



Rencontres de Noirmoutier - 01/06/26



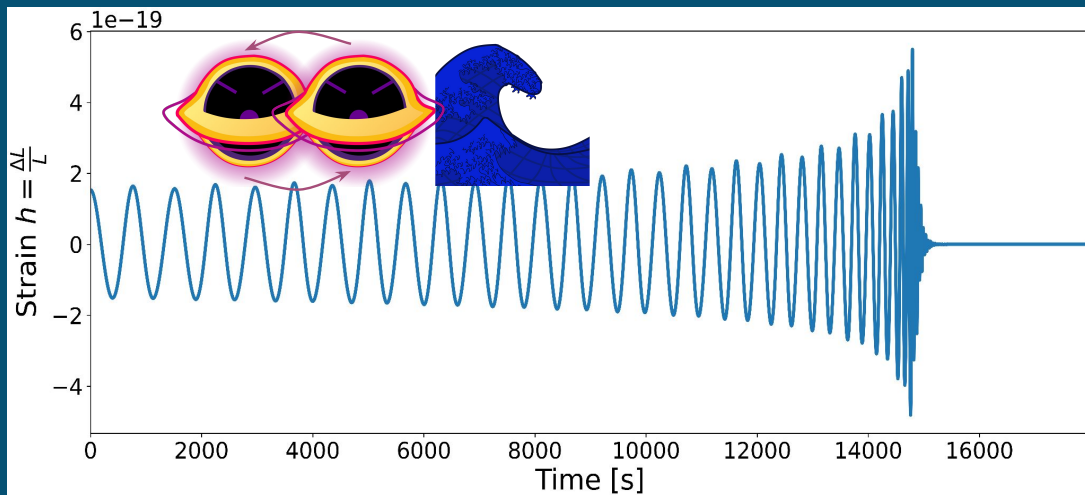
Detecting the memory effect with LISA

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Gravitational waves from MBHBs

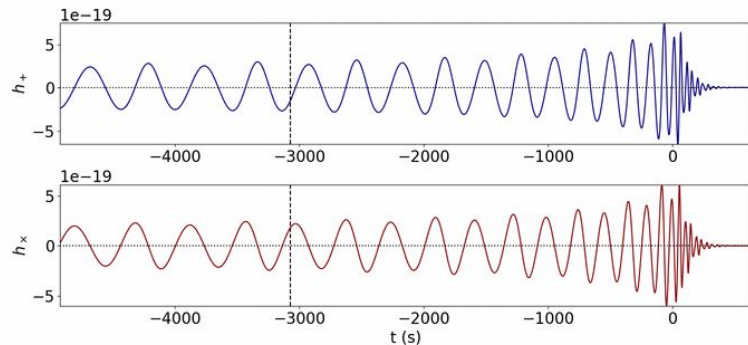
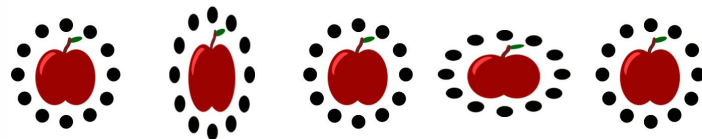
(Massive Binary Black Holes)



Real duration: 5565.0s = 92.75min = 1.55h

Time acceleration: 185.5×

Wave amplification: $10^{18.0} \times$



THE SPECTRUM OF GRAVITATIONAL WAVES

You are here



Observatories
& experiments

Ground-based
experiment



Space-based observatory



Pulsar timing array



Cosmic microwave
background polarisation



Timescales

milliseconds

seconds

hours

years

billions of years

Frequency (Hz)

100

1

10^{-2}

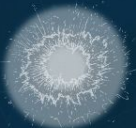
10^{-4}

10^{-6}

10^{-8}

10^{-16}

Cosmic
sources



Supernova



Pulsar



Compact object falling
onto a supermassive
black hole



Merging supermassive black holes



Merging neutron
stars in other galaxies



Merging stellar-mass black holes
in other galaxies



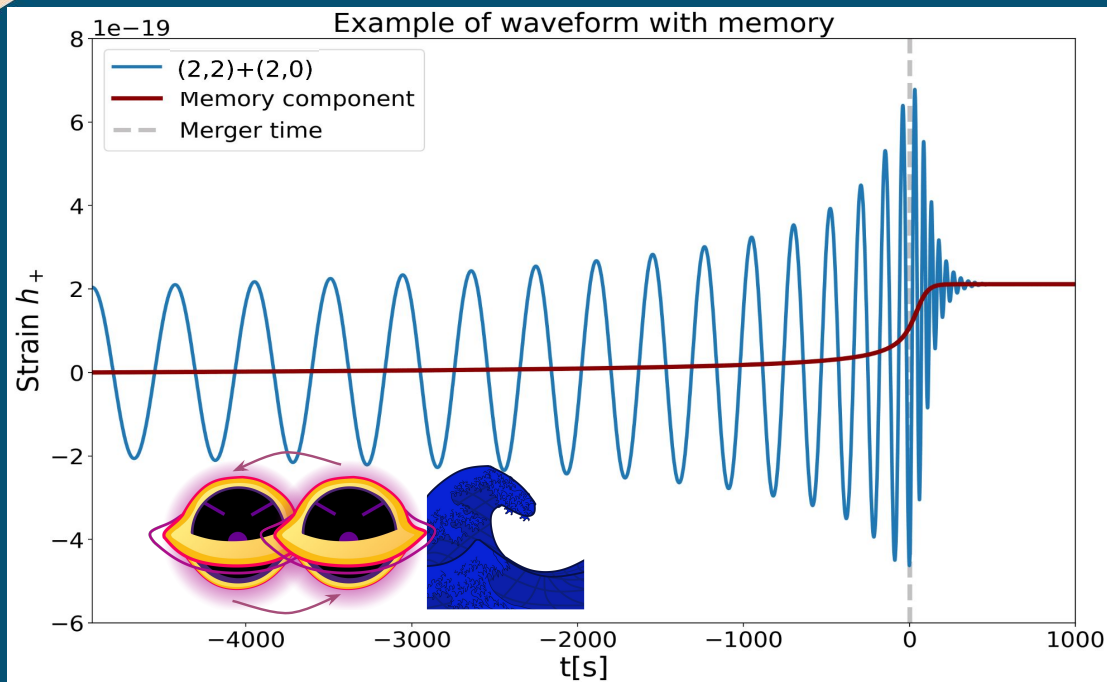
Merging white dwarfs
in our Galaxy

#lisa





What is memory effect ?



★ Permanent strain remaining after the passage of Gravitational Waves

☆ Predicted by GR

☆ Low frequency component of the GW

★ For MBHB, it looks like a sort of sigmoid step, mostly built during the merger.

★ Linked to asymptotic symmetries of General Relativity (BMS symmetries).

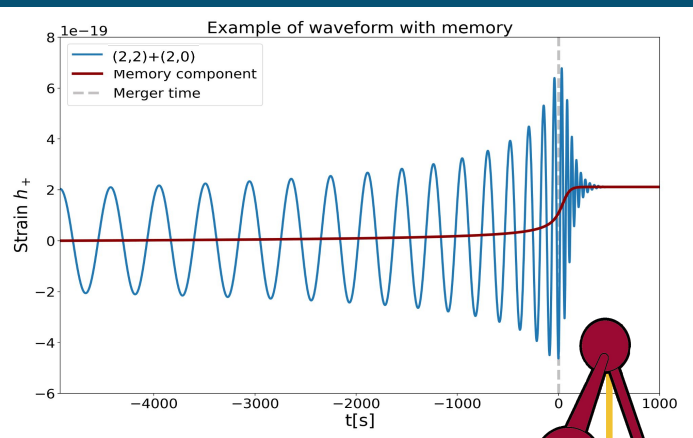
☆ Note: Parameters used:

$Q = 1.5; \chi_{1z} = \chi_{2z} = 0.7; M = 10^6 M_\odot; d_L = 10^4 \text{Mpc}; \iota = \pi/2; \psi = 0$

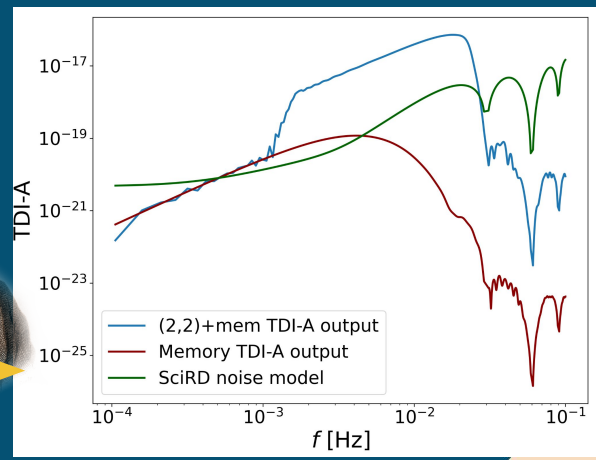
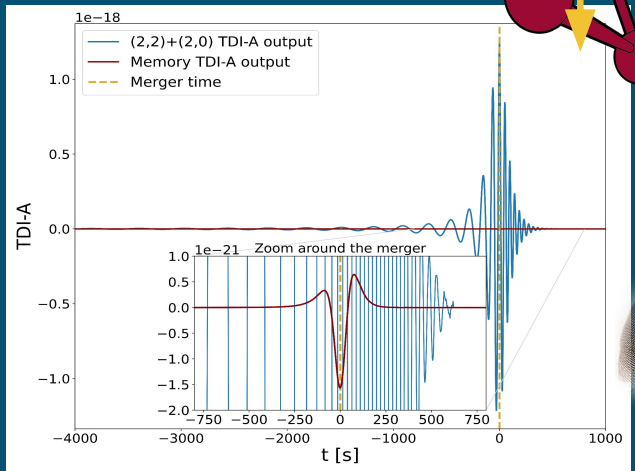
☆ Note: Here with NRHybSur3dq8_CCE, restricted to (2,2) + memory



Observing memory with LISA



LISA response
+
Time-Delay
Interferometry





Analysis choices: Waveforms and HM

Waveforms	Considered modes
<i>NRHybSur3dq8_CCE</i>	(2,2)
<i>NRHybSur3dq8_CCE</i>	(2,2) + HM: (2,1), (3,3), (3,2), (4,4), (4,3)
<i>SEOBNRv5HM</i>	(2,2) + HM: (2,1), (3,3), (3,2), (4,4), (4,3)

★ Time-domain waveforms for spin-aligned binaries.

