Machine Learning for Transient signal analysis in Gravitational Wave data

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June 9th - 11th
11th Iberian Gravitational Waves Meeting

Image credit: NSF/LIGO/Sonoma State University/A. Simonnet
Outline

- Transient Gravitational Wave signals
- Gravitational Wave data and detection strategy
- GW alert system
- Machine learning and its application to
  - Transient noise
  - Core Collapse Supernovae
  - Compact Binary Coalescences
  - Astrophysical Stochastic Background
Gravitational Wave Transient signal sources

Compact binary coalescences

Credit
LIGO/Caltech/MIT/R. Hurt (IPAC)

Core collapse Supernovae

Credit
ESA/XMM-Newton & NASA/Chandra (X-ray);
NASA/WISE/Spitzer (Infrared)
Gravitational Wave Transient signals

CBC signals

![Graph of CBC signals](image)

CCSN signals

![Graph of CCSN signals](image)

Image from less, Cuoco, Morawski, Powell (2020)
GW detector data

- Time series sequences... noisy time series with low amplitude GW signal buried in
Detector Noise

- Thermal noise
- Seismic noise
- Electromagnetic noise
- Control noise
- Environmental noise
- Laser noise
- ...

Glitches

How we detect transient signals: modeled search

- pyCBC (Usman et al, 2015)
- MBTA (Adams et al. 2015)
- gstlal-SVD (Cannon et al. 2012)

**Matched-filter**

\[
\rho(t) = 4 \int_0^{\infty} \eta^*(f) \frac{\hat{h}^*(f)}{S_n(f)} e^{2\pi i ft} df
\]

**CBC search**
To cover in efficient way the parameters space, we build a templates bank requiring that the signal can be detected with a maximum loss of 3% of its SNR.

How many templates?

~250000 waveforms used for GW150914

How we detect transient signals: un-modeled search

- **Strategy:** look for excess power in single detector or coherent/coincident in network data

- **Example cWB** ([https://gwburst.gitlab.io/](https://gwburst.gitlab.io/))
  - Time-domain data preprocessed
  - Wavelet decomposition
  - Event reconstruction

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**Burst search**

Phys. Rev. D 93, 042004 (2016)
Class. Quant. Grav. 25:114029, 2008
Detection to date

- **O1** (~ 4 months): - 3 BBHs ·
- **O2** (~ 8 months) - 7 BBHs - 1 BNS ·
- **O3a** (~ 6 months) - 1 BNS (GW190425) - 2 BH + lighter object (GW190814, GW190426152155) - 36 BBHs

- Given the increased sensitivity, the detection of 39 candidate events during O3a is consistent with GWTC-1 (O1 + O2) LVC GWTC-2 paper; arXiv:2010.14527 7
- 23 public alerts released during O3b
- O3b Analysis still on going

B.P. Abbott et al. (LIGO Scientific Collaboration and Virgo Collaboration)
Phys. Rev. Lett. 119, 161101 – Published 16 October 2017
Low latency analysis

**Pipelines running in real time**
- 4 low-latency CBC search pipelines: GstLAL, MBTAOnline, PyCBC Live, and SPIIR
- 1 GW burst search pipeline: cWB (Coherent WaveBurst)

**Pipelines assess the significance of candidate**
- False Alarm Rate (FAR) based on empirically measured noise properties
- The initial searches focus on detection, not on estimating the parameters of the source

**Data Quality evaluated autonomously for initial alert**
- GCN notice
- Initial alert released on order of 1 minute; Notice on order of 10 minutes

