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Fast Machine Learning for Gravitational Waves

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Fast Machine Learning Workshop, Fermilab
September 10th 2019

XSEDE

Extreme Science and Engineering Discovery Environment

NSF

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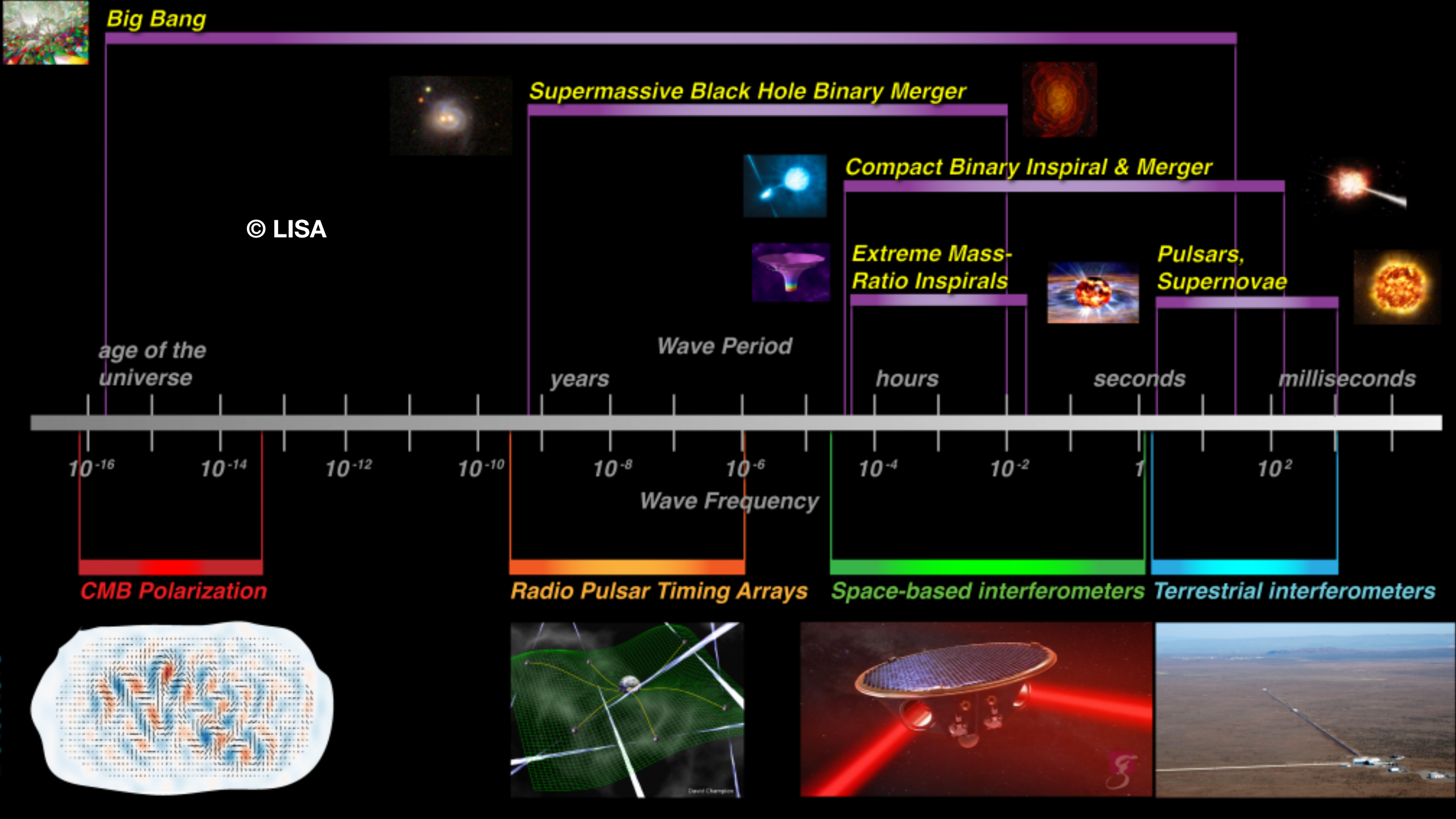
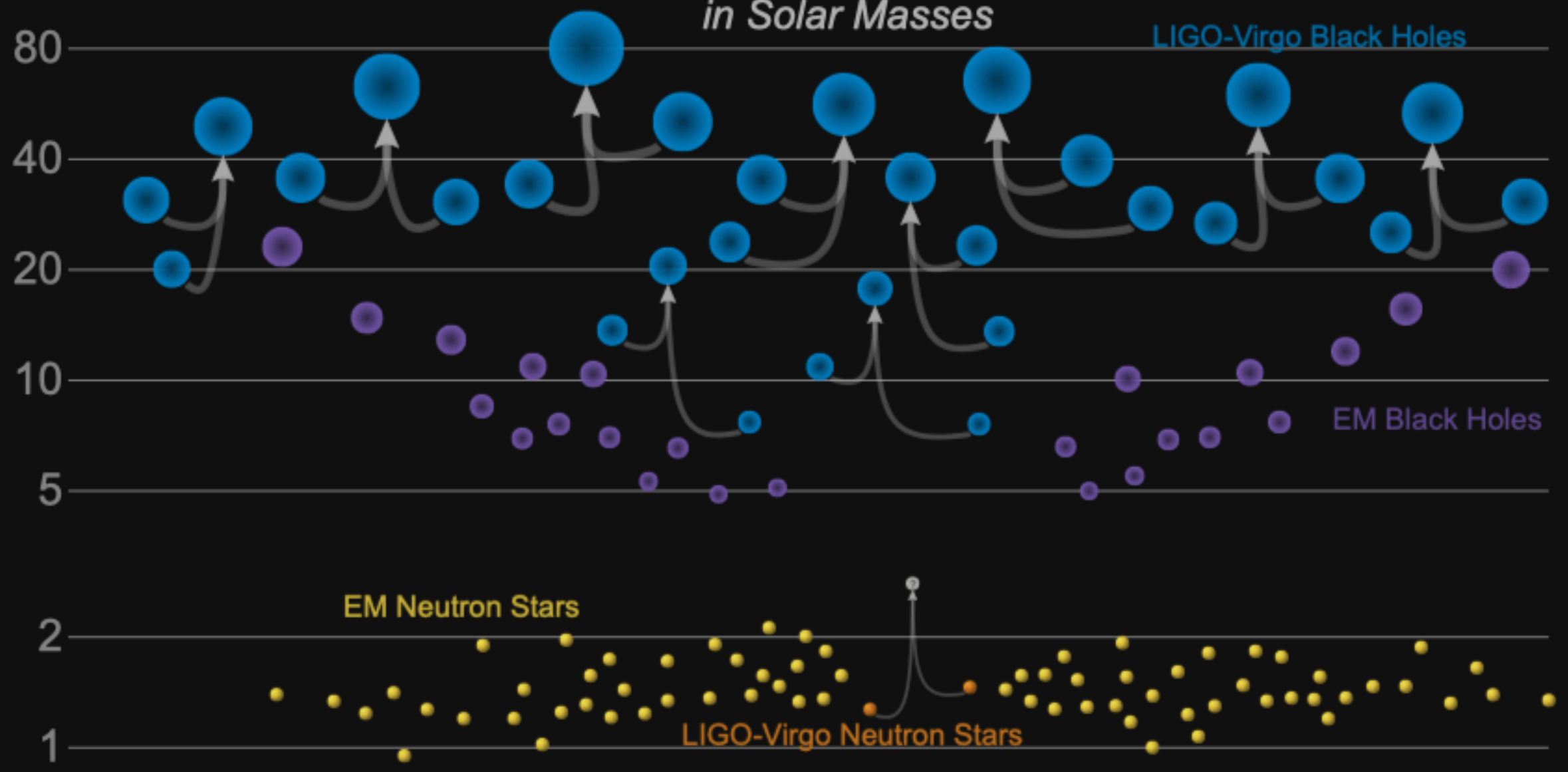

Big Bang
Supermassive Black Hole Binary Merger
Compact Binary Inspiral & Merger
© LISA
Extreme Mass-Ratio Inspirals
Pulsars, Supernovae
age of the universe
Wave Period
years
hours
seconds
milliseconds
10-16
10-14
10-12
10-10
10-8
10-6
10-4
10-2
1
10 2
Wave Frequency
CMB Polarization
Radio Pulsar Timing Arrays
Space-based interferometers
Terrestrial interferometers

Masses in the Stellar Graveyard

in Solar Masses



LIGO-Virgo | Frank Elavsky | Northwestern

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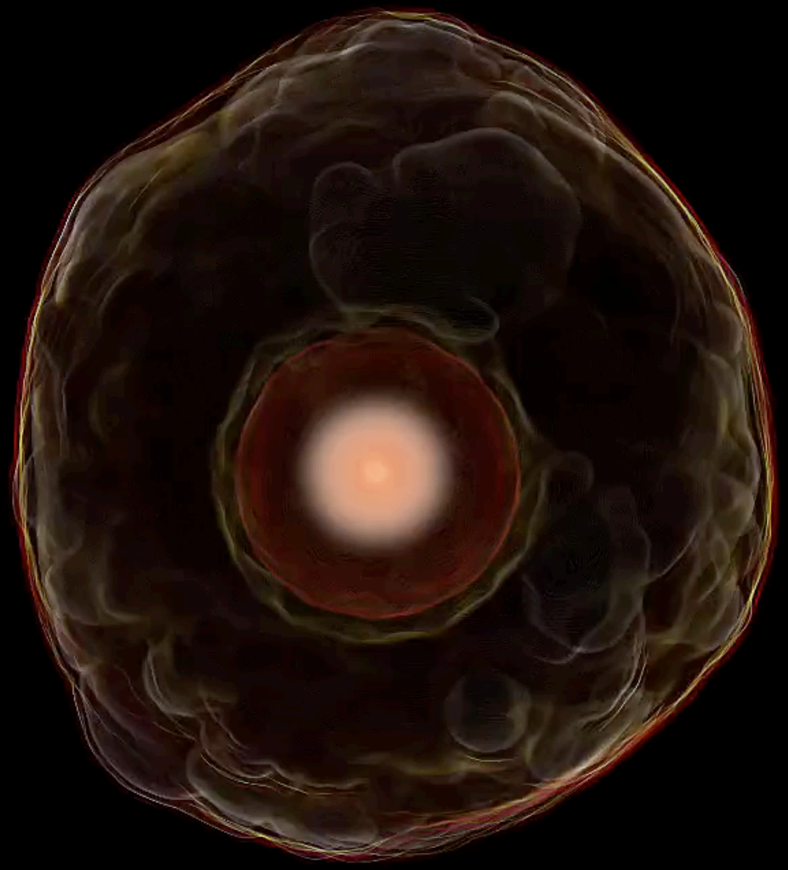

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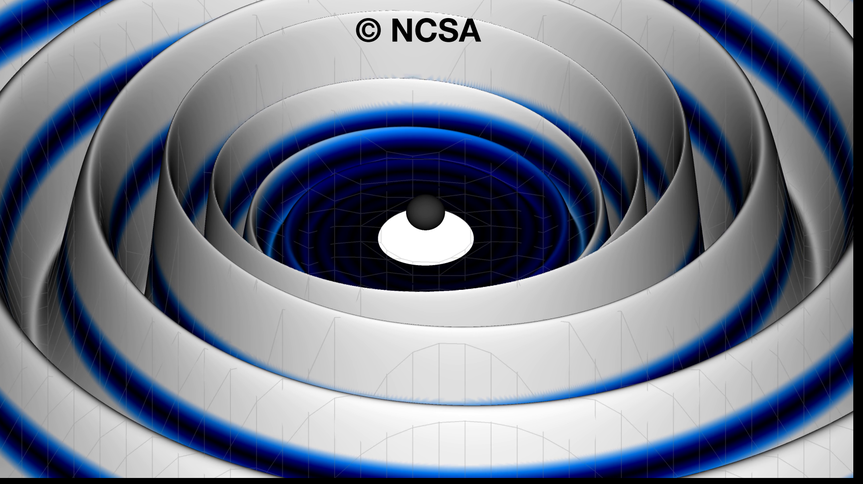
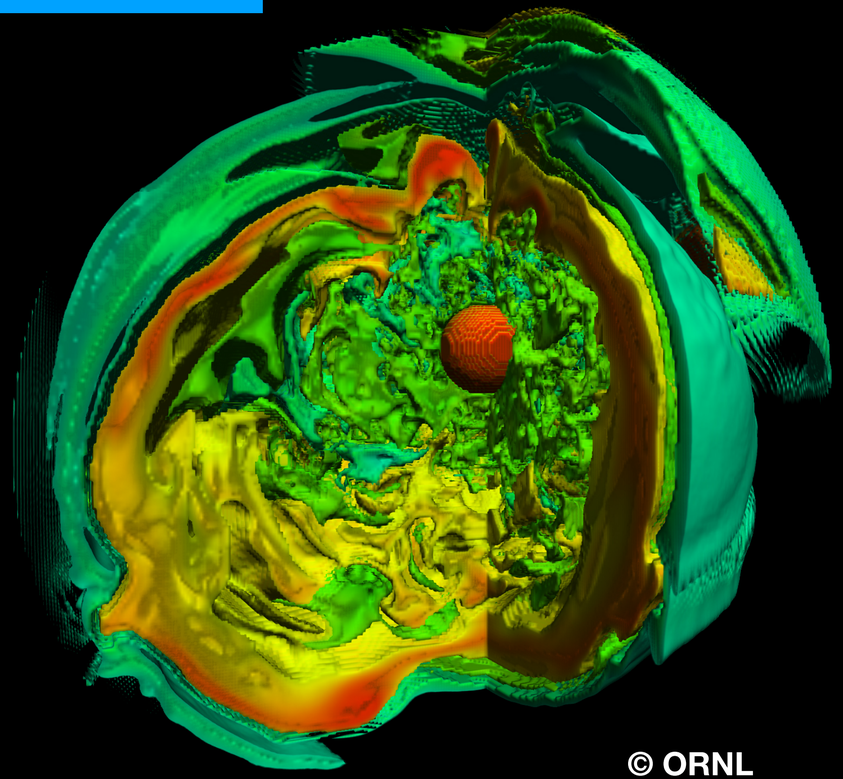


