Extracting the properties of compact binary coalescences with phenomenological waveform models

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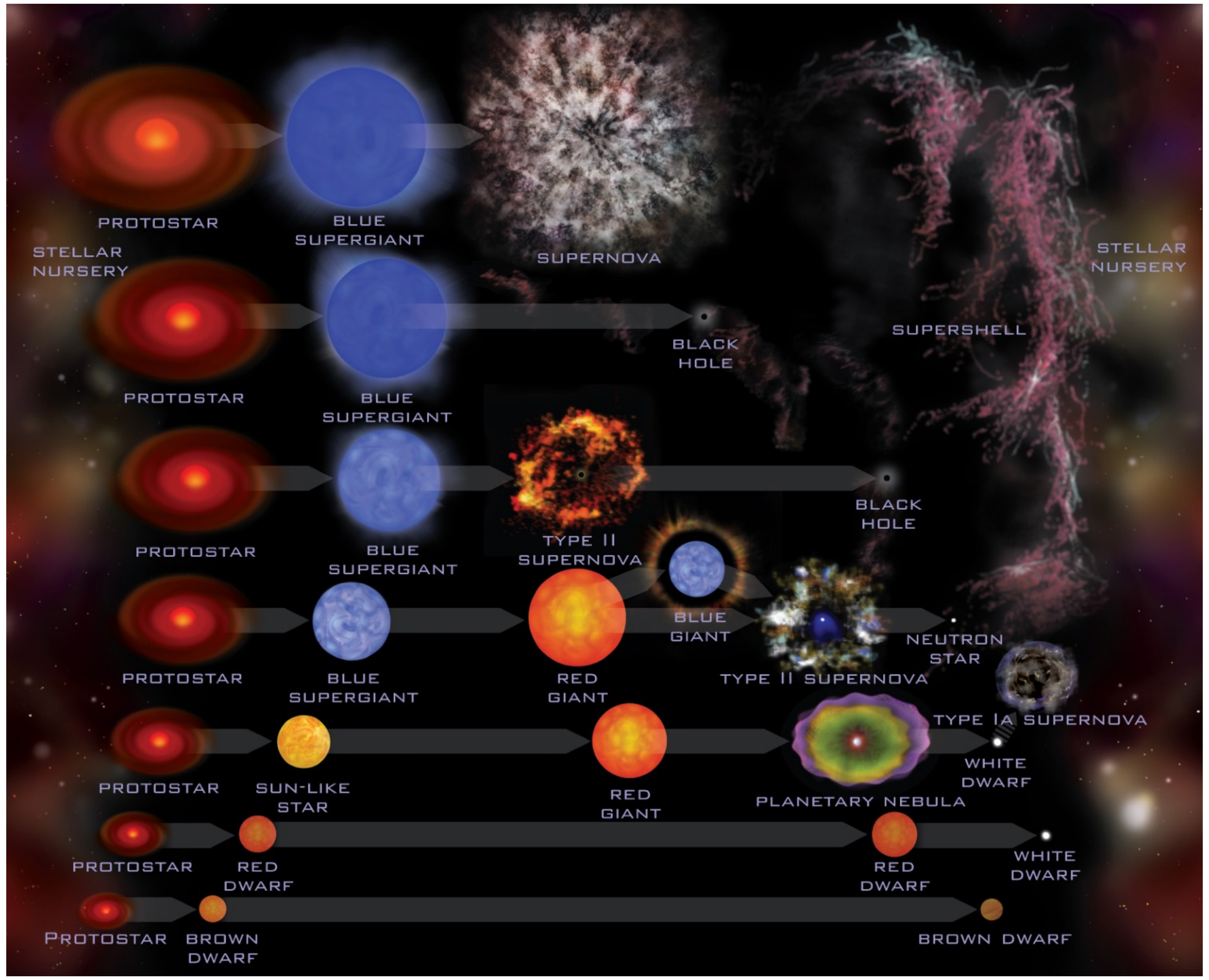
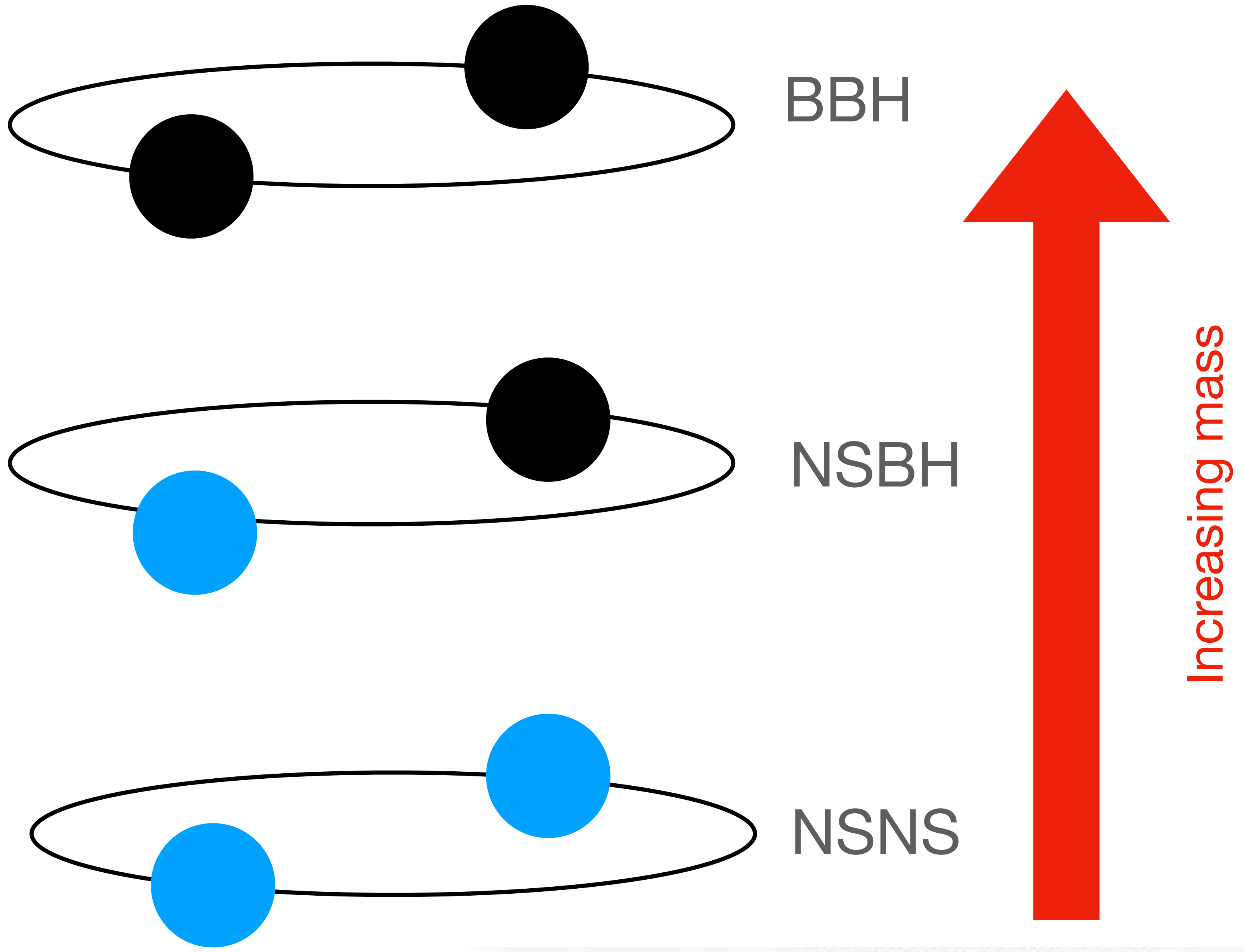
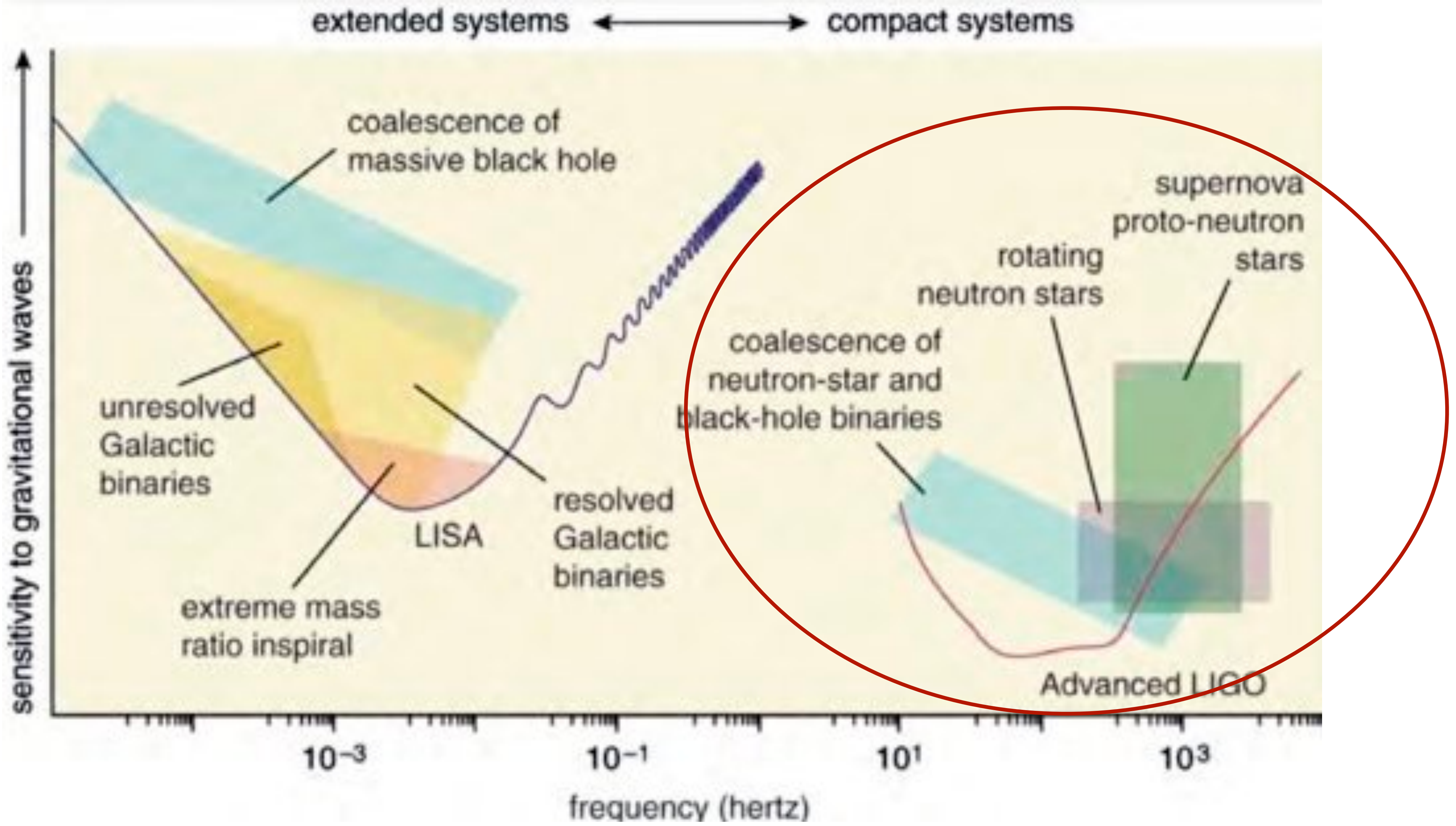
JURES 22, Caceres, Spain

