

Explainable Deep-learning: Monte Carlo methods for Gravitational-Wave Inference

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My 250 word abstract goes here...

I. INTRODUCTION

Figs: Hunter's Vit Schematic

Remember to signpost rest of paper at end of this section!

A. VITAMIN: User-Friendly Inference

II. THEORETICAL FRAMEWORK

Need to mention metropolis hastings it seems!

Don't apply it to our situation at this stage, just straight theory and equations (Section III deals with taking these eqns arnd applying them to our situation)

A. Monte Carlo Framework

B. SIR Framework

Do theory on normal IS and then say that SIR is an monte carlo approach/approx to normal IS then give equations for bot (talk about the NEW IMPROVED SIR method (link to Section V))

III. METHODOLOGY

Apply the intro/theory material to our case, JUSTIFY scientific decisions like number of samples, batch size, npars!!

A. Model Training

Figs: loss plot

Tables: training hypers in table

Figs: initial corner plot? (to talk about params and how posteriors aren't perfect)

Need this cornerplot here to talk about how it doesn't 'get' the multimodal dists, which after resampling it does!

B. Likelihood Estimates

Figs: Monte flowchart

C. Importance Resampling

IV. RESULTS

A. Self-consistency

Figs: Self consist corner plot

B. Reproducibility

Talk about how 'binning' is preventing proper error profile across the likelihood range, (not present in the DYNesty case)

Figs: sigma gaussians for different z batch

Figs: scatter vit vit

Figs: scatter vit dynesty

C. Importance Resampling

Figs: Final corner plot (big)

V. FUTURE WORK

As we find ourself in a proof-of-concept mode, there is justification of a section dedicated to the next steps leading towards production of this code.

VI. CONCLUSIONS

This is section has to encapsulate everything we did so that after the abstract a reader can go here and see if they want to buy the paper or not!

VII. ACKNOWLEDGEMENTS

Thanks to Chris and Hunter and Michael and Daniel.
Paragraph on the software used BILBY [1]

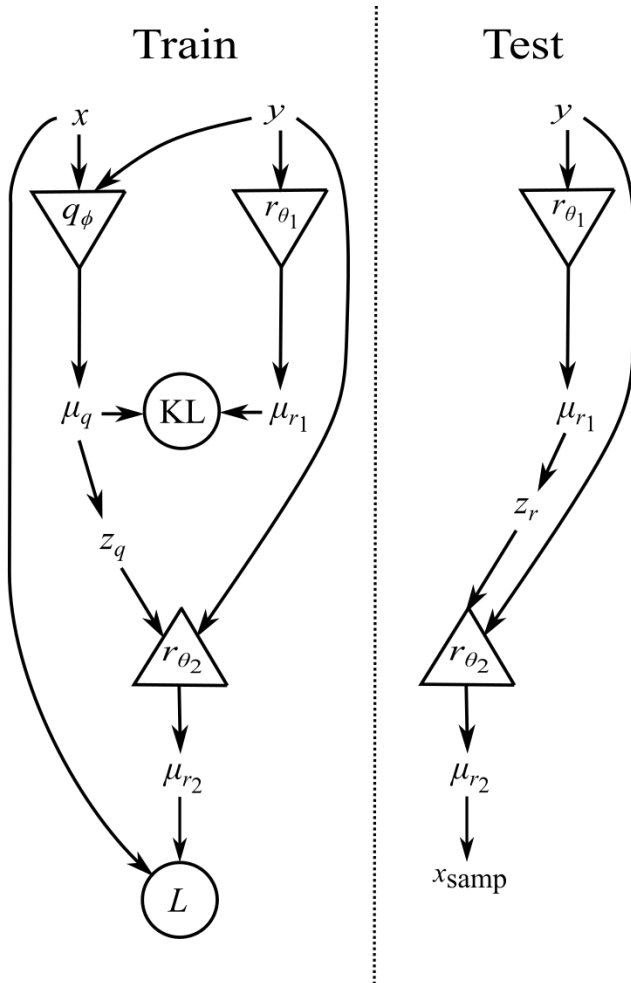


FIG. 1. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour for the current *worst point* shown in orange. **Middle:** samples drawn from a truncated Gaussian within the iso-likelihood contour in and mapped to using the inverse mapping. **Bottom:** pool of accepted samples after applying rejection sampling until 1000 points are obtained shown in both and .

