기계학습을 이용한 중력파 데이터 분석

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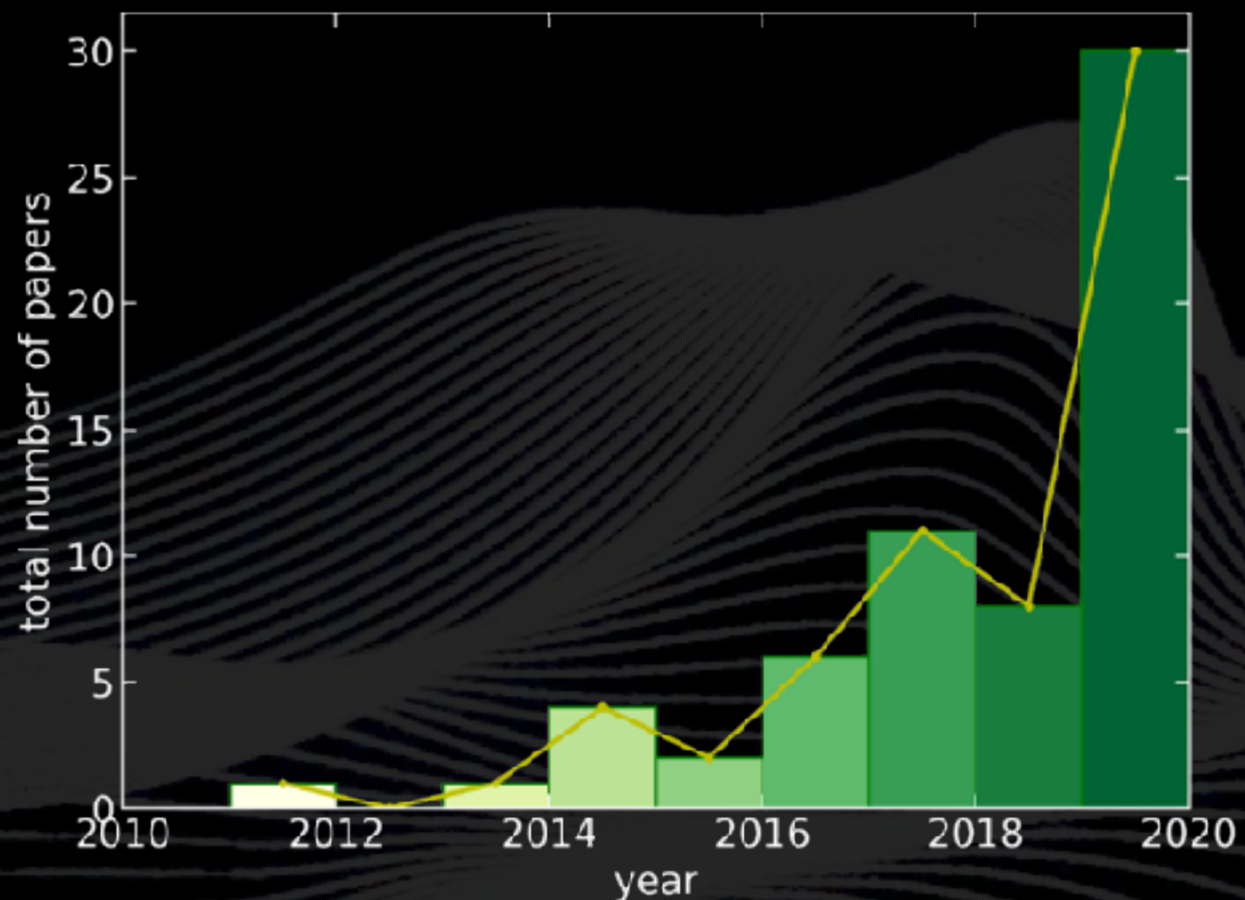
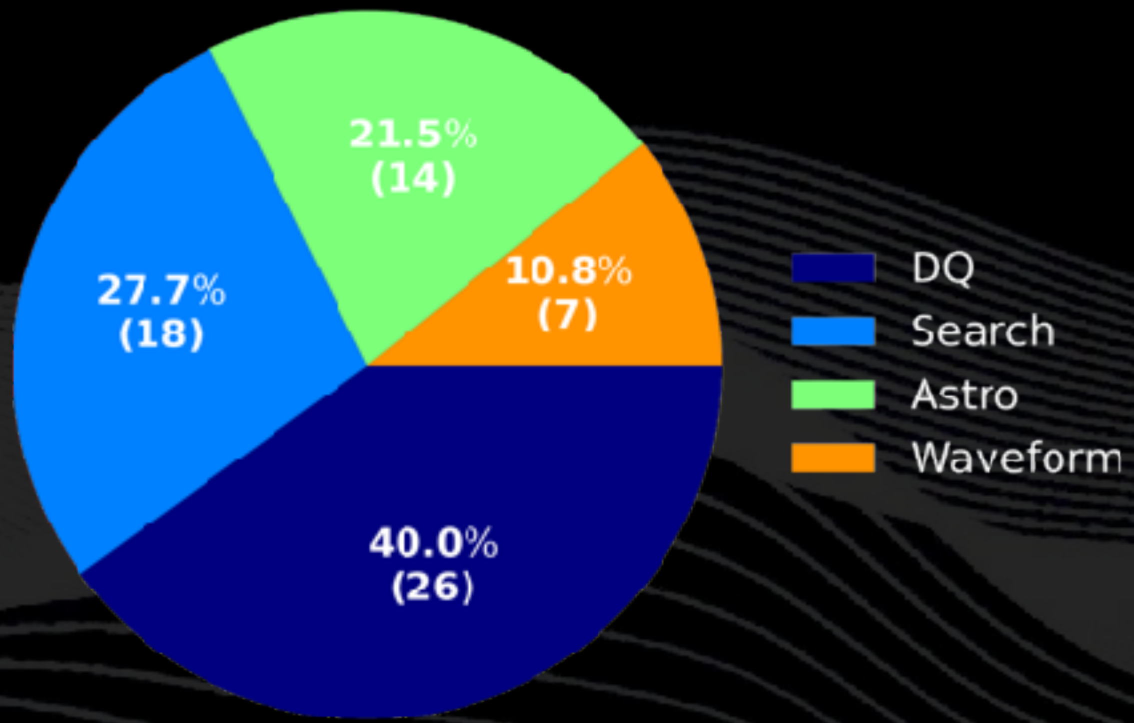
Additional read: '중력파 과학에도 인공지능이?!' (물리학과 첨단기술 2021년 6월 30권 6호)

Overview

- Publications summarized in E. Cuoco+ (2021; but as of May 2020)…





"Number of publications is rapidly increasing!"

"Applications of ML have been conducted for more or less all topics of GW sciences!"

- To date, more papers have appeared in public, for example,
  - K. Kim+, ApJ (2021) (Search & Astro),
  - J. Lee+, PRD (2021) (Waveform).

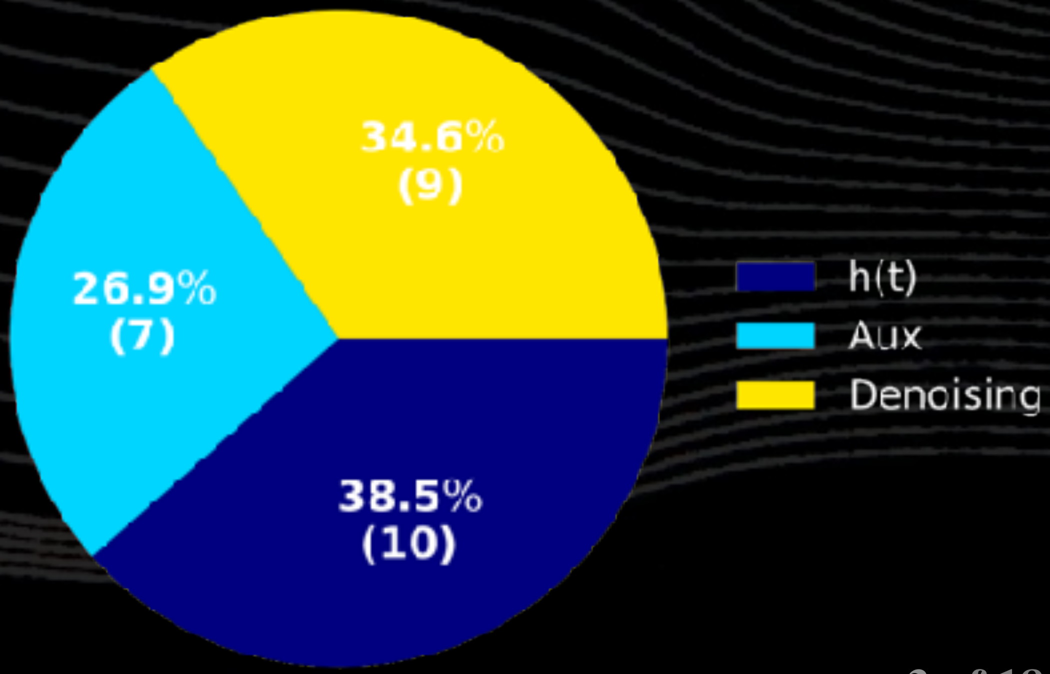
Data Quality Improvement

- <u>**Challenges**</u>
  - characterize non-stationary & non-Gaussian noise transients (a.k.a. *glitches*)
  - subtract and denoise glitches

