

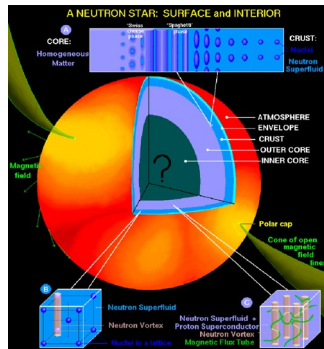
Conformal prediction, neural networks, and emulators for few-body systems

Alex Gezerlis



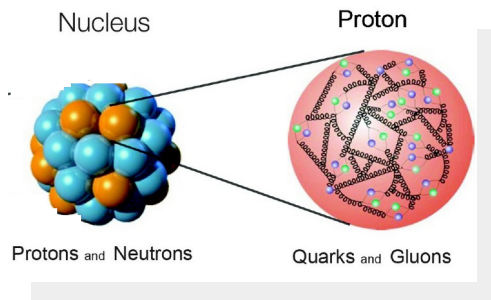
“Next generation *ab initio* nuclear theory” workshop
ECT*, Trento, Italy
July 15, 2025

Outline

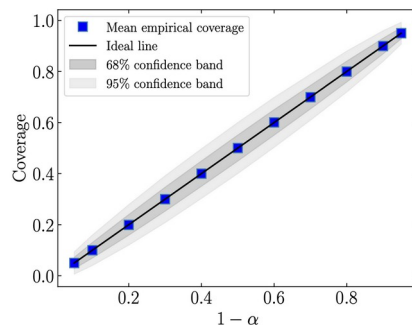


Credit: Dany Page

Motivation

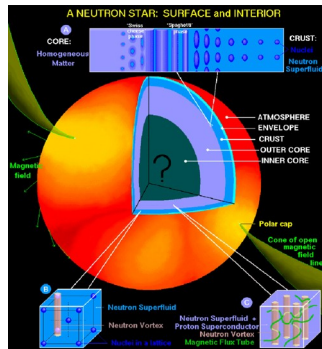


Nuclear methods



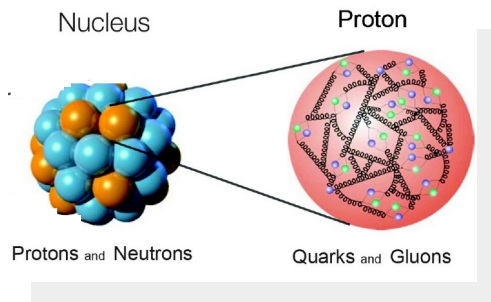
Recent results

Outline

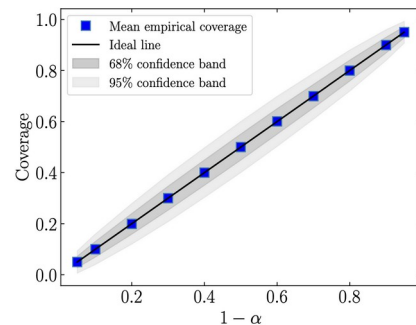


Credit: Dany Page

Motivation



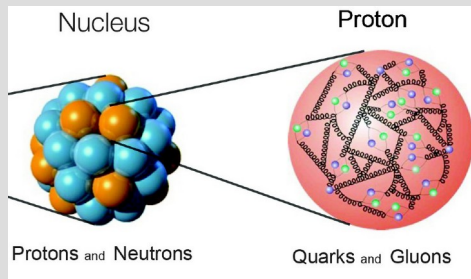
Nuclear methods



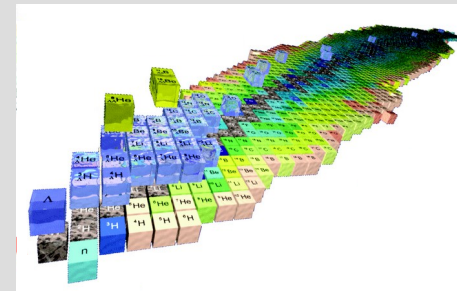
Recent results

Physical systems studied

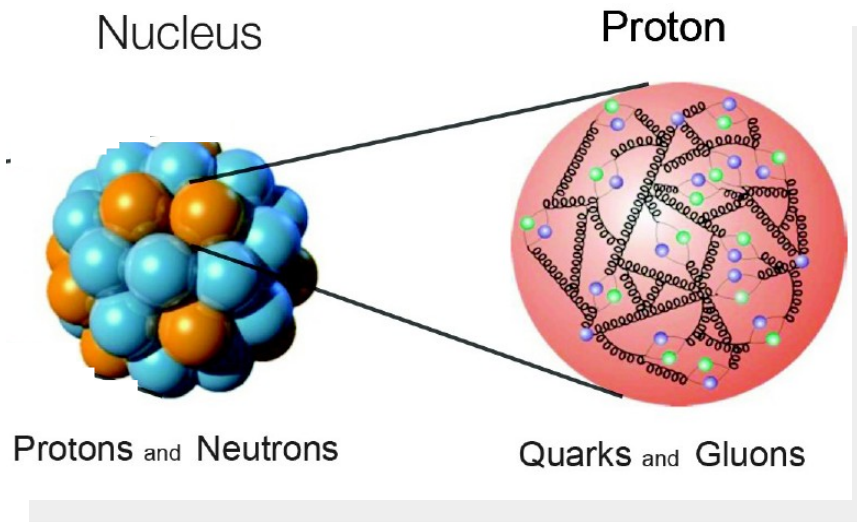
Nuclear forces



Nuclear structure

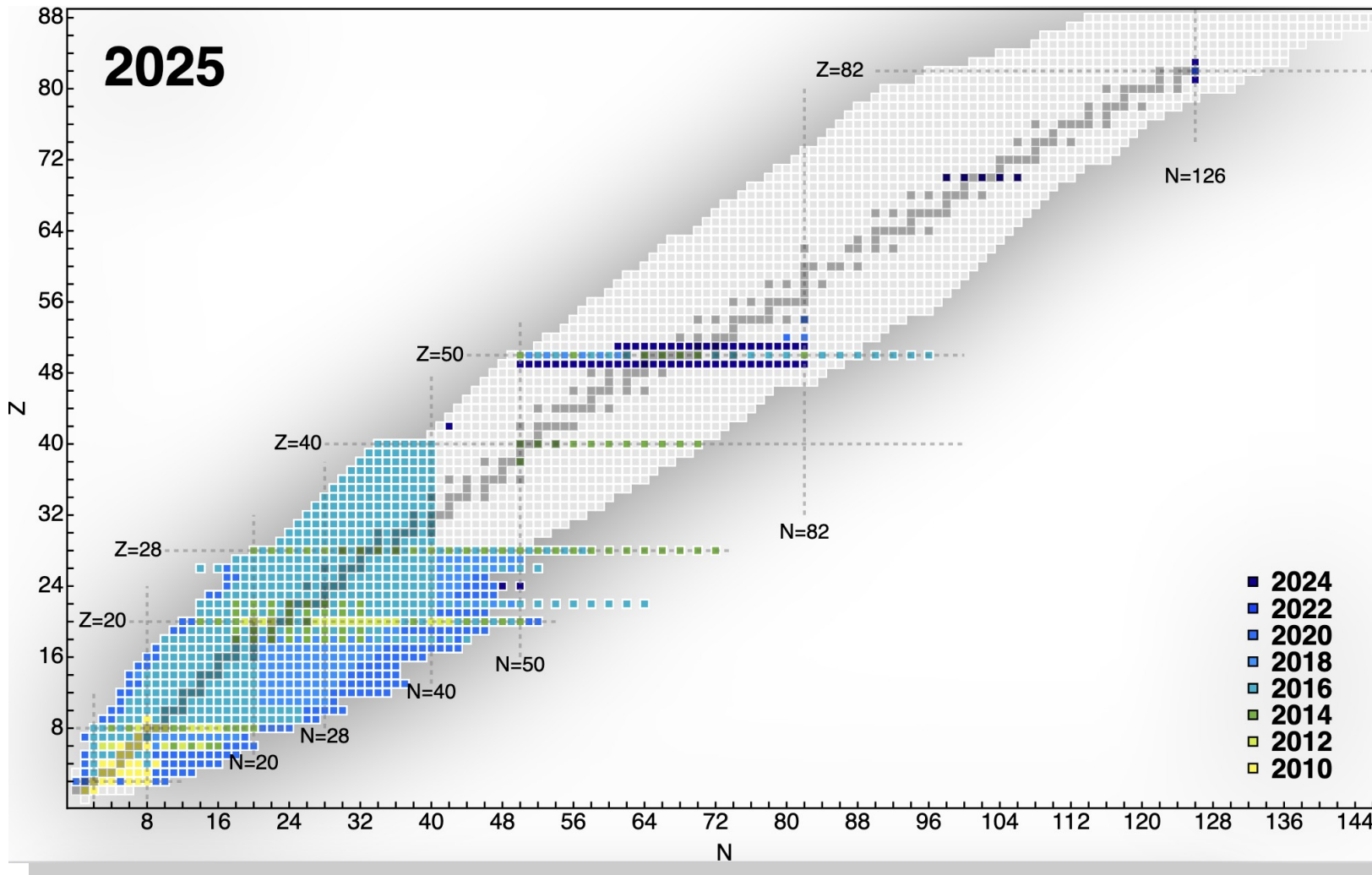


Key system: few nucleons



- No unique nuclear potential
- Preferable to use combination of phenomenological (high-quality) and more modern (conceptually clean) approach
