

Rapid Online Estimation of Astrophysical Source Category and Compact Binary Parameters

[arXiv: 2203.10080](https://arxiv.org/abs/2203.10080)

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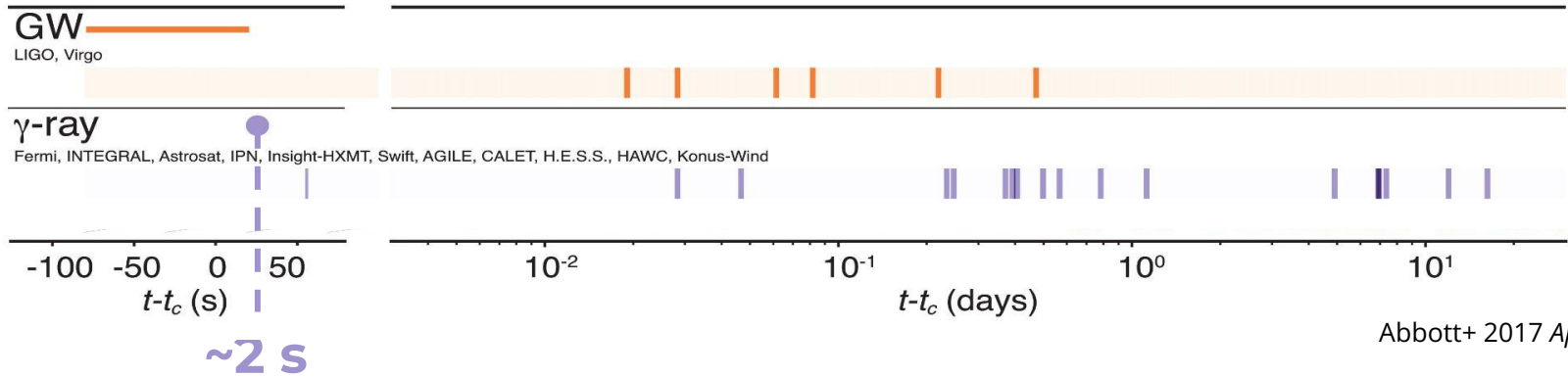
12th Iberian GW Meeting, 7th June 2022

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Motivation: Rapid Follow-up

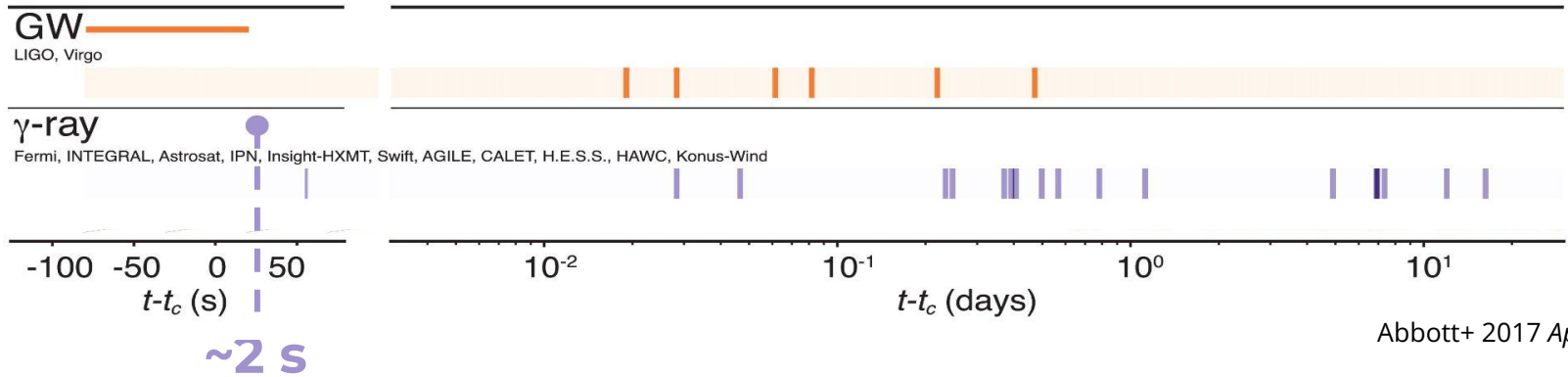
First EM counterpart - **GW170817**: γ -ray burst with ~ 2 s latency



Abbott+ 2017 *ApJL* 848 L12

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Challenge

Look for events with potential EM or neutrino counterparts (high probability of containing a NS) in **very low-latency**

Candidates Identification

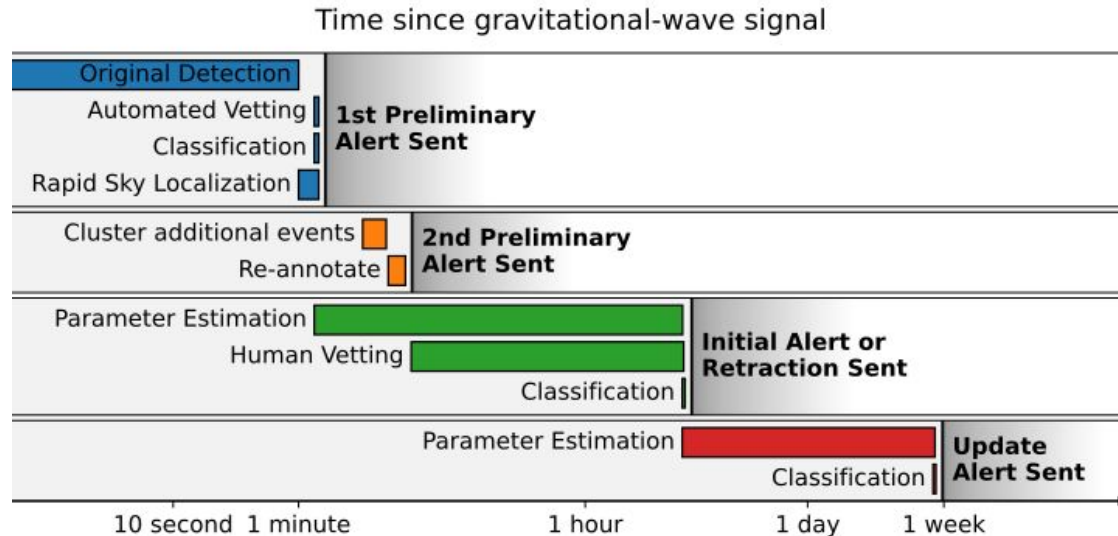
Searches perform candidate identification on two timescales:

- **Low-latency** → Generates public alerts within minutes
- **Offline** →
 - Reanalysis with better data quality and/or more detailed methods
 - Takes hours to weeks

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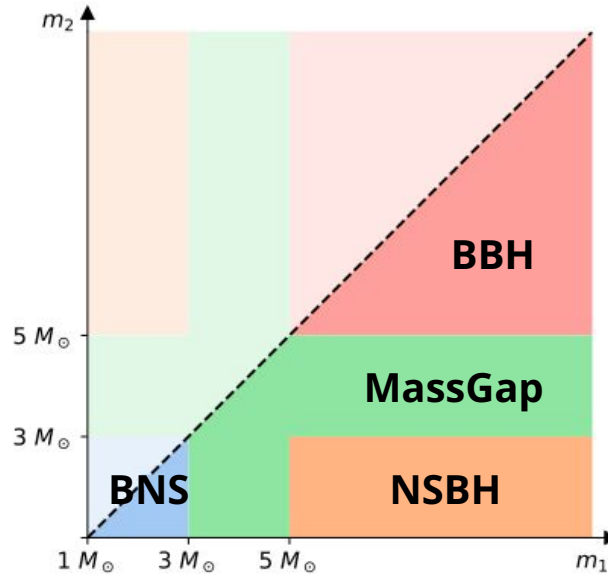


