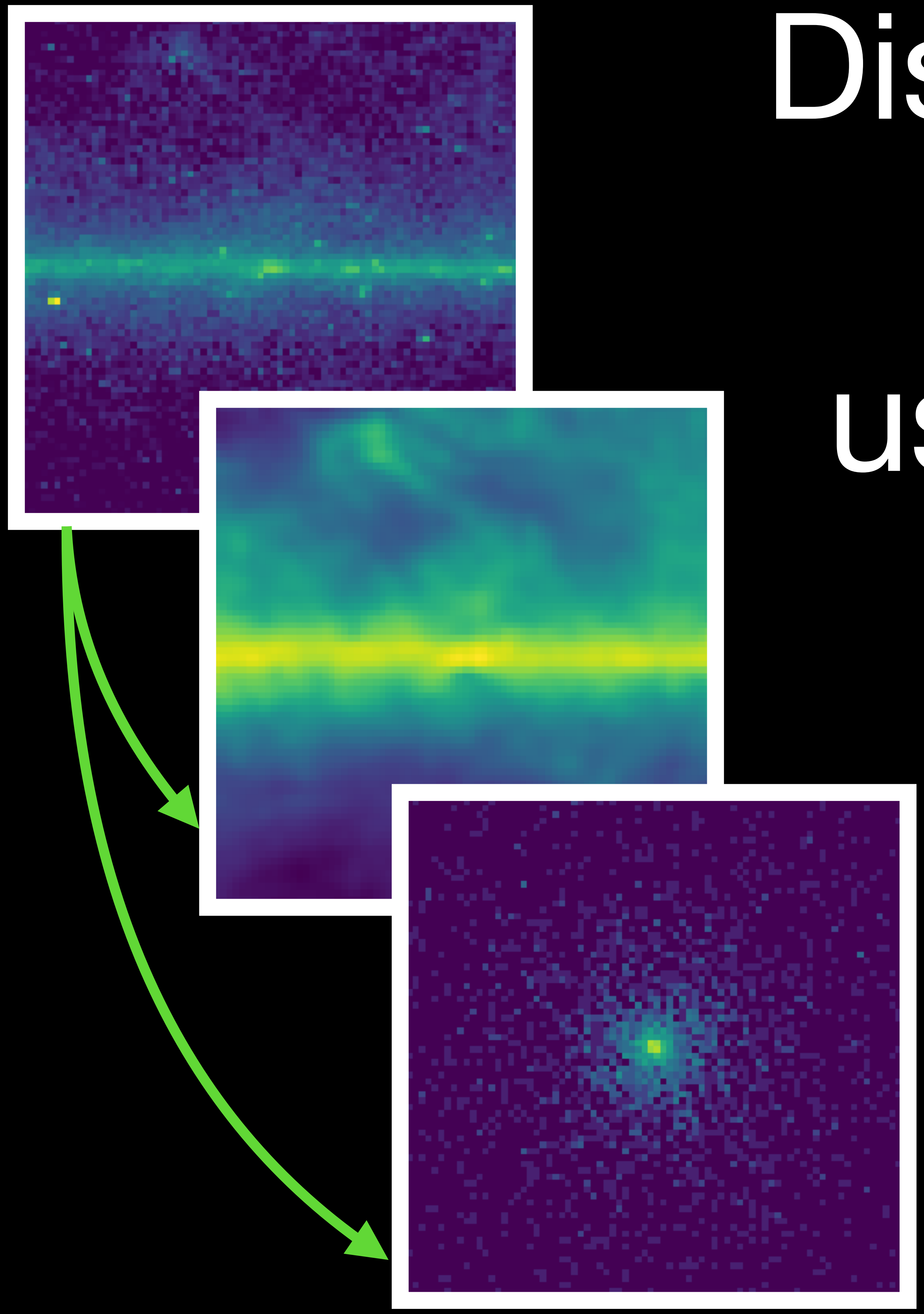


Disentangling γ-ray observations of the Galactic Center using differentiable probabilistic programming

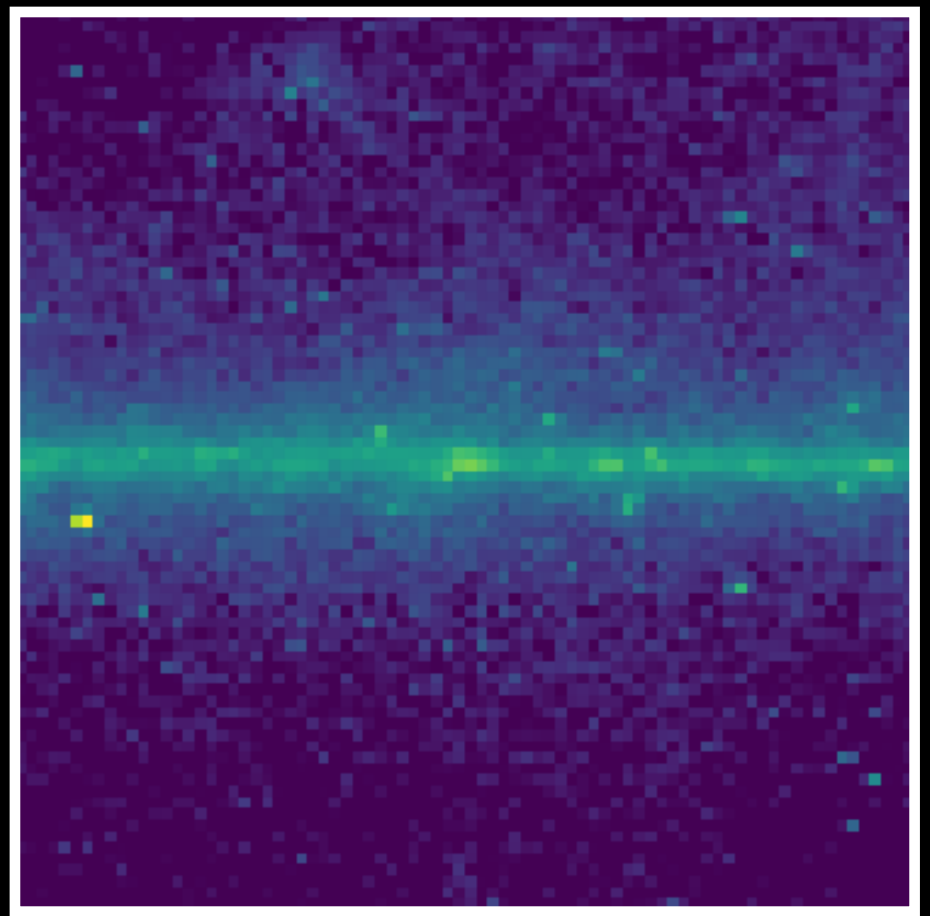
Yitian Sun with
Siddharth Mishra-Sharma
Tracy Slatyer and Yuqing Wu

Imperial College London

Machine Learning for Astrophysics @ ICML 2023

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

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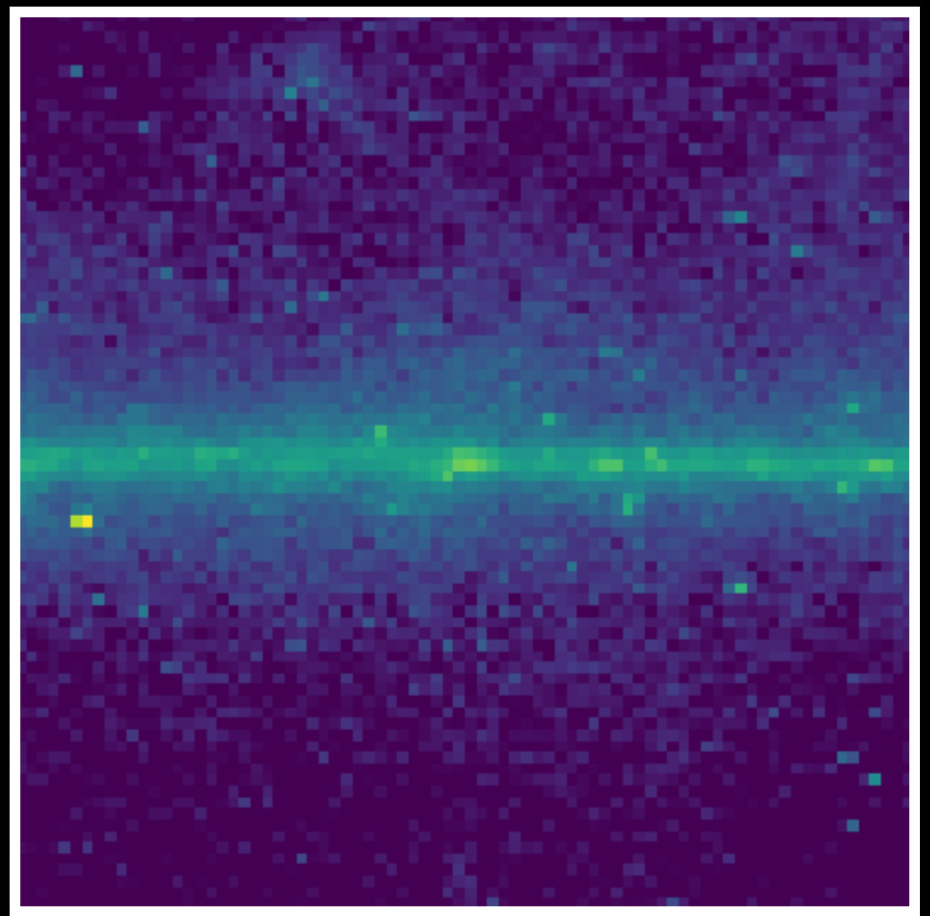

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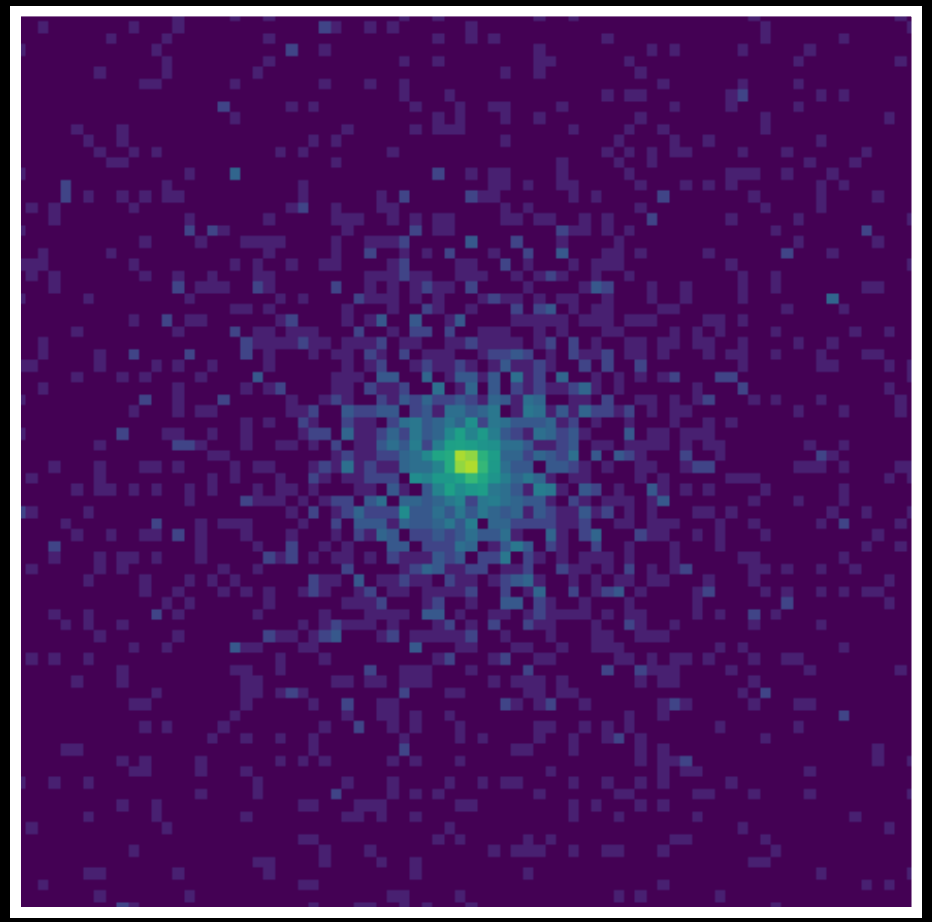

morphology:
spherical-like,
extended up to 15°

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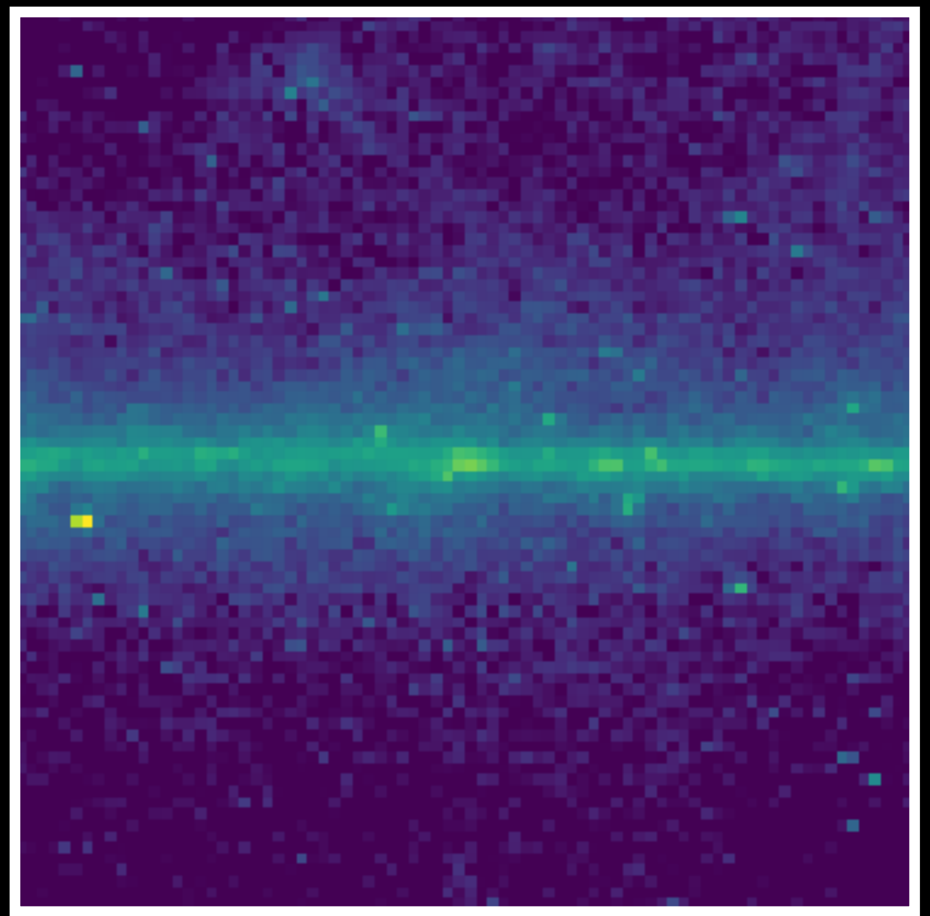

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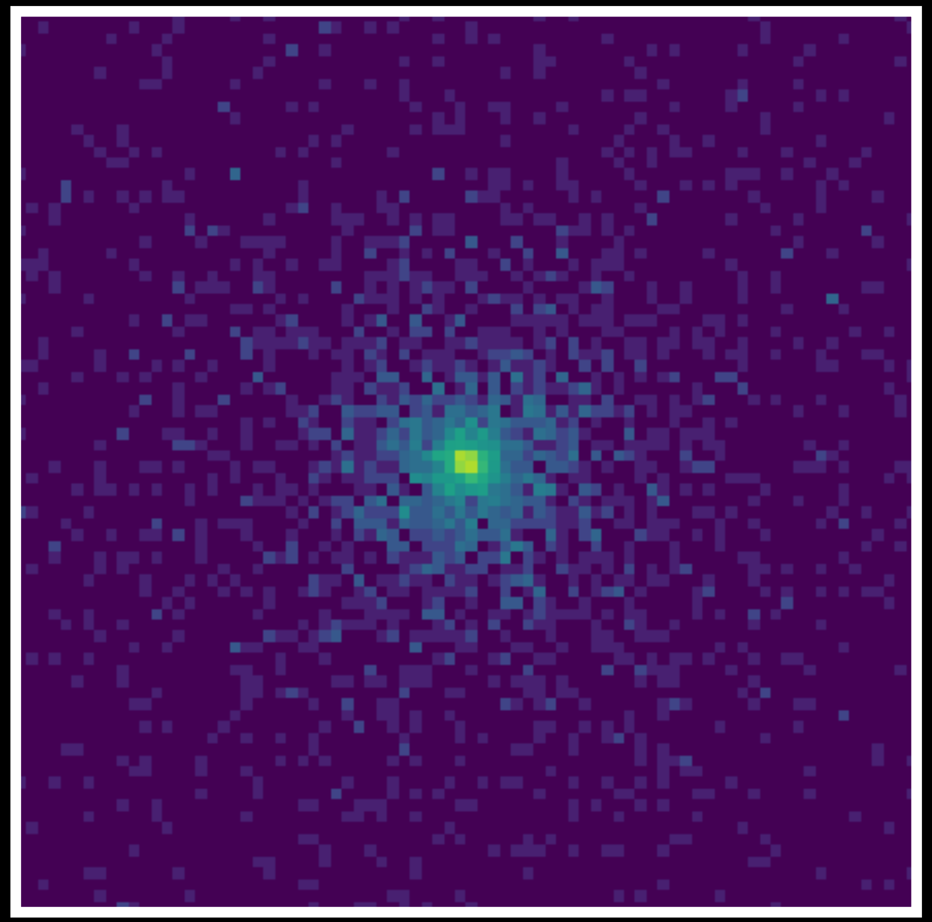

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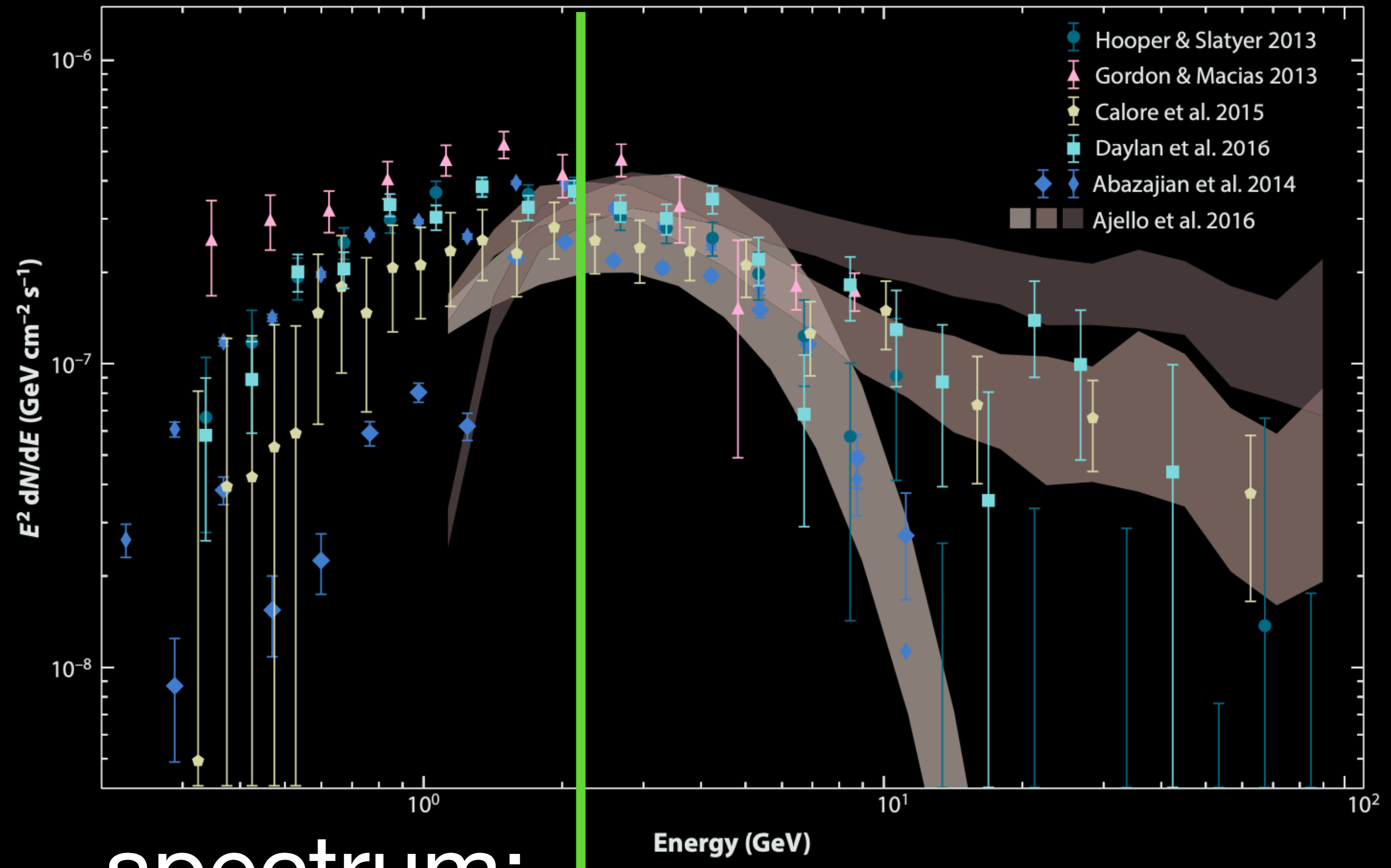

spectrum:
peak at 2 GeV,
tails uncertain

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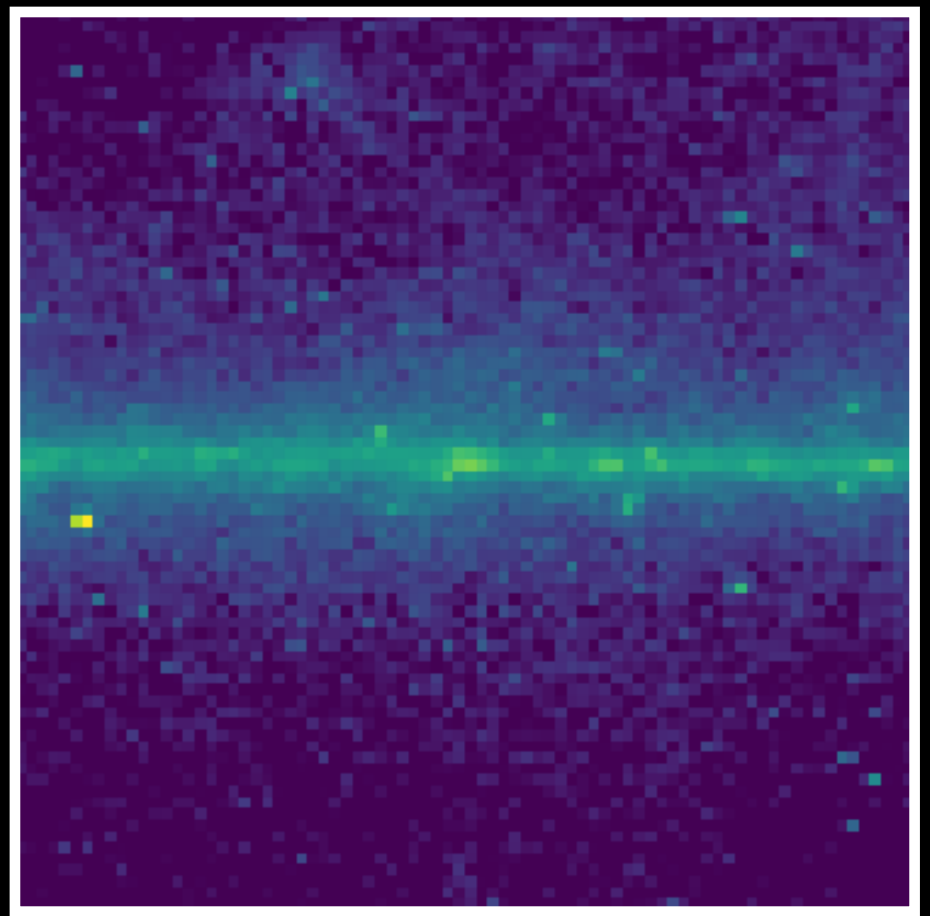