- ***h*(*t*) glitch characterization and classification**
  - (convolutional) neural networks, wavelet detection filter, elastic-net based ML for understanding, …

- **Glitch characterization and classification with auxiliary channels**
  - neural networks, random forest, support vector machine, genetic programming (GP), …
  - R. Biswas+ (PRD ’13)

- **Non-stationary noise subtraction and denoising**
  - deep neural networks, recurrent neural networks (RNN), toatal-variation method, dictionary learning, autoencoder, …

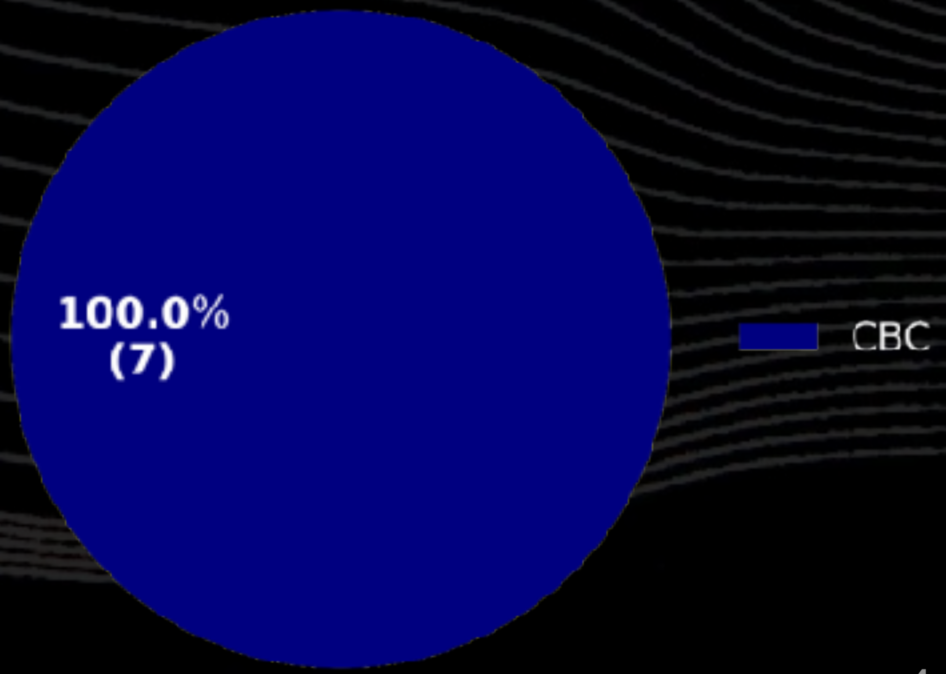


Waveform Modeling

- **Importance**
  - searches for CBC-GWs and estimation of source parameters require waveform templates.
- **Challenge**
  - need accurate and computationally efficient models

- **Compact Binary Coalescence (CBC) only so far**
  - RNN-based dual-decoder sequence-to-sequence, Gaussian process regression, (deep) neural networks, hierarchical ML, …
  - J. Lee+ (PRD '21)

- **Burst and continuous waves (tentative)**
  - K. Kim+
  - under discussion/development (no concrete idea yet)



Signal Searches

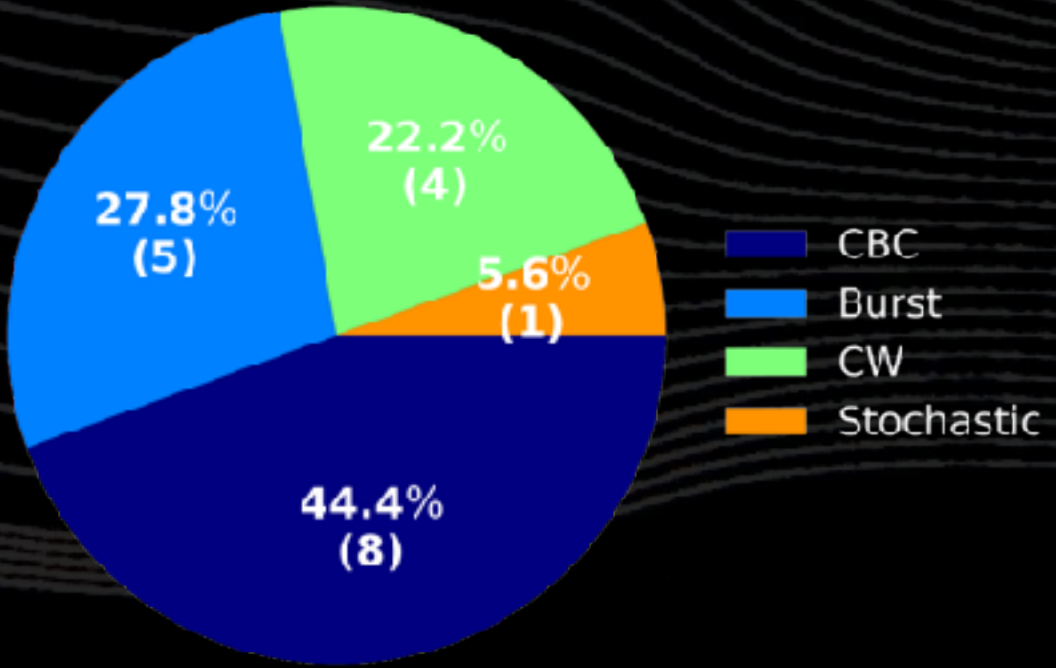
- **Challenge**
  - enhance searches for four different types of GW signals

- **CBC**
  - random forest, (shallow/deep, convolutional) neural networks, …
  - K. Kim+ (CQG ’15)
  - K. Kim+ (PRD ’20)
  - K. Kim+ (ApJ ’21)

- **Burst**
  - convolutional neural networks (CNN), GP, wavelet detection filter, …

- **Continuous wave**
  - CNN, region-based CNN, …

- **Stochastic background**
  - Gaussian mixture model, …



Astrophysical Interpretation of Sources

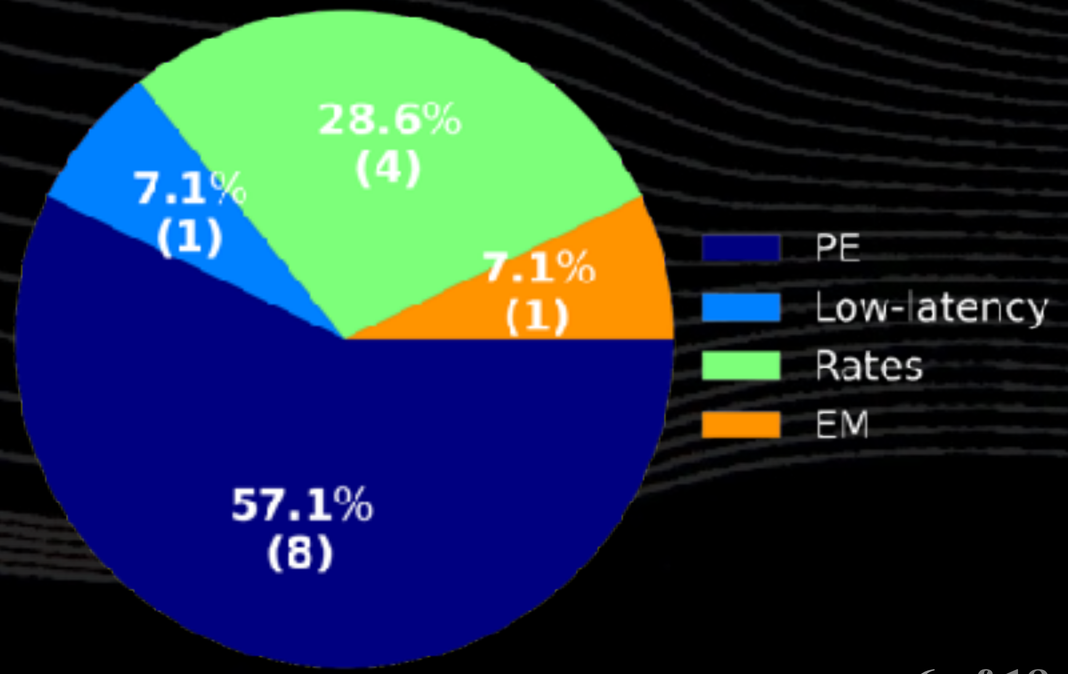
- **Challenges**
  - measure/infer the parameters/properties of the source accurately and fastly
  - estimate detection/event rates properly for population analysis

