Deep Learning for Extracting Hidden Signals: Detecting Gravitational Waves

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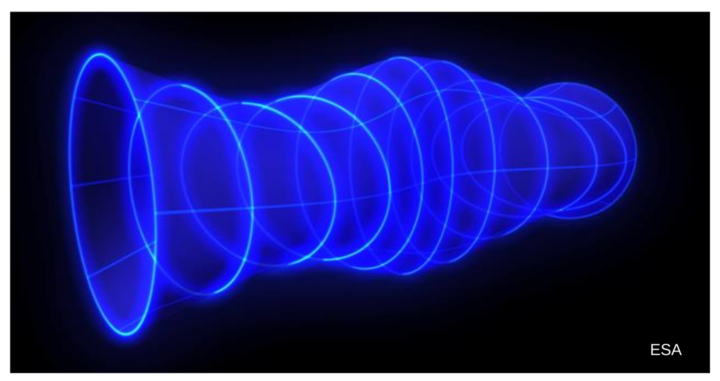
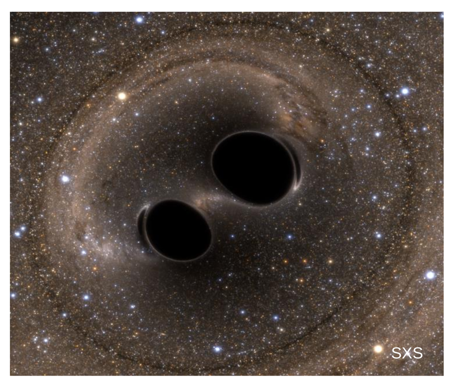
INTRODUCTION

We introduce a new method for time-domain signal processing, based on deep learning convolutional neural networks trained with HPC simulations, that can detect and extract parameters of signals which are much weaker than the background noise.

Gravitational Waves

Ripples in the fabric of space-time produced by violent events such as supernovae or the mergers of black holes or neutron stars. Predicted by Einstein in 1916 and first observation by LIGO in 2015 won the Nobel prize in 2017.

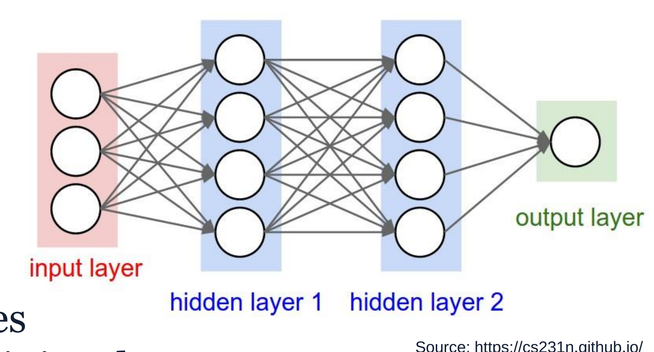




Deep Learning with Neural Networks

A machine learning technique based on interconnected networks of artificial neurons. The deeper layers can learn highly abstract features.

Extremely successful for artificial intelligence applications.



Can learn optimal strategies automatically from raw training data.

AIM

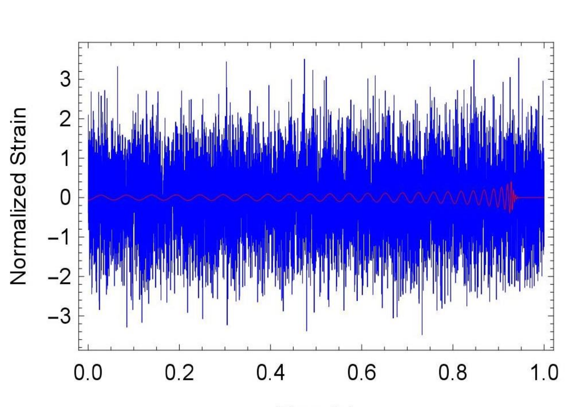
To detect gravitational waves and estimate astrophysical properties of the source in real-time given time-series data measured by detectors.

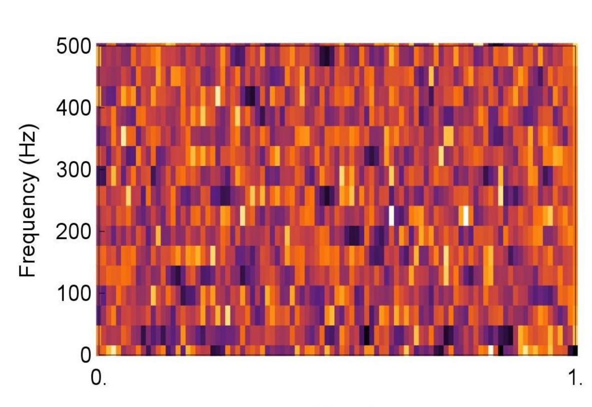
Challenges

Signals are extremely weak and embedded in highly non-Gaussian noise with periodic glitches.

