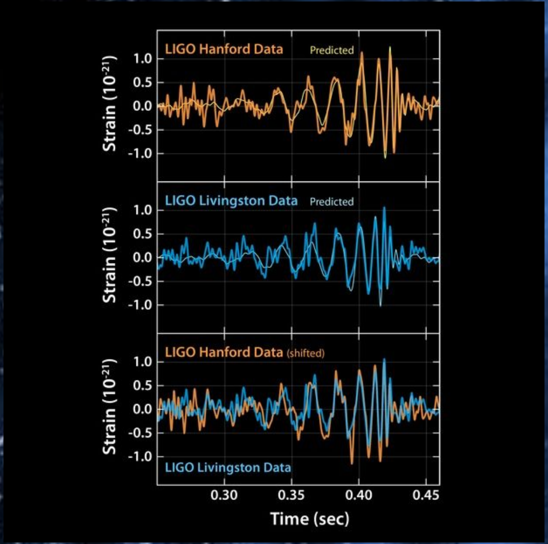
Tools and Results for Real-Time DL in Gravitational-Wave Physics

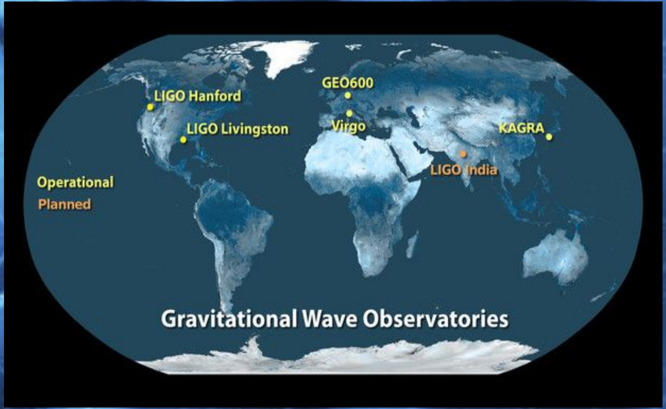
Alec Gunny, Ethan Marx, Will Benoit, Rafia Omer, Deep Chatterjee, Muhammed Saleem, Eric A. Moreno, Katya Govorkova, Ryan Raikman, Dylan Rankin, Michael Coughlin, Erik Katsavounidis, Philip Harris

Gravitational wave physics

Large scale astrophysical events ripple the fabric of spacetime



International Gravitational Wave Observatory Network (IGWN) set up to detect, locate, and characterize events



Measure timeseries of unitless quantity - gravitational wave **strain**

ML for GW-physics is nothing new…

- [Staats & Cavaglià (2018) [38] (Commun. Comput. Phys.)] - Finding the origin of noise transients in LIGO data with machine learning (**Karoo GP**)
- **[Mukund et al. (2017) [39] (PRD)]** - Transient classification in LIGO data using difference boosting neural network (**Wavelet-DBNN, India**)
- **[Llorens-Monteagudo et al. (2019) [40] (CQG)]** - Classification of gravitational-wave glitches via dictionary learning (**Dictionary learning**)
- Low latency transient detection and classification (I. Pinto, V. Pierro, L. Troiano, E. Mejuto-Villa, V. Matta, P. Addesso)
- **[George et al. (2018) [33] (PRD)]** - Classification and unsupervised clustering of LIGO data with Deep Transfer Learning (**Deep Transfer Learning**)
- **[Astone et al. (2018) [41] (PRD)]** - New method to observe gravitational waves emitted by core collapse supernovae (**RGB image SN CNN**)
- **[Colgan et al. (2020) [42] (PRD)]** - Efficient gravitational-wave glitch identification from environmental data through machine learning
- **[Bahaadini et al. (2017) [43] (IEEE)]** - Deep Multi-View Models for Glitch Classification
- **[Bahaadini et al. (2018) [44] (Info. Sci.)]** - Machine learning for Gravity Spy: Glitch classification and dataset
- **[Bahaadini et al. (2018) [45] (IEEE)]** - DIRECT: Deep Discriminative Embedding for Clustering of LIGO Data
- Young-Min Kim - Noise Identification in Gravitational wave search using Artificial Neural Networks (PDF) (4th K-J workshop on KAGRA @ Osaka Univ.)
- **[Biswas et al. (2020) [46] (CQG)]** - New Methods to Assess and Improve LIGO Detector Duty Cycle
- **[Morales-Alvarez et al. (2020) [47] (IEEE)]** - Scalable Variational Gaussian Processes for Crowdsourcing: Glitch Detection in LIGO
- **[Marianer et al. (2020) [48] (Mon. Not. Roy. Astron. Soc.)]** - A Semisupervised Machine Learning Search for Never-seen Gravitational-wave Sources
- **[Mesuga & Bayanay (2021) [49] (2107.01863)]** - On the Efficiency of Various Deep Transfer Learning Models in Glitch Waveform Detection in Gravitational-wave Data
- **[Sankarapandian & Kulis (2021) [50] (2107.10667)]** - β-Annealed Variational Autoencoder for Glitches
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- **[Merritt et al. (2021) [53] (PRD)]** - Transient Glitch Mitigation in Advanced LIGO Data
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- **[Davis et al. (2022) [55] (2204.03091)]** - Incorporating Information from LIGO Data Quality Streams into the PyCBC Search for Gravitational Waves
- **[Bahaadini et al. (2022) [56] (2205.13672)]** - Discriminative Dimensionality Reduction Using Deep Neural Networks for Clustering of LIGO Data

Glitch cancellation / GW denosing

- Pending:
  - **[Cuoco et al. (2001) [68] (CQG)]** - On-line power spectra identification and whitening for the noise in interferometric gravitational wave detectors
  - **[Torres-Forné (2016) [69] (PRD)]** - Denoising of Gravitational Wave Signals Via Dictionary Learning Algorithms
  - **[Torres et al. (2014) [70] (PRD)]** - Total-Variation-Based Methods for Gravitational Wave Denoising
  - **[Torres-Forné (2018) [71] (PRD)]** - Total-variation methods for gravitational-wave denoising: Performance tests on Advanced LIGO data
  - **[Torres-Forné (2020) [72] (PRD)]** - Application of dictionary learning to denoise LIGO's blip noise transients
  - **[Shen et al. (2019) [73] (IEEE)]** - Denoising Gravitational Waves with Enhanced Deep Recurrent Denoising Auto-encoders
  - **[Wei & Huerta (2020) [74] (PLB)]** - Gravitational wave denoising of binary black hole mergers with deep learning
  - **[Vajente et al. (2020) [75] (PRD)]** - Machine-learning nonstationary noise out of gravitational-wave detectors
  - **[Alimohammadi et al. (2021) [76] (Scientific Reports)]** - A Template-Free Approach for Waveform Extraction of Gravitational Wave Events
  - **[Ormiston et al. (2020) [77] (PRR)]** - Noise Reduction in Gravitational-Wave Data via Deep Learning
  - **[Essick et al. (2020) [78] (Mach. learn.: sci. technol.)]** - iDQ: Statistical Inference of Non-gaussian Noise with Auxiliary Degrees of Freedom in Gravitational-wave Detectors
  - **[Mogushi et al. (2021) [79] (Mach. learn.: sci. technol.)]** - NNETFIX: an artificial neural network-based denoising engine for gravitational-wave signals
  - **[Chatterjee et al. (2021) [80] (PRD)]** - Extraction of Binary Black Hole Gravitational Wave Signals from Detector Data Using Deep Learning
  - **[Mogushi (2021) [81] (2105.10522)]** - Reduction of Transient Noise Artifacts in Gravitational-wave Data Using Deep Learning
  - **[Colgan et al. (2022) [82] (2203.05086)]** - Detecting and Diagnosing Terrestrial Gravitational-Wave Mimics Through Feature Learning
  - **[Lopez et al. (2022) [83] (2203.06494)]** - Simulating Transient Noise Bursts in LIGO with Generative Adversarial Networks
  - **[Yu & Adhikari (2022) [84] (Front. Artif. Intell.)]** - Nonlinear Noise Cleaning in Gravitational-Wave Detectors With Convolutional Neural Networks
  - **[Lopez et al. (2022) [85] (2205.09204)]** - Simulating Transient Noise Bursts in LIGO with Gengli
  - **[Vajente (2022) [@PhysRevD.105.102005] (PRD)]** - Data Mining and Machine Learning Improve Gravitational-Wave Detector Sensitivity
  - **[Bacon et al. (2022) [86] (2205.13513)]** - Denoising Gravitational-Wave Signals from Binary Black Holes with Dilated Convolutional Autoencoder
  - **[Kato et al. (2022) [87] (Astron. Comput.)]** - Validation of Denoising System Using Non-Harmonic Analysis and Denoising Convolutional Neural Network for Removal of Gaussian Noise from Gravitational Waves Observed by LIGO

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- [Kapadia et al. (2017) [125] (PRD)] - Classifier for Gravitational-wave Inspiral Signals in Nonideal Single-detector Data
- [Cao et al. (2018) [126] (JHNU)] - Initial study on the application of deep learning to the Gravitational Wave data analysis
- [Fan et al. (2019) [127] (SCI CHINA PHYS MECH)] - Applying deep neural networks to the detection and space parameter estimation of compact binary coalescence with a network of gravitational wave detectors
- [Luo et al. (2019) [128] (Front. Phys.)] - Extraction of gravitational wave signals with optimized convolutional neural network
- [Lin et al. (2019) [129] (Front. Phys.)] - Binary Neutron Stars Gravitational Wave Detection Based on Wavelet Packet Analysis and Convolutional Neural Networks
- [Wang et al. (2019) [130] (New J. Phys.)] - Identifying Extra High Frequency Gravitational Waves Generated from Oscillons with Cuspy Potentials Using Deep Neural Networks
- [Rebei et al. (2019) [131] (PRD)] - Fusing numerical relativity and deep learning to detect higher-order multipole waveforms from eccentric binary black hole mergers
- [Krastev (2020) [132] (PLB)] - Real-time Detection of Gravitational Waves from Binary Neutron Stars Using Artificial Neural Networks
- [Mytidis et al. (2019) [133] (PRD)] - Sensitivity Study Using Machine Learning Algorithms on Simulated r-mode Gravitational Wave Signals from Newborn Neutron Stars
- [Gebhard et al. (2017) [134] (Workshop)] - Convwave: Searching for gravitational waves with fully convolutional neural nets
- [Gebhard et al. (2019) [135] (PRD)] - Convolutional Neural Networks: A Magic Bullet for Gravitational-wave Detection?
- [Bresten & Jung (2019) [136] (1910.08245)] - Detection of Gravitational Waves Using Topological Data Analysis and Convolutional Neural Network: An Improved Approach
- …3.09995)] - Gravitational Wave Detection and Information Extraction via Neural Networks
- …ert Syst. Appl.)] - Scalable Auto-Encoders for Gravitational Waves Detection from Time
- …hina Phys. Mech. Astron.)] - Machine Learning for Nanohertz Gravitational Wave Detection …h Pulsar Timing Array
- …PLB)] - Deep learning Gravitational Wave Detection in the Frequency Domain
- …] - Gravitational-Wave Signal Recognition of LIGO Data by Deep Learning
- … Ranking Candidate Signals with Machine Learning in Low-latency Searches for …npact Binary Mergers
- …Thesis)] - Analysis of Gravitational-Wave Signals from Binary Neutron Star Mergers Using
- …)] - Detection of Gravitational-wave Signals from Binary Neutron Star Mergers Using
- …Detection of Gravitational Waves Using Bayesian Neural Networks
- …5889)] - Deep Learning Model to Make Gravitational Wave Detections from Weak Time-
- …eur

