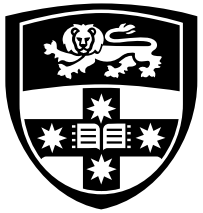
Wising up to CatWISE

Using simulation-based inference to measure the cosmic dipole

Oliver Oayda
oliver.oayda@sydney.edu.au

PhD Candidate
Sydney Institute for Astronomy
The University of Sydney

Supervised by
Geraint Lewis
Tara Murphy



THE UNIVERSITY OF SYDNEY

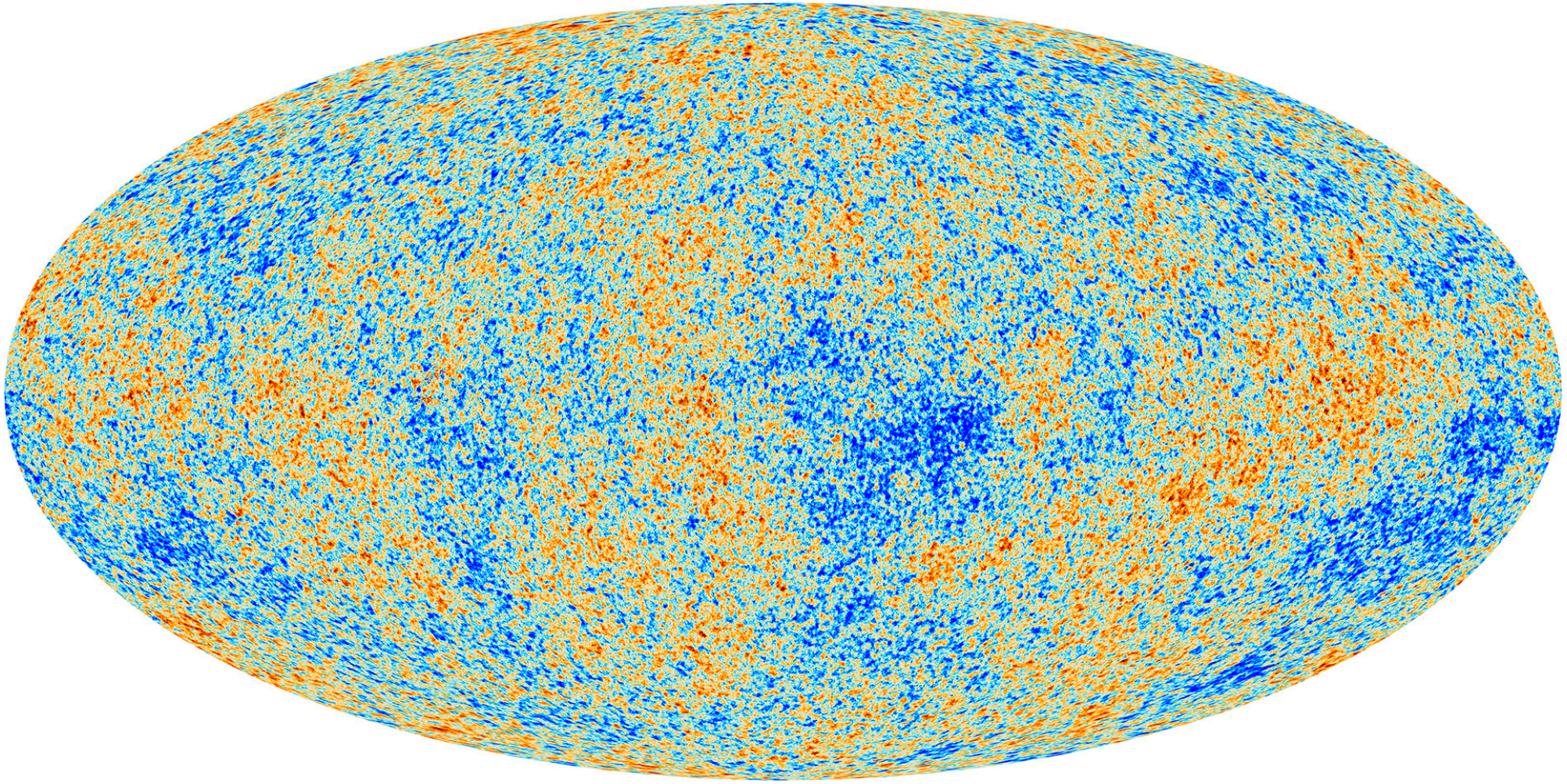
CosmoVerse@Bilbao

September 15, 2026



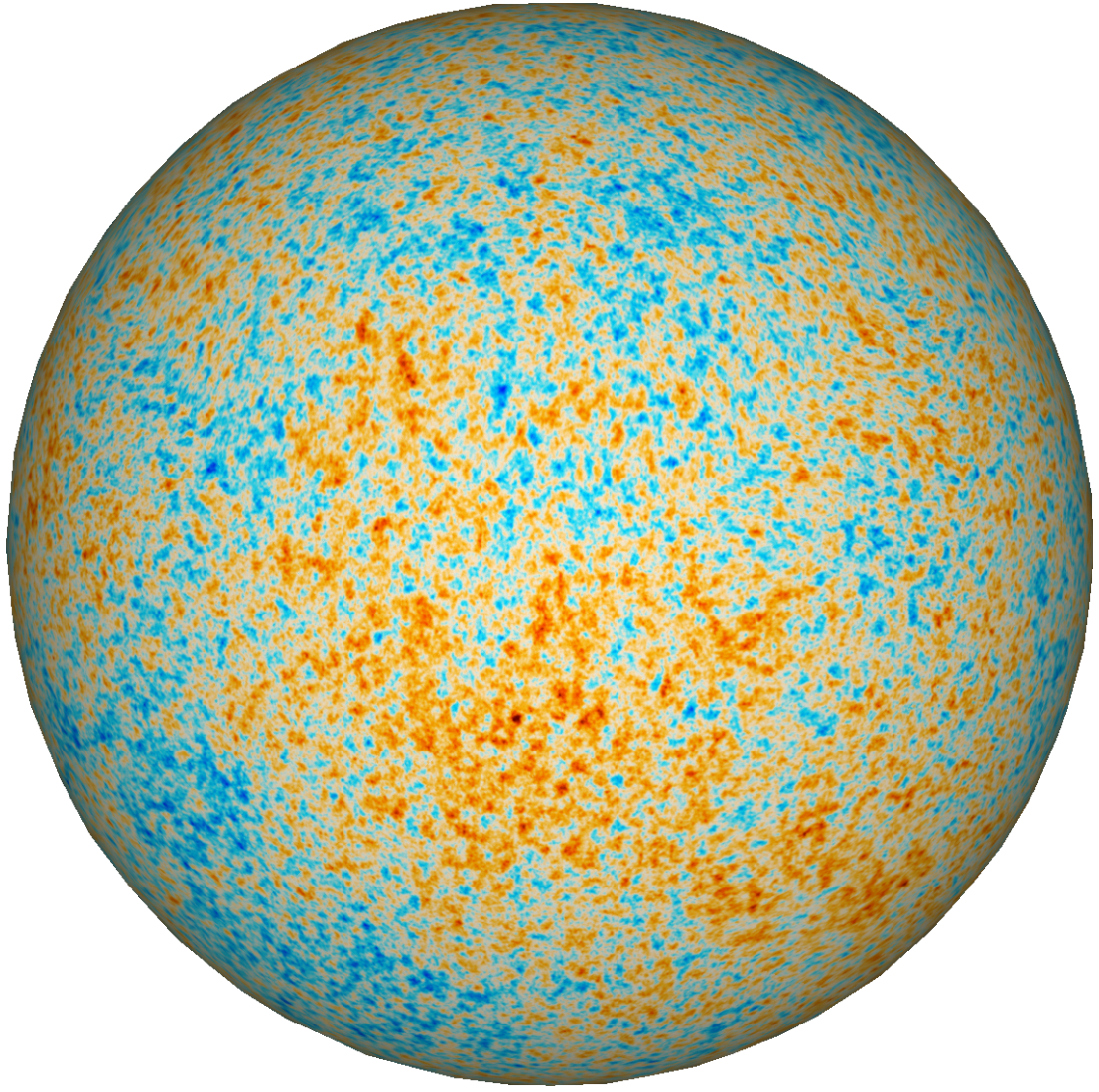
Simulation-based inference resolves systematics.

The Kinematic Dipole



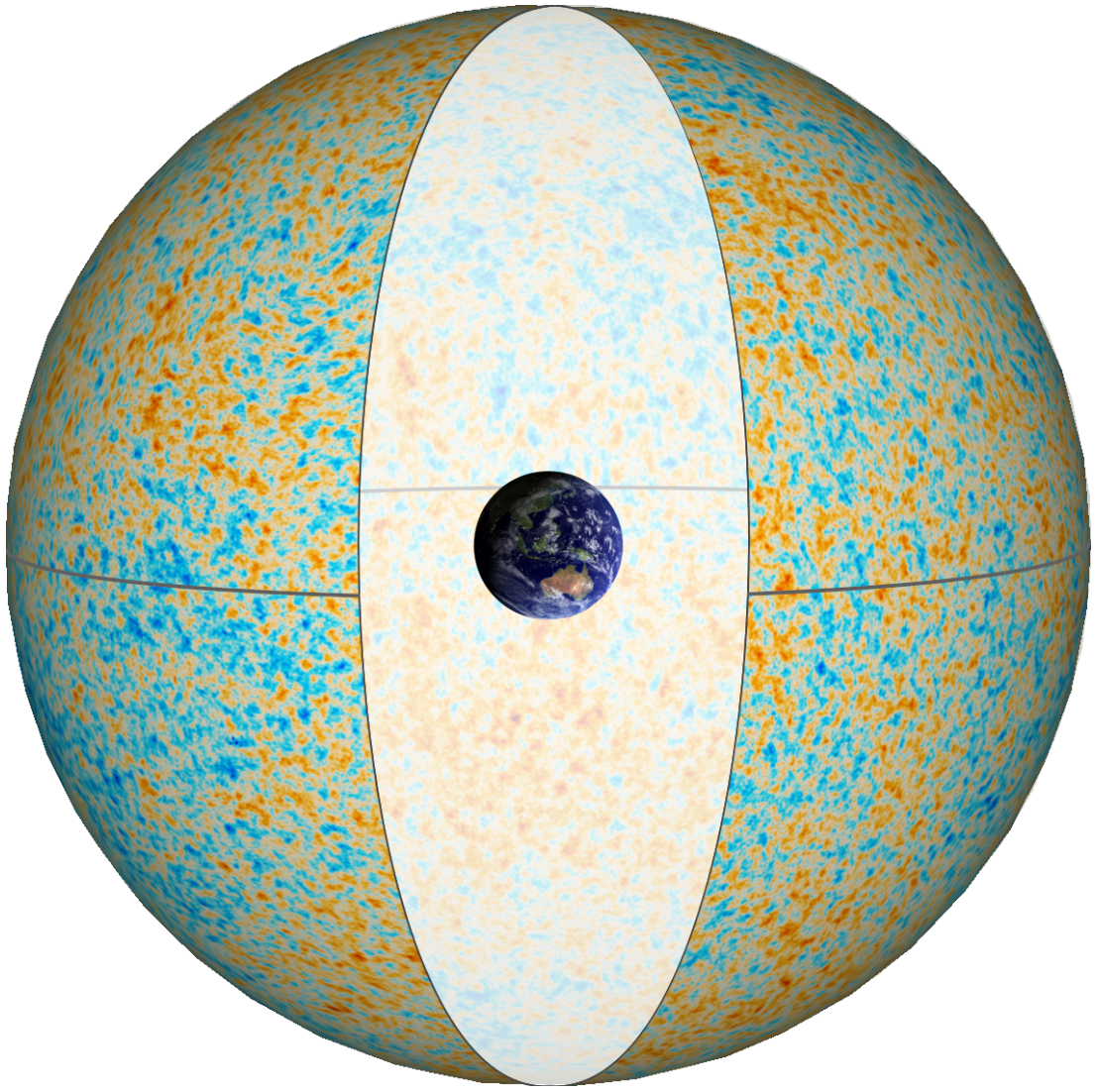
CMB temperature map (Planck satellite)

The Kinematic Dipole



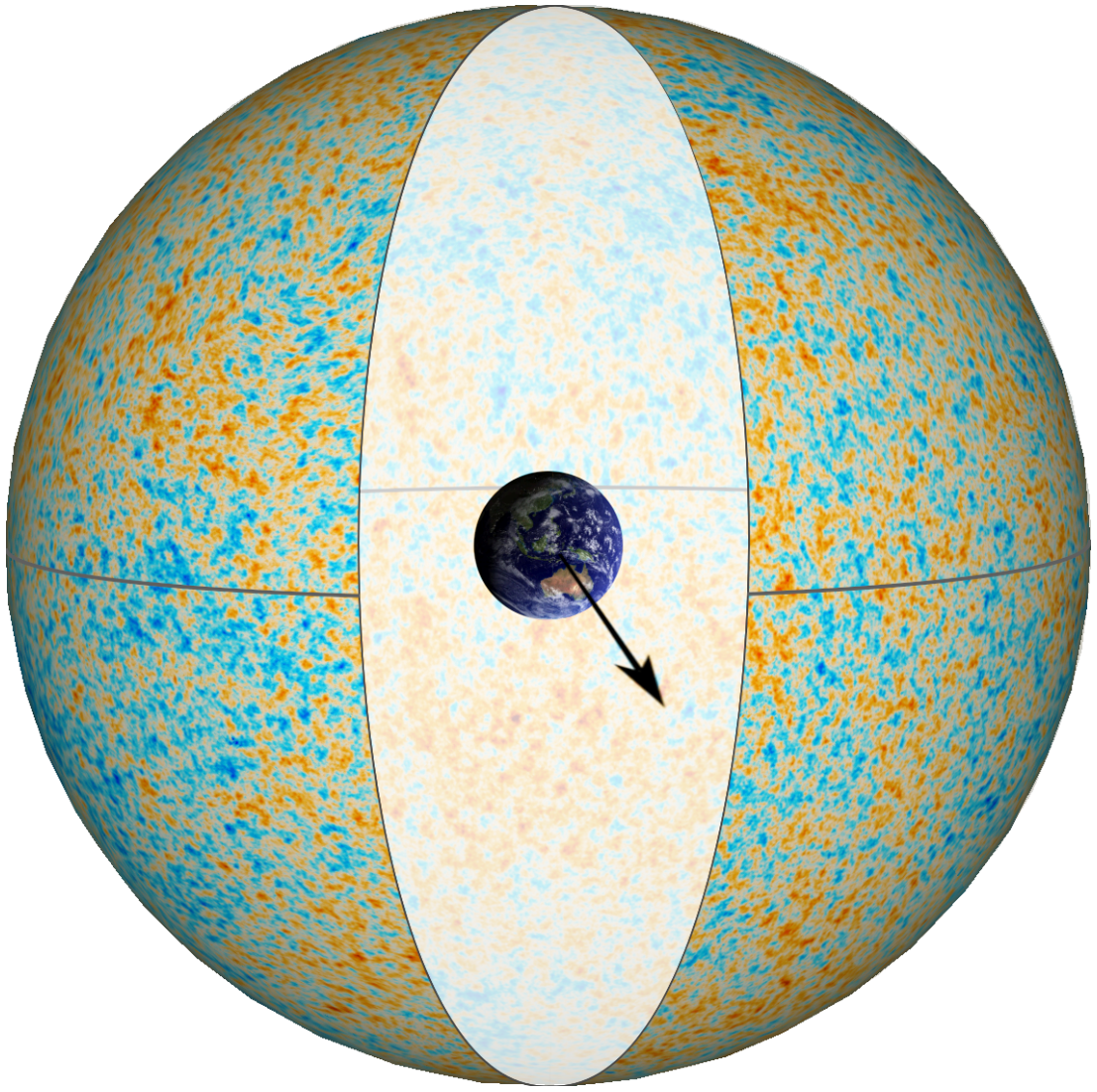
CMB as a sphere

The Kinematic Dipole



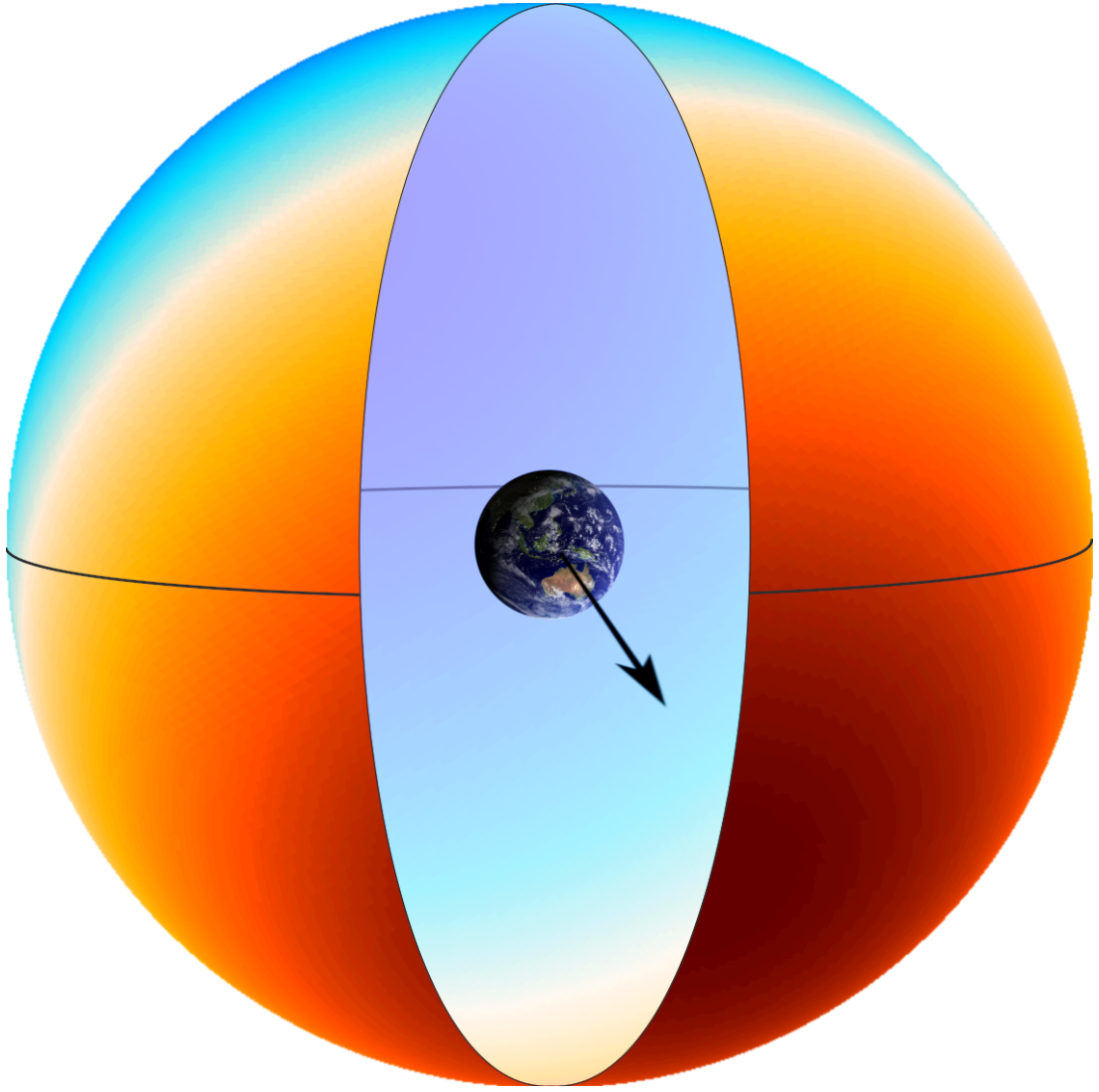
CMB as a sphere (Earth inside)

The Kinematic Dipole



We’re moving through the Universe!

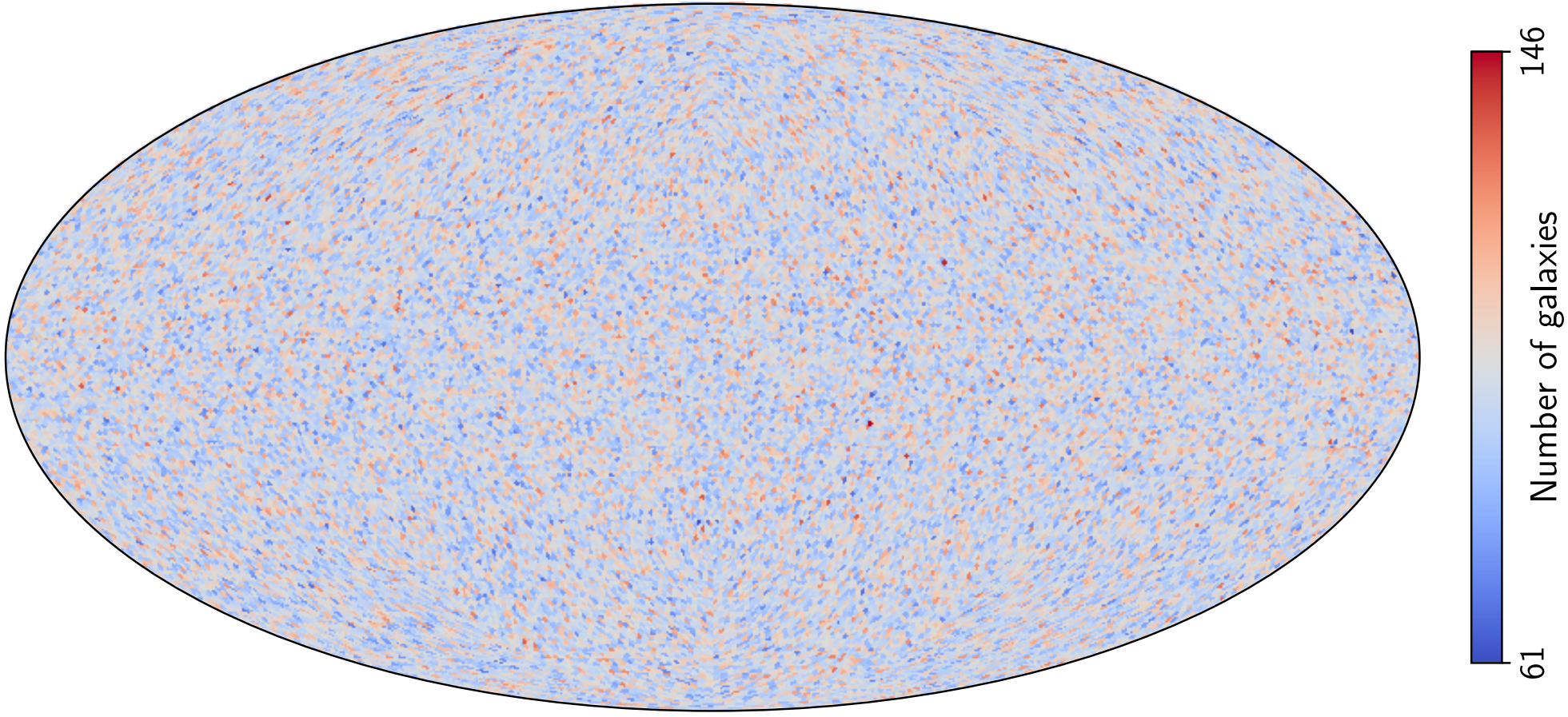
The Kinematic Dipole



Kinematic dipole as a sphere (Earth inside)

