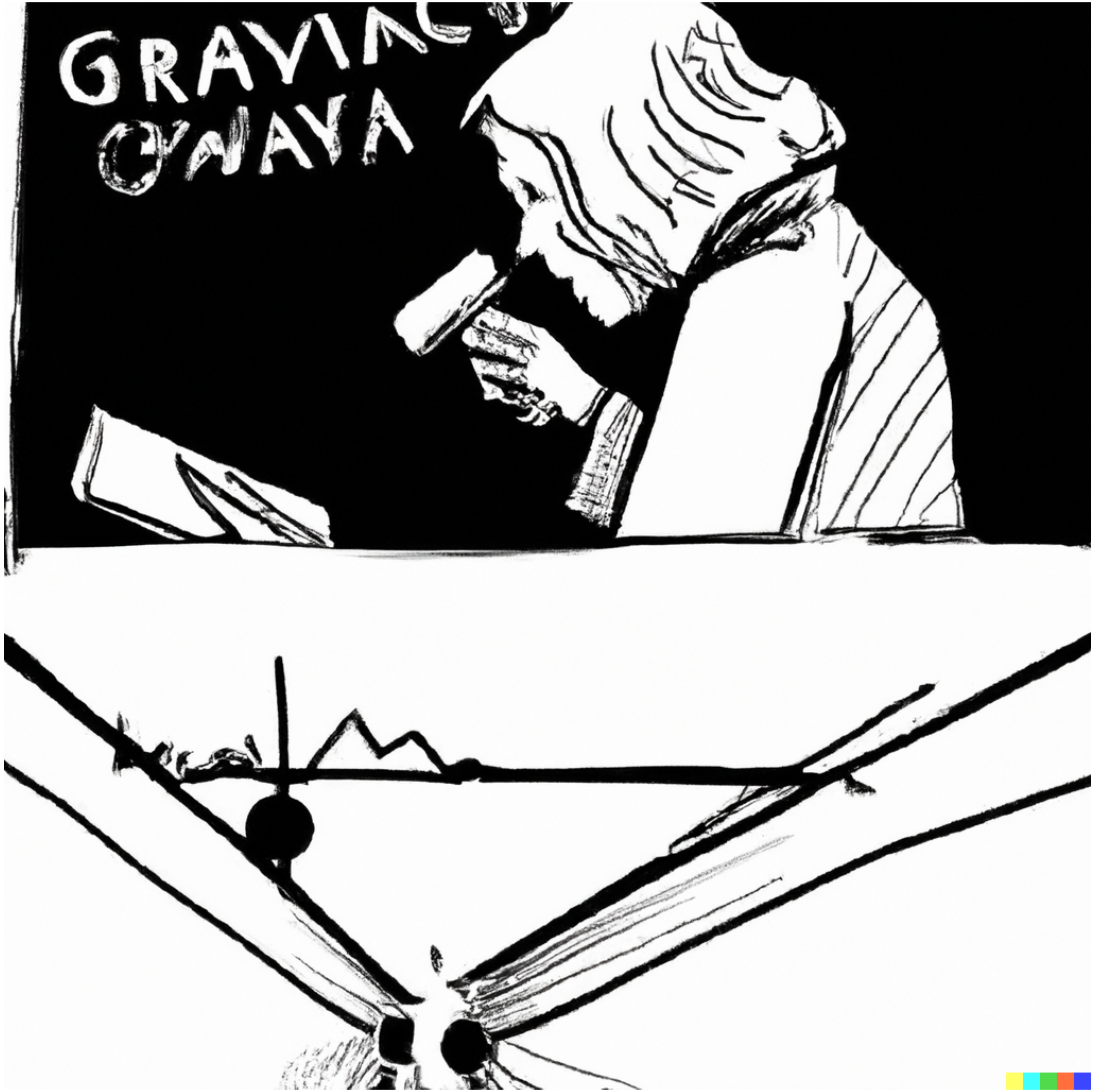
AI-Powered Gravitational-Wave Detection: Bridging Traditional Pipelines and Neural Networks

