Characterizing the Galactic Center γ-ray Excess using Probabilistic Programming

Yitian Sun

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

May 9th | PHENO 2023

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Imperial College London

Part I

Part II

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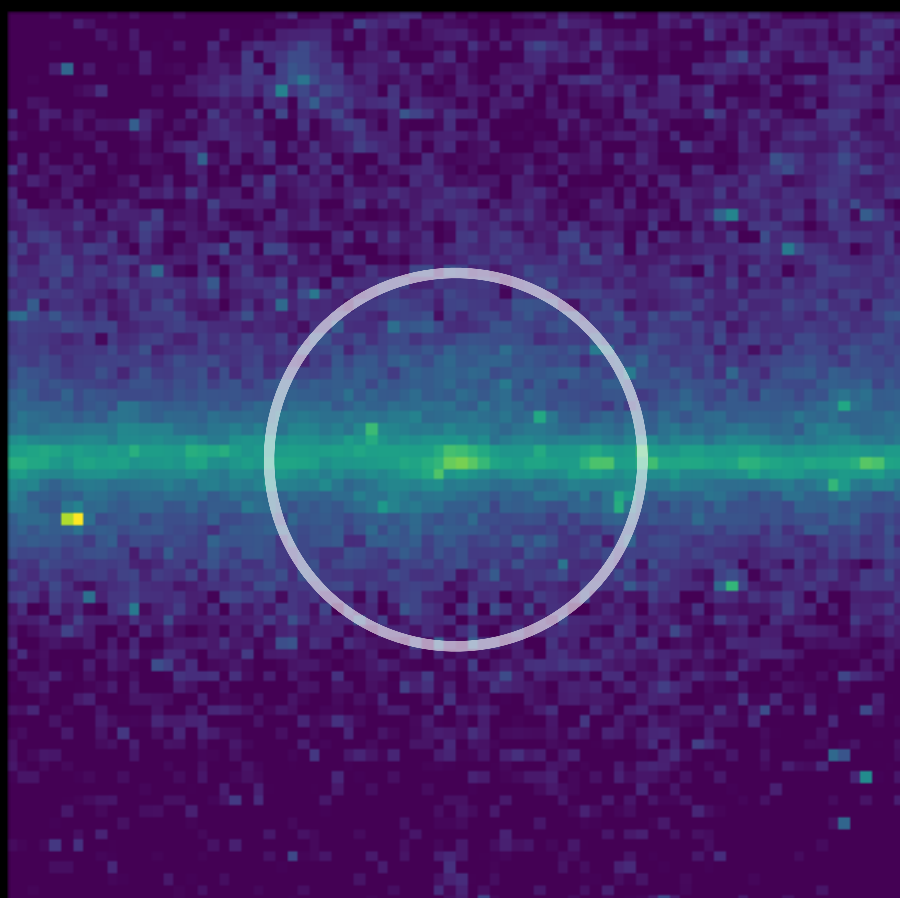
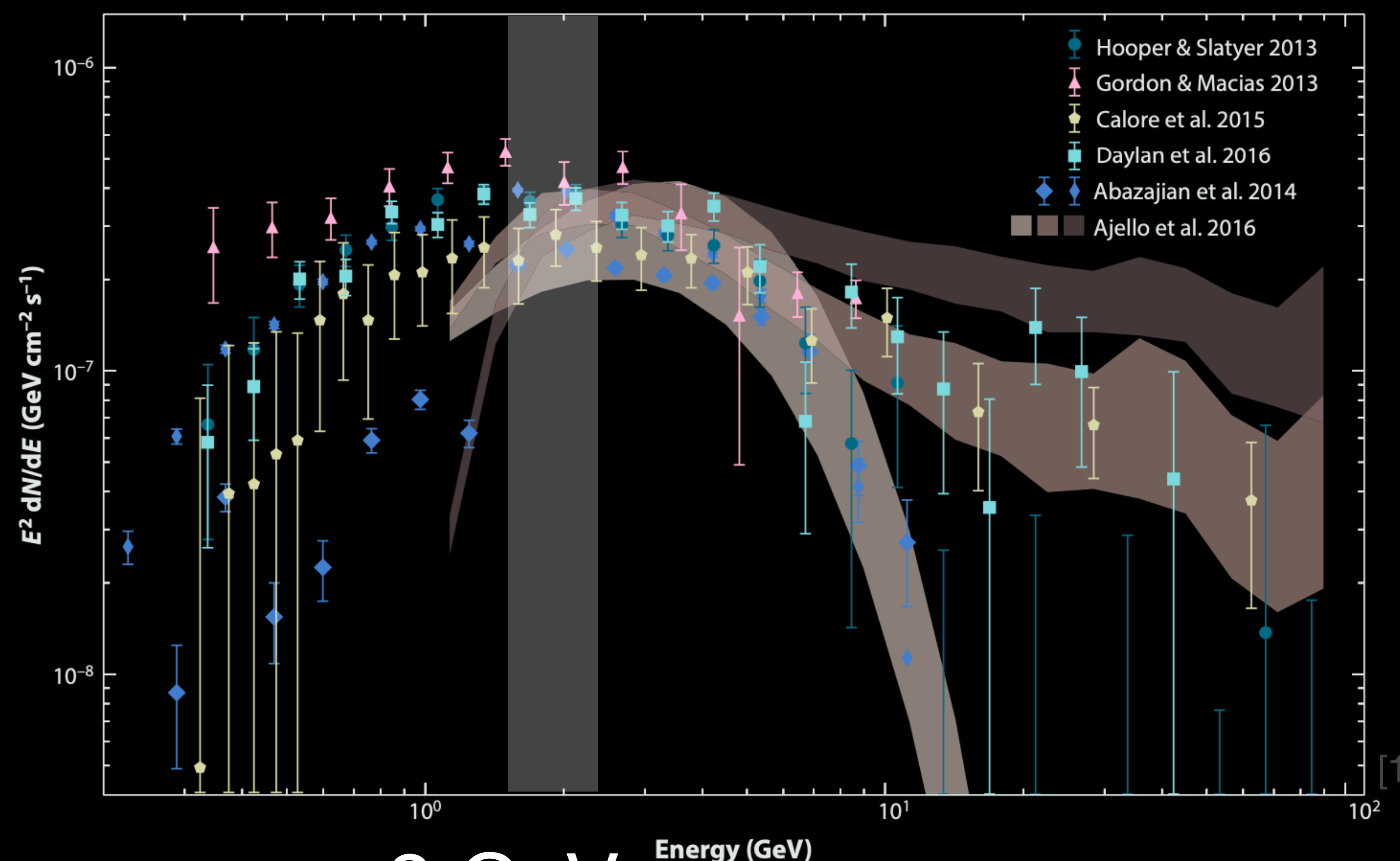
Part I: What is the GCE





>15°   ~ 2 GeV

- Extended, ~ spherical morphology.
- Centered around 2 GeV, may continue higher.

[1] Murgia, Simona. "The Fermi–LAT Galactic Center Excess: Evidence of Annihilating Dark Matter?." Annual Review of Nuclear and Particle Science 70 (2020): 455-483.

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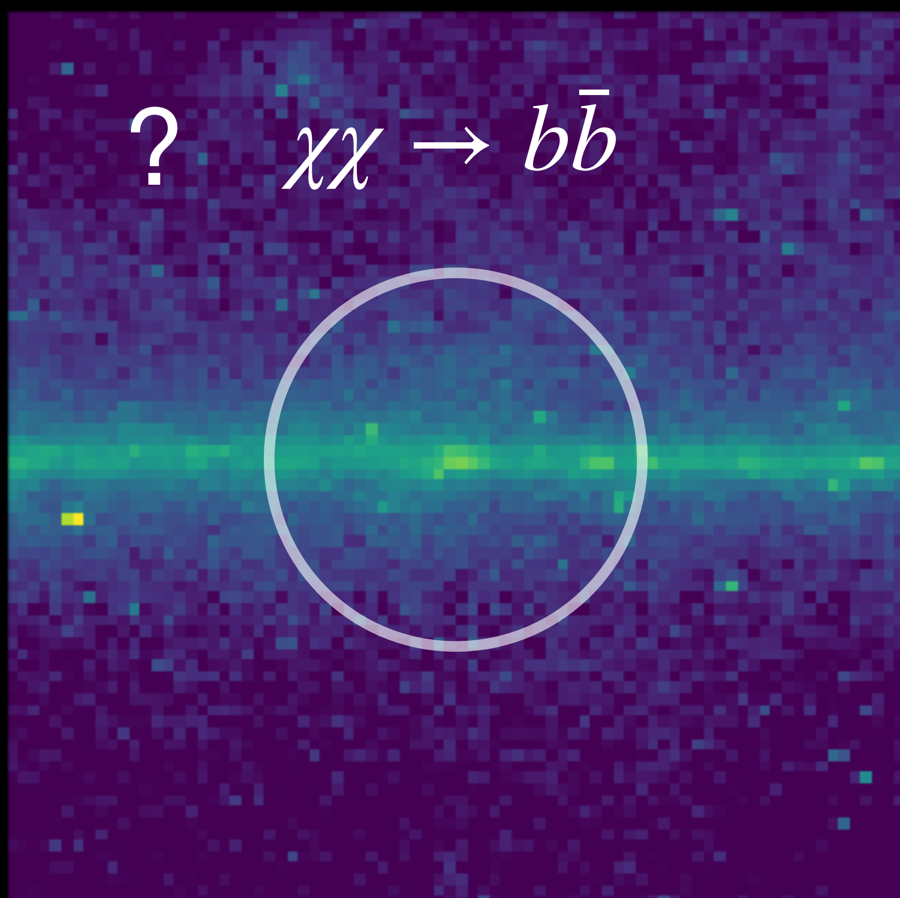

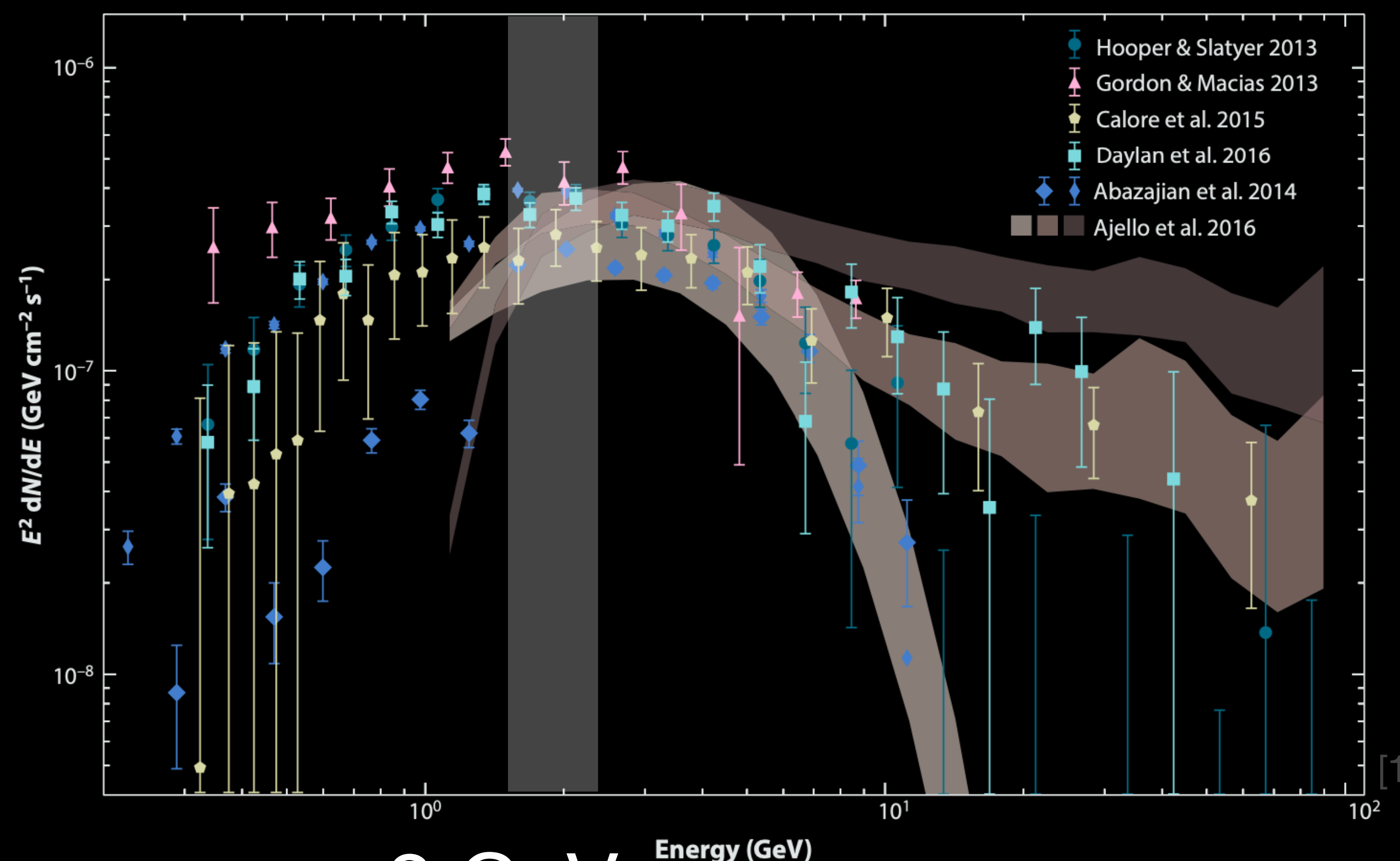

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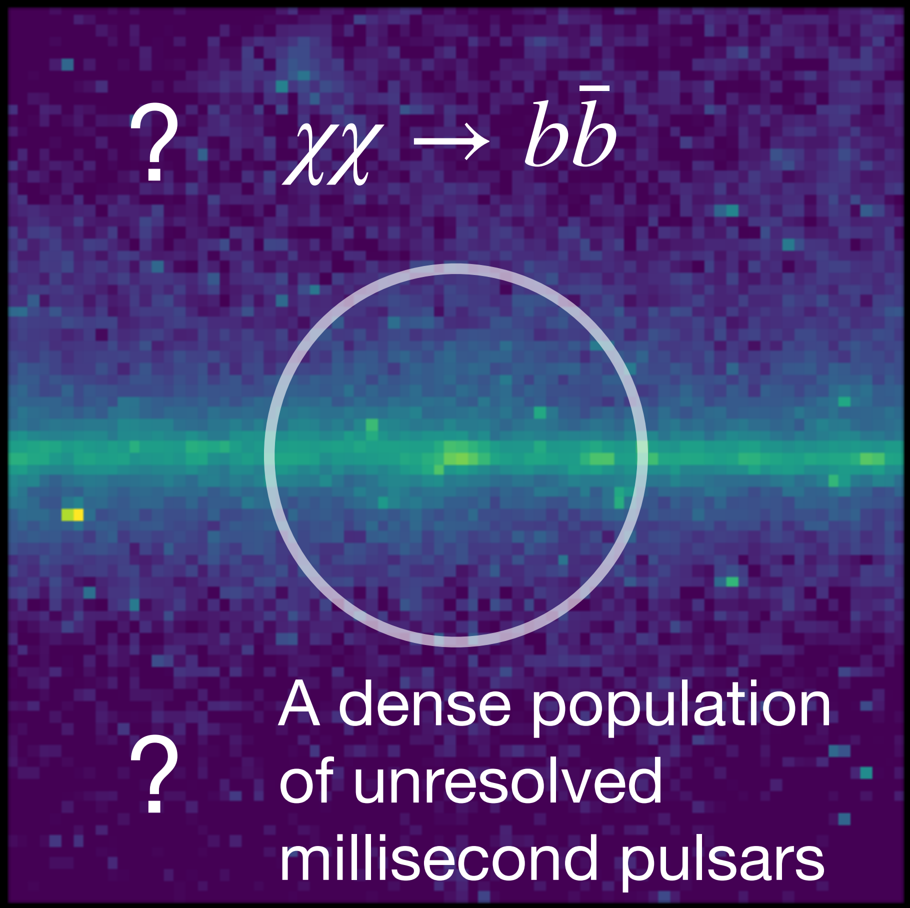

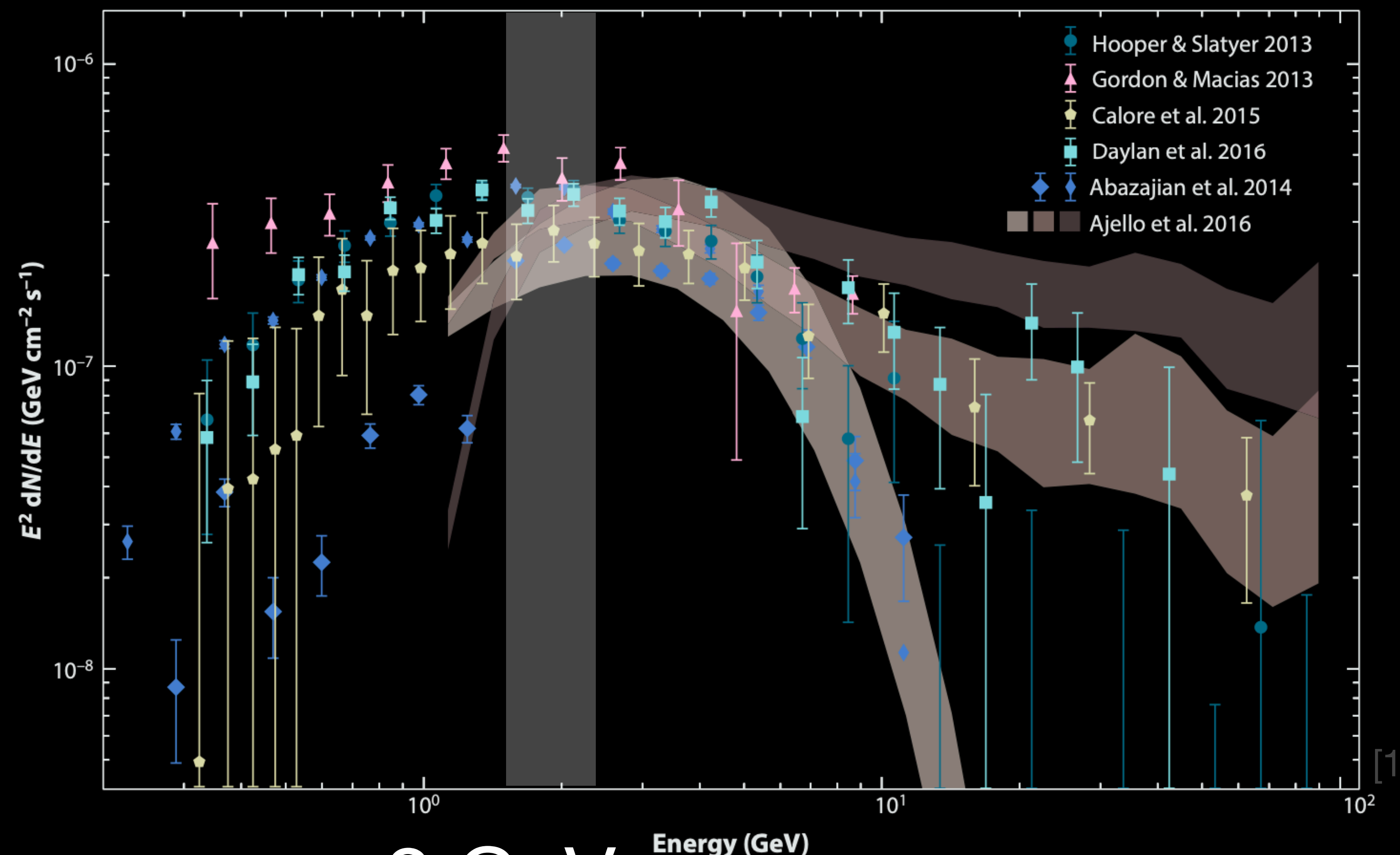

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Foregrounds: cosmic ray γ + …