- **Parameter estimation**
  - Gaussian process, random forest, neural networks, conditional variational autoencoder, multivariate Gaussian posterior model, …
  - K. Kim+ (ApJ '21)
  - K. Kim+ (under discussion)

- **Low-latency source properties inference**
  - KNeighbors, …

- **Rates and populations of GW sources**
  - Gaussian mixture, deep generative network, …

- **Identification of EM counterparts**
  - neural networks, …

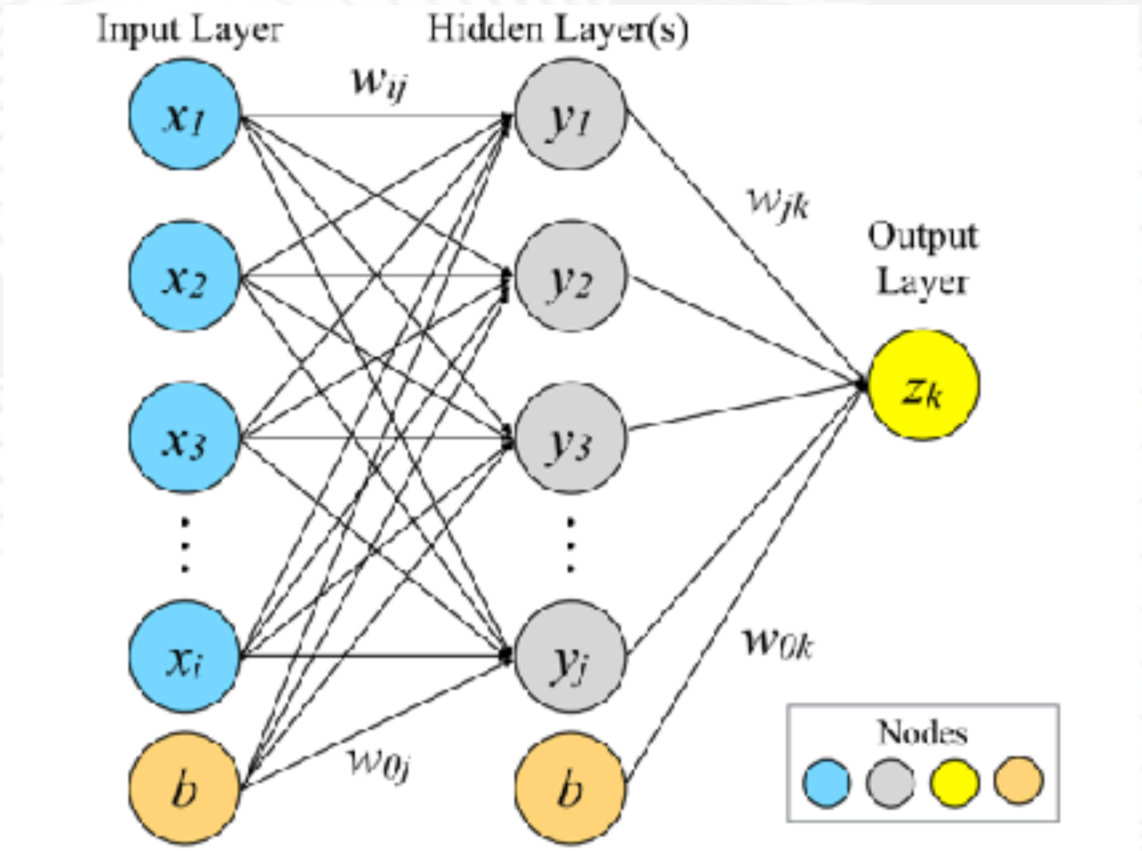


Application of Machine Learning to GW Science - Examples -

ML for GW Search Related to Short GRBs

KK+, CQG **32** (2015) 24, 245002

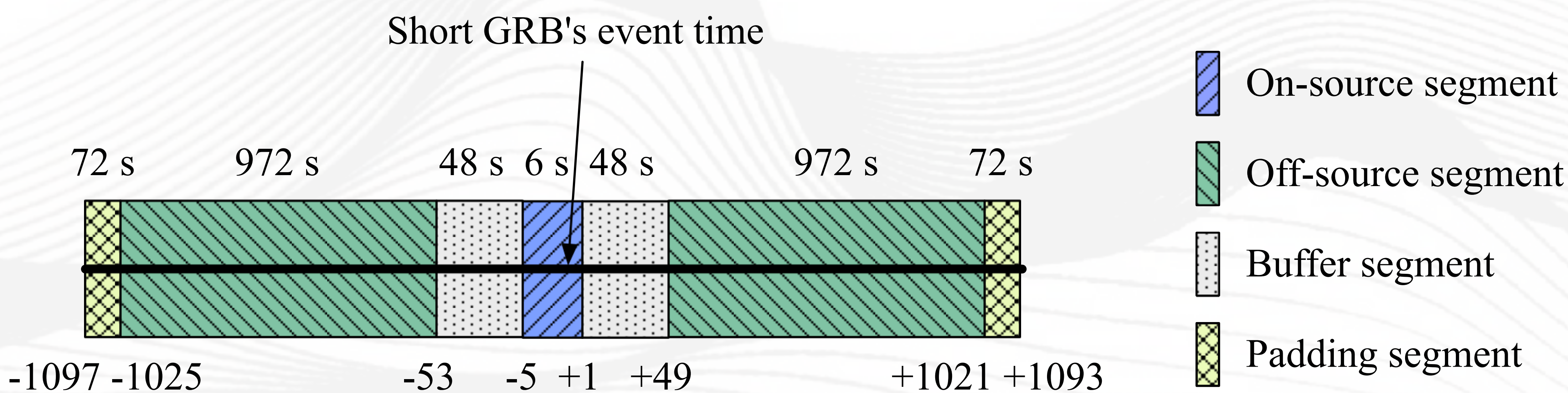
- Motivation
  - Progenitors of short GRBs can radiate both GW and EM waves.
    - proved by GW170817 and GRB170817 later on.
  - Previous searches for LIGO's S5 & S6 and Virgo's VSR1, VSR2, & VSR3 data couldn't find any evidence from the candidate triggers (events) evaluated by a ranking statistics of a matched-filtering-based search method (Abadie+ (2010, 2012); Aasi+ (2014)).
  - Neural networks can be a new ranking method for candidate events.