Compact binaries within the reach of current ground-based detectors



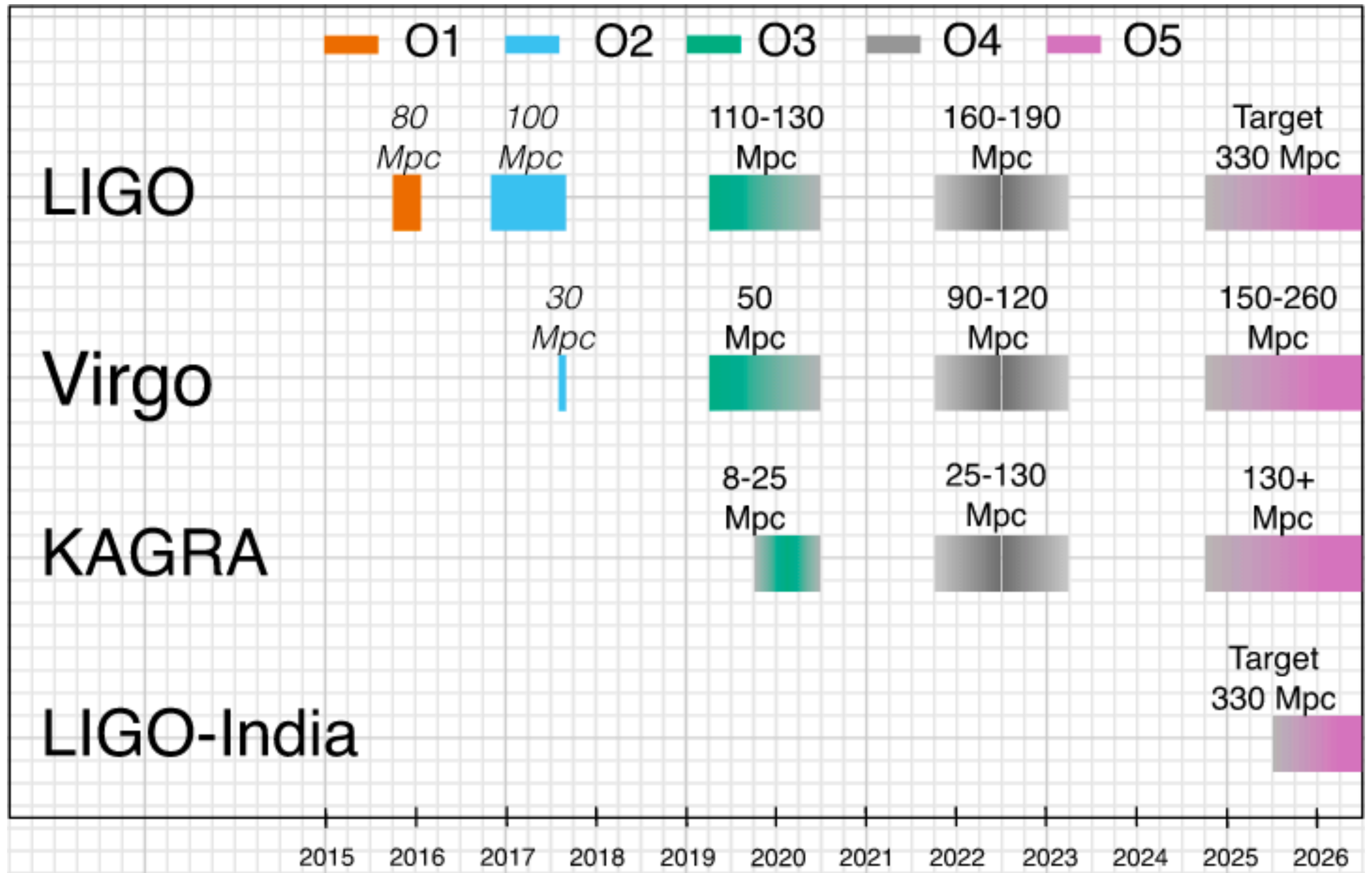
Credit: NASA

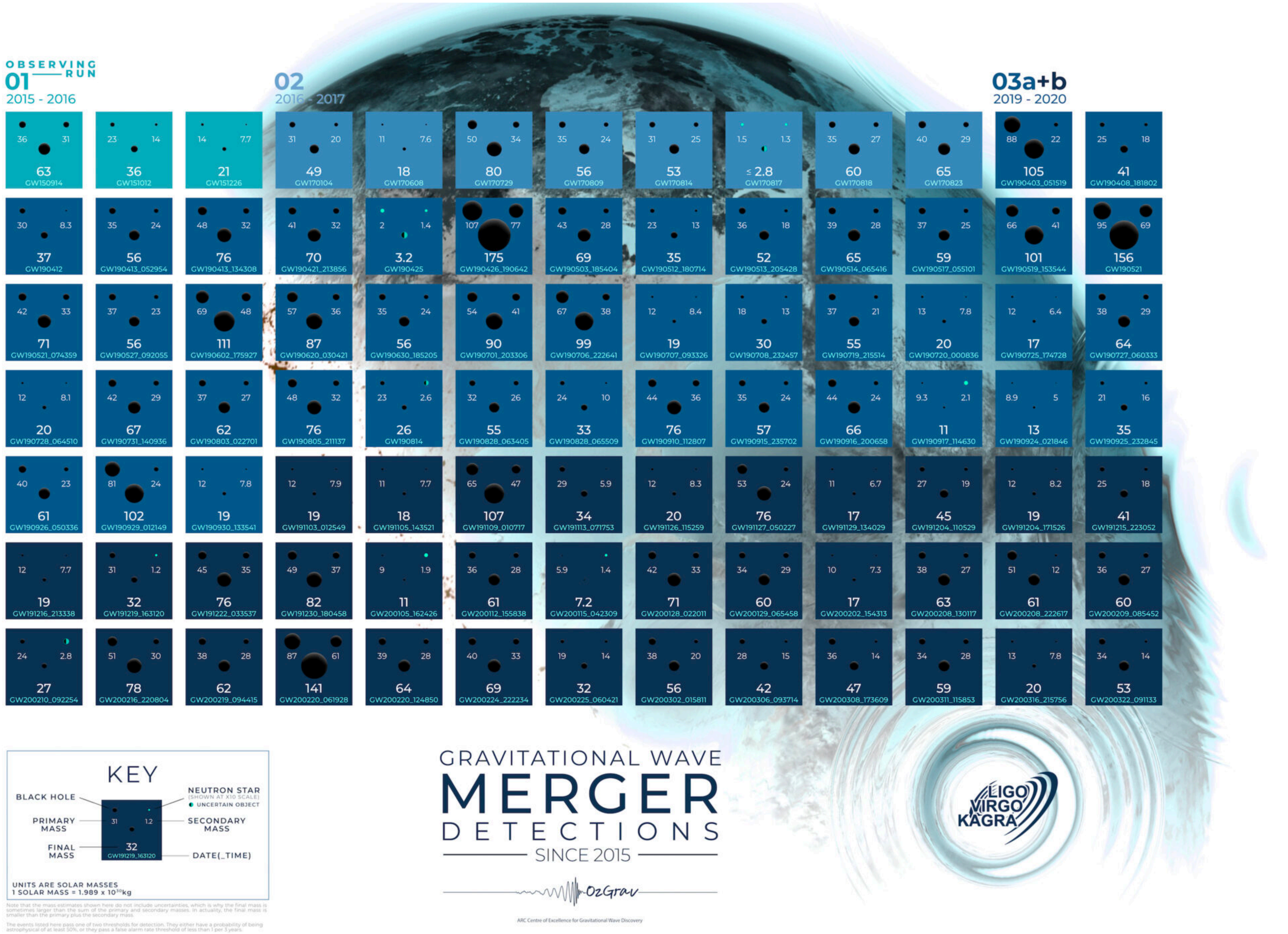




Credit: LISA

The story so far





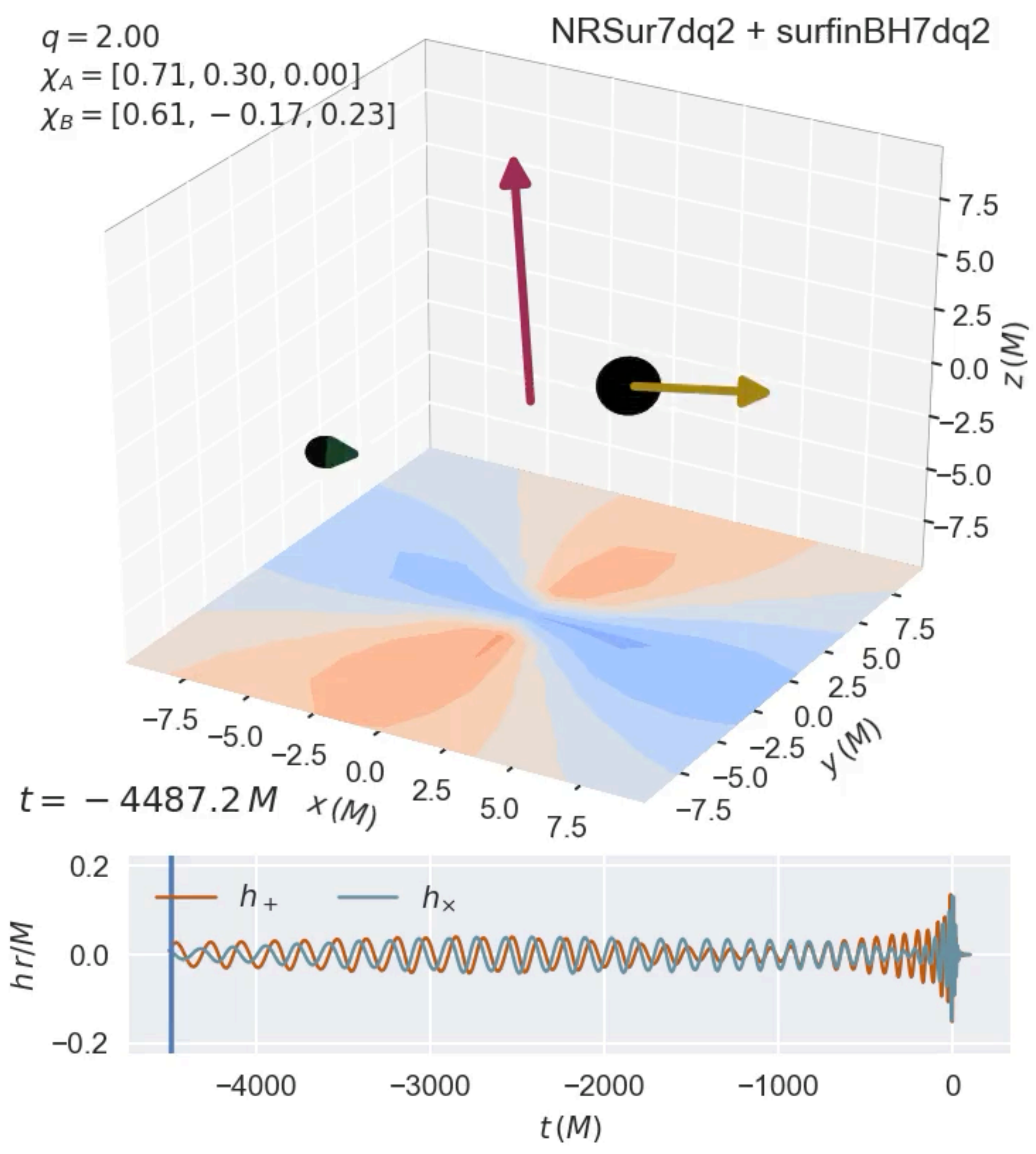
A large parameter space

“Who” “What” “When” “Where”

- 15 parameters to fully describe a generic black-hole binary

  - **Who** and **What: masses** and **spin vectors**
  - **When: coalescence time**
  - **Where:** the **sky location** (right ascension, declination, luminosity distance), but also the **inclination of the orbital plane**, the **coalescence phase** and **polarisation angle** of the signal