- [Xia et al. (2020) [158] (PRD)] - Improved Deep Learning Techniques in Gravitational-wave Data Analysis
- [Alvares et al. (2020) [159] (CQG)] - Exploring Gravitational-wave Detection and Parameter Inference Using Deep Learning Methods
- [Wang et al. (2019) [130] (New J. Phys.)] - Identifying Extra High Frequency Gravitational Waves Generated from Oscillons with Cuspy Potentials Using Deep Neural Networks
- LIGO & Virgo provide two probabilities in low-latency. [Chatterjee et al. (2020) [160] (ApJ)] The probability that there is a neutron star in the CBC system, P(HasNS). The probability that there exists tidally disrupted matter outside the final coalesced object after the merger, P(HasRemnant). Matched filter searches give point estimates of mass and spin but they have large errors! To solve this a machine learning classification is used. (scikit learn K nearest neighbours, also tried random forest). A training set is created by injecting fake signals into gravitational wave data and performing a search. This then produces a map between true values and matched filter search point estimates which is learnt by the classifier.
- [Wei et al. (2020) [161] (ApJ)] - Deep Learning with Quantized Neural Networks for Gravitational Wave Forecasting of Eccentric Compact Binary Coalescence
- [Menéndez-Vázquez et al. (2020) [162] (PRD)] - Searches for Compact Binary Coalescence Events Using Neural Networks in the LIGO/Virgo Second Observation Period
- [Krastev et al. (2020) [163] (PLB)] - Detection and Parameter Estimation of Gravitational Waves from Binary Neutron-Star Mergers in Real LIGO Data Using Deep Learning
- [Dodia (2021) [164] (2101.00195)] - Detecting Residues of Cosmic Events Using Residual Neural Network
- [Kulkarni et al. (2019) [165] (PRD)] - Random Projections in Gravitational Wave Searches of Compact Binaries (Random projections)
- [Rzeza et al. (2021) [166] (2101.03226)] - Random Projections in Gravitational Wave Searches from Compact Binaries II: Efficient Reconstruction of Detection Statistic within LLOID Framework (Random projections)
- [Zhan et al. (2021) [167] (2103.03557)] - The Response of the Convolutional Neural Network to the Transient Noise in Gravitational Wave Detection
- [Morawski et al. (2021) [168] (Mach. learn.: sci. technol.)] - Anomaly Detection in Gravitational Waves Data Using Convolutional Autoencoders
- [Baltus et al. (2021) [169] (PRD)] - Convolutional Neural Networks for the Detection of the Early Inspiral of a Gravitational-wave Signal
- [Yan et al. (2021) [170] (PRD)] - Generalized Approach to Matched Filtering Using Neural Networks
- [Yu et al. (2021) [171] (PRD)] - Early Warning of Coalescing Neutron-star and Neutron-star-black-hole Binaries from Nonstationary Noise Background Using Neural Networks
- [Fan et al. (2021) [172] (ICPR)] - Improving Gravitational Wave Detection with 2d Convolutional Neural Networks
- [Baltus et al. (2021) [173] (IEEE)] - Detecting the Early Inspiral of a Gravitational-wave Signal with Convolutional Neural Networks
- [Schäfer et al. (2021) [174] (2106.03741)] - Training Strategies for Deep Learning Gravitational-wave Searches
- [Goyal et al. (2021) [175] (PRD)] - Rapid Identification of Strongly Lensed Gravitational-wave Events with Machine Learning
- [Dodia et al. (2021) [176] (2107.03607)] - Specgrav – Detection of Gravitational Waves Using Deep Learning
- [Van Lieshout (2021) [177] (Master Thesis)] - Sparse, Deep Neural Networks for the Early Detection of Gravitational Waves

- Supernova Search

Some burst searches are for targeted sources like supernovae. There is not enough supernova waveforms to match filter search but some supernova waveform features are known. The known features from supernova simulations can be incorporated into supernova searches using machine learning.

- [Astone et al. (2018) [41] (PRD)] enhance the efficiency of cWB using a neural network. The network is trained on phenomenological waveforms that represent the g-mode emission in supernova waveforms. They use cWB to prepare images of the data. They use colours to determine which detectors find the signal. They find their method increases the sensitivity of traditional cWB.
- [Iess et al. (2020) [321] (Mach. learn.: sci. technol.)] have a different approach that does not involve cWB. They use a trigger generator called WDF to find excess power in the detector. Then they do a neural network classification to decide if the trigger is a signal or noise. They train directly on supernova waveforms. They use both time series and images of data. They obtain high accuracies with both methods and include glitches.
- [Chan et al. (2019) [322] (PRD)] also train directly on supernova waveforms. They use only the time series waveforms from different explosion mechanisms.
- [Cavaglia et al. (2020) [323] (Mach. learn.: sci. technol.)] - Improving the background of gravitational-wave searches for core collapse supernovae: a machine learning approach
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- [Loperz et al. (2021) [327] (IEEE)] - Deep Learning Algorithms for Gravitational Waves Core-collapse Supernova Detection
- [Antelis et al. (2021) [328] (PRD)] - Using Supervised Learning Algorithms As a Follow-up Method in the Search of Gravitational Waves from Core-collapse Supernovae

- [Nousi et al. (2022) [210] (2211.01520)] - Deep Residual Networks for Gravitational Wave Detection
- [Kim (2022) [211] (2211.02655)] Search for Microlensing Signature in Gravitational Waves from Binary Black Hole Events

- Machine Learning Parameter Estimation
  - **The current "holy grail" of machine learning for GWs.**
  - BAMBI: blind accelerated multimodal Bayesian inference combines the benefits of nested sampling and artificial neural networks. **[Graff et al. (2012) [220] (Mon. Not. Roy. Astron. Soc.)]** An artificial neural network learns the likelihood function to increase significantly the speed of the analysis. **[Graff (2012) [221] (PhD Thesis)]**
  - Chua et al. **[Chua & Vallisneri (2020) [222] (PRL)]** produce Bayesian posteriors using neural networks.
  - Gabbard et al. **[Gabbard et al. (2019) [223] (Nature Physics)]** use a conditional variational autoencoder pre-trained on binary black hole signals. We use a variation inference approach to produce samples from the posterior. It does NOT need to be trained on precomputed posteriors. It is ~6 orders of magnitude faster than existing sampling techniques. For Chris Messenger, it seems completely obvious that all data analysis will be ML in 5-10 years.
  - **[Chatterjee et al. (2020) [160] (ApJ)]** - A Machine Learning-based Source Property Inference for Compact Binary Mergers
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  - **[Green et al. (2020) [224] (PRD)]** - Gravitational-Wave Parameter Estimation with Autoregressive Neural Network Flows
  - **[Carrillo et al. (2016) [225] (GRG)]** - Parameter estimates in binary black hole collisions using neural networks
  - **[Carrillo et al. (2018) [226] (INT J MOD PHYS D)]** - One parameter binary black hole inverse problem using a sparse training set
  - **[Chatterjee et al. (2019) [227] (PRD)]** - Using deep learning to localize gravitational wave sources
  - **[Yamamoto & Tanaka (2020) [228] (2002.12095)]** - Use of conditional variational auto encoder to analyze ringdown gravitational waves
  - **[Haegel & Husa (2020) [229] (CQG)]** - Predicting the properties of black-hole merger remnants with deep neural networks
  - **[Belgacem et al. (2020) [230] (PRD)]** - Gaussian processes reconstruction of modified gravitational wave propagation
  - **[Chen et al. (2020) [139] (Sci. China Phys. Mech. Astron.)]** - Machine Learning for Nanohertz Gravitational Wave Detection and Parameter Estimation with Pulsar Timing Array
  - **[Khan et al. (2020) [231] (PLB)]** - Physics-inspired deep learning to characterize the signal manifold of quasi-circular, spinning, non-precessing binary black hole mergers

- [Rover et al. (2009) [329] (PRD)] - Bayesian reconstruction of gravitational wave burst signals from simulations of rotating stellar core collapse and bounce

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] - Machine Learning for Nanohertz Gravitational Wave Detection
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spinning, non-precessing binary black hole mergers

al. (2022) [213] (2211.13789)] - Detection of Einstein Telescope Gravitational Wave Signals from Binary
Jsing Deep Learning
(2022) [214] (ICPR)] - Convolutional Transformer for Fast and Accurate Gravitational Wave Detection
asona et al. (2022) [@2022Andres-CarcasonaSearchesMassAsymmetricCompact] (2212.02829)] -
Mass-Asymmetric Compact Binary Coalescence Events Using Neural Networks in the LIGO/Virgo Third
Period
(2022) [@PhysRevD.106.122002] (PRD)] - Deep Learning Model Based on a Bidirectional Gated Recurrent
etection of Gravitational Wave Signals
2023) [215] (2302.00295)] - Self-Supervised Learning for Gravitational Wave Signal Identification
n et al. (2023) [216] (2302.00666)] - Rapid Identification and Classification of Eccentric Gravitational Wave
Machine Learning
(2022) [217] (IEEE)] - Optimizing Large Gravitational-Wave Classifier through a Custom Cross-System

- Machine Learning Parameter Estimation
  - **The current "holy grail" of machine learning for GWs.**
  - BAMBI: blind accelerated multimodal Bayesian inference combines the benefits of nested sampling and artificial neural networks. **[Graff et al. (2012) [220] (Mon. Not. Roy. Astron. Soc.)]** An artificial neural network learns the likelihood function to increase significantly the speed of the analysis. **[Graff (2012) [221] (PhD Thesis)]**
  - Chua et al. **[Chua & Vallisneri (2020) [222] (PRL)]** produce Bayesian posteriors using neural networks.
  - Gabbard et al. **[Gabbard et al. (2019) [223] (Nature Physics)]** use a conditional variational autoencoder pre-trained on binary black hole signals. We use a variation inference approach to produce samples from the posterior. It does NOT need to be trained on precomputed posteriors. It is ~6 orders of magnitude faster than existing sampling techniques. For Chris Messenger, it seems completely obvious that all data analysis will be ML in 5-10 years.
  - **[Chatterjee et al. (2020) [160] (ApJ)]** - A Machine Learning-based Source Property Inference for Compact Binary Mergers
  - **[Fan et al. (2019) [127] (SCI CHINA PHYS MECH)]** - Applying deep neural networks to the detection and space parameter estimation of compact binary coalescence with a network of gravitational wave detectors
  - **[Green et al. (2020) [224] (PRD)]** - Gravitational-Wave Parameter Estimation with Autoregressive Neural Network Flows
  - **[Carrillo et al. (2016) [225] (GRG)]** - Parameter estimates in binary black hole collisions using neural networks
  - **[Carrillo et al. (2018) [226] (INT J MOD PHYS D)]** - One parai training set
  - **[Chatterjee et al. (2019) [227] (PRD)]** - Using deep learning t
  - **[Yamamoto & Tanaka (2020) [228] (2002.12095)]** - Use of co gravitational waves
  - **[Haegel & Husa (2020) [229] (CQG)]** - Predicting the properti
  - **[Belgacem et al. (2020) [230] (PRD)]** - Gaussian processes r
  - **[Chen et al. (2020) [139] (Sci. China Phys. Mech. Astron.)]** - and Parameter Estimation with Pulsar Timing Array
  - **[Khan et al. (2020) [231] (PLB)]** - Physics-inspired deep learr spinning, non-precessing binary black hole mergers

- **[Xia et al. (2020) [158] (PRD)]** - Improved Deep Learning Techniques in Gravitational-wave Data Analysis
- **[Alvares et al. (2020) [159] (CQG)]** - Exploring Gravitational-wave Detection and Parameter Inference Using Deep Le Methods
- **[Wang et al. (2019) [130] (New J. Phys.)]** - Identifying Extra High Frequency Gravitational Waves Generated from Os with Cuspy Potentials Using Deep Neural Networks
- LIGO & Virgo provide two probabilities in low-latency. **[Chatterjee et al. (2020) [160] (ApJ)]** The probability that there neutron star in the CBC system, P(HasNS). The probability that there exists tidally disrupted matter outside the fi coalesced object after the merger, P(HasRemnant). Matched filter searches give point estimates of mass and sp they have large errors! To solve this a machine learning classification is used. (scikit learn K nearest neighbours, tried random forest). A training set is created by injecting fake signals into gravitational wave data and performin search. This then produces a map between true values and matched filter search point estimates which is learnt classifier.
- **[Wei et al. (2020) [161] (ApJ)]** - Deep Learning with Quantized Neural Networks for Gravitational Wave Forecasting Eccentric Compact Binary Coalescence
- **[Menéndez-Vázquez et al. (2020) [162] (PRD)]** - Searches for Compact Binary Coalescence Events Using Neural Ne in the LIGO/Virgo Second Observation Period
- **[Krastev et al. (2020) [163] (PLB)]** - Detection and Parameter Estimation of Gravitational Waves from Binary Neutro Mergers in Real LIGO Data Using Deep Learning
- **[Dodia (2021) [164] (2101.00195)]** - Detecting Residues of Cosmic Events Using Residual Neural Network
- **[Kulkarni et al. (2019) [165] (PRD)]** - Random Projections in Gravitational Wave Searches of Compact Binaries (**Ran projections**)
- **[Rzeza et al. (2021) [166] (2101.03226)]** - Random Projections in Gravitational Wave Searches from Compact Binai Efficient Reconstruction of Detection Statistic within LLOID Framework (**Random projections**)
- **[Zhan et al. (2021) [167] (2103.03557)]** - The Response of the Convolutional Neural Network to the Transient Noise Gravitational Wave Detection
- **[Morawski et al. (2021) [168] (Mach. learn.: sci. technol.)]** - Anomaly Detection in Gravitational Waves Data Using Convolutional Autoencoders
- **[Baltus et al. (2021) [169] (PRD)]** - Convolutional Neural Networks for the Detection of the Early Inspiral of a Gravitational-wave Signal
- **[Yan et al. (2021) [170] (PRD)]** - Generalized Approach to Matched Filtering Using Neural Networks
- **[Yu et al. (2021) [171] (PRD)]** - Early Warning of Coalescing Neutron-star and Neutron-star-black-hole Binaries from Nonstationary Noise Background Using Neural Networks
- **[Fan et al. (2021) [172] (ICPR)]** - Improving Gravitational Wave Detection with 2d Convolutional Neural Networks
- **[Baltus et al. (2021) [173] (IEEE)]** - Detecting the Early Inspiral of a Gravitational-wave Signal with Convolutional Neural Networks
- **[Schäfer et al. (2021) [174] (2106.03741)]** - Training Strategies for Deep Learning Gravitational-wave Searches
- **[Goyal et al. (2021) [175] (PRD)]** - Rapid Identification of Strongly Lensed Gravitational-wave Events with Machine Learning
- **[Dodia et al. (2021) [176] (2107.03607)]** - Specgrav – Detection of Gravitational Waves Using Deep Learning
- **[Van Lieshout (2021) [177] (Master Thesis)]** - Sparse, Deep Neural Networks for the Early Detection of Gravitational Waves

