Why using artificial intelligence in the search for gravitational waves?

Elena Cuoco, EGO and SNS

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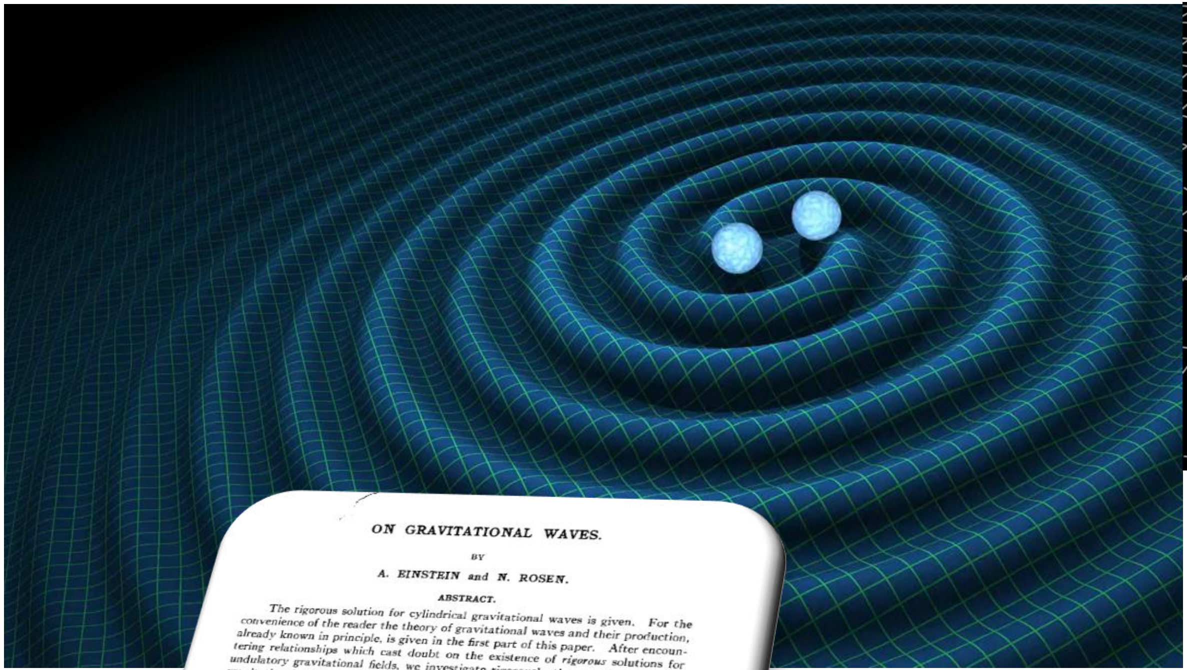
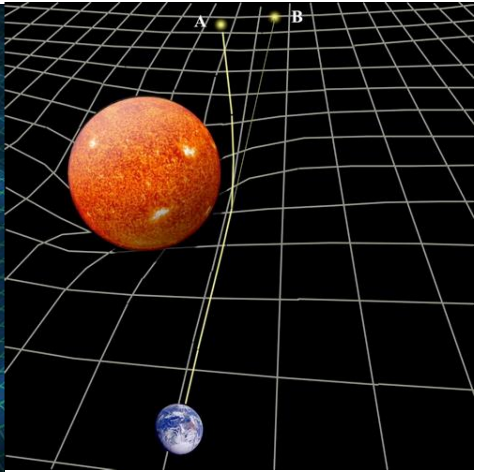
EGO EUROPEAN GRAVITATIONAL OBSERVATORY

SCUOLA NORMALE SUPERIORE

VIRGO

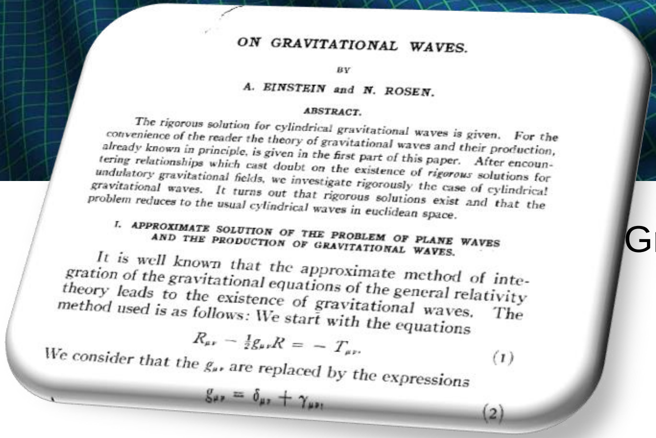
What are Gravitational Waves (GWs)?





General Relativity (1915)

$$G_{m} = \frac{8pG}{c^{4}} T_{m}$$



ON GRAVITATIONAL WAVES.

BY

A. EINSTEIN and N. ROSEN.

ABSTRACT.

The rigorous solution for cylindrical gravitational waves is given. For the convenience of the reader the theory of gravitational waves and their production, already known in principle, is given in the first part of this paper. After encountering relationships which cast doubt on the existence of *rigorous* solutions for undulatory gravitational fields, we investigate rigorously the case of cylindrical gravitational waves. It turns out that rigorous solutions exist and that the problem reduces to the usual cylindrical waves in euclidean space.

I. APPROXIMATE SOLUTION OF THE PROBLEM OF PLANE WAVES AND THE PRODUCTION OF GRAVITATIONAL WAVES.

It is well known that the approximate method of integration of the gravitational equations of the general relativity theory leads to the existence of gravitational waves. The method used is as follows: We start with the equations

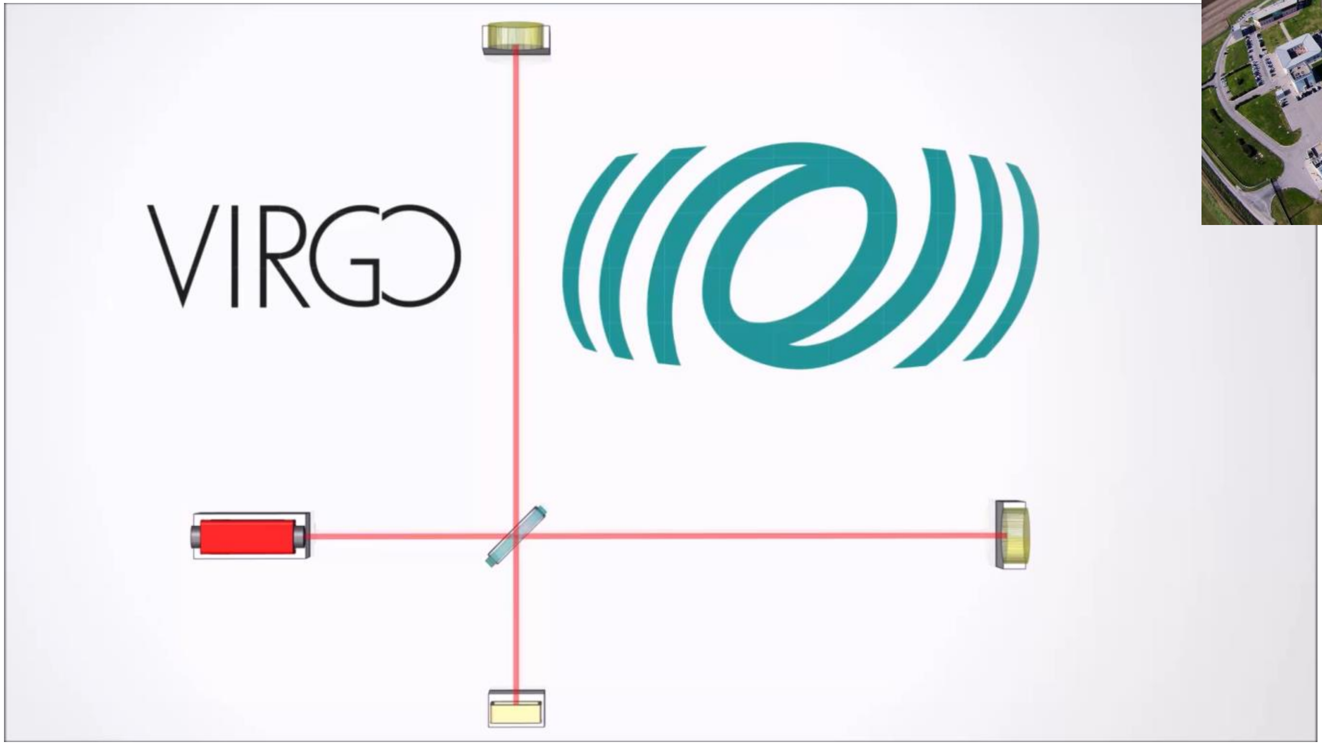
$$R_{\mu\nu} - \tfrac{1}{2}g_{\mu\nu}R = - T_{\mu\nu}. \qquad (1)$$

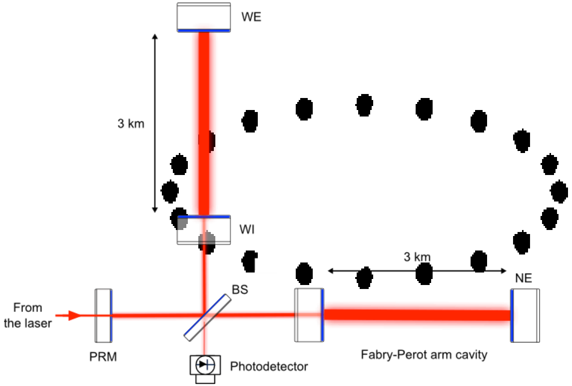
We consider that the $g_{\mu\nu}$ are replaced by the expressions

$$g_{\mu\nu} = \delta_{\mu\nu} + \gamma_{\mu\nu}, \qquad (2)$$

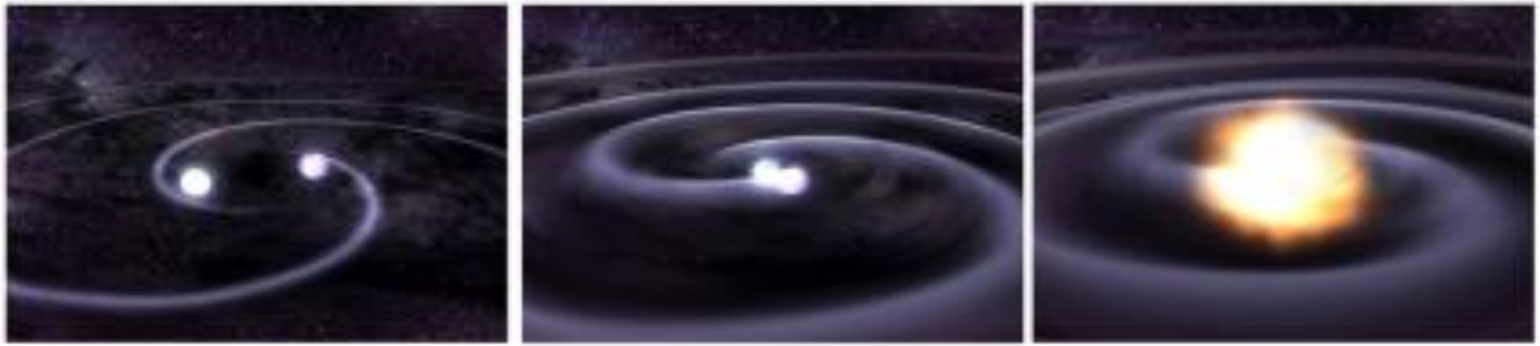
Gravitational Waves (1916)

How we detected GWs?

