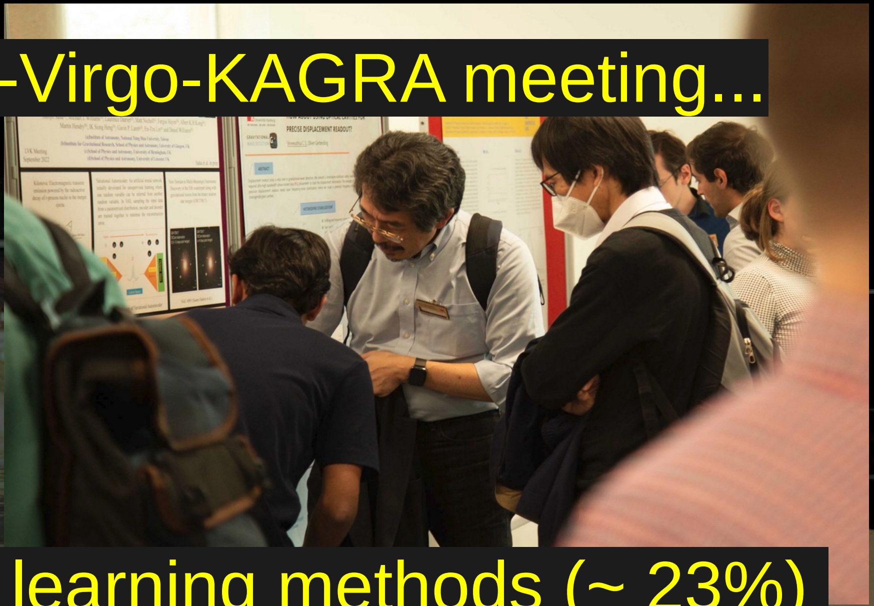
Discovering gravitational waves with Machine Learning

Marco Cavaglià
Missouri University of Science and Technology

Two weeks ago at the LIGO-Virgo-KAGRA meeting...

Photo credits: Cardiff University.

Two weeks ago at the LIGO-Virgo-KAGRA meeting...



75 posters → 17 on machine learning methods (~ 23%)

Photo credits: Cardiff University.

LIGO
DCC

Document List by Topic

Home Reserve Number Search Recent Changes Topics Events Public Help

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These documents on Machine Learning (subtopic of Data Analysis) are available:
(List events on Machine Learning)

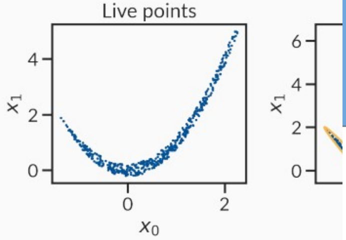
LIGO-Number	Title	Author(s)
G1700088-v1	LIGO detector characterization with genetic programming (Detchar group presentation)	Marco Cavaglia *et al.*
G1700628-v1	Genetic programming	Marco Cavaglia *et al.*
G1700632-v1	PCAT (Principal Component Analysis for Transients)	Marco Cavaglia *et al.*
G1700634-v1	Recording of MLA call 2017-04-05	Marco Cavaglia *et al.*
G1700717-v1	Recording of MLA call 2017-04-19	Marco Cavaglia *et al.*
G1700936-v1	MLA meeting recording 17 May 2017	Ra Inta *et al.*
G1701049-v1	MLA meeting recording 01 Jun 2017	Ra Inta *et al.*

321 documents with machine learning tag after 5 years!

nessai

nessai: Nested Sampling with Artificial Intelligence

Core idea: train a normalising flow to learn likelihood contou
sample directly from those contours to produce new sample



M. J. Williams - LVK September 2022

Deep Learning for LIGO's Lock Acquisition

Machine Learning for non-linear dynamic controls.

Peter Ma | Supervisor: Dr. Gabriele Vajente

Rapid localization of gravitational wave sources from compact binary coalescences using deep learning

Chayan Chatterjee,* Linqing Wen,† and Damon Beveridge‡
Department of Physics, OzGrav-UWA, The University of Western Australia, 35 Stirling Hwy, Crawley, Western Australia 6009, Australia

Foivos Diakogiannis§
The Commonwealth Scientific and Industrial Research Organisation 7 Conlon St, Waterford, WA, Australia

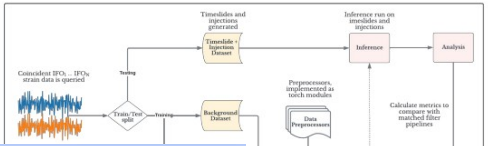
Kevin Vinsen¶
International Centre for Radio Astronomy Research, The University of Western Australia M468, 35 Stirling Hwy, Crawley, WA, Australia

(Dated: July 21, 2022)

A Machine Learning Software Infrastructure for Gravitational Wave Signal Discovery

Ethan Marx

How can ML detection algorithms achieve results comparable to matched filter



A convolutional neural network to distinguish glitches from minute-long gravitational wave bursts

Vincent Boudart

PhD student
University of Liège, Belgium

UNIVERSITY OF ILLINOIS URBANA-CHAMPAIGN — MISSOURI S&T — MONTCLAIR STATE UNIVERSITY

GRITS: Genetic Rapid Inference for Trigger Sources

A machine learning algorithm to identify GW signals with EM counterpart

Sushant Sharma Chaudhary[1], Marco Cavaglia[1], Deep Chatterjee[2], Shaon Ghosh[3]
[1]Missouri University of Science and Technology,
[2]Center for AstroPhysical Surveys, NCSA, University of Illinois Urbana-Champaign, [3]Montclair State University

IFAE — EGO

Searches for Compact Binary Coalescence Events using Neural Networks in LIGO/Virgo Third Observation Period

M. Andrés-Carcasona[1], A. Menéndez-Vázquez[1], M. Martínez[1,2], Ll. M. Mir[1]
[1] Institut de Física d'Altes Energies (IFAE), Barcelona Institute of Science and Technology, E-08193 Barcelona, Spain
[2] Catalan Institution for Research and Advanced Studies (ICREA), E-08010 Barcelona, Spain

UNIVERSITY PRIFYSGOL CAERDYDD

MLy-Pipeline , a new transient search pipeline for O4

Vasileios Skliris[1,2], Patrick Sutton[1] , Michael Norman[1] ,
Kyle Willetts[1] , Wasim Javed[1] , Amin B
1. Gravity Exploration Institute, Cardiff Univ
2. Data Innovation Institute, Cardiff Unive

Overview

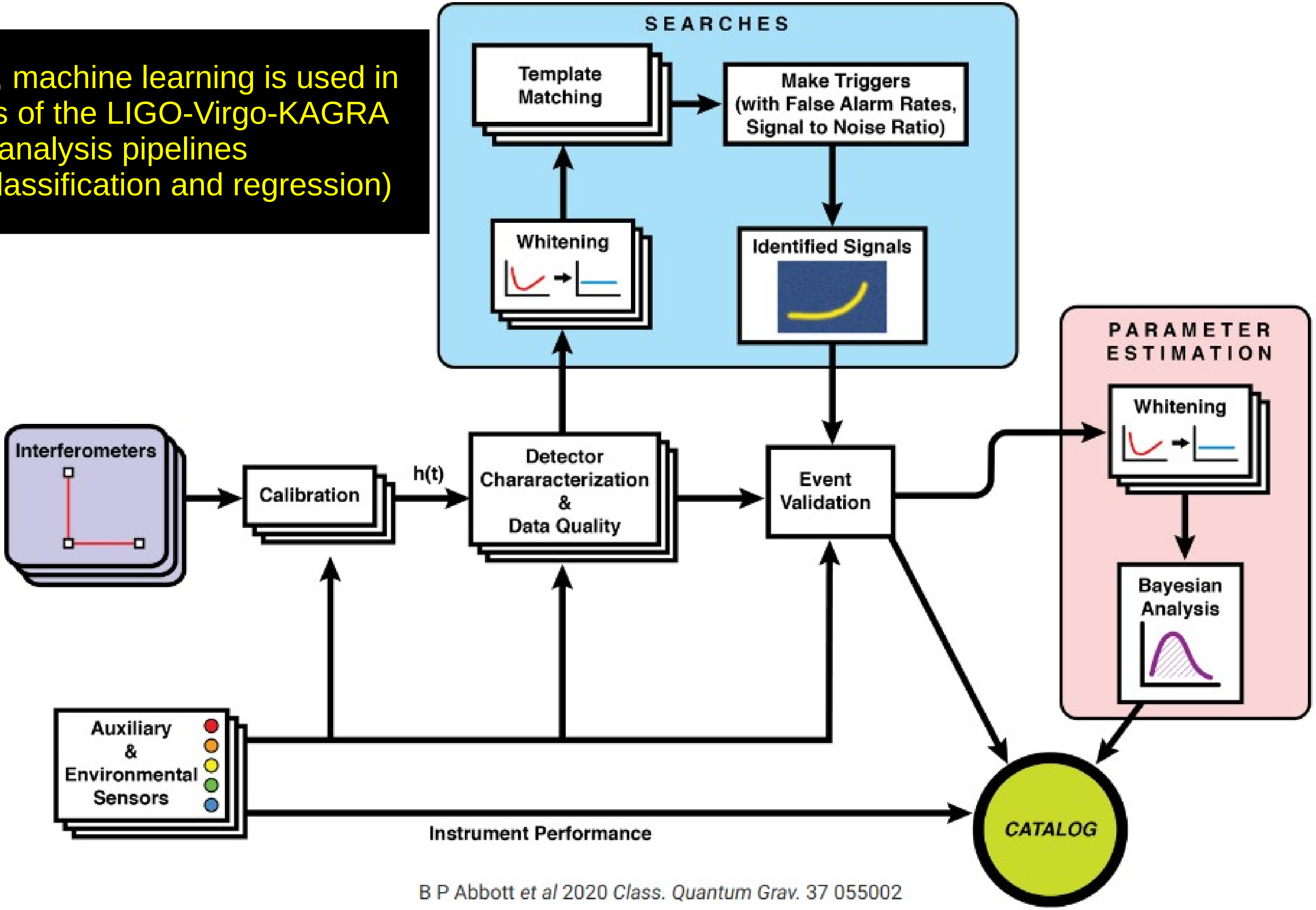
MLy-pipeline is an exclusively machine learning pipeline that is used to quickly identify generic transient signals from detector noise. Its function is provided by a combination of a residual CNN and a simple CNN model classifier. [1] For a given positive classification,

MLy-pipelir
To measur
minimum
which mea

All-sky search for gravitational-wave bursts in the third Advanced LIGO-Virgo run with coherent WaveBurst enhanced by Machine Learning

Marek J. Szczepańczyk,[1] Francesco Salemi,[2,3,a] Sophie Bini,[2,3] Tanmaya Mishra,[1] Gabriele Vedovato,[4] V. Gayathri,[1] Imre Bartos,[1] Shubhagata Bhaumik,[1] Marco Drago,[5,6] Odysse Halim,[7,8] Claudia Lazzaro,[9,10] Andrea Miani,[2,3] Edoardo Milotti,[7,8] Giovanni A. Prodi,[11,3] Shubhanshu Tiwari,[12] and Sergey Klimenko[1]
[1]*Department of Physics, University of Florida, PO Box 118440, Gainesville, FL 32611-8440, USA*
[2]*Università di Trento, Dipartimento di Fisica, I-38123 Povo, Trento, Italy*

Nowadays, machine learning is used in all aspects of the LIGO-Virgo-KAGRA analysis pipelines
(both for classification and regression)



B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

An (incomplete) overview of machine learning in gravitational-wave science

IOP Publishing   *Mach. Learn.: Sci. Technol.* **2** (2021) 011002   https://doi.org/10.1088/2632-2153/abb93a

MACHINE LEARNING
Science and Technology

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RECEIVED
7 May 2020

REVISED
31 July 2020

ACCEPTED FOR PUBLICATION
16 September 2020

PUBLISHED
1 December 2020

TOPICAL REVIEW

Enhancing gravitational-wave science with machine learning

Elena Cuoco[1,2,3], Jade Powell[4], Marco Cavaglià[5], Kendall Ackley[6,7], Michał Bejger[8], Chayan Chatterjee[7,9], Michael Coughlin[10,11], Scott Coughlin[12], Paul Easter[6,7], Reed Essick[13], Hunter Gabbard[14], Timothy Gebhard[15,16], Shaon Ghosh[17], Leïla Haegel[18], Alberto Iess[19,20], David Keitel[21], Zsuzsa Márka[22], Szabolcs Márka[23], Filip Morawski[8], Tri Nguyen[24], Rich Ormiston[25], Michael Pürrer[26], Massimiliano Razzano[3,27], Kai Staats[12], Gabriele Vajente[10] and Daniel Williams[14]

1 European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy.
2 Scuola Normale Superiore (SNS), Piazza dei Cavalieri, 7 - 56126 Pisa, Italy.
3 Istituto Nazionale di Fisica Nucleare, Sezione di Pisa, Pisa, I-56127, Italy.

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TOPICAL REVIEW

Outdated!

Enha … machine learning

Elena C… Ma…o Cavaglià[5], Kendall Ackley[6,7], Michał Bejger[8], Chayan C…[9], …el Coughlin[10,11], Scott Coughlin[12], Paul Easter[6,7], Reed Essick[13], Hunter Gabb…[14], Timothy Gebhard[15,16], Shaon Ghosh[17], Leïla Haegel[18], Alberto Iess[19,20], David Keitel[21], Zsuzsa Márka[22], Szabolcs Márka[23], Filip Morawski[8], Tri Nguyen[24], Rich Ormiston[25], Michael Pürrer[26], Massimiliano Razzano[3,27], Kai Staats[12], Gabriele Vajente[10] and Daniel Williams[14]

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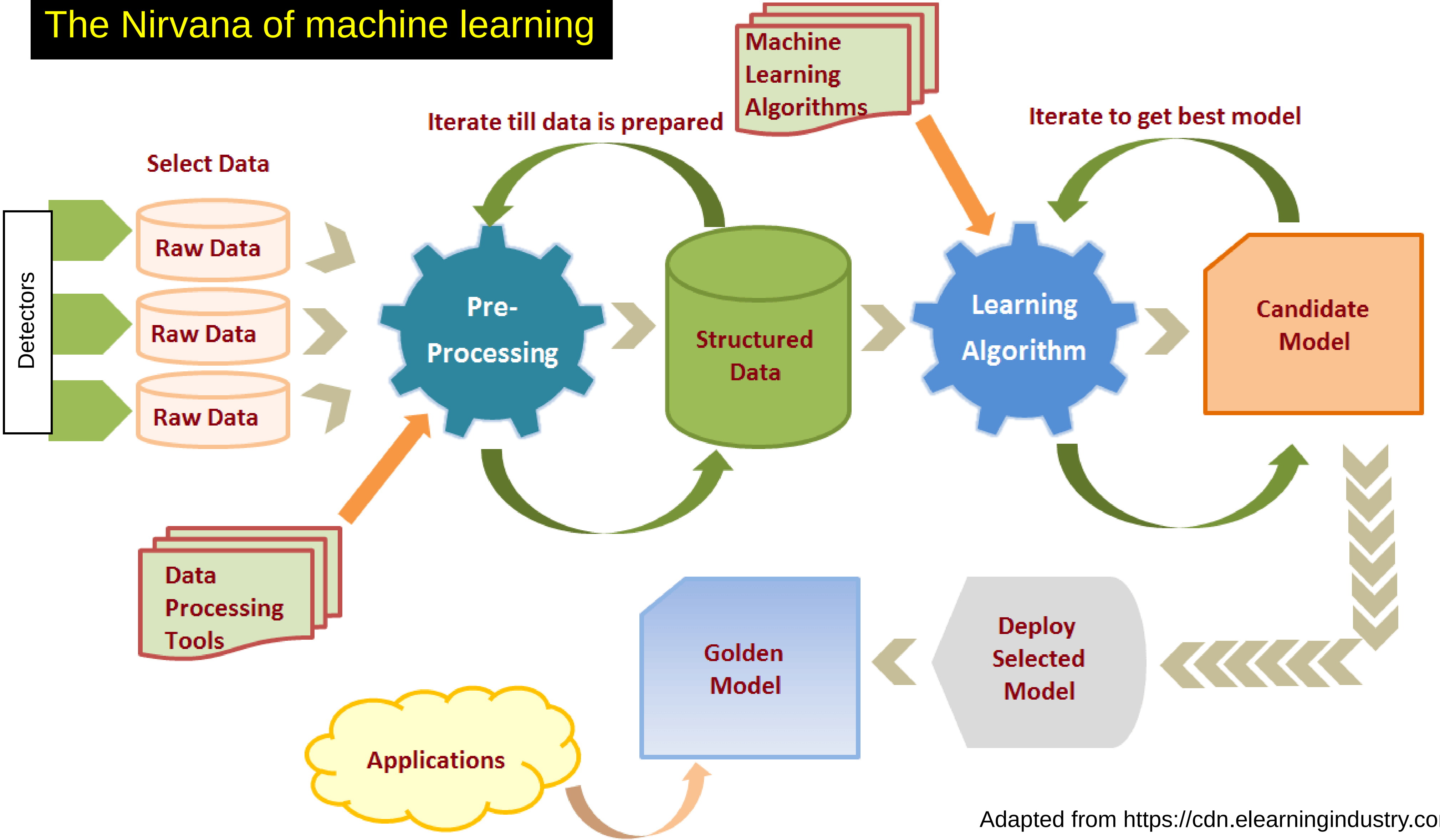
The Nirvana of machine learning



Adapted from https://cdn.elearningindustry.com/

The Nirvana of machine learning

nirvana noun

nir·va·na nir-ˈvä-nə (ˌ)nər-

often capitalized

1 : the final beatitude (see BEATITUDE sense 1a) that transcends suffering, karma, and samsara and is sought especially in Buddhism through the extinction of desire and individual consciousness

2 **a** : a place or state of oblivion to care, pain, or external reality

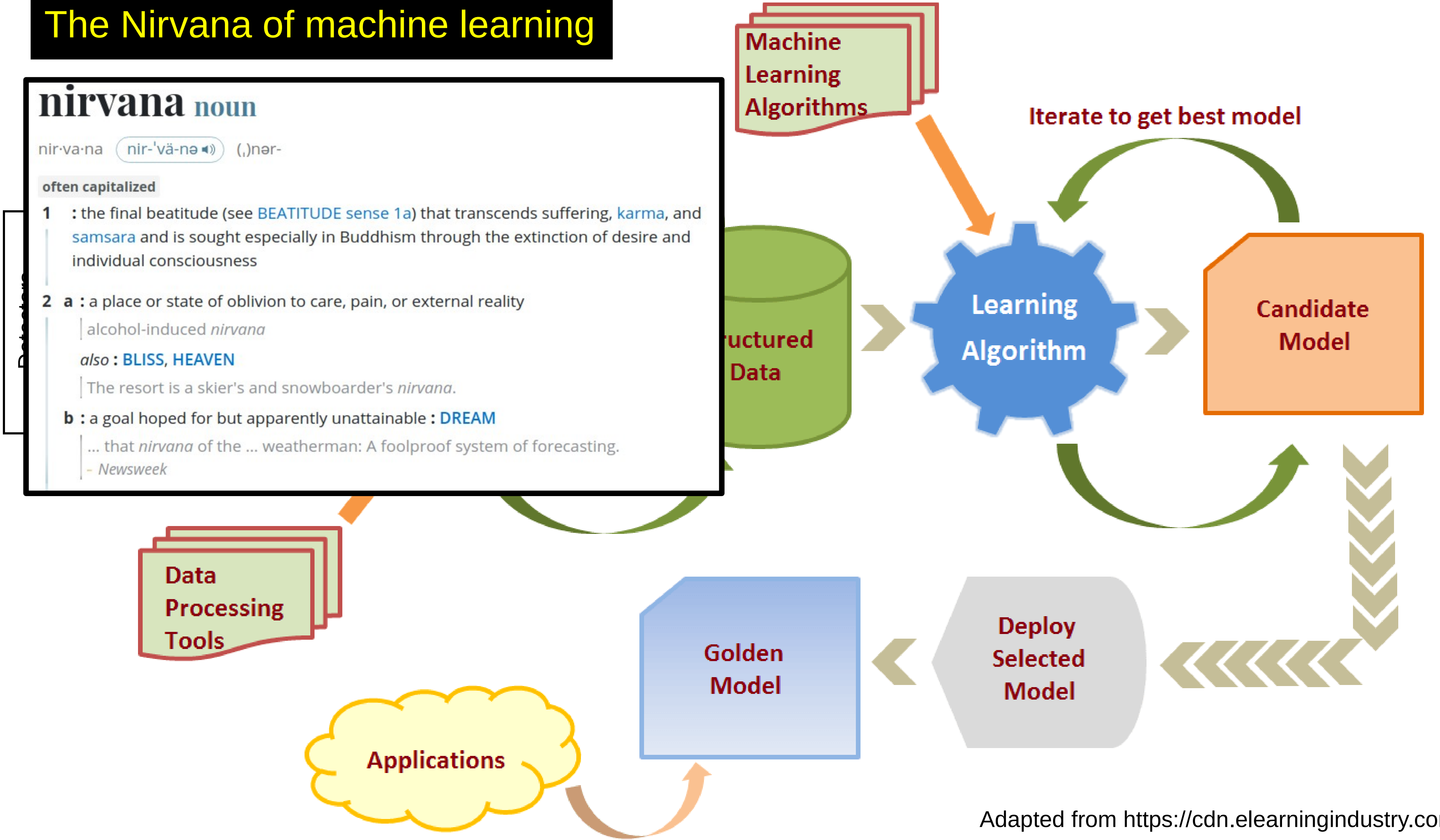
alcohol-induced *nirvana*

also : BLISS, HEAVEN

The resort is a skier's and snowboarder's *nirvana*.