Gravitational Wave Detection
Gravitational Waves

- **[Kapadia et al. (2017) [125] (PRD)]** - Classifier for Gravitational-wave Inspiral Signals in Nonideal Single-detector Data
- **[Cao et al. (2018) [126] (JHNU)]** - Initial study on the application of deep learning to the Gravitational Wave data analysis
- **[Fan et al. (2019) [127] (SCI CHINA PHYS MECH)]** - Applying deep neural networks to the detection and space parameter estimation of compact binary coalescence with a network of gravitational wave detectors

- **[Kapadia et al. (2017) [125] (PRD)]** - Classifier for Gravitational-wave Inspiral Signals in Nonideal Single-detector Data
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- **[Fan et al. (2019) [127] (SCI CHINA PHYS MECH)]** - Applying deep neural networks to the detection and space parameter estimation of compact binary coalescence with a network of gravitational wave detectors
- **[Luo et al. (2019) [128] (Front. Phys.)]** - Extraction of gravitational wave signals with optimized convolutional neural network
- **[Lin et al. (2019) [129] (Front. Phys.)]** - Binary Neutron Stars Gravitational Wave Detection Based on Wavelet Packet Analysis and Convolutional Neural Networks
- **[Wang et al. (2019) [130] (New J. Phys.)]** - Identifying Extra High Frequency Gravitational Waves Generated from Oscillons with Cuspy Potentials Using Deep Neural Networks
- **[Rebei et al. (2019) [131] (PRD)]** - Fusing numerical relativity and deep learning to detect higher-order multipole waveforms from eccentric binary black hole mergers
- **[Krastev (2020) [132] (PLB)]** - Real-time Detection of Gravitational Waves from Binary Neutron Stars Using Artificial Neural Networks
- **[Mytidis et al. (2019) [133] (PRD)]** - Sensitivity Study Using Machine Learning Algorithms on Simulated r-mode Gravitational Wave Signals from Newborn Neutron Stars
- **[Gebhard et al. (2017) [134] (Workshop)]** - Convwave: Searching for gravitational waves with fully convolutional neural nets
- **[Gebhard et al. (2019) [135] (PRD)]** - Convolutional Neural Networks: A Magic Bullet for Gravitational-wave Detection?
- **[Bresten & Jung (2019) [136] (1910.08245)]** - Detection of Gravitational Waves Using Topological Data Analysis and Convolutional Neural Network: An Improved Approach
- **[Santos et al. (2020) [137] (2003.09995)]** - Gravitational Wave Detection and Information Extraction via Neural Networks
- **[Corizzo et al. (2020) [138] (Expert Syst. Appl.)]** - Scalable Auto-Encoders for Gravitational Waves Detection from Time Series Data
- **[Chen et al. (2020) [139] (Sci. China Phys. Mech. Astron.)]** - Machine Learning for Nanohertz Gravitational Wave Detection and Parameter Estimation with Pulsar Timing Array
- **[Marulanda et al. (2020) [140] (PLB)]** - Deep learning Gravitational Wave Detection in the Frequency Domain
- **[Wang et al. (2020) [141] (PRD)]** - Gravitational-Wave Signal Recognition of LIGO Data by Deep Learning
- **[Kim et al. (2020) [142] (PRD)]** - Ranking Candidate Signals with Machine Learning in Low-latency Searches for Gravitational Waves from Compact Binary Mergers
- **[Schäfer (2019) [143] (Masters Thesis)]** - Analysis of Gravitational-Wave Signals from Binary Neutron Star Mergers Using Machine Learning
- **[Schäfer et al. (2020) [144] (PRD)]** - Detection of Gravitational-wave Signals from Binary Neutron Star Mergers Using Machine Learning
- **[Lin & Wu (2020) [145] (PRD)]** - Detection of Gravitational Waves Using Bayesian Neural Networks
- **[Chauhan (2020) [146] (2007.05889)]** - Deep Learnin series Data

- **[Dodia et al. (2021) [176] (2107.03607**
- **[Van Lieshout (2021) [177] (Master The**
- **[Schäfer et al. (2020) [144] (PRD)]** - Machine Learning
- **[Lin & Wu (2020) [145] (PRD)]** - Dete
- **[Chauhan (2020) [146] (2007.0588** series Data

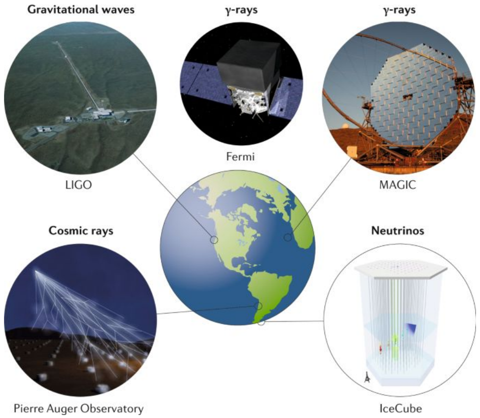
- **[Alimohammadi et al. (2021) [76] (Scientific Reports)]** - A Template-Free Approach for Waveform Extraction of Gravitational Wave Events
- **[Ormiston et al. (2020) [77] (PRR)]** - Noise Reduction in Gravitational-Wave Data via Deep Learning
- **[Essick et al. (2020) [78] (Mach. learn.: sci. technol.)]** - iDQ: Statistical Inference of Non-gaussian Noise with Auxil Degrees of Freedom in Gravitational-wave Detectors
- **[Mogushi et al. (2021) [79] (Mach. learn.: sci. technol.)]** - NNETFIX: an artificial neural network-based denoising e gravitational-wave signals
- **[Chatterjee et al. (2021) [80] (PRD)]** - Extraction of Binary Black Hole Gravitational Wave Signals from Detector Dat Deep Learning
- **[Mogushi (2021) [81] (2105.10522)]** - Reduction of Transient Noise Artifacts in Gravitational-wave Data Using Dee Learning
- **[Colgan et al. (2022) [82] (2203.05086)]** - Detecting and Diagnosing Terrestrial Gravitational-Wave Mimics Throug Feature Learning
- **[Lopez et al. (2022) [83] (2203.06494)]** - Simulating Transient Noise Bursts in LIGO with Generative Adversarial Ne
- **[Yu & Adhikari (2022) [84] (Front. Artif. Intell.)]** - Nonlinear Noise Cleaning in Gravitational-Wave Detectors With Convolutional Neural Networks
- **[Lopez et al. (2022) [85] (2205.09204)]** - Simulating Transient Noise Bursts in LIGO with Gengli
- **[Vajente (2022) [@PhysRevD.105.102005] (PRD)]** - Data Mining and Machine Learning Improve Gravitational-Wa Detector Sensitivity
- **[Bacon et al. (2022) [86] (2205.13513)]** - Denoising Gravitational-Wave Signals from Binary Black Holes with Dilate Convolutional Autoencoder
- **[Kato et al. (2022) [87] (Astron. Comput.)]** - Validation of Denoising System Using Non-Harmonic Analysis and Denoising Convolutional Neural Network for Removal of Gaussian Noise from Gravitational Waves Observed by LIGO

- **[Staats & Cavaglià (2018) [38] (Commun. Comput. Phys.)]** - Finding the origin of noise transients in LIGO data with machine learning (**Karoo GP**)
- **[Mukund et al. (2017) [39] (PRD)]** - Transient classification in LIGO data using difference boosting neural network (**Wavelet-DBNN, India**)
- **[Llorens-Monteagudo et al. (2019) [40] (CQG)]** - Classification of gravitational-wave glitches via dictionary learning (**Dictionary learning**)
- Low latency transient detection and classification (I. Pinto, V. Pierro, L. Troiano, E. Mejuto-Villa, V. Matta, P. Addesso)
- **[George et al. (2018) [33] (PRD)]** - Classification and unsupervised clustering of LIGO data with Deep Transfer Learning (**Deep Transfer Learning**)
- **[Astone et al. (2018) [41] (PRD)]** - New method to observe gravitational waves emitted by core collapse supernovae (**RGB image SN CNN**)
- **[Colgan et al. (2020) [42] (PRD)]** - Efficient gravitational-wave glitch identification from environmental data through machine learning
- **[Bahaadini et al. (2017) [43] (IEEE)]** - Deep Multi-View Models for Glitch Classification
- **[Bahaadini et al. (2018) [44] (Info. Sci.)]** - Machine learning for Gravity Spy: Glitch classification and dataset
- **[Bahaadini et al. (2018) [45] (IEEE)]** - DIRECT: Deep Discriminative Embedding for Clustering of LIGO Data
- Young-Min Kim - Noise Identification in Gravitational wave search using Artificial Neural Networks (PDF) (4th K-J workshop on KAGRA @ Osaka Univ.)
- **[Biswas et al. (2020) [46] (CQG)]** - New Methods to Assess and Improve LIGO Detector Duty Cycle
- **[Morales-Alvarez et al. (2020) [47] (IEEE)]** - Scalable Variational Gaussian Processes for Crowdsourcing: Glitch Detection in LIGO
- **[Marianer et al. (2020) [48] (Mon. Not. Roy. Astron. Soc.)]** - A Semisupervised Machine Learning Search for Never-seen Gravitational-wave Sources
- **[Mesuga & Bayanay (2021) [49] (2107.01863)]** - On the Efficiency of Various Deep Transfer Learning Models in Glitch Waveform Detection in Gravitational-wave Data
- **[Sankarapandian & Kulis (2021) [50] (2107.10667)]** - β-Annealed Variational Autoencoder for Glitches
- **[Yu & Adhikari (2021) [51] (2111.03295)]** - Nonlinear Noise Regression in Gravitational-Wave Detectors with Convolutional Neural Networks
- **[Sakai et al. (2021) [52] (2111.10053)]** - Unsupervised Learning Architecture for Classifying the Transient Noise of Interferometric Gravitational-wave Detectors
- **[Merritt et al. (2021) [53] (PRD)]** - Transient Glitch Mitigation in Advanced LIGO Data
- **[Colgan et al. (2022) [54] (2202.13486)]** - Architectural Optimization and Feature Learning for High-Dimensional Time Series Datasets
- **[Davis et al. (2022) [55] (2204.03091)]** - Incorporating Information from LIGO Data Quality Streams into the PyCBC Search for Gravitational Waves
- **[Bahaadini et al. (2022) [56] (2205.13672)]** - Discriminative Dimensionality Reduction Using Deep Neural Networks for Clustering of LIGO Data

Convolutional Autoencoder
- **[Kato et al. (2022) [87] (Astron. Comput.)]** - Validation of Denoising System Using Non-Harmonic Analysis and Denoising

But where are the online algorithms?

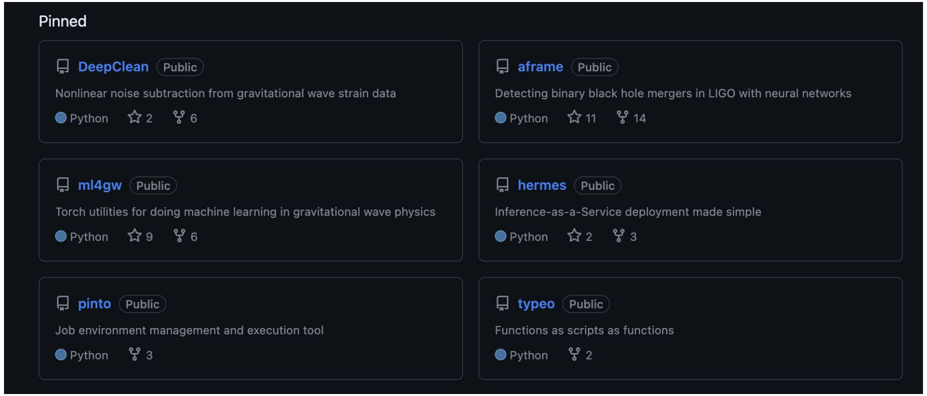
- Multi-Messenger Astrophysics (MMA) requires **low-latency alerts**.
- With LIGO Observing Run 4 starting, GW signals are no longer “rare” - MMA collaborators require accurate alerts, parameter estimation, event probabilities.
- **Seems like a perfect application for ML … however the implementation is complicated!**
- GW-physics is not a high statistics field. Everything needs to be trained/validated on years - decades of detector data.



My opinion

Online (real-time) ML for GW hasn't happened because there is *was* no team dedicated to making the GW-ecosystem ML-friendly. This leads to issues in data loading, simulation, inference, validation, optimization, etc.

