What can we learn about nuclear Hamiltonians from neutron star observations?

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04/30/2026, Nuclear Hamiltonians for Advancing Nuclear Physics and Beyond

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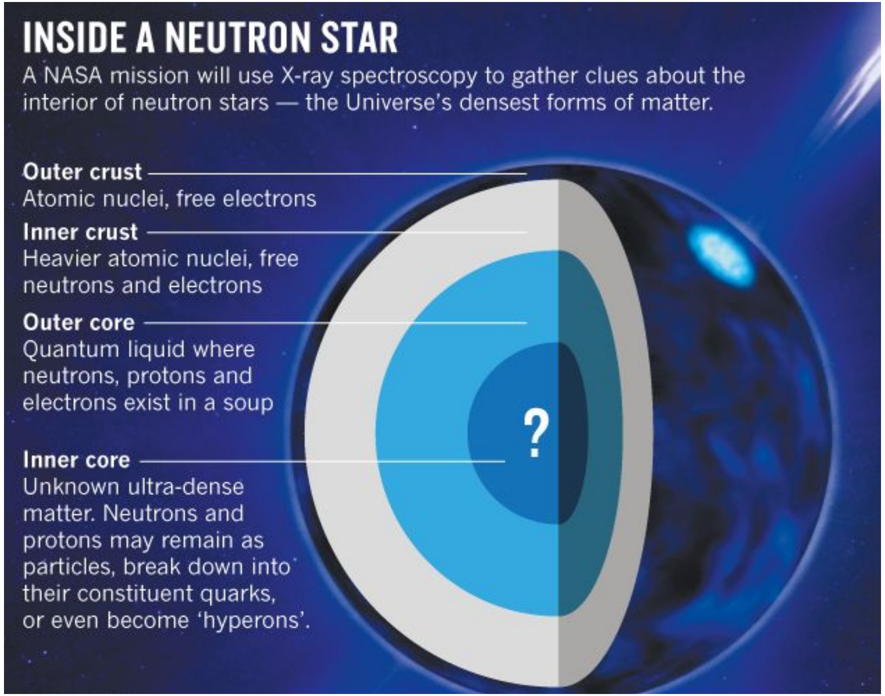
LA-UR-25-31265

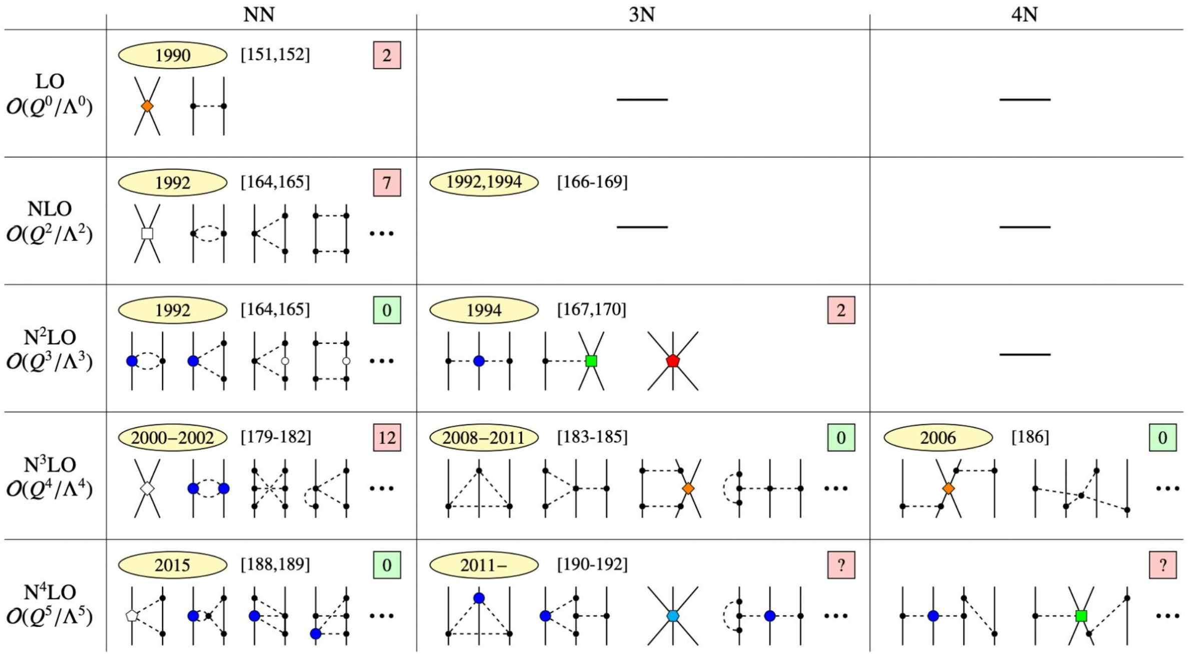
Neutron stars are unique nuclear systems

- Densest matter in the universe, with densities as high as $5n_{sat}$ to $8n_{sat}$
- Highly neutron rich, with the proton fraction ~5%
- Many different observables: glitches, cooling curves etc. But Mass-Radius measurements are “clean” EOS measurements
- Exciting era of “multi-messenger” astronomy: gravitational waves, X-ray observations, electromagnetic signals, etc.



Implications for the nuclear Hamiltonian

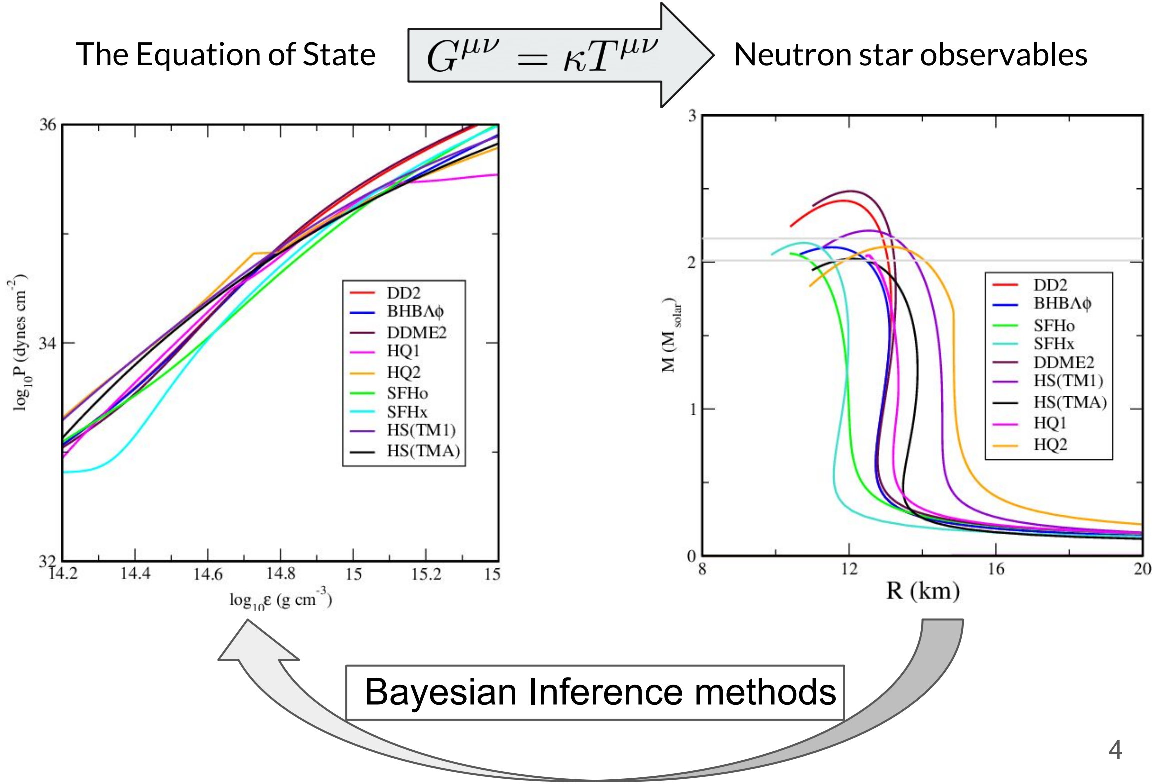
- Calibrate higher order LECs
- Understand how EFT breaks down in dense matter: $Q = K_F/\Lambda_B$ and K_F/Λ_C
- Probe "new" physics: Hyperon-Nucleon couplings, phase transitions, etc.



Hebeler, Phys.Rept. 890 (2021) 1-116

Non-trivial inverse problem

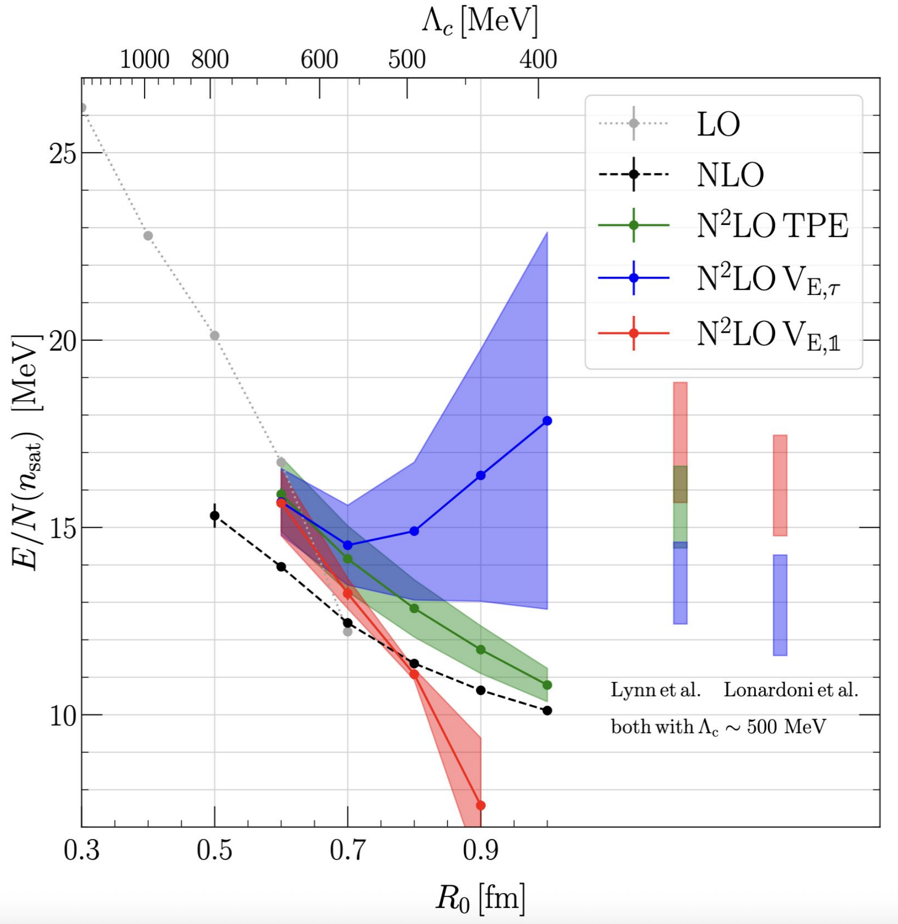
- For a given EOS, there is a single M-R curve which all neutron stars should obey
- This is an ill-defined inverse problem: crossing points, etc.
- We need an uncertainty-aware (Bayesian) framework



We’ll focus on “High” cutoff local interactions

- Local regulators violate the Fierz rearrangement freedom. This can have a drastic effect in the 3-body sector

- Different operator structures are possible for the same 3N force, V_E. This ambiguity should vanish in the limit of infinite cutoff.



