Glitch removal in ground-based interferometric gravitational-wave detectors

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Missouri University S&T

Gravitational waves

Selected for a Viewpoint in *Physics*
PRL **116,** 061102 (2016) PHYSICAL REVIEW LETTERS week ending 12 FEBRUARY 2016

Observation of Gravitational Waves from a Binary Black Hole Merger

B. P. Abbott *et al.*[*]
(LIGO Scientific Collaboration and Virgo Collaboration)
(Received 21 January 2016; published 11 February 2016)

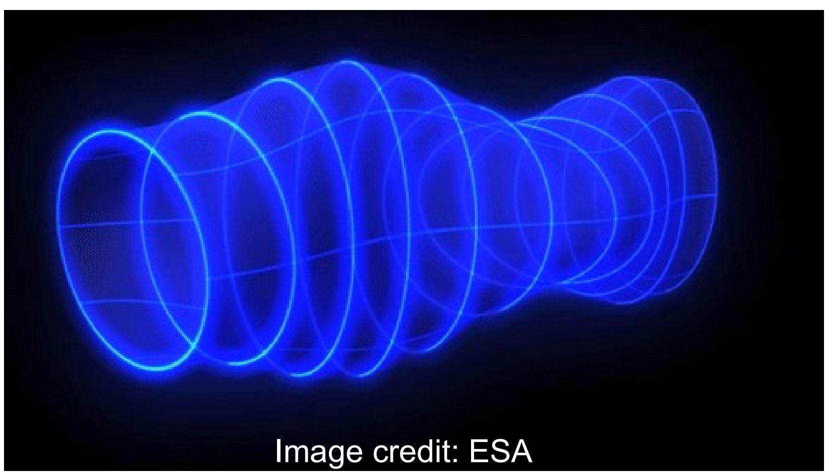


Image credit: ESA


Image credit: LIGO/Caltech/MIT/R. Hurt (IPAC)

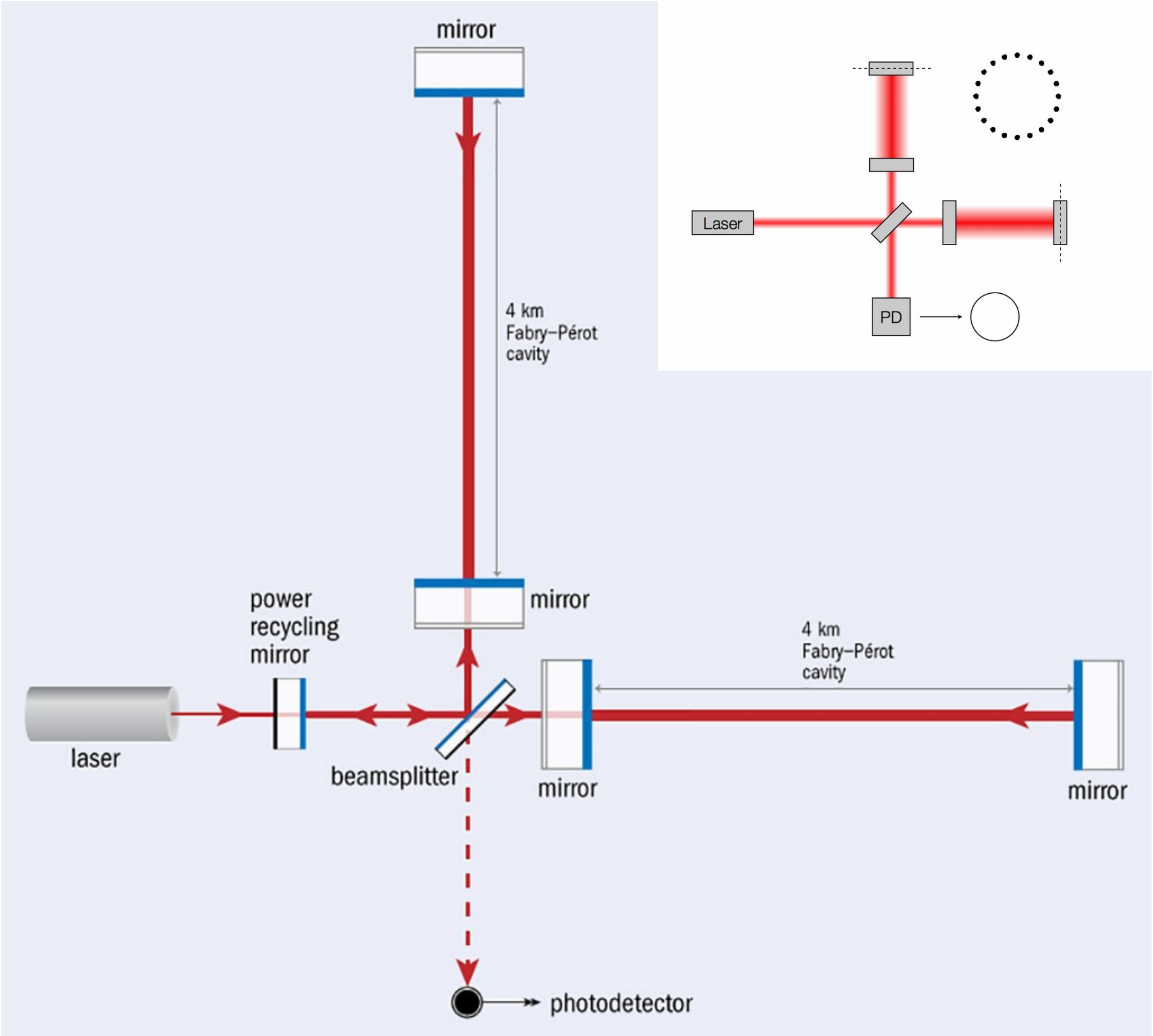
Typical strain of 10^{-22} around 100 Hz.

Detectors


LIGO-Hanford

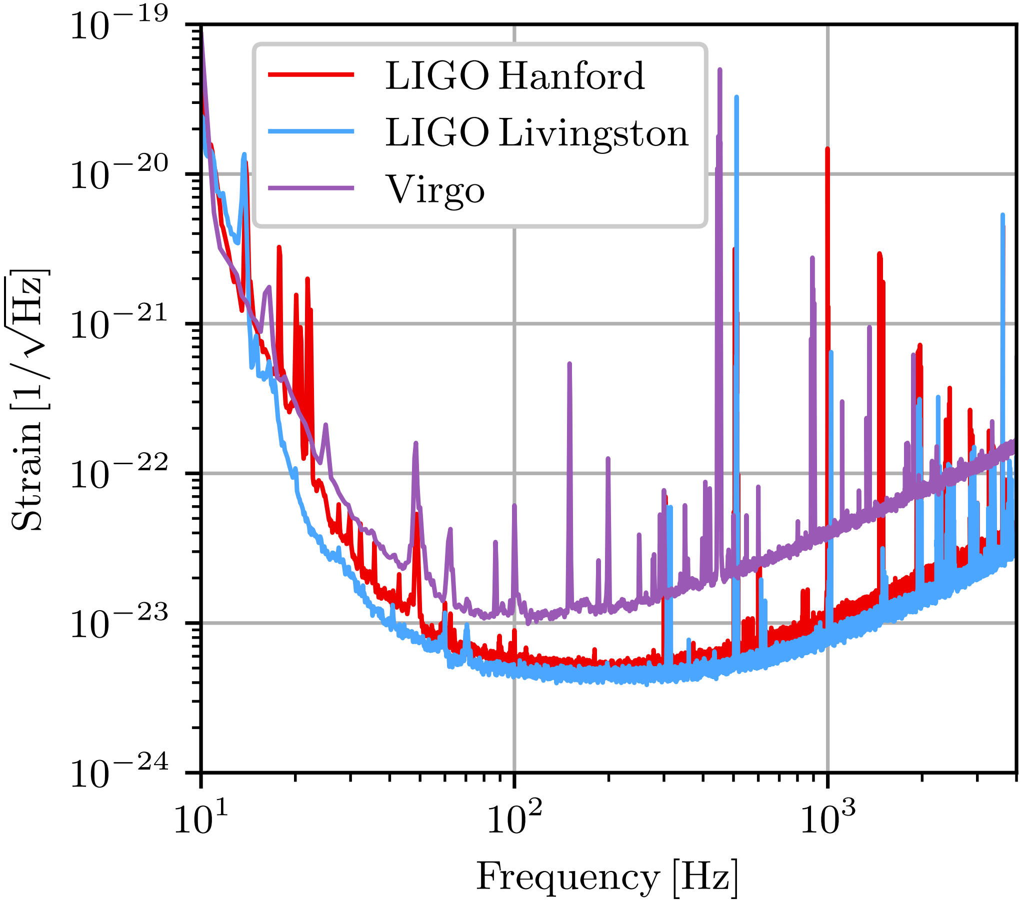

LIGO-Livingston


Virgo


mirror
4 km
Fabry–Pérot
cavity
power
recycling
mirror
mirror
4 km
Fabry–Pérot
cavity
laser
beamsplitter
mirror
mirror
photodetector
Laser
PD