Listen to the Dark Sector of the Universe

Listen to and observe cosmic mergers

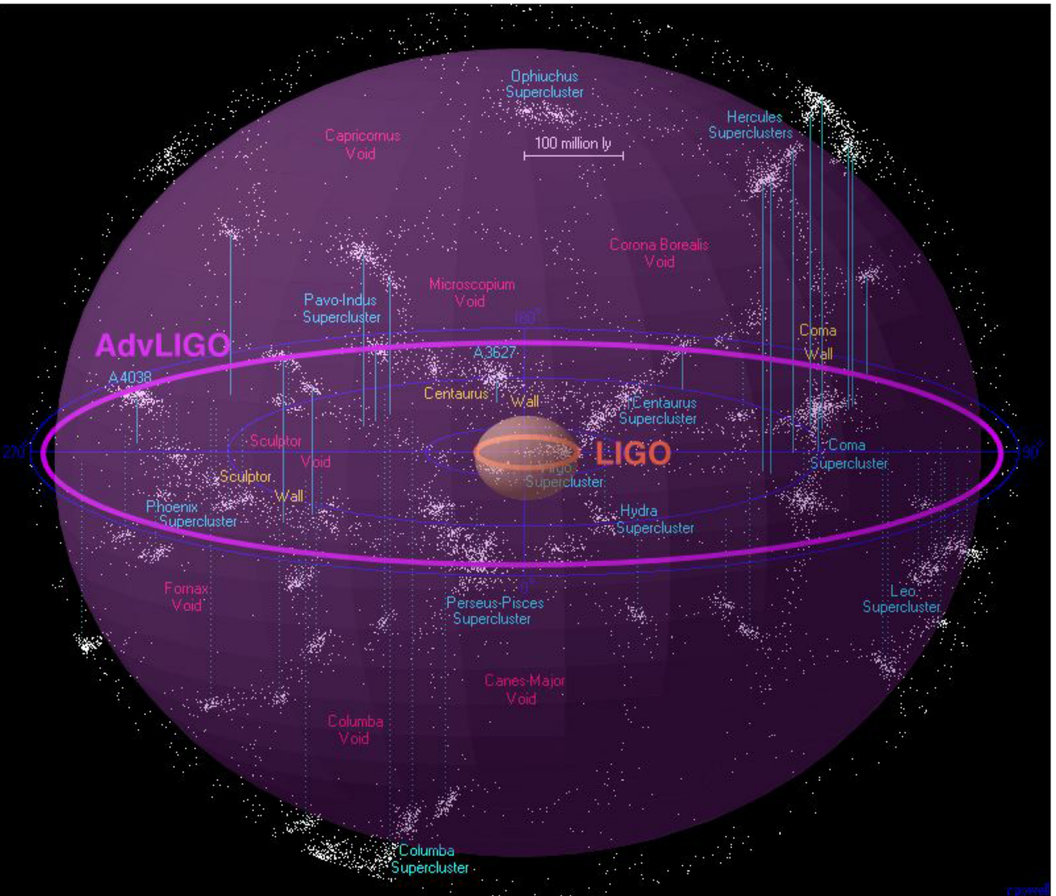


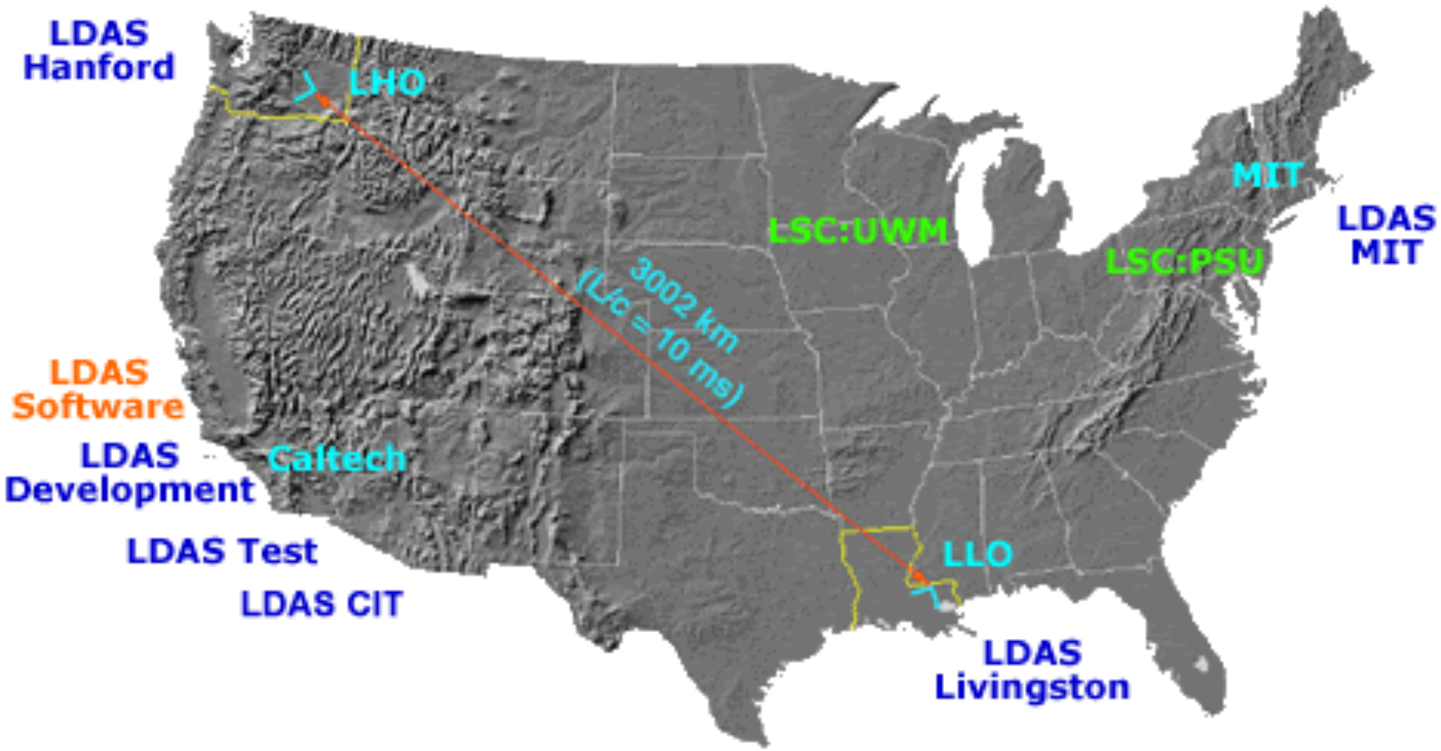
Listen to, observe and feel cosmic explosions in the nearby Universe

Sources, Signals and *Searches*

Number of observations increases with more sensitive detectors

Localization improves with a global detector network





Challenges and Opportunities

Higher-dimensional signal manifold

Weak signals embedded in non-Gaussian and non-stationary noise

Existing algorithms cover a shallow signal manifold due to their lack of scalability and compute-intensive nature

Multi-Messenger searches are time-sensitive

Sociological

What can we learn from the Big Data Revolution?

Innovations in signal-processing tools have driven breakthroughs in industry and technology

Leverage software and hardware developments to tackle computational grand challenges across disciplines

Plenty of room for innovation in AI

Sociological

In any community of scientists, there are some individuals who are bolder than most

These scientists, judging that a crisis exists, embark on revolutionary science, exploring alternatives to long-held, obvious-seeming assumptions

Occasionally this generates a rival to the established framework of thought

The new candidate paradigm will appear to be accompanied by numerous anomalies, partly because it is still so new and incomplete

The majority of the scientific community will oppose any conceptual change, and so they should

To fulfill its potential, a scientific community needs to contain both individuals who are bold and individuals who are conservative. There are many examples in the history of science in which confidence in the established frame of thought was eventually vindicated

It is almost impossible to predict whether the anomalies in a candidate for a new paradigm will eventually be resolved

Those scientists who possess an exceptional ability to recognize a theory's potential will be the first whose preference is likely to shift in favor of the challenging paradigm

There typically follows a period in which there are adherents of both paradigms. In time, if the challenging paradigm is solidified and unified, it will replace the old paradigm, and a paradigm shift will have occurred

Thomas Kuhn, The Structure of Scientific Revolution

Multi-Messenger Astrophysics has taken off!

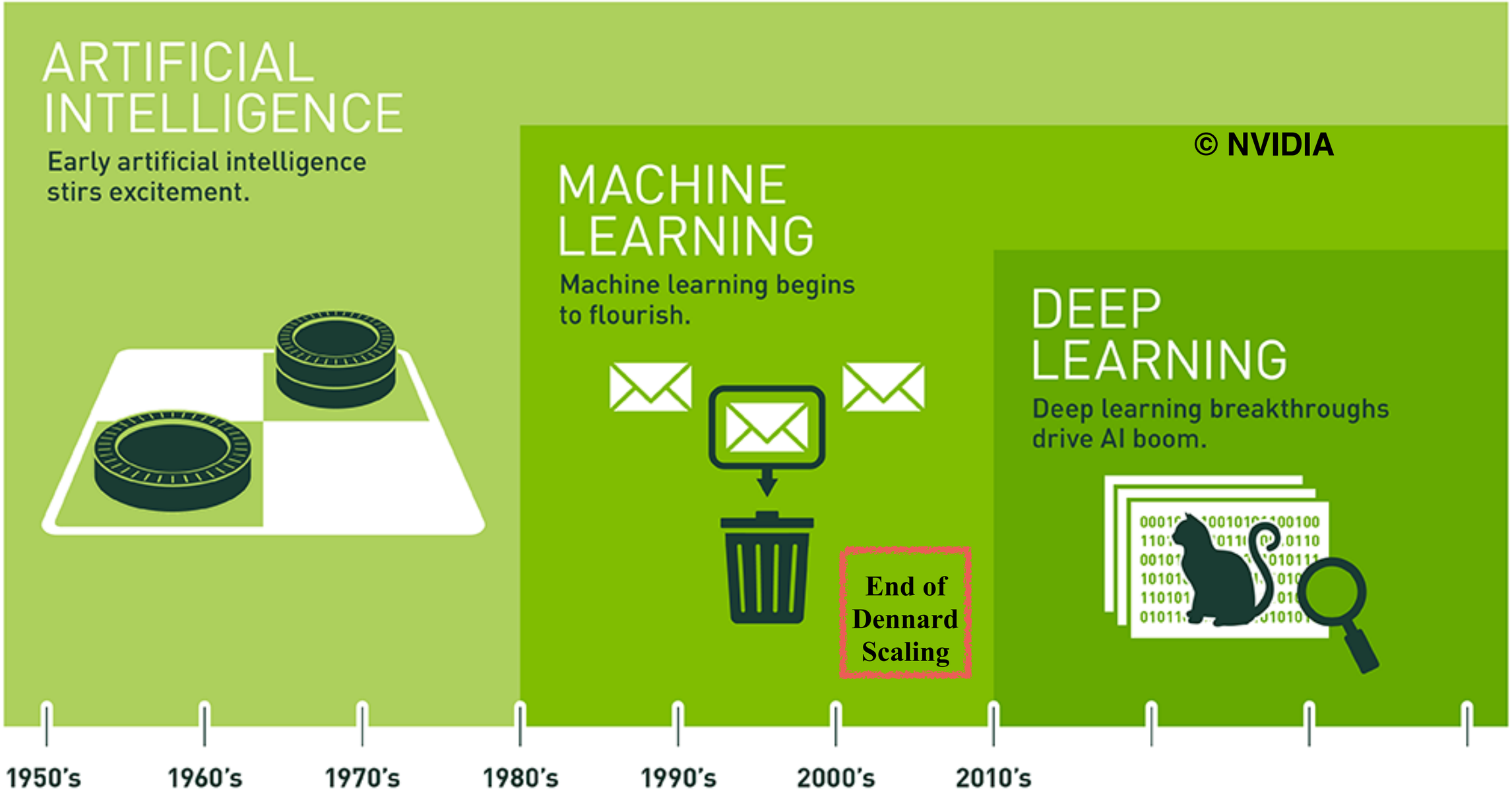
Swift transition from “first detection era” to discovery at scale

Binary black holes observations are now routine!

