

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

Project No: 628
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My 250 word abstract goes here...

I. INTRODUCTION

Figs: Hunter's Vit Schematic

Tables: Params and their defn

Tables: Compare inference speeds like in vit paper

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

Use gen pap to intro CVAE in context, CONTEXT IS KEY HERE

Need to mention metropolis hastings it seems!

Introduce equations directly to our specifics, we don't have space to intro them blind then again to specifics...

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 ??))

II. 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. Likelihood Reweighting

III. 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)

IV. CONCLUSIONS

This 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!

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

ACKNOWLEDGEMENTS

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

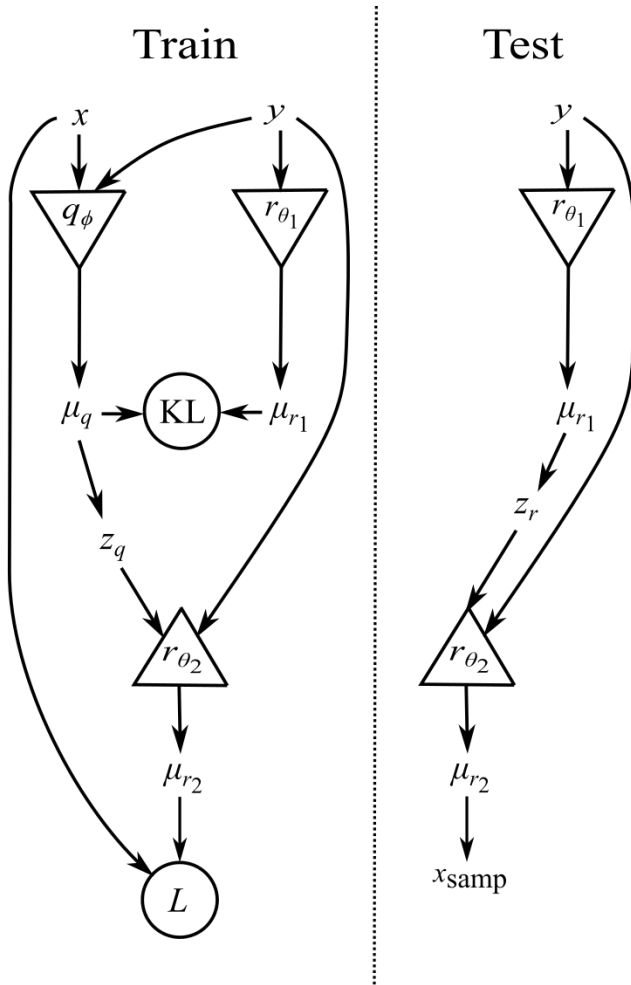


FIG. 1. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour 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 .

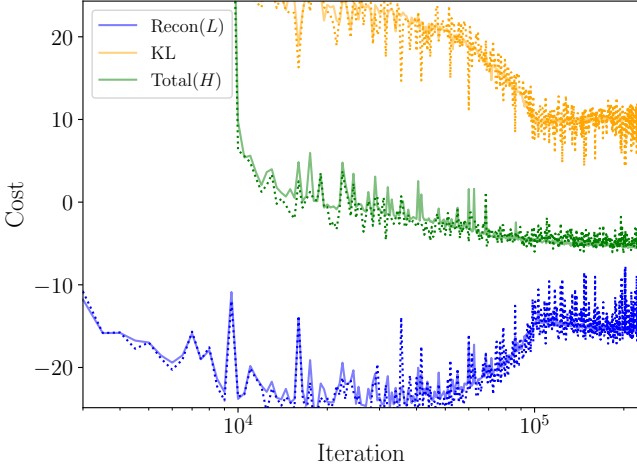


FIG. 2. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour 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 .