- Desirable to make contact with underlying level
- New era, where practitioners design interactions themselves

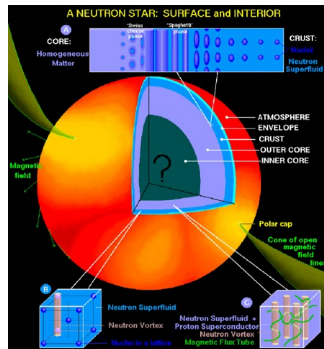
Key system: nuclei



Heiko Hergert's
propaganda plot

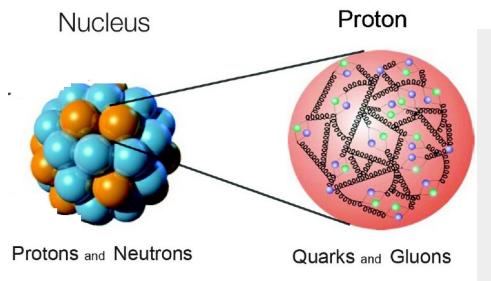
- Lots of recent progress
- Open-shell nuclei are the current frontier
- Goal is to study nuclei *from first principles* (when possible)

Outline

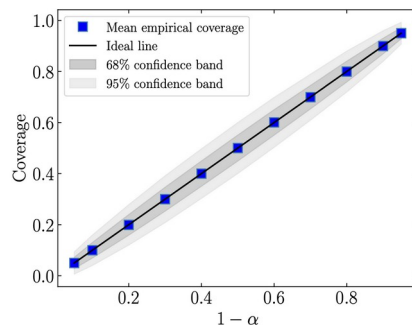


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Motivation

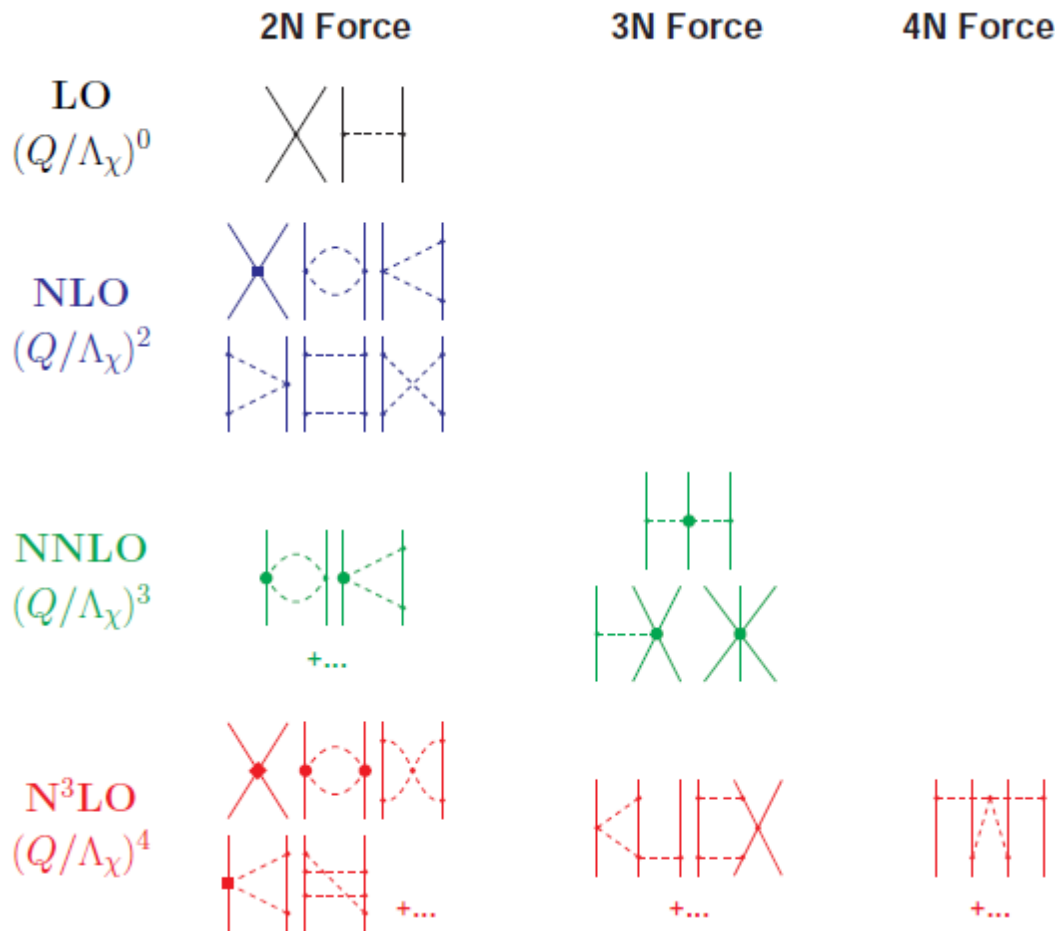


Nuclear methods



Recent results

Nuclear interactions



- Attempts to connect with underlying theory (QCD)
- Low-momentum expansion
- Naturally emerging many-body forces
- Low-energy constants from experiment or lattice QCD
- Now available in non-local, local, or semi-local varieties
- Power counting's relation to renormalization actively investigated