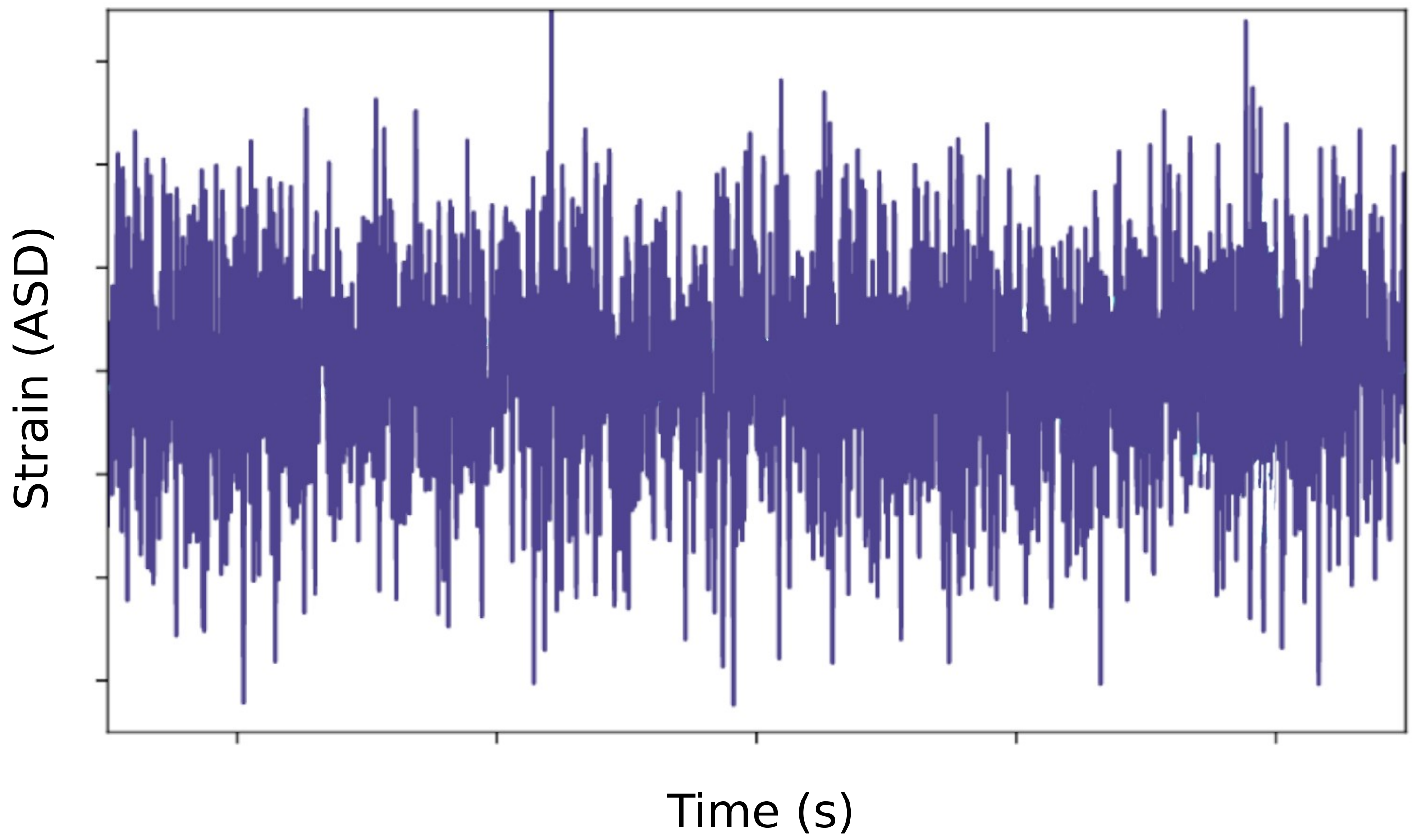
Detectors - II

LIGO-Virgo O3a representative sensitivity spectrum



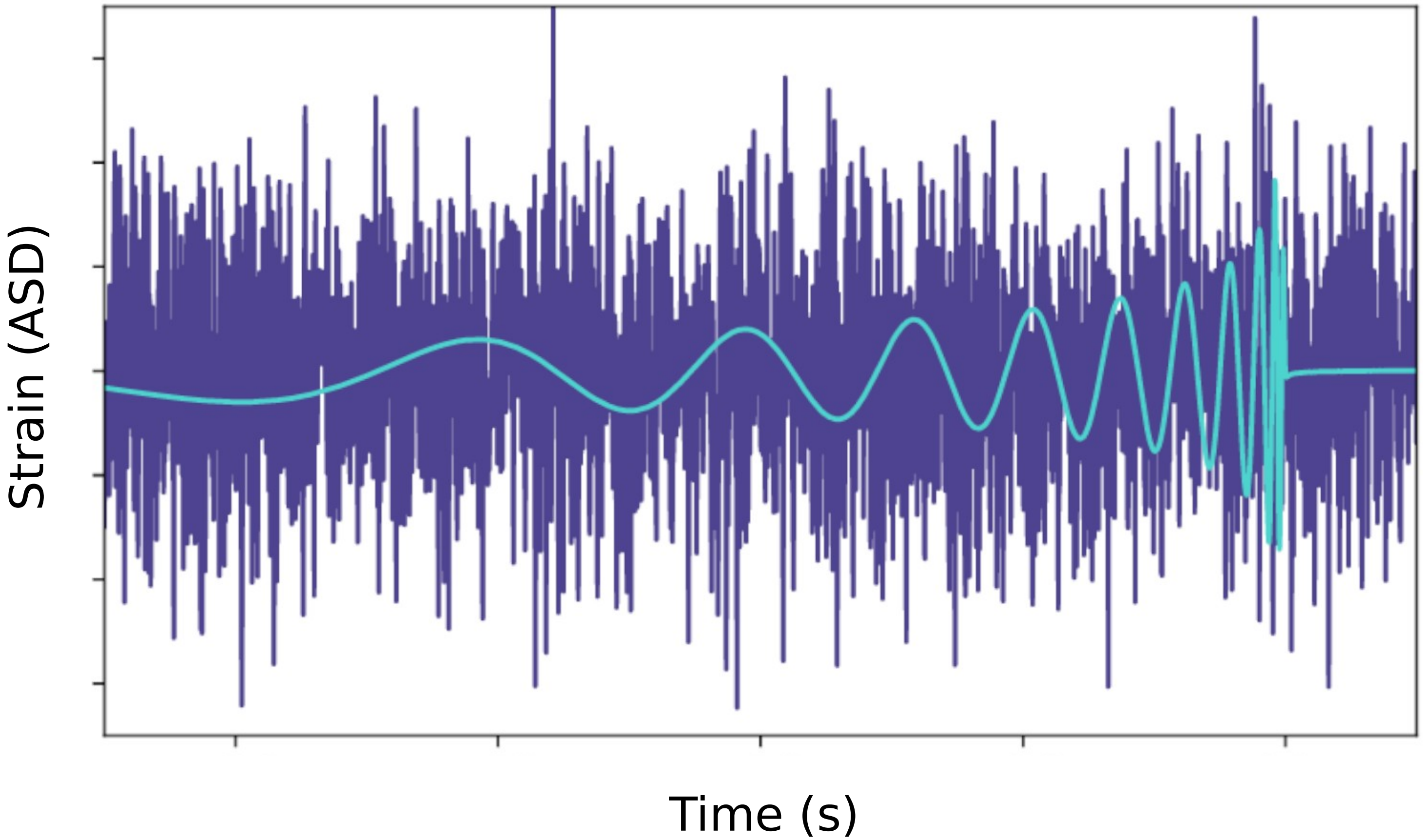
GWTC-2: Compact Binary Coalescences Observed by LIGO and Virgo During the First Half of the Third Observing Run, LIGO Scientific and Virgo Collaborations (R. Abbott et al.) e-Print: 2010.14527 [gr-qc]

Detectors - II



Enhancing Gravitational-Wave Science with Machine Learning, Elena Cuoco et al. [Mach.Learn.Sci.Tech. 2 (2021) 1, 011002]

Detectors - II

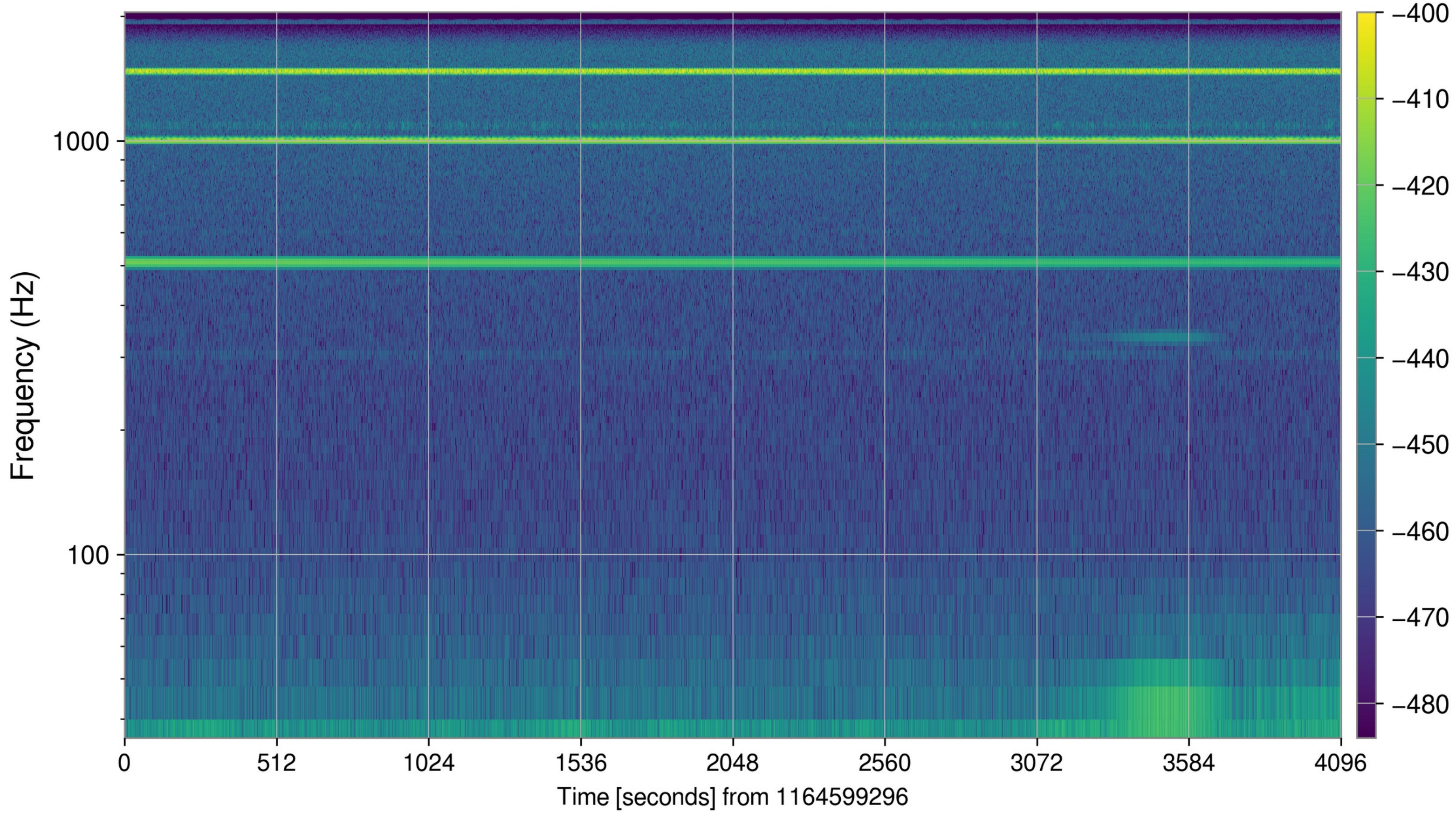


Signals are typically buried in the noise

Enhancing Gravitational-Wave Science with Machine Learning, Elena Cuoco et al. Mach.Learn.Sci.Tech. 2 (2021) 1, 011002