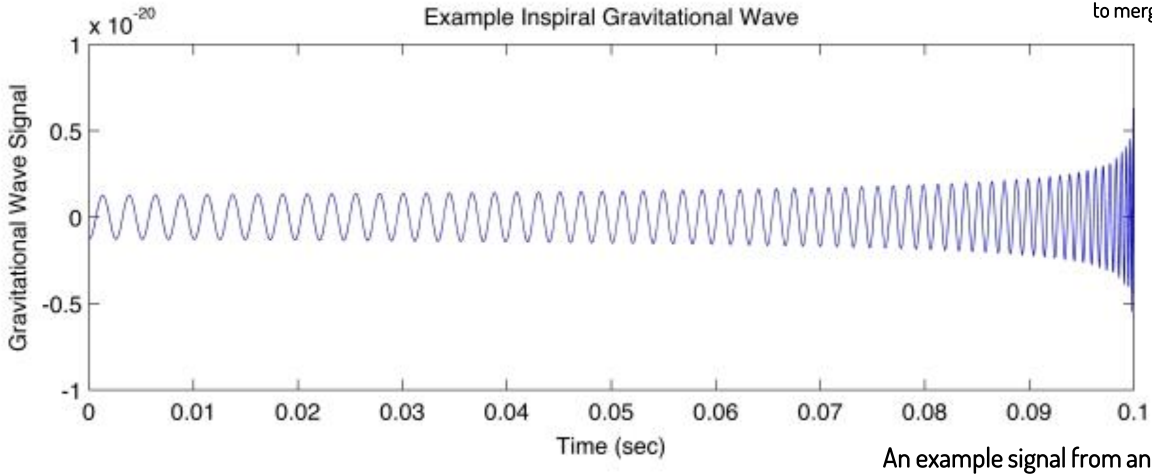


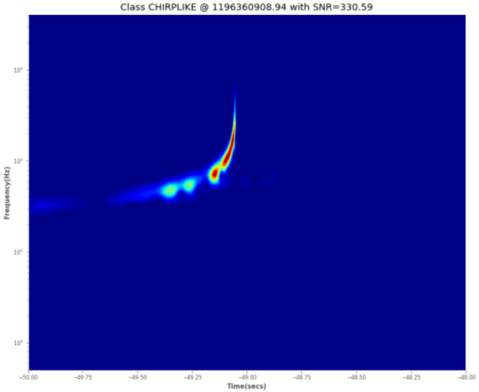


Astrophysical Gravitational Wave signals



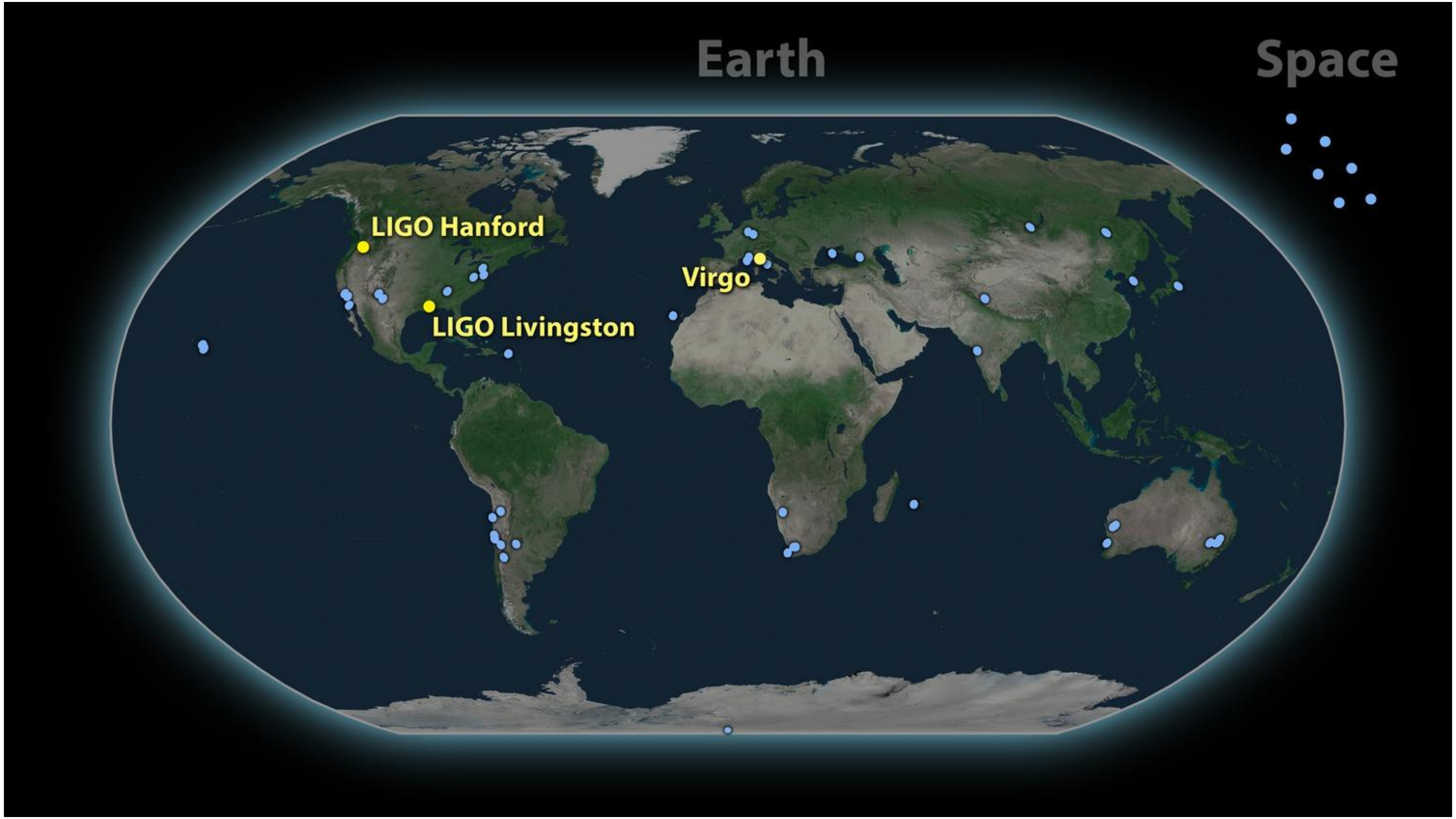
An artist's impression of two stars orbiting each other and progressing (from left to right) to merger with resulting gravitational waves. [Image: NASA/CXC/GSFC/T.Strohmayer]



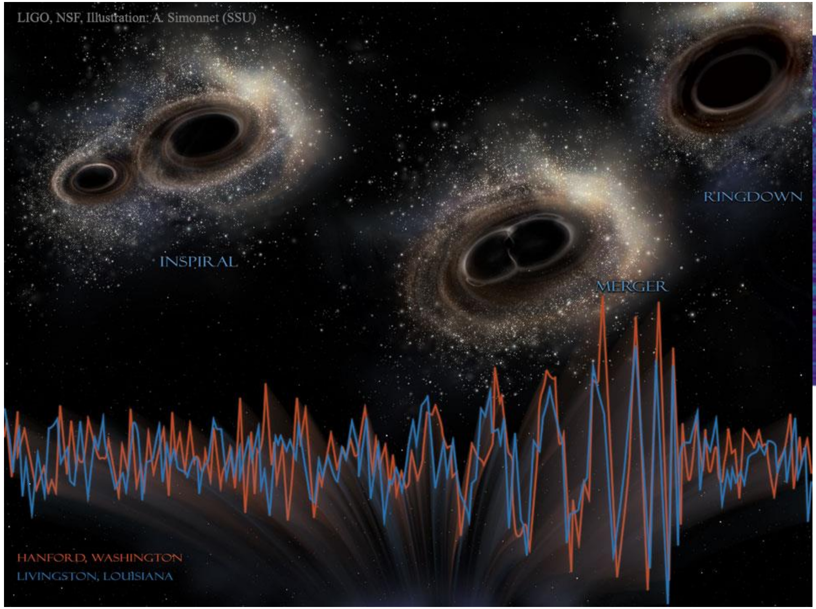


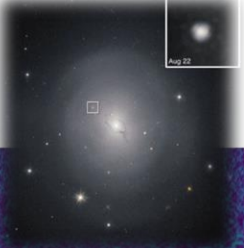
An example signal from an inspiral gravitational wave source. [Image: A. Stuver/LIGO]

International Collaboration

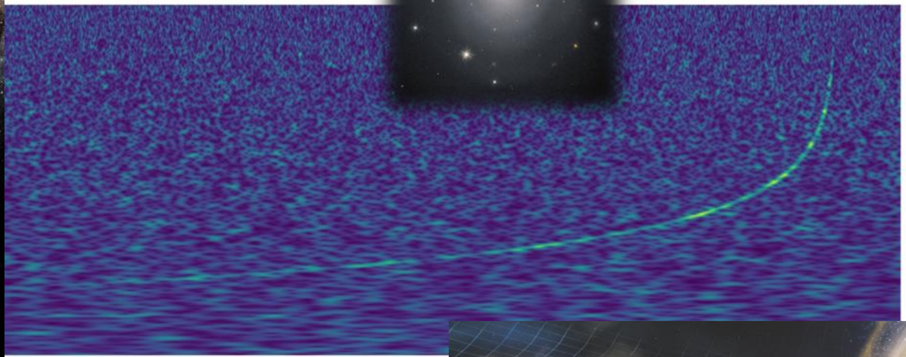


GW150914 and GW170817

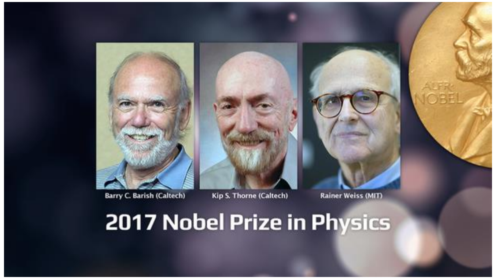




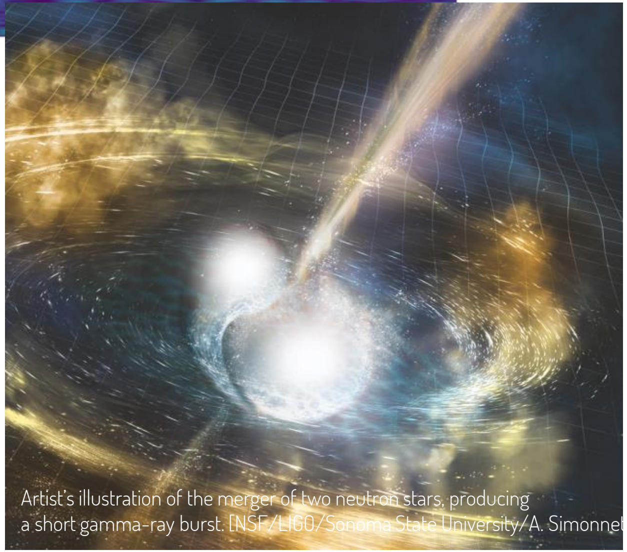
NGC 4993 GRB170817A
Hubble telescope



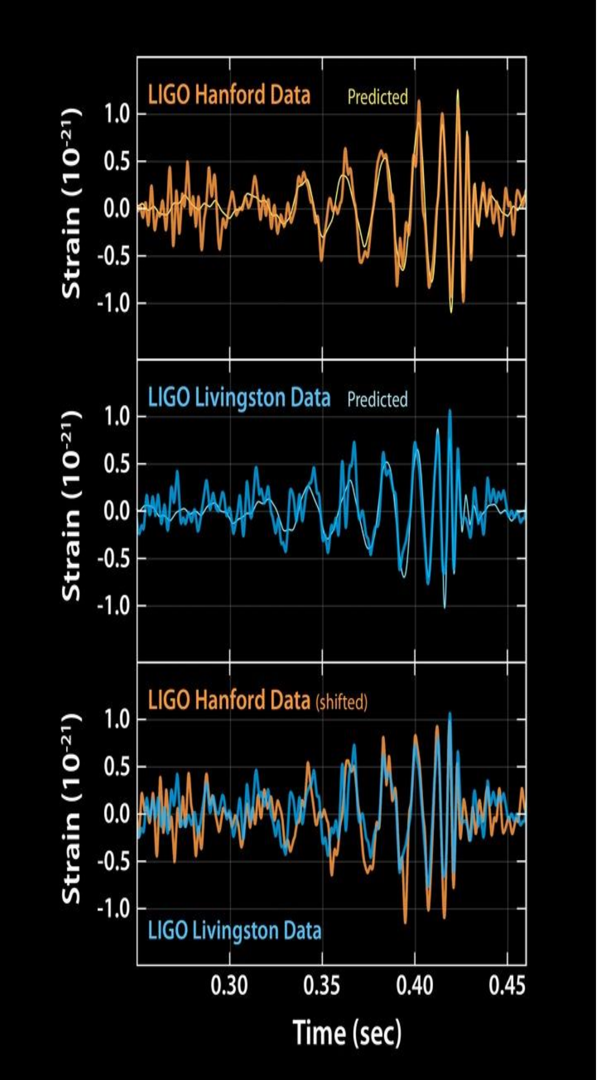
First Detection of Gravitational Waves from 2 colliding Neutron Stars
~1.5-2 Solar mass each



First Detection of Gravitational Waves!
2 colliding Black Holes
~30Solar mass each



Artist's illustration of the merger of two neutron stars, producing a short gamma-ray burst. [NSF/LIGO/Sonoma State University/A. Simonnet



Why Machine Learning in Gravitational Wave research

VIRGO Elena Cuoco

Outline

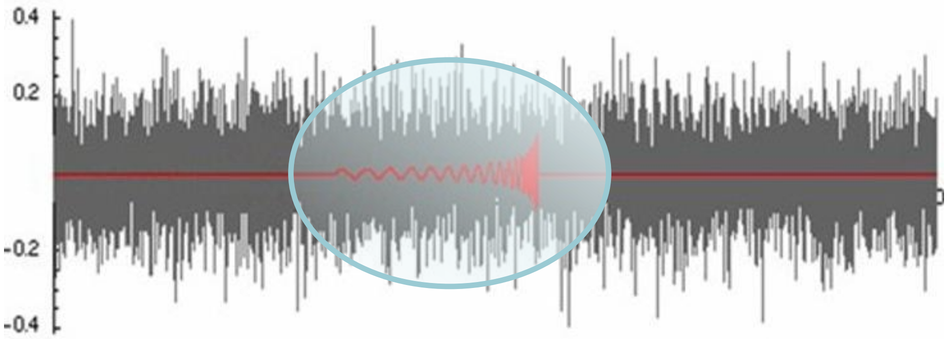
Glitches classification
- Image-based
- Wavelet-based

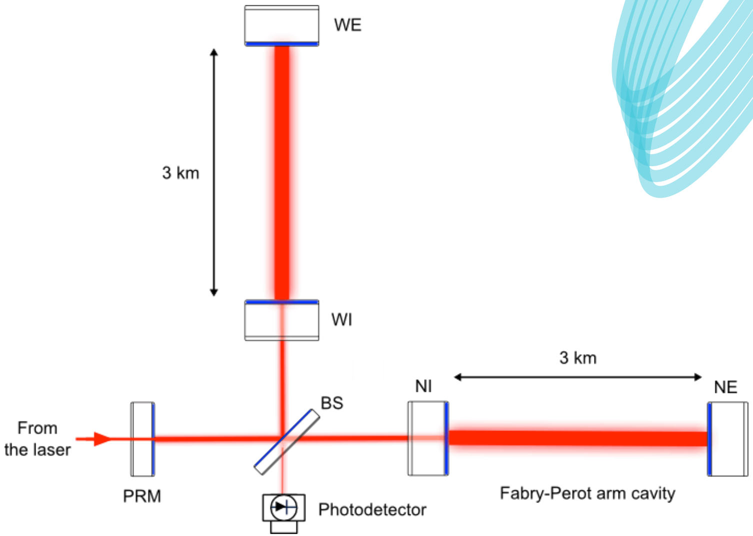
New ideas and possible collaborations in COST action framework

Machine learning for Gravitational Wave Data analysis

Noise Removal

Real time analysis (on going work)





LIGO/Virgo data

are time series sequences… **noisy time series** with low amplitude GW signal buried in

Our "signals"