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- [1] G. Ashton, M. Huebner, P. D. Lasky, Colm Talbot, K. Ackley, Sylvia Biscoveanu, Q. Chu, A. Divarkala, P. J. Easter, Boris Goncharov, Francisco Hernandez Vivanco, J. Harms, M. E. Lower, Grant D. Meadors, D. Melchor,

E. Payne, M. D. Pitkin, J. Powell, N. Sarin, Rory J. E. Smith, and E. Thrane, *Astrophys. J. Supp.* **241**, 27 (2019).

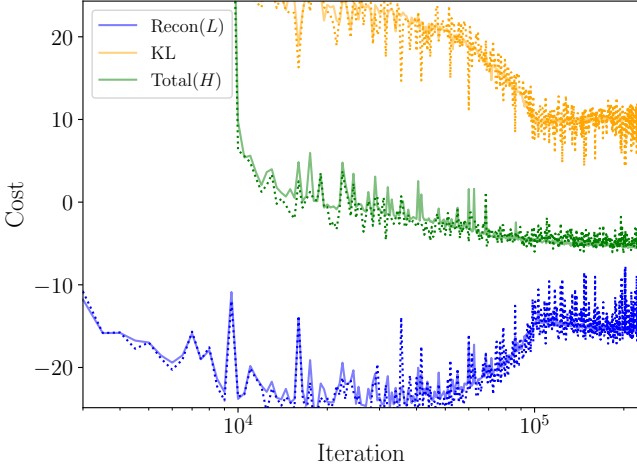


FIG. 2. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour for the current *worst point* shown in orange. **Middle:** samples drawn from a truncated Gaussian within the iso-likelihood contour in and mapped to using the inverse mapping. **Bottom:** pool of accepted samples after applying rejection sampling until 1000 points are obtained shown in both and .