Several Multi-Messenger observations may take place in LIGO-Virgo third observing run

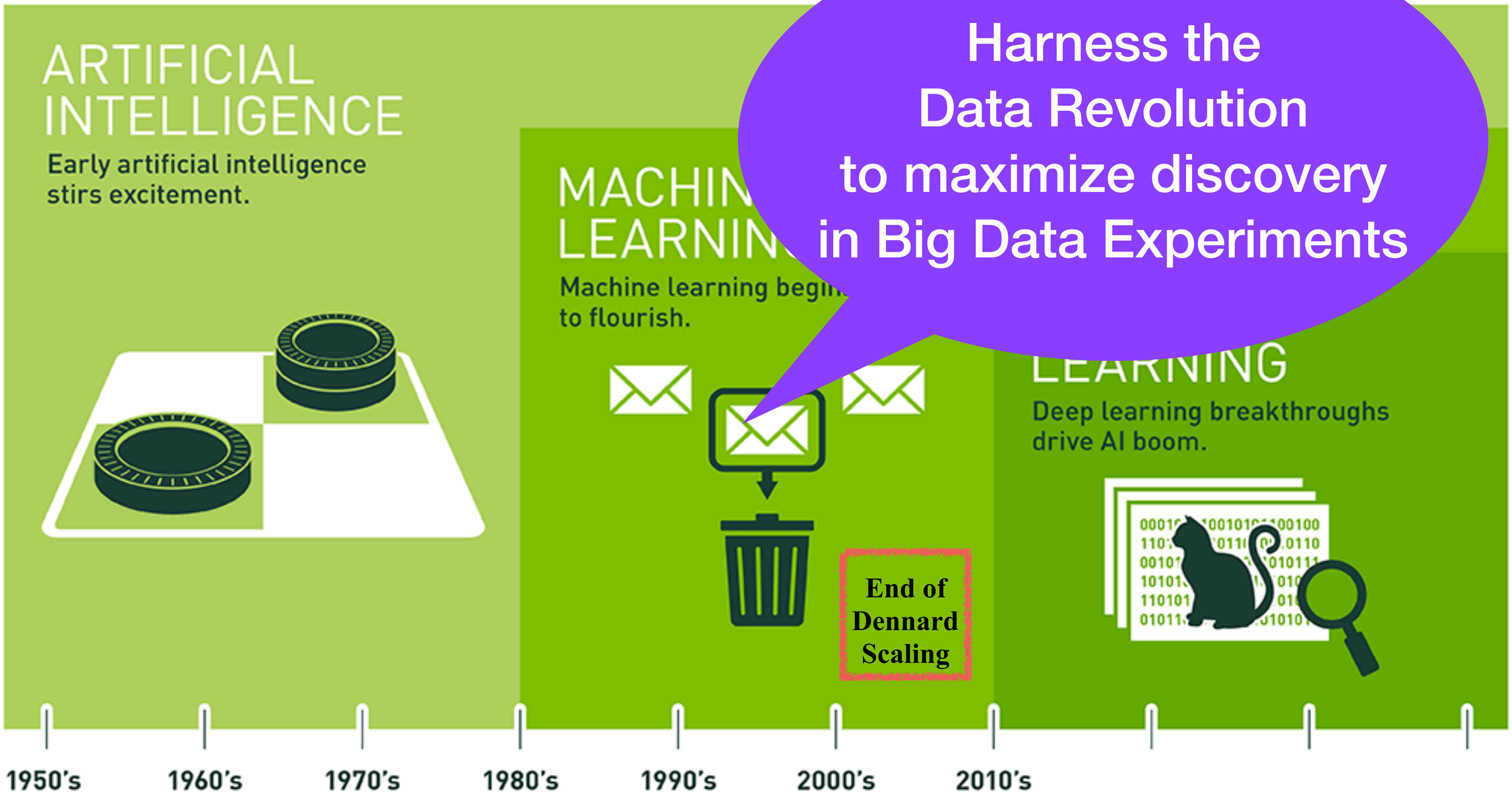
Pressing need to maximize discovery

Deep Learning
From optimism to breakthroughs in technology and science



Deep Learning

From optimism to breakthroughs in t[illegible] science



Harness the Data Revolution to maximize discovery in Big Data Experiments

High Performance Computing

Understand sources with numerical relativity

Datasets of numerical relativity waveforms to train and test neural nets

Train neural nets with distributed computing

Innovative Hardware Architectures

Develop state-of-the-art neural nets with large datasets

Accelerate data processing and inference

Fully trained neural nets are computationally efficient and portable

Applicable to any time-series datasets

Faster then real time classification and regression

Faster and deeper gravitational wave searches

The rise of deep learning for gravitational wave astrophysics

Deep learning for real-time *classification and regression* of gravitational waves in simulated LIGO noise
George & Huerta, *Phys. Rev.* D
January 2017

Deep learning for real-time *classification and regression* of gravitational waves in real advanced LIGO noise
George & Huerta, *Physics Letters B*
November 2017

Why relevant?

First demonstration that deep learning may be used for regression of time-series data

Application for real-time analysis of gravitational waves

Deep Learning for Gravitational Wave Astrophysics

2017 First Place Research Competition. Association for Computing Machinery at US Conferences

2018 Third Place Research Competition. Association for Computing Machinery at Conferences around the World

The rise of deep learning for gravitational wave astrophysics

Deep learning for real-time *classification and regression* of gravitational waves in simulated LIGO noise
George & Huerta, *Phys. Rev.* D
January 2017

Deep learning for real-time *classification and regression* of gravitational waves in real advanced LIGO noise
George & Huerta, *Physics Letters B*
November 2017

Deep learning at scale for real-time gravitational wave parameter estimation and tests of general relativity
Shen, Huerta & Zhao
March 2019
arXiv:1903.01998

Deep Learning for Gravitational Wave Astrophysics

Training requires tens of thousands of modeled waveforms

64 GPUs sufficient to finalize training in 30mins

Evaluation time is faster than real-time

Training requires tens of millions of modeled waveforms

1024 nodes at Theta finalize training in 30 mins

Evaluation time is 2 ms per event

Prototypes → **Production Scale**

First generation of neural network models for gravitational wave detection

Simple architectures 2-D black hole binary signal manifold ...ets

George & Huerta, Phys. Rev. D 97, 044...
Classification and regression in simulated LIG...

See Sawn Condon's talk tomorrow

George & Huerta, Physics Letters B, 778 64-70
Classification and regression in real advanced LIGO noise

Follow-up studies a year later:

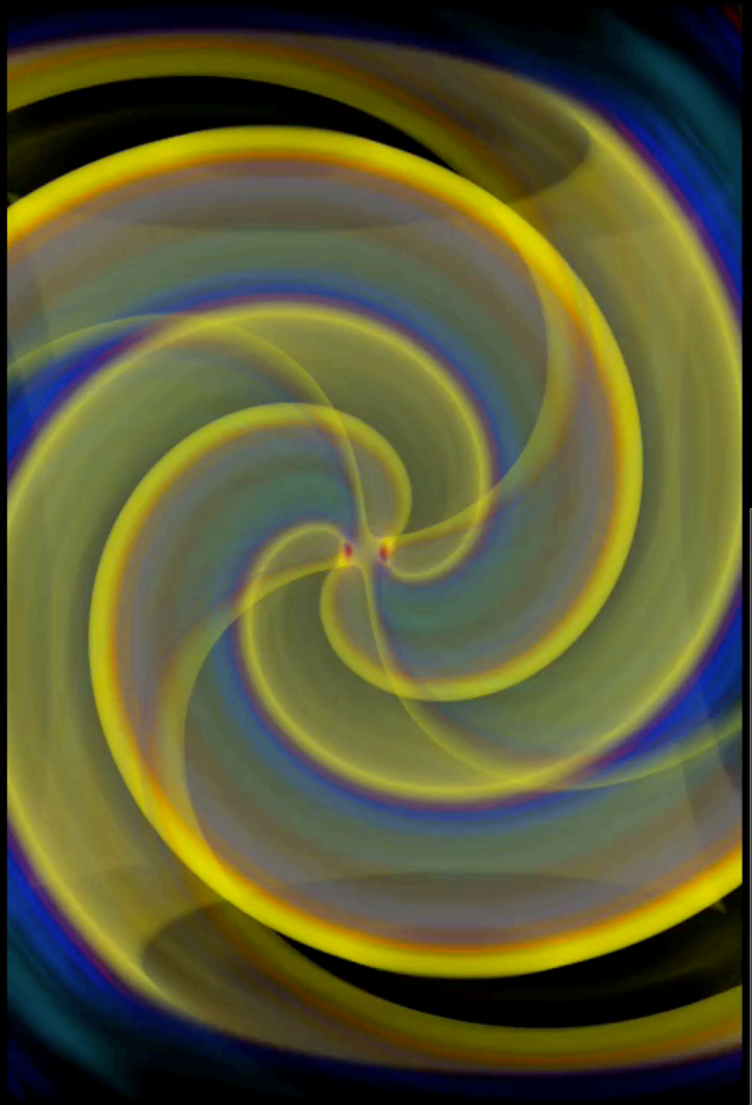
Classification of 2-D BBH signals in simulated LIGO noise:

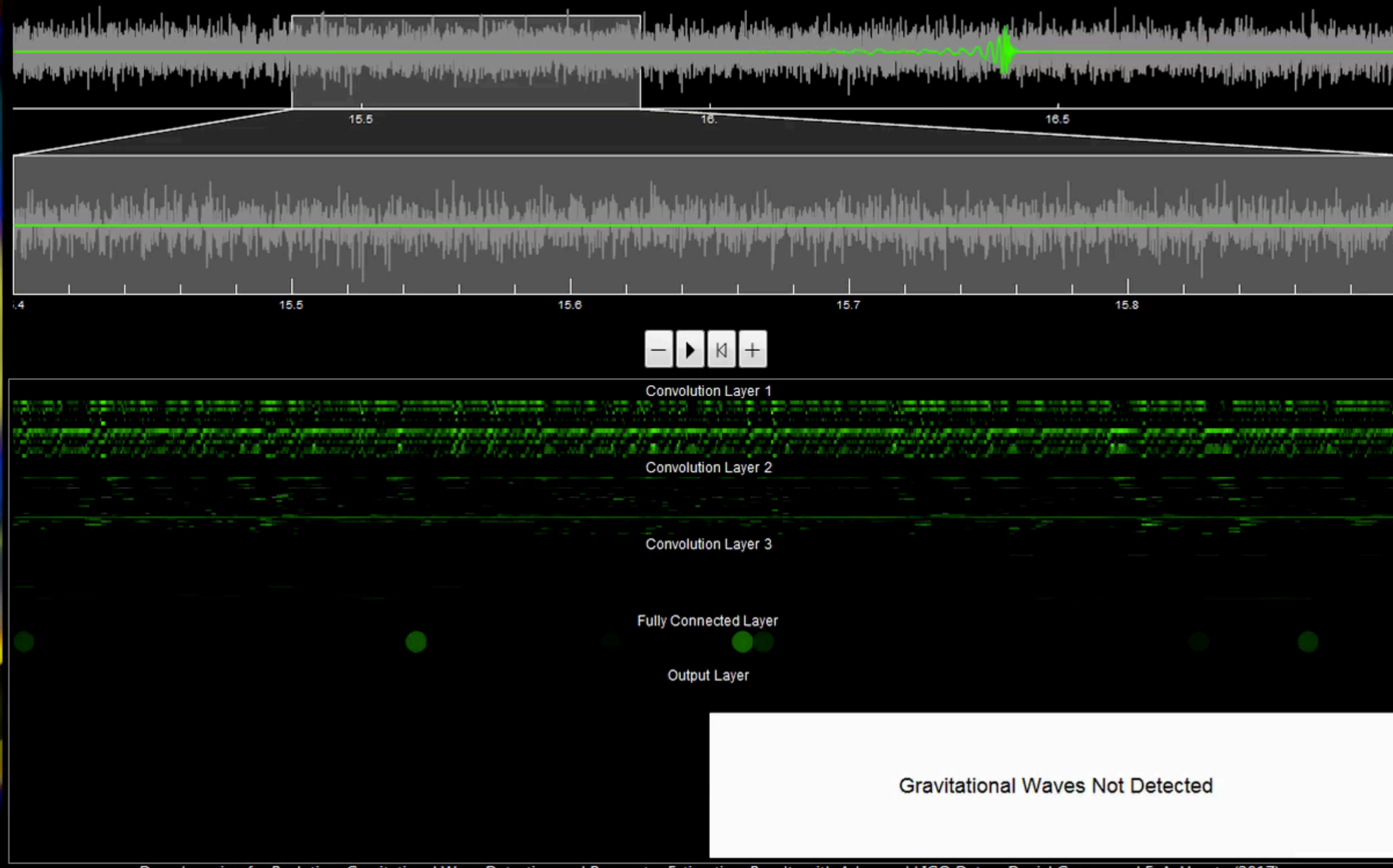
Gabbard *et al.*, PRL 120, 141103 (2018)