b : a goal hoped for but apparently unattainable : DREAM

… that *nirvana* of the … weatherman: A foolproof system of forecasting.
– *Newsweek*



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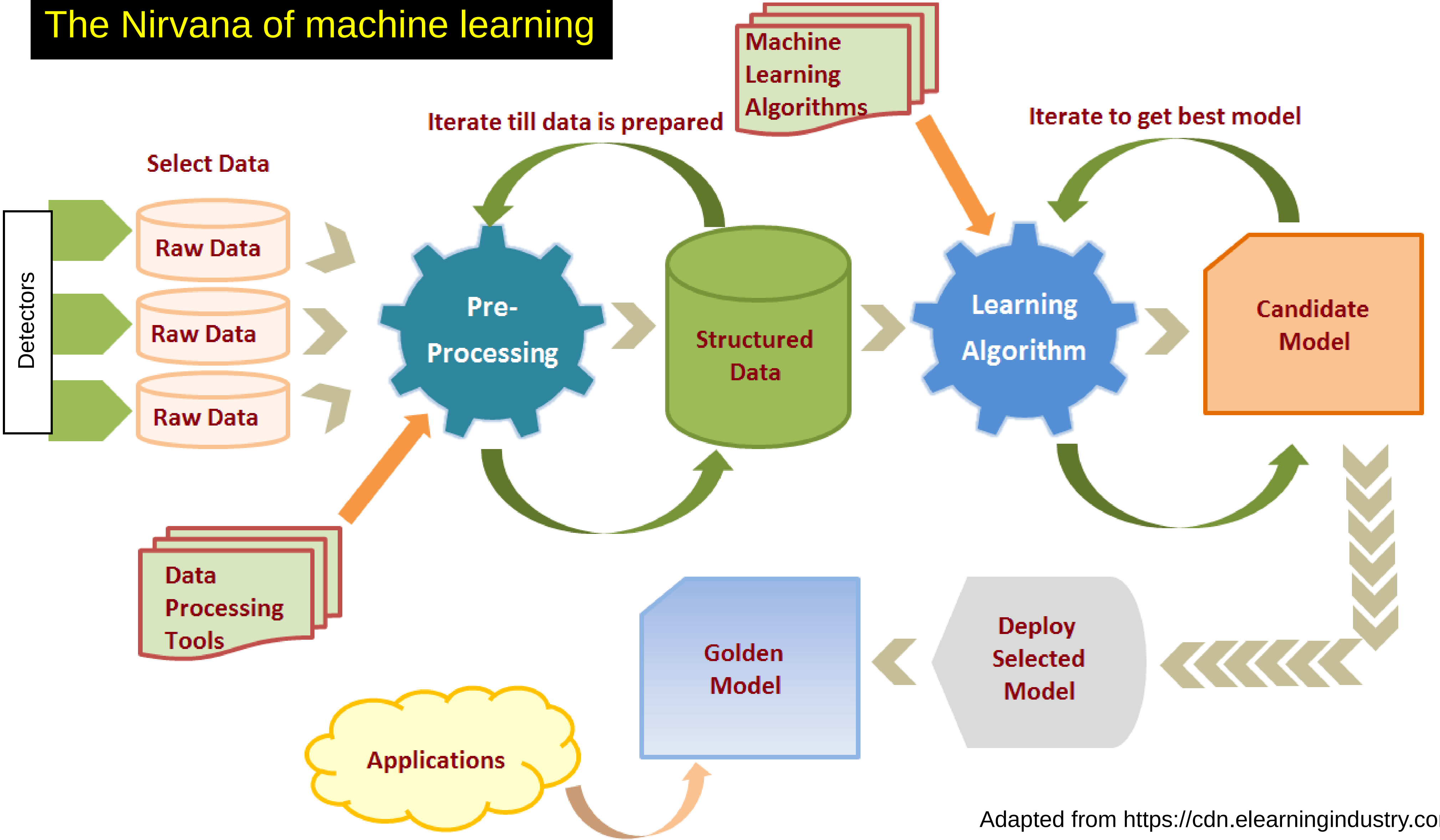
The Nirvana of machine learning



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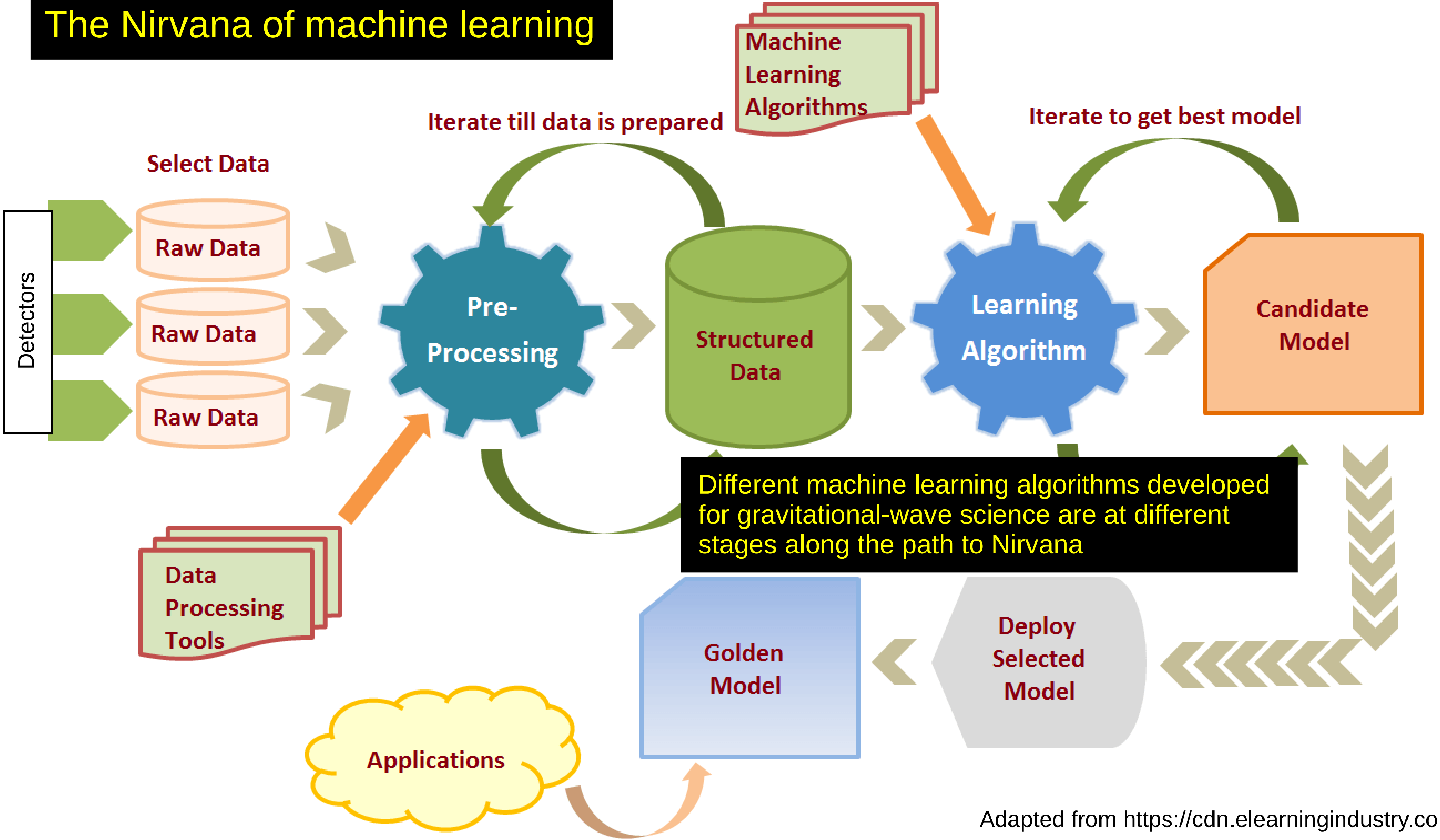
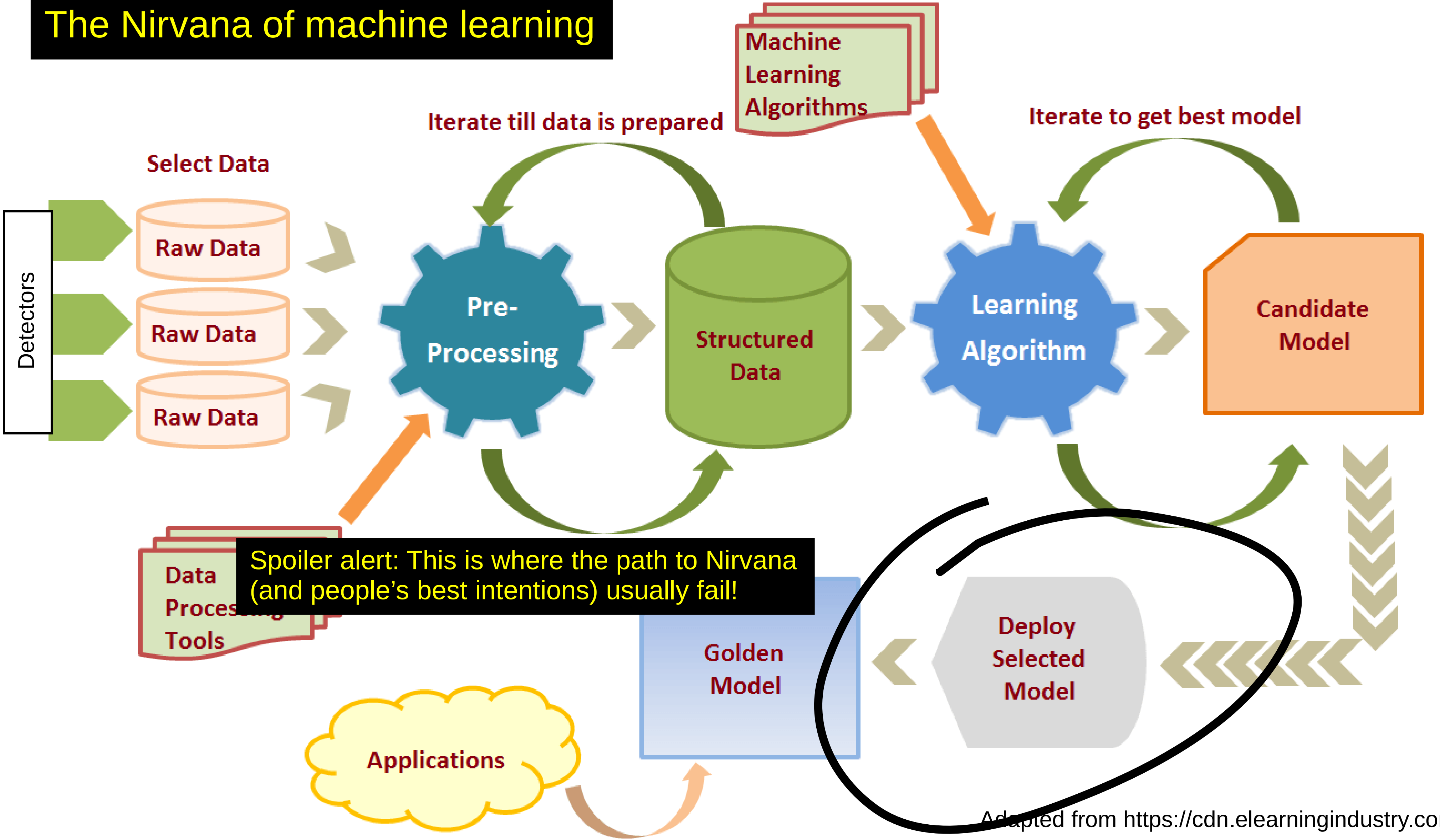
The Nirvana of machine learning



Different machine learning algorithms developed for gravitational-wave science are at different stages along the path to Nirvana

Adapted from https://cdn.elearningindustry.com/

The Nirvana of machine learning



Spoiler alert: This is where the path to Nirvana (and people's best intentions) usually fail!

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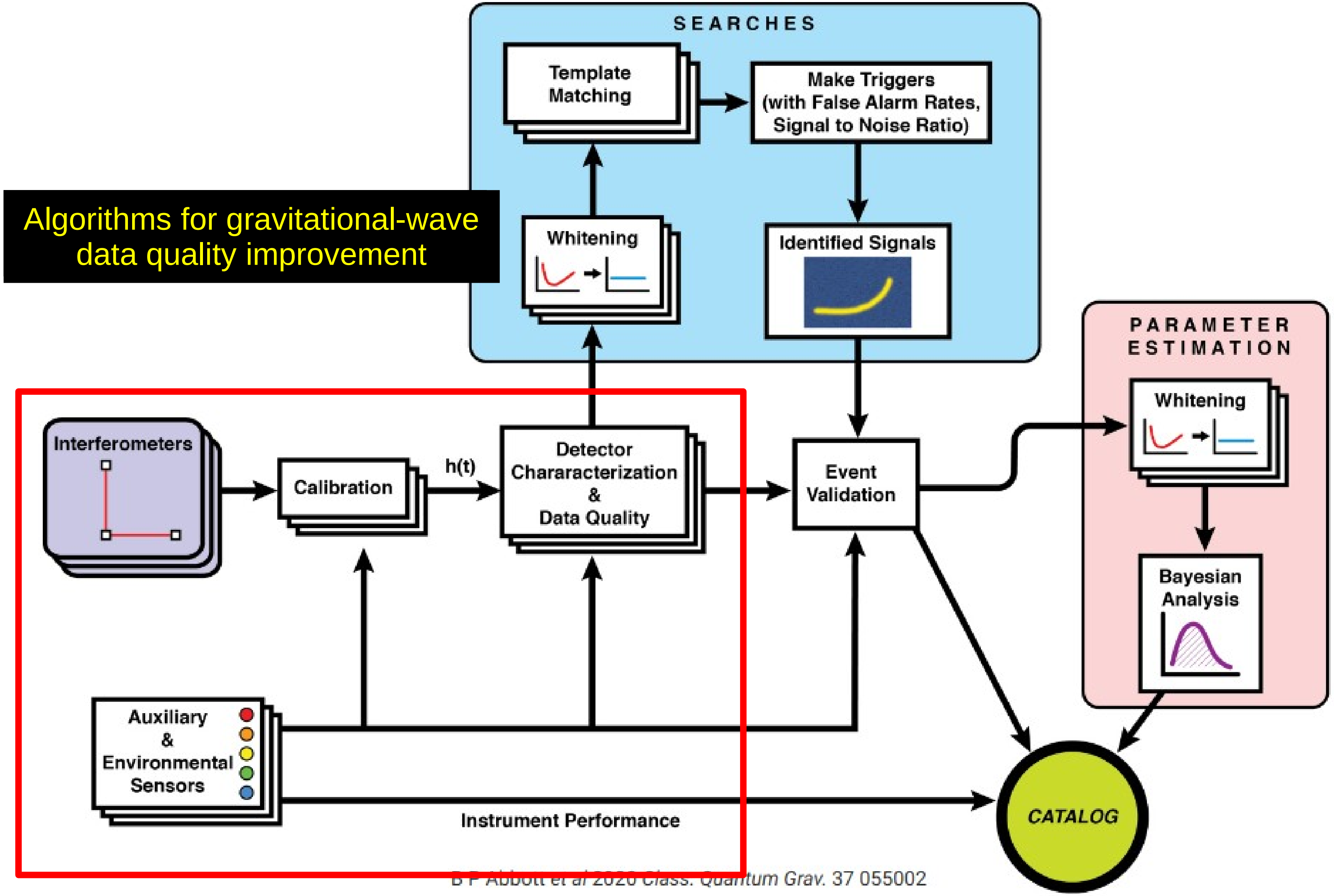
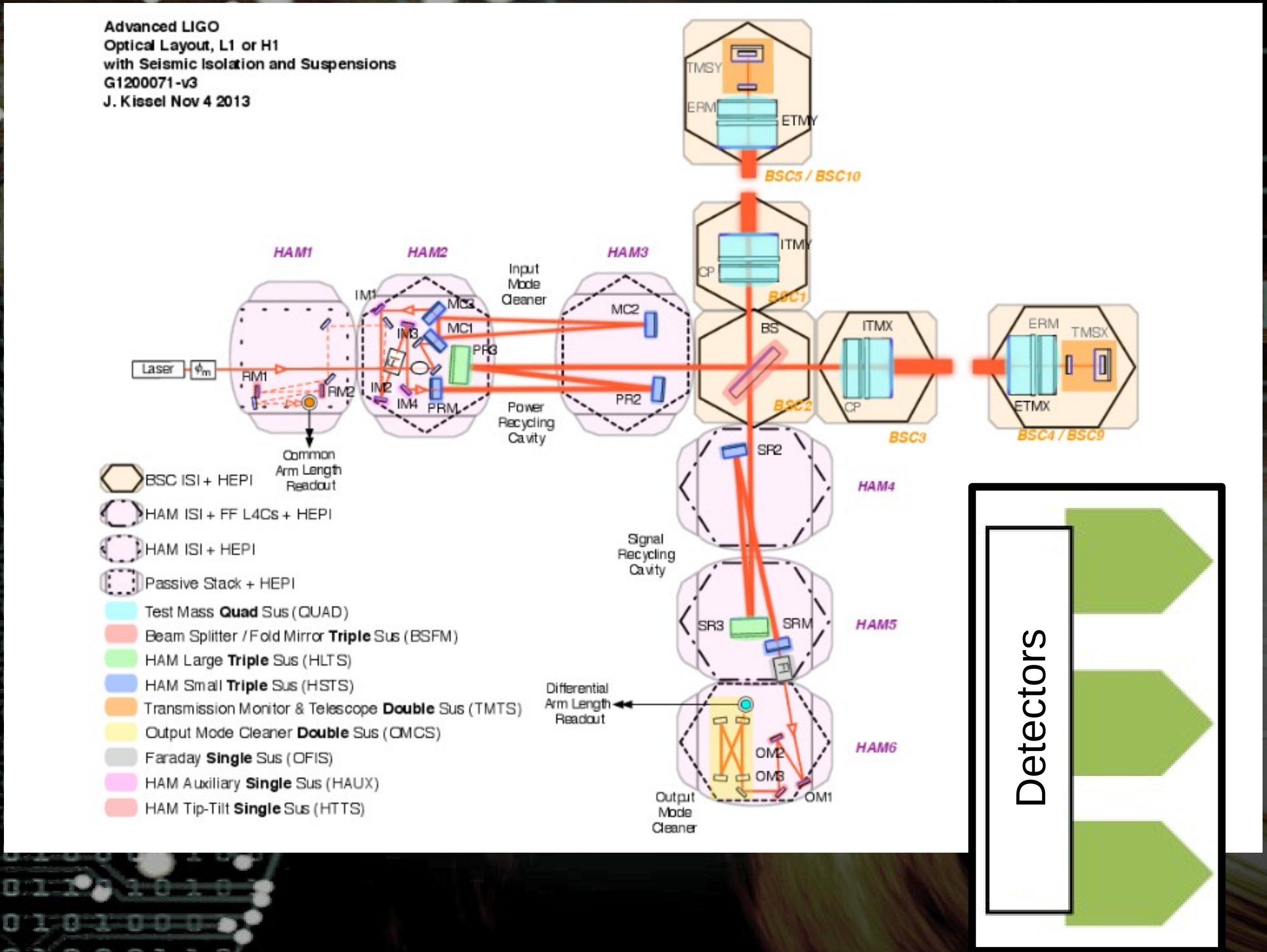
Algorithms for gravitational-wave data quality improvement



B P Abbott et al 2020 Class. Quantum Grav. 37 055002

Algorithms for gravitational-wave data quality improvement

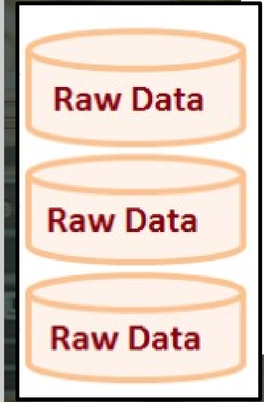


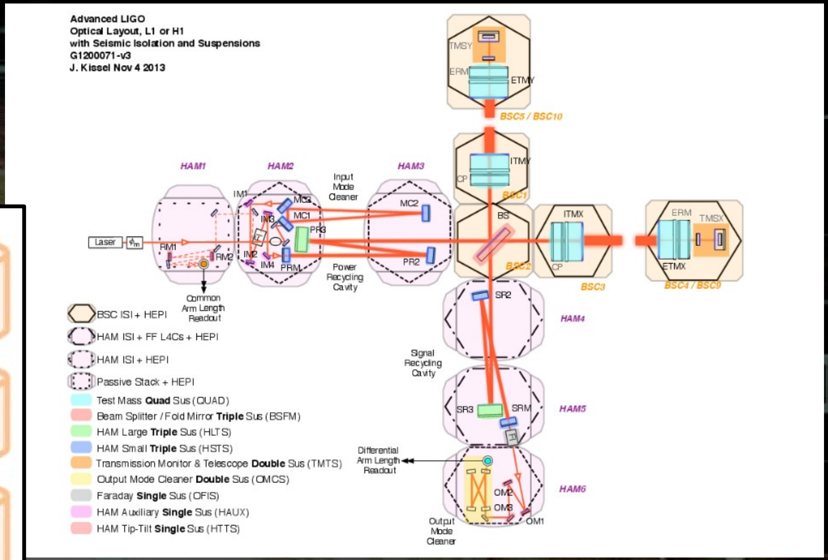
- Sensors continuously monitor the behavior of the detectors and their environment.
- Sensor data are used to characterize noise that may negatively impact searches and signal estimation.
- Information is in the form of time series.
- Invalid data due to detector malfunctions, calibration errors, data acquisition are be removed from analyses.
- Flags are created according to different levels of data quality.

