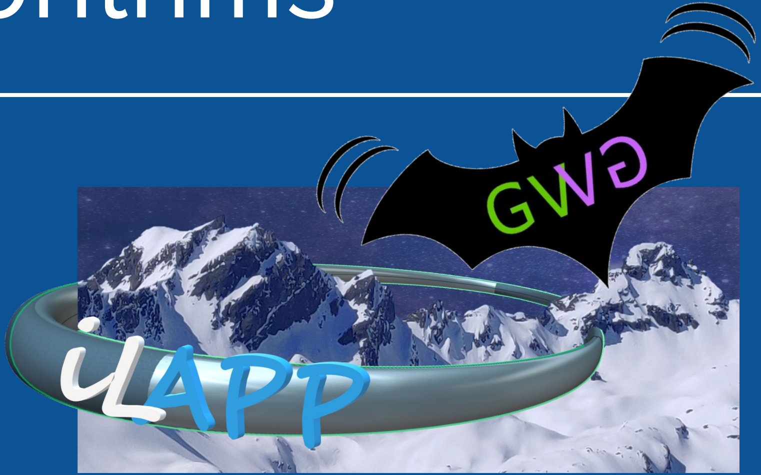
Detection of Gravitational Waves with Machine Learning/Deep Learning Algorithms

Osvaldo Freitas



23 September 2022
University of Minho

Outline

1. An introduction to gravitational waves

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2. Gravitational wave detectors

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3. Challenges

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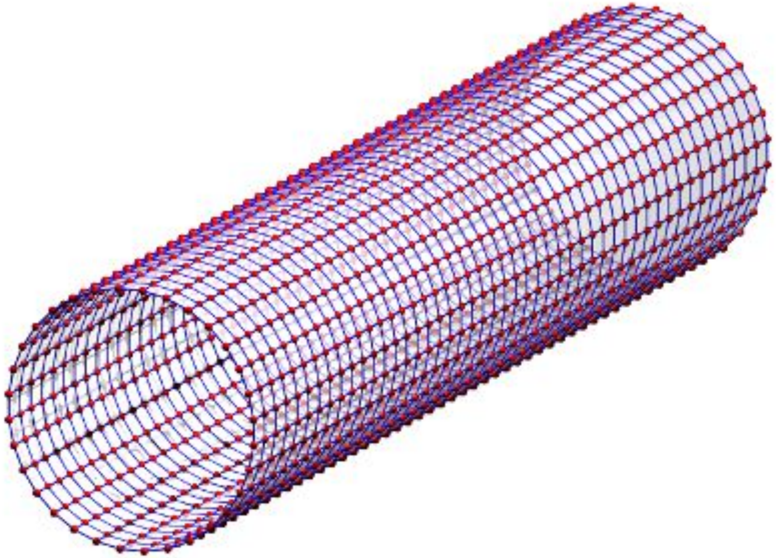
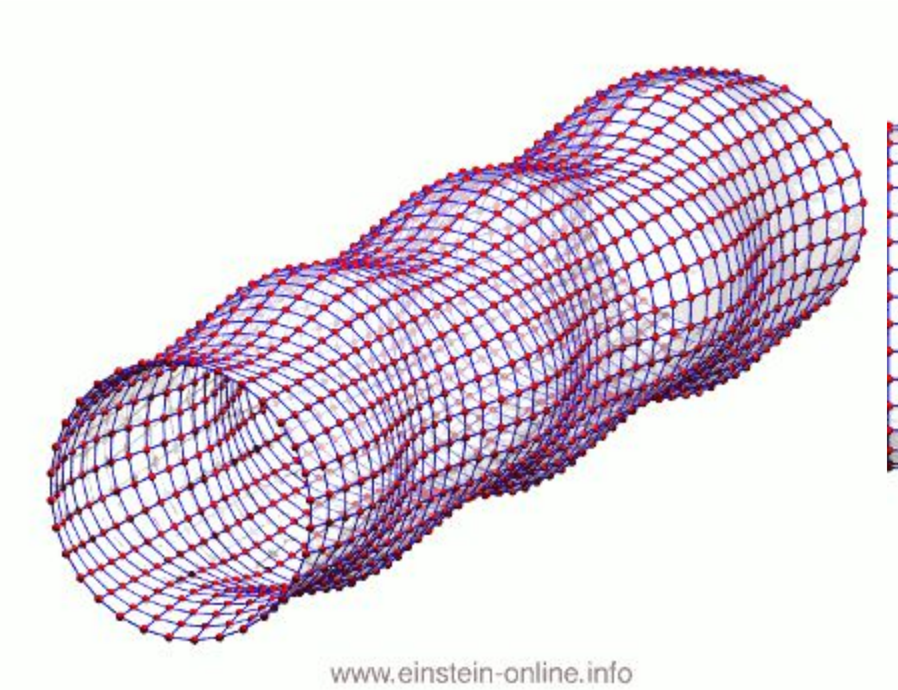
3. Challenges
4. Deep learning
5. Applications to GW astronomy

