

Detection and Analysis of Gravitational Waves in the Era of Multi-Messenger Astronomy

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The Banff International Research Station for Mathematical Innovation and Discovery (BIRS) “Detection and Analysis of Gravitational Waves in the Era of Multi-Messenger Astronomy: From Mathematical Modeling to Machine Learning (24w5177),” took place in Banff, Alberta, Canada, from Sunday, November 17, through Friday, November 22, 2024. About six dozen participants from all continents (except Antarctica) attended the meeting, with thirty-eight of them in person at the beautiful BIRS headquarters and the remaining joining on Zoom. The focus of the discussions was the latest advances in the development of machine learning algorithms for the analysis and interpretation of gravitational wave (GW) data.

1 Overview

On February 11, 2016, one hundred years and a few months after Einstein’s publication of the General Relativity Theory, the Laser Interferometer Gravitational-wave Observatory (LIGO) Scientific Collaboration (LSC) [1] and the European Virgo Collaboration [2] announced the first direct detection of GWs from a pair of coalescing black holes [3], marking the beginning of GW astronomy. Eight years and a few months later, at the time of the 24w5177 workshop, GW observations from a variety of astrophysical sources (black hole mergers, neutron star mergers, and mixed binary systems) had surpassed one hundred and counting [4]. This plethora of detections has allowed scientists to confirm astrophysical conjectures (e.g., the origin of gamma-ray bursts), put stringent limits on physical theories (e.g., the speed of GWs), test the behavior of matter at high densities and low temperatures (e.g., the equation of state of neutron stars), perform precision measurements of physical constants (e.g., the Hubble constant), and test the frontiers of high-energy physics (e.g., alternative theories of gravity). In spite of these achievements, LIGO and Virgo’s discoveries have left many questions unanswered. In fact, GW astronomy has raised new questions. What physical process led to the formation of intermediate-mass black holes? Where in their galaxies do stellar-mass black holes reside? What is the nature of low-mass gap objects, too heavy to be neutron stars but too light to be black holes formed by stellar collapse? Can we use gravitational sirens to measure the expansion of the universe with the

precision required to solve the Hubble tension? When will we detect GW signals from non-binary merger sources?

The increase in detector sensitivity and the development of novel and more powerful search algorithms are key to answering these questions; scientists will be able to study the population of GW emitters through statistical means by building a large catalog of observations. However, this program is not free of challenges. Paraphrasing a well-known catchphrase, “With great data comes great needs.” Handling hundreds of new detections and extracting physical information from them will require the creation of new mathematical algorithms, the development of sophisticated data analysis techniques, and the deployment of advanced computational techniques. New discoveries will only be possible by the interplay and simultaneous advancement of all these elements. In this context, Machine Learning (ML) is poised to play an ever-increasing role in GW astronomy [5].

In November 2021, the authors of this report organized the first BIRS workshop on the detection and analysis of GWs in Oaxaca, Mexico. The first workshop focused on the development of analytical, numerical, and computational methods for GW physics in preparation for the LIGO-Virgo-KAGRA (LVK) fourth observation run. The workshop emphasis was on numerical relativity and ML. By the time of the second workshop in Banff, some of the machine learning techniques discussed in Oaxaca had been implemented in the GW data analysis pipelines or were close to their final implementation: algorithms for rapid detection and classification of electromagnetically (EM)-bright signals, procedures for speeding up the extraction of physical parameters from the signals, and data analysis methods for signal denoising and detector characterization.

Three years after Oaxaca’s workshop, the time was ripe to discuss how these algorithms performed, assess their effectiveness in the ongoing fourth observing run, and discuss lessons learned. These topics were discussed from different perspectives by gathering participants with common ML interests but complementary expertise and skills. The list of invited participants and speakers included experts in the field of General Relativity (GR) and GW data analysis, as well as applied ML. Many of the participants were members of the LVK collaborations, but invitations were extended to members of the scientific community who were not directly involved with GW searches. This interdisciplinarity allowed the workshop participants to discuss the progress of the field from different angles and create a useful dialectic between theory- and experiment-oriented researchers. With this in mind, the workshop program included a mix of invited talks and ample time for discussions. The participant demographic was wide both in terms of geographic distribution, gender distribution, and career stage; workshop participants were a mix of late-stage experts in the field and junior researchers at the graduate and postdoctoral levels.

