Studying binary neutron star systems with future ground-based gravitational-wave detectors

GRASS Trento
2nd Oct 2024

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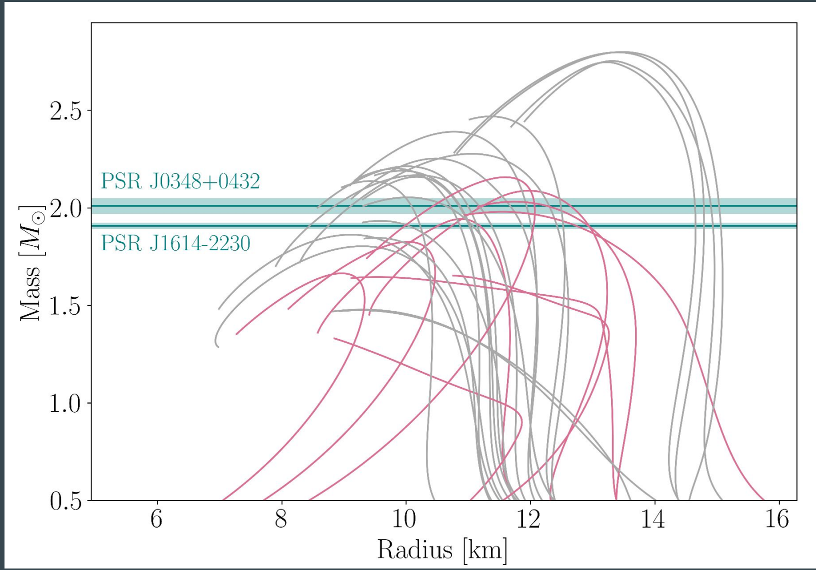
- *Phys.Rev.D* 108 (2023) 2, 023018
- arXiv:2408.10678

Neutron Stars Equation of State



Neutron stars: supranuclear-dense matter

Equation of state:

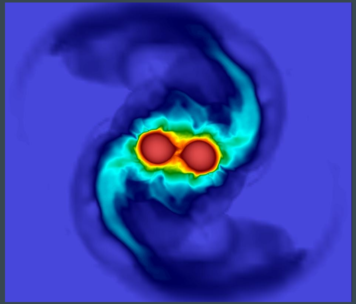
relation between pressure and density

⇕

parameters of the neutron stars

↔ mass-radius

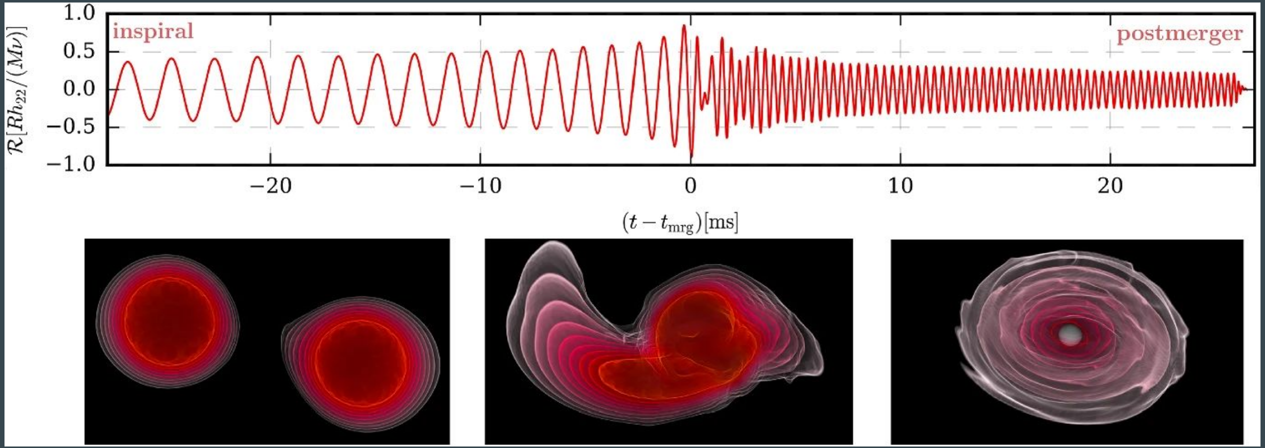
↔ mass - tidal deformability



University of Birmingham

Gravitational Waves from binary neutron stars

Gen. Rel.Grav. 53, 27 (2021)



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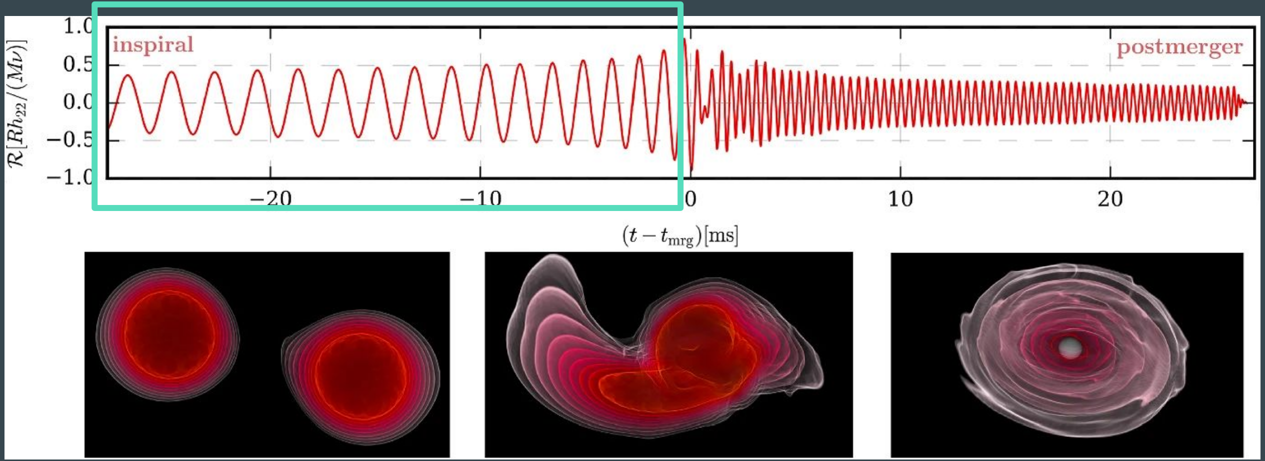

Inspiral

- parameters measurements (mass, tidal deformability)

