

# Statistical inference of astrophysical point-sources

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GABRIEL COLLIN

A solid orange horizontal bar at the bottom of the slide.

# What is a point source

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Any object so small that it can be approximated as a mathematical point.

Thus, it is always located inside exactly one pixel.

However, instrumentation effects (PSF) means that it can contribute to more than one pixel. Eg:

- Diffraction spikes (seen in JWST image)
- Atmospheric diffraction
- Limited focusing (X-rays and gamma-rays)



Stars in foreground are point-sources.  
Galaxies in background are not point-sources.

# Statistics of a point-source

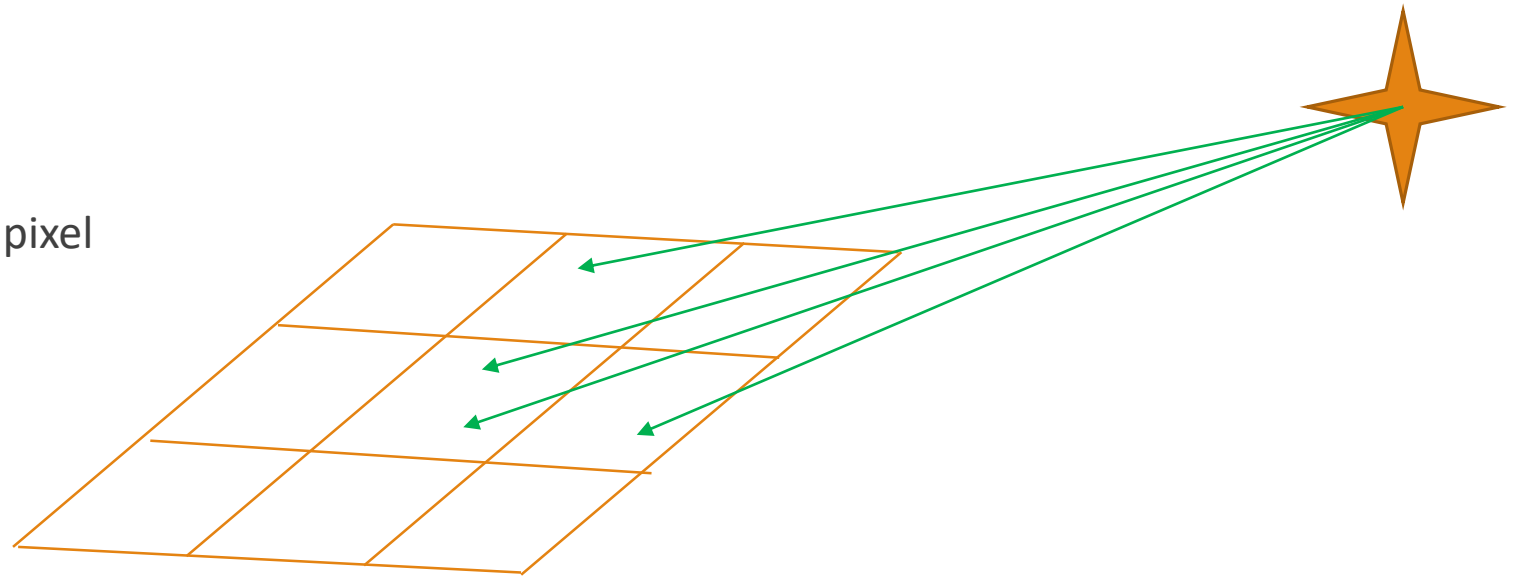
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A single point-source is usually treated as a Poisson distribution.

- If the flux is constant
  - (a usual approximation that we make)
- Then the arrival time of the gamma-rays is exponentially distributed.

For a pixelated detector

- There is Poisson distribution per pixel
- Weighted by
  - PSF
  - Effective area
  - Detection probability



# Point sources

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Any group of point sources that have common properties is called a population.

The most familiar point source population is the stars in the night sky that are visible to the naked eye.

Here, stars are well separated.

- Images intuitively reflect the mathematical modelling of points.
- We can simply count all the stars and list their positions, in a database known as a *catalogue*.