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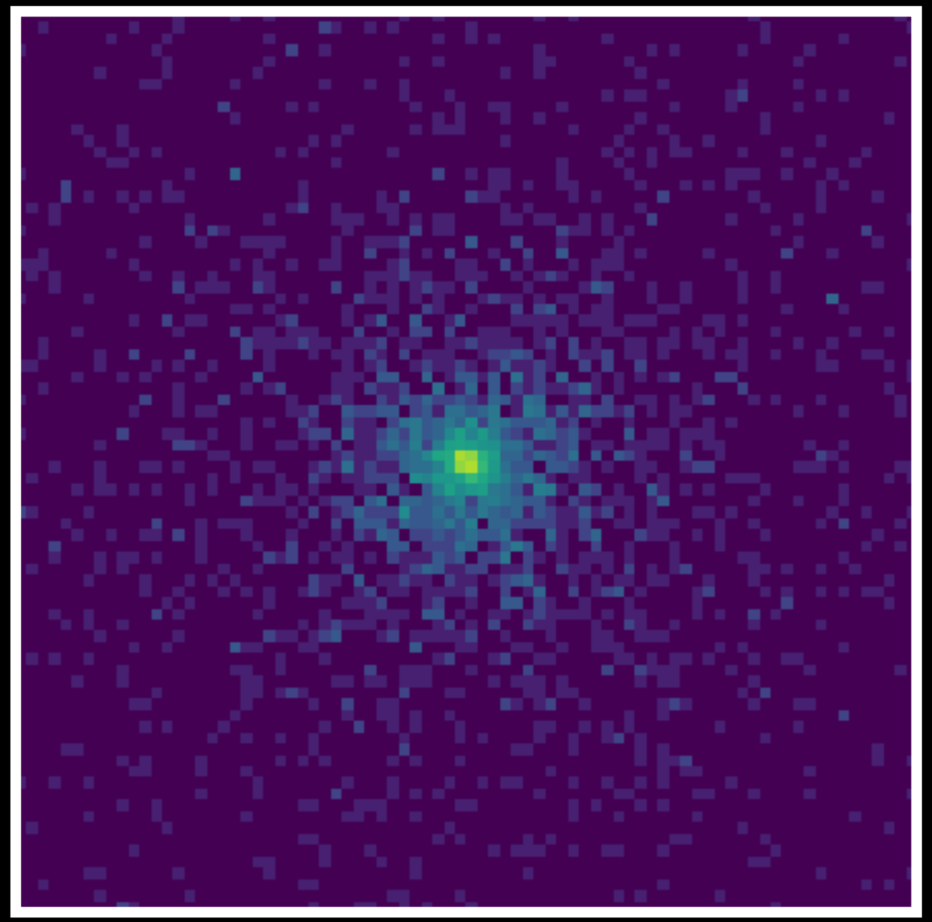

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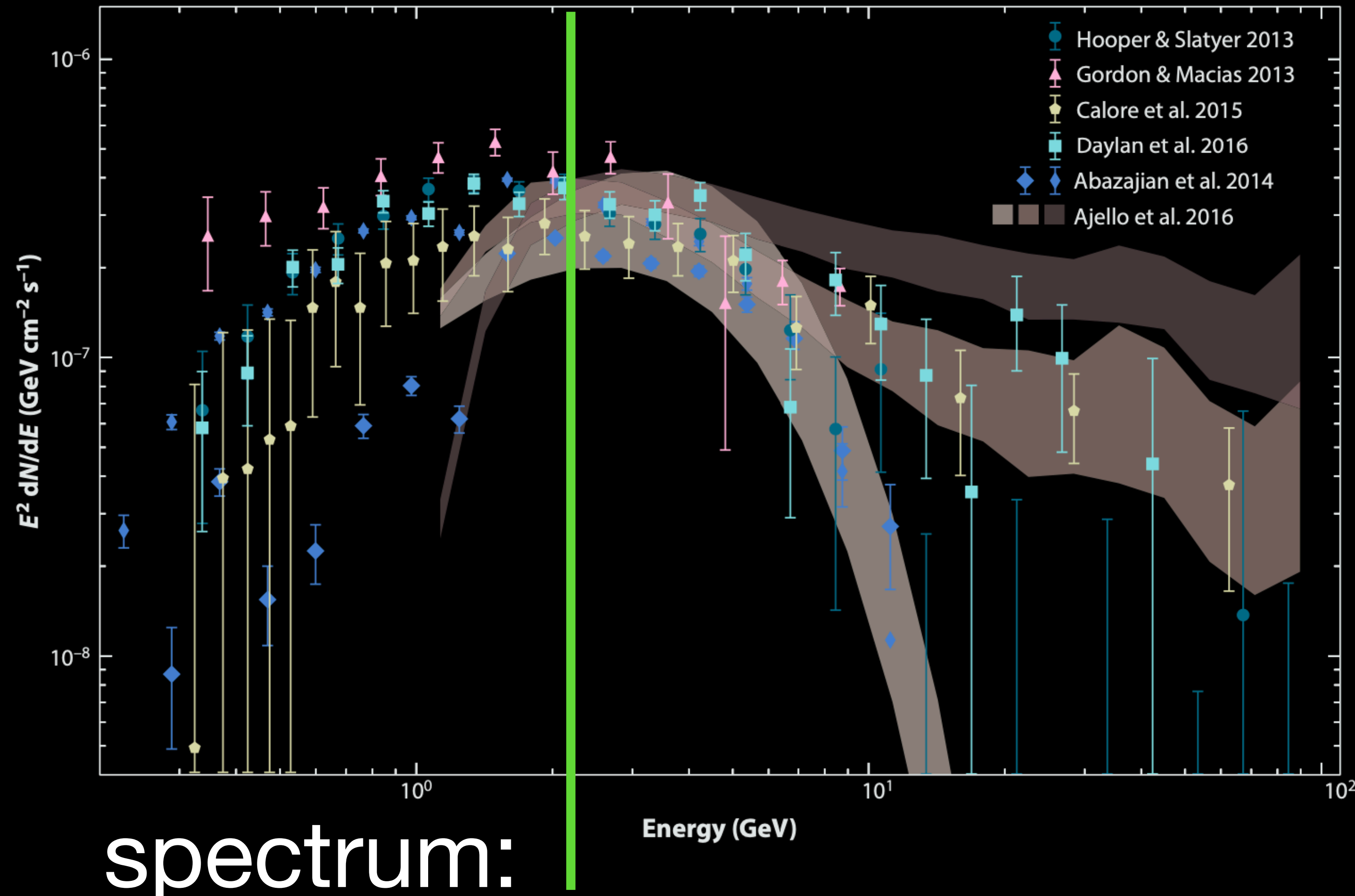

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Hypothesis I: An otherwise unseen, unresolved population of millisecond pulsars (point sources).

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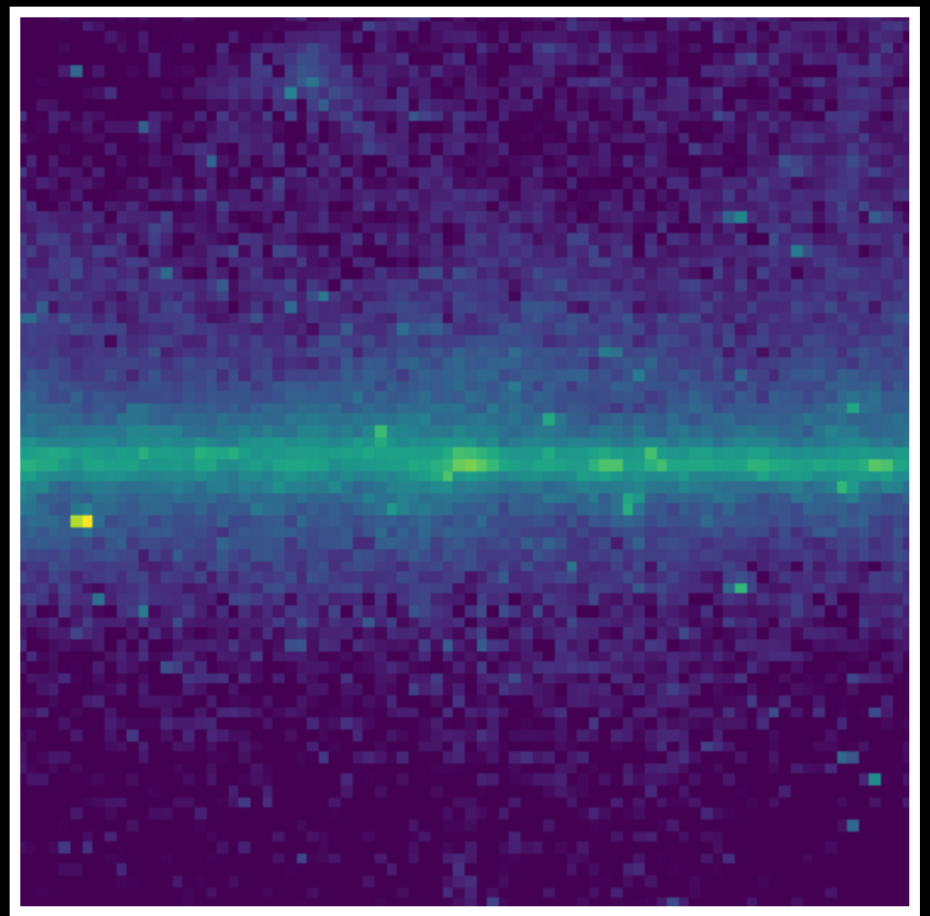

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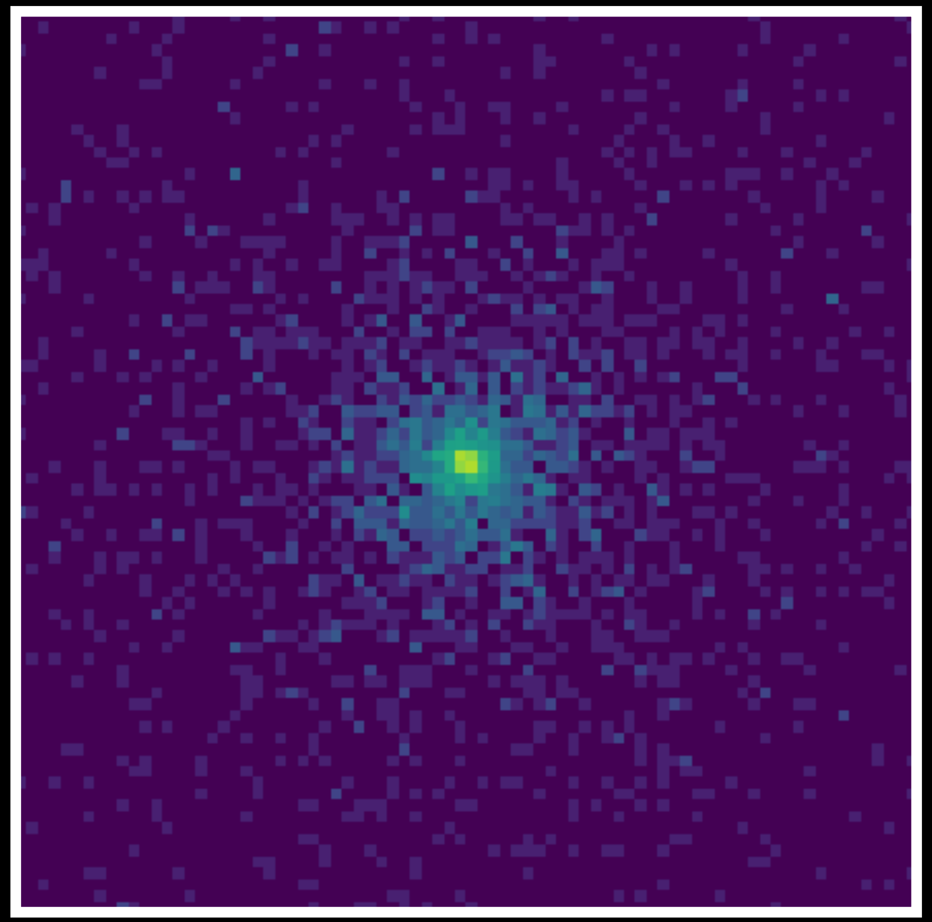
$\supset$



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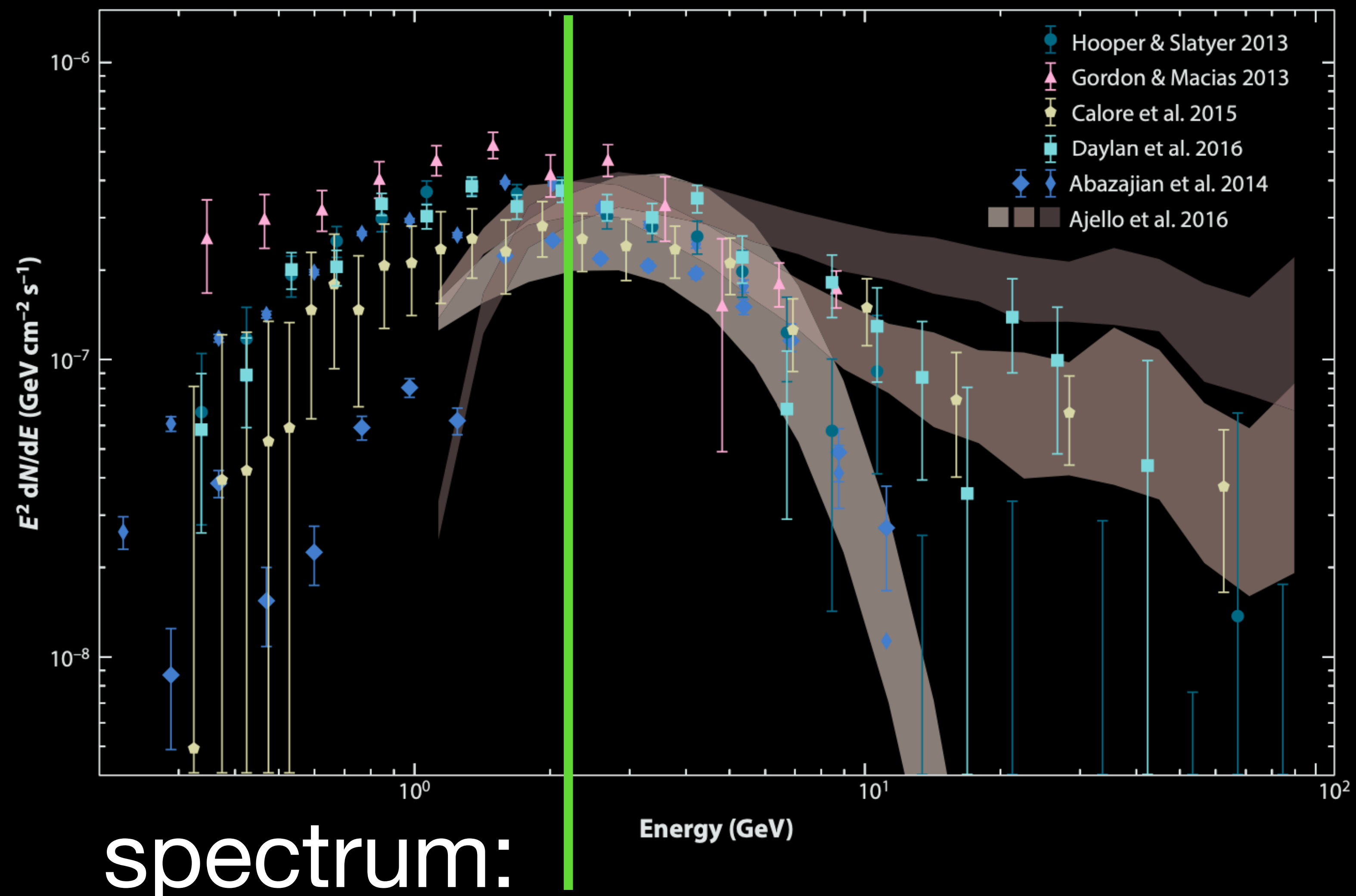

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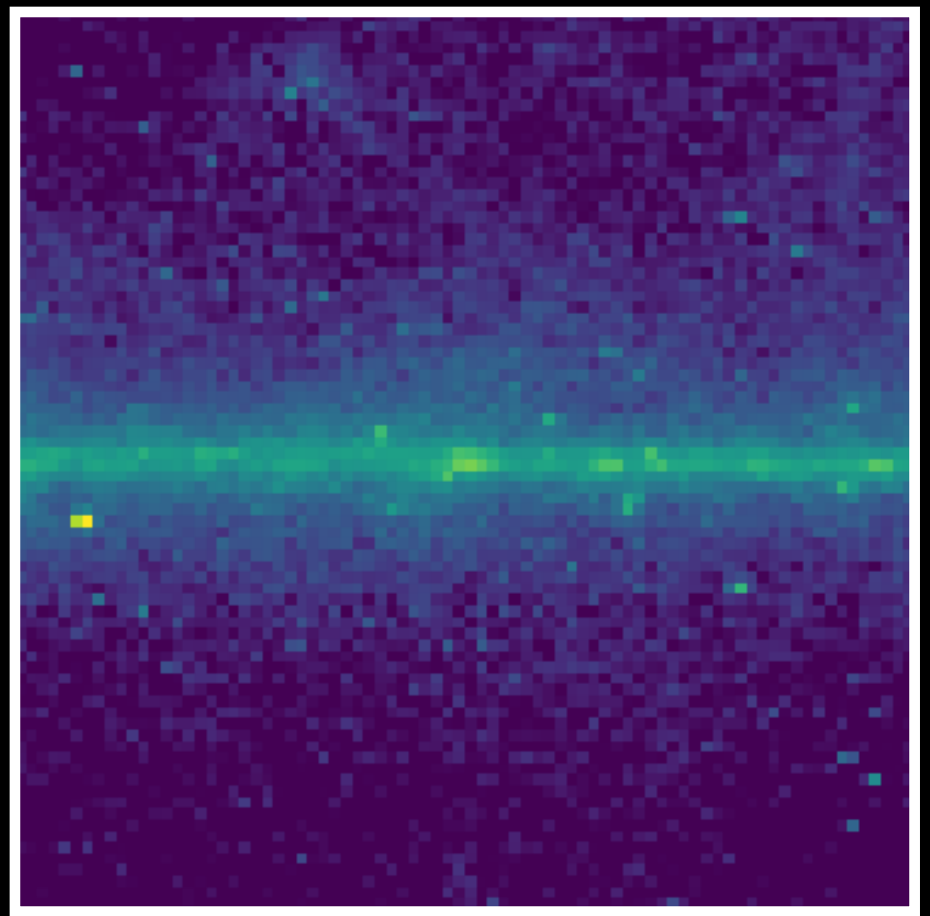
Hypothesis I: An otherwise unseen, unresolved population of millisecond pulsars (point sources).
Hypothesis II: Dark Matter annihilation, e.g. $\chi\chi \to b\bar{b}$, with mass ~ 40 GeV (diffuse source).

