

Spanning the full range of neutron star properties within a microscopic description

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Tuhin Malik, Márcio Ferreira, Constança Providência

Universidade de Coimbra, Portugal

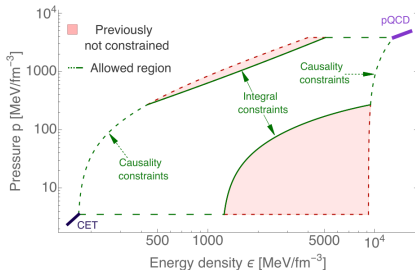


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The dense matter equation of state (EOS)

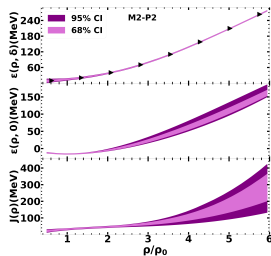
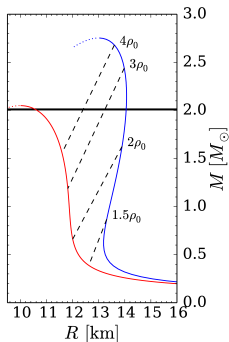
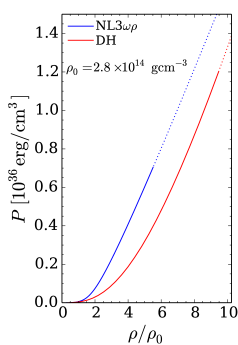
- ▶ A neutron star (NS), also known as a pulsar, is one of the densest and most compact objects in the universe.
- ▶ A significant probe to reduce uncertainty can be the NS maximum mass, radii, moments of inertia, and tidal Love numbers, which are all accessible to observation.
- ▶ The NS core composition remains a mystery



Phys. Rev. Lett. 128, 202701 (2022), 2111.05350

Probing the interior of Neutron Stars

- ▶ Neutrons stars provide a laboratory for testing
 - ▶ nuclear physics: high density, highly asymmetric matter
 - ▶ QCD: deconfinement, quark matter, superconducting phases
- ▶ mass-radius \rightarrow equation of state \rightarrow composition?



Sk Md Adil Imam et al PRC 105, 015806 (2022)
see also

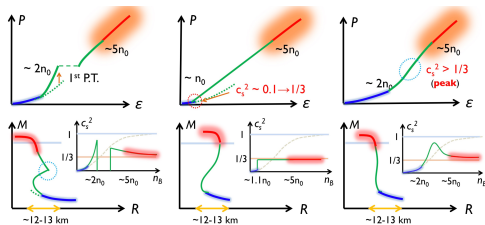
- ▶ Tovar et al PRD 104 (2021)
- ▶ Mondal & Gulminelli PRD 105 (2022)
- ▶ Essick PRL 127 192701 (2021)

The possible scenario

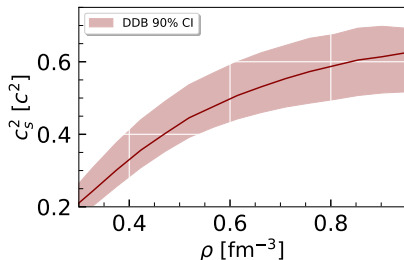
- ▶ **nucleon**: Malik et al and B.K. Agrawal et al *Astrophys.J.* 930 (2022), Malik and B.K. Agrawal et al *PRC Letter* 106 (2022), Bikram Keshari Pradhan and Debarati Chatterjee et al *Nucl.Phys.A* 1030 (2023)
- ▶ **hyperons**: S. Weissenborn et al *NPA* 881 (2012), Micaela Oertel et al *EPJA* 52 (2016), Malik and Providência *PRD* 106 (2022)
- ▶ **quark matter**: Annala et al *Nature Phys.*, 16, 907 (2020), Gorda et al *arXiv:2212.10576* (2022)
- ▶ **(anti) kaons**: Banik et al. *Phys.Rev.C* 78 (2008), Char & Banik *Phys. Rev. C* 90(2014), Banik & Bandyopadhyay, *Phys.Rev.C* 64 (2001)
- ▶ **dark matter**
 - ▶ **admixed**: Arpan Das et al *Phys.Rev.D* 99 (2019), Violetta Sagun et al *Phys.Rev.D* 102 (2020)
 - ▶ **two fluid**: Arpan Das et al *Phys.Rev.D* 105 (2022), Violetta Sagun et al *Phys.Rev.D* 105 (2022)
- ▶ **modified gravity**: K. Nobleson et al *JCAP* 08 (2021)