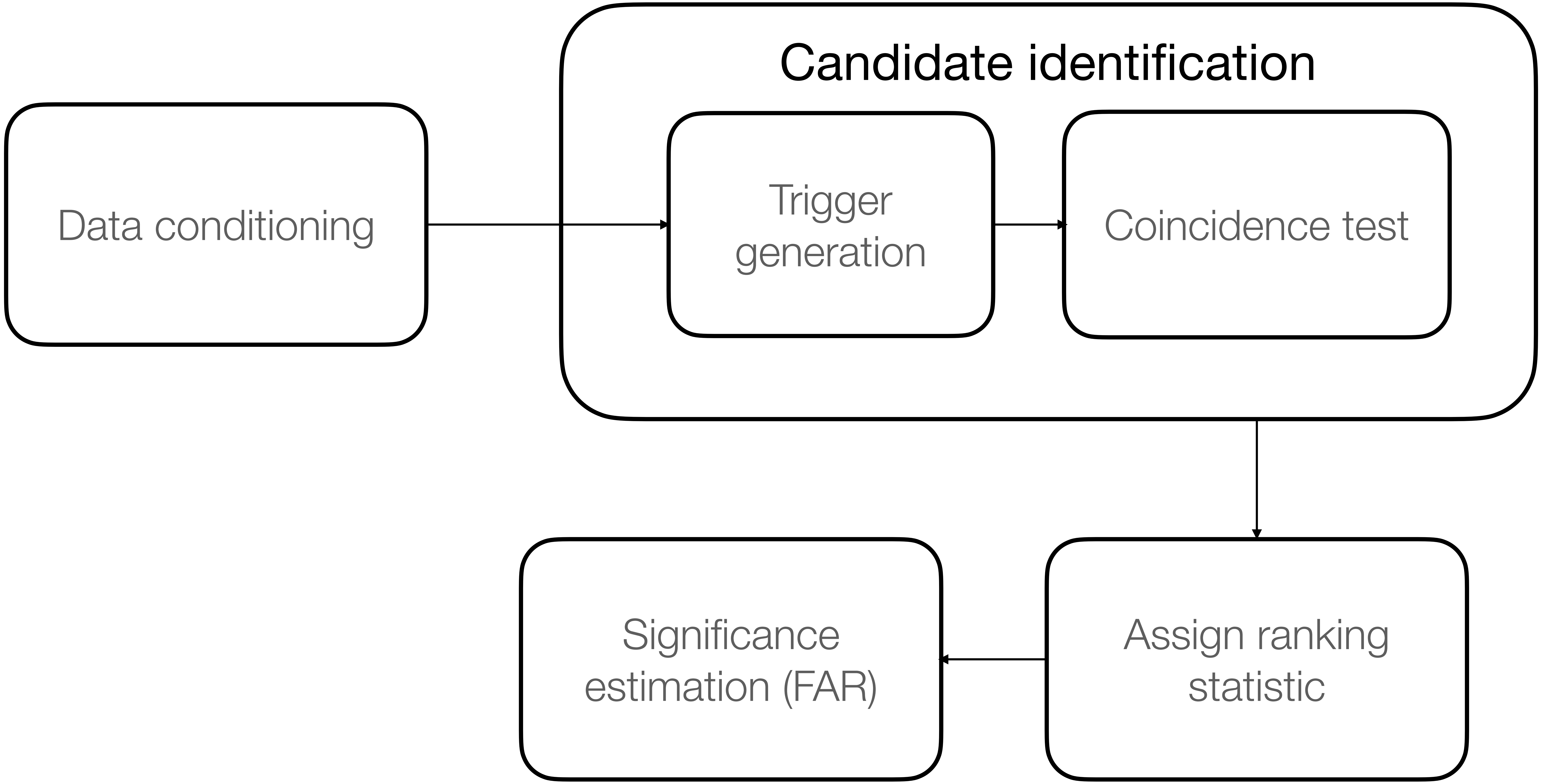


ICERM: Scientific Machine learning for gravitational waves
June 2, 2025

Surabhi Sachdev

Georgia Tech

Search pipelines for compact binaries

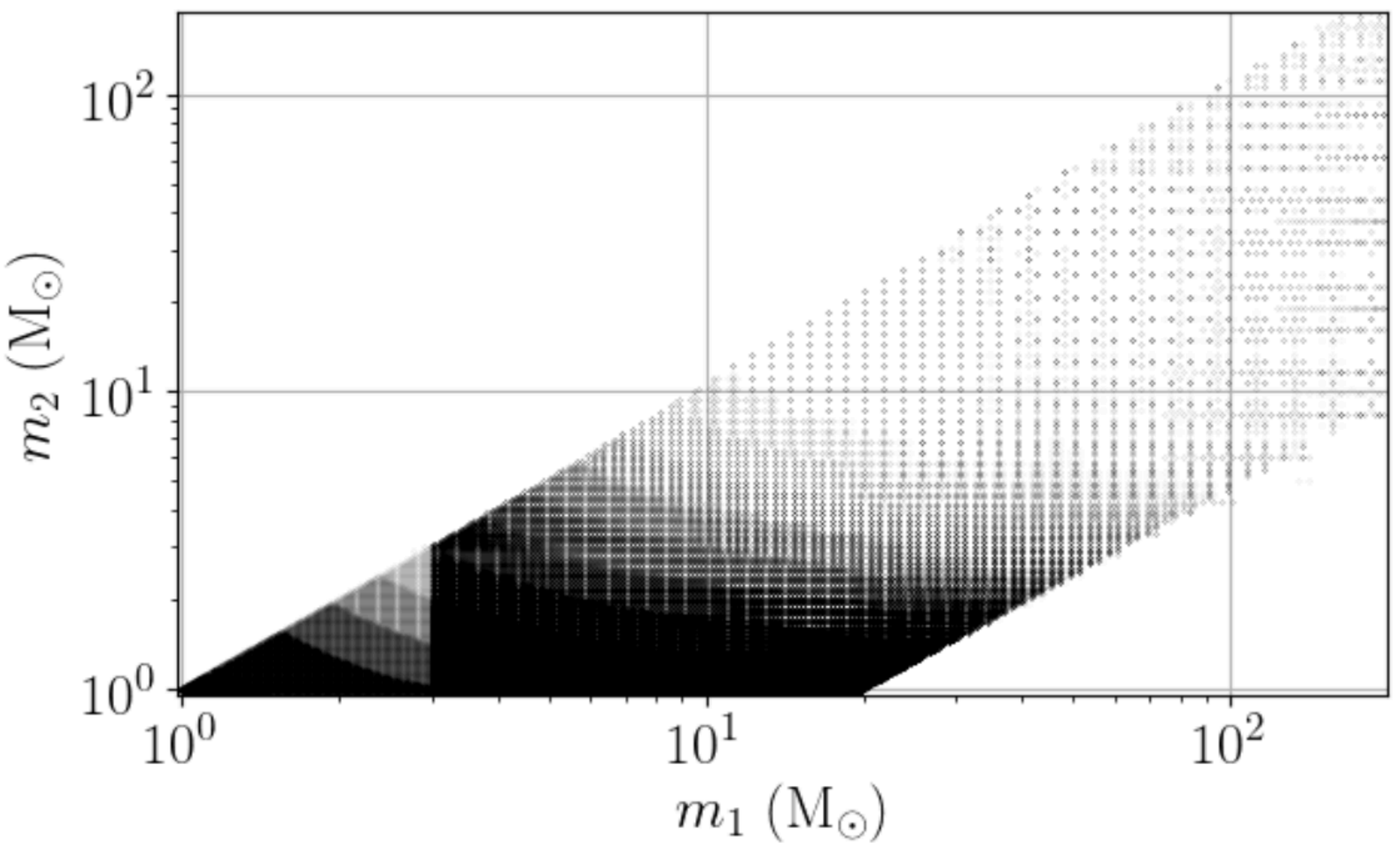


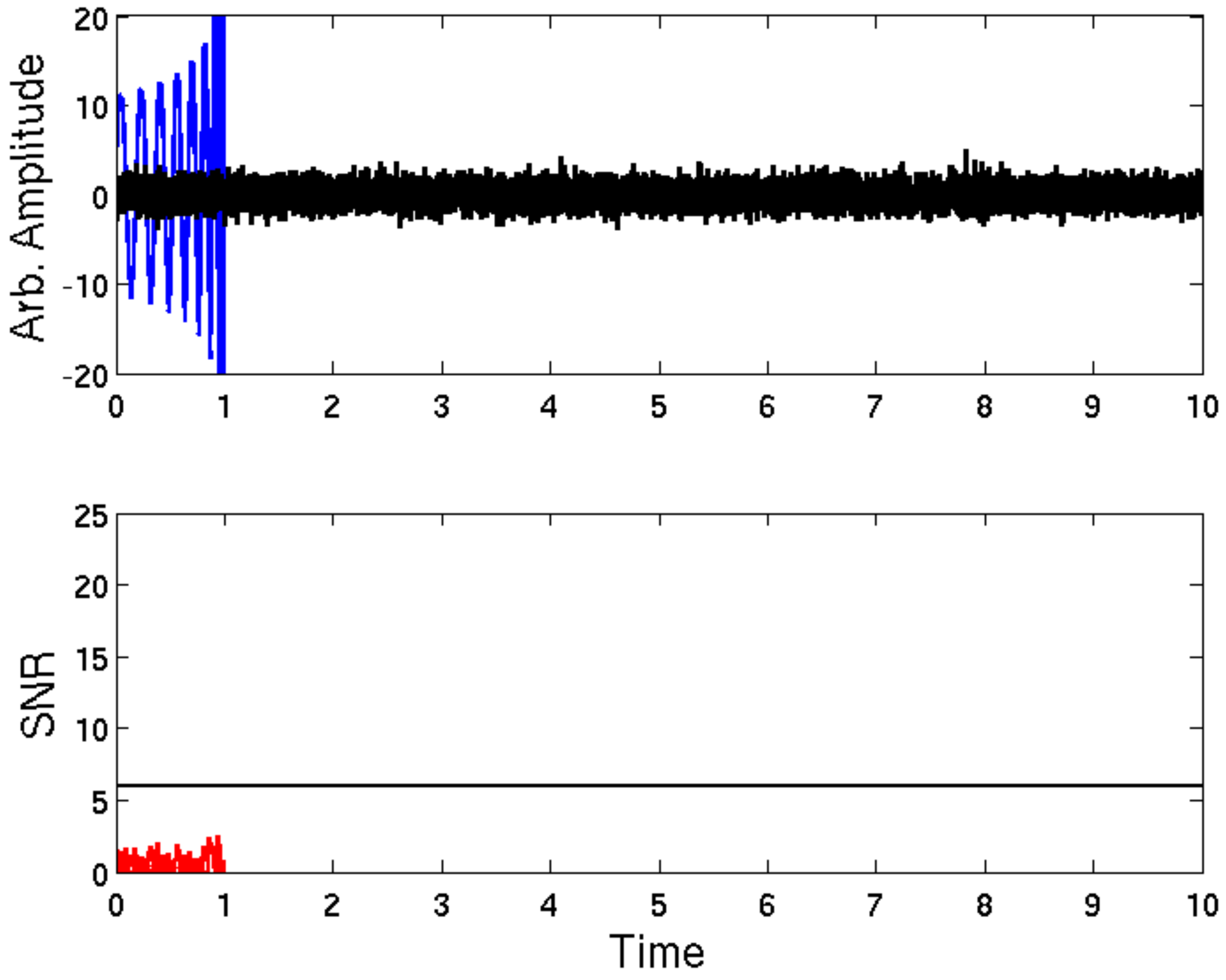
Matched-filtering

Trigger Identification stage

- Trigger identification: uses matched-filtering of data with templates in a template bank
- Candidates are formed after demanding time and template coincidence