Galactic Center γ-ray: components



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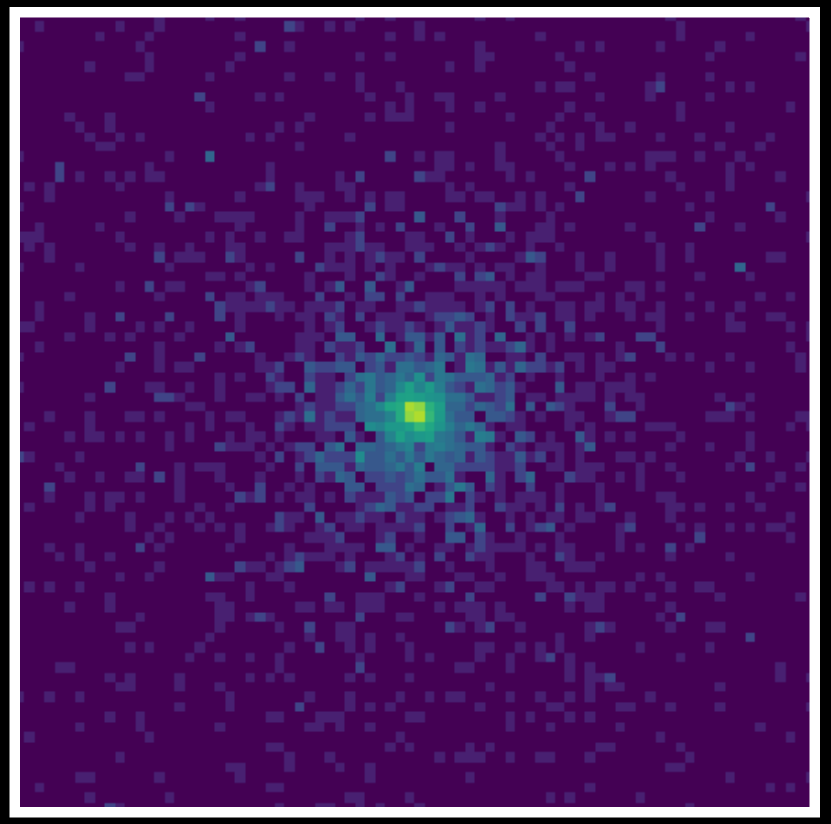

excess

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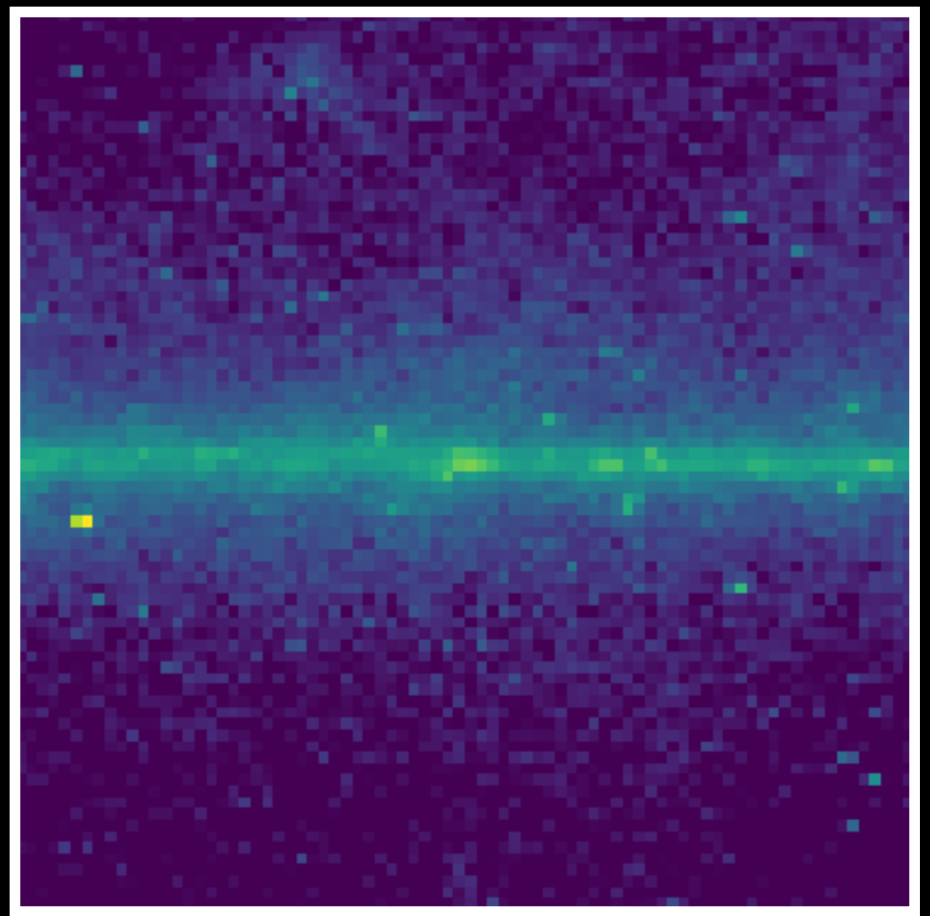

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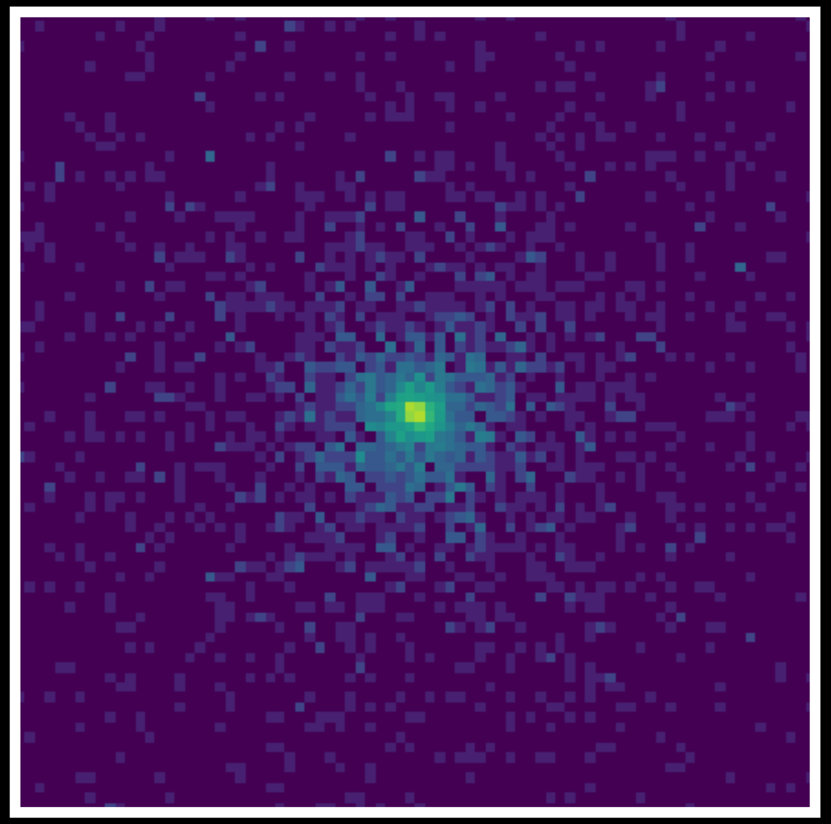
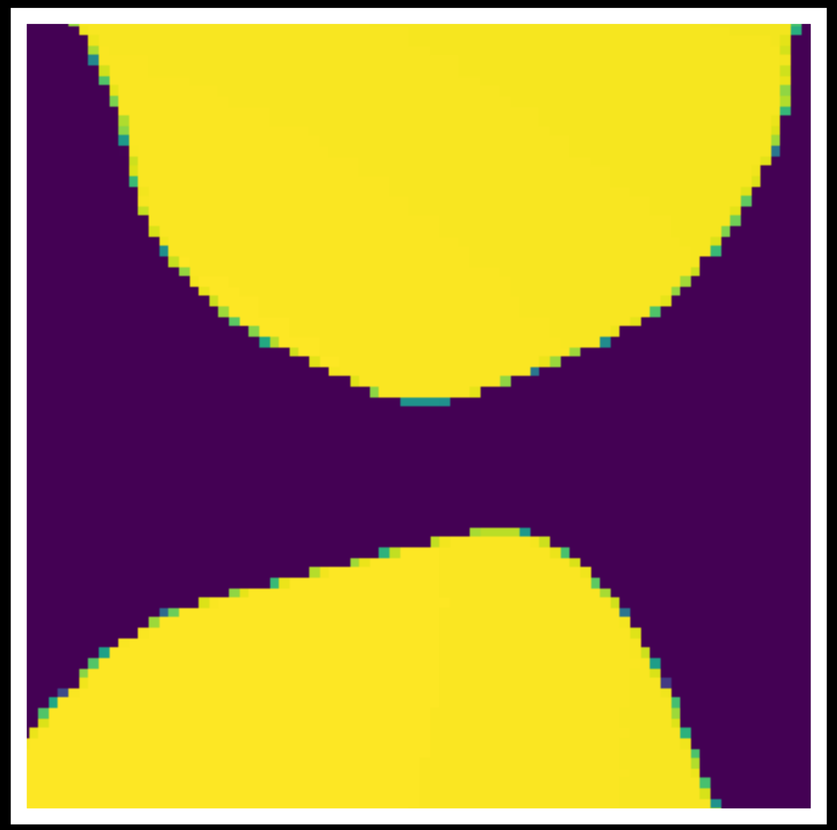


excess

$+$



Fermi bubble

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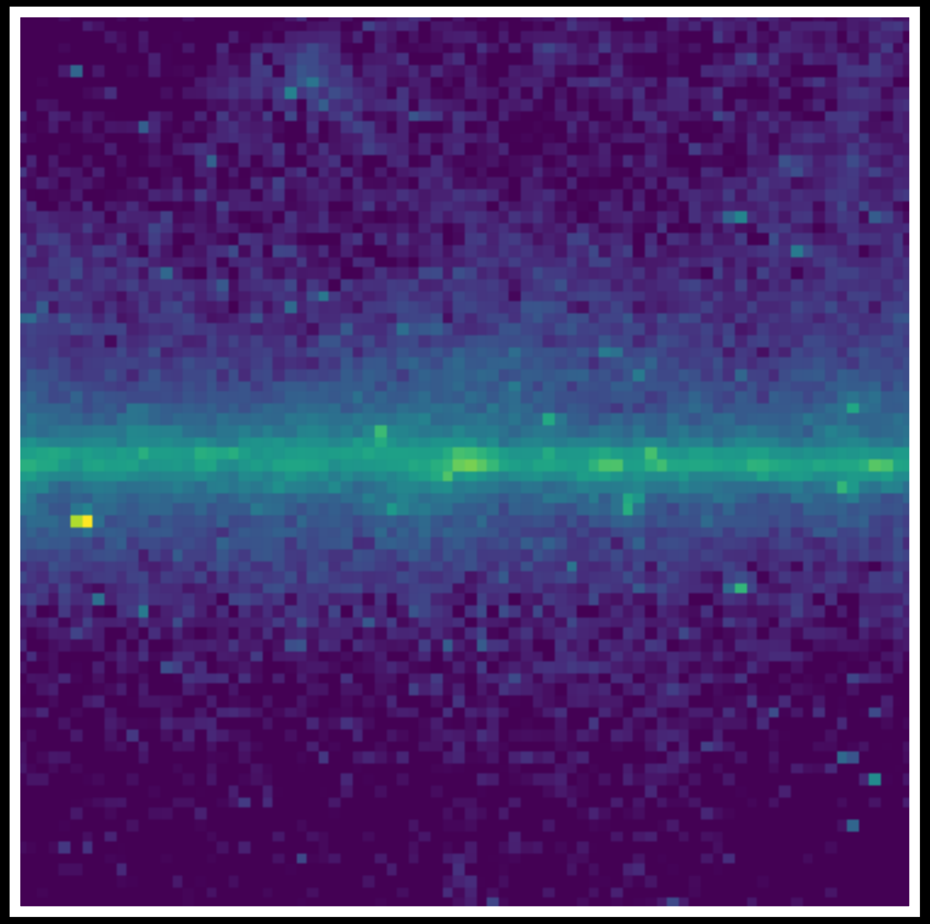

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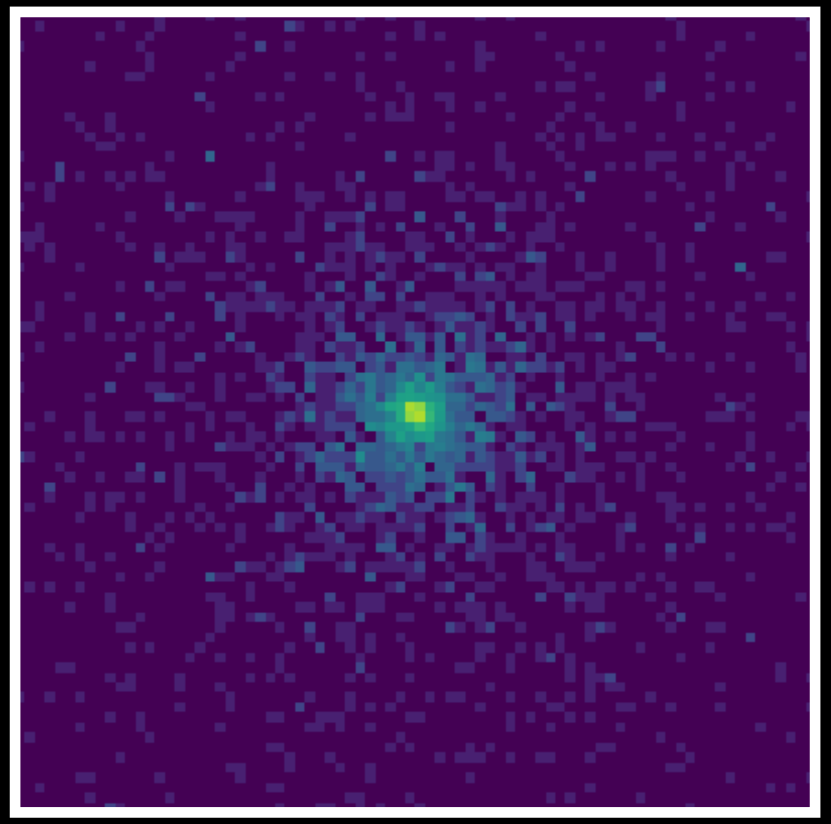

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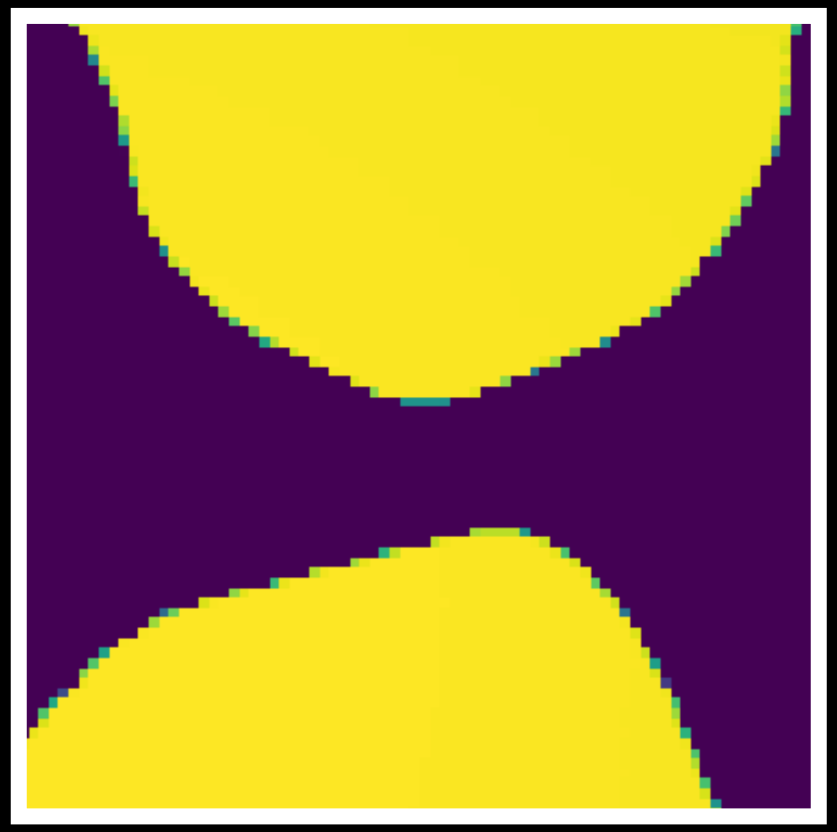

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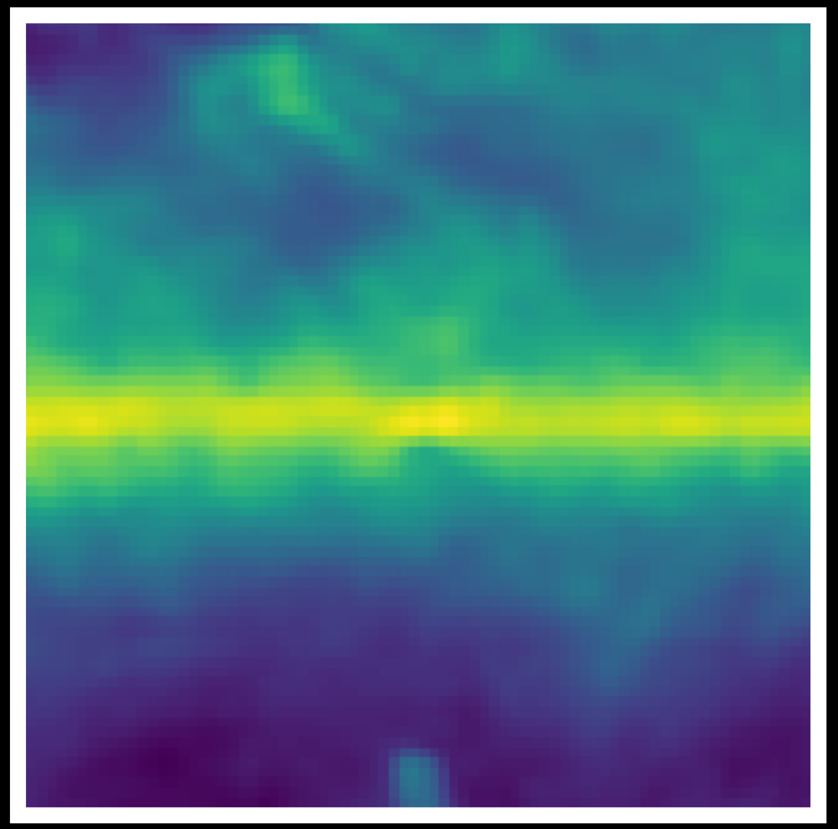
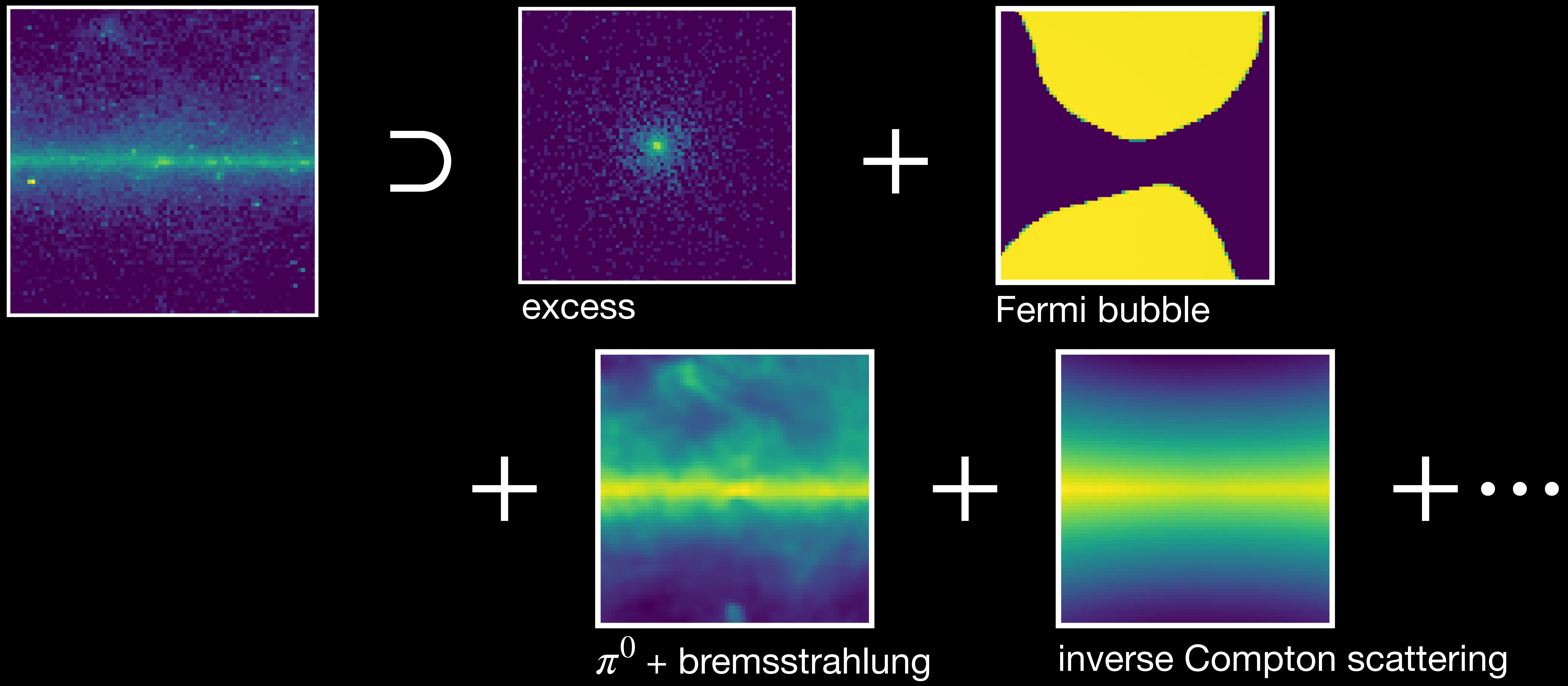