# Crowded fields

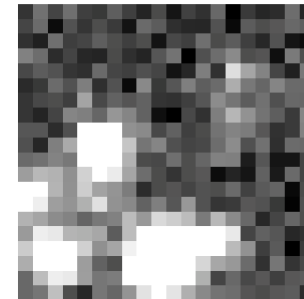
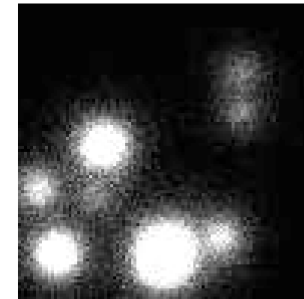
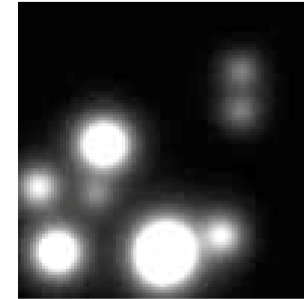
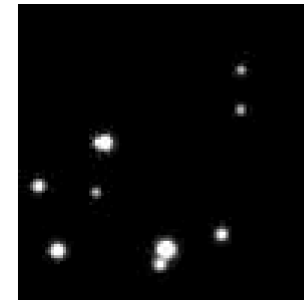
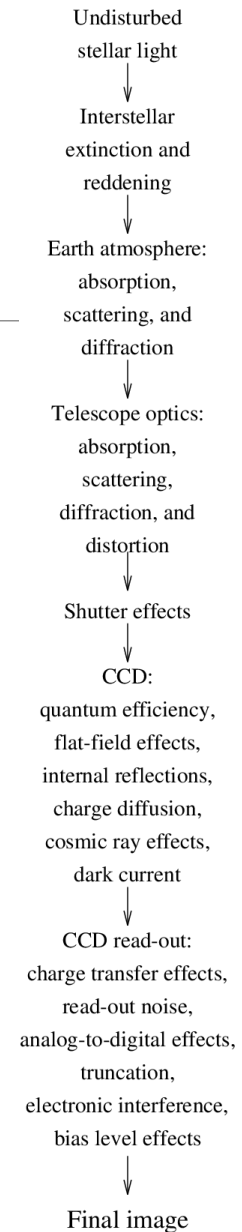
When many point sources are near each other, it can be difficult to distinguish them.

This is called a *crowded field*.

- It is entirely caused by experimental issues, such as the angular resolution of the instrument.

This kind of situation is becoming more common, as instruments push the limits.

- Cheaper, smaller experiments.
- Experiments that look deeper into the universe.

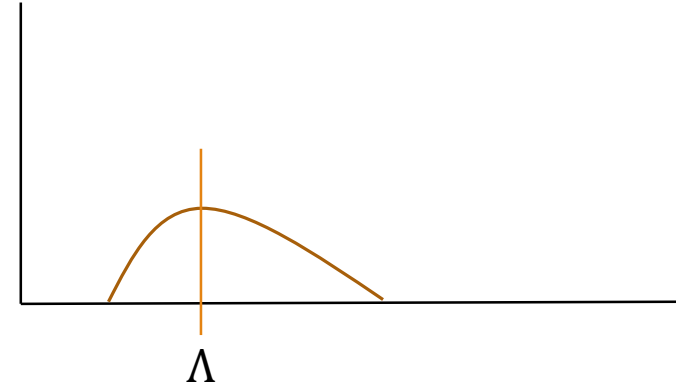


Snel 1998

# Statistics of N sources

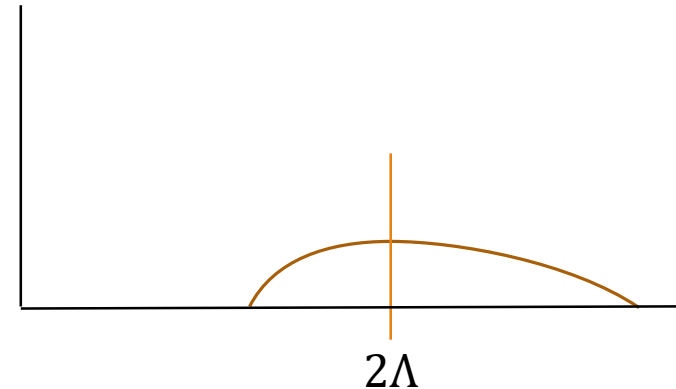
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For one point-source, we get a Poisson distribution with mean  $\Lambda$



For two point-sources, we get a Poisson distribution with mean  $2\Lambda$

- (Assuming, for simplicity, the flux is the same for both)



