Virgo Group of the University of Valencia

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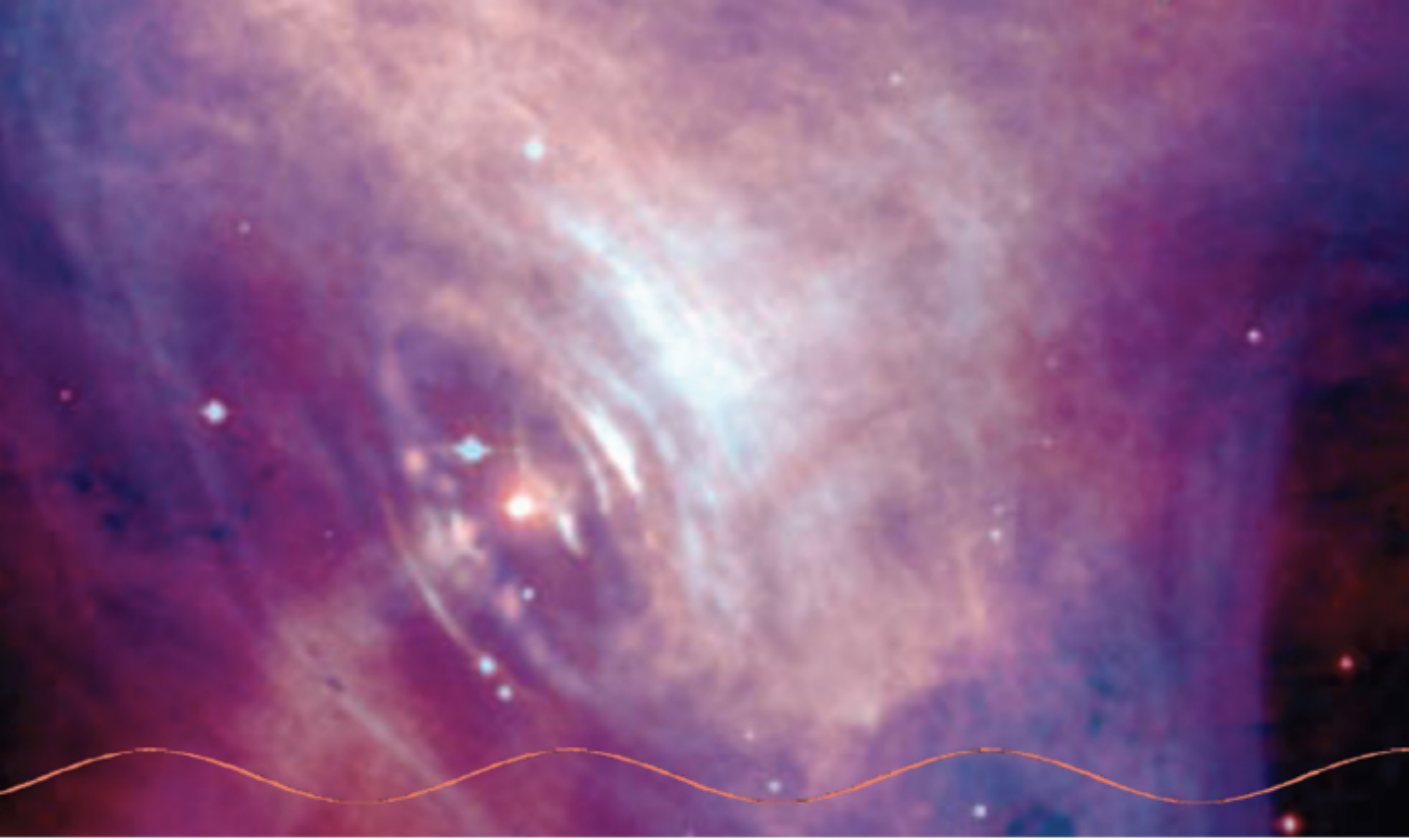
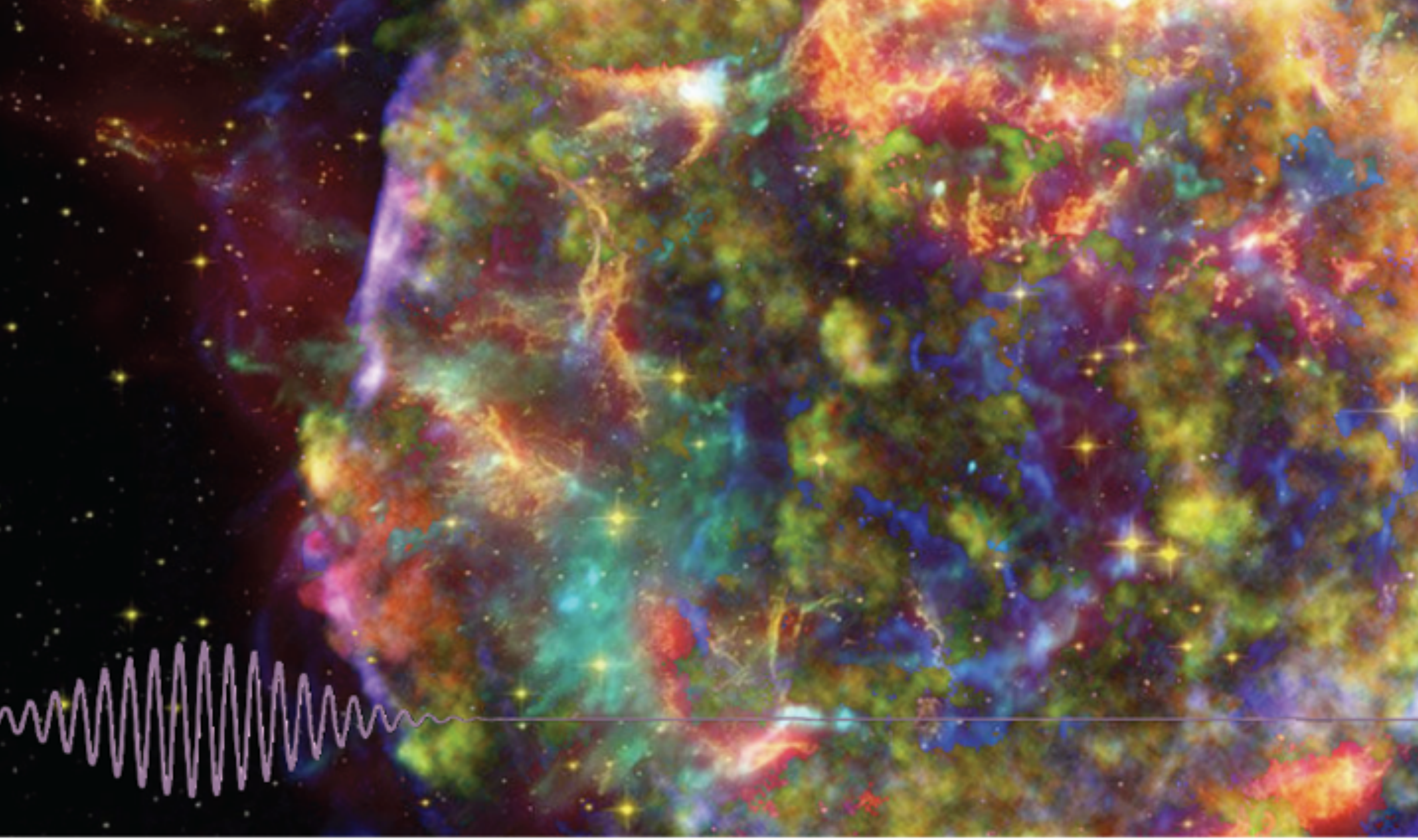
Advanced Virgo