Source Classification of CBC

- **Source Classification:** probability that the source belongs to the different Astrophysical categories or is of Terrestrial origin

Source Classification of CBC

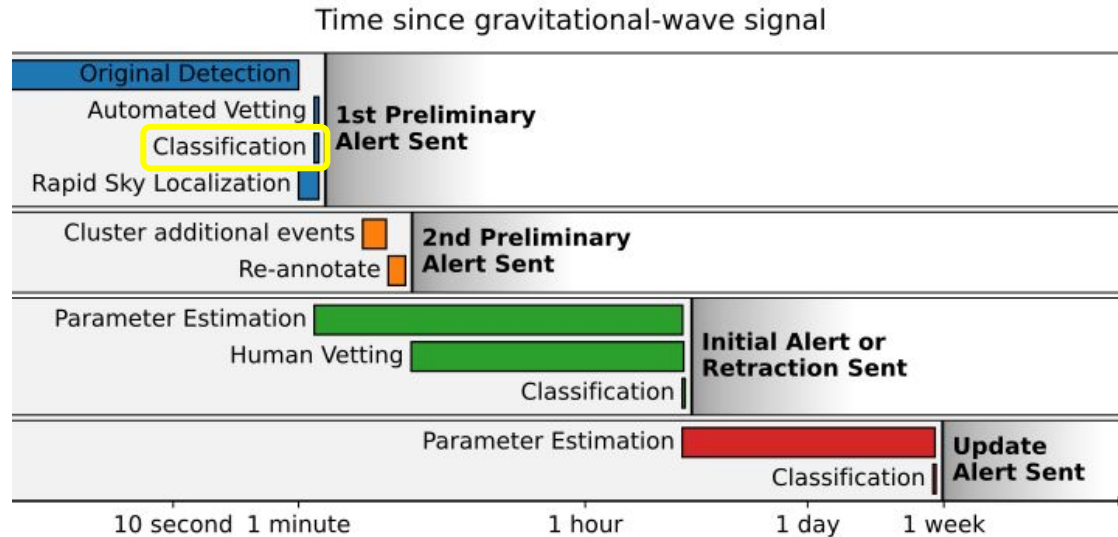
- **Source Classification:** probability that the source belongs to the different Astrophysical categories or is of Terrestrial origin
- Astrophysical Categories of CBC during O3: **BNS**, **NSBH**, **MassGap**, **BBH**



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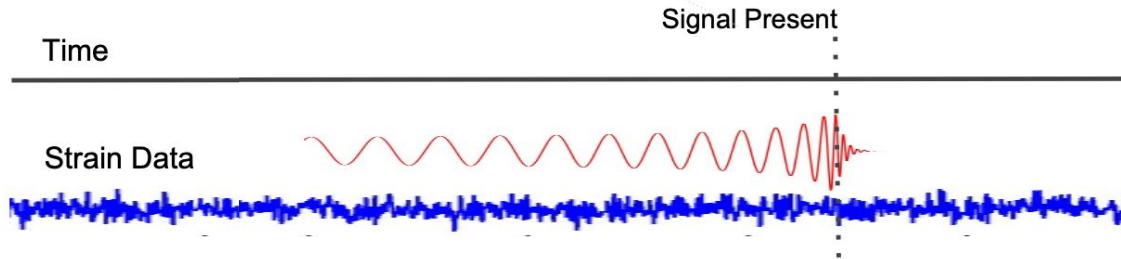
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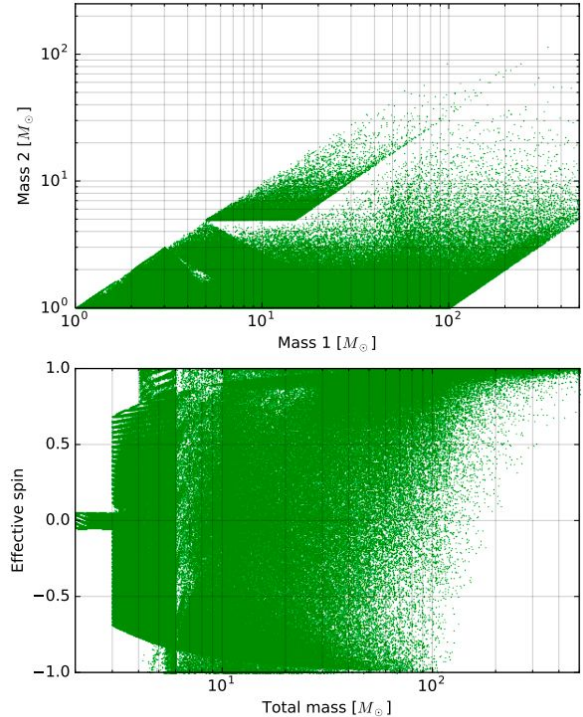
Source Classification in PyCBC Live

PyCBC Live:

- Online all-sky modelled search for CBC's
- Uses matched filtering with a bank of templates



- Each template has component masses and spins

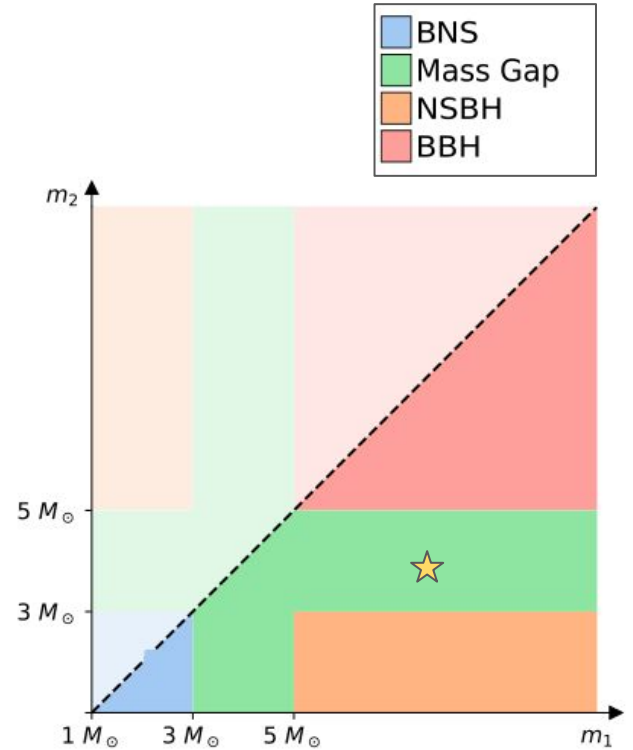


Source Classification in PyCBC Live during O3

“Hard-cuts” method:

- Uses point (template) estimates of **component masses**

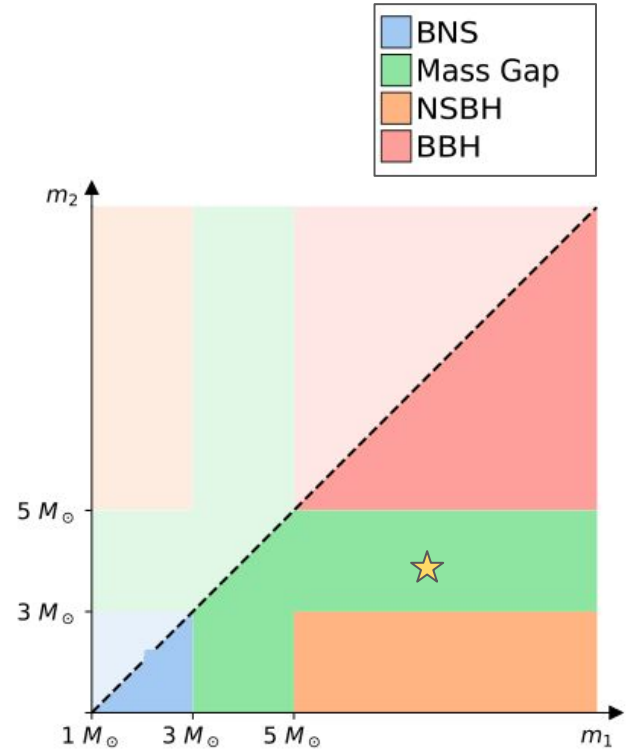
$m_1 m_2$



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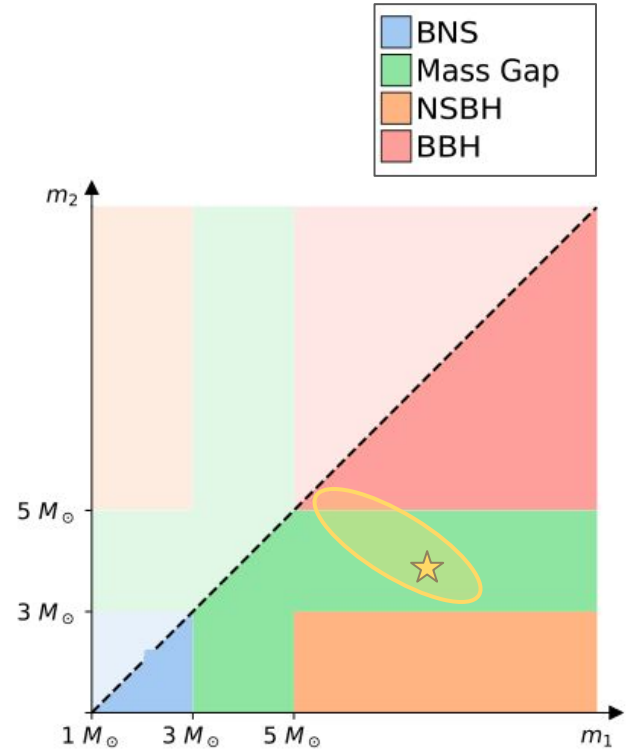
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Drawbacks:

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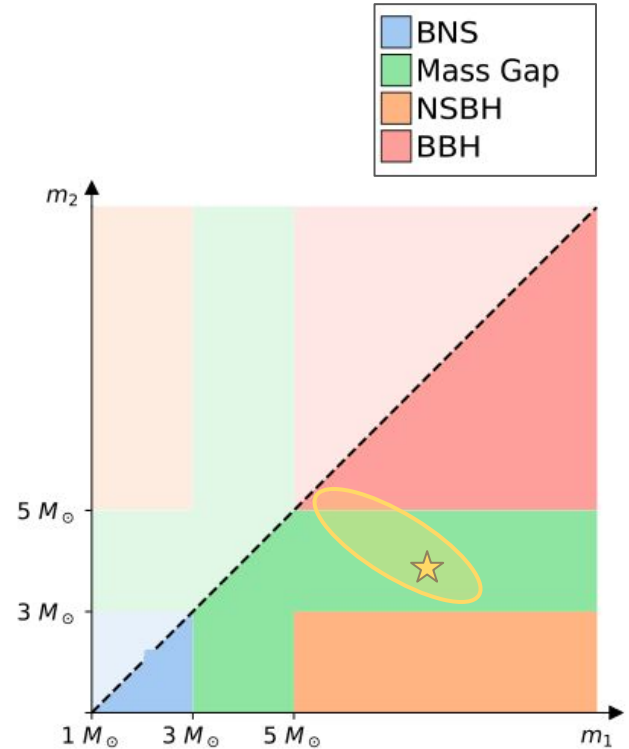
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- Does not account for **redshift bias**

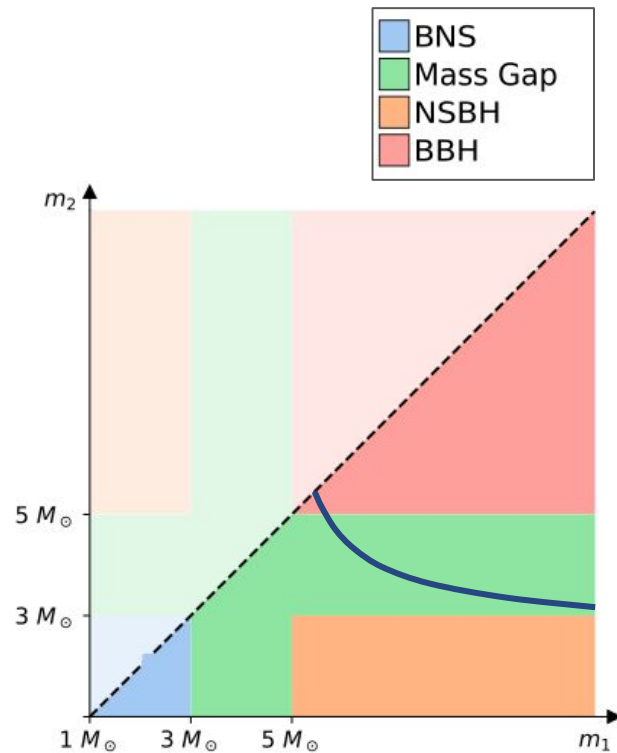


New Classification Method

“Chirp-mass based” method:

- Uses point estimates of **chirp mass**

$$\mathcal{M} = \frac{(m_1 m_2)^{3/5}}{(m_1 + m_2)^{1/5}}$$



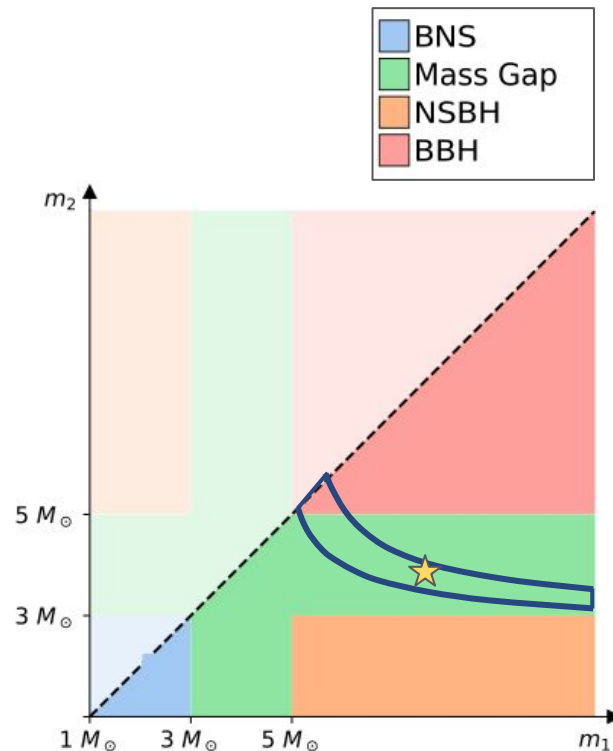
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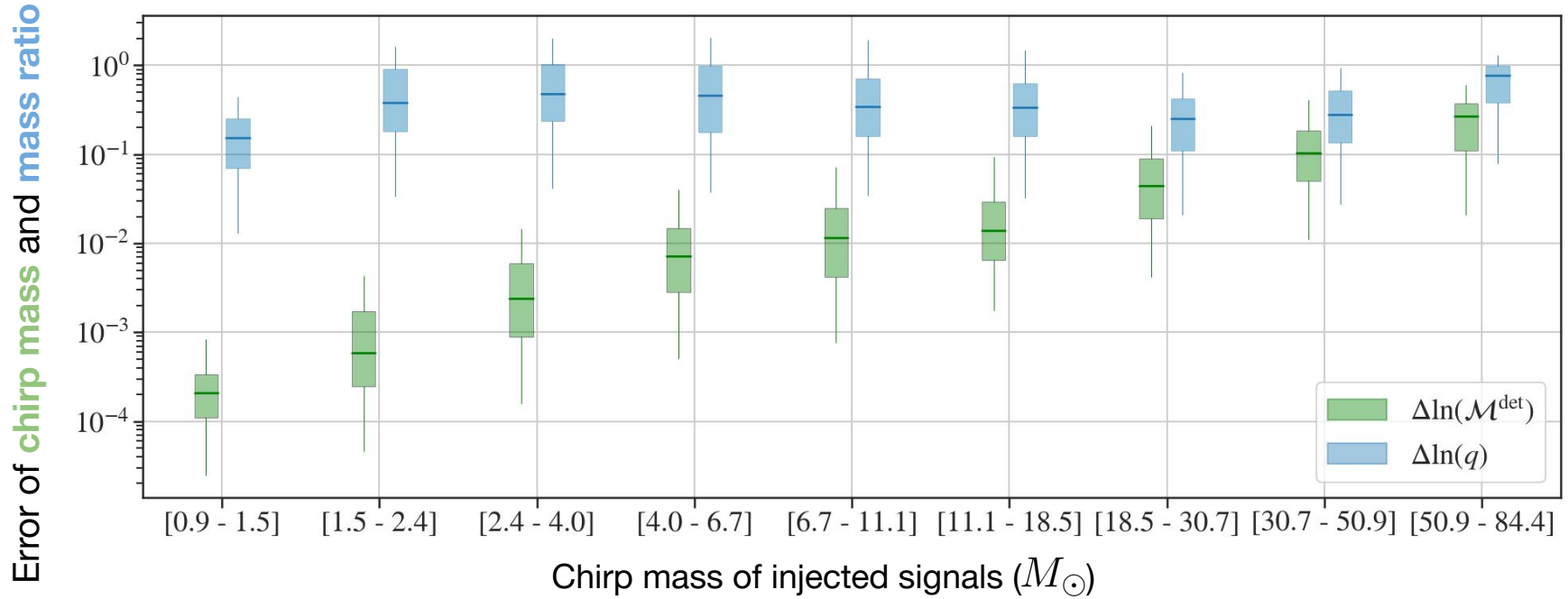
- Uses point estimates of **chirp mass**

