Characterization of LIGO/Virgo selection effects with neural networks

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Machine learning in GW search: g2net next challenges

Pisa, Italy

We are like any other observatory

- We wish to infer the **global** properties of some objects (BHs)…
- …by observing only **some** of them.

For a review: Vitale, **DG**+ 2020

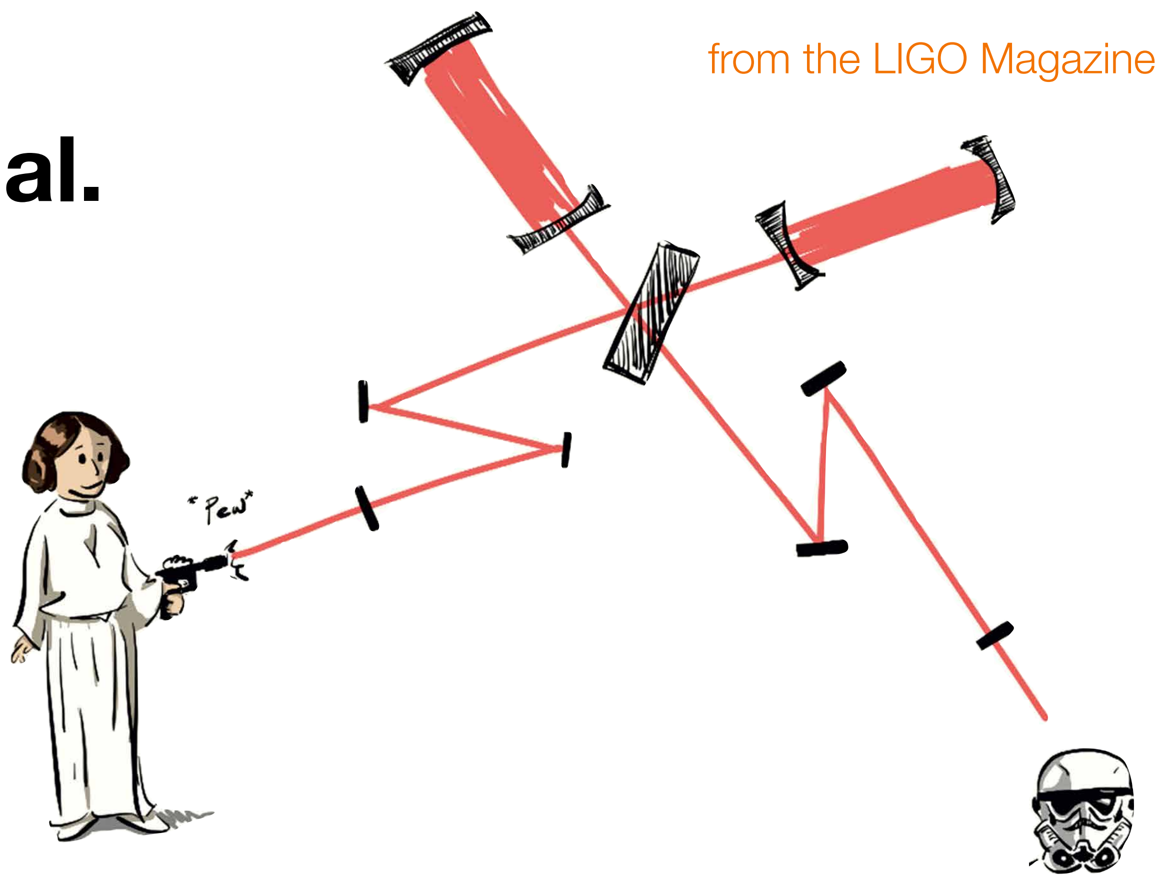
Accurate inference relies on accurate knowledge of the detector response

from the LIGO Magazine

Not all BH binaries are created equal.

Some are easier to see:

- Large masses (but still on stellar scales)
- Large aligned spins (waveform is longer)
- Inclination: face on/off
- Preferred locations in the sky



Detection probability

The key quantity we want: $p_{\mathrm{det}}(\theta, \xi, z)$

Probability that LIGO/Virgo will observe a source

- θ: Intrisic parameters (masses, spins,...)
- ξ: Extrinsic parameters (sky location, inclination,...)
- z: Redshift (or distance)

Two strategies:

- Software injections (same procedure used for detection!)
- Used to calibrate a ranking statistics

SNR $\rho^2 = 4 \int \frac{\tilde{h}(f)\tilde{h}^*(f)}{S(f)}$

Detectable: $\rho > 8$ (single LIGO)

$\rho > 12$ (LIGO/Virgo network)

LIGO/Virgo 2016, 2018, Chen+ 2017

Many pdet's

Thresholding the SNR $$p_{\rm det}(\theta, \xi, z) = \Theta[\rho(\theta, \xi, z) - \rho_{\rm thr}]$$

We (usually at least) are not interested in the extrinsic parameters:

$$p_{\rm det}(\theta, z) = \int p(\xi) p_{\rm det}(\theta, \xi, z) d\xi$$

And at the end of the day we just want a population average

See Matt's talk in a bit!