# Statistics of a population of sources

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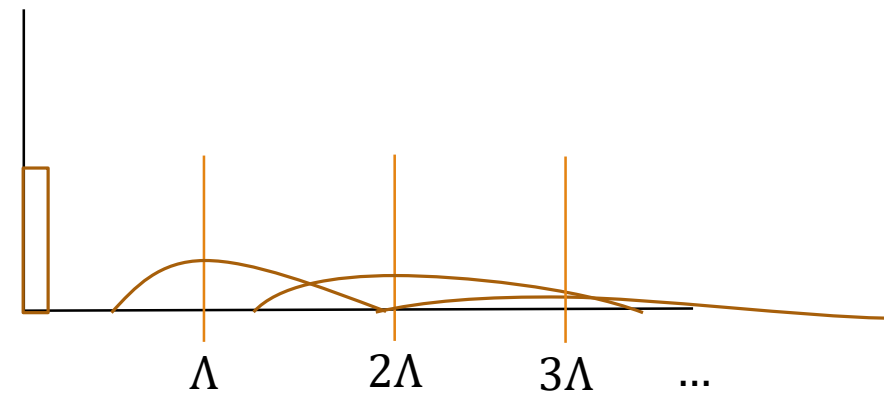
For zero point-sources, we get a Poisson distribution with a mean of zero.

- All probability mass is concentrated at  $k = 0$



If we don't know the number of sources, we need to add all of these together to account for all possibilities.

- This is very different looking to a single Poisson distribution.
- There are many humps.
- Large gap between zero and the first hump.



# In numbers

Example provided by Tracy Slatyer

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I expect 10 photons per pixel, in some region of the sky.

- What is my probability of finding 0 photons? 12 photons? 100 photons?

Case 1: Dark matter, Poissonian statistics

- $P(12 \text{ photons}) = 10^{12} e^{-10}/12! \sim 0.1$
- $P(0 \text{ photons}) \sim 5 \times 10^{-5}$ ,
- $P(100 \text{ photons}) \sim 5 \times 10^{-63}$

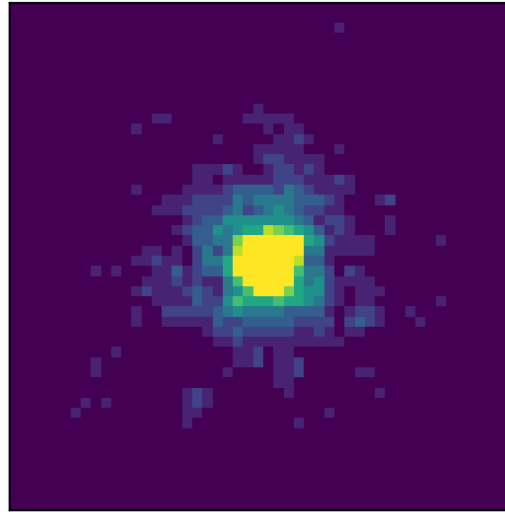
Case 2: population of rare sources.

- Expect 100 photons/source, 0.1 sources/pixel - same expected # of photons
- $P(0 \text{ photons}) \sim 0.9$ ,
- $P(12 \text{ photons}) \sim 0.1 \times 100^{12} e^{-100}/12! \sim 10^{-29}$ ,
- $P(100 \text{ photons}) \sim 4 \times 10^{-3}$
- (plus terms from multiple sources/pixel, which I am not including in this quick illustration)

