

Detecting gravitational-wave signals with stochastic sampling

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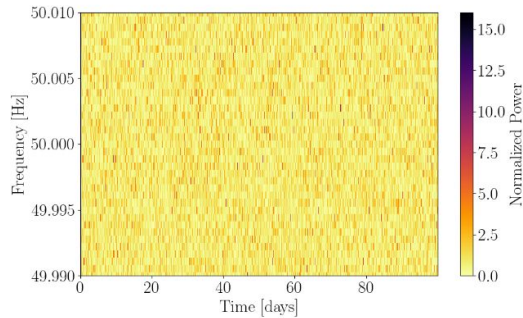
Overview

Gravitational-wave astronomy is an exciting field when it comes to data analysis:

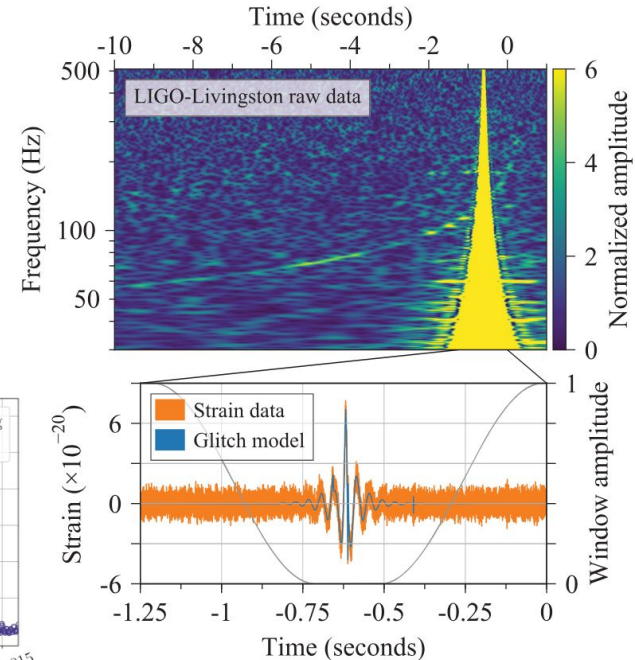
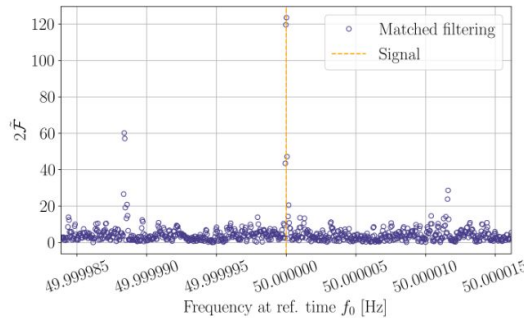
- Well-known models for the expected signals (Black-hole/Neutron star mergers).
- Complicated noise and detector response.

This talk: **Follow-up of continuous gravitational-wave candidates.**

1. What are continuous waves (CWs)? Why do we care?
2. How do we search for CW?
3. Follow-up of GW candidates using MCMCs
4. How to quantify the “success” of an MCMC follow-up
5. Setup and sensitivity optimisation



Search f_0



<https://arxiv.org/pdf/1710.05832>

Gravitational waves : a quick introduction

Gravitational waves : a quick introduction

GWs: traveling perturbations of the spacetime geometry predicted by General Relativity (A. Einstein, ca. 1915) and detected using LIGO [LIGO-Virgo Collaboration [arxiv:1602.03837](https://arxiv.org/abs/1602.03837)]

Source: “Time-dependent quadrupolar accelerations.”

Extremely weak, need extreme phenomena at astrophysical scales:

- Mergers of black holes or neutron stars.
- Supernovae explosions.
- Rapidly rotating non-axisymmetric neutron stars.

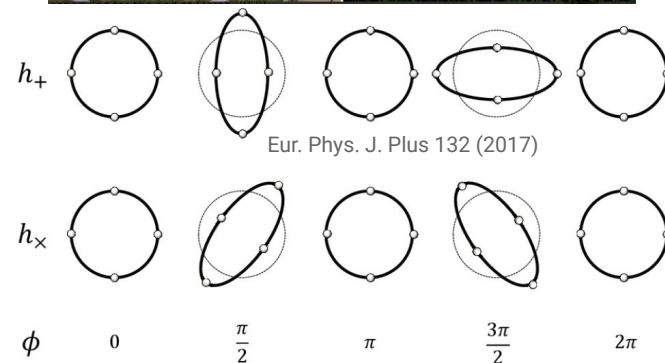
Complementary information to EM channels:

- How often do Black holes/Neutron stars merge?
- How spherical are neutron stars?
- What happens during a supernova explosion?
- Direct dark matter detection, exotic physics...

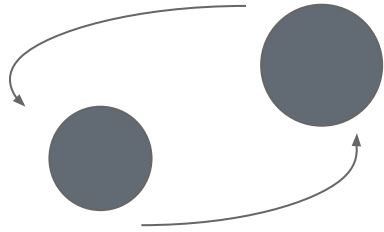
Observable effect: Relative displacement of test masses.

Interferometric detectors (LIGO, Virgo, KAGRA):

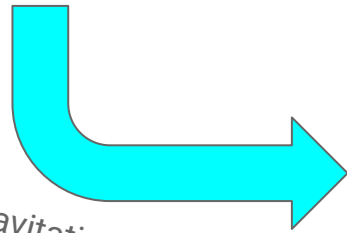
- Test masses==mirrors, use lasers to measure their position.