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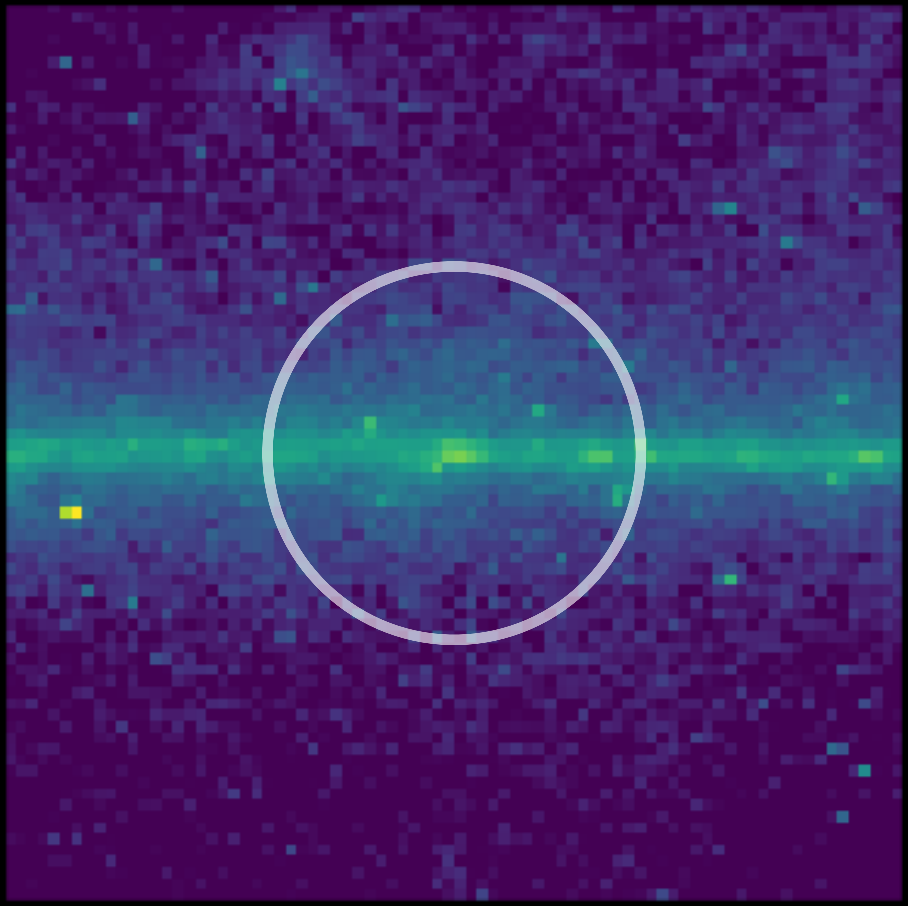

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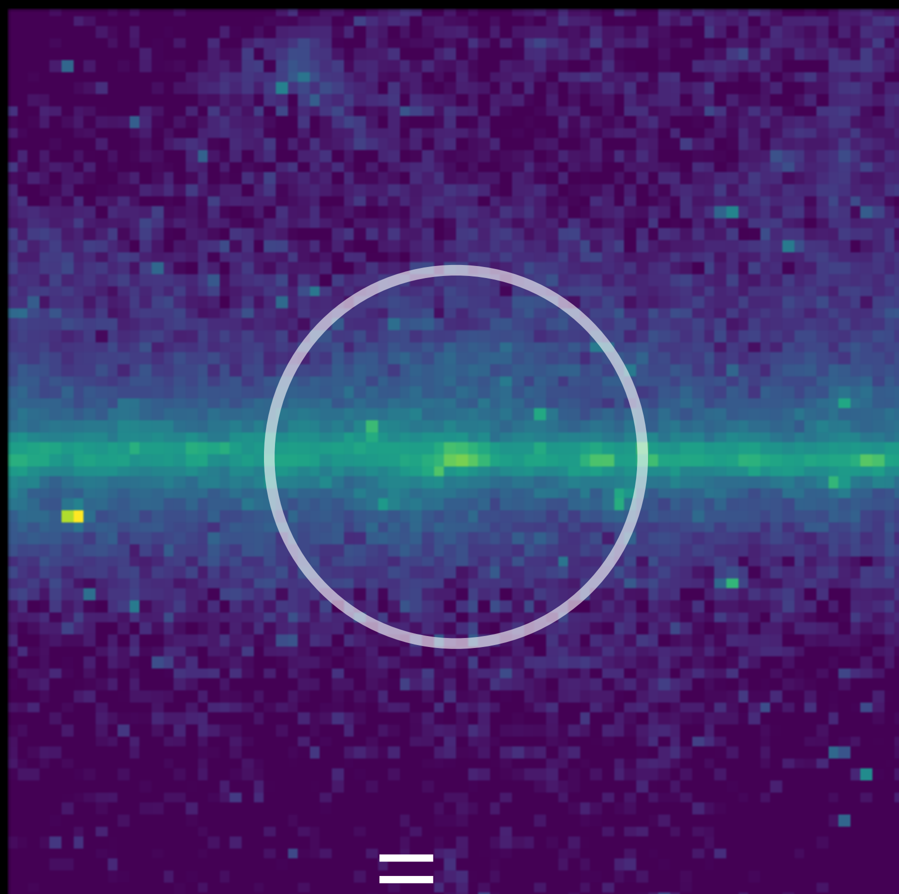

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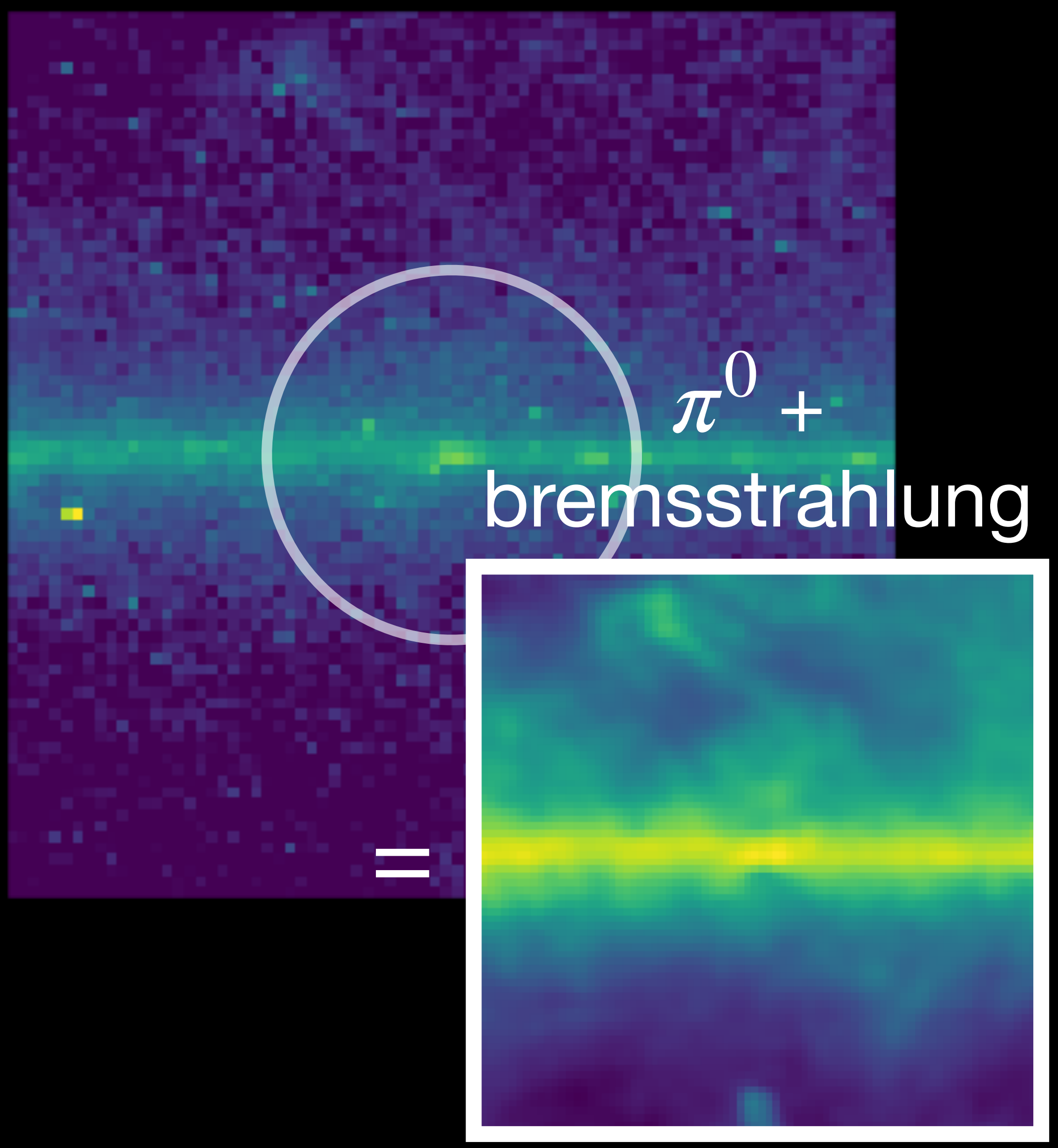

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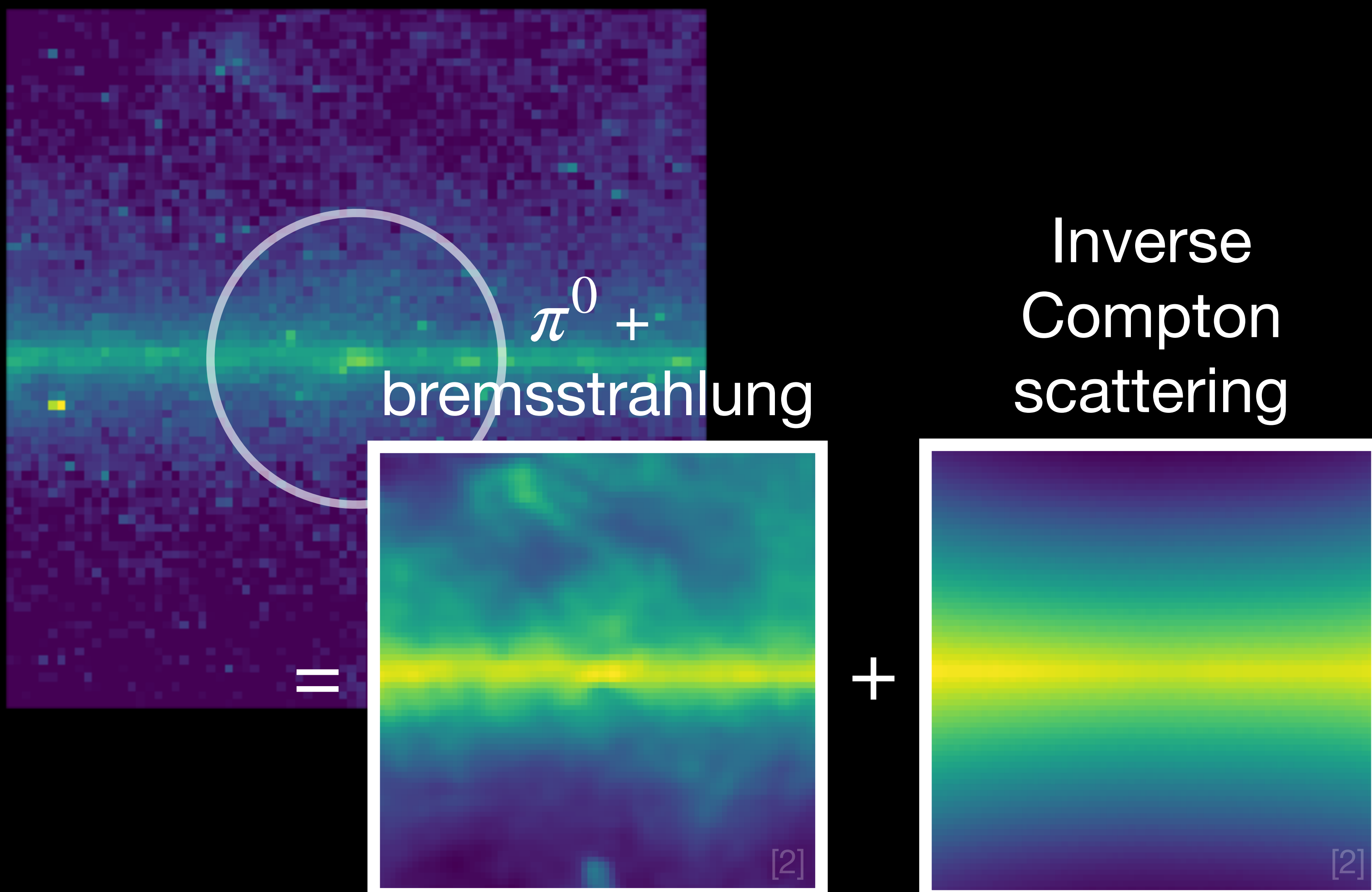

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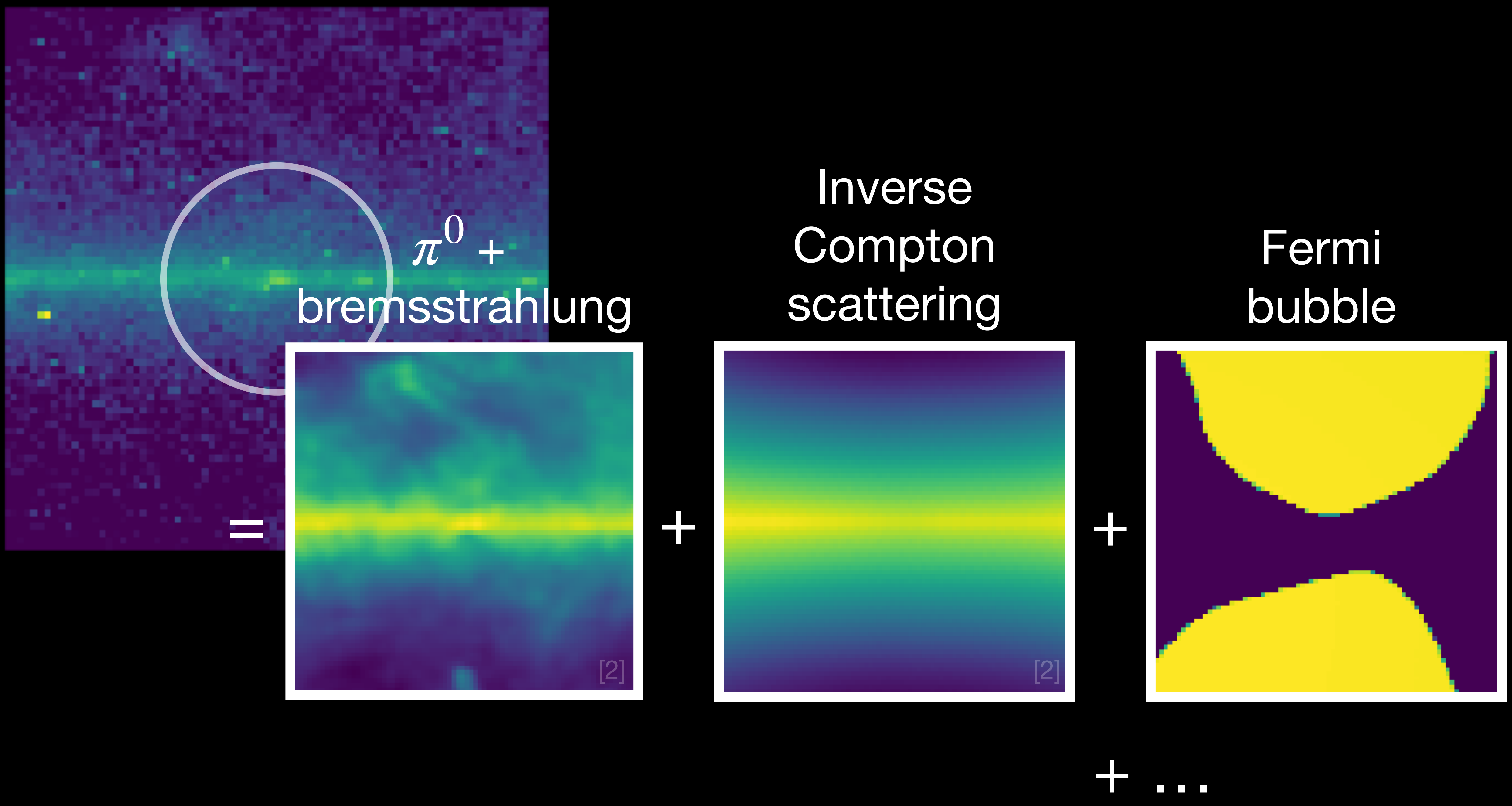

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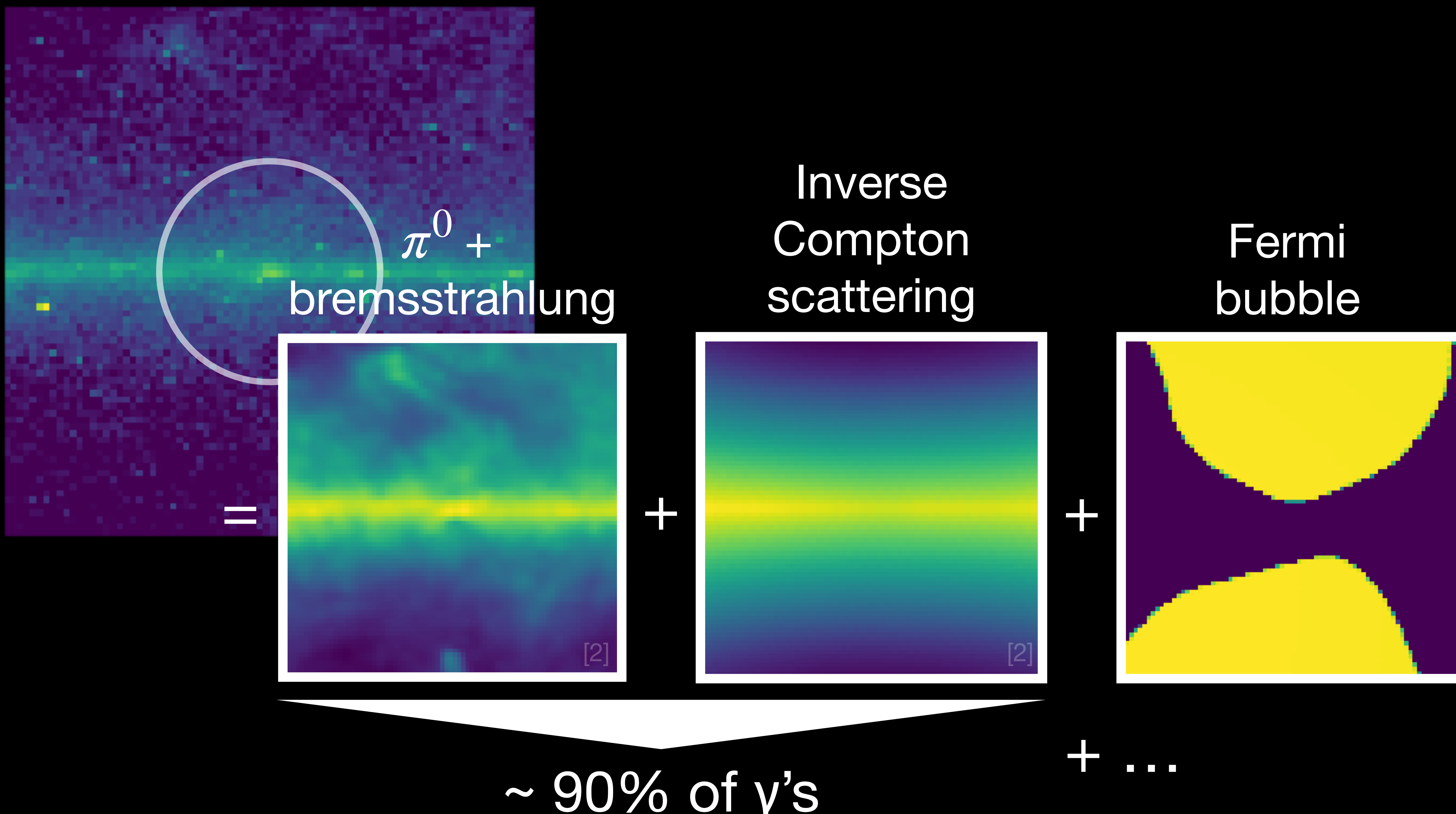

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Diffuse vs. Point Source emissions