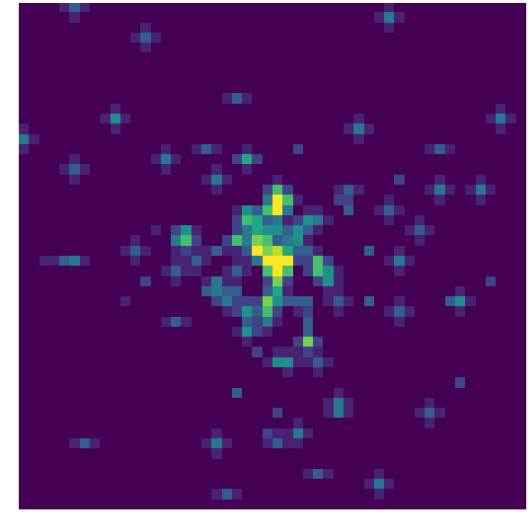


# An intuitive view

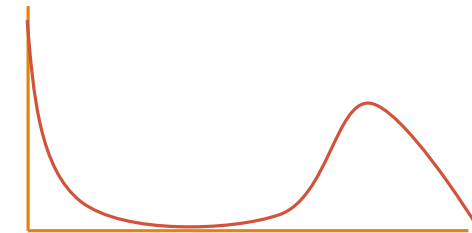
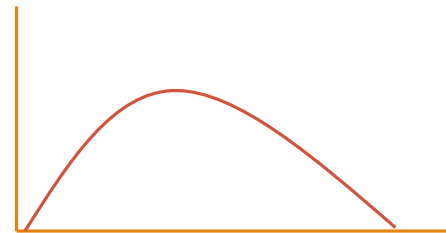
Extended source



Population of point sources



Freq.




Counts

# Compound Poisson Generators

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Full details and alternative derivation at

 > astro-ph > arXiv:2104.04529

**Astrophysics > Instrumentation and Methods for Astrophysics**

*[Submitted on 9 Apr 2021 (v1), last revised 27 Jun 2022 (this version, v2)]*

## **A Compound Poisson Generator approach to Point-Source Inference in Astrophysics**

Gabriel H. Collin, Nicholas L. Rodd, Tyler Erjavec, Kerstin Perez

# How to build a distribution

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We need some way to combine the Poisson distributions for each choice of  $N$  together.

- While accounting for the fact that  $N$  is itself a random variable
  - (because we don't know how many point-sources there are).

There's an easy way to do this.

- Using **generating functions**.

The generating function for a distribution  $p(k)$  is

$$G(z) = \sum_{k=0}^{\infty} p(k) z^k$$
$$p(k) = \frac{1}{k!} \frac{d^k}{dz^k} G(z) \Big|_{z=0} = \sum_{n=0}^{\infty} p(n) \frac{1}{k!} \frac{d^k}{dz^k} z^n \Big|_{z=0} = \sum_{n=0}^{\infty} p(n) \delta_{nk}$$

# The generating function

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The full point-source population generating function is

$$G_{k_B}(z) = \exp \left[ \underbrace{N}_{\text{Mean no. of sources}} \left( \int dF \int d\varepsilon e^{\varepsilon F(z-1)} \underbrace{\mu_B(\varepsilon)}_{\text{Effective area distribution}} \underbrace{p(F)}_{\text{Flux distribution}} - 1 \right) \right]$$

Mean no. of sources

Effective area distribution

Flux distribution

(required to be broken power law)

All instrumental effects summarised in effective area distribution

$$\mu_B(\varepsilon) = \int dx \underbrace{T(x)}_{\text{Spatial template}} \delta \left( \varepsilon - \underbrace{\kappa(x)}_{\text{Effective area}} \int_{\Omega_B} dy \underbrace{\eta(y)}_{\text{Detection prob.}} \underbrace{\phi(y|x)}_{\text{PSF}} \right)$$

Spatial template

Effective area

Detection prob.

PSF

Most often needs to be simulated

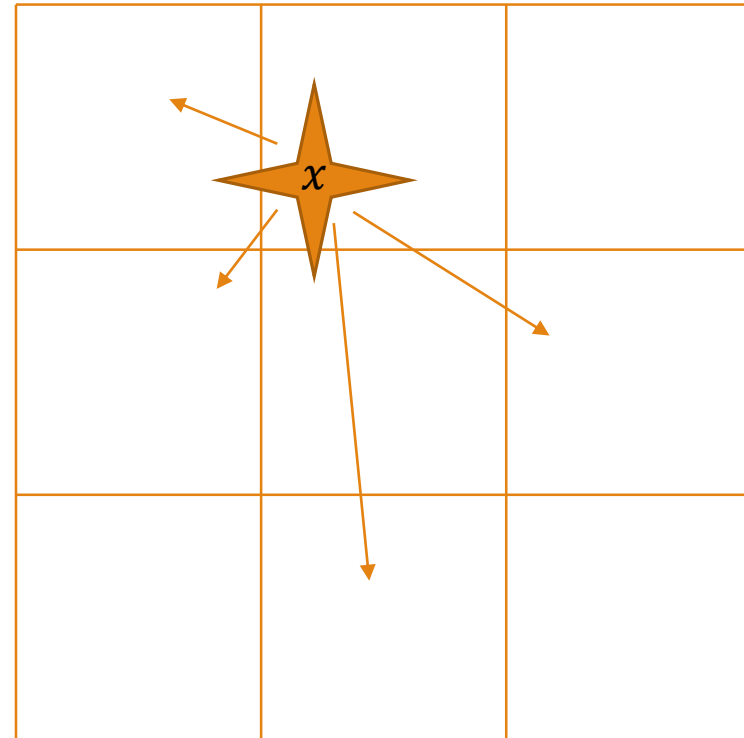
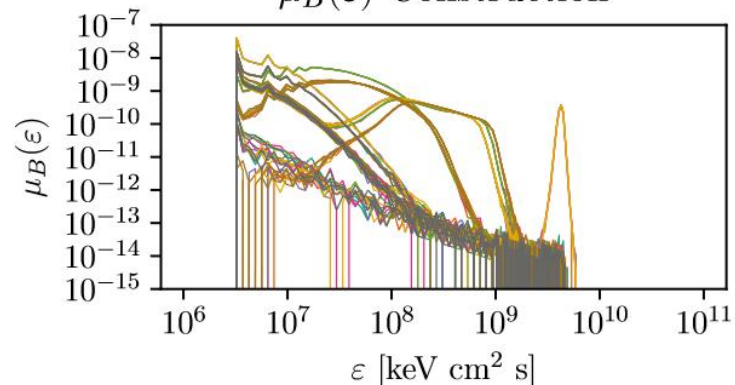
# Simulating the effective effective-area

