Universiteit van Amsterdam

PEREGRINE

Gravitational Wave Parameter Inference with Neural Ratio Estimation

Sequential simulation based inference for gravitational waves

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Based on **2304.02035, 2308.06318**

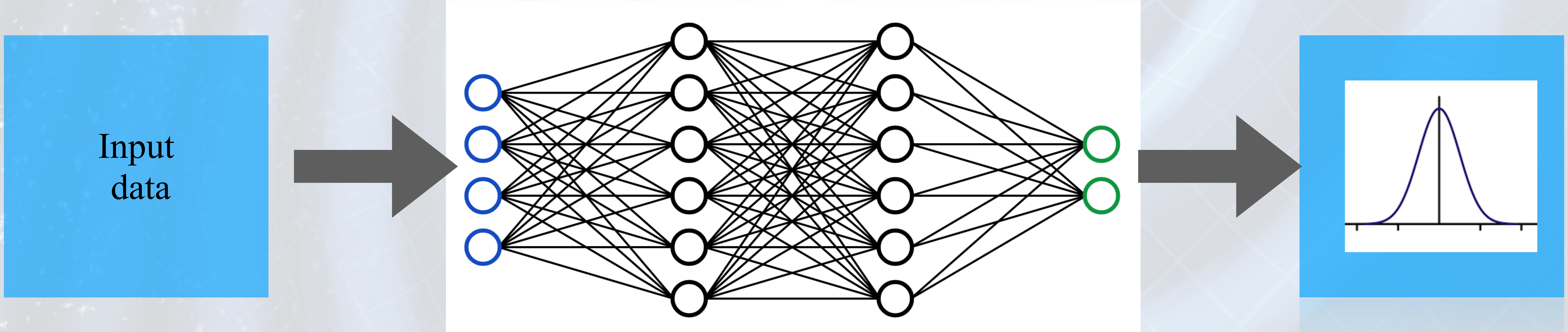
PEREGRINE

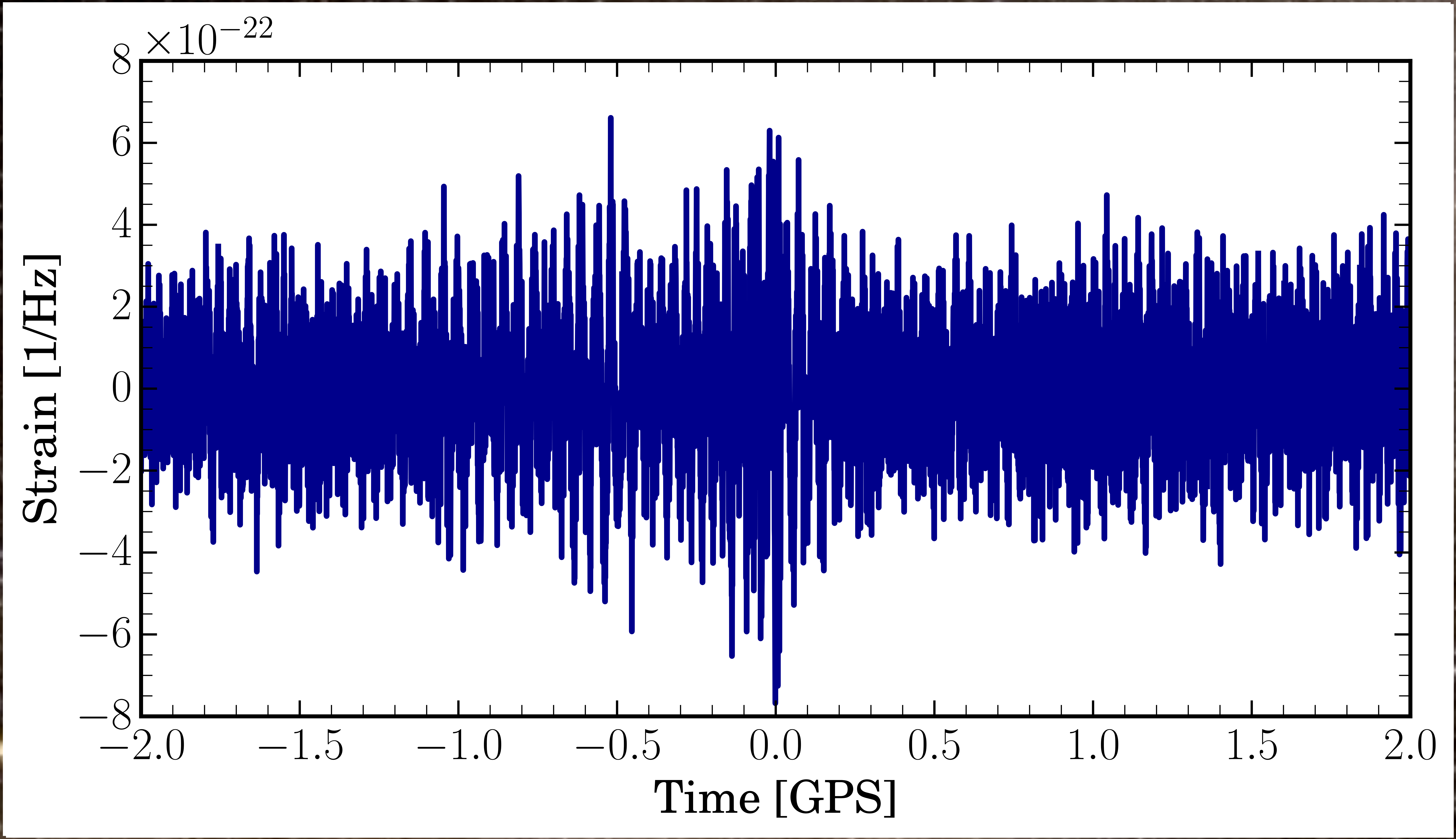
Gravitational Wave Parameter Inference with Neural Ratio Estimation