Enter: [ML4GW]()



Requirements for ML deployment

Training

- Load time-series data from disk and efficiently move it to GPU
- Leverage simulations to create robust datasets
- Implement signal processing operations on GPU

Inference

- Offline - produce predictions on O(months-years) of data
- Online - produce predictions on real-time data in O(ms)
- Stream time-series data into NN
- Heterogeneous backends/dtypes

Design Goals

Intuitive - maps on to familiar, physically meaningful concepts

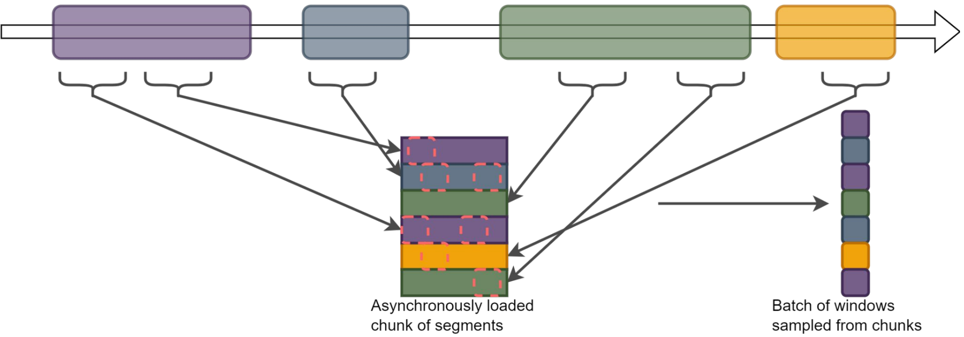
Composable - hierarchical layers of abstraction support new use cases seamlessly

Integrated - ecosystem of tools following same standards and nomenclature

Efficient - make the most out of parallel computing resources

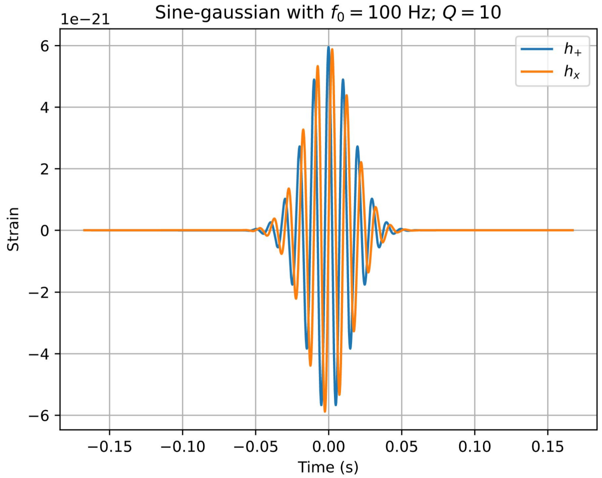
ml4gw - Torch training utilities

Transitioning to larger datasets



Chunked loading of background data

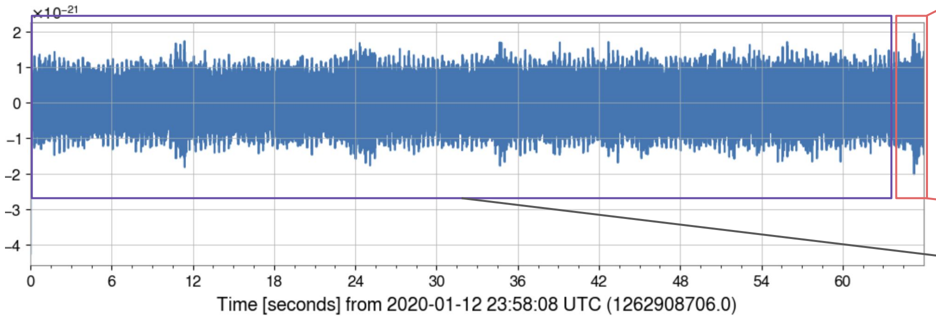
Tradeoff between memory, I/O, and randomness

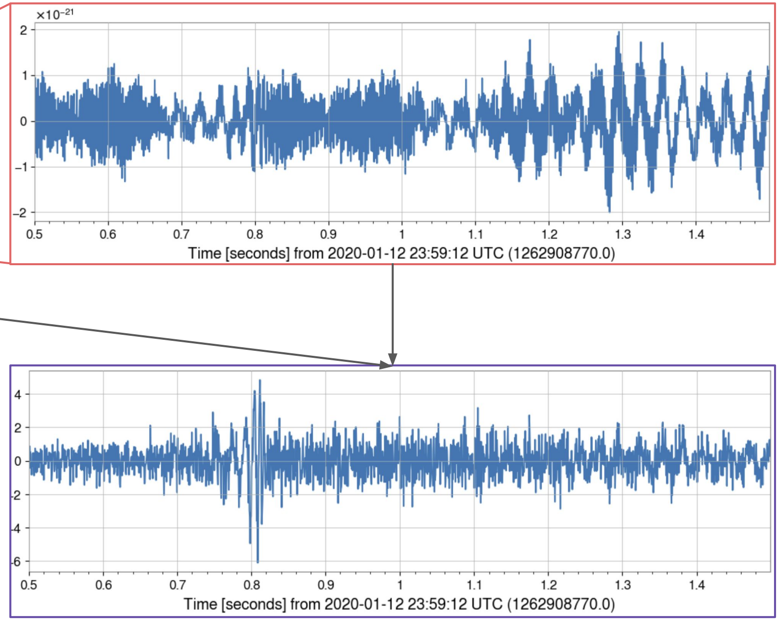


Fully on-the-fly generation of waveforms for unlimited training signal data

`ml4gw` - Torch training utilities

More training data requires more flexibility when **whitening data**





Whiten data using background PSDs computed on-the-fly

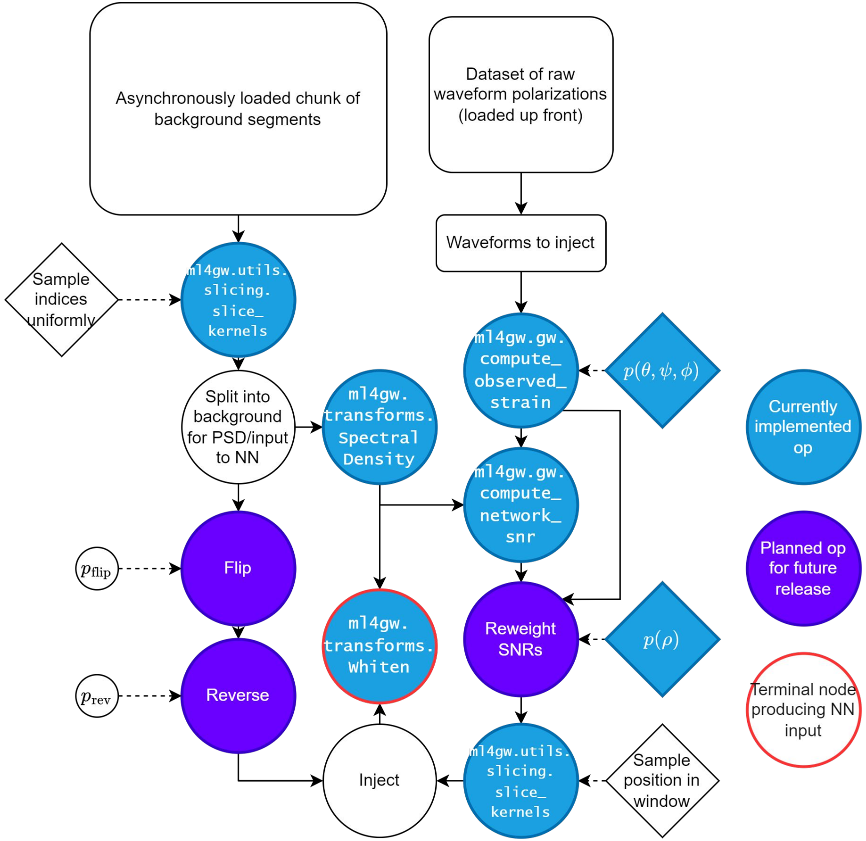
Faster than previous implementation because executed in frequency domain - FFTs are faster than large convolutions

`ml4gw` - Torch training utilities

Example use case: dataloading for binary black hole detection (`aframe`)

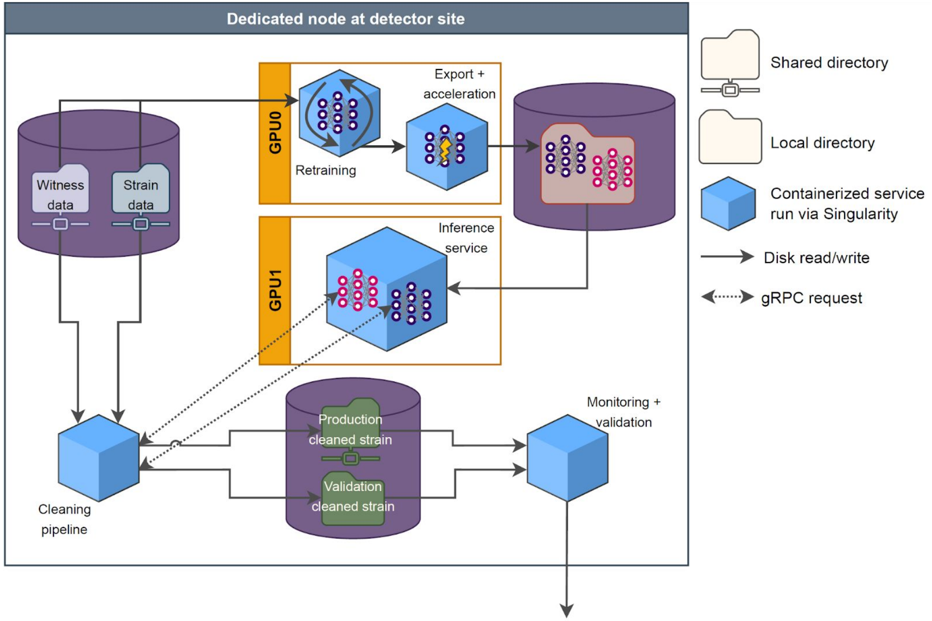
Complex data flow simplified by intuitive transform `Modules`

Efficient GPU implementations ensure strong utilization, shift bottleneck to NN forward/backward step

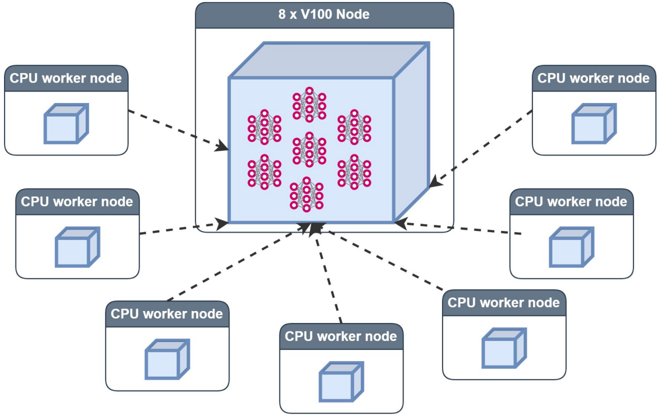


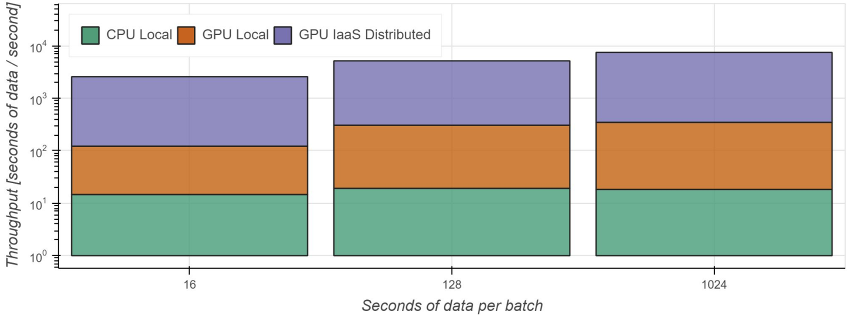
hermes - Inference-as-a-Service deployment tools