Algorithm:

- Draw a point-source location from  $T(x)$
- Distribute effective area  $\kappa(x)$  among all pixels
  - By drawing photons according to the PSF  $\phi(y|x)$
  - weighted by the detection probability  $\eta(y)$
- Repeat multiple times.

Now each pixel has a list of effective areas.

- Histogram this list for each pixel.  $\mu_B(\varepsilon)$  Construction
- This forms  $\mu_B(x)$



# The total likelihood

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Straightforward to get probability over pixels.

- Computationally unfeasible to account for correlations.

Instead

- Get probability for one pixel.
- Take product over all pixels.

$$p(\{n_i\}) = \prod p_i(n_i)$$

- Mean-field approximation
- Does not take into account correlations between pixels.

$p_0(n)$	$p_1(n)$	$p_2(n)$
$p_3(n)$	$p_4(n)$	$p_5(n)$
$p_6(n)$	$p_7(n)$	$p_8(n)$

# Application to galactic gamma-ray excess

Excess of gamma-rays at the galactic center

- Could be dark matter decay
- Could just be a population of previously unknown point-sources

Similar existing method called

Non-Poissonian Template Fitting (NPTF)

Existing analysis prefers point source

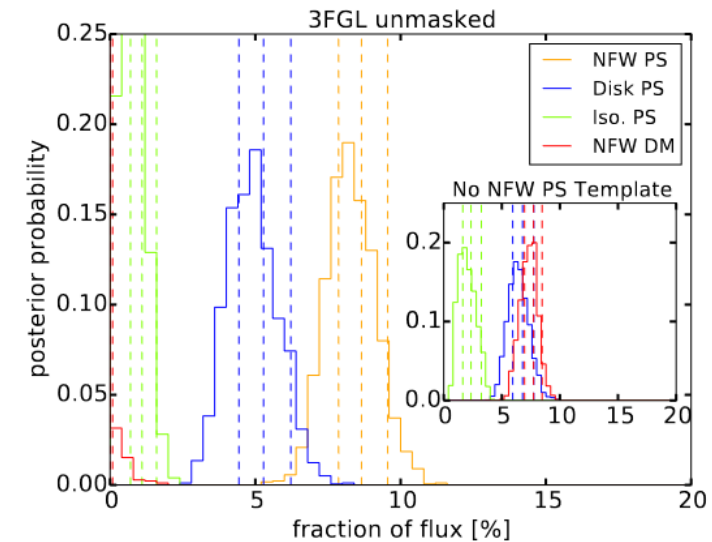
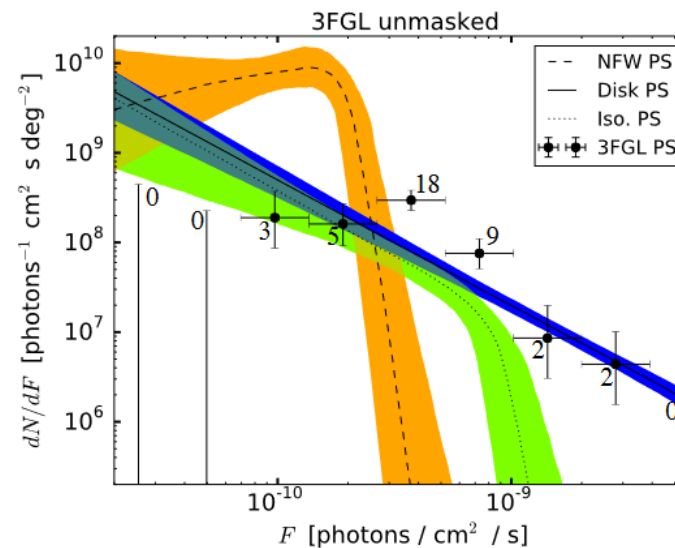
arXiv > astro-ph > arXiv:1506.05124

