Chapter 7

MACHINE LEARNING IN COSMOLOGY AND GRAVITATIONAL WAVE ASTRONOMY: RECENT TRENDS

Alvina Burgazli, PhD, Olga Sergijenko, PhD, Iryna Vavilova, Prof. *
Main Astronomical Observatory of the NAS of Ukraine

April 30, 2022

Abstract

The machine learning methods both supervised/unsupervised and reinforcement have invaded and conquered many scientific fields. During the last decade, novel algorithms and codes were developed and intended since huge observational sky surveys and databases have been conducted. Machine Learning methods are widely used to study the cosmological parameters and models, modified gravity theories, cosmic microwave background radiation in Big Bang cosmology, the gravitational lensing effect, photometry and image-based morphological classification of galaxies in various spectral range including gamma-ray and transient objects, large-scale structures of the Universe (galaxies, galaxy clusters and superclusters, filaments and voids) with their distance moduli at the cosmological scales, gravitational wave signals detection from merging black hole star and other events. It allows us to obtain a more structured picture of the evolutionary properties of these celestial bodies and the Universe as a whole. Classification accuracy (success rate) of machine learning is varied depending on the mathematical subtleties of the applied methods and the quality of astronomical data samples. Improvement of these methods and their limitations/correctness help us to interpret an astrophysical essence of results. In this context, we discuss the recent trends of machine learning applications in cosmology and gravitational wave astronomy.

PACS 01.50.hv, 01.75.+m, 02.70.-c, 04.30.Tv, 89.20.Ff, 95.30.Sf, 95.35.+d, 95.36.+x, 95.80.+p, 98.80.-k Keywords: machine learning, cosmology, gravitational wave science

AMS Subject Classification: 68-81, 85-08, 85A40, 83-08, 83C35

*E-mail address: aburgazli@gmail.com, olka@mao.kiev.ua, irivav@mao.kiev.ua

1. Machine Leaning in Cosmology

Modern cosmology is a relatively young branch of astronomy that involves the origin and evolution of the Universe from the Big Bang to the present time and on into the future. Current challenges it faces are, in general, about:

- the Dark Matter and the Dark Energy nature;
- growth of structures from inflation;
- formation of galaxies and stars;
- astrophysical feedback;
- Hubble tension.

Basically, what cosmology wants to know are the answers to the following questions:

- How did the Universe begin?
- How was the structure formed in the very early Universe? What were the initial conditions?
- How did all those structures grow? (This is a function of cosmic content, so the things that make up the Universe are neutrinos, baryons, and dark matter - all the components of the Universe.)
- How the Universe then evolved and the dynamics of the Universe (both in terms of growth of structure, but also globally the background dynamics, because the expansion geometry of the Universe is an essential clue to what is going to happen, what is dark energy, why the Universe is accelerating its expansion today)?

In contrast to the situation of just over a decade, the lack of data is no longer the bottleneck for cosmological knowledge. There are numerous current and upcoming experiments and missions dedicated to studying more about the Universe with significant datasets with observational data as an output. Among them, which are related to the modern cosmology, the most important and well-known are:

Planck (Planck Collaboration et al. (2020)) – is the third space mission (after COBE - COsmic Background Explore (a NASA space mission) and WMAP - Wilkinson Microwave Anisotropy Probe (a NASA Explorer mission)), which mapped the anisotropy of the cosmic microwave background (CMB) at microwave and infrared frequencies, with high sensitivity and small angular resolution. The space observatory was launched and operated by the European Space Agency (ESA) in 2009-2013.

Euclid (Euclid Collaboration et al. (2022)) – is a visible to near-infrared space telescope developed by the ESA and the Euclid Consortium. The Euclid mission is a Medium class astronomy and astrophysics space mission that aims at understanding the nature of the late Universe's accelerated expansion, planned for launch in 2023. The imprints of the dark energy and gravity will be tracked by using two complementary cosmological probes to capture signatures of the expansion rate of the Universe and the growth of the cosmic structures: Weak gravitational Lensing and Galaxy Clustering (Baryonic Acoustic Oscillations, BAO, and Redshift Space Distortion).

Square Kilometre Array, SKA (de Lera Acedo et al. (2020)) – is the world's largest telescope co-located primarily in Western Australia and South Africa. SKA will be a collection of hundreds of thousands of radio antennas with a combined collecting area equivalent to approximately one million square meters.

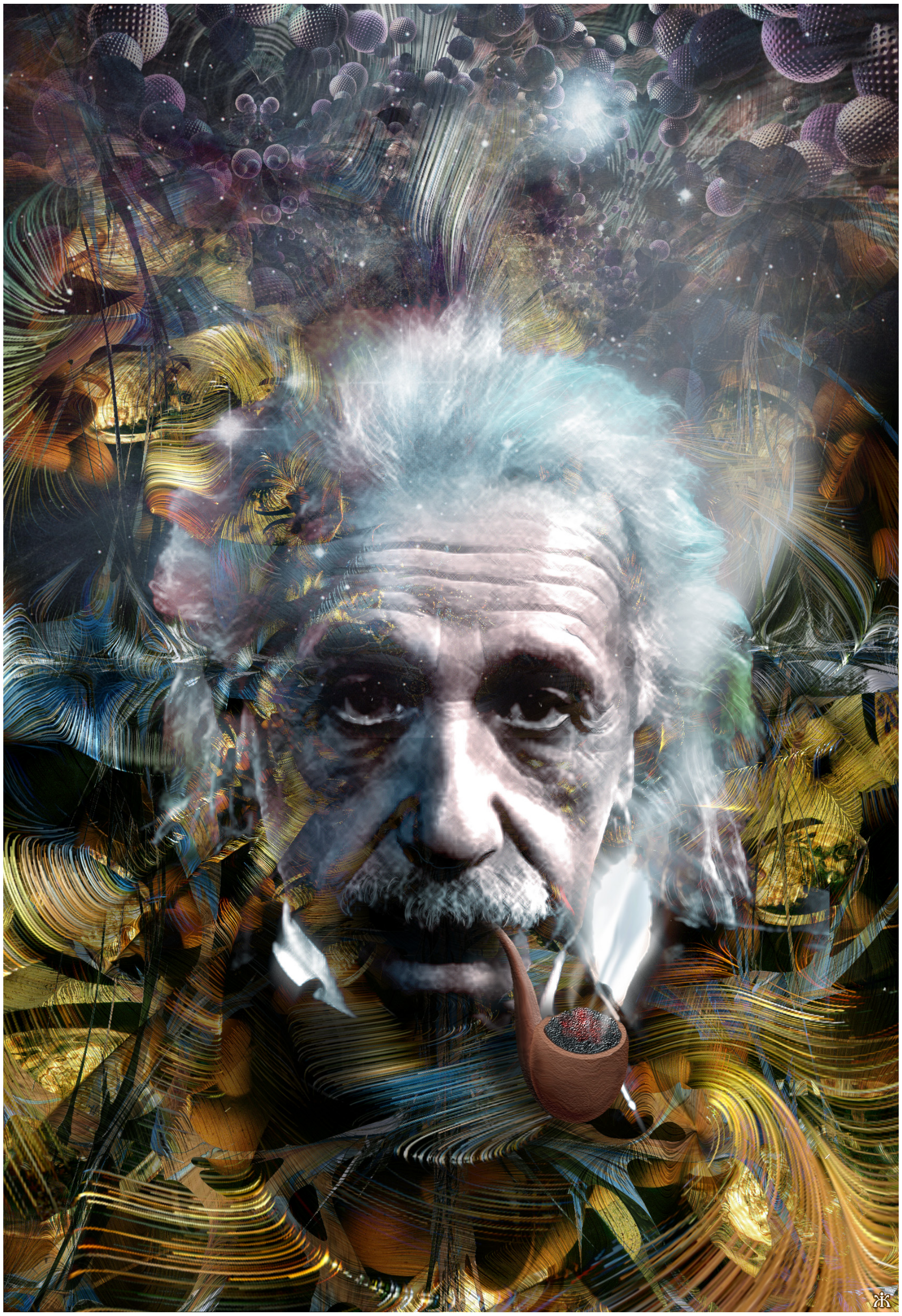

Figure 1. Albert Einstein. Computer Art Painting.
Credit: Ihor T. Zhuk (Institute for Space Research of the NAS of Ukraine)

Dark Energy Spectroscopic Instrument, DESI (DESI Collaboration et al. (2016) and Dey et al. (2019)) – is dedicated to obtaining optical spectra for tens of millions of galaxies and quasars, constructing a 3D map spanning the nearby Universe to 11 billion light-years to measure the effect of dark energy on the expansion of the Universe. The survey is being conducted on the Mayall 4-m telescope at Kitt Peak National Observatory in the United States.

Sloan Digital Sky Survey, SDSS I, II, III, IV, V (Blanton et al. (2017)) – is a multi-spectral imagining and spectroscopic redshift sky survey performed by Apache Point Observatory (New Mexico, the United States) with a 2.5-m wide-angle optical telescope. It provided the community with multi-color images of $\sim 1/3$ of the sky and high-resolution spectra of millions of Galactic and extra-galactic objects.

Canada France Hawaii Telescope Legacy Survey, CFHTLS (Everett et al. (2022)) – the scientific collaboration between Canada and France joined a large fraction of their dark and grey telescope time from mid-2003 to early 2009 for a large project. The data acquisition and calibration have been a major undertaking for the Canadian and French communities: more than 2300 hours over 5 years (an equivalent of 450 nights) have been devoted to the survey using the wide-field optical imaging camera MegaCam, a 1-degree by 1-degree field of view 340 Megapixel camera.

Cosmic Microwave Background-S4 (Chang et al. (2022)) – is the Stage-IV ground-based CMB polarization experiment. It will allow measuring the CMB temperature fluctuations with unprecedented precision, mapping the visible and dark matter seeds, and recovering for signatures of primordial gravitational waves.

Large Synoptic Survey Telescope, LSST (Ivezić et al. (2019)) – is the Vera C. Rubin astronomical Observatory currently under construction in Chile that features an 8.4-meter telescope, a 3200-megapixel camera, an automated data processing system, and an online public engagement platform. The Rubin Observatory will advance science in four main areas: the nature of dark matter and understanding of dark energy, cataloging the Solar System, exploring the "changing" sky, and Milky Way structure and formation (entire operations for the ten-year survey commencing in October 2022).

Dark Energy Survey, DES (Müller and Schnider (2021) and S. J. Schmidt et al. (2020)) – is an astronomical survey designed to constrain the properties of dark energy. It uses images taken in the near-ultraviolet, visible, and near-infrared to measure the expansion of the Universe using Type Ia supernovae, baryon acoustic oscillations, weak gravitational lensing, the galaxy clusters and other elements of the large-scale structure (LSS) of the Universe. The collaboration comprises research institutions and universities from the United States, Australia, Brazil, the United Kingdom, Germany, Spain, and Switzerland.

Nancy Grace Roman Space Telescope (previously known as - the Wide Field Infrared Survey Telescope, WFIRST) (Spergel et al. (2013)) – is an infrared space telescope currently in development by NASA and scheduled to launch in 2027. In its present incarnation, a significant fraction of the Joint Dark Energy Mission (JDEM) between NASA and the Department of Energy (DOE) will be focused on probing the expansion history of the Universe and the growth of cosmic structure with multiple methods in overlapping redshift ranges with the goal of precisely measuring the effects of dark energy, the consistency of general relativity, and the curvature of space-time.

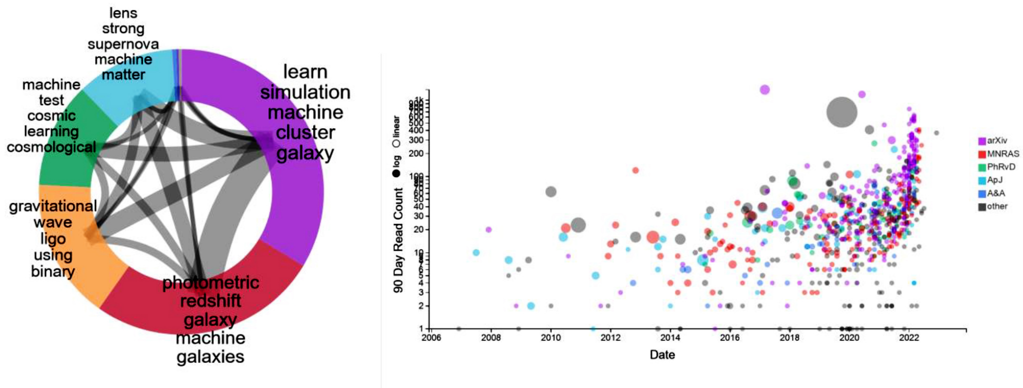

Figure 2. Network and graph of 780 publications related to "cosmology" and "machine learning" search words over last 15 years, which are indexed in the SAO/NASA Astronomical Data System

The cosmological observables we can use the information about are such as LSS surveys, precise redshifts of galaxies and galaxy clusters in a wide cosmological scale, 21-cm absorption and brightness mapping, weak lensing, quasars, Lyman-α Forest, CMB spectral distortions, neutrino background, primordial gravitational waves, etc.

What we know about the cosmological parameters soon will be no longer limited by the amount of data but by our ability to analyze it, use it, and interpret it. In such an arrangement, the machine learning (ML) methods provide us with new perspectives in modern science (e.g., Carleo et al. (2019), Fluke and Jacobs (2020), and I. Vavilova, Dobrycheva, et al. (2020)). The most important feature of ML techniques in general and in cosmology in particular, is the inference directly from data, without summary statistics required by "former" cosmological approaches. The rapid growth of relevant publications during the last 15 years is clearly demonstrated in Fig. 2.

There are three main types of machine learning being categorized: supervised, unsupervised, and reinforcement learning.

Unsupervised machine learning describes algorithms that are used to learn complex relationships that exist in the dataset, with no labels or tags set up manually. Unsupervised learning can be used to describe the extraction of features and parameters or characteristics and for such tasks as clustering, dimensionality reduction, and anomaly detection, which are potentially important since they can extract new knowledge and cause insights and discoveries. This type of machine learning has been used within spectroscopy for dimensionality reduction (e.g., Kaderali et al. (2019)), outlier and novel source detection (e.g., Giles and Walkowicz (2019)), and other purposes (e.g., Kügler and Gianniotis (2016) and Vadai et al. (2017)).

Supervised machine learning algorithms typically seek to classify or label/flag some data using regression tasks. In other words, supervised machine learning algorithms are used to learn a mapping from a set of features to a target variable, based on example input-output pairs provided manually. While classification organizes data into different groups, regression tasks label data with continuous quantities. Random forest and neural networks are among the most popular and widely used algorithms for these tasks. Neutral networks have an expansive hierarchy of varieties (e.g., convolutional, recurrent, generative adversarial networks). Similarly, random forest and other tree-based methods allow several possible algorithmic choices.