Part I: What is the GCE made of

dark
matter

unresolved
pulsar

Diffuse vs. Point Source emissions

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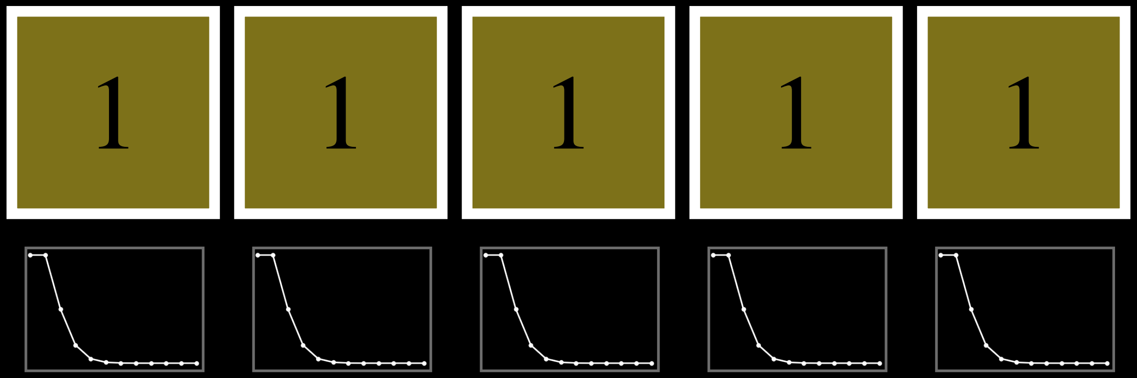
dark matter



diffuse source

unresolved pulsar

Diffuse vs. Point Source emissions

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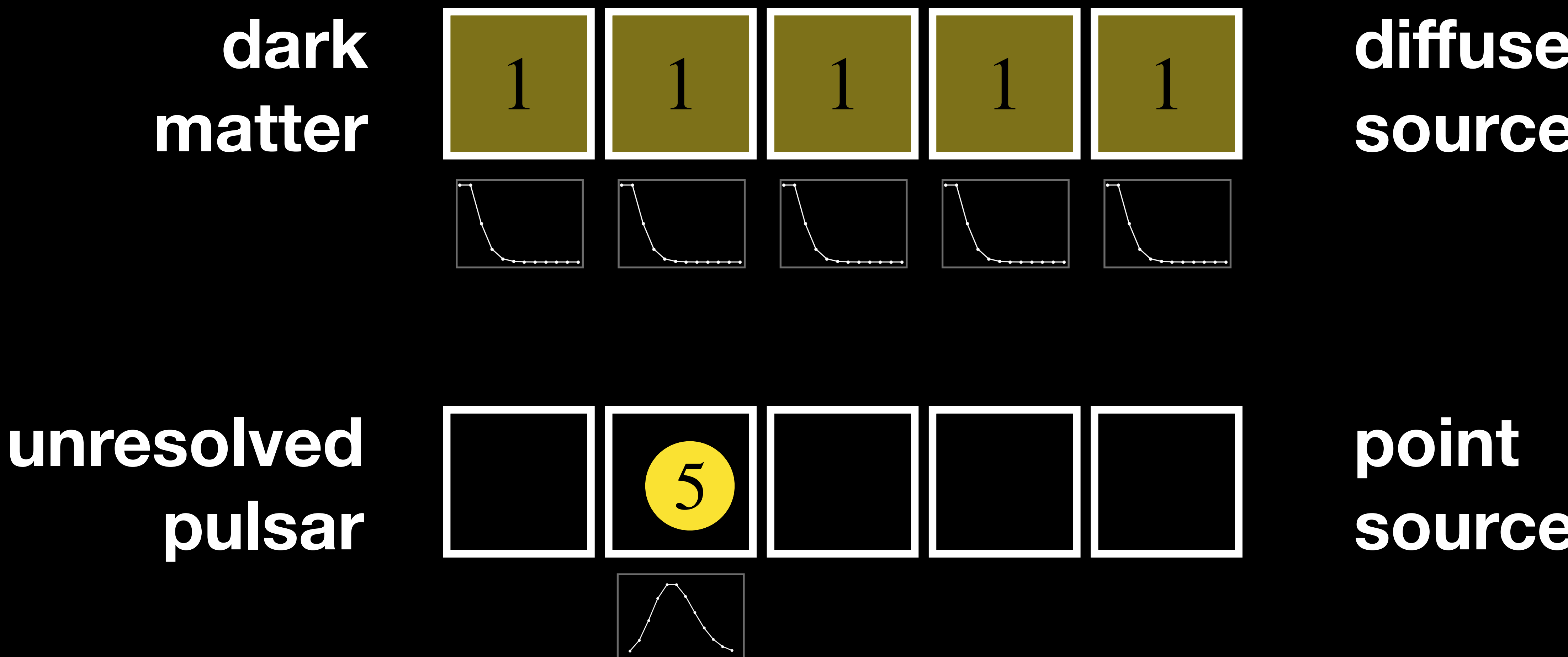

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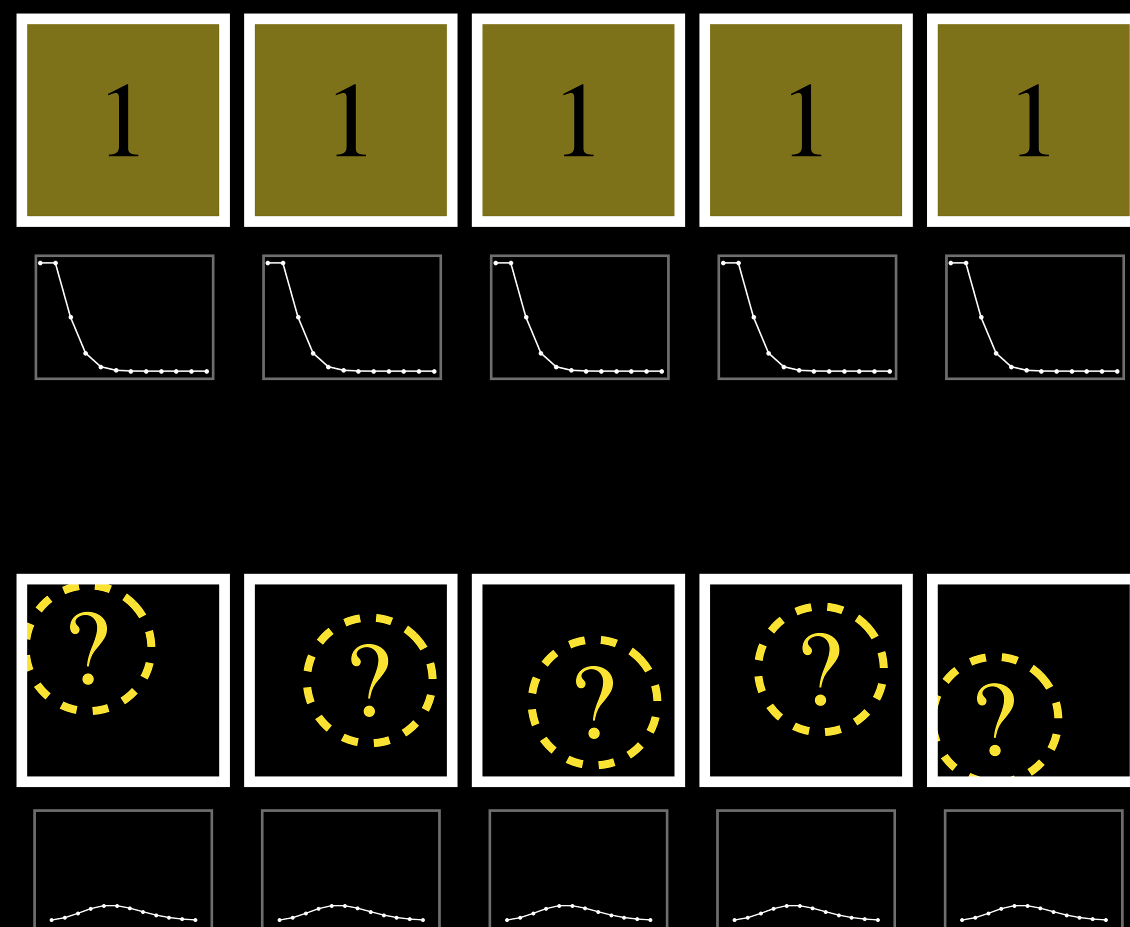

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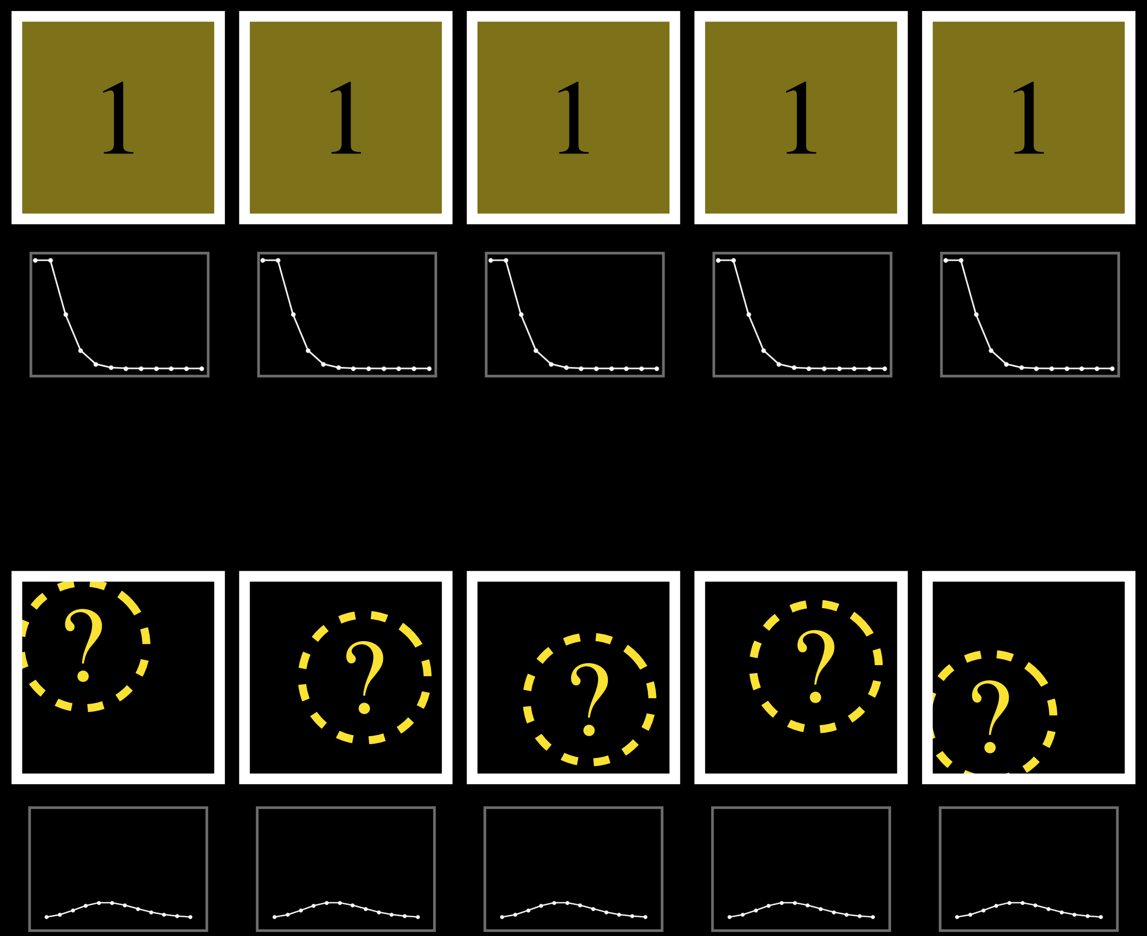

diffuse source

unresolved pulsar

point source

The point source photon count distribution is **Non-Poissonian**.

How is the GCE

Part I: What is the GCE

How is the GCE analyzed

Part I: What is the GCE

How is the GCE analyzed

Part I: What is the GCE

- Previous: Inflexible, singular templates for PSs:
  - Likelihood (with point sources) quite computationally expensive.
  - Marginalizing over too many parameters = curse of dimensionality.

How is the GCE analyzed

Part I: What is the GCE

- Previous: Inflexible, singular templates for PSs:
  - Likelihood (with point sources) quite computationally expensive.
  - Marginalizing over too many parameters = curse of dimensionality.
- However, fits to the GCE are <u>not great</u> (compared to expected likelihood of a perfect fit, e.g.).
  - Need more flexible templates for both foreground & source.
  - Need a unified framework to understand systematics.
  - Need to avoid the curse of dimensionality.

Part II: Probabilistic Programs

are frameworks for doing inference on probabilistic models

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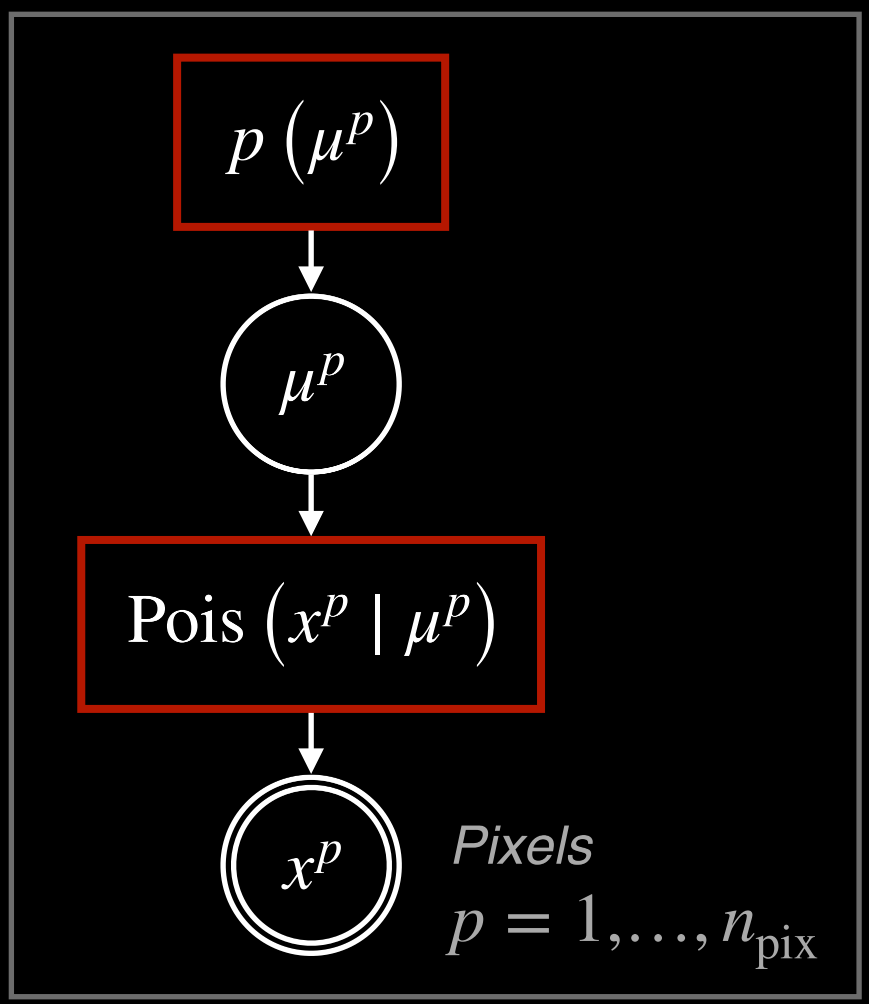
are frameworks for doing inference on probabilistic models

Example: inferring
expected photon counts



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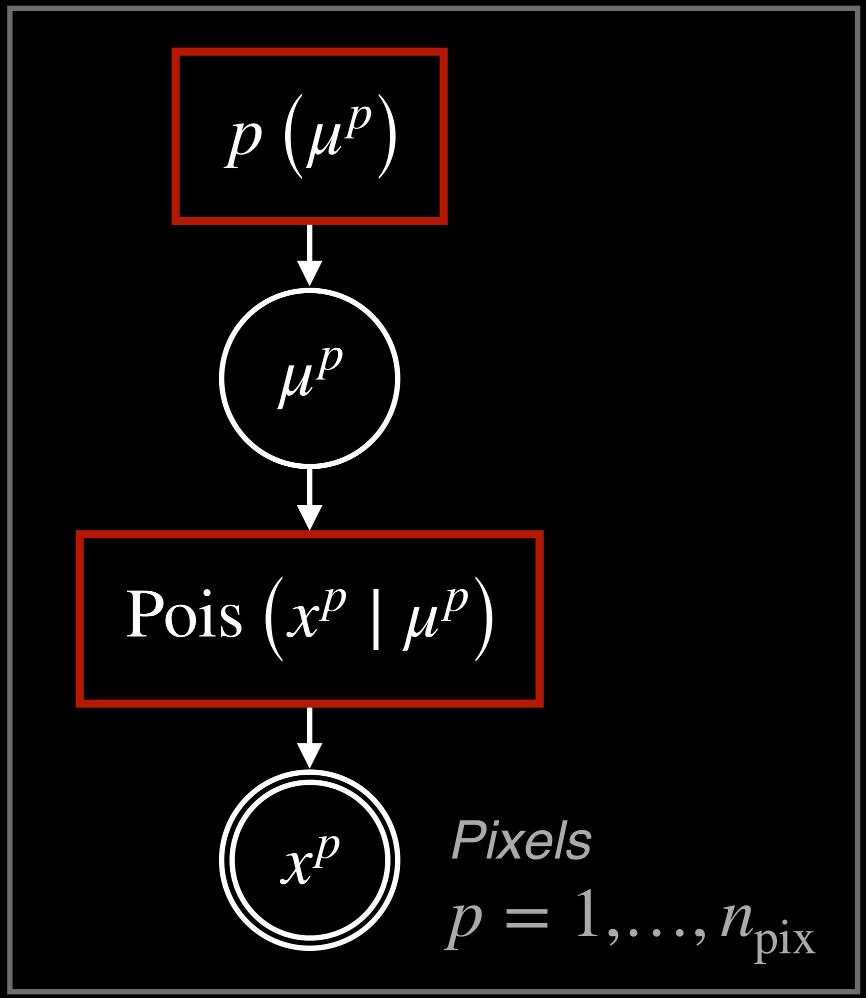
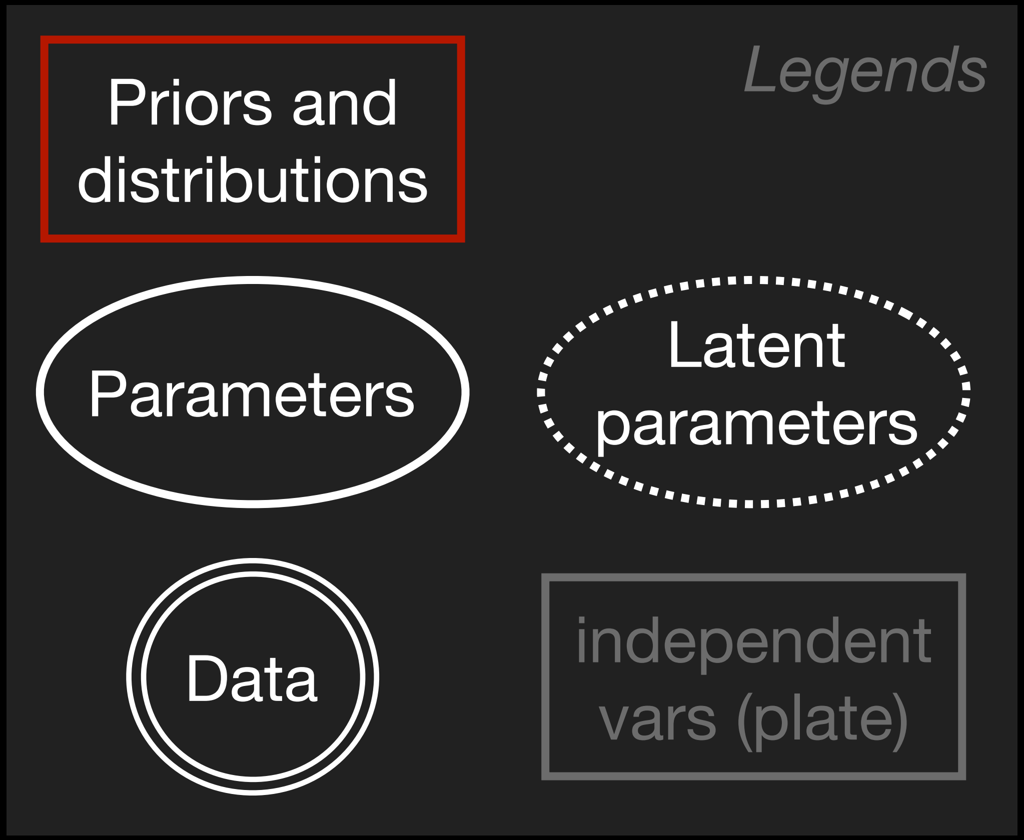
Example: inferring expected photon counts





