Bayesian model selection of population synthesis models of CBCs

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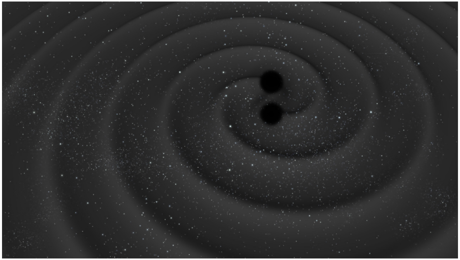
Ripples in Spacetime

- The detection of GWs by LIGO opens up a new window to observe the Universe.
- Start of the era of GW astronomy.
- Along with advLIGO and adv VIRGO, a worldwide network of GW detectors with LIGO-India and KAGRA at Japan by the next decade.



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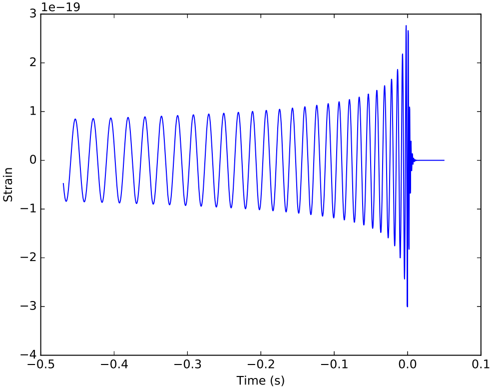
Credit: ESA-C. Carreau

GWs from compact binary sources

- Merger of two compact objects (BBH, NSBH, NSNS) is the main source for GWs for LIGO detectors.
- The waveform for BBH merger with masses $(m_1, m_2) = (20M_\odot 10M_\odot)$ looks like:



Population Synthesis Models for Compact Binaries

- The physical and astrophysical processes governing the evolution of compact binaries are poorly understood.
- Population synthesis codes aim to simulate these processes and provide predictions of the galactic merger rates and mass distribution for NS-NS, NS-BH, and BH-BH mergers.
- The rates differs for the different models which are characterized by various unknown parameters such as metalicity, binding energy of the envelope, maximum mass of the neutron star, etc.
- Advanced LIGO is expected to detect many events. This will provide us an opportunity to constrain parameter space of these models.

Synthetic Universe

- Dominik et al., 2012 provided publicly available population synthesis models for compact binaries with simulations using StarTrack code.
  www.syntheticuniverse.org
- Distribution of masses and spins of compact binaries along with merger rates for 64 different models (16 models with 4 submodels of each) which are characterized by various parameters.
- We consider the BBH mass distribution predicted by each model and develop a Bayesian method to rank these models based on the observed GW events.

Classification of population synthesis models

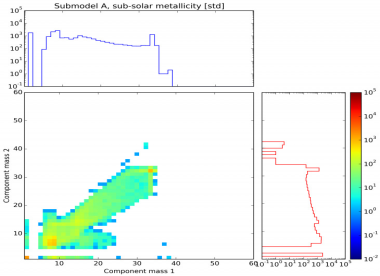
TABLE 1
SUMMARY OF MODELS[a]

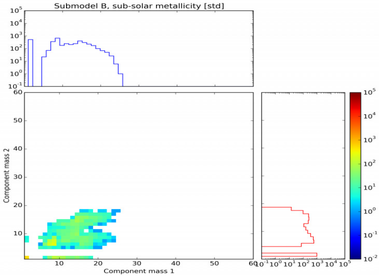
Model	Parameter	Description
S	Standard	$\lambda =$*Nanjing*, $M_{\rm NS,max} = 2.5$ M$_\odot$, $\sigma = 265$ km s^{-1} BH kicks: variable, SN: Rapid half-cons mass transfer
V1	$\lambda = 0.01$	very low λ: fixed
V2	$\lambda = 0.1$	low λ: fixed
V3	$\lambda = 1$	high λ: fixed
V4	$\lambda = 10$	very high λ: fixed
V5	$M_{\rm NS,max} = 3.0$ M$_\odot$	high maximum NS mass
V6	$M_{\rm NS,max} = 2.0$ M$_\odot$	low maximum NS mass
V7	$\sigma = 132.5$ km s^{-1}	low kicks: NS/BH
V8	full BH kicks	high natal kicks: BH
V9	no BH kicks	no natal kicks: BH
V10	Delayed SN	NS/BH formation: Delayed SN engine
V11	weak winds	Wind mass loss rates reduced to 50%
V12	cons MT	Fully conservative mass transfer
V13	non-cons MT	Fully non-conservative mass transfer
V14	$\lambda \times 5$	*Nanjing* λ increased by 5
V15	$\lambda \times 0.2$	*Nanjing* λ decreased by 5

[a] All parameters, except for the one listed under "Description", retain their Standard model ("S") values.

