Applications of Machine Learning to Gravitational Wave Physics: Detection and Parameter Estimation

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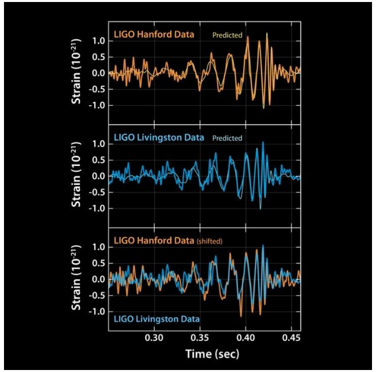
Accelerated AI Algorithms for Data-Driven Discovery

Event Detection

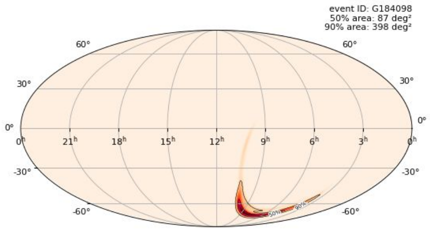


Identify astrophysical gravitational wave (GW) signals with high confidence

Machine learning offers low latency, high throughput, scalability

aframe - Framework for optimizing neural networks to detect compact binary coalescences (CBCs) in GW strain

Parameter Estimation



Extract information about astrophysical source (e.g. sky localization)

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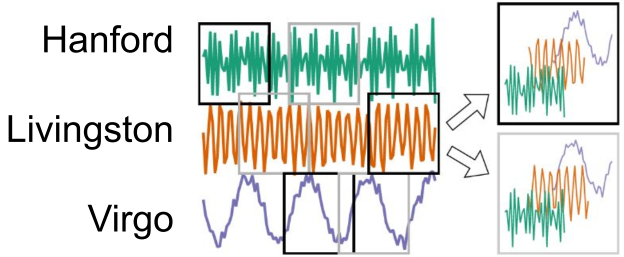
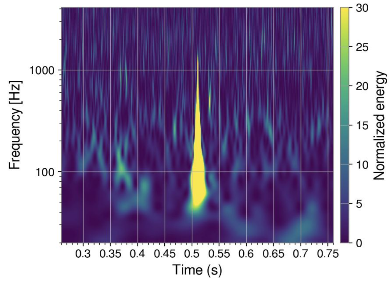
mlpe - Parameter estimation of *unmodeled* GW sources using normalizing flows

Data Augmentation: Noise

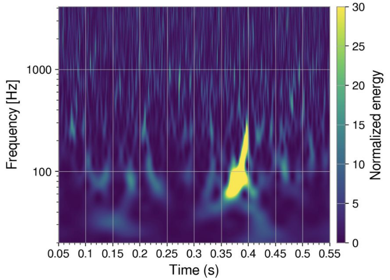
Sample kernels from each interferometer ***independently*** to create more noise instances



Oversample glitches, which can mimic true astrophysical signals

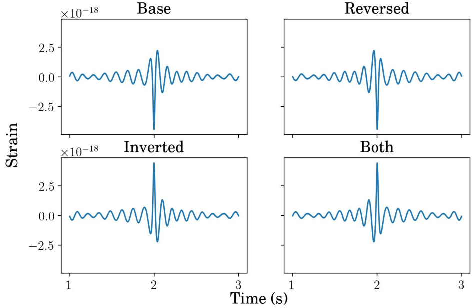


Blip Glitch



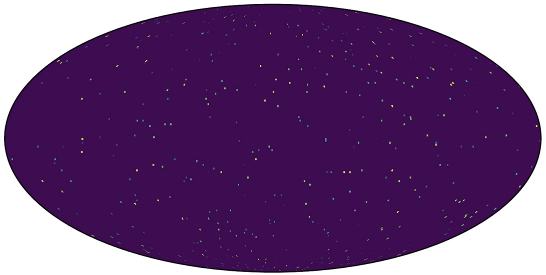
Binary Black Hole

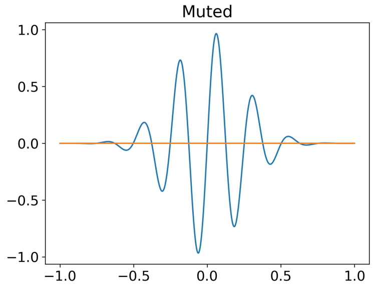
Reverse and ***invert*** noise samples to create more diversity of noise instances