Tews et al., Phys.Rev.Res. 7 (2025) 3, 033024

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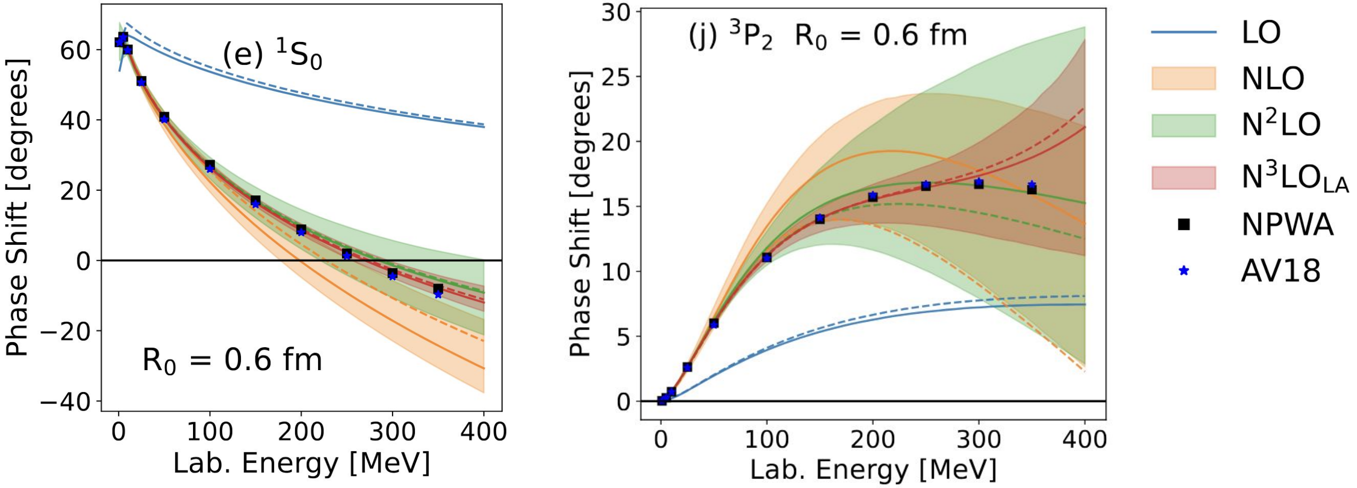


$$\mathcal{L} \propto \prod_i \exp\left\{ -\frac{1}{2}\left(\frac{X_i^{\rm exp} - X_i^{\rm theo}}{\sigma_i}\right)^2\right\}, \quad \sigma^2 = \sigma^2_{\rm exp} + \sigma^2_{\rm theo},$$

<u>EFT Truncation error:</u>

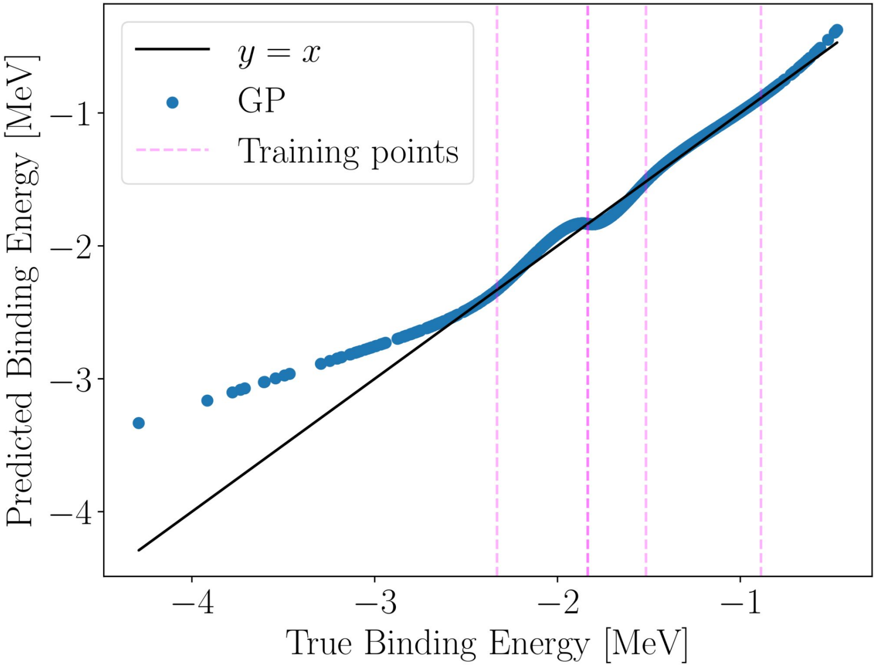
$$X(p) = X_{\rm ref}(p) \sum_{n=0}^{k} c_n Q^n(p) \qquad \Delta X^k_{\rm EKM} = X_{\rm ref}\, Q^j \max\big(|c_0|, |c_1| \ldots, |c_k|\big)$$

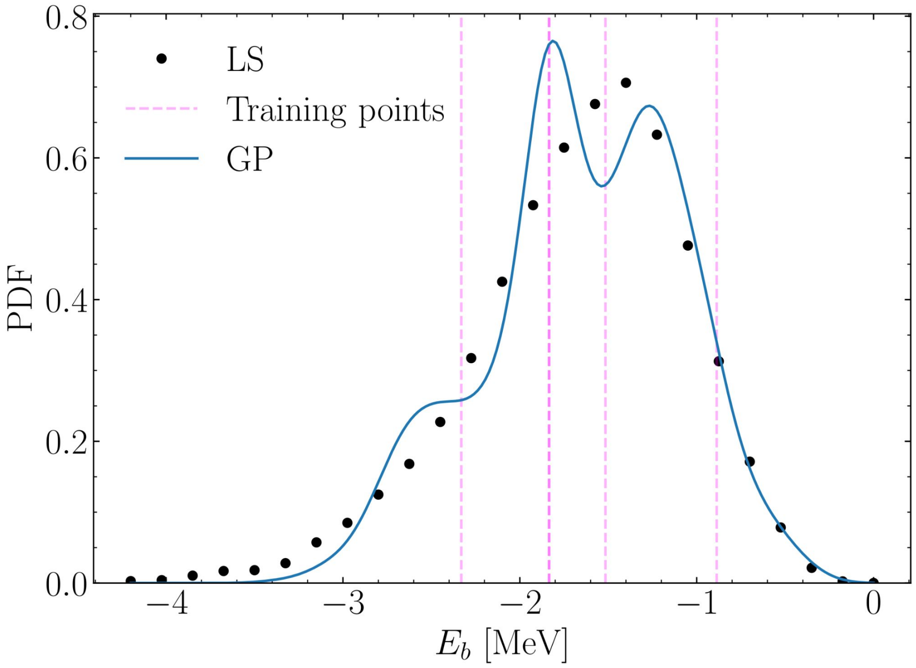
$$\text{where } j = \max(2, k+1)$$

RS et al., Phys.Rev.C 109 (2024) 3, 3

Emulators with scarce data: The Deuteron at leading order

- Goal: Build emulator for QMC with ~5 - 10 training points
- A baseline GP fails to accurately interpolate and extrapolate between training points



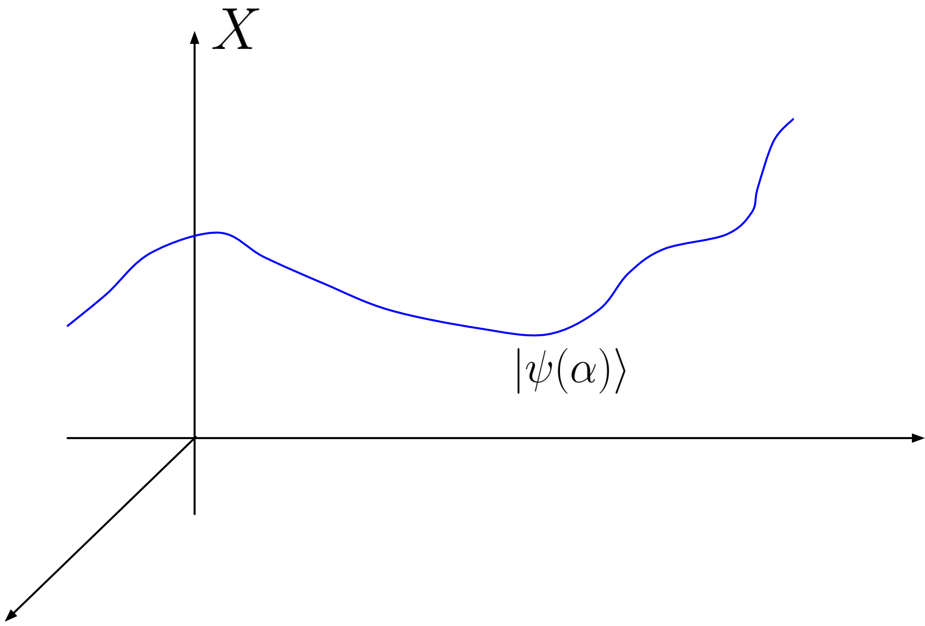


RS et al., Phys.Lett.B 866 (2025) 139558

Emulators with scarce data: Reduced basis methods

- Start with the full Schrödinger equation

$$H|\psi\rangle = E|\psi\rangle$$



Emulators with scarce data: Reduced basis methods

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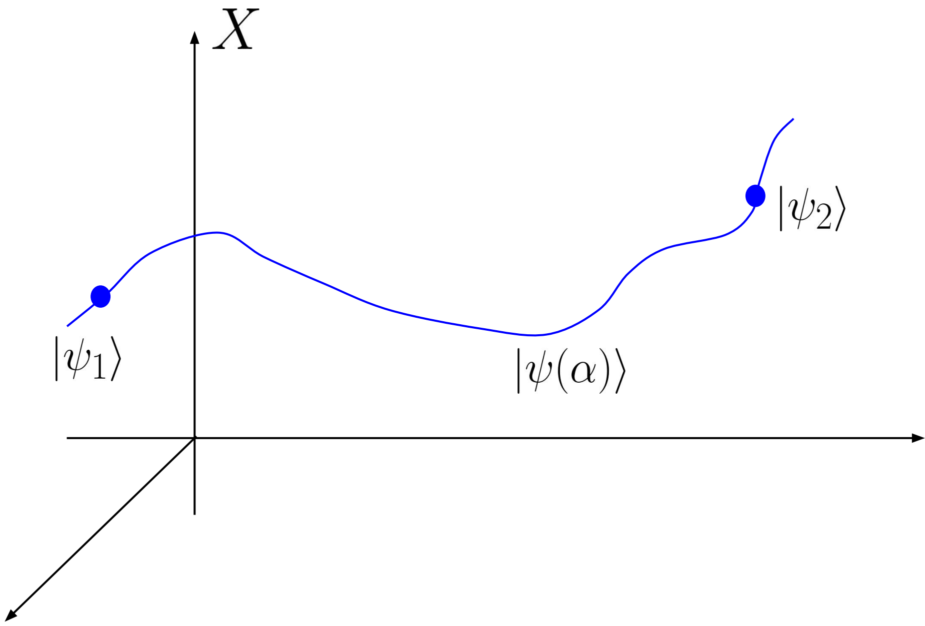
- Compute N training functions or ‘snapshots’ $|\psi_j\rangle$



