CALIBRATING THE GLOBAL BEHAVIOUR OF EOS IN A MACHINE LEARNING APPROACH

Adil Imam

Based on : arXiv:2407.08553



INTRODUCTION : SIMPLISTIC VIEW OF PHASE DIAGRAM



THE DENSITY LADDER



arXiv:2304.05441v1

MICRO-MACRO COLLISION



THE EOS FOR NS MATTER :

NUCLEONIC CORE COMPOSITION

■ The NS core is composed of neutron (n), proton(p), electron(e) and muon(µ)

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- The NS core is composed of neutron (n), proton(p), electron(e) and muon(µ)
- The EoS is determined by the features of nucleon-nucleon (N-N) interaction

THE PARABOLIC APPROXIMATION :

Energy per nucleon for neutron star matter at a given nucleon density ρ and asymmetry $\delta = \left(\frac{\rho_n}{\rho} - \frac{\rho_p}{\rho}\right)$ can be written as,

$$\varepsilon(\rho,\delta) = \sum \frac{\partial^n}{\partial \delta^n} \varepsilon(\rho,\delta)|_{\delta=0} = \boldsymbol{e}(\rho,0) + \boldsymbol{e}_{sym}(\rho)\delta^2 + \dots,$$

 $e(\rho, 0)$: Energy for SNM and $e_{sym}(\rho) = \varepsilon(\rho, 1) - e(\rho, 0)$: Density dependent symmetry energy

THE PARABOLIC APPROXIMATION :



FIGURE: Energy per nucleon for Symmetric Nuclear Matter (SNM)((green curve) and symmetry energy (blue curve)

I Nuclear Matter Parameters(NMPs) $\propto \frac{\partial^n}{\partial \rho^n} e(\rho, 0)$ or $\propto \frac{\partial^n}{\partial \rho^n} e_{sym}(\rho)$

NUCLEAR MATTER PARAMETERS (NMPS) :

Taylor expansion :
$$\varepsilon(\rho, \delta) = \sum_{n=0}^{4} (a_n + b_n \delta^2) (\frac{\rho - \rho_0}{3\rho_0})^n$$

NUCLEAR MATTER PARAMETERS (NMPS) :

- **Taylor expansion** : $\varepsilon(\rho, \delta) = \sum_{n=0}^{4} (a_n + b_n \delta^2) (\frac{\rho \rho_0}{3\rho_0})^n$
- SNM parameters (at ho_0) :
- $e_0 \equiv \text{Binding energy} = e(\rho, 0)|_{\rho=\rho_0} = a_0$
- $K_0 \equiv$ Incompressibility coefficient $\propto \frac{\partial^2 e(\rho, 0)}{\partial \rho^2}|_{\rho=\rho_0} = a_2$
- $Q_0(Z_0) \equiv \text{Third}(\text{Fourth}) \text{ order derivative} = a_3(a_4)$
- Symmetry Energy parameters (at ρ_0) :
- **J**₀ \equiv Symmetry energy $= e_{sym}(\rho)|_{\rho=\rho_0} = b_0$
- **I** $L_0 \equiv$ Slope of symmetry energy $\propto \frac{\partial e_{sym}(\rho)}{\partial \rho}|_{\rho=\rho_0} = b_1$
- $K_{sym,0} \equiv \text{Curvature of symmetry energy} \propto \frac{\partial^2 e_{sym(\rho)}}{\partial \rho^2}|_{\rho=\rho_0} = b_2$
- $\blacksquare Q_{sym,0}(Z_{sym,0}) \equiv \text{Third}(\text{Fourth}) \text{ order derivative} = b_3(b_4)$

The $\frac{n}{3}$ Expansion model :

a $\frac{n}{3}$ Expansion: $\varepsilon(\rho, \delta) = \sum_{n=2}^{6} (c_n + d_n \delta^2) (\frac{\rho}{\rho_0})^{n/3}$