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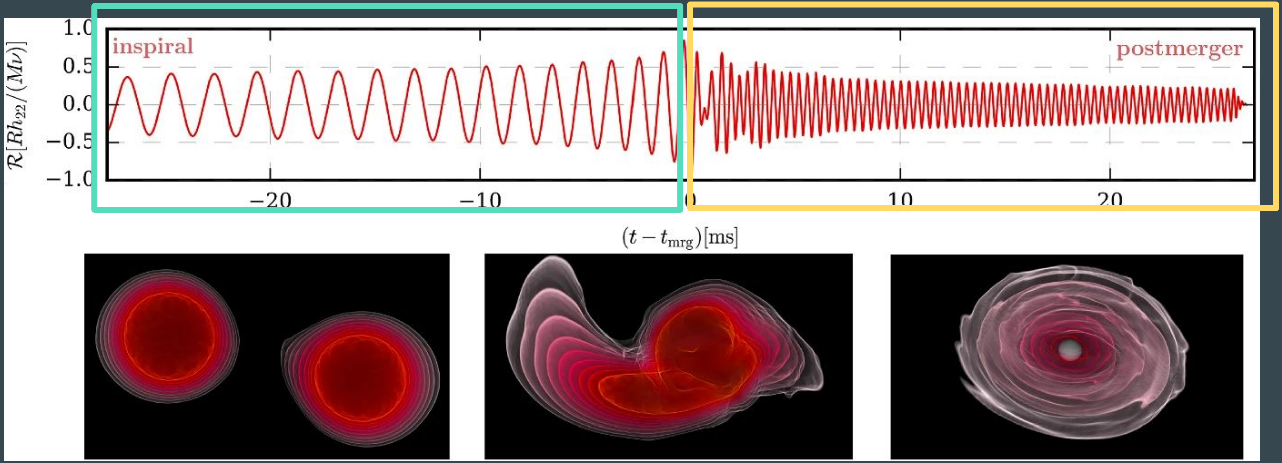

Inspiral

- parameters measurements (mass, tidal deformability)

Postmerger

- different density and temperature regime

Gravitational Waves from binary neutron stars

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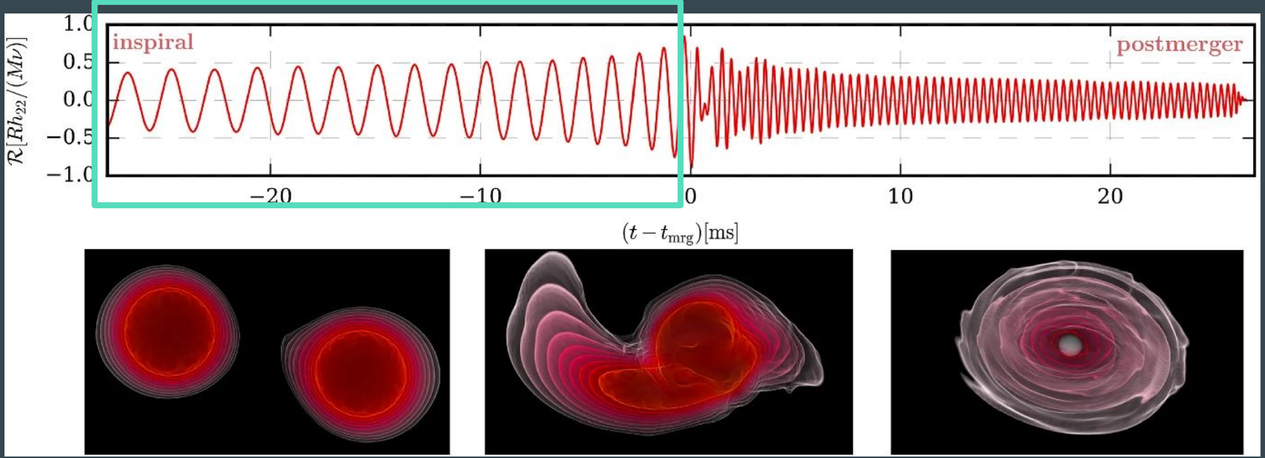


Inspiral

- parameters measurements (mass, tidal deformability)

How well can future detectors measure binary neutron stars parameters?

[*Phys.Rev.D* 108 (2023) 2, 023018]

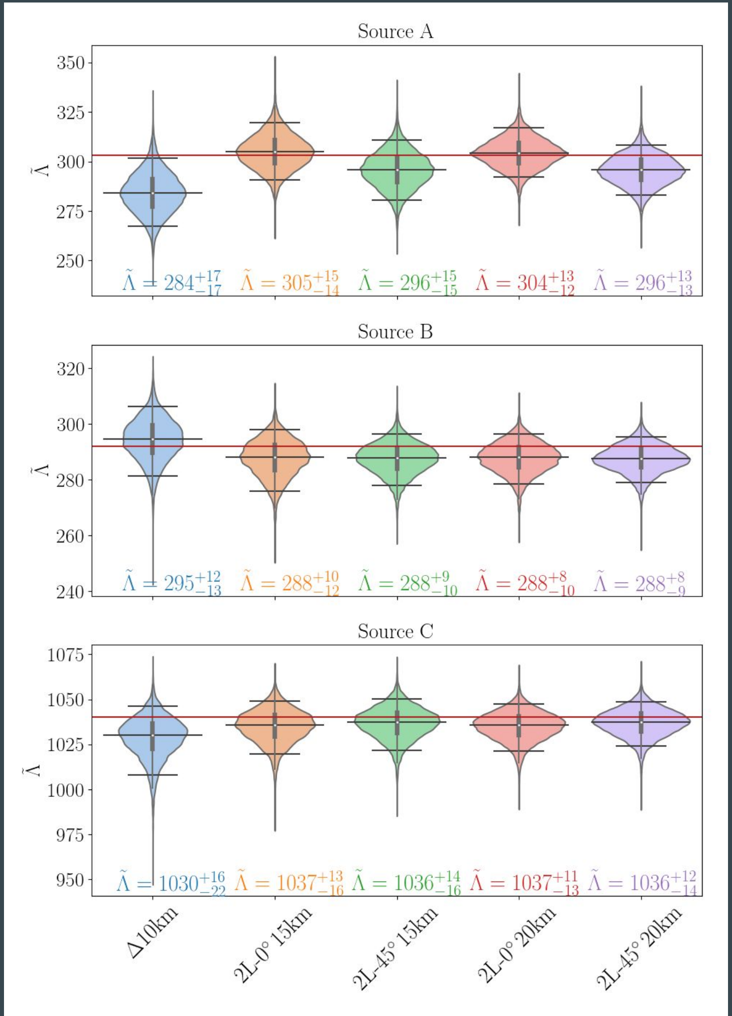
Tidal deformability recovery

- Parameter estimation analysis with ET
- Simulate signals for 3 different sources (ET analysis computationally very expensive)
- Mass-weighted tidal deformability
- Repeat analysis with the different ET $\tilde{\Lambda}$ configurations (triangular 10 km, 2L aligned 15 or 20 km, 2L misaligned: 15 or 20 km)

Comparison

GW170817: $\tilde{\Lambda} = 300^{+420}_{-230}$

[Phys. Rev. X 9, 011001 (2019)]



