From Astrometry to Distances

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ISSS 2019
L'Aquila 06/04/19

Structure

- Astrometric measurement
- Bayesian Inference
- Prior for distance inference
- 6d phasespace including error propagation

Credit: ESA

Gaia vision

- Motion of the star on the sky as seen from L2

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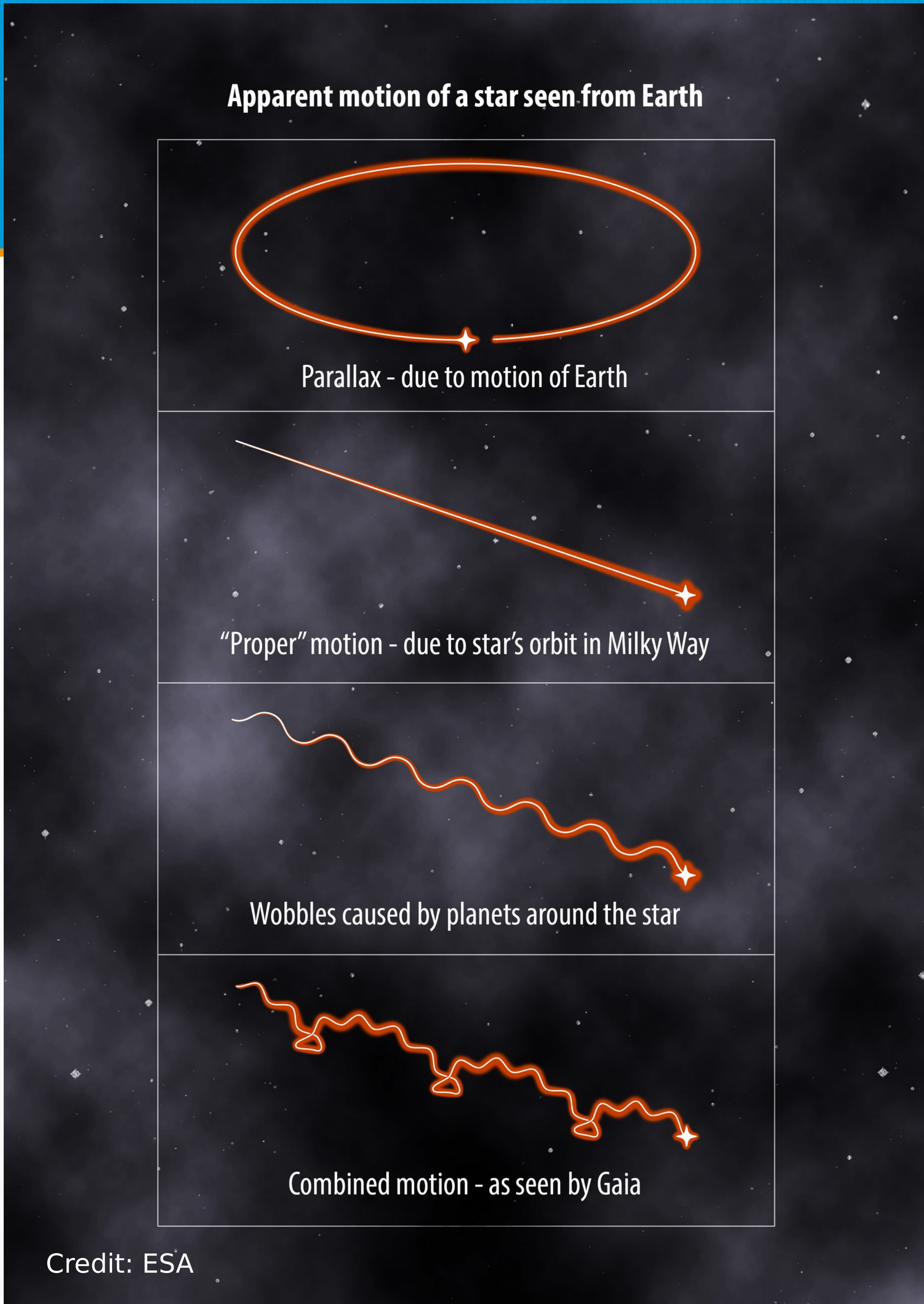

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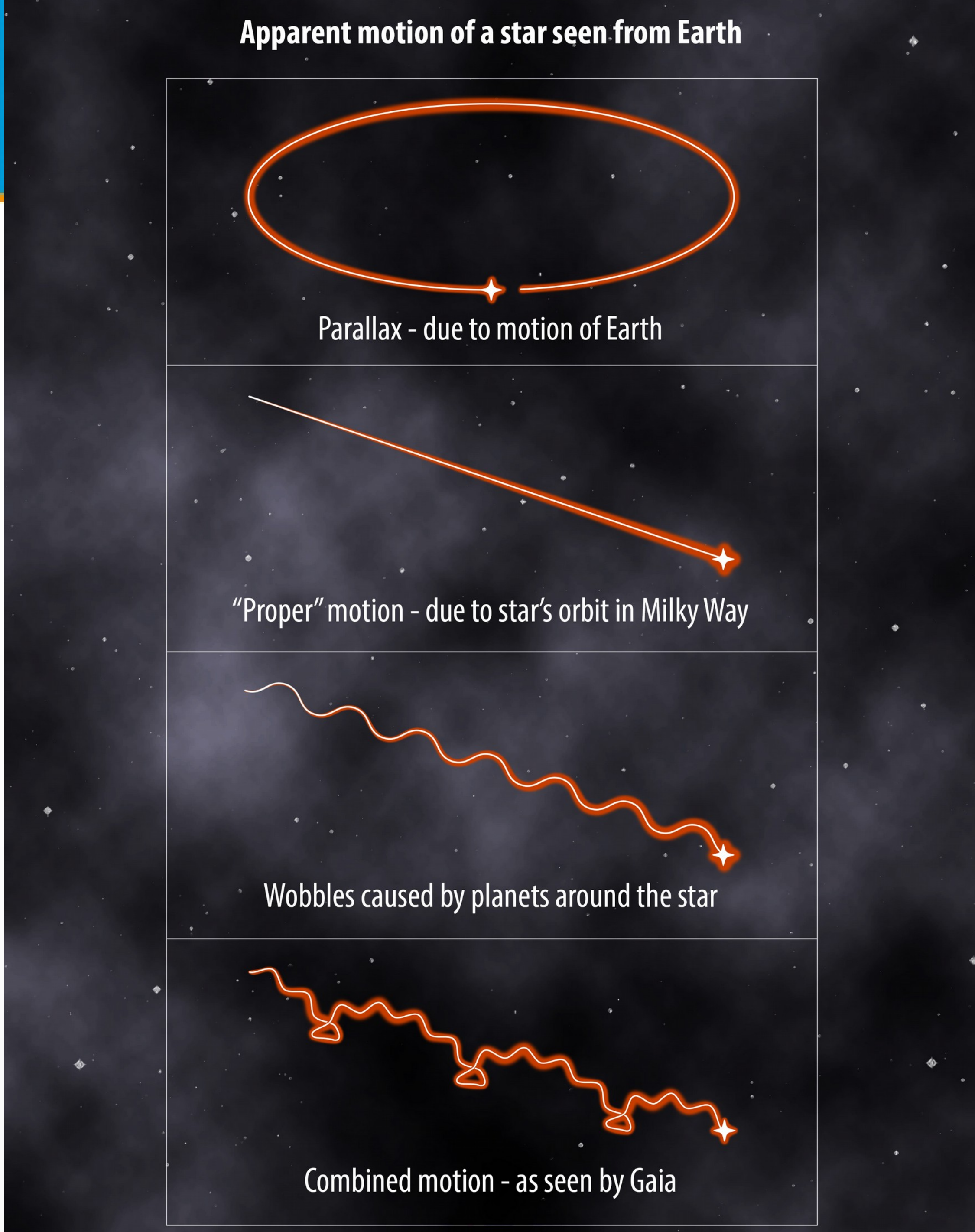
- Motion of the star on the sky as seen from L2
- parsec (pc) → arcsec (as)
  - 30 arcmin ~ Moon / Sun
  - 1 arcmin ~ eye's resolution
  - 1 as ~ 1cent in 4km
  - 20 µas ~ Gaia uncertainty



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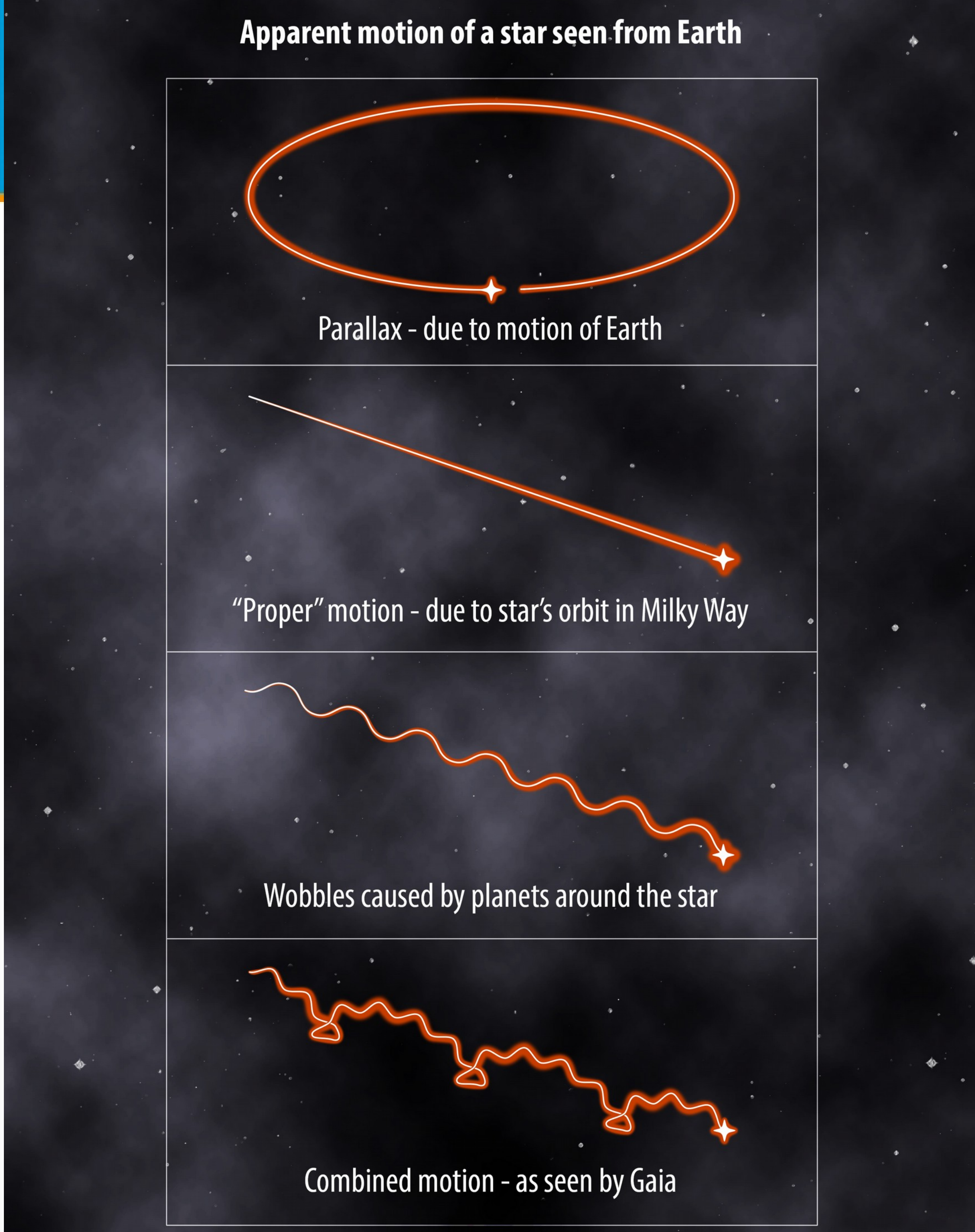

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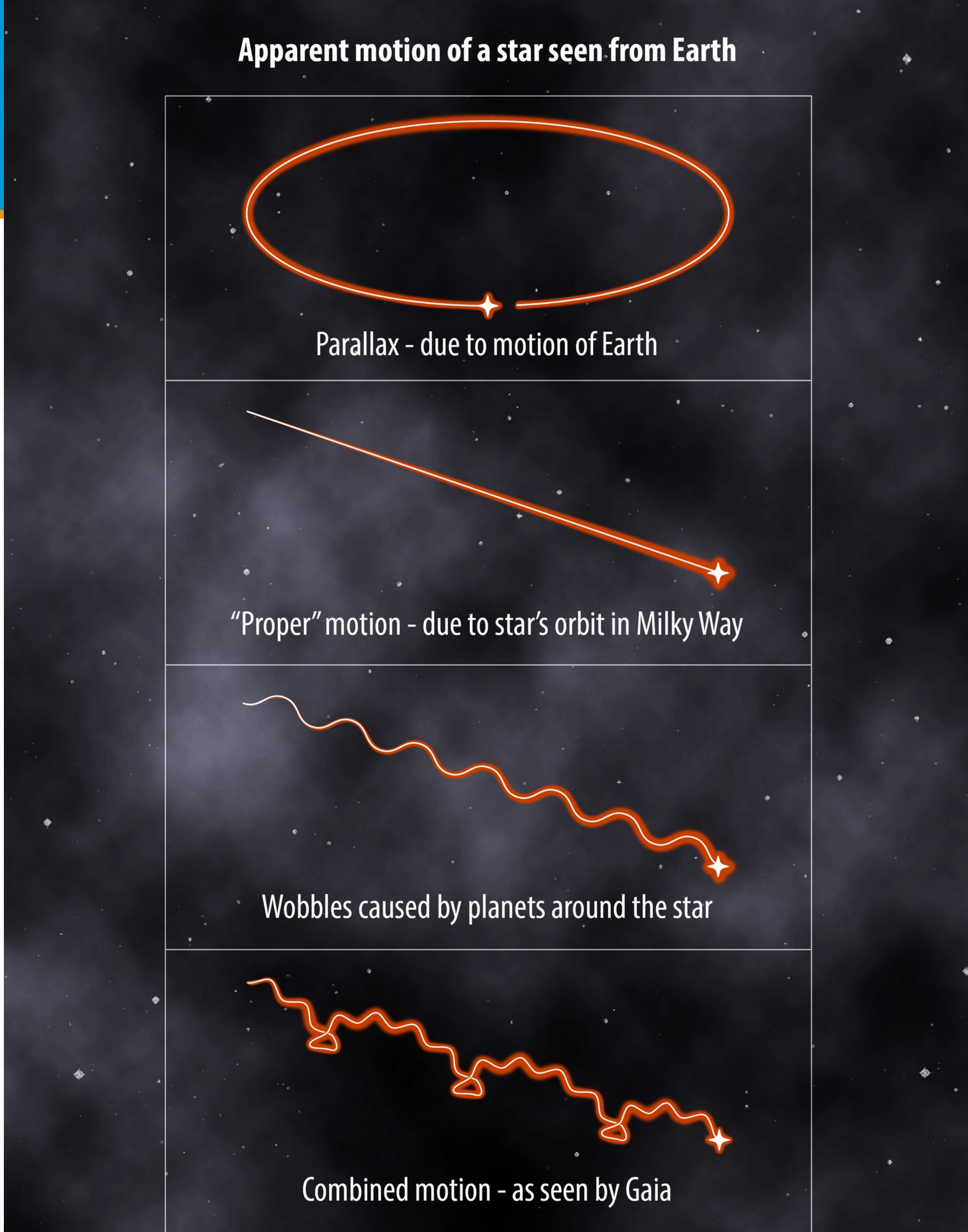
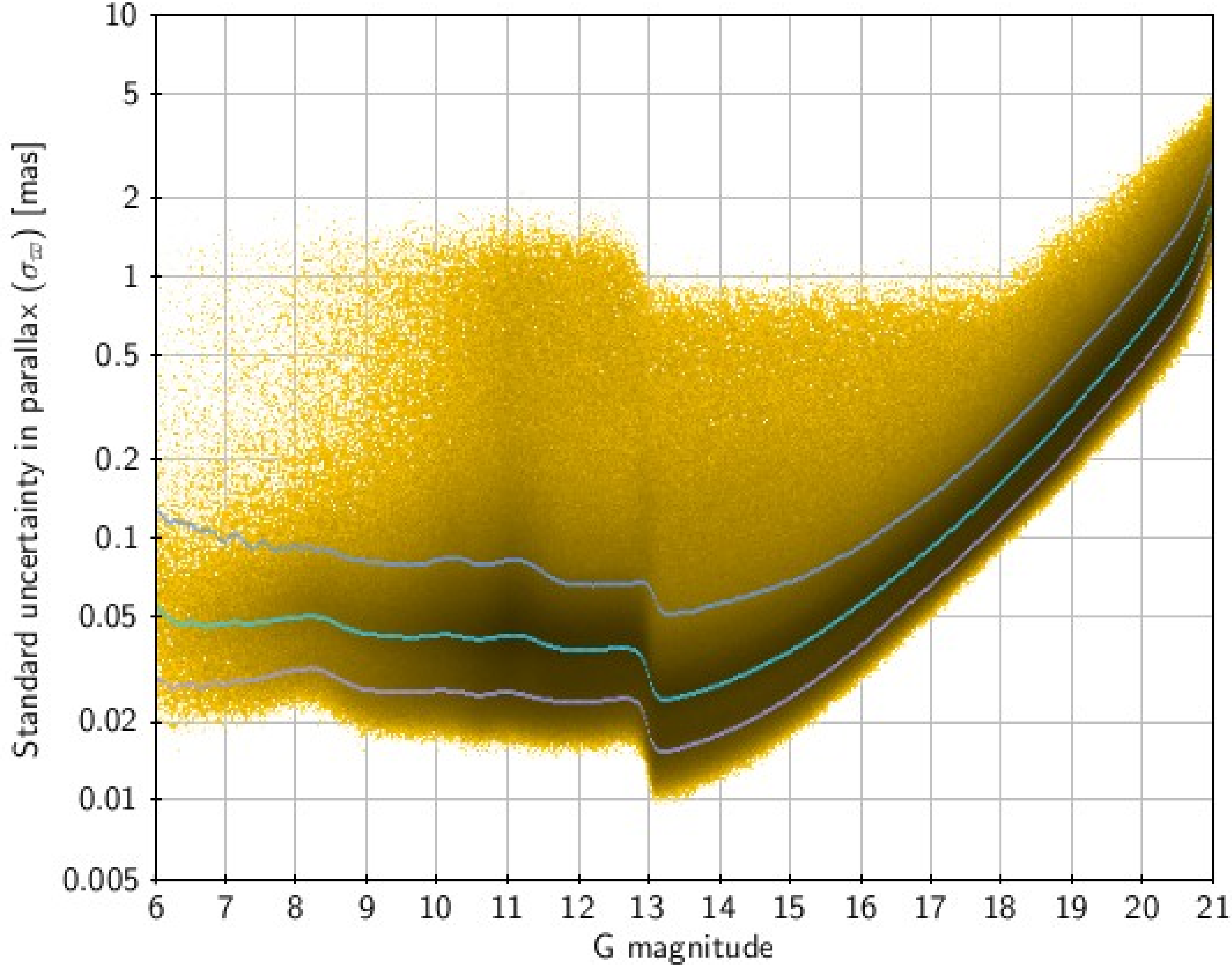
- Parallax uncertainty dependent on G and N_obs



