Need new tools for old problems

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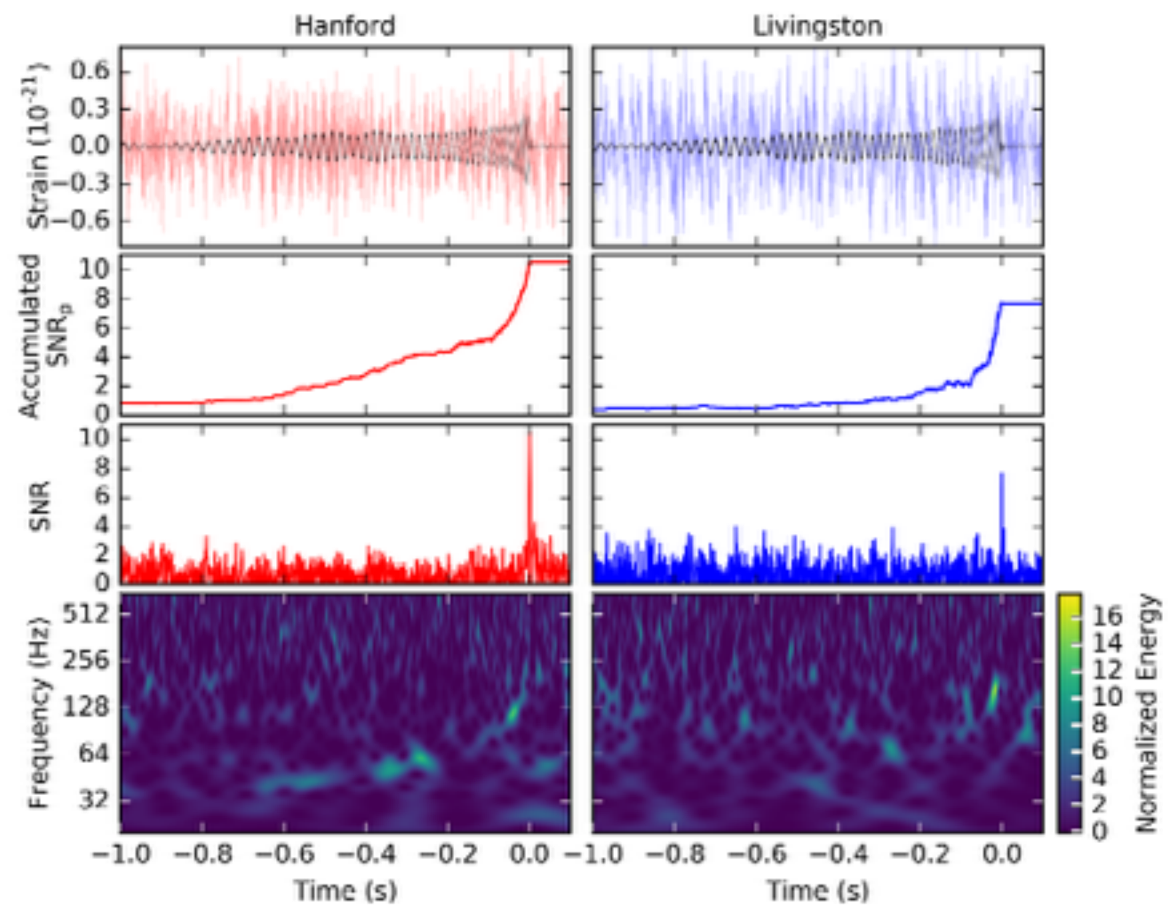
Template placement

gridding the parameter space

$$\rho_i(t) = \langle d | h_i \rangle$$

Data Template



Template bank

$$T \equiv \{h_i\}$$

Waveforms are described by many parameters
How do we grid a multi-dimensional manifold efficiently?