Implementing a supervised machine learning model typically involves training, validation, and testing sets of data to train, optimize, and test the performance of a model for a given task. Overall, understanding and labeling new data is the main goal for such model development. While training, the relationship between the data and the labels that describe the data is captured by the model. A validation set is used to optimize the parameters of the model (the so-called hyperparameters). The test set of data is unseen data labeled utilizing the model. Test sets are typically used to assess the performance of the model. Numerous metrics can be used to quantify the performance of a supervised machine learning model, including the metrics specific to classification (e.g., accuracy and precision) and regression (e.g., R-square and bias). The choice of evaluation metrics is often particular to the particular uses and goals of the model.

Reinforcement learning is a field of machine learning related to how intelligent agents should act in the environment to maximize the notion of cumulative reward. Unlike supervised learning, reinforcement learning does not require the presence of labeled input/output pairs and does not require explicit correction for suboptimal actions. In the absence of a training dataset, it is bound to learn from its experience, in other words, by seeking a balance between exploration of the unknown and exploitation of current knowledge. The combination of the advantages of supervised and reinforcement learning algorithms is defined as partially supervised reinforcement learning algorithms.

The environment is usually specified in a Markov Decision Process (MDP) because many reinforcement learning algorithms for this context use dynamic programming techniques. The main difference between classical active programming methods and reinforcement learning is that the latter does not require knowledge of the exact MDP mathematical model and is aimed at large MDPs, where precise methods become impossible.

The main problems of ML learning at the stage of data processing can be divided into two categories. The first one is related to dataset preparation, which includes: determining the parameters that are the best for dividing objects into classes, selecting a homogeneous dataset for classification parameters, creating a sub-directory for training algorithms, cleaning the sub-list of ”undesired” (misclassified) objects, determining the best ML methods for the task, and selecting the best ML features to build training sample. The second category includes problems related to the individual peculiarities of selected objects and to the quality of their explored data.

The classic methods in cosmology are primarily about summary statistic processing, while the analytical models are complicated to use and provide only qualitative understanding due to the limited model complexity. With all the diversity of cosmological and astrophysical surveys to process and the number of data available, the question of looking for more advanced technologies seems reasonable and rightful while the goal is to extract the maximum information from the data sets and scale up our abilities. Thus, the ML techniques, while most of them learn (e.g. Convolutional Neural Networks (CNN)) from the “raw data”, with no need to be fed with any summaries, are considered a powerful tool to help us solve cosmological problems that are intractable nowadays.

Many traditional applications of machine learning elements can be implemented in cosmology: classification, regression, clustering analyses, outlier detection, data mining, data compression, also data and model emulation. While still facing a lot of uncertainties and concerns (cosmology, as every science, cares about detailed uncertainty quantification, reliability/trust, and understanding of the models and approaches), there are substantial successes of machine learning applications in cosmology that have been archived recently. They illustrate the potential for sophisticated machine learning data-analysis tools to make significant strides in cosmology (see, computer art painting in Fig. 3).

The list of the most important achievements includes the results about the gravitational lensing (Barnacka (2018), Bonnett (2015), Jacobs et al. (2019), and Khramtsov et al. (2019), CMB (Ciuca and Hernández (2017), Douspis et al. (2022), Hortúa et al. (2020), and A. Mishra et al. (2019)), cosmological parameters and models (Angulo and Hahn (2022), Ansari et al. (2019), Burgazli et al. (2015), Doux et al. (2021), Sergijenko and Novosyadlyj (2009), Tsizh et al. (2020), Villaescusa-Navarro et al. (2022), Wandelt (2008), and Zaninetti (2019)), photometry and image-based morphological classification of galaxies in various spectral range (Aniyan and Thorat (2017), Barchi et al. (2020), Manning et al. (2020), I. B. Vavilova et al. (2021), Vega-Ferrero et al. (2021), and Walmsley et al. (2022)) including gamma-ray and transient objects (Bellm et al. (2019), Kang et al. (2019), Krause et al. (2017), Mahabal et al. (2019), A. L. Miller et al. (2019), Mukund et al. (2017), Ruhe (2020), and Schlickeiser et al. (2012)), large-scale structures such as galaxies, galaxy clusters and superclusters, filaments and voids (He et al. (2019), Kremer et al. (2017), Matthews (2014), Saulder et al. (2016), Sergijenko et al. (2009), Sorce et al. (2017), and Tully et al. (2019)), galaxy distance moduli and the Zone of Avoidance of our Galaxy (Brescia et al. (2021), A. A. Elyiv et al. (2020), Huertas-Company et al. (2018), Jones et al. (2019), Lee and Shin (2022), Salvato et al. (2019), Schawinski et al. (2017), I. B. Vavilova et al. (2018), and I. Vavilova, Dobrycheva, et al. (2020)), the investigation of the epoch of reionization (Billings et al. (2021)), topological data analysis (Fussell and Moews (2019), Pranav (2022), and Wilding et al. (2021)), ML supernova classification (Kessler and Scolnic (2017), Kodi Ramanah et al. (2022), and Lochner et al. (2016)), gravitational wave astronomy (see, Section 2), and significant success on cosmological simulations both N-body and hydrodynamical ones (e.g. Angulo and Hahn (2022), Doux et al. (2021), Lazanu (2021), Ntampaka and Vikhlinin (2022), and Villaescusa-Navarro et al. (2021)).

Modern cosmology has relied on computer simulations for more than a decade, which is an effective tool to predict the structure formation of the Universe. Two different types of cosmological simulations are based on the N-body simulations approach and hydrodynamics. Both approaches have their own advantages and limitations. For example, while the N-body simulations consider the influence of gravity only, the hydrodynamics simulations are more computationally expensive but can enrich the data also with fluid dynamics and astrophysics. Hydrodynamics simulations are valid on all resolved scales and can shed light on such a problem as galaxy formation, while the N-body simulations are valid in the regime not affected by baryons, and are used to investigate the structure formation and halo formation.

The well-known problems with the N-body simulations (such as Uchuu, Bacco, Quijote, Flagship, Aemulus, and many more) are storage needs, high resolution, and parameter space/total volume. Machine learning has been shown to develop some kind of emulators (such as CosmoPower, DarkEmulator, etc.) of summary statistics to estimate the power spectrum. The future challenges in using ML for N-body simulations are about covering the development of the field-level emulators (based, for example, on such parameters as gas temperature and gas metallicity).

Among the most used hydrodynamical simulations, are the ones such as Illustris and IllustrisTNG, Magneticum, SIMBA, Romulus25, EAGLE, Massiveblack-II, Horizon-AGN, and more. The problem the science faces here is the small volume, storage needs, and high resolution (even more significant than for N-body simulations), and that's expensive to cover parameter space / with no control of uncertainties. The small volume problem can be solved within a baryonification approach while using N-body to reproduce the power spectrum for hydrodynamics. This approach does not require any ML implementation. Still, an impressive application of machine learning and/or deep learning techniques is about creating a bridge to convert N-body simulations into hydrodynamical ones. Basically, the idea is about running standard N-body simulations and "painting" gas and other components (such as halo, galaxies, etc.) to reproduce the hydrodynamics. The halo-galaxy connection was one of the first applications of reinforcement learning in astrophysics and cosmology. It is based on the idea of running the N-body simulations, finding dark matter halos, taking galaxies from the actual data, and using reinforcement learning to train how to paint galaxies on top of the dark matter halos. For example, the dark matter halos formation problem has been recently studied within ML application by Lucie-Smith et al. (2020) while trying to bring insights into dark matter halo collapse from machine learning and CNN. The approach for this investigation is about training the machine learning algorithms to learn the mapping between the initial condition and dark matter halos from N-body simulations, and the aim was to gain new physical insights into dark matter halo formation.

It is worth mentioning the advantages and disadvantages of Convolutional Neural Networks here. The critical advantage of this technique is about no featurization approach - CNNs learn directly from initial conditions, so they use the "raw data". Also, CNNs identify which initial conditions features are relevant for halo mass. The main problem of deep learning applications is that DL algorithms are always some kind of "black-box" algorithm. Also, there is an essential question: how do we extract physical knowledge from a deep learning algorithm?

In general, extracting the maximum amount of information from current and upcoming experiments is crucial to constrain the value of the cosmological parameters with the highest accuracy. Still, there are some problems related to this task.

Cosmology and Astrophysics with Machine Learning Simulations (CAMELS) are among the most potent ML application projects (Villaescusa-Navarro et al. (2022)) designed for machine learning applications in cosmology that help resolve some of those issues. The project is a suite of more than 4,000 N-body and hydrodynamic simulations run with three different codes (GADGET III for N-body simulation, AREPO (IllistrisTNG), and GIZMO (SIMBA) for hydrodynamic simulations), that contains more than 140 000 snapshots, more than 200 Tb of data (with approximately 10 millions CPU hours), and more than 100 billion particles over $(400Mpc/h)^3$. The main scientific goals of the CAMELS project are:

- Provide theory predictions for statistics, or fields, as a function of cosmology and astrophysics.

- Extract cosmological information while marginalizing over baryonic effects.

- Find the mapping between N-body and hydrodynamical simulations.

- Quantify the dependence of galaxy formation and evolution on astrophysics and cosmology.

- Use machine learning to efficiently calibrate subgrid parameters in cosmological hydrodynamic simulations to match a set of observations.

One of the problems with the survey processing is that the optimal summary statistic is unknown. CAMELS approach is about training neural networks to search through all possible summary statistics and extract the maximal amount of cosmological information at the field level.

Lots of information on small scales is affected by baryonic processes, which are poorly understood, and the CAMELS project offers training the NNs to marginalize over uncertainties in baryonic effects and extract cosmological information down to the smaller scales. To capture the baryonic effects for arbitrary observables on large cosmological volumes more efficiently than within the standard approach, CAMELS is about developing the ML techniques to find the mapping between N-body simulations and hydrodynamic simulations with full baryonic physics as a function of model implementation and feedback parameters. Besides N-body simulations (based on GADGET III simulations), CAMELS covers also cosmological hydrodynamical simulations. Based on two codes - IllustrisTNG and SIMBA, that both are plausible models (reproducing galaxy observables), CAMELS is about covering thousands of simulation runs with different galaxy formation implementations and model parameter variation, to cover the range of plausible baryonic effects in the real Universe.

Based on the CAMELS application, the following summary of ML usage in cosmological simulation can be made - neural networks can extract information and marginalize over baryonic effects at the field level. Neural network also can infer the value Ω_m and σ_8 with a few percent accuracies from $(25h^(- 1)Mpc)^2$ 2D maps for most of the fields from cosmological hydrodynamical simulations. Also, the combination of the fields can constrain Ω_m better than maps from dark matter-only simulations. Besides that, estimators are not robust for some fields, but they are for the total matter. And at least 10% accuracy can also be obtained from the combination of galaxy clustering statistics.

Machine learning is performed to reduce scatter in cluster mass estimates compared to more traditional methods while studying galaxy clusters, that are sensitive to the underlying cosmological model, where the low-scatter cluster mass proxies are one essential ingredient in using these objects to constrain parameters (Ho et al. (2019) and Ntampaka and Vikhlinin (2022)).

Weak gravitational lensing is a powerful probe of the large-scale cosmic matter distribution. The weak lensing maps can shed light on the fundamental nature of gravity and cosmic acceleration. Apart from the already mentioned works, we note work by Peel et al. (2019), where ML was applied with such maps to discriminate between standard and modified gravity models that generate statistically similar observations. Also, the non-Gaussianities in weak lensing maps can encode cosmological information, but it is hard to measure or parameterize. ML has been shown to tighten parameter constraints by a factor of five or more by harnessing these non-Gaussianities (Gupta et al. (2018) and Ribli et al. (2019)).

The strong gravitational lensing probes cosmic structure along the lines of sight, where the strong lensing is a source of uncertainty. ML was the most effective method for correctly

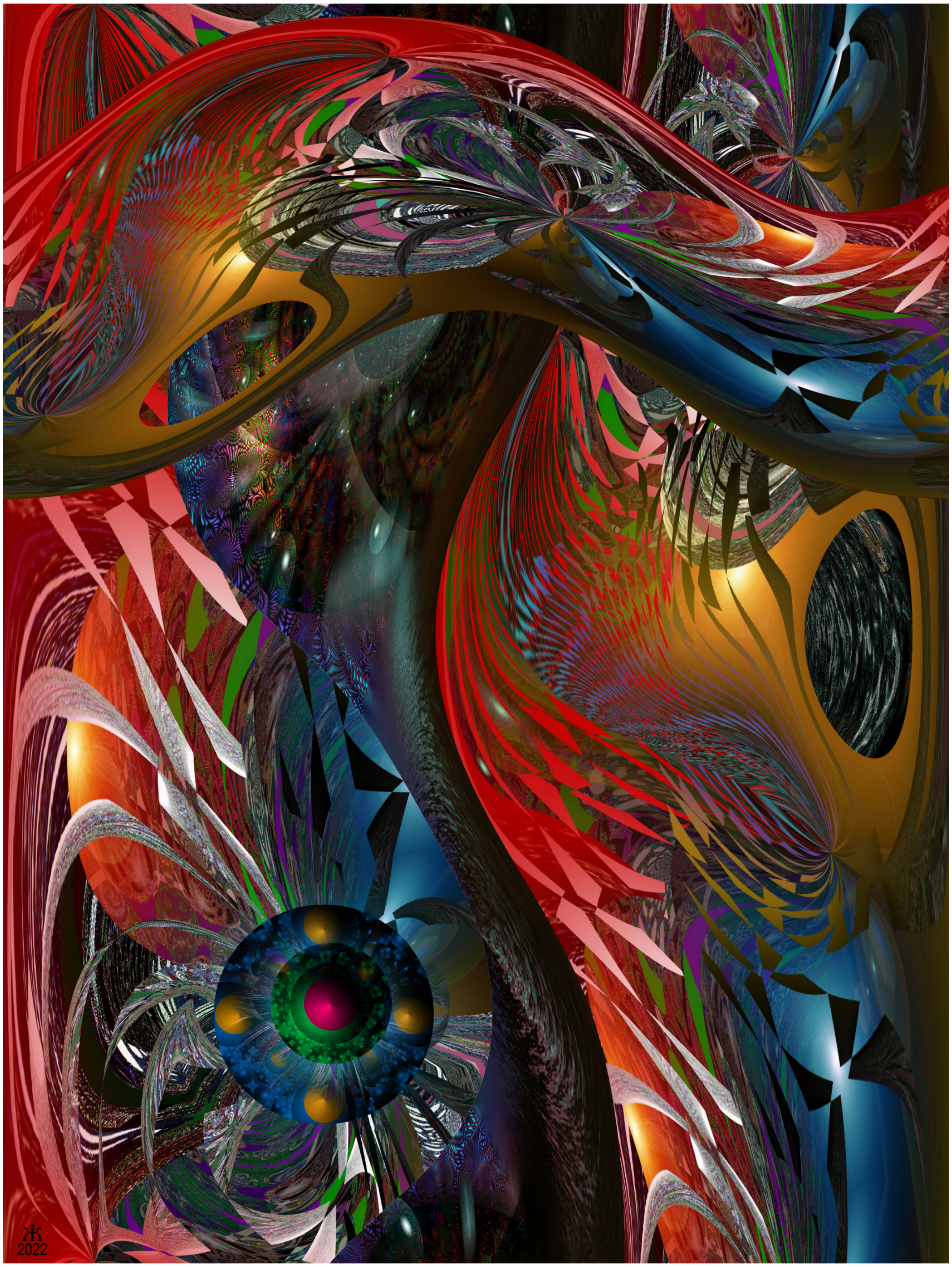

Figure 3. Curvature of space-time of the Universe. Computer Art Painting.
Credit: Ihor T. Zhuk (Institute for Space Research of the NAS of Ukraine)

identifying strong lensing arcs in a recent data challenge, outperforming humans at this classification task (Lanusse et al. (2018)). ML analyzes strong lensing systems 10 million times faster than the state-of-the-art method (see, for example, Hezaveh et al. (2017) and Perreault Levasseur et al. (2017)).