Astrophysics > High Energy Astrophysical Phenomena

[Submitted on 16 Jun 2015 (v1), last revised 3 Feb 2016 (this version, v3)]

## Evidence for Unresolved Gamma-Ray Point Sources in the Inner Galaxy

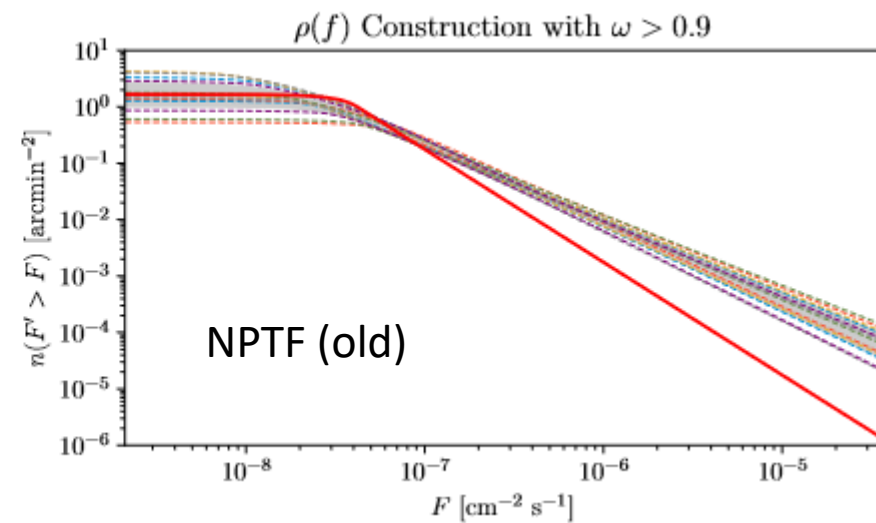
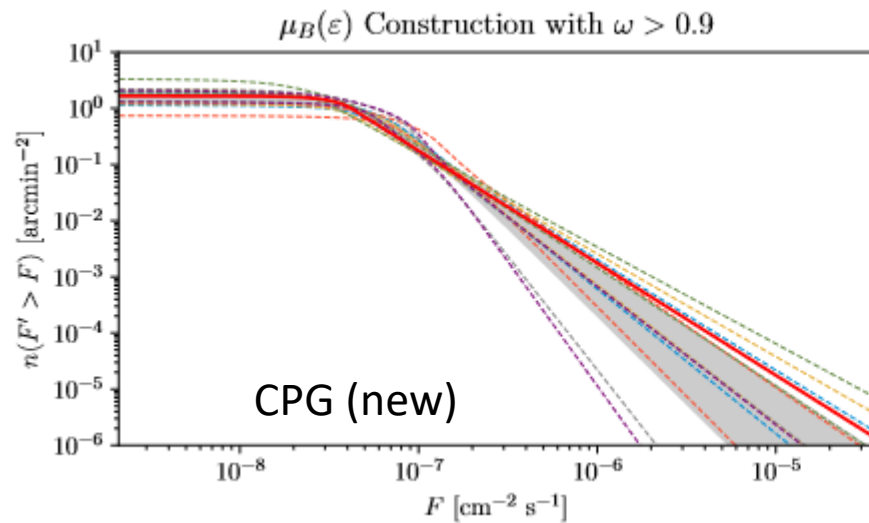
Samuel K. Lee, Mariangela Lisanti, Benjamin R. Safdi, Tracy R. Slatyer, Wei Xue