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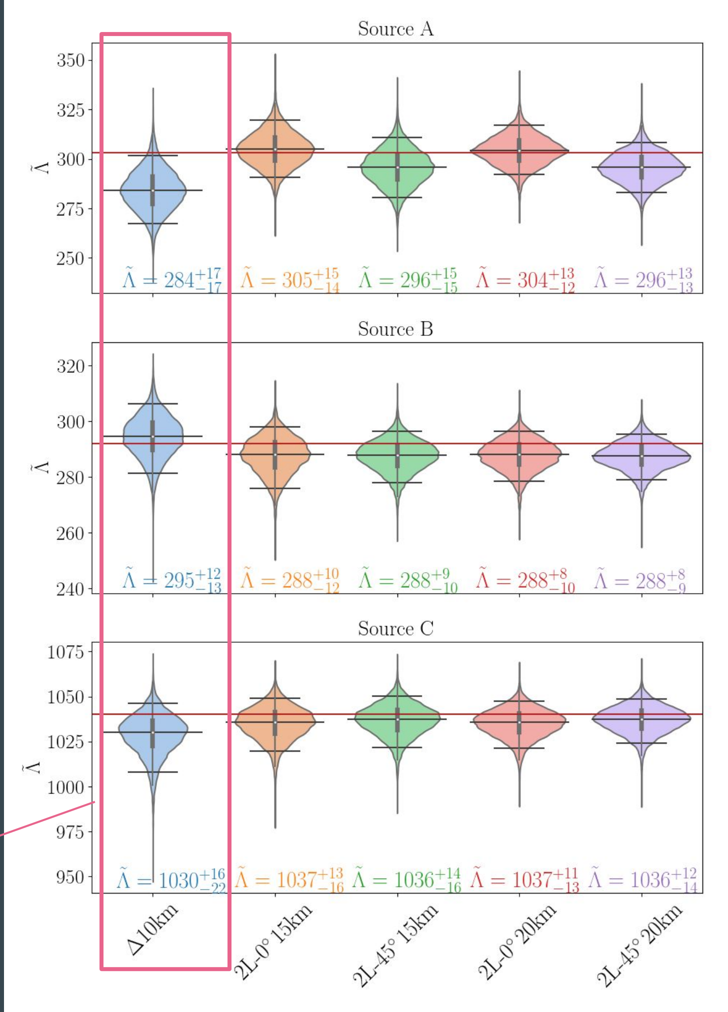
Triangular 10 km: wider posterior



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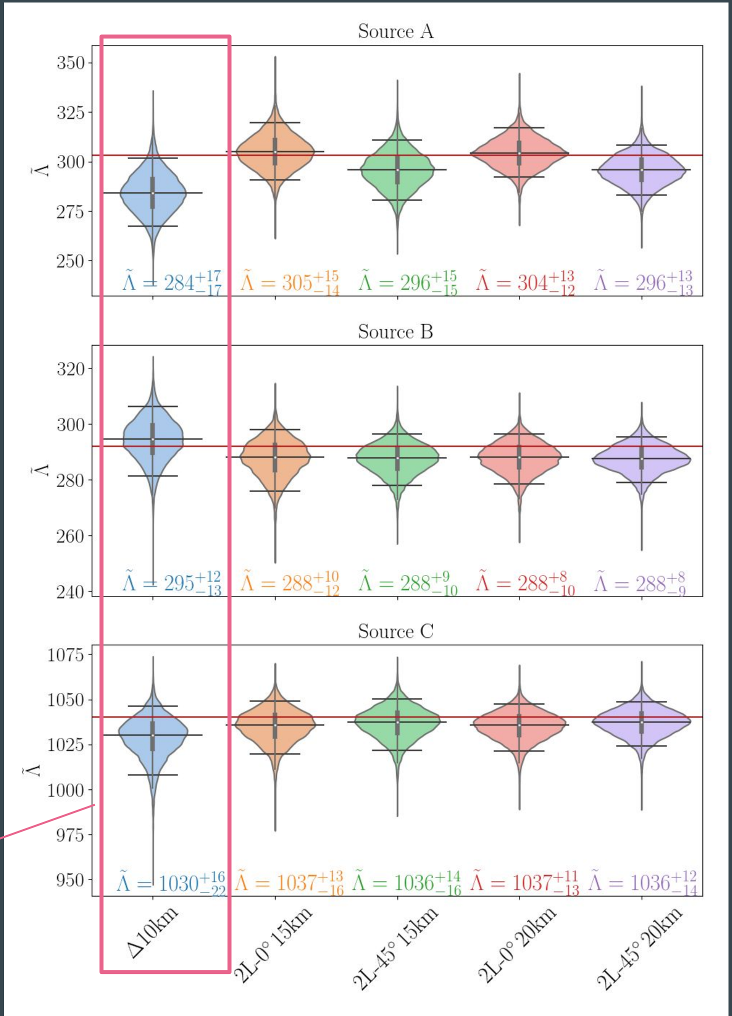
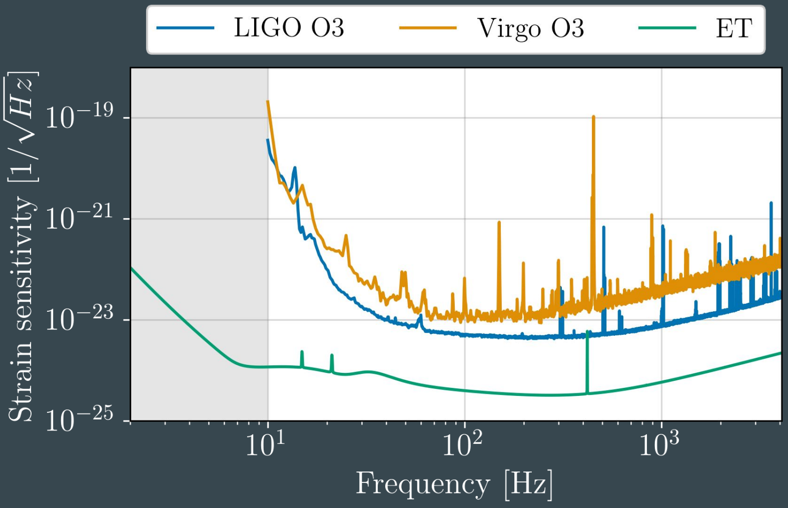
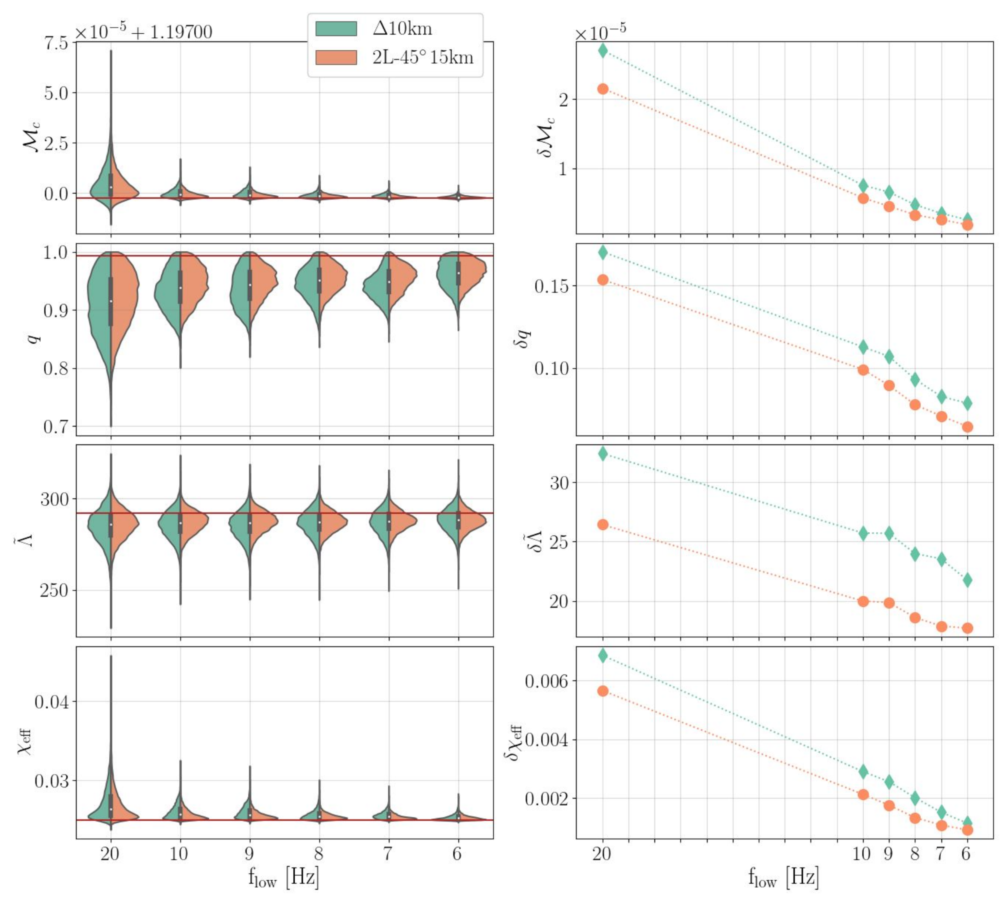