Some Issues with marquee searches

- Optimal searches for fully spinning binary blackholes:

$$h(t;\vec{\theta}_i) : \vec{\theta}_i \equiv \{m_1, m_2, \vec{s}_1, \vec{s}_2\}$$

- Instead, spins can be combined to one scalar parameter to form a lower dimensional space
- Template placement can be mapped to sphere packing with overlap in a non-flat space.
- How do we find good coordinates to place templates?
- For higher dimensions, use a stochastic template placement. How can we use geometrical placement? (Important for aLIGO era)
- Effective lower dimensional manifolds. Dimensional reduction.
- SVD (utilize the fact that templates are linearly dependent)
- Data fusion: Multi band analysis

A new paradigm on the horizon

Deep Neural Networks to Enable Real-time Multimessenger Astrophysics

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(Dated: January 5, 2017)

We introduce a new method for time-domain signal processing, based on deep learning neural networks, which has the potential to revolutionize data analysis in science. To demonstrate how this enables real-time multimessenger astrophysics, we designed two deep convolutional neural networks that can analyze time-series data from observatories including advanced LIGO. The first neural network recognizes the presence of gravitational waves from binary black hole mergers, and the second one estimates the mass of each black hole, given weak signals hidden in extremely noisy time-series inputs. We highlight the advantages offered by this novel method, which outperforms matched-filtering or conventional machine learning techniques, and propose strategies to extend our implementation for simultaneously targeting different classes of gravitational wave sources while ignoring anomalous noise transients. Our results strongly indicate that deep neural networks are highly efficient and versatile tools for directly processing any raw noisy data streams. We also pioneer a new paradigm to accelerate scientific discovery by combining high-performance simulations on traditional supercomputers and artificial intelligence algorithms that exploit innovative hardware architectures such as deep-learning-optimized GPUs. This unique approach immediately provides a natural framework to unify multi-spectrum observations in real-time thus enabling coincident detection campaigns of gravitational waves sources and their electromagnetic counterparts.