Expectations

Key words: simulation efficiency, sequential-SBI, truncation, marginals

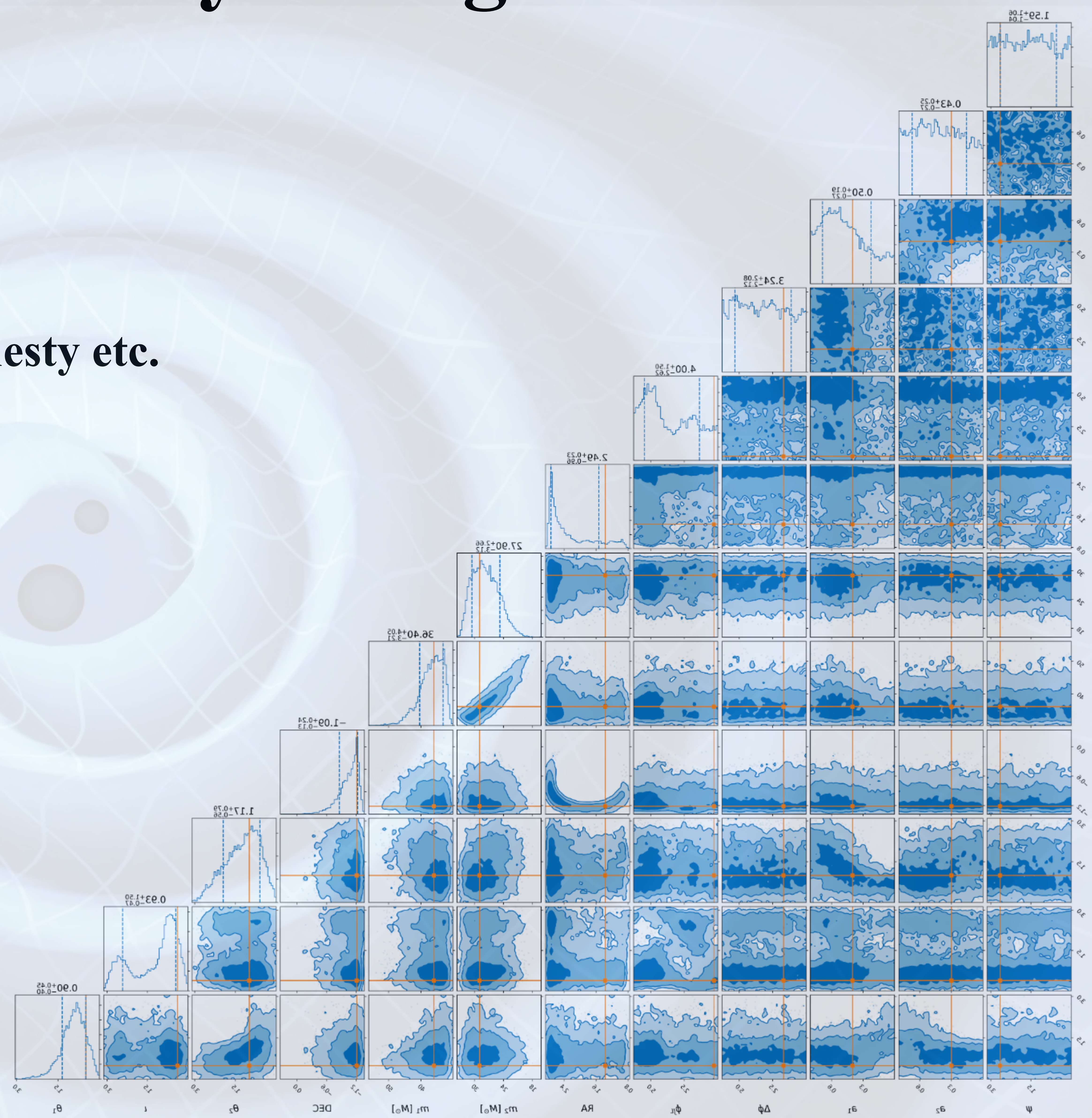
- Gravitational wave (GW) parameter inference: LIGO, Virgo and Lord Bayes
- Simulation based inference for GW physics: A(n) (explicit-)likelihood-free future
- A sequence of steps towards the truth: Staying on target
- Conclusions and promises




×10^−22
8
6
4
2
0
−2
−4
−6
−8
Strain [1/Hz]
−2.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Time [GPS]

GW inference works! Why change it?

- **Bayesian inference task:** $P(\theta \mid d) = \dfrac{\mathscr{L}\pi}{\mathscr{Z}}$
- $d = h(\theta_{GW}) + n_{detector} \mid \theta_{GW} = (M_i, S_{ji}, d_L \ldots)$
- **Inference via traditional samplers : MCMC, multinest, dynesty etc.**
- **O($10^6 - 10^7$) waveform evaluations**



❓ How long of a signal?

❓ How complicated can $\mathscr{L}$ be?

❓ How many dimensions?

❓ How many detections?

Surely not all of them together?

The sampling problem

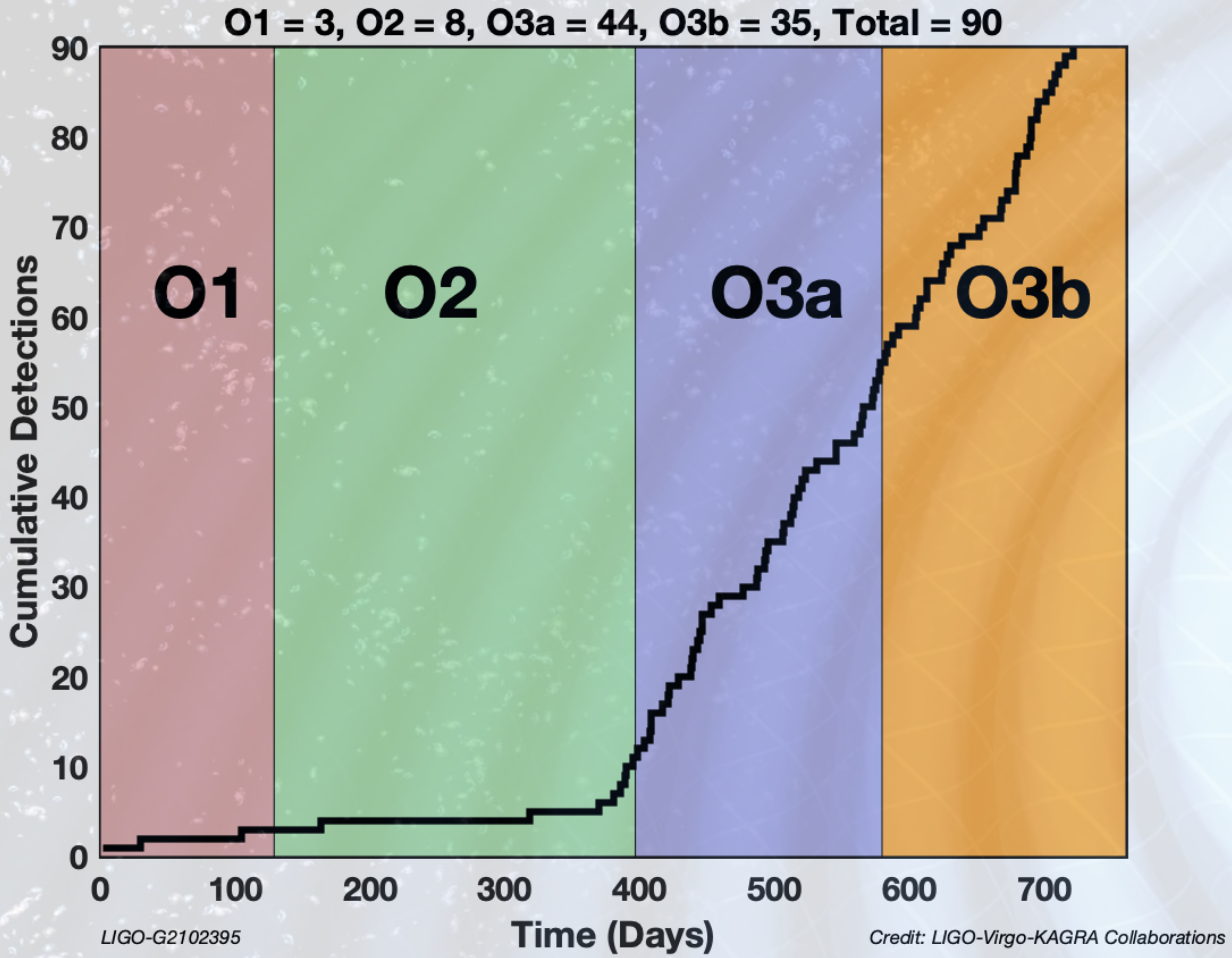


Figure: Cumulative distribution of LVKC GW detections over time. Projected value for 10 years of LVKC operations is O($10^3 - 10^4$).
Credit: LVKC