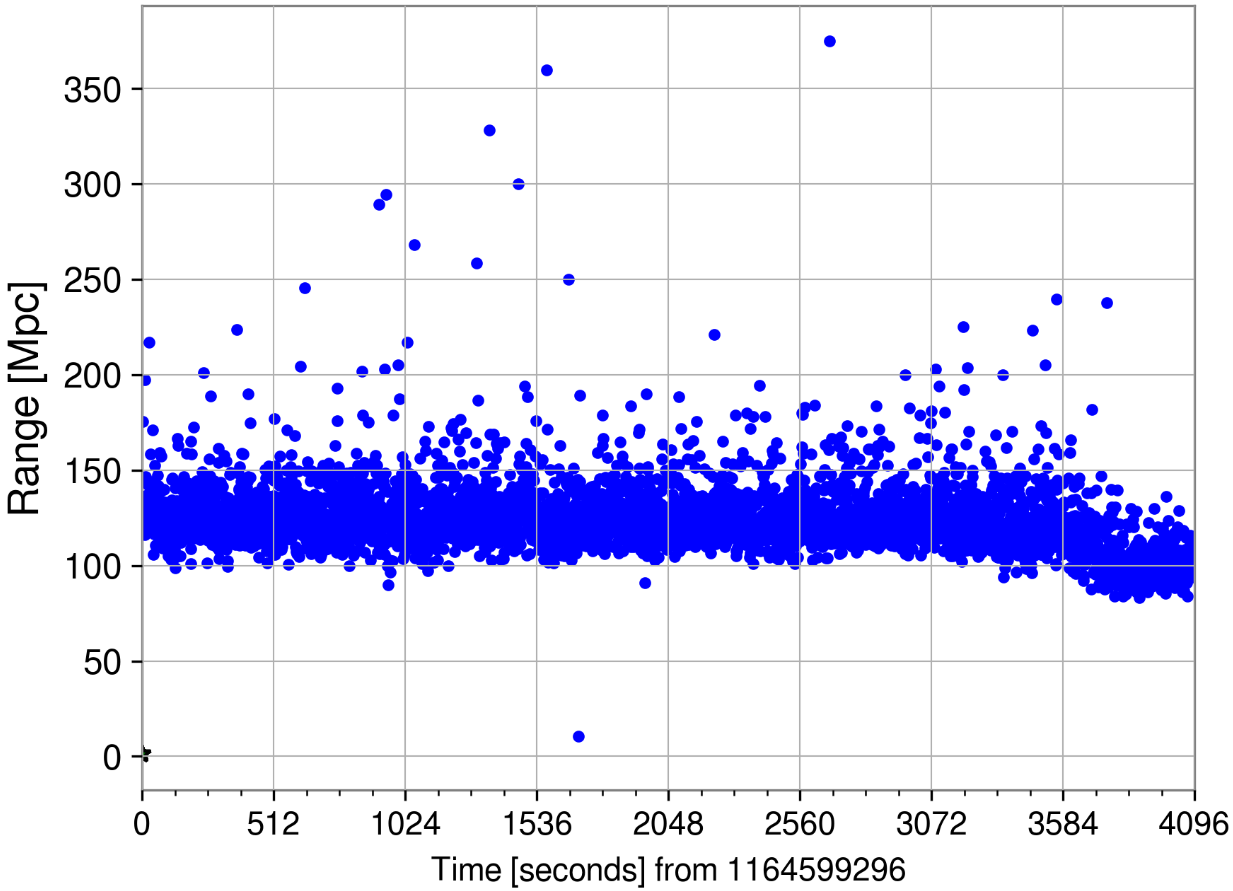
Detector noise

Non-Gaussian and non-stationary on short- and long-time scales



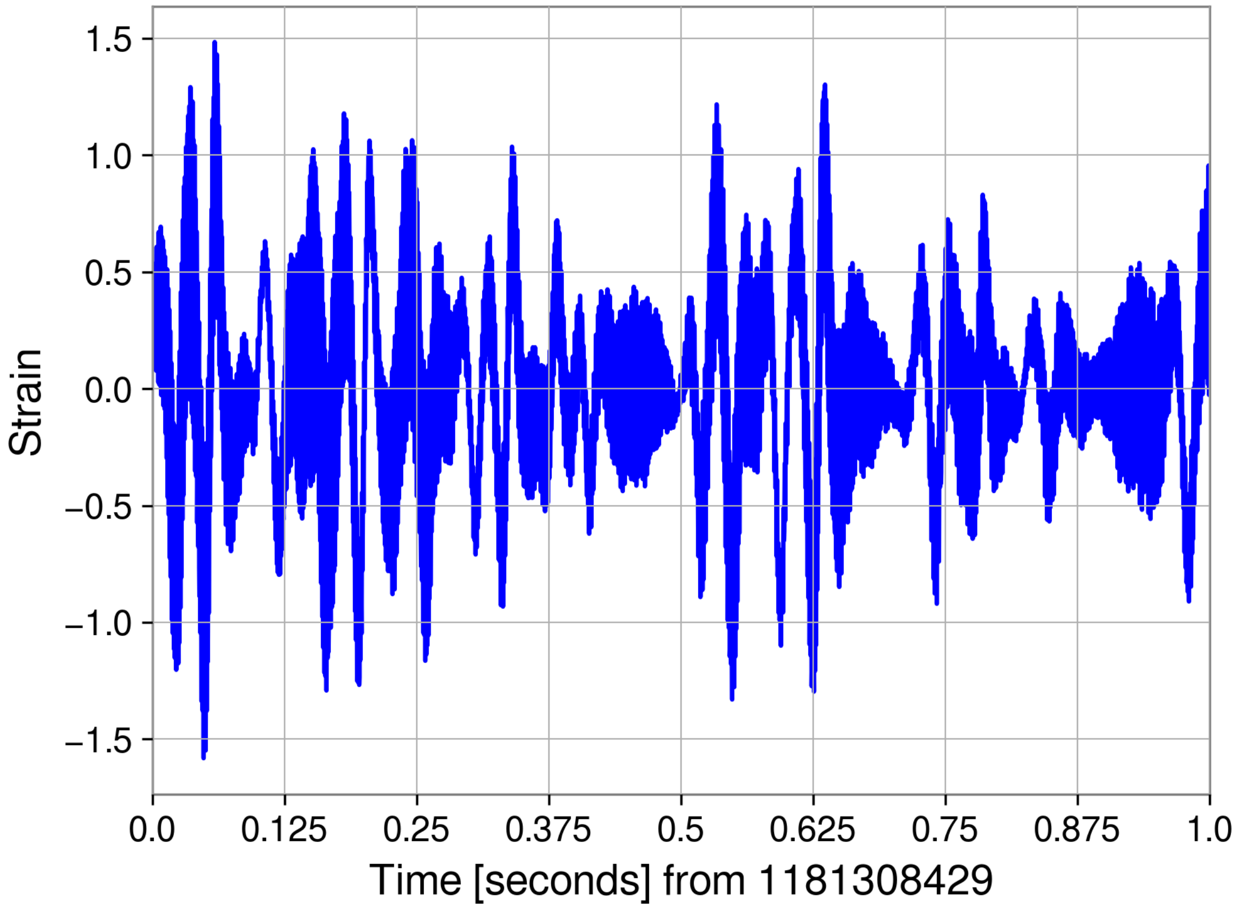
Detector noise

Non-Gaussian and non-stationary on short-time and long-time scales



Detector noise

Non-Gaussian and non-stationary on short-time and long-time scales



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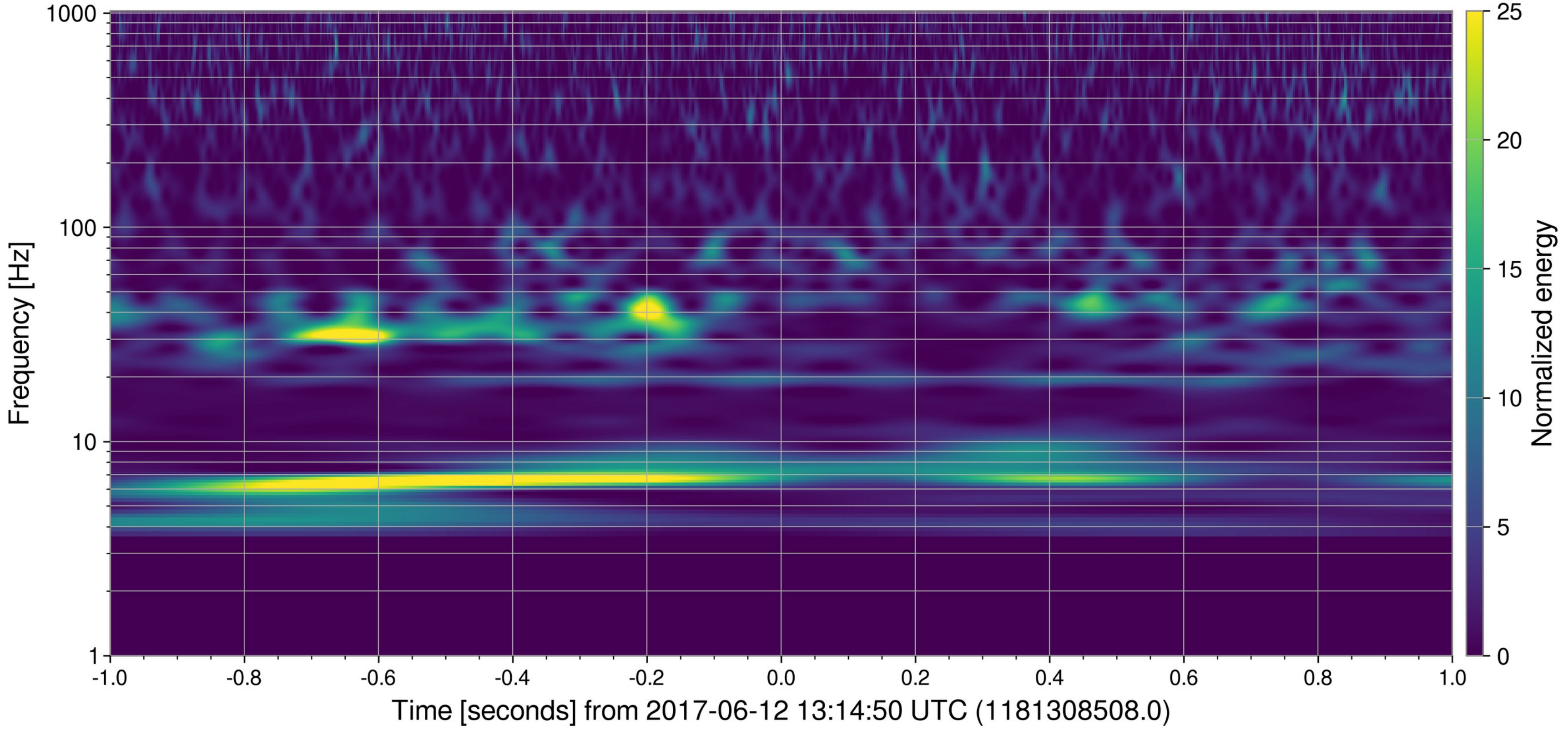
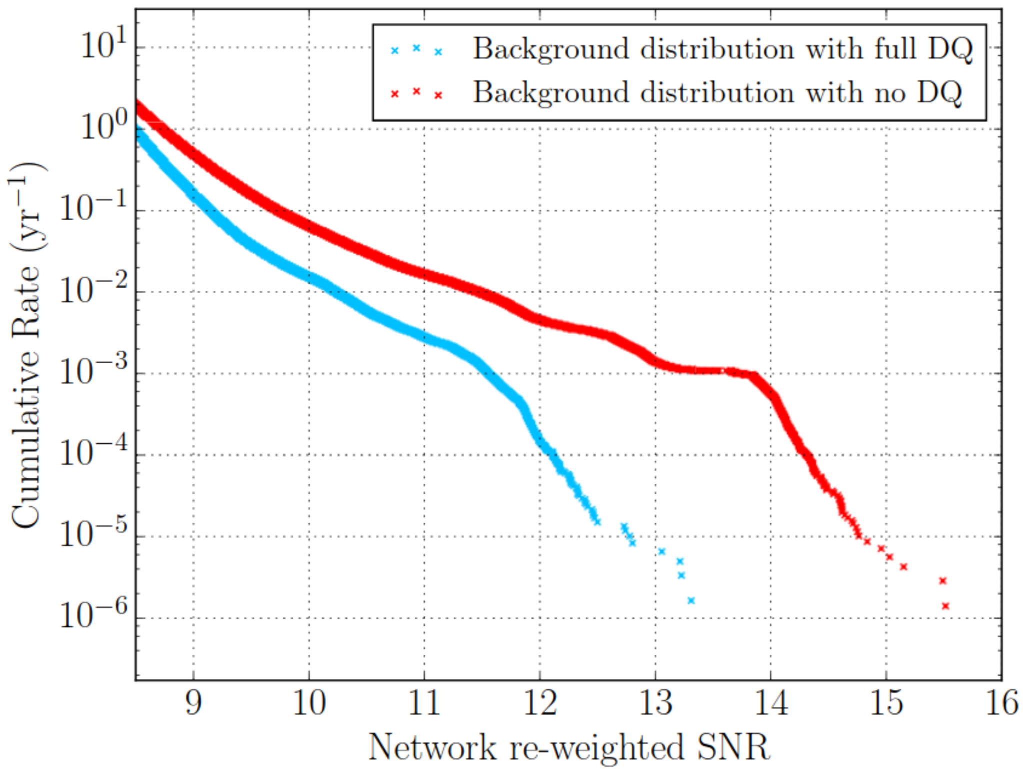
Non-Gaussian and non-stationary on short-time and long-time scales



Why do we want to de-noise?

Background reduction



Effects of data quality vetoes on a search for compact binary coalescences in Advanced LIGO's first observing run, LIGO Scientific and Virgo Collaborations (BP Abbott et al), Class.Quant.Grav. 35 (2018) 6, 065010.

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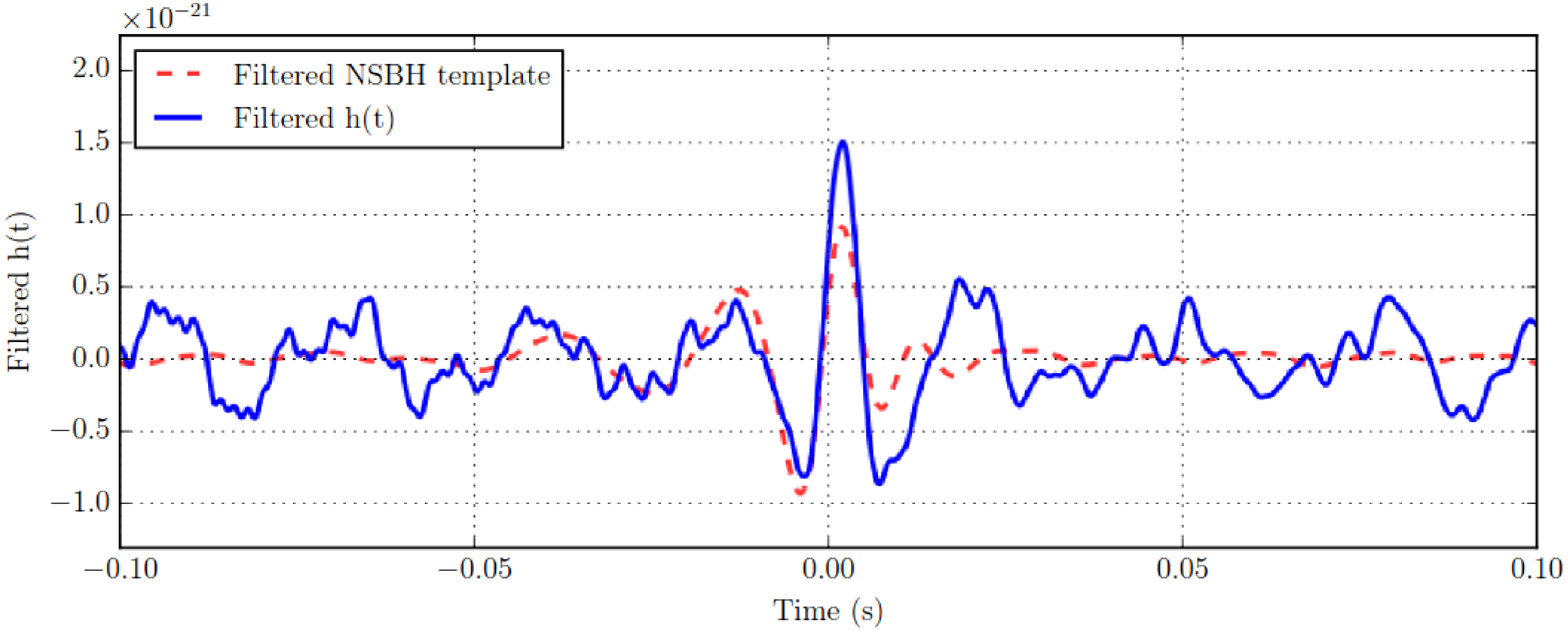

Effects of data quality vetoes on a search for compact binary coalescences in Advanced LIGO's first observing run, LIGO Scientific and Virgo Collaborations (BP Abbott et al), [Class.Quant.Grav. 35 (2018) 6, 065010](#).

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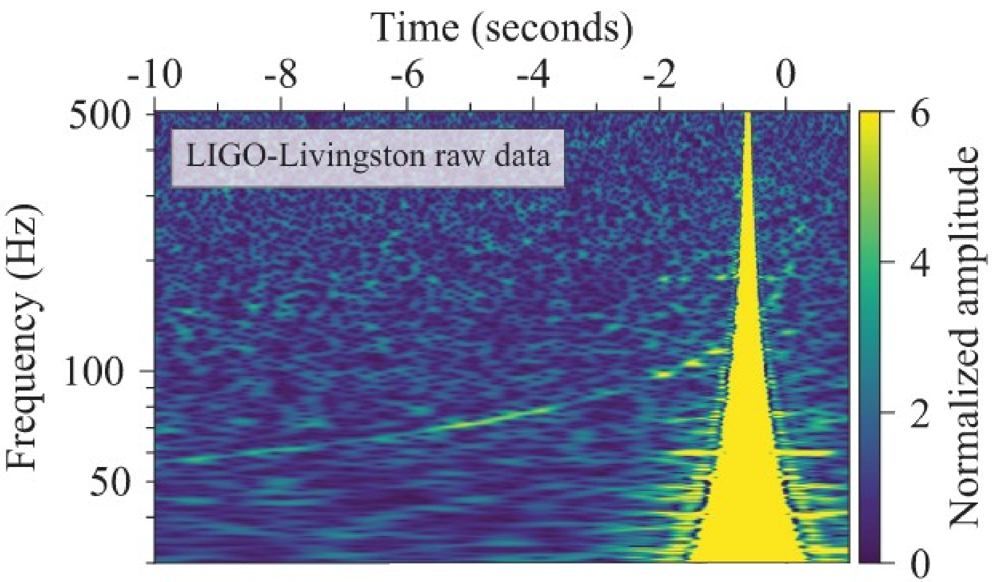
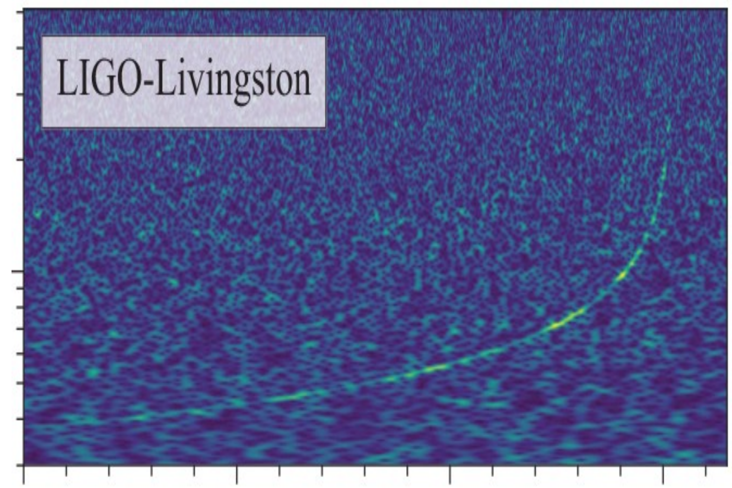