Known GW signals

Compact coalescing binaries has known theoretical waveforms

↓

Optimal filter: Matched filter

↓

Too many templates to test

Unknown GW signals

Core collapse supernovae

↓

No Optimal filter

↓

Parameters estimation

Noise

Moving lines

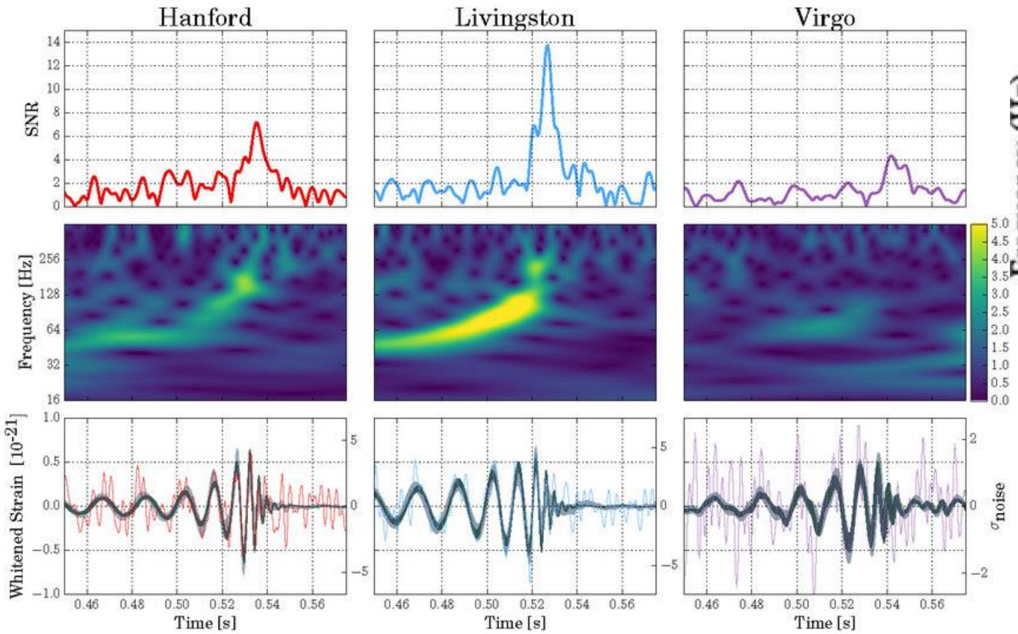
Broad band noise

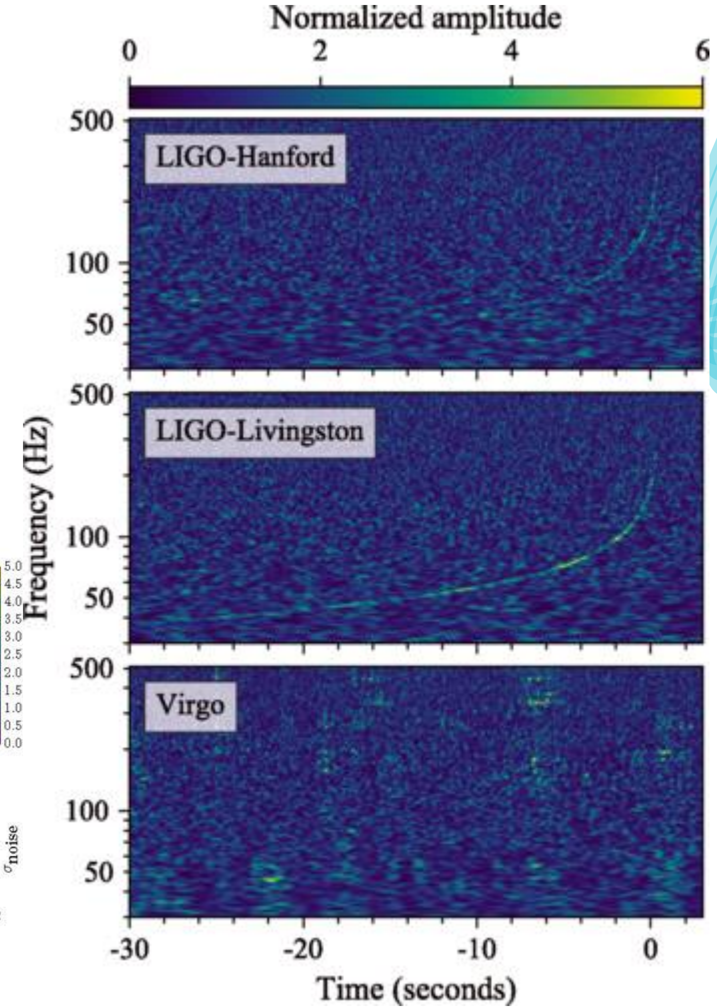
Glitch noise

↓

"Pattern recognition" by visual inspection

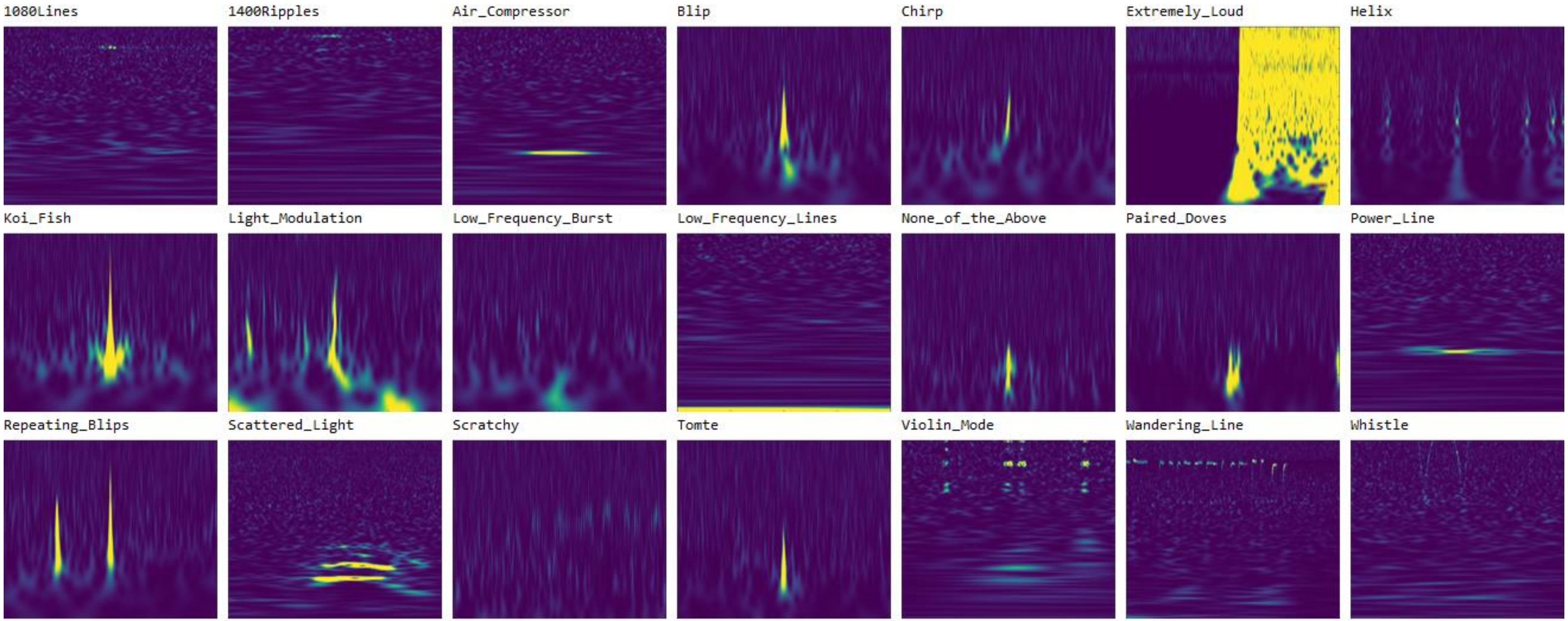
Example of GW signals in Time-Frequency plots



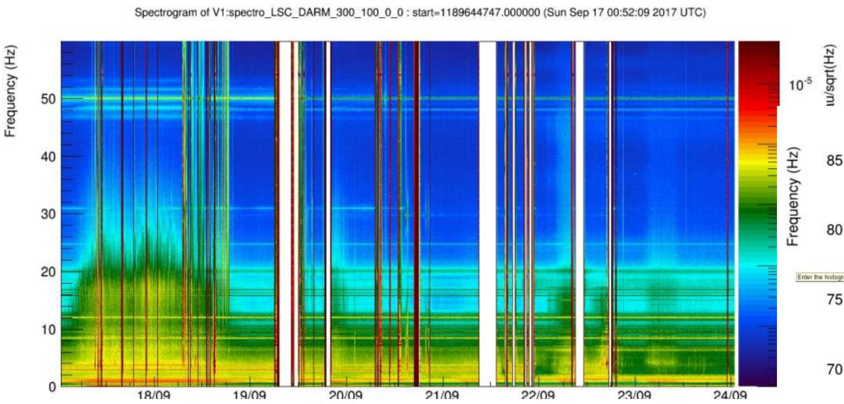


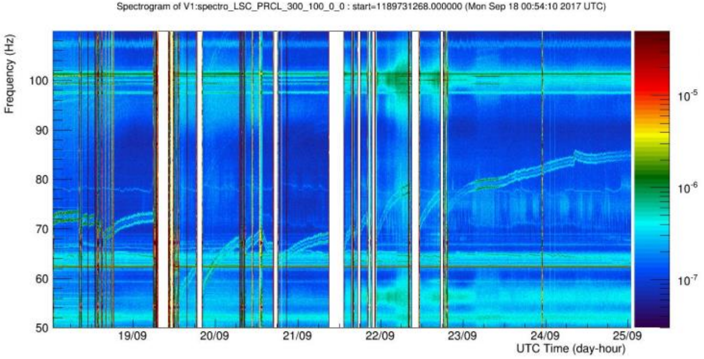
https://www.zooniverse.org/projects/zooniverse/gravity-spy

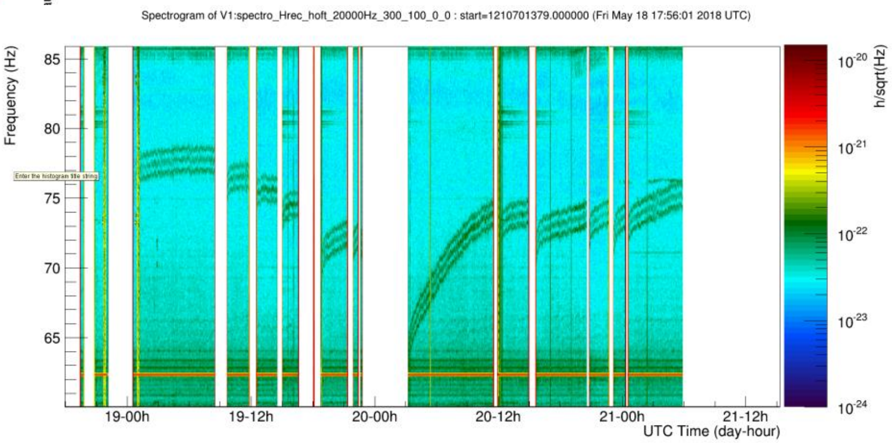
Example of Glitch signals



Example of other noise signals







I. Fiori courtesy

Numbers about data

Data Stream Flux	Data on disk	Number of events	Number of glitches
• 50MB/s	• 1-3PB	• 1/week • 1/day?	• 1/sec • 0.1/sec?

Should be analysed in less than 1min

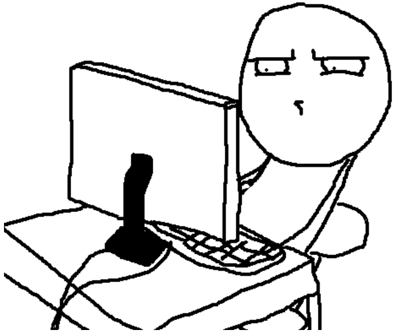
How Machine Learning can help

Data conditioning

- Non linear noise coupling
- Use Neural Network to learn noise
- Use Neural Network to remove noise

Signal Detection/Classification/PE

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



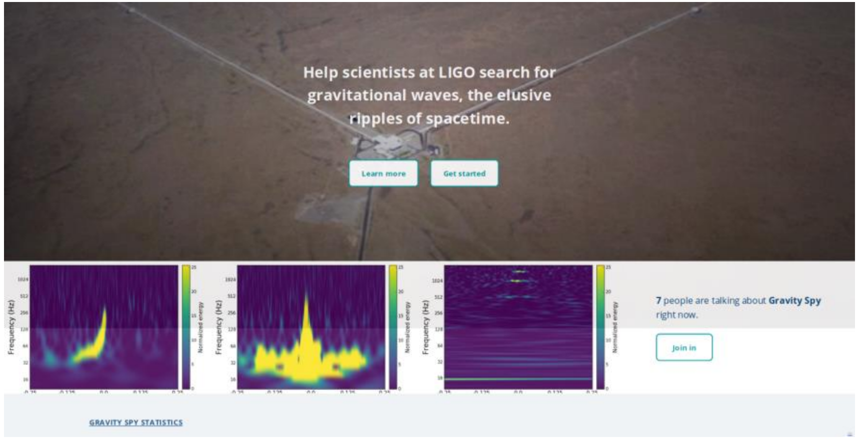
What is going in the ML LIGO/Virgo group

