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DNN classification of signals and glitches in time-domain gravitational-wave data

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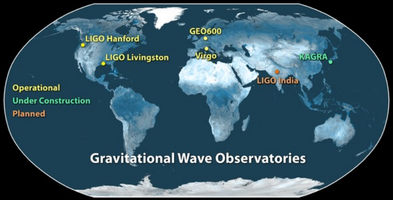
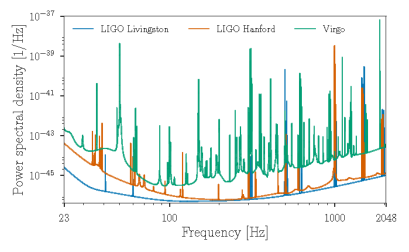
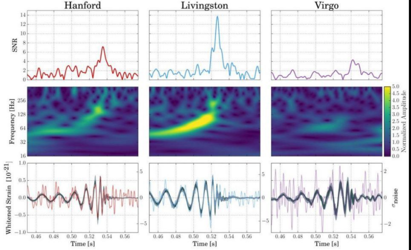
Gravitational-wave astronomy



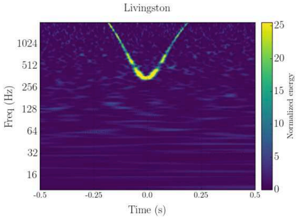


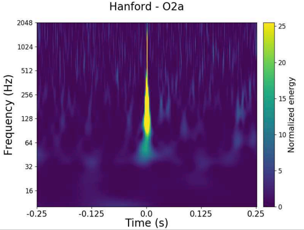


5 binary black hole mergers and 1 binary neutron star merger detected so far!

Glitches representation

- Studies to apply machine learning to the problem of the glitch identification are mainly based on spectrograms (GravitySpy, DeepLearning,..)
  - ✓ Deep-learning performs well on images
  - ✓ Disadvantages:
    - Volume of data (big images)
    - Spectrogram parameters/choice dependent
    - Risk of loosing information due to manipulation
    - Deep learning algorithms learn on raw data
- Time series representation
  - ✓ full information
  - ✓ Reduced volume of data



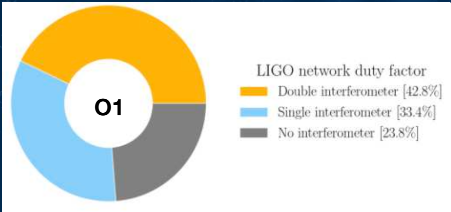


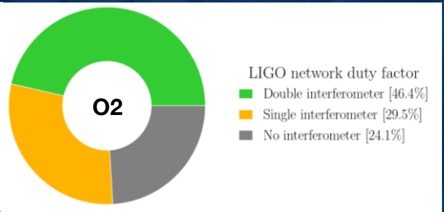
General ideas

- Study, identify and reduce the transient noise present in the gravitational wave detectors through deep learning techniques
  - ✓ Raw time-series as input instead of frequency-time representations (spectrograms)
  - ✓ Both strain data and auxiliary channels
  - ✓ Try different kind of deep-learning algorithms
- Final goal: analyse single-detector data

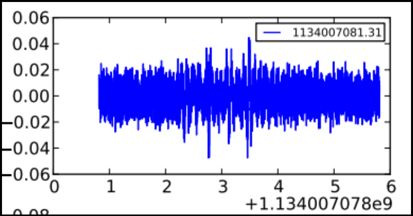
Single-detector time

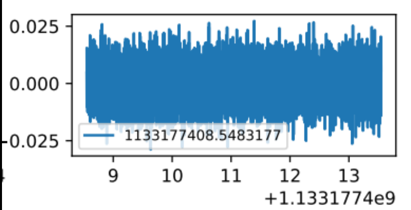
- Transient noise (behaviour of the instruments or complex interactions between the instruments and their environment)
  - ✓ “instrumental glitches”, non-Gaussian short duration artefacts
  - ✓ mimic the gravitational wave signal.
- Current pipelines: signal has to appear in coincidence in two or more detectors
  - ✓ distinguish true astrophysical signals from the transient noise
  - ✓ highly reduces the number of false positives allowing to detect gravitational waves with very high statistical confidence.
- Single-detector time marginally exploited
  - ✓ 2.7 months in O1+O2 => could contain 3 events

