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

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My 250 word abstract goes here...

#### I. INTRODUCTION

Figs: LIGO Cumulative events 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 mateiral 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!

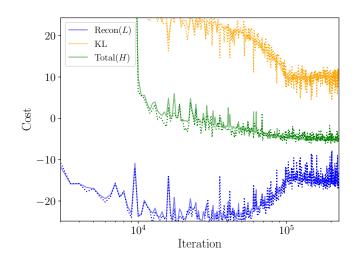


FIG. 1. Example of how a normalising flow trained on a set of live points can produce samples within current iso-likelihood contour for simple two-dimensional parameter space. **Top:** example of training samples in the physical space and learned mapping to the latent space with the iso-likelihood contour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

### 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 acorss the likelihood range, (not present in the DYNESTY case)

Figs: z batch vs sigma

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

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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).