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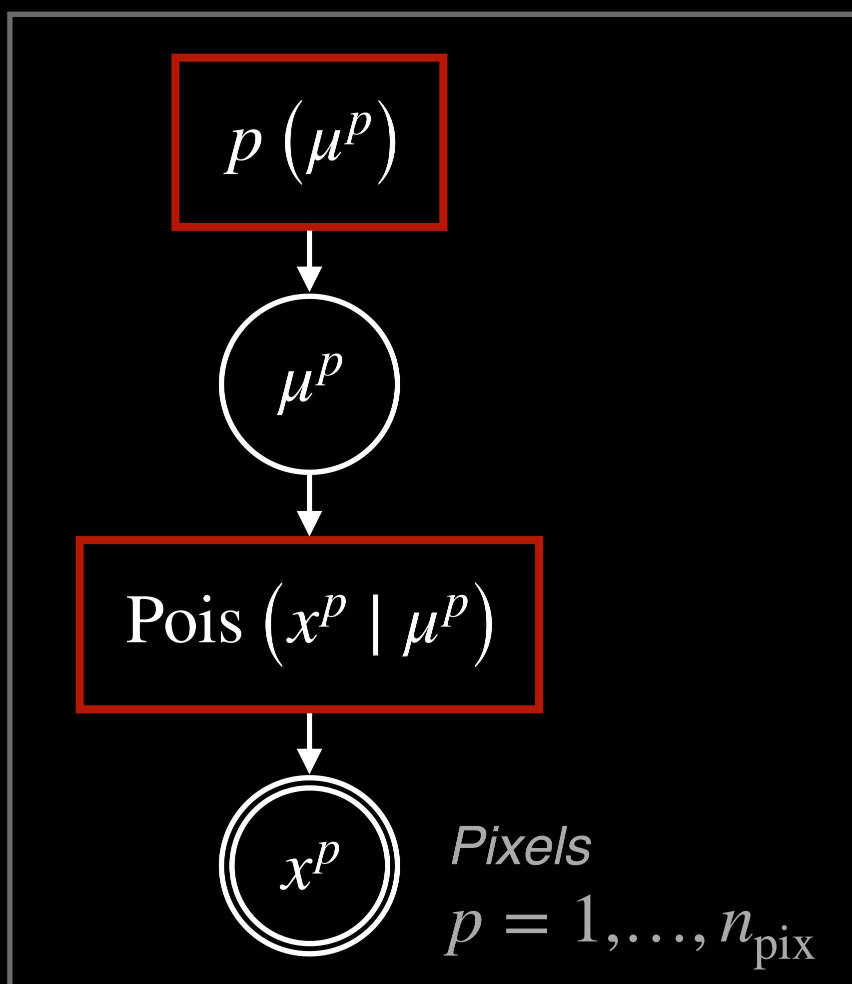
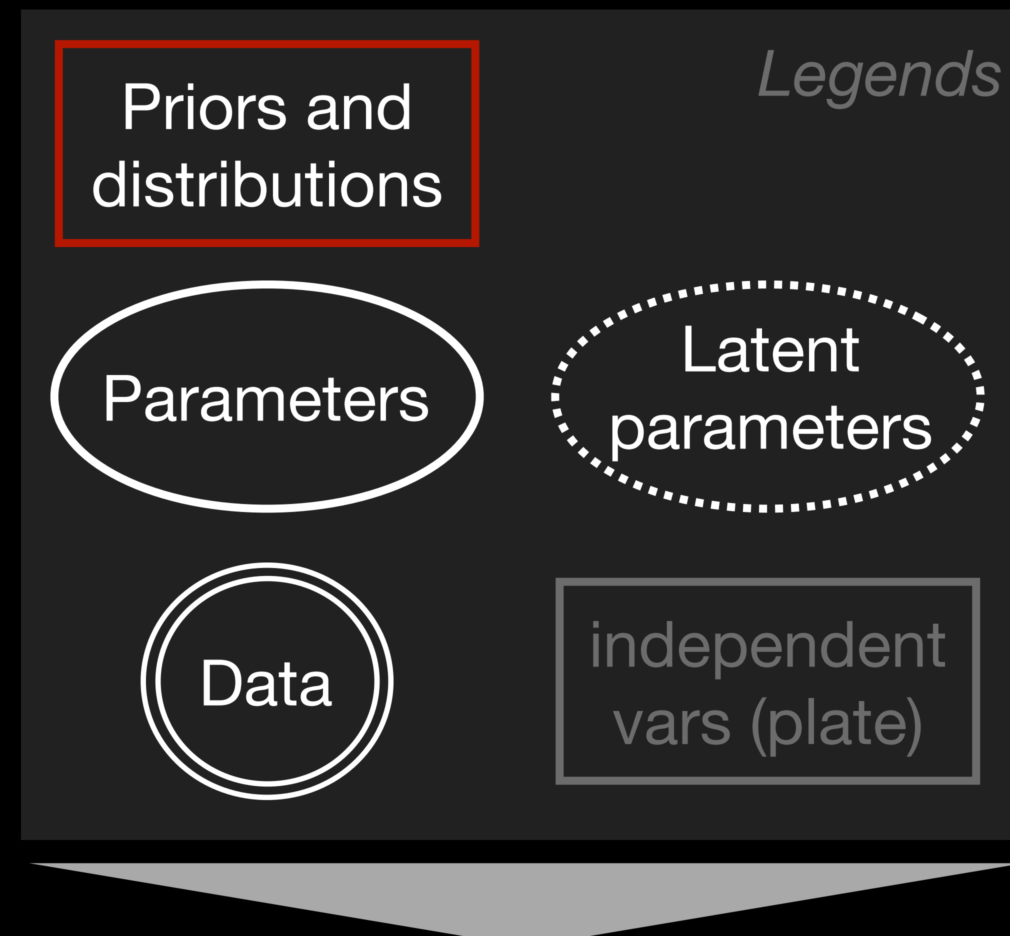
Example: inferring expected photon counts



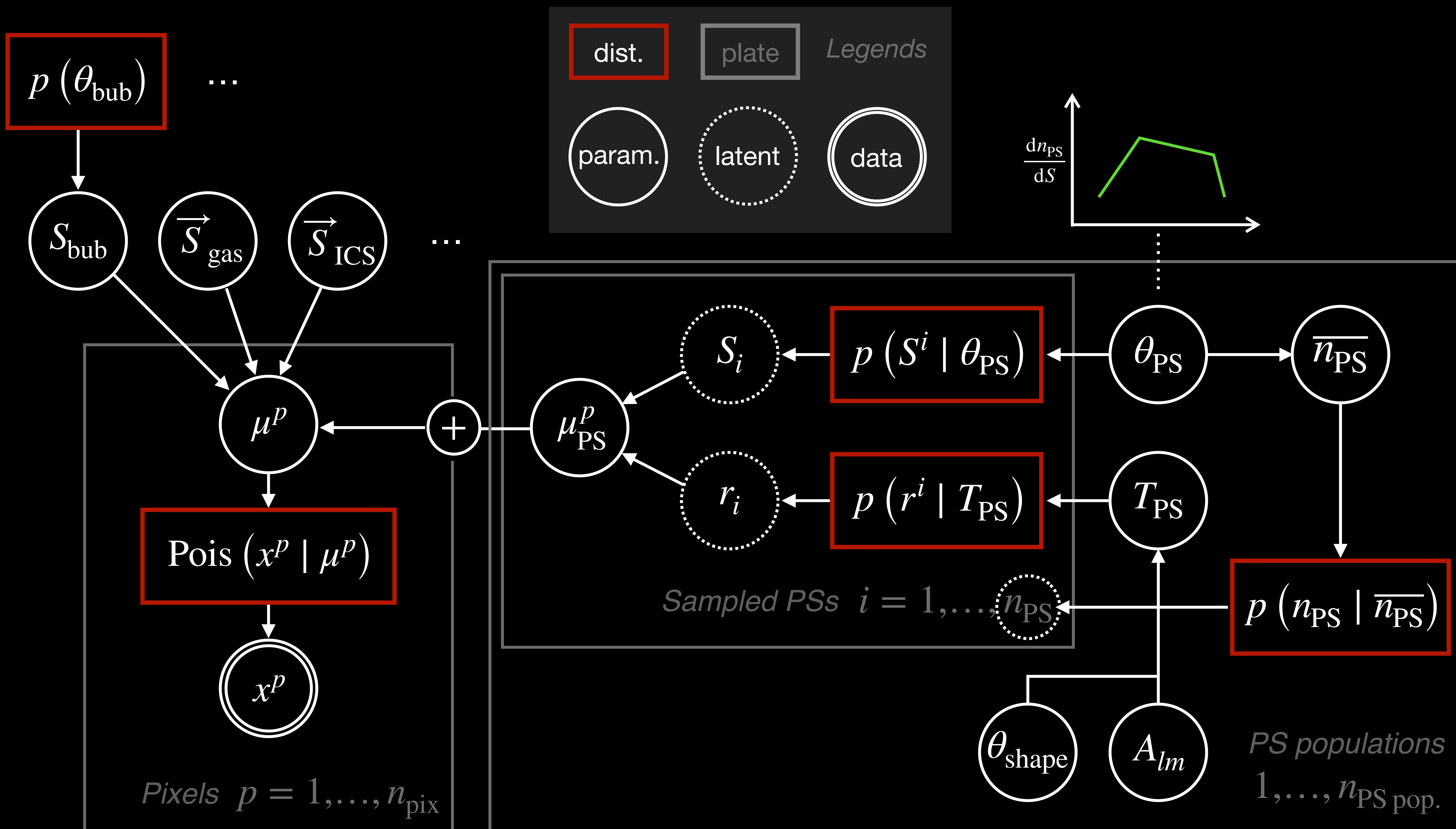


All first class objects / primitives

NumPyro JAX

Our probabilistic model

Part II: Prob. Programs: Flexible model



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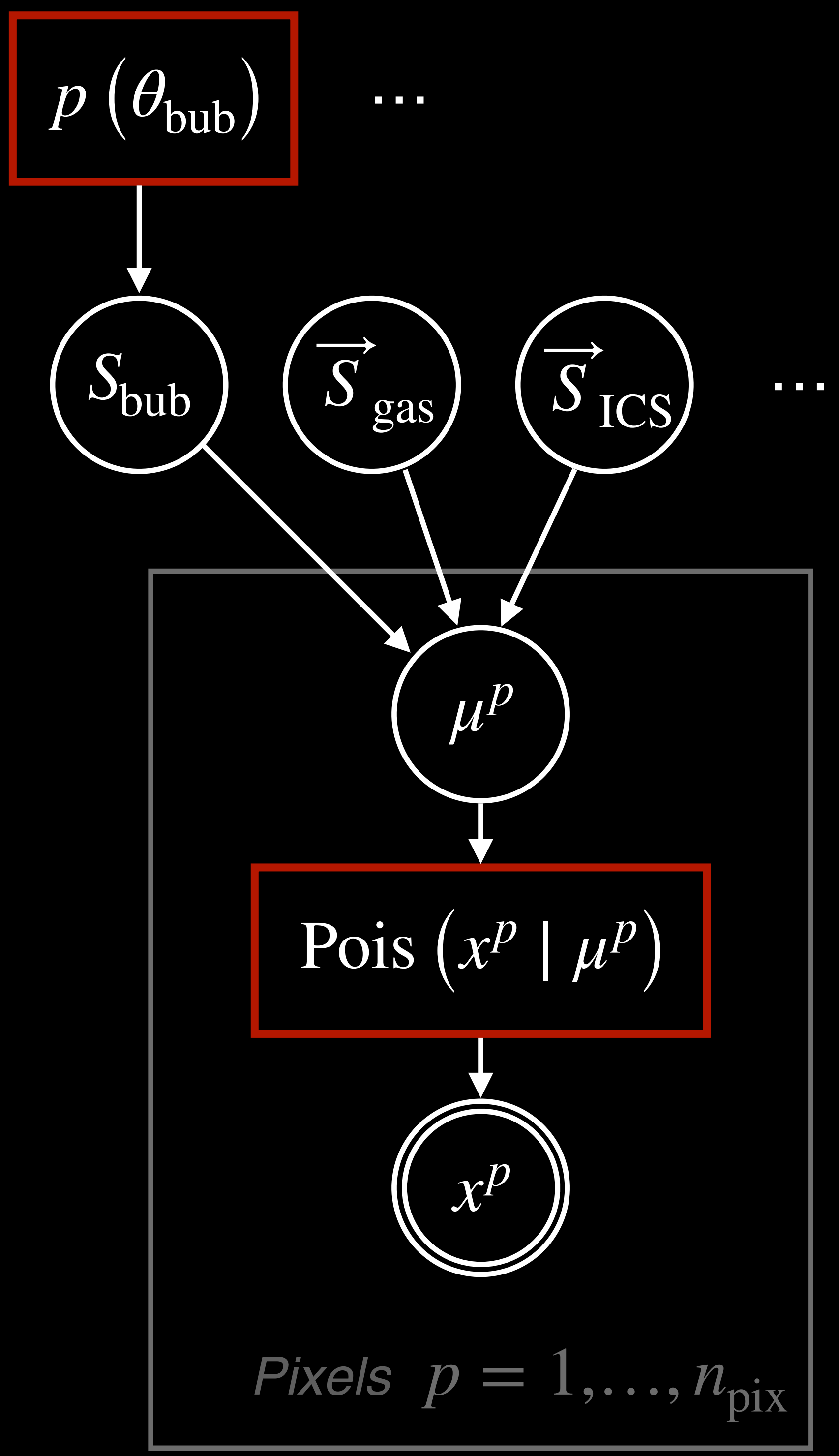

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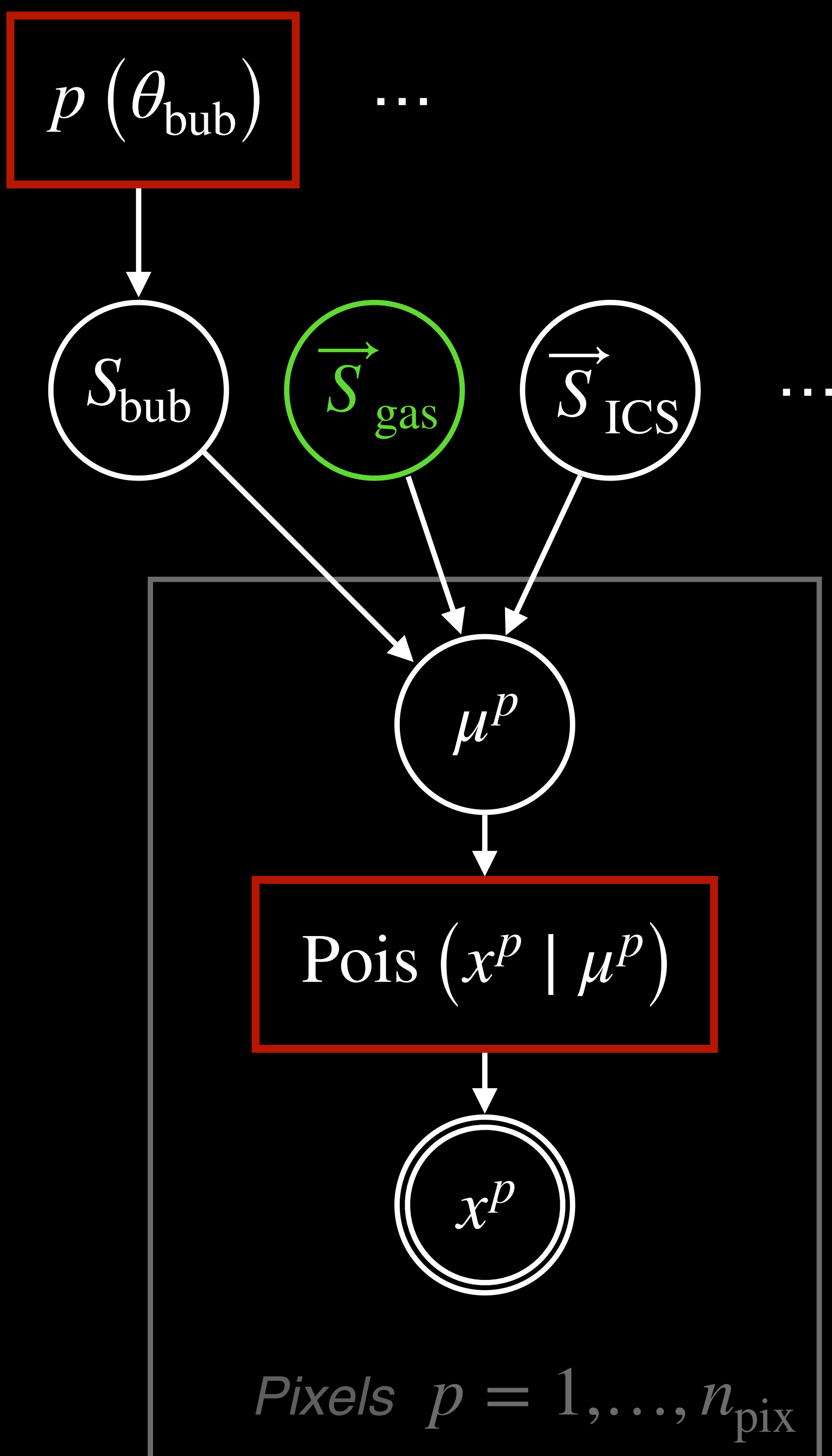
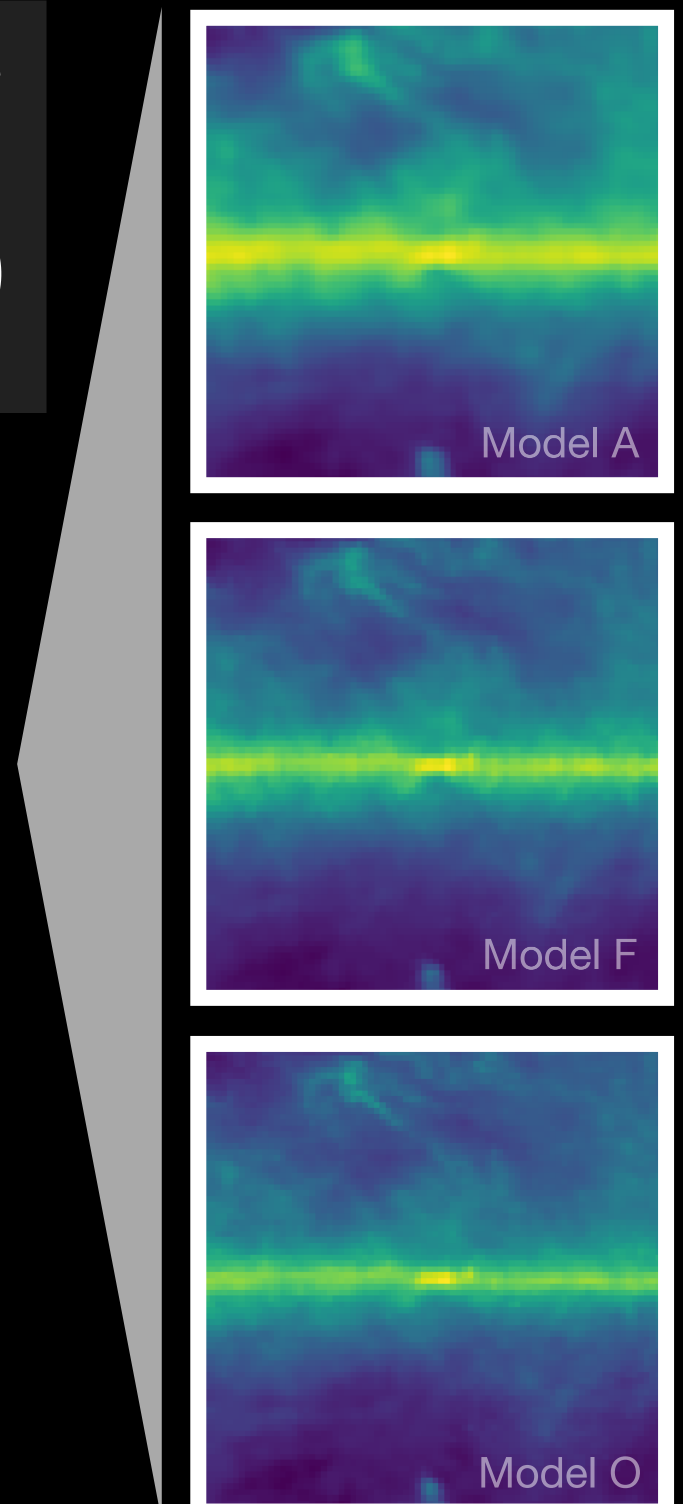


e.g. π^0+ brem.
templates:



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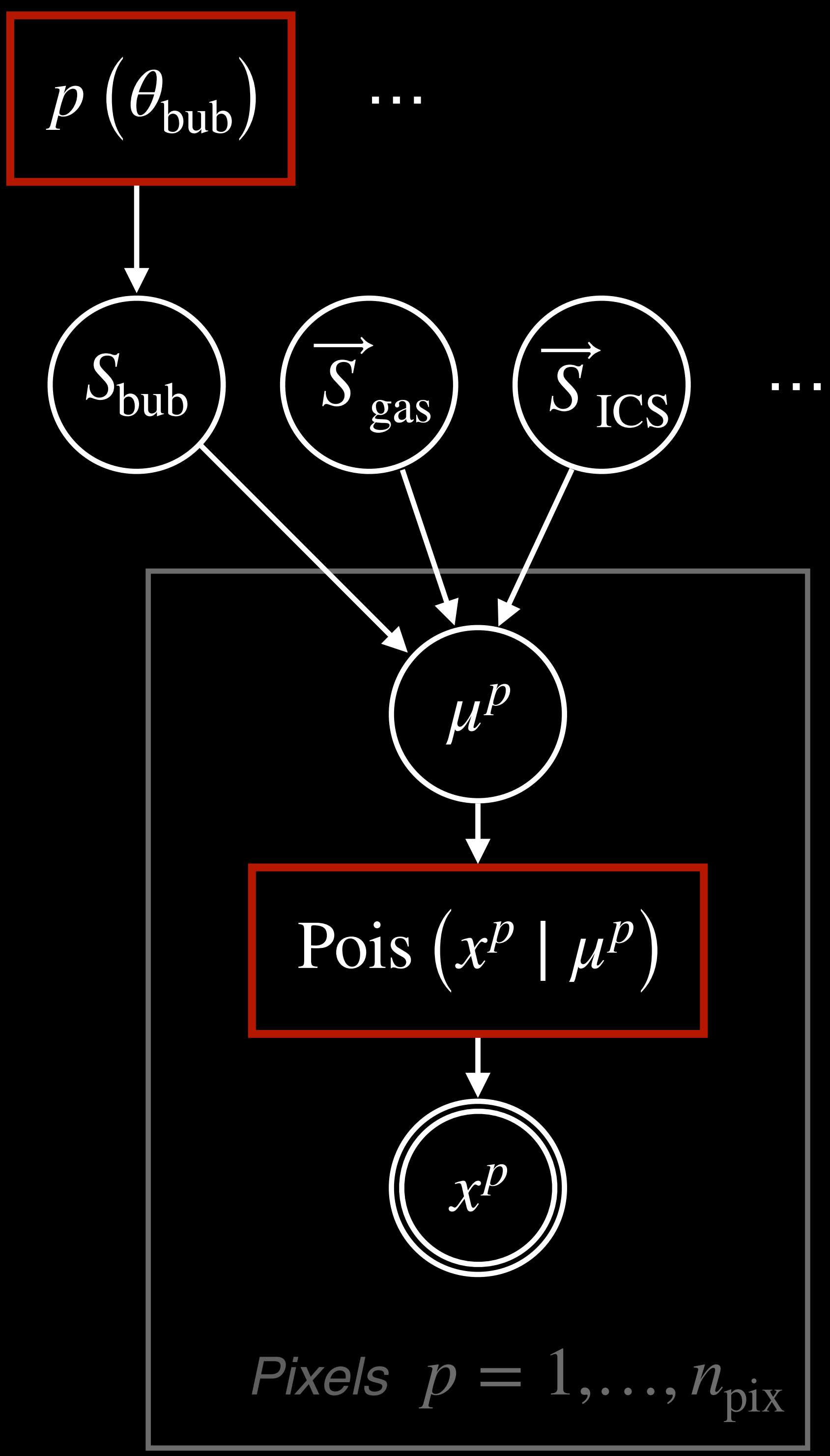

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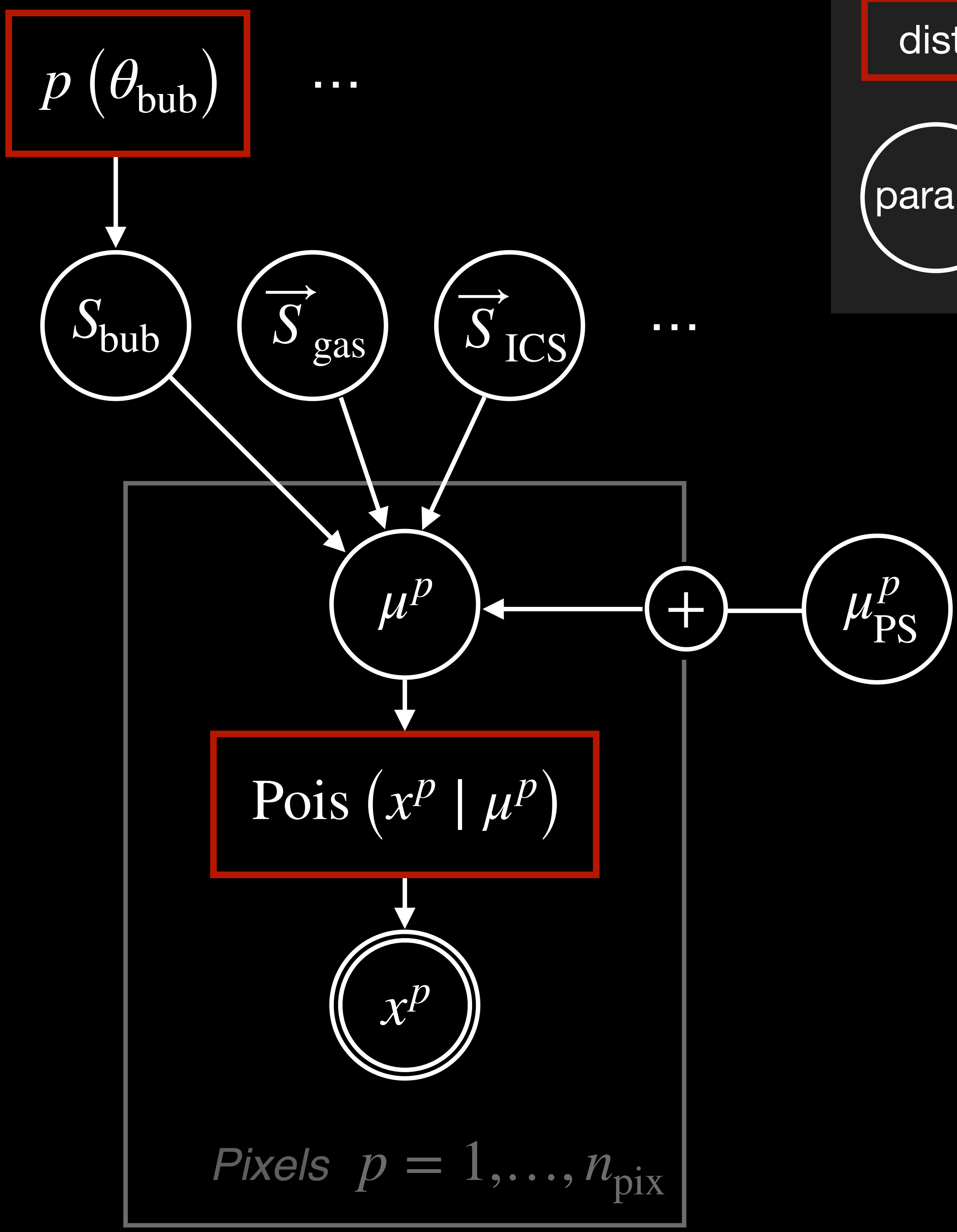

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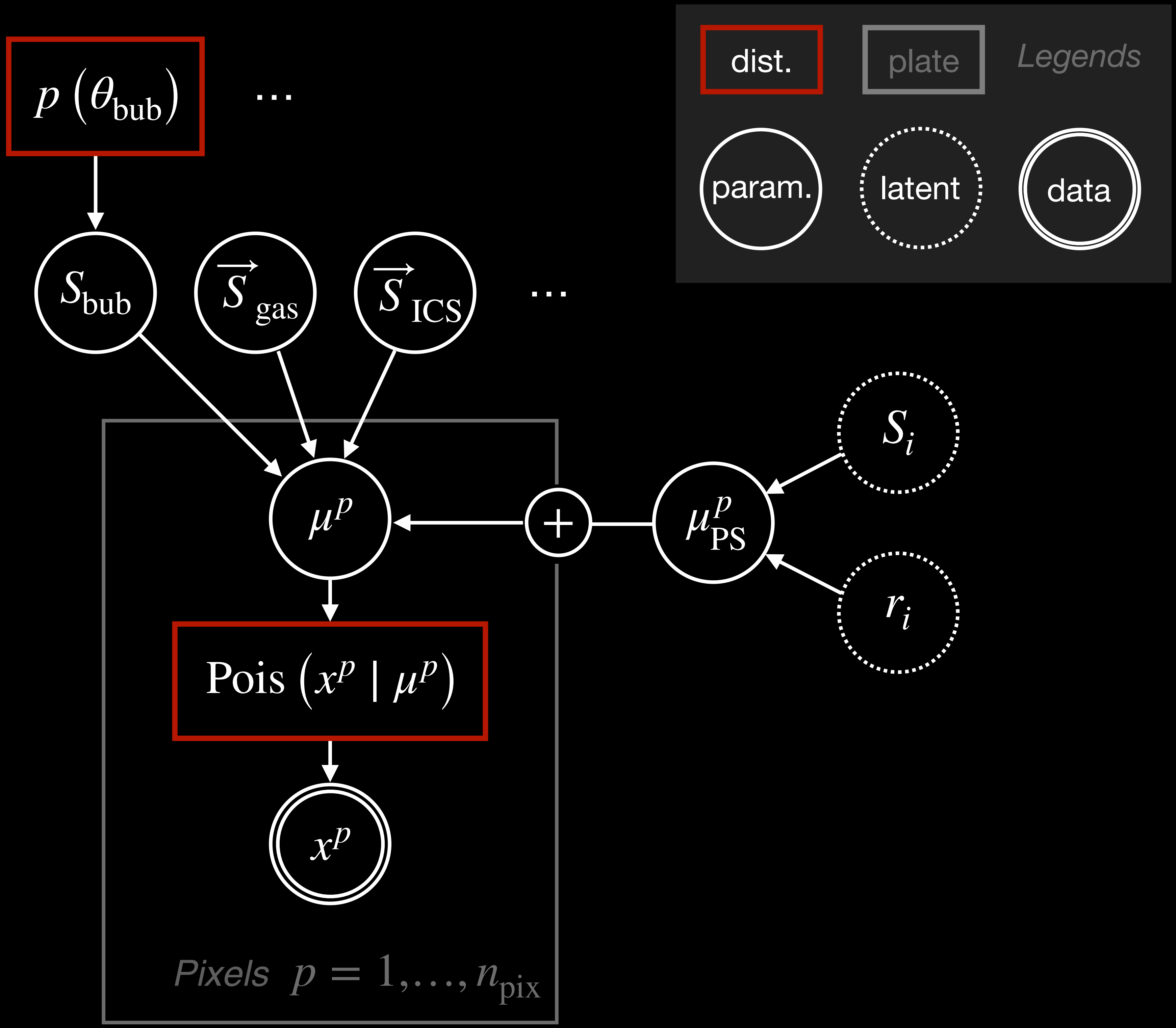

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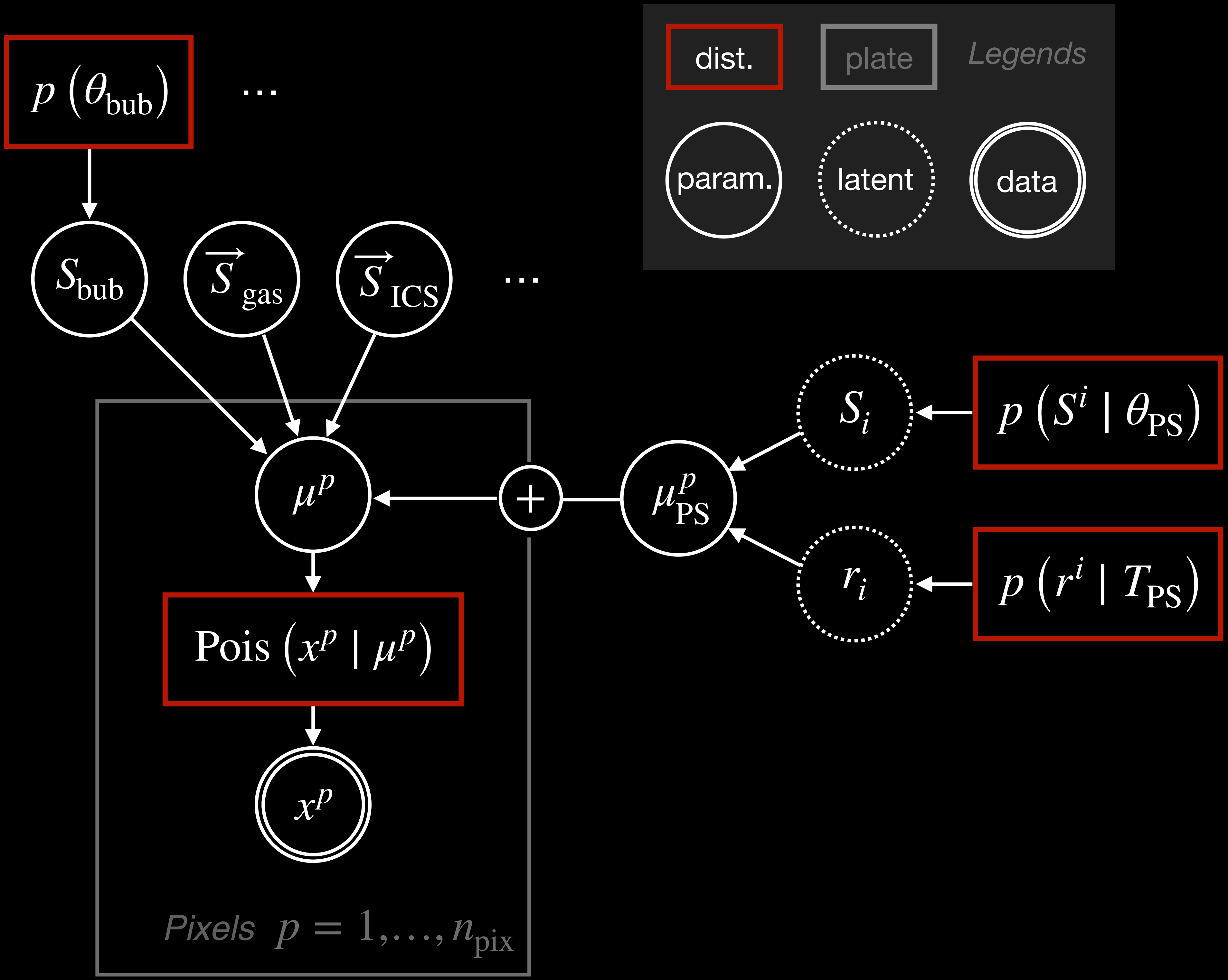

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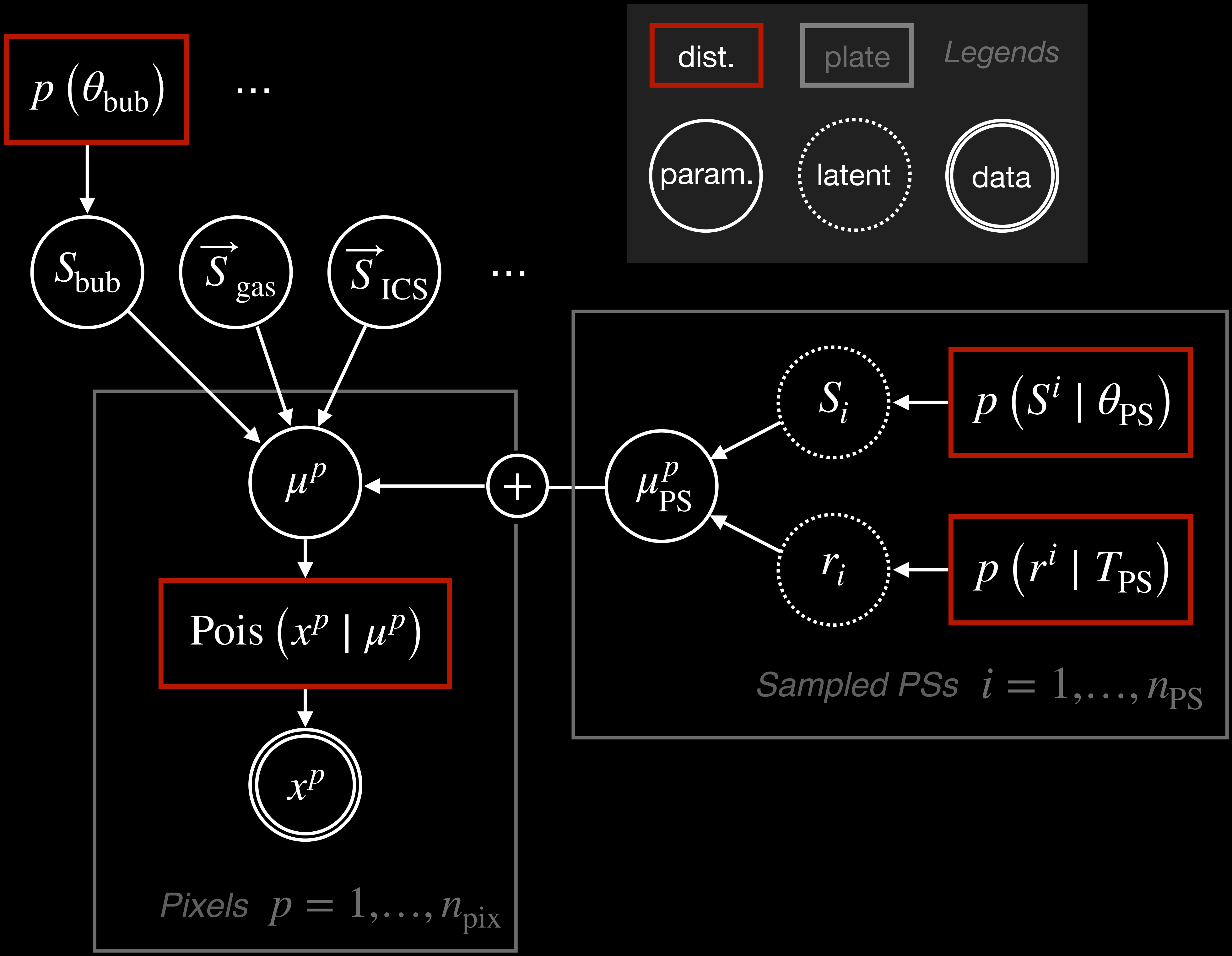

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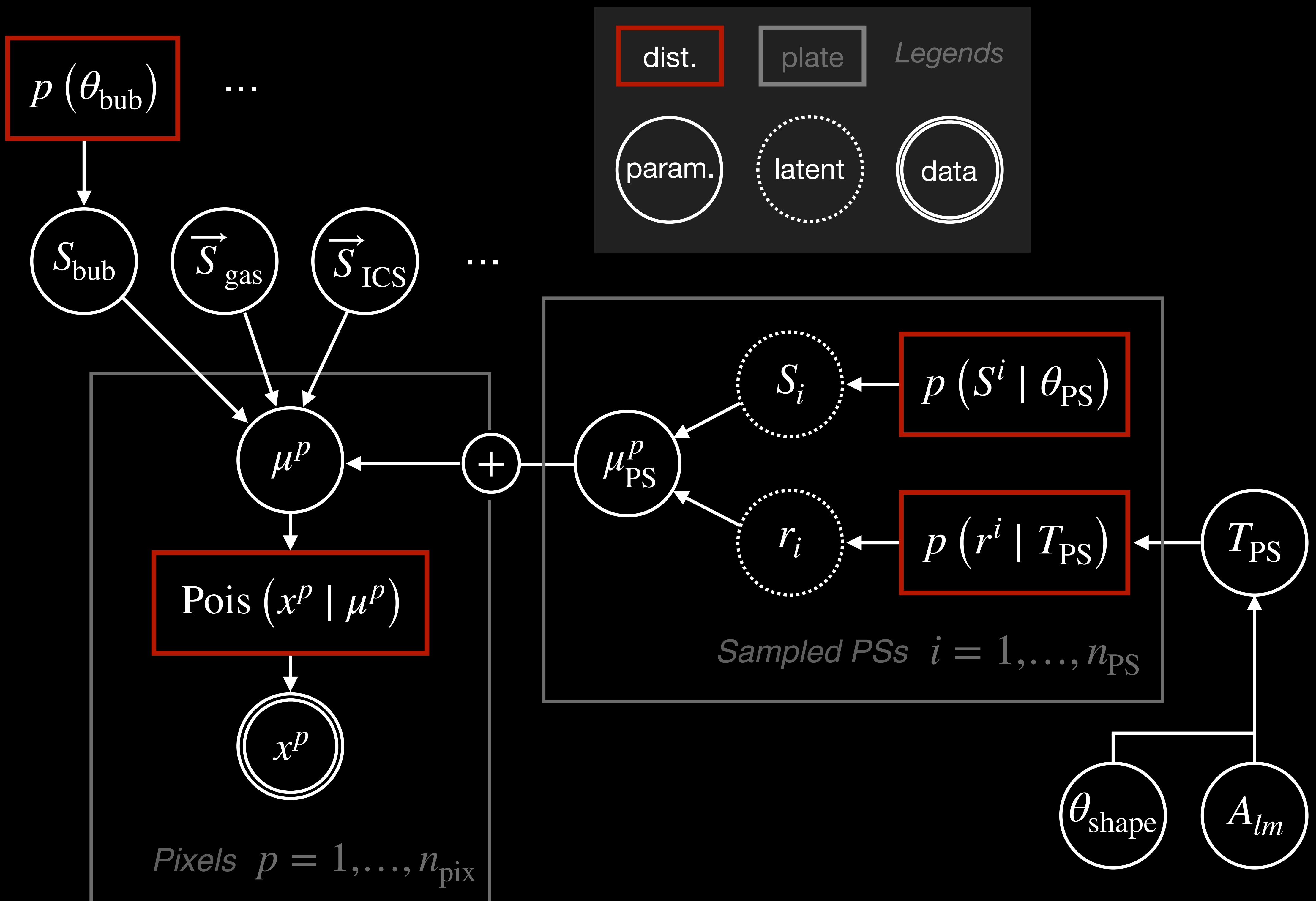