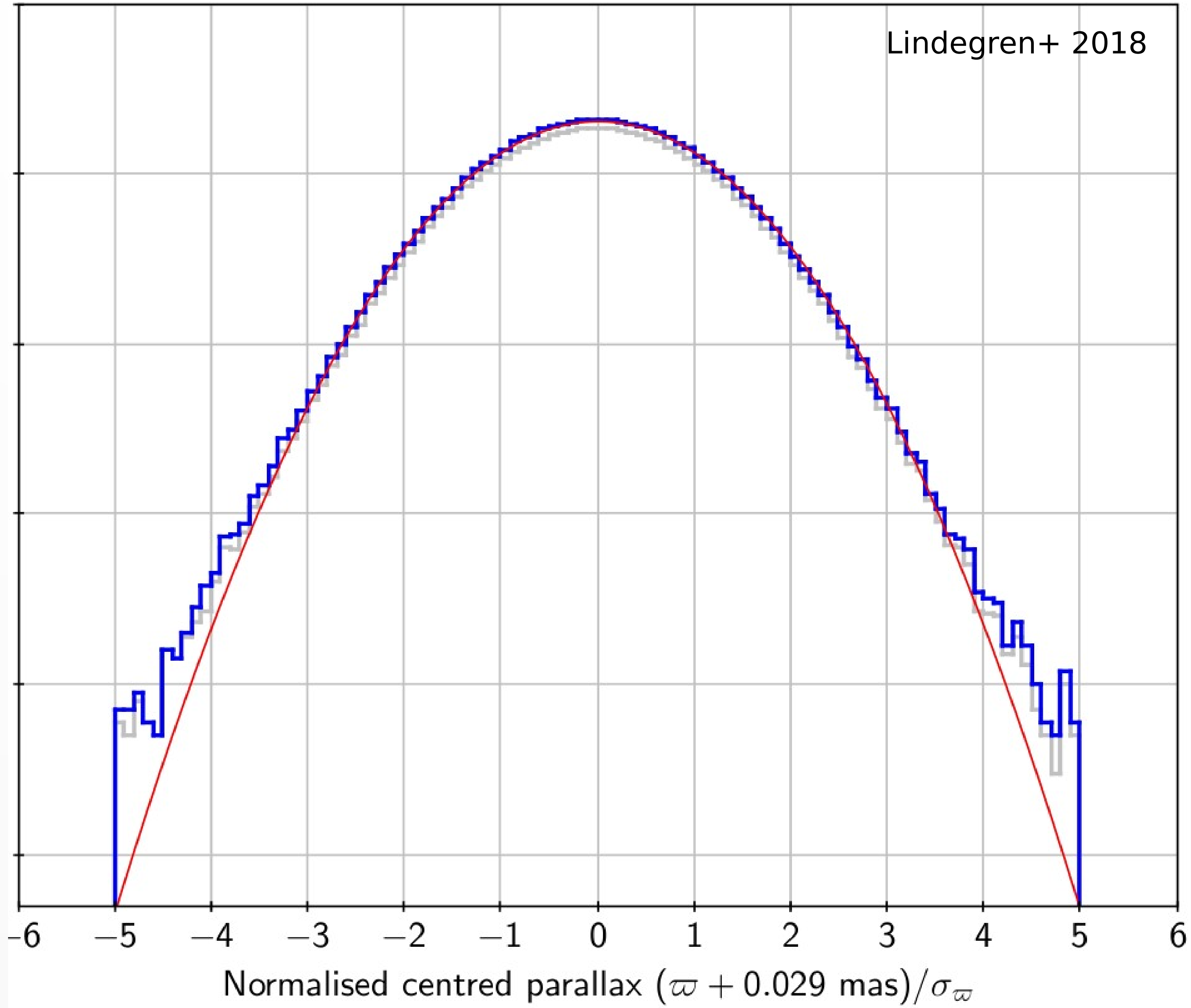
Credit: ESA

Parallax uncertainty



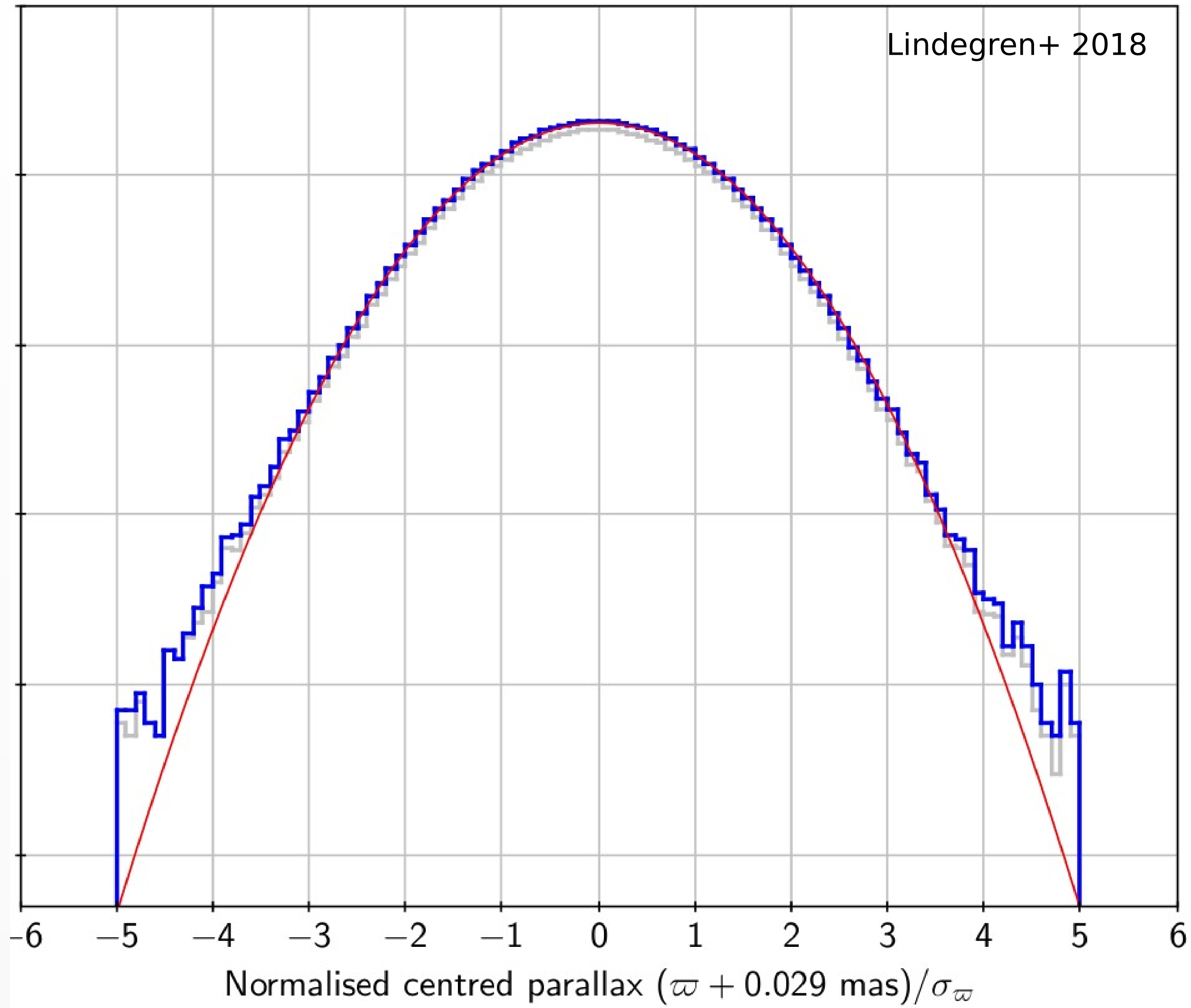
Lindegren+ 2018

Parallax measurement



Parallax measurement

- Is Gaussian



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- Is Gaussian
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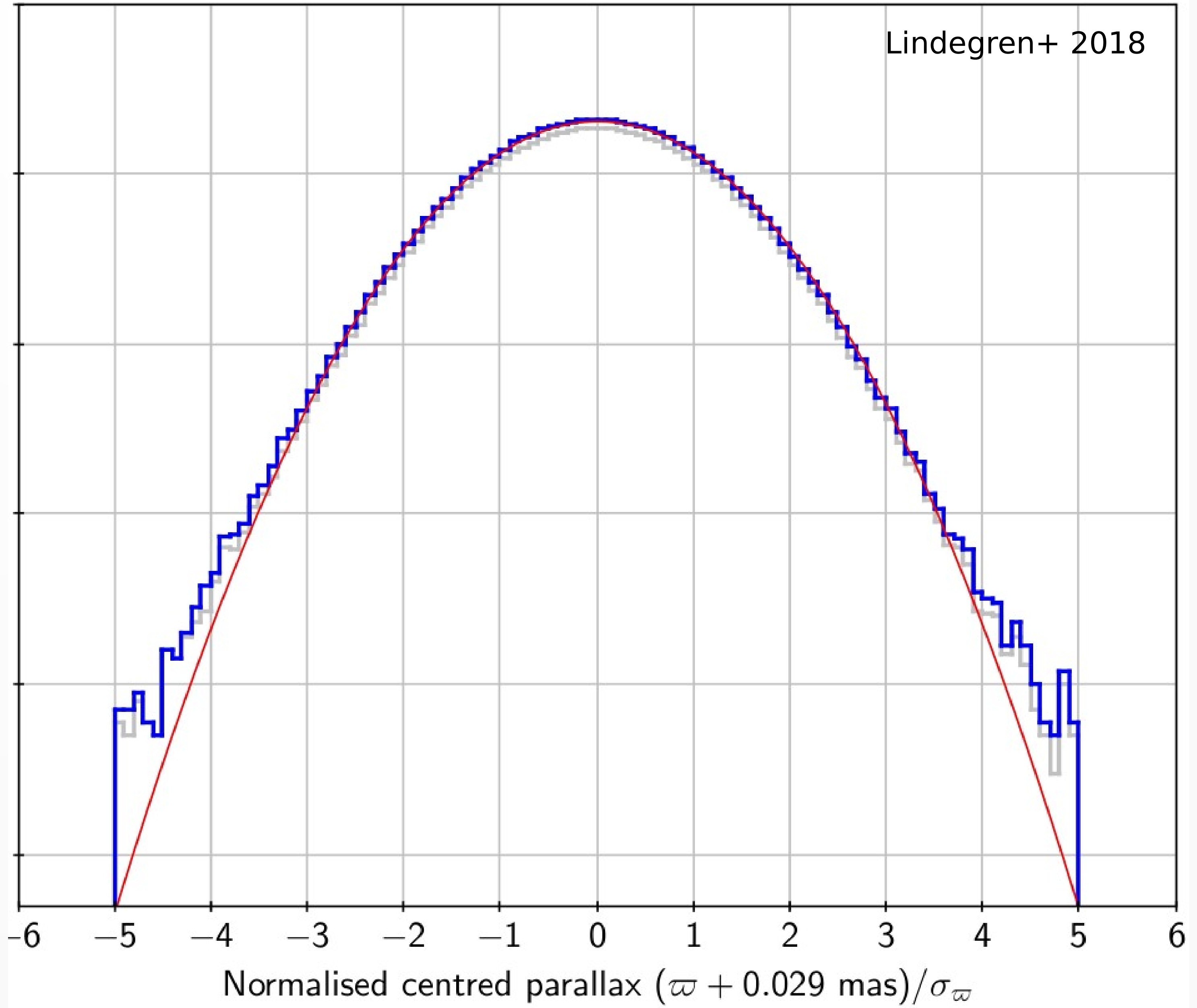

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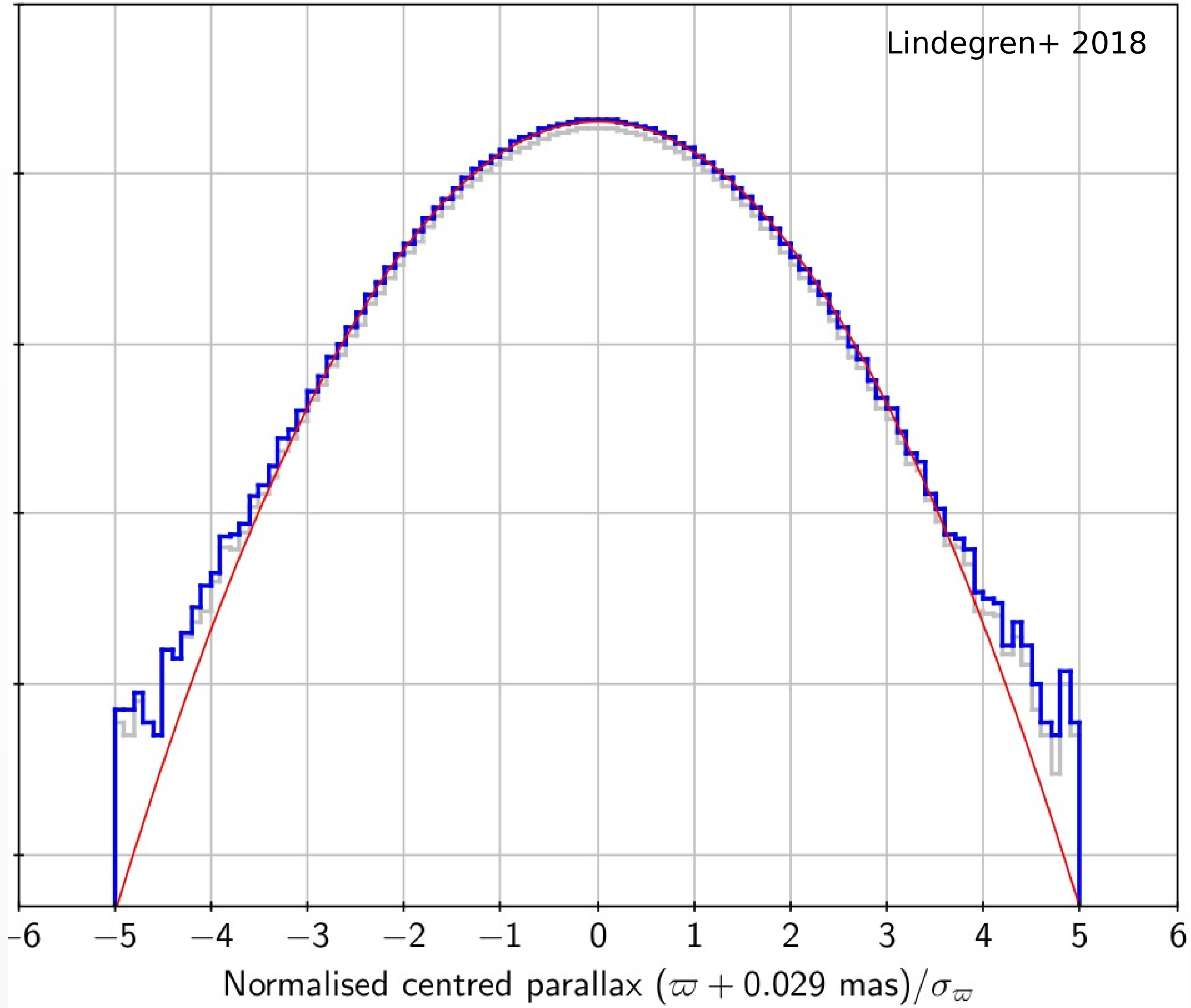

