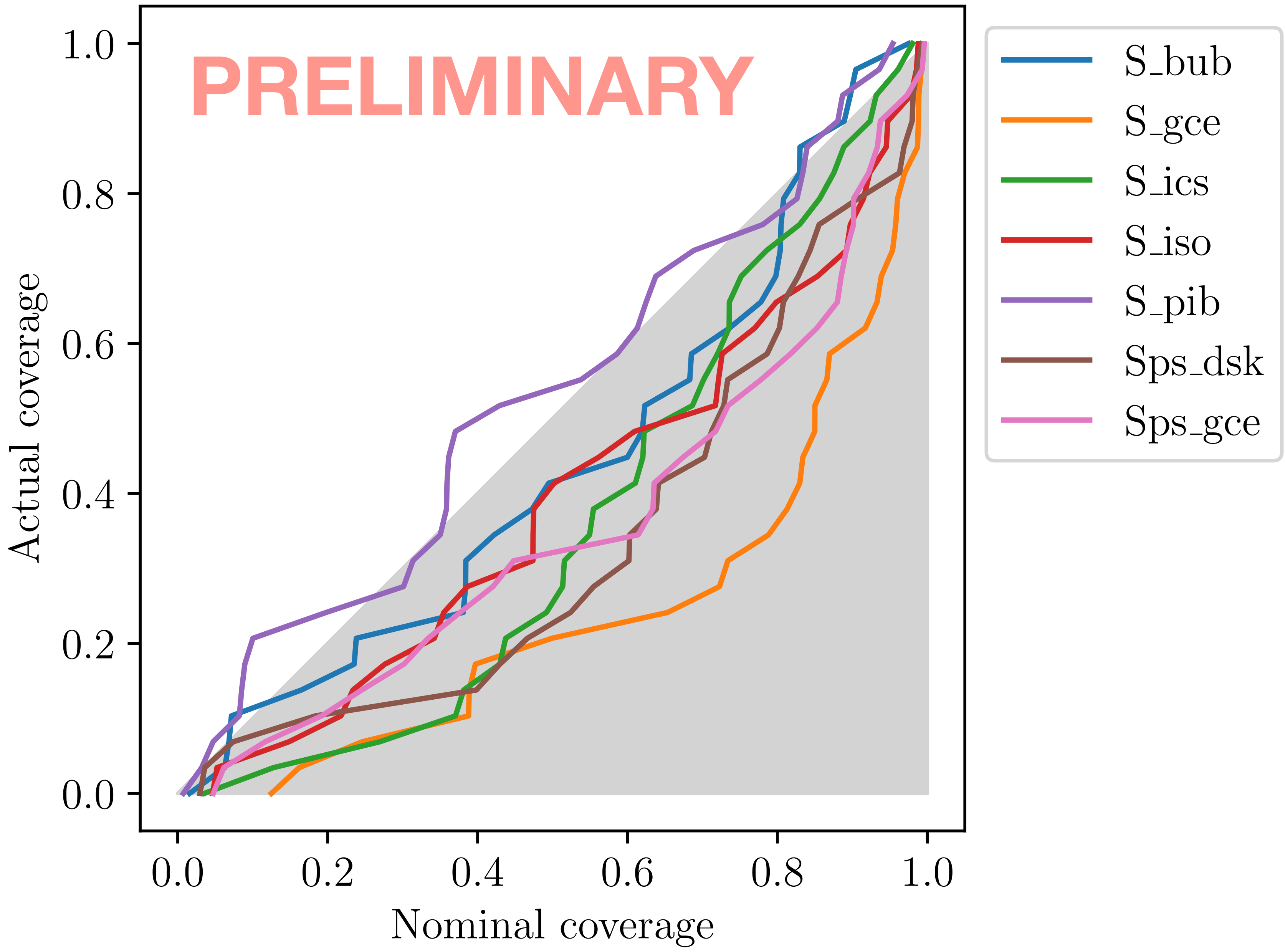



Pointed out in Collin et al 2018

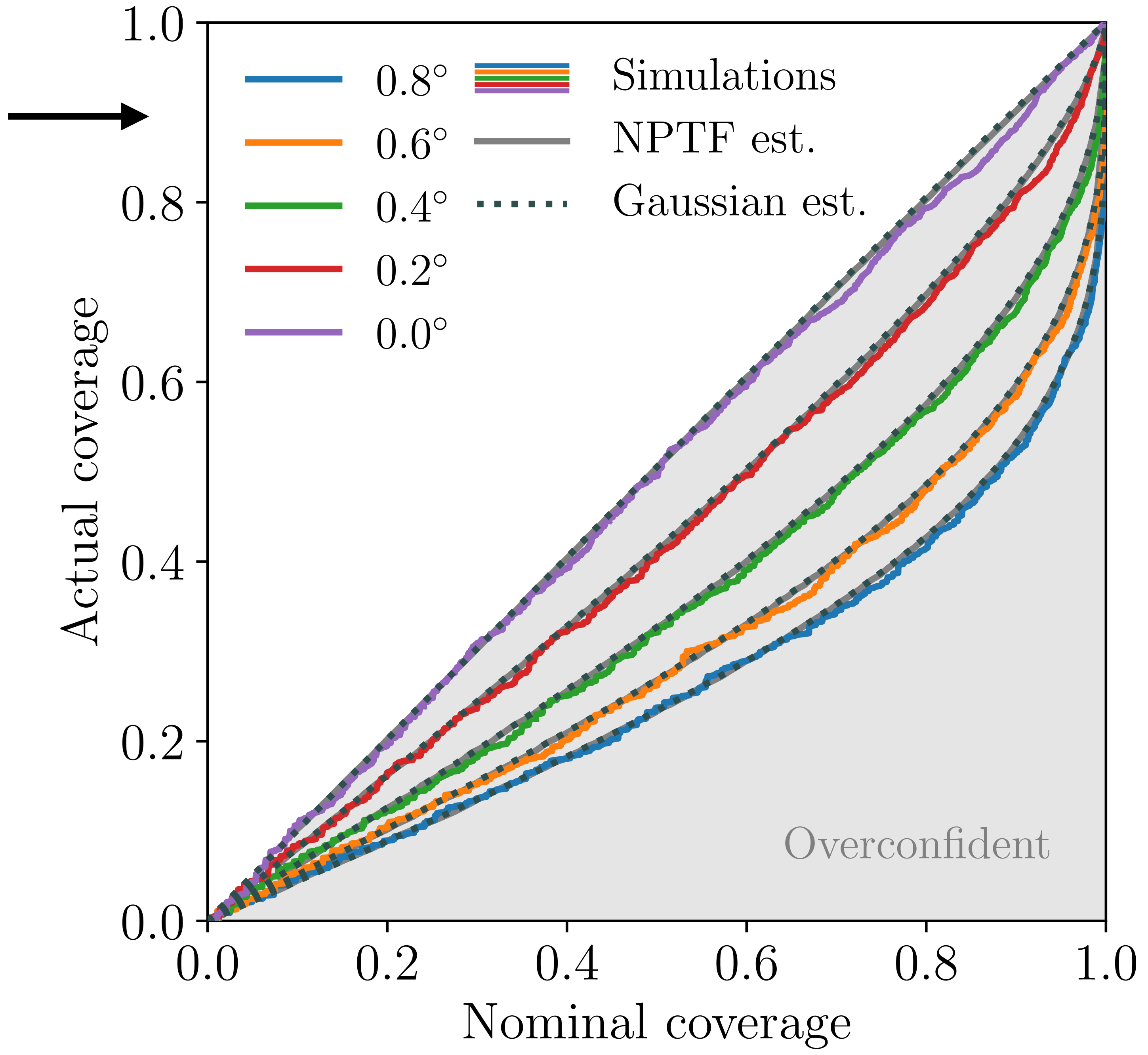
For this talk, I will focus on one of sources of NPTF's overconfidence: un-modeled inter-pixel correlations.

# A toy example: a single uniform population of PS

We fit for overall normalization, against simulated data, to test coverage.

PSF $\sigma = 0.8^\circ$ $\sigma = 0.6^\circ$ $\sigma = 0.4^\circ$ $\sigma = 0.2^\circ$ $\sigma = 0.0^\circ$

coverage



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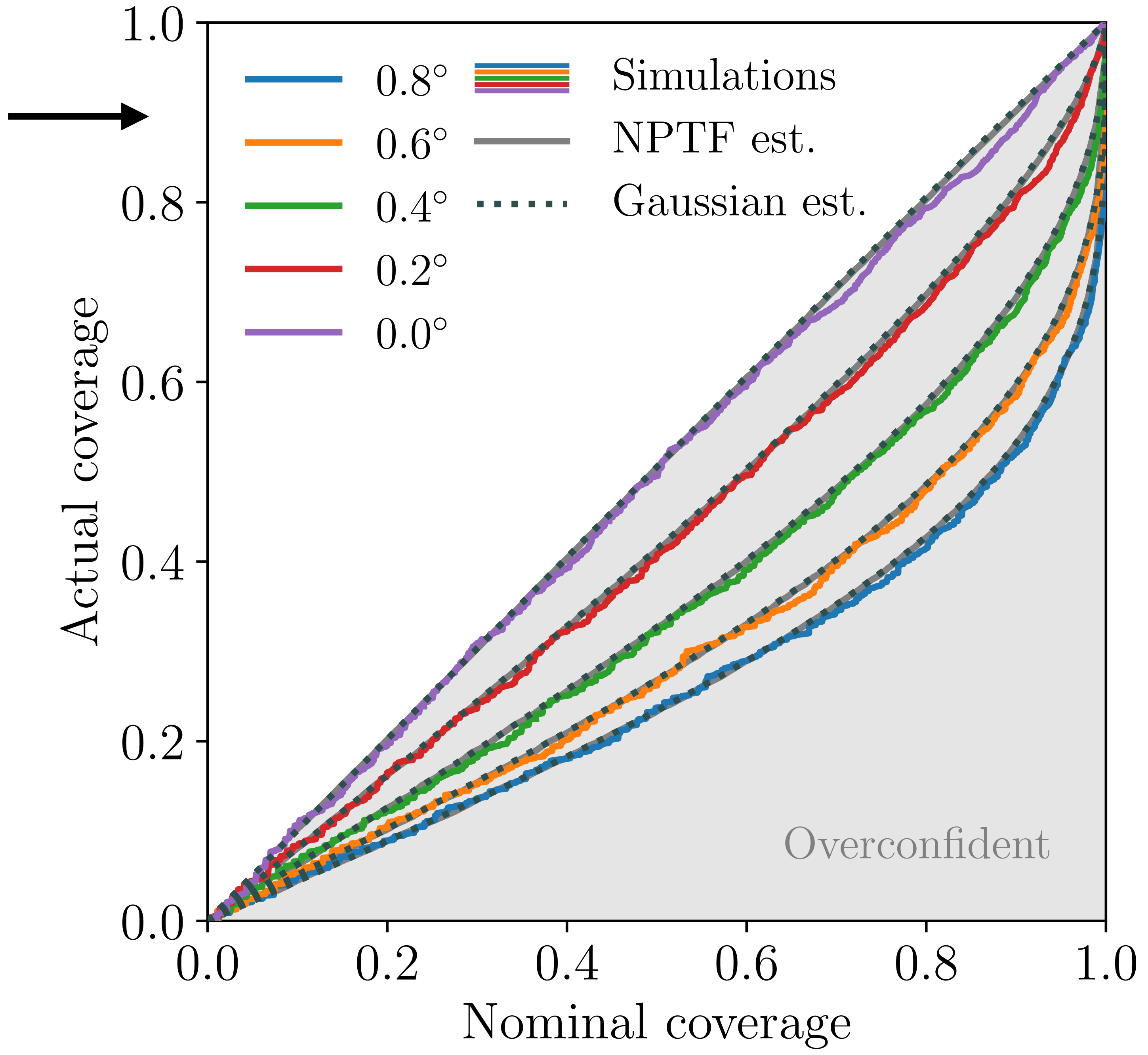


With a single template, fitted normalization ~ total count.

Total count likelihood given by NPTF is overconfident!