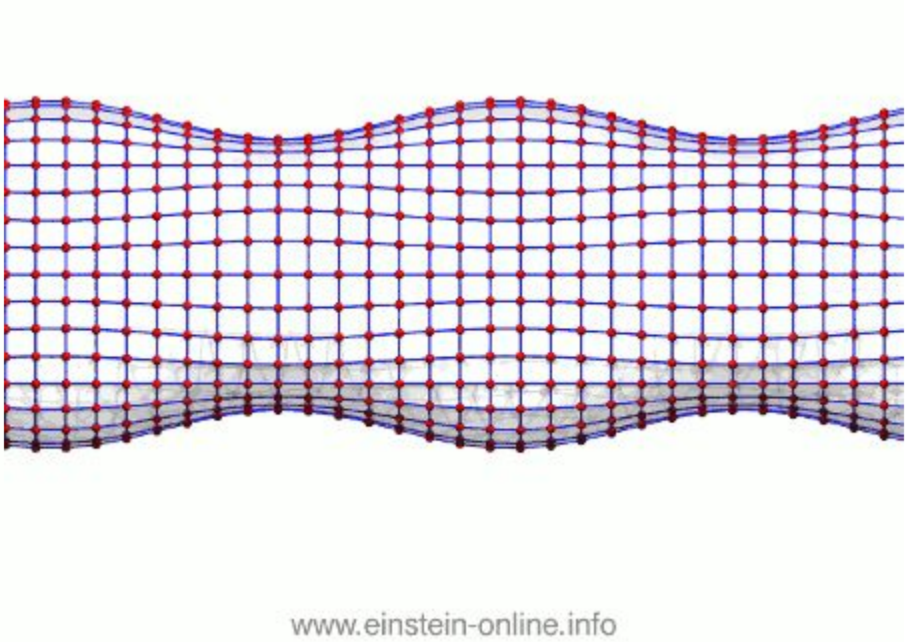
Gravitational waves



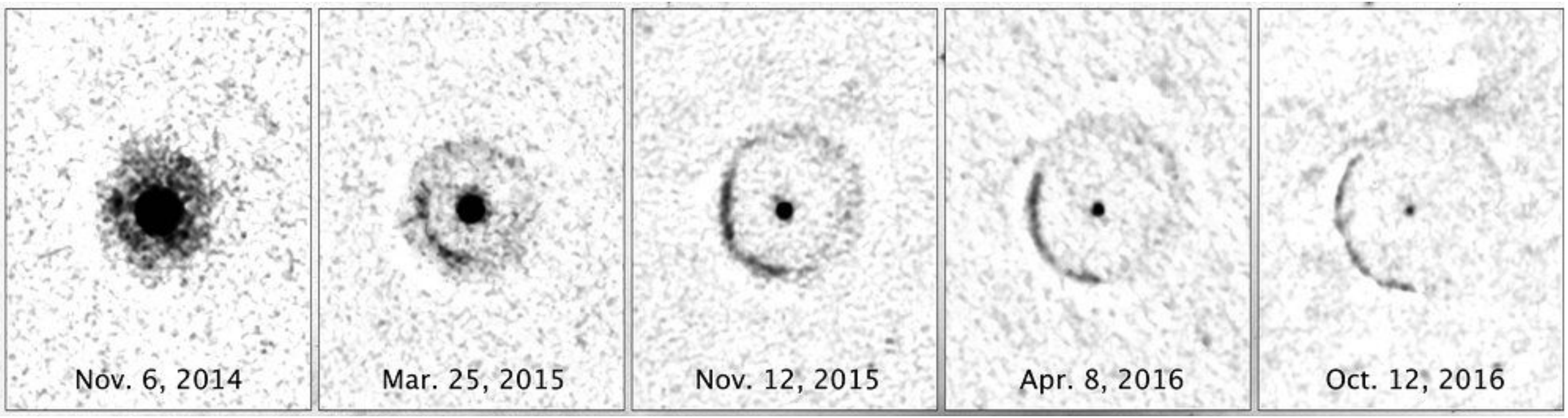
www.einstein-online.info

Gravitational waves



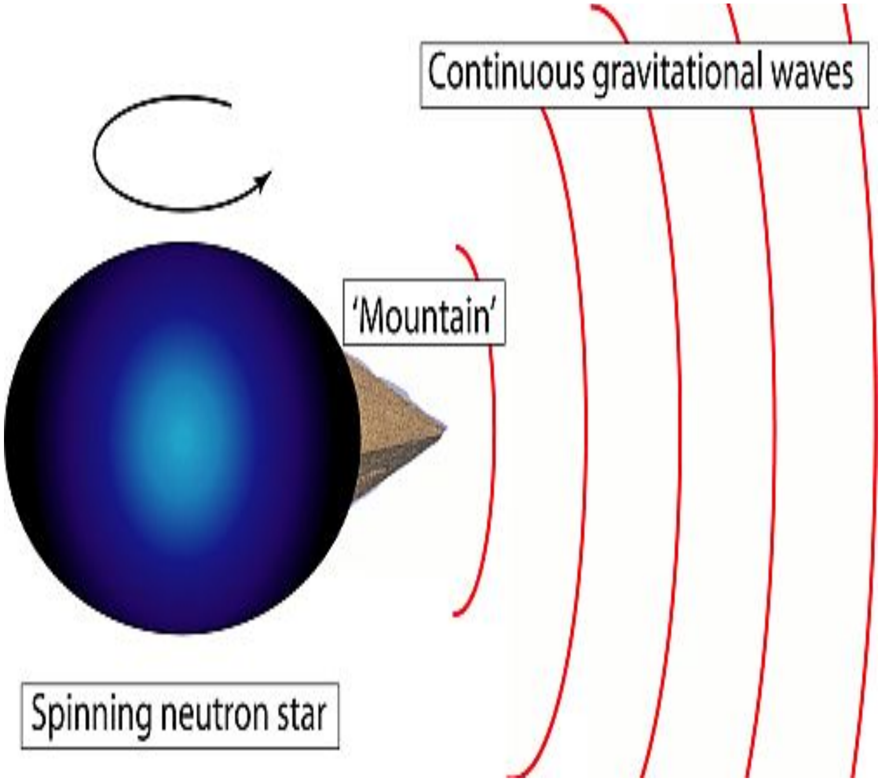


Sources of gravitational waves - Supernovae

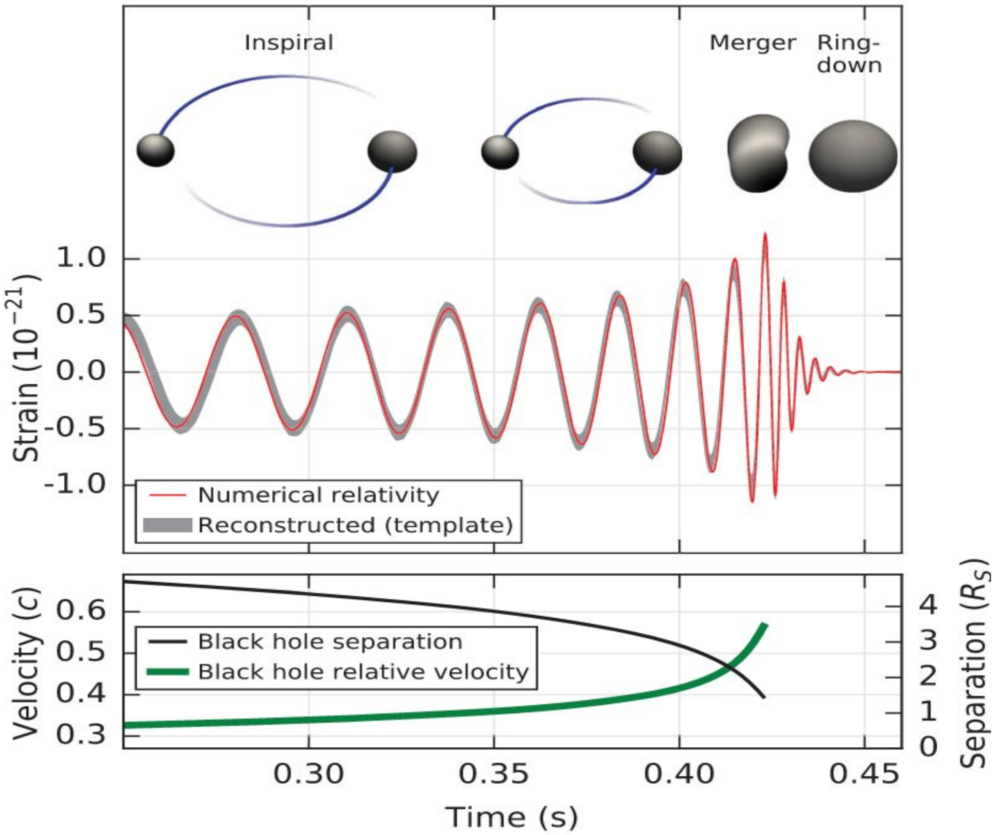


esahubble.org

Sources of gravitational waves - Spinning neutron stars



Sources of gravitational waves - Binary systems



Abbott BP. *et al.* 2016. Observation of gravitational waves from a binary black hole merger. *Phys. Rev. Lett.* 116, 061102 (10.1103/PhysRevLett.116.061102)

Gravitational wave detections

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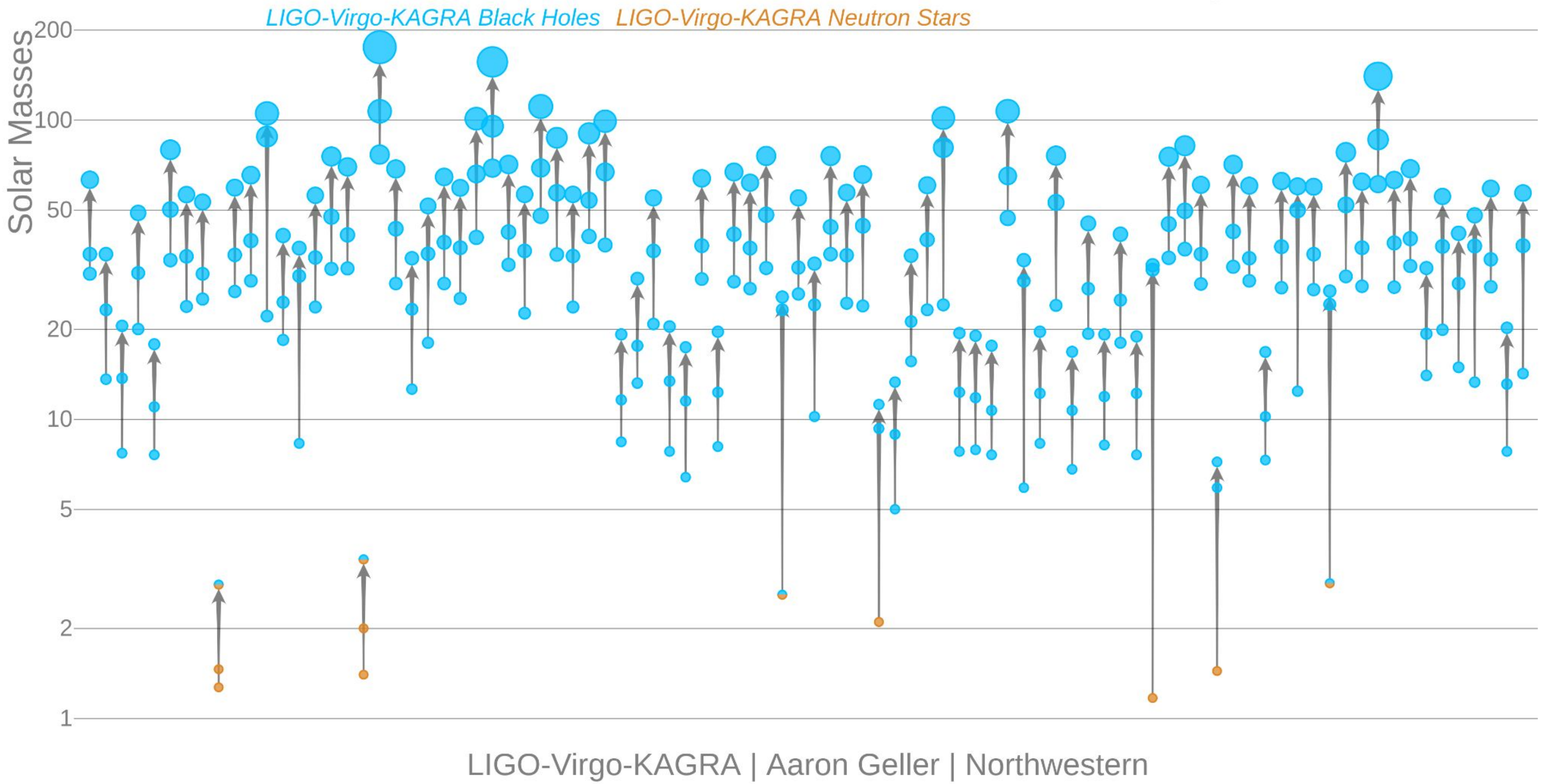
- Detectors will improve further
- Wholly new detectors are in the work

Challenges

- Detection rate will increase significantly!

Masses in the Stellar Graveyard



Network	GW events		Joint GW-GRB events	
	Flat	Gaussian	Flat	Gaussian
HLVKI	768	814	14	15

Table 1. Number of GW events detected by second generation (2G) networks in 10 years, and the expected GW-GRB coincidences obtained by assuming a GRB detector with the characteristics of Fermi-GBM. We show detection rates for BNS populations generated using O2 rates corresponding to both flat and Gaussian mass distributions.

E. Belgacem, Y. Dirian, S. Foffa, E. J. Howell, M. Maggiore, and T. Regimbau, *Cosmology and Dark Energy from Joint Gravitational Wave-GRB Observations*, J. Cosmol. Astropart. Phys. **2019**, 015 (2019).

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Network	GW events		Joint GW-GRB events	
	Flat	Gaussian	Flat	Gaussian
ET	621,700	688,426	389 (128)	511 (169)
ET+CE+CE	5,420,656	7,077,131	644 (213)	907 (299)

Table 2. Number of GW BNS events detected by third generation (3G) networks in 10 years of data taking (assuming a 80% duty cycle for each detector) and the corresponding GW-GRB coincidences obtained by assuming a GRB detector with the characteristics of THESEUS-XGIS; numbers in parenthesis show the number of sources with arcmin localisation. BNS populations are generated using the O2 rates corresponding to 'flat' and 'Gaussian' mass distributions.