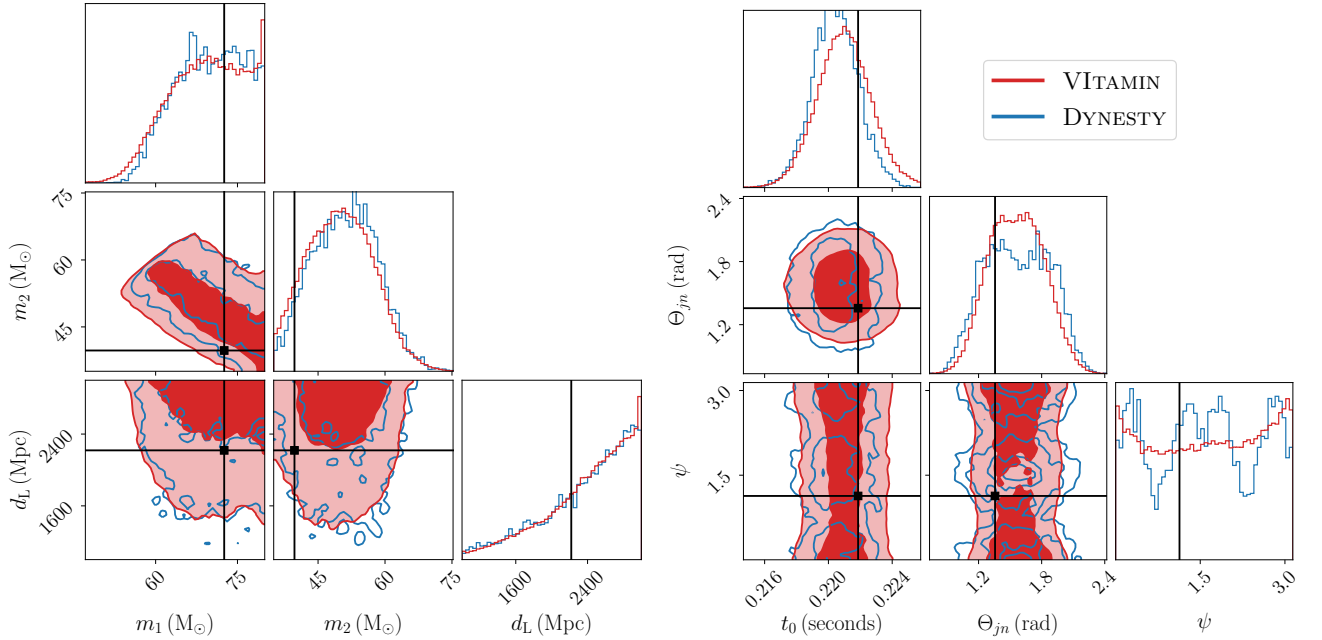


FIG. 3. Probability-probability (P-P) plot showing the confidence interval versus the fraction of the events within that confidence interval for the posterior distributions obtained using our analysis NESSAI for 128 simulated compact binary coalescence signals produced with BILBY and BILBY_PIPE. The 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.