Shio Sakon et al. 2024 Phys. Rev. D 109, 044066



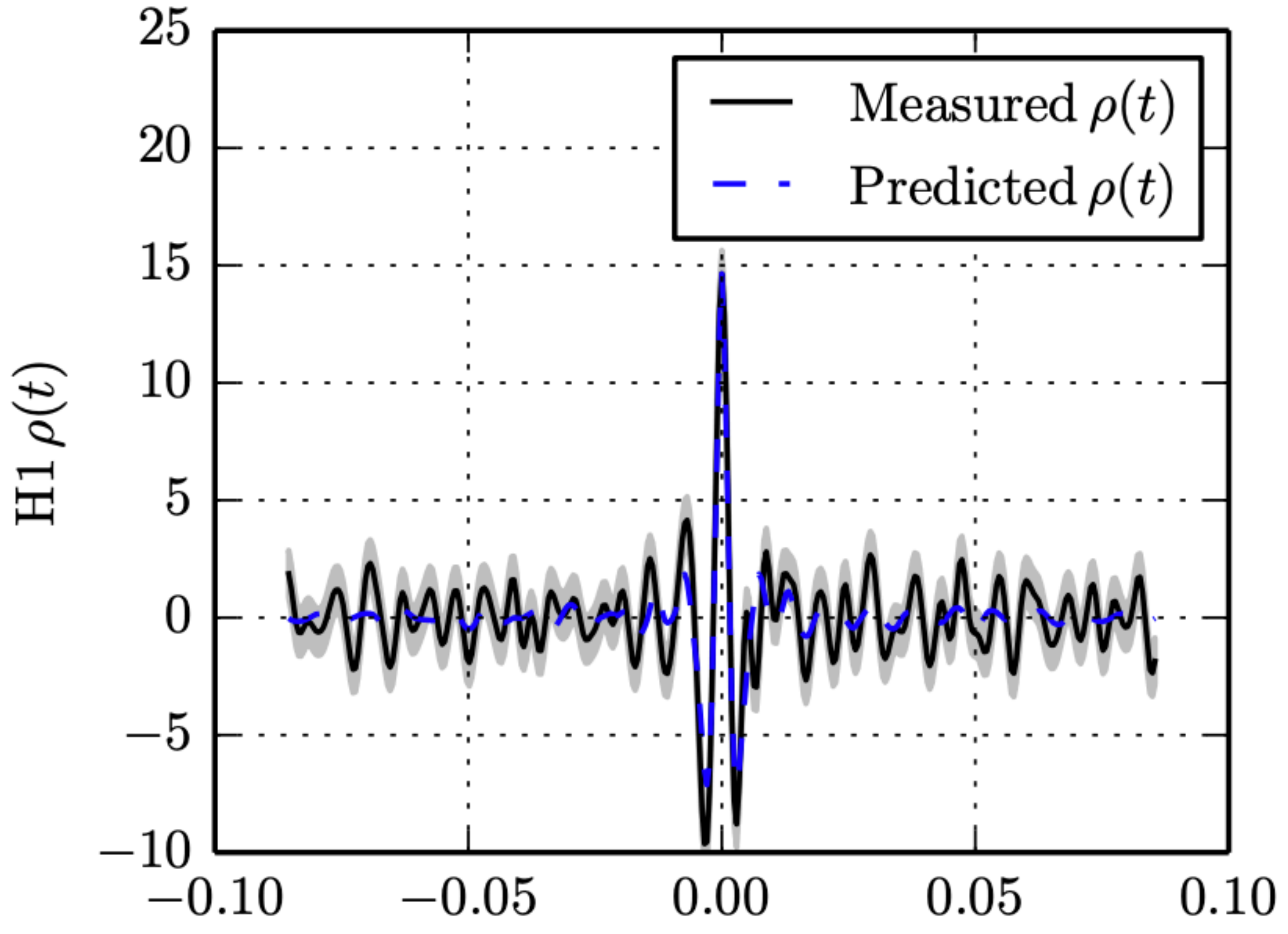


Assigning ranking statistic

Beyond SNR

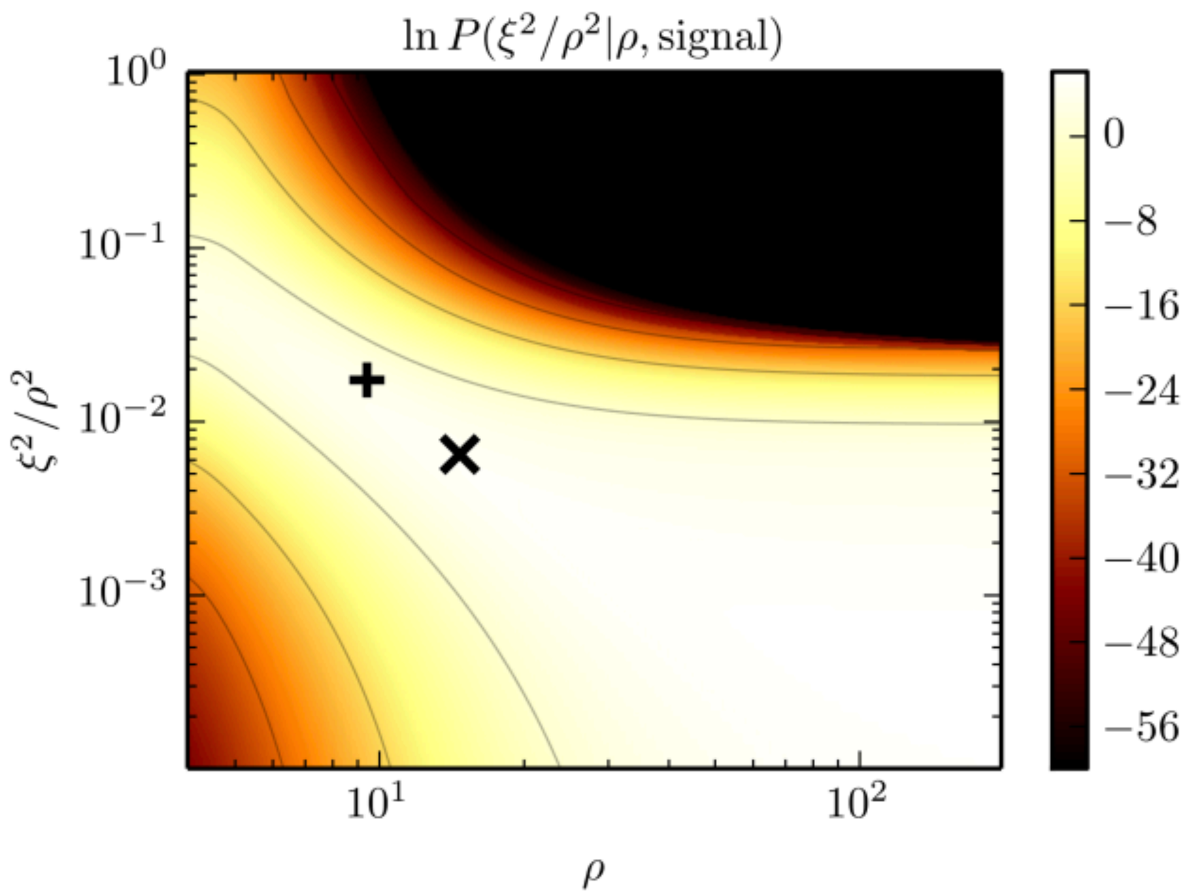
If noise were stationary & Gaussian, SNR could be used as a ranking statistic

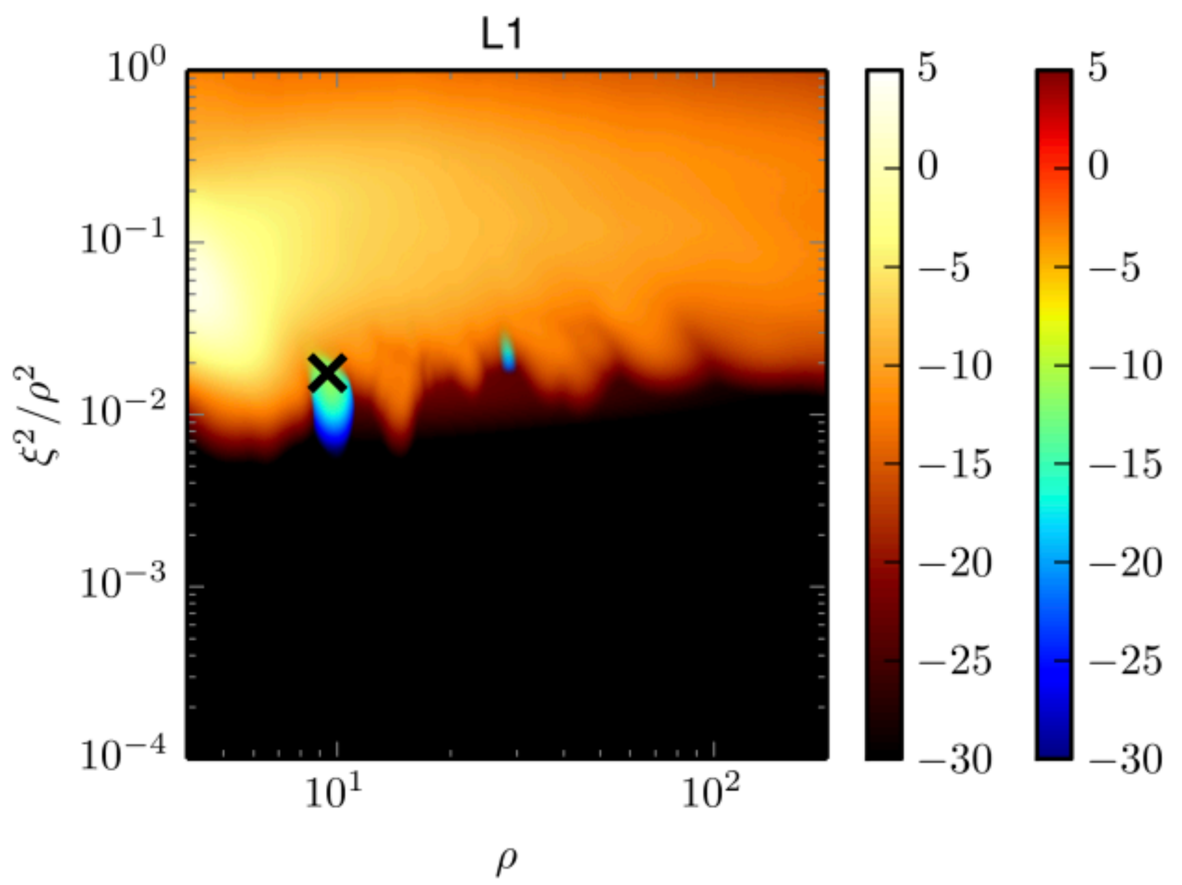
Noise is not Gaussian, we use **a ranking statistic** that includes SNR, signal-based vetoes, and other factors



For example in GstLAL, a likelihood-ratio statistic is used:

$$\mathcal{L} = \frac{P(\vec{D_H}, \vec{O}, \vec{\rho}, \vec{\xi^2}, \vec{\phi}, \vec{t} \mid \mathrm{s})}{P(\vec{D_H}, \vec{O}, \vec{\rho}, \vec{\xi^2}, \vec{\phi}, \vec{t} \mid \mathrm{n})}$$