Gravitational waves : a quick introduction

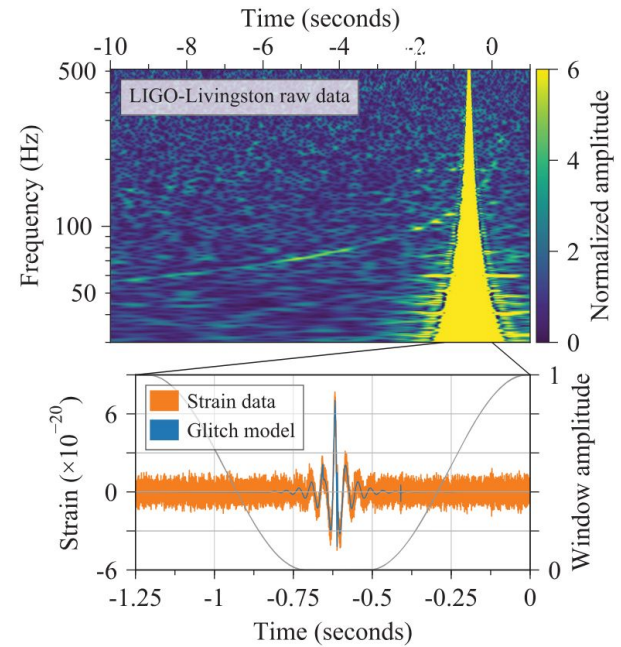


Binary neutron star,
~40 Mpc away



Gravitational waves
travelling through
spacetime
 $h \sim 1e-21$

LIGO/Virgo/KAGRA
detectors
(~3-4 km long)



Laser interferometry,
displacement $\sim 1e-5$ * proton radius

Continuous gravitational-wave signals (CWs)

Continuous gravitational-wave signals

So far (2025), detected GW signals come from merging binaries.

Neutron stars (NSs) *may* sustain surface deformations while they spin hundreds of time per second (see e.g. millisecond pulsars).

Non-axisymmetric deformation + rapid spin == GW emission!

Long-duration (continuous!) GW signal.

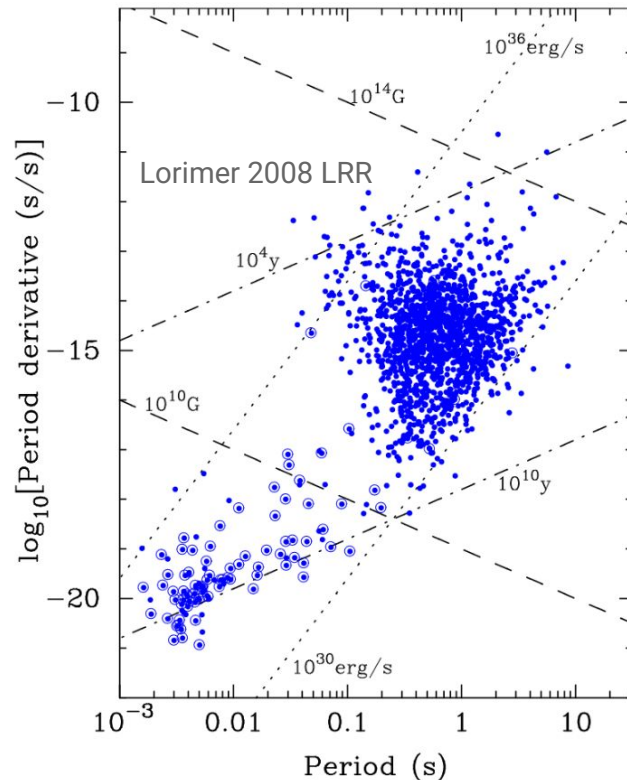
Implications:

- We are missing ~ 100 million NS, we may observe them using GW.
- NS interiors are *very* complicated and can be observed using GWs! (superconducting inner fluids? Rosby-mode oscillations? nuclear pasta? glitches?)

Deformation \sim NS ellipticity (ϵ). Theoretical models: $\log_{10}(\epsilon) < -6$
[Gittins arxiv:2401.01670]

$$h_0 = \frac{4\pi^2 G}{c} \frac{I_z \epsilon}{d} [2f_{\text{rot}}]^2 \simeq 4.2 \cdot 10^{-26} \left(\frac{\epsilon}{10^{-6}} \right) \left(\frac{f_{\text{rot}}}{100 \text{ Hz}} \right)^2 \left(\frac{d}{1 \text{ kpc}} \right)^{-1}$$

at least ~ 5 orders of magnitude weaker than BNS.
Need to integrate *long* data periods to detect.



Continuous gravitational-wave signals

Morphology:

- Quasi-monochromatic signal.
- Frequency modulation due to Earth's motion around the Sun.
- Amplitude modulation due to detector's antenna pattern.

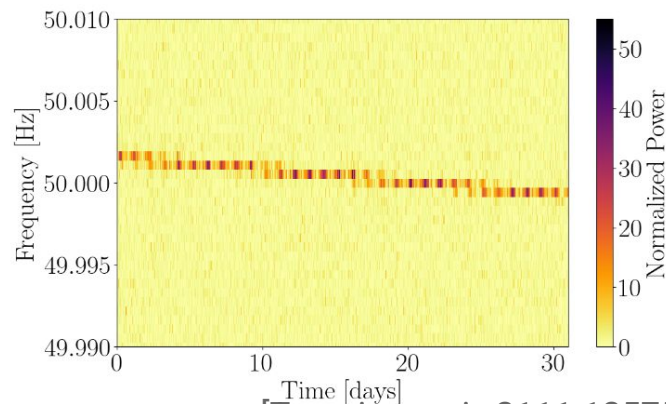
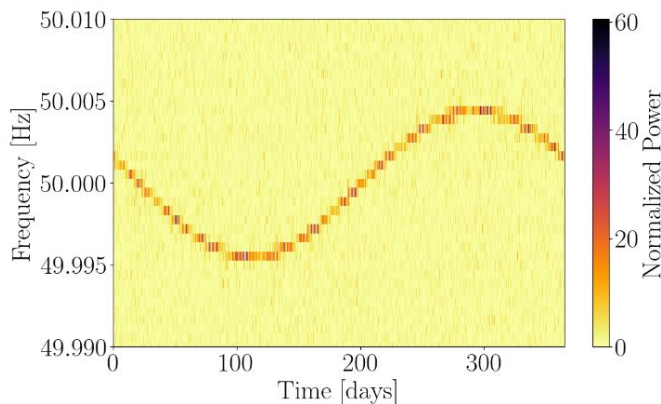
Search using *matched-filtering*:

- 1) **Propose**/select a specific set of **signal parameters** (*template*).
- 2) Subtract corresponding signal from data.
- 3) Check if result is consistent with noise
(i.e. compute **detection statistic**!)

$\lambda = \{\text{Frequency, spindown, sky position, ...}\}$

Multiple ways:

- EM observations.
- Interesting sky regions.
- Optimize sensitivity.
- ...