Selected for a Viewpoint in *Physics*

PRL **119,** 161101 (2017) PHYSICAL REVIEW LETTERS week ending 20 OCTOBER 2017

GW170817: Observation of Gravitational Waves from a Binary Neutron Star Inspiral

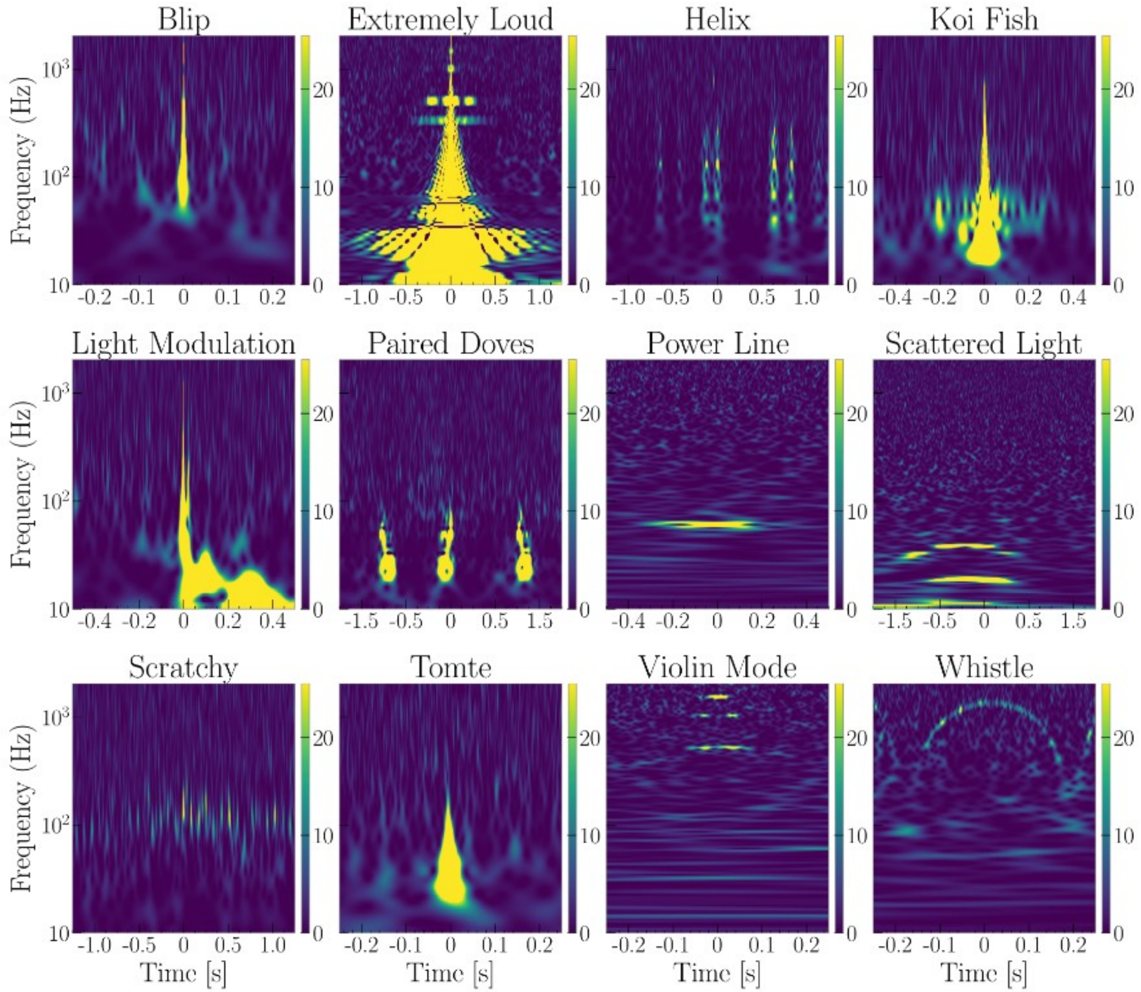
B. P. Abbott *et al.**

(LIGO Scientific Collaboration and Virgo Collaboration)

(Received 26 September 2017; revised manuscript received 2 October 2017; published 16 October 2017)

Detector noise

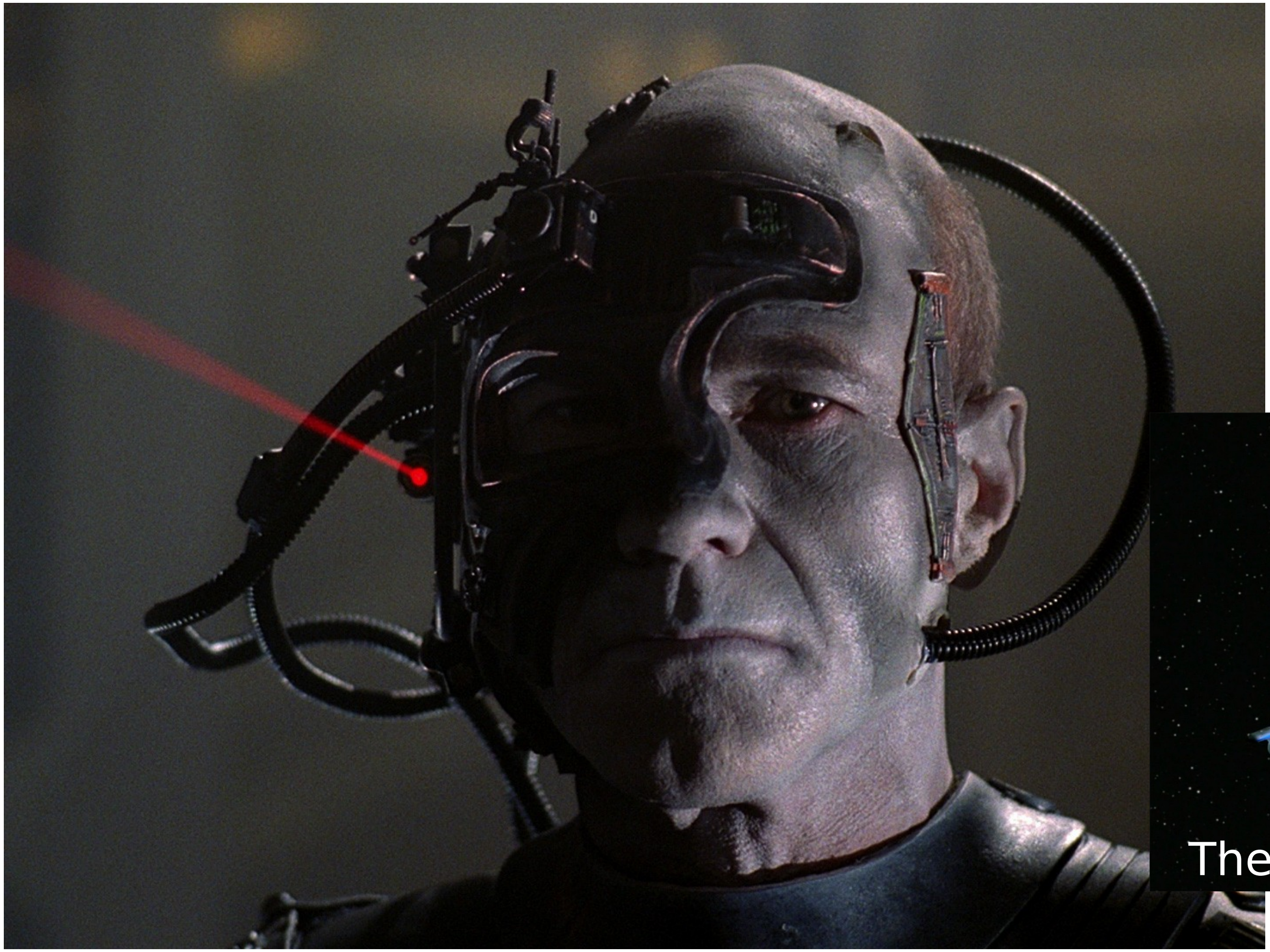
A zoo of short-time “glitches”

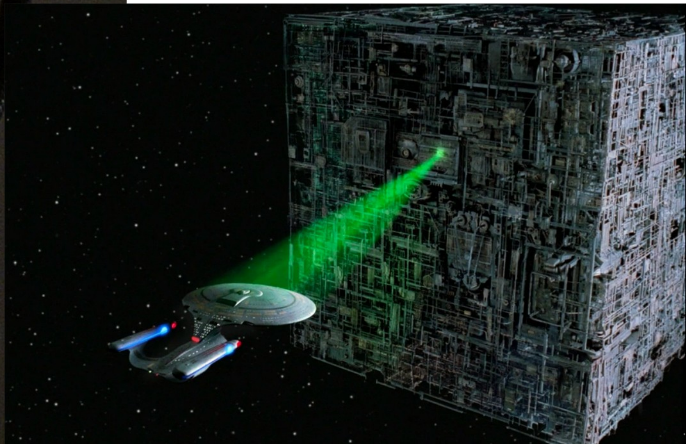


Enhancing Gravitational-Wave Science with Machine Learning, Elena Cuoco et al. [Mach.Learn.Sci.Tech. 2 (2021) 1, 011002]

Detector noise

Is resistance futile?

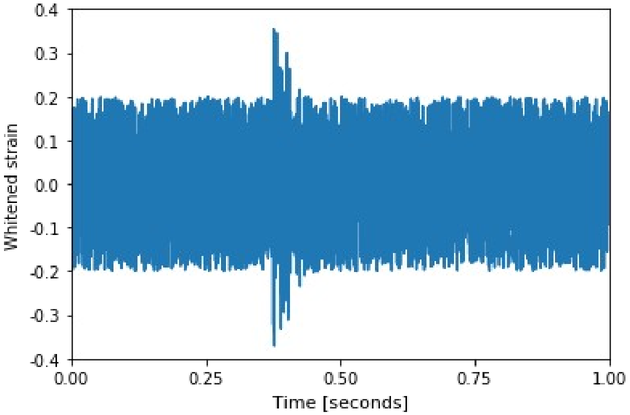




The interferometer noise

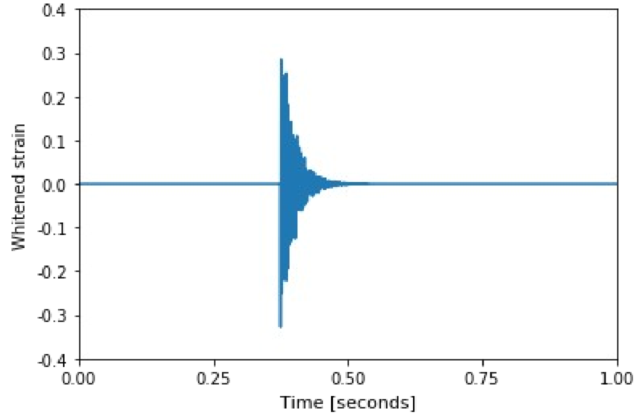
The battle for denoising: The strain-based approach

strain data



-

some model



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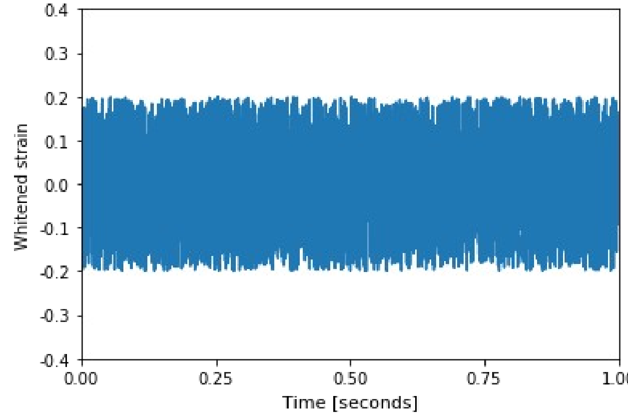
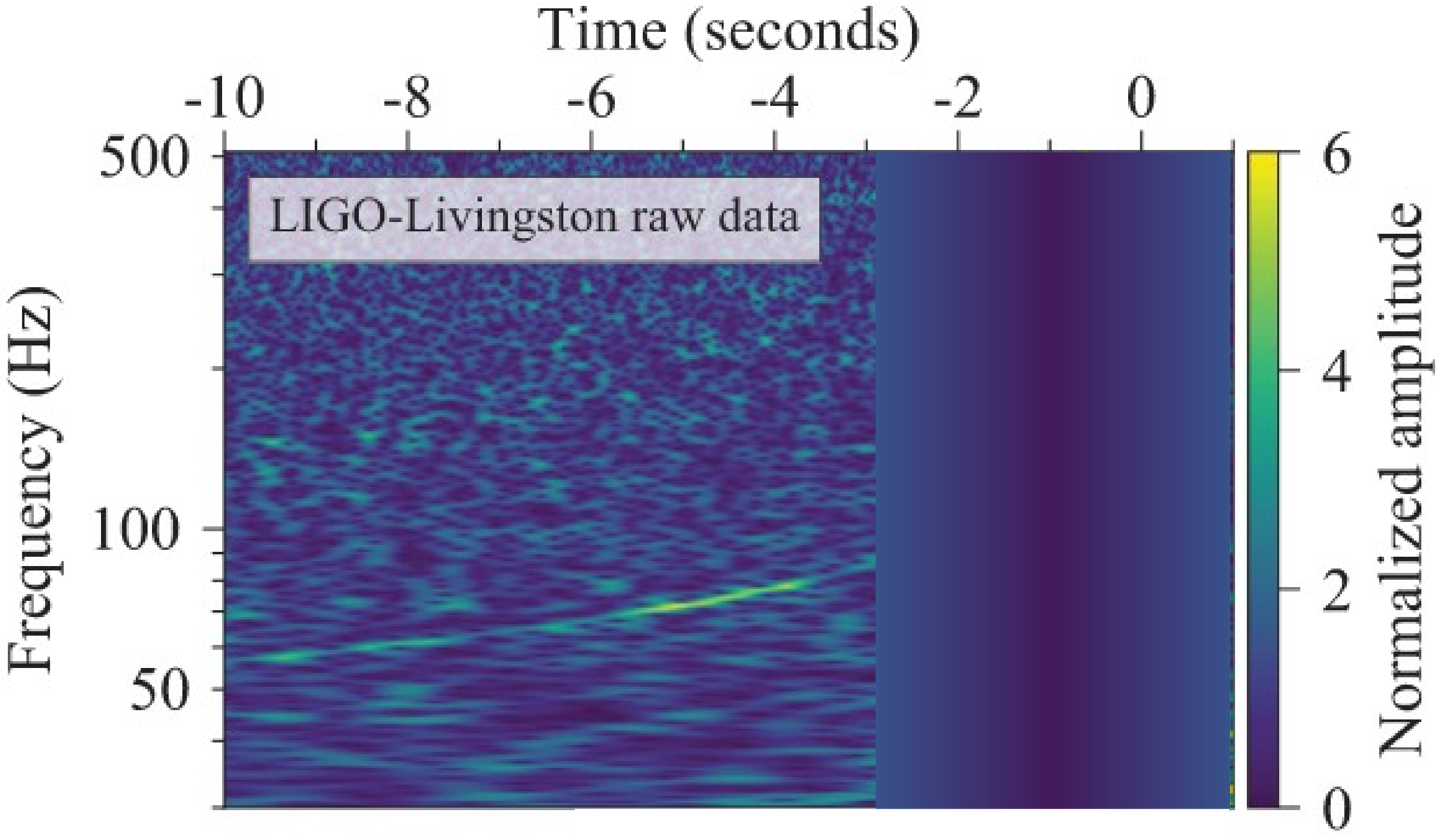
clean data