Cody Messick et al. Phys. Rev. D ***95****, 042001*

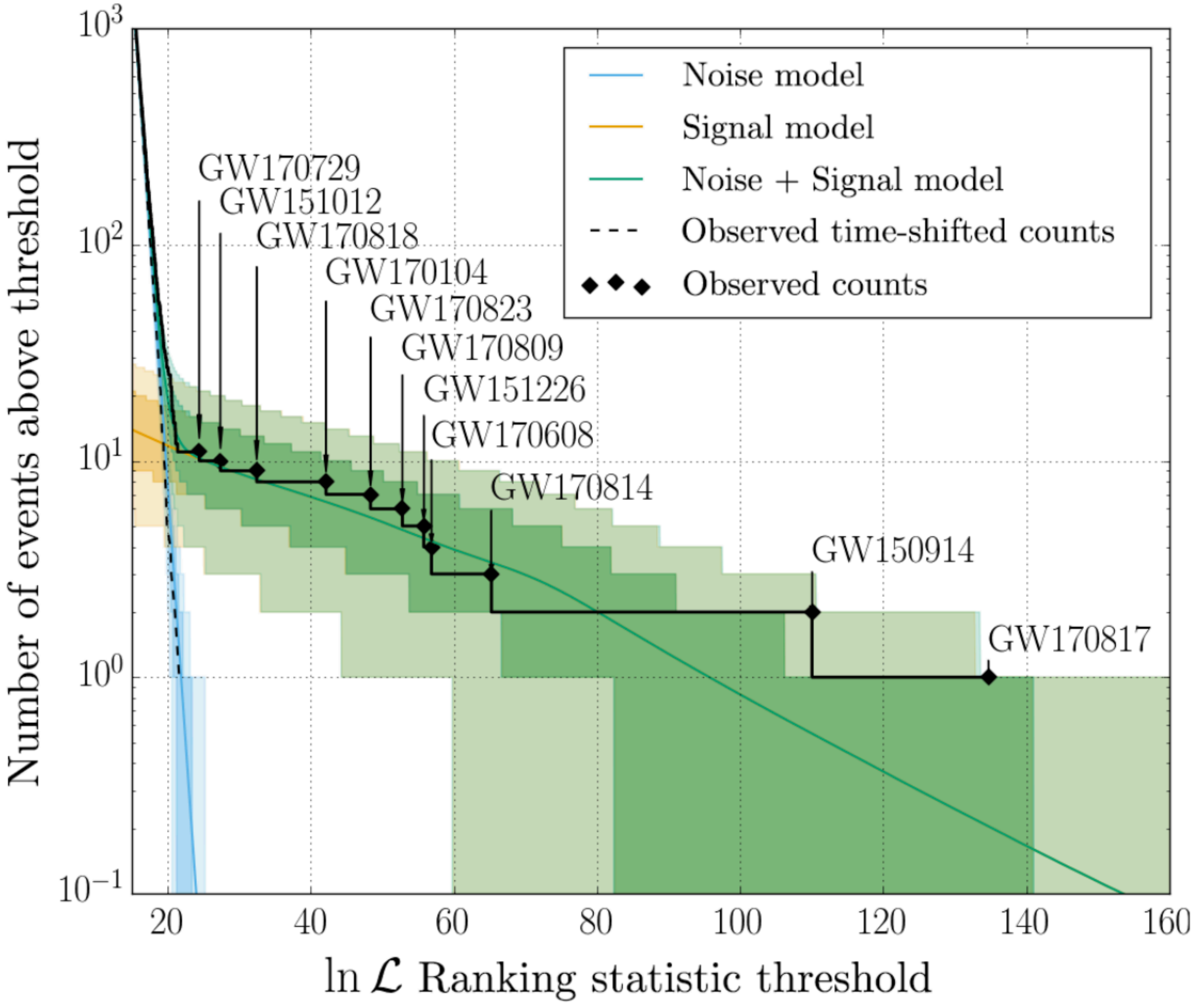
Significance estimation

False-alarm rate

LVK GWTC-1

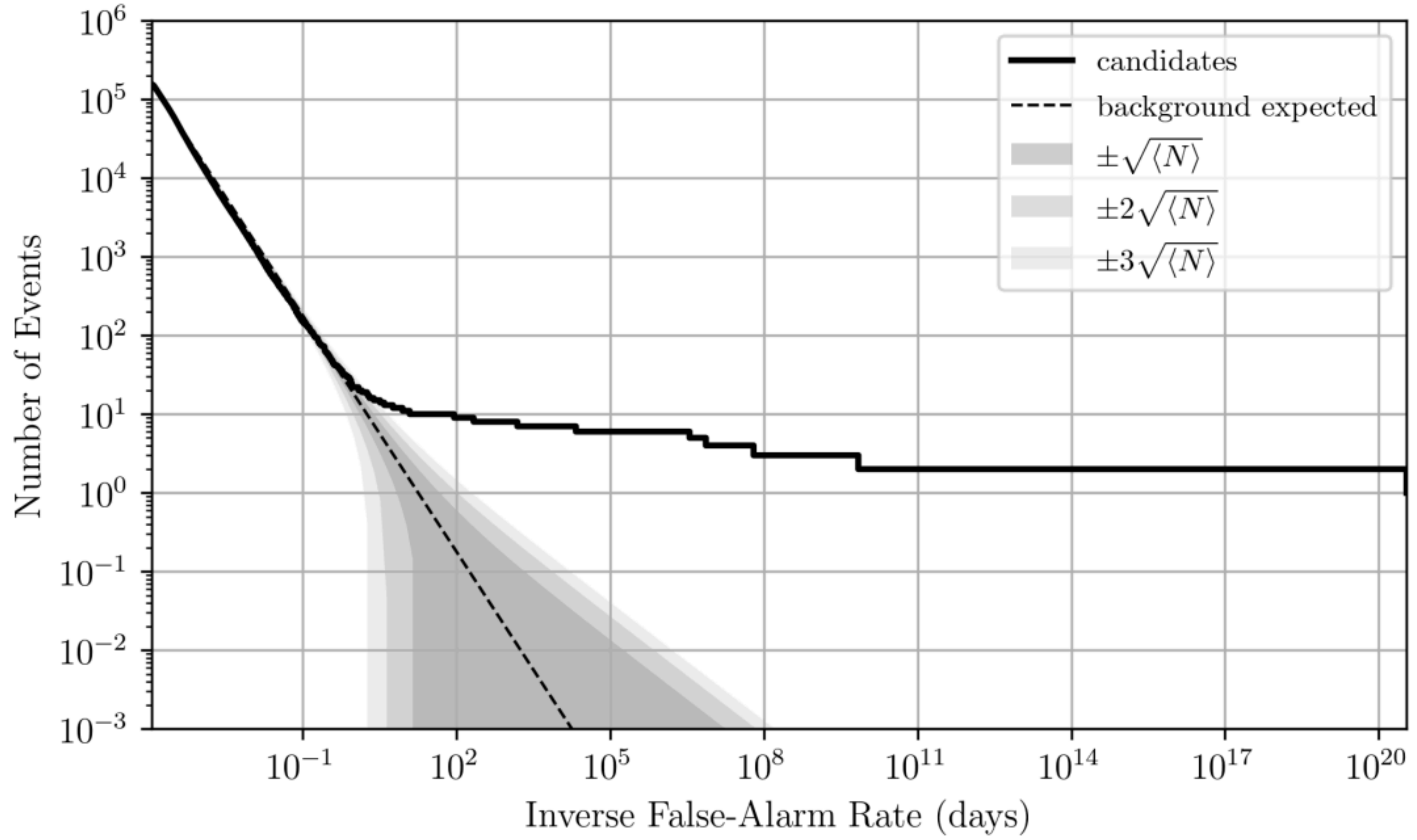
False-alarm rate of an event: Rate at which noise produces candidates at least as significant as the event

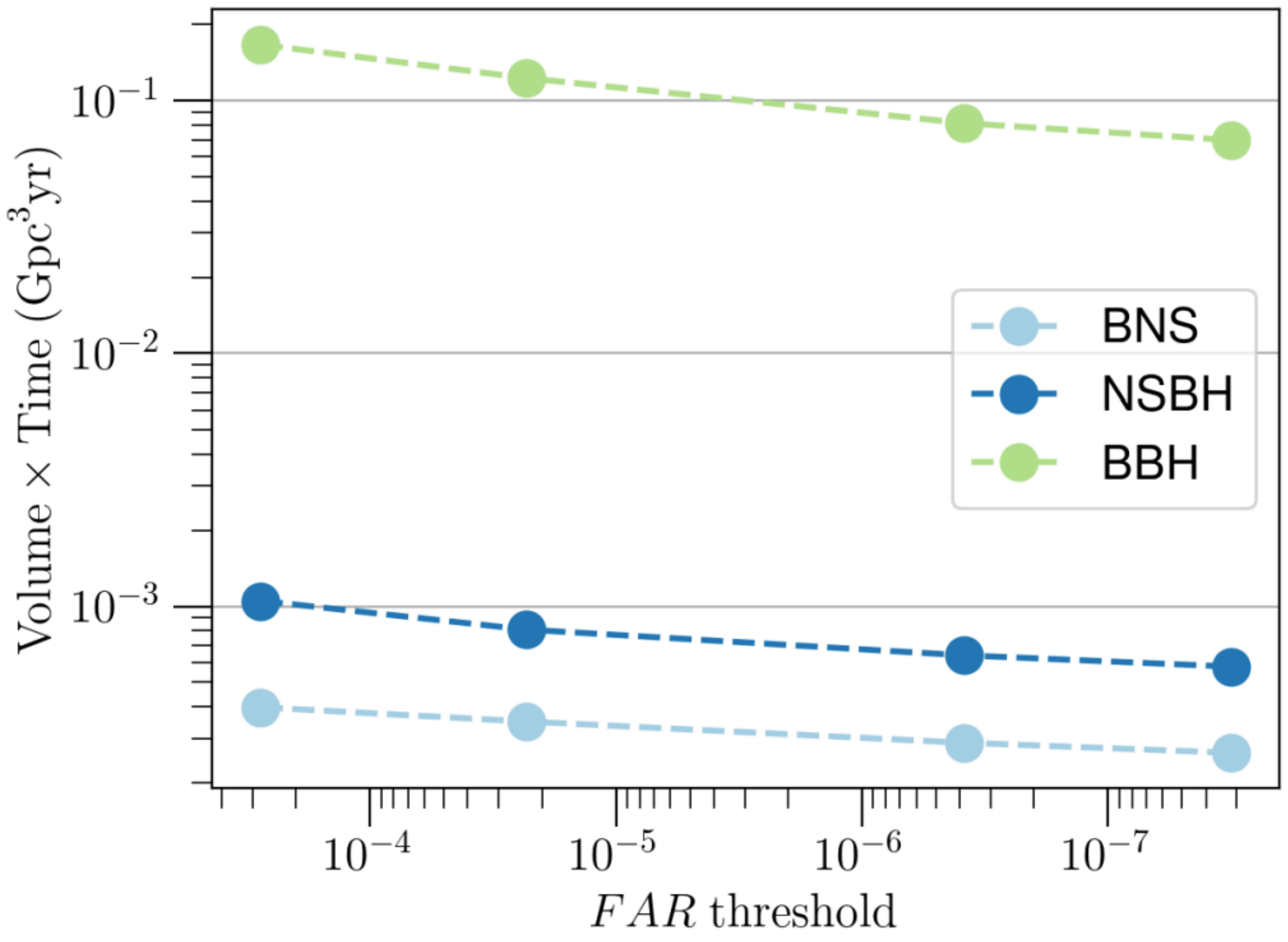
In order to calculate FAR, we need to estimate the distribution of ranking statistic for noise: sample from noise distributions of parameters (SNR< chisq, etc.) to simulate many noise events or use time slides (as in PyCBC, MBTA, and SPIIR)