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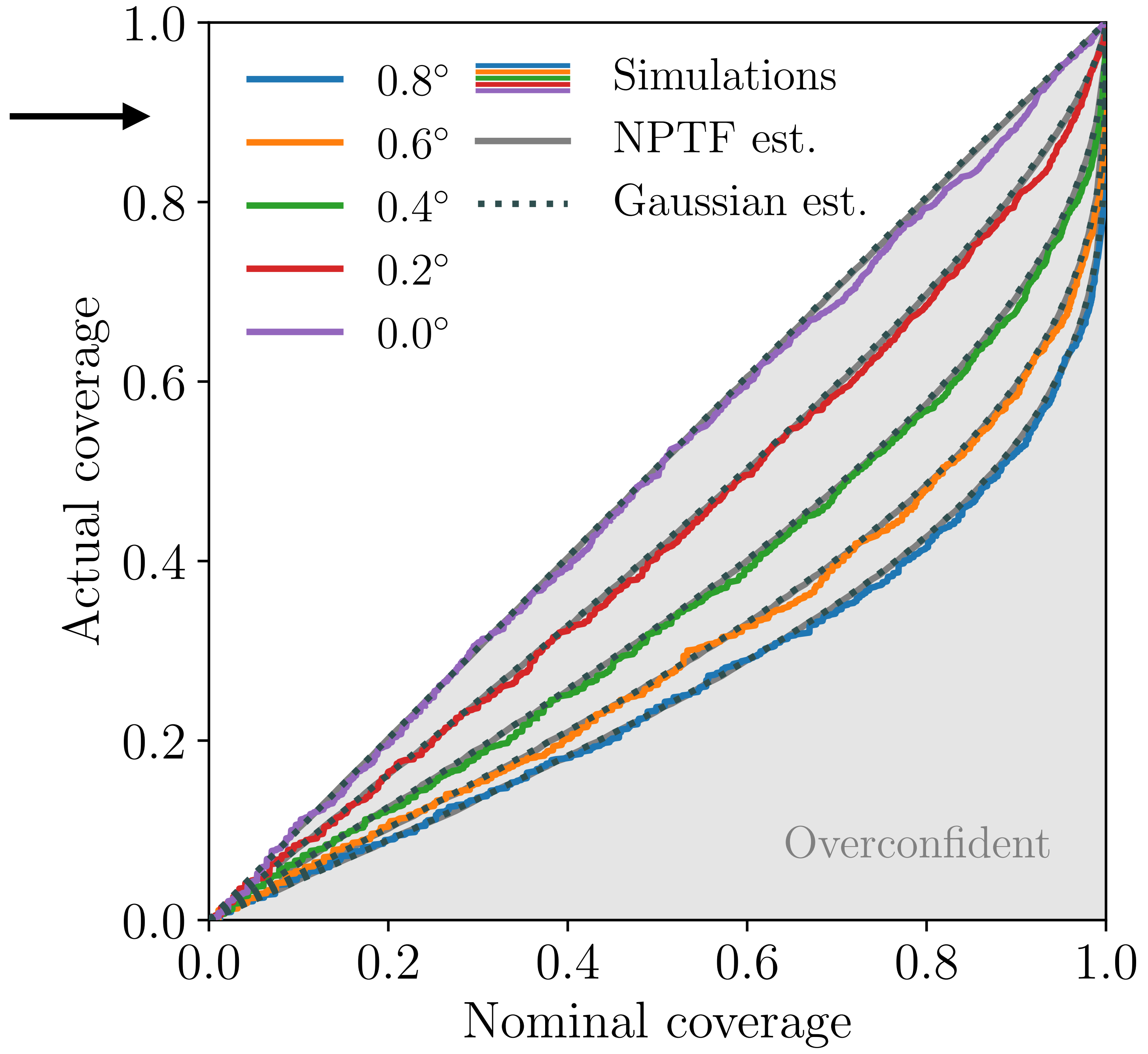


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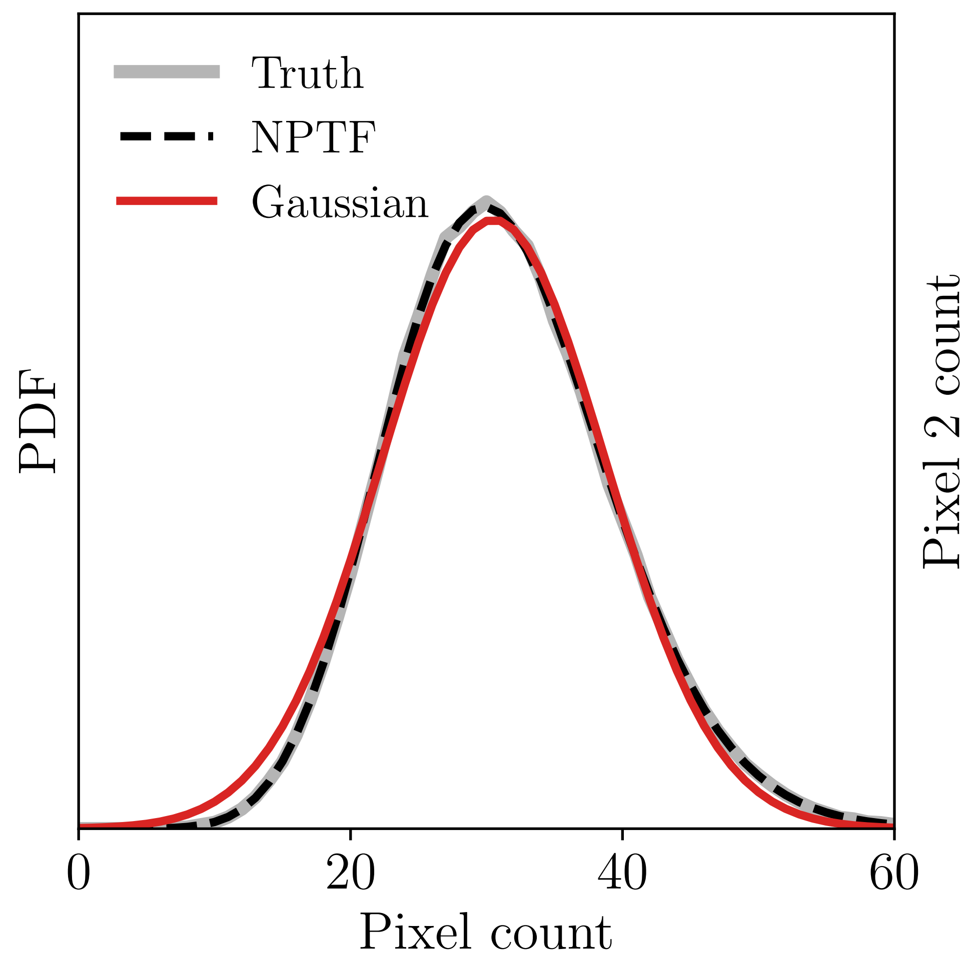
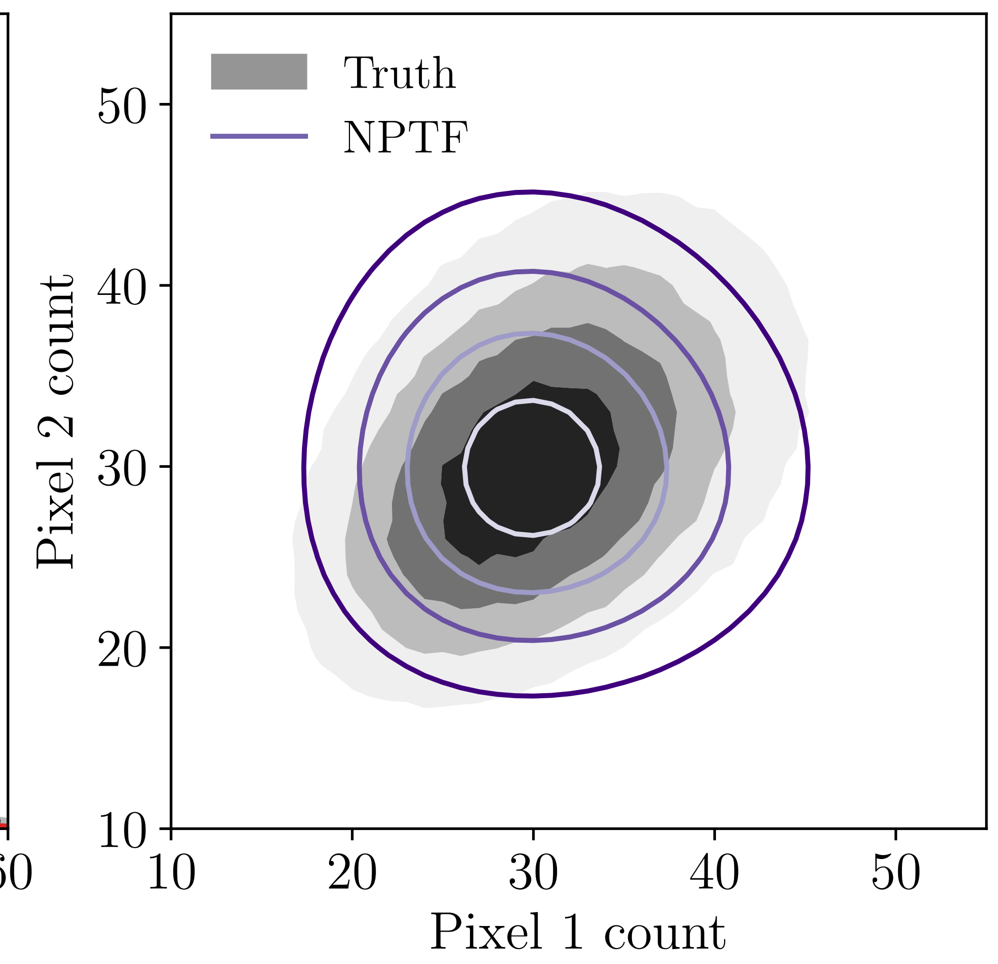
1-pixel (marginal) likelihood




2-pixel joint likelihood



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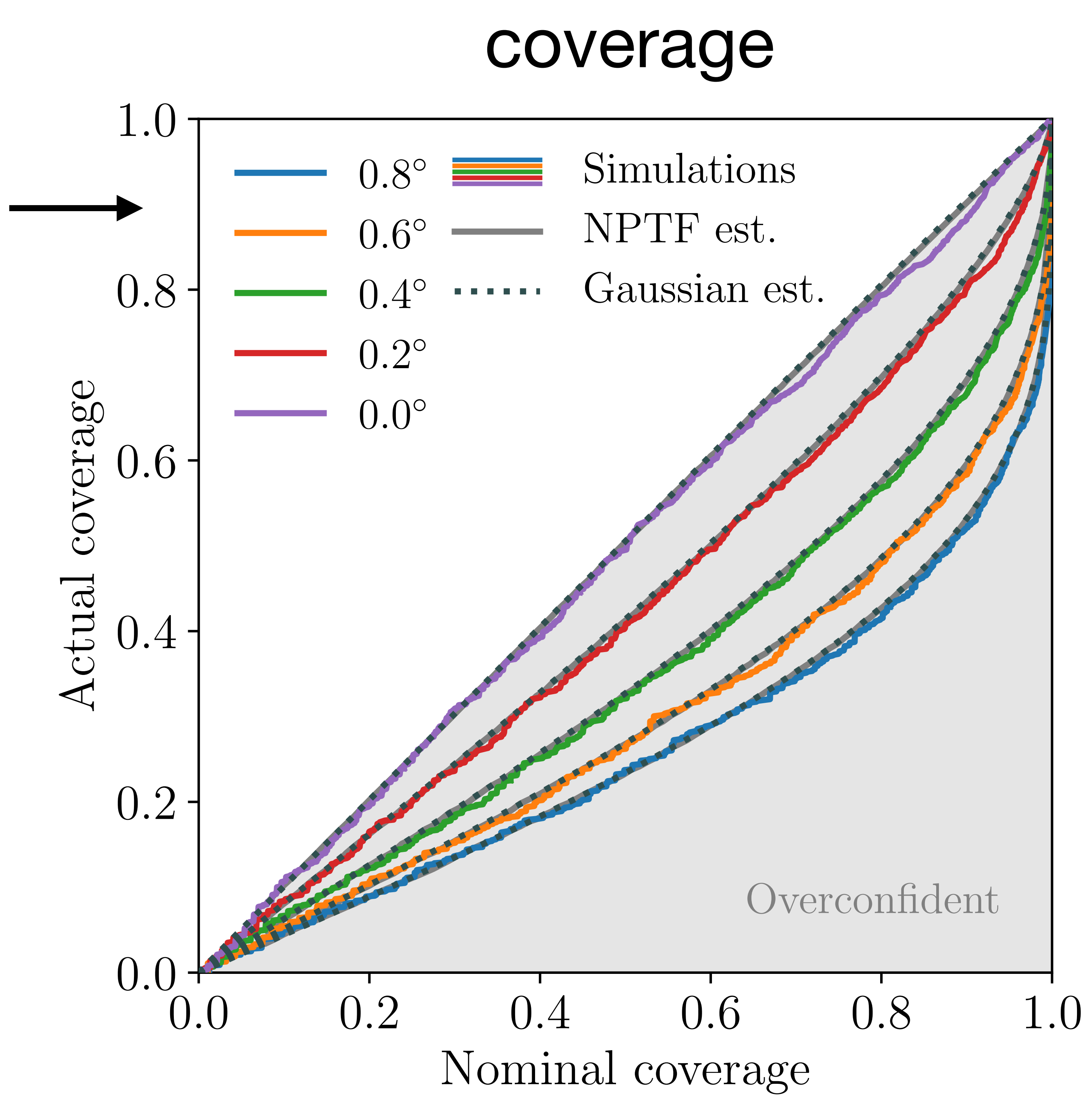