★ Memory is **mainly contained in the (2,0)-mode** , and **mainly sourced by the (2,2)-mode** of the waveform.

☆ up to ~10% improvement with Higher Modes

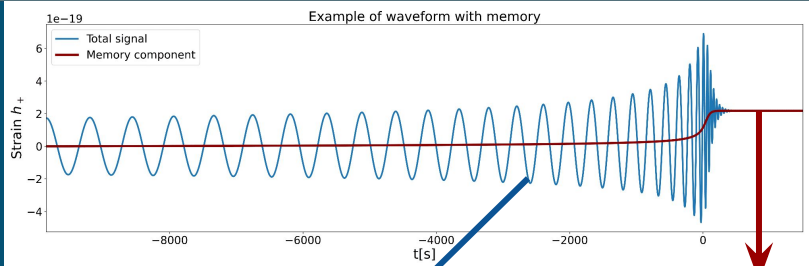
+ associated memory component:

$$h_{20}^{(\text{mem})}(t) = \int_{-\infty}^t dt' \left[\frac{1}{7} \sqrt{\frac{5}{6\pi}} |\dot{h}_{22}|^2 - \frac{1}{14} \sqrt{\frac{5}{6\pi}} |\dot{h}_{21}|^2 + \frac{5}{4\sqrt{42\pi}} \left(\dot{h}_{22} \dot{h}_{32}^* + \dot{h}_{22}^* \dot{h}_{32} \right) + \frac{1}{2\sqrt{10\pi}} \left(\dot{h}_{33} \dot{h}_{43}^* + \dot{h}_{33}^* \dot{h}_{43} \right) - \frac{2}{11} \sqrt{\frac{2}{15\pi}} |\dot{h}_{44}|^2 \right]$$

See Zosso et al. [[arXiv:2601.23019](https://arxiv.org/abs/2601.23019) / DOI: [10.1103/51xv-zlfy](https://doi.org/10.1103/51xv-zlfy)]



Signal-to-noise ratio hints



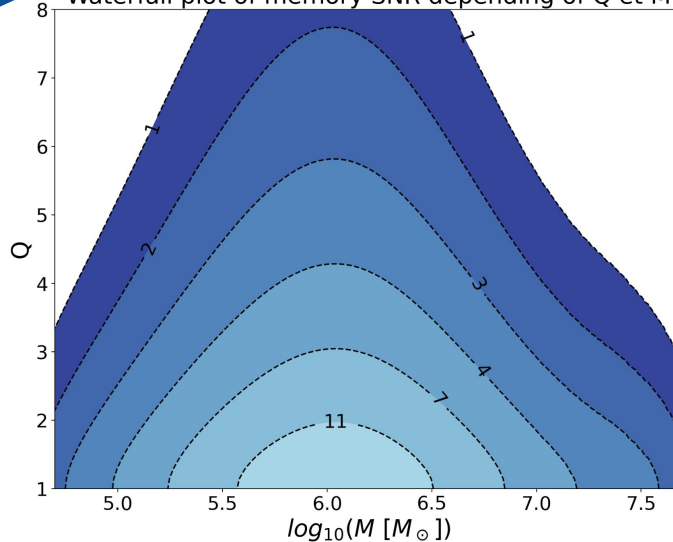
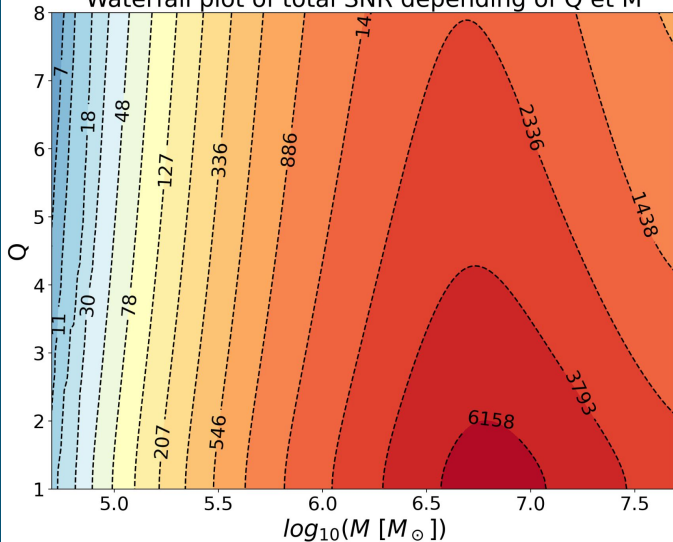
See Inchauspé et al. (2025)
DOI: 10.1103/PhysRevD.111.044044

SNR_{tot}

SNR_{mem}

Waterfall plot of total SNR depending of Q et M

Waterfall plot of memory SNR depending of Q et M



Encouraging results but
it assumes that we can
perfectly disentangle
memory from the
oscillatory signal.

Q mass ratio,
 $Q = m_1/m_2 > 1$

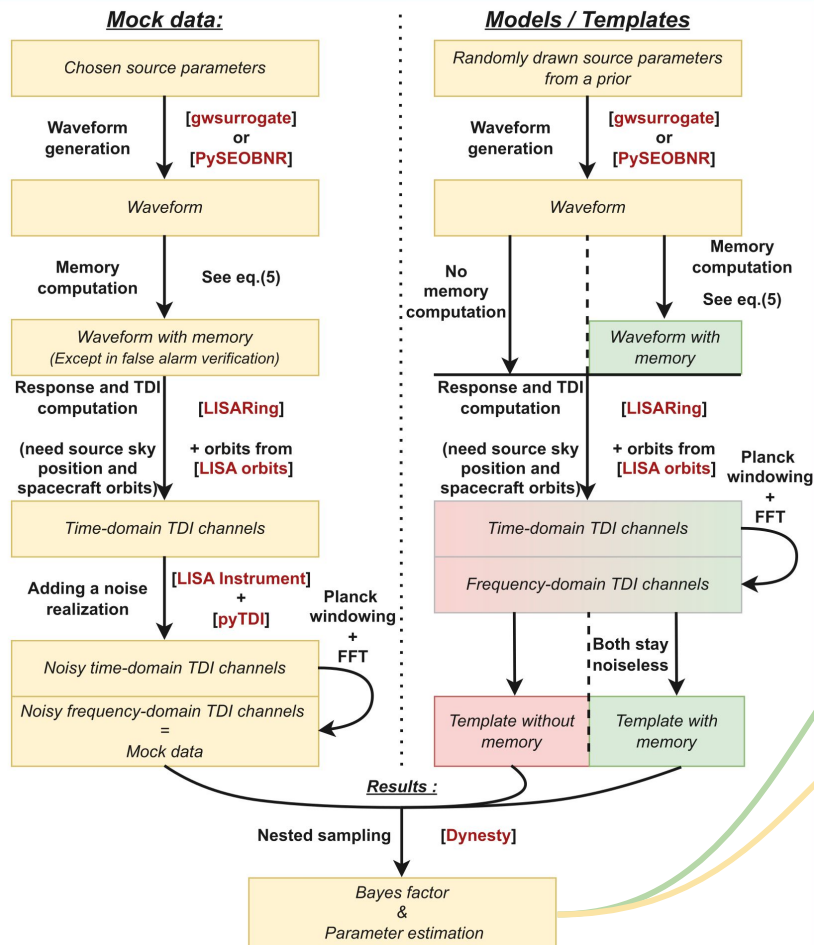
M total mass,
in detector-frame

$d_L = 10^4$ Mpc
inclination $\iota = \pi/3$
spins $\chi = 0.4$

☆ Note: Here with NRHybSur3dq8_CCE,
restricted to (2,2) + memory



Bayesian Analysis



(See Yves Lemière's talk on Friday)

Posterior distributions

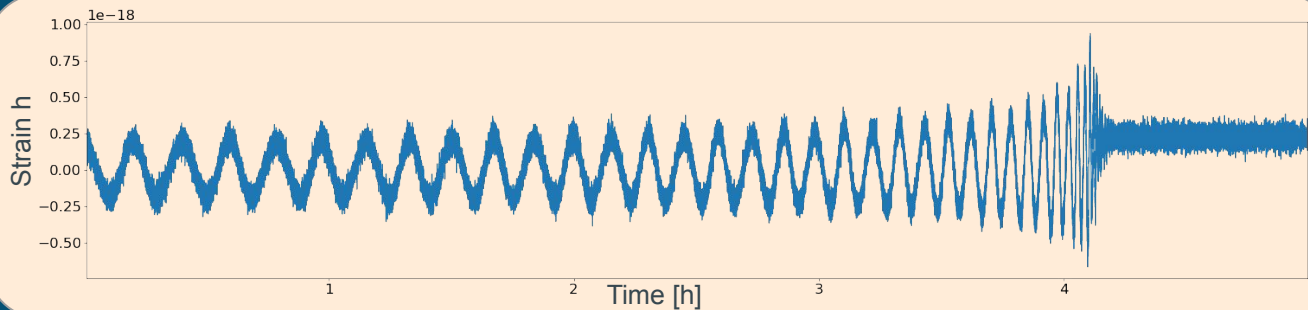
$$\log_{10} \mathcal{B} = \log_{10} \mathcal{Z}_{o+m} - \log_{10} \mathcal{Z}_o$$