Next-generation cosmic microwave background (CMB) experiments will have lower noise and therefore increased sensitivity, enabling improved constraints on fundamental physics parameters such as the sum of neutrino masses and the tensor-to-scalar ratio r. Achieving optimal conditions on these parameters requires high signal-to-noise extraction of the projected gravitational potential from the CMB maps. The application of CNNs here provides a few innovations - the machine learning techniques have been used to provide competitive methods for this extraction and are expected to excel in capturing hard-to-model non-Gaussian foreground and noise contributions (Caldeira et al. (2019)). While the accurate estimation of cosmological parameters of the Universe is traditionally done with large-scale matter distribution usage, by calculating summary statistics of the observed structure traced by galaxies and then compared to the analytical theory, the ML application can help distribute them directly from the distribution of matter - from the large-scale structure field and find more stringent constraints on the cosmological parameters, that opens the way to estimate the parameters of the Universe with higher accuracy (Ravanbakhsh et al. (2016)).

The information on the earliest luminous sources can be taken from the observations of the Epoch of Reionization. Within CNN, it's possible to classify the types of sources driving reionization (Hassan et al. (2018)) and measure the duration of reionization to within 10%, given a semi-analytic model and a strong prior on the midpoint of reionization. These results have exciting impacts on estimating τ, the optical depth to the CMB, which can help constrain other cosmological parameters (La Plante and Ntampaka (2019)).

Topological Data Analysis (TDA) comprises a set of ML techniques and statistical methods, whose ability to extract robust geometric information has to led novel insights in the analysis of complex data. TDA has been useful for discriminating dark energy models on simulated data (van de Weygaert et al. (2013)), isolating structures of the cosmic web (A. Elyiv et al. (2009), Libeskind et al. (2018), Sousbie et al. (2011), and I. Vavilova et al. (2021)), and defining new types of structures in the cosmic web such as filament loops (Xu et al. (2019)). TDA may also help constrain the sum of neutrino masses (Asselmeyer-Maluga and Król (2019)).

At the end of the 20th century, extragalactic distance measurements based on type Ia supernovae (SNe Ia) provided the first evidence that our Universe is currently undergoing an accelerated expansion. A result was subsequently confirmed by a series of independent probes, each contributing with different pieces of what is known as the standard model of cosmology.

Nevertheless, two decades into the 21st century, a fundamental theory concerning the physics of dark energy – the energy component causing cosmic acceleration – is still missing. In a remarkable community effort, astronomers have devoted a significant fraction of their resources to imposing more restrictive constraints over cosmological parameters – in the hope that they might shed some light on the properties of dark energy. In this new scenario, SNe Ia continues to play a central role as cosmological standardizable candles – and consequently, feature among the main targets of modern large-scale sky surveys.

Supernova classification is a critical step in obtaining cosmological constraints from type Ia supernovae in photometric surveys such as LSST. ML has proven to be a powerful tool (Lochner et al. (2016)) and has been successfully applied to the current largest public supernova dataset (Narayan et al. (2018)). The public has become heavily involved in developing new classification techniques (Malz et al. (2019) and The PLAsTiCC team et al. (2018)).

Machine learning can be used for tasks that are about high-dimension interpolation or lower storage needs operating with big astroinformatics data resource (Feigelson et al. (2021) and I. Vavilova, Pakuliak, et al. (2020)), where we would like to speed up simulations, find anomalies, generate new synthetic data, or, thus, learn more with modern computing about dark energy, distribution and properties of dark and baryonic matter, the consistency of General Theory of Relativity, and complex physics of the Universe as a whole (e.g. Alexandrov et al. (2015), Amendola and Tsujikawa (2015), Andersson (2019), M. C. Miller and Yunes (2021), Mo et al. (2010), Novosyadlyj et al. (2014), S. Schmidt et al. (2021), and I. B. Vavilova et al. (2015)).

2. Machine Leaning in the Gravitational Wave Astronomy

The ML applications to gravitational wave (GW) science have grown explosively over the past few years (Fig. 4). Describing briefly some significant results in this review, we do not touch the glitch classification and noise mitigation as well as speed-up of the waveform generation and search for continuous GWs.

Real-time detection and parameter estimation are among the most important applications of ML techniques to GW data analysis. They are critical for prompt follow-up of the electromagnetic (EM) and astroparticle counterparts to binary neutron-star and black-hole neutron-star mergers. One of the key challenges is the computational cost of conventional approaches: matched-filtering and Bayesian inference.

Deep Filtering, a highly scalable method for end-to-end time-series signal processing based on a system of two deep CNNs, has been proposed by George and Huerta (2018b) for classification and regression to rapidly detect and estimate parameters of signals in highly noisy time-series data streams. They demonstrated a novel training scheme with gradually increasing noise levels a transfer learning procedure between the two networks. Deep Filtering significantly outperforms conventional ML techniques and achieves similar performance as the matched-filtering while being several orders of magnitude faster extending the range of gravitational wave signals detectable with the ground-based GW detectors. In the other work (George and Huerta (2018a)), the Deep Filtering has been exploited with the real data from LIGO. The ability of ML to detect and estimate the true parameters of real binary black hole (BBH) mergers observed by LIGO has been demonstrated for the first time.

Krastev (2020) used deep learning to rapidly identify transient GW signals from binary neutron star (BNS) mergers in noisy time series representative of typical GW detector data. It has been shown that the deep CNN trained on 100,000 data samples can promptly identify BNS GW signals and distinguish them from noise and signals from merging BBHs.

The possibility of EM and astroparticle counterparts based on the presence of an NS component and remnant matter post-merger in real time was reported by D. Chatterjee et al. (2020) with supervised ML. Also, a real-time GW detection of spinning BBH mergers deep learning ensembles has been studied by Wei et al. (2021). Their analysis consisted of training independent neural networks that simultaneously process strain data from multiple detectors, with the output combined and processed to identify significant noise triggers. The deep learning ensemble has been trained with millions of modeled waveforms that describe quasi-circular, spinning, non-precessing, and binary black hole mergers. The method has been applied to O2 and O3 open-source data available at the Gravitational-Wave Open Science Center. The performance has been benchmarked by processing 200 hours of open-source advanced LIGO noise from August 2017 to find that the approach identifies real GW sources in advanced LIGO data with a false positive rate of 1 misclassification for every 2.7 days of searched data (a follow-up of these misclassifications identified them as glitches).

Krastev et al. (2021) have demonstrated, for the first time, that artificial neural networks (ANNs) can promptly detect and characterize BNS GW signals in real LIGO data and distinguish them from noise and signals from coalescing BBHs: the deep learning framework classifies correctly all GW events from the Gravitational-Wave Transient Catalog GWTC-1. Using this LIGO-Virgo GWTC-1, the eight GW events were analyzed by Dax et al. (2021) with neural networks as surrogates for Bayesian posterior distributions. A very close quantitative agreement with the standard inference codes has been achieved, while the inference times have been reduced from O(day) to a minute per event. The networks were trained on simulation data including an estimate of the detector noise characteristics near the events to enable inference for any observed data consistent with the training distribution, accounting for the noise non-stationarity from event to event. The developed algorithm DINGO should enable further real-time data analysis without sacrificing accuracy.

The performance of two ML methods, random forest, and neural networks, has been benchmarked for ranking of the candidate GW events by Kim et al. (2020). For both methods, the evaluation time takes tens of milliseconds for $\sim$45000 evaluation samples. The classification efficiency of both ML methods and a conventional low-latency search method has been compared with respect to the true positive rate at a given false positive rate: about 10% improved efficiency can be achieved at lower false positive rate $\sim 2 \times 10^{-5}$ with both ML methods and the search sensitivity can be enhanced by about 18% at $\sim$10-11 Hz false alarm rate. Applying only publicly available information from the LIGO-Virgo open public alerts, a real-time framework GWSkyNet was introduced by Cabero et al. (2020) to distinguish between astrophysical events and instrumental artefacts. It consists of a non-sequential CNN involving sky maps and metadata attaining a prediction accuracy of 93.5% on a testing data set.

Chua and Vallisneri (2020) trained a deep neural network to take as input a signal+noise data drawn from the astrophysical source-parameter prior and the sampling distribution of detector noise. They relied on compact representation of the data, which are based on the reduced-order modeling, and generated with a separate neural-network waveform interpolant to output a parametrized approximation of the corresponding posterior (see, also, their work on using fully relativistic extreme-mass-ratio-inspiral waveform templates for LISA data by Chua et al. (2021)).

There are many attempts to use ML to improve GW detection and parameter inference

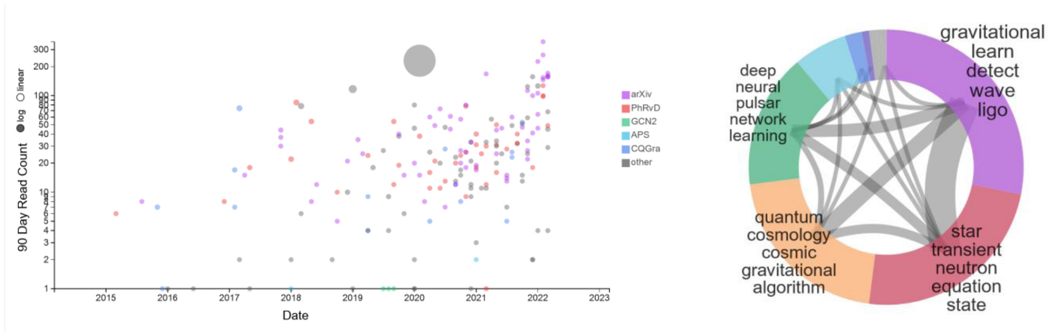

Figure 4. Network and results graph of 260 publications related to "gravitational waves" and "machine learning" search words over last 7 years, which are indexed in the SAO/NASA Astronomical Data System

efficiency. So, Gabbard et al. (2018) constructed a deep CNN, which is able to reproduce the sensitivity of a matched-filtering search for BBH GW signals. Wang et al. (2020) applied a deep learning to LIGO O1 data. Lin and Wu (2021) proposed the detection of GW from BNS mergers based on wavelet packet (WP) decomposition and CNN: the scheme is more than 960 times faster than the matched filtering. Singh et al. (2021) developed CNNs, which were trained to predict the physical parameters of GW events (the maximum accuracy reached 90.93%, with a validation accuracy of 89.97%). Bayley et al. (2020) analyzed the robustness of their new ML algorithm to detect continuous GW.

A combination of results of the three-detector network in a unique RGB image and deep networks to the advanced LIGO O2 public data with injected GW signal waveforms allows to improve the single detector performance by as much as 70% (Álvares et al. (2021)). As well, Morales et al. (2021) exploited CNNs to detect GW signals of compact binary coalescences using single-interferometer data from LIGO. They found after a post-analysis that for SNR$\geq$21.80 with H1 data and SNR$\geq$26.80 with L1 data the developed CNNs could remain tentative alternatives for detecting GW signals. However, the use of CNNs as a tool to search for merging black holes has been critically analyzed by Gebhard et al. (2019): its strengths and limitations have been identified as well as some common pitfalls in translating between ML and GW astronomy was highlighted in their article.

A novel neural network algorithm using time series strain data from GW detectors has been proposed for the detection of signals from the non-spinning BNS mergers by Schäfer et al. (2020). For the advanced LIGO design sensitivity, the network has an average sensitive distance of 130 Mpc at a false alarm rate of 10 per month. As compared to other state-of-the-art ML algorithms, it demonstrates an improvement by a factor of 4 in sensitivity to signals with a signal-to-noise ratio between 8 and 15. Results of the search for the coalescence of compact binary mergers using CNNs in the O2 LIGO/Virgo data were presented by Menéndez-Vázquez et al. (2021). They explored 2D images in time and frequency as input and trained two sets of neural networks separately for low mass (0.2 – 2.0 M_{Sun}) and high mass (25 – 100 M_{Sun}) events. A scan over the full O2 dataset demonstrates that the performance of the CNNs is compatible with traditional pipelines using matched filtering techniques.

T. Mishra et al. (2021) proposed a new ML approach to optimize the sensitivity of the Coherent WaveBurst (cWB) – search algorithm identifying generic GW signals in the LIGO-Virgo strain data – to BBH mergers. The ML-enhanced cWB search was tested on strain data from the O1 and O2 runs of advanced LIGO. It has successfully recovered all BBH events previously reported by cWB with higher significance. For the simulated events with a false alarm rate of less than 1 per year, the improvement in detection efficiency of 26% for stellar-mass BBH mergers and 16% for intermediate mass BBH mergers was attained.

Results on training a neural network conditional density estimator to model posterior probability distributions over the full 15-dimensional space of BBH system parameters are presented by Green and Gair (2021). These authors exploited strain data from multiple detectors using the method of normalizing flows, specifically, a neural spline normalizing flow, which allowed them for rapid sampling and density estimation. Training the network is likelihood-free, and requires only samples from the data generative process. The detector noise power spectral density was estimated at the time of GW150914 and conditioned on the event strain data. The neural network has been able to generate accurate posterior samples consistent with analyses using conventional sampling techniques. Marulanda et al. (2020) proposed a new frequency CNN domain (FCNN) to predict the merger masses from the spectrogram of the detector signal and compared to the time domain neural networks (TCNN). FCNNs are trained using spectrograms, therefore the dimension of the input is reduced with respect to TCNNs, implying a substantially lower number of model parameters and less over-fitting. The additional time due to the spectrogram computation is approximately compensated by the lower execution time of the FCNNs.

The mass and spin magnitude of Kerr black holes resulting from the BBH coalescence have been estimated for the first time using a deep neural network by Haegel and Husa (2020). The model was trained on a dataset containing 80% of the full publicly available catalog of numerical simulations of GW emission by BBHs including full precession effects for spinning binaries. The network predicts the remnant black hole mass and spin with an error less than 0.04% and 0.3% for 90% of values in the non-precessing test dataset, 0.1% and 0.3% respectively in the precessing test dataset.

