

Inferring three-nucleon couplings from multi-messenger neutron-star observations

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25 February 2025

PAINT25 workshop: TRIUMF, Vancouver, 25-28 February 2025



TECHNISCHE
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Two topics:

Main topic: Inference of $3N$ couplings

Towards the end: uncertainty quantification for many-body perturbation theory
(*feedback appreciated, talk to me over coffee?*)

Chiral effective field theory and nuclear forces

Low-energy constants (LECs) need to be inferred from data:

- Nucleon-nucleon (NN) LECs fit to NN scattering data
- $3N$ LECs fit to properties of light nuclei (e.g. triton, helium)
- πN (pion-nucleon) LECs fit to πN scattering data

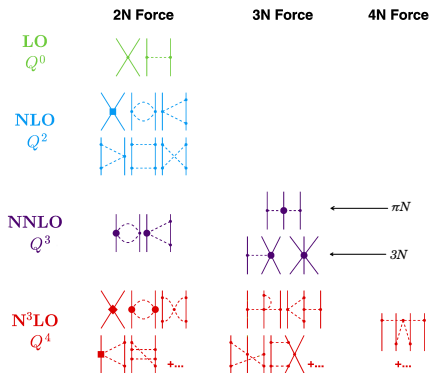


Figure adapted from Entem et al., Phys. Rev. C **96** (2017).

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- πN (pion-nucleon) LECs fit to πN scattering data
- πN LECs can (in principle) also be fit to neutron-star (NS) data

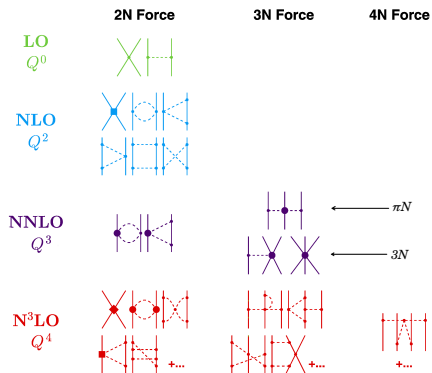


Figure adapted from Entem et al., Phys. Rev. C **96** (2017).

arXiv > nucl-th > arXiv:2410.00247 Search... Help | Ad

Nuclear Theory

[Submitted on 30 Sep 2024]

Inferring three-nucleon couplings from multi-messenger neutron-star observations

Rahul Somasundaram, Isak Svensson, Soumi De, Andrew E. Deneris, Yannick Dietz, Philippe Landry, Achim Schwenk, Ingo Tews

Understanding the interactions between nucleons in dense matter is one of the outstanding challenges of theoretical physics. Effective field theories have emerged as the dominant approach to address this problem at low energies, with many successful applications to the structure of nuclei and the properties of dense nucleonic matter. However, how far into the interior of neutron stars these interactions can describe dense matter is an open question. Here, we develop a framework that enables the inference of three-nucleon couplings in dense matter directly from astrophysical neutron-star observations. We apply this formalism to the LIGO/Virgo gravitational-wave event GW170817 and the X-ray measurements from NASA's Neutron-Star Interior Composition Explorer and establish direct constraints for the couplings that govern three-nucleon interactions in chiral effective field theory. Furthermore, we demonstrate how next-generation observations of a population of neutron-star mergers can offer stringent constraints on three-nucleon couplings, potentially at a level comparable to those from laboratory data. Our work directly connects the microscopic couplings in quantum field theories to macroscopic observations of neutron stars, providing a way to test the consistency between low-energy couplings inferred from terrestrial and astrophysical data.