Emulators with scarce data: Reduced basis methods

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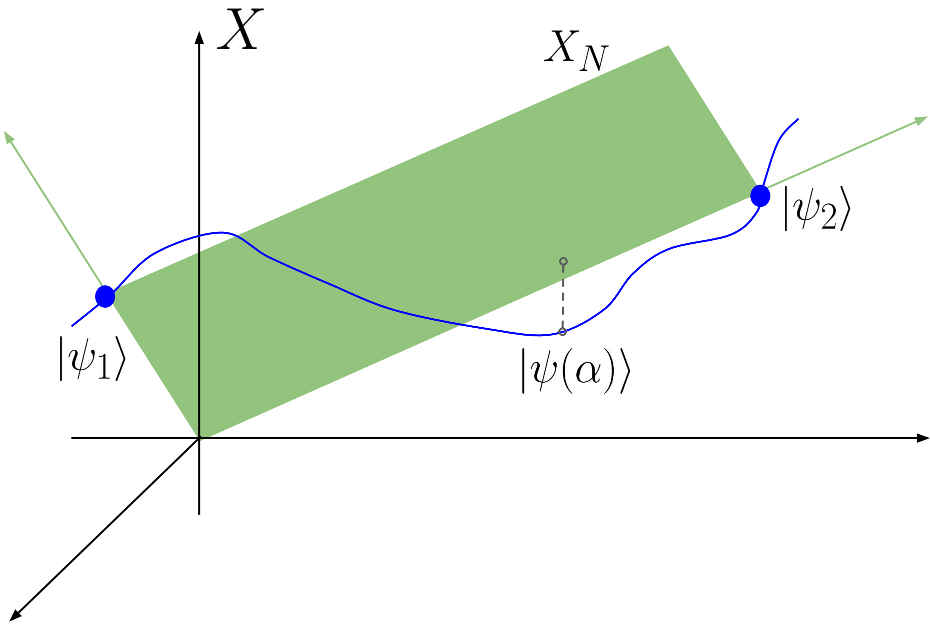
- Project the Hamiltonian into the reduced space spanned by $|\psi_j\rangle$

  Mathematically, this corresponds to computing the matrix

$$M_{ij} \equiv \langle\psi_i|H|\psi_j\rangle$$

Petrov-Galerkin projection method



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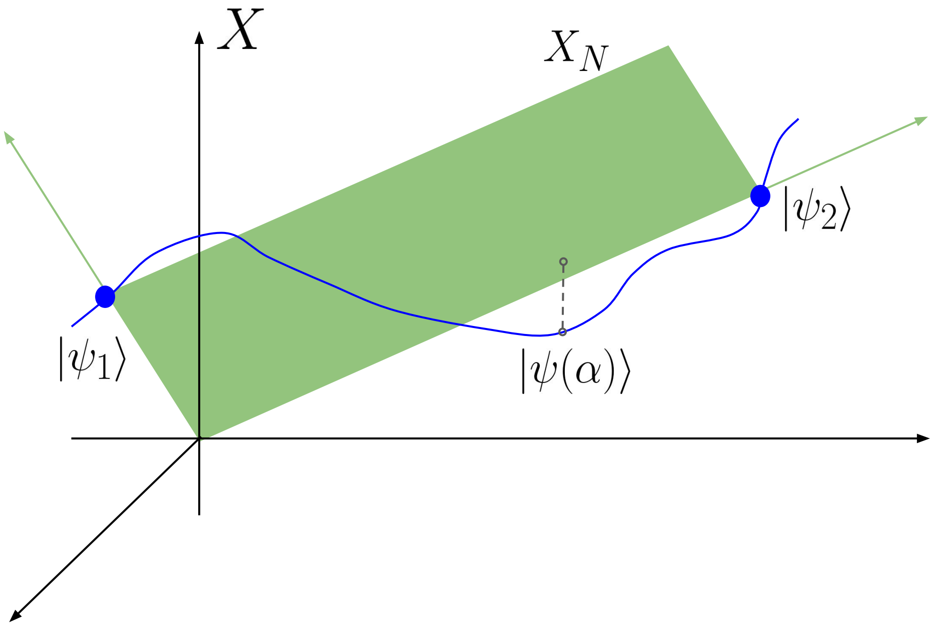
Petrov-Galerkin projection method

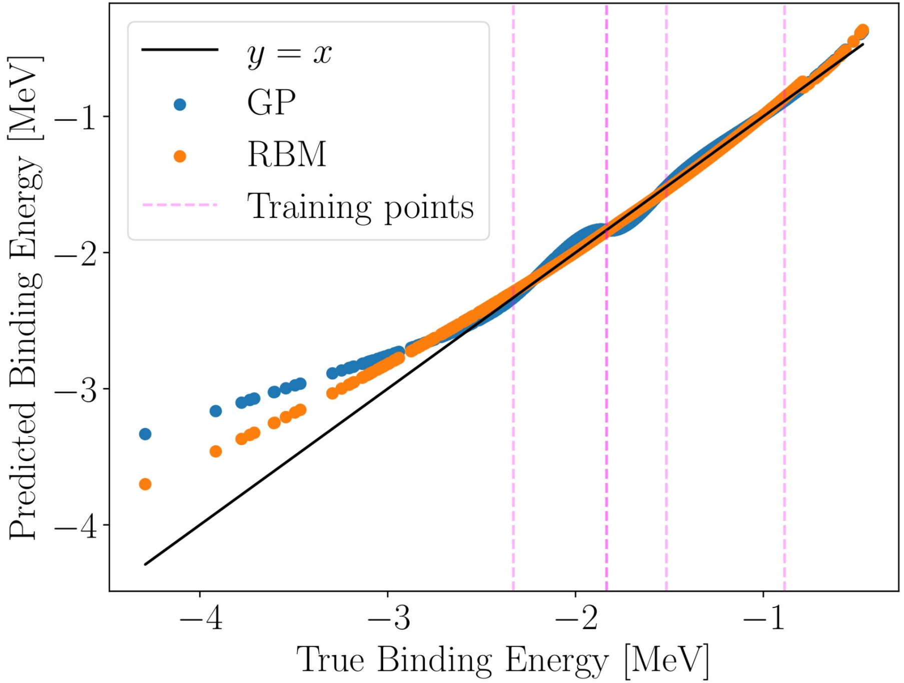


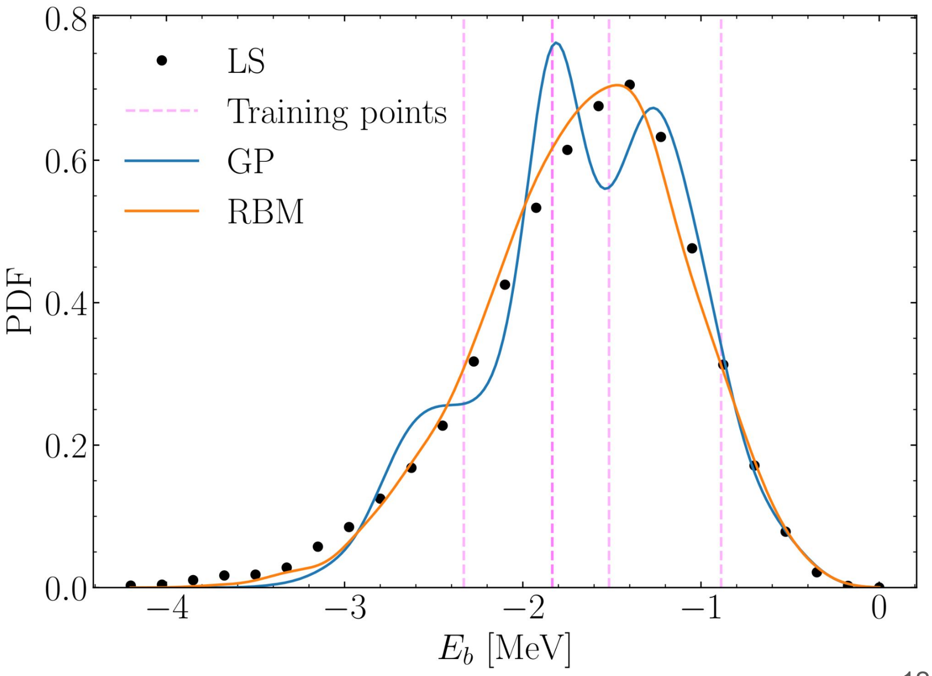
- For QMC, M_{ij} is dominated by stochastic noise and cannot be calculated. We therefore implemented a Petrov-Galerkin projection method for this problem:

$$\tilde{M}_{ij} = \langle\psi_i^T|H|\psi_j\rangle$$

Emulators with scarce data: Reduced basis methods

- This RBM outperforms the GP
- This RBM is capable of interpolating but fails to extrapolate away from training points. Note that this is <u>NOT</u> Eigenvector Continuation





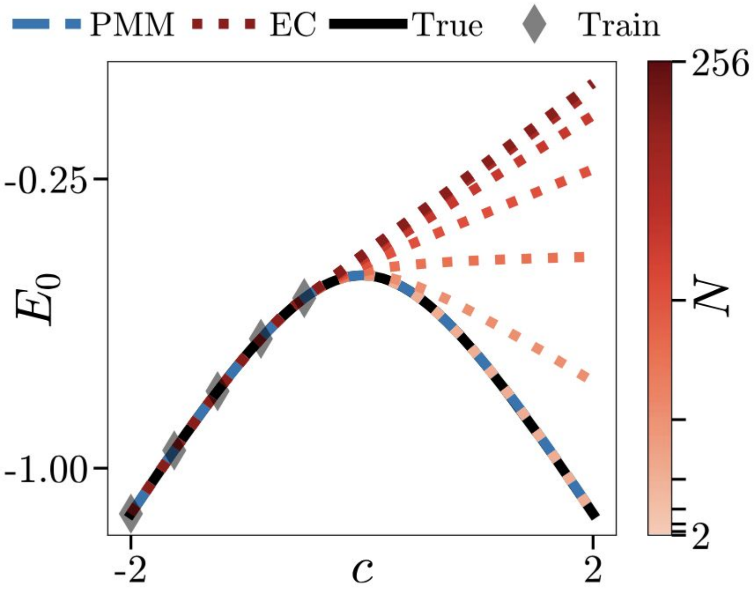
RS et al., Phys.Lett.B 866 (2025) 139558

Emulators with scarce data: Hybrid models

- Combine elements of RBMs with data-driven emulators
- We employ the recently proposed parametric matrix models

$$M(\vec{\alpha}) = M_0 + \sum_i \alpha_i M_i$$

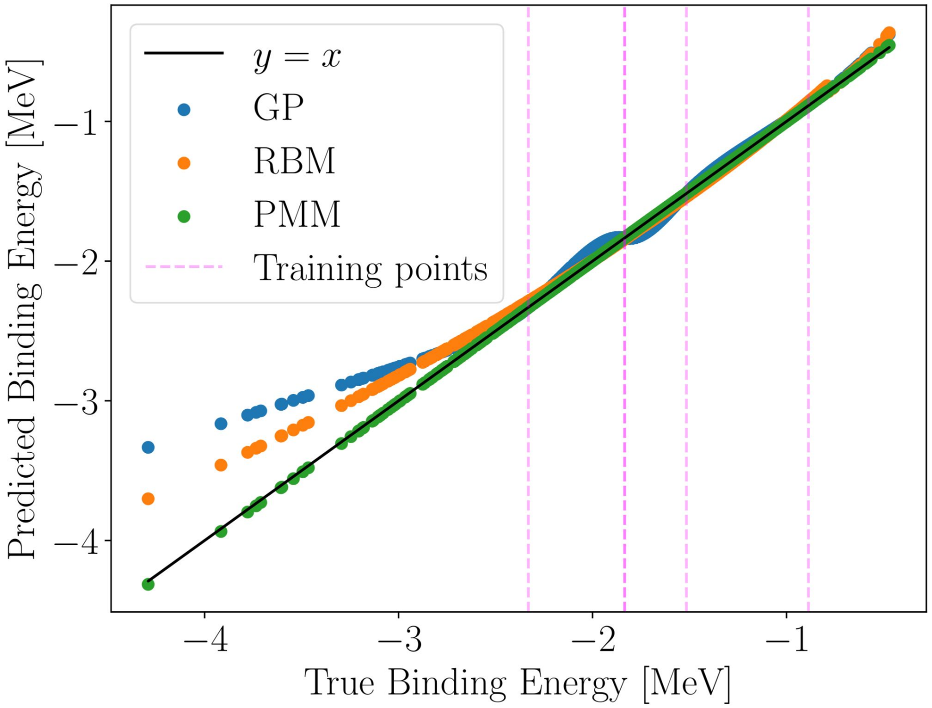
- The form of the reduced subspace matrix is inspired by RBMs. However, we do not directly compute the projections, i.e. we do not compute the subspace matrix elements
- Instead they are learned in some manner from the data

