Identification of binary neutron star mergers

using object-detection machine learning models

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Contents

The theory of general relativity predicts the emission of wave-like perturbations in the space-time fabric, which we call gravitational-waves (GW).

A few examples of predicted sources or occurrences of GW include:

- *Background* radiation
- Periodic emitters (e.g. pulsars)
- Gravitational collapse (e.g. stellar core collapse)
- Compact Binary Coalescences (CBC) (e.g. Binary Neutron Star (BNS) systems)

Based on a Michelson Interferometers:

- In anti-phase
- Arms generally $l \sim 10^0 - 10^1$km
- Usually include *Fabry-Perot* cavities

A GW generates an asymmetrical variation of the light path in each arm.

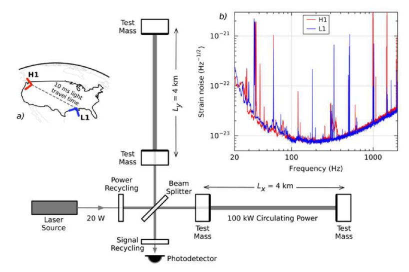


Figure 1: Simplified diagram of an Advanced LIGO detector (Credits: LIGO)

(At least) three large experiments currently:

- **LIGO** - USA
- **Virgo** - Italy
- **KAGRA** - Japan

Frequency range:

$$f \sim 10^1 - 10^4 \text{Hz}$$

GW150914: First detection of GW - binary black holes ($M_1 \approx 36\, M_\odot$ and $M_2 \approx 29\, M_\odot$).

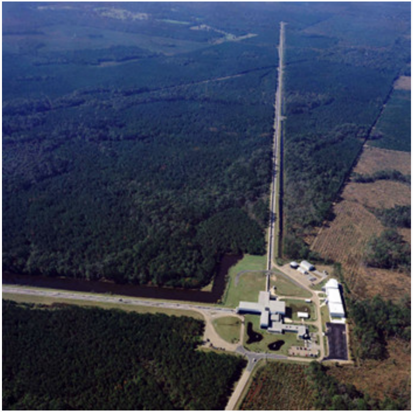


Figure 2: LIGO Livingston observatory. Louisianna, USA.

The search for GW events is done applying Bayesian matched-filtering approaches. This has been proven to be effective, but:

- It is computationally expensive and requires a large computation infrastructure for real-time detection;
- It may be affected by glitches/transient noise.

Deep Learning (DL) is a subset of **Machine Learning (ML)** where usually complex neural networks are trained to perform a specific task by using large amounts of data. The training process it is comprised of an iterative process where the network weights are adjusted to minimize a loss function that defines the performance of the network.

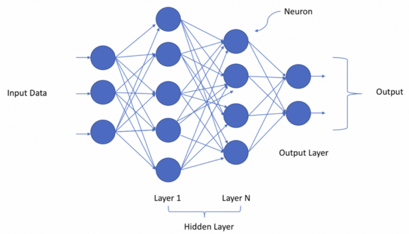


Figure 3: Example of the structure of a neural network used in deep learning tasks.

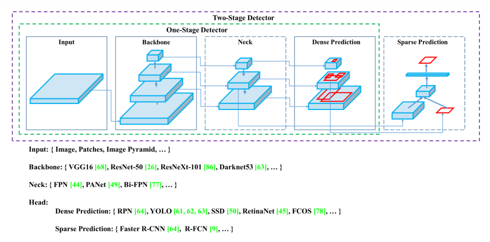


Figure 4: Structure of a generic object detection pipeline.

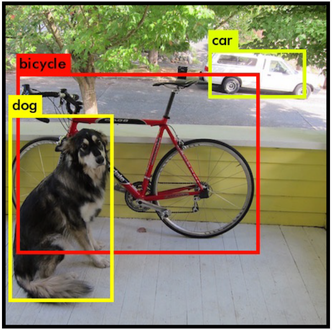


Figure 5: Example of the output of an object detection network.

Can we use object detection to detect and locate a GW signals?

There are a few problems:

- The GW data must be represented as images;
- For ML tasks we require a very large dataset.