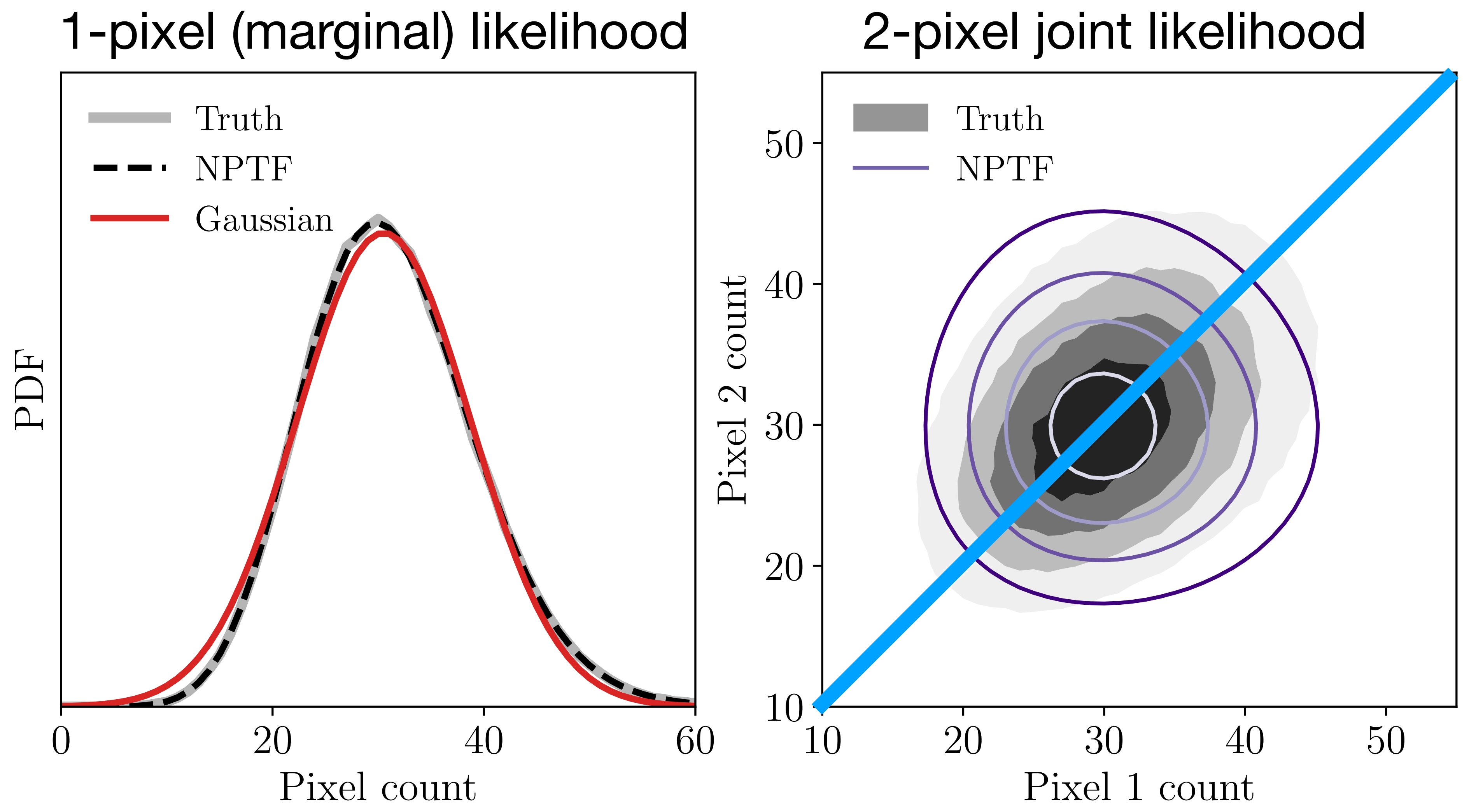


Total count ~ marginalization in the diagonal direction

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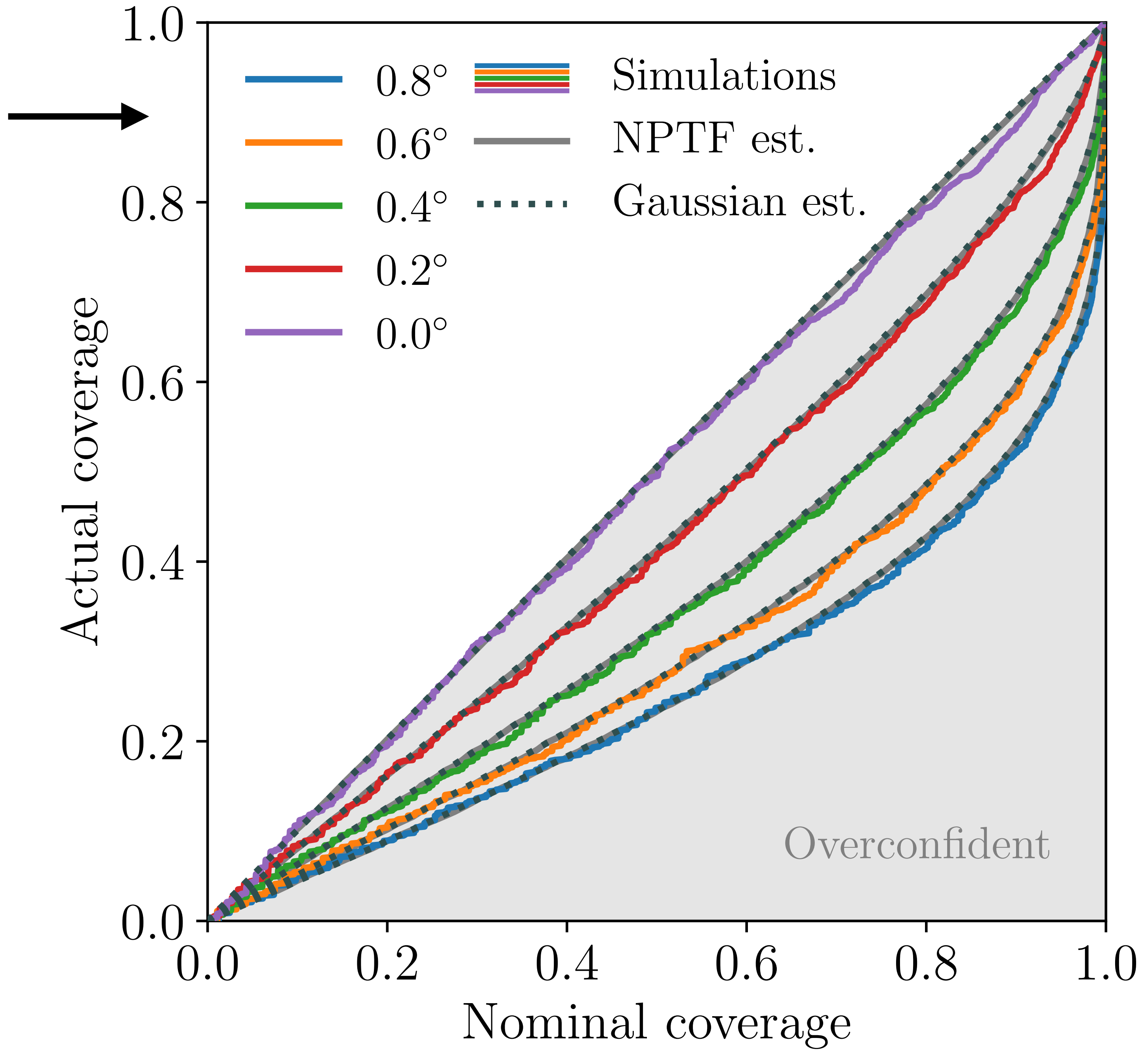


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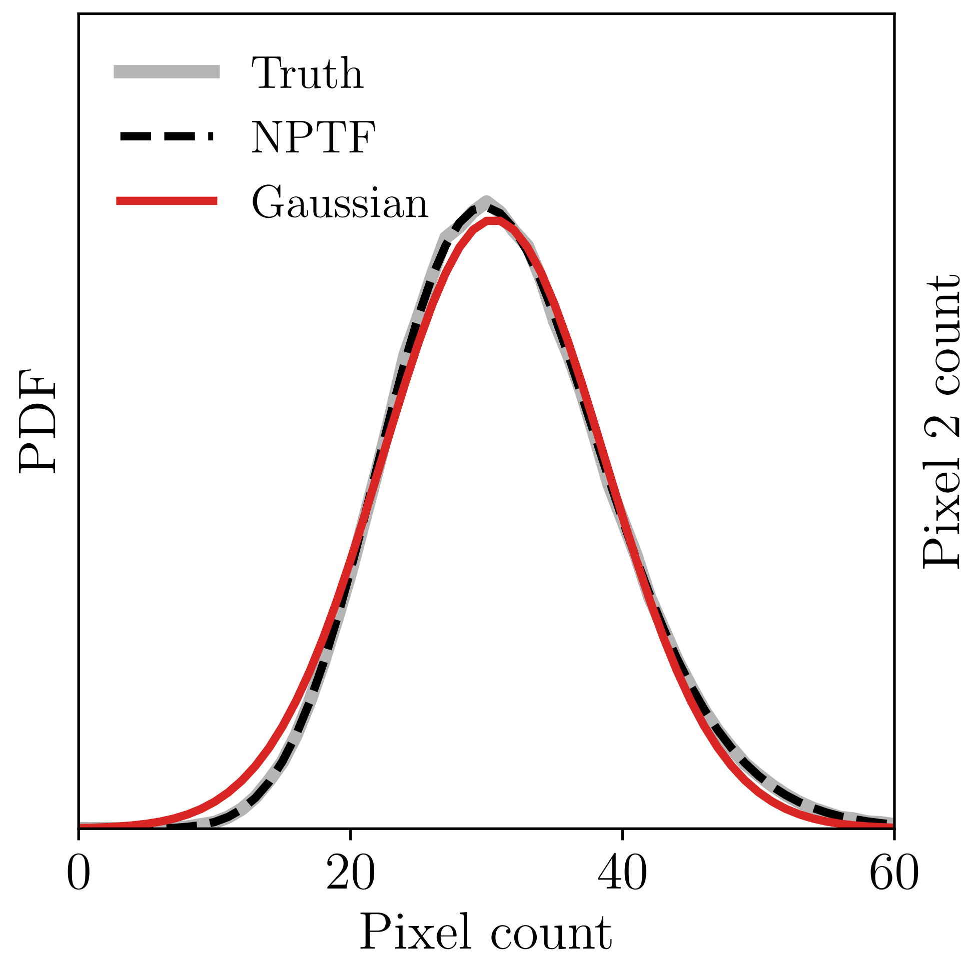


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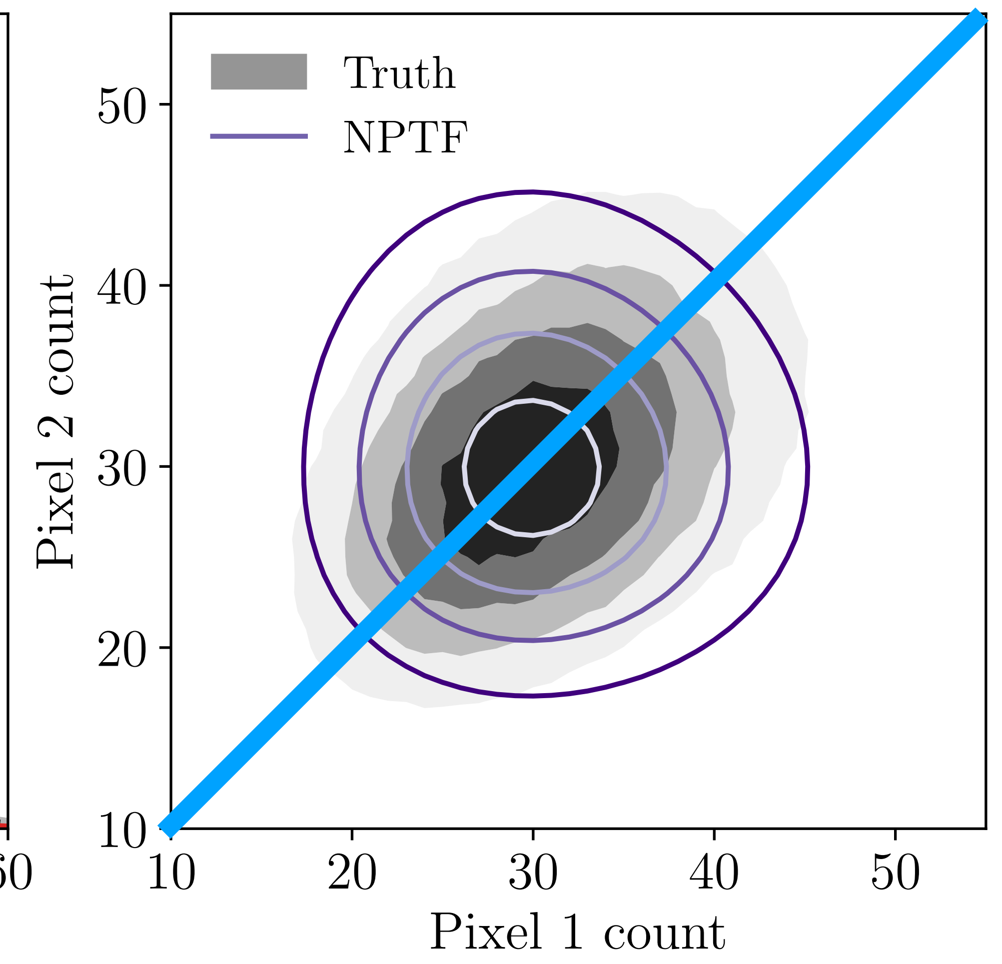


Total count ~ marginalization in the diagonal direction

Un-modeled positive correlation -> overconfidence!

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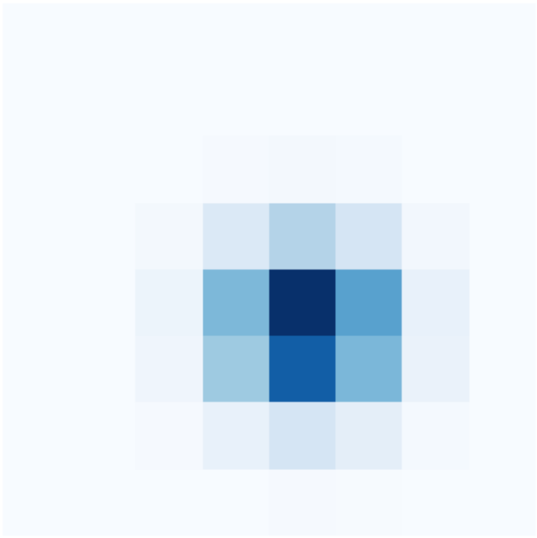
We fit for overall normalization, against simulated data, to test coverage.