S. Weinberg, U. van Kolck, E. Epelbaum, N. Kaiser ...

**But even with the interaction in place,
how do you solve the many-body problem?**

Nuclear many-body problem

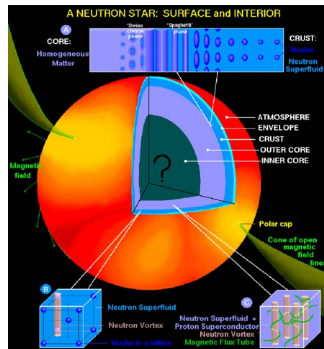
$$H\Psi = E\Psi$$

where

$$H = \sum_i K_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk}$$

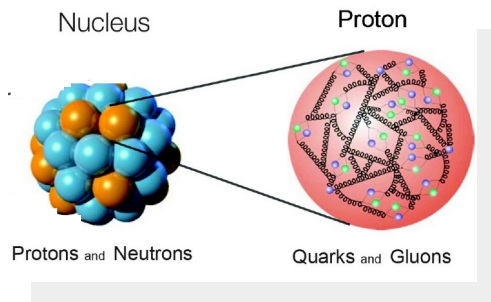
Wave function depends on coordinates, spin projections, and isospin projections, so we are faced with a large number of complex coupled second-order differential equations

Outline

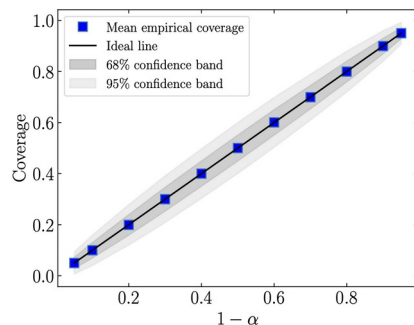


Credit: Dany Page

Motivation



Nuclear methods



Recent results

Recent results

- **Conformal prediction for nucleon-nucleon scattering**
- **Neural-network wave functions for light nuclei**
- **Emulators for the triton**

Conformal prediction for nucleon-nucleon scattering

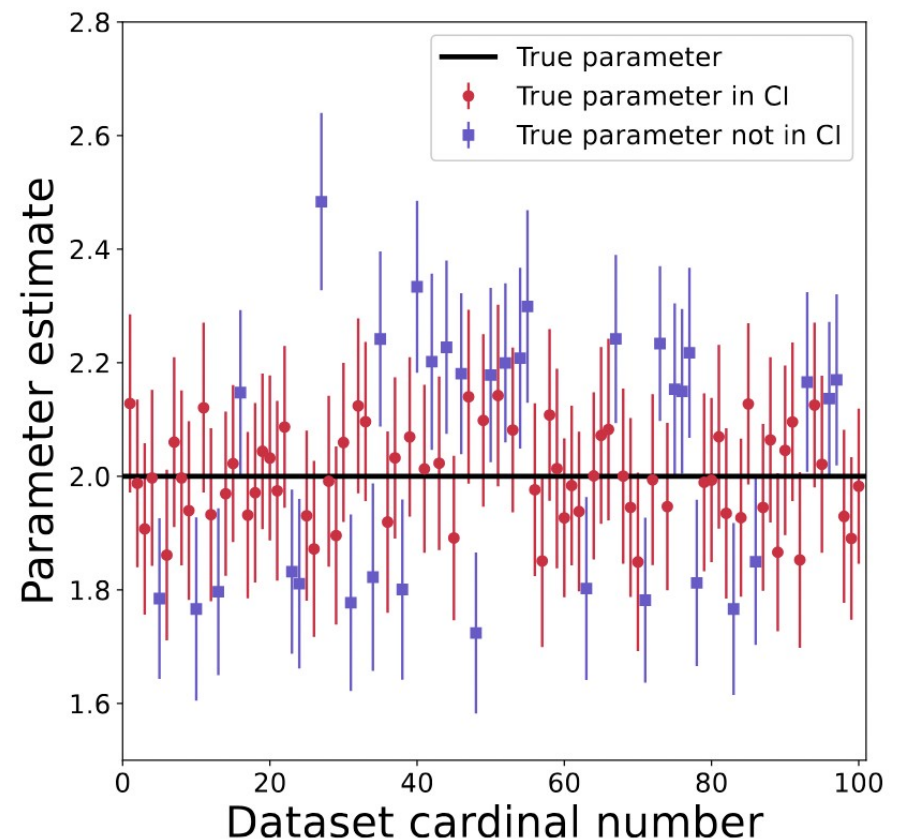
H. Yousefi Dezdarani, R. Curry, and A. Gezerlis, arXiv:2507:08085

A hint of the philosophy of statistics

(Frequentist) confidence interval

E.g., maximize likelihood and take an $n\sigma$ error bar around that point.

Confidence interval *does not* imply degree of belief about our single dataset, but *does* provide guaranteed coverage across datasets.



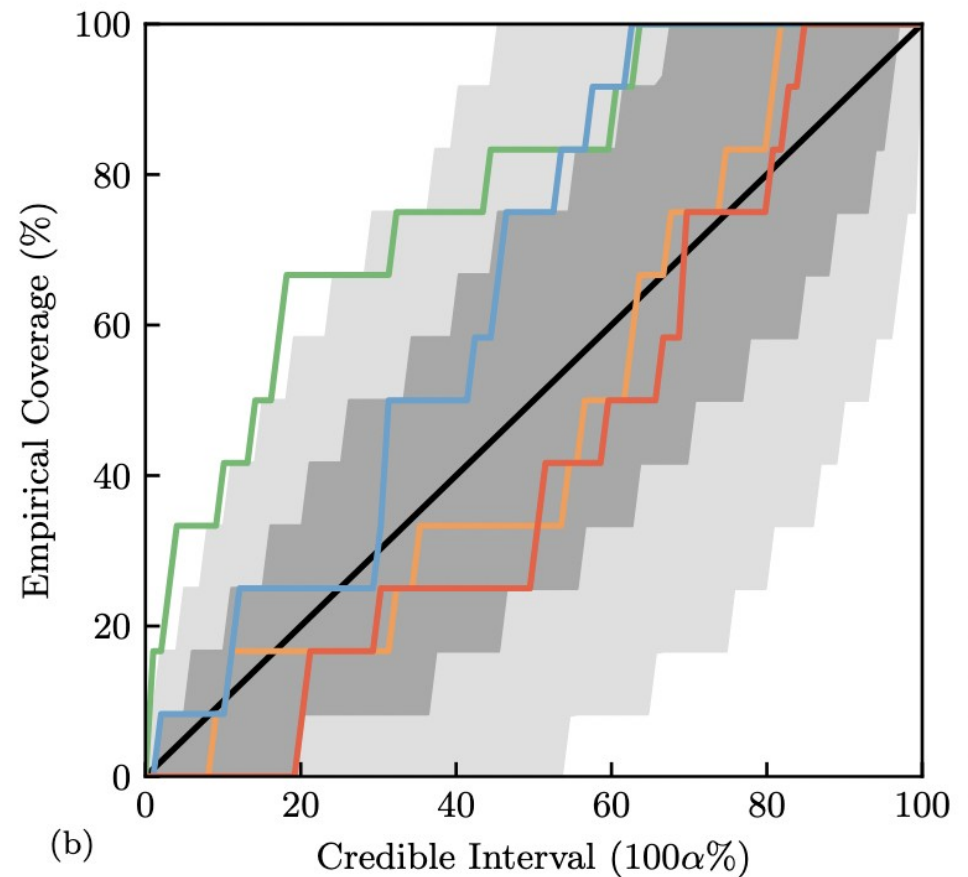
A hint of the philosophy of statistics

(Bayesian) credible interval

E.g., maximize posterior and take an $n\sigma$ error bar around that point.