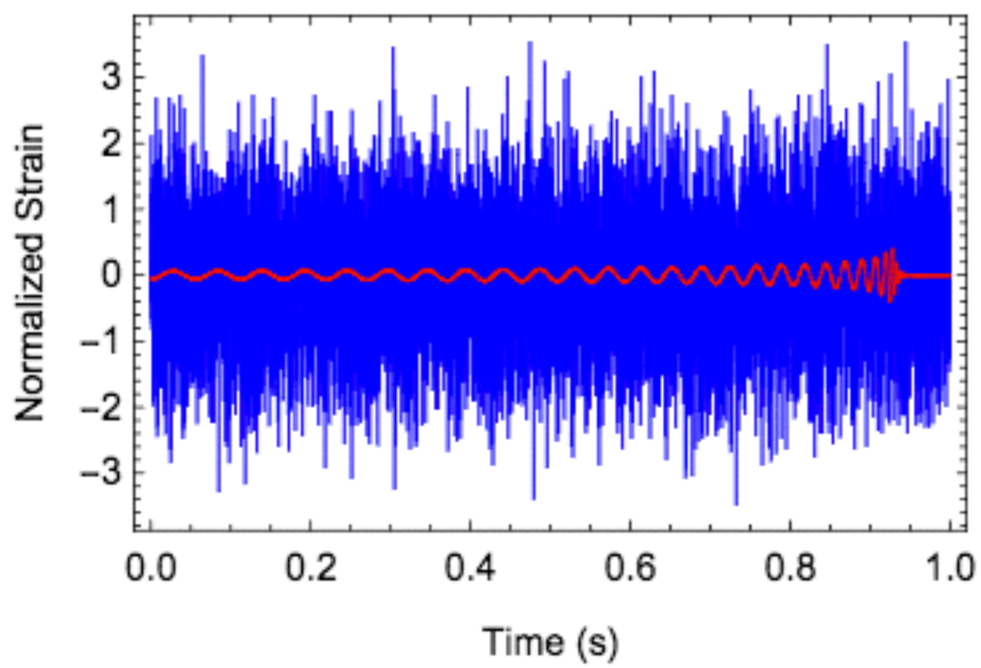
I. INTRODUCTION

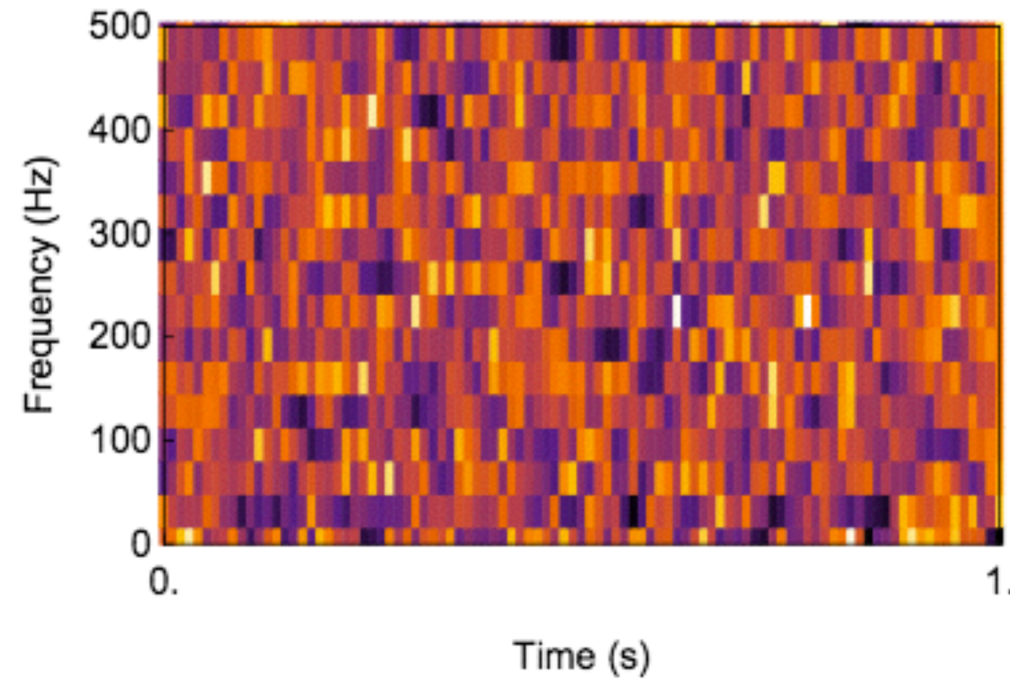
Gravitational wave (GW) science has reshaped the landscape of observational astronomy and theoretical astrophysics. During the first observing run of the advanced Laser Interferometric Gravitational wave Obser-

ativity and to get better insights into stellar evolution processes. However, the emphasis of multimessenger astrophysics will be on *extraordinary* events, such as the mergers of binary neutron stars (BNSs), NSBH, intermediate mass black holes (IMBHs) with masses between $100M_{\odot}-500M_{\odot}$, IMBHs and stellar mass BHs or NSs, as

Deep Learning Networks

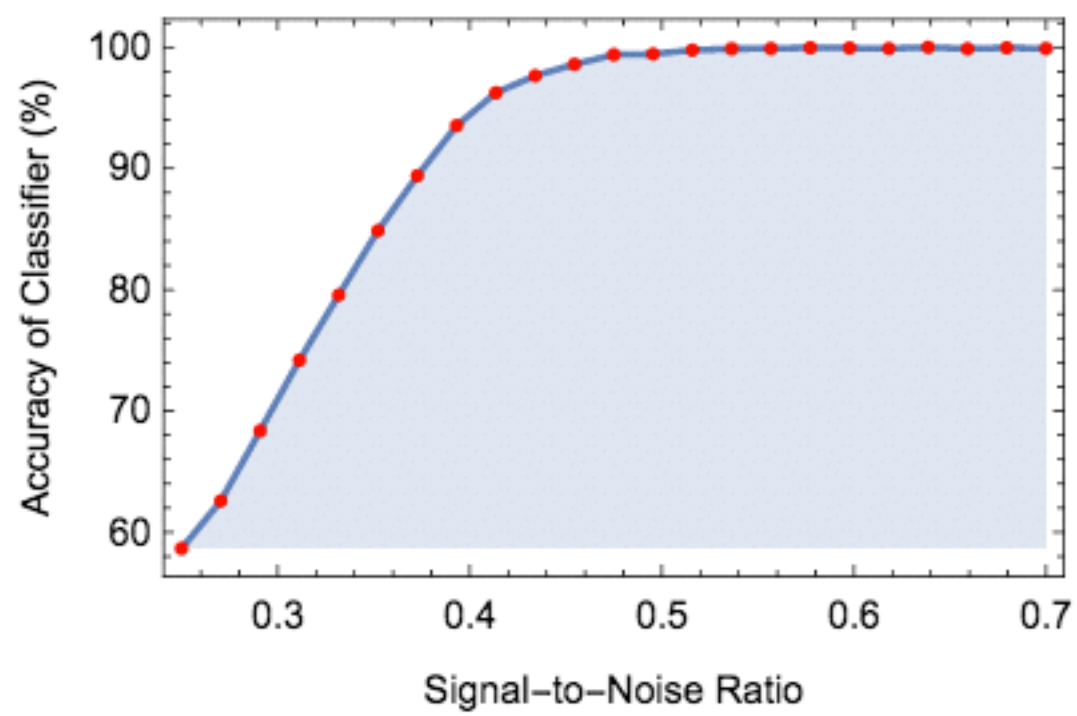
- Time domain signal processing based on deep learning neural networks
- Can be the next big thing
- Potential to facilitate multi-messenger astronomy
- Implementation for **simultaneously targeting different classes** of gravitational wave sources while ignoring anomalous noise transients
- Our results strongly indicate that deep neural networks are highly efficient and versatile tools for directly processing any raw noisy data streams.