Algorithms for gravitational-wave data quality improvement

Over 200,000 auxiliary channels per detector!

- Different data rates from few Hz to 65536 Hz. (Strain is at 16384 Hz).
- Different units.
- Different acquisition systems.
- Safe and unsafe channels.





<u>A full, manual analysis</u> of auxiliary channel data is generally <u>impracticable</u> because of the huge number of instrumental and environmental monitoring sensors. The power of machine learning to handle huge data sets has recently been exploited to analyze auxiliary channel data.

Algorithms for gravitational-wave data quality improvement

To complicate matters…

- Fundamental noise sources inherent to the detector’s design, e.g.,
  - Quantum sensing noise
  - Suspension thermal noise
  - Mirror coating thermal noise
  - Gravity gradient noise

- Additional noise sources related to the detector’s control or environment, e.g.,
  - Feedback control system noise
  - Electronic or mechanical noise
  - Seismic noise and gravity gradient noise
  - Anthropogenic noise
  - Weather

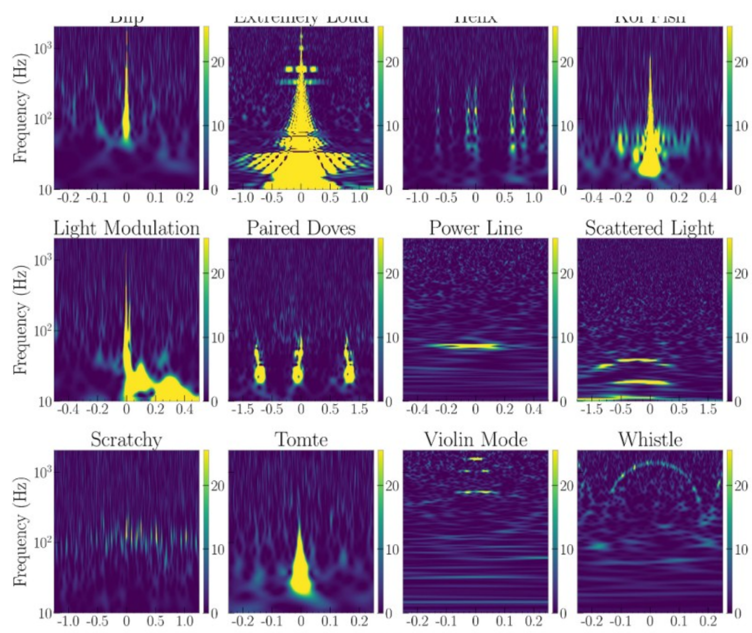


Figure 1. Time-frequency representations of different types of glitches occurring in GW data. (Examples from the GravitySpy project [45]). ML algorithms can help identify the origin of these glitches and increase the sensitivity of GW transient searches.

Elena Cuoco et al. 2021 Mach. Learn.: Sci. Technol. 2 011002

- Most of these noise sources are non-stationary over a range of time scales.
- They typically couple to the detector strain in a nonlinear way.
- Short-lived excess noise is referred as “transient noise” or more colloquially “glitches”.
- Persistent excess noise confined to certain frequencies is referred as “spectral lines”.
- How can machine learning help?

Algorithms for gravitational-wave data quality improvement

Noise transient classification on strain

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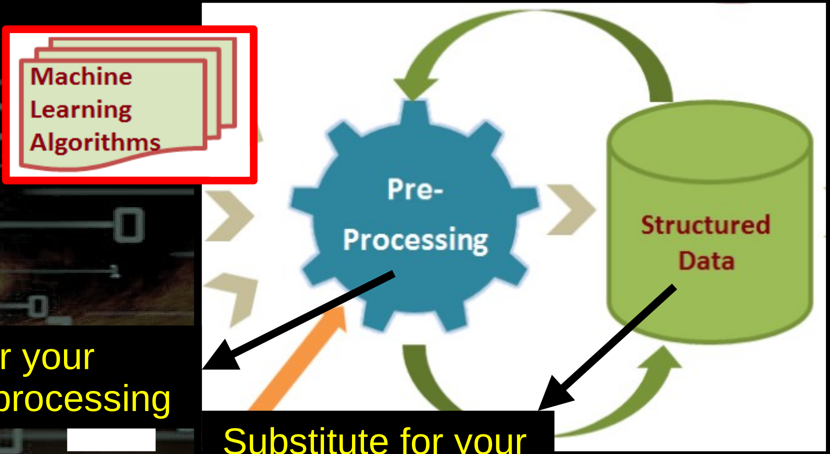
Classical and Quantum Gravity
Class. Quantum Grav. 32 (2015) 215012 (20pp)
doi:10.1088/0264-9381/32/21/215012

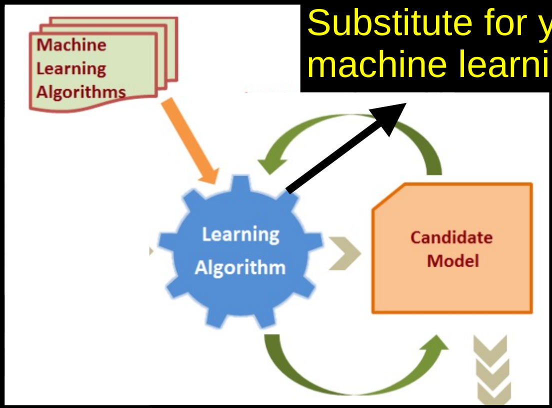
Classification methods for noise transients in advanced gravitational-wave detectors

Jade Powell[1], Daniele Trifirò[2,3], Elena Cuoco[4,5], Ik Siong Heng[1] and Marco Cavaglià[3]

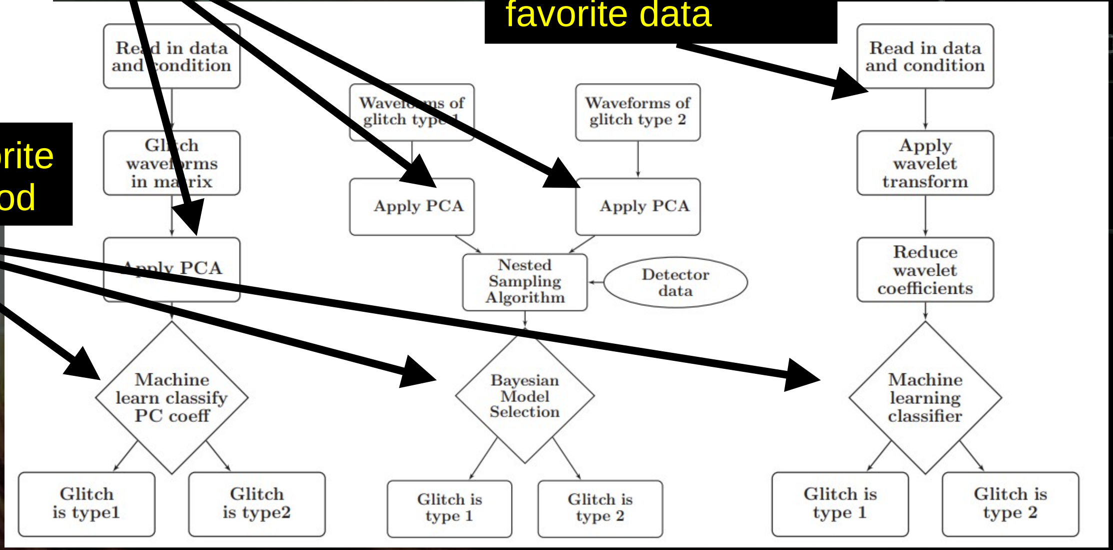


Substitute for your favorite pre-processing

Substitute for your favorite data



Substitute for your favorite machine learning method

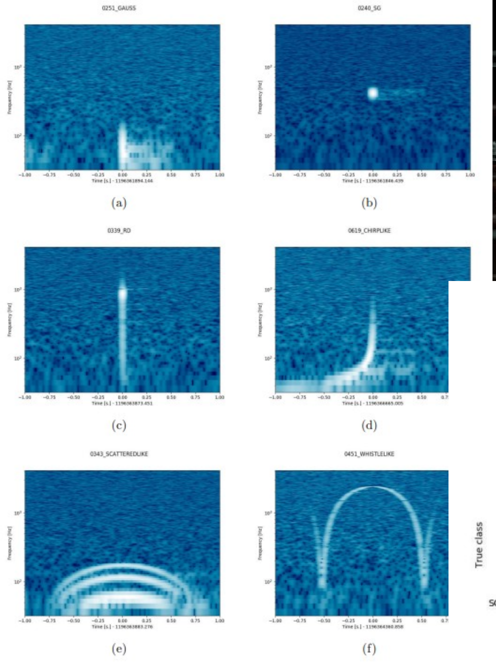


Algorithms for gravitational-wave data quality improvement

Noise transient classification on strain: deep learning approach

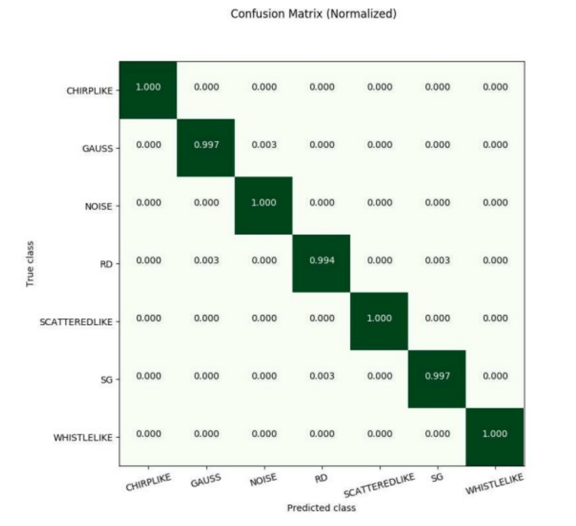
Image-based deep learning for classification of noise transients in gravitational wave detectors

Massimiliano Razzano[1,3] and Elena Cuoco[2,3]
Department of Physics, University of Pisa, Pisa I-56127, Italy
European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy
Istituto Nazionale di Fisica Nucleare, Sezione di Pisa, Pisa I-56127, Italy
E-mail: massimiliano.razzano@unipi.it



Machine Learning Algorithms

simulated glitches + Gaussian noise



Use 2D matrices (images) for classification purposes, e.g., spectrograms, Q-transforms

CNNs have an unique power to automatically extract the most significant features from an image, which can be used to distinguish between different images.

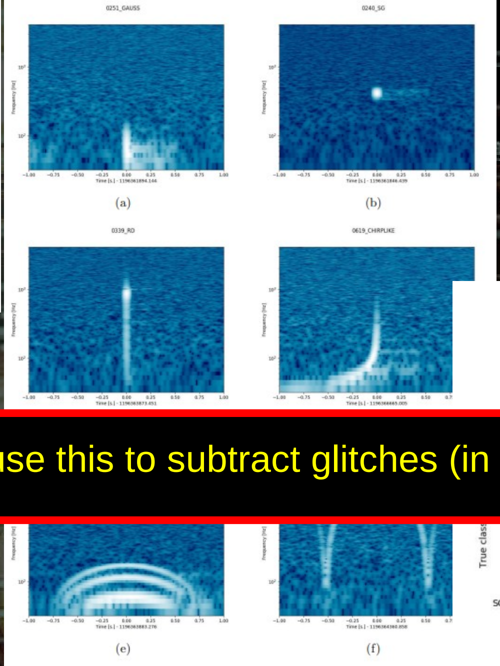
Several image-based detection and classification pipelines have been built on 2D CNN layers.

Algorithms for gravitational-wave data quality improvement

Noise transient classification on strain: deep learning approach

Image-based deep learning for classification of noise transients in gravitational wave detectors

Massimiliano Razzano[1,3] and Elena Cuoco[2,3]
Department of Physics, University of Pisa, Pisa I-56127, Italy
European Gravitational Observatory (EGO), I-56021 Cascina, Pisa, Italy
Istituto Nazionale di Fisica Nucleare, Sezione di Pisa, Pisa I-56127, Italy
E-mail: massimiliano.razzano@unipi.it



Machine Learning Algorithms

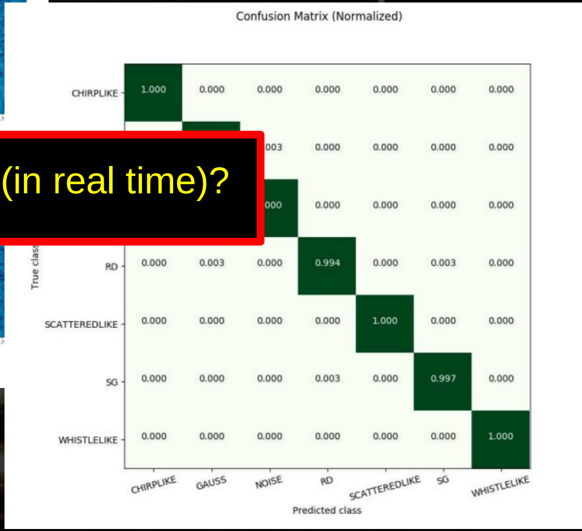
simulated glitches + Gaussian noise

Use 2D matrices (images) for classification purposes, e.g., spectrograms, Q-transforms

CNNs have an unique power to automatically extract the most significant features from an image, which can be used to distinguish between different images.

Several image-based detection and classification pipelines have been built on 2D CNN layers.

Can we use this to subtract glitches (in real time)?

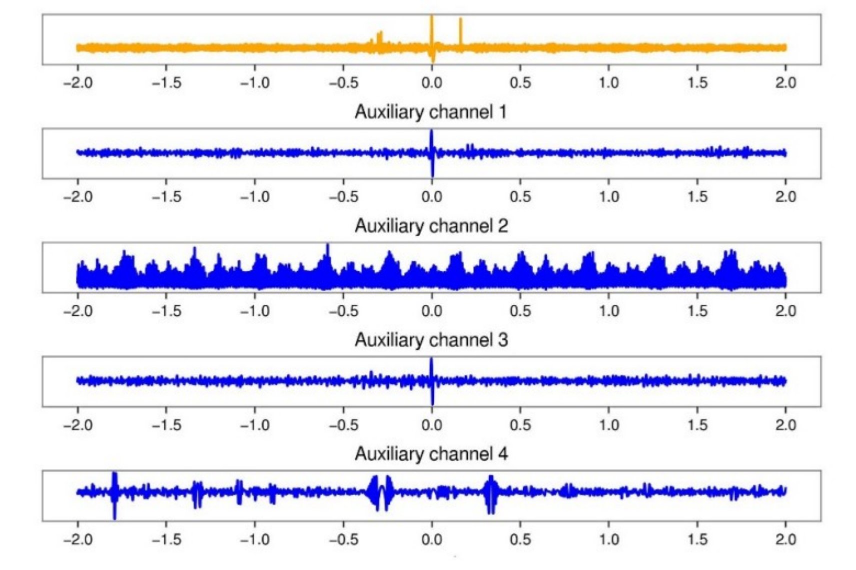


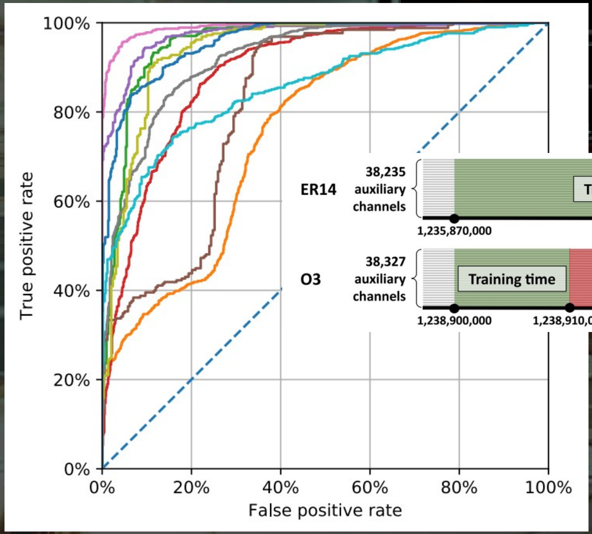
Algorithms for gravitational-wave data quality improvement

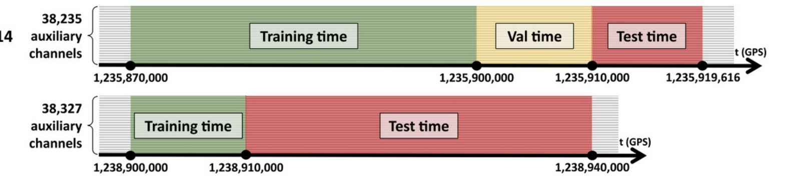
Noise transient classification on auxiliary channels

Machine Learning Algorithms

Logistic regression and Omicron event trigger generator







PHYSICAL REVIEW D **88**, 062003 (2013)

Application of machine learning algorithms to the study of noise artifacts in gravitational-wave data

Rahul Biswas,[1] Lindy Blackburn,[2] Junwei Cao,[3] Reed Essick,[4] Kari Alison Hodge,[5] Erotokritos Katsavounidis,[4] Kyungmin Kim,[6,7] Young-Min Kim,[8,7] Eric-Olivier Le Bigot,[3] Chang-Hwan Lee,[8] John J. Oh,[7] Sang Hoon Oh,[7] Edwin J. Son,[7] Ye Tao,[9] Ruslan Vaulin,[4,*] and Xiaoge Wang[9]

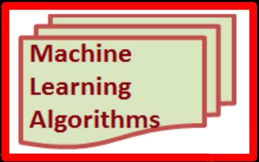
PHYSICAL REVIEW D **101,** 102003 (2020)

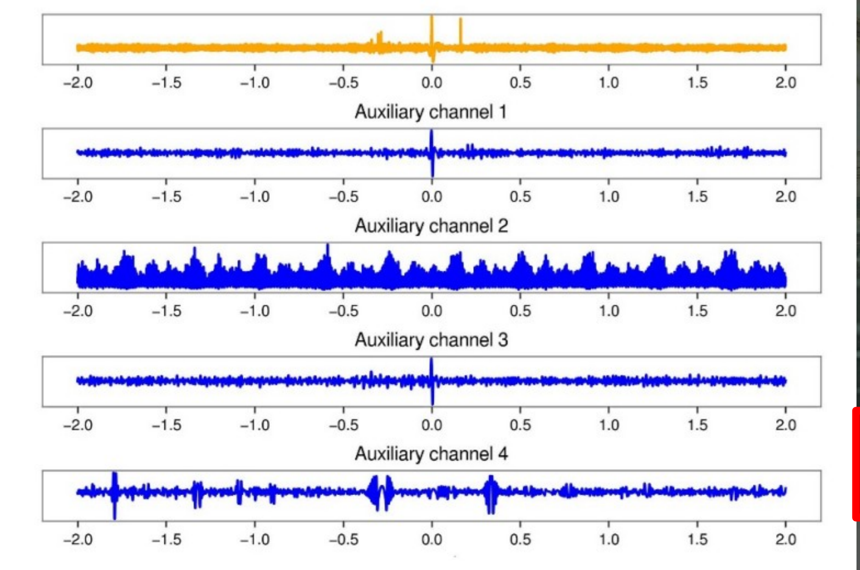
Efficient gravitational-wave glitch identification from environmental data through machine learning

Robert E. Colgan,[1,2] K. Rainer Corley,[3,4] Yenson Lau,[2,5] Imre Bartos,[6] John N. Wright,[2,5] Zsuzsa Márka,[4] and Szabolcs Márka[3]

Algorithms for gravitational-wave data quality improvement

Noise transient classification on auxiliary channels





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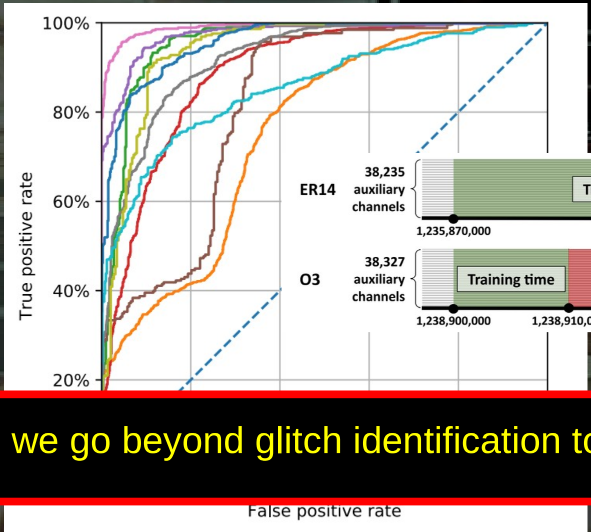
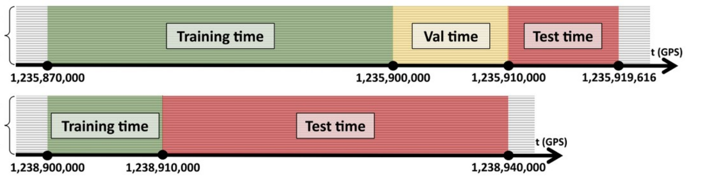
Logistic regression and Omicron event trigger generator





Can we go beyond glitch identification to glitch subtraction?