<table>
<thead>
<tr>
<th>Root</th>
<th>lvc:/osa,e.gfc:ac/LVC(f7,M)5Y0928bc-(f7,2.3)- (Preliminary,Initial,Update,Preliminary-Retraction)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rule</td>
<td>[observation, test]</td>
</tr>
<tr>
<td>Date</td>
<td>Time sent (UTC, ISO-8601), e.g. 2018-11-31T12:36:45</td>
</tr>
<tr>
<td>Author</td>
<td>LIGO Scientific Collaboration and Virgo Collaboration</td>
</tr>
<tr>
<td>Where/When</td>
<td>Time of signal (UTC, ISO-8601), e.g. 2018-11-31T12:22:46.684437</td>
</tr>
<tr>
<td>What</td>
<td></td>
</tr>
<tr>
<td>GraceID</td>
<td>Gracedb ID: (f7,M)5Y0928bc. Example: M518181abc</td>
</tr>
<tr>
<td>Packet Type</td>
<td>GCN Notice type: (Preliminary, Initial, Update)</td>
</tr>
<tr>
<td>Notice Type</td>
<td>Numerical equivalent of GCN Notice type: 1559, 1551, 1552</td>
</tr>
<tr>
<td>FAR</td>
<td>Estimated false alarm rate in Hz</td>
</tr>
<tr>
<td>Sky Map</td>
<td>URL of HEALPix FITS localization file</td>
</tr>
<tr>
<td>Group</td>
<td></td>
</tr>
<tr>
<td>Pipeline</td>
<td></td>
</tr>
<tr>
<td>CentralFreq</td>
<td>N/A</td>
</tr>
<tr>
<td>Duration</td>
<td></td>
</tr>
<tr>
<td>Flux</td>
<td></td>
</tr>
<tr>
<td>BNS, NSBH, BH, Noise</td>
<td>Probability that the source is a BNS, NSBH, NSBH merger, or terrestrial (i.e., noise) respectively</td>
</tr>
<tr>
<td>Halo/He Remnant</td>
<td>Probability, under the assumption that the source is not noise, that at least one of the compact objects was a neutron star, and that the system ejected a nonzero amount of neutron star matter, respectively.</td>
</tr>
</tbody>
</table>
# LIGO/Virgo O3 Public Alerts

Detection candidates: 35

<table>
<thead>
<tr>
<th>Event ID</th>
<th>Possible Source (Probability)</th>
<th>UTC</th>
<th>GCN</th>
<th>Location</th>
<th>PAR</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>S191117f</td>
<td>NSBH (&gt;90%)</td>
<td>Nov. 17, 2019 06:08:22 UTC</td>
<td>GCN Circulars</td>
<td><img src="image1.png" alt="Image" /></td>
<td>1 per 2.8433e+10 years</td>
<td>RETRACTED</td>
</tr>
<tr>
<td>S191110af</td>
<td>NSBH (&gt;90%)</td>
<td>Nov. 10, 2019 23:06:44 UTC</td>
<td>GCN Circulars</td>
<td><img src="image2.png" alt="Image" /></td>
<td>No public skymap image found.</td>
<td>RETRACTED</td>
</tr>
<tr>
<td>S191110x</td>
<td>MassGap (&gt;90%)</td>
<td>Nov. 10, 2019 18:08:42 UTC</td>
<td>GCN Circulars</td>
<td><img src="image3.png" alt="Image" /></td>
<td>1 per 1081.7 years</td>
<td>RETRACTED</td>
</tr>
<tr>
<td>S191108f</td>
<td>BBH (&gt;99%)</td>
<td>Nov. 9, 2019 01:07:17 UTC</td>
<td>GCN Circulars</td>
<td><img src="image4.png" alt="Image" /></td>
<td>1 per 2.062e+05 years</td>
<td></td>
</tr>
<tr>
<td>S191105e</td>
<td>BBH (95%), Terrestrial (5%)</td>
<td>Nov. 5, 2019 14:35:21 UTC</td>
<td>GCN Circulars</td>
<td><img src="image5.png" alt="Image" /></td>
<td>1 per 1.3881 years</td>
<td></td>
</tr>
<tr>
<td>S190930f</td>
<td>NSBH (74%), Terrestrial (26%)</td>
<td>Sept. 30, 2019 14:34:07 UTC</td>
<td>GCN Circulars</td>
<td><img src="image6.png" alt="Image" /></td>
<td>1 per 2.6536 years</td>
<td></td>
</tr>
</tbody>
</table>

GW alert system

Time since gravitational-wave signal

Original Detection
Set Preferred Event
Automated Vetting
Classification
Rapid Sky Localization

Parameter Estimation
Human Vetting
Classification
Initial Alert or Retraction Sent

