*Link to these slides*: [www.tiny.cc/LIGO](www.tiny.cc/LIGO)

# Deep Learning with Neural Networks For Gravitational Wave Astrophysics


## Daniel George

dgeorge5@illinois.edu

PhD student in the Department of Astronomy
Computational Science and Engineering Fellow, NVIDIA Fellow
NCSA Gravity Group - gravity.ncsa.illinois.edu
University of Illinois at Urbana-Champaign


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# AI for Gravitational Wave Analysis:

1) Deep Neural Networks to Enable Real-time Multimessenger Astrophysics

*Physical Review D (February 2018)* - Daniel George and E. A. Huerta

Foundational article pioneering deep learning for gravitational wave detection.
First to show neural networks can **outperform** matched-filtering, enabling new physics

2) Deep Learning for Real-time Gravitational Wave Detection and Parameter Estimation: Results with Advanced LIGO Data

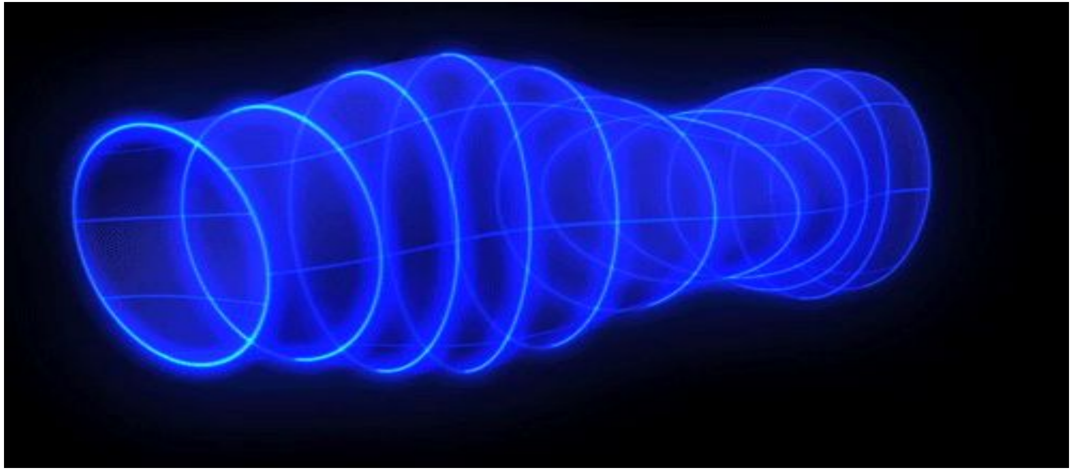
*Physics Letters B (March 2018)* - Daniel George and E. A. Huerta

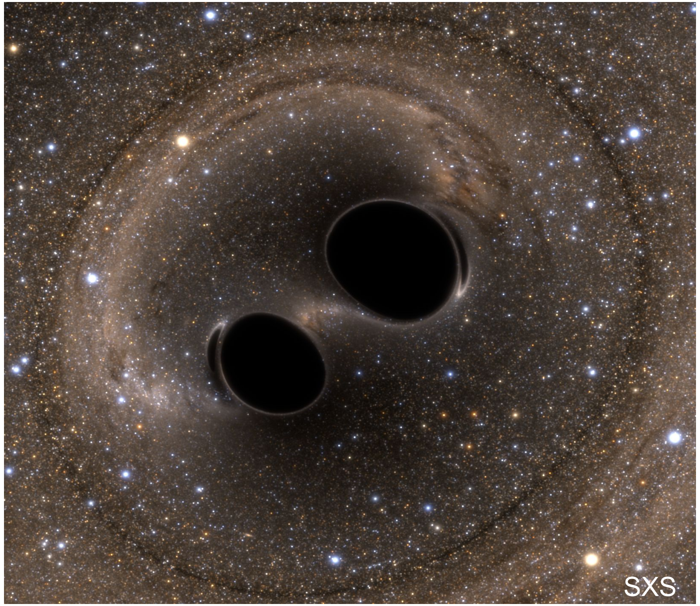
First application of deep learning to detect true gravitational waves in **real** LIGO data

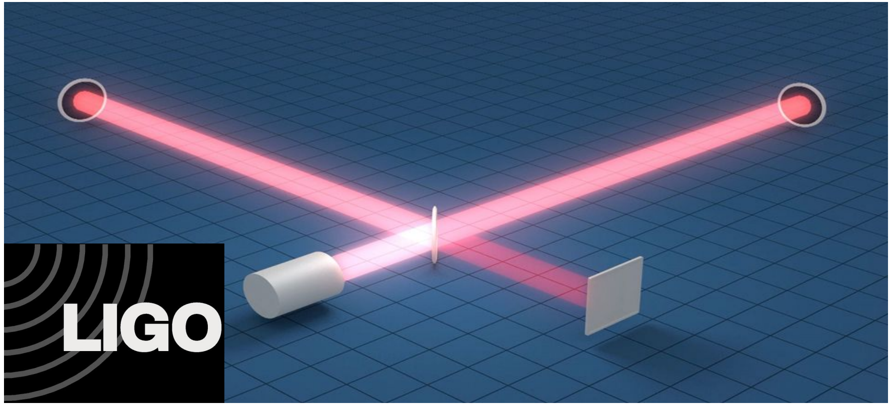


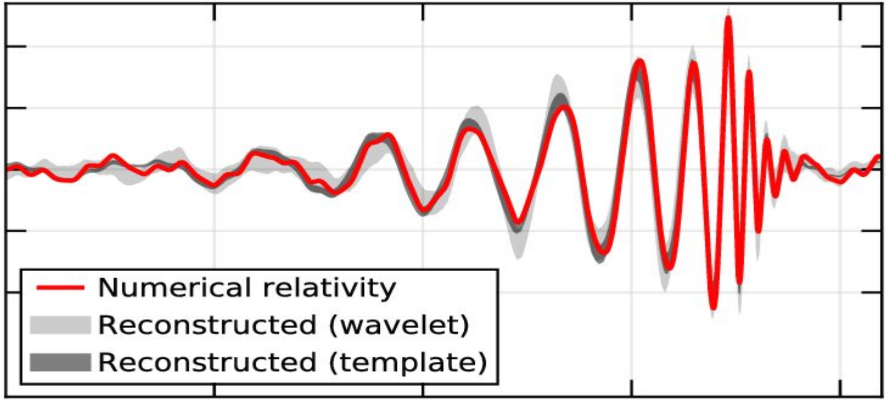
*Link to these slides*: www.tiny.cc/LIGO