Xilong Fan et al., Sci.China Phys.Mech.Astron. 62 (2019)

Detecting Gravitational Waves in Real–Time with Deep Learning

Data from a LIGO Interferometer around the first event (GW150914)





Deep Learning for Real–time Gravitational Wave Detection and Parameter Estimation: Results with Advanced LIGO Data – Daniel George and E. A. Huerta (2017)

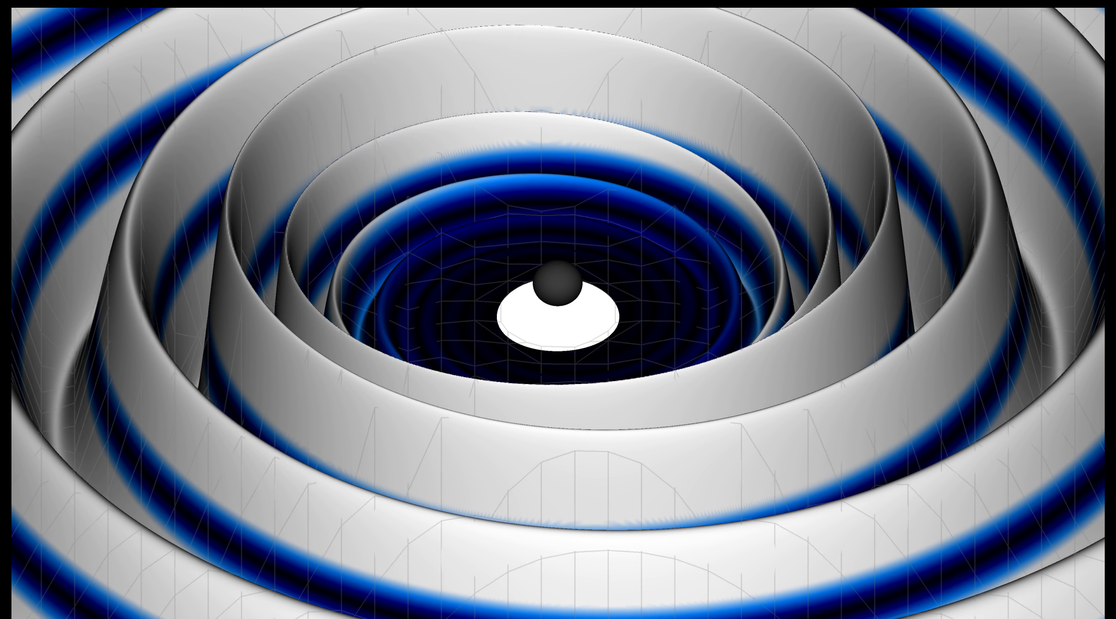
Deep learning at scale for gravitational wave astrophysics

First application of deep learning at scale to characterize a 4-D signal manifold with 10M+ templates
Shen, Huerta and Zhao, arXiv:1903.01998



Inference of the properties of the binary components before and after merger

Parameter estimation studies are now endowed with a solid statistical backbone



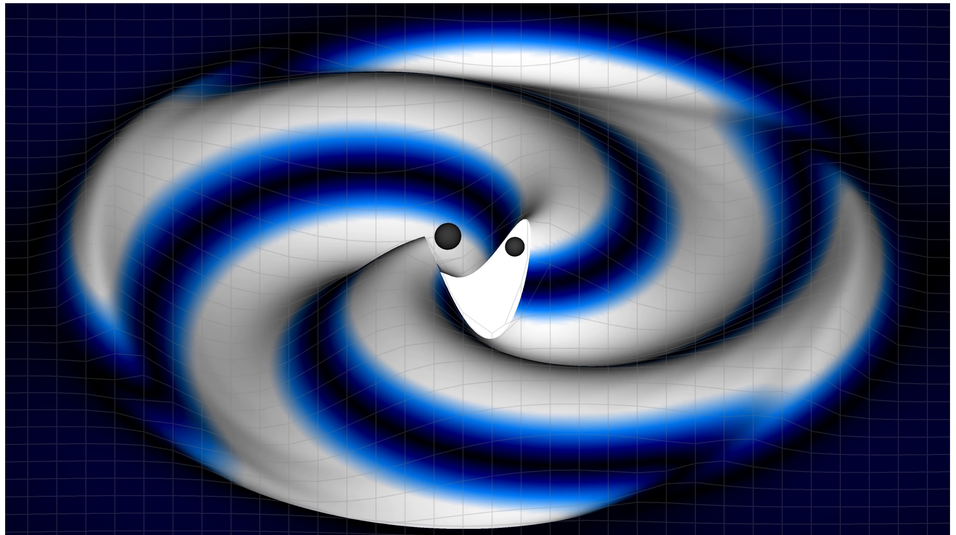
Machine Learning for waveform generation

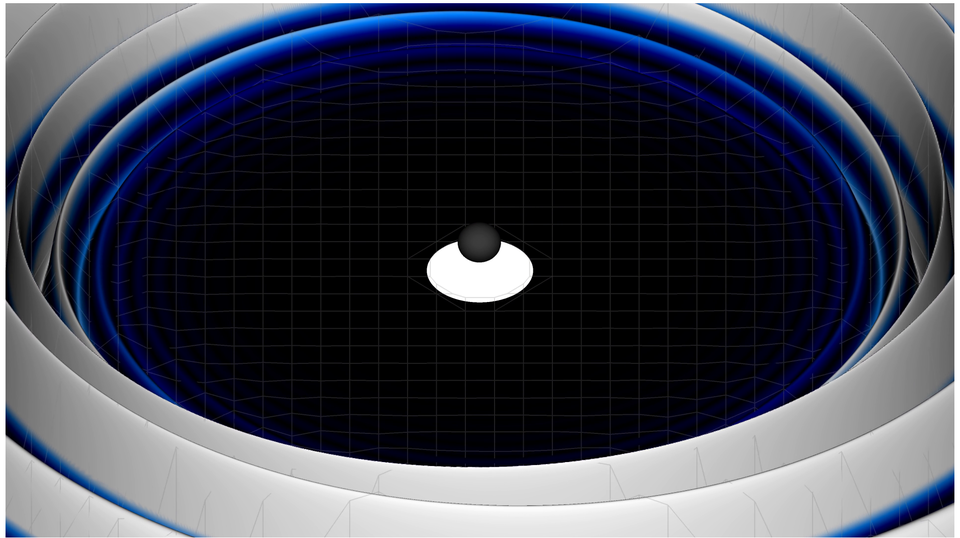
- Deep learning models perform optimally when trained with high quality data
- Use optimal waveform generators, i.e., machine learning models trained with numerical relativity waveforms
  - Blackman *et al.*, Phys. Rev. D **95**, 104023 (2017)
  - Huerta *et al.*, Phys. Rev. D **97**, 024031 (2018) [For eccentric black hole mergers]
  - Varma *et al.*, Phys. Rev. D **99**, 064045 (2019)
  - Varma *et al.*, arXiv:1905.09300

Deep learning at scale for gravitational wave astrophysics

Hongyu Shen, EA Huerta, Jane Zhao and Elise Jennings, arXiv:1903.01998

Event Name	$m_1[M_\odot]$	$m_2[M_\odot]$	a_f	ω_R	ω_I
GW150914	37.46 [4.13| 0.06]	30.80 [0.43|-1.65]	0.689 [0.037| 0.17]	0.5362 [0.0127|-0.20]	0.0798 [0.0011| 0.16]
GW151012	23.89 [0.35| 1.65]	17.34 [0.56| 1.44]	0.653 [0.009| 0.25]	0.5214 [0.0030| 0.15]	0.0810 [0.0003|-0.15]
GW151226	17.60 [2.01| 0.87]	14.14 [2.85| 0.73]	0.646 [0.006| 1.53]	0.5188 [0.0021| 1.51]	0.0812 [0.0001|-1.60]
GW170104	36.45 [1.54|-0.76]	21.83 [3.54|-0.56]	0.661 [0.080|-0.84]	0.5185 [0.0306|-0.48]	0.0816 [0.0029| 0.57]
GW170608	13.96 [1.13| 1.10]	11.96 [1.07| 1.56]	0.697 [0.025|-1.28]	0.5278 [0.0154|-0.95]	0.0809 [0.0011|-0.67]
GW170729	48.61 [1.58|-1.61]	37.69 [1.82|-0.28]	0.694 [0.019|-0.47]	0.5102 [0.0107|-0.50]	0.0812 [0.0019|-0.16]
GW170809	31.01 [3.29| 0.60]	22.42 [4.56| 1.85]	0.698 [0.034|-1.23]	0.5428 [0.0163|-1.15]	0.0779 [0.0016|-1.05]
GW170814	35.07 [1.75| 0.84]	21.50 [0.52| 0.99]	0.718 [0.010|-1.89]	0.5377 [0.0108|-1.38]	0.0794 [0.0003| 1.76]
GW170818	40.05 [1.29|-1.57]	24.08 [0.93|-1.33]	0.656 [0.015| 0.73]	0.5129 [0.0043| 1.21]	0.0816 [0.0005|-1.02]
GW170823	39.56 [1.75|-1.44]	30.14 [0.53|-1.68]	0.740 [0.002|-1.76]	0.5510 [0.0007|-1.74]	0.0782 [0.0001| 1.75]

