



Deep Learning at Scale: A Paradigm Shift for Multi-Messenger Astrophysics

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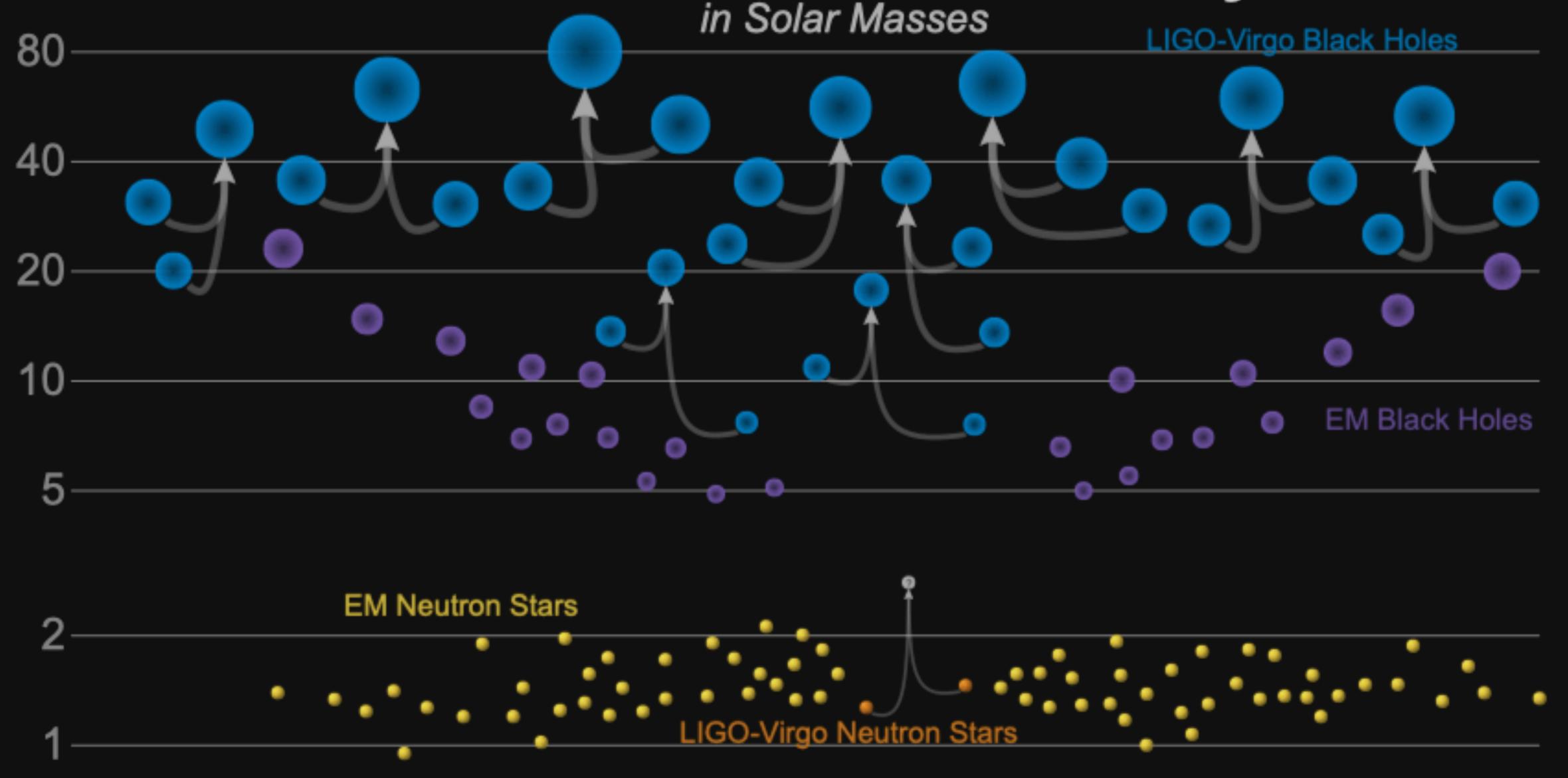
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NCSA Blue Waters Symposium for Petascale Science and Beyond June 4th 2019



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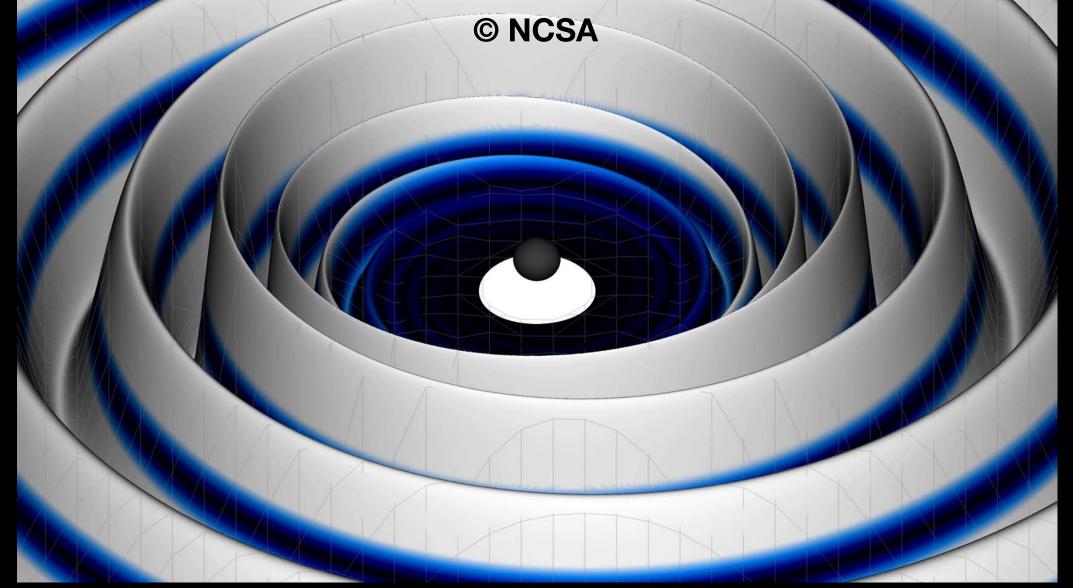
Masses in the Stellar Graveyard in Solar Masses LIGO-Virgo Black