λ : Population (hyper) parameters

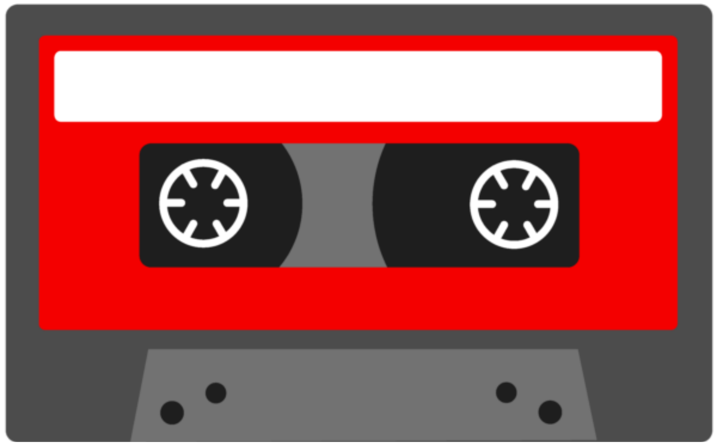
$$\sigma(\lambda) = \int p_{\rm pop}(\theta, z|\lambda) p_{\rm det}(\theta, z)$$

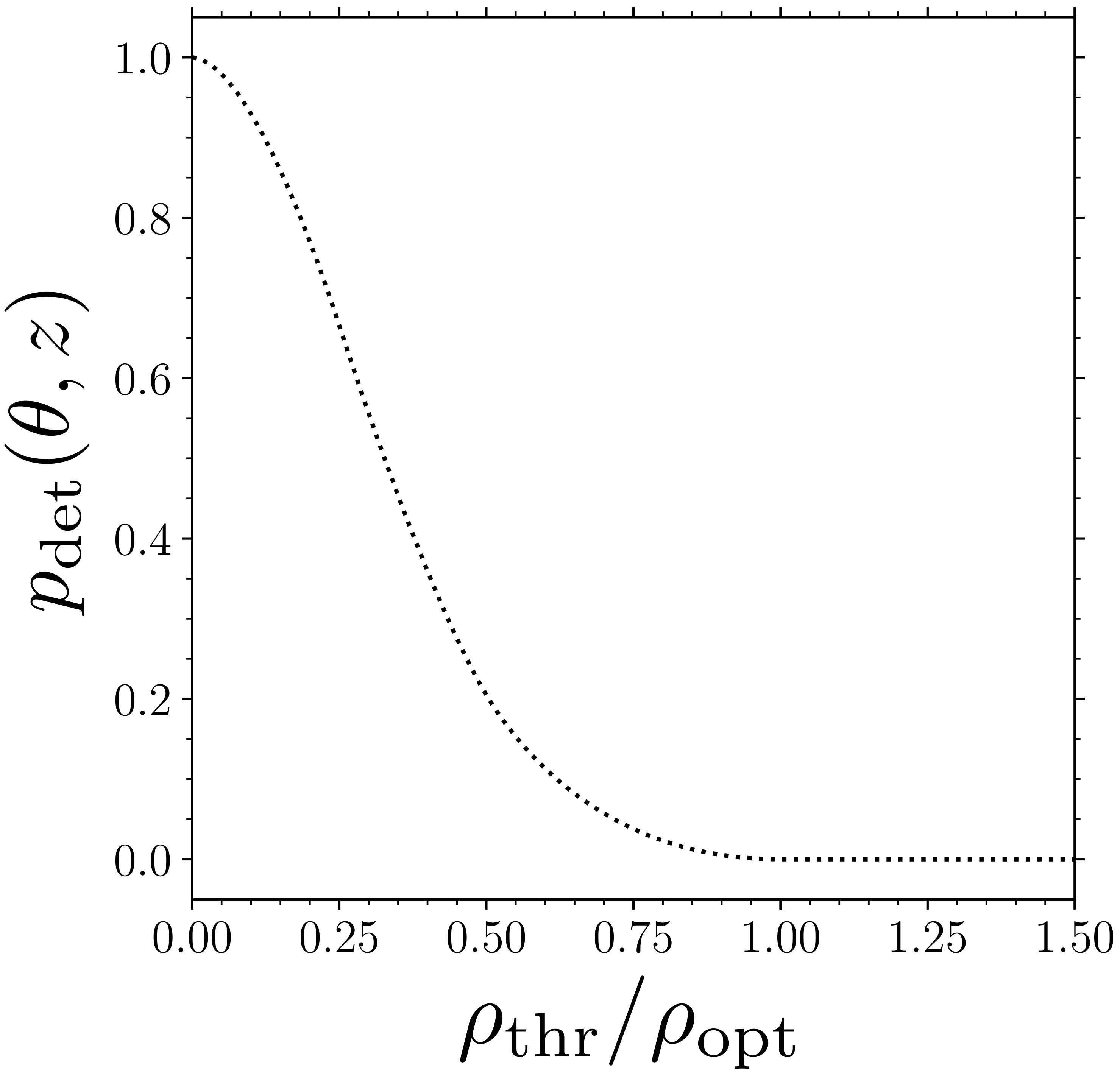
Key ingredients:

- Compute the SNR $\rho(\theta, \xi, z)$
- Pdf of the extrinsic parameters (usually easy: isotropic) $p(\xi)$
- Pdf of the intrinsic parameters (specific population model) $p_{\rm pop}(\theta, z|\lambda)$

Semi-analytic pdet

Rewind from the 90s: Finn Chernoff 1993, Chernoff 1996





Still state-of-art for O1-O2 LIGO analyses
LVK O3a/b used injections
Still used very much nonetheless!

Key assumptions:

- Single detector
- Dominant mode only
- No spin precession

Key results:

- Universal curve
- Cheap! One needs to compute a single SNR

Machine-learning classifiers

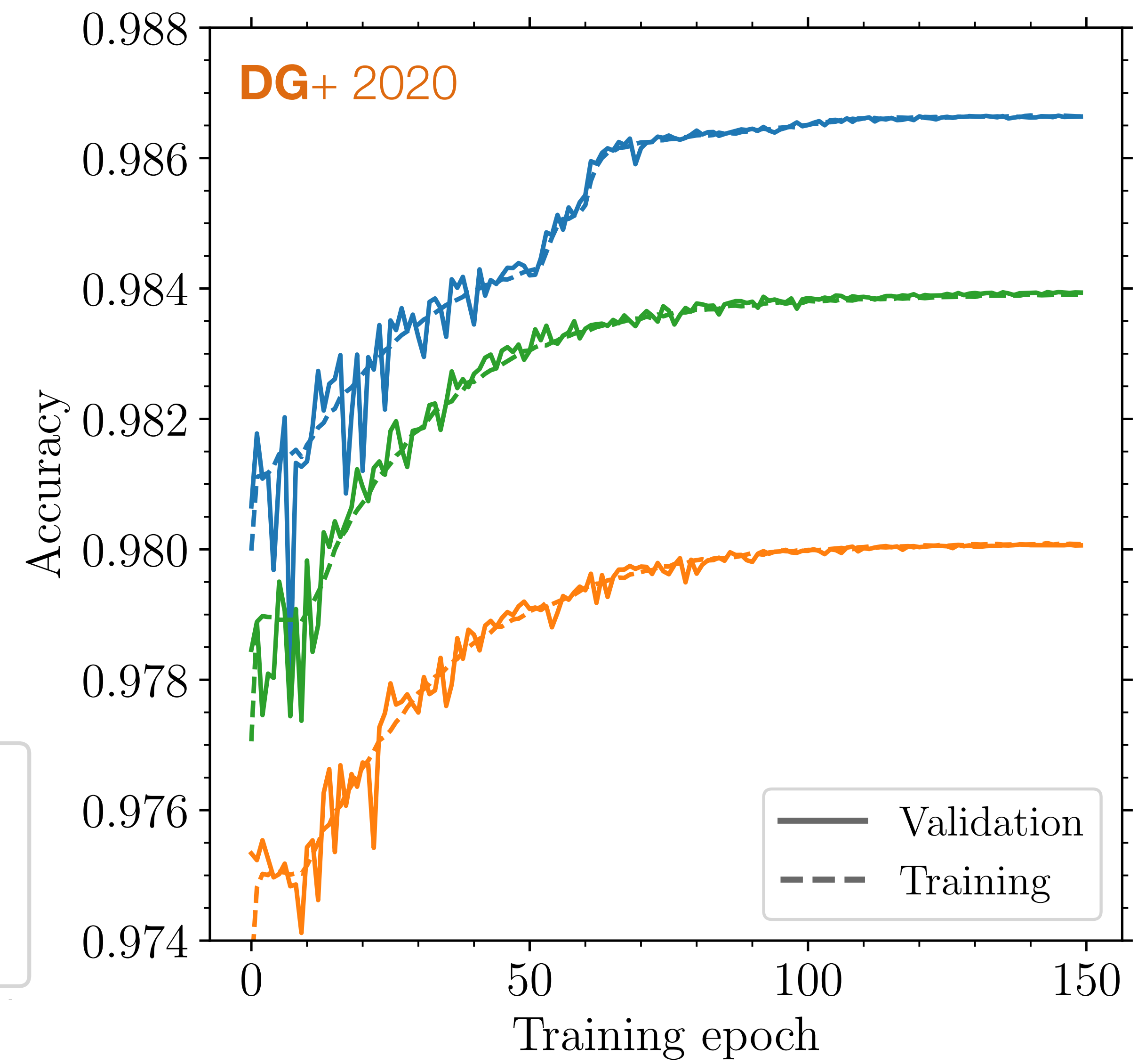
Including spin precession, three detectors and higher-order modes with machine learning