Figure: Dominik et. al., Astrophys. J., **759**, 1

Component mass distribution for standard model





Using Bayesian inference to rank models

The probability of parameter θ given data d and a population synthesis a model M, is given by,

$$P(\theta|d,M) = \frac{P(\theta|M)\mathcal{L}(d|\theta,M)}{P(d|M)} \tag{1}$$

Using Bayesian inference to rank models

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The quantity in denominator,

$$P(d|M) := \int P(\theta|I)\mathcal{L}(d|\theta,I)d\theta \quad (2)$$

is called the marginal likelihood of the model M, or the evidence of M.

Accounting for selection Bias (...In Progress)

- Observed mass distribution does not represent the true mass distribution.
- Avoid selection bias by accounting non-detection and perform full Bayesian analysis. [**Messenger, C and Veitch J.**]
- Selection function using large number of injections in data analysis pipeline.

Challenges

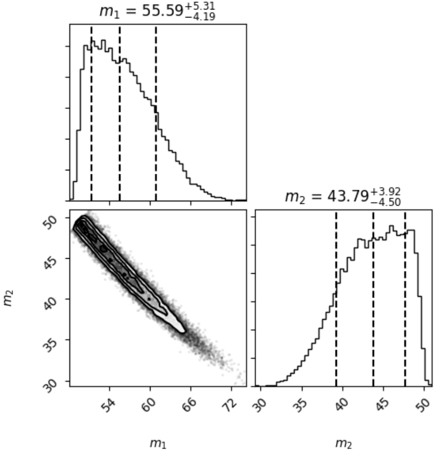
- *How to account for selection bias in an efficient way.*
- *Accounting for uncertainties due to poorly understood astrophysics.*

Using Bayesian inference methods to rank models

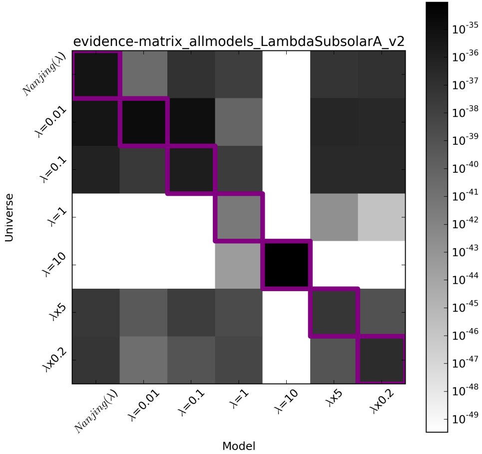
- We simulate populations of BBHs with mass distributions predicted by various population synthesis models. (spatially distributed uniformly in comoving volume).
- We calculate evidence for each model and rank them accordingly as models with higher evidence rank higher.
- For large number of detections, we expect to recover the fiducial model and expect that we can distinguish between different models also.

LALInference runs for simulated events

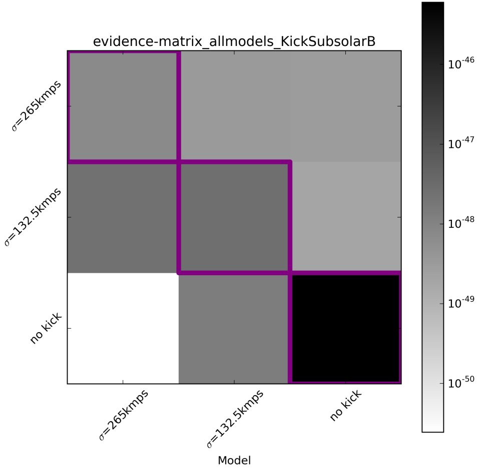
- Nested Sampling implementation in LALInference
- Posterior distribution for one simulated event



15 simulated observations , SNR $>$ 15



24 simulated observations , SNR $>$ 15



Summary

- As we enter the era of GW astronomy, the future detections of GWs from compact binaries can be used to distinguish between some of the population synthesis models.
- With large number of detections ($\sim \mathcal{O}(100)$) one can not only distinguish different population synthesis models but can rule out many models.
- It will have implication for astrophysics as it can constrain various astrophysical parameters used in the evolution of these population synthesis models.

Thank you!