

Symbolic Regression Is All You Need: From Simulations to Scaling Laws in Binary Neutron Star Mergers

Gravitational wave sources with electromagnetic counterparts have highlighted the need for predictive, interpretable models linking the parameters of compact binary systems to post-merger remnants and mass outflows. In this work, we explore AI-driven symbolic regression (SR) frameworks to derive updated analytical relations for disk ejecta mass in binary neutron star mergers, trained on state-of-the-art numerical relativity simulations. Our method reveals a set of compact equations that outperform existing fitting formulae across multiple statistical metrics while remaining physically interpretable. Notably, SR also enables alternative predictor sets (e.g., $\{M_1, M_2, \tilde{\Lambda}\}$) that match or exceed the accuracy of models relying solely on compactness of the lightest neutron star (C_1), enabling new parameter constraints from electromagnetic observations. Unlike traditional black-box machine learning models, these closed-form expressions generalize robustly to regions of the parameter space not represented in the training data, offering a physics-informed tool for multimessenger observations and constraints on the neutron star equation of state.

Author: DARC DE MATOS, Phelipe Antonie (Centro Brasileiro De Pesquisas Físicas)

Co-authors: Prof. FRAGA, Bernardo (CBPF); Prof. KILPATRICK, Charles (Northwestern university); Prof. DE BOM, Clecio R (CBPF); S. TEIXEIRA, Gabriel (CBPF)

Presenter: DARC DE MATOS, Phelipe Antonie (Centro Brasileiro De Pesquisas Físicas)