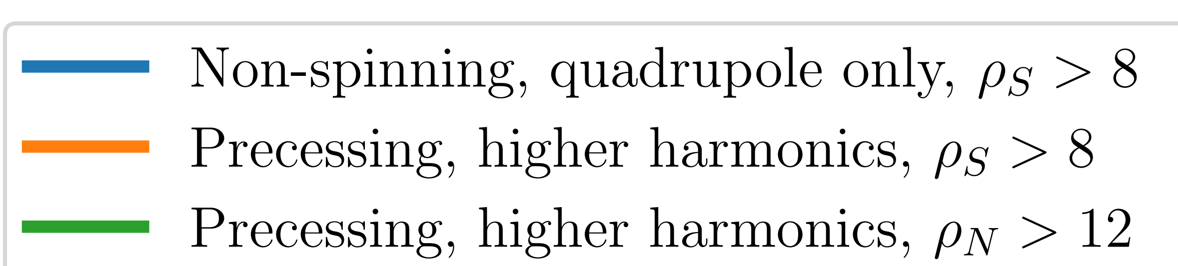
$$(\theta, \xi, z) \to \rho(\theta, \xi, z) > \rho_{\rm thr}$$

$$(\theta, \xi, z) \to \rho(\theta, \xi, z) < \rho_{\rm thr}$$

Network architecture

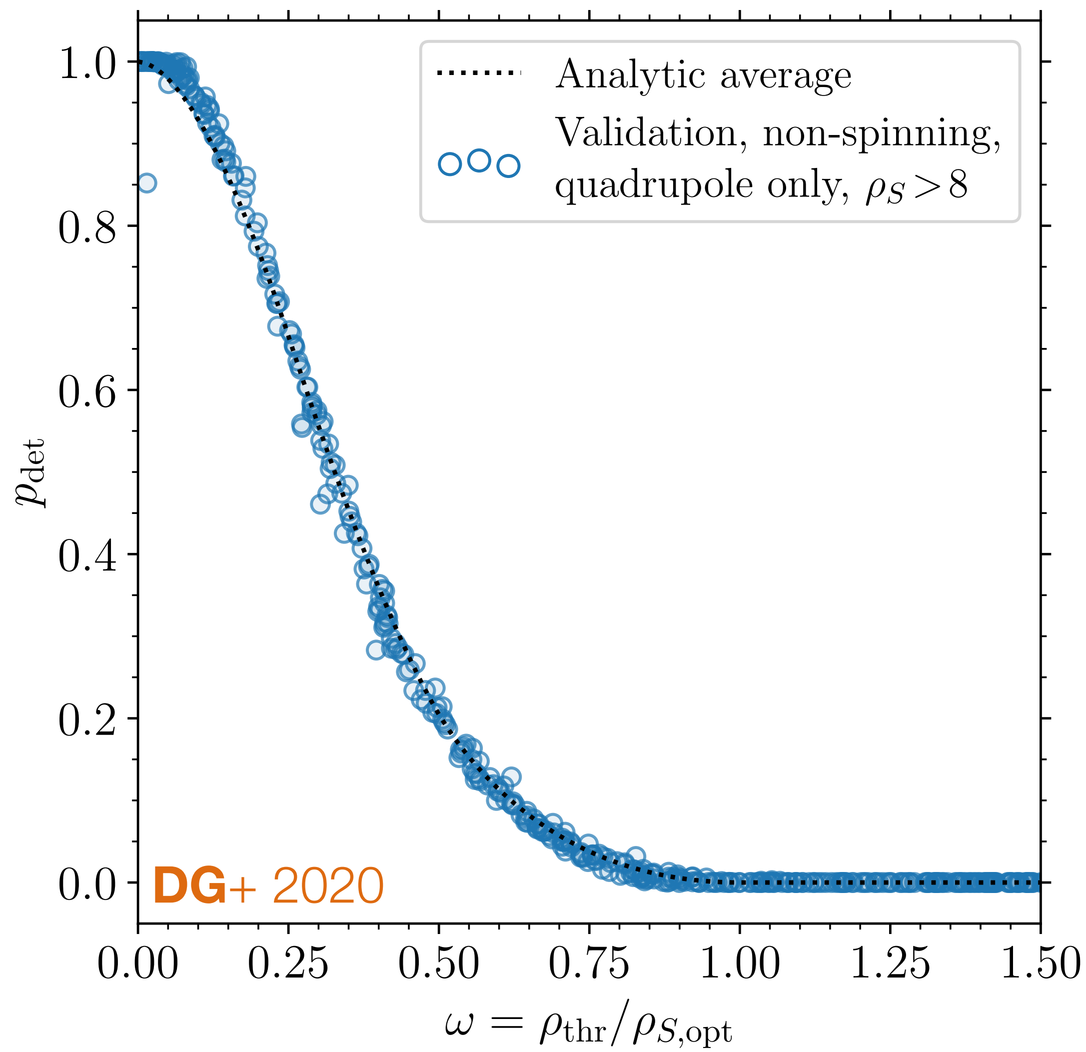
- Fully connected neural network (MPL)
- Implemented in TensorFlow
- One hidden layer with 32 neurons
- Adam optimizer
- Glorot initializer
- Tanh activation function