What makes a good search pipeline

- FARs are reliable: we test this by looking at IFAR plots
- At a given FAR, we want to maximize sensitivity





Becca Ewing et al. 2024, Phys. Rev. D ***109****, 042008, arXiv: 2305.05625*

Limitations with traditional approach

- Computationally expensive and scales linearly with number of templates - infeasible to deploy for parameter spaces that require large template bank
  - Current best searches have latencies O(12 s) ***
- Only sensitive to signals present in the template banks: for example current flagship searches do not look for eccentric binaries or precessing binaries
- Struggle with noise artifacts that sometimes lead to retractions

New pipeline in development has shown latency 4-5 s *(arXiv: 2410.16416 Huang et al. 2024)*

Long history of machine learning implementations

- Earliest efforts used machine learning to design ranking statistics:

Application of artificial neural network to search for gravitational-wave signals associated with short gamma-ray bursts

Kyungmin Kim[1], Ian W Harry[2], Kari A Hodge[3], Young-Min Kim[4], Chang-Hwan Lee[4], Hyun Kyu Lee[1], John J Oh[5], Sang Hoon Oh[5], Edwin J Son[5]

The Search for Gravitational Waves from the Coalescence of Black Hole Binary Systems in Data from the LIGO and Virgo Detectors Or: A Dark Walk through a Random Forest

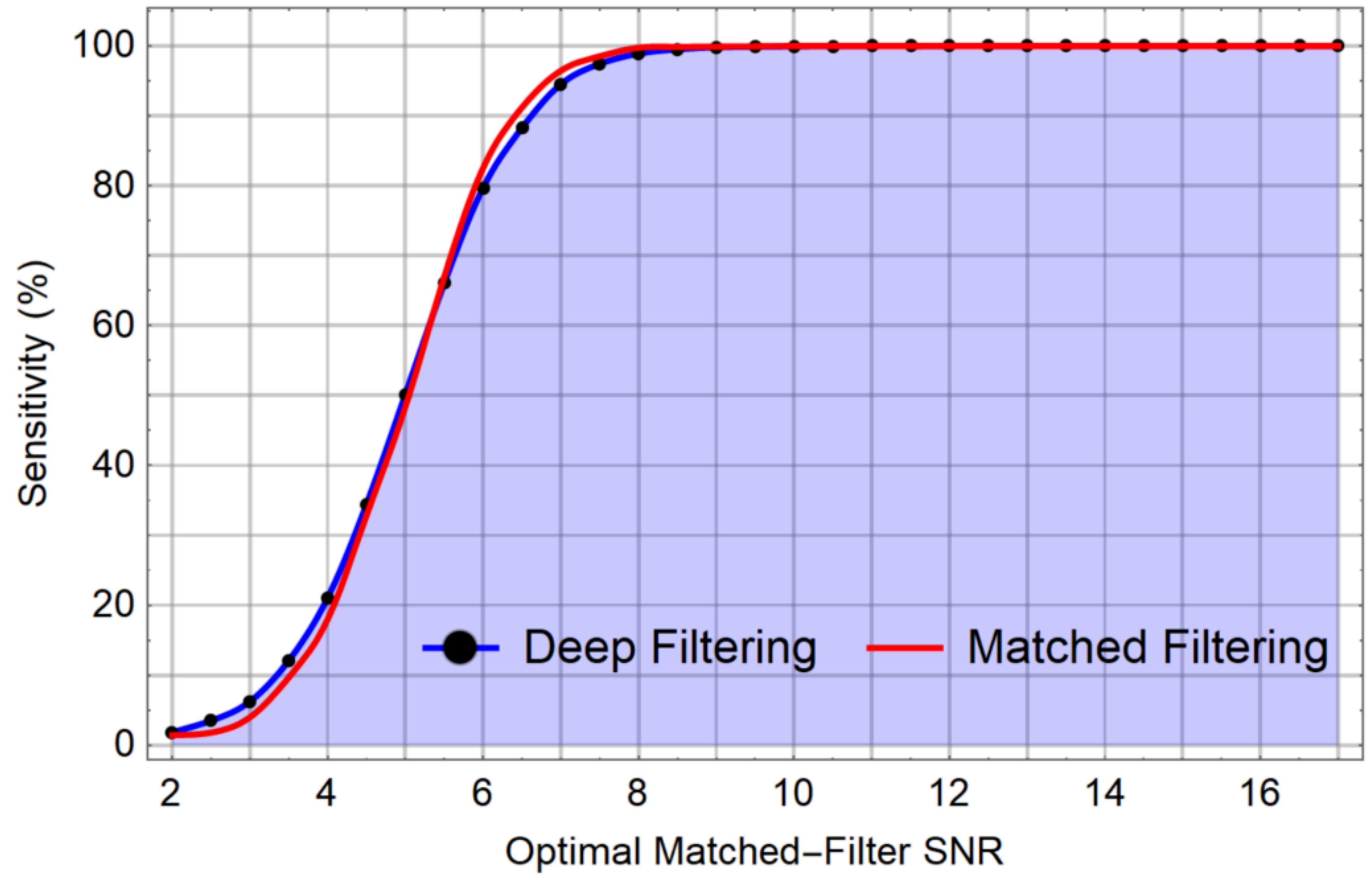
Thesis by

Kari Alison Hodge

Deep Neural Networks to Enable Real-time Multimessenger Astrophysics

Daniel George[1,2] and E. A. Huerta[2]

- Introduced `Deep Filtering` for stellar mass BBHs based on CNNs and compared against matched-filtering
- First attempt at replacing matched-filtering for detection of gravitational waves; first use of CNN for gravitational-wave data analysis
- Was able to detect signals beyond training set: moderately eccentric and moderately precessing waveforms

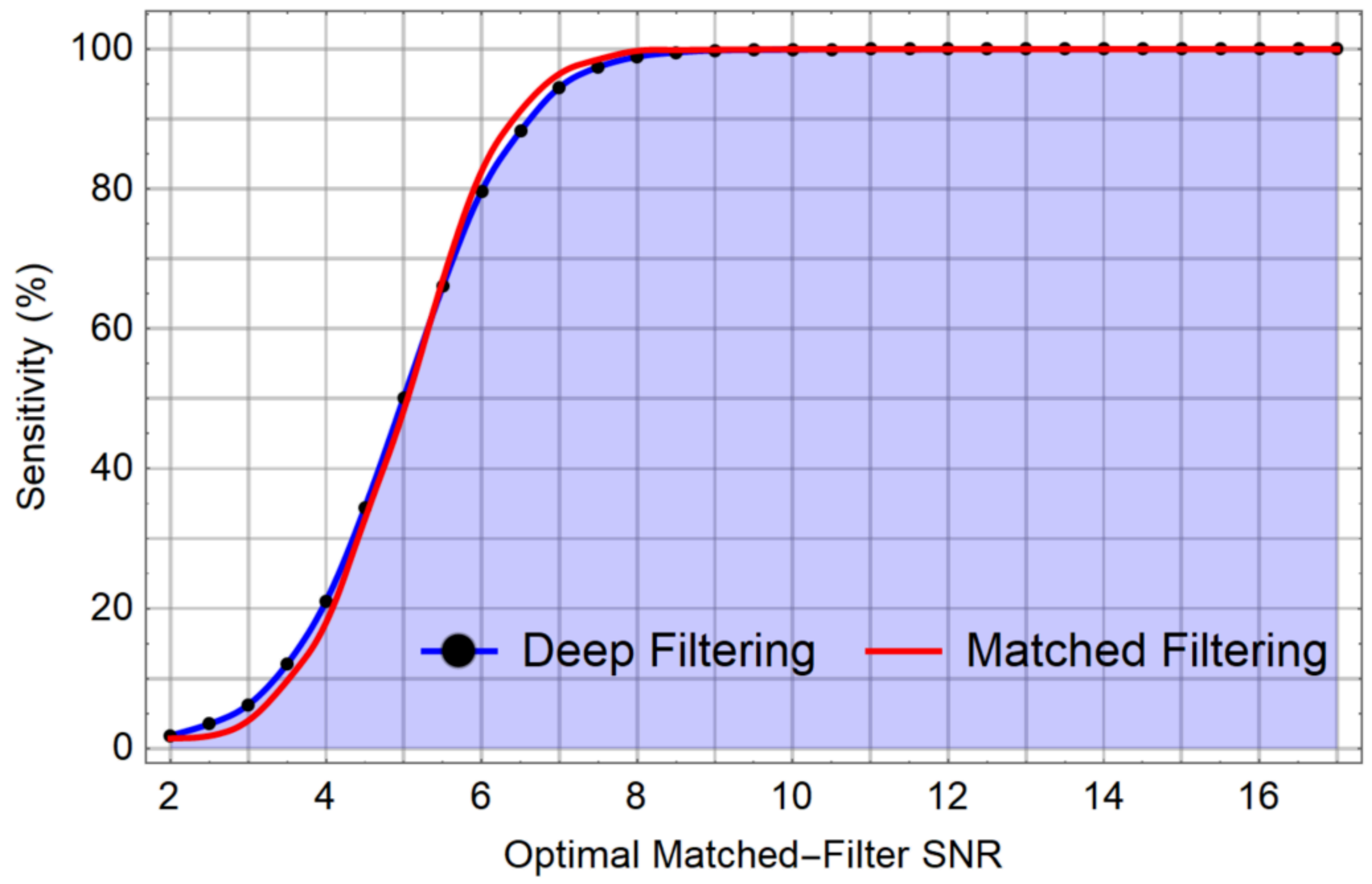


George and Huerta et al. 2018, Phys. Rev. D ***97****, 044039, arXiv:1701.00008*

Deep Neural Networks to Enable Real-time Multimessenger Astrophysics

Daniel George[1,2] and E. A. Huerta[2]