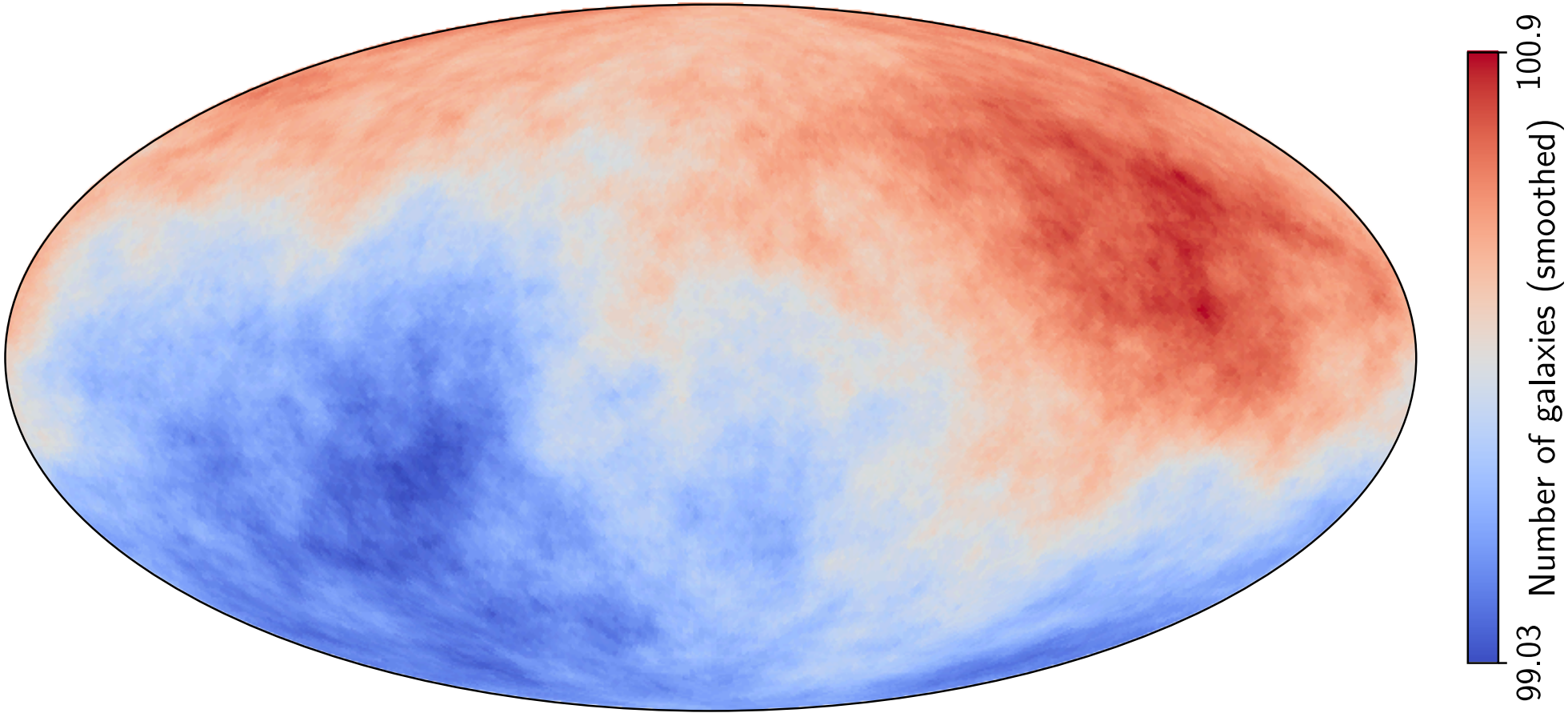
Counting Galaxies

$$N_i = \overline{N}(1 + \mathcal{D}\cos\theta_i)$$



Counting Galaxies

$$N_i = \overline{N}(1 + \mathcal{D}\cos\theta_i)$$



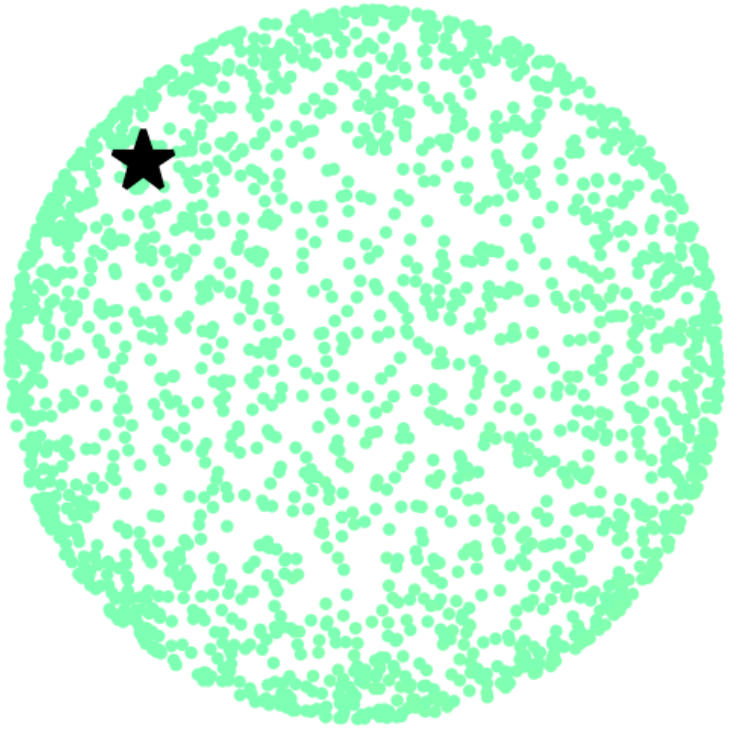
Special Relativity

Aberration

Doppler boosting

Special Relativity

Aberration

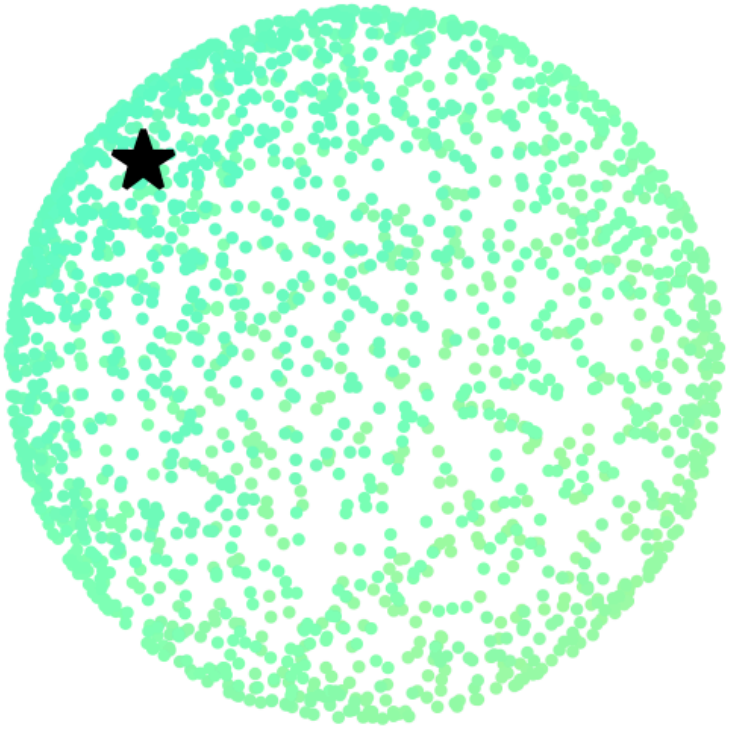


Speed (c) 0.025

Doppler boosting

Special Relativity

Aberration

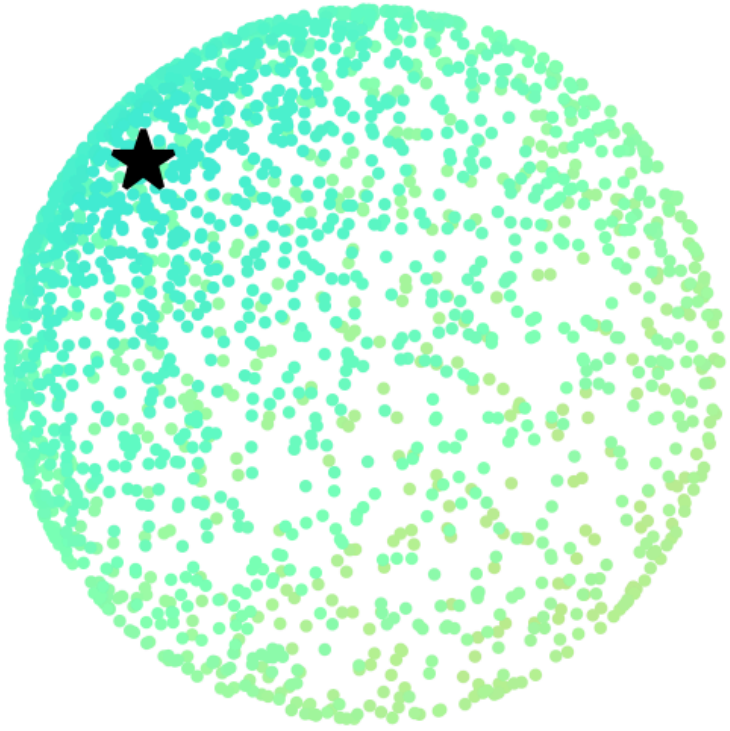


Speed (c) 0.244

Doppler boosting

Special Relativity

Aberration

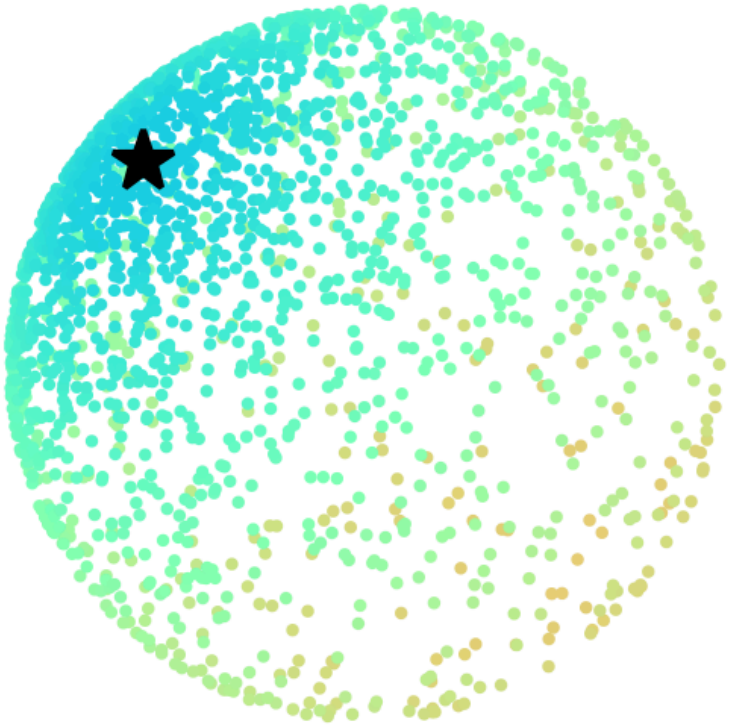


Speed (c) 0.462

Doppler boosting

Special Relativity

Aberration

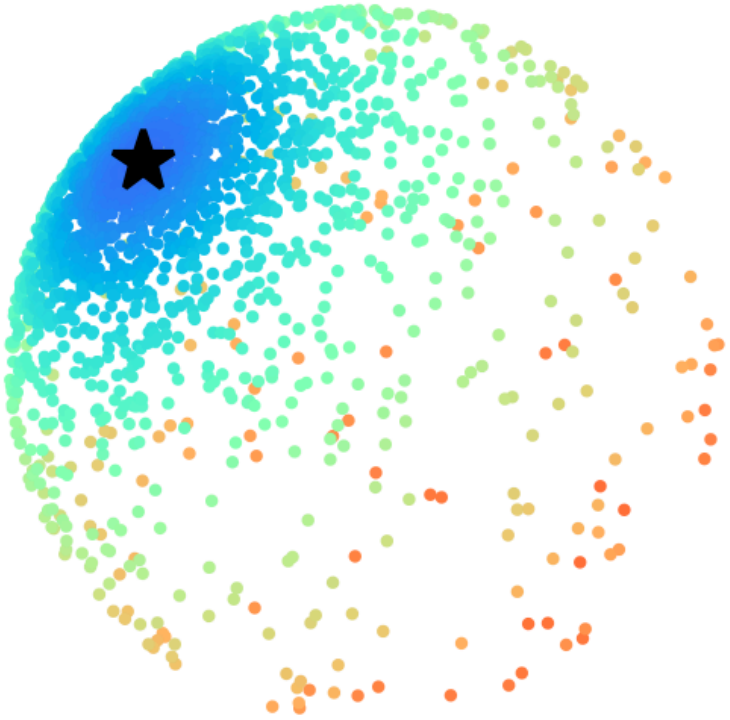


Speed (c) 0.681

Doppler boosting

Special Relativity

Aberration

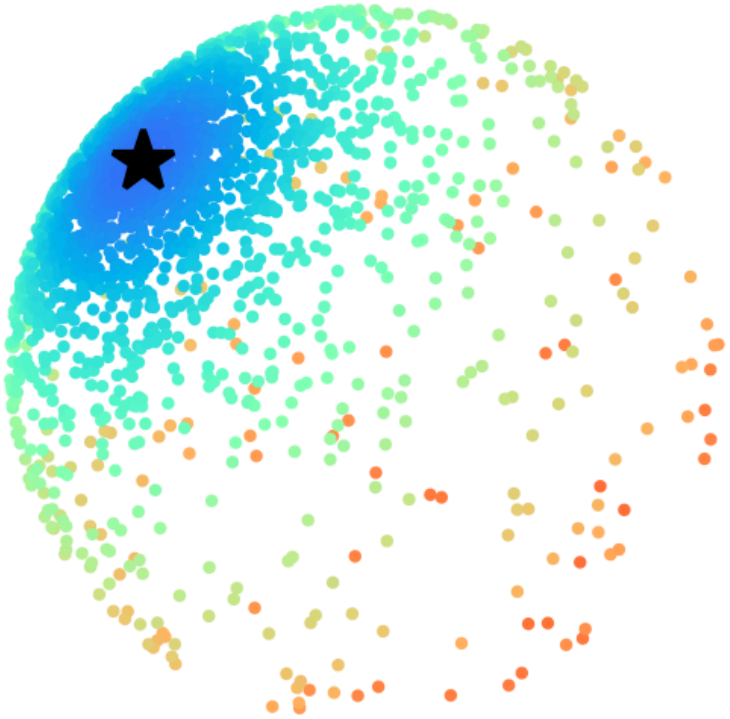


Speed (c) 0.9

Doppler boosting

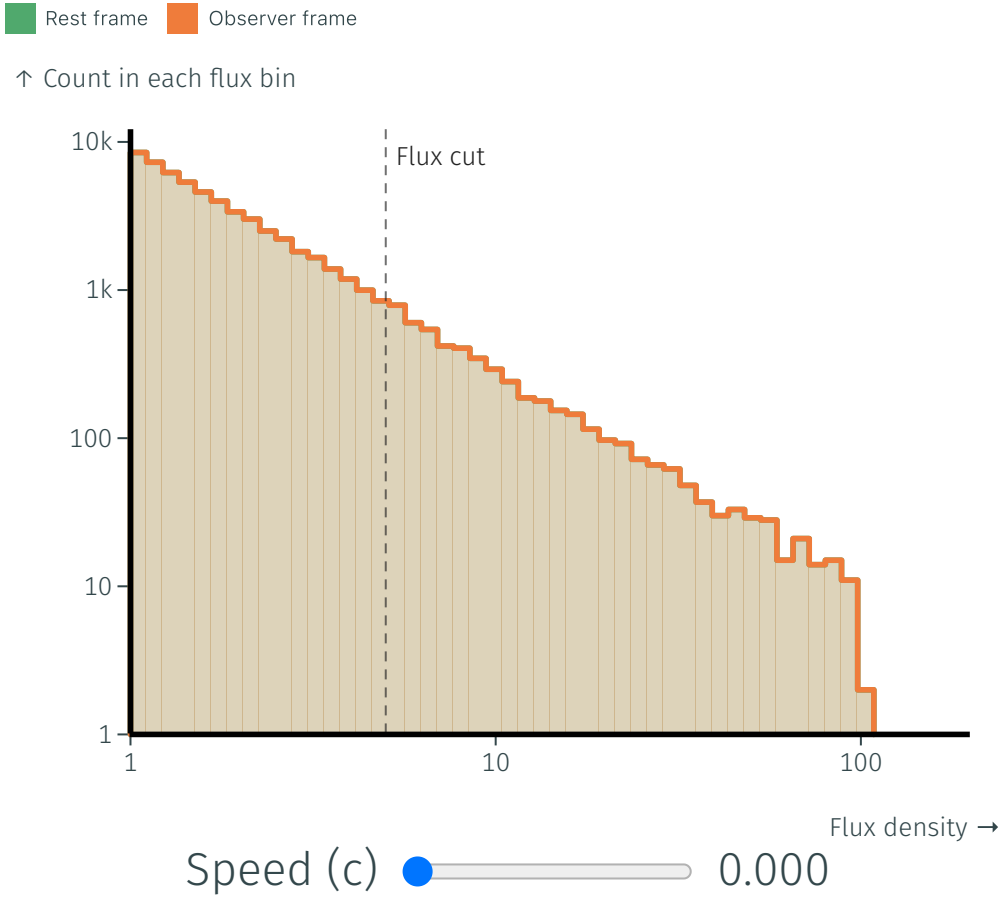
Special Relativity

Aberration



Speed (c) 0.9

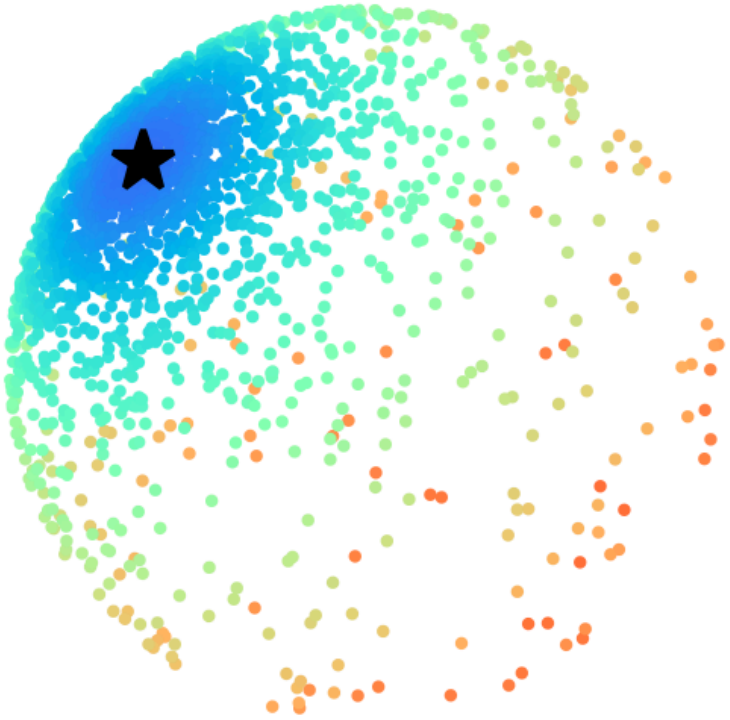
Doppler boosting



Speed (c) 0.000

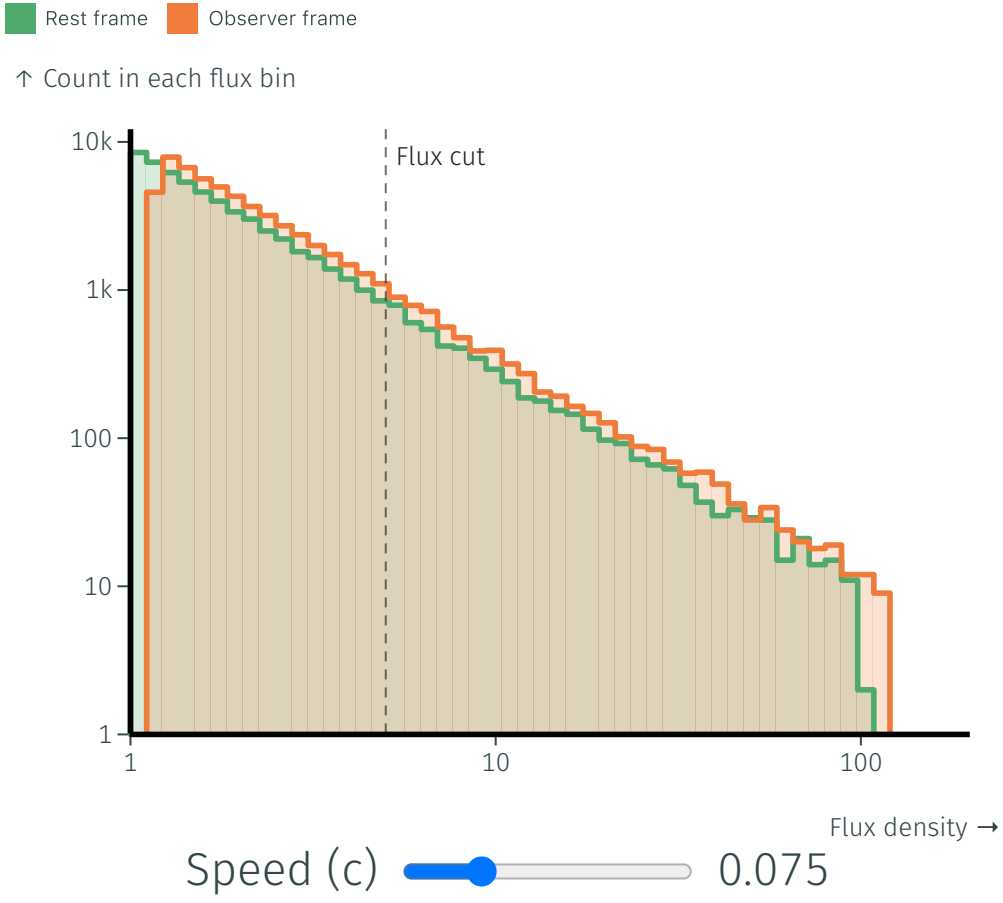
Special Relativity

Aberration



Speed (c) 0.9

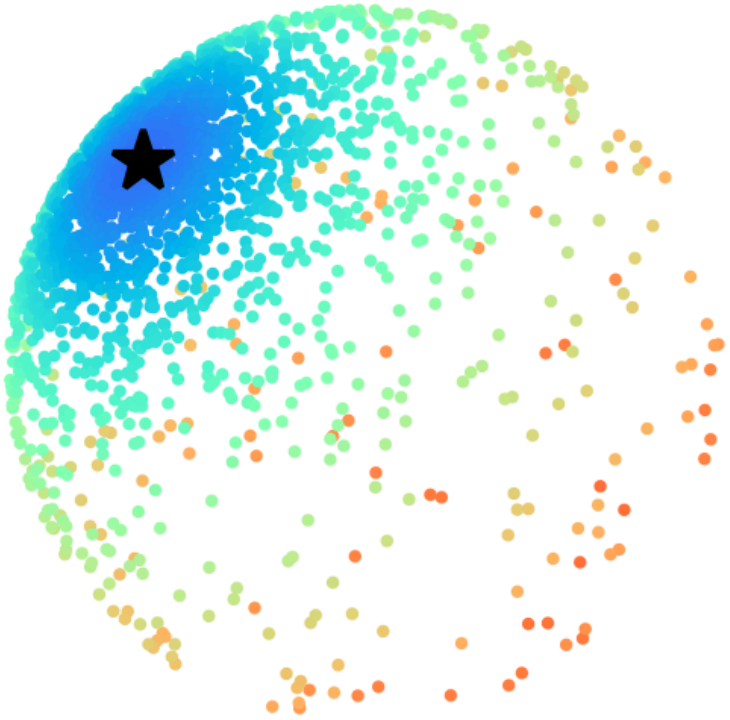
Doppler boosting



Speed (c) 0.075

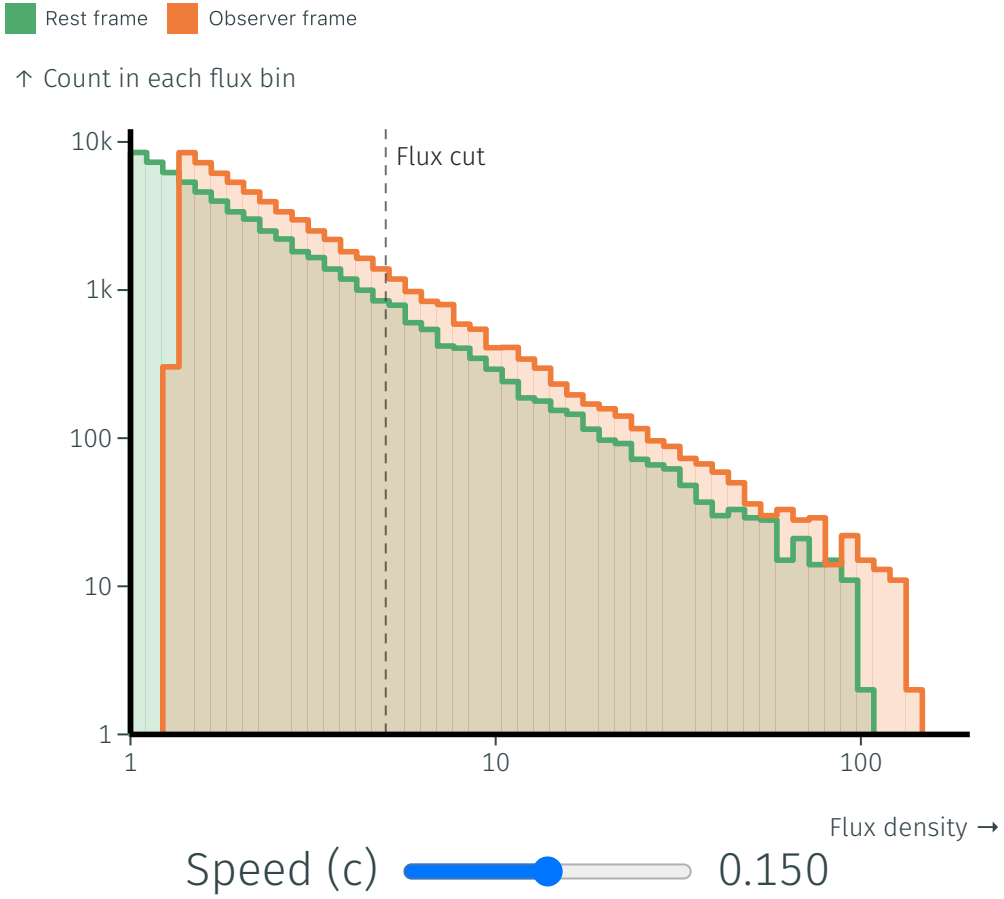
Special Relativity

Aberration



Speed (c) 0.9

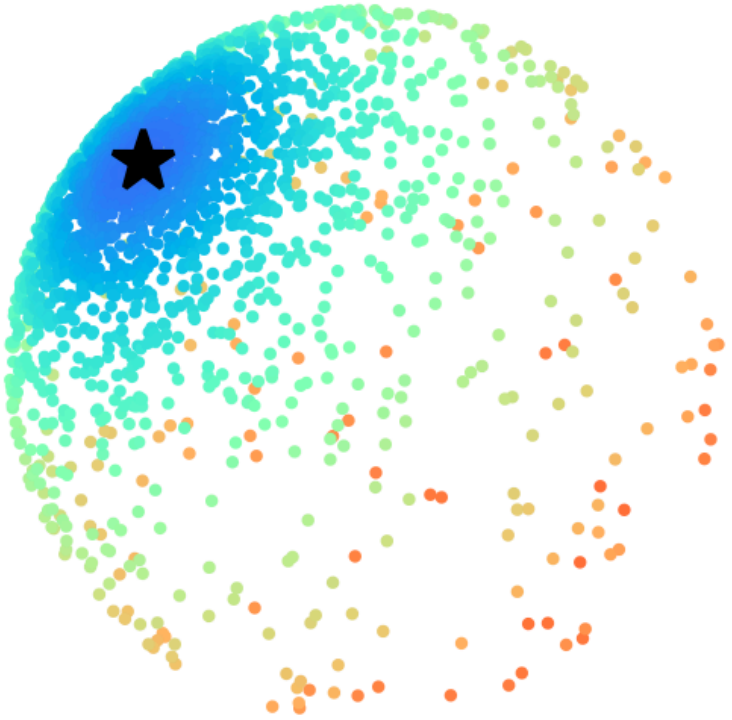
Doppler boosting



