# Astrophysics with joint analysis of multi-messenger observations

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### Outline

#### • Brief introduction

- Short gamma-ray burst (sGRB) jet structure inference via joint analysis with gravitational wave observations
- Inferring kilonova parameters including BNS merger time
- Additional collaborations presented in talks by
  - En-Tzu Lin: X-ray afterglow joint analysis
  - Surojit Saha: autoencoders for kilonova light curves





#### Multi-messenger astronomy with GW170818



#### Joint GW-GRB inference

- We previously showed that, for joint short GRB-BNS detection, we can obtain the short GRB intrinsic luminosity using GW information: Fan, Messenger & Heng PRL (2017) arXiv:1706.05639
- We have also demonstrated that the short GRB luminosity function can be accurately determined from a population of joint short GRB-GW observations of BNS mergers



## Inferring sGRB jet structure

- We can combine the information from population of GW observations of BNS with the corresponding GRB observation to see to investigate the GRB jet structure
- To demonstrate this, we consider two **observed** structured jet models:
  - Gaussian jet (GL)
  - Power law (PL)
- We simulate a BNS merger population and draw their corresponding GRB luminosities based on the assumed jet structure model
- Details of hierarchal Bayesian analysis in F. Hayes *et al.*, ApJ 891 (2020)





#### Jet structure models

$$y(\theta) = e^{-\frac{1}{2} \left(\frac{\theta}{\theta_w}\right)^2}$$

$$y(\theta) = \begin{cases} 1 & \text{if } 0 \le \theta \le \theta_{in}, \\ \left(\frac{\theta}{\theta_{in}}\right)^{-k} & \text{if } \theta_{in} < \theta \le \theta_{out}, \\ 0 & \text{if } \theta_{out} < \theta. \end{cases}$$

Fix k = 2 for this analysis.



#### Bayesian model selection

• Bayes' theorem where for desired model, *M*<sub>A</sub>, and some observational data, *D*, we have

$$posterior \\ p(M_A|D,I) = \frac{p(D|M_A,I) \times p(M_A|I)}{p(D|I)} \\ \frac{p(D|I)}{evidence}$$

- The posterior probability represents the state of our knowledge of the model ("the truth") in light of our observed data
- If we have a competing model or hypothesis, we use the ratio of the posterior probabilities for each model

$$\frac{p(M_A|D,I)}{p(M_B|D,I)} = \begin{bmatrix} p(M_A|I) \\ p(M_B|I) \end{bmatrix} \times \begin{bmatrix} p(D|M_A,I) \\ p(D|M_B,I) \end{bmatrix}$$
prior odds Bayes factor

• If Bayes factor > 1,  $M_A$  is preferred. If Bayes factor < 1,  $M_B$  is preferred



#### Model comparison

- We calculate the Bayes factor for two datasets, each with 100 BNS detections
  - Dataset  $D_{GJ}$  universe of sGRBs with Gaussian jet structures
  - Dataset D<sub>PL</sub> universe of sGRBs with power-law jet structures





#### Parameter estimation

• We can also estimate the jet structure parameters using the correct model



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- Gravitational wave observations have provided us with an estimate of the rate of BNS and NSBH mergers.
- Can we combine these rates with the rate of sGRBs to learn about the jet structure?
  - Selection effects are included when calculating BNS and NSBH rates from GW observations
  - Selection effects for sGRB rate are a little tricky since it is also a function of the jet structure
- Previous work assuming top-hat jets: Williams et al., ApJ 858 (2018)
- For structured jets, we base our analysis on the formalism laid out by K. Mogushi *et al.*, ApJ 880 (2019)
- We construct a likelihood which is a Poisson distribution with the number of observed sGRBs, *N*<sub>obs</sub>, as the distribution mean
- Aim to evaluate Bayes factor comparing different jet structure models; can also obtain jet structure model parameters