# Gravitational Waves








Source: ligo.org

The Royal Swedish Academy of Sciences has decided to award the

# 2017 NOBEL PRIZE IN PHYSICS

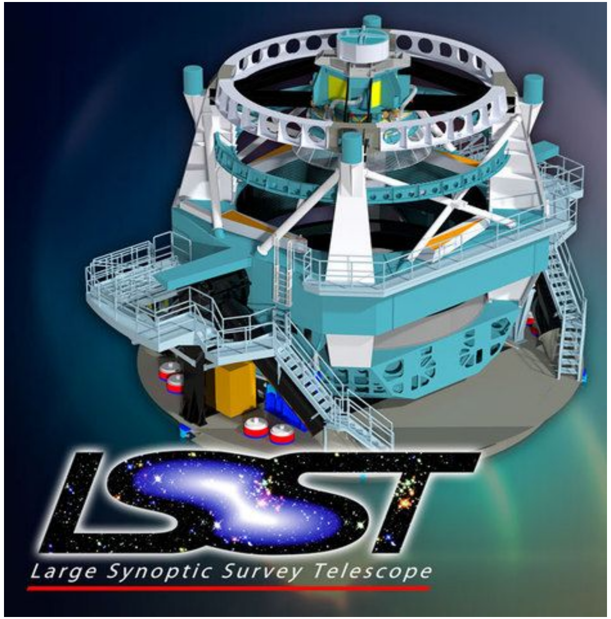
to:

# Enable Real-time Multimessenger Astrophysics

***Hear*** **gravitational waves**

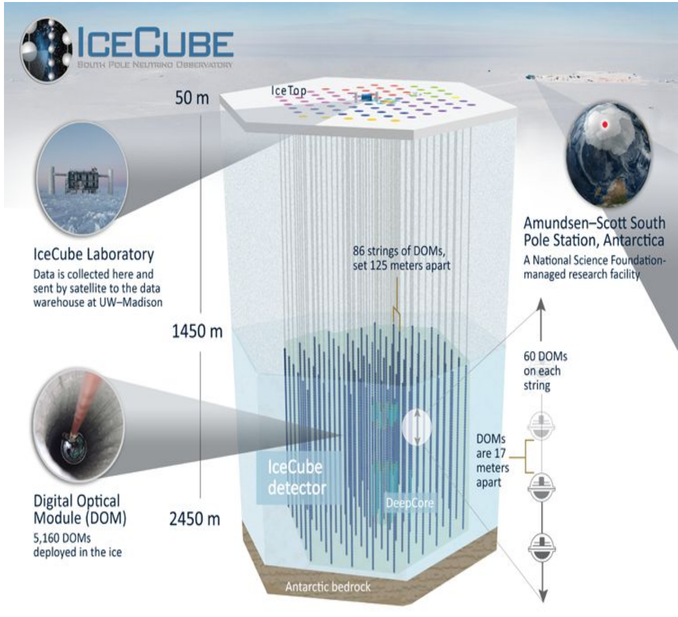
**LIGO, VIRGO, KAGRA, eLISA**

***See*** **electromagnetic waves**



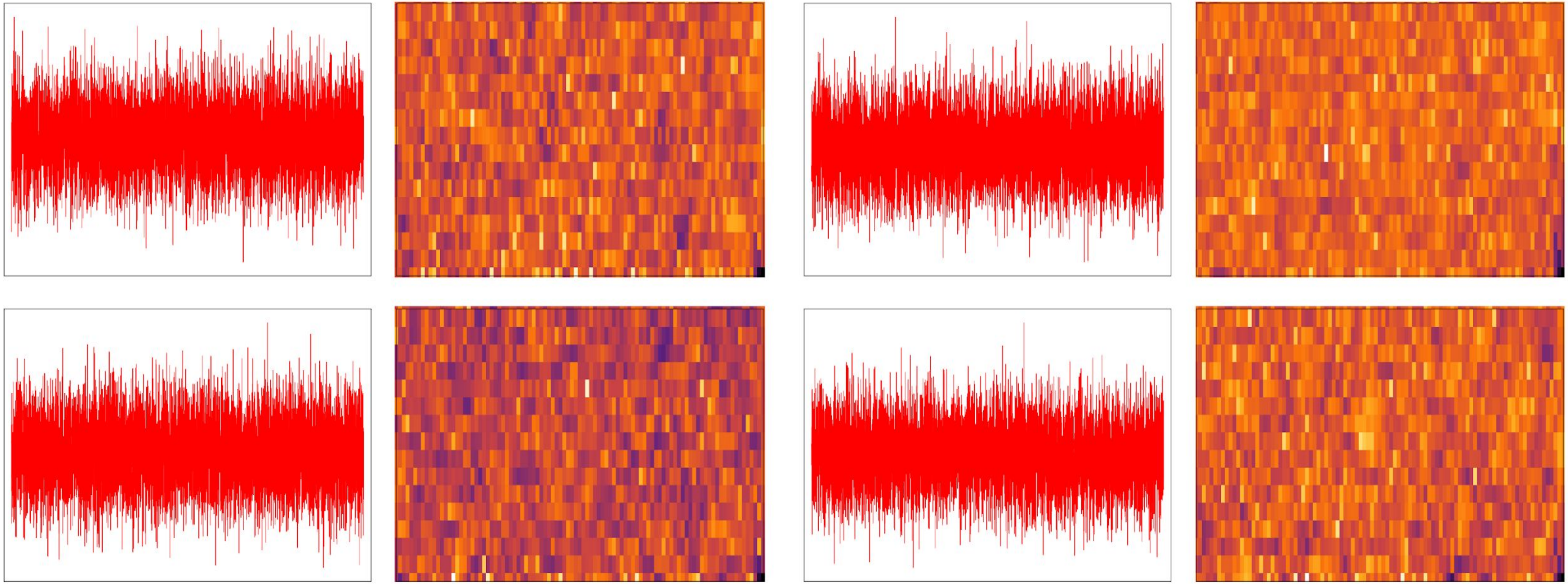

**DES, LSST, JWST, WFIRST**

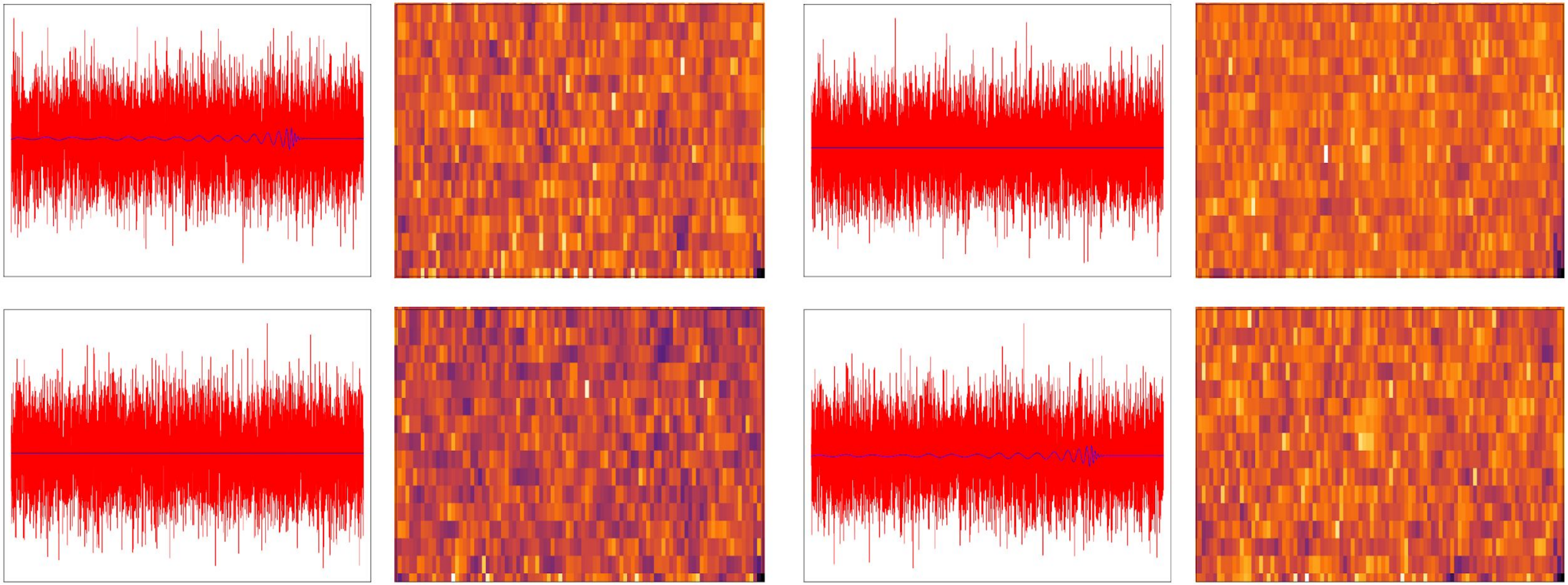
***Feel*** **astroparticles**




**IceCube (neutrinos)**

# Challenge





# Method?

## Matched-Filtering:

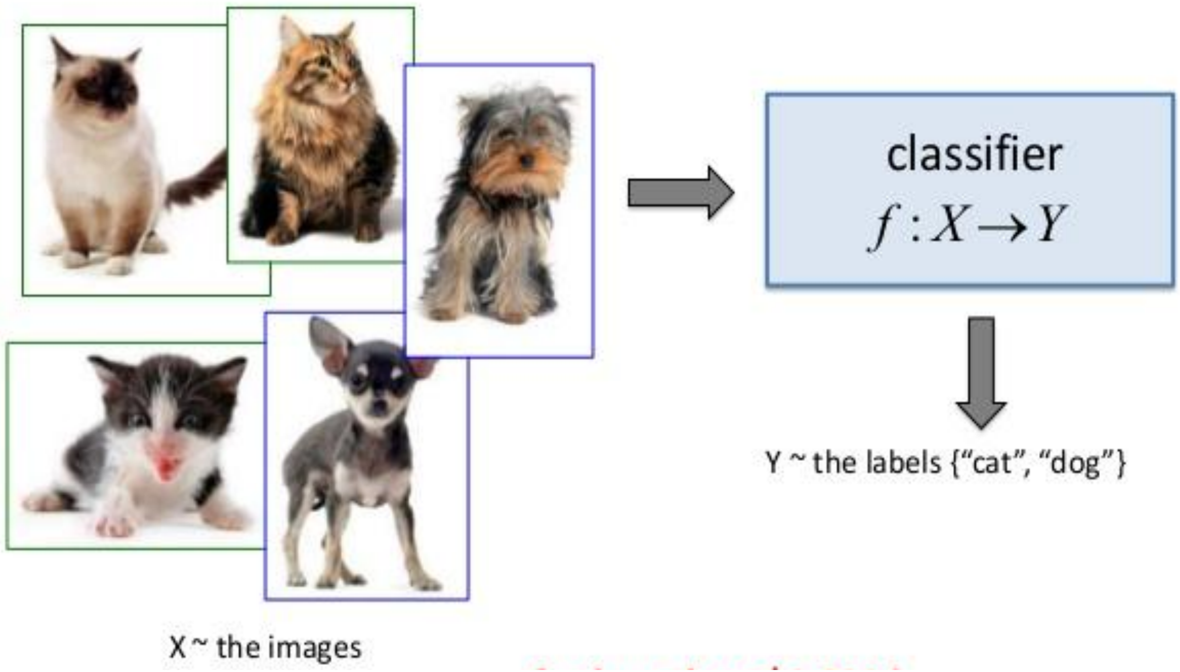
Compare every input with millions of templates.

Limited to small subset of signals

**Template matching is not scalable and is very slow**

## Solution:

**Deep Learning with Artificial Neural Networks!**






*Source*: https://www.slideshare.net/andrewgardner5811/deep-learning-for-data-scientists-dsatl-talk-alpharetta-20140108


A person riding a motorcycle on a dirt road.

A herd of elephants walking across a dry grass field.