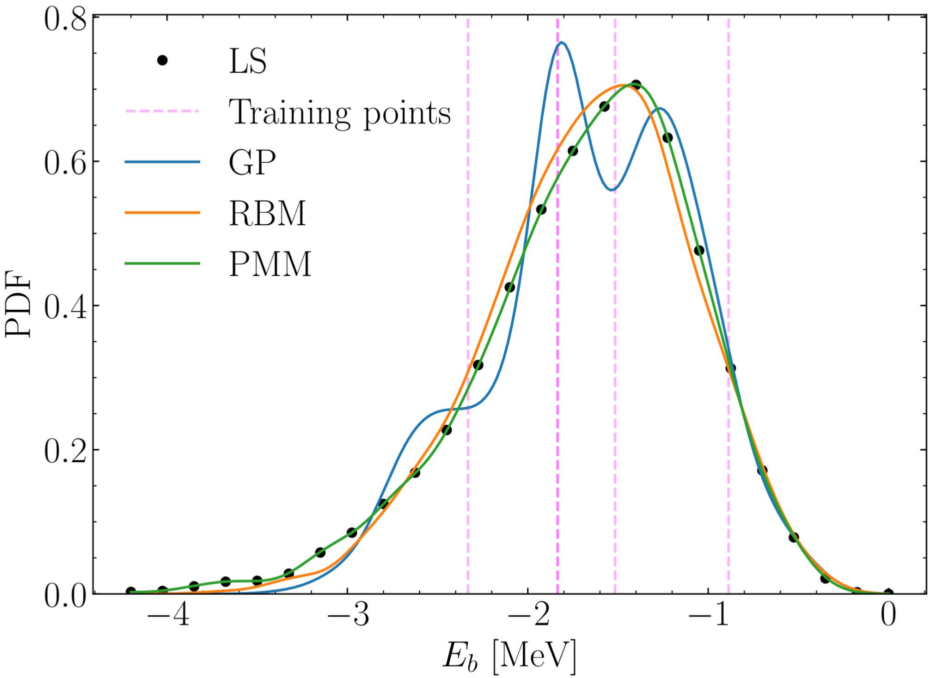


Cook et al., Nature Commun. 16 (2025) 1, 5929

Emulators with scarce data: Hybrid models

- The PMM outperforms both the GP and our RBM
- It interpolates well but also gives excellent results for extrapolation!





RS et al., Phys.Lett.B 866 (2025) 139558

Emulators with scarce data: Hybrid models. The Deuteron at N^2LO

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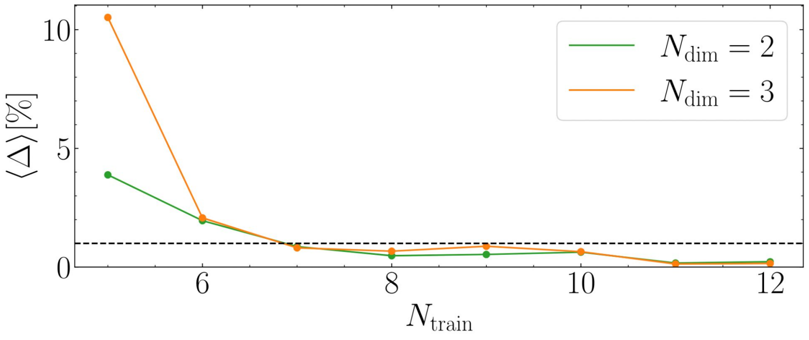
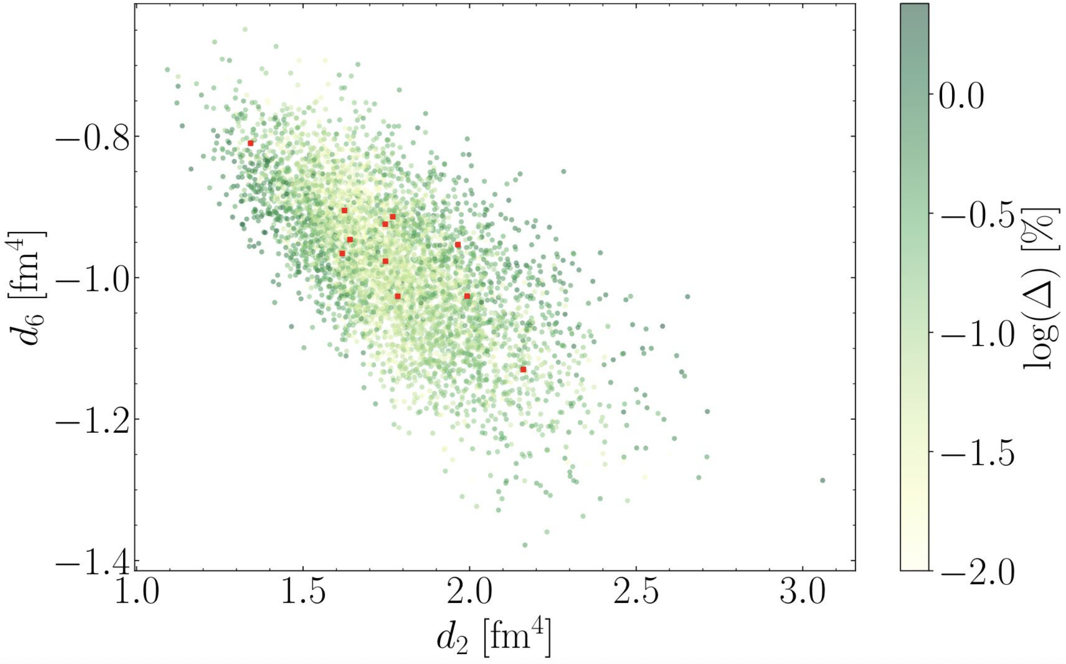


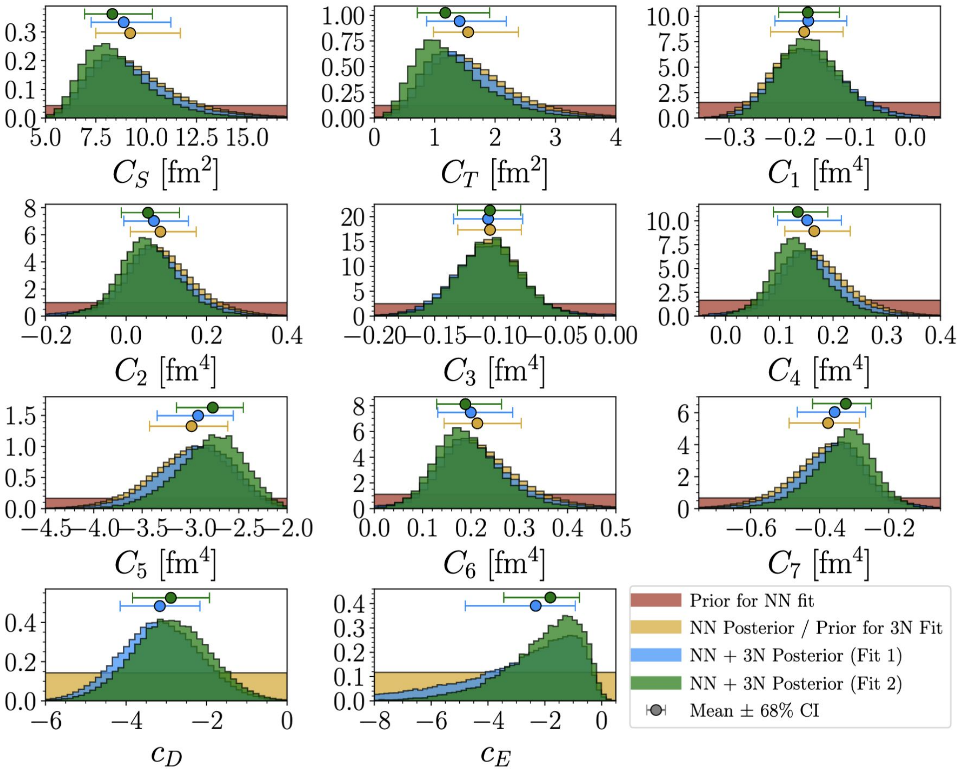


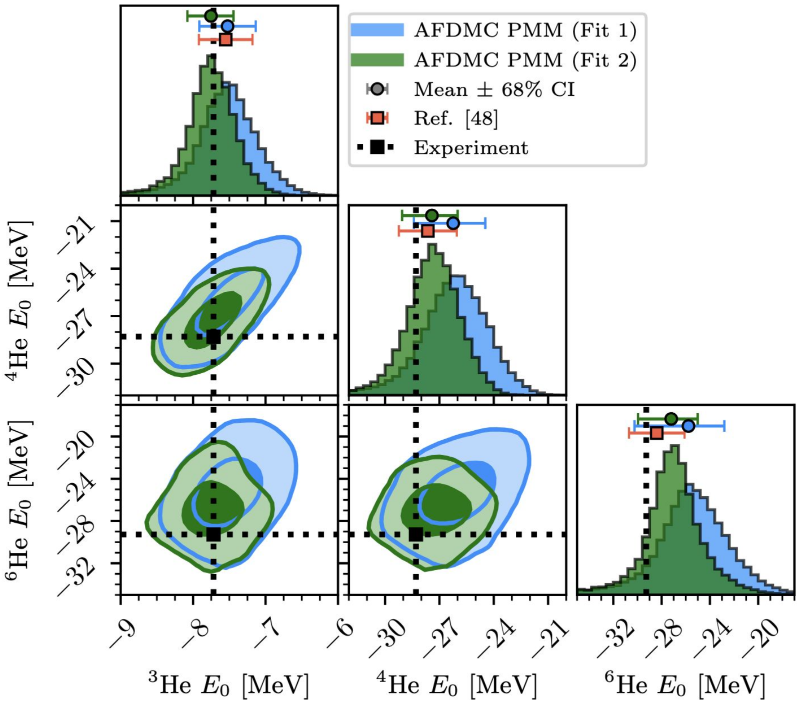
- We found that our PMM generalises very well to at least 4 - 5 dimensional parameter spaces.

RS et al., Phys.Lett.B 866 (2025) 139558

Using PMMs for light nuclei

$$P(\alpha_{3N}, \alpha_{2N}|D) \propto \mathcal{L}(\alpha_{3N}, \alpha_{2N}|D_L)\Pi(\alpha_{3N})P(\alpha_{2N}|D_S)$$