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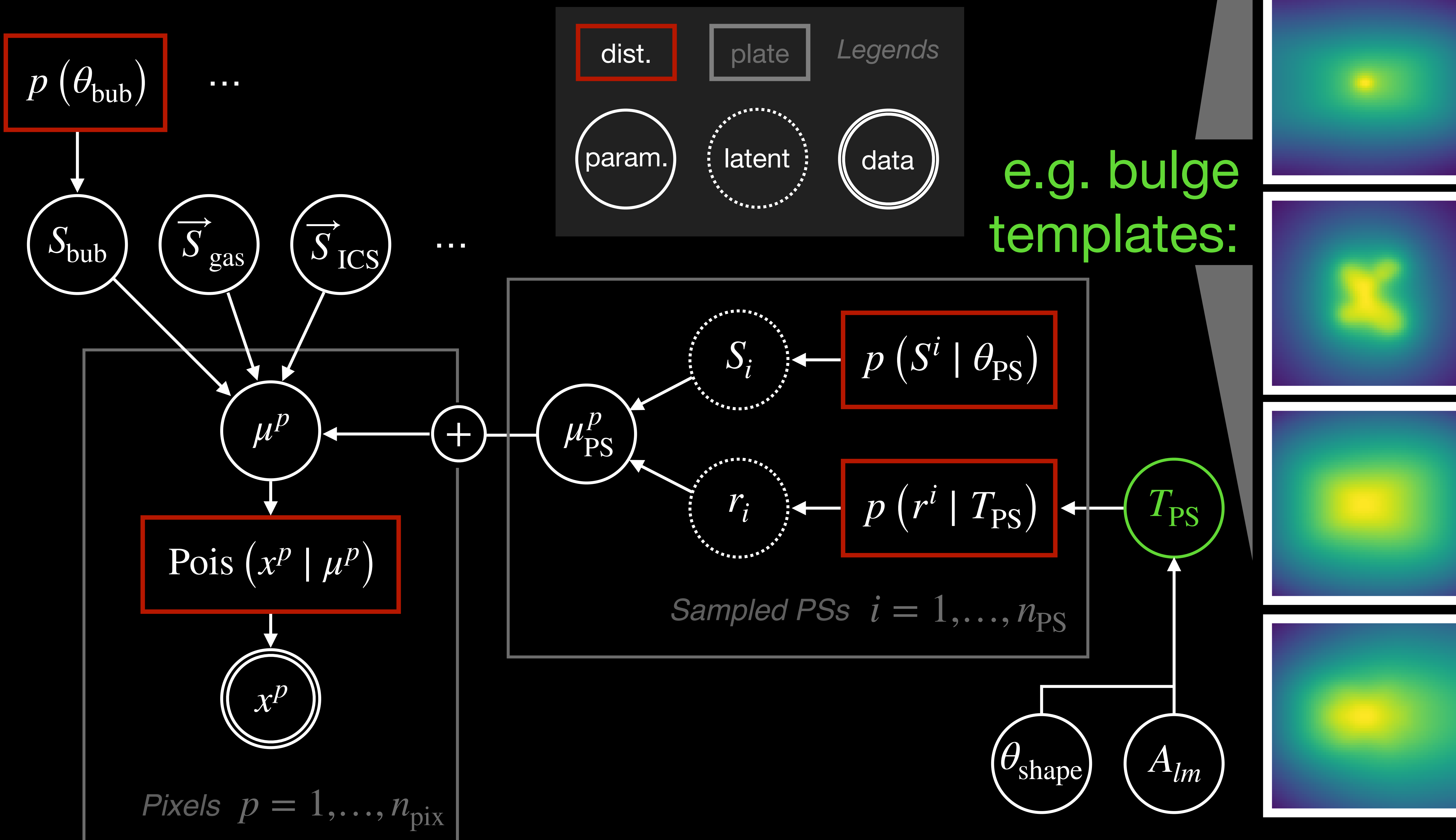

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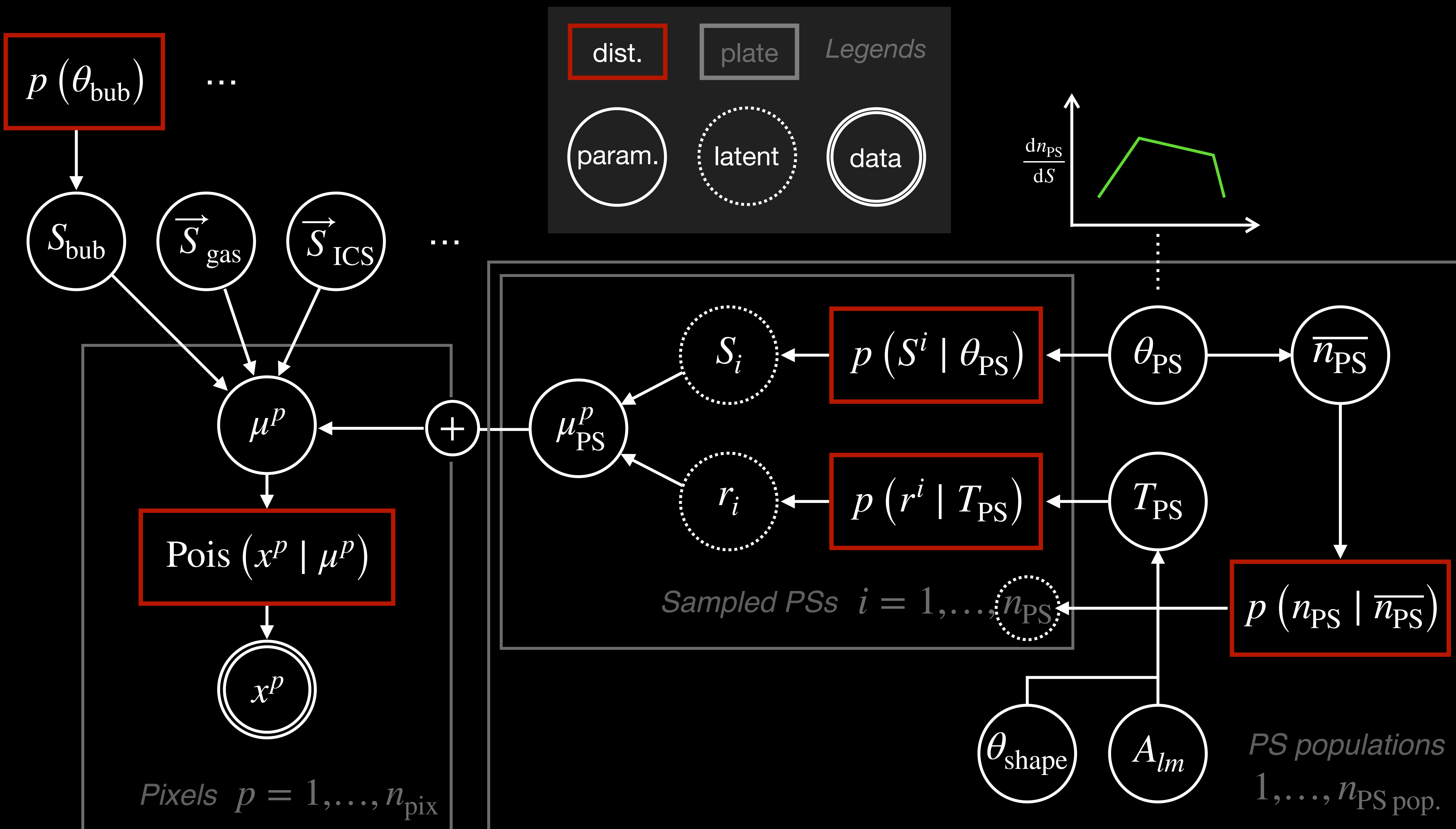

Stochastic Variational Inference

Part II: Prob. Programs: Avoiding the curse of dimensionality

- Guess the posterior q_λ.
- Optimize parameters λ so that q_λ looks like the true posterior.
- Equivalent to maximizing the ELBO (evidence lower bound).

Stochastic Variational Inference

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

Stochastic Variational Inference

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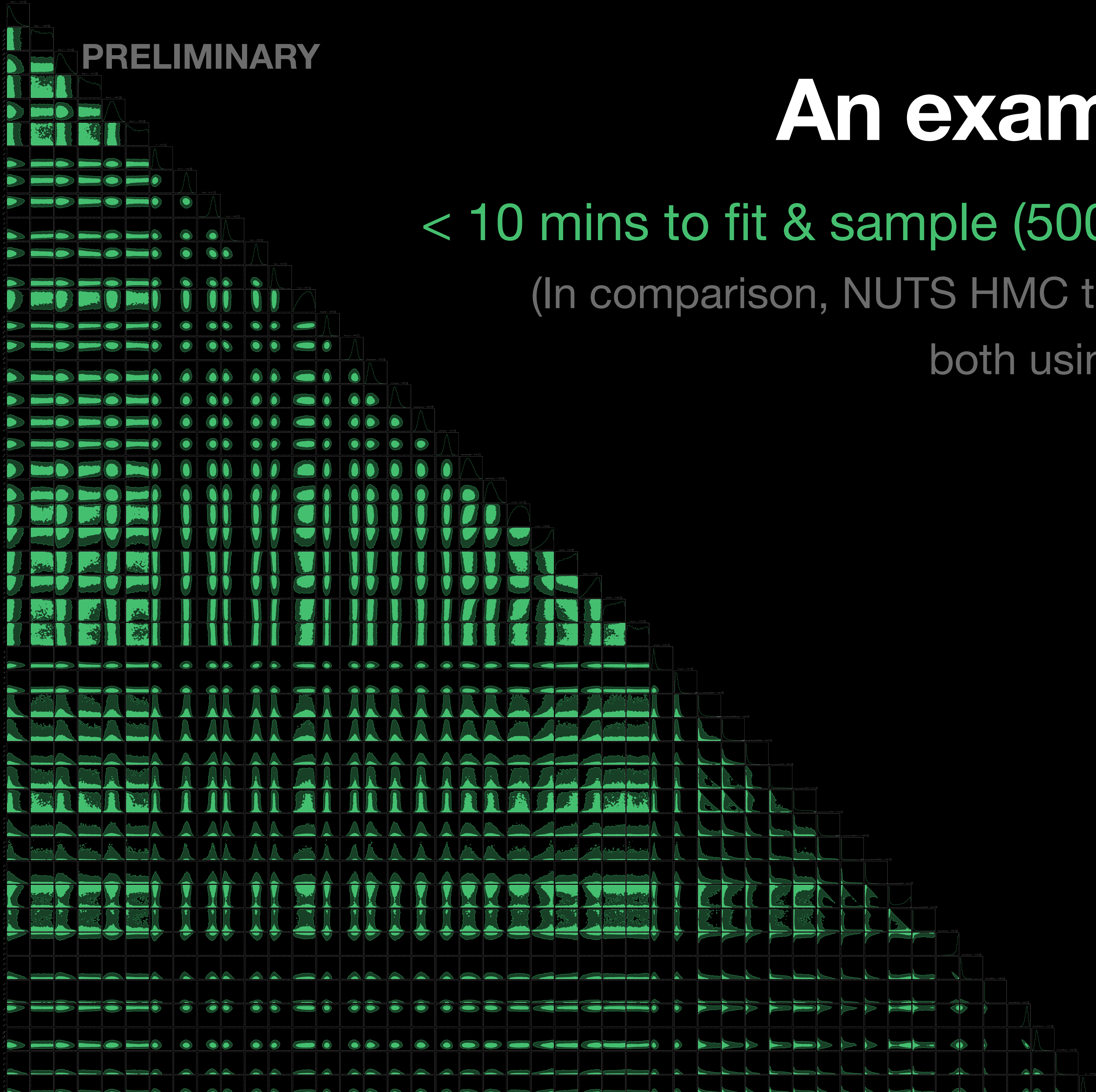
- Parametrize q_λ as a inverse autoregressive flow (IAF) on some base distribution…
  - …allowing an expressive guess posterior
  - …and a way of estimating $\mathbb{E}_{q_\lambda}[\ldots]$ in training.

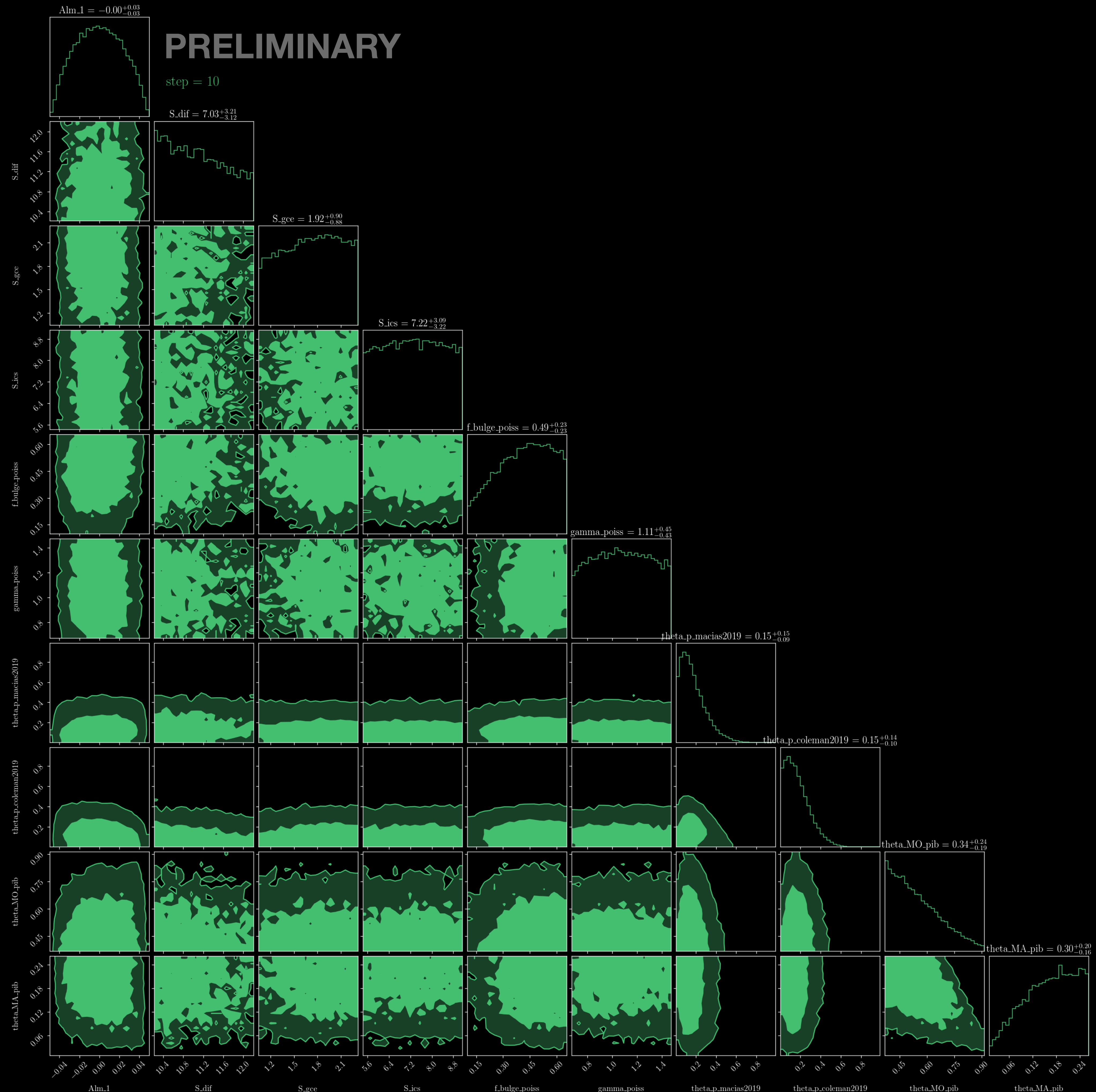


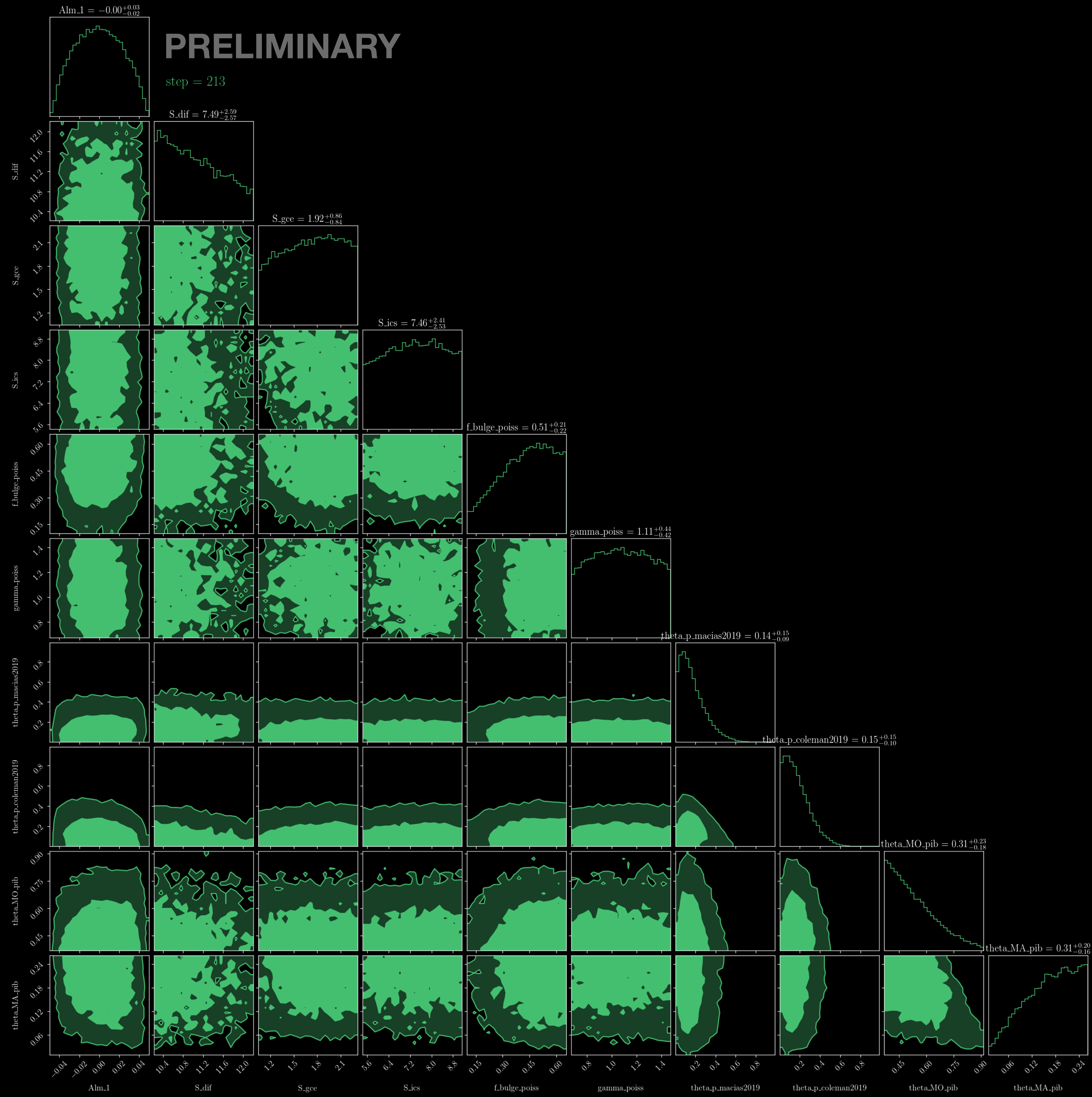
An example run

< 10 mins to fit & sample (50000 samples)