- If there are neutron stars in the pair, we have to add in their **tidal deformabilities**

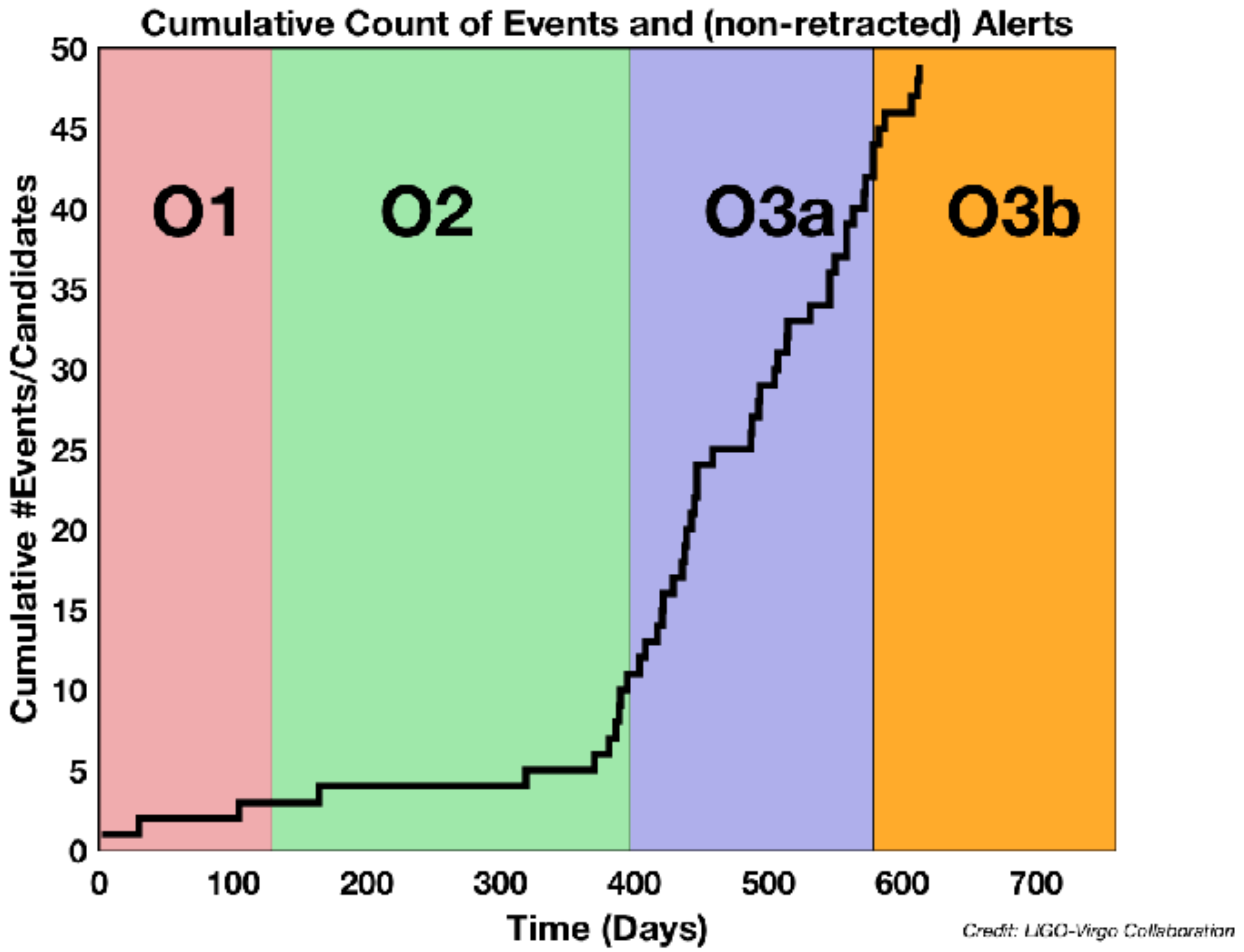


Credit: binaryBHexp, Varma et al., arXiv:1811.06552

Extracting the properties of the source

“Who” “What” “When” “Where”

- Detectors are being constantly improved: more sensitive instruments yield more detections
- Two ingredients:
  - Accurate and fast models: we "match" them to the signals
  - Reliable and computationally efficient parameter estimation codes



