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REVIEW ARTICLE

Applications of machine learning in gravitational-wave research with current interferometric detectors

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Abstract

This article provides an overview of the current state of machine learning in gravitational-wave research with interferometric detectors. Such applications are often still in their early days, but have reached sufficient popularity to warrant an assessment of their impact across various domains, including detector studies, noise and signal simulations, and the detection and interpretation of astrophysical signals. In detector studies, machine learning could be useful to optimize instruments like LIGO, Virgo, KAGRA, and future detectors. Algorithms could predict and help in mitigating environmental disturbances in real time, ensuring detectors operate at peak performance. Furthermore, machine-learning tools for characterizing and cleaning data after it is taken have already become crucial tools for achieving the best sensitivity of the LIGO–Virgo–KAGRA network. In data analysis, machine learning has already been applied as an alternative to traditional methods for signal detection, source localization, noise reduction, and parameter estimation. For some signal types, it can already yield improved efficiency and robustness, though in many other areas traditional methods remain dominant. As the field evolves, the role of machine learning in advancing gravitational-wave research is expected to become increasingly prominent. This report highlights recent advancements, challenges, and perspectives for the current detector generation, with a brief outlook to the next generation of gravitational-wave detectors.

Keywords Gravitational waves · Machine learning · Signal processing · Interferometric detectors

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1 Introduction

The first direct detection of Gravitational Waves (GWs), the Binary Black Hole (BBH) coalescence event GW1501914 (Abbott et al. 2016b), was made on September 14, 2015, by the twin detectors of the Laser Interferometer Gravitational-wave Observatory (LIGO), located in Livingston, Louisiana, and Hanford, Washington, USA. In 2017, the Virgo detector in Italy joined the global network of GW detectors, and August 2017 brought the first multi-messenger event, the Binary Neutron Star (BNS) inspiral GW170817 (Abbott et al. 2017c) with rich electromagnetic (EM) counterparts (Abbott et al. 2017d). Since then, the LIGO-Virgo-KAGRA (LVK) Collaboration has published over 90 GW signals caused by Compact Binary Coalescences (CBCs), with most of them due to BBH mergers (Abbott et al. 2019a, 2021c, 2023b, 2024a), but also including several BNS (Abbott et al. 2017c, 2020b) and Neutron Star-Black Hole (NSBH) (Abbott et al. 2021d) events. As of the submission of this review, LIGO (Aasi et al. 2015), Virgo (Acernese et al. 2014), and KAGRA (Akutsu et al. 2021) are performing their fourth observing run O4[1] after undergoing further upgrades to improve their sensitivity. We anticipate that many more events will be detected, including some multi-messenger events like GW170817 (Abbott et al. 2018b).

Besides the construction, commissioning and characterization of the detectors, GW astronomy relies on a variety of signal modeling and data analysis techniques (Abbott et al. 2020a; LIGO Scientific Collaboration, Virgo Collaboration, KAGRA Collaboration 2023). Most of these have been developed in the frameworks of Frequentist statistics or Bayesian statistics statistics. For some signal types, such as CBCs and Continuous Gravitational Waves (CWs) from spinning neutron stars, predictive waveform models of varying accuracy are available. In these cases, matched filter techniques (Wiener 1949) are typically used, though model mismatch can be a concern and continued development of these models is of crucial importance, see e.g. Dhani et al. (2024). On the other hand, a variety of cross-correlation and pattern-recognition techniques are used for less well-understood sources, such as transient GW bursts from a variety of sources, as well as Stochastic Gravitational-Wave Backgrounds (SGWBs) (Creighton and Anderson 2011a).

In recent years, several novel Machine Learning (ML) approaches have been explored as alternatives for noise mitigation, source modeling, signal detection and characterization in GW astronomy. A first survey of these developments was presented a few years ago (Cuoco 2021). Now with this review article, we aim to provide an updated comprehensive summary of where the field stands. We focus on applications for the current LVK network and the near future, though we also briefly comment on future ground- and space-based GW detectors towards the end of the article (Sect. 10).

ML for GW astronomy fits within a wider context of such methods gaining ground in physics and astronomy. Various papers and other resources have been dedicated to making concepts, methods and software from the ML world more

[1] https://observing.docs.ligo.org/plan/.

accessible to astronomers, including both general reviews and introductory articles (Baron 2019; Sen et al. 2022; Smith and Geach 2023) as well as those about individual methods, e.g. transformers (Tanoglidis et al. 2023) – the reader is also kindly referred to our glossary at the end of this review for short definitions and additional basic references on methods and concepts. A useful set of recommendations for reliable and impactful ML applications in astronomy are made by Huppenkothen et al. (2023). Criticisms to the indiscriminate application of ML in the physical sciences, and possible answers, are discussed in Hogg and Villar (2024).

In this review, we mainly focus on concrete applications of ML in the GW context. However, we also provide a few introductory sections that briefly summarize the status of both fields. These do not aim to be comprehensive didactic treatments, but just to offer sufficient context for the later sections and pointers for the reader to study the rest of the literature. In this understanding, in Sect. 2 we provide a brief general introduction to GW detector data and the various standard methods both for preprocessing it and for detecting astrophysical signals in it. In Sect. 3, we provide a concise overview of the principal ML methods employed within the context of our review. This includes, but is not limited to, supervised learning, unsupervised learning, and reinforcement learning techniques. The goal of Sect. 4 is to present a conceptional and visual summary of the domains where ML is presently utilized in GW astronomy, or could potentially find application in the near future.

These different domains are then discussed in detail in the remaining sections of this review. In Sect. 5 we will demonstrate the considerable focus of numerous studies on utilizing ML to clean data and mitigate noise contributions. Section 6 discusses the application of ML techniques for efficiently simulating astrophysical GW sources and the emitted waveforms, as well as simulating realistic detector noise. In Sect. 7 we explore ML applications for GW signal searches and in Sect. 8 we address aspects related to source interpretation, including the Parameter Estimation (PE) of individual GW signals as well as wider inference tasks such as multi-messenger, population and cosmology studies, which are crucial areas where ML can significantly impact outcomes. Faster PE algorithms can open the way for discoveries in new physics, facilitate real-time studies, and enhance alert systems. In particular, in Sect. 8.4, we outline the preliminary framework for a multimodal machine learning application in multimessenger astrophysics, where faster PE will have a fundamental role. Throughout these sections, we mainly aim to give a general overview of the historical development and current state of the art of ML applications in the GW context, rather than detailed comparisons against other established techniques, though performing such comparisons case-by-case is a crucial step for the adoption of ML methods as tools for routine practical use.

In Sect. 9, we explore the links of the realm of citizen science with ML strategies, motivated by the growing need for labeled datasets. This demand is being addressed through the engagement of volunteers in citizen science initiatives. Furthermore, these activities could potentially connect the expertise of data scientists outside the GW community. A concise outlook towards applications of ML to next-generation GW detectors is provided in Sect. 10. Like much of this review, this section in particular will continue to evolve significantly in the coming years, as we face new challenges arising from the upgraded sensitivity of GW detectors.

We provide our overall perspective on the role and significance of ML for GW astronomy in the summary and outlook of Sect. 11.

2 A brief primer on GW data and searches

Advanced LIGO (Aasi et al. 2015), Advanced Virgo (Acernese et al. 2014) and KAGRA (Akutsu et al. 2021) are second-generation laser-interferometric detectors specifically designed for the detection of GW signals. They utilize the Michelson interferometer technique, which allows them to be highly sensitive to the strain in space-time caused by passing GWs (Saulson 2017). This strain causes fluctuations in the relative lengths of the interferometer arms, which in turn lead to corresponding power variations in the interferometer's output. To precisely capture these fluctuations, photo-diodes are used to measure changes in the intensity of the laser light (Abbott et al. 2020a). The signal obtained from these photo-diodes, after calibration (Viets et al. 2018; Acernese et al. 2018), serves as the readout for detecting GWs.

However, alongside astrophysical GW signals, these detectors are also susceptible to a variety of environmental noises: terrestrial forces can also directly cause time-varying variations in the lengths of the interferometer arms. These variations pose a challenge in accurately identifying astrophysical signals amidst the noise (Abbott et al. 2016a, 2020a; Davis et al. 2021; Acernese et al. 2023a; Covas et al. 2018). Hence, the detector output also functions as an error signal for controlling the relative lengths of the arms. This continuous monitoring and adjustment of the arm lengths based on the control signal allow the detectors to optimize their sensitivity to GWs while minimizing the impact of unwanted noise sources. In addition to the control signal, a vast array of auxiliary monitoring channels is employed to track and monitor noise sources, aiming to reduce their influence on the GW strain.

2.1 Preprocessing techniques

The photo-diode output in the interferometer yields time-series data, recorded at a designated sampling rate, covering a wide spectrum of emissions originating from diverse astrophysical sources. LIGO, Virgo, and KAGRA commonly sample their data at a rate of 16384 Hz. For most astrophysical analyses, the frequency range of interest typically spans only from 20 to 2000 Hz, where sensitivity is best. (Calibration is typically valid from 10 Hz on, but due to the steep sensitivity losses at lower frequencies, few analyses go that low in practice (Abbott et al. 2020a).) Thus, in practice, when it comes to analyzing this wealth of data, most GW analysis pipelines employ a down-sampling process, reducing the data to a lower sampling rate, e.g. 4096 Hz. This down-sampling approach effectively condenses the information in the time series while retaining essential details, enabling researchers to focus on GW signals within a frequency range that extends up to half the chosen sampling rate, also known as the Nyquist frequency (Shannon 1949).

This down-sampling strategy serves several crucial purposes in the field of GW research. Firstly, it helps manage the computational demands of data analysis, as the original high-frequency data can be extremely data-intensive and challenging to process. If the signal has no contributions above the Nyquist frequency, by reducing the sampling rate, analysis pipelines become more computationally manageable.

Secondly, this down-sampling aligns with the fact that many astrophysical sources of GWS fall within the frequency range preserved by the lower sampling rate. The down-sampling strategy can be applied with different sampling rates, depending on the type of astrophysical signal search being conducted or if the data analysis involves detector characterization procedures.

This strategy of down-sampling achieves a balance between data efficiency and the capability to detect and investigate GW signals emitted by diverse astrophysical phenomena.

Another step that is often useful is to reduce the bandwidth of interest for analysis. This is done by using digital filters with different purposes, such as high-pass, low-pass or band-pass filters, which allow greater efficiency on the area of interest for searching gravitational signals and can reduce the computational cost of subsequent operations.

Another important aspect to improve the sensitivity and robustness of GW analyses is to mitigate the impact of certain spectral lines (Covas et al. 2018) due to the presence of noise of a persistent nature at certain frequencies, such as those created by the power grid frequency, mirror suspension resonances, and other sources. This can be done in a variety of ways best suited to each analysis pipeline, e.g. by simple notch filters on the frequencies to be removed (Ogata 2001), veto techniques at analysis time (see e.g. Leaci 2015 for an overview for the case of CW searches), or the ML noise subtraction methods discussed in Sect. 5.4.

The extraction of GW signals from the background noise requires sophisticated signal processing techniques due to the relatively low amplitudes of the gravitational signals of interest, since the signals usually have a signal-to-noise ratio close to one. These techniques involve advanced algorithms and analyses to separate and identify the desired signals from the noise, ensuring accurate detection and characterization of GWs, and are linked to the kind of signals we are looking for (Abbott et al. 2020a).

One important preprocessing procedure that is applied in some GW searches for transient signals is the whitening algorithm. The purpose of the whitening procedure is essentially to remove the contribution of stationary noise associated with the second-order statistics of the data, information encapsulated in the Power Spectral Density (PSD) of the data. Thus, whitening transforms colored noise, which includes stationary and Gaussian noise contributions, into white noise, meaning it becomes delta-correlated.

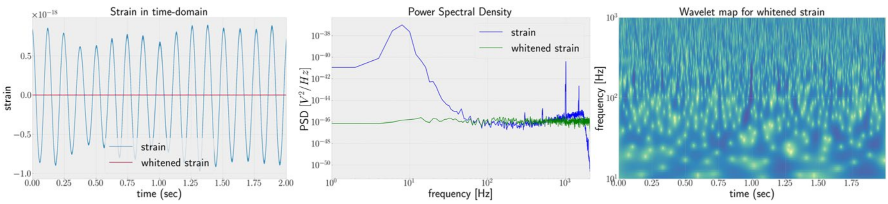
This is done by applying a filter that compensates for the frequency-dependent response of the detector, and can be accomplished through techniques applied either in the frequency domain (Abbott et al. 2020a) or in the time domain (Cuoco et al. 2001). Whitening is an intrinsic part of modeled matched filter techniques while for most unmodeled detection algorithms an explicit whitening preprocessing step significantly improves pipeline efficiency.

The data in the time domain is frequently subjected to various transformations to gain deeper insights and extract valuable information useful for the signal detection or characterization algorithms. Two common domains in which these transformations occur are the frequency domain and the time-frequency domain. The frequency domain is typically achieved through the Fourier transform, a mathematical technique that decomposes a signal into its constituent frequencies, allowing for the analysis of its frequency components. The time-frequency domain provides a representation of the signal that captures both time and frequency information simultaneously. This is particularly useful for analyzing non-stationary signals. Techniques used in this domain include the Short-Time Fourier Transform (STFT), which divides the signal into short segments and applies the Fourier transform to each segment; the Q-transform, which provides a time-frequency representation with variable resolution; and wavelet transforms, which use wavelet functions to analyze signals at different scales and positions, offering a more flexible approach to time-frequency analysis. In Cornish (2020), the various methodologies for time-frequency representation in the field of GW are described. The choice between these time-frequency analysis techniques depends on the specific characteristics of the data and the research objectives. They all offer unique advantages in terms of revealing temporal and spectral information that may be hidden in the original time series. Transforming time-series data into different domains, such as frequency or time-frequency representation, can help uncover hidden patterns, track changes over time, and gain deeper insights into the underlying dynamics of the data. Very often the time-frequency transformation is used before ML applications based on image classification.

In Fig. 1 we show different representations of a GW signal in the time domain, the frequency domain and in time-frequency domain, as a wavelet map. The wavelet transform was utilized after signal whitening to improve the visibility of transient signals.

2.2 GW searches

The exploration of detector data in search of astrophysical gravitational signals involves distinct methodologies, depending on the specific nature of the signals under investigation. Broadly speaking, GW signals are categorized into three main types: continuous signals, transient signals, and stochastic signals (Creighton and Anderson 2011b). A more nuanced classification arises from our understanding of the signal's source and



(a) Time domain (b) Frequency domain (c) Time-Frequency domain

Fig. 1 The image shows the identical not whitened and whitened strain data represented in the time domain **a** and frequency domain **b**. In **c** we illustrated, as time-frequency representation, the mapping to a Morlet continuous wavelet basis of the whitened strain our ability to model its waveform accurately. Consequently, research efforts are further stratified into two overarching domains: the examination of signals characterized by known waveforms and those characterized by unknown waveforms.

The matched filter technique (see Wiener 1949; Wainstein and Zubakov 1962 for general mathematical background and Abbott et al. 2020a for a modern, GW-focused review) is designed for scenarios where a known signal waveform and known noise background can be assumed, with the noise typically characterized as a stationary and Gaussian (but possibly colored) distribution It represents the optimal choice under these constraints in the Neyman–Pearson sense (Neyman and Pearson 1933) of maximizing detection probability at fixed false-alarm probability. In the LVK different pipelines implement the matched filter for CBC signals in real time (also called "online" mode) (Nitz et al. 2018; Cannon et al. 2021; Aubin 2021b; Chu et al. 2022). Many more implementations exist for "offline" analyses, where the data is reanalyzed at higher latency (also called "archival" searches), for both CBCs and CWs. In this review however, we will mostly focus on ML alternatives to this kind of approach.

When dealing with signals characterized by unknown waveforms, the requirements shift towards more generic algorithms capable of identifying signal excess over a background of noise, with coherence across multiple detectors valuable to take into account. One example of this kind of pipeline is coherent WaveBurst (Klimenko et al. 2008; Drago et al. 2021), based on wavelet transform. Another important class of algorithms is based on cross-correlation techniques (Dhurandhar et al. 2008), used mainly for unmodeled transients (bursts) and stochastic signals, but also for complicated cases of CWs such as those from Neutron Stars (NSs) in binary orbits.

We will not go further into the details of these existing pipelines in the rest of this review. Instead, our focus is to outline various solutions based on ML approaches that have been researched and implemented in the community. These solutions aim to enhance existing search pipelines, either by complementing them or by serving as potential new pipelines integrated into the standard framework.

Observations of transient signals from the first three observing runs have been reported in, so far, four releases of the Gravitational-Wave Transient Catalog (GWTC) (Abbott et al. 2019a, 2021c, 2023b, 2024a), all corresponding to CBCs. The full cumulative catalog is also available online at https://gwosc.org/eventapi/html/GWTC/. An overview of all LVK observational results, including more detailed papers on individual events as well as upper limits on other GW signal types, can be found at https://pnp.ligo.org/ppcomm/Papers.html and a live catalog of detection candidates from O4 and future runs is provided at https://gracedb.ligo.org/. Data releases of archival LVK data (Abbott et al. 2021e, 2023c) can be found in the Gravitational Wave Open Science Center, https://gwosc.org/, along with pointers to the software used in obtaining LVK results.

3 A brief overview of machine learning techniques

ML offers a diverse range of approaches for solving complex problems across numerous domains, each tailored to specific types of problems and data characteristics. For a general introduction to machine learning, the reader may consider reading Theobald (2017) or, with more of a focus on astronomy applications, Baron (2019); Sen et al. (2022); Smith and Geach (2023). Deep learning (Goodfellow et al. 2016) is a subfield of machine learning that focuses on training Artificial Neural Networks (ANNs) with multiple layers to learn complex patterns and representations from data. Deep learning algorithms automatically learn hierarchical representations of the data directly from raw inputs. This ability to automatically discover intricate, nonlinear patterns makes deep learning particularly well-suited for tasks involving large amounts of data, such as image and speech recognition, natural language processing, and reinforcement learning (Nielsen 2015).

The rise of ML and, in particular, deep learning methods has been closely linked with the use of highly-parallelized high-performance Graphical Processing Unit (GPU) hardware for general computation and data processing applications. Their ability to perform numerous calculations simultaneously allows for faster training times and the execution of sophisticated models that were previously impractical with traditional CPU-based systems. On the software side, ML applications in GW astronomy are often built on standard libraries from other fields, which we however do not review in detail here. The further embedding of GW applications into existing online computing infrastructures optimized for ML is also a promising approach, as discussed e.g. by Gunny et al. (2022).

Below, we present a concise overview of the primary approaches utilized in GW machine learning applications. The glossary of this article also collects the main definitions and references.

3.1 Supervised methods

Supervised learning involves training a model on a labeled dataset, where the input data is paired with corresponding output labels. The goal of supervised learning is to learn a mapping from input data to output labels, such that the algorithm can make accurate predictions on new, unseen data. Examples of supervised learning algorithms include linear regression, Decision Trees (Fürnkranz 2010), Random Forests (Breiman 2001), and Support Vector Machines Support Vector Machine (SVM) (Cristianini and Ricci 2008). A comparison among the different techniques for supervised methods is reported in Osisanwo et al. (2017). Deep learning neural network models like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) are also often used in supervised modes, though they can also form building blocks for unsupervised or reinforcement learning approaches. Many ML applications in GW science are based on supervised methods, which will be discussed in the following sections.

Neural networks and other supervised methods with explicit training stages can depend a lot, both in the ease and speed of training and in their eventual performance, on the design of the training data set. Besides general rules like ensuring that the training set is large enough and representative of (but statistically independent from) the eventual evaluation and application cases, specific tricks have been developed in the ML community to enhance training. For example, “curriculum learning” (Bengio et al. 2009) first presents the algorithm or model to be trained with an “easy” training set (e.g., in the GW contest, simulated data with high signal-to-noise ratios or with simple Gaussian noise only), and then moves onto another training stage with a second, more difficult set. More than two stages are also possible. This is, in principle, also applicable to the unsupervised methods discussed next. For another popular enhancement, data augmentation, see Sect. 3.5 below.

3.2 Unsupervised methods

Unsupervised learning involves training a model on an unlabeled dataset, where the model must learn the underlying structure or patterns in the data without explicit guidance. Unlike supervised learning, there are no explicit output labels provided during training. Instead, the model identifies relationships or clusters among the input data points. Common tasks in unsupervised learning include clustering, where the algorithm groups similar data points together, and dimensionality reduction, where the algorithm reduces the number of features while preserving the essential information. Examples of unsupervised learning algorithms include k-means clustering (Jin and Han 2010), hierarchical clustering, Principal Component Analysis (PCA) (Maćkiewicz and Ratajczak 1993), and auto-encoders (Li et al. 2023a).

3.3 Semi-supervised methods

Semi-supervised learning techniques (van Engelen and Hoos 2020) work with both labeled and unlabeled data for training. Its goal is to recover the information present in both labeled and unlabeled data to improve the performance of the learning algorithm. The availability of unlabeled data can be advantageous in scenarios where data labeling is expensive or time-consuming, as it allows the model to learn from a larger pool of examples. Semi-supervised learning algorithms aim to exploit the underlying structure or relationships within the data to make predictions on both labeled and unlabeled instances. One prevalent strategy in semi-supervised learning involves utilizing the unlabeled data to generate additional training examples or to regularize the learning process. Semi-supervised learning has applications in various domains, including natural language processing, computer vision, and speech recognition.

3.4 Reinforcement learning

Reinforcement Learning (RL) (Arulkumaran et al. 2017) involves training an agent to interact with an environment to achieve a specific goal. The agent receives feedback in the form of rewards or penalties based on its actions, and the goal is to learn a policy that maximizes cumulative reward over time. Unlike supervised and unsupervised learning, reinforcement learning is focused on learning through trial and error rather than explicit input–output mappings. Reinforcement Learning has applications in areas such as robotics, game playing, autonomous driving, and resource management. A reinforcement learning control system strategy for non-linear systems is discussed in Hwang et al. (2003), which could have applications for GW detector control (see Sect. 5.3).