Deterministic vs. machine learning methods

Strain-based approach - I

Simple gate



Advantages/disadvantages

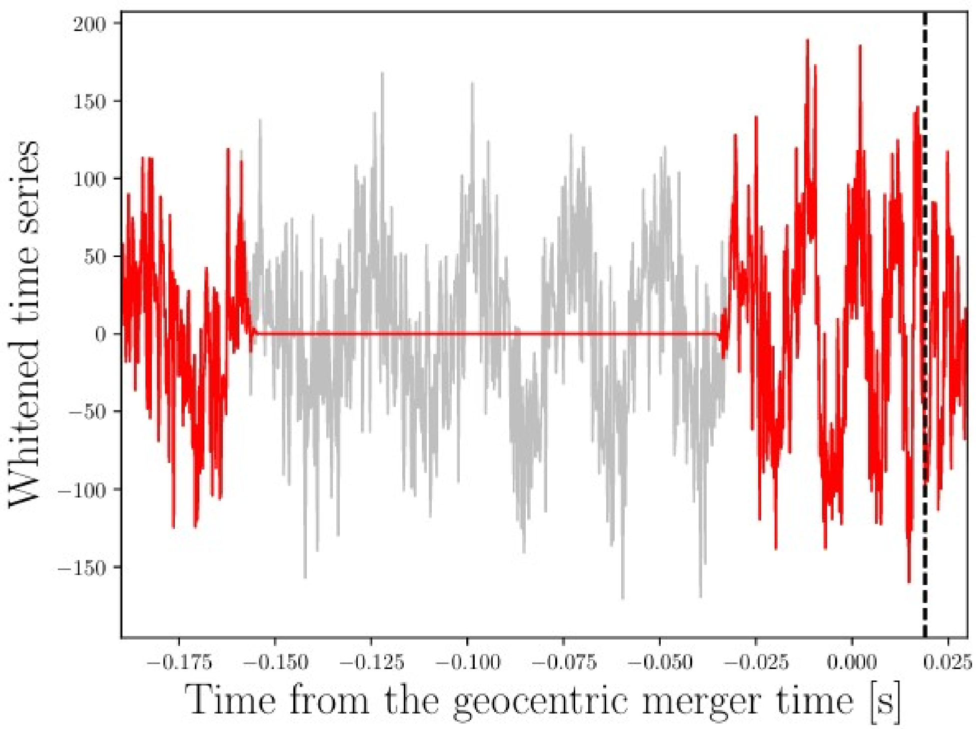
- Easy to apply, very low latency
- Works for any type of glitch and sources
- Does not depend on long-time scale effects
- Does not need training or special algorithms

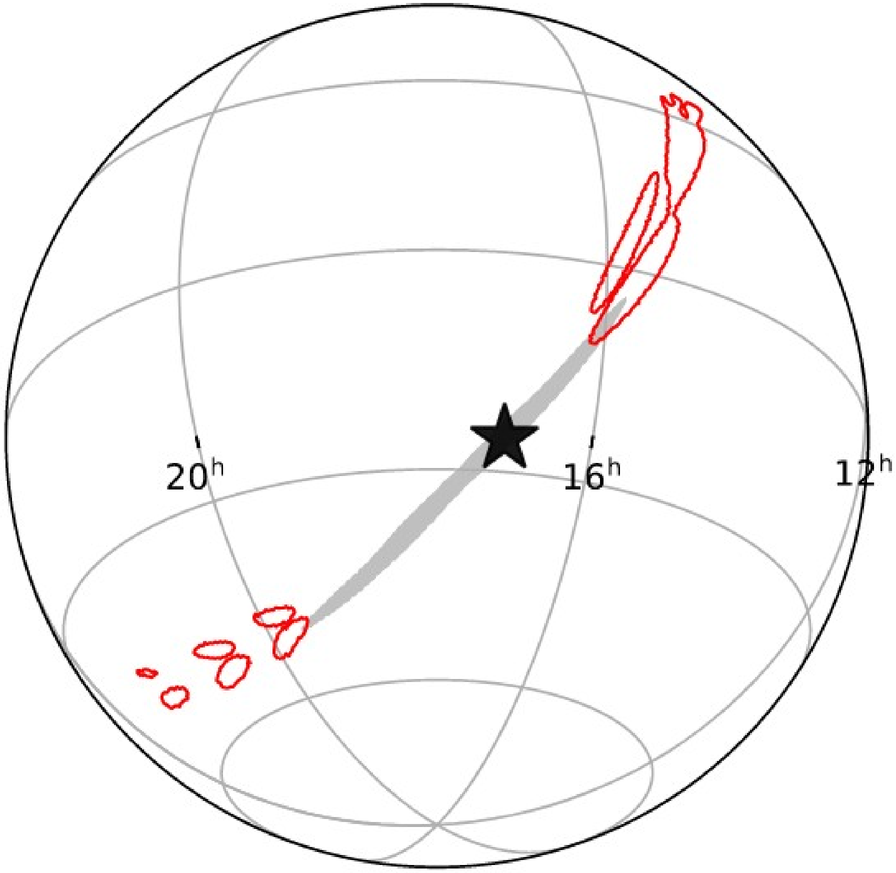
Advantages/disadvantages

- Easy to apply, very low latency ✓
- Works for any type of glitch and sources ✓
- Does not depend on long-time scale effects ✓
- Does not need training or special algorithms ✓
- Loss of data (SNR) ✗
- Affects sky localization, source parameter estimation... ✗

Advantages/disadvantages

Binary black hole coalescence with network SNR = 42.4 and masses = (35, 29) $M_\odot$
130 ms-long gate at 30 ms before merger

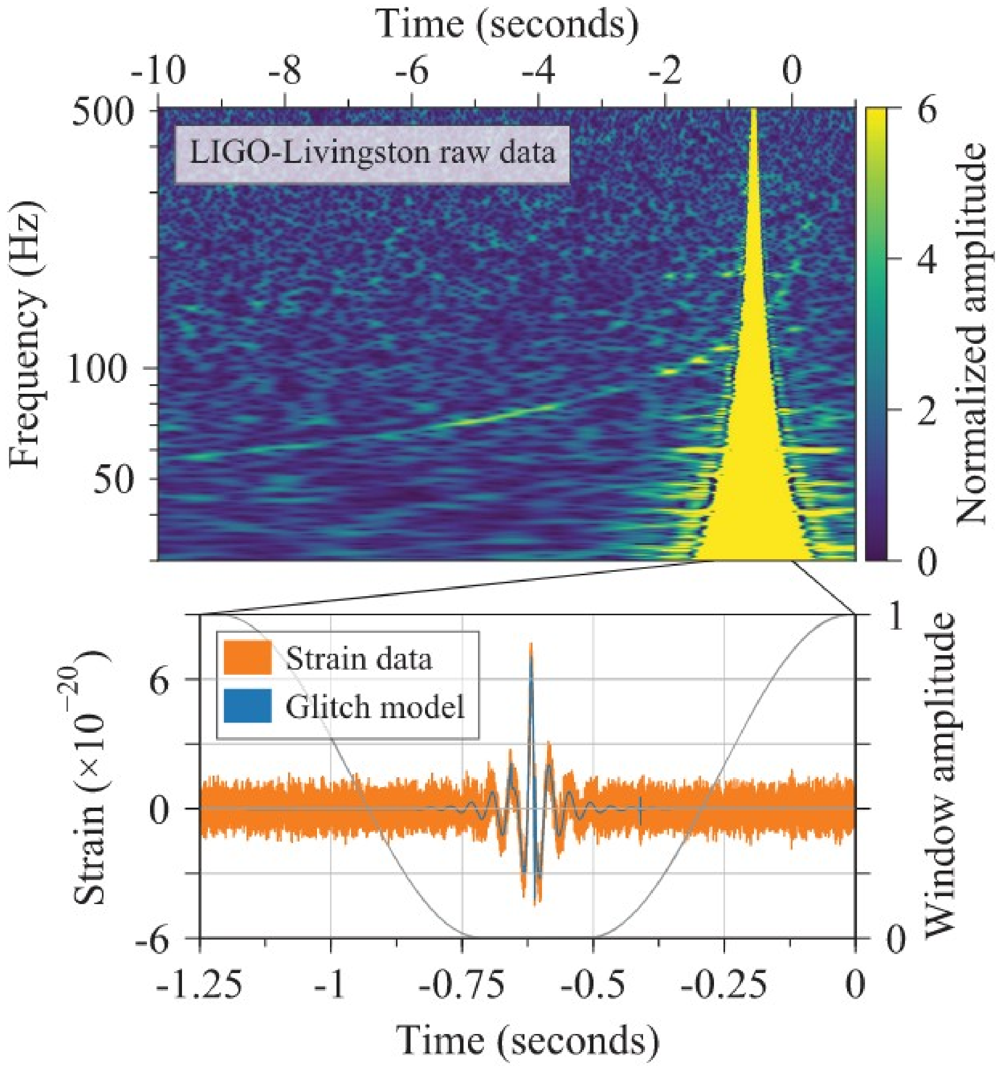




NNETFIX: An artificial neural network-based denoising engine for gravitational-wave signals, K. Mogushi et al, e-Print: 2101.04712 [gr-qc]

Strain-based approach - II

- **Model (specific) transient and subtract**



GW170817: Observation of Gravitational Waves from a Binary Neutron Star Inspiral, LIGO Scientific and Virgo Collaborations, B.P. Abbott (LIGO Lab., Caltech) et al., Phys.Rev.Lett. 119 (2017) 16, 161101

Advantages/disadvantages

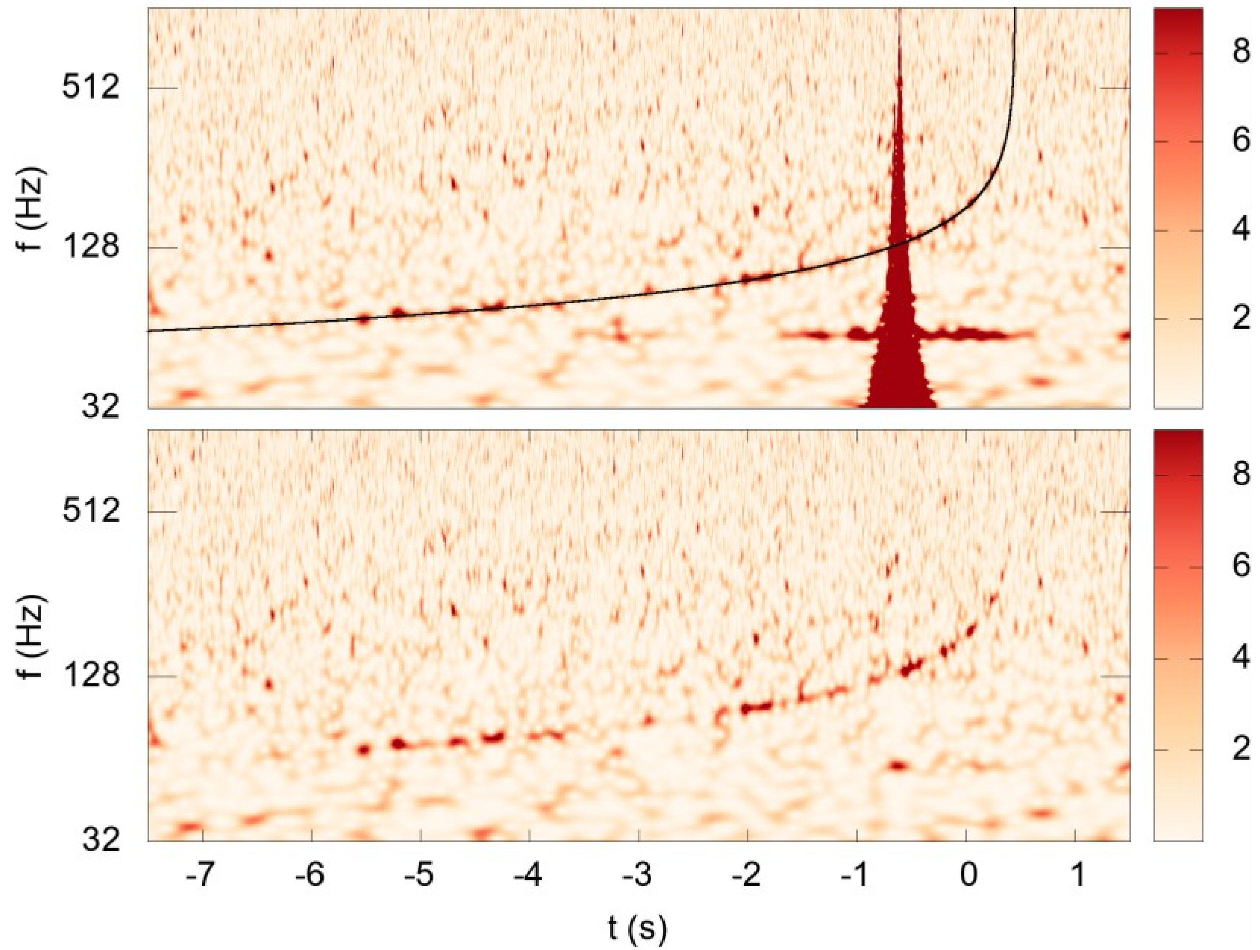
- Deterministic ✔
- Does not depend on long-time scale effects ✔