PHYSICAL REVIEW D **101,** 102003 (2020)

Efficient gravitational-wave glitch identification from environmental data through machine learning

Robert E. Colgan,[1,2] K. Rainer Corley,[3,4] Yenson Lau,[2,5] Imre Bartos,[6] John N. Wright,[2,5] Zsuzsa Márka,[4] and Szabolcs Márka[3]

Algorithms for gravitational-wave data quality improvement

Deepclean

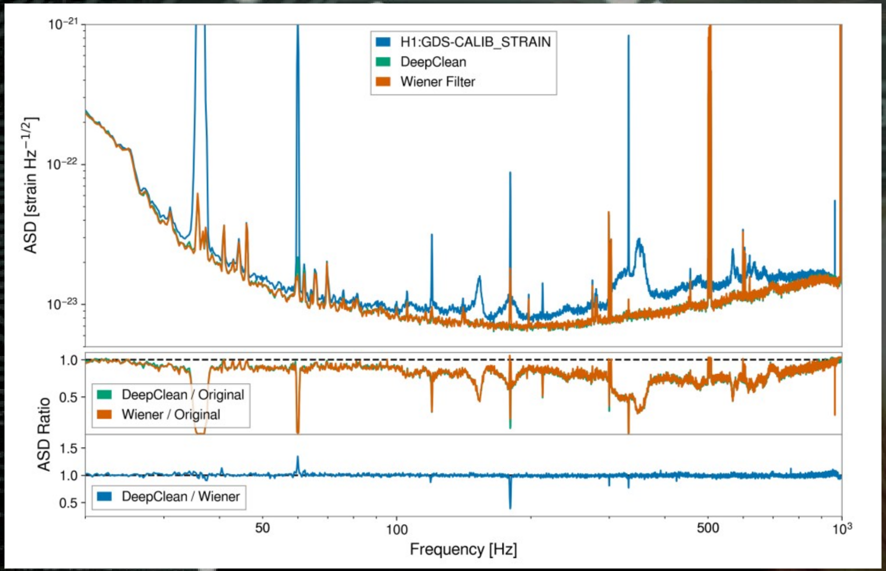
Candidate Model

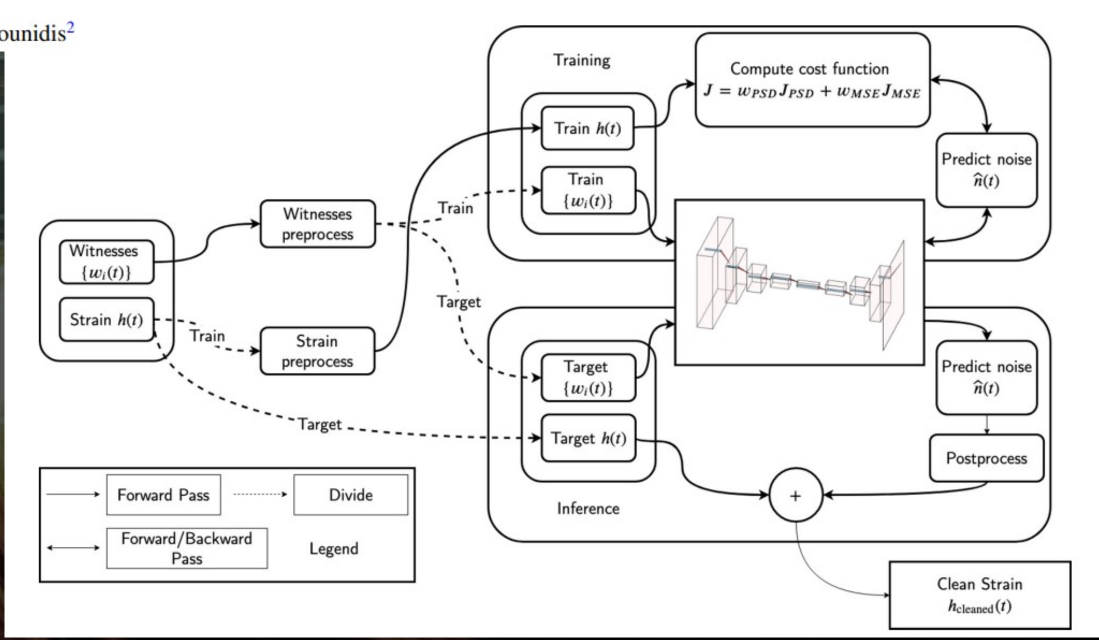
PHYSICAL REVIEW RESEARCH **2**, 033066 (2020)

Noise reduction in gravitational-wave data via deep learning

Rich Ormiston,[1] Tri Nguyen,[2] Michael Coughlin,[1,3] Rana X. Adhikari,[3] and Erik Katsavounidis[2]

One-dimensional Convolutional Neural Network which takes a specified set of witness channels and subsequently outputs the predicted noise in strain.





Algorithms for gravitational-wave data quality improvement

Data set preparation

Classical and Quantum Gravity

PAPER

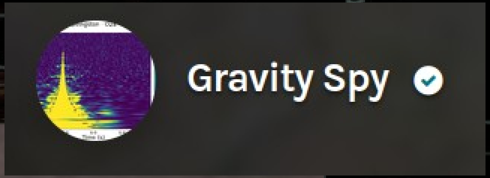
Gravity Spy: integrating advanced LIGO detector characterization, machine learning, and citizen science

M Zevin[1], S Coughlin[1], S Bahaadini[2], E Besler[2], N Rohani[2], S Allen[3], M Cabero[4], K Crowston[5], A K Katsaggelos[2], S L Larson[1,3] + Show full author list

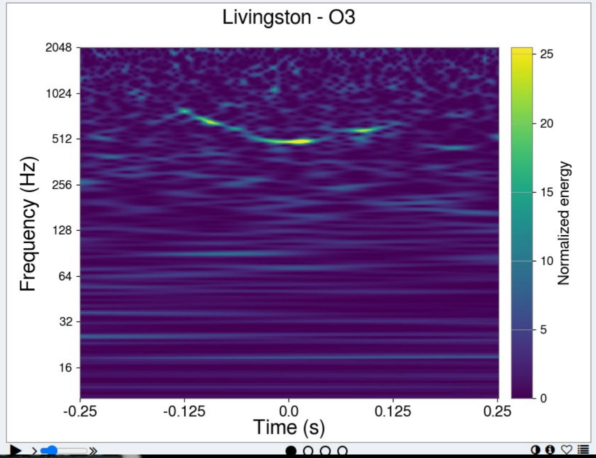
Published 28 February 2017 • © 2017 IOP Publishing Ltd
Classical and Quantum Gravity, Volume 34, Number 6
Citation M Zevin *et al* 2017 *Class. Quantum Grav.* **34** 064003

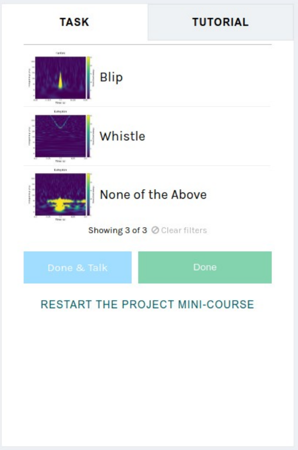
Citizen science! A crowdsource classifier plus a convolutional neural network model.

Gravity Spy dataset publicly released. It includes 8583 of images of LIGO glitches and the specifications for 22 glitch classes.



Help scientists at LIGO search for gravitational waves, the elusive ripples of spacetime.





REINFORCE
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Algorithms for gravitational-wave data quality improvement

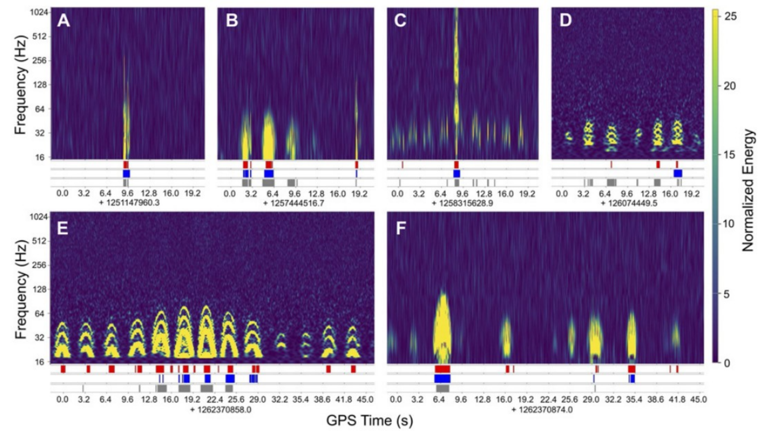
Machine Learning Algorithms

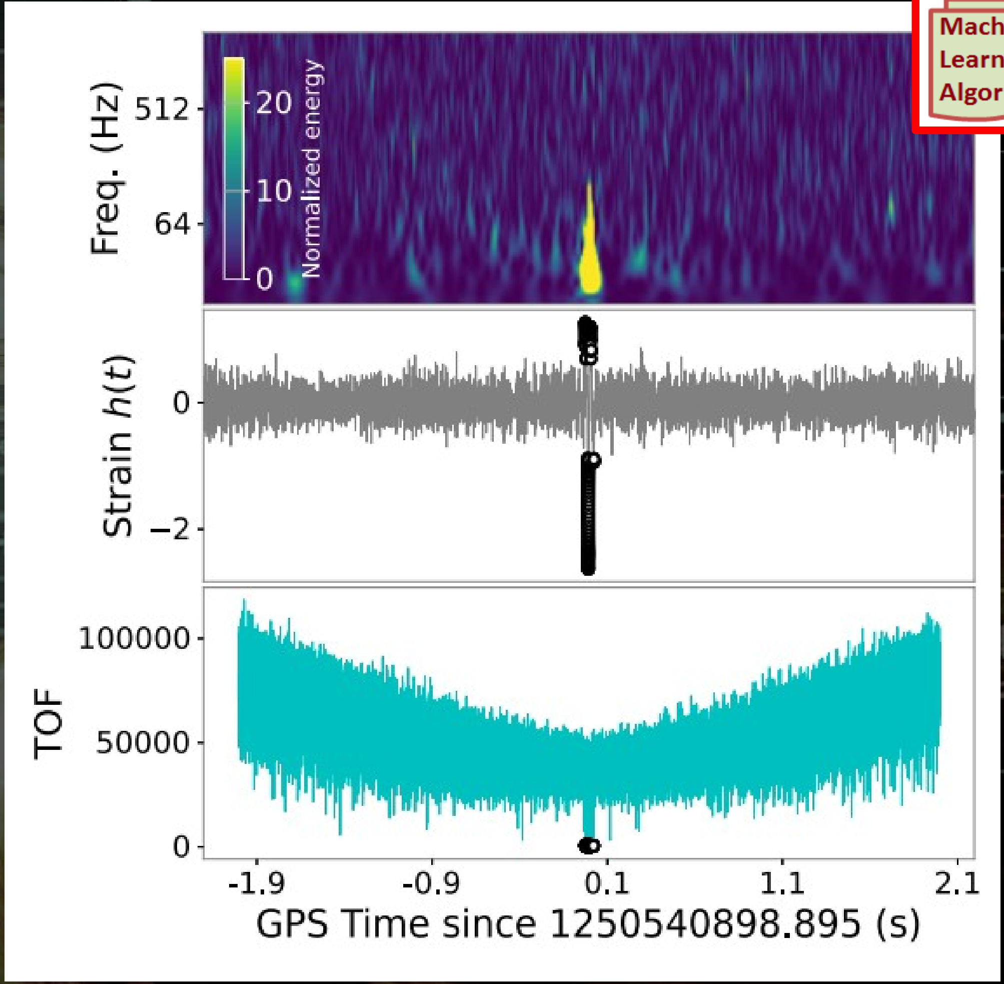
Anomaly detection

OPEN ACCESS
IOP Publishing
Classical and Quantum Gravity
Class. Quantum Grav. 39 (2022) 135011 (14pp)
https://doi.org/10.1088/1361-6382/ac7278

UniMAP: model-free detection of unclassified noise transients in LIGO-Virgo data using the temporal outlier factor

J Ding[1,2,*], R T Ng[2] and J McIver[1]





Algorithms for gravitational-wave data quality improvement

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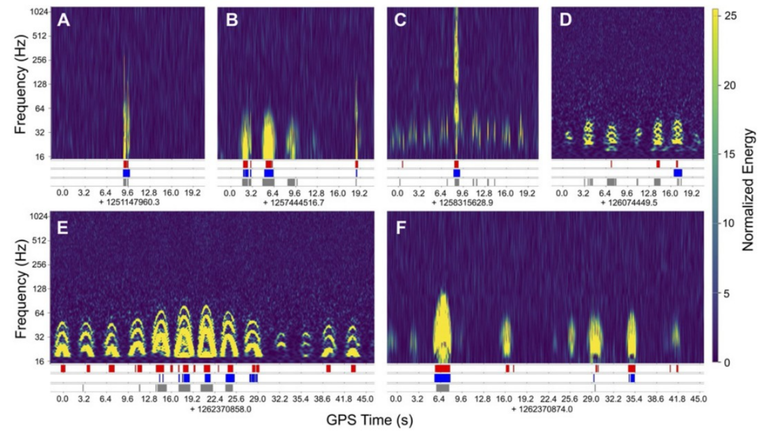
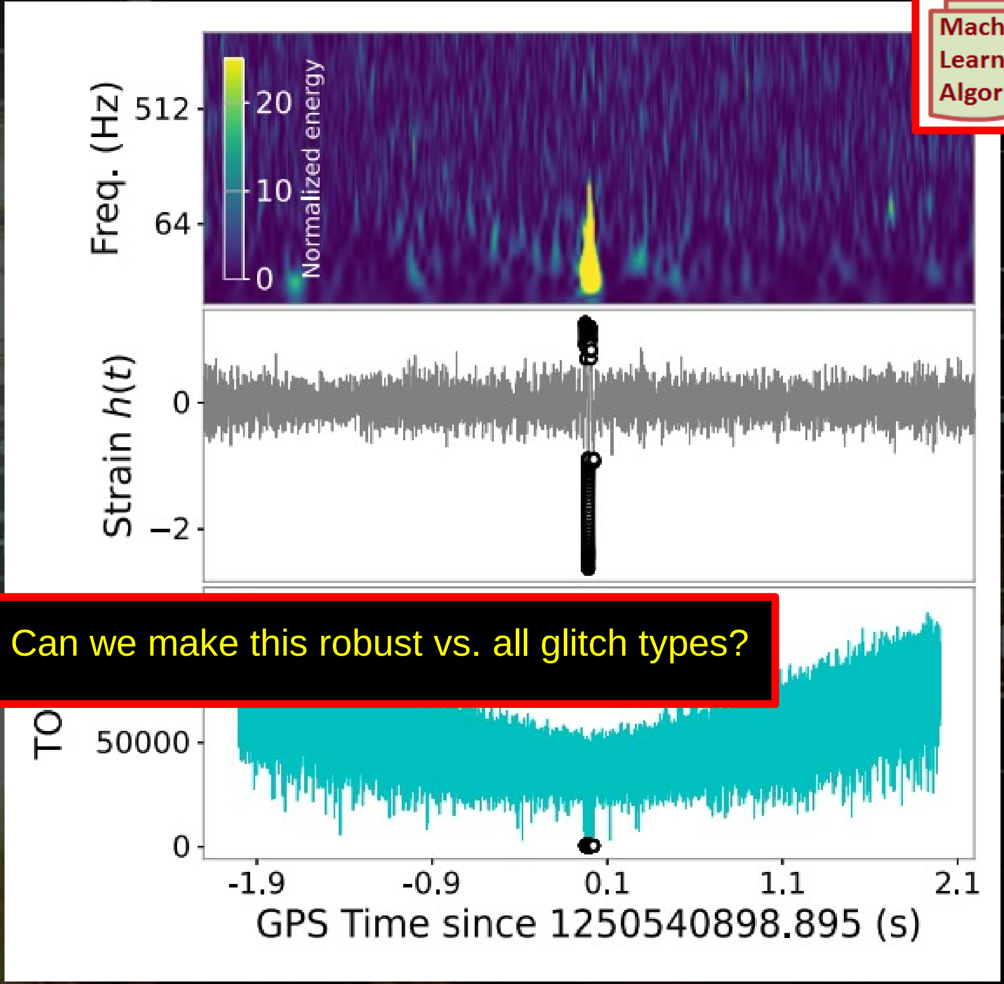




Can we make this robust vs. all glitch types?

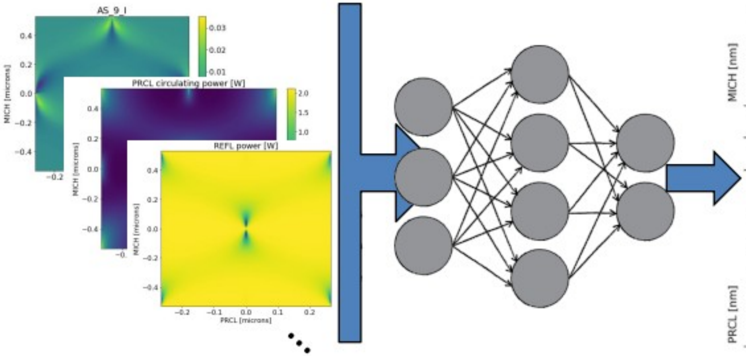
Algorithms for detector control

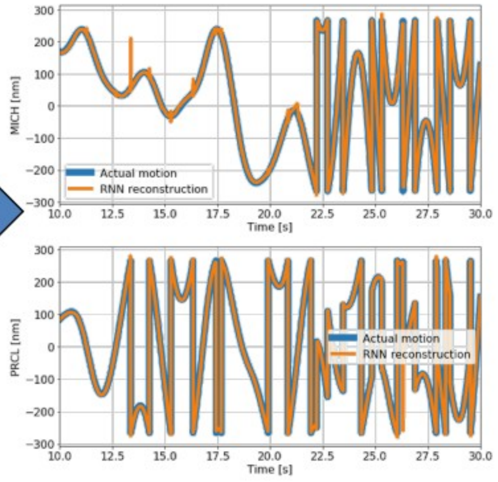
Machine Learning Algorithms

Machine Learning for Lock Acquisition

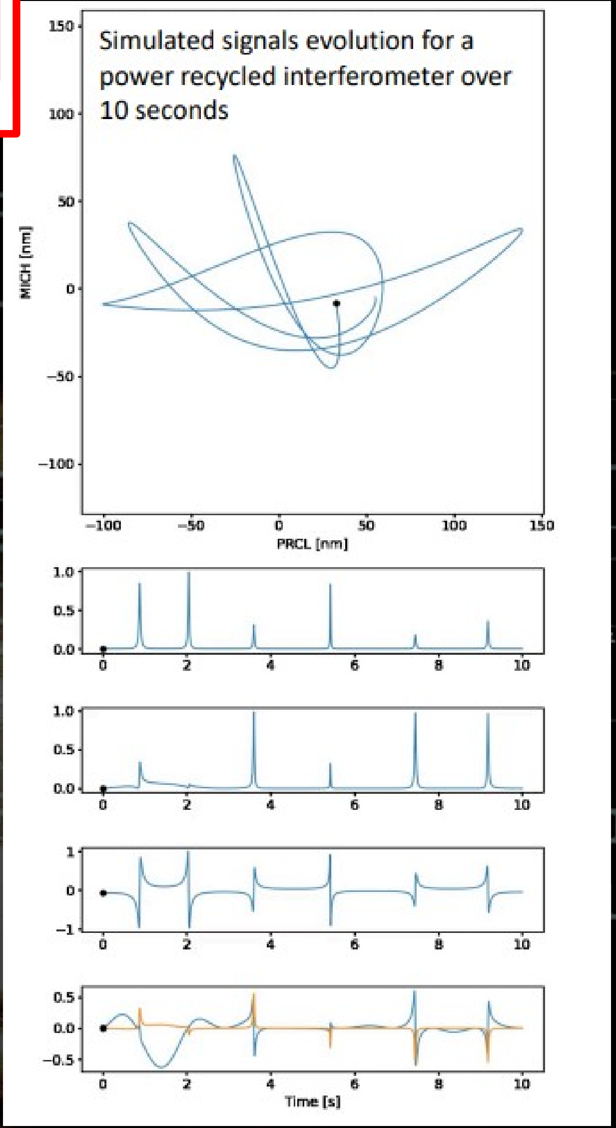
Non-linear control problem: drive the system into a narrow region of the 5d phase space, where linear control is possible

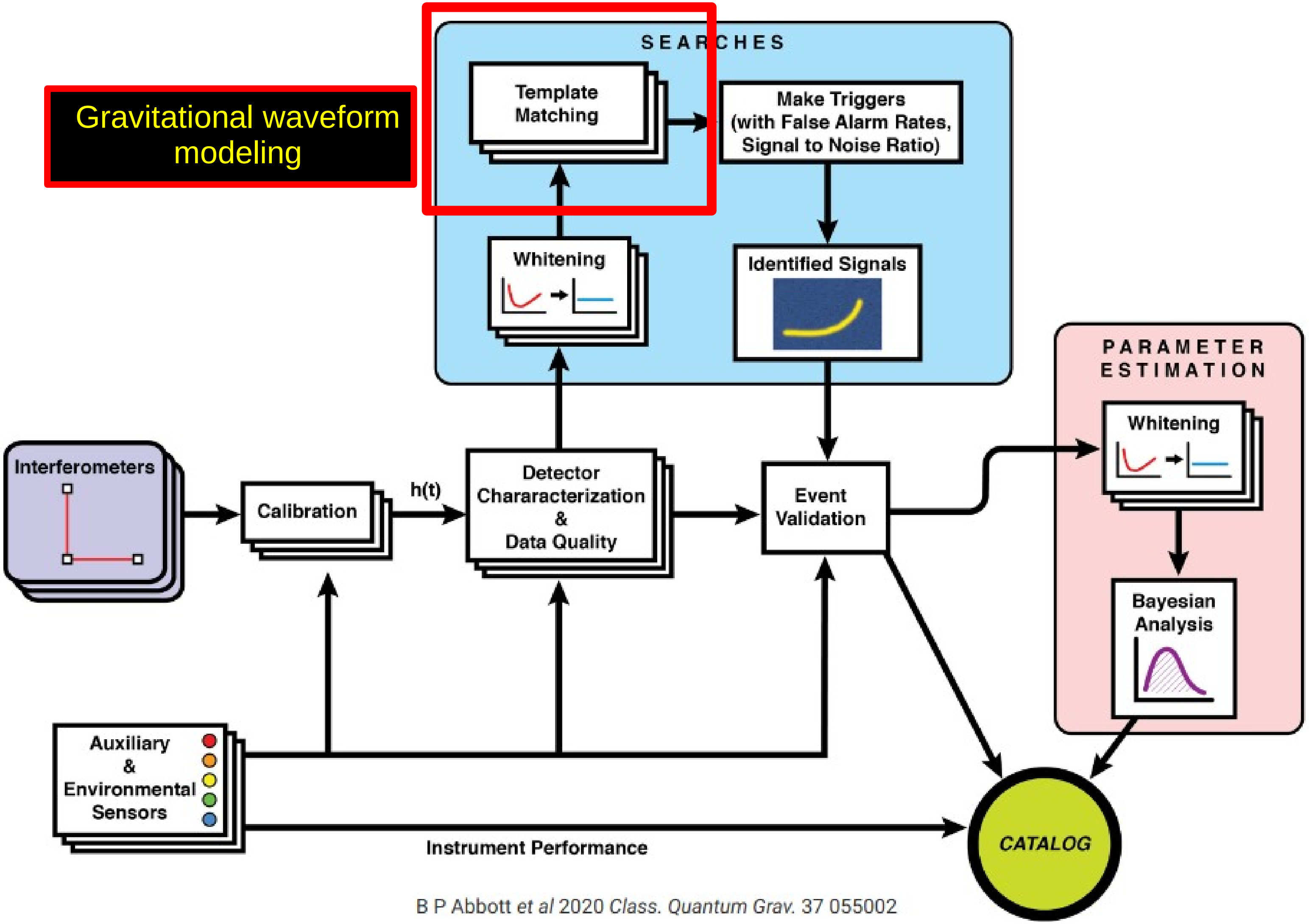
- Construct a **non-linear state estimator**: use all available signals as input, build an estimate of the degree of freedom positions that works (almost) everywhere





