GW Parameter Estimation

Group ...

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Abstract

The multi-messenger follow-up of gravitational waves (GW) requires rapidly estimating source parameters like component masses, distance, and sky-localization. Deep learning based pipelines provide an efficient method to carry out this task due to reduced computational power. This project aims to develop one such pipeline that uses a normalizing flow model. The pipeline uses LIGO O3 MDC data along with IMRPhenomD waveforms. Computationally expensive parameters like time-of-arrival are marginalized using a similarity embedding network. Finally, the model is trained using a normalizing flow model, which is a generative deep learning algorithm. This pipeline demonstrates the key features of a more developed AMPLFI pipeline.

Introduction

The discovery of gravitational waves (GWs) has opened an unprecedented window into the universe. Rapid and accurate parameter estimation (PE) of GW events is important for enabling timely electromagnetic follow-up observations. Traditionally, PE relies on likelihood-based inference methods. These approaches are often computationally expensive and slow. This latency poses a significant limitation for real-time multi-messenger astronomy. Recently, likelihood-free inference (LFI) has emerged as a promising alternative. Instead of explicitly evaluating the likelihood, LFI methods use machine learning models, such as normalizing flows, to learn the posterior distribution directly from simulated data. This enables fast inference once the model is trained, greatly reducing the time-to-alert for GW discoveries.

In this project, the architecture combines similarity-based embedding with normalizing flows to model complex gravitational wave data distributions effectively. The embedding network marginalizes computationally expensive parameters like time-of-arrival and irrelevant ones like spins. Doing so enables us to focus on estimating the component masses and sky-localization. It also reduces data dimensionality for the flow model. This similarity embedding is achieved by pre-training the encoder to prioritize feature structures that capture meaningful relationships using VICReg loss [1] function. Once embedded, a normalizing flow is applied to the latent space to model its probability density. This two-step architecture allows the model to preserve important physical similarities while simultaneously enabling accurate sampling, density estimation, and uncertainty quantification within the complex parameter space of gravitational wave events.

Timeline

Week1
Everyone- Set up Delta accounts
Shrey - Get LIGO O3 Data, create container and environment
Steven - Work with BILBY pipeline
Yiwen and Calvin - Data Preprocessing (whitening and FFT)

Week2
Everyone - Presentation
Shrey and Steven - Set up Normalizing flow architecture
Yiwen and Calvin - Similarity embedding network

Week3
Everyone - Hyper-parameter tuning and Write-up