Advantages/disadvantages

- Deterministic ✓
- Does not depend on long-time scale effects ✓
- Requires glitch model ✗
- Little control on accuracy of subtraction ✗

QuickCBC

Wavelet-based de-noising + Bayesian inference



Rapid and Robust Parameter Inference for Binary Mergers, Neil J. Cornish, e-Print: [2101.01188] [gr-qc]

Advantages/disadvantages

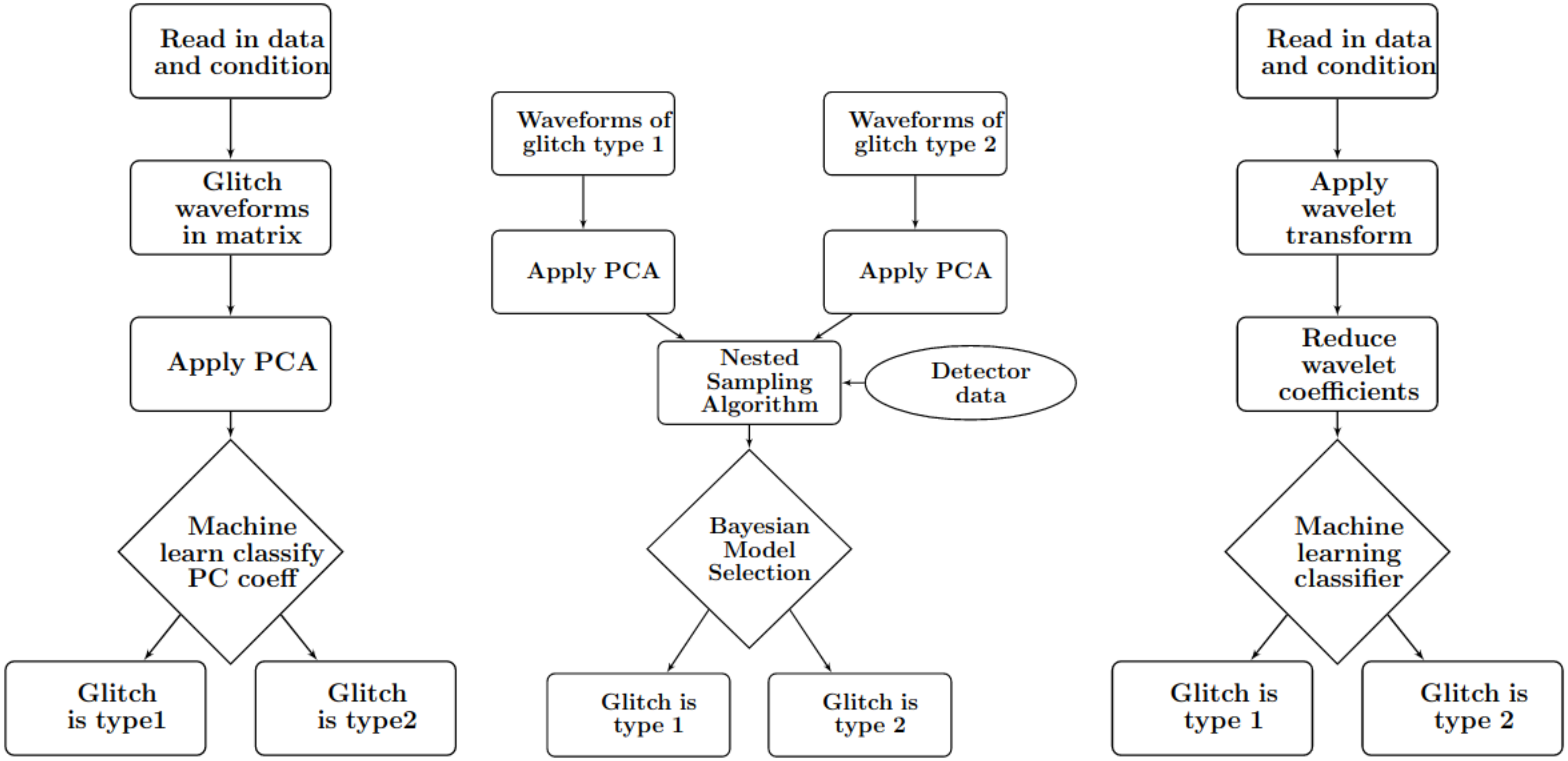
- Deterministic ✓
- Does not depend on long-time scale effects ✓

Advantages/disadvantages

- **Deterministic** ✓
- **Does not depend on long-time scale effects** ✓
- **Requires separating coherent vs. incoherent part of signal** ✗
- **Does not work for single-interferometer events** ✗
- **Requires source and/or glitch model** ✗

Strain-based approach - III

- **Combination of deterministic and supervised / unsupervised machine-learning methods**
- **Model classes of noise transients, then subtract**



Classification methods for noise transients in advanced gravitational-wave detectors II: performance tests on Advanced LIGO data, Jade Powell et al., Class.Quant.Grav. 34 (2017) 3, 034002

Advantages/disadvantages

- **Can outperform the performance of deterministic methods**
- **Re-training may takes care of long-time scale non-stationarity**

Advantages/disadvantages

- Can outperform the performance of deterministic methods
- Re-training may takes care of long-time scale non-stationarity
- Supervised methods works only for known types of noise
- Unsupervised methods may not be accurate depending on type and severity of glitch

Strain-based approach - IV

- **Excise and reconstruct**
- **Single-interferometer**
- **Machine learning-based**

Machine Learning: Science and Technology

ACCEPTED MANUSCRIPT • OPEN ACCESS

NNETFIX: An artificial neural network-based denoising engine for gravitational-wave signals

Kentaro Mogushi[1], Ryan Quitzow-James[1], Marco Cavaglia[2], Sumeet Kulkarni[3] and Fergus Hayes[4]

Accepted Manuscript online 26 February 2021 • © 2021 The Author(s). Published by IOP Publishing Ltd

NNETFIX

$$s_f(t) \qquad s_g(t) \qquad s_r(t)$$

full strain (noise + signal) | gated strain | reconstructed strain (noise + signal)

Build the map

$$s_r(t) := F\left[s_g(t)\right]$$

by training an ANN on full / gated strain such that

$$s_r(t) \sim s_f(t)$$

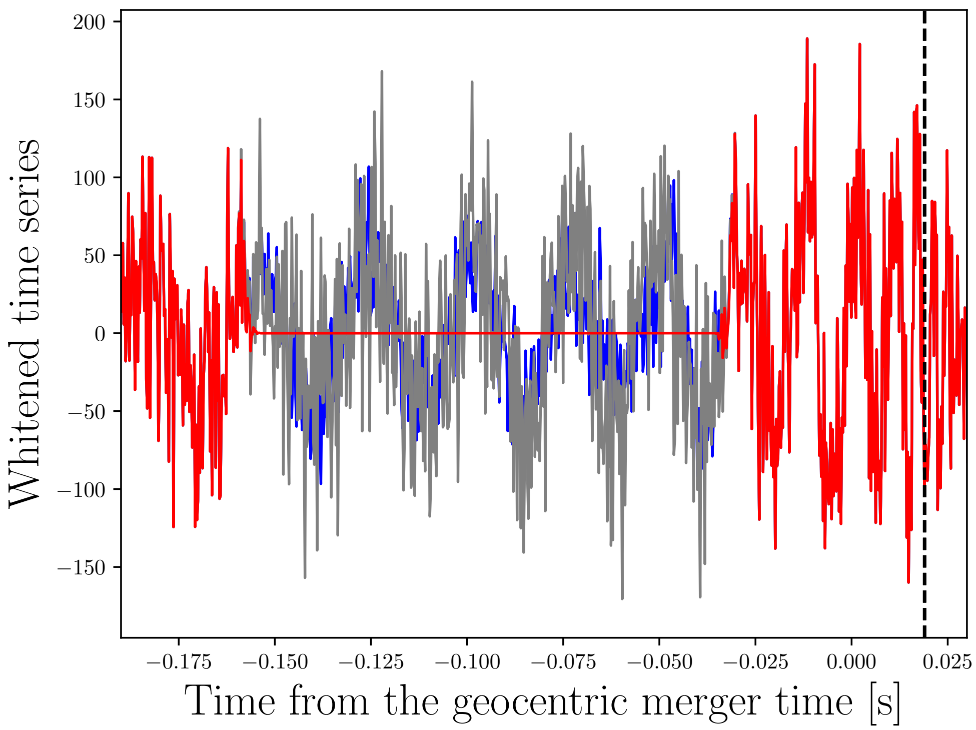
NNETFIX

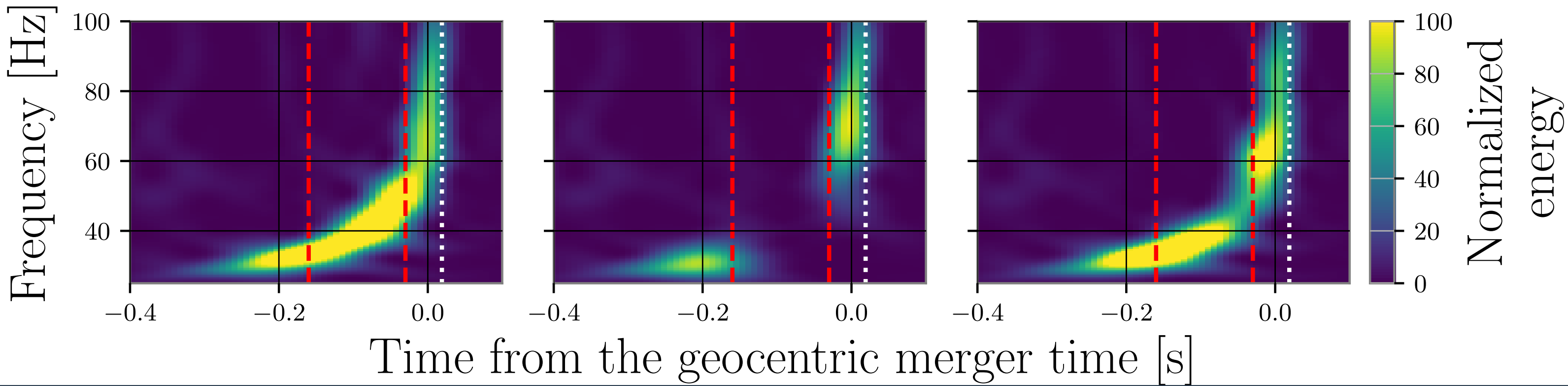
- **One hidden layer containing 200 neurons**
- **Rectified linear unit activation function**
- **ADAM stochastic gradient-based optimizer with learning rate of 10^{-3}**
- **60%+10%+30% for training, internal validation and testing**
- **Non-spinning IMRphenomD BBH merger waveforms**
- **3 distinct template banks (low, medium, high BBH component masses) each with 12 sets of waveforms injected into 50 distinct realizations of advanced LIGO recolored Gaussian noise at design sensitivity + (pure) noise time series**
- **12 combinations of gate durations (50, 75, 130) ms and gate end-times before merger (15, 30, 90, 170) ms**
- **Further testing on 108 additional independent exploration sets with network SNR (11.3, 28.3, 42.4) and component masses (12, 10), (20, 15), (35, 29) $M_\odot$**

	m_1 $[M_\odot]$	m_2 $[M_\odot]$	n_s	n_n	Set dimension $(n_s \times 50 + n_n)$
Low	10–15	8–12	348	1900	19300
Medium	15–25	12–18	251	1350	13900
High	28–42	23–35	61	300	3350

NNETFIX

Red: Original
Grey: Gated
Blue: Reconstructed





NNETFIX – SNR recovery

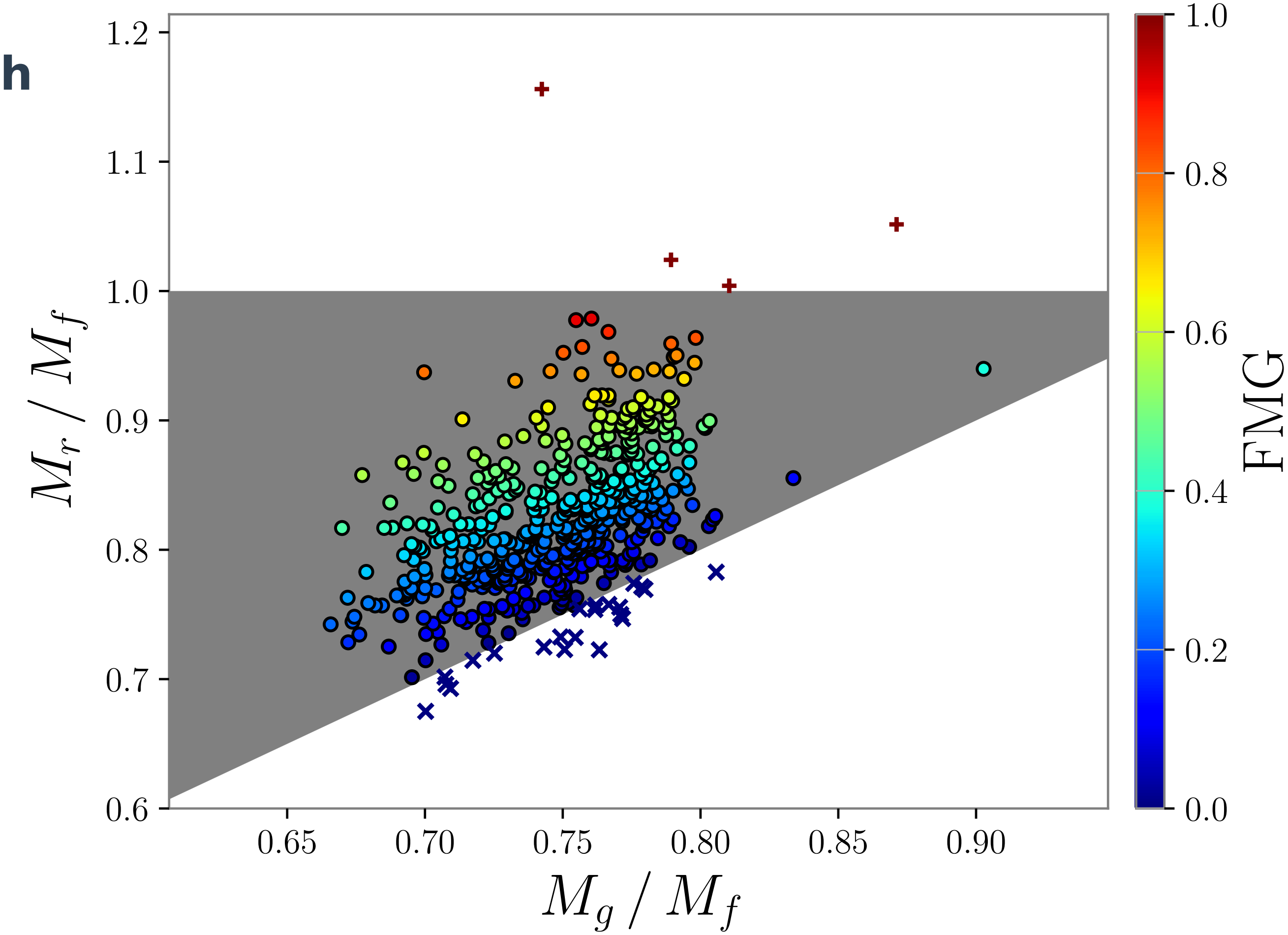
Signal/waveform match

$$M_i = \frac{\langle s_i | h \rangle}{\sqrt{\langle s_i | s_i \rangle \langle h | h \rangle}}$$