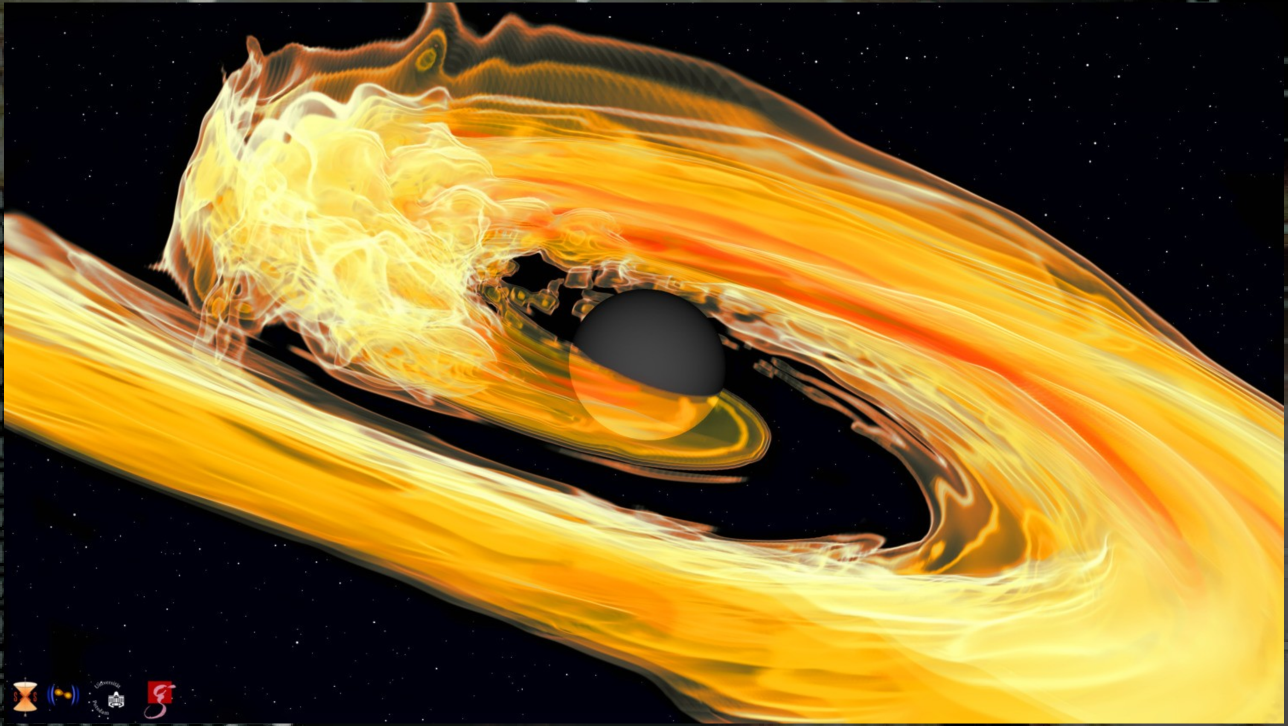
In simulation we have both **input signals** and **target coordinates**: supervised learning





B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

Gravitational waveform modeling



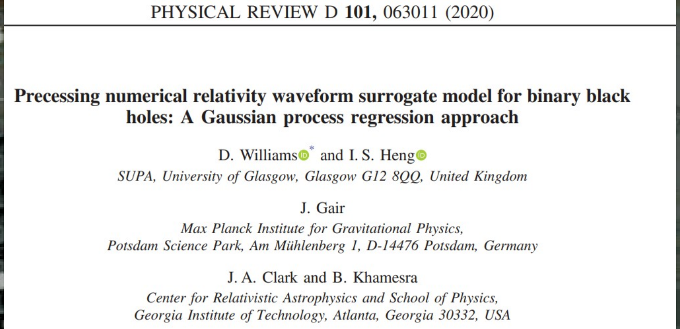
Credit: Scientific visualization: T. Dietrich (Potsdam University and Max Planck Institute for Gravitational Physics), N. Fischer, S. Ossokine, H. Pfeiffer (Max Planck Institute for Gravitational Physics), T. Vu. Numerical-relativity simulation: S.V. Chaurasia (Stockholm University), T. Dietrich (Potsdam University and Max Planck Institute for Gravitational Physics)

- GW detection of binary systems relies on matched-filter analysis. Template accuracy is crucial!
- Accurate solutions of the Einstein equations for binary sources can be obtained with Numerical Relativity (NR) simulations.
- High computational cost prevent the production of NR waveforms catalogs spanning the full parameter space.
- LIGO and Virgo rely on approximate solutions that are traditionally obtained through the effective-one-body or phenomenological modeling approaches.
- How can machine learning help?

Gravitational waveform modeling

Machine Learning Algorithms

Waveform building


PHYSICAL REVIEW D **101**, 063011 (2020)

Precessing numerical relativity waveform surrogate model for binary black holes: A Gaussian process regression approach

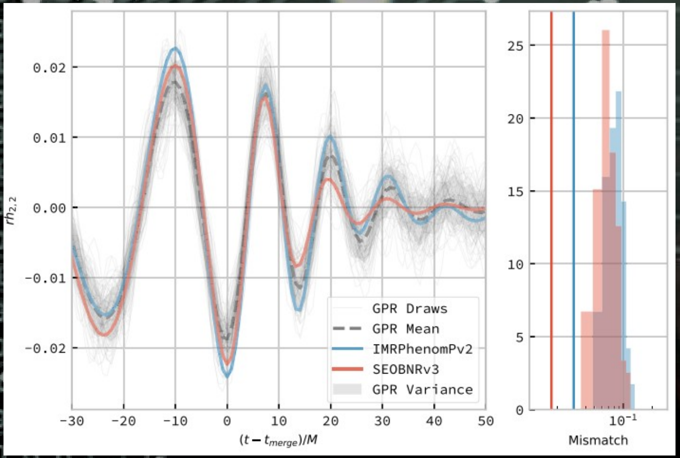
D. Williams* and I. S. Heng
SUPA, University of Glasgow, Glasgow G12 8QQ, United Kingdom

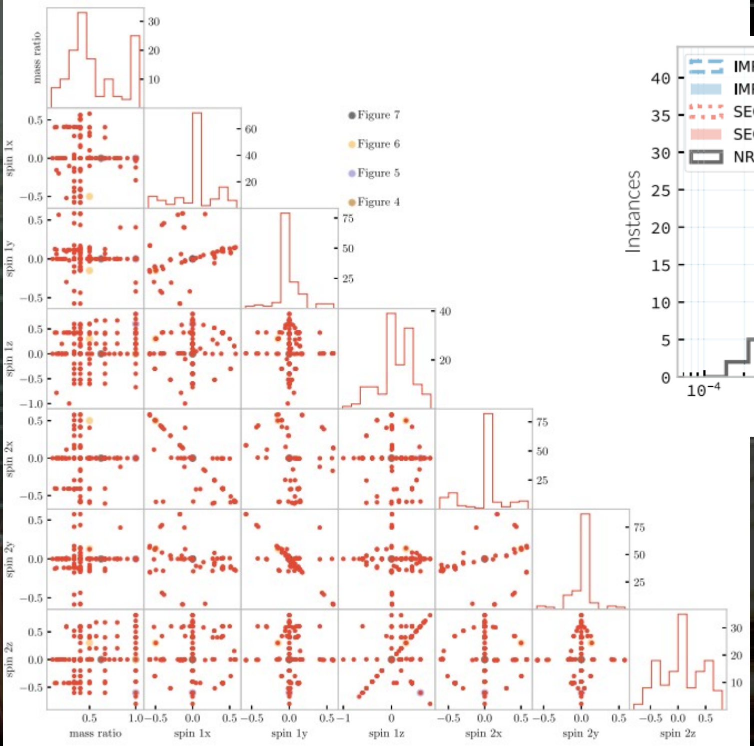
J. Gair
Max Planck Institute for Gravitational Physics, Potsdam Science Park, Am Mühlenberg 1, D-14476 Potsdam, Germany

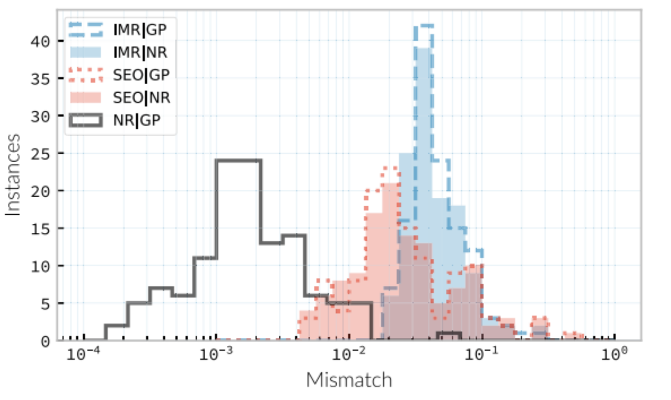
J. A. Clark and B. Khamesra
Center for Relativistic Astrophysics and School of Physics, Georgia Institute of Technology, Atlanta, Georgia 30332, USA

Gaussian process regression to compute the waveform at points of the parameter space not covered by numerical relativity.

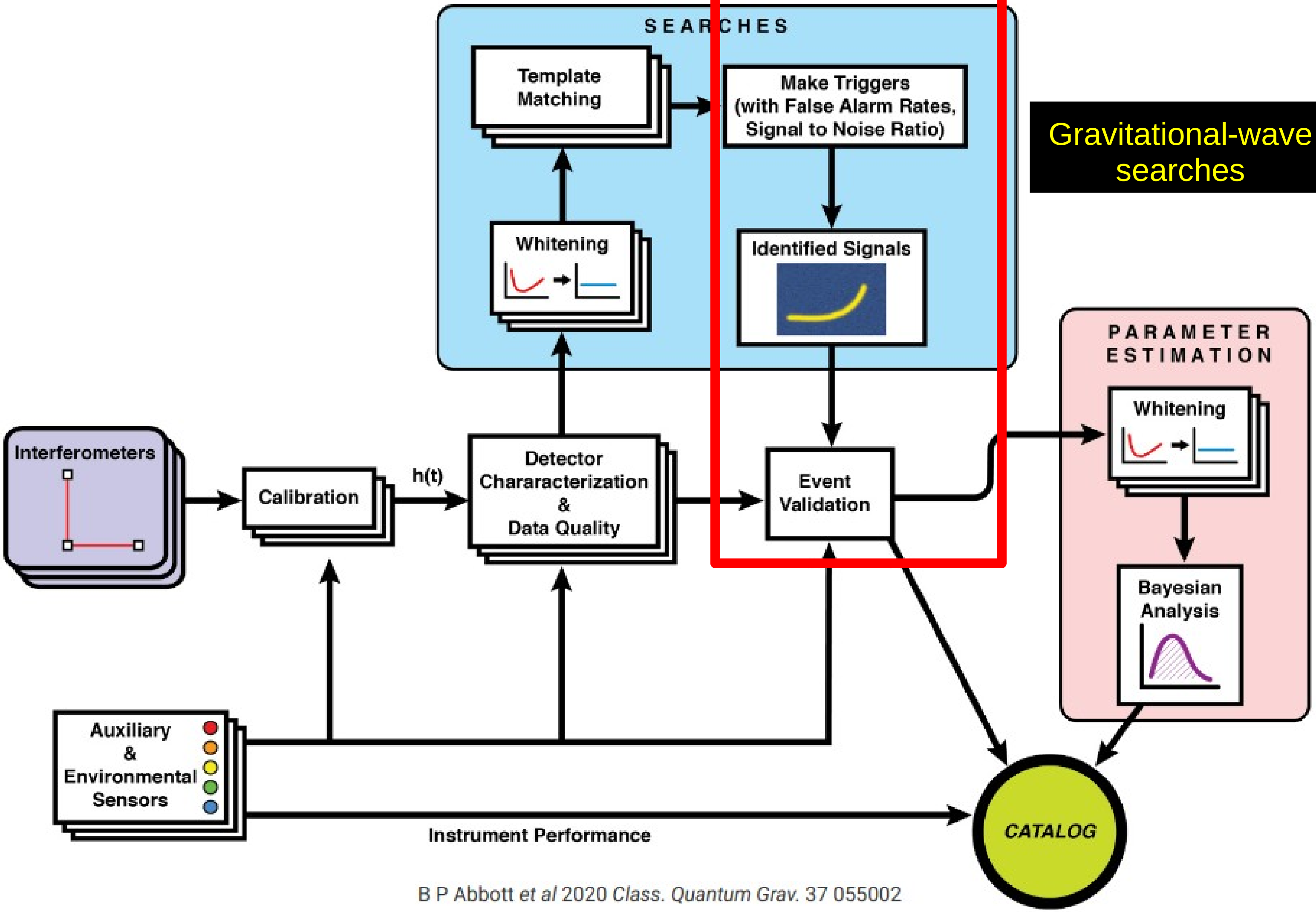
GPR has been used to build surrogate models of both non-precessing and precessing BBH systems.







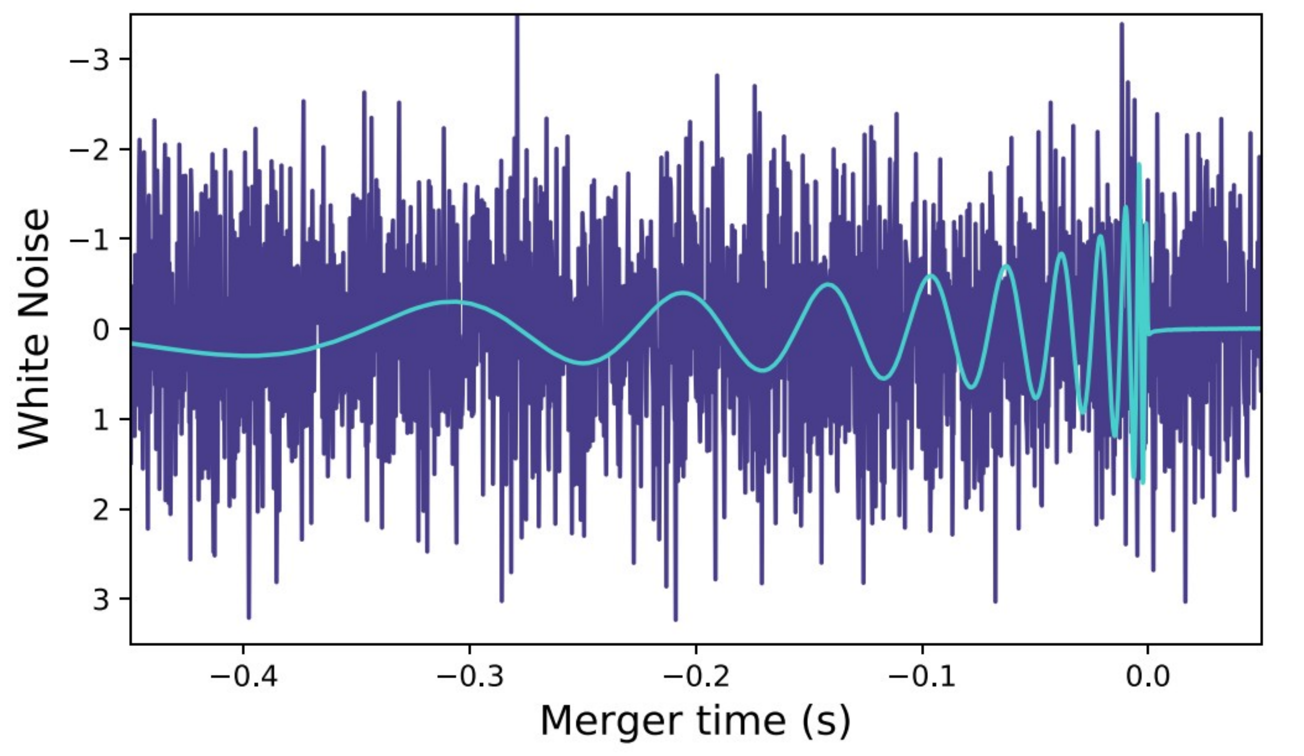
See also:
Z. Doctor et al, “Statistical gravitational waveform models: What to simulate next?” Phys. Rev. D 96, 123011 (2017)



Gravitational-wave searches

B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

Gravitational-wave searches



- Four different types of searches: compact binary coalescences, bursts, continuous waves, stochastic. Each has its own challenges.
- CBC: Matched filter. Computationally expensive. Relies on accuracy of templates.
- Burst: How to detect an unmodeled signal in a sea of (unmodeled) noise. Relies on coherence.
- Continuous waves: Hard to detect, need to process long stretches of data. Huge computational cost
- Stochastic: Searches based on cross-correlation.
- How can machine learning help?

Gravitational-wave searches

Candidate
Model

Detection of binary mergers

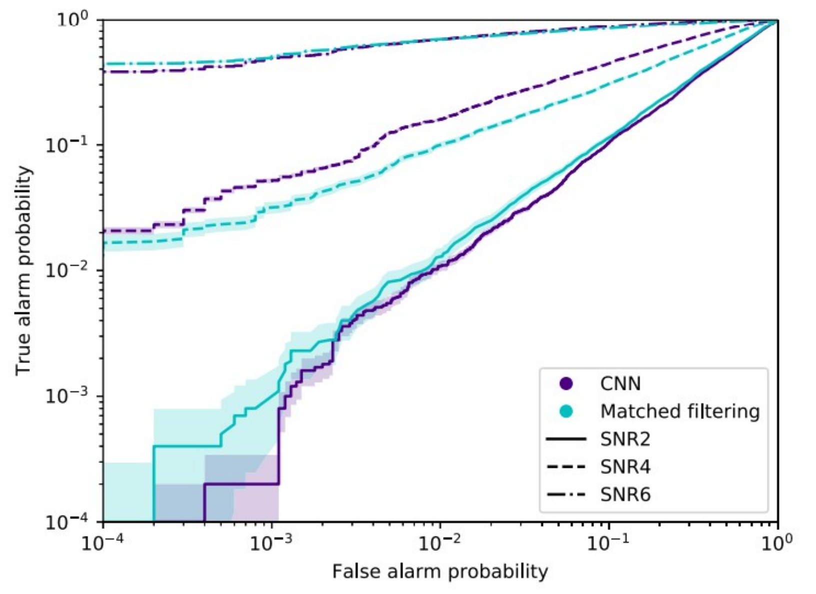
PHYSICAL REVIEW LETTERS **120,** 141103 (2018)

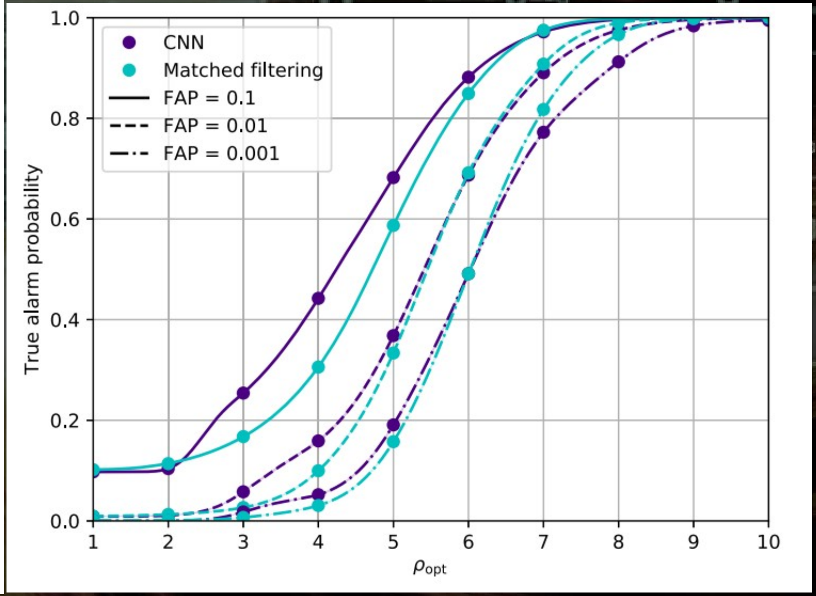
Editors' Suggestion

Matching Matched Filtering with Deep Networks for Gravitational-Wave Astronomy

Hunter Gabbard,* Michael Williams, Fergus Hayes, and Chris Messenger
SUPA, School of Physics and Astronomy, University of Glasgow, Glasgow G12 8QQ, United Kingdom

- Deep convolutional neural network to search for binary black hole gravitational-wave signals.
- Input is the whitened time series of measured gravitational-wave strain in Gaussian noise.
- Sensitivity comparable to match filtering.