Update Alert Sent

10 second 1 minute 1 hour 1 day 1 week
How Machine Learning can help

Data conditioning

- Identify Non linear noise coupling
- Extract useful features to clean data

Signal Detection/Classification/PE

- A lot of fake signals due to noise
- Fast alert system
- Manage parameter estimation

You can find more here:
E.Cuoco, J.Powell, M. Cavaglià et al  
https://doi.org/10.1088/2632-2153/abb93a
Machine learning workflow for signal classification
Outline

- Time-series based classification
- Image based classification with Deep Learning
- Application on Simulated data
- Application on Real Data
Two different approaches

- Images

  Image-based deep learning for classification of noise transients in gravitational wave detectors, Massimiliano Razzano, Elena Cuoco, Class.Quant.Grav. 35 (2018) no.9, 095016

- Time series

  Wavelet-based Classification of Transient Signals for Gravitational Wave Detectors, Elena Cuoco, Massimiliano Razzano and Andrei Utina, #1570436751 accepted reviewed paper at EUSIPCO2018
How we started...
Data simulation: signal families + Detector colored Noise

waveform
Gaussian
Sine-Gaussian
Ring-Down
Chirp-like
Scattered-like
Whistle-like
NOISE (random)

To show the glitch time-series here we don’t show the noise contribution

Razzano M., Cuoco E. CQG-104381.R3
Data preprocessing

- Many spectral features
- Non stationary and non linear noise

![Graph showing strain vs frequency with different sensitivities over time](image1)

![Spectrogram showing frequency and time domain analysis](image2)
On-line power spectra identification and whitening for the noise in interferometric gravitational wave detectors

DOI 10.1088/0264-9381/18/9/309

Classical and Quantum Gravity
Signals in whitened data

Not Whitened

Whitened
Images as input data

Why Image-based classification
Glitches and citizen science

Citizen scientists contribute to classify glitches

More details in Zevin+17 10.1088/1361-6382/aa5cea

https://doi.org/10.1016/j.ins.2018.02.068
Building the images

- Spectrogram for each image
- 2-seconds time window to highlight features in long glitches
- Data is whitened
- Optional contrast stretch

Simulations now available on FigShare

Deep learning: Convolutional Neural Network

2-D CNN

Spectrogram images

Alberto Iess courtesy
**Pipeline structure**

**Input GW data**
- Image processing
- Time series whitening
- Image creation from time series (FFT spectrograms)
- Image equalization & contrast enhancement

**Classification**
- A probability for each class, take the max
- Add a NOISE class to crosscheck glitch detection

**Network layout**
- Tested various networks, including a 4-block layers

**Run on GPU Nvidia GeForce GTX 780**
- 2.8k cores, 3 Gb RAM
- Developed in Python + CUDA-optimized libraries

M. Razzano courtesy
Classification accuracy

Normalized Confusion Matrix

Deep CNN

Razzano M., Cuoco E. CQG-104381.R3
### Application Test on Real data: O1 run

<table>
<thead>
<tr>
<th>Glitch name</th>
<th># in H1</th>
<th># in L1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Air compressor</td>
<td>55</td>
<td>3</td>
</tr>
<tr>
<td>Blip</td>
<td>1495</td>
<td>374</td>
</tr>
<tr>
<td>Chirp</td>
<td>34</td>
<td>32</td>
</tr>
<tr>
<td>Extremely Loud</td>
<td>266</td>
<td>188</td>
</tr>
<tr>
<td>Helix</td>
<td>3</td>
<td>276</td>
</tr>
<tr>
<td>Koi fish</td>
<td>580</td>
<td>250</td>
</tr>
<tr>
<td>Light Modulation</td>
<td>568</td>
<td>5</td>
</tr>
<tr>
<td>Low_frequency_burst</td>
<td>184</td>
<td>473</td>
</tr>
<tr>
<td>Low_frequency_lines</td>
<td>82</td>
<td>371</td>
</tr>
<tr>
<td>No_Glitch</td>
<td>117</td>
<td>64</td>
</tr>
<tr>
<td>None_of_the_above</td>
<td>57</td>
<td>31</td>
</tr>
</tbody>
</table>