Effect of varying minimum frequency

Extended frequency band





Gravitational Waves from binary neutron stars

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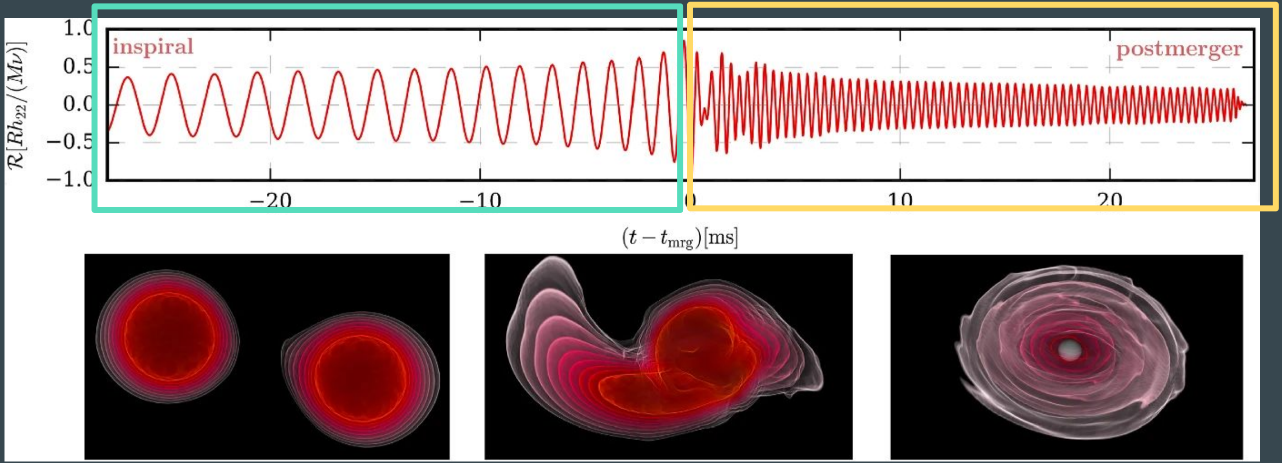

Inspiral
- parameters measurements (mass, tidal deformability)

Postmerger
- different density and temperature regime

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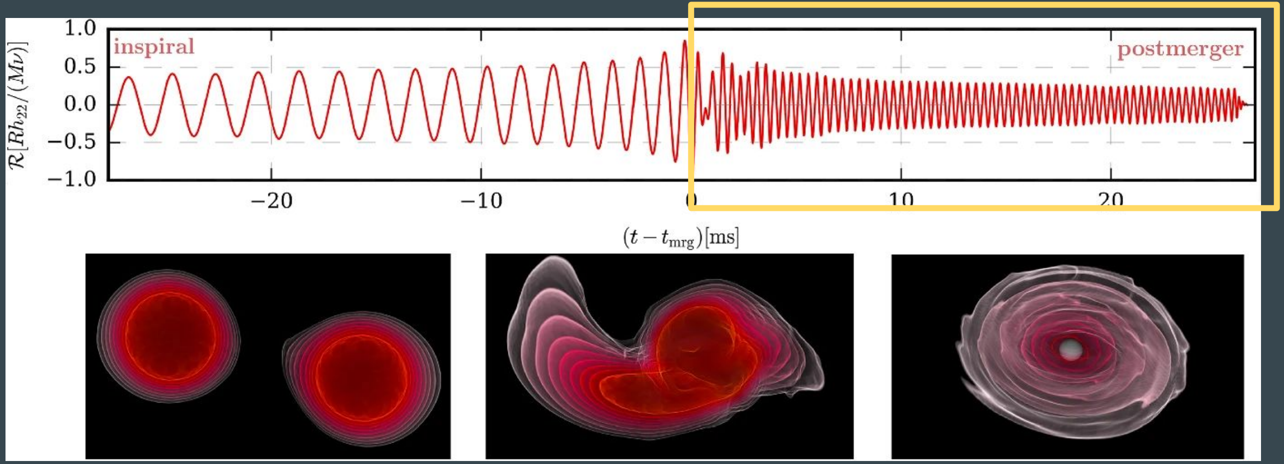
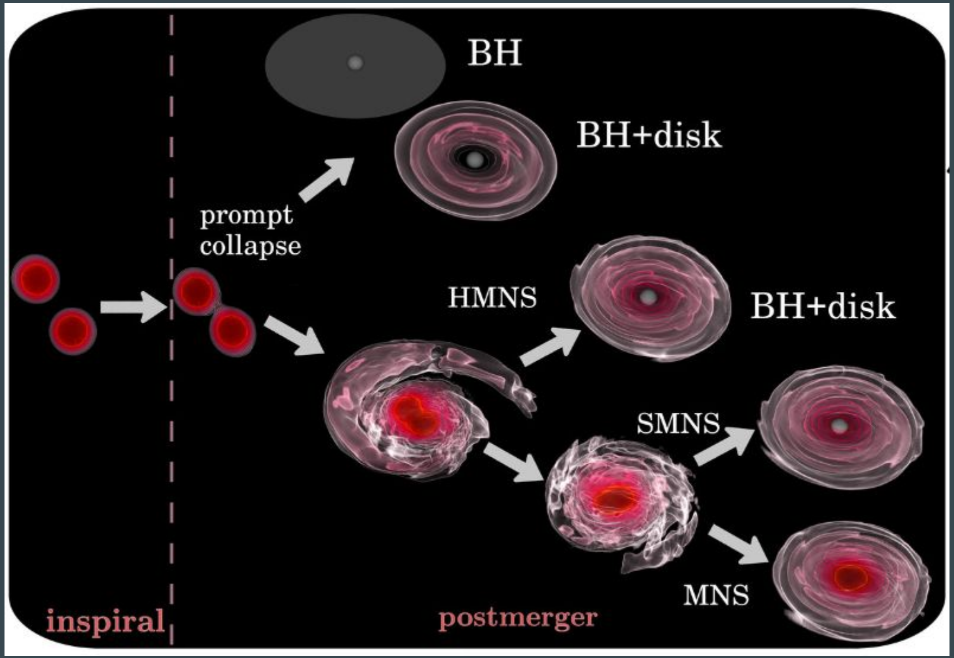