Data Augmentations: Waveforms

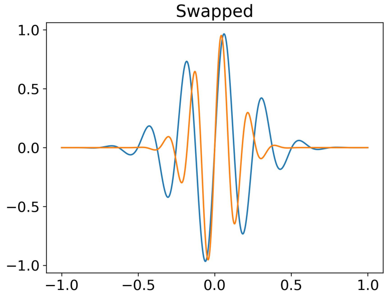
Randomly project waveforms using different sky localizations at training time - leverage larger effective dataset





Zero out one interferometers waveform - label as noise to enforce coincidence

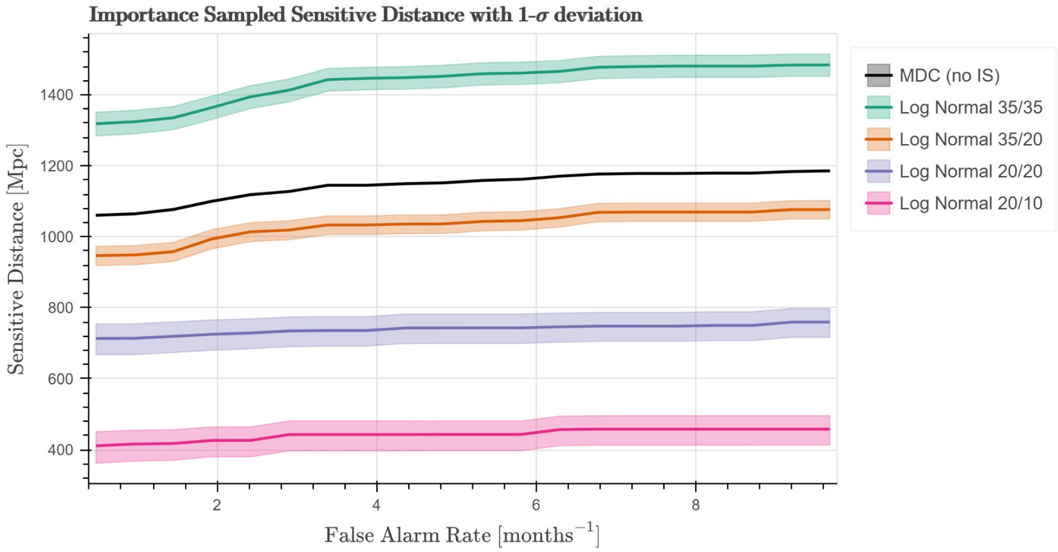
Replace one interferometers waveform with that of another template - label as noise to enforce coherence



