Source-Classification and Source-Properties in low-latency

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What are these quantities

- Source-Classification - Identification of a source as a BNS, NSBH or BBH, or with a member in the mass-gap (MG), or as non-astrophysical (Terrestrial)

    - Source-Classification is computed by **`p-astro`** (cf. `p_astro.json`)

    - NS := mass <= 3.0 solar mass; BH := mass >= 5.0 solar mass;
      MG := 3.0 < mass < 5.0 solar mass.

- Source-Properties - Attributing properties of the binary that are pointers for observers: namely, **is there a neutron star**, and was there **remnant matter** due to tidal disruption, **assuming that the source is <u>astrophysical in origin</u>**.

    - Computed by **`EM-Bright`** (cf. **`em_bright.json`**). There are three versions of this available:

    - EM-Bright from point estimate - currently in use

    - EM-Bright from Machine Learning - Soon to be deployed

    - EM-Bright from PE - Recently approved.

Source-Classification

p-astro

- Extension of a counting formalism first presented by FGMC.

- Suppose there are N events $\overrightarrow{x}_N$ above detection threshold
  Where, $\overrightarrow{x}_N$ are the detection-statistics values.

- Posterior on the Poisson expected counts, $\Lambda_0, \overrightarrow{\Lambda}$:

terrestrial

astrophysical

$$P_N\left(\Lambda_0, \overrightarrow{\Lambda} \,|\, \overrightarrow{x}_N\right) \propto p\left(\Lambda_0, \overrightarrow{\Lambda}\right) \prod_{j=1}^{N} [\Lambda_0 + \overrightarrow{\Lambda} \,.\, \overrightarrow{K}(x_j)] e^{-\Lambda_0 - \overrightarrow{\Lambda} . \overrightarrow{u}}, \quad K_\beta(x_j) = \frac{f(x_j)}{b(x_j)} \times \frac{w_\beta(m_j)}{w_{\mathrm{terr}}(m_j)}$$

- p-astro for a new event :

$$P_\beta\left(x_{N+1} \,|\, \overrightarrow{x}_{N+1}\right) = \frac{\langle \Lambda_\beta \rangle_N K_\beta(x_{N+1})}{\langle \Lambda_0 \rangle_N + \overrightarrow{K}(x_{N+1}) \,.\, \langle \overrightarrow{\Lambda} \rangle_N}$$

Issue with **S190728q**

- Computation of source-classification requires the weights for the different astrophysical categories.

- The weights $(w_{\rm terr}, w_{\beta})$ in low-latency are computed from injection campaign, conducted with O2 data, by studying the mass bins that are triggered by the injections. Thus the weights are sensitive to the choice of the template banks.

- Recently the template-bank changed for the gstlal pipeline. However, due to a logistical error the old weights were used, which led to incorrect result in **S190728q** for `p-astro`, wrongly identifying the system as a mass-gap object with ~50% probability.

- **We apologize for this mistake,** and are making changes to make sure this does not happen again.

