Comparing Parameter Inference Techniques in the Context of Reionization

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Background

The onset of Cosmic Dawn is marked by the formation of the first luminous structures, such as star forming galaxies. The photons they emitted ionized the predominantly neutral hydrogen that comprised the intergalactic medium (IGM), facilitating the Universe's last phase transition from neutral to ionized. This period is called the Epoch of Reionization.[1]

The goal is to get the best-fit model of Reionization based on observational constraints including the **volume-averaged neutral hydrogen fraction (x_{HI})**, the **ionizing emissivity ($\dot{N}_{ion}$)**, the **optical depth to Thomson scattering (τ)**, and the **UV luminosity density (ρ_{UV})**, compiled from HST, JWST, and Planck surveys.[1]

In this project, we utilize and compare two inference techniques, **emcee** and **Nautilus**, to get the best-fit parameters of our model.

Model

We use a model derived from radiative transfer simulations of reionization.[1][2][4]

$$\frac{R_{ion}}{M_h} = A(1+z)^D \left(\frac{M_h}{B}\right)^C exp\left[-\left(\frac{M_h}{B}\right)^{-3}\right]$$

- R_{ion} = Rate of Ionization
- M_h = Halo Mass
- z = Redshift
- A = Amplitude of R_{ion}, scales the ionizing emissivity over the entire halo mass range at a given redshift by same amount
- B = Determines minimum halo mass, the quenching mass scale due to feedback from star formation and photoionization heating
- C = Quantifies slope of (R_{ion}-M_h) relation, which controls the contribution of different mass scales to total emissivity.
- D = Accounts for redshift dependence of ionization rate for a given halo mass

Inference Techniques

emcee

emcee is a python implementation of the Markov Chain Monte Carlo (MCMC) method.[3]