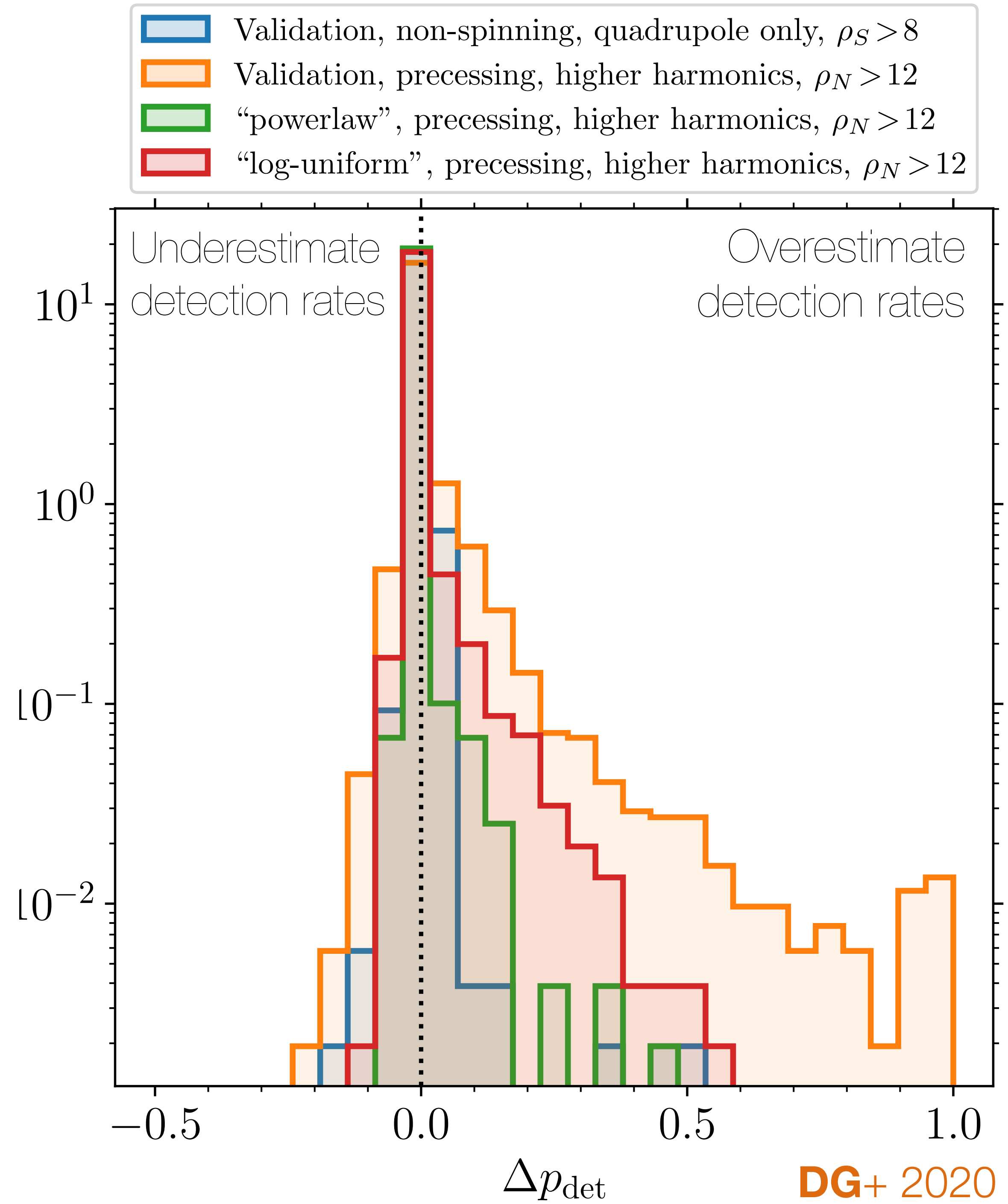




Lessons learned

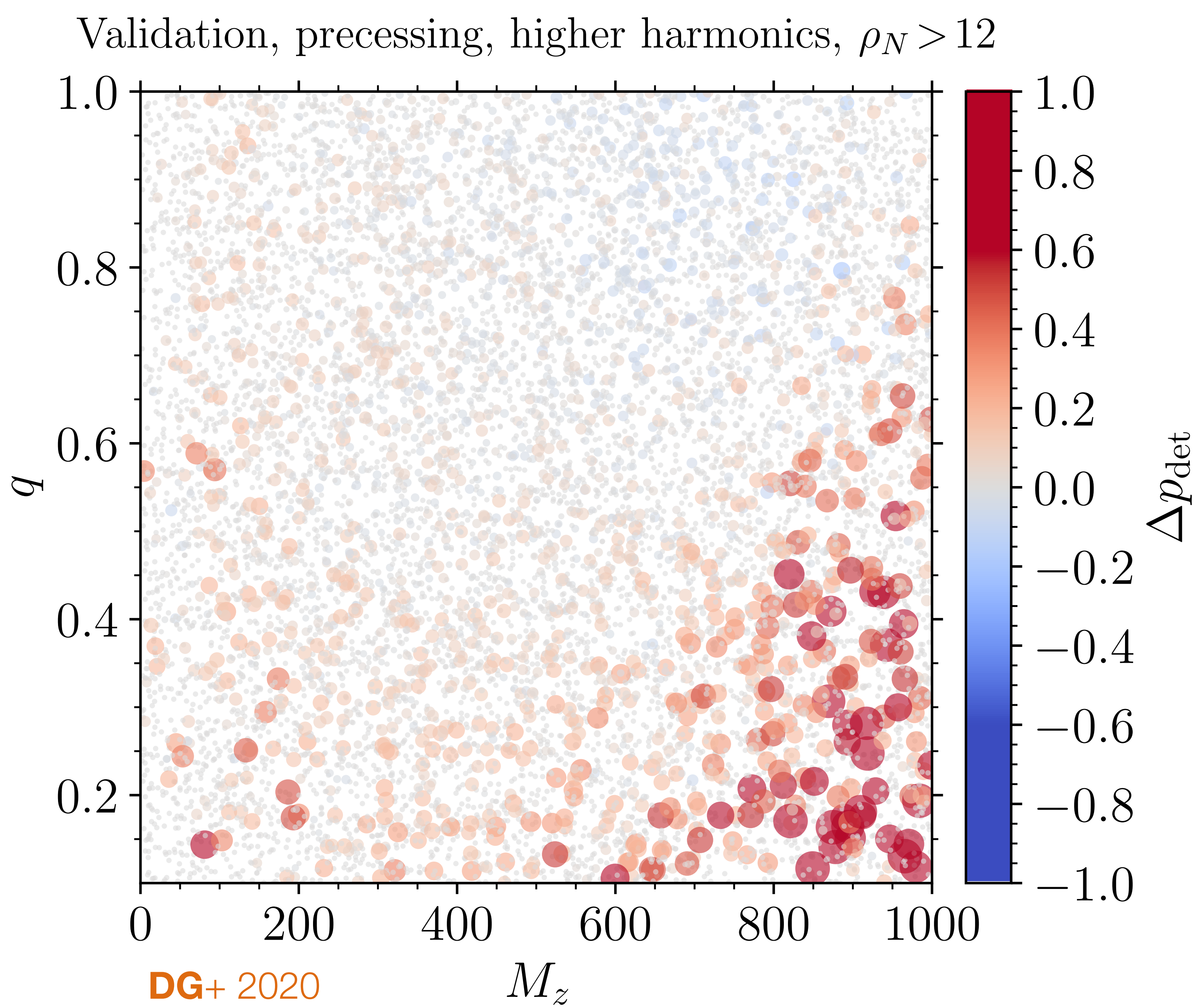
Reproduces the analytics for the non-spinning single-detector case