3.5 Data augmentation

Data augmentation is not a specific kind of ML algorithm, but a technique used in various approaches to increase the diversity and size of a training dataset by applying various transformations to the existing data samples. The objective of data augmentation is to improve the robustness and generalization capability of ML models by exposing them to a wider range of variations in the input data. Data augmentation is particularly useful in scenarios where the training data set is limited or when the data distribution is unbalanced. By introducing variations to the training data, data augmentation helps prevent over-fitting (Ying 2019) and improves the model's ability to generalize to unseen data. Mumuni and Mumuni (2022) report a comprehensive review of data augmentation methods specifically tailored to computer vision domains, with a focus on recent and advanced techniques, including a comparative analysis of several state-of-the-art augmentation methods.

3.6 Simulation-based inference and neural posterior estimation

Estimating the parameters of GW detections, and other more general inference tasks such as those at a population level, are traditionally done by Bayes' theorem and stochastic sampling techniques (Jaynes 2003; Gregory 2005), requiring an explicit likelihood model for the data containing noise and signal contributions. Since realistic detector noise can be difficult to model (see Sect. 6.3) and signal models can be expensive to evaluate, or even too complicated to fully express, alternative likelihood-free inference schemes are attractive. One class of such alternatives is referred to as Simulation Based Inference (SBI), which inverts the usual approach of Bayesian inference: instead of evaluating a large number of models on each observation, large numbers of fake data realizations are generated in advance and then each observation is compared to this ensemble. One popular implementation is neural posterior estimation, where neural networks (often normalizing flows, and variational auto-encoders, which are designed to deal with continuous distributions such as needed for Bayesian posteriors) are trained to learn the mapping from data to a posterior distribution in parameter space and can then typically be evaluated extremely quickly for each new observation, as long as it falls within the training space. A brief overview of the SBI approach is given by Cranmer et al. (2020). For an early introduction of the ideas of neural posterior estimation, see e.g. Papamakarios and Murray (2016), though we discuss GW applications more concretely in Sect. 8.2.

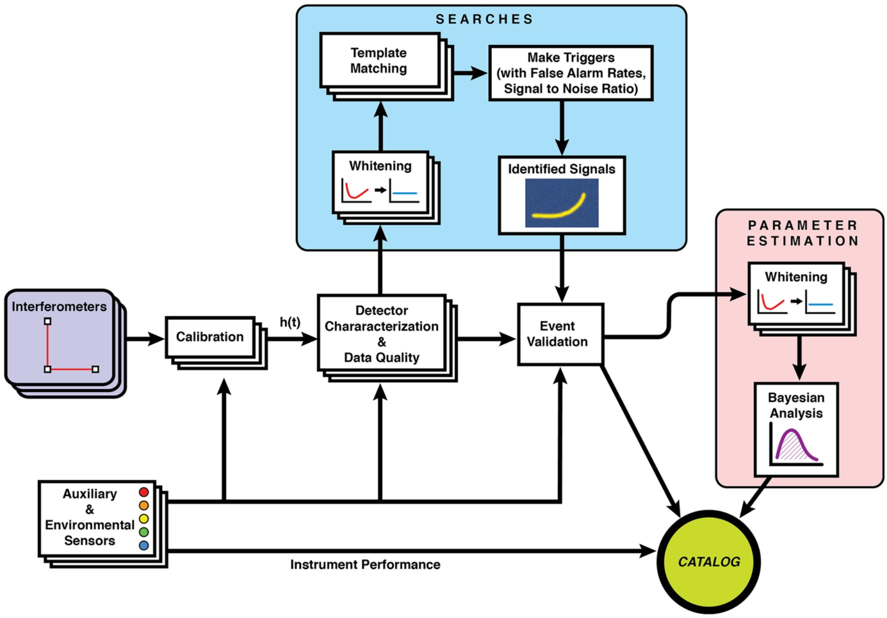


Fig. 2 Typical analysis workflow for the data from GW detectors. Image reproduced with permission from Abbott et al. (2020a), copyright by the author(s)

3.7 Explainable/interpretable machine learning

ML methods are often perceived as "black boxes", where the researcher applying a trained model has little insight into how it comes to a certain result given certain inputs, and sometimes the same may even be true for the developer who trained a neural network. Particularly in fundamental physics with its traditional emphasis on deep understanding of the underlying processes and the ability to forward-model many of the systems being studied, a real or perceived lack of interpretable algorithm behavior can be a hurdle to the adoption of ML solutions. A broad trend in the wider ML landscape are so-called explainable or interpretable algorithms and models. These can range from additional tools that allow to study the responses of networks trained in standard ways to novel architectures designed from the ground up to ease the understanding of their inner workings. See e.g. Murdoch et al. (2019); Linardatos et al. (2020) for a review and some clarifications on the related concepts and nomenclature.

4 Machine learning applications in the GW data analysis workflow

Figure 2 illustrates the standard GW data analysis workflow as outlined in Abbott et al. (2020a), delineating the principal areas involved. Our objective in this paper is to showcase the latest advancements in ML applications across the diverse domains depicted within the same figure. We aim to outline the ever-growing significance of ML methodologies in the GW data analysis framework.

As discussed in Sect. 2, the output from the detection photodiodes in GW detectors comprises a time series that may contain GW signals, but also many sources of instrumental and environmental noise. Alongside the primary channel (strain) which contains the GW signals, numerous other channels are acquired with varying sampling rates to facilitate detector operation. Some channels serve as control signals for machine operation, while others monitor environmental conditions. All of these channels contain valuable information that can be utilized for data quality checks and cleaning procedures.

Following an initial stage involving calibration, cleaning, and vetting through data quality checks, the data is prepared for detection algorithms. The approaches employed vary, as elaborated in Sect. 2. For the specific case of applying a matched filter, it is also necessary to input a template bank of signals generated in a parameter space suitable to cover the possible waveform parameters. After detecting the signal, a comprehensive parameter estimation procedure is initiated, including sky localization.

At each stage outlined above, there exists the opportunity to either adopt an equivalent ML approach or to utilize ML techniques to enhance the speed and efficiency of existing processes. This concept is illustrated in Fig. 3, where we have

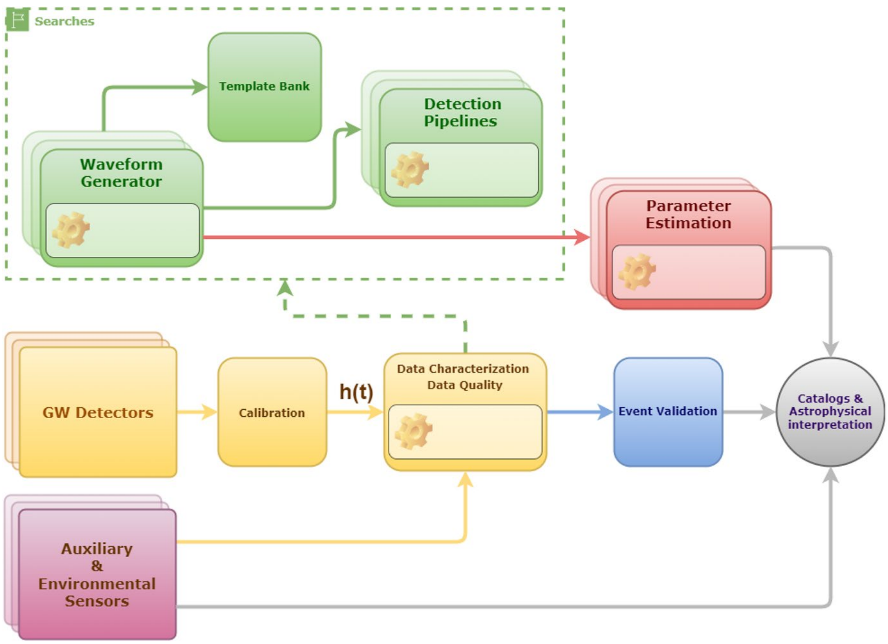


Fig. 3 Example of where machine learning fits in the workflow for GW detectors and data analysis. The gear in the picture indicates the parts of the data analysis chain where ML could be used. It is not the full picture covering all the ML-based solutions. Most of the kinds of ML applications studied will be described in the following sections of the paper

incorporated typical ML solutions that have already been explored in GW science. These ML solutions will be elaborated upon in greater detail in the subsequent sections of this paper. By integrating ML methods into our workflow, we aim to optimize various aspects of GW data analysis and enhance our ability to extract meaningful insights from the acquired data.

In this review article, our aim is not to show a detailed quantitative comparison with the standard techniques widely used in GW data analysis. We mainly aim to report a general overview of the state of the art of ML algorithms that have been studied and tested as alternatives or complementary to the techniques already in use.

5 Strategies for noise mitigation

The background noise in the instrument band of interest of a GW detector determines its sensitivity. Ideally, this background noise is Gaussian, stationary, and determined by the detector's design (Abbott et al. 2020a). For instance, the quantum noise of the laser light, the thermal noise of the mirror coatings and optic suspensions, the electronic and feedback control system designs, and the inevitable seismic noise all limit the background floor of current ground-based GW interferometric detectors (Aasi et al. 2015; Acernese et al. 2014; Abe et al. 2022). However, the noise floor of GW detectors is not actually Gaussian nor stationary in practice. Most noise sources that couple to the detector, whether they be environmental or instrumental, vary over various time scales (Nguyen et al. 2021). The detector may also experience non-linear coupling from noise sources, which can for example cause sidebands, i.e. frequencies that appear on both sides of a carrier frequency during modulation, carrying the actual information of the signal, at frequencies close to other known disturbances (Davis et al. 2021). These extra noise artifacts result in a decrease in a GW detector's duty cycle and in its design sensitivity at specific frequencies or times (Acernese et al. 2023a; Davis et al. 2021). Even if such artifacts are correctly identified, the simplest approach of dealing with them by excising certain time or frequency ranges from analysis will lead to a reduced duty cycle (fraction of usable data over the total run duration) or frequency coverage. Hence, more advanced mitigation strategies are highly valuable.

Among transient noise phenomena, shifts in the noise floor are usually referred to as "non-stationarities", while the term "glitches" refers to various types of excess noise that are more-or-less well-localized in the time domain. These have an impact particularly on searches for burst signals and CBCs because their presence increases the false alarm rate in both modeled and unmodeled searches (Abbott et al. 2016a, 2018a; Nitz 2018; Davis et al. 2020; Mozzon et al. 2020, 2022; Kumar et al. 2022). A glitch overlapping with a signal, or in close vicinity to it, can also significantly impact the accuracy of low-latency alerts to astronomer partners for EM follow-up (Macas et al. 2022) and the fidelity of parameter estimation, both in terms of sky localization and estimates of intrinsic parameters. The GW170817 BNS detection (Abbott et al. 2017c) is a well-known example, where an improved parameter estimation was obtained after subtracting the time-frequency wavelet reconstruction of an instrumental glitch from the LIGO-Livingston data (Fig. 4). Such instances

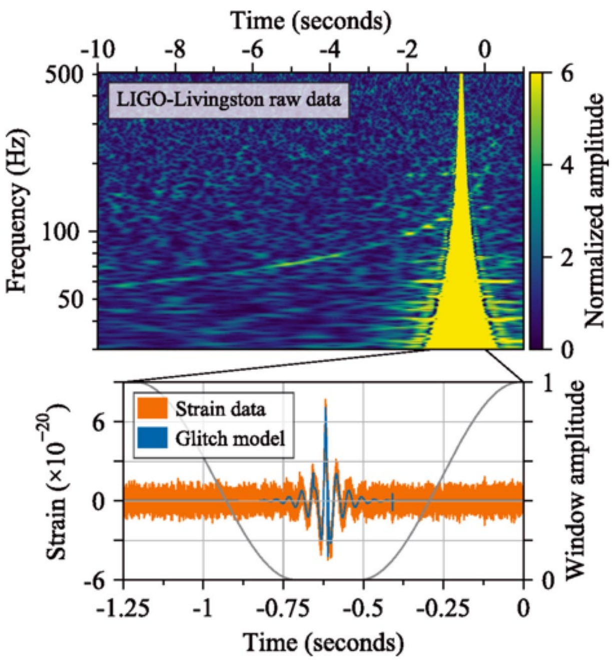


Fig. 4 Top panel: Time-frequency representation (Chatterji et al. 2004) of the LIGO-Livingston data at the time of the GW170817 binary neutron star merger. The time-frequency track of GW170817 shows the typical chirp-like shape. A loud glitch occurs 1.1 s before the coalescence time. Bottom panel: Strain data in the time domain (orange curve) band passed between 30 Hz and 2 kHz. To mitigate the glitch, the raw detector data were initially multiplied by an inverse Tukey window represented by the gray curve. A model of the glitch based on a wavelet reconstruction (blue curve) was later subtracted from the data to mitigate the glitch in the measurement of the source's properties. Image reproduced with permission from Abbott et al. (2017c); copyright by the author(s)

become more common as the detectors improve, reducing their noise background and increasing the rate of detectable astrophysical signals, but also uncovering new types of transient noise artifacts.

On the other hand, excess localized noise in the frequency domain, e.g., narrow spectral lines or other narrow-band features, are the main contaminants in searches for continuous GWs, long-lived GW transients, and the SGWB, where they can also massively increase the false-alarm rate if not adequately accounted for through advance mitigation or post-processing strategies.

For all these reasons, a critical step in any real-time and follow-up GW detection workflow is the understanding and mitigation of detector non-astrophysical excess noise in the instrument band of sensitivity (Abbott et al. 2016a). Hence, characterizing non-astrophysical noise, enhancing the quality of GW search data, and commissioning detectors are major areas of focus for the GW collaborations (Davis 2021; Acernese et al. 2023a; Klimenko et al. 2008). These tasks are all completed by the detector characterization team, which is part of the joint collaboration operation division. Here, spectral features and unwanted glitches that taint GW searches are recognized, categorized, and reduced by a collaborative effort between instrumentalists, commissioners, and data analysts.

The data from the GW detector output and numerous instrumental and environmental auxiliary data streams are typically mined to complete these tasks. To accomplish these tasks, GW researchers have created and applied a variety of signal processing techniques and algorithms over time (Slutsky et al. 2010; Davis et al. 2021; Acernese et al. 2023b). A few of the data quality tools are available online and are capable of rapidly assessing the interferometers' state for low-latency searches (Chaudhary et al. 2024). For follow-up with GW candidates and deeper searches, an alternative set of tools is utilized offline. The findings of these studies are then shared with data analysts operating GW searches, detector commissioners, and operators to help mitigate undesired non-astrophysical disturbances.

However, current data quality methods based on conventional signal processing techniques will probably prove inadequate for the tasks ahead due to the increase in detections of CBC and the discovery of GWs from other types of astrophysical sources. Investigating the use of sophisticated techniques based on computational learning theory as a complement to conventional signal processing methods is one way to enhance the way GW collaborations perform in the area of data quality.

Machine learning algorithms are effective instruments for identifying patterns and analyzing large volumes of data. They are made to carry out specified tasks and, through the use of adaptive techniques and iterative procedures, automatically enhance their performance. Furthermore, because models created to address one problem can be readily modified to address another, they are adaptable, robust, and portable to a variety of scenarios. Because of these features, machine learning techniques are ideal for developing novel approaches to non-astrophysical noise reduction (Cuoco 2021).

Under this framework, a crucial step towards implementing new techniques and improving GW detector operations is the creation of self-contained algorithms that can be incorporated into already-existing searches or noise investigation processes.

5.1 Noise characterization with detector strain data (transient and continuous)

Thus far, the majority of ML algorithm applications to the characterization of GW interferometric detector noise have concentrated on the identification and classification of glitches in the time domain. ML applications to spectral line characterization have mainly focused on noise line subtraction. These studies will be described in 5.4.

Developing and implementing algorithms for the identification and predictive modeling of detector noise is the ultimate goal of detector characterization. If the source of the excess noise is found, it might be possible to design software or hardware upgrades that remove it. Various methods can be used to accomplish this aim.

Most ML algorithms that are publicly accessible have been explored throughout the years, covering the primary categories outlined in Sect. 3. As a result, a substantial body of literature has been written on this topic (see Cuoco 2021; Benedetto

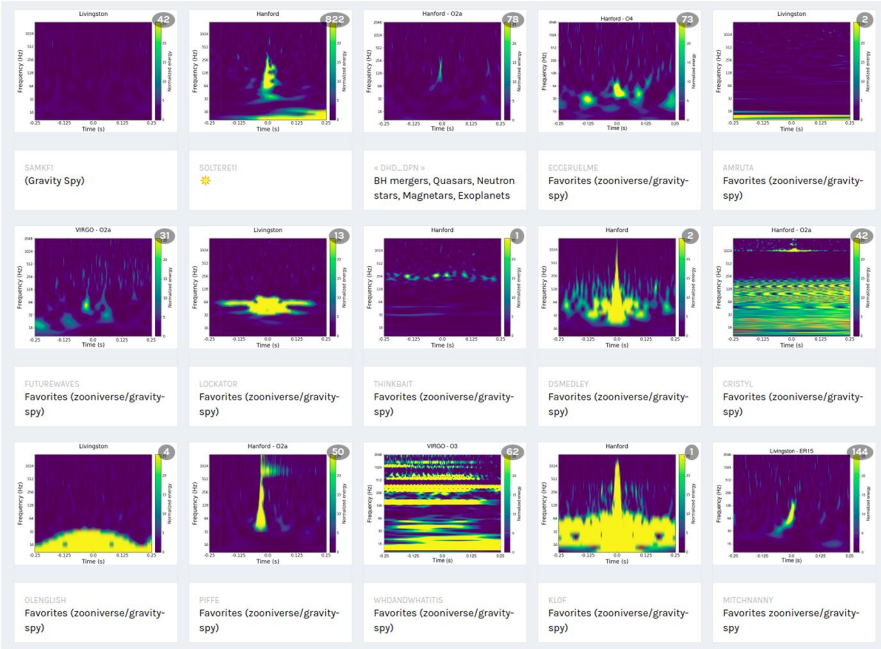


Fig. 5 A snapshot from the Gravity Spy website with a few examples of citizen science classifications of glitches. Retrieved February 20, 2024 from https://www.zooniverse.org/projects/zooniverse/gravity-spy/favorites

et al. 2023 and references therein). The classification of glitches in the detector output, as well as the separation of astrophysical signals from detector glitches, were the primary goals of early ML applications to detector characterization (Powell et al. 2015, 2017; Cuoco et al. 2017; Biswas et al. 2013; Kapadia et al. 2017). Several of these notable methods that have advanced to the point of being implemented in GW searches and/or helped characterize real interferometric data in various observing runs include Gravity Spy (Zevin et al. 2017), GWSkyNet (Cabero et al. 2020; Abbott et al. 2022d) and deep learning algorithms.

Gravity Spy (Zevin et al. 2017; Zevin et al. 2024; Wu et al. 2024; Bahaadini et al. 2017) is a project that combines GW science with machine learning and citizen science. Utilizing citizen scientists' voluntary efforts, Gravity Spy aims to categorize LIGO's glitches and produce an ever-expanding labeled data set (see Fig. 5) that can be used as input for machine learning algorithms (Glanzer et al. 2023). A similar effort, GWitchHunters, has been developed in the Virgo community, with citizens assisting in labeling glitch data sets (Razzano et al. 2023).

Time-frequency images, specifically Omega Scans (Chatterji et al. 2004), are used in the Gravity Spy framework to represent glitches. Volunteers manually label these images using a predetermined list of glitch classes (Jackson et al. 2020) and perform their own investigations. One of the useful tools for this is the Similarity Search, which finds similar images using distance in the feature space (Coughlin et al. 2019).

Gravity Spy employs a deep learning model with CNN layers, a Rectified Linear Unit (RELU) activation function, and a fully connected final layer to train the algorithm over the images. For glitches that do not fall into any of the established categories, a “None of the Above” class is supplied. This makes it possible for citizen scientists to identify new glitch classes (Soni et al. 2021). The machine learning algorithms are retrained to include these newly discovered glitch categories in the data set. As a result, the Gravity Spy product becomes a dynamic set that incorporates variations in the detectors’ noise characteristics over time.

Neural network algorithms are designed to extract features from two-dimensional matrices and use their features for classification purposes. Thus, like GravitySpy, the majority of neural network-based techniques rely on time-frequency transform images for the classification of glitches.

One of the first attempts at glitch classification using deep learning is described in Razzano and Cuoco (2018), where the authors present a classification pipeline utilizing CNNs to categorize glitches based on their time-frequency evolution, represented as images. This earlier application demonstrated that deep learning can accurately identify glitches, paving the way for real-time detector characterization and advanced algorithm implementation.

A recent application of deep learning to glitch classification was reported in Fernandes et al. (2023). Here, the Residual neural network (ResNet) architecture is used to classify glitches in both supervised and unsupervised modes. The supervised algorithm is directly trained on Gravity Spy public images with the Fastai library (Howard et al. 2024). In unsupervised mode, the algorithm is pre-trained with automatically generated labels before being fine-tuned with Gravity Spy labels.

In recent years, there has been a great deal of interest in developing complementary strategies to detection pipelines for discriminating GW signals from noise artifacts (Schäfer et al. 2023). This issue has been addressed using a variety of ML architectures, from Gaussian Process regression (Lopez et al. 2022a) and Random Forest (Shah et al. 2023) to Genetic Programming (Cavaglià et al. 2020) and deep learning (Andres-Carcasona et al. 2023; Chatterjee et al. 2023; Jadhav et al. 2023; Trovato et al. 2024; Baltus et al. 2021), and targeting both modeled and unmodeled GW sources as well as signals of varying durations (Boudart 2023; Boudart and Fays 2022; Skliris et al. 2020). See Sect. 7 for more discussion of search pipelines incorporating such techniques to increase robustness against noise artifacts.

Two promising recent examples of deep learning applications are SiGMa-Net (Choudhary et al. 2023) and GSpyNetTree (Álvarez-López et al. 2024; Álvarez-López 2023). Both these algorithms use CNN architectures and input from Gravity Spy to distinguish GW signals from noise artifacts.

SiGMa-Net uses sine-Gaussian projections as the deep learning neural network’s input to distinguish binary black hole signals from short-lived “blip” glitches for potential applications in low latency.

GSpyNetTree uses spectrograms with varying durations; the same input feature set as Gravity Spy. Based on a GW candidate’s estimated merger mass, these spectrograms are then sent to one of a set of classifiers with multi-label architecture, tuned to identify GWs and glitches of different characteristic durations (Jarov et al. 2023). The classifier returns a series of scores indicating the likelihood that the data contains a GW and/or noise artifacts. GSpyNetTree is currently used in the validation of LIGO-Virgo event candidates.