Motivation

- ▶ Sound speed describes how stiff matter is.
- ▶ The determination of the sound speed c_s^2 in NS is an important unresolved issue.
- ▶ At asymptotically high densities, the conformal symmetry of QCD is restored, and the sound speed approaches $c_s^2 = 1/3$, which is realized in ultrarelativistic fluids.
- ▶ Generally, in the microscopic model, c_s^2 tends to increase monotonically or saturates.



arxiv: 2011.10940



Malik et al *Astrophys.J.* 930 (2022) 1, 17

Motivation

- ▶ The agnostic approach:
 - ▶ L. Lindblom et al, Phys. Rev. D 86, 084003 (2012), arXiv:1207.3744.
 - ▶ A. Kurkela et al, Astrophys. J. 789, 127 (2014), arXiv:1402.6618.
 - ▶ E. R. Most et al, Phys. Rev. Lett. 120, 261103 (2018), arXiv:1803.00549.
 - ▶ E. Lope Oter et al, J. Phys. G 46, 084001 (2019), arXiv:1901.05271.
 - ▶ E. Annala et al, Nature Phys. 16, 907 (2020), arXiv:1903.09121., E. Annala et al, arXiv:2105.05132
 - ▶ Rahul Somasundaram et al, arXiv : 2112.08157
 - ▶ Sinan Altiparmak et al, arXiv: 2203.14974
- ▶ What do a minimal set of nuclear matter constraints together with a $2M_{\odot}$ condition tell us about the NS EOS based on a microscopic model?
- ▶ Can we extract nuclear matter properties from neutron star matter EOS?

Synopsis

To answer the motivation questions we:

- ▶ Will generate a set of EOS based on a microscopic model
- ▶ Include causality
- ▶ Restrict parameters imposing minimal constraints
- ▶ Access to nuclear saturation properties of different orders
- ▶ Analyze the speed of sound of generated EOS

RMF EOS from a Bayesian approach

EOS: relativistic mean field description

RMF Lagrangian for stellar matter

- ▶ **Lagrangian density**

- ▶ Lorentz-covariant Lagrangian with baryon densities and meson fields
- ▶ causal by construction

$$\mathcal{L} = \mathcal{L}_N + \mathcal{L}_M + \mathcal{L}_{NL},$$

- ▶ **Baryonic contribution:**

$$\mathcal{L}_N = \bar{\Psi} \left[\gamma^\mu (i\partial_\mu - \mathbf{g}_\omega \omega_\mu - \mathbf{g}_\rho \mathbf{t} \cdot \boldsymbol{\rho}_\mu) - (m - g_\sigma \phi) \right] \Psi,$$

- ▶ **Meson contribution**

$$\begin{aligned} \mathcal{L}_M = & \frac{1}{2} \left[\partial_\mu \phi \partial^\mu \phi - m_\sigma^2 \phi^2 \right] - \frac{1}{4} F_{\mu\nu}^{(\omega)} F^{(\omega)\mu\nu} + \frac{1}{2} m_\omega^2 \omega_\mu \omega^\mu \\ & - \frac{1}{4} \mathbf{F}_{\mu\nu}^{(\rho)} \cdot \mathbf{F}^{(\rho)\mu\nu} + \frac{1}{2} m_\rho^2 \boldsymbol{\rho}_\mu \cdot \boldsymbol{\rho}^\mu. \end{aligned}$$

$$\begin{aligned} \mathcal{L}_{NL} = & -\frac{1}{3} b g_\sigma^3 (\sigma)^3 - \frac{1}{4} c g_\sigma^4 (\sigma)^4 + \frac{\xi}{4!} (g_\omega \omega_\mu \omega^\mu)^4 \\ & + \Lambda_\omega g_\rho^2 \boldsymbol{\rho}_\mu \cdot \boldsymbol{\rho}^\mu g_\omega^2 \omega_\mu \omega^\mu \end{aligned}$$