Credible interval *does* imply degree of belief about our single dataset, but *does not* provide guaranteed coverage across datasets.

N.B. BUQEYE collaboration interprets coverage order-by-order



A hint of the philosophy of statistics

Summarizing attractive features

- (Frequentist) confidence interval has guaranteed coverage across datasets
- (Bayesian) credible interval combines prior and likelihood to encapsulate degree of belief about our single dataset

A hint of the philosophy of statistics

Summarizing attractive features

- (Frequentist) confidence interval has guaranteed coverage across datasets
- (Bayesian) credible interval combines prior and likelihood to encapsulate degree of belief about our single dataset

Can you get the best of both worlds?

- Yes (*contra* Betteridge's law of headlines)
- Conformal prediction is a tool that post-processes any pre-trained model to produce guaranteed coverage

Conformal prediction

- Distribution-free and model-agnostic uncertainty-quantification method
- Provides finite-sample prediction intervals with guaranteed coverage
- It accomplishes this by employing the quantile function (inverse of the cumulative distribution function) in an ingenious way:

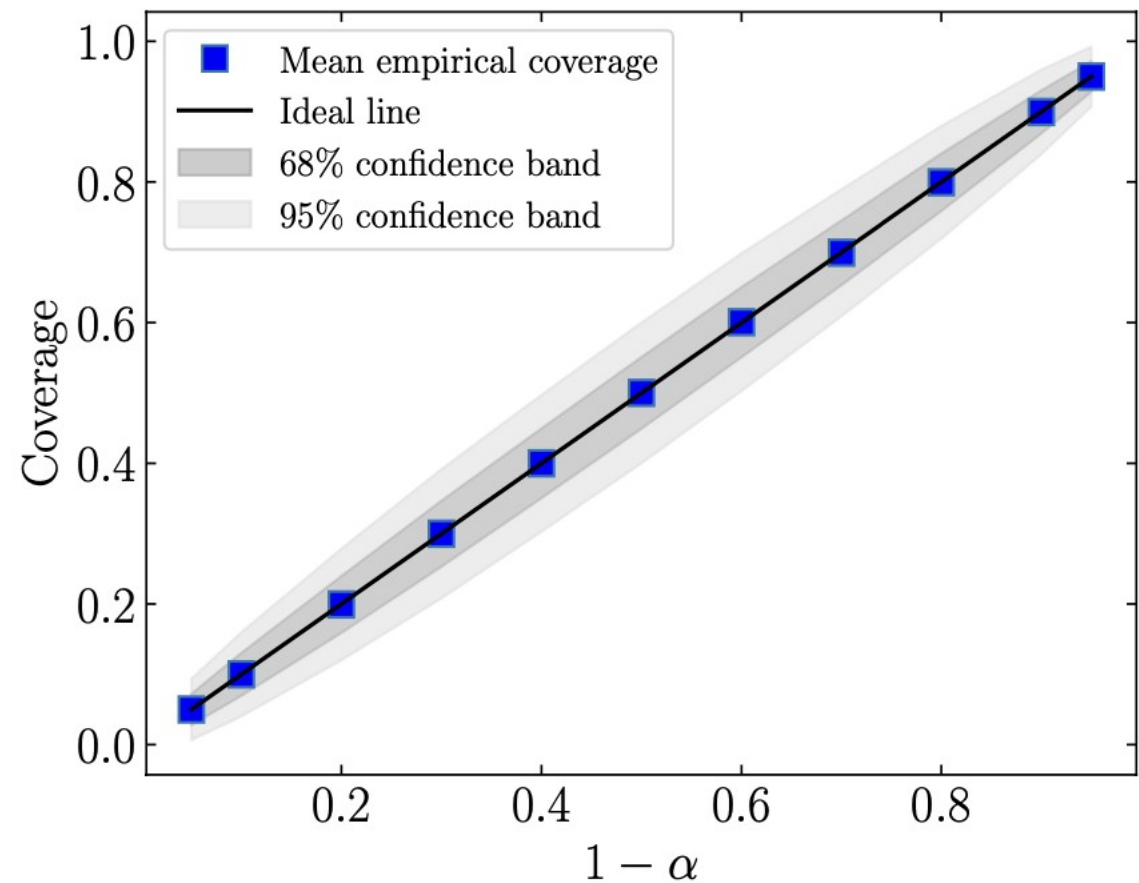
$$C(X_{n+1}) = [Q_Y \left(\frac{\alpha}{2} \mid X_{n+1} \right) - q, Q_Y \left(1 - \frac{\alpha}{2} \mid X_{n+1} \right) + q]$$

$$\text{where } q = Q_S(1 - \alpha)$$

Conformal prediction

Application: BUQEYE pointwise model

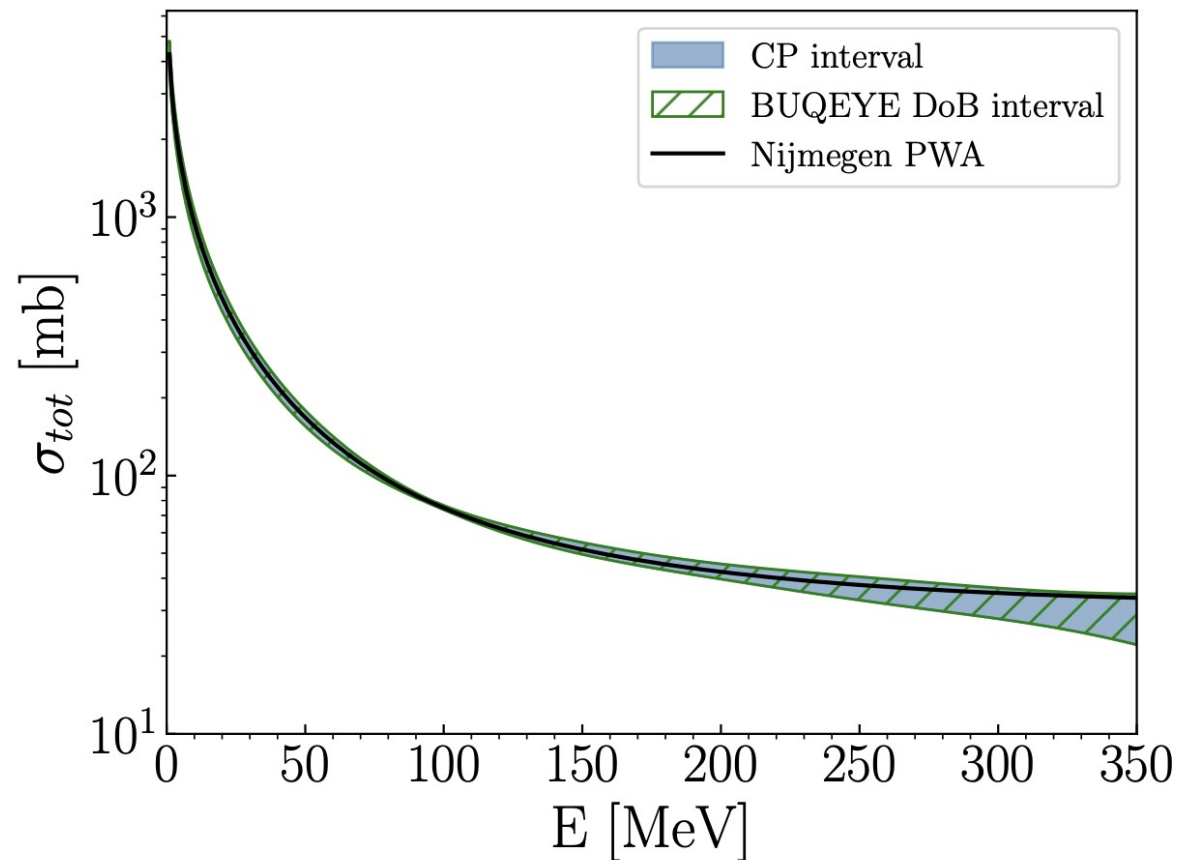
- Two-nucleon total cross section at $E = 50$ MeV
- Empirical coverage over 4000 independent trials
- There is near-perfect alignment between empirical coverage and ideal line