Speed (c) 0.150

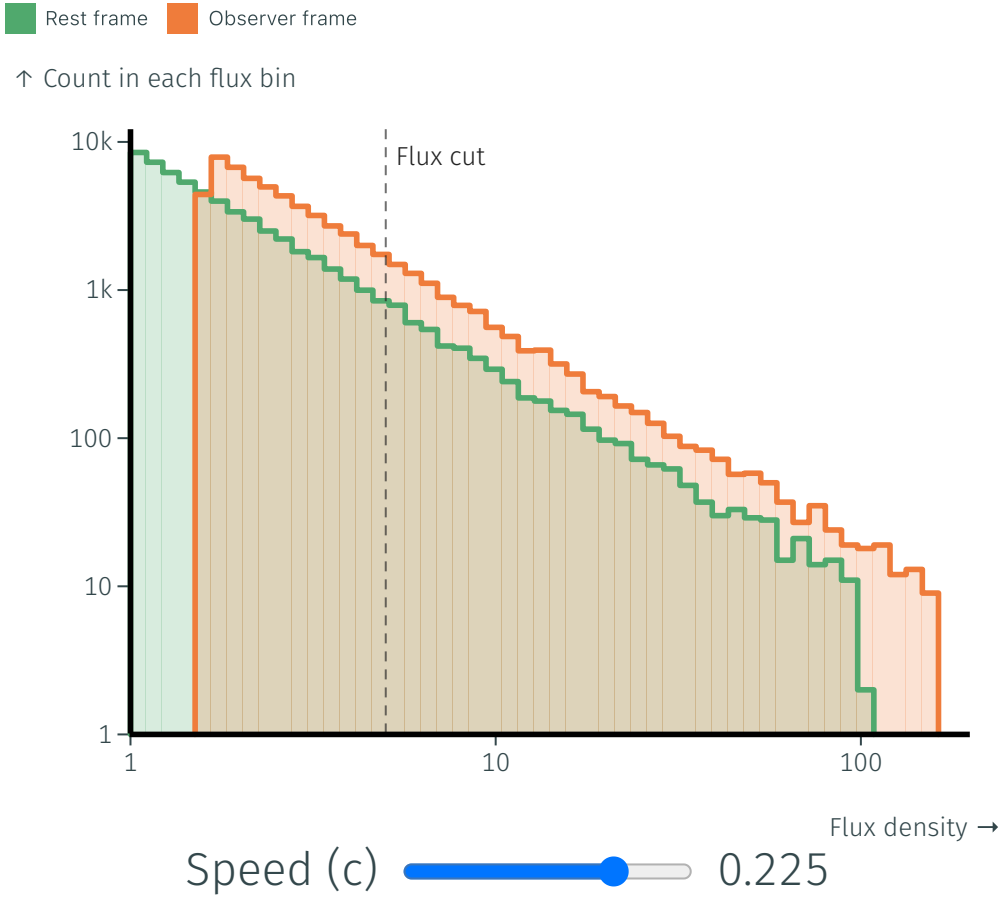
Special Relativity

Aberration



Speed (c) 0.9

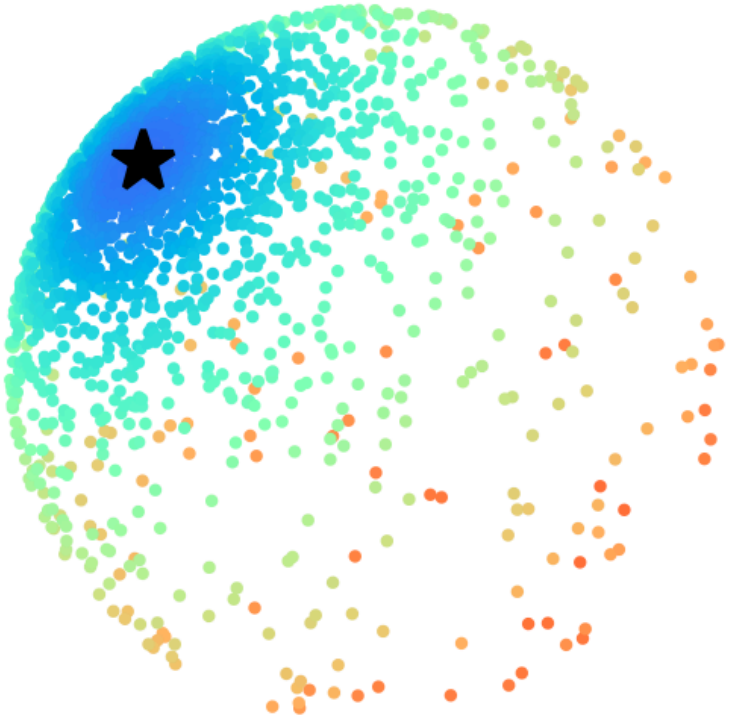
Doppler boosting



Speed (c) 0.225

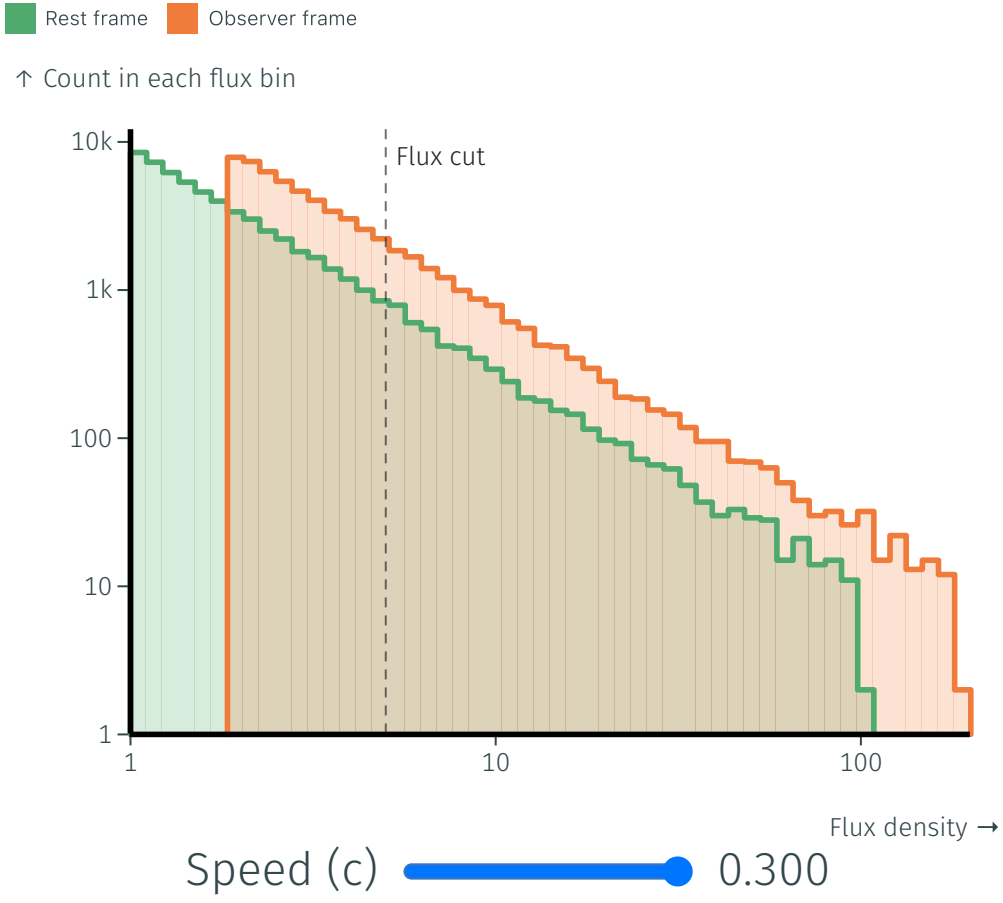
Special Relativity

Aberration



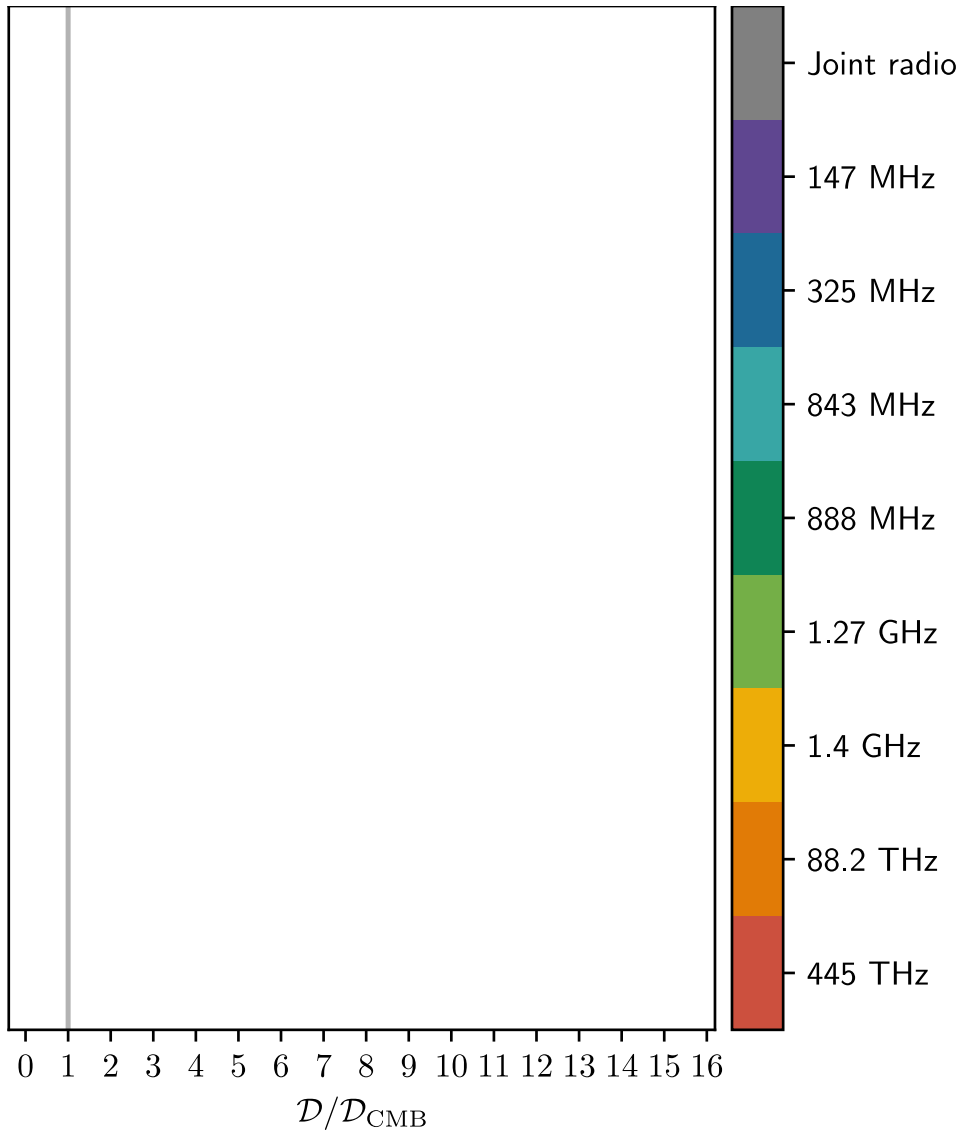
Speed (c) 0.9

Doppler boosting



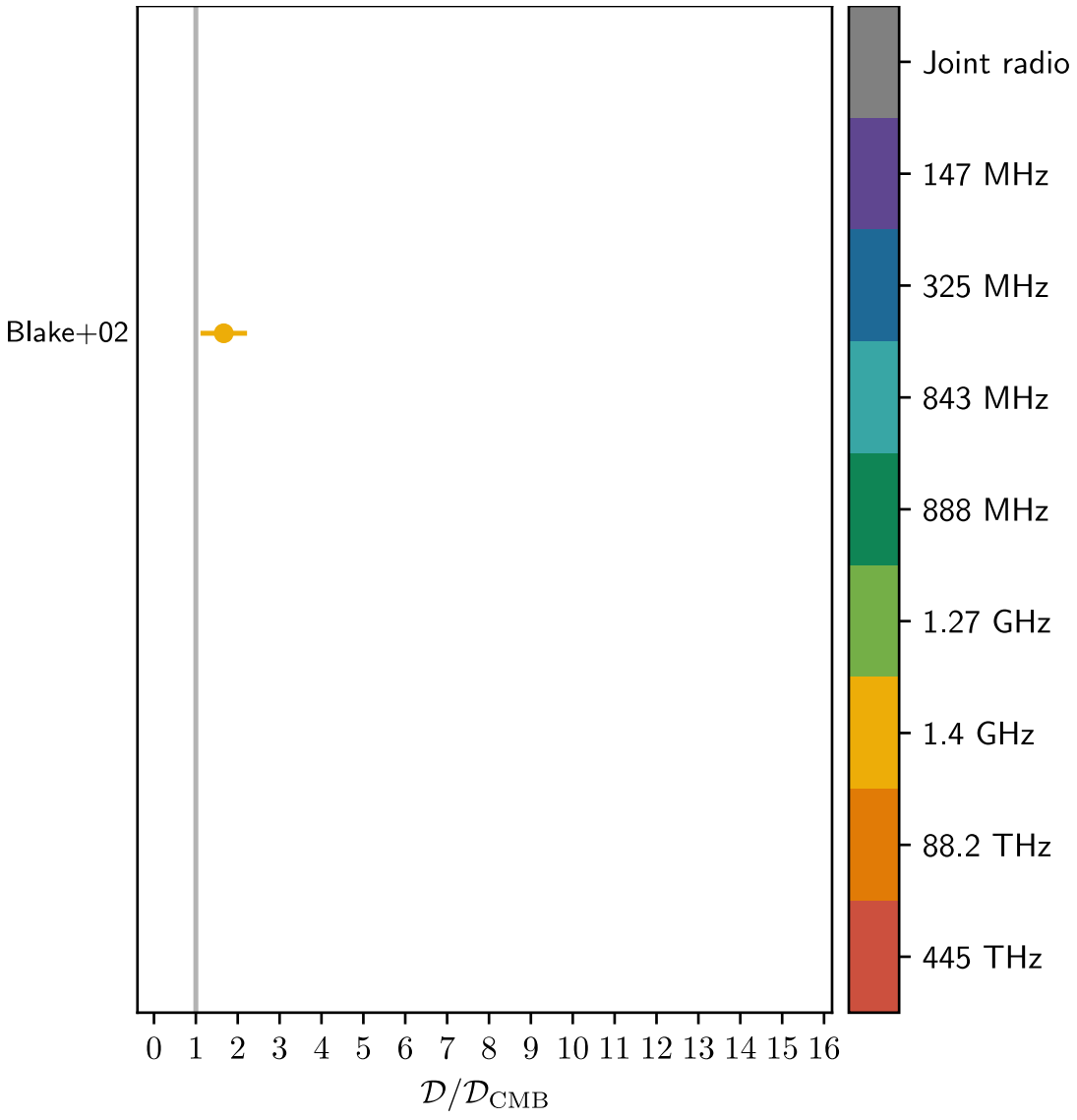
Speed (c) 0.300

The Amplitude Excess



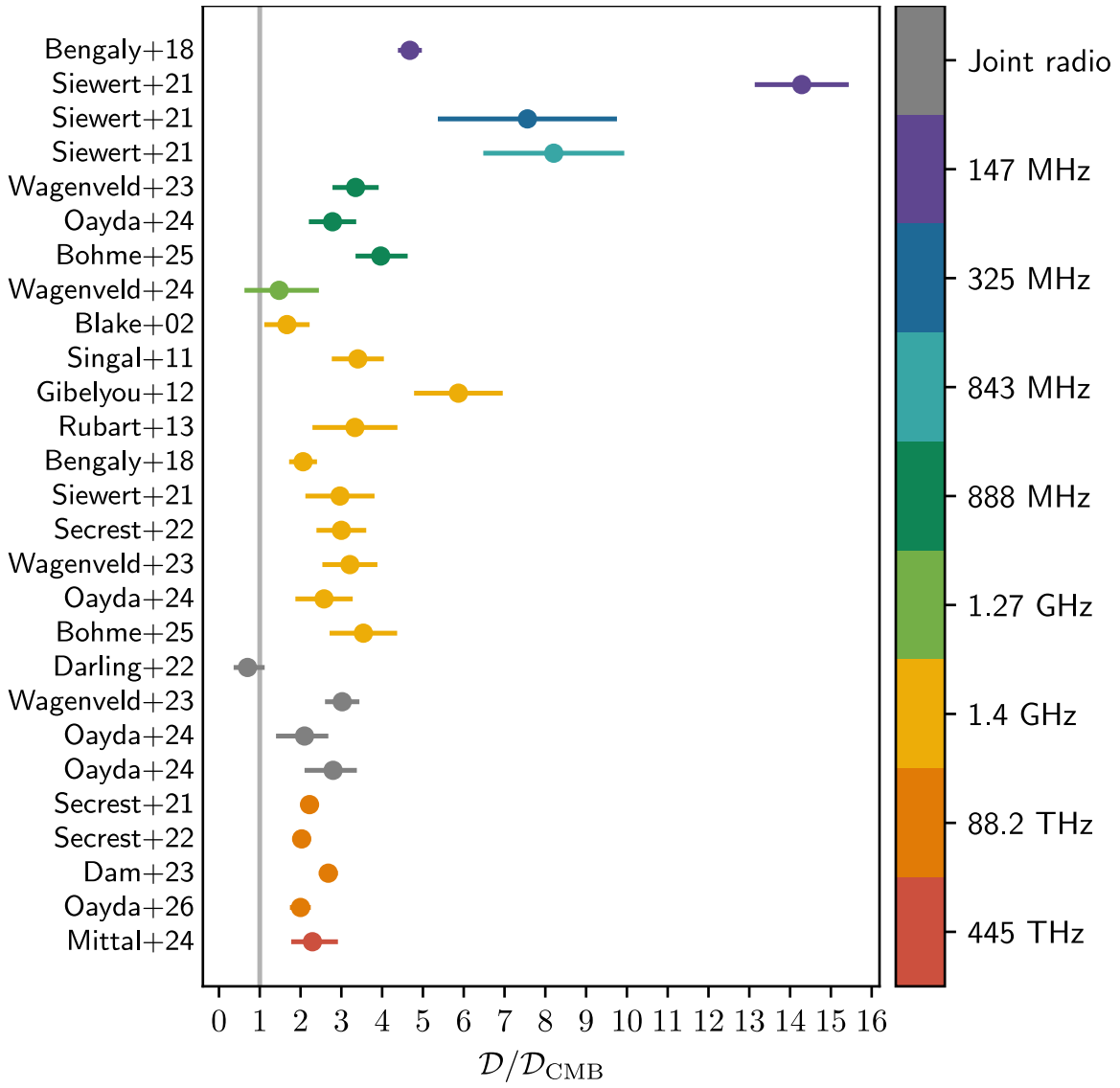
The cosmic dipole should be consistent with the CMB dipole.

The Amplitude Excess



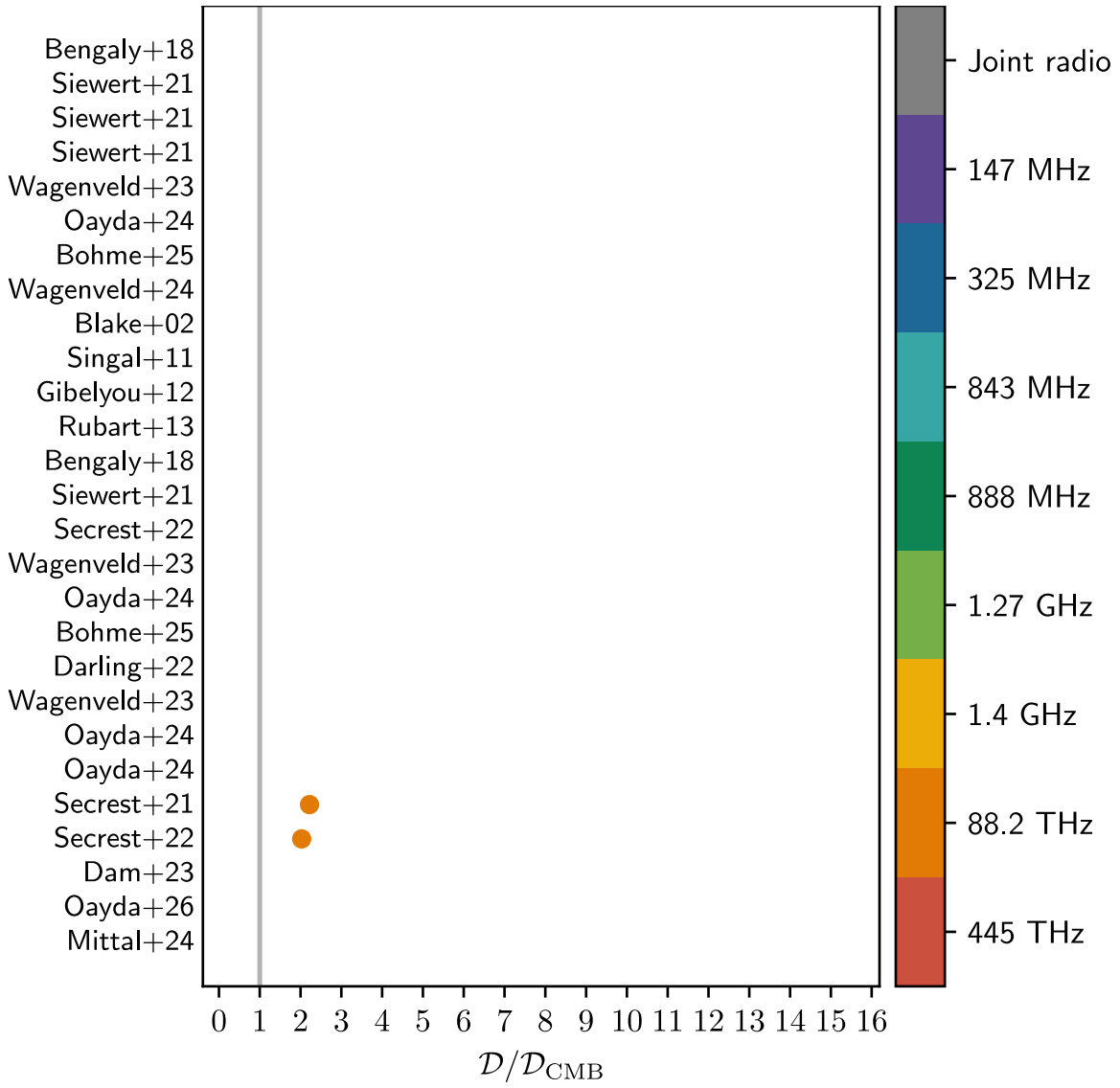
All is well!

The Amplitude Excess



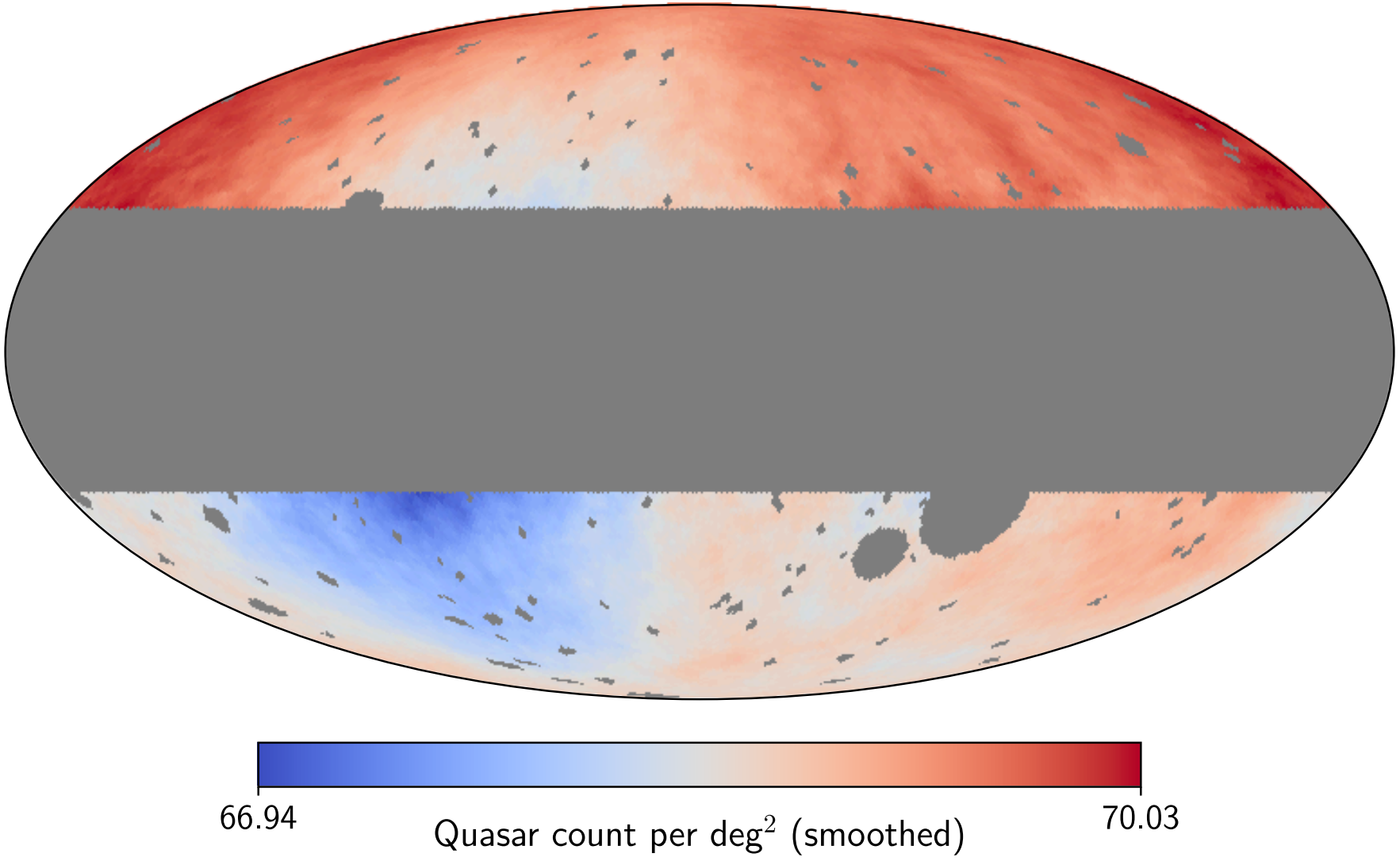
Wait...

The Amplitude Excess



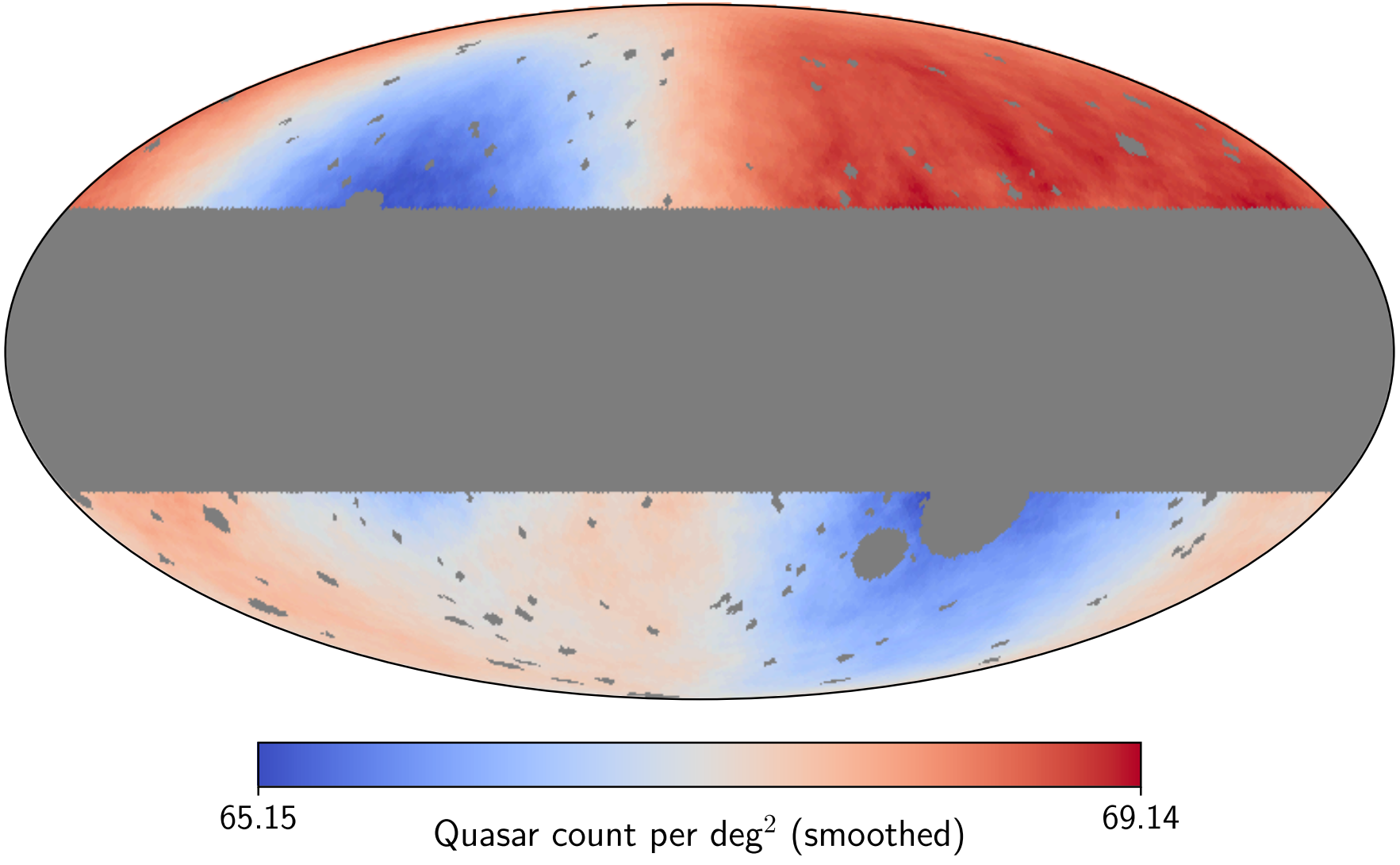
Focus: Secrest+21/22, CatWISE2020

The CatWISE Sample



CatWISE quasar map from Secrest+21

The CatWISE Sample



CatWISE quasar map, no linear weighting

Correcting for the Bias

The Astrophysical Journal Letters, 908:L51 (6pp), 2021 February 20 https://doi.org/10.3847/2041-8213/abdd40
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A Test of the Cosmological Principle with Quasars

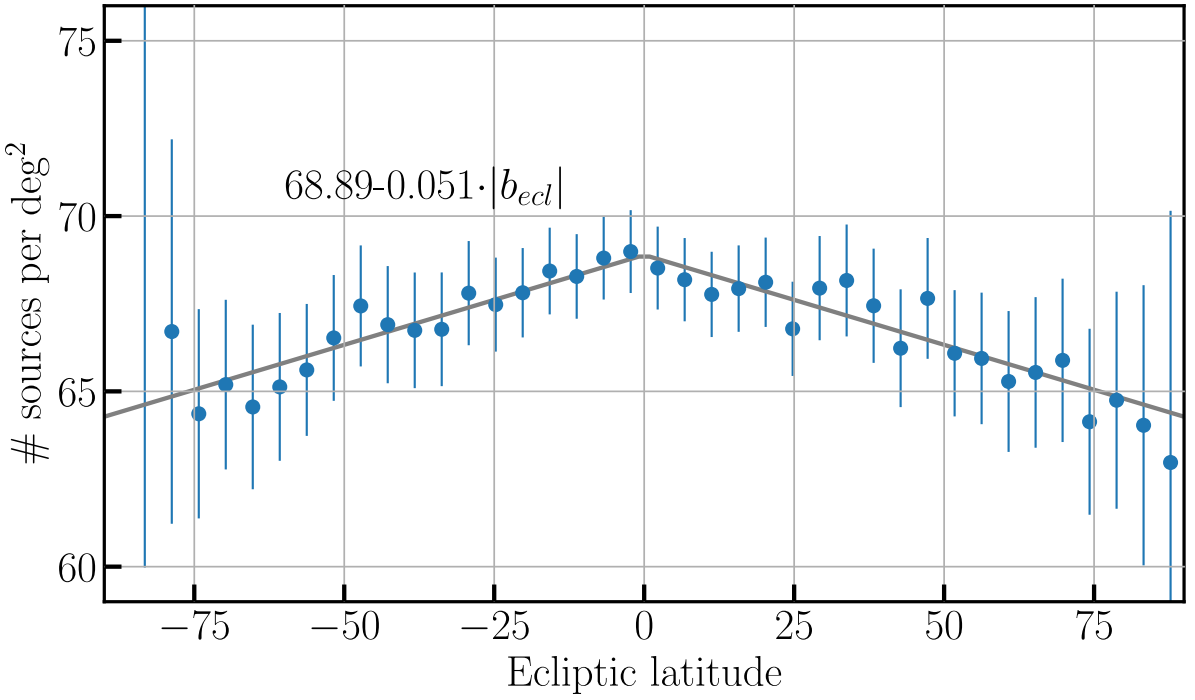
Nathan J. Secrest[1], Sebastian von Hausegger[2,3,4], Mohamed Rameez[5], Roya Mohayaee[3], Subir Sarkar[4], and Jacques Colin[3]

