A Machine Learning Model for discriminating between gravitational wave signals from core collapse supernovae and detector noise

Michael Benjamin, Shahrear Khan Faisal, Gaukhar Nurbek and Oscar Valdez
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Introduction

Core collapse supernovae (CCSN) are highly anticipated sources of gravitational waves (GW) during the fourth observation run (O4). CCSN signals are weak and unmodeled and the rate of occurrence in our galaxy is 2 per century.Thus, detection of GW from CCSN is a challenging problem. CCSN waveform simulations are used to test the detection pipeline in the event a CCSN is detected during O4. CCSN GW signals are often indistinguishable from the noise sources present in GW data. Machine Learning (ML) techniques are useful in addressing this problem. We have used a Convolutional Neural Network (CNN) to train two CCSN signals from Powell and Müller [1, 2], 3D simulations using a 39 solar mass progenitor and an 18 solar mass progenitor, which are injected into data from the third observation run (O3). We also trained our CNN with background triggers from O3. Our network is currently able to correctly classify CCSN signals in more than 97% of cases.

m39 waveform

The m39 waveform is a 3D, general relativistic simulation using a 39 solar mass progenitor. This is a rapidly rotating model. It has an explosion energy of 7.5e-10 (M_sol * c^2). It has f and g modes, standing accretion shock instability (SASI), prompt convection components. The peak frequency is at 674 Hz.
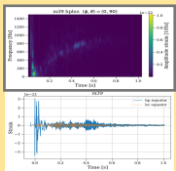

s18 waveform

The s18 waveform is a 3D, general relativistic simulation using an 18 solar mass progenitor. The peak frequency for this model is 872 Hz with a duration of 980 ms. The explosion energy is 1.6×10^{-8} M☉c2. g modes are observed.
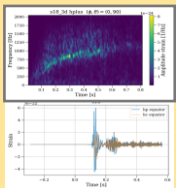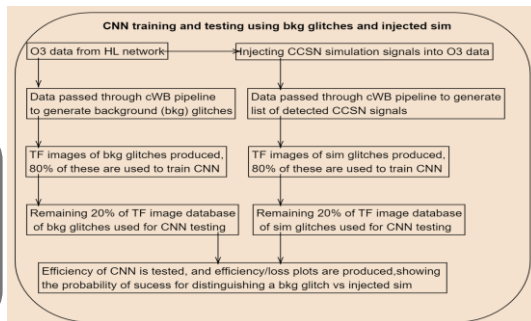

References

1. Jade Powell, Bernhard Müller, Gravitational wave emission from 3D explosion models of core-collapse supernovae with low and normal explosion energies, *Monthly Notices of the Royal Astronomical Society*, Volume 487, Issue 1, July 2019, Pages 1178–1190, https://doi.org/10.1093/mnras/stz1304
2. Jade Powell, Bernhard Müller, Three-dimensional core-collapse supernova simulations of massive and rotating progenitors, *Monthly Notices of the Royal Astronomical Society*, Volume 494, Issue 4, June 2020, Pages 4665–4675, https://doi.org/10.1093/mnras/staa104
3. Drago, M. & V, Gayathri & Klimenko, S. & Lazzaro, C. & Milotti, Edoardo & Mitselmakher, G. & Necula, V. & O'Brian, B. & Prodi, G. & Salemi, Francesco & Szczepanczyk, M. & Tiwari, Shubhanshu & Tiwari, Vimlesh & Vedovato, Gabriele & Yakushin, Igor. (2020). Coherent WaveBurst, a pipeline for unmodeled gravitational-wave data analysis.
4. Soma Mukherjee, Gaukhar Nurbek, and Oscar Valdez, Study of efficient methods of detection and reconstruction of gravitational waves from nonrotating 3D general relativistic core collapse supernovae explosion using multilayer signal estimation method, Phys. Rev. D **103**, 103008, 2021
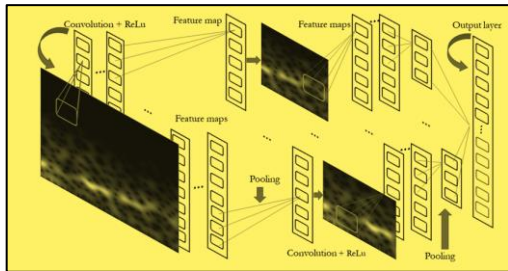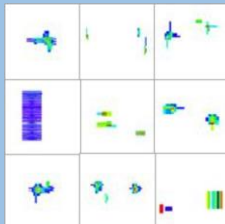
What is a Convolutional Neural Network?

Step 1: **Convolution**: The image is broken down into a matrix of numbers or weights. A kernel (a smaller dimension matrix) is chosen to move over the full image to do convolution at each step to create a 'feature map'.

Step 2: **Pooling**: The feature map is further reduced by a pooling layer where either a maximum (max-pooling) or an average (average pooling) is computed from all over the image.

Step 3: **A Rectified Linear Unit** is applied to introduce more non-linearity and the matrix from the pooled layer is flattened i.e., a nxn matrix is converted into n^2x1 matrix to produce the fully connected layer.

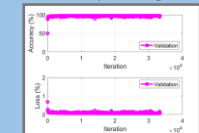**Step 4:** Ready for **classification using the softmax**, which is a weighted exponential function.

CNN training and testing using bkg glitches and injected sim

O3 data from HL network → Injecting CCSN simulation signals into O3 data

Data passed through cWB pipeline to generate background (bkg) glitches | Data passed through cWB pipeline to generate list of detected CCSN signals

TF images of bkg glitches produced, 80% of these are used to train CNN | TF images of sim glitches produced, 80% of these are used to train CNN

Remaining 20% of TF image database of bkg glitches used for CNN testing | Remaining 20% of TF image database of sim glitches used for CNN testing

Efficiency of CNN is tested, and efficiency/loss plots are produced,showing the probability of sucess for distinguishing a bkg glitch vs injected sim

Examples of BKG images

Examples of s18 images
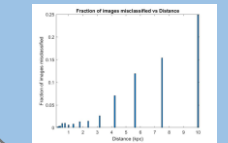

Examples of m39 images
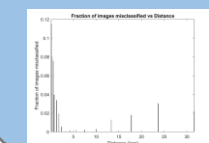

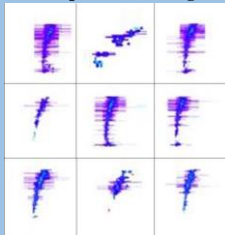### S18 accuracy & loss plots

M39 accuracy & loss plots

s18 fractions of misclassifications

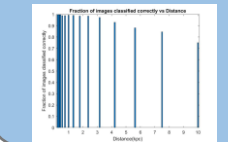### m39 fraction of misclassifications
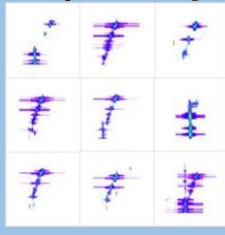

s18 fractions of correct classifications

m39 fraction of correct classifications
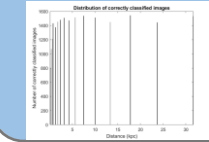
Conclusions

1. S18 waveforms are classified with 98.50 % accuracy
2. M39 waveforms are classified with 97.97 % accuracy
3. The CNN model is fully integrated with the MuLaSECC analysis pipeline, expected to run in O4
4. CNN is found to be an effective discriminator for CCSN waveforms.
5. More CCSN waveforms to be tested in the HLV and HLVK networks

Acknowledgements