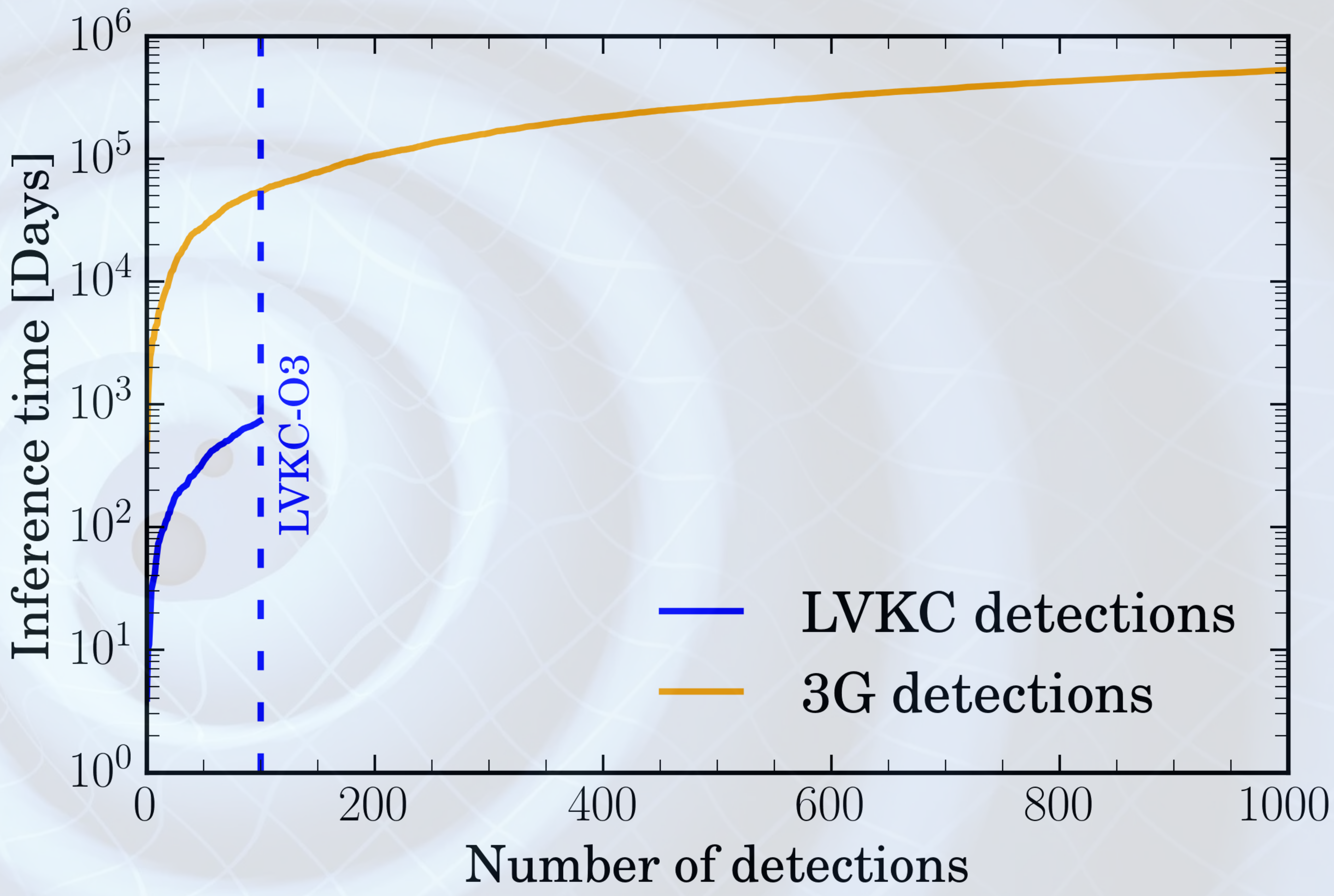
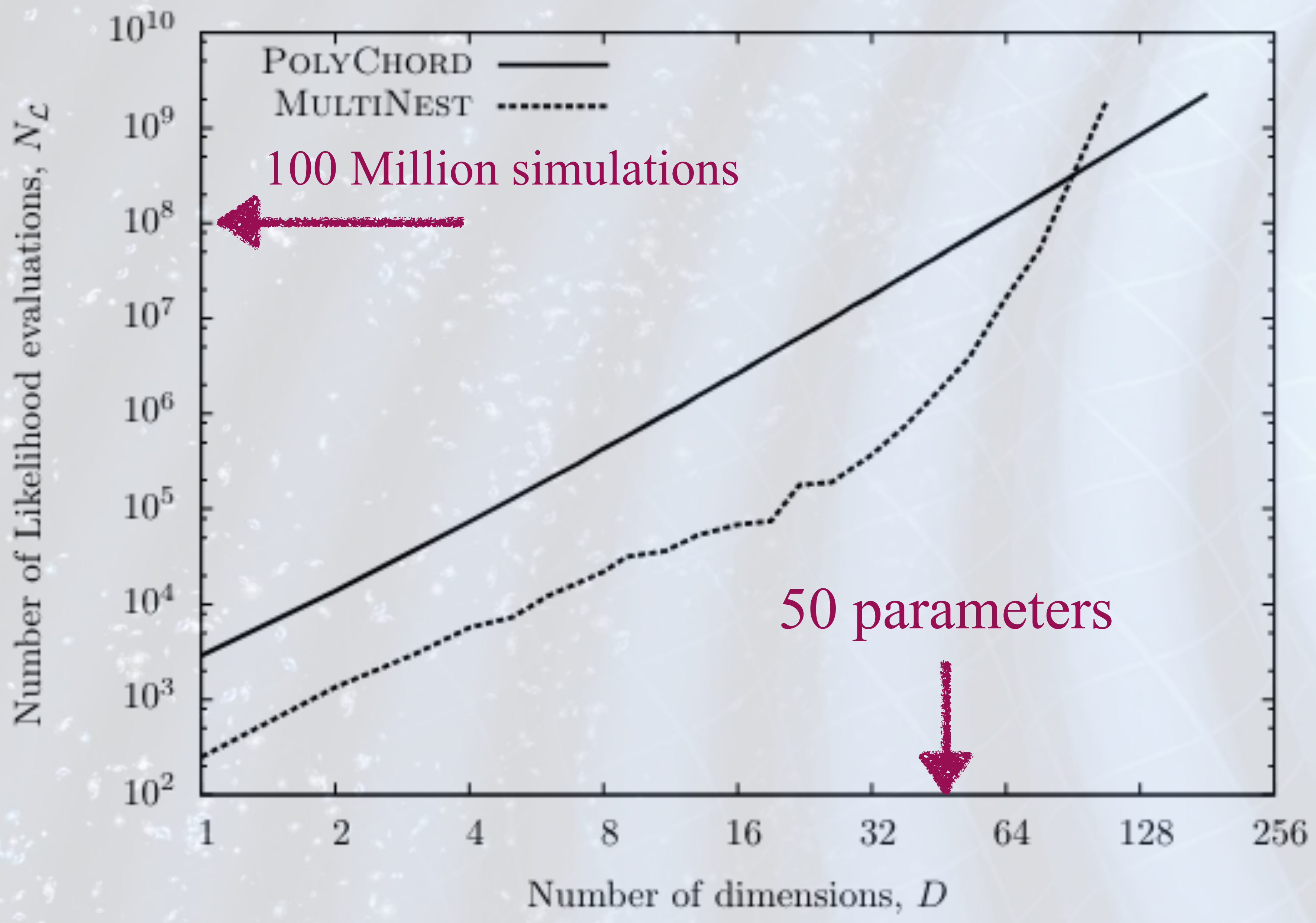


