Binary Black Holes mergers from Population III stars

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Universidad Andrés Bello — August 6, 2024

I introduce myself

And many others…

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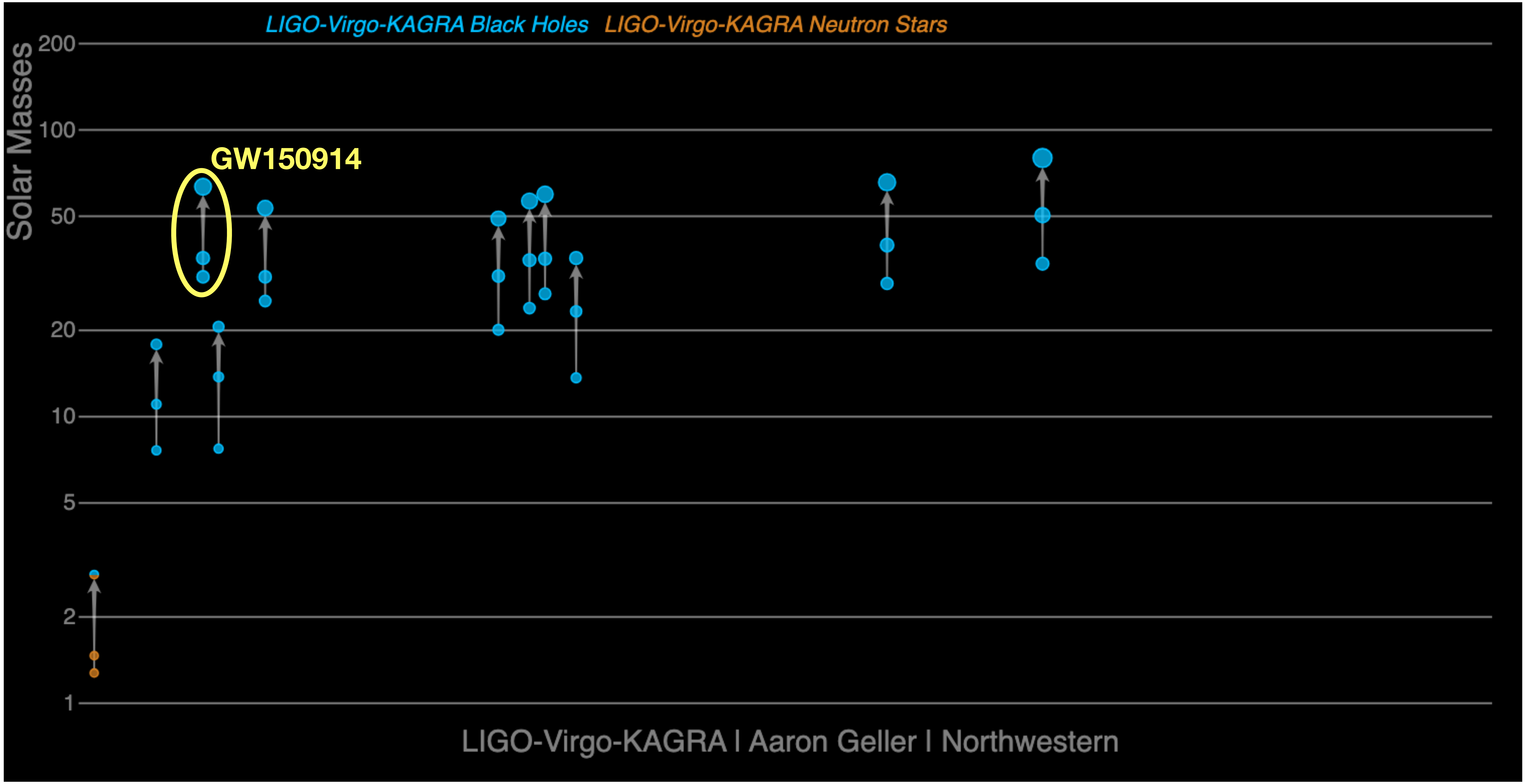
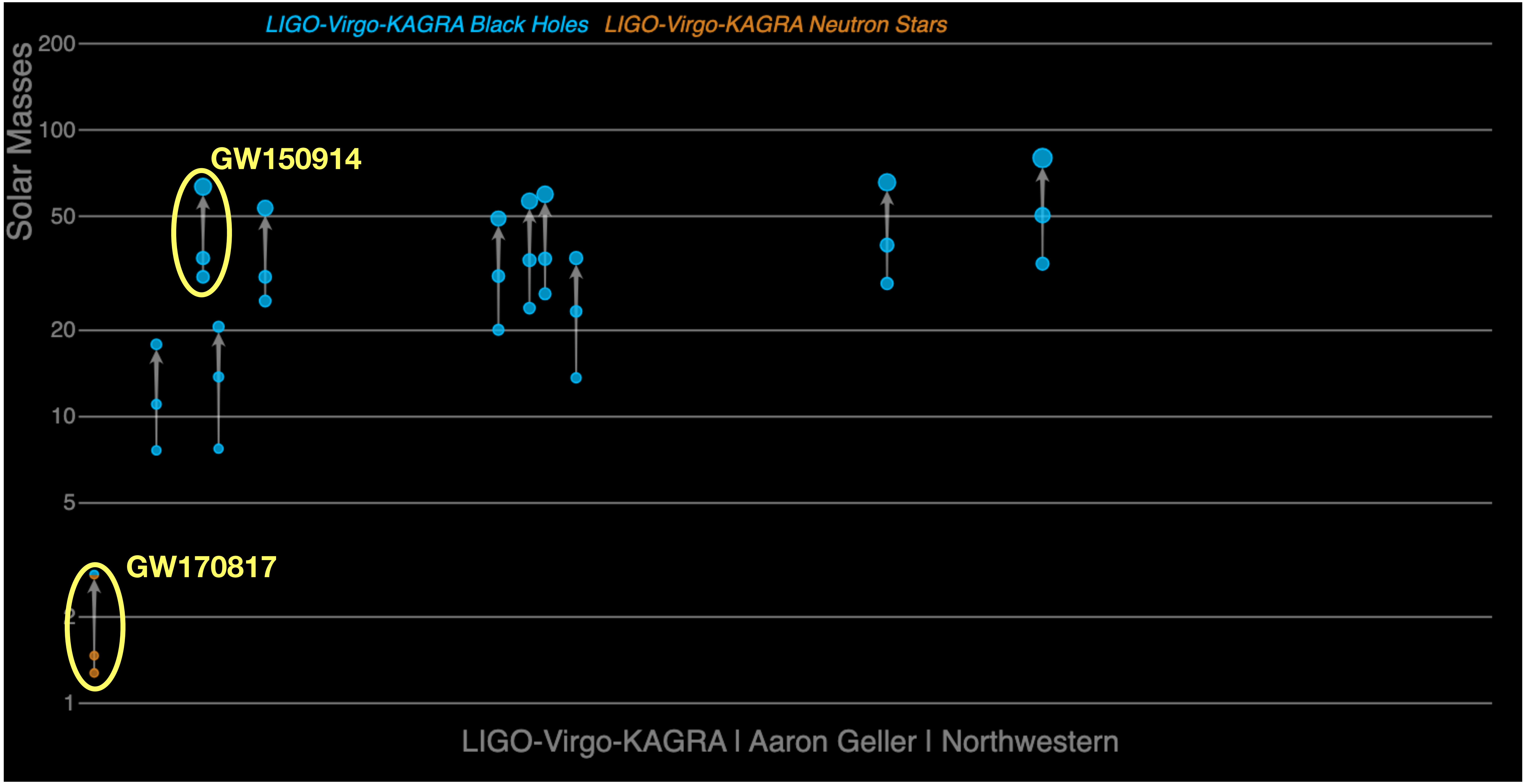
Gravitational Wave Astrophysics

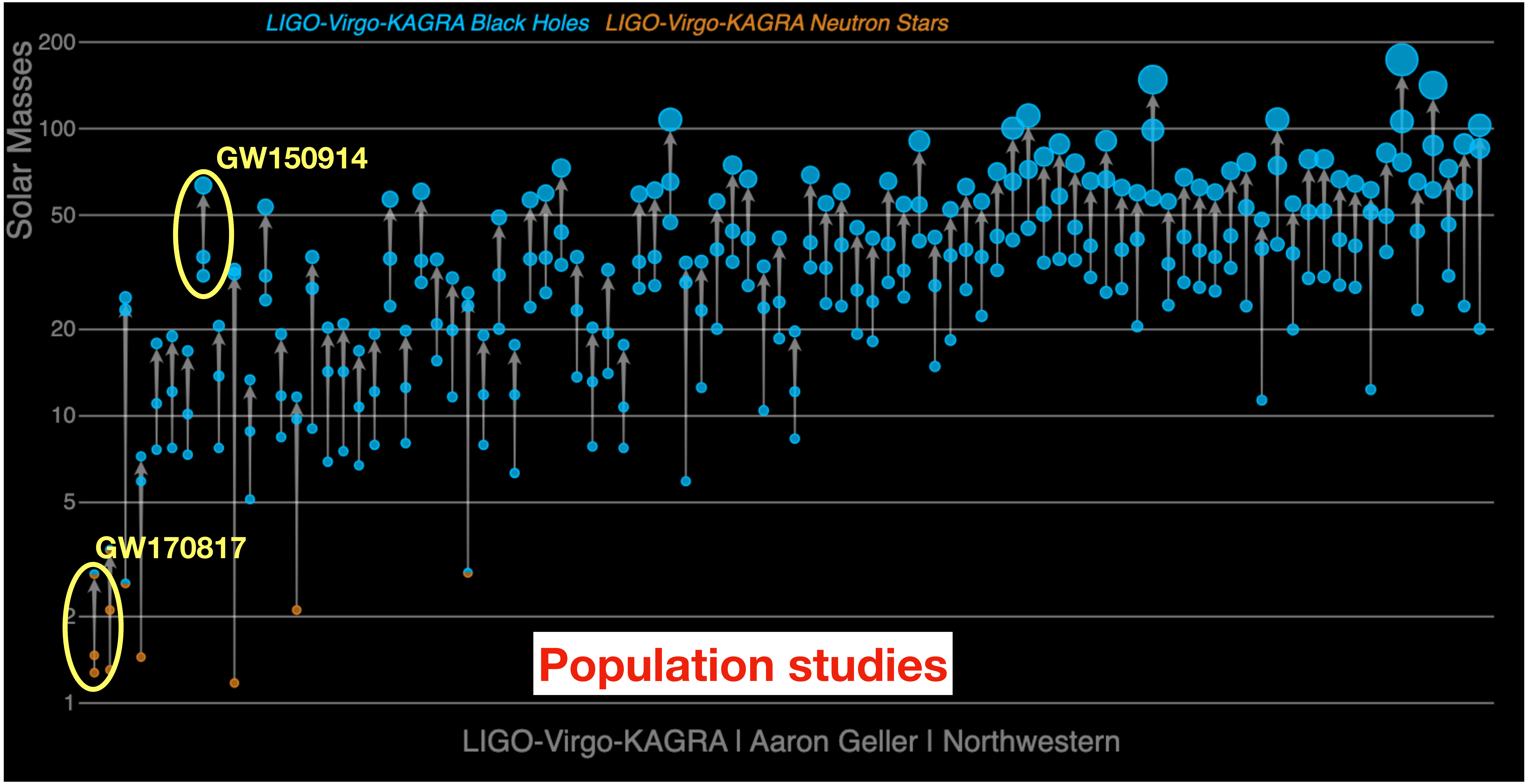


Gravitational Wave Astrophysics



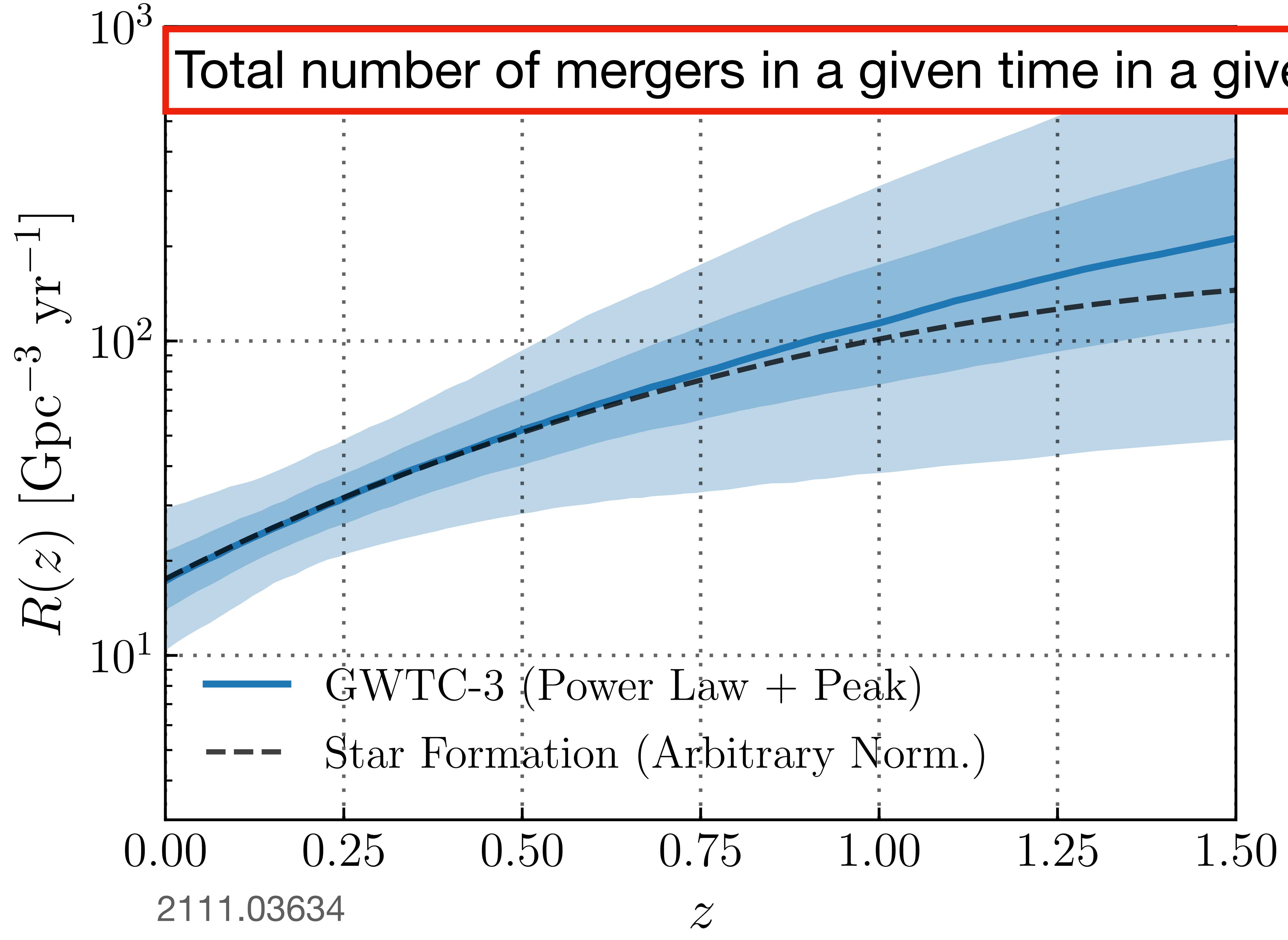
Refs: [*Abbott et al. 2017*]

Gravitational Wave Astrophysics



Merger rate density

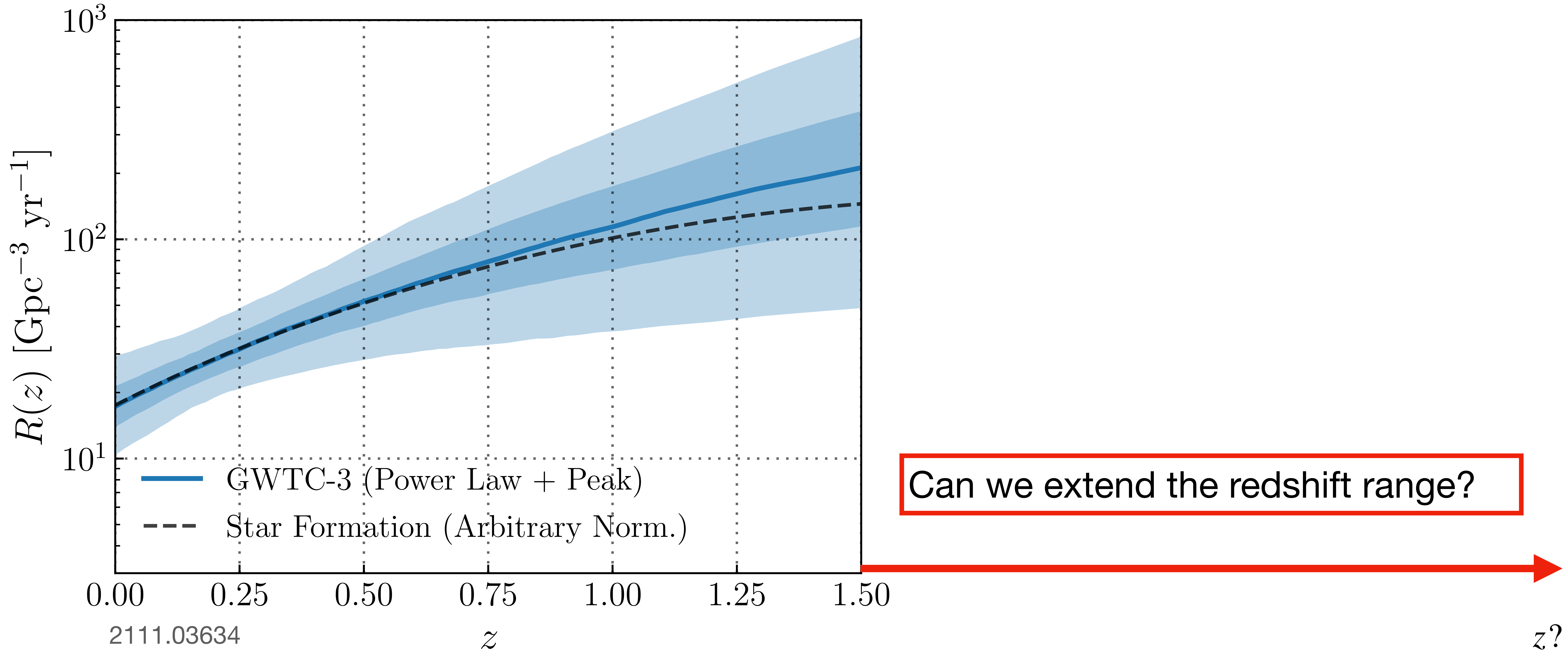
Total number of mergers in a given time in a given volume



2111.03634

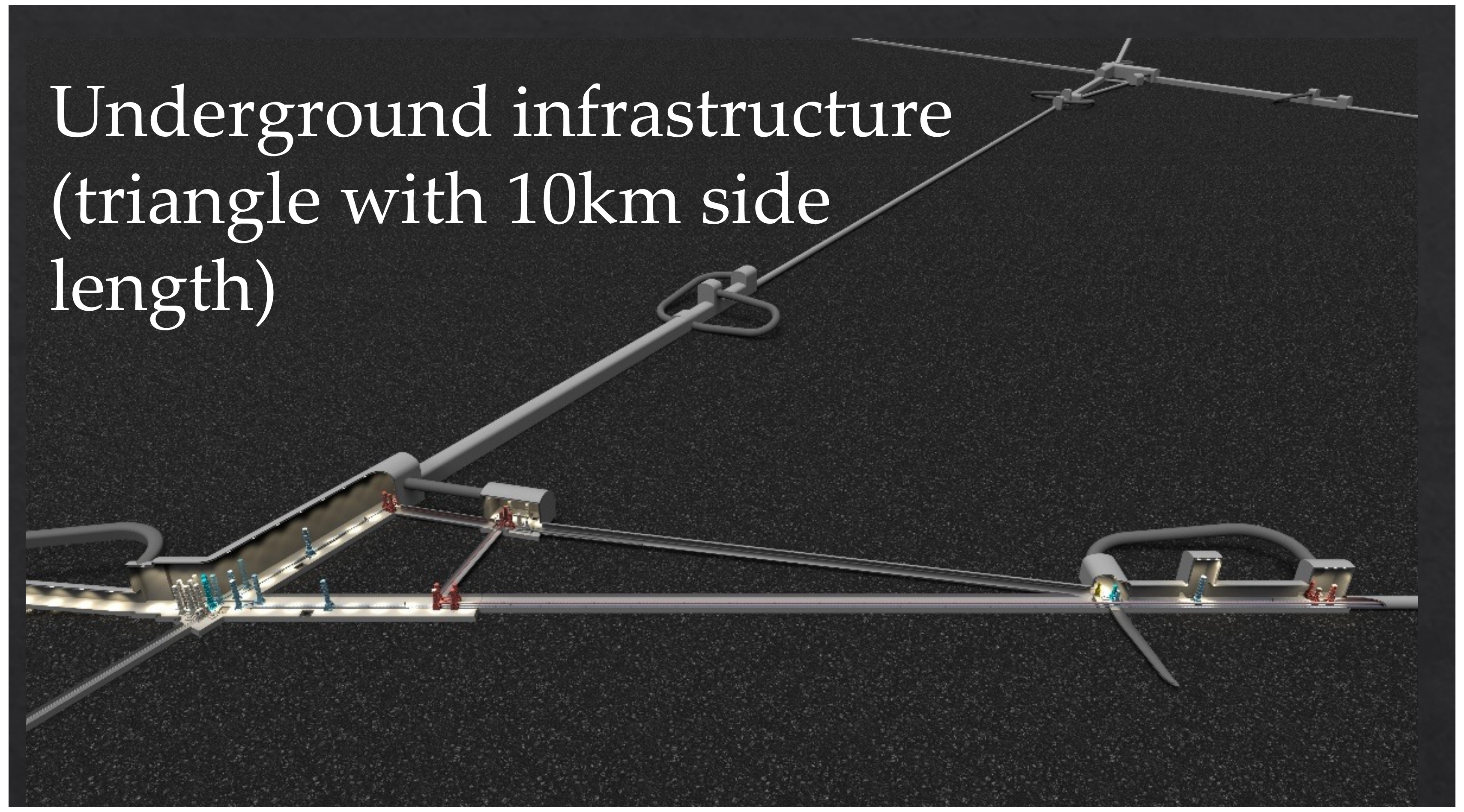
- $\mathscr{R}(z) = \mathscr{R}^0(1+z)^\kappa$
- $\kappa > 0$ at 99% credibility