PSF $\sigma = 0.8^\circ$ simulation

PSF of one source



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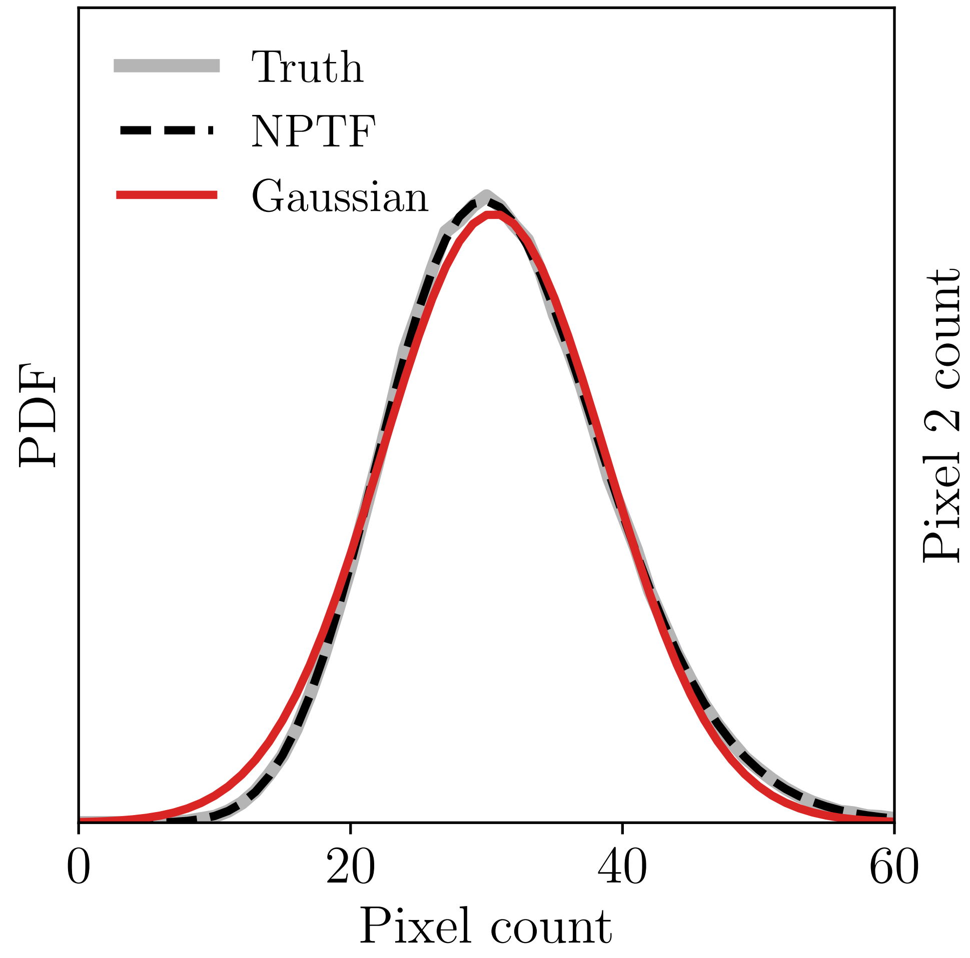


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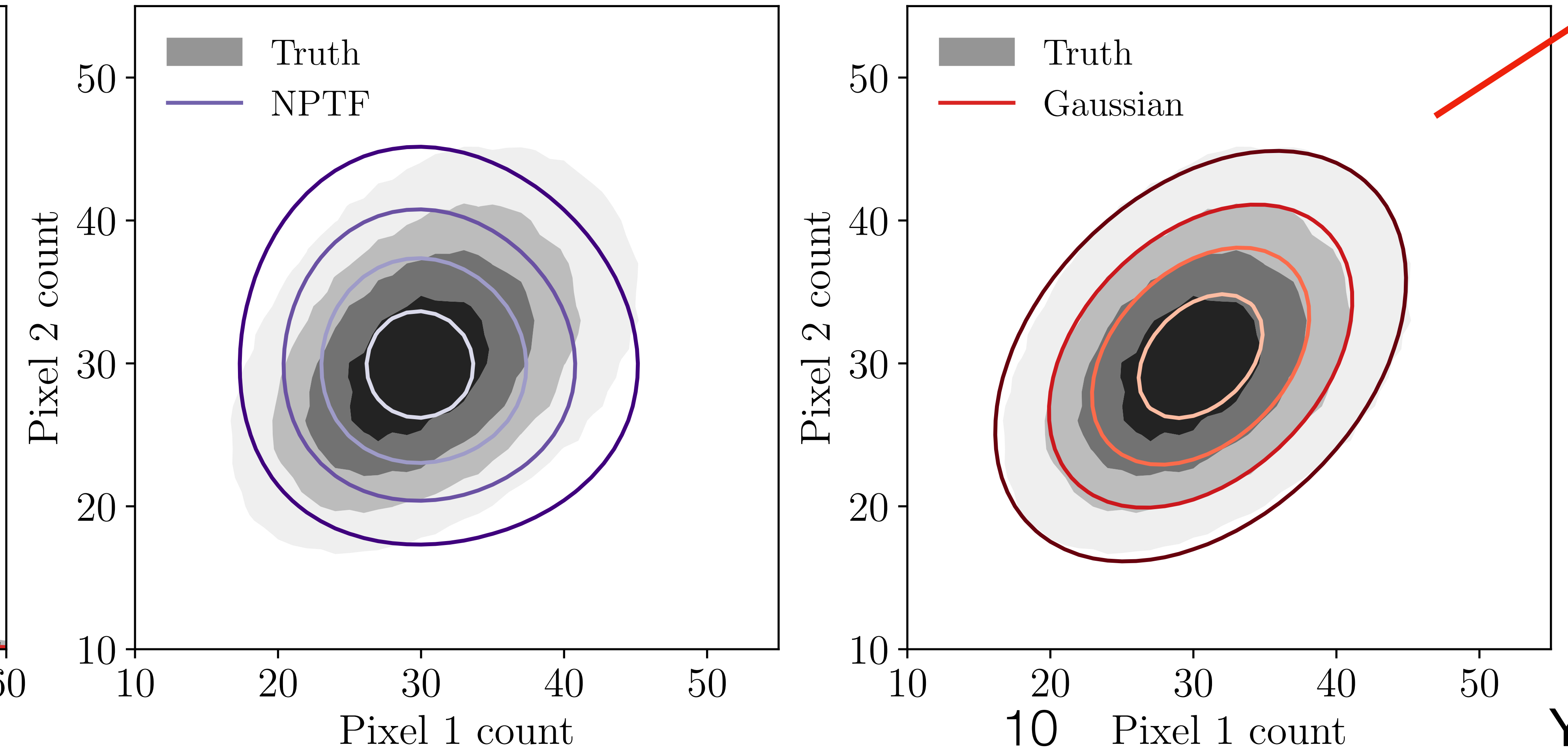


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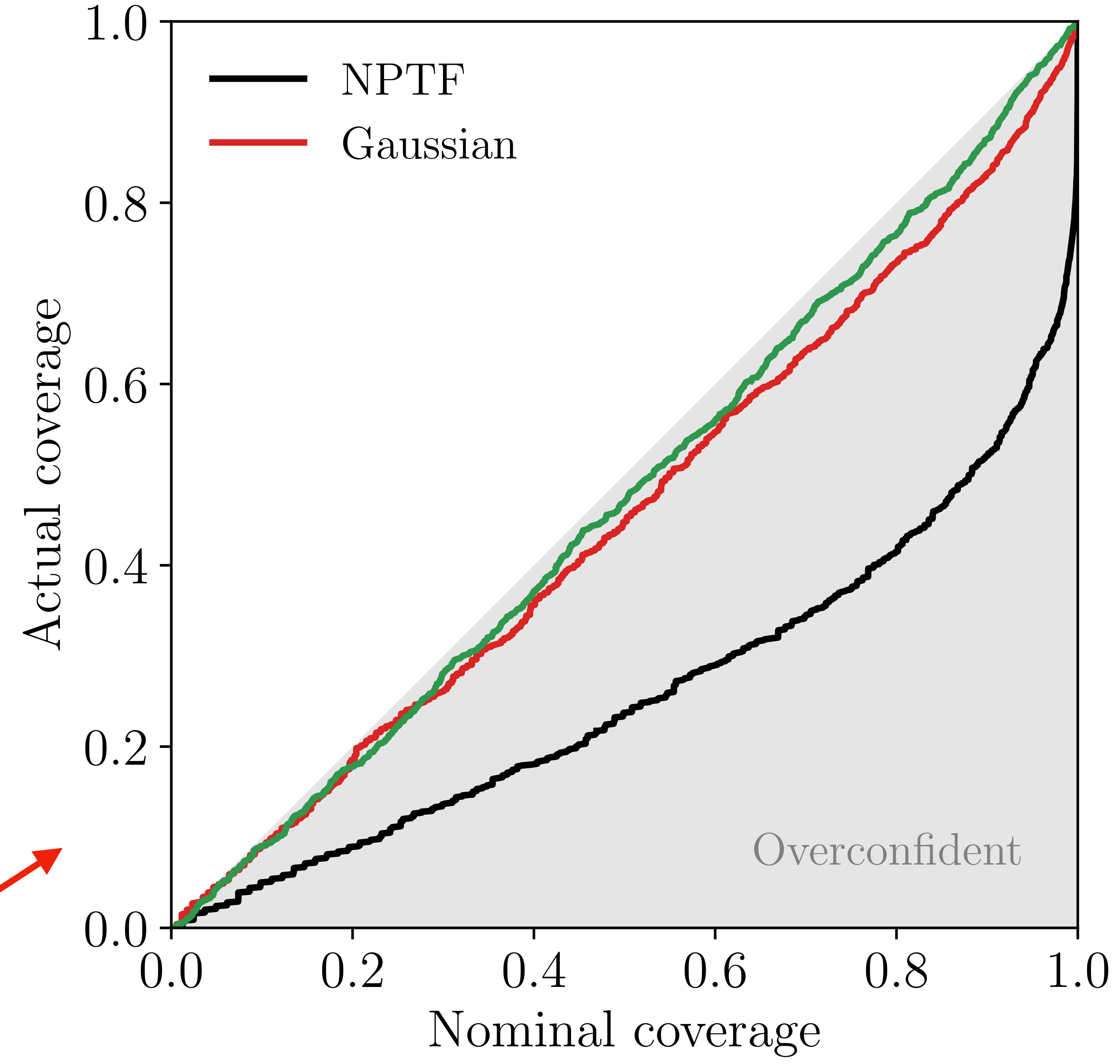


In this toy example, 2-pixel correlation can be recaptured with an Gaussian approximation to the image likelihood, yielding a fairly well-calibrated fit.

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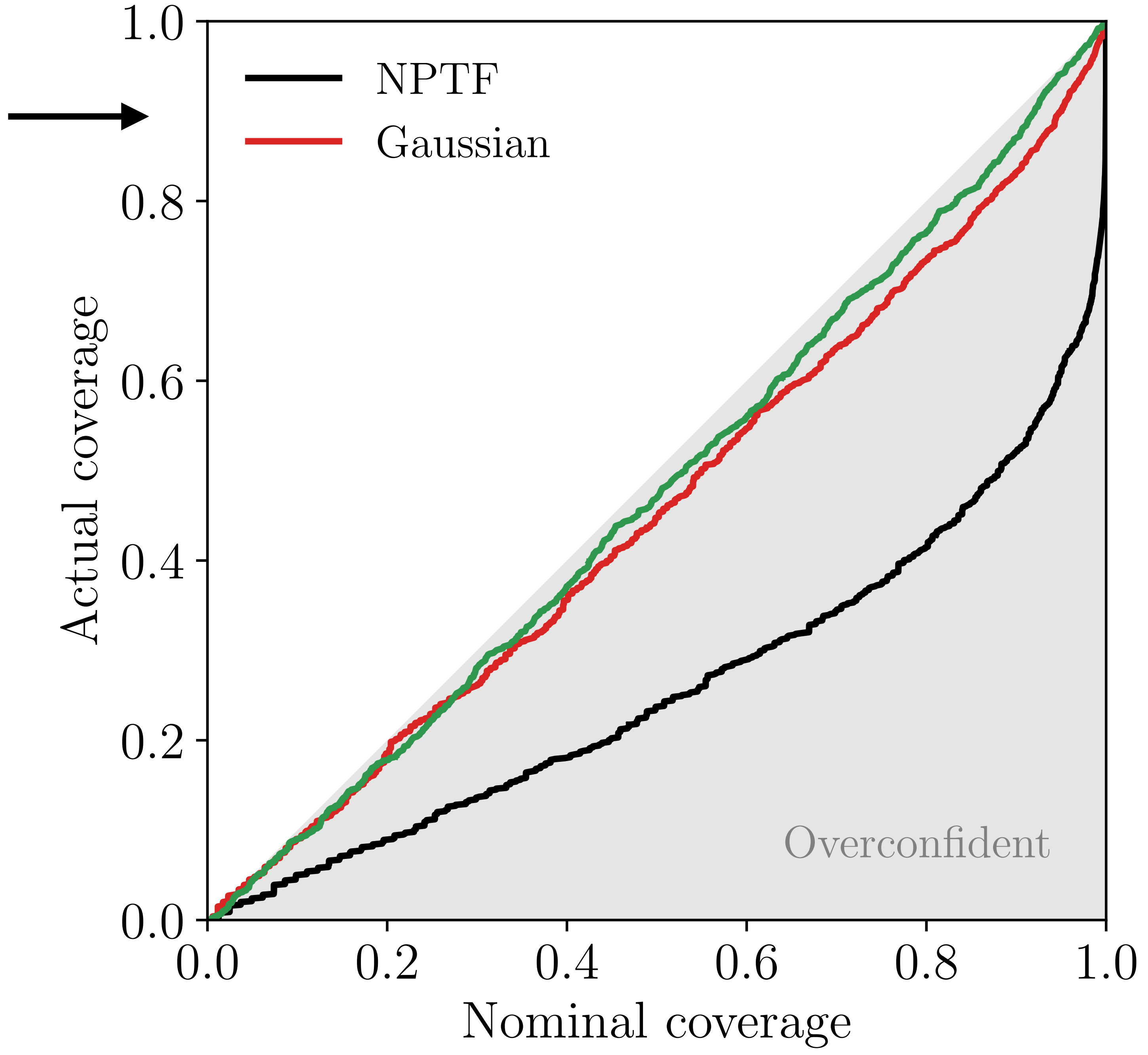
Aside: share the same total count likelihood profile

