Global Sensitivity Analysis of Bulk Properties of an Atomic Nucleus

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Presenting work from collaboration with

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Overview

- Fast and accurate emulation using eigenvector continuation (EC)
- Sub-space projected coupled cluster theory (SP-CC)
- Global sensitivity analysis of the ground-state energy/radius of 16-Oxygen
- Recent developments:SP-CC and excited states, Bayesian parameter estimation, GPUs

Physics questions

- How do properties of atomic nuclei depend on the underlying interaction between protons and neutrons?
- What is the predictive power of ab initio nuclear theory?
- Some interaction models work better than others, but only for selected types of observables and in limited regions of the nuclear chart, e.g. NNLO_{sat}, 1.8/2.0 (EM), ΔNNLO_{go}. Why?

Summary

The sub-space projected coupled-cluster method enables emulation of Hamiltonians at unprecedented speed:

- Ground-state energy
- Ground-state radius
- Excited state energies ullet
- A global sensitivity analysis indicates that the NNLO description of the radius of 16-0 depends sensitively on higher order correlations between the LECs.
- **Bayesian inference** in nuclear physics is rapidly moving forward.
- **Outlook**: sophisticated statistical computation in ab initio nuclear theory!

- **nuclear observables** at different values of the coupling constants in chiral

(Next talk by C. Forssén)

Bayesian inference: from likelihood & prior to posterior.

- Collect N data points that we gather in a data vector **D** lacksquare
- Propose some model M to explain the data, depending on the parameter vector $\boldsymbol{\alpha}$
- Apply Bayes' theorem

Likelihood Prior Marginal likelihood

Posterior $P(\vec{\alpha}|D, M) = \frac{P(D|\vec{\alpha}, M) \cdot P(\vec{\alpha}|M)}{P(D|M)}$

- The prior encodes our knowledge about the parameter values before analyzing the data -
- The likelihood of the data given a set of parameters
- The marginal likelihood (or model evidence) provides normalization of the posterior
- The posterior is the complete inference and resulting probability density for the parameters α

Computing nuclei: the curse of dimensionality

Solving the Schrödinger equation for a large collection of strongly interacting nucleons is an interesting challenge that typically requires substantial high-performance computing resources.

 $H|\Psi_i\rangle$

Rigorous uncertainty quantification and sensitivity analyses require a large number of model samples. The demand also increases exponentially with the number of uncertain model parameters. Clearly, this is not feasible given the computational cost of existing many-body methods.

$$=E_i|\Psi_i\rangle$$



2004

"Eigenvector Continuation as an Efficient and Accurate Emulator for Uncertainty Quantification"

S. König, et al. arXiv:1909.08446 [nucl-th]



Eigenvector continuation: emulating nuclei

We have a Hamiltonian that depends smoothly on some LECs $\hat{H}(\vec{lpha})$



D. Frame, et al. Phys. Rev. Lett. 121, 032501 (2018)

(See S. König talk)

- For the potential models we can often write the LEC dependence as $\hat{H}(\vec{\alpha}) = \hat{H}_0 + \sum_{i=1}^N \alpha_i \hat{H}_i$
- We seek the lowest energy and wavefunction in a given symmetry class for some target value $ec{lpha}_{ ext{target}}$
 - Project each term \hat{H}_i to the eigenvector subspace, represented here by a 4-by-4 matrix, and **quickly** solve for the eigenvalues and eigenvectors at any $ec{lpha}_{ ext{target}}$
 - Tremendous gain: replaced original large space eigenvalue problem with a generalized eigenvalue problem of considerably smaller dimension.

$$\Psi(\vec{\alpha}_{\text{target}})\rangle = E_{\text{target}}N|\tilde{\Psi}(\vec{\alpha}_{\text{target}})\rangle$$



Eigenvector continuation: example (Nparameters=16)

-250Regression prediction (MeV) 16 dimensions, 64 training data -500Eigenvector Continuation Polynomial Interpolation -750Gaussian Process -1000-1250-1500-200-150

0



⁴He NNLO(450)

S. König, et al. arXiv:1909.08446 [nucl-th]



What about heavier systems?