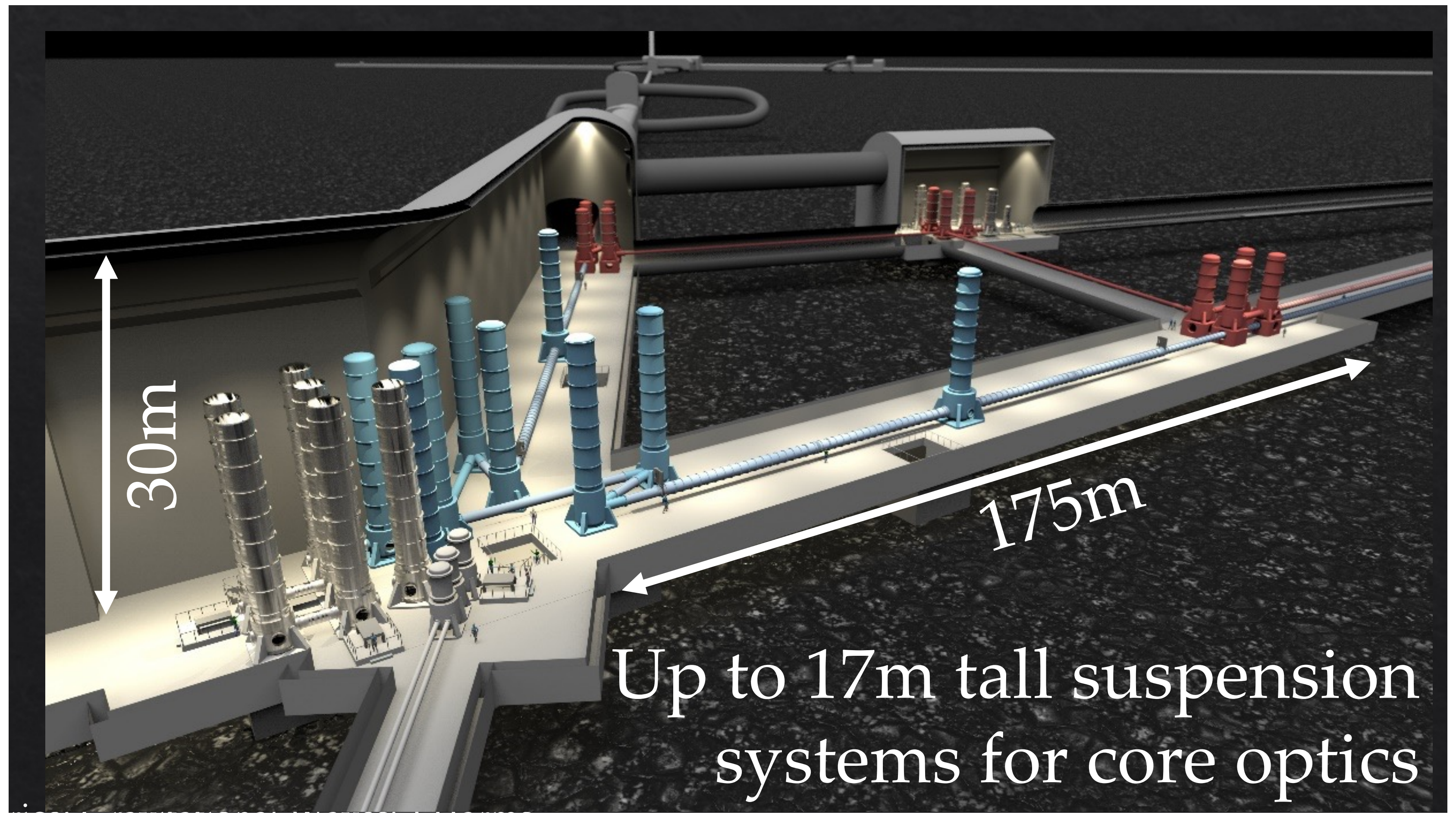
Merger rate density



Can we extend the redshift range?

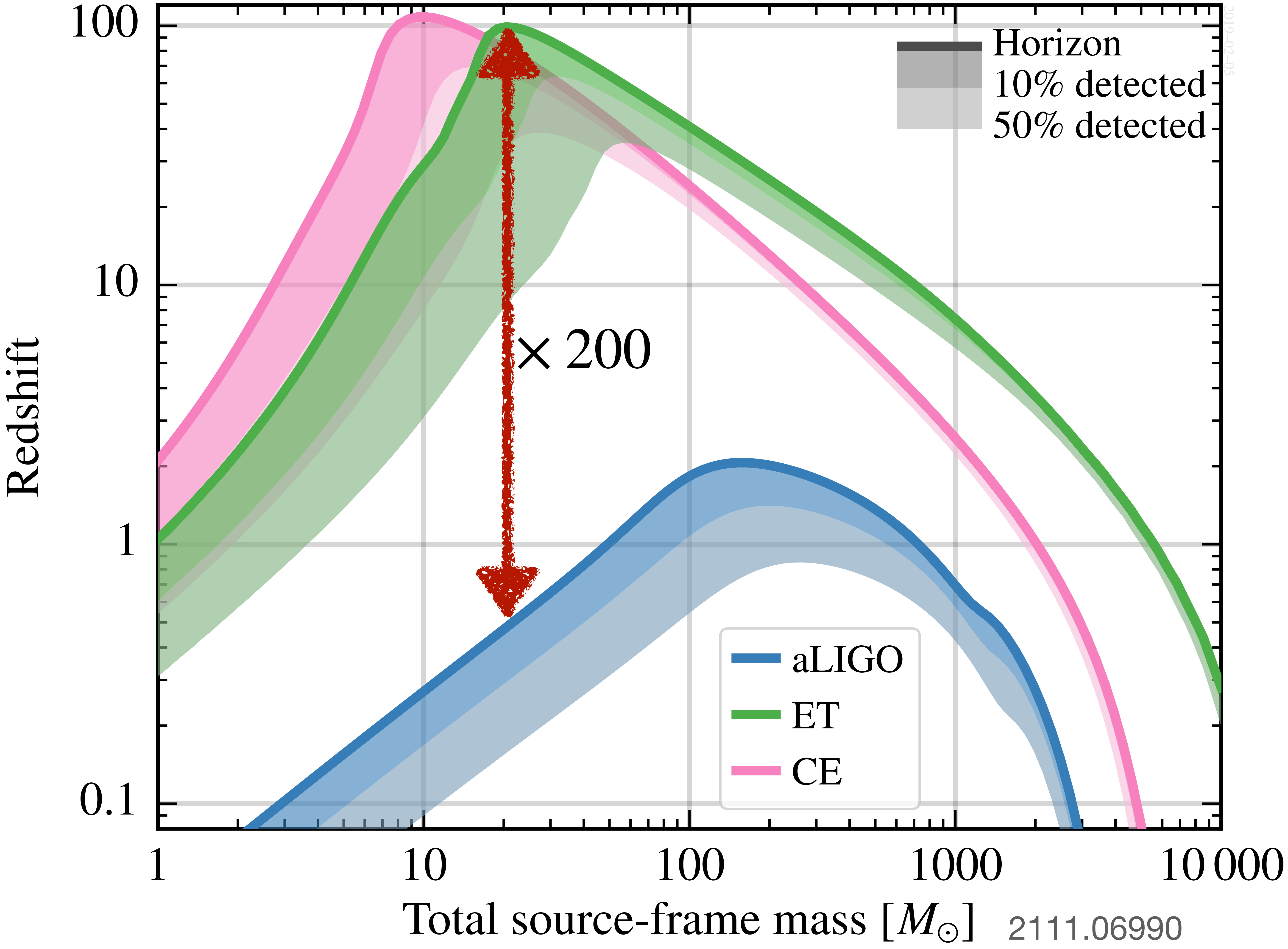
The Einstein Telescope





Credits: Jan Harms

Third-generation detectors



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Population III stars

- Population III stars are believed to be the first generation of stars formed at **high redshift** $(z > 20)$
- They are massive and formed from pristine gas (i.e. **zero metallicity**)
- They are still undetected *(traces of their existence with JWST)*
- Modelled through cosmological simulations

Ref. ***Klessen & Glover 2023***, ***Bromm & Larson 2004***, ***Zackrisson et al. 2023***, ***Maiolino et al. 2024***

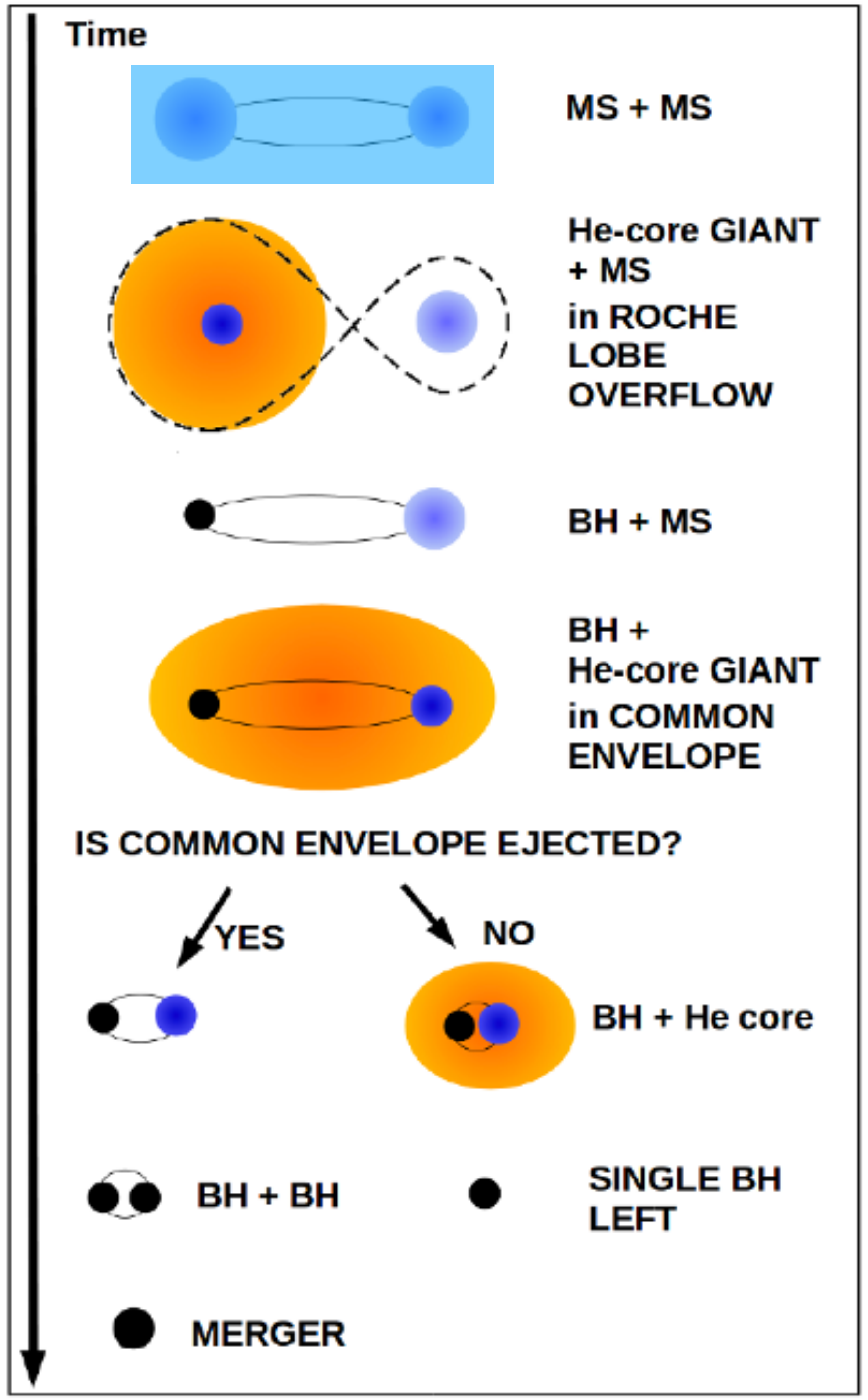
Our goals

- Large **parameter space exploration** of Pop. III BBHs
- **merger rate density**
- **evolution of mass** spectrum **with redshift**
- expected **detection rates** with Einstein Telescope

Isolated formation channel

- Two massive stars form in the **same binary system** and evolve together

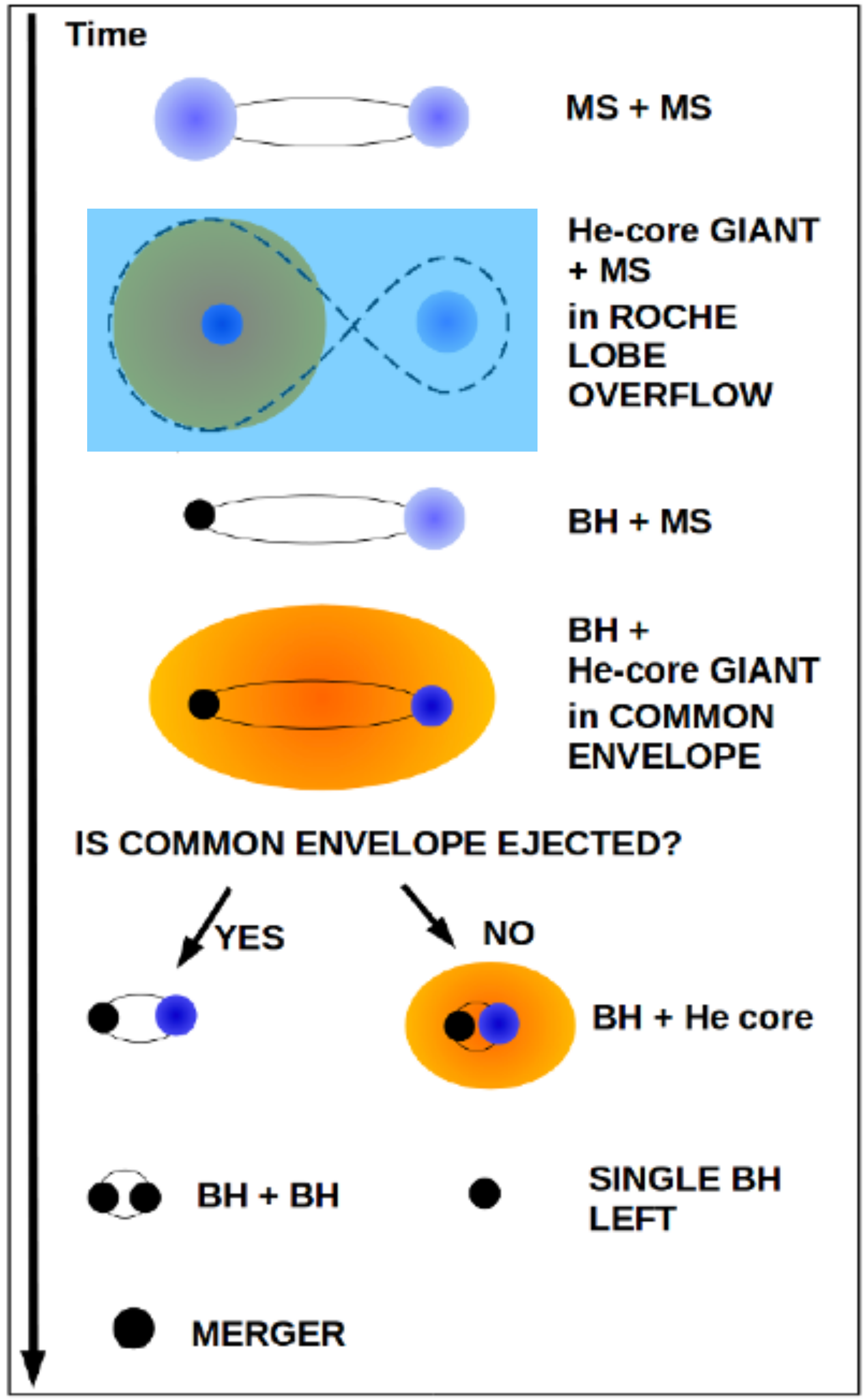
- *Let’s see an example*



Isolated formation channel

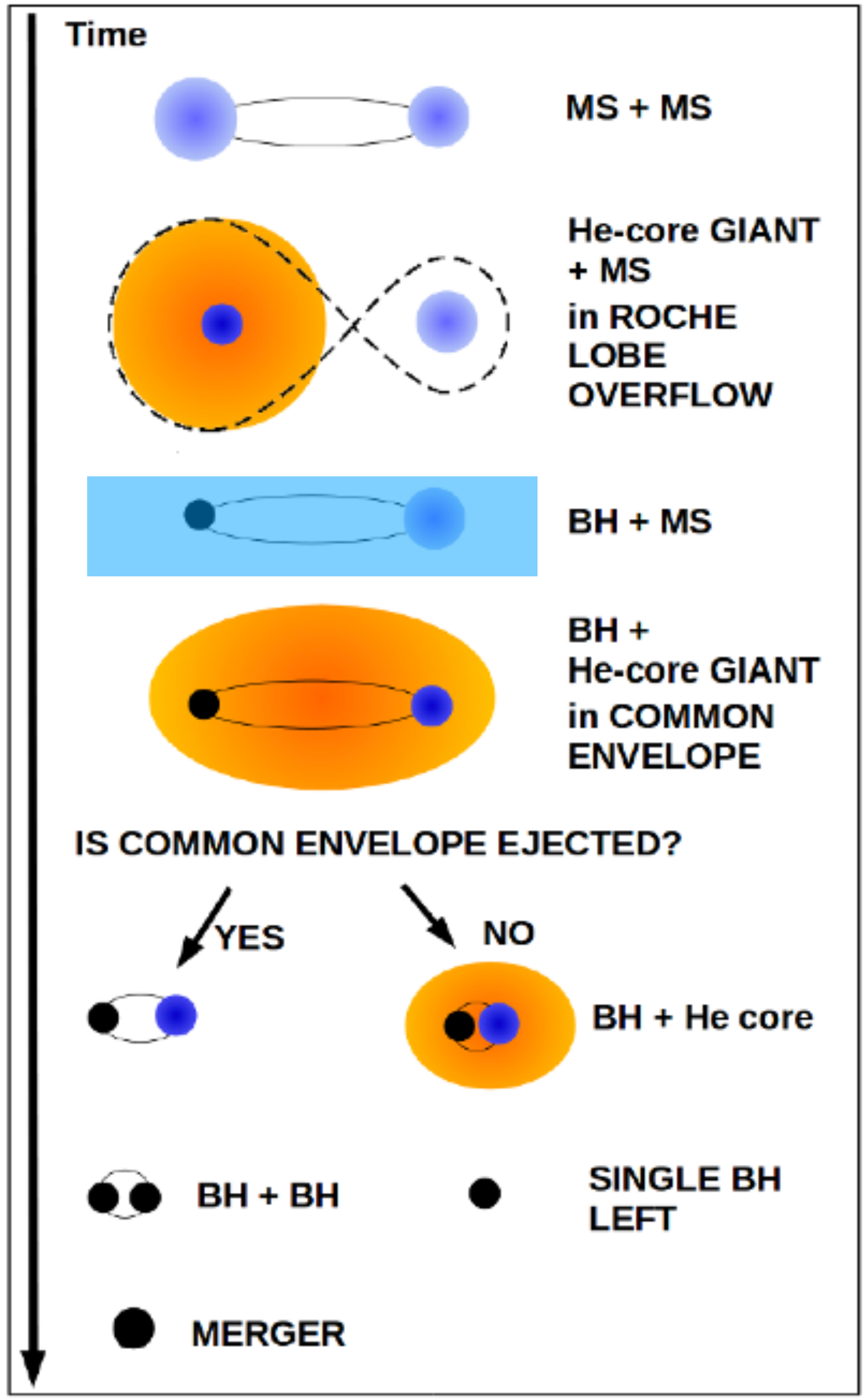
- Following radius expansion, one star can transfer mass to the other in a **stable mass transfer**