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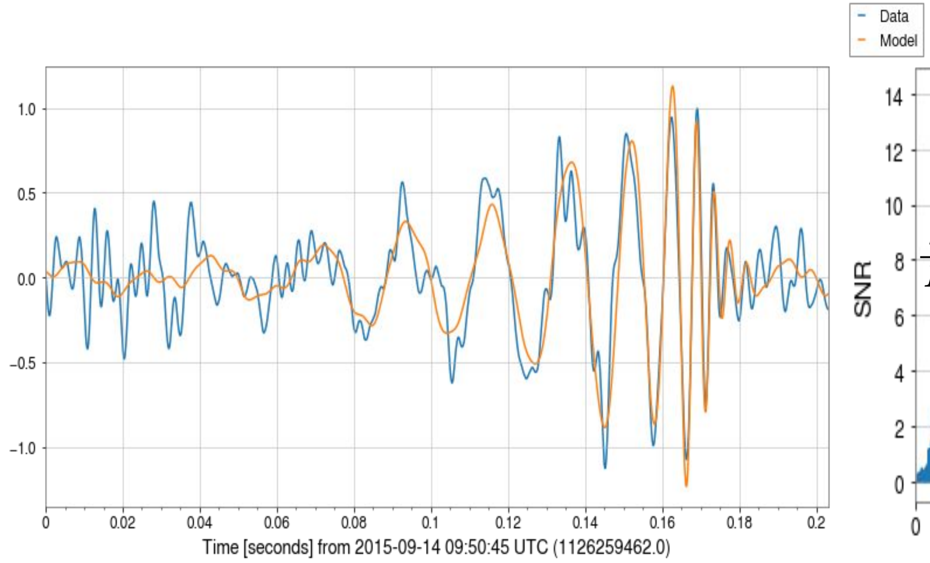

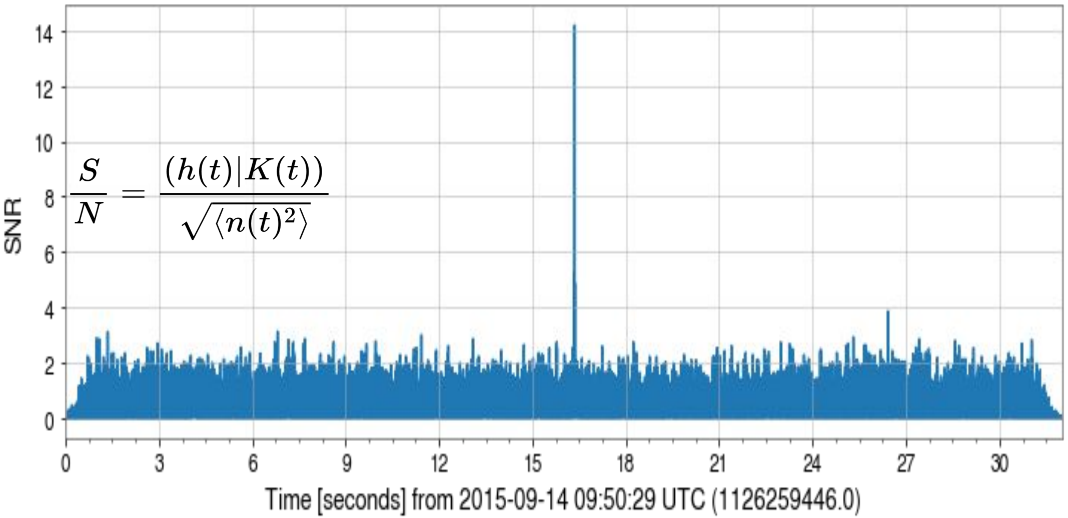

$$\frac{S}{N} = \frac{(h(t)|K(t))}{\sqrt{\langle n(t)^2 \rangle}}$$

Challenges

- Detection rate will increase significantly!
- Current methods use extensive template banks
- We must deal with large amounts of data efficiently
  - Unmodeled searches
  - Accelerated parameter estimation
  - Fast template generation

Machine Learning (basically statistics but it sounds cooler)

- Algorithms can be trained to extract meaningful information from data.

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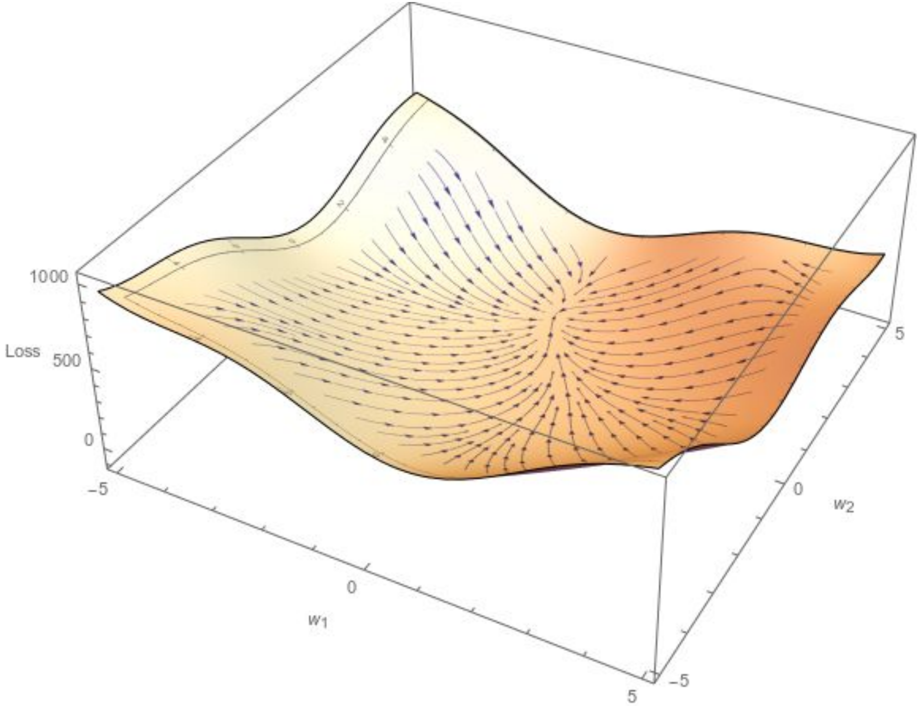