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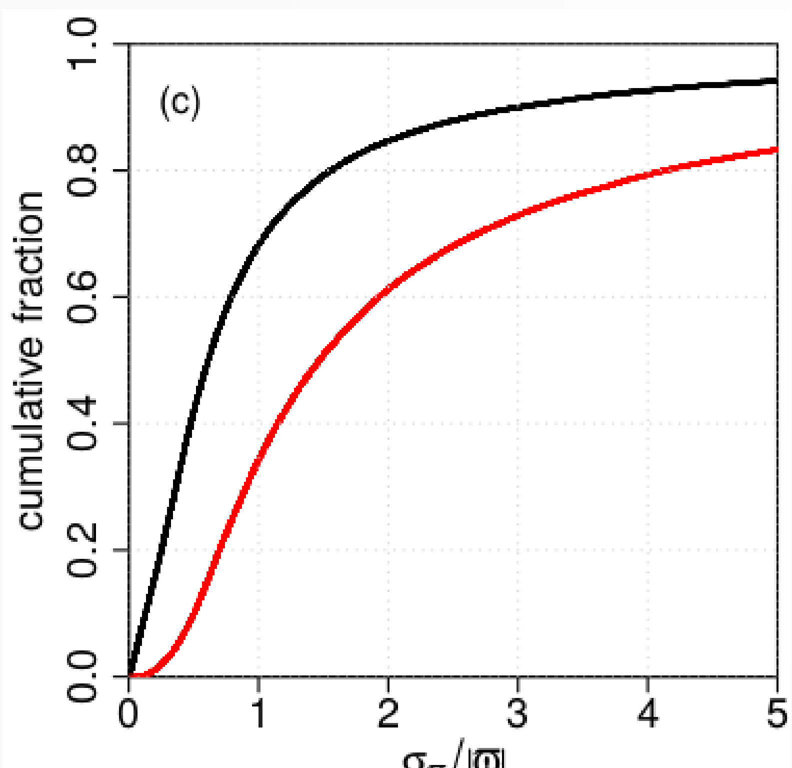
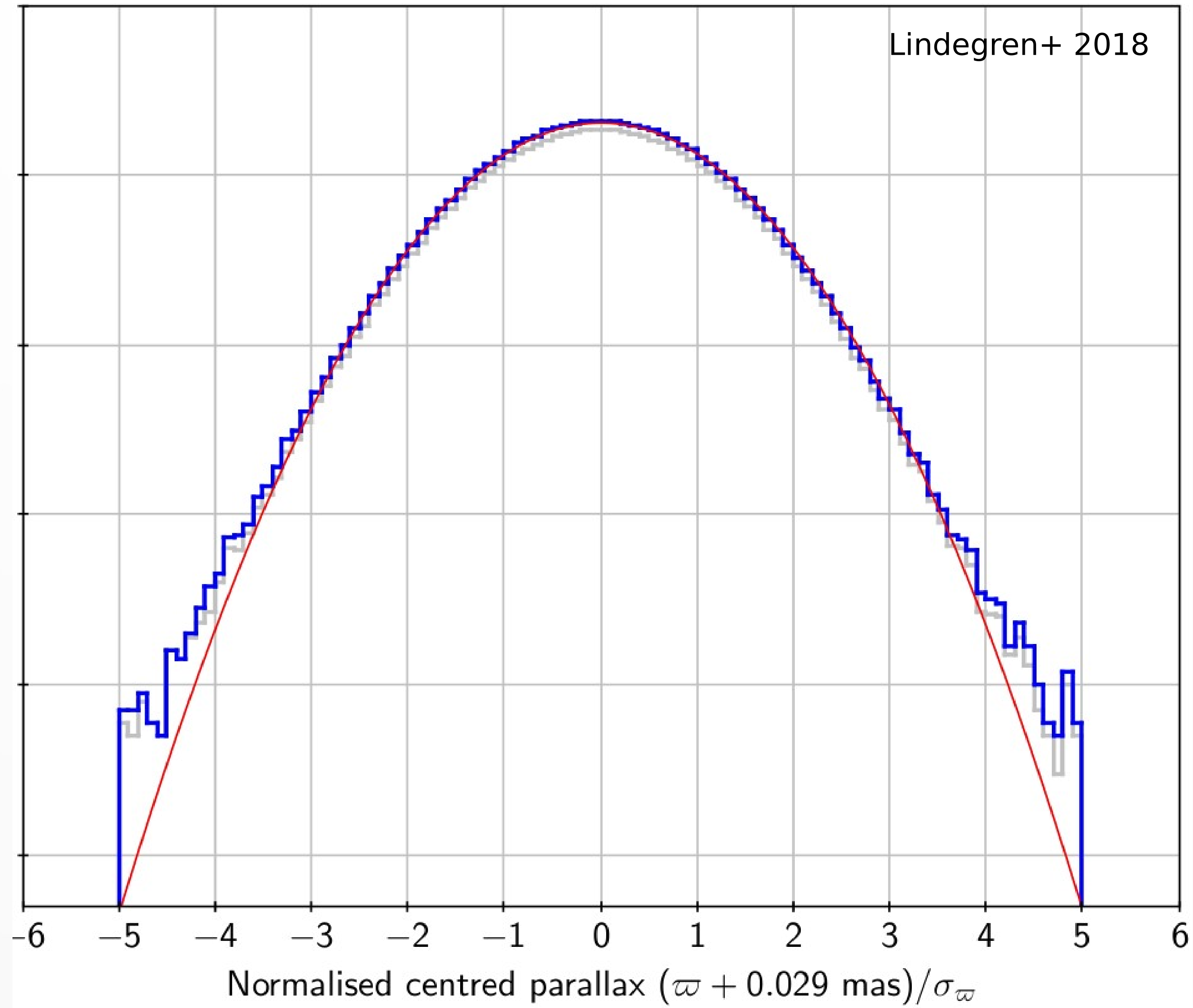
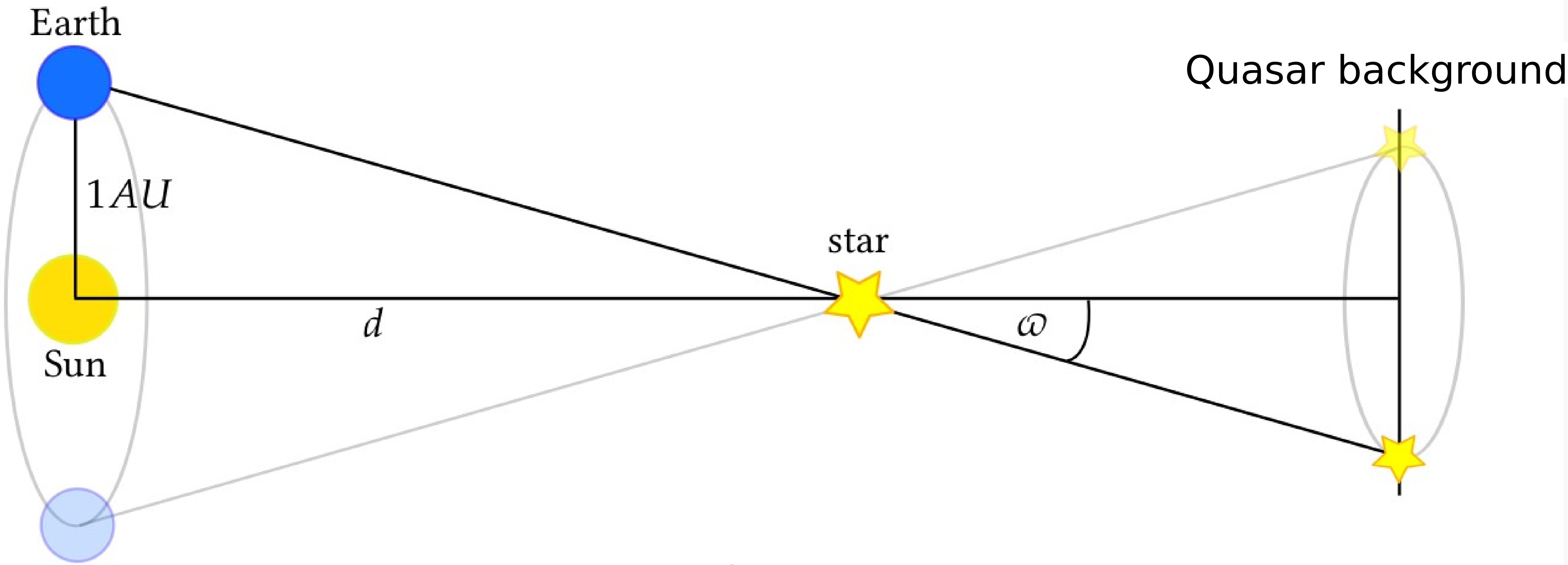




Measurement model

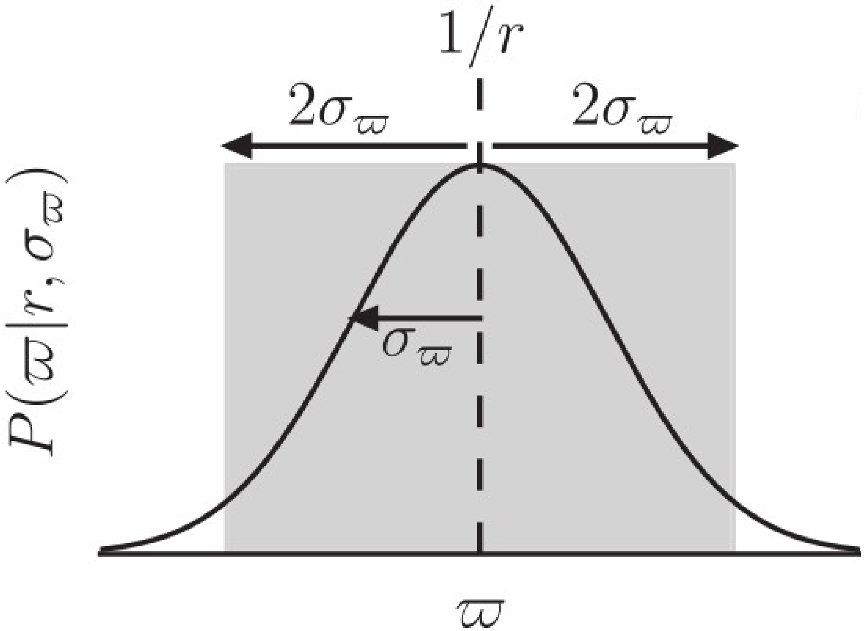


$$\frac{AU}{d} = \tan(\varpi) \simeq \varpi$$

$$d[pc], \varpi[as]$$

Likelihood function

$$P(\varpi|r, \sigma_\varpi) = \frac{1}{\sqrt{2\pi}\,\sigma_\varpi} \exp\left[-\frac{1}{2\sigma_\varpi^2}\left(\varpi - \frac{1}{r}\right)^2\right], \quad \sigma_\varpi \geqslant 0$$



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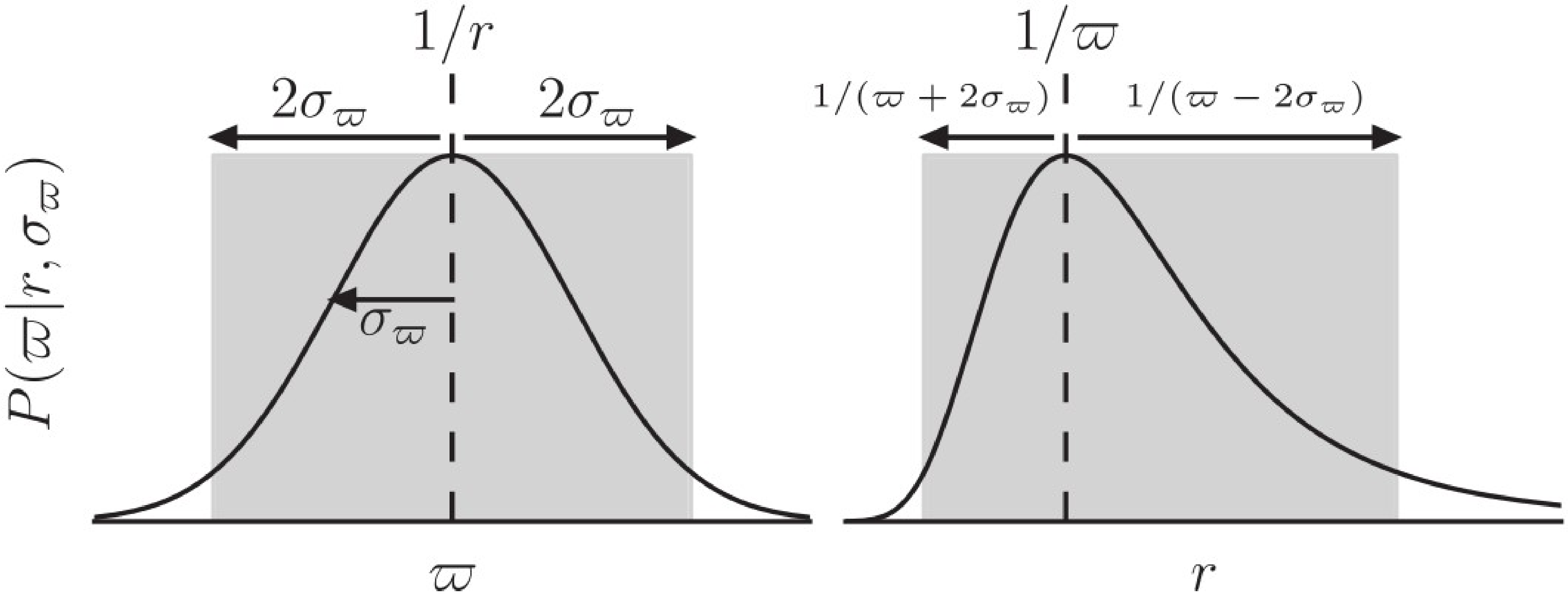
$\sigma_{\varpi}/\varpi = 0.2$



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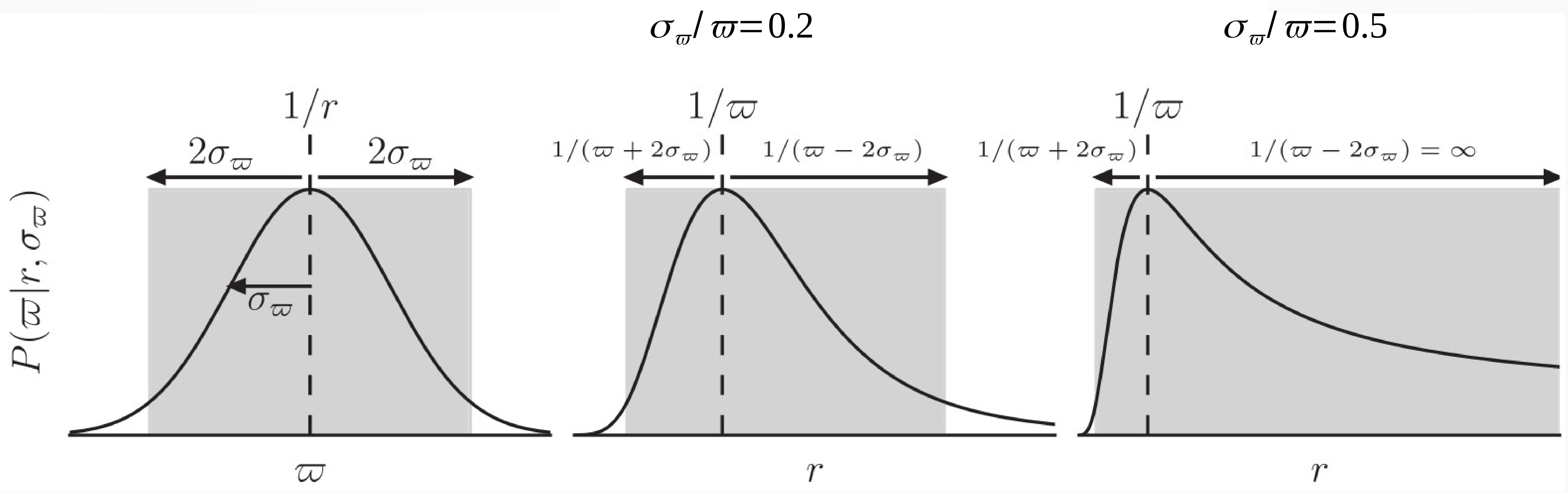