π^0 + bremsstrahlung

Galactic Center γ-ray: components



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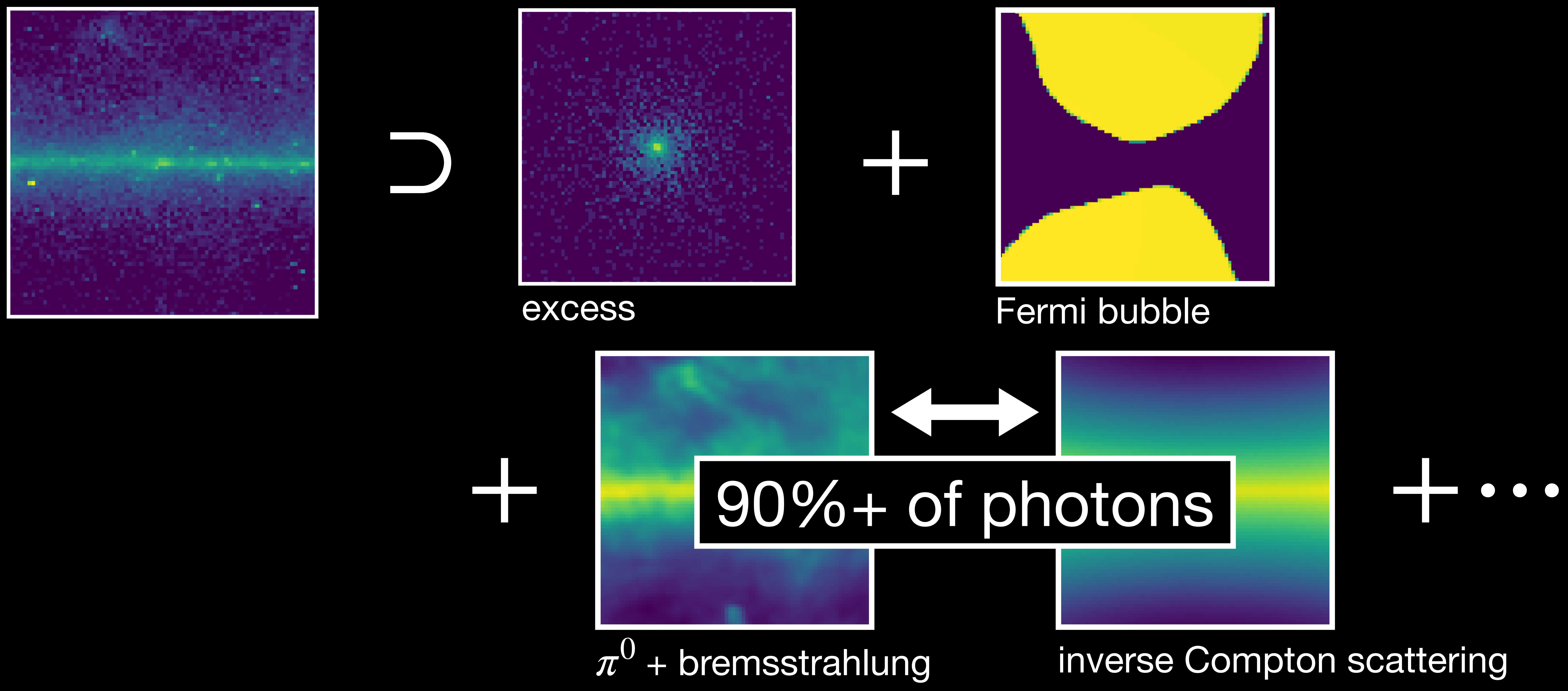

Question 1: morphology of GCE

Point sources: millisecond pulsars may traces known stellar distributions in the galactic bulge

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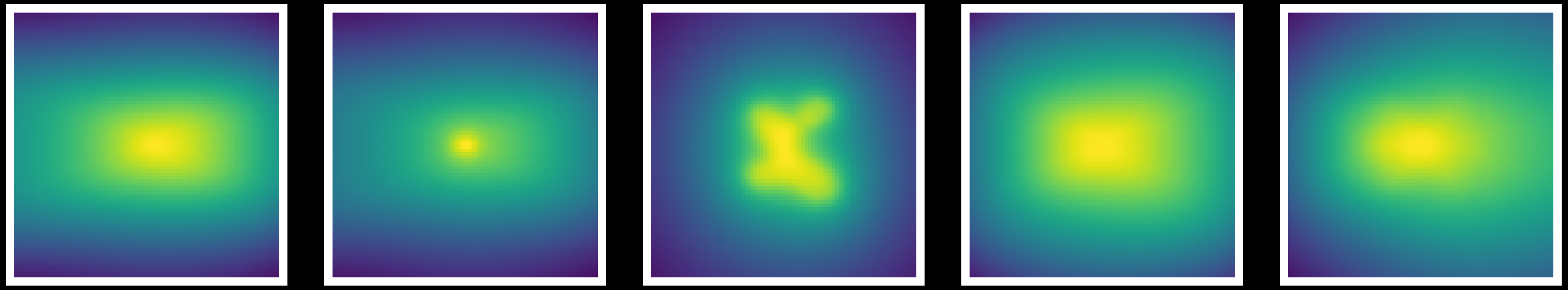
examples: 

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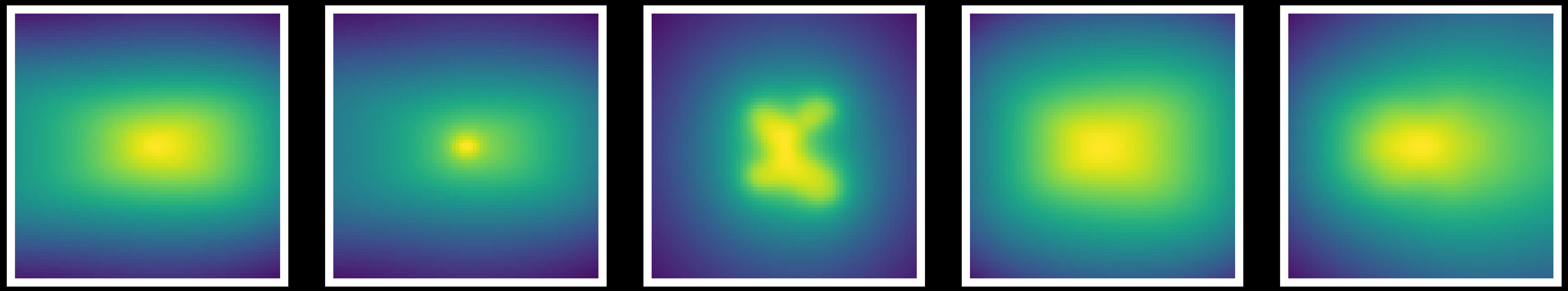
examples: 

Dark matter: Generalized NFW with inner slope parameter γ ~ 1.2 ($\rho \propto r^{-\gamma}$ for small r).

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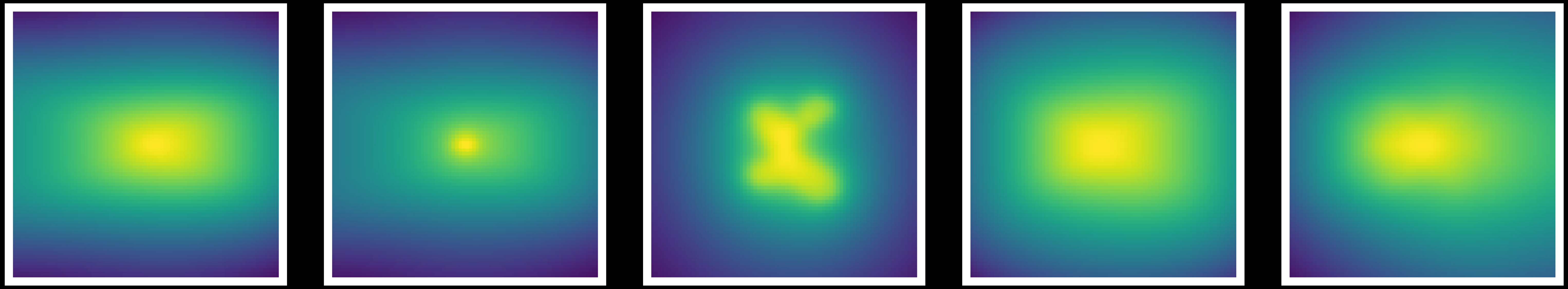

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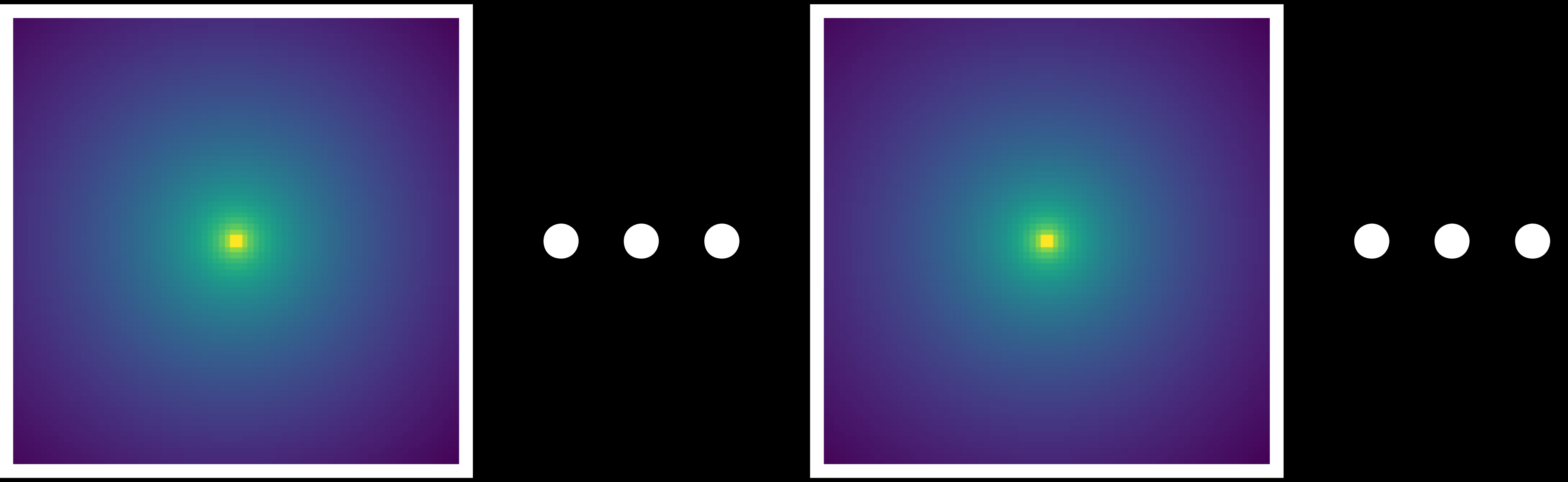

γ = 1.0 γ = 1.2

Question 2: diffuse or point source

Dark matter
(diffuse source)

Unresolved pulsars
(point sources, known location)

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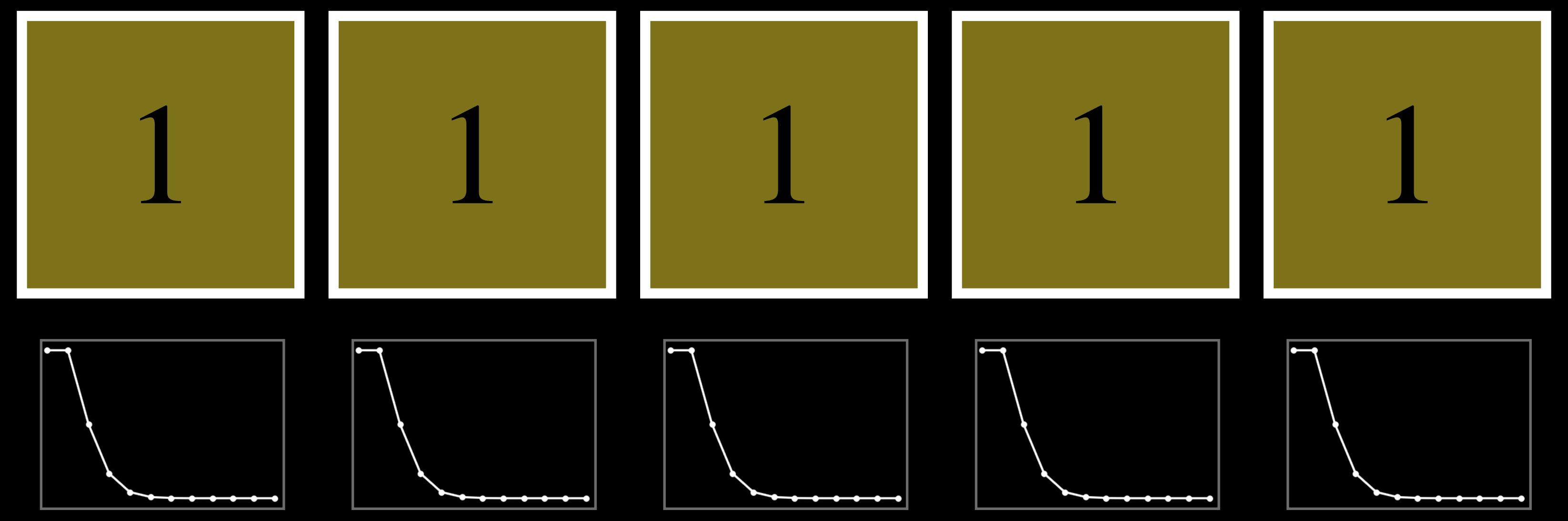

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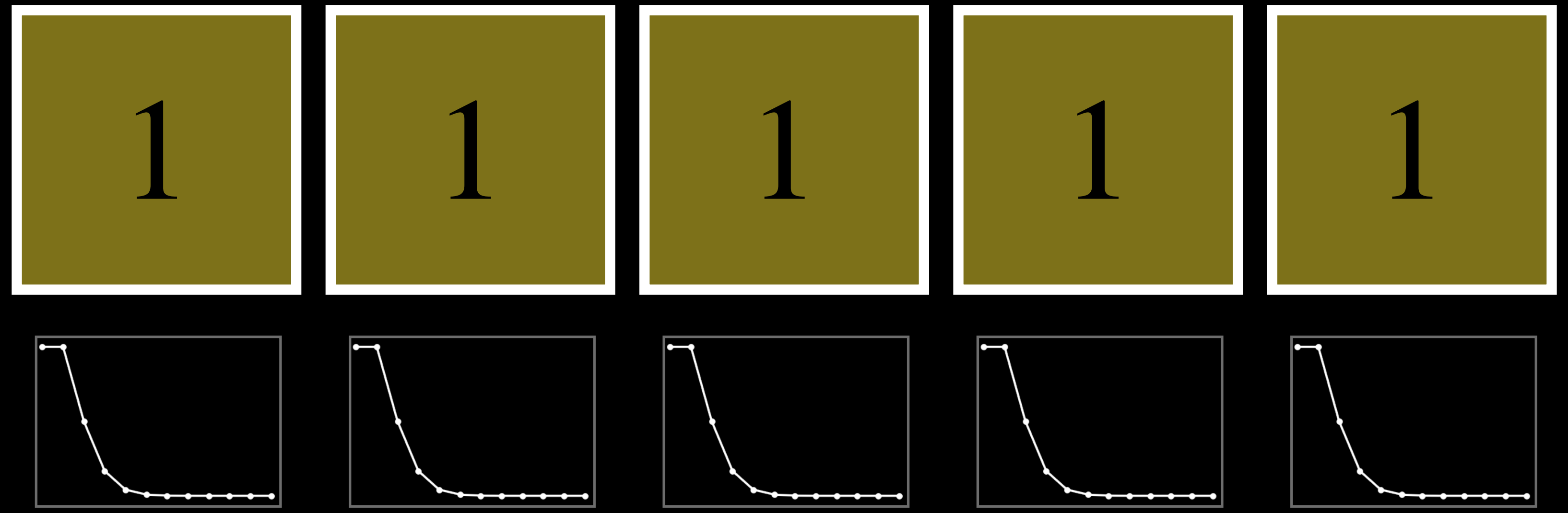

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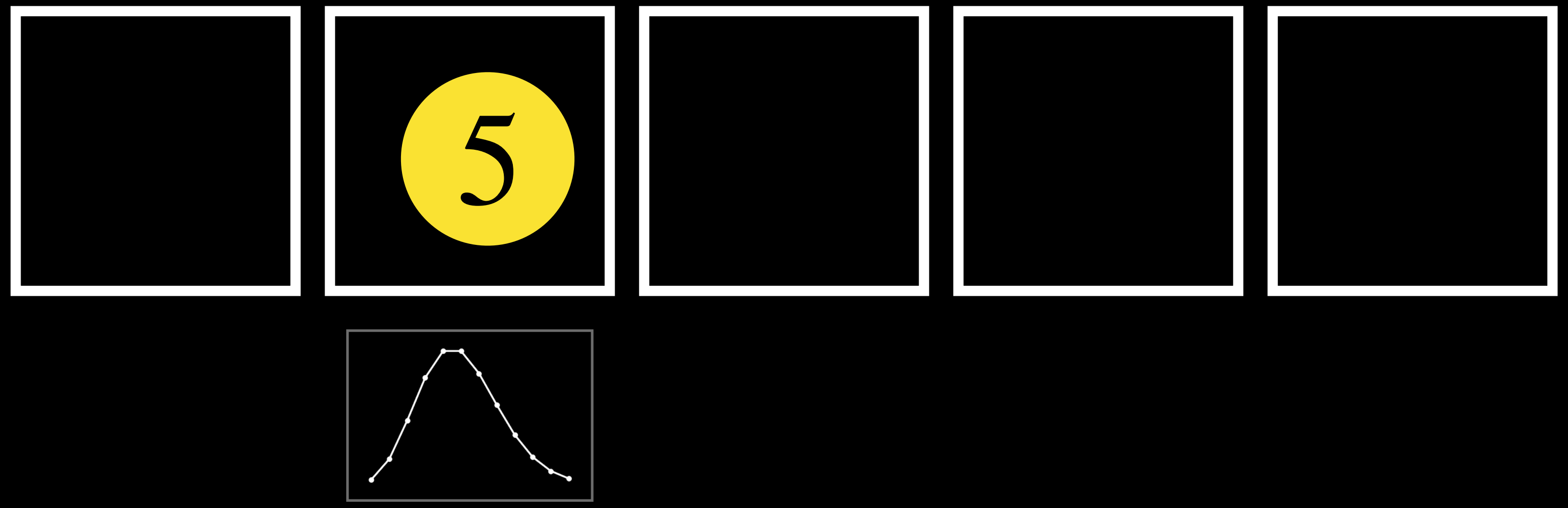

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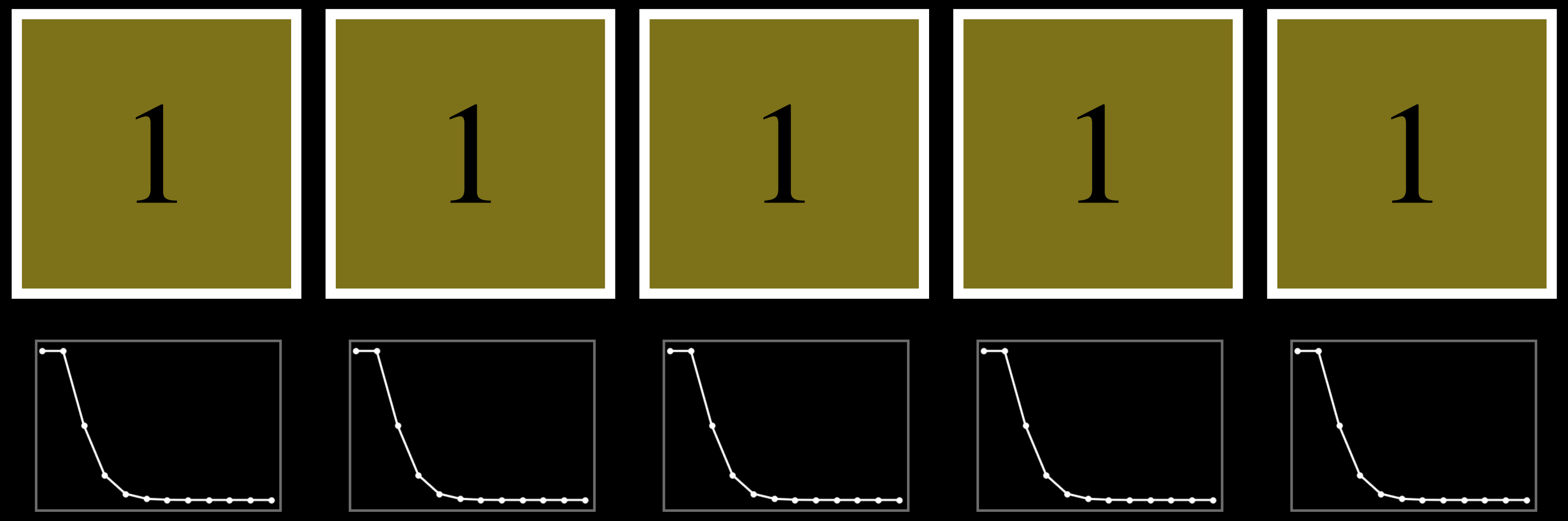

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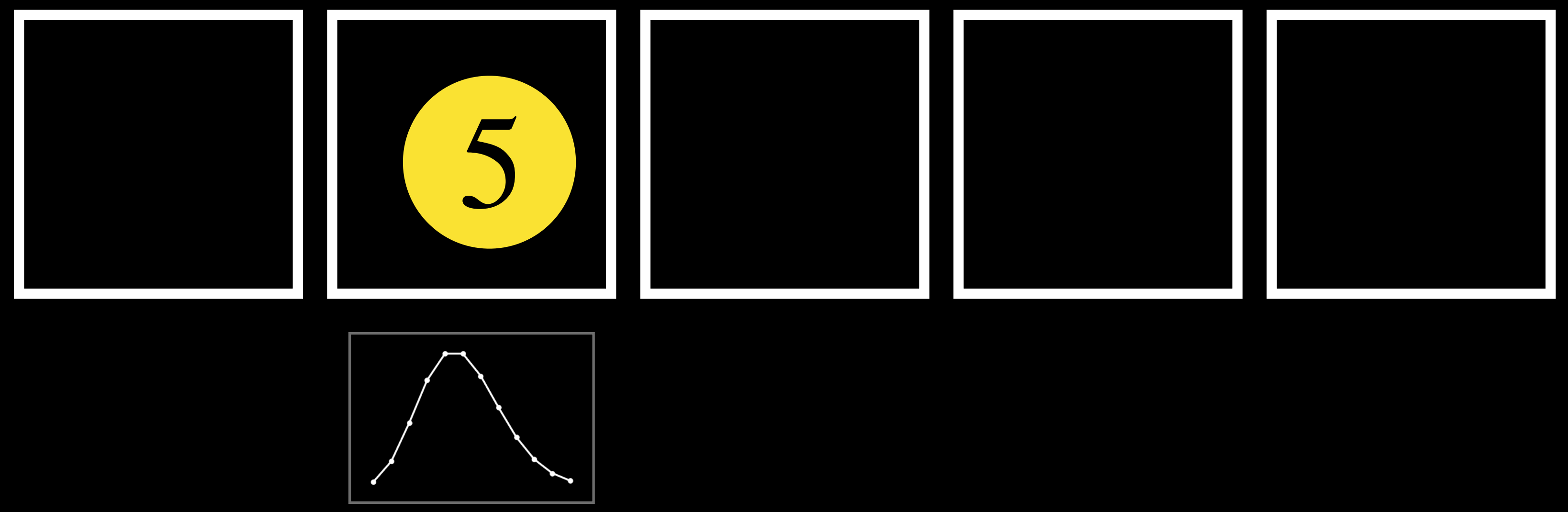