Current methods are based on matched-filtering which is computationally prohibitive beyond a small range of signals. Accurate parameter estimation takes several days to months.

Most signals are too weak to be visible in a spectrogram (see below for an example with signal-to-noise ratio = 0.5)



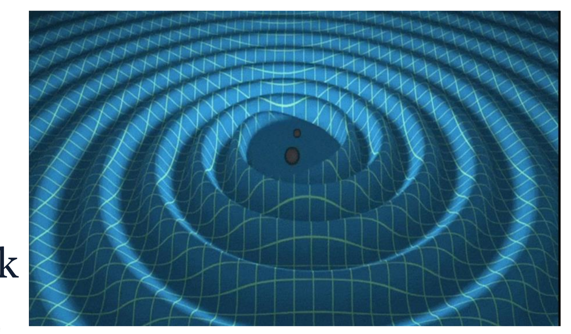


METHOD

Numerical Relativity Simulations

Einstein's Field Equations must be solved numerically to predict gravitational waves generated by different events.

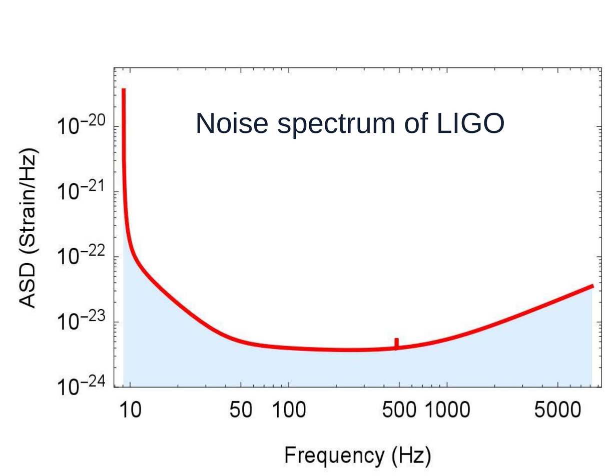
These waveforms are used to infer parameters of observed gravitational wave signals.

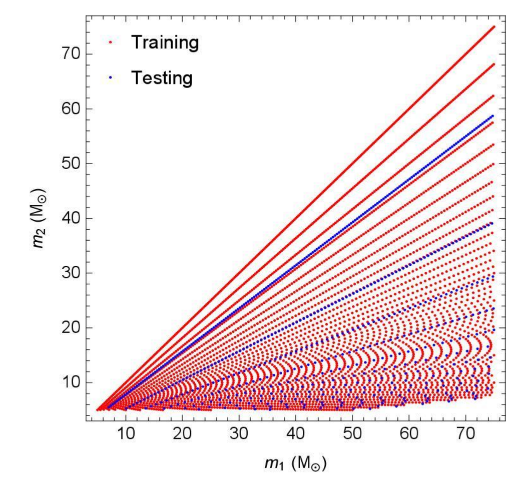


We performed large scale black hole merger simulations using open-source Einstein Toolkit on supercomputers including Blue Waters and XSEDE.

Training Data

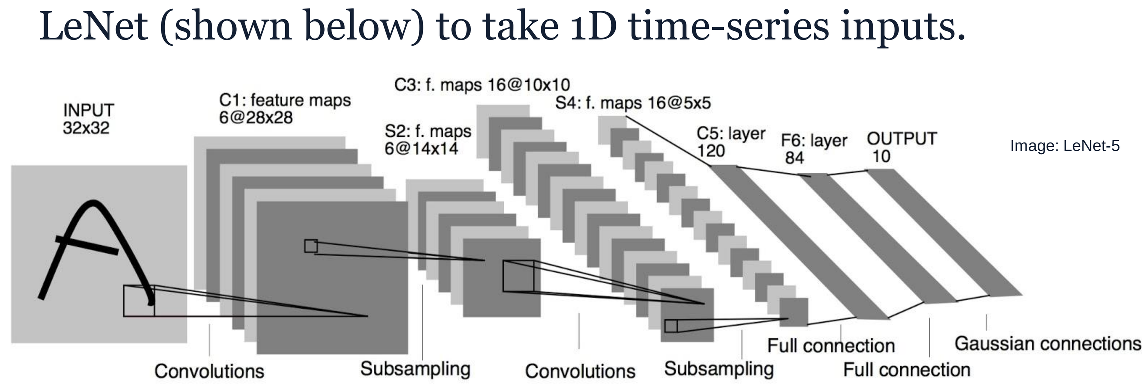
Generated gravitational wave templates of binary black hole mergers calibrated with numerical relativity simulations and added real+simulated LIGO noise.