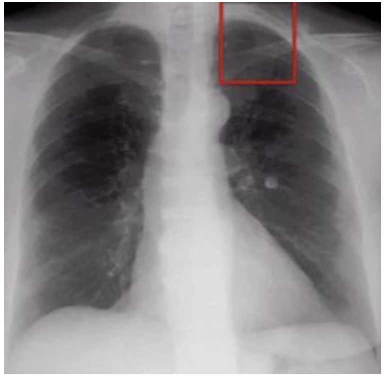
A group of young people playing a game of frisbee.

Two hockey players are fighting over the puck.

amazon

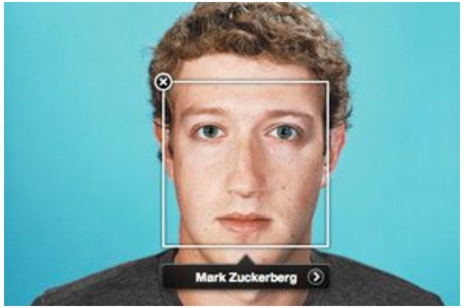
Google Translate

YouTube



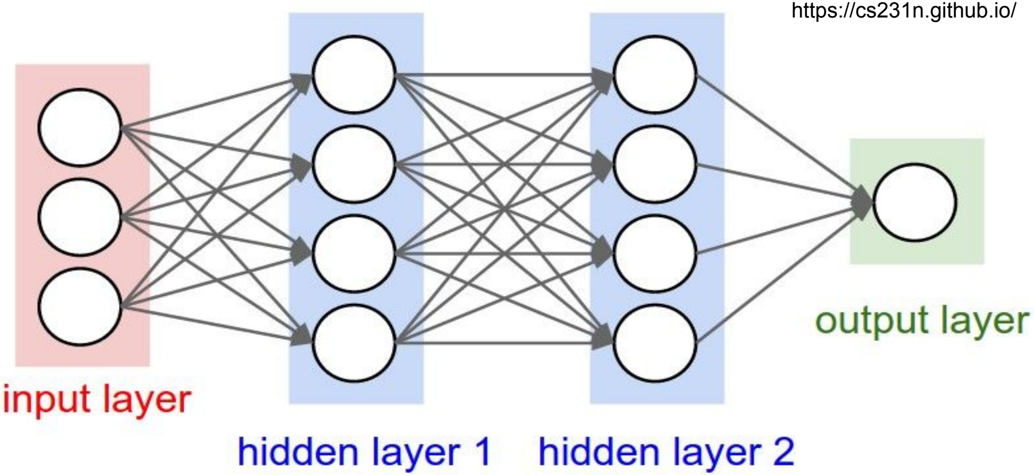
SwiftKey

AlphaGo


# Deep Learning: An AI Revolution

Source: https://cs231n.github.io/




- Very long networks of artificial neurons (dozens of layers)
- State-of-the-art algorithm for image processing, natural language understanding, speech recognition and synthesis, web search engines, self-driving cars, games (AlphaGo)
- **We discovered this technique can be adapted to detect gravitational waves!**

- Does not require hand-crafted features to be extracted first
- Automatic end-to-end learning
- Deeper layers can learn highly abstract functions

# Designing neural net

Proposed the use of convolutional neural nets with time-series inputs for gravitational wave detection

Train using signals + noise

Tested on real data

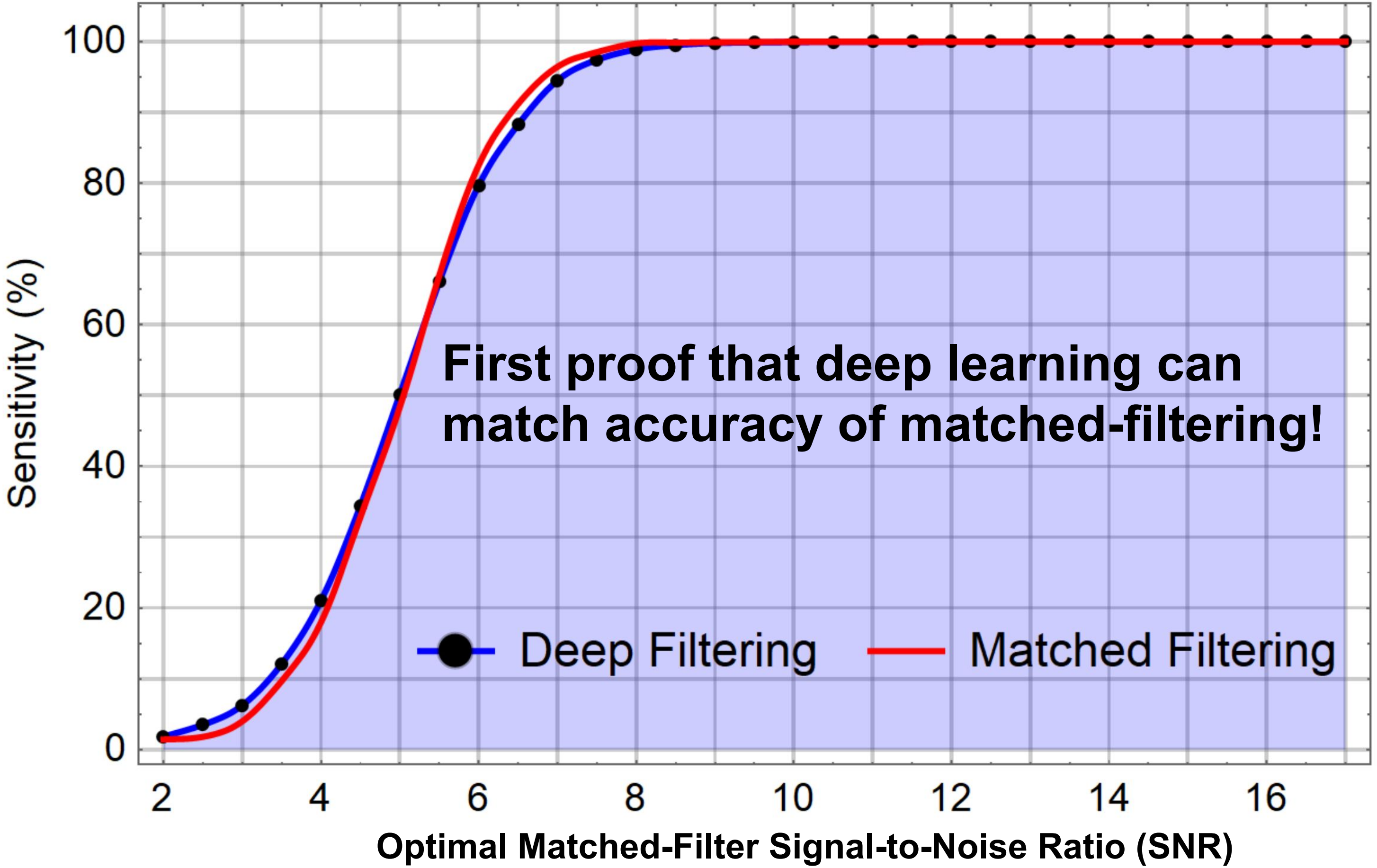
**Designed 2 networks**:

*Classifier* for detecting signals

*Predictor* for estimating source parameters

| | | |
|---|---|---|
| | Input (1s, 8192Hz) | vector (size: 8192) |
| 1 | Reshape Layer | tensor (size: $1 \times 1 \times 8192$) |
| 2 | Convolution Layer | tensor (size: $16 \times 1 \times 8177$) |
| 3 | Pooling Layer | tensor (size: $16 \times 1 \times 2045$) |
| 4 | Ramp | tensor (size: $16 \times 1 \times 2045$) |
| 5 | Convolution Layer | tensor (size: $32 \times 1 \times 2017$) |
| 6 | Pooling Layer | tensor (size: $32 \times 1 \times 505$) |
| 7 | Ramp | tensor (size: $32 \times 1 \times 505$) |
| 8 | Convolution Layer | tensor (size: $64 \times 1 \times 477$) |
| 9 | Pooling Layer | tensor (size: $64 \times 1 \times 120$) |
| 10 | Ramp | tensor (size: $64 \times 1 \times 120$) |
| 11 | Flatten Layer | vector (size: 7680) |
| 12 | Linear Layer | vector (size: 64) |
| 13 | Ramp | vector (size: 64) |
| 14 | Linear Layer | vector (size: 2) |
| 15 | Softmax Layer | vector (size: 2) |
| | Output | vector (size: 2) |