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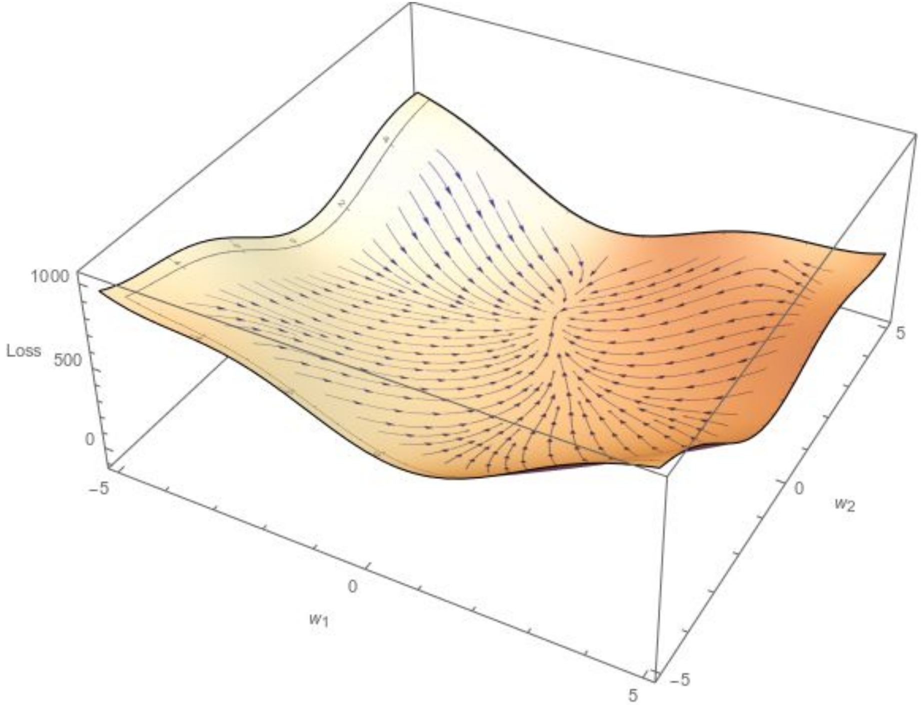
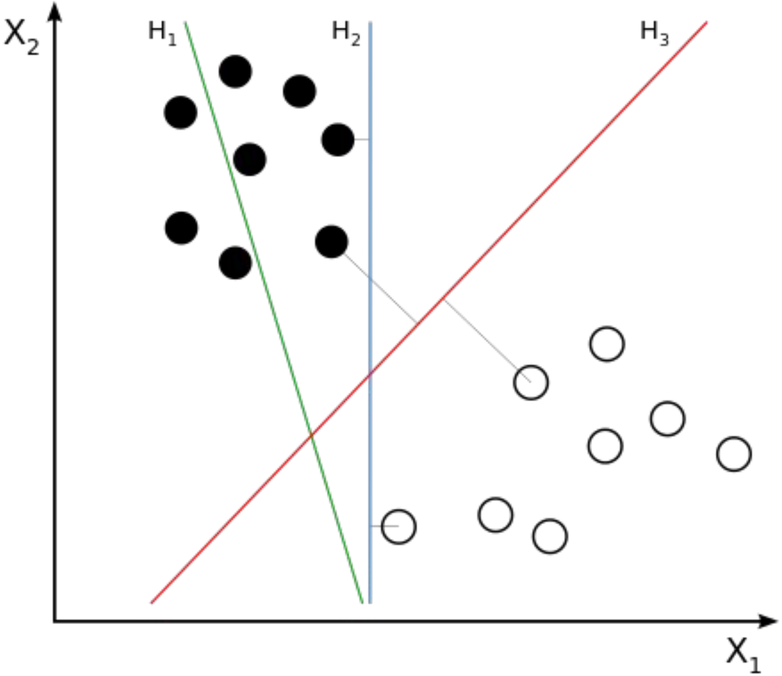
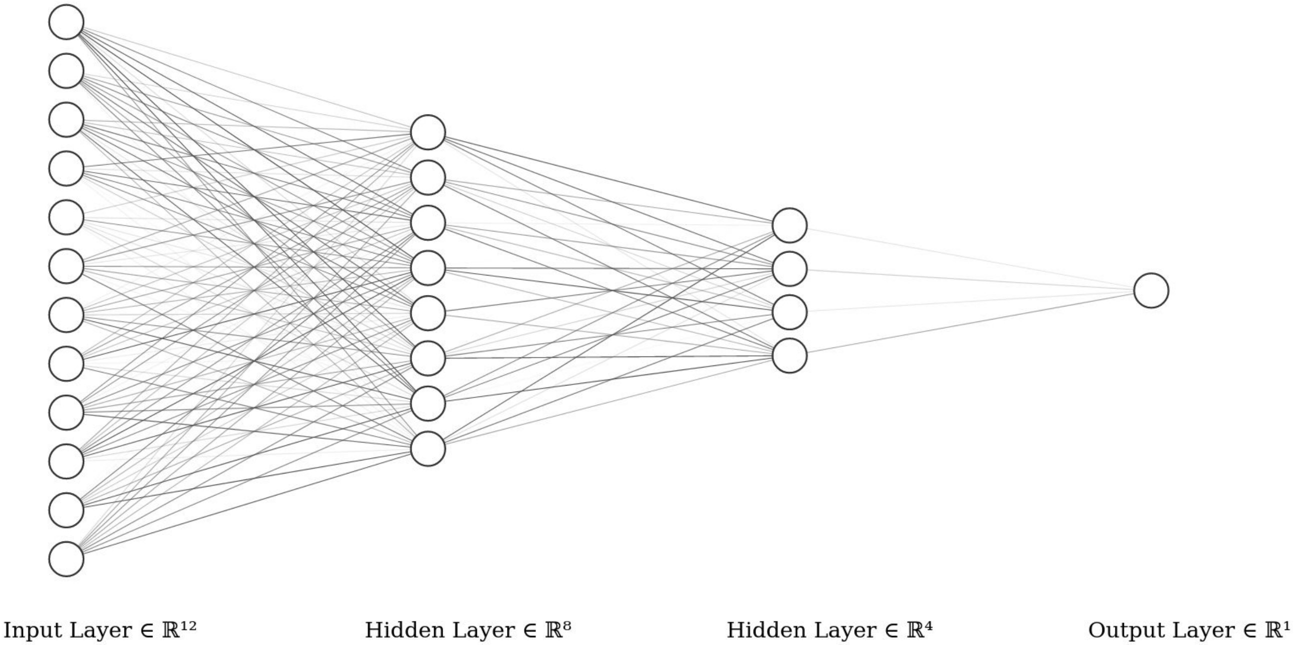