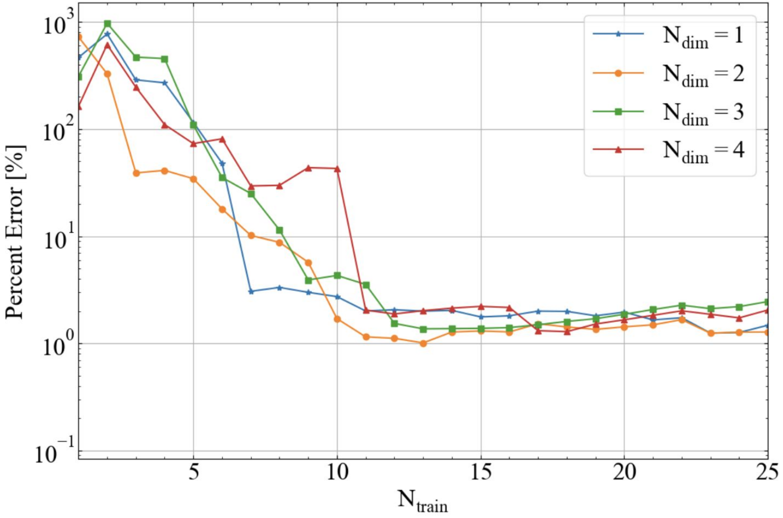


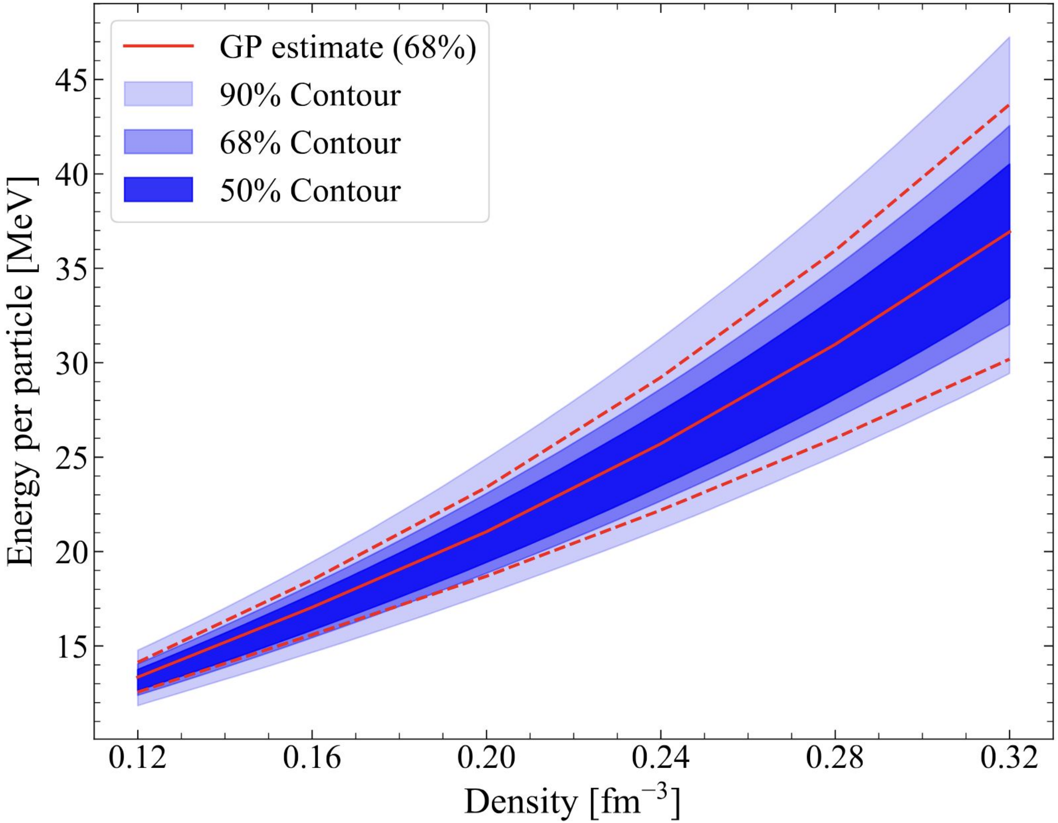


Curry et al., arXiv:2510.15860

Using PMMs for neutron matter

Joint posterior distribution on 6 two-body spectral LECs propagated to pure neutron matter.

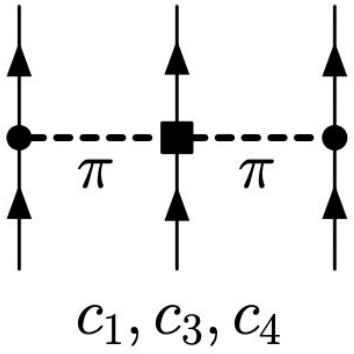


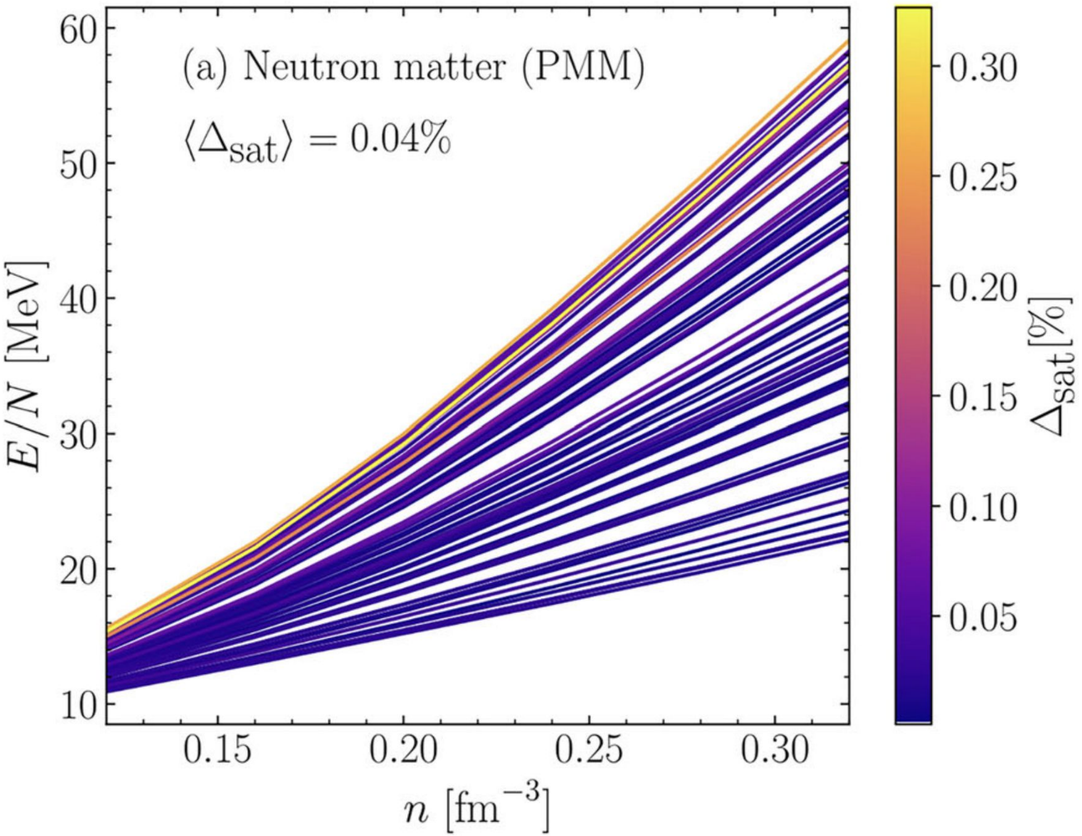


Armstrong et al., Phys.Rev.Lett. 135 (2025) 14, 142501

Using PMMs for neutron matter (MBPT calculations)

- N^2LO interaction of Entem, Machleidt, and Nosyk. Λ_C = 450 MeV
- We kept NN part fixed. There are then two parameters that determine the 3N sector in PNM





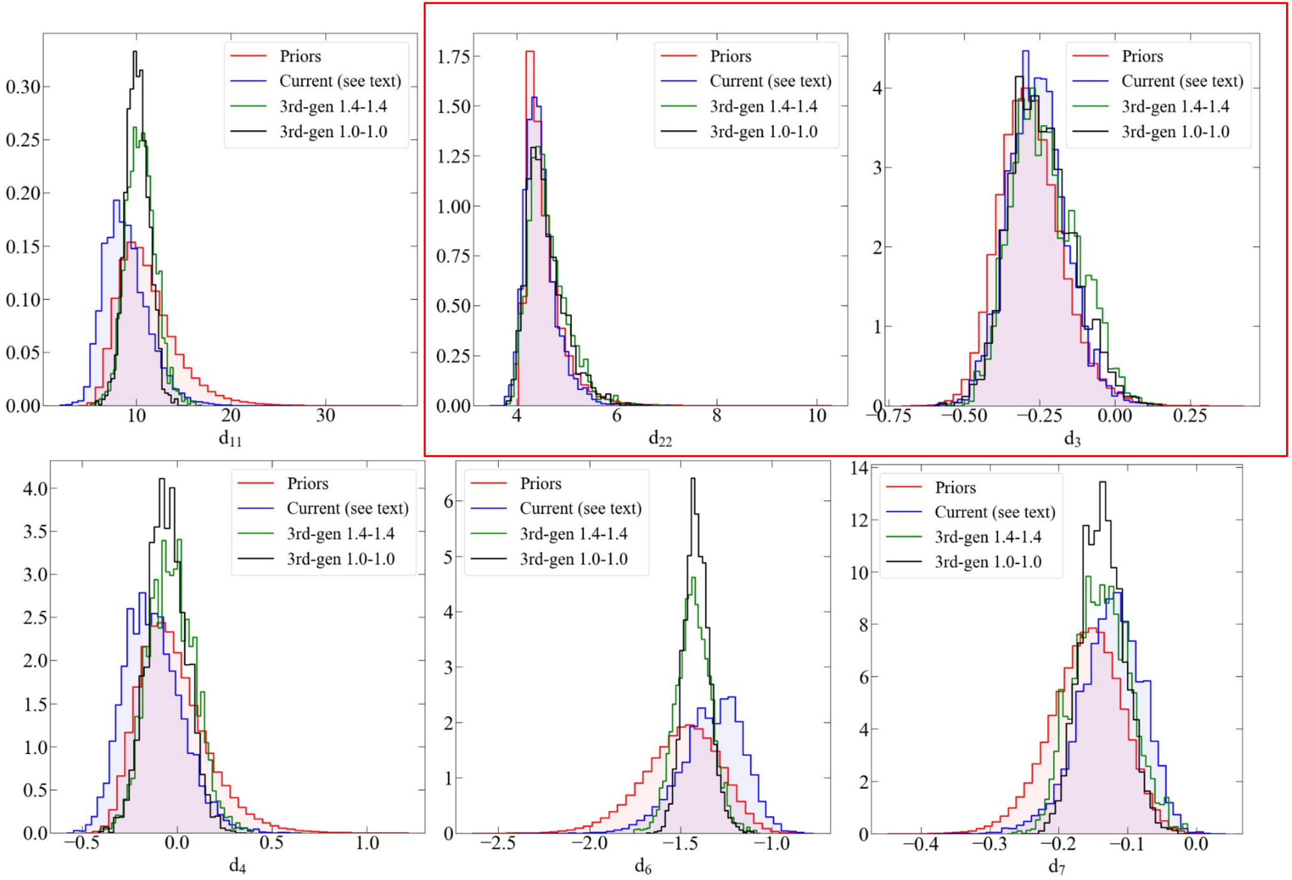
RS and Isak Svensson, et al. Nature Commun. 16 (2025) 1, 9819

Impact of neutron star data

Astrophysical data includes:

- GW170817
- NICER
  - PSR J0030
  - PSR J0740
  - PSR J0437
  - PSR J0614
- Radio observations ($M_{TOV} > 2\ M_{sun}$)
- Simulated next-generation events from Cosmic Explorer and Einstein Telescope