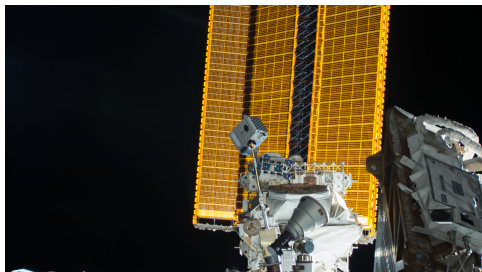
First time inferring χ EFT LECs from non-microscopic data

We keep things relatively simple for now:

- no EFT truncation errors included
- N^2 LO
- Δ -less EFT

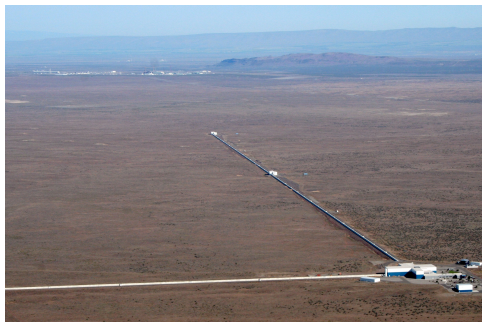
Neutron star observatories

Neutron Star Interior Composition Explorer (NICER), an X-ray telescope for neutron star mass and radius



NICER aboard the ISS. Image: NASA

Laser Interferometer Gravitational-Wave Observatory (LIGO)



LIGO, Hanford

Bayesian inference

χ EFT calculations of neutron matter depend on πN LECs c_1, c_3
—→ In principle, neutron-star observables can constrain c_1, c_3

From LECs to NS observables:

- ➊ Input LECs into χ EFT
- ➋ Compute neutron-matter equation of state (EOS) using MBPT
- ➌ Solve Tolman-Oppenheimer-Volkoff (TOV) and quadrupolar tidal perturbation equations
- ➍ Output: neutron-star masses and tidal deformabilities

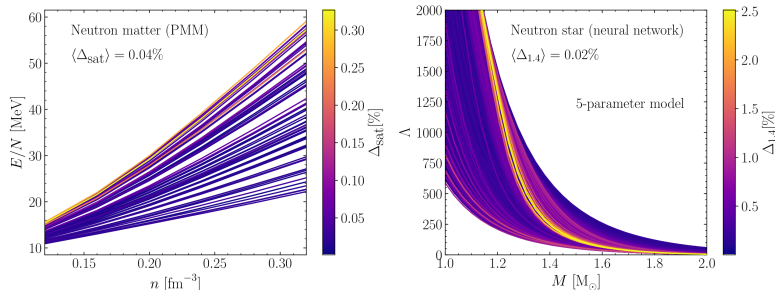
With Bayesian inference, we can go from neutron-star data to LECs

Problem: huge computational cost: $\mathcal{O}(10^2)$ CPU-h for MBPT(3)

Solution: emulators, allow us to calculate $\mathcal{O}(10^8)$ samples

Emulators for the EOS (energy per particle): parametric matrix models (PMM)¹

Emulators for NS observables: neural networks²



Very good accuracy in both cases ($< 0.05\%$ on average)

¹Cook et al., arXiv:2401.11694 (2024), Somasundaram et al., arXiv:2404.11566 (2024).

²Reed et al., arXiv:2405.20558 (2024)

PMM emulators for the EOS

PMM combines ideas from eigenvector continuation with machine learning:

$$M = M_0 + c_1 M_1 + c_3 M_3 \quad (1)$$

- M_0 : diagonal 2×2 matrix
- M_1 and M_3 : symmetric 2×2 matrices
- In total, 8 elements are optimized to reproduce the behavior of MBPT
- Lowest eigenvalue of M is the (neutron matter) energy per particle

The emulators are trained on 30 EOS curves and validated with 70 curves computed using 3rd-order MBPT³

Average emulator error: 15 keV (significantly less than the uncertainty of MBPT itself)

³Drischler et al., Phys. Rev. Lett. **122** (2019); Keller et al., Phys. Rev. Lett. **130** (2023); Alp, Dietz, et al. (in preparation)

