Machine-Learning Classification Of Core-Collapse Supernovae And Detector Glitches

Alberto Iess[1,2], Elena Cuoco[3,4], Filip Morawski[4,5], Massimiliano Razzano[6,7], Jade Powell[8]

[1] *Università di Roma Tor Vergata, I-00133 Roma, Italy*
[2] *INFN, Sezione di Roma Tor Vergata, I-00133 Roma, Italy*
[3] *European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy*
[4] *Scuola Normale Superiore, Piazza dei Cavalieri 7, I-56126 Pisa, Italy*
[5] *Nicolaus Copernicus Astronomical Center, Polish Academy of Sciences, 00-716, Warsaw, Poland*
[6] *Università di Pisa, I-56127 Pisa, Italy*
[7] *INFN, Sezione di Pisa, I-56127 Pisa, Italy*
[8] *OzGrav, Swinburne University of Technology, Hawthorn, VIC 3122, Australia.*

Abstract

Gravitational wave (GW) interferometers have successfully observed signals generated by binary black-hole (BBH) and binary neutron stars (BNS) mergers. The AdLIGO and AdVirgo detectors have undergone upgrades in view of the coming observing run O3. Galactic Core-Collapse Supernovae (CCSN) are expected to emit a signal which may be observable by AdLIGO and AdVirgo and future generation detectors. Differently from binary mergers, CCSN searches should not be based on traditional matched filtering techniques, due to large uncertainty on the expected burst waveform. A variety of models exist for different progenitors and GW emission mechanisms. In recent years, machine-learning (ML) obtained remarkable results in classification tasks. In this work we test the performance of a ML approach in classifying CCSN signals and other burst-like signals present in interferometric data, such as detector glitches. The analysis is carried on for a single detector. We inject CCSN waveforms from 3-D simulations by Powell et al. 2018, which reach far into the explosion phase, onto simulated gaussian noise and afterwards onto real data from the O2 observing run. We use a Wavelet Detection Filter (WDF) to provide event triggers for ML algorithms.We test the performance of different ML algorithms working both with raw timeseries and in the time-frequency domain. We analyse its performance in terms of source distance and position to provide detection limits. We also test its robustness in the more realistic case of a strongly unbalanced dataset.