- This shrinks the orbit of the binary system



Isolated formation channel

- The first black is formed after core **collapse supernova**

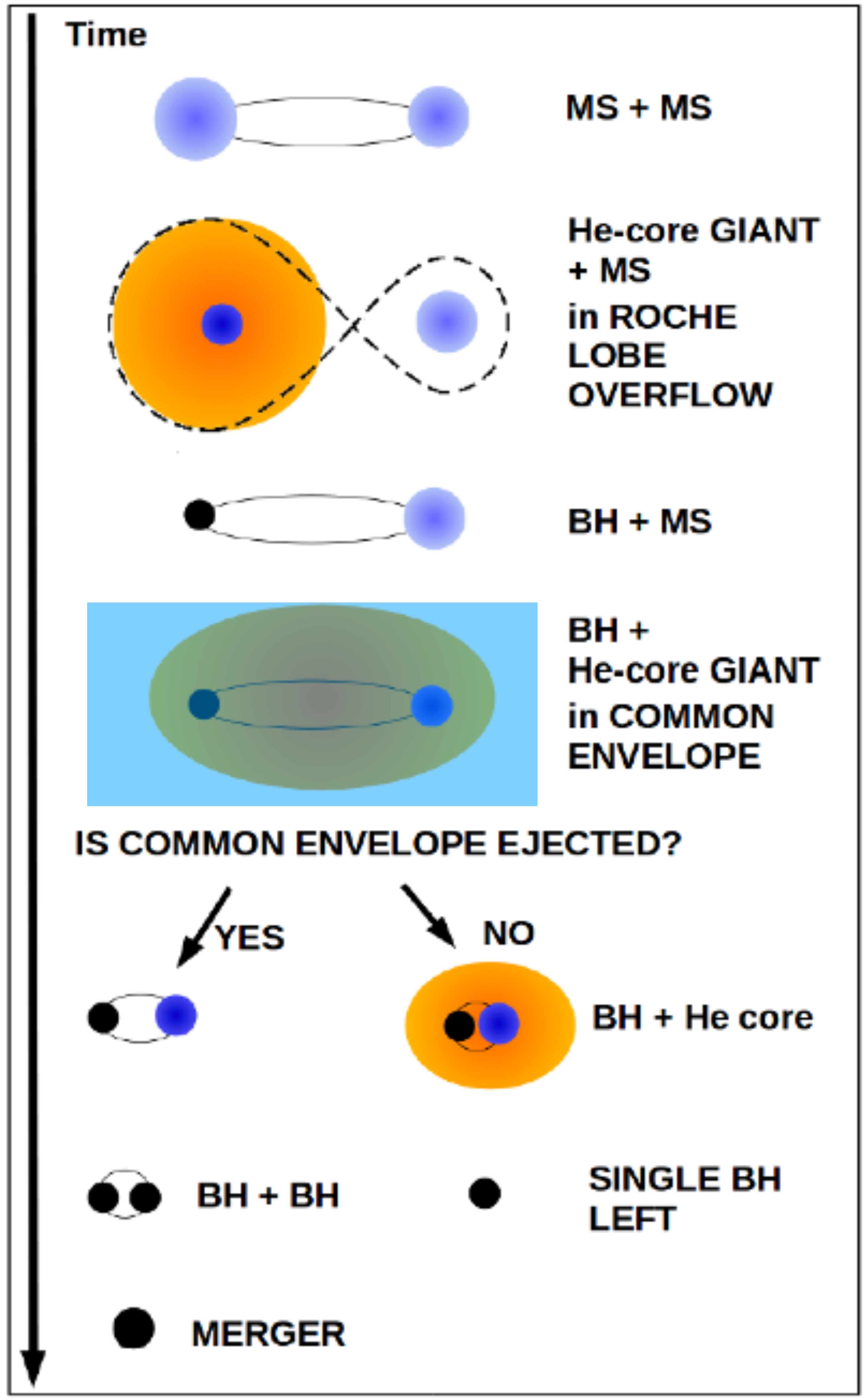


Ref. *Mapelli 2018*, *Spera et al. 2022*, *Costa et al. 2023*

Credits: Michela Mapelli

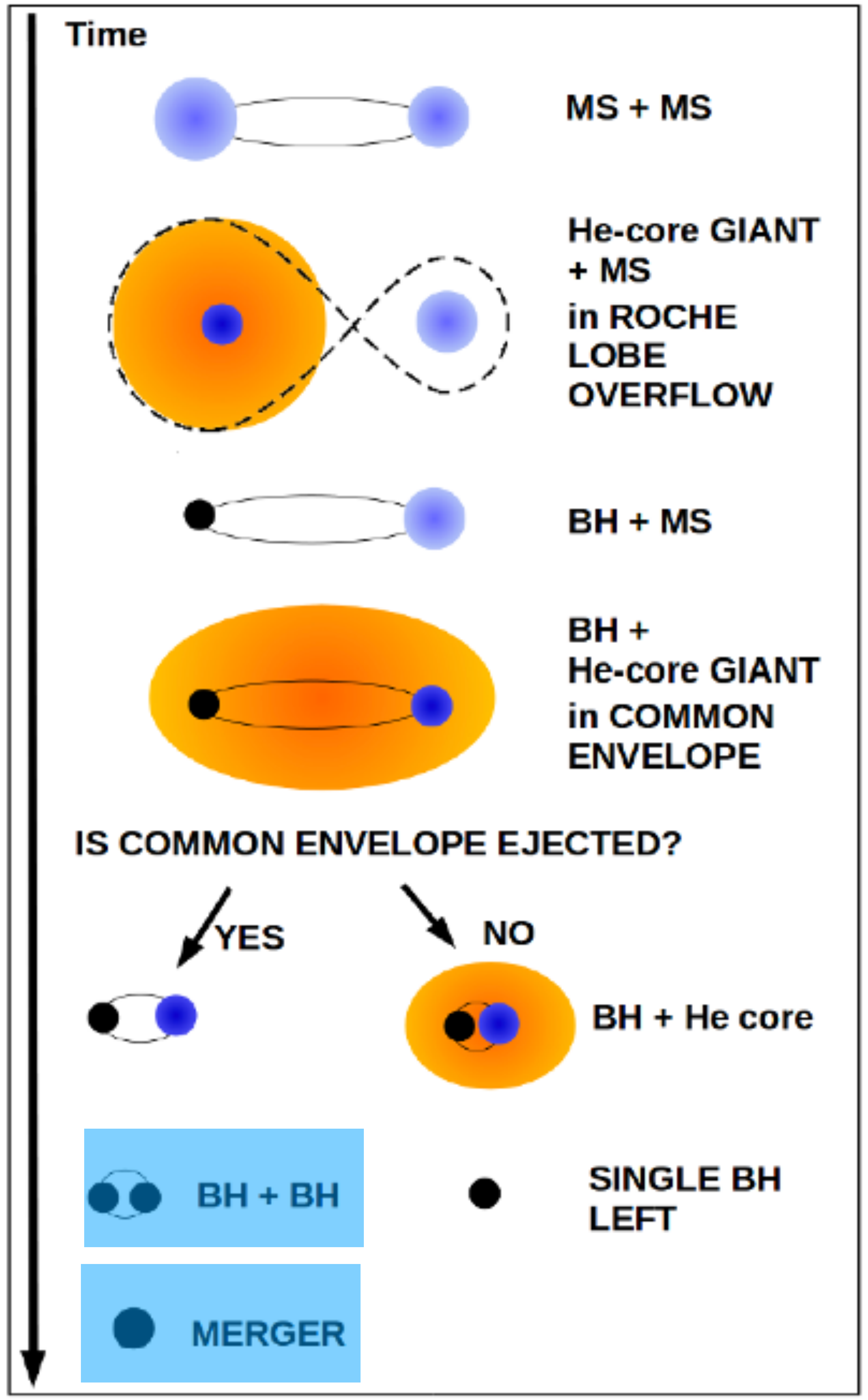
Isolated formation channel

- The other star starts transferring mass through **unstable mass transfer**
- Beginning of the **common envelope phase**
- A **drag force** is exerted between the black hole and the stellar core.
- This phase further shrinks the binary systems



Isolated formation channel

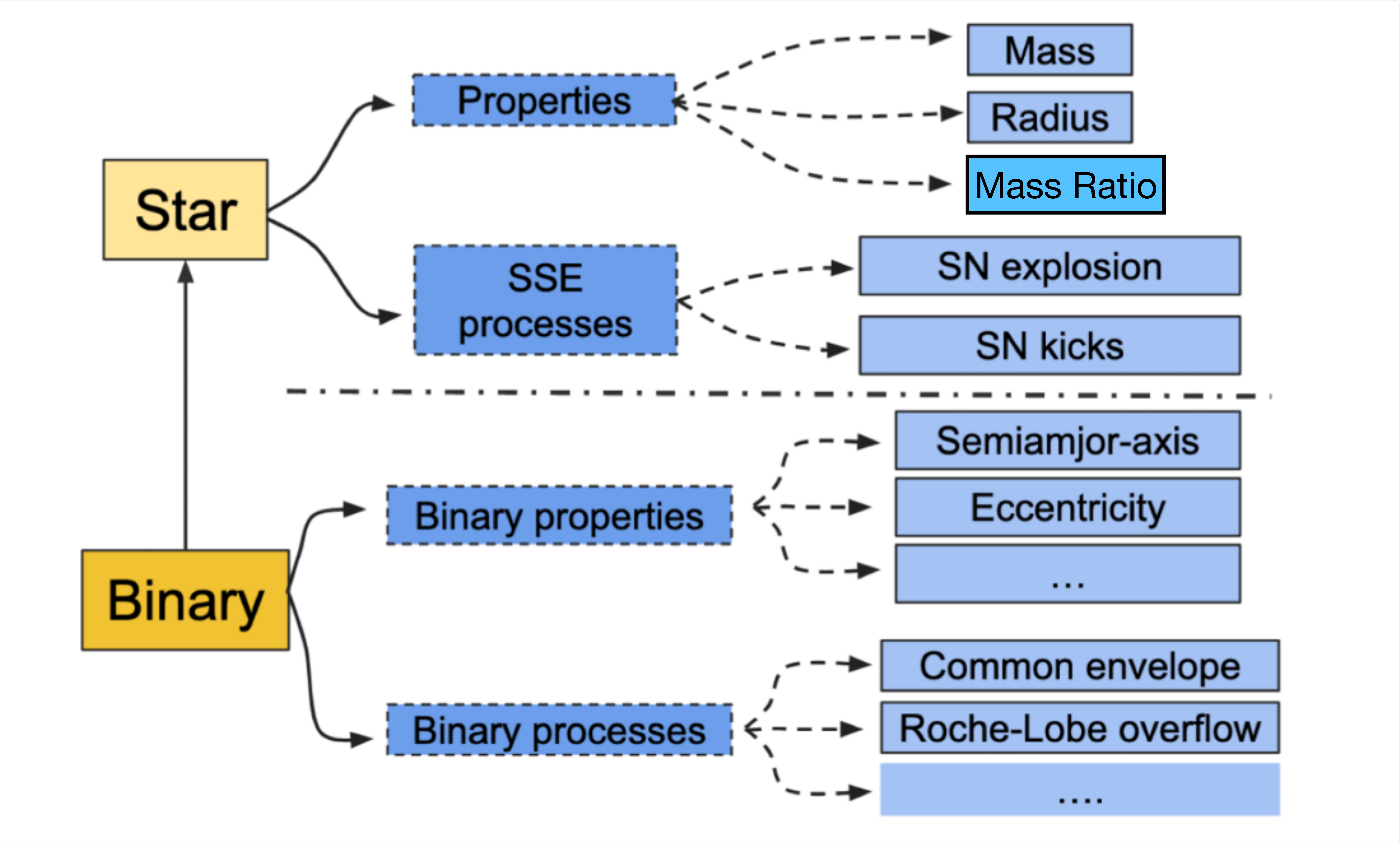
- The second black hole forms
- The binary system starts to loose energy through **gravitational wave radiation emission**
- The **two black holes** might **merge** within an Hubble time



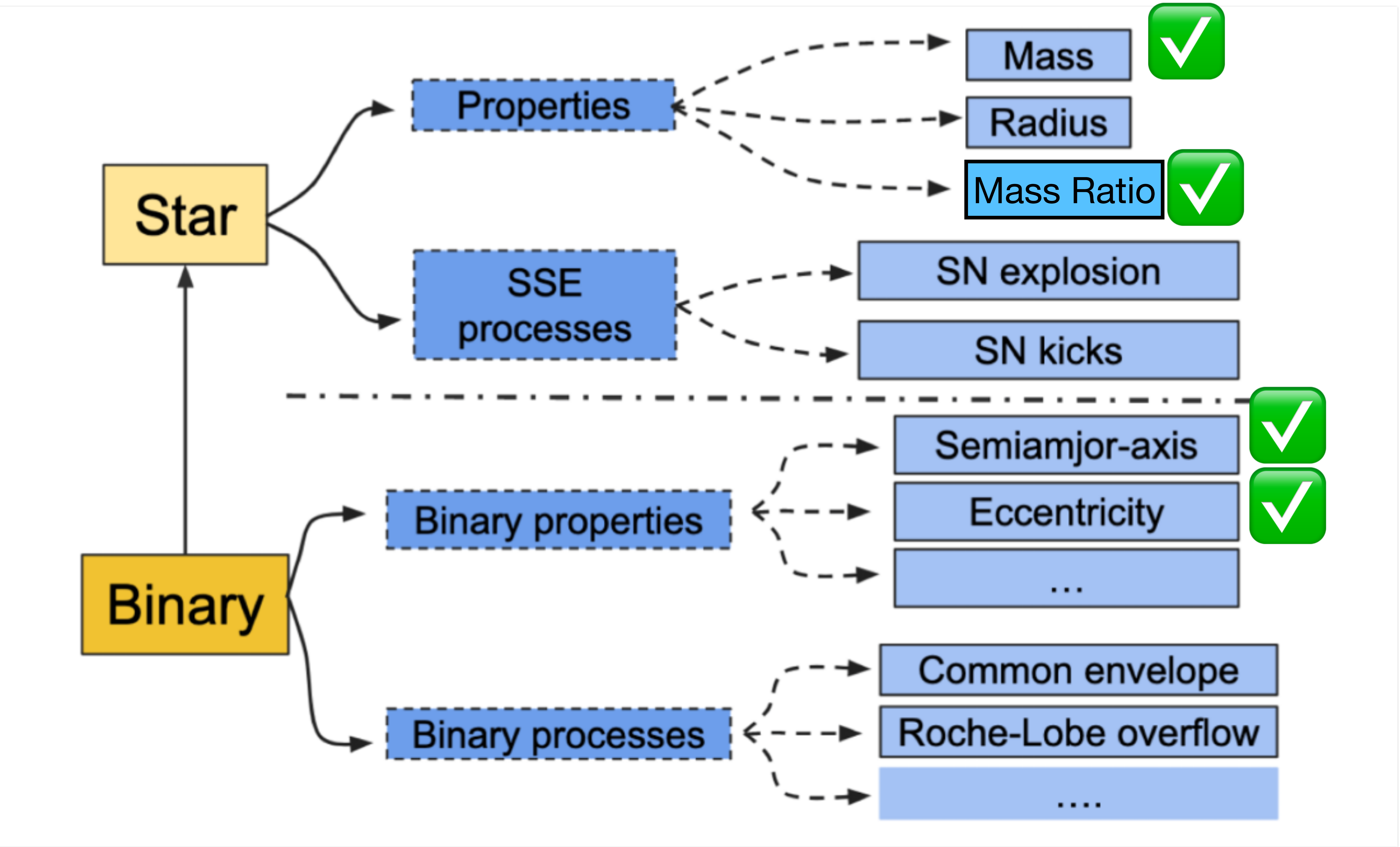
Population synthesis

- SEVN: population-synthesis code with **stellar tracks**
- *Costa et al. 2023* generated a new set of Pop. III stellar tracks
- We evolve a large set of Pop III. binary stars