Mismodeling for multiple detectors, precessing sources, and higher-order modes

Highly non-uniform selection bias



DG+ 2020

Affects specific parts of the parameter space more prominently than others

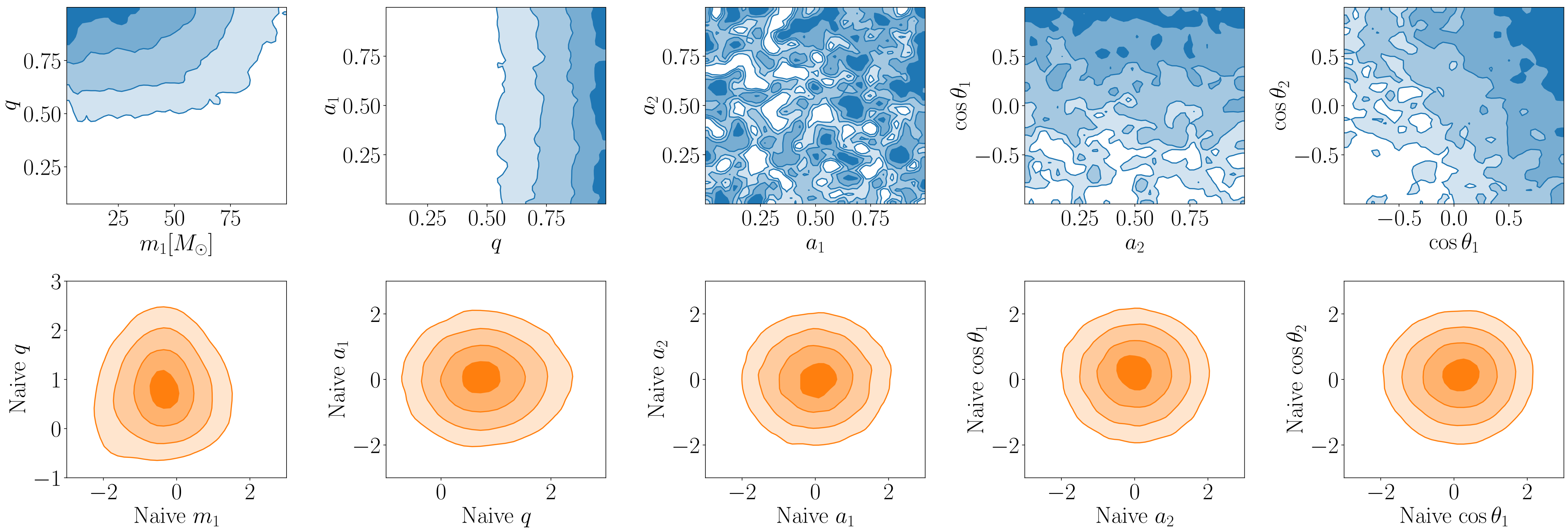
- Large masses
- Small mass ratios

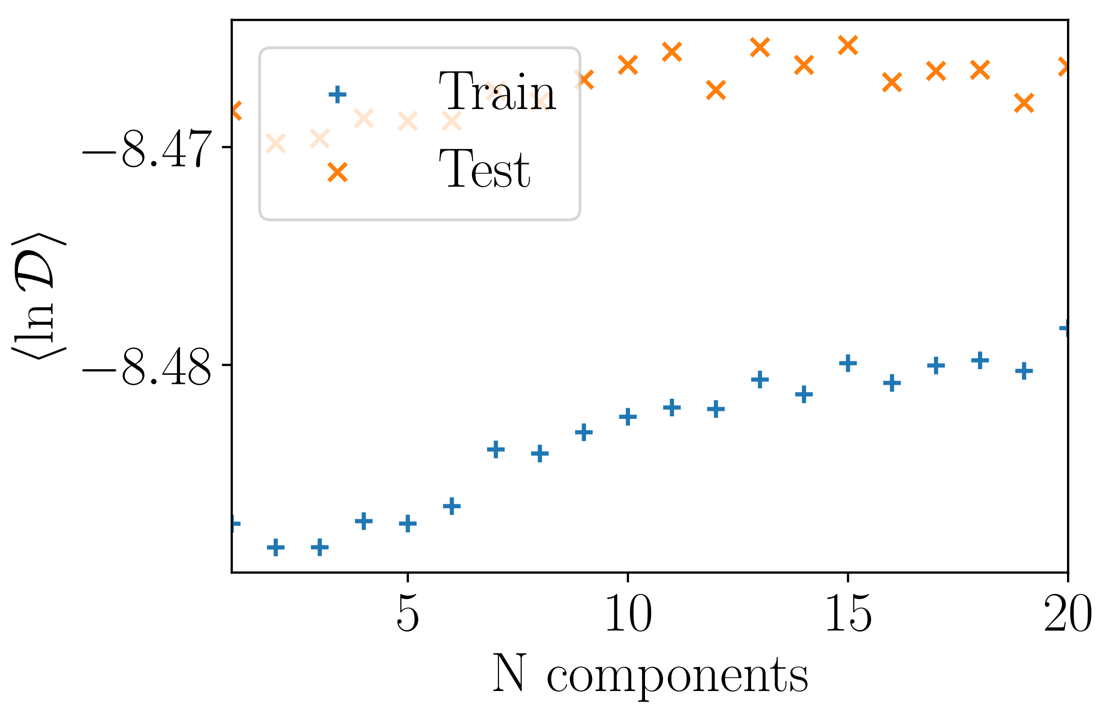
Are current event rates (slightly) overestimated?