Green et al. (2020) introduced how to use the autoregressive normalizing flows for rapid likelihood-free inference of the BBH system parameters from GW data with deep neural networks. As well, Khan et al. (2020) introduced a modified version of WaveNet trained with a novel optimization scheme incorporating general relativistic constraints of the BH spin properties. It allows quantifying the suitability of deep learning to estimate the individual spins, effective spin, and mass ratio of quasi-circular, spinning, non-precessing BBH mergers. Another powerful dimension reduction technique – the Random projection (RP), which is widely used in the analysis of high dimensional data – was explored by Kulkarni et al. (2019) to improve the computational efficiency of GW searches from compact BBHs and BNSs. A novel ML approach to estimate selection effects in GW observations, including the effect of spin precession, higher-order modes, and multiple detectors, is proposed by Gerosa et al. (2020). These authors discussed also the limitations, which lead to the overestimation of the inferred merger rate in selected regions of the parameter space.

We also note several works, where Bayesian neural networks were exploited. A conditional variational autoencoder (CVAE), which was pre-trained on BBH signals, can return

Bayesian posterior probability estimates $\sim$6 orders of magnitude faster than traditional techniques as concluded by Gabbard et al. (2022). A new model of Bayesian neural networks allowing the compact binary coalescence events in GW data was proposed by Lin and Wu (2021). It's able to identify the full length of the event duration including the inspiral stage. This Bayesian approach has been incorporated into the CLDNN classifier integrating CNN and the Long Short-Term Memory Recurrent Neural Network (LSTM).

ML techniques can also help with enhancing the significance of detection. Vinciguerra et al. (2017) applied a multivariate analysis based on ANNs to classify GW waves emitted in compact binary coalescences, enhancing by orders of magnitude the significance of signals against the noise background or, at a given level of misclassification of noise events, detecting about 1/4 more of the total signal population. In recent work, Jadhav et al. (2021) described the first ML-based search making a clean detection of GW151216 (not significant enough to be included in the GWTC-1 catalog). Transfer learning along with curriculum learning has been used to re-train the InceptionV3 network for the classification of continuous wavelet transform maps of transients in the LIGO data and MLStat (a new coincident ranking statistics). It incorporates information into the coincident search likelihood used by the standard PYCBC search. In own turn, it leads to at least an order of magnitude improvement in the inverse false-alarm-rate for the "low significance" events GW151012, GW170729, and GW151216, and, as has been shown by the injection study, bringing the average improvement in the sensitive volume of $\sim$10% for low chirp masses (0.8–5 M_{Sun}) and $\sim$30% for higher masses (5–50 M_{Sun}).

GW observations of BNS mergers constrain the NS equation of state (EoS) by enabling measurement of the tidal deformation of each NS, well approximated by the tidal deformability Λ parameter. Hernandez Vivanco et al. (2020) combined the data from GW170817 and GW190425 to place constraints on the NS EoS. They applied an ML algorithm to derive interpolated marginalized likelihoods for each event allowing for results from multiple GW signals to be easily combined. The radius of a fiducial $1.4M_{Sun}$ NS has been constrained to $11.6^{+1.6}_{-0.9}$ km and the pressure at twice the nuclear saturation density to $3.1^{+3.1}_{-1.3} \times 10^{34}$ dyne/cm^2 at the confidence level of 90%.

GW signals from the BNS mergers cannot be easily distinguished from those from comparable-mass mixed binary mergers, in which one of the companions is a black hole (NS-BH). In this context, Fasano et al. (2020) developed a new data analysis strategy employing Bayesian inference and ML. It allows for the identification of NS-BH systems with the distribution of tidal deformability parameters inferred from the GW observations. Kapadia et al. (2017) described a multivariate classifier for the candidate events. It exploits a templated search for the GW inspiral signals from the NS-BH systems in data, whereas detectors have a sensitivity limited by the non-Gaussian noise transients.

The Random Forest classifier has been evaluated on a set of single-detector events from the realistic simulations of advanced LIGO data, using simulated NS-BH signals added to the data. It detects a factor of 1.5-2 more signals at low false positive rates compared to the standard "re-weighted SNR" statistics.

Early warning of coalescing neutrons star and neutron star – black hole binaries can significantly improve the chances of detecting GW signals and their EM and astroparticle counterparts. Baltus et al. (2021) analyzed the possibility of a combination of small CNNs, trained on the whitened detector strain in the time domain, to detect and classify early inspirals. Yu et al. (2021) found that the neural networks with simulated data representing the real LIGO detectors allow a typical binary neutron star (neutron star – black hole) to be detected 100 s (10 s) before the merger at a distance of 40 Mpc (160 Mpc).

A small fraction of the GW signals detectable by 2G and 3G detectors are expected to be strongly lensed by galaxies and clusters, producing multiple observable copies, processing of which is computationally expensive for large numbers of possible pairs. That's why an ML approach to rapidly rule out a vast majority of candidate lensed pairs has been proposed by Goyal et al. (2021),

As well, we mention a significant work by Huerta et al. (2021). These authors developed a workflow connecting the Data and Learning Hub for Science, a repository for publishing AI models, with the Hardware Accelerated Learning (HAL) cluster, using funcX as a universal distributed computing service. It allows an ensemble of the four openly available AI models to be run on HAL to process August 2017 data of advanced LIGO in 7 minutes, identifying all 4 BBHs previously identified in this dataset and reporting no misclassifications.

Precise localization of a GW source is also crucial for the follow-up of the EM and astroparticle counterparts. C. Chatterjee et al. (2019) constructed a deep ANN to localize simulated GW signals in the sky with high accuracy. The sky has been modeled as a sphere divided into 18, 50, 128, 1024, 2048, and 4096 sectors. The sky direction of the GW source was estimated by classifying the signal into one of these sectors based on its right ascension and declination. The proposed model is able to classify GW samples not used in the training process into the correct sectors with high accuracy ($>$90%) for coarse angular resolution using 18, 50, and 128 sectors.

ML can also be used to enhance the traditional MCMC and nested sampling techniques. Ashton and Talbot (2021) introduced the Bilby-MCMC, an MCMC sampling algorithm tuned for the GW analysis from merging compact objects. It provides a parallel-tempered ensemble Metropolis-Hastings sampler with access to a block-updating proposal library including problem-specific and ML proposals allowing for over a 10-fold improvement in efficiency by reducing the autocorrelation time. Williams et al. (2021) proposed a novel method for sampling iso-likelihood contours in nested sampling with normalizing flows. It was incorporated into the sampler Nessai, designed for problems where computing the likelihood is computationally expensive and, therefore, the cost of training a normalizing flow is offset by the overall reduction in the number of likelihood evaluations. The sampler has been validated on 128 simulated GW signals from compact binary coalescence. Compared to results obtained with dynesty, the Nessai results are in good agreement whilst requiring 2.07 times fewer likelihood evaluations.

The ML methods are very effective in extending the duty cycle of the GW detectors. Local seismic disturbances cause GW detectors to lose light resonance in one or more of their component optic cavities and make them unable to take data until resonance is recovered. Biswas et al. (2020) identified a minimal set of optic cavity control signals and data features capturing the interferometer behavior leading to a loss of light resonance (or lock loss). These channels have been explored to accurately distinguish between lock loss events and quiet interferometer operating times via both supervised and unsupervised ML methods. The state of the component optical cavities is found to be a better predictor of lockloss than ground motion trends. The prediction accuracy is 98% for times just prior to

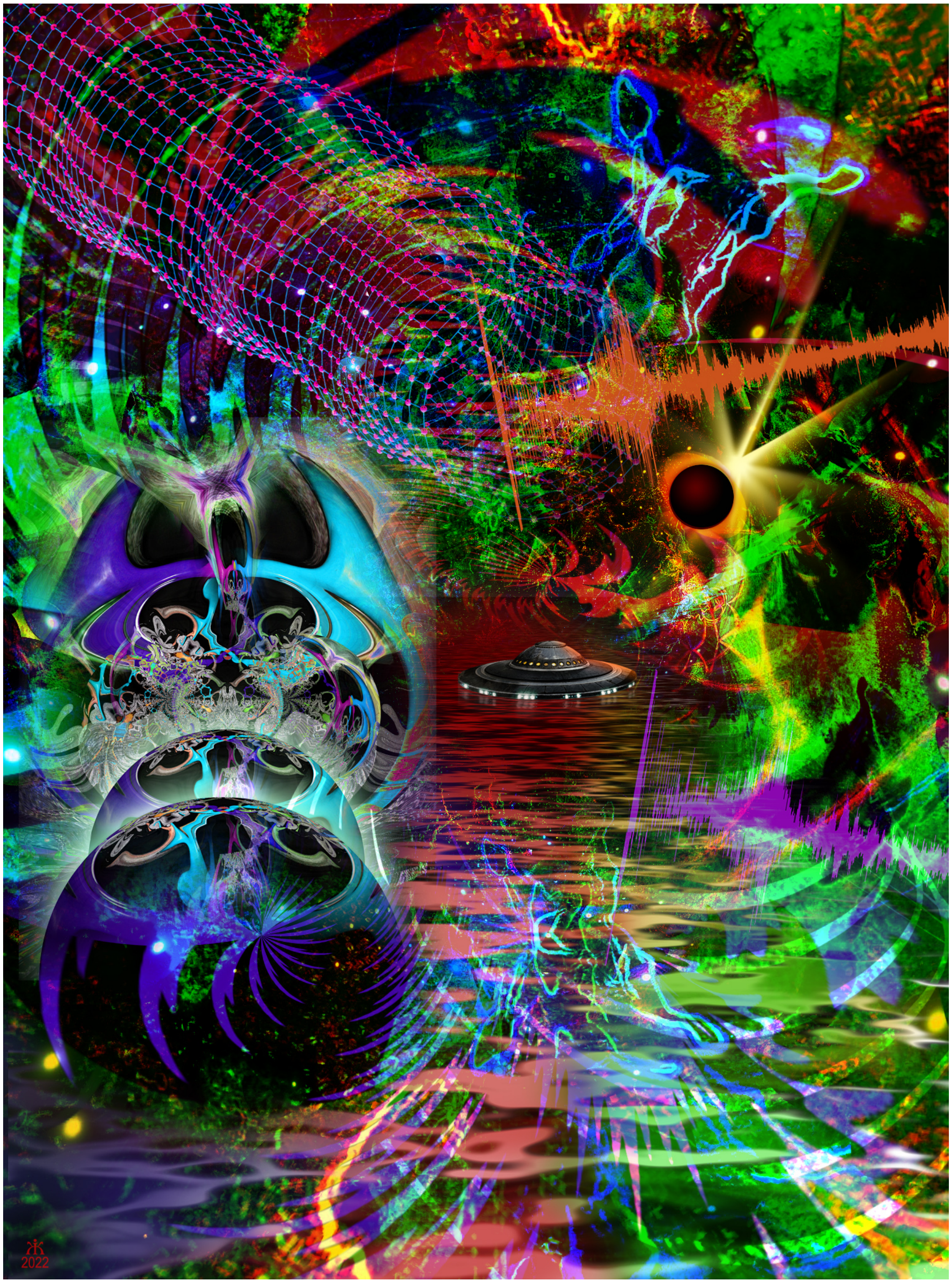

Figure 5. Gravitational waves. Computer Art Painting.
Credit: Ihor T. Zhuk (Institute for Space Research of the NAS of Ukraine)

lockloss, and 90% for times up to 30 seconds prior to lockloss.

The interesting problem in a technical sense was investigated by Mukund et al. (2019). They applied various machine learning algorithms to archival seismic data for prediction of the ground motion and the state of the GW interferometer during the event of an earthquake. An improvement from a factor of 5 to a factor of 2.5 in scatter of the error in the predicted ground velocity over a previous model fitting-based approach has been demonstrated. The analysis of IRIS seismic network data (Incorporated Research Institutions for Seismology) yields similar levels of agreement between the estimated and the measured amplitudes.

ML techniques are also applied in cosmology with GWs. Apart of the articles mentioned in Section 1, we note yet several works.

Negative results of the search for WIMPs revived the interest to other dark matter candidates, e.g. primordial black holes (PBHs) formed in the early Universe. Wong et al. (2021) exploited the GWTC-2 dataset from the O3 run of the LIGO-Virgo Collaboration. They found the constraints on PBH formation models based on deep learning techniques and hierarchical Bayesian inference framework. The upper limit on the fraction of PBHs in this study is 0.3% of the total dark matter.

The potential of arrays of future GW detectors to study the cosmological and modified gravity models using the catalogs of standard sirens has been forecasted by Yang (2021) through the Gaussian process (GP) with the ANN reconstruction. The results showed that the GP reconstructions can already give comparable results with the traditional MCMC approach as well as the modified GW propagation can be a powerful probe of dark energy and modified gravity. Belgacem et al. (2020) applied the GP technique to measurements of the GW luminosity distance from simulated joint GW-GRB detections combined with measurements of the photometric (luminosity) distance by simulated DES data has demonstrated a remarkable discovery potential of the proposed 3G detector Einstein Telescope (ET). In own turn, Cañas-Herrera et al. (2021) explored the possibility of joint reconstruction of the modified GW propagation law and the linear bias of GW sources using the ML technique for a network of ETs combined with a high-redshift galaxy survey ($z \lesssim 3$). Arjona et al. (2021) used two ML approaches, Genetic Algorithms (GAs) and GPs, to reconstruct the mock data of strongly lensed GW events from ET and to demonstrate how the luminosity and angular diameter distances can be combined to test in a model-independent manner deviations from the cosmic distance duality relation. Both approaches are found to be capable of correctly recovering the underlying fiducial model and able to provide percent-level constraints at intermediate redshifts.

Gravitational waves have been detected from mergers of BBHs, BNSs, and BHNS, but signals from the most energetic explosions in the modern Universe – core-collapse supernovae (CCSNe) – remain undetected. Astone et al. (2018) proposed the new method based on a classification procedure of the time-frequency images of the LIGO, Virgo, and KAGRA network data performed by a CNN. It allows to recognition of the signal for enhancing the detection efficiency of the GW signal emitted by CCSNe. The method has been validated with phenomenological waveforms injected in Gaussian noise, whose spectral properties are those of the LIGO and Virgo advanced detectors. Its performance is better than the present algorithm for GW selection of a transient signal. The simulated time series of GW detectors and the waveforms in the training of CNN were used by Chan et al. (2020). These authors showed that the network of KAGRA and advanced LIGO and VIRGO, or the network of LIGO A+, advanced VIRGO and KAGRA is likely to detect a magnetorotational CCSN within the Large and Small Magellanic Clouds, or a Galactic event if the explosion mechanism is neutrino-driven. For the CNN with waveforms not used for training, the true alarm probabilities are 52% and 83% at 60 kpc for the waveforms R3E1AC and R4E1FC L and are 70% and 93% at 10 kpc for the waveforms s20 and SFHx. False alarm probability equals to 10%.