2 Workshop outcomes

The workshop was unique in its genre, as it responded to a well-defined research need (application of ML techniques in GW science) while providing a strategic synergism between theoretical physicists, applied mathematicians, and researchers directly involved with the analysis of multi-messenger GW data. A tangible outcome of the workshop was to spur the development of novel analysis techniques that will allow GW scientists to extract more efficiently physical information from the upcoming data as well as increase the astrophysical reach of the detectors in the next observing runs planned for the late part of this decade. The workshop created new synergies between the GW scientists attending the event. In particular, the workshop dealt with these specific topics:

- The future of GW multi-messenger astronomy; what do GW scientists and the EM astronomers expect to learn from new GW observations? How can ML help the communication between these two intertwined communities?
- The potential of ML in extracting physical information on possible beyond-Einstein’s GR signatures in future observations; What new physics can ML help to detect in GW signals? Can ML methods reach the required level of accuracy to detect beyond-GR effects?
- Methods to increase the sensitivity of GW detectors; Can ML be used to control the instruments and improve their calibration? What are the most effective ML algorithms to reduce instrumental background and denoise data?

- Numerical and computational algorithms for the detection of GW signals at future expected rates; What are the desirable or required refinements in ML applications for the next observing runs? Can ML algorithms be used to achieve complete automatization of GW searches with next-generation detectors?
- Debriefing and next steps in ML-based data analysis algorithms; What were the lessons learned in ML-based data analysis? How can we use ML to improve the extraction of physical information from GW observations?

These questions were addressed during the presentation as well as discussion sessions. To facilitate progress and improve synergy among the participants, the workshop schedule included five open mic roundtable discussions on the above topics:

1. “Multimessenger astronomy in the era of design sensitivity and beyond,” chaired by Michael Coughlin (University of Minnesota).
2. “New avenues in physics beyond general relativity,” chaired by Anuradha Gupta (University of Mississippi);
3. “Applications of machine learning in GW instrumentation, calibration, and detector characterization,” chaired by Gabriele Vajente (California Institute of Technology);
4. “Addressing demands of analyses in O5 and beyond,” chaired by Jess McIver (University of British Columbia);
5. “Applications of machine learning in gravitational wave data analysis,” chaired by Ik Siong Heng (Glasgow University).

These sessions were independently organized by each chair and made use of various interactive techniques to stimulate the conversation among participants and summarize the outcomes. For example, the roundtable on the applications of ML in GW instrumentation, calibration, and detector characterization used a padlet to emphasize the connections between various proposed ML techniques and the problems facing their applications to GW instrumentation (see Fig.1). The roundtable on addressing demands of future analyses used a “breakout room setting” where workshop participants were asked to split into separate groups and work within their groups to determine the top three biggest hurdles of future GW analyses before reporting to the whole assembly at the end of the session.

3 Presentation Highlights

The workshop included 29 invited presentations about multi-messenger astronomy, ML algorithms applied to GW science, and current and novel techniques for searches in GW data, detector characterization, and control. We highlight the invited presentations in the workshop’s five thematic areas section below.

3.1 Multimessenger astronomy in the era of design sensitivity and beyond

Ben Farr (University of Oregon) focused on the potential of normalizing-flow-based ML techniques to overcome the limitations of current probabilistic catalogs of posterior samples for GW observations and provide more usable catalogs of GW events for the broader community. Along the same lines, Anarya Ray (Northwestern University) presented a novel neural network-based emulator to learn the mapping between astrophysical input parameters and the resulting population of GW emitters and discussed future applications for larger GW catalogs and more realistic population synthesis simulations.

Challenges and progress in the detection of GWs and their joint analysis in conjunction with EM observations were the subject of Ik Siong Heng and Christopher Messenger’s (Glasgow University) presentations. Joint analyses of GW and EM observations, as well as parameter estimation of the sources, can be computationally intensive, leading to latencies that make the analysis unfeasible for near-real-time follow-ups. Heng’s talk presented ML tools that have been deployed to facilitate rapid computation for multi-messenger astronomy, including population analyses for GRB jet structures, rapid EOS inference, and kilonova light

