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

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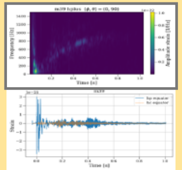
Introduction

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.

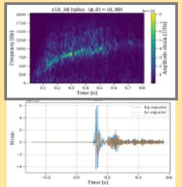
m39 waveform

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

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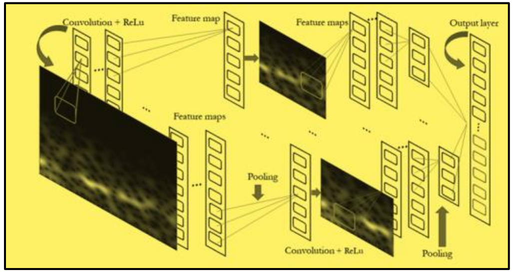


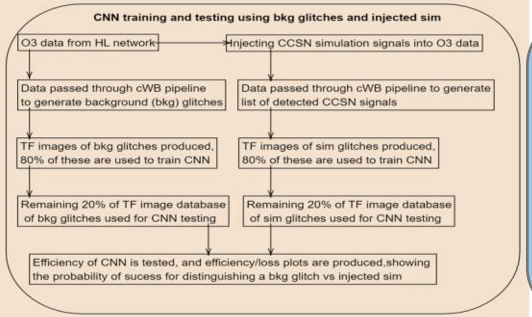
What is a Convolutional Neural Network?

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'.

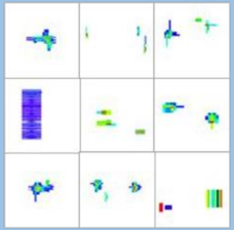
Step 2: **Pooling**: The feature map is further reduced by a pooling layer where either a maximum (max-pooling) or an average (average pooling) is computed from all over the image.

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.

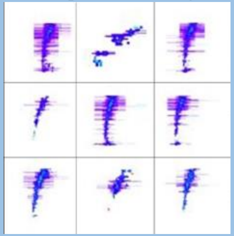
Step 4: Ready for **classification using the softmax**, which is a weighted exponential function.



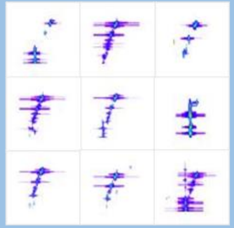
Examples of BKG images



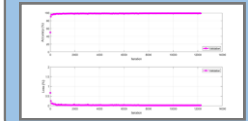
Examples of s18 images



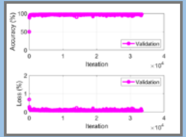
Examples of m39 images



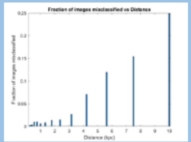
S18 accuracy & loss plots



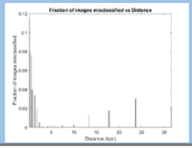
M39 accuracy & loss plots



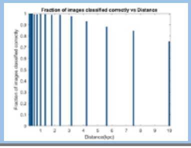
s18 fractions of misclassifications



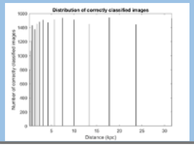
m39 fraction of misclassifications



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

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