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

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Outline

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A (Very) Brief Introduction

Parameter Estimation (PE)

Inferring intrinsic and extrinsic parameters from their waveform signature.

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$p(x|y) \propto p(y|x)p(x)$. $x =$ parameters, $y =$ waveform data.

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Stochastic algorithms timescale $\mathcal{O}$(days/weeks), `Dynesty*` $\mathcal{O}$(10hrs).

*J. S. Speagle MNRAS Volume 493, Issue 3, April 2020

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Motivation for Deep-Learning

Multimessenger Astronomy (MMA) benefits from fast sky localisation.

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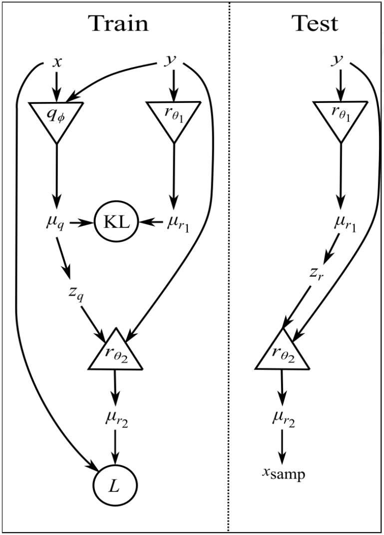
VItamin Structure & Training

CVAE Conditional Variational Autoencoder

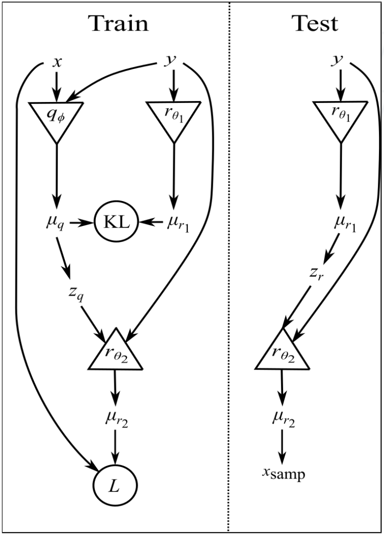


H.Gabbard *et al.* arXiv preprint arXiv:1909.06296 (2019).

VItamin Structure & Training

CVAE	Conditional Variational Autoencoder
KL	Kullback-Leibler Divergence
L	Reconstruction Loss
H	Cost Function

$$\boxed{H \lesssim \frac{1}{N_\mathrm{b}} \sum_{n=1}^{N_\mathrm{b}} (L + KL)}$$



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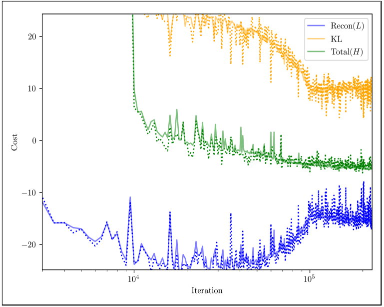

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VItamin Results

$$\tilde{p}(x|y) = \int dz\, r_{\theta_1}(z|y) r_{\theta_2}(x|y,z)$$

VItamin Results

- **Plot Factfile:**
  - 6 parameters
  - 1 detector
  - 5000 samples
- **Choice of Parameters:**
  - Less sampling time
  - All have flat priors
  - Phase marginalisation
- **Result Quality:**
  - Good for unimodal
  - "Misses" psi
  - Incomplete training

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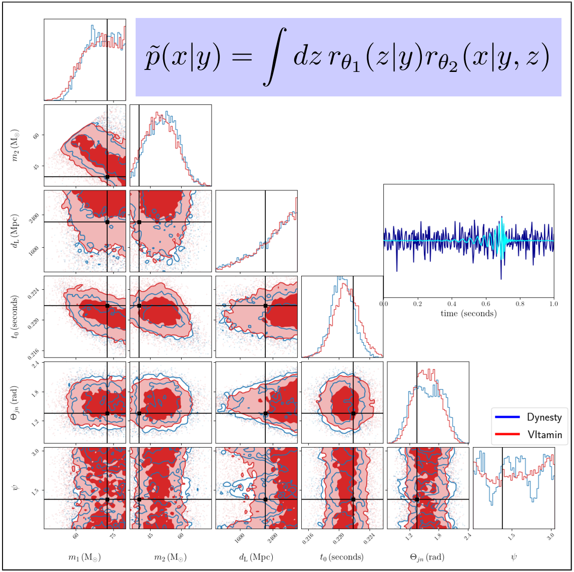

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1. Introduction & Background
2. Our software: `VItamin`
   - `VItamin` Structure & Training
   - `VItamin` Results
3. Monte Carlo Methods for Explainable Deep-learning
   - Monte Carlo Framework
   - Interim Results & Ongoing Work

Monte Carlo Maths

$$I = \int dx\, h(x) f(x)$$

- Probability density

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$$\tilde{p}(x|y) \sim \tilde{p}(y|x)$$

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- **Plot Quality:**
  - Qualatitive Success
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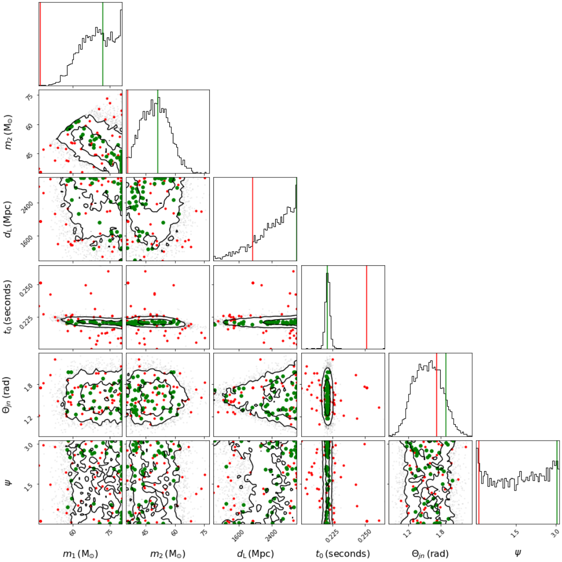

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Brief Summary & Ongoing/Future Work

Recap

1. Focus on faster PE for MMA.

2. Have trained `VItamin` to learn posterior by minimising H.

3. Generated `VItamin` samples and approximated their likelihood using Monte Carlo methods.

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Ongoing Work

- Reweigh likelihoods using `Dynesty` samples via Importance Sampling.
- Quantitative tests of likelihood reproducibility with batch size.
- Rewrite code in `keras.tensorflow` for `VItamin_c`.
- Increase parameter space by accounting for non-flat priors.

Thanks for Listening

VItamin Repo

https://github.com/hagabbar/vitamin_c

Just been updated to VItamin_c pre-release, go check it out!

I look forwarding to answering any questions you may have!