ACCELERATED FULLY-COHERENT SEARCH FOR COMPACT BINARY COALESCENCES

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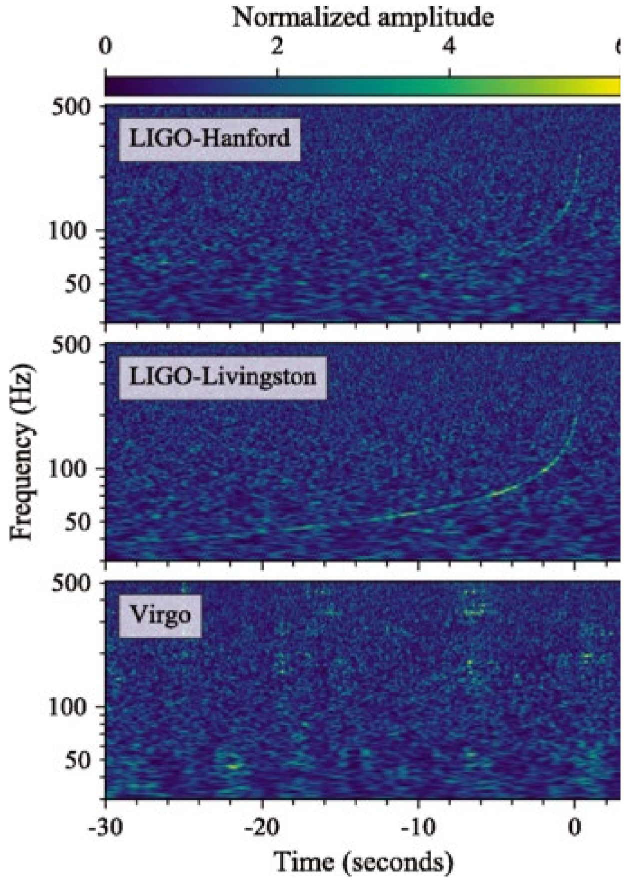
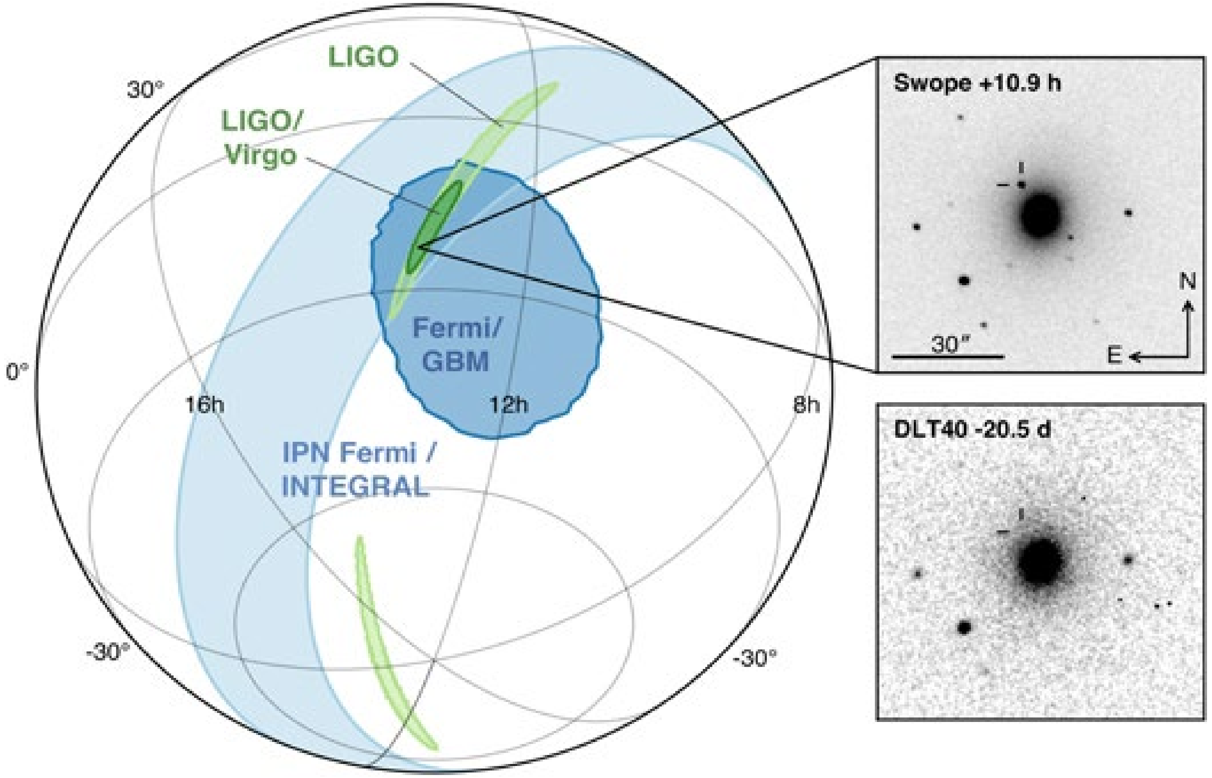
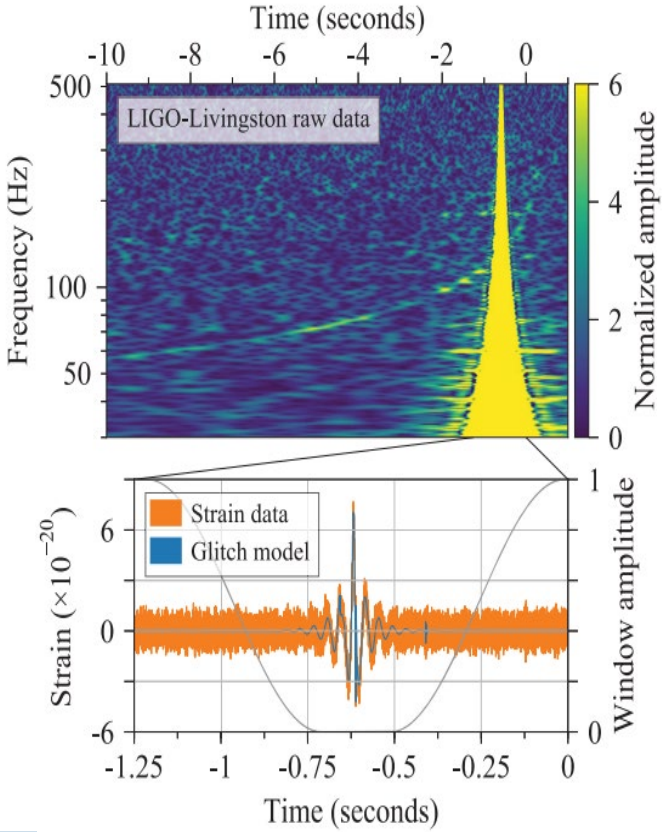
OBJECTIVES

- GW astronomy has seen spectacular success since 2015
- Data analysis algorithms form a critical component of the technological base behind these successes
- We will walk through a key data analysis challenge for ground-based IFOs to illustrate the critical role of data analysis in GW astronomy
- Techniques developed for solving these challenges have broad applicability

GW170817: DOUBLE NEUTRON STAR INSPIRAL AND MERGER





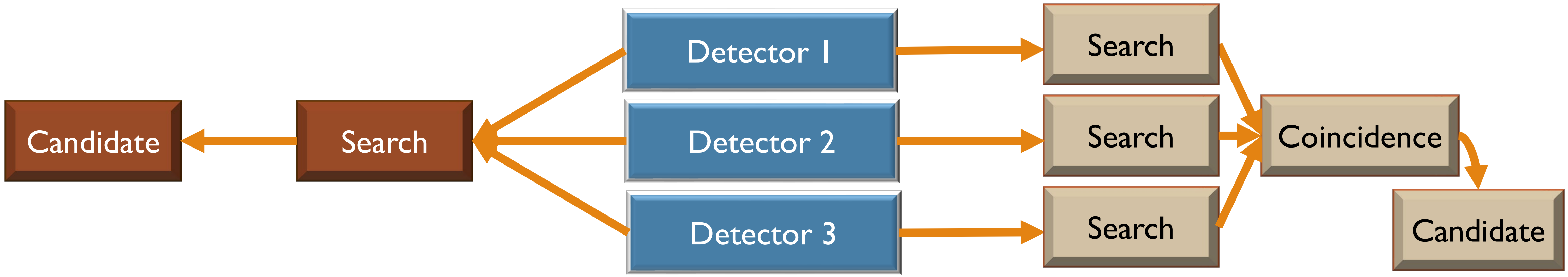


- Noise dominated data
- 2nd Gen detectors: signals appear rarely

- Localization needs data from a network of detectors
- Multi-messenger astronomy: Low-latency GW detection needed

Data artifacts, such as glitches, must be mitigated for better sensitivity

B. P. Abbott *et al.* (LIGO Scientific Collaboration and Virgo Collaboration), Phys. Rev. Lett. **119**, 161101



Coherent analysis

- Pai, Bose, Dhurandhar, Physical Review D, 64, 042004 (2001)
- Klimenko, Mohanty, Rakhmanov, Mitselmakher, Physical Review D 72, 122002 (2005)
- In theory: more sensitive, simpler