136 LIGO/Virgo members

30 active projects

Example of interesting works

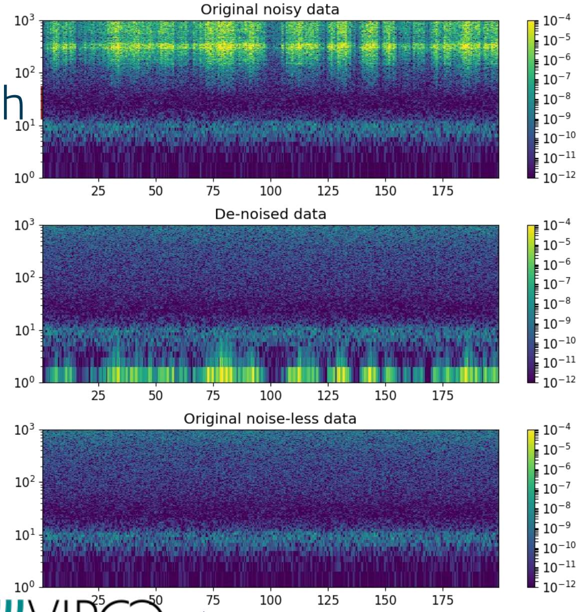
- Labelling glitches: Gravity Spy



S. Coughlin courtesy

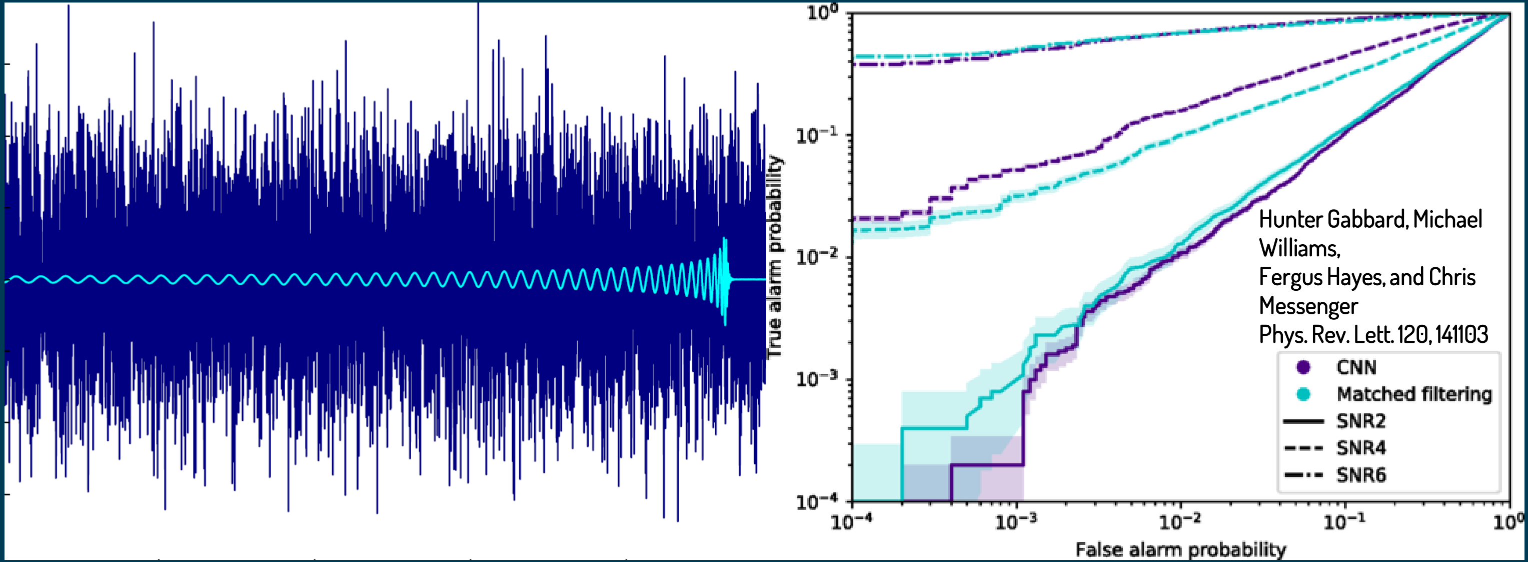
- Noise Removal

Non-linear and non-stationary noise subtraction with Learning



G. Vajente courtesy

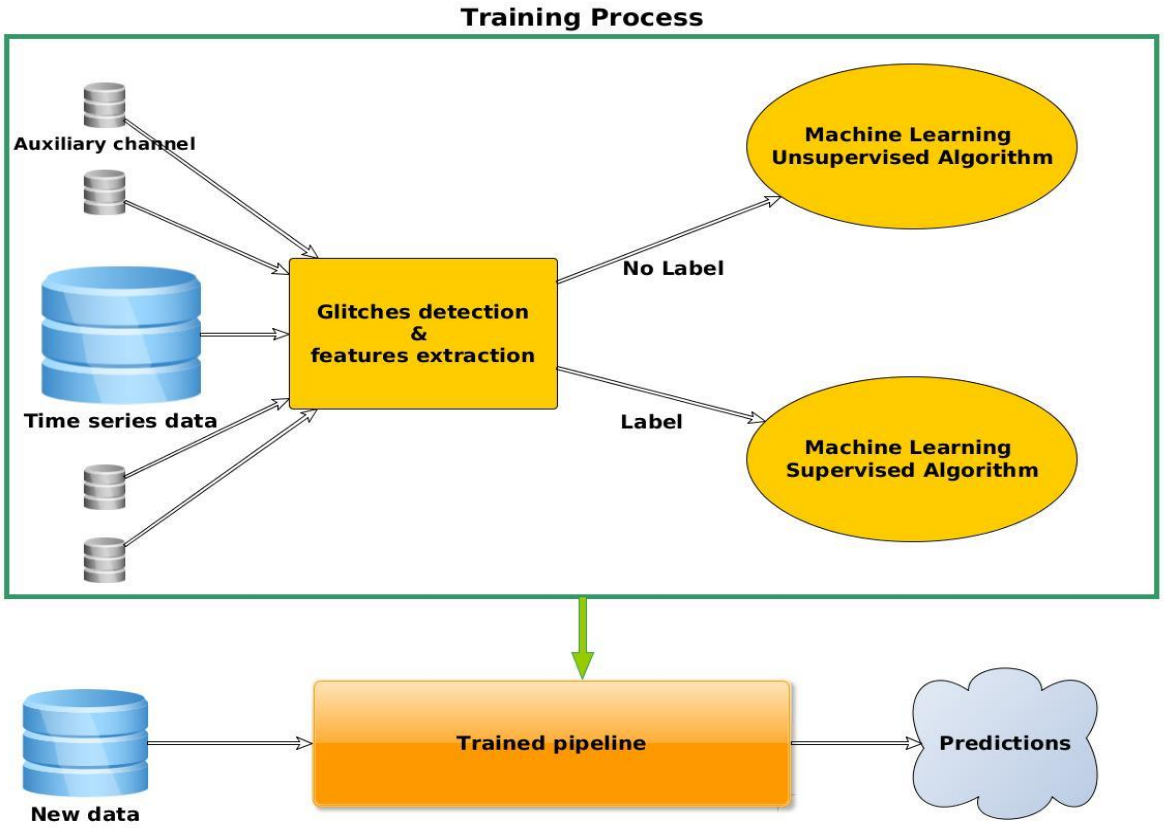
Signal detection



Hunter Gabbard, Michael Williams, Fergus Hayes, and Chris Messenger
Phys. Rev. Lett. 120, 141103

- Deep learning procedure requiring only the raw data time series as input with minimal signal pre-processing.
- Performance similar to Optimal Wiener Filter

Glitches Classification Strategy

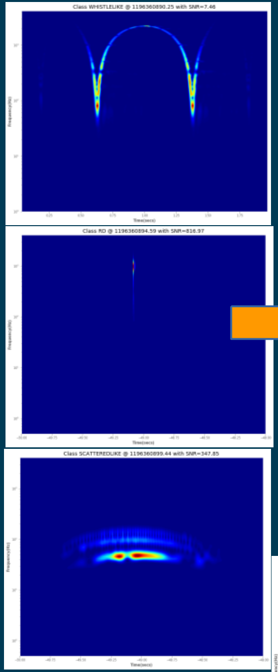


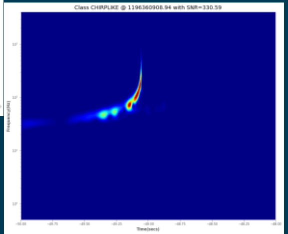
Glitches classification efforts in LIGO/Virgo Community

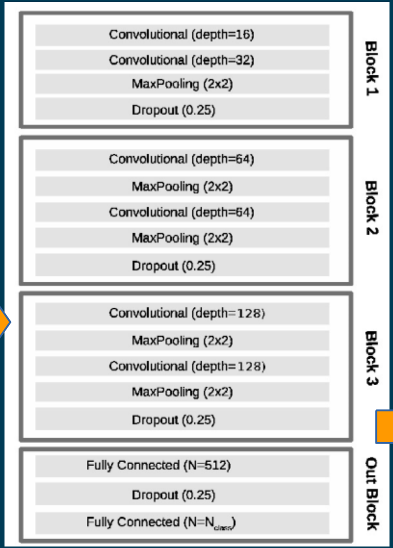
- Gravity Spy (M. Zevin,S. Coughlin,J. R. Smith, A. Lundgren, D. Macleod, V. Kalogera)
- WDF-ML (E. Cuoco, A. Torres)
- WDFX (E. Cuoco, M. Razzano, A. Utina)
- PCAT (M.Cavaglià, D. Trifirò)
- Karoo GP (K. Staats, M. Cavaglià)
- Wavelet-DBNN (N. Mukund S. Abraham S. Mitra et al)
- ImageGlitch CNN (M. Razzano, E. Cuoco)
- Low latency transient detection and classification (I. Pinto, V. Pierro, L. Troiano, E. Mejuto-Villa, V. Matta, P. Addesso)
- Deep Transfer Learning (Daniel George, Hongyu Shen, E.A. Huerta)
- Gstlal-iDQ (P. Godwin, R. Essick, D. Meacher, S. Chamberlain, C. Hanna, E. Katsavounidis, L. Wade, M. Wade, D. Moffa, K. Rose)
- New ranking statistic for gstlal (K. Kim, T.G.F. Li, R.K.-L. Lo, S. Sachdev, R.S.H. Yuen)
- RGB image SN CNN (P. Astone, S. Frasca, C. Palomba, F. Ricci, M. Drago, I. Di Palma, F. Muciaccia, Pablo Cerda-Duran)

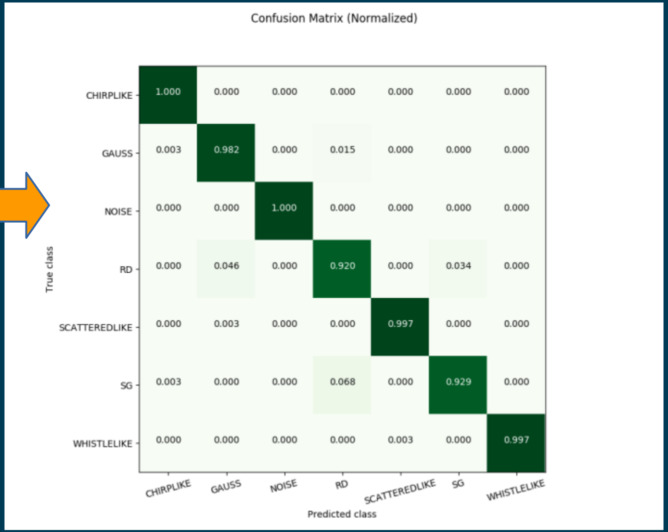
Images-based glitch classification

Deep learning with CNN





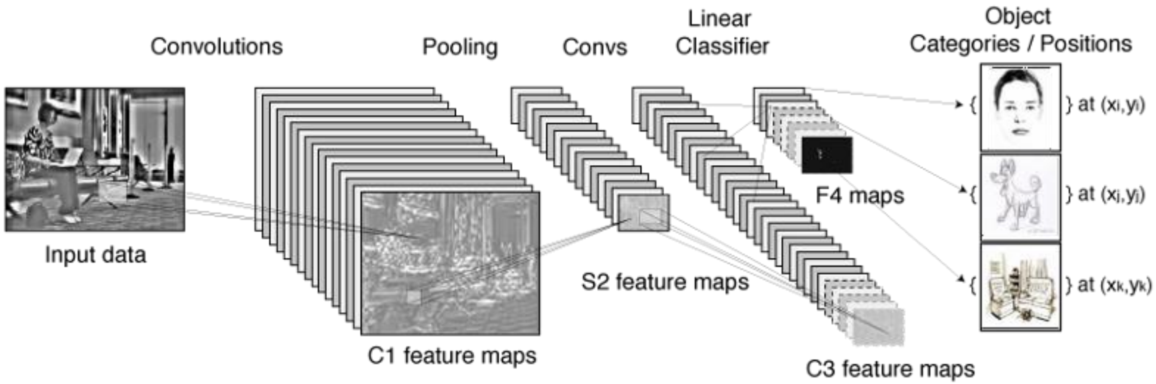




Massimiliano Razzano and Elena Cuoco
2018 Class. Quantum Grav. 35 095016

Deep learning for Glitch Classification

- Many approaches to data: we choose image classification of time frequency images
- The architecture is based on Convolutional deep Neural Networks (CNNs).
- CNNs are more complex than simple NNs but are optimized to catch features in images, so they are the best choice for image classification



Pipeline structure

Input GW data

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

Classification

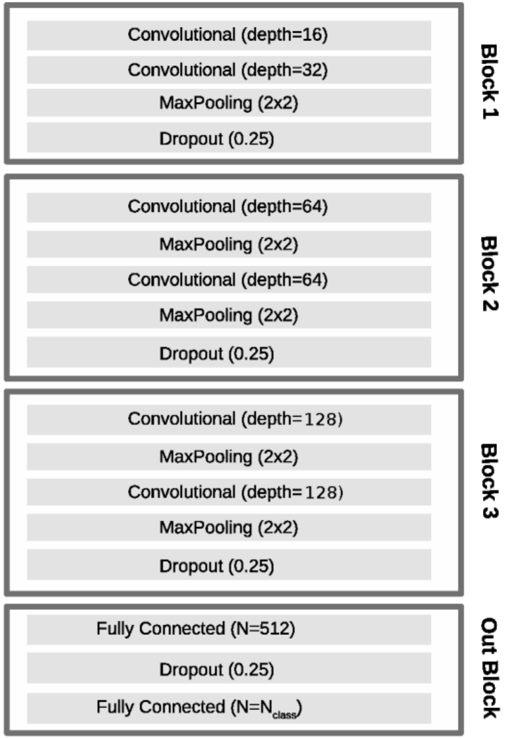
- A probability for each class, take the max
- Add a NOISE class to crosscheck glitch detection