Beyond glitches and other time-domain non-stationarities, spectral lines are of concern to all GW searches, but particularly to those for persistent stochastic backgrounds or CW. Many line investigation tools have been developed (Covas et al. 2018; Davis et al. 2021; Accadia et al. 2012) that can then feed either into instrumental mitigation interventions or the creation of lists of affected frequencies that need to be vetoed in astrophysical searches. Computing cross-correlations or coherence measures with additional instrumental and environmental monitoring channels is often crucial for safe line identification, as the methods should not falsely dismiss true astrophysical narrow-band signals like CWs. The NoEMI (Noise Frequency Event Miner) framework (Accadia 2012) was developed for Virgo detector characterization. It automatically monitors Fourier-transformed data for spectral features and creates a database of identified features, but does not include advanced ML techniques. Most tools developed on the LIGO side (Covas et al. 2018; Davis et al. 2021) rely heavily on human interaction and visual inspection. One exception is the CNN implemented by Bayley et al. (2020) for three-way candidate classification as background noise, spectral lines or astrophysical CWs in the Officially not an acronym but can be assumed to stand for Snakes On A Plane (SOAP) pipeline (Bayley et al. 2019), discussed further in Sects. 7.4 and 8.3.

5.2 Noise characterization with auxiliary channels

All the above implementations discussed in the previous section have as a common denominator the classification of short-lived glitches (either time series or time-frequency transforms) from the detector's main output that may impact burst or CBC searches.

Although the upstream classification of glitches in the detector output can provide some insight into their origins and relationships to the environment and the instrument, this process rarely makes it possible to identify how these glitches are coupled to the different detector components and ultimately come up with solutions to remove them. Utilizing the data supplied by auxiliary channels monitoring the different detector subsystems is the obvious next step (Fig. 6).

Different ML algorithms have been investigated to uncover correlations between the upstream interferometer output and auxiliary channels. Again, investigations have used a variety of algorithms, from tree-based classifiers to neural network architectures, for real-time or offline identification of excess noise.

iDQ (Essick et al. 2020a) is a supervised learning algorithm that can autonomously identify noise artifacts in GW detectors in real time by leveraging data from thousands of detector auxiliary data streams. During the first four advanced-detector observing runs, iDQ has been running in real-time and has produced probabilistic statements on the presence of excess noise in LIGO data. iDQ uses wavelet-based extractors to generate feature tables from auxiliary channels. Different supervised classifier models are then applied to these high-dimensional representations of the detector's state to evaluate the probability of observing a

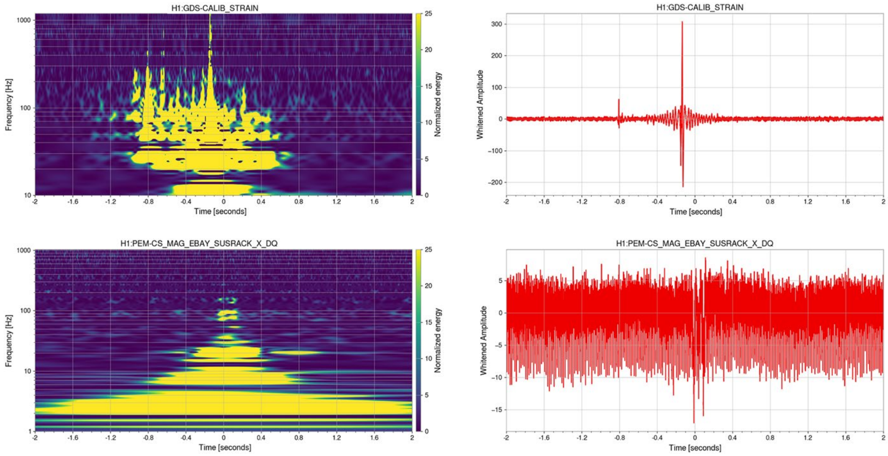


Fig. 6 Example of a glitch appearing in the main output of the LIGO-Hanford detector (`H1:GDS_CALIB_STRAIN`) as well as in one of the environmental magnetometer auxiliary channel (`PEM-CS_MAG_EBAY_SUSRACK_X_DQ`). The left panels show Omega Scan (Chatterji et al. 2004) representations of the glitch. The right panels are the corresponding whitened time series. The plots were obtained with the *GWDetChar* Python package (Urban and Macleod 2023). *GWDetChar* is distributed under the GNU General Public License, Copyright 2023, Alex Urban, Duncan Macleod

specific instance of excess noise. The classifiers are regularly retrained to detect excess noise without human involvement. Supporting multiple modes of operation and accommodating any supervised learning algorithm that works with tabular data are two of iDQ's key advantages.

A significant amount of work has gone into creating offline, on-demand techniques for the identification and characterization of glitches in real time, in addition to iDQ and other online algorithms. For the sake of brevity, we will just describe a few examples of methods developed over the past decade.

The first use of an ML algorithm for offline noise excess identification with auxiliary detector channels dates back to the initial GW detector era (Biswas et al. 2013). ANN, SVM, and Random Forest classifiers were used to identify and remove noise artifacts during four weeks of LIGO's fourth science run and one week of LIGO's sixth science run, demonstrating the feasibility of using ML for the detection of instrumental and environmental excess glitches with auxiliary channels.

Subsequent studies examined ready-to-use algorithms for the identification and classification of excess noise. In this case, having straightforward, adaptable algorithms at hand is essential so that new noise artifacts in the interferometer data can be quickly and easily addressed. One of the desired features of this approach is the ability to train the algorithm with small datasets.

Examples of ML algorithms to identify the origin of the noise artifacts and infer the relevant mechanical couplings in the detector were presented in Cavaglià et al. (2018) and Colgan et al. (2020). In these methods, event trigger generators operating on auxiliary channels provide input to ML binary classification algorithms like

Random Forests, Genetic Programming, and logistic regression to either rank the channels according to their correlation to the GW channel (Cavaglià et al. 2018) or produce a probability estimate to classify data periods as glitchy or clean (Colgan et al. 2020). In the former approach, several instances of classifiers are run with a fixed number of estimators, and the channels with importance below a pre-defined threshold are removed iteratively from the results. In the latter approach, a predictive model is trained by iteratively minimizing the residual error between predicted class probability and ground truth via gradient descent.

Unsupervised ML methods have recently been used to learn the underlying distribution of glitches. Unsupervised algorithms have the advantage of not making prior assumptions about data distribution. Catalogs of glitches can be constructed using tensor and matrix factorization techniques (Gurav et al. 2022). Deep-learning methods, such as auto-encoders, can be used to find anomalous time periods that deviate significantly from the general trend as they can discover structures and patterns in unlabeled datasets. Their performance is typically evaluated by comparing their output to that of supervised classifiers, which serve as the benchmark. For example, the unsupervised algorithm in Laguarta et al. (2024) is benchmarked against Gravity Spy high-confidence classifications. In that case, the information from safe auxiliary channel time series is first encoded in their fractal dimension (Cavaglià 2022) to reduce the dimensionality of the data set. Then, similar to neural network algorithms acting on time-frequency transforms, a convolutional auto-encoder algorithm is applied to a "time-fractalgram" to identify the anomalous periods.

As detectors evolve and become more sensitive, the ability to characterize their noise in real time will become increasingly important. In this context, it is expected that machine learning methods, particularly unsupervised methods, will continue to gain traction as tools for the noise characterization of detectors. These methods are highly general and are likely to be used in the characterization of the upcoming generation of GW detectors.

5.3 Interferometer control

One area of experimental GW physics where machine learning might be useful is detector control. Although the detector is intrinsically nonlinear, most detector control techniques rely on linear controllers. Machine learning algorithms may be able to approximate instrumental nonlinear behavior around the planned mode of operation.

Deep learning approaches have recently been applied to the problem of LIGO lock acquisition (Ma and Vajente 2024) and lock loss prediction (Coughlin et al. 2017; Biswas et al. 2020). Interferometer lock is usually obtained by controlling the detector's longitudinal translational degrees of freedom (Staley et al. 2014). This requires knowing the state of the mirrors and then making use of that knowledge to drive their motion to the operational point using an appropriate model. This method has traditionally been handled with case-by-case procedures that are difficult to scale to more complicated systems. Lock acquisition can take a few minutes to tens of minutes due to the variability of initial boundary conditions.

A Gated Recurrent Unit (GRU) was used in Ma and Vajente (2024) to provide an accurate non-linear state assessment of LIGO's mirror locations. The approach is precise enough, according to simulations, to allow quick lock acquisition of the interferometer's power-recycled cavity. This approach has two advantages: it can obtain a detector lock without requiring an expert's understanding of the instrument, and it may be scalable to other detector designs. Additional hardware testing is planned to validate the simulated results.

Noise reduction by machine learning non-linear control is another use of machine learning techniques that has been investigated. The complexity of the mathematical equations required in modeling the system typically hampers detector non-linear control. As a result, only a few non-linear systems can be analytically characterized. This could be avoided with neural networks. Noise reduction via detector control is still in its early stages. Proof-of-concept studies are currently being conducted at the LIGO laboratories on simple setups such as seismometers used to measure seismic motion.

5.4 Methods for denoising

The removal of excess noise is the next desirable step in the GW detection workflow after noise identification and characterization. Machine learning techniques can help with this task by creating algorithms for modeling and removing non-astrophysical noise.

Machine learning algorithms may be especially effective at removing instrumental and technical noise that couples to the detector in nonlinear or nonstationary ways without previous knowledge of the physical mechanisms of the noise. Because the majority of excess noise in the interferometer's output does not always result from linear couplings, standard signal processing techniques such as Wiener filtering may be incapable of removing this type of noise. Because of machine learning's ability to detect nonlinear patterns in data, it may be possible to develop machine learning-based "transfer functions" for the nonlinear components of excess noise. The algorithm can then be used to subtract those nonlinear couplings from the output data, thereby reducing the noise floor of the detector.

Machine learning-based denoising methods fall into two categories: methods for removing persistent noise, such as spectral lines like the 60 Hz line, and methods for removing glitches, either to reduce search backgrounds or to improve GW signal parameter estimation.

5.4.1 Algorithms for denoising of persistent noise

DeepClean (Ormiston et al. 2020) and NonSENS are the two primary algorithms that have been developed for line noise subtraction of GW interferometers.

DeepClean (Ormiston et al. 2020) employs a one-dimensional CNN algorithm that takes the detector auxiliary channels as input and produces an estimate of the

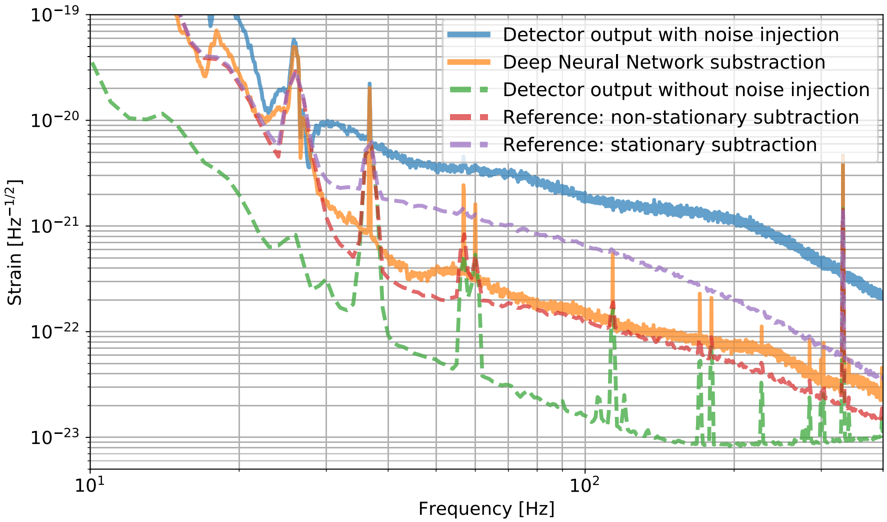


Fig. 7 Noise subtraction of persistent noise with the NonSENS algorithm (Vajente et al. 2020). The curves show a comparison between the Deep Neural Network-based subtraction and the stationary noise subtraction. Image reproduced with permission from Vajente et al. (2020), copyright by APS

excess noise in the GW strain data, which can then be filtered out. To deal with non stationary noise couplings, the algorithm is designed to be easily retrained on time scales smaller than the duration of the analyzed data. On a standard GPU, training on 300–1024 s of training data takes roughly 2-6 min (including data preprocessing). After training the data, the inference process takes a few seconds. This makes the algorithm suitable for use in both offline and real-time subtraction. DeepClean was tested on data collected by the LIGO detectors during their second and third observation runs, and it was shown to be capable of removing broadband beam jitter noise as well as the 60 Hz linear coupling and its sidebands (Saleem et al. 2024). A similar, CNN-based approach has been used in Yu and Adhikari (2022) to mitigate noise in the aLIGO angular control system, one of the major noise sources limiting the sensitivity of the detector in the sub-30 Hz band.

NonSENS (NON-Stationary Estimation of Noise Subtraction) (Vajente et al. 2020), like DeepClean, is a Deep Neural Networks-based algorithm designed to characterize non-stationary noise couplings in auxiliary witness data streams and perform time-domain noise subtraction in the target detector's strain (Fig. 7). The algorithm can model noise coupling modulations sensed by slowly varying witness sensors and applies to both linear and stationary couplings. The algorithm determines the best Infinite Impulse Response (IIR) filters to use for subtraction in the time domain. So far, it has been used in the third observing run to subtract the 60 Hz power line and sidebands, LIGO's Alignment Sensing and Control (ASC) dither lines, and ASC and Length Sensing and Control (LSC) control noise. After training a noise subtraction model, current NonSENS implementations can either generate subtracted frame file data with a script that runs on

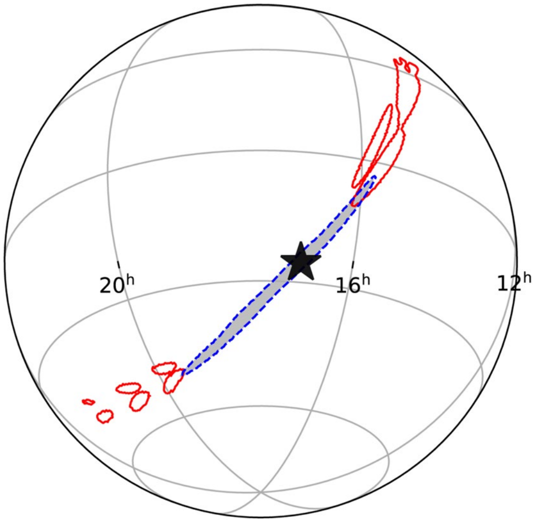


Fig. 8 The 90% sky localization error region of a simulated BBH signal in a two-detector Advanced LIGO network (gray region). The black star indicates the true location of the injected signal. The red empty contours show the localization area when a 130 ms gate is applied 30 ms before the geocentric merger time in one of the two detectors. The dashed-blue contour indicates the signal localization area after the missing portion of the signal has been reconstructed with NNETFIX. Image reproduced with permission from Mogushi et al. (2021), copyright by the author(s)

low-latency data or use LIGO's frontend model to subtract noise in real time. During the first six months of Advanced LIGO's O3 run, nonstationary subtraction of the 60 Hz line and its sidebands effectively enhanced astrophysical sensitivity, extending the detector's range for high-mass binary black hole systems by 25 Mpc and increasing the observable volume by 11%.

5.4.2 Algorithms for signal denoising

The idea behind machine learning methods for glitch subtraction is to train the algorithm on a set of glitches in the interferometer's main output or auxiliary channels to reconstruct the excess noise in strain data.

Dictionary Learning (DL) (Torres-Forné et al. 2020) and ANNs (Mogushi et al. 2021) were two of the earliest machine learning techniques that were suggested for removing glitches from GW signals. A similar approach based on a recurrent neural net denoising auto-encoder was reported in Wei and Huerta (2020)

To represent the input data, the DL approach (Dumitrescu and Irofti 2018) uses a linear combination of basic elements known as atoms. Data are mathematically represented as a linear combination of a small set of basis functions (atoms) in a higher-dimensional space (the dictionary). The training process is optimized to identify the most effective dictionary that reduces reconstruction error while preserving sparsity. DL has proven effective in a range of applications including image and signal processing, as well as data reduction.

In Torres-Forné et al. (2020), DL is used to identify and subtract "Blip" glitches, which are one of the most prevalent short-lived glitches detected in LIGO detector data and can interfere with transient GW searches. In most of the detector frequency bands, the approach can remove the noise contribution of blip glitches.

NNETFIX (Mogushi et al. 2021) is an ANN technique used to reconstruct data with a binary black hole merging signal overlapping with a glitch as if the latter were not present. The algorithm is trained to predict the fraction of the signal that must be gated owing to the existence of excess noise. The neural network's output is a full-time series of the signal, which may subsequently be utilized as input to other algorithms to generate sky localization maps or parameter estimates. Figure 8 illustrates a comparison of a sky localization error region obtained using NNETFIX reconstructed data to one obtained with (incomplete) gated data.

Bacon et al. (2023) recently investigated the use of a convolutional neural network in an encoder-decoder architecture to denoise merging binary black hole signals. The method is trained and evaluated on a population of several thousand synthetic astrophysical signals injected into interferometric noise, as well as real events from the first two LIGO-Virgo observation runs. The denoised output, like NNETFIX, might be used as an input for parameter estimate pipelines.

6 Modeling and data generation

Many GW data analysis methods, especially for CBCs and CWs, rely on matched filtering of the detector data against predicted waveform templates. Modeling of astrophysical sources is an important contribution to GW astrophysics, both to provide these waveform models and more generally to understand the physical behavior of these extreme physical systems, which can be useful even in guiding the design of template-free searches and in the astrophysical interpretation of any analysis results.

Due to the often complex physics of GW sources, conventional modeling approaches tend to combine a large array of analytical approximations and numerical methods. ML methods are making inroads in these research areas, but with a few notable exceptions, they still have many challenges to overcome to become competitive. We will split the discussion of these efforts into first source modeling on its own, and then specific GW signal models.

Another nontrivial problem is the realistic simulation of detector noise, which to first approximation is colored Gaussian noise, but in reality has many non-stationary aspects and contains various types of artifacts. See, again, Abbott et al. (2020a) for a general summary of GW detector noise characteristics. Here, traditional approaches have been very limited, and ML solutions are already considered the state of the art. Generative noise modeling is also closely related to the noise mitigation and data characterization tasks discussed in Sect. 5, as the ability to simulate large sets of realistic noise samples is often a requirement for training those tools.

6.1 Modeling of astrophysical sources

GW sources span a broad range of astrophysical systems, even if just focusing on the sensitive band of current detectors: CBCs, individual NSs, Core-Collapse

SuperNovas (CCSNs), exotic sources such as cosmic strings or dark matter condensates, and early-universe physics.

We will first focus on works regarding the modeling of the only type of GW signals detected so far by the LVK network, CBCs.[2] This requires solving the orbital dynamics of close binaries in the strong-field dynamic regime of general relativity, including gravitational back-reaction. The nominally "simplest", yet already enormously challenging case are BBHs, which are pure gravity systems. On the other hand, BNSs and NSBHs additionally require the modeling of matter and EM effects. Analytic approximations can be obtained for the inspiral phase from post-Newtonian theory, as well as the self-force and effective one-body approaches. See Blanchet (2024); Barack and Pound (2019); Damour and Nagar (2016) for reviews of these three frameworks, respectively. On the other hand, the more complicated merger and postmerger phases require numerical simulations: pure numerical relativity (NR) for BBHs, and general relativistic magnetohydrodynamics (GRMHD) when NSs are involved. See e.g. Shibata (2016) for a textbook treatment and Duez and Zlochower (2019) for a review of this field. Adequately covering the full parameter space of generic BBHs (especially when including spin precession and orbital eccentricity) with high-fidelity NR simulations remains a formidable challenge, and even more so for BNSs and NSBHs.

Due to the physical and numerical complexity of these systems, on the one hand ML approaches appear very promising as they could allow us to work around limitations of the classical approaches, or at least to reduce the amount of algorithmic and initial data fine-tuning needed. On the other hand, decades of progress on the established methods mean that ML has a high standard to reach to be a valid alternative, and the more abstract and intuitive aspects of a trained physicist's domain knowledge can prove quite difficult to encode in a way that benefits an algorithmic learning scheme.

One class of approaches that have received attention across the broader physics community in recent years are Physics-Informed Neural Networks (PINNs) (Raissi et al. 2017; Markidis 2021) and the closely related physics-informed neural operators (PINOs) (Rosofsky et al. 2023). In the most general sense, this covers neural networks used to solve any type of differential equations that describe a physical law. The major advantage compared to traditional differential equation solvers lies in using the power of automatic differentiation, which is available in highly optimized form in all standard ML packages, as an alternative to other numerical differentiation schemes. Training may work in supervised or unsupervised modes. A common setup is to construct the PINN out of two building blocks, a "surrogate network" that provides solutions to the equation and a "residual network" that evaluates the cost function associated with deviations from these solutions, see Fig. 9. For more detailed overviews of the concepts and sub-classes, see Raissi et al. (2017); Markidis (2021); Rosofsky et al. (2023).

[2] Evidence has also been found for a stochastic GW background – see Agazie et al. (2024) and references therein – but through the very different approach of pulsar timing arrays, which we do not cover in detail in this review.