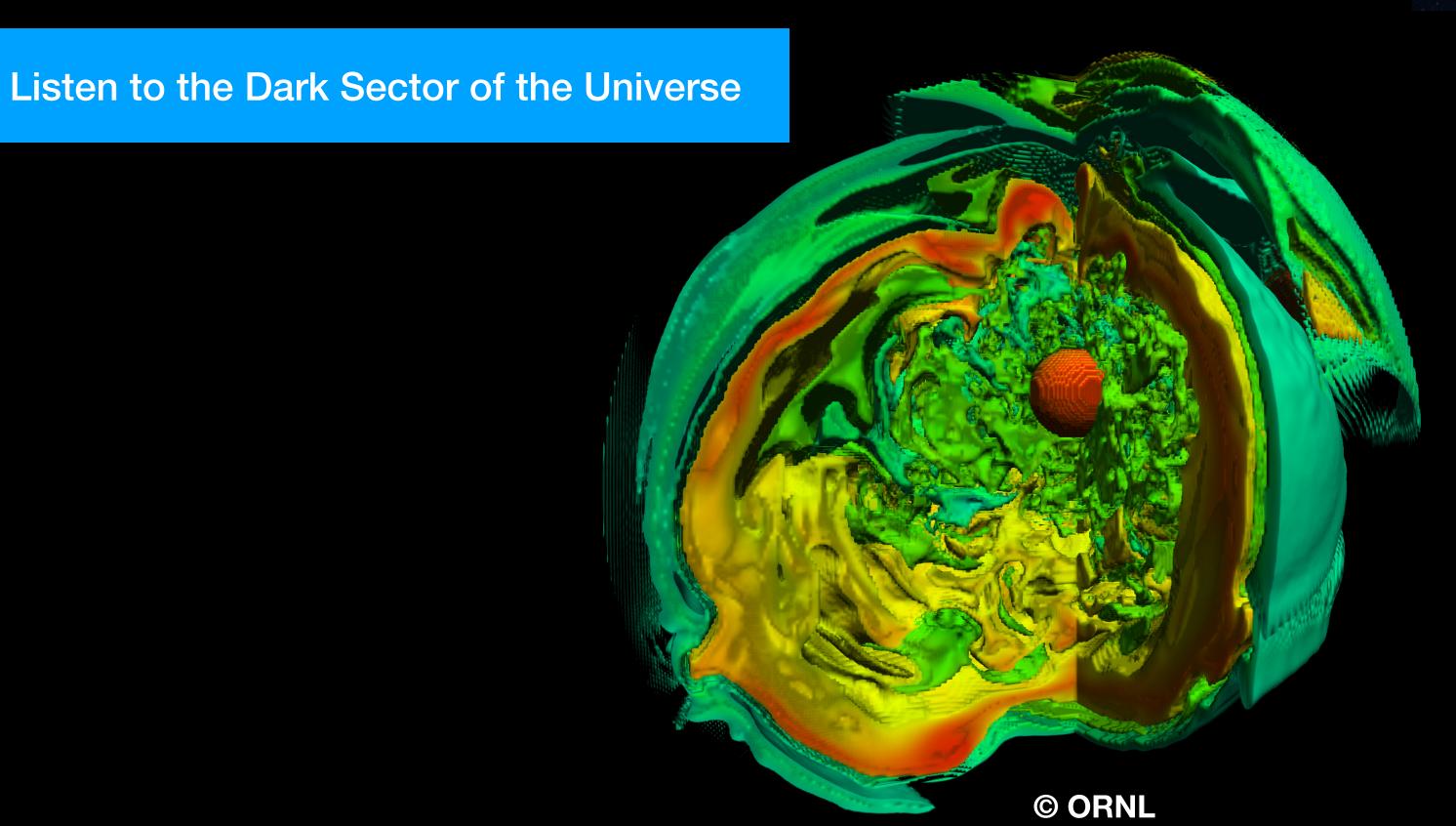




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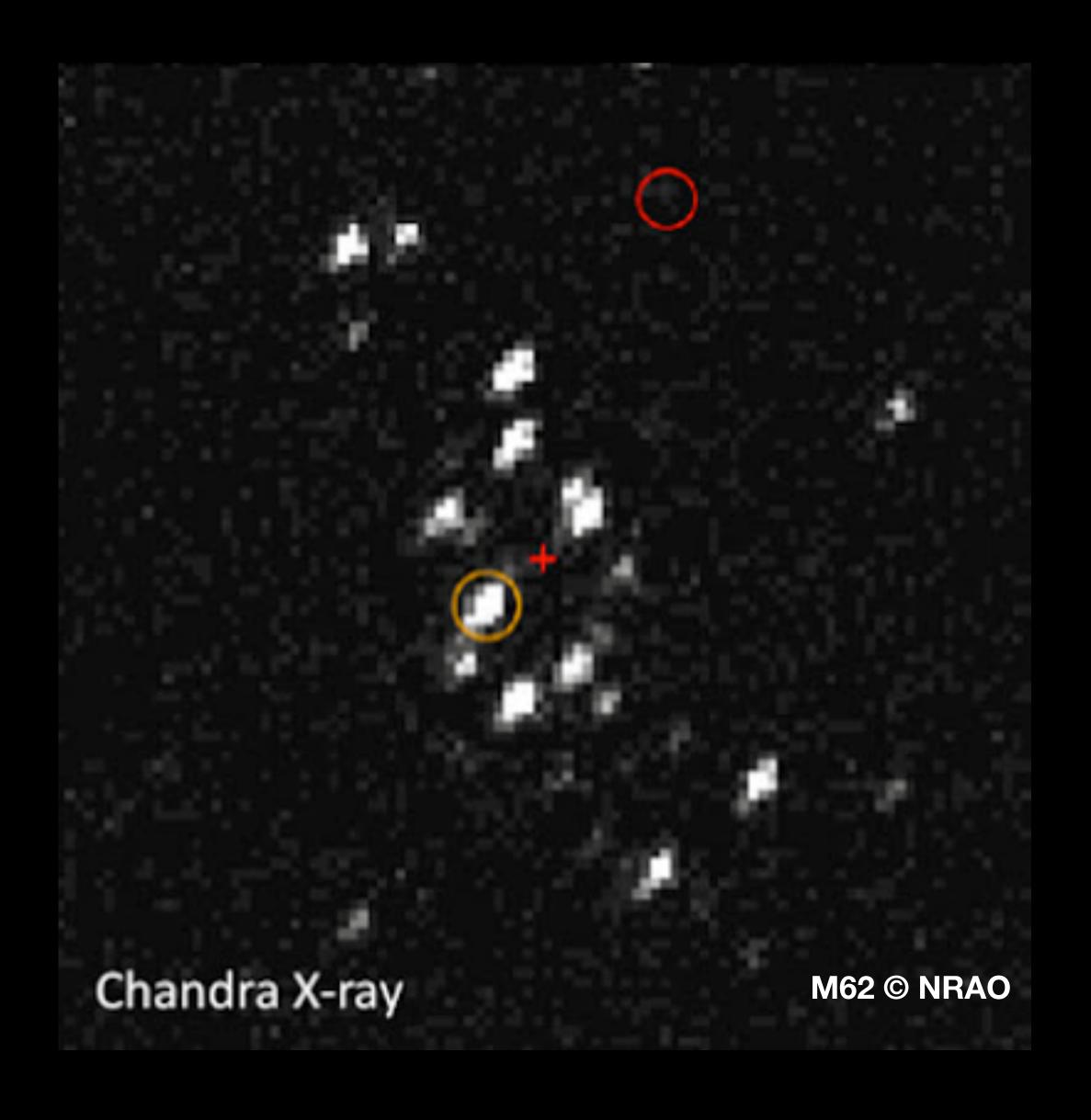


Listen to and observe cosmic mergers

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

Gravitational Wave Astrophysics

- 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?



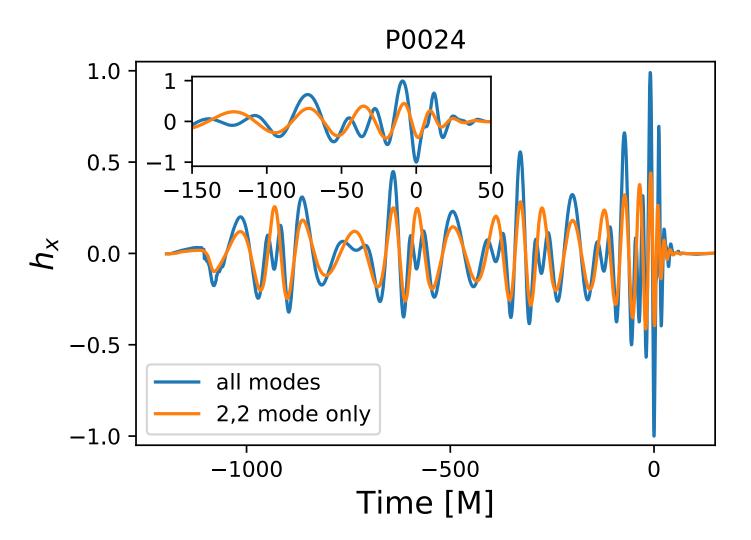
Physics of Eccentric Binary Black Hole Mergers