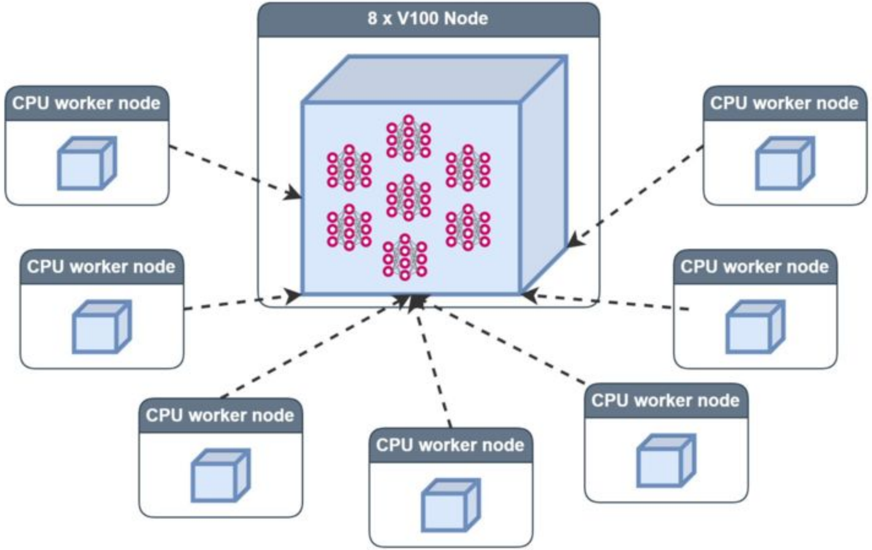
Performance Metric

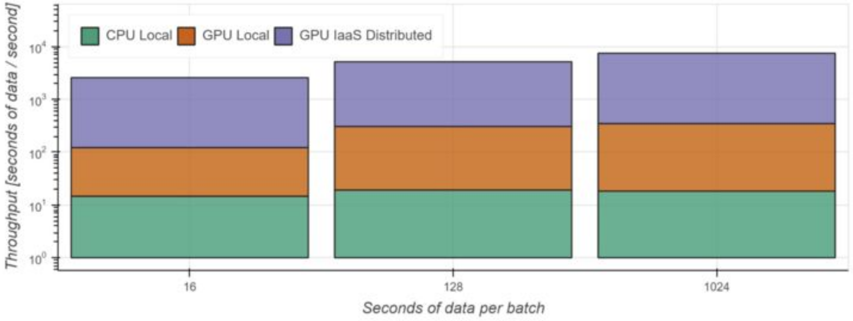
Sensitive Volume - Measure effective volume V at some false alarm rate F probed by search algorithm to a population ϕ of sources

$$V\left(\mathcal{F}\right) = \int d\boldsymbol{x} d\boldsymbol{\Lambda}\ \epsilon\left(\mathcal{F}; \boldsymbol{x}, \boldsymbol{\Lambda}\right) \phi\left(\boldsymbol{x}, \boldsymbol{\Lambda}\right)$$



GPU Distributed Inference





Parallelize inference of segments across multiple GPUs to allow analysis of larger volumes of data

Scalable: have seen approximately linear returns with the number of GPUs

Looking Forward

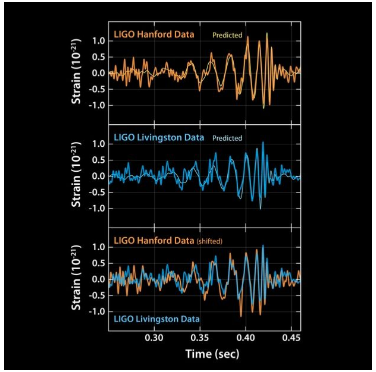
1. Online deployment

2. Scaling up quantity of background data

3. End to end analysis of previous observing runs

Stop by my poster later today to discuss details!

Event Detection



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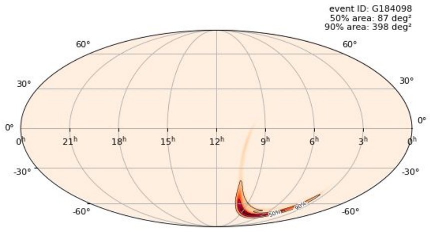

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Unmodeled "Burst" Sources

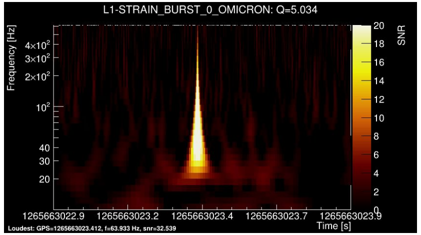
Minimally or poorly modeled GW emission

e.g. Core Collapse Supernovae, Neutron Star Glitches

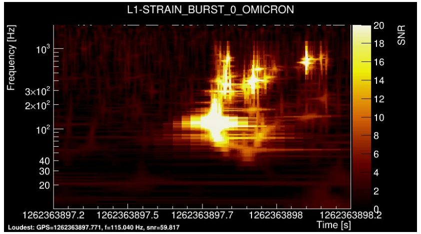
Use a complete basis of minimal uncertainty wavelets to decompose data, and search for coherent excess power between multiple detectors

$$h_+(t) \propto cos(2\pi f_0(t-t_0)+\phi_0)e^{(-t-t_0)^2/\tau^2}$$

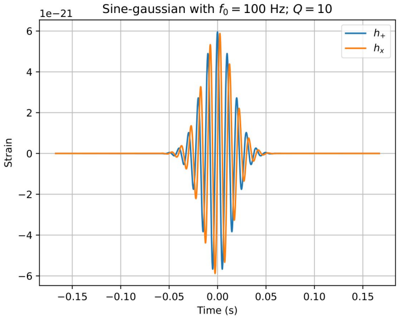
$$h_\times(t) \propto sin(2\pi f_0(t-t_0)+\phi_0)e^{(-t-t_0)^2/\tau^2}$$