Population synthesis

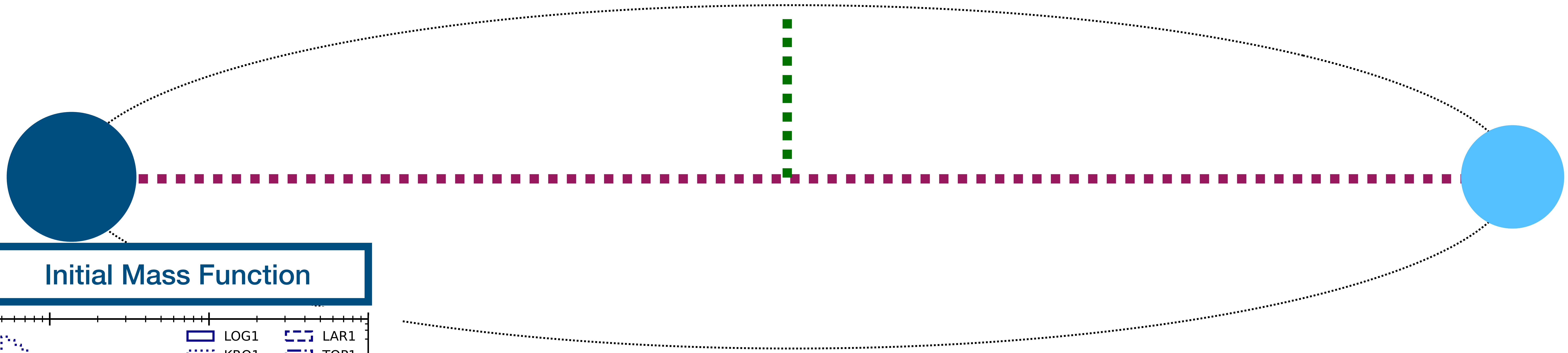


Population synthesis

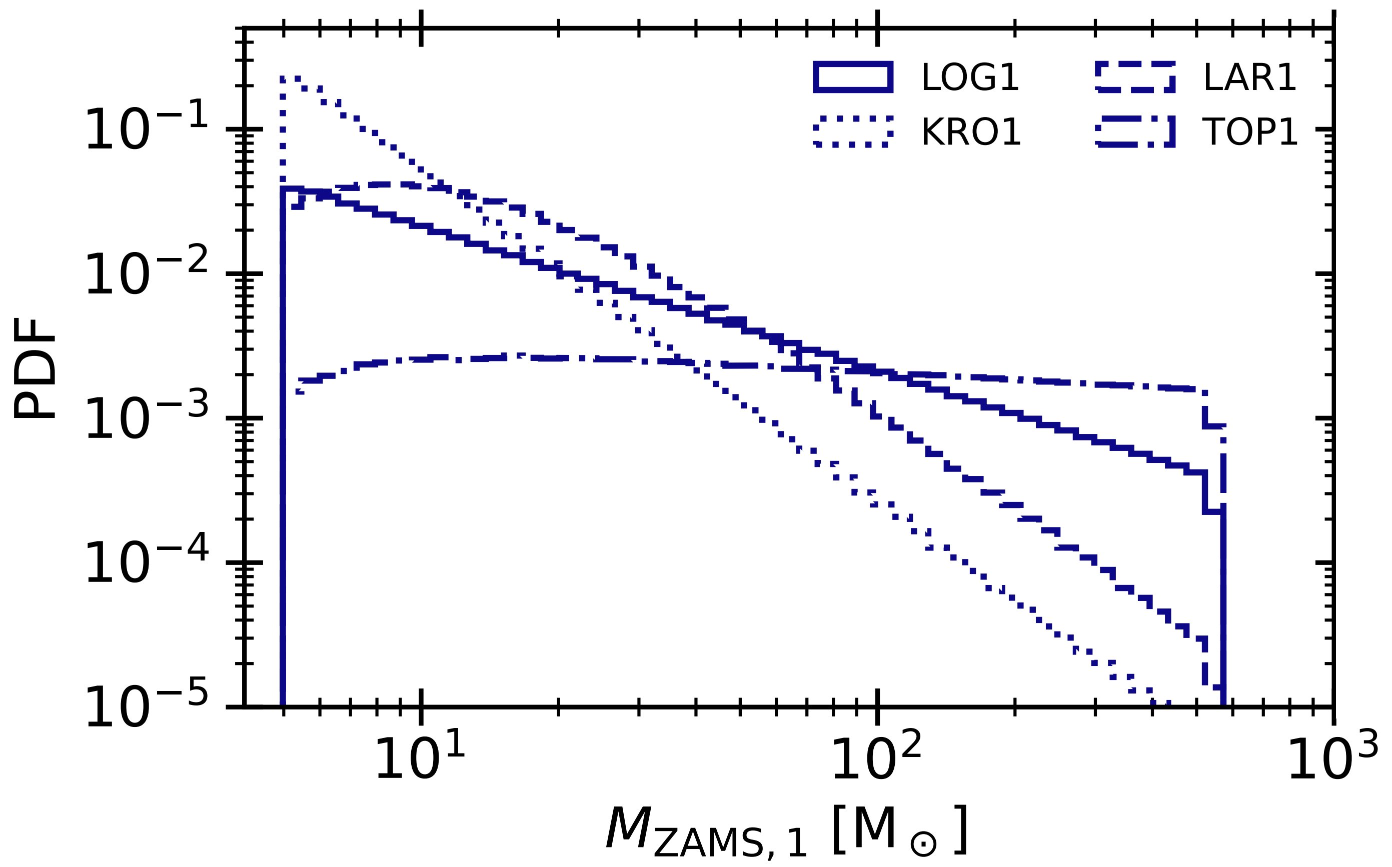


Exploring initial conditions

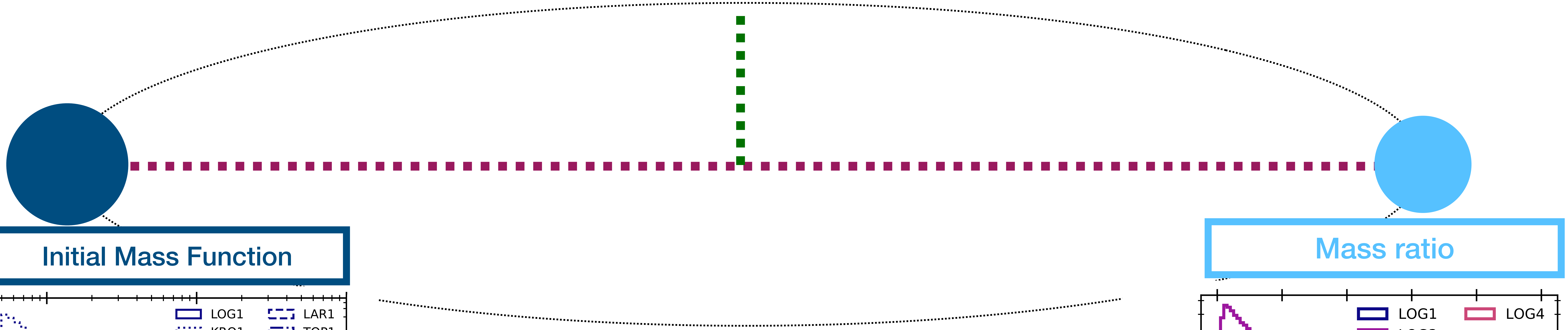
Initial conditions

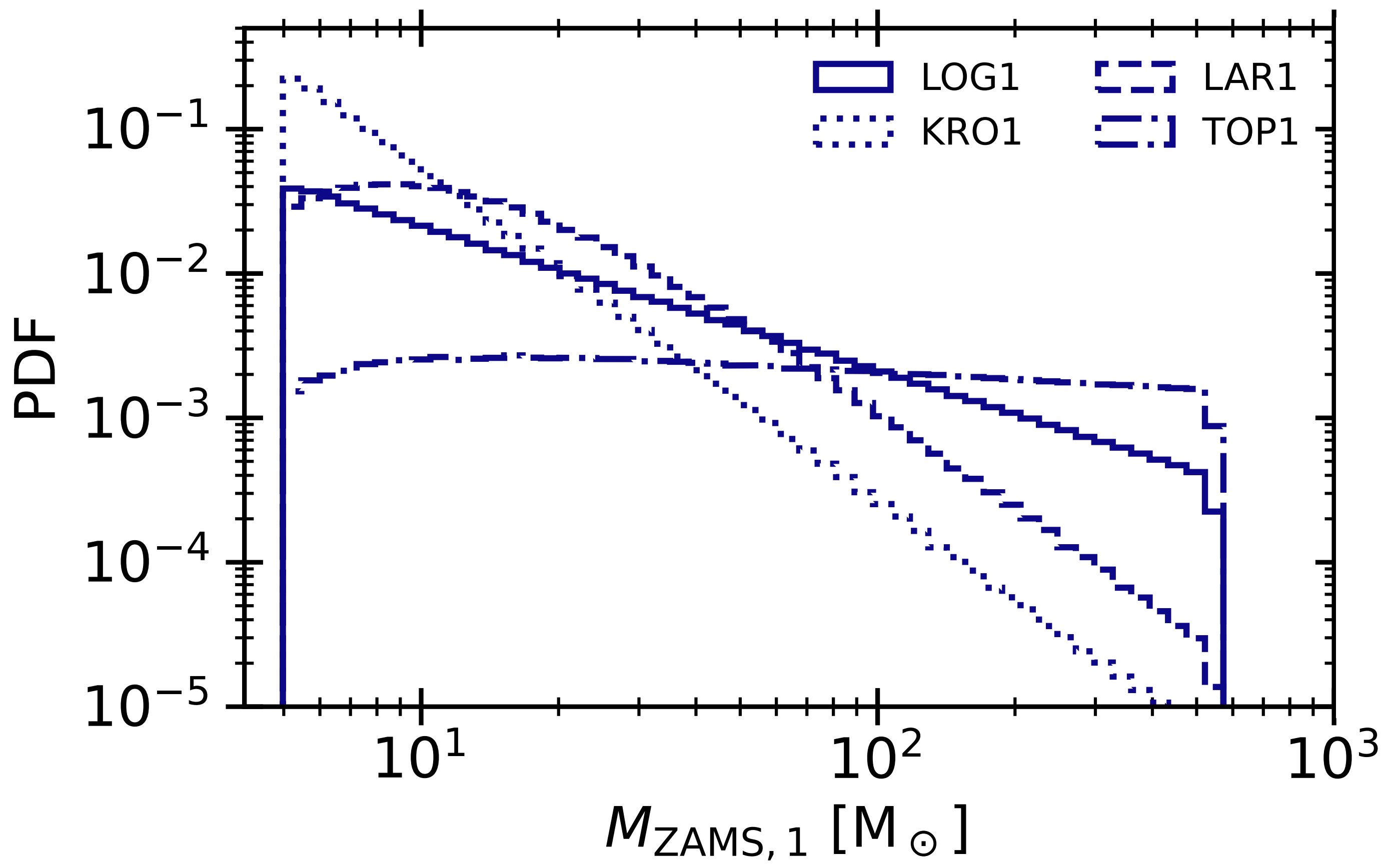


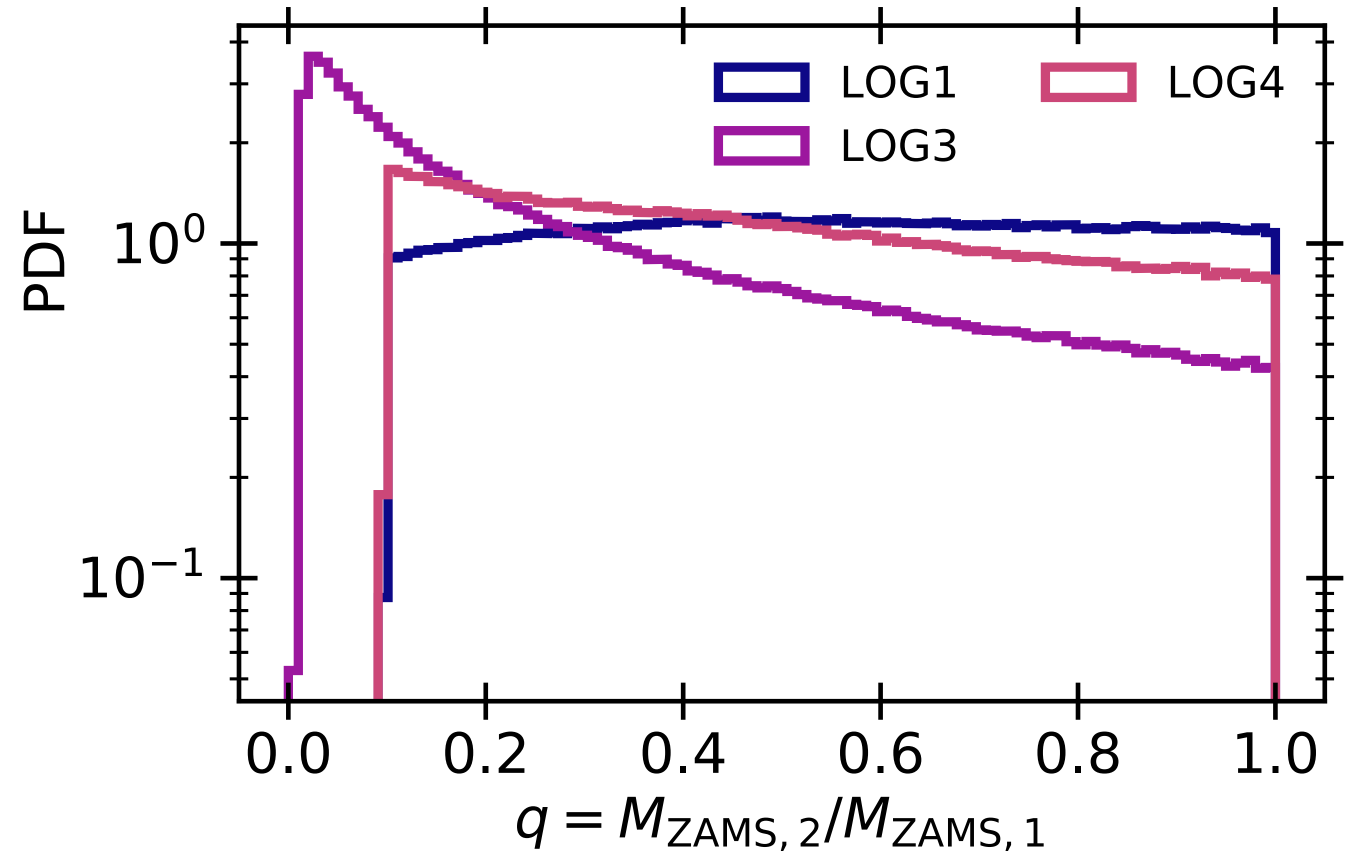
Initial Mass Function



Initial conditions







Initial conditions

COSMORATE

$$\mathcal{R}(z) = \int_{z_{\max}}^{z} \left[\int_{Z_{\min}}^{Z_{\max}} \boxed{\mathrm{SFRD}(z', Z)} \boxed{\mathcal{F}(z', z, Z)} \mathrm{d}Z \right] \frac{\mathrm{d}t(z')}{\mathrm{d}z'} \mathrm{d}z'$$

Output from SEVN

Catalogs of merging BBHs:
primary mass, secondary mass,
delay time

COSMORATE

$$\mathcal{R}(z) = \int_{z_{\max}}^{z} \left[\int_{Z_{\min}}^{Z_{\max}} \boxed{\mathrm{SFRD}(z', Z)} \boxed{\mathcal{F}(z', z, Z)} \mathrm{d}Z \right] \frac{\mathrm{d}t(z')}{\mathrm{d}z'} \mathrm{d}z'$$

$$\mathrm{SFRD}(z, Z) = \boxed{\psi(z)} \boxed{p(Z|z)}$$

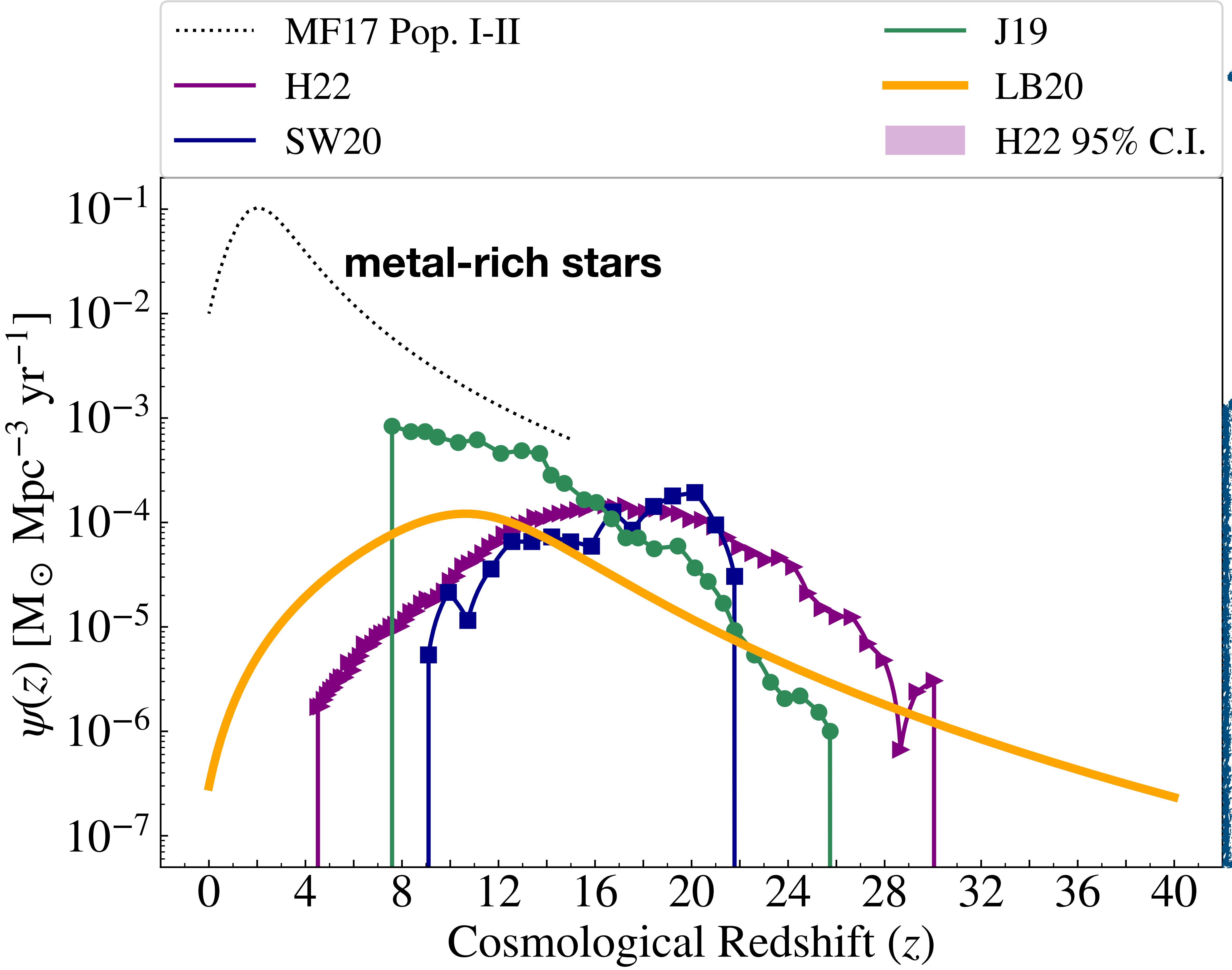
Evaluated from SEVN catalogs

COSMORATE

$$\mathcal{R}(z) = \int_{z_{\max}}^{z} \left[\int_{Z_{\min}}^{Z_{\max}} \boxed{\mathrm{SFRD}(z', Z)}\, \boxed{\mathcal{F}(z', z, Z)}\, \mathrm{d}Z \right] \frac{\mathrm{d}t(z')}{\mathrm{d}z'} \mathrm{d}z'$$

$$\mathrm{SFRD}(z, Z) = \boxed{\psi(z)}\, \boxed{p(Z|z)}$$

Evaluated from SEVN catalogs



4 different Pop. III SFRD:

H22 - *Hartwig et al. 2022*

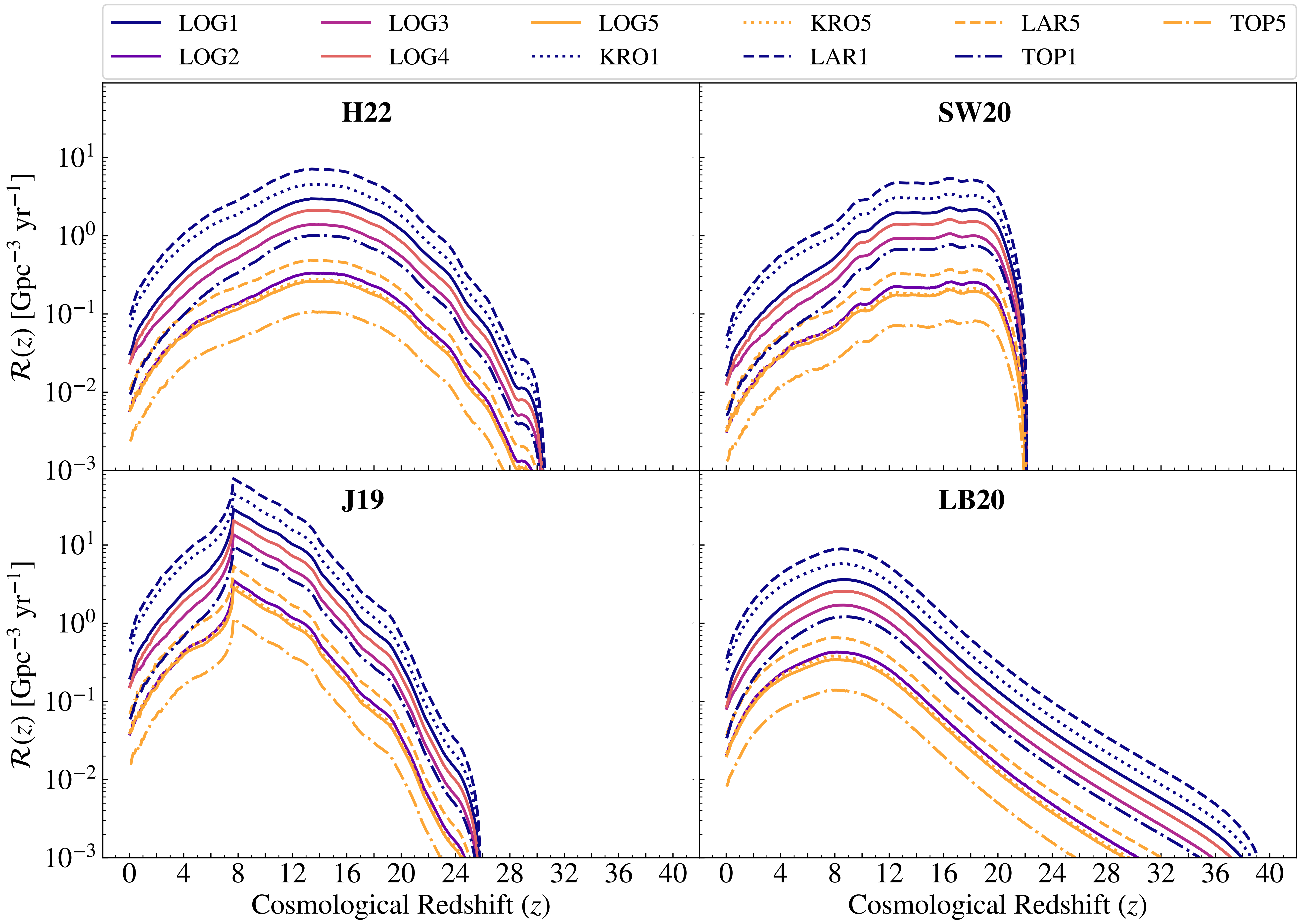
J19 - *Jaacks et al. 2019*

LB20 - *Liu & Bromm 2020*

SW20 - *Skinner & Wise 2020*

different assumptions on baryonic physics + cosmic variance

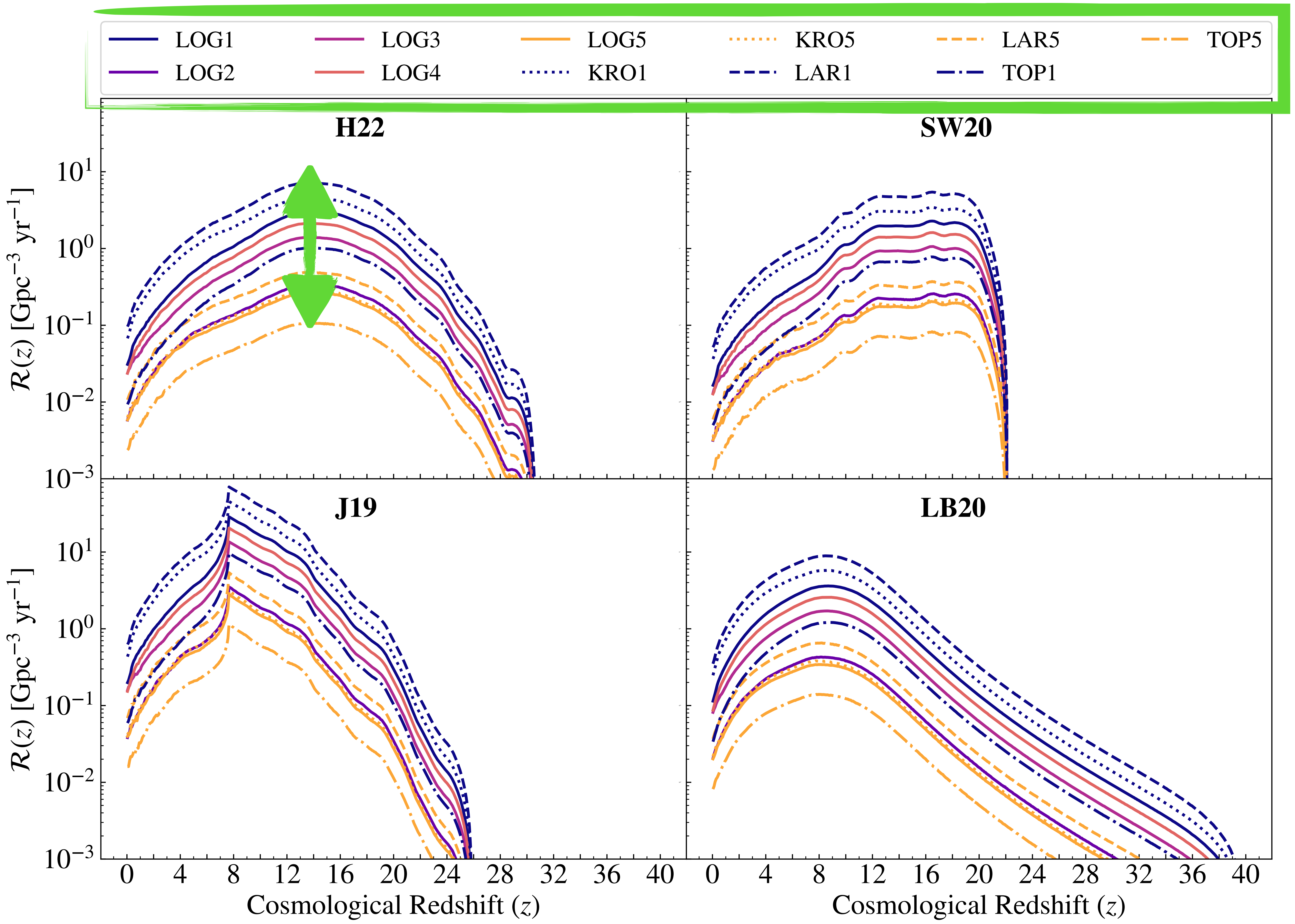
Merger rate density



Merger rate density

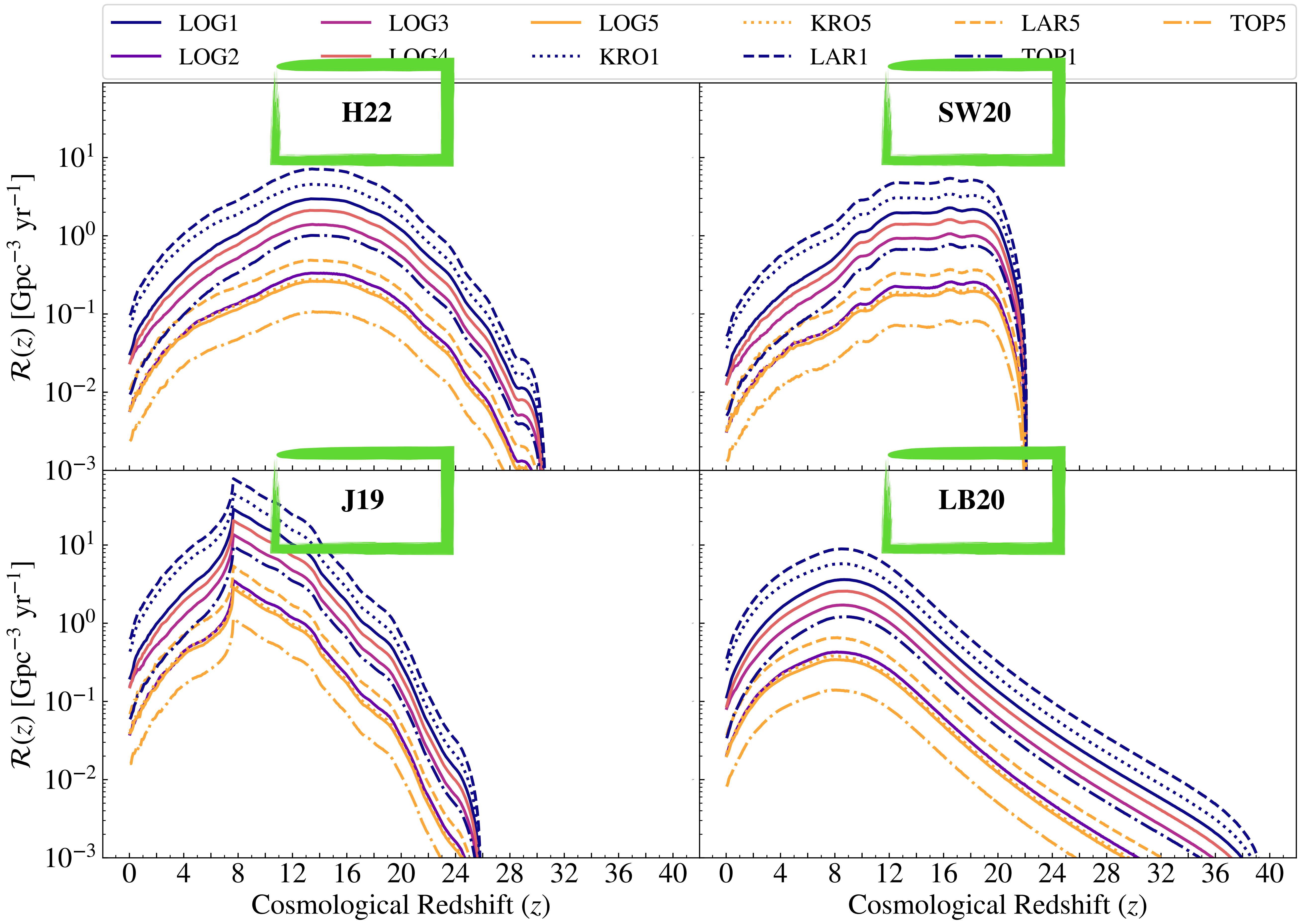
initial conditions

impact ~2 orders of magnitude

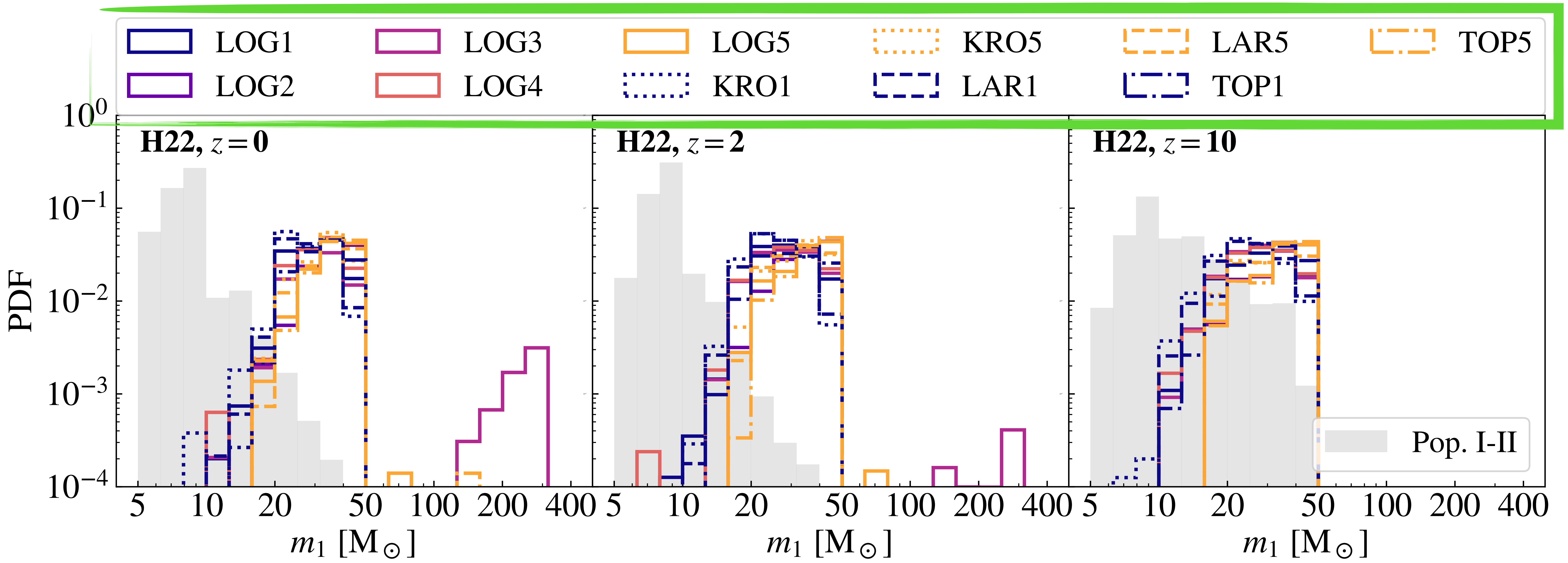


Merger rate density

star formation history impacts shape and normalisation

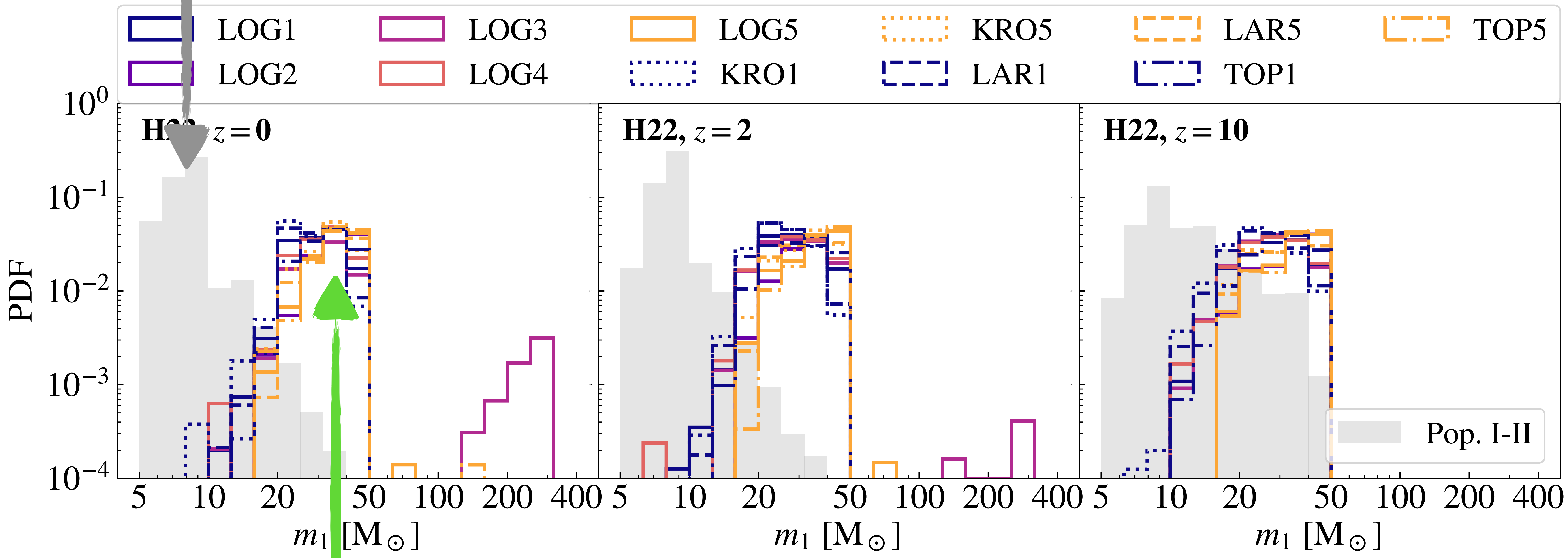


Primary mass



Primary mass

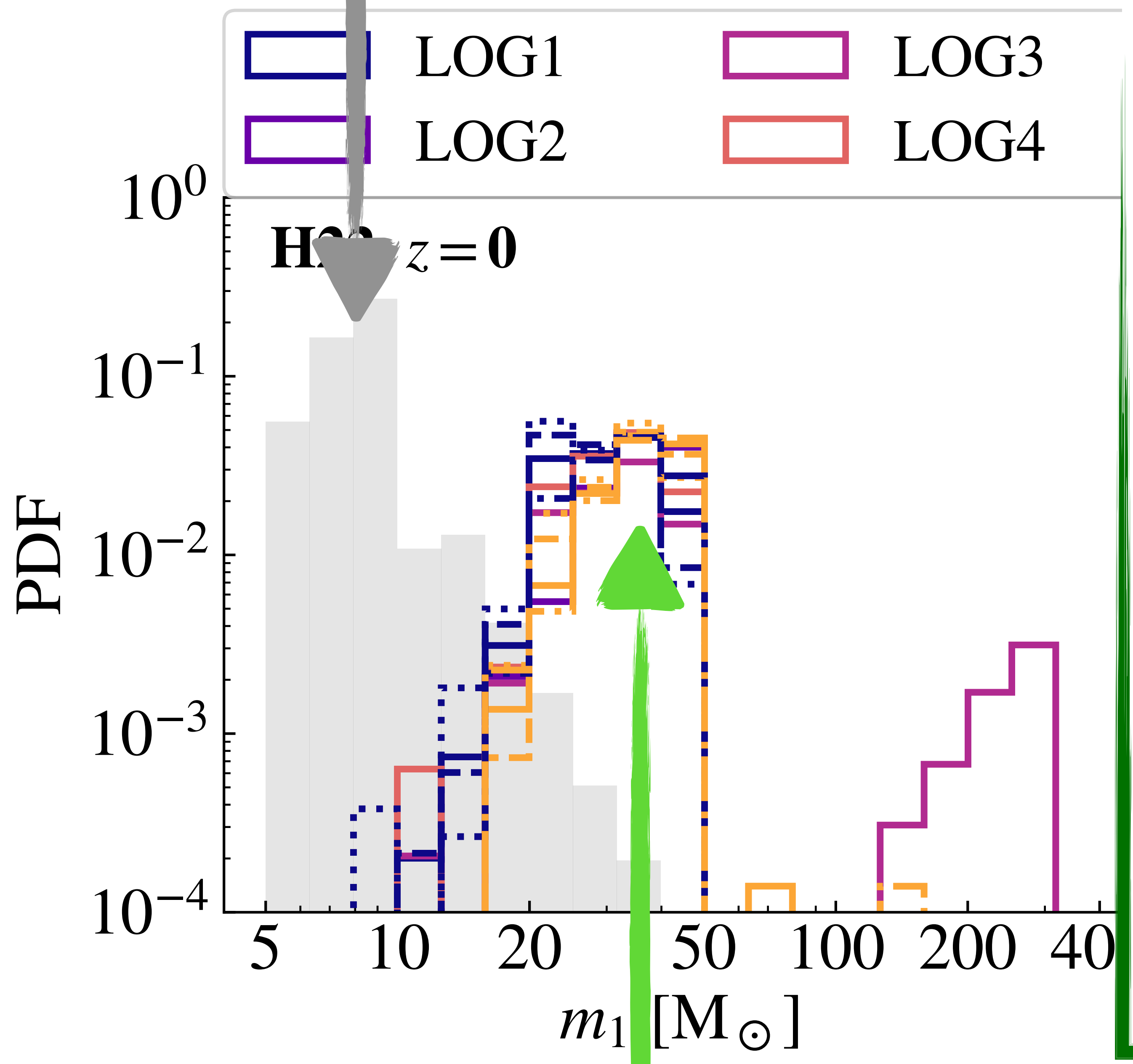
At $z = 0$, **Pop. I-II** BBHs show a **main peak at 8 – 10** $\mathrm{M}_{\odot}$

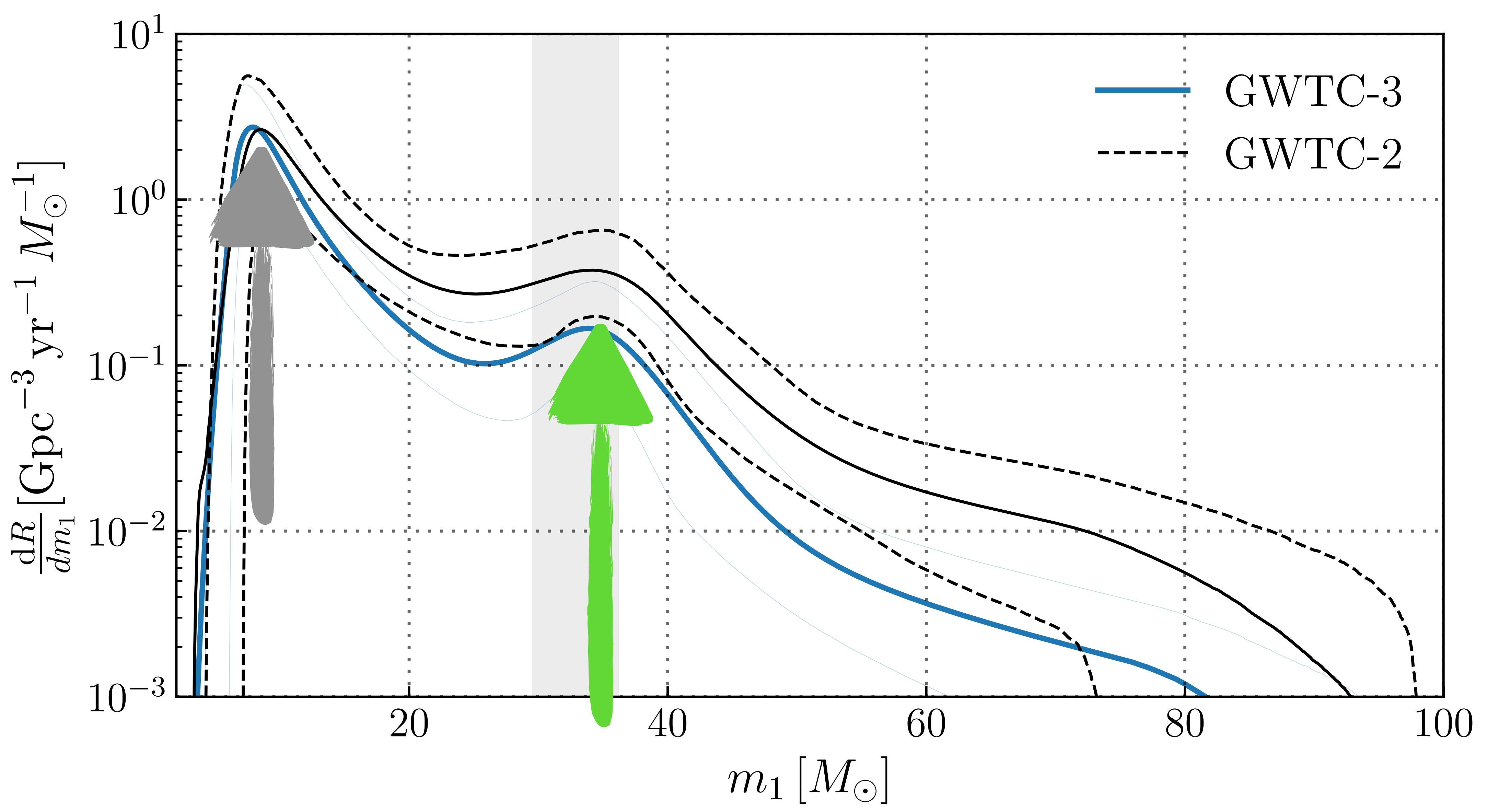


Pop. III BBHs show a **main peak at 30 – 35** $\mathrm{M}_{\odot}$

Primary mass

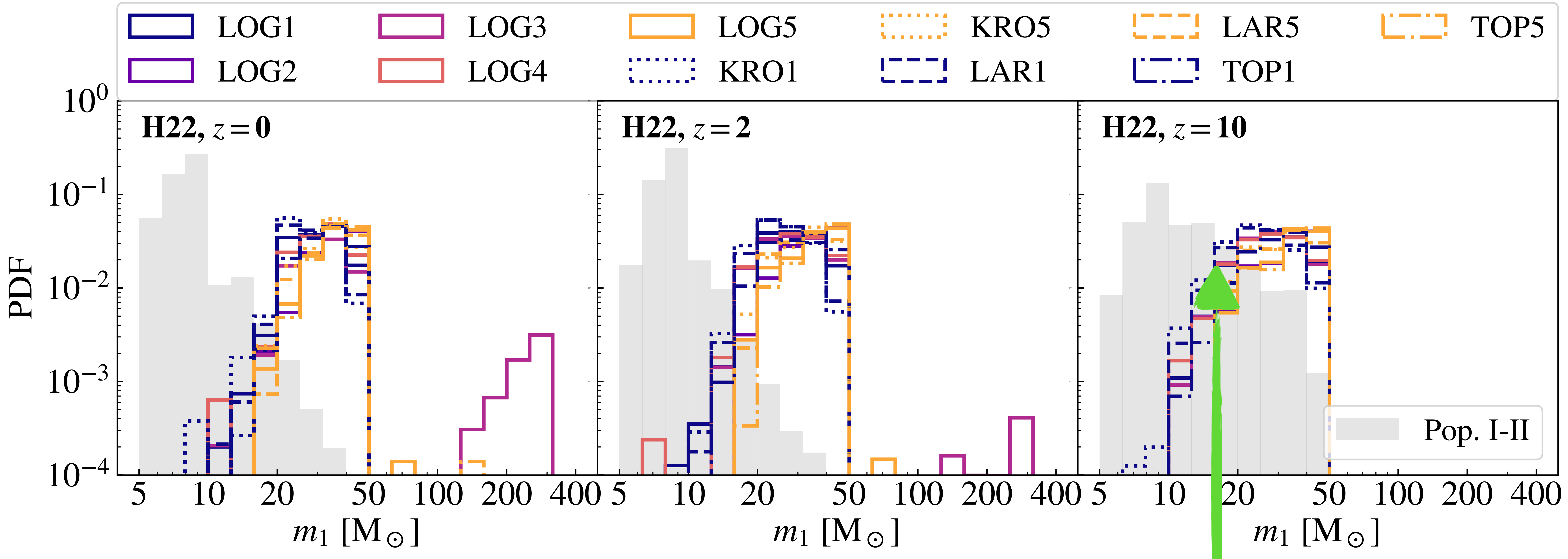
At $z = 0$, **Pop. I-II** BBHs show a **main peak at 8 – 10** $\mathrm{M}_\odot$





Pop. III BBHs show a **main peak at 30 – 35** $\mathrm{M}_\odot$

Primary mass

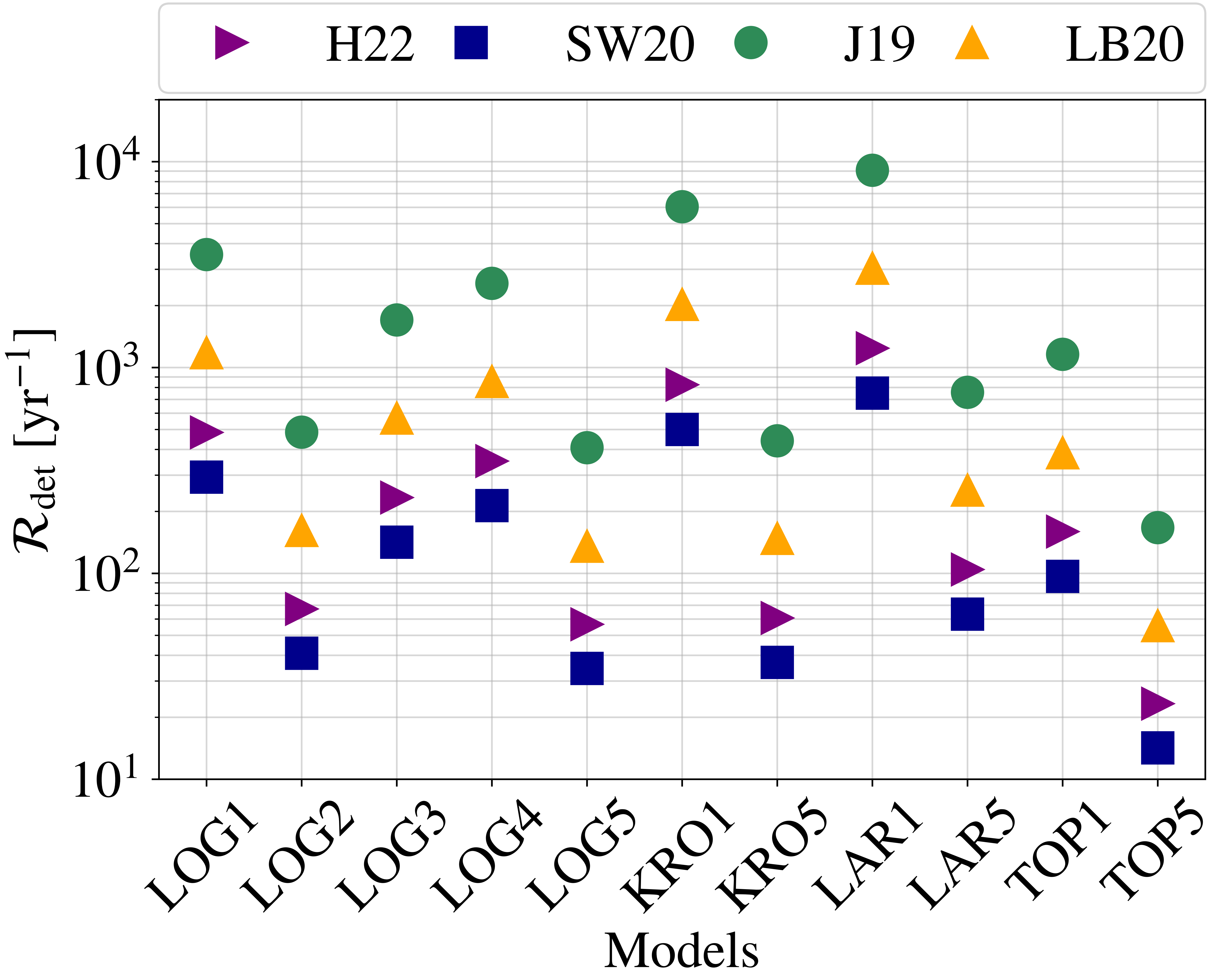


At high redshift, overlap increases

Detection rate

- **Einstein Telescope will detect 10 – 10^4** Pop. III BBH mergers per year

- We expect between **23%** and **73% of detections to** occur at redshift z **> 8**