Huerta *et al.*, arXiv: 1901.07038



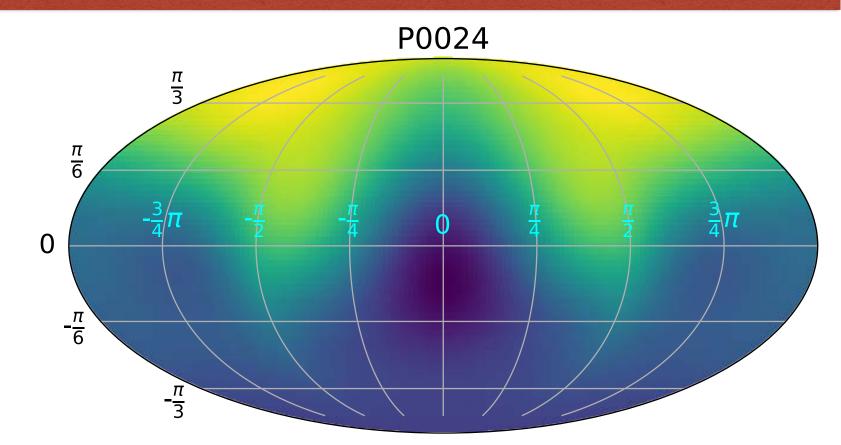
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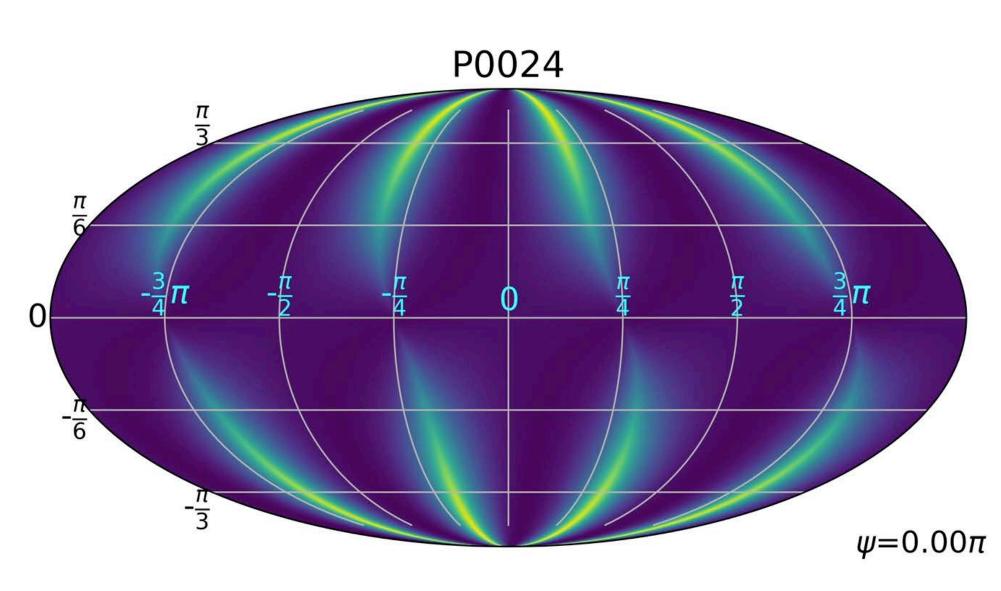
Gravitational Wave Astrophysics

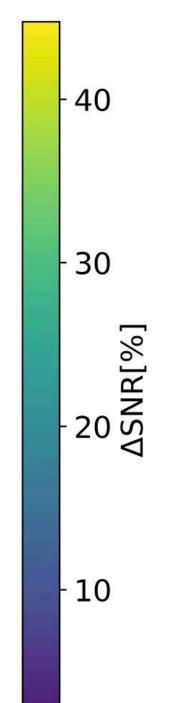


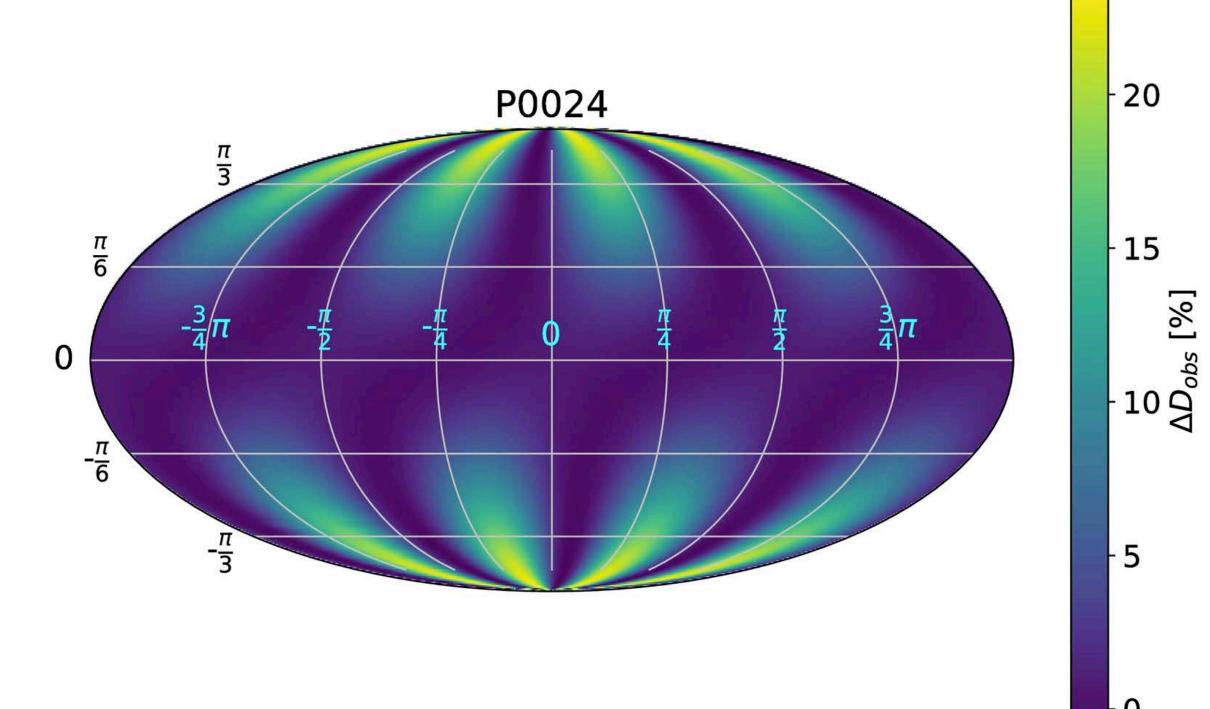
Rebei, Huerta, Wang, et al., arXiv:1807.09787

$$h(t) = \sum_{i=\{+,\times\}} h_i(\theta,\phi) F_i(\alpha,\beta,\psi)$$
$$SNR^2 = 4\Re \int_{f_0}^{f_{\text{max}}} \frac{\tilde{h}\tilde{h}^*}{S_n(f)} df$$