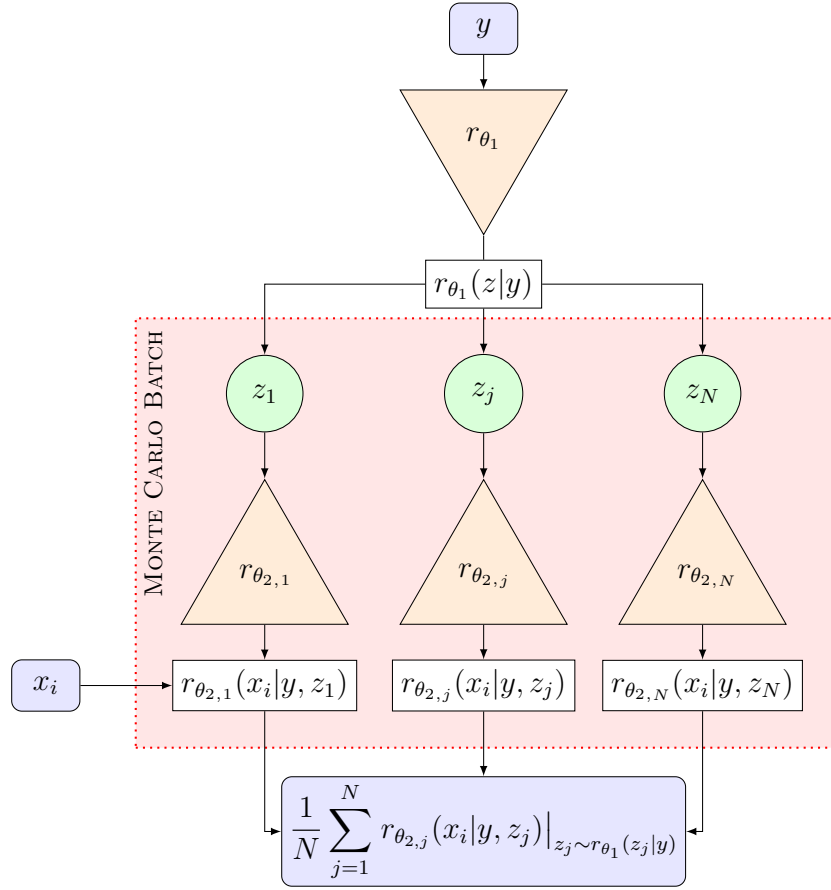


FIG. 4. Diagram of a normalising flow $f(x)$ composed of four coupling transforms which maps an n input vector x to an n latent vector z . Each transform splits x in two $[x_{1:m}, x_{m+1:n}]$ and updates one part conditioned on the other. In the first and third transforms $x_{1:m}$ is used as the input 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. [In my caption, link to previous sections and equations](#)

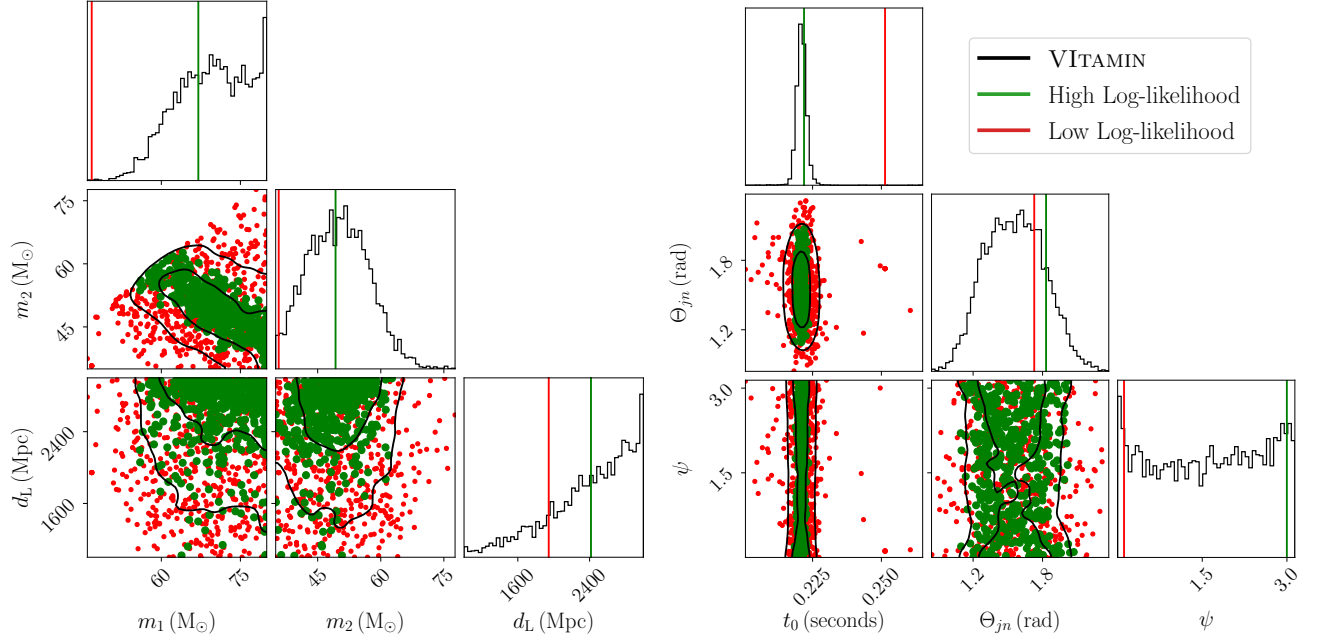


FIG. 5. Probability-probability (P-P) plot showing the confidence interval versus the fraction of the events within that confidence interval for the posterior distributions obtained using our analysis NESSAI for 128 simulated compact binary coalescence signals produced with BILBY and BILBY-PIPE. The 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.