What is the remnant?
[arXiv:2408.10678]

Postmerger

- different density and temperature regime

BNS fate after the merger



Gen.Rel.Grav. 53 (2021) 3, 27

Depends mainly on:

- equation of state
- total mass

-> Information about the EOS
-> Different processes involved
-> Different electromagnetic signatures
-> Which GW events follow up

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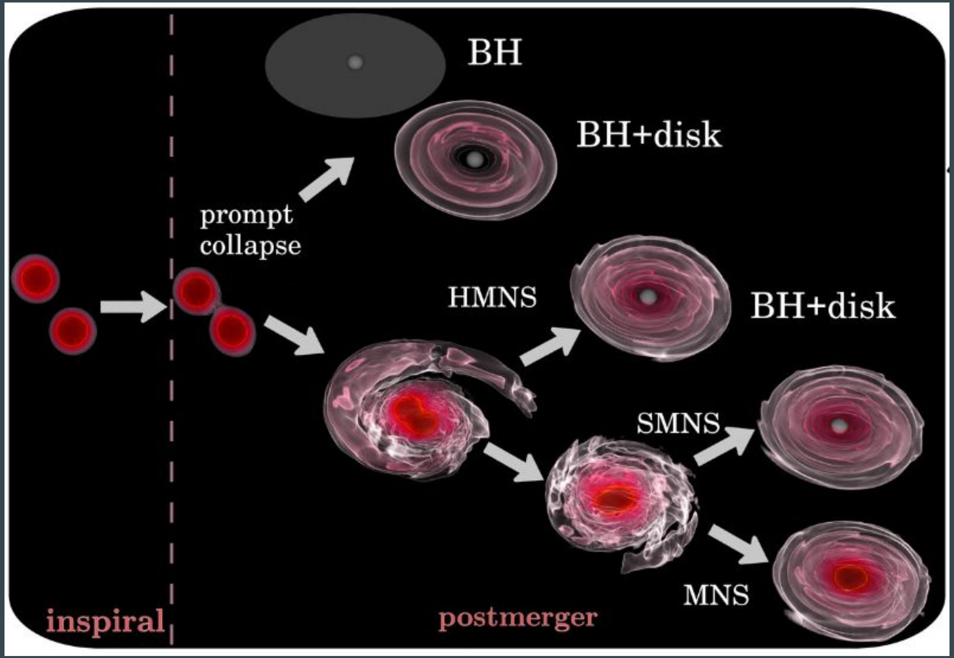

Gen.Rel.Grav. 53 (2021) 3, 27

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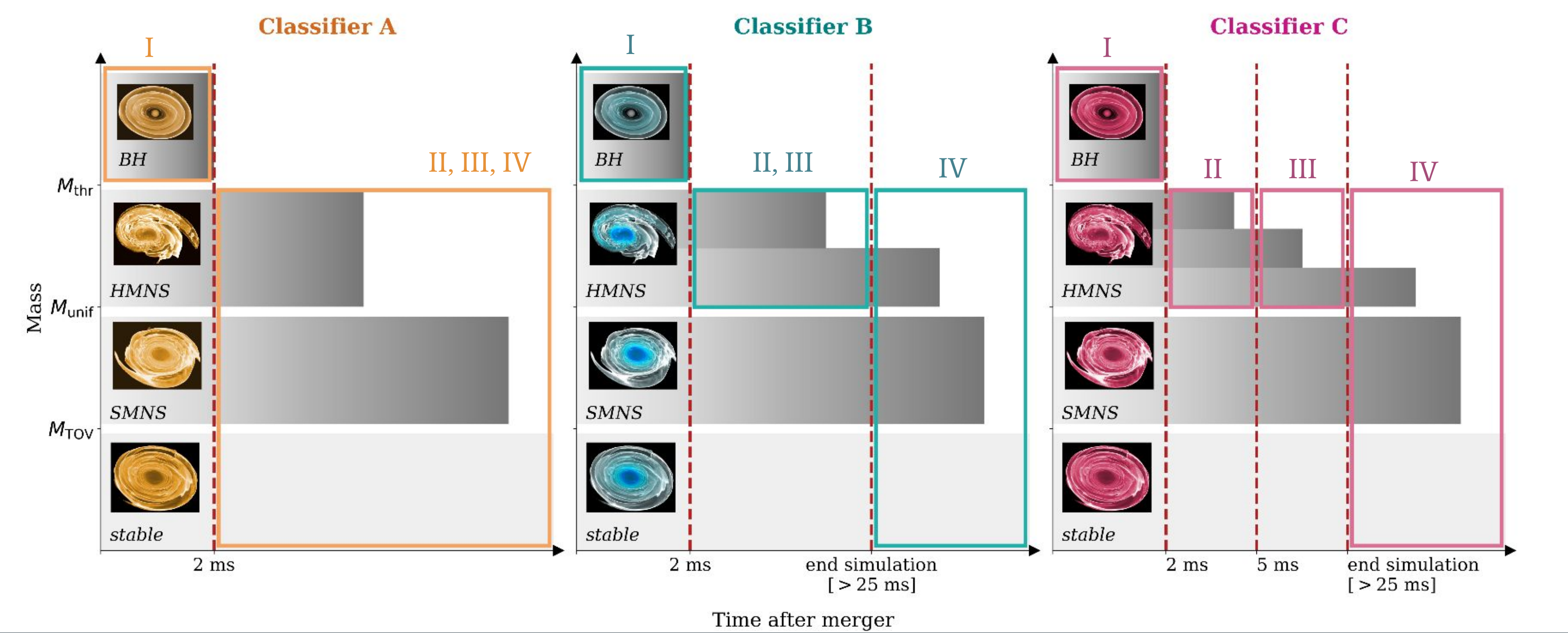
Goal

Use numerical-relativity data to build a classifier to predict the remnant based on parameters measured from inspiral GWs

Following *Phys.Rev.D* 83 (2011) 124008, classification based on collapse time t_{BH}:

I. $t_{BH} < 2$ ms: prompt collapse
II. 2 ms $< t_{BH} < 5$ ms: short-lived HMNS
III. $t_{BH} > 5$ ms: long-lived HMNS
IV. no collapse within simulation time



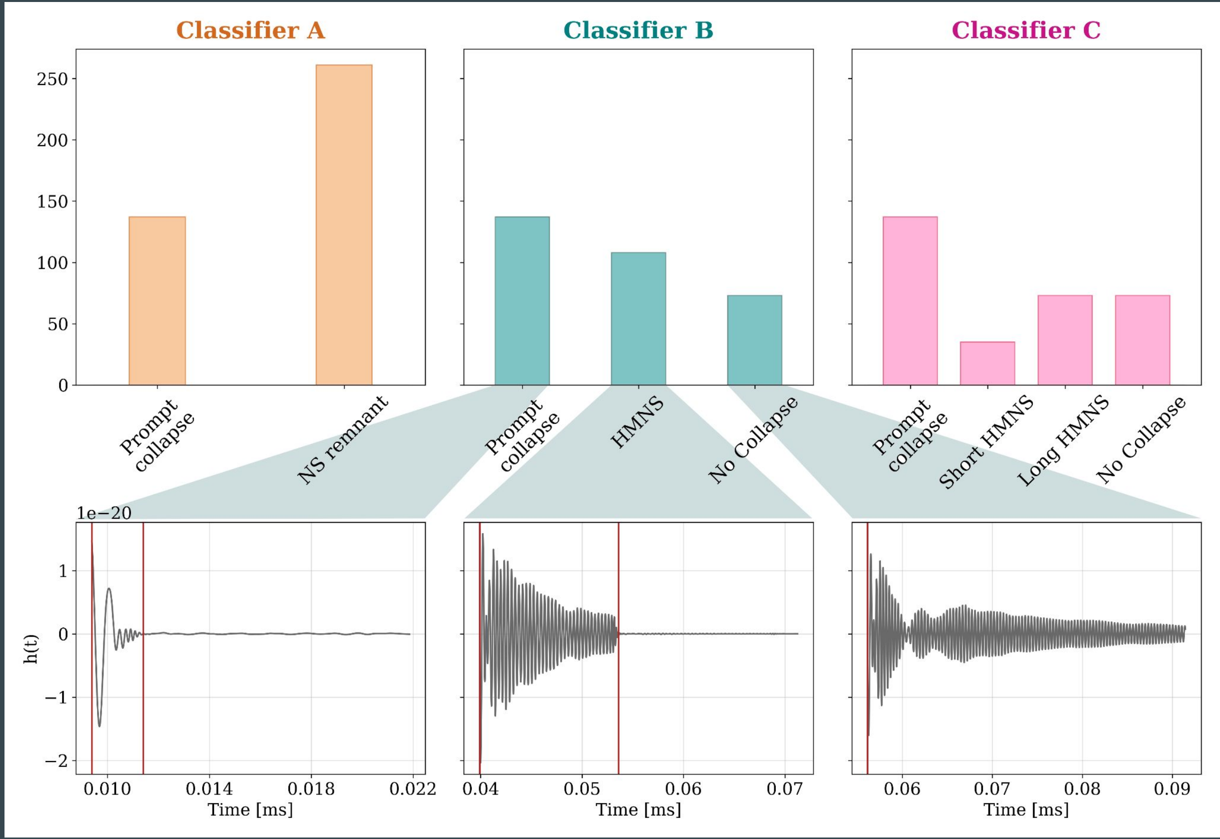
Data and algorithm

- NR simulations data from CoRe and SACRA database, together with data from *Phys.Rev.D* 106 (2022) 4, 044026 and *Phys.Rev.D* 109 (2024) 12, 123011
- Highest resolution, ignore eccentric systems and mis-aligned spins
- Total: 398
- For classifier B and C, remove points in class IV with short simulation time ($>$ 25 ms, total points 318)

Parameters from GWs inspiral as features : total mass, $\tilde{\Lambda}$ [EOS information], mass ratio, effective inspiral spin $\chi_{\rm eff}$

Data and algorithm

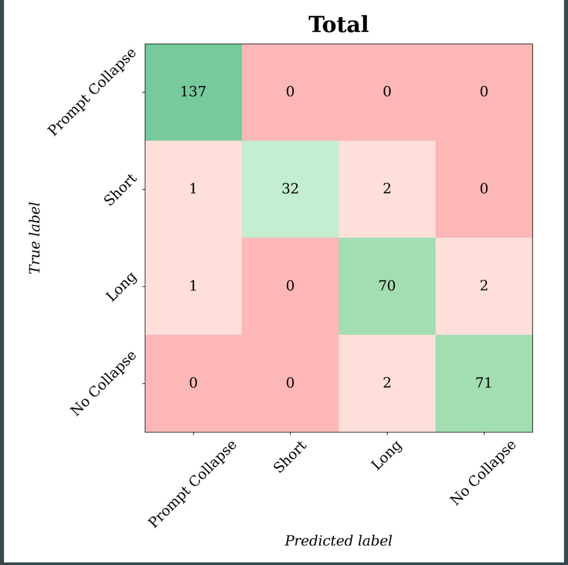
- Gradient Boosted Trees Classifier in `sklearn`
- 90% training and 10% validation



Results

	Validation set		Total	
	α	MCC	α	MCC
Classifier A	97.6%	0.946	99.8%	0.994
Classifier B	94.1%	0.909	99.1%	0.985
Classifier C	88.2%	0.831	97.5%	0.964

α: accuracy
MCC: Matthews Correlation Coefficient (accounts for correct/wrong classifications distribution among different classes)



Real events

$$p_i = \frac{n_i}{n_{\rm tot}}$$

i: over posterior samples

	Classifier A		Classifier B			Classifier C			
	$p_{\rm PCBH}$	$p_{\rm RNS}$	$p_{\rm PCBH}$	$p_{\rm HMNS}$	$p_{\rm NC}$	$p_{\rm PCBH}$	$p_{\rm SHORT}$	$p_{\rm LONG}$	$p_{\rm NC}$
GW170817	39.8%	60.2%	39.7%	57.5%	2.8%	41.7%	15.6%	39.8%	3.7%

Include information about equation of state and electromagnetic counterparts

$\Longrightarrow$ posterior samples from Koehn et al. [arxiv:2402.04172]

Real events

	Classifier A		Classifier B			Classifier C			
	p_{PCBH}	p_{RNS}	p_{PCBH}	p_{HMNS}	p_{NC}	p_{PCBH}	p_{SHORT}	p_{LONG}	p_{NC}
GW170817	39.8%	60.2%	39.7%	57.5%	2.8%	41.7%	15.6%	39.8%	3.7%
GW170817+EoS	9.0%	91.0%	8.8%	90.5%	0.7%	11.6%	38.7%	49.2%	0.5%
GW170817+EoS+KN	0.9%	99.1%	0.9%	98.9%	0.2%	1.3%	42.8%	55.8%	0.2%
GW170817+EoS+KN+GRB	0.1%	99.9%	0.2%	99.5%	0.3%	0.5%	50.8%	48.6%	0.1%
GW190425	59.5%	40.5%	66.2%	7.4%	26.4%	71.9%	0.3%	11.1%	15.7%
GW190425+EoS	98.2%	1.8%	98.6%	0.2%	1.1%	97.3%	0.0%	0.1%	2.5%