Conformal prediction

Application: BUQEYE Gaussian-process model

- Two-nucleon total cross section at N²LO 0.9 fm EKM potential
- BUQEYE's GP is a non-parametric model
- To generate the conformal prediction bands we drew posterior samples using the BUQEYE open-source code



Neural-network wave functions for light nuclei

P. Weng, A. Gezerlis, and J. Holt, arXiv:2505.11442

Quantum Monte Carlo in one slide

Variational Monte Carlo

Encode parameters in trial wave function Ψ_V and use Rayleigh-Ritz principle to minimize expectation value of Hamiltonian

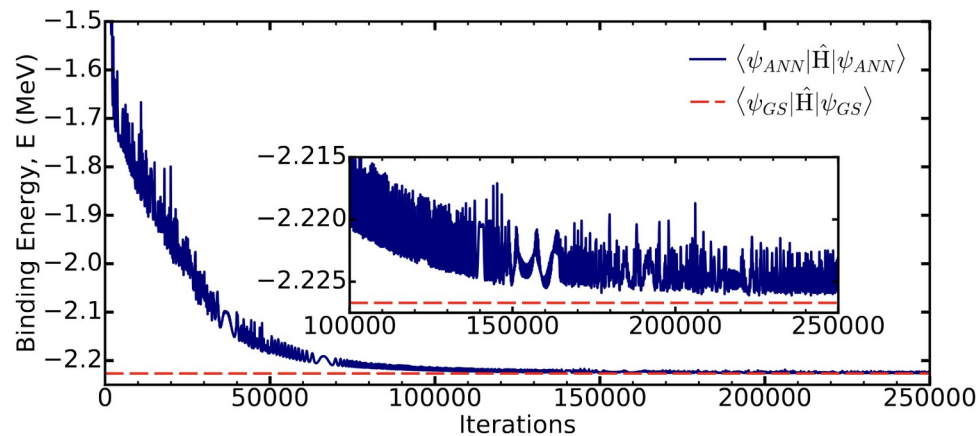
Diffusion Monte Carlo

Project out excited-state contributions, to reach the ground state

$$\Psi(\tau \rightarrow \infty) = \lim_{\tau \rightarrow \infty} e^{-(\mathcal{H} - E_T)\tau} \Psi_V$$

Earlier work

Deuteron



J. W. T. Keeble and A. Rios,
Phys. Lett. B **809**, 135743 (2020)

Light nuclei

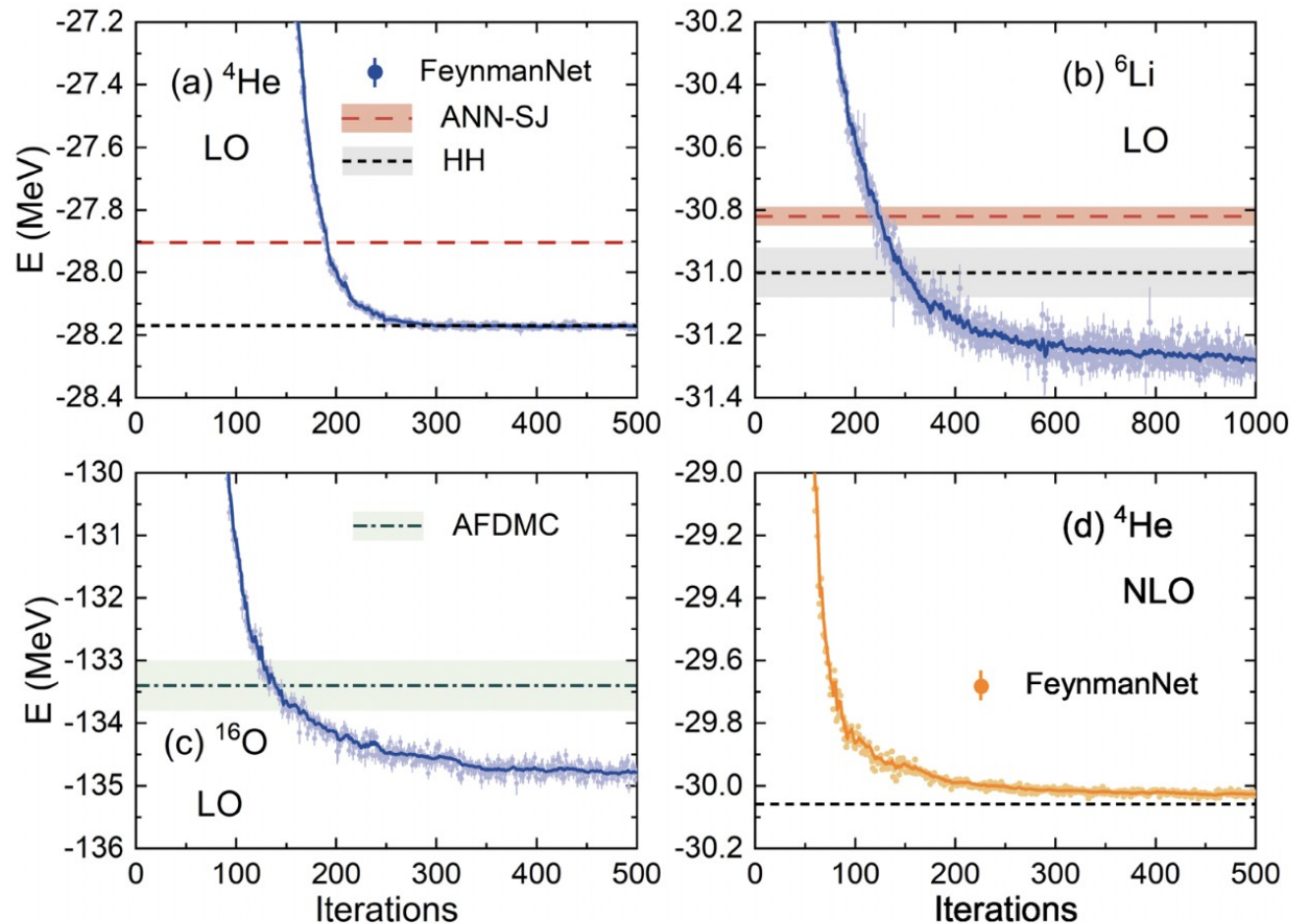
| | Λ | VMC-ANN | VMC-JS | GFMC | GFMC _c |
|---------------|--------------------|-----------|-----------|-----------|-------------------|
| ^2H | 4 fm ⁻¹ | -2.224(1) | -2.223(1) | -2.224(1) | - |
| | 6 fm ⁻¹ | -2.224(4) | -2.220(1) | -2.225(1) | - |
| ^3H | 4 fm ⁻¹ | -8.26(1) | -7.80(1) | -8.38(2) | -7.82(1) |
| | 6 fm ⁻¹ | -8.27(1) | -7.74(1) | -8.38(2) | -7.81(1) |
| ^4He | 4 fm ⁻¹ | -23.30(2) | -22.54(1) | -23.62(3) | -22.77(2) |
| | 6 fm ⁻¹ | -24.47(3) | -23.44(2) | -25.06(3) | -24.10(2) |

