Calculating Gravitational Wave Bias With TNG Simulation

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Outline

Motivation: The Gravitational Wave Era

- Gravitational waves (GW) from binary black hole (BBH) mergers are now routinely detected by observatories like LIGO and Virgo.
- These events aren't just fascinating on their own; they offer a new opportunity to probe the **large-scale structure** of the Universe.

Understanding GW Bias

- We assume BBH mergers don't happen randomly; they are expected to *trace the underlying matter distribution* in the Universe.
- This connection is quantified by the gravitational wave bias parameter (b_{GW}).
- Think of it as a clustering multiplier: if $b_{GW} > 1$, GW sources are more clustered than the underlying matter; if $b_{GW} < 1$, they are less clustered.
- This parameter is a critical link between the properties of host galaxies and the large-scale clustering of GW events.

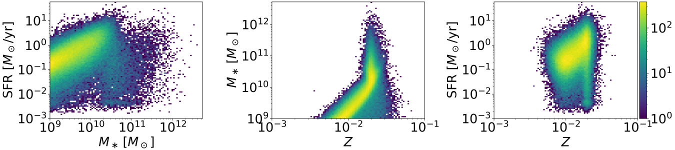
Project Goal

- Our aim is to simulate a realistic population of GW sources to measure their bias.
- We do this using the **TNG300 simulation**, a massive cosmic simulation that models galaxies and dark matter.
- We developed a **probabilistic model** to assign BBH mergers to specific galaxies based on their properties.
- Finally, we study the clustering of these simulated GW sirens by computing b_{GW} across:
  - Redshift
  - Host galaxy properties
    - Stellar Mass
    - Star Formation Rate
    - Metallicity

Galaxies from TNG300

- We extracted galaxy (subhalo) properties from the simulation.
- We selected galaxies with a stellar mass $> 10^9 M_\odot$.

Distributions of galaxies with respect to key properties at $z = 0$



- We validated our dataset against existing literature [1-4] to ensure good agreement with observational trends.

Dark Matter and Data Processing

Dark Matter Particles

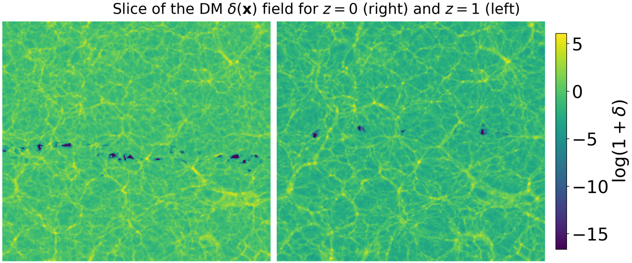
- We also extracted the spatial positions of dark matter particles from the simulation.
- We used 10 snapshots spanning the redshift range from $z = 0$ to $z = 1$.

Next Steps

- With both galaxy and dark matter data, we can now compute the smoothed density fields.
- This allows us to quantify the large-scale clustering of both populations and calculate the bias parameter.

Density Field

- We compute the smoothed matter density field $\rho(\mathbf{x})$ for dark matter, galaxies, and GW sirens.
- Employed the Cloud-In-Cell (CIC) mass assignment scheme using the `Pylians` library on `Python`.



- The overdensity field is defined as: $\delta(\mathbf{x}) = \rho(\mathbf{x})/\bar{\rho} - 1$

Power Spectrum and Bias

Power Spectrum

- The power spectrum, $P(k)$, quantifies density fluctuations as a function of spatial scale.
- We compute $P(k)$ for dark matter, galaxies, and GW sirens using the `Pylians` library [5].

$$\langle\tilde{\delta}(\mathbf{k})\tilde{\delta}^*(\mathbf{k}')\rangle = (2\pi)^3\delta^{(3)}(\mathbf{k}-\mathbf{k}')P(k)$$

Gravitational Wave Bias

- We characterize how well GW sirens and galaxies trace the matter distribution with the scale-dependent bias:

$$b_{\text{obj}}(k) = \sqrt{P_{\text{obj}}(k)/P_{\text{dm}}(k)}$$

- We fit for a non-linear bias, $b(k) = b_0 + b_1 k$, over the range $0.04 < k < 1.0$ using a χ^2 minimization.
- We define $b_{GW} := b(k = 0.1\mathrm{h/Mpc})$.