Source-Properties

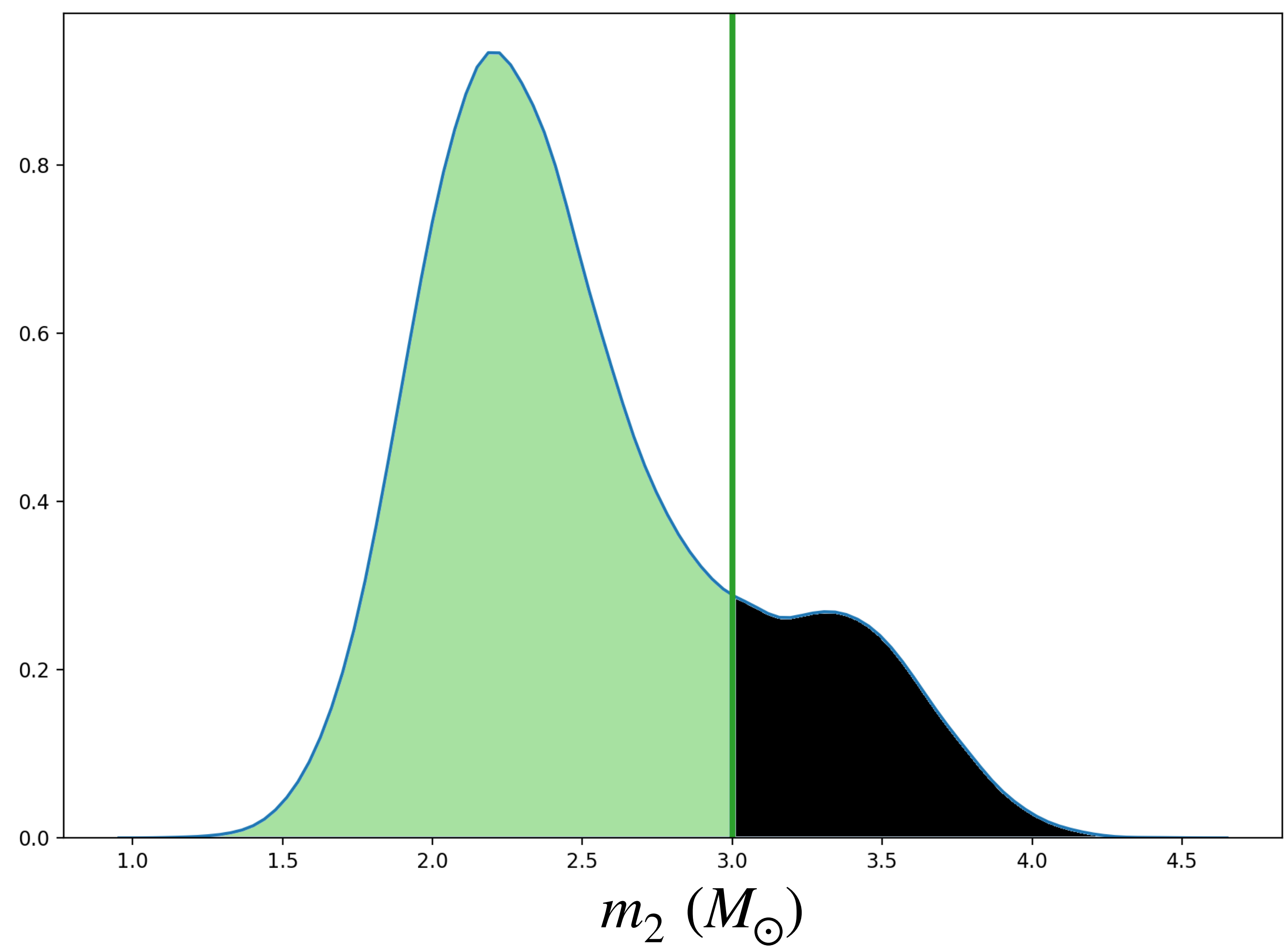
EM-Bright computation

- In the beginning of O3 we implemented machine learning based classifier to compute the probability of a binary harboring a neutron star, and the probability that the neutron star was tidally disrupted (using Foucart, Hinderer and Nissanke, 2018).

- Predicted presence of remnant matter for S190408an and S190412m, both BBH, when we expect none. Switched to best matching template-based inference.

- The machine learning based classifier is currently under review, expected to be approved in two weeks. Things are now working (results **here** and **here**).

- Higher-latency: We can simply count the fraction of the samples that have masses consistent with at least one neutron star.



Comparison for GSTLAL events

	Superevent	p_astro_NS		p_astro_Terr	HasNS	HasNS_ML	HasNS_PE
1	S190408an	0.0		0.0	0.0	0.0	0.0
2	S190412m	0.0		0.0	0.0	0.0	0.0
3	S190425z	0.99		0.0	1.0	1.0	1.0
4	S190426c	0.62		0.1401	1.0	1.0	1.0
5	S190503bf	0.00		0.0	0.0	0.0	0.0
6	S190510g	0.42		0.58	1.0	1.0	1.0
7	S190513bm	0.0		0.0	0.0	0.0	0.0
8	S190517h	0.0		0.0	0.0	0.0	0.0
9	S190630ag	0.0		0.0	0.0	0.0	0.0
10	S190718y	0.02		0.98	1.0	1.0	N.A
11	S190727h	0.0		0.0	0.0	0.0	0.0
12	S190728q	0.0		0.0	0.0	0.0	0.0
13	S190814bv	0.0	**p_MG = 1.0**	0.0	0.0	0.62	0.99

Comparison for other pipeline events

	Superevent	p_astro_NS	p_astro_Terr	HasNS	HasNS_ML	HasNS_PE
1	S190512at	0.0	0.01	0.0	0.0	0.0
2	S190707q	0.0	0.0	0.0	0.0	0.0
3	S190519bj	0.0	0.04	0.0	0.0	0.0
4	S190720a	0.0	0.01	0.0	0.0	0.0
5	S190421ar	0.0	0.96	0.0	0.0	0.0
6	S190521r	0.0	0.0	0.0	0.0	0.0
7	S190701ah	0.0	0.07	0.0	0.0	0.0
8	S190602aq	0.0	0.01	0.0	0.0	0.0
9	S190706ai	0.0	0.01	0.0	0.0	0.0

Conclusion

- The true masses of the detected binary are quite uncertain until parameter estimation is conducted. The challenge is to get the best possible inference for `p-astro` and `EM-Bright` in low-latency despite these uncertainties.