### Dataset from GravitySpy images

<table>
<thead>
<tr>
<th>Glitch name</th>
<th># in H1</th>
<th># in L1</th>
</tr>
</thead>
<tbody>
<tr>
<td>Paired doves</td>
<td>27</td>
<td>-</td>
</tr>
<tr>
<td>Power_line</td>
<td>274</td>
<td>179</td>
</tr>
<tr>
<td>Repeating blips</td>
<td>249</td>
<td>36</td>
</tr>
<tr>
<td>Scattered_light</td>
<td>393</td>
<td>66</td>
</tr>
<tr>
<td>Scratchy</td>
<td>95</td>
<td>259</td>
</tr>
<tr>
<td>Tomte</td>
<td>70</td>
<td>46</td>
</tr>
<tr>
<td>Violin_mode</td>
<td>179</td>
<td>-</td>
</tr>
<tr>
<td>Wandering_line</td>
<td>44</td>
<td>-</td>
</tr>
<tr>
<td>Whistle</td>
<td>2</td>
<td>303</td>
</tr>
</tbody>
</table>
Full CNN stack

Consistent with Zevin+2017
The importance of glitch analysis

Ligo Livingston

GW 170817

Glitch mitigation

Alberto Iess courtesy

Abbott et al. (2017)
GW Astrophysical signal classification

Compact Binary Coalescences

Core Collapse Supernovae

This is Cassiopeia A, a core collapse supernova remnant with a neutron star in its center. Located in the Milky Way only some 11,000 light-years away from Earth, it originally exploded about 330 years ago.

Credit
LIGO/Caltech/MIT/Sonoma State (Aurore Simonnet)

NASA/CXC/UNAM/IUFFE/D. PAGE, P. SHTERNIN ET AL
GWs from Core Collapse Supernovae

- Waveform depends on progenitor star
- Different emission mechanisms (Proto-neutron star oscillation, Standing Accretion Shock Instability (SASI),...)
- Largely Stochastic
- Best waveform models from computationally expensive 3D simulations
- Different simulation models
- Rare (~100 yrs in Milky Way)

Need an alternative to matched filter approach

Ott et al. (2017)
Core-Collapse Supernovae models

- **Andresen s11**: Low amplitude, non-exploding, peak emission at lower frequencies
- **Radice s13**: Non-exploding, lower amplitudes
- **Radice s25**: Late explosion time, standing accretion shock instability (SASI), high peak frequency
- **Powell s18**: High peak frequency, exploding model
- **Powell He3.5**: Ultra-stripped helium star, high peak frequency, exploding model

*Alberto Iess courtesy*
Time frequency waveforms

Alberto Iess courtesy

Iess, Cuoco, Morawski, Powell,
https://doi.org/10.1088/2632-2153/ab7d31
MDC and CCSN GW simulations

\[ h(t) = F_+ h_+(t) + F_\times h_\times(t) \]

- Distances:
  - VO3 0.01 kpc to 10 kpc
  - ET 0.1 kpc to 1000 kpc
- Random sky localization
- Large SNR range

SINE GAUSSIAN & SCATTERED LIGHT GLITCHES

\[ h_{SG}(t) = h_0 \sin(2\pi f_0(t - t_0)) e^{-\frac{(t-t_0)^2}{2\sigma^2}} \]

\[ h_{SL}(t) = h_0 \sin(\phi_{SL}) e^{-\frac{(t-t_0)^2}{2\tau}} \quad \phi_{SL} = 2\pi f_0(t - t_0)[1 - K(t - t_0)^2] \]

BACKGROUND STRAIN: simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Alberto Iess courtesy

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\[ h_{SL}(t) = h_0 \sin(\phi_{SL}) e^{-\frac{(t-t_0)^2}{2\tau}} \quad \phi_{SL} = 2\pi f_0(t - t_0)[1 - K(t - t_0)^2] \]

BACKGROUND STRAIN: simulated data sampled at 4096 Hz built from VO3 and ET projected sensitivities

Alberto Iess courtesy
Pipeline Workflow

- STRAIN
- WAVEFORMS
- RESAMPLING, FILTERING
- WHITENING & TRIGGER GENERATION (WDF)
- TRAINING
- MACHINE-LEARNING CLASSIFIER