[Tenorio+ arxiv:2111.12575]

Continuous gravitational-wave signals

Example search: Search in O4a LIGO data targeted at known pulsars.
LVK [arxiv:2501.01495](https://arxiv.org/abs/2501.01495). ~ 6 months of integration time.

No detection: Set upper limits on ϵ for known pulsars.

Crab pulsar (for example):

- Distance to the source ~ 2kpc .
- Less than 1% of the energy is loss as CW signals.
- $\epsilon < 6e-6$.
- NS Radius ~ 10km \rightarrow “Mountain height” < 6cm

“Imagine a flat Milano - Lecco road with less than 6cm imperfections”

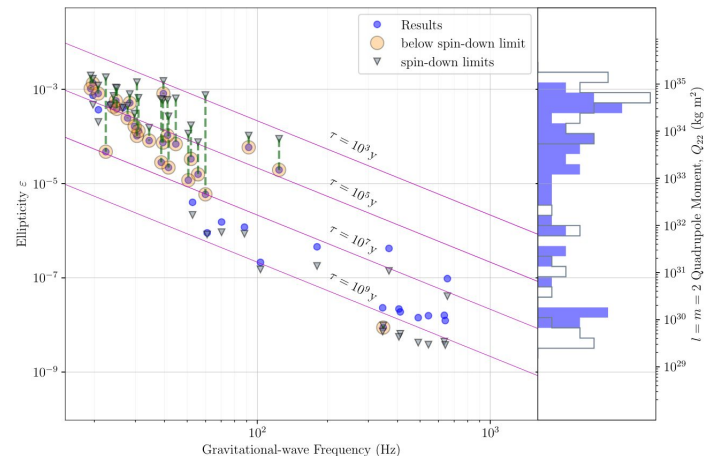
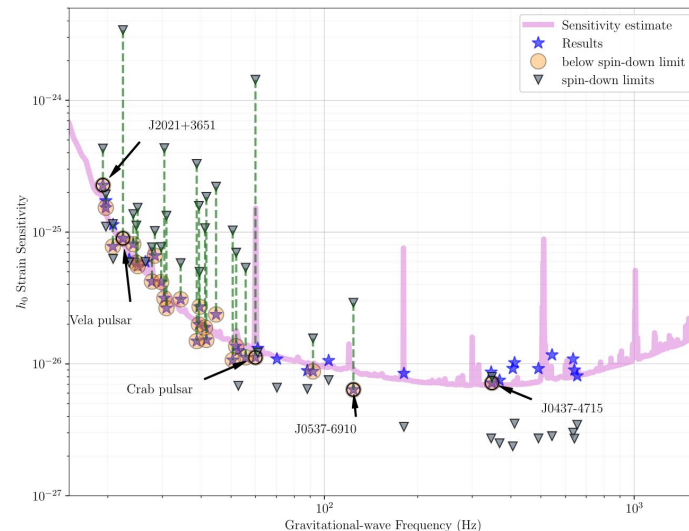
Summary:

- LIGO can set constraining upper limits on nearby NSs.
- Observed NS (pulsars) are very spherical.
- ...?

Can we look for NS from unknown sources?

Would they behave like pulsars?

What if they are more extreme?



All-sky CW searches

All-sky CW searches

Wette [arxiv:2305.07106](https://arxiv.org/abs/2305.07106)

Historical set of CW searches
(2003 - 2023)

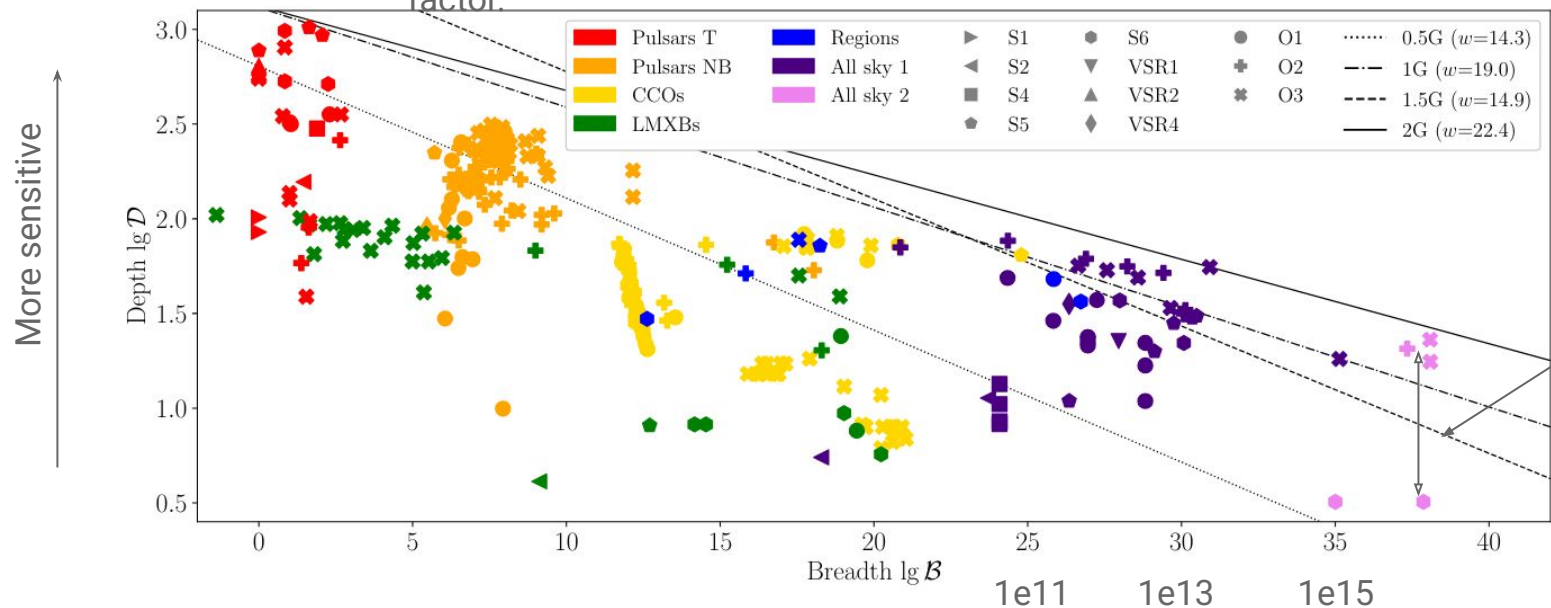
Breadth == Number of templates

Depth == (Noise amplitude) / (Signal amplitude)

Clear *downward* trend:

Broader space → Broader priors → Bigger Occam factor.

$$\mathcal{D} = \frac{\sqrt{S_h/\text{Hz}}}{h_0^C}$$



All-sky CW searches

The less we *assume* about a source (bigger prior), the more complicate is to detect it (\sim bigger Occam's factor).