A newly developed Mini-Inception Resnet neural network has been trained by López et al. (2021) with the time-frequency images corresponding to injections of simulated phenomenological signals that mimic the waveforms obtained in 3D numerical simulations of CCSNe. Robustness has been tested by injecting signals in the real noise data taken by the Advanced LIGO-Virgo network during the O2 run. This algorithm is able to identify signals from both phenomenological template banks and numerical 3D simulations of CCSNe. For SNR higher than 15 the detection efficiency is 70% at the false alarm rate lower than 5%. In the case of O2 run it would have been possible to detect events at a distance of 1 kpc. Lowering the efficiency down to 60%, the distance reach grows to 14 kpc.

Apart from compact binary mergers, there might be other sources for which there are no reliable models, either expected to exist but to be very rare (e.g., SNe) or totally unanticipated. No unmodeled sources have been discovered so far, but the search for such sources is much more difficult and less sensitive. In this context, Marianer et al. (2021) presented a search for unmodeled GW signals with semi-supervised ML methods. Deep learning and outlier detection algorithms are applied to the labeled spectrograms of GW strain data. About 13% of the public coincident data from the O1 and O2 runs have been searched for the spectrograms with anomalous patterns, and no candidates of GW signals have been detected.

We noted in this brief review the research, which only contours the recent trends of effective ML application in GW astronomy. A more extensive description of ML methods for the analysis of ground-based GW detector data and multi-messenger astrophysics can be found in works by Cuoco et al. (2021), Huerta et al. (2019), Huerta and Zhao (2021), and Soni et al. (2021).

3. Computer Art and General Relativity

Instead of a conclusion, we illustrate our vision of cosmology and gravitational waves through the computer art paintings "Albert Einstein" (Fig. 1), "The curvature of the Universe" (Fig. 3), and "Gravitational waves" (Fig. 5) created by Dr. Ihor Zhuk. Modern cosmology and gravitational wave science owe their appearance to Albert Einstein and the General Theory of Relativity. The significance of achievements in these fields of knowledge for mankind is indirectly confirmed by the Nobel Prizes in Physics awarded over the past two decades: J.C. Mather and G.F. Smoot "for their discovery of the blackbody form and anisotropy of the cosmic microwave background radiation" (2006); S. Perlmutter, B.P. Schmidt and A.G. Riess "for the discovery of the accelerating expansion of the Universe through observations of distant supernovae" (2011); R. Weiss, B.C. Barish and K.S.

Thorne “for decisive contributions to the LIGO detector and the observation of gravitational waves” (2017); J. Peebles “for theoretical discoveries in physical cosmology” (2019); R. Penrose “for the discovery that black hole formation is a robust prediction of the General Theory of Relativity”, R. Genzel and A. Ghez “for the discovery of a supermassive compact object at the center of our galaxy” (2020).

The new mathematical tools and algorithms as machine learning have invaded and conquered cosmology, extragalactic astronomy, astrophysics, and gravitational wave astronomy since the huge observational sky surveys and databases have been conducted. Today machine Learning methods are widely used to study the cosmological parameters and models, modified gravity theories, cosmic microwave background radiation in Big Bang cosmology, the gravitational lensing effect, photometry, and image-based morphological classification of galaxies in various spectral ranges including gamma-ray and transient objects, large-scale structures of the Universe (galaxies, galaxy clusters and superclusters, filaments and voids) with their distance moduli at the cosmological scales, gravitational wave signals detection from merging black hole star and other events. It allows us to obtain a more structured picture of the evolutionary parameters and nature of these celestial bodies as well as to provide new revolutionary discoveries of properties of the Universe as a whole.

Acknowledgements. The authors gratefully thank Dr. Ihor Zhuk for his wonderful computer art paintings on cosmology and GW astronomy. Vavilova I.B. thanks the Wolfgang Pauli Institute, Vienna, Austria, for the grant in a frame of “The Pauli Ukraine Project” (2022) under the “Models in Plasma, Earth and space science” program. This work was partially supported in the frame of the program of the NAS of Ukraine “Support for the development of priority fields of scientific research” (Project “ActivPhys”, 2022-2023). The use of the SAO/NASA Astrophysics Data System was extensively applicable.

References

Alexandrov, A. N., Vavilova, I. B., Zhdanov, V. I., Zhuk, A. I., Kudrya, Y. N., Parnovsky, S. L., Fedorova, E. V., & Yatskiv, Y. S. (2015). *General Relativity Theory: Recognition through Time*. Kyiv: Naukova Dumka.

Álvares, J. D., Font, J. A., Freitas, F. F., Freitas, O. G., Morais, A. P., Nunes, S., Onofre, A., & Torres-Forné, A. (2021). Exploring gravitational-wave detection and parameter inference using deep learning methods. *Classical and Quantum Gravity*, *38*(15), Article 155010, 155010. https://doi.org/10.1088/1361-6382/ac0455

Amendola, L., & Tsujikawa, S. (2015). *Dark Energy*. Cambridge: Cambridge University Press.

Andersson, N. (2019). *Gravitational-Wave Astronomy: Exploring the Dark Side of the Universe*. Oxford: Oxford University Press. https://doi.org/10.1093/oso/9780198568032.001.0001/oso-9780198568032

Angulo, R. E., & Hahn, O. (2022). Large-scale dark matter simulations. *Living Reviews in Computational Astrophysics*, *8*(1), Article 1, 1. https://doi.org/10.1007/s41115-021-00013-z

Aniyan, A. K., & Thorat, K. (2017). Classifying Radio Galaxies with the Convolutional Neural Network. *Astrophys. J. Suppl. Ser.*, *230*(2), Article 20, 20. https://doi.org/10.3847/1538-4365/aa7333

Ansari, R., Choyer, A., Habibi, F., Magneville, C., Moniez, M., Plaszczynski, S., Renault, C., Ricol, J.-S., & Souchard, J. (2019). Impact of photometric redshifts on the galaxy power spectrum and BAO scale in the LSST survey. *Astronomy & Astrophysics*, *623*, Article A76, A76. https://doi.org/10.1051/0004-6361/201833732

Arjona, R., Lin, H.-N., Nesseris, S., & Tang, L. (2021). Machine learning forecasts of the cosmic distance duality relation with strongly lensed gravitational wave events. *Phys. Rev. D*, *103*(10), 103513. https://doi.org/10.1103/PhysRevD.103.103513

Ashton, G., & Talbot, C. (2021). B ilby-MCMC: an MCMC sampler for gravitational-wave inference. *Mon. Not. Roy. Astron. Soc.*, *507*(2), 2037–2051. https://doi.org/10.1093/mnras/stab2236

Asselmeyer-Maluga, T., & Król, J. (2019). A topological approach to neutrino masses by using exotic smoothness. *Modern Physics Letters A*, *34*(13), Article 1950097-63, 1950097–63. https://doi.org/10.1142/S0217732319500974

Astone, P., Cerdá-Durán, P., Di Palma, I., Drago, M., Muciaccia, F., Palomba, C., & Ricci, F. (2018). New method to observe gravitational waves emitted by core collapse supernovae. *Phys. Rev. D*, *98*(12), 122002. https://doi.org/10.1103/PhysRevD.98.122002

Baltus, G., Janquart, J., Lopez, M., Reza, A., Caudill, S., & Cudell, J.-R. (2021). Convolutional neural networks for the detection of the early inspiral of a gravitational-wave signal. *Phys. Rev. D*, *103*, 102003. https://doi.org/10.1103/PhysRevD.103.102003

Barchi, P. H., de Carvalho, R. R., Rosa, R. R., Sautter, R. A., Soares-Santos, M., Marques, B. A. D., Clua, E., Gonçalves, T. S., de Sá-Freitas, C., & Moura, T. C. (2020). Machine and Deep Learning applied to galaxy morphology - A comparative study. *Astronomy and Computing*, *30*, Article 100334, 100334. https://doi.org/10.1016/j.ascom.2019.100334

Barnacka, A. (2018). Gravitational lenses as high-resolution telescopes. *Physical Reports*, *778*, 1–46. https://doi.org/10.1016/j.physrep.2018.10.001

Bayley, J., Messenger, C., & Woan, G. (2020). Robust machine learning algorithm to search for continuous gravitational waves. *Phys. Rev. D*, *102*(8), Article 083024, 083024. https://doi.org/10.1103/PhysRevD.102.083024

Belgacem, E., Foffa, S., Maggiore, M., & Yang, T. (2020). Gaussian processes reconstruction of modified gravitational wave propagation. *Phys. Rev. D*, *101*(6), 063505. https://doi.org/10.1103/PhysRevD.101.063505

Bellm, E. C., Kulkarni, S. R., Graham, M. J., Dekany, R., Smith, R. M., Riddle, R., Masci, F. J., Helou, G., Prince, T. A., Adams, S. M., Barbarino, C., Barlow, T., Bauer, J., Beck, R., Belicki, J., Biswas, R., Blagorodnova, N., Bodewits, D., Bolin, B., … Zolkower, J. (2019). The Zwicky Transient Facility: System Overview, Performance, and First Results. *Publications of the Astronomical Society of the Pacific*, *131*(995), 018002. https://doi.org/10.1088/1538-3873/aaecbe

Billings, T. S., La Plante, P., & Aguirre, J. E. (2021). Extracting the Optical Depth to Reionization τ from 21 cm Data Using Machine Learning Techniques. *arXiv e-prints*, Article arXiv:2103.14563.

Biswas, A., McIver, J., & Mahabal, A. (2020). New methods to assess and improve LIGO detector duty cycle. *Class. Quant. Grav.*, *37*(17), 175008. https://doi.org/10.1088/1361-6382/ab8650

Blanton, M. R., Bershady, M. A., Abolfathi, B., Albareti, F. D., Allende Prieto, C., Almeida, A., Alonso-García, J., Anders, F., Anderson, S. F., Andrews, B., Aquino-Ortíz, E., Aragón-Salamanca, A., Argudo-Fernández, M., Armengaud, E., Aubourg, E., Avila-Reese, V., Badenes, C., Bailey, S., Barger, K. A., … Zou, H. (2017). Sloan Digital Sky Survey IV: Mapping the Milky Way, Nearby Galaxies, and the Distant Universe. *Astron. J.*, *154*(1), Article 28, 28. https://doi.org/10.3847/1538-3881/aa7567

Bonnett, C. (2015). Using neural networks to estimate redshift distributions. An application to CFHTLenS. *Mon. Not. R. Astron. Soc.*, *449*, 1043–1056. https://doi.org/10.1093/mnras/stv230

Brescia, M., Cavuoti, S., Razim, O., Amaro, V., Riccio, G., & Longo, G. (2021). Photometric redshifts with machine learning, lights and shadows on a complex data science use case. *Frontiers in Astronomy and Space Sciences*, *8*, Article 70, 70. https://doi.org/10.3389/fspas.2021.658229

Burgazli, A., Eingorn, M., & Zhuk, A. (2015). Rigorous theoretical constraint on constant negative EoS parameter and its effect for the late Universe. *European Physical Journal C*, *75*, Article 118, 118. https://doi.org/10.1140/epjc/s10052-015-3335-7

Cabero, M., Mahabal, A., & McIver, J. (2020). GWSkyNet: a real-time classifier for public gravitational-wave candidates. *Astrophys. J. Lett.*, *904*(1), L9. https://doi.org/10.3847/2041-8213/abc5b5

Caldeira, J., Wu, W. L. K., Nord, B., Avestruz, C., Trivedi, S., & Story, K. T. (2019). DeepCMB: Lensing reconstruction of the cosmic microwave background with deep neural networks. *Astronomy and Computing*, *28*, Article 100307, 100307. https://doi.org/10.1016/j.ascom.2019.100307

Cañas-Herrera, G., Contigiani, O., & Vardanyan, V. (2021). Learning How to Surf: Reconstructing the Propagation and Origin of Gravitational Waves with Gaussian Processes. *Astrophys. J.*, *918*(1), 20. https://doi.org/10.3847/1538-4357/ac09e3

Carleo, G., Cirac, I., Cranmer, K., Daudet, L., Schuld, M., Tishby, N., Vogt-Maranto, L., & Zdeborová, L. (2019). Machine learning and the physical sciences. *Reviews of Modern Physics*, *91*(4), Article 045002, 045002. https://doi.org/10.1103/RevModPhys.91.045002

Chan, M. L., Heng, I. S., & Messenger, C. (2020). Detection and classification of supernova gravitational wave signals: A deep learning approach. *Phys. Rev. D*, *102*(4), 043022. https://doi.org/10.1103/PhysRevD.102.043022

Chang, C. L., Huffenberger, K. M., Benson, B. A., Bianchini, F., Chluba, J., Delabrouille, J., Flauger, R., Hanany, S., Jones, W. C., Kogut, A. J., McMahon, J. J., Meyers, J., Sehgal, N., Simon, S. M., Umilta, C., Abazajian, K. N., Ahmed, Z., Akrami, Y., Anderson, A. J., … Zhang, C. (2022). Snowmass2021 Cosmic Frontier: Cosmic Microwave Background Measurements White Paper. *arXiv e-prints*, Article arXiv:2203.07638.

Chatterjee, C., Wen, L., Vinsen, K., Kovalam, M., & Datta, A. (2019). Using Deep Learning to Localize Gravitational Wave Sources. *Phys. Rev. D*, *100*(10), 103025. https://doi.org/10.1103/PhysRevD.100.103025

Chatterjee, D., Ghosh, S., Brady, P. R., Kapadia, S. J., Miller, A. L., Nissanke, S., & Pannarale, F. (2020). A Machine Learning Based Source Property Inference for Compact Binary Mergers. *Astrophys. J.*, *896*(1), 54. https://doi.org/10.3847/1538-4357/ab8dbe

Chua, A. J. K., Katz, M. L., Warburton, N., & Hughes, S. A. (2021). Rapid generation of fully relativistic extreme-mass-ratio-inspiral waveform templates for LISA data analysis. *Phys. Rev. Lett.*, *126*(5), 051102. https://doi.org/10.1103/PhysRevLett.126.051102

Chua, A. J. K., & Vallisneri, M. (2020). Learning Bayesian posteriors with neural networks for gravitational-wave inference. *Phys. Rev. Lett.*, *124*(4), 041102. https://doi.org/10.1103/PhysRevLett.124.041102

Ciuca, R., & Hernández, O. F. (2017). A Bayesian framework for cosmic string searches in CMB maps. *Journal of Cosmology and Astroparticle Physics*, *2017*(8), Article 028, 028. https://doi.org/10.1088/1475-7516/2017/08/028

Cuoco, E. et al. (2021). Enhancing Gravitational-Wave Science with Machine Learning. *Mach. Learn. Sci. Tech.*, *2*(1), 011002. https://doi.org/10.1088/2632-2153/abb93a

Dax, M., Green, S. R., Gair, J., Macke, J. H., Buonanno, A., & Schölkopf, B. (2021). Real-Time Gravitational Wave Science with Neural Posterior Estimation. *Phys. Rev. Lett.*, *127*(24), 241103. https://doi.org/10.1103/PhysRevLett.127.241103

de Lera Acedo, E., Pienaar, H., Razavi Ghods, N., Abraham, J., Beltran, E. C., Mort, B., Dulwich, F., Virone, G., Fiorelli, B., Arts, M., Craeye, C., van Ha, B., Grainge, K., Dewdney, P., Wagg, J., Grazia Labate, M., Faulkner, A., Geralt bij de Vaate, J., & Gerbers, M. (2020). SKA LFAA Station Design Report. *arXiv e-prints*, Article arXiv:2003.12744.