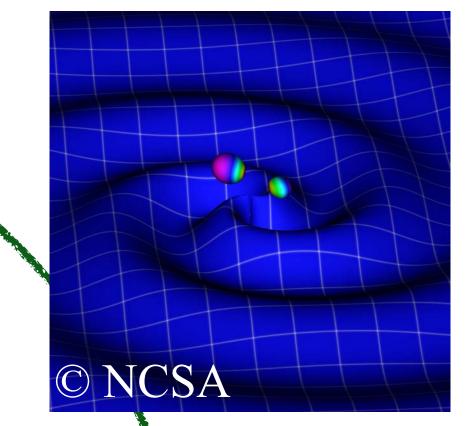




Observations

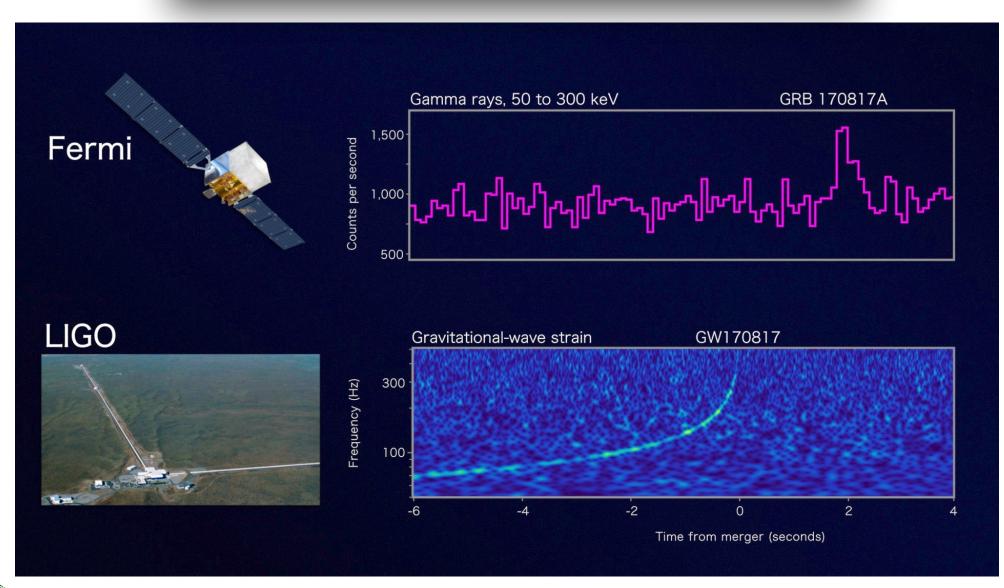


Models and simulations



Scientific Discovery







Theory

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

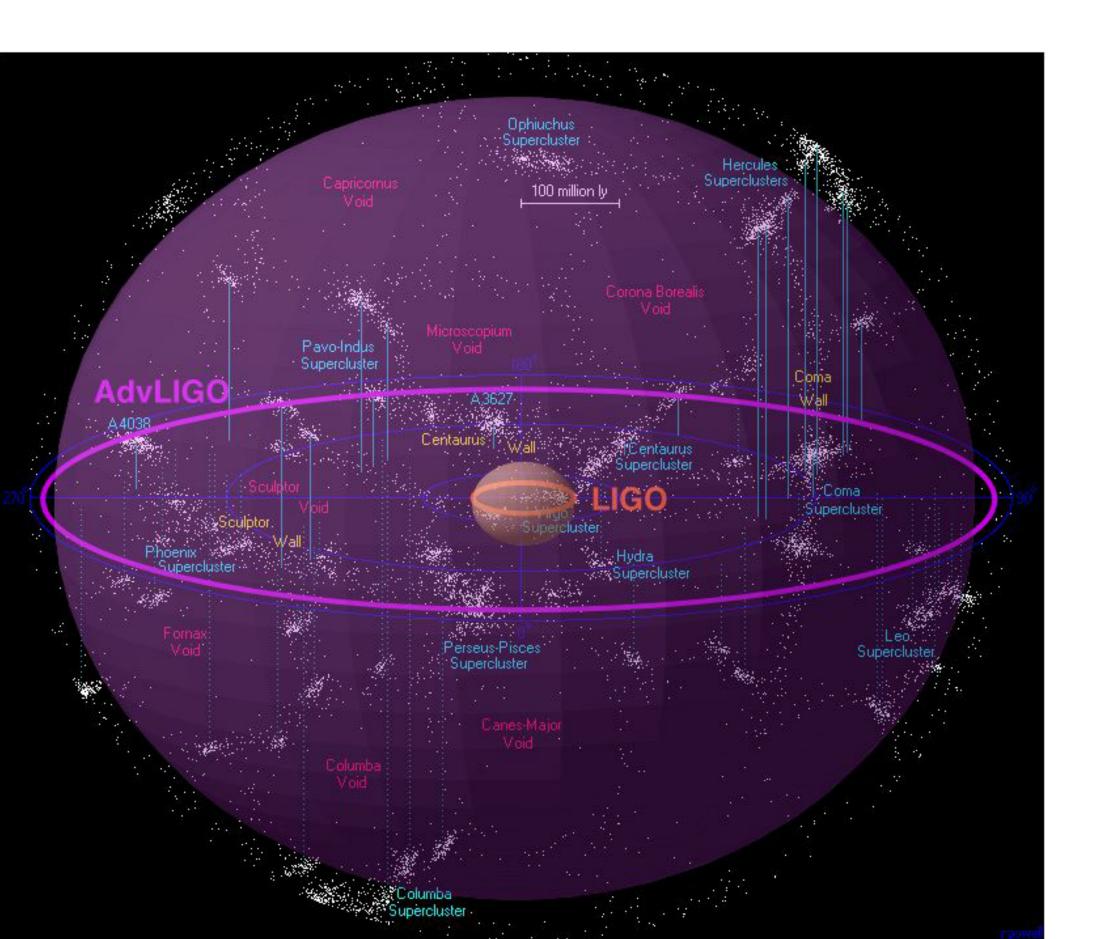
Routine: black hole and neutron star collisions
Future: supernovae, oscillating neutron

stars....

Sources, Signals and Searches

Number of observations increases with the detectors' sensitivity

Localization improves with a global detector network





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Thomas Kuhn, The Structure of Scientific Revolution

Multi-Messenger Astronomy has taken off!

Swift transition from "first detection era" to discovery at scale

Binary black holes observations are now routine!

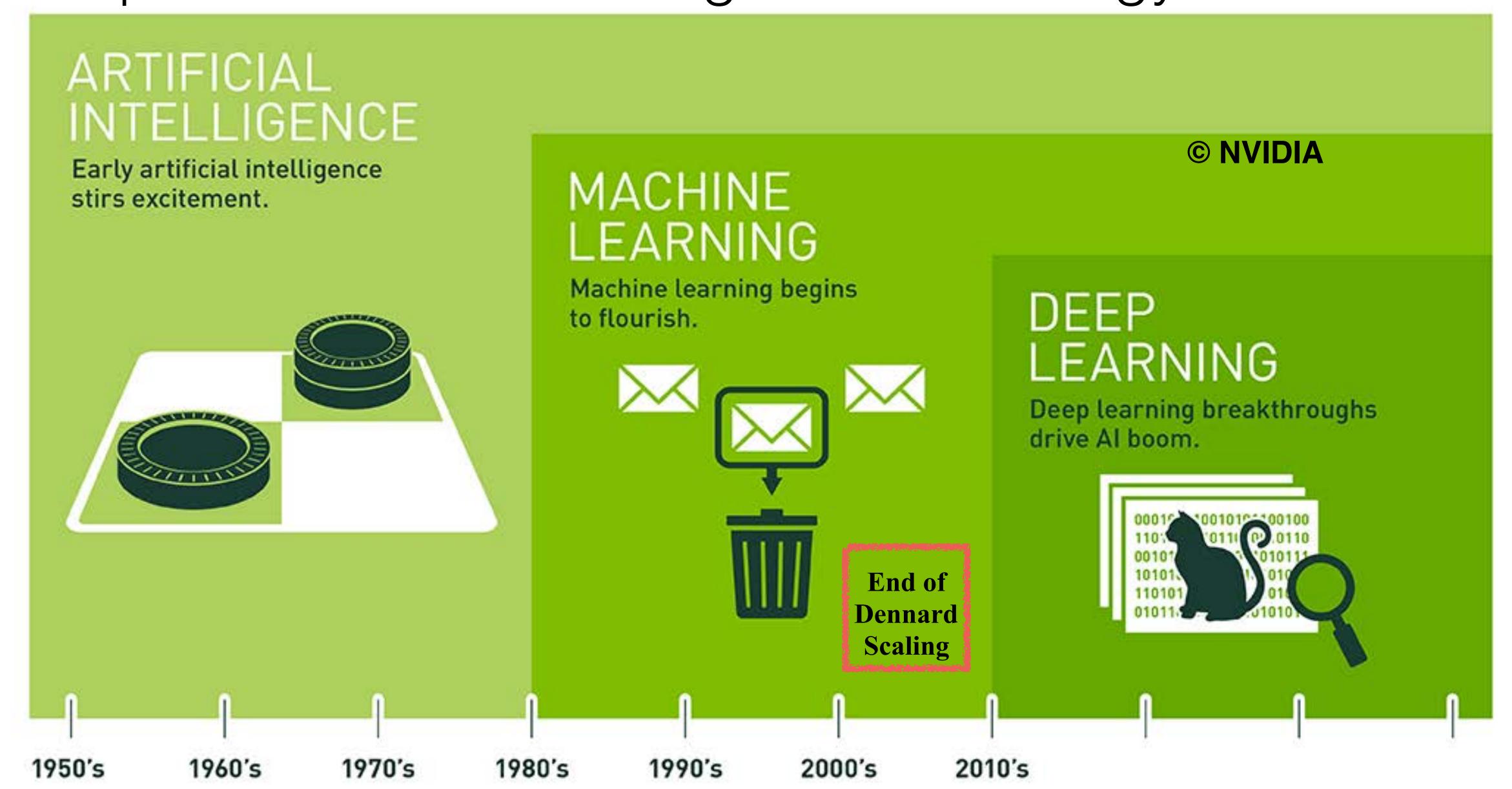
Several Multi-Messenger observations may take place in LIGO-Virgo third observing run