# Not the end of the story

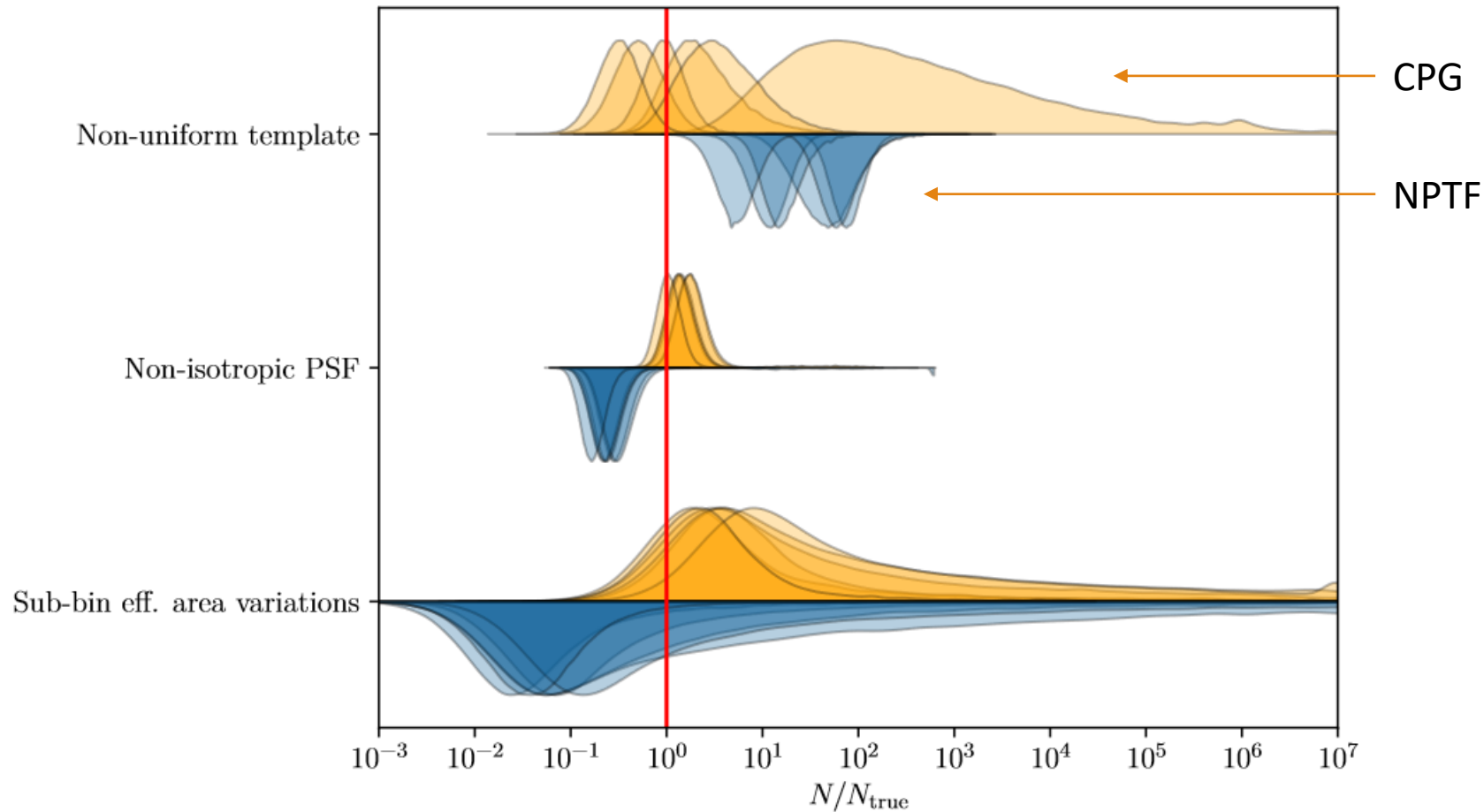
Since then, we found that NPTF has significant problems.