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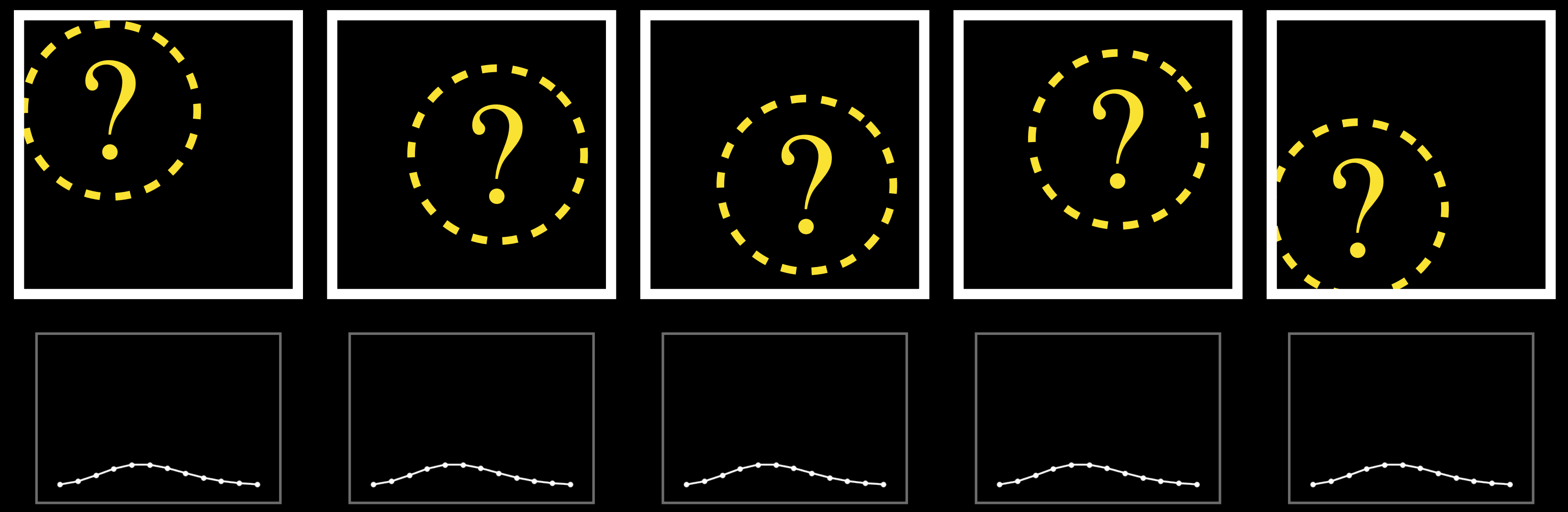

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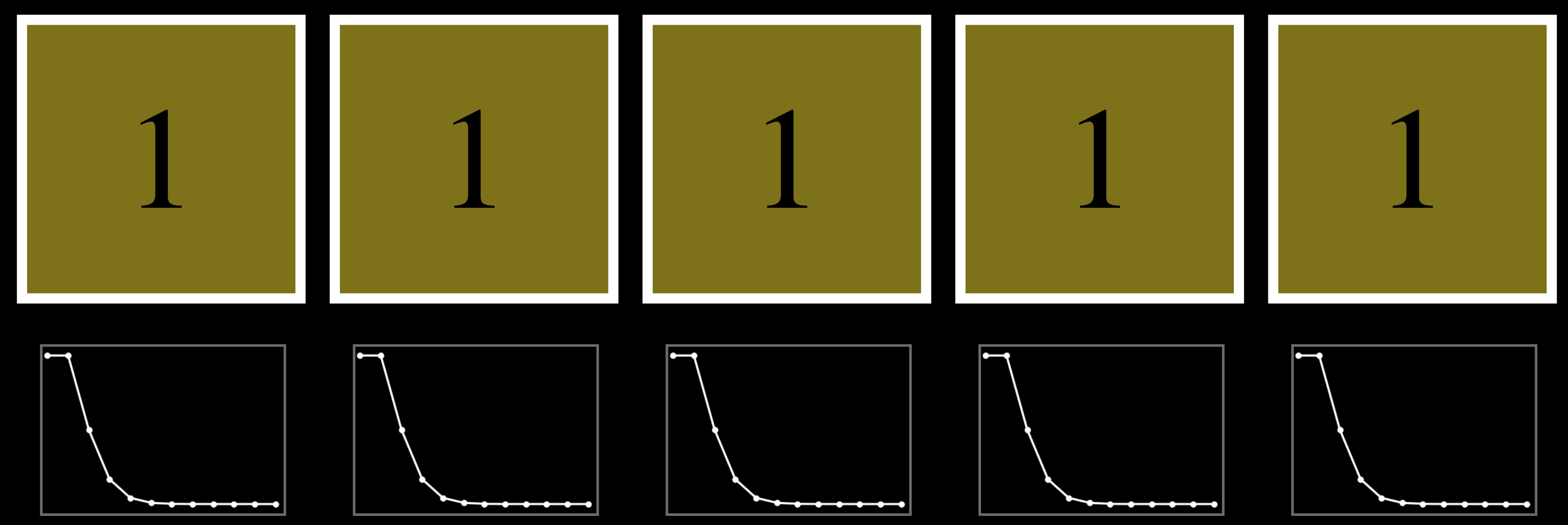

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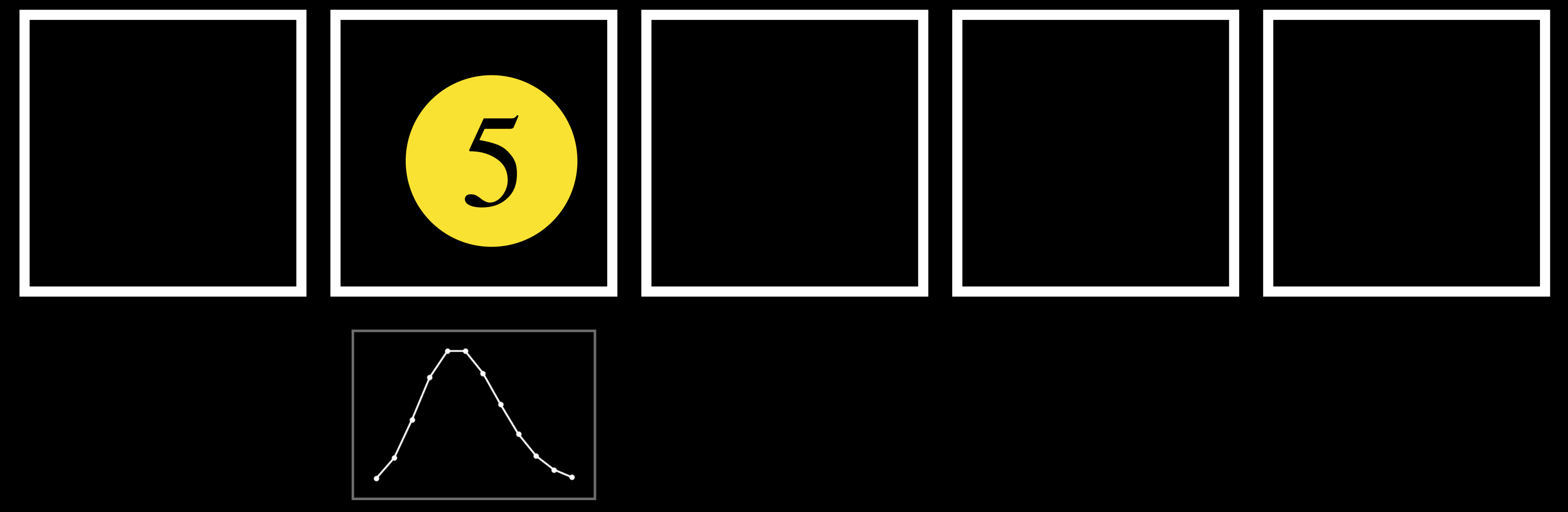

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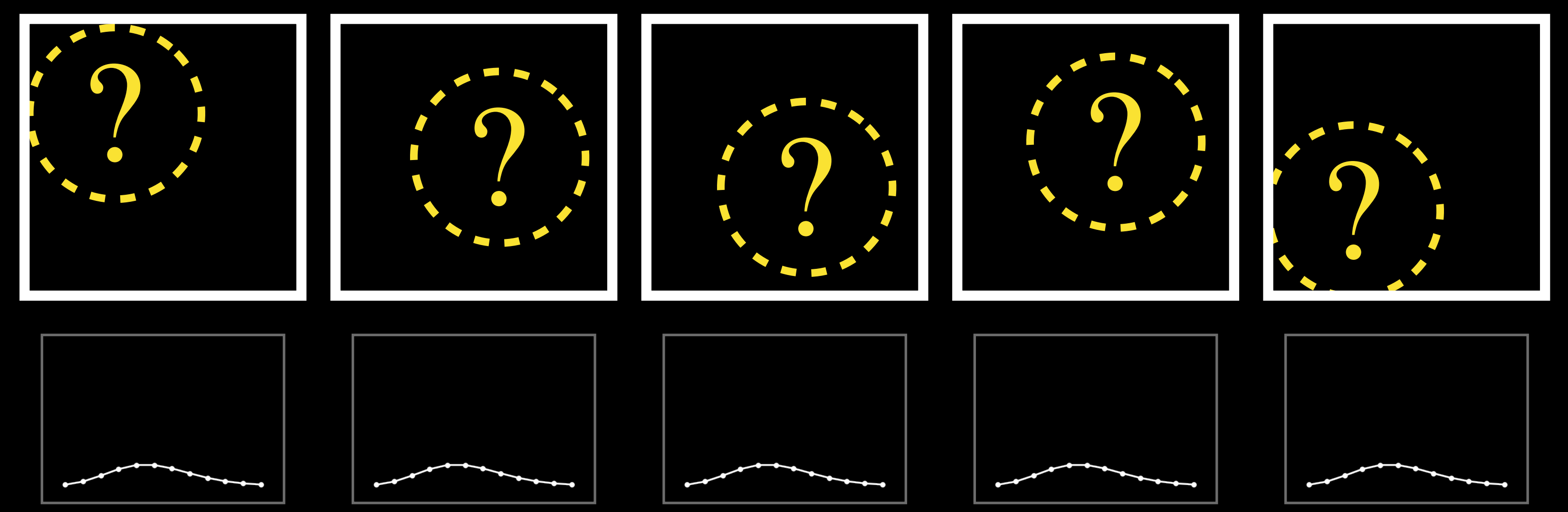
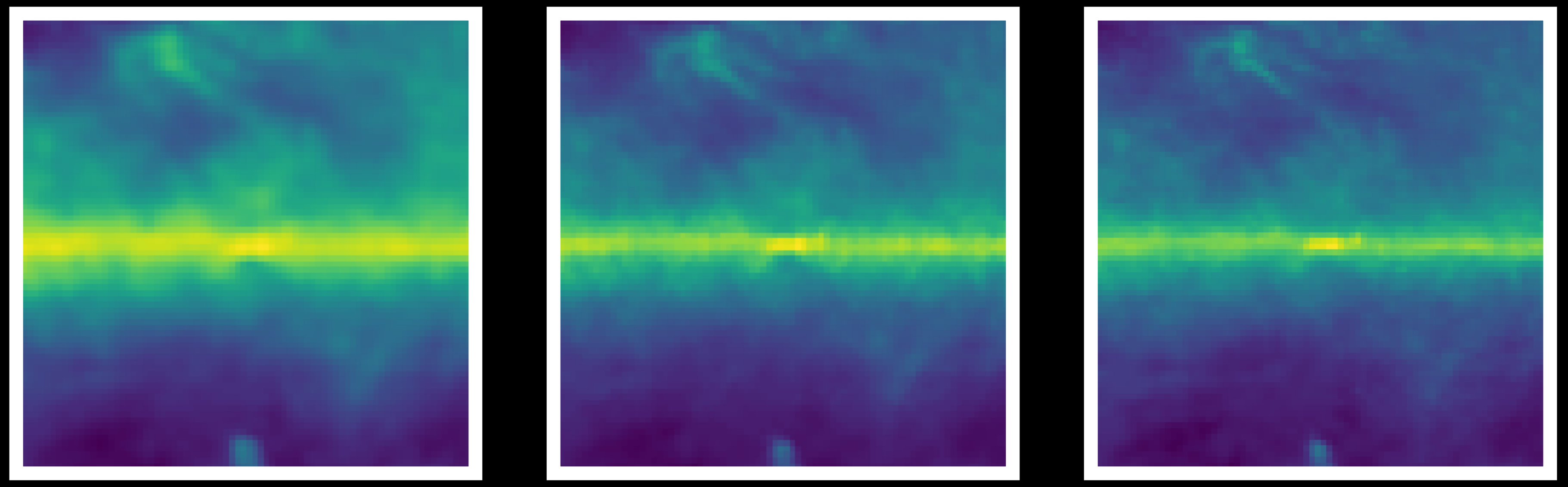


Computing point source
(non-poissonian) likelihood is expensive! →

Question 0: modeling gas-correlated emissions

Different groups have reconstructed gas-correlated emissions (π^0+bremsstrahlung) using different physics & fitting assumptions.



Model A [1] Model F [1] Model O [2]

[1] Calore Cholis Weniger (2015)
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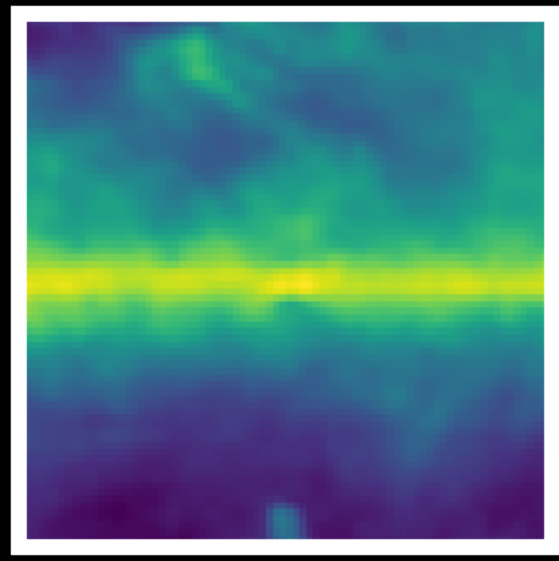

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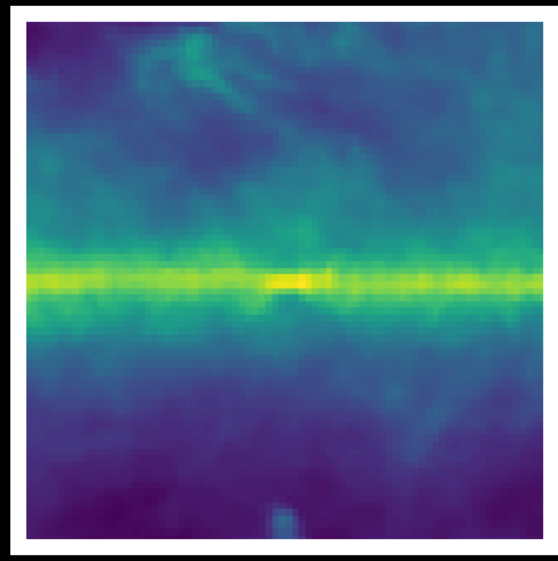
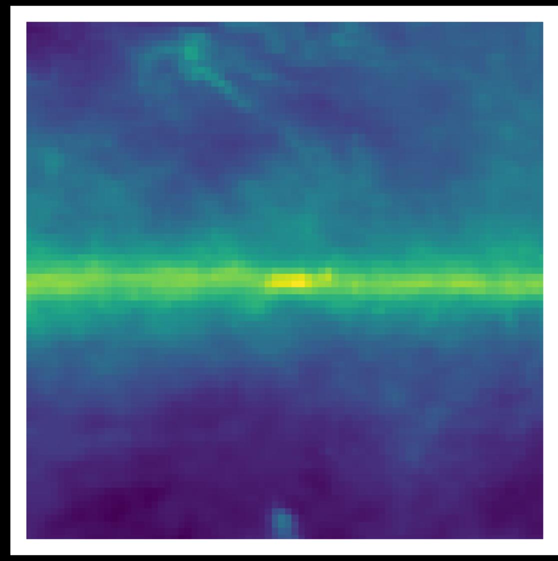
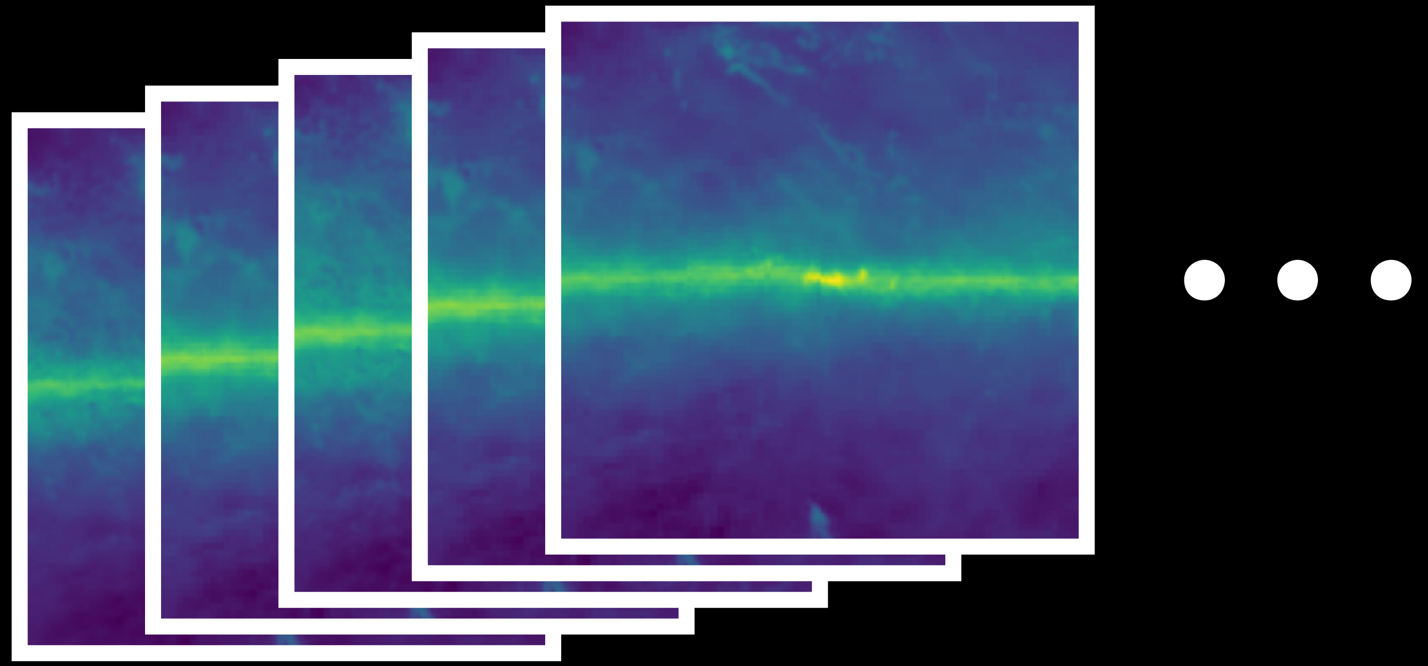


Model F [1]



Model O [2]



“Return of the templates” [3]
(varying physical parameters in galprop)

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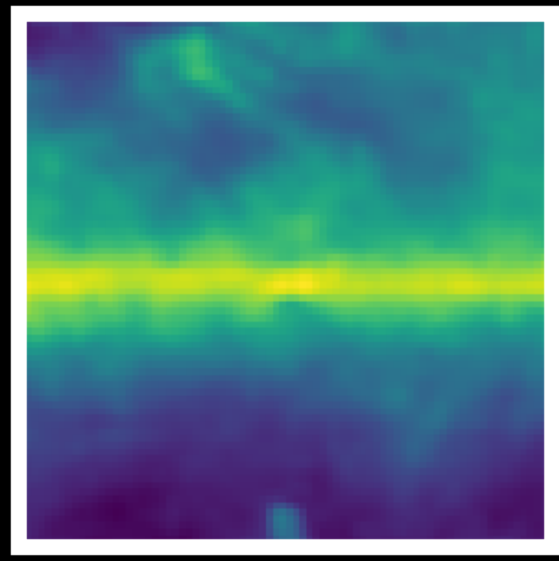

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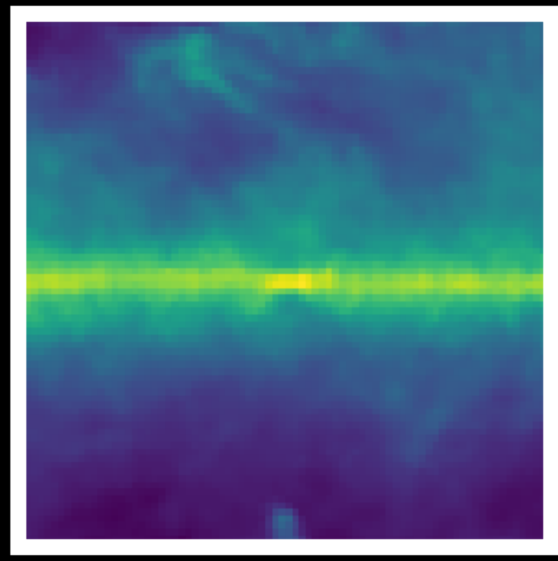