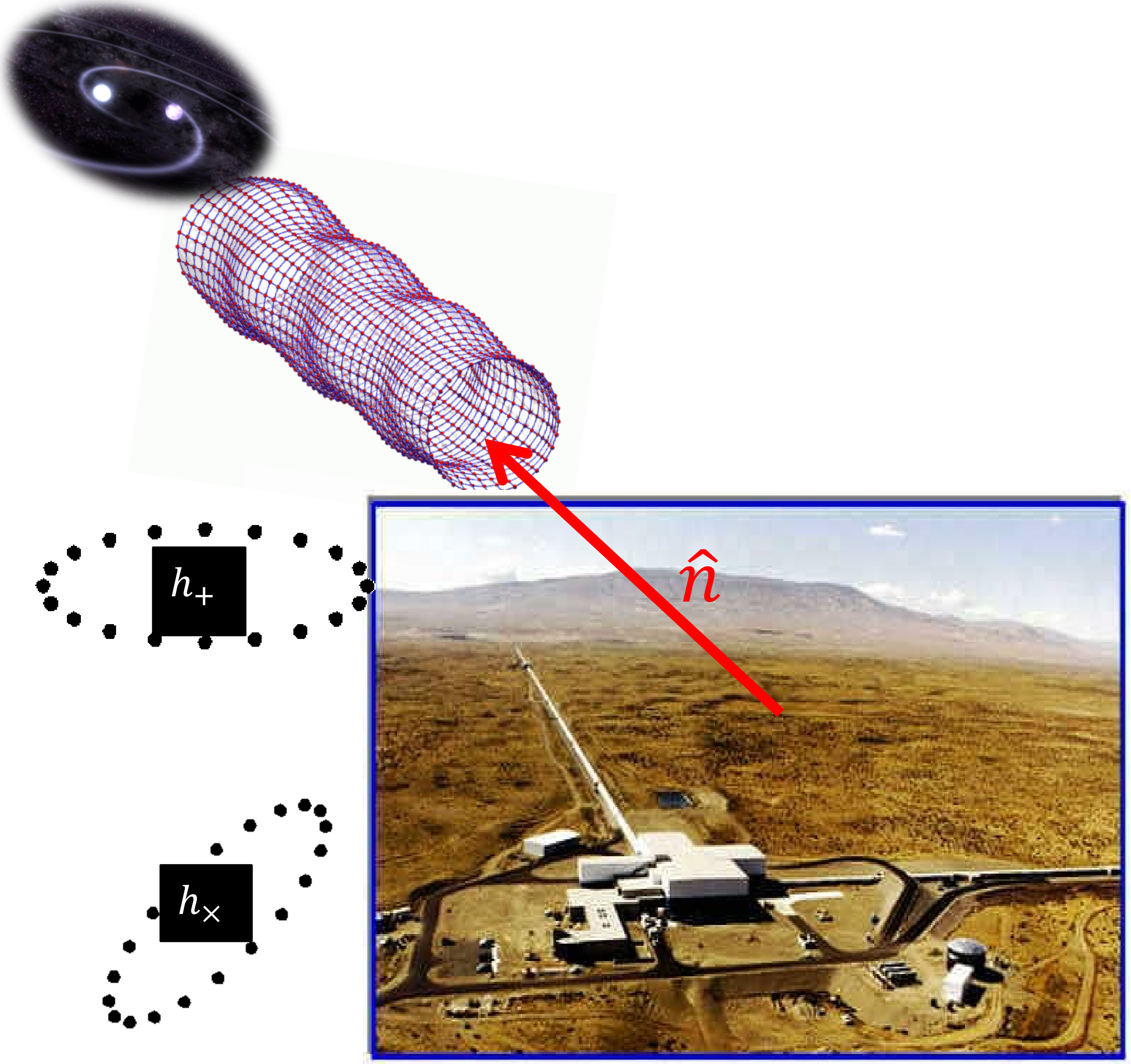
Semi-coherent analysis

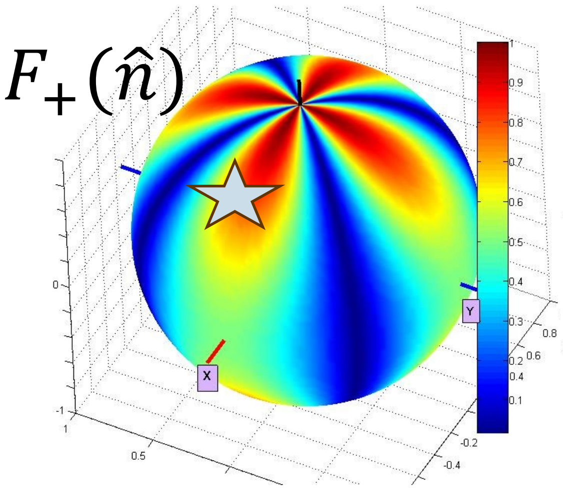
- Most current flagship pipelines (GstLAL, PyCBC, MBTA)
- SPIIR uses coherent analysis for candidate events (plus a segmented time-domain matched filter approach)
- In theory: less sensitive, complex

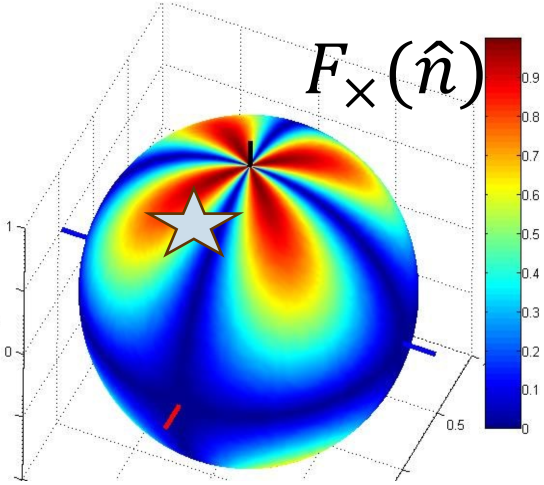
Problem: ≈ 2000x more expensive

HIGHLIGHTS

- **Problem solved**: Accelerated Fully-Coherent All-sky (FCAS) search: $\approx$**50x faster than real-time** (4-detector network; 4096Hz sampling frequency)
  a. $\Rightarrow$**Low latency FCAS search now possible on all data** → potentially higher detection sensitivity
  b. *Normandin, Mohanty, PRD, 2020; Normandin, Mohanty, Weerathunga, PRD, 2018; Weerathunga, Mohanty, PRD, 2017*
- **Novel glitch veto**: byproduct of the FCAS search instead of an add-on algorithm

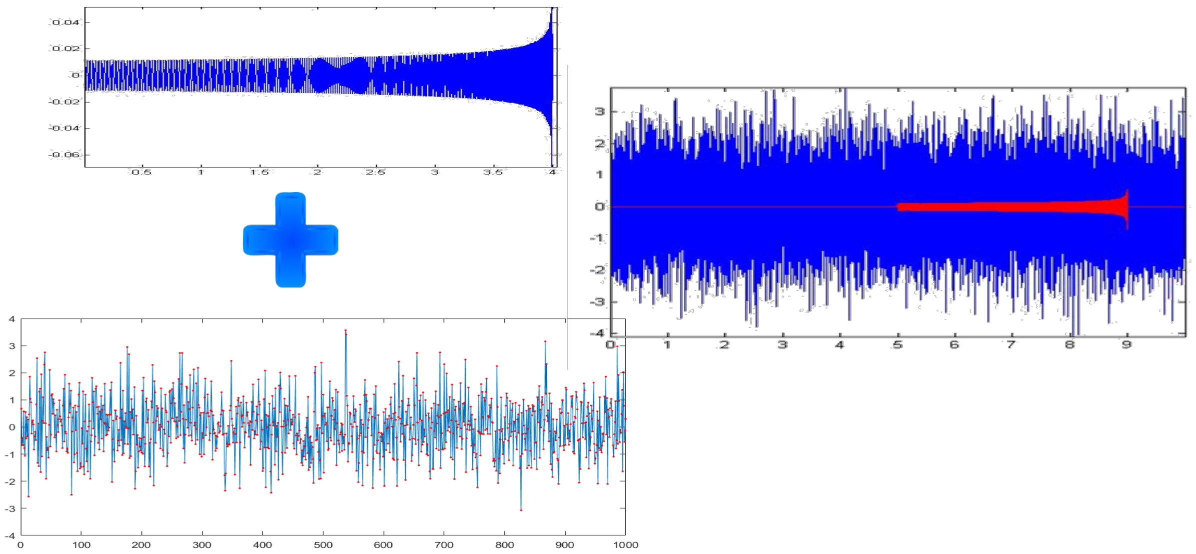






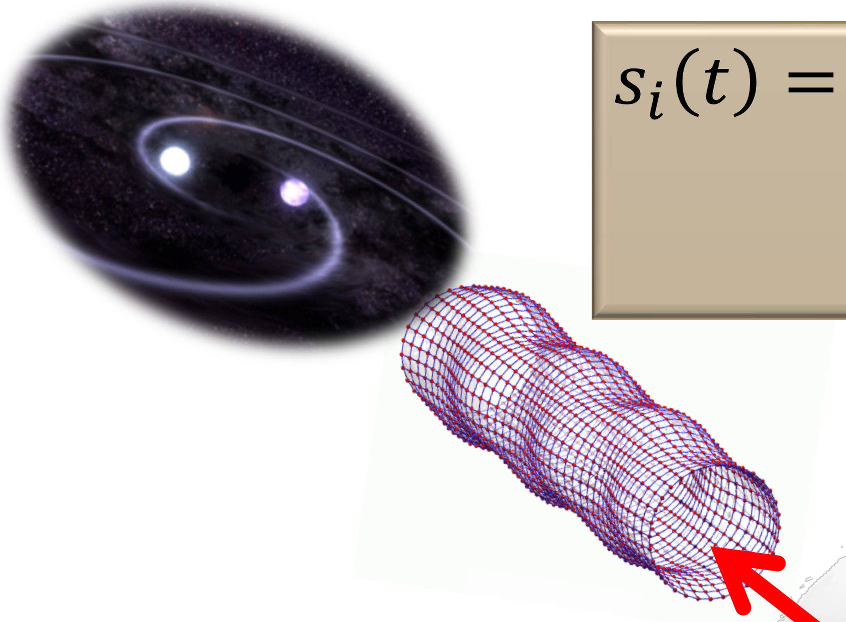
$$s(t) = F_+(\hat{n})h_+(t) + F_\times(\hat{n})h_\times(t)$$