See also:
D. George and E.A. Huerta
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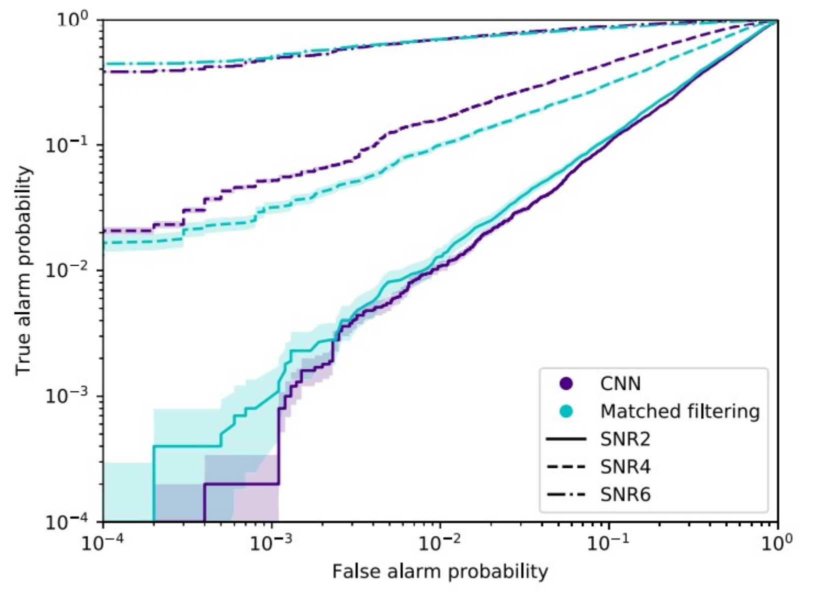
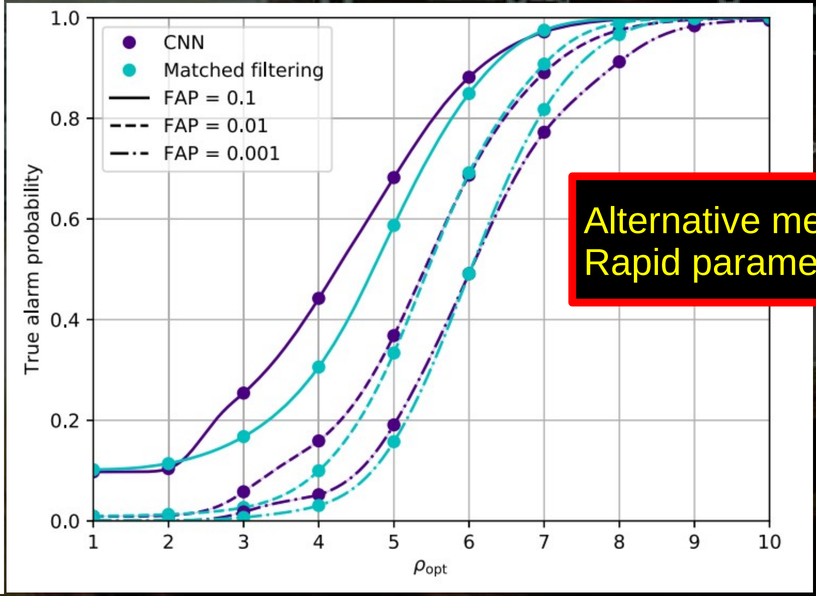




Alternative methods?
Rapid parameter estimation?

See also:
D. George and E.A. Huerta
Phys. Lett. B 778 64–70 (2018)

Gravitational-wave searches

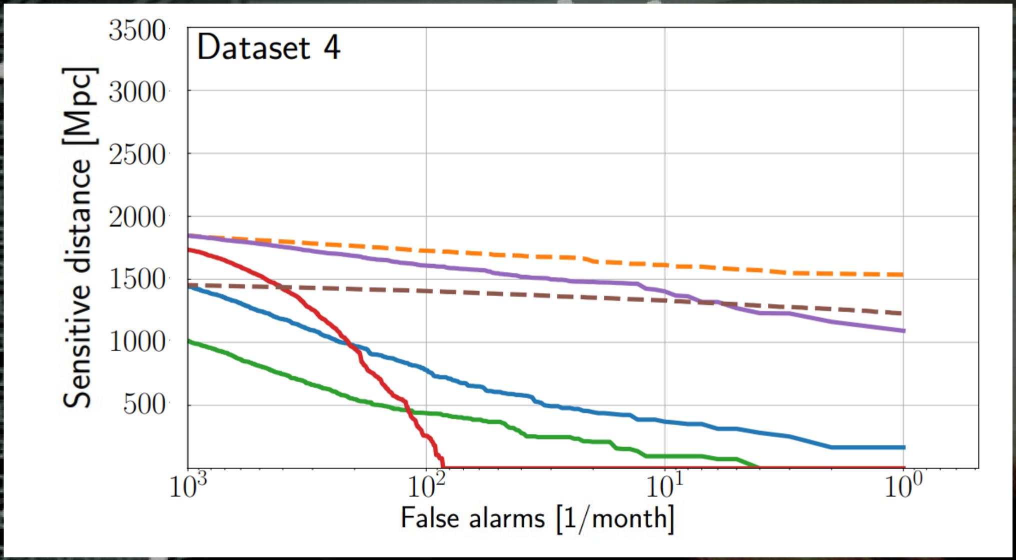
Candidate Model

Detection of binary mergers

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]

- Comparison of 6 algorithms for binary black hole searches.
- Four different data sets of different complexity (from Gaussian noise to varying real detector PSD)
- Benchmark data set for algorithm testing.



A few excerpts form the paper conclusions:

- Machine learning search algorithms are competitive in sensitivity compared to state-of-the-art searches on simulated data and the limited parameter space explored in this challenge.
- Most of the tested machine learning algorithms struggle to effectively handle real noise, which is contaminated with non-Gaussian noise artifacts.
- Traditional search algorithms are capable of detecting signals at lower FARs, thus making detections more confident.
- The tested machine learning searches struggle to identify long duration signals.

Gravitational-wave searches

Machine
Learning
Algorithms

Rapid localization of sources

Rapid localization of gravitational wave sources from compact binary coalescences using deep learning

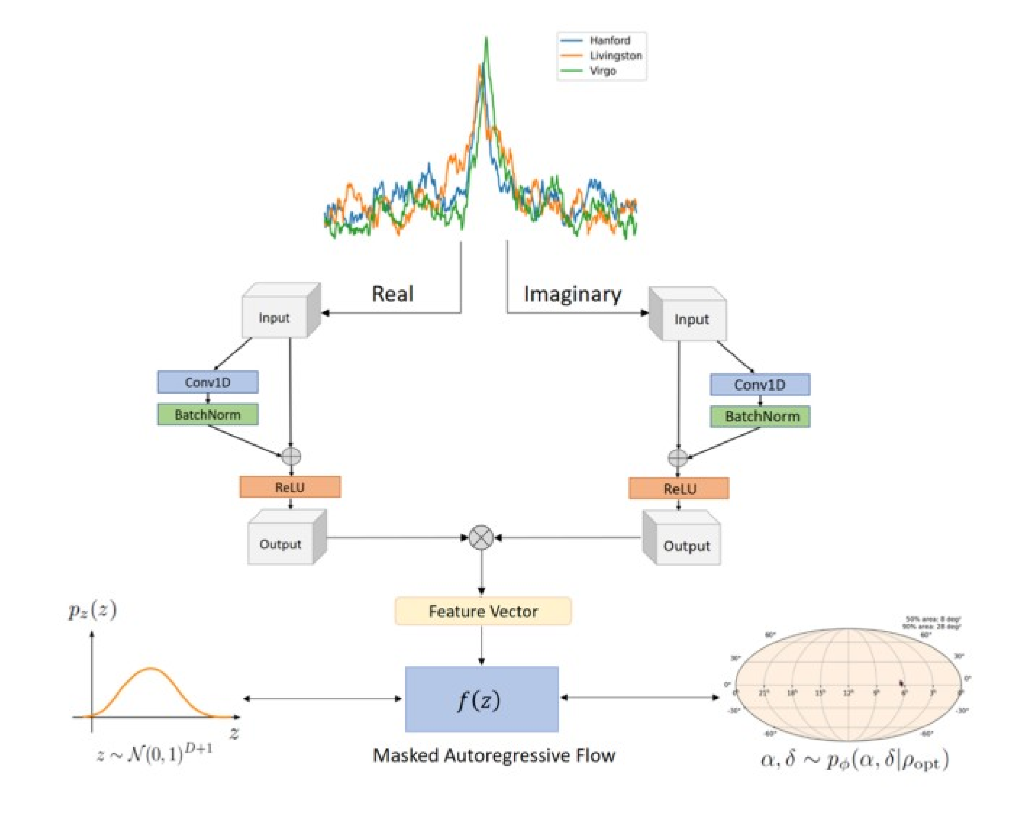
Chayan Chatterjee,* Linqing Wen,† and Damon Beveridge‡
Department of Physics, OzGrav-UWA, The University of Western Australia, 35 Stirling Hwy, Crawley, Western Australia 6009, Australia

Foivos Diakogiannis§
The Commonwealth Scientific and Industrial Research Organisation 7 Conlon St, Waterford, WA, Australia

Kevin Vinsen¶
International Centre for Radio Astronomy Research, The University of Western Australia M468, 35 Stirling Hwy, Crawley, WA, Australia

(Dated: August 1, 2022)

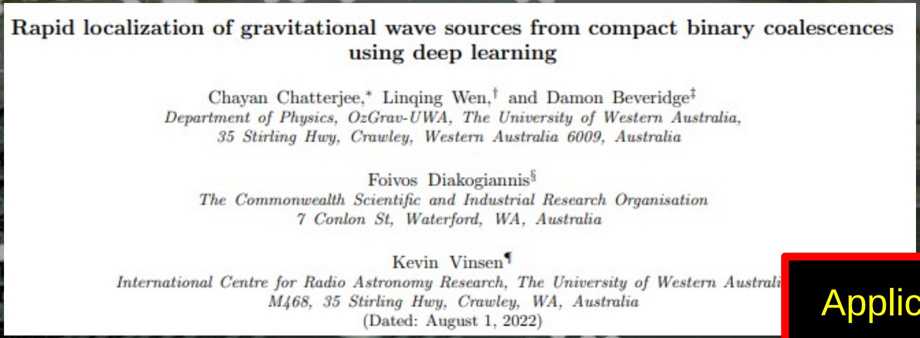
- Deep learning-based approach for sky localization of binary coalescences
- Train and test a normalizing flow model on matched-filtering output from GW searches.
- Fast sky localizations.



Gravitational-wave searches

Machine Learning Algorithms

Rapid localization of sources


Rapid localization of gravitational wave sources from compact binary coalescences using deep learning

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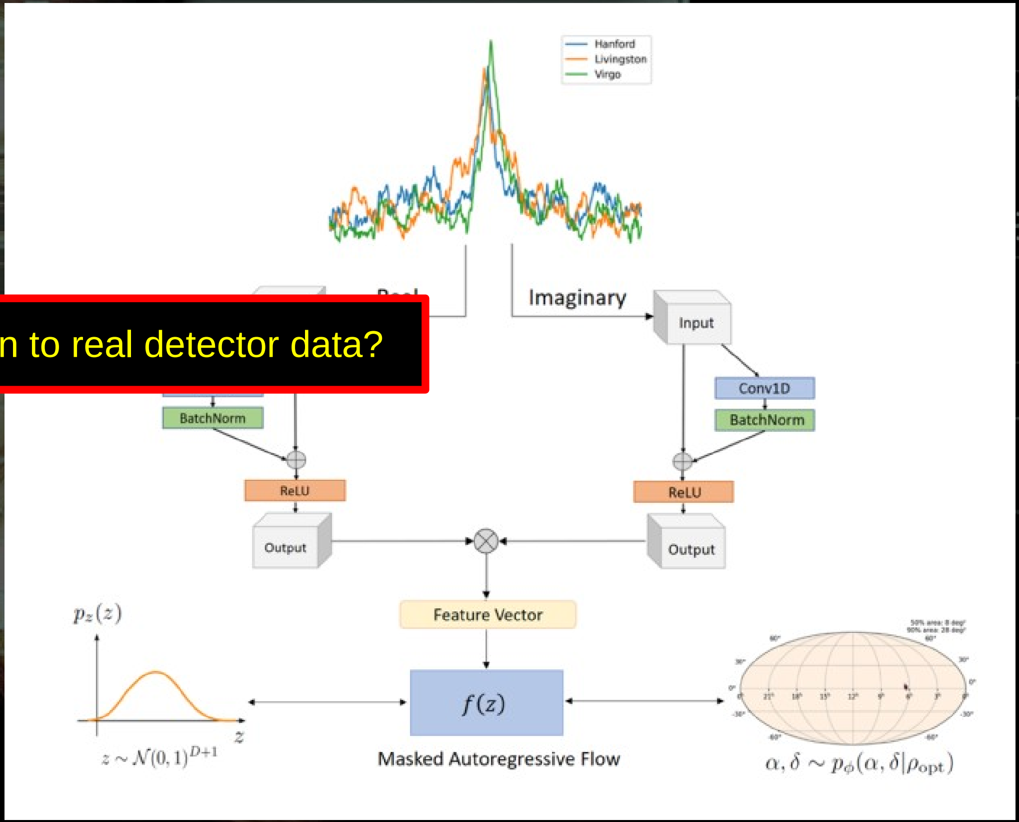
Application to real detector data?



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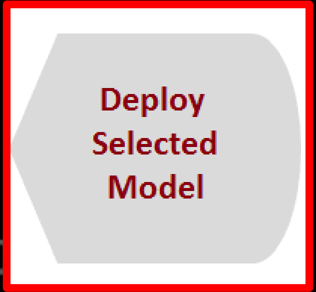
Gravitational-wave searches

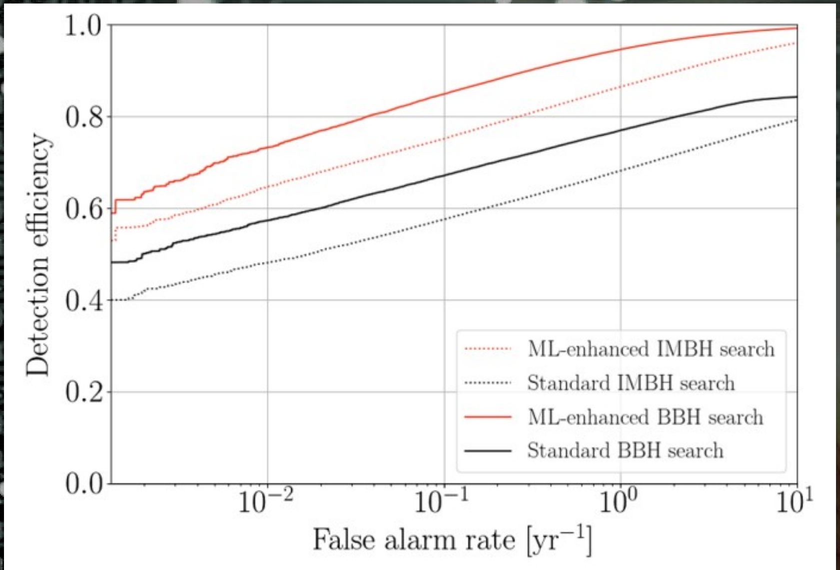


Burst searches

PHYSICAL REVIEW D **105**, 083018 (2022)

Search for binary black hole mergers in the third observing run of Advanced LIGO-Virgo using coherent WaveBurst enhanced with machine learning

T. Mishra,[1] B. O'Brien,[1] M. Szczepańczyk,[1] G. Vedovato,[2] S. Bhaumik,[1] V. Gayathri,[1] G. Prodi,[3,4] F. Salemi,[5,4] E. Milotti,[6,7] I. Bartos,[1] and S. Klimenko[1]



- Decision tree-based machine learning algorithm (eXtreme-Gradient Boost) to automate signal vs. noise classification in coherent WaveBurst searches for binary black hole mergers.
- Post-processing application replacing standard veto techniques.

	Standard cWB	ML-enhanced cWB		
Event	FAR (yr^{-1})	FAR (yr^{-1})	SNR	P_{astro}
GW190408_181802	$<9.5\times10^{-4}$	$<1.0\times10^{-3}$	14.8	0.999
GW190412	$<9.5\times10^{-4}$	$<1.0\times10^{-3}$	19.7	0.999
GW190421_213856	3.0×10^{-1}	1.8×10^{-2}	9.3	0.997
GW190503_185404	1.8×10^{-3}	$<9.9\times10^{-4}$	11.5	0.999
GW190512_180714	3.0×10^{-1}	1.8×10^{-1}	10.7	0.941
GW190513_205428	...	$1.0\times10^{+0}$	11.5	0.703
GW190517_055101	6.5×10^{-3}	6.2×10^{-4}	10.7	0.999
GW190519_153544	3.1×10^{-4}	$<1.0\times10^{-4}$	14.0	1.000
GW190521	2.0×10^{-4}	$<1.0\times10^{-4}$	14.4	1.000
GW190521_074359	$<1.0\times10^{-4}$	$<1.0\times10^{-4}$	24.7	0.999
GW190602_175927	1.5×10^{-2}	$<8.8\times10^{-4}$	11.1	0.999
GW190701_203306	5.5×10^{-1}	1.1×10^{-2}	10.2	0.997
GW190706_222641	$<1.0\times10^{-3}$	$<1.1\times10^{-3}$	12.7	0.999
GW190707_093326	...	1.1×10^{-1}	11.2	0.976
GW190727_060333	8.8×10^{-2}	3.4×10^{-3}	11.4	0.998
GW190728_064510	...	2.6×10^{-2}	10.5	0.993
GW190828_063405	$<9.6\times10^{-4}$	$<1.1\times10^{-3}$	16.6	0.999

Gravitational-wave searches

Machine Learning Algorithms

Supernova searches

Mach. Learn.: Sci. Technol. **1** (2020) 015005 https://doi.org/10.1088/2632-2153/ab527d

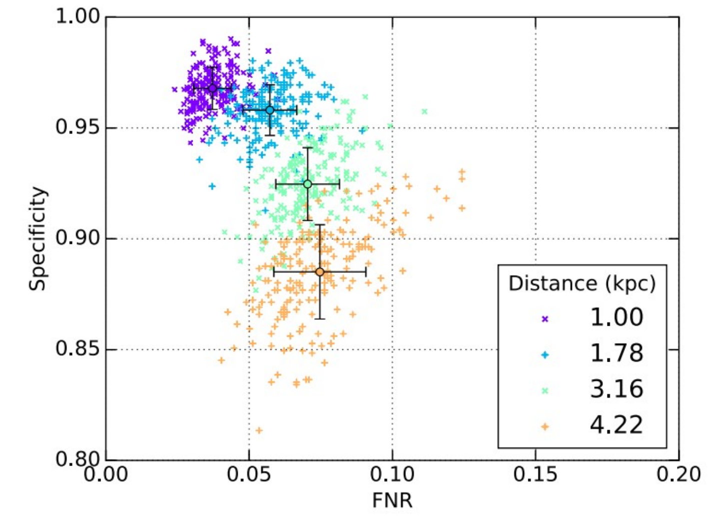
MACHINE LEARNING Science and Technology

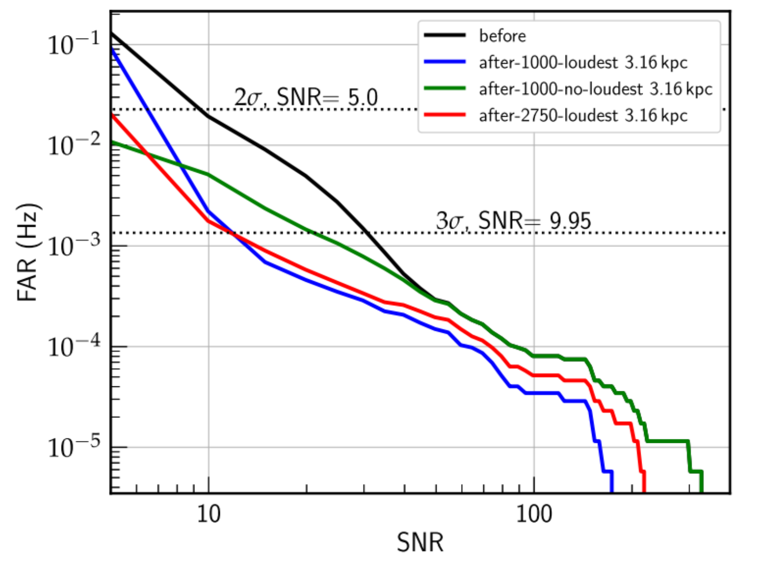
PAPER

Improving the background of gravitational-wave searches for core collapse supernovae: a machine learning approach

M Cavaglià[1,5], S Gaudio[2], T Hansen[2], K Staats[3], M Szczepańczyk[4] and M Zanolin[2]

- Genetic evolutionary algorithm to perform single-interferometer supernova searches.
- Post-processing method on top of cWB.