C. Adams, G. Carleo, A. Lovato, N. Rocco,
Phys. Rev. Lett. **127**, 022502 (2021)

N.B. Limited to pionless Hamiltonian

Earlier work

More on light nuclei



Y. L. Yang and P. W. Zhao, Phys. Rev. C **107**, 034320 (2023)

N.B. Also limited to pionless Hamiltonian

Neural networks for light nuclei

Spin-isospin correlations

$$|\psi\rangle = \mathcal{S} \prod_{i < j} \left(1 + \sum_{\mathbf{x}} u_{ij}^{(\mathbf{x})} \hat{O}_{ij}^{(\mathbf{x})} \right) f_{ij}^{(c)} |\Phi\rangle$$

$$|\psi\rangle \rightarrow \left(1 + \sum_{i < j < k} \sum_{\text{cyc}} \sum_{\mathbf{x}} \epsilon^{(\mathbf{x})} \hat{V}_{ijk}^{(\mathbf{x})} \right) |\psi\rangle$$

for N²LO chiral Hamiltonian

P. Weng, A. Gezerlis, and J. Holt, arXiv:2505.11442

Neural networks for light nuclei

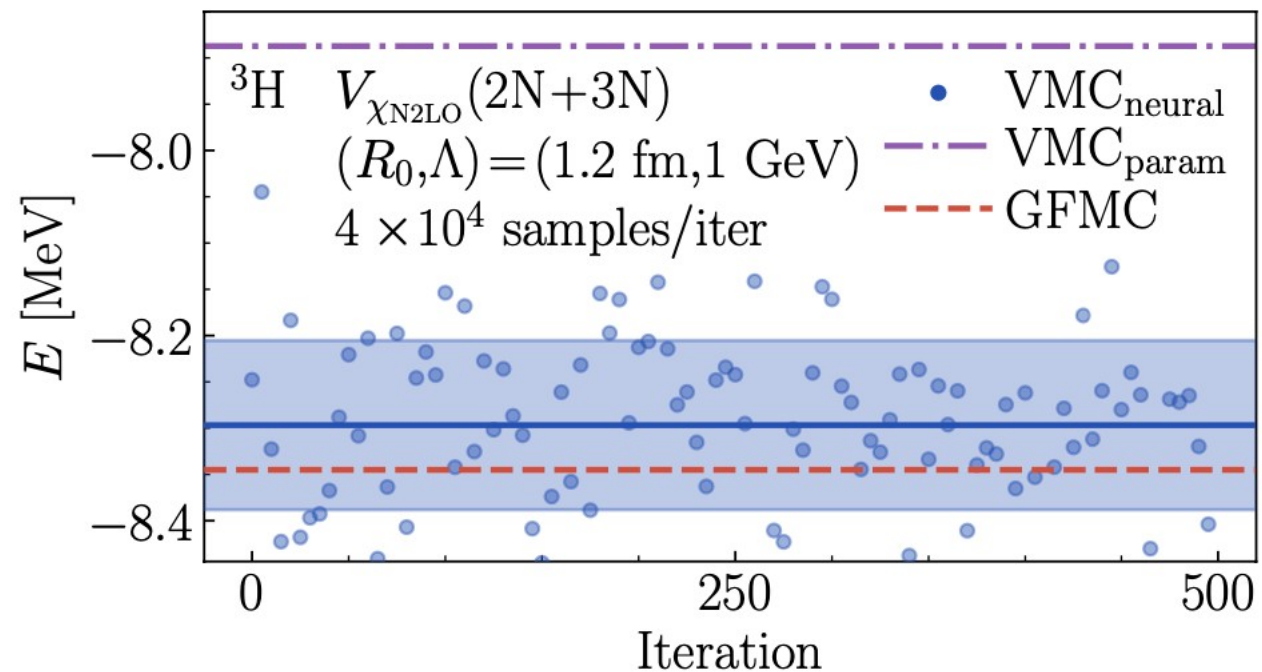
Nearly reproduces GFMC results
already at the VMC level

| $E = E_k + V_{\chi\text{N}^2\text{LO}}(2\text{N})$ | | | | |
|--|------------|---------------------------|-------------------------|--------------------------------|
| | R_0 [fm] | E_{neural} [MeV] | E_{GFMC} [MeV] | $ \Delta E / E_{\text{GFMC}} $ |
| ${}^3\text{H}$ | 1.0 | -7.338 ± 0.008 | -7.554 ± 0.007 | 2.9% |
| | 1.1 | -7.500 ± 0.006 | -7.625 ± 0.005 | 1.6% |
| | 1.2 | -7.678 ± 0.005 | -7.740 ± 0.005 | 0.8% |
| ${}^2\text{H}$ | 1.0 | -2.217 ± 0.005 | -2.21 ± 0.02 | 0.3% |
| | 1.2 | -2.212 ± 0.004 | -2.20 ± 0.03 | 0.5% |