Example GW emission from cosmic string cusp



Example GW emission from core collapse supernovae simulation



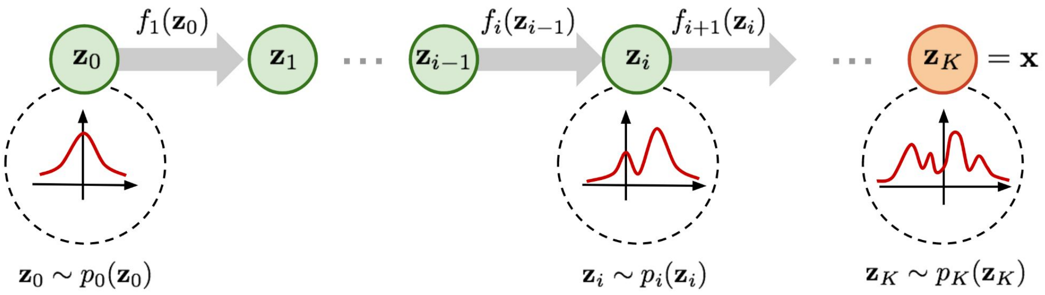
Simulation Based Inference

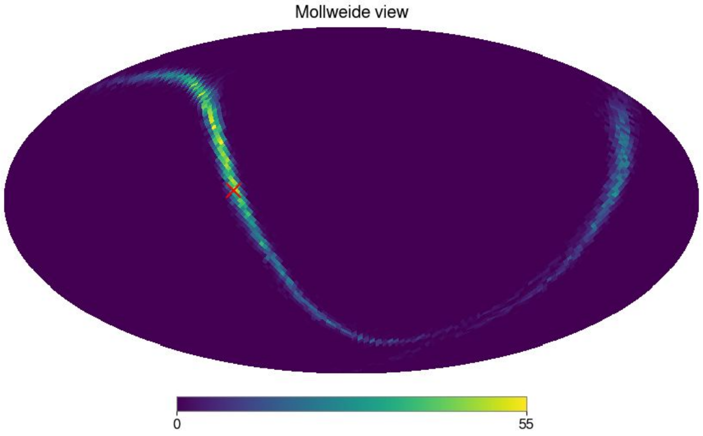
Simulate data from the likelihood, train neural network to approximate posterior

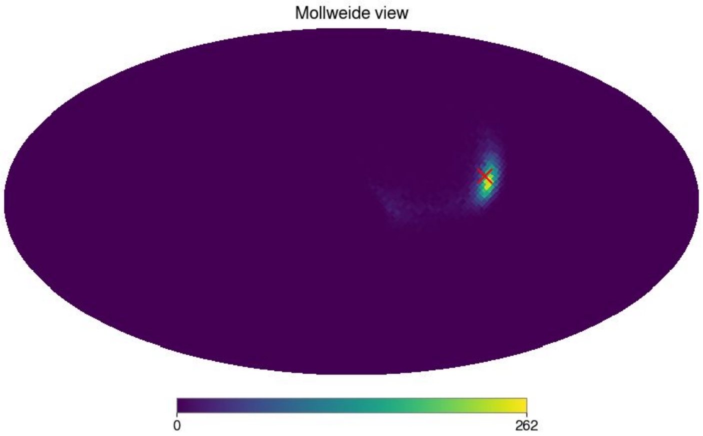
$$d \sim p(d|\theta) \qquad d = h(\theta) + n$$

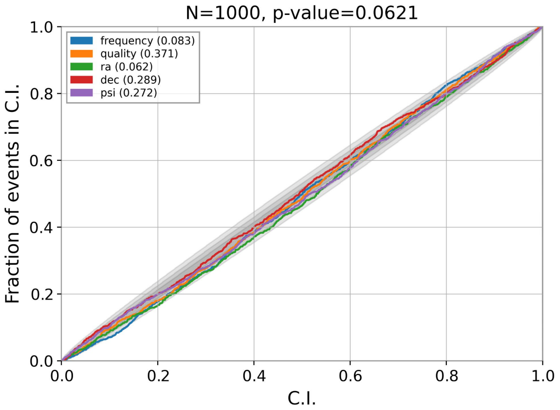
$$q_\phi(\theta|d) \sim p(\theta|d) \quad L \approx -\frac{1}{N}\sum_{i=1}^{N} \log q_\phi(\theta^{(i)}|d)$$

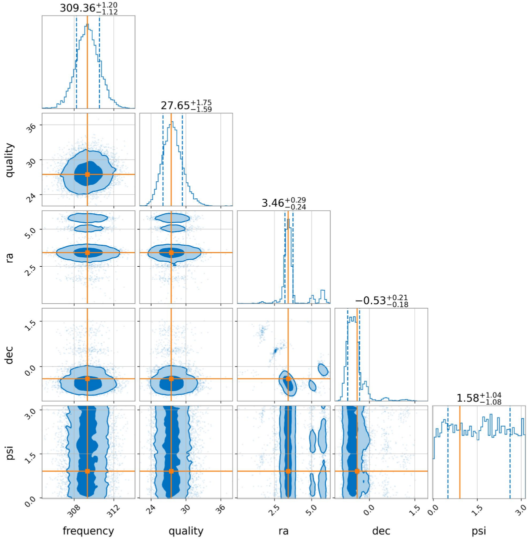
Normalizing flows: invertible transforms map simple distribution to complex distribution