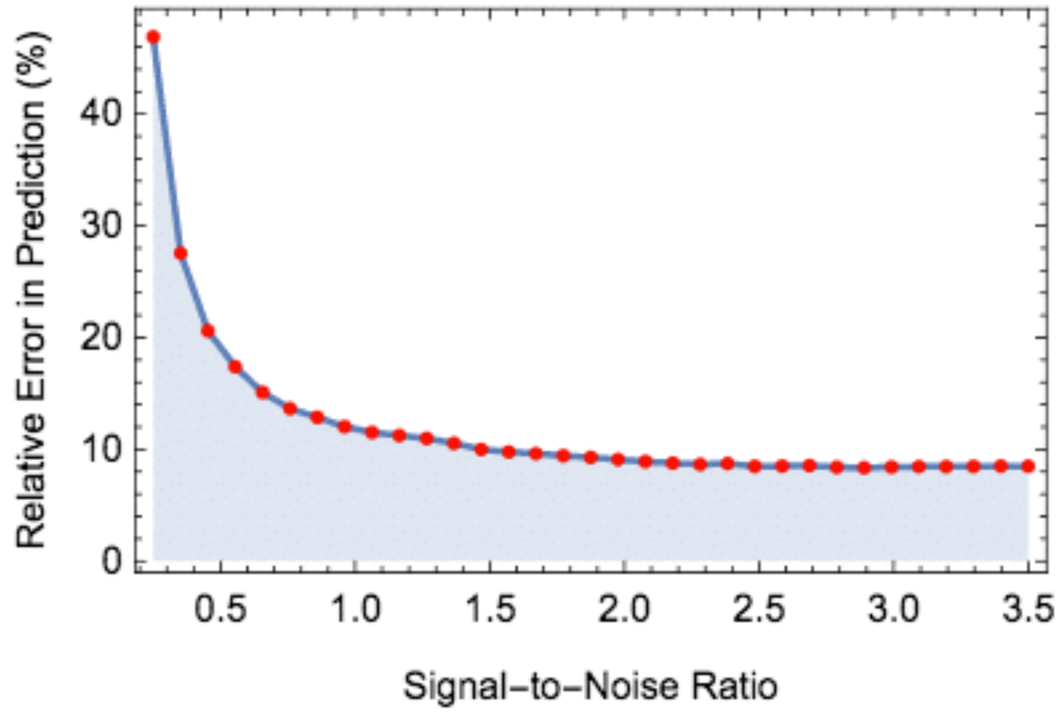


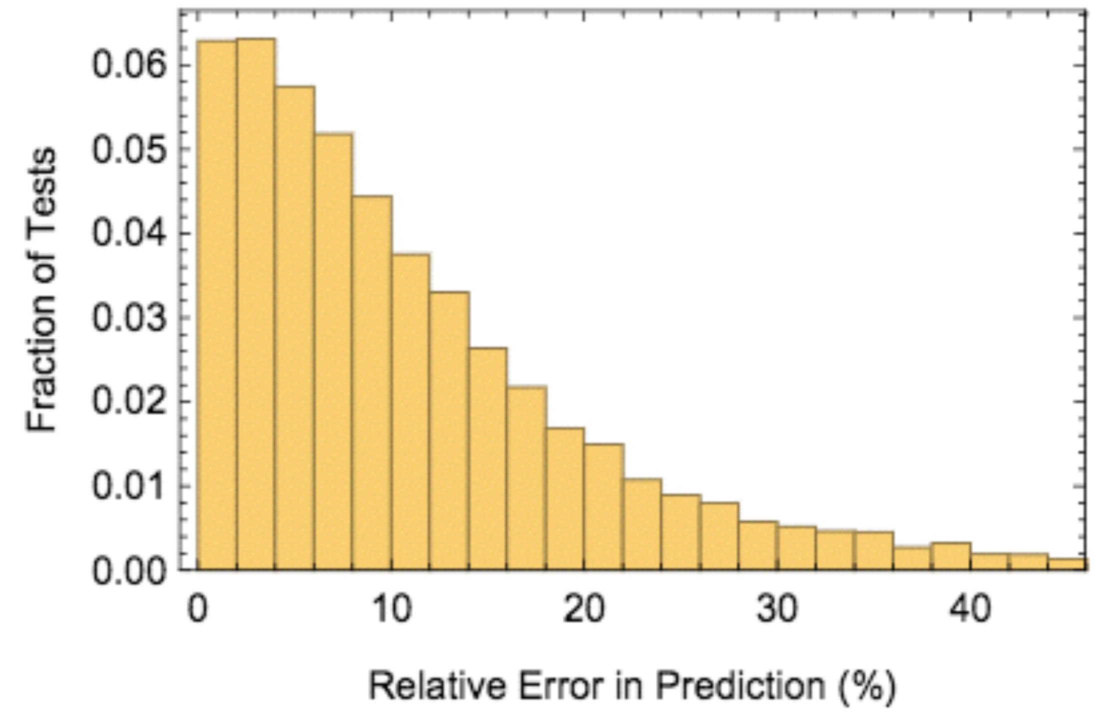


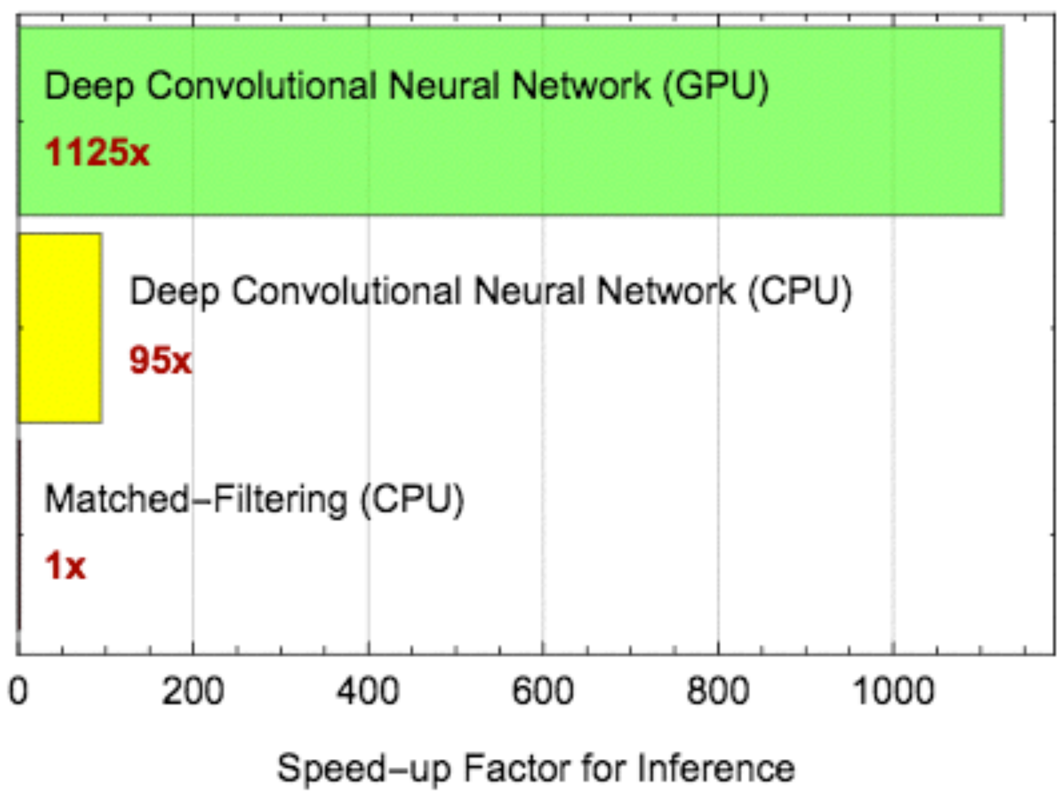
Time Frequency
Track Search
Excess Power

Dig deep into the noise









Discovery potential!