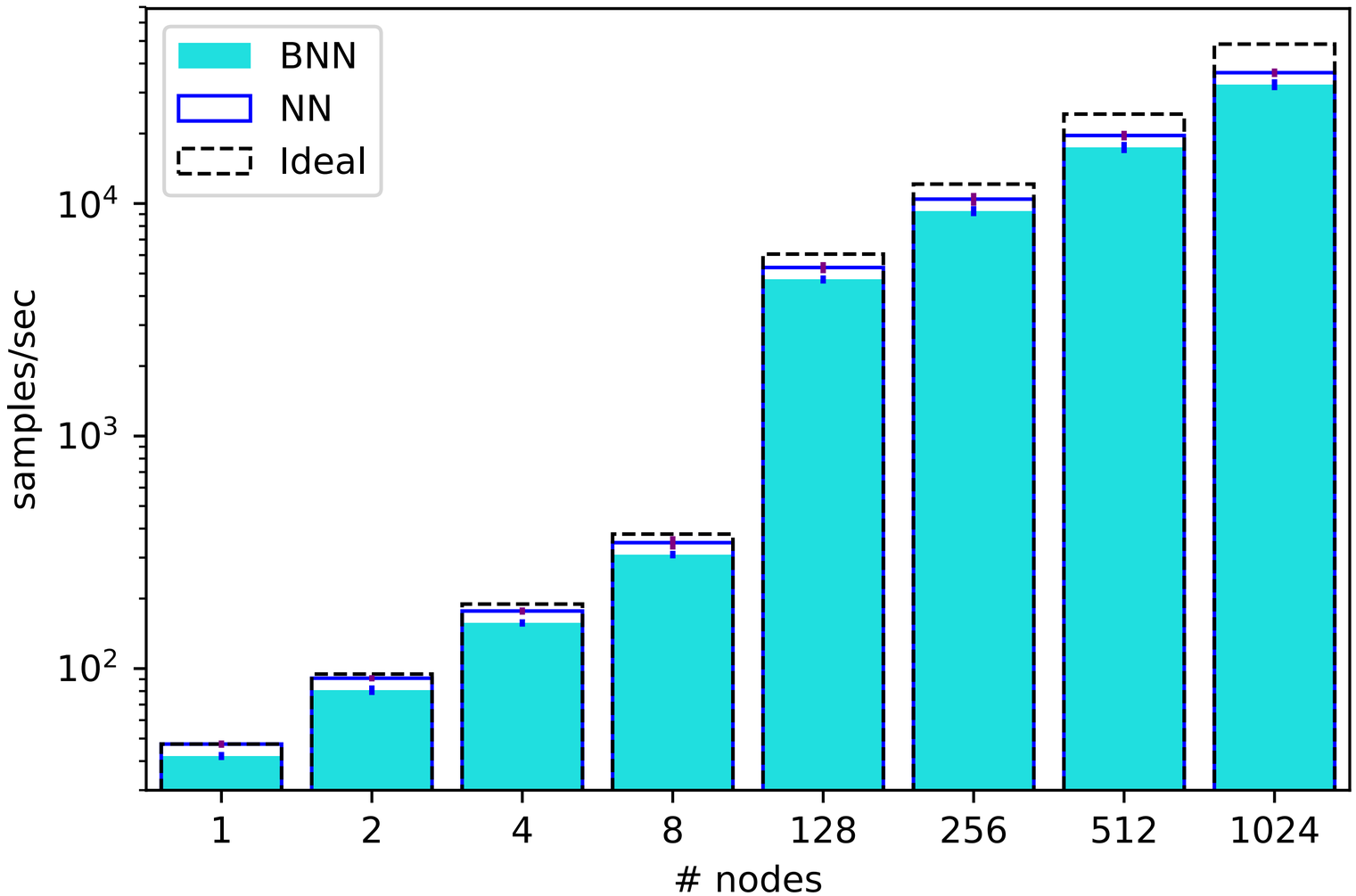




Deep learning at scale for gravitational wave astrophysics

Hongyu Shen, EA Huerta, Jane Zhao and Elise Jennings, arXiv:1903.01998

NCSA-ALCF Data Science Program



First Bayesian Neural Network model for gravitational wave parameter estimation

Trained with over ten million waveforms using 1024 nodes (64 processors/node) on an HPC platform optimized for deep learning research (Theta at Argonne National Lab)

Inference time is 2 milliseconds for each gravitational wave detection using a single GPU

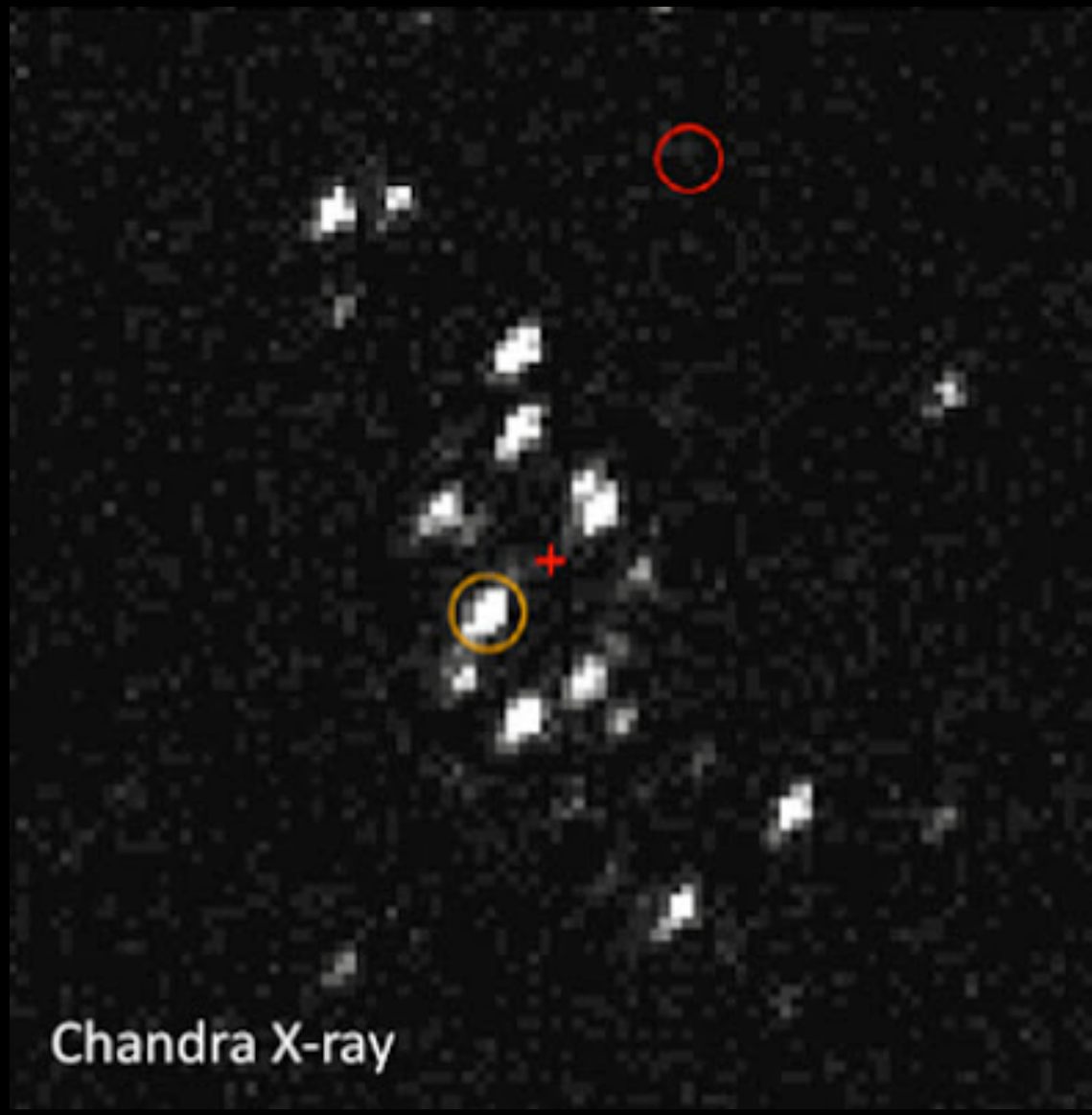
Gravitational Wave Astronomy

Dynamical assembly of black hole and neutron star binaries in dense stellar environments

Use gravitational waves to probe the existence of these sources

Can we actually detect these signals with available algorithms?

What can we learn from the observation of dynamically assembled compact binaries?



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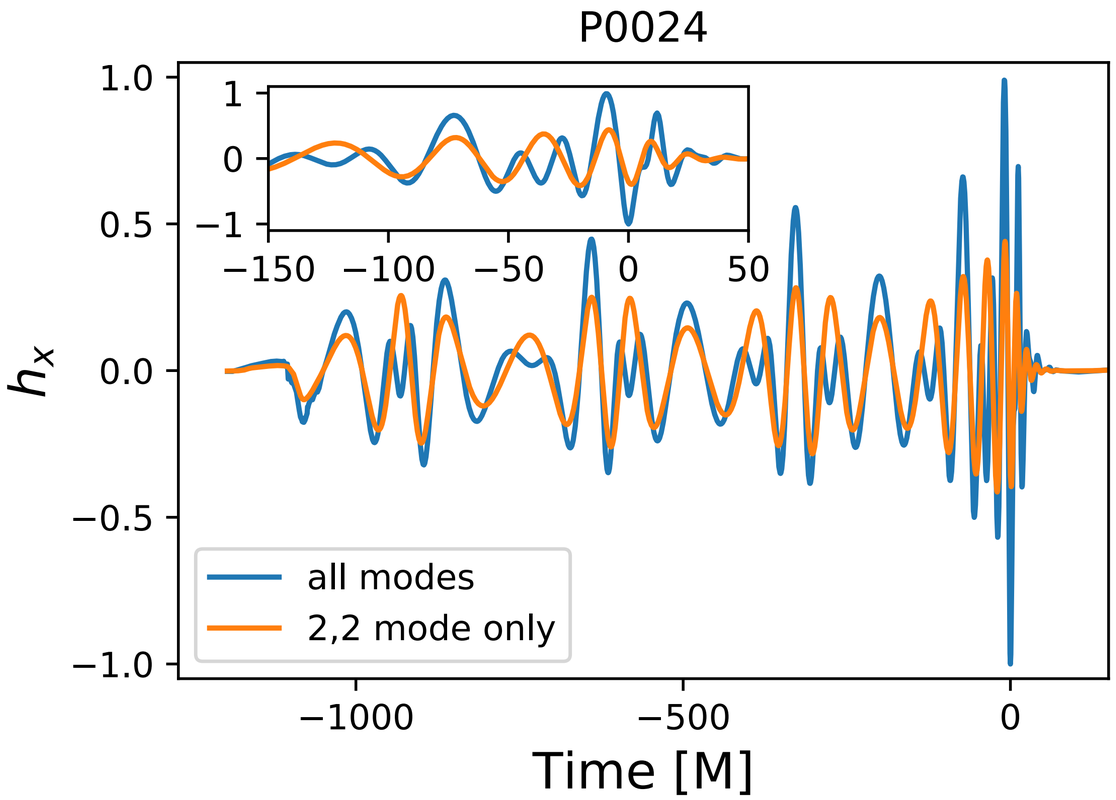
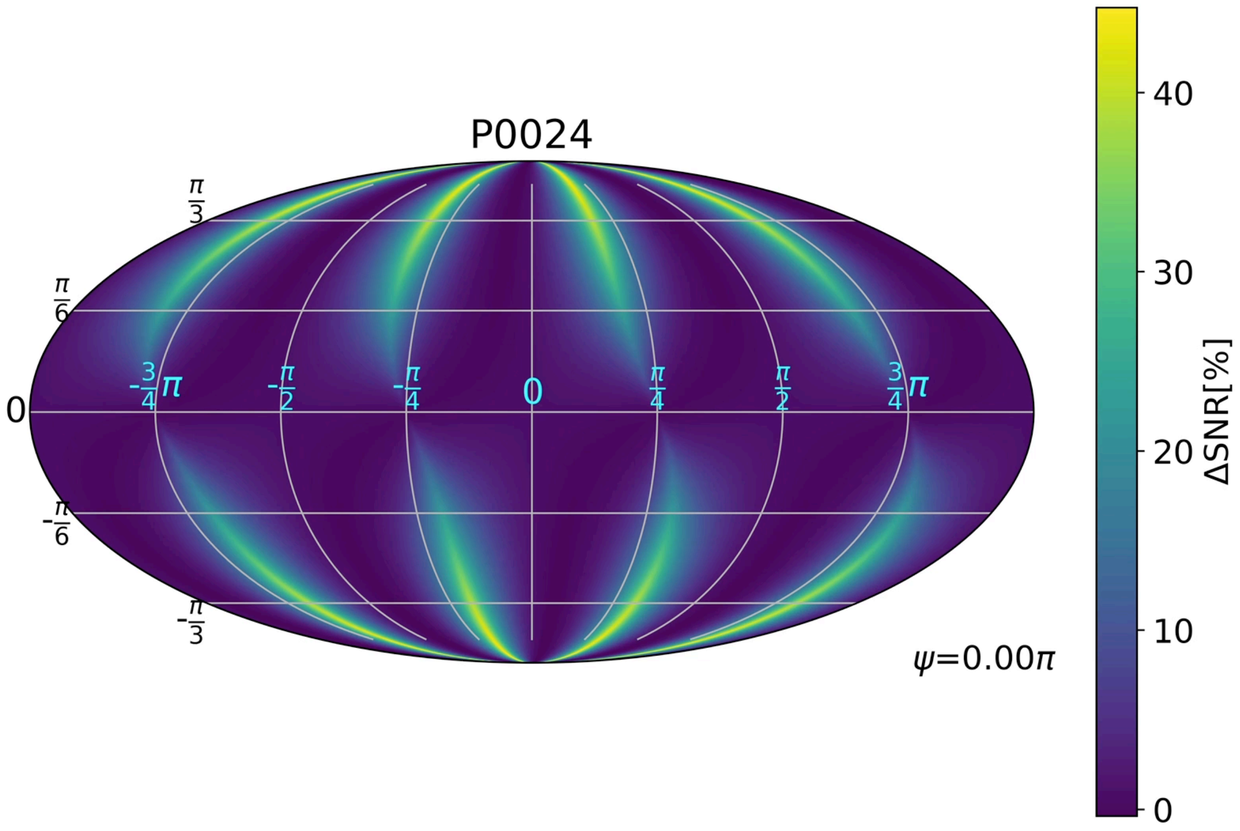
Physics of Eccentric Binary Black Hole Mergers