Detector in Cascina, near Pisa (Italy)



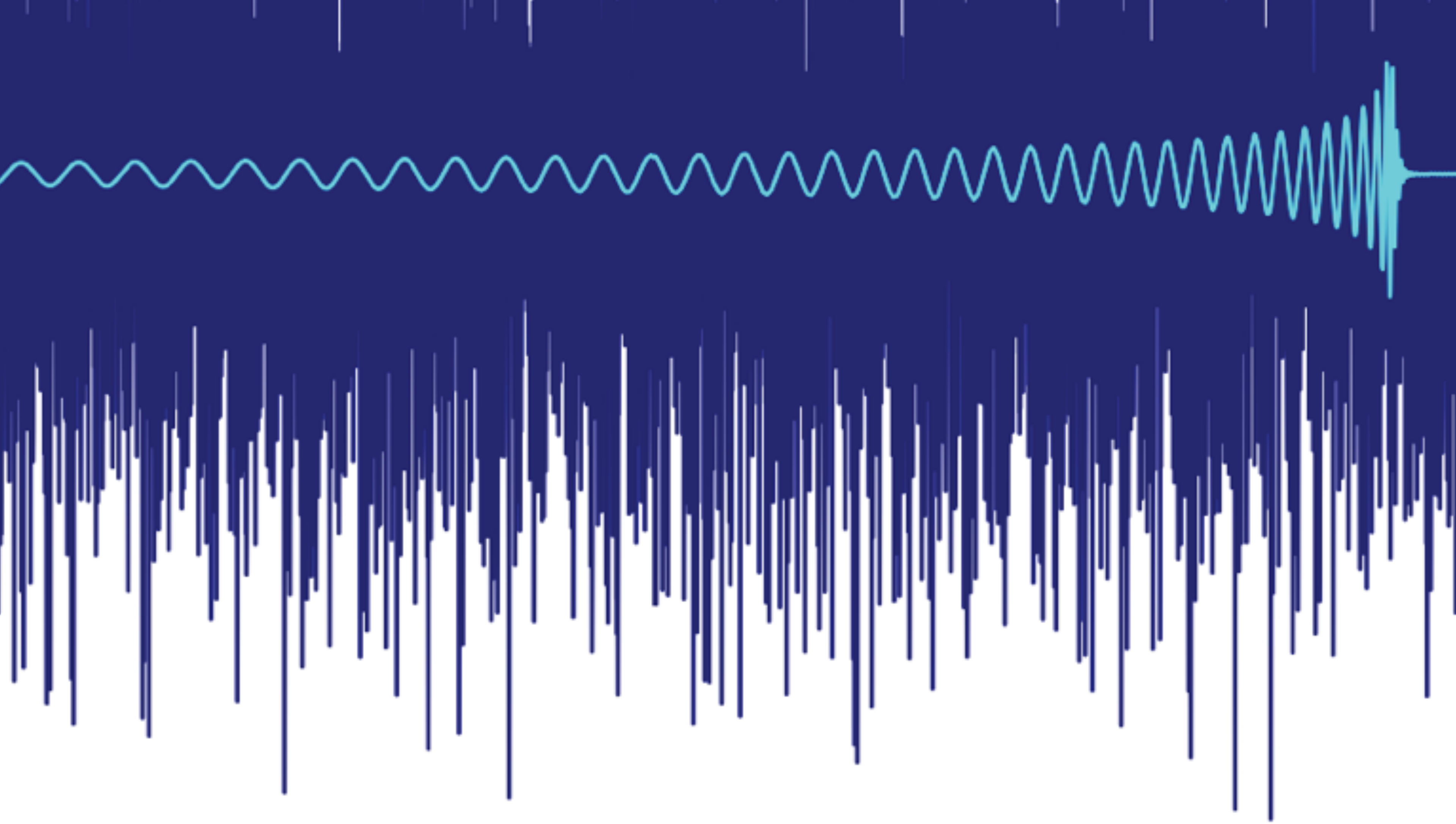
Continuous waves

Weak but always there



Burst searches

An ideal ML problem?



Compact Binaries

These are the ones we’ve detected

Main activities of the VVG

- Numerical simulation of astrophysical sources of gravitational radiation (Einstein equations + GRMHD).

- Waveform generation of astrophysical signals employing numerical relativity techniques.

- Inference of astrophysical parameters: CCSN, CBC.

- Data analysis with Total Variation and Machine Learning algorithms:

    - Gravitational wave denoising.
    - Waveform reconstruction.
    - Glitch classification and mitigation (DetChar).

Our mid-term goal within the LVK

Development of a **pipeline** for GW data analysis using total-variation, dictionary-learning, and deep-learning methods.