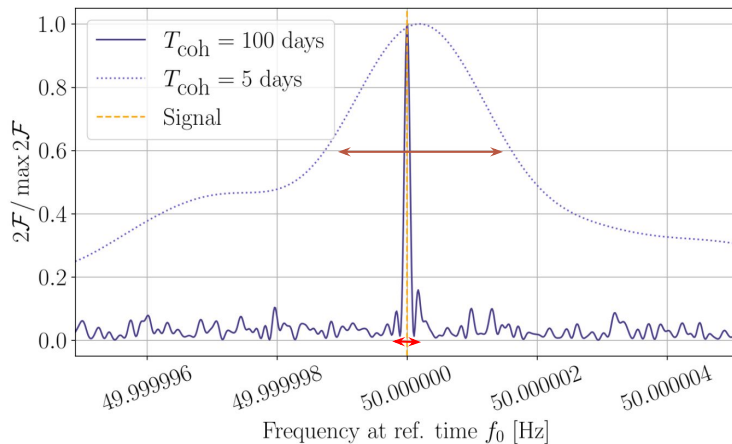
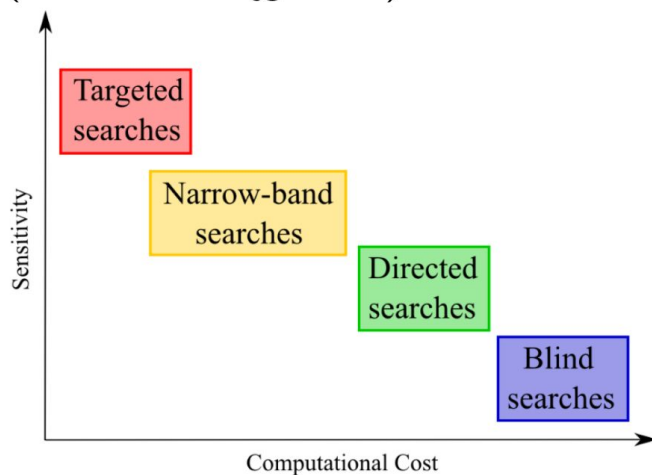
We can look for CW sources across the whole sky and LIGO sensitive band to look for *unknown* NSs.

How many frequencies/sky positions/spindowns (*templates*) should we evaluate? We count them!

We can *simulate* a signal and study how much we can deviate from the true parameters before the detection statistic degrades too much (mismatch).

Different detection statistics will have different resolution requirements.

(Sieniawska & Bejger 2019)



All-sky CW searches

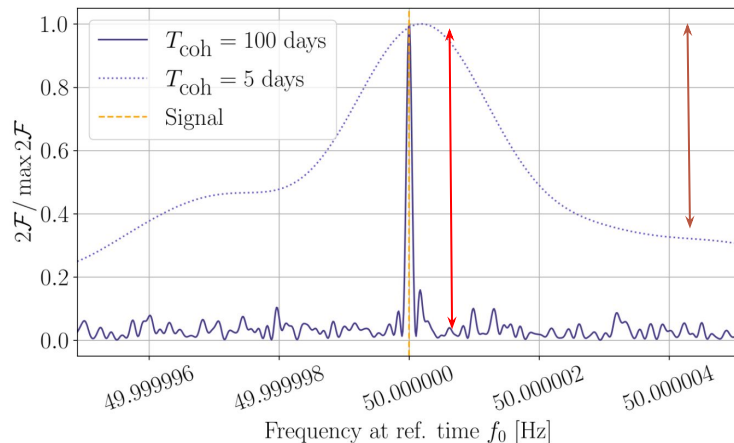
Cost of a detection statistic on 1 template $\sim 1\text{ms}$.
Typical budget ~ 1 million CPU hours ~ 1 CPU century.

Optimal statistic:

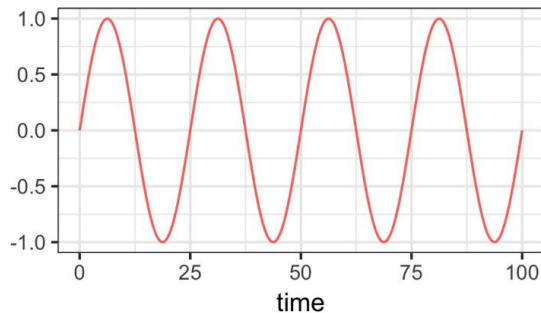
$\sim 10^{20}$ templates $\Rightarrow 3\text{k}$ millennia. \rightarrow No.

Semicoherent statistic:

$\sim 10^{15}$ templates $\Rightarrow 0.3$ century \rightarrow Ok :)

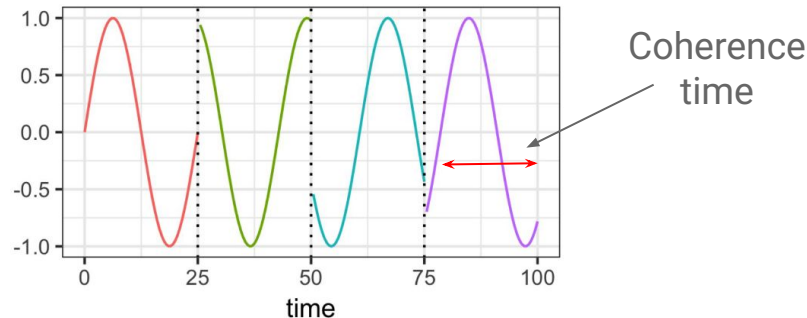


Coherent strategy



Very expensive, less false alarms.

