Application of a hierarchical MCMC follow-up to Advanced LIGO continuous gravitational-wave candidates arXiv:2105.13860 [gr-qc] (submitted to PRD)

#### Rodrigo Tenorio David Keitel Alicia M. Sintes

Departament de Física, Institut d'Aplicacions Computacionals i de Codi Comunitari (IAC3), Universitat de les Illes Balears, and Institut d'Estudis Espacials de Catalunya (IEEC), Carretera de Valldemossa km 7.5, E-07122 Palma, Spain

11th Iberian Gravitational Waves Meeting, 11th June 2021

# Introduction

- Continuous waves (CWs) are long-duration quasi-monochromatic gravitational waves (GWs). No direct detection up to date.
- Expected sources are Neutron Stars (NS) presenting a non-axisymmetry (crust deformations, r-modes, free precession).
- $\bullet\,$  CWs are described by amplitude  ${\cal A}$  and phase-evolution  $\lambda$  parameters:
  - $\mathcal{A} \rightarrow$  source orientation  $(\cos \iota, \psi, \phi_0)$ , nominal GW amplitude  $h_0$ .
  - $\lambda \rightarrow \text{source spinup/spindown } (f_0, f_1, \dots)$ , Doppler modulation due to the Earth's motion  $(\alpha, \delta)$ , Doppler modulation due to a binary companion.



# Introduction

### Simple example of a CW search

- Set up a template bank covering the parameter space of interest (Note: A can be maximized out analytically, so only look for λ).
- Evaluate a statistic (e. g. matched filter)  $2\tilde{\mathcal{F}}$  on each template.
- Retrieve outliers for further inspection.



The number of required templates (computing cost) in order not to lose a signal scales with a strong power of the observing time. Matched filtering is unfeasible for wide parameter-space searches.

rodrigo.tenorio@ligo.org (UIB)

arXiv:2105.13860 [gr-qc]

### Semicoherent $\mathcal{F}$ -statistic

- Divide the data stream into  $N_{\rm seg}$  segments with a duration of  $T_{\rm coh}.$
- Sum the result of filtering the data stream x against a signal template  $h(\lambda)$  in each of these segments  $2\hat{\mathcal{F}}(\lambda;x) = \sum_{s=1, \dots, N_{\text{seg}}} 2\tilde{\mathcal{F}}(\lambda;x(s)).$
- Shorter  $T_{\rm coh} \rightarrow$  Less constraining templates  $\rightarrow$  Wider maxima.
- Semicoherent statistics allow to use coarser template banks (less computing cost), but are more susceptible to false alarms.



Hierarchical approach:

- Sweep wide regions with low coherence time.
- Focus on concrete outliers using longer coherence times.

### A Bayesian perspective

- $\hat{\mathcal{F}}(\lambda; x)$  is similar to a Bayes factor updating our prior knowledge on  $\lambda$ .
- Sampling the posterior  $P(\lambda|x) \propto \hat{\mathcal{F}}(\lambda;x) P(\lambda)$  is equivalent to an adaptive grid search.
- PyFstat [D. Keitel + J. Open Source Softw. (2021)] implements this procedure using the ptemcee sampler [W. Vousden + MNRAS Vol. 455 1919-1937 (2016)]



Using an MCMC sampler simplifies the overall setup: its effectiveness essentially depends on the number of templates within the prior volume.

rodrigo.tenorio@ligo.org (UIB)

arXiv:2105.13860 [gr-qc]

5/15

#### Hierarchical follow-up

- After running a search using  $T_{\rm coh}^{(0)}$ , a follow-up can be run using  $T_{\rm coh}^{(1)} > T_{\rm coh}^{(0)}$ , refining the effective parameter-space resolution.
- Coherence time can be increased as the MCMC sampler narrows down the outlier parameters until a fully-coherent follow-up is reached.



#### Hierarchical follow-up

- After running a search using  $T_{\rm coh}^{(0)}$ , a follow-up can be run using  $T_{\rm coh}^{(1)} > T_{\rm coh}^{(0)}$ , refining the effective parameter-space resolution.
- Coherence time can be increased as the MCMC sampler narrows down the outlier parameters until a fully-coherent follow-up is reached.



So...?

What can we conclude about a set of follow-up stages with different  $T_{\rm coh}$ ?

rodrigo.tenorio@ligo.org (UIB)

arXiv:2105.13860 [gr-qc]

#### Bayes factor

Suppose we run a complete MCMC follow-up and the loudest candidate returns an  $\mathcal{F}$ -statistic value of  $2\hat{\mathcal{F}}^*$  from a semicoherent stage and the final fully-coherent  $2\tilde{\mathcal{F}}^*$  stage.

- $(\mathcal{H}_N)$  If there is no signal,  $2\tilde{\mathcal{F}}^*$  is the maximum of  $\mathcal{N}$  random variables (one for each template sampled).
- $(\mathcal{H}_S)$  If there is a signal, the retrieved value of  $2\tilde{\mathcal{F}}^*$  has to be consistent with the value implied by  $2\hat{\mathcal{F}}^*$ .

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

 $\mathcal{B}^*_{\mathrm{S/N}}$  can be easily evaluated to distinguish interesting candidates.