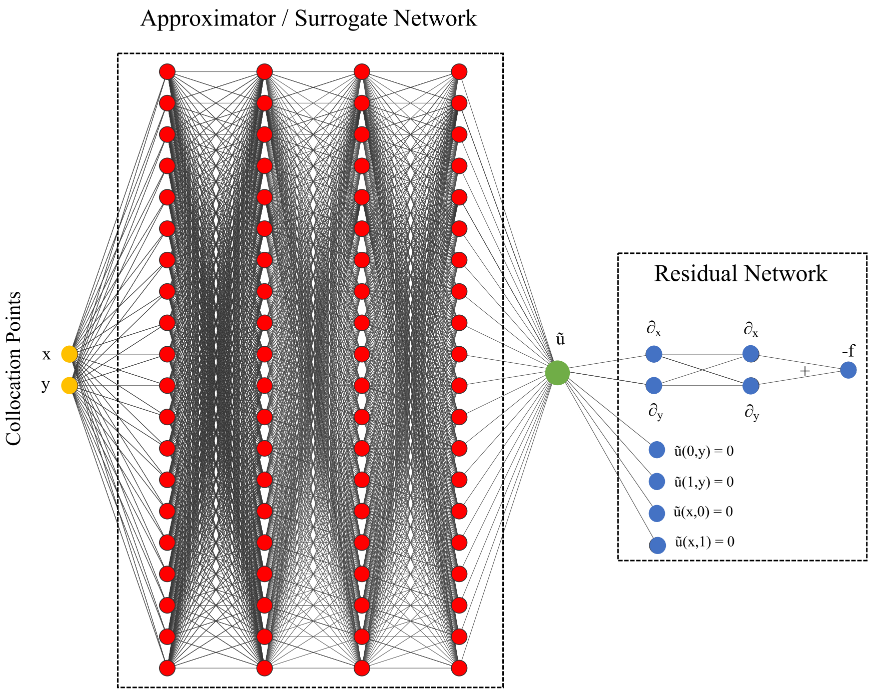


Fig. 9 Example of the common two-block layout for a PINN. The approximator/surrogate network produces approximate solutions for the differential equation under study, with the cost function necessary for its training evaluated by the residual network. Image reproduced with permission from Markidis (2021), copyright by the author(s)

The first applications of PINNs with more or less direct relevance to GW astrophysics include Cornell et al. (2022); Patel et al. (2024) for quasi-normal modes of non-rotating black holes, Luna et al. (2023) for the Teukolsky equation (linear perturbations of the spinning Kerr metric), Dieselhorst et al. (2021) for relativistic hydrodynamics (without gravity or EM fields), Rosofsky and Huerta (2023) for magnetohydrodynamics (without gravity), Auddy et al. (2024) for Newtonian self-gravitating hydrodynamic systems, Urbán et al. (2023); Stefanou et al. (2023) for pulsar magnetospheres and Li et al. (2023b) for obtaining the Schwarzschild metric from the Einstein equations. The promise of PINNs is that they could eventually solve broader families of such differential equations for a variety of physical systems more efficiently, more robustly, or in cases where no traditional solution is known. But in practice, these examples are mostly still proofs of concept applied to cases for which long-established solution methods already exist. Applications to more complicated GW-emitting systems without known solutions are still to be demonstrated.

Besides PINNs, other ML methods can be used for emulating the solutions to differential equations. For example, Reed et al. (2024) studied neural networks, Gaussian Process and a reduced-basis method for the Tolman–Oppenheimer–Volkoff equation describing neutron stars. Yet another different approach was taken in another proof-of-concept study (Keith et al. 2021) demonstrating the concept of "inverse modeling", where real data is used as the main input to find an appropriate physical model. The generic dynamics of BBH systems were phrased as a hyper-model of possible differential equations, parameterized via feed-forward neural networks, which are then trained on observed GW data.

ML can also be used as a tool to improve NR codes and catalogs. Anomaly detection in NR catalogs was considered in Pereira and Sturani (2024), using a U-Net network (Ronneberger et al. 2015) to identify types of data quality issues in NR waveforms. In Ferguson (2023), a deep neural network (15 layers) was used to optimize the placement of new simulations based on mismatches between the entries of an existing catalog. The same goal was pursued in Doctor et al. (2017) based on where a new simulation would most reduce the uncertainties of a Gaussian Process surrogate waveform model (see next subsection). Another fruitful approach could be to use ML tools to improve internal aspects of NR simulation codes, such as initial data generation or grid setups. But to the knowledge of the authors, no such works had been published as of the writing of this article.

One of the key aspects of NS physics, the equation of state of dense nuclear matter (Lattimer 2021) (of relevance both to CBC and CW studies), can – besides many more classical interpolation approaches – also be modeled or inferred from observational data with ML methods. Many such works have been published following an initial study by Fujimoto et al. (2018) which used a 5-layer deep feed-forward network trained to infer the functional dependency from mock sets of mass–radius measurement. These works have used a wide variety of algorithms, with varying emphasis on the modeling or inference aspects. For studies focusing on combining GW and EM observations in a multi-messenger approach, see also Sect. 8.4. To highlight here just two more examples of how the equation of state can be modelled in a flexible way by ML approaches, the influential work by Essick et al. (2020b) used a non-parametric Gaussian process model, while Han et al. (2023) trained a predictive variational auto-encoder as a general representation of the equation of state. This is a very active and rapidly evolving field, and one where ML-based or at least ML-adjacent methods (not all practitioners in the field agree whether Gaussian processes should be considered ML) are already playing a highly significant role. The flexibility of ML approaches in this context also helps to extend the formalism to neutron stars in theories beyond general relativity, as for example done with neural network surrogates in Liodis et al. (2024); Biswas et al. (2024); Stergioulas (2024) which can help to efficiently analyze the higher-dimensional parameter space of neutron star properties and alternative gravity theories.

For GW sources beyond CBCs, the physics can be even more complicated and poorly understood, e.g. for CCSNs. Various ML approaches have been explored for supernova modeling in general, and especially for the turbulent aspects of the involved stellar hydrodynamics (Karpov et al. 2021, 2022), as well as for the prediction of EM lightcurves (Demianenko et al. 2023).

Furthermore, ML methods can be helpful for simulating complex astrophysical source populations, and there is fruitful interaction between pure simulation methods and SBI approaches. Not many dedicated ML-based works on population simulations alone exist yet in GW astronomy, but similar approaches feed directly into the inference of source populations from GW observations, for which see Sect. 8.5.

6.2 Modeling of GW signals

The GW signal models needed for matched filter methods, and many other data analysis tasks, have to be based on an understanding of astrophysical sources. They can either be based purely on numerical simulations, purely on analytical work, or combine both kinds of inputs. Simple expressions are typically used for CWs – Taylor expansions, see the general CW review of Riles (2023) – and CW-like long-duration transients – e.g power laws (Lasky et al. 2017) or piece-wise expressions (Grace et al. 2023) for long-lived BNS remnants. For CBCs the signals are more complicated. A basic introduction and review of waveform modeling for BBHs is given in Schmidt (2020) and a broader review of its history, current state and open challenges is given in the Laser Interferometer Space Antenna (LISA) collaboration's white paper (Afshordi et al. 2023). While the latter focuses on the signals detectable at the mHz frequencies where LISA will be sensitive, much lower than for ground-based interferometers, it also covers many aspects relevant to the LVK science case. However, some aspects of waveform modeling are unique to the LVK band, for example the matter effects in the late inspiral, merger and post-merger phases of binaries involving neutron stars. For the BNS and NSBH cases, respectively, such effects and associated modeling approaches are reviewed in Dietrich et al. (2021) and Kyutoku et al. (2021).

For CBCs specifically, the traditional modeling approaches for full inspiral-merger-ringdown waveforms have long combined analytical approximations with NR simulation results. A key tool in constructing these models are fitting (regression) methods. such as the one developed in Jiménez-Forteza et al. (2017); Keitel et al. (2017) for the fourth generation of the "IMRPhenom" model family (Pratten et al. 2020, and other works building on it), or as described for the latest "SEOBNR" model (Ramos-Buades et al. 2023) in Pompili et al. (2023) and for the "TEOBResumS" model in Nagar (2018). Regression methods in this context have also been compared quantitatively in Setyawati et al. (2020), including both traditional interpolation and fitting schemes (e.g. least squares) as well as two ML frameworks: Gaussian Processes and neural networks. Especially for EOBNR models, since these are typically computationally more expensive than IMRPhenom models, reduced-order-modeling based on Singular Value Decomposition (SVD) has often been used as an intermediate step between the initial calibrated model and practical applications in GW searches and PE, starting from Pürrer (2014, 2016).

These approaches have been joined by a more strongly data-driven approach to waveform modeling, the NRSurrogate model family (see, e.g., Field et al. 2014 for the initial work and Varma et al. 2019a for the "NRSur7dq4" model most often used in data analysis up to now). These use a variety of techniques to construct a reduced basis that is sufficient to interpolate an input set of waveforms from other methods at discrete parameter-space points for evaluation at any other point within the fitted domain. Initially, mainly traditional parametric fits and spline interpolation (e.g. in Blackman et al. 2017a, b) were used. However, Varma et al. (2019c) introduced a surrogate for the BBH merger remnant properties based on Gaussian Process regression (Rasmussen and Williams 2006), which is considered by many (though not universally) as a ML technique. This remnant surrogate then served as an additional ingredient to the full precessing waveform surrogate of Varma et al. (2019a). Other works that have used a pure Gaussian Process approach for fitting and interpolation include Doctor et al. (2017) who used spin-aligned IMRPhenomD waveforms (Husa et al. 2016; Khan et al. 2016) as the input, and Williams et al. (2020); Khan (2024) who both applied a similar approach to constructing fully precessing NR surrogates. An example from Williams et al. (2020) is shown in Fig. 10, illustrating the probabilistic nature of a Gaussian process model but also the level of match achieved with NR and other models. As an added bonus, Gaussian process regression also provides uncertainty estimates on the waveforms, which can then be marginalized over in PE (Moore and Gair 2014; Moore et al. 2016; Liu et al. 2023) for more robust results.

Initial studies have also considered neural networks to further accelerate surrogate models. Fragkouli et al. (2023) have used a 4-layer neural network for finding the coefficients in the parameterized interpolation scheme from Field et al. (2014). On the other hand, Nousi et al. (2022) have again followed the basic surrogate approach from Field et al. (2014) but used auto-encoders. They noticed a “spiral” pattern in the dependence of fitting coefficients on the mass ratio, which was exploited via the autoencoder’s differentiable transformation from input to output parameters for a faster and more precise regression of the fitting coefficients. See

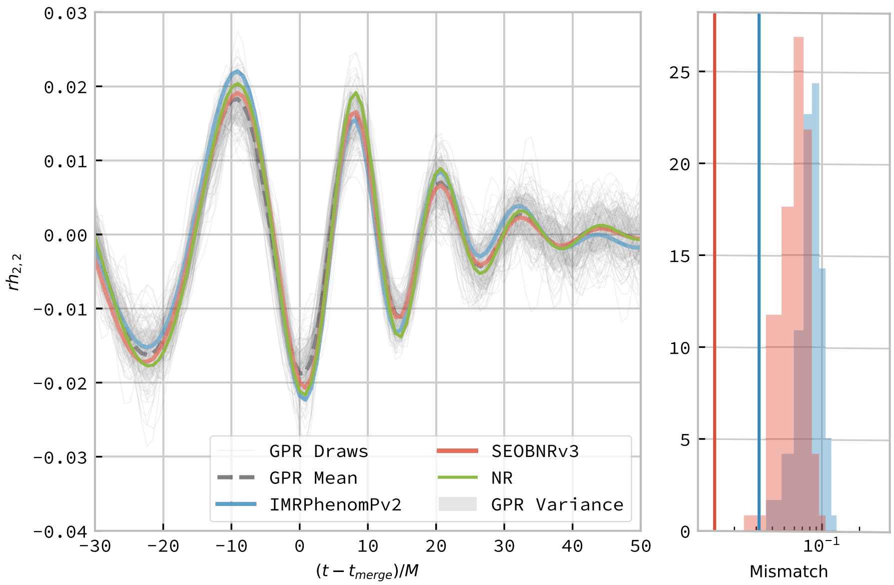


Fig. 10 Example of a Gaussian Process waveform model, for a non-spinning binary, illustrating the variance over 100 draws from the GP and a comparison with full NR and two other waveform models. Image reproduced with permission from Williams et al. (2020), copyright by APS

also Stergioulas (2024) for a summary of these developments. However, neither of these neural-accelerated surrogates has found practical adoption yet, and it remains to be seen whether these or similar techniques will become an important ingredient of future waveform model generations.

Besides full waveform models, surrogates are also available to predict the remnant properties (final mass and spin, kick velocity) of BBH mergers (Varma et al. 2019c; Islam et al. 2023) and their peak luminosity (Taylor and Varma 2020; Islam et al. 2023). These four works all use Gaussian Process regression. An independent approach to ML modeling of BBH remnant properties was introduced by Haegel and Husa (2020), using a four-layer neural network, with the eventual aim of improving the parameter-space fitting in "IMRPhenom" waveform models..

ML waveform models have also been trained on top of other inspiral-merger-ringdown models, with the main goal of providing for accelerated evaluation. The GP approach mentioned above for NR simulation placement (Doctor et al. 2017) used IMRPhenomD waveforms (Husa et al. 2016; Khan et al. 2016) as a proof of concept. We provide here a representative, but not necessarily exhaustive, list of other combinations of architectures and input waveforms that have been the subject of at least proof-of-concept studies: in Khan and Green (2021), a fully-connected neural network was trained on SEOBNRv4 (Bohé et al. 2017) waveforms, and Lee et al. (2021) adapted a deep learning model previously developed for natural language processing to emulate the same waveform model. SEOBNRv4 and TEOBResumS (Nagar et al. 2018) waveforms were used in Schmidt et al. (2021) with a "mixture of experts" (Jacobs et al. 1991) approach, where the training is on the coefficients of a weighted combination of a number of linear regression functions. in Thomas et al. (2022) SEOBNR4PHM waveforms (Ossokine 2020) were used to train fully-connected neural networks. A transformer network (Vaswani et al. 2017) was built in Khan et al. (2022) for the NRHybSur3dq8 surrogate model (Varma et al. 2019b). In the future, ML-accelerated models like these could be used for ML-accelerated Bayesian parameter estimation as discussed in Sect. 8.2. However, for now, most applications rely instead on direct GPU acceleration of the original waveform models, see e.g. Edwards et al. (2024).

At the interface of waveform modeling and data analysis, in Wong et al. (2020) explicit reproduction of the full waveform was skipped, and instead a fully-connected network was trained to reproduce optimal Signal-to-Noise Ratios (SNRs) as given by the IMRPhenomD (Husa et al. 2016; Khan et al. 2016) and SEOBNRv4 models. This differs from signal detection methods, as discussed below in Sect. 7.1, in that optimal SNRs do not take into account a particular data realization, but solely depend on the source parameters and a reference PSD for a detector.

Other areas in which waveform modeling faces challenges in physical and numerical complexity are for example GW signals from BNS remnants (Easter et al. 2019; Sarin and Lasky 2021) and from ultralight dark matter particles forming clouds around spinning black holes via the superradiance process (Siemonsen et al. 2023). ML methods could conceivably contribute to studying these as well. For example, Whittaker et al. (2022) trained a Conditional Variational Auto-Encoder (CVAE) on NR simulations of hyper-massive NS remnants.

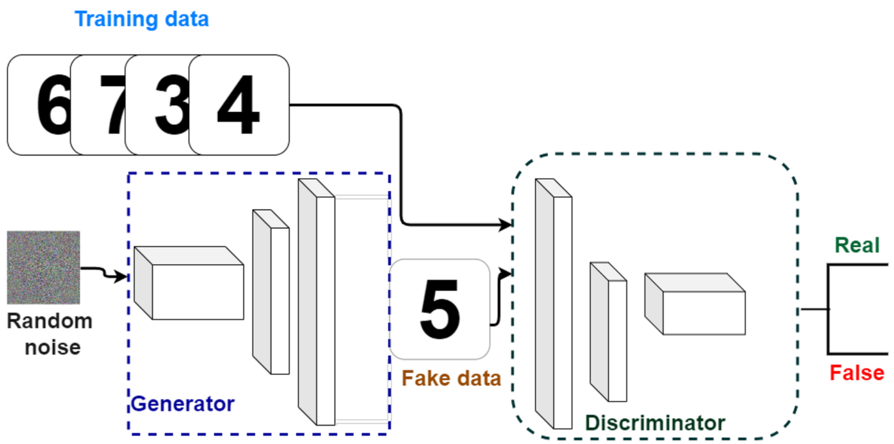


Fig. 11 Example of basic GAN architecture

In summary, it is not always clear where to draw the dividing line between "traditional" and ML methods in waveform modelling. At least if considering surrogates as an ML approach, then waveform modeling has proven to be one of the areas where ML methods are already very productively contributing to practical progress in GW astronomy. A healthy competition between different modeling approaches is driving the field forward towards meeting the challenges imposed by higher-sensitivity and lower-frequency future detectors (Afshordi et al. 2023) – see also Sect. 10. Both pure ML approaches and judicious combinations of such novel techniques and the strengths of traditional modelling expertise are likely to play an increasing role in these regimes.

6.3 Tools for noise generation

One key importance of having simulated datasets is the ability to understand and mitigate systematic errors or biases in data analysis pipelines. By generating synthetic data that mimics the characteristics of real observations, we can stress-test our detection or parameter estimation pipelines. In particular, transient noise perturbations can make it more difficult to detect signals or obtain good parameter estimation. Therefore, different groups work on creating tools to generate realistic data, which contains also non-stationary behavior and, in particular, loud transient noise signals (glitches).

For example, Lopez et al. (2022) addresses a significant challenge in the field of GW searches: the so-called "blip glitches" which occur at a rate of approximately 1 per minute and hinder the detection of astrophysical signals. Due to the huge impact of these glitches on data quality, there is a pressing need for improved modeling and incorporation of glitches into large-scale studies. The authors employ a Generative Adversarial Network (GAN) to generate blip glitches in the time domain. They make the trained network available through an accessible open-source software package called “gengli”[3] and provide practical examples of its application. In Fig. 11, a typical GAN workflow is illustrated.

Another work that addresses the issue of glitches in GW data is Powell et al. (2023) The authors propose a solution using GANs to simulate glitches. They create synthetic images representing the 22 most common glitch types observed in LIGO, Virgo, and KAGRA detectors. These images are then converted into time series data, facilitating their integration into simulations and mock data challenges. Through neural network classification, the authors demonstrate that their artificial glitches closely resemble real glitches, achieving an average classification accuracy of 99.0% across all 22 types. This work suggests that incorporating GAN-generated glitches could enhance the reliability of GW searches and parameter estimation algorithms.

McGinn et al. (2021) introduced the use of Conditional Generative Adversarial Networks (CGAN) for the generation of generalized GW bursts in the time domain. The CGAN in this work was conditioned on five classes of time-series signals commonly used in GW burst searches: sine-Gaussian, ringdown, white noise burst, Gaussian pulse, and binary black hole merger. An example application was presented where a CNN classifier was trained on burst signals generated by the CGAN. The results showed that a CNN classifier trained solely on the standard five signal classes exhibits lower detection efficiency compared to one trained on a population of generalized burst signals drawn from the combined signal class space.

7 Strategies for signal detection

As discussed in Sect. 2, searches for GW signals with the current ground-based LVK detector network have traditionally been separated into the four categories of modeled transients (CBCs), unmodeled transients (bursts), CWs and stochastic long-duration signals. The observational science White Paper of the LVK collaboration (LIGO Scientific Collaboration, Virgo Collaboration, KAGRA Collaboration 2023) can be used for an overview of efforts in all four areas.

This section covers the main ML alternatives developed in the community for searches in these four areas. However, there are also fairly generic ML approaches that do not necessarily fall within any one search type. For example, Morawski et al. (2021) use convolutional auto-encoders for generic detection of transient anomalies which could be of either noise or astrophysical origin.

7.1 Methods for modeled transient searches (CBC, real-time and offline)

The application of ML to the problem of CBC detection has arguably been the most popular area of ML research in the GW community since the recent acceleration of ML technology through the use of GPUs. In most cases, the problem of signal detection is approached in terms of a classification problem in ML. In the early

[3] https://git.ligo.org/melissa.lopez/gengli.

examples and through to the most recent state-of-the-art applications, neural networks are trained via supervised learning to identify between the 2 main classes of data – a piece of data containing detector noise and a piece of data containing detector noise plus a CBC event. We will now discuss the main developments in the field and highlight the different approaches taken.

The first work on this topic (George and Huerta 2018) laid the foundations for the analysis pipelines under development today. It consisted of a relatively basic, but highly appropriate, deep convolutional neural network architecture made of 2 convolutional layers and 2 fully connected output layers. These were interspersed with a series of max pooling layers used to reduce the feature space as the data passed through the network. The output was the result of a softmax layer applied to the pair of final layer neurons and was interpreted as a probability for each of the 2 classes (0 =noise or 1 =noise plus signal). As is standard in binary classification problems, the loss function to be minimized during training was the binary cross entropy defined as

$$L_{\mathrm{BCE}} = \frac{1}{N}\sum_{i=1}^{N}\left[y_i \log \hat{y}_i + \left(1 - y_i\right) \log \hat{y}_i\right] \tag{1}$$

where y and $\hat{y}$ represent the true (0 or 1) and predicted labels respectively of each of N training data items. The input data came in the form of 1-second long segments of whitened GW strain time-series sampled at 8192 Hz and each sample labeled as 1 contained a signal whose mass and time of arrival parameters were sampled from a specified prior distribution. The whitening process used the average PSD of real noise measured from LIGO data during the O1 observing run. The trained network performance indicated that this emerging technology could already rival the sensitivity of the traditional matched filtering approach and set the bar for competing ML approaches.

Soon after the initial work on this, Gabbard et al. (2018) were able to independently reproduce the results and converged on a similar structure and complexity of network for the classification task. In this work, the emphasis was on providing a comparison with matched filtering that probed lower false alarm rates to indicate the performance of CNN approaches in more realistic detection scenarios. One limitation of both studies (George and Huerta 2018; Gabbard et al. 2018) was the choice to train separate networks for different signal SNRs. The results presented indicated that ML could achieve the same sensitivity as matched filtering under a range of conditions. However, as presented in both papers, in practical terms one would need to run each network separately on data since the SNR of an as-yet undetected signal was unknown. The authors did not provide a scheme for combining the outputs of each network into a single detection statistic.

In the years following the first work on this topic, there was much work placed on reproducing and enhancing the power of ML for CBC detection. One notable study (Gebhard et al. 2019) made efforts to place limitations on the potential impact of ML and CNNs specifically to the field of CBC detection. They conclude that such approaches should not be used to quantify the statistical significance of GW detections, due to the high false positive rate. However, they do note that networks such as the CNN that they present, due to their computational efficiency, provide a useful and promising tool to produce real-time triggers for detailed analysis and follow-up searches.

Jadhav et al. (2021) demonstrate possible improvements in search sensitivity by integrating deep learning with a conventional template based search pipeline. They construct a new coincident ranking statistic that incorporates information from an ML model trained to identify multiple known transient noise features. The effect is to achieve a considerable reduction in background leading to elevated significance of events. Apart from recovering the GWTC-1 events (Abbott et al. 2019a), the search was also able to confidently detect an additional event, viz., GW151216, identified in the GWTC-1 catalogue as “low significance” and previously observed by Venumadhav et al. (2020) and the OGC analyses (Nitz et al. 2019, 2020a). In Jadhav et al. (2023), the problem of model reliability was addressed through stage-wise training of the network for CBC detection. The authors also tested the fragility of the network and proposed a novel GAN based setup for improved robustness.