$$\langle s_i | s_j \rangle = 4\Re \int_{f_1}^{f_N} \frac{\tilde{s}_i(f) \tilde{s}_j{}^*(f)}{S(f)} df$$

Fractional match gain

$$\mathrm{FMG} = \frac{M_r - M_g}{M_f - M_g}$$



Exploration set: $\rho_N = 42.4,\ (m_1, m_2) = (20, 15)\ M_\odot,\ t_d = 130$ ms and $t_e = 30$ ms.

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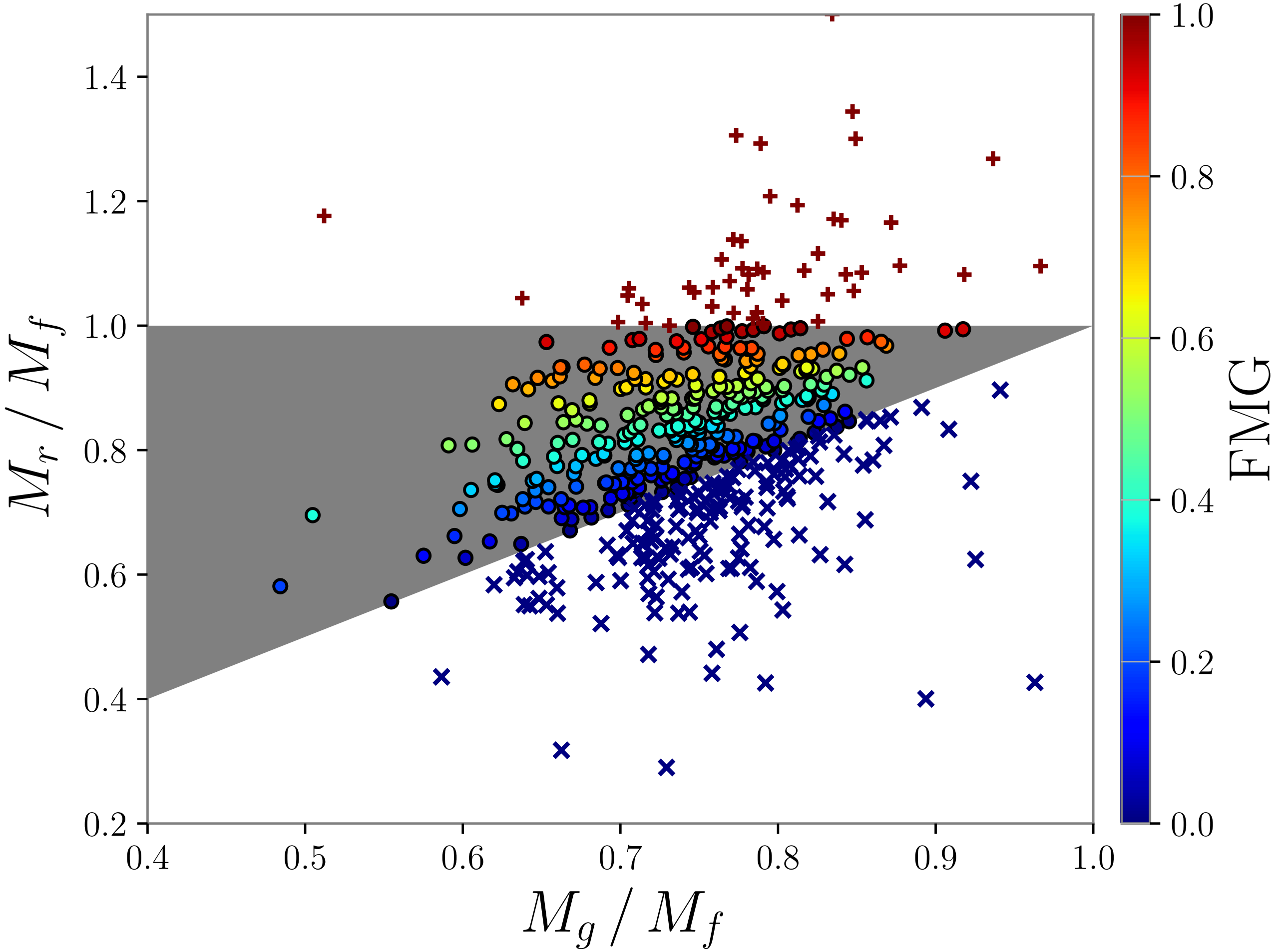

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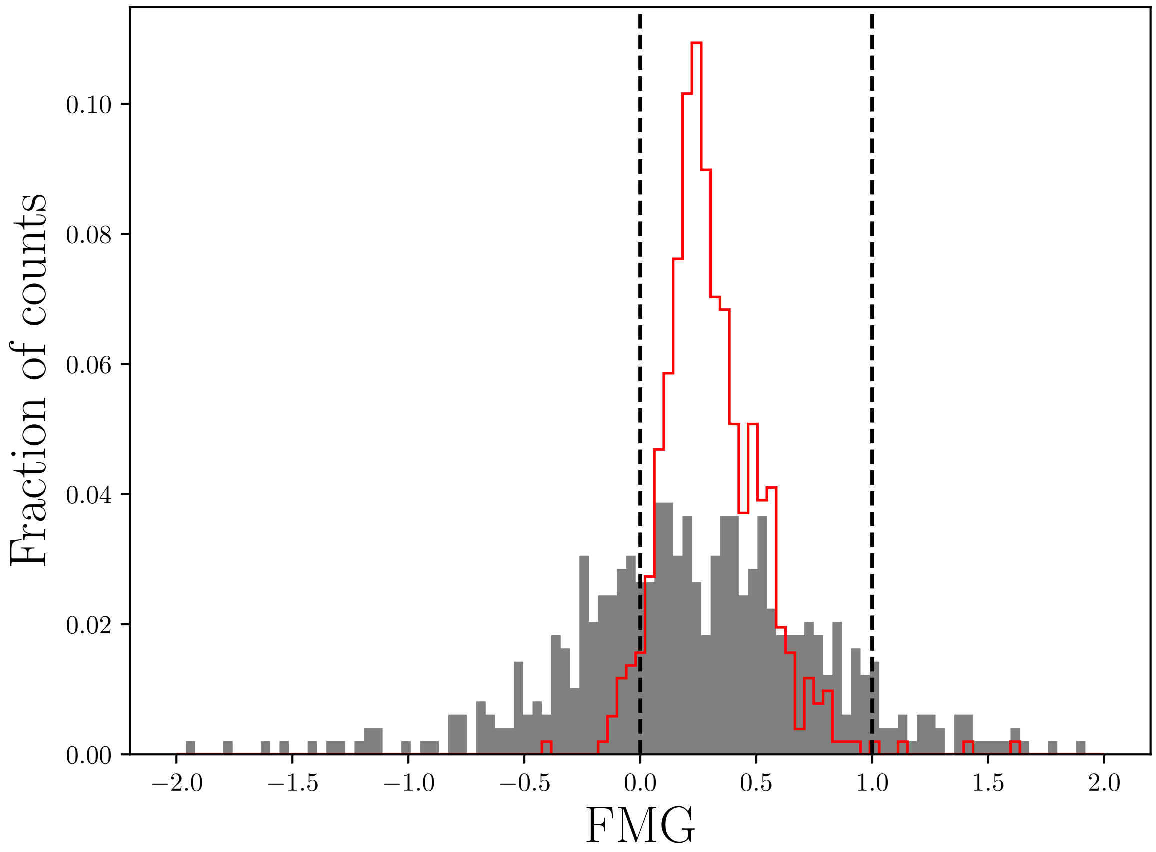

SNR = 11.3 (gray-filled) vs SNR = 42.4 (red)

NNETFIX – SNR recovery

Signal/waveform match

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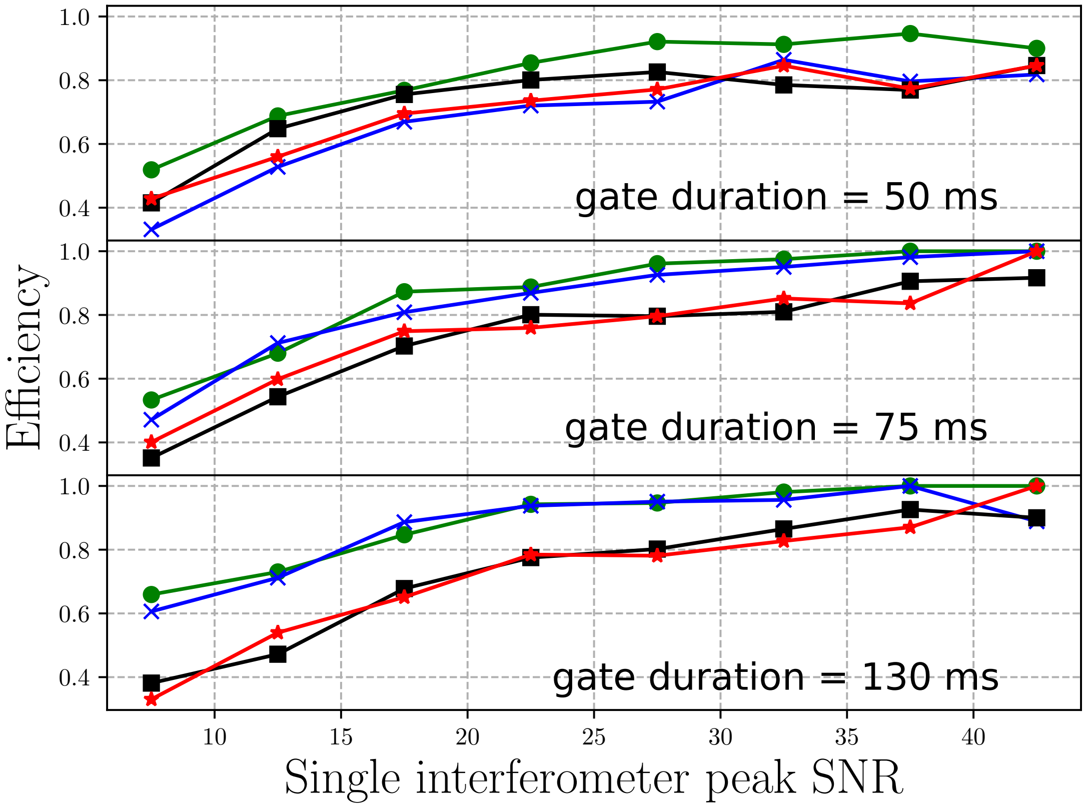


Exploration set with component masses (20,15) $M_\odot$
Gate end-times: Green circles =15 ms, blue crosses = 30 ms, black squares = 90 ms, red stars = 170 ms