ML for GW Search Related to Short GRBs

KK+, CQG **32** (2015) 24, 245002

- Date preparation
  - We use some triggers generated by the existing analysis pipeline which produces
    - on-source triggers: regarded as containing a candidate GW signal
    - off-source triggers: estimating background distribution around the candidate
    - software injection triggers: evaluating the performance of the search pipeline



- We use the software injection triggers as signal samples and the off-source triggers as background samples.
  - software injection: considering both BNS and NSBH systems

ML for GW Search Related to Short GRBs

KK+, CQG **32** (2015) 24, 245002

For both neutron star binary (BNS) and neutron star - black hole binary (NSBH)…

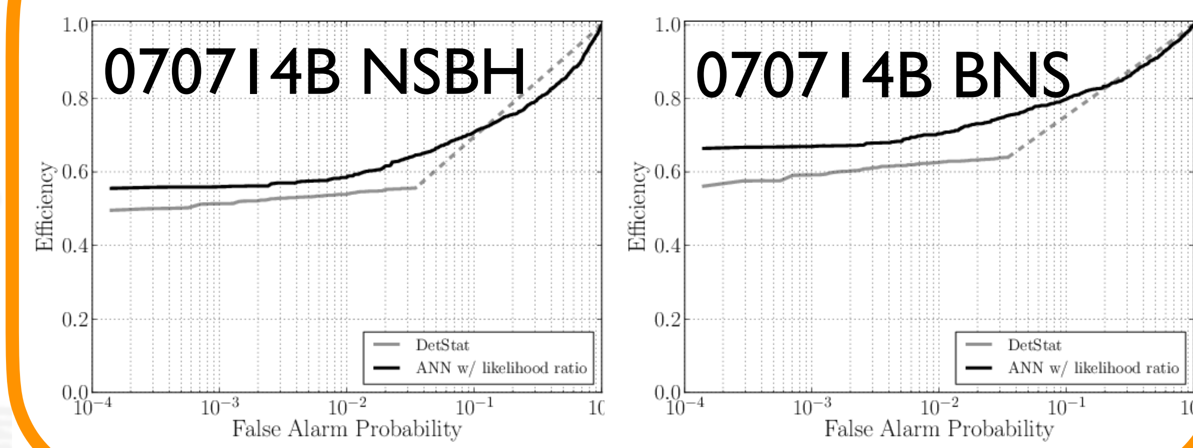
Signal samples (~2 000 samples) / Background samples (~7 000 samples)
+
10 Feature Parameters from CBC-GRB triggers

- Single IFO's SNRs
- Coherent SNR, New SNR
- Coherent χ^2-test, bank χ^2-test, auto-correlation χ^2-test value
- Mass 1 and Mass 2 of BNS or NSBH

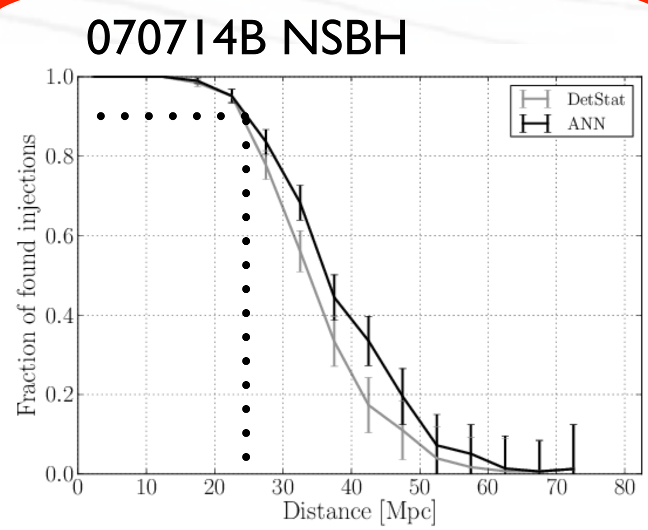
with two S5 & VSR1 triple-coincidence data (070714B & 070923)

Classification with Neural Network as post-processing

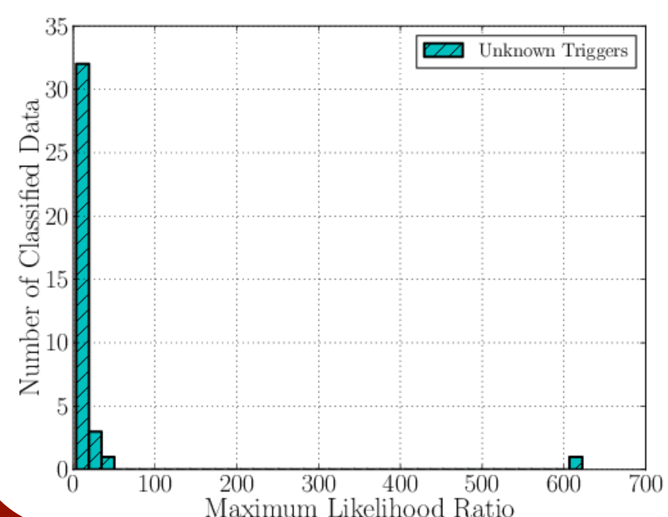
~5% — 10% improved efficiency



Sensitivity



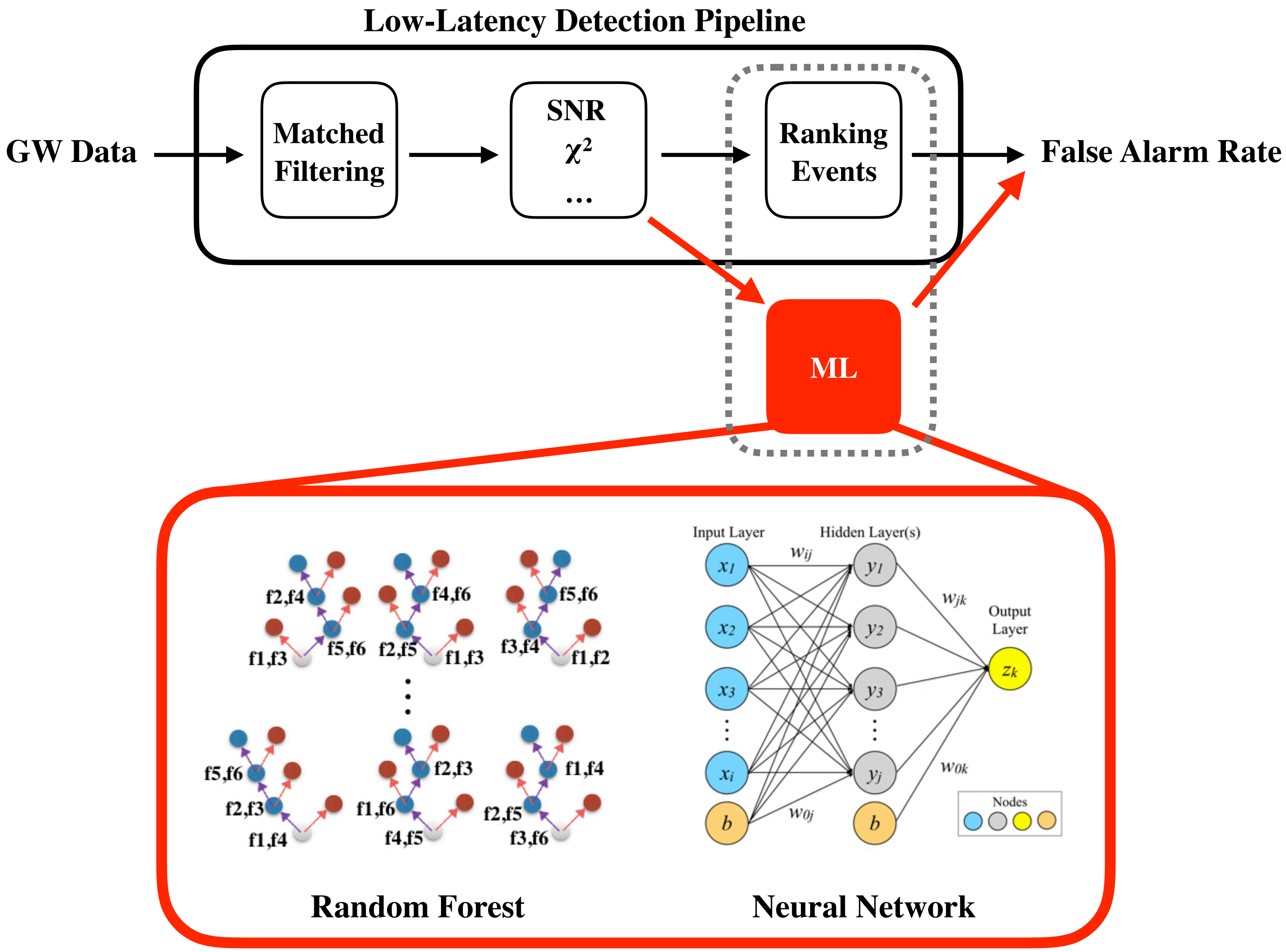
Evaluating Unknown Triggers



ML for Low-Latency GW Search

KK+, Phys. Rev. D **101** (2020) 8, 083006

- Motivation
  - Low-latency search (detection) pipeline: real-time (online) search pipeline which produce candidate event triggers within $\mathcal{O}$(min).
    - c.f., offline search takes $\mathcal{O}$(hrs) – $\mathcal{O}$(days)
    - GstLAL inspiral pipeline (Messick+ '17)
  - Similar to the previous work, we assume the output of machine learning algorithms can be used to rank candidate events of low-latency pipeline.
    - In this work, we consider random forest and neural networks.