Nuclear matter properties at saturation

- Taylor expansion, parabolic approximation

$$\frac{E_{\text{nuc}}}{A}(n, \delta) = \frac{E_{\text{SNM}}}{A}(n) + S(n) \delta^2,$$

$$S(n) = \frac{1}{2} \left. \frac{\partial^2 E_{\text{nuc}}/A}{\partial \delta^2} \right|_{\delta=0},$$

$$\frac{E_{\text{SNM}}}{A}(n) = E_0 + \frac{K_0}{2} \eta^2 + \frac{J_0}{3!} \eta^3 + \frac{Z_0}{4!} \eta^4,$$

$$S(n) = E_{\text{sym}} + L_{\text{sym}} \eta + \frac{K_{\text{sym}}}{2} \eta^2 + \frac{J_{\text{sym}}}{3!} \eta^3 + \frac{Z_{\text{sym}}}{4!} \eta^4,$$

$$\delta = (n_p - n_n)/n, \quad \eta = (n - n_0)/(3n_0)$$

Bayesian estimation of model parameters

Bayesian Inference:

$$P(\theta | D) = \frac{\mathcal{L}(D | \theta)P(\theta)}{\mathcal{Z}}$$

- ▶ The θ is the model parameter vector and D is the set of fit data.
- ▶ $P(\theta | D)$ is the joint posterior distribution of the parameters.
- ▶ $\mathcal{L}(D | \theta)$ is the likelihood function.
- ▶ $P(\theta)$ is the prior distribution for the model parameters.
- ▶ \mathcal{Z} is the evidence. It can be obtained by complete marginalization of the likelihood function.

The marginalized posterior distribution for a parameter θ_i :

$$P(\theta_i | D) = \int P(\theta | D) \prod_{k \neq i} d\theta_k$$

Gaussian likelihood function

$$\mathcal{L}(D | \theta) = \prod_j \frac{1}{\sqrt{2\pi\sigma_j^2}} e^{-\frac{1}{2} \left(\frac{d_j - m_j(\theta)}{\sigma_j} \right)^2}$$

- ▶ The index j runs over all the data points.
- ▶ The d_j and m_j are the data and corresponding model values, respectively.
- ▶ The σ_j are the uncertainties for every data point.

THE BAYESIAN SETUP

By updating a prior belief (i.e., a prior distribution) with given information (i.e., observed or fit data) and optimizing a likelihood function, a posterior distribution can be obtained according to Bayes' theorem.

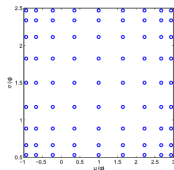
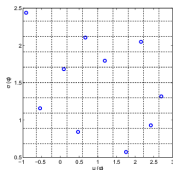
- ▶ The prior
- ▶ The fit data
- ▶ The Log-Likelihood
- ▶ The sampling algorithm

The prior

The uniform prior

The prior preparation:

- ▶ The model parameters:
 g_σ , g_ω , g_ρ , b , c , ξ , and Λ_ω
- ▶ Latin hypercube sampling (Loh, W.-L. 1996, AnSta, 24, 2058).
- ▶ Which provides relatively wide nuclear matter saturation properties.



No	Parameters	Set 0	
		min	max
1	g_σ	6.5	15.5
2	g_ω	6.5	15.5
3	g_ρ	6.5	15.5
4	B	0.5	9.0
5	C	-4.0	4.0
6	ξ	0.0	0.04 *
7	Λ_ω	0	0.12

*Note: We have also performed three identical studies but for three different ranges of a uniform prior for parameter ξ : i) $\xi \in [0, 0.004]$ (Set 1), ii) $\xi \in [0.004, 0.015]$ (Set 2) and iii) $\xi \in [0.015, 0.04]$ (Set 3).