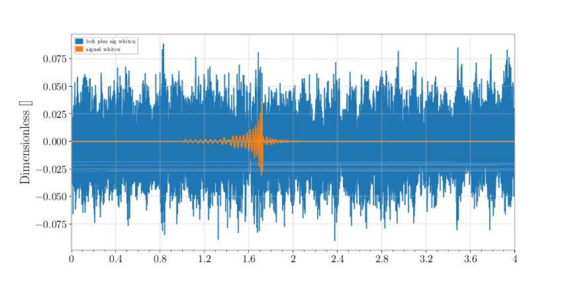




Glitches, noises and signals







Current activity

- First step: prepare samples for the training and test
  - ✓ Training on the basis of the <u>strain morphology</u>

- Generator of 3 classes of events only:
  - ✓ Detector noise without loud glitches (<u>Gaussian-noise</u>)
    - Taken from real data when nor glitches nor signals are present
  - ✓ <u>Gaussian-noise + glitches</u>
    - Glitches occurring times taken from cWB analysis
  - ✓ <u>Gaussian-noise + astrophysical signals</u>
    - Signals = BBH with randomised parameter

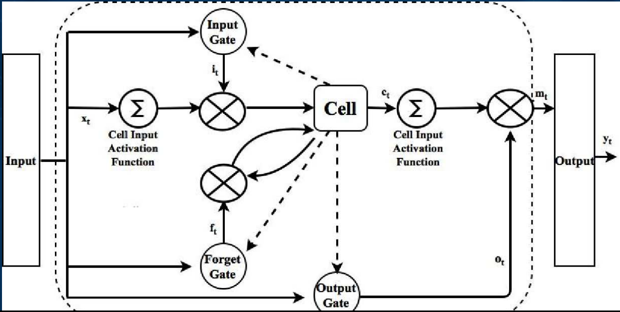
- Generator able to produce each of the 3 classes selecting randomly a piece of random noise and, if needed, adding randomly glitches or signals
  - ✓ Data whitened and accompanied by the PSD to calculate the SNR

Ongoing / next steps

- ⋆ setup a 1D Convolutional Neural Network (CNN) to distinguish the 3 classes of events,
- ⋆ try other algorithms: recurrent neural networks (RNN), Long-Short Term Memory (LSTM),
- ⋆ Add features:
  - ⋆ environmental channels (multi-instance learning),
  - ⋆ more complicated signal/glitch morphologies,
  - ⋆ study causality (not only corelation) between channels,
  - ⋆ Compression to decrease the size of DNN (e.g. Bayesian compression, `arXiv:1705.08665`).

RNN - LSTM

- Neural networks for processing sequential data
  - ✓ Keep a summary of the past sequence in their memory or so-called hidden state, which is updated whenever a new input token is presented.
  - ✓ LSTMs incorporate a gating mechanism which controls to what extent the new input is stored in memory and the old memory is forgotten.



Environmental channels

- Hundreds of thousands auxiliary data streams, auxiliary channels, monitors status of the detector (e.g, state of the control loops) and of its physical environment.

- Now: correlation-based techniques used to identify the coupling of a noise source with an observed disturbance
  - ✓ UPV and Excavator: based on time coincidence only (Virgo)
  - ✓ Weak points: need many (100) glitches to find correlation
  - ✓ Fail to find long-duration (> few sec) glitches because those are always in coincidence with something happening in the witness channels

- Deep-learning algorithms: in principle able to learn and evidence non-linear couplings