ML for Low-Latency GW Search

KK+, Phys. Rev. D **101** (2020) 8, 083006

Input Data

- Signal samples: mock data of GW150914 using GstLAL inspiral pipeline (~ 5 000 samples)
- Background samples: time-slide data around the GPS times of injections of the MDC (~ 172 000 samples)
- Features: mass1, mass2, spin1z, spin2z, snr, and chisq (6 features)
- Train/Test data: 75%/25% of shuffled samples (no validation data)

Training

- Time for training (w/ ~ 122 000 samples of 6 features) on MacBook Pro
  - Random Forest (scikit-learn): **~ 6—7 hrs** for running GridSearchCV with 288 combinations
  - Neural Network (TensorFlow): **~ 7—10 mins**

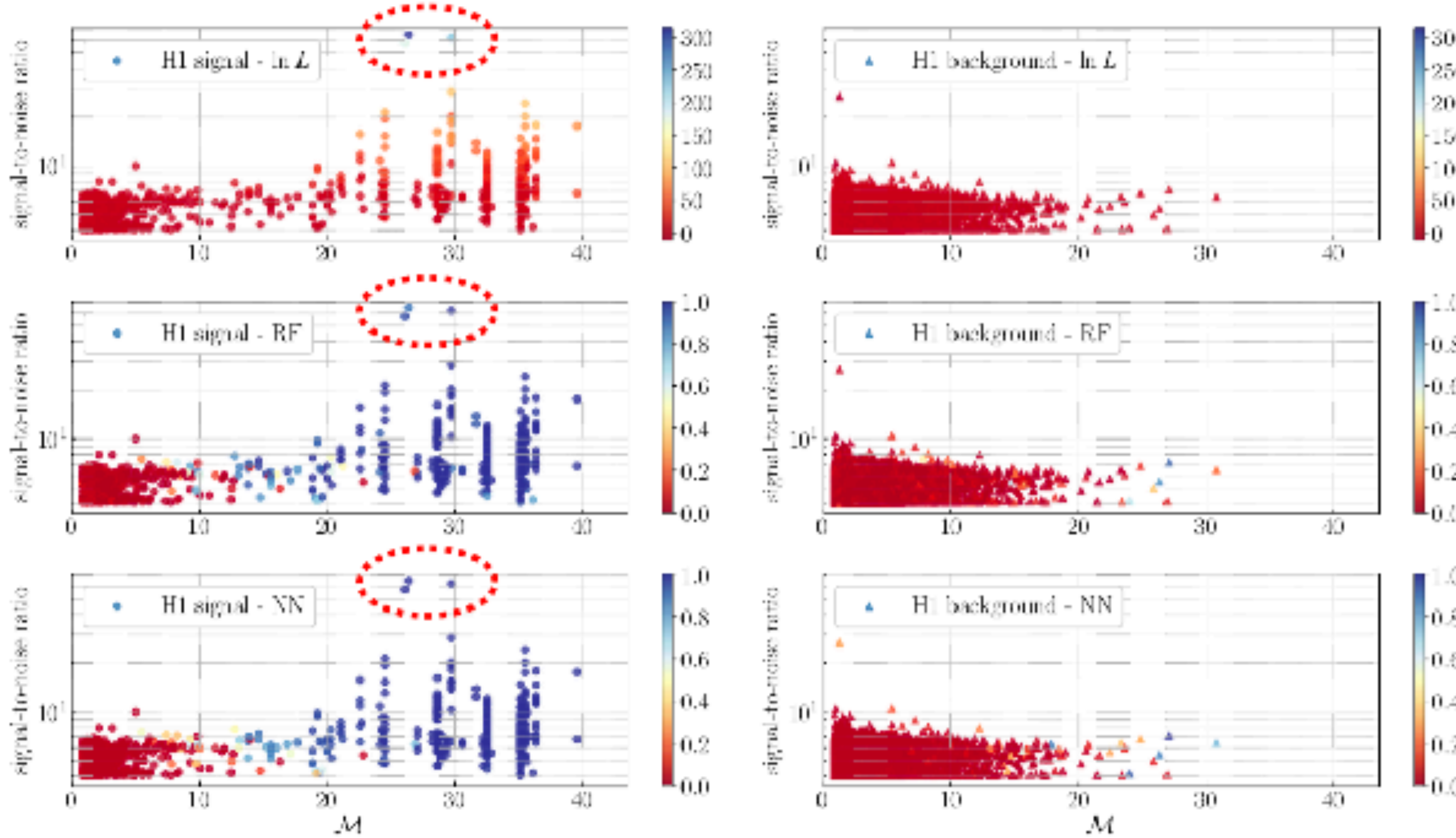
Evaluation

- Time for evaluation (w/ ~ 45 000 samples of 6 features): **~ O(100) ms**
- Output: probabilistic prediction between 0 and 1 → **rank**
- For the performance test of the evaluation result, 3 figure-of-merits were used:
  - Confusion matrix,
  - 2-D histogram: ln L vs. rank of ML,
  - Receiver Operation Characteristic (ROC) curve.

ML for Low-Latency GW Search

KK+, Phys. Rev. D **101** (2020) 8, 083006

Performance Test on Classification



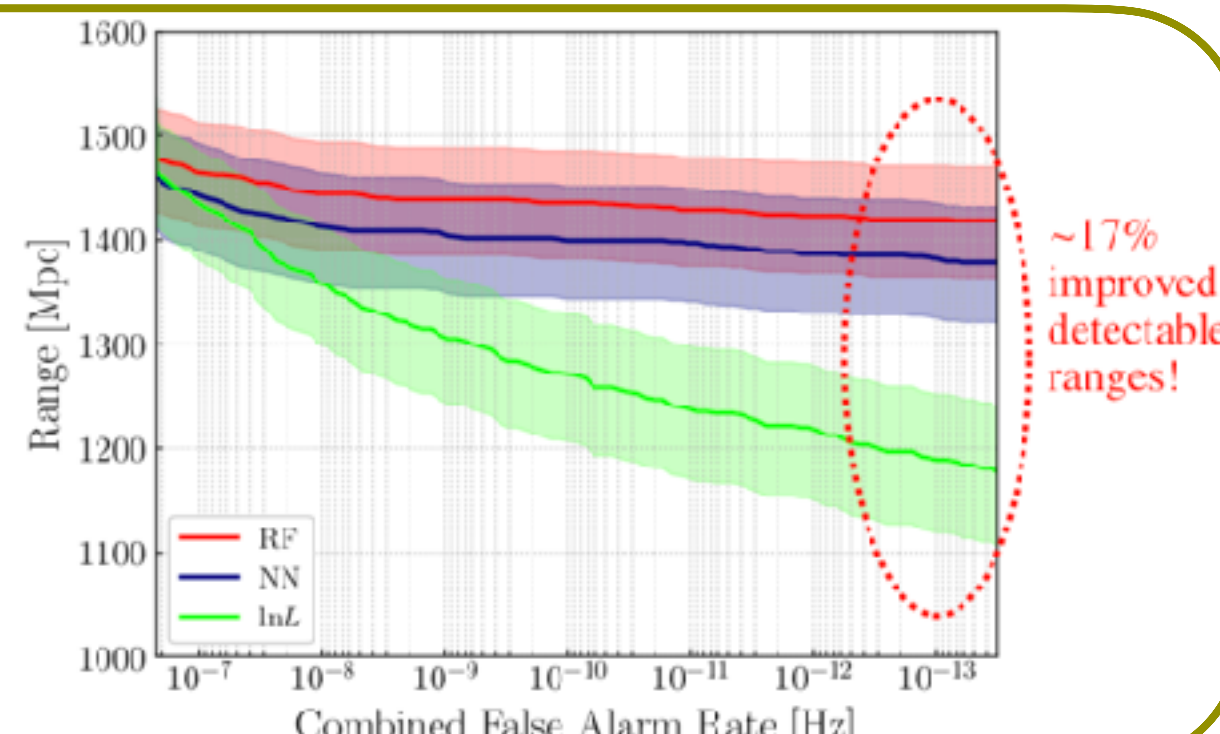
Remarks

- MLAs found high ranks candidate signals of GstLAL pipeline as well.
- MLAs found more candidates signals of lower signal-to-noise ratios than GstLAL pipeline.
- Similar performance on identifying noise samples.