1. GW data analysis in upcoming LIGO/Virgo science runs.
2. New algorithms for GW denoising (TV, dictionary-learning, and DL methods).
3. Application to LIGO/Virgo data. Performance assessment for glitch denoising.
4. Development of pipelines for AdV detector monitoring activities.
5. Joint observing scenarios involving GW and EM emission from transient sources.

Initial work with Virgo group at ICCUB.

Objectives:

The central aim of this proposal is to **develop and apply ML and DL techniques to analyze existing and upcoming GW data and to reinforce the chances of detection of new GW signals**, including signals from Compact Binary Coalescences (CBC) and yet undetected burst signals such as CCSN, during the next observational periods of advanced LIGO-Virgo-KAGRA and beyond (i.e. based on third-generation detectors such as the Cosmic Explorer or the Einstein Telescope).

For this purpose this proposal will build a computational framework to test and exploit different ML and DL approaches which remain unexplored within the LIGO-Virgo-KAGRA collaboration.

Objective 1:

Automatic identification of g-modes and p-modes in proto-neutron stars (PNS) using ML classification algorithms.

PNS properties can be inferred from the features observable in numerically-simulated GWs from CCSN.

This requires the analysis of eigenmodes of PNS and convective instabilities and their relationship with the typical frequencies observed in the GW spectra of CCSN simulations.

Universal relations for gravitational-wave asteroseismology of proto-neutron stars
A. Torres-Forné, P. Cerdá-Durán, M. Obergaulinger, B. Müller, and J.A. Font
Physical Review Letters, **123**, 051102 (2019)

Towards asteroseismology of core-collapse supernovae with gravitational-wave observations - II. Inclusion of spacetime perturbations
A. Torres-Forné, P. Cerdá-Durán, A. Passamonti, M. Obergaulinger, and J.A. Font
Monthly Notices of the Royal Astronomical Society, **482**, 3967-3988 (2019)

Towards asteroseismology of core-collapse supernovae with gravitational-wave observations - I. Cowling approximation
A. Torres-Forné, P. Cerdá-Durán, A. Passamonti, and J.A. Font
Monthly Notices of the Royal Astronomical Society, **474**, 5272-5286 (2018)

PNS asterosismology

At the VVG we have developed a method to analyze modes of oscillation of PNS employing results from numerical-relativity simulations of CCSN.

- Automatically classifies modes: g-modes (*buoyancy-driven*) y p-modes (*pressure-driven*)
- `GREAT` code (**G**eneral **R**elativistic **E**igenmode **A**nalysis **T**ool)

Ongoing:

Improve the classification algorithm employing Machine Learning techniques.

Machine Learning and stellar core-collapse asteroseismology – focused on the application of clustering techniques (K-Means and Gaussian Mixture) to classify oscillation modes of CCSN with GWs. TFG M. López (UV)

We plan on implementing another technique called *Support Vector Machine*. If the data is linearly separable, this algorithm divides it in two different classes. This is not always the case, but we can always use a mathematical transformation to make our data linearly separable in a higher hyperspace.

Detection of CCSNe using machine learning

Collaboration with U. Rome (I. Di Palma, F. Muciaccia, C. Palomba, F. Ricci) and GSSI (M. Drago)

Method based on Convolutional Neural Networks (CNN), a classification procedure of time-frequency images with neural networks).

New method to observe gravitational waves emitted by core collapse supernovae, Astone, P.; **Cerdá-Durán, P.**; Di Palma, I.; Drago, M.; Muciaccia, F.; Palomba, C.; Ricci, F., Physical Review D **98**, 122002 (2018)

Ongoing work to enhance this method. M. López has implemented smaller versions of some neural networks such as Inception v2, ResNet and Inception-Resnet v3.