Example use case: online deployment of DeepClean noise subtraction algorithm



Example use case: offline deployment of `aframe`





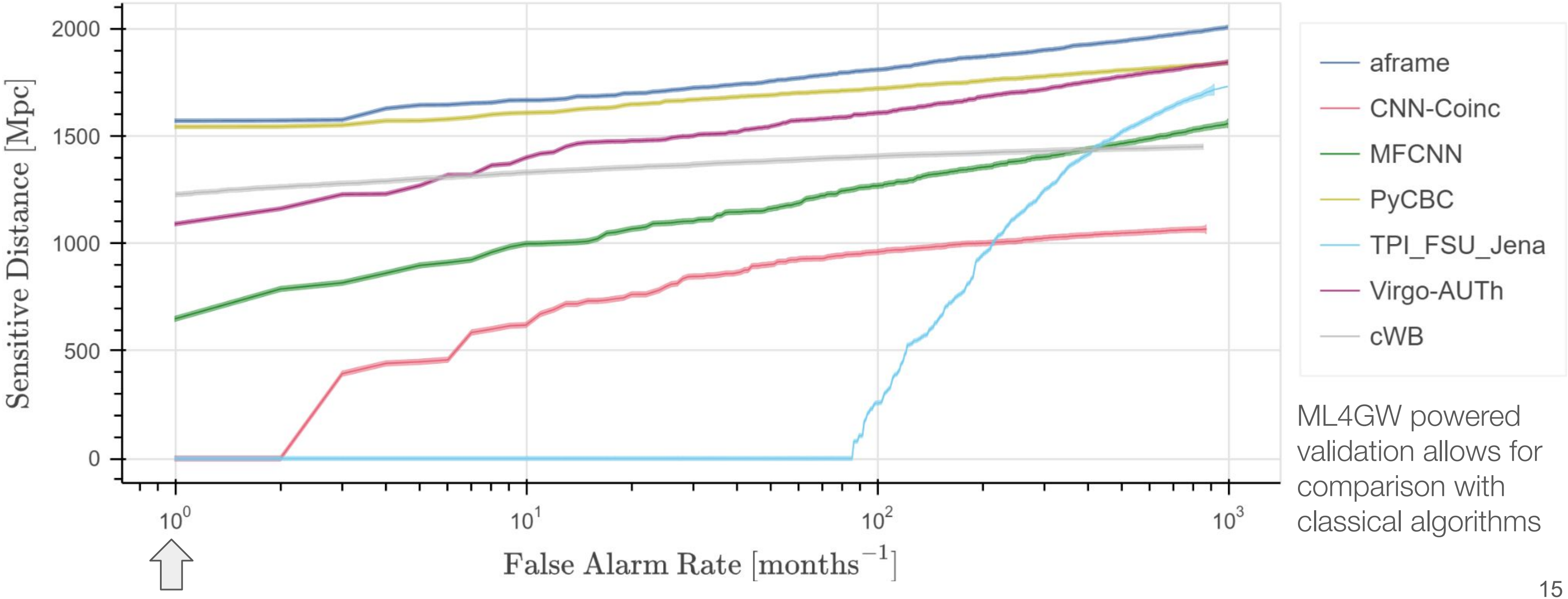
Ensemble versioning allows newly trained models to be validated/deployed asynchronously

`ml4gw` - Example cases

1. **Supervised Detection of Binary mergers - *Aframe***
2. Real-time Parameter Estimation
3. Real-time data noise regression - *DeepClean*
4. Unsupervised/Semi-Supervised Anomaly Detection - *GWAK* (covered in earlier talk)

Performance on ML-Mock-Data-Challenge

Aframe: ResNet CNN Architecture



ML4GW powered validation allows for comparison with classical algorithms

ML4GW at work

ML-based Sensitive Distance Comparison

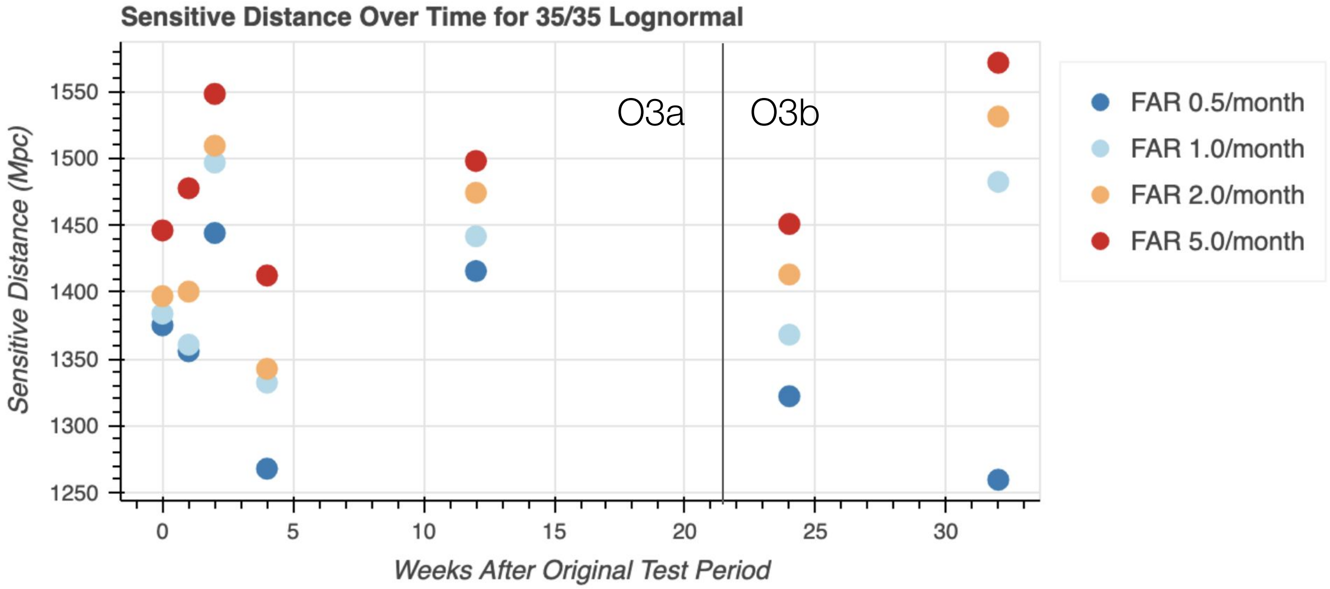
Created 1 year worth of timeslide data with background from **May 9th, 2019** to **June 8th, 2019**. **All measurements in units of Mpc**.

	Minutes to Hours				Milliseconds	
Mean masses	**PyCBC-BBH**	**MBTA**	**GstLAL**	**cWB**	**Aframe @ FAR=1/month**	**Aframe @ FAR=1/year**
35/35	1445	1321	1360	1336.5	**1461 ± 128**	1355 ± 141
35/20	1206	1080	1122	1074	**1229.5 ± 152**	1050± 186
20/20	**999**	916.5	937	801	847.5 ± 78	719 ± 89
20/10	**770**	709.5	717	604	584 ± 95	477 ± 111

Pipeline sensitive distances at GW astrophysical probability p_{astro} >0.5

Aframe sensitive distances at multiple false alarm thresholds.

Stability Over Time



Train *one model* on 10 days of data at beginning of O3a

Evaluate sensitive distance at intervals across O3 observing run

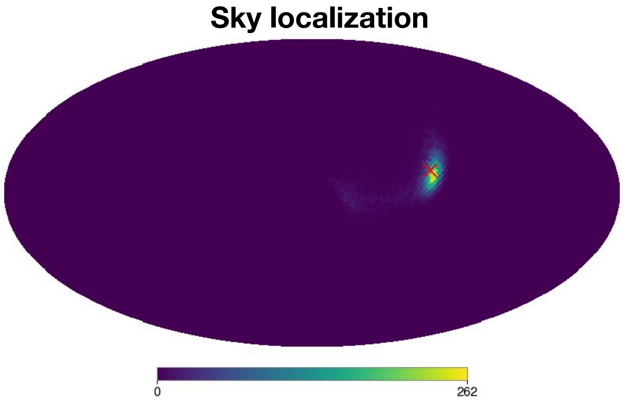
`ml4gw` - Example cases

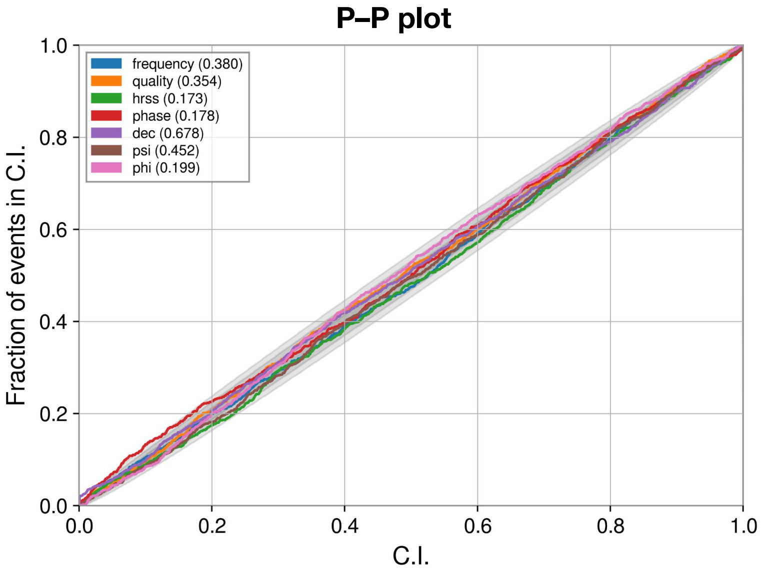
1. Supervised Detection of Binary mergers - *Aframe*
2. **Real-time Parameter Estimation**
3. Real-time data noise regression - *DeepClean*
4. Unsupervised/Semi-Supervised Anomaly Detection - *GWAK* (covered in earlier talk)

Likelihood-Free Inference

- Using auto-regressive flows, we can perform **parameter estimation of Sine-Gaussian signals in real detector noise.**
- Measurement accuracy is comparable to stochastic sampling at significantly faster run-time which is suitable for real-time applications (ms vs days)

[code here]





`ml4gw` - Example cases

1. Supervised Detection of Binary mergers - *Aframe*
2. Real-time Parameter Estimation
3. **Real-time data noise regression - *DeepClean***
4. Unsupervised/Semi-Supervised Anomaly Detection - *GWAK* (covered in earlier talk)

Data Cleaning

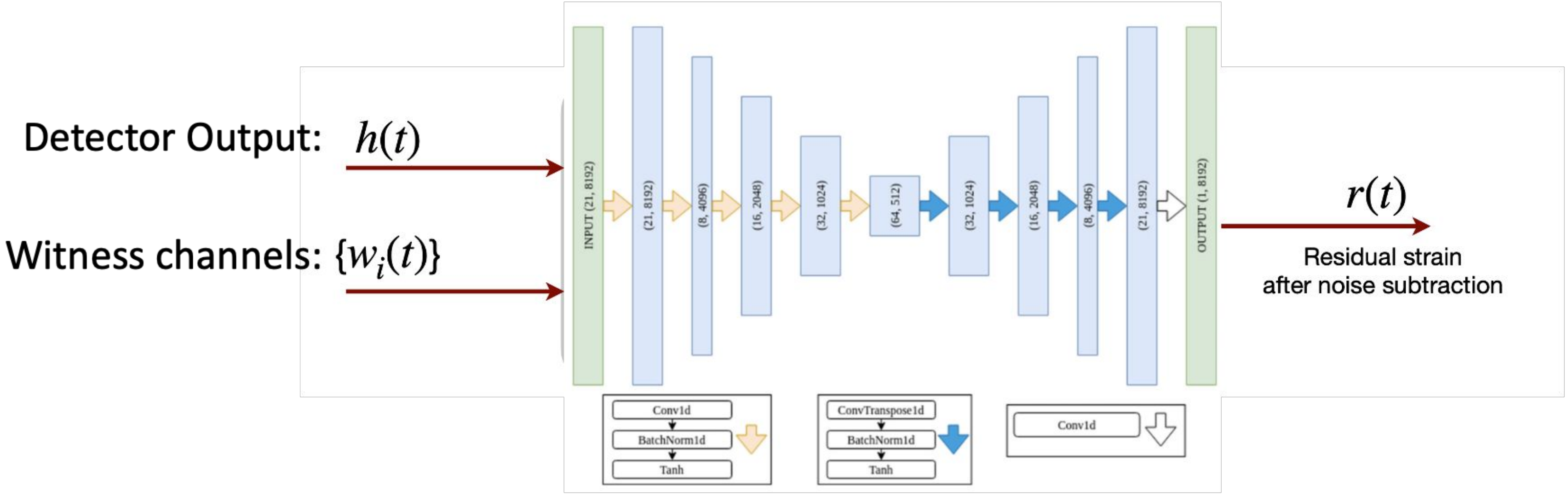
- The output reconstructed from an interferometer contains:

$$h(t) = s(t) + n_w(t) + n_f(t)$$

Possible GW Signal Witness Noise Fundamental Noise (non-removable)

- Objective: recover $s(t)$ with best possible signal-to-noise ratio by minimizing $n_w(t)$ with AEs.
- Real-time/Offline noise reduction can provide quicker detections, more accurate GW parameters, find signals below the noise.