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- Chirp mass is measured with **little uncertainty ~0.1-1%**
 - $m_1 m_2$ constrained to a interval of constant $\mathcal{M} \pm \Delta\mathcal{M}$
 - We assume $\Delta\mathcal{M} = 1\%$



Uncertainties on template masses

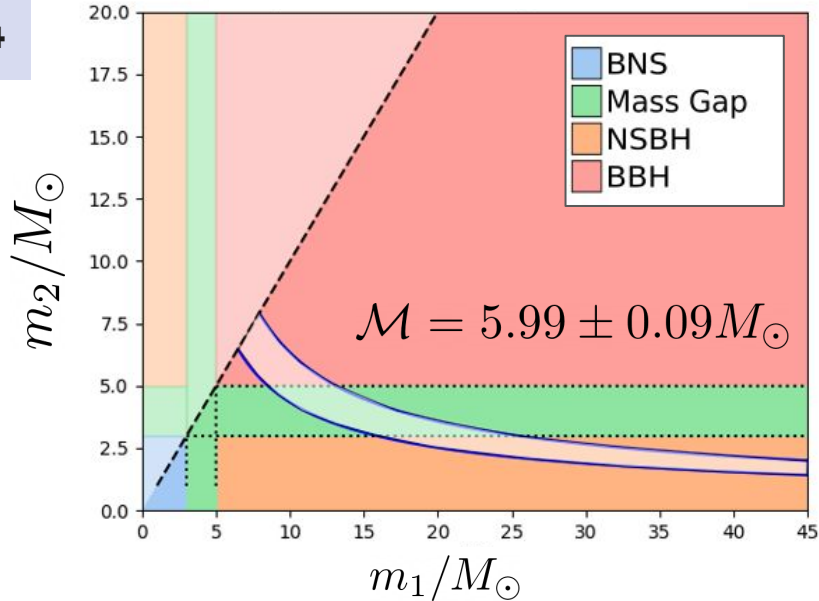


Source Probabilities from Chirp Mass

Assuming **uniform density prior** of candidate signals over $m_1 m_2$ plane:

Probabilities proportional to the area of each region inside contour of chirp mass

GW190814

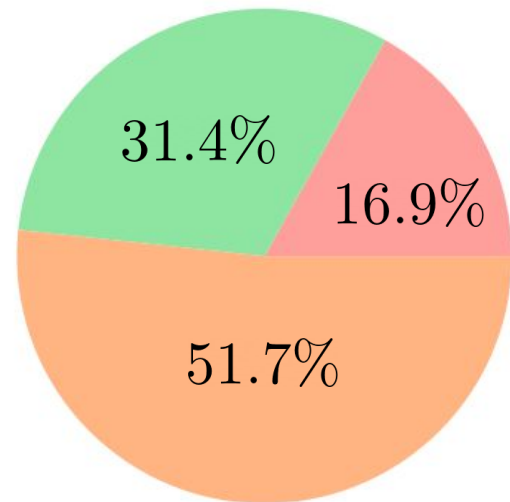
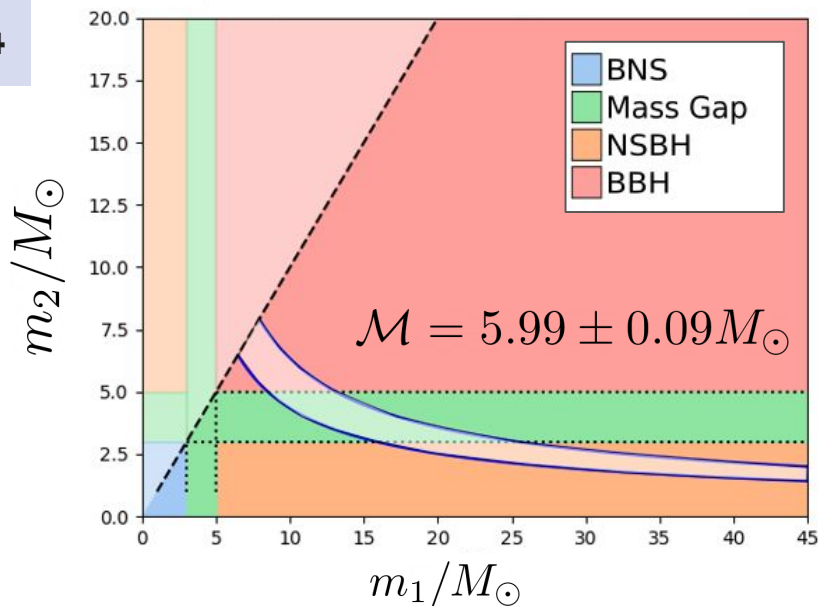


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PyCBC Live recovers **effective distances** to the source:

$$D_{\text{eff},i} = D_L \left[F_{+,i}^2 \left(\frac{1 + \cos^2 \iota}{2} \right)^2 + F_{\times,i}^2 \cos^2 \iota \right]^{-1/2}$$

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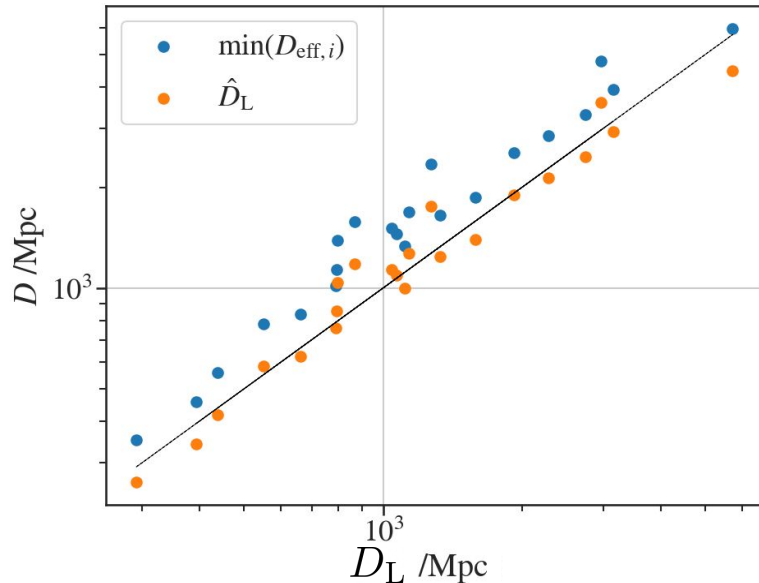
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- One for each detector i
- $D_{\text{eff},i} \geq D_L$ so we can take the minimum one