MACHINE-LEARNING FOR CORE-COLLAPSE SUPERNOVAE IN THE ERA OF GRAVITATIONAL-WAVE ASTRONOMY (LVK efforts)

a) Automatic classification of the oscillation modes of PNS using ML algorithms (UV)

b) Development of Dictionary Learning techniques for CCSN GW signals (UV)

c) Development of Convolutional Neural Networks for CCSN GW signals (UV, Università di Roma "Sapienza")

d) Investigations of non-astrophysical noise in the LIGO and Virgo detectors (University of Mississippi)

e) R&D of new methods to improve parameter estimation (U. of Mississippi, ARC Centre of Excellence for Gravitational Wave Discovery - OzGrav)

f) Reconstruction of CCSN GW signals with the Supernova Model Evidence Extractor (SMEE) (OzGrav, University of Glasgow)

g) ML approaches to generate GW signals from CCSN (University of Glasgow)

h) Deep Learning for CCSN GW signals (EGO, Università di Pisa)

i) Advanced ML Techniques in Multimessenger Astronomy with CCSN (Columbia University)

Objective 2:

Exploration of DL methods for **GW detection** from CBC (i.e. BBH, BNS and BH-NS mergers) and for unmodelled GW sources (namely CCSN) using a Residual Network with a regression algorithm (e.g. xResNet18) that can identify the presence of GW signals through spectrograms and perform parameter estimation of the sources' properties.

Exploring gravitational-wave detection and parameter inference using Deep Learning methods
J.D. Alvares, J.A. Font, F.F. Freitas, O.G. Freitas, A.P. Morais, S. Nunes, A. Onofre, and A. Torres-Forné
Classical and Quantum Gravity, submitted (2020)

Sources of noise

The sensitivity of GW detectors is limited by diverse sources of noise.

<u>Fundamental Noises:</u>

I. *Displacement Noises*

$\Delta L(f)$

- Seismic noise
- Radiation Pressure
- Thermal noise
    - Suspensions
    - Optics