Data Cleaning



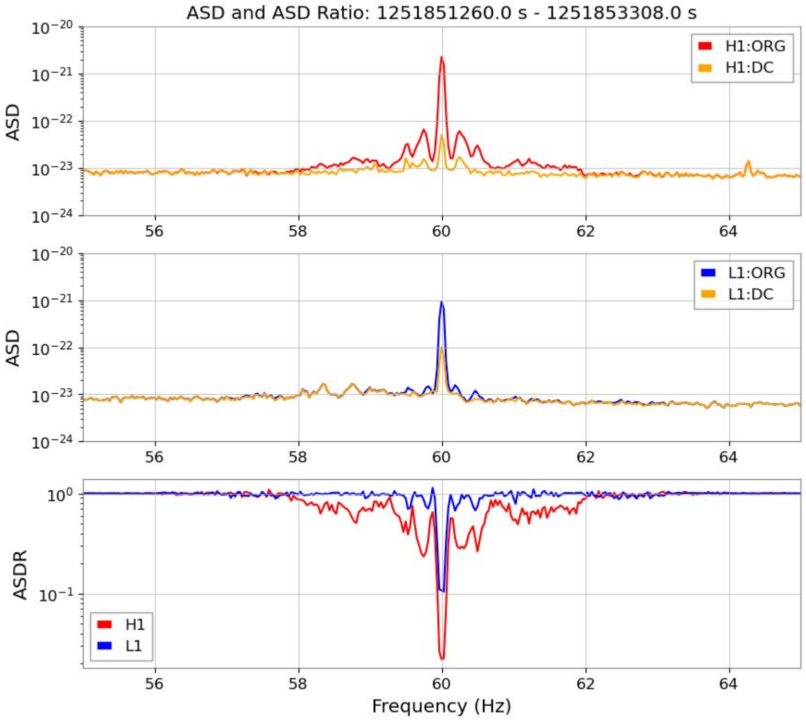
Fully convolutional auto-encoder maps the witness channels $\{w_i(t)\}$ into the noise predictions $n_w(t)$ which are then subtracted from detector output $h(t)$

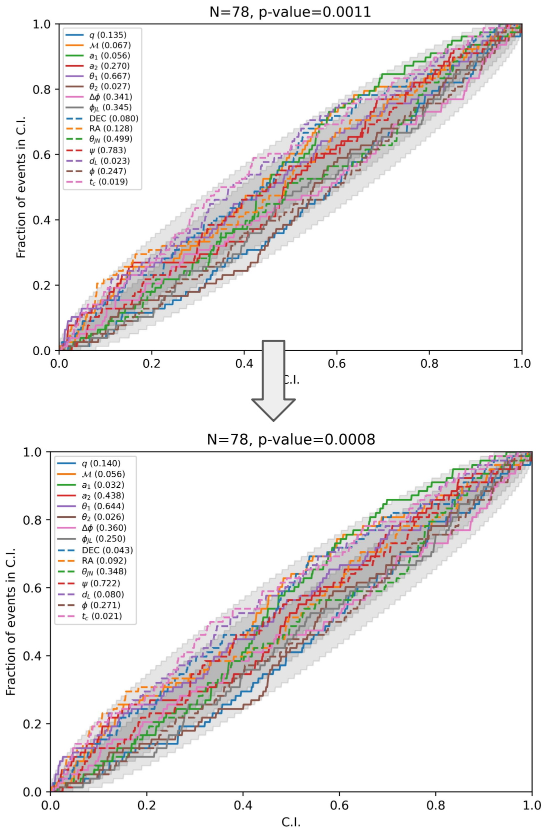
[code here]

DeepClean - improving PE

[Ormiston et al. (2020)]
[Saleem et al. (2023)]

Step 1: Clean 60 Hz Noise





Step 2: Improve Parameter Estimation!

Conclusions

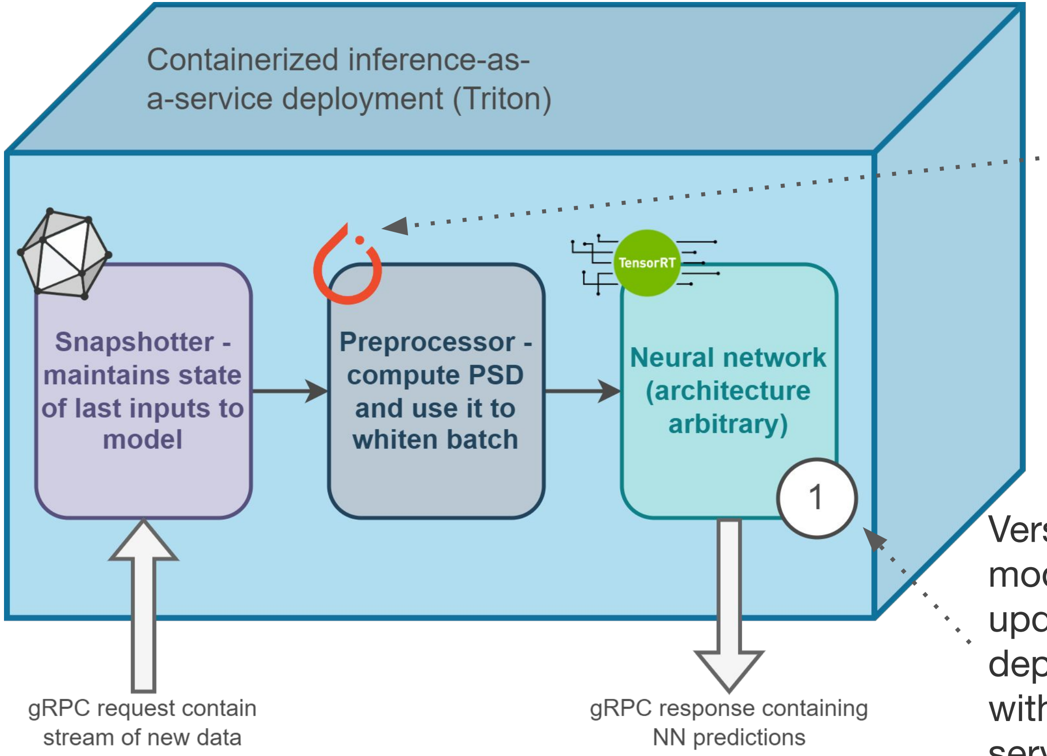
- ML4GW is helping GW physicists (around the world) by providing utilities/support for commonly used ML tools.
- Multiple real-time algorithms are ready to run/running thanks to the capabilities of ML4GW:
  - GW-detection
  - Parameter Estimation
  - Noise Regression
  - Anomaly Detection
- ML4GW allows us to ensure that ML is actually working!

Backup

`hermes` - Inference-as-a-Service deployment tools

`hermes` is a set of APIs for assisting in the acceleration, export, serving, and requesting of models using Triton Inference Server. New features include:

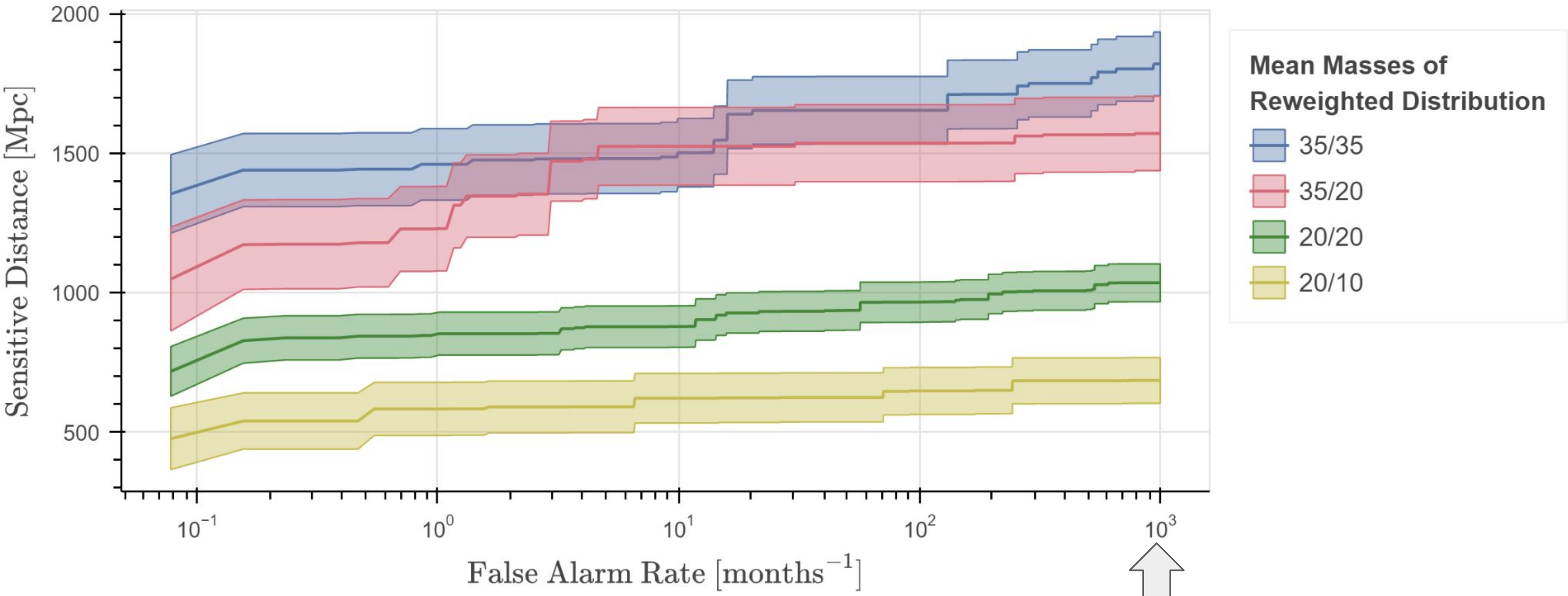
Example deployment: binary black hole detection (`aframe`)



Support for Torchscript export format due to lack of support for FFT ops in ONNX

Version specification in model ensembles - update individual deployed models without interrupting service

Full Aframe Performance



ML4GW at work

Pipeline Details

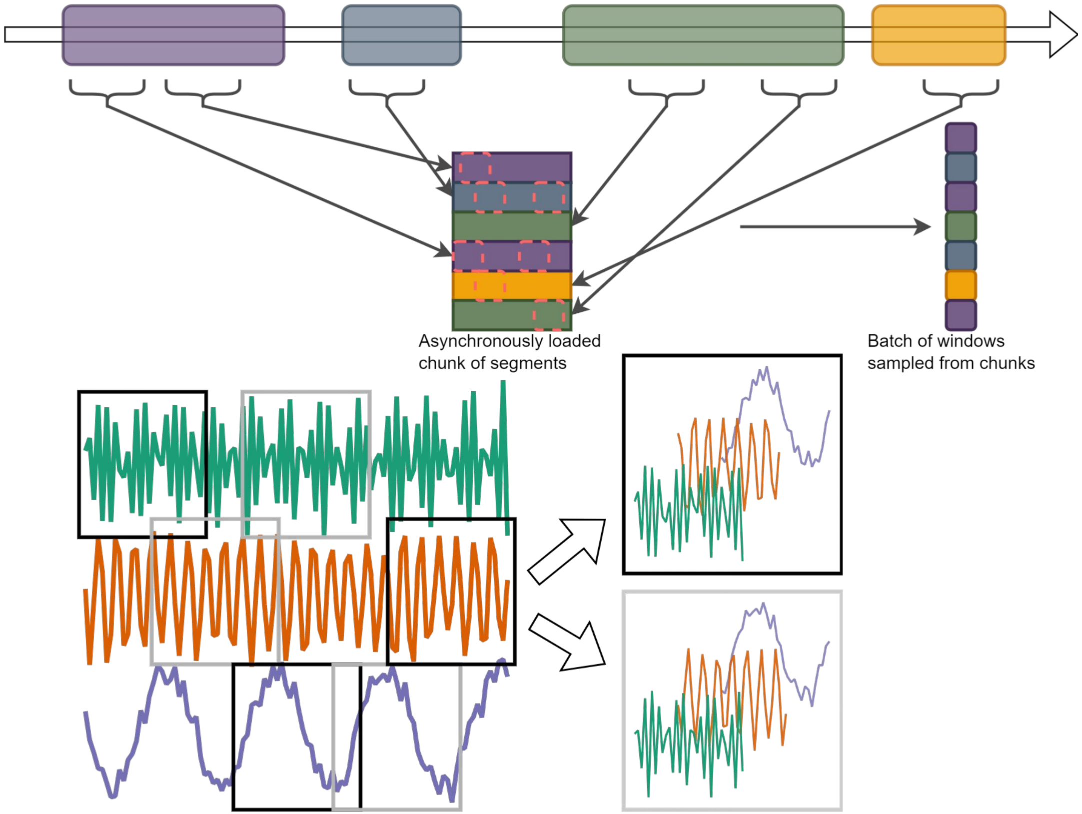
Training

- Emphasis on extracting the most information out of the available data

- Use of population models, simulations, and large amounts of background noise to achieve more robust models

- Encode familiar concepts like coincidence and coherence through data augmentations

Robust Noise Sampling



Background chunks loaded from disjoint segments

Batches of windows or “kernels” sampled from chunks, with each IFO sampled independently in time