Deep Convolutional Neural Networks

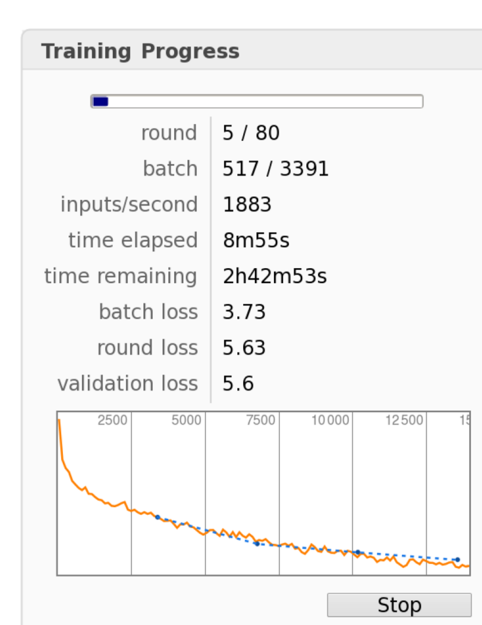
State-of-the-art method for image processing. Each neuron looks at a small section of the previous layer. We modified LeNet (shown below) to take 1D time-series inputs.



Architecture of Neural Network

Tested designs with up to 4 *1D* convolutional layers and 3 fully connected layers. Used the Wolfram Language based on MXNet to train the neural networks.

	Input	vector (size: 8192)
1	Reshape Layer	tensor (size: 1 × 1 × 8192)
2	Convolution Layer	tensor (size: 16 × 1 × 8177)
3	Pooling Layer	tensor (size: 16 × 1 × 2045)
4	Ramp	tensor (size: 16 × 1 × 2045)
5	Convolution Layer	tensor (size: 32 × 1 × 2017)
6	Pooling Layer	tensor (size: 32 × 1 × 505)
7	Ramp	tensor (size: 32 × 1 × 505)
8	Convolution Layer	tensor (size: 64 × 1 × 477)
9	Pooling Layer	tensor (size: 64 × 1 × 120)
10	Ramp	tensor (size: 64 × 1 × 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)