Bayesian parameter estimation

$$Posterior: P(r \mid \varpi) = \frac{Likelihood \cdot Prior}{Evidence}$$

Bayesian parameter estimation

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$$Likelihood: P(\varpi|r)$$

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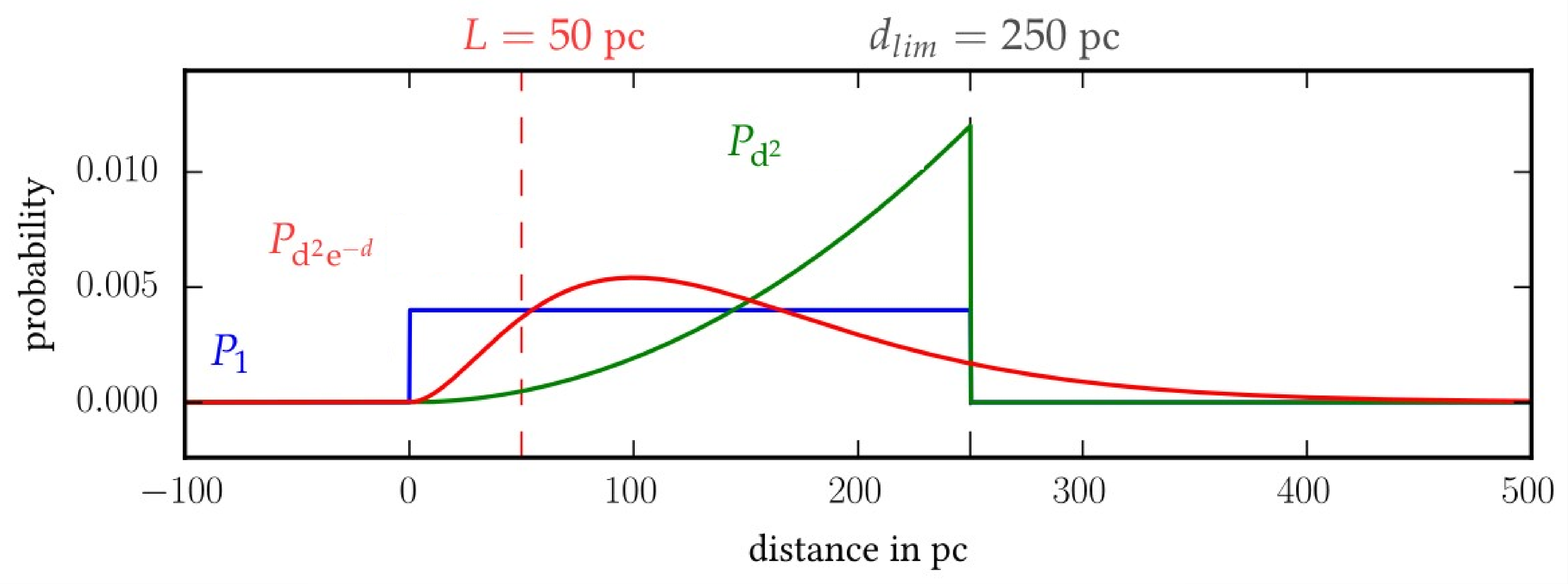
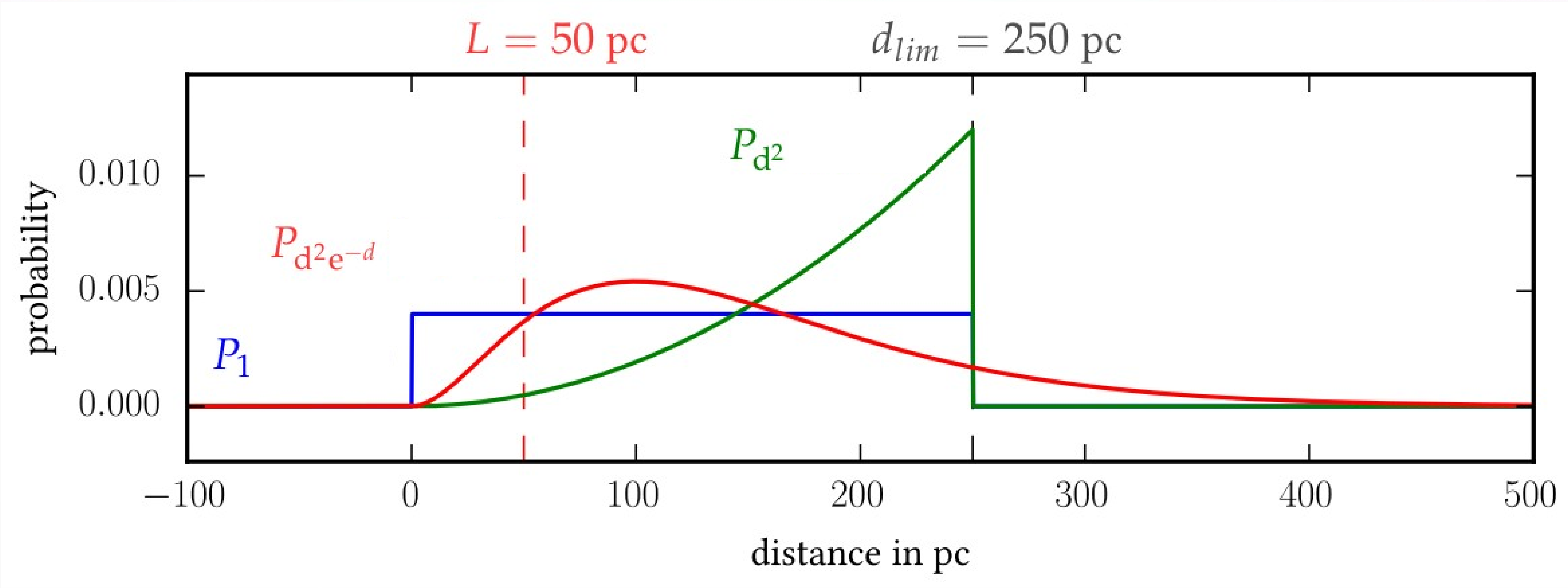
$$Evidence: \int_{r=0}^{r=\infty} Posterior$$

Prior



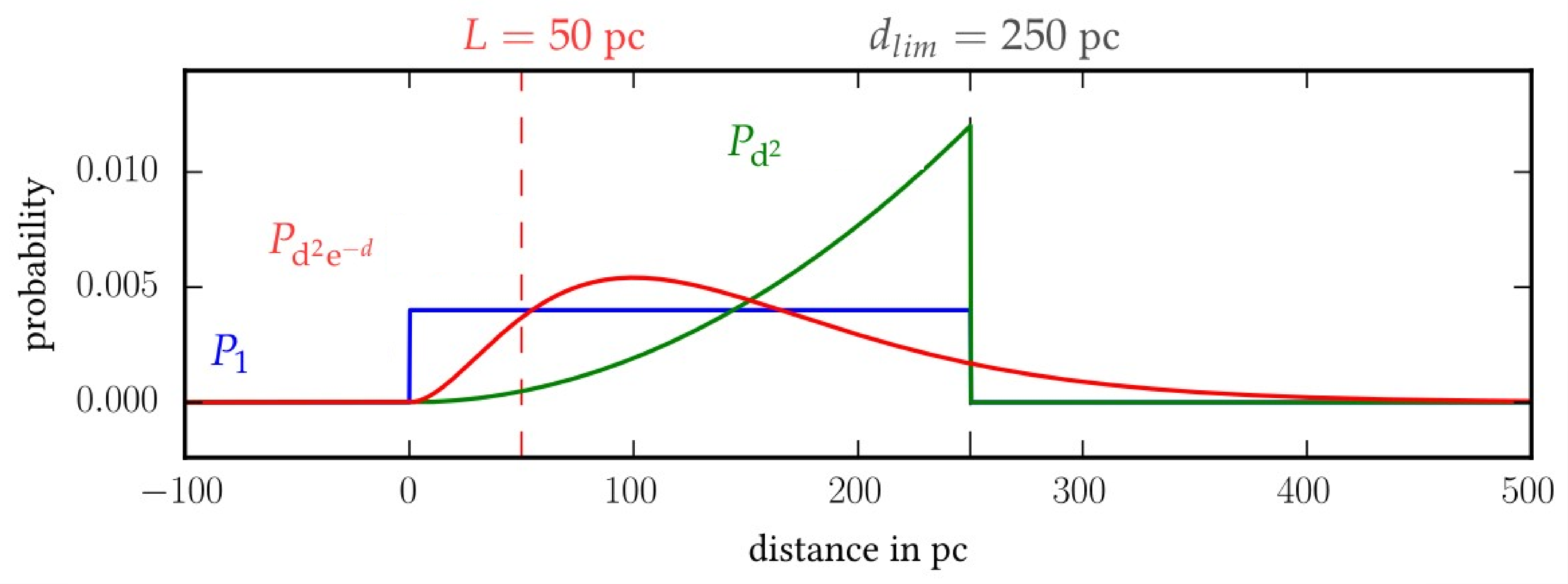
$L = 50$ pc
$d_{lim} = 250$ pc
P_{d^2}
$P_{d^2e^{-d}}$
P_1
probability
0.010
0.005
0.000
−100
0
100
200
300
400
500
distance in pc

Prior



- Exponentially decreasing volume density prior

Prior



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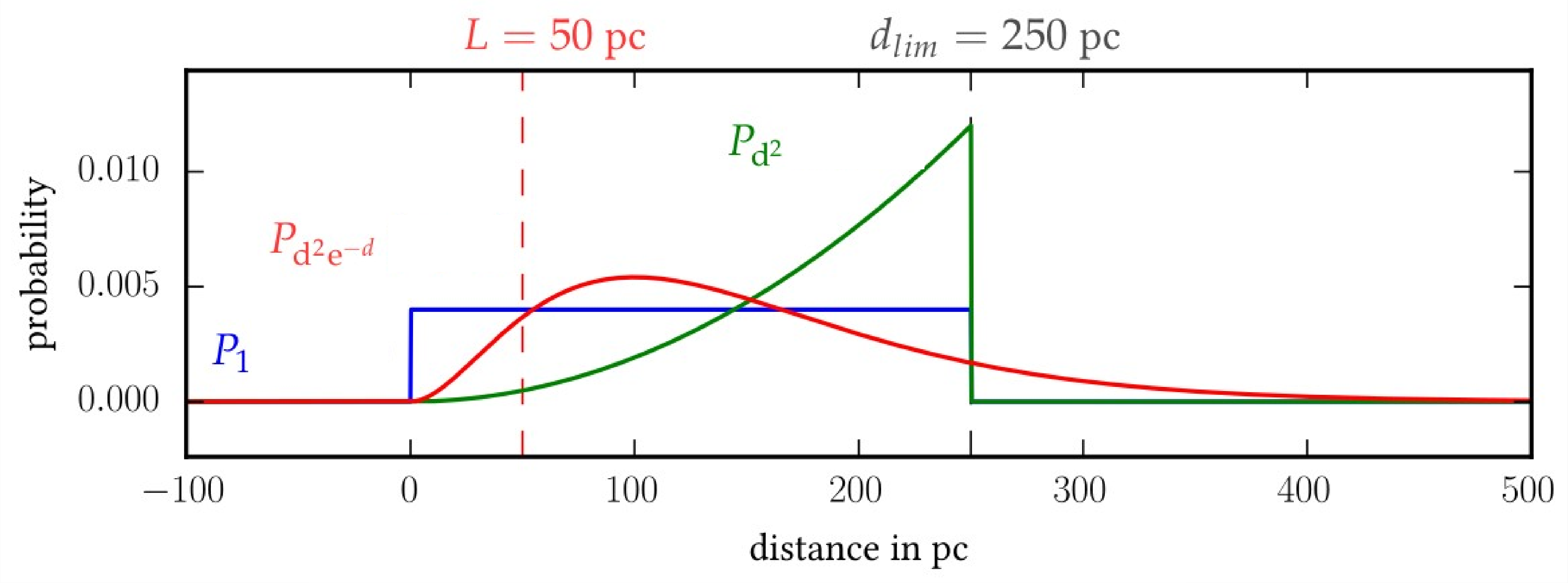
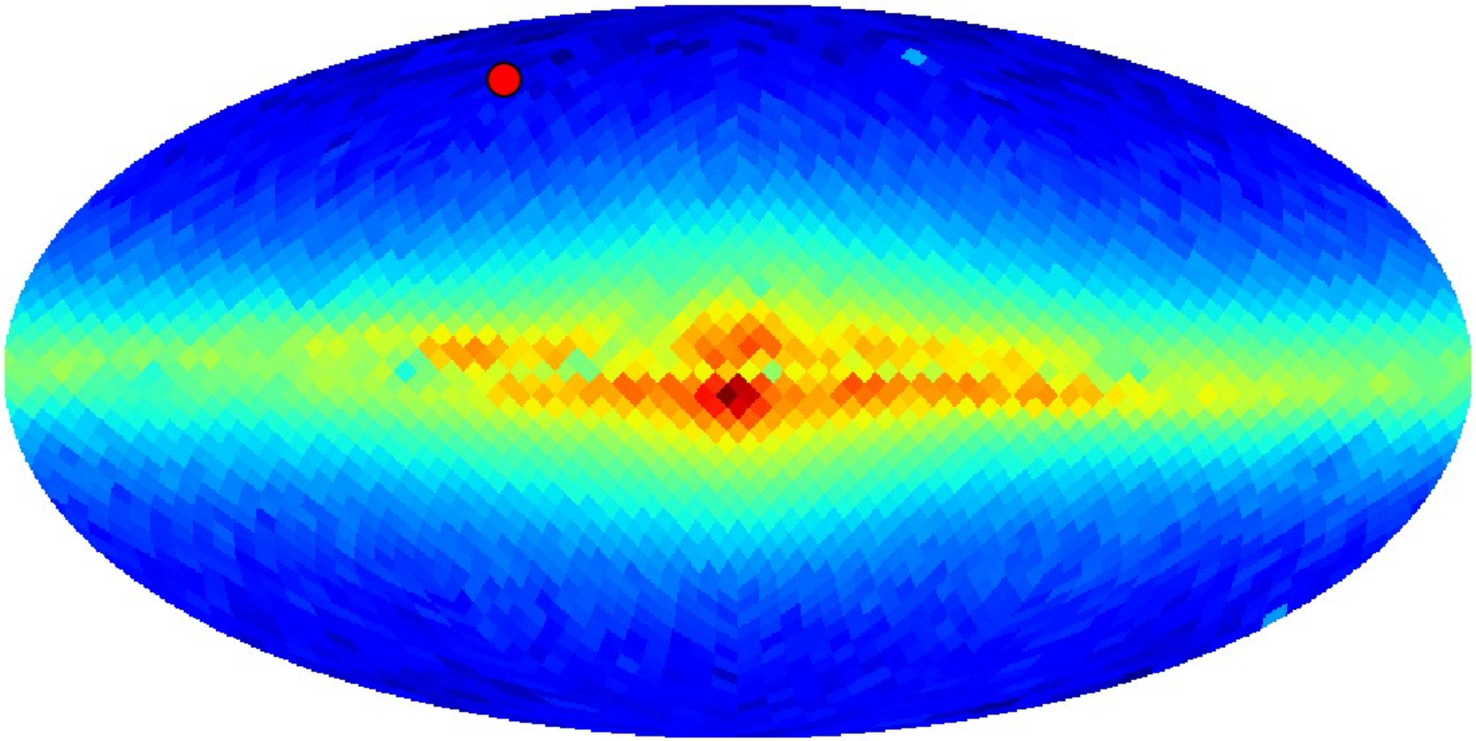
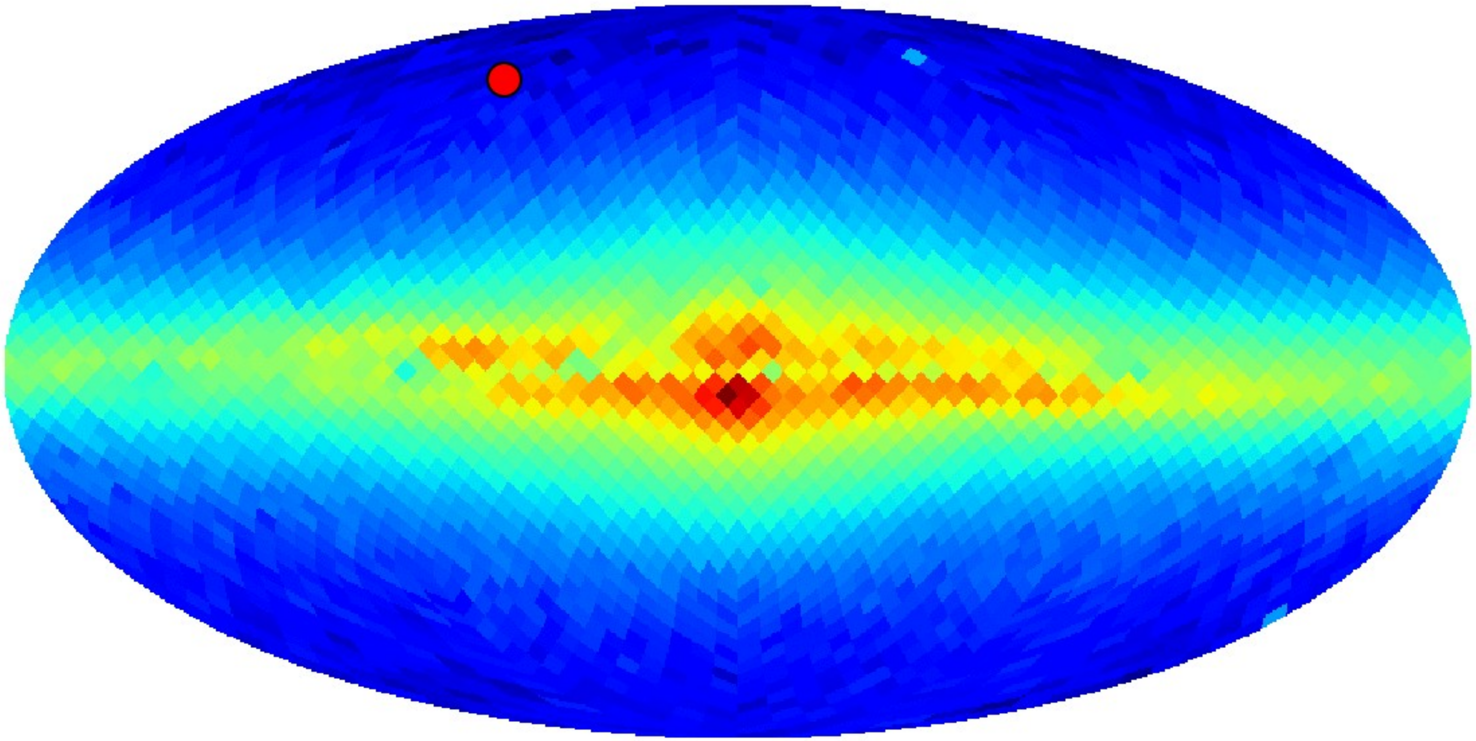
- Bailer-Jones+2018: L_prior(l,b)