# Accuracy of Detecting Signals

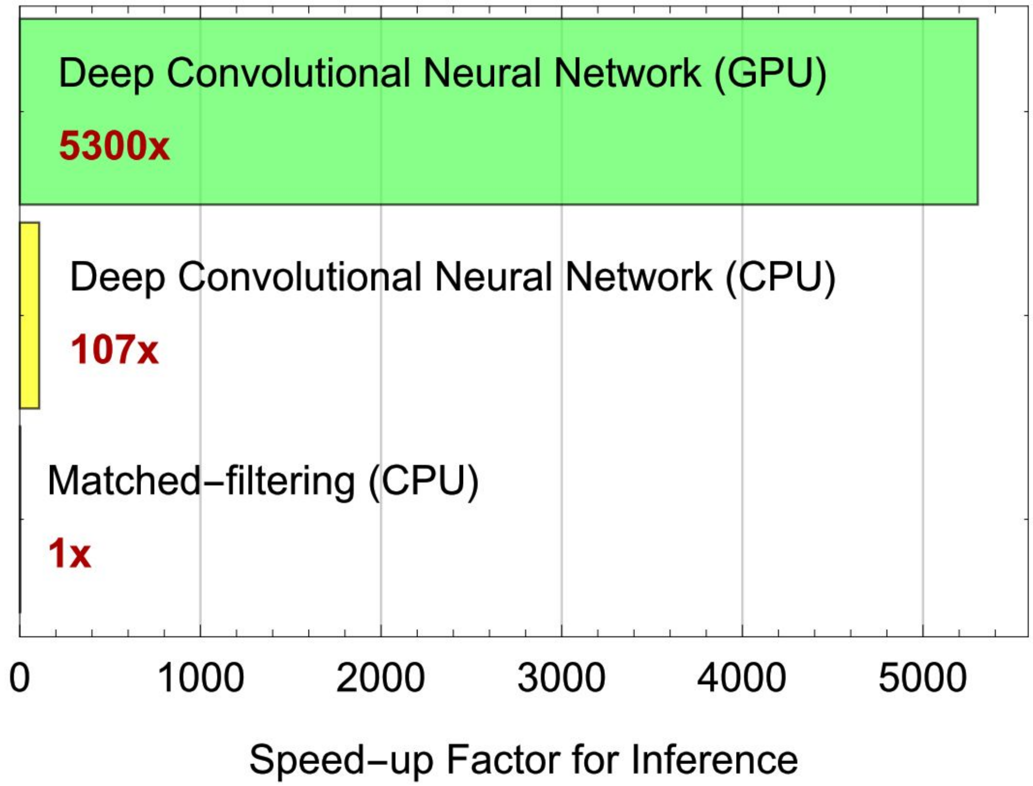



**100% Sensitivity for SNR > 10**

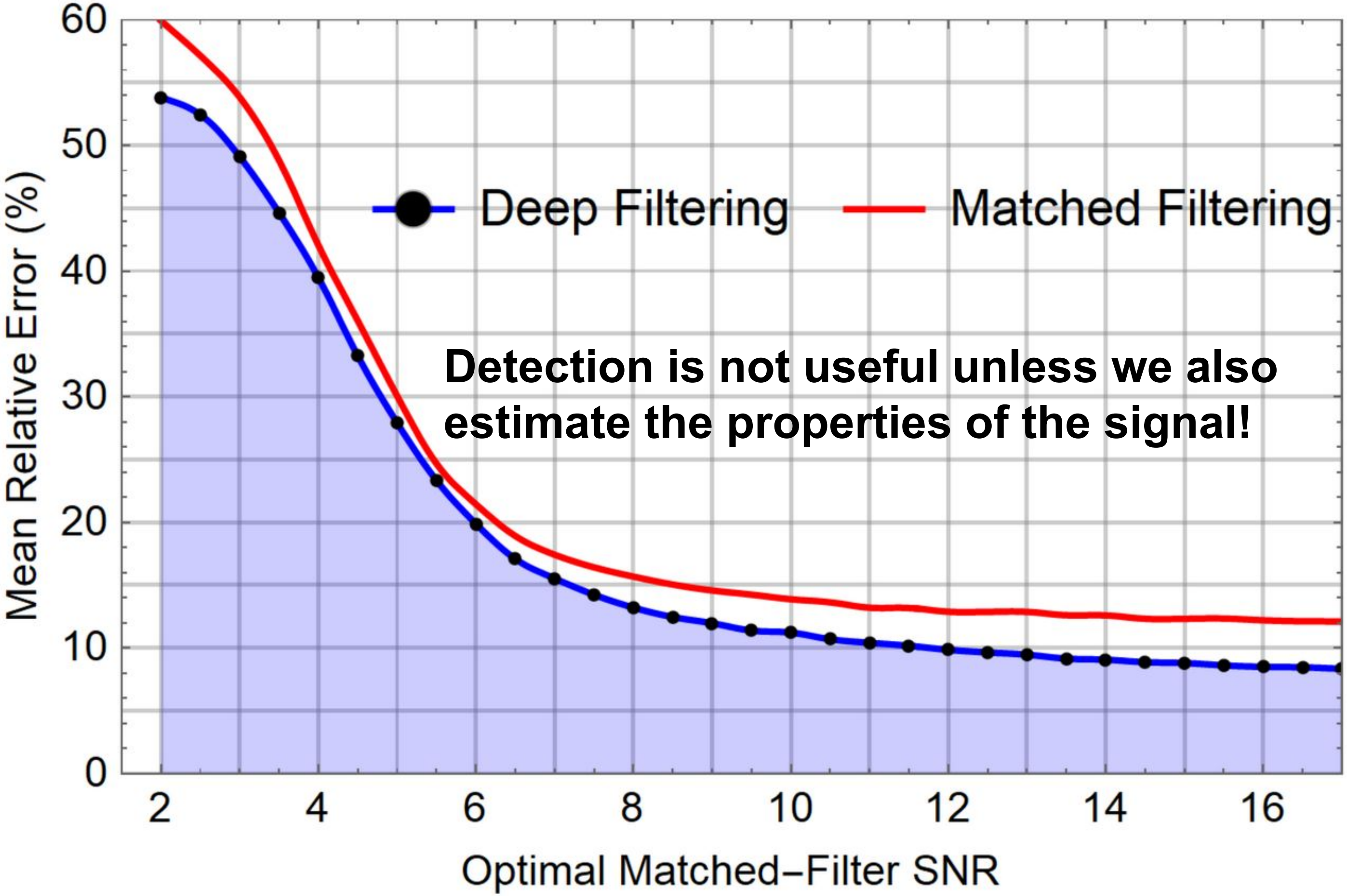
**False Alarm Rate < 0.6%**

# Orders of Magnitude Faster!

- Real-time analysis (milliseconds).
- Constant time regardless of number of templates, after training once.
- Thousands of inputs can be processed at once on a cheap GPU.
- Dedicated inference engines can offer additional speed-up.