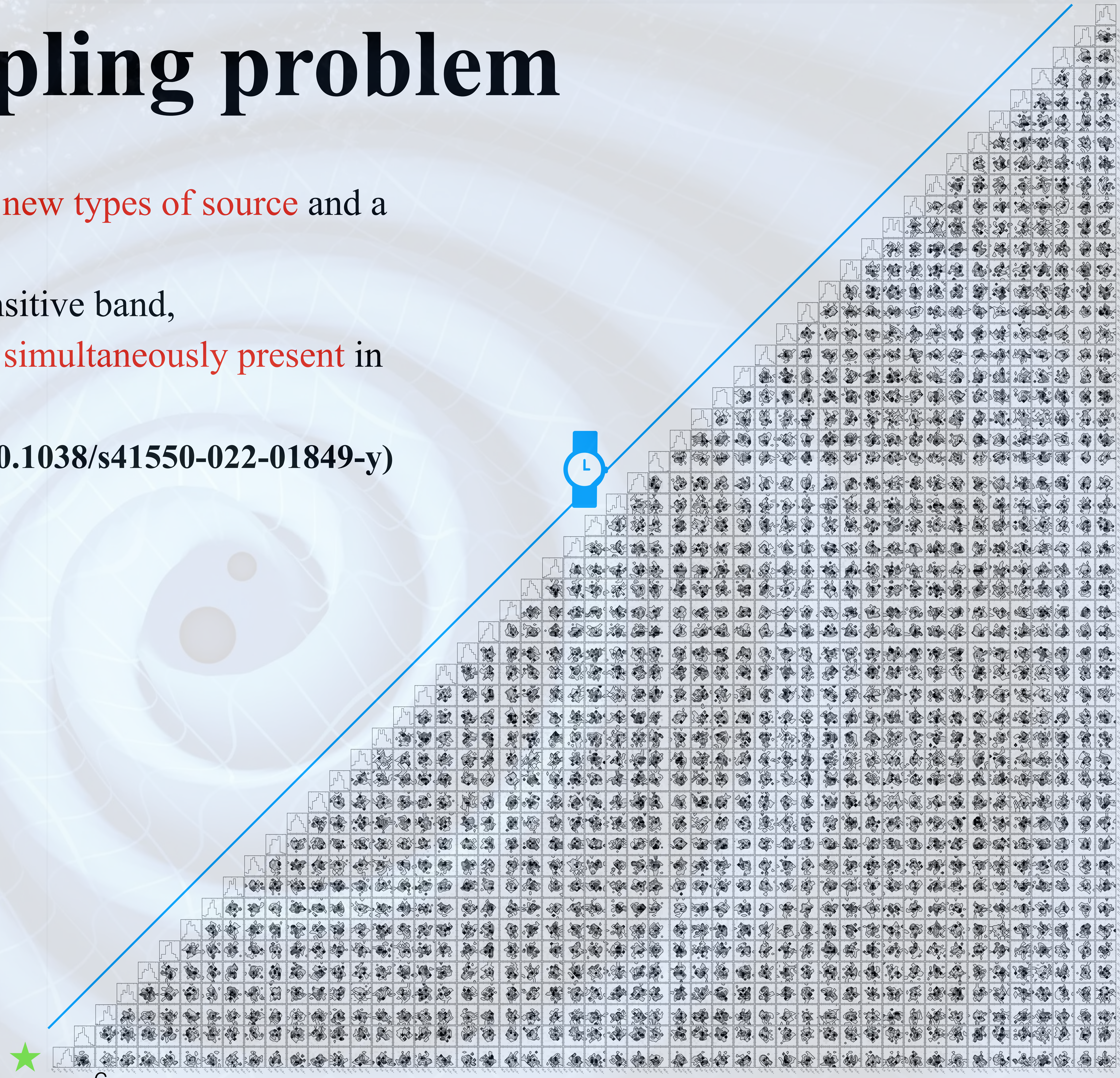
Figure: Inference time vs number of GW detections (estimated for traditional samplers using current LVKC resources)

The sampling problem

- Near-future detector efforts will lead to the detection of new types of source and a steep increase in the detection rate.
- Signals will linger for much longer in the detectors' sensitive band,
- Highly likely that signals from different sources will be simultaneously present in the data.

- Speri+ (Nat. Ast., 10.1038/s41550-022-01849-y)

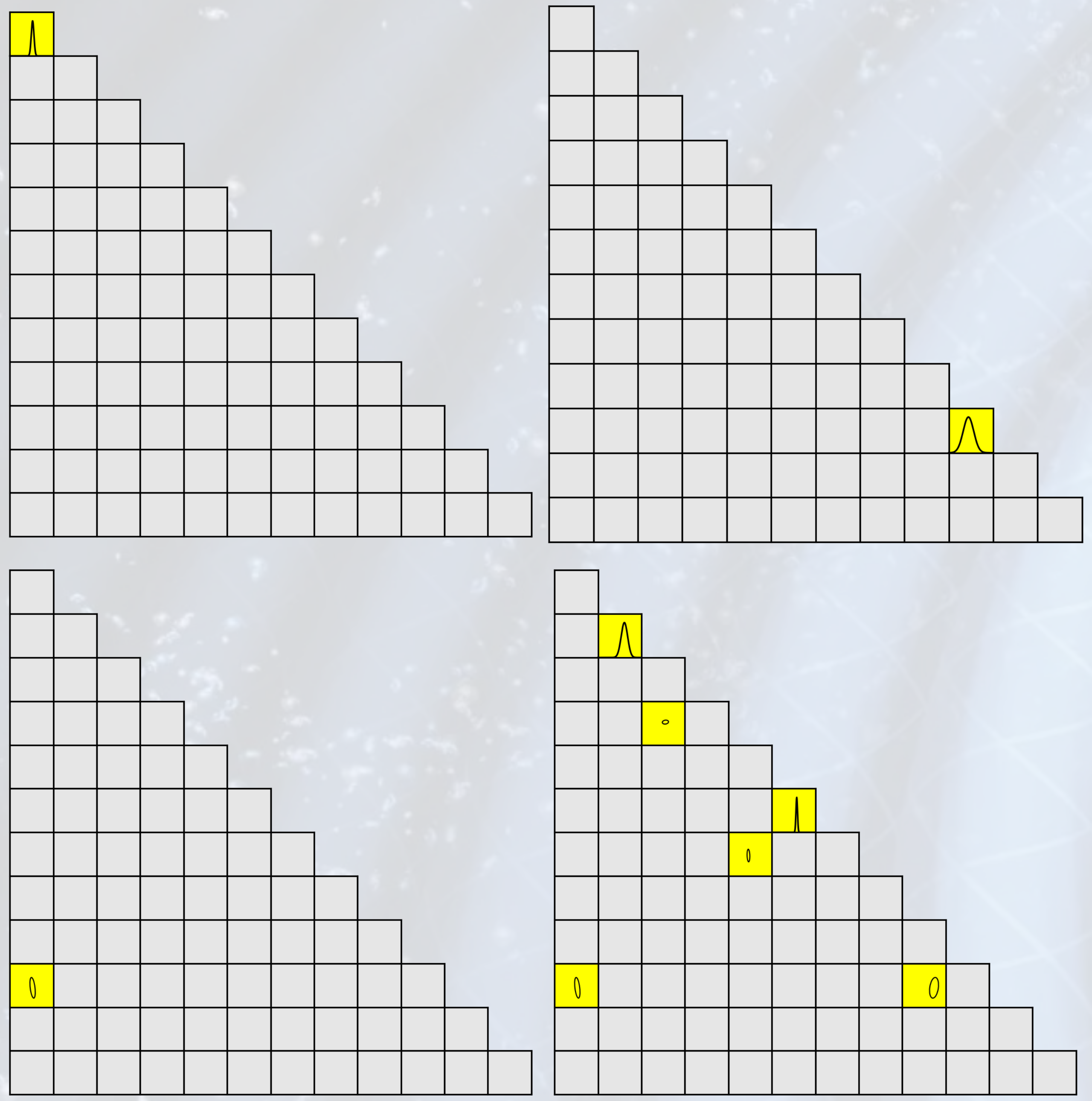




Feroz+ 0809.3437 (MultiNest)
Handley+ 1502.01856 (PolyChord)
Figure credit: C. Weniger

TMNRE performs precision analysis sequentially

(Marginal) Neural Ratio Estimation $r(d;\theta) = \frac{p(x|\theta)}{p(d)} = \frac{p(\theta|d)}{p(\theta)} = \frac{p(d,\theta)}{p(d)p(\theta)}$



Binary classification task: Given a pair (θ, d), did θ generate d ?