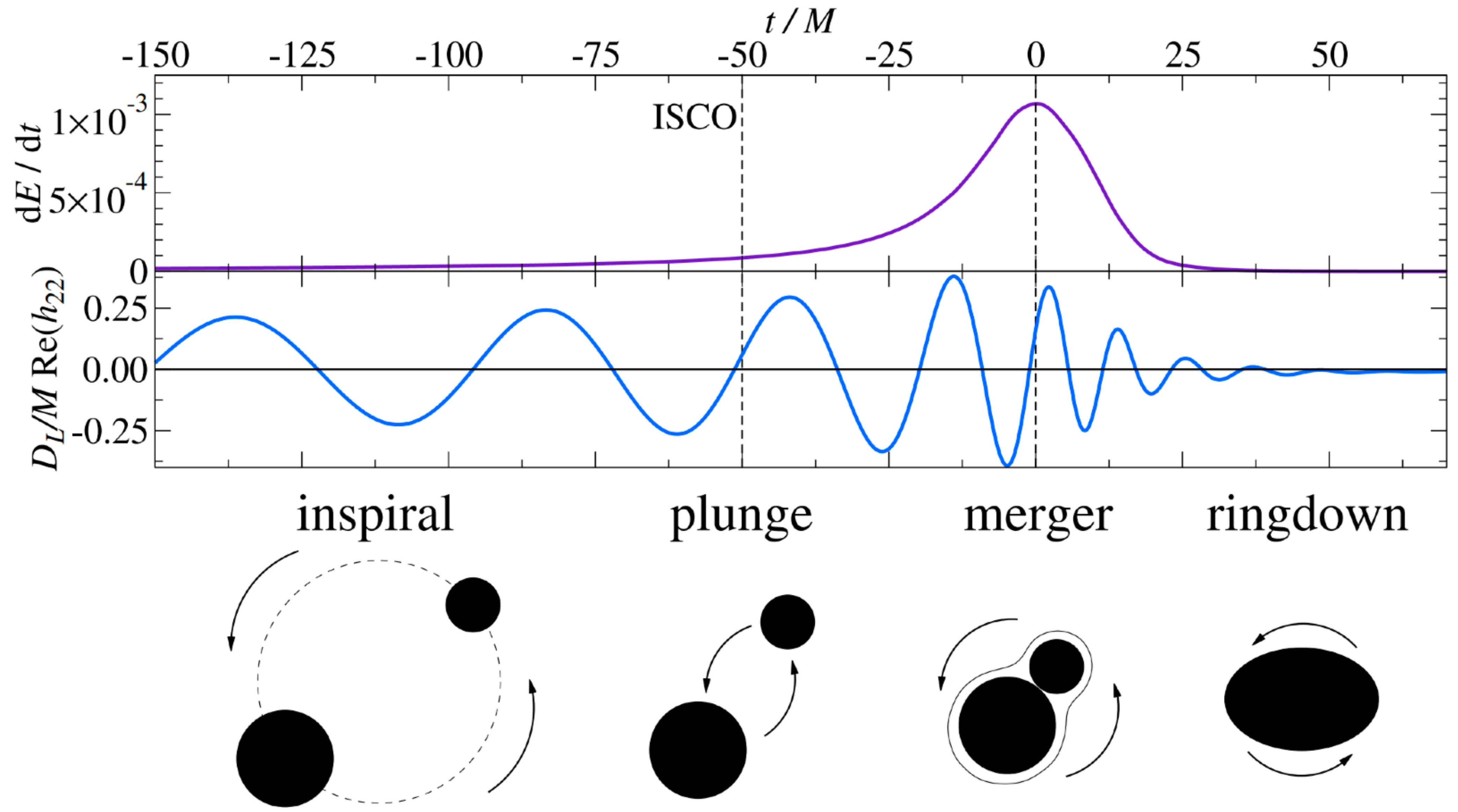
I will focus on "phenomenological" models

Phenomenological waveform models

For people in a hurry

Credit: A. Taracchini, PhD thesis

- Numerical Relativity (NR) simulations are expensive!
- Find simple analytical descriptions to model the **amplitude** and **phase** of the signal
- Several iterations over the years. UIB team delivered the latest version IMRPhenomX* (Pratten+ arXiv:2001.11412, Garcia-Quirós+ arXiv:2001.10914, Pratten+ arXiv:2004.06503)



Post-Newtonian Numerical Relativity Perturbation theory

Parameter estimation: some tools for gravitational-wave inference

- We estimate the properties of the source within a Bayesian framework and calculate their posterior distributions

- Codes we used in our works (many more exist!)

  - `LALinference` (Veitch+ arXiv:1409.7215), C code

  - `BILBY` (serial, Ashton+ arXiv:1811.02042, Romero-Shaw+ arXiv:2006.00714, Ashton+ arXiv:2106.08730) & `pBILBY` (parallelised nested sampling, Smith+ arXiv:1909.11873), `python`

- Stochastic samplers:

  - Markov Chain Monte Carlo (MCMC)

  - Nested sampling (Skilling, Bayesian Anal. 1(4): 833-859, 2006)

Need cross-checks between codes/ samplers

Our experience

The use of HPC resources + `pBILBY` was a good combination to meet the tight deadlines of collaboration projects

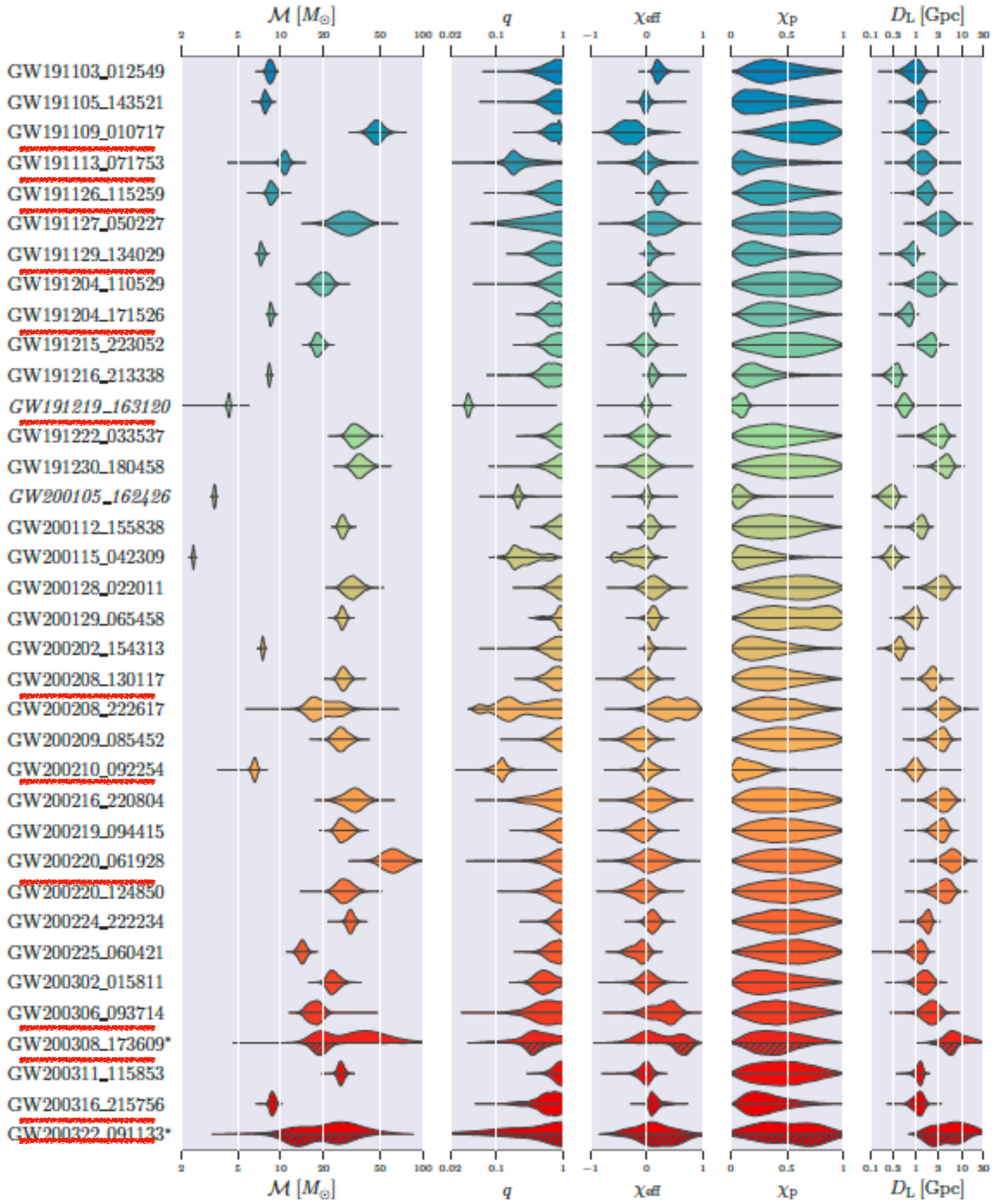
What drives cost up?