Trigger time	n_+	$P(s\|n_+)$	Actual
1137221362.849899	0	0.03	BKG
1137221296.450439	12	0.35	BKG
1137221270.478584	7	0.26	BKG
1137221270.315765	0	0.03	BKG
1137221256.461151	0	0.03	BKG
1137221254.992889	0	0.03	BKG
1137221206.790939	0	0.03	BKG
1137221187.891924	0	0.03	BKG
1137088411.819580	0	0.03	BKG
1137088400.326843	91	0.50	BKG
1137123606.447540	146	0.50	SIG (Yak, 3.16 kpc)
1137234559.739685	188	0.65	SIG (Yak, 3.16 kpc)
1137250081.748009	167	0.52	SIG (Yak, 3.16 kpc)
1137215815.308205	188	0.65	SIG (Yak, 1 kpc)
1137240747.519287	188	0.65	SIG (Yak, 1 kpc)
1137251495.131439	188	0.65	SIG(Yak, 1 kpc)
1137232392.167053	188	0.65	SIG (Yak, 1 kpc)
1137237558.365189	186	0.62	SIG (Yak, 1 kpc)

Gravitational-wave searches

Machine
Learning
Algorithms

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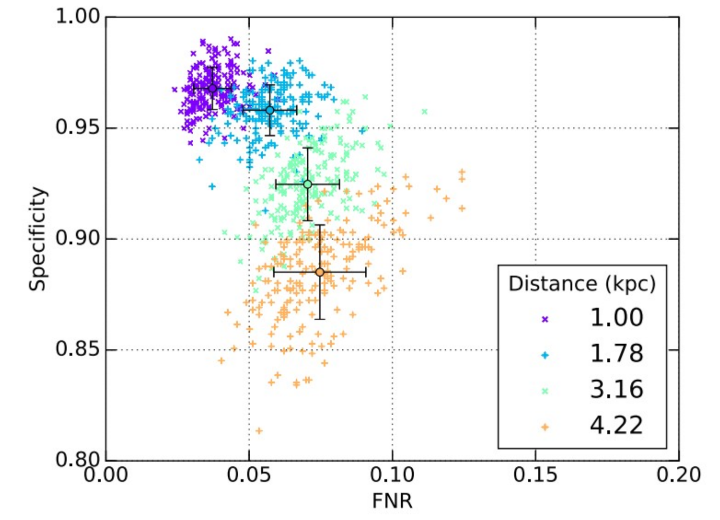

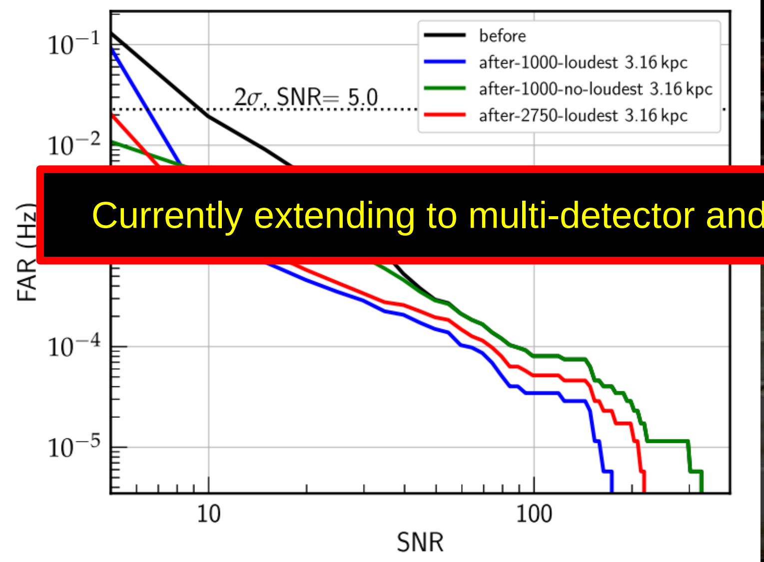

Currently extending to multi-detector and applying to O3 data

Trigger time	n_+	$P(s\|n_+)$	Actual
1137221362.849899	0	0.03	BKG
1137221296.450439	12	0.35	BKG
1137221270.478584	7	0.26	BKG
[illegible]	[illegible]	[illegible]	BKG
[illegible]	[illegible]	[illegible]	BKG
[illegible]	[illegible]	[illegible]	BKG
[illegible]	[illegible]	[illegible]	BKG
1137221187.891924	0	0.03	BKG
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Gravitational-wave searches

Machine
Learning
Algorithms

Supernova searches

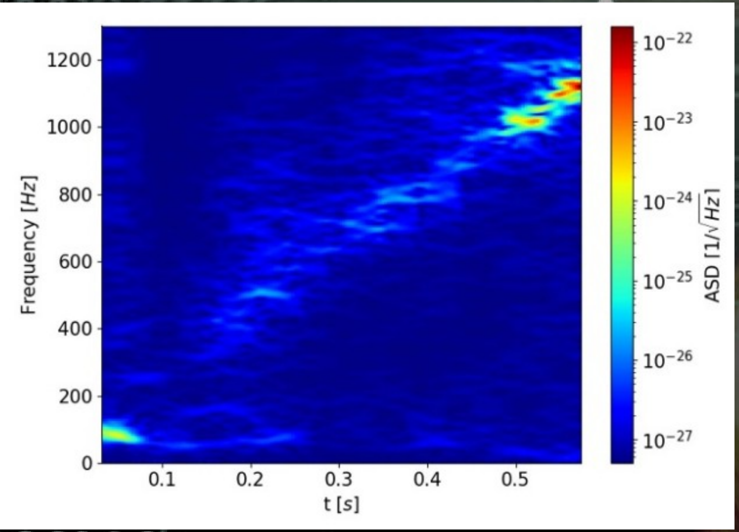
Mach. Learn.: Sci. Technol. **1** (2020) 025014 https://doi.org/10.1088/2632-2153/ab7d31

MACHINE LEARNING Science and Technology

Core-Collapse supernova gravitational-wave search and deep learning classification

Alberto Iess[1,2], Elena Cuoco[3,4], Filip Morawski[5] and Jade Powell[6]

- 1D (time series) and 2D (images) CNN classification.
- Training with simulations of signal and glitches in Gaussian noise.
- Detection with wavelet detection filter.



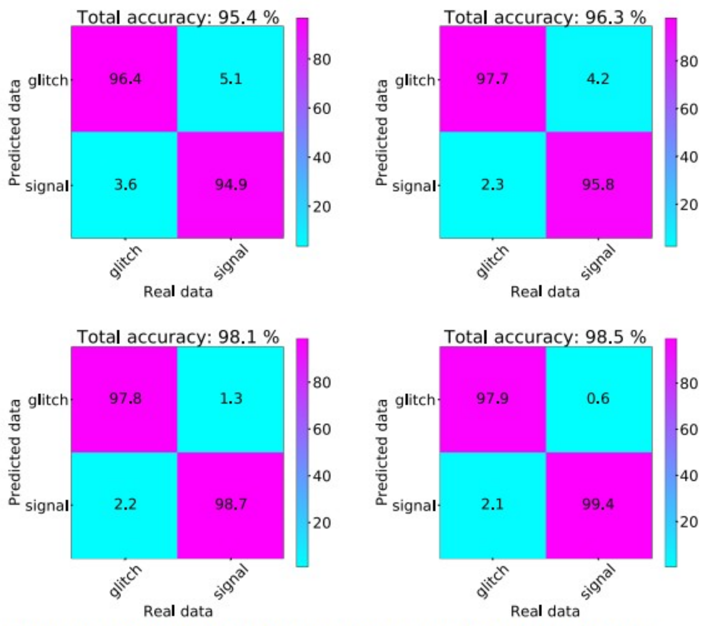
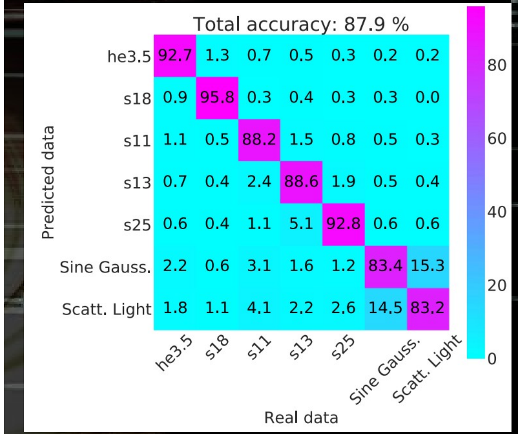


Figure 7. Binary 1D CNN (*left*) and 2D CNN (*right*) classification of glitches and CCSN signals from all considered models, added to simulated Virgo O3 (*top*) and Einstein Telescope (*bottom*) noise background.



Gravitational-wave searches

Machine Learning Algorithms

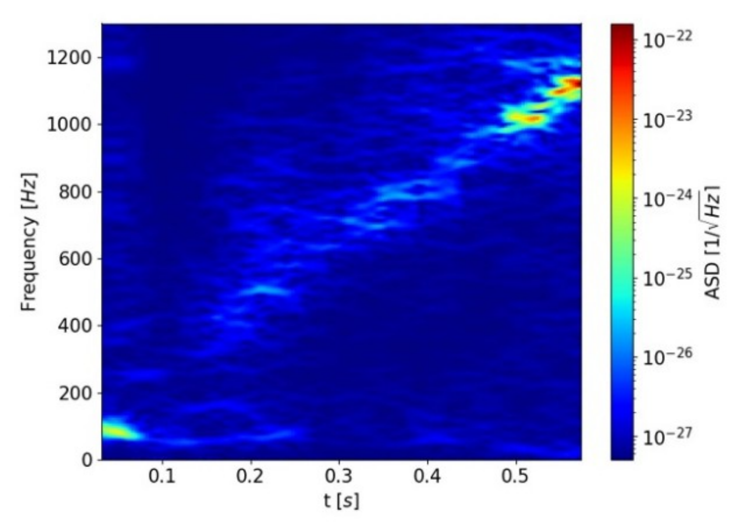
Supernova searches

Mach. Learn.: Sci. Technol. 1 (2020) 025014 https://doi.org/10.1088/2632-2153/ab7d31

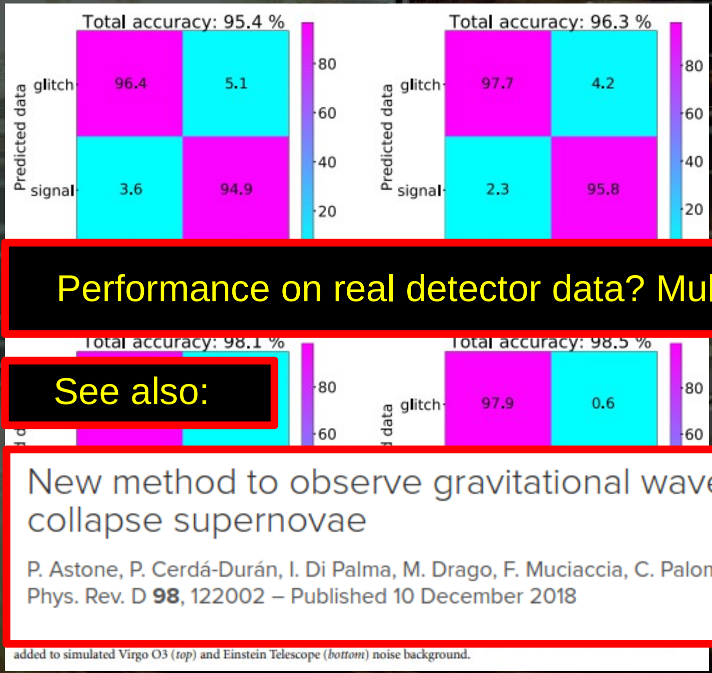
MACHINE LEARNING Science and Technology

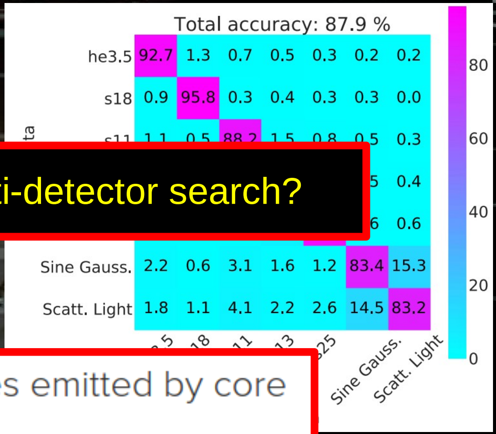
Core-Collapse supernova gravitational-wave search and deep learning classification

Alberto Iess[1,2], Elena Cuoco[3,4], Filip Morawski[5] and Jade Powell[6]



- 1D (time series) and 2D (images) CNN classification.
- Training with simulations of signal and glitches in Gaussian noise.
- Detection with wavelet detection filter.





Performance on real detector data? Multi-detector search?

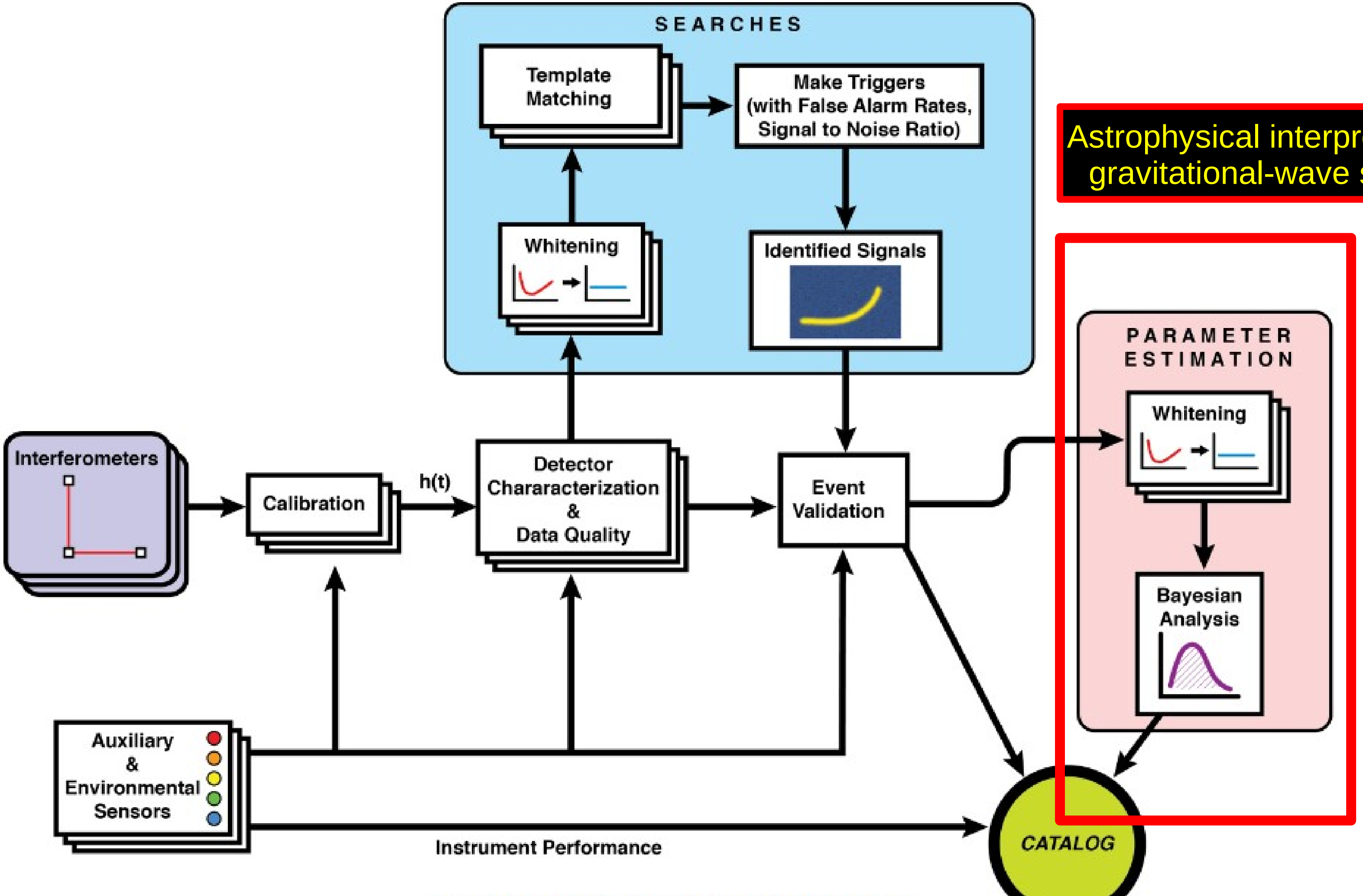
See also:

New method to observe gravitational waves emitted by core collapse supernovae

P. Astone, P. Cerdá-Durán, I. Di Palma, M. Drago, F. Muciaccia, C. Palomba, and F. Ricci

Phys. Rev. D **98**, 122002 – Published 10 December 2018

Astrophysical interpretation of gravitational-wave sources



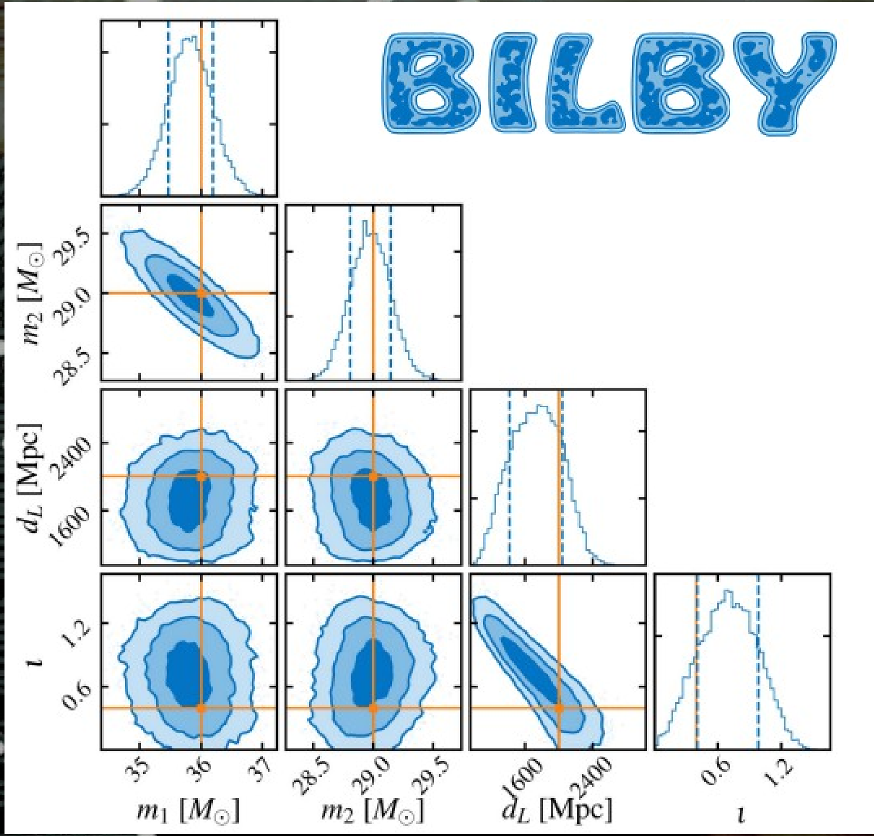
B P Abbott *et al* 2020 *Class. Quantum Grav.* 37 055002

Astrophysical interpretation of gravitational-wave signals

THE ASTROPHYSICAL JOURNAL SUPPLEMENT SERIES, 241:27 (13pp), 2019 April https://doi.org/10.3847/1538-4365/ab06fc

BILBY: A User-friendly Bayesian Inference Library for Gravitational-wave Astronomy

Gregory Ashton[1,2], Moritz Hübner[1,2], Paul D. Lasky[1,2], Colm Talbot[1,2], Kendall Ackley[1,2], Sylvia Biscoveanu[1,2,3], Qi Chu[4,5], Atul Divakarla[1,2,6], Paul J. Easter[1,2], Boris Goncharov[1,2], Francisco Hernandez Vivanco[1,2], Jan Harms[7,8], Marcus E. Lower[1,9,10], Grant D. Meadors[1,2], Denyz Melchor[1,2,11], Ethan Payne[1,2], Matthew D. Pitkin[12], Jade Powell[9,10], Nikhil Sarin[1,2], Rory J. E. Smith[1,2], and Eric Thrane[1,2]



PHYSICAL REVIEW D 91, 042003 (2015)

Parameter estimation for compact binaries with ground-based gravitational-wave observations using the LALInference software library

J. Veitch,[1,2,*] V. Raymond,[3] B. Farr,[4,5] W. Farr,[1] P. Graff,[6] S. Vitale,[7] B. Aylott,[1] K. Blackburn,[3] N. Christensen,[8] M. Coughlin,[9] W. Del Pozzo,[1] F. Feroz,[10] J. Gair,[11] C.-J. Haster,[1] V. Kalogera,[5] T. Littenberg,[5] I. Mandel,[1] R. O'Shaughnessy,[12,13] M. Pitkin,[14] C. Rodriguez,[5] C. Röver,[15,16] T. Sidery,[1] R. Smith,[3] M. Van Der Sluys,[17] A. Vecchio,[1] W. Vousden,[1] and L. Wade[12]

Publications of the Astronomical Society of the Pacific, 131:024503 (16pp), 2019 February https://doi.org/10.1088/1538-3873/aaef0b

PyCBC Inference: A Python-based Parameter Estimation Toolkit for Compact Binary Coalescence Signals

C. M. Biwer[1,2], Collin D. Capano[3], Soumi De[2], Miriam Cabero[3], Duncan A. Brown[2], Alexander H. Nitz[3], and V. Raymond[4,5]

Rapid and accurate parameter inference for coalescing, precessing compact binaries

J. Lange,[1] R. O'Shaughnessy,[1] and M. Rizzo[1]
[1]Center for Computational Relativity and Gravitation, Rochester Institute of Technology, Rochester, New York 14623, USA

- Current parameter estimation techniques for compact binary coalesce signals rely on Bayesian analysis (posteriors + evidence).
- Computationally costly!
- Need to dramatically speed up the process!
- How can machine learning help?