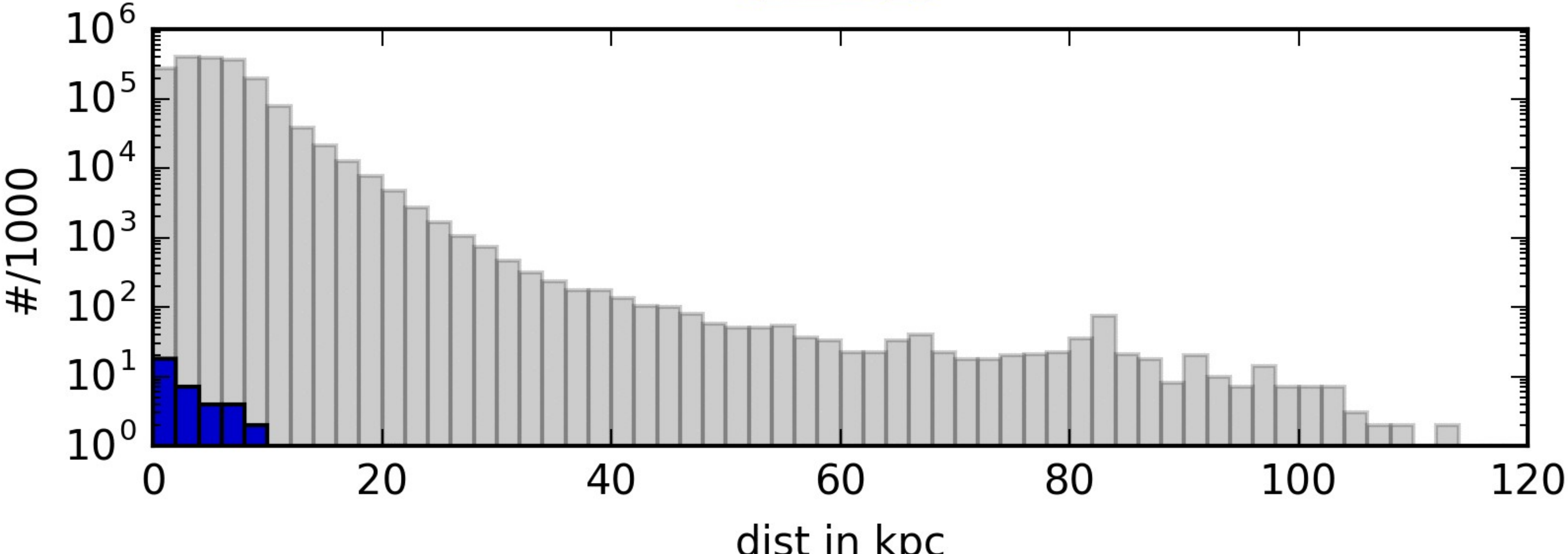
Prior



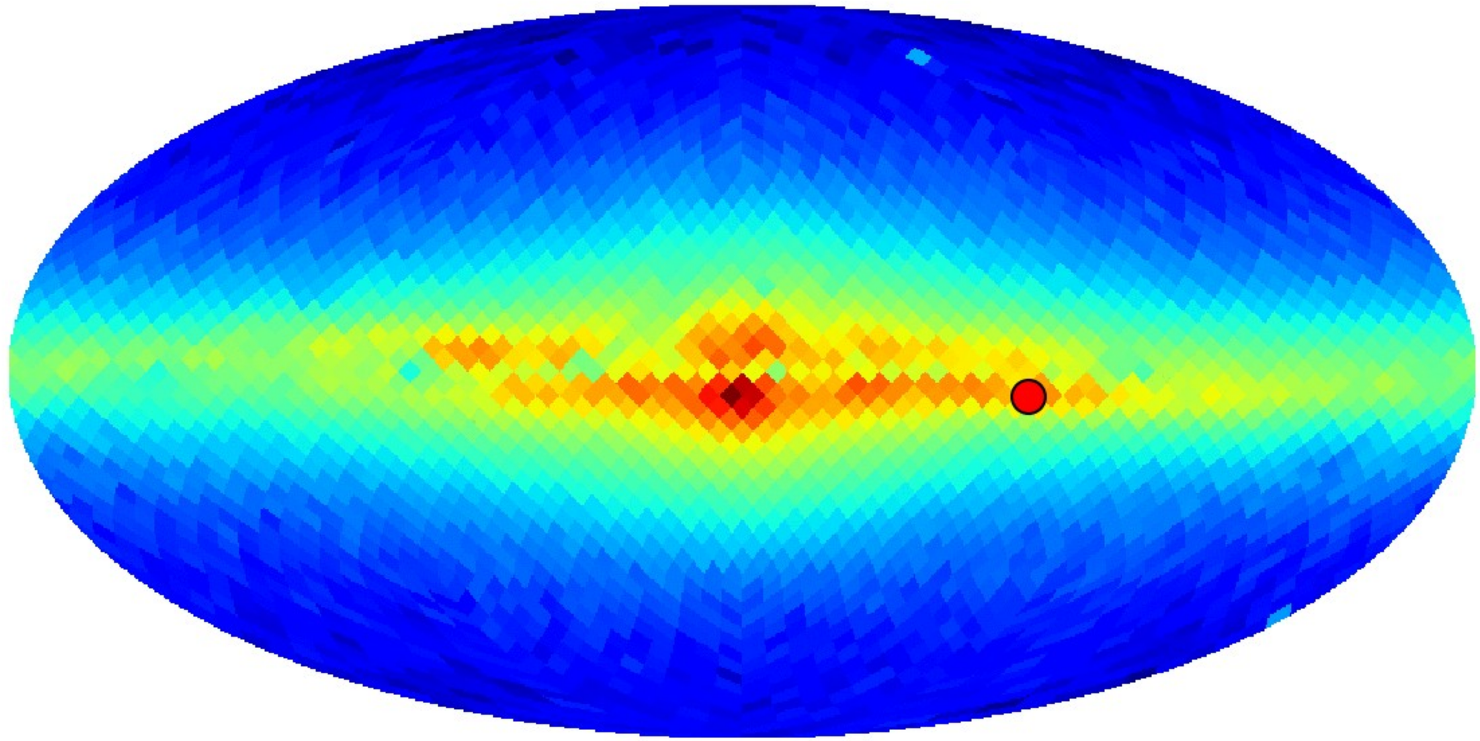
- Exponentially decreasing volume density prior
- Bailer-Jones+2018: L_prior(l,b)
- GDR2mock as spin-off (Rybizki+ 2018)

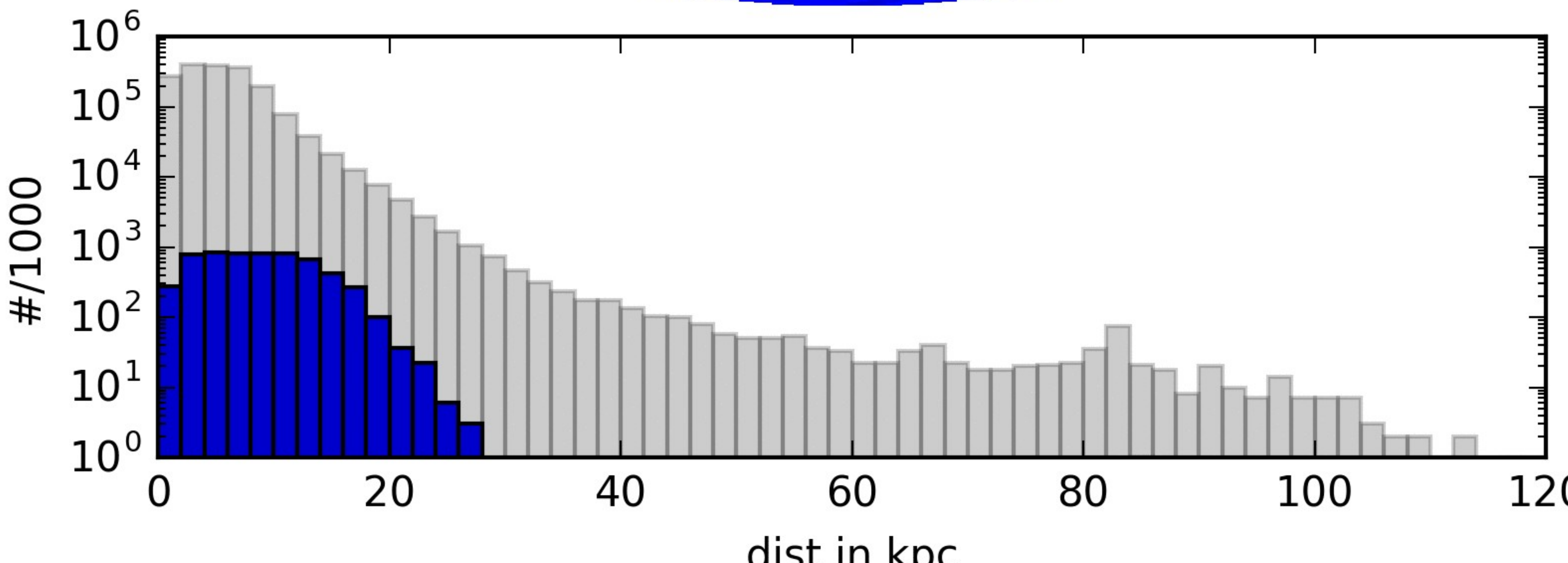






10^6
10^5
10^4
10^3
10^2
10^1
10^0
#/1000
0
20
40
60
80
100
120
dist in kpc





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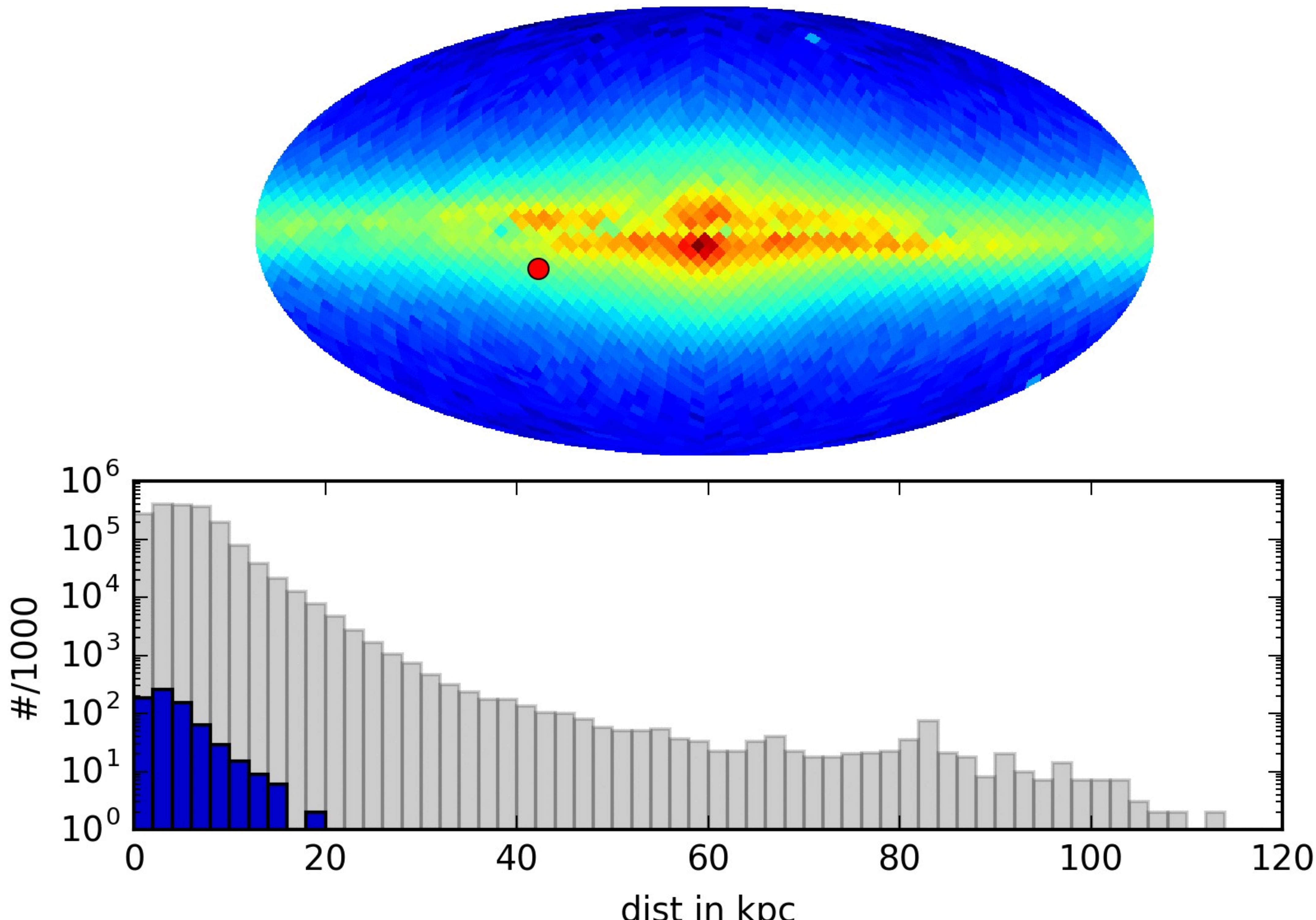

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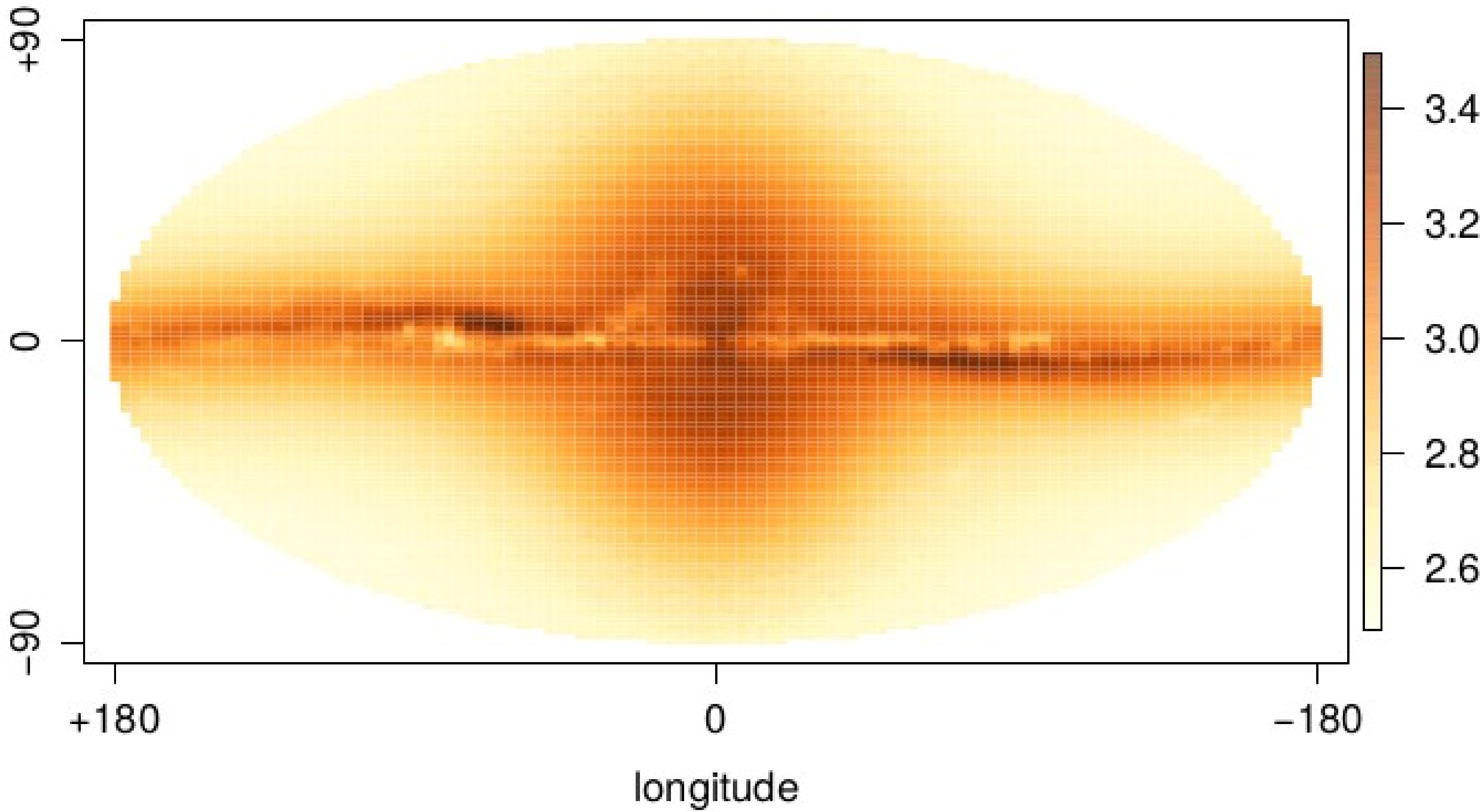
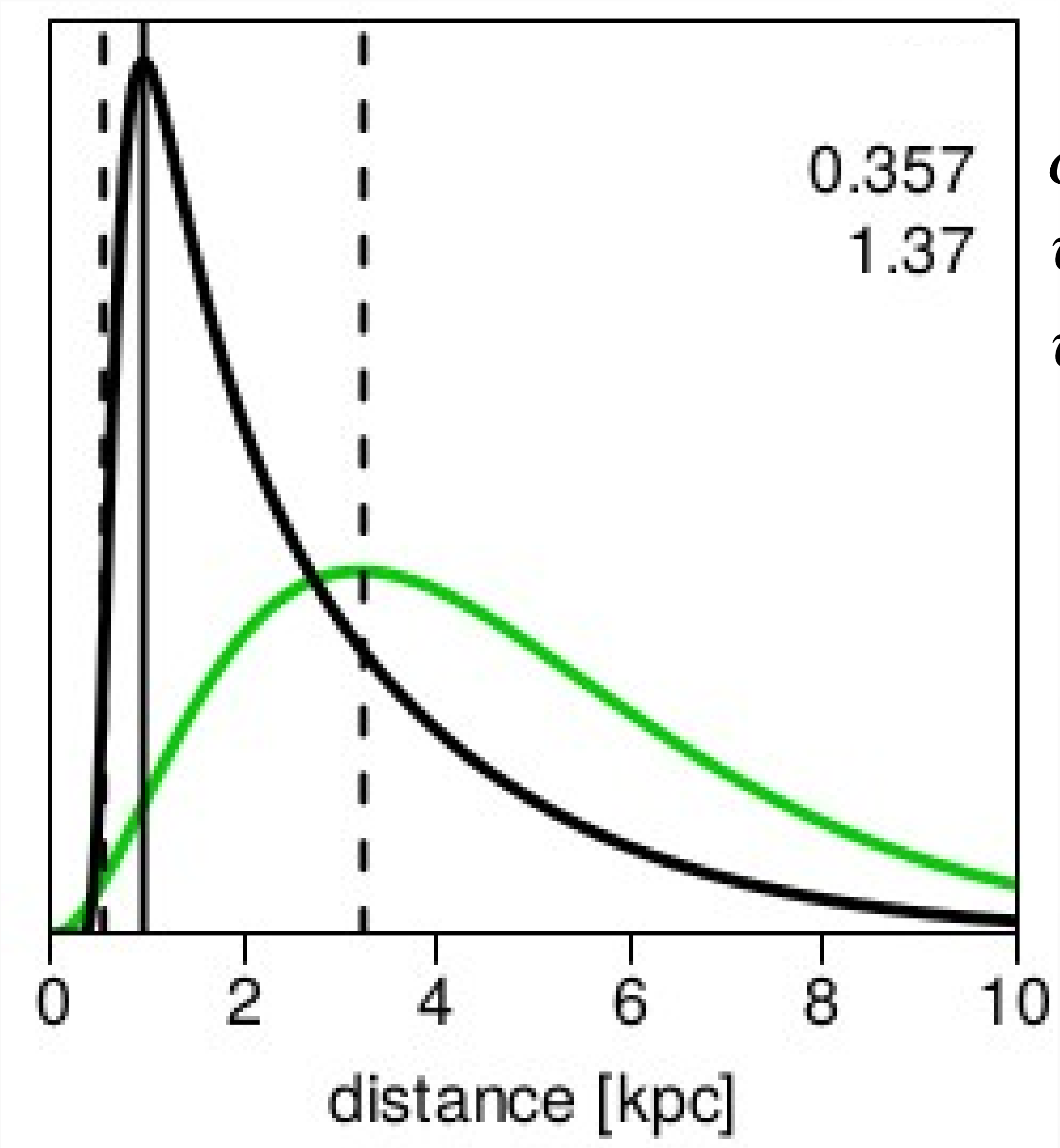
Prior Lengthscale(l,b)