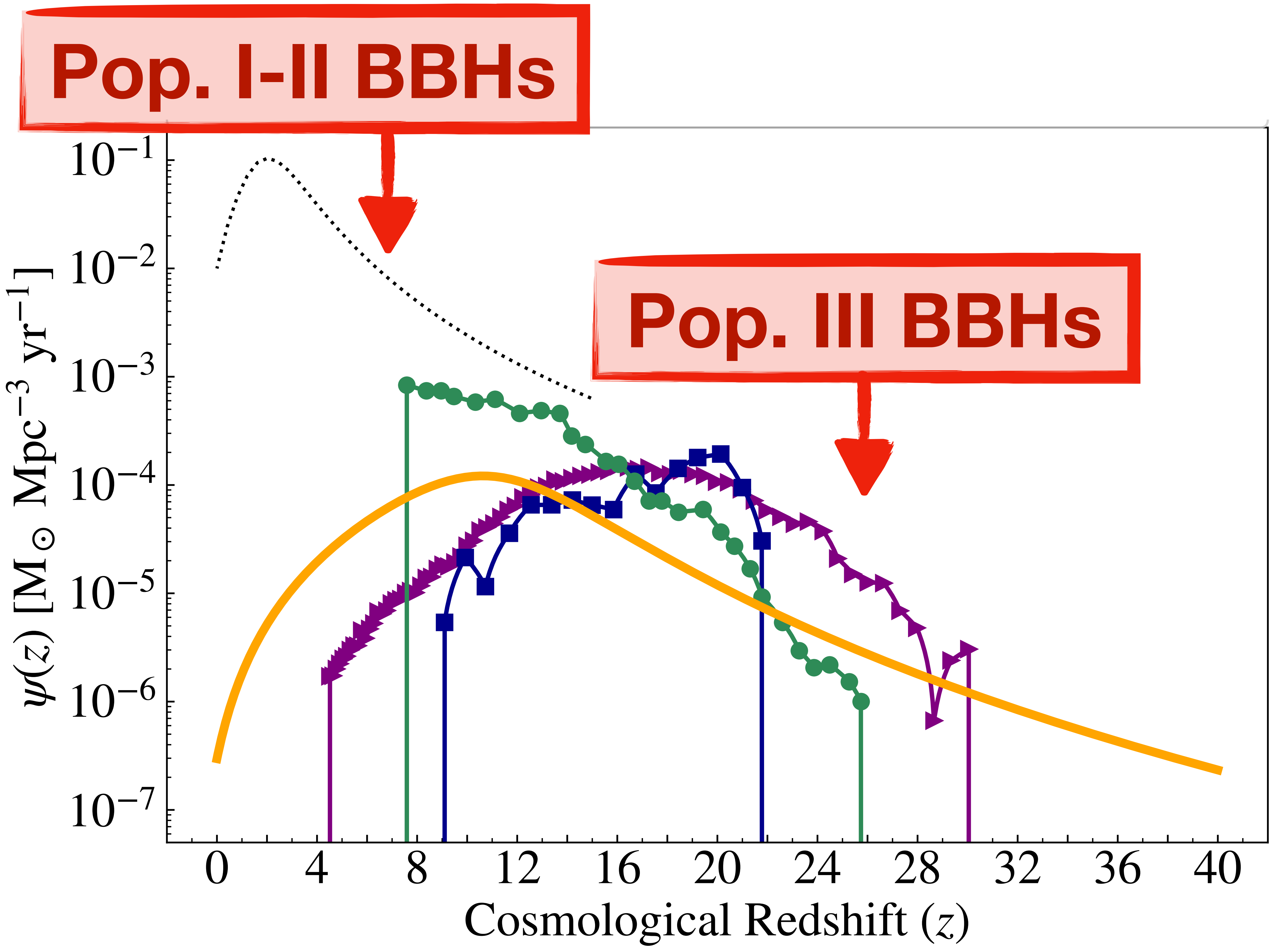


Can we distinguish Pop. III BBHs?

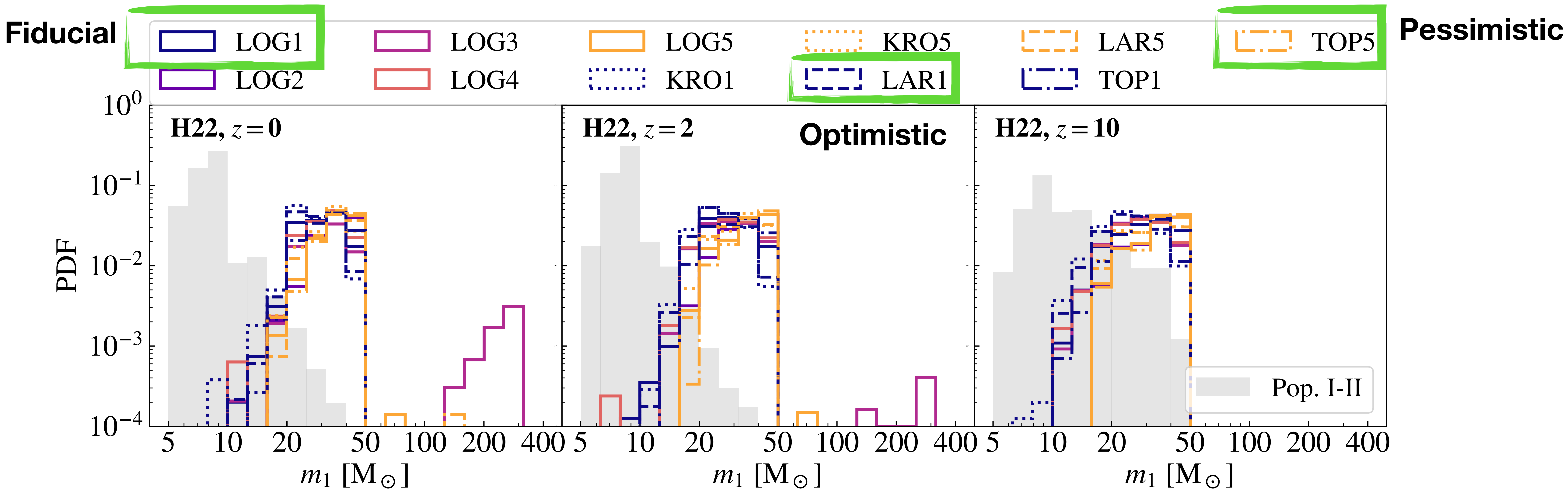
- **Einstein Telescope** will detect BBH mergers up to $z \sim 100$
- **high-redshift sources** with **low-SNR** and poor estimate of d_{L}
- **inferring the origin** of individual GW detections will not be granted

Ref. ***Maggiore et al. 2020***, ***Ng et al. 2021***, ***2022***, ***Branchesi et al. 2023***, ***Mancarella et al. 2023***

Goal: classification



Simulation-based classification



Classification

$$\boxed{p(j \in k \,|\, d_i, \{\beta\})} = \int p(j \in k \,|\, x, d_j, \{\beta\}) \; p(x \,|\, d_j, \{\beta\})$$

This is the probability that the event j is a Pop. III BBH

Classification

Mixing fraction

$$p(j \in k \,|\, d_i, \boxed{\{\beta\}}) = \int p(j \in k \,|\, x, d_j, \{\beta\})\; p(x \,|\, d_j, \{\beta\})$$

Fiducial ~4% $\beta_{III} \propto N_{\text{Pop. III}} \sim 400$

$\beta_{I-II} \propto N_{\text{Pop. I–II}} \sim 10^4$

Classification

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\}) \, \boxed{p(x \,|\, d_j, \{\beta\})}$$

This is the posterior of waveform parameters ➡️ parameter-estimation **performance of ET**

Fisher Information Matrix approximation

Classification

$$p(j \in k \,|\, d_i, \{\beta\}) = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

This is the probability that links waveform parameters to Pop. III BBHs

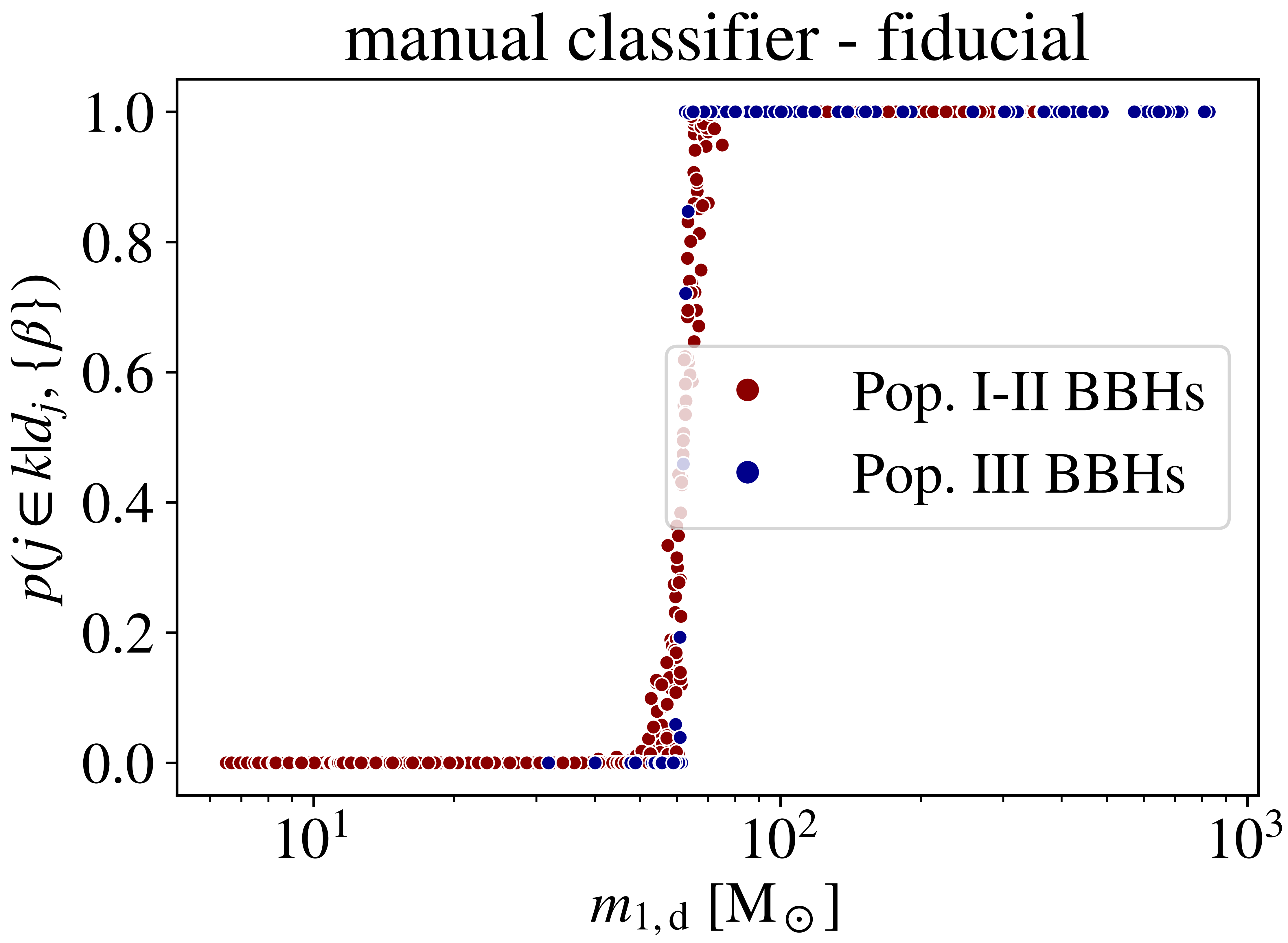
➡️ easiest approach is to consider a fix threshold

$$p(j \in k \,|\, d_i, \{\beta\}) = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\; p(x \,|\, d_j, \{\beta\})$$

$$= 1 \quad \text{if} \quad m_{1,\mathrm{d}} \gtrsim 60\ \mathrm{M}_\odot$$

$$\boxed{p(j \in k \,|\, d_i, \{\beta\})} = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

$= 1 \quad \text{if} \quad m_{1,\mathrm{d}} \gtrsim 60\ \mathrm{M}_\odot$



⚠️ low performances: precision is ~ 0.16

$$p(j \in k \,|\, d_i, \{\beta\}) = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

we can use Machine Learning

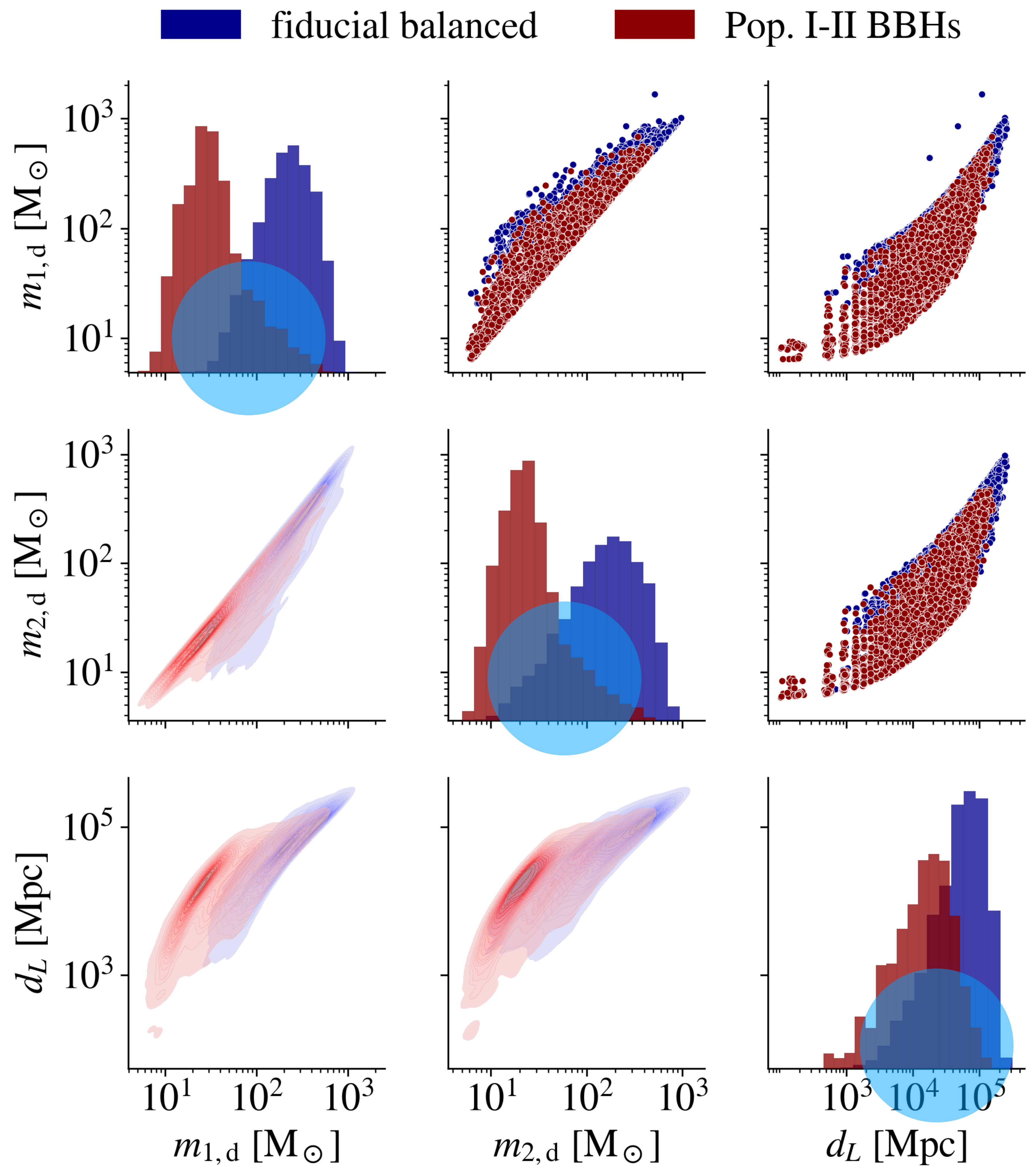
XGBoost

supervised ML based on decision trees

Ref. *Santoliquido et al. 2024*, *Chen et al. 2016*, *Pedregosa et al. 2012*, *Antonelli et. al 2023*

$$p(j \in k \,|\, d_i, \{\beta\}) = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

Using Machine Learning



* trained and tested on balanced classes + re-balancing

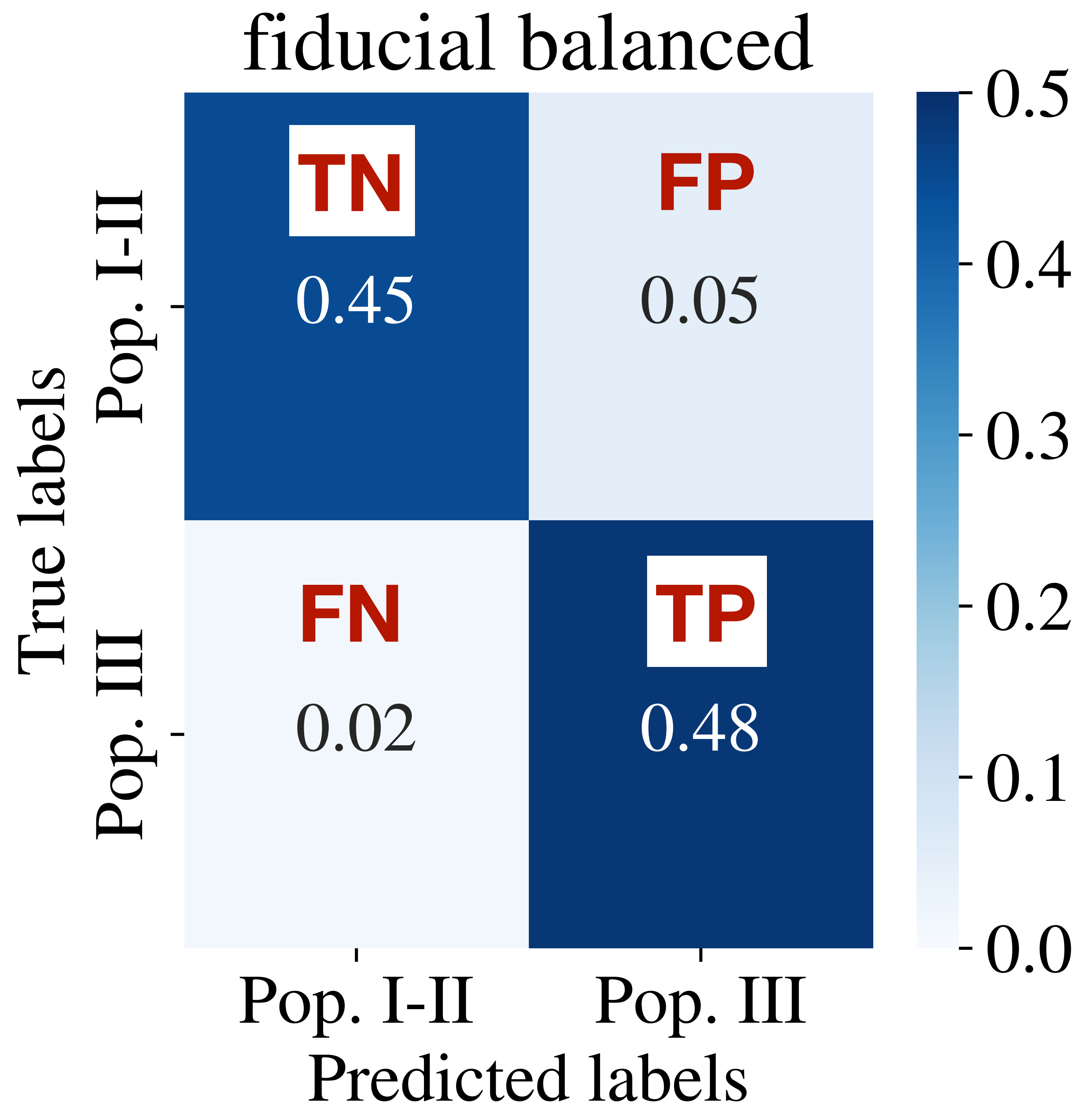
* instances: > 10^4

$$p(j \in k \,|\, d_i, \{\beta\}) = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