Largely, we see consistency between astrophysical data and np scattering



Armstrong et al., arXiv:2601.05999

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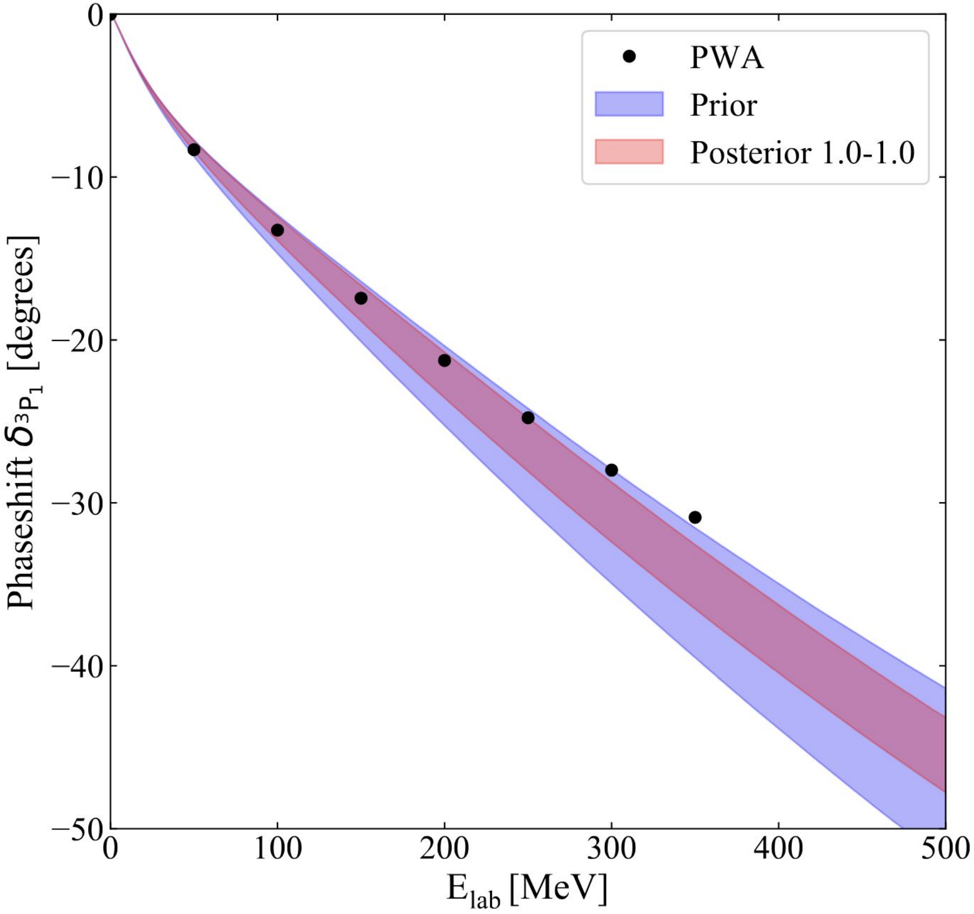

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Impact of neutron star data (EMN, 450 MeV)

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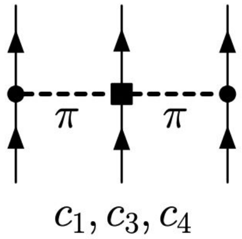

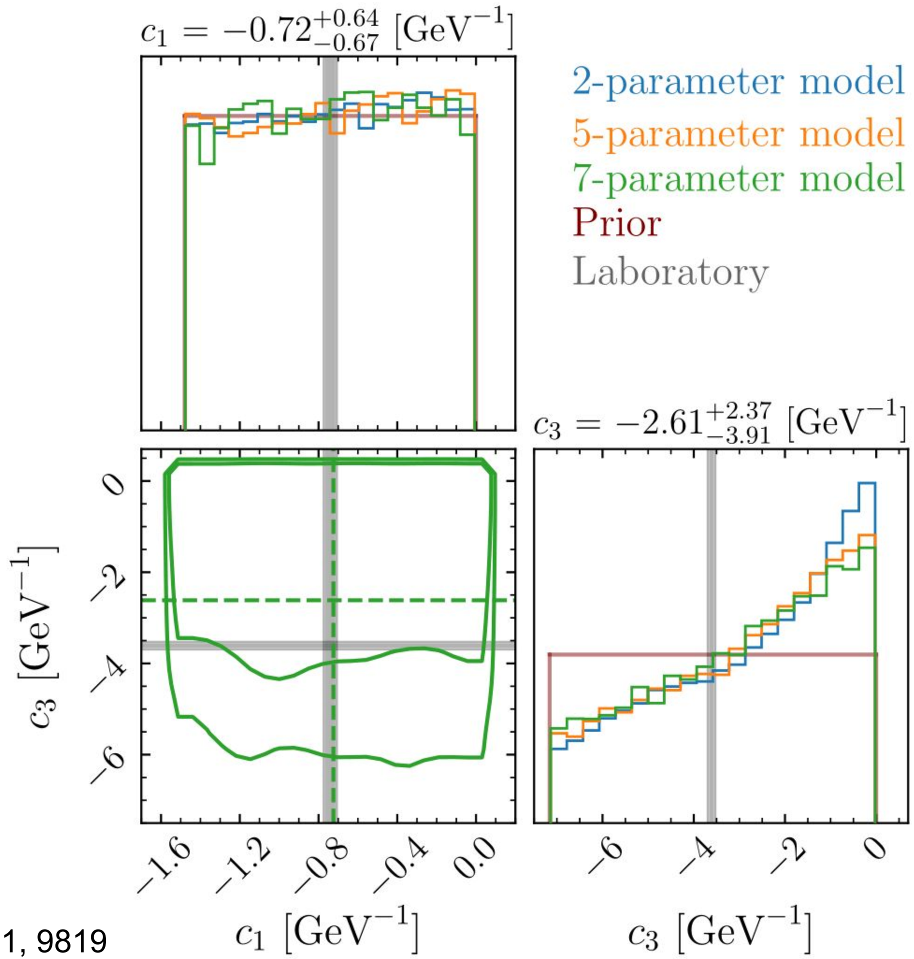

RS and Isak Svensson, et al. Nature Commun. 16 (2025) 1, 9819

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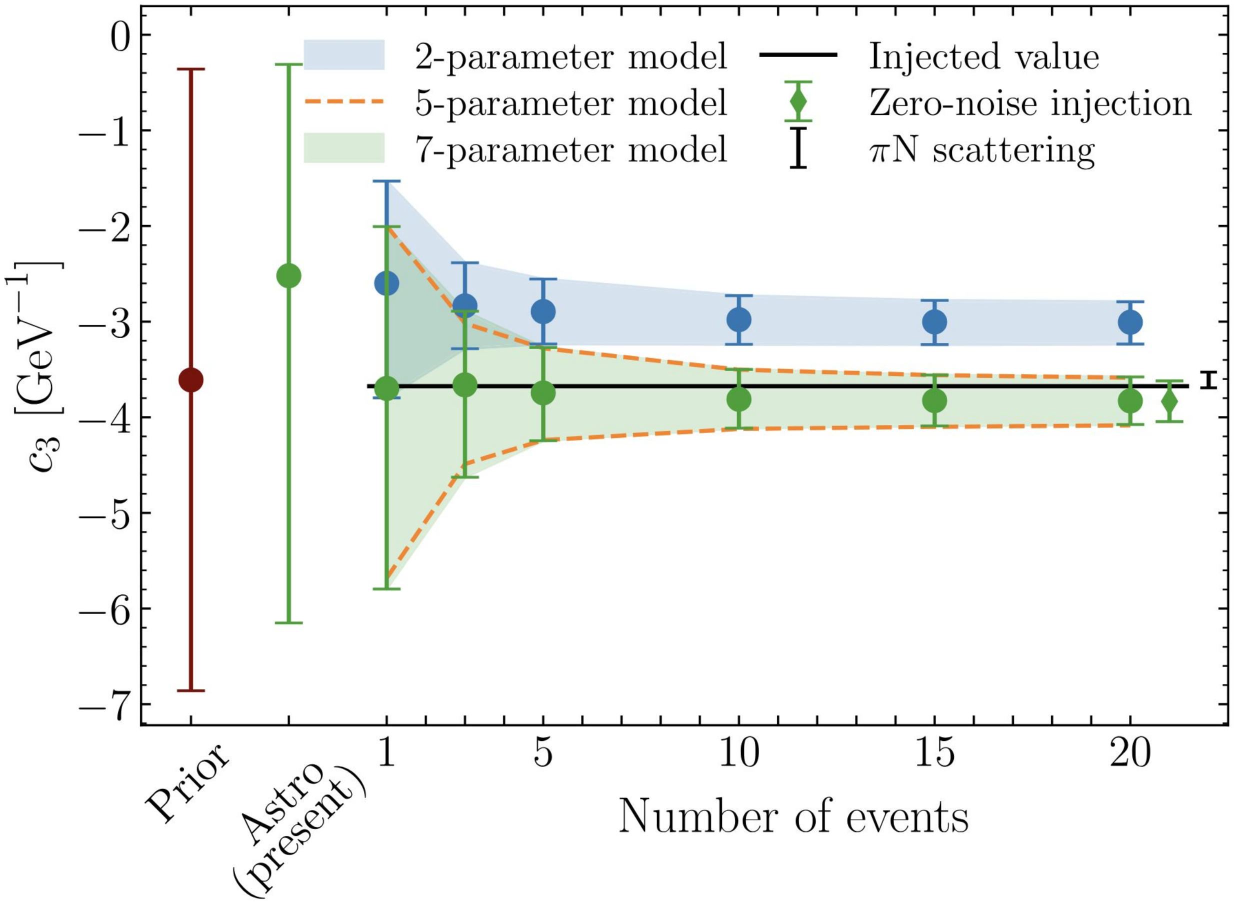

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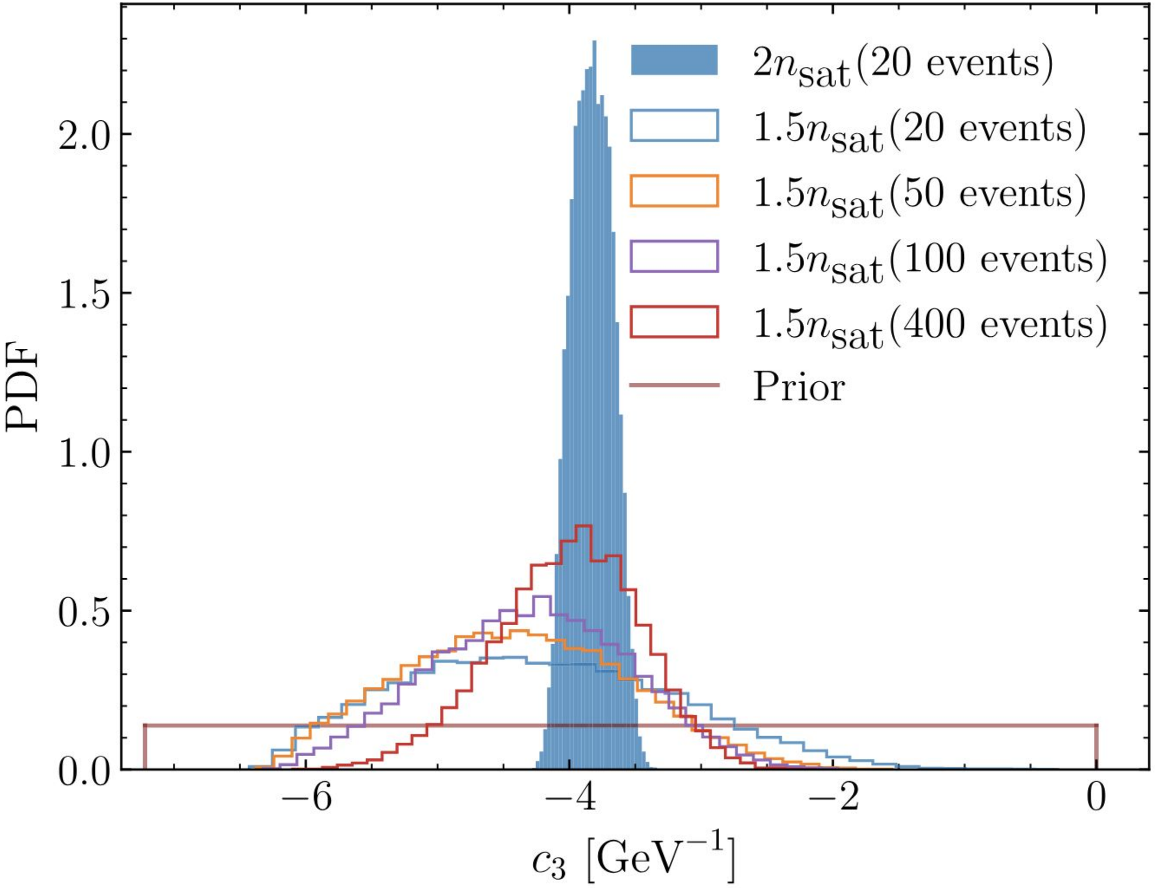
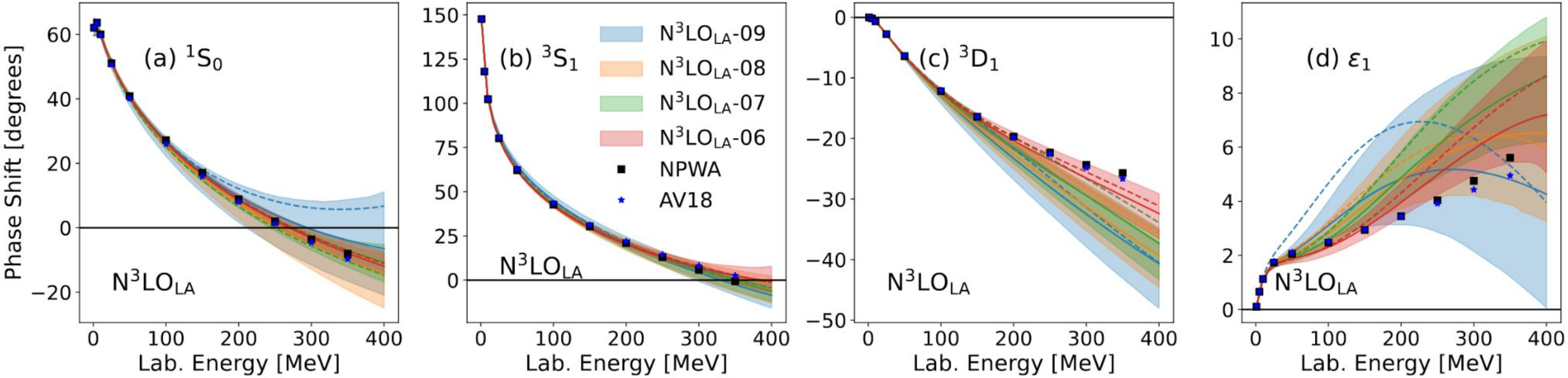
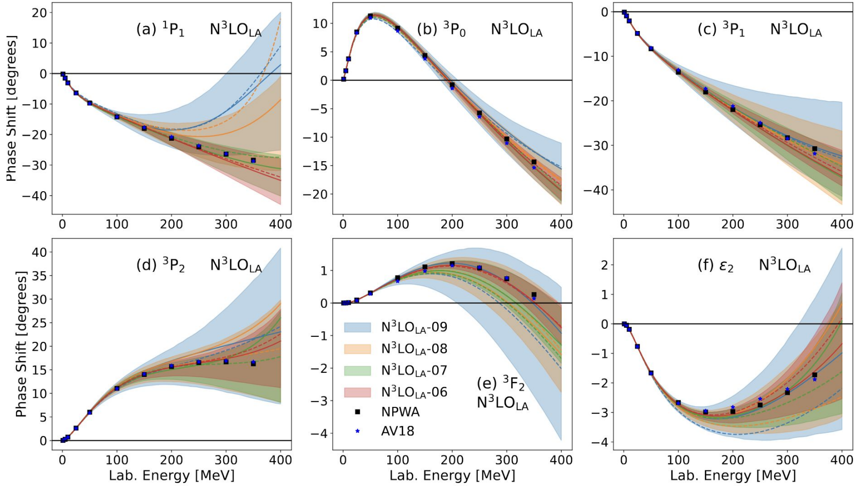