- No physical significances assigned
- This has been compared to only one ingredient that makes a search pipeline: the trigger identification stage; overall would suffer from high false alarms when using in real data
- Could potentially suffer from mis-classification of parameters due to training choices



George and Huerta et al. 2018, Phys. Rev. D **97**, 044039, arXiv:1701.00008

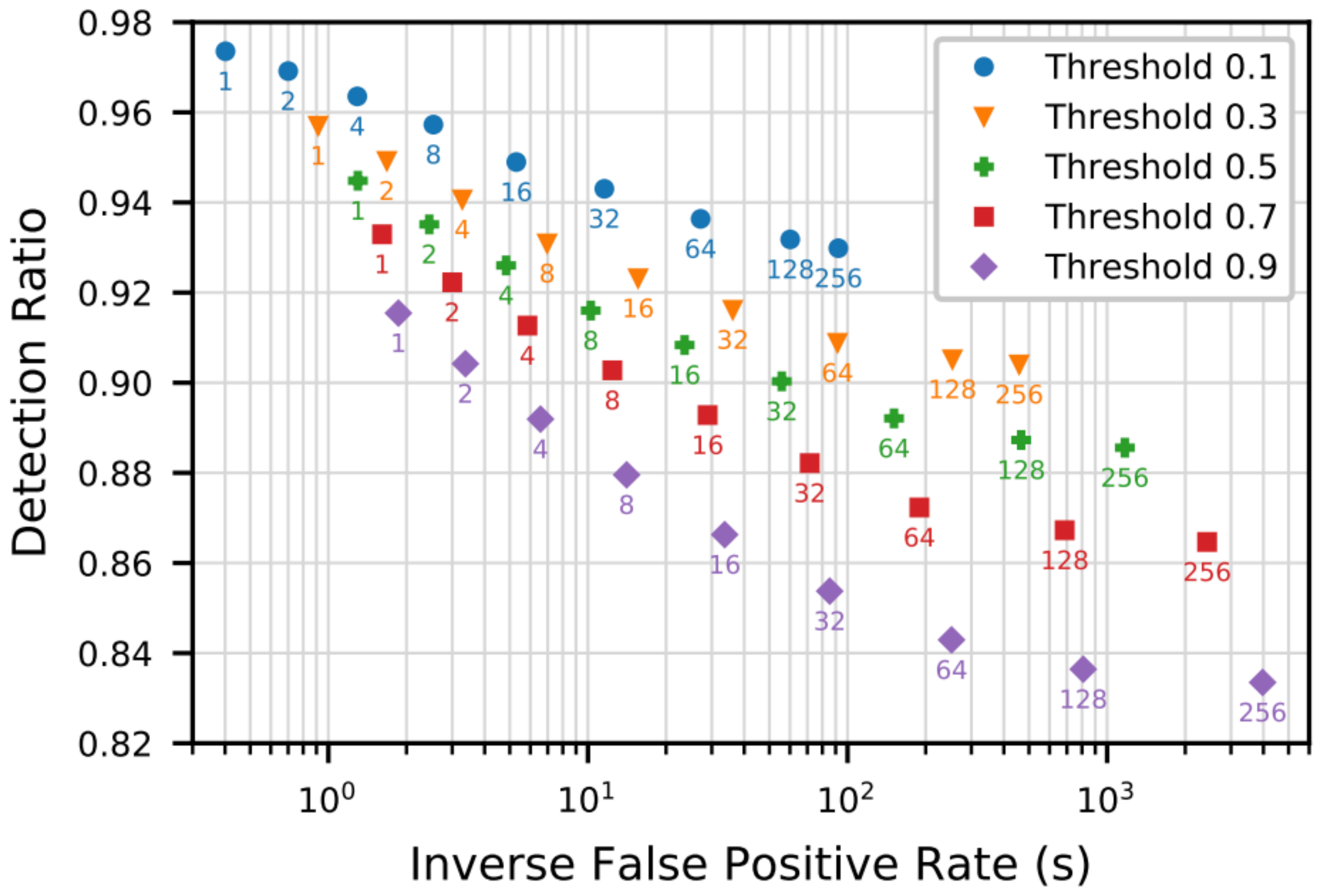
Convolutional neural networks: A magic bullet for gravitational-wave detection?

Timothy D. Gebhard,[1,2,*] Niki Kilbertus,[1,3,*] Ian Harry,[4,5] and Bernhard Schölkopf[1]

- Argues that CNNs should not be used standalone for GW detection: inability to assign individual event FARs; some training choices in the publications discussed could be problematic for real applications

- Previous Literature does not explain how to go from binary classification example to sliding window approach on streaming data

- Creates a CNN based algorithm and shows what detection ratio can be achieved at different false positive rates

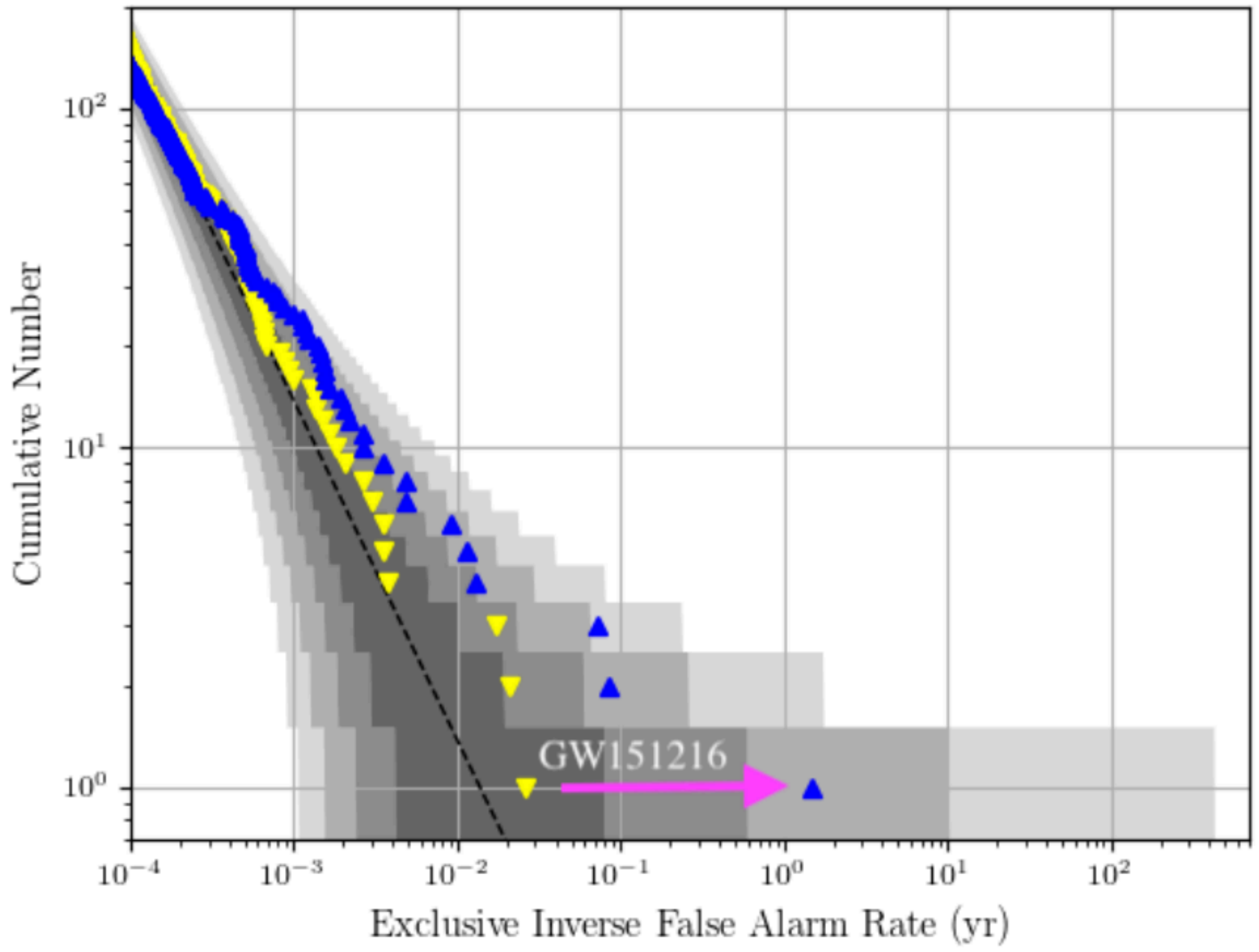


Gebhard et al. 2019, Phys. Rev. D **100**, 063015, arXiv:1904.08693

Improving significance of binary black hole mergers in Advanced LIGO data using deep learning : Confirmation of GW151216