Alberto Iess courtesy
Wavelet Detection Filter (WDF) as event trigger generator

**WDF (Cuoco et al. 2015)**

- Whitening
- Wavelet decomposition

\[
\langle s|\psi_{a,b}\rangle = \int_{-\infty}^{+\infty} s(t) \frac{1}{\sqrt{b}} \psi^* \left( \frac{t-a}{b} \right) dt
\]

\[t = \sqrt{2 \log N \hat{\sigma}} \quad \text{(Donoho, Johnstone 1994)}\]

- Trigger generation based on threshold (tunable). WDF signal-to-noise ratio:

\[
\text{SNR}_w = \frac{\sum_i w_i^2}{\hat{\sigma}}
\]

- Window 0.25 s, overlap 0.0625 s

**GPS TIMES OF TRIGGERS**

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Alberto Iess courtesy

Iess, Cuoco, Morawski, Powell, [https://doi.org/10.1088/2632-2153/ab7d31](https://doi.org/10.1088/2632-2153/ab7d31)
Neural Network architecture

- **Train, Validation, Test sets:** 60%, 10%, 30%
- 3 or 4 Convolutional layers
- Activation function $f$: ReLU
- Adam optimizer, learning rate $\alpha = 0.001$, decay rate of 0.066667
- Early stopping
- Batch Size: 64 or 128
- Loss function: Categorical-cross entropy

Dataset: chunks of 3 hr data with 1000 injections/h

GPU: Tesla k40
Binary Classification

• Train on all CCSNe waveforms and glitches.
• Test on all.

Test samples → TRAINED CNN MODEL

TRAINED CNN MODEL

ET

VO3

• Training time: ~ 30 min

Alberto Iess courtesy

https://doi.org/10.1088/2632-2153/ab7d31
MultiLabel classification

- Train on all (4 CCSNe waveform models + glitches).
- Test on all.

Test samples → TRAINED CNN MODEL

- he3.5
- s18
- s11
- s13
- s25
- Sine gauss.
- Scatt. light

COMPLEX TASK → LONGER TRAINING (> 1 hr)

Alberto Iess courtesy

ET, MERGED 1D & 2D CNN

Total accuracy: 89.6 %

he3.5: 92.6, 17, 3.3, 1.9, 0.8, 0.3, 0.3
s18: 1.6, 92.2, 0.0, 0.4, 0.7, 0.1, 0.0
s11: 1.1, 0.7, 84.1, 2.3, 2.0, 0.2, 0.2
s13: 2.0, 1.0, 5.9, 88.4, 2.2, 0.5, 0.4
s25: 1.3, 1.8, 2.6, 3.1, 91.6, 0.1, 0.5
Sine Gauss: 0.9, 2.0, 1.5, 0.7, 0.9, 87.8, 8.7
Scatt. Light: 0.5, 0.6, 2.6, 3.1, 1.9, 11.0, 89.9

Real data

Iess, Cuoco, Morawski, Powell, https://doi.org/10.1088/2632-2153/ab7d31
REAL NOISE FROM O2 SCIENCE RUN

- 44 segments (4096s per segment) from O2 science run.
- Added m39, y20, s18np models (Powell, Mueller 2020).
- **Fixed distance of 1 kpc.**
- Added LSTM Networks, suited for timeseries data.
- **Added Three ITF classification.**

- *Powell s18np*: differs from s18 since simulation does not include perturbations from the convective oxygen shell. As a result, this model develops strong SASI after collapse.
- *Powell m39*: rapidly rotating Wolf-Rayet star with an initial helium star mass of 39 solar masses

*Alberto Iess courtesy*
REAL NOISE FROM O2 SCIENCE RUN

- Noise PSD is non stationary.
- Multiple Glitch Families.
- SNR distribution is affected by ITF antenna pattern.
- Dataset: ~15000 samples.
- Imbalanced Dataset due to different model amplitudes.