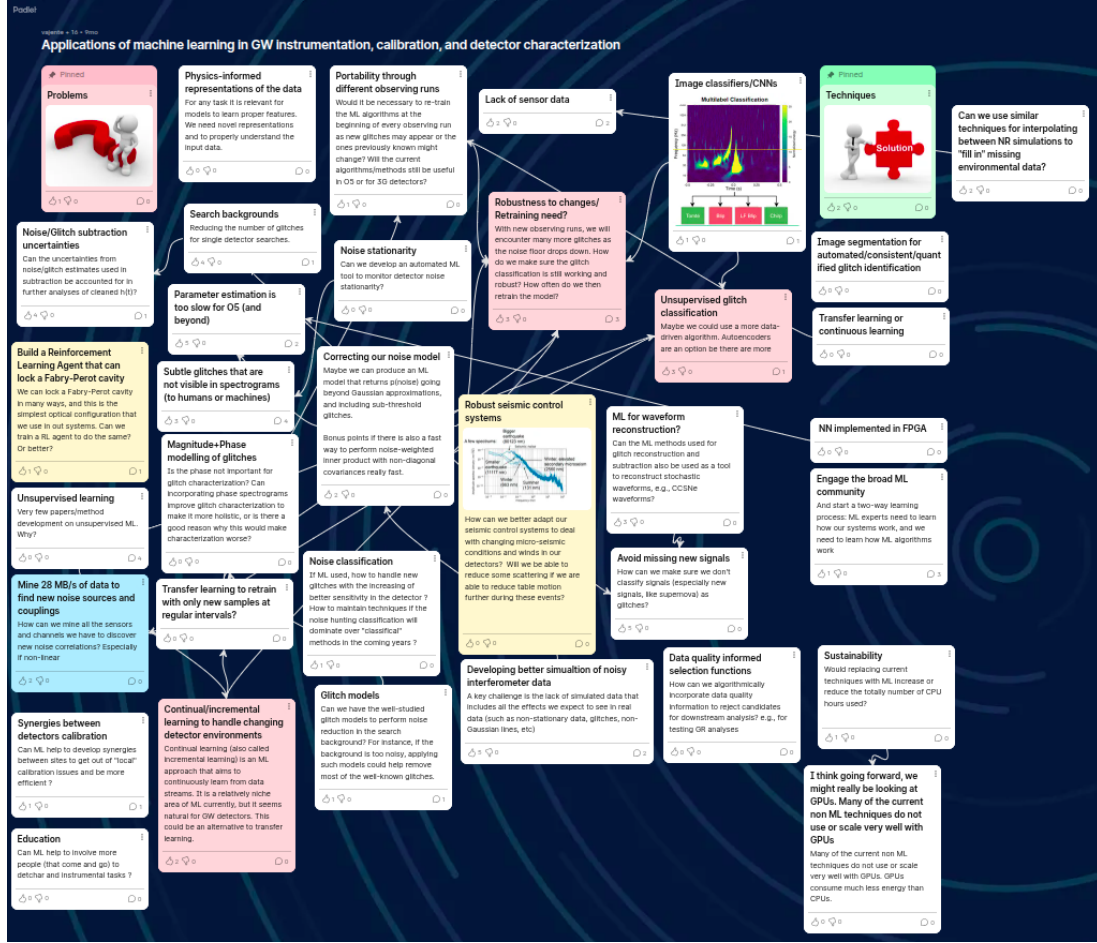


Figure 1: The padlet used for the discussion on the applications of ML in GW instrumentation, calibration, and detector characterization on the second day of the workshop.

curve predictions. Messenger’s presentation focused on a novel deep learning algorithm to complement or replace matched-filtering techniques for optimal detection of GW signals.

Barbara Patricelli (University of Pisa) and Nikhil Sarin (Nordita-Stockholm)’s presentations focused on multi-messenger astronomy. Patricelli reviewed the challenges and the status of the searches for very high-energy EM counterparts to GWs and the prospects for future detections of gamma-ray bursts in coincidence with GWs with next-generation instruments such as the Cherenkov Telescope Array. Sarin discussed what can be learned from observations of mergers seen directly in GWs or indirectly as gamma-ray bursts and/or kilonovae. The signatures of EM and GW emissions we can expect from future observations, and the tools required to maximally extract physics from these observations, were also discussed.

3.2 New avenues in physics beyond general relativity

Aaron Zimmerman (University of Texas at Austin), Ajith Parameswaran (ICTS, Bangalore), and Anuradha Gupta (University of Mississippi) discussed searching for new, yet-undetected, GW signals. Zimmerman focused on GWs from exotic stars, and Parameswaran discussed gravitationally lensed GW signals and how the observation (as well as non-observation) of lensed GWs can probe different aspects of cosmology, including primordial black holes, dark matter, and cosmic expansion rate. Gupta discussed challenges in claiming violations of GR using GW observations, in particular the required statistical confidence to claim the observation of beyond-Einstein effects in a GW detection. She discussed various causes that could potentially lead to a false GR violation and possible ways to mitigate them.