In 2021 the first mock data challenge for the detection of CBC signals using ML was launched through Kaggle and is discussed in Sect. 9.1.1. This challenge was limited to semi-realistic cases and the aim was to cultivate interest and expertise in GW detection from the ML community. This was followed by a realistic data challenge (Schäfer et al. 2023) targeted at the GW community itself to bring together the existing efforts within the field and calibrate them against one of the standard CBC detection tools (Usman et al. 2016; Nitz et al. 2017; Aubin et al. 2021a). The challenge consisted of 4 datasets, each representing different levels of difficulty. The first contained non-spinning BBH signals with mass ranging from 10–50$M_{\odot}$ in Gaussian noise with known detector PSD and the fourth extended the mass range down to $7\,M_{\odot}$, including spinning systems, and used real O3 LIGO noise. The challenge attracted 6 teams using independent analysis tools, 2 of which were existing non-ML algorithms (PyCBC, Nitz et al. 2017, and coherent WaveBurst, Klimenko et al. 2008) with the remainder being newly developed ML applications. The primary metric used for comparison was the sensitive distance – a chirp-mass weighted approximation to the range in the universe out to which each algorithm can detect signals. This quantity is itself represented as a function of the false alarm rate and showed that when applied to the most challenging dataset (dataset 4) one of the existing non-ML tools, PyCBC, achieved the highest sensitive distance at all false alarm rates (limited by the background to be $\geq$ 1/month and exceeding the equivalent sensitive distance from the best ML approach by a factor of ≈ 1.4). However, for challenges 1–3 which did not include real detector noise, two ML analyses (Schäfer et al. 2022; Nousi et al. 2023) using deep residual networks achieved almost equivalent results in terms of sensitive distance, e.g., obtaining sensitive distances of up to 95% of those achieved by PyCBC at false alarm rates of 1 per month. In both cases, however, the duration of signals considered as input data for training was 1 sec, far shorter than the maximum length of signal contained within the data challenge ($\sim$ 12 sec). We note that following the publication of the initial challenge results, two of the analyses used in the challenge have since been updated (Zelenka et al. 2024; Nousi et al. 2023). For the Virgo-AUTh approach the sensitive distances at false alarm rates $\geq 1\,\text{month}^{-1}$ all exceed those of the traditional PyCBC implementation from the challenge. More recently studies into neural network approaches to the analysis of periods when only single detectors are operational (Trovato et al. 2024) have assessed the applicability of different network architectures. Additionally, two deep neural network analysis pipelines were developed (Marx et al. 2024; Koloniari et al. 2024) that successfully detected gravitational-wave signals in real, publicly available data, demonstrating their potential as pipeline detection tools.

The most compelling motivation for the use of ML in GW searches for CBC events is the possibility to front-load the computational expense in training such that at run-time the search can be performed in real-time with relatively low computational cost. As an example we can take the mock data challenge of Schäfer (2023) where pre-trained ML tools can run at $\mathcal{O}(1000)$ times faster than real time assuming 16 CPU cores. This can be compared to the run times of PyCBC within that challenge that were $\mathcal{O}(10)$ times faster than real time. The potential to detect signals with minimal computational cost and potentially before the binary stars merge (i.e., using only the information from the inspiral part of the signal) would be a powerful tool for multi-messenger astronomy. This need is most relevant for CBC systems that contain one or more neutron stars since they, unlike BBH systems, are expected to produce an electromagnetic counterpart signal that could be observed by ground or space-based telescopes (Mészáros et al. 2019). The challenge in such cases is the length of the expected signal in the GW detector band, especially for BNS systems. The first BNS detection (Abbott et al. 2017c) spent $\mathcal{O}(100)$ sec (Abbott et al. 2019b) in band and as the low frequency sensitivity of ground based detectors improves, the duration will grow, e.g, for a detector with sensitivity at 2 Hz (e.g., the Einstein Telescope (ET Steering Committee 2020)) a BNS signal could last for $\sim$ 1 day. Recent efforts have attempted to address this issue and have made improvements in the signal duration considered within ML detection algorithms. Work has extended the initial consideration of 1 sec long signal durations to 2 sec (Fan et al. 2019), 4 sec (Lin et al. 2020), and 10 sec (Krastev 2020; Krastev et al. 2021). It is also worth mentioning work specifically on early warning detection of CBC events, where detection can be claimed before the merger (Sachdev et al. 2020; Magee et al. 2021; Nitz et al. 2020b; Kovalam et al. 2022), with a neural network approach (Yu et al. 2021). In Baltus et al. (2021); Alfaidi and Messenger (2024) it is shown that both CNNs and Long Short Term Memorys (LSTMs) can be very effective in the analysis of long time-series and could return confident detection statements after only analyzing a fraction of the waveform.

Often, ML algorithms and neural networks for CBC detection are treated as black boxes that are purely judged on how they compete with each other, and with existing non-ML methods, in terms of high-level summary statistics such as detection performance at fixed false-alarm rate. But understanding their detailed responses, e.g. in terms of the activation patterns of subnetworks or even individual neurons, can also be very enlightening to design better solutions – following the general approach of explainable or interpretable ML, for which see Murdoch et al. (2019); Linardatos et al. (2020) and also Sect. 3.7. For example, Gebhard et al. (2019) used activation maximization and feature visualization techniques (Zeiler and Fergus 2014; Olah et al. 2017) to study the actual response patterns of the network they were using. They also tested its behaviour to so-called “adversarial attacks” (Szegedy et al.

2013), where the network is exposed to test cases deliberately designed to cause otherwise rare failure modes and elucidate the problematic associations it has learned. The work of Safarzadeh et al. (2022) focused on similar approaches to study the detailed responses of the two-branched architecture introduced in Huerta et al. (2021) for BBH signals, by visualizing the layer-by-layer activation response of the networks and detailed neuron-level sensitivity maps.

A special case of CBC searches is those for gravitationally lensed signals (Grespan and Biesiada 2023) where, as for EM radiation, GWs can also be lensed by massive celestial objects. Strong lensing magnifies signals, making the sources of binary merger signals appear closer and more massive, and can create multiple instances of the same event, separated by minutes to years, but appearing to come from similar sky locations. Microlensing introduces small time delays, causing overlapping waveforms and produces "beating" patterns in the signals. Besides many matched filtering methods developed so far and applied e.g. in two LVC/LVK searches (Abbott et al. 2021f, 2024b), there are also some based on ML methods. Two works have proposed neural network spectrogram classifiers to identify microlensing beating patterns in individual GW events (Singh et al. 2019; Kim et al. 2021). For strongly lensed image pairs, another classifier (Goyal et al. 2021) combines information from spectrograms and sky maps and was already used in Abbott et al. (2024b) as a complementary first-stage classifier for potentially lensed event pairs, together with the traditional KDE-based Bayesian posterior overlap method (Haris et al. 2018). Here the superimposed spectrograms of the two events are first passed through a separate CNN for each detector (starting from pretrained DenseNet201 (Huang et al. 2016) networks), and the three outputs then passed to the XGBoost algorithm (Chen and Guestrin 2016); while for the skymaps three feature statistics are defined which summarize the similarity and differences between the two maps and then XGBoost is applied to these. The final ranking statistic is the product of the two XGBoost outputs. An alternative implementation (Magare et al. 2024) also combines two classifiers, one working on Q-transforms (time-frequency representations of detector data) and sine-Gaussian projections (which transform to a space characterized by the central frequency and quality factor of sine-Gaussian model functions), whose output in terms of probability for lensing are then simply multiplied with each other for the final ranking. In all these cases, an input catalog of GW events is used; direct searches for additional candidate lensed events from the full strain data sets have so far not been proposed with ML methods.

XGBoost is also used in conjunction with a version of cWB that focuses on the detection of BBH events (Mishra et al. 2021, 2022). The results, reported in Mishra et al. (2022). show an improved sensitivity including the recovery of BBH events previously missed by the standard cWB search.

7.2 Methods for GW searches associated with core-collapse supernovae

CCSNs are extremely complex phenomena (Burrows and Vartanyan 2021; Boccioli and Roberti 2024) and modelling them is challenging, though great advances in numerical relativity models have managed to incorporate a wide range of the physics required for predicting the result GW signal morphology. A recent review article by Mezzacappa and Zanolin (2024) provides a good overview of simulating and detecting GW signals associated with core-collapse supernovae. GW emissions from CCSNs are usually considered under the category of Burst GW signals since GW signal waveforms from CCSNs simulations are not yet suitable for generating template banks used by the matched filtering for CBC sources. Furthermore, the stochastic nature of the processes involved in a CCSN requires search pipelines that make minimal assumptions on the GW signal waveform.

Iess et al. (2020) explore the use of 1D and 2D CNNs and of LSTM networks for multilabel classification of CCSNs signals obtained from 3D simulations. The classification procedure is carried out after preprocessing and trigger generation by a wavelet based algorithm, the Wavelet Detection Filter (Cuoco et al. 2018), using real data from the second observing run.

Similarly, Drago et al. (2023) simulated core-collapse GW signals were processed by the coherent WaveBurst algorithm to produce a list of events with excess coherent energy in data from multiple detectors before the attributes of these events are then analyzed by a fully connected neural network. In this work, the training data used for the training network was augmented by a novel method of generation of expected long SASI GW signal so as to allow the neural network to achieve competitive sensitivities. López et al. (2021) performed a variation of this work which used a mini-inception ResNet on the time-frequency images of the data.

Antelis et al. (2022) used linear discriminant analysis and support vector machines and characterized the effectiveness of these approaches as a supervised follow-up approach for coherent WaveBurst events originating from CCSN signals. Chan et al. (2020) used a convolution neural network on time series data and demonstrated the ability of convolutional neural network to distinguish between GW signals corresponding to different explosion mechanisms (rapidly-rotating vs neutrino-driven) and also characterized the sensitivity of their approach. Cavaglià et al. (2020) proposed a single-detector CCSN GW signal search based on a combination of coherent WaveBurst and Genetic Programming. Mukherjee et al. (2017) introduced the harmonic regeneration noise reduction approach for reconstructing (denoising) supernova waveform signals and later proposed a convolutional neural network to improve the noise rejection ability of their proposed analysis (Mukherjee et al. 2021).

There have also been some efforts comparing and interpreting machine learning approaches for supernova. Powell et al. (2024) compared different methods of classifying the CCSN explosion mechanisms. Among the classification methods compared was a method based on dictionary learning and another method involving a convolutional neural network. All methodologies were able to correctly classify the corresponding explosion mechanism for the majority of the simulated GW signals. The convolutional neural network approach was better at correctly classifying GW signals from rapidly rotating stars while dictionary learning was better at classifying gravitational-wave signals from non-exploding CCSN simulations. Dictionary learning for GWs, in particular CCSNs, was first proposed by Torres-Forné et al. (2016) and later used to classify CCSN signals (Saiz-Pérez et al. 2022). Additionally, Sasaoka et al. (2023) used the Class Activation Mapping approach to investigate and interpret how a CNN classifies GW signals from CCSN.

7.3 Methods for unmodeled transient searches (burst, real-time and offline)

Burst signals, by definition, do not have a well-modeled waveform. Traditional burst search techniques rely on the principle that GW signals are correlated between multiple, widely-spaced detectors while noise originating from the detector or the local environment is uncorrelated. The burst parameter space is defined by a range of proxy waveforms (e.g. sine gaussians, ringdowns, white-noise bursts) which try to capture the main features of the wide parameter space. An overview of the burst search techniques and these proxy waveforms can be found in Abadie et al. (2012)

The lack of a well-defined signal waveform poses a challenge for many machine learning approaches which tend to be trained to detect specific signal morphologies that are simulated in the training data set. Machine learning use in Burst searches fall into two broad categories. The first category involves the direct application of machine learning techniques to the calibrated strain data, typically time series. These approaches are trained on one or more sets of simulated data with proxy waveforms injected (e.g. sine-gaussian signals). This class of machine learning approaches take additional steps to ensure generalisation of the approach and prevent overfitting on the training data set.

The second category of burst machine learning techniques involve existing burst detection methodologies (e.g. coherent WaveBurst) being enhanced by machine learning techniques to improve the search sensitivity. These approaches ingest various event attributes with the goal of finding a mapping of these attribute values that best differentiates background noise events and simulated signal events.

7.3.1 Direct application of machine learning

Li et al. (2020) used a wavelet basis to decompose simulated GW strain data as input to a classification CNN to detect simulated transient signals. The network was trained and characterized using only a decaying sinusoidal signal. Nonetheless, this is one of the first examples of CNN applications for Burst GW searches.

MLy, developed by Skliris et al. (2020), is an ML pipeline to search for Burst GW signals. MLy consists of two CNNs, each trained to identify critical features of Burst GW signals. One CNN is trained to detect the presence of transient signals in data from multiple GW detectors. A second CNN uses both the whitened detector time series data and the corresponding Pearson correlation between data from pairs of detectors to distinguish between correlated GW signals and uncorrelated spurious noise. A novel aspect of this approach is that the hyperparameters for this search pipeline were optimized using a Genetic Algorithm. This approach has been shown to be competitive for online searches with false alarm rates of 1 per year.

The Gravitational Wave Anomalous Knowledge (GWAK) is a semi-supervised anomaly detection approach which uses deep recurrent auto-encoders to encode the different signals and glitches into a latent space which captures the physical signatures of the different signal classes (Raikman et al. 2024). The encoding is informed by priors based on GW signal features to allow for robust signal recovery of unmodeled transients. GWAK has been shown to have comparable burst signal sensitivity to MLy and can identify CBCs.

Additionally, ALBUS (Boudart and Fays 2022; Boudart 2023) is an approach which uses fourier time-frequency maps (spectrograms) as inputs to a CNN to detect long-transient GW signals which can last for many minutes.

Marianer et al. (2020) have presented a search for unmodeled GW signals using semi-supervised machine learning, processing first a set of labeled spectrograms and then searching for anomalies in the remaining dataset.

7.3.2 Machine learning enhanced burst searches

The Coherent WaveBurst (cWB) algorithm (Klimenko et al. 2008; Drago et al. 2021) looks for signals using excess coherent energy between detectors in the time-frequency wavelet domain. This algorithm outputs a set of events which correspond to time-frequency locations of excess coherent energy. These triggers are characterized by a list of event attributes such as the event time, central frequency and strength of coherent energy. Until the 3rd observing run (O3), the standard approach for optimising cWB's sensitivity for transient burst searches was to manually tune threshold for a set of trigger attributes This approach relied on experience and intuition built up over many years of performing burst searches on data from GW observatories (for latest results see Abbott et al. 2023b, 2021a). However, with the advent of machine learning and multi-variate approaches, new data-driven methodologies were developed to optimise search sensitivities.

Gaussian Mixture Modeling (GMM) have been used as a supervised machine learning postprocessing analysis for the cWB pipeline (Gayathri et al. 2020). GMMs are probabilistic models which use a sum of uni-modal Gaussian distributions to statistically model the multi-dimensional attribute space for background and signal data from cWB. These models are applied to data to calculate log-likelihood statistics, and a single detection statistic that distinguishes likely GW triggers from noisy background glitches. The addition of GMM improves on the overall search sensitivity of standard signals in the all-sky short search, and removes the need for manual selection of triggers through binning and cuts which occurred in standard cWB post-production previously. The benefits of GMM to the cWB analysis are further exemplified in Lopez et al. (2022b), where a comparison between standard cWB and cWB + GMM has been presented for the O3a all-sky short search. In this work it is shown that the addition of GMM enhances the detection efficiency for all standard injections, with improvements in detection efficiencies of between 5% and 10% for sine gaussian waveforms and about 100% for gaussian pulses at a false alarm rate of 1 event per 100 years. The detection efficiencies for supernova waveforms were also improved by a few percent at false alarm rates of 1 event per 100 years.

Recently, the cWB pipeline was upgraded with XGBoost (Chen and Guestrin 2016), an ensemble based boosted decision-tree algorithm, to automate the signal-noise classification of cWB events (Mishra et al. 2021, 2022; Szczepańczyk et al. 2023). Two types of input data are used: signal events from simulations and noise events from background estimations. For each event, a selected subset of cWB summary statistics/attributes is used by XGBoost as input features to train a signal-noise classification model. The output of XGBoost is incorporated into an overall detection statistic by multiplying the standard cWB ranking statistic with the XGBoost weighting factor. Therefore, this approach uses the XGBoost output as a penalty factor which applies a weight between 0 (noise) and 1 (signal) to the cWB ranking statistic. This enhanced cWB pipeline was tuned to search for generic GW bursts in O3 data, where it demonstrated robustness as a model-agnostic search, and improved the all-sky search sensitivity across the broad spectrum of simulated signals, ranging from a few percent improvement for sine Gaussian waveforms up to factors of about 3 for gaussian pulses (Szczepańczyk et al. 2023). The authors also report the most stringent constraints on isotropic emission of GW energy from short-duration burst sources with the enhanced cWB pipeline, improving on previous constraints by about 5 to 10% depending on the frequency of the GW signal. Moreover, Bini et al. trained a version of the cWB+XGBoost pipeline on GW signals from hyperbolic encounters between compact objects (Bini et al. 2024). These scattering events are expected to occur in dense stellar environments releasing a GW burst signal. The authors used O3b data to obtain the first observational upper limit on the rate density of hyperbolic encounters in the local universe.

In addition to using XGBoost, Bini et al. (2023) combined cWB with an autoencoder which was trained on specific transient noise morphologies (blip glitches). The autoencoder allowed for better discrimination between known glitch classes and noise. The authors show that the sensitivity volume can be improved by up to 30% for signal morphologies similar to blip glitches at a false alarm rate of 1 event per 50 years. In Astone et al. (2018), time-frequency maps from cWB were studied with a CNN classifier.

7.4 Methods for continuous-wave searches

GW signals are typically considered as CWs when they have longer duration than typical CBC or burst transients, with slow amplitude and frequency evolution. For a broad review of CW research see Riles (2023), and for other recent reviews with different focus areas see Tenorio et al. (2021b); Piccinni (2022); Haskell and Bejger (2023); Wette (2023).

A specific minimum duration for calling a signal a CW can however not easily be given. The classical case are true, fully persistent CWs: as long as, or longer than, a typical observing run of our GW detectors. A crucial aspect of searching for these are the time-varying Doppler shifts and antenna patterns from the Earth's diurnal rotation an orbital motion. However, over the past decade data analysis methods from the CW regime have increasingly also been applied to transient signals of varying duration. and CW-like transients together as a single category is that they are *quasi-monochromatic*: at any given time, the signal is limited to a narrow frequency band, even if that frequency evolves slowly over time. Such CW-like transients can be days to months long, maintaining the importance of correcting for Earth's motion, but they can also be as short as seconds and hence the regime of interest overlaps with CBC and burst analysis methods.

The prototypical sources for both fully-persistent and CW-like transiemt signals, with ground-based detectors, are spinning NSs with non-axisymmetric deformations or oscillation modes. Other possible sources include glitching pulsars or newborn strongly deformed NSs (both yielding short- or long-duration CW-like transients), exotic compact objects, boson clouds around spinning black holes, and the early slowly varying inspiral phase of low-mass binaries, such as primordial black holes. Dark matter directly interacting with the interferometric detectors could also be observed through CW-like detection methods. The more exotic cases will be discussed in Sect. 8.6.

ML applications in the CW context fall into two main categories: (i) improvements to individual aspects of existing workflows, typically in post-processing steps after an initial matched filter search; (ii) attempts at stand-alone ML searches from input data that has been preprocessed to varying degrees. For both categories, it is important to realize that most current CW searches (except for targeted searches for known pulsars with well-constrained frequency evolution from EM observations) are severely computationally limited: The weak expected signals from typical astrophysical sources make it necessary to precisely track the signal over long integration times in order to achieve significant SNR. For templated methods like matched filter and cross-correlation, this requires a very dense covering of the search space, reaching over 10^{18} templates for the deepest all-sky blind searches (Steltner et al. 2023). Hence, all methods applied to wide-parameter space CW searches are by necessity statistically sub-optimal, making trade-offs between sensitivity and computational efficiency. While for CBC searches, "matching matched filtering" (Gabbard et al. 2018) can be considered the main benchmark, for CWs there is a large gap between current practical algorithms and the theoretical optimum of a fully-coherent matched filter, where ML methods could potentially find better sensitivity-efficiency tradeoffs. Thus, they could actually be crucial for opening up a new detection space with current GW detectors.

Regarding improvements to existing workflows, one promising area is candidate clustering. Various supervised or unsupervised clustering algorithms have been developed (Singh et al. 2017; Beheshtipour and Papa 2020, 2021; Tenorio et al. 2021c; Steltner et al. 2022) to reduce the number of candidates that need to be followed up further (Papa et al. 2016; Walsh et al. 2019; Tenorio et al. 2021a). These make use of the fact that both true CW signals and detector noise artifacts typically excite several nearby templates. Some are based on nearest-neighbor techniques or graph theory (Tenorio et al. 2021c). On the other hand, the method from Beheshtipour and Papa (2020, 2021) used a neural network architecture called "Mask R-CNN" (He et al. 2017), which is designed specifically to find and bound regions of interest. This method is so far limited to directed searches (for sources with known sky location), applied e.g. in Ming et al. (2022) to the supernova remnant G347.3, while for the more challenging all-sky case a more conventional binned approach (Steltner et al. 2022) is still preferred by the same analysis group (Steltner et al. 2023).

An intermediate approach combining traditional and ML methods is taken by Morawski et al. (2020), who trained CNNs on the per-frequency-band outputs of the matched filter time-domain $\mathcal{F}$-statistic (Jaranowski et al. 1998) search and then each band is classified as containing either pure Gaussian noise, line-like noise artifacts (Covas 2018), or a CW signal, with the latter two on top of Gaussian noise.