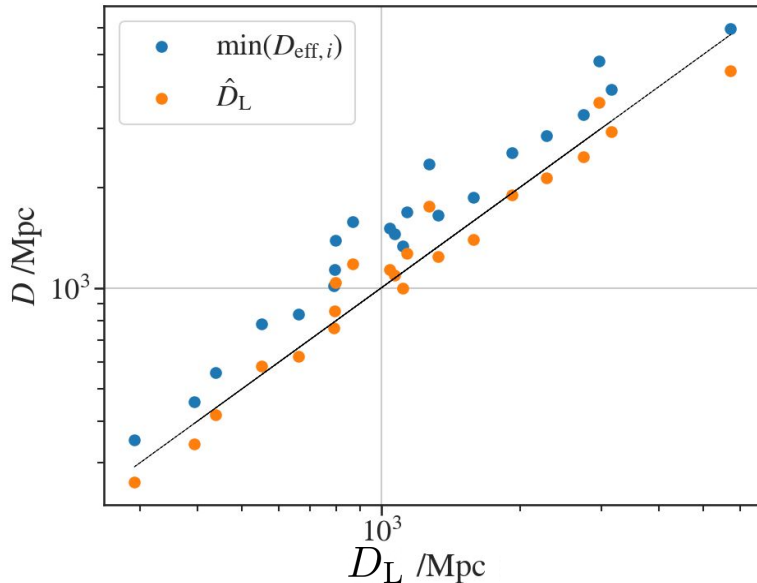
Luminosity Distance Estimation

- We fit a relationship between estimated D_L and minimum effective distances
 - $\tilde{D}_L = C_D \cdot \min(D_{\text{eff},i})$
 - Data from O3a events

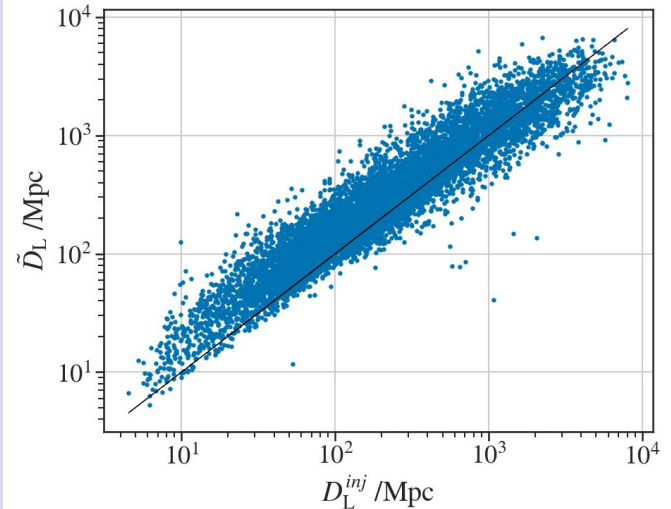


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Check with simulated signals

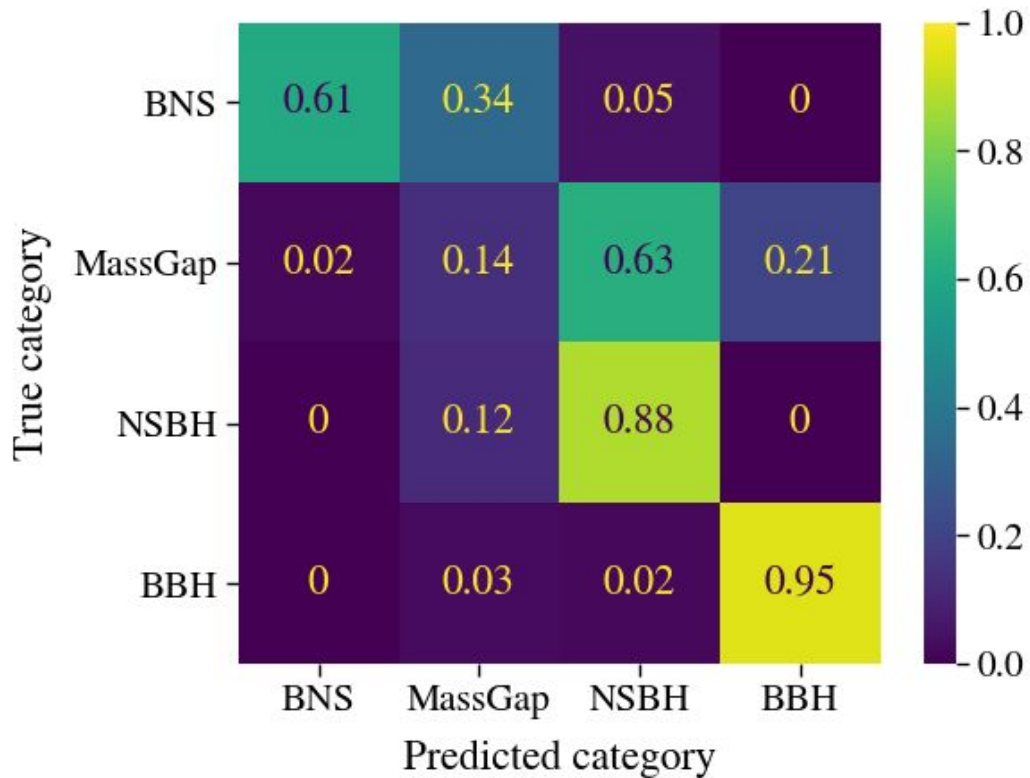


Method applied to simulated signals

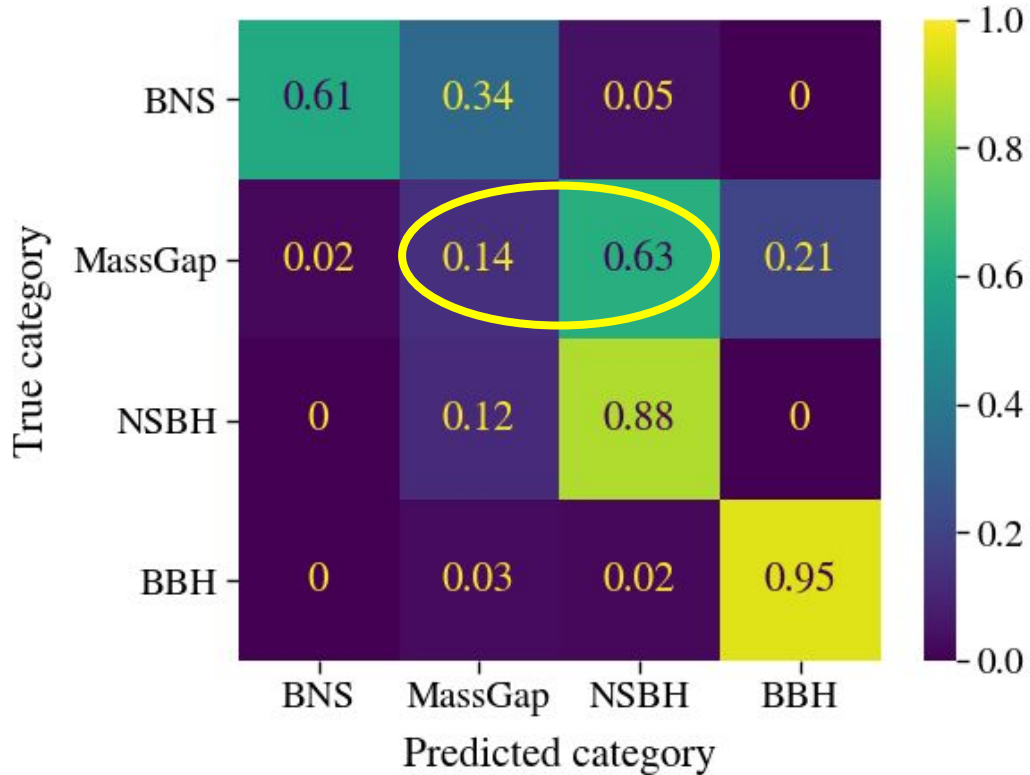
Simulated signals injected into O3a data recovered with PyCBC Live:

- $m(\text{NS}) \in [1-3] M_{\odot}$
- $m(\text{BH}) \in [3-97] M_{\odot}$
- Uniform in **chirp distance**

Confusion Matrix

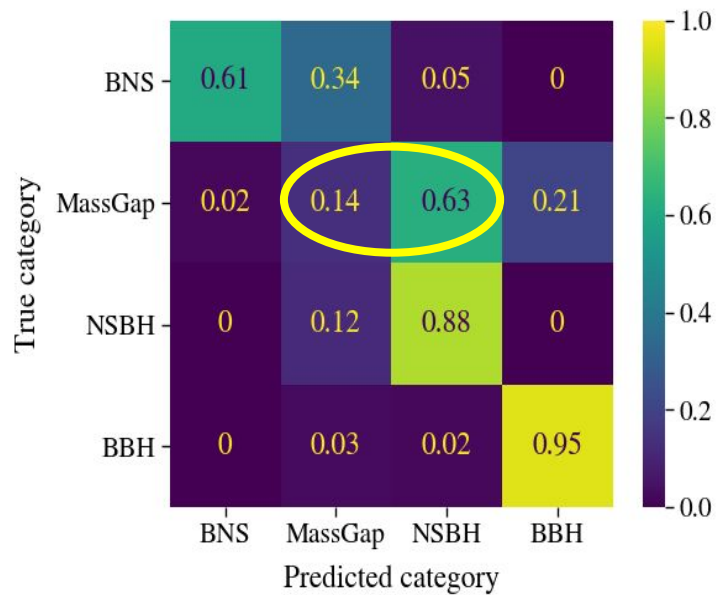


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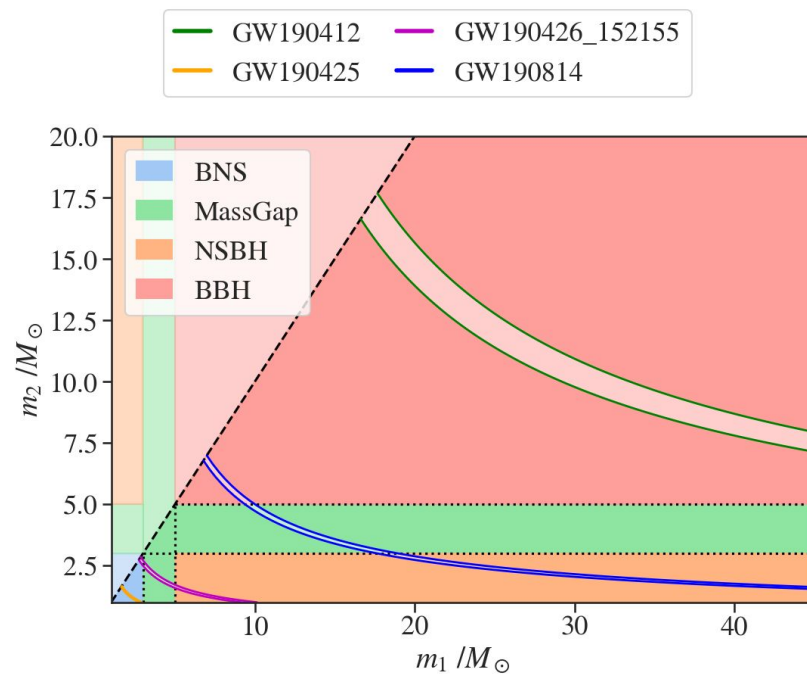


MassGap and NSBH always overlap with other regions

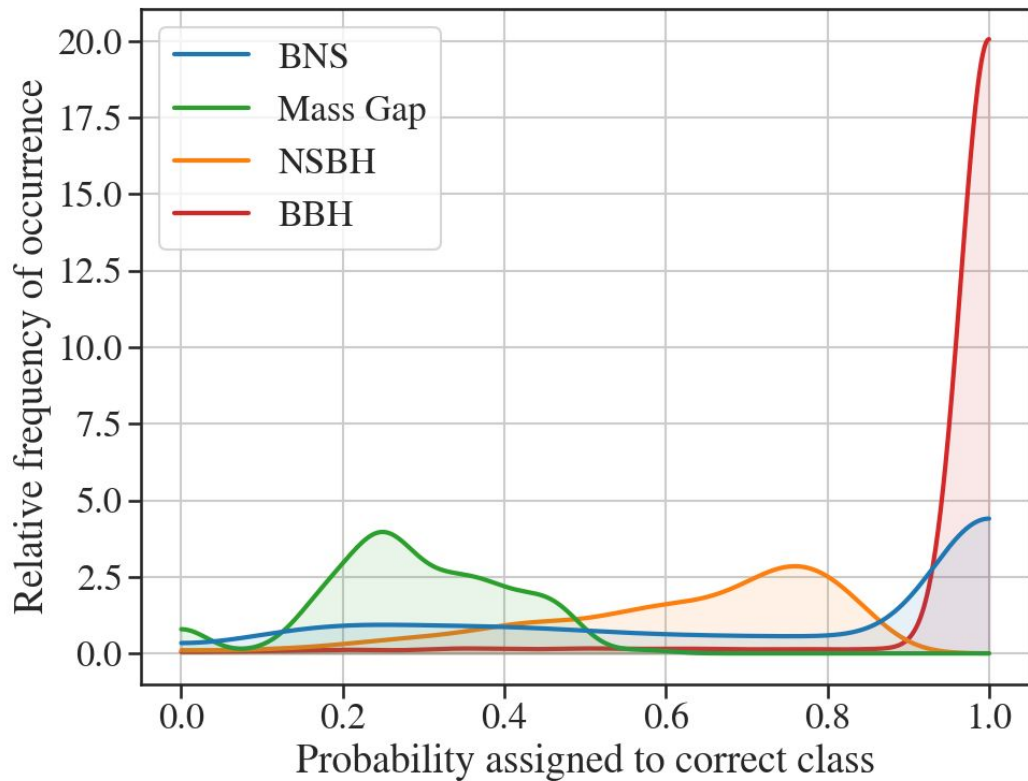
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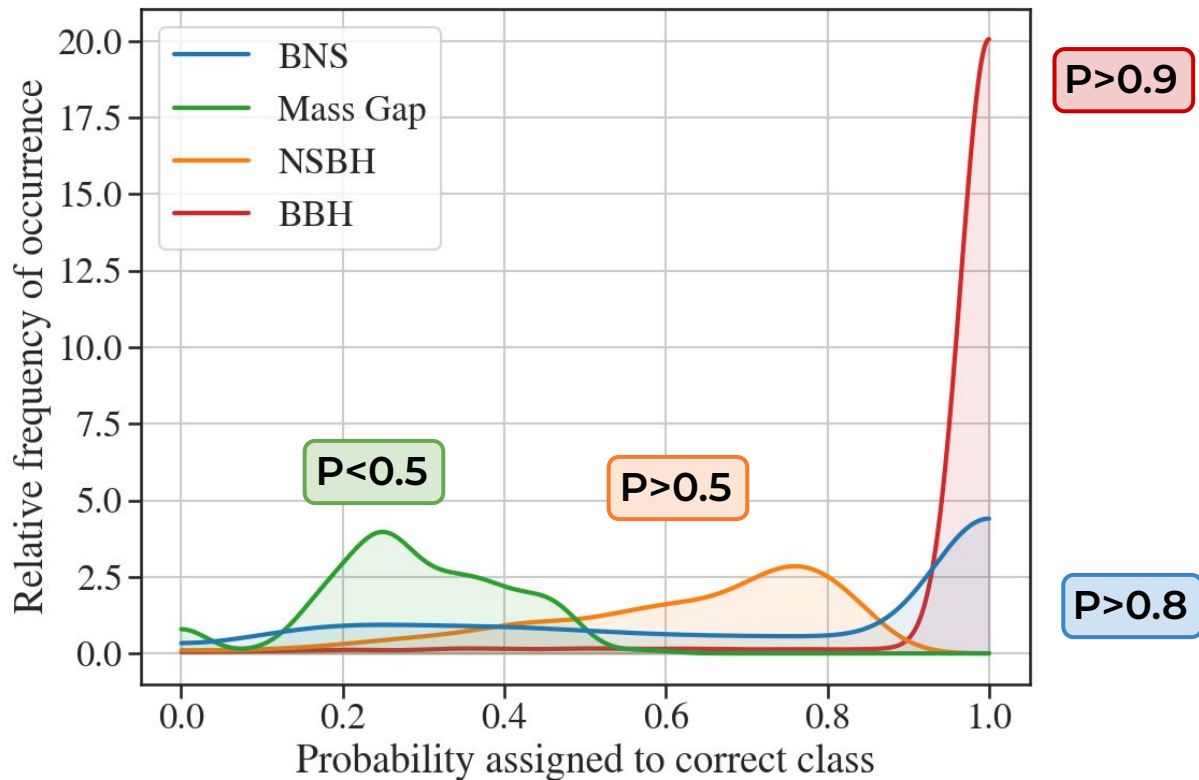
Overlap between regions