Correcting for the Bias

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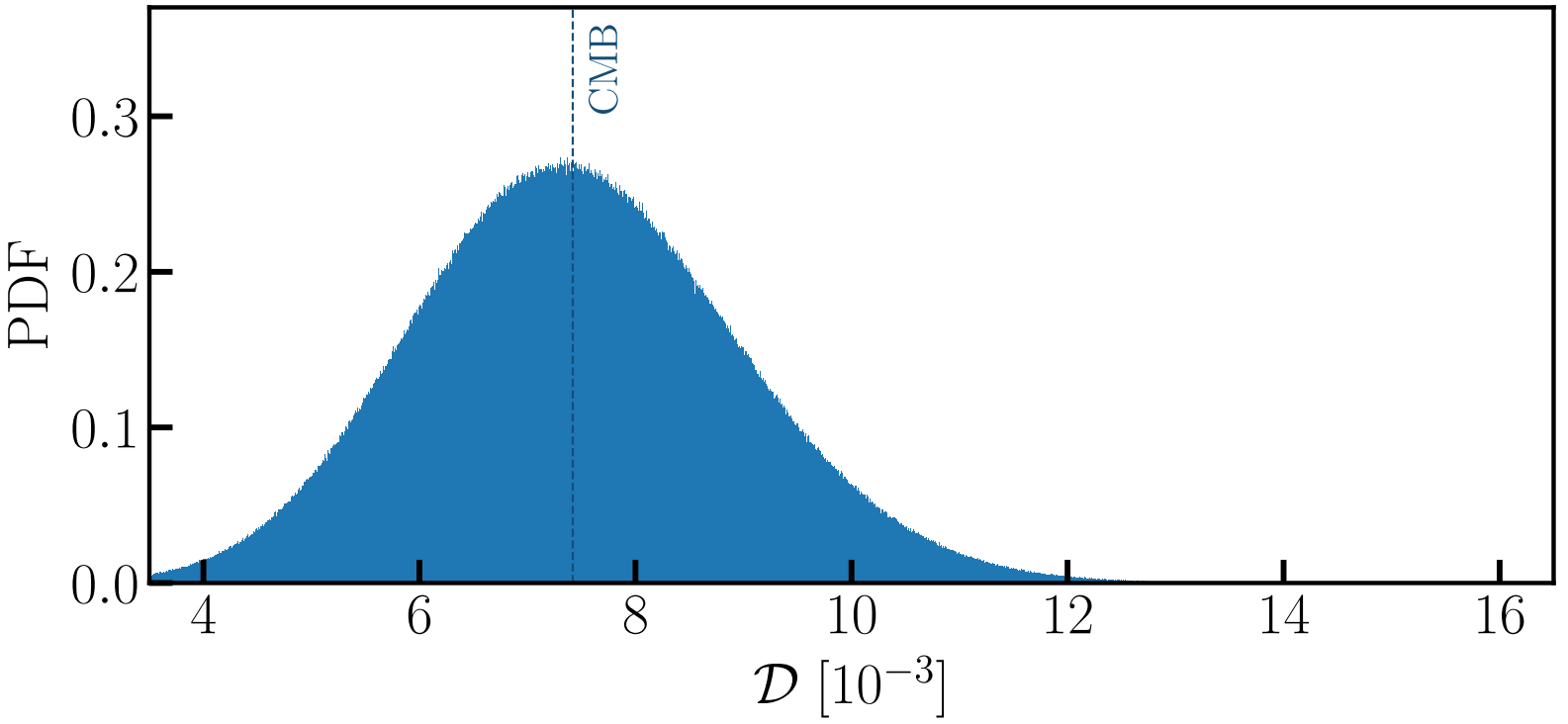
Linear fit to density vs. declination

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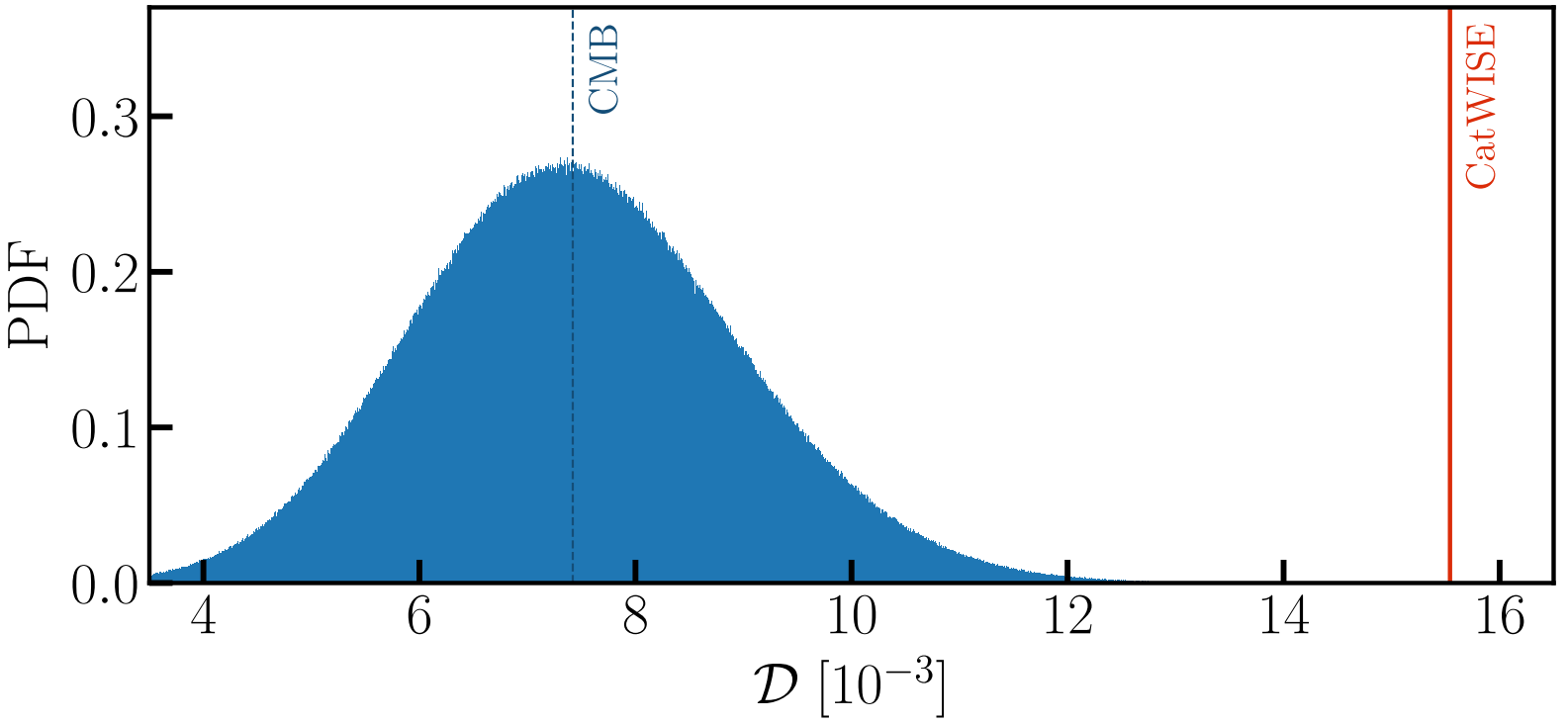
Null hypothesis test for the dipole amplitude

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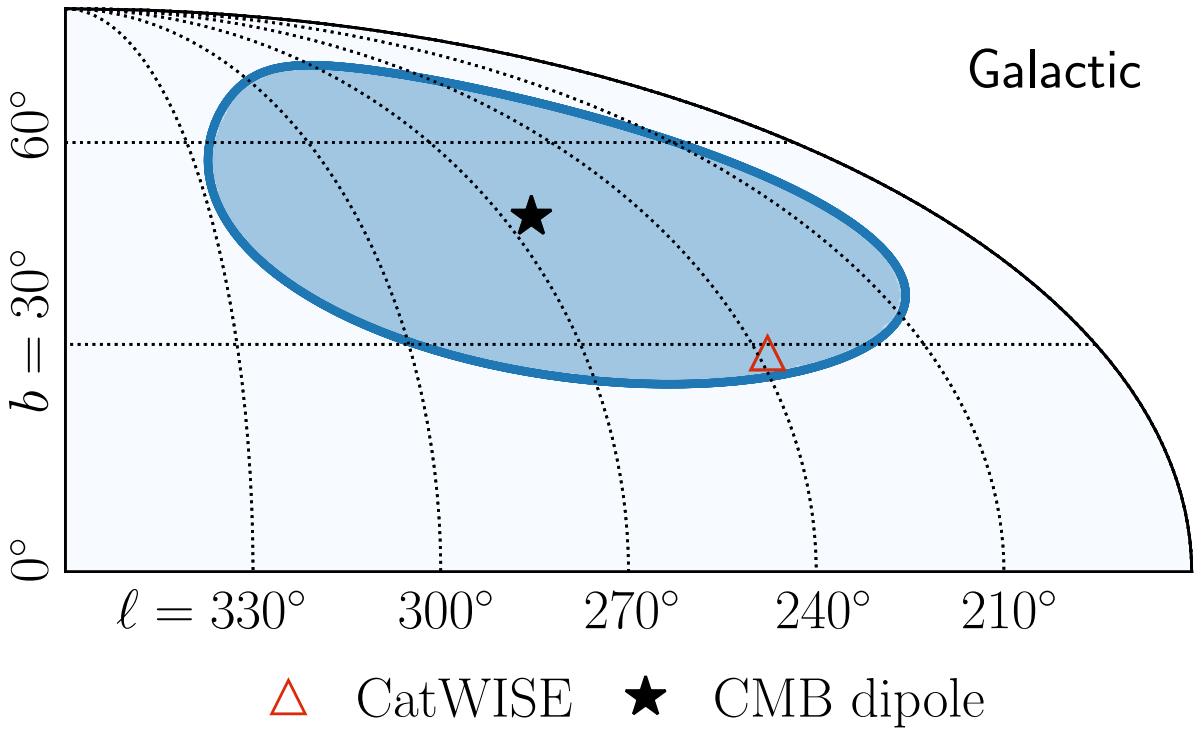
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A Test of the Cosmological Principle with Quasars

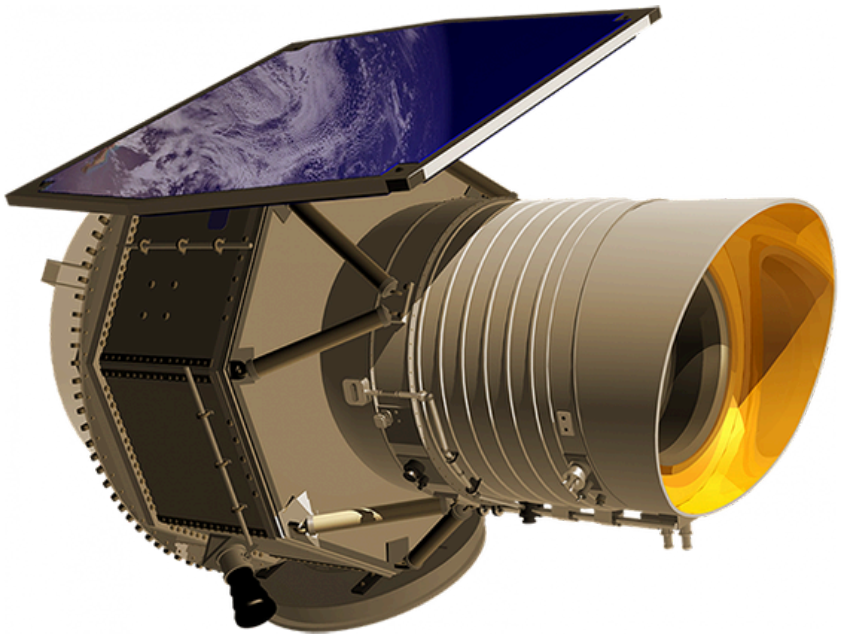
Nathan J. Secrest[1], Sebastian von Hausegger[2,3,4], Mohamed Rameez[5], Roya Mohayaee[3], Subir Sarkar[4], and Jacques Colin[3]



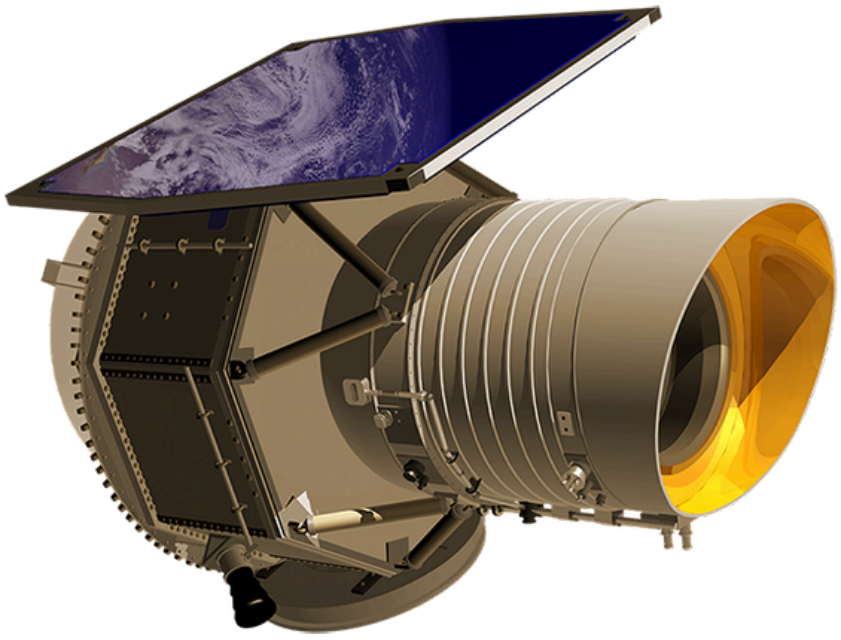
Null hypothesis test for the dipole direction

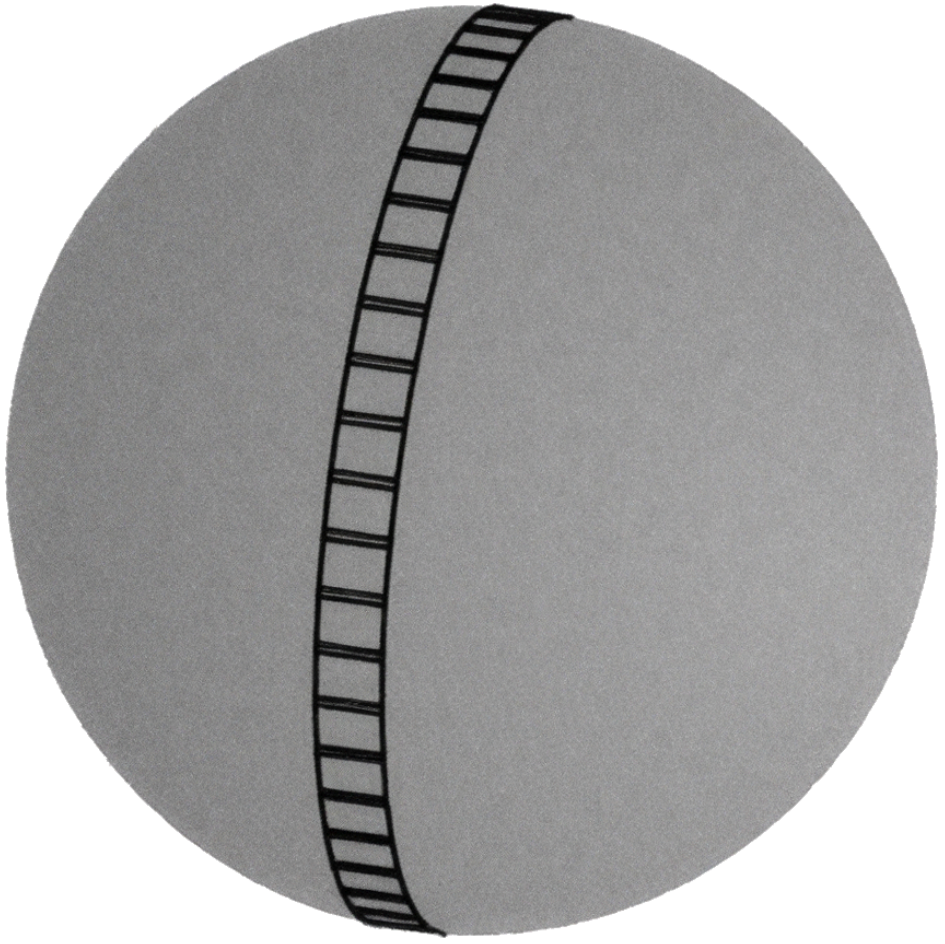
Is it good enough to make an ad hoc correction after the fact?