Please explore! github.com/dgerosa/pdetclassifier

We're not the only ones

Results from another group Talbot, Thrane 2020



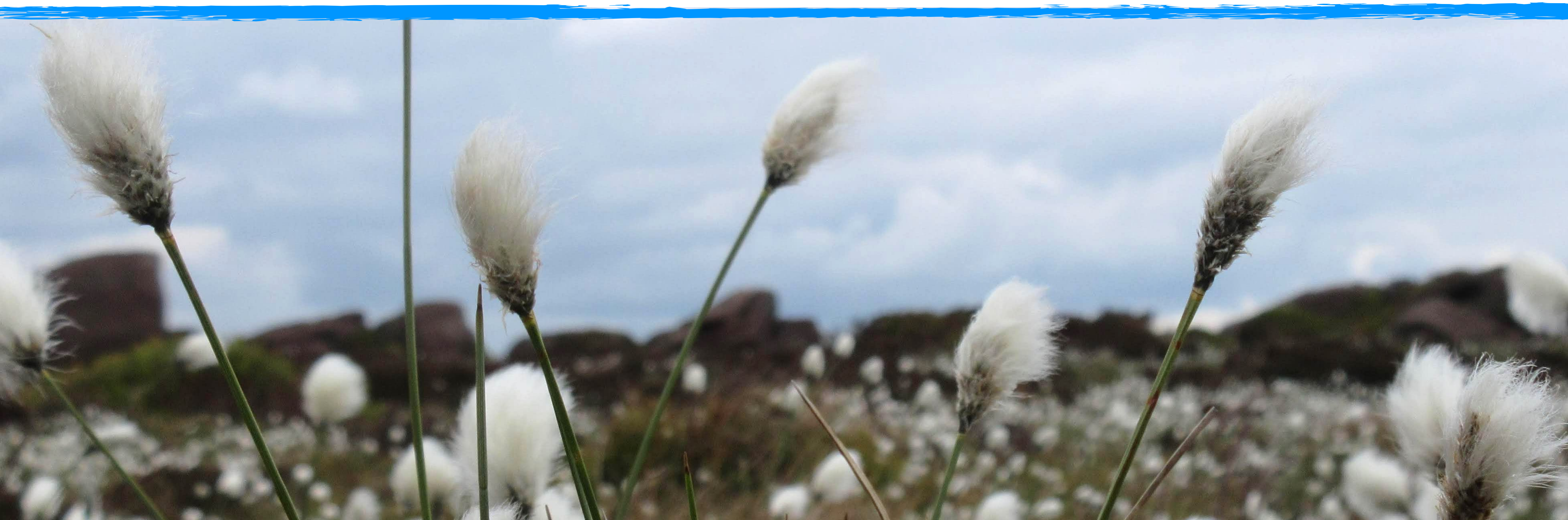


- Data pre-process designed for the GW problem
- Fit with Kernel density estimation + Gaussian mixtures
- Higher level, fit the population-average pdet directly

Next

1. LIGO/Virgo injections are now public! Can we machine-learn them?
2. Should we instead machine-learn the population average? See Matt's talk in a bit!
3. Common approximations lead to an overestimate of the detection rate
4. Careful with selection biases in specific regions of the parameter space

arXiv:2007.06585 github.com/dgerosa/pdetclassifier



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How we put things together

θ **Single-event parameters:** masses, spins, redshifts

λ **Population parameters:** spectral index of mass distribution, cutoffs

Inhomogeneous Poisson process:

Loredo 2004, Mandel+ 2019, Thrane, Talbot 2019, Vitale, **DG**+ 2022,

$$\underbrace{p(\lambda|d)}_{\text{Population posterior}} \propto \underbrace{\pi(\lambda)}_{\text{Population prior}}\sigma^{-N}(\lambda) \underbrace{\prod_{i=1}^{N}}_{\text{N events...}} \int \underbrace{p_{\rm pop}(\theta|\lambda)}_{\text{Population model}}\underbrace{\mathcal{L}(d_i|\theta)}_{\text{Single-event likelihood}}\,\mathrm{d}\theta$$

Selection effects: $\sigma(\lambda) = \int p_{\rm pop}(\theta|\lambda)\underbrace{p_{\rm det}(\theta)}_{\text{Detection probability}}\mathrm{d}\theta$

Semi-analytic calculation

Response

$$h(t) = F_+ h_+(t) + F_\times h_\times(t)$$

Beam patterns

$$F_+ = \frac{1}{2}\left(1+\cos^2\vartheta\right)\cos 2\phi \cos 2\psi - \cos\vartheta \sin 2\phi \sin 2\psi$$

$$F_\times = \frac{1}{2}\left(1+\cos^2\vartheta\right)\cos 2\phi \sin 2\psi + \cos\vartheta \sin 2\phi \cos 2\psi$$

GW emission

$$h_+(t) = A(t)\frac{1+\cos^2\iota}{2}\cos\Phi(t) \qquad h_\times(t) = A(t)\cos\iota\sin\Phi(t)$$

Projection

$$\rho(\theta,\xi,z) = \omega\rho_{\rm opt}(\theta,z) \qquad \omega = \sqrt{\left(F_+\frac{1+\cos^2\iota}{2}\right)^2 + (F_\times\cos\iota)^2}$$

Result

$$p_{\rm det}(\theta,z) = \int_{\rho_{\rm thr}/\rho_{\rm opt}}^{1} p(\omega)\,d\omega$$