Sensitivity in Detection Range

Remarks

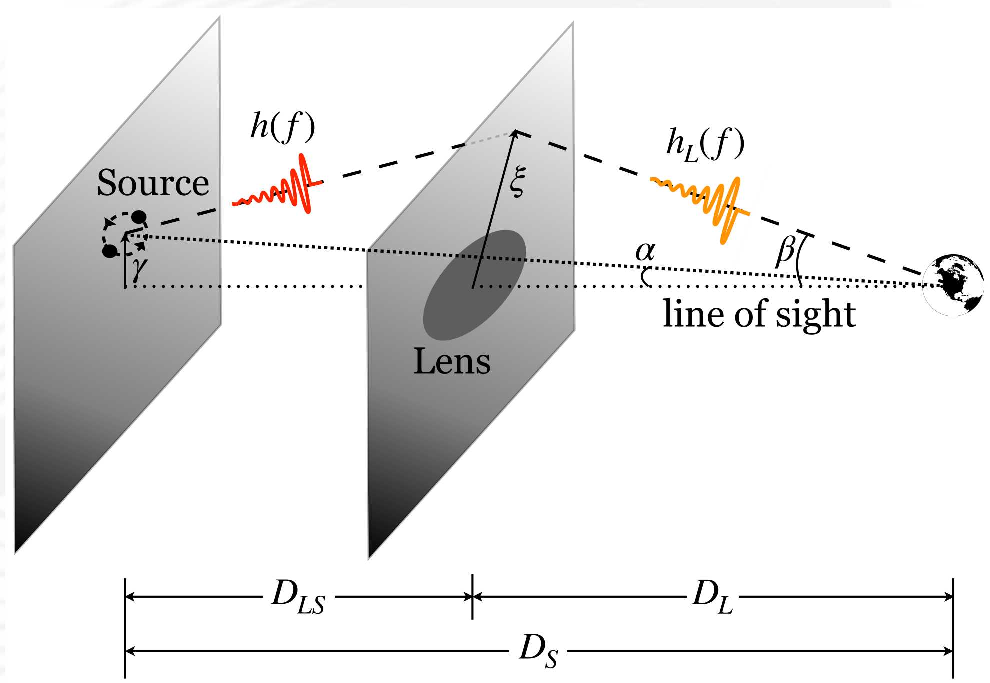
- MLAs could capture more candidate signals generated from sources at farther distances at lower false alarm rate than GstLAL pipeline.

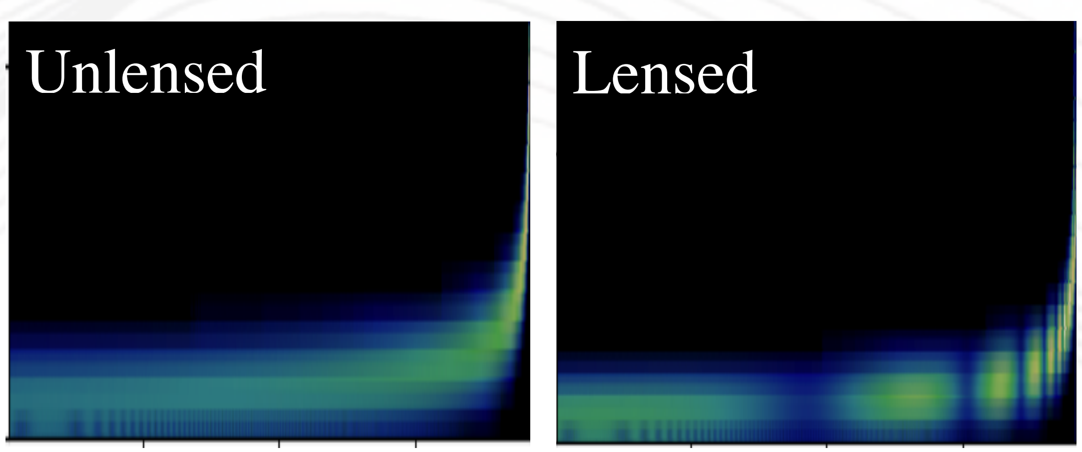


ML for Identification of Lensed GWs

KK+, ApJ **915** (2021) 2, 119

- Motivation
  - If GWs propagate around heavy mass systems, they can be lensed like EM waves.
  - If the time delay of two lensed images is short enough (~ms), the images would be superposed.





- Thin lens approximation
- Strain amplitude of lensed GW in frequency domain

$$h_L(f) = F(f)h(f)$$

where $F(f)$ is the ***amplification factor*** which is determined by the surface mass density and the position parameter y:

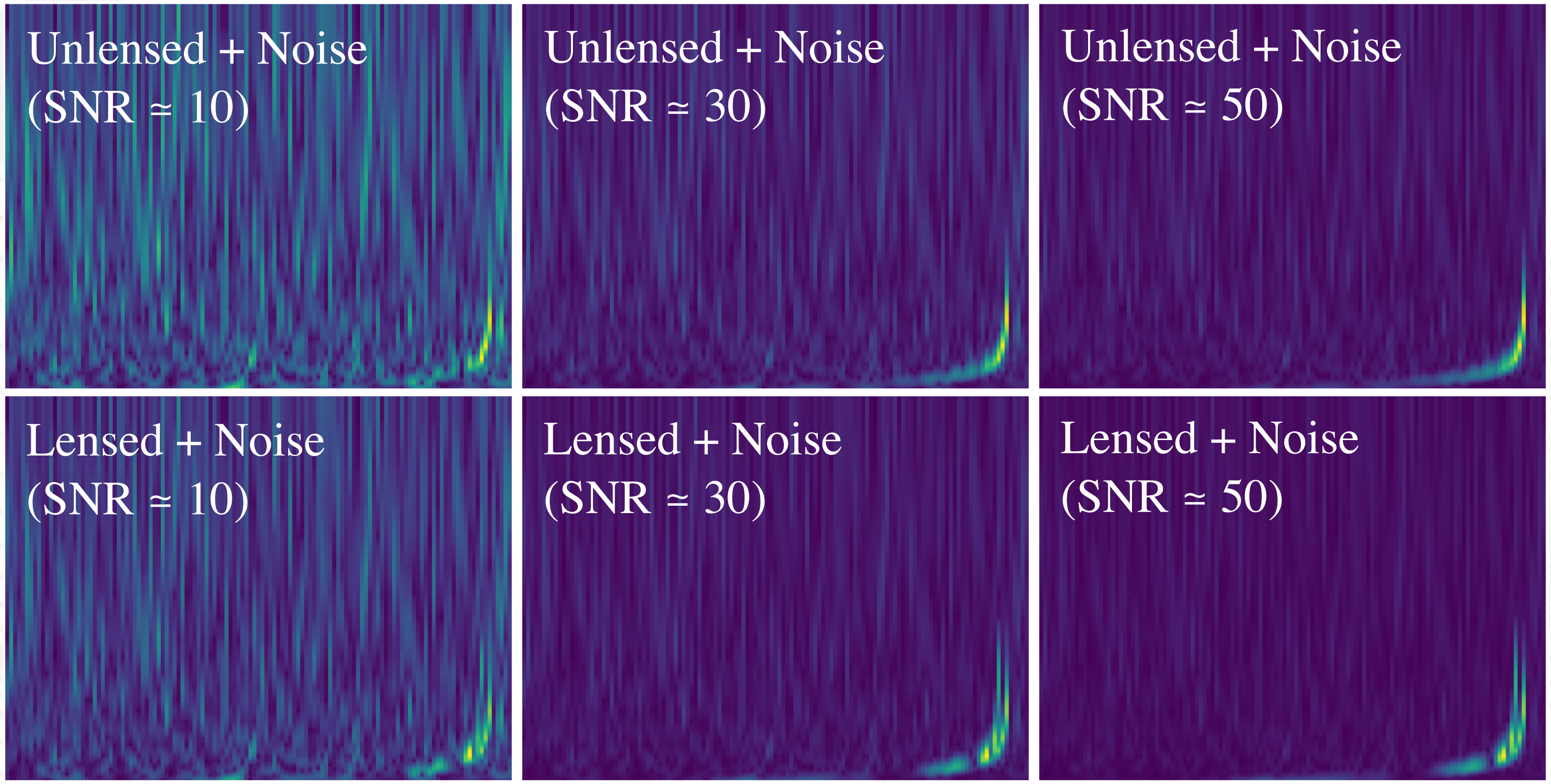
$$y = \frac{\gamma D_L}{\xi_0 D_S}$$

where $\xi_0 = \sqrt{(4GM_L/c^2)D_{LS}D_L/D_S}$ is the Einstein radius of a lens

ML for Identification of Lensed GWs

KK+, ApJ **915** (2021) 2, 119

- Input data: spectrogram using IMRPhenomPv2 and constant-Q transform
  - unlensed+non-precessing (U_N), unlensed+precessing (U_P), and lensed+non-precessing (L)
  - Poin Mass model and Singular Isothermal Sphere model
  - Parameters
    - m_1, m_2: $5-55M_\odot$
    - D_L: $10-1000$Mpc
    - D_{LS}: $10-1000$Mpc
    - M_L: $10^3-10^5M_\odot$
    - γ: $10^{-6}-0.5$pc
  - Noise: aLIGO's DetHighPower model
    - $10 \leq \mathrm{SNR} \leq 50$ (c.f. ≤ 23.6 for BBHs in GWTC-1)
  - # of samples: 45,000 for each type and each lens model
    - training (80%), validation (10%), and evaluation (10%)