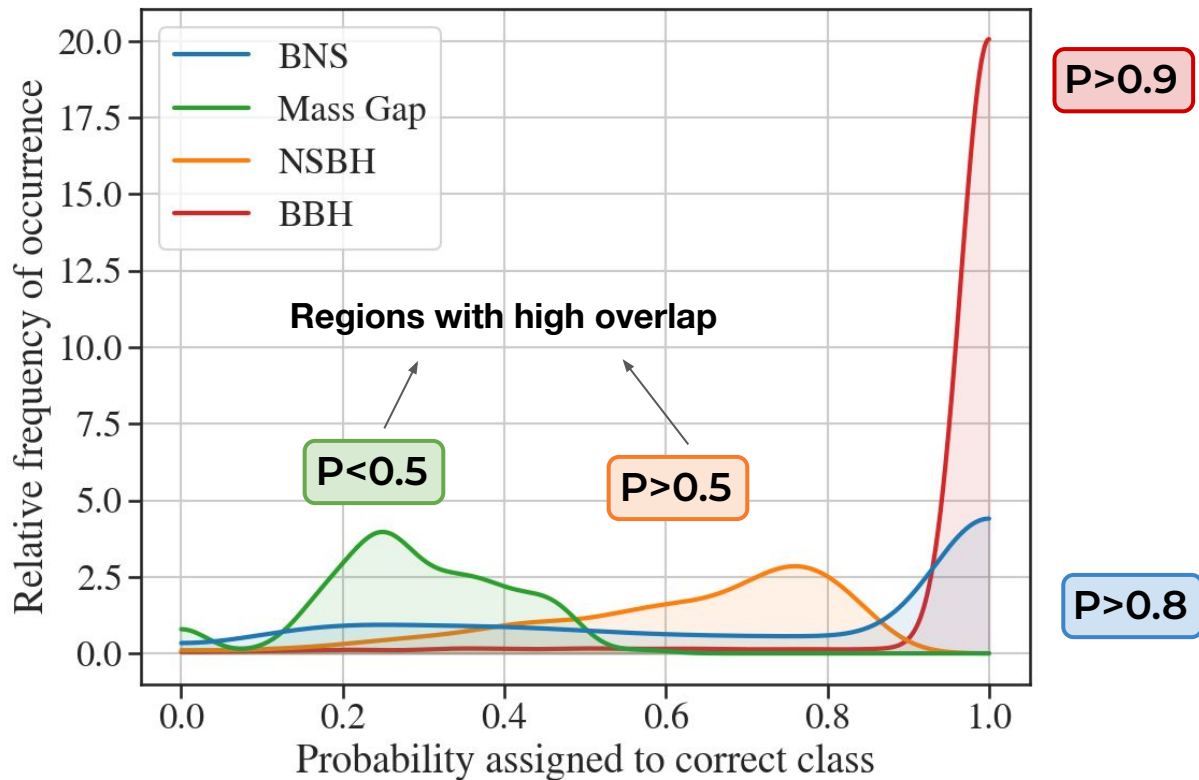
Kernel Density Estimation (KDE)



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Results for low-mass O3 events

- Results for O3 events **sent in LVC Public Alerts** with chirp masses less than $9 M_{\odot}$.
- We compare probabilities (%) computed with **our method** with the ones sent on **LVC Public Alerts** and the ones from PE results for **catalogs GWTC-2 and GWTC-3**

Results for low-mass O3 events

Event Name	Our method				Public Alerts				GWTC-2&3 PE				$\mathcal{M}(M_{\odot})$
	BNS	MG	NSBH	BBH	BNS	MG	NSBH	BBH	BNS	MG	NSBH	BBH	
GW190425	100	0	0	0	100	0	0	0	> 99	< 1	0	0	1.4
GW190426_152155	6	40	54	0	57	28	15	0 ^a	1	29	64	0	2.4
					15	25	60	0 ^b					
GW190707_093326	0	46	7	47	0	0	0	100	0	< 1	0	> 99	8.5
GW190720_000836	0	47	4	49	0	0	0	100	0	< 1	0	> 99	8.9
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GW190924_021846	0	30	56	14	0	100	0	0	0	45	4	51	5.8
GW190930_133541	0	44	14	42	0	100	0	0	0	8	< 1	92	8.5
GW200115_042309	7	41	52	0	0	100	0	0	< 1	28	71	0	2.4
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^a Initial Public Alert ^b Preliminary PE

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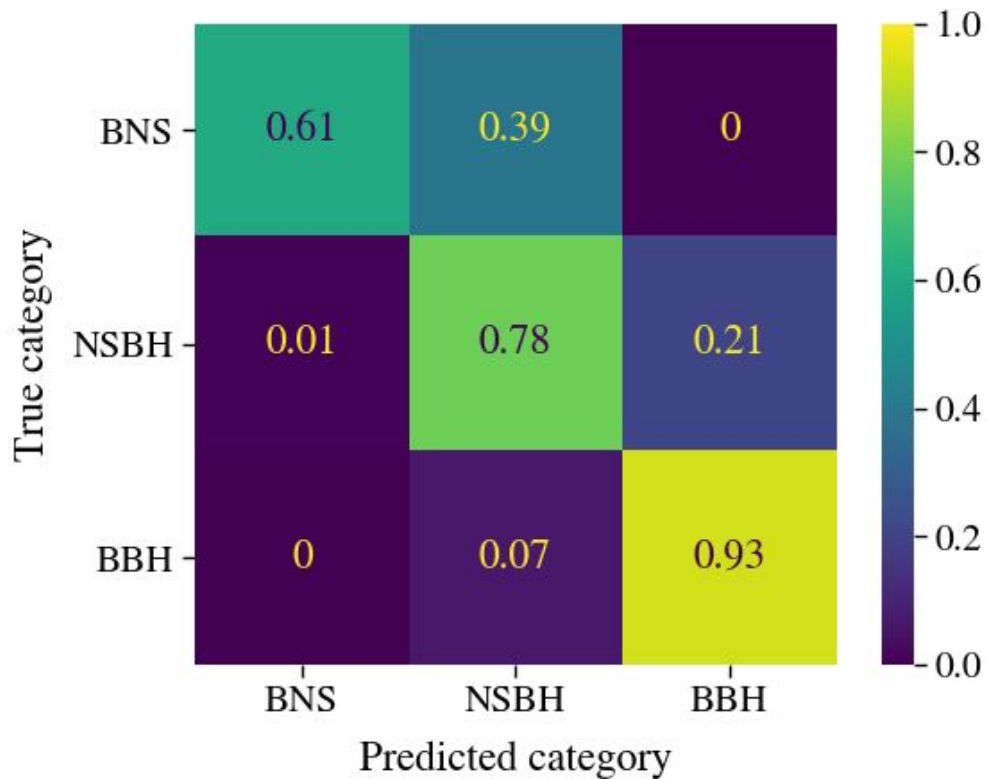
Summary