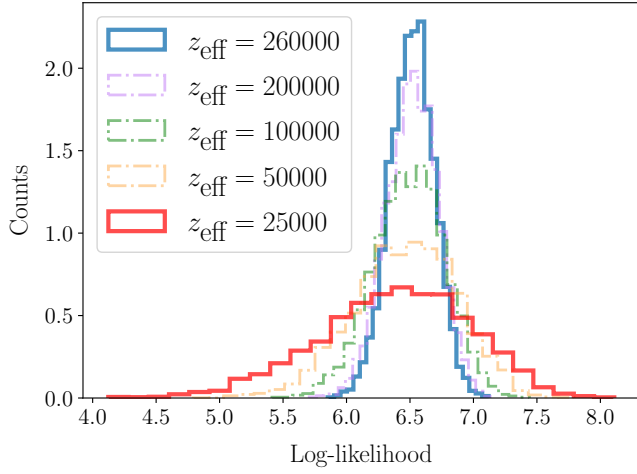


FIG. 6. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour 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 .

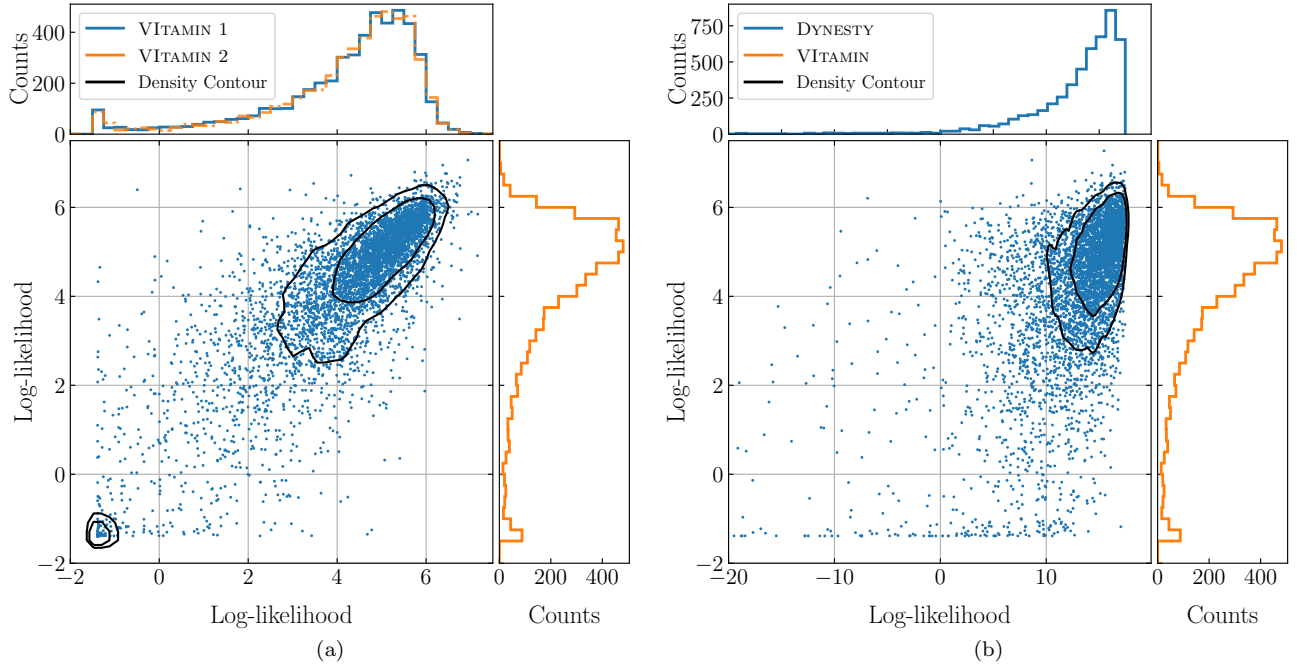


FIG. 7. Probability-probability (P-P) plot showing the confidence interval versus the fraction of the events within that confidence interval for the posterior distributions obtained using our analysis NESSAI for 128 simulated compact binary coalescence signals produced with BILBY and BILBY_PIPE. The 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.