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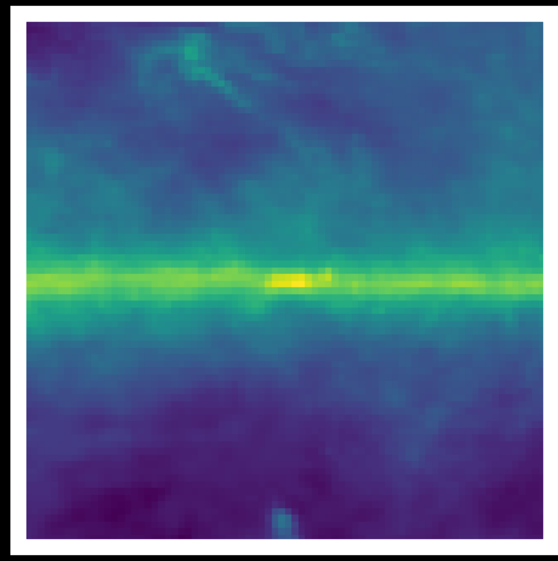
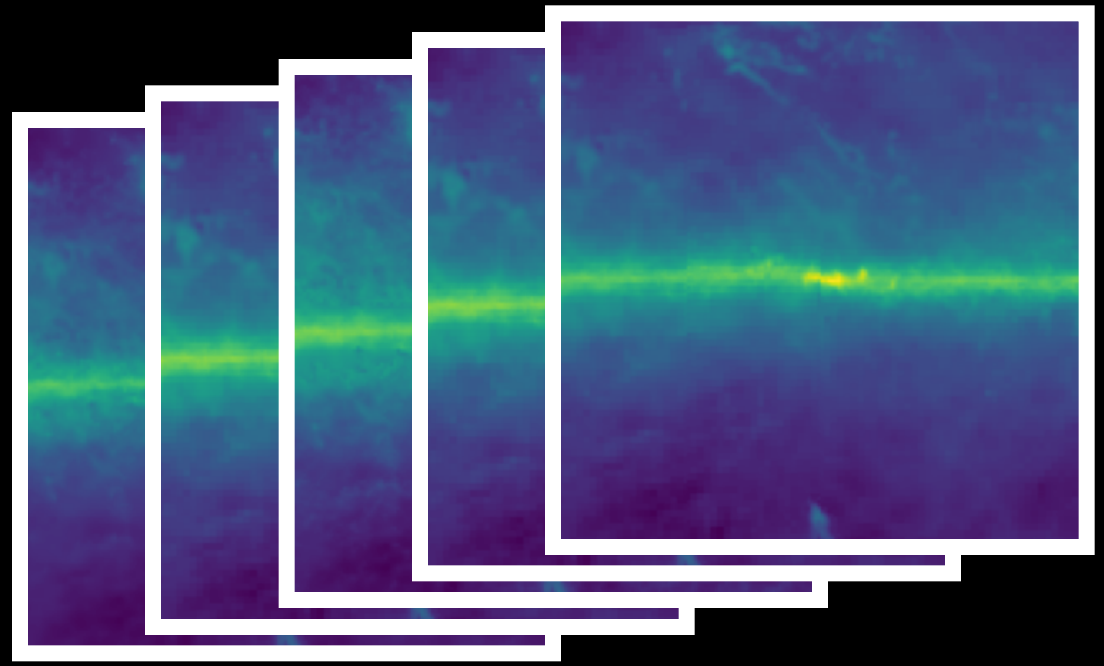


Model O [2]



…

“Return of the templates” [3]
(varying physical parameters in galprop)

Uncertainties on modeling interstellar gas emission can greatly affect fits of the GCE, due to the photon number difference.

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Challenges in GCE

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will increase γ-ray model parameters

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Challenges in GCE

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} will increase γ-ray model parameters

- Need for faster computation of point source (non-poissonian) likelihood
- Need a unified framework to understand systematics
- We use GPU-accelerated differentiable probabilistic programming to specify flexible models and perform efficient inference on them.

Our model in differentiable probabilistic programming

Our model in differentiable probabilistic programming

a common framework for bayesian inference problems

NumPyro JAX

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a common framework for bayesian inference problems

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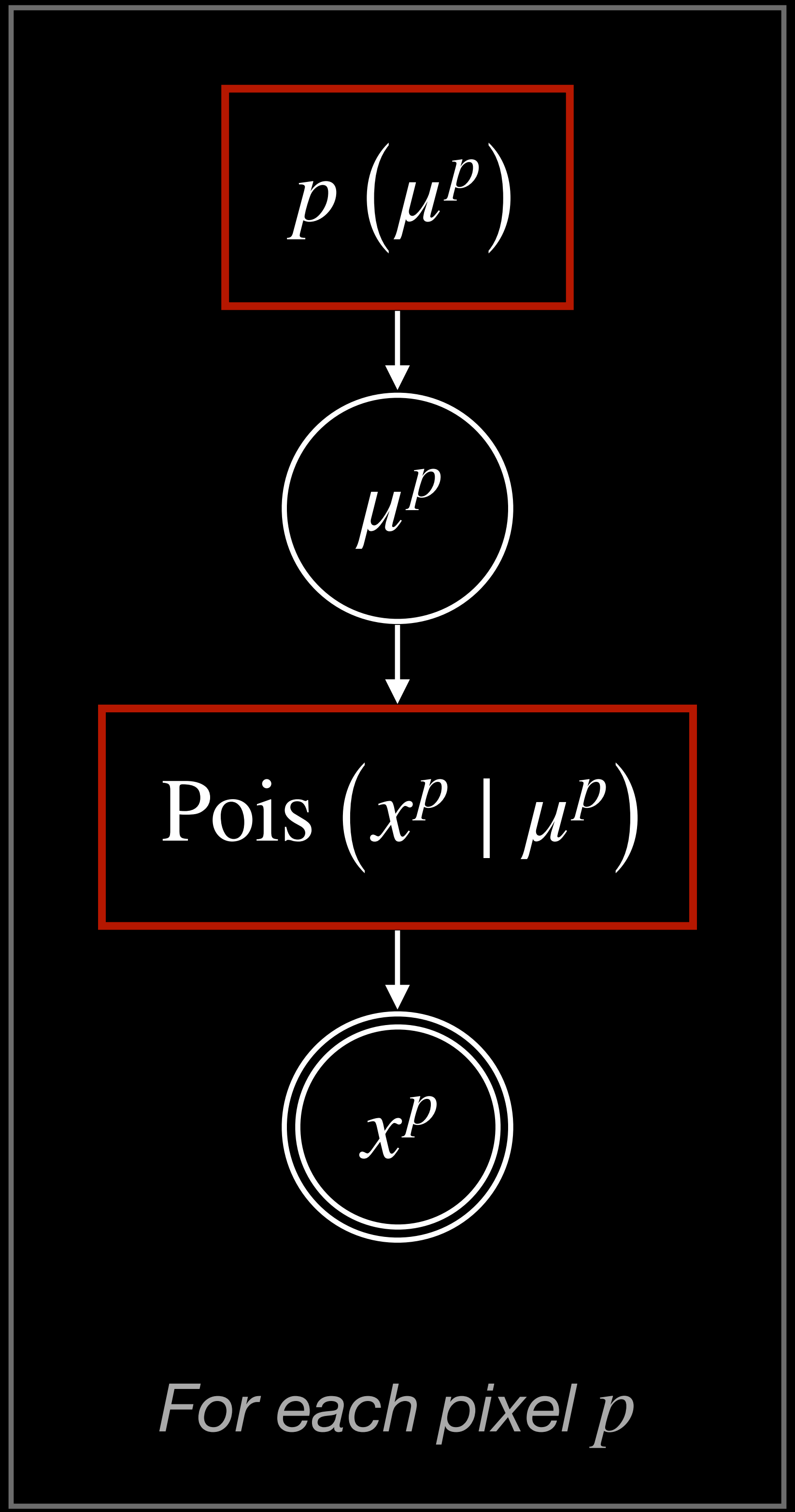

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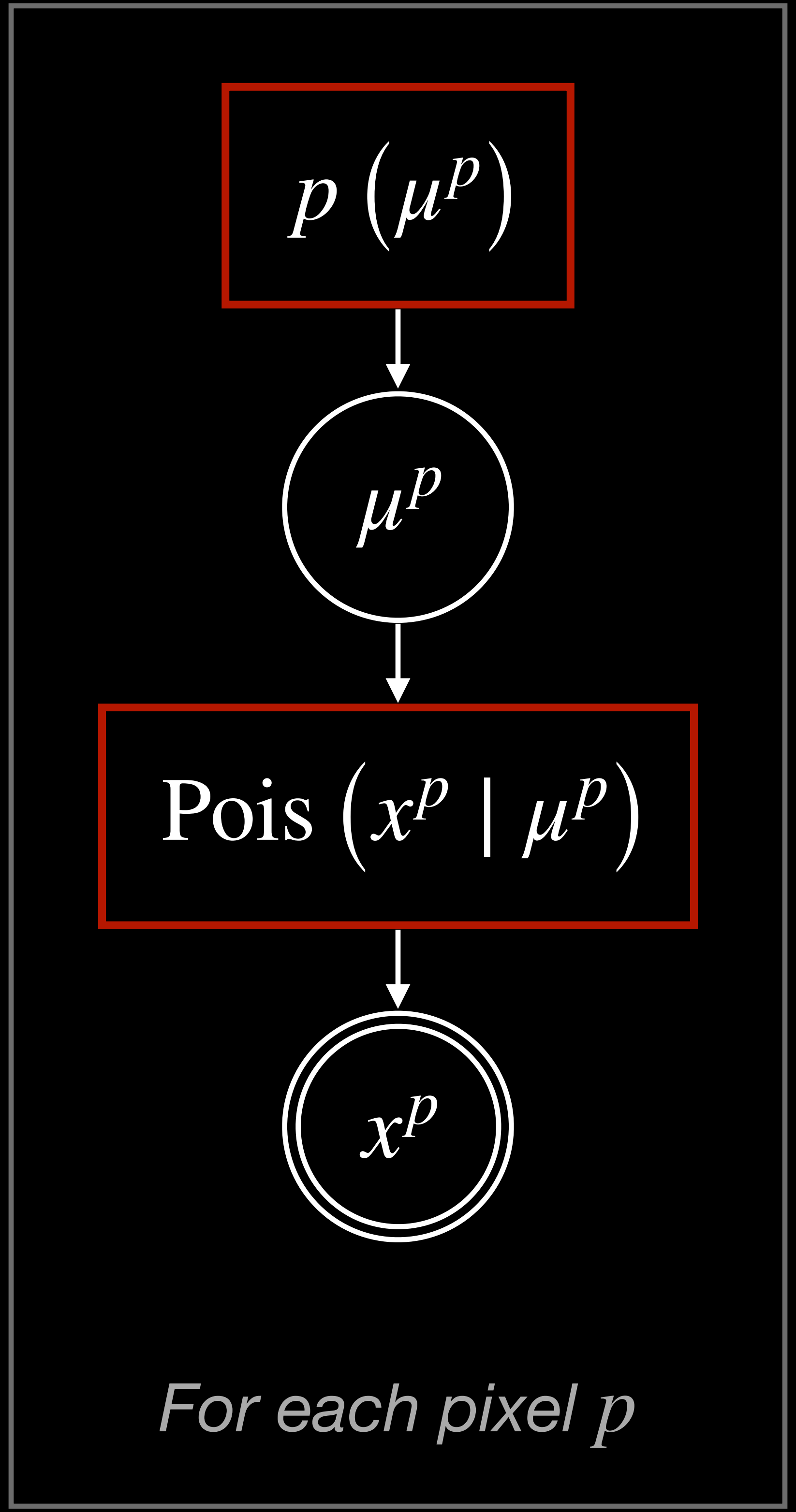

prior distribution

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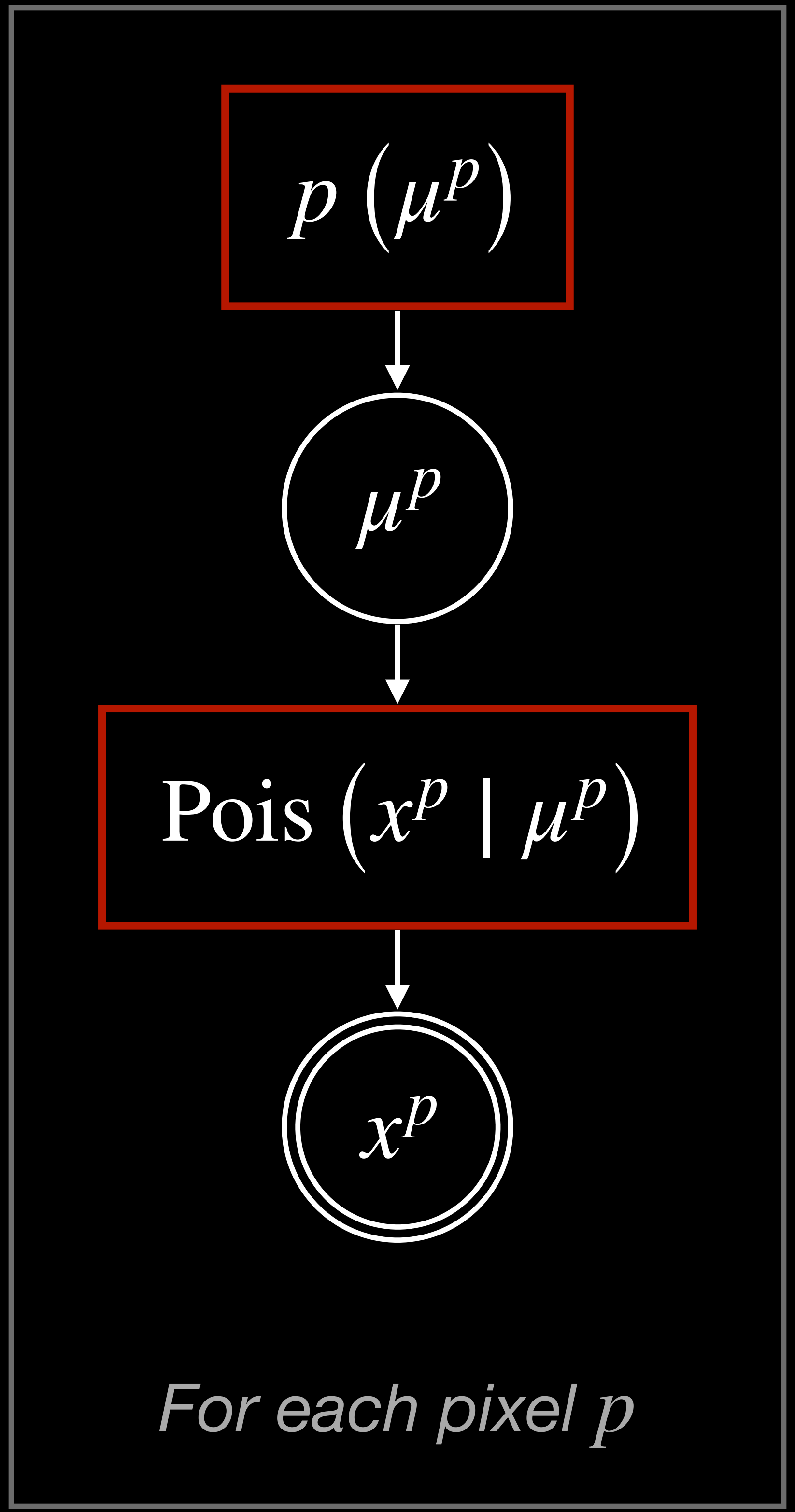

prior distribution

expected photon #

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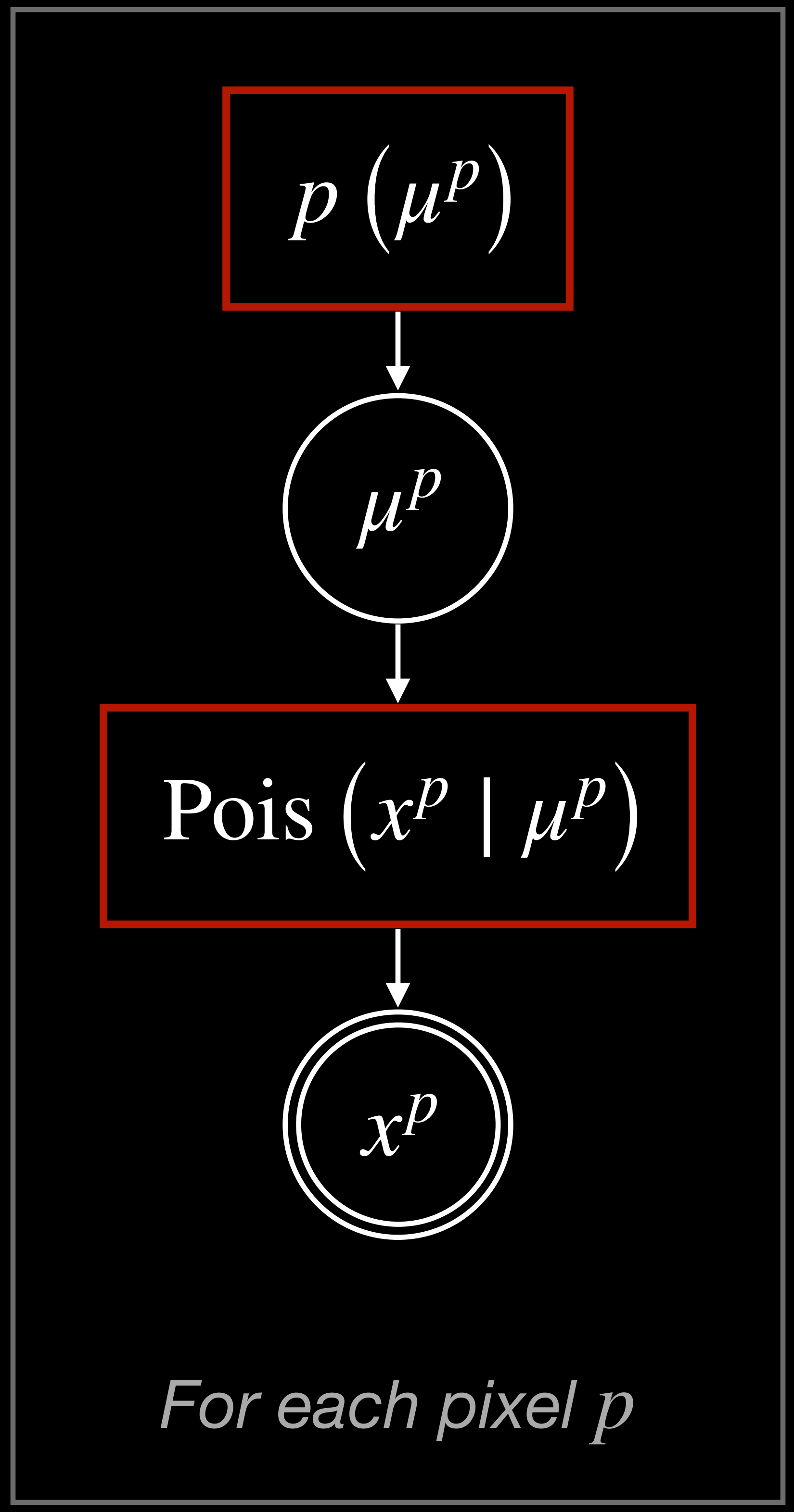

prior distribution

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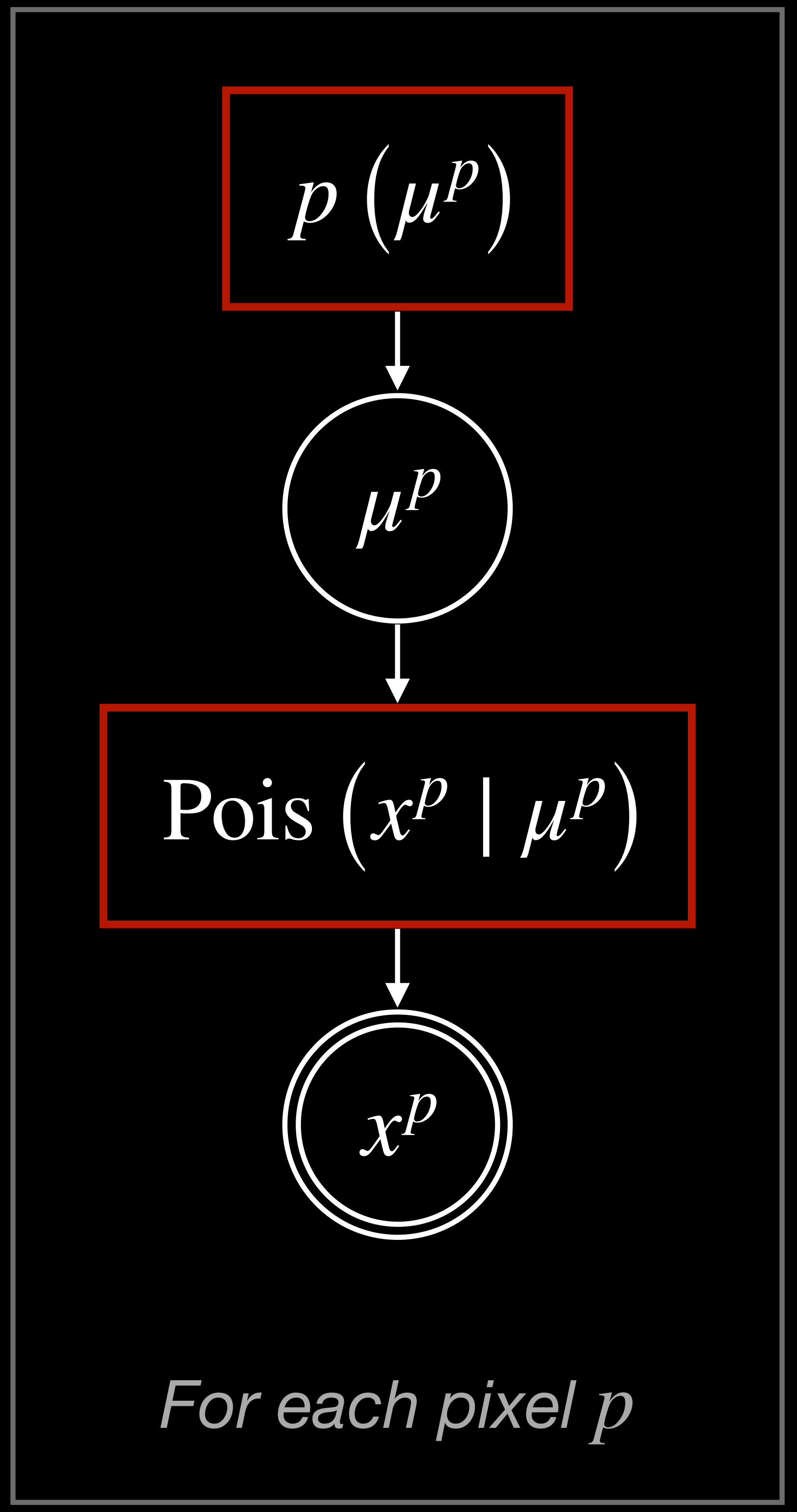

prior distribution

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realization (compare with data)

