# CLUSTERING COMPACT-BINARY OBJECTS IN THE PARAMETER SPACE THROUGH PROBABILISTIC HOUGH TRANSFORM Marco Canducci, Ilya Mandel and Peter Tiňo



### Motivation

#### Masses and Spins distributions of simulated compact-binaries.

N = 1000 simulated binaries via population synthesis code, corrupted by realistic noise. These observations are mock posteriors on future LIGO data sets.



FIGURE 1: Posteriors on future LIGO datasets in masses (left) and spins (right) spaces.

Finding prototypical systems in the parameter space and clustering the models w.r.t. the prototypes could provide useful model-independent information about the population [2].

#### Building a probabilistic model for each simulated binary.

Each model is a mixture of five gaussians with means aligned along the principal direction and full covariance matrices.



FIGURE 2: Gaussian mixture contours for a single posterior in both parameter spaces.

For each observation we then have a probabilistic model of the form:

$$q_i = \sum_{k=1}^5 p_k \mathcal{N}(\mu_k, \Sigma_k)$$

## References

mxc743@cs.bham.ac.uk Ilya.Mandel@monash.edu P.Tino@cs.bham.ac.uk School of Computer Science, University of Birmingham, Birmingham B15 2TT, UK School of Physics and Astronomy, Monash University, Melbourne, Asutralia

Methodology

### Probabilistic Hough-Transform

(1)

FIGURE 4:  $T - N_{Peaks}$  curve for  $m_1 - m_2$  parameter space, showing a knee at Threshold  $\approx$  1, corresponding to 5 detected peaks.

Following the work by [1], each parameter space is covered by a uniform grid and each cell (identified by the vector  $\vec{x}$ ) contains the summation of the responsibilities of all the 1000 models  $\mathcal{O}_{i=1}^N$  for that cell:

 $P(\vec{x}) = \sum_{i=1}^{N} p(i)q(\vec{x}|\mathcal{O}_i)$ 

The prior p(i) is assumed to have a flat distribution and is fixed to 1/N for every  $\mathcal{O}_i$ .



FIGURE 3: PHT for both parameter spaces: masses (left) and spins (right).

The obtained map of the reponsibilities on each parameter space is the Probabilistic Hough-Transform (PHT, [3]).

#### Peak detection and optimal number of clusters

Treating the PHT as a grey-scale image, the number of connected components in it, are the number of peaks  $(c_i)$  in the map and thus the clusters prototypes. We can estimate the number of relevant peaks by letting a threshold T vary from the maximum to the minimum of the PHT and looking for a 'knee' in the  $T - N_{Peaks}$  curve.



[2] I. Mandel, W. M. Farr, A. Colonna, S. Stevenson, P. Tiňo, and J. Veitch. Model-independent inference on compactbinary observations. MNRAS, 465(3):3254–3260, Mar 2017.

$$)$$
 (2)



FIGURE 5: PHT with overposed detected optimal peaks.

For each peak we can now compute its responsibility w.r.t. every model:

$$p(c_j|\mathcal{O}_i) = \frac{\frac{q(c_j|O_i)}{\sum_{k=1}^N q(c_j|\mathcal{O}_k)}}{\sum_{l=1}^M \frac{qc(c_l|\mathcal{O}_l)}{\sum_{a=1}^M q(c_l|\mathcal{O}_a)}}$$
(3)

The clusters are formed by assigning the models to the peak  $c_i$  for which  $p(c_i|\mathcal{O}_i)$  is maximum, obtaining:



FIGURE 6: Posteriors clustered w.r.t. the detected peaks.

first BMVC 1990.



# PHT Peaks and associated clusters

# Results

<sup>[1]</sup> R. T. Ibrahem, P. Tino, R. J. Pearson, T. J. Ponman, and A. Babul. Automated detection of galaxy groups through probabilistic hough transform. In S. Arik, T. Huang, W. K. Lai, and Q. Liu, editors, Neural Information Processing, pages 323–331, Cham, 2015. Springer International Publishing.