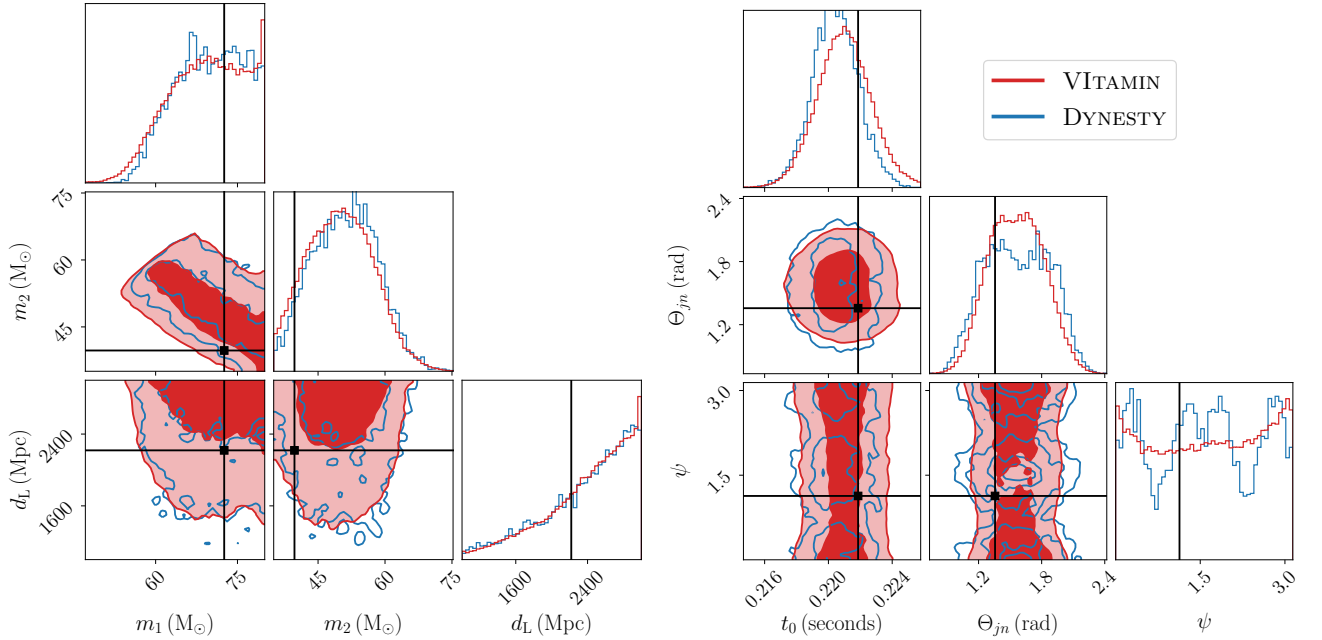


FIG. 3. Probability-probability (P-P) plot showing the confidence interval versus the fraction of the events within that confidence interval for the posterior distributions obtained using our analysis NESSAI for 128 simulated compact binary coalescence signals produced with BILBY and BILBY_PIPE. The 1-, 2- and 3- σ confidence intervals are indicated by the shaded regions and p -values are shown for each of the parameters and the combined p -value is also shown.

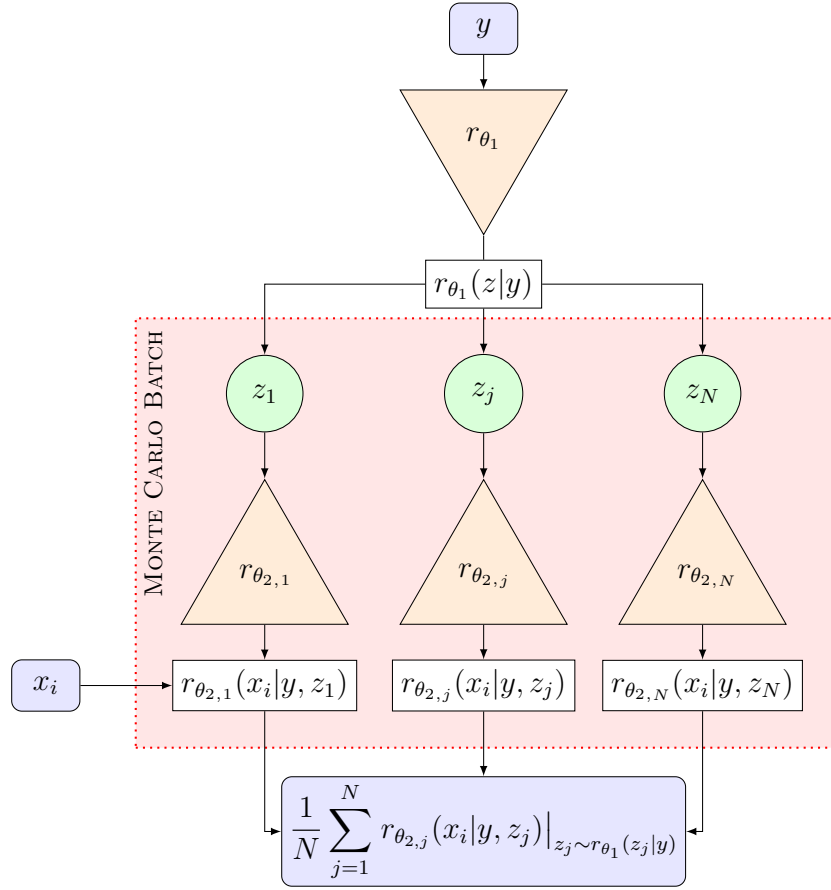


FIG. 4. Diagram of a normalising flow $f(x)$ composed of four coupling transforms which maps an n input vector x to an n latent vector z . Each transform splits x in two $[x_{1:m}, x_{m+1:n}]$ and updates one part conditioned on the other. In the first and third transforms $x_{1:m}$ is used as the input to a neural network (NN) which then produces the scale s and translation t vectors of length m . The element-wise product (\odot) is then computed between $x_{1:m}$ and $\exp(s)$ followed by the sum of the output and t . This is shown in the left transform. In the second and fourth transforms $x_{1:m}$ is updated conditioned on $x_{m+1:n}$ as shown in the right transform.