Pressing need to maximize discovery



Deep Learning

From optimism to breakthroughs in technology and science



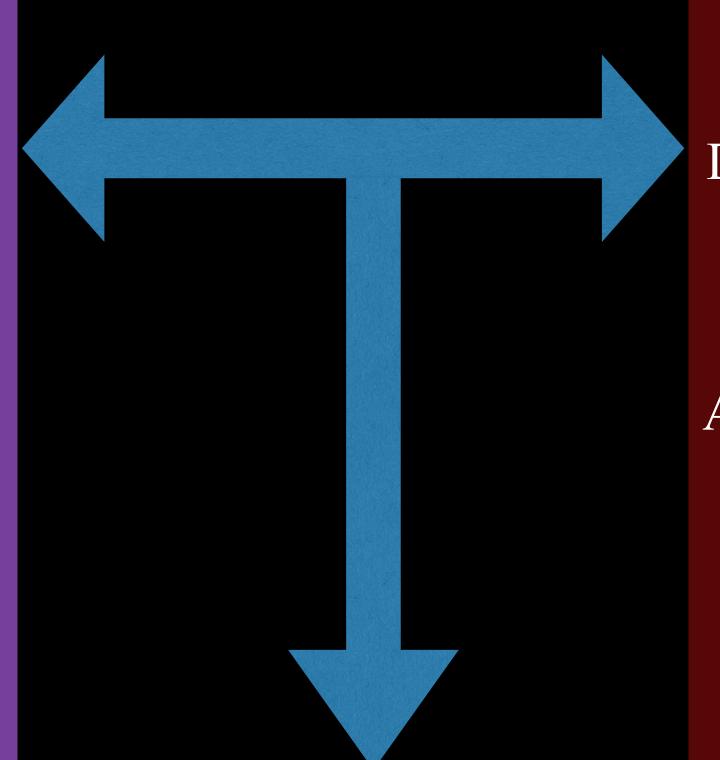
Deep Learning From optimism to breakthroughs in Harness the Data Revolution to ARTIFICIAL INTELLIGENCE maximize discovery Early artificial intelligence in the MACHINE stirs excitement. LEARNING Big Data Era Machine learning begins to flourish. LEARNING Deep learning breakthroughs drive Al boom. 00101 10101 **End of** 110101 Dennard **Scaling** 1950's 1960's 1970's 1980's 1990's 2000's 2010's

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

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

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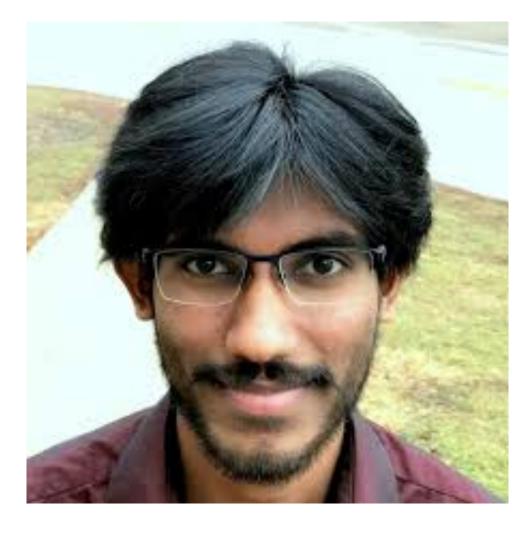
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Deep Learning for Gravitational Wave Astrophysics

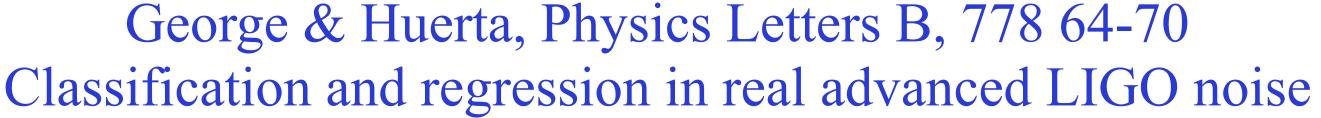
Deep learning for classification of gravitational waves in simulated noise Gabbard et al., *PRL*, December 2017

First generation of neural network models for gravitational wave detection

Simple architectures 2-D black hole binary signal manifold Small training data sets



George & Huerta, Phys. Rev. D 97, 044039 Classification and regression in simulated 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)

From pioneering work to production scale applications

First application of deep learning at scale to characterize a 4-D signal manifold with 10M+ templates

Shen, Huerta and Zhao, arXiv:1903.01998

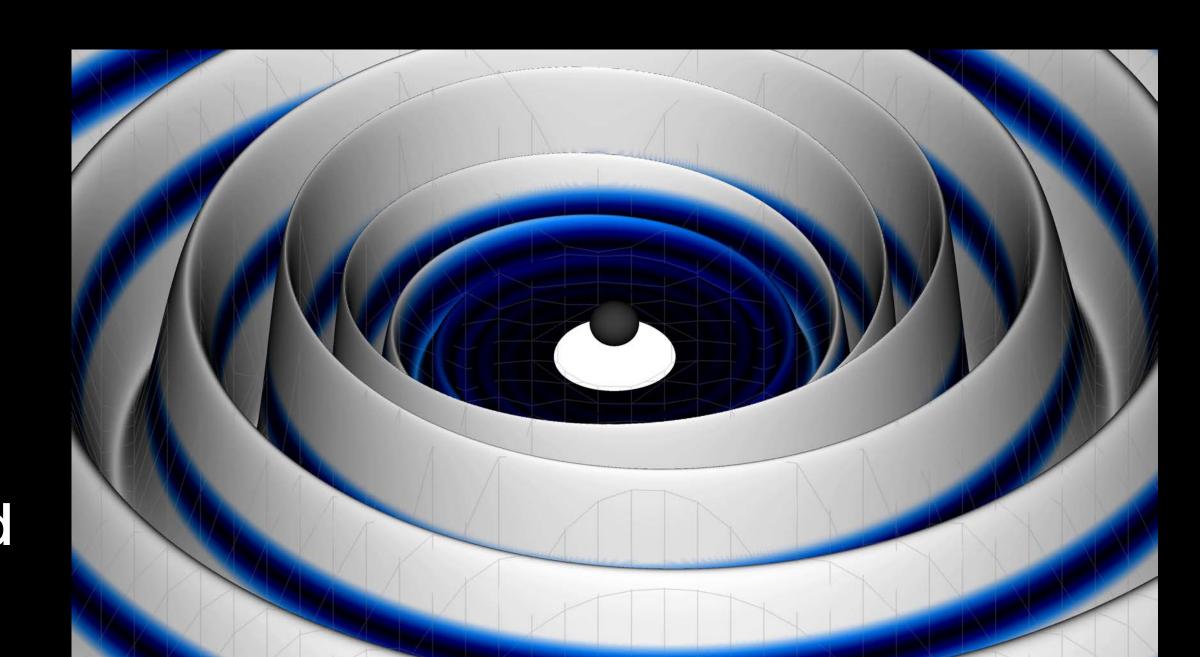






Inference of the properties of the binary components before and after merger

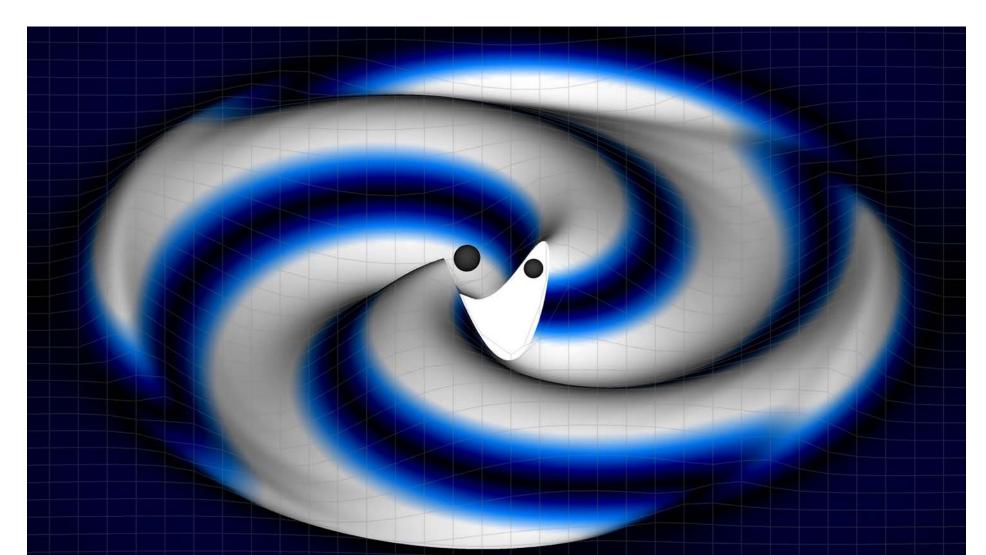
Parameter estimation studies are now endowed with a solid statistical backbone