3.3 Applications of machine learning in GW instrumentation, calibration, and detector characterization

Gabriele Vajente and Derek Davis (Caltech) reviewed current ML-based techniques for interferometer control, calibration, and detector characterization. Denoising of GW data in real time was the main focus of Davis' presentation; rapid data quality assessment is becoming more important as the detection rate of signals in GW detectors increases. While numerous techniques are currently employed to identify and mitigate problems in GW data, these procedures will need to evolve to address new problems that will arise with improved detector sensitivities. ML-based techniques could provide a solution to the big data challenges on the horizon.

Tom Dooney (Utrecht University) presented a novel deep learning algorithm to reconstruct time-domain GW signals and detector glitches in GW data. Reconstructing transient features is essential for a range of scientific analyses. The algorithm is designed to reconstruct power excess as a precursor to parameter estimation pipelines as well as enable large-scale simulations or mock data challenges of noise artifacts.

Melissa Lopez (Nikhef) discussed LIGO noise detection with autoencoders. The unsupervised algorithm relies on information provided by auxiliary channels monitoring the state of the interferometers to find anomalous glitches. Using the noise fractal dimension as a feature, near-real-time detection of data anomalies can be performed using an autoencoder with cyclic periodic convolutions. This approach could provide a flexible framework for glitch discovery.

Francesco Di Renzo (Institut de Physique des 2 Infinis de Lyon) reviewed data quality and event validation in the ongoing LVK observational campaign, including their impact on the detection of astrophysical signals and the significance and reliability of astrophysical parameter estimates. He also discussed how advances in signal processing and artificial intelligence (AI) will enhance these procedures in future observational campaigns.

3.4 Addressing demands of analyses in O5 and beyond

Shrobana Ghosh (Max Planck Institute for Gravitational Physics, Hannover) and Koustav Chandra (Penn State University) discussed data analysis challenges and progress towards better models of GWs from astrophysical transients in the next generation of detectors. Ghosh discussed the state-of-the-art in producing more accurate waveforms with the addition of new physics, such as the asymmetric emission of GWs. Chandra focused on parameter estimation and detection sensitivity of overlapping signals – a real possibility in future instruments due to the expected increase in detection rates. New features in GW waveforms and novel methods to detect them were the subject of Sharan Banagiri (Northwestern University) and Amitesh Singh (University of Mississippi). Banagiri focused on effective models to detect evidence for misalignment of binary black hole spins with the system's orbital angular momentum. Singh discussed modeling of binary systems with eccentric orbits.

3.5 Applications of machine learning in gravitational wave data analysis

This part of the workshop saw presentations on different aspects of ML algorithm applications to GW science. Jess McIver and Mervyn Chan (University of British Columbia) discussed new ML codes, GWSkyNet, GWSkyNet-Multi, and GSpyNetTreeS. McIver focused on the ongoing multidisciplinary approach to probe the algorithm explainability in real-time estimation of GW signals. Chan's presentation focused on the identification and classification of noise and astrophysical transients in GW data as well as their removal and subtraction. Sarah Antier (Observatoire de la Côte d'Azur) presented ML and AI methods for alert monitoring, decision-making, image analysis, and parameter extraction of multi-messenger sources as well as their use by astronomical collaborations. AI will be critical in upcoming observational campaigns, such as the Vera Rubin Observatory, which will generate vast volumes of alerts. Marco Serra (INFN Sezione di Roma) discussed deep learning techniques to detect long-duration transient GWs, namely signals from rapidly rotating newborn magnetars that can last from minutes to hours and change rapidly in frequency. ML methods could provide a workable alternative to computationally demanding matched filter techniques. Soichiro Morisaki (University of Tokyo) presented new results in black hole spin distribution inference.

Real-time estimation of GW signals and source inference were the subject of Andrew Toivonen (University of Minnesota), Miquel Miravet-Tenés (University of Southampton), and Sushant Sharma Chaudhary (Missouri University of Science and Technology). Toivonen’s presentation focused on low-latency GW data products for ongoing LVK multi-messenger searches, including gamma-ray bursts and kilonovae. He presented a summary of open public alerts, the current data products used to classify compact binary mergers, and those under current development. Miravet-Tenés presented a new ML-based scheme to promptly identify the properties of GW sources, such as component masses and spins. He discussed two new implementations of supervised machine learning algorithms, K-nearest neighbors and random forest, which can provide Bayesian probabilities for the presence of a neutron star and post-merger matter remnant in LVK low-latency searches. Sharma Chaudhary presented an ML approach to estimate GW parameters in real time. The method is based on a quantile regression neural network model that provides dynamic confidence bounds on key parameters such as chirp mass, mass ratio, and total mass of the GW binary source with over 95% accuracy while decreasing the overall time required for parameter estimation.