Posterior Highest Density Interval



σ_{ϖ} / ϖ

$\varpi [mas]$

$\varpi^{-1} = 0.73\, kpc$

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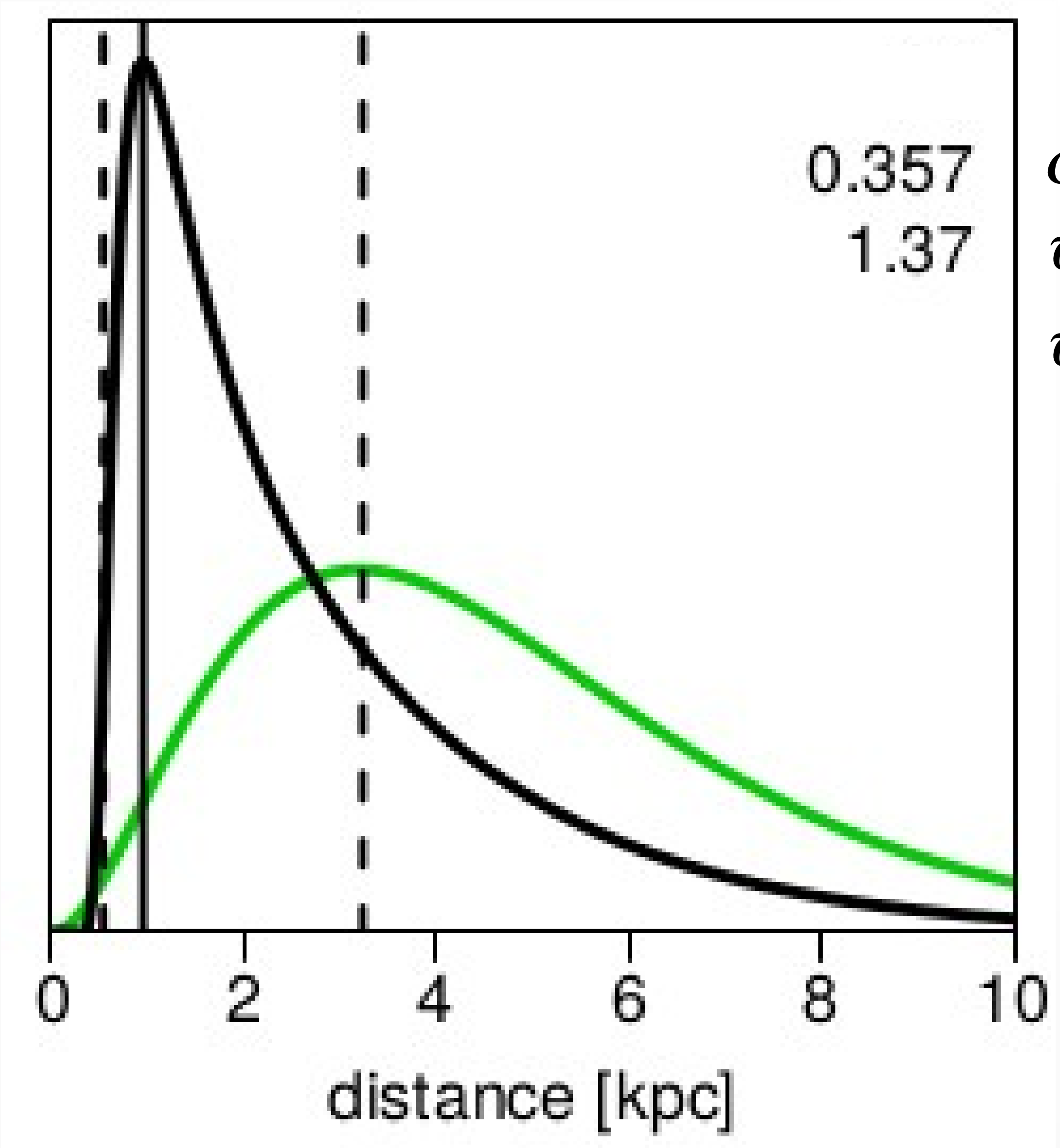

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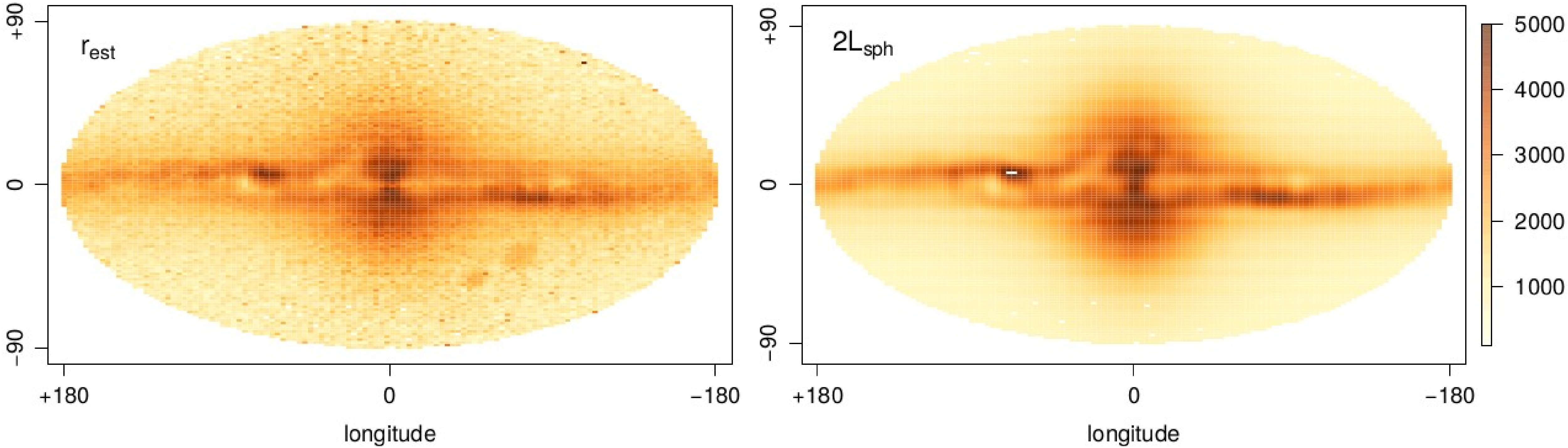
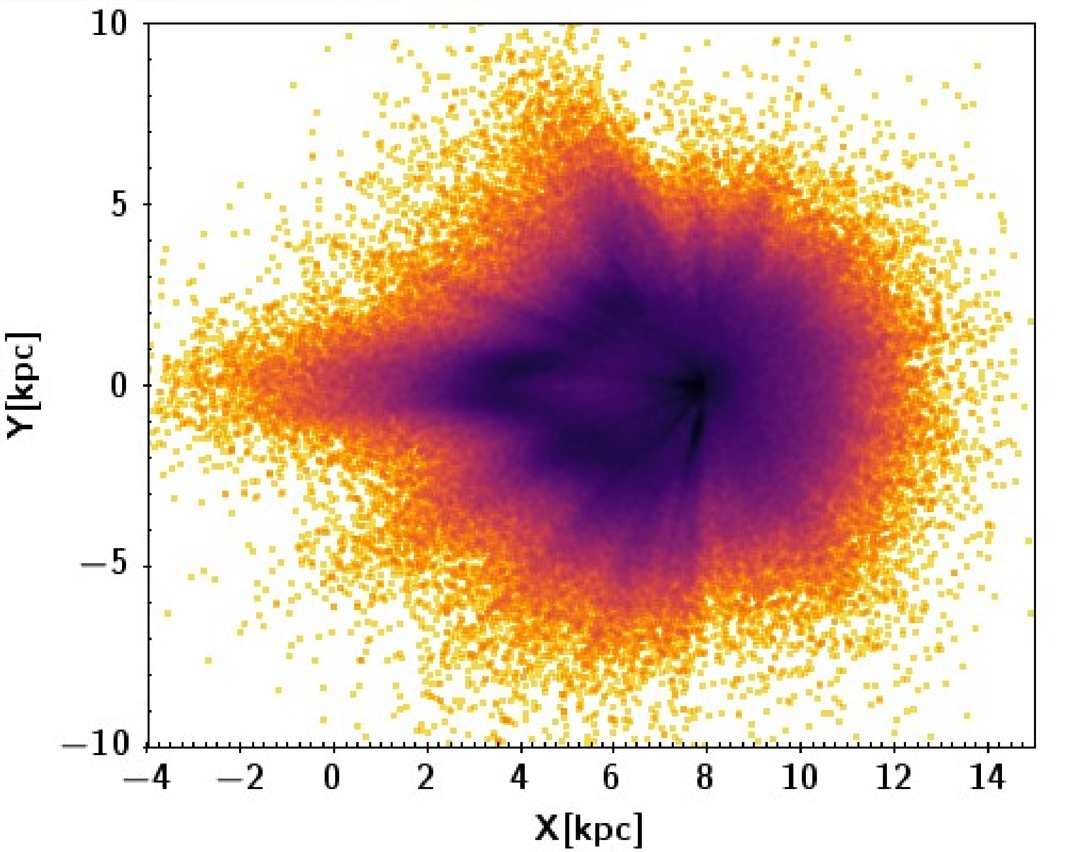
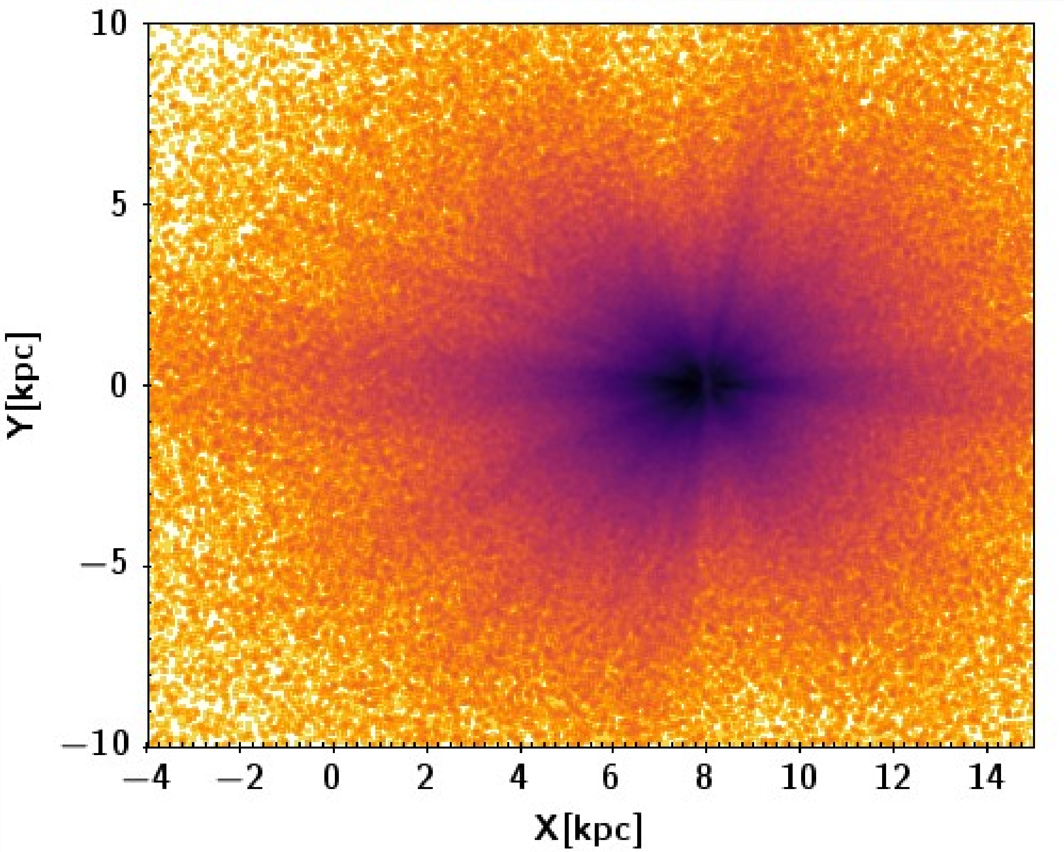
Catalog entries:
Source ID, r_est, r_lo, r_hi, r_len,
result_flag [mode, mean], modality_flag

Prior vs. Posterior



r_est vs. 1/parallax





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- Provides probable distance range for stars
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- A baseline against which to compare other distances
- 3D space distribution of a set of stars
  - Distances are inferred independently but prior is correlated on small scales (and parallaxes may as well)

Don’ts with the catalog

- Infer cluster distance from a set of probable cluster members using our distances

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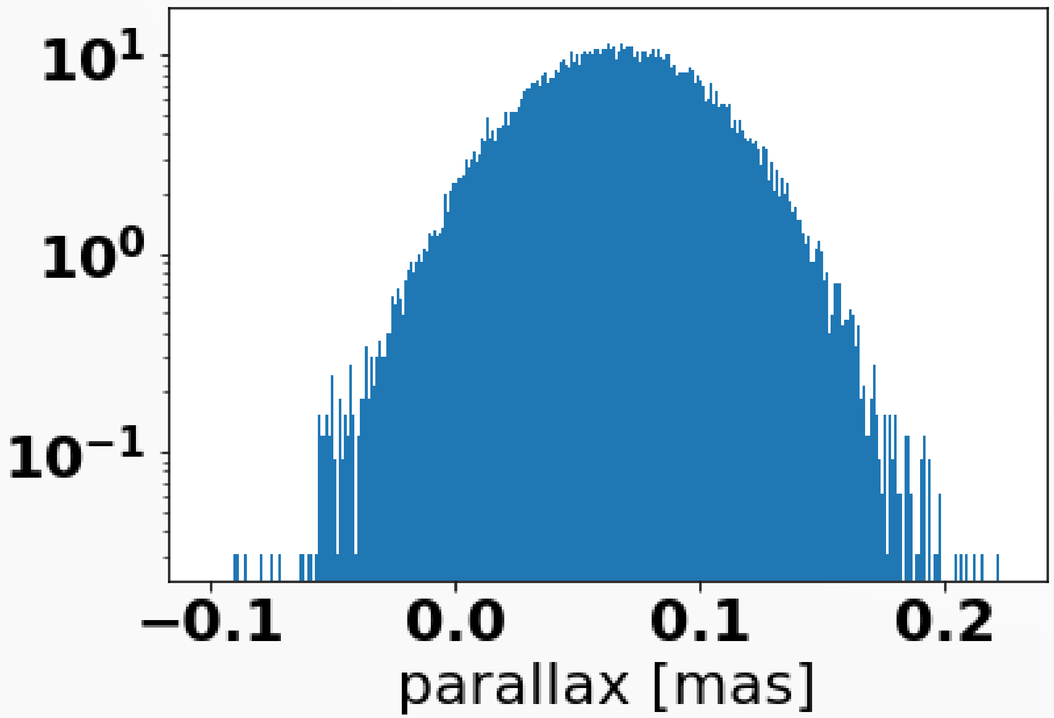