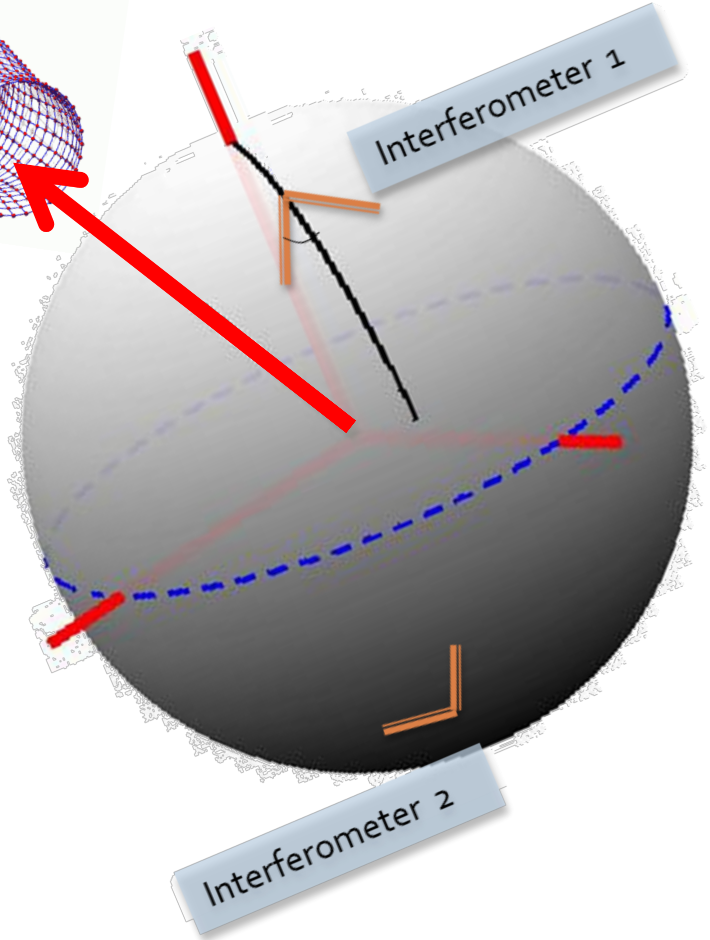
Long-wavelength approximation

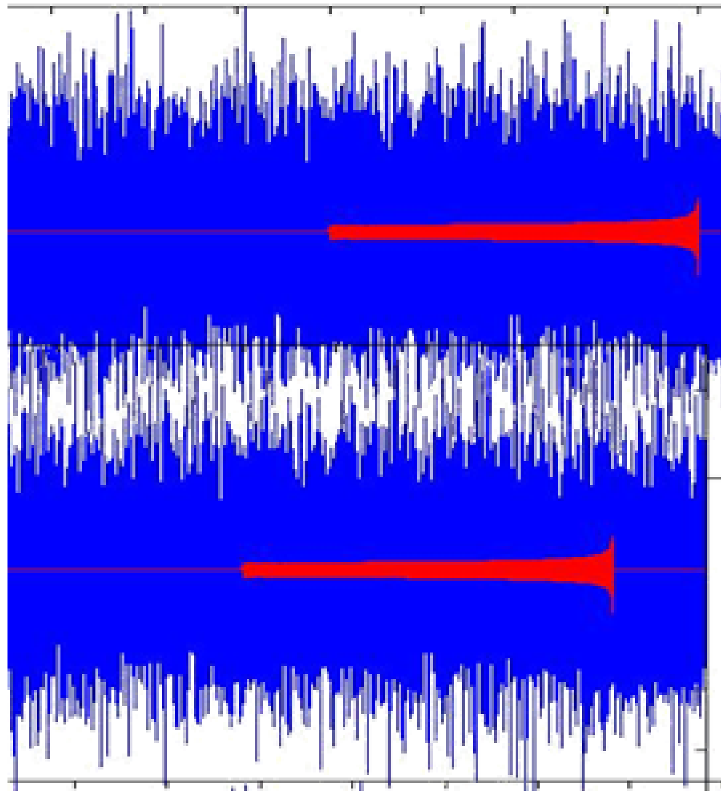


$$s_i(t) = F_{+,i}(\hat{n})B[\Delta_{\mathrm{i}}(\hat{n})]h_+(t) + F_{\times,i}(\hat{n})B[\Delta_{\mathrm{i}}(\hat{n})]h_\times(t))$$

$$B[\delta]f(t) = f(t-\delta)$$







NETWORK ANALYSIS INVERSE PROBLEM

$$\begin{pmatrix} x_1(t) \\ \vdots \\ x_N(t) \end{pmatrix} = \begin{pmatrix} F_{+,1}(\hat{n})B[\Delta_1(\hat{n})] & F_{\times,1}(\hat{n})B[\Delta_1(\hat{n})] \\ \vdots & \vdots \\ F_{+,N}(\hat{n})B[\Delta_N(\hat{n})] & F_{\times,N}(\hat{n})B[\Delta_N(\hat{n})] \end{pmatrix} \begin{pmatrix} h_+(t) \\ h_\times(t) \end{pmatrix} + \begin{pmatrix} n_1(t) \\ \vdots \\ n_N(t) \end{pmatrix}$$

GW network data

GW strain signal

Noise

- Inverse problem: infer $\hat{n}$, $h_{+,\times}(t)$ given the network data
- Bayesian or Fisherian approach: likelihood function
- Detection: significance of the inverted solution

NETWORK LOG-LIKELIHOOD

$\boldsymbol{x_1}, \boldsymbol{x_2}, \ldots, \boldsymbol{x_D} \in \mathbb{R}^N$

Joint PDF $p(x|\Theta) = p_{Noise}(x - s(\theta))$

Detection: $\max_{\theta}(\ldots)$

Estimation: $\arg\max_{\theta}(\ldots)$

<u>Linear</u>

$\bar{a}$: Reparametrized Distance, initial phase, orbital inclination, and polarization angles

<u>Non-linear</u>

chirp times $\boldsymbol{\tau}$ (functions of component masses), spins, orbital eccentricity,…, **sky location ($\hat{n}$)**, **time of arrival** (t_a)

$$\max_{\{\tau,\hat{n}\}} \max_{t_a} \max_{\bar{a}} \ln(p(x|\Theta)) = \max_{\{\tau,\hat{n}\}} \max_{t_a} \overbrace{H(\hat{n}, t_a, \tau)}^{1\times 4} \overbrace{M^{-1}(\hat{n})}^{4\times 4} H^T(\hat{n}, t_a, \tau)$$

Gaussian noise

$\hat{n}$ dependent linear combinations of $\mathrm{IFFT}(\tilde{z}_i .* \tilde{q}_r^{\dagger}(\tau)), r = 1,2$

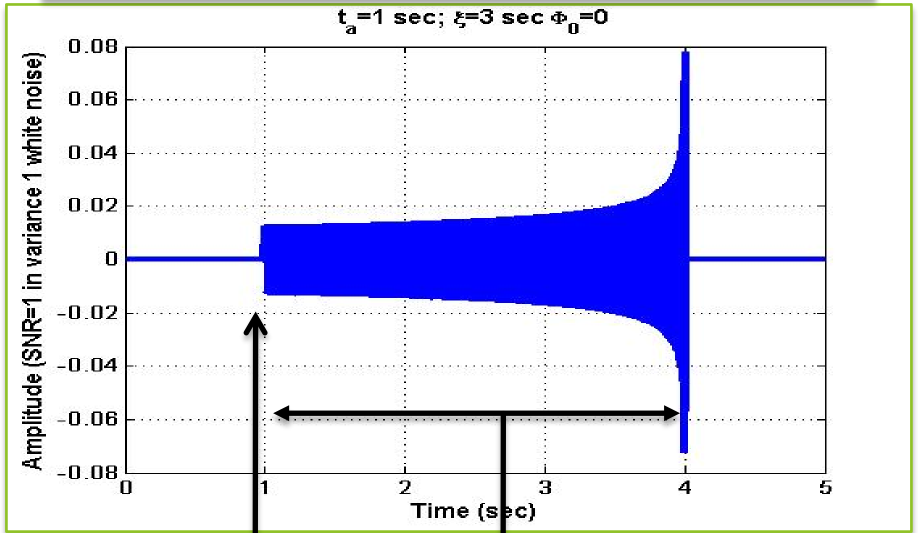
$\tilde{b} = \mathrm{FFT}(b)$

$\tilde{z}_i[k] = \tilde{x}_i[k]/PSD_i[k]$

Quadrature *templates* (0 and $\frac{\pi}{2}$ initial phase signals)