The fit data

Constraints			
Quantity		Value/Band	Ref
NMP (MeV)	ρ_0	0.153 ± 0.005	Typel & Wolter (1999)
	ϵ_0	-16.1 ± 0.2	Dutra et al. (2014)
	K_0	230 ± 40	Todd-Rutel & Piekarewicz (2005); Shlomo et al. (2006)
PNM (MeV fm^{-3})	$J_{\text{sym},0}$	32.5 ± 1.8	Essick et al. (2021a)
	$P(\rho)$	$2 \times \text{N}^3\text{LO}$	Hebeler et al. (2013)
NS mass (M_\odot)	M_{max}	>2.0	Fonseca et al. (2021)

The Log-Likelihood

The equation 1 shows the log-likelihood function, except for the low-density PNM data and the maximum mass of NS. Our approach has been to use the box function probability as given in equation 2 for the PNM data from χ EFT. We also used the step function probability for the NS mass.

$$\text{Log}(\mathcal{L}) = -0.5 \times \sum_j \left\{ \left(\frac{d_j - m_j(\theta)}{\sigma_j} \right)^2 + \text{Log}(2\pi\sigma_j^2) \right\} \quad (1)$$

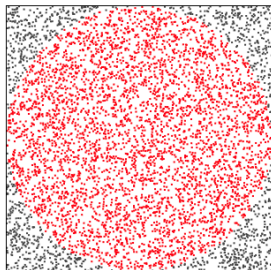
$$\text{Log}(\mathcal{L}) = \text{Log} \left\{ \prod_j \frac{1}{2\sigma_j} \frac{1}{\exp\left(\frac{|d_j - m_j(\theta)| - \sigma_j}{0.015}\right) + 1} \right\} \quad (2)$$

†

†It is important to understand that when sampling the posterior, the normalization of the log-likelihood, which is done in equations 1 and 2 is irrelevant. However, to calculate the Bayes *evidence* it is mandatory and in some cases, it also reduces the computation time.

Sampling

Monte Carlo sampling:



- ▶ Generate random uniform samples in the parameter hyperspace.
- ▶ Apply filter
- ▶ Analyze filtered samples' properties

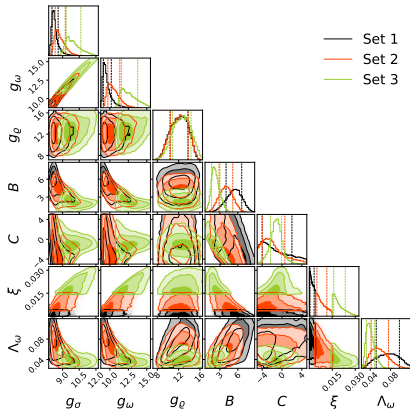
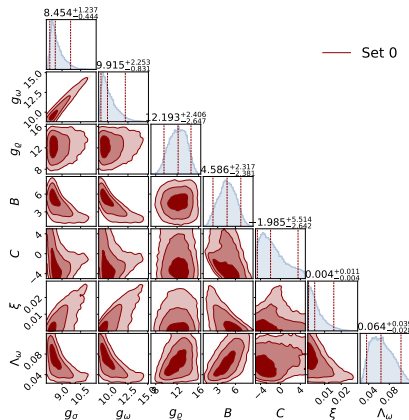
Markov Chain Monte Carlo sampling:

- ▶ Cost-function guided random walk
- ▶ Sample the posterior

we use the nested sampling algorithm, first proposed in J Skilling, American Institute of Physics Conference Series, Vol. 735, edited by R. Fischer, R. Preuss, and U. V. Toussaint (2004) pp. 395–405.

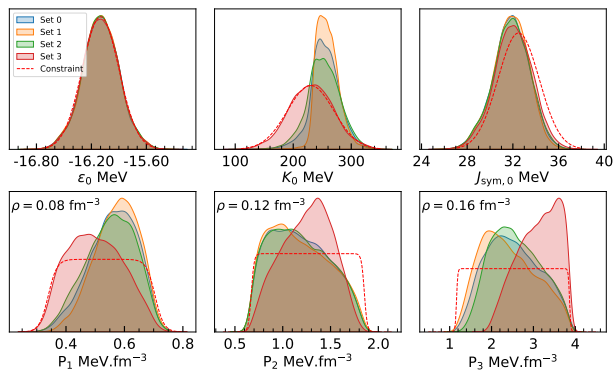
- ▶ suitable for low-dimensional problems
- ▶ approximately 17000 samples we have obtained in the posterior

Results



Corner plot for the three sets of models with Set 0 (dark red), Set 1 (black), Set 2 (orange), and Set 2 (green) comparing the posteriors of the parameters g_σ , g_ω , g_ρ , $B = b \times 10^3$, $C = c \times 10^3$, and Λ_ω of the RMF model used in present study. The vertical lines represent the 68% CIs, and the light and dark intensities represent the 1σ , 2σ , and 3σ CIs, respectively.