RS and Isak Svensson, et al. Nature Commun. 16 (2025) 1, 9819

Local interactions at N^{3}LO



Work in progress: Extend calculations to maximally local N^{3}LO interactions. This includes 4 non-local operators that need to be treated perturbatively.

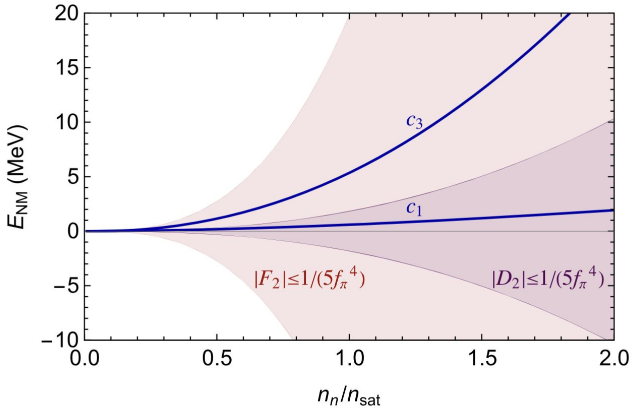


RS et al., Phys.Rev.C 109 (2024) 3, 3

Outlook

- Infer the breakdown scale directly in dense nuclear matter. Study cutoff dependency and compare local vs non-local interactions

- Study RG invariance of 3N forces in dense matter



Cirigliano et al., Phys.Rev.Lett. 135 (2025) 2, 022501

Challenges

- What other observables should we be focusing on? Can we study multi-nucleon scattering?

- How do we sample large parameter spaces (at high orders) and how much data should we include?

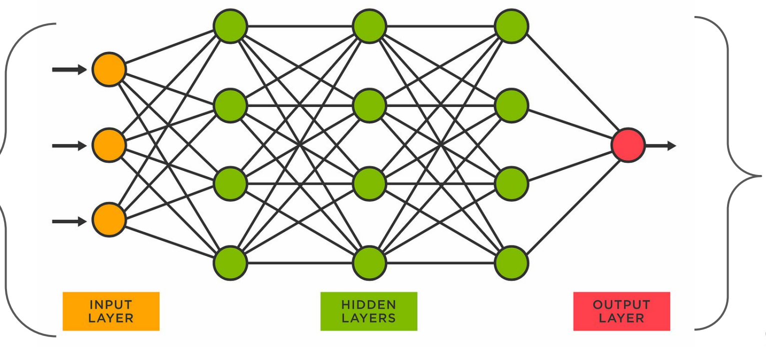
- Can we “sample” over the space of operators to study different power counting schemes?

Backup Slides

Emulating the TOV equations: Deep ensembles of Multilayer Perceptrons

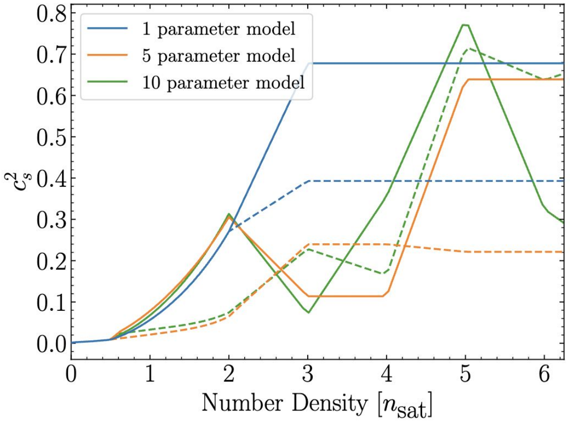
Multilayer Perceptrons (MLP) are the simplest, dense, feedforward neural networks. We use the method of deep ensembles where we use a set of 100 MLPs

Equation of State parameters

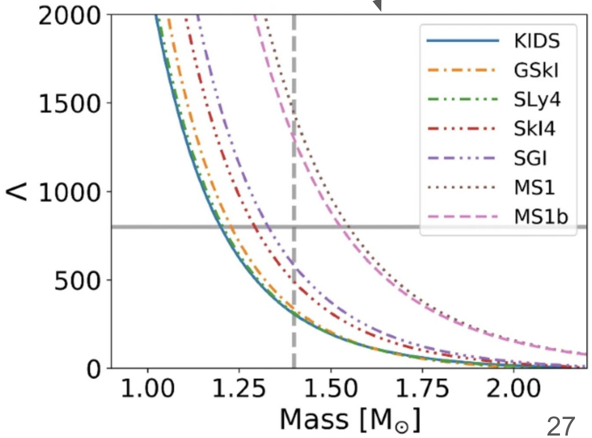


The neutron star tidal deformability

(x100)

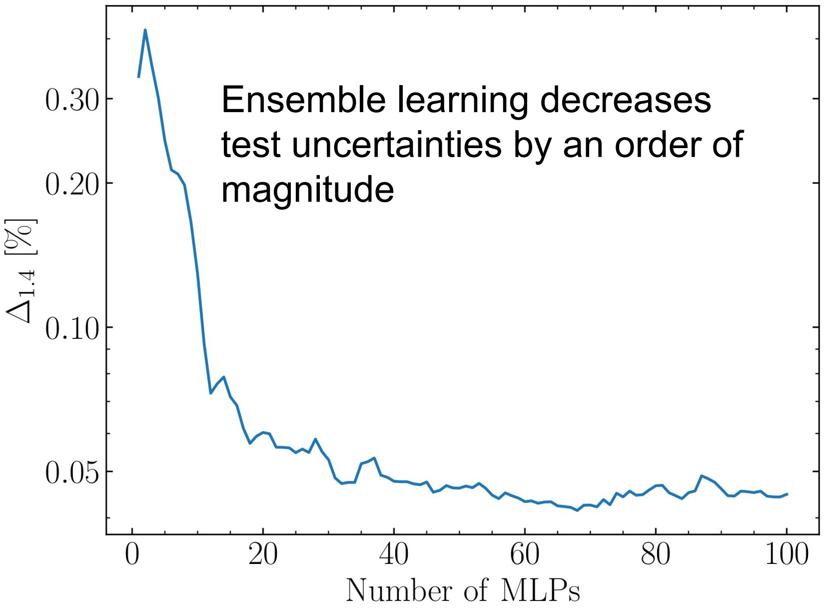


We generated 200K samples, randomly split into training and test data

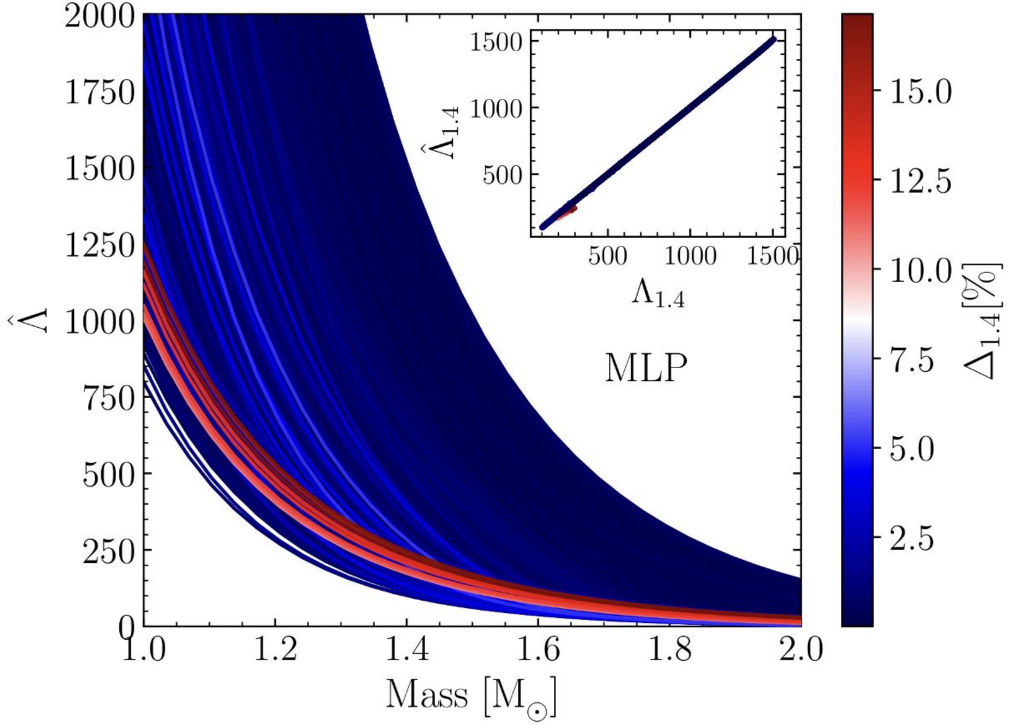


Reed et al., Astrophys.J. 974 (2024) 2, 285

Deep ensembles of Multilayer Perceptrons



$$\Delta[\%] \equiv \left| \frac{\Lambda - \hat{\Lambda}}{\Lambda} \right| \times 100$$