- We are interested in the distribution of  $2\tilde{\mathcal{F}}^* = \max_{\mathcal{N}} 2\tilde{\mathcal{F}}$ .
- $\bullet$  Under the noise hypothesis,  $2\tilde{\mathcal{F}}\sim\chi_4^2$  , which means

$$P(2\tilde{\mathcal{F}}^*|\mathcal{H}_N) = \mathcal{N} \cdot \chi_4^2(2\tilde{\mathcal{F}}^*) \cdot \left[\int_0^{2\tilde{\mathcal{F}}^*} d\xi \ \chi_4^2(\xi)\right]^{\mathcal{N}-1}$$

- This approach, however, only works if the  $\mathcal{N}$  templates are completely independent. By construction, templates are correlated to ensure a good parameter-space coverage.
- A usual work around is to evaluate a template bank on Gaussian noise and fit the distribution using an *effective* number of templates  $\mathcal{N}'$ , but this is known to give inaccurate results (see Appendix A of arXiv:2105.13860 [gr-qc]).

## Noise Hypothesis using Extreme Value Theory

- The distribution of  $\max_{\mathcal{N}} 2\tilde{\mathcal{F}}^*$  for  $\mathcal{N} \gg 1$  is  $\operatorname{Gumbel}(\mu_N, \sigma_N)$ .
- Background noise samples can be generated by evaluating the template bank on sky positions away from that of the outlier ("off-sourcing" M. Isi + Phys. Rev. D 102, 123027 (2020)).
- $P(2\tilde{\mathcal{F}}^*|\mathcal{H}_N)$  is constructed by fitting a Gumbel distribution to the maximum of off-sourced evaluations.



# Signal Hypothesis [R. Prix LIGO-T1700236]

- The presence of a signal with (squared) SNR  $\rho^2$  shifts the  $\mathcal{F}$ -statistic distribution to a non-central  $\chi^2$  distribution  $2\hat{\mathcal{F}} \sim \chi^2_{4N_{\text{ser}}}(\rho^2)$ .
- The basic idea to construct a probability distribution is  $2\hat{\mathcal{F}} \rightarrow \rho^2 \rightarrow 2\tilde{\mathcal{F}}$ , which translates to  $P(2\tilde{\mathcal{F}}|\mathcal{H}_S) \propto \int_0^\infty d\rho^2 P(2\tilde{\mathcal{F}}|\rho^2) P(2\hat{\mathcal{F}}|\rho^2, N_{seg}) P(\rho^2)$ .
- This integral can be numerically evaluated as all the involved probabilities are analytically known.
- $\bullet\,$  In the strong signal regime  $\rho^2 \gg 1$  this expression simplifies to a Gaussian distribution

$$P(2\tilde{\mathcal{F}}^*|\mathcal{H}_S) = Gauss(2\tilde{\mathcal{F}}^*; \mu_S, \sigma_S)$$

# Bayes factor: Qualitative description



### Basic behavior of $\ln \mathcal{B}^*_{S/N}$

a)  $\xi_N < \xi_S \rightarrow \ln \mathcal{B}^*_{S/N} < 0$  and the signal hypothesis is disfavoured. b)  $\xi_S \sim 0 \rightarrow \ln \mathcal{B}^*_{S/N} \propto \xi_N$  and the signal hypothesis favours with SNR. c)  $\xi_S \gg 0 \rightarrow \ln \mathcal{B}^*_{S/N} \simeq -\frac{1}{2}\xi_S^2 + \xi_N$  disfavouring signal hypothesis.

rodrigo.tenorio@ligo.org (UIB)

# Bayes factor

### O2-like injection campaign

• 100 CW signals were injected into 9 months of Gaussian noise at three depth values  $\mathcal{D} = (40, 60, 80)1/\sqrt{\text{Hz}}$ .



- We apply our new follow-up method to 30 outliers from open data searches on O2 LIGO data, using the same configuration as in the injection campaign.
- O2 Searches:
  - Mid-frequency Falcon search Dergachev & Papa Phys. Rev. Lett. 125, 171101 (2020).
  - High-frequency Falcon search Dergachev & Papa Phys. Rev. D 103, 063019 (2021).
  - Directed Einstein@Home search м. А. Рара + АрJ 897 22 (2020).
  - Fomalhaut b Viterbi search D. Jones & L. Sun Phys. Rev. D 103, 023020 (2021).
  - H.E.S.S. sources Viterbi search D. Beniwal + Phys.Rev.D 103 083009 (2021).
- Falcon & E@H are wide-parameter space searches reporting outliers as parameter-space points (with uncertainty regions).
- Viterbi searches are directed towards a particular sky position and use a Hidden Markov Model to model the frequency evolution of a CW.

# Outliers in O2 LIGO data



- Safe threshold at  $\ln {\cal B}^*_{\rm S/N} = 90$  from the injection campaign.
- All but three H.E.S.S. Viterbi outliers are below threshold.
  - Outlier at  $f_0 \simeq 20 \text{ Hz}$ corresponds to a known instrumental comb.
  - Outlier at  $f_0 \simeq 26.34 \text{ Hz}$  due to a very strong hardware injection.
  - Outlier at  $f_0 \simeq 15.4~{\rm Hz}$  was manually inspected and is consistent with an instrumental artifact.
- The next two outliers, also from H.E.S.S. Viterbi, can be related to a 1 Hz comb.

< < >>

14/15

# Conclusion

- We present the first complete framework to conduct hierarchical MCMC follow-ups on outliers stemming from generic CW searches.
- The results are evaluated using a novel Bayes factor. The probability distribution of the signal hypothesis is derived from first principles; the noise hypothesis' is constructed using extreme value theory.
- The follow-up is applied to a set of 30 outliers produced by several CW searches on open O2 LIGO Data.
- Only three of the outliers end up above threshold: One of them is due to an identified instrumental artifact, another one is produced by a strong hardware injection. Manual inspection suggests an instrumental origin for the third one as well, but we could not identify the cause.
- This new tool allows for the routine use of long coherence-time follow-ups on general CW searches, vastly simplifying the setup of post-processing steps.