Semicoherent strategy

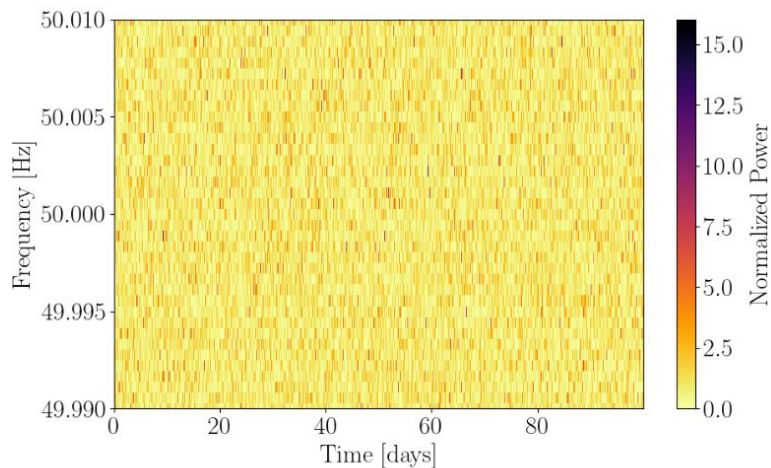


Less expensive, more false alarms.

All-sky CW searches

Situation so far (i.e. summary!):

- Want to find CW signals from unknown sources.
- *Must* use sub-optimal methods to fit within budget.
- Initial Tcoh ~ 30 min.
- The search will produce *many* false alarms.

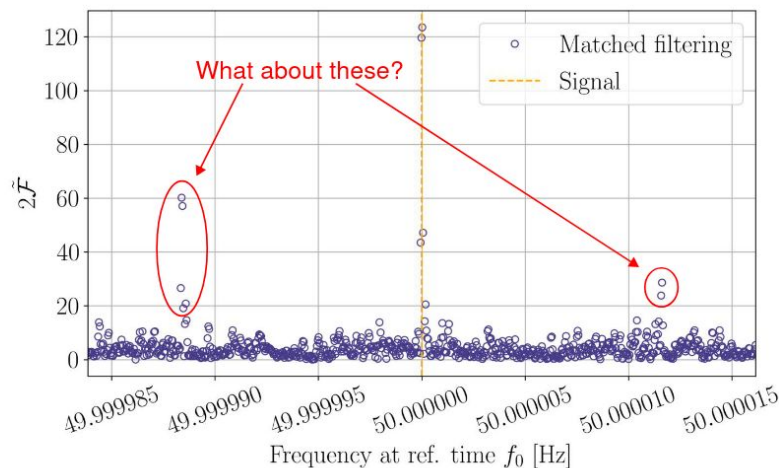


Search f_0 \rightarrow

(+ sky position, spin down, ...)

How do we deal with false alarms?

Increase coherence time in a *controlled* manner.
Place templates efficiently using probabilistic methods.



MCMC Follow-up of CW candidates

MCMC Follow-up of CW candidates

Asthon & Prix arxiv:1802.05450
<https://github.com/PyFstat/PyFstat>

Run a search → Identify interesting candidates → Run another “search” around with longer Tcoh.

Increase Tcoh → Need more templates to cover the region, increasing computing cost.

Is there a “cheap” way to run this search cheaply?

Simple idea: *Detection statistics* are related to *Posterior distributions* by an “unimportant” factor.

$$P(\boldsymbol{\lambda}|\mathbf{x}, \mathcal{H}_S) \propto B_{S/G}(\mathbf{x}; \boldsymbol{\lambda}) P(\boldsymbol{\lambda}|\mathcal{H}_S)$$

↓
Signal parameters
after looking at the
data

↓
Detection
statistic

↓
Prior on signal
parameters

$$B_{S/G}(\mathbf{x}) \equiv \frac{P(\mathbf{x}|\mathcal{H}_S)}{P(\mathbf{x}|\mathcal{H}_G)}$$

Higher detection statistic → Higher posterior probability.

$$B_{S/G}(\mathbf{x}; \boldsymbol{\lambda}, N_{\text{seg}}) \equiv \left(\frac{70}{\hat{\rho}_{\text{max}}^4} \right)^{N_{\text{seg}}} e^{\hat{\mathcal{F}}}$$

Can we use a Markov-Chain Monte Carlo to place templates “smartly”?

$$P(\theta|\mathbf{x}, \mathcal{H}) = \frac{P(\mathbf{x}|\theta, \mathcal{H}) P(\theta|\mathcal{H})}{P(\mathbf{x}|\mathcal{H})}$$

MCMC Follow-up of CW candidates

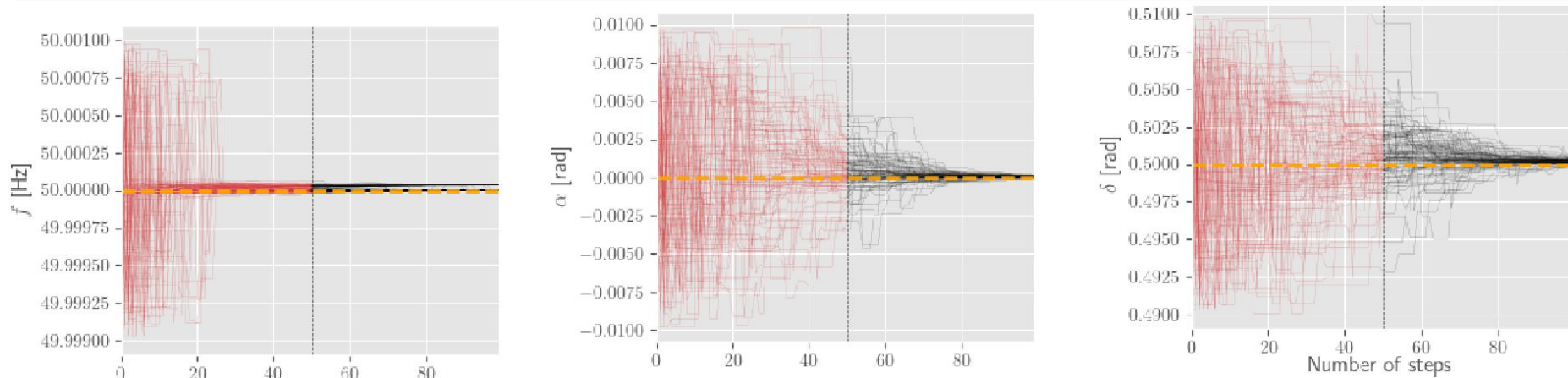
Tenorio+ arxiv:2105.13860

We use ptemcee [Vousden+ arxiv:1501.05823], a parallel-tempered ensemble MCMC.