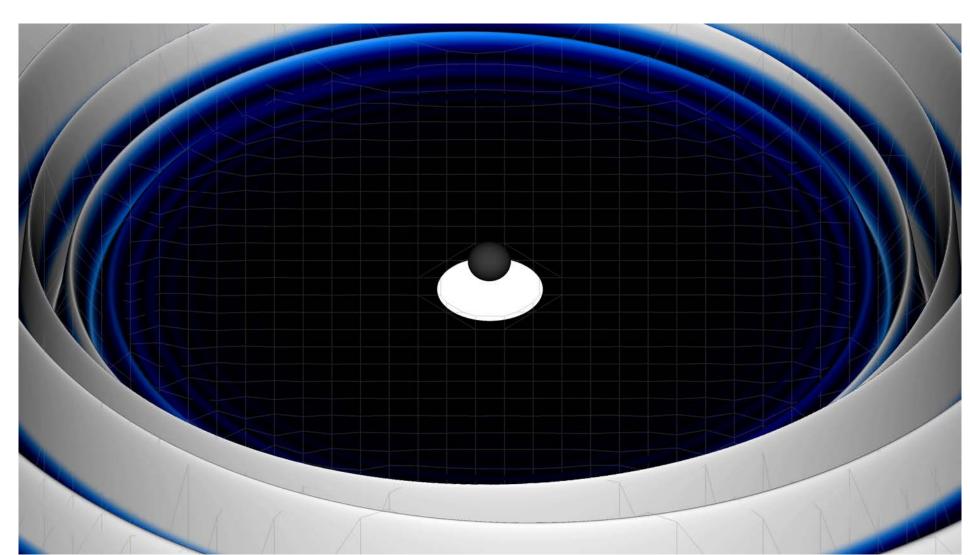


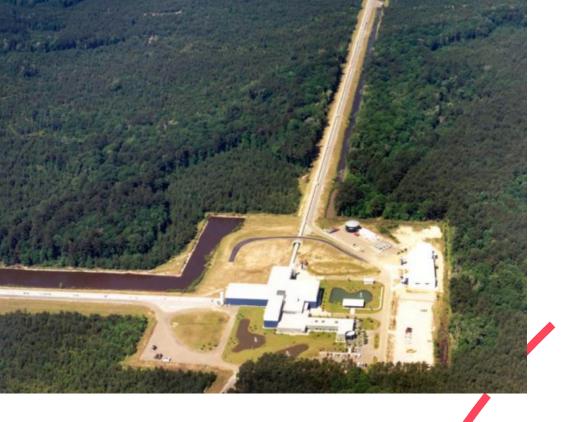
From pioneering work to production scale applications

Shen, Huerta and Zhao, arXiv:1903.01998

EVENT NAME	$m_1[{ m M}_{\odot}]$	$m_2[{ m M}_{\odot}]$	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]
$\underline{\text{GW}170823}$	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]



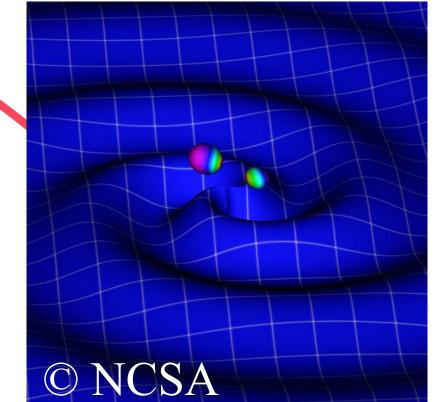




Training and testing datasets from numerical relativity simulations

Convergence of HPC and HDA





Observational data to train, validate and test neural network models







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

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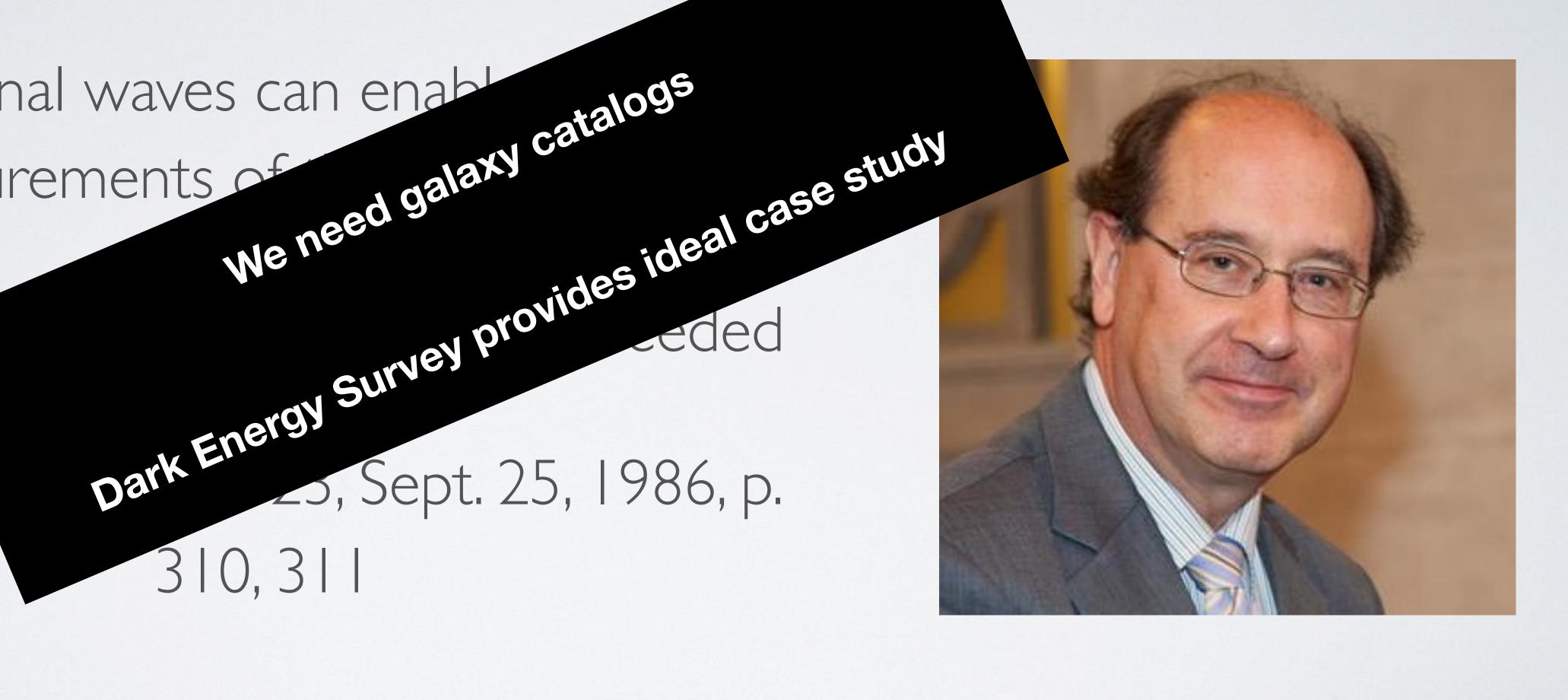