but NPTF with different PSF gives different results
(gives correct result for no PSF case)

coverage

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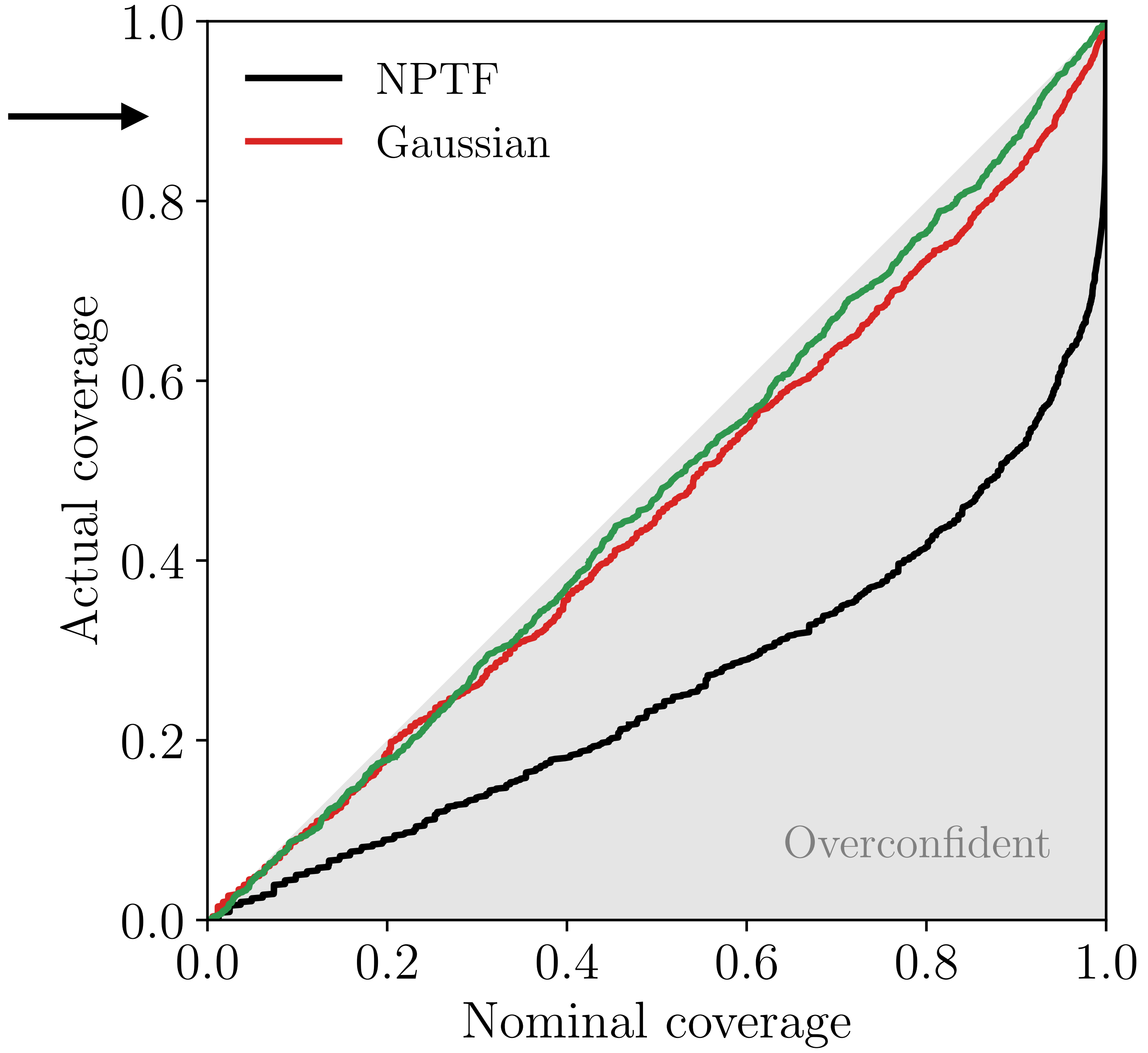


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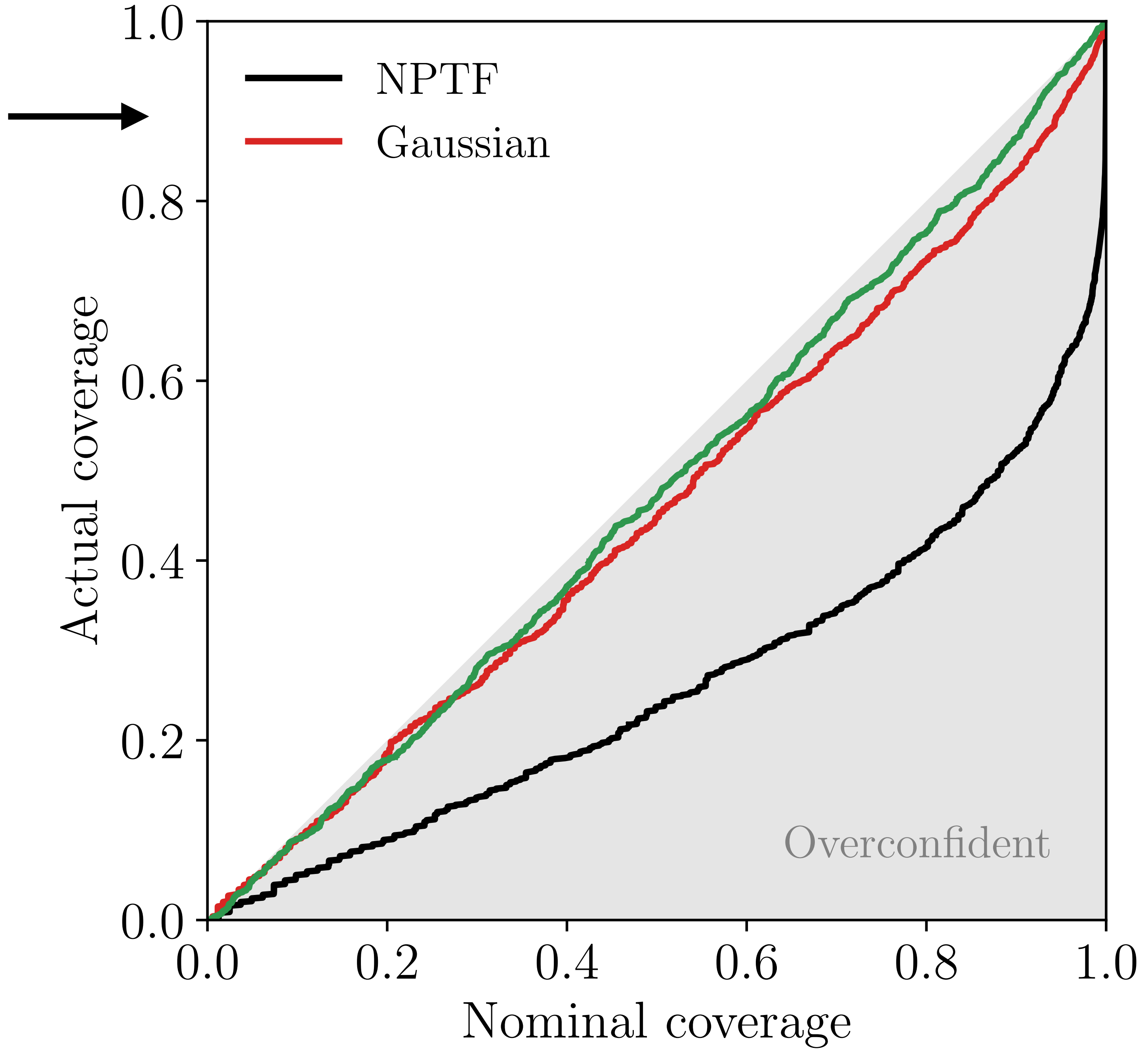


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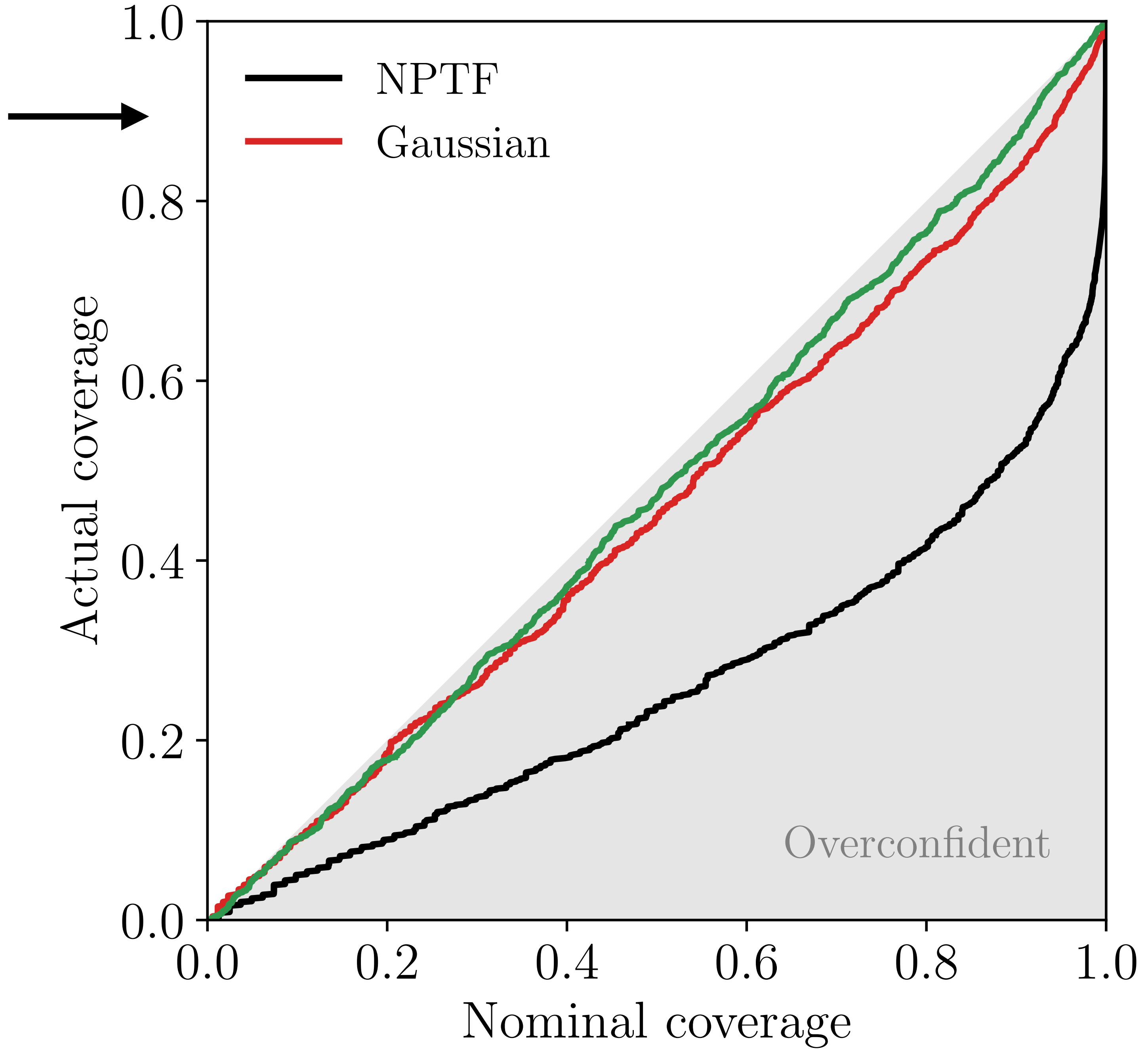