Machine Learning (basically statistics but it sounds cooler)

- Algorithms can be trained to extract meaningful information from data.
- Very efficient at runtime; computational cost concentrated in training process

Deep Learning



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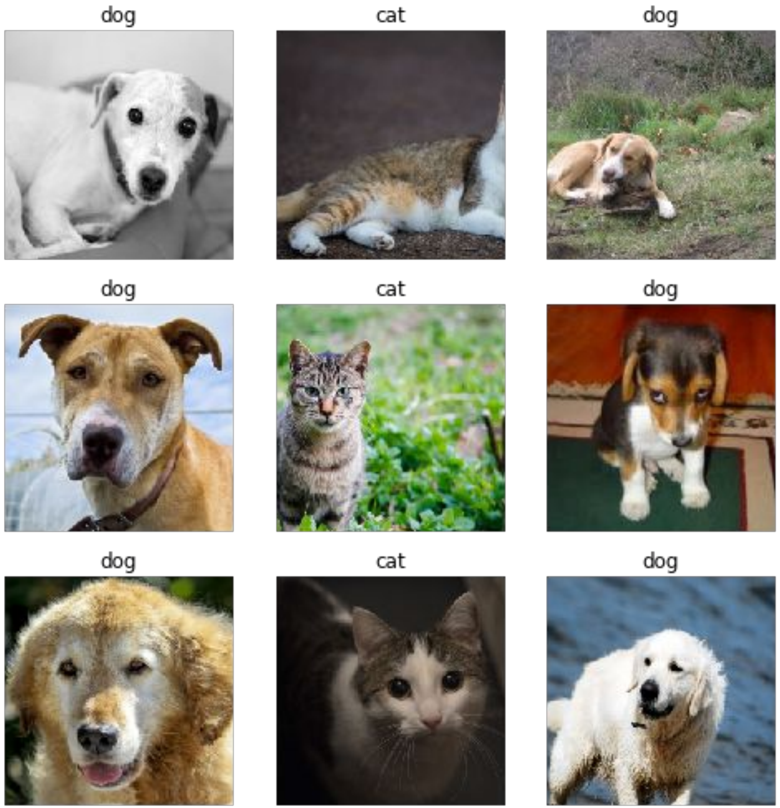

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DL applications to GW astronomy

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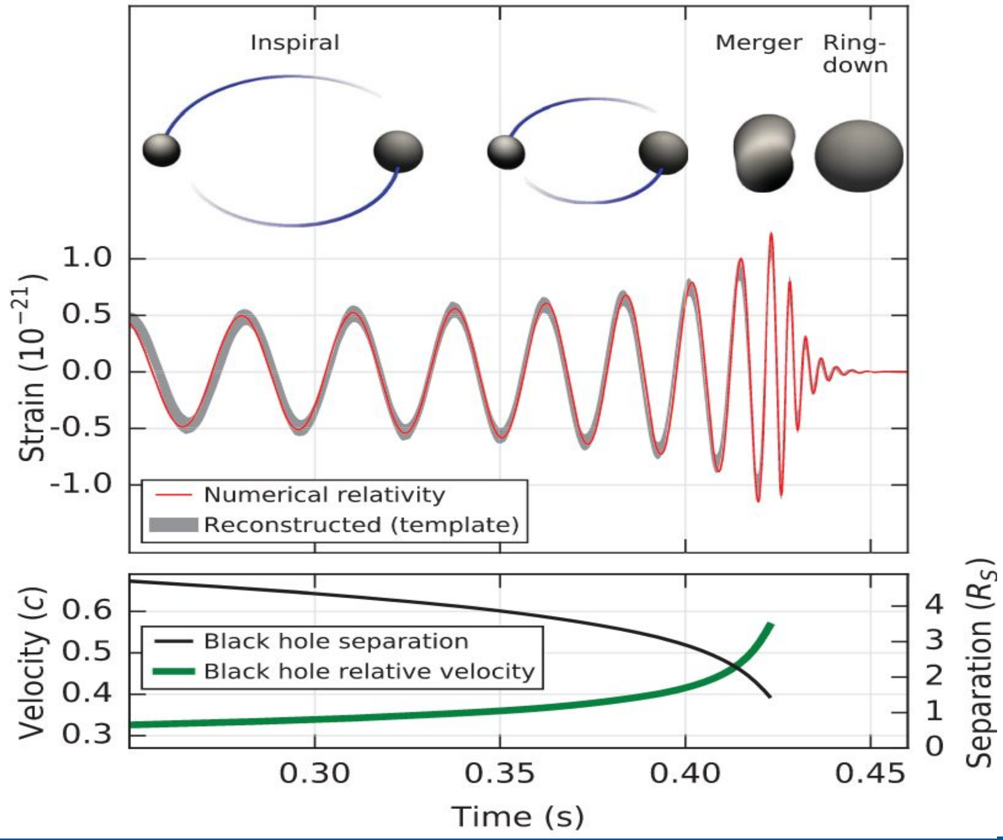

