



Vitamin: Rapid Bayesian parameter estimation for CBC signals

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Overview

- Introduction
- CVAEs and Vitamin
- Results
- Summary



Brief Intro

We are interested in CBC signals and estimating their parameters

O(100) signals in total, more expected from O4.





The problem

For full parameter estimation this can be slow - hours to days

Quick alerts are important for followup by EM partners

Not to be compared with fast sky only methods [Singer & Price PRD, 93, 2 (2016)]





VItamin

Variational Inference (tamin)

Uses: Conditional Variational Auto Encoders (CVAE)

Bayesian parameter estimation using conditional variational autoencoders for gravitational-wave astronomy

Hunter Gabbard¹², Chris Messenger¹, Ik Siong Heng¹, Francesco Tonolini² and Roderick Murray-Smith²

With the improving sensitivity of the global network of gravitational-wave detectors, we expect to observe hundreds of transient gravitational-wave events per year. The current methods used to estimate their source parameters employ optimally sensitive but computationally costly Bayesian inference approaches, where typical analyses have taken between 6 h and 6 d. For binary neutron star and neutron star-black hole systems prompt counterpart electromagnetic signatures are expected on timescales between 1s and 1min. However, the current fastest method for alerting electromagnetic follow-up observers can provide estimates in of the order of 1min on a limited range of key source parameters. Here, we show that a conditional variational autoencoder pretrained on binary black hole signals can return Bayesian posterior probability estimates. The training procedure need only be performed once for a given prior parameter space and the resulting trained machine can then generate samples describing the posterior distribution around six orders of magnitude faster than existing techniques.

https://www.nature.com/articles/s41567-021-01425-7

Initially developed by Hunter Gabbard, Chris Messenger and others.





Defining our model



Want to find minimum entropy between posterior and output of network.

$$H(p,r) = \int p(x \mid y) \log r_{\theta}(x \mid y) dx$$

Rewrite target distribution

$$r_{\theta}(x \mid y) = \int r_{\theta_1}(z \mid y) r_{\theta_2}(x \mid z, y) dz$$

Introduce recognition function

 $q_{\phi}(z \mid x, y)$

With some rearranging

$$H < -\frac{1}{N} \sum_{n=1}^{N} \{ \log r_{\theta_2}(x_n \mid z_n, y_n) - KL [q_{\phi}(z \mid x_n, y_n) \parallel r_{\theta_1}(z \mid y_n) \} \}$$



Training

Generate 1e7 training examples with parameters drawn from prior distribution

Augmented on

• $D_L, t_c, \alpha, \delta, \psi, \phi$

Run on 3 detectors at 1024 Hz for 1s.

Name	Symbol	Min	Max	Unit
Mass 1	m_1	10	100	Solar Mass
Mass 2	m_2	10	100	Solar Mass
Luminosity	D_L	0.5	5	Gpc
Coalescent time	t_c	0.65	0.85	Seconds
Phase	ϕ	0	2π	radian
Right ascension	α	0	2π	radian
Declination	δ	$-\pi/2$	$\pi/2$	radian
Inclination	l	0	π	radian
Polarisation	Ψ	0	π	radian
Spin magnitude 1	a_1	0	0.99	
Spin magnitude 2	a_2	0	0.99	
Tilt 1	θ_1	0	π	radian
Tilt 2	θ_2	0	π	radian
Azimuth angle	ϕ_{12}	0	2π	radian
Azimuth position	ϕ_{jl}	0	2π	radian

Training

Training takes around 1 day on a single GPU

Although realistically need to train for a bit longer.

Red line is expected minimum loss.

Can calculate the expectation value of crossentropy from Dynesty samples.



VItamin posteriors

Dynesty (blue)

Vitamin (red)

Takes less than a second to generate posteriors



Can test the statistical consistency of posteriors.

Test over the marginal posteriors.



Comparison of JS divergence between different samplers



Summary

- Currently a problem of speed in PE for CBC signals.
- Use Vitamin to generate Bayesian posteriors for BBH signals in less than a second.
- Demonstrated to perform similarly to traditional samplers.
- Currently testing on real data.
- Plan to extend to BNS signals in the future