Neural network emulators for computing NS observables

We use standard neural network techniques

- ➊ draw 200,000 samples of the LECs
- ➋ compute EOS using PMM emulators
- ➌ solve TOV/tidal deformability equations with high-fidelity solver
- ➍ use 100,000 samples to train a neural network; 100,000 samples for validation
- ➎ output: masses, tidal deformabilities

EOS modeling

χ EFT may break down somewhere around $\sim 2n_{\text{sat}}$

Necessary to model the high-density EOS somehow

We use three models for the EOS:

- “2-parameter”: χ EFT results extended to $10n_{\text{sat}}$
- “5-” and “7-parameter”: speed-of-sound parametrization above $2n_{\text{sat}}$
- Parameters are speed of sound (squared) on two different grids above $2n_{\text{sat}}$

Use a metamodel⁴ to provide smooth interpolation of EOS and extrapolation to matter in beta equilibrium

⁴Margueron et al., Phys. Rev. C **97** (2018)

Input data: multimessenger observations

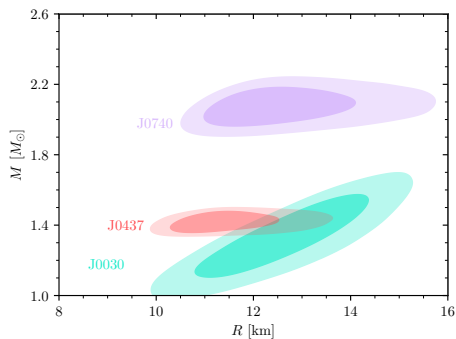
We use gravitational wave data: GW170817, Abbott et al., PRL **119** (2017)

And three NICER pulsars (mass-radius):

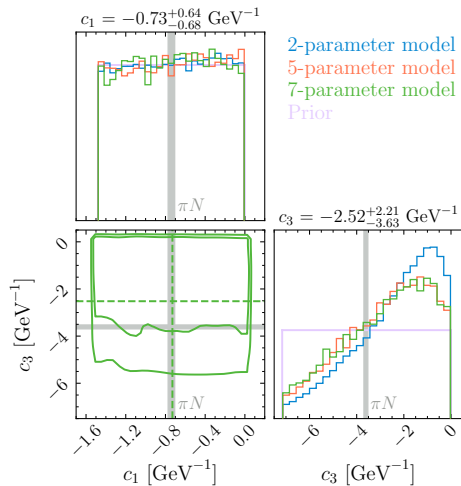
- PSR J0740, Salmi et al., ApJ **941** (2022)
- PSR J0437, Choudhury et al., ApJ Lett. **971** (2024)
- PSR J0030, Riley et al., ApJ Lett. **887** (2019), Vinciguerra et al., Astrophys. J. **961** (2024)

Three different results for J0030 are available, we have compared them

LEC posteriors using currently available data

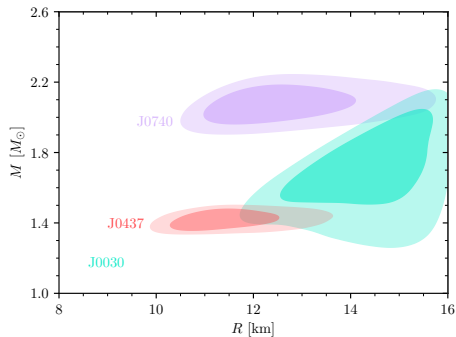


No constraints on c_1 , but
clear preference for less negative c_3
(less repulsive $3N$ force)

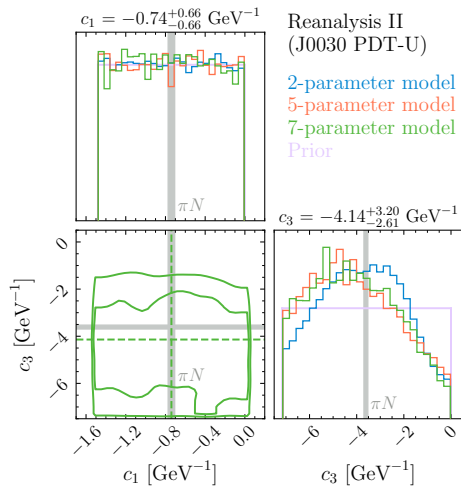


Uncertainties shown as 90% intervals.
 πN result from Siemens et al., Phys.
Lett. B **770** (2017).

