EGU23-7939, updated on 29 Feb 2024
https://doi.org/10.5194/egusphere-egu23-7939
EGU General Assembly 2023

Towards Bayesian Full-Waveform Source Inversion using Simulation-Based Inference

Alex Saoulis[1], Ana Ferreira[2], Benjamin Joachimi[1], Alessio Spurio Mancini[1,3,4], and Davide Piras[5]
[1]Physics & Astronomy, University College London, London, UK (a.saoulis@ucl.ac.uk)
[2]Earth Sciences, University College London, London, UK
[3]Mullard Space Science Laboratory, University College London, London, UK
[4]Astrophysics Group, Cavendish Laboratory, Cambridge, UK
[5]University of Geneva, Geneva, Switzerland

Bayesian inference provides a pathway toward accurate predictions of source parameters (e.g., location and moment tensor), along with principled, well-calibrated uncertainty estimates. Unfortunately, standard Bayesian inference techniques can often require O(10^5) simulations per full waveform inversion, making the method infeasible when studying large numbers of events due to the high computational cost of seismological forward modelling. Machine Learning (ML) has emerged as a promising solution to this issue, with recent work demonstrating that ML-based emulators of the physics simulation can be used as rapid-executing surrogates of the forward model in the Bayesian inference workflow. It has been demonstrated that such models, in conjunction with an assumed likelihood model (e.g. Gaussian), can be used to efficiently perform Bayesian posterior inference over seismological source parameters.

This work explores an extension to the above method, often referred to as “likelihood-free” or “simulation-based” inference, which removes any assumptions about the likelihood model. This approach leverages a class of neural networks known as Neural Density Estimators (NDEs) to estimate the likelihood density directly given some representation of the observables. To simplify training of these NDEs, a compression technique that can reduce the observables (i.e., full seismograms) into a small set of parameters is required. This work investigates “classical” and ML-based compression techniques for creating a reduced dimension representation. It then demonstrates simulation-based inference on the problem of source location inversion applied to synthetic examples based on a recent seismic swarm on the São Jorge island in the Azores. Comparisons between the proposed approach and other inversion techniques are also presented.