

Core-Collapse Supernova Waveform Generation Using Machine Learning

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Faculty of Physics, University of Warsaw

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Introduction

Excellent Talks Covering Fundamentals of CCSN !!!

Motivation

- **CCSN simulations are computationally expensive.**
- **Looking for an alternate method to quickly generate the waveforms across EOS and other physical parameter.**
- **Potential application in parameter estimation.**
- **An approach to combine the current CCSN models for further application.**

Workflow

- **Prepare a CCSN GW data.**
- **Choose the required physical parameter space.**
- **Built the neural network.**
- **Perform training, test and validation.**
- **Generate waveforms with the neural network.**
- **Verify the results with measured values.**

Data

Data has been adopted from Richers et al. 2017 <https://zenodo.org/records/201145>

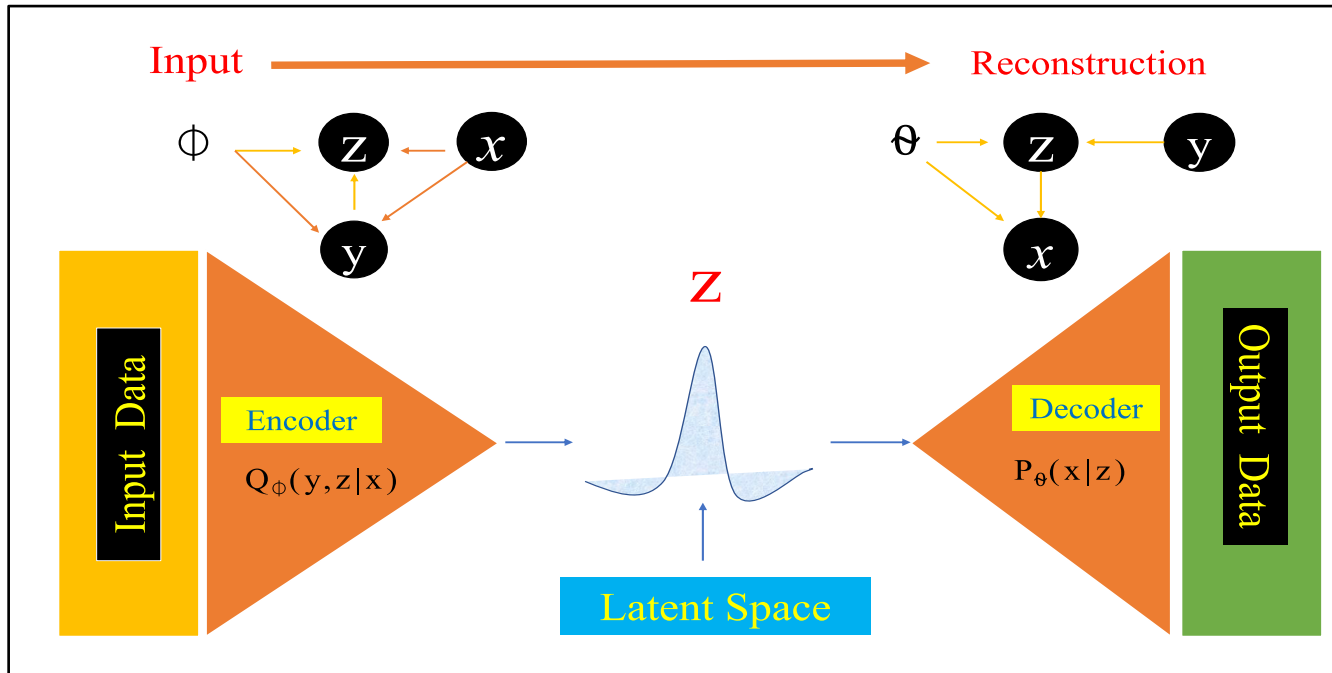
- 2D GR Hydrodynamic Simulation.
- 12- M_0 progenitor model.
- 18 different EOS
- 98 different rotational profile with differential rotation and maximum rotation.