Taking one step further towards pure ML-based searches, Modafferi et al. (2023) used the so-called $\mathcal{F}$-statistic atoms (Prix et al. 2011), which are intermediate short-duration matched filter data products, as inputs to a CNN producing an emulated SNR-like detection statistic for long-duration CW-like transients from glitching NSs. This is a computationally limited search type, with the CNN evaluating much faster even than a straight GPU port (Keitel and Ashton 2018) of the pure MF method from Prix et al. (2011). A curriculum learning approach using simulated Gaussian data first and then adding real data allowed for preserving performance in a search of real O2 data, but the study was limited to a narrow frequency band.

From such hybrid solutions, it is a gradual but quite challenging step to fully stand-alone ML searches. One possible input are time-frequency maps with differing degrees of preprocessing. An early study (Mytidis et al. 2019) used such maps as produced by the STAMP pipeline (Thrane et al. 2011) for transient CW-like signals from neutron star r-mode oscillations, and compared three ML methods: a shallow neural network with one hidden layer, SVMs and Constrained Subspace Classifierss (CSCs). Similarly, Miller et al. (2019) used a CNN on time-frequency maps to search for long-duration transients from BNS merger remnants, obtaining results on real data competitive with other algorithms for the same target signal that had been developed until that point. Attadio et al. (2024) studied similar signals from newborn neutron stars, again using time-frequency maps, and found that combining a classifier CNN with a previous denoising stage (see Sect. 5.4) is beneficial to increase sensitivity towards weaker signals.

Working directly on the full detector strain data was pioneered by Dreissigacker et al. (2019); Dreissigacker and Prix (2020) who trained deep neural networks (modified versions of ResNet (He et al. 2016) and Inception-ResNet (Szegedy et al. 2016)) for all-sky and directed wide-parameter space searches. To overcome limitations encountered in these two works, which we will also discuss below, Joshi and Prix (2023) took a step back and considered the simpler case of targeted known-pulsar searches, constructing a simpler neural network. It uses spectrograms with well-chosen bandwidth as inputs and various improvements such as on-the-fly regeneration of Gaussian training data at each training epoch. This allowed for nearly "matching matched filtering" sensitivity at different points in parameter space, up to signal durations of 10 days, but still in stationary Gaussian noise and not for full observing-run length data sets.

In follow-up work (Joshi and Prix 2024), the same authors kept for the moment the limitation to 10 days of observation time but extended the method to be able to cover wide parameter spaces, thus competing directly with traditional fully-coherent

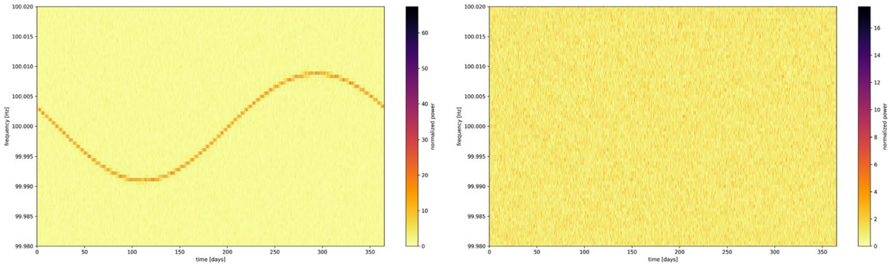


Fig. 12 Example spectrograms of CW signals, illustrating the difficulty of detecting these with pattern recognition algorithms focusing on local structure. The left panel shows a signal that is extremely strong for CW standards (depth $\sqrt{S_\mathrm{n}}/h_0 = 5\,\mathrm{Hz}^{-1/2}$, see Dreissigacker et al. 2018 for a discussion of this quantity), already illustrating the extended and narrow structure in time-frequency space. The right panel with a depth of 50 $\mathrm{Hz}^{-1/2}$ (a realistic value for current semi-coherent all-sky CW searches), the signal track is in addition not visible by eye above the noise, even though it is purely Gaussian. Graphs generated with PyFstat (Keitel et al. 2021)

matched filters for which a similar maximum duration applies in practice due to computational constraints (see, e.g., Owen et al. 2022) and which are more usually replaced with semi-coherent methods to cover a full observing run (Tenorio et al. 2021b; Riles 2023; Wette 2023). In Joshi and Prix (2024), both directed (known sky position) and all-sky searches are considered, and tested for 20–1000 Hz. The network architecture is made up of three blocks following the design principles from Joshi and Prix (2023). Resulting sensitivity depths at 1% false-alarm probability per 50 mHz band and 10% false-dismissal probability reach around $\sqrt{S_\mathrm{n}}/h_0 \approx 30\,\mathrm{Hz}^{-1/2}$ at 20 Hz, while still falling off to $\approx 20\ \mathrm{Hz}^{-1/2}$ towards higher frequencies where the signal tracks are more challenging. For comparison, a fully-coherent matched filter reaches $\approx 40\ \mathrm{Hz}^{-1/2}$ across the frequency band. This work demonstrates that a certain gap in sensitivity remains to be caught up, but that the proposed architecture can generalize already quite well in signal strength, frequency and sky position.

In an independent approach, Yamamoto and Tanaka (2021) combined excess-power detection on short-time Fourier transform data with a CNN for sky localization. A similar network was used directly on Fourier-transformed data in Yamamoto et al. (2022), serving as a four-class classifier for pure Gaussian noise, CW signals, line artifacts, or CWs plus lines. They found comparable sensitivity to established semi-coherent all-sky search methods in quiet data, but with significant degradation in the presence of (simulated) noise lines.

Occupying a space between traditional CW search methods and pure ML, the class of Viterbi searches (Viterbi 1967; Suvorova et al. 2016, 2017; Sun et al. 2018; Sun and Melatos 2019; Bayley et al. 2019; Sun et al. 2019; Melatos et al. 2021) considers detector data as the output of a hidden Markov model, with the true frequency evolution of the source as the hidden state. The main attraction is robustness to non-deterministic source behavior, such as NS spin wandering. These are essentially semi-coherent searches that can be run either in a fully unmodeled mode with short-time Fourier transforms as the input, or on the outputs of coherent matched filter analyses over limited coherence-time segments (the $\mathcal{F}$-statistic and variants of it). The Viterbi-based SOAP pipeline (Bayley et al. 2019) for all-sky searches is in its latest iteration also being combined with two deep learning stages (Bayley et al. 2020, 2022), one for spectral line suppression and another for performing PE on the most significant remaining candidates at the end of the search pipeline (after line suppression), for which see Sect. 8.3.

In summary, ML has started to establish itself as a useful tool for optimizing and generalizing various steps of typical CW search workflows. End-to-end ML searches that could fully replace traditional algorithms are however still in their infancy, with several crucial challenges identified so far (Joshi and Prix 2023; Yamamoto et al. 2022): The defining characteristics of CW signals– being weak, long-duration and narrow-band– makes them fundamentally more challenging for some popular ML architectures, especially CNNs and any other networks that learn the local structure of data sets. This is illustrated in Fig. 12. Furthermore, the complicated Doppler modulations produced by the Earth's motion over long observing times lead to very diverse signal patterns across parameter space, so that fully-coherent analyses of year-long data sets by stand-alone neural network classifiers have remained out of reach so far. On translating methods from simulated Gaussian noise to real data, sensitivity also often takes a significant hit, as nonstationarities in the detector noise floor as well as stationary line detector artifacts (Covas 2018) make for very different characteristics. The last point, though, is not a unique challenge of ML methods, as the outputs of traditional CW searches are usually dominated by candidates produced by noise lines too, and much development has been put over the years into making them more robust in this regard (Keitel et al. 2014; Leaci 2015; Zhu et al. 2017; Intini et al. 2020; Jones et al. 2022).

See also Sect. 8.3 for PE methods on CW signal candidates. Furthermore, CW searches were also covered in a Kaggle challenge as described in Sect. 9.1.2. The winning submissions turned out to be more closely related to established CW analysis methods than to typical ML approaches, also indicating that finding competitive pure ML solutions is still an open problem in this field.

7.5 Methods for stochastic searches

Like CWs, searches for stochastic GWs are generally considered to cover long-term persistent signals, but in contrast lack deterministic signal models. These cover both the SGWB (stochastic backgrounds – either of cosmological nature, i.e. from early-universe physics, or the stochastic superposition of unresolved signals from individual astrophysical sources such as CBCs) and individual, but unmodeled signals. The latter category includes searches for persistent point sources without the strict model assumptions of CW searches and various types of long-duration transients. Recent reviews of stochastic search methods and the current observational status can be found in Renzini et al. (2022); van Remortel et al. (2023).

There are no mainstream analysis pipelines for stochastic backgrounds based on ML techniques in use by the LVK yet. A first exploration of different deep learning frameworks (Utina et al. 2021a) has compared three architectures: 1D and 2D CNNs and a LSTM network. Meanwhile, a good example for cases that might be considered as instances of ML by some, but not by others, has appeared in the context of a proposed optimal Bayesian search (Smith and Thrane 2018) for astrophysical backgrounds (superposed CBC signals)The method itself is firmly based on traditional Bayesian PE methods. Additionally, a Gaussian Mixture Model (GMM) approach has been used to predict detection prospects and to simulate data realizations for testing the analysis. For the regime of intermittent, non-Gaussian backgrounds, Yamamoto et al. (2023) have compared three neural network architectures with different structures: two CNNs of varying depth and a residual network, which was found to perform best for detection purposes. Another neural network was tested for signal classification and PE (in the sense of estimating the duty cycle and SNR of the background).

Since stochastic background searches typically rely on observing cross-correlations (Allen and Romano 1999) between the data of two or more GW observatories, it is crucial to control possible correlated noise sources across sites (e.g. through atmospheric magnetic channels), as is the reduction of low-frequency noise components such as Newtonian noise. ML can play an important role in this kind noise mitigation, as explored e.g. in Badaracco et al. (2020) with surrogate Wiener filtering.

Work is also ongoing on using ML for stochastic background searches in other GW frequency bands, e.g. with LISA (Alvey et al. 2024) and Pulsar Timing Arrays (Chen et al. 2020; Shih et al. 2024).

Long-duration transient searches with stochastic-style methods, for targets such as magnetar bursts (Quitzow-James et al. 2017; Abbott et al. 2024c) or BNS post-merger remnants (Abbott et al. 2019c; Banagiri et al. 2019) typically involve pattern recognition tasks in GW spectrograms, similar to shorter-duration burst searches (Sect. 7.3). As such, the STAMP pipeline, first introduced in Thrane et al. (2011) and recently reimplemented in python (Macquet et al. 2021), uses either seeded or seedless clustering techniques (Khan and Chatterji 2009; Thrane and Coughlin 2013) for detecting GW transients as time-frequency tracks. At the shorter duration end ($\sim \mathcal{O}$(minutes)), this overlaps with the regime where neural networks are being applied for burst-type searches (Boudart and Fays 2022; Boudart 2023).

8 Strategies for source interpretation

Once a GW signal candidate has been detected with sufficient confidence, additional methods are needed to characterize the parameters of its physical source in detail. Here, we discuss how ML methods are starting to make an impact on the classification of candidates into different possible source types and the detailed estimation of parameters, for both the transient and continuous signal case. We also discuss in this section applications for multi-messenger physics, population inference, cosmology and new physics beyond the standard model.

8.1 Source classification (online/offline)

In the last two observing runs, the LVK has been issuing prompt public alerts for GW transient candidates crossing a pre-determined false alarm rate (FAR) significance (Chaudhary et al. 2024). Preliminary alerts are issued seconds after the merger, with annotations released as additional and more accurate information becomes available. Since the fourth observing run, additional specialized searches (Magee et al. 2021; Sachdev et al. 2020; Nitz et al. 2020b; Kovalam et al. 2022) have been set up to issue "early warning" alerts when they detect sufficiently strong signal candidates before they reach the merger stage. In cases of positive confirmation of the candidate following human vetting, update notices are generally issued on time scales of a few hours with improved estimates of sky localization, detection significance, or source classification.

The classification of GW candidate events and source property inference in real time present various issues, as the necessity for precision clashes with the need to release information as soon as feasible. These are situations where machine learning-based classifiers may be effective in obtaining accurate results that would otherwise be unachievable.

The LVK low-latency pipeline (Chaudhary et al. 2024) for compact binary coalescence events (Chatterjee et al. 2020a) currently uses two supervised learning algorithms: a k-nearest-neighbor (KNN) (Shakhnarovich et al. 2005) algorithm is used to infer the presence of a neutron star as one of the binary components and of possible post-remnant matter, and a Random Forest algorithm (Breiman 2001) to infer the presence of an object with mass in the "gray" region between the lowest-mass black holes and the heaviest neutron stars (Chaudhary et al. 2024). Binary classification scores for these metrics are generated from the output of detection pipelines and equation of state models. The algorithms are typically trained using hundreds of thousands of simulated CBC signals that are coherently inserted into real detector noise. The validity of an event's classification outcome is then evaluated by means of features of the algorithm's confusion matrix and the receiver operating characteristic curve. The benefit of this approach is its capacity to accommodate statistical and systematic errors in the search pipeline parameters. It also provides for a significant speed gain over the semi-analytic effective Fisher formalism technique used in the first two LVK observing runs (Chatterjee et al. 2020b). Recent advancements have concentrated on improving this method and obtaining actual conditional Bayesian probabilities for the source property measures that are more simply interpretable than scores (Berbel et al. 2024).

8.2 Source parameter estimation (transient signals)

Our understanding of the compact binary systems that produce the GWs detected by the LVK Collaboration hinges on our ability to perform Bayesian inference. The de-facto standard algorithm used for this task is nested sampling within a range of different implementations (Skilling 2006; Ashton et al. 2022; Veitch et al. 2015; Ashton et al. 2019) which, for standard CBC signals, take of order days to weeks.

The bottleneck in nested sampling is two-fold: evaluating the likelihood for CBC signals is computationally expensive and drawing a new sample from the likelihood-constrained prior typically requires using random walks that may need up to thousands of steps, which also require evaluating the likelihood. This, in conjunction with the expected increase in the number of detected events that will result from improvements to existing detectors and next generation detectors, presents a significant computational challenge.

Multiple strategies have been suggested and demonstrated that harness the power of ML within the existing nested sampling algorithm. Targeting the bottleneck associated with repeatedly drawing samples from the likelihood-constrained prior, it has been shown (Williams et al. 2021; Ashton and Talbot 2021; Williams et al. 2023) that incorporating ML in the process of drawing new samples can provide significant speed-ups. In this case, a type of generative machine learning algorithm called normalising flows is used allowing a normalising flow to learn the distribution of samples within likelihood-constrained prior during sampling and, in-turn, sample from the learned distribution. This eliminates the need for random walks and improves the efficiency of drawing new samples. Comparisons of the Nessai algorithm (Williams et al. 2021) with the standard nested sampler (Speagle 2020) used in current LVK analyses (Abbott et al. 2023b, 2024a) show that Bayesian posterior distributions are accurately recovered whilst requiring two-times fewer likelihood evaluations. The follow-up implementation (known as i-nessai (Williams et al. 2023)) improves this factor to a range of between 2.68 and 13.3 times fewer likelihood evaluations.

The alternative speed enhancement that can be applied to nested-sampling is to optimise the likelihood calculation at the core of the algorithm. This can come in 2 forms: using new techniques to learn the likelihood function itself, or to optimise the generation of CBC waveforms. In the former case, much non-ML work has been done on Reduced Order Models that allow for rapid evaluation of the likelihood by finding computationally efficient representations of the waveform model. In the latter case it has been shown that significant speed-ups can be obtained using ML approaches. Khan and Green (2021) demonstrated that an order of magnitude speed-up could be achieved for BBH signal generation over Reduced Order Quadrature (ROQ) techniques which was further enhanced if generating many thousands of waveforms in batches on a GPU. This area of research has since been extended to include multi-modal precessing waveforms (Thomas et al. 2022).

An additional scientific benefit of incredibly rapid parameter estimation for CBC events, specifically those containing a NS component, is the possibility to perform parameter estimation quickly enough to be able to alert EM astronomers of the locations of the source. Non-ML and ML methods alike are being developed to achieve the goal of accurate posterior estimation within $\mathcal{O}(1)$ sec and potentially even prior to merger. One way to tackle this problem is to look at completely new approaches using solely ML algorithms.

One of the first ML approaches to address the issue of rapidly generating samples from a joint Bayesian posterior on CBC source parameters (Gabbard et al. 2022) utilized a type of neural network known as a CVAE. This CVAE implementation (known as Vitamin) and a form of simulation based inference only needs to be trained once and can be applied many times with a computational cost orders of magnitude faster than standard techniques at runtime. The process of training requires the choice of signal parameter prior distributions and assumptions on the detector network and noise properties, and so will require retraining if those assumptions change.

A standard approach to the comparison of Bayesian inference tools has been to compute the JS-divergence between 1-dimensional marginalised posterior distributions. The JS divergence between the distributions $p(x)$ and $q(x)$ is defined as

$$\mathrm{JS}(p, q) = \frac{1}{2}\left[\mathrm{KL}(p, m) + \mathrm{KL}(q, m)\right] \tag{2}$$

and has units of nats (the natural unit of information) where $m = (p + q)/2$ and the KL-divergence is

$$\mathrm{KL}(p, m) = \int p(x)\frac{\log p(x)}{\log q(x)}dx. \tag{3}$$

Identical distributions have $\mathrm{JS}(p, p) = 0$ and in the opposite extreme with maximally differing distributions the JS becomes log(2).

Vitamin posterior distributions have been compared with existing techniques such as Markov Chain Monte Carlo (MCMC) and nested sampling (Gabbard et al. 2022) when applied to inference of the type of BBH systems detected by the LVK. These comparisons have shown JS-divergences between 1-dimensional marginalised posteriors of $\mathcal{O}(10^{-2})$ nats and can be compared to the findings of Romero-Shaw et al. (2020) where for different sets of samples drawn from the same Gaussian distribution, values of > 0.002 nats were considered statistically significant.

At present the state-of-the-art application of ML to Bayesian parameter estimation is done using neural posterior inference (Green et al. 2020; Dax et al. 2021, 2023). The first work on this application incorporated autoregressive flows within a variational auto-encoder framework but was subsequently developed into a dedicated spline coupling normalizing flow incorporating an embedding network to compress the conditional input GW timeseries data. This approach allows for the analysis of 8 sec of data from a network of GW detectors compressed into 128 features to be input as the normalizing flow conditional data. The normalizing flow is expected to accurately model the GW parameters posterior for any likely signal and noise realisation, and hence compression is crucial to helping the normalizing flow by representing the conditional timeseries data in a compact and information-rich form. Results from the pipeline (known as DINGO) applied to real LIGO-Virgo detections provide posteriors that match incredibly well with benchmark analyses, returning JS-divergences between 1-dimensional marginalized posteriors of $\mathcal{O}(10^{-3})$ nats.

Parallel applications of the DINGO framework have included the addition of an importance sampling component that essentially uses DINGO as a highly efficient tool for sampling from an approximate posterior distribution (Dax et al. 2023). Then through comparison with the likelihood obtained from analytic models (the same models used within MCMC and NS algorithms) at those sample locations, can be used to obtain a corrected posterior. The motivation behind such an approach is to hedge against the known "imperfect" nature of current ML applications where despite rigorous testing, the behaviour of generative models cannot be guaranteed in all regions of parameter space. The additional computational cost of using the analytic likelihood model in this scenario is minimal in comparison to traditional techniques (MCMC and NS) where $\mathcal{O}(10^6)$ likelihood evaluations may be required. Depending on the accuracy of the normalizing flow approximate (proposal) distribution this can be reduced to $\mathcal{O}(10^3)$ evaluations (that can also be parallelised) therefore adding minutes to the inference latency. The disadvantages beyond the additional computational cost (minimal in comparison with traditional techniques but significant in terms of the normalizing flow) are that in order to use an analytic likelihood, one must assume a specific form for the noise model. This limits the ways that real (non-Gaussian) detector noise can be used in training the model where no assumption is made on the mathematical form of the noise distribution which includes transient detector noise artifacts (glitches). In other words, this approach can no longer be classified as "likelihood free" inference.

Yamamoto and Tanaka (2020) used CVAE for estimating quasi-normal-mode frequencies from the ringdown portion of BBH signals.

One challenge of likelihood-free/simulation-based inference is that the ML models trained for it (e.g., normalizing flows) can get quite large. Chatterjee et al. (2023) suggested that "Self-supervised Neural Symmetry Embeddings" can mitigate this problem by exploiting intrinsic symmetries of the problems studied. Mao et al. (2024) demonstrated that auto-encoders and ANNs can also help in calibrating the coverage of posterior credible intervals for GW parameter estimation – the example application was for LISA, but the methods should translate to ground-based detectors as well.

8.3 Source parameter estimation (continuous signals)

Beyond simple maximum-likelihood parameter estimates (Jaranowski et al. 1998; Prix 2018), the PE problem for CW signals has so far been less explored than for CBCs. As for Bayesian approaches, nested sampling is used for analyzing known pulsars in a time-domain pipeline (Pitkin et al. 2017; Pitkin 2022), either at a single frequency-evolution template or in a very narrow band, combining the traditionally separate detection and PE steps into a single analysis. An alternative frequency-domain implementation based on the $\mathcal{F}$-statistic (Jaranowski et al. 1998) was recently presented (Ashok et al. 2024), also using nested sampling. In addition, parallel-tempered ensemble MCMC sampling (Foreman-Mackey et al. 2013; Vousden et al. 2016) is used for the hierarchical follow-up of candidates from wide-parameter space searches with the PyFstat package (Ashton and Prix 2018; Keitel et al. 2021; Tenorio et al. 2021a; Mirasola and Tenorio 2024). Here, the chains are typically run only for a limited time, not necessarily reaching the level of convergence needed for robust parameter estimates, with the main goal of excluding/confirming signal candidates for passing from one stage to the other. An alternative implementation if

Bayesian PE for CWs has been presented by Covas et al. (2024), accessing a larger variety of samplers through the bilby package (Ashton et al. 2019).

The first application of ML-based PE for CW-like signals has been implemented for the weakly modeled Viterbi-based SOAP pipeline (Bayley et al. 2019) (see also Sect. 7.4), proceeding in two steps: First, a CNN is used to eliminate spurious candidates caused by instrumental lines (Bayley et al. 2020); then, a CVAE delivers posterior estimates for the frequency-evolution ("Doppler") parameters of a CW signal candidate (Bayley et al. 2022). Like the SOAP search itself, this approach so far works only for relatively high SNRs (low search depths of around $\sqrt{S_{\mathrm{n}}}/h_0 = 10\,\mathrm{Hz}^{-1/2}$, compare Fig. 12).