Class 1: Matching (data, parameter) pairs

(😽, cat) (🐈, dog)

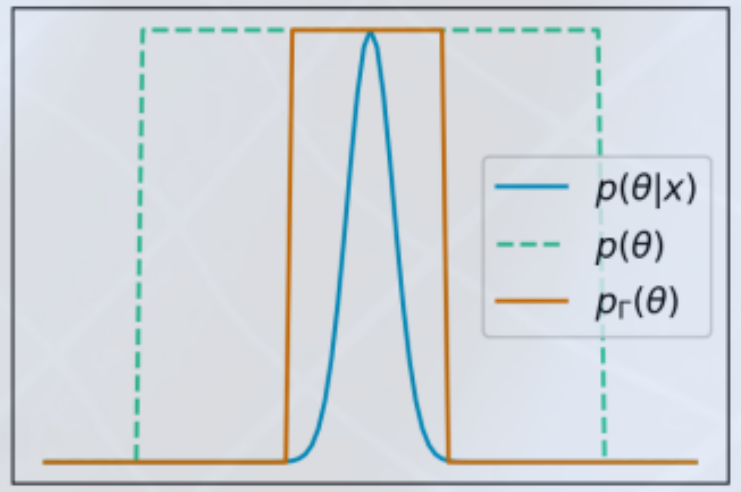
(⭐, star)

Class 0: Scrambled (data, parameter) pairs

(😽, dog) (🐈, star)

(⭐, cat)

Truncated Marginal Neural Ratio Estimation (TMNRE)



swyft : **Miller et al. (2021, 2022)**
arXiv:2011.13951
arXiv:2107.01214
Slide credit: C. Weniger

Schematic

TRUNCATED MARGINAL NEURAL RATIO ESTIMATION (TMNRE) WITH PEREGRINE

Gravitational Wave Parameter Inference with Neural Ratio Estimation

STEP 1: (RE-) SIMULATE

- Sample parameters $\vec{\theta}$ from (truncated) prior $p(\vec{\theta})$
- Simulate data $d(\vec{\theta}) \sim p(d\,|\,\vec{\theta})$

STEP 2: RATIO ESTIMATION

- Train ratio estimators $r(d, \theta_i)$ on simulated data to approximate the posterior-to-prior ratio $r(d, \theta_i) \sim p(\theta_i\,|\,d)/p(\theta_i)$ for each parameter of interest θ_i

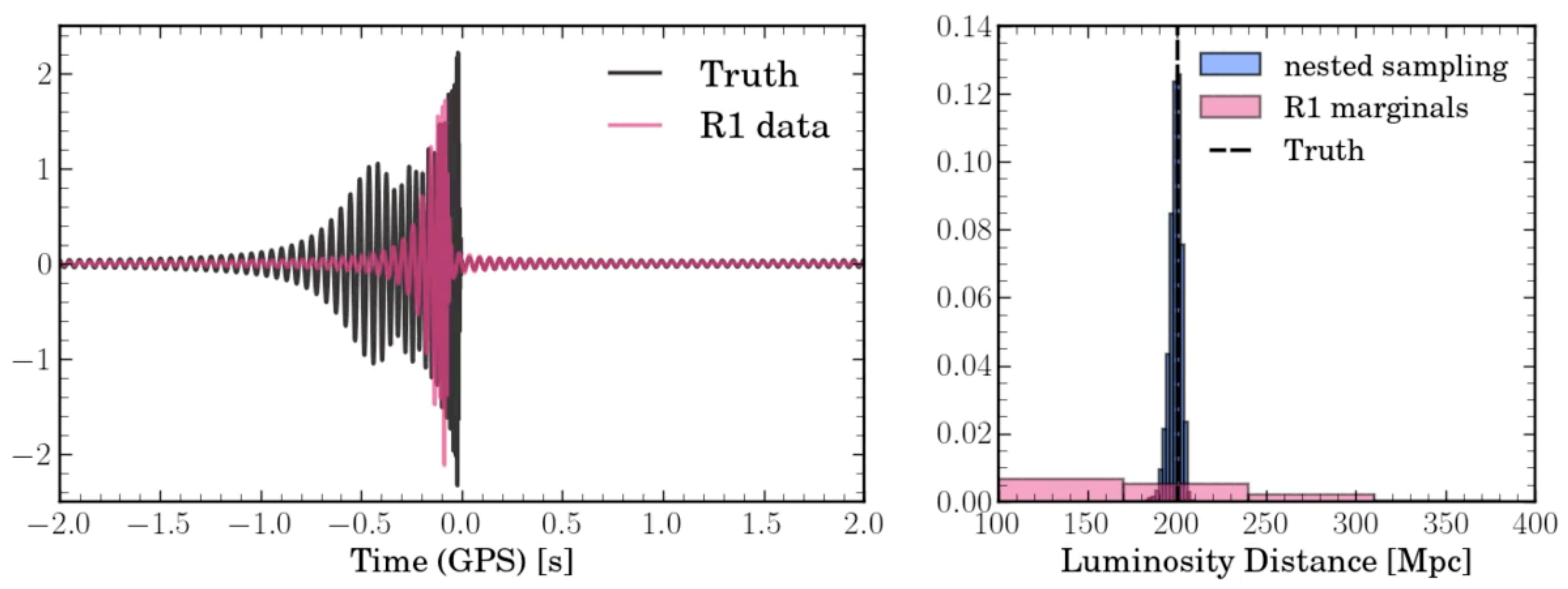
STEP 3: INFERENCE

- Obtain a prior sample from $p(\theta_i)$
- Target a specific observation and compute the ratios $r(d_0, \theta_i)$ across the prior sample
- Weight the samples according to this ratio

STEP 4: TRUNCATION

- Use ratios $r(x_0, \theta_i)$ to remove regions with extremely low posterior density
- If this leads to a reduction in prior volume, re-simulate from Step 1 with truncated prior

Sequential SBI for GW parameter inference



- ~ 700k simulations constitute training data over subsequent TMNRE rounds
- Achieve precision via truncation onto HPD regions

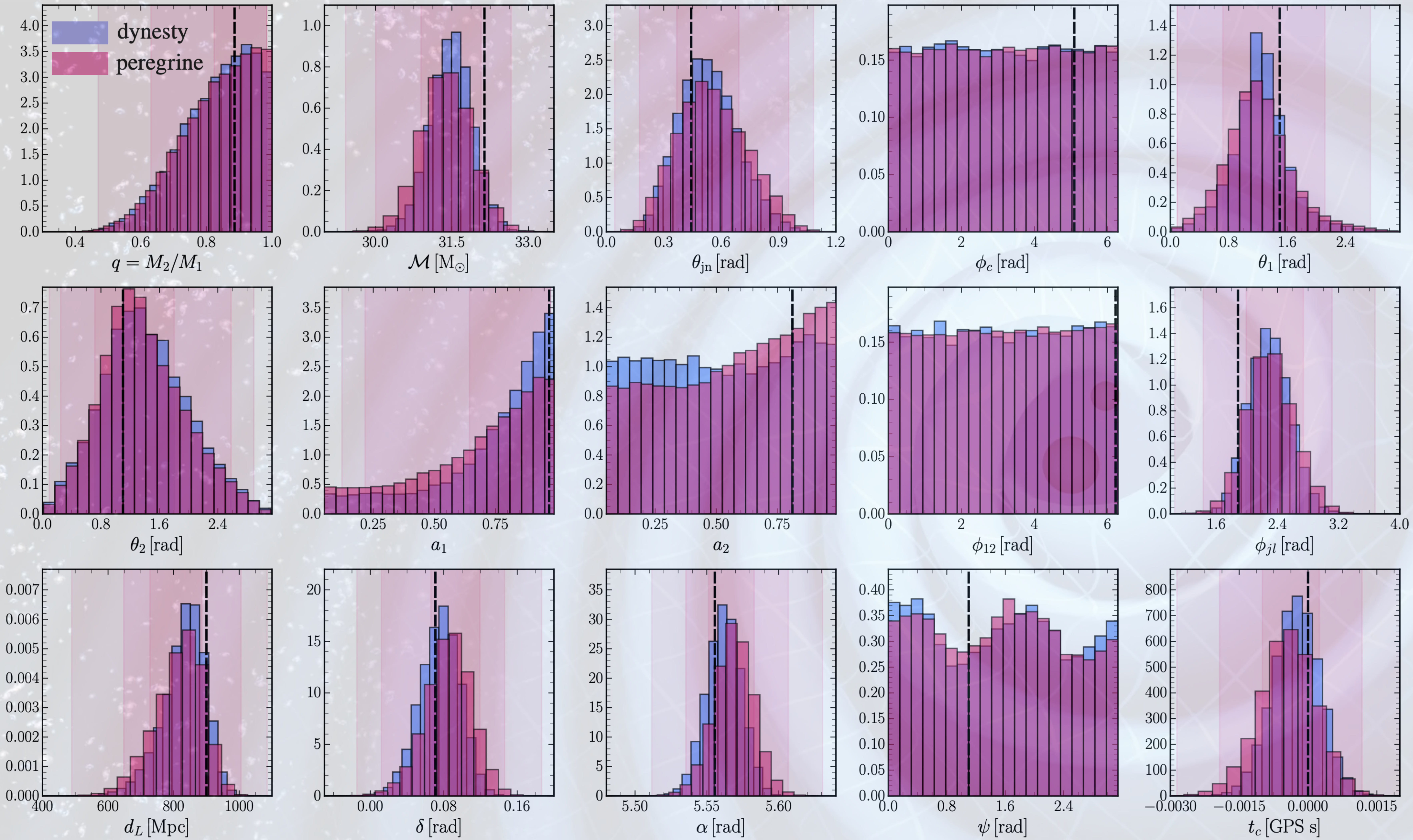
~98% reduction in waveform evaluations!!