- There is very good consistency between the `EM-Bright` and the `p-astro` results for all the CBC pipelines for events that we have sent out. **This consistency extends to parameter estimation results.**

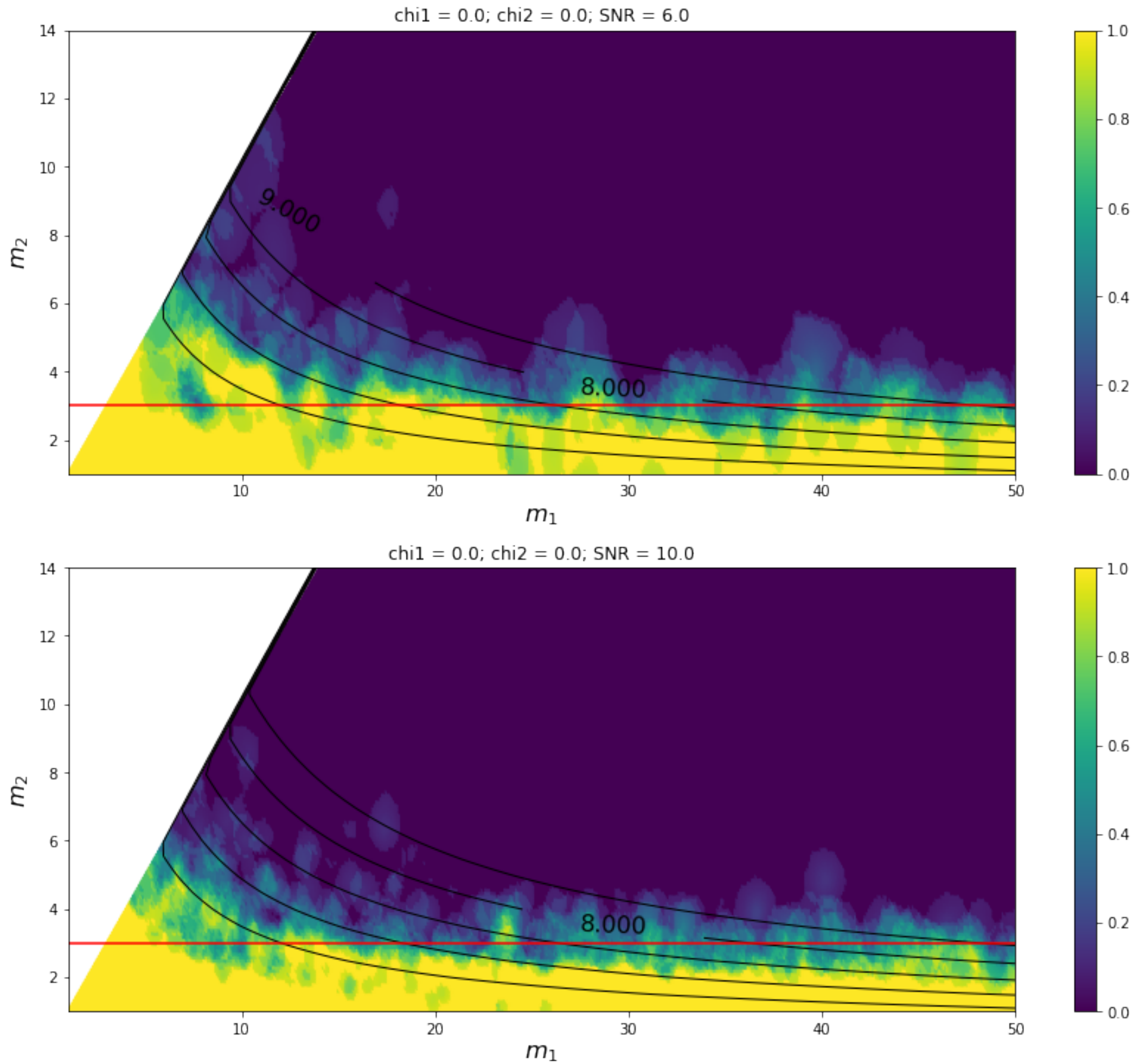
- There were some hiccups in the beginning of O3 with both the source-properties (`EM-Bright`) and the source-classification (`p-astro`) results.

- We saw some bugs in the recent past in `p-astro`. Each case of problematic `p-astro`, has been due to logistical-errors, most often due to outdated files being used.

- We sincerely apologize for these errors, and are taking steps to make sure they do not happen in the future.

Performance of ML based EM-Bright

- The performance of the Machine Learning classifier.
- The classifier learns from injection campaign to classifier a system having a NS and having remnant matter.
- Systems found near the boundary of NS and BH (red-line) are the ones that are affected by the machine learning.
- In absence of the ML all points below the red line will be classified as HasNS = 1.0 and all points above as HasNS = 0.0



Status in low-latency

Events in July

Superevent	Event	Pipeline	Latency (s) (EM-Bright)	Latency (s) (p-astro)
S190728q	G345315	gstlal	1	13
S190727h	G345173	gstlal	2	21
S190720a	G344656	pycbc	2	2
S190718y	G344538	gstlal	2	42
S190707q	G338000	MBTA	1	1
S190706ai	G337913	pycbc	2	2
S190701ah	G337515	pycbc	6	6