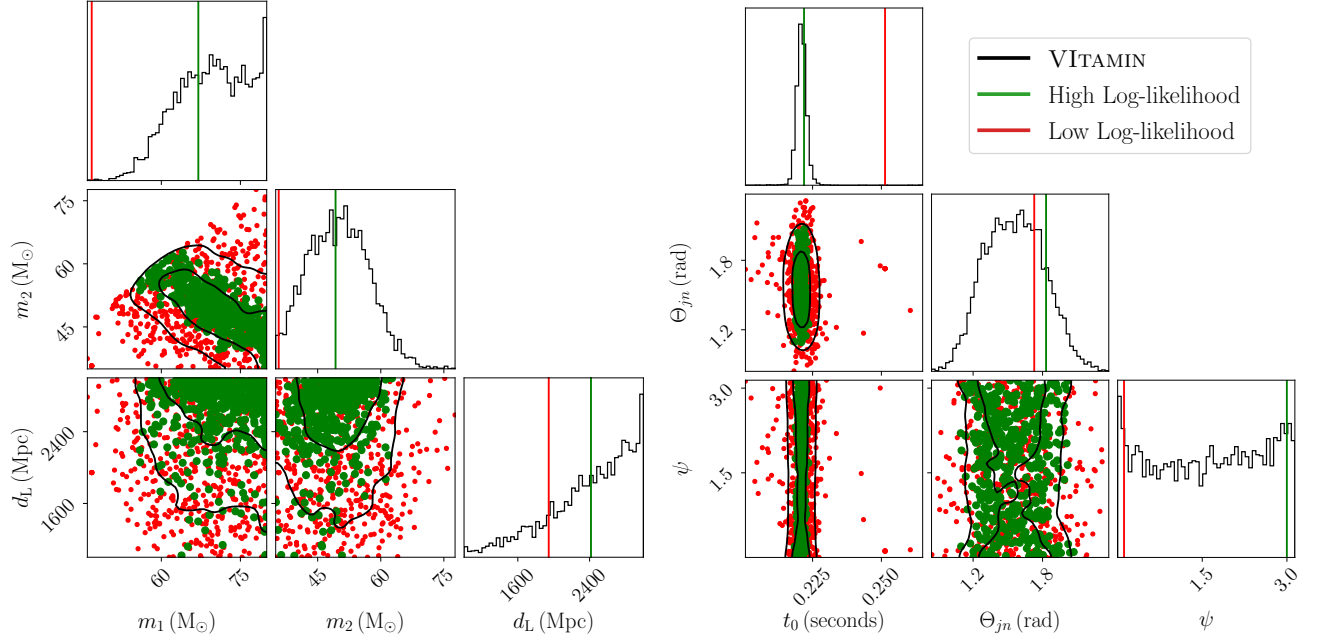


FIG. 5. Probability-probability (P-P) plot showing the confidence interval versus the fraction of the events within that confidence interval for the posterior distributions obtained using our analysis NESSAI for 128 simulated compact binary coalescence signals produced with BILBY and BILBY-PIPE. The 1-, 2- and 3- σ confidence intervals are indicated by the shaded regions and p -values are shown for each of the parameters and the combined p -value is also shown.