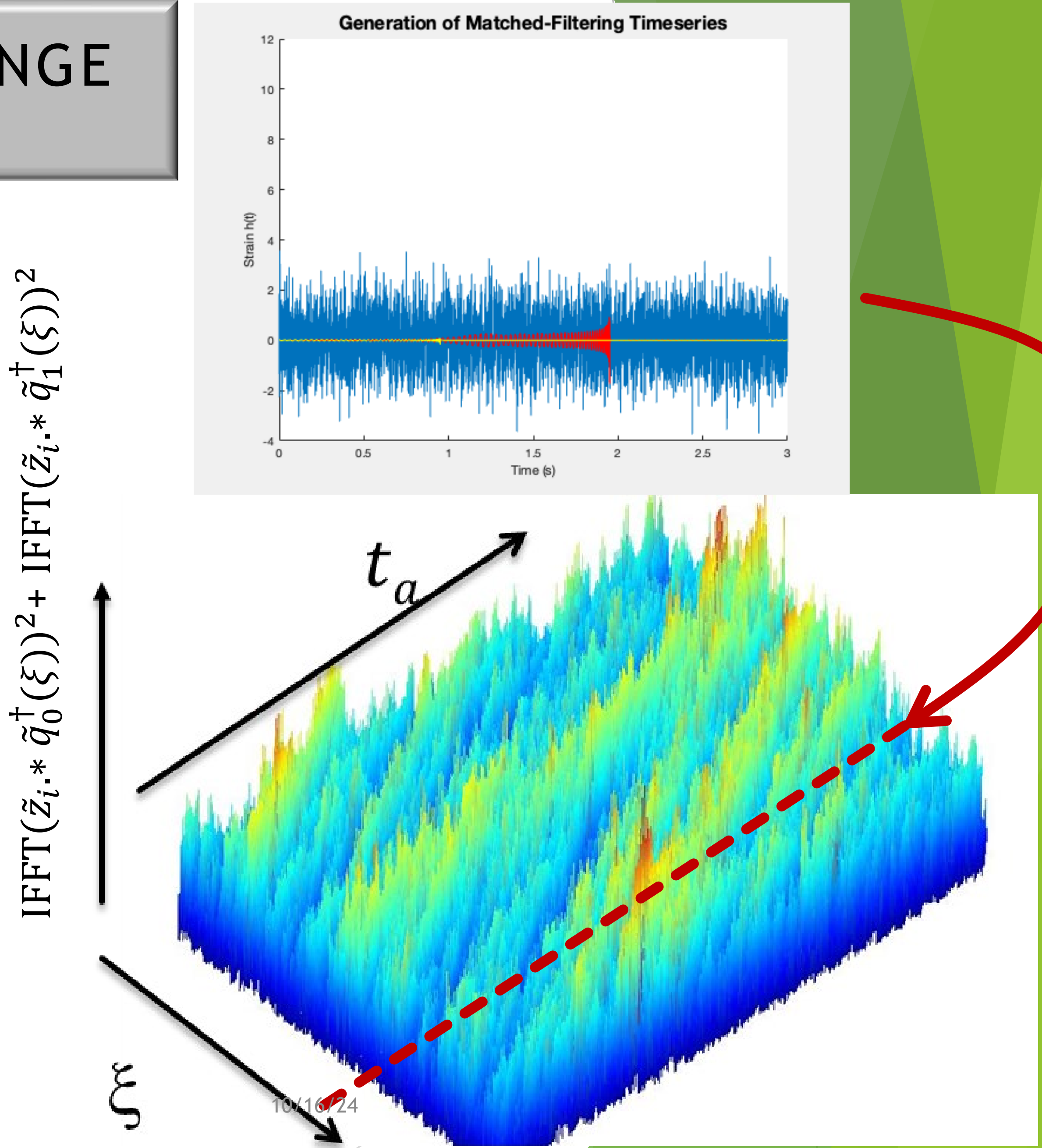
GLOBAL OPTIMIZATION CHALLENGE
SINGLE DETECTOR SEARCH

Newtonian signal model



t_a : time of arrival

ξ : Chirp time



REGULARIZATION

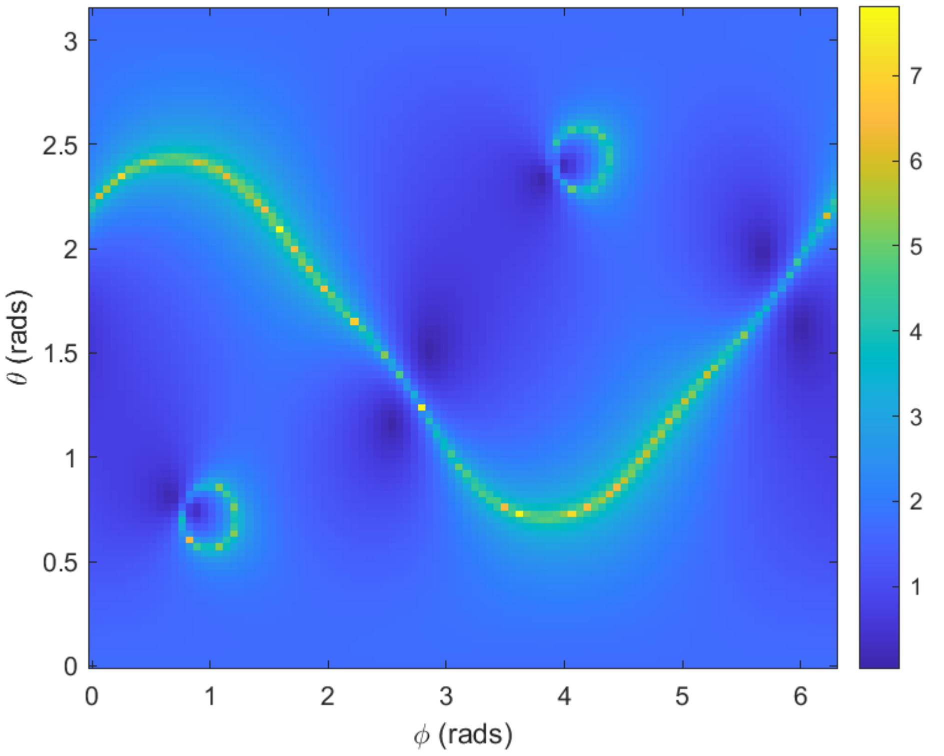
$$H(\hat{n}, t_a, \tau)\boldsymbol{M}^{-1}(\hat{\boldsymbol{n}})H^T(\hat{n}, t_a, \tau)$$

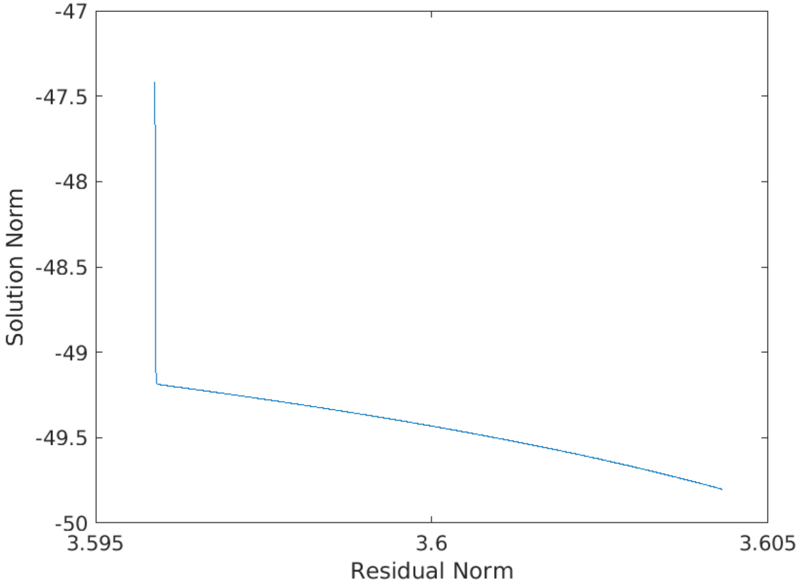
- $M(\hat{n})$ can become ill-conditioned
- Especially serious for the LIGOs due to their close alignment

<u>Regularization</u>

$$H(\hat{n}, t_a, \theta)(M + \boldsymbol{\lambda P})^{-1}H^T(\hat{n}, t_a, \theta)$$

- Penalty matrix (P): user-defined
- Regulator gain (λ): how to select?
- L-curve: Balance Residual (data – estimated signal) norm against Solution norm $\bar{a}P\bar{a}^T$
- Regularization: Bias-Variance trade-off





ACCELERATING COHERENT NETWORK ANALYSIS

Deterministic searches

- Grid-based:
  - Not scalable
  - Exponential growth in cost with number of parameters
- Gradient-based methods: Trapped by local maxima