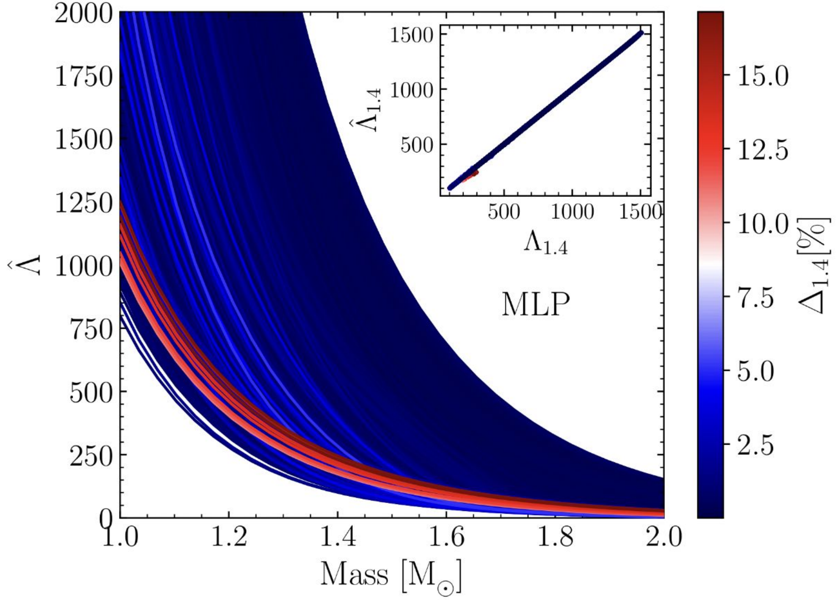


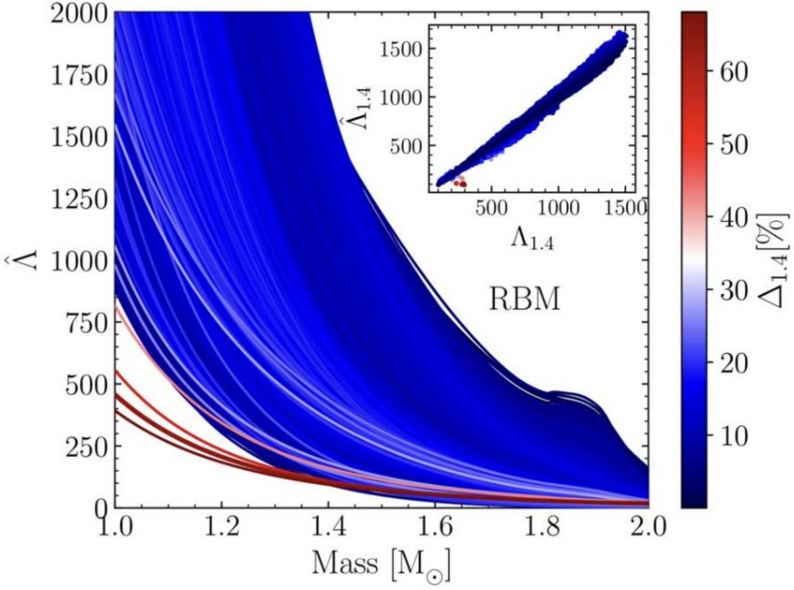
- Average uncertainty on test samples is 0.04 %
- 0.01% of test samples are outliers (uncertainty > 10%)

Reed et al., Astrophys.J. 974 (2024) 2, 285

Deep ensemble versus RBMs

Overall, our deep ensemble also performs better on test samples, with better validation scores.

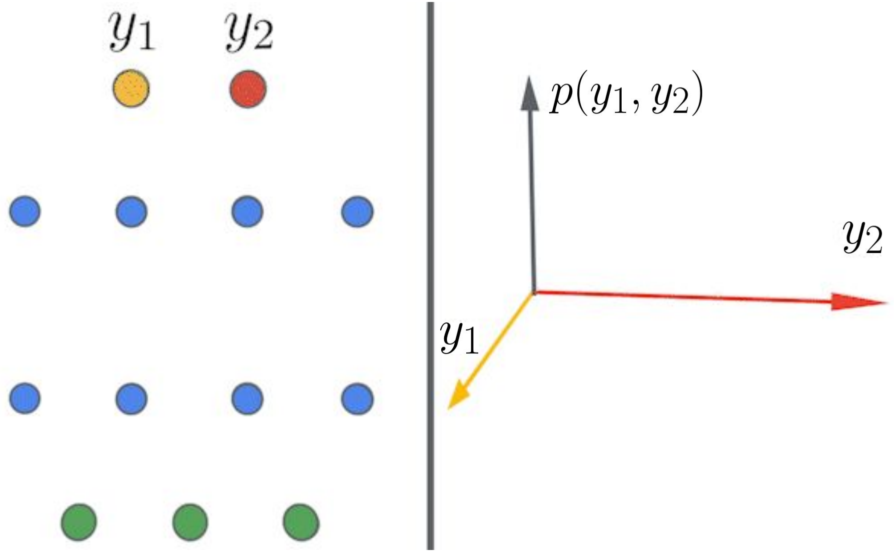




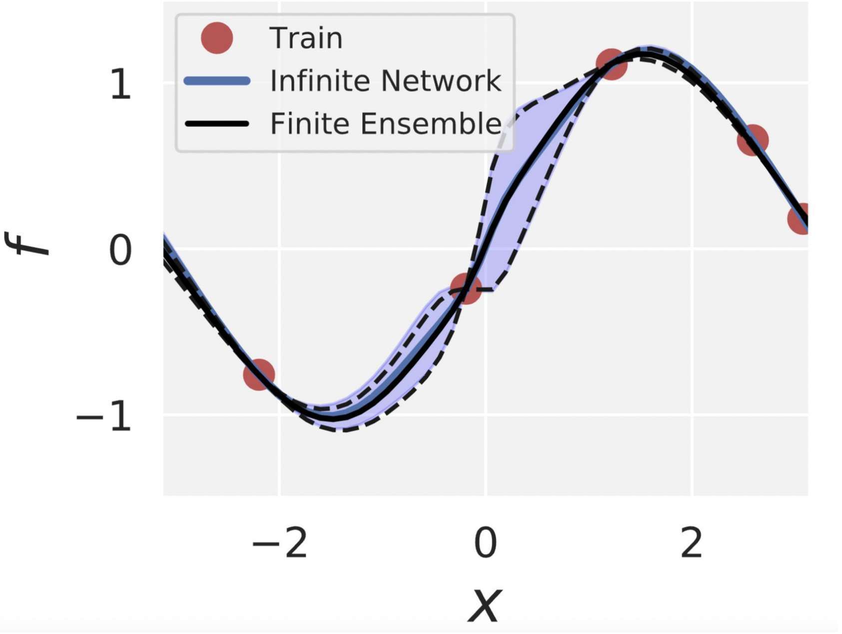
Reed et al., Astrophys.J. 974 (2024) 2, 285

Uncertainty quantification using deep ensembles

- In the limit of infinite neural network width, deep ensembles are mathematically equivalent to Gaussian Processes



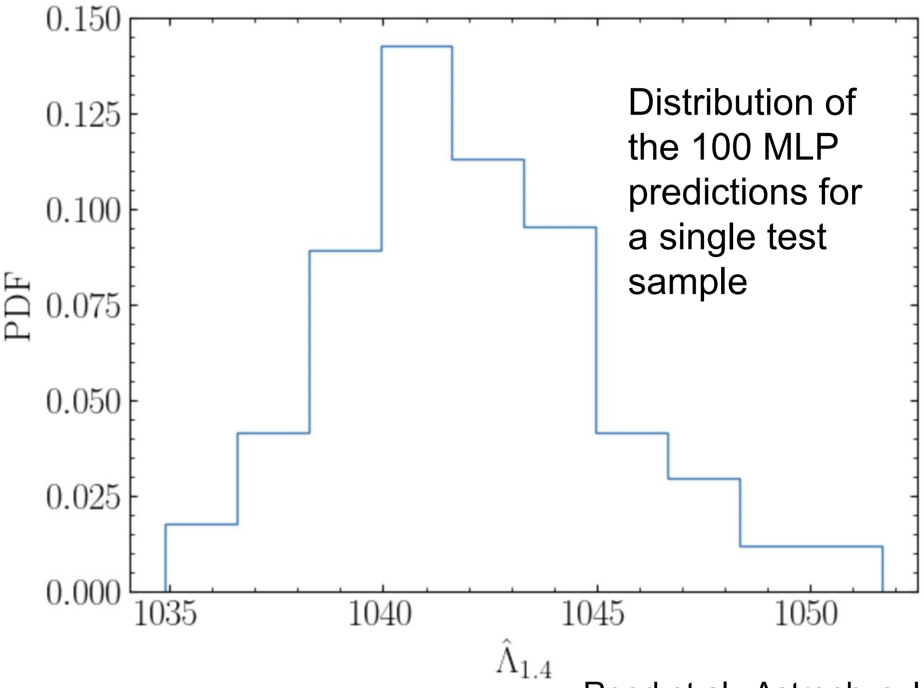
Google Research



Lee et al., arXiv:1902.06720

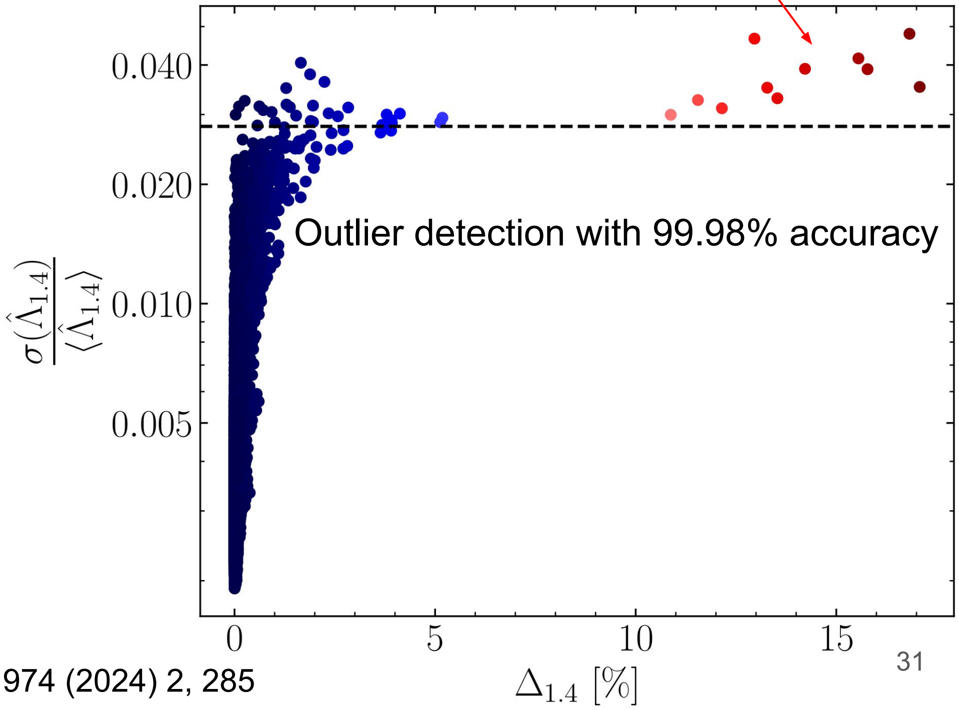
Uncertainty quantification using deep ensembles

We use MLPs with a width of 64 neurons. Therefore, our predictions are not exactly Gaussian distributed



Distribution of the 100 MLP predictions for a single test sample

Outliers can be detected using variance among the MLPs



Outlier detection with 99.98% accuracy

Reed et al., Astrophys.J. 974 (2024) 2, 285