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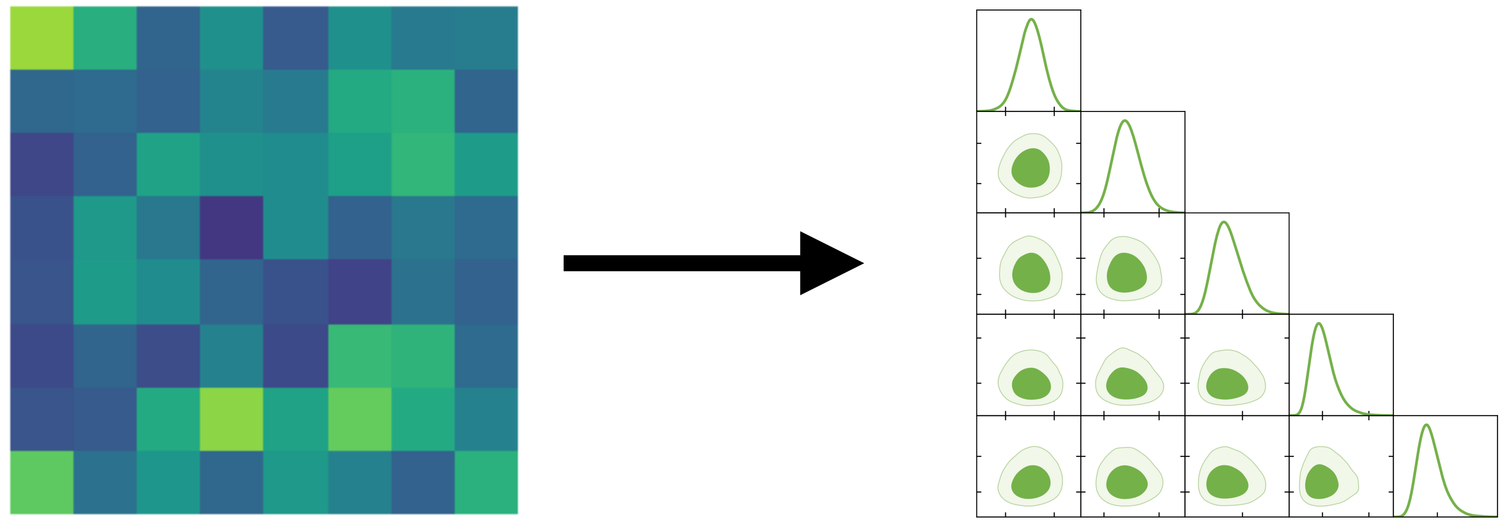

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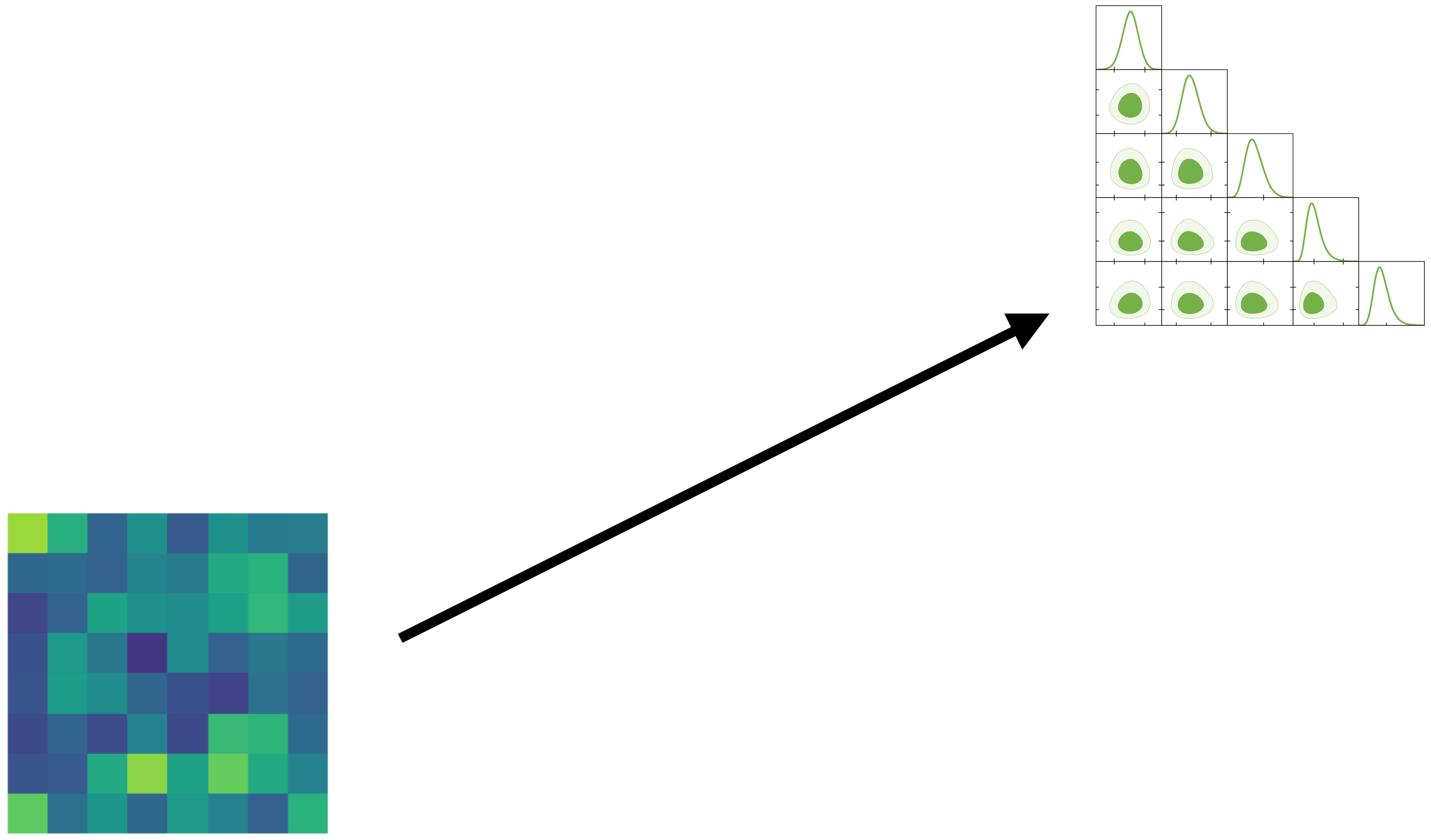
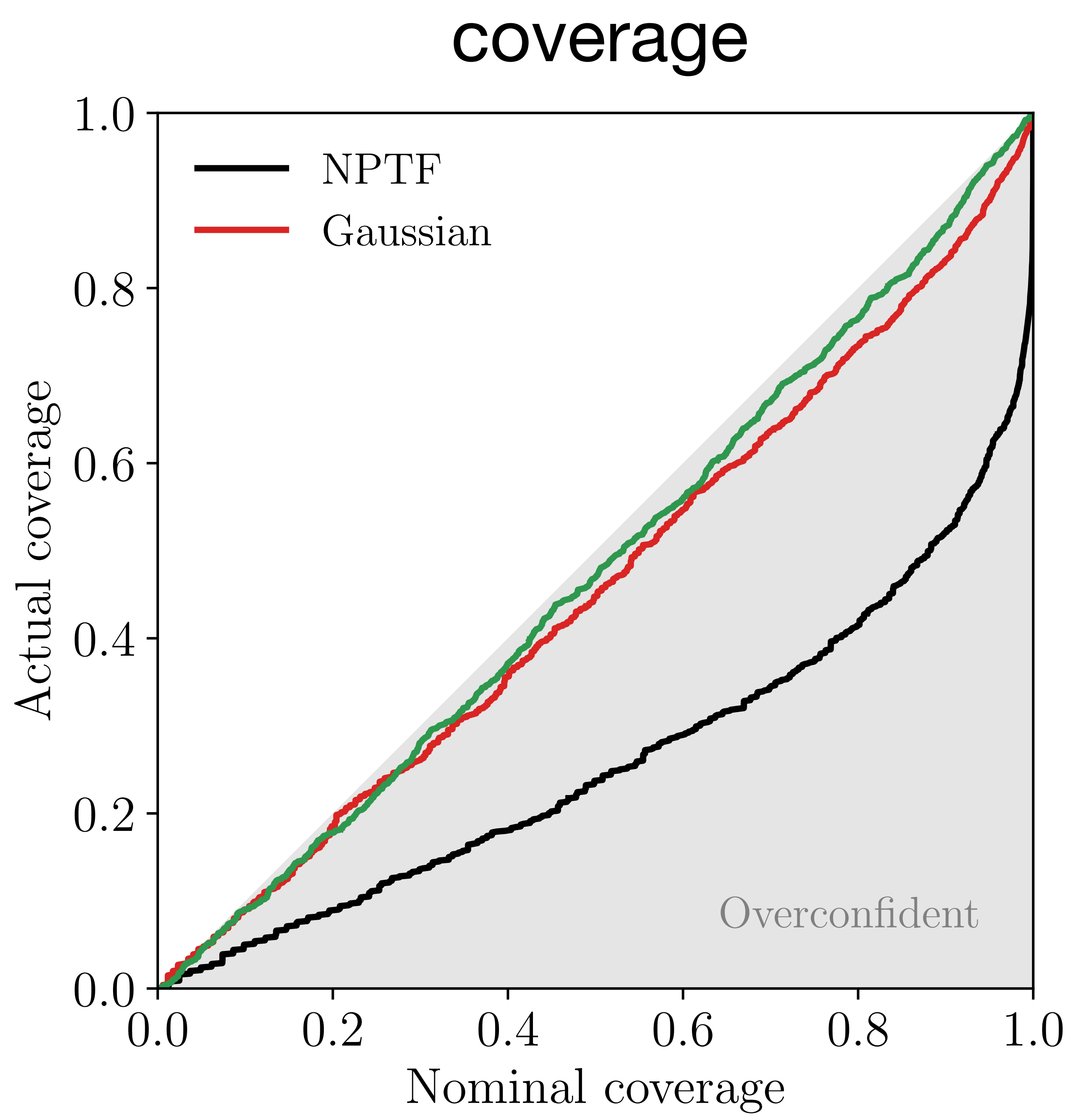
# Simulation-Based Inference as a solution

Neural Posterior Estimator (as an example for SBI)





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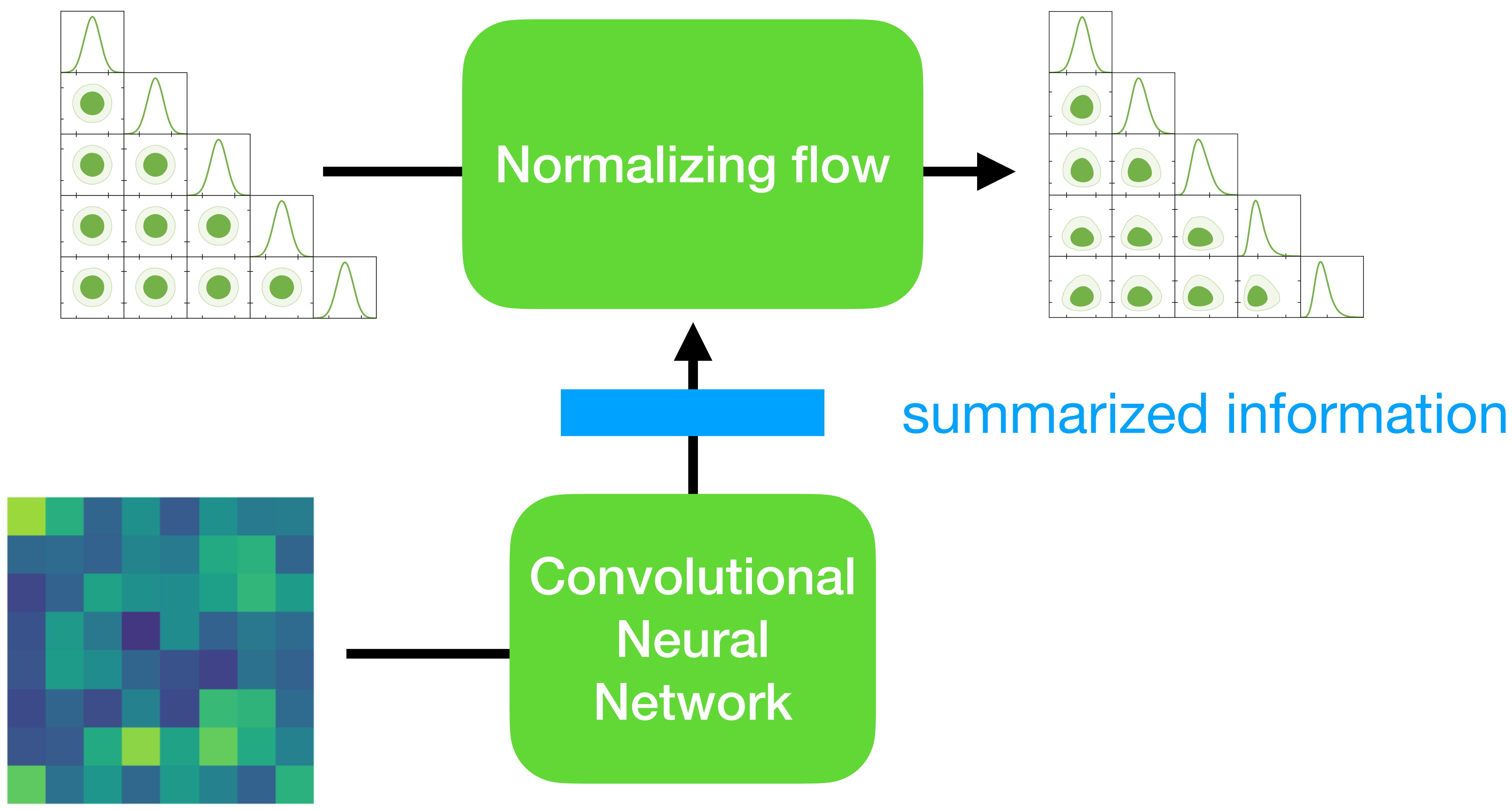