Shreejit Jadhav[1,a] Nikhil Mukund[2,1,b] Bhooshan Gadre[3,1,c] Sanjit Mitra[1,d] and Sheelu Abraham[1,e]

- Develop a machine learning classifier to distinguish GW events from noise events
- Incorporate output of the classifier into coincident search likelihood used by PyCBC
- Repeat PyCBC GWTC-1 analysis with the new ranking statistic leads to:
  - a confident detection of GW151216 which was not included in GWTC-1 due to low-significance
  - improvement in the significance of GW151012 and GW170729



Jadhav et al. 2021, Phys. Rev. D **104**, 064051, arXiv: 2010.08584

MLGWSC-1: The first Machine Learning Gravitational-Wave Search Mock Data Challenge

Marlin B. Schäfer[1,2], Ondřej Zelenka[3,4], Alexander H. Nitz[1,2], He Wang[5], Shichao Wu[1,2], Zong-Kuan Guo[5], Zhoujian Cao[6], Zhixiang Ren[7], Paraskevi Nousi[8], Nikolaos Stergioulas[9], Panagiotis Iosif[10,9], Alexandra E. Koloniari[9], Anastasios Tefas[8], Nikolaos Passalis[8], Francesco Salemi[11,12], Gabriele Vedovato[13], Sergey Klimenko[14], Tanmaya Mishra[14], Bernd Brügmann[3,4], Elena Cuoco[15,16,17], E. A. Huerta[18,19], Chris Messenger[20], Frank Ohme[1,2]

Datasets (1 month; 2 detectors H1 and L1)

- Gaussian noise recolored to design LIGO sensitivity (`aLIGOZeroDetHighPower`); non-spinning BBHs between 10 and 50 Msun; signal duration about 1s
- Gaussian noise recolored to O3a PSD; spinning BBHs between 7 and 50 Msun; duration up to 20s
- Gaussian noise recolored to O3a PSD but PSDs allowed to vary over time; precessing BBHs between 7 and 50 Msun; including higher order modes
- Real O3a data with the same injection set as 3

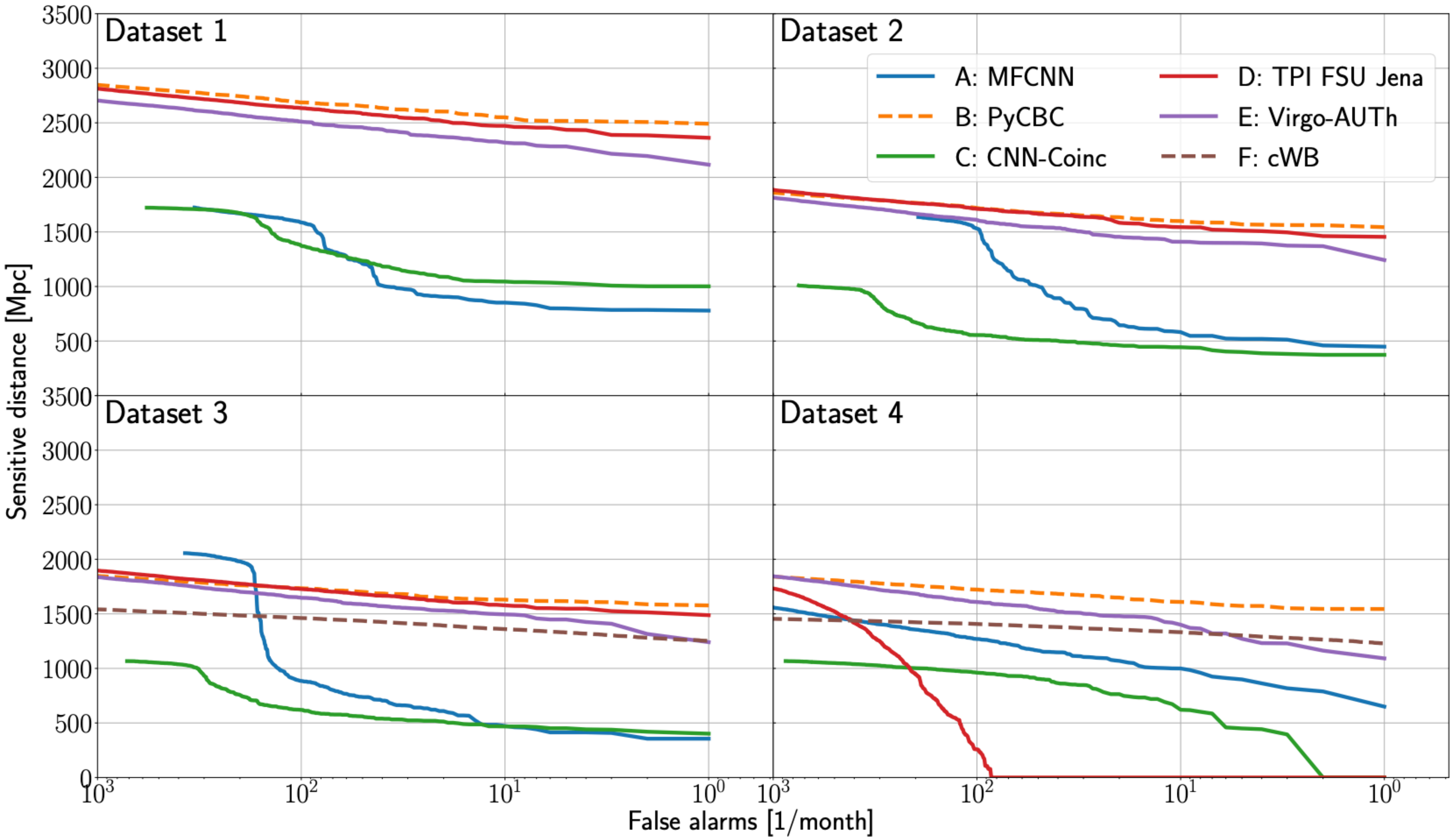
Submission requirements

- Each team has to submit three 1-d datasets of equal lengths containing: “time”, “stat”, “var”

*Schafer et al. 2023, Phys. Rev. D **107**, 023021, arXiv: 2209.11146*

MLGWSC-1 pipelines and results

- MFCNN
- PyCBC
- CNN-Coinc
- TPI FSU Jena
- Virgo-AUTh
- cWB



Schafer et al. 2023, Phys. Rev. D ***107****, 023021, arXiv: 2209.11146*

A machine-learning pipeline for real-time detection of gravitational waves from compact binary coalescences

Ethan Marx,[1,2] William Benoit,[3] Alec Gunny,[1,2] Rafia Omer,[3] Deep Chatterjee,[1,2] Ricco C. Venterea,[3,4] Lauren Wills,[3] Muhammed Saleem,[3] Eric Moreno,[1,2] Ryan Raikman,[1,5] Ekaterina Govorkova,[1,2] Dylan Rankin,[6] Michael W. Coughlin,[3] Philip Harris,[1] and Erik Katsavounidis[1,2]

- Modified ResNet54 architecture by replacing 2D with 1D convolutions and replacing Batch Normalization layers with Group Normalization layers
  - GN performs better when testing data (which is typically noise dominated) is not the same as training data (which contains many more signals)

- Uses time slides to extrapolate background

- Curriculum learning: Learn with high SNR signals first

- Data augmentation during training: Noise instances are sampled independently from each IFO; additionally each noise instance has a probability to be inverted -h(t) or reversed h(-t)