Using Machine Learning

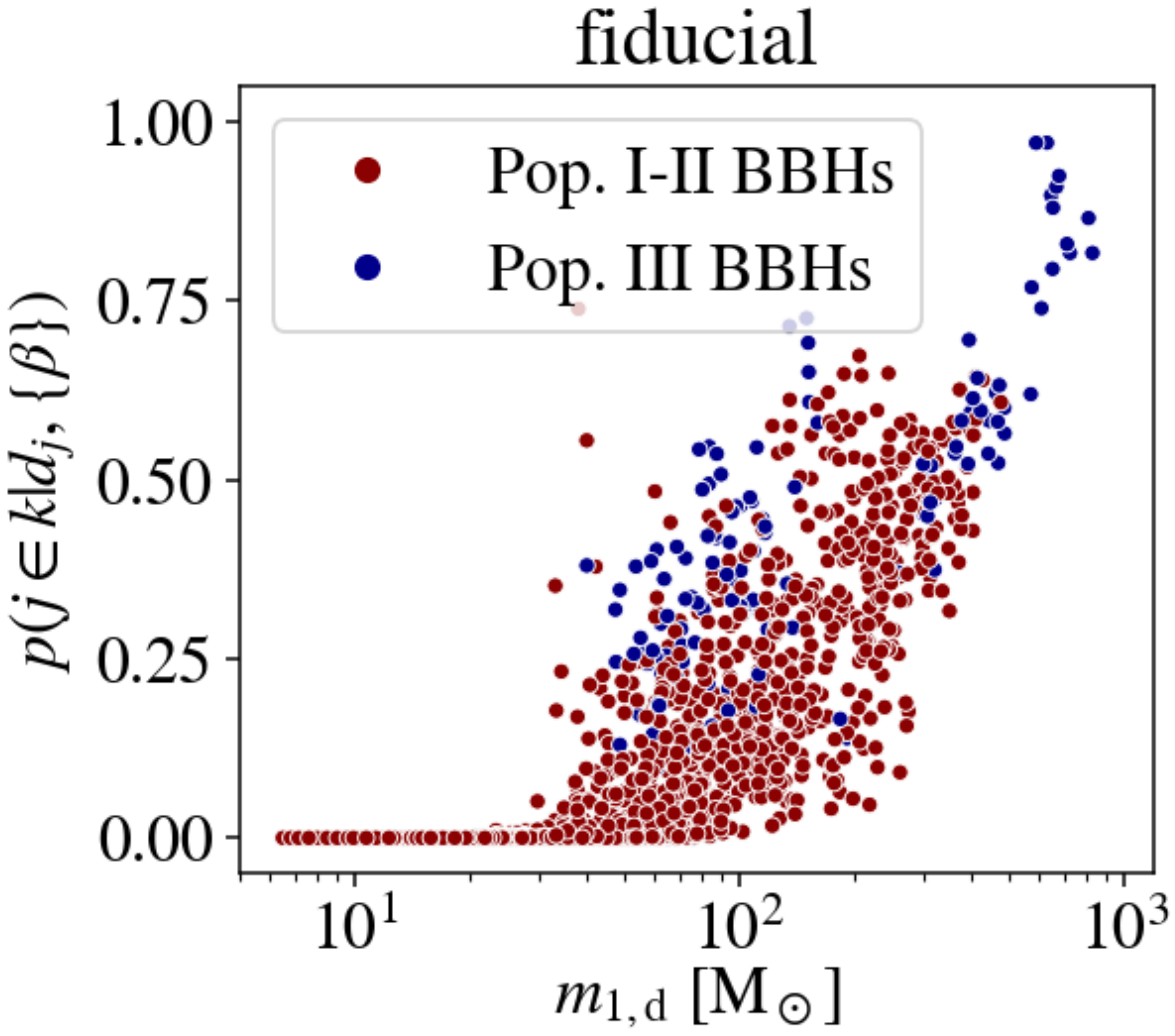
precision = TP/(TP+FP)

high precision > 0.90



$$\boxed{p(j \in k \mid d_i, \{\beta\})} = \int \boxed{p(j \in k \mid x, d_j, \{\beta\})}\, p(x \mid d_j, \{\beta\})$$

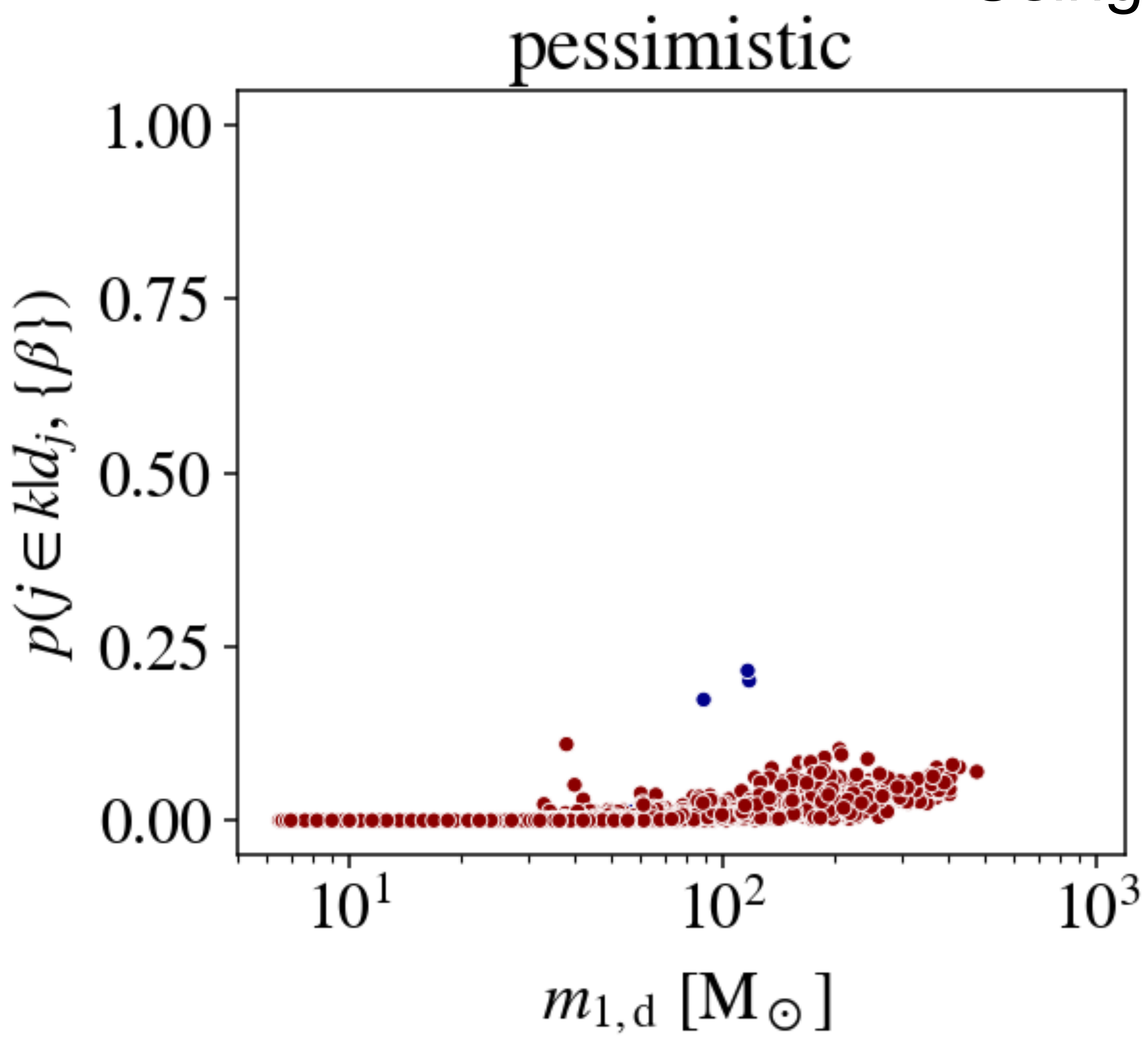
Using Machine Learning



~10% of detected sources are classified with precision > 0.90

$$\boxed{p(j \in k \,|\, d_i, \{\beta\})} = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

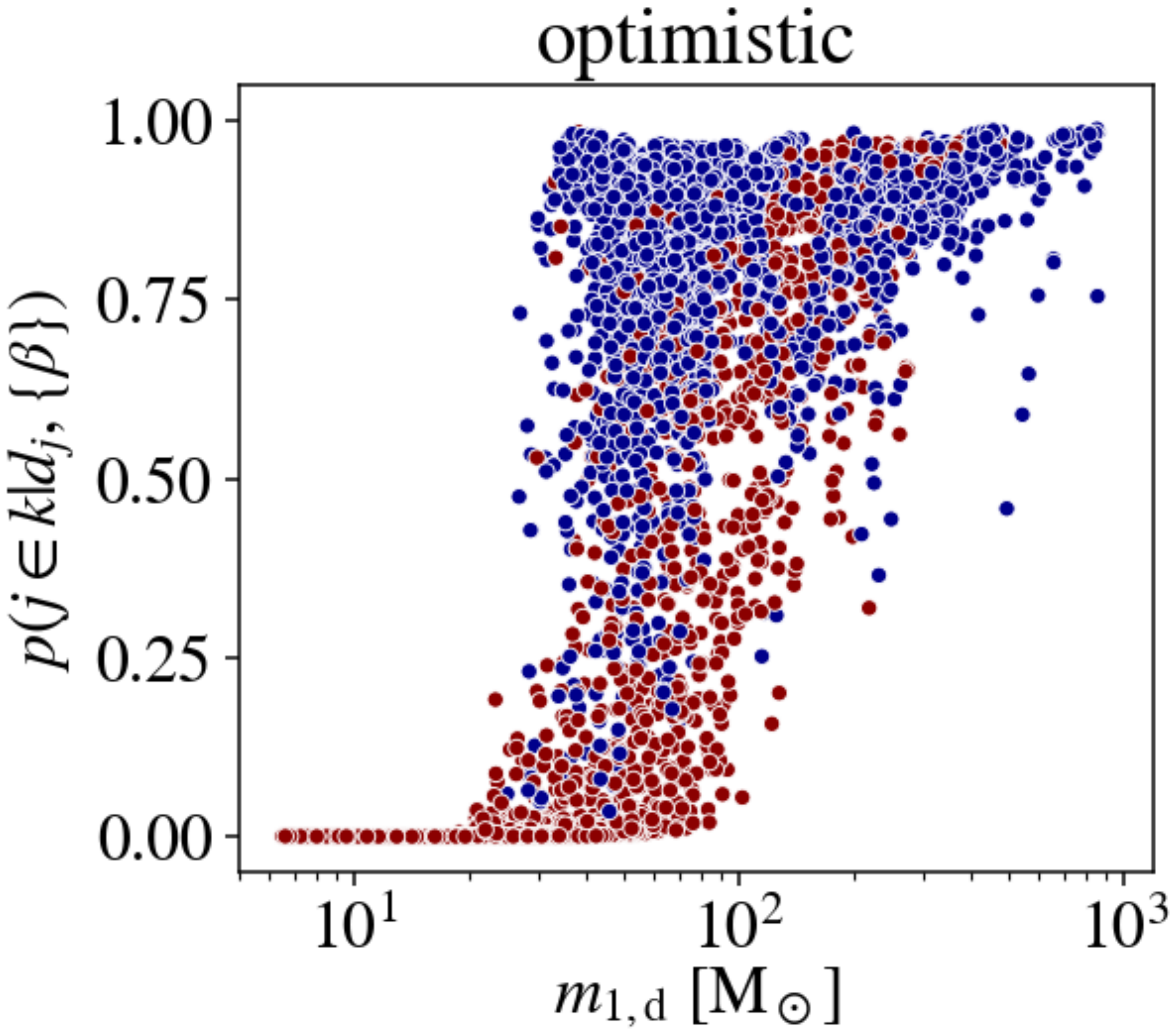
Using Machine Learning



~30% of detected sources are classified with precision > 0.90

$$\boxed{p(j \in k \,|\, d_i, \{\beta\})} = \int \boxed{p(j \in k \,|\, x, d_j, \{\beta\})}\, p(x \,|\, d_j, \{\beta\})$$

Using Machine Learning



~45% of detected sources are classified with precision > 0.90

Contributions

- First **large parameter exploration of Pop. III BBHs**
  - **SFRD** affects **normalisation and shape** of **merger rate density**
  - primary mass of Pop. III **BHs** is **substantially massive**
- **ET will detect** these sources and **machine learning** boosts our ability to classify them

Ref. ***Costa et al. 2023***, ***Santoliquido et al. 2023***, ***Santoliquido et al. 2024***

Backup slides

$\alpha\lambda$ formalism for modelling the common envelope

- $\Delta E = \alpha(E_{\rm b,f} - E_{\rm b,i}) = \alpha \frac{G m_{\rm c1} m_{\rm c2}}{2} \left(\frac{1}{a_{\rm f}} - \frac{1}{a_{\rm i}} \right)$ This is the orbital energy before and after the common envelope phase
- $E_{\rm env} = \frac{G}{\lambda} \left[\frac{m_{\rm env,1} m_1}{R_1} + \frac{m_{\rm env,2} m_2}{R_2} \right]$ This is the binding energy of the envelope
- By imposing $\Delta E = E_{\rm env}$, $\frac{1}{a_{\rm f}} = \frac{1}{\alpha\lambda} \frac{2}{m_{\rm c1} m_{\rm c2}} \left[\frac{m_{\rm env,1} m_1}{R_1} + \frac{m_{\rm env,2} m_2}{R_2} \right] + \frac{1}{a_i}$
- If α is larger, $a_{\rm f}$ is larger, following $a_{\rm f} \sim \frac{\alpha}{1+\alpha}$. Therefore larger α gets wider binaries
- Where λ is the parameter which measures the concentration of the envelope (the smaller λ is, the more concentrated is the envelope).
- The $\alpha\lambda$ formalism is a simplified prescription. When $\alpha > 1$, we account for other sources of energy that make the envelope less bind, for instance recombination energy. Recent works (e.g. *Fragos et al. 2019*) suggest that $\alpha > 1$ is necessary to reproduce the final orbital separation obtained with hydrodynamical simulations.

Initial conditions

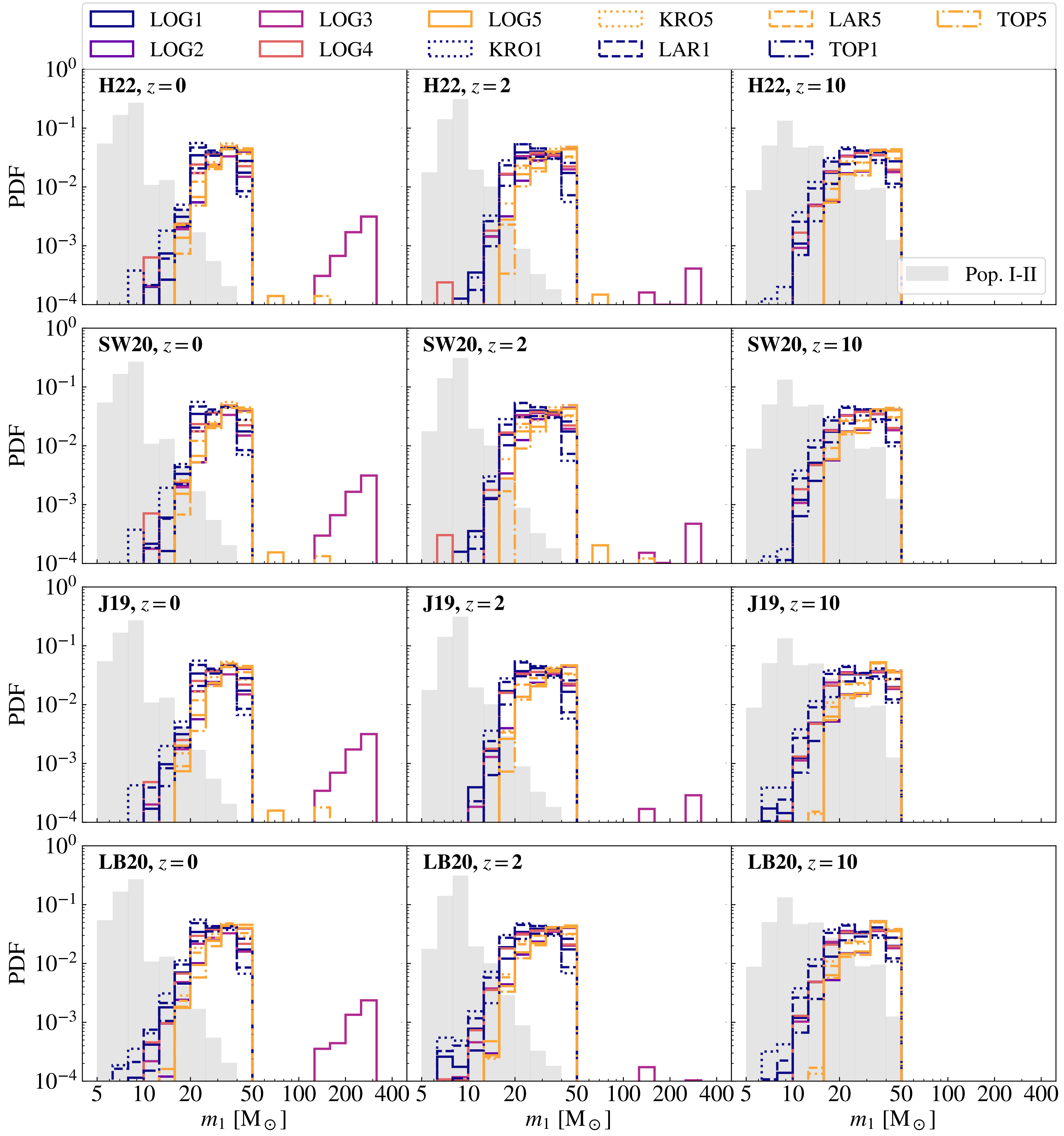
Table 1. Initial conditions.

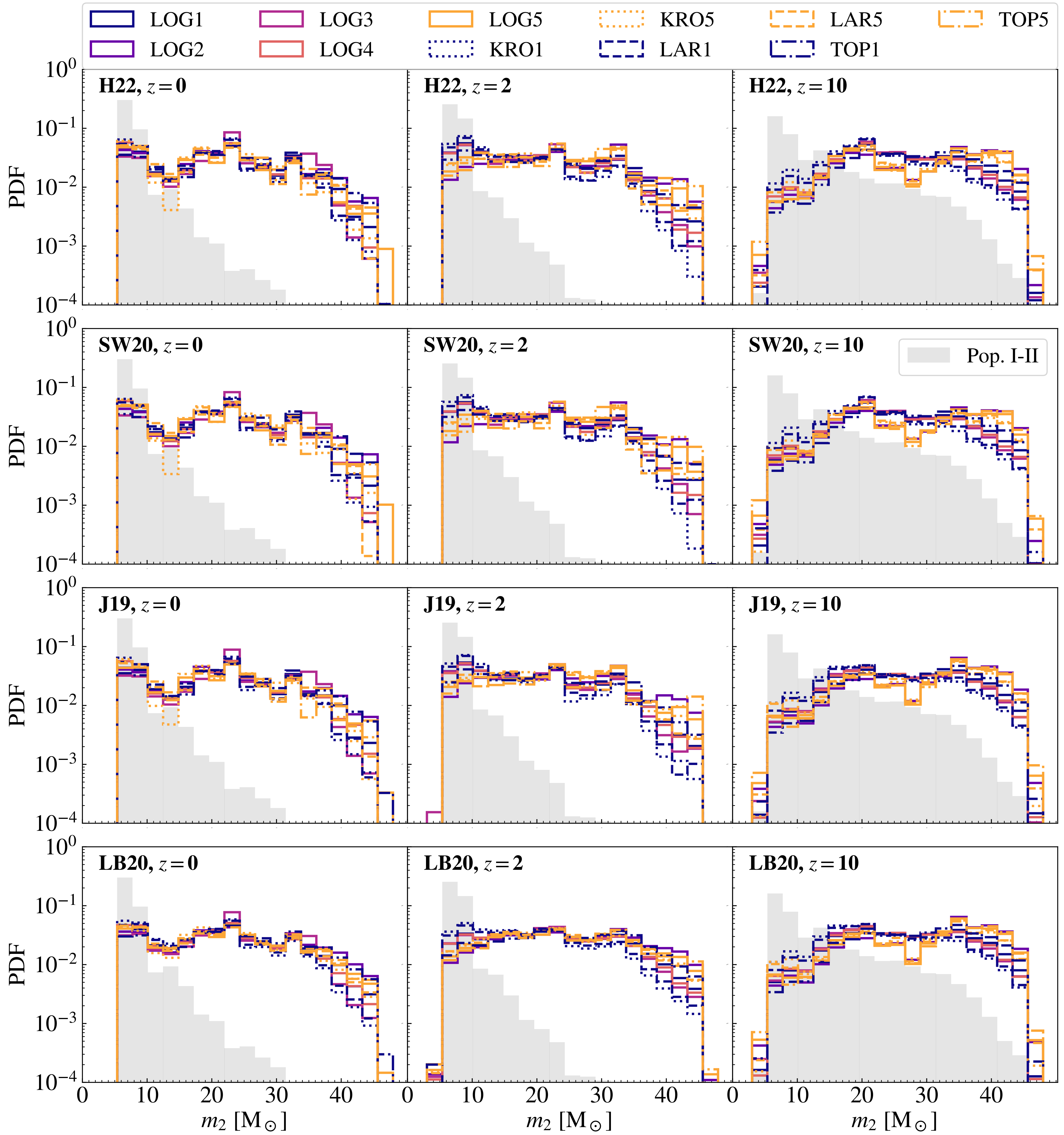
Model	$M_{\mathrm{ZAMS},1}$	M_{ZAMS}	q	P	e
LOG1	Flat in log	–	S12	S12	S12
LOG2	Flat in log	–	S12	SB13	Thermal
LOG3	–	Flat in log	Sorted	S12	S12
LOG4	Flat in log	–	SB13	S12	Thermal
LOG5	Flat in log	–	SB13	SB13	Thermal
KRO1	K01	–	S12	S12	S12
KRO5	K01	–	SB13	SB13	Thermal
LAR1	L98	–	S12	S12	S12
LAR5	L98	–	SB13	SB13	Thermal
TOP1	Top heavy	–	S12	S12	S12
TOP5	Top heavy	–	SB13	SB13	Thermal

Column 1 reports the model name. Column 2 describes how we generate the ZAMS mass of the primary star (i.e., the most massive of the two members of the binary system). Column 3 describes how we generate the ZAMS mass of the overall stellar population (without differentiating between primary and secondary stars). We follow this procedure only for model LOG3 (see the text for details). Columns 4, 5, and 6 specify the distributions we used to generate the mass ratios q, the orbital periods P and the orbital eccentricity e. See Section 2.2 for a detailed description of these distributions.