Selected Data

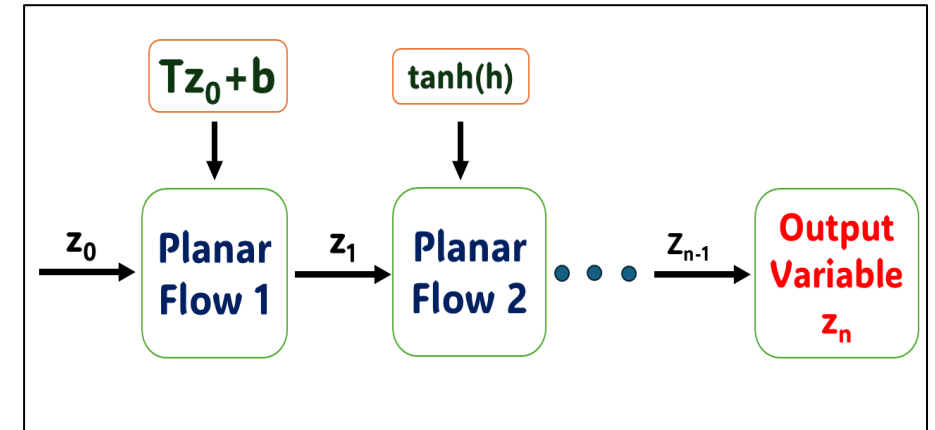
- **EOS Considered:** HDSS2, SFHo, GShenNL3, BHBLP, HSTMA, LS220, LS180, LS375, HSTMA, HSNL3, GShenFSU1.7, SFHx, SFHo_ecapture_0.1, SFHo_ecapture_1.0, SFHo_ecapture_10
- **Differential Rotation A** : 300, 467, 634, 1268 and 10000 (km)
- **Maximum Rotation Ω_0** : 0.5-15.5 rad/s
- **98 combinations** of physical parameter sets with A , Ω_0 for each EOS.
- **Thus 98 waveforms** for each EOS.

Training Methodology

Conditional Variational Autoencoder + Planar Normalizing Flow (Generative Models)



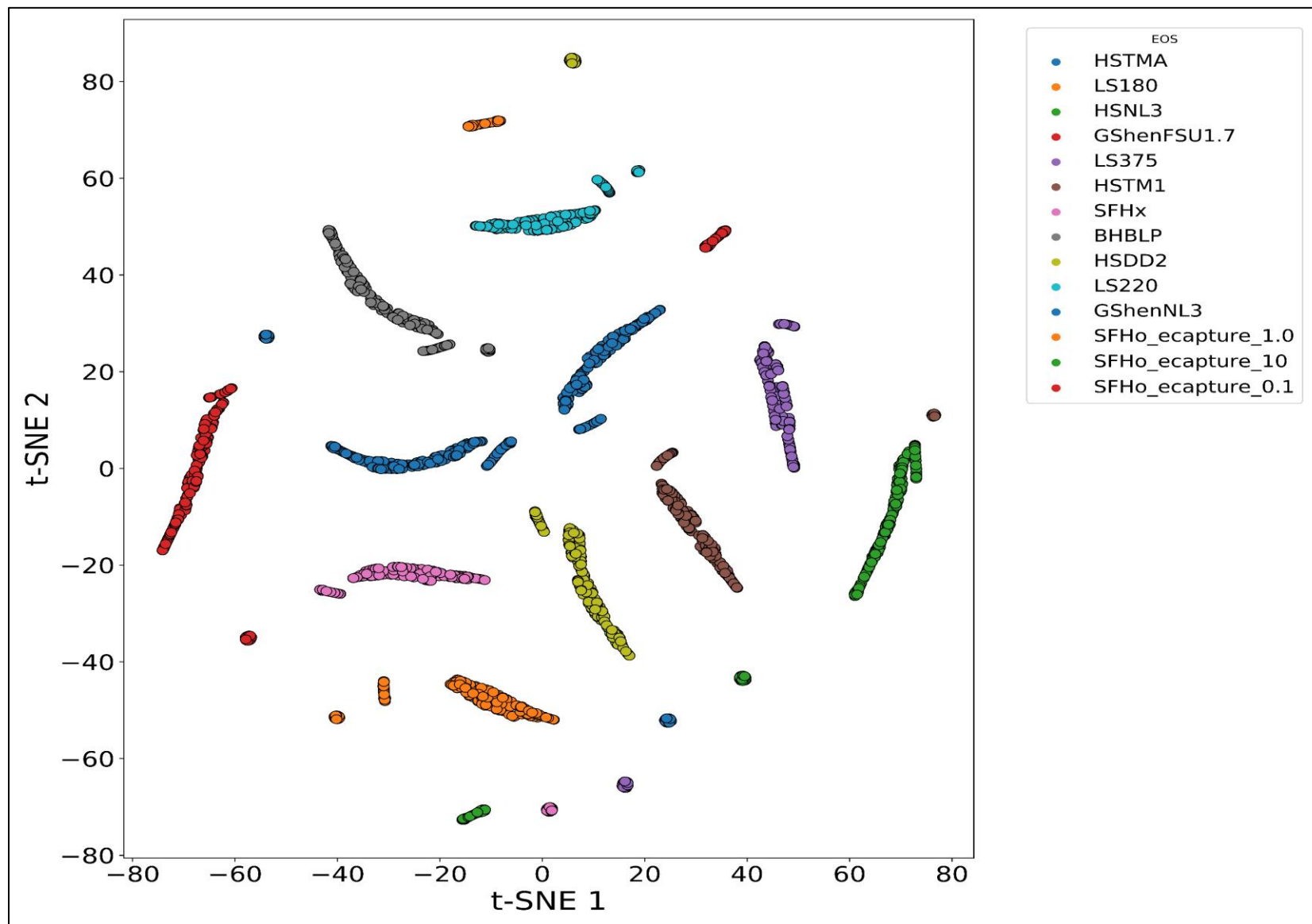
(Saha et al. 2024)