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$$\begin{pmatrix} e_0 \\ 0 \\ K_0 \\ Q_0 \\ Z_0 \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 & 1 \\ 2 & 3 & 4 & 5 & 6 \\ -2 & 0 & 4 & 10 & 18 \\ 8 & 0 & -8 & -10 & 0 \\ -56 & 0 & 40 & 40 & 0 \end{pmatrix} \begin{pmatrix} c_0 \\ c_1 \\ c_2 \\ c_3 \\ c_4 \end{pmatrix}$$

$$\begin{pmatrix} J_0 \\ L_0 \\ K_{\text{sym},0} \\ Q_{\text{sym},0} \\ Z_{\text{sym},0} \end{pmatrix} = \begin{pmatrix} 1 & 1 & 1 & 1 & 1 \\ 2 & 3 & 4 & 5 & 6 \\ -2 & 0 & 4 & 10 & 18 \\ 8 & 0 & -8 & -10 & 0 \\ -56 & 0 & 40 & 40 & 0 \end{pmatrix} \begin{pmatrix} d_0 \\ d_1 \\ d_2 \\ d_3 \\ d_4 \end{pmatrix} .$$

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Each EoS must satisfies :

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- Symmetry energy : $e_{sym}(\rho) > 0$
- M_{TOV} ≥ mass of observed massive NS (non-rotating) (M_{TOV} = maximum mass in the stable branch)

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- The parameters which are known within about 10 percent: J_0 , K_0
- The parameters which are known within about 50 percent: L₀
- The parameters which are almost unknown: $Q_0, Z_0, K_{sym,0}, Q_{sym,0}, Z_{sym,0}$

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\begin{array}{c} \mathsf{NMPs} \longrightarrow \mathsf{f}(\mathsf{NMPs}) \longrightarrow \mathsf{Observable} \ (\mathsf{EoS} \ \mathsf{or} \ \mathsf{NS}) \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & \\ & & & \\ & & & \\ & & \\ & & & \\ & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & \\ & & & & \\ & & & &
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We use a machine learning approach : Symbolic Regression

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To choose the best equation one has to perform a goodness of fit

Symbolic Regression:

$$R^2 = 1 - rac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

 y_i : observed or actual value \hat{y}_i : predicted value for the ith data point \bar{y} : mean of the n observed values

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$$\text{RMSE} = \sqrt{\frac{\sum (y_i - \hat{y}_i)^2}{n}}$$

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$$\begin{split} M_{\text{max}} &= 0.14\hat{K}_0 - 0.02\hat{L}_0 + 0.27\hat{Q}_0 + 0.16\hat{Z}_0 + 2.33\\ R_{1.4} &= -0.31(\hat{J}_0 - \hat{Q}_0 - \hat{Q}_{\text{sym0}}) - 0.62\hat{K}_{\text{sym0}} + 1.75\hat{L}_0 + 14.22\\ \Lambda_{1.4} &= -54.02(\hat{J}_0 - \hat{K}_0 - \hat{Q}_0 - \hat{Q}_{\text{sym0}}) + 76.09\hat{K}_{\text{sym0}}\\ &+ 178.12\hat{L}_0 + 737.93 \end{split}$$

DATA FOR BAYESIAN INFERENCE :

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- GW170817, mass-radius posterior data from NICER

$MAPPING \ NS \ PROPERTIES \ TO \ NMPS$

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FIGURE: Variation of incompressibility coefficient, K with density.

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TABLE: S_0 : All the data except E_{pnm} and M_c ; S_{ALL} : All the data.

	Scenario	K ₀	Q ₀	J ₀	L ₀	K _{sym0}
ref	-	266	-90	33.17	67	-47
$\mathcal{T}_{\mathrm{SRM}}$	S ₀	256^{+46}_{-56}	-148 ⁺²⁵⁵ -266	$32.92^{+1.36}_{-1.33}$	65^{+14}_{-14}	-27 ⁺⁸¹ -79
	S _{ALL}	262^{+21}_{-23}	-167^{+175}_{-194}	32.97 ^{+1.29} -1.26	65^{+14}_{-14}	$\textbf{-26}^{+79}_{-80}$
$\mathcal{T}_{\mathrm{TOV}}$	S _{ALL}	262^{+20}_{-20}	-203^{+182}_{-176}	$32.74^{+1.24}_{-1.24}$	63^{+14}_{-13}	-34^{+76}_{-74}

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Bayesian inferences are performed with realistic data including E_{pnm} and M_c

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TOV VS SYMBOLIC REGRESSION MODELS :



FIGURE: Posterior obtained using symbolic regression models and TOV solutions

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- Symbolic regression based equations are constructed to replace EoS computation and solutions of TOV equations
- Using TOV and SRMs in Bayesian inference give comparable results while SRMs provides results within 20 minutes which is 100 times faster than the traditional TOV approach

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- 2. Dr. Tuhin Malik
- 3. Dr. Naresh K. Patra

Thank You