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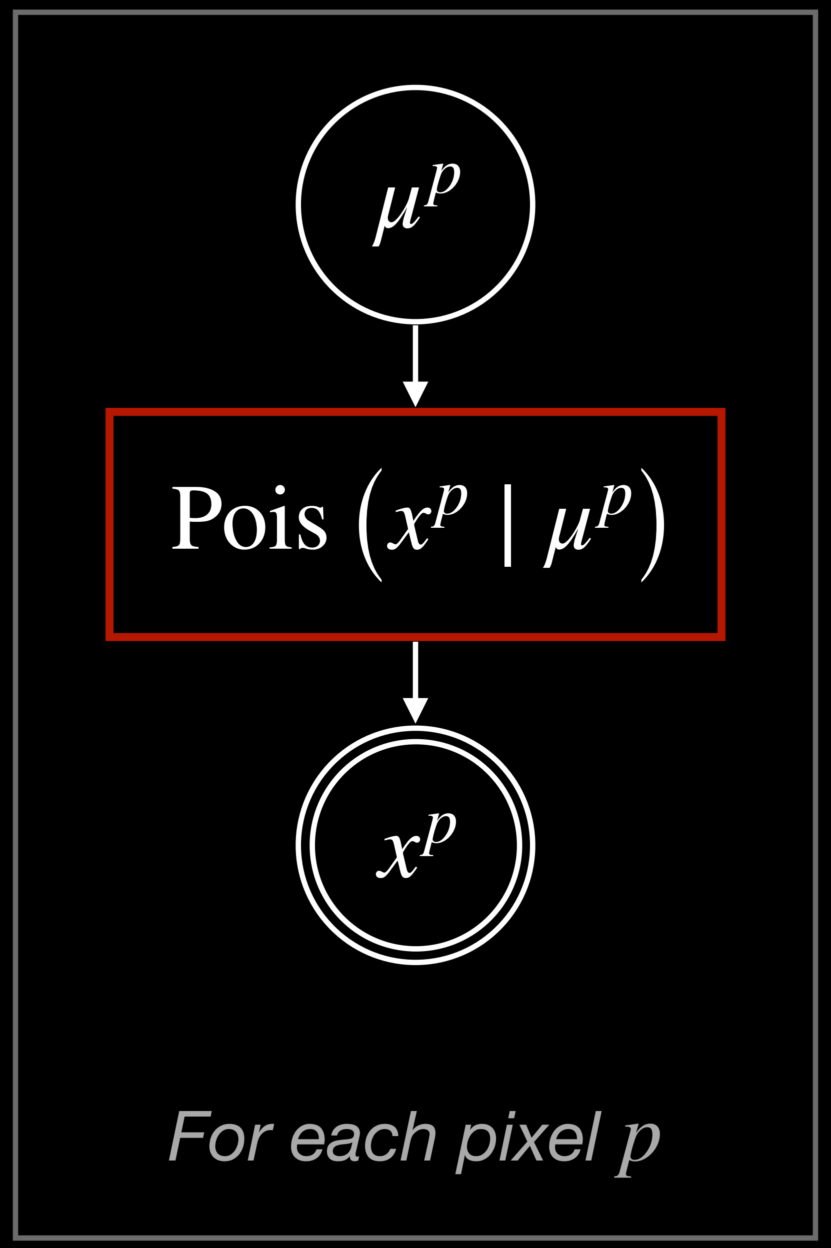

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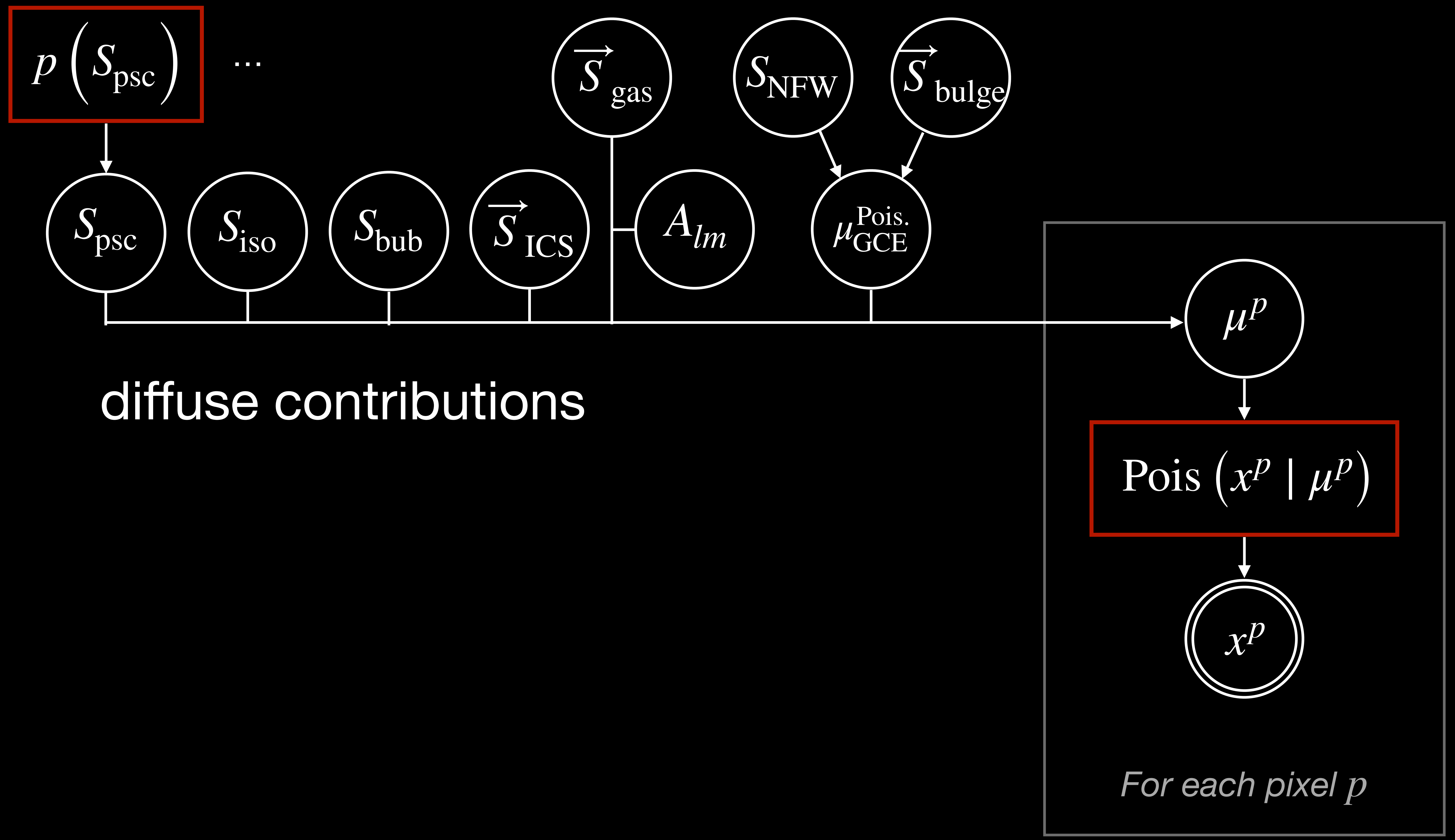

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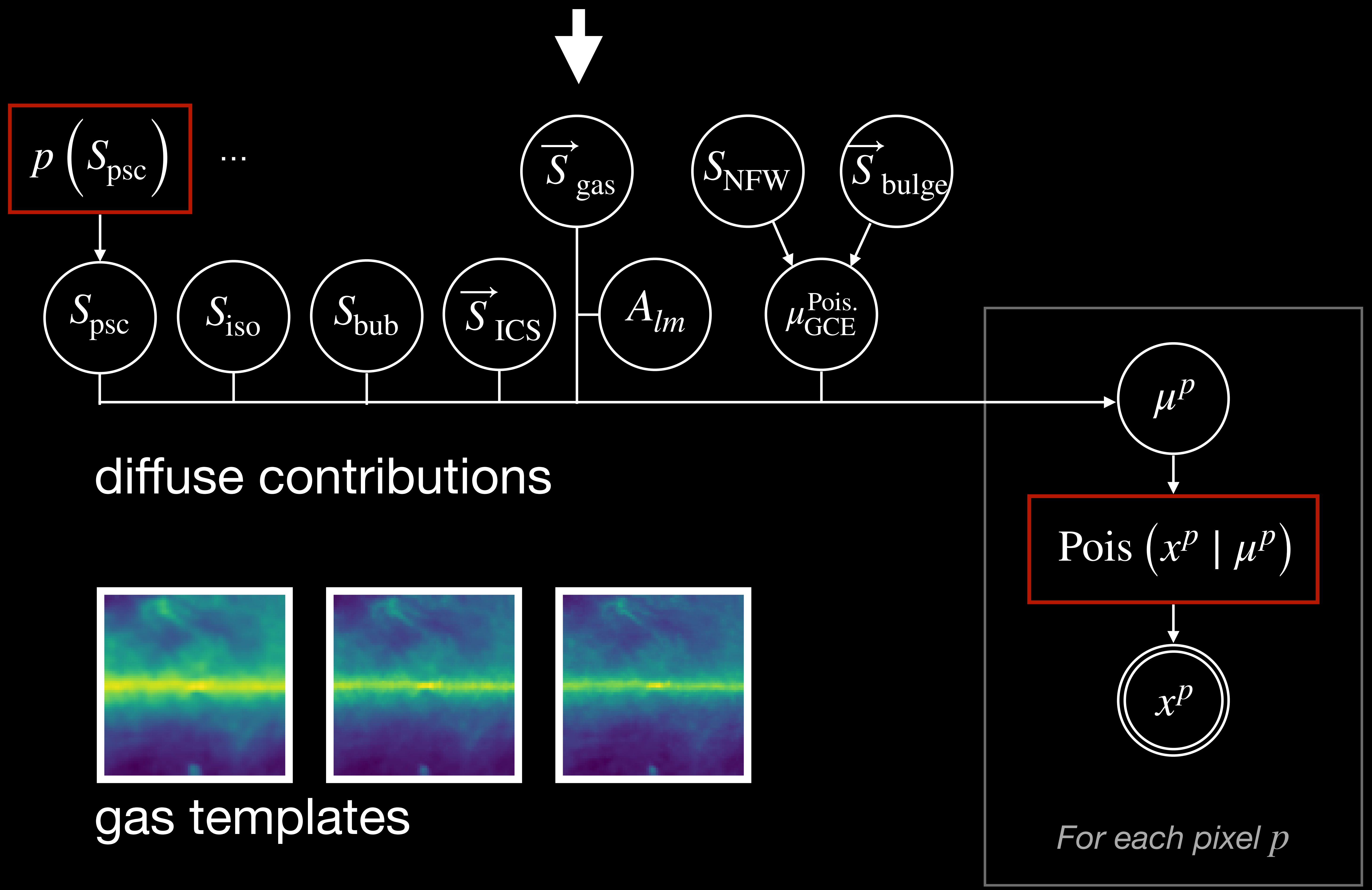

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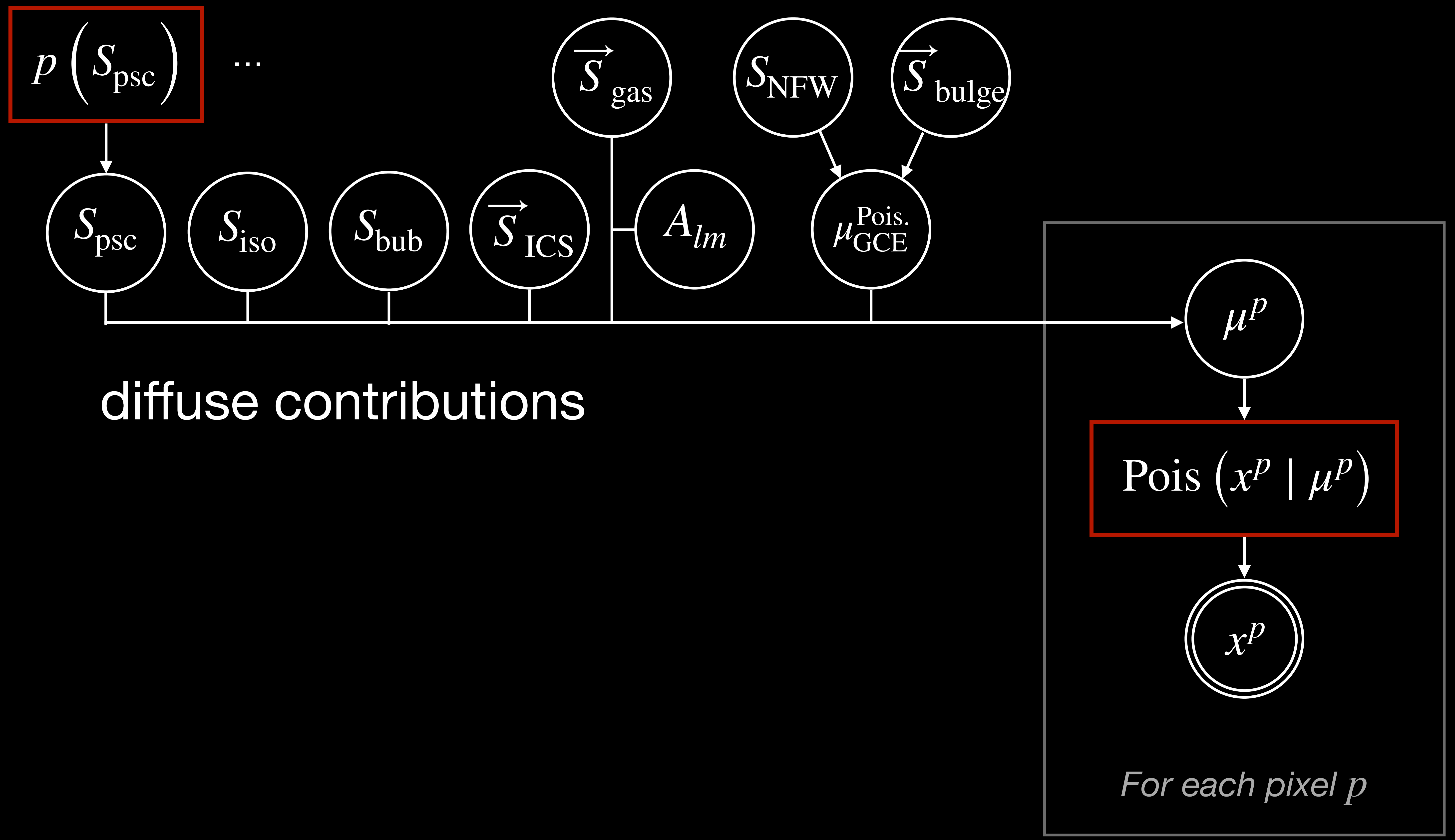

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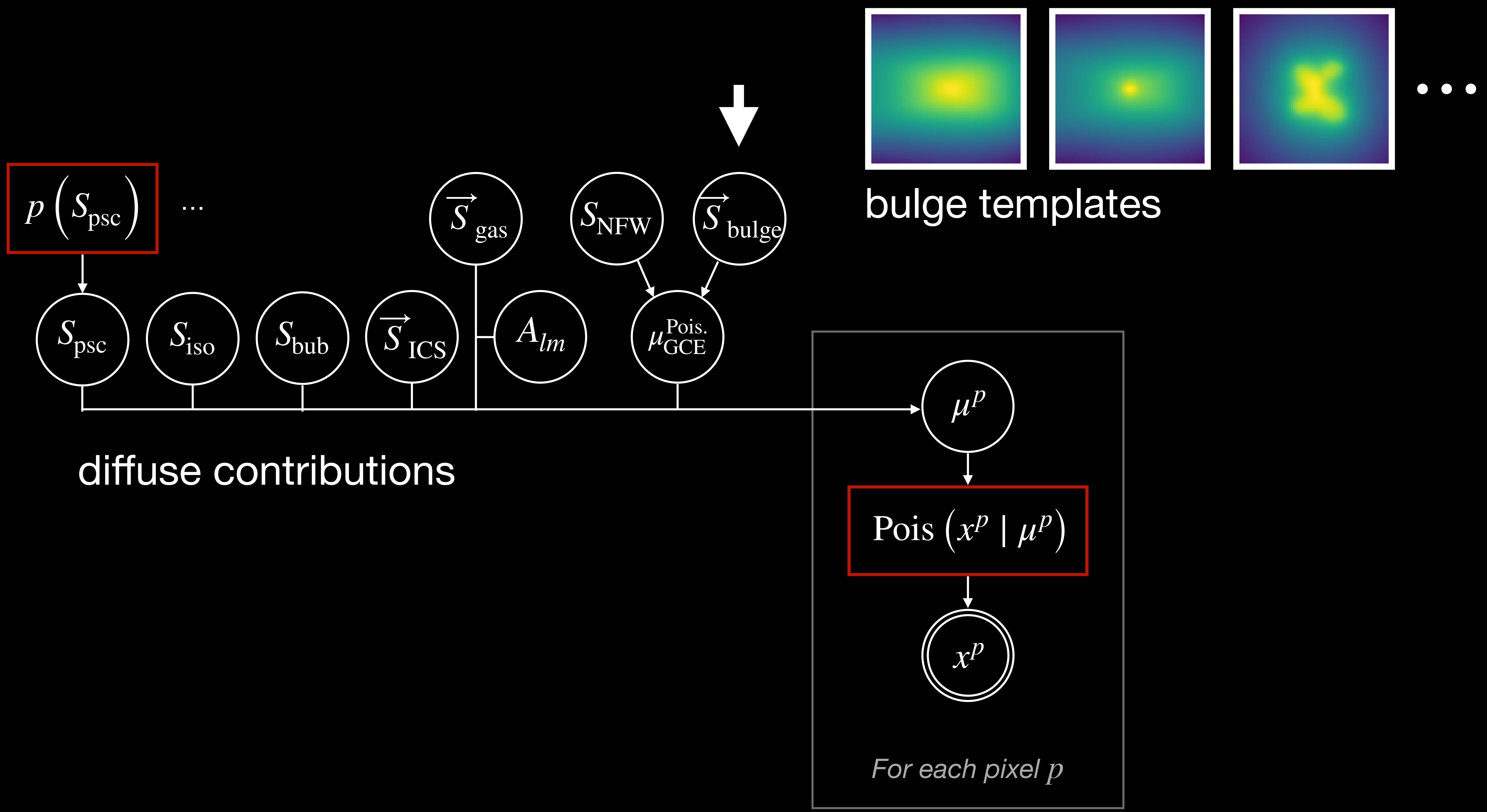

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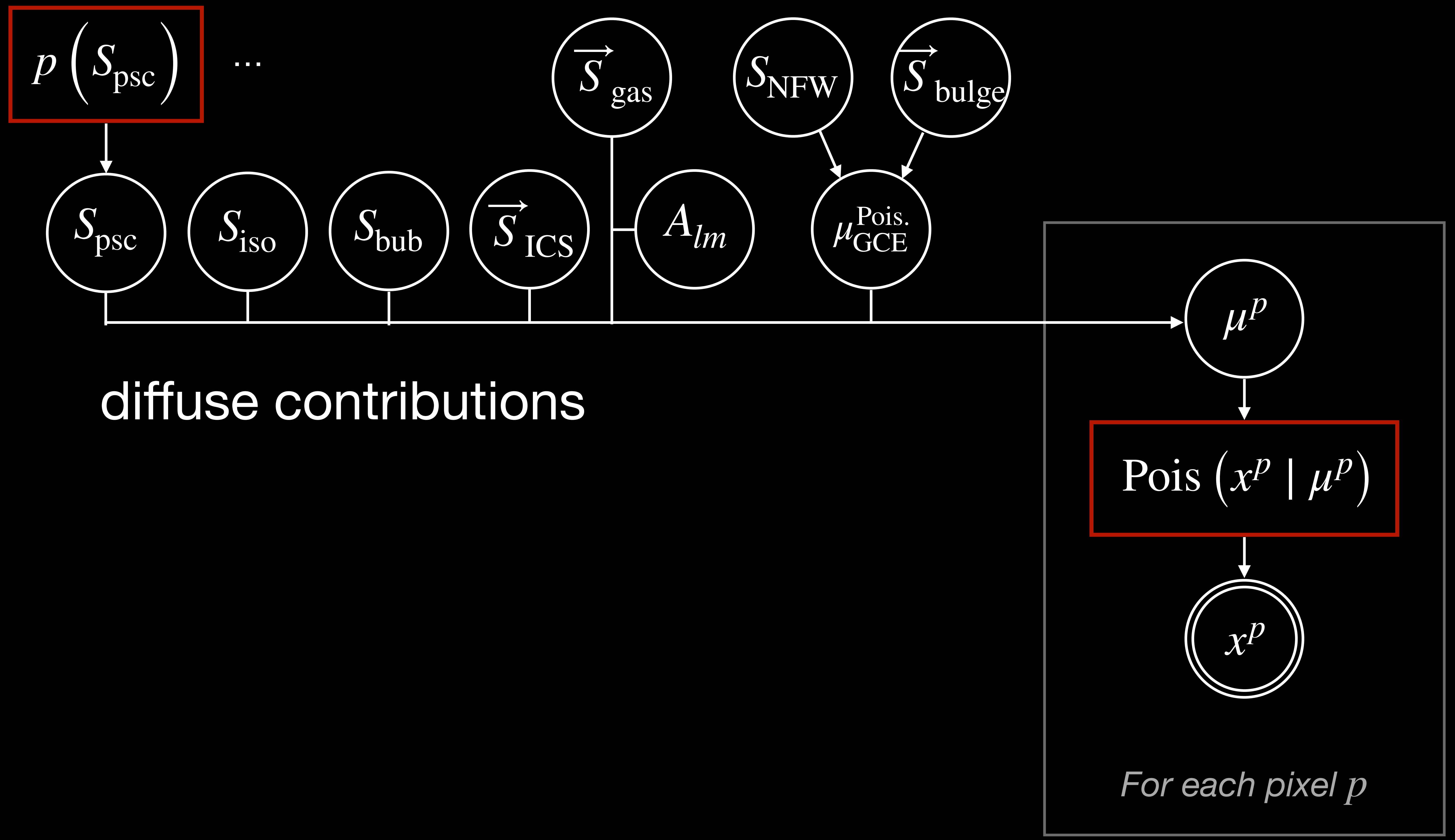