Simulating the GW Siren Population

Number of Mergers

- We simulate the GW siren population by assigning binary mergers to galaxies in simulation snapshots.
- The expected number of sirens, N_{GW}, is calculated using the merger rate density, $R_{GW}(z)$, and the observation time, t_{obs}:

$$N_{GW}(z) = V_{box} \cdot \frac{R_{GW}(z) t_{obs}}{1+z}$$

GW Host Probability Function

- Hosts are selected using a *broken power-law probability distribution* based on stellar mass [6]:

$$P(M_*) \propto \begin{cases} M_*^{1/\delta_l} & \text{if } M_* < M_K \\ M_*^{-1/\delta_h} \cdot M_K^{1/\delta_l + 1/\delta_h} & \text{if } M_* \geq M_K \end{cases}$$

- The parameters δ_l and δ_h are the slopes of the power law, and M_K is the pivot mass.

Merger Rate and Counts: The Equations

Merger Rate Density The merger rate density of GW sources at a given merger redshift, z_m, can be written as:

$$R_{GW}(z_m) = \mathcal{A}_0 \int_{z_m}^{\infty} P_D(t_d) \frac{dt_f}{dz_f} R_{SFR}(z_f) dz_f \quad (1)$$

Where:

- $P_D(t_d)$: The delay time probability distribution.
- $R_{SFR}(z_f)$: The cosmic star formation rate density.
- $\mathcal{A}_0$: A normalization factor to match the local observed merger rate.

Merger Rate: Key Parameters

Star Formation Rate (SFR) The redshift dependence of the cosmic SFR density is given by the Madau-Dickinson relation:

$$R_{SFR}(z) = 0.015 \frac{(1+z)^{2.7}}{1+[(1+z)/2.9]^{5.6}} \; M_\odot \; \mathrm{yr}^{-1} \; \mathrm{Mpc}^{-3} \tag{2}$$

Cosmological Factors The Jacobian for the change of variable from time to redshift is:

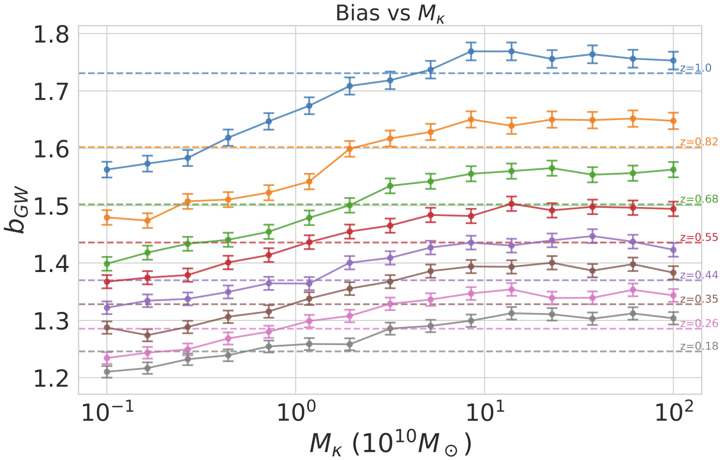
$$\frac{dt_f}{dz_f} = \frac{1}{H_0} \frac{1}{(1+z_f)E(z_f)} \tag{3}$$

where

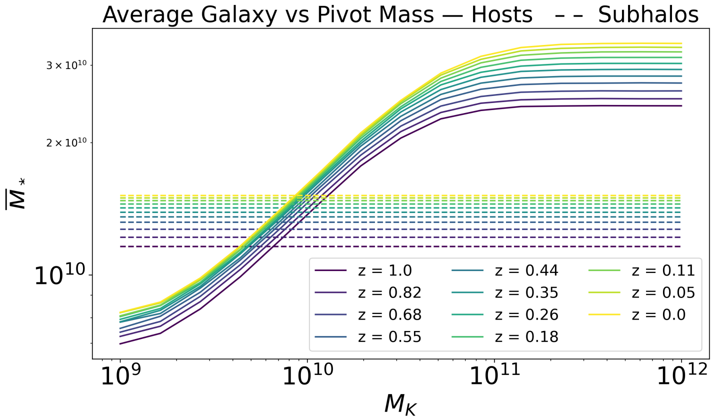
$$E(z) = \sqrt{\Omega_m(1+z)^3 + \Omega_r(1+z)^4 + \Omega_\Lambda + \Omega_K(1+z)^2} \tag{4}$$

We use a cosmology with vanishing curvature and radiation density parameters $(\Omega_K, \Omega_r \approx 0)$.