Waveform Distribution

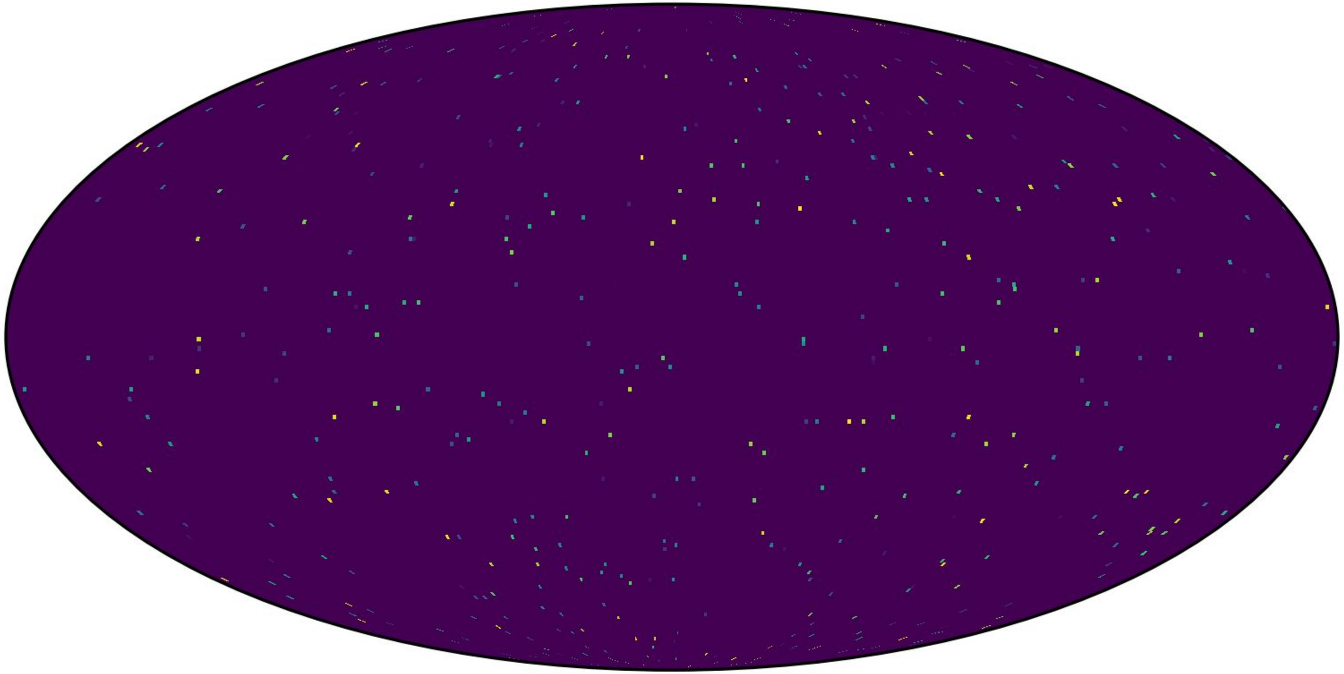
Parameter	Prior	Limits	Units
m_1	$m_1^{-2.35}$	$(5, 100)$	$M_\odot$
m_2	m_2	$(5, m_1)$	$M_\odot$
z	Comoving	$(0, 2)$	-
ψ	Uniform	$(0, \pi)$	rad.
$a_{1,2}$	Uniform	$(0, 0.998)$	-
$\theta_{1,2}$	Sine	$(0, \pi)$	rad.
ϕ_{12}	Uniform	$(0, 2\pi)$	rad.
ϕ_{JL}	Uniform	$(0, 2\pi)$	rad.
ϕ	Uniform	$(0, 2\pi)$	rad.
RA	Uniform	$(0, 2\pi)$	rad.
Dec	Cosine	$(-\pi/2, \pi/2)$	rad.
θ_{JN}	Sine	$(0, \pi)$	rad.

Matches the distribution used by the R+P group for injections campaigns at the end of O3

IMRPhenomPv2

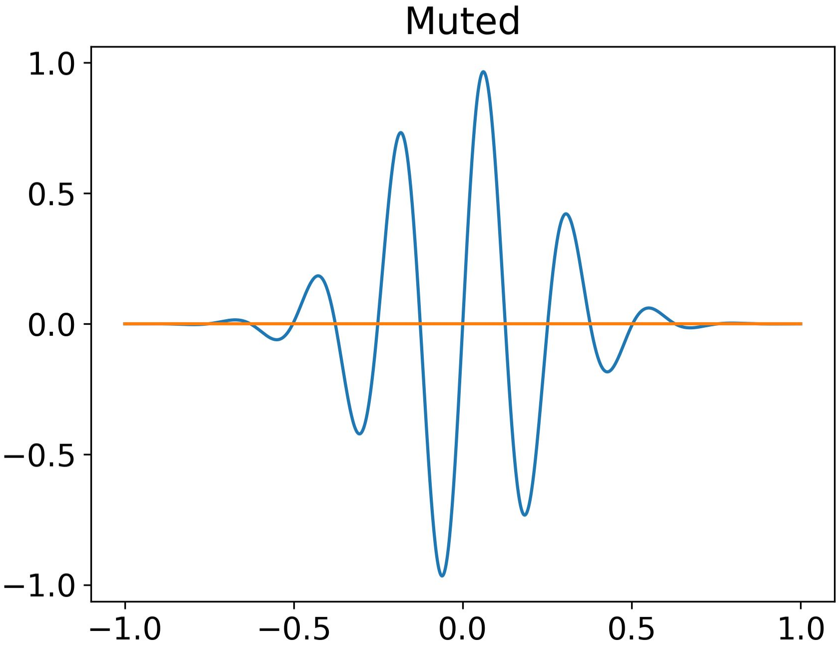
Allow coalescence time to be placed randomly within some offset from center of window

Location Augmentations

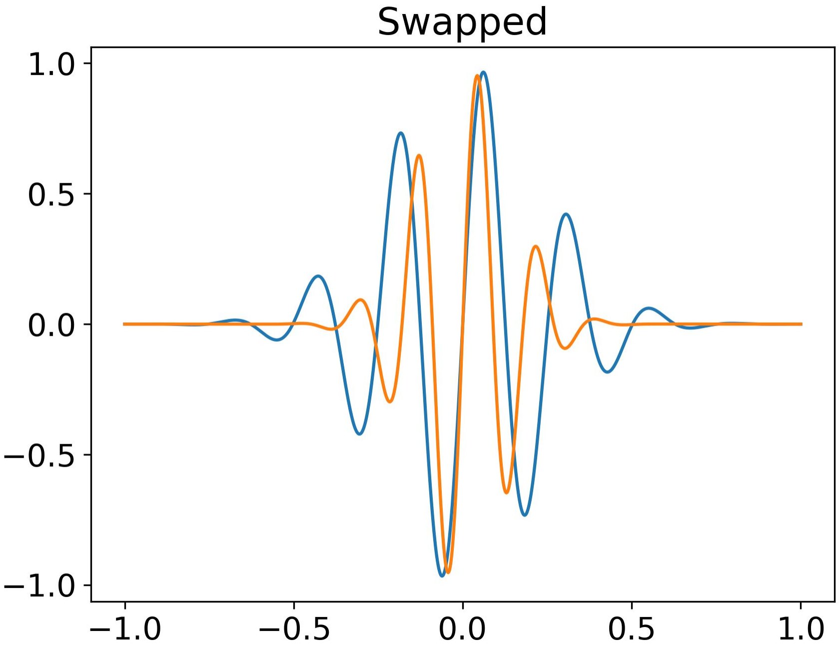


One waveform, many sky locations and distances

Coherence/Coincidence Augmentations

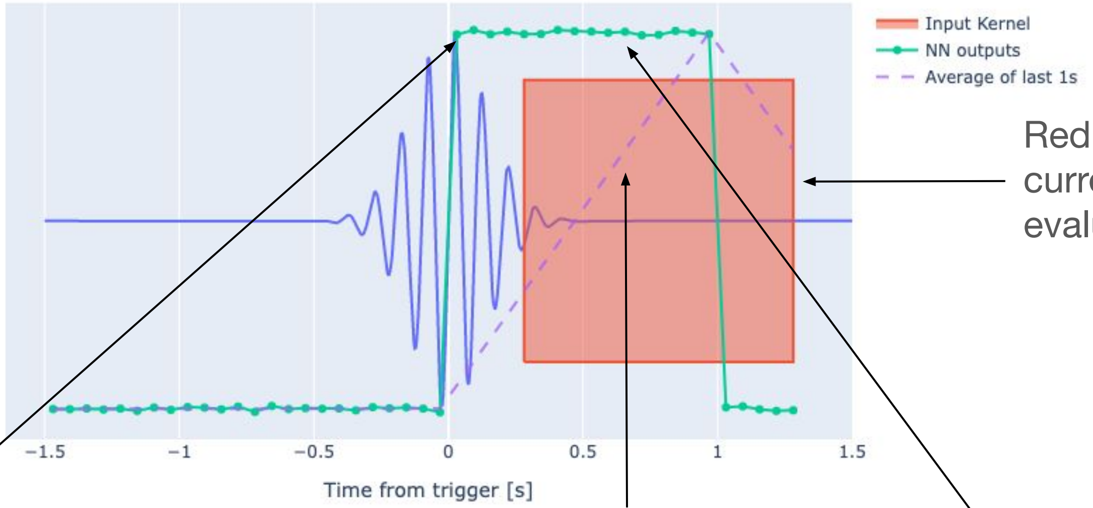


Coincidence



Coherence

What is an event?



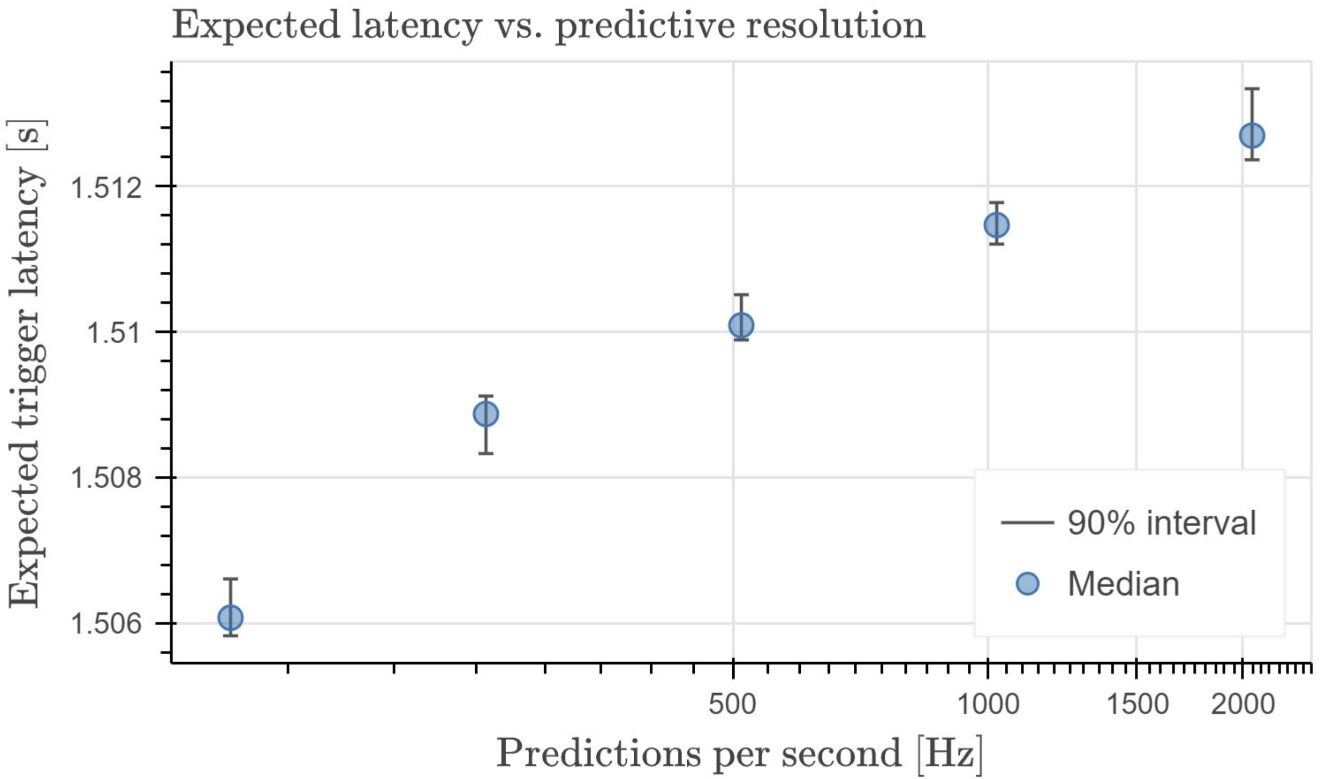
Red sliding kernel represents current window of data evaluated by network