WISE's Scanning Law



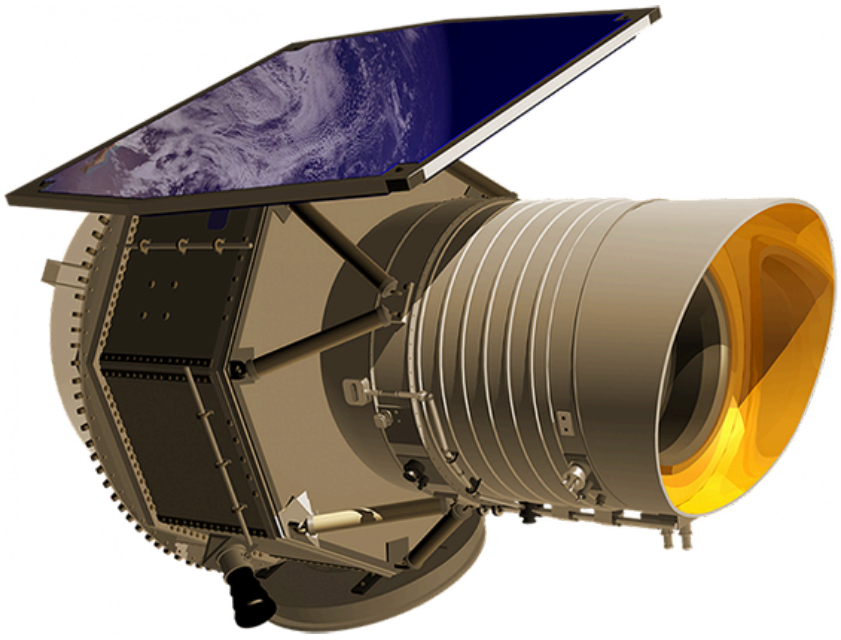
WISE's Scanning Law

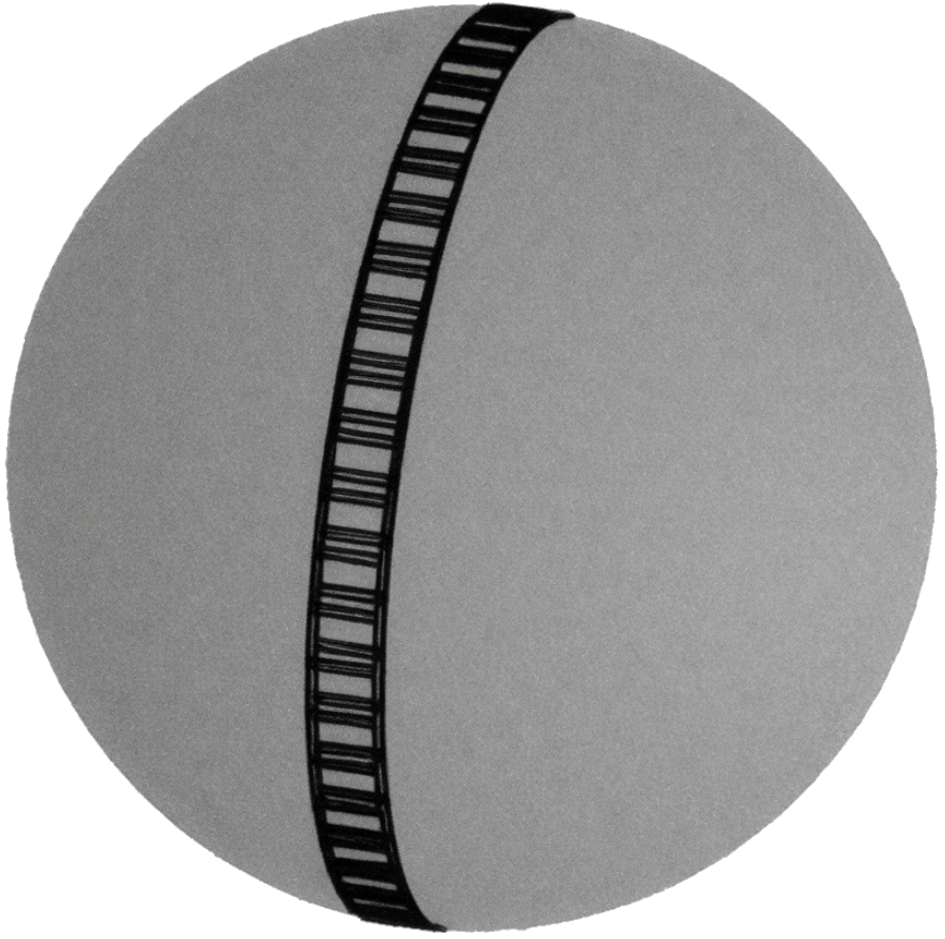




Frames over 1 orbit

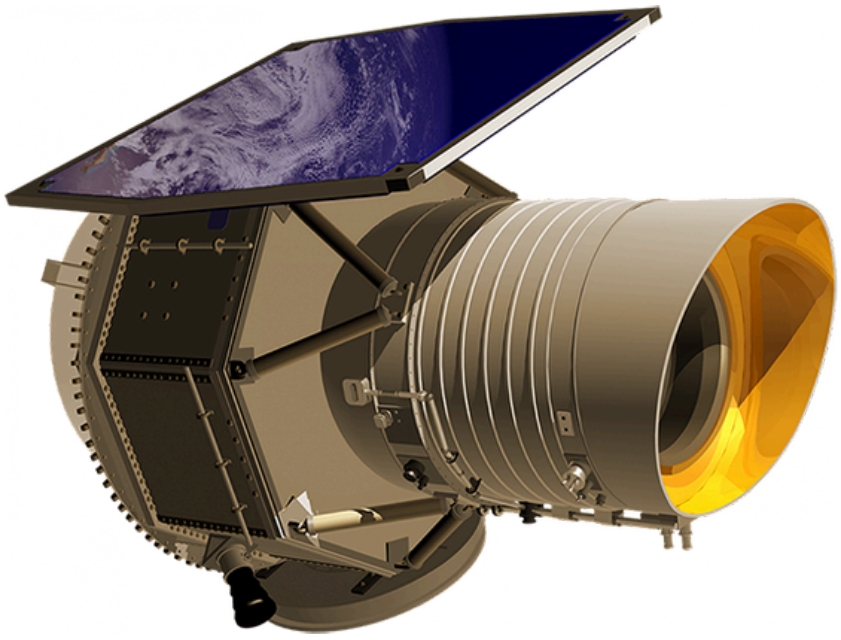
WISE's Scanning Law

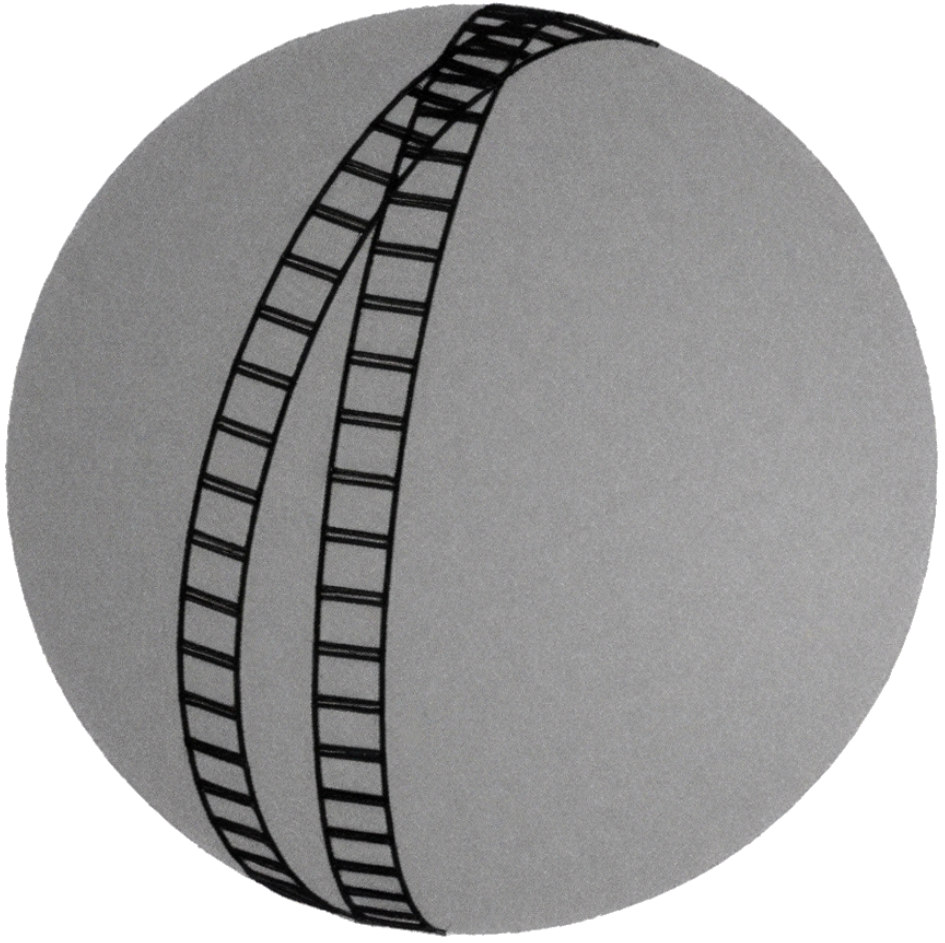




Frames over 2 orbits

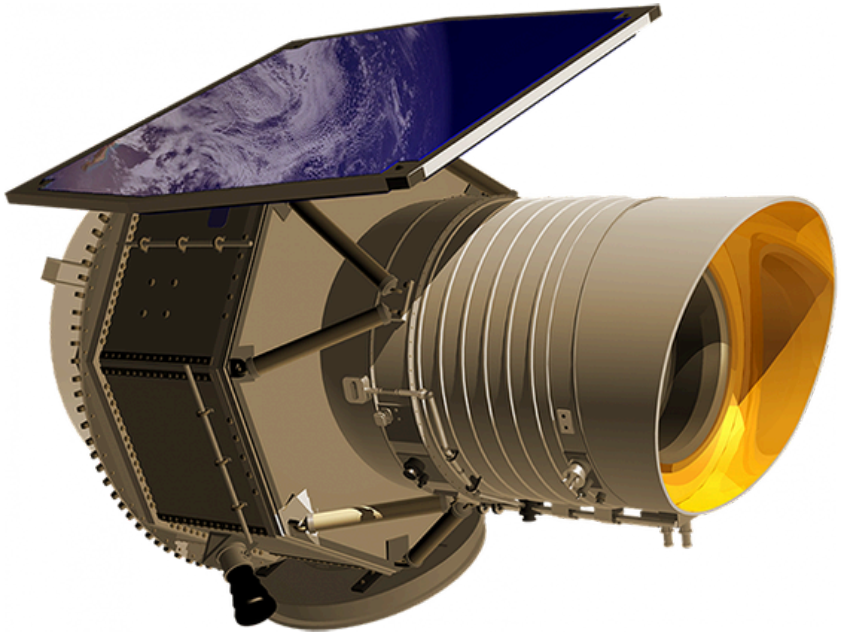
WISE's Scanning Law

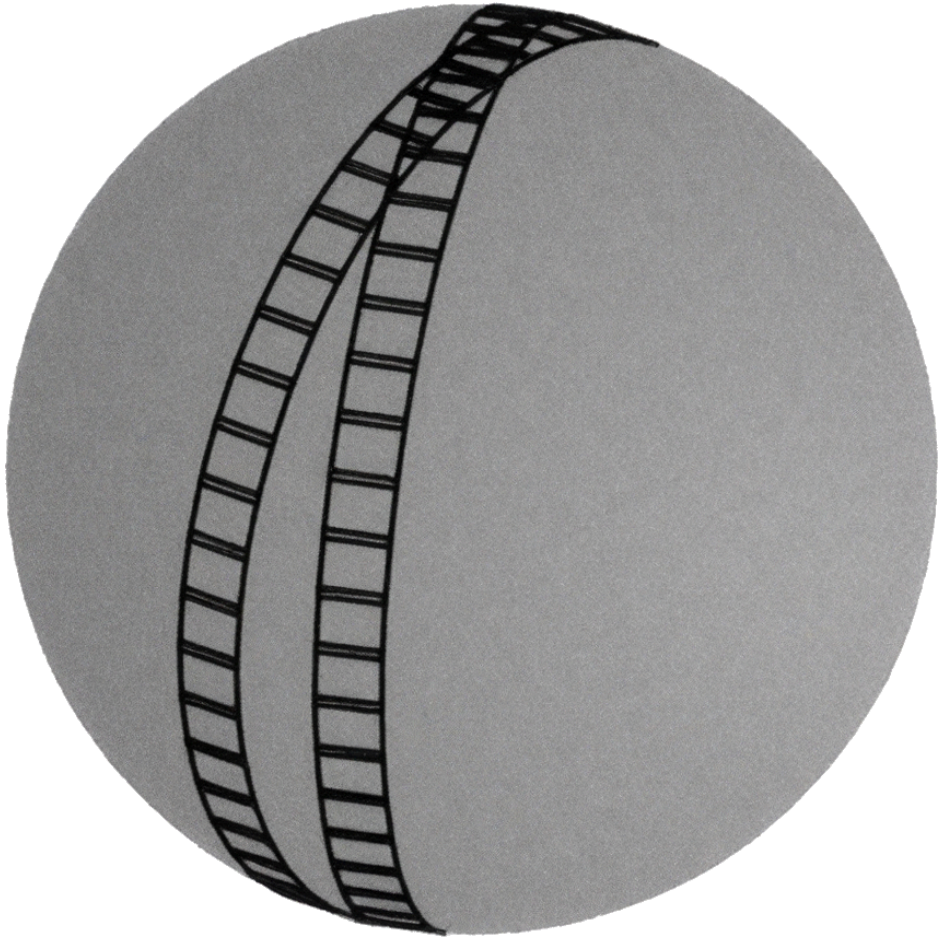




Frames over 2 orbits 20 days apart

WISE's Scanning Law

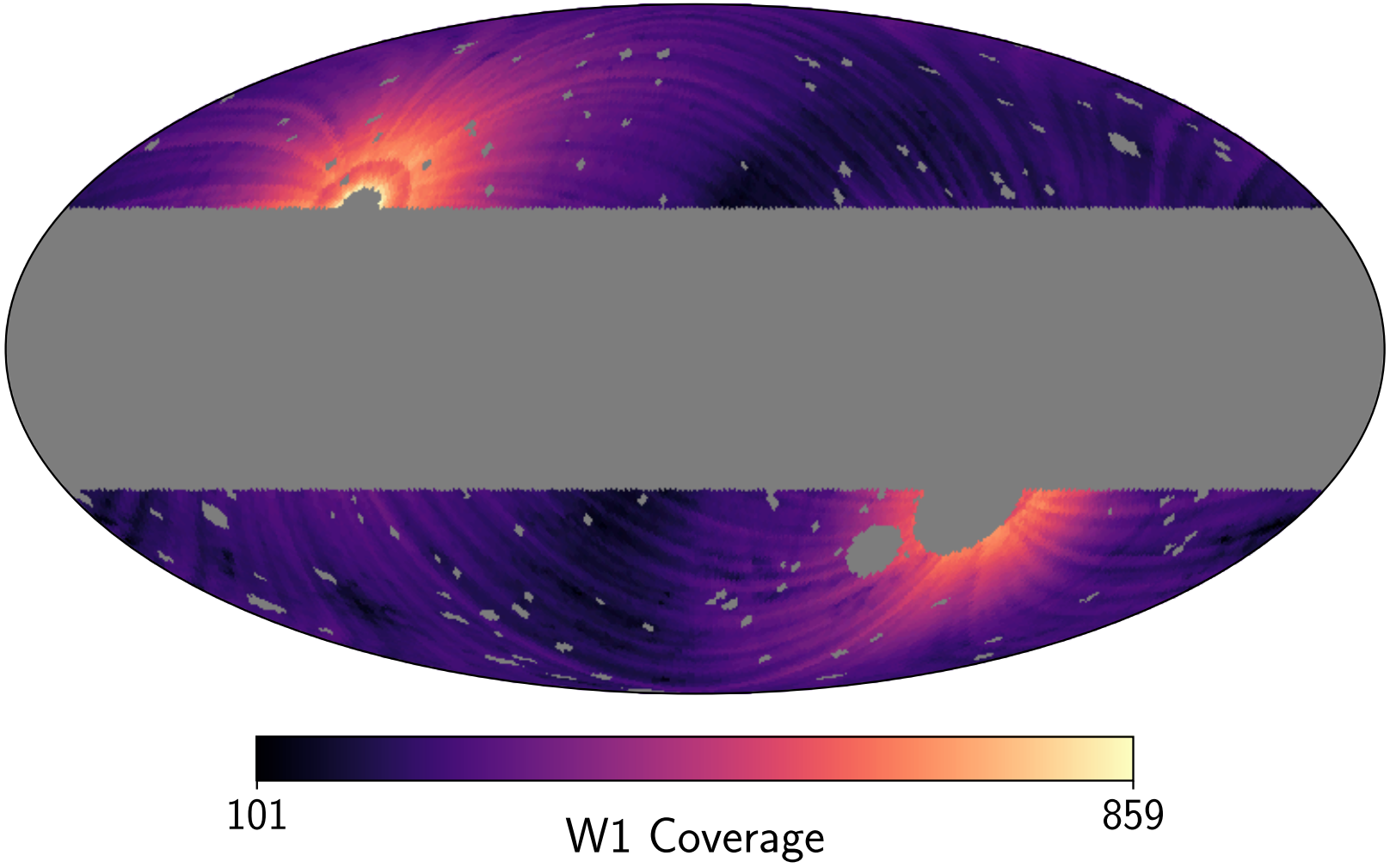




Frames over 2 orbits 20 days apart

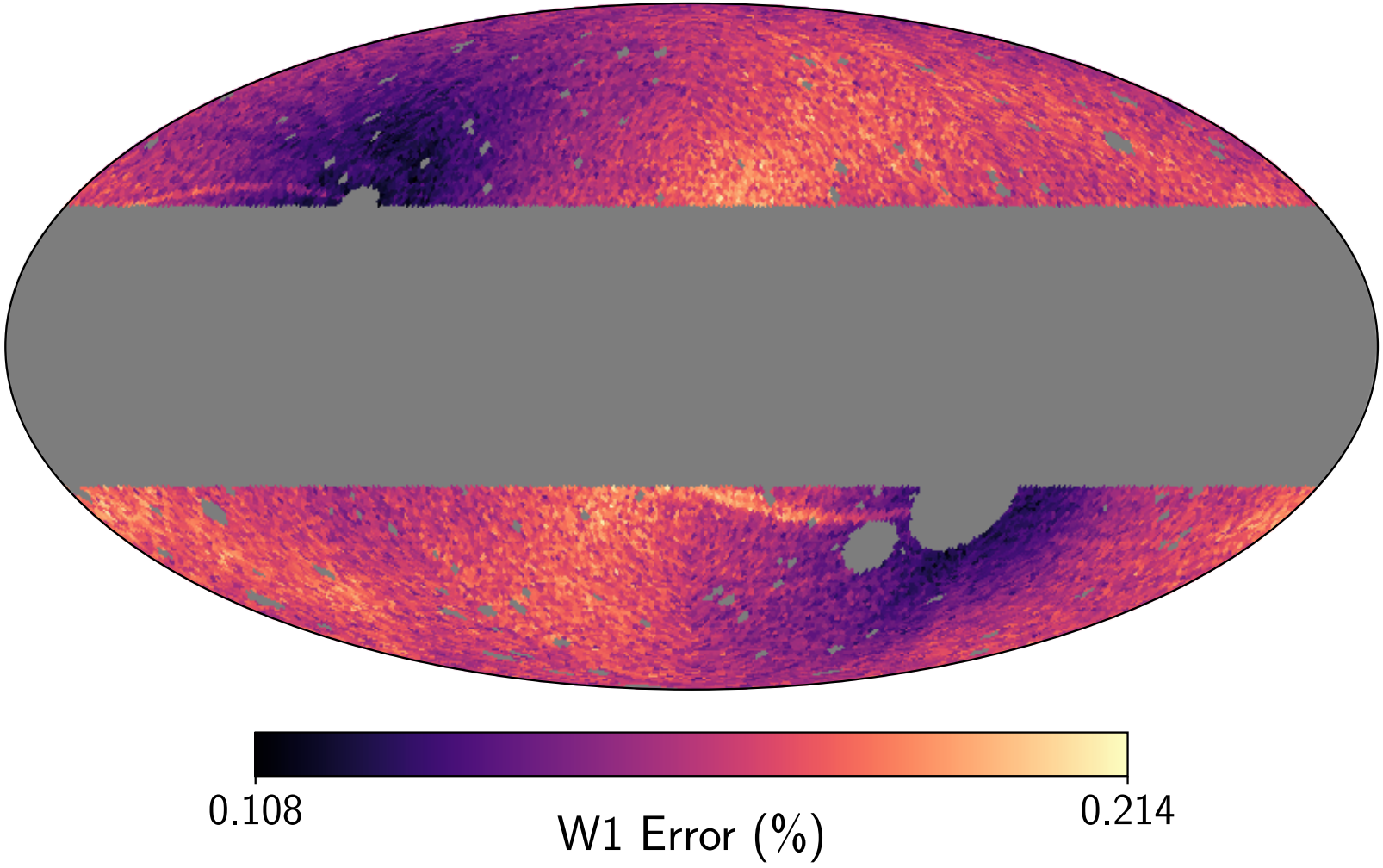
Obeys a scanning law over the survey's lifetime

Photometric Errors



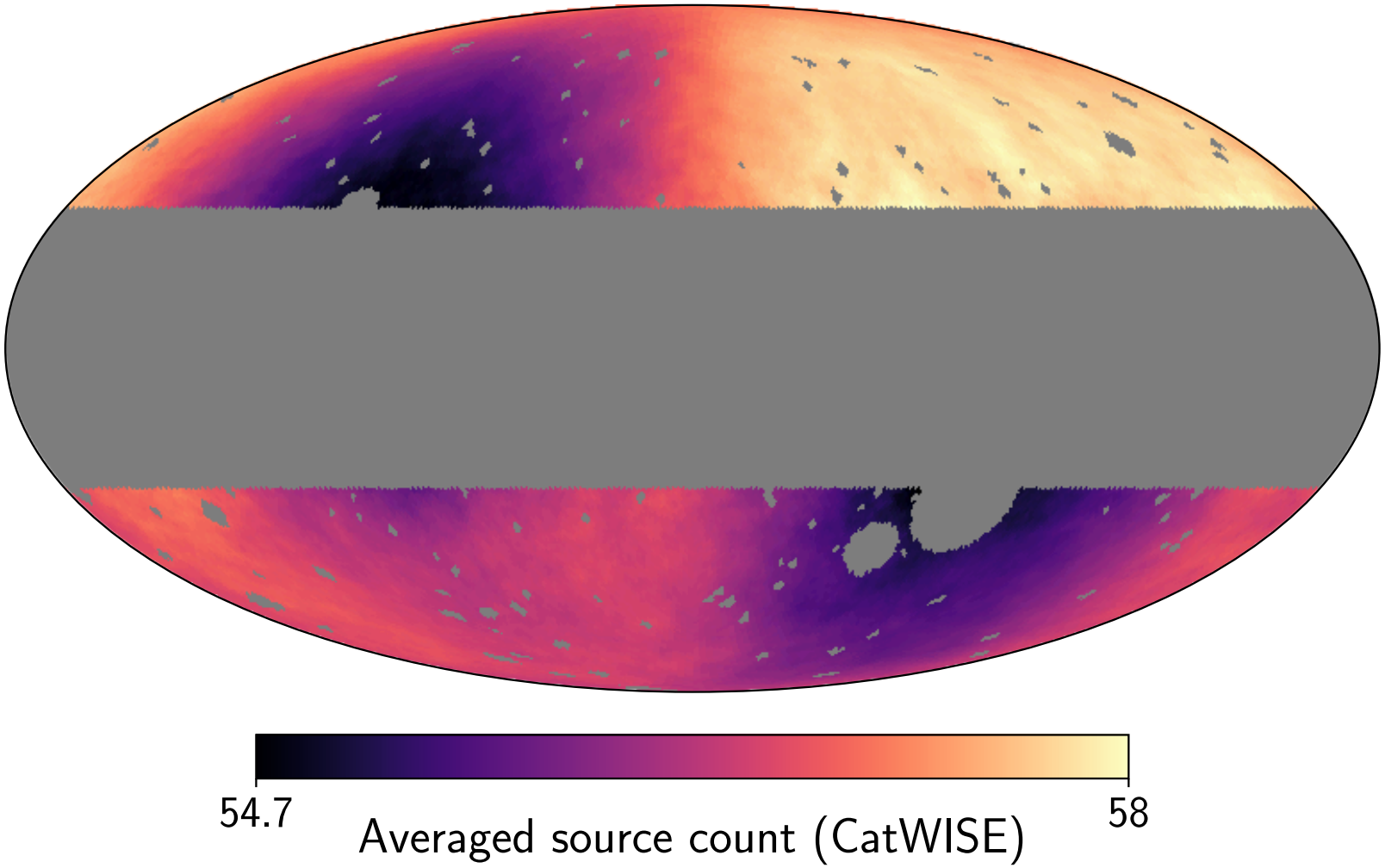
WISE coverage in W1 band for the Secrest+21 sample