# Error in Predicting Masses (Regression)



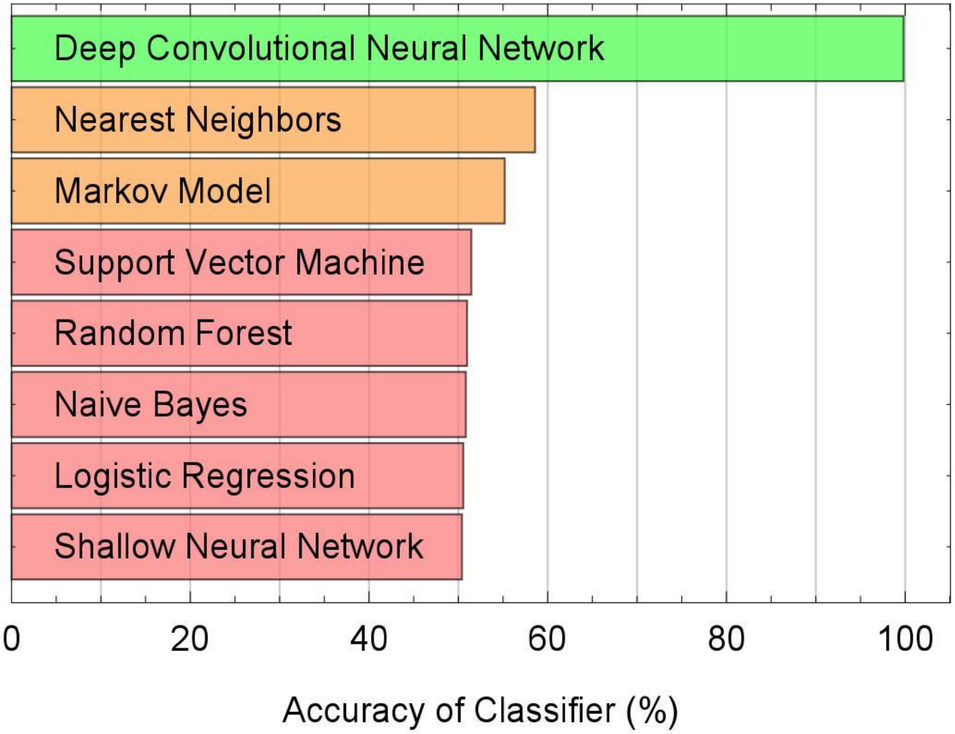

**Detection is not useful unless we also estimate the properties of the signal!**

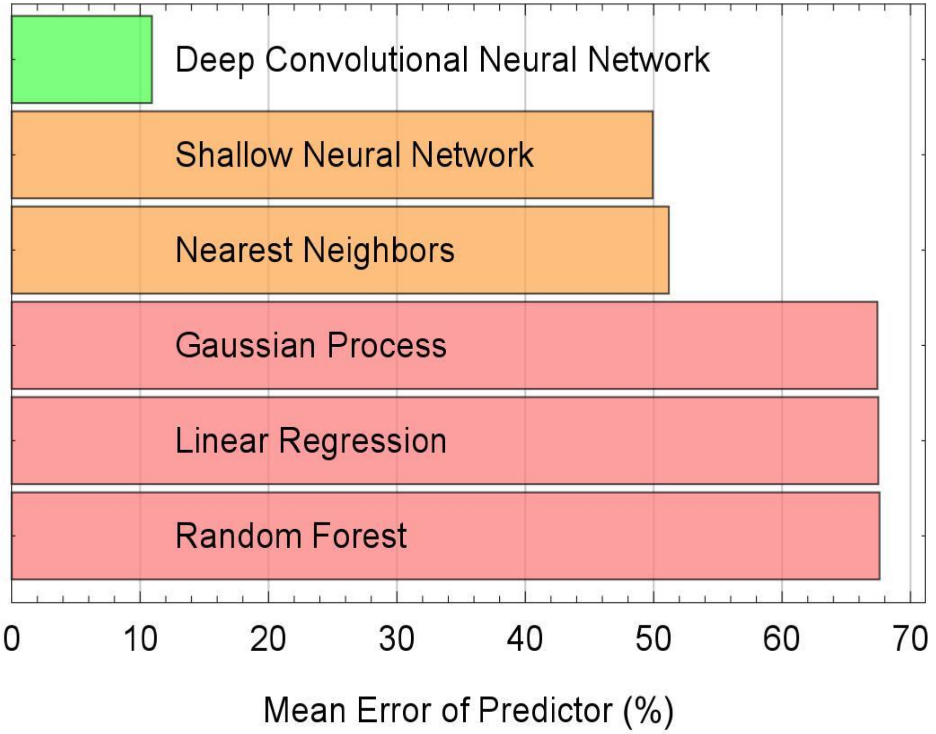
**CNN error < 5% for SNR>50**

**Can interpolate between templates!**

**Matched-Filtering error with same template bank is always > 11%**

# Detection and Parameter Estimation



# Live Demo Detecting GW150914: [www.tiny.cc/DLGW](http://www.tiny.cc/DLGW)

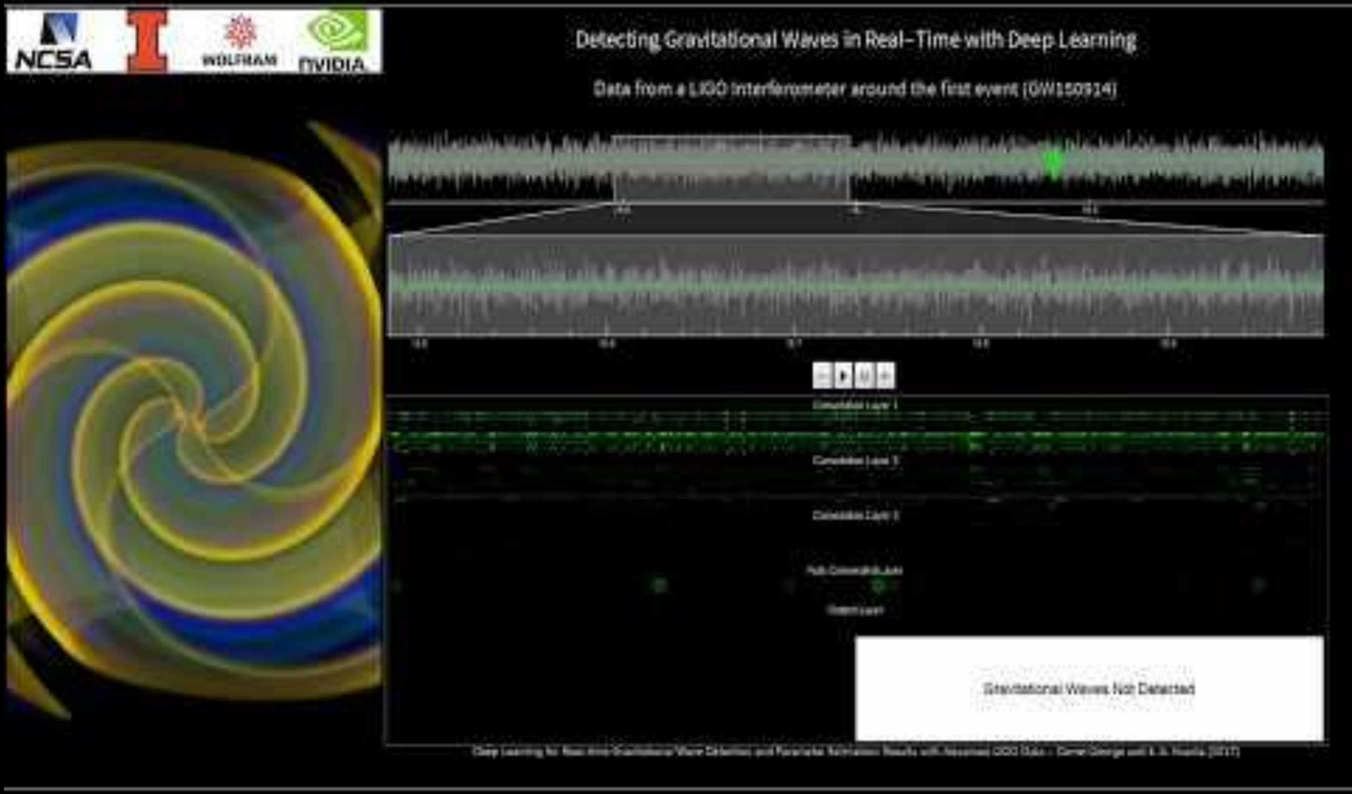
Data not included in training

Trained with only non-spinning, non-eccentric simulated signals

~1s to analyze 4096s of data

Masses predicted correct within error bars

No False Alarms with two detector data!