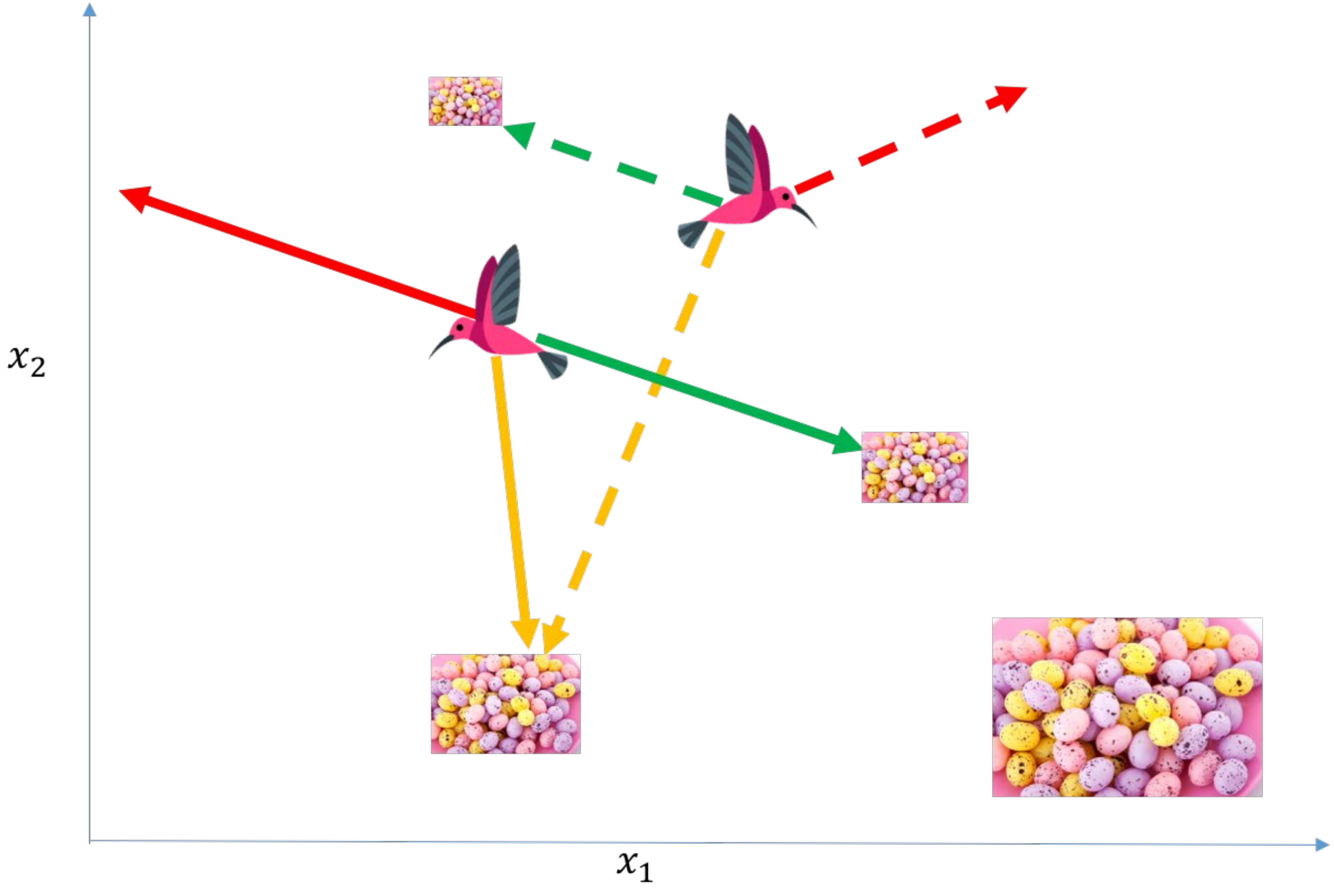
Stochastic searches

- Markov Chain Monte Carlo (MCMC): Currently used (LALInference) for parameter estimation
- Surrogates of full MCMC (e.g., BayeStar) by imposing some approximation on the posterior

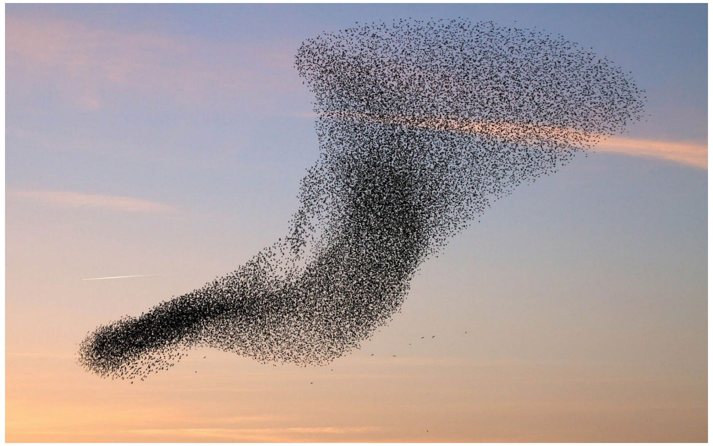
1. Particle Swarm Optimization (Kennedy, Eberhart, IEEE, 1995; 88,885 citations)
   - 10x fewer likelihood evaluations compared to grid-based searches
2. Graphics Processing Units (GPUs)

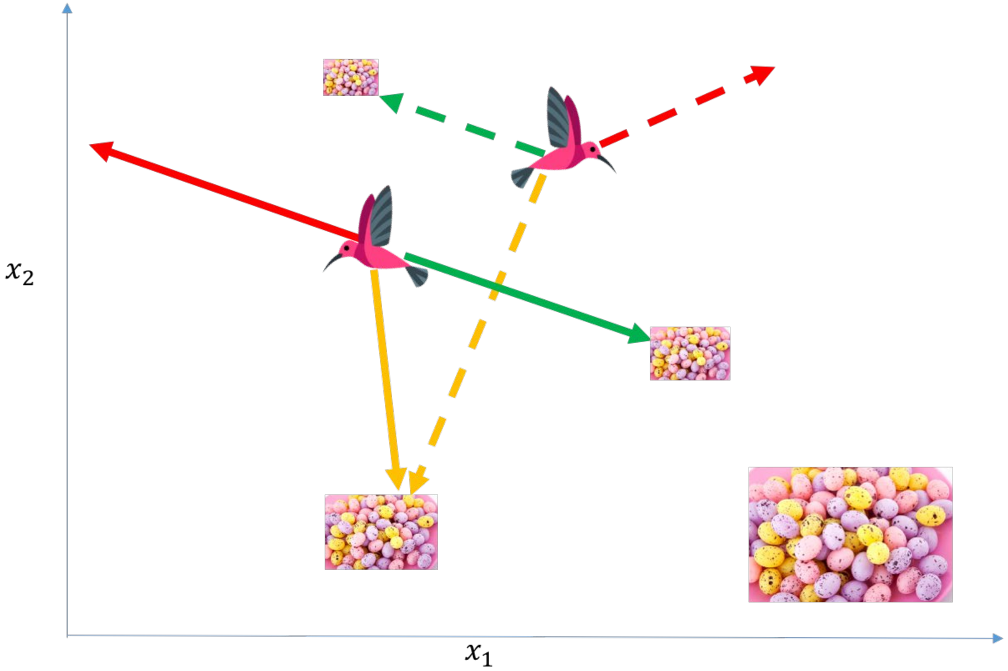
PARTICLE SWARM OPTIMIZATION

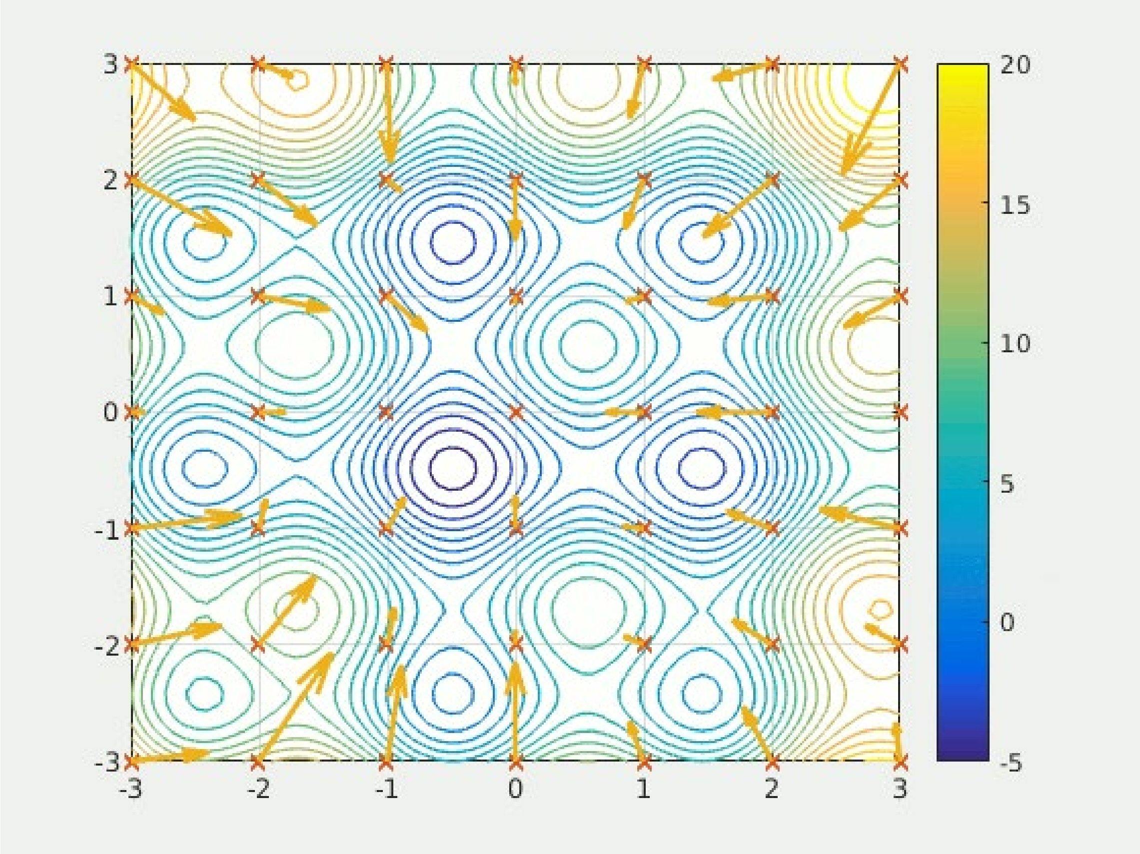
- Global optimization algorithm inspired by emergent behavior of bird flocks
- Evolution of flocking behavior driven by optimization challenges