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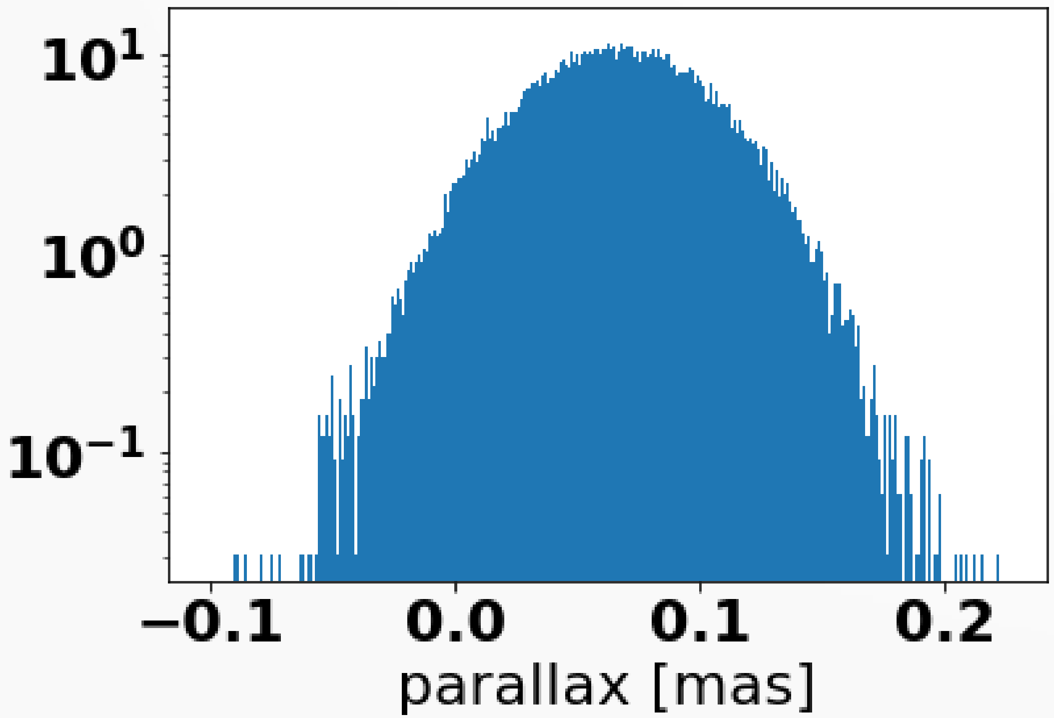
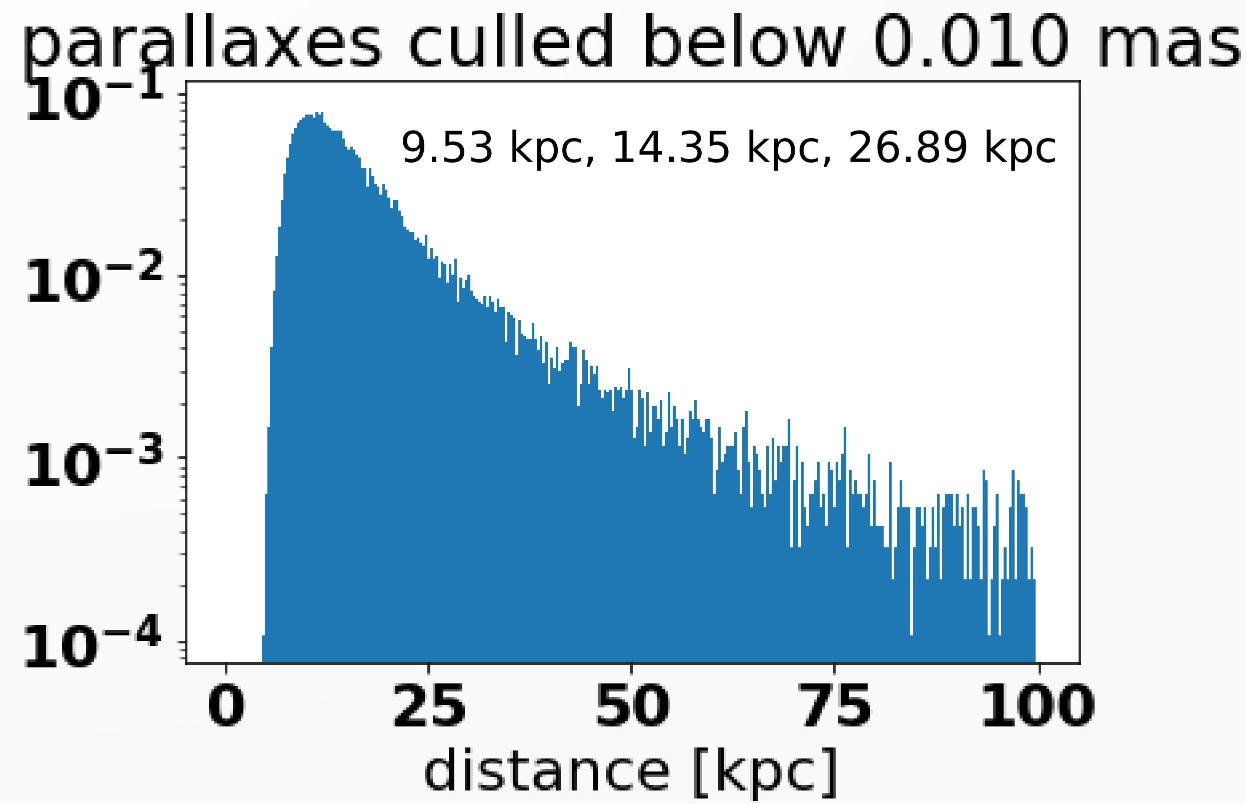
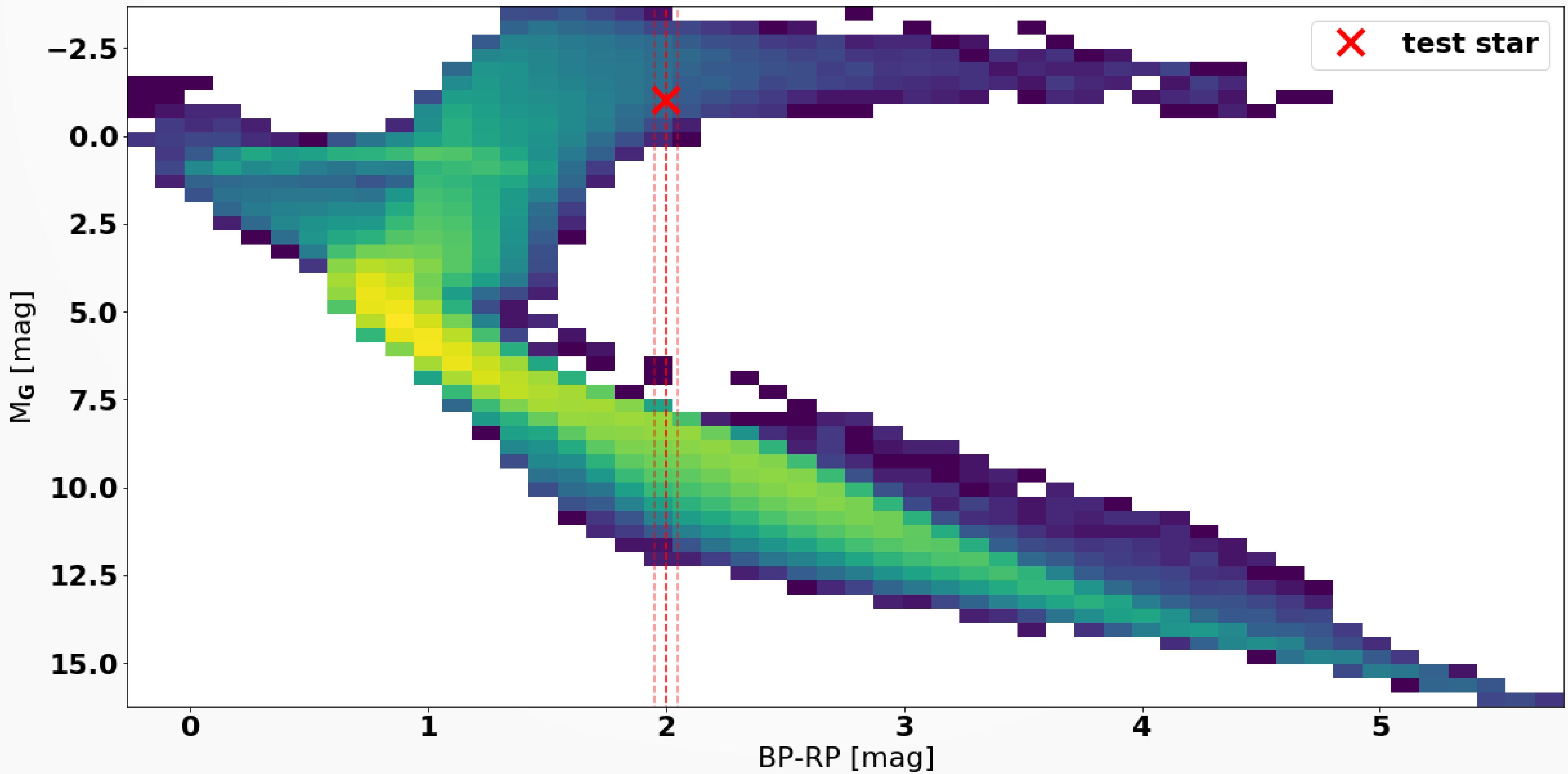
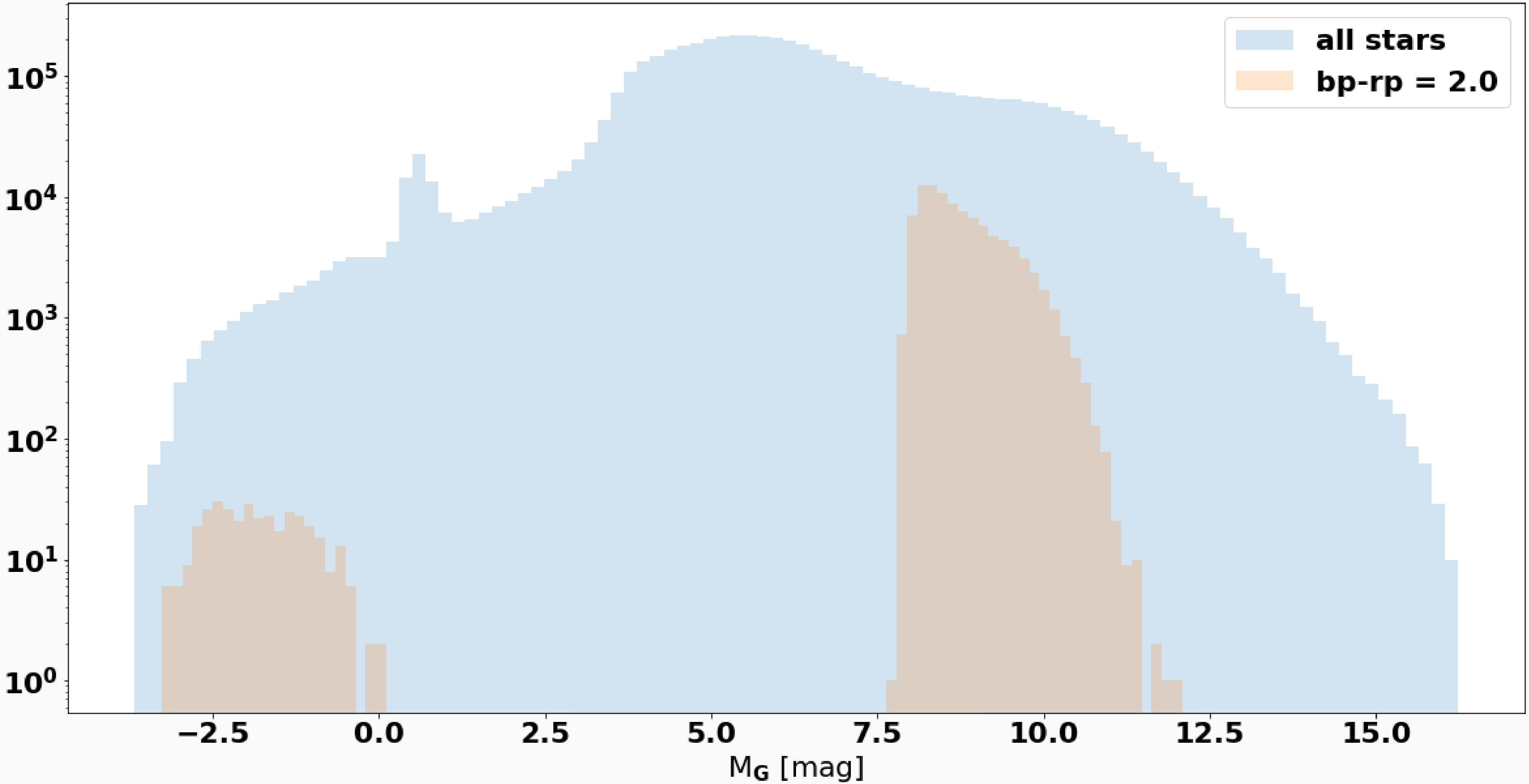




Mock CMD



MG distribution



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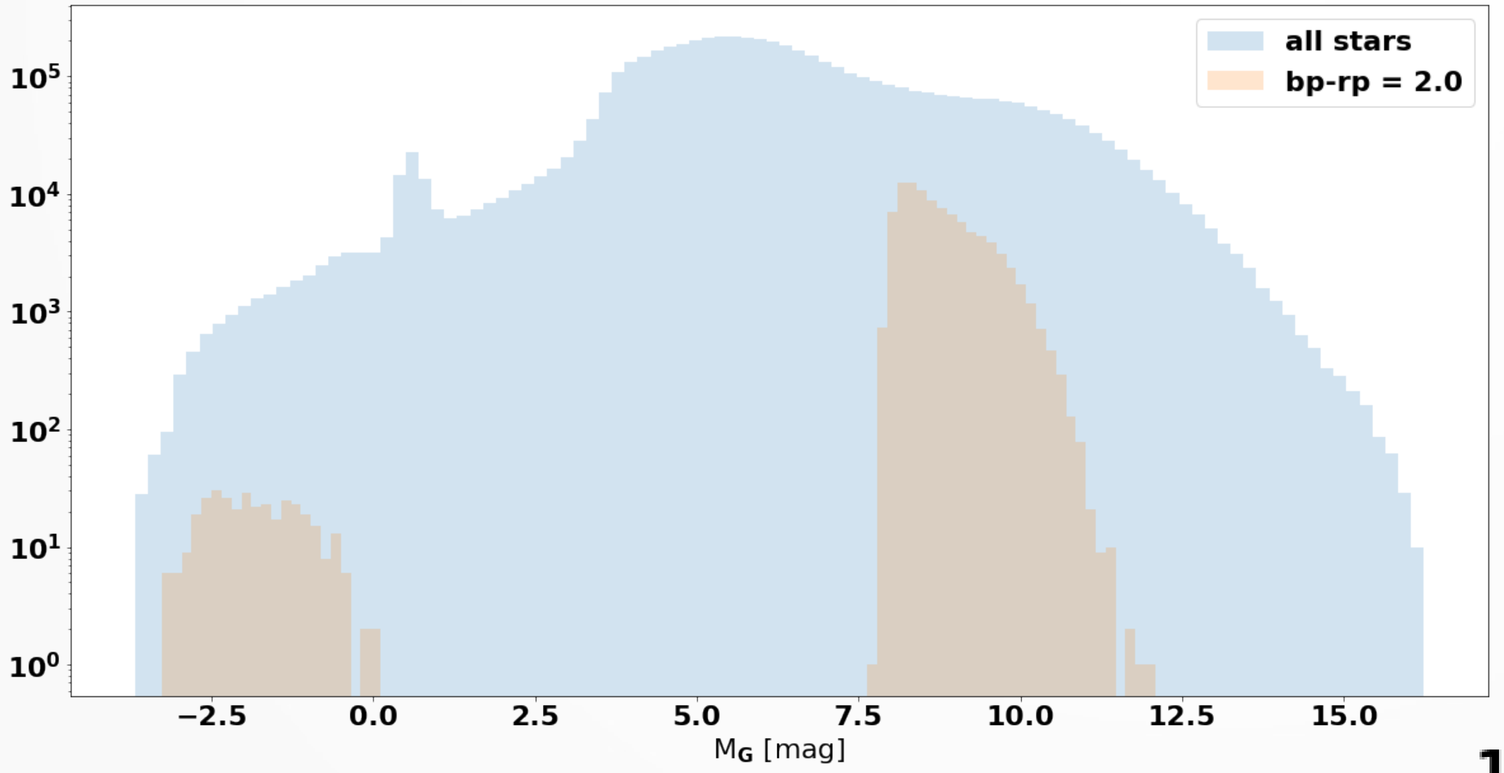
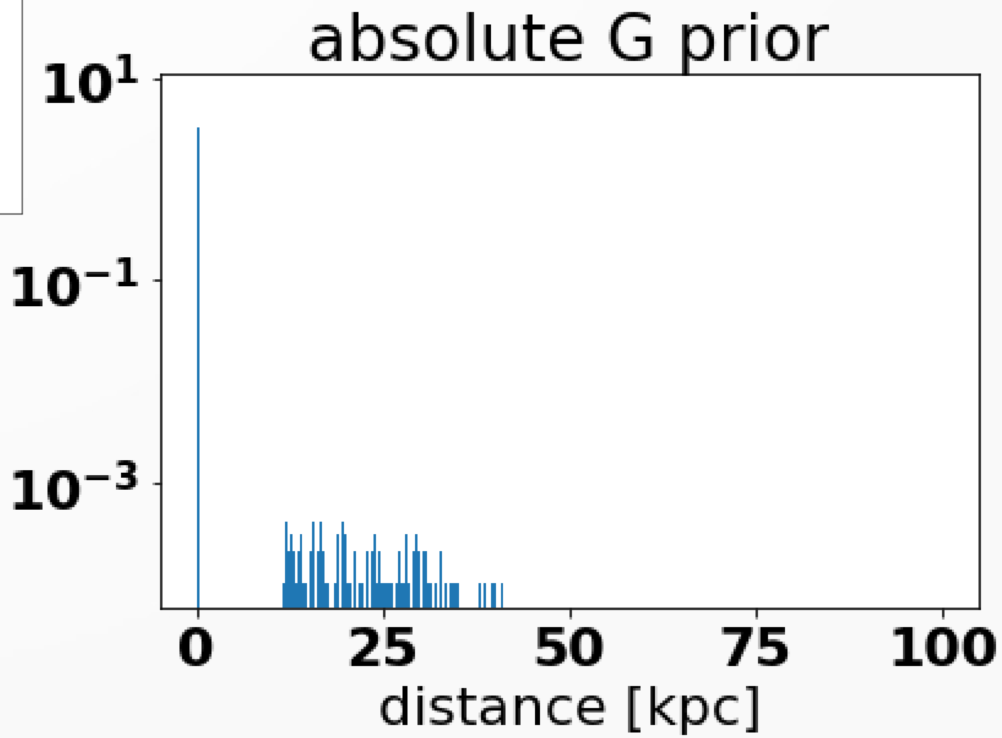
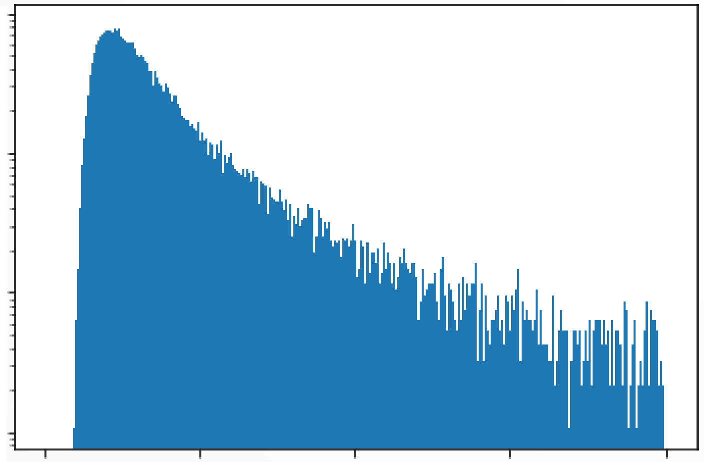