- Train the waveforms being conditioned on EOS, A and Ω_0
- Generate 1000 GW waveforms for selected parameter set.
- Compare the true and generated waveforms visually and with other metrics.

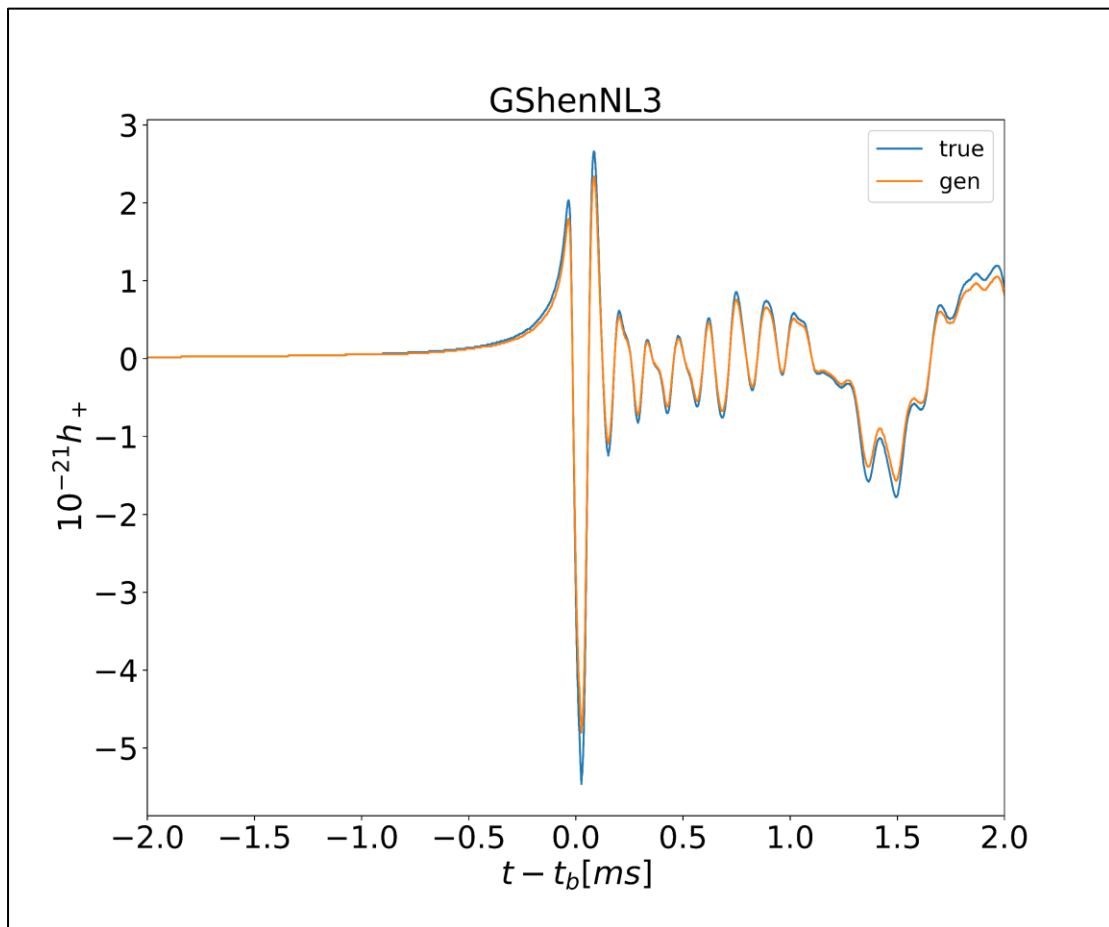
Results 1

t-SNE Plot

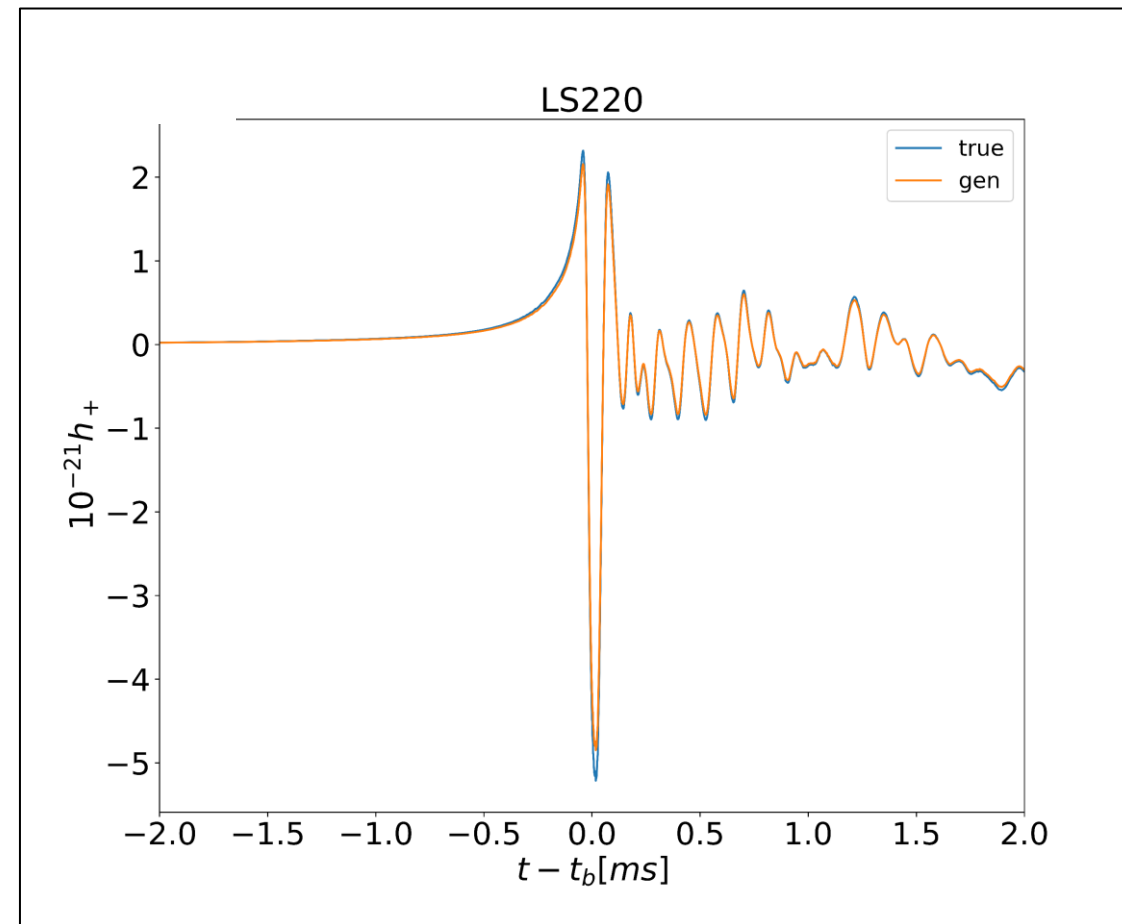