Gravitational Wave Cosmology

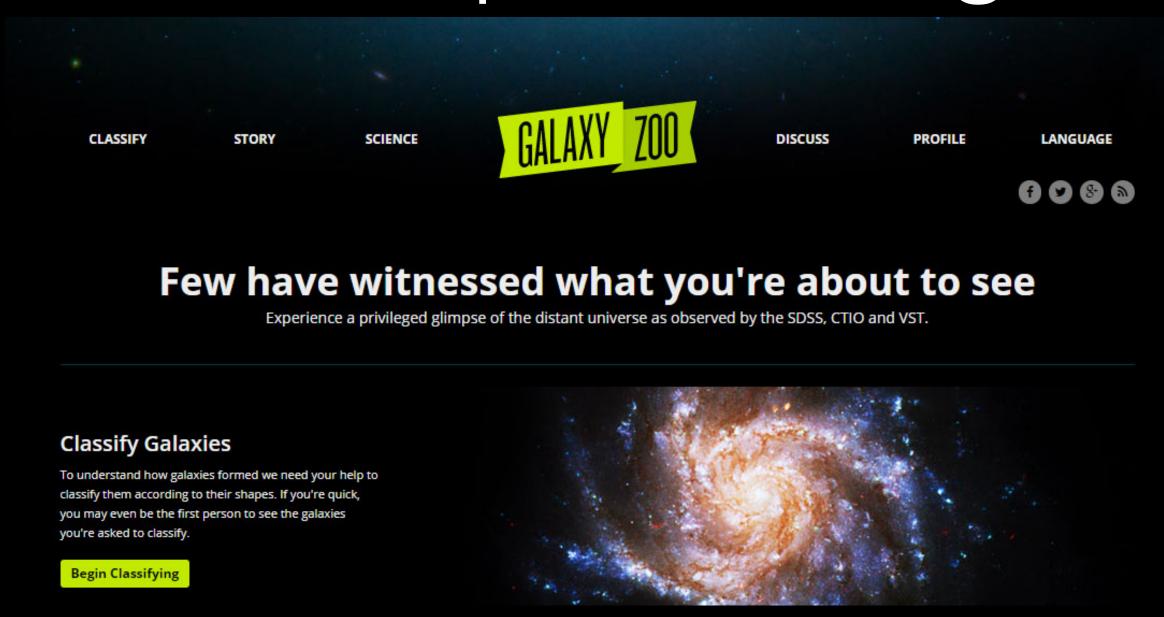
We need galaxy catalogs Gravitational waves can enable siren measurements of

No ele

Schutz, N

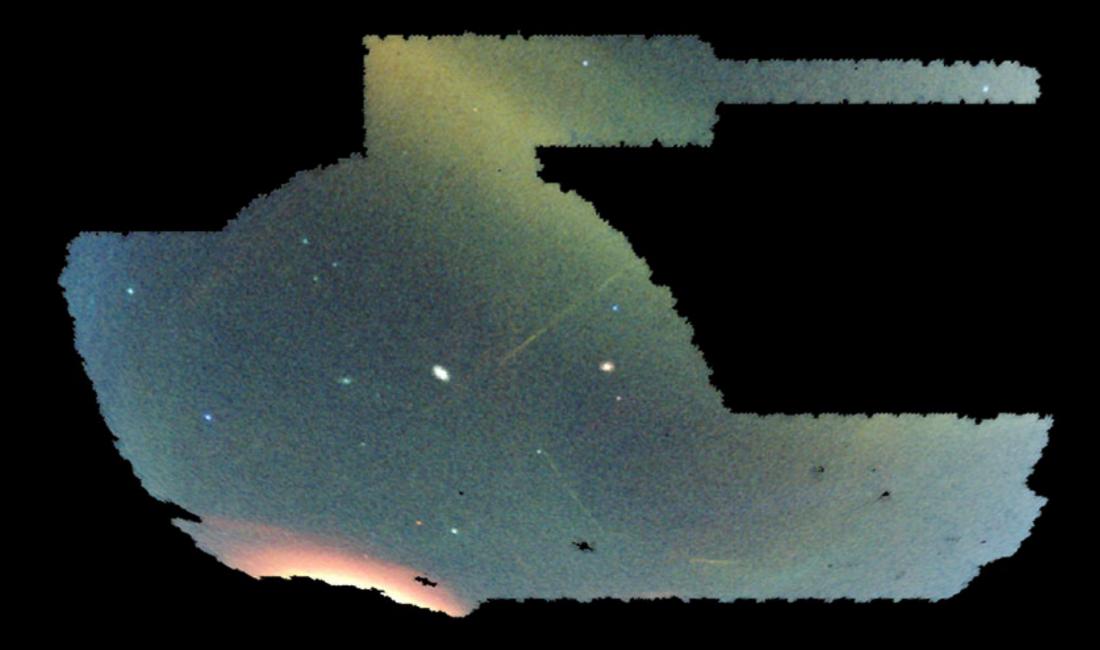


Deep Learning for DES data science

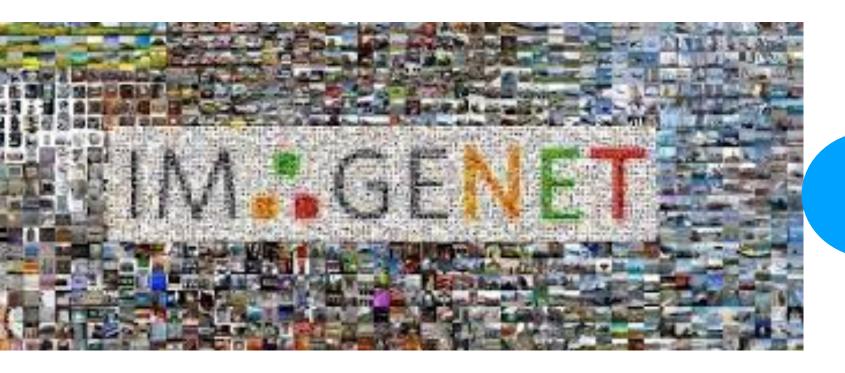


From the citizen science revolution using the Sloan Digital Sky Survey...

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



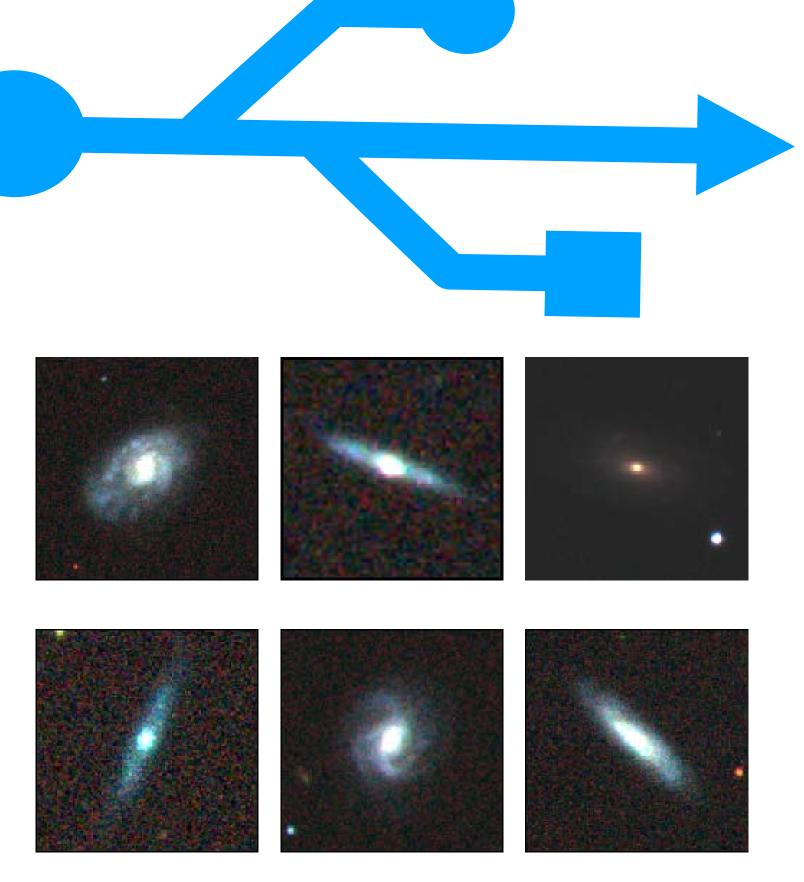
Khan, Huerta, Wang, Gruendl, Jennings and Zheng, arXiv:1812.02183 Accepted to Physics Letters B