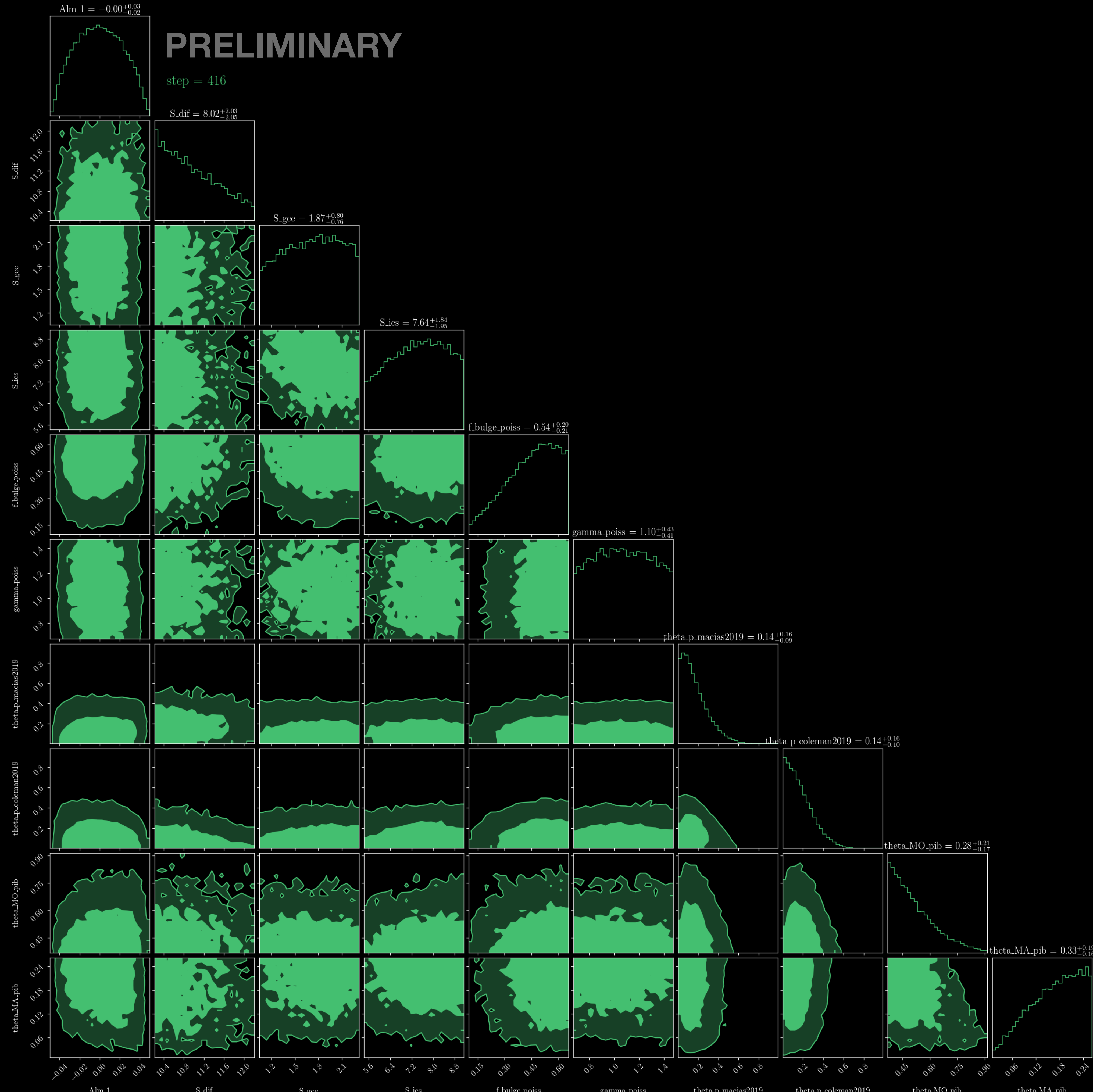
(In comparison, NUTS HMC takes ~ 5 hours)

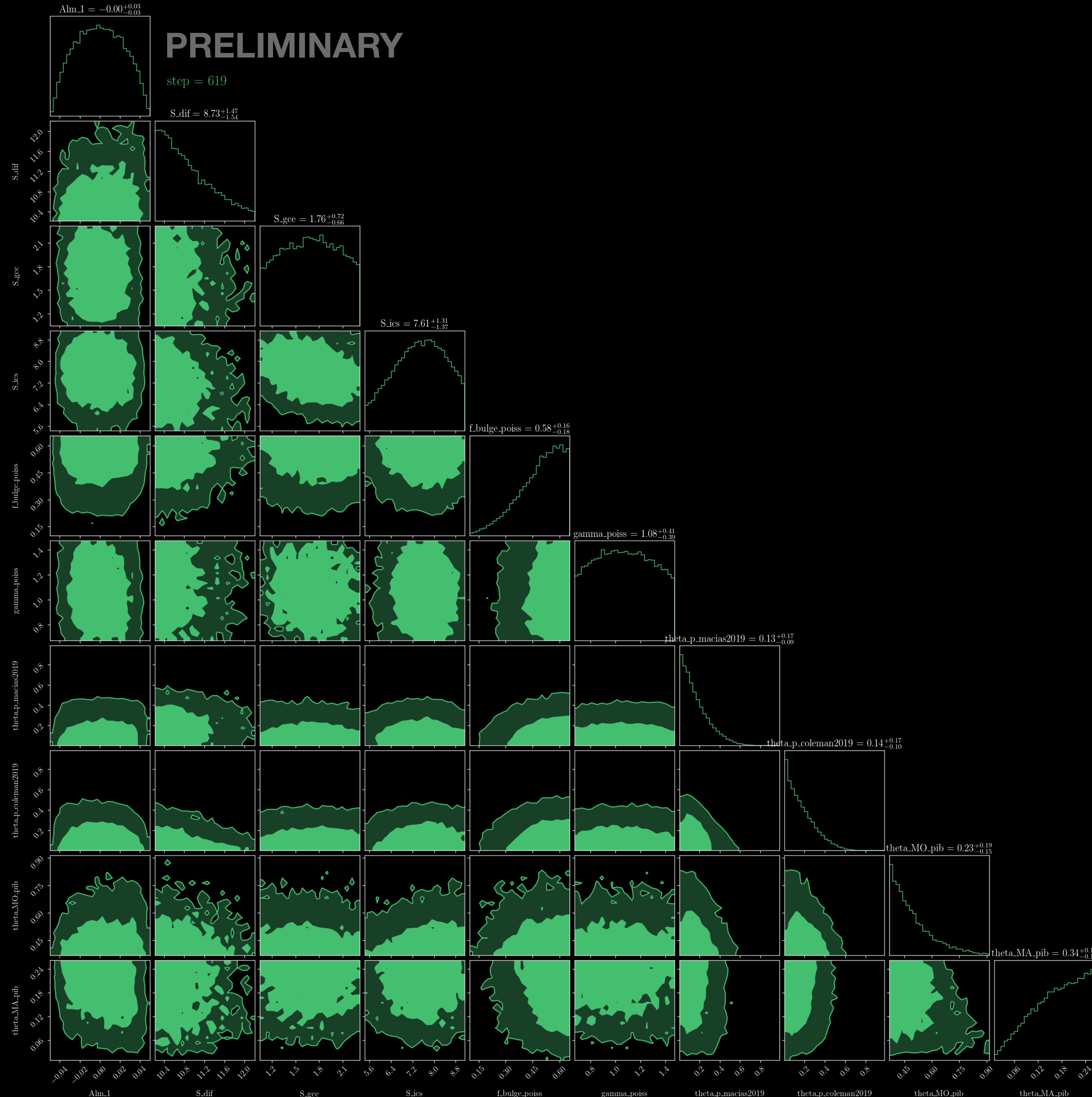
both using a A100 GPU

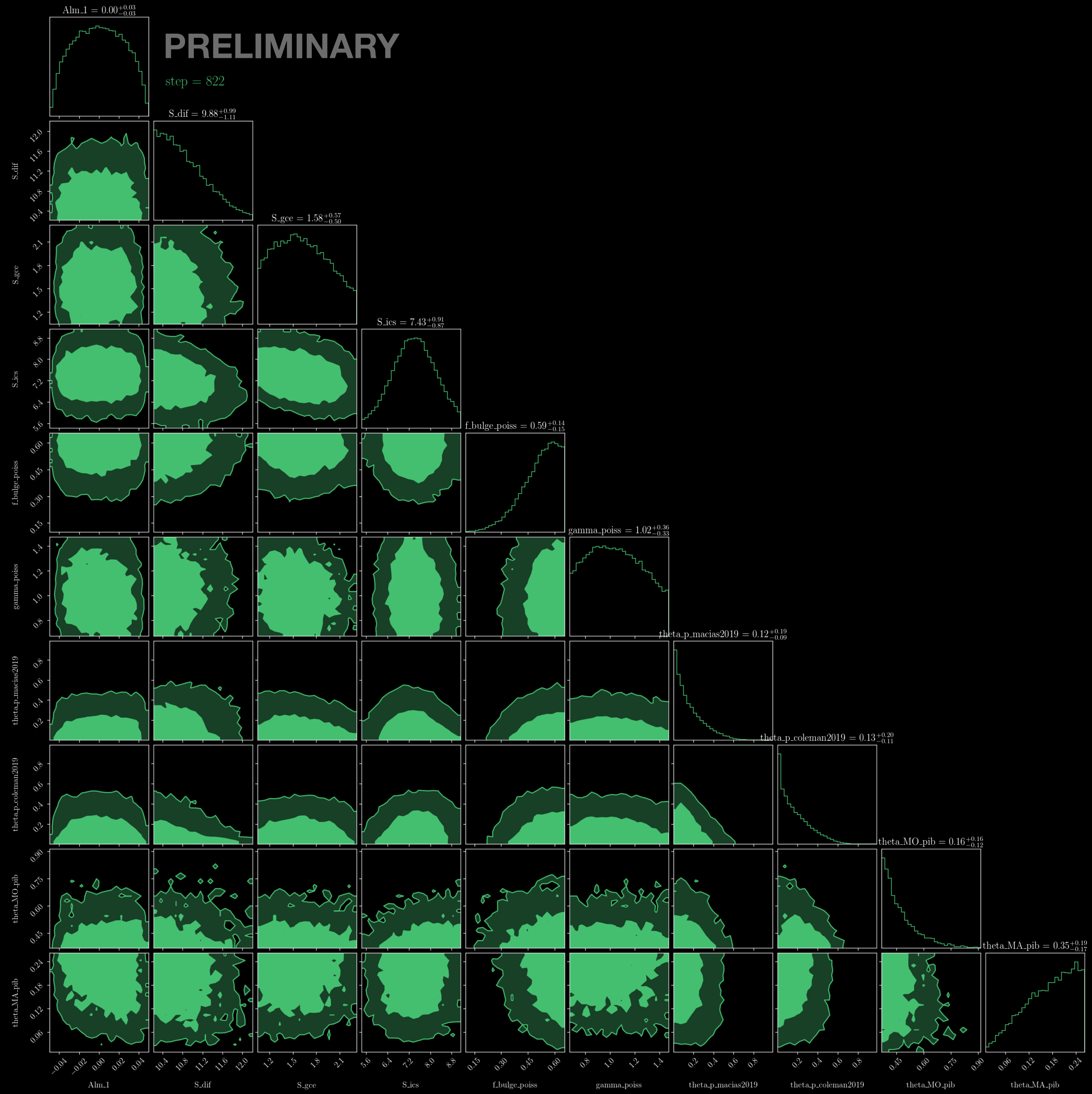

PRELIMINARY
step = 10
Alm_1 = −0.00$^{+0.03}_{-0.03}$
S_dif = 7.03$^{+3.21}_{-3.12}$
S_gce = 1.92$^{+0.90}_{-0.88}$
S_ics = 7.22$^{+3.09}_{-3.22}$
f_bulge_poiss = 0.49$^{+0.23}_{-0.23}$
gamma_poiss = 1.11$^{+0.45}_{-0.43}$
theta_p_macias2019 = 0.15$^{+0.15}_{-0.09}$
theta_p_coleman2019 = 0.15$^{+0.14}_{-0.10}$
theta_MO_pib = 0.34$^{+0.24}_{-0.19}$
theta_MA_pib = 0.30$^{+0.20}_{-0.16}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib



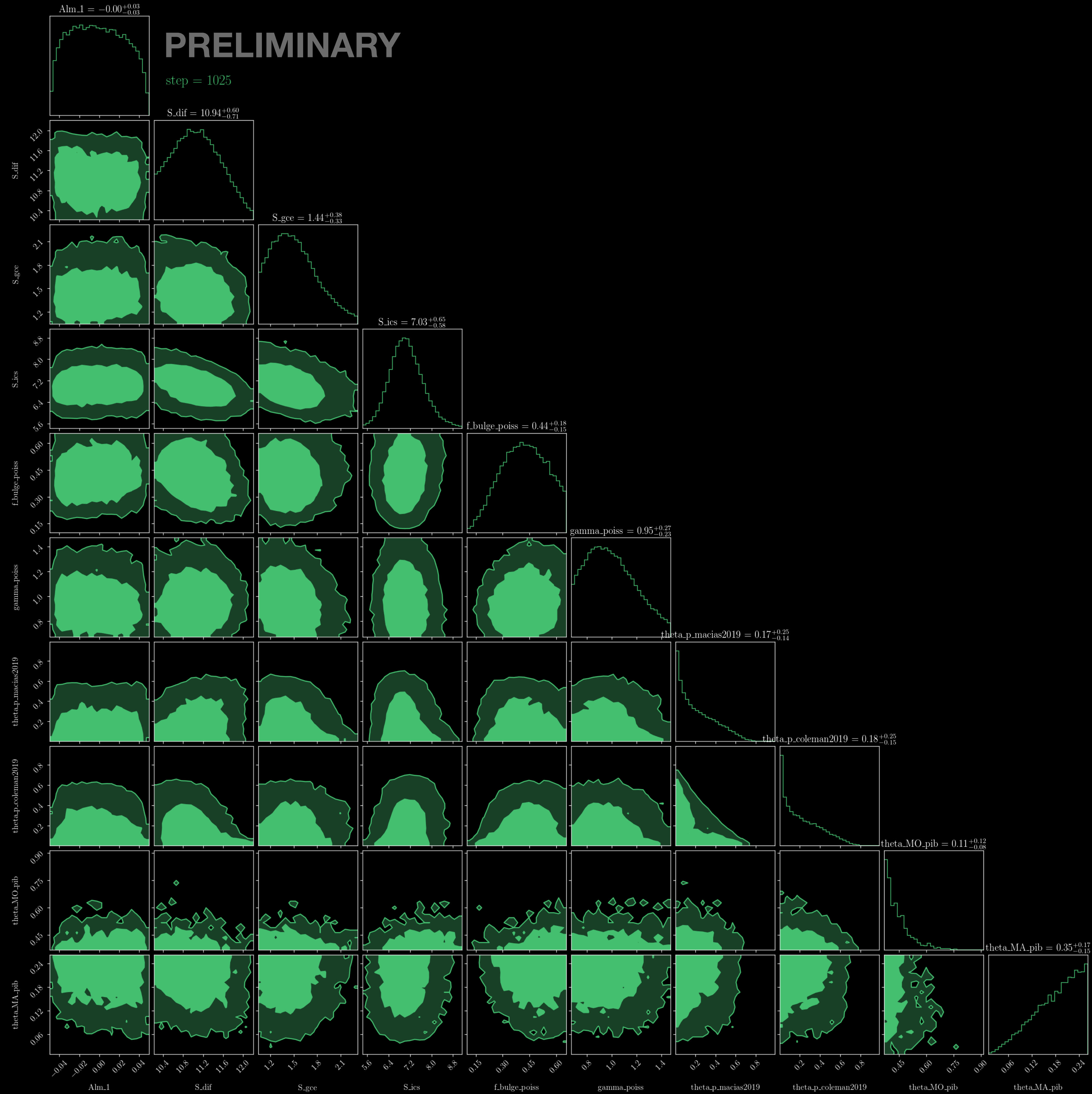
PRELIMINARY
step = 213
Alm_1 = −0.00 +0.03 −0.02
S_dif = 7.49 +2.59 −2.57
S_gce = 1.92 +0.86 −0.84
S_ics = 7.46 +2.41 −2.53
f_bulge_poiss = 0.51 +0.21 −0.22
gamma_poiss = 1.11 +0.44 −0.42
theta_p_macias2019 = 0.14 +0.15 −0.09
theta_p_coleman2019 = 0.15 +0.15 −0.10
theta_MO_pib = 0.31 +0.23 −0.18
theta_MA_pib = 0.31 +0.20 −0.16
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib


PRELIMINARY
step = 416
Alm_1 = −0.00 +0.03 −0.02
S_dif = 8.02 +2.03 −2.05
S_gce = 1.87 +0.80 −0.76
S_ics = 7.64 +1.84 −1.95
f_bulge_poiss = 0.54 +0.20 −0.21
gamma_poiss = 1.10 +0.43 −0.41
theta_p_macias2019 = 0.14 +0.16 −0.09
theta_p_coleman2019 = 0.14 +0.16 −0.10
theta_MO_pib = 0.28 +0.21 −0.17
theta_MA_pib = 0.33 +0.19 −0.16
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib

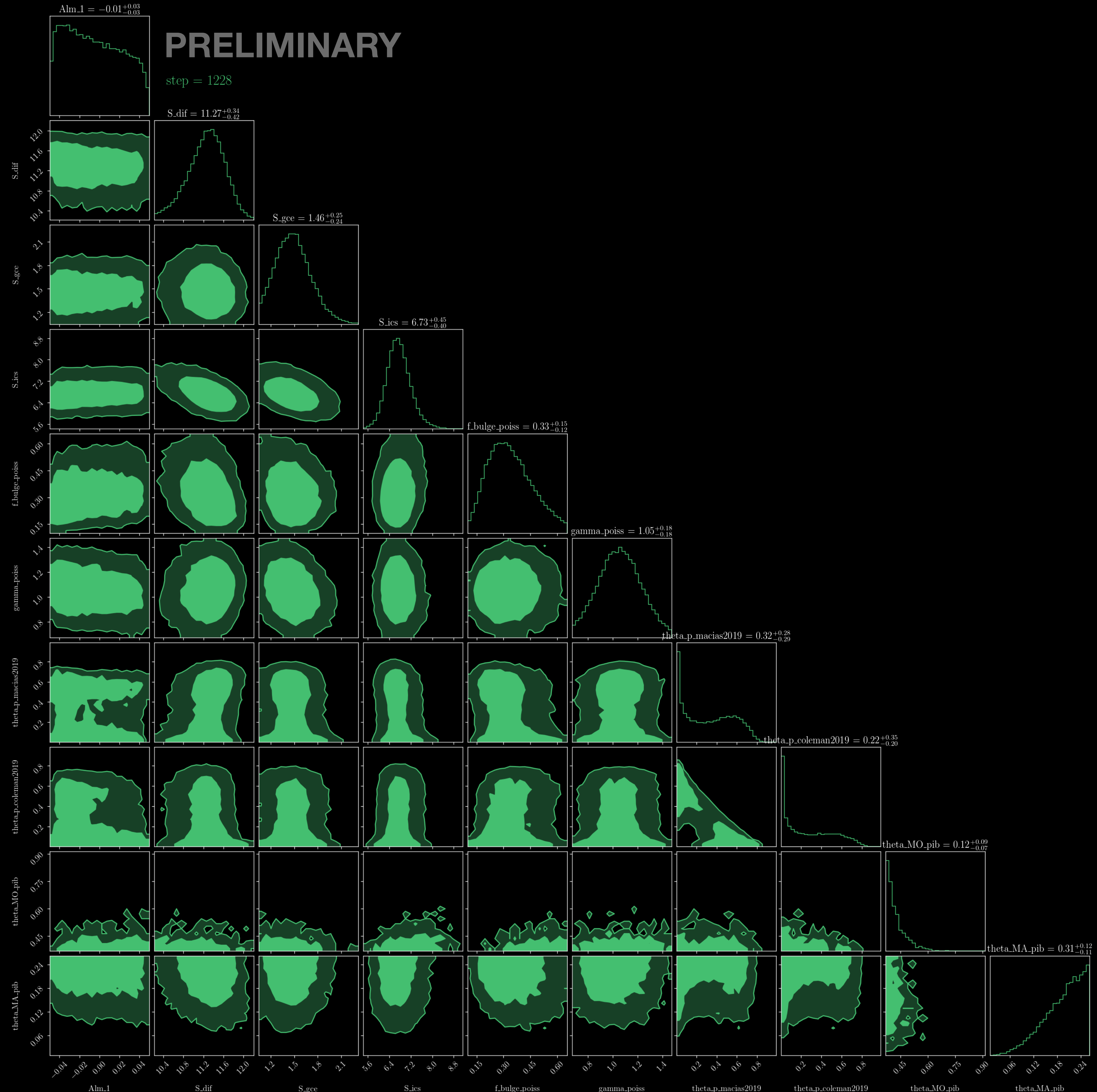

PRELIMINARY
step = 619
Alm_1 = $-0.00^{+0.03}_{-0.03}$
S_dif = $8.73^{+1.47}_{-1.54}$
S_gce = $1.76^{+0.72}_{-0.66}$
S_ics = $7.61^{+1.31}_{-1.37}$
f_bulge_poiss = $0.58^{+0.16}_{-0.18}$
gamma_poiss = $1.08^{+0.41}_{-0.39}$
theta_p_macias2019 = $0.13^{+0.17}_{-0.09}$
theta_p_coleman2019 = $0.14^{+0.17}_{-0.10}$
theta_MO_pib = $0.23^{+0.19}_{-0.15}$
theta_MA_pib = $0.34^{+0.19}_{-0.17}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib

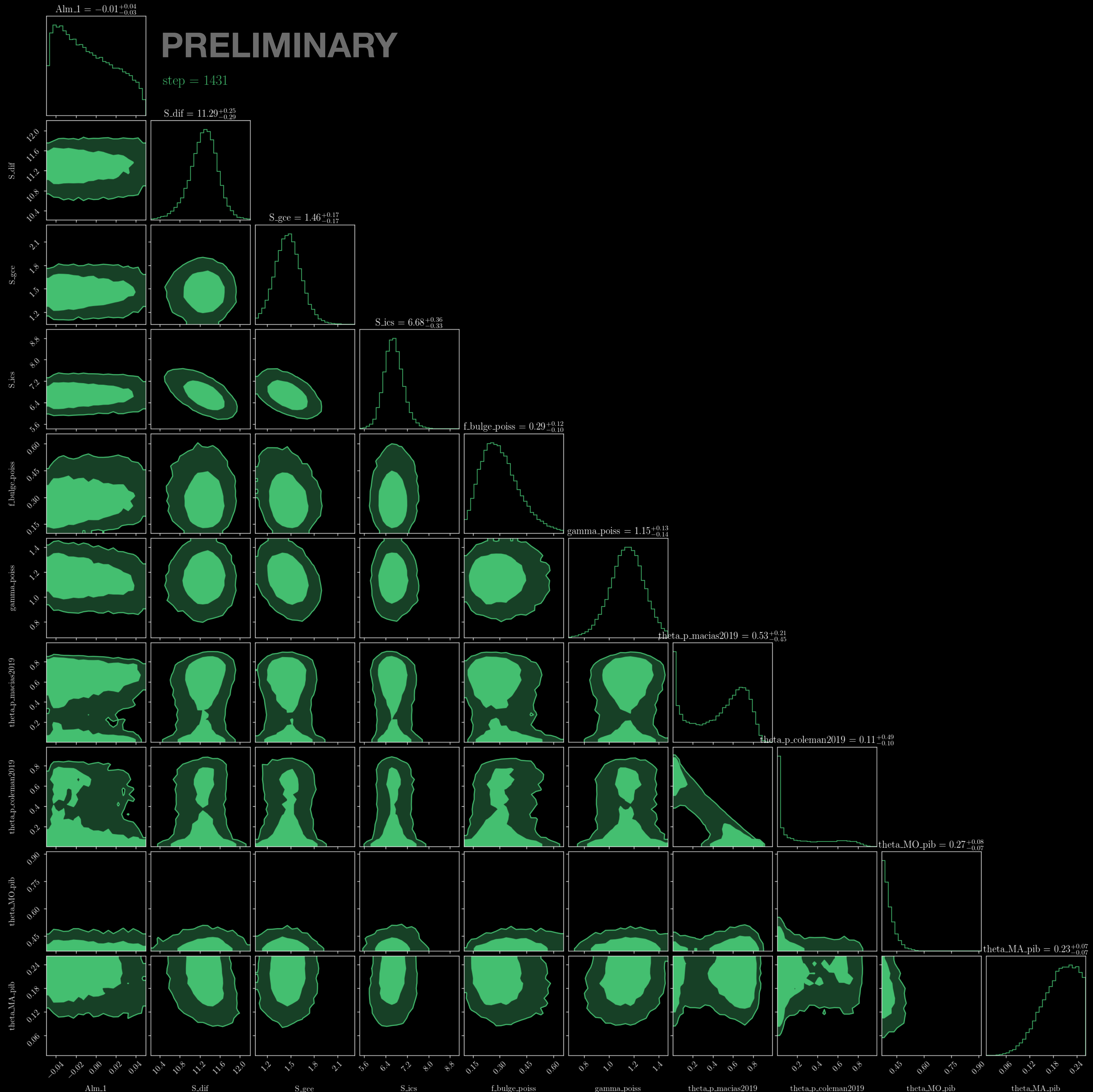


PRELIMINARY
step = 822
Alm_1 = $0.00^{+0.03}_{-0.03}$
S_dif = $9.88^{+0.99}_{-1.11}$
S_gce = $1.58^{+0.57}_{-0.50}$
S_ics = $7.43^{+0.91}_{-0.87}$
f_bulge_poiss = $0.59^{+0.14}_{-0.15}$
gamma_poiss = $1.02^{+0.36}_{-0.33}$
theta_p_macias2019 = $0.12^{+0.19}_{-0.09}$
theta_p_coleman2019 = $0.13^{+0.20}_{-0.11}$
theta_MO_pib = $0.16^{+0.16}_{-0.12}$
theta_MA_pib = $0.35^{+0.19}_{-0.17}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib

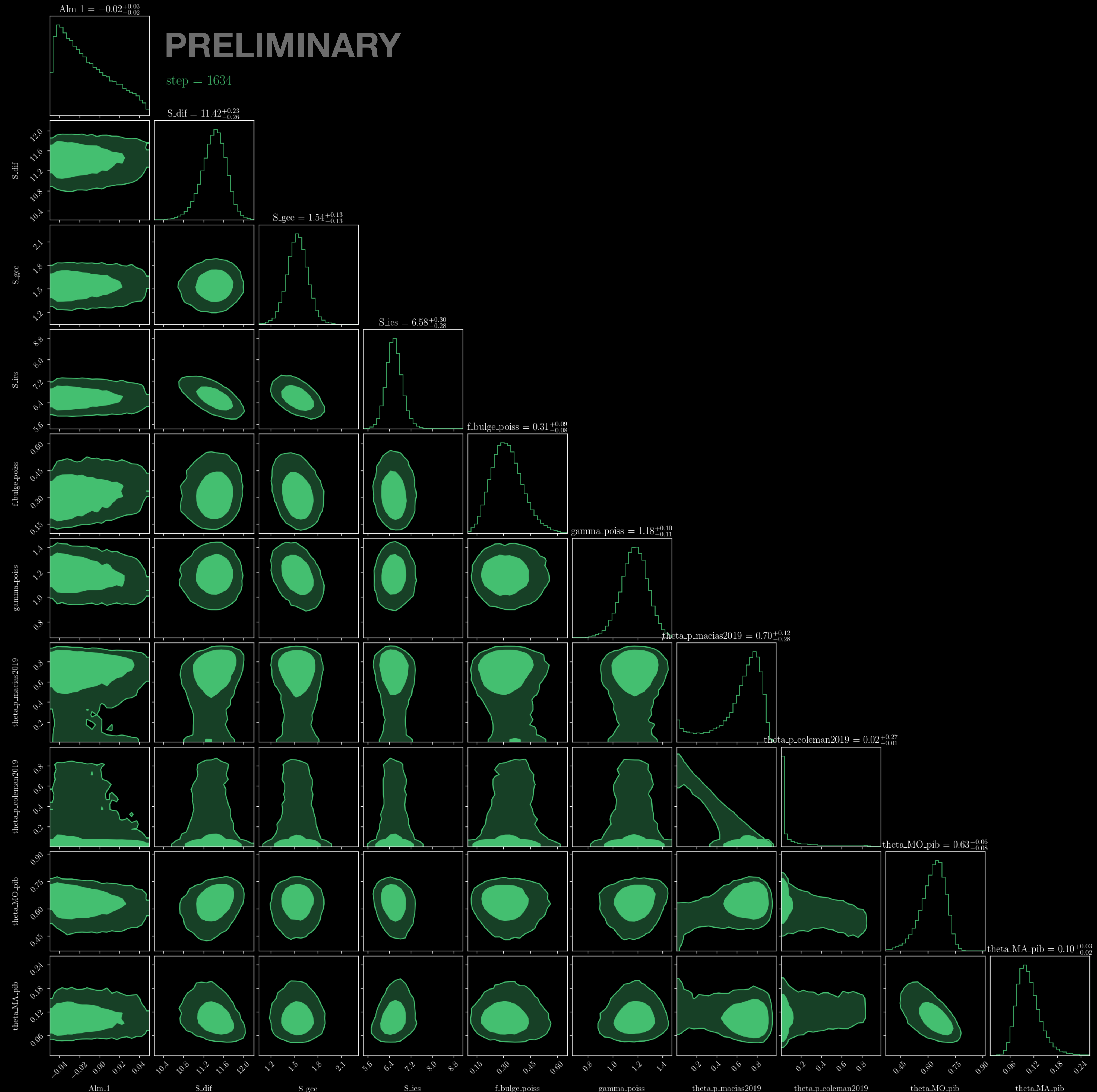


PRELIMINARY
step = 1025
Alm_1 = −0.00^{+0.03}_{−0.03}
S_dif = 10.94^{+0.60}_{−0.71}
S_gce = 1.44^{+0.38}_{−0.33}
S_ics = 7.03^{+0.65}_{−0.58}
f_bulge_poiss = 0.44^{+0.18}_{−0.15}
gamma_poiss = 0.95^{+0.27}_{−0.23}
theta_p_macias2019 = 0.17^{+0.25}_{−0.14}
theta_p_coleman2019 = 0.18^{+0.25}_{−0.15}
theta_MO_pib = 0.11^{+0.12}_{−0.08}
theta_MA_pib = 0.35^{+0.17}_{−0.15}
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib

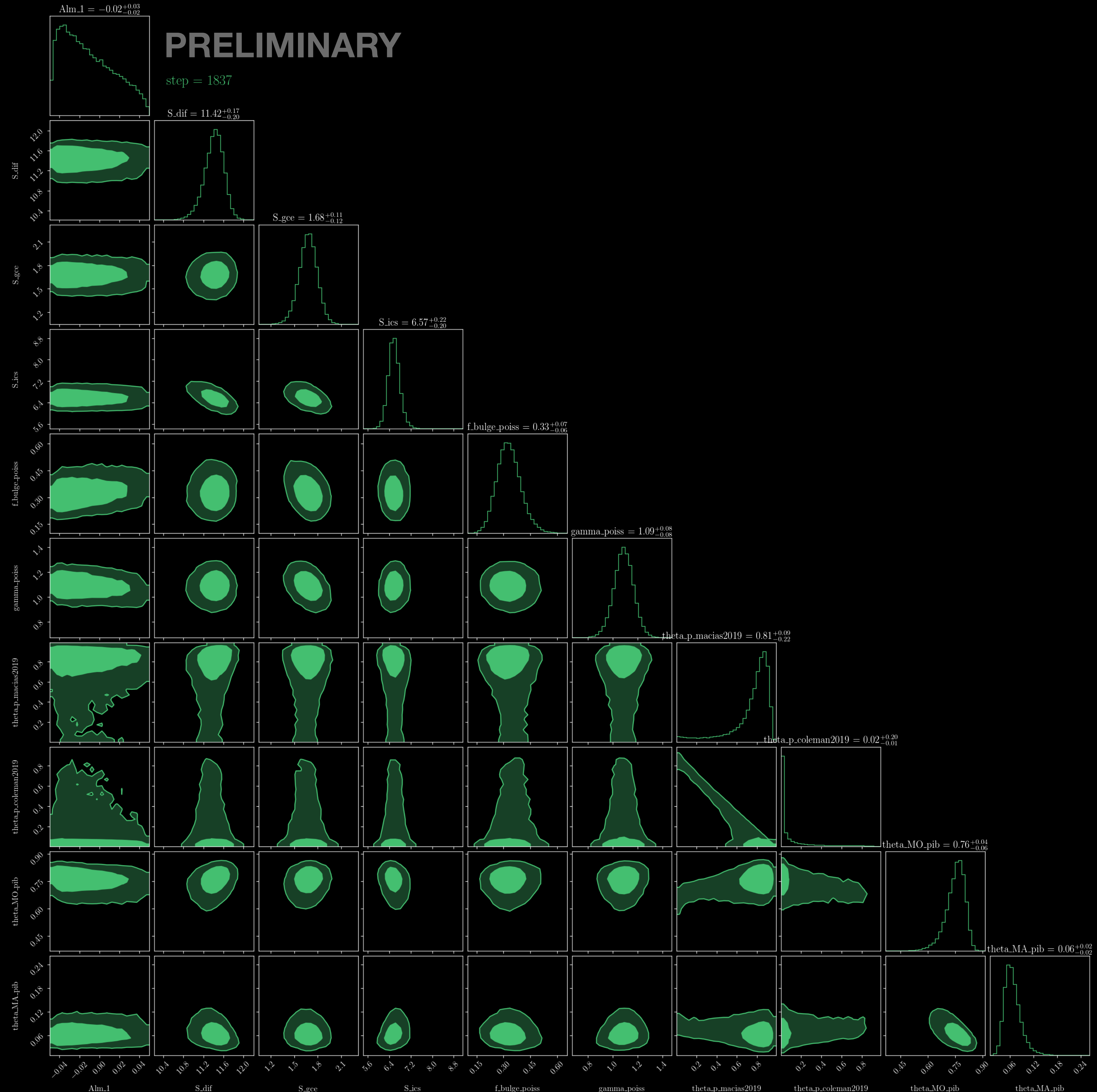

PRELIMINARY
step = 1228
Alm_1 = $-0.01^{+0.03}_{-0.03}$
S_dif = $11.27^{+0.34}_{-0.42}$
S_gce = $1.46^{+0.25}_{-0.24}$
S_ics = $6.73^{+0.45}_{-0.40}$
f_bulge_poiss = $0.33^{+0.15}_{-0.12}$
gamma_poiss = $1.05^{+0.18}_{-0.18}$
theta_p_macias2019 = $0.32^{+0.28}_{-0.29}$
theta_p_coleman2019 = $0.22^{+0.35}_{-0.20}$
theta_MO_pib = $0.12^{+0.09}_{-0.07}$
theta_MA_pib = $0.31^{+0.12}_{-0.11}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib

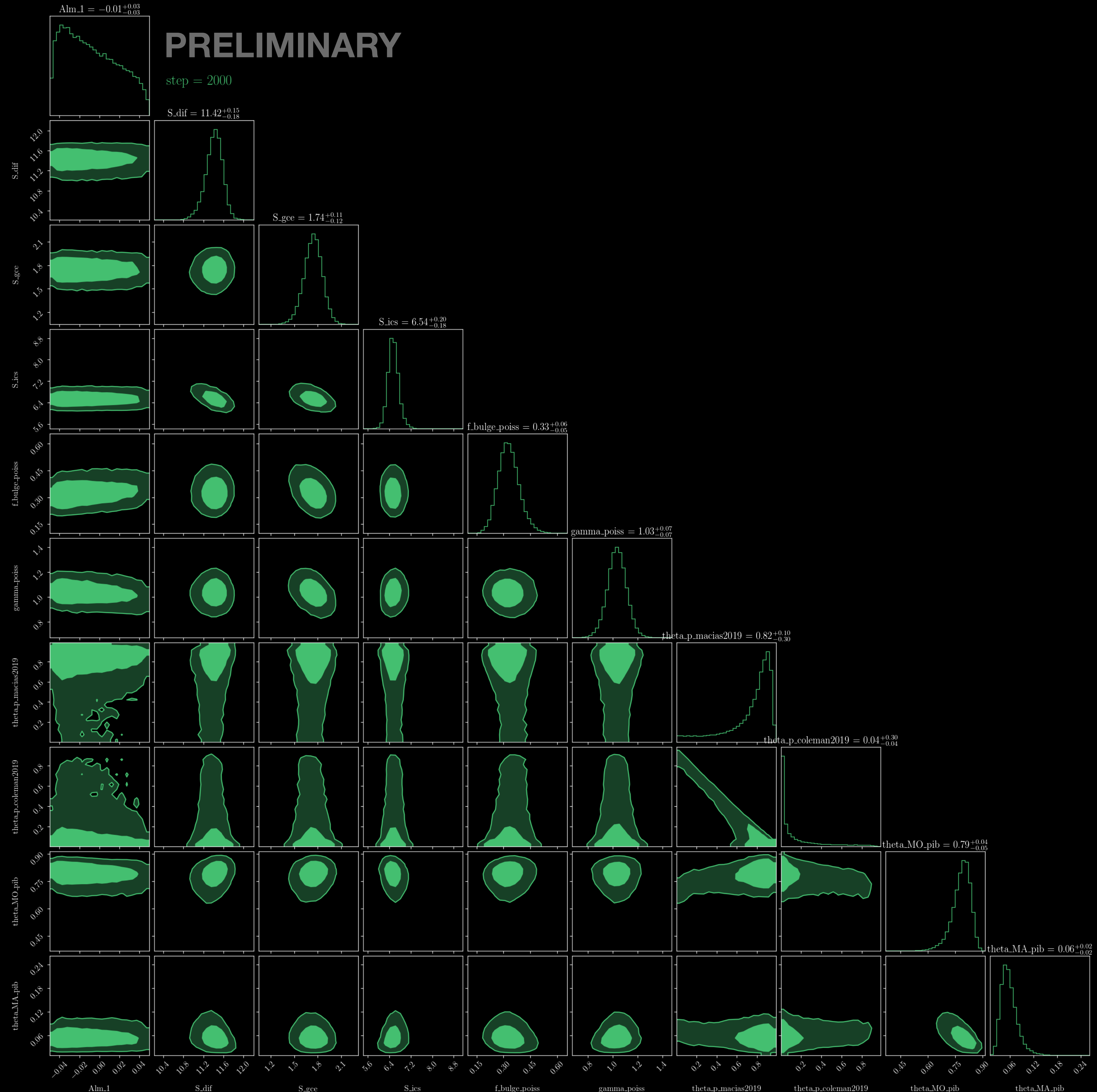


PRELIMINARY
step = 1431
Alm_1 = $-0.01^{+0.04}_{-0.03}$
S_dif = $11.29^{+0.25}_{-0.29}$
S_gce = $1.46^{+0.17}_{-0.17}$
S_ics = $6.68^{+0.36}_{-0.33}$
f_bulge_poiss = $0.29^{+0.12}_{-0.10}$
gamma_poiss = $1.15^{+0.13}_{-0.14}$
theta_p_macias2019 = $0.53^{+0.21}_{-0.45}$
theta_p_coleman2019 = $0.11^{+0.49}_{-0.10}$
theta_MO_pib = $0.27^{+0.08}_{-0.07}$
theta_MA_pib = $0.23^{+0.07}_{-0.07}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib



PRELIMINARY
step = 1634
Alm_1 = $-0.02^{+0.03}_{-0.02}$
S_dif = $11.42^{+0.23}_{-0.26}$
S_gce = $1.54^{+0.13}_{-0.13}$
S_ics = $6.58^{+0.30}_{-0.28}$
f_bulge_poiss = $0.31^{+0.09}_{-0.08}$
gamma_poiss = $1.18^{+0.10}_{-0.11}$
theta_p_macias2019 = $0.70^{+0.12}_{-0.28}$
theta_p_coleman2019 = $0.02^{+0.27}_{-0.01}$
theta_MO_pib = $0.63^{+0.06}_{-0.08}$
theta_MA_pib = $0.10^{+0.03}_{-0.02}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib


PRELIMINARY
step = 1837
Alm_1 = −0.02+0.03 −0.02
S_dif = 11.42+0.17 −0.20
S_gce = 1.68+0.11 −0.12
S_ics = 6.57+0.22 −0.20
f_bulge_poiss = 0.33+0.07 −0.06
gamma_poiss = 1.09+0.08 −0.08
theta_p_macias2019 = 0.81+0.09 −0.22
theta_p_coleman2019 = 0.02+0.20 −0.01
theta_MO_pib = 0.76+0.04 −0.06
theta_MA_pib = 0.06+0.02 −0.02
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib


PRELIMINARY
step = 2000
Alm_1 = $-0.01^{+0.03}_{-0.03}$
S_dif = $11.42^{+0.15}_{-0.18}$
S_gce = $1.74^{+0.11}_{-0.12}$
S_ics = $6.54^{+0.20}_{-0.18}$
f_bulge_poiss = $0.33^{+0.06}_{-0.05}$
gamma_poiss = $1.03^{+0.07}_{-0.07}$
theta_p_macias2019 = $0.82^{+0.10}_{-0.30}$
theta_p_coleman2019 = $0.04^{+0.30}_{-0.04}$
theta_MO_pib = $0.79^{+0.04}_{-0.05}$
theta_MA_pib = $0.06^{+0.02}_{-0.02}$
Alm_1
S_dif
S_gce
S_ics
f_bulge_poiss
gamma_poiss
theta_p_macias2019
theta_p_coleman2019
theta_MO_pib
theta_MA_pib

Summary

In order to better fit the GCE and understand the its systematics…

We built a probabilistic programming model with flexible template for point source and diffuse emission, and were able to quickly obtain posterior distribution using SVI.

Summary

In order to better fit the GCE and understand the its systematics…

Step 1. We built a probabilistic programming model with flexible template for point source and diffuse emission, and were able to quickly obtain posterior distribution using SVI.

Step 2. Profit?