Results 2

GShenNL3, $A = 467$ km, $\Omega_0 = 6$ rad/sec



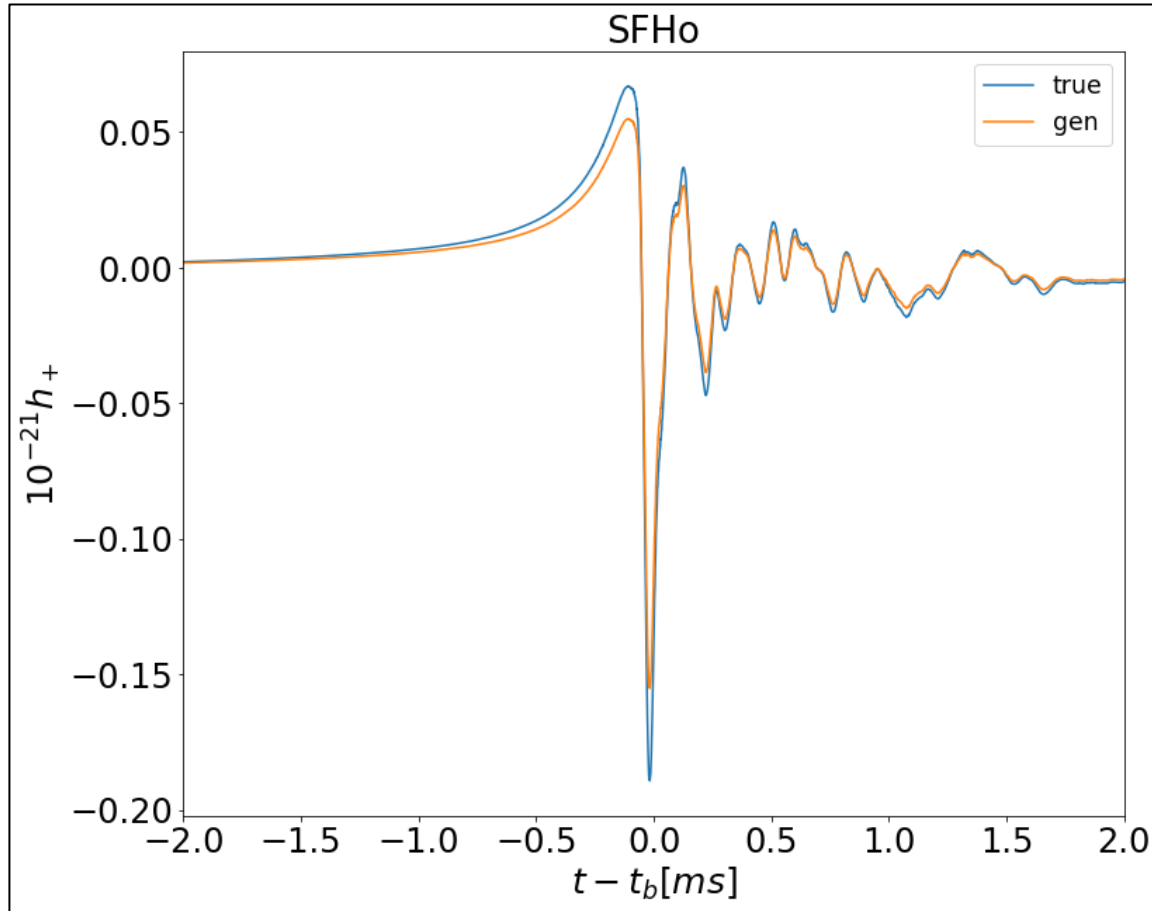
LS220, $A = 634$ km, $\Omega_0 = 6$ rad/sec