Sparse representations

Dictionary learning

Given a dataset **X**, one finds a dictionary **D** and a representation **R** such that, $||X - DR||$ is minimised and the representations $R = [r_1, \ldots, r_k]$ are sparse enough.

Denoising of gravitational wave signals via dictionary learning algorithms

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Gravitational wave astronomy has become a reality after the historical detections accomplished during the first observing run of the two advanced LIGO detectors. In the following years, the number of detections is expected to increase significantly with the full commissioning of the advanced LIGO, advanced Virgo and KAGRA detectors. The development of sophisticated data analysis techniques to improve the opportunities of detection for low signal-to-noise-ratio events is hence a most crucial effort. We present in this paper one such technique, dictionary-learning algorithms, which have been extensively developed in the last few years and successfully applied mostly in the context of image processing. However, to the best of our knowledge, such algorithms have not yet been employed to denoise gravitational wave signals. By building dictionaries from numerical relativity templates of both, binary black holes mergers and bursts of rotational core collapse, we show how machine-learning algorithms based on dictionaries can be also successfully applied for gravitational wave denoising. We use a subset of signals from both catalogs, embedded in non-white Gaussian noise, to assess our techniques with a large sample of tests and to find the best model parameters. The application of our method to the actual signal GW150914 shows promising results. Dictionary-learning algorithms could be a complementary addition to the gravitational wave data analysis toolkit. They may be used to extract signals from noise and to infer physical parameters if the data are in good enough agreement with the morphology of the dictionary atoms.