PARTICLE SWARM OPTIMIZATION







Swarm Intelligence methods for statistical regression, Mohanty, CRC press (2019)

IMPLEMENTATION

- Parallelization hierarchy

$$\underbrace{\text{MPI □ OpenMP}}_{CPU}\rightarrow\underbrace{\text{CUDA}}_{GPU}$$

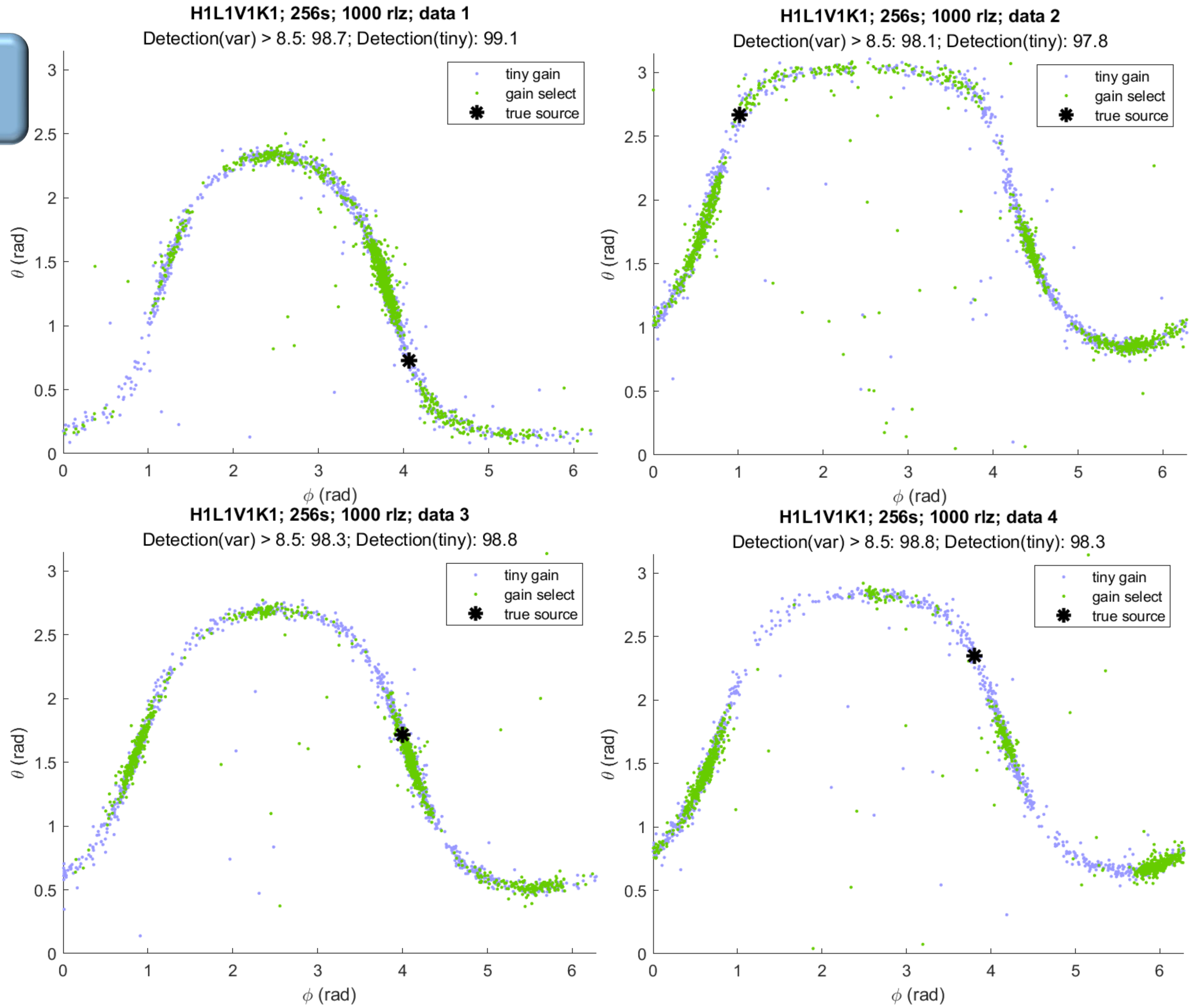
- 8 parallel PSO runs per data segment $\rightarrow$ pick the best run
  - 8xGPU ≈ 50x faster than CPU code
  - PSO+GPU: ≈500x faster than grid-based search

CRADLE

- NSF + DoD: $1.25 million
- Total: 96 NVIDIA A100
  - 32 GPUs interlinked with NVLink: AI workloads
- Dedicated
  - 64 NVIDIA A100 80GB
  - 8 GPUs per node

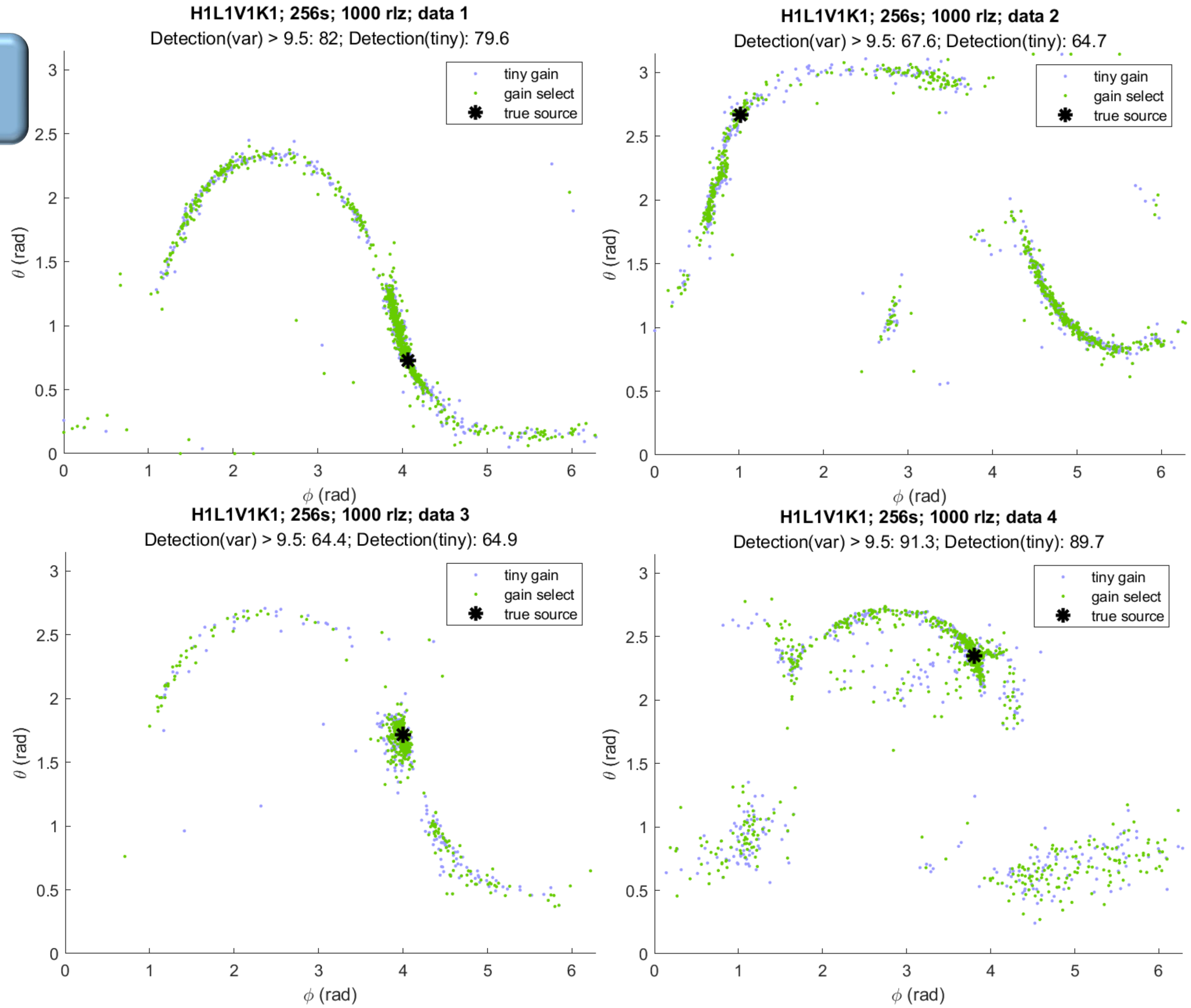
2-DETECTOR NETWORK

- LIGO-Hanford, LIGO-Livingston
- Sky localization with and without gain selection
- Simulated Gaussian stationary noise with design Power Spectral Densities