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

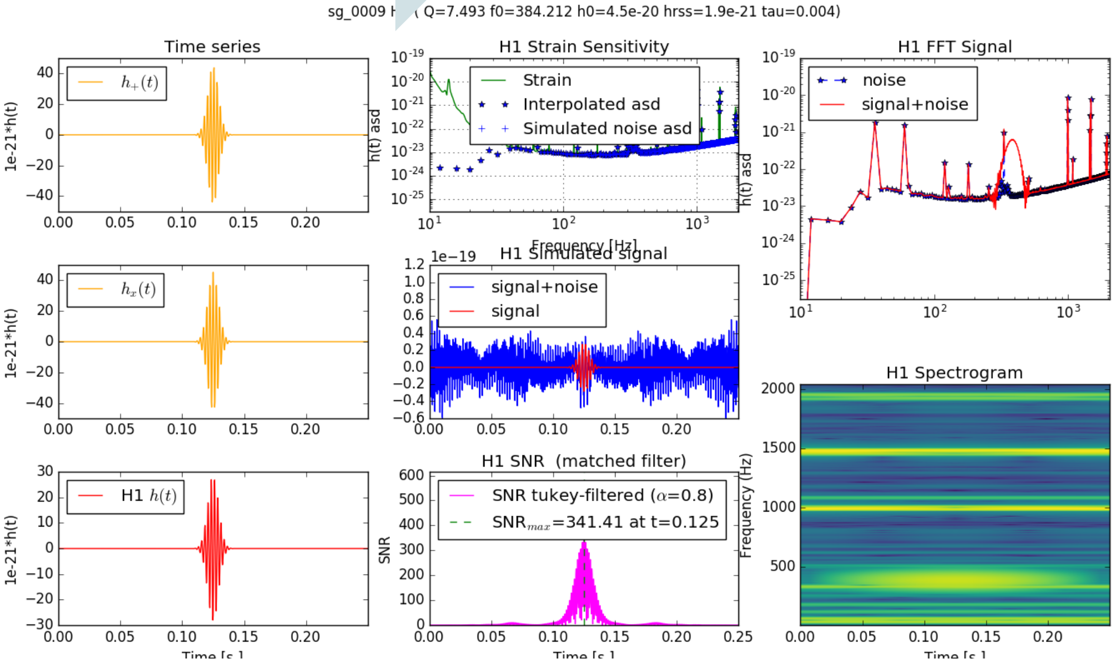


Test on simulation

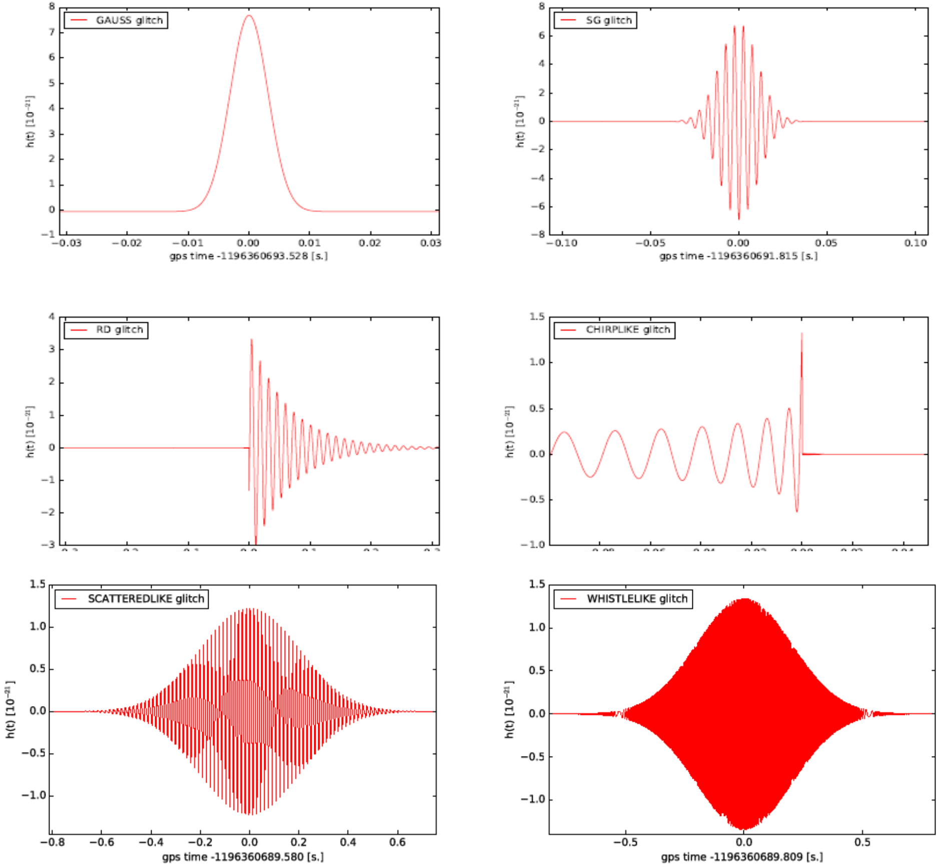
To test the pipeline, we prepared ad-hoc simulations

Simulate colored noise using public H1 sensitivity curve

Add 6 different classes of glitch shapes



Simulated signal families



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

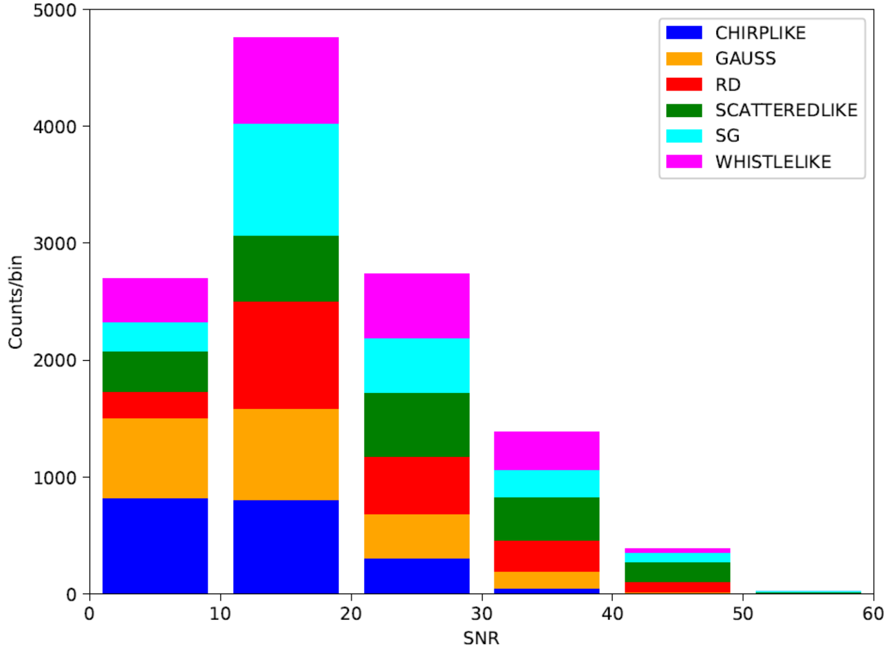
Signal distribution

Simulated time series with 8kHz sampling rate

Glitches distributed with Poisson statistics m=0.5 Hz

2000 glitches per each family

Glitch parameters are varied randomly to achieve various shapes and Signal-To-Noise ratio



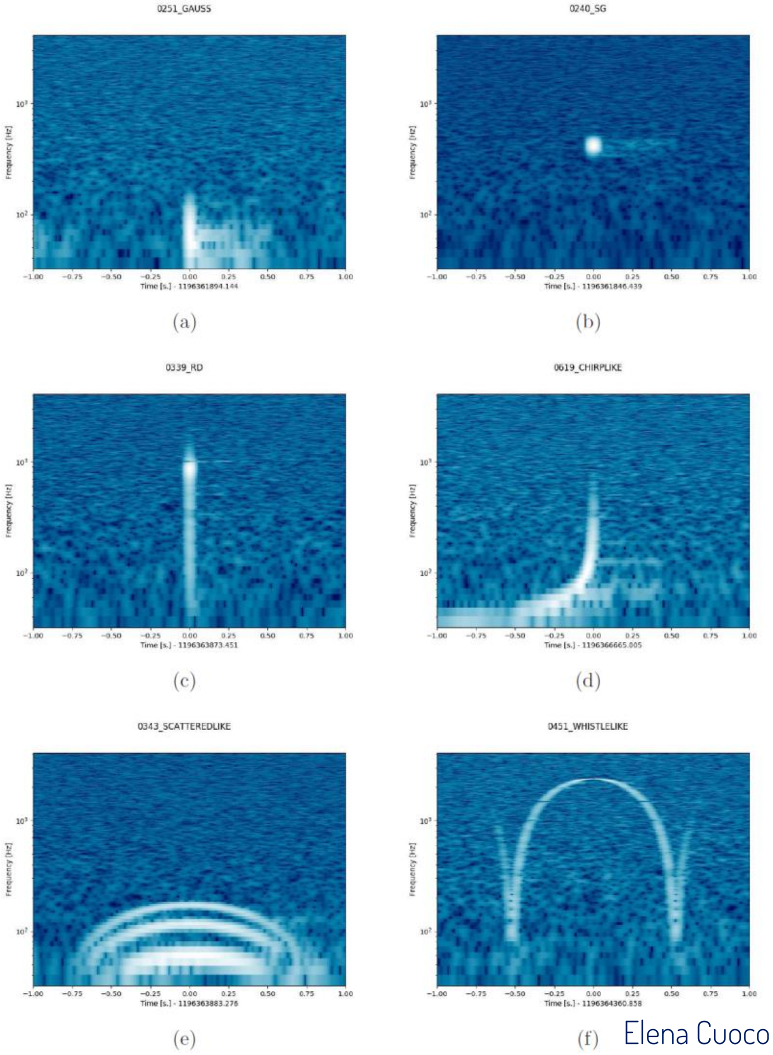
Building the images

Spectrogram for each image

2-seconds time window to highlight fatures in long glitches

Data is whitened

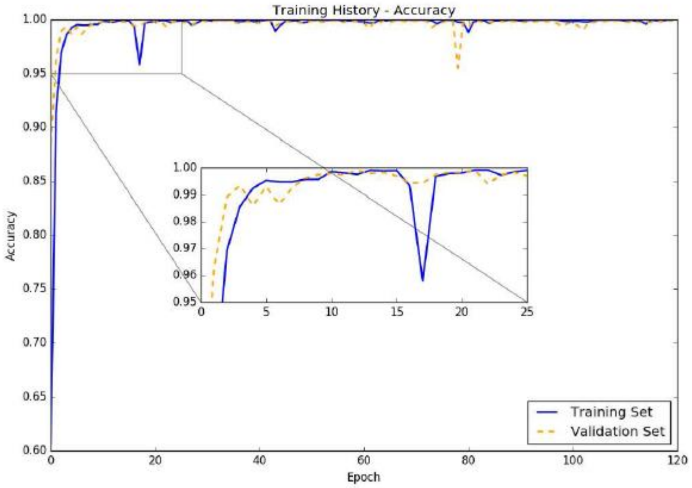
Optional contrast stretch

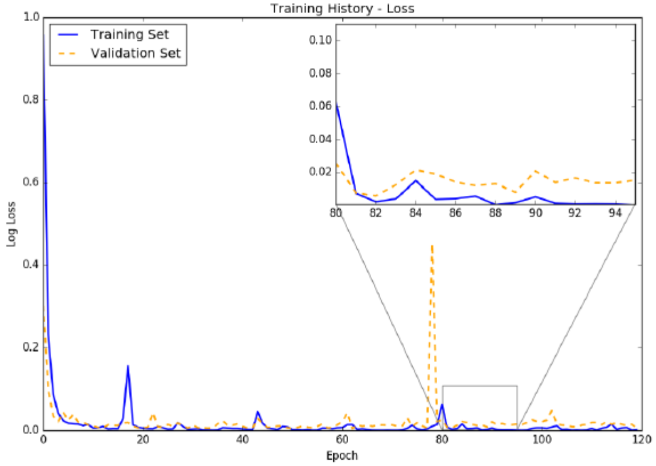


Elena Cuoco

Training the CNN

- ✓ Datasets of 14000 images
- ✓ Training/validation/test → 70/15/15
- ✓ Image size 241px x 513px
- ✓ Reduced the images by a factor 0.55 due to memory constraints
- ✓ Use validation set to tune hyperparameters
- ✓ On our hardware, training time ~8 hrs for ~100 epochs
- ✓ When training is done, classification requires ~1 ms/image (on our configuration)





Classification Results

We compared classification performances with simpler architectures

Linear Support Vector Machine

CNN with 1 hidden layer

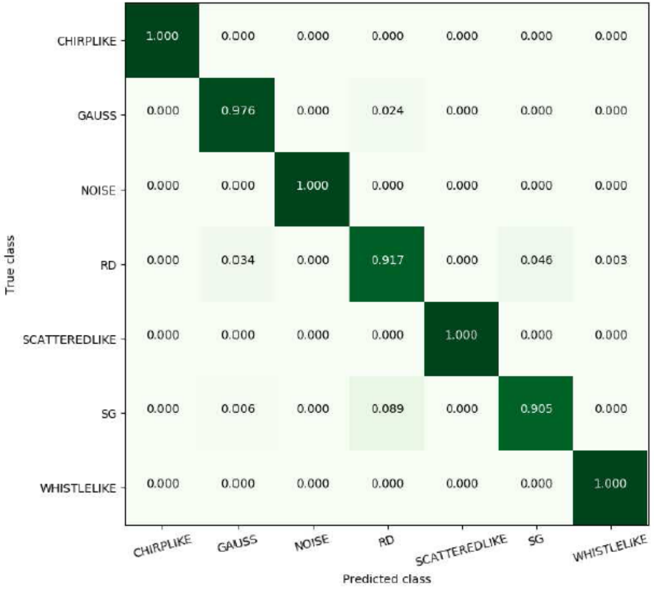
CNN with one block
(2 CNNs+Pooling&Dropout)

Deep 4-blocks CNNs

Metric	Accuracy	Precision	Recall	F1 score	Log loss
SVM	0.971	0.972	0.971	0.971	0.08
Shallow CNN	0.986	0.986	0.986	0.986	0.04
1 CNN block	0.991	0.991	0.991	0.991	0.02
3 CNN blocks	0.998	0.998	0.998	0.998	0.008