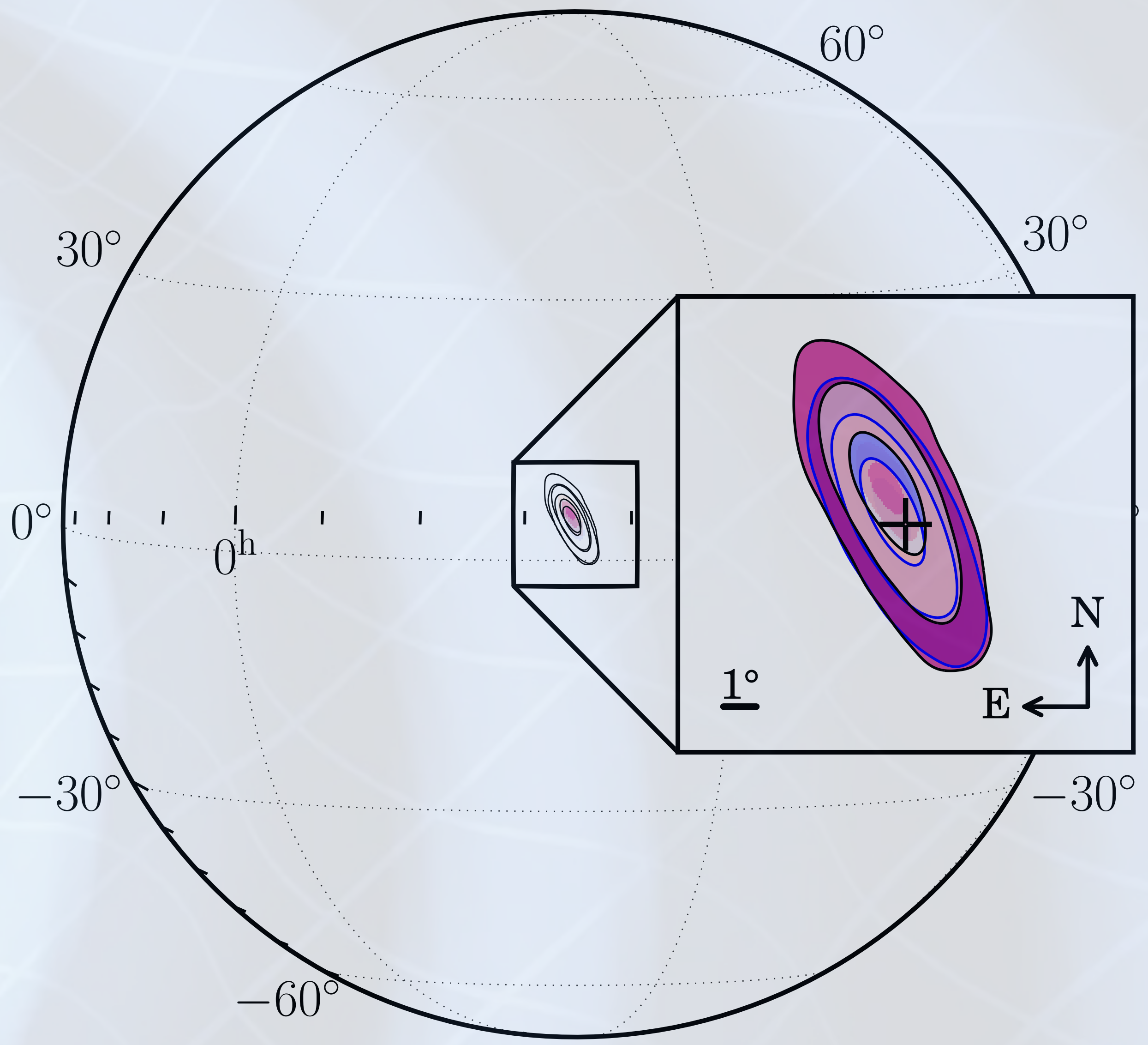
- ~ 45 million waveform computations for dynesty!

Bhardwaj, Alvey, et al. (2023)