DESI Collaboration, Aghamousa, A., Aguilar, J., Ahlen, S., Alam, S., Allen, L. E., Allende Prieto, C., Annis, J., Bailey, S., Balland, C., Ballester, O., Baltay, C., Beaufore, L., Bebek, C., Beers, T. C., Bell, E. F., Bernal, J. L., Besuner, R., Beutler, F., … Zu, Y. (2016). The DESI Experiment Part I: Science,Targeting, and Survey Design. *arXiv e-prints*, Article arXiv:1611.00036.

Dey, A., Schlegel, D. J., Lang, D., Blum, R., Burleigh, K., Fan, X., Findlay, J. R., Finkbeiner, D., Herrera, D., Juneau, S., Landriau, M., Levi, M., McGreer, I., Meisner, A., Myers, A. D., Moustakas, J., Nugent, P., Patej, A., Schlafly, E. F., … Zhou, Z. (2019). Overview of the DESI Legacy Imaging Surveys. *Astron. J.*, *157*(5), Article 168, 168. https://doi.org/10.3847/1538-3881/ab089d

Douspis, M., Salvati, L., Gorce, A., & Aghanim, N. (2022). Retrieving cosmological information from small-scale CMB foregrounds. I. The thermal Sunyaev Zel'dovich effect. *Astronomy & Astrophysics*, *659*, Article A99, A99. https://doi.org/10.1051/0004-6361/202142004

Doux, C., Baxter, E., Lemos, P., Chang, C., Alarcon, A., Amon, A., Campos, A., Choi, A., Gatti, M., Gruen, D., Jarvis, M., MacCrann, N., Park, Y., Prat, J., Rau, M. M., Raveri, M., Samuroff, S., DeRose, J., Hartley, W. G., … Wilkinson, R. D. (2021). Dark energy survey internal consistency tests of the joint cosmological probes analysis with posterior predictive distributions. *Mon. Notic. R. Astron. Soc.*, *503*(2), 2688–2705. https://doi.org/10.1093/mnras/stab526

Elyiv, A., Melnyk, O., & Vavilova, I. (2009). High-order 3D Voronoi tessellation for identifying isolated galaxies, pairs and triplets. *Mon. Notic. R. Astron. Soc.*, *394*(3), 1409–1418. https://doi.org/10.1111/j.1365-2966.2008.14150.x

Elyiv, A. A., Melnyk, O. V., Vavilova, I. B., Dobrycheva, D. V., & Karachentseva, V. E. (2020). Machine-learning computation of distance modulus for local galaxies. *Astronomy & Astrophysics*, *635*, Article A124, A124. https://doi.org/10.1051/0004-6361/201936883

Euclid Collaboration, Ilić, S., Aghanim, N., Baccigalupi, C., Bermejo-Climent, J. R., Fabbian, G., Legrand, L., Paoletti, D., Ballardini, M., Archidiacono, M., Douspis, M., Finelli, F., Ganga, K., Hernández-Monteagudo, C., Lattanzi, M., Marinucci, D., Migliaccio, M., Carbone, C., Casas, S., … Zucca, E. (2022). Euclid preparation. XV. Forecasting cosmological constraints for the Euclid and CMB joint analysis. *Astronomy & Astrophysics*, *657*, Article A91, A91. https://doi.org/10.1051/0004-6361/202141556

Everett, S., Yanny, B., Kuropatkin, N., Huff, E. M., Zhang, Y., Myles, J., Masegian, A., Elvin-Poole, J., Allam, S., Bernstein, G. M., Sevilla-Noarbe, I., Splettstoesser, M., Sheldon, E., Jarvis, M., Amon, A., Harrison, I., Choi, A., Hartley, W. G., Alarcon, A., … Wilkinson, R. D. (2022). Dark Energy Survey Year 3 Results: Measuring the Survey Transfer Function with Balrog. *Astrophys. J. Suppl. Ser.*, *258*(1), Article 15, 15. https://doi.org/10.3847/1538-4365/ac26c1

Fasano, M., Wong, K. W. K., Maselli, A., Berti, E., Ferrari, V., & Sathyaprakash, B. S. (2020). Distinguishing double neutron star from neutron star-black hole binary populations with gravitational wave observations. *Phys. Rev. D*, *102*(2), 023025. https://doi.org/10.1103/PhysRevD.102.023025

Feigelson, E. D., de Souza, R. S., Ishida, E. E. O., & Jogesh Babu, G. (2021). 21st Century Statistical and Computational Challenges in Astrophysics. *Annual Review of Statistics and Its Application*, *8*, 493–517. https://doi.org/10.1146/annurev-statistics-042720-112045

Fluke, C. J., & Jacobs, C. (2020). Surveying the reach and maturity of machine learning and artificial intelligence in astronomy. *WIREs Data Mining and Knowledge Discovery*, *10*(2), Article e1349, e1349. https://doi.org/10.1002/widm.1349

Fussell, L., & Moews, B. (2019). Forging new worlds: high-resolution synthetic galaxies with chained generative adversarial networks. *Mon. Notic. R. Astron. Soc.*, *485*(3), 3203–3214. https://doi.org/10.1093/mnras/stz602

Gabbard, H., Messenger, C., Heng, I. S., Tonolini, F., & Murray-Smith, R. (2022). Bayesian parameter estimation using conditional variational autoencoders for gravitational-wave astronomy. *Nature Phys.*, *18*(1), 112–117. https://doi.org/10.1038/s41567-021-01425-7

Gabbard, H., Williams, M., Hayes, F., & Messenger, C. (2018). Matching matched filtering with deep networks for gravitational-wave astronomy. *Phys. Rev. Lett.*, *120*(14), 141103. https://doi.org/10.1103/PhysRevLett.120.141103

Gebhard, T. D., Kilbertus, N., Harry, I., & Schölkopf, B. (2019). Convolutional neural networks: a magic bullet for gravitational-wave detection? *Phys. Rev. D*, *100*(6), 063015. https://doi.org/10.1103/PhysRevD.100.063015

George, D., & Huerta, E. A. (2018a). Deep Learning for Real-time Gravitational Wave Detection and Parameter Estimation: Results with Advanced LIGO Data. *Phys. Lett. B*, *778*, 64–70. https://doi.org/10.1016/j.physletb.2017.12.053

George, D., & Huerta, E. A. (2018b). Deep Neural Networks to Enable Real-time Multi-messenger Astrophysics. *Phys. Rev. D*, *97*(4), 044039. https://doi.org/10.1103/PhysRevD.97.044039

Gerosa, D., Pratten, G., & Vecchio, A. (2020). Gravitational-wave selection effects using neural-network classifiers. *Phys. Rev. D*, *102*(10), 103020. https://doi.org/10.1103/PhysRevD.102.103020

Giles, D., & Walkowicz, L. (2019). Systematic serendipity: a test of unsupervised machine learning as a method for anomaly detection. *Mon. Notic. R. Astron. Soc.*, *484*(1), 834–849. https://doi.org/10.1093/mnras/sty3461

Goyal, S., D., H., Kapadia, S. J., & Ajith, P. (2021). Rapid identification of strongly lensed gravitational-wave events with machine learning. *Phys. Rev. D*, *104*(12), 124057. https://doi.org/10.1103/PhysRevD.104.124057

Green, S. R., & Gair, J. (2021). Complete parameter inference for GW150914 using deep learning. *Mach. Learn. Sci. Tech.*, *2*(3), 03LT01. https://doi.org/10.1088/2632-2153/abfaed

Green, S. R., Simpson, C., & Gair, J. (2020). Gravitational-wave parameter estimation with autoregressive neural network flows. *Phys. Rev. D*, *102*(10), 104057. https://doi.org/10.1103/PhysRevD.102.104057

Gupta, A., Zorrilla Matilla, J. M., Hsu, D., & Haiman, Z. (2018). Non-Gaussian information from weak lensing data via deep learning. *Phys. Rev. D*, *97*(10), Article 103515, 103515. https://doi.org/10.1103/PhysRevD.97.103515

Haegel, L., & Husa, S. (2020). Predicting the properties of black-hole merger remnants with deep neural networks. *Class. Quant. Grav.*, *37*(13), 135005. https://doi.org/10.1088/1361-6382/ab905c

Hassan, S., Liu, A., Kohn, S., & La Plante, P. (2018). Identifying Reionization Sources from 21cm Maps using Convolutional Neural Networks. In A. D. Kapinska (Ed.), *The 34th annual new mexico symposium* (p. 7).

He, S., Li, Y., Feng, Y., Ho, S., Ravanbakhsh, S., Chen, W., & Póczos, B. (2019). Learning to predict the cosmological structure formation. *Proceedings of the National Academy of Science*, *116*(28), 13825–13832. https://doi.org/10.1073/pnas.1821458116

Hernandez Vivanco, F., Smith, R., Thrane, E., & Lasky, P. D. (2020). A scalable random forest regressor for combining neutron-star equation of state measurements: A case study with GW170817 and GW190425. *Mon. Not. Roy. Astron. Soc.*, *499*(4), 5972–5977. https://doi.org/10.1093/mnras/staa3243

Hezaveh, Y. D., Perreault Levasseur, L., & Marshall, P. J. (2017). Fast automated analysis of strong gravitational lenses with convolutional neural networks. *Nature*, *548*(7669), 555–557. https://doi.org/10.1038/nature23463

Ho, M., Rau, M. M., Ntampaka, M., Farahi, A., Trac, H., & Póczos, B. (2019). A Robust and Efficient Deep Learning Method for Dynamical Mass Measurements of Galaxy

Clusters. *Astrophys. J.*, *887*(1), Article 25, 25. https://doi.org/10.3847/1538-4357/ab4f82

Hortúa, H. J., Volpi, R., Marinelli, D., & Malagò, L. (2020). Parameter estimation for the cosmic microwave background with Bayesian neural networks. *Phys. Rev. D.*, *102*(10), Article 103509, 103509. https://doi.org/10.1103/PhysRevD.102.103509

Huerta, E. A., Allen, G., Andreoni, I., Antelis, J. M., Bachelet, E., Berriman, G. B., Bianco, F. B., Biswas, R., Carrasco Kind, M., Chard, K., Cho, M., Cowperthwaite, P. S., Etienne, Z. B., Fishbach, M., Forster, F., George, D., Gibbs, T., Graham, M., Gropp, W., … Zhao, Z. (2019). Enabling real-time multi-messenger astrophysics discoveries with deep learning. *Nature Reviews Physics*, *1*(10), 600–608. https://doi.org/10.1038/s42254-019-0097-4

Huerta, E. A., Khan, A., Huang, X., Tian, M., Levental, M., Chard, R., Wei, W., Heflin, M., Katz, D. S., Kindratenko, V., Mu, D., Blaiszik, B., & Foster, I. (2021). Accelerated, scalable and reproducible AI-driven gravitational wave detection. *Nature Astronomy*, *5*, 1062–1068. https://doi.org/10.1038/s41550-021-01405-0

Huerta, E. A., & Zhao, Z. (2021). Advances in machine and deep learning for modeling and real-time detection of multi-messenger sources. *Handbook of Gravitational Wave Astronomy*, 1–27. https://doi.org/10.1007/978-981-15-4702-7_47-1

Huertas-Company, M., Primack, J. R., Dekel, A., Koo, D. C., Lapiner, S., Ceverino, D., Simons, R. C., Snyder, G. F., Bernardi, M., Chen, Z., Domínguez-Sánchez, H., Lee, C. T., Margalef-Bentabol, B., & Tuccillo, D. (2018). Deep Learning Identifies High-z Galaxies in a Central Blue Nugget Phase in a Characteristic Mass Range. *Astrophys. J.*, *858*(2), Article 114, 114. https://doi.org/10.3847/1538-4357/aabfed

Ivezić, Ž., Kahn, S. M., Tyson, J. A., Abel, B., Acosta, E., Allsman, R., Alonso, D., AlSayyad, Y., Anderson, S. F., Andrew, J., Angel, J. R. P., Angeli, G. Z., Ansari, R., Antilogus, P., Araujo, C., Armstrong, R., Arndt, K. T., Astier, P., Aubourg, É., … Zhan, H. (2019). LSST: From Science Drivers to Reference Design and Anticipated Data Products. *Astrophys. J.*, *873*(2), Article 111, 111. https://doi.org/10.3847/1538-4357/ab042c

Jacobs, C., Collett, T., Glazebrook, K., McCarthy, C., Qin, A. K., Abbott, T. M. C., Abdalla, F. B., Annis, J., Avila, S., Bechtol, K., Bertin, E., Brooks, D., Buckley-Geer, E., Burke, D. L., Carnero Rosell, A., Carrasco Kind, M., Carretero, J., da Costa, L. N., Davis, C., … DES Collaboration. (2019). Finding high-redshift strong lenses in DES using convolutional neural networks. *Mon. Notic. R. Astron. Soc.*, *484*(4), 5330–5349. https://doi.org/10.1093/mnras/stz272

Jadhav, S., Mukund, N., Gadre, B., Mitra, S., & Abraham, S. (2021). Improving significance of binary black hole mergers in Advanced LIGO data using deep learning: Confirmation of GW151216. *Phys. Rev. D*, *104*(6), 064051. https://doi.org/10.1103/PhysRevD.104.064051

Jones, D., Schroeder, A., & Nitschke, G. (2019). Evolutionary Deep Learning to Identify Galaxies in the Zone of Avoidance. *arXiv e-prints*, Article arXiv:1903.07461.