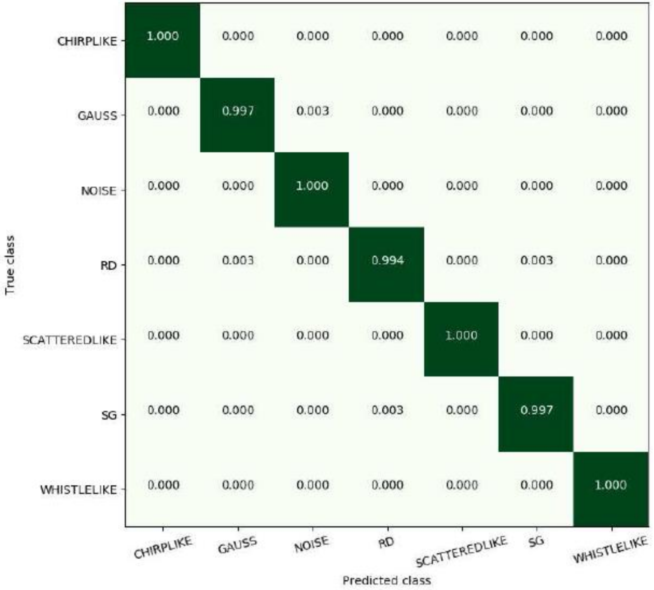
Classification accuracy

Normalized Confusion Matrix



SVM

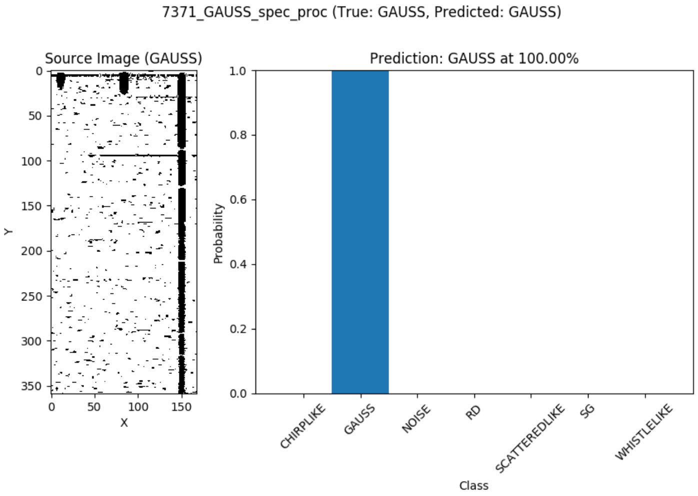
Deep CNN

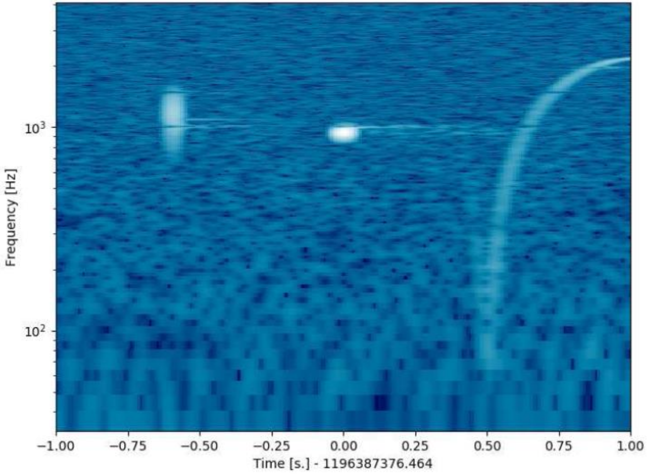


Deep CNN better at distinguishing similar morphologies

Example of classification results

Some cases of more glitches in the time window, always identify the right class



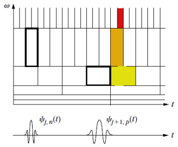


100% Sine-Gaussian

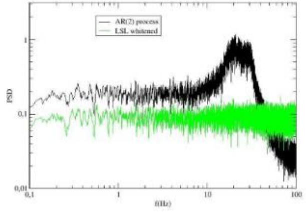
Wavelet Detection Filter (WDF) workflow

$$x_i = h_i + n_i, \quad i = 0, 1, \ldots N-1,$$

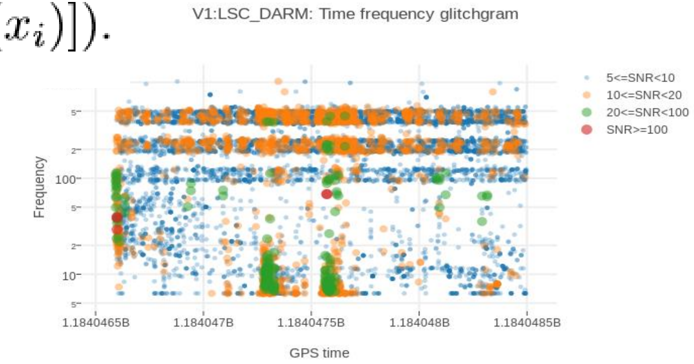
$$Wf(a,b) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(t) \frac{1}{\sqrt{b}} \psi^* \left(\frac{t-a}{b} \right) \, dt,$$



Data → Whitening in time domain → Wavelet transform → De-noising → Parameter estimation → Trigger list

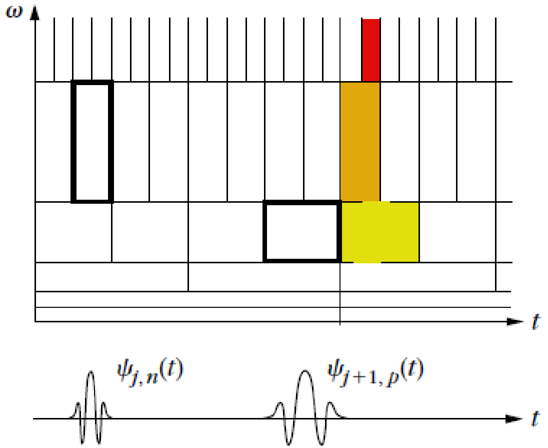


$$\hat{h}_i = W^{-1}(t[W(x_i)]).$$



Wavelet Detection Filter

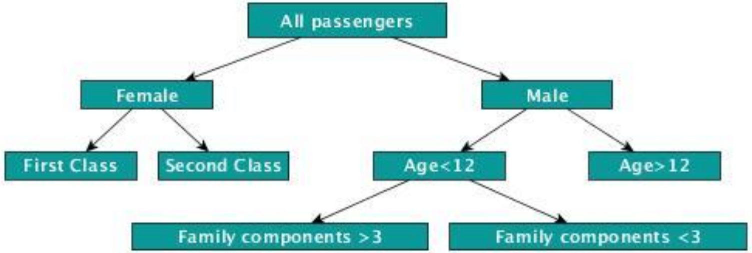
- Wavelet transform in the selected window size
- Retain only coefficients above a fixed threshod (Donoho-Johnston denoise method)
- Create a metrics for the energy using the selected coefficients and give back the trigger with all the wavelet coefficients.
- In the wavelet plane, select the highest values and closest coefficients to build the event
- Put to zero all the other coefficients
- Inverse wavelet transform
- Estimate mean and max frequency and snr max of the cleaned event



Gps, duration, snr, snr@max, freq_mean, freq@max, wavelet type triggered + corresponding wavelets coefficients.

eXtreme Gradient Boosting

- https://github.com/dmlc/xgboost
- Tianqi Chen and Carlos Guestrin. XGBoost: A Scalable Tree Boosting System. In 22nd SIGKDD Conference on Knowledge Discovery and Data Mining, 2016
- XGBoost originates from research project at University of Washington, see also the Project Page at UW.

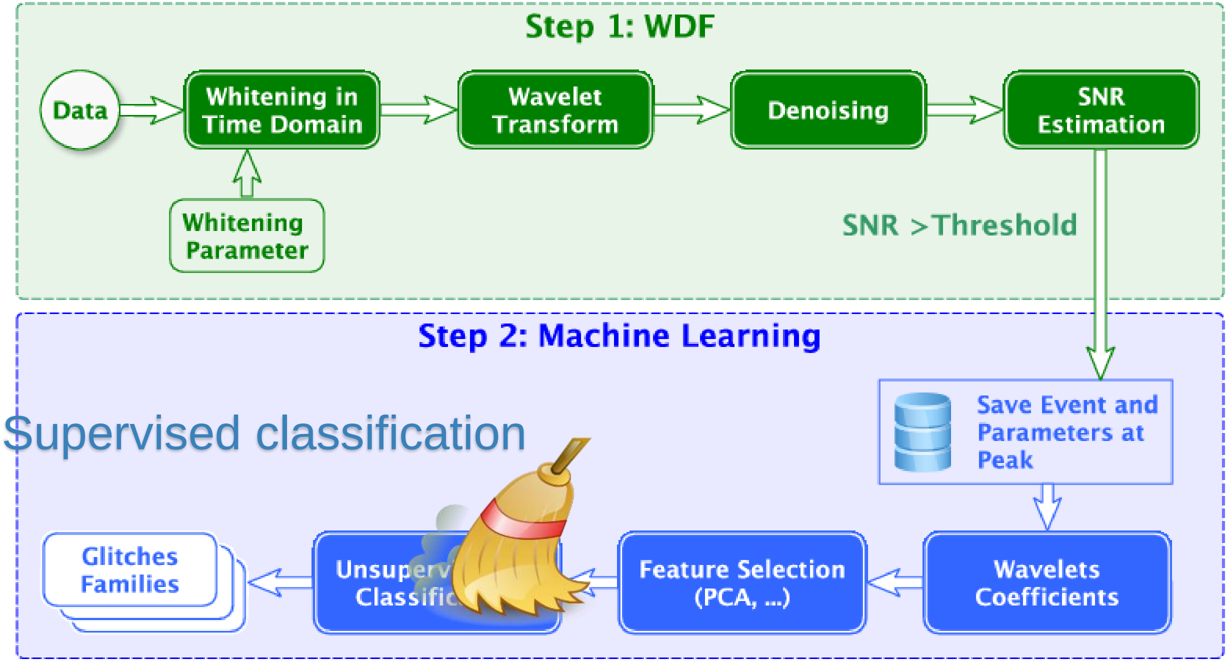


Tree Ensemble

$$y_n = \sum_{k=1}^{K} f_k(x_n)$$

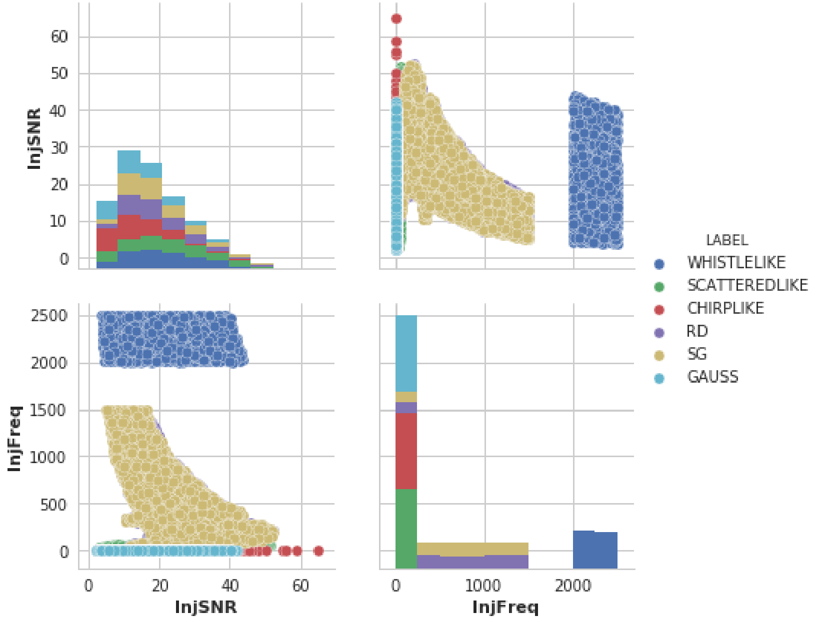
dmlc XGBoost

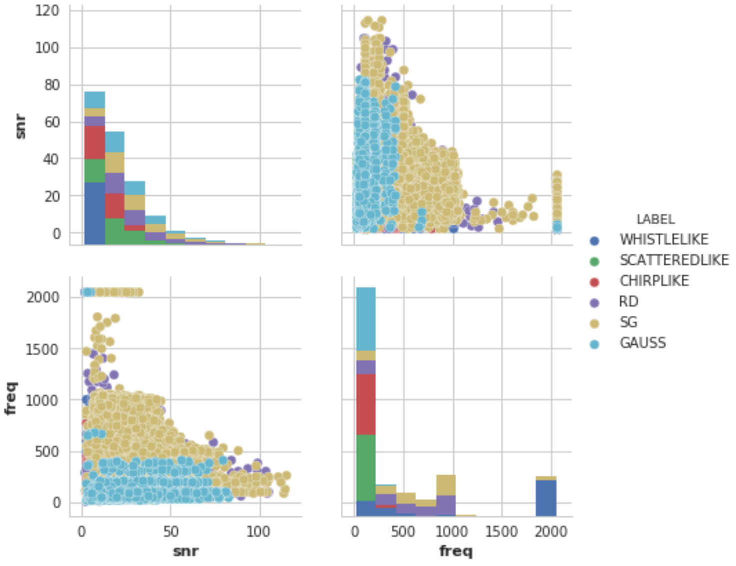
Wavelet Detection Filter and XGBoost (WDFX)



WDF results

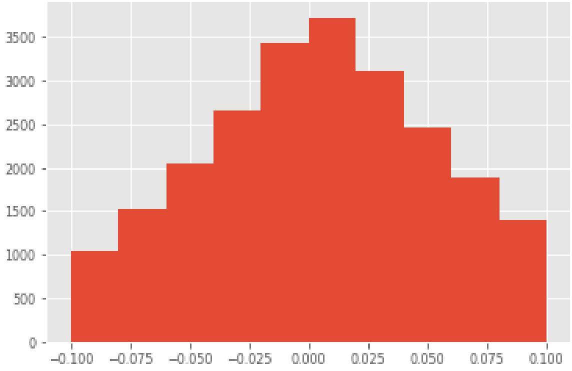
- Detected 97% of injected signals (some with SNR=1)
- False alarm rate: 10% for a time window shift of 1sec
- Good parameters estimation