II. Sensing Noises

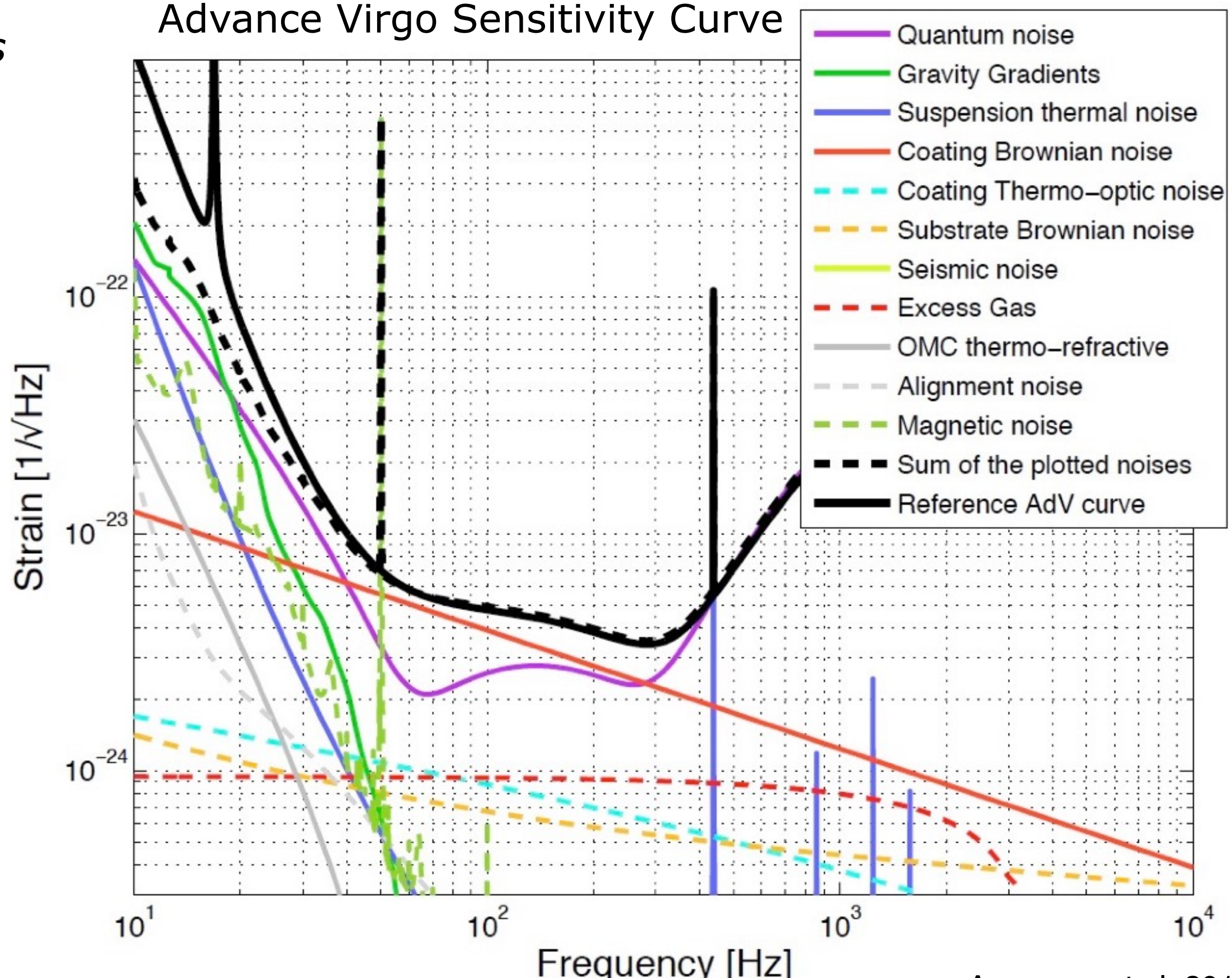
$\Delta t_{photon}(f)$

- Shot Noise
- Residual Gas

<u>Technical Noises:</u>

→ Hundreds of them…

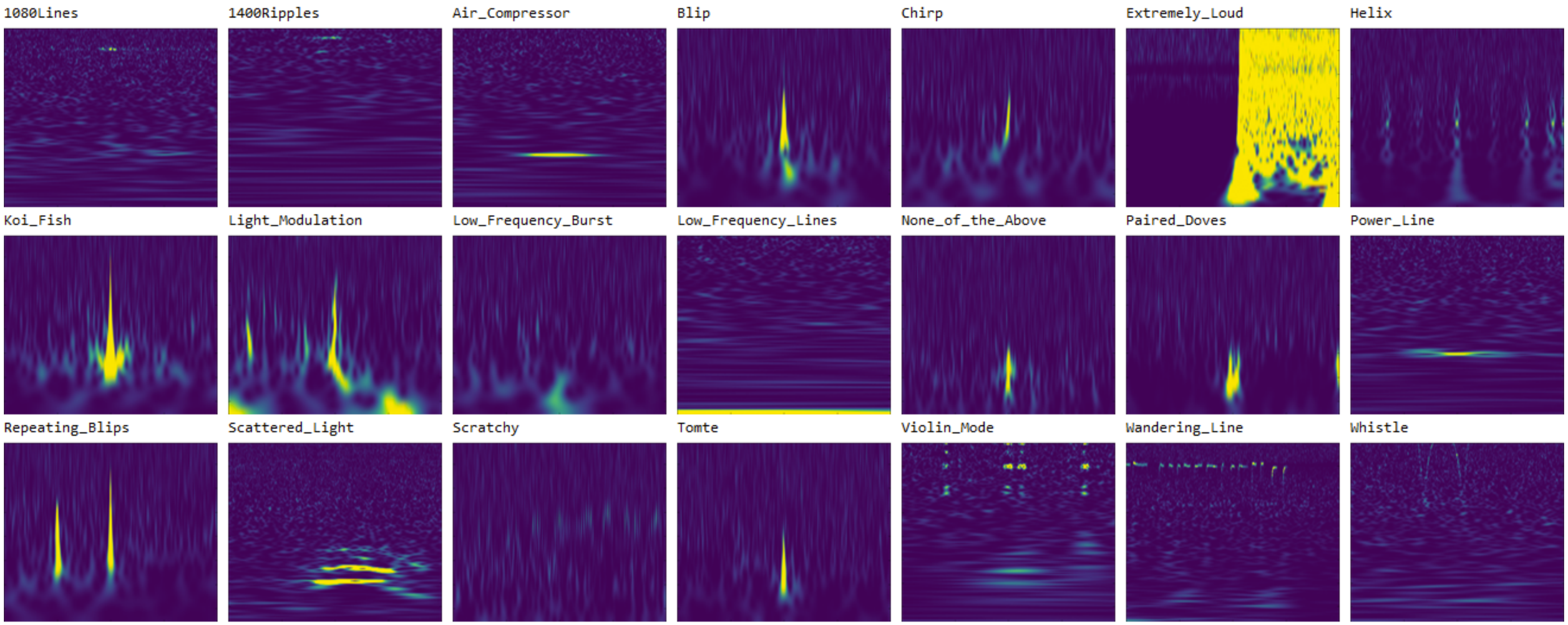
Advance Virgo Sensitivity Curve