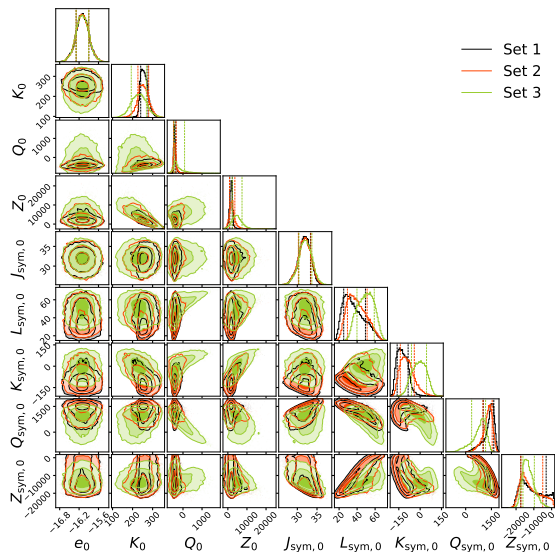
Results



The comparison of the corresponding target distribution for the constraints imposed in the Bayesian inference analysis.

Nuclear matter properties

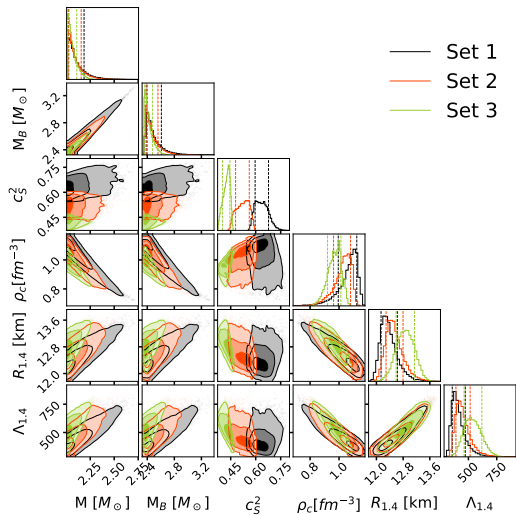
Posterior



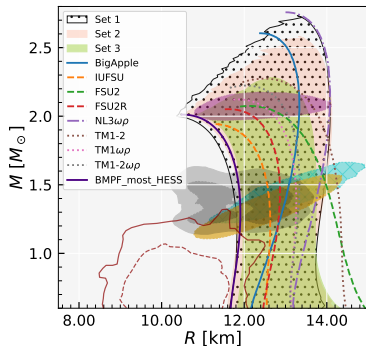
- ▶ Set 3 presents larger values of Q_0 and Z_0
- ▶ an anti-correlation between Z_0 and K_0 : the lower values of K_0 are compensated by larger Z_0
- ▶ Set 3 also shows a slight positive correlation between $L_{\text{sym},0}$ and $K_{\text{sym},0}$. Similar behavior has been shown in Vidana et al, Phys.Rev.C 80 (2009) 045806.
- ▶ a strong correlation is obtained between $L_{\text{sym},0}$ and $Q_{\text{sym},0}$ for all three sets.

The NS properties

Posterior



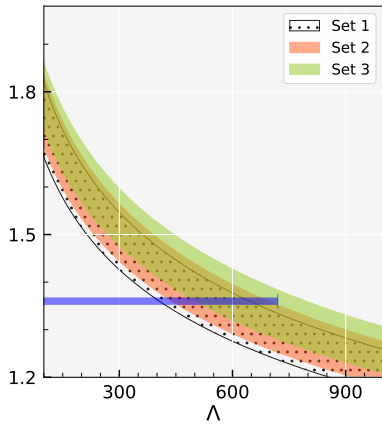
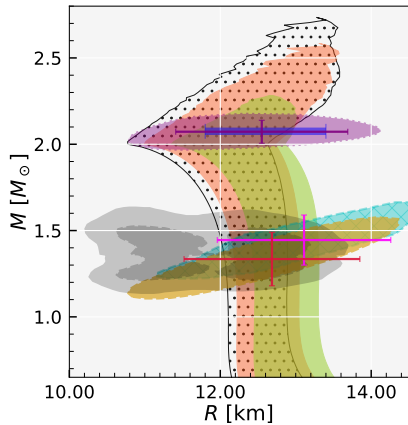
- Set 1
- Set 2
- Set 3