☆ Note: o = oscillatory
m = memory



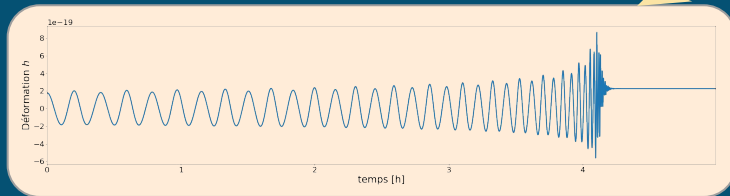
Bayesian Analysis

Noisy data

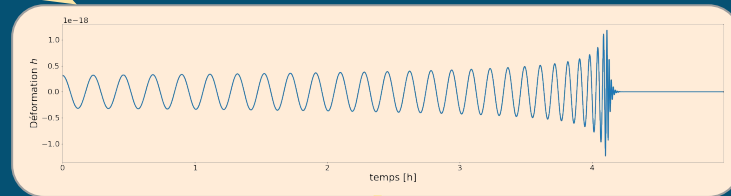


(For illustration only,
in practice we work in
Frequency Domain)

Template with memory



Template without memory



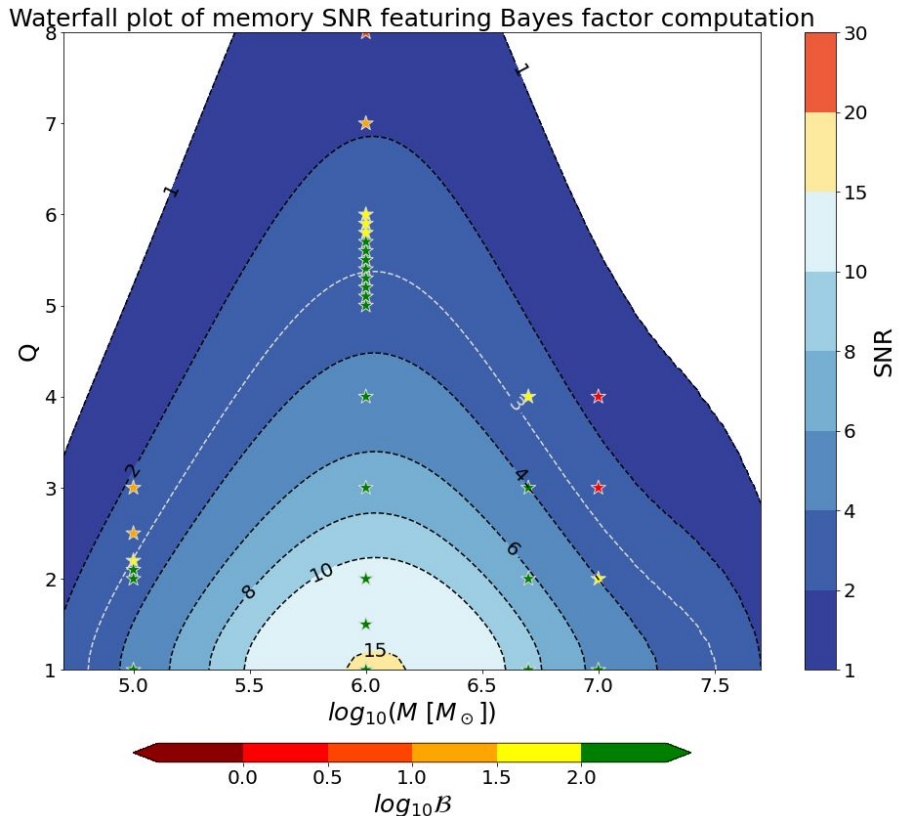
$$\log_{10} \mathcal{Z}_{o+m}$$

$$\log_{10} \mathcal{Z}_o$$

$$\log_{10} \mathcal{B} = \log_{10} \mathcal{Z}_{o+m} - \log_{10} \mathcal{Z}_o$$



Bayesian detectability criterion



★ Need Bayes factor to evaluate model preference.

$$\log_{10}\mathcal{B} = \log_{10}\mathcal{Z}_{oscill+mem} - \log_{10}\mathcal{Z}_{oscill}$$

★ On top of the previous memory map, we add some results of the Bayesian analysis (→ stars).

★ **Memory is detected when $\log_{10}\mathcal{B} > 2$ (=green stars)**, using the threshold value from Jeffrey's scale.

Bayes factor	[1,3]	[3,10]	[10,32]	[32,100]	[100, +∞[
log ₁₀ Bayes factor	[0, ½]	[½, 1]	[1, 3/2]	[3/2, 2]	[2, +∞[
Interpretation	Barely worth mentioning	Substantial	Strong	Very strong	Decisive





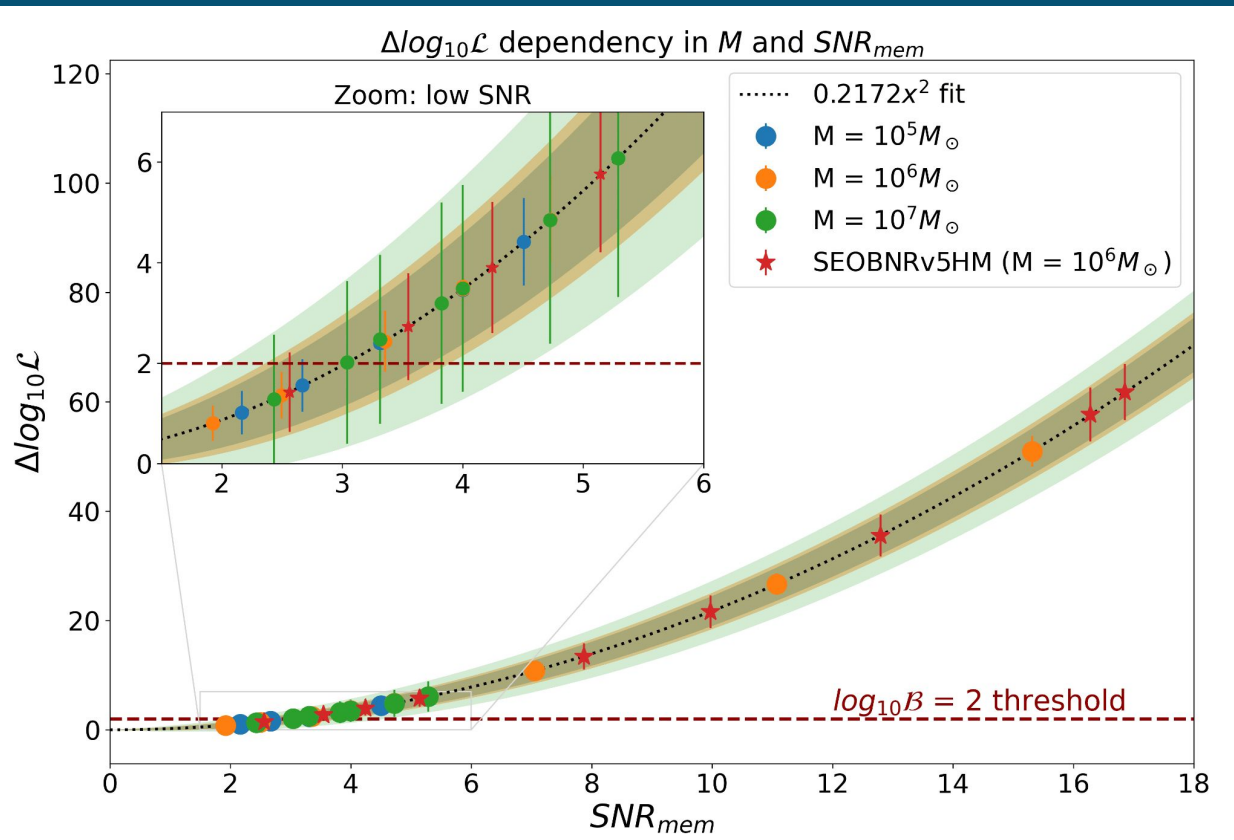
Using SNR_{mem} as a proxy

★ Power law relation between the (mean) Bayes factor value and the SNR of memory, SNR_{mem} .

★ Noise dispersion also depends on the total mass (= the frequencies where memory lies)

★ Favourable to detection for events with $\text{SNR}_{\text{mem}} \geq 3$

★ Expected detection for every event with $\text{SNR}_{\text{mem}} \geq 5$!