Increase coherence time from 30min to 0.5 days (Detection statistic cost $\sim 10\text{ms}$).

Ensemble of ~ 100 walkers running for ~ 100 steps through 3 temperatures $\rightarrow \sim 30,000$ templates.
(cf. initial $\sim 1\text{e}15$).

Seems to do a good job, right? \rightarrow Standard situation: How do we quantify that?



MCMC Follow-up of CW candidates

Mirasola & Tenorio arxiv:2405.18934

Detection criterion: “Detection statistic high enough to be incompatible with noise”.

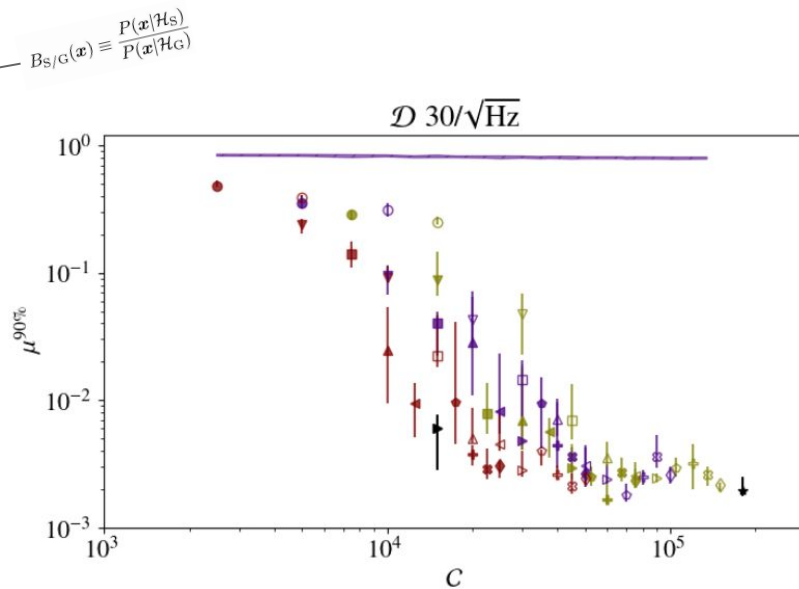
We don't *need* convergence in terms of autocorrelation time, we only need the MCMC to *find* the peak.

We quantify “how close” the MCMC gets to the peak using the *mismatch*:

$$\mu(\Delta\lambda; \lambda_s) = \frac{2\hat{\mathcal{F}}(\lambda_s) - 2\hat{\mathcal{F}}(\lambda_s + \Delta\lambda)}{2\hat{\mathcal{F}}(\lambda_s) - 4N_{\text{seg}}} \leftarrow B_{S/G}(x) \equiv \frac{P(x|H_S)}{P(x|H_G)}$$

We compute the resulting mismatch for each configuration using software-simulated signals.

These are compared to semianalytical estimates at a given false alarm and false dismissal (blue region), and then validated using simulations in real data.

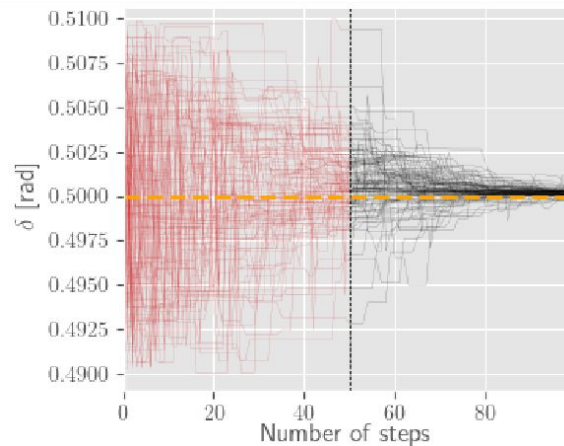
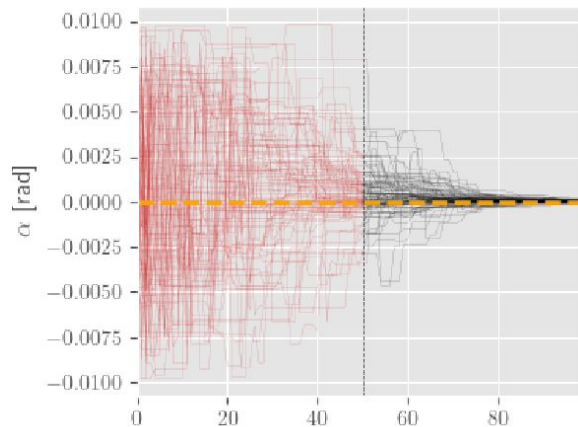
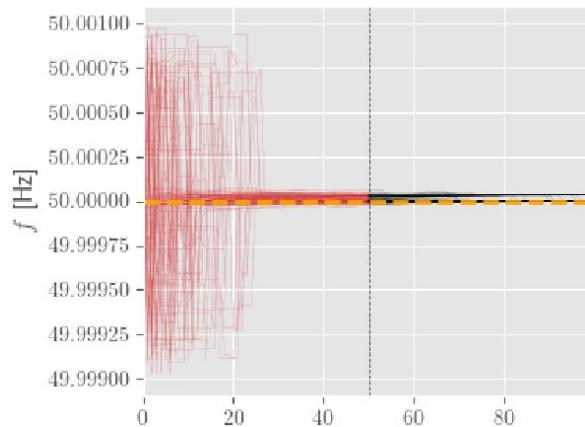


Right, now we know it has *finished* and we know the maximum detection statistic value.

What is the *result*? Was this a signal? Or was it only noise?

Two options:

1. Run another stage with longer coherence time and postpone the question.
2. Construct a Bayes factor to *decide* whether you have a signal or not. → We go directly to this one



Assume we ran a few MCMC follow-ups increasing T_{coh} .

Upon finishing an MCMC run, my *detection statistic* (2Fmax) is given by the *loudest* template:

$$\{2F_{\text{max}}[i], i=\text{run } 0, \text{run } 1, \dots\}$$

If the data contains a signal, 2Fmax values will be *correlated*, as they are looking at *the same signal*.