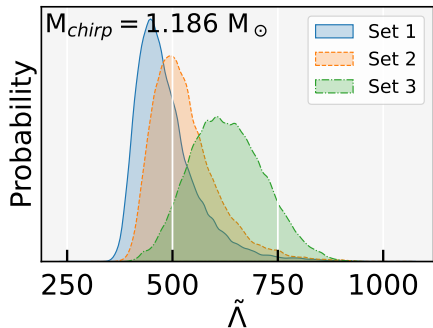
The NMP and NS properties

Quantity	Units	Set 1			Set 2			Set 3			
		median	90% CI		median	90% CI		median	90% CI		
			min	max		min	max		min	max	
NMP	ρ_0	fm^{-3}	0.152	0.145	0.160	0.152	0.145	0.160	0.153	0.145	0.161
	m^*	...	0.76	0.69	0.78	0.72	0.64	0.76	0.63	0.55	0.69
	ε_0		-16.10	-16.43	-15.76	-16.10	-16.43	-15.76	-16.10	-16.43	-15.77
	K_0		257	234	293	252	205	300	232	169	295
	Q_0		-444	-497	-301	-438	-548	-256	-319	-562	483
	Z_0		1766	435	3054	2161	65	5521	4698	739	9623
	$J_{\text{sym},0}$	MeV	31.87	29.10	34.22	31.90	29.05	34.44	32.05	29.19	34.75
	$L_{\text{sym},0}$		35	21	57	39	25	58	50	35	64
	$K_{\text{sym},0}$		-126	-177	-57	-96	-160	4	-6	-89	71
	$Q_{\text{sym},0}$		1438	640	1736	1328	722	1661	866	-88	1303
	$Z_{\text{sym},0}$		-12118	-19290	236	-13057	-19030	-1147	-13422	-17643	-6877
	NS	M_{max}	M_{\odot}	2.073	2.013	2.306	2.064	2.011	2.244	2.048	2.010
$M_{\text{B,max}}$		M_{\odot}	2.457	2.378	2.772	2.437	2.367	2.677	2.400	2.348	2.546
c_s^2		c^2	0.63	0.58	0.70	0.52	0.46	0.58	0.43	0.39	0.45
ρ_c		fm^{-3}	1.079	0.914	1.138	1.036	0.899	1.099	0.972	0.883	1.035
ε_c		MeV fm^{-3}	1377	1169	1462	1302	1127	1394	1198	1084	1288
R_{max}			10.75	10.46	11.52	11.03	10.69	11.74	11.47	11.07	11.97
$R_{1.4}$			12.34	12.03	12.89	12.50	12.17	13.05	12.87	12.42	13.30
$R_{1.6}$		km	12.21	11.89	12.86	12.39	12.04	13.02	12.77	12.31	13.26
$R_{1.8}$			11.98	11.62	12.79	12.18	11.79	12.93	12.57	12.09	13.14
$R_{2.075}$			11.67	10.96	12.86	11.88	11.21	12.92	12.25	11.65	12.96
$\Lambda_{1.4}$			399	338	545	439	366	587	535	420	672
$\Lambda_{1.6}$			156	129	233	174	141	250	215	166	284
$\Lambda_{1.8}$...	62	49	107	71	55	114	89	67	127
$\Lambda_{2.075}$			17	9	42	20	12	43	26	16	43
$\tilde{\Lambda}_{q=1.0}$		474	402	639	519	434	688	631	497	787	