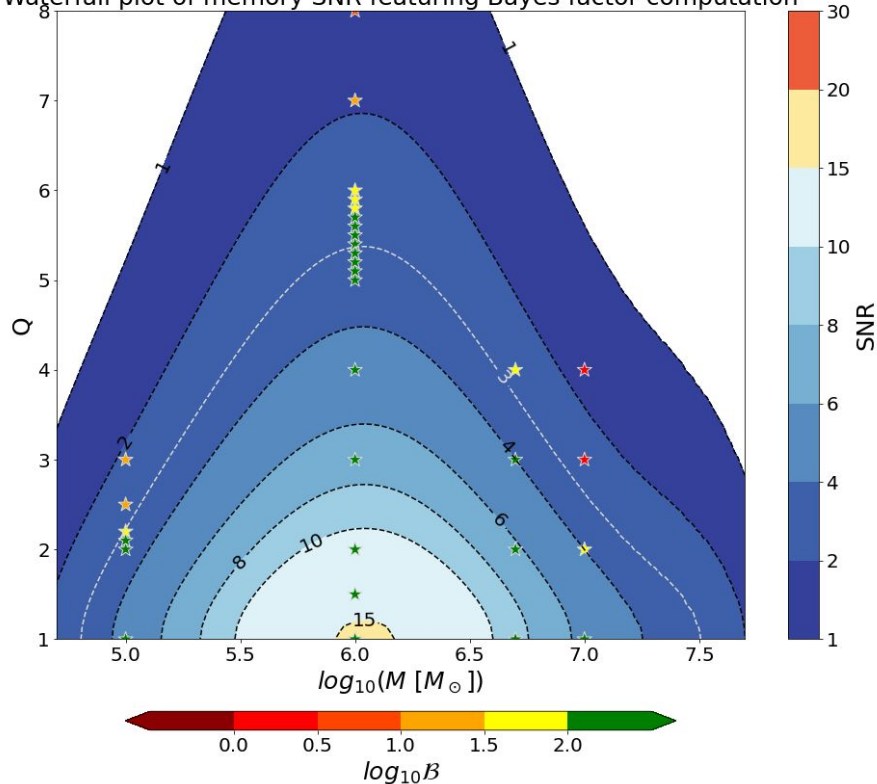


★ Note: Done with NRHybSur3dq8_CCE, restricted to (2,2) + memory, validated with SEOBNRv5HM

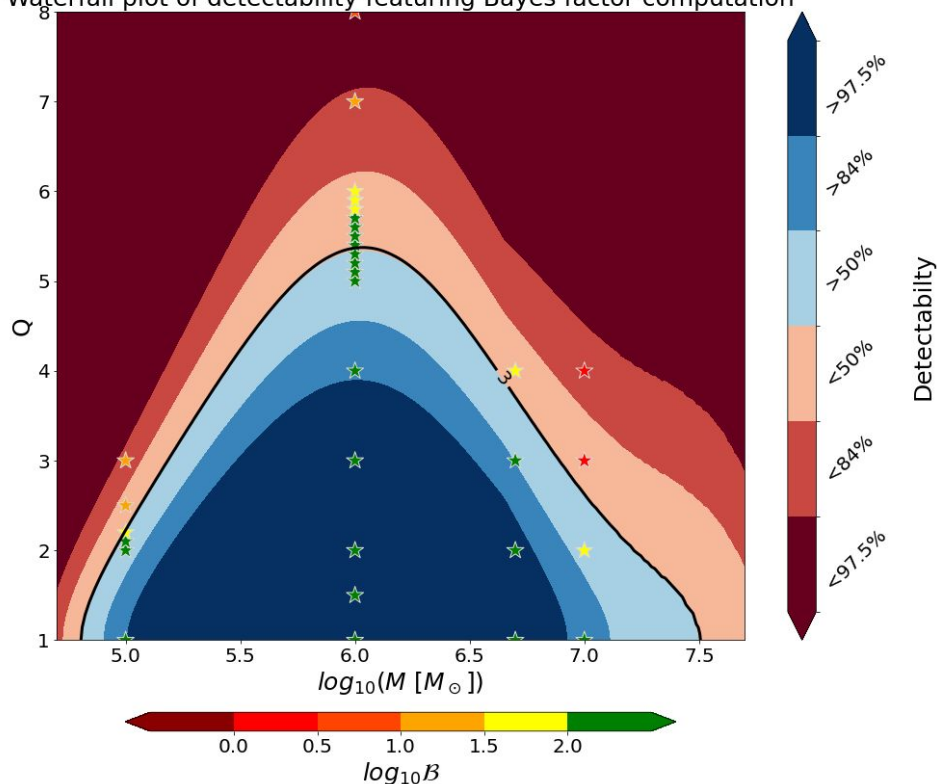


Detectability map

Waterfall plot of memory SNR featuring Bayes factor computation

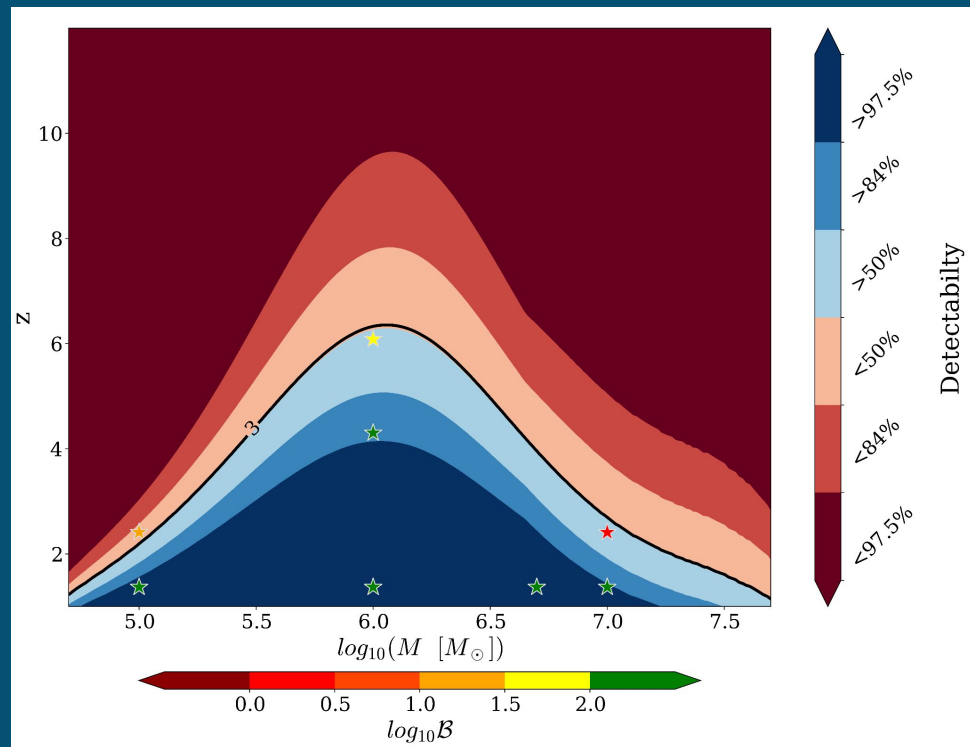
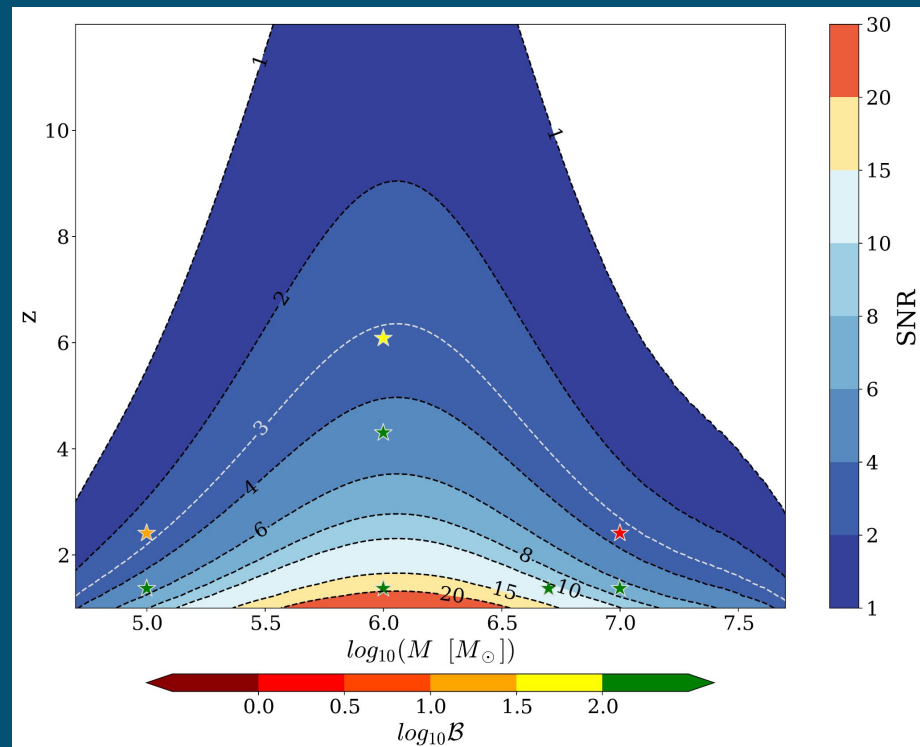


Waterfall plot of detectability featuring Bayes factor computation





Redshift waterfall plots





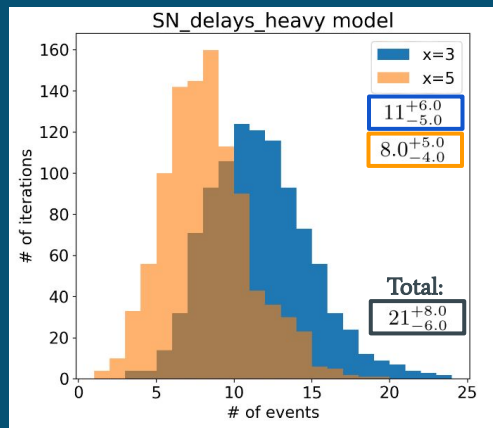
Forecast using population models

Thanks to E. Barausse for the population models.
See Barausse et al. (2020) DOI: [10.3847/1538-4357/abba7f](https://doi.org/10.3847/1538-4357/abba7f)

★ We used 8 different population models, combining 3 different properties.