EA Huerta, Roland Haas, *et al.*, Phys. Rev. D 100, 064003 (2019)

Detection of eccentric binary black hole mergers

Adam Rebei, EA Huerta, Sibo Wang, *et al.*, Phys. Rev. D 100, 044025 (2019)





Detection of eccentric binary black hole mergers

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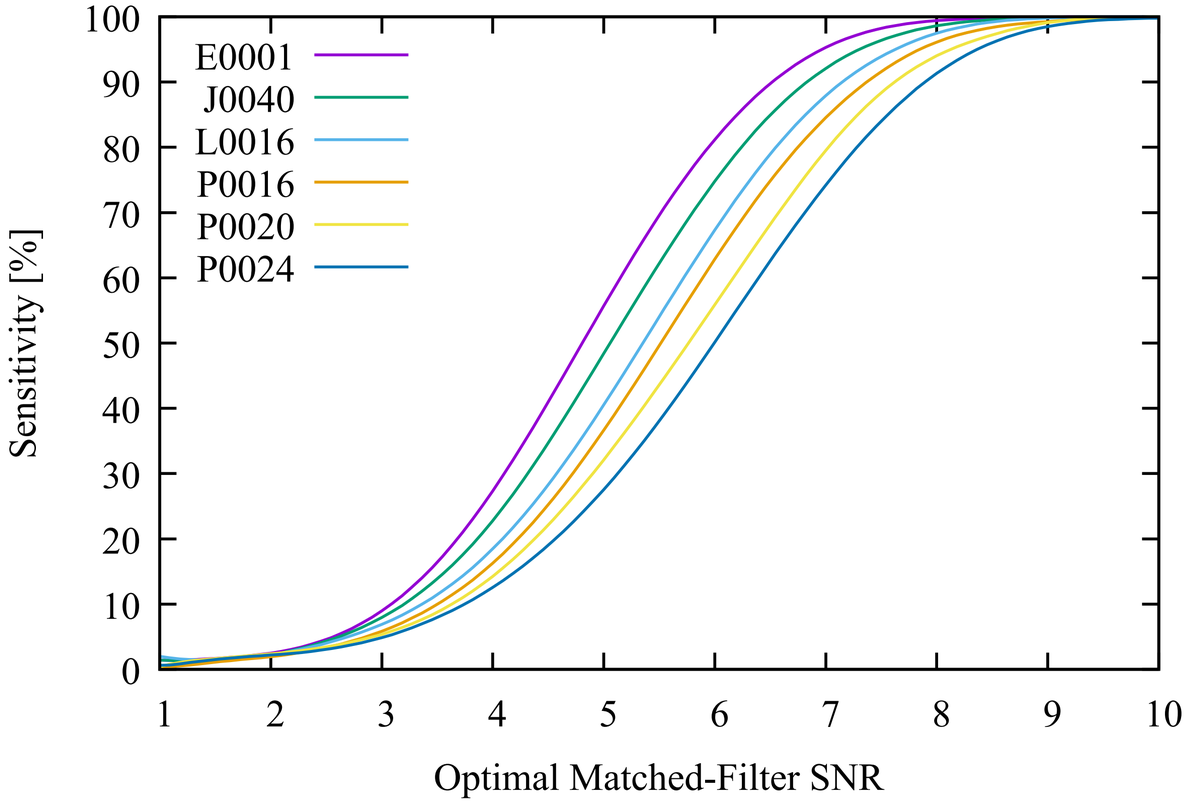
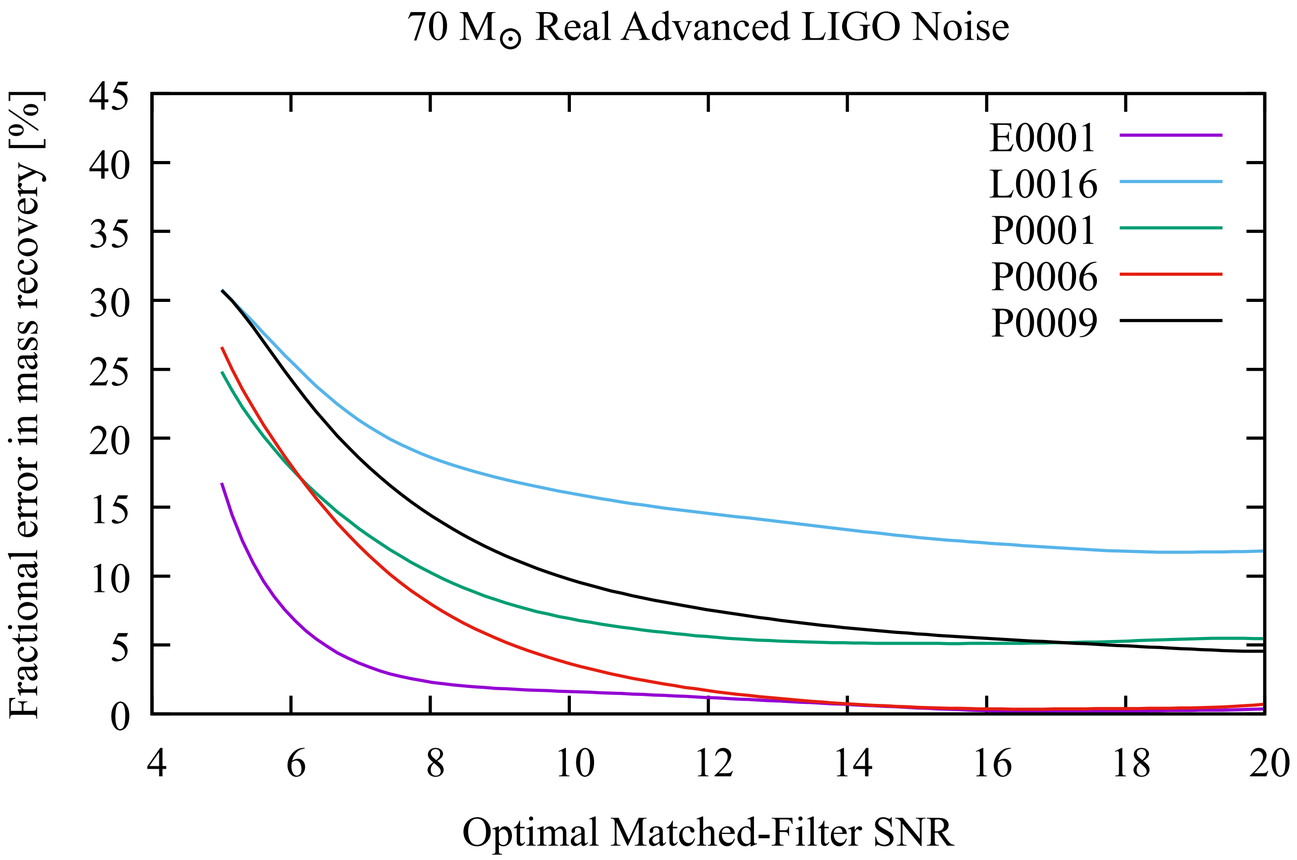
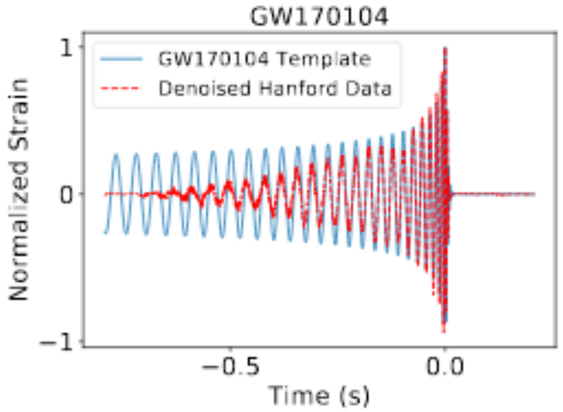


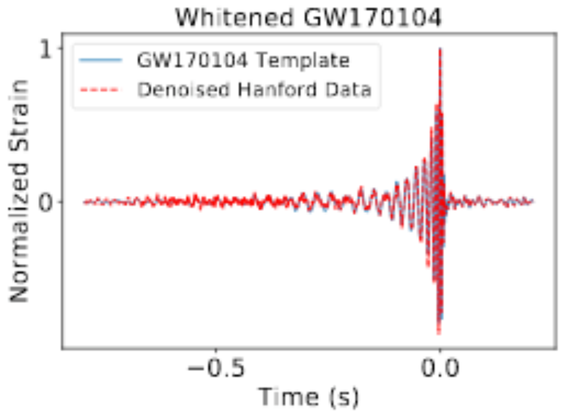


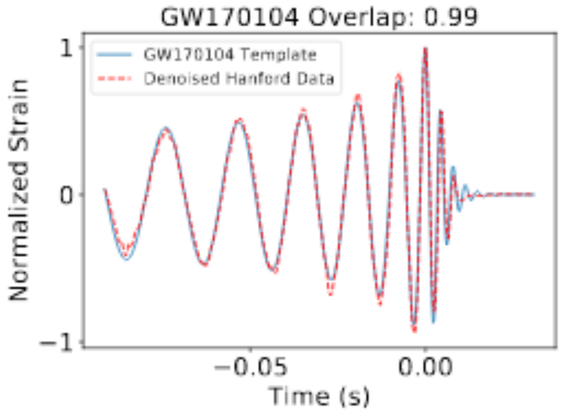
Gravitational wave denosing

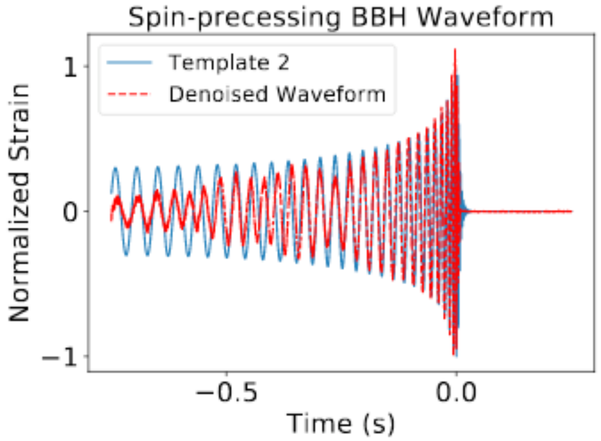
Wei Wei & EA Huerta, arXiv:1901.00869

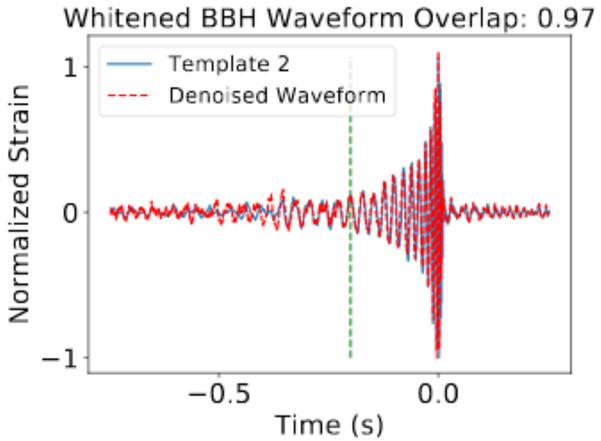
$\mathbf{s_1} = (0.4,\ 0.6,\ 0.8),\ \mathbf{s_2} = (0.4,\ -0.6,\ 0.7)$