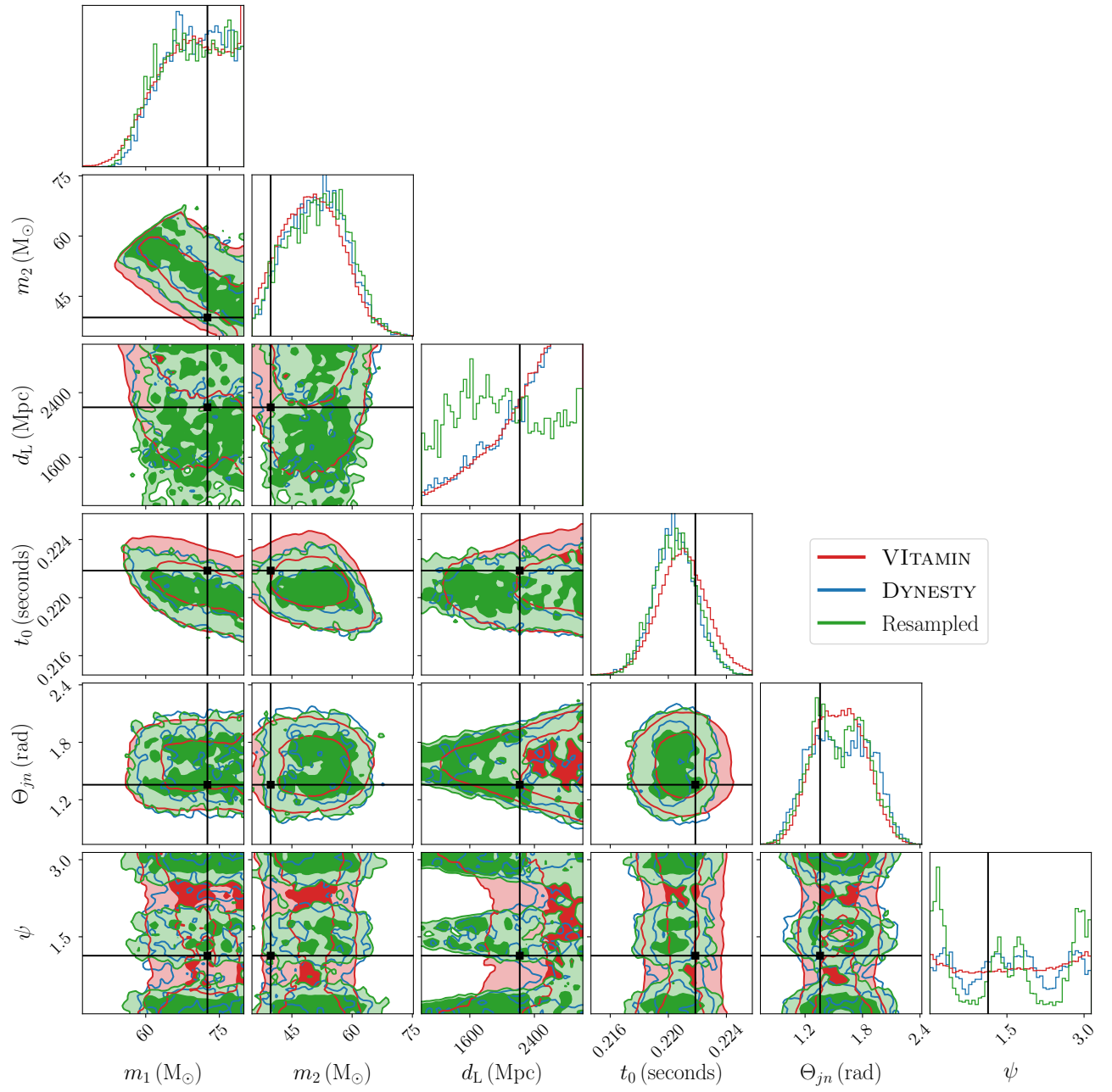


FIG. 8. Corner plot comparing the posterior distributions produced with DYNesty (blue) and our sampler NESSAI (red). The phase is marginalised and remaining 14 parameters are shown, see app:priors for details on the parameters. The respective 16% and 84% quantiles are also shown in the 1 marginalised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