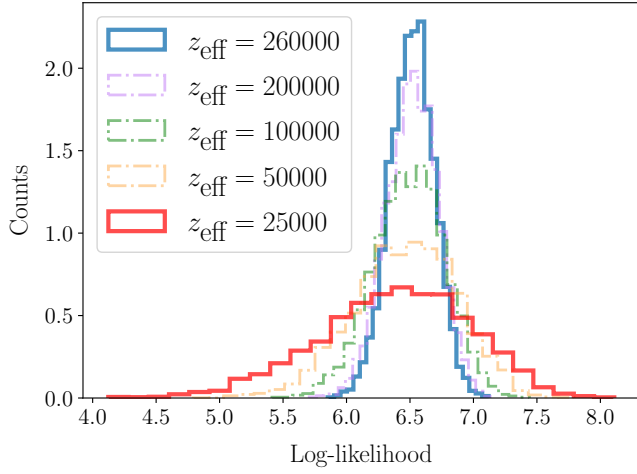


FIG. 6. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour for the current *worst point* shown in orange. **Middle:** samples drawn from a truncated Gaussian within the iso-likelihood contour in and mapped to using the inverse mapping. **Bottom:** pool of accepted samples after applying rejection sampling until 1000 points are obtained shown in both and .

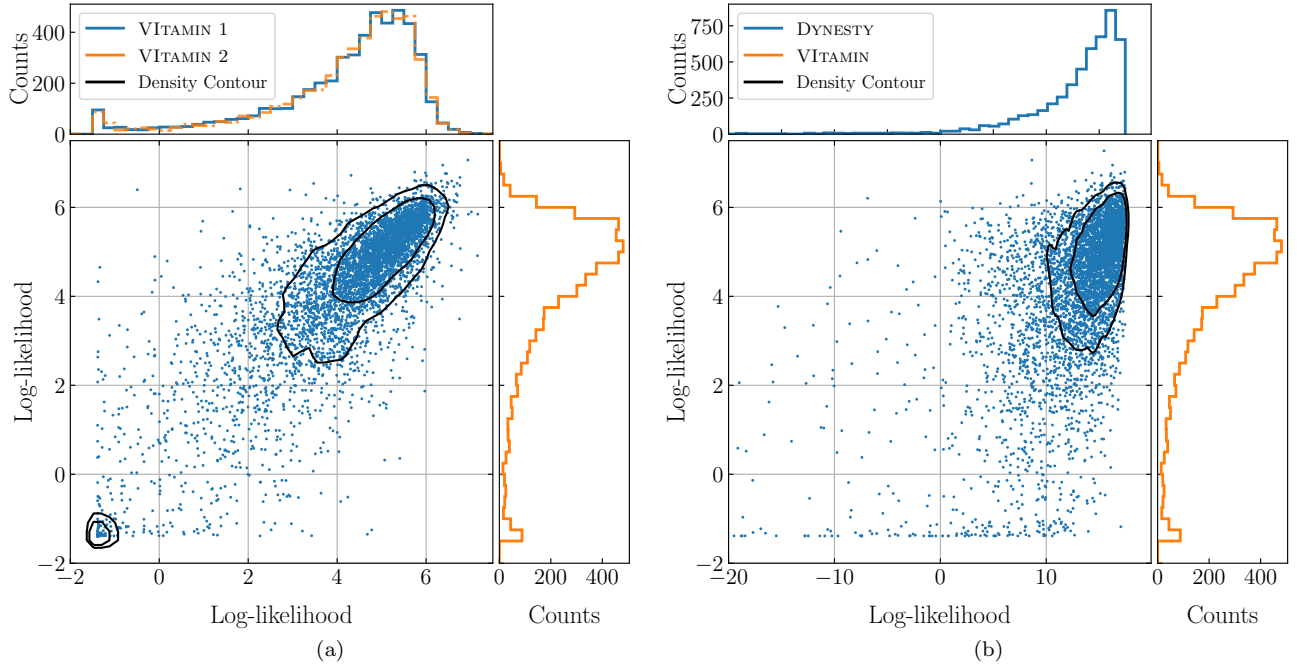


FIG. 7. Probability-probability (P-P) plot showing the confidence interval versus the fraction of the events within that confidence interval for the posterior distributions obtained using our analysis NESSAI for 128 simulated compact binary coalescence signals produced with BILBY and BILBY_PIPE. The 1-, 2- and 3- σ confidence intervals are indicated by the shaded regions and p -values are shown for each of the parameters and the combined p -value is also shown.