Marx et al. 2025, Phys. Rev. D ***111****, 042010, arXiv:2403.18661*

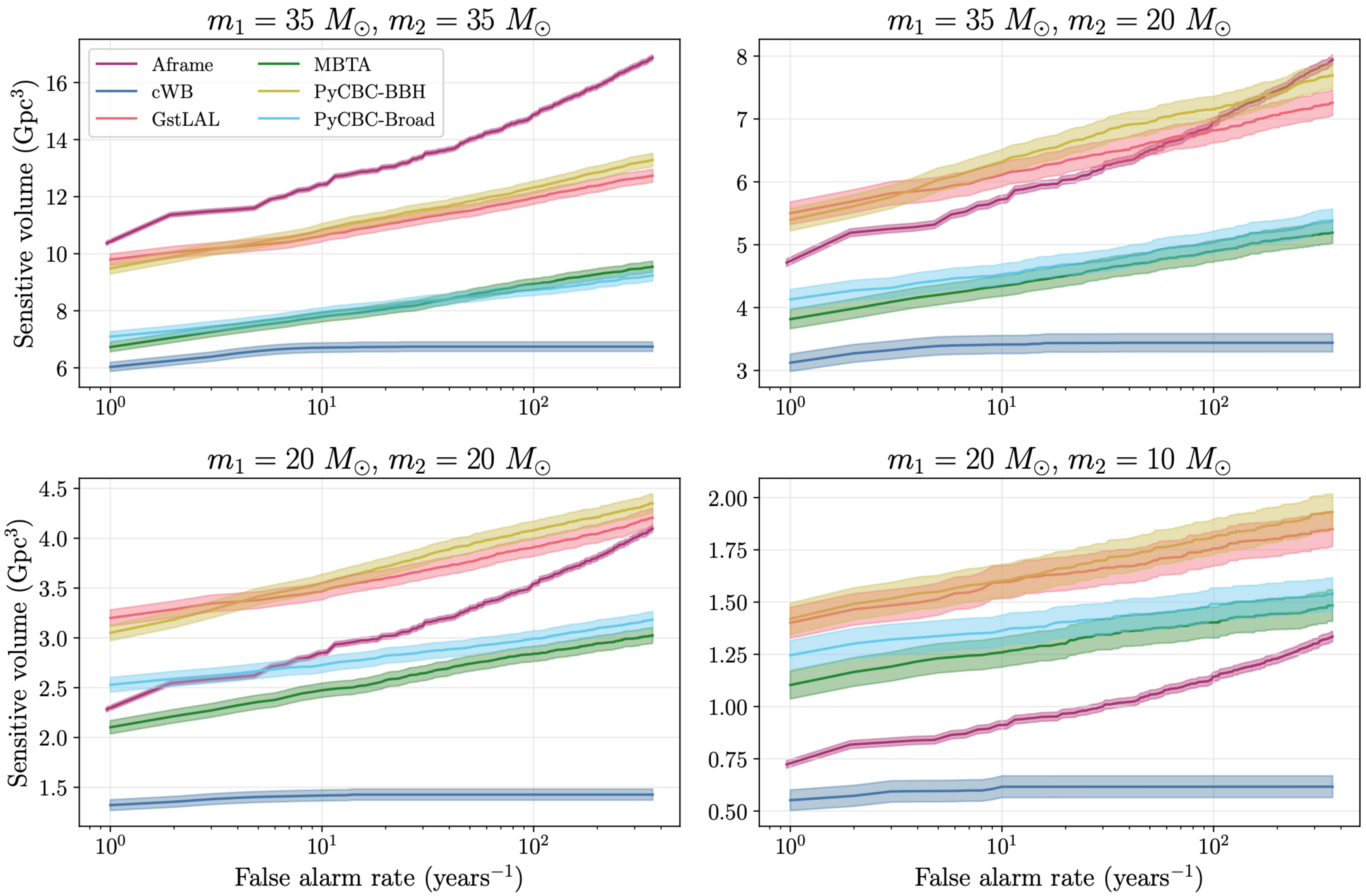
AFRAME

- Glitch mitigation:
  - Muting: For a fraction, mute BBHs in one detector and label as noise
  - Swapping: For a fraction, swap one IFO response with response from a different signal and label as noise

- Select neural network during validation stage: between individually trained networks and also while performing hyperparameter search

*Marx et al. 2025, Phys. Rev. D **111**, 042010, arXiv:2403.18661*

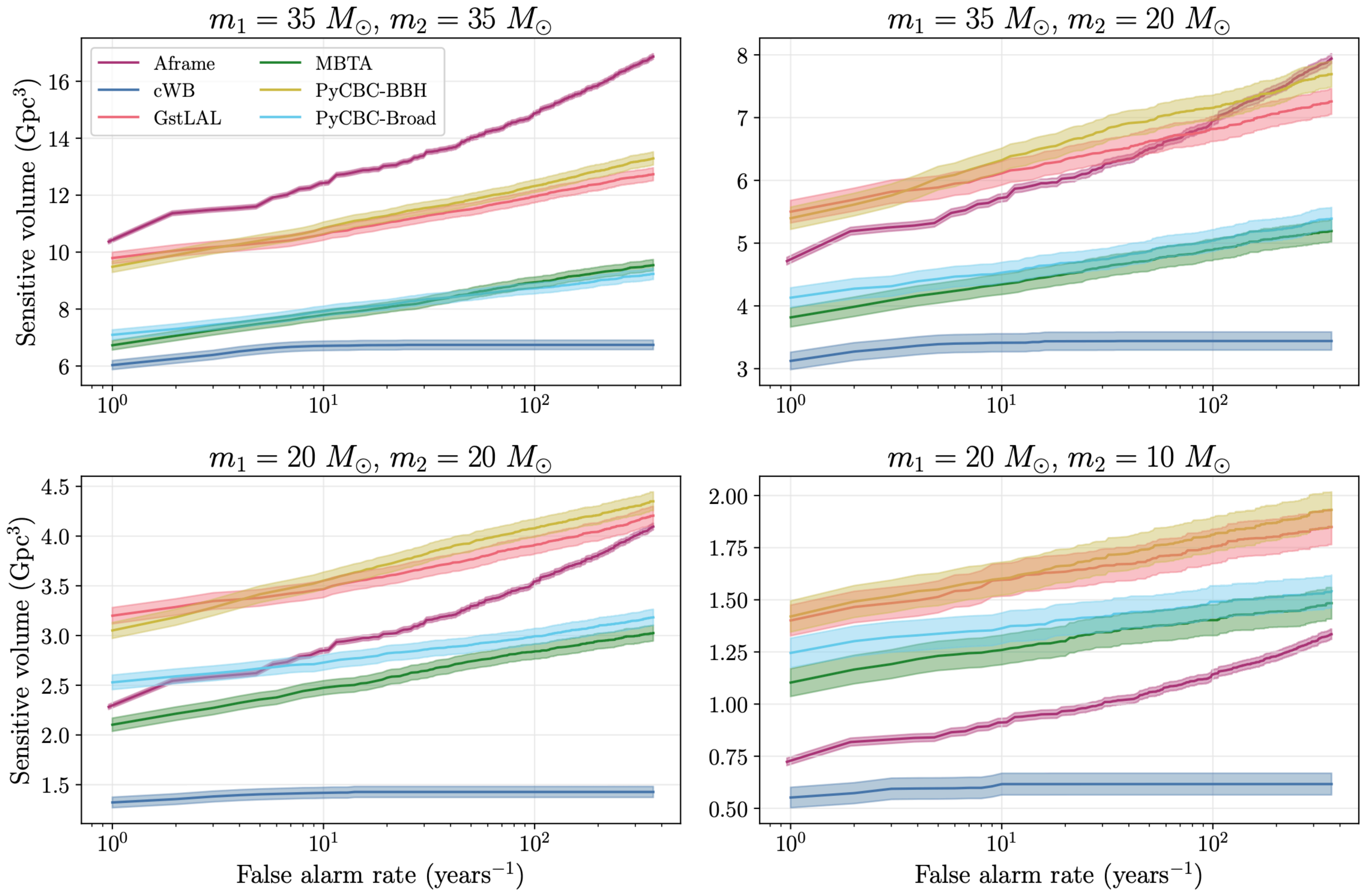
AFRAME: Results



- Comparable/better results for high-mass BBHs
- Median latency for uploading to GraceDB is 3.9s for MDC compared to ~12s for other pipelines
- Throughput of 500 s of data from two detectors on a single GPU

Marx et al. 2025, Phys. Rev. D ***111****, 042010, arXiv:2403.18661*

AFRAME: Results



- Since other pipelines are also looking for BNSs and NSBHs, they incur a higher trials factor due to those templates, need to account for this
- Newer implementations of traditional pipelines are seeing latencies of 4-5s

Marx et al. 2025, Phys. Rev. D ***111****, 042010, arXiv:2403.18661*

Precessing signals

Detection of Gravitational Wave Signals from Precessing Binary Black Hole Systems using Convolutional Neural Network

Chetan Verma,[1,*] Amit Reza,[2,3,†] Gurudatt Gaur,[4,5,‡] Dilip Krishnaswamy,[6,§] and Sarah Caudill[7,¶]

Early warning

Early warning of coalescing neutron-star and neutron-star-black-hole binaries from nonstationary noise background using neural networks

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TAPIR, Walter Burke Institute for Theoretical Physics,
MC 350-17 California Institute of Technology, Pasadena, CA 91125, USA

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Yanbei Chen
TAPIR, Walter Burke Institute for Theoretical Physics,
Mailcode 350-17 California Institute of Technology, Pasadena, CA 91125, USA
(Dated: April 20, 2021)

Long Short-Term Memory for Early Warning Detection of Gravitational Waves

Reem Alfaidi[1,2] and Christopher Messenger[1]

[1] School of Physics and Astronomy, University of Glasgow, Glasgow G12 8QQ, UK
[2] The Department of Physics ,Tiba University, Madinah, Saudi Arabia

Convolutional neural networks for the detection of the early inspiral of a gravitational-wave signal

Grégory Baltus[1],* Justin Janquart[2,3],† Melissa Lopez[2,3],‡
Amit Reza[2,3],§ Sarah Caudill[2,3],¶ and Jean-René Cudell[1]**
[1] *STAR Institut, Bâtiment B5, Université de Liège, Sart Tilman B4000 Liège, Belgium*
[2] *Nikhef, Science Park 105, 1098 XG Amsterdam, The Netherlands and*
[3] *Institute for Gravitational and Subatomic Physics (GRASP),*
Utrecht University, Princetonplein 1, 3584 CC Utrecht, The Netherlands

Outlook

- Machine learning use in gravitational-wave detection has come a long way
- Ideas that combine traditional methods (for example combining output from IFOs and putting them through another layer of CNN; time slides for background estimation) and neural networks seem to be the way forward
- For high-mass binary black holes, machine learning pipelines have shown comparable performance in real settings: need to check the event rate is consistent though
- For production use: more testing needs to happen and pipelines need to demonstrate they are operationally stable
- How to get the machine learning pipelines work for longer signals which are typically of more interest for MMA
- Offers exciting prospects: lowered latency for MMA, prospects for searches over parameter spaces where template banks become prohibitively large, prospects for searching for signals with added physical effects such as eccentricity and precession

This material is in part based upon work supported by NSF’s LIGO Laboratory which is a major facility fully funded by the National Science Foundation