We use the well-established Ultralytics YOLOv5 model and we focus on detecting BNS mergers.

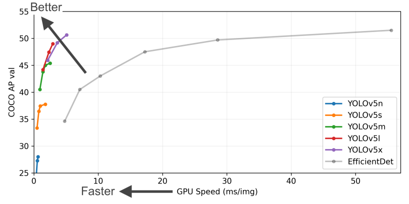


Figure 6: Performance comparison of YOLOv5 variants and the EfficientDet model in the COCO val2017 dataset.

Our approach to BNS GW detection | Dataset generation

We generate noise and strain (injection) samples using PyCBC, obtaining simulated CBC GW waveforms.

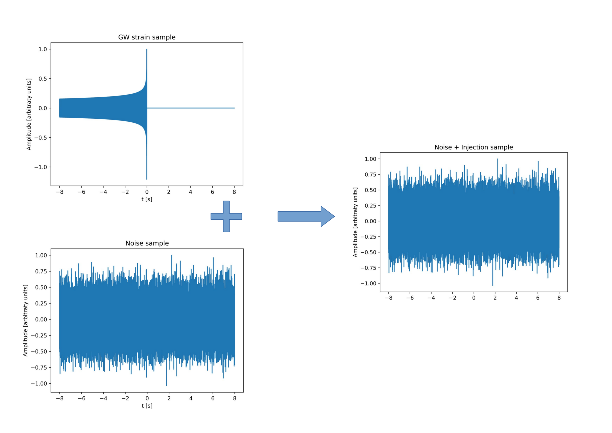


Figure 7: Generation of GW CBC waveforms

We use the Constant Q-Transform to convert the waveform into a spectrogram image.

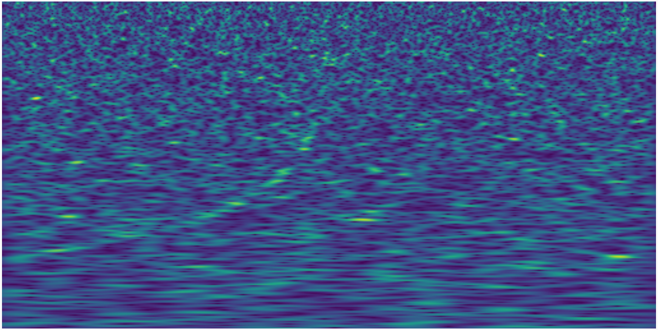


Figure 8: Spectrogram generated using the Constant Q-Transform

Since we know where the merger occurs, we can make any cut we desire and know where the event is located in the final image.

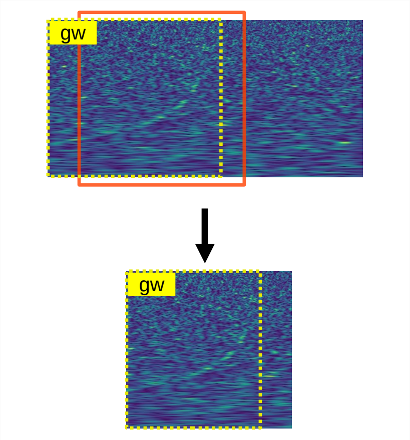


Figure 9: Automatic labelling of the injection object

Our approach to BNS GW detection | Results

Table 1: Precision, Recall, Mean Average Precision [0.50] ($mAP_{0.50}$), and Mean Average Precision [0.50:0.95] ($mAP_{0.50:0.95}$) values for the best epoch (200) for the validation dataset

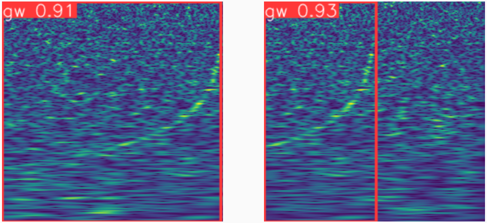
Precision	Recall	$mAP_{0.5}$	$mAP_{0.5:0.95}$
0.922	0.823	0.945	0.893

Table 2: Precision, Recall, Mean Average Precision [0.50] ($mAP_{0.50}$), and Mean Average Precision [0.50:0.95] ($mAP_{0.50:0.95}$) values of the test dataset with ratio 50/50($\%_{obj}/\%_{bg}$) of object/background samples, for a total of 20000 samples.