Conclusions

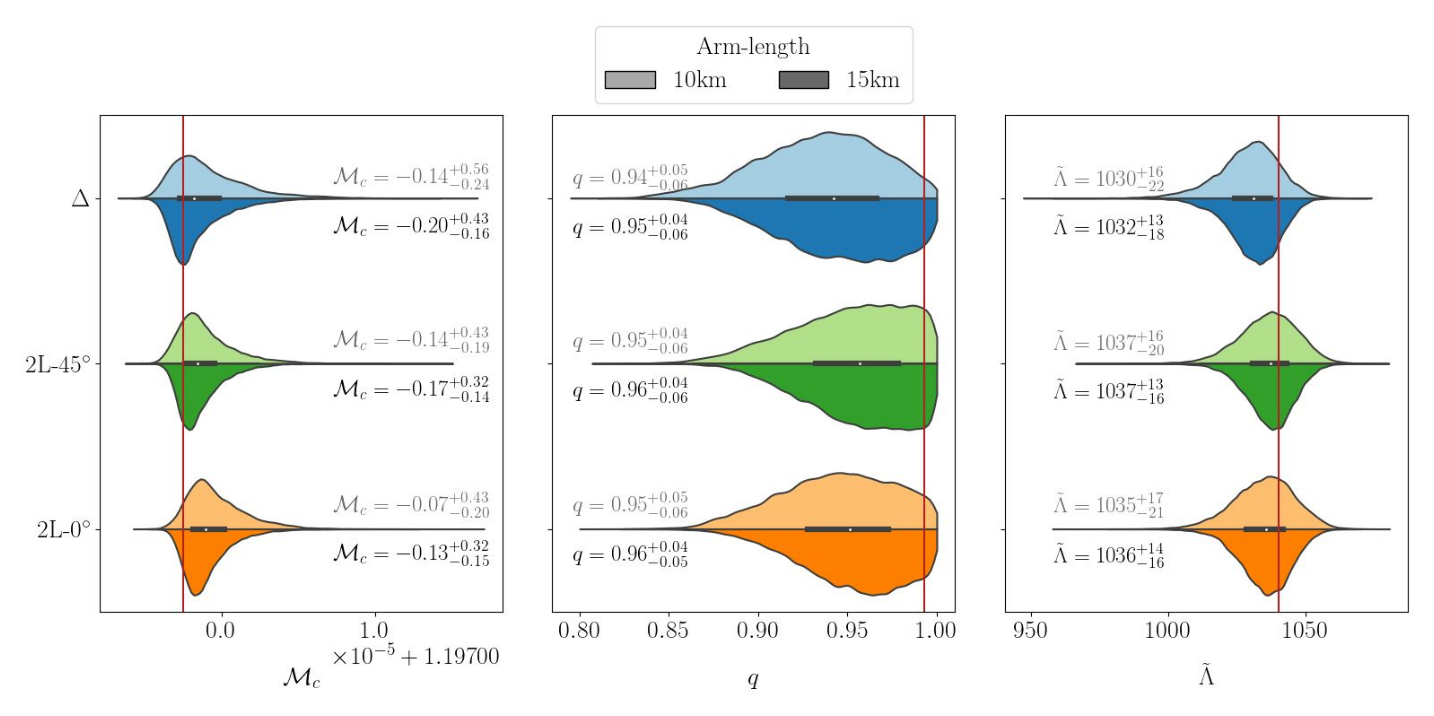
Inspiral parameter estimation

- Tidal deformability recovered with very high accuracy
- The accuracy depends on the detector's arm-length, but not on its geometry
- Starting the analysis at lower frequencies brings an additional improvement

Postmerger remnant

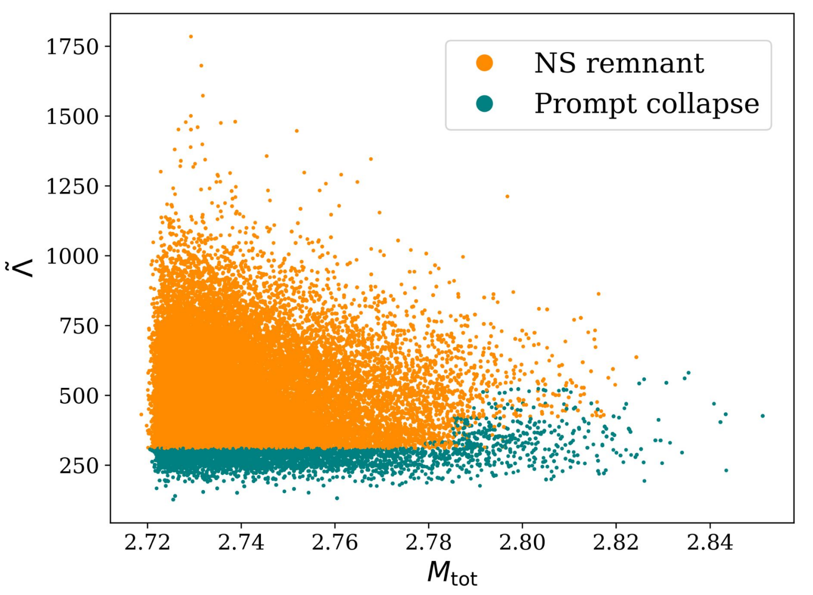
- We employed numerical-relativity data and Gradient Boosted Decision Trees to build a classifier to predict the outcome of BNS mergers
- Features = parameters inferred from GW inspiral signal (no need of a post-merger detection)
- Three different classifiers, all with very high accuracy and MCC
- When applied to real events (possibly including additional information)
  - ↳ GW170817: formed a hyper-massive NS, with roughly same probability of being short- or long-lived
  - ↳ GW190425: prompt collapse to black hole