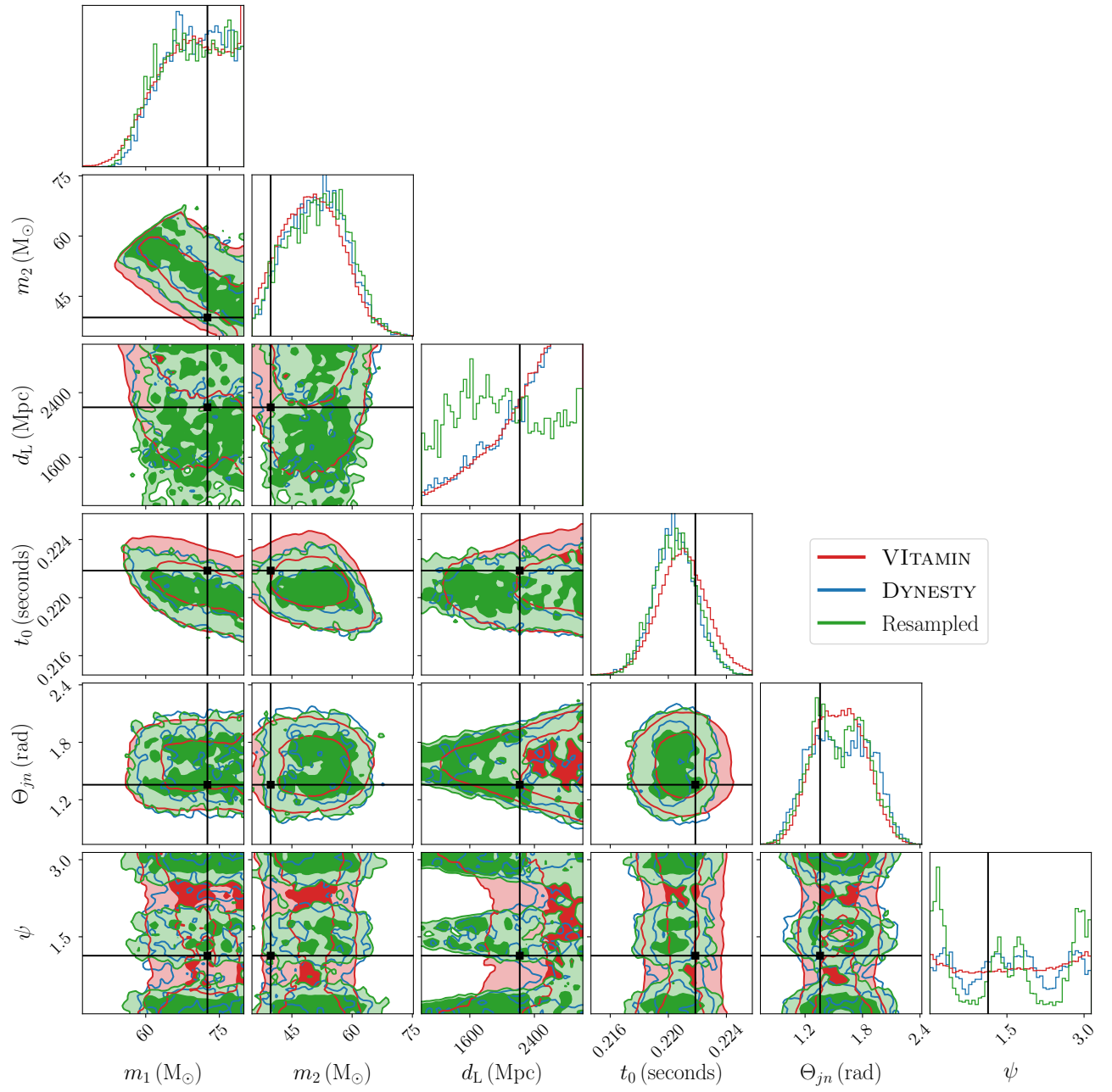


FIG. 8. Corner plot comparing the posterior distributions produced with DYNESITY (blue) and our sampler NESSAI (red). The phase is marginalised and remaining 14 parameters are shown, see app:priors for details on the parameters. The respective 16% and 84% quantiles are also shown in the 1 marginalised posteriors.