Posterior

parallaxes culled below 0.010 mas



9.53 kpc, 14.35 kpc, 26.89 kpc

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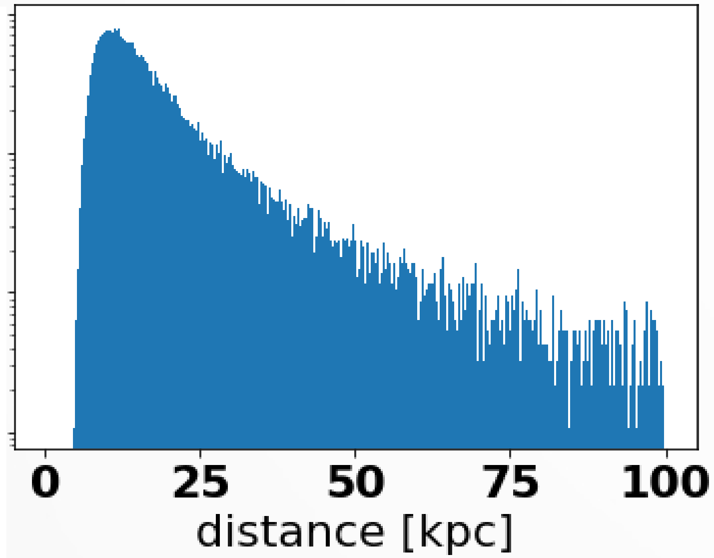

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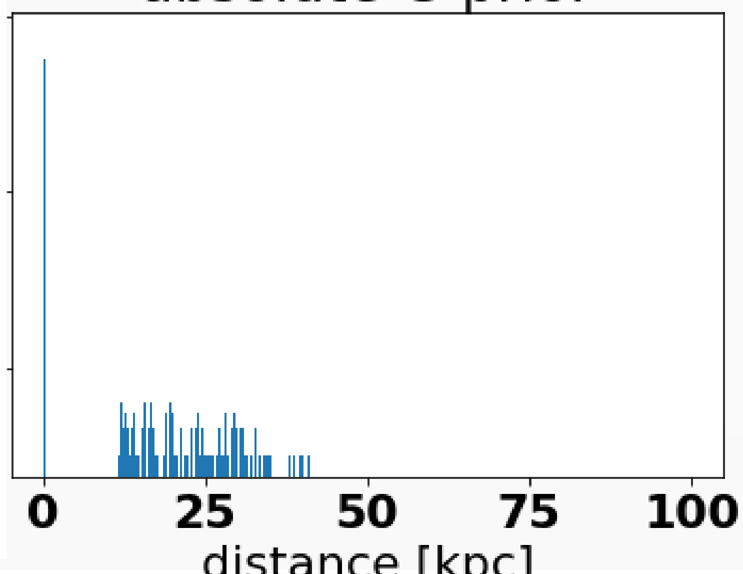
absolute G prior



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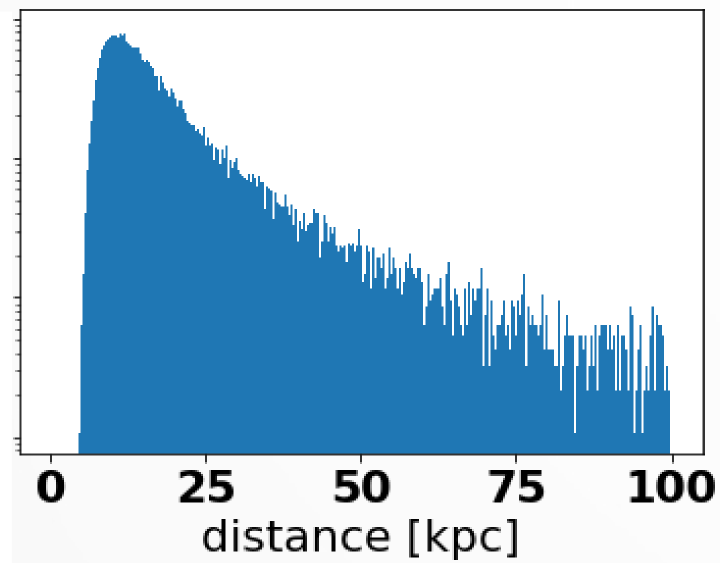

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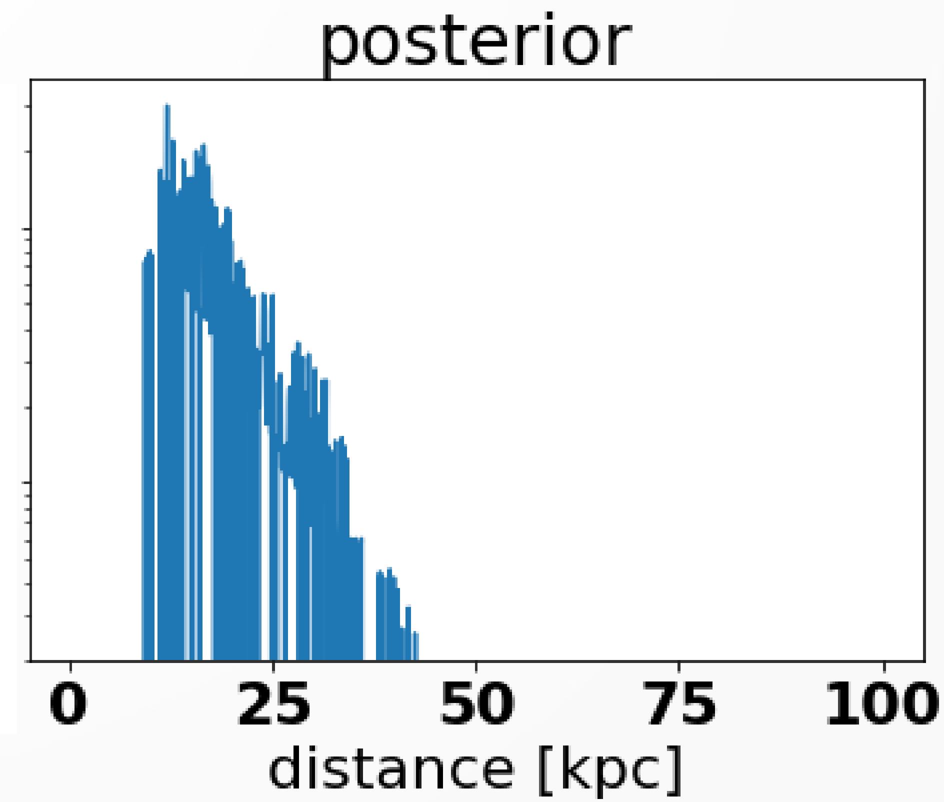

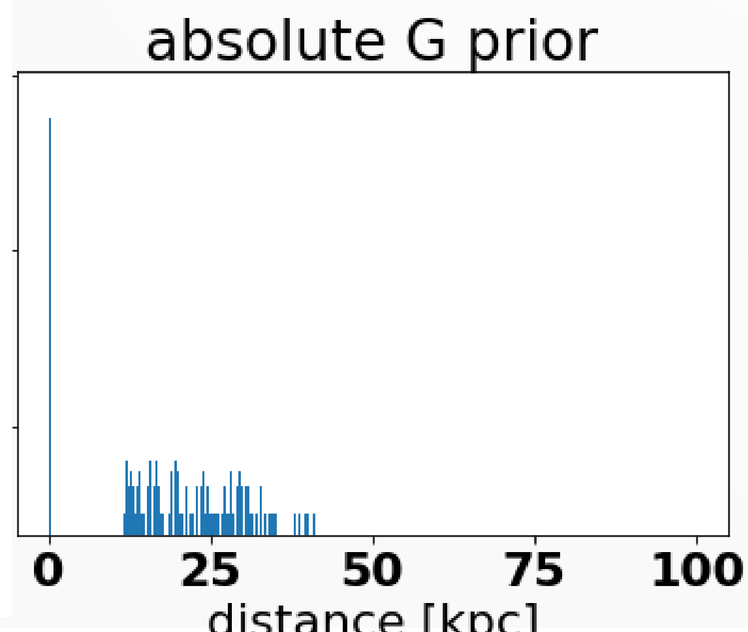

12.35 kpc, 16.55 kpc, 24.25 kpc

6d phasespace

- Plugin astrometry and rv and sample the correlated uncertainties

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- Example code including orbit integration can be found here: https://bit.ly/312UiCc

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- Example code including orbit integration can be found here: https://bit.ly/312UiCc
- For distant stars (> 5 kpc) usually spectro-photometric distance inferences are more precise:
  - Green+ 2019 https://arxiv.org/abs/1905.02734
  - Anders+2019 https://arxiv.org/abs/1904.11302
  - Leung+2019 https://arxiv.org/abs/1902.08634

Summary

- Distance is not observable → inference problem

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- Frame your prior assumptions

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- Distance is not observable → inference problem
- Frame your prior assumptions
- Geometric distance inference has its limits

Thanks for your attention

Parallax measurement

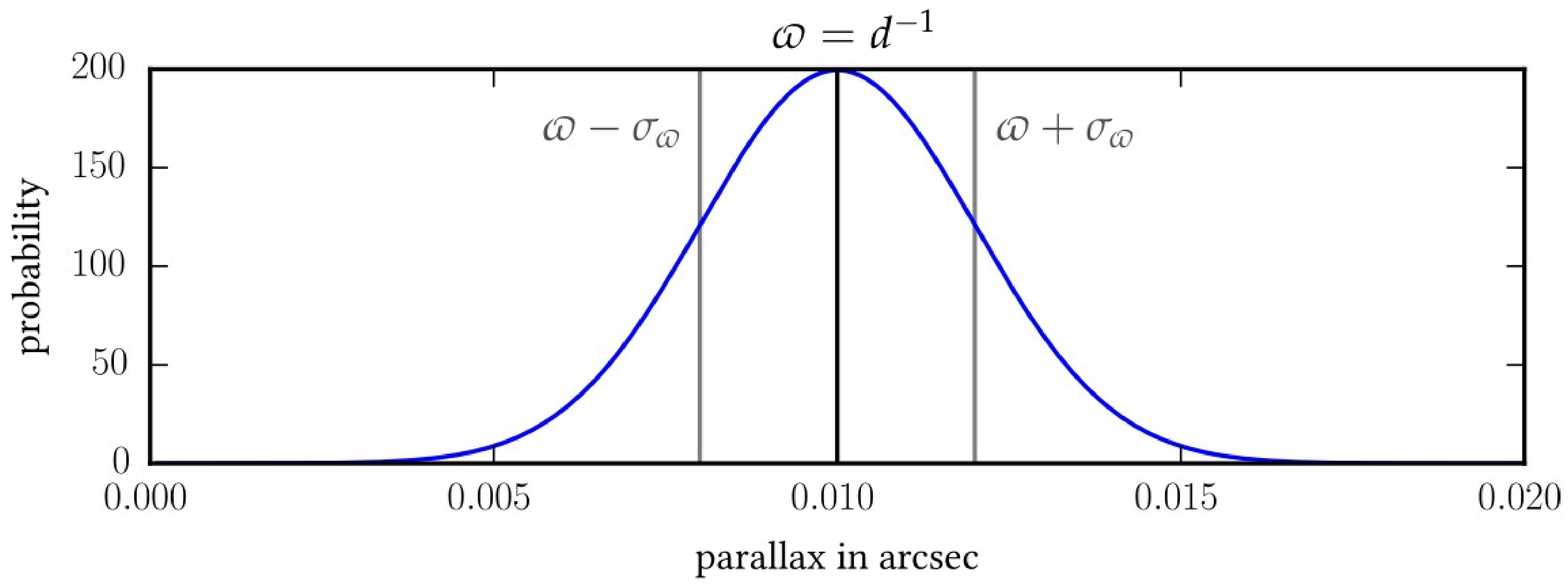

Figure 2.3: Probability distribution for true distance of 100 pc (equivalently a true parallax of 0.01 arcsec) and a relative error, $\frac{\sigma_\varpi}{\varpi}$, of 0.2

Negative parallaxes

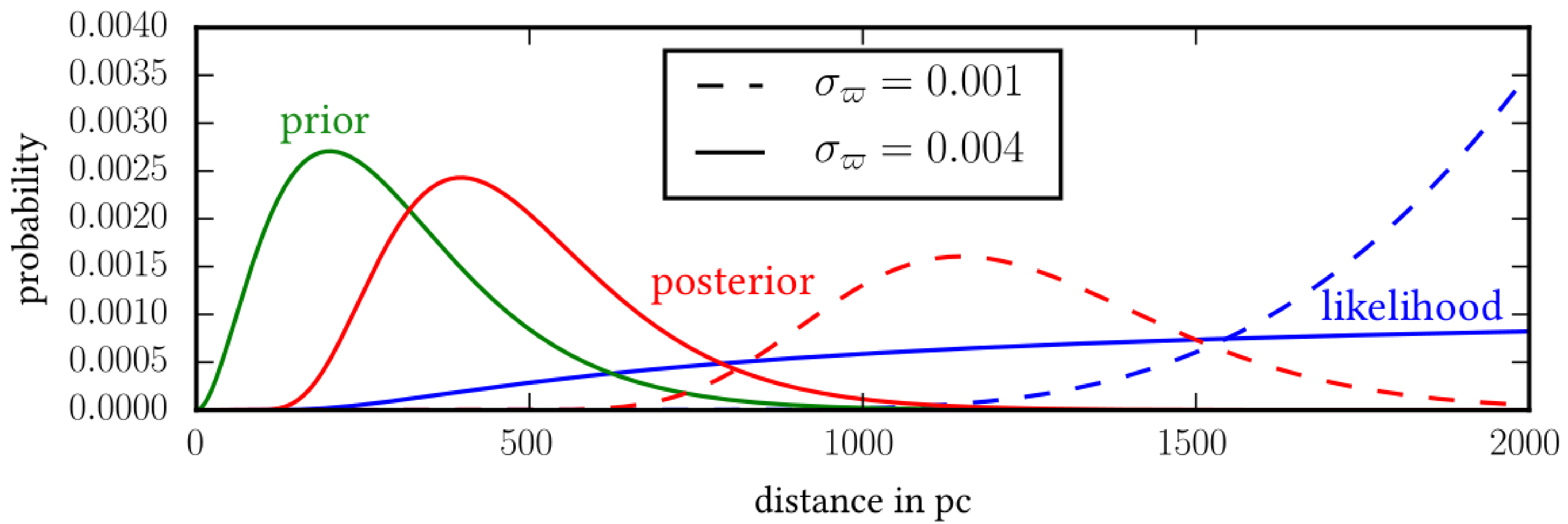

Figure 2.7: Likelihood in blue and posterior in red for negative parallax, $\varpi = -0.01$, and different relative parallax errors, $\frac{\sigma_\varpi}{\varpi} = 10\,\%$ in dashed lines and $40\,\%$ in solid lines. The prior in green stays unaffected. What is visible of the likelihoods as functions of distance is arbitrarily normalised to unity.

$$P(\varpi|d,\sigma_\varpi) = \frac{1}{\sqrt{2\pi\sigma_\varpi^2}} \exp\left(-\frac{\left(\varpi - \frac{1}{d}\right)^2}{2\sigma_\varpi^2}\right)$$