With updated NICER data



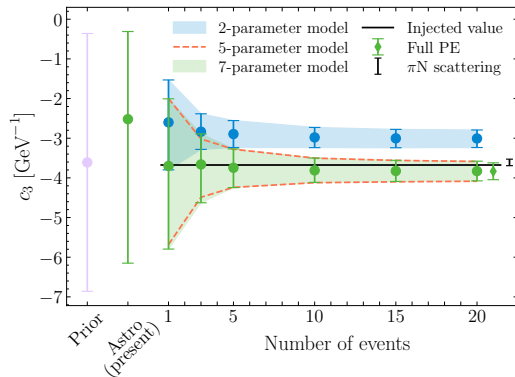
This posterior for c_3 prefers more repulsion (higher NS pressure)



Can we improve this with more and better GW data?

Next, use **simulated** next-generation GW data from Einstein Telescope⁵ and Cosmic Explorer⁶, ~ 1 year of observation

- Select 20 highest-SNR events, perform Bayesian inference
- c_3 converges quickly with number of observed events
- Final constraints almost comparable with πN scattering constraints
- Must marginalize over high-density parameters; 2-parameter model has large systematic uncertainty



Uncertainties given as 90% credibility intervals. (PE = Parameter Estimation)

⁵Punturo et al., *Class. Quant. Grav.* **27** (2010)

⁶Reitze et al., *Bull. Am. Astron. Soc.* **51**, (2019)

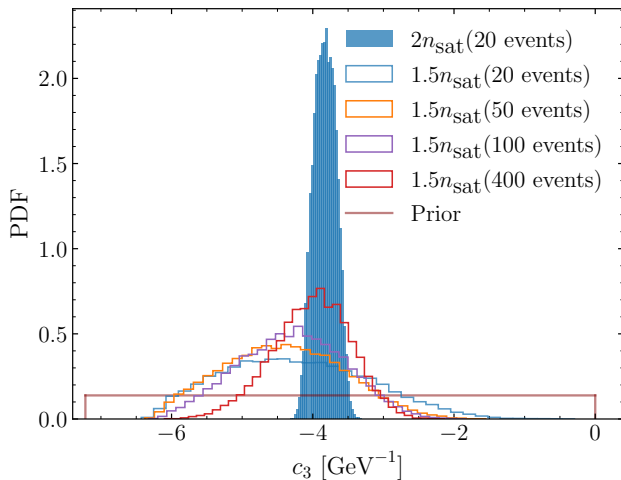
What if χ EFT breaks down earlier than $2n_{\text{sat}}$?

Before we used χ EFT up to $2n_{\text{sat}}$

If we instead trust χ EFT only to $1.5n_{\text{sat}}$ then **constraints on c_3 become much weaker**

Demonstrates the importance of learning the breakdown scale

Distributions appear to **converge to the same value**



(events = number of simulated GW events)

Truncation errors for MBPT

Short different topic:

Uncertainty quantification for MBPT calculations of, in this case, finite nuclei
(Preliminary)

Infering hyperparameters for MBPT truncation errors

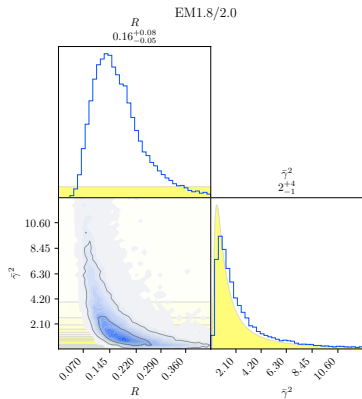
BUQEYE model for EFT truncation error^a:

$$y = y_{\text{ref}} \sum_{i=0}^{\nu} c_i Q^i, \quad \delta y = y_{\text{ref}} \sum_{i=\nu+1}^{\infty} c_i Q^i$$