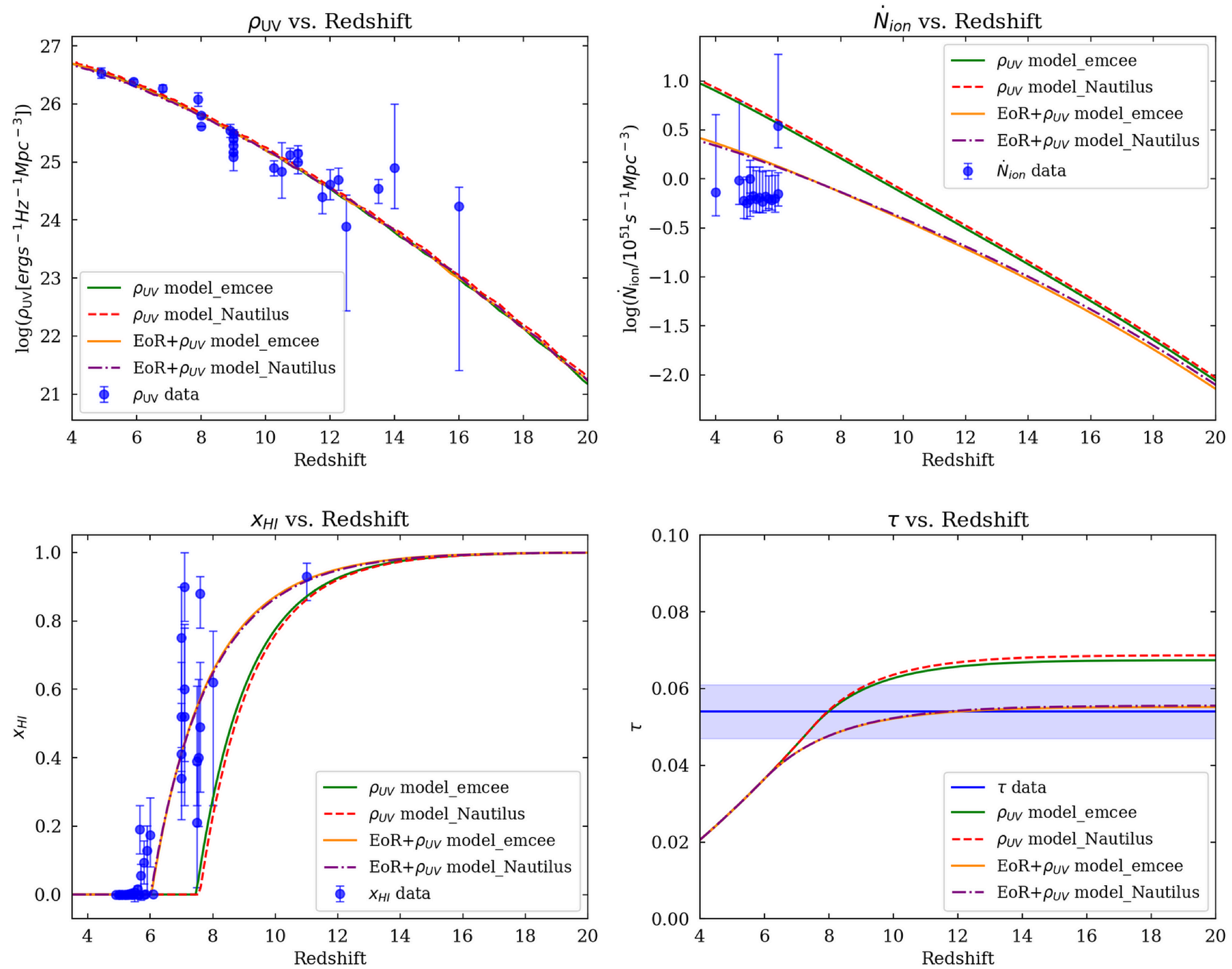
NAUTILUS

Nautilus employs Importance Nested Sampling (INS) and incorporates neural networks to improve sampling efficiency and convergence.[5]

Both are Bayesian parameter inference techniques that use the likelihood function and prior function to compute the posterior probability distribution of the model parameters.

