Parameter estimation of binary black hole systems using numerical relativity surrogates and a rapid inference framework

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Ongoing MS Thesis Project supervised by

- Scott Field (UMass Dartmouth)

Joint work with

- Jacob Lange (RIT) (RIFT+ILE)
- Richard O'Shaughnessy (RIT) (RIFT+ILE)
- Vijay Varma (Caltech) (NR Surrogate Model)

Introduction

GW Parameter Estimation

- Figuring out what are the properties of the binary sources using the data
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Parameters include

- Masses and spins of black holes
- Luminosity distance to binary D_L
- Inclination angle ι
- RA and dec (position in sky)
- ..and so on

Introduction

Why do we need parameter estimation?

- Accurate parameter estimation required for science (eg. population studies, tests of GR)
- Fast algorithms can help follow-up observations

Bayes' Theorem

Updating and maximizing our knowledge from the data and our prior belief

$$p_{post}(\lambda, \theta) = \frac{\mathcal{L}(\lambda, \theta) p(\theta) p(\lambda)}{\int d\lambda d\theta \mathcal{L}(\lambda, \theta) p(\lambda) p(\theta)}$$

- Posterior p_{post} - probability of parameter value to be correct given the data. This is what we are looking for
- Likelihood $\mathcal{L}$ - probability of data assuming model is true i.e. how well does the model parameter fit the data
- Prior $p(\theta)p(\lambda)$ - what we think the model parameter PDF looks like
- Evidence - normalization constant, important for model selection

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- λ - Intrinsic parameters, describes dynamics of binary
- θ - Extrinsic parameters, describes space and time orientation

Models

Templates for aligned spin

- SEOBNRv4 - Effective-one-body model
- IMRPhenomD
- Numerical Relativity (NR) simulations - solving Einstein's equations on a computer. Very expensive to compute, but gives most accurate results

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- Surrogate models

Surrogate Models

- Fast and accurate evaluation using reduced order modeling (ROM)
- No assumptions of underlying model
- Will converge to the model by improving representation
- Need to specify model and range of parameters
- Non-intrusive
- gwsurrogate - Publicly available package

NR Surrogate Models

NRHybSur3dq8

- Aligned spin hybrid model made by stitching together PN for early inspiral, NR simulation for the rest
- Contains higher modes upto lmax $\leq$ 5
- Training region: 1 $\leq$ q $\leq$ 8, 0.8 $\leq \chi_{1z/2z} \leq$ 0.8.

NRHybSur3dq8

ModelErrors.png

NRHybSur3dq8

SurrogateTrainingSet.png

Inference algorithms

LALInference (LIGO)

- Using variants of optimized MCMC and nested sampling
- Well-tested and reliable
- Doesn't scale well to massive ($>$1000) core counts
- Model must be made available in LALSimulation (need low level C to interface)

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gwin (in development, Capano et al.)

- Next gen python package for parameter estimation

Inference algorithms

ILE+RIFT

- Specify and separate intrinsic and extrinsic parameters
- Lay out grid on intrinsic parameters
- Independent, Parallelized, Log-Likelihood calculation over each grid point using Monte Carlo Integration and marginalization of extrinsic parameters
- Gaussian Process Regression to interpolate over grid points with high likelihood
- Setup for next iteration over new interpolated grid

MGHPCC

Massachusetts Green High Performance Computing Center

- Developed as a joint venture of Boston University, Harvard, MIT, Northeastern, and the University of Massachusetts system
- Can be accessed by UMass students under participating faculty

mghpcc.jpg

Figure: The MGHPCC facility at Holyoke, Massachusetts

Progress so far

- Interfacing the new model with the codebase
- Performing test runs on a local cluster at RIT
- Setting up the codebase at MGHPCC to begin PE runs

Preliminary Results

- Preliminary is the key word here
- Signal injected and PE study done using same model
- Sparse grid, only 5 points per dimension
- SNR 20
- $m_1 = 56$
- $m_2 = 14$
- $\chi_{1z} =$ -0.5
- $\chi_{2z} = 0.5$

mspin.png

mcetachiE.png

Conclusion

Remarks

- First PE study with this new model
- NR surrogates provide fast and accurate waveform models
- ILE+RIFT performs rapid parameter estimation using parallelized computation in order of hours

Future Outlook

- Investigate effects of higher harmonic modes
- Understand bias in PE studies using statistical techniques
- Compare with other models