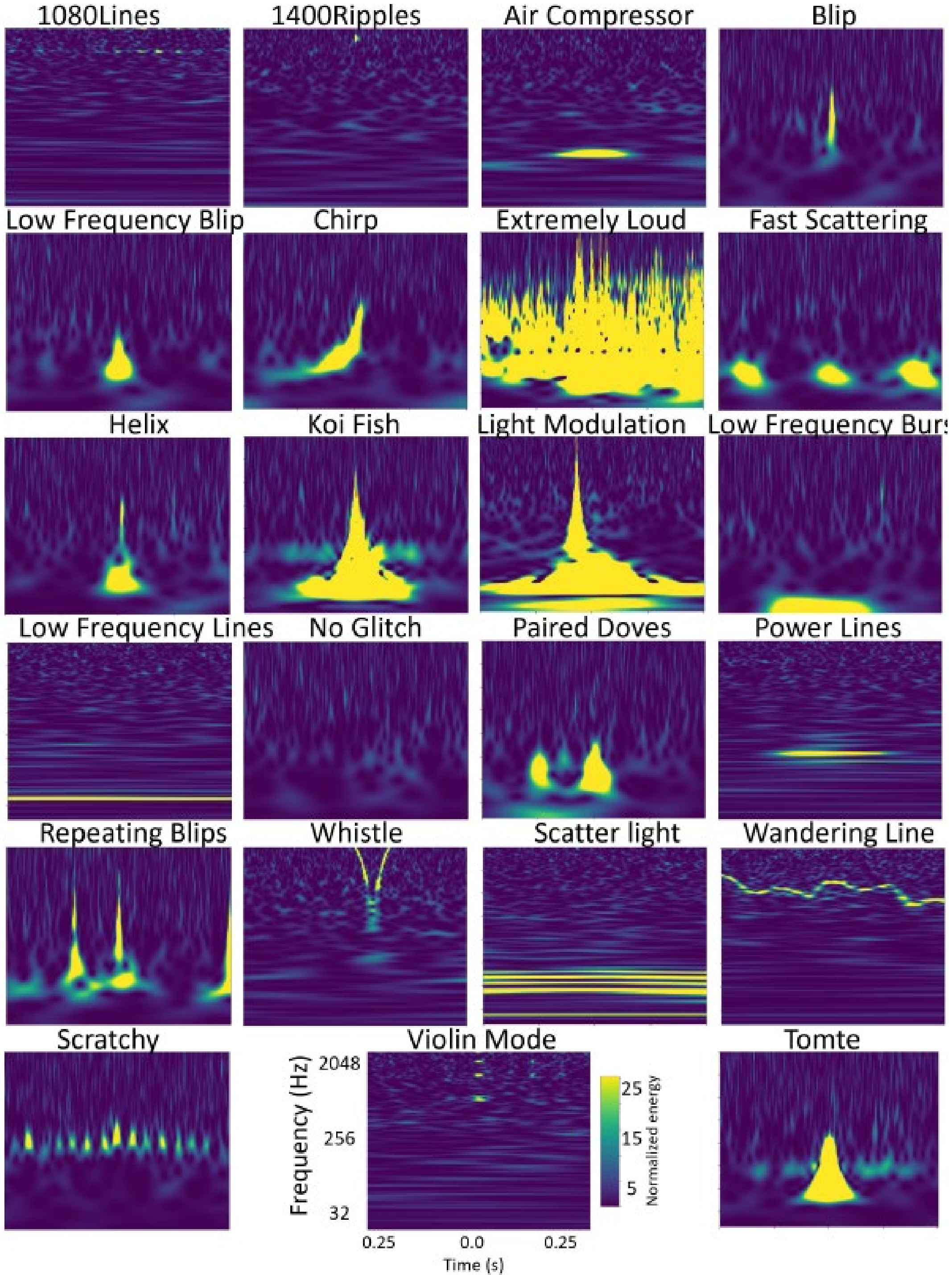
4-DETECTOR NETWORK

- LIGO-Hanford, LIGO-Livingston, Virgo, KAGRA
- Sky localization with and without gain selection
- Simulated Gaussian stationary noise with design Power Spectral Densities
- Realistic error estimation beyond Fisher Information



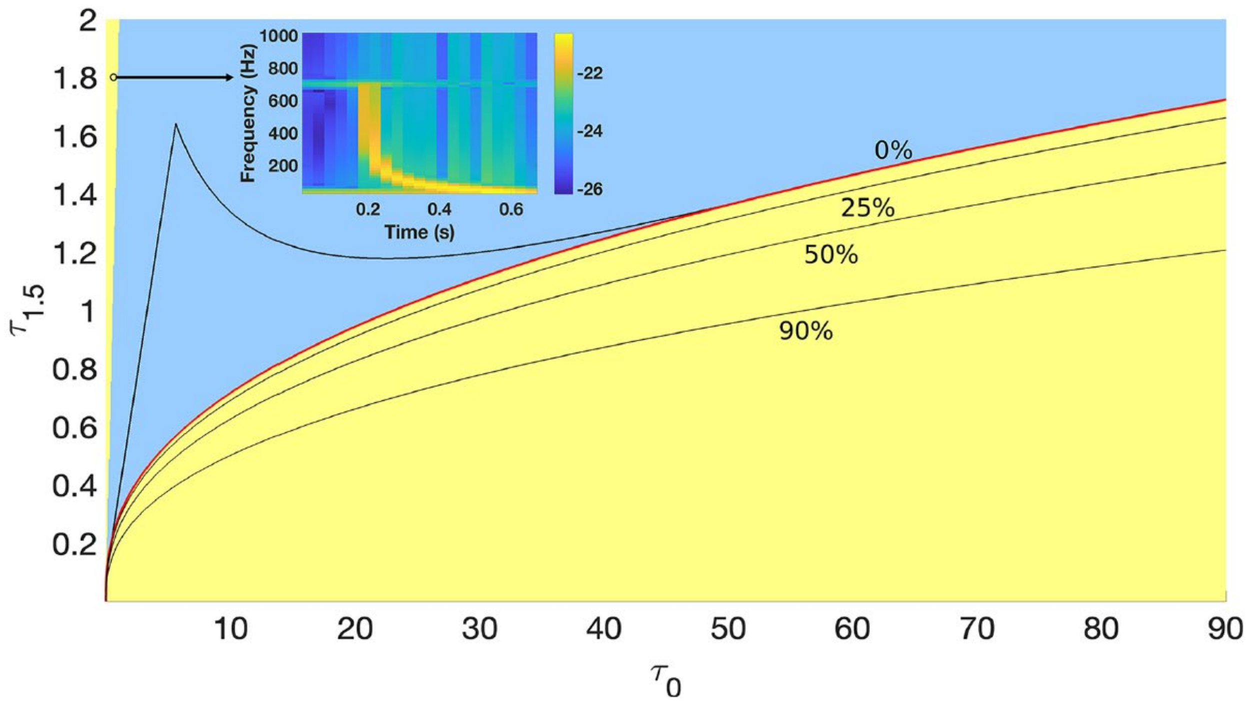
GLITCH MITIGATION

- Ground-based IFOs are affected by frequent interference signals from instrumental and environmental sources.
- Wu et al, ArXiv: 2401.12913v1