Therefore, as of 2024, a full solution to PE across the full parameter space of modeled CW signals is still lacking, using either traditional or ML approaches.

As discussed in Sect. 7.5, a first application of neural networks to intermittent, non-Gaussian stochastic backgrounds was presented by Yamamoto et al. (2023) (along with detection methods).

8.4 Applications for multi-messenger physics

BNSs represent a unique laboratory for probing the fundamental physics governing the dynamics of compact objects, nuclear astrophysics and the synthesis of heavy elements in the universe. The detection of GW signals coupled with the observation of their accompanying electromagnetic counterparts, and in particular gamma-ray bursts, has opened a new era of multi-messenger astronomy (Abbott et al. 2017d, b).

For multi-messenger astronomy, GW analyses must be able to provide information on detection candidates as quickly as possible to enable follow-up searches for electromagnetic and neutrino counterparts, and to enable multi-messenger studies of a compact binary merger. Astronomers must decide quickly whether to follow the low-latency Open Public Alerts for significant GW candidate events. In Abbott et al. (2022e) GWSkyNet-Multi, an advanced ML model was presented as an extension of the earlier GWSkyNet (Cabero et al. 2020). It classifies potential GW events detected by the LIGO and Virgo observatories, using the limited data from low-latency Open Public Alerts to quickly determine whether an event represents a black hole merger, a merger involving neutron stars, or simply a non-physical incident. Specifically, GWSkyNet-Multi uses the following information from the alerts: image representations of the skymap and three volume-projected versions of it, along with four corresponding normalization factors; the available GW detectors; distance information; and two Bayes factors for the signal-vs-noise and coherent-vs-incoherent hypothesis tests. In Raza et al. (2024), a study was conducted on how the complex GWSkyNet-Multi network uses input features to make a correct prediction. Factors such as the localization area of the sky maps and the computed coherence versus incoherence Bayes factors play a key role in distinguishing between authentic events and glitches. In addition, the estimated distance to the source helps to distinguish between different types of glitches.

Multimodal machine learning is a cutting-edge approach in artificial intelligence where models are designed to process and understand information from multiple

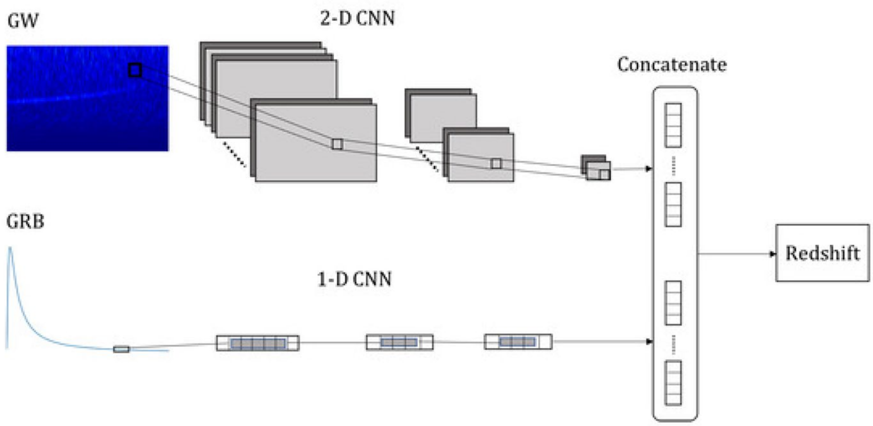


Fig. 13 The analysis from Cuoco et al. (2022) employs a multimodal ML model to calculate the redshifts of joint GW and gamma-ray burst (GRB) sources. This model integrates two distinct types of data – images and time series – to effectively address the regression problem. A schematic of the architecture of the neural network used is shown

modalities in input, such as text, images, audio, and sensor data. By integrating diverse sources of information, multimodal learning enables Artificial Intelligent systems to capture a more complete understanding of the world, mimicking human-like perception (Baltrusaitis et al. 2019) The multimodal approach could offer complementary information on the merger process and provide constraints on the properties of neutron stars and the nature of the resulting remnant or help in parameter inference. Cuoco et al. (2022) introduced the idea of applying the multimodal machine learning (MMML) approach to multi-messenger data where there is the emission of GW signals and electromagnetic or neutrino counterpart. Cuoco et al. (2021) introduced the first approach of multimodal machine learning to joint analysis of signals emitted as GW and as gamma-ray electromagnetic signals to produce a proof of concept of this approach (Fig. 13).

On the other hand, as already discussed in Sect. 6.1, neutron star properties (especially the equation of state) can also be inferred by combining more indirectly the measurements from GW and EM observations of different objects. ML-based examples of this rapidly growing field include, e.g., a random-forest based approach (Hernandez Vivanco et al. 2020), a predictive variational auto-encoders (Han et al. 2023), or Bayesian Neural Networks (Han et al. 2021; Carvalho et al. 2023), which have all been chosen with a mind to being flexible enough to combine the mass–radius constraints from the observations of BNSs and radio pulsars.

8.5 Population inference and cosmology

The main developments in the application of ML to population inference and cosmology are very recent. As with a large fraction of ML applications in GW astrophysics, the aim in the area of cosmology is an improvement in the speed of analysis when compared to the accurate existing benchmark analyses and the correlated issue of efficiency when the number of detections and the complexity of the cosmological models is increased. Regarding population analysis, speed is of less motivation and model flexibility through the use of normalizing flows and GPUs appears to be the driving force. In both areas the techniques share many commonalities and all work discussed in this section falls under the category of Hierarchical Bayesian inference. This is where the input to these algorithms comes in the form of samples from Bayesian posteriors on the source parameters of individually detected events.

Stachurski et al. (2024) use a normalising flow model trained to learn the true prior distribution of GW source parameters given knowledge of the distribution of mass in the local universe and conditioned on the Hubble constant. The results of the process then allow for the rapid calculation of the posterior distribution on the Hubble constant using posterior samples from detected BBH events. The posterior samples are initially processed by undoing the priors applied on the GW samples during the event PE process. Then the Hubble constant dependent normalising flow model priors are applied allowing the extraction of the posterior probability directly from the normalizing flow model marginalized over the event uncertainties. The paper focuses on the task of accurately comparing their results with those of the benchmark analysis (Abbott et al. 2023a) which only provided inference on the Hubble constant. The authors compare with the benchmark results and provide JS-divergence measurements of $\mathcal{O}$(few) nats over 42 BBH events.

Although the normalizing flow model in Stachurski et al. (2024) was presented as a Hubble constant inference tool, it is easily generalisable to additional cosmological and population parameters. At the heart of the analysis is the generation of training data for the model which crucially incorporates the fact that GW sources within sky and distance regions that would likely be contained within galaxy catalogs (specifically the GLADE+ catalog; Dálya et al. 2022). Data generation therefore includes samples from the GW parameter prior that follow the mass distribution described by the distribution and magnitude properties of known galaxies. Those generated samples whose location and host galaxy properties would not be within the catalog are sampled according to a uniform in comoving volume distribution. Data generation is also restricted such that samples must be detectable by the assumed network of GW detectors. In this sense the authors require that a training data signal within an assumed detector network would achieve an SNR above a predefined threshold. An identical SNR threshold criteria must then be applied to any signals analysed (or tested) by the trained model. Ultimately these processes form a prior distribution of GW event parameters conditional on sources being detectable but also conditional on the assumed cosmological and population parameters which are represented by random draws from their respective priors for each generated sample.

The choice to use training data conditional on being detectable naturally limits the volume of space considered. However, the evaluation of the detectability of each prior sample is costly since it requires the simulation of a gravitational waveform in order to calculate the SNR. To avoid this significant bottleneck in the speed of data generation an additional ML tool was used. To compute the optimal SNR of each sample rapidly, a Multi-Layer Perceptron (MLP) model was used to approximate the SNR function (from the *poplar* package developed by Chapman-Bird et al. 2023, and similar to Gerosa et al. 2020). This same tool is used to evaluate the probability of detection when processing event posterior samples through the normalizing flow model and accounts for the selection bias imposed by the original SNR threshold[4] used for determining detections.

Work done in parallel (Leyde et al. 2024) applied the same normalizing flow technology but used a different approach to the training data. Here the authors make use of a previously discussed ML tool used for rapid Bayesian PE for CBC events, DINGO (Dax et al. 2021). This allows them to sample from a prior distribution of both cosmological and population parameters from which they can then sample the prior parameters of GW events conditional on the cosmology and population. In this first work they do not consider information from galaxy catalogs although in principle they could be incorporated in a similar way to Stachurski et al. (2024). They can then very quickly simulate GW signals in noise and generate $\mathcal{O}(1000s)$ of posterior samples from each event. The normalizing flow model is designed to take as conditional input an embedded representation of event posteriors from n events, each contributing a set of posterior samples. So in contrast to Stachurski et al. (2024), where a normalizing flow was trained to process batches of single posterior samples conditional on cosmological parameters, here the network is conditional on input batches that are composed of many events with each event represented by many posterior samples. The outputs in this case are samples drawn from the posterior on the cosmological and population parameters and results can be obtained in ~minutes.

Regarding population analyses, the first approach to apply machine learning techniques was Wong et al. (2020), where a normalizing flow model was used to emulate a phenomenological population model governed by 4 hyper-parameters. Each instance of the model predicts the distribution of 6 GW observables (the primary mass, mass ratio, spin magnitudes, and spin tilts) which are modeled as being measured in the high SNR limit and therefore with no uncertainty. Their normalizing flow method was validated against an analytic phenomenological model where the only difference is the likelihood function (learned for the normalizing flow versus analytic). It is concluded that the normalizing flow model can emulate the phenomenological model accurately and efficiently.

A non-parametric binned Gaussian Process approach is used in Ray et al. (2023) to model the joint mass and redshift distribution of compact binary coalescences. They account for the significant measurement uncertainties in the GW input data (posteriors), and using a Gaussian process allows them to make very few assumptions about the functional form of the distribution model. The flexibility of their model allows them to probe the possible correlations between the mass and redshift distribution, e.g, a cosmologically evolving mass distribution. They applied their model to data from the GWTC-3 catalog (Abbott et al. 2023b) but concluded that more events are required to confidently assert that correlations are present.

In Ruhe et al. (2022) normalizing flows were used to model the mass, redshift, and spin distributions of detected CBC events taken from the GWTC-3 catalog

[4] In reality an SNR threshold is not used for determining whether GW events have been detected. This decision is made based on a false alarm rate leading to a correlated but variable threshold on the matched-filter SNR.

(Abbott et al. 2023b). The input in this case were the posterior samples on the event parameters under the assumption of a fixed and known cosmology. Despite not including selection effects in their model, the authors claim that they have been able to recover posterior structure that agrees with existing phenomenological modeling results.

Motivated by the growth of the observed catalog of GW events, in Cheung et al. (2022) a Gaussian process and a normalizing flows approach are compared in a population study mock events and a subset of events from GWTC-2 (Abbott et al. 2021c). They consider a phenomenological model of the mass and redshift parameters and use posterior samples from the simulated (and real) events as input to the analysis. They were able to conclude that the normalizing flows model could recover the correct posterior distributions with up to 300 mock events but had a tendency to underestimate the uncertainty (or width) of the posterior for real data. The Gaussian process model struggled in all but low-dimensional cases.

We also briefly mention an application of ML to population synthesis (Gerosa et al. 2018; Wong and Gerosa 2019) where in the latter work a Gaussian Process is trained on a small but state-of-the-art, set of population-synthesis predictions of BBH systems formed in isolation. The resultant hierarchical Bayesian analysis uses the Gaussian Process model to interpolate between simulations allowing the construction of a smooth posterior on the input hyper-parameters of the population synthesis model conditioned on BBH data from O1 and O2 detections. In this case the inferred hyper-parameter was the strength of natal kick that black holes receive at birth.

One aspect that is becoming increasingly clear with the development of new ML techniques in the areas of GW population and cosmological inference is the realistic possibility of merging the 2 areas of research. As research has developed it is clear that cosmological analyses have made fixed model assumptions about the underlying source population. Similarly, population studies have often assumed a fixed cosmology. Work specifically on the cosmology side, e.g. Leyde et al. (2024) is leveraging the power of ML to bridge the gap and simultaneously perform inference on a joint cosmological and population parameter-space. This will allow us to properly account for our lack of accuracy in either area and correctly account for how these uncertainties correlate between cosmological and population parameters.

8.6 New physics

Beyond the traditional astrophysical targets and search types, terrestrial GW detectors can also probe many interesting "new physics" scenarios not expected under standard astrophysical scenarios, or even beyond the standard model of particle physics. This includes the manifold imprints of early-universe physics on stochastic backgrounds (Renzini et al. 2022; van Remortel et al. 2023) as well as dedicated searches for such diverse physics as the early inspiral or full coalescence of binary Primordial Black Holess (PBHs) (García-Bellido 2017; Bird et al. 2016; Abbott et al. 2022c; Miller et al. 2022, 2024) (depending on their mass scale), cosmological defects such as cosmic strings (Vachaspati and Vilenkin 1985; Abbott et al. 2021b) and domain walls (Grote and Stadnik 2019), indirect detection of particle dark matter as emitters of GWs from boson clouds around spinning black holes (Brito et al. 2020; Abbott et al. 2022a), and direct detection of particle dark matter interacting with the hardware of the detectors rather than through any propagating GW channel (Pierce et al. 2018; Guo et al. 2019; Vermeulen et al. 2021; Abbott et al. 2022b; Miller and Mendes 2023; Abac et al. 2024). These references are only a limited set of examples, as the ongoing research in these directions would merit several dedicated review articles. For example, see also Maggiore (2000); Roshan and White (2025) for probing the early universe with GWs, and for anything black-hole related see also Barack et al. (2019).

Most of these scenarios have only been investigated relatively recently, and the search methods employed so far are mostly based on direct transfer of established traditional methods from the CBC, burst, CW or stochastic domains. This approach bears the risk of a "searching under the streetlights" or "hammer in search of a nail" effect, where only new physics that produces signals that are qualitatively similar to known types get searched for. One ML-adjacent algorithm that is already being fruitfully applied as a computationally efficient alternative to PBH searches (Alestas et al. 2024) is the Viterbi method, as previously discussed for CW searches in Sect. 7.4. One could in general expect that fairly generic ML approaches, such as those discussed in Sects. 7.3 and 7.5 for the detection of unmodelled signals, will generalize well to such new physics signals. This includes e.g. anomaly detection techniques, which by definition look for any type of unexpected signals, and neural networks with training sets that follow simple phenomenological signal models, such as sine-Gaussians or a Taylor expansion for quasi-monochromatic CW-like signals, but are independent of specific physical scenarios. However, detailed studies remain to be done to see if this expectation will be borne out. On the other hand, in the future, more dedicated ML methods for specific new physics scenarios could lead to notable progress in the field, especially in areas where fully explicit waveform models over a broad parameter space are difficult to obtain, e.g. requiring a large new set of computationally costly numerical simulations and lots of human effort to construct an explicit model, but ML interpolation schemes or SBI may be more feasible starting from a relatively sparse set of simulations and skipping the manual modelling step. Again, it remains to be seen in the coming years if fruitful applications will be found.

9 Citizen science & machine learning

We have already mentioned the Gravity Spy and the GWitchHunters projects in Sect. 5.1 as two examples of applications of citizen science to the characterization of detector strain data.

A study by Soni et al. (2021) analyses the impact of glitches on GW searches during the O3 run of the Advanced LIGO detectors. Two new classes of glitches were identified, fast scattering/crowns and low-frequency blips. Gravity Spy's ML algorithm for glitch classification was updated using training sets from detector monitoring and citizen-science volunteers. Reclassification of the data based on the updated model reveals that about 27% of glitches at LIGO- Livingston belongs to the fast scattering class, while about 8% belongs to the low-frequency blip class. The results underline the potential of glitch classification to improve the data quality of GW detectors and demonstrate the value of citizen-science contributions in analyzing large datasets.

Different strategies have also been employed to involve scientists or citizens outside of the GW community, with efforts to engage the advanced data scientist community. The approach of the G2net COST Action CA17137[5] was to engage external participants through data challenges for GW data on the Kaggle platform.[6]

9.1 Kaggle challenges

Kaggle is a data science competition platform and online community of data scientists and machine learning practitioners under Google LLC. Kaggle works together with academics and business to develop self-contained data analysis challenges for this community. As of 2023 Kaggle has over 15 million registered participants who are encouraged to tackle these challenges for rewards of either cash or Kaggle credits. Example competitions currently active on the platform include the identification of text generated from large language models, predicting how small molecules change gene expression in different cell types, predicting US stocks closing movements, and helping to evaluate tackling tactics and strategy in the American National Football League. Since the founding of Kaggle in 2017 they have hosted over 600 competitions.

In a typical challenge, participants are provided with an example (training) dataset or the means to generate artificial data, a description of the aims of the challenge, and a clearly defined metric by which to judge a submitted set of analysis results. These results are obtained through the analysis of a testing dataset, uploaded via the Kaggle competition site where the metric is evaluated. Competitions are open for ~ 3 months (although this can vary) and participants can track their performance relative to other participants (or teams of participants) via a leaderboard that is constantly updated based on the latest submissions.

As a challenge developer, the process of designing the challenge within the Kaggle infrastructure takes place whilst working with a small team of Kaggle employees over a number of months. During this time the feasibility of the challenge is assessed in terms of a number of factors including practical issues such as the volume of training and testing data to be made available, the difficulty of the challenge, the appropriate metric by which to judge the results, and how intrinsically interesting the challenge will be to the Kaggle community. Prior to the competition launch, documentation for participants must be provided and the datasets carefully examined by Kaggle developers to catch errors and to specifically eliminate any leakage.[7] Once

[5] https://www.g2net.eu and https://www.cost.eu/actions/CA17137.

[6] https://www.kaggle.com/.

[7] Leakage in this context is the use of information in the model training process which would not be expected to be available at prediction time.

the challenge is launched, competition hosts are able to interact with participants through the competition online forum in order to answer any questions or address any remaining issues with the data.

In order to engage with the broader ML community and in an effort to gain independent perspectives on how to approach GW data analysis problems, a series of Kaggle challenges have been developed within the G2net COST action. To date two such challenges have been hosted on the Kaggle platform, each tackling a different aspect of ground based GW data analysis. Both were classification (detection) problems with the first on the topic of compact binary coalescence of black holes (BBHS), and the second on the detection of continuously emitted GWs (CWs) from rapidly rotating NSs.

9.1.1 Challenge 1: binary black holes

The first G2Net Kaggle challenge (Messenger et al. 2021) was launched on 30th June 2021 and was the first public GW based data analysis targeted at the machine learning community. It was designed to build upon the growing interest in applying neural network classification algorithms for the problem of transient GW signal detection, specifically the case of stellar mass BBHs. The task was to determine the presence or absence of a BBH signal in simulated advanced-detector Gaussian noise and the metric used to rank submissions was the *Area under the ROC curve* (AUC). This measure can be constructed from a submitted list of probability estimates for the presence of a signal in each piece of test data. At the conclusion of the challenge 1501 competitors spread between 1219 teams participated in the challenge.

In this competition, the participants were provided with a training set of time series data containing simulated GW measurements from a network of 3 detectors (LIGO-Hanford, LIGO-Livingston, and Virgo). Each time series contained either just detector noise or detector noise plus a simulated GW signal. The BBH parameters that were varied for each simulated signal were the masses, sky location, distance, black hole spins, binary orientation angle, polarisation, time of arrival, and phase at coalescence (merger). These 15 parameters were randomized according to astrophysically motivated prior distributions (not known to the participants) and used to generate the simulated signals present in the data. Each data sample contained three time series (one for each detector) and each spanned 2 sec and was sampled at 2048 Hz. The distribution of integrated SNR values for the data containing signals was not astrophysically motivated but tuned by varying the distances of each signal such that the challenge contained a range of easy and hard to detect cases. It was also designed so that the bulk of signals would have SNRs close to the sensitivity region of known matched filter searches (SNR ~ 8).

At the time of writing, the results of the first challenge have yet to be published.

9.1.2 Challenge 2: continuous waves

Following the success of the first challenge, which attracted strong interest from the Kaggle community, a more difficult challenge was introduced in the second G2Net competition (Tenorio et al. 2022). This focused on continuous gravitational wave detection, where recent ML efforts (Dreissigacker et al. 2019; Dreissigacker and Prix 2020) have shown promise but have yet to overcome the significant computational hurdles of traditional search methods – see Sect. 7.4.

The second challenge was similar to the first in that it was a classification task to detect CW signals in simulated advanced-detector Gaussian noise, using the Area under the ROC curve for ranking. However, the datasets were much larger, and the parameter space was more complex, making it significantly more difficult. Special efforts were made to increase the realism of the challenge by using real advanced-detector noise for the test data and simplifying the application of winning solutions to real GW data.

In this competition, participants received time-frequency data from two gravitational-wave detectors (LIGO-Hanford & LIGO-Livingston) over a 3-month period, containing either real or simulated noise and possibly a simulated CW signal. The data consisted of Short-time Fourier Transforms (SFTs) (Allen et al. 2022) and GPS timestamps, with realistic gaps due to detectors not always operating. Simulated signals, if present, spanned the entire dataset, and were defined by eight parameters including source location, frequency, and amplitude, drawn from astrophysical priors. The SNR distribution was tuned to include stronger signals that were easier for beginners, while more challenging signals were aimed at experienced Kaggle teams.

The results of this challenge are still pending, but like the first, it drew significant interest with 1,181 competitors across 936 teams. Surprisingly, most top-ranked teams concluded that ML wasn't the best approach for this problem. Competitors initially tested standard ML methods, but the weak CW signal and large search space made them ineffective. This led many to explore more traditional data analysis techniques inspired by physical principles and gGW literature. The winning method incorporated existing state-of-the-art CW techniques, simplifying complex procedures and achieving faster computation using smart algorithm design and GPU parallelism.

10 Next-generation GW detectors

Beyond the current LVK network, new third-generation ground-based detectors like the Einstein Telescope (ET) (Punturo et al. 2010) in Europe and Cosmic Explorer (CE) (Abbott et al. 2017a) in the US are in planning. These will be designed to bring great improvements in sensitivity, but will also create completely new challenges in data analysis due to the huge event rates (Maggiore 2020), much higher achievable SNRs which require more accurate waveform models and processing techniques (Pürrer and Haster 2020), and the much longer in-band duration of CBC signals due to the lower minimum frequency. The latter, for example, makes it necessary to include the Earth's movement in CBC studies (Zhao and Wen 2018; Chen and Johnson-McDaniel 2024), an aspect that for the LVK is usually limited to CW analyses.