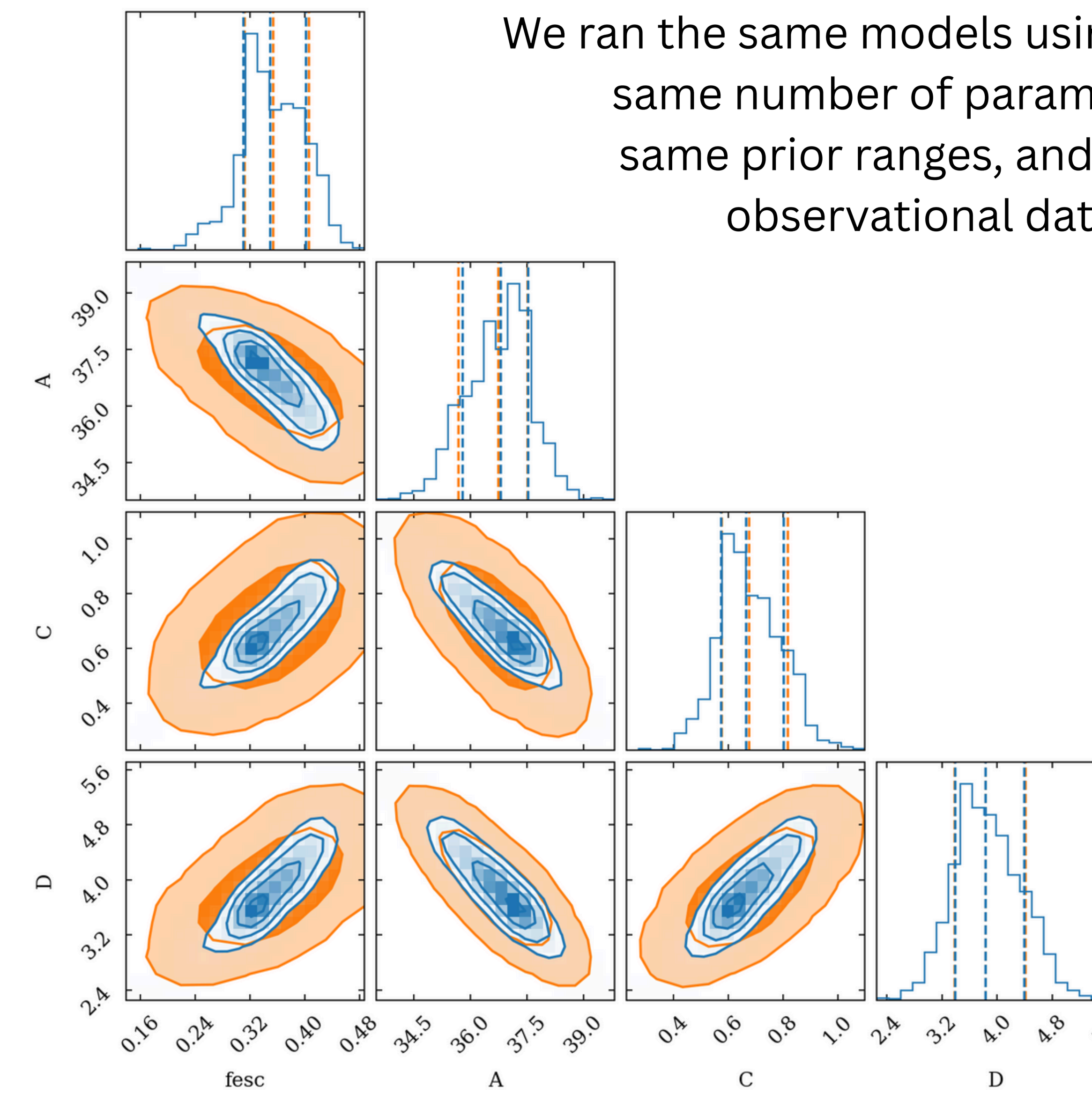
Results

EoR = x_{HI} + $\dot{N}_{ion}$ + τ



These curves represent the best-fit models considering different observations in the likelihoods, which we found using emcee and Nautilus.

Comparison Between the Techniques



We ran the same models using the same number of parameters, same prior ranges, and same observational datasets.

Time per N_{eff} for above EoR+ρ_{UV} model:

- emcee : ~3.993 s per N_{eff} point
- Nautilus : **~0.258 s** per N_{eff} point

Summary

- The two different sets of observational data result in two different reionization timelines.
- The model fits the data better when more observational contraints are considered in the likelihood.
- Nautilus computed the same values as emcee in less time: **>15x** faster than emcee in this case.
- Nautilus provides more information such as weighted likelihoods.

References

[1] Ankita Bera, Sultan Hassan, Aaron Smith, Renyue Cen, Enrico Garaldi, Rahul Kannan, and Mark Vogelsberger. Bridging the Gap between Cosmic Dawn and Reionization Favors Models Dominated by Faint Galaxies. , 959(1):2, December 2023.
[2] Kristian Finlator, Laura Keating, Benjamin D Oppenheimer, Romeel Dave, and Erik Zackrisson. Reionization in technicolor. Monthly Notices of the Royal Astronomical Society, 480(2):26282649, 07 2018.
[3] D. Foreman-Mackey, D. W. Hogg, D. Lang, and J. Goodman. emcee: The mcmc hammer. PASP, 125:306–312, 2013.
[4] Sultan Hassan, Romeel Dav ´e, Kristian Finlator, and Mario G. Santos. Epoch of reionization 21 cm forecasting from MCMC-constrained semi-numerical models., 468(1):122–139, June 2017.
[5] Johannes U. Lange. NAUTILUS: boosting Bayesian importance nested sampling with deep learning. , 525(2):3181–3194, October 2023.

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