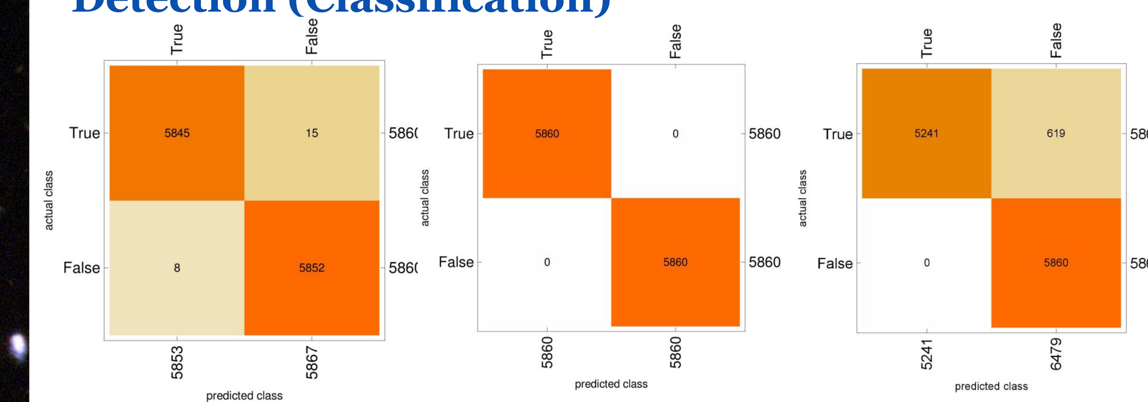
RESULTS

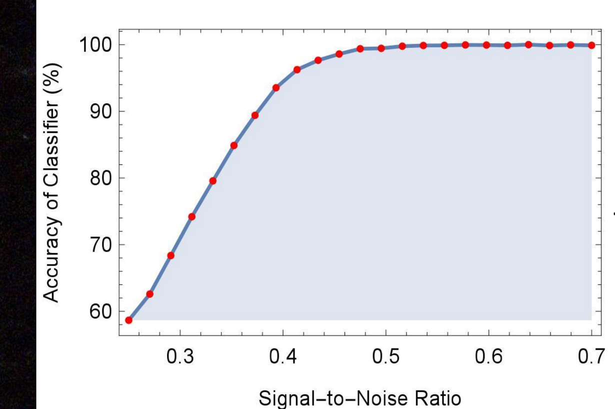
Summary

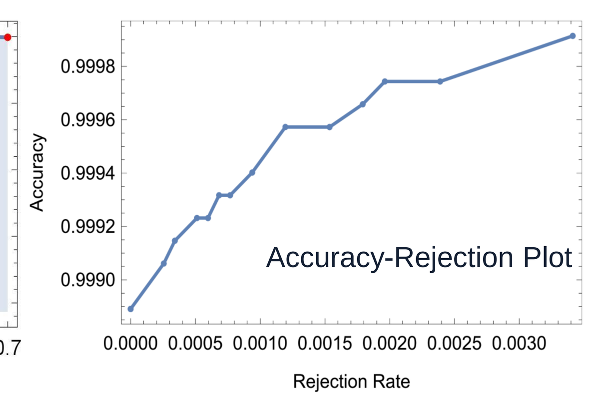
Obtained excellent performance for both classification (detection) and regression (parameter estimation) even at signal-to-noise ratio (SNR, ratio of peak signal amplitude divided by standard deviation of noise) as low as 0.5

Outperformed all conventional machine learning methods. Over 100 times faster than matched-filtering (template matching). Accurately detected GW150914.

Detection (Classification)

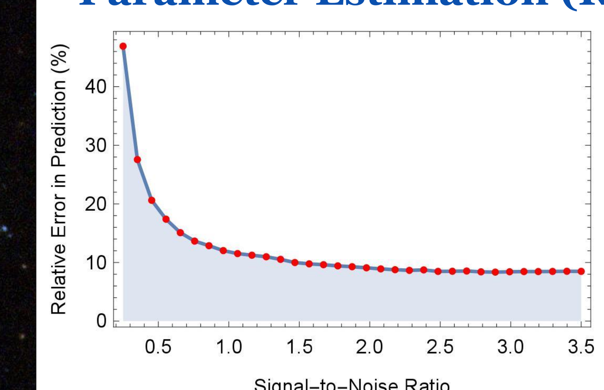


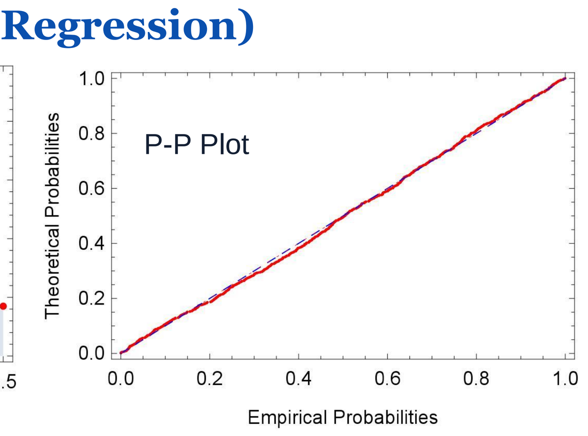




Obtained 100% accuracy at SNR greater than 0.6

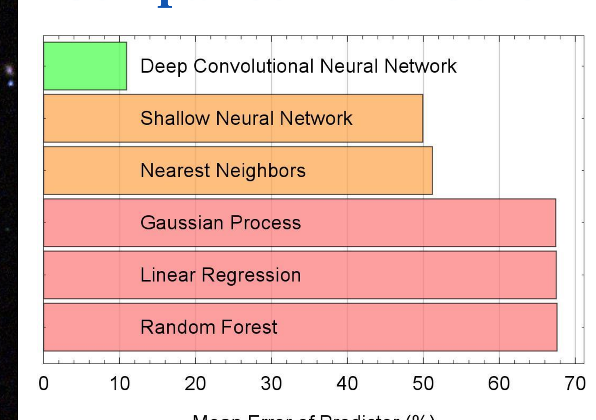
Parameter Estimation (Regression)