Supernovae feedback	Delay between host galaxies merger and MBHB merger	Black hole seeding
Yes {SN} // No {noSN}	Short delays {short} // Intermediate delays {delays}	Light seed {light} // Heavy seed {heavy}

★ Method and example:



☆ Compute SNRs for 1000 universe realizations of 4 years of data



☆ Count how many of them see x events

$$\begin{matrix} 11^{+6.0} \\ -5.0 \end{matrix}$$

Nb of memory event:
 $\text{SNR}_{\text{mem}} \geq 3$ (resp. 5)

$$\begin{matrix} 8.0^{+5.0} \\ -4.0 \end{matrix}$$

$$\begin{matrix} 21^{+8.0} \\ -6.0 \end{matrix}$$

Nb of total events:
 $\text{SNR}_{\text{tot}} \geq 8$

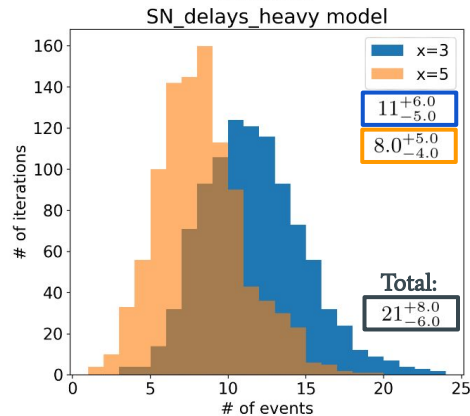
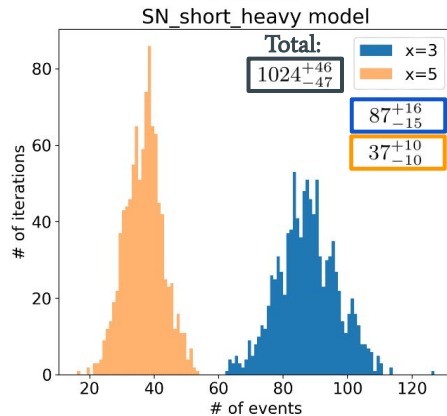
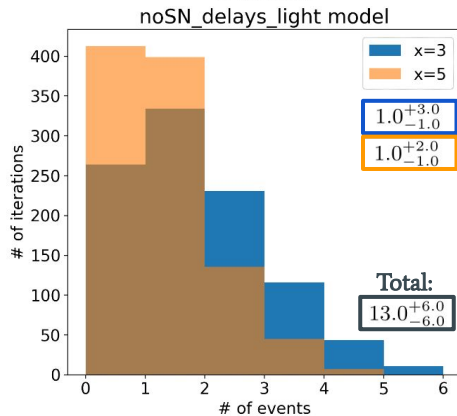
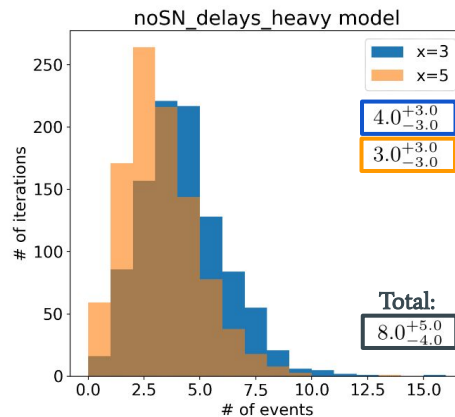
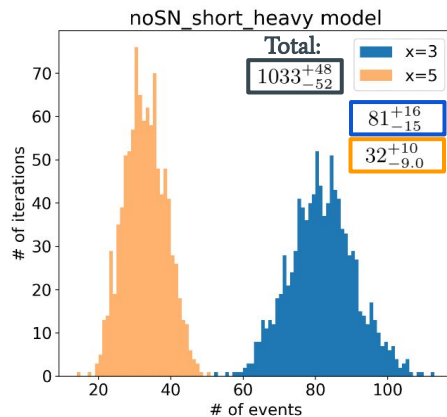
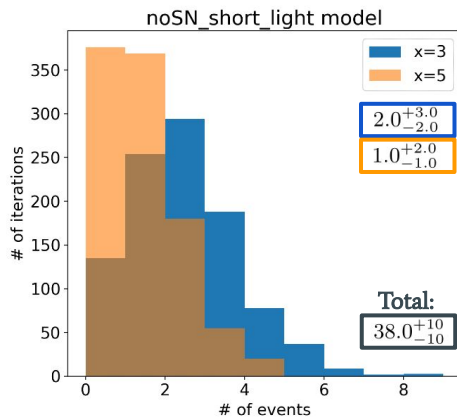


Forecast using population models

- ★ 6 out of the 8 different models present detectable memory event.
- ☆ In particular, **heavy seed models** are really favourable to memory detection.

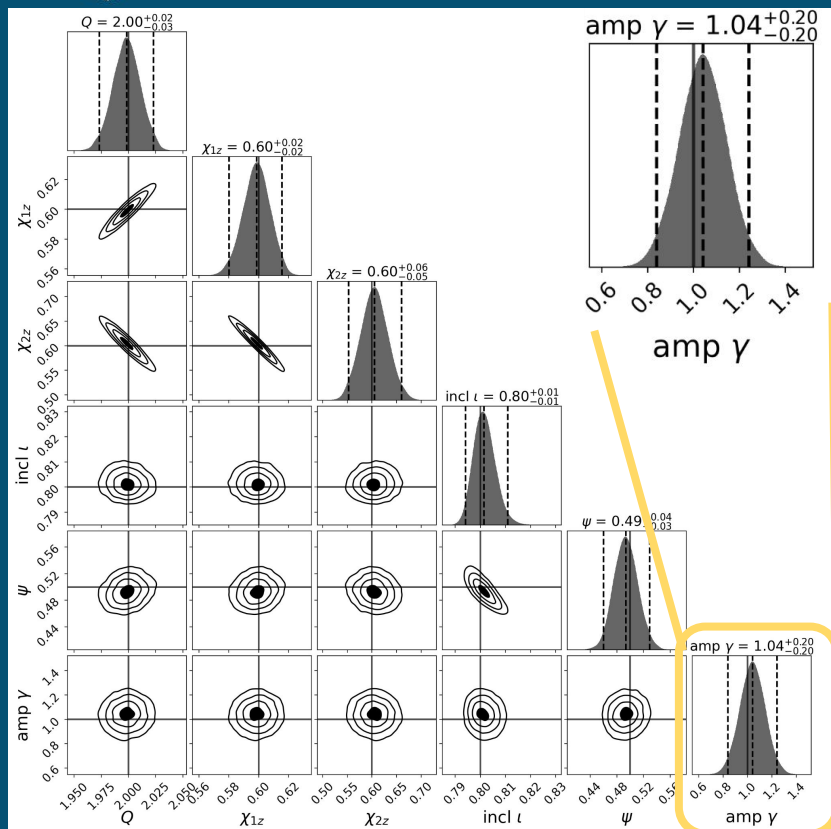
☆ 4 years realization s

☆ Total =
Nb of
sources
with
 $\text{SNR}_{\text{tot}} > 8$





Probing GR through memory



- ★ Possibility to define a free parameter to describe the amplitude of the memory. Here we define γ as:

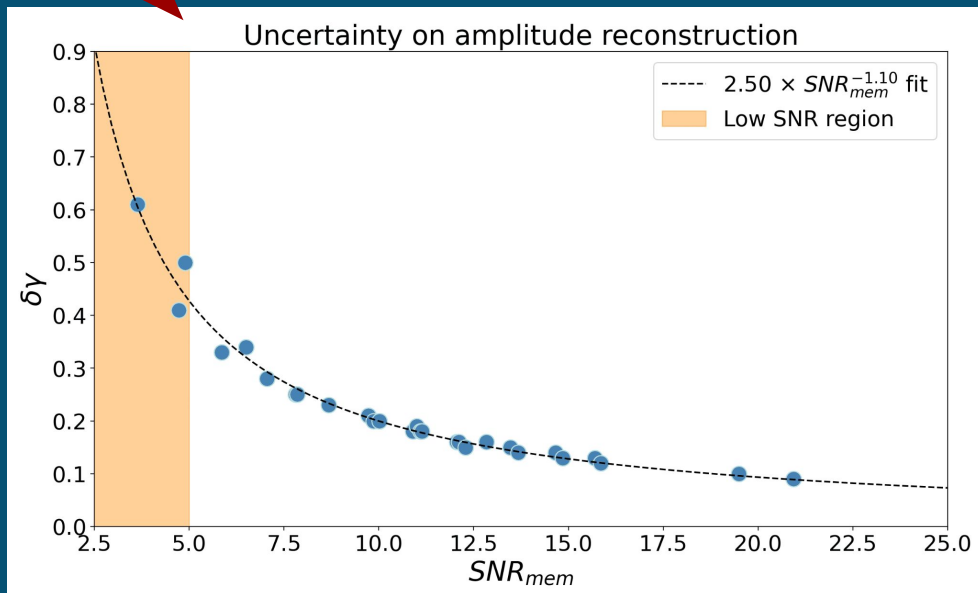
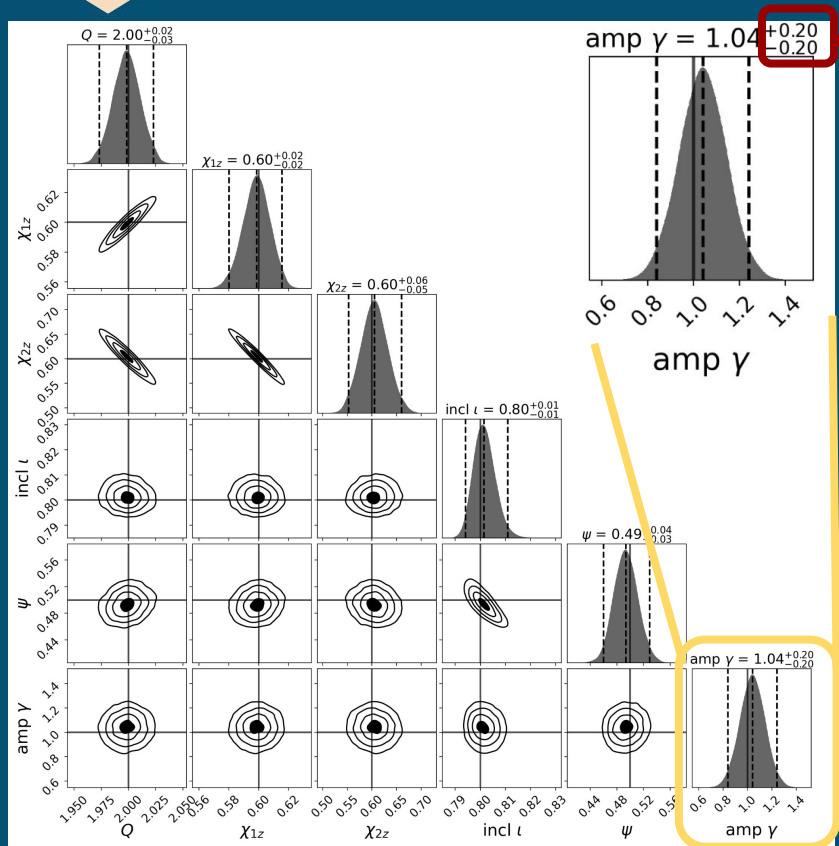
$$h_{mem}(t) = \gamma \times h_{mem}^{GR}(t)$$



Probing GR through memory

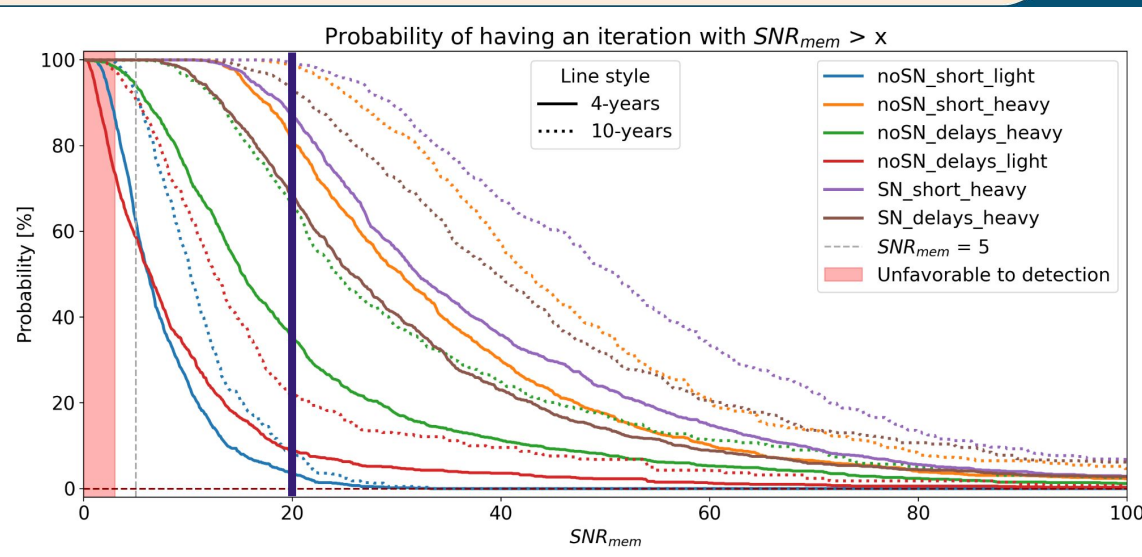
★ We can also monitor the uncertainty $\delta\gamma$ on the reconstructed γ . As a result, $\delta\gamma$ only depend on SNR_{mem} following:

$$\delta\gamma = 2.5 \times \text{SNR}_{\text{mem}}^{-1.1}$$



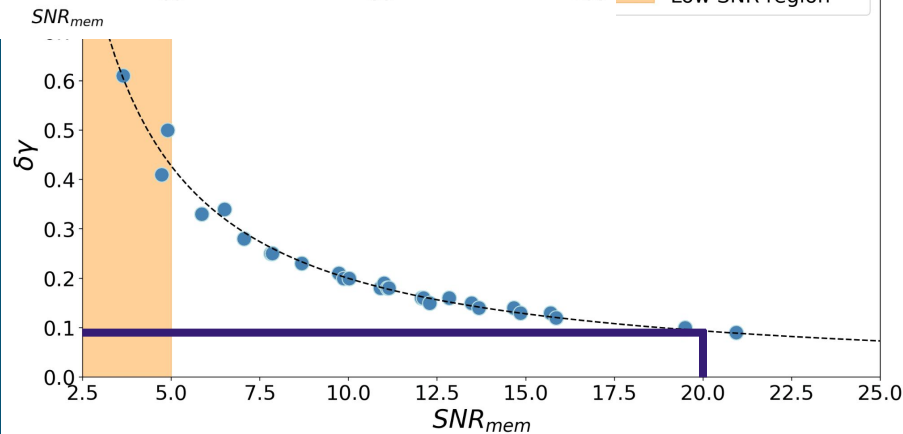


Probing GR through memory



Instruction

- $2.50 \times SNR_{mem}^{-1.10}$ fit
- Low SNR region



★ $SNR_{mem} = 20 \Rightarrow \approx 10\%$
constraint on amplitude



Take home message & Prospects

- ★ LISA will be able to identify the memory for a significant region of the parameter space.
- ★ Population models predicts MBHBs within the favourable region. The number of expected events will depend on the specific model but at least one event is very likely.
- ★ Observing memory is already a test of GR, but first attempts to characterize the shape of the memory signal offers promising perspectives.



- ☆ Taking into account precessing MBHB and the memory contribution in every mode.
- ☆ Build a toy-model for memory that allow to test the shape of the memory.



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Thanks for your attention !

Any question ? :)

And if you want more details: [[arXiv:2601.23230](#) / DOI: [10.1103/b9ld-dqq4](#)]
Companion theory paper [[arXiv:2601.23019](#) / DOI: [10.1103/51xv-zlfy](#)]



Forecast using population models

SN	Delays	Seeds	Nb of events detected	Nb of events with $SNR_{mem} > 3$	Nb of events with $SNR_{mem} > 5$	Nb of events to reach $\log_{10} B^{cumul} > 2$
Yes	Short delays	Light	$0.0^{+0.0}_{-0.0}$	$0.0^{+0.0}_{-0.0}$	$0.0^{+0.0}_{-0.0}$	N\A
		Heavy	1024^{+46}_{-47}	87^{+16}_{-15}	37^{+10}_{-10}	$7.0^{+0.7}_{-0.6}$
	Delays	Light	$0.0^{+0.0}_{-0.0}$	$0.0^{+0.0}_{-0.0}$	$0.0^{+0.0}_{-0.0}$	N\A
		Heavy	$21^{+8.0}_{-6.0}$	$11^{+6.0}_{-5.0}$	$8.0^{+5.0}_{-4.0}$	$1.7^{+0.7}_{-0.4}$
No	Short delays	Light	38.0^{+10}_{-10}	$2.0^{+3.0}_{-2.0}$	$1.0^{+2.0}_{-1.0}$	$10.8^{+8.7}_{-4.5}$
		Heavy	1033^{+48}_{-52}	81^{+16}_{-15}	$32^{+10}_{-9.0}$	$7.3^{+0.8}_{-0.7}$
	Delays	Light	$13.0^{+6.0}_{-6.0}$	$1.0^{+3.0}_{-1.0}$	$1.0^{+2.0}_{-1.0}$	$5.2^{+4.6}_{-2.2}$
		Heavy	$8.0^{+5.0}_{-4.0}$	$4.0^{+3.0}_{-3.0}$	$3.0^{+3.0}_{-3.0}$	$1.8^{+1.4}_{-0.6}$

★ Even if we don't observe an event alone, observing $\mathcal{O}(10)$ mergers should be enough to statistically assess the presence of memory.