ML techniques may play crucial roles in dealing with these new challenges, and work is picking up in the community to develop new solutions. To give just a few examples, some studies of ML applications in this new observational regime include Alhassan et al. (2022, 2024) who adapted several off-the-shelf neural network for

BBH detection with ET and found ResNet to perform best, which was then tested on the first Einstein Telescope Mock Data Challenge (Regimbau et al. 2012). In Meijer et al. (2024), a deep-learning model was used to distinguish between GW signals from cosmic string cusps and simulated blip glitches in ET data, using a realistic population of glitches for this future detector.

The sensitivity of these future ground-based GW detectors at frequencies below approximately 10 Hz may still be constrained by the Newtonian coupling of ground vibrations to the core optics of the detectors. This contribution of Newtonian noise varies depending on the specific site and is influenced by the ambient seismic field, which, in turn, is contingent upon the geological makeup of the site and the distribution of surface and underground seismic-noise sources. Van Beveren et al. (2023) used ML for one of the candidate ET sites to learn alongside seismic sensor networks and to predict seismic displacement noise at specific surface and underground locations. Additionally, a deep neural network has been developed to subtract Newtonian noise from the measured GW strain data, showing its effectiveness in predicting Newtonian noise.

Utina et al. (2021b) explored the search for a GW background using deep neural networks, focusing on simulated astrophysical backgrounds generated by many BBH coalescences. Specifically, the study examined the detection pipeline designed to isolate signal data from noisy detector backgrounds, utilizing three classes of deep neural network algorithms: a 1D CNN, a 2D CNN, and a LSTM network. Results indicate that all three algorithms can effectively distinguish signals from noise with high precision for the ET sensitivity level.

Several space-based detectors, including LISA (Amaro-Seoane et al. 2017), Taiji (Hu and Wu 2017), Tianqin (Luo et al. 2016), and DECIGO (Kawamura et al. 2011), are being planned to access the GW spectrum at frequencies lower than those accessible to ground-based detectors – with LISA firmly adopted by ESA for launch in the 2030 s. These next-generation detectors target a rich science case in a completely different regime than the LVK, including novel sources (Amaro-Seoane et al. 2023; Afshordi et al. 2023; Ruan et al. 2020; Mei et al. 2021), such as supermassive black hole binaries and the very long-duration, highly complex Extreme Mass Ratio Inspirals (EMRIs) (Amaro-Seoane 2018). LISA and the analysis of its data will function very differently from the LVK detectors, with each space craft receiving and sending out individual laser beams rather than them being reflected at each end point, time-delay interferometry (Tinto and Dhurandhar 2021) as a crucial ingredient to obtain sensitive strain measurements, and the time- and frequency-dependent detector response adding significant complications. In addition, it is expected to operate in a signal-dominated regime, where many transients of different duration and characteristics overlap in time and a strong foreground of galactic sources dominates part of the sensitive band, leading to the "global fit" challenge (Cornish and Crowder 2005; Vallisneri 2009) of modelling and extracting all these contributions together. And even more so than for third-generation ground-based detectors, the extremely high SNRs expected for some LISA detections pose stringent requirements on the accuracy of waveform models and analysis techniques (Afshordi et al. 2023).

So far, deep neural networks are already emerging as a popular approach for studying the new signal types accessible with LISA, see for example Zhang et al. (2022); Zhao et al. (2023); Yun et al. (2025); Mao et al. (2024); Sun and Li (2023); Korsakova et al. (2024); Xu et al. (2024); Ruan and Guo (2024). Besides evaluating individual waveforms, neural networks can also be useful to speed up population studies (like those discussed for the LVK case in Sect. 8.5), see e.g. Chapman-Bird et al. (2023) for using neural networks for SNR estimation and selection effects in studying EMRI populations. As for ground-based detectors, glitch mitigation (see Sect. 5) in detectors like LISA can also be approached with ML methods (Houba et al. 2024). But much work remains to be done to see how ML approaches can help with the overall challenges and fit into the overall LISA data analysis pipeline. They clearly carry great promises to deal with the complicated noise and detector properties and the more complicated signal types like EMRIs, but realistic end-to-end testing and integration with global fits will be crucial to realize this potential.

ML and related methods can also be useful in the design of future detectors. For example, Krenn et al. (2023) have used a gradient-descent optimization algorithm to explore the sensitivity of many possible configurations of interferometric GW detectors. Such algorithms are also typically used in many training-based ML approaches, though in this case direct optimization is performed over a large parameter space, without a training stage, so the authors categorize their work more generally as artificial intelligence.

11 Summary and outlook

The ML revolution is rapidly changing the picture related to data analysis and, above all, the ability to provide increasingly reliable real-time answers in different fields. In this review, we have provided an overview of the application of ML techniques in the field of GW astronomy, discussing various ML algorithms and methods used to address key challenges in GW data analysis, including noise reduction and mitigation, signal detection, parameter estimation (pe), classification and interpretation of astrophysical sources. We have only covered works released by the summer of 2024. More recent works will be considered in future updates of this living review.

The main promises of ML are twofold: greater speed, and greater flexibility and robustness where signal and noise models may be incomplete.

Many proof-of-principle studies have shown that ML algorithms can be useful and computationally efficient instruments for identifying weak signals from noisy data and provide high-sensitivity GW searches, supplementing classical signal processing techniques. Full end-to-end analyses and detailed comparisons against existing pipelines, to judge sensitivity and reliability in different parts of parameter space, have initially been scarce, but are now also increasingly appearing in the literature. Kaggle challenges and other mock data sets are important to this end, as are end-to-end searches on real open data.

Moreover, ML methods can identify and suppress noise artifacts, and remove non-stationary and non-linear noise, giving thereby a better overall data quality. They can also facilitate the PE process for GW events by enabling faster determination of key parameters such as the masses and spins of CBCs. This capability is essential for extracting detailed astrophysical information from observed signals. By training on labeled data sets, ML models can distinguish between various source populations, aiding in the identification and categorization of observed events, and helping us in the classification task of different GW signals. ML will also be able to help us with increasingly complex detector architectures, in identifying and reducing non-linear couplings in various noise sources.

Efficient real-time processing capabilities will be indispensable, especially for future detectors, when we will be forced to analyze many events per day and provide increasingly precise parameter estimates in a short timeframe to electromagnetic observing partners. As the sensitivity of GW detectors increases, particularly at low frequencies, we will also be faced with the problem of analyzing increasingly long transient events and even overlapping signals. ML applications in this area may be one of the solutions to untangle signals of particular interest from the astrophysical background. At the same time, "multimodal" ML methods that use multiple inputs from different observational domains to characterize the same astrophysical object, or populations of similar events or sources, may be a key advance for multi-messenger astronomy.

In addition to computational efficiency, ML also holds the promise of making GW data analysis more robust towards the complications of real detector noise, and to signal model limitations. Generative noise models can help overcome the limitations of standard techniques based on Gaussian likelihoods. Where complete and accurate signal models are difficult to obtain, ML techniques may help with better inter- and extrapolation properties, though the details highly depend on the structure of the parameter space under study and the amount of physical intuition that can go into constructing the algorithms and, if applicable, their training data.

In general, across GW astrophysics it is too early to say that the traditional data analysis methods have been replaced or superseded by ML techniques. While they have demonstrated their importance and usefulness as being more efficient and faster for some applications, in others they are merely another alternative in a large toolbox with certain benefits, but not necessarily superior overall. Also, any new algorithms proposed to a large collaboration like the LVK – not limited to ML – must always undergo a thorough review process before becoming an official and production-level analysis line. Examples where ML is already used as a production tool by the LVK include noise subtraction techniques and the low-latency classification of compact binary coalescence alerts. For search pipelines and parameter estimation, various ML methods are gearing up for production use, and this is likely to become a growing trend before the next observing run (O5).

So, we expect that in the coming years, ML will see an increasingly deep application in production pipelines for GW detection, classification and PE, both inside the LVK and in the wider GW community. Still, such broad adaptation will also confront us with choices for the technical solutions best suited to this type of analysis. The availability of increasingly high-performance and specific hardware for data analysis algorithms may also determine the best choices for innovative strategies, distinguishing algorithms as dedicated to real-time or offline analysis. Many areas such as persistent GW signals and searches with GW detectors for new physics also are still in very early stages for exploring ML solutions, and we expect more progress in the coming years.

On the technical side, many more recent innovations from the wider ML community are still making their way into GW practice. Initial studies have often focused on a few select classifier algorithms and neural network architectures, with CNNs initially particularly prominent, but a more diverse array of algorithms and network models are now being explored. Certainly, in the coming years new innovative techniques will continue to be either newly developed or adapted from other fields.

Meanwhile, it will be increasingly important to work on the the remaining conceptual and practical challenges of ML techniques. For example, while very computationally efficient at evaluation time, neural networks in particular can have immense computing costs for training, leading to high computing budgets overall, bottlenecks on GPUs which are still comparatively rare on many computing clusters used within the GW community, and possibly severe climate impacts. More fundamentally, questions have been raised about the capability of ML-based GW signal searches to provide reliable significance estimates on their own, or at least about how well these extrapolate from standard training/testing workflows to real applications. Another often-raised criticism is the lacking reproducibility and explainability of many results obtained with ML techniques, including the possibility of unforeseen failure modes. We expect in the years to come that an increasing emphasis will be placed on improving these aspects, with the adoption of best practices and novel architectures from the growing field of explainable/interpretable ML/AI research, and also the need to make them part of the standard pipeline of ML-based analyses.

In summary, we look forward to an increasingly permeating role of ML in the field of GW research and we expect an evolution of techniques also related to the deployment of next-generation detectors.

Glossary

ANN	Artificial Neural Network: A machine learning algorithm that is based on the structure and function of biological neural networks in the human brain.
Auto-encoder	A type of machine learning algorithm that combines two networks, one for encoding and one for decoding, to transform between inputs/outputs and a lower-dimensional latent representation space. See e.g. Michelucci (2022) for an introduction.
Bayesian statistics	One approach to statistics, where probability is interpreted as degrees of belief. In the gravitational-wave context, most parameter estimation techniques are Bayesian. See Jaynes (2003); Gregory (2005).
BBH	Binary Black Hole: A binary composed of two black holes, typically of interest to us as a source of a compact binary coalescence signal. Purely described by general

	relativity without matter effects. The prototypical example was GW1501914 (Abbott et al. 2016b).
BNS	Binary Neutron Star: A binary composed of two neutron stars, typically of interest to us as a source of a compact binary coalescence signal, of longer duration inside the detector band than a binary black hole and with more complicated waveforms due to matter effects. First multimessenger detection with GW170817 (Abbott et al. 2017c).
Burst	A short transient gravitational-wave signal, typically those for which no explicit waveform model is available.
CBC	Compact Binary Coalescence: A binary of two compact objects radiating away orbital energy in the form of gravitational waves, getting increasingly closer, producing chirp-like gravitational-wave signals with the three characteristic phases of inspiral, merger and ringdown.
CCSN	Core-Collapse SuperNova: The explosion at the end of a massive star's life, which due to asymmetries can emit gravitational-wave bursts.
CE	Cosmic Explorer: A planned third-generation gravitational-wave detector in the United States, see Abbott et al. (2017a).
CGAN	Conditional Generative Adversarial Networks: A variant of generative adversarial networks (see below) where the networks are provided with additional information, e.g. labels of the training data. See Mirza and Osindero (2014).
CNN	Convolutional Neural Network: Neural networks that convolve the input data with kernels representing local perceptive fields. A popular method for image recognition tasks and hence also often used on intermediate gravitational-wave data products such as spectrograms. See e.g. Venkatesan and Li (2017) for a general introduction.
CSC	Constrained Subspace Classifiers: A class of algorithms for classification.
Curriculum Learning	A procedure to improve the training of, e.g., a neural network, by presenting it with two or more separate training sets of increasing difficulty. See Bengio et al. (2009).
CVAE	Conditional Variational Auto-Encoder: A version of auto-encoders (see above) where "variational" refers to considering distributions as the central objects of interest, and the network is "conditional" on specific observations. See Tonolini et al. (2019); Pagnoni et al. (2018).
CW	Continuous Gravitational Wave: Persistent or at least very long-duration gravitational-wave signals from individual

spinning deformed neutron stars or other, more exotic sources. See Riles (2023) for a comprehensive review.

Deep learning Machine-learning methods based on deep, i.e. many-layered, neural networks. See Goodfellow et al. (2016) for an introduction.

DL Dictionary Learning: A machine learning method that sparsely represents data in a higher-dimensional space by using an optimal set of basis functions.

EM electromagnetic: Physical interactions mediated by photons. In our context also used as a shorthand for the methods and observatories of classic astronomy ranging from radio to γ-ray wavelengths.

EMRI Extreme Mass Ratio Inspiral: Binary mergers with very high mass ratios, e.g. higher than 10^4 following (Afshordi et al. 2023). They are mainly accessible to space-based gravitational-wave detectors.

ET Einstein Telescope: A planned third-generation gravitational-wave detector in Europe, see Punturo et al. (2010).

Frequentist statistics one approach to statistics, where probability is interpreted as the limiting fraction in infinitely repeated experiments. Often referred to as the opposite of Bayesian.

GAN Generative Adversarial Network: An unsupervised machine learning method where two networks are designed to train through competing with each other, a generator trying out new signals and a discriminator trying to classify them. See Goodfellow et al. (2020).

Gaussian Process Nonparametric supervised learning method. For a review see Rasmussen and Williams (2006).

Genetic Algorithm An algorithm that uses rules inspired by reproductive processes and natural selection to improve a population of candidate solutions.

Genetic Programming An approach to problem solving based on evolving an initial population of computer programs.

GMM Gaussian Mixture Model: The approach of approximating arbitrary data sets or probability distributions by a sum of a variable number of Gaussian functions. See Sect. 16 of Press (2007). In the limit of a large and adaptively chosen number of Gaussians, this becomes comparable to Gaussian Kernel Density Estimators (KDEs).

GPU Graphical Processing Unit: Computer hardware originally designed for 3D graphics, with massively parallel processing capabilities, which also makes them ideal for machine learning applications.

GRU Gated Recurrent Unit: A type of recurrent neural network architecture with a simpler architecture and fewer parameters than long short-term memory networks.

GW	Gravitational Wave: Ripples in space-time, i.e. propagating solutions of Einstein's equations. The types of astrophysical signals we are considering.
GWTC	Gravitational-Wave Transient Catalog: The catalogs of high-probability gravitational-wave candidates published by LIGO, Virgo and KAGRA, with all entries in the four releases from observing runs O1–O3 (Abbott et al. 2019a, 2021c, 2024a, 2023b) so far being compact binary coalescences. These catalogs are considered cumulative, e.g. GWTC-3 contains events from O1–O3, even though the individual publications typically focus on the most recent subset of events.
k-means clustering	A popular clustering algorithm that iteratively refines an initial set of clusters, see Jin and Han (2010).
KAGRA	A 3 km armlength underground gravitational-wave detector in Japan, described in Akutsu et al. (2021).
KNN	k-nearest-neighbor: A non-parametric supervised classification/regression method, see Shakhnarovich et al. (2005).
LIGO	Laser Interferometer Gravitational-wave Observatory: Two 4 km armlength gravitational-wave detectors in the US. Upgraded to Advanced LIGO by 2015, as described in Aasi et al. (2015).
LISA	Laser Interferometer Space Antenna: A space-based gravitational-wave detector scheduled for launch in the 2030 s by ESA and NASA, targeting lower frequencies than current terrestrial detectors.
LSTM	Long Short Term Memory: Recurrent neural network family.
LVK	LIGO–Virgo–KAGRA: The current global network of interferometric gravitational-wave detectors. Also used as a joint acronym for the three collaborations who build and operate them and analyze their data.
Matched Filter	The optimal linear solution to finding weak signals in a noise background of known properties, by "filtering" the full (noise+signal) input data with a model for the expected signal. See Wiener (1949); Wainstein and Zubakov (1962) for the general concept, Allen et al. (2012) for the compact binary coalescence case and Jaranowski and Krolak (2009) for continuous waves.
MCMC	Markov Chain Monte Carlo: A stochastic sampling method, often used for parameter estimation of gravitational-wave signals, using one or more chains exploring the parameter space with a jump probability depending only on the current position, not the previous history (Markovian). See e.g. Chapter 12 of Gregory (2005).

ML	Machine Learning: The set of data-driven analysis methods we review here.
MLP	Multi-Layer Perceptron: Another term for neural networks made out of multiple layers, each including multiple neurons. Traditionally, a perceptron is a neuron with various binary inputs and one binary output.
Multi-messenger	Astronomical observations that use signals from at least two of the following categories: electromagnetic, gravitational waves, and/or astroparticles (neutrinos, cosmic rays, ...). See Corsi et al. (2024) for a recent review.
Nested sampling	A stochastic sampling technique often used as an alternative to Markov Chain Monte Carlo algorithms in gravitational-wave parameter estimation, introduced by Skilling (2006). It is particularly well suited for evidence calculation, as needed in model selection. See also Ashton et al. (2022) for a pedagogical review.
Newtonian Noise	Environmental noise that is produced by tiny fluctuations of the Earth's gravitational field, such as those generated by the motion of air and soil. Newtonian noise couples to ground-based interferometric gravitational-wave detectors limiting their sensitivity at low frequencies. It is expected to become the dominant source of noise in the low-frequency band in third-generation detectors.
Normalizing Flow	A technique to build up representations of complex probability distributions by learning the necessary transformations from a simpler base distribution (e.g. a Gaussian). See Papamakarios et al. (2021).
NR	numerical relativity: Methods for solving the Einstein equations with computers, most importantly for cases such as compact binary coalescences where no full analytical solutions exist. NR simulation results are one of the main ingredients for inspiral-merger-ringdown waveform models. See Palenzuela (2020) for an introduction.
NS	Neutron Star: The extremely dense remnant of a massive star, but not massive enough to collapse to a black hole. Promising gravitational-wave emitters either in a compact binary binary neutron stars or neutron star – black hole binaries or individually for continuous-wave signals.
NSBH	Neutron Star-Black Hole: A mixed compact binary consisting of one black hole and one neutron star. A possible multi-messenger source. First detected during the O3 observing run (Abbott et al. 2021d).
PBH	Primordial Black Holes: Black Holes that have not formed through stellar evolution, but are remnants from early universe physics.

PCA	Principal Component Analysis: A popular dimensionality reduction algorithm, see e.g. Jolliffe (2013).
PE	Parameter Estimation: Determining the physical properties of the sources. Usually Bayesian.
PINN	Physics-Informed Neural Network: Neural networks used to solve differential equations dwhich describe physical laws. See Raissi et al. (2017); Markidis (2021).
PSD	Power Spectral Density: A frequency-domain description of the fluctuation power in a time series, e.g. for detector noise or signal strength, with units 1/Hz. This is the square of the also commonly used Amplitude Spectral Density (ASD). For gravitational-wave applications, see Abbott et al. (2020a).
Random Forest	An ensemble learning method for classification and regression based on a set of decision trees. See Breiman (2001).
Reinforcement Learning	Deep learning approach based on trial-and-error and objective-based reward/penalty feedback. See Arulkumaran et al. (2017).
RELU	Rectified Linear Unit: A type of activation function often used for neural networks, defined as $\max(0, x)$.
ResNet	Residual neural network: A deep learning architecture in which the neural network layers learn residual functions based on their inputs. This technique enables the model to bypass one or more layers, allowing the network to be trained on a large number of layers without compromising performance.
RNN	Recurrent Neural Network: Deep learning structure with information exchange between layers. It is frequently used to process and model speech, text, and time series in general.
ROQ	Reduced Order Quadrature: A technique to speed up likelihood-based inference in gravitational-wave parameter estimation by precomputing ingredients to the signal likelihood for a given waveform model.
SBI	Simulation Based Inference: A version of likelihood-free inference that is useful when explicit parametrized models are computationally prohibitive or difficult to write down, while forward-simulating noise+signal realizations is easy and hence neural network methods, such as normalizing flows, can be trained to perform the analysis. See Cranmer et al. (2020).
SGWB	Stochastic Gravitational-Wave Background: A non-deterministic gravitational-wave signal corresponding to a universal background made of many overlapping signals, either from astrophysical processes or early-universe

	physics. See Renzini et al. (2022); van Remortel et al. (2023) for recent reviews.
SNR	Signal-to-Noise Ratio: A common measure for signal detectability. Note that this can be defined quite differently for different applications, including different conventions on expectation values in pure noise and scaling with amplitude or with power/energy (amplitude squared). For example, see Allen et al. (2012) for the standard definition in the context of compact binary coalescences and Riles (2023) for the continuous waves case.
SOAP	Officially not an acronym but can be assumed to stand for Snakes On A Plane: An algorithm for detecting continuous-wave signals as time-frequency tracks, introduced by Bayley et al. (2019). It involves a discrete number of time steps, where the states at each step are computed with the highest probability given the data. The algorithm got its name as a joke on the observation that the signal tracks, with their Doppler modulation, have snake-like shapes in the time-frequency plane, and the 2006 American action thriller film “Snakes on a Plane” directed by David R. Ellis and starring Samuel L. Jackson.
SVD	Singular Value Decomposition: A standard matrix decomposition of linear algebra that can also be used for dimensionality reduction, by chosing a reduced subset of the obtained basis set.
SVM	Support Vector Machine: A class of algorithms for classification, see e.g. Chapter 5 of Vapnik (2013).
Transformer	A deep learning architecture based on the multi-head attention mechanism, proposed by Vaswani et al. (2017).
Virgo	A 3 km armlength gravitational-wave detector in Italy, later upgraded to Advanced Virgo as described in Acernese et al. (2014).
Viterbi	A dynamic programming algorithm that can efficiently find the highest-probability signal path through an observed data set, e.g. a gravitational-wave spectrogram. Originally introduced for communications decoding by Viterbi (1967).
Waveform	A signal model for the time-domain strain time series or frequency-domain amplitude and phase evolution of gravitational waves from a specific source. For the case of compact binary coalescences, these are either taken directly from numerical relativity simulations or combine these with analytical relativity information. See Schmidt (2020) for a brief review and Afshordi et al. (2023) for a more in-depth overview, though focused on the case of the space-based LISA observatory.

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