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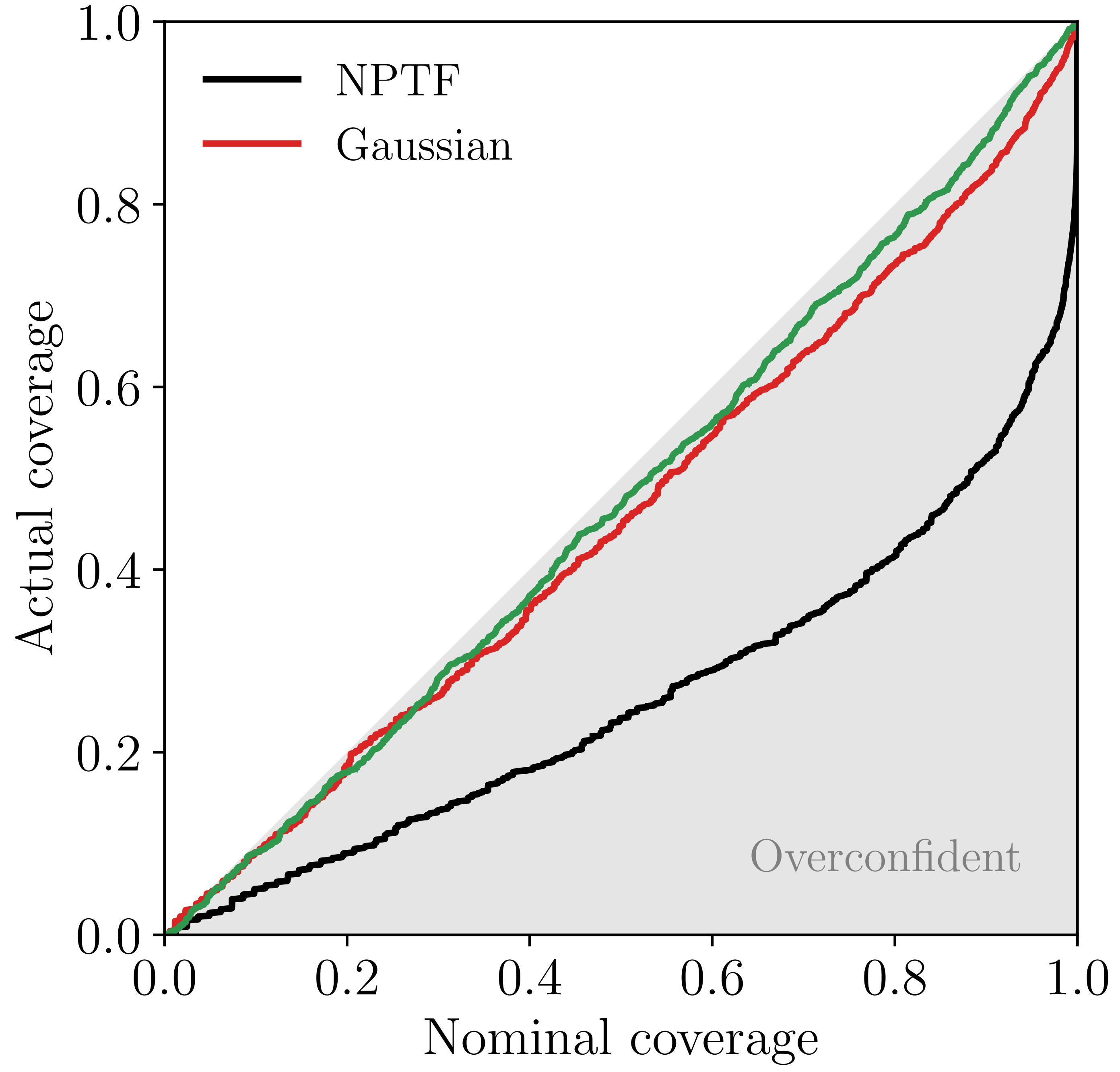

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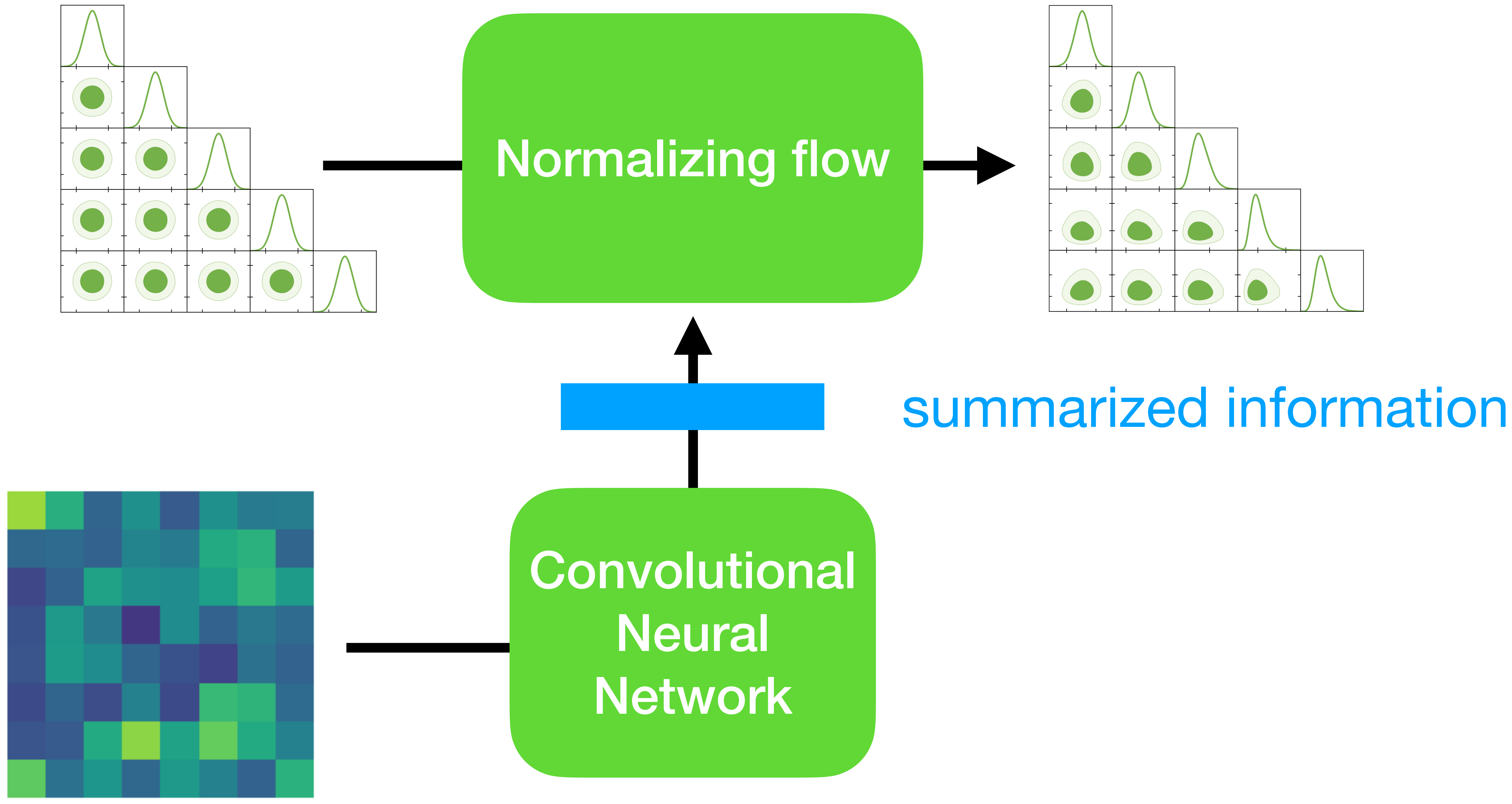


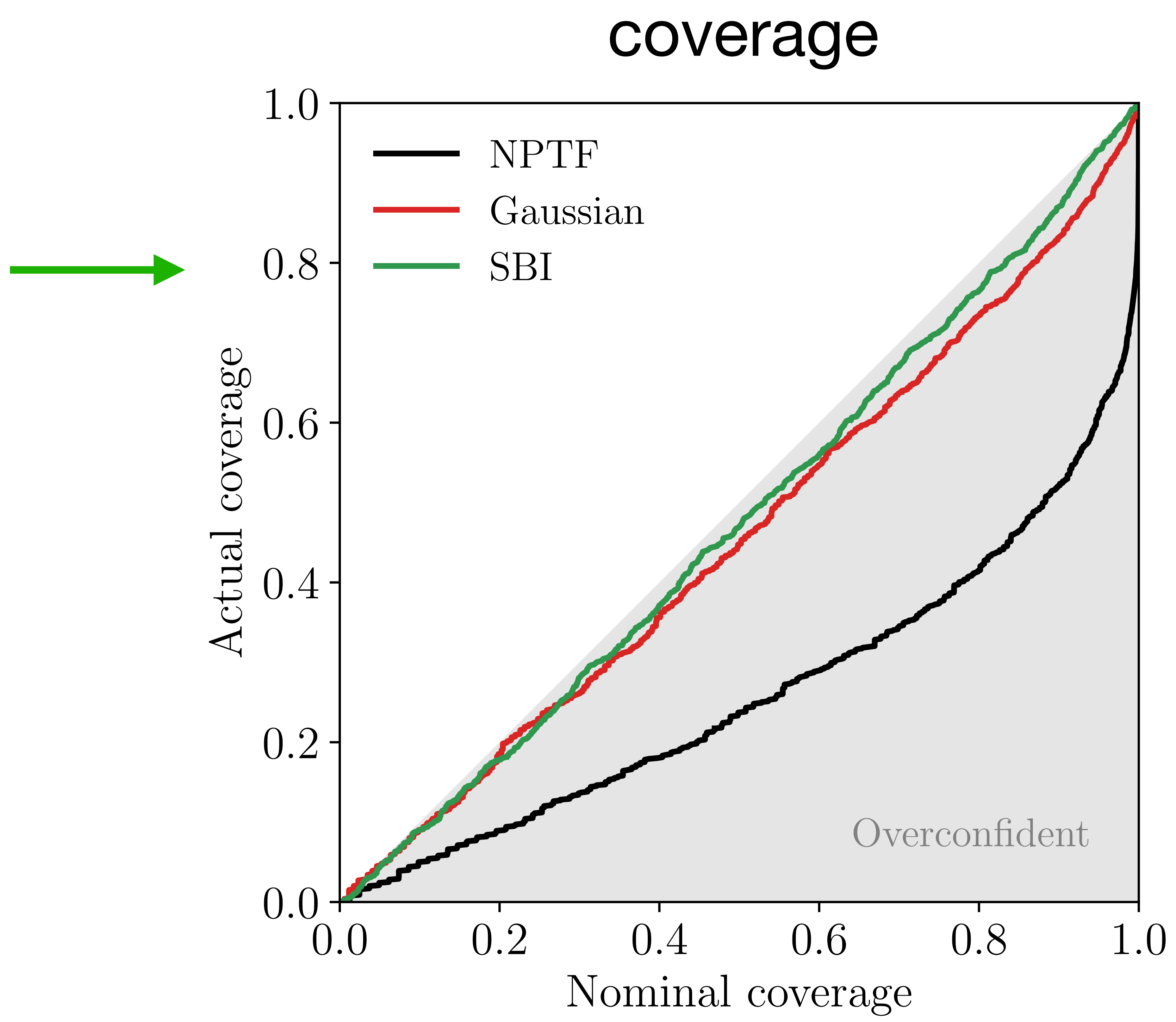

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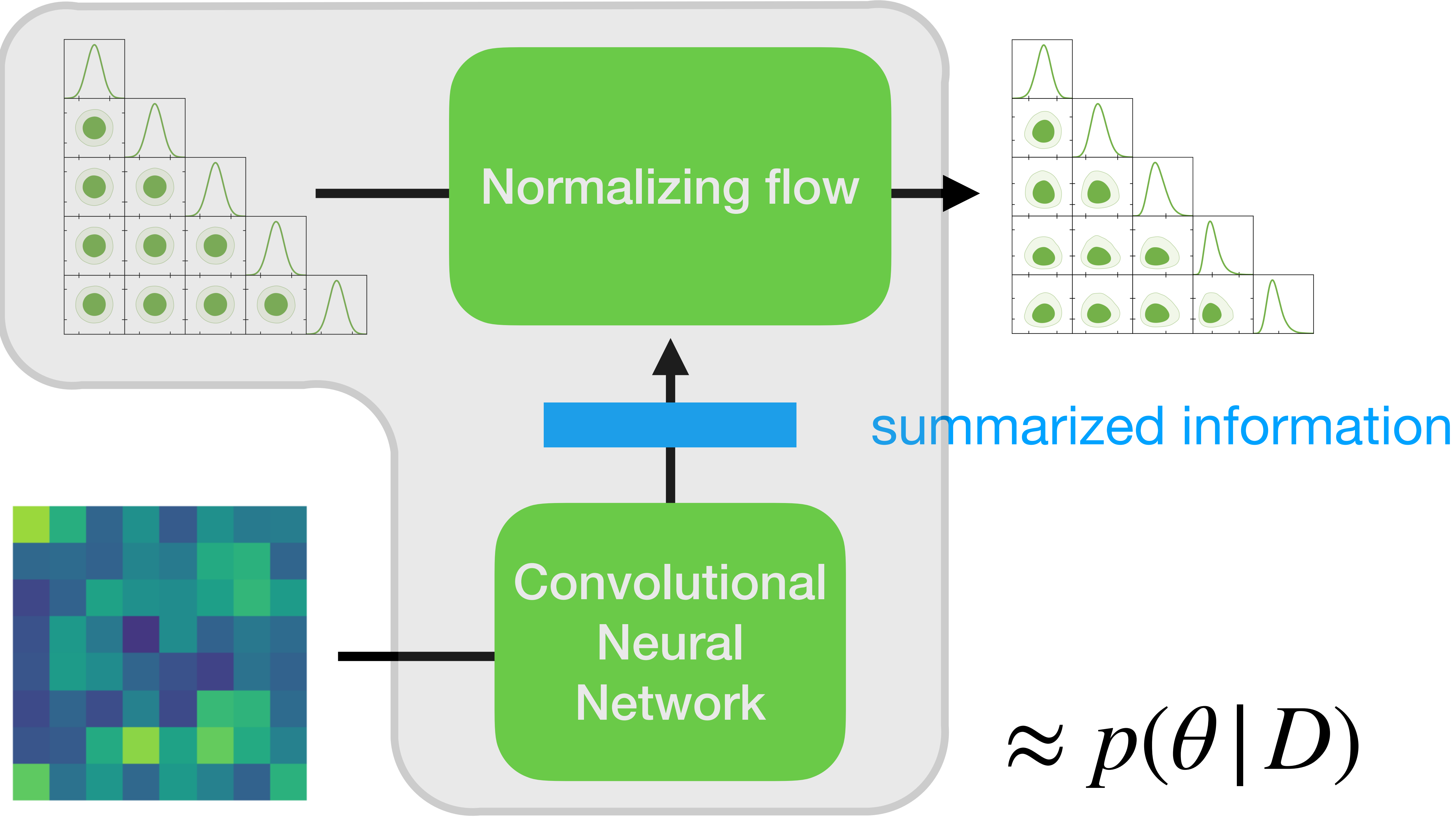