Kaderali, S., Hunt, J. A. S., Webb, J. J., Price-Jones, N., & Carlberg, R. (2019). Rediscovering the tidal tails of NGC 288 with Gaia DR2. *Mon. Not. R. Astron. Soc.*, *484*(1), L114–L118. https://doi.org/10.1093/mnrasl/slz015

Kang, S.-J., Fan, J.-H., Mao, W., Wu, Q., Feng, J., & Yin, Y. (2019). Evaluating the Optical Classification of Fermi BCUs Using Machine Learning. *Astrophys. J.*, *872*(2), Article 189, 189. https://doi.org/10.3847/1538-4357/ab0383

Kapadia, S. J., Dent, T., & Dal Canton, T. (2017). Classifier for gravitational-wave inspiral signals in nonideal single-detector data. *Phys. Rev. D*, *96*(10), 104015. https://doi.org/10.1103/PhysRevD.96.104015

Kessler, R., & Scolnic, D. (2017). Correcting Type Ia Supernova Distances for Selection Biases and Contamination in Photometrically Identified Samples. *Astrophys. J.*, *836*(1), Article 56, 56. https://doi.org/10.3847/1538-4357/836/1/56

Khan, A., Huerta, E. A., & Das, A. (2020). Physics-inspired deep learning to characterize the signal manifold of quasi-circular, spinning, non-precessing binary black hole mergers. *Phys. Lett. B*, *808*, 0370–2693. https://doi.org/10.1016/j.physletb.2020.135628

Khramtsov, V., Sergeyev, A., Spiniello, C., Tortora, C., Napolitano, N. R., Agnello, A., Getman, F., de Jong, J. T. A., Kuijken, K., Radovich, M., Shan, H., & Shulga, V. (2019). KiDS-SQuaD. II. Machine learning selection of bright extragalactic objects to search for new gravitationally lensed quasars. *Astronomy & Astrophysics*, *632*, Article A56, A56. https://doi.org/10.1051/0004-6361/201936006

Kim, K., Li, T. G. F., Lo, R. K. L., Sachdev, S., & Yuen, R. S. H. (2020). Ranking candidate signals with machine learning in low-latency searches for gravitational waves from compact binary mergers. *Phys. Rev. D*, *101*(8), 083006. https://doi.org/10.1103/PhysRevD.101.083006

Kodi Ramanah, D., Arendse, N., & Wojtak, R. (2022). AI-driven spatio-temporal engine for finding gravitationally lensed type Ia supernovae. *Mon. Not. R. Astron. Soc.*, *512*(4), 5404–5417. https://doi.org/10.1093/mnras/stac838

Krastev, P. G. (2020). Real-Time Detection of Gravitational Waves from Binary Neutron Stars using Artificial Neural Networks. *Phys. Lett. B*, *803*, 135330. https://doi.org/10.1016/j.physletb.2020.135330

Krastev, P. G., Gill, K., Villar, V. A., & Berger, E. (2021). Detection and Parameter Estimation of Gravitational Waves from Binary Neutron-Star Mergers in Real LIGO Data using Deep Learning. *Phys. Lett. B*, *815*, 136161. https://doi.org/10.1016/j.physletb.2021.136161

Krause, M., Pueschel, E., & Maier, G. (2017). Improved γ/hadron separation for the detection of faint γ-ray sources using boosted decision trees. *Astroparticle Physics*, *89*, 1–9. https://doi.org/10.1016/j.astropartphys.2017.01.004

Kremer, J., Stensbo-Smidt, K., Gieseke, F., Steenstrup Pedersen, K., & Igel, C. (2017). Big Universe, Big Data: Machine Learning and Image Analysis for Astronomy. *arXiv e-prints*, Article arXiv:1704.04650, arXiv:1704.04650.

Kügler, S. D., & Gianniotis, N. (2016). Modelling multimodal photometric redshift regression with noisy observations. *arXiv e-prints*, Article arXiv:1607.06059, arXiv:1607.06059.

Kulkarni, S., Phukon, K. S., Reza, A., Bose, S., Dasgupta, A., Krishnaswamy, D., & Sengupta, A. S. (2019). Random projections in gravitational wave searches of compact binaries. *Phys. Rev. D*, *99*(10), 101503. https://doi.org/10.1103/PhysRevD.99.101503

La Plante, P., & Ntampaka, M. (2019). Machine Learning Applied to the Reionization History of the Universe in the 21 cm Signal. *Astrophys. J.*, *880*(2), Article 110, 110. https://doi.org/10.3847/1538-4357/ab2983

Lanusse, F., Ma, Q., Li, N., Collett, T. E., Li, C.-L., Ravanbakhsh, S., Mandelbaum, R., & Póczos, B. (2018). CMU DeepLens: deep learning for automatic image-based galaxy-galaxy strong lens finding. *Mon. Not. R. Astron. Soc.*, *473*(3), 3895–3906. https://doi.org/10.1093/mnras/stx1665

Lazanu, A. (2021). Extracting cosmological parameters from N-body simulations using machine learning techniques. *Journal of Cosmology and Astroparticle Physics*, *2021*(9), Article 039, 039. https://doi.org/10.1088/1475-7516/2021/09/039

Lee, J., & Shin, M.-S. (2022). Estimation of Photometric Redshifts. II. Identification of Out-of-distribution Data with Neural Networks. *Astron. J.*, *163*(2), Article 98, 98. https://doi.org/10.3847/1538-3881/ac4335

Libeskind, N. I., van de Weygaert, R., Cautun, M., Falck, B., Tempel, E., Abel, T., Alpaslan, M., Aragón-Calvo, M. A., Forero-Romero, J. E., Gonzalez, R., Gottlöber, S., Hahn, O., Hellwing, W. A., Hoffman, Y., Jones, B. J. T., Kitaura, F., Knebe, A., Manti, S., Neyrinck, M., … Yepes, G. (2018). Tracing the cosmic web. *Mon. Not. R. Astron. Soc.*, *473*(1), 1195–1217. https://doi.org/10.1093/mnras/stx1976

Lin, Y.-C., & Wu, J.-H. P. (2021). Detection of gravitational waves using Bayesian neural networks. *Phys. Rev. D*, *103*(6), 063034. https://doi.org/10.1103/PhysRevD.103.063034

Lochner, M., McEwen, J. D., Peiris, H. V., Lahav, O., & Winter, M. K. (2016). Photometric Supernova Classification with Machine Learning. *Astrophys. J. Suppl. Ser.*, *225*(2), Article 31, 31. https://doi.org/10.3847/0067-0049/225/2/31

López, M., Di Palma, I., Drago, M., Cerdá-Durán, P., & Ricci, F. (2021). Deep learning for core-collapse supernova detection. *Phys. Rev. D*, *103*, 063011. https://doi.org/10.1103/PhysRevD.103.063011

Lucie-Smith, L., Peiris, H. V., Pontzen, A., Nord, B., & Thiyagalingam, J. (2020). Deep learning insights into cosmological structure formation. *arXiv e-prints*, Article arXiv:2011.10577.

Mahabal, A., Rebbapragada, U., Walters, R., Masci, F. J., Blagorodnova, N., van Roestel, J., Ye, Q.-Z., Biswas, R., Burdge, K., Chang, C.-K., Duev, D. A., Golkhou, V. Z., Miller, A. A., Nordin, J., Ward, C., Adams, S., Bellm, E. C., Branton, D., Bue, B., … Wright, D. (2019). Machine Learning for the Zwicky Transient Facility. *Publications of the Astronomical Society of the Pacific*, *131*(997), 038002. https://doi.org/10.1088/1538-3873/aaf3fa

Malz, A. I., Hložek, R., Allam, J., T., Bahmanyar, A., Biswas, R., Dai, M., Galbany, L., Ishida, E. E. O., Jha, S. W., Jones, D. O., Kessler, R., Lochner, M., Mahabal, A. A., Mandel, K. S., Martínez-Galarza, J. R., McEwen, J. D., Muthukrishna, D., Narayan, G., Peiris, H., … Variable Stars Science Collaboration. (2019). The Photometric LSST Astronomical Time-series Classification Challenge PLAsTiCC: Selection of a Performance Metric for Classification Probabilities Balancing Diverse Science Goals. *Astron. J.*, *158*(5), Article 171, 171. https://doi.org/10.3847/1538-3881/ab3a2f

Manning, S. M., Casey, C. M., Hung, C.-L., Battye, R., Brown, M. L., Jackson, N., Abdalla, F., Chapman, S., Demetroullas, C., Drew, P., Hales, C. A., Harrison, I., Riseley, C. J., Sanders, D. B., & Watson, R. A. (2020). SuperCLASS - II. Photometric redshifts and characteristics of spatially resolved μJy radio sources. *Mon. Not. R. Astron. Soc.*, *495*(2), 1724–1736. https://doi.org/10.1093/mnras/staa657

Marianer, T., Poznanski, D., & Prochaska, J. X. (2021). A semisupervised machine learning search for never-seen gravitational-wave sources. *Mon. Not. R. Astron. Soc.*, *500*(4), 5408–5419. https://doi.org/10.1093/mnras/staa3550

Marulanda, J. P., Santa, C., & Romano, A. E. (2020). Deep learning merger masses estimation from gravitational waves signals in the frequency domain. *Phys. Lett. B*, *810*, 135790. https://doi.org/10.1016/j.physletb.2020.135790

Matthews, D. J. (2014). *Exploring the distant universe with cross-correlation statistics* (Doctoral dissertation). University of Pittsburgh.

Menéndez-Vázquez, A., Kolstein, M., Martínez, M., & Mir, L. M. (2021). Searches for compact binary coalescence events using neural networks in the LIGO/Virgo second observation period. *Phys. Rev. D*, *103*(6), 062004. https://doi.org/10.1103/PhysRevD.103.062004

Miller, A. L. et al. (2019). How effective is machine learning to detect long transient gravitational waves from neutron stars in a real search? *Phys. Rev. D*, *100*(6), 062005. https://doi.org/10.1103/PhysRevD.100.062005

Miller, M. C., & Yunes, N. (2021). *Gravitational Waves in Physics and Astrophysics: An artisan's guide*. IOP Publishing. https://doi.org/10.1088/2514-3433/ac2140

Mishra, A., Reddy, P., & Nigam, R. (2019). CMB-GAN: Fast Simulations of Cosmic Microwave background anisotropy maps using Deep Learning. *arXiv e-prints*, Article arXiv:1908.04682.

Mishra, T., O'Brien, B., Gayathri, V., Szczepanczyk, M., Bhaumik, S., Bartos, I., & Klimenko, S. (2021). Optimization of model independent gravitational wave search for binary black hole mergers using machine learning. *Phys. Rev. D*, *104*(2), 023014. https://doi.org/10.1103/PhysRevD.104.023014

Mo, H., van den Bosch, F. C., & White, S. (2010). *Galaxy Formation and Evolution*. Cambridge University Press.

Morales, M. D., Antelis, J. M., Moreno, C., & Nesterov, A. I. (2021). Deep Learning for Gravitational-Wave Data Analysis: A Resampling White-Box Approach. *Sensors*, *21*(9), 3174. https://doi.org/10.3390/s21093174

Mukund, N., Abraham, S., Kandhasamy, S., Mitra, S., & Philip, N. S. (2017). Transient Classification in LIGO data using Difference Boosting Neural Network. *Phys. Rev. D*, *95*(10), 104059. https://doi.org/10.1103/PhysRevD.95.104059

Mukund, N., Coughlin, M., Harms, J., Biscans, S., Warner, J., Pele, A., Thorne, K., Barker, D., Arnaud, N., Donovan, F., Fiori, I., Gabbard, H., Lantz, B., Mittleman, R., Radkins, H., & Swinkels, B. (2019). Ground motion prediction at gravitational wave observatories using archival seismic data. *Class. Quant. Grav.*, *36*(8), Article 085005, 085005. https://doi.org/10.1088/1361-6382/ab0d2c

Müller, O., & Schnider, E. (2021). Dwarfs from the Dark (Energy Survey): a machine learning approach to classify dwarf galaxies from multi-band images. *The Open Journal of Astrophysics*, *4*(1), Article 3, 3. https://doi.org/10.21105/astro.2102.12776

Narayan, G., Zaidi, T., Soraisam, M. D., Wang, Z., Lochner, M., Matheson, T., Saha, A., Yang, S., Zhao, Z., Kececioglu, J., Scheidegger, C., Snodgrass, R. T., Axelrod, T., Jenness, T., Maier, R. S., Ridgway, S. T., Seaman, R. L., Evans, E. M., Singh, N., . . . ANTARES Collaboration. (2018). Machine-learning-based Brokers for Real-time Classification of the LSST Alert Stream. *Astrophys. J. Suppl. Ser.*, *236*(1), Article 9, 9. https://doi.org/10.3847/1538-4365/aab781

Novosyadlyj, B., Sergijenko, O., Durrer, R., & Pelykh, V. (2014). Constraining the dynamical dark energy parameters: Planck-2013 vs WMAP9. *Journal of Cosmology and Astroparticle Physics*, *2014*(5), Article 030, 030. https://doi.org/10.1088/1475-7516/2014/05/030

Ntampaka, M., & Vikhlinin, A. (2022). The Importance of Being Interpretable: Toward an Understandable Machine Learning Encoder for Galaxy Cluster Cosmology. *Astrophys. J.*, *926*(1), Article 45, 45. https://doi.org/10.3847/1538-4357/ac423e

Peel, A., Lalande, F., Starck, J.-L., Pettorino, V., Merten, J., Giocoli, C., Meneghetti, M., & Baldi, M. (2019). Distinguishing standard and modified gravity cosmologies with machine learning. *Phys. Rev. D*, *100*(2), Article 023508, 023508. https://doi.org/10.1103/PhysRevD.100.023508

Perreault Levasseur, L., Hezaveh, Y. D., & Wechsler, R. H. (2017). Uncertainties in Parameters Estimated with Neural Networks: Application to Strong Gravitational Lensing. *Astrophys. J.*, *850*(1), Article L7, L7. https://doi.org/10.3847/2041-8213/aa9704

Planck Collaboration, Aghanim, N., Akrami, Y., Arroja, F., Ashdown, M., Aumont, J., Baccigalupi, C., Ballardini, M., Banday, A. J., Barreiro, R. B., Bartolo, N., Basak, S., Battye, R., Benabed, K., Bernard, J. .-., Bersanelli, M., Bielewicz, P., Bock, J. J., Bond, J. R., . . . Zonca, A. (2020). Planck 2018 results. I. Overview and the cosmological legacy of Planck. *Astronomy & Astrophysics*, *641*, Article A1, A1. https://doi.org/10.1051/0004-6361/201833880

Pranav, P. (2022). Anomalies in the topology of the temperature fluctuations in the cosmic microwave background: An analysis of the NPIPE and FFP10 data releases. *Astronomy & Astrophysics*, *659*, Article A115, A115. https://doi.org/10.1051/0004-6361/202140291

Ravanbakhsh, S., Lanusse, F., Mandelbaum, R., Schneider, J., & Poczos, B. (2016). Enabling Dark Energy Science with Deep Generative Models of Galaxy Images. *arXiv e-prints*, Article arXiv:1609.05796.