MBPT truncation error:

$$y = y_{\text{ref}} \sum_{i=0}^k \gamma_i R^i, \quad \delta y = y_{\text{ref}} \sum_{i=k+1}^{\infty} \gamma_i R^i$$

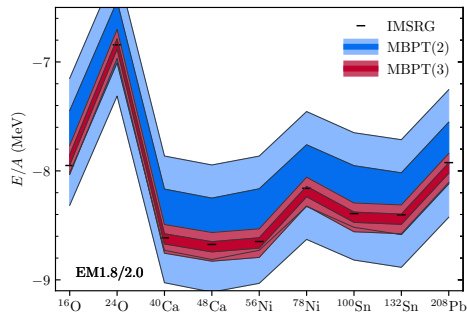
We infer $\text{pr}(R, \bar{\gamma}^2)$ from order-by-order differences similar to how $\text{pr}(Q, \bar{c}^2)$ was inferred in Wesolowski et al., Phys. Rev. C **104** (2021)



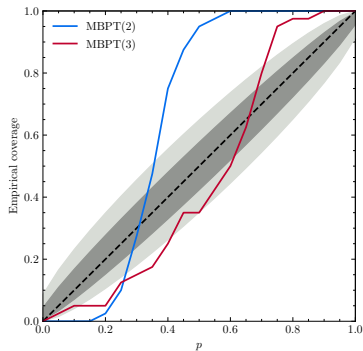
Joint prior (yellow) and posterior (blue) for $(R, \bar{\gamma}^2)$. Input data is ^{16}O , ^{48}Ca , ^{132}Sn . Interpretation: each new MBPT order is expected to be suppressed by a factor of ~ 0.1 – 0.2 (interaction dependent!)

^aFurnstahl et al., Phys. Rev. C **92** (2015)

How well does our error model work?



PPDs at 2nd and 3rd order for select nuclei. IMSRG and bare MBPT results from Arthuis et al., arXiv:2401.06675



Empirical coverage ("weatherman") plot comparing our predictions against all 40 available IMSRG results. p is the expected coverage, and the empirical coverage is what we actually observe.

Here we take the IMSRG results to be "exact", even though they are not (no exact results exist!)

Summary

- We have developed a framework to infer $3N$ couplings from NS observations
- Current and future data can provide constraints on c_3 , but not c_1
- Provides constraints complementary to πN scattering, enables nontrivial consistency checks for χ EFT
- Work-in-progress: statistically rigorous quantification of MBPT method errors

Outlook

- investigate EFT breakdown scale for EOS calculations
- repeat investigation with Δ -full χ EFT and/or N³LO
- compare different many-body methods
- Long-term: use actual new multimessenger data to infer c_3
- Validation of MBPT UQ model, better handling of correlated errors, application to nuclear matter

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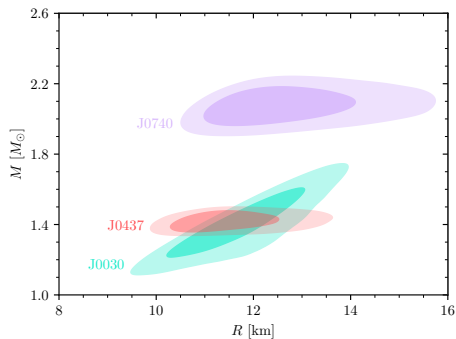
Thank you to my collaborators:

3*N* inference: Rahul Somasundaram, Soumi De, Andrew E. Deneris, Yannick Dietz, Philippe Landry, Achim Schwenk, Ingo Tews

MBPT UQ: Alex Tichai, Kai Hebeler, Achim Schwenk

Extra slides

With updated NICER data



Very similar to the previous result