- Increasingly **complex waveform models** are more computationally expensive.
- Some signals have a **higher number of observable cycles**.
- A single waveform might take from ms to s. We work within a Bayesian framework: we typically needs **millions of likelihood evaluations.** The cost quickly escalates. Without further optimisations, some models might take weeks/months to complete a single analysis!
- Challenges
  - Large parameter space
  - Correlation among some parameters
  - Multimodalities

RES projects

- Activities we performed thanks to RES allocations
  - Parameter estimation
  - Numerical Relativity simulations
  - Injection studies and waveform systematics

Parameter estimation



Some of our contributions

- In O3, the Gravity group @UIB was in charge of the final parameter estimation runs for several events presented in the latest catalog "GWTC-3"
- MareNostrum was acknowledged as one of the key computational resources

> The authors gratefully acknowledge the support of the NSF, STFC, INFN and CNRS for provision of computational resources. Computing was performed on the OzSTAR Australian national facility at Swinburne University of Technology, which receives funding in part from the Astronomy National Collaborative Research Infrastructure Strategy (NCRIS) allocation provided by the Australian Government. We thankfully acknowledge the computer resources at MareNostrum and the technical support provided by Barcelona Supercomputing Center (RES-AECT-2021-2-0021).

- The CPU time of a single analysis ranged from a few thousands to ~600K CPU hrs

LVK Collaboration, arXiv:2111.03606

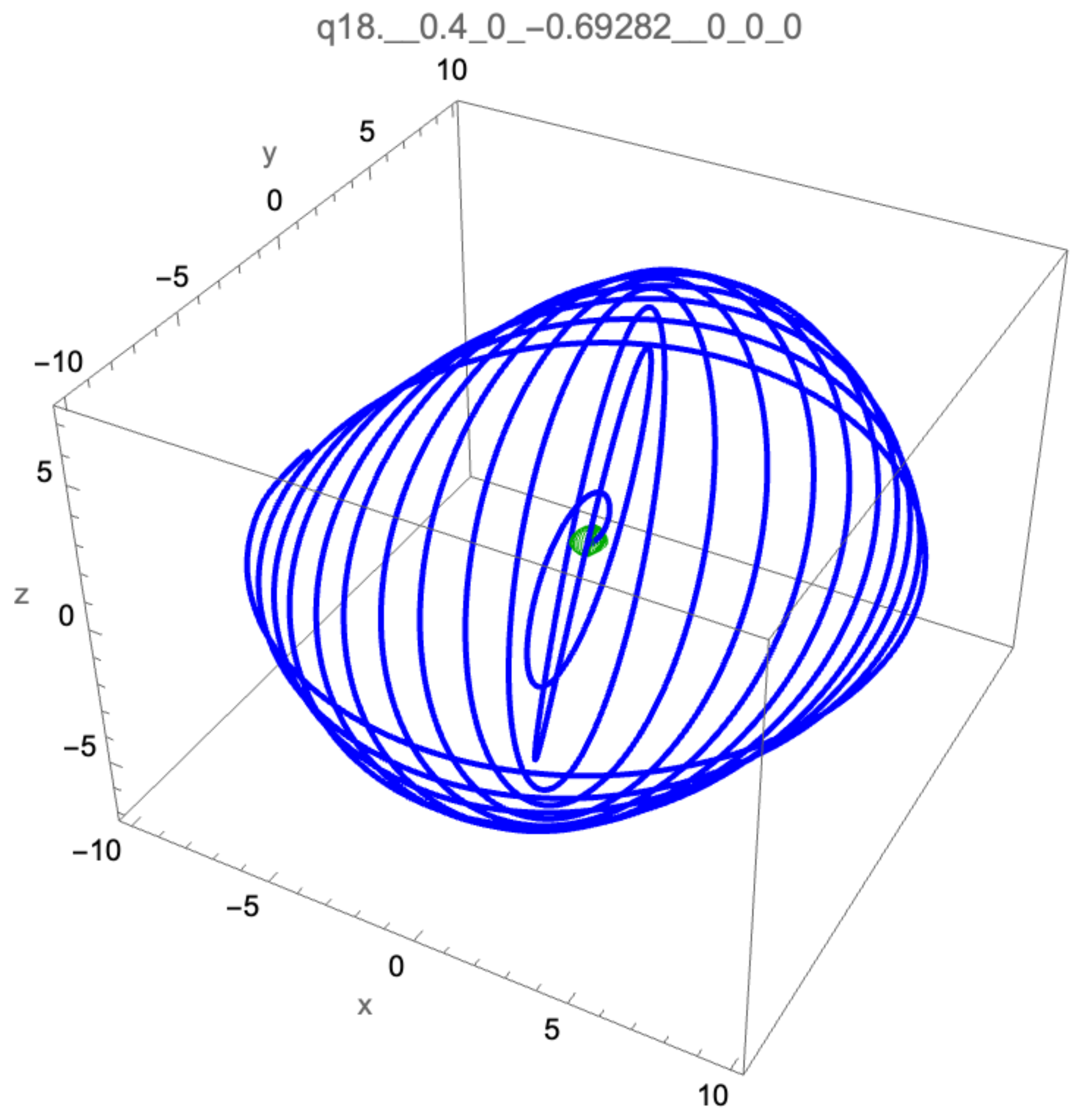
Numerical Relativity simulations

Numerical Relativity simulations

Use open source framework Einstein Toolkit to evolve black hole binaries + compute GW signal.

- Solve Einstein equations as coupled hyperbolic PDEs (also elliptic constraints for initial data).
- 8th order FD, 4th order RK, 384 - 480 cores, mesh refinement to resolve BHs.

- Current focus: precession - situations where the orbital plane (almost) flips over
  - not well captured by models, effects on parameter bias not known.
  - happens for high mass ratios - simulate Q=4, 6, 8, 18 (current upper limit of calibrating models to NR, UIB-Cardiff)
  - also relevant for BH-neutron star systems.
  - Long evolutions/many orbits are required to connect with perturbative regime.
  - Challenging simulations
  - 0.8 - 1.2 million hours for medium resolution, lower and higher resolution required for convergence tests - continue through next funding period.