Photometric Errors



Source photometric error (%) in W1 band for the Secrest+21 sample

Photometric Errors

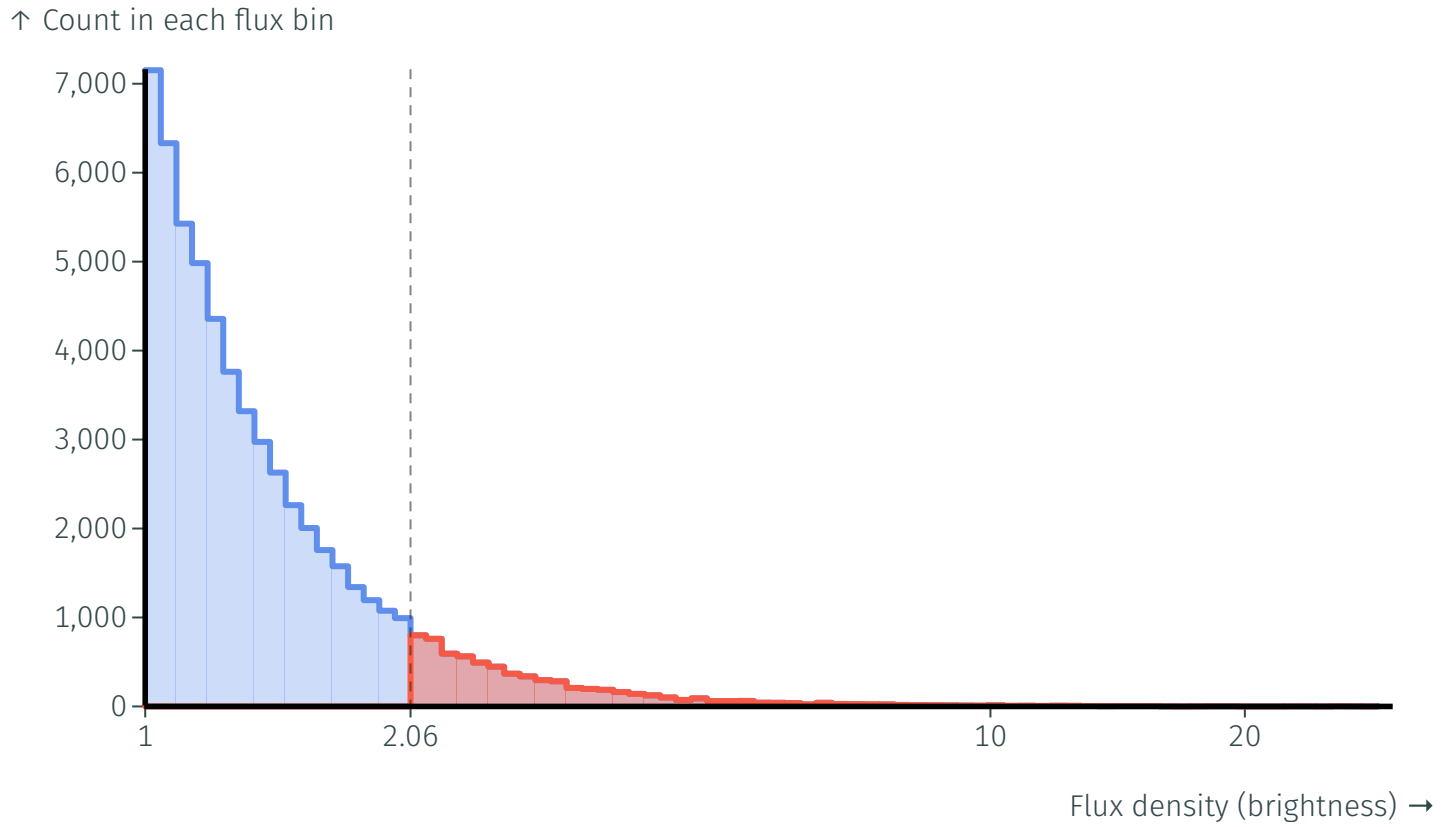


CatWISE quasar map, no linear weighting

Eddington Bias

Sampled flux = True flux + Noise

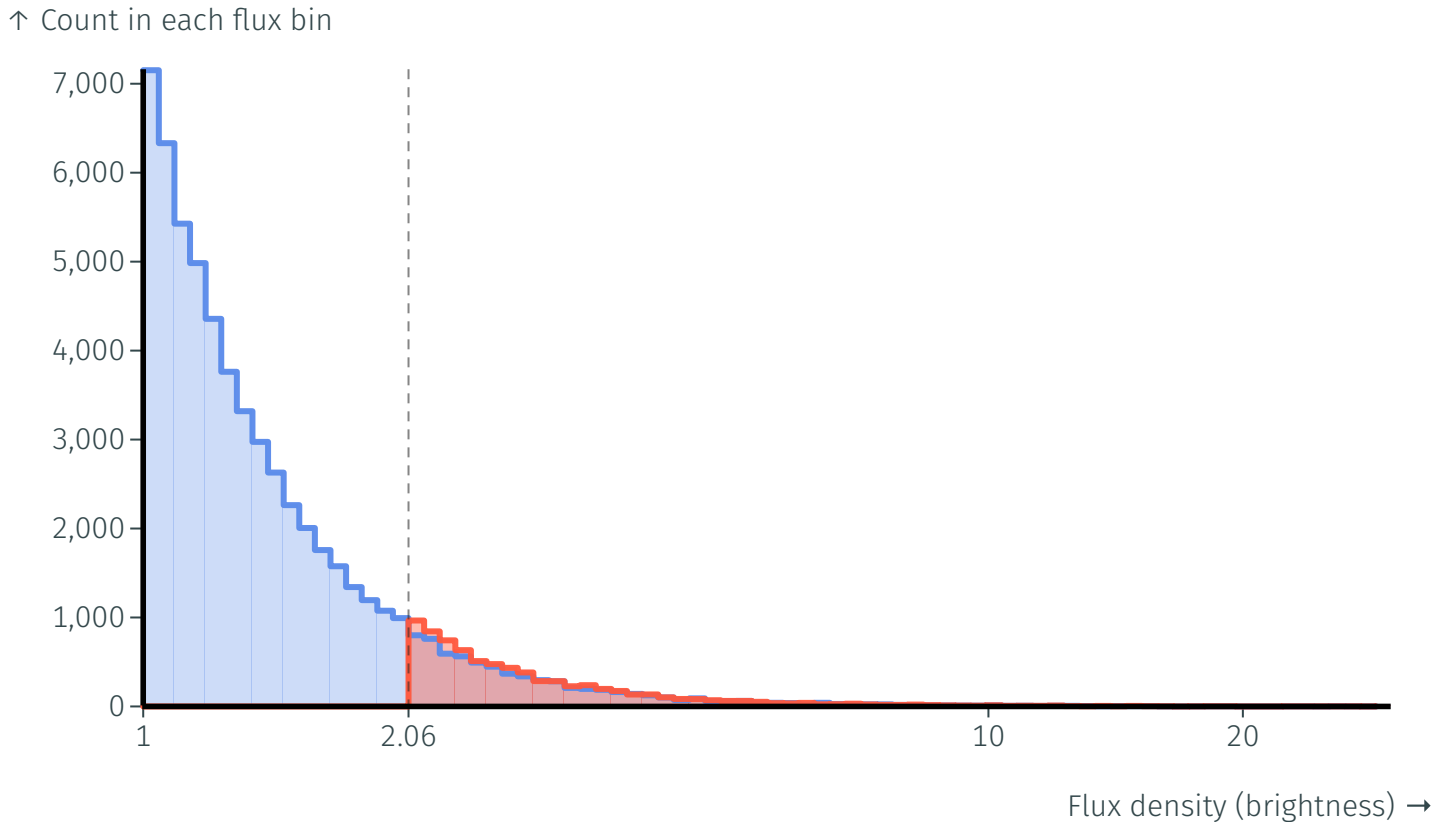
Flux cut 2.06 Noise 0.00



Eddington Bias

Sampled flux = True flux + Noise

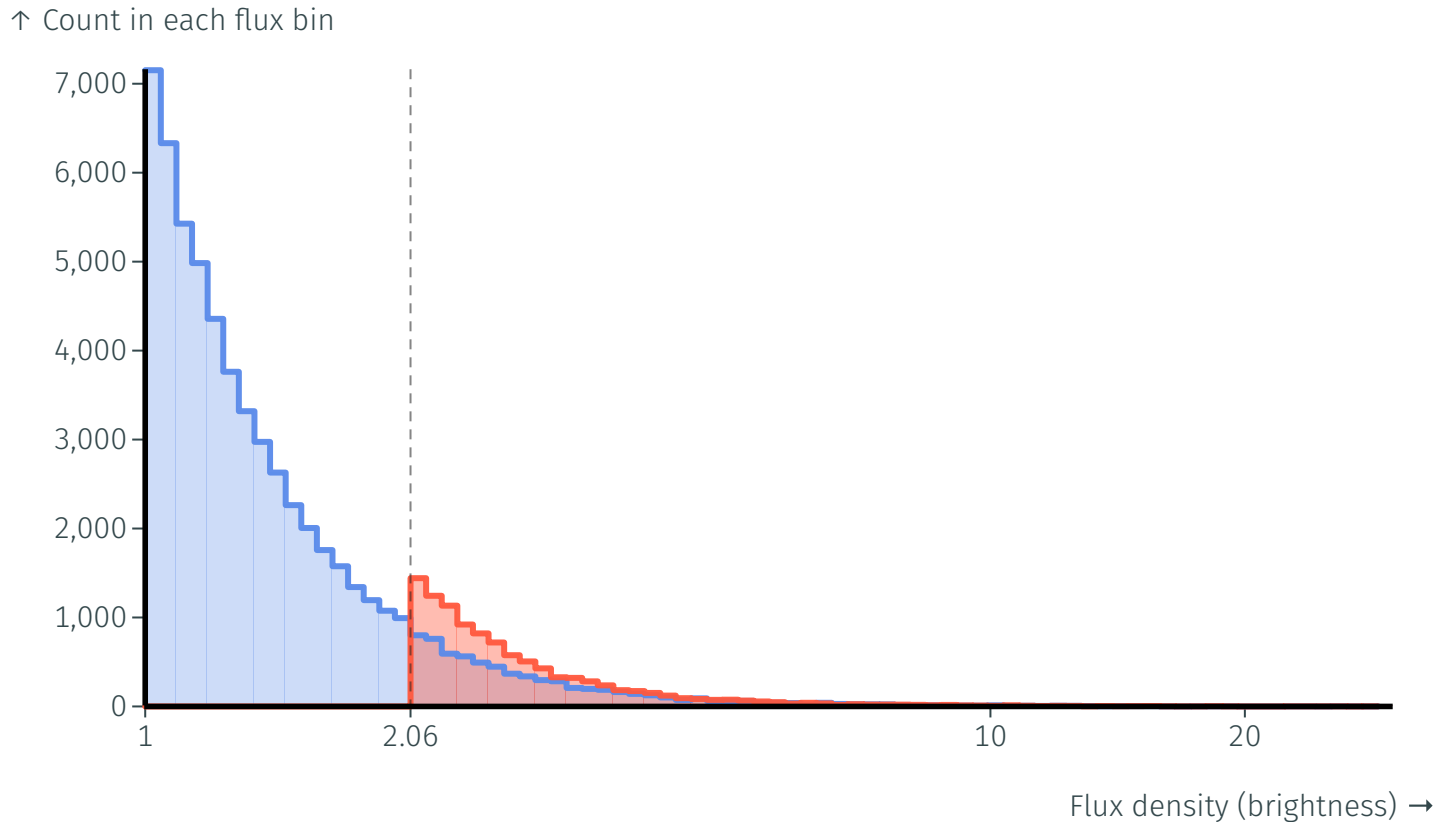
Flux cut 2.06 Noise 0.25



Eddington Bias

Sampled flux = True flux + Noise

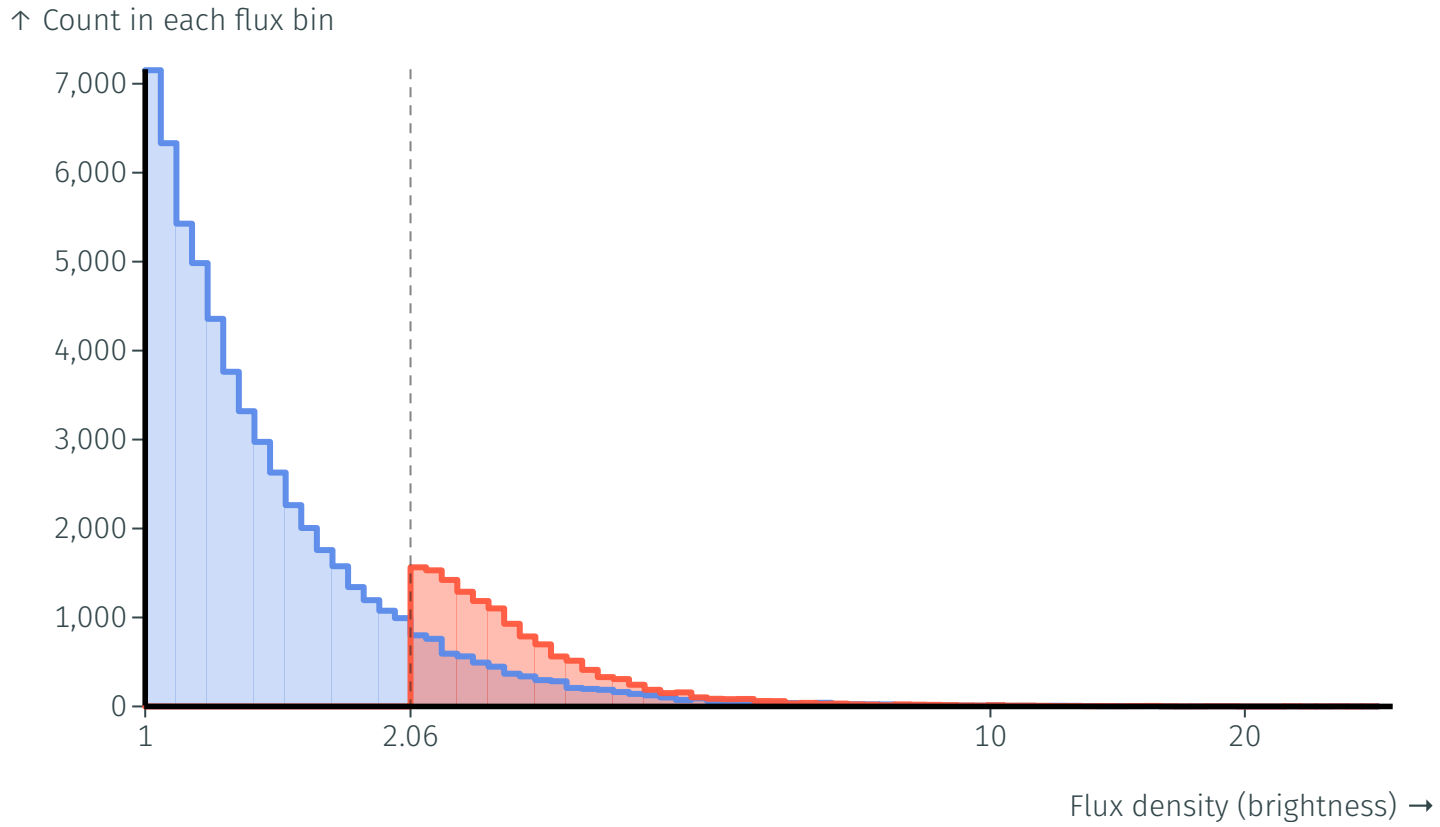
Flux cut 2.06 Noise 0.50



Eddington Bias

Sampled flux = True flux + Noise

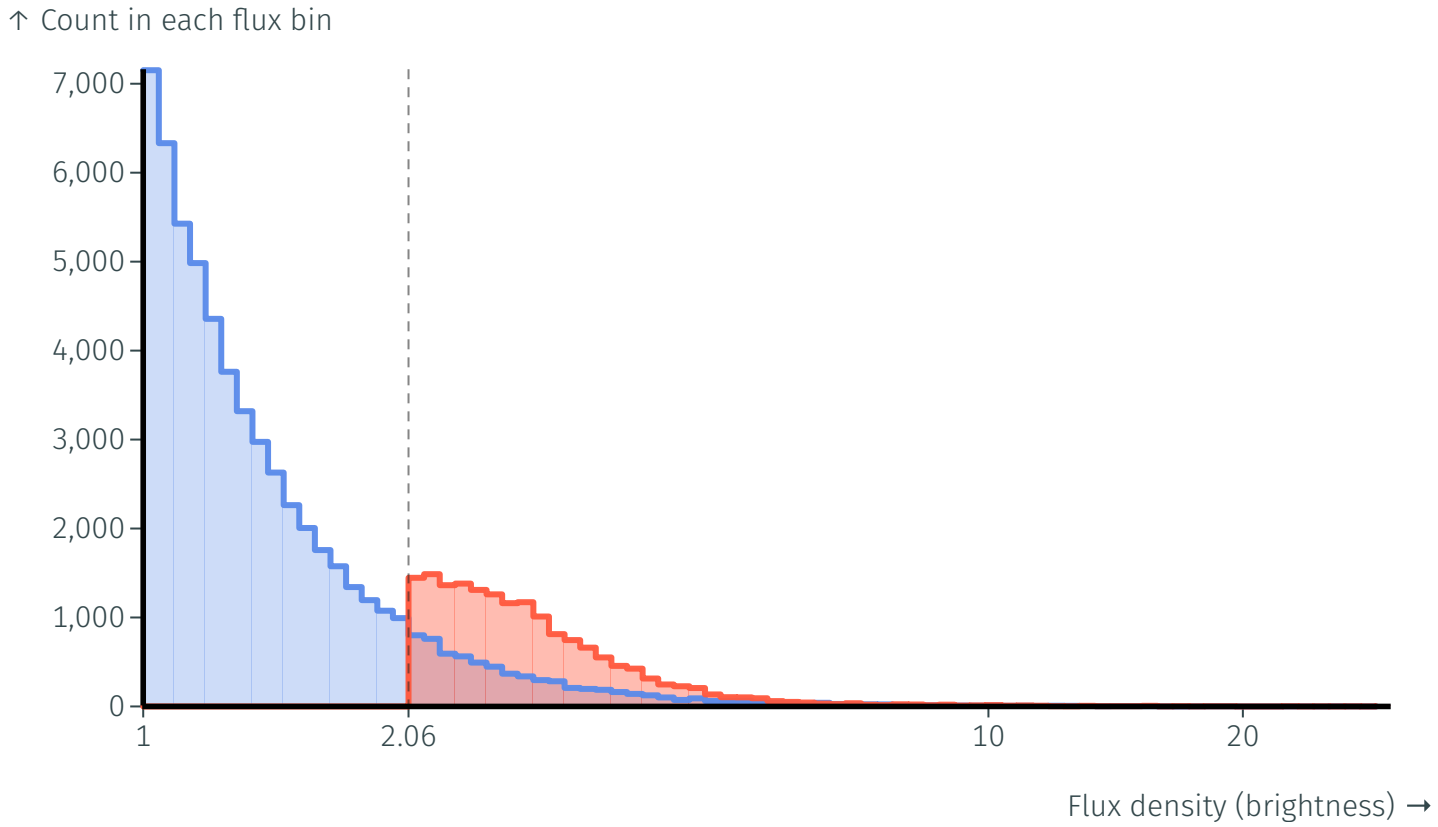
Flux cut 2.06 Noise 0.75



Eddington Bias

Sampled flux = True flux + Noise

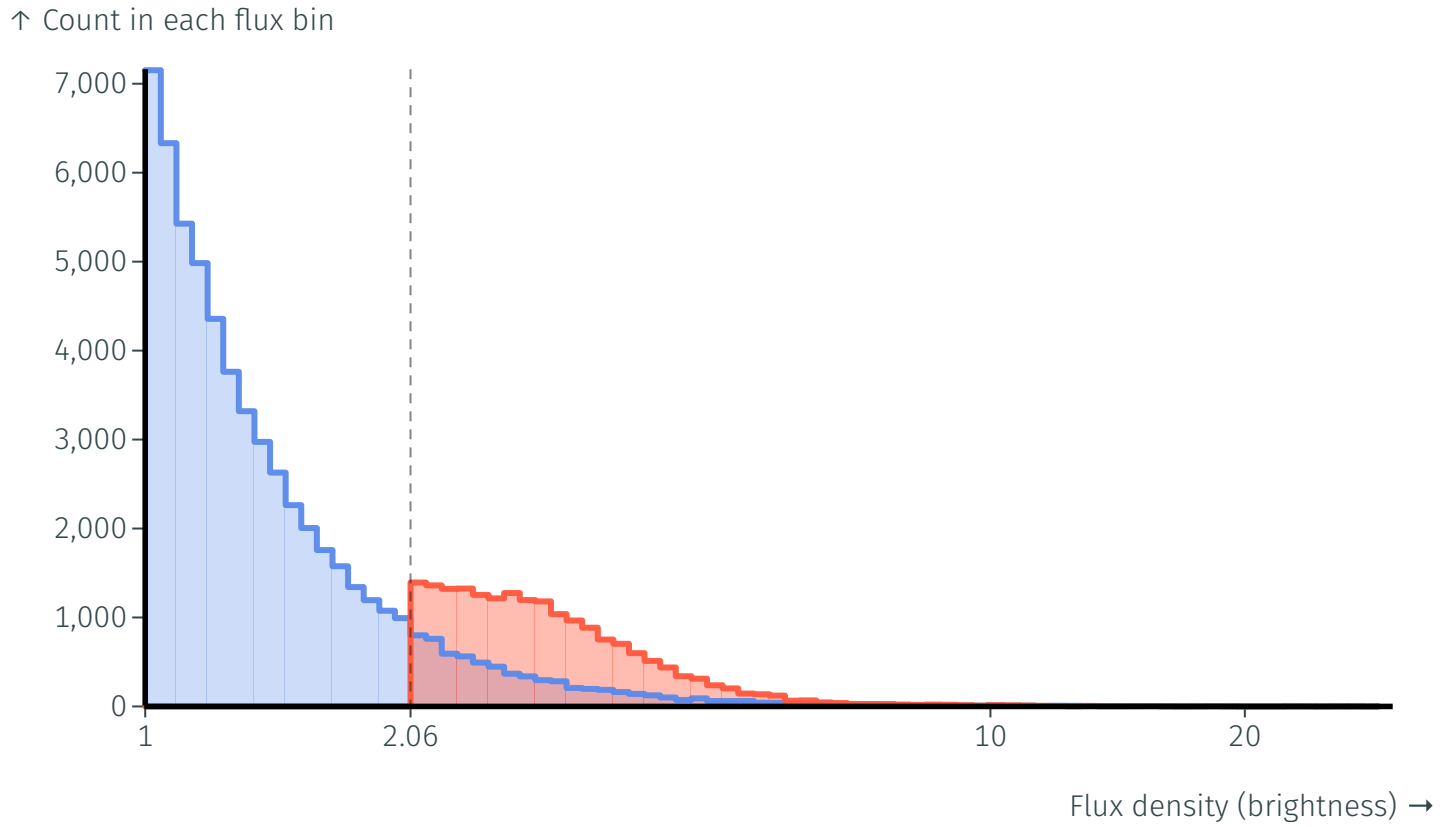
Flux cut 2.06 Noise 1.00



Eddington Bias

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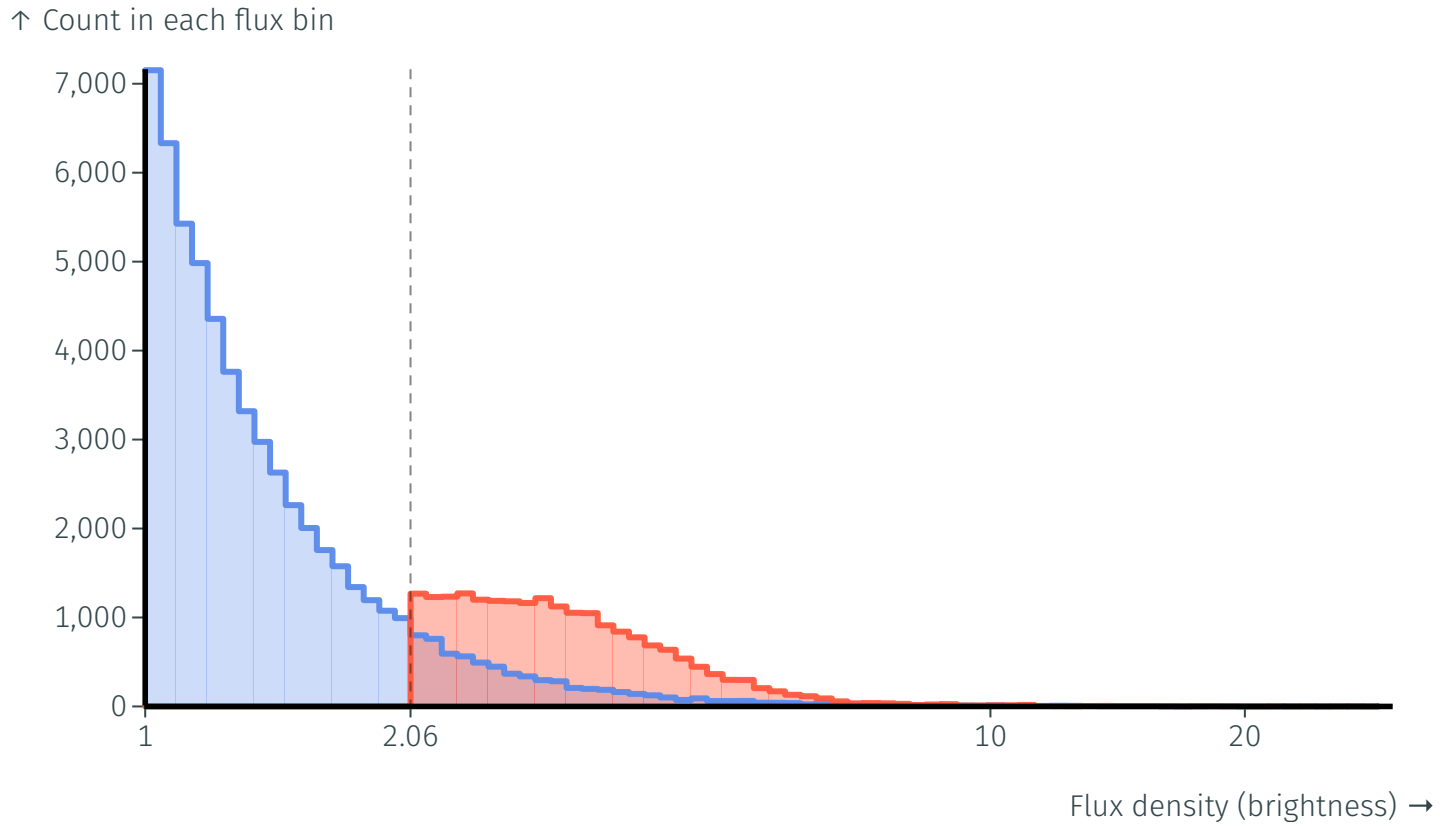
Flux cut 2.06 Noise 1.25



Eddington Bias

Sampled flux = True flux + Noise

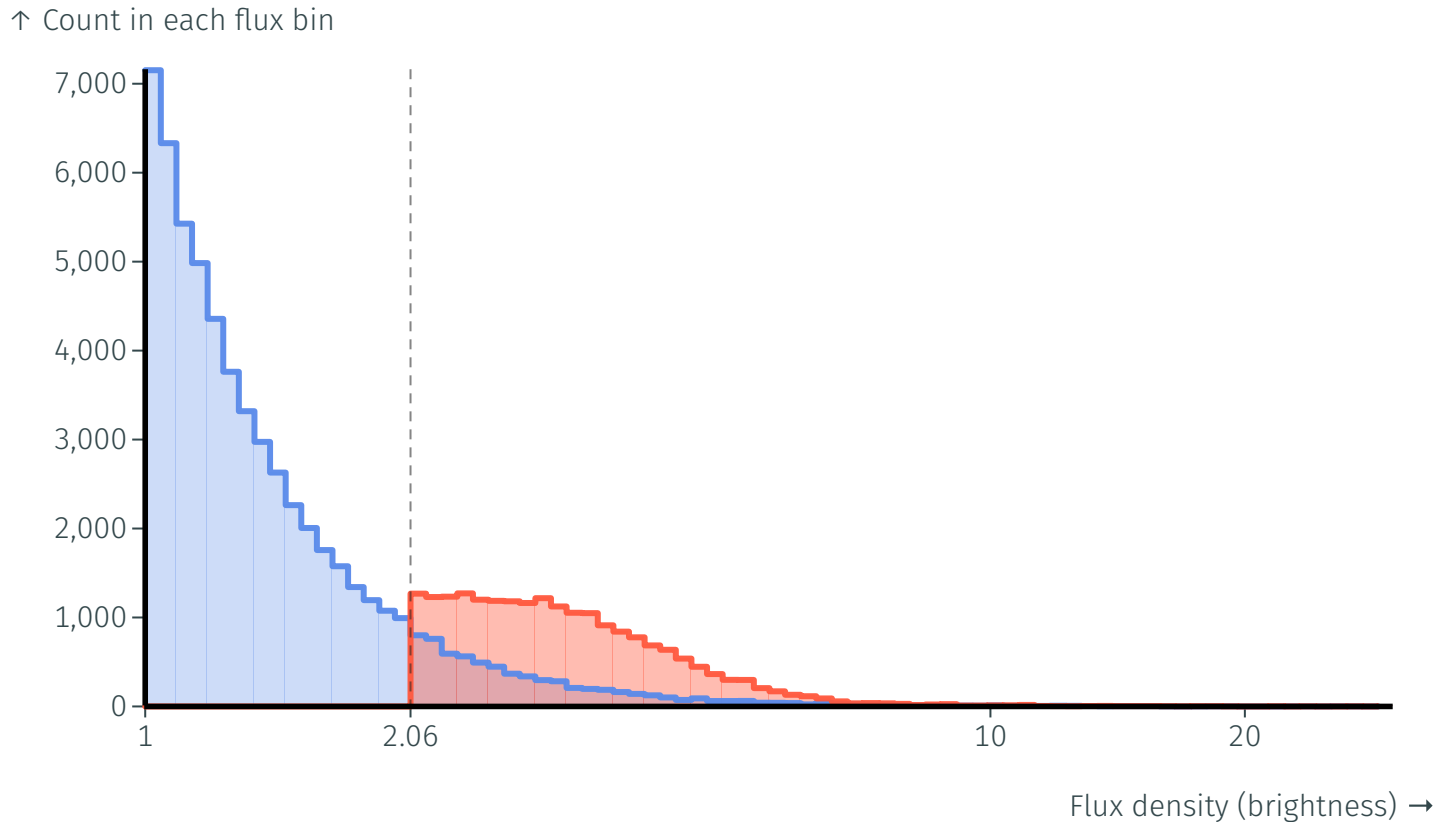
Flux cut 2.06 Noise 1.50



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Flux cut 2.06 Noise 1.50



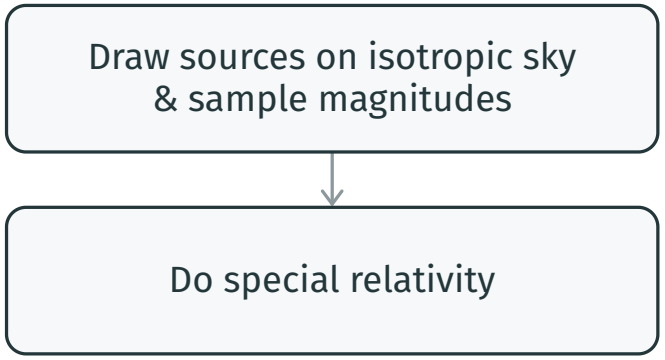
What if the noise varies over the sky? 🤔

This is just something we can simulate!

Simulations

Draw sources on isotropic sky
& sample magnitudes

Simulations



Simulations

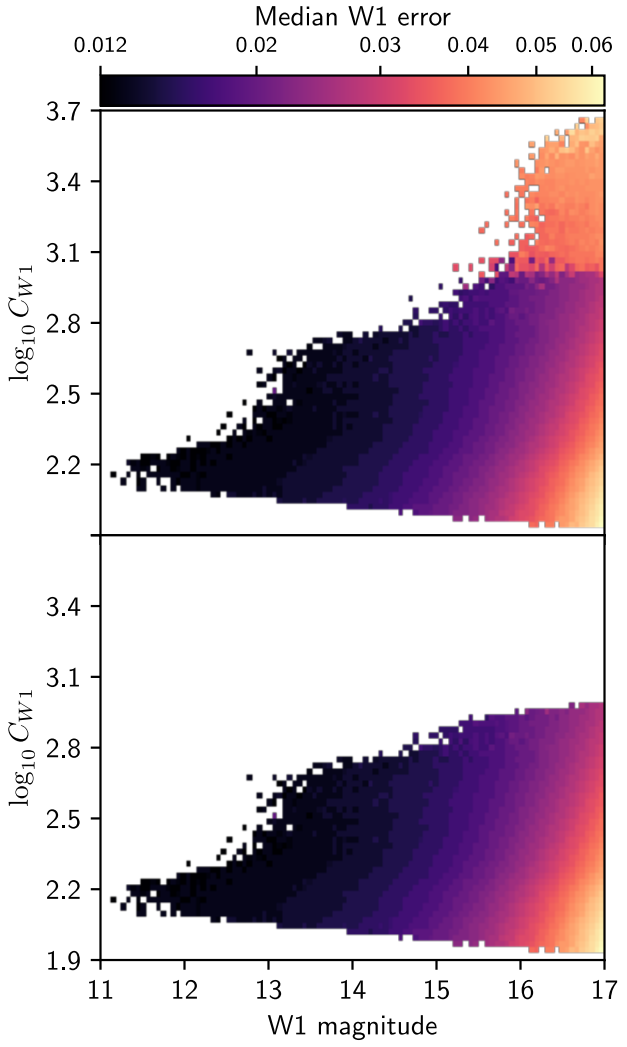
Draw sources on isotropic sky & sample magnitudes

↓

Do special relativity

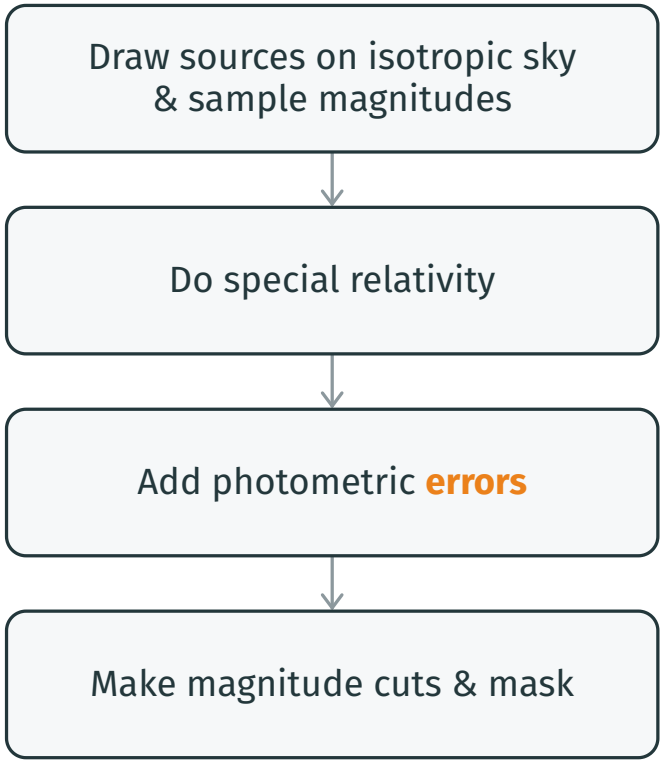
↓

Add photometric **errors**



$$m'_\nu \to m'_\nu + \Delta m'_\nu$$

Simulations



Simulations

Draw sources on isotropic sky & sample magnitudes

↓

Do special relativity

↓

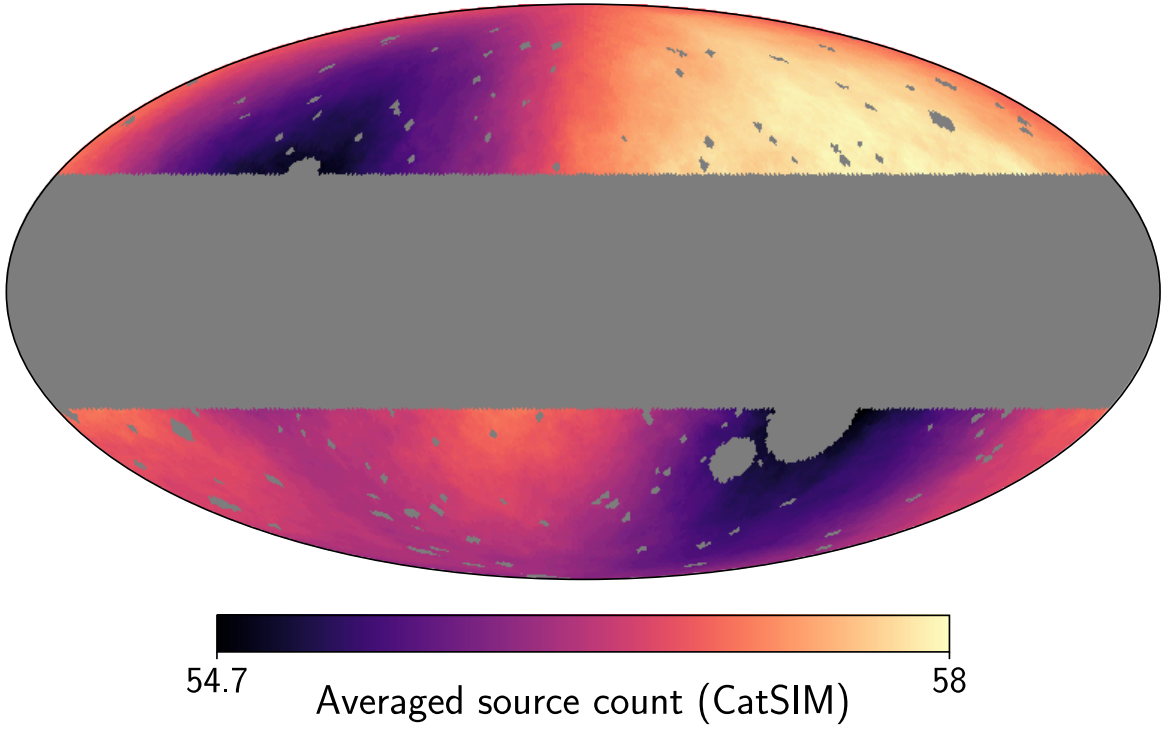
Add photometric **errors**

↓

Make magnitude cuts & mask

↓

Output: CatSIM density map



Simulated quasar map

Simulations

Draw sources on isotropic sky & sample magnitudes

↓

Do special relativity

↓

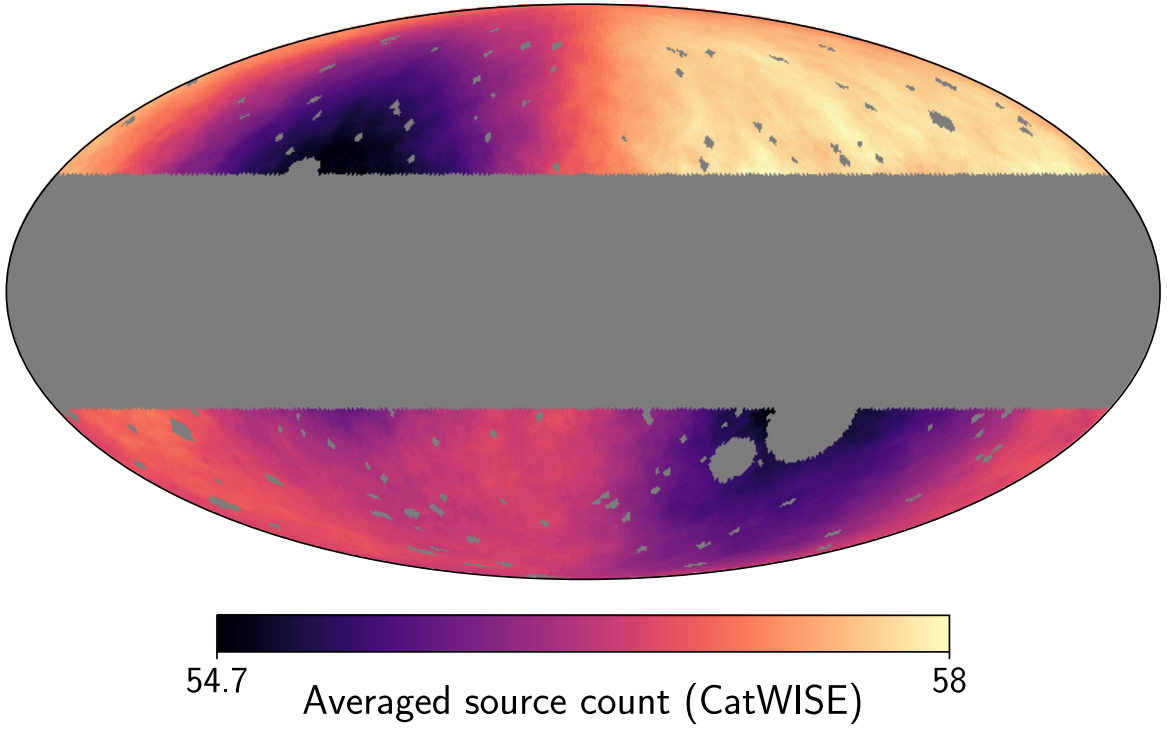
Add photometric **errors**

↓

Make magnitude cuts & mask

↓

Output: CatSIM density map



Actual quasar map

One Thing Left To Do...