- We developed a new Source Classification method that improves the previous “hard-cuts”:
 - Offers a **spectrum of probabilities**
 - Accounts for **redshift bias** by estimating the **source distance**
- The method is **implemented in PyCBC Live** and it is available to run in O4
- Only adds **<50 ms** to the latency of the pipeline - **very low-latency**
- **Next step:**
 - To obtain a more accurate classification, we are investigating how to include information on the **binary mass ratio q** and account for **component spins**
 - For that we are considering a higher dimensional parameter space

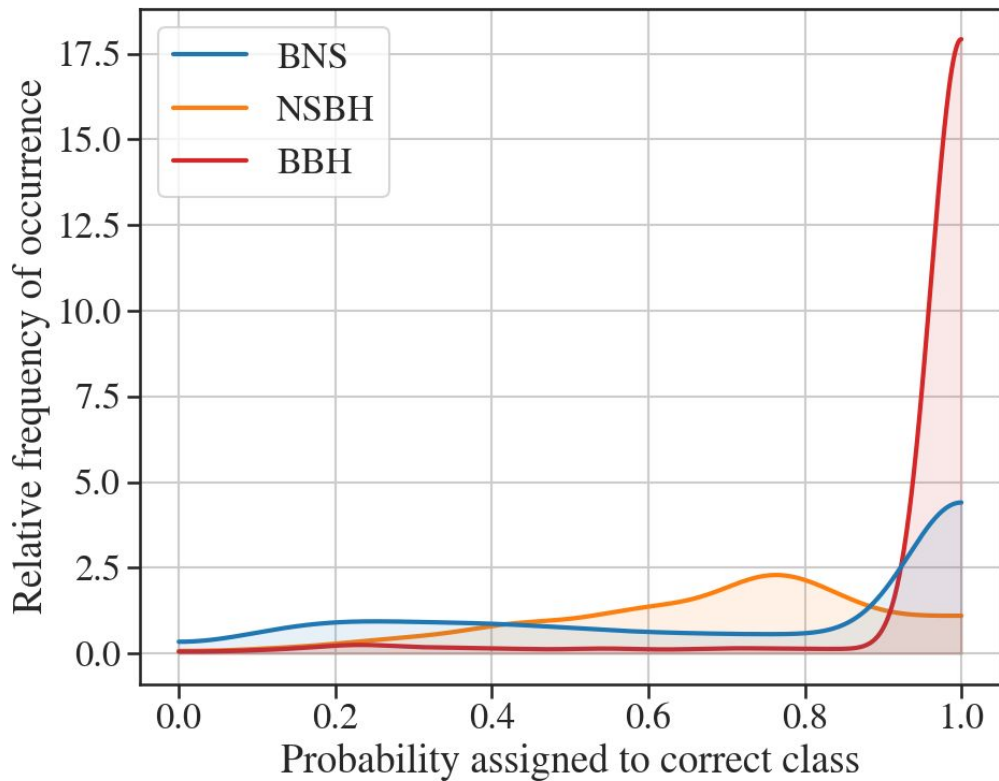
Thank you for your attention!

EXTRA SLIDES

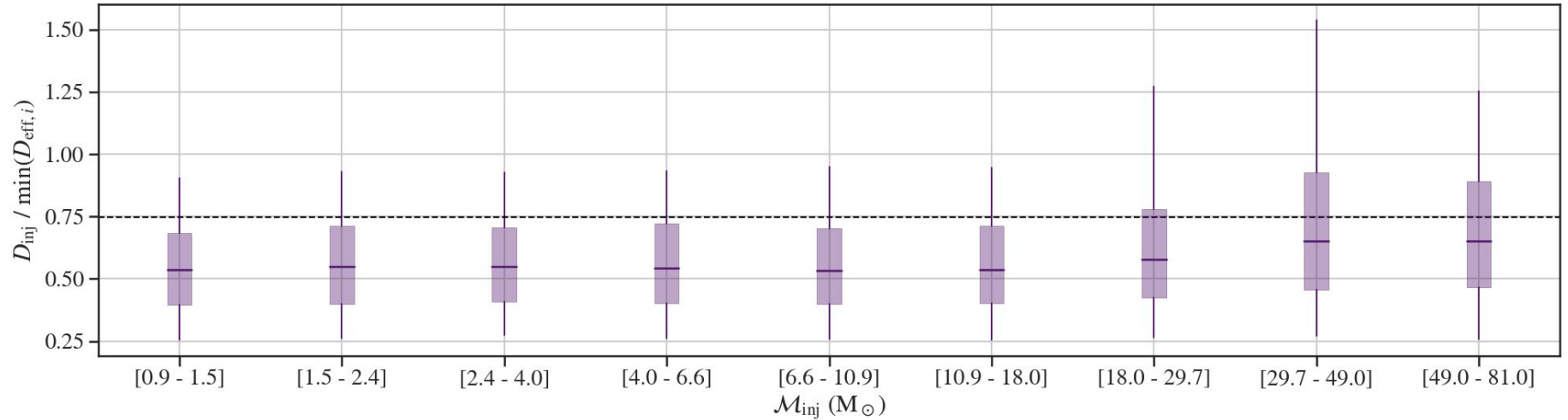
Results without MassGap



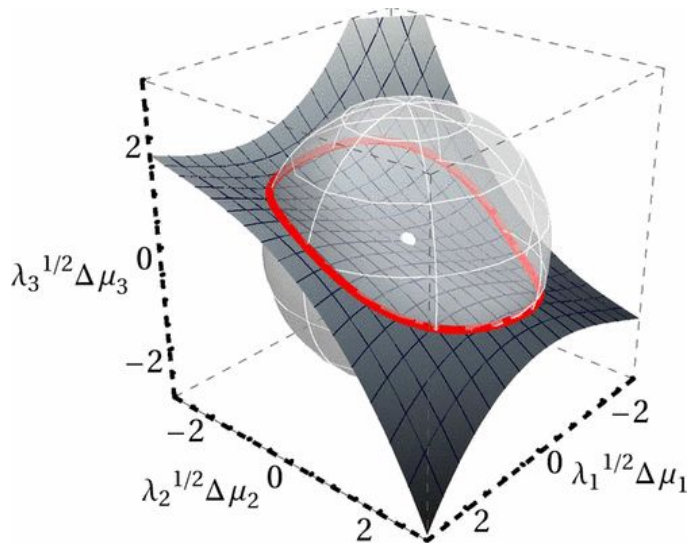
Results without MassGap



Check of distance fit with injections



Future Work



Expect to get better estimates of parameter errors by computing template mismatches in higher dimensional space
- (space based on PN coefficients)