arxiv.2304.02035

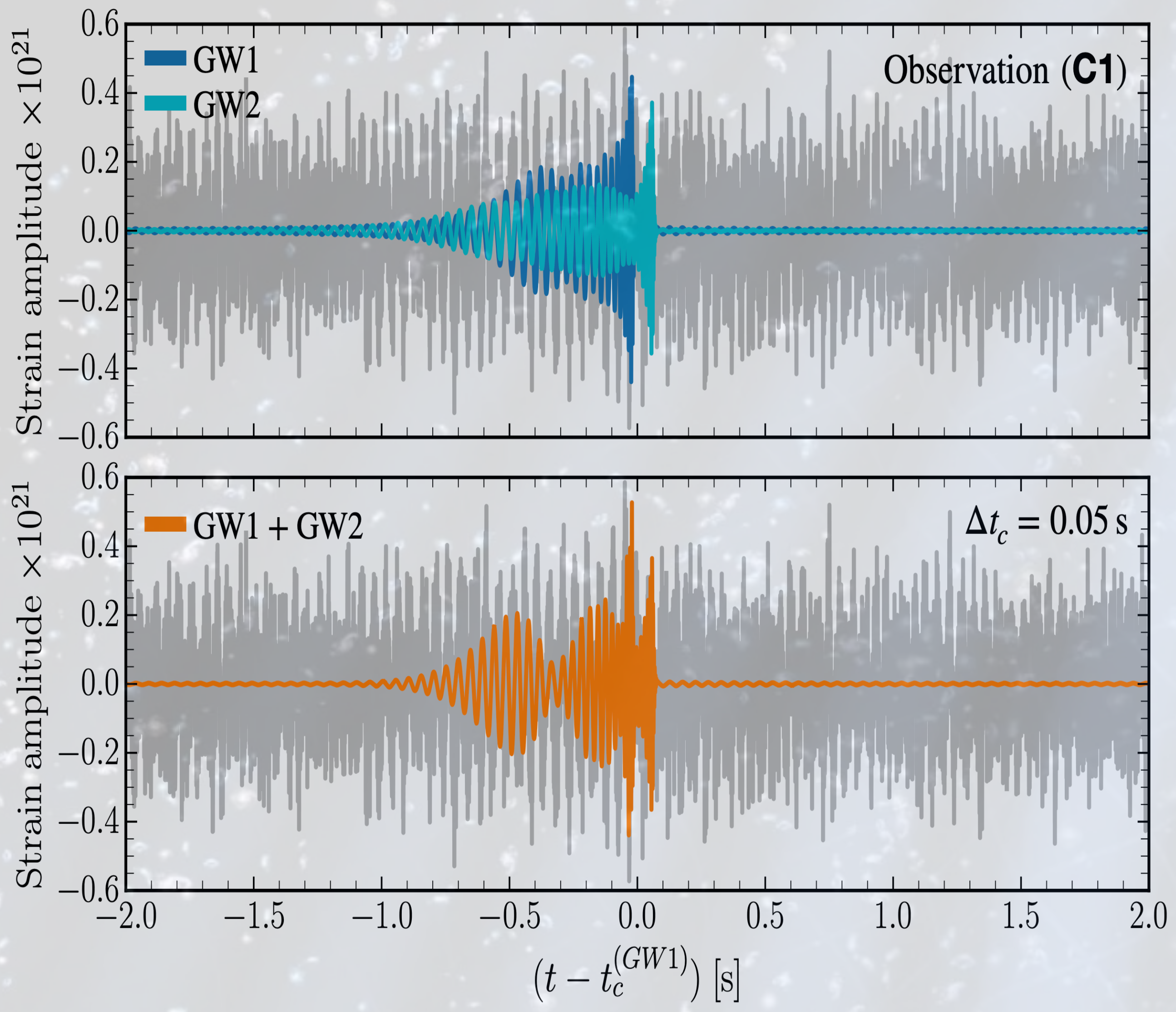
Results

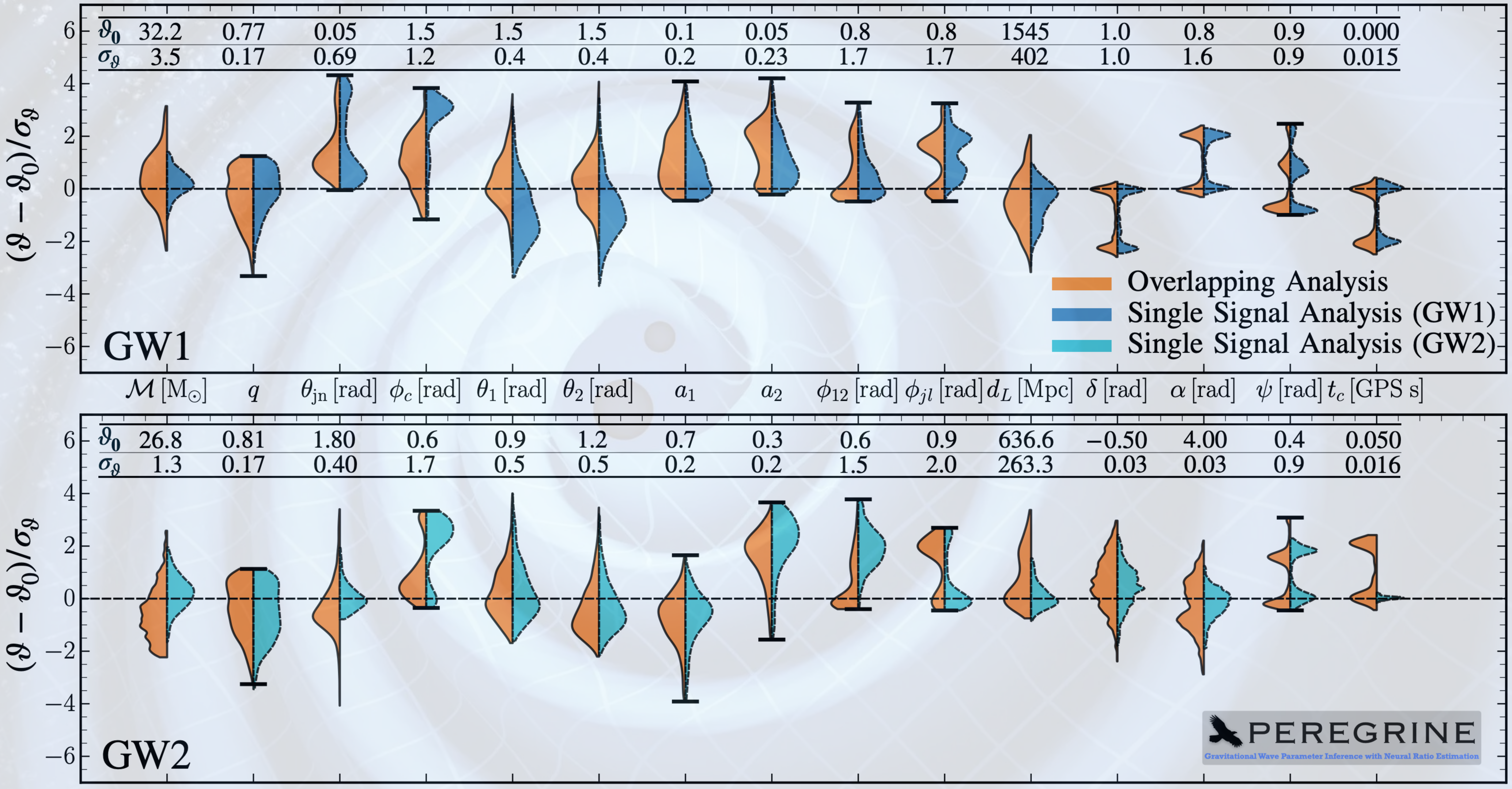




Alvey, Bhardwaj et al. (2023)
arxiv.2308.06318

Results





	$\mathcal{M}$ [M$_\odot$]	q	θ_{jn} [rad]	ϕ_c [rad]	θ_1 [rad]	θ_2 [rad]	a_1	a_2	ϕ_{12} [rad]	ϕ_{jl} [rad]	d_L [Mpc]	δ [rad]	α [rad]	ψ [rad]	t_c [GPS s]
GW1 ϑ_0	32.2	0.77	0.05	1.5	1.5	1.5	0.1	0.05	0.8	0.8	1545	1.0	0.8	0.9	0.000
GW1 σ_ϑ	3.5	0.17	0.69	1.2	0.4	0.4	0.2	0.23	1.7	1.7	402	1.0	1.6	0.9	0.015
GW2 ϑ_0	26.8	0.81	1.80	0.6	0.9	1.2	0.7	0.3	0.6	0.9	636.6	−0.50	4.00	0.4	0.050
GW2 σ_ϑ	1.3	0.17	0.40	1.7	0.5	0.5	0.2	0.2	1.5	2.0	263.3	0.03	0.03	0.9	0.016

Thank you

Takeaway:

- A need to re-think GW inference for the future
- Focusing on marginals for physical conclusions rather than high dimensional correlations
- Sequential approach to precision analysis. TMNRE
- **Obtain reliable posteriors identical to those obtained via traditional methods at a fraction of the cost!**
- **Crucial for solving significant analysis challenges facing next-gen detectors** e.g. overlapping signals, SGWB searches, very long signals (O(weeks)!), non-gaussian correlated noise

PEREGRINE

Gravitational Wave Parameter Inference with Neural Ratio Estimation

https://github.com/PEREGRINE-GW/peregrine

- Sequential simulation based inference for gravitational waves (*arxiv.2304.02035:* Bhardwaj, Alvey, et al.)
- What to do when things get crowded? Scalable joint analysis of overlapping gravitational wave signals (*arxiv.2308.06318:* Alvey, Bhardwaj et al.)
- Simulation-based inference for stochastic gravitational wave background data analysis (*arxiv.2309.07954:* Alvey, Bhardwaj et al.)