Santoliquido et al. 2023:
https://arxiv.org/pdf/2303.15515.pdf

Pop. III BBHs: mass evolution





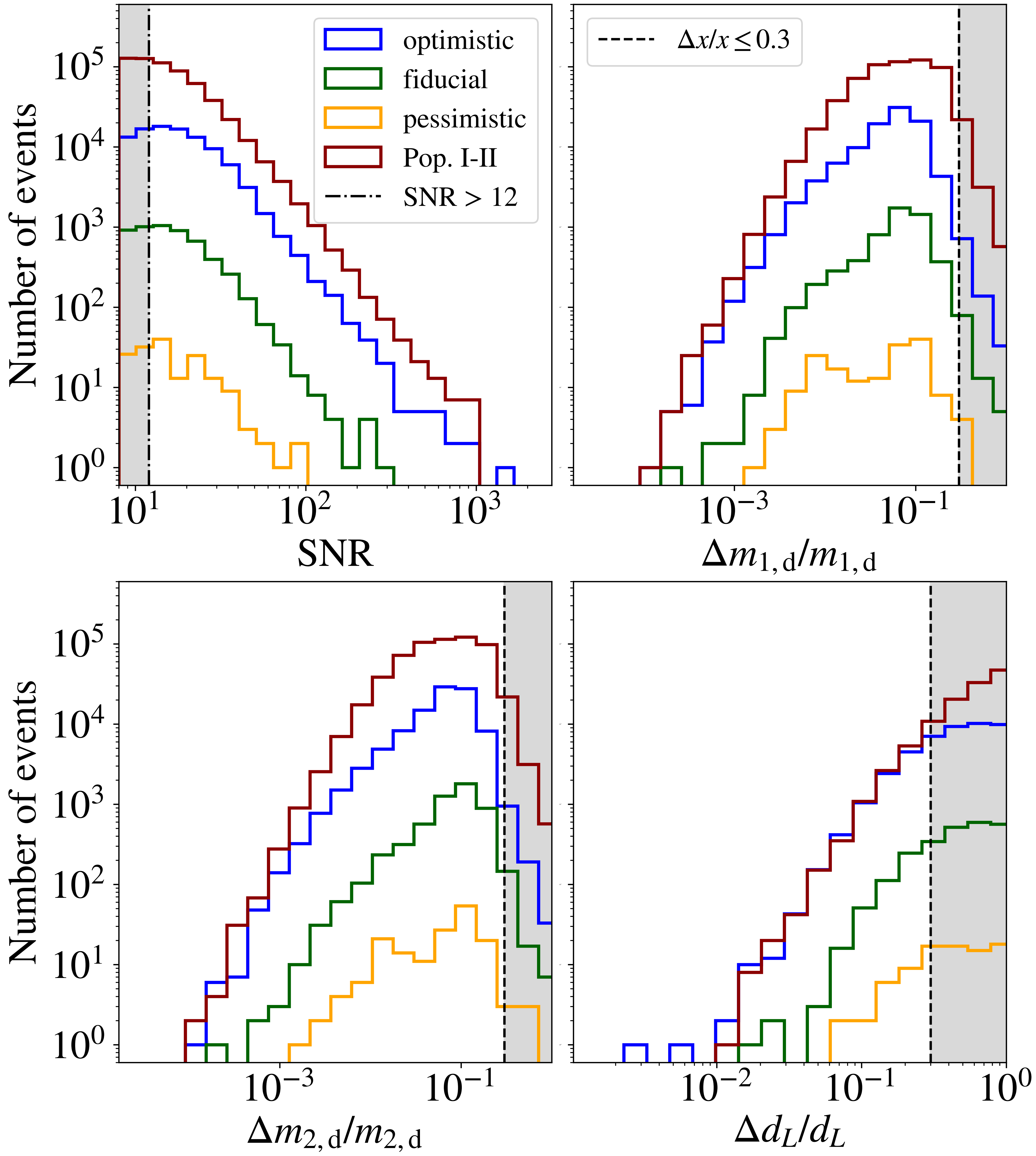
detection rate

$$\mathcal{R}_{\rm det} = \int \frac{{\rm d}^2\mathcal{R}(m_1, m_2, z)}{{\rm d}m_1 {\rm d}m_2} \frac{1}{(1+z)} \frac{{\rm d}V_c}{{\rm d}z}\, p_{\rm det}(m_1, m_2, z)\, {\rm d}m_1\, {\rm d}m_2\, {\rm d}z$$

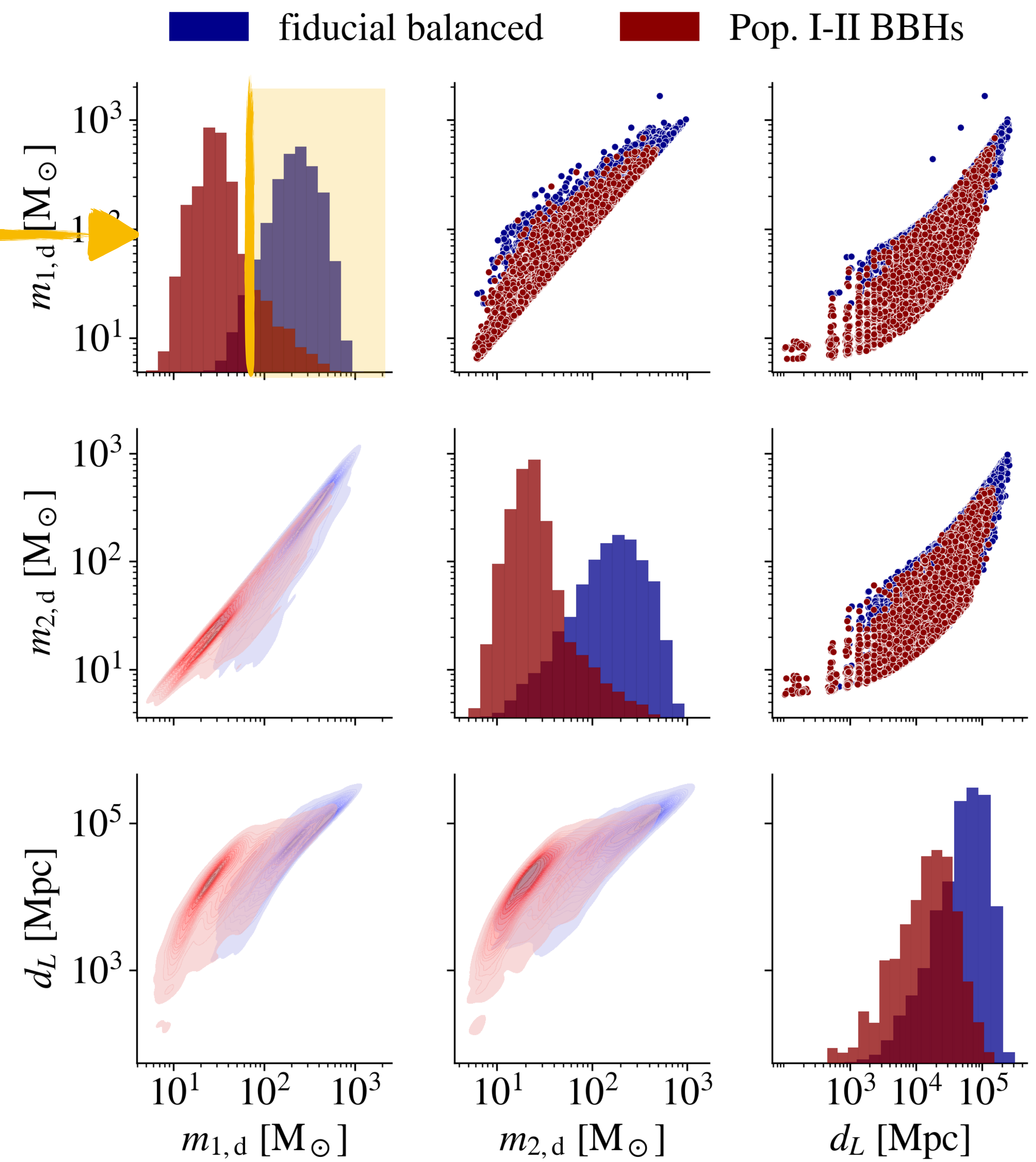
$$\frac{{\rm d}^2\mathcal{R}(m_1, m_2, z)}{{\rm d}m_1 {\rm d}m_2} = \mathcal{R}(z)\, p(m_1, m_2|z)$$

$$\rho = \rho_{\rm opt}\sqrt{\omega_0^2 + \omega_1^2 + \omega_2^2}$$

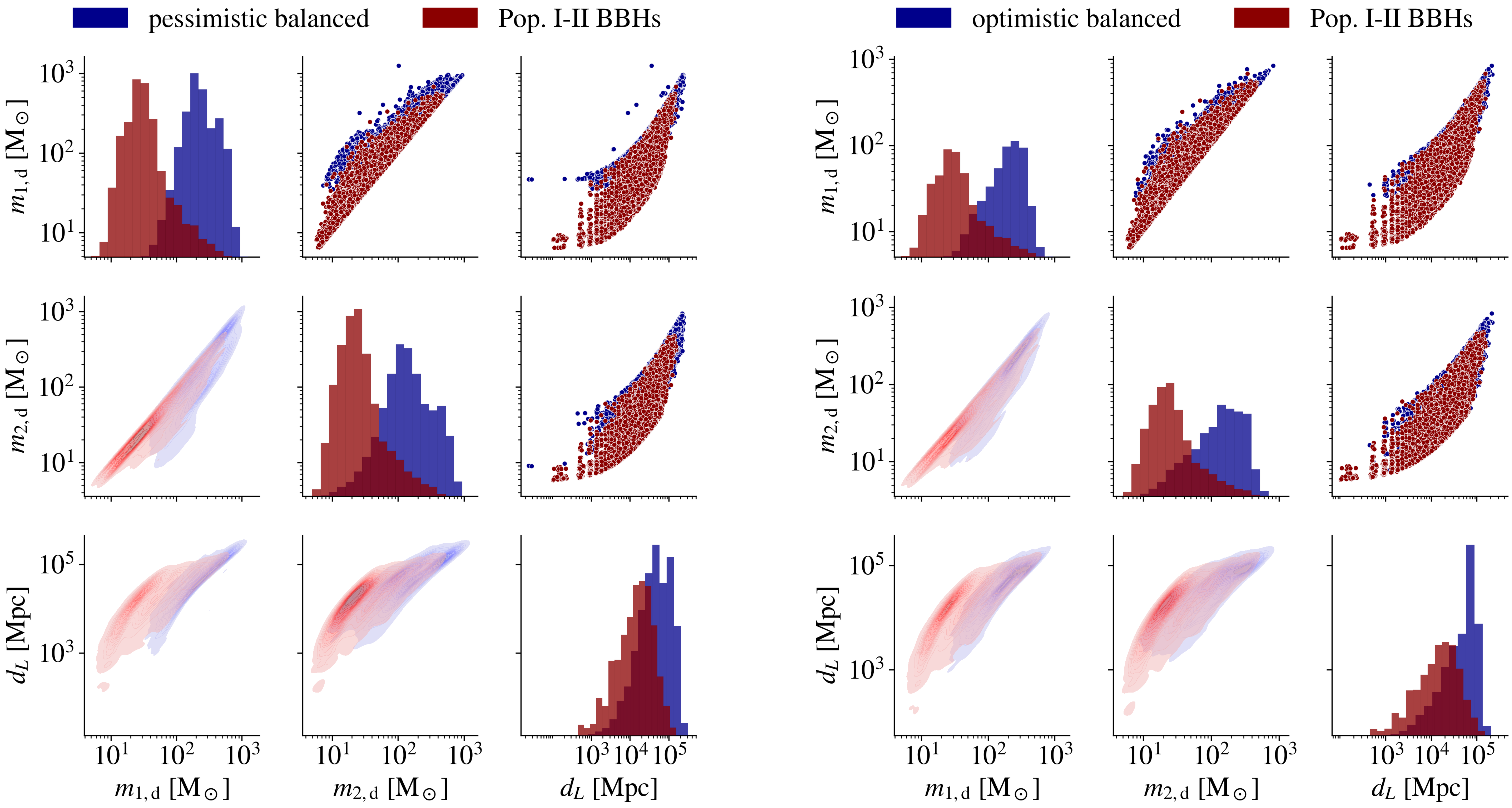
$$\rho_{\rm opt}^2 = 4\int_{f_{\rm low}}^{f_{\rm high}} {\rm d}f\, \frac{|\tilde{h}(f)|^2}{S_n(f)}$$


optimistic
fiducial
pessimistic
Pop. I-II
SNR > 12
Number of events
SNR
Δx/x ≤ 0.3
Δm1,d/m1,d
Δm2,d/m2,d
ΔdL/dL

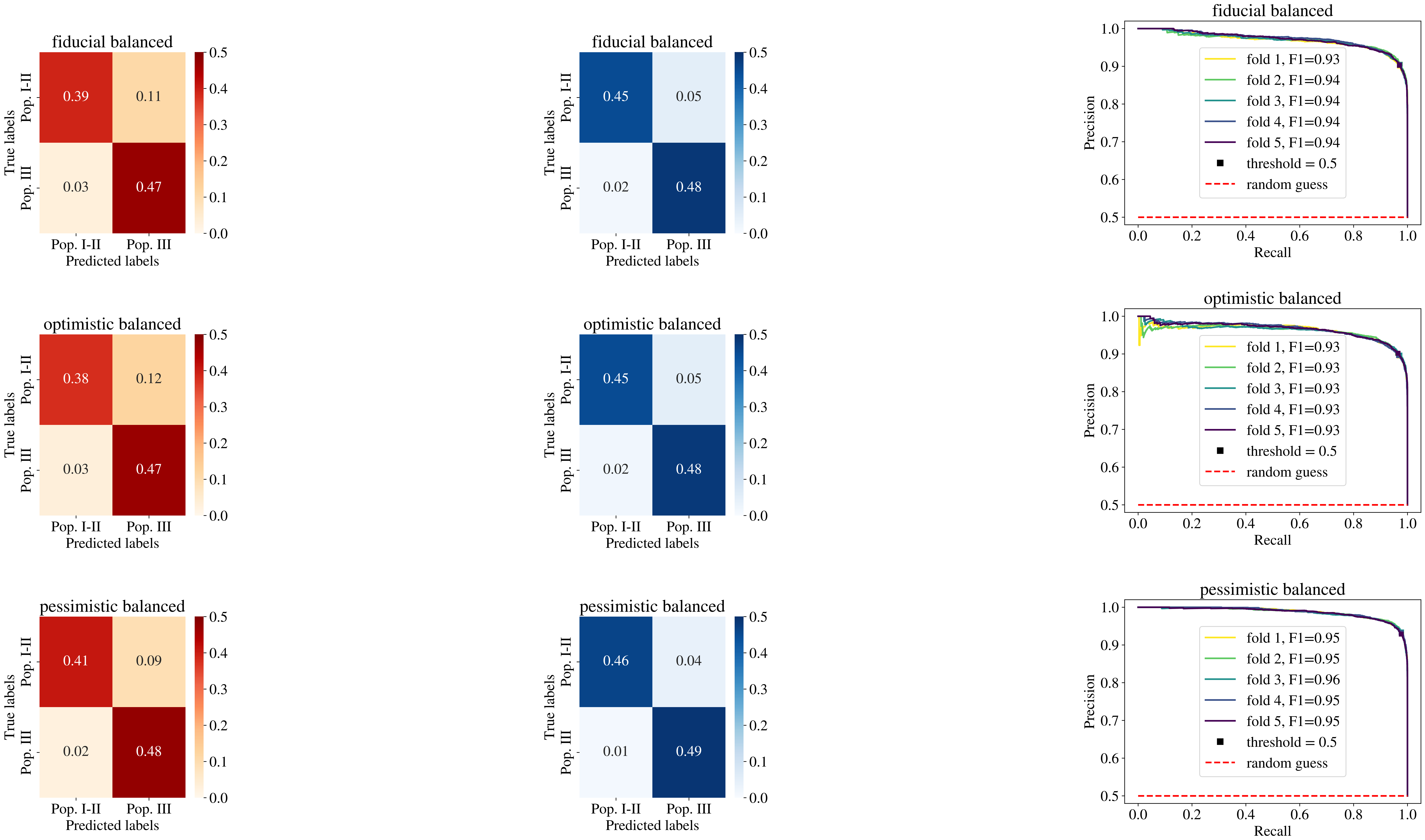
$$p(j \in k \,|\, x, d_j, \{\beta\}) = 1 \quad \text{if} \quad m_{1,\mathrm{d}} \gtrsim 60\ \mathrm{M}_\odot$$

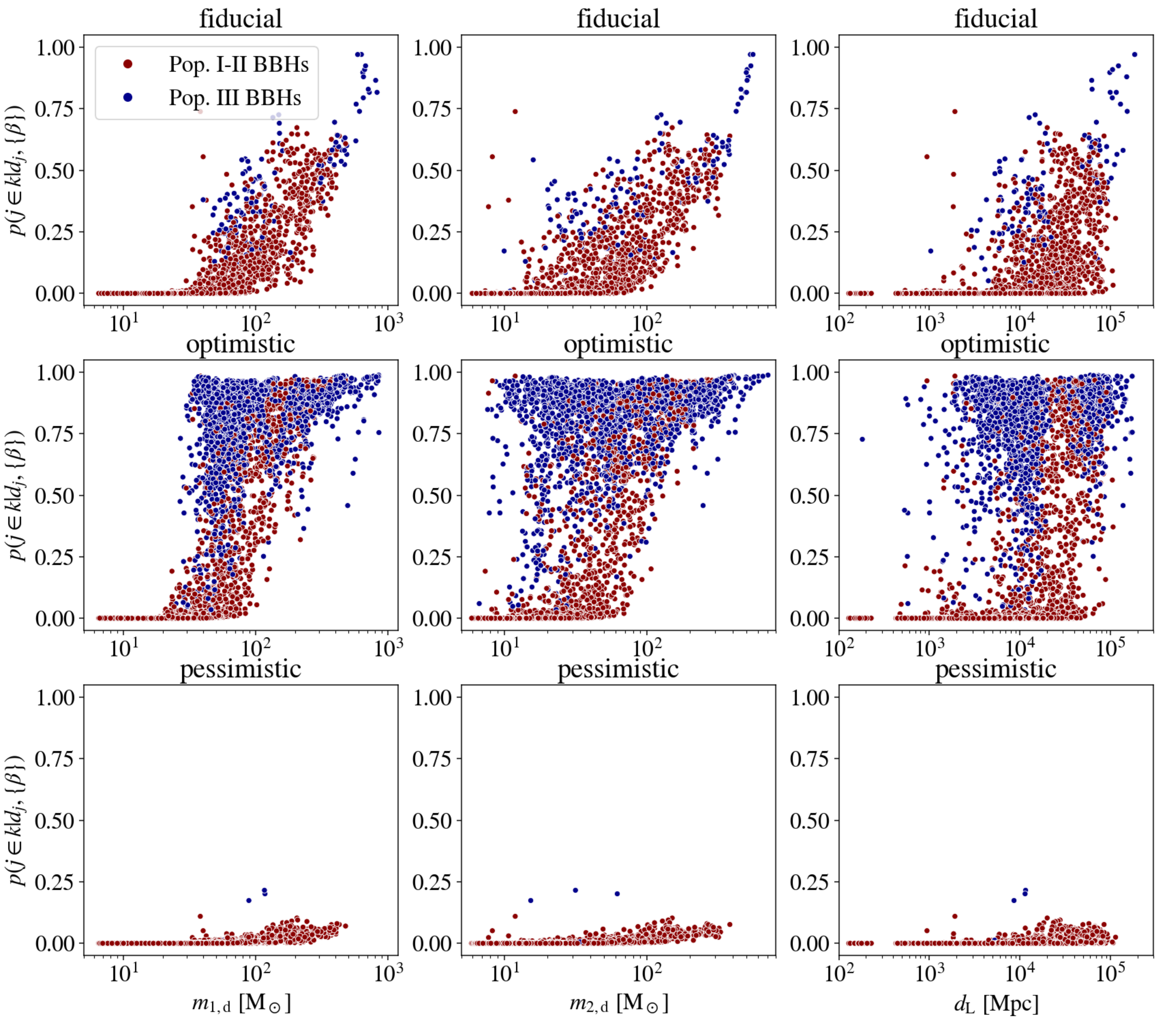


Ref. [Santoliquido et al. 2024]



pessimistic balanced
Pop. I-II BBHs
optimistic balanced
Pop. I-II BBHs
$m_{1,\mathrm{d}}$ [M$_\odot$]
$m_{2,\mathrm{d}}$ [M$_\odot$]
d_L [Mpc]
10^1
10^2
10^3
10^3
10^4
10^5


fiducial balanced
True labels
Predicted labels
Pop. I-II
Pop. III
0.39
0.11
0.03
0.47
0.45
0.05
0.02
0.48
0.5
0.4
0.3
0.2
0.1
0.0
Precision
Recall
fold 1, F1=0.93
fold 2, F1=0.94
fold 3, F1=0.94
fold 4, F1=0.94
fold 5, F1=0.94
threshold = 0.5
random guess
optimistic balanced
0.38
0.12
0.03
0.47
0.45
0.05
0.02
0.48
fold 1, F1=0.93
fold 2, F1=0.93
fold 3, F1=0.93
fold 4, F1=0.93
fold 5, F1=0.93
threshold = 0.5
random guess
pessimistic balanced
0.41
0.09
0.02
0.48
0.46
0.04
0.01
0.49
fold 1, F1=0.95
fold 2, F1=0.95
fold 3, F1=0.96
fold 4, F1=0.95
fold 5, F1=0.95
threshold = 0.5
random guess



Fiducial

Thr.	%TP	%TN	%FP	%FN	Precision	Recall
0.1	96	85	15	4	0.20	0.96
0.2	86	90	10	14	0.26	0.86
0.5	33	98	2	67	0.43	0.33
0.7	11	100	0	89	0.94	0.11
0.9	3	100	0	97	1.00	0.03

Optimistic

Thr.	%TP	%TN	%FP	%FN	Precision	Recall
0.1	100	77	23	0	0.80	1.00
0.2	99	80	20	1	0.81	0.99
0.5	95	85	15	5	0.85	0.95
0.7	87	89	11	13	0.88	0.87
0.9	46	96	4	54	0.91	0.46

Pessimistic

Thr.	%TP	%TN	%FP	%FN	Precision	Recall
0.1	50	100	0	50	0.60	0.50
0.2	33	100	0	67	1.00	0.33
0.5	0	100	0	100	0	0
0.7	0	100	0	100	0	0
0.9	0	100	0	100	0	0