"Global Sensitivity Analysis of Bulk Properties of an Atomic Nucleus"

A. Ekström and G. Hagen Phys. Rev. Lett. **123**, 252501 (2019)



Sub-space projected coupled-cluster theory

The no-core shell-model for nuclei corresponds to fully diagonalizing the nuclear Hamiltonian. Straightforward, although computationally expensive with increasing mass number.

The sub-space projected coupled-cluster (SP-CC) Hamiltonian, which we end up diagonalizing, is non-hermitian and given by

$$\langle \tilde{\Psi}' | H(\vec{\alpha}_{target}) | \Psi \rangle = \langle \Phi_0 | (1 + \Lambda(\vec{\alpha}')) e^{-T(\vec{\alpha}') + T(\vec{\alpha})} \overline{H}(\vec{\alpha}_{target}) | \Phi_0 \rangle$$
Large-space CCSD states
at $\vec{\alpha}'$ and $\vec{\alpha}$

- **Coupled-cluster (CC)** theory exploits a similarity transformed Hamiltonian $\bar{H}(\vec{\alpha}) = e^{-T(\vec{\alpha})}H(\vec{\alpha})e^{T(\vec{\alpha})}$
- Where in the singles and doubles approximation (CCSD) the cluster operator is $T(\vec{\alpha}) = T_1(\vec{\alpha}) + T_2(\vec{\alpha})$

A. Ekström and G. Hagen Phys. Rev. Lett. **123**, 252501 (2019)





















































±20% variation in all parameters with respect to a well-know point

Two sets of exact CCSD calculations to setup two sub-space projected CCSD Hamiltonians

SPCC(64)SPCC(128)

Takes a few milliseconds to diagonalize exactly

Incorporate prior information: $H_{\rm nn} \approx H_{\rm np} \approx H_{\rm pp}$ Coupled-cluster singles and doubles approximation CCSD N_{max}=10, hw=16 MeV, E_{3max}=14

Harmonic oscillator basis

A. Ekström and G. Hagen Phys. Rev. Lett. **123**, 252501 (2019)

Cross-validation

SPCCSD matrices for ¹⁶O available

Global sensitivity analysis (GSA)

<u>Sensitivity analysis</u> addresses the question 'How much does each model parameter contribute to the uncertainty in the prediction?'

<u>Uncertainty analysis addresses the question 'How uncertain is the prediction?'</u>

<u>Variance-based methods</u> for GSA decompose the variance of a certain model output in terms of each input and their combinations.

<u>Global</u> methods deal with the uncertainties of the outputs due to input variations over the whole domain.

Sobol sensitivity analysis

Given models for some observable(s)

$$E = f_E(\alpha_1, \alpha_2, \dots, \alpha_N)$$
$$R = f_R(\alpha_1, \alpha_2, \dots, \alpha_N)$$

Decompose the total variance:

$$\operatorname{Var}[Y] = \sum_{i}^{N} V_i + \sum_{i < j}^{N} V_{ij} + \dots$$

Basically requires multiple model evaluations across some pre-determined parameter domain

Compute the variance integrals using MC sampling, which is the computationally expensive part

$$V_i = \operatorname{Var}[\mathbb{E}_{\vec{\alpha} \sim \alpha_i}[Y|\alpha_i]]$$

 $V_{ij} = \operatorname{Var}[\mathbb{E}_{\vec{\alpha} \sim (\alpha_i, \alpha_j)}[Y|\alpha_i, \alpha_j]] - V_i - V_j$

We find it necessary to do ~1 Million computations of ¹⁶O to extract statistically significant variances With SPCCSD(68), 1 hour on my MacBook Pro (2016) I. M. Sobol Mathematic and Computers in in Simulation 55, 271 (2001)

Sensitivity indices

$$S_{ij} = \frac{V_{ij}}{\operatorname{Var}[Y]}$$

$$S_{Ti} = S_i + S_{ij} -$$

Easier to compute the sum

progressively more difficult to compute

"Main effect"

A number between 0 and 1

Second order index Another number between 0 and 1

$$-\sum_{i < j < k} S_{ijk} + \dots$$

$$+S_{ijk}+\ldots$$

"Total effect"

More recent developments

Including Δ -isobars and CC triples: ground states

(See C. Forssén talk for details)