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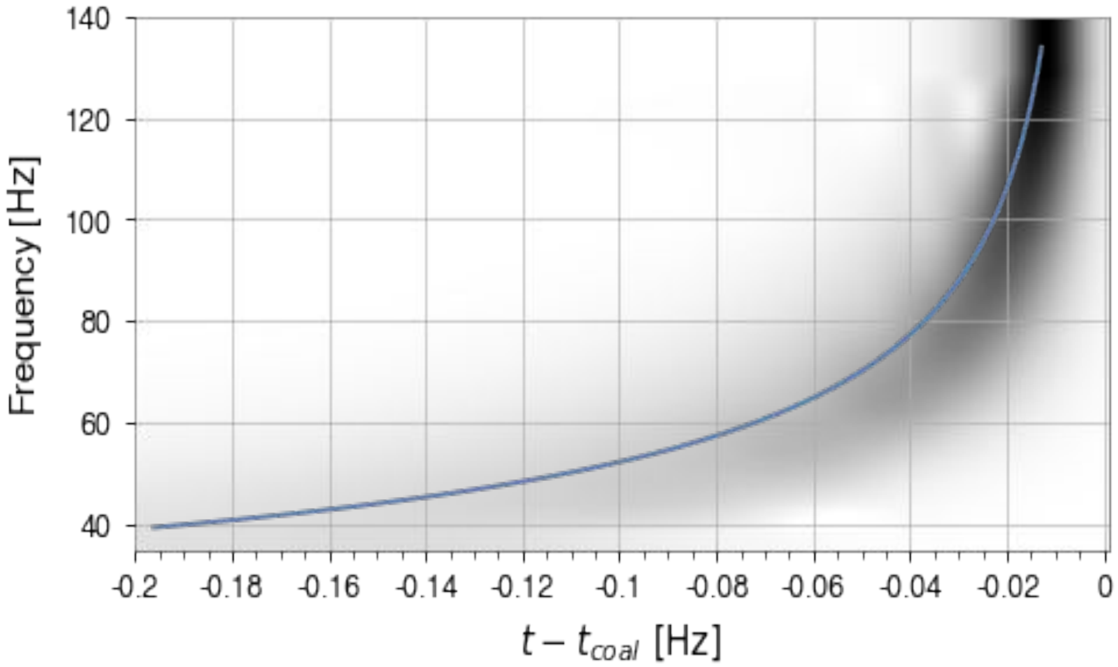
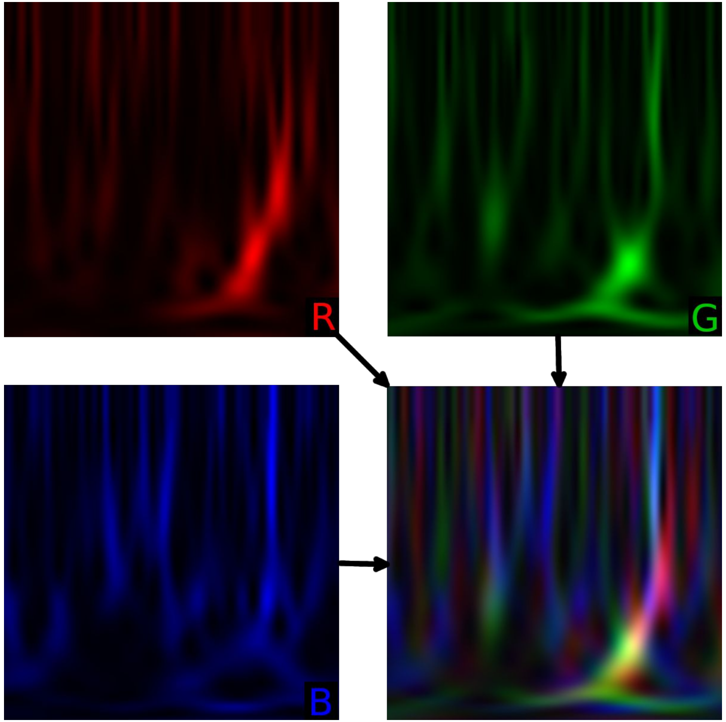


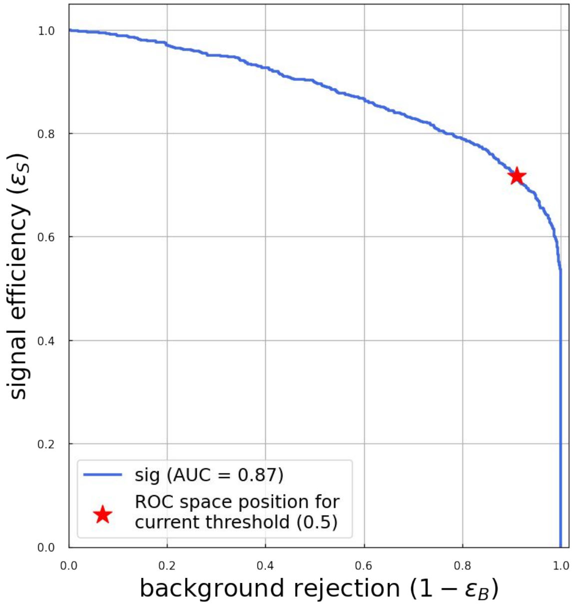
DL applications to GW astronomy

- We can reappropriate computer vision tools...

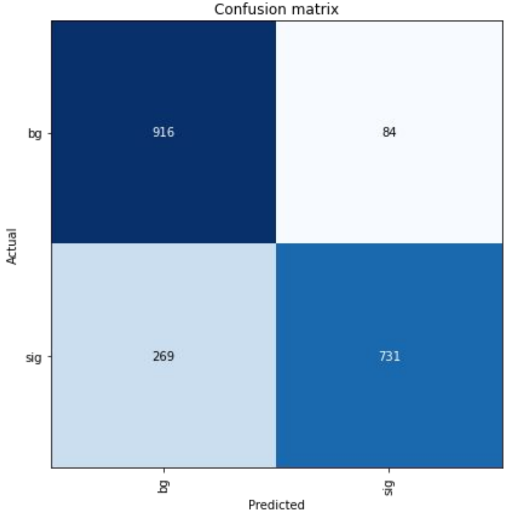


DL applications to GW astronomy

- We can reappropriate computer vision tools… for classification



$\mathrm{FPR} \approx 0.08$



$\mathrm{PPV} = 0.9$

$\varepsilon_S = \mathrm{TPR} \approx 0.73$

Álvares, J.D., Font, J.A., Freitas, F.F., Freitas, O.G., Morais, A.P., Nunes, S., Onofre, A., Torres-Forné, A., 2021. Exploring gravitational-wave detection and parameter inference using deep learning methods. Class. Quantum Grav. 38, 155010. https://doi.org/10.1088/1361-6382/ac0455