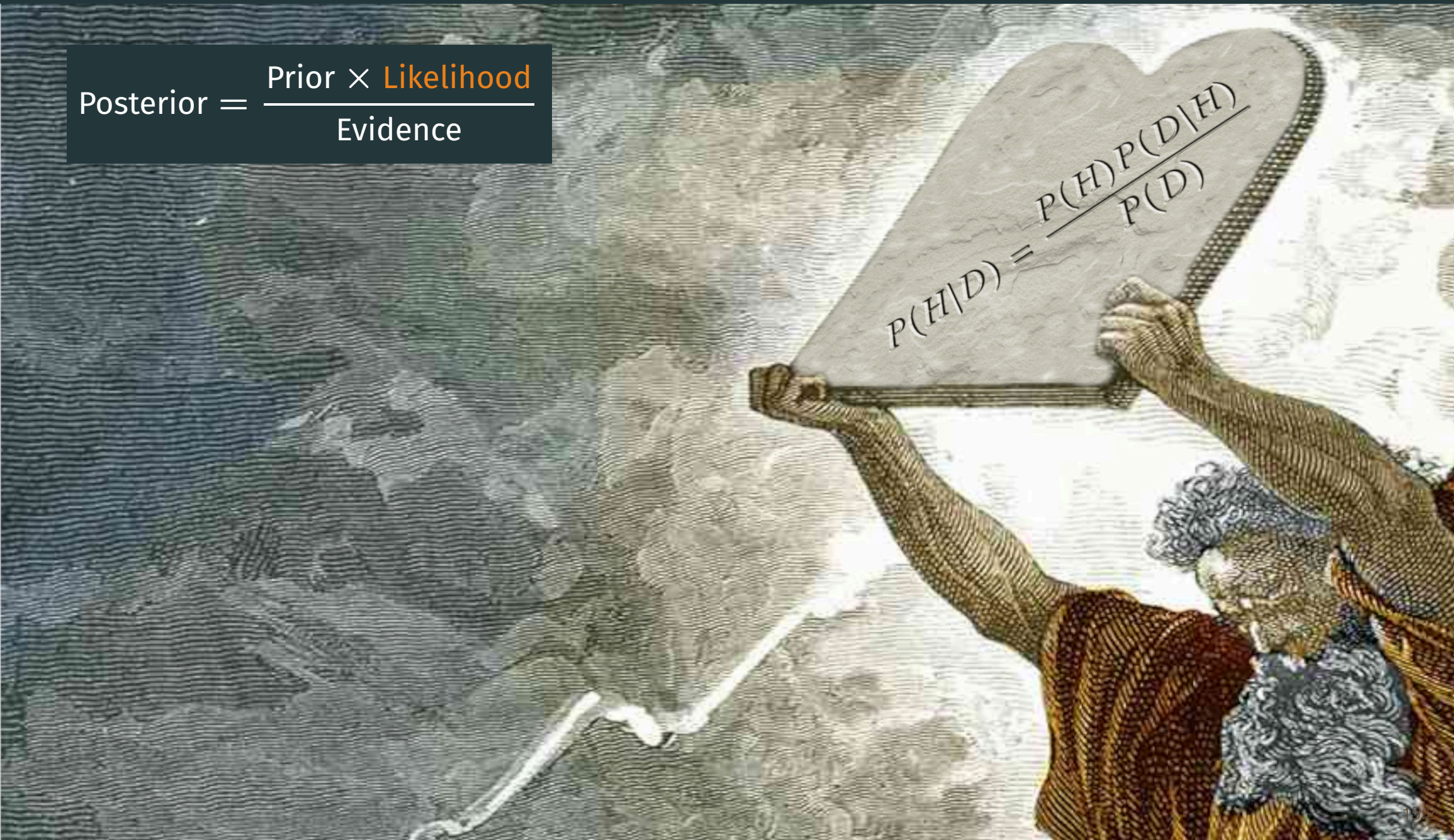


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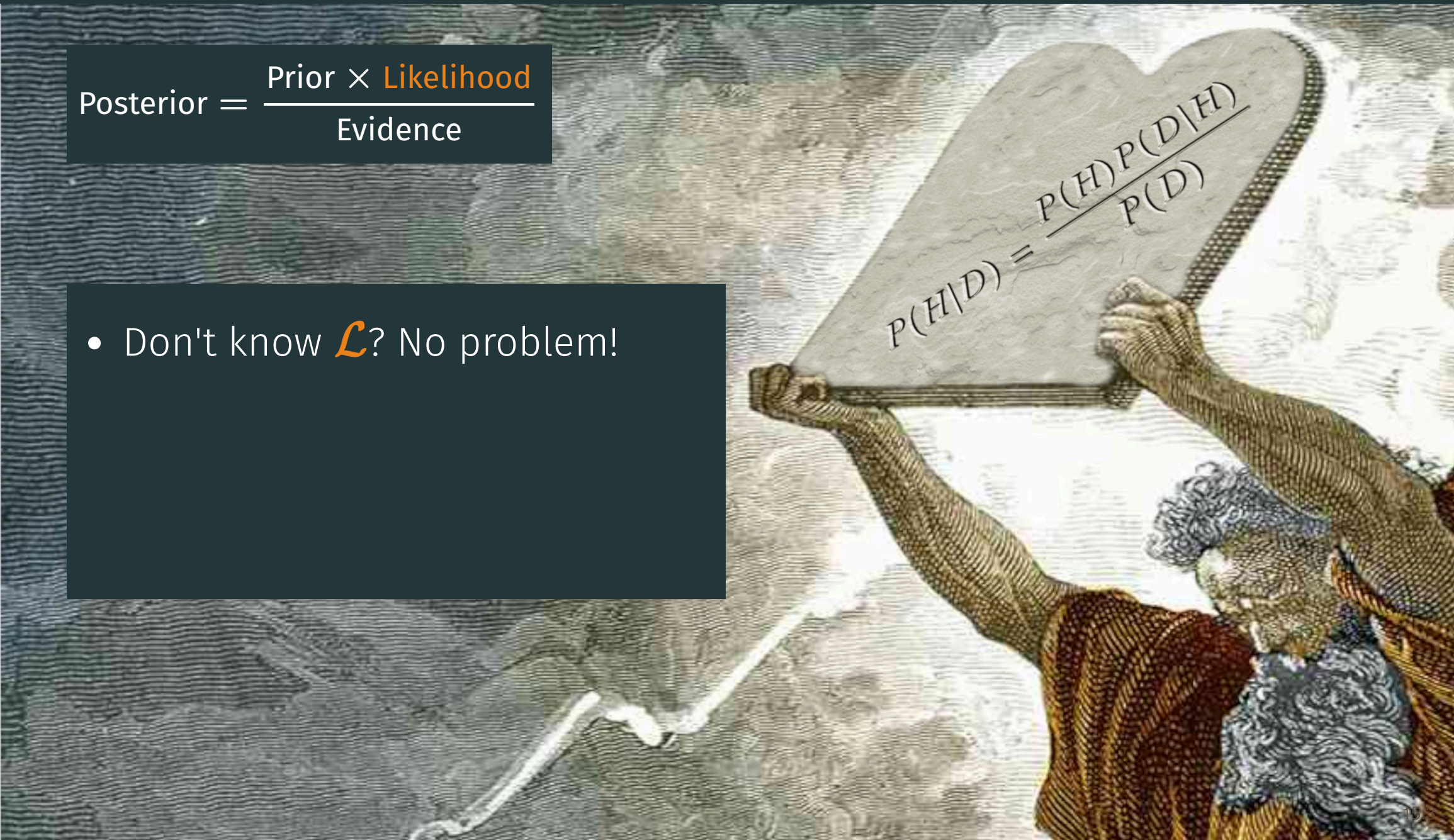
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$$\text{Posterior} = \frac{\text{Prior} \times \text{Likelihood}}{\text{Evidence}}$$



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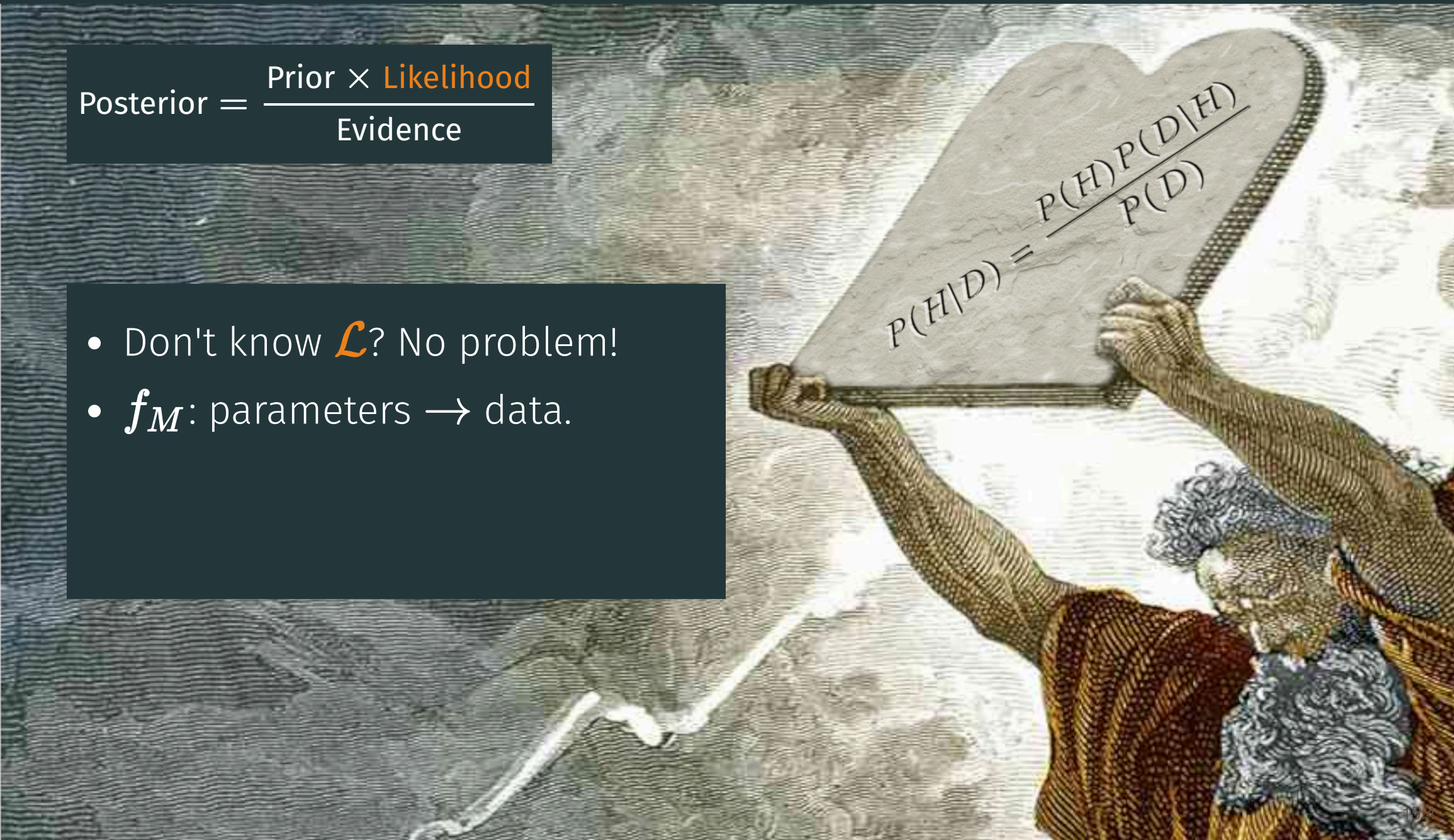
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- Don't know $\mathcal{L}$? No problem!

One Thing Left To Do...

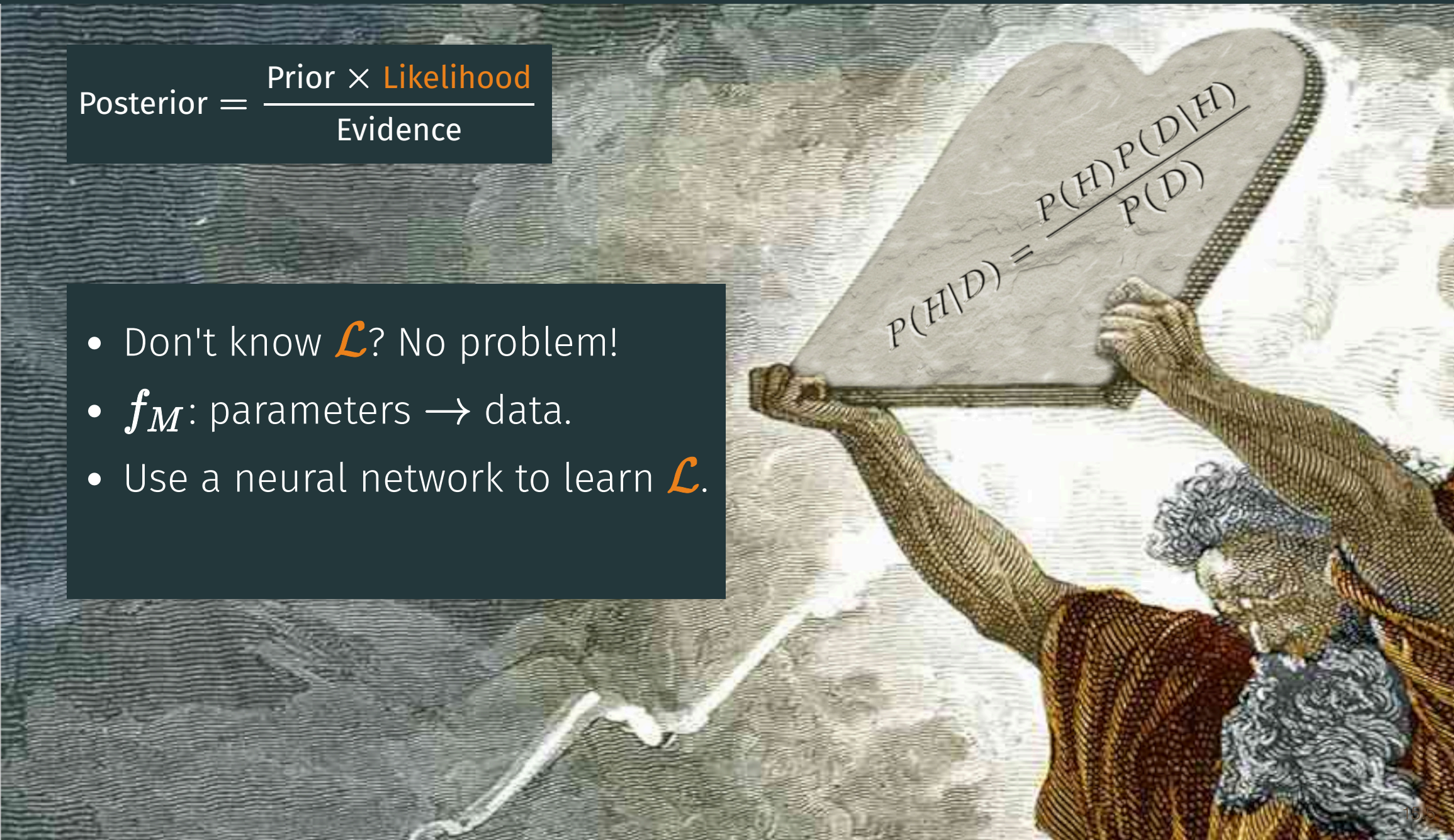
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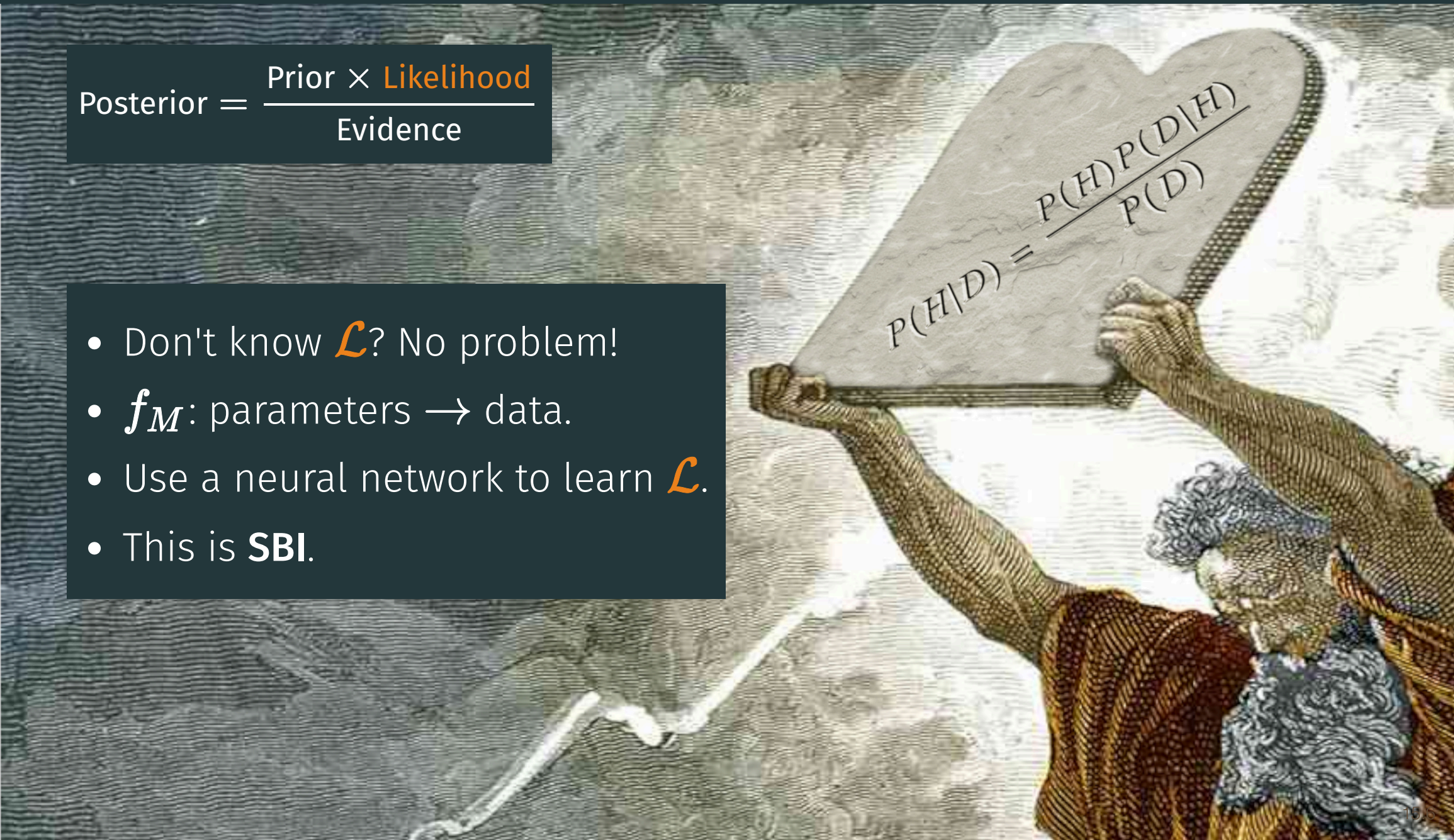
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- This is **SBI**.

Normalising Flows

Normalising Flows

- **Goal:** describe the distribution $\mathcal{L}(\boldsymbol{x} \mid \boldsymbol{\theta})$ for data $\boldsymbol{x}$ and parameters $\boldsymbol{\theta}$

Normalising Flows

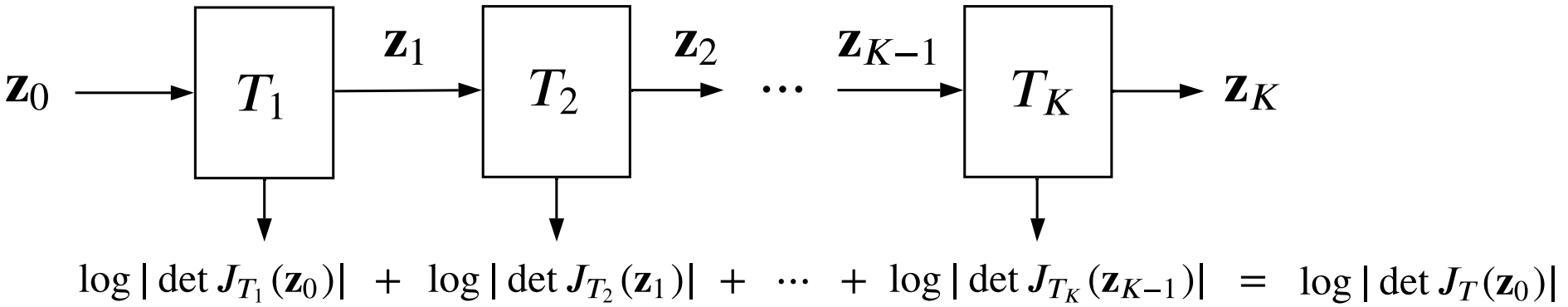
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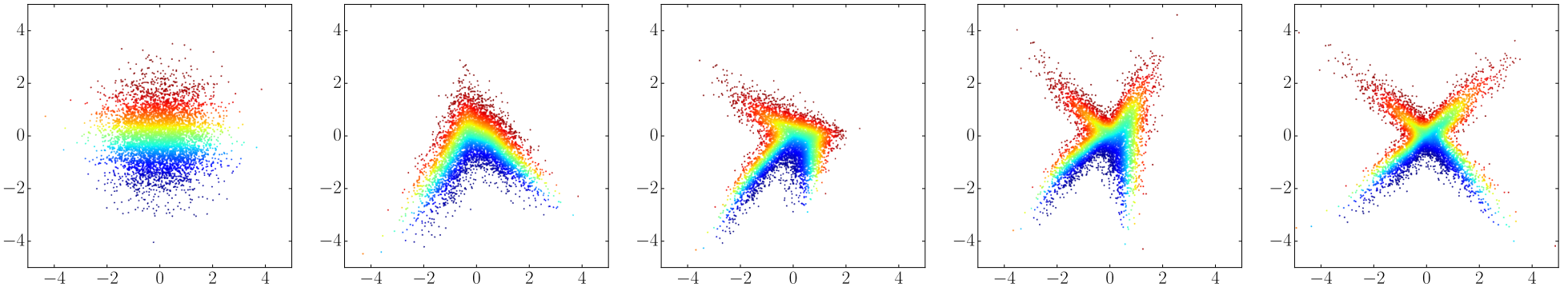
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Composing individual bijections, adapted from Papamakarios et al. (2019).

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The Nuts & Bolts

Algorithm: Sequential Neural Likelihood Estimator (SNLE)

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- learn approx. likelihood $\mathcal{L}_\phi$ using all pairs

$$\begin{aligned}\text{Loss}(\phi) &= -\frac{1}{N}\sum_{i=1}^{N} \ln \mathcal{L}_\phi(x_i \mid \theta_i) \\ &\approx -\mathbb{E}_{\mathcal{J}}\left[\ln \mathcal{L}_\phi\right] \\ &= \mathbb{E}_{\pi}\left[D_{\text{KL}}\left(\mathcal{L} \,\|\, \mathcal{L}_\phi\right)\right] + \text{const.}\end{aligned}$$

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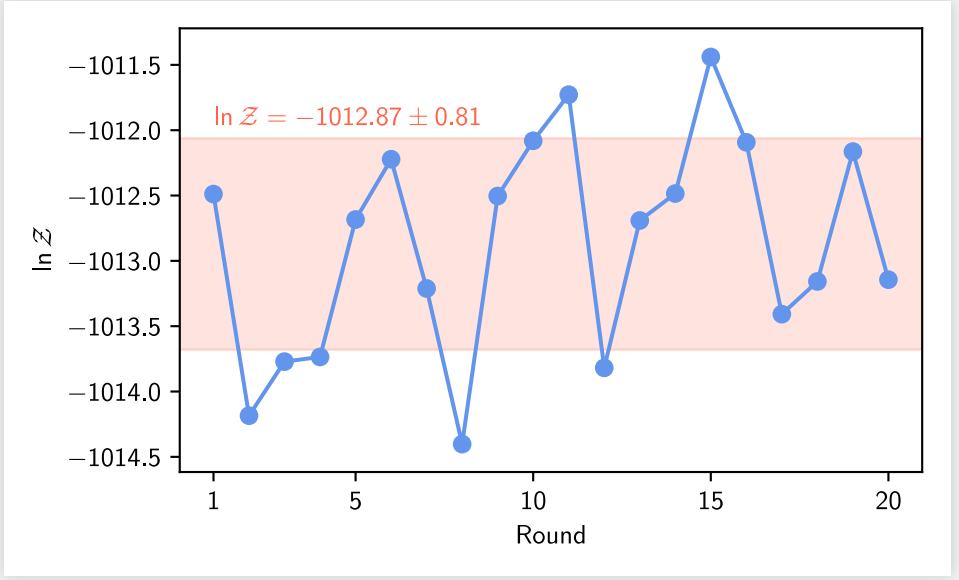
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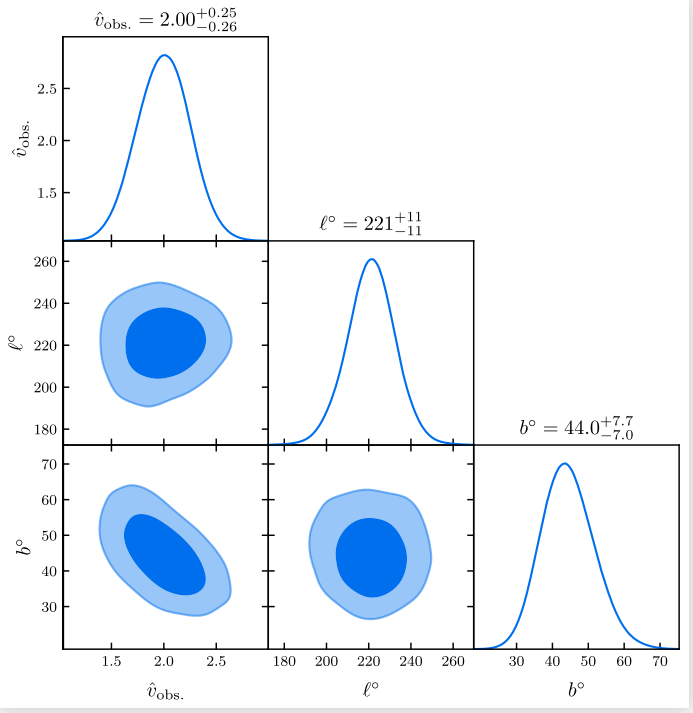
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Let proposal = prior

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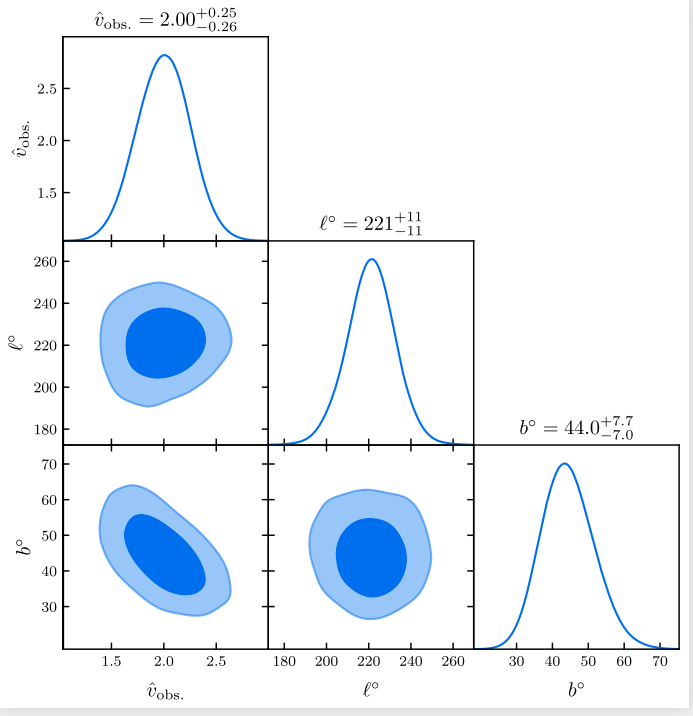
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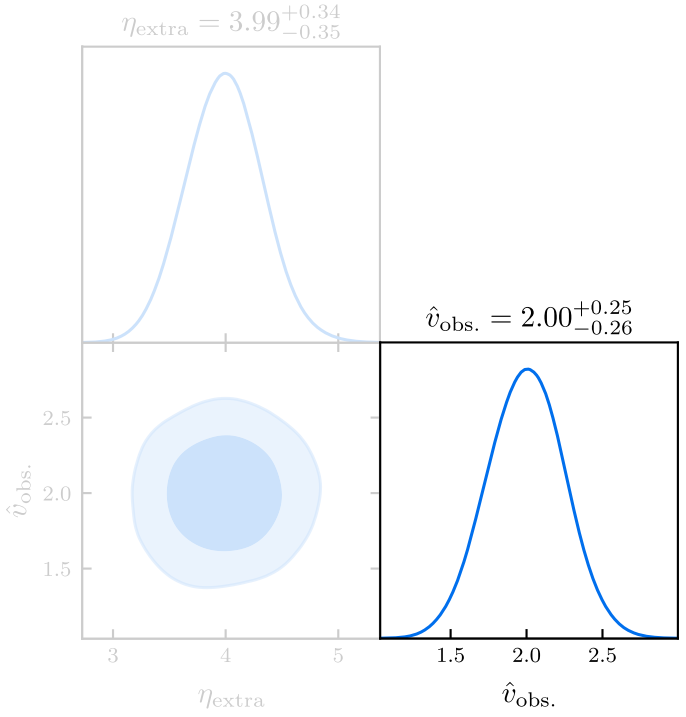
return final posterior & evidence estimate