TMNRE @ GRAPPA

Uddipta Bhardwaj, James Alvey
Gravitational waves

Uddipta Bhardwaj
Standard sirens, MMA

Noemi Anau Montel
Strong Lensing +

James Alvey, Mathis Gerdes
Stellar streams

Benjamin Kurt Miller
swyft

Guillermo F. Abellan, Oleg Savchenko
Cosmological simulations

PEREGRINE-GW/
peregrine

A simulation-based Inference (SBI) library designed to perform analysis on a wide class of gravitational wave signals

1 Contributor · 0 Issues · 2 Discussions · 5 Stars · 0 Forks

undark-lab/**swyft**

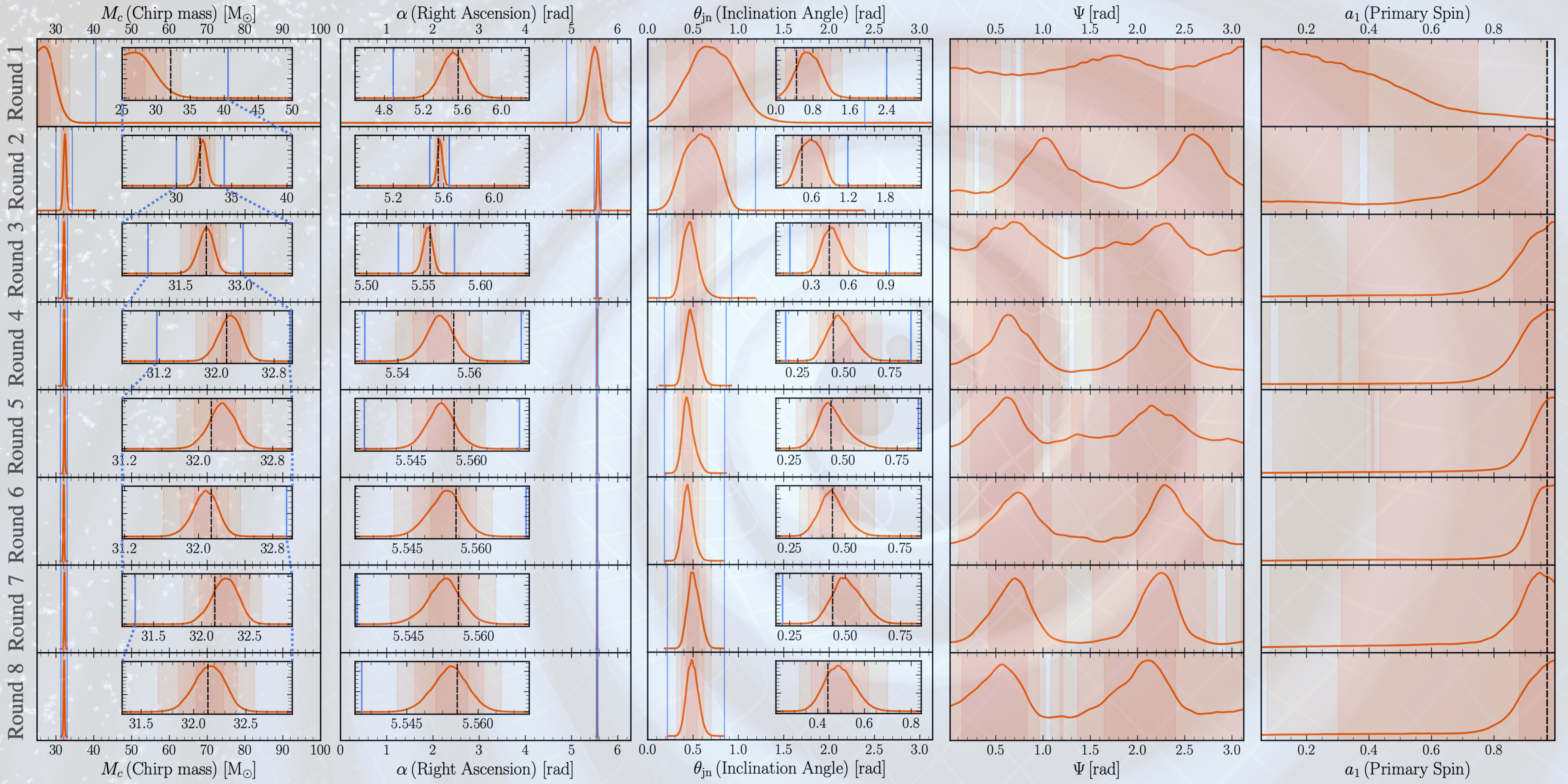
A system for scientific simulation-based inference at scale.

8 Contributors · 9 Issues · 2 Discussions · 116 Stars · 10 Forks

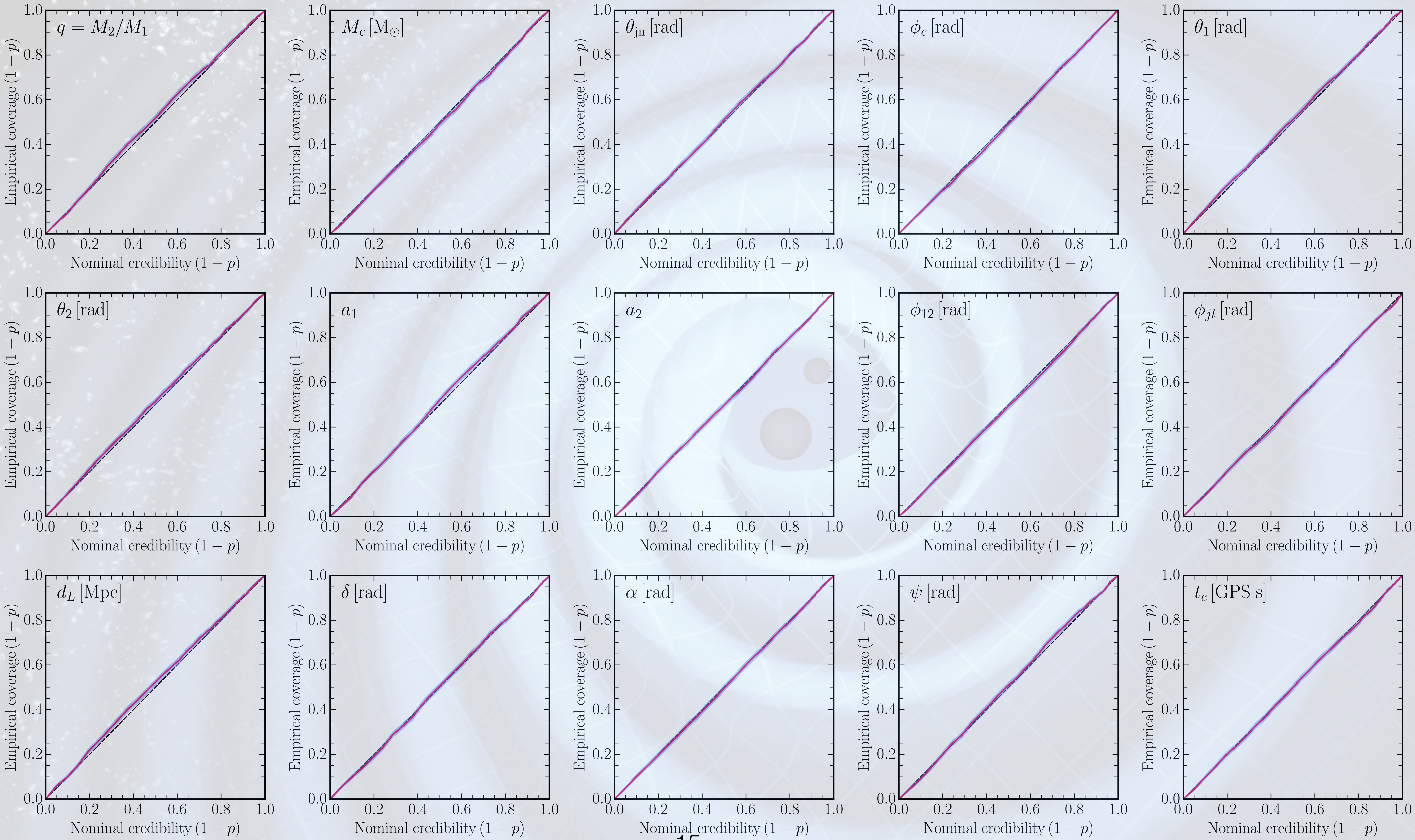
 

Christoph Weniger, Samaya Nissanke

B1: Truncation



B2: Coverage tests



B3: Quantitative comparisons

JSD [10^{-3} nat]	peregrine	dynesty	dynesty (re-run)	ptemcee	cpnest
peregrine		18.0	13.1	21.0	20.6
dynesty	9.75		4.02	10.0	35.2
dynesty (re-run)	10.9	0.55		10.6	29.9
ptemcee	16.5	7.01	7.56		35.9
cpnest	6.82	3.52	4.46	8.60	