If the data does not contain a signal, 2Fmax will be the *maximum* of a set of N random variables.

I want a Bayes factor that compares these two hypotheses:

$$\ln \mathcal{B}_{\text{S/N}}^* = \ln \frac{P(2\tilde{\mathcal{F}}^* | \mathcal{H}_{\text{S}})}{P(2\tilde{\mathcal{F}}^* | \mathcal{H}_{\text{N}})}$$

Can I construct probability distributions for those two cases?

Signal case: Detection statistic values are correlated.

Any pair of detection statistics depends on the signals SNR ρ , so we can write the following integral:

$$\begin{aligned} P(2\tilde{\mathcal{F}}|\mathcal{H}_S) &= \int_0^\infty d\rho^2 P(2\tilde{\mathcal{F}}|\rho^2, 2\hat{\mathcal{F}}, N_{\text{seg}}) P(\rho^2|2\hat{\mathcal{F}}, N_{\text{seg}}) \\ &\propto \int_0^\infty d\rho^2 P(2\tilde{\mathcal{F}}|\rho^2) P(2\hat{\mathcal{F}}|\rho^2, N_{\text{seg}}) P(\rho^2) , \end{aligned}$$

If both det. stats. are high at
the same ρ value, the
probability is high.

You'll have to believe me on this one.

tl;dr We can compute the probability under the signal hypothesis.

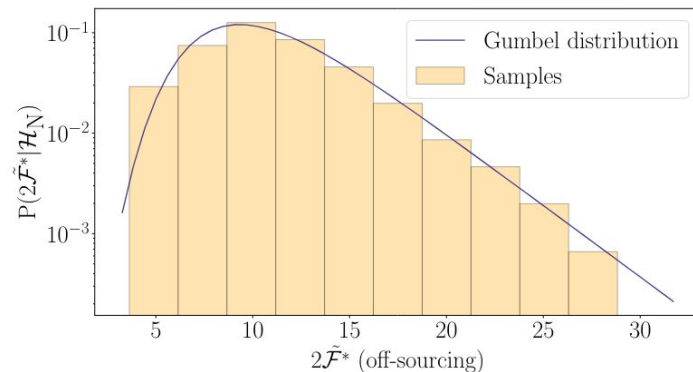
Noise case: Fisher-Tippett-Gnedenko Theorem

It's like the central limit theorem, but for min/max instead of for averages!
(checkout Extreme Value Theory).

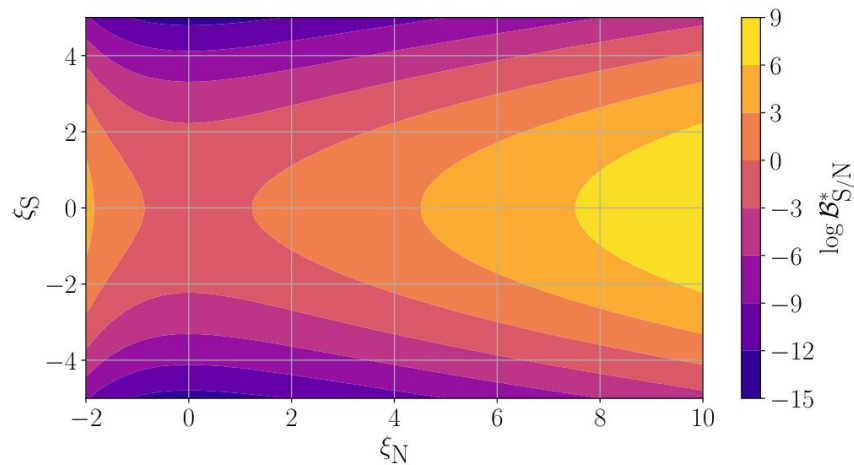
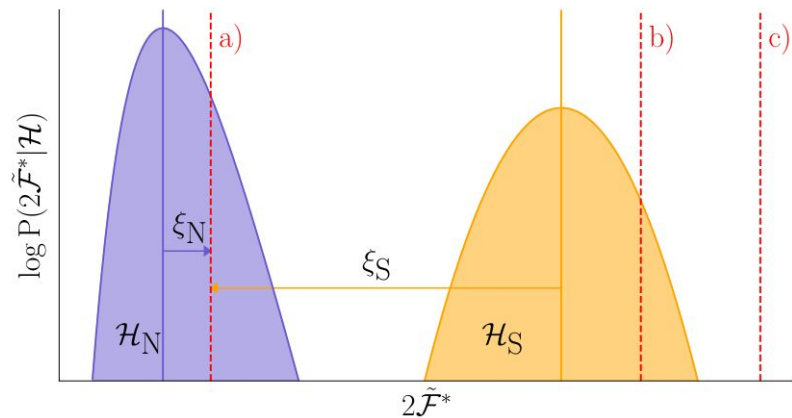
The maximum of N variables, in this case, converges to a Gumbel distribution:

$$P(2\tilde{\mathcal{F}}^*|\mathcal{H}_N) = \frac{1}{\sigma_N} \exp \left[- \left(\frac{2\tilde{\mathcal{F}}^* - \mu_N}{\sigma_N} \right) - e^{-\left(\frac{2\tilde{\mathcal{F}}^* - \mu_N}{\sigma_N} \right)} \right]$$

We can point away from the candidate in the sky and run an MCMC to generate “independent” noise samples [Isi+[arxiv.org:2010.12612](https://arxiv.org/abs/2010.12612)] and fit the result using a Gumbel distribution [Tenorio+ arxiv:2111.12032].