- Many instrumental effects can throw off the NPTF method.
- In X-ray astronomy these problems are most pronounced





# Instrumental effects, in detail

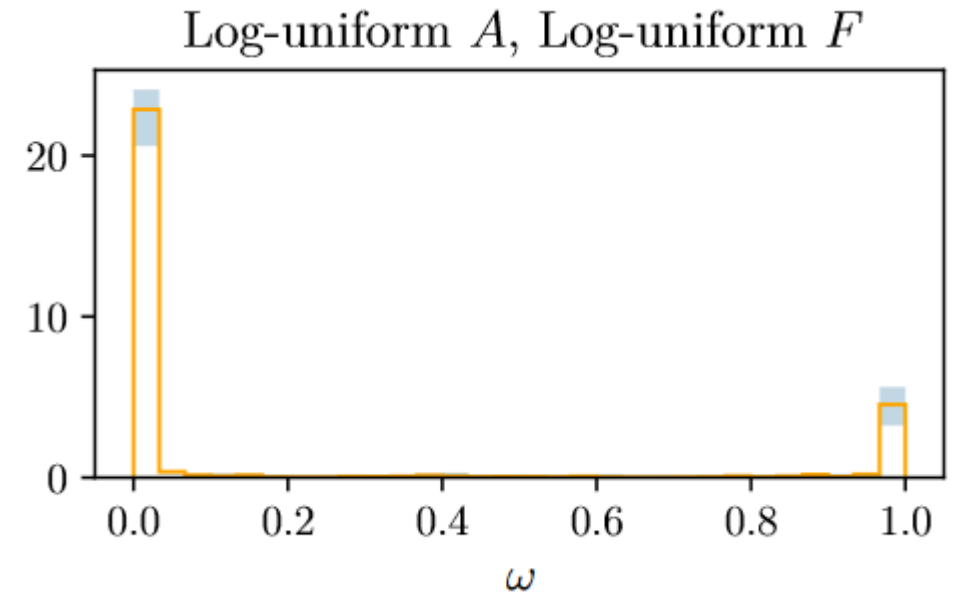


# Priors also a concern

Priors specified in terms of quantities that are not qualitatively relevant.

- Gives unexpected priors in relevant quantities!
- Always try to specify priors in quantities that you plan to plot

$$\frac{dN}{dF} = A \begin{cases} \left[ \prod_{j=2}^m \left( \frac{F_{b(j+1)}}{F_{b(j)}} \right)^{-n_j} \right] \left( \frac{F}{F_{b(m)}} \right)^{-n_m} & F \in [0, F_{b(m)}] \\ \vdots \\ \left[ \prod_{j=2}^i \left( \frac{F_{b(j+1)}}{F_{b(j)}} \right)^{-n_j} \right] \left( \frac{F}{F_{b(i)}} \right)^{-n_i} & F \in (F_{b(i+1)}, F_{b(i)}] \\ \vdots \\ \left( \frac{F}{F_{b(2)}} \right)^{-n_2} & F \in (F_{b(3)}, F_{b(2)}] \\ \left( \frac{F}{F_{b(2)}} \right)^{-n_1} & F > F_{b(2)} \end{cases}$$



Fraction of flux assigned to point-sources over diffuse (dark-matter like)

# Also not the only method

Probabilistic cataloguing is a different approach

- Requires less assumptions.
- Potentially more sensitive.
- Much more computationally demanding.

Directly estimates the locations of every potential point-source.

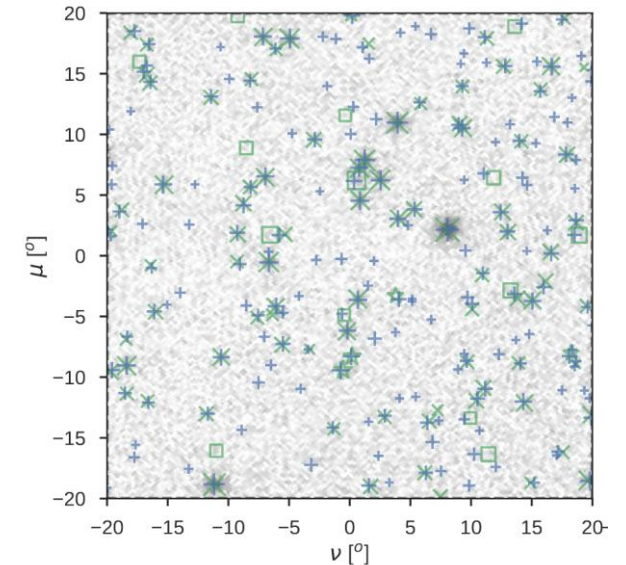
- Means many thousands of parameters that need to be estimated!
- Requires advanced trans-dimensional statistical inference method.

arXiv:1607.04637

Simulation

Green marks: True point-source locations.

Blue marks: One sample from the posterior.



But, might be a better choice if expected no. of sources is low.