Precision	Recall	$mAP_{0.5}$	$mAP_{0.5:0.95}$
0.933	0.820	0.947	0.894

Our approach to BNS GW detection | Detecting GW170817

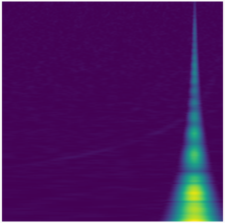
Applying the trained model to the GW170817 event data of the LIGO Hanford (H1) detector, we obtain a successful detection with a very high confidence value.



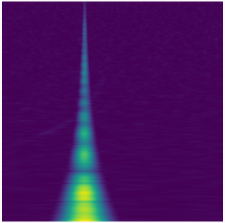
(a) $t_e - 8s < t < t_e$ (b) $t_e - 4s < t < t_e + 4s$

Figure 10: Spectrograms of the GW170817 event data from the LIGO H1 detector and respective event detection bounding boxes and confidence value obtained by applying the trained YOLOv5 model

Doing the same for the LIGO Livingston (L1) detector, we get no detection mainly due to the large glitch overlapping the event.



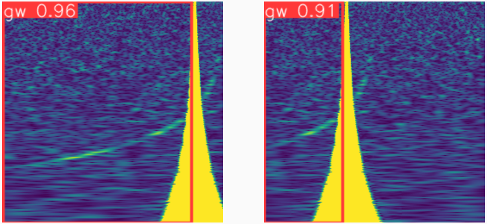
(a) $t_e - 8s < t < t_e$



(b) $t_e - 4s < t < t_e + 4s$

Figure 11: Spectrograms of the GW170817 event data from the LIGO L1 detector with visible glitch

Despite this, if we limit the pixel values to a reasonable value for true GW data, the GW strain becomes visible and the model is able to correctly detect it, even in the presence of the glitch.



(a) $t_e - 8s < t < t_e$ **(b)** $t_e - 4s < t < t_e + 4s$

Figure 12: Spectrograms of the GW170817 event data from the LIGO L1 detector limited to $x_{ij} = 256$ and respective event detection bounding boxes and confidence value obtained by applying the trained YOLOv5 model

Conclusions and future work

With this proof of concept we have concluded that:

- CV object-detection pipelines can be used for detecting events in GW spectrograms
- The detection can be done extremely quickly and efficiently
- It can be robust to glitches or partial degradation of the signal

A few improvements and future work may include:

- Find ways to improve low SNR performance
- Apply this model in other classes of object (e.g. glitches)
- Test the classification capabilities of the model
- Test other object-detection models
- Study the impact of the image conversion process on the performance of the network

Identification of Binary Neutron Star Mergers in Gravitational-Wave Data Using YOLO One-Shot Object Detection

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Precision, Recall, and Average Precision (AP)

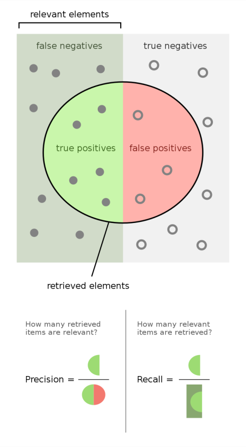
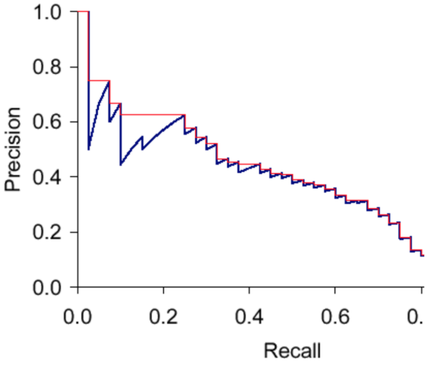


Figure 13: Precision and recall



The area under this Precision-Recall curve gives you the “Average Precision”.

Figure 14: Precision/recall curve