P. Weng, A. Gezerlis, and J. Holt, arXiv:2505.11442

Neural networks for light nuclei

Dramatic improvement over
standard/parametric VMC
employed before, e.g., AFDMC



P. Weng, A. Gezerlis, and J. Holt, arXiv:2505.11442

Emulators for the triton

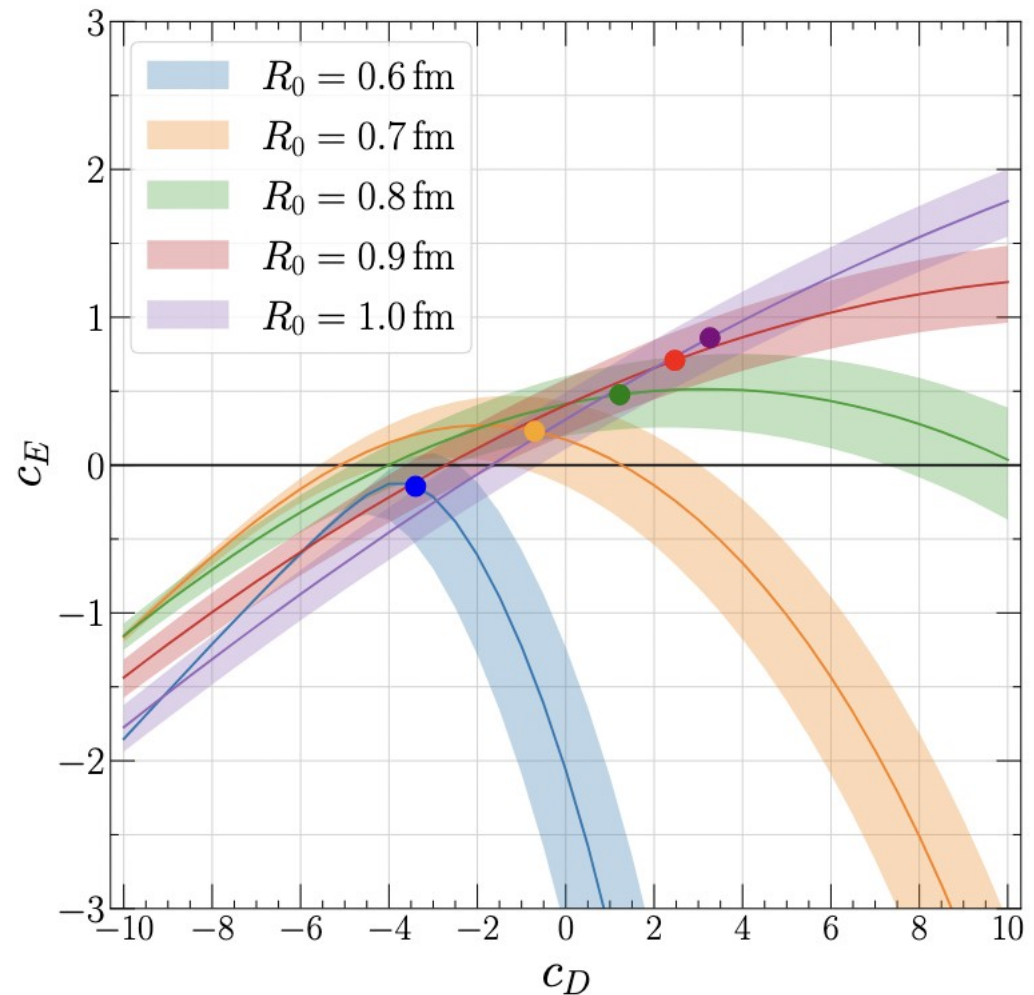
R. Curry, A. Gezerlis, K. Hebeler, A. Schwenk, R. Somasundaram, and I. Tews, *in preparation*

Fitting the three-nucleon interaction

Solve Faddeev equations for triton binding energy to find a curve

Employ triton beta-decay half-life to single out a point (for each interaction)

This process is computationally quite costly



Tews, Somasundaram, Lonardon, Goettling, Seutin, Carlson, Gandolfi, Hebeler, Schwenk, Phys. Rev. Research 7, 033024 (2025)

Emulators in one slide

I'm probably running out of time, so I refer to the previous two talks for a summary of previous applications of emulators to nuclear physics.

- **Parametric Matrix Model (PMM):** use approximate model with matrices of chosen dimensionality:

$$\hat{H} = H_0 + c_D H_D + c_E H_E$$

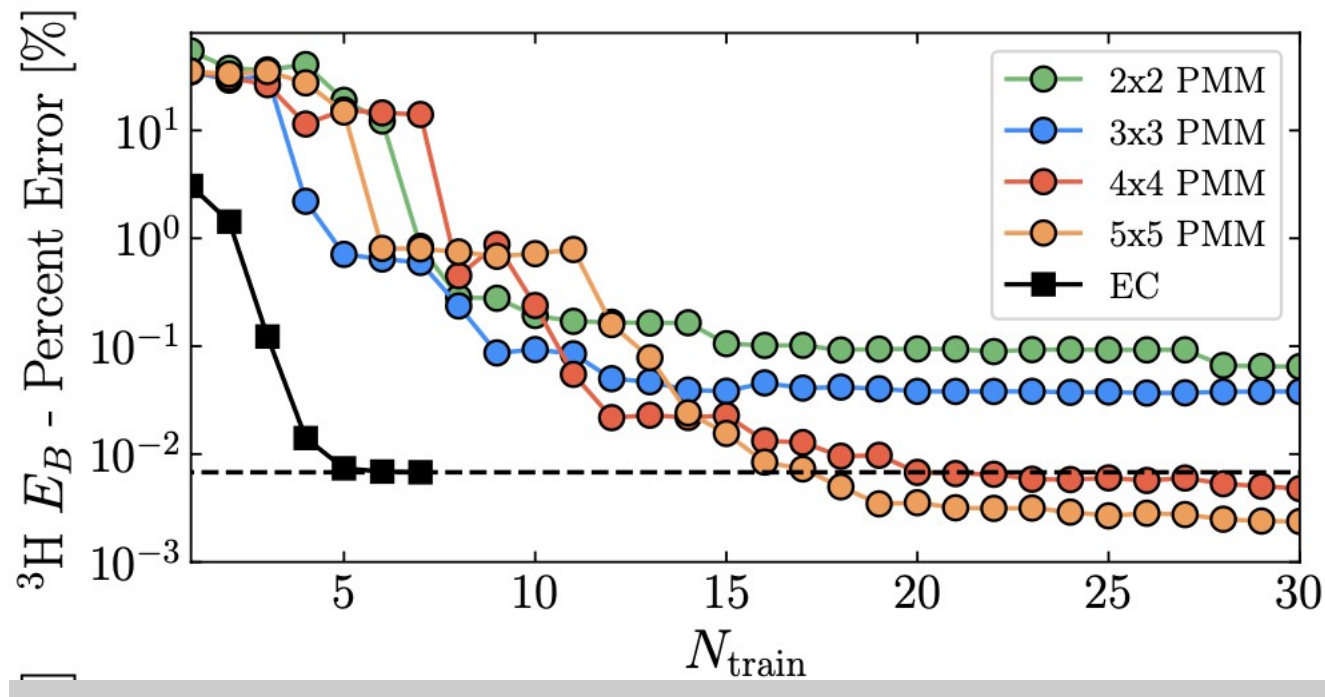
- **Eigenvector continuation (EC):** Solve within a subspace (leading to generalized eigenvalue problem):

