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NSF HDR ML A3D3: Detecting Anomalous Gravitational Wave Signals

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NSF HDR Hackathon in Taiwan@2024/12/23



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GW Dataset

References

Gravitational Wave Detectors



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Gravitational Wave Detectors



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Sources of Gravitational Waves

- Compact Binary Coalescence:
 - Black Hole-Black Hole Mergers,
 - Neutron Star-Neutron Star Mergers,
 - Black Hole-Neutron Star Mergers.
- Bursts:
 - Core-collapse Supernovae, Neutron Star Glitches, etc.
- Continuous Waves:
 - Spinning Neutron Stars, etc.
- Stochastic Background:
 - Cosmological background, Astrophysical background, etc.

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Multi-Messenger Astronomy (MMA)



Sky localization of the "Known GW Sources" from their GW signals and send out alerts in low latency for the EM telescopes to capture the follow-up EM wave signals.

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Searching for Anomalous GW Signals

- The unknown "Unknown GW Sources" are called "Anomalous". The conventional way to search such unmodelled GW signals is "Coherence Search" which analyze the coherenece between different detectors simultaneously.
- Now we would like to develop a semi-supervised approach to discover anomalous signals without explicit modelling.

Data Preprocessing

- Whitening: The original time series are transformed by the Power Spectral Density (PSD) so different frequency components are comparably scaled.
- Bandpassing: The filter is then applied to remove the low-frequency (< 30*Hz*) and high-frequency (> 1500*Hz*) components which are too noisy.

 2-second time series with the sampling rate = 4096 Hz



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Background Dataset

- The data is diveded into segments of 50 milliseconds, which contains 200 data points $(50 \times 10^{-3} s \times 4096 \text{ samples/s} \approx 200 \text{ samples.})$
- The dimension of the input data is (N, 200, 2) where N is the number of the data segments. The last 2 corresponds to the data streams from the 2 LIGO detectors: Hanford (H1) and Livingston (L1).



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Anomalous GW	GW Dataset ○○●○

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Signal Dataset

- The data is diveded into segments of 50 milliseconds, which contains 200 data points $(50 \times 10^{-3} s \times 4096 \text{ samples/s} \approx 200 \text{ samples.})$
- The dimension of the input data is (N, 200, 2) where N is the number of the data segments. The last 2 corresponds to the data streams from the 2 LIGO detectors: Hanford (H1) and Livingston (L1).



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Example Submission

	import numpy as np
	class Model:
	<pre>definit(self):</pre>
	# You could include a constructor to initialize your model here, but all calls will be made to the load method
	<pre>self.clf = None</pre>
	<pre>def predict(self, X):</pre>
	# This method should accept an input of any size (of the given input format) and return predictions appropriately
	<pre>return np.array([0 for _ in range(len(X))])</pre>
	def load(self):

Github Link

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References

- Codabench: https://www.codabench.org/competitions/2626/
- Notebook:

https://colab.research.google.com/drive/1hatkYT5Xq6qauDXY6x

- Paper: MLST 10.1008/2632-2153/ad3a31
- Github issue:

https://github.com/a3d3-institute/HDRchallenge/issues

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