 The number of observed sGRBs is related to a redshift dependent sGRB rate R<sub>GRB</sub>(z) by

$$N_{\rm obs}(\theta_M) = T\hat{F}R_0 \int_0^{z_{\rm max}} \int_{-1}^1 \int_{L_{\rm th}(\theta_M, z, \cos\theta)}^{\infty} \frac{R_{\rm GRB}(z)}{1+z} \frac{dV(z)}{dz} \mathcal{N}(L) dz d(\cos\theta) dL$$

• The effect of the jet structure enters via a luminosity threshold used to determine detection

$$L_{\rm th}(\theta_M, z, \cos \theta) = 4\pi d_L(z)k(z)F_{\rm min}\frac{y_{M,0}}{y_M(\theta)}$$

• Also,

 $R_0 = \epsilon_{\rm BNS} R_{\rm BNS} + \epsilon_{\rm NSBH} R_{\rm NSBH}$ 

- where  $\varepsilon_{\text{BNS}}$  is fraction of BNS mergers that produce a GRB and similarly for eNSBH
  - assume  $\epsilon_{BNS} = 1$ ,  $\epsilon_{NSBH}$  is unknown (typically 0.1-0.3)
- BNS/NSBH rates taken from GWTC-1

 $N(z, \cos\theta, L)$ : sGRB number density z: redshift  $\theta$ : viewing angle L: intrinsic luminosity *L*<sub>th</sub>: luminosity threshold  $R_{\text{GRB}}(z)$ : normailised sGRB rate where  $R_{\text{GRB}}(0) = 1$  $R_0$ : sGRB rate at z = 0T: observation duration  $\hat{F}$ : time-averaged detector response V: redshift volume  $y_{M}(\theta)$ : jet structure for model M yM,0:  $\theta_{M}$ : jet structure model parameters  $d_L$ : luminosity distance k: k-correction factor  $F_{\min}$ : minimum flux required for detection



• Test case with simulated number of observed sGRBs for validation



Gaussian jet structure where  $\theta_c$  is the width of the gaussian

- Jet structure function and rates used to simulate the number of observed sGRBs
- This simulated value is combined with GW priors on BNS and NSBH rates to obtain parameter posteriors



• Test case with simulated number of observed sGRBs for validation



#### Kilonovae

- We expect a number of BNS to be subthreshold (edge-on) or single detector events - an associated EM counterpart could confirm one of these detections as an event.
- We expect a number of untriggered kilonova detections associated with such subthreshold or one detector events. (Setzer *et al.*, 2019)
- Depth and field of view of LSST searches make it ideal for serendipitous kilonova discoveries

L. Datrier et al., in prep.



## Methdology

- We use the 2017 Kasen models to simulated observed light curves, and try to recover model parameters for varying cadences
- Two components (red, blue) with 3 ejecta parameters each:
  - Ejecta velocity
  - Ejecta mass
  - Lanthanide fraction
- 1 magnitude uncertainty on models



- Models on evaluated on a grid expanded with Gaussian Process Regression.
- Simulate apparent magnitude for different types of kilonovae from time resolved spectra, focusing at g,r,i bands
- Use LSST single exposure magnitude limits to determine when light curve is no longer detectable
- Consider different cadences and observing start times (time of first observation in days most-merger)



### Test with AT2017gfo

- Full parameter estimation on truncated AT 2017 gfo light curves for g,r,i DECam data.
- Start of observations t = 1.45 days after merger
- Recovered t =  $1.21^{+1.14}_{-0.82}$  days



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#### Summary

- Multi-messenger analysis of joint observations can uncover astrophysical insight which may not be accessible otherwise
  - population of GRB-GW observations will allow us to probe jet strucure
  - joint analysis of GRB, GW, X-ray,... observations will improve parameter estimation for individual events
- Kilonova model uncertainties have a significant impact on the ability to determine the merger time
  - Other factors include number of observing bands, kilonova brightness,...
- Multi-messenger analysis can also improve inference on distance, inclination,... and lead to better interpretation (eg. cosmology)