Injection studies

Injection and recovery: check how well a model does

- "Injections" of known signals are a standard tool to check a model performance and accuracy
- Typically, we inject signals elaborated from trusted NR simulations
- We can study several aspects
    - Dis/agreement among **different waveform models**
    - Impact of specific **approximations** (e.g. to the precession dynamics) on the estimated source properties
    - How **noise properties** impact our ability to determine the properties of the source

Scaling tests

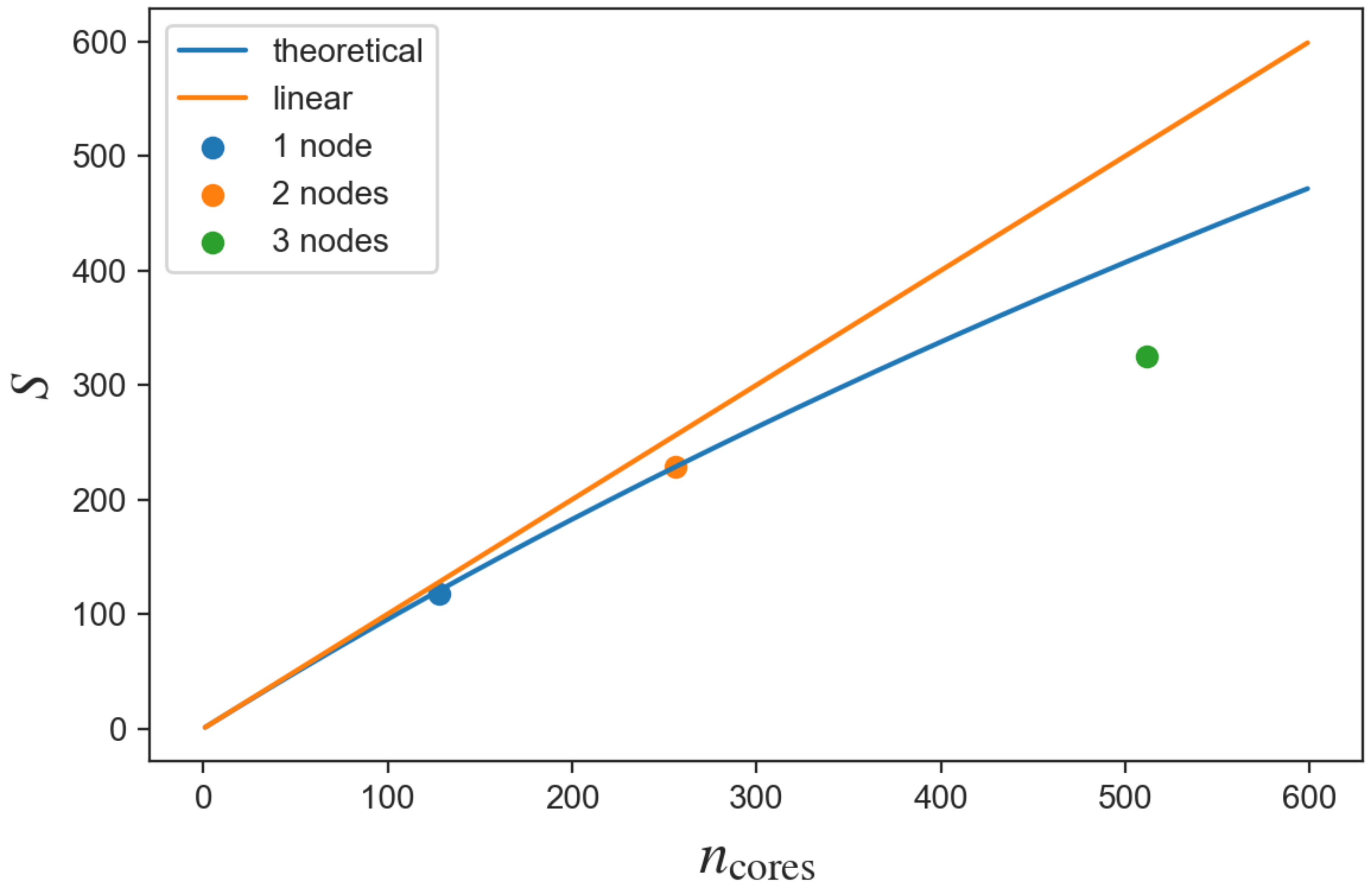
- We tested the scaling of `pBILBY` on a simulated signal (chunk of 4 s) in PICASSO
  - Lenovo SR645 nodes: 128 cores (AMD EPYC 7H12 @ 2.6GHz), 512 GB of RAM. InfiniBand HDR100 network
  - Bull R282-Z90 nodes: 128 cores (AMD EPYC 7H12 @ 2.6GHz), 2 TB of RAM. InfiniBand HDR200 network

(https://www.scbi.uma.es/site/scbi/documentation#HARDWARE)

- We can check if wall-time gets reduced with no. cores according to our expectations

Sampling time (wall-time)

128 cores	256 cores	512 cores
~3h 30	~1h 51	~1h 18



A precessing black-hole binary

PRELIMINARY

- We want to compare the "goodness" of different ways to describe precession effects.
- We take a NR simulation (SXS:BBH:0057, https://data.black-holes.org/waveforms) with clear signs of precession and simulate a binary with a total mass of 150 $M_\odot$
- We simulate a network of detectors and inject the waveform "as it is" (i.e. without adding any extra noise). We analyse **4 s** of data. Runs performed in Picasso.