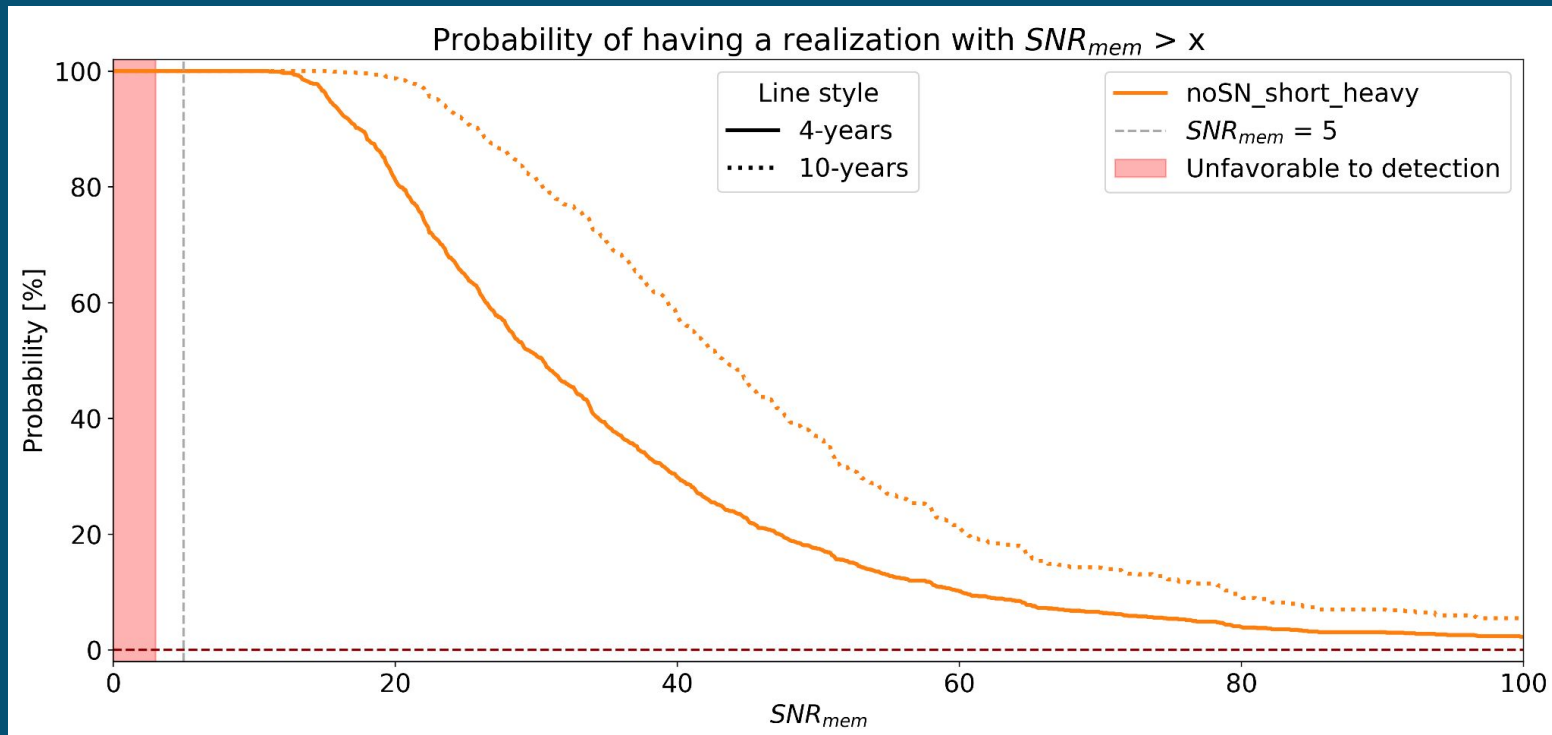
☆ For LVK, it's $\mathcal{O}(2000)$ events*.

* See Cheung et al. (2024)
DOI: [10.1088/1361-6382/ad3ffe](https://doi.org/10.1088/1361-6382/ad3ffe)



Possibility of loud memory events

★ We can expect loud memory event, especially under the heavy seed hypothesis

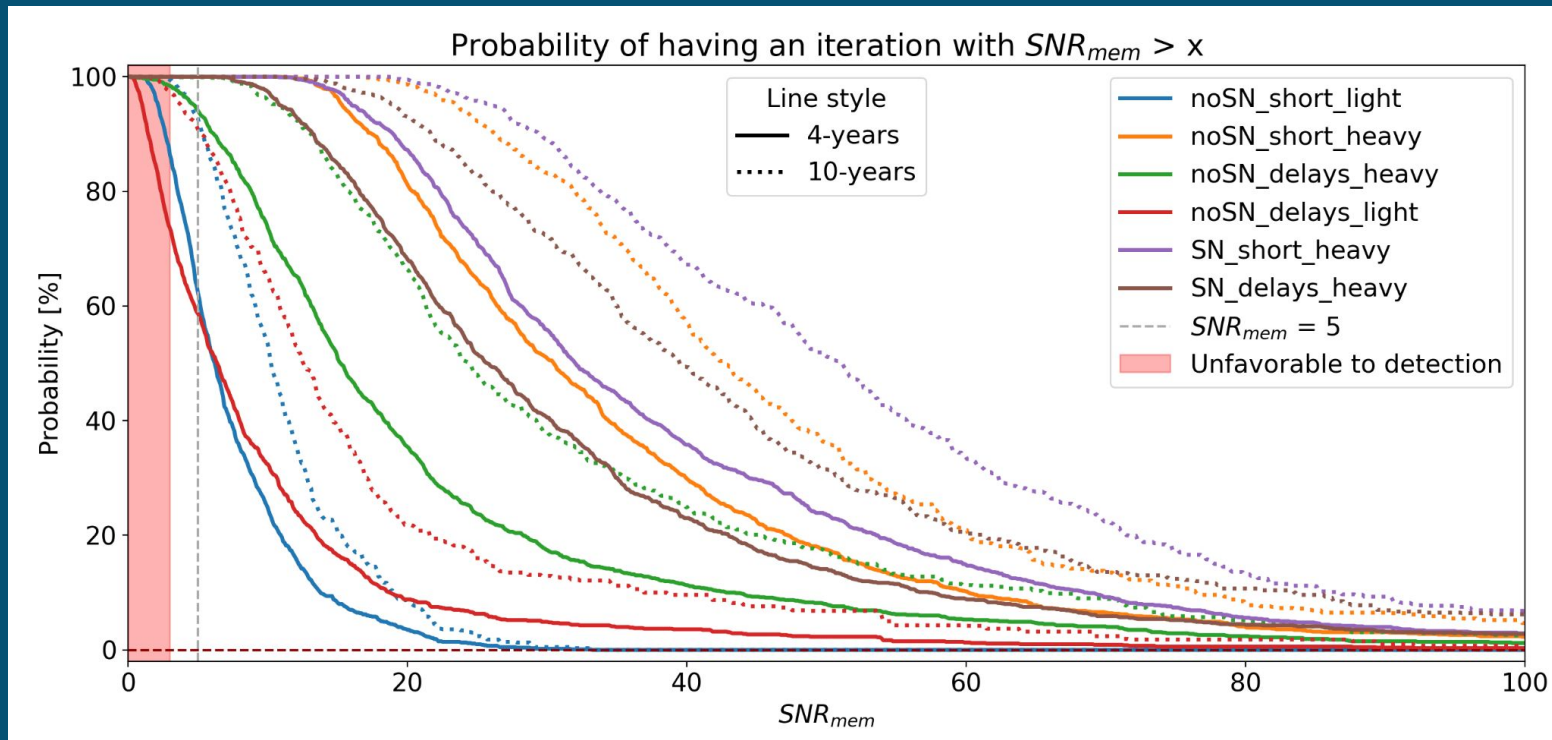


☆ Note: Probability estimated using 1000 realizations for each model



Possibility of loud memory events

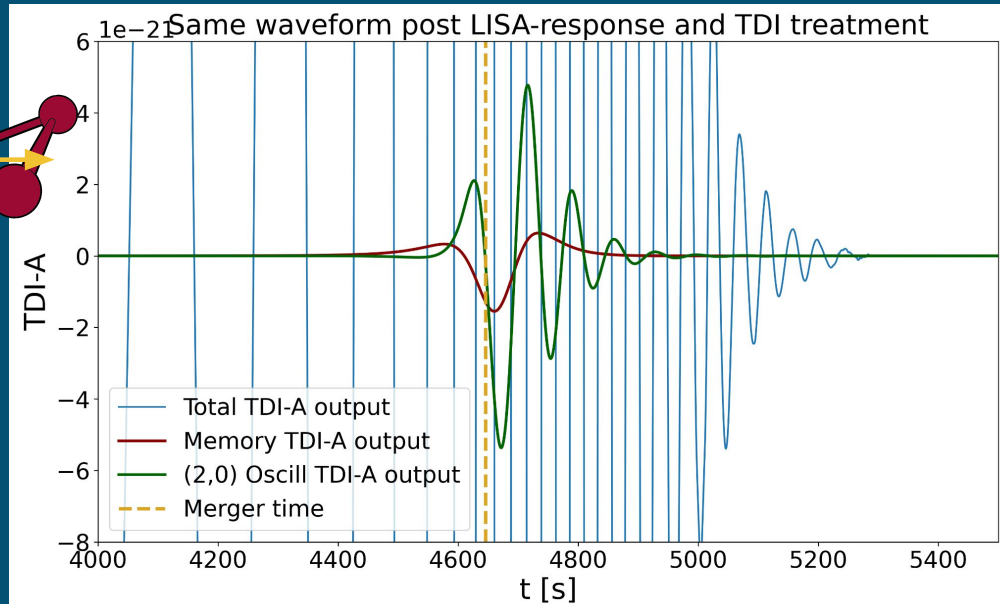
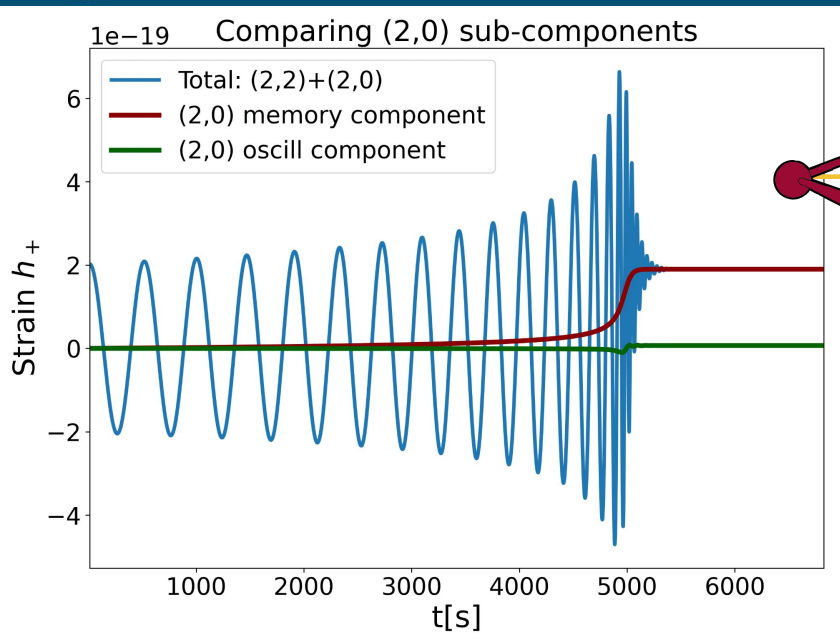
★ We can expect loud memory event, especially under the heavy seed hypothesis