NNETFIX – Sky map recovery

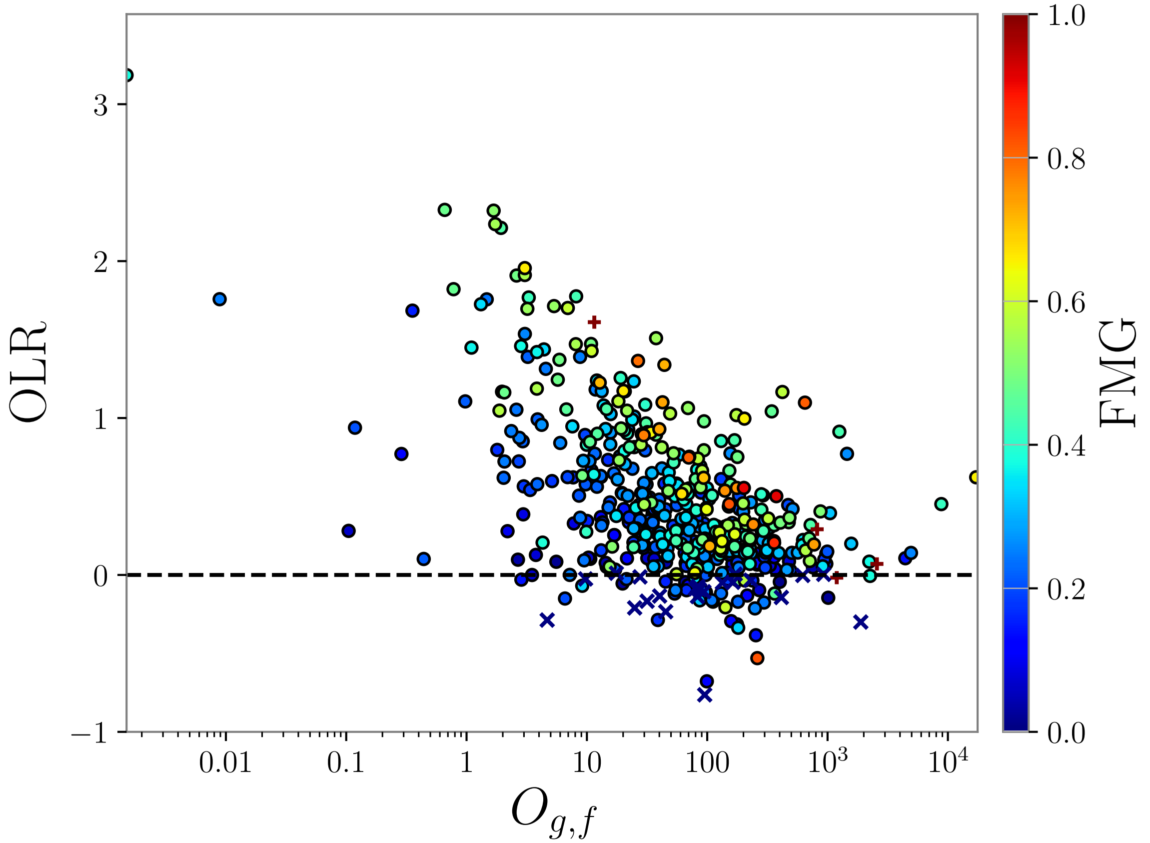
Skymap overlap

$$O_{1,2} = \frac{4\pi \int p_1(\Omega) p_2(\Omega)\, \mathrm{d}\Omega}{\int p_1(\Omega)\, \mathrm{d}\Omega \int p_2(\Omega)\, \mathrm{d}\Omega}$$

$$= N \sum_{i=1}^{N} P_{1i} P_{2i}$$

Overlap log ratio

$$\mathrm{OLR} = \log_{10} \frac{O_{r,f}}{O_{g,f}}$$



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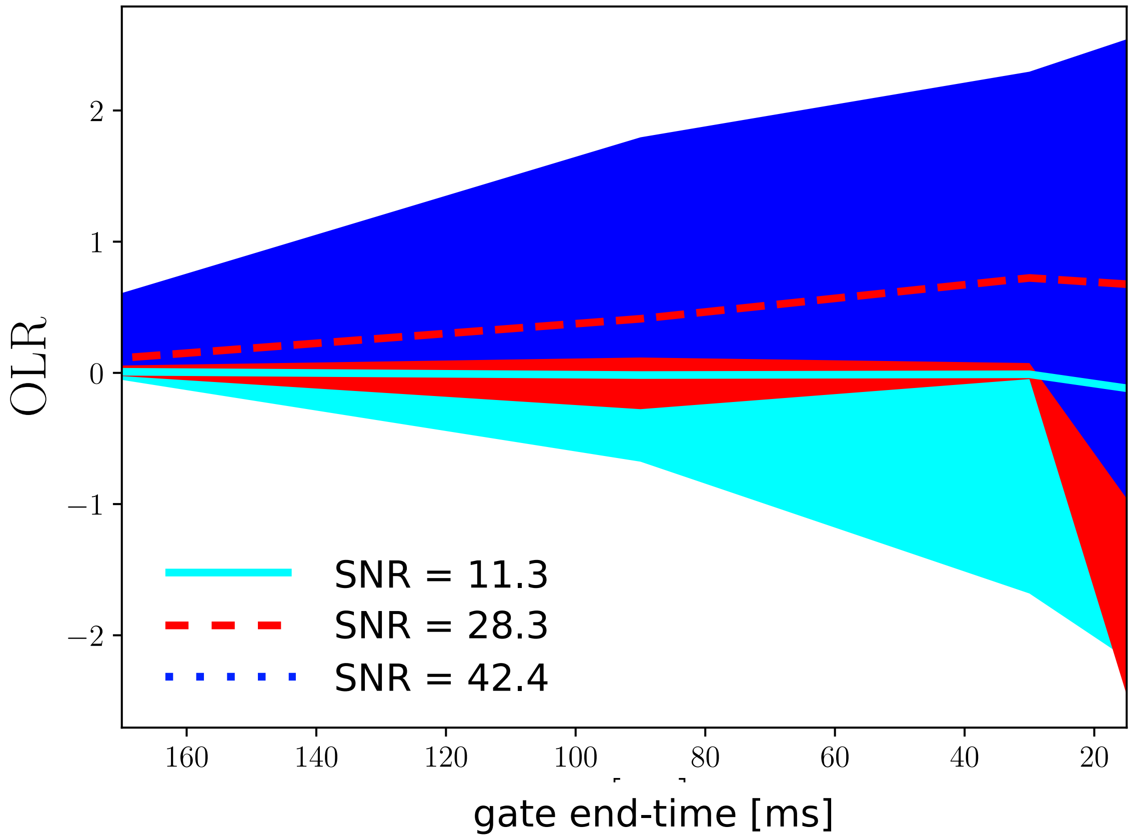

Exploration set with component masses (35,29) $M_\odot$
gate duration = 130 ms

NNETFIX – Sky map recovery

Skymap overlap

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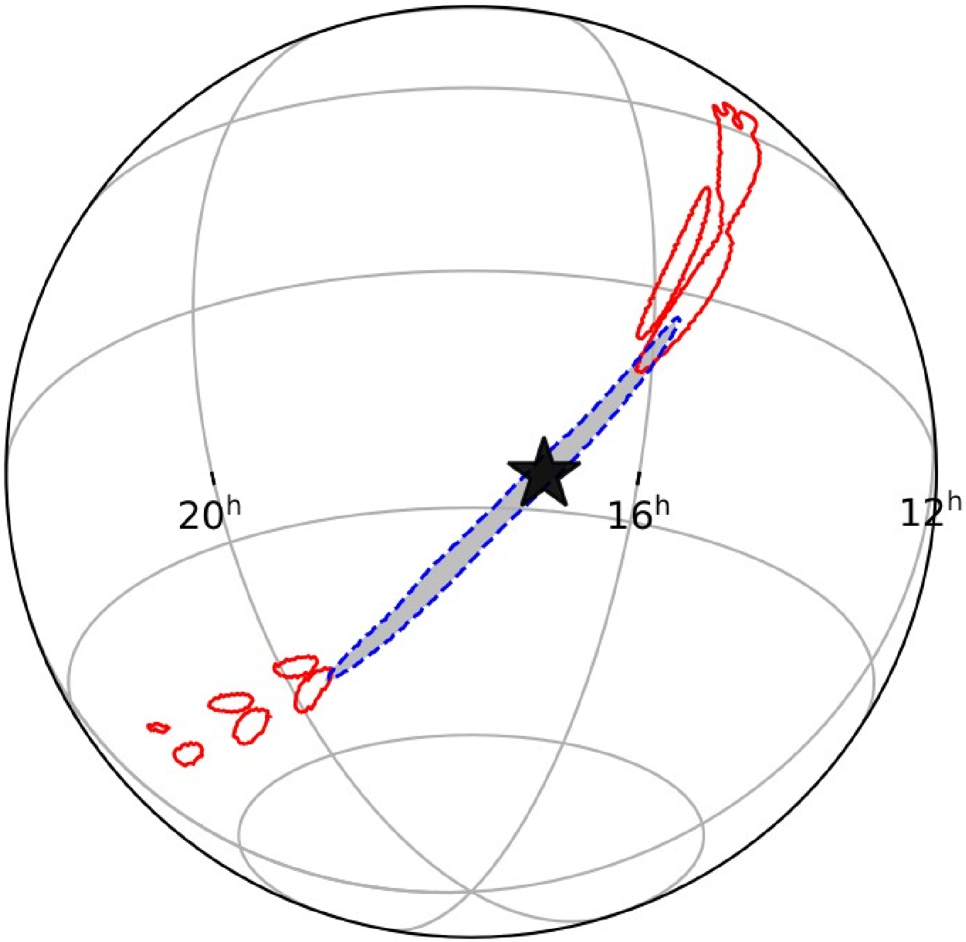


BBH with network SNR = 42.4 and masses = (35, 29) $M_\odot$
with 130 ms gate at 30 ms before merger

Advantages/disadvantages

- **Works for any type of glitch**
- **Works also for single interferometer**
- **Recovers SNR and sky localization**
- **Re-training takes care of long-time scale non-stationarity**

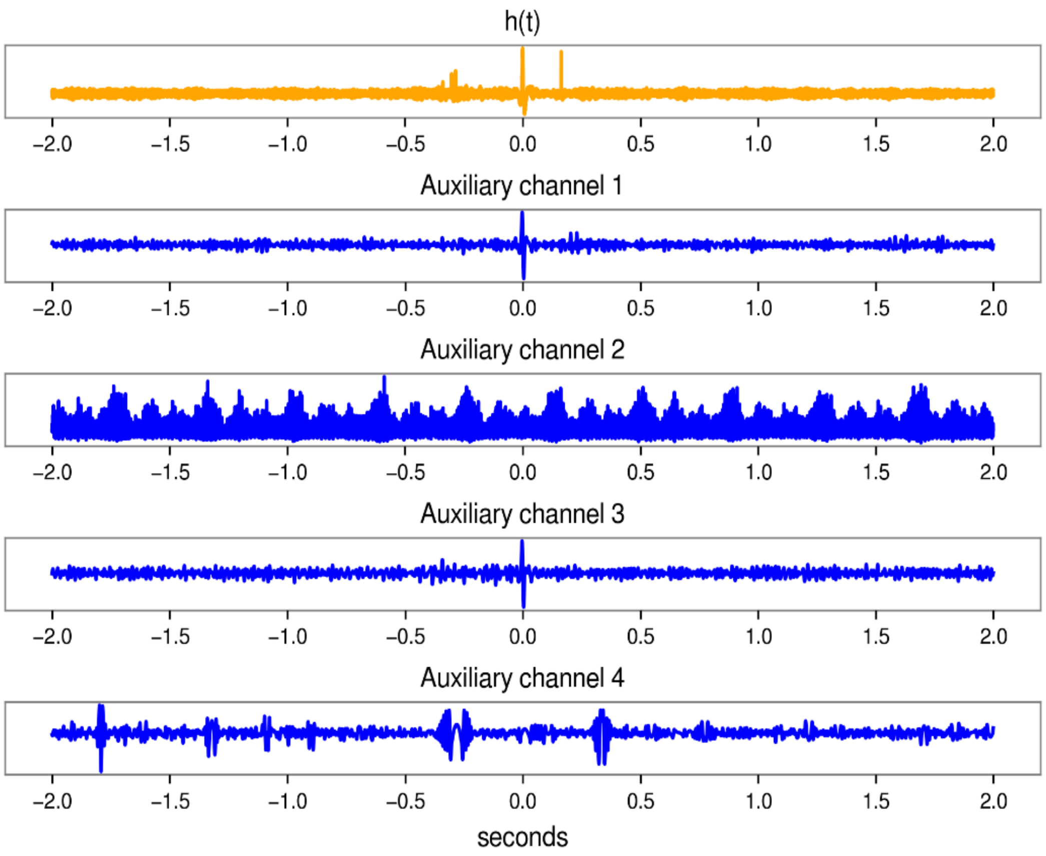
Advantages/disadvantages

- Works for any type of glitch ✓
- Works also for single interferometer ✓
- Recovers SNR and sky localization ✓
- Re-training takes care of long-time scale non-stationarity ✓
- Requires source modeling ✗
- May not be accurate for long-duration glitches or glitches very close to merger ✗

We may need to go beyond strain-based methods

Auxiliary channel-based methods

Identify in aux



Model in aux subtract in strain

Auxiliary channel-based approach

- **Model classes of glitches in auxiliary channels**
- **Map to strain, then subtract**
- **Can be deterministic and/or machine learning-based**

$$s(t) = n_s(t) + g_s(t) + h(t)$$
$$a(t) = n_a(t) + g_a(t)$$

strain + aux data

$$\rightarrow \quad g_s(t) = g_s[(a(t)-n_a(t))^{-1}]$$

map aux to strain

$$\rightarrow \quad s_c(t) = n_s(t) + h(t)$$

subtract in strain

Advantages/disadvantages

- **Does not use information from strain**
- **Large amount of information available from auxiliary channels**
- **Re-training takes care of long-time scale non-stationarity**
- **Does not require source modeling**
- **It should work for any type of glitch and sources**
- **Similar scheme used to remove non-stationary power line at 60 Hz and 4 Hz-wide sidebands**

(Machine-learning non-stationary noise out of gravitational-wave detectors, G. Vajente et al, Phys. Rev. D 101, 042003 (2020))

Advantages/disadvantages

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- **Similar scheme used to remove non-stationary power line at 60 Hz and 4 Hz-wide sidebands** ✓

  (Machine-learning non-stationary noise out of gravitational-wave detectors, G. Vajente et al, Phys. Rev. D 101, 042003 (2020))
- **What if there are no witness channels?** ✗

Thank you!

The battle continues...

The author thankfully acknowledges the human and material resources of the LIGO Scientific Collaboration and the Virgo Collaboration that have made possible the results presented in this talk, and the National Science Foundation for its continuous support of LIGO science and basic and applied research in the United States.
This work has been partially supported by NSF grants PHY-1921006 and PHY-2011334.

LIGO VIRGO

NSF

LSC

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Thank you!

The battle continues…

The author thankfully acknowledges the human and material resources of the LIGO Scientific Collaboration and the Virgo Collaboration that have made possible the results presented in this talk, and the National Science Foundation for its continuous support of LIGO science and basic and applied research in the United States.
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LIGO VIRGO NSF LSC

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