<table>
<thead>
<tr>
<th>Detector</th>
<th>Signal</th>
<th>Noise</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Virgo V1</td>
<td>9273</td>
<td>47901</td>
<td>57174</td>
</tr>
<tr>
<td>Ligo L1</td>
<td>10480</td>
<td>3810</td>
<td>14290</td>
</tr>
<tr>
<td>Ligo H1</td>
<td>10984</td>
<td>4103</td>
<td>15087</td>
</tr>
<tr>
<td>L1, H1, V1</td>
<td>5647</td>
<td>675</td>
<td>6322</td>
</tr>
</tbody>
</table>

CCSN Classification on Simulated and Real O2 Data with CNNs and LSTMs

A. iess, E. Cuoco, F. Morawski, C. Nicolaou, O. Lahav, submitted to MLST
LONG SHORT TERM MEMORY (LSTM) NETWORK

Pros

- Keeps track of dependencies in time-series.
- Avoids the Vanishing Gradient problem.

Cons

- Many parameters to train, long training times.
- Hyperparameter tuning can be challenging.

Prediction

\[ o_t = \sigma \left( W_o \left[ h_{t-1}, x_t \right] + b_o \right) \]

\[ h_t = o_t \cdot \tanh (C_t) \]

MULTILABEL CLASSIFICATION ON REAL O2 NOISE (SINGLE ITF, LIGO H1, DIFFERENT MODELS)

- **Bi-LSTM**, 2 recurrent layers
  - $\sim$10 ms/sample
  - Best weights over 100 epochs

- **1D-CNN**, 4 convolutional layers
  - $\sim$2 ms/sample
  - Best weights over 20 epochs

- **2D-CNN**, 4 convolutional layers
  - $\sim$3 ms/sample
  - Best weights over 20 epochs

3 ITF MERGED MODEL MULTILABEL CLASSIFICATION ON REAL O2 NOISE

- Dataset breakdown:
  675 noise, 329 s18p, 491 s18np, 115 he3.5, 1940 m39, 1139 y20, 76 s13, 1557 s25.
- Input to NNs have additional dimension (ITF)

Anomaly Detection in Gravitational Waves data using Convolutional AutoEncoders

Example for detection/classification for CBC signals

- Create a deep learning pipeline allowing detection of anomalies defined in terms of transient signals: gravitational waves as well as glitches.
- Additionally: Consider reconstruction of the signal for the found anomalies.

Pipeline Workflow

Detector

strain

+

Whitening

GW
waveforms

Deep Learning
Neural Network

Training

Anomaly

Noise

Autoencoder


Filip Morawski courtesy

**Concept**

Model input

Model prediction

Filip Morawski courtesy
Real or simulated strain with injected anomalies – BBH GW.

Mass range: 26–40 M\(_\odot\)

Distance: 200–800 Mpc

Sampling rate: 1024 Hz
Simulations - reconstructed signal

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
Simulations – Mean Squared Error Distributions

Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,

02 data - reconstructed signal
Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,

O2 data - MSE Distributions
GW150914

LIGO Livingston

LIGO Hanford


Filip Morawski courtesy
**GW170806**

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**Interesting! GW170806 Has Much Lower Masses!**

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Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
Filip Morawski, Michał Bejger, Elena Cuoco, Luigia Petre,
Deep learning searches for gravitational waves stochastic backgrounds

Andrei Utina, Filip Morawski, Alberto Iess, Francesco Marangio, Tania Regimbau, Elena Cuoco, Giuseppe Fiameni
MDC package was used to generate time-series data of detector noise and BBH coalescences.

Data was simulated for Handford O3 sensitivity and ET-D design sensitivity starting at 30 Hz.

A full duration of a simulated dataset was 2048 seconds, sampled at 4096 Hz.

The time interval between successive events defined three datasets:
- BBH10s for a Poisson parameter of 0.1
- BBH4s for a Poisson parameter of 0.25
- BBH1s for a Poisson parameter of 1

Recovered signals from a Welch method are shown by the blue and black curves above. For reference, ET-D design sensitivity is shown by the orange curve and the H1 O3 measured strain on Sep 05 2019 at 36.6 W input power and 2 dB of squeezing.
After processing, the library of feature and label vectors were created.