BBH

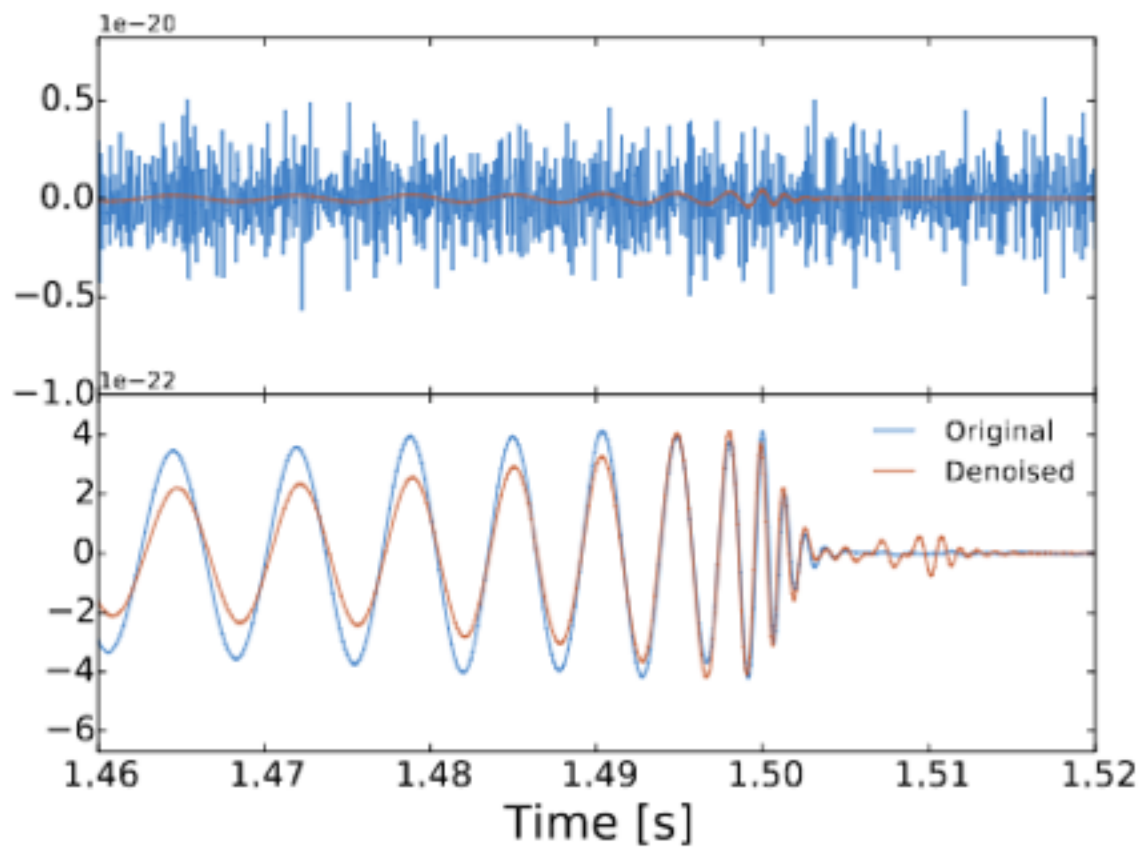


FIG. 7: Denoising of the test signal #2 taken from the BBH catalog. The SNR is set to 20 in a 2 s frame. The value of λ used is 0.01 with TV averaging. The values of MSE and SSIM are 0.031×10^{-3} and 0.86 respecrespectively.

Supernovae

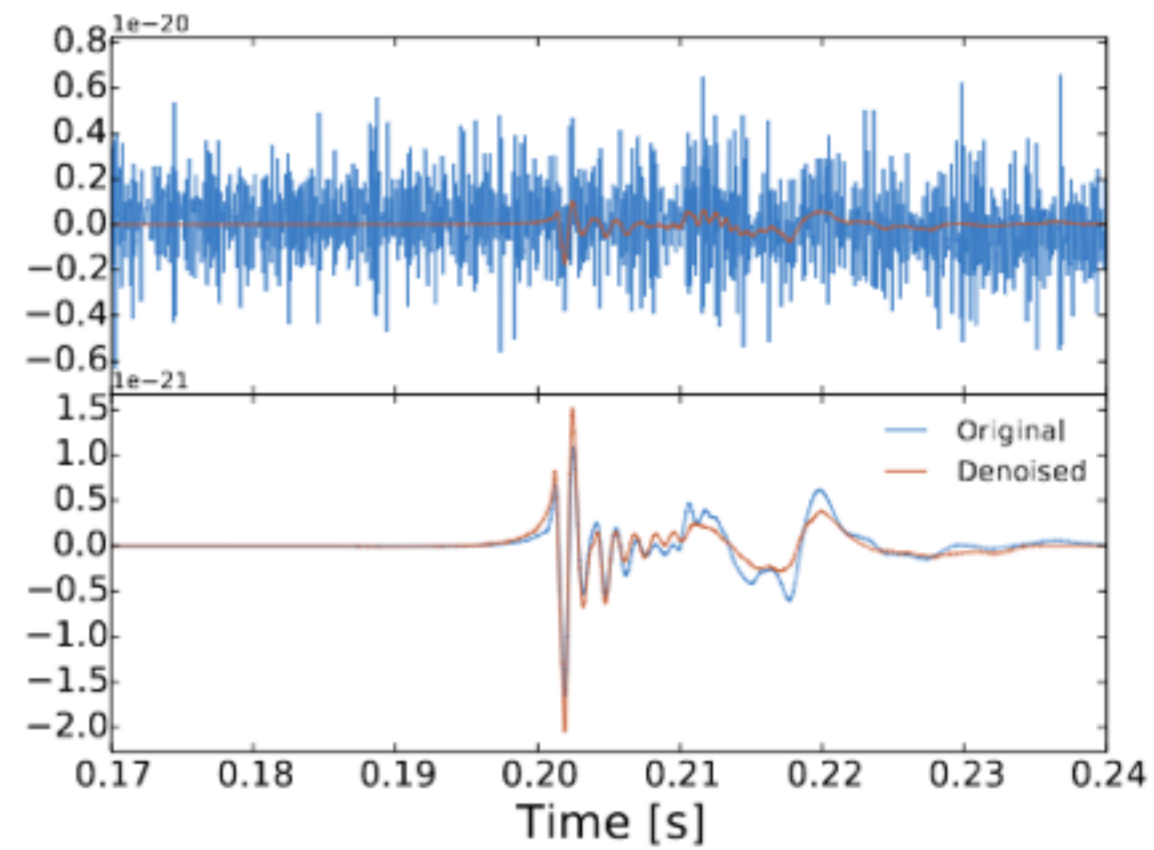
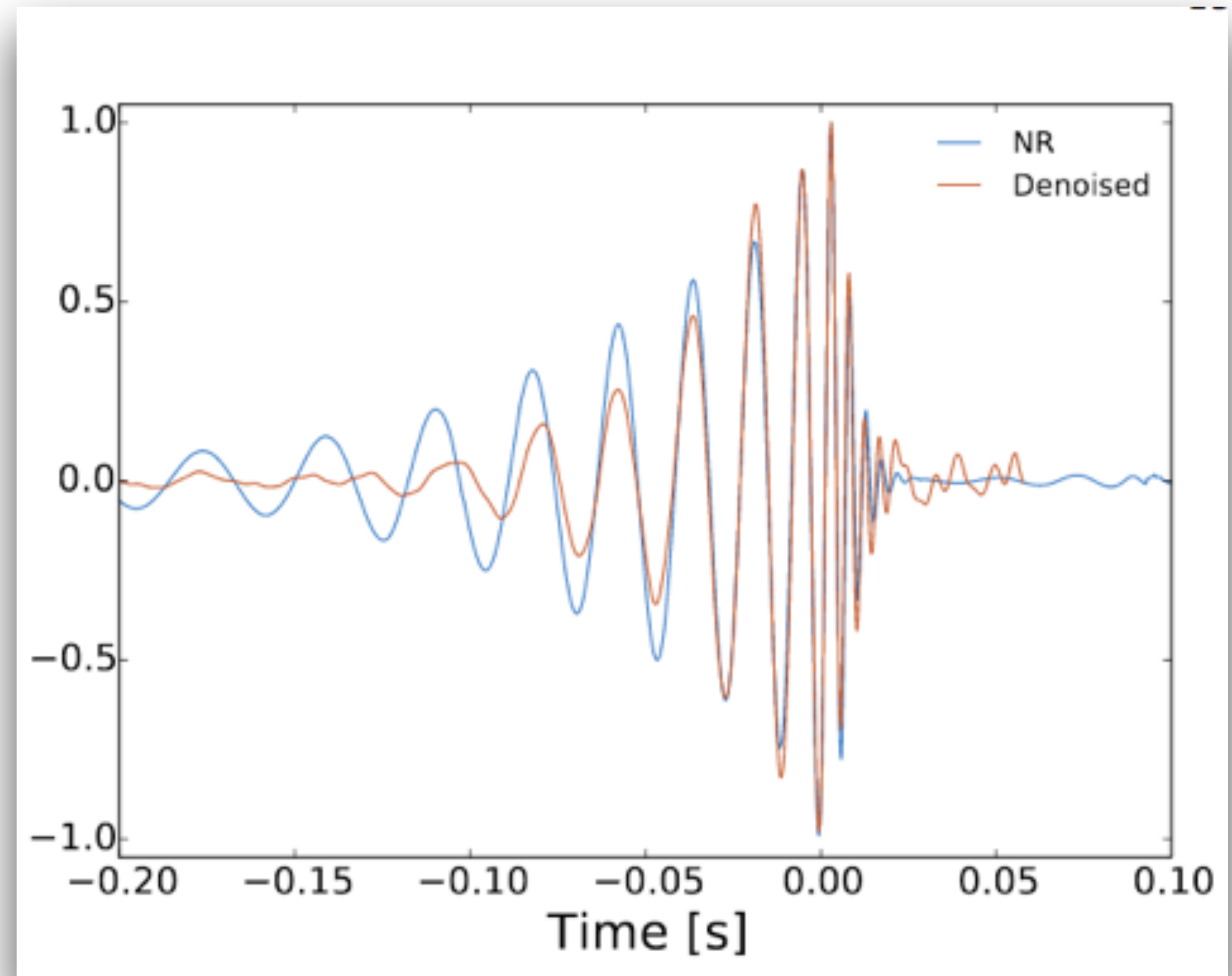


FIG. 8: Denoising of a burst signal from the core collapse catalog of [52] using a dictionary generated from a different catalog [43]. The arrival time is random, the SNR is 20 and $\lambda = 0.03$.

Denoising GW150914



Implications for waveform based tests of GR and source reconstruction!

- Early days for machine learning algorithms applied to GW astronomy
- Potentially useful for many aspects of GW astronomy
    - GW searches
    - Parameter estimation
    - Discovery potentials
    - Improvement in data quality [*Sajeeth Philip and collaborators*]
- Challenge - exponential increase in search volume. Search and parameter estimation. Electromagnetic follow-ups require “quick” estimation and sky localization. Waveform extraction for tests of GR. Many opportunities for doing good science.
    - what can time domain analysis teach?
    - Can one think of other search paradigms which have not been tried in GWave data analysis?