

Machine Learning Emulator For Neutron Star Tidal Deformability

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Introduction

Our work aims at predicting macroscopic properties of neutron stars such as tidal deformability. Understanding the properties of dense nuclear matter is fundamental for the study of neutron stars (NSs). Recent multimessenger observations, including gravitational waves from binary neutron star mergers and electromagnetic counterparts, have highlighted the necessity of accurately constraining the EOS to interpret astrophysical data [1, 2].

Accurate determination of the tidal deformability of neutron stars is a key requirement for constraining the dense-matter equation of state (EOS) and interpreting multimessenger observations such as gravitational wave signals from binary neutron star mergers [1, 2].

Recent studies have explored machine learning techniques to accelerate this process, enabling rapid mapping from microscopic NMPs to macroscopic NS observables. In particular, Support Vector Regression (SVR) is a machine learning method derived from Support Vector Machines (SVM) that is well-suited for regression problems with complex, nonlinear relationships. Instead of trying to exactly fit all training data points, SVR maps the input features into a higher-dimensional space using kernel functions. This study focuses on the development and evaluation of SVR-based em-

ulators trained on varying sets of NMPs to predict neutron star tidal deformabilities with minimal computational cost. To systematically investigate the dependence of neutron star tidal deformability on the nuclear EOS, we construct machine learning models using two distinct sets of nuclear matter parameters (NMPs). These parameters encode the bulk properties of nuclear matter around saturation density and its higher-order density derivatives, which are critical for constraining stellar observables.

Methodology

In this work, we use Support Vector Regression (SVR) to map nuclear matter parameters (NMPs) to neutron star tidal deformabilities. Two different sets of models were considered:

5-NMP Model: Includes K_0 (incompressibility), Q_0 (skewness), $J_{\text{sym}0}$ (symmetry energy), $L_{\text{sym}0}$ (slope of symmetry energy), and $K_{\text{sym}0}$ (curvature of symmetry energy).

10-NMP Model: Incorporates the above five parameters along with ρ_0 (saturation density), E_0 (binding energy per nucleon), Z_0 (fourth-order EOS derivative), $Q_{\text{sym}0}$ (skewness of symmetry energy), and $Z_{\text{sym}0}$ (higher-order isovector term).

The reduced 5-NMP set captures the essential isoscalar and isovector contributions,

but it neglects the finer density evolution of the symmetry energy at supranuclear densities. In contrast, the 10-NMP model accounts for higher-order terms such as $Q_{\text{sym}0}$ and $Z_{\text{sym}0}$, which govern the nonlinear density dependence of the symmetry energy.

The SVR models were trained on the RMF-DDME and NL3 datasets using an averaging technique, and subsequently applied to the RMF-DBE model. Each model predicts tidal deformabilities $\Lambda_{1.2}$, $\Lambda_{1.4}$, $\Lambda_{1.6}$, $\Lambda_{1.8}$, and $\Lambda_{2.0}$ corresponding to neutron stars of masses 1.2–2.0 M_{\odot} .

Model performance was evaluated using the mean absolute error percentage (MAE) and root mean square error (RMSE) metrics.

Results and Discussion

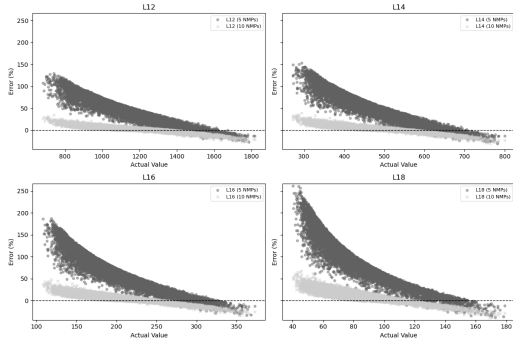


Figure 1: Percentage prediction errors for neutron-star tidal deformability obtained using SVR models trained on 5-NMP (circle) and 10-NMP (cross) input sets.

Two models were trained on the RMF-DDME and NL3 dataset: (i) a reduced 5-NMP set consisting of K_0 , Q_0 , $J_{\text{sym}0}$, $L_{\text{sym}0}$, and $K_{\text{sym}0}$, and (ii) an extended 10-NMP set incorporating higher-order parameters ρ_0 , E_0 , Z_0 , $Q_{\text{sym}0}$, and $Z_{\text{sym}0}$.

Model performance was evaluated using mean absolute error (MAE) and root mean square error (RMSE) across $\Lambda_{1.2}$ – $\Lambda_{2.0}$. The reduced

Λ	MAE (%)		RMSE	
	5-NMP	10-NMP	5-NMP	10-NMP
$\Lambda_{1.2}$	43.05	5.88	497.64	82.24
$\Lambda_{1.4}$	51.50	7.16	240.01	40.16
$\Lambda_{1.6}$	63.24	9.46	122.74	21.77
$\Lambda_{1.8}$	84.84	13.87	66.78	12.75
$\Lambda_{2.0}$	147.86	22.89	37.88	7.29

Table 1: Prediction errors for Λ using 5-NMP and 10-NMP models.

5-NMP model showed large deviations, with MAE percentage in the range of 30–150%, reflecting its inability to capture higher-order EOS dependencies. In contrast, the 10-NMP model substantially improved accuracy, achieving MAE of only 5–20% [Figure 1] and RMSE reductions of nearly an order of magnitude [Table 1].

The extended 10-NMP framework provides a reliable bridge between microscopic nuclear physics and macroscopic astrophysical constraints from gravitational-wave data [3]. The improved performance of the 10-NMP model indicates that inclusion of higher-order nuclear matter parameters significantly enhances the predictive reliability of tidal deformabilities.

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