Mairi Sakellariadou (King’s College London) presented sparse dictionary learning methods to reconstruct merger waveforms in the presence of galactic confusion noise, rapid detection of GWs, and reconstruction of long-duration GWs from extreme mass ratio inspirals. Ryan Magee (California Institute of Technology) discussed the role of ML as a tool to bolster GW detection pipeline outputs. Magee’s focus was on two distinct applications of ML to detection pipeline outputs: how simple neural networks can accurately interpolate across the GW signal space used by search pipelines, facilitating local signal-to-noise ratio maximization, and how convolutional neural networks can accurately classify signals and noise.

4 Summary

ML is playing an important role in GW astronomy and multi-messenger astronomy. ML algorithms are applied to a variety of problems, from detector science to data analysis. Current ML methods have matured enough to be able to rival standard conventional techniques used for detection and parameter estimation of GW astrophysical sources. They can effectively deal with large data sets and the need for high accuracy, which is required in performing searches at the limit of the instrument sensitivity and extracting the physics from the data. The BIRS workshop successfully provided a forum to review the latest advances in this field, as well as the challenges and open questions that need to be solved to render these techniques even more robust and widely applicable.

The workshop supported the participation of researchers and students at different stages of their careers and from diverse institutions. Its hybrid nature allowed for the participation of several international participants who otherwise would not have had the chance of attending the workshop and for a couple of last-minute dropouts due to travel impediments.

Overall, the workshop was successful in its original intents; it put together a balanced program with invited talks and open discussions on the main thematic areas of ML-related GW science, set up an environment to encourage exchanges of ideas, facilitated the interaction between GW scientists with different backgrounds and research approaches, and encouraged participation of early career researchers.

Ten years after the first detection of GWs, ML is well on course to play an ever-increasing role in expanding our understanding of the universe. The BIRS workshop has been pivotal in pushing the field forward.

Acknowledgements

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All workshop participants would also like to acknowledge the traditional territory of the Stoney Nakoda Nations of Wesley, Chiniki, and Bearspaw; three Blackfoot Confederacy nations: the Pikani, Kainai, and Siksika; the Tsuut’ina First Nations, and the Métis Nation of Alberta. Before provincial boundaries were established, the Ktunaxa and Maskwacis people also lived in this territory. For decades, all these peoples

have contributed to preserving this land, honoring and cherishing it as a place of knowledge and healing. We are honored and humbled to have had the opportunity to partake in this heritage.

Appendix: Participants

In-person invited participants:

1. Ackley, Kendall (University of Warwick)
2. Antier, Sarah (Observatoire de la Côte d'Azur, France)
3. Banagiri, Sharan (Northwestern University, USA, & Monash University, Australia)
4. Baylor, Amanda (University of Wisconsin-Milwaukee, USA)
5. Brady, Patrick (University of Wisconsin-Milwaukee, USA)
6. Cavaglia, Marco (Missouri University of Science and Technology, USA)
7. Chan, Mervyn (University of British Columbia, Canada)
8. Coughlin, Michael (University of Minnesota, USA)
9. Davis, Derek (California Institute of Technology, USA)
10. Di Renzo, Francesco (Institut de Physique des 2 Infinis de Lyon, France)
11. Dooney, Tom (Utrecht University, Netherlands)
12. Ghosh, Shrobona (Max Planck Institute for Gravitational Physics (AEI) Hannover, Germany)
13. Gupta, Anuradha (University of Mississippi, USA)
14. Heng, Ik Siong (University of Glasgow, UK)
15. Lopez, Melissa (Nikhef, Netherlands)
16. Magee, Ryan (California Institute of Technology, USA)
17. Malakar, Dishari (Missouri University of Science and Technology, USA)
18. McIver, Jessica (The University of British Columbia, Canada)
19. Messenger, Christopher (University of Glasgow, UK)
20. Messick, Cody (University of Wisconsin-Milwaukee, USA)
21. Miravet-Tenés, Miquel (University of Southampton, UK)
22. Morisaki, Soichiro (University of Tokyo, Japan)
23. Pannarale, Francesco (Sapienza University of Rome & INFN, Italy)
24. Parameswaran, Ajith (International Center for Theoretical Sciences (ICTS), Bangalore, India)
25. Patricelli, Barbara (University of Pisa, Italy)
26. Powell, Jade (Swinburne University of Technology, Australia)
27. Ray, Anarya (Northwestern University, USA)
28. Sakellariadou, Mairi (King's College London, UK)
29. Sarin, Nikhil (Nordita-Stockholm, Sweden)