☆ Note: Probability estimated using 1000 realizations for each model



Analysis choices: Native memory

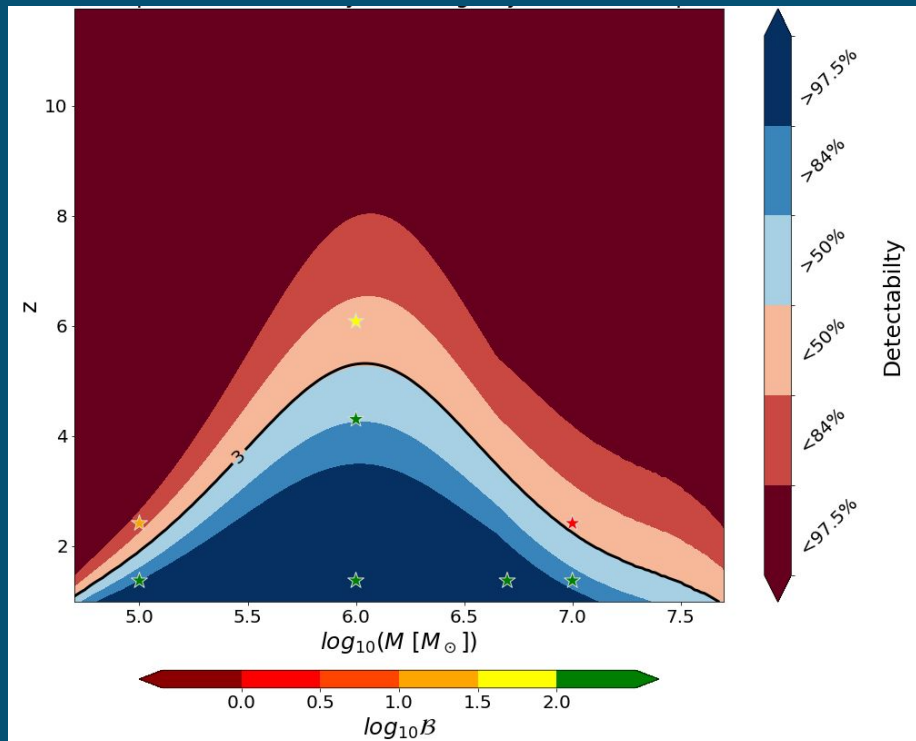


★ Post-response and TDI, (2,0) oscillatory component is far less damped than memory and therefore should really not be neglected.

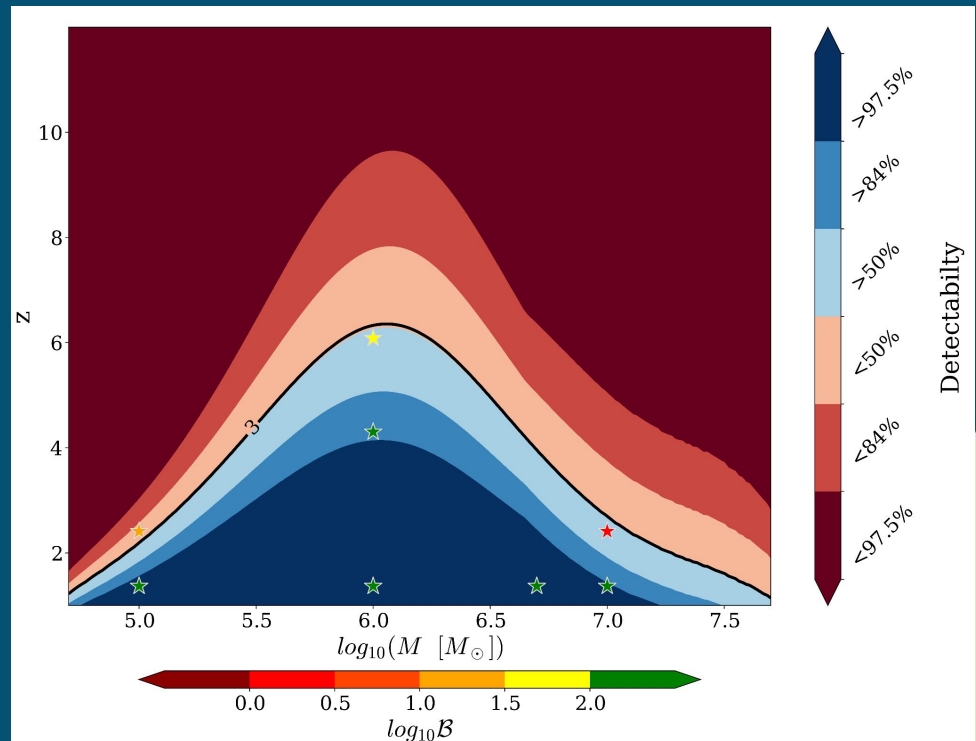


Redshift waterfall plots

☆ Without HM



☆ With HM



☆ Note: Done with NRHybSur3dq8_CCE

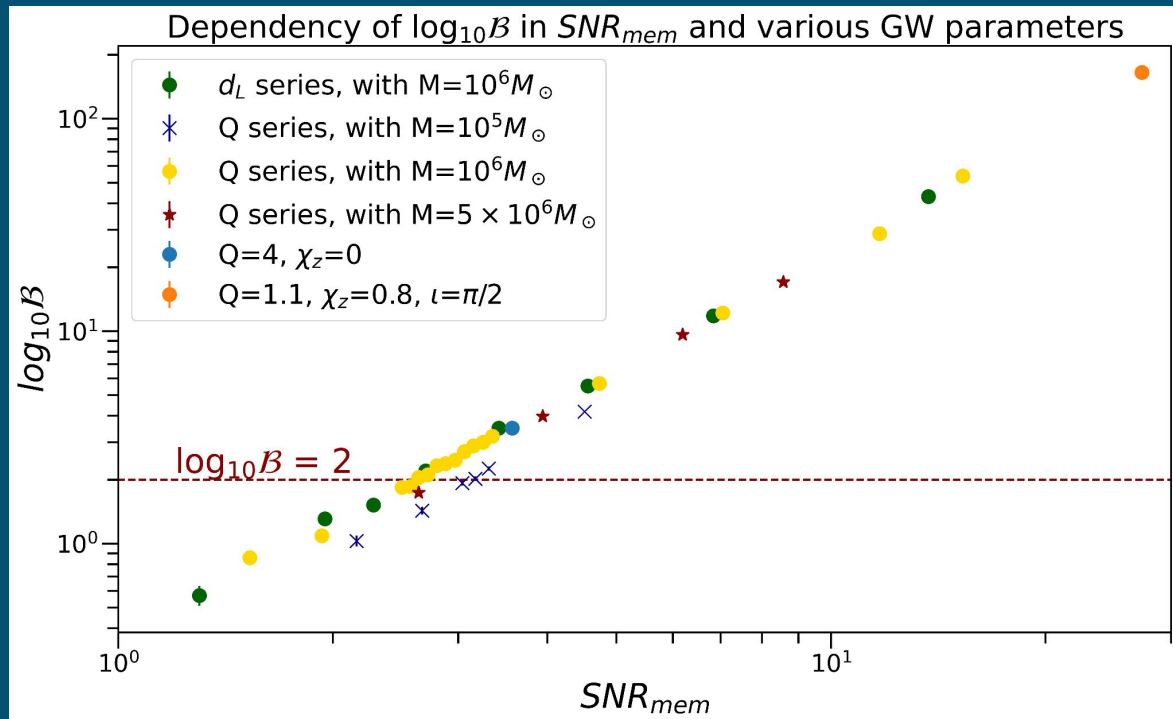


Using SNR_{mem} as a proxy

★ We observed a power law relation between the Bayes factor value and the SNR of memory, SNR_{mem} .

★ For the usual case of MBHB in LISA, we have bright sources ($SNR_{tot} > 100$), this implies that the likelihood function is highly peaked and so the evidence –the integration of the likelihood over parameter space– is dominated by the injected source parameters θ_{source} .
Allowing this approximation:

$$\log_{10} \mathcal{B} = \Delta \log_{10} \mathcal{Z} \approx \Delta \log_{10} \mathcal{L}(\theta_{source})$$



☆ Note: Done with NRHybSur3dq8_CCE, restricted to (2,2) + memory



Loglikelihood approximation