Astrophysical interpretation of gravitational-wave signals

Rapid inference of source properties

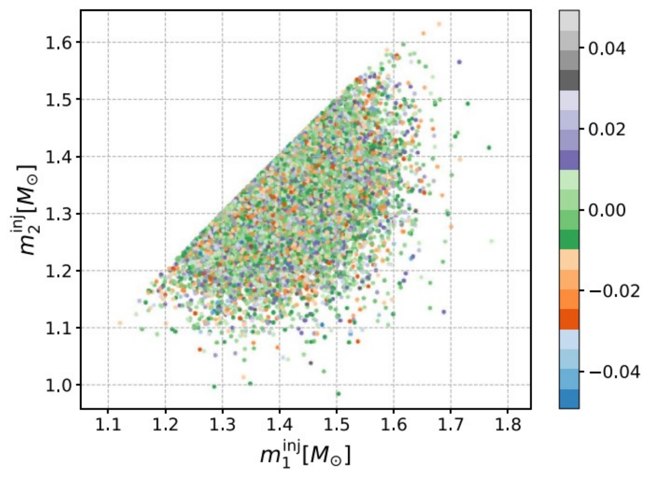
- Classifiers (Kneighbors, genetic, random forests) for HasNS and HasRemnant properties of sources in low-latency
- Train and test on LIGO-Virgo online MDC
- Integrate in the LVK low-latency infrastructure and run in O4

The Astrophysical Journal, 896:54 (10pp), 2020 June 10 https://doi.org/10.3847/1538-4357/ab8dbe

A Machine Learning-based Source Property Inference for Compact Binary Mergers

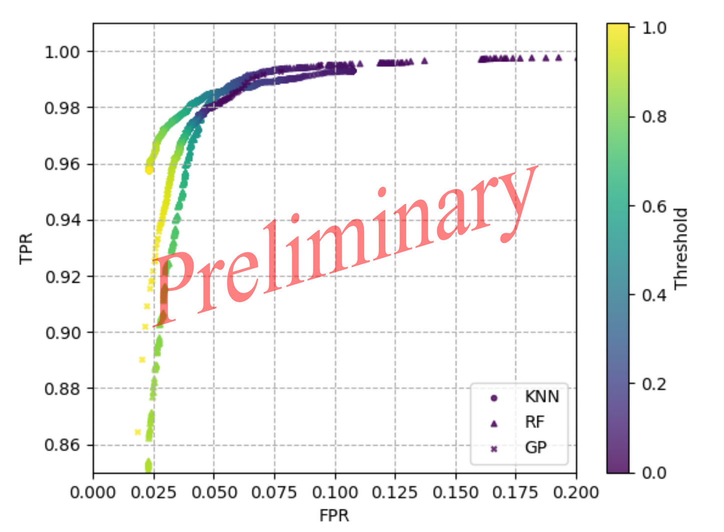
Deep Chatterjee[1], Shaon Ghosh[1,2], Patrick R. Brady[1], Shasvath J. Kapadia[1,3], Andrew L. Miller[4], Samaya Nissanke[5], and Francesco Pannarale[6,7]
[1] Department of Physics, University of Wisconsin–Milwaukee, Milwaukee, WI 53211, USA
[2] Department of Physics and Astronomy, Montclair State University, 1 Normal Avenue, Montclair, NJ 07043, USA
[3] International Centre for Theoretical Sciences, Tata Institute of Fundamental Research, Bangalore 560012, India
[4] Centre for Cosmology, Particle Physics and Phenomenology (CP3), Université Catholique de Louvain, Chemin du Cyclotron, 2 B-1348 Louvain-la-Neuve, Belgium
[5] GRAPPA, Anton Pannekoek Institute for Astronomy and Institute of High-Energy Physics, University of Amsterdam, Science Park 904, 1098 XH Amsterdam, The Netherlands
[6] Dipartimento di Fisica, Università di Roma "Sapienza," Piazzale A. Moro 5, I-00185 Roma, Italy
[7] INFN Sezione di Roma, Piazzale A. Moro 5, I-00185 Roma, Italy
Received 2019 October 31; revised 2020 April 24; accepted 2020 April 26; published 2020 June 12

Deploy Selected Model



O3 event	p(HasNS)	p(HasRemnant)
GW190425	0.999	0.9959
GW190426	0.9676	0.0029
GW190421	0.0057	0.0012
GW190915	0.0057	0.0012
GW200115	0.967	0.0029
GW20012	0.0057	0.0012

Preliminary



See also:
S. Sharma Chaudhary, MC, D. Chatterjee, S. Ghosh, in preparation

Astrophysical interpretation of gravitational-wave signals

Parameter estimation

- Deep neural networks to infer the relationship between the initial BBHs parameters and the remnant final mass and fina spin of a binary black hole merger.
- Trained with publicly available NR catalogs.

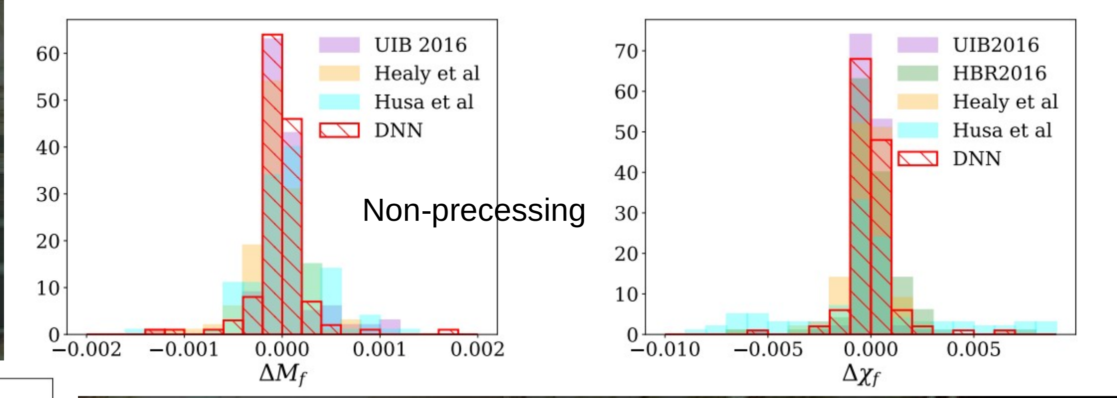
Classical and Quantum Gravity

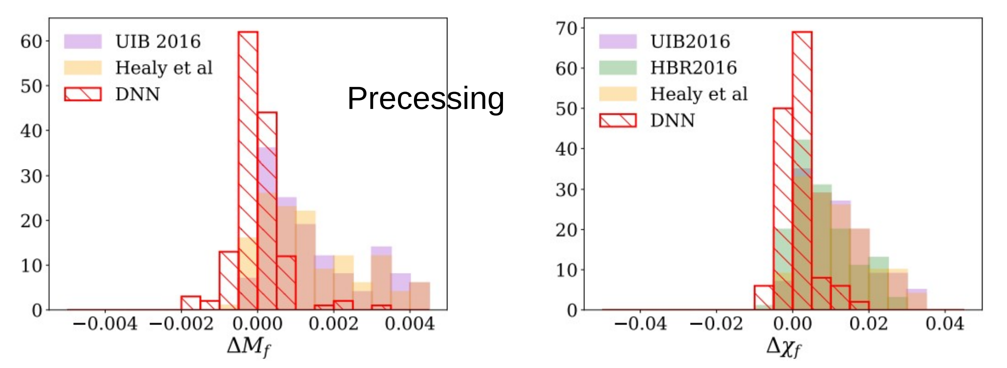
PAPER

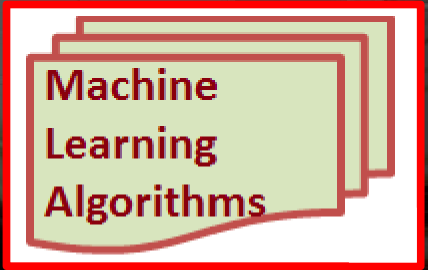
Predicting the properties of black-hole merger remnants with deep neural networks

L Haegel[3,1,2] and S Husa[1]

Published 10 June 2020 • © 2020 IOP Publishing Ltd
Classical and Quantum Gravity, Volume 37, Number 13
Citation L Haegel and S Husa 2020 *Class. Quantum Grav.* **37** 135005

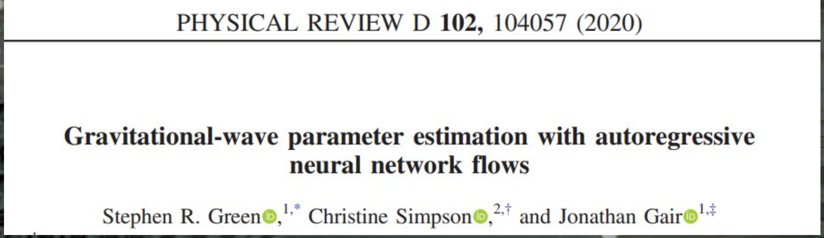






Astrophysical interpretation of gravitational-wave signals

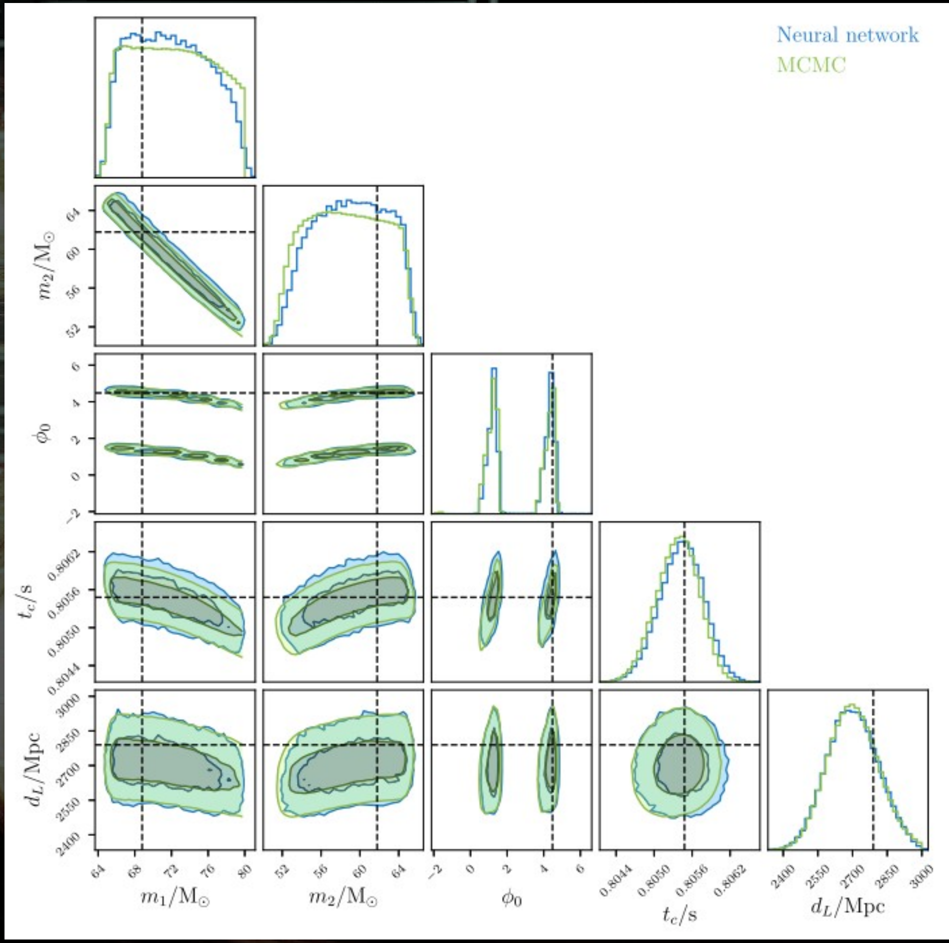
Parameter estimation


PHYSICAL REVIEW D **102,** 104057 (2020)

Gravitational-wave parameter estimation with autoregressive neural network flows

Stephen R. Green,[1,*] Christine Simpson,[2,†] and Jonathan Gair[1,‡]

- Autoregressive normalizing flows for rapid likelihood-free inference of binary black hole system parameters.
- Maps a multivariate standard normal distribution into the posterior distribution of system parameters.
- Performance comparable to Markov chain Monte Carlo.



Astrophysical interpretation of gravitational-wave signals

Parameter estimation

Candidate Model

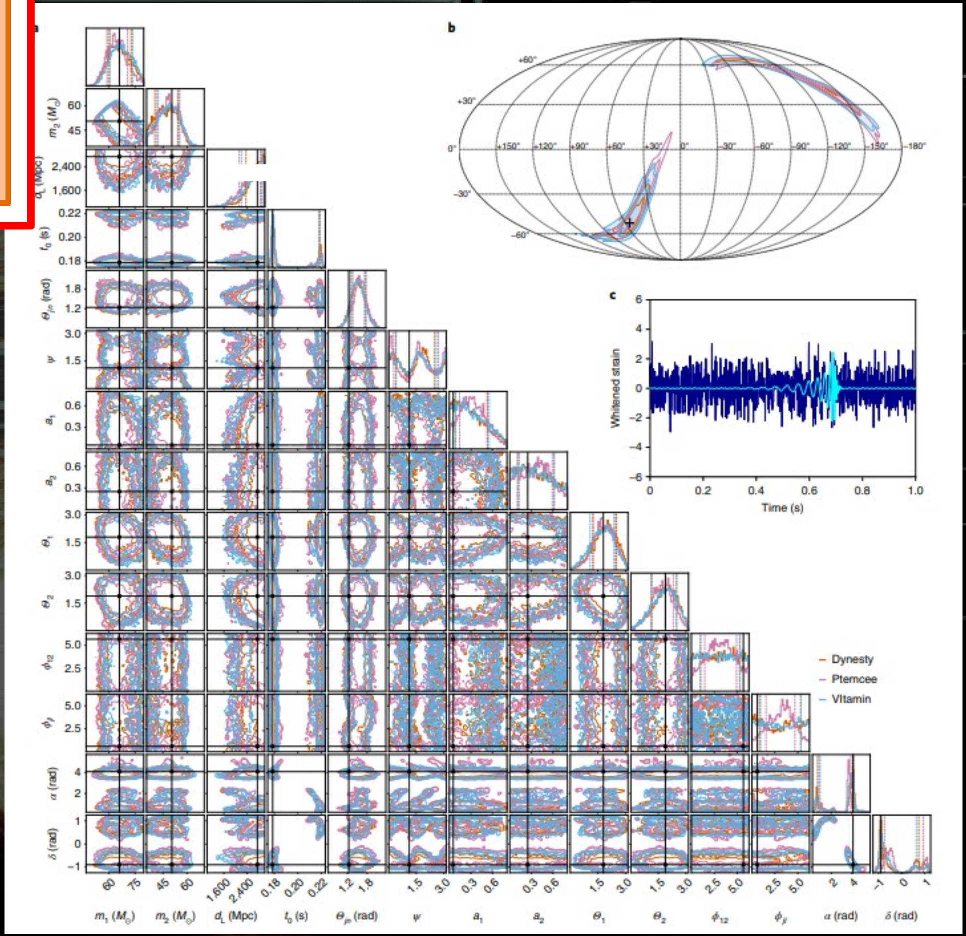
ARTICLES
nature physics
https://doi.org/10.1038/s41567-021-01425-7
Check for updates

Bayesian parameter estimation using conditional variational autoencoders for gravitational-wave astronomy

Hunter Gabbard[1], Chris Messenger[1], Ik Siong Heng[1], Francesco Tonolini[2] and Roderick Murray-Smith[2]

Table 2 | Durations required to produce samples from each of the sampling approaches

Sampler	Run time (s)			Ratio $\frac{\tau_{\text{VItamin}}}{\tau_X}$
	Min.	Max.	Median	
Dynesty[a,7]	21,564	261,268	45,607[b]	2.2×10^{-6}
emcee[8]	16,712	39,930	19,821	5.1×10^{-6}
ptemcee[9]	2,392	501,632	41,151.0	2.4×10^{-6}
CPNest[6]	10,309	437,008	83,807	1.2×10^{-6}
VItamin[c]	1×10^{-1}			1



- Pre-trained conditional variational autoencoder
- Standard advanced detector power spectral density.
- Full-parameter estimation ~ 1 s.

Astrophysical interpretation of gravitational-wave signals

Parameter estimation

ARTICLES
https://doi.org/10.1038/s41567-021-01425-7
nature physics
Check for updates

Bayesian parameter estimation using conditional variational autoencoders for gravitational-wave astronomy

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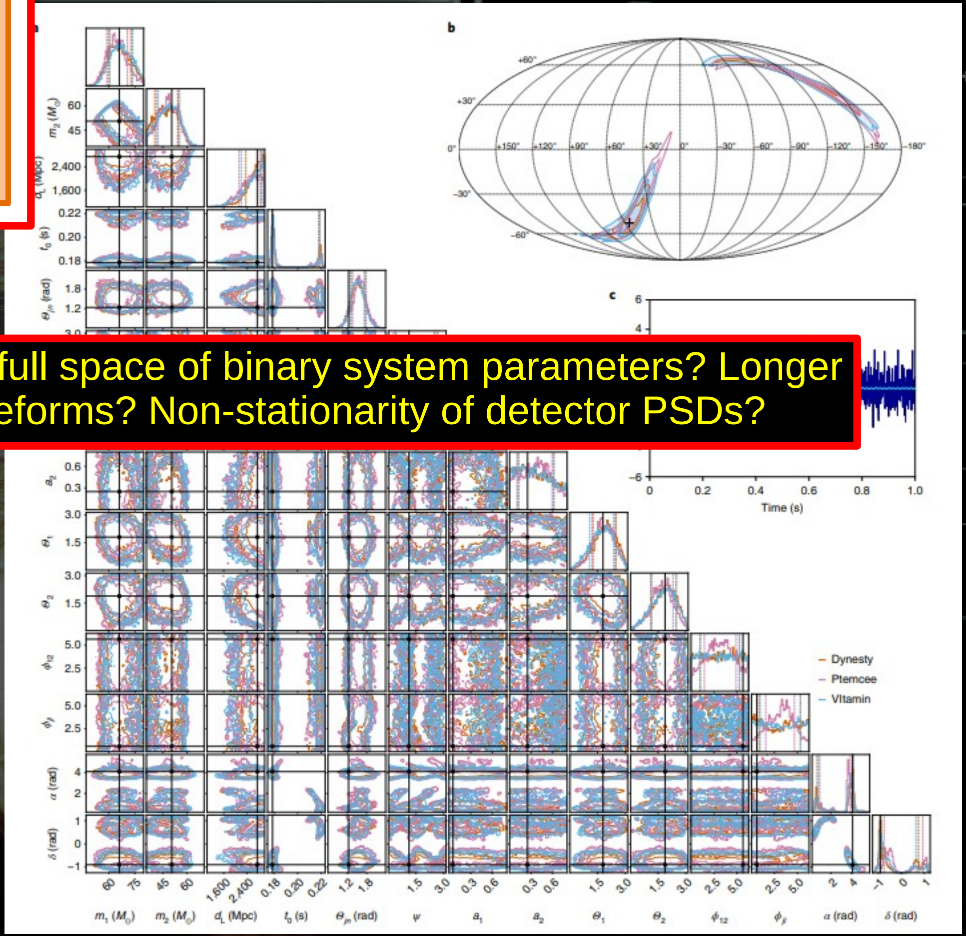
Candidate Model



Extension to full space of binary system parameters? Longer duration waveforms? Non-stationarity of detector PSDs?

- Pre-trained conditional variational autoencoder
- Standard advanced detector power spectral density.
- Full-parameter estimation ~ 1 s.

What do we need to do to reach gravitational-wave machine learning Nirvana?

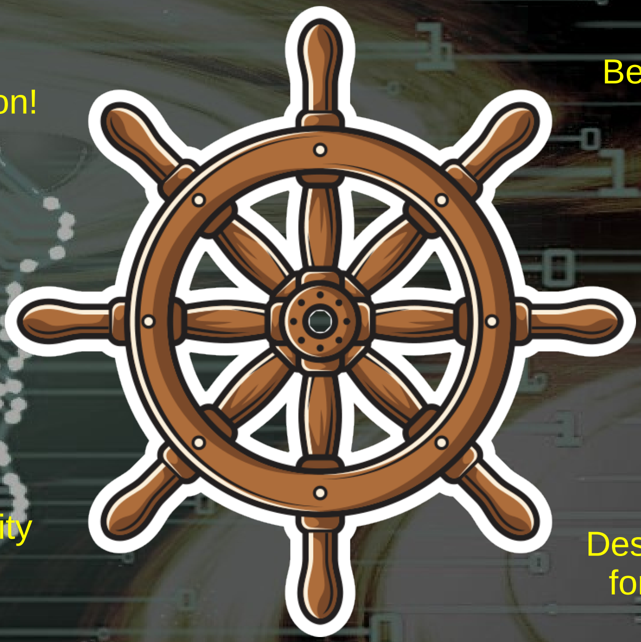
The eightfold path to machine learning enlightenment

What do we need to do to reach gravitational-wave machine learning Nirvana?

Show better performance than conventional techniques on the full parameter space!

Go beyond classification!

Be careful about overfitting!



Make sure your algorithm speaks the language of physicists!

Test on real data!

Favor interpretability over accuracy!

Design algorithms for low latency!

Implement in production mode!

The eightfold path to machine learning enlightenment

MISSOURI S&T

Institute for Multi-messenger Astrophysics and Cosmology

Thank you!

The author thankfully acknowledges the human and material resources of the LIGO Scientific Collaboration and the Virgo Collaboration that have made possible the results presented in this talk, and the National Science Foundation for its continuous support of LIGO science, and basic and applied research in the United States. This work has been partially supported by NSF grant PHY-2011334.