DL applications to GW astronomy

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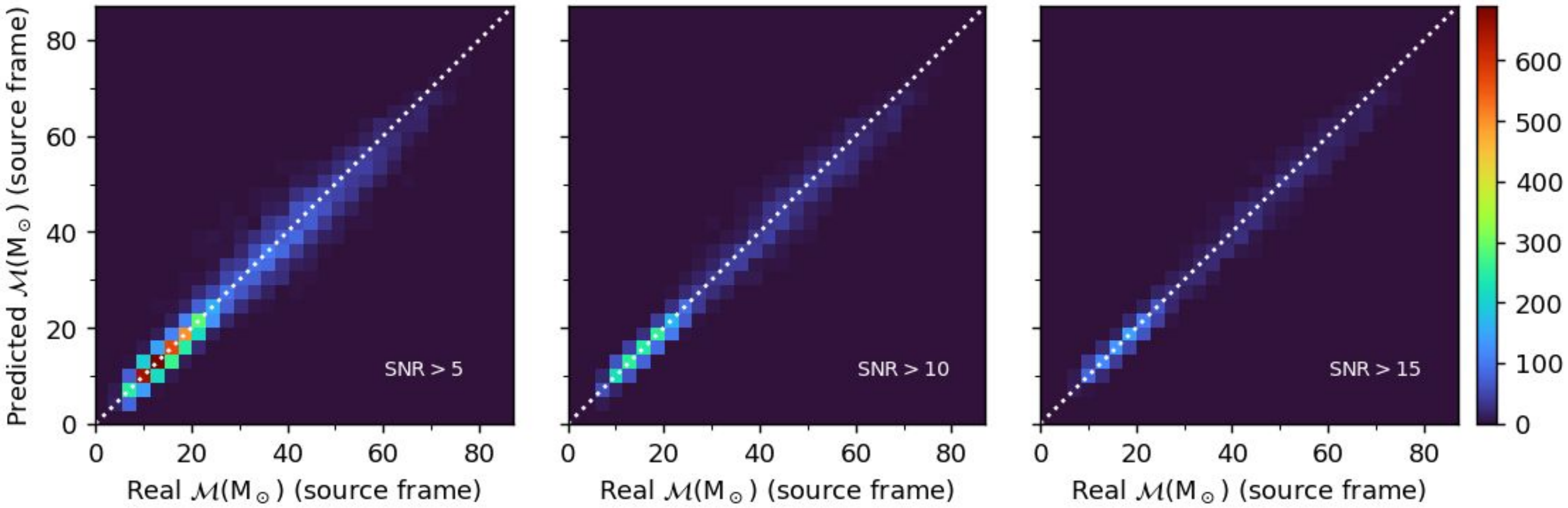

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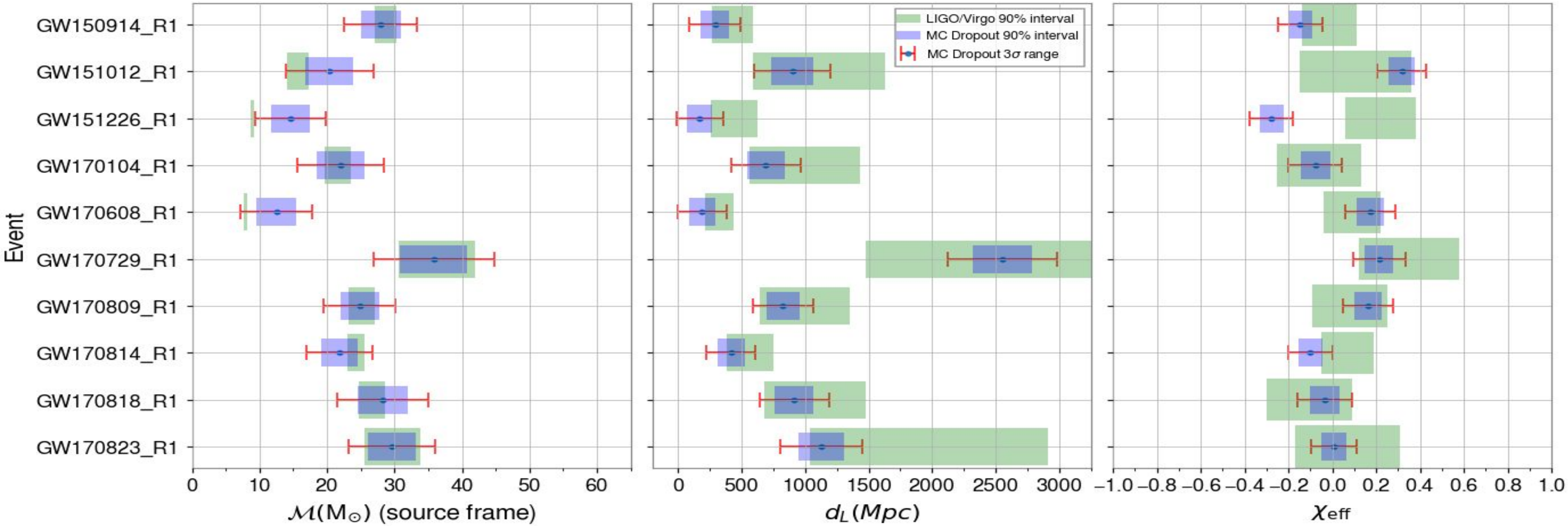

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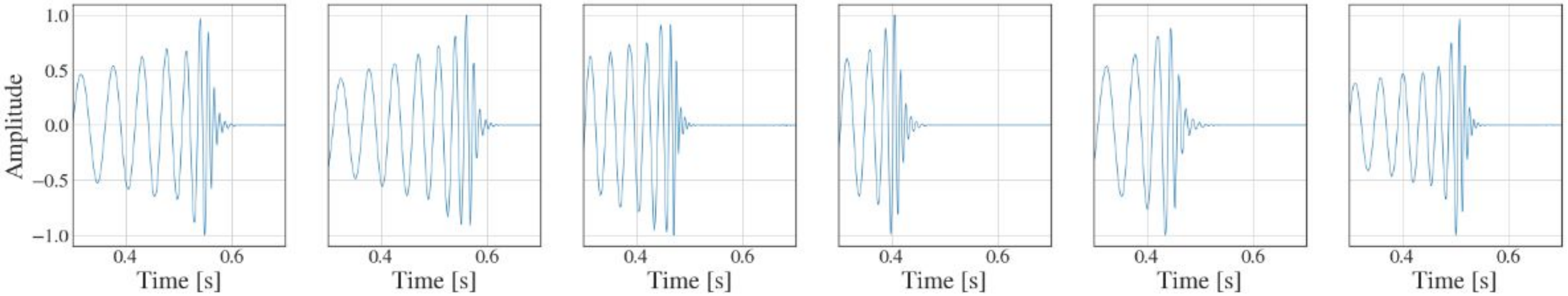
DL applications to GW astronomy

- Efforts ongoing to generate GW models with DL



McGinn, J., Messenger, C., Heng, I.S., Williams, M.J., 2021. Generalised gravitational burst generation with Generative Adversarial Networks. Class. Quantum Grav. 38, 155005. https://doi.org/10.1088/1361-6382/ac09cc

Summing up:

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- Amount of relevant data will increase (absurdly)

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- Amount of relevant data will increase
- DL has already proved promising for the future of GW astronomy

Thank you!

help