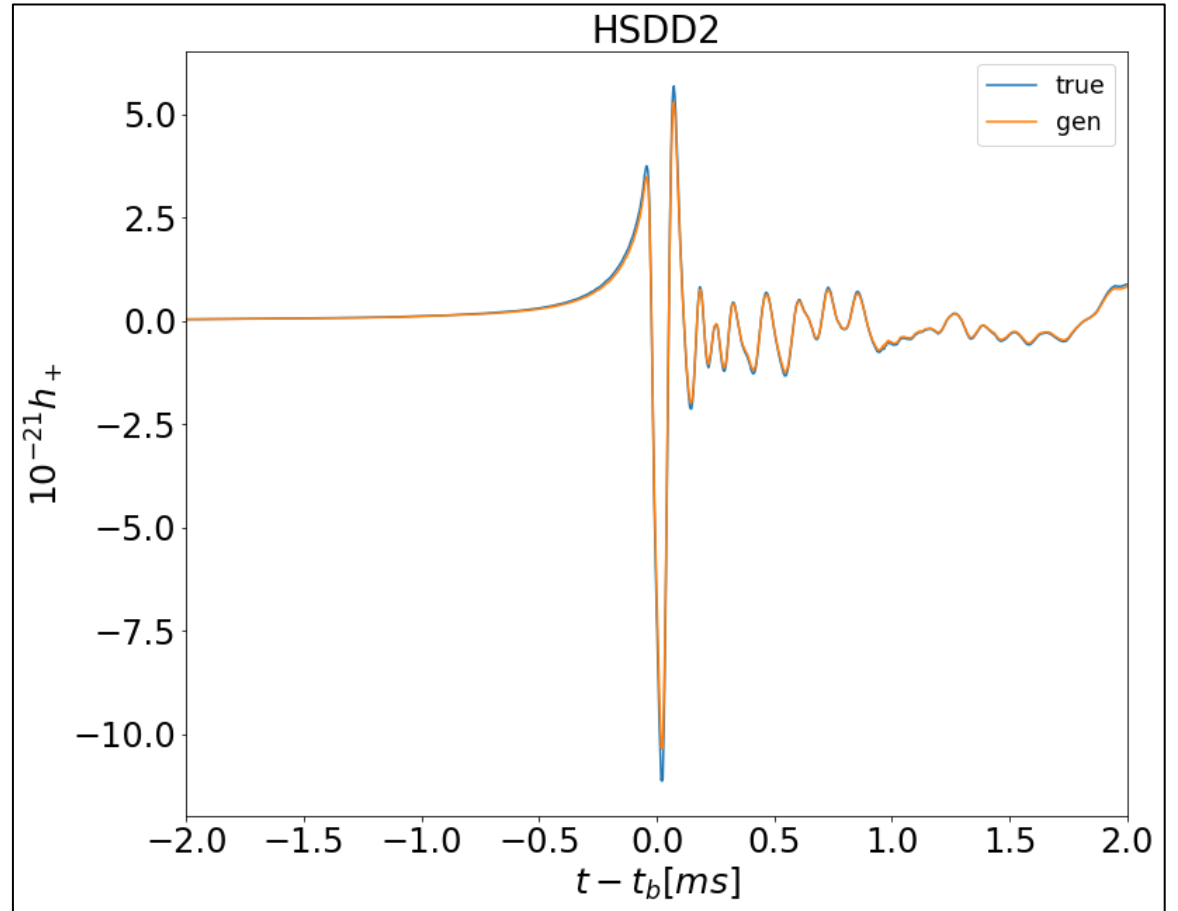
Extent of overlap between the true and generated waveforms

Results 3

SFHo, $A = 634$ km, $\Omega_0 = 9$ rad/sec



HSDD2, $A = 467$ km, $\Omega_0 = 6$ rad/sec



Extent of overlap between the true and generated waveforms

Results 4

Calculated values of mean squared error and MAPE between the true and generated waveform across EOS

EOS	Range of MSE [1e-41]	Range of MAPE (%)
HSDD2	0.0083~0.0088	1.5~2
GShenNL3	0.0077~0.0080	0.8-1.2
BHBLP	0.007~0.0073	0.9~1.25
SFHo	0.008~0.009	1.32~1.75
HSTMA	0.0065~0.0072	0.7~1.1
LS220	0.0092~0.0097	1.12~1.5
LS180	0.006~0.0065	1.09~1.45

Summary

- **Currently, training takes ~2 hrs.**
- **Generation of waveforms take ~milliseconds.**
- **MSE and MAPE provide evidence for accurate generation.**

Future Works

- **Include CCSN waveforms from other models.**
- **Generate waveforms across other models based on EOS.**

**Thank You For Your
Attention**