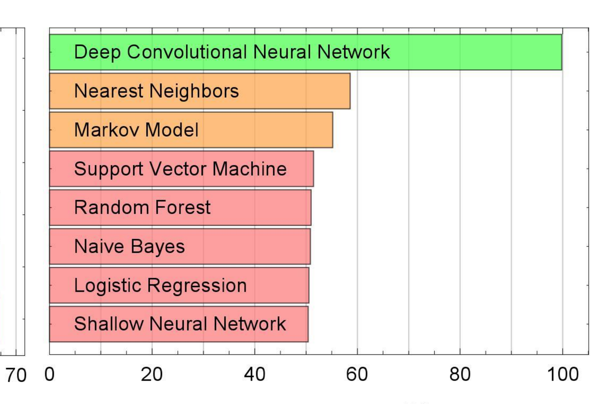




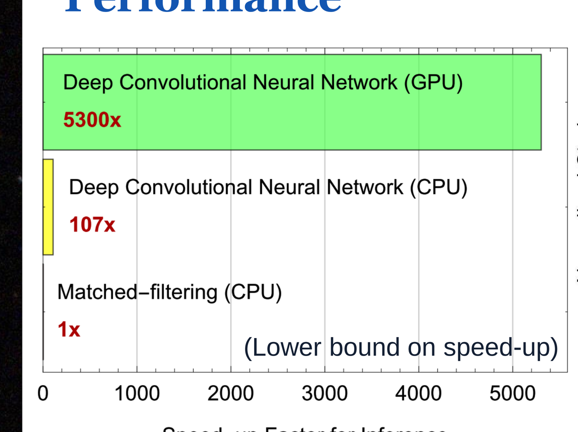
Mean error at SNR > 1 is less than 11% and it is a Gaussian normal distribution. Obtained ~ 1% error for high SNR.

Comparison with Other Methods

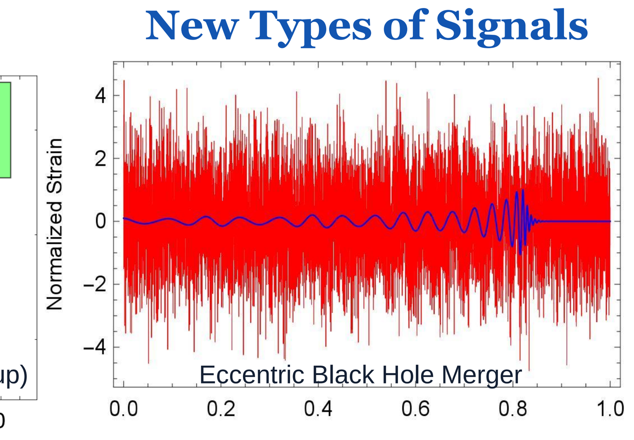




Performance



New Types of Signals



Learned to extrapolate to entirely new classes of signals!

DISCUSSION

Scope for Improvements

Multitask learning can unify classification of different sources and noise as well as parameter estimation.

Transients such as glitches and blips can be injected for training to incorporate real-time noise characteristics.

Datasets from HPC covering the full parameter space of sources like supernovae, neutron stars can be used.

Complex topologies such as LSTM recurrent neural networks may improve performance for variable length signals and non-Gaussian noise transients (glitches).

Enabling Multimessenger Astrophysics

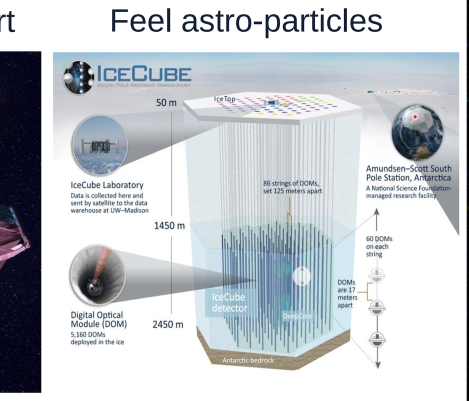
Hear gravitational waves

LIGO, VIRGO, eLISA

See optical counterpart

JWST, DECam, LSST

Feel astro-particles



IceCube (neutrinos)

This provides a unified framework for simultaneously analyzing big data from all observational instruments enabling real-time alerts and efficient follow-up of events.

CONCLUSION

- New method for directly analyzing noisy time-series data
- Deep learning applied for scientific signal processing
- Convolutional neural networks are excellent for time-series
- Alternative to existing methods for LIGO data analysis
- Need catalogs of massively-parallel HPC simulations
- Extensive scope for research on deep learning for science
- Can exploit rapid advances in deep learning and AI

ACKNOWLEDGEMENTS

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We utilized NVIDIA GPUs in the Innovative Systems Lab at NCSA for training the neural networks.

REFERENCE

Deep Neural Networks to Enable Real-time Multimessenger Astrophysics
- Daniel George and E. A. Huerta

Background image: The Hubble Deep Field