30. Serra, Marco (INFN Sezione di Roma, Italy)
31. Sharma Chaudhary, Sushant (Missouri University of Science and Technology, USA)
32. Singh, Amitesh (University of Mississippi, USA)
33. Toivonen, Andrew (University of Minnesota, USA)
34. Vajente, Gabriele (California Institute of Technology, USA)
35. Winborn, Charlie (Missouri University of Science and Technology, USA)
36. Wysocki, Daniel (University of Wisconsin - Milwaukee, USA)
37. Zheng, Yanyan (Missouri University of Science and Technology, USA)
38. Zimmerman, Aaron (University of Texas at Austin, USA)

Remote invited participants:

1. Chandra, Koustav (Penn State University, USA)
2. Cuoco, Elena (European Gravitational Observatory, Italy)
3. Farr, Ben (University of Oregon, USA)
4. Ghosh, Shaon (Montclair State University, USA)

Other remote participants:

1. Afzal, Adeela (Quaid-i-Azam University Islamabad, Pakistan)
2. Aleman, Brianna (Cal State Northridge, USA)
3. Bachhar, Ritesh (University of Rhode Island, USA)
4. Bessa, Pedro (CBPF, Brasil)
5. Borghetto, Giulia (University of Swansea, UK)
6. Canizares, Priscilla (University of Cambridge, UK)
7. Cardoso, Vitor (University of Lisbon, Portugal)
8. Caudill, Sarah (University of Massachusetts Dartmouth, USA)
9. Chowdhury, Sourav Roy (Southern Federal University, India)
10. Chowdhury, Debika (Indian Institute of Astrophysics, India)
11. Cordero-Carrión, Isabel (University of Valencia, Spain)
12. Dejarah, Rafid H. (Ankara University, Turkey)
13. Emma, Mattia (Royal Holloway University of London, UK)
14. Kumar, Bhuvnesh (University of Malaysia, Malaysia)
15. Laguna, Pablo (University of Texas at Austin, USA)
16. Lyu, Zhenwei (Dalian University of Technology, China)
17. Millhouse, Meg (Georgia Institute of Technology, USA)
18. Moon, Yashasvi (Missouri State University, USA)

19. Nagarajan, Narenraju (University of Glasgow, UK)
20. Noureen, Tayyaba (Lahore University of Management Sciences, Pakistan)
21. Razzano, Massimiliano (University of Pisa, Italy)
22. Rivera, Marco Immanuel (ARTEMIS/OCA, France)
23. Roulet, Javier (California Institute of Technology, USA)
24. Sathyaprakash, Bangalore (Pennsylvania State University, USA)
25. Scialpi, Matteo (University of Ferrara, Italy)
26. Shoemaker, Deirdre (University of Texas at Austin, USA)
27. Soni, Kanchan (Syracuse University, USA)
28. Tang, Yong (ICTP-AP, India)
29. Teofilo, F. Enrico (University of Pisa, Italy)
30. Ubach, Helena (University of Barcelona, ICCUB, Spain)
31. Wadekar, Digvijay (Johns Hopkins University, USA)
32. Wang, He (University of Chinese Academy of Sciences, China)

References

- [1] J. Aasi *et al.* [LIGO Scientific Collaboration], Advanced LIGO, *Class. Quant. Grav.* **32** (2015), 074001.
- [2] F. Acernese [Virgo Collaboration], The Advanced Virgo detector, *J. Phys. Conf. Ser.* **610** (2015), 012014.
- [3] B. P. Abbott *et al.* [LIGO Scientific and Virgo Collaborations], Observation of Gravitational Waves from a Binary Black Hole Merger, *Phys. Rev. Lett.* **116** (2016), 061102.
- [4] R. Abbott *et al.* [LIGO Scientific and Virgo Collaborations], GWTC-3: Compact Binary Coalescences Observed by LIGO and Virgo During the Second Part of the Third Observing Run, [arXiv:2111.03606 [gr-qc]] (2021).
- [5] E. Cuoco, M. Cavaglia, I. S. Heng, D. Keitel and C. Messenger, *Living Rev. Rel.* **28**, no.1, 2 (2025) doi:10.1007/s41114-024-00055-8 [arXiv:2412.15046 [gr-qc]].