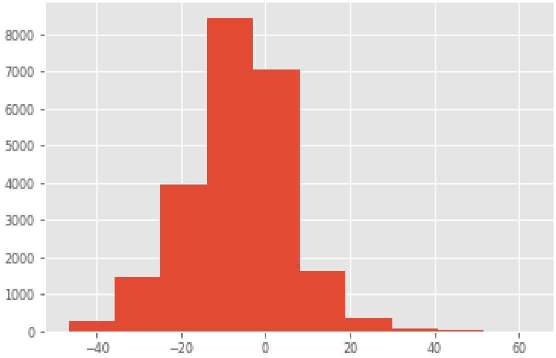




Parameters estimation

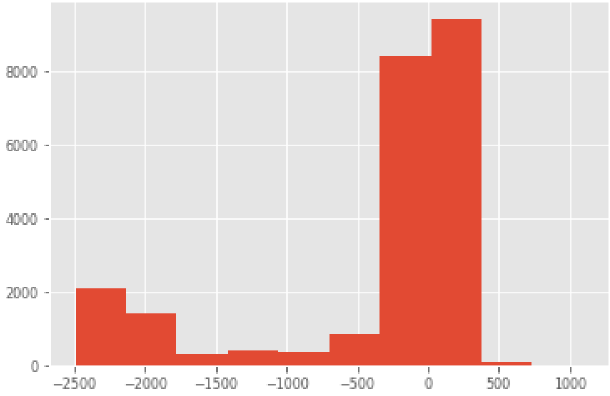
Time difference distribution





SNR difference distribution

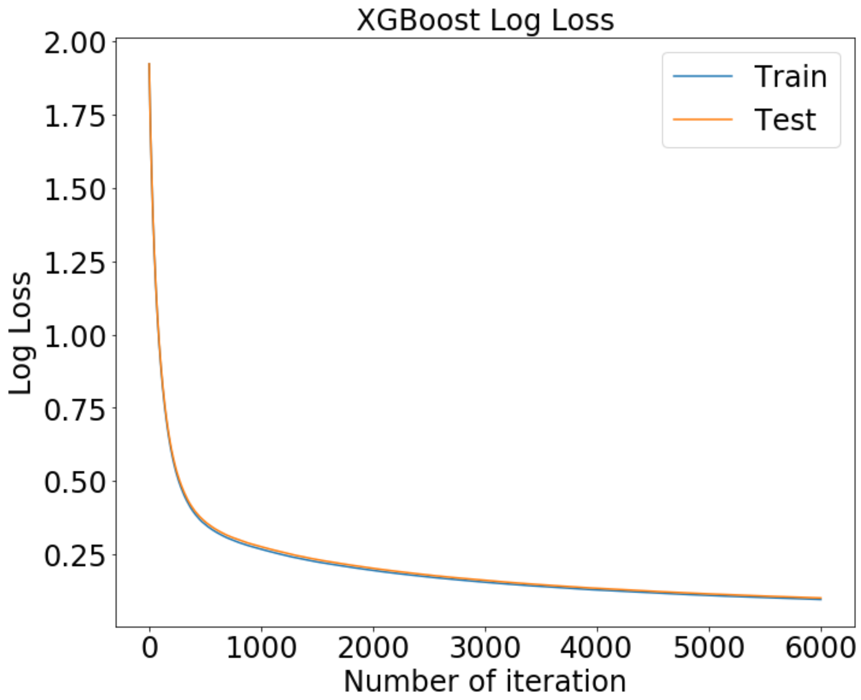
Frequency difference distribution



Machine learning

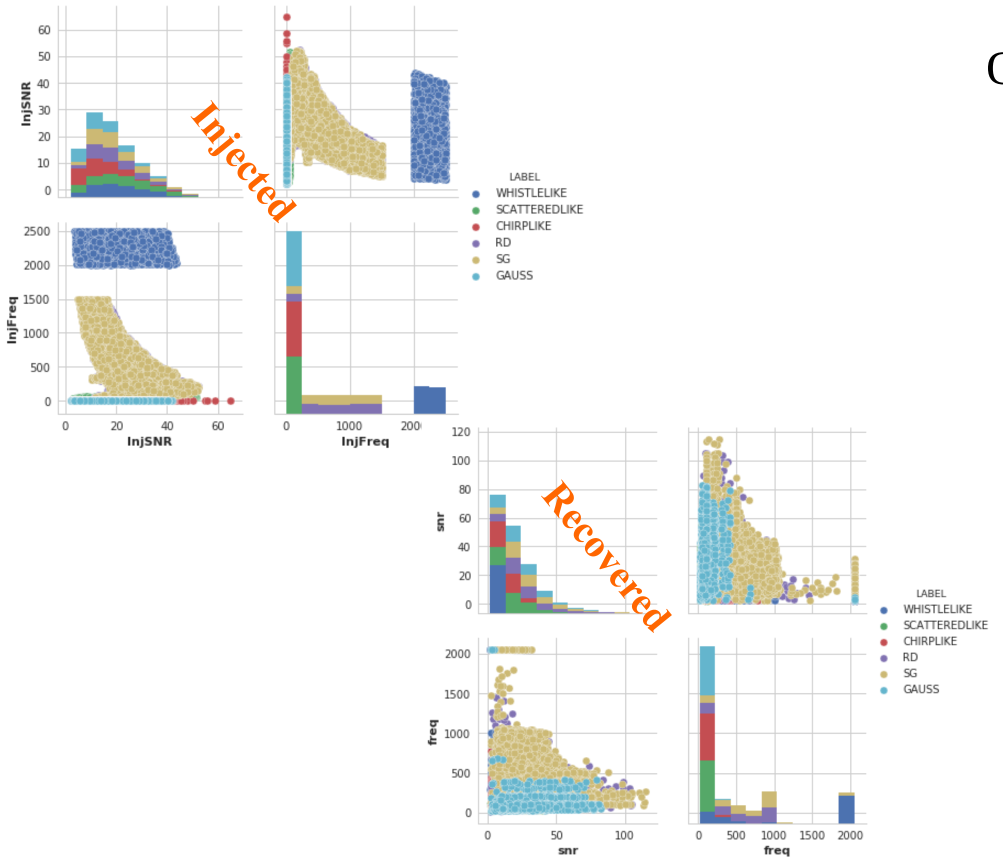
$$L = -\frac{1}{N}\sum_{1}^{N}((y_i \log(p_i) + (1 - y_i)(log(1 - p_i)) + \Omega$$

Train/validation/test set: 70/15/15

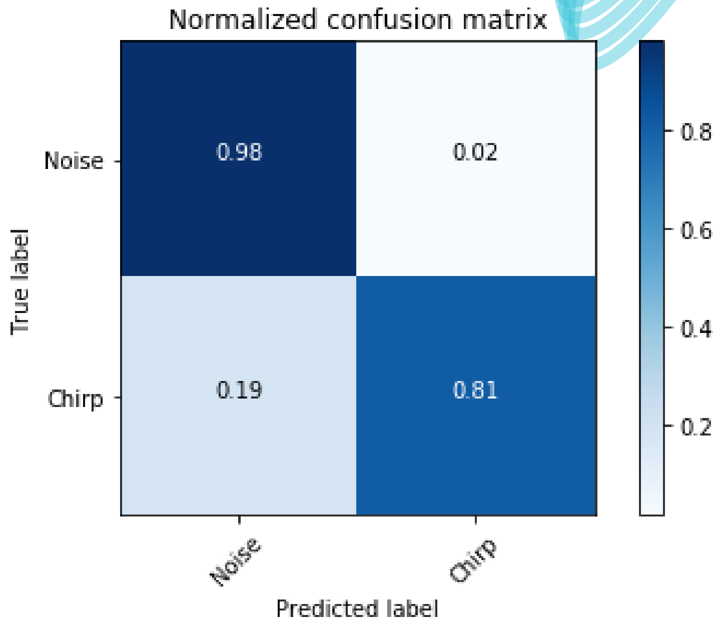


task	Classes	Learning-rate	Max_depth	estimators
Binary	2	0.01	7	5000
Multi-label	7	0.01	10	6000

WDFX: Binary Classification Results



Overall accuracy >90%



WDFX Results: Multi-Label Classification

Overall accuracy >80%

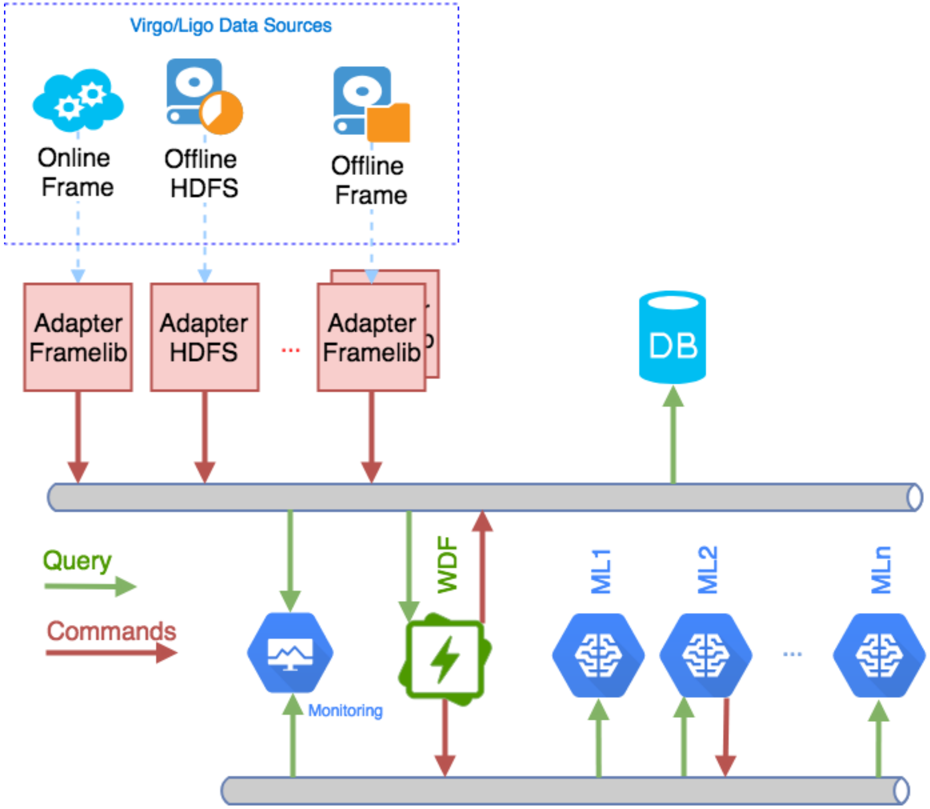
Wavefier

Real time Gravitational Wave transient signal classifier

- release an end to end framework for the glitches identification, classification and archiving ML classification schemes for GW glitches.
- To evaluate possible HPC solutions for DL pipelines for online glitch classification.

Draft

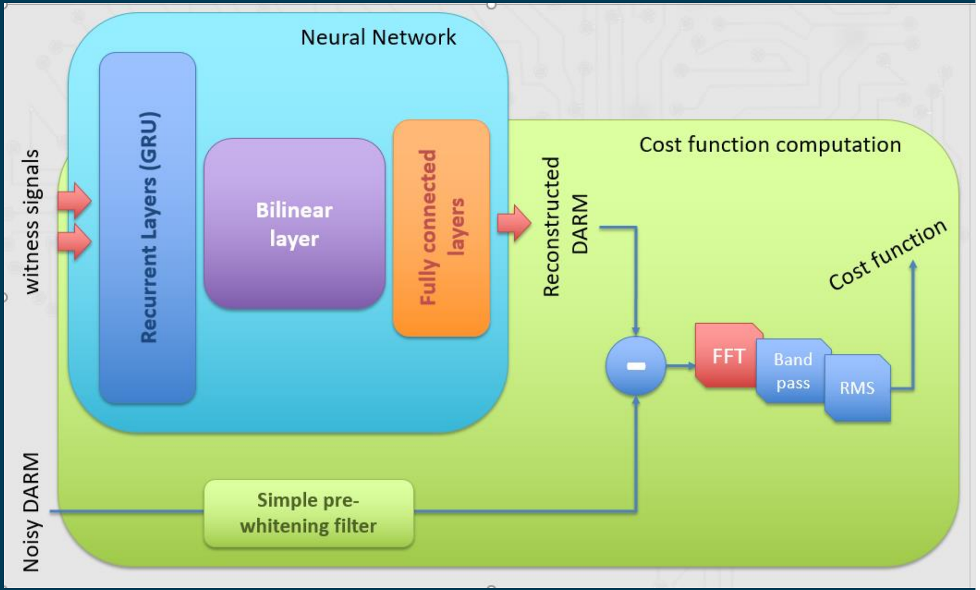
LAPP, Trust-IT Services company, EGO

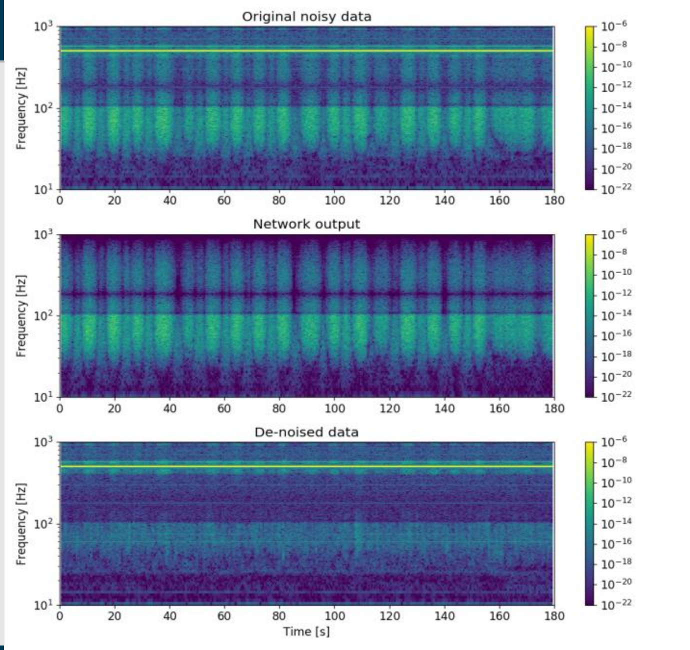


Noise removal trough Deep learning

Gabriele Vajente[1],
Michael Coughlin[1],
Rich Ormistom[2]
[1]LIGO Laboratory Caltech
[2]University of Minnesota Twin Cities

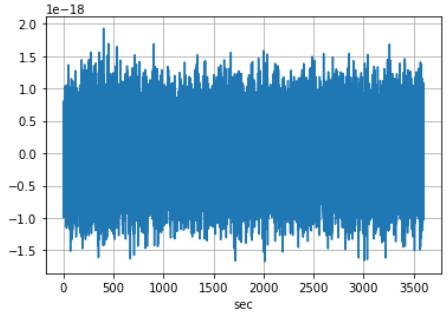
Same work for Virgo.
A. Iess et al. with the help of Gabriele





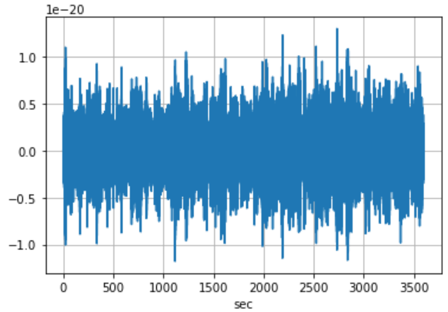
Recurrent Neural Networks for noise cancellation