Conditional probabilities $P(R|M)$ and $P(\Lambda|M)$



The Probability distribution of combined tidal deformability in BNS

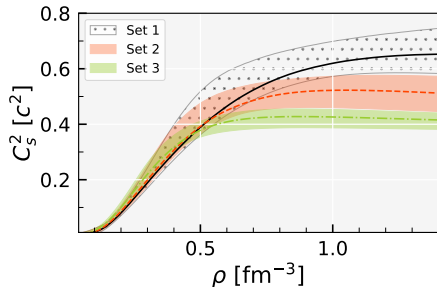
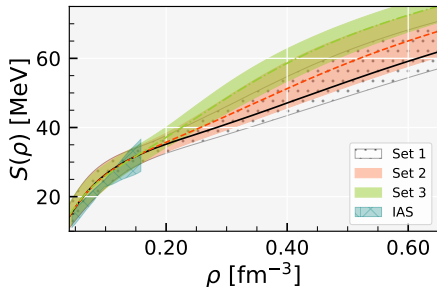
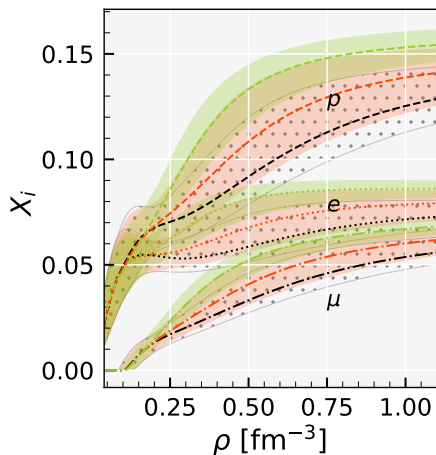


The $\tilde{\Lambda}$ in a Binary is plotted for a given *chirp* mass $M_{chirp} = 1.186 M_{\odot}$.

- ▶ For each and every mass-radius curve, and fixing the chirp mass at $1.186 M_{\odot}$, we select all possible combinations of the mass m_1 and m_2 and calculate the combined tidal deformability. For each EOS we have 44 combinations of m_1 and m_2 .
- ▶ The median and 90% CI for $\tilde{\Lambda}$ are:
 - 471 ${}_{-71}^{+163}$ (Set 1)
 - 516 ${}_{-84}^{+166}$ (Set 2)
 - 626 ${}_{-132}^{+154}$ (Set 3).

The proton fraction, symmetry energy and speed-of-sound

Posterior



The correlation between the central density and its radius

The correlation coefficient between the central density of the maximum mass star ρ_c and its radius R_{\max} is of the order of 0.9.

A similar result by J.-L. Jiang, C. Ecker, and L. Rezzolla, (2022), arXiv:2211.00018

$$\frac{\rho_c}{0.16 \text{ fm}^{-3}} = d_0 \left[1 - \left(\frac{R_{\max}}{10 \text{ km}} \right) \right] + d_1 \left(\frac{R_{\max}}{10 \text{ km}} \right)^2,$$

with $d_0 = 27.6$ and $d_1 = 7.5$ and a 3.7% standard deviation of relative residual over the central value zero.

- ▶ Performing a similar analysis with Set 0, we have obtained $d_0 = 28.89 \pm 0.02$ and $d_1 = 7.73 \pm 0.01$.
- ▶ However, the linear relation shows a chi-square fit similar to the quadratic relation.

$$\frac{\rho_c}{0.16 \text{ fm}^{-3}} = m_0 \left(\frac{R_{\max}}{10 \text{ km}} \right) + c_0,$$

with $m_0 = -11.618 \pm 0.018$ and $c_0 = 19.255 \pm 0.019$.

Conclusion and future work

- ▶ The high-density behavior of nuclear matter is analyzed within a relativistic mean-field description with non-linear meson interactions
- ▶ Depending on the strength of the non-linear higher-order scalar vector field contribution, we have found three distinct classes of EOSs, each one correlated to different speed-of-sound density behavior.
- ▶ A weak non-linear vector contribution gives a monotonically increasing speed of sound
- ▶ The nuclear matter saturation properties (NMP) are very much model-dependent.
- ▶ Machine-Learning can be used to quantify the uncertainty of NMP due to different models and observations.

ACKNOWLEDGMENTS

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Data availability

- ▶ arXiv:2301.08169 (2023)
- ▶ The final posterior of the model parameters, the equation of states, and the solutions for the star properties obtained with prior Set 0 can be obtained from the link (<http://e.pc.cd/moqotalk>).

Thank you!

Obrigado!