Acernese et al. 2014

Noise transients - glitches

Non-Gaussian transients of noise. Large variety of morphologies.



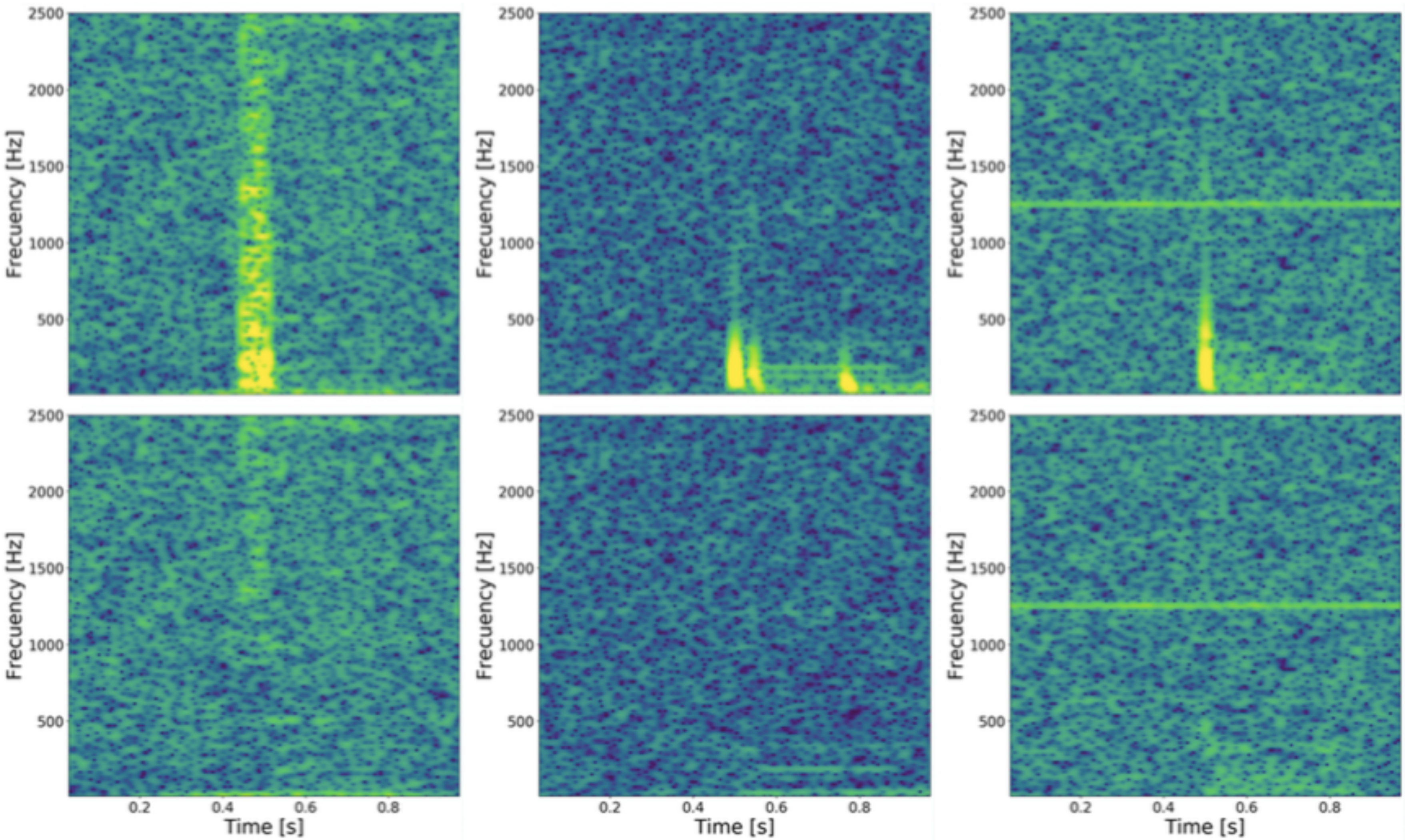
Gravity Spy, Zevin et al (2017) www.zooniverse.org/projects/zooniverse/gravity-spy