Tidal deformability recovery



Configuration does not affect results, but arm-length does

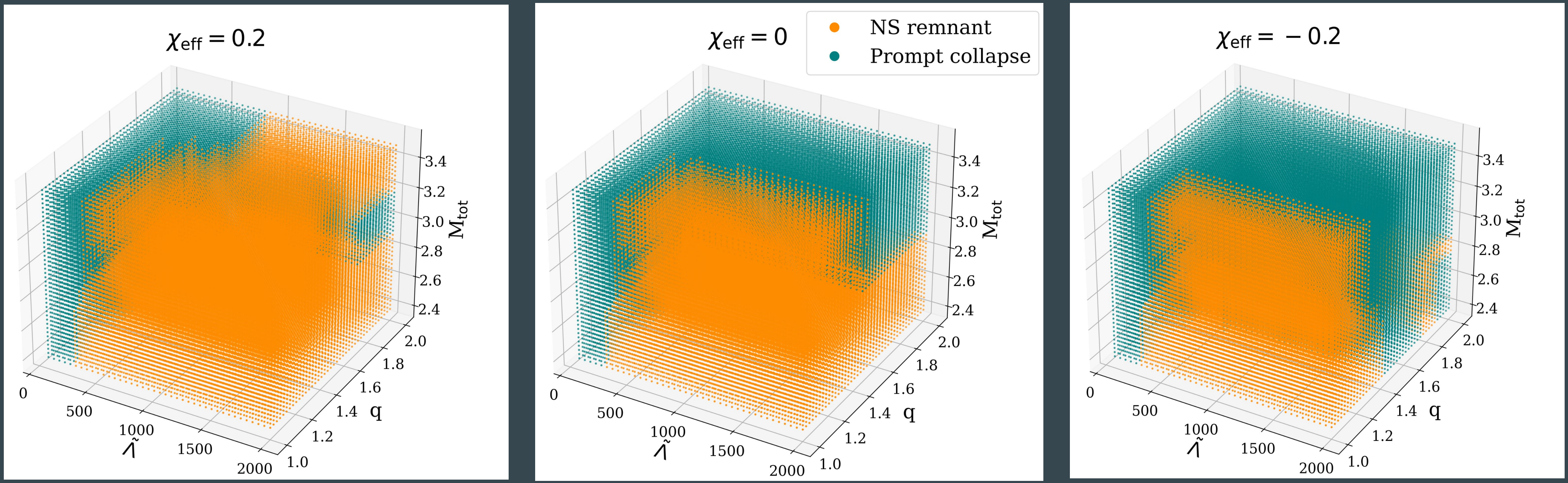
Prompt collapse: effect of parameters



GW170817+EoS samples

$$\tilde{\Lambda}_{\rm thr} \sim 310$$

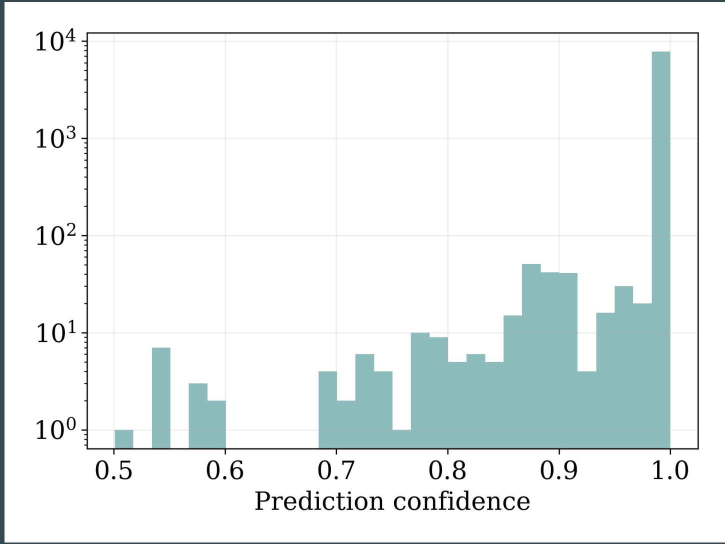
Prompt collapse: effect of parameters



Extra: Confidence of predictions

The classifier predict the probability of an input $\mathbf{x}$ to belong to each class:

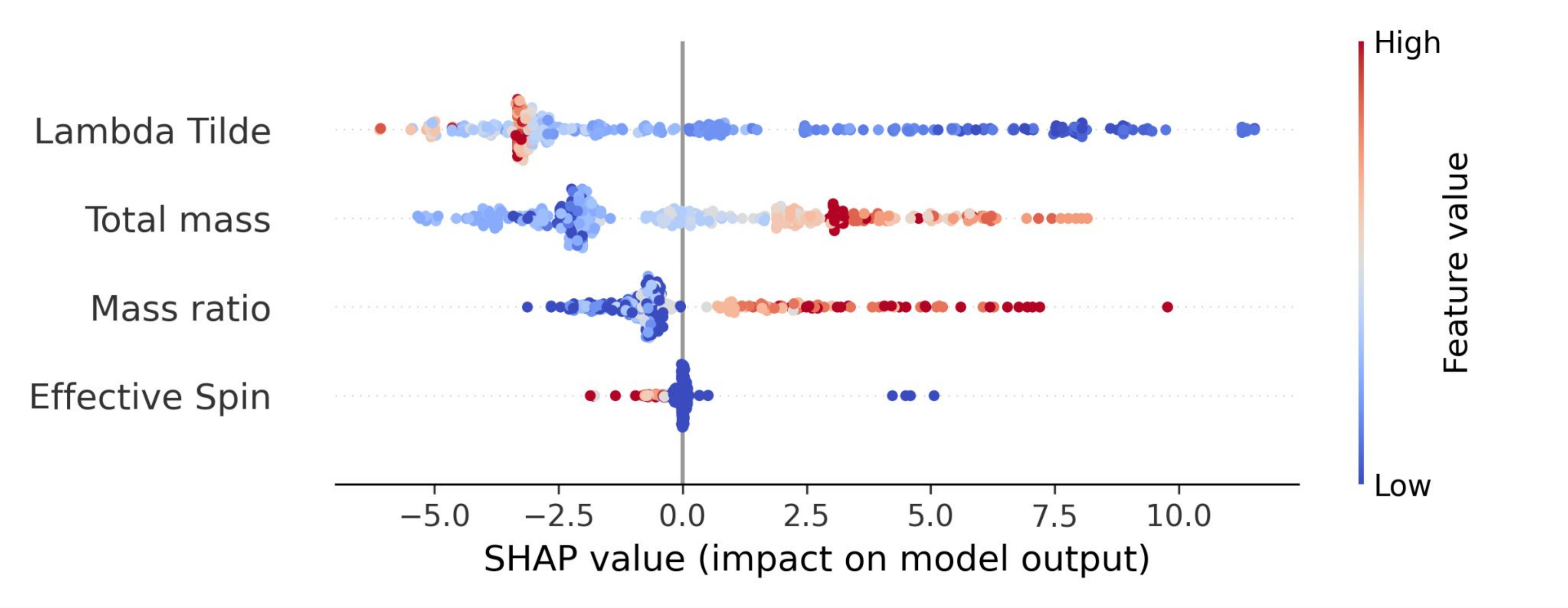
- final predictions: $\mathbf{x}$ belongs to class with largest probability
- likelihood of preferred class $\Longleftrightarrow$ confidence of prediction [1]



Classifier A on GW170817: mean $\Downarrow$ confidence ~99%

[1] A. Manilin, Uncertainty Estimation in Deep Learning with application to Spoken Language Assessment, (2019).

SHAP values



Lambda Tilde
Total mass
Mass ratio
Effective Spin
−5.0
−2.5
0.0
2.5
5.0
7.5
10.0
SHAP value (impact on model output)
High
Low
Feature value