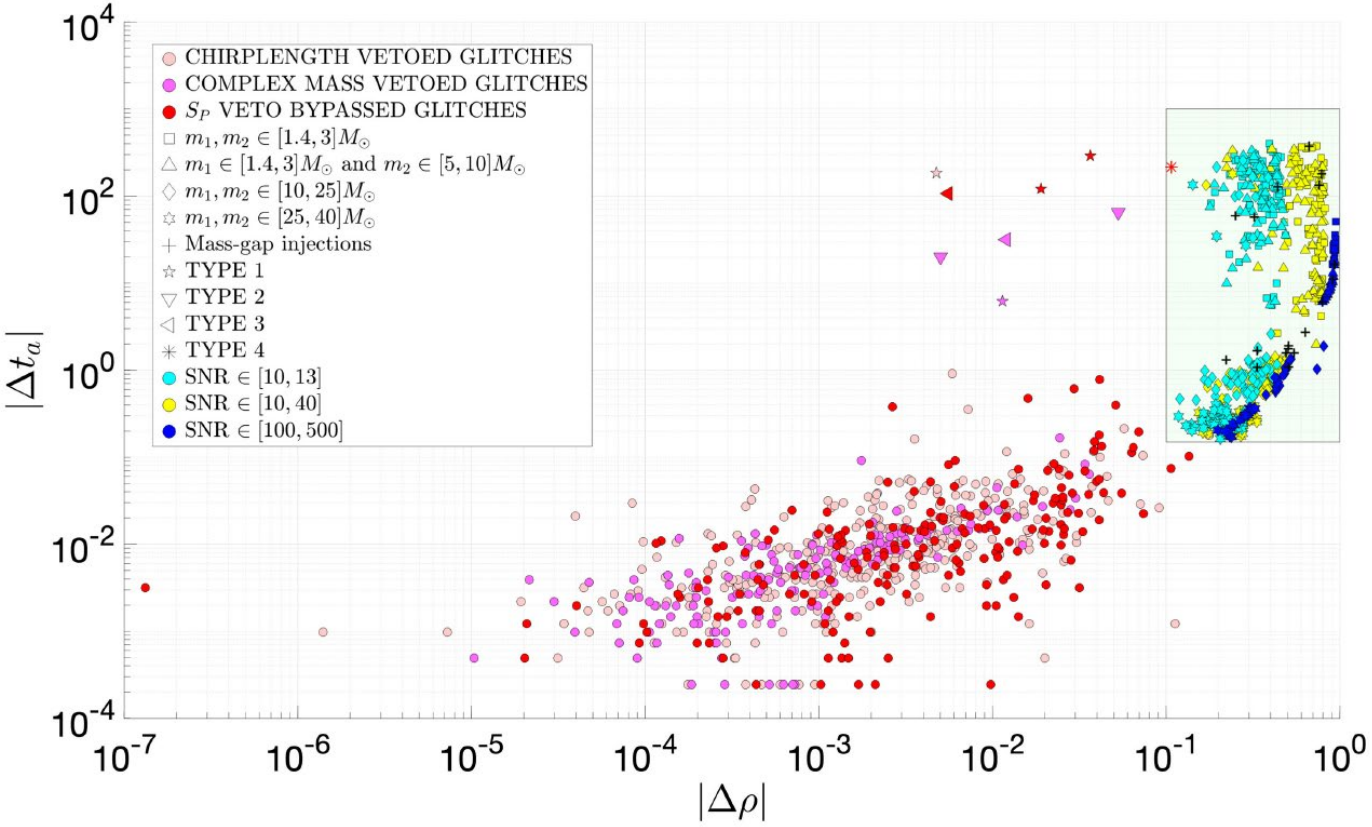
GLITCH VETO USING UNPHYSICAL TEMPLATES

- Masses to chirp times map is one-to-one but not onto $\Rightarrow$ unphysical sectors in chirp time space
- PSO performs better for hypercubical spaces $\Rightarrow$ unphysical sectors covered at **no extra cost**
- One can augment the search space using the negative chirp time quadrant
- Glitches match physical & unphysical templates; GW signals do not



GLITCH VETO USING UNPHYSICAL TEMPLATES

- Girgaonkar, Mohanty, Physical Review D 110, 023037 (2024)
- 131 hours of LIGO data (L1, H1, all O-runs)
- 99.9% rejection of glitches with no loss in detections (injected signals $\leq 80\ M_\odot$ total mass)

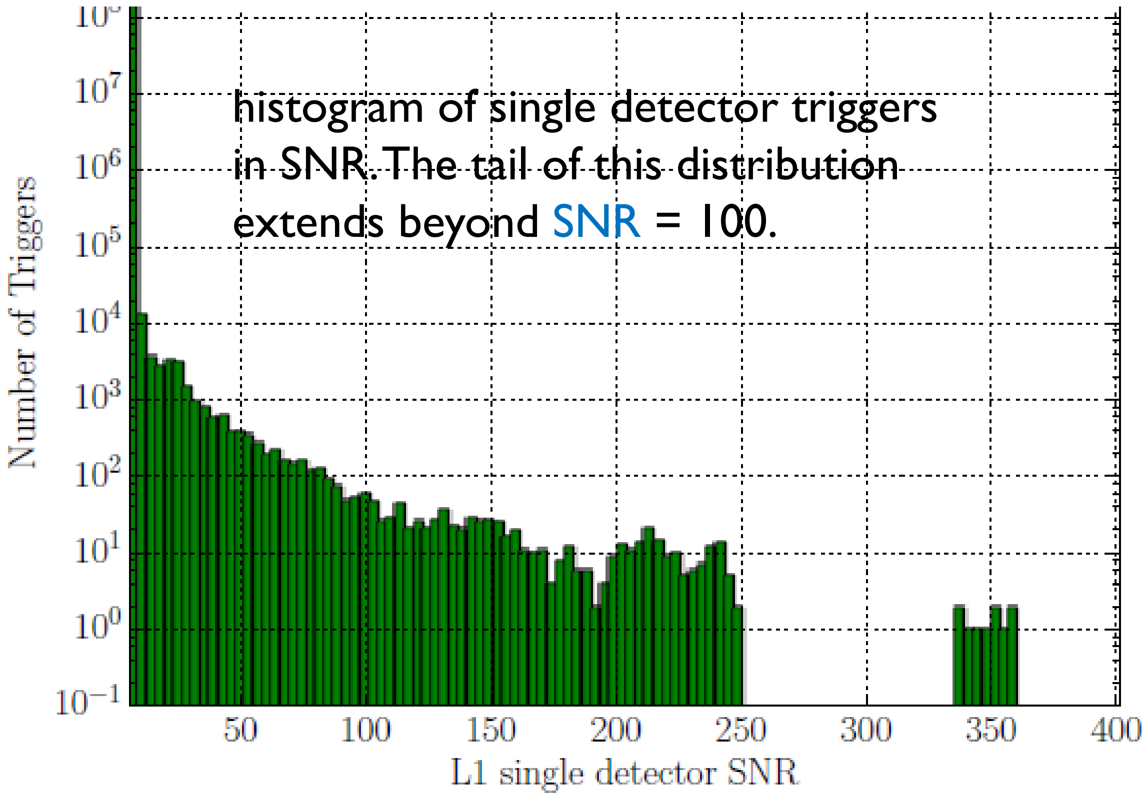


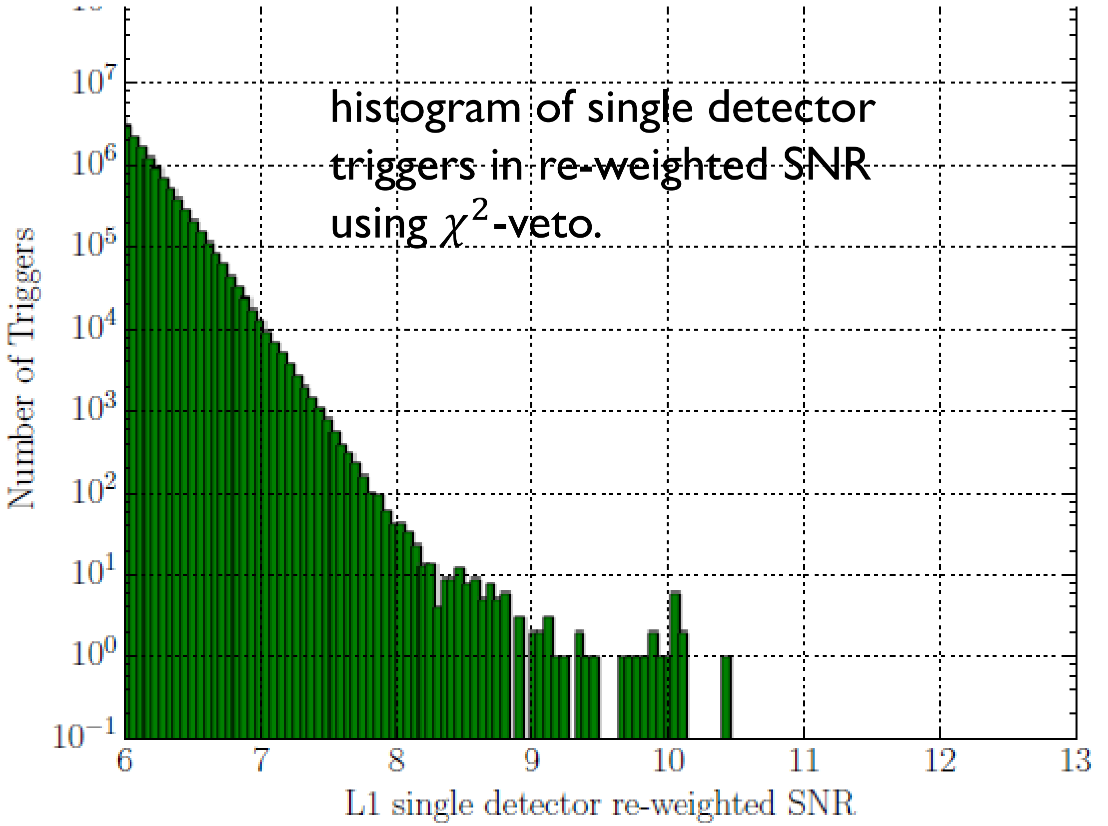
SUMMARY

- Data analysis is a critical component of GW astronomy and computational bottlenecks often limit us from reaching higher search sensitivity
- Nature inspired optimization heuristics are powerful techniques for addressing some of the key challenges
- GPU acceleration is extremely significant and should be adopted where possible
- Open challenges abound. Examples:
  - 3rd generation detectors: longer signals with higher rate → Glitch mitigation problem becomes harder
  - Space-based detectors: Embarrassment of riches but only if the data analysis problems are solved

THANK YOU!
QUESTIONS?

EFFECT OF GLITCHES ON DETECTION SENSITIVITY





- arXiv:1710.02185v3 [gr-qc]
- Histograms of single detector PyCBC triggers from the Livingston (L1) detector.