Xception neural network model

François Chollet, arXiv:1610.02357

State-of-the-art model for computer vision



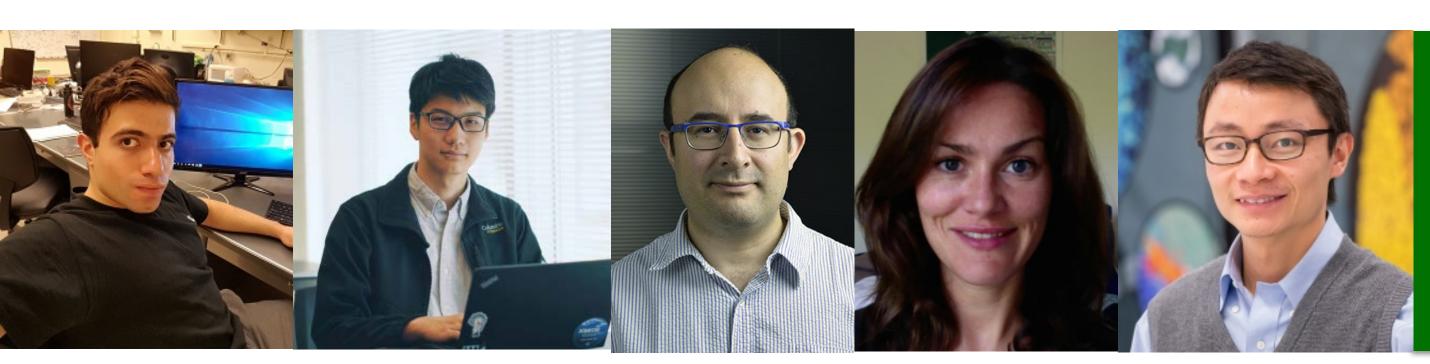
Convergence of deep transfer learning, distributed training, data clustering, and recursive training

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

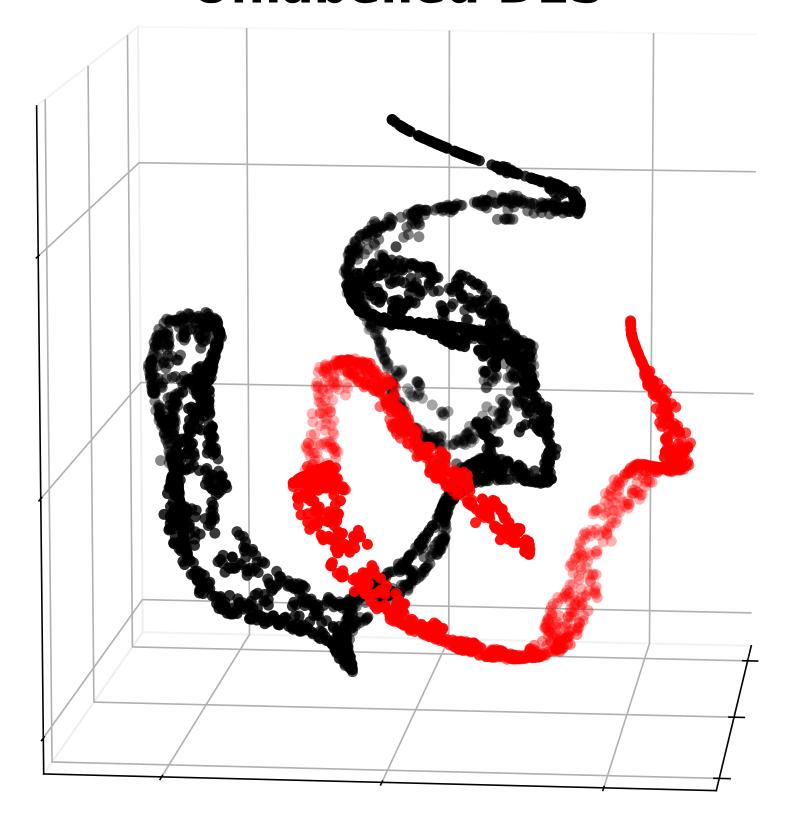
Deep Learning for DES data science



Khan, Huerta, Wang, Gruendl, Jennings and Zheng, arXiv:1812.02183

NCSA-Argonne Data Science Program

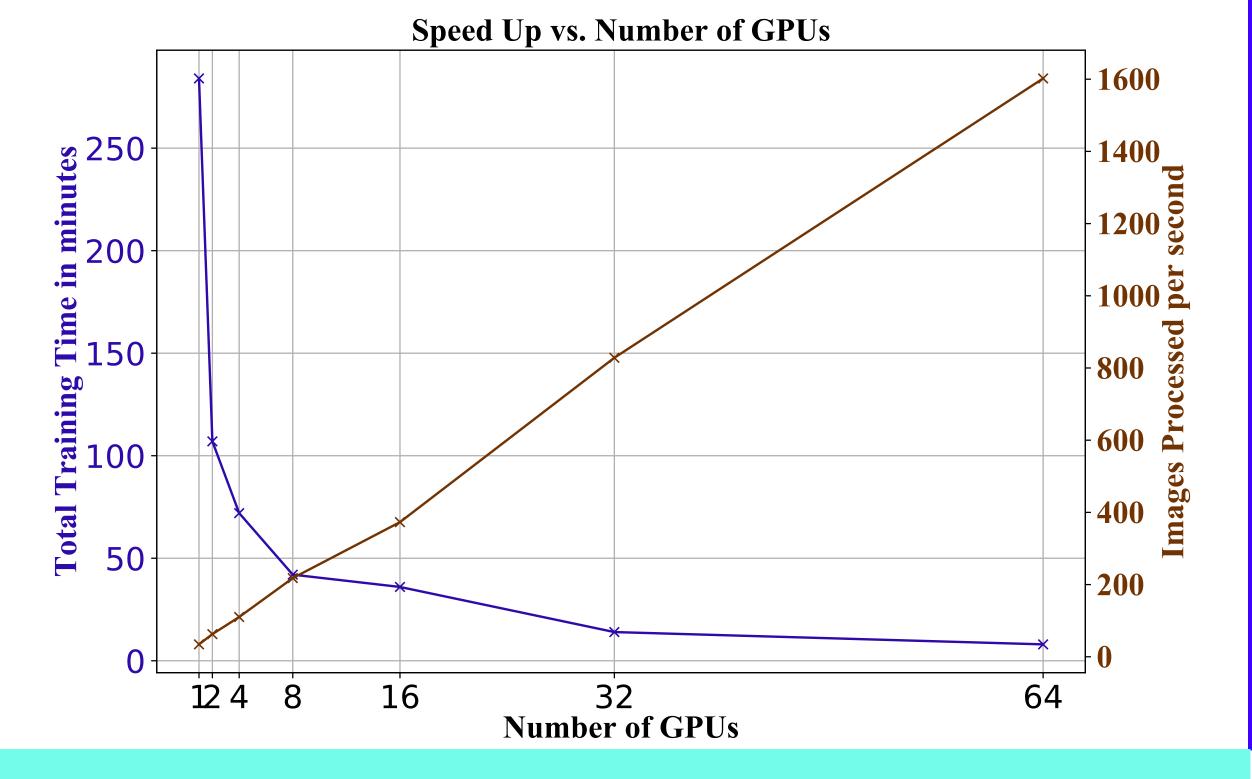
Unlabelled DES



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

See viz at https://www.youtube.com/watch?v=n5rl573i6ws



Predicted DES elliptical galaxies by our neural network model

Khan, Huerta, Wang, Gruendl, Jennings and Zheng, arXiv:1812.02183

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



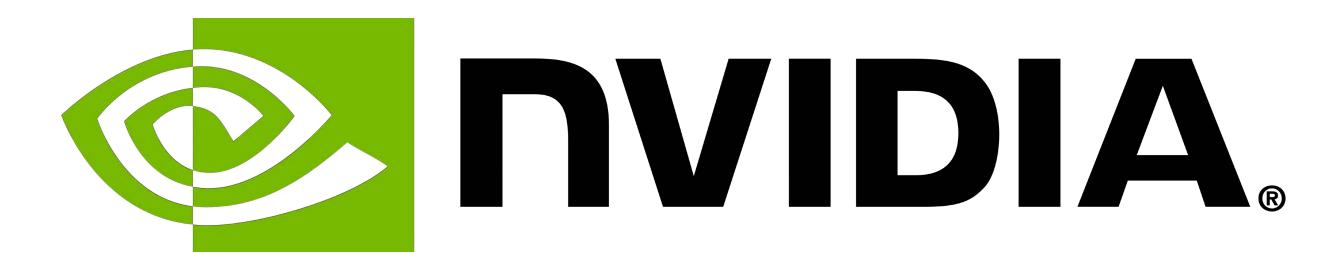
Conclusions

- Deep learning can be seamlessly applied to enhance the science reach of gravitational wave astrophysics and gravitational wave cosmology
- Harnessing the data revolution encompass data fusion, and convergence of deep learning with large scale computing
- Design a new type of deep learning algorithms at scale to characterize 4-D+ signal manifolds
- Deep learning for Multi-Messenger Astrophysics is just taking off!

















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