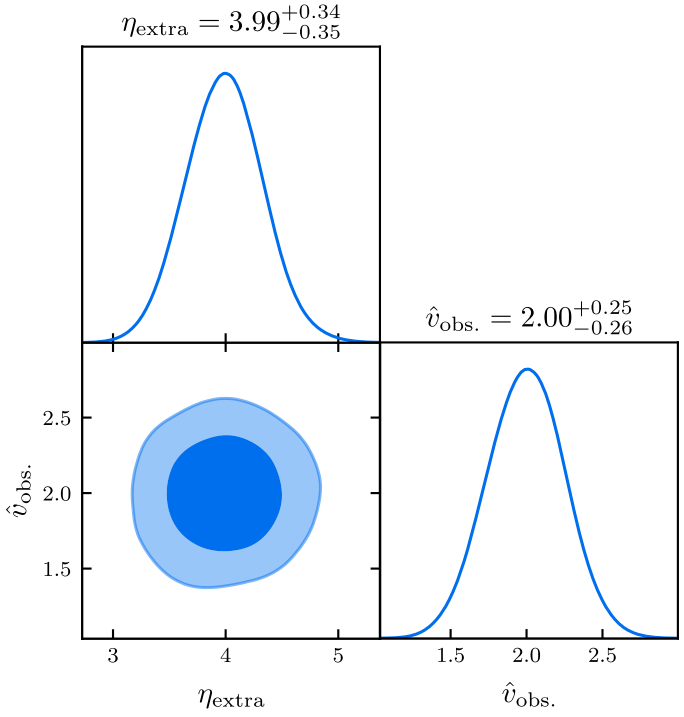
Results

CatSIM Results

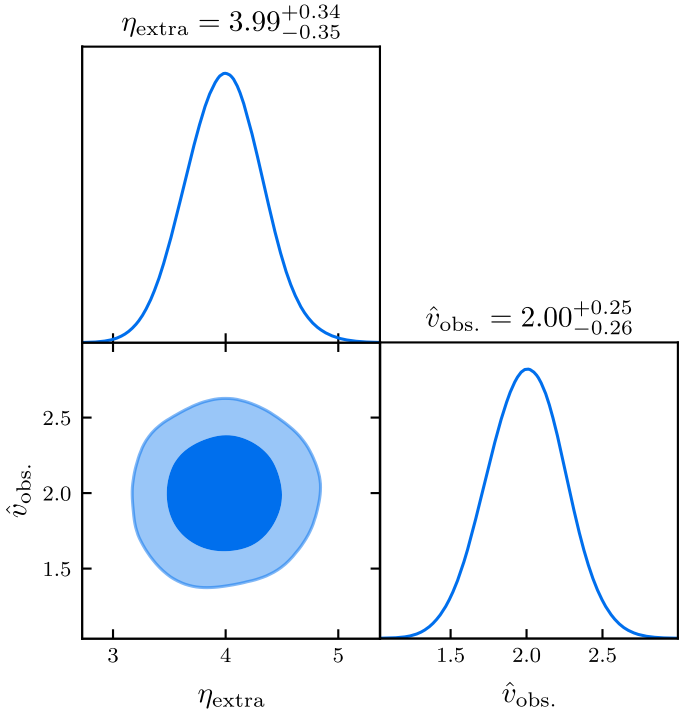
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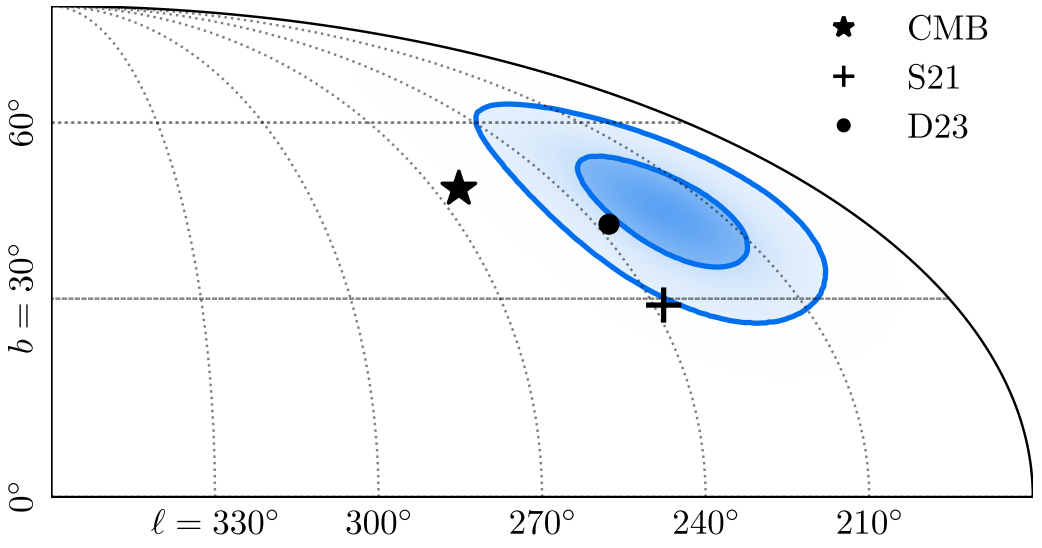


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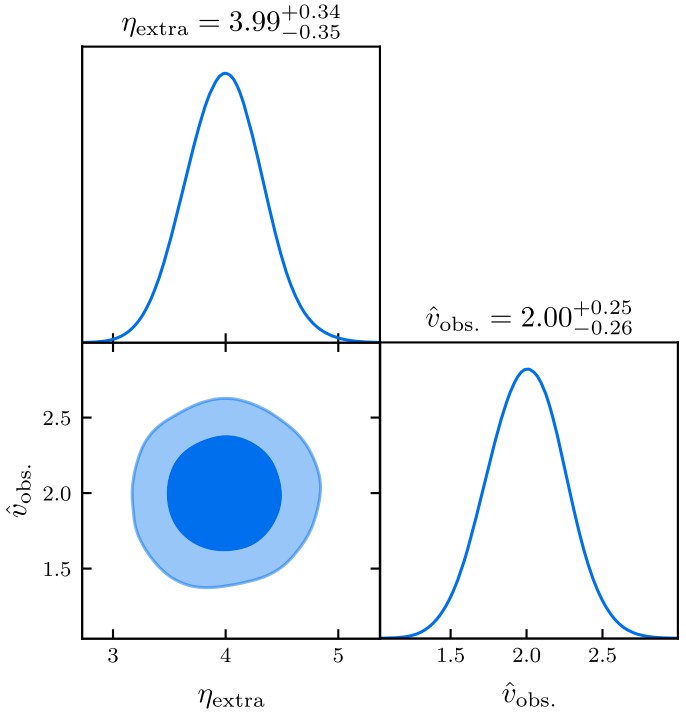


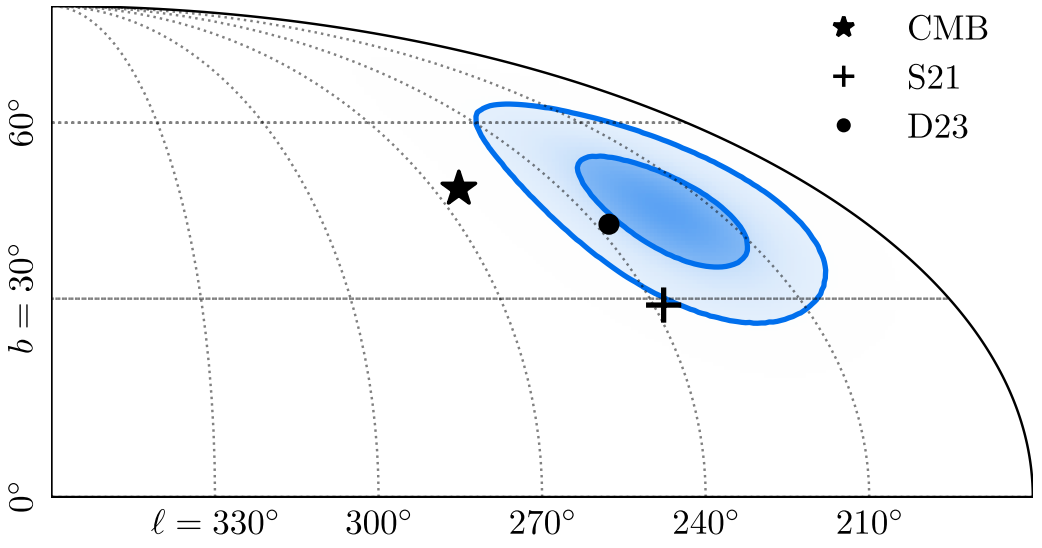
CatSIM Results





CatSIM Results





Confirms cosmic dipole tension.

Bayes Factors

Model	$\ln \mathcal{B}$

Bayes factors with respect to the fiducial model.

Bayes Factors

Model	$\ln \mathcal{B}$
Dipole with free parameters	0.0 ± 0.0

Bayes factors with respect to the fiducial model.

Bayes Factors

Model	$\ln \mathcal{B}$
Dipole from Secrest+21	2.8 ± 0.9
Dipole from Dam+23	1.9 ± 0.8
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CMB velocity & direction	-8.3 ± 0.9

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CMB direction, free velocity	-2.4 ± 0.9
CMB velocity & direction	-8.3 ± 0.9

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Free dipole but no extra error	-113.6 ± 6.4

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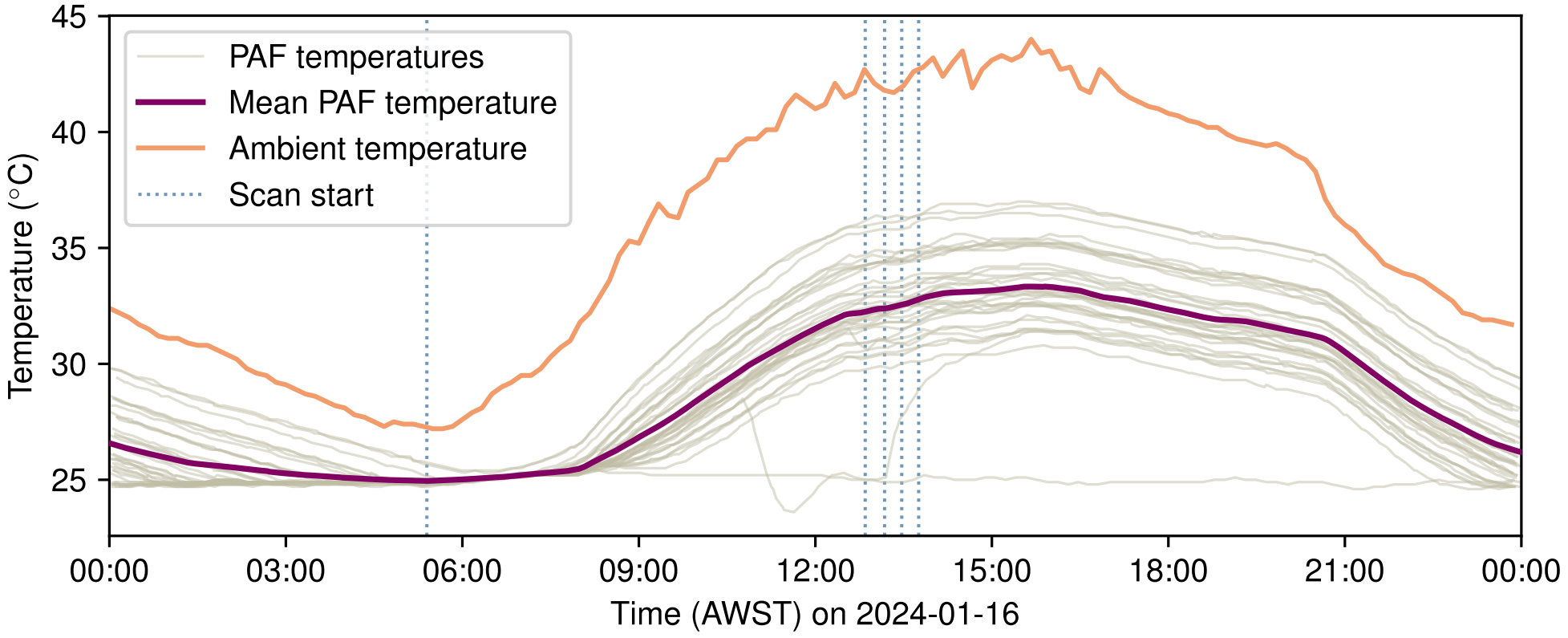
Bayes factors with respect to the fiducial model.

- *We need an **extra error** term to explain the data.*
- CMB dipole is ruled out convincingly.

We've got to be careful of our instruments!

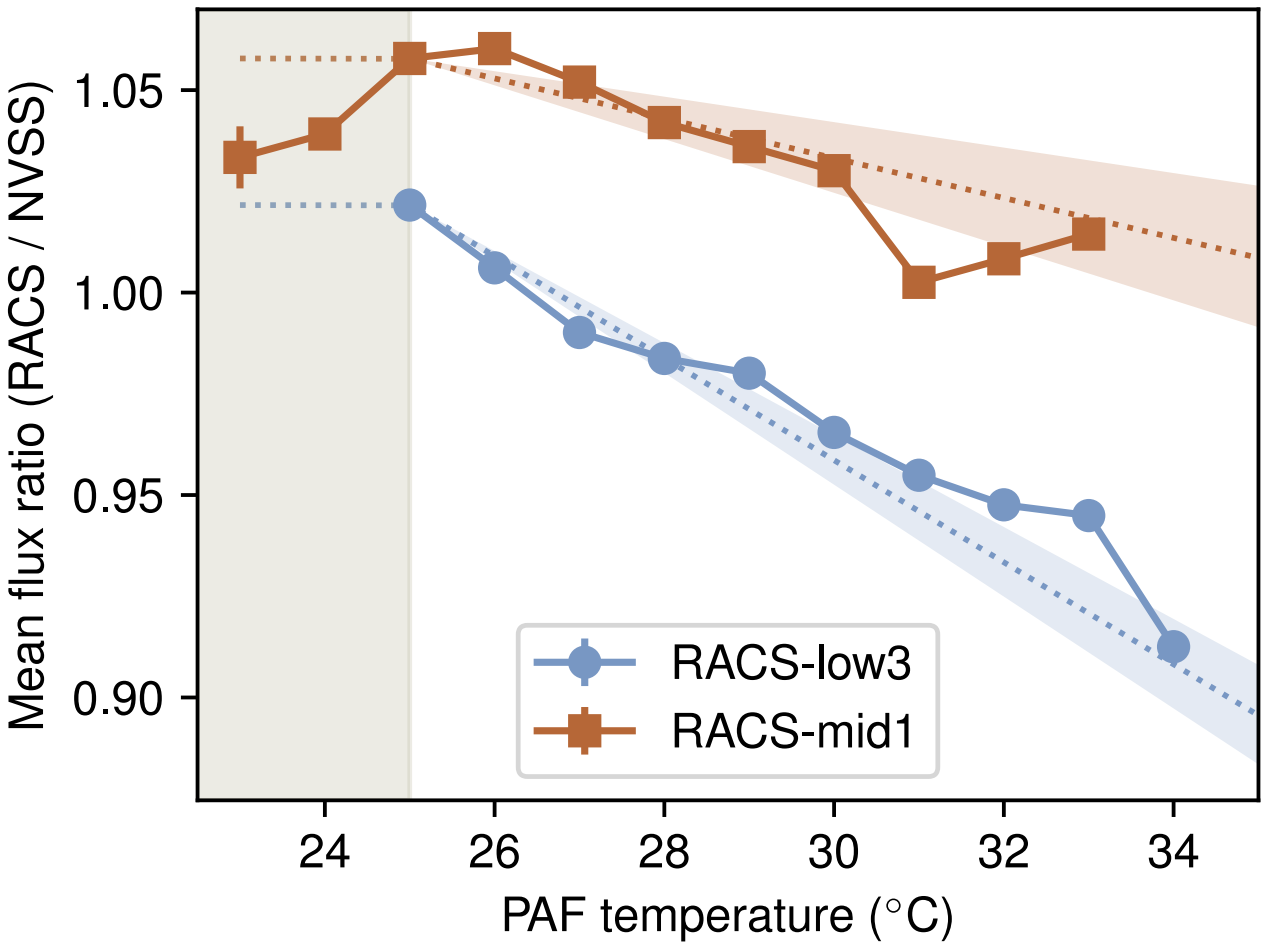
Cracking into RACS?

Cracking into RACS?



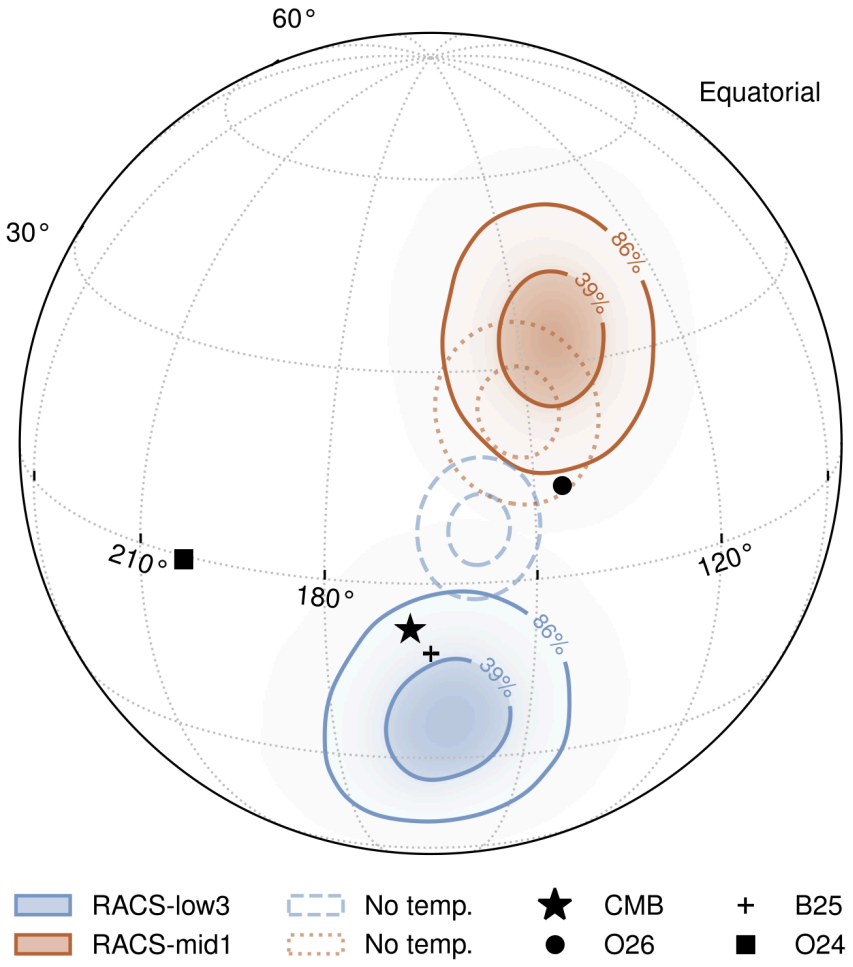
RACS observations get warmer as the day progresses...

Cracking into RACS?



... which leads to a systematic suppression of flux density...

Cracking into RACS?



... and impacts the cosmic dipole! (Oayda et al., in prep.)

Monthly Notices of the ROYAL ASTRONOMICAL SOCIETY

MNRAS **546,** 1–16 (2026) https://doi.org/10.1093/mnras/stag248
Advance Access publication 2026 February 9

Wising up to CatWISE: using simulation-based inference to interpret the ecliptic bias and confirm the cosmic dipole excess

Oliver T. Oayda ★ and Geraint F. Lewis

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- Describe and account for ecliptic bias ✓

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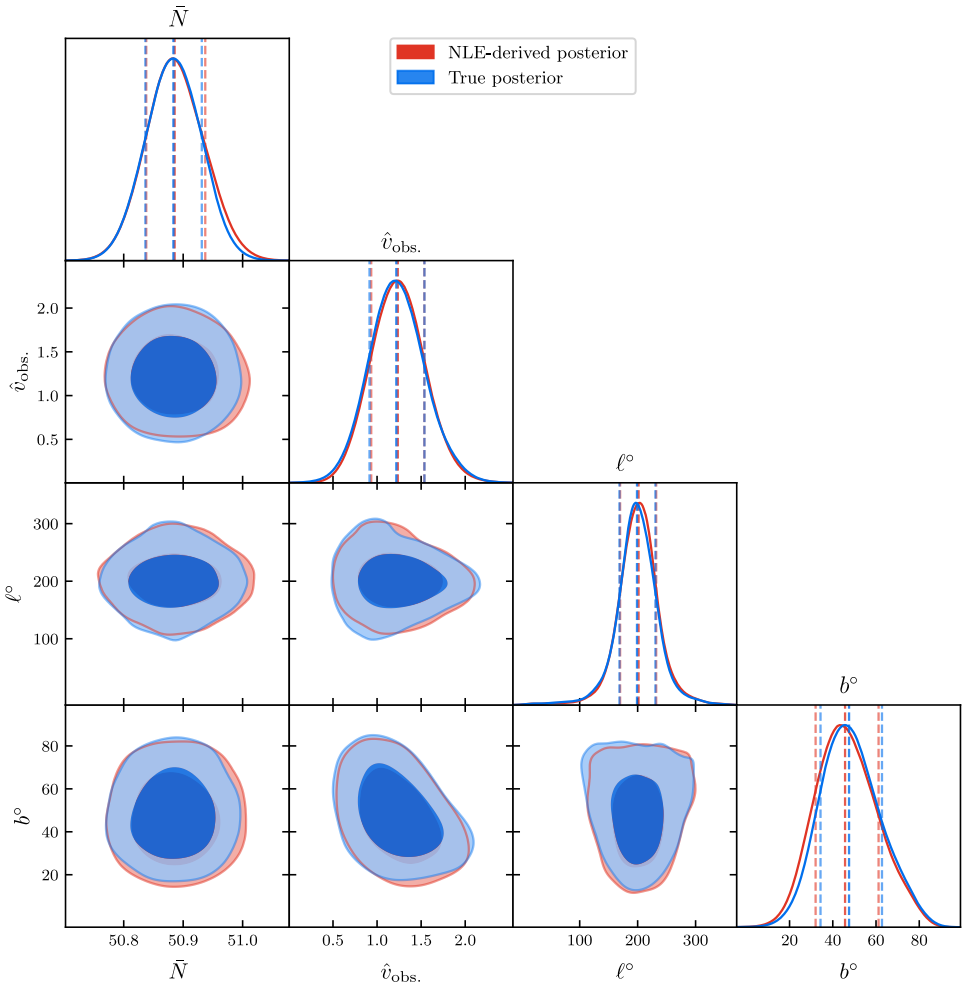
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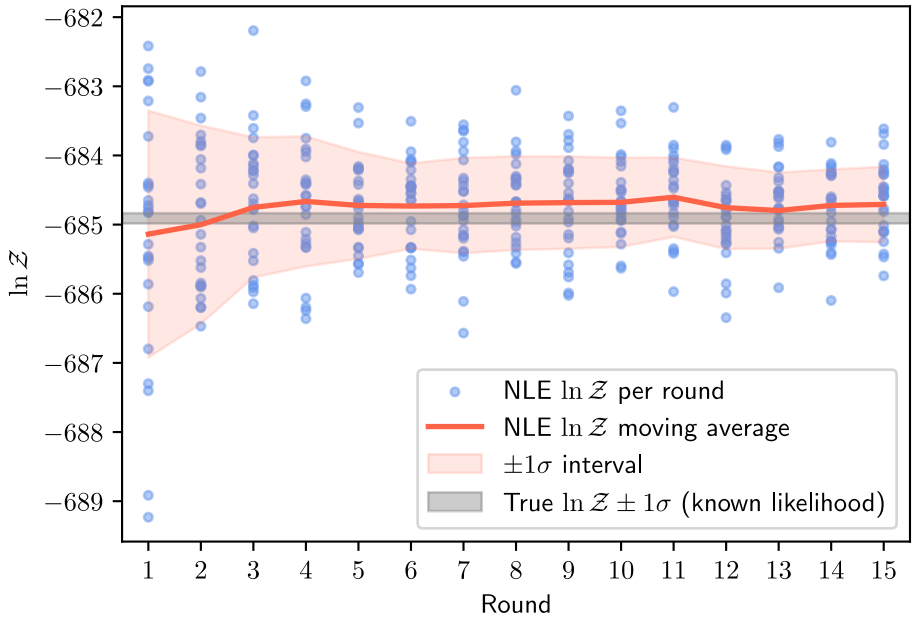
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Appendix

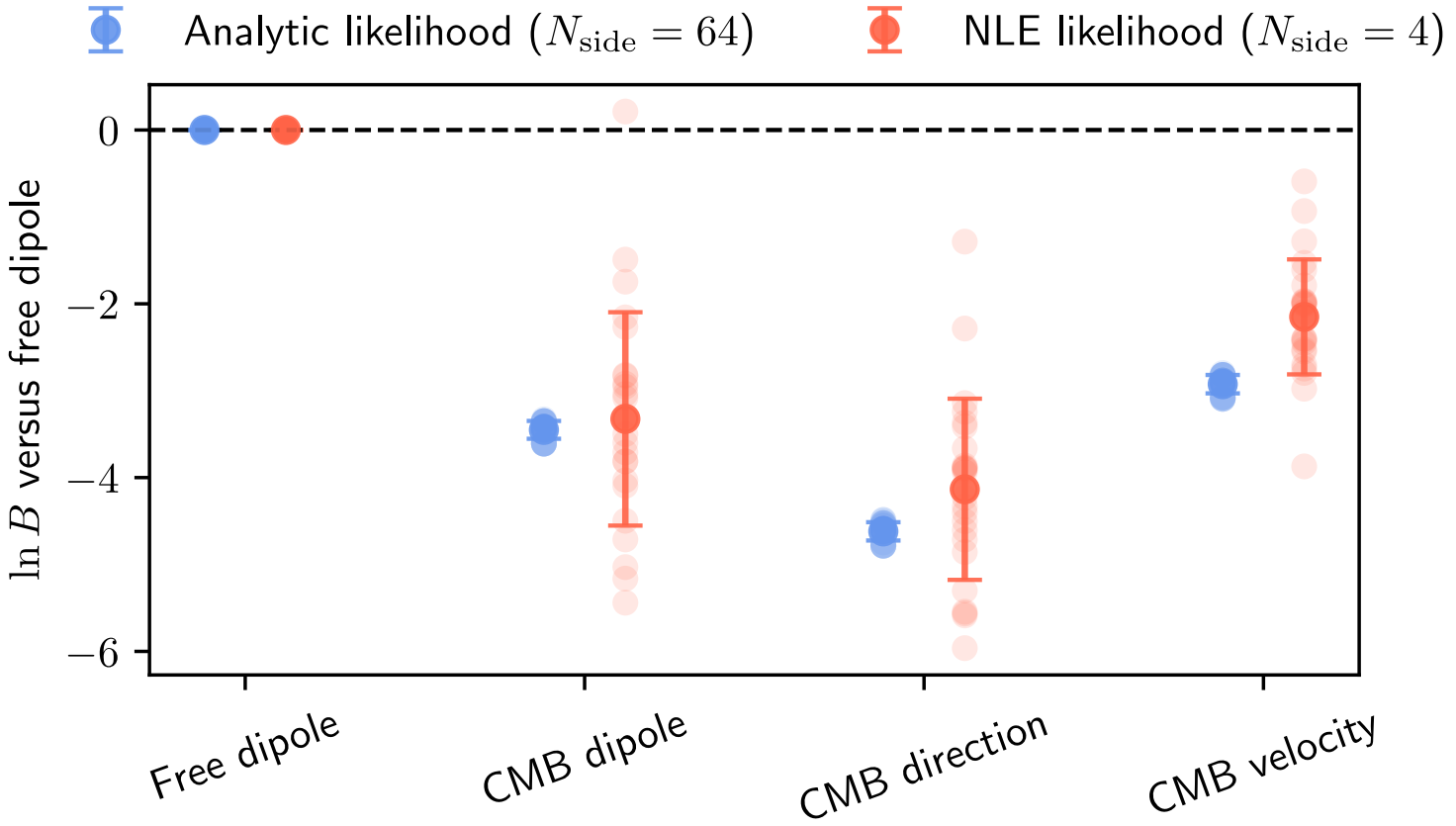
Validation


NLE-derived posterior
True posterior
$\bar{N}$
$\hat{v}_{\mathrm{obs.}}$
$\ell°$
$b°$


NLE $\ln \mathcal{Z}$ per round
NLE $\ln \mathcal{Z}$ moving average
$\pm 1\sigma$ interval
True $\ln \mathcal{Z} \pm 1\sigma$ (known likelihood)
$\ln \mathcal{Z}$
Round

Consistency Check: Bayesian Evidence

- SBI likelihood $\approx$ analytic likelihood
- $N_{\text{side}} = 4 \iff N_{\text{side}} = 64$



Fiducial Model: SNLE vs. SNPE