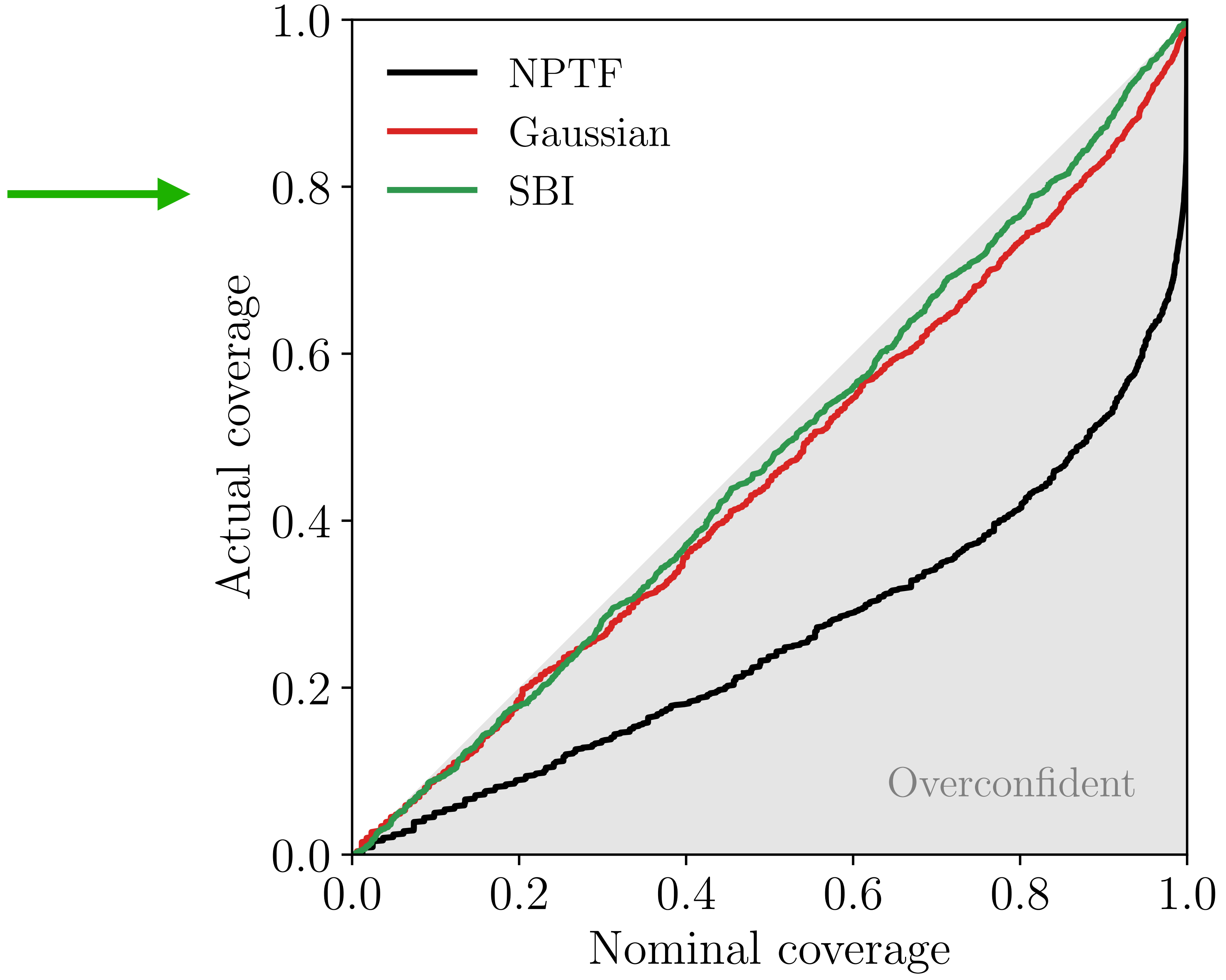

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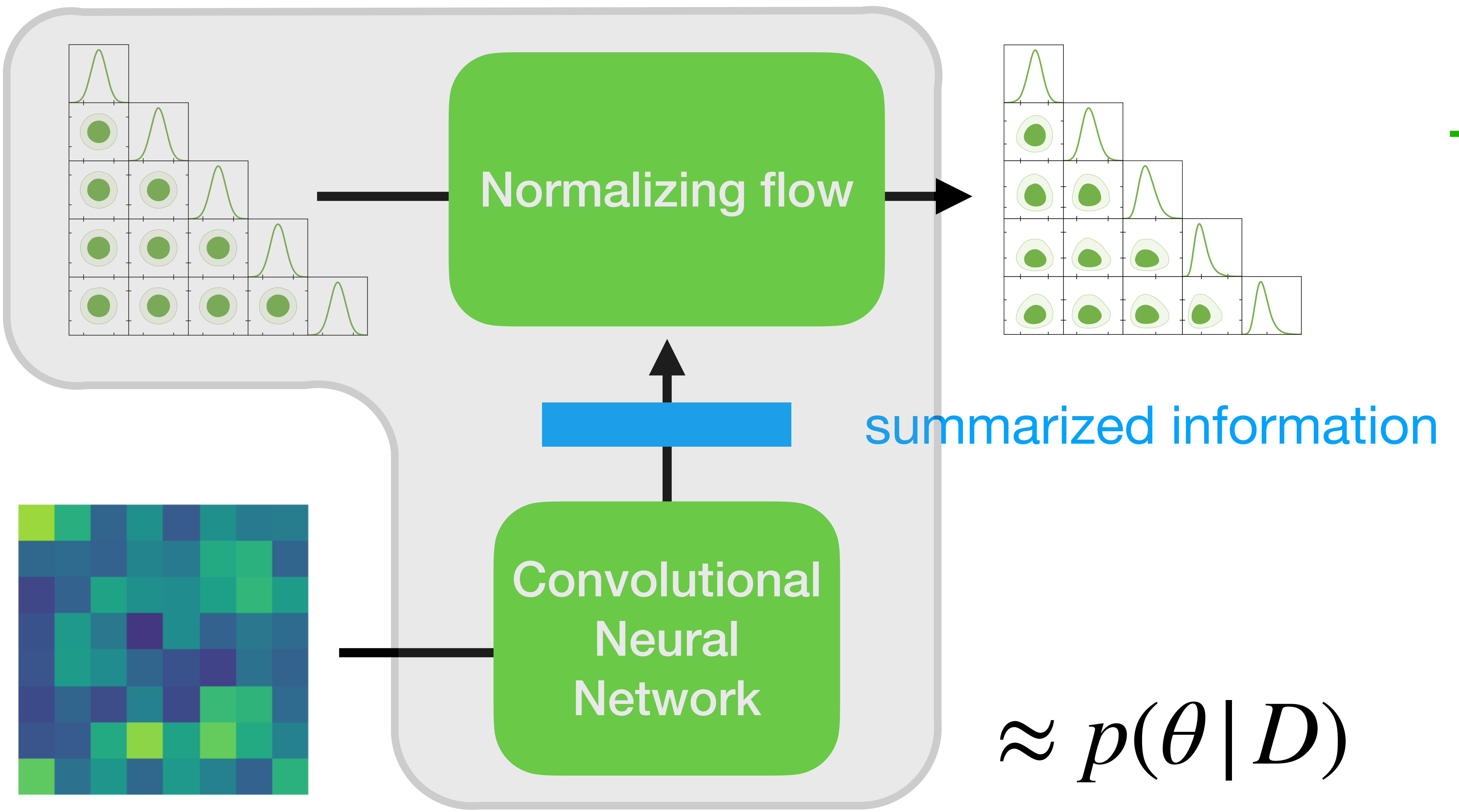


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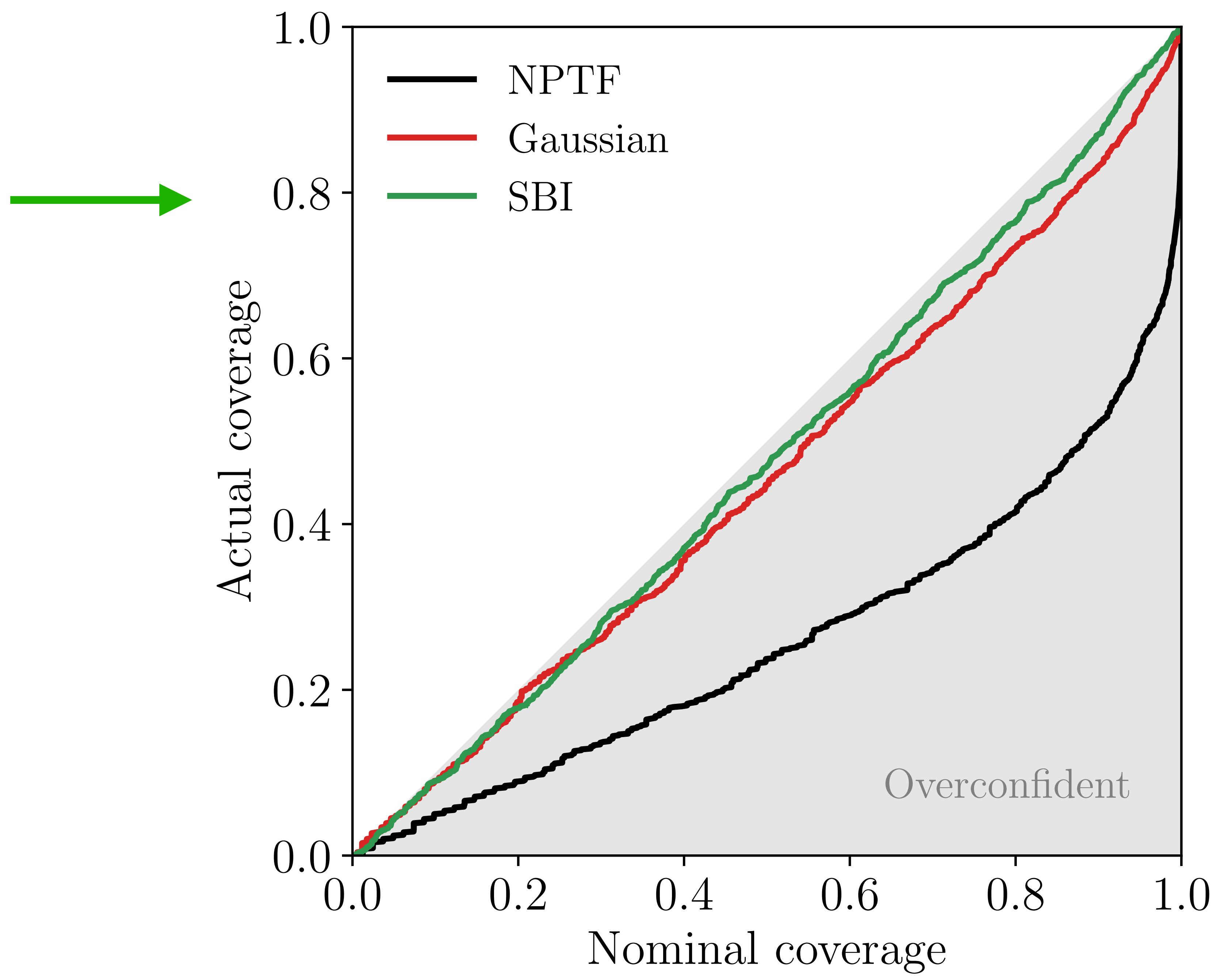


With energy binning: even more complicated correlations.

# Summary

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- Un-modeled positive correlations between pixels causes the likelihood for point source template normalization to be overconfident.
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Thank you!

# Backup slides

# NPTF fitting de-correlated data in toy example