$$\sum_i H |\psi_j\rangle = E \sum_j |\psi_j\rangle$$

Varying the three-nucleon interaction

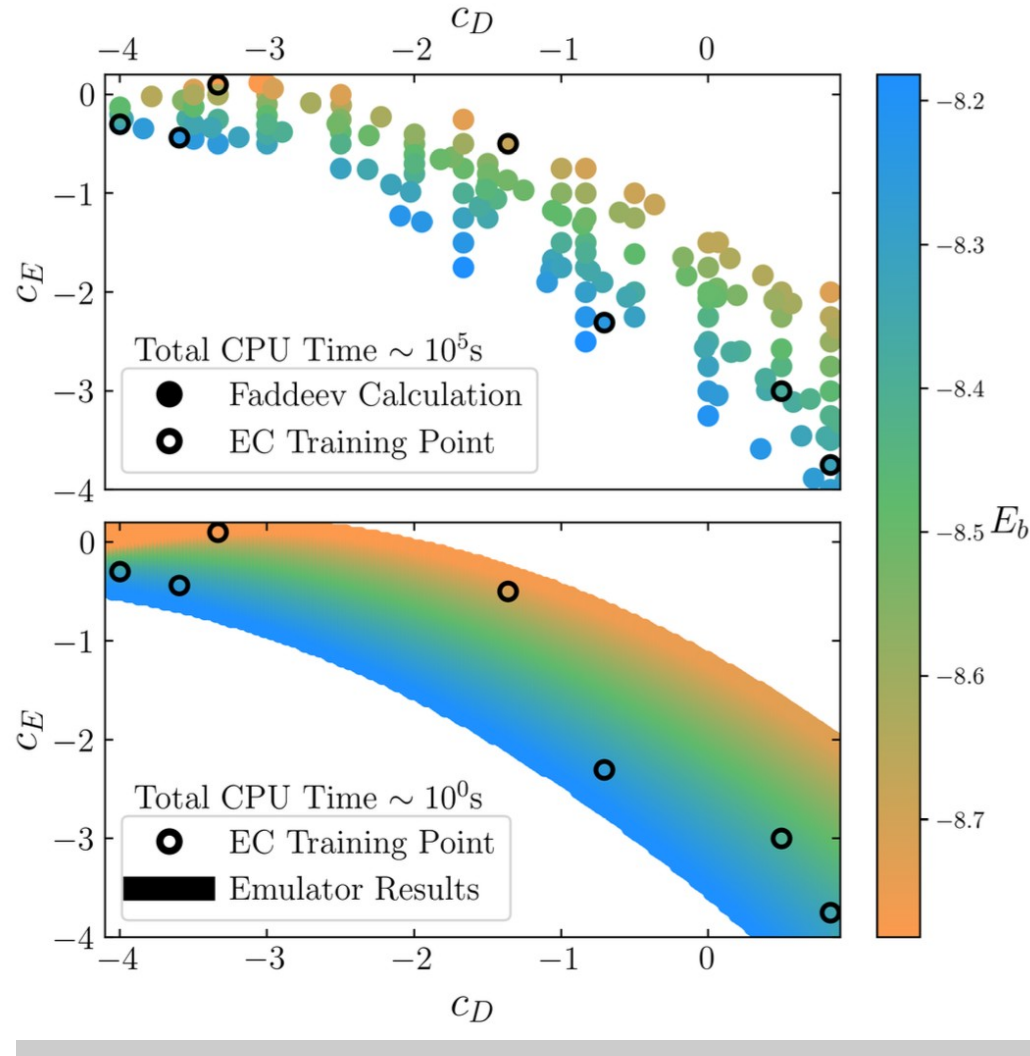
150 training data points + 75 test data points

New criterion for how to reject linearly dependent new training points



Varying the three-nucleon interaction

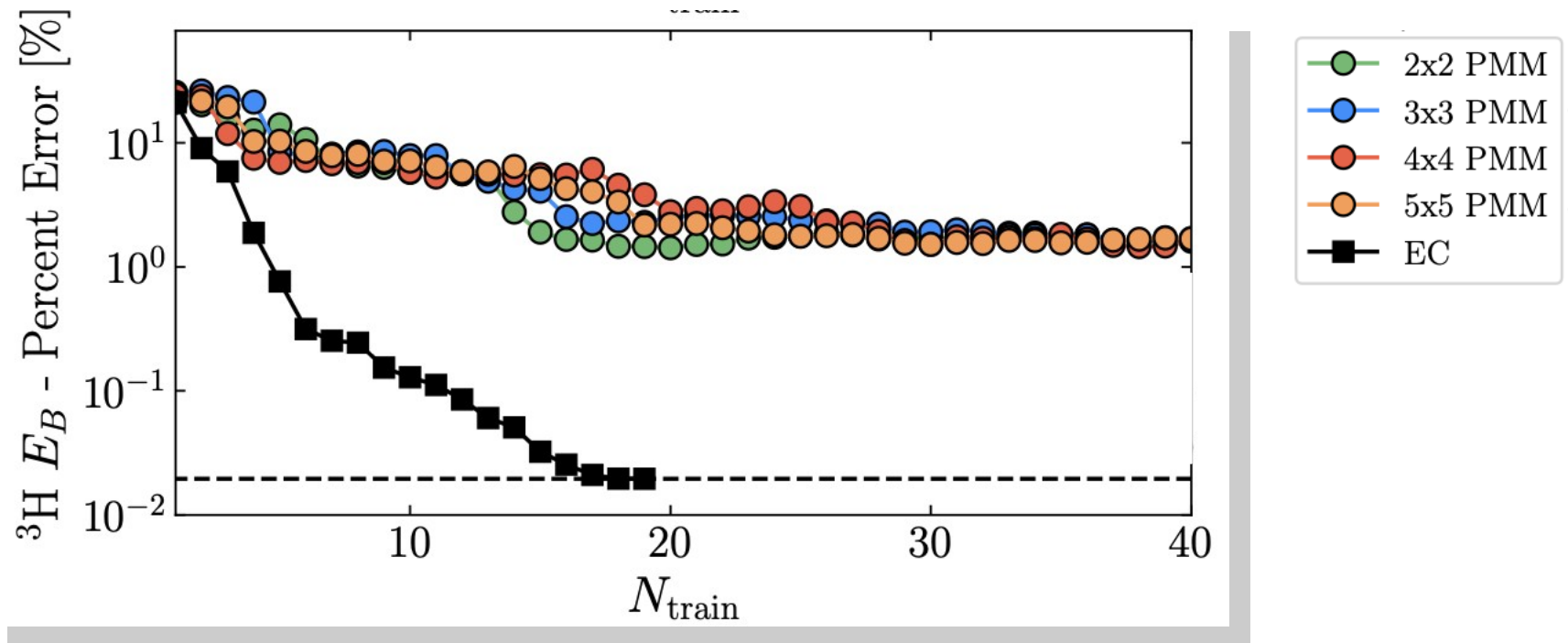
Now that the calculation is so cheap, we can fill out the plot:



Varying the full interaction

Release the full interaction, leading to 11 matrices:

$$\hat{H} = H_0 + c_S H_S + c_T H_T + \sum_{i=1}^7 c_i H_i + c_D H_D + c_E H_E$$



Conclusions

- We applied conformal prediction to nuclear physics
- We used chiral Effective Field Theory interactions in neural-network studies of light nuclei
- We used PMM and EC emulators for the three-nucleon problem

Acknowledgments

Collaborators

Guelph

- Ryan Curry
- Habib Yousefi Dezdaran

Los Alamos

- Rahul Somasundaram
- Ingo Tews

Texas A&M

- Jeremy Holt
- Pengsheng Weng

TU Darmstadt

- Kai Hebler
- Achim Schwenk

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MINISTRY OF RESEARCH AND INNOVATION
MINISTÈRE DE LA RECHERCHE ET DE L'INNOVATION

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