Putting all together:

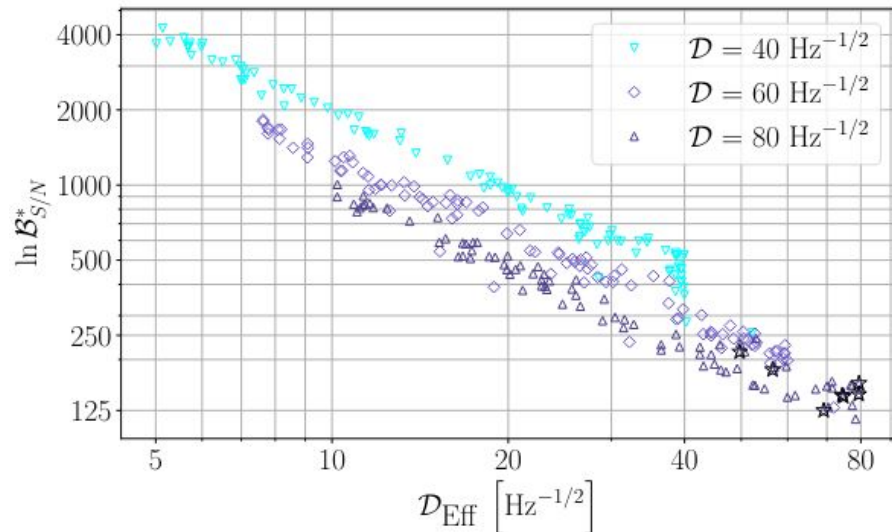
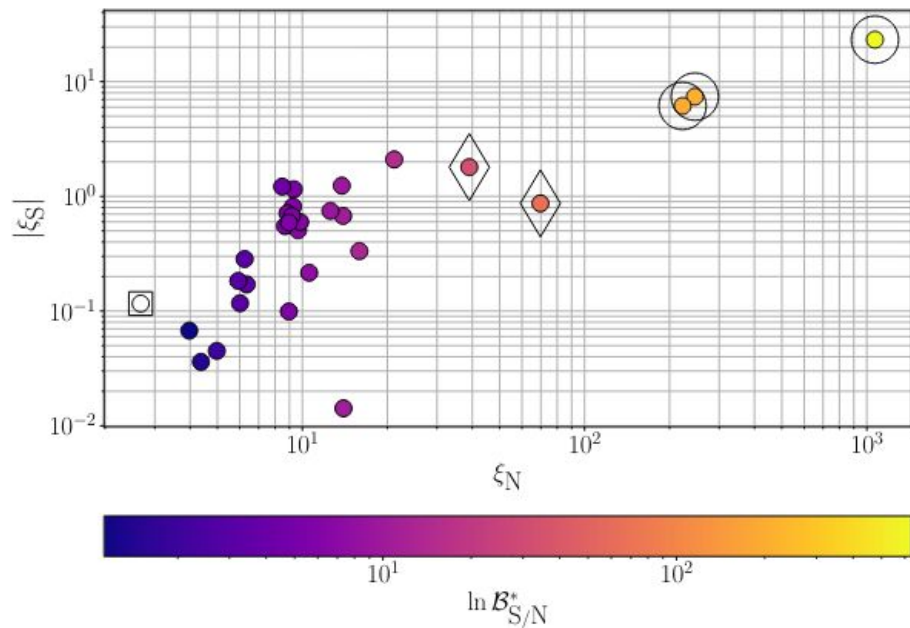


We end up with a sound Bayes factor to quantify the result of MCMC follow-ups!

MCMC Follow-up of CW candidates

Tenorio+ arxiv:2105.13860

Pilot application: ~ 30 outliers produced in LIGO O2 searches.
Our Bayes factor disfavors an astrophysical origin for *all* of them.



Impact

Impact

MCMC follow-up is a *systematic search-independent* approach to assess the astrophysical origin of a CW candidate.

First of its kind, this approach was used in O(10) LVK searches in O3 data, vastly simplifying their analyses.

Before, manual checks and ad-hoc vetoes where the norm.

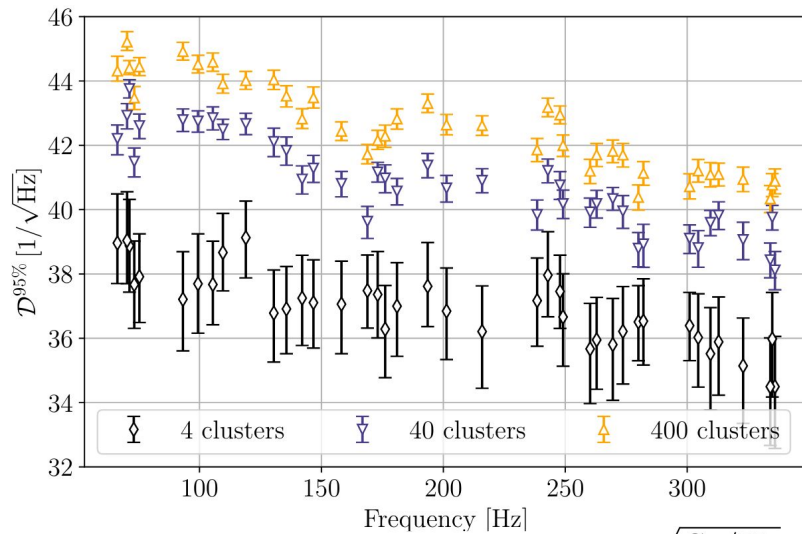
Due to its high computing efficiency, it is now feasible to increase the *false alarm probability* of a search, as the MCMC follow-up will rapidly lower it again in a few stages.

More false alarms → More probability of detection!

Specifically, $\sim(10-15)\%$ sensitivity increase *at negligible computing cost* after calibrating the MCMC follow-up.

Increase of $\sim(30-50)\%$ in surveyed volume!

Mirasola & Tenorio arxiv:2405.18934



$$\mathcal{D} = \frac{\sqrt{S_h/\text{Hz}}}{h_0^C}$$

Conclusion

Conclusion

Gravitational-wave astronomy is an exciting field when it comes to data analysis:

Complicated noise, intricate signal models, vast parameter spaces, ...

We discussed the use of MCMC to follow-up CW candidates. In particular:

- How to decide whether the setup is “good”.
- How to decide if the candidate is “astrophysical” or not.

This involved the application of multiple probability results:

- Bayes factors and Bayesian probability in general.
- Extreme-value theory.
- Numerical simulations to estimate probabilities.

The resulting method has tangible impact:

- *Simpler* and more systematic CW follow-ups.
- Significant increase of the search sensitivity at a negligible computing cost.

This is just a small percentage of GW’s data-analysis potential, there’s many more avenues to explore!

(low-latency/FPGA/GPU computing, machine-learning for detection and mitigation of non-Gaussianities, GenAI as a sampler... ask if interested!).