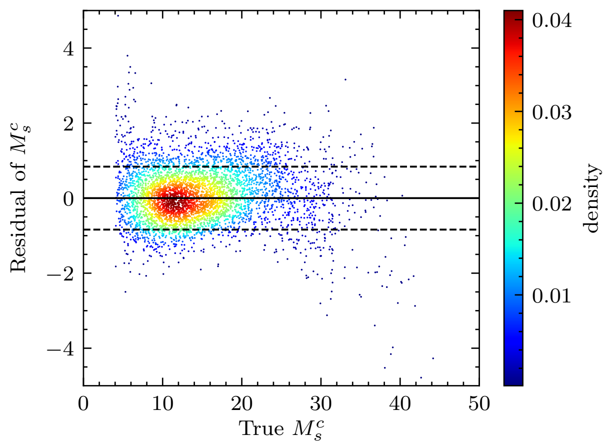
↖ $m_1 = m_2 = 20M_\odot$; $M_L = 10^4M_\odot$
$D_S = 1$Gpc; $D_L = 800$Mpc

ML for Identification of Lensed GWs

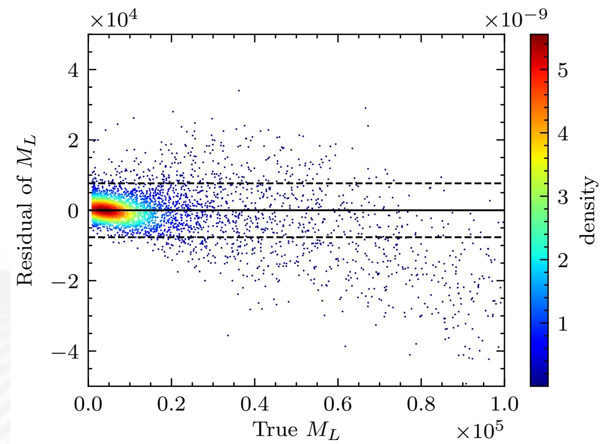
KK+, ApJ **915** (2021) 2, 119

Regression for Parameter Estimation

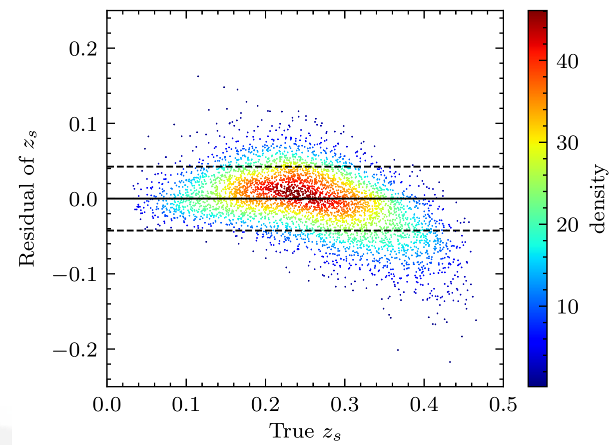
Chirp mass of source



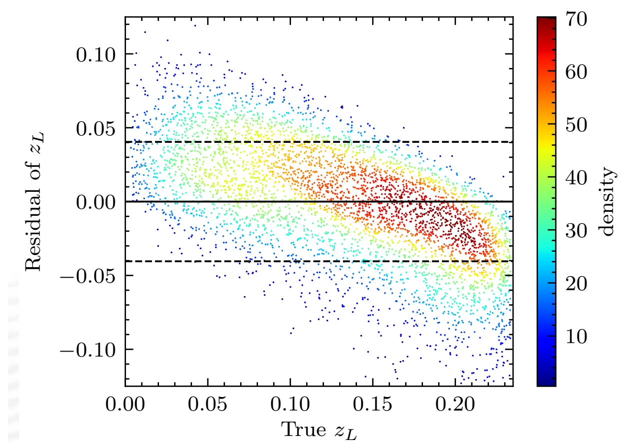
Lens mass



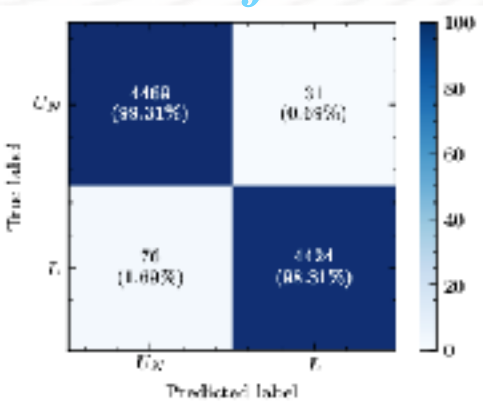
Redshift of source



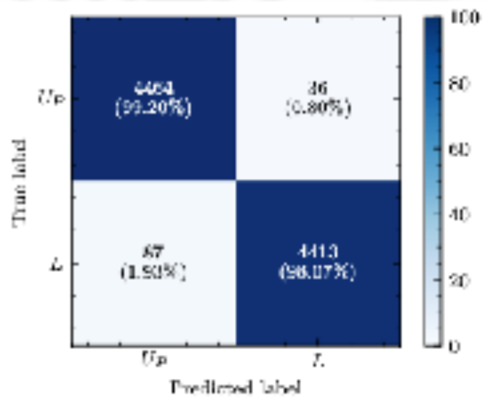
Redshift of Lens



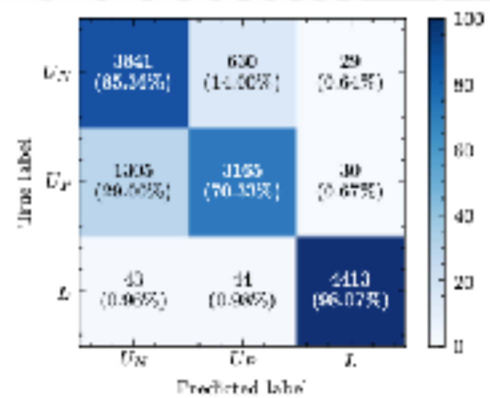
Classification



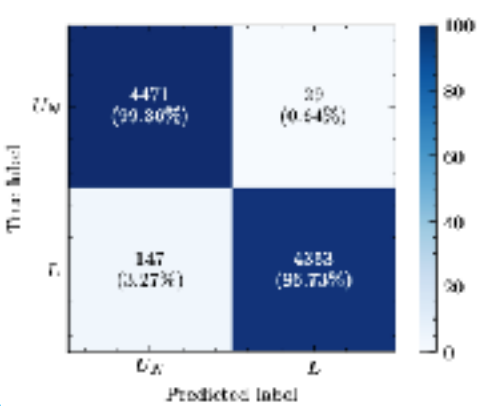
(a) Case I - PM



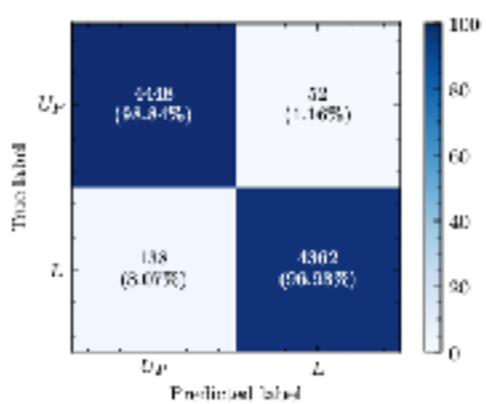
(b) Case II - PM



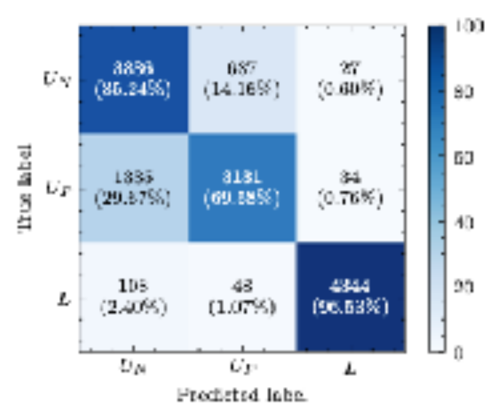
(c) Case III - PM



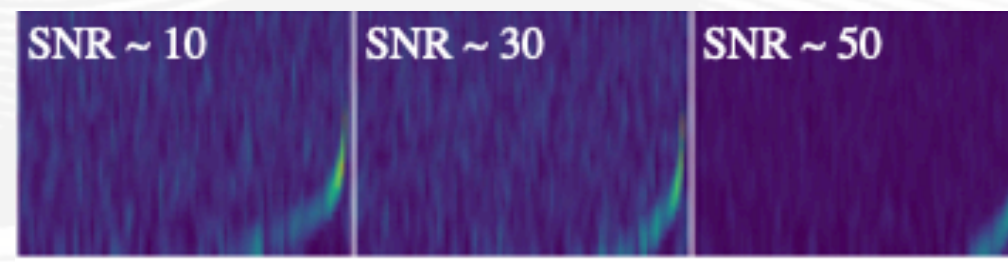
(d) Case I - SIS



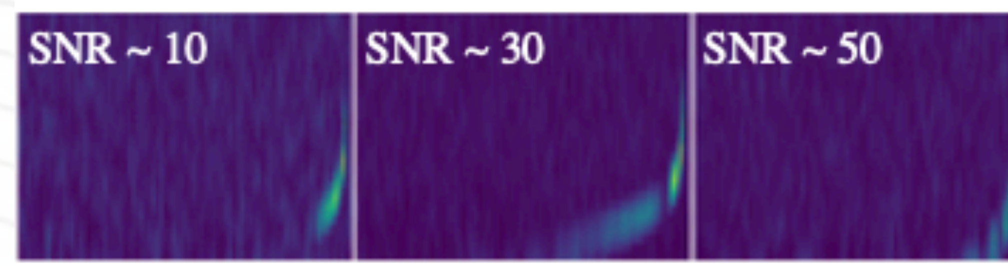
(e) Case II - SIS



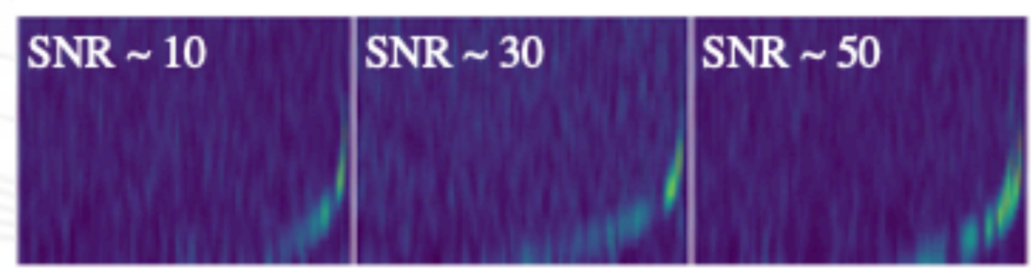
(f) Case III - SIS



(a) Case I - U_N (correct)