As coalescence time enters window, network begins to ring

Dotted purple line shows average of last 1 second of network outputs

Green dots show network outputs

Online Throughput and Latency

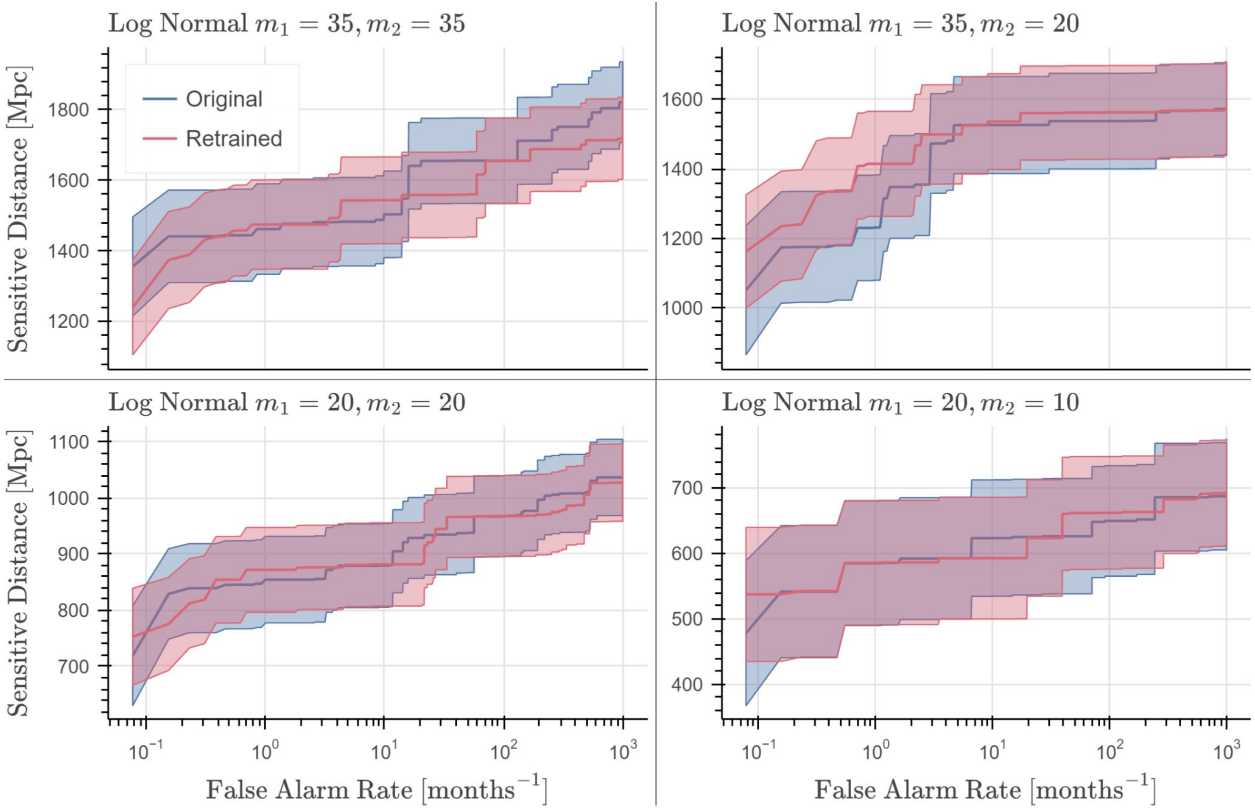


Inference time for our neural network is < 10ms

Latency is dominated by integration window (1s) and whitening settle-in (0.5s)

Plan to investigate tradeoff between inference frequency, integration length, and sensitivity to optimize compute

Stability Between Training Seeds



Train 2 models that differ only in the model initialization seed

Testing performance consistent with error bars

Aframe Computing Statistics

All measurements collected on 16GB NVIDIA V100 GPUs

Training: ~**24 hours** on 1 GPU

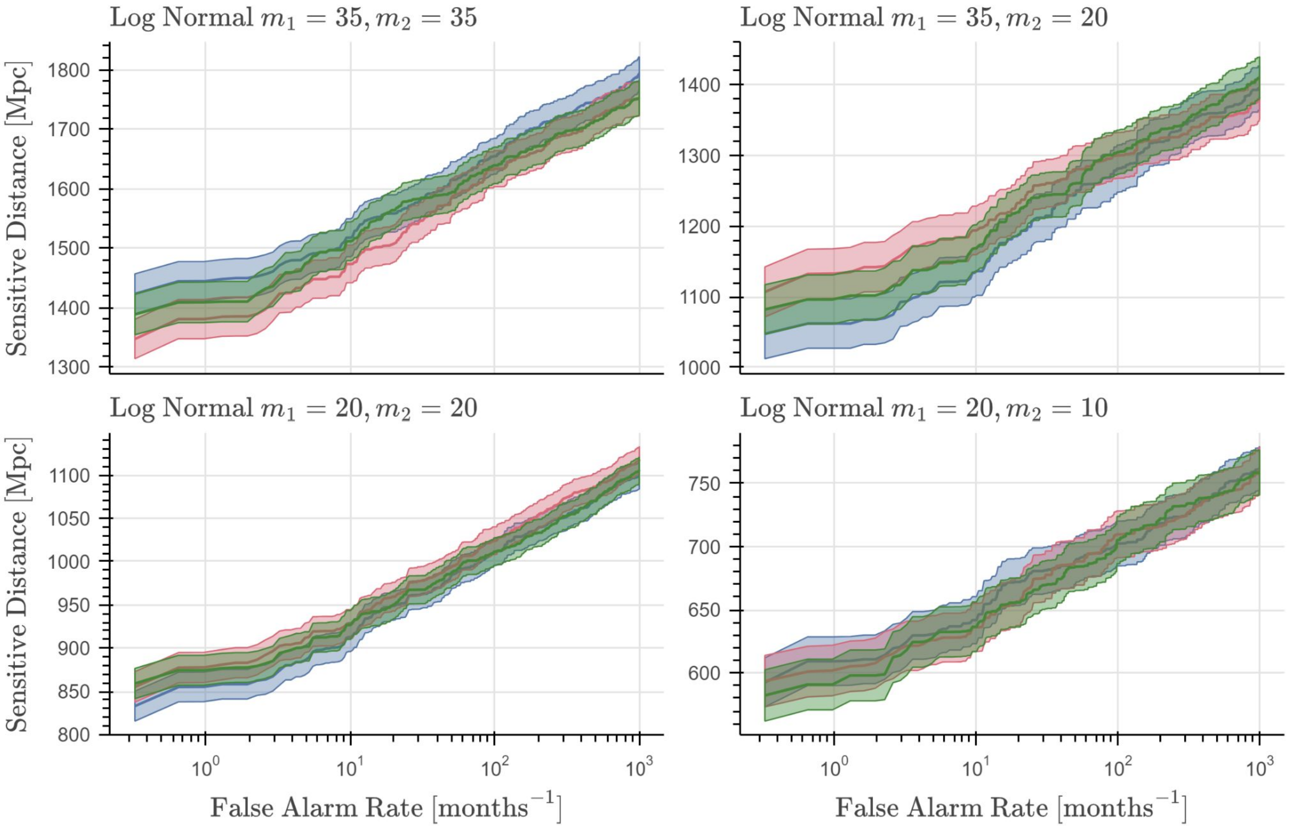
Evaluation: ~16 hours for 2 years of livetime (1 year each of background/injections) on 8 GPUs

- ~**1100** seconds of data processed per second

Online deployment: **6-10ms** latency for real-time throughput on 1 GPU

- Non-computing based sources of latency discussed later

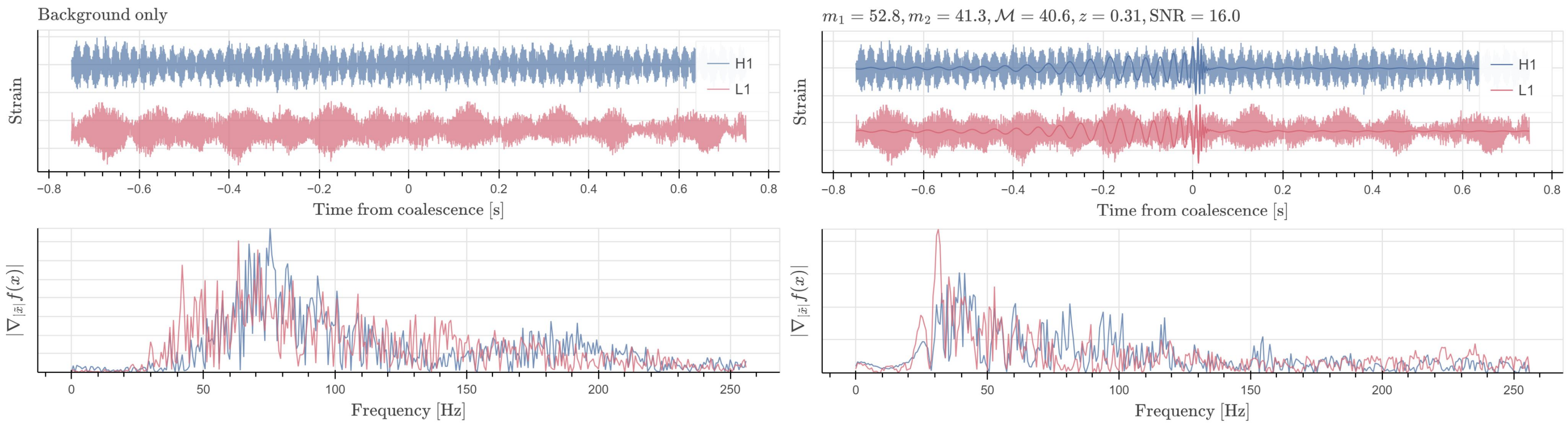
Evaluating significance of uncertainty



Evaluate same model between multiple testing sets generated with different seeds

Results are consistent within error bars

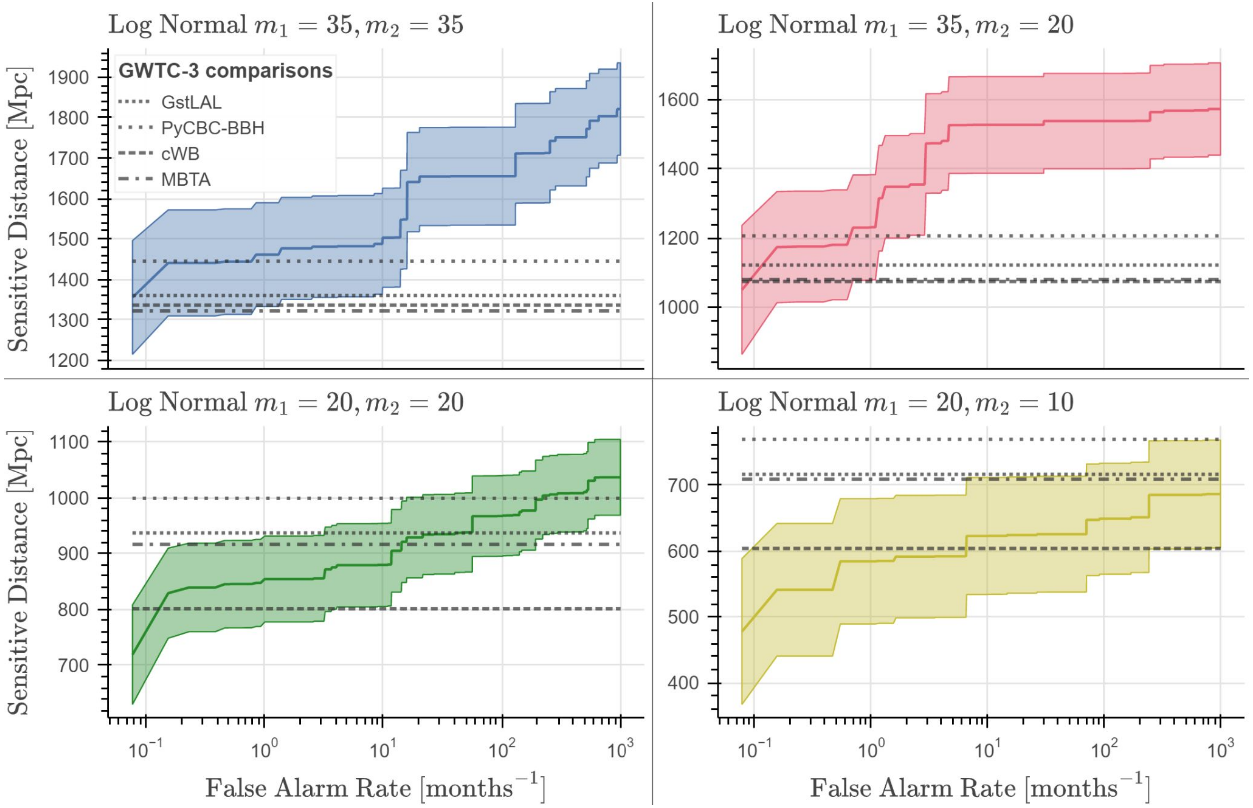
Saliency Maps for Interpreting Network Output



Gradient of network output wrt frequency content of input can provide insight into features the network is using to inform decision making

Potentially useful for understanding failure modes and guiding iteration/development

Performance on 1 year of O3 Background



Create 1 years worth of timeslide data with background from May 9th, 2019 to June 8th, 2019

Inject distribution used by the R+P group for GWTC-3

Re-weight sensitive distance over injections to various mass bins

Likelihood-Free Inference

- Draw parameters, $\boldsymbol{\Theta} = \{Q, f_0, \text{Sky loc.}, \ldots\}$ from priors and generate signals.
- Simulate data, $\mathbf{d}$; inject signal into real detector noise
- Train auto-regressive flow to learn joint distribution, $p(\boldsymbol{\Theta}, \mathbf{d})$, from simulated pairs $\{\boldsymbol{\Theta}_i, \mathbf{d}_i\}$.
- During training, maximize likelihood, $p(\mathbf{d}_i|\boldsymbol{\Theta}_i)$.
- Given new data, $\mathbf{d}_{\text{new}}$, draw posterior samples, $p(\boldsymbol{\Theta}|\mathbf{d}_{\text{new}})$, from learned joint distribution, i.e. $\{\boldsymbol{\Theta}_j\}$, .
- Unlike stochastic sampling, drawing posterior samples does not involve computing likelihood every time, which may be expensive.
- Suited for real-time applications.