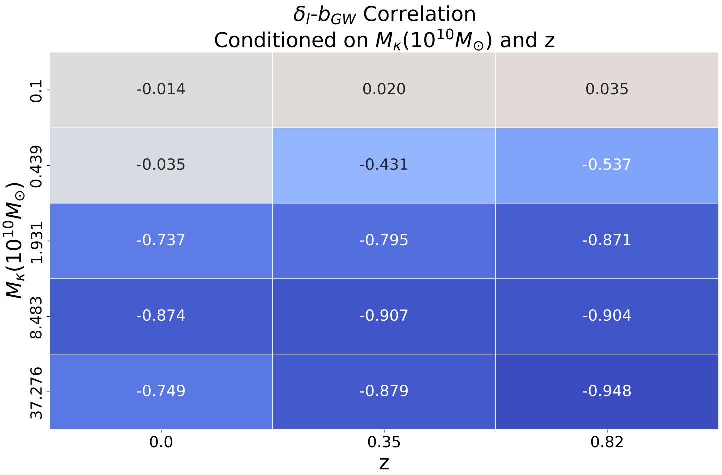
GW Bias vs. Pivot Mass



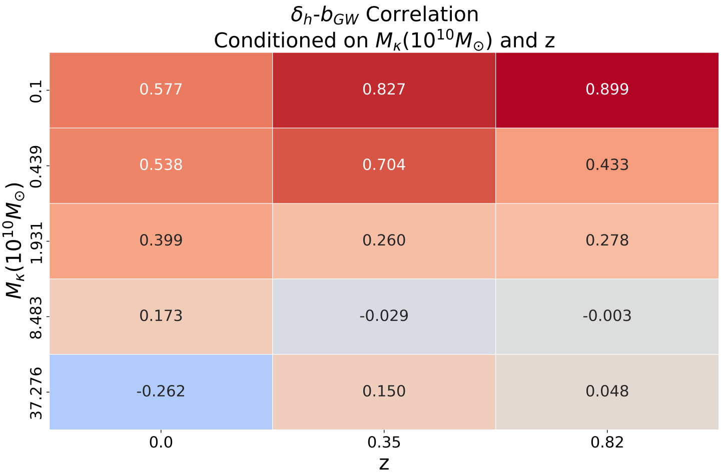
Host Mass and Pivot Point



Correlation with Low-Mass Slope



Correlation with High-Mass Slope



Key Findings and Interpretation

Main Conclusions

- $\boldsymbol{b_{GW}}$ increases with redshift, consistent with the expected galaxy bias trend.
- A **higher pivot stellar mass (M_K)** leads to stronger clustering of sirens, as it selects more massive galaxies.
- $\boldsymbol{b_{GW}}$ shows a non-trivial positive correlation with M_K and a weak dependence on the power-law slopes (δ_l, δ_h).
- The correlation of b_{GW} with δ_l and δ_h depends on the value of M_K relative to the mean stellar mass of galaxies.

Limitations

- Our results are specific to the chosen broken power-law probability model.
- We consider the dependence of probability model on mass, SFR, and metallicity to be uncorrelated.

Future Work

- Explore other galaxy host probability models.
- Figure out the correlations by training an ML model on available data and reproduce the sampling distribution.
- Analyze more snapshots and larger simulation boxes.
- Compare with observational data from future GW detectors.
- Consider other metrics instead of bias

$$\mathrm{Cor}(\mathrm{obj}, \mathrm{dm})(k) = \langle \delta_{\mathrm{obj}}(k)^* \delta_{\mathrm{dm}}(k) \rangle$$

and others.

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