Ribli, D., Pataki, B. Á., & Csabai, I. (2019). An improved cosmological parameter inference scheme motivated by deep learning. *Nature Astronomy*, *3*, 93–98. https://doi.org/10.1038/s41550-018-0596-8

Ruhe, T. (2020). Application of machine learning algorithms in imaging Cherenkov and neutrino astronomy. *International Journal of Modern Physics A*, *35*(33), Article 2043004-778, 2043004–778. https://doi.org/10.1142/S0217751X20430046

Salvato, M., Ilbert, O., & Hoyle, B. (2019). The many flavours of photometric redshifts. *Nature Astronomy*, *3*, 212–222. https://doi.org/10.1038/s41550-018-0478-0

Saulder, C., van Kampen, E., Chilingarian, I. V., Mieske, S., & Zeilinger, W. W. (2016). The matter distribution in the local Universe as derived from galaxy groups in SDSS DR12 and 2MRS. *Astronomy & Astrophysics*, *596*, Article A14, A14. https://doi.org/10.1051/0004-6361/201526711

Schäfer, M. B., Ohme, F., & Nitz, A. H. (2020). Detection of gravitational-wave signals from binary neutron star mergers using machine learning. *Phys. Rev. D*, *102*(6), 063015. https://doi.org/10.1103/PhysRevD.102.063015

Schawinski, K., Zhang, C., Zhang, H., Fowler, L., & Santhanam, G. K. (2017). Generative adversarial networks recover features in astrophysical images of galaxies beyond the deconvolution limit. *Mon. Not. R. Astron. Soc.*, *467*(1), L110–L114. https://doi.org/10.1093/mnrasl/slx008

Schlickeiser, R., Elyiv, A., Ibscher, D., & Miniati, F. (2012). The Pair Beam Production Spectrum from Photon-Photon Annihilation in Cosmic Voids. *Astrophys. J.*, *758*(2), Article 101, 101. https://doi.org/10.1088/0004-637X/758/2/101

Schmidt, S. J., Malz, A. I., Soo, J. Y. H., Almosallam, I. A., Brescia, M., Cavuoti, S., Cohen-Tanugi, J., Connolly, A. J., DeRose, J., Freeman, P. E., Graham, M. L., Iyer, K. G., Jarvis, M. J., Kalmbach, J. B., Kovacs, E., Lee, A. B., Longo, G., Morrison, C. B., Newman, J. A., … LSST Dark Energy Science Collaboration. (2020). Evaluation of probabilistic photometric redshift estimation approaches for The Rubin Observatory Legacy Survey of Space and Time (LSST). *Mon. Not. R. Astron. Soc.*, *499*(2), 1587–1606. https://doi.org/10.1093/mnras/staa2799

Schmidt, S., Breschi, M., Gamba, R., Pagano, G., Rettegno, P., Riemenschneider, G., Bernuzzi, S., Nagar, A., & Del Pozzo, W. (2021). Machine Learning Gravitational Waves from Binary Black Hole Mergers. *Phys. Rev. D*, *103*(4), 043020. https://doi.org/10.1103/PhysRevD.103.043020

Sergijenko, O., Kulinich, Y., Novosyadlyj, B., & Pelykh, V. (2009). Large-scale structure formation in cosmology with classical and tachyonic scalar fields. *Kinemat. Physics Celest. Bodies*, *25*(1), 17–27. https://doi.org/10.3103/S0884591309010036

Sergijenko, O., & Novosyadlyj, B. (2009). Perturbed dark energy: Classical scalar field versus tachyon. *Phys. Rev. D*, *80*(8), Article 083007, 083007. https://doi.org/10.1103/PhysRevD.80.083007

Singh, S., Singh, A., Prajapati, A., & Pathak, K. N. (2021). Deep learning for estimating parameters of gravitational waves. *Mon. Not. Roy. Astron. Soc.*, *508*(1), 1358–1370. https://doi.org/10.1093/mnras/stab2417

Soni, S. et al. (2021). Discovering features in gravitational-wave data through detector characterization, citizen science and machine learning. *Class. Quant. Grav.*, *38*(19), 195016. https://doi.org/10.1088/1361-6382/ac1ccb

Sorce, J. G., Colless, M., Kraan-Korteweg, R. C., & Gottlöber, S. (2017). Predicting structures in the Zone of Avoidance. *Mon. Not. R. Astron. Soc.*, *471*(3), 3087–3097. https://doi.org/10.1093/mnras/stx1800

Sousbie, T., Pichon, C., & Kawahara, H. (2011). The persistent cosmic web and its filamentary structure - II. Illustrations. *Mon. Not. R. Astron. Soc.*, *414*(1), 384–403. https://doi.org/10.1111/j.1365-2966.2011.18395.x

Spergel, D., Gehrels, N., Breckinridge, J., Donahue, M., Dressler, A., Gaudi, B. S., Greene, T., Guyon, O., Hirata, C., Kalirai, J., Kasdin, N. J., Moos, W., Perlmutter, S., Postman, M., Rauscher, B., Rhodes, J., Wang, Y., Weinberg, D., Centrella, J., … Shaklan, S. (2013). WFIRST-2.4: What Every Astronomer Should Know. *arXiv e-prints*, Article arXiv:1305.5425.

The PLAsTiCC team, Allam, J., Tarek, Bahmanyar, A., Biswas, R., Dai, M., Galbany, L., Hložek, R., Ishida, E. E. O., Jha, S. W., Jones, D. O., Kessler, R., Lochner, M., Mahabal, A. A., Malz, A. I., Mandel, K. S., Martínez-Galarza, J. R., McEwen, J. D., Muthukrishna, D., Narayan, G., ... Variable Stars Science Collaboration. (2018). The Photometric LSST Astronomical Time-series Classification Challenge (PLAsTiCC): Data set. *arXiv e-prints*, Article arXiv:1810.00001.

Tsizh, M., Novosyadlyj, B., Holovatch, Y., & Libeskind, N. I. (2020). Large-scale structures in the ΛCDM Universe: network analysis and machine learning. *Mon. Not. R. Astron. Soc.*, *495*(1), 1311–1320. https://doi.org/10.1093/mnras/staa1030

Tully, R. B., Pomarède, D., Graziani, R., Courtois, H. M., Hoffman, Y., & Shaya, E. J. (2019). Cosmicflows-3: Cosmography of the Local Void. *Astrophys. J.*, *880*(1), Article 24, 24. https://doi.org/10.3847/1538-4357/ab2597

Vadai, Y., Poznanski, D., Baron, D., Nugent, P. E., & Schlegel, D. (2017). The effect of interstellar absorption on measurements of the baryon acoustic peak in the Lyman α forest. *Mon. Not. R. Astron. Soc.*, *472*(1), 799–807. https://doi.org/10.1093/mnras/stx2088

van de Weygaert, R., Vegter, G., Edelsbrunner, H., Jones, B. J. T., Pranav, P., Park, C., Hellwing, W. A., Eldering, B., Kruithof, N., Bos, E. G. P., Hidding, J., Feldbrugge, J., ten Have, E., van Engelen, M., Caroli, M., & Teillaud, M. (2013). Alpha, Betti and the Megaparsec Universe: on the Topology of the Cosmic Web. *arXiv e-prints*, Article arXiv:1306.3640.

Vavilova, I. B., Bolotin, Y. L., Boyarsky, A. M., Danevich, F. A., Kobychev, V. V., Tretyak, V. I., Babyk, I. V., Iakubovskyi, D. A., Hnatyk, B. I., & Sergeev, S. G. (2015). *Dark matter: Observational manifestation and experimental searches*. Kyiv: Akademperiodyka.

Vavilova, I. B., Dobrycheva, D. V., Vasylenko, M. Y., Elyiv, A. A., Melnyk, O. V., & Khramtsov, V. (2021). Machine learning technique for morphological classification of galaxies from the SDSS. I. Photometry-based approach. *Astronomy & Astrophysics*, *648*, Article A122, A122. https://doi.org/10.1051/0004-6361/202038981

Vavilova, I. B., Elyiv, A. A., & Vasylenko, M. Y. (2018). Behind the Zone of Avoidance of the Milky Way: what can we Restore by Direct and Indirect Methods? *Russian Radio Physics and Radio Astronomy*, *23*(4), 244–257. https://doi.org/10.15407/rpra23.04.244

Vavilova, I., Dobrycheva, D., Vasylenko, M., Elyiv, A., & Melnyk, O. (2020). Multiwavelength Extragalactic Surveys: Examples of Data Mining. In P. Škoda & F. Adam (Eds.), *Knowledge discovery in big data from astronomy and earth observation* (pp. 307–323). Elsevier. https://doi.org/10.1016/B978-0-12-819154-5.00028-X

Vavilova, I., Elyiv, A., Dobrycheva, D., & Melnyk, O. (2021). The Voronoi tessellation method in astronomy. In I. Zelinka, M. Brescia, & D. Baron (Eds.), *Intelligent astrophysics* (pp. 57–79). Springer, Cham. https://doi.org/10.1007/978-3-030-65867-0_3

Vavilova, I., Pakuliak, L., Babyk, I., Elyiv, A., Dobrycheva, D., & Melnyk, O. (2020). Surveys, Catalogues, Databases, and Archives of Astronomical Data. In P. Škoda & F. Adam (Eds.), *Knowledge discovery in big data from astronomy and earth observation* (pp. 57–102). Elsevier. https://doi.org/10.1016/B978-0-12-819154-5.00015-1

Vega-Ferrero, J., Domínguez Sánchez, H., Bernardi, M., Huertas-Company, M., Morgan, R., Margalef, B., Aguena, M., Allam, S., Annis, J., Avila, S., Bacon, D., Bertin, E., Brooks, D., Carnero Rosell, A., Carrasco Kind, M., Carretero, J., Choi, A., Conselice, C., Costanzi, M., … Wilkinson, R. D. (2021). Pushing automated morphological classifications to their limits with the Dark Energy Survey. *Mon. Not. R. Astron. Soc.*, *506*(2), 1927–1943. https://doi.org/10.1093/mnras/stab594

Villaescusa-Navarro, F., Anglés-Alcázar, D., Genel, S., Spergel, D. N., Somerville, R. S., Dave, R., Pillepich, A., Hernquist, L., Nelson, D., Torrey, P., Narayanan, D., Li, Y., Philcox, O., La Torre, V., Maria Delgado, A., Ho, S., Hassan, S., Burkhart, B., Wadekar, D., … Bryan, G. L. (2021). The CAMELS Project: Cosmology and Astrophysics with Machine-learning Simulations. *Astrophys. J.*, *915*(1), Article 71, 71. https://doi.org/10.3847/1538-4357/abf7ba

Villaescusa-Navarro, F., Genel, S., Anglés-Alcázar, D., Thiele, L., Dave, R., Narayanan, D., Nicola, A., Li, Y., Villanueva-Domingo, P., Wandelt, B., Spergel, D. N., Somerville, R. S., Zorrilla Matilla, J. M., Mohammad, F. G., Hassan, S., Shao, H., Wadekar, D., Eickenberg, M., Wong, K. W. K., … Vogelsberger, M. (2022). The CAMELS Multifield Data Set: Learning the Universe's Fundamental Parameters with Artificial Intelligence. *Astrophys. J. Suppl. Ser.*, *259*(2), Article 61, 61. https://doi.org/10.3847/1538-4365/ac5ab0

Vinciguerra, S., Drago, M., Prodi, G. A., Klimenko, S., Lazzaro, C., Necula, V., Salemi, F., Tiwari, V., Tringali, M. C., & Vedovato, G. (2017). Enhancing the significance of gravitational wave bursts through signal classification. *Class. Quant. Grav.*, *34*(9), Article 094003, 094003. https://doi.org/10.1088/1361-6382/aa6654

Walmsley, M., Lintott, C., Géron, T., Kruk, S., Krawczyk, C., Willett, K. W., Bamford, S., Kelvin, L. S., Fortson, L., Gal, Y., Keel, W., Masters, K. L., Mehta, V., Simmons, B. D., Smethurst, R., Smith, L., Baeten, E. M., & Macmillan, C. (2022). Galaxy Zoo DECaLS: Detailed visual morphology measurements from volunteers and deep learning for 314 000 galaxies. *Mon. Not. R. Astron. Soc.*, *509*(3), 3966–3988. https://doi.org/10.1093/mnras/stab2093

Wandelt, B. D. (2008). Precision Parameter Estimation and Machine Learning. In C. A. L. Bailer-Jones (Ed.), *Classification and discovery in large astronomical surveys* (pp. 339–344). https://doi.org/10.1063/1.3059073

Wang, H., Wu, S., Cao, Z., Liu, X., & Zhu, J.-Y. (2020). Gravitational-wave signal recognition of LIGO data by deep learning. *Phys. Rev. D*, *101*(10), 104003. https://doi.org/10.1103/PhysRevD.101.104003

Wei, W., Khan, A., Huerta, E. A., Huang, X., & Tian, M. (2021). Deep Learning Ensemble for Real-time Gravitational Wave Detection of Spinning Binary Black Hole Mergers. *Phys. Lett. B*, *812*, 136029. https://doi.org/10.1016/j.physletb.2020.136029

Wilding, G., Nevenzeel, K., van de Weygaert, R., Vegter, G., Pranav, P., Jones, B. J. T., Efstathiou, K., & Feldbrugge, J. (2021). Persistent homology of the cosmic web - I. Hierarchical topology in ΛCDM cosmologies. *Mon. Not. R. Astron. Soc.*, *507*(2), 2968–2990. https://doi.org/10.1093/mnras/stab2326

Williams, M. J., Veitch, J., & Messenger, C. (2021). Nested sampling with normalizing flows for gravitational-wave inference. *Phys. Rev. D*, *103*(10), 103006. https://doi.org/10.1103/PhysRevD.103.103006

Wong, K. W. K., Franciolini, G., De Luca, V., Baibhav, V., Berti, E., Pani, P., & Riotto, A. (2021). Constraining the primordial black hole scenario with Bayesian inference and machine learning: the GWTC-2 gravitational wave catalog. *Phys. Rev. D*, *103*(2), 023026. https://doi.org/10.1103/PhysRevD.103.023026

Xu, X., Cisewski-Kehe, J., Green, S. B., & Nagai, D. (2019). Finding cosmic voids and filament loops using topological data analysis. *Astronomy & Computing*, *27*, Article 34, 34. https://doi.org/10.1016/j.ascom.2019.02.003

Yang, T. (2021). Gravitational-Wave Detector Networks: Standard Sirens on Cosmology and Modified Gravity Theory. *Journal of Cosmology and Astroparticle Physics*, *05*, 044. https://doi.org/10.1088/1475-7516/2021/05/044

Yu, H., Adhikari, R. X., Magee, R., Sachdev, S., & Chen, Y. (2021). Early warning of coalescing neutron-star and neutron-star-black-hole binaries from the nonstationary noise background using neural networks. *Phys. Rev. D*, *104*(6), 062004. https://doi.org/10.1103/PhysRevD.104.062004

Zaninetti, L. (2019). A New Analytical Solution for the Distance Modulus in Flat Cosmology. *International Journal of Astronomy and Astrophysics*, *9*, 51–62. https://doi.org/10.4236/ijaa.2019.91005