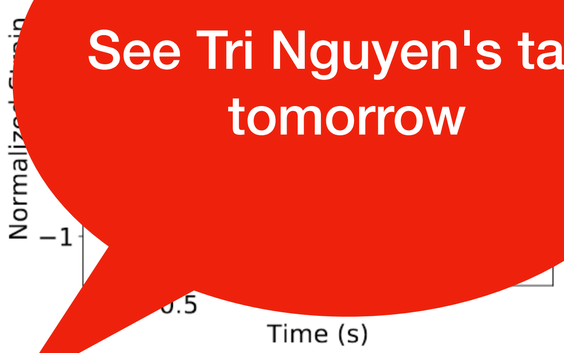




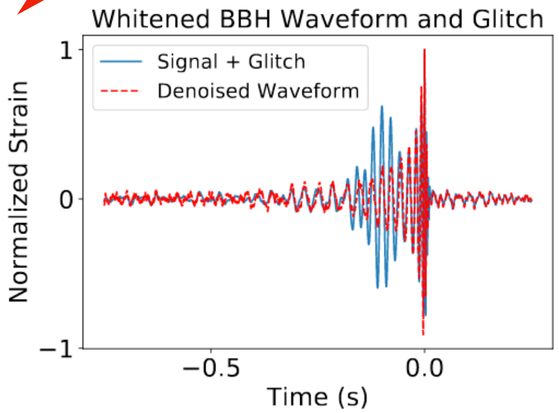


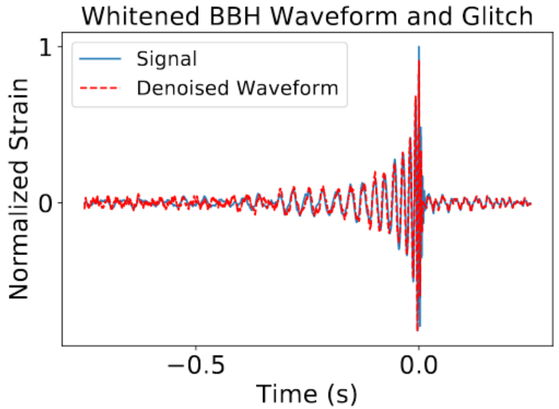




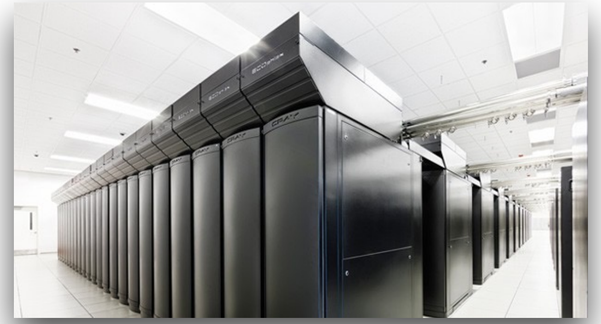


See Tri Nguyen's talk tomorrow

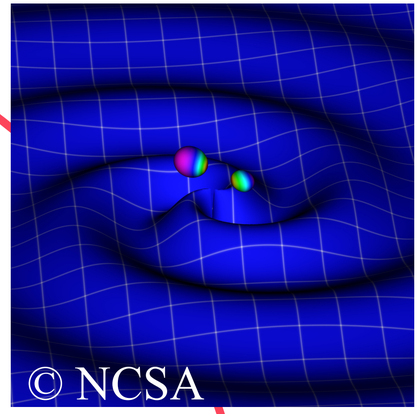




Convergence of AI and HPC



Training and testing datasets from numerical relativity simulations



Observational data to train, validate and test neural network models

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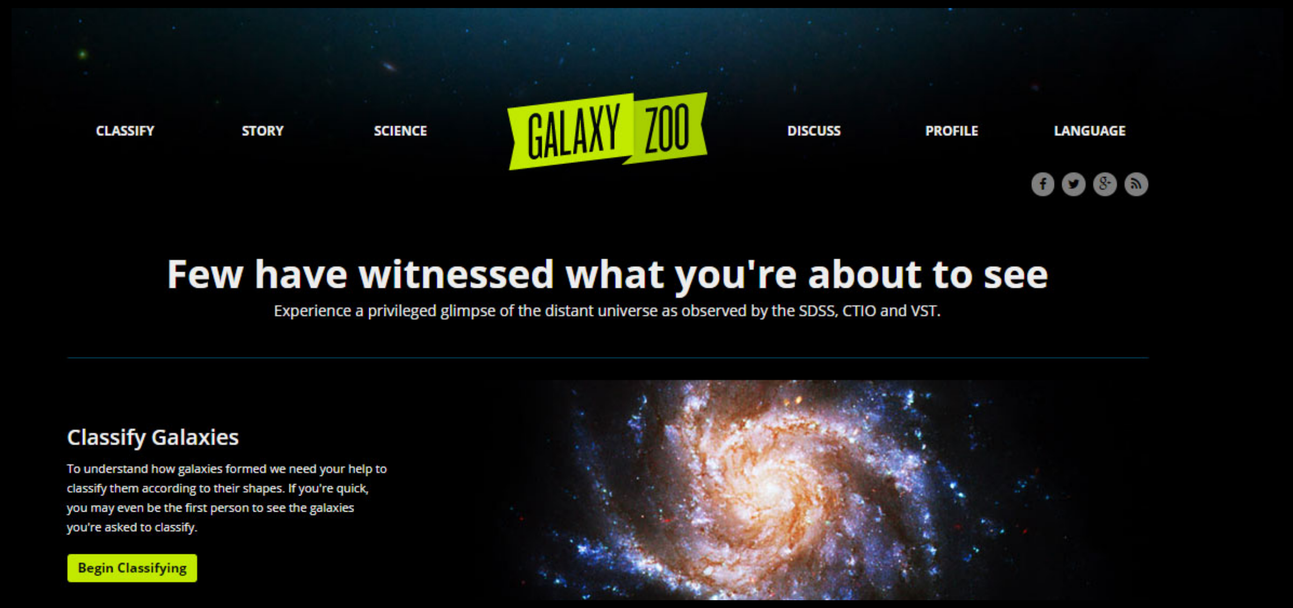
Theory to inform the design of deep learning models

$G_{\mu\nu} = 8\pi T_{\mu\nu}$

Routine: black hole and neutron star collisions

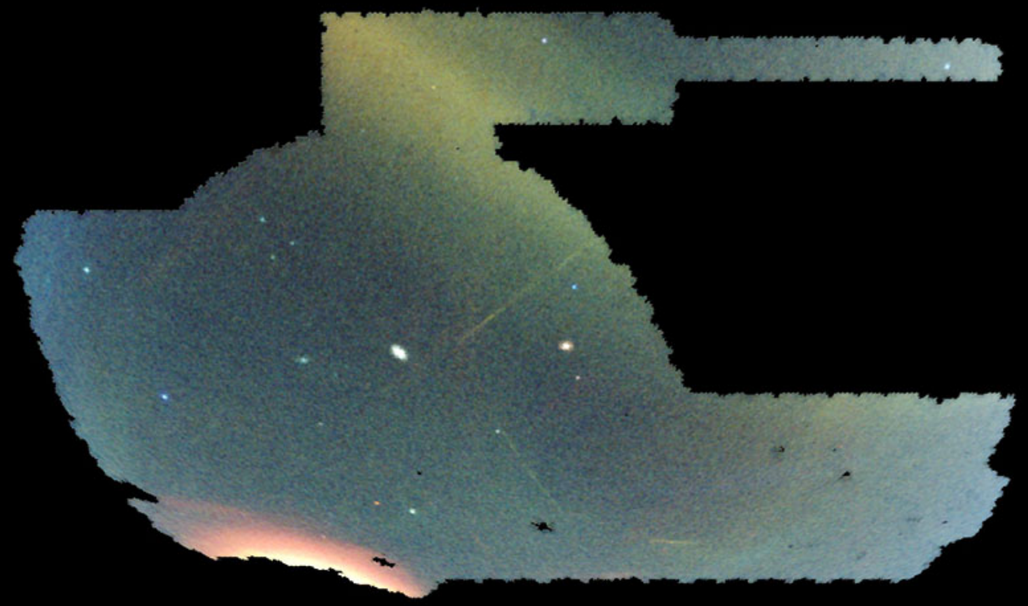
Future: supernovae, oscillating neutron stars….

Deep Learning for Gravitational Wave Cosmology



From the citizen science revolution using the Sloan Digital Sky Survey…

… to large scale discovery using unlabeled images in the Dark Energy Survey using deep learning

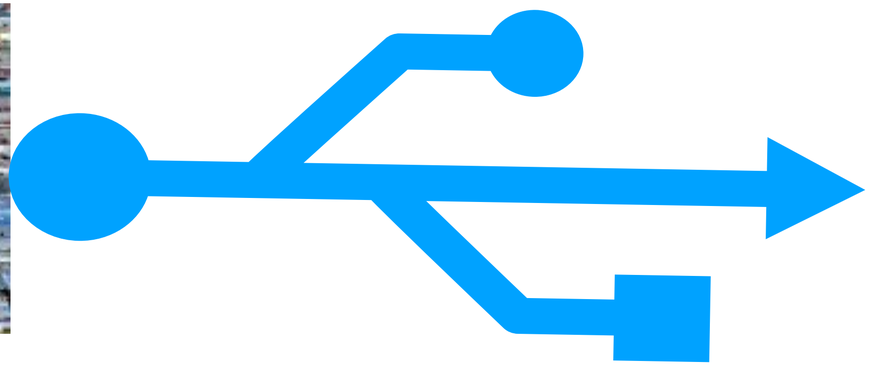


Khan, Huerta, Wang, Gruendl, Jennings and Zheng, Physics Letters B 795 (2019) 248-258

Xception neural network model

François Chollet, arXiv:1610.02357

State-of-the-art model for computer vision



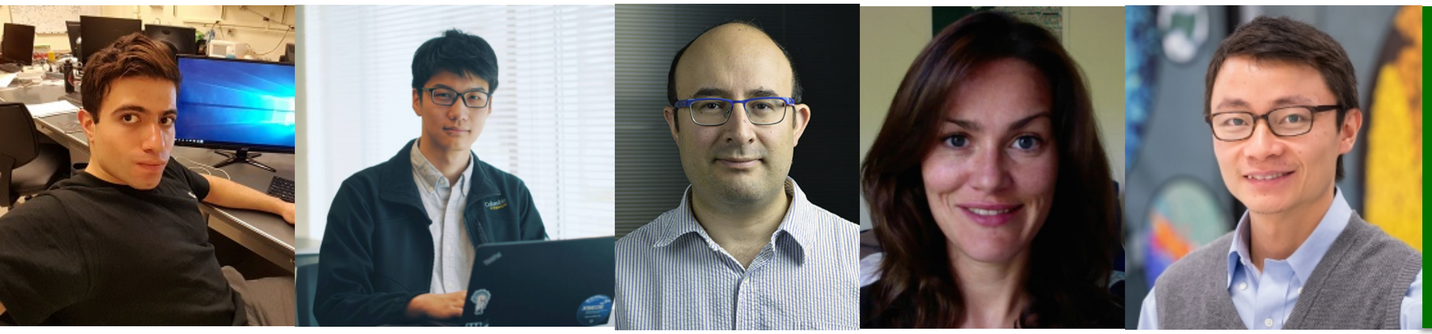
Convergence of deep transfer learning, distributed training, data clustering, and recursive training

State-of-the-art galaxy classification

Scalable method for the construction of galaxy catalogs in the Dark Energy Survey

Platform for next-generation electromagnetic surveys

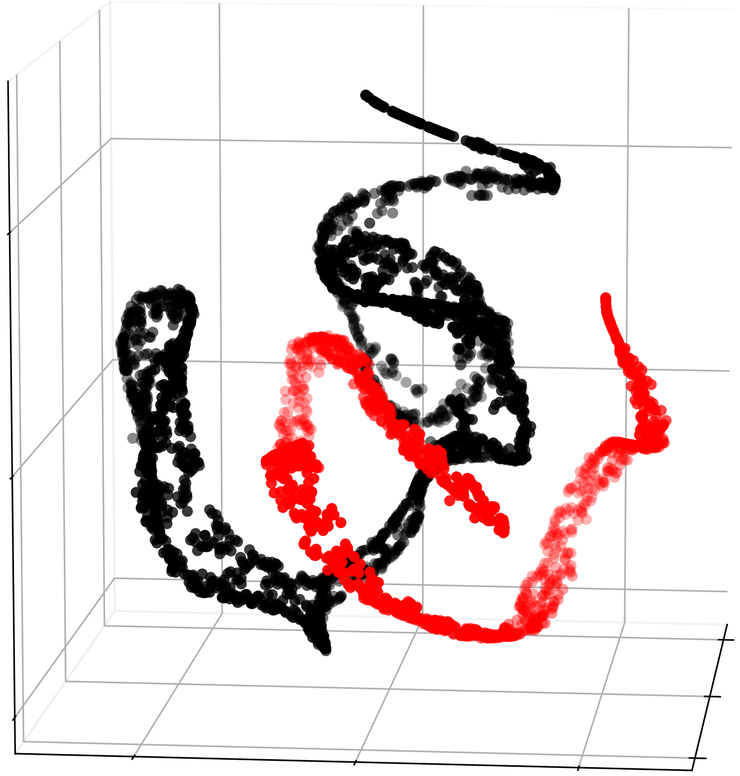
Deep Learning for DES data science



Khan, Huerta, Wang, Gruendl, Jennings and Zheng, Physics Letters B 795 (2019) 248-258