<u>A. Iess (PhD student)</u>, G. Vajente, E. Cuoco, V.Fafone

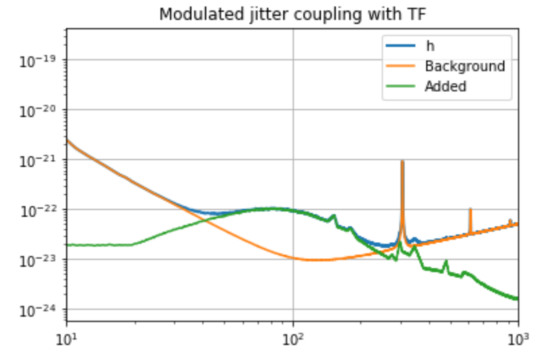


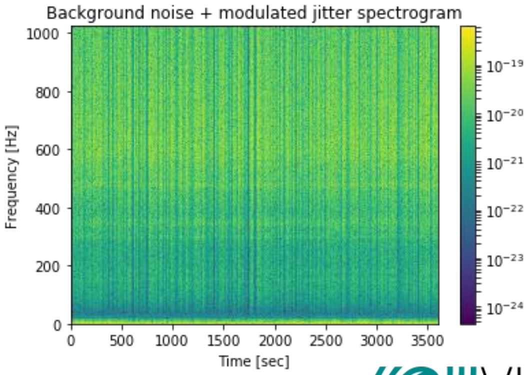
Gaussian background
(from Ad Virgo sensitivity curve)

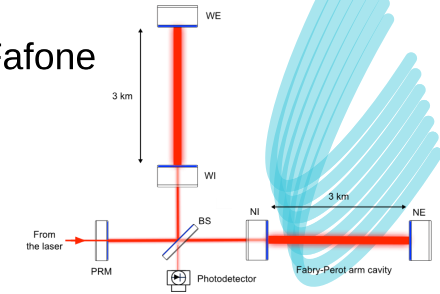
+

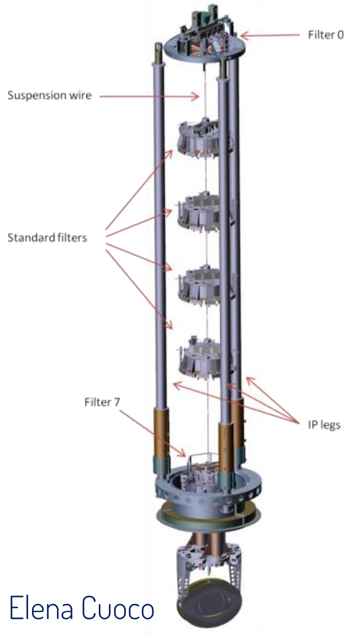


Beam Jitter Noise modulated by suspension transfer function
(simulated)









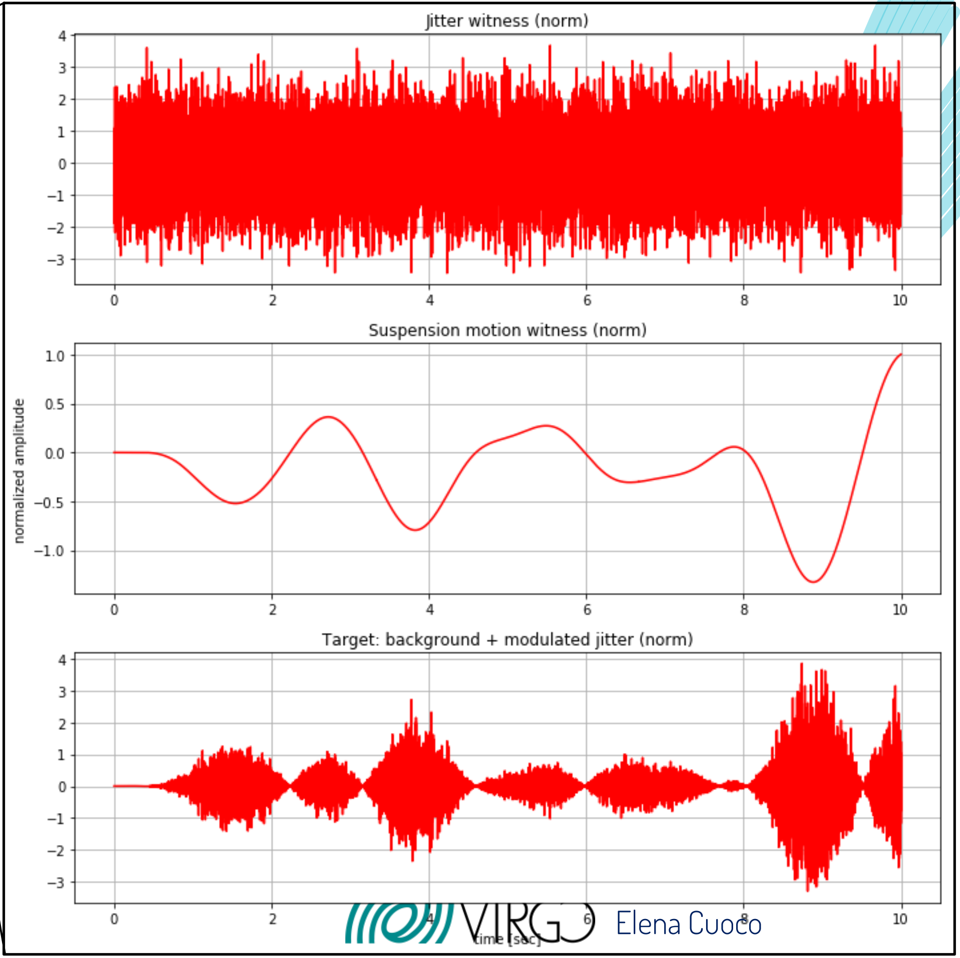
A. Iess courtesy

3 WITNESS CHANNELS (INPUTS)

1. Beam Jitter
2. Suspension motion
3. Seismic modulation

RECURRENT NEURAL NETWORK

h PREDICTION (OUTPUT)



A. Iess courtesy

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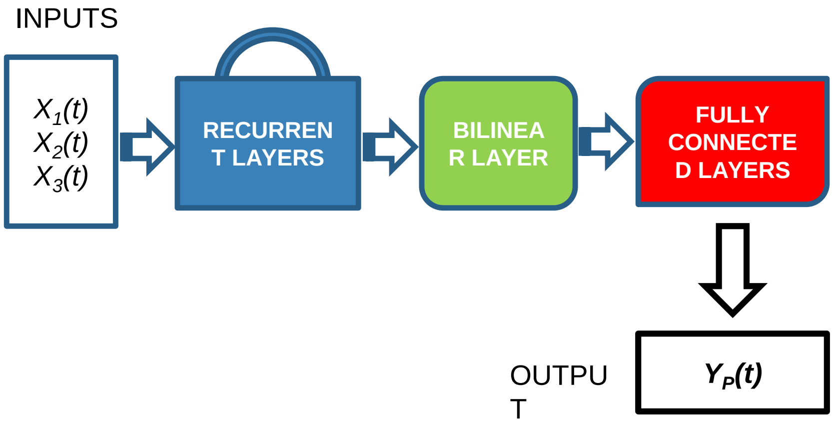
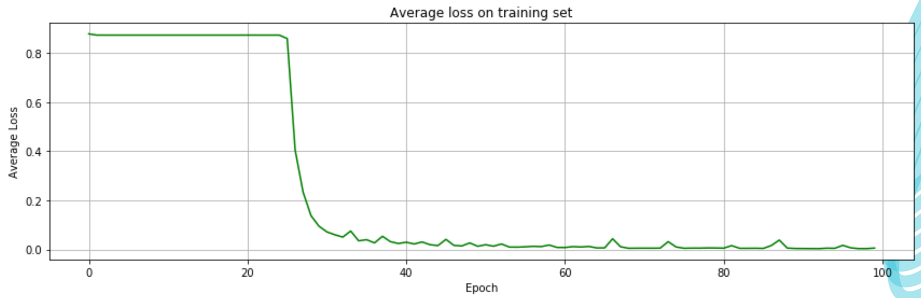


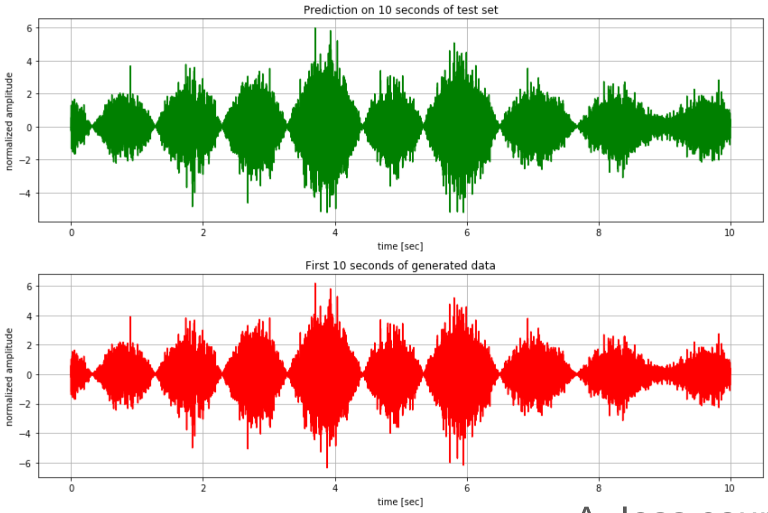
- ***PyTorch 0.4.0***
- Number of Epochs: 100
- Optimizer: ***ADAM*** (ADAptive Moment estimation)
- Initial learning rate: **0.004**
- Learning rate decay: factor 1.0 every 15 epochs
- Loss function: ***Squared Error***
- 3 Recurrent layers (Elman/GRU/LSTM+ 1 Bilinear + 4 Fully connected layers
- Batch size: 1 second

A. Iess courtesy

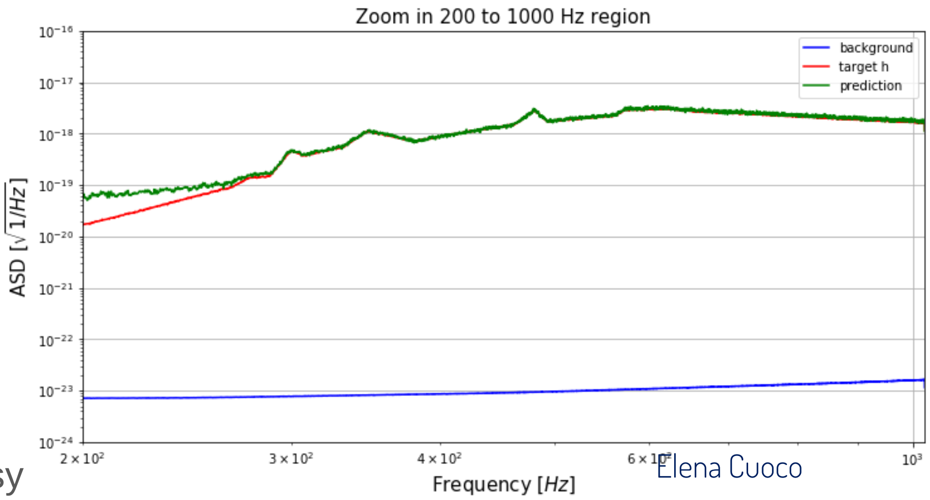
- RNNs good for time-series prediction, retain memory through *context units*
- Bilinear layer to model non-linear noise coupling
- Computational load concentrated in training step
- Wiener filters bad for removing non-linear noise



Prediction: Time Domain



Prediction: Frequency Domain



A. Iess courtesy

Elena Cuoco

Cost Action 17137

G2net: A network for Gravitational Waves, Geophysics and Machine Learning

cost
EUROPEAN COOPERATION IN SCIENCE & TECHNOLOGY

Action Chair: E. Cuoco, EGO and SNS
Vice Chair: C. Messenger, Glasgow University

G2net: goals of the ACTION

Facilitate conceiving innovative solutions for the analysis of the data of Gravitational Wave (GW) detectors.

Investigate possible solutions to monitor the low-frequency Newtonian noise through the use of adaptive robots.

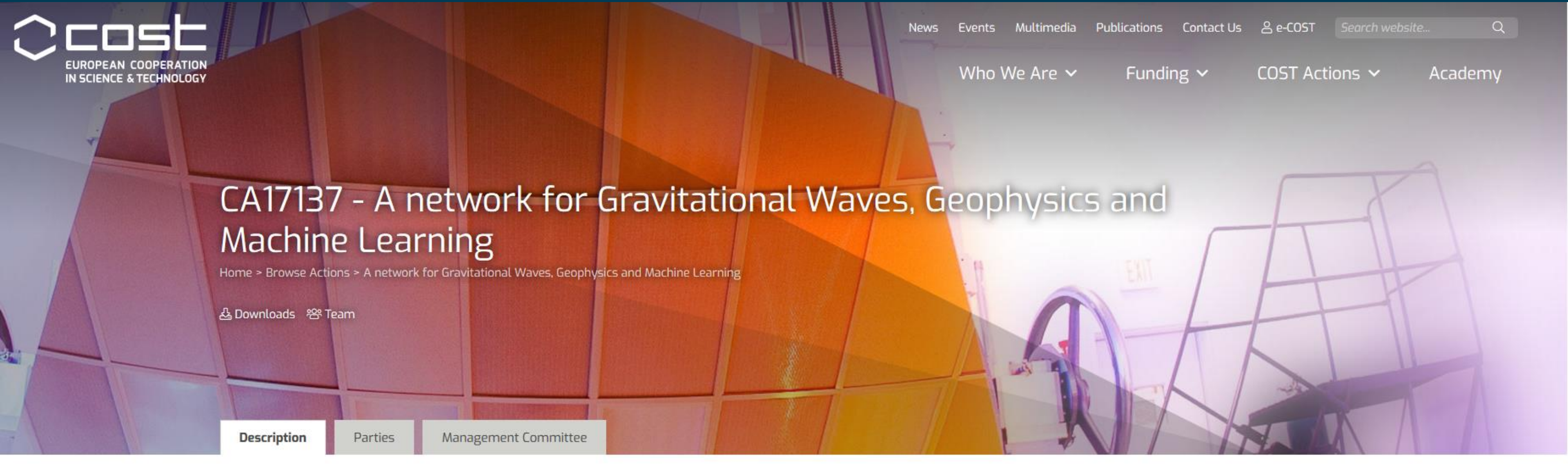
Train a new generation of young scientists with broad skills in Machine Learning, GW, Control and Robotics.

Investigate new strategies for the handling/suppression of instrumental and environmental noise using Machine Learning techniques.

Bridge the gap between the disciplines of GW physics, geophysics, computer science and robotics

G2net more info

https://www.cost.eu/actions/CA17137



Thanks!