Our model in differentiable probabilistic programming

sampling -> optimization via built-in SVI

NumPyro

SVI = Stochastic Variational Inference:

sampling -> optimization via built-in SVI

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- Guess a posterior q_λ. We use an Inverse Autoregressive Flow.

sampling -> optimization via built-in SVI

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- Minimize $D_{KL}(q_\lambda \,||\, \text{true posterior})$ by maximizing ELBO (evidence lower bound).

sampling -> optimization via built-in SVI

NumPyro

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- Guess a posterior q_λ. We use an Inverse Autoregressive Flow.
- Minimize $D_{KL}(q_\lambda \,||\, \mathrm{true\ posterior})$ by maximizing ELBO (evidence lower bound).

$$\log \mathrm{evidence} = \mathbb{E}_{q_\lambda}\left[\mathrm{likelihood} \cdot \mathrm{prior}\right] + \mathbb{H}[q_\lambda] + D_{\mathrm{KL}}(q_\lambda \,||\, \mathrm{true\ posterior})$$

sampling -> optimization via built-in SVI

NumPyro

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ELBO

Performance

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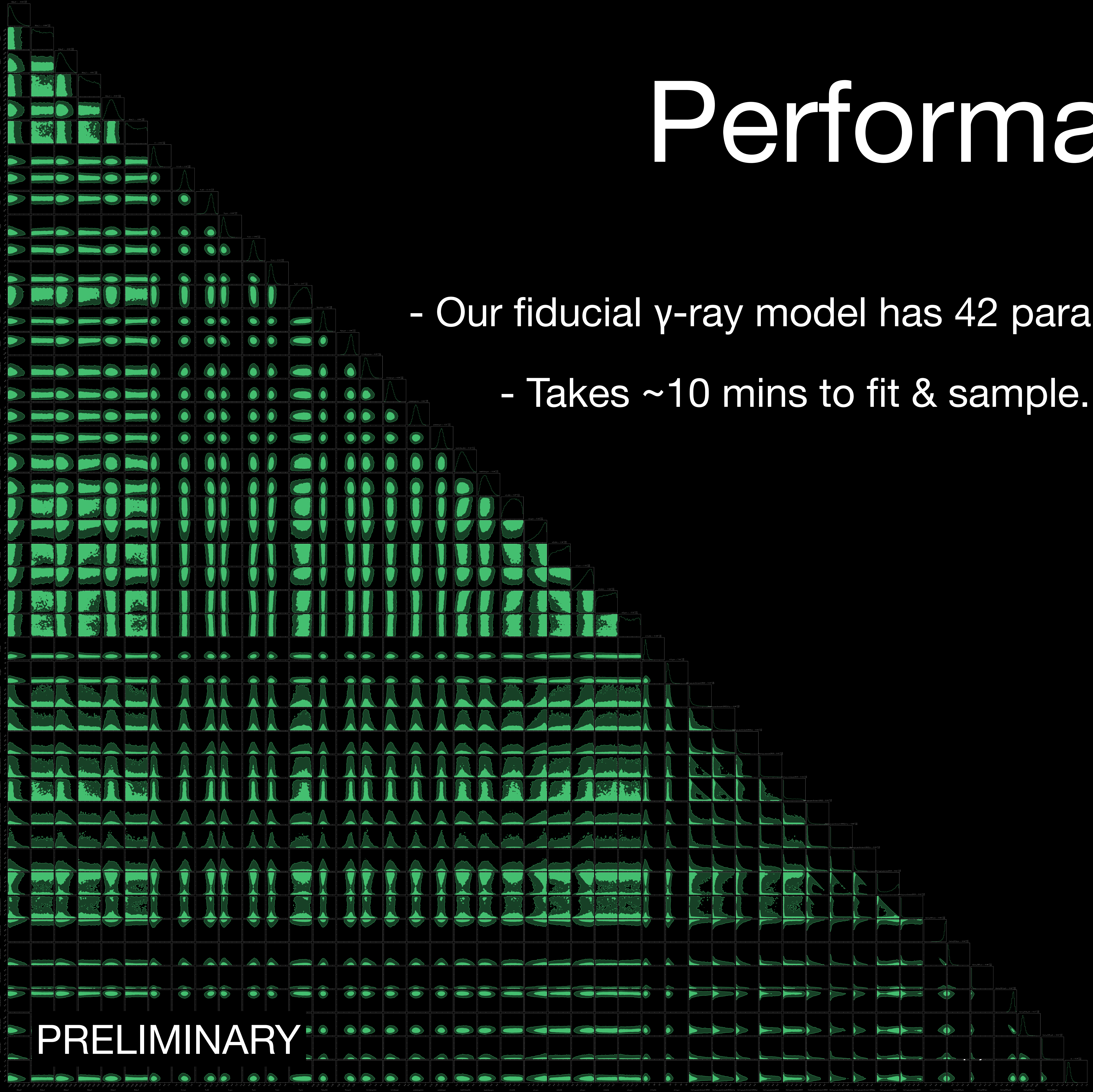

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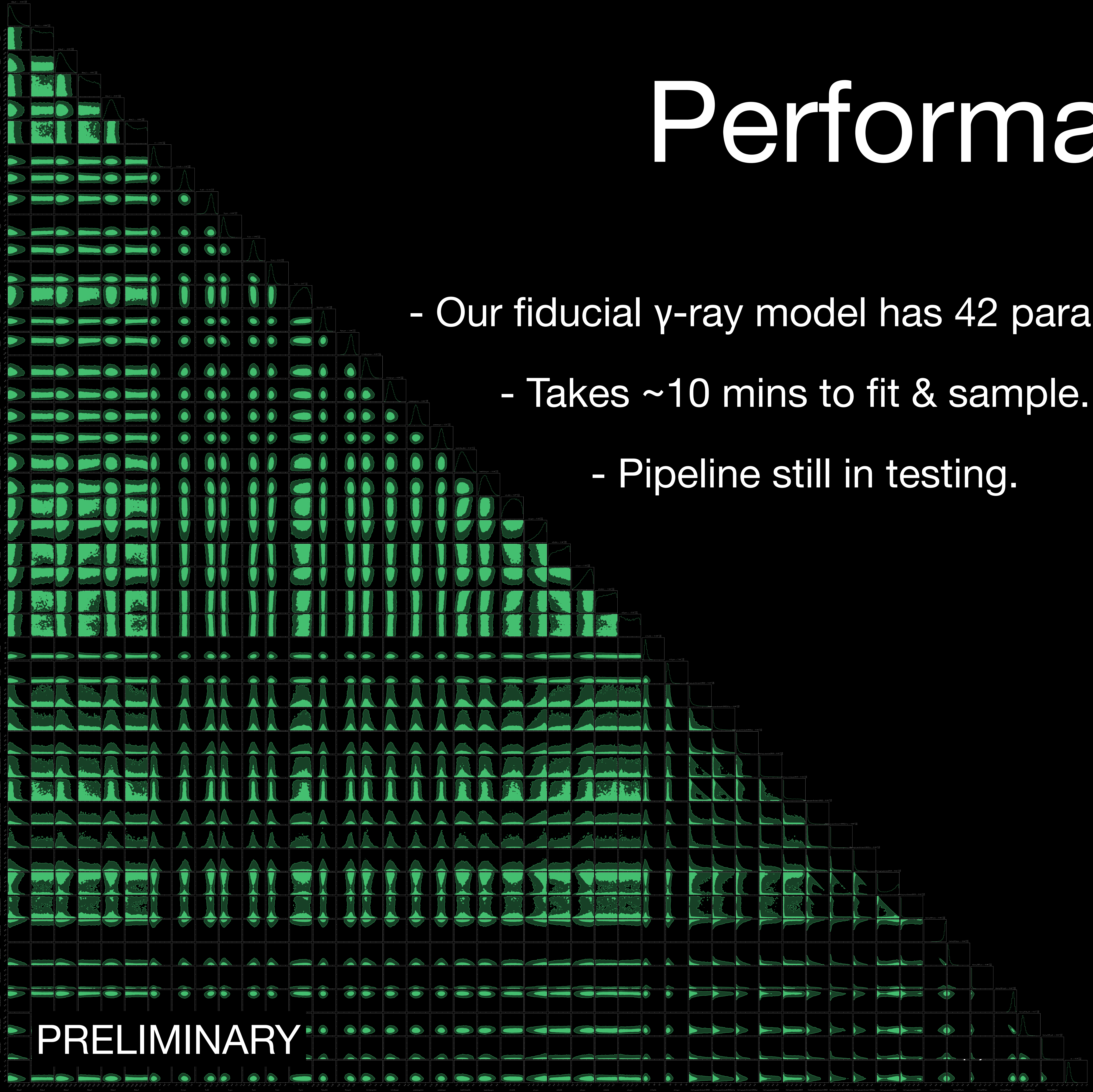

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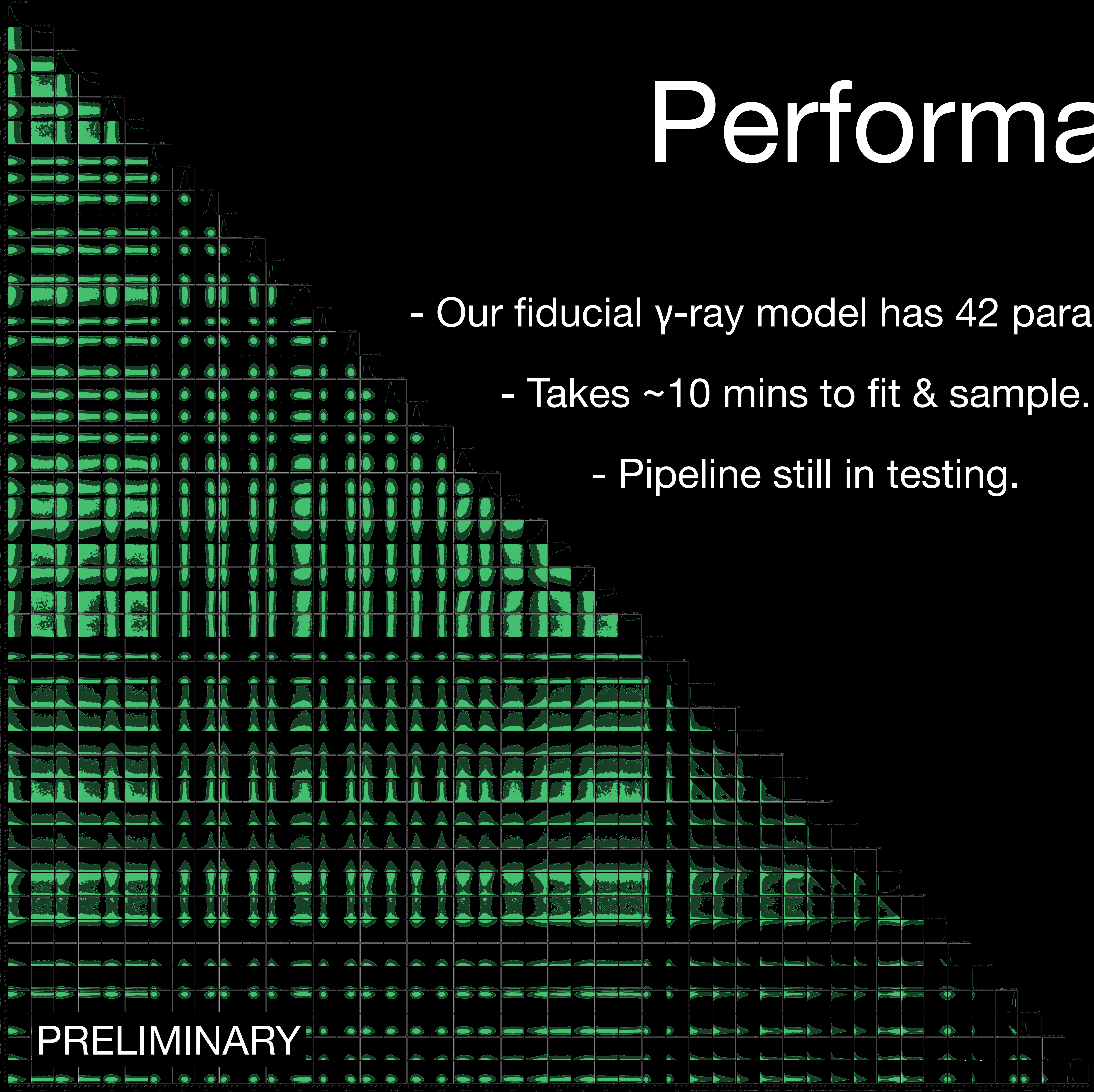

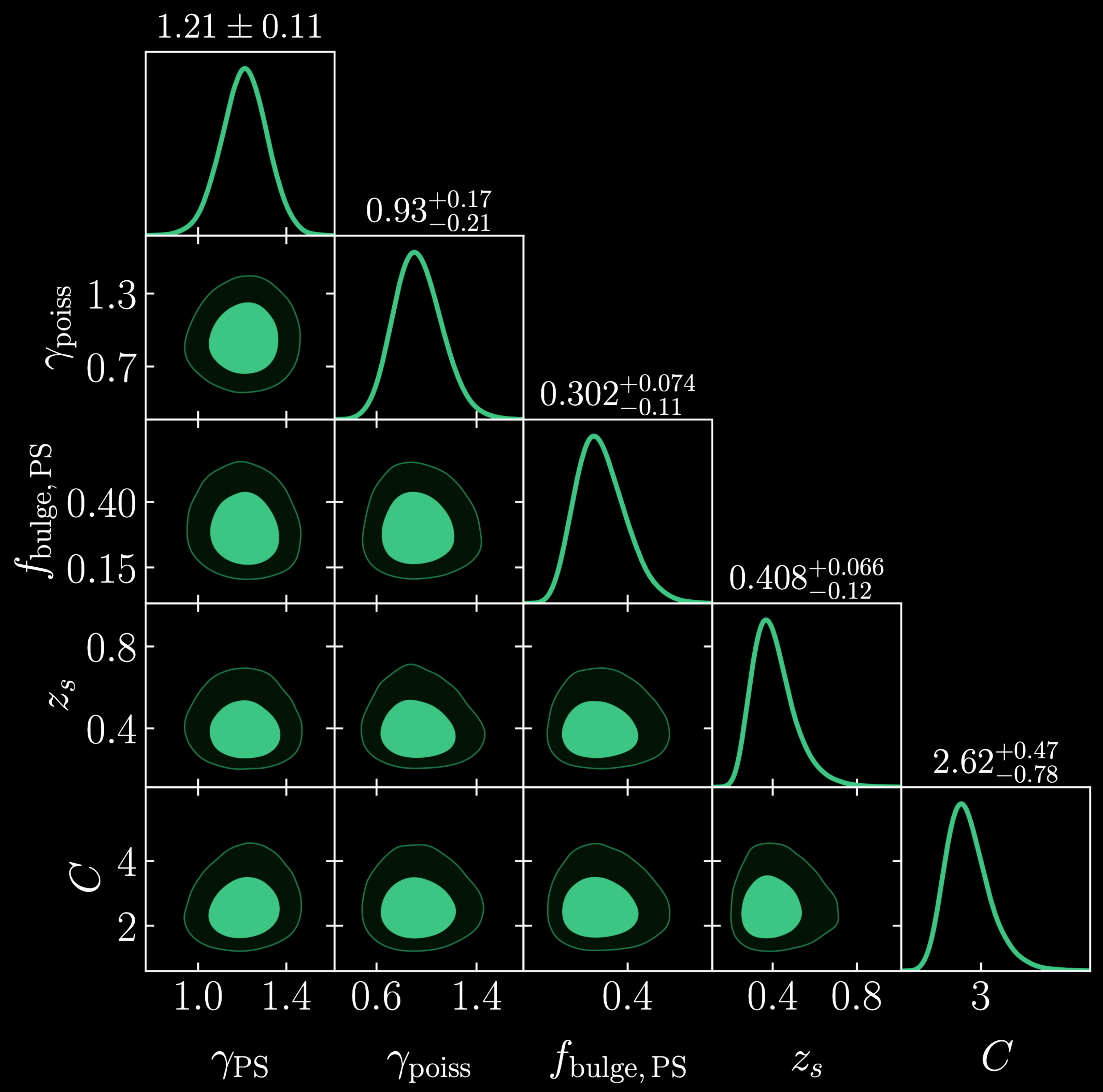

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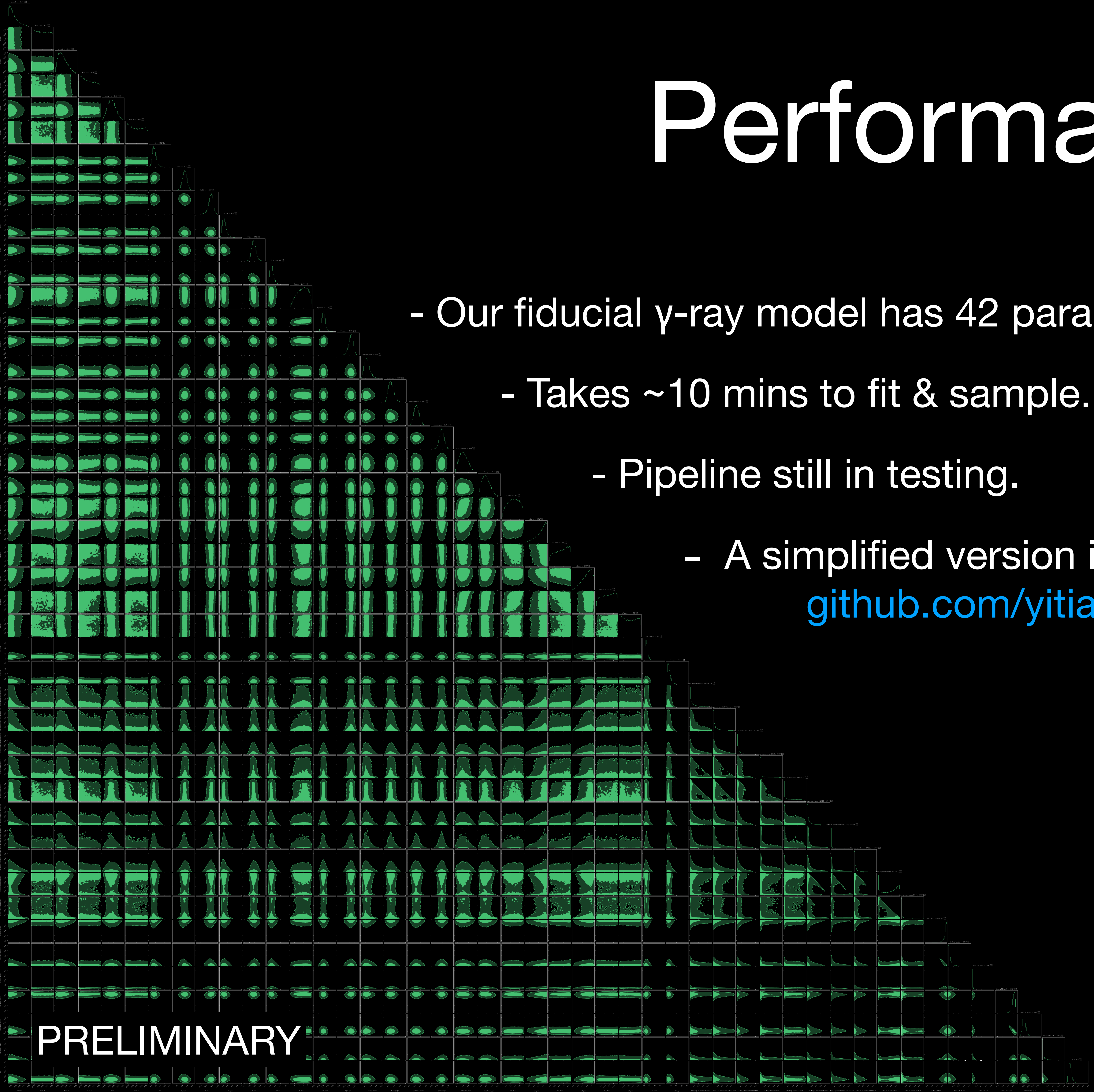

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            - A simplified version is available on github
              github.com/yitiansun/gce-prob-prog

Summary

- We model gamma-ray emission in the Galactic Center using differentiable probabilistic programming.
- We can specify flexible forward models and efficiently do inference on them, with a unified framework to probe systematics.
- Goal: Robustly understand the nature of the Galactic Center Excess signal.