The duration of each data instance was set to 2 seconds. For performance reasons, in the case of the LSTM algorithm, the length was set to 1 second.

The 2-D space of the spectrogram representation gives the input for the CNN2D algorithm:
- Top left shows a high SNR chirp signal for ET.
- Top right shows a similar signal but for LIGO.

The 1-D time-series representation is the input for the CNN1D algorithm and the LSTM algorithm.
We chose Convolutional Neural Networks (CNN) and Long-Short-Term Memory Networks (LSTM) as the test deep learning algorithms.

The full sets were split into 70% training set, 10% validation set and 20% test set.

The performance of the algorithms strongly relies on the tuning of the hyperparameters:

- We hypertuned over a multi-dimensional parameter space including the number and type of perceptron layers, the filter numbers and sizes, the learning rate and the optimizers.

- The tuning was performed using Hyperband, a random search algorithm that assigns resources adaptively.

- The hypertuning was performed on the whitened 4s and 10s datasets.

All the computations were performed on the Marconi100 HPC cluster of CINECA.
CNN Architectures

### CNN1D
- **Time-series Input**
- Conv layer
  - Input: (130, 40)
  - (250, 16) → (120, 16) → (80, 16) → (60, 16) → (40, 16) → (30, 16) → (20, 16) → (10, 16) → (5, 16) → (2, 16) → (1, 16)
  - (130, 40) → (250, 16) → (120, 16) → (80, 16) → (60, 16) → (40, 16) → (30, 16) → (20, 16) → (10, 16) → (5, 16) → (2, 16) → (1, 16)
- MaxPool layer
  - (2, 2)
- Flatten layer
- Dense layer
- Output

### CNN2D
- **Spectrogram Input**
- Conv layer
  - Input: (40, (4*4)) → (20, (3*3)) → (10, (2*2)) → (5, (1*1))
  - (40, (4*4)) → (20, (3*3)) → (10, (2*2)) → (5, (1*1))
- Spatial Dropout
- Flatten layer
- Dense layer
- Output

Output example: The confusion matrix from the classification

Predicted Values
- BBH: 2.1, 94.0
- Noise: 97.9, 6.0

Real Values
- Total accuracy: 96.0

Andrei Utina courtesy
LSTM Architecture

Input time-series
0
.
.
1

First layer connection

Second layer connection

Two bidirectional LSTM layers with dimensions 64 and 32

4 FC layers

Output, similar performance metric as in the CNN architectures

Softmax activation
We look at the percentages of the true rates for each Poisson intensity parameter, i.e., the correct predictions given either noise or signal plus noise inputs.

The H1 O3 detections are either 100% for noise (LSTM) or 50%–50% (not convergent) for both noise and signal with noise.

With increasing the Poisson intensity parameter, the detection accuracy increases significantly for both noise and signal.

All three algorithms showed similar results for the 1s dataset.

The detection efficiencies of the CNNs were similar: 67%+ for 10s, 75%+ for the 4s and 95%+ for the 1s datasets.

<table>
<thead>
<tr>
<th>Chosen Detector</th>
<th>Whitened Data Results</th>
<th>CNN2D Results</th>
<th>CNN1D Results</th>
</tr>
</thead>
<tbody>
<tr>
<td>ET</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1s</td>
<td>99.0 %</td>
<td>97.9 %</td>
<td>97.9 %</td>
</tr>
<tr>
<td>4s</td>
<td>94.5 %</td>
<td>89.2 %</td>
<td>87.5 %</td>
</tr>
<tr>
<td>10s</td>
<td>94.5 %</td>
<td>88.3 %</td>
<td>90.2 %</td>
</tr>
<tr>
<td>LIGO H O3</td>
<td>100 %</td>
<td>50 %</td>
<td>50 %</td>
</tr>
<tr>
<td>1s</td>
<td>100 %</td>
<td>50 %</td>
<td>50 %</td>
</tr>
<tr>
<td>4s</td>
<td>100 %</td>
<td>50 %</td>
<td>50 %</td>
</tr>
<tr>
<td>10s</td>
<td>100 %</td>
<td>50 %</td>
<td>50 %</td>
</tr>
</tbody>
</table>

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Results
Thanks

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