NCSA-Argonne Data Science Program

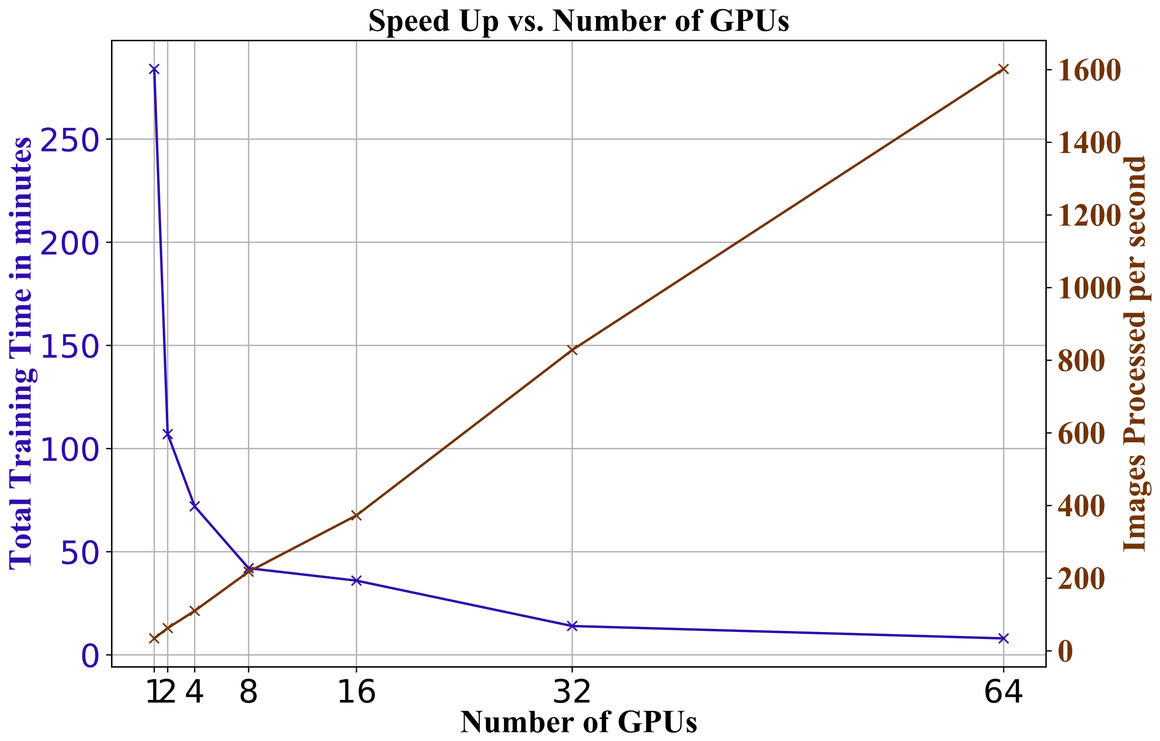
Unlabelled DES



10k+ raw, unlabeled galaxy images from DES clustered according to morphology using RGB filters

Scalable approach to curate datasets, and to construct large-scale galaxy catalogs

Visualization: https://www.youtube.com/watch?v=1F3q7M8QjTQ

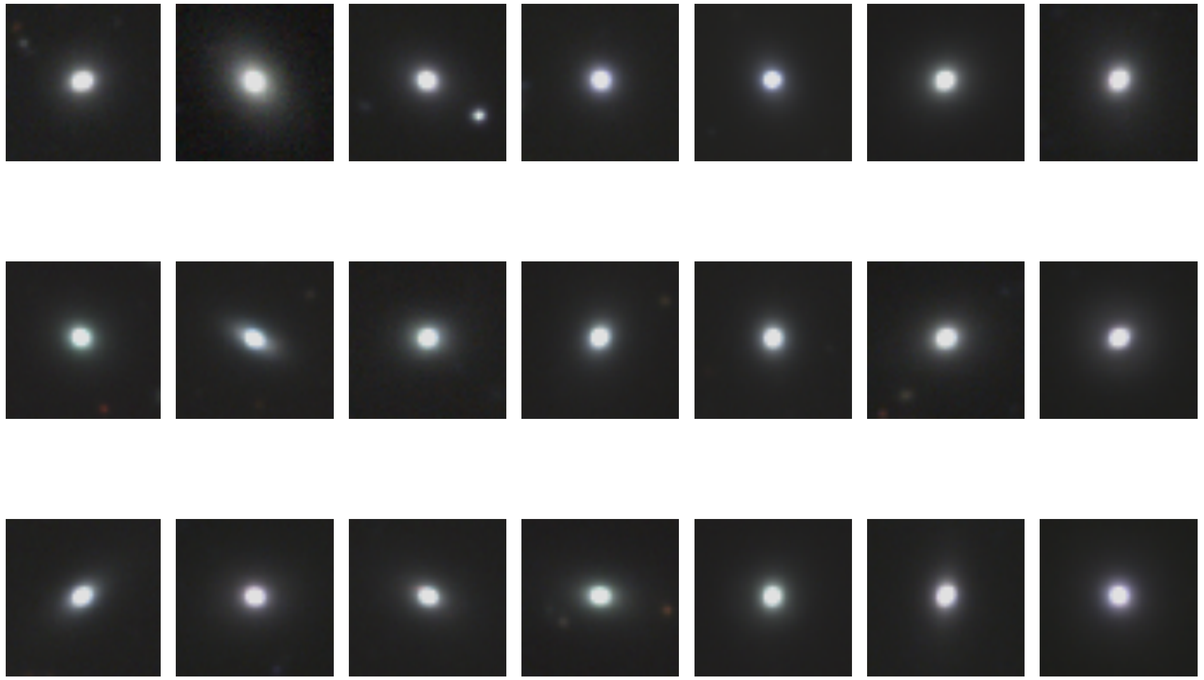


Deep transfer learning combined with distributed training for cosmology

Training is completed within 8 minutes achieving state-of-the-art classification accuracy

Training done at the Cooley supercomputer at Argonne National Lab

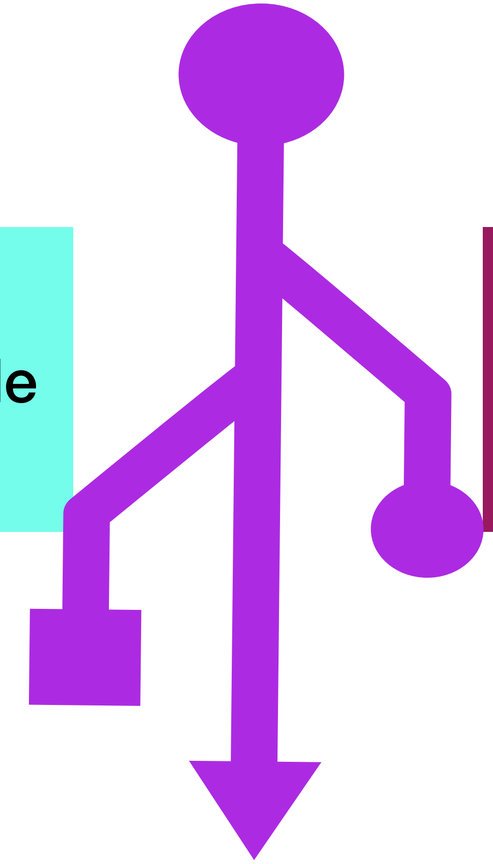
Predicted DES elliptical galaxies by our neural network model



Khan, Huerta, Wang, Gruendl, Jennings and Zheng, Physics Letters B 795 (2019) 248-258

Visualization: https://www.youtube.com/watch?v=1F3q7M8QjTQ

Deep Learning for Gravitational Wave Cosmology

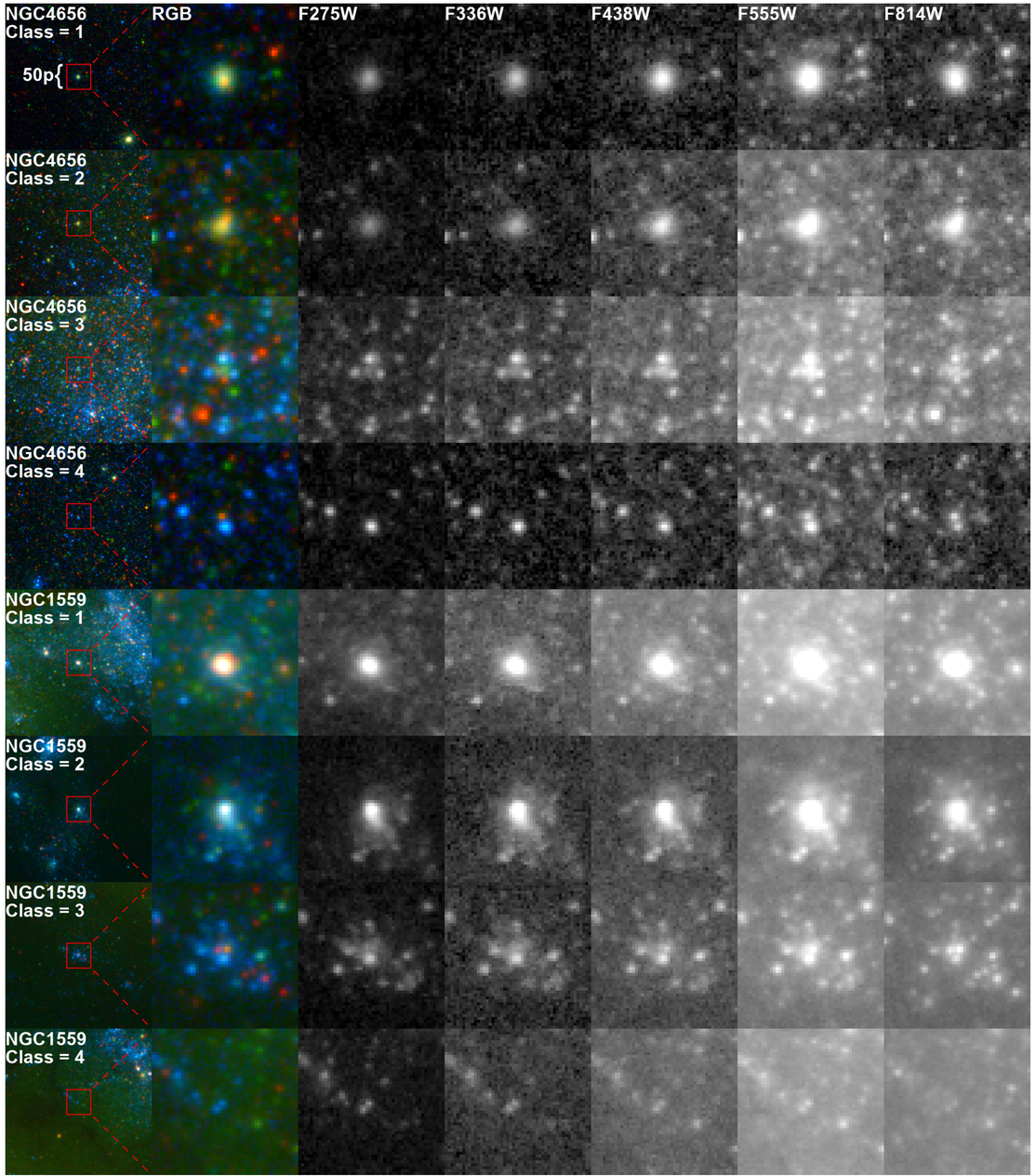


Real-time detection and characterization of binary black hole mergers

Classification and regression of galaxies across redshift in DES/LSST-type surveys

Hubble constant measurements with probabilistic neural network models

NCSA-IPAC-STScI-MPI



Wei Wei, EA Huerta, *et al.*, arXiv:1909.02024

Star cluster classification has been predominantly done by human experts

We have designed neural network models that outperform, for the first time, human performance for star cluster classification

Worldwide collaboration of experts in deep learning, astronomy, software and data

Stay tuned…

Several new applications to be presented throughout the Fall

New computing frameworks to accelerate convergence of AI & HPC

Applications of AI & HPC for multi-messenger astrophysics, cosmology, and astronomy

Branching out to new areas including geoscience and medicine

In any community of scientists, there are some individuals who are bolder than most

These scientists, judging that a crisis exists, embark on revolutionary science, exploring alternatives to long-held, obvious-seeming assumptions

Occasionally this generates a rival to the established framework of thought

The new candidate paradigm will appear to be accompanied by numerous anomalies, partly because it is still so new and incomplete

The majority of the scientific community will oppose any conceptual change, and so they should

To fulfill its potential, a scientific community needs to contain both individuals who are bold and individuals who are conservative. There are many examples in the history of science in which confidence in the established frame of thought was eventually vindicated

It is almost impossible to predict whether the anomalies in a candidate for a new paradigm will eventually be resolved

Those scientists who possess an exceptional ability to recognize a theory's potential will be the first whose preference is likely to shift in favor of the challenging paradigm

There typically follows a period in which there are adherents of both paradigms. In time, if the challenging paradigm is solidified and unified, it will replace the old paradigm, and a paradigm shift will have occurred

Thomas Kuhn, The Structure of Scientific Revolution