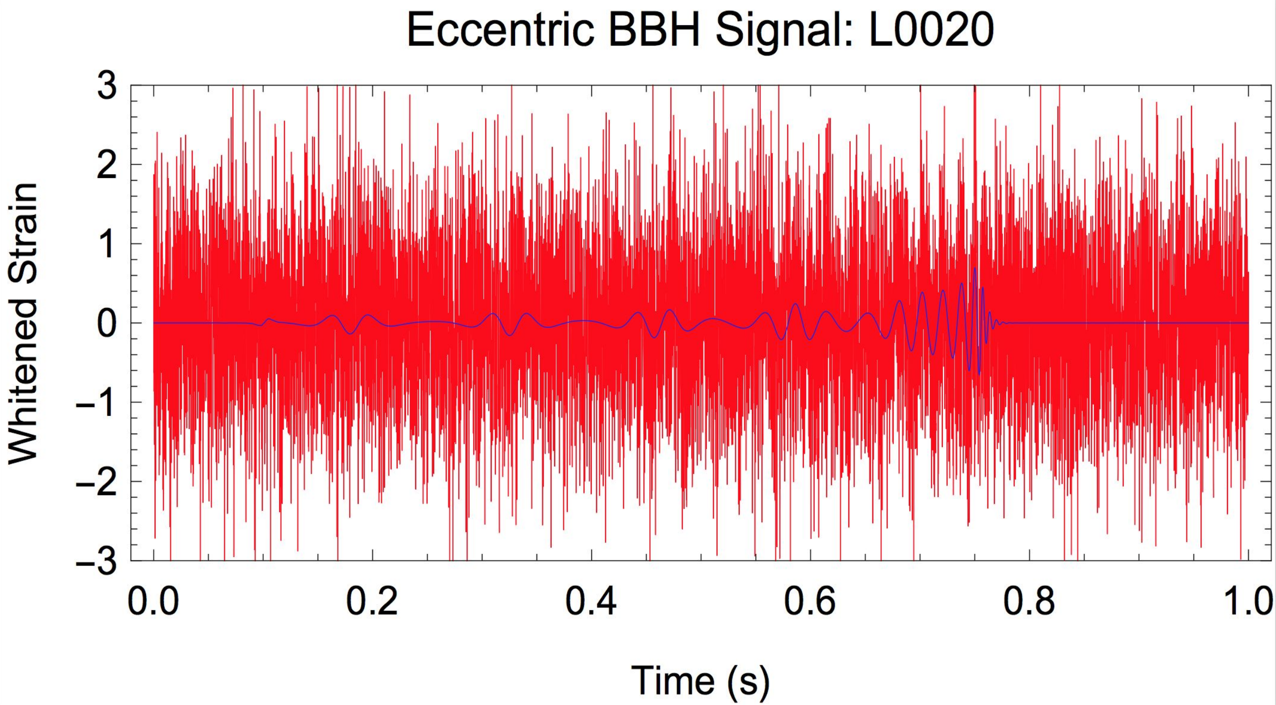
# New Physics!

## Seeing new types of gravitational waves

**Eccentric, Spinning black holes produced in new astrophysical environments:**

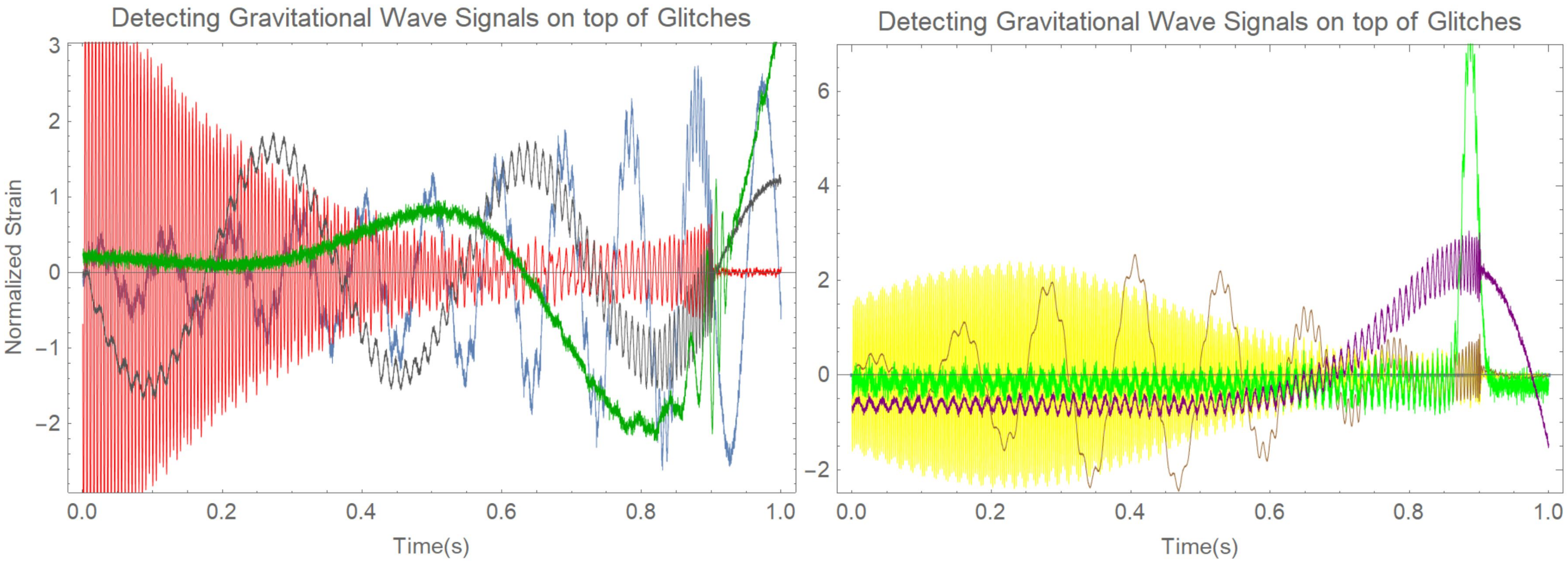
Can automatically learn to identify new types of signals missed by current methods

Same accuracy of detection!




**Can detect eccentric spin-precessing signals with same sensitivity of matched-filtering, without using these templates!**

# Works in bad data contaminated by glitches!




***Successfully recovered ~80% of signals injected in real noise plus glitches (anomalies)***

***Mean relative error of parameter estimation during glitches < 30% for SNR > 10***

**False Alarm Rate with glitches in the data:** Matched-Filter = **30%**, Deep Learning = **1%**

# Advantages of using deep learning

1) **Speed**: Enables real-time analysis with a single CPU/GPU. Enable rapid follow-up

2) **Covering more parameters**: Scalable to full range of signals since the one-time training process can be carried out with billions of templates or more

3) **Generalization to new sources**: Can automatically detect spin-precessing and/or eccentric compact binary mergers with same sensitivity without extra training

4) **Resilience to non-Gaussian noise and glitches**: Can learn and adapt to the characteristics of non-Gaussian noise in LIGO and thus outperform matched-filtering

5) **Interpretability**: Validate with matched-filtering with single predicted template, i.e., accelerate existing pipelines. Can constrain search space of templates

# Conclusion

**Artificial Intelligence (*Deep Learning*)**
**=> Real-time Big Data Analysis for Science!**

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# Pioneering AI for Gravitational Waves

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