Including Δ -isobars and CC triples: ground states

(See C. Forssén talk for details)

Including Δ-isobars and CC triples: excited states

(See C. Forssén talk for details)

Bayesian estimation of c_D and c_E

 $c_D = -0.77, c_E = -0.31$ 0.0 **NN-NNLO**sat -0.1Fixed all LECs but cD/cE Use EC for likelihood evaluations -0.2

$$We gie Ct \ 2 LEC$$

$$-0.3$$

$$-0.4$$

$$-0.5$$

$$P(c_D, c_E | \mathbf{y}_{exp}, I)$$

$$-0.6$$

$$-2.0$$

$$-1.5$$

$$-1.0$$

$$-0.5$$

$$0.0$$

 C_D

S Wesolowski et al., J. Phys. G: Nucl. Part. Phys. 46, 045102 (2019)

In progress, and preliminary

S. Wesolowski, Chalmers, et al.

1.0 Data: energy/radius of ⁴He, energy of ³H Potential model: NNLO, only vary c_D & c_E (Using EC) - 0.8 Log-likelihood proportional to:

0.6
$$(\mathbf{y}_{exp} - \mathbf{y}_{th})^T (\mathbf{\Sigma}_{exp} + \mathbf{\Sigma}_{th})^{-1} (\mathbf{y}_{exp} - \mathbf{y}_{th})$$

Assume uncorrelated LEC and truncation errors

 $\Sigma_{\rm th} = \Sigma_{\rm LEC} + \Sigma_{
m truncation}$

$$\mathbf{2} \qquad (\mathbf{\Sigma}_{\text{th}})_{ij} = (\mathbf{\Sigma}_{\text{LECs}})_{ij} + \left[\frac{\bar{c}_i^2 (y_{\text{ref}})_i^2 Q_i^2}{1 - Q_i^2}\right] \delta_{ij}$$

$$Q = \frac{m_{\pi}}{\Lambda_b}, \ \Lambda_b = 600 \,\mathrm{MeV}, \ \bar{c}_i = 1 \,\mathrm{for \,\,all} \,i$$

ToDo: add LEC errors study prior dependencies

0.4

0.

0.0

Observable posteriors

In progress, and preliminary

bound state momentum scale?

EC emulation of NCSM calculations of triton beta-decay $fT_{1/2}[^{3}\mathrm{H} \rightarrow {}^{3}\mathrm{He}] (\mathrm{s})$ **Cross validation** Eigenvector continuation

Including triton beta decay

In progress, and preliminary

Bayesian LEC estimation using HMC

NLO(500), select np scattering data with T_{lab}<100 MeV Normal LEC prior: mean=0,variance=5 Uncorrelated truncation errors $\bar{c} = 1.55$

 $(\Sigma_{\text{th,uncorr.}})_{ij} = (\mathbf{y}_{\text{ref}})_i^2 \, \bar{c}^2 \sum_{n=k+1}^{k_{\text{max}}} Q_i^{2n} \delta_{ij} \xrightarrow[k_{\text{max}} \to \infty]{} \frac{(\mathbf{y}_{\text{ref}})_i^2 \, \bar{c}^2 \, Q_i^{2k+2}}{1 - Q_i^2} \, \delta_{ij}$

S Wesolowski et al., J. Phys. G: Nucl. Part. Phys. 46, 045102 (2019)

Questions/ToDo:

HMC/MCMC convergence diagnostics Identifying multiple modes (History Matching?) Posterior predictive distribution with theory errors

In progress, and preliminary

ISak Svensson

GPU/Wave-packet computation of NN scattering cross sections

"Computation via an approximate method and batched CUDA calls" GPU challenge: efficient diagonalization of many small (< '100 x 100') matrices

0. A. Rubtsova et al. Annals of Physics 360, 613–654, (2015)

Sean Miller

Looking ahead

The SP-CC method and eigenvector continuation enables sophisticated statistical computation in ab initio nuclear theory. This can help reveal which data would reduce the uncertainty in Hamiltonian models the most and provide key insights for understanding how the properties of atomic nuclei depend on the underlying interaction between protons and neutrons.

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Thank You for Your Attention!

- **nuclear observables** at different values of the coupling constants in chiral

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