Mollweide view
0
55


Mollweide view
0
262


N=1000, p-value=0.0621
frequency (0.083)
quality (0.371)
ra (0.062)
dec (0.289)
psi (0.272)
Fraction of events in C.I.
C.I.


$309.36^{+1.20}_{-1.12}$
$27.65^{+1.75}_{-1.59}$
$3.46^{+0.29}_{-0.24}$
$-0.53^{+0.21}_{-0.18}$
$1.58^{+1.04}_{-1.08}$
quality
ra
dec
psi
frequency
quality
ra
dec
psi

Looking Forward

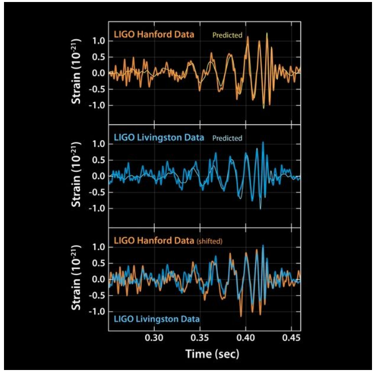
1. Validate model on astrophysical waveforms

2. Exploit symmetries for faster training convergence

3. Paper in prep

See Deep Chatterjee’s poster today for more details!

Event Detection



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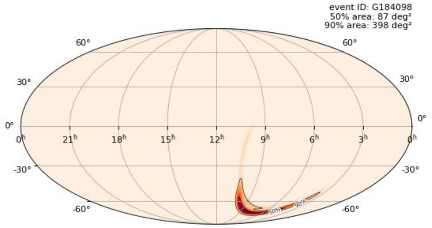

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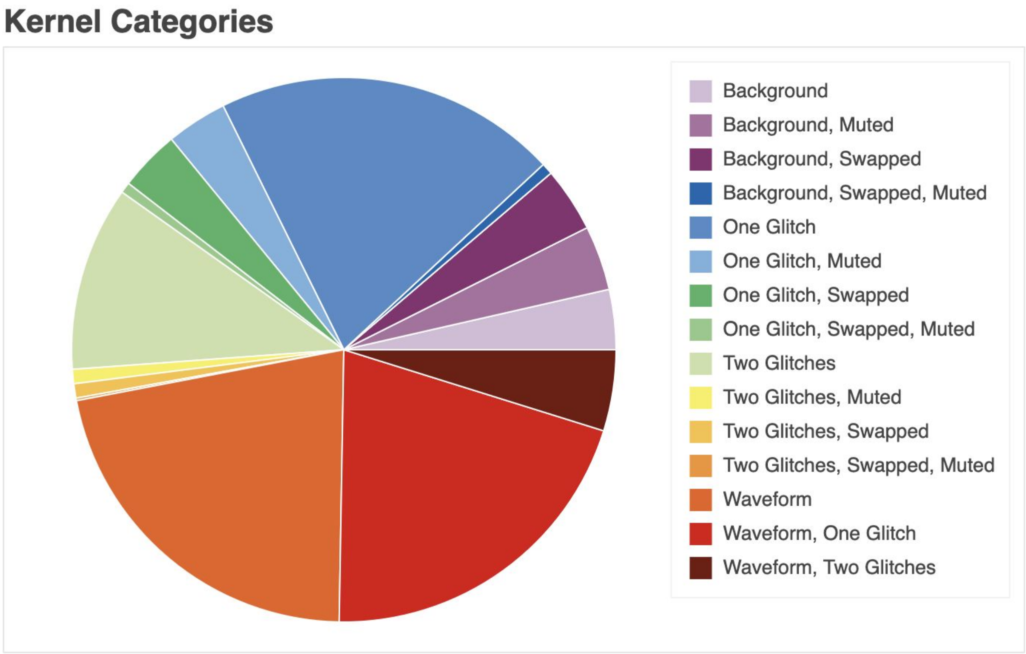
Backups

Taxonomy of Training Batch



Taxonomy of training data determined by hyperparameters that can easily be searched