Effect on detectors

1. Reduce significance of candidate GW events.
2. Affect estimation of physical parameters.
3. Reduce amount of usable data.

Prompt characterization of noise critical for improving sensitivity.
Fast methods for glitch classification are needed.

Glitch denoising and mitigation



Application of dictionary learning to denoise LIGO's blip noise transients, Toores-Forné et al (in preparation)

Objective 3:

Exploration of DL methods in conjunction with **total-variation methods** for GW **denoising** and **signal reconstruction**.

This subproject will make use of the same GW injections in real LIGO-Virgo data as in objective #2 but using a recurrent neural network instead.

The combination of this network with standard GW detections methods from the LIGO-Virgo Collaboration might be attempted depending on the performance of the network when applied in isolation.

Total-variation methods and dictionary-learning methods for GW data analysis

Total-variation-based methods for gravitational wave denoising
A. Torres, A. Marquina, J.A. Font, and J.M. Ibánez
Physical Review D, **90**, 084029 (2014)

Denoising of gravitational wave signals via dictionary learning algorithms
A. Torres-Forné, A. Marquina, J.A. Font, and J.M. Ibánez
Physical Review D, **94**, 124040 (2016)

Total-variation methods for gravitational-wave denoising: performance tests on Advanced LIGO data
A. Torres-Forné, E. Cuoco, A. Marquina, J.A. Font, and J.M. Ibánez
Physical Review D, **98**, 084013 (2018)

Classification methods for noise transients in advanced gravitational-wave detectors II: performance tests on Advanced LIGO data
J. Powell, A. Torres-Forné, R. Lynch, D. Trifiro, E. Cuoco, M. Cavaglia, I.S. Heng, and J.A. Font
Classical Quantum Gravity, **34**, 034002 (2017)

Classification of gravitational-wave glitches via dictionary learning
M. Llorens-Monteagudo, A. Torres-Forné, J.A. Font, and A. Marquina
Classical Quantum Gravity, **36**, 075005 (2019)

Objective 4:

Development of generative ML algorithms and their application for **waveform generation** and GW detection.

Generative Adversarial Networks will be built for waveform generation of CCSN and CBC sources, sidestepping the need to perform costly numerical-relativity simulations of those systems.

Objective 5:

Development and application of acceleration algorithms to carry out efficient **parameter estimation** of GW signals from CBC sources.

With a significant increase in the number of CBC detections in upcoming LIGO-Virgo-KAGRA observing runs (O4 and O5) parameter estimation is foreseen to be an extremely CPU-demanding task, demanding the urgent development of efficient algorithms to ameliorate those requirements.

Objective 6

Machine learning to infer astrophysical parameters using gravitational waveforms.

Problem case:

- BBH waveforms (NR simulations; few 1000s)
- BNS waveforms (NR simulations; few 100s)
- Waveforms from actual detections (sample still poor)
- Use existing NR catalogs.

Outcome: network prediction for

- new waveform models
- masses and spins (BBH)
- final remnant (BNS)
- EOS (BNS)

Previous work with BBH catalogs:

- Using Deep Neural Network (Haegel & Husa, arXiv:1911.01496)

NR code	non-precessing	precessing
SpEC	592	2015
LazEv	280	0
MayaKranc	125	0
BAM	47	0
$\eta \to 0$	300	0
Total	1344	2015

Our ongoing work:

We are currently looking into this problem (waveform generation) using Generative Adversarial Networks (TensorFlow, Keras). First network generates new waveforms and second network discriminates.