Injection and recovery: planned follow-up

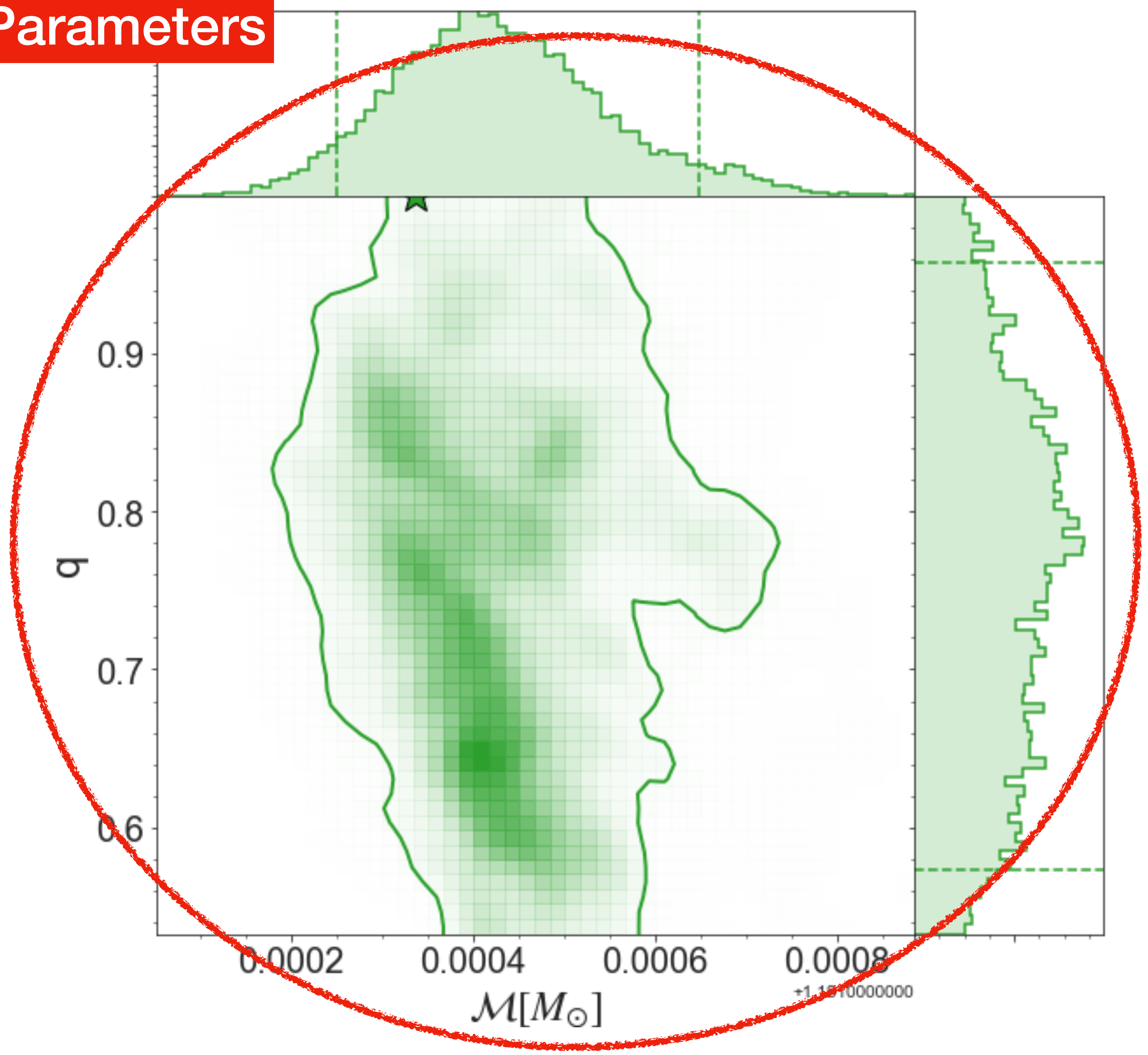
- Need to study the impact of
  - **Binary's orientation** (whether we're seeing the binary face-on or edge-on)
  - **Total mass**: if we have a heavy binary, we will detect only very few cycles!
  - **Noise**: what if we add some fake noise to the data? In real life our signals are buried in noise!

A neutron star binary

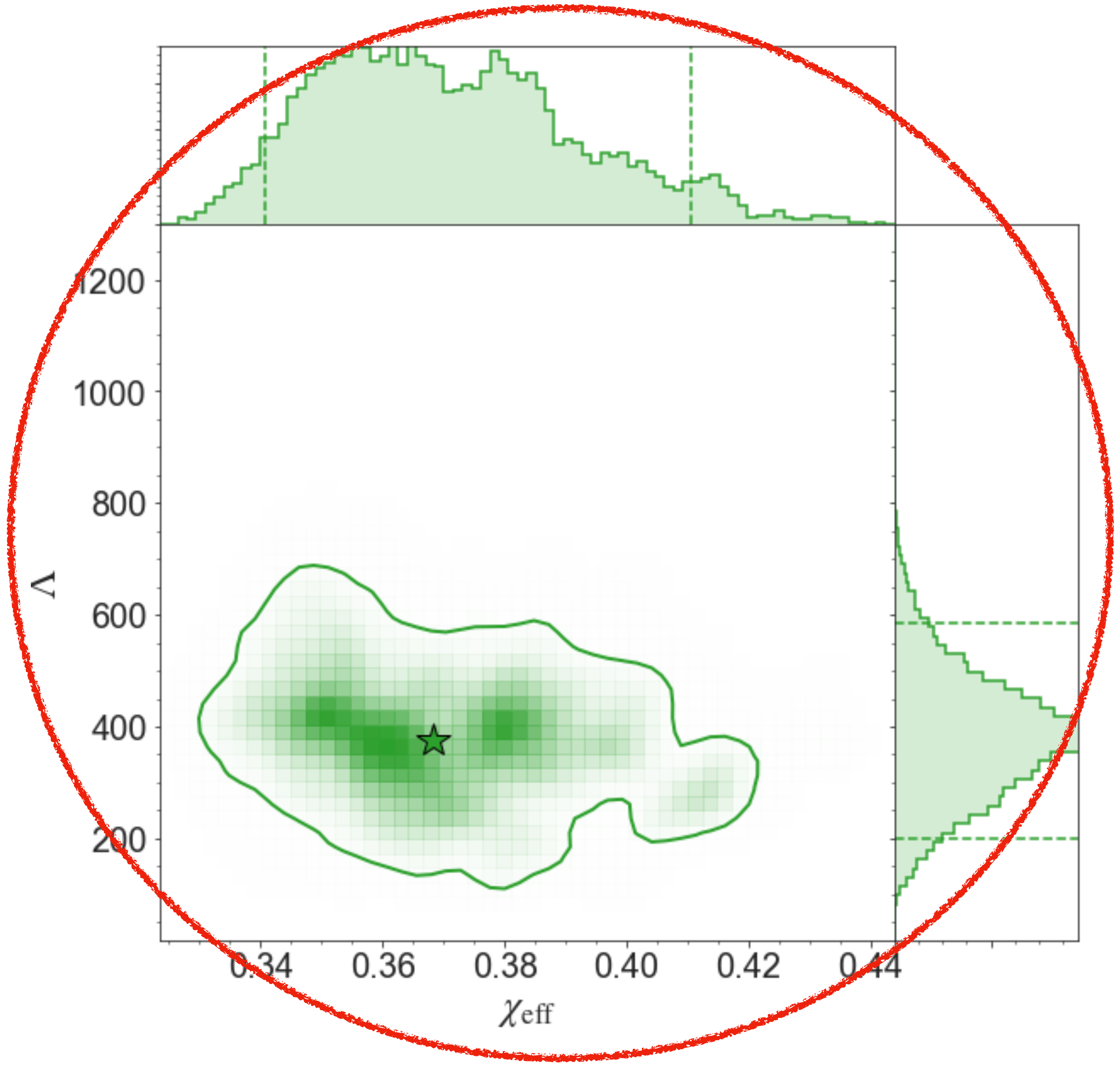
PRELIMINARY

- We inject and recover a signal corresponding to a spinning (though non-precessing) binary neutron star and we recover it with our tidal model, PhenomX+NRTidalv2 (Dietrich+ 1905.06011, Dudi+ arXiv:2108.10429)
- We simulate a network of detectors and inject the waveform "as it is" (i.e. without adding any extra noise). We analyse a long segment of simulated data: **128 s**
- Runs in MareNostrum on 16 nodes (48 cores). In combination with `pBILBY` the sampling time is well **below 2 days**

Mass Parameters



Spin & combined tidal deformability



Conclusions

- Thanks to RES allocations, Spanish computational resources played an important role in flagship papers produced by the LIGO-Virgo-KAGRA collaboration
- We plan to perform more injection studies to understand strengths and weaknesses of our models in preparation for future observing runs
- We plan to run more NR simulations to calibrate our models
- We will extend our investigations to future detectors (e.g. Einstein Telescope)
- Big thanks to the technical support!

Acknowledgments

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