(c) Case I - $L_{\rm PM}$ (correct)



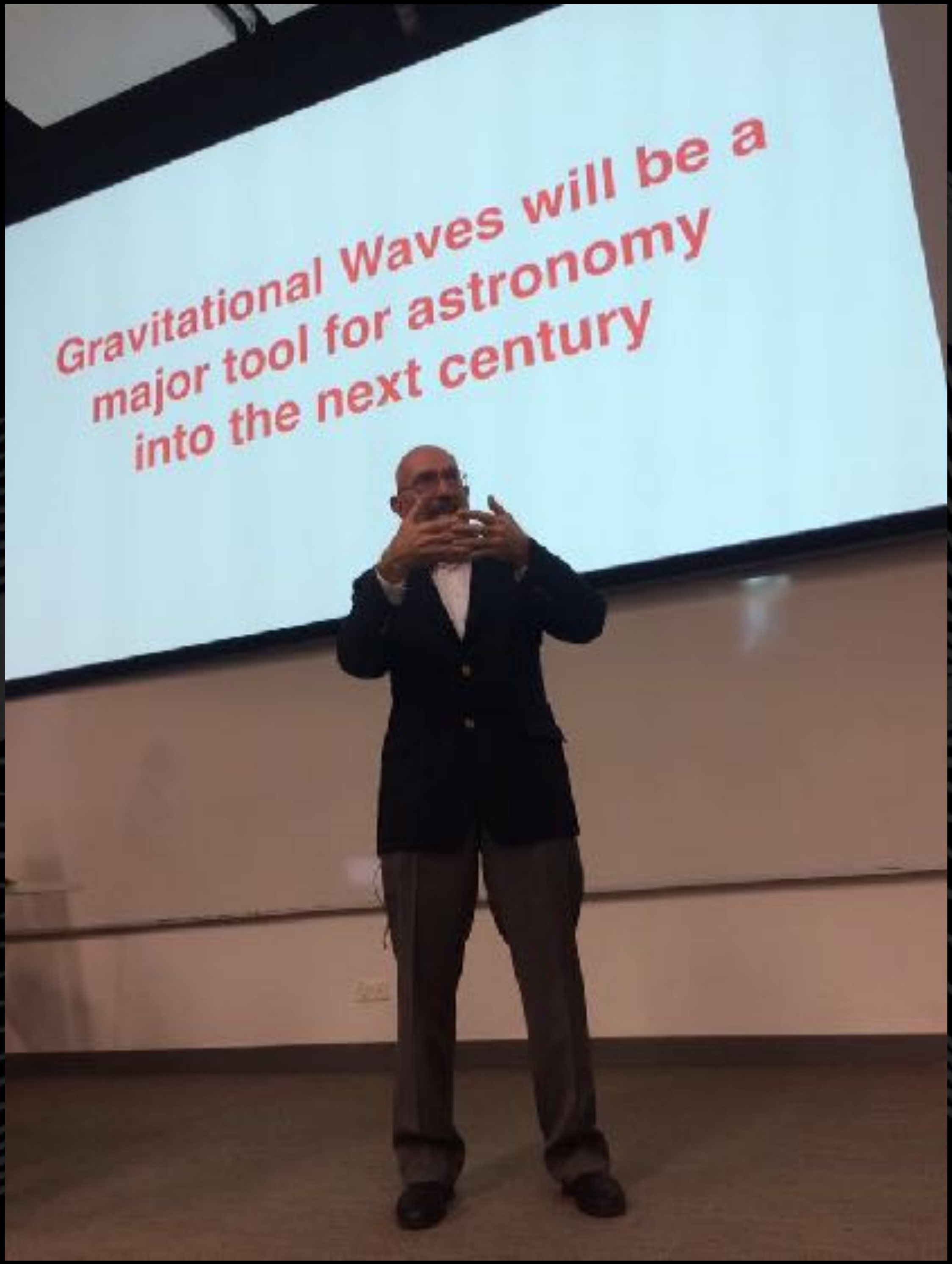
(e) Case I - $L_{\rm SIS}$ (correct)

Summary

- ML is an exciting area of development in the field of multi-messenger astrophysics.
- ML can be used to
  - improve the quality of data,
  - predict the GW waveforms in areas of the signal parameter space not covered by full numerical relativity,
  - search GW signals where the exact signal morphology is unknown,
  - speed up parameter estimation of GW signals,
  - determine the populations of GW sources and their properties, and
  - find EM counterparts to GW signals.
- ML techniques are poised to become essential tools in GW science and multi-messenger astrophysics.

"There are still many untouched topics where we can be the pioneer and make canonical achievements!"

Kip Thorne said...



"Gravitational Waves will be a major tool for astronomy into the next century."

September 30, 2016
Public lecture @ CUHK, Hong Kong

Thank you

for

your attention!