

## **BAYESIAN POSTERIORS IN THE NUCLEON-NUCLEON SECTOR**

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## Outline

Part 1:

Many-body systems in finite oscillator spaces

- IR extrapolations at fixed UV cutoff
- Low-momentum scales of finite nuclei



#### Part 2:

Bayesian data analysis in the nucleon-nucleon sector

- Proof-of-principle demonstration with posterior sampling, error propagation.
- Outlook

#### Progress report



#### The NCSM curse of dimensionality – explicit matrix storage



#### 6-Li ground-state observables



From  $N_{max}$ =20 to 22 the variational minimum changes by < 90 keV

## **Convergence in finite oscillator spaces**

- What is the equivalent of Lüscher's formula for the harmonic oscillator basis? [Lüscher, Comm. Math. Phys. 104, 177 (1986)]
- Convergence in momentum space (UV) and in position space (IR) needed
   [Stetcu et al. (2007); Coon et al. (2012); Furnstahl et al. (2012, 2015); König et al. (2014)]
- Choose regime ( $N, \hbar \omega$ ) with negligible UV corrections.
- > The infrared error term is universal for short range Hamiltonians.
- It can be systematically corrected and resembles error from putting system into an infinite well.

$$E(L) = E_{\infty} + Ae^{-2k_{\infty}L} + \mathcal{O}(e^{-4k_{\infty}L})$$
$$\langle r^{2} \rangle_{L} \approx \langle r^{2} \rangle_{\infty} [1 - (c_{0}\beta^{3} + c_{1}\beta + c_{2})e^{-\beta}]$$

## What (precisely) is the IR scale L?

**Key idea**: compute eigenvalues of kinetic energy and compare with *corresponding* (hyper)spherical cavity to find L.

What is the corresponding cavity?

Single particle	A particles (product space)	A particles in No-core shell model
Diagonalize T <sub>kin</sub> =p <sup>2</sup>	Diagonalize A-body T <sub>kin</sub>	Diagonalize A-body T <sub>kin</sub>
3D spherical cavity	A fermions in 3D cavity	3(A-1) hyper-radial cavity
	$\left( \sum_{2} \right)^{1/2}$	2

$$L_{2} = \sqrt{2(N+3/2+2)}b \quad L_{\text{eff}} = \left(\frac{\sum_{nl}\nu_{nl}a_{l,n}}{\sum_{nl}\nu_{nl}\kappa_{l,n}^{2}}\right) \quad L_{\text{eff}} = b\frac{X_{1,\mathcal{L}}}{\sqrt{T_{1,\mathcal{L}}(N_{\text{max}}^{\text{tot}})}}$$

More, Ekström, Furnstahl, Hagen, Papenbrock, PRC 87, 044326 (2013) Furnstahl, Hagen, Papenbrock, Wendt, J. Phys. G 42, 034032 (2015) Wendt, Forssén, Papenbrock, Sääf, PRC 91, 061301(R) (2015)

## A practical approach to IR extrapolations

- In practice it is often challenging to fulfill:
  - 1.... being UV converged
  - 2. ... reaching asymptotically large values of  $k_\infty L$
- Moreover, we lack a physical interpretation of  $k_{\infty}$  for many-body systems.
- Perform instead the extrapolation at a fixed (not necessarily UV converged) value of Λ
- The LO IR extrapolation becomes

$$E(L,\Lambda) = E_{\infty}(\Lambda) + a(\Lambda) \exp\left[-2k_{\infty}(\Lambda)L\right]$$

#### Hyperradial well, explains low-momentum scale



NCSM: hyper-radial well 
$$\vec{\rho}^2 = \sum_{j=1}^{A-1} \vec{\rho}_j^2$$
.  $e^{-k_1 |\vec{\rho_1}|}$ 

Separation energy for lowest threshold

$$S = \frac{\hbar^2 k_\infty^2}{2m}$$

 $\mathcal{V}$ 

See also König and Lee, arXiv:1701.00279 for volume dependence of N-Body Bound States in lattice calculations.

#### **Results:** A=3 — ground-state energy





#### **Results: 6Li — ground-state energy**





# **BAYESIAN POSTERIORS IN THE NUCLEON-NUCLEON SECTOR**



## **Overview of our research efforts**

- Does nuclear-physics phenomena emerge in a "from few to many" ab initio approach?
- Is available few-body data sufficient to constrain this model? Does the model become fine-tuned?

We aim to develop the technology and ability to:

Diversify and extend the **statistical analysis** of chiral-EFT based nuclear interactions in a **data-driven** approach.



- Can/should emergent phenomena be used to constrain the model?
- How to quantify systematic uncertainties in such an approach?

Explore alternative strategies of informing the model about lowenergy many-body observables.



#### Inference

"the act of passing from one proposition, statement, or judgment considered as true to another whose truth is believed to follow from that of the former" (Webster)

Do premises  $A, B, \ldots \rightarrow$  hypothesis, H?

- Inductive inference: Premises bear on truth/falsity of H, but don't allow its definite determination
- Statistical Inference: Quantify the strength of inductive inferences from data and other premises to hypotheses about the phenomena producing the data.
- Quantify via probabilities, or averages calculated using probabilities. Frequentists and Bayesians use probabilities very different for this.

- Assume that hypothesis H<sub>i</sub> is a model M<sub>i</sub> with parameters
  α<sub>i</sub>.
- In frequentist statistics we devise a procedure to choose among H<sub>i</sub> using data D. Apply this procedure to D<sub>obs</sub>.
- Report long-run performance (e.g., how often it is correct, how "far" the choice is from the truth on average).

#### **FREQUENTIST CHI-SQUARED MINIMZATION**

#### Low-energy constants (LECs) need to be fitted to experimental data.

$$\chi^{2}(\vec{p}) \equiv \sum_{i} r_{i}^{2}(\vec{p}) = \sum_{j \in NN} r_{j}^{2}(\vec{p}) + \sum_{k \in \pi N} r_{k}^{2}(\vec{p}) + \sum_{l \in 3N} r_{l}^{2}(\vec{p})$$



- Efficient minimization algorithms (Levenberg-Marquardt, Newton), and statistical error analysis require **derivatives.** We use Automatic Differentiation (AD) for this purpose.
- There is a possibility to find several minima in the various channels; They will then multiply into many local minima that don't necessarily disappear when doing simultaneous optimisation of all parameters to all data.

#### **Parametric models**

- Assume that hypothesis  $H_i$  is a model  $M_i$  with parameters  $\alpha_i$ .
- In frequentist statistics we devise a procedure to choose among H<sub>i</sub> using data D. Apply this procedure to D<sub>obs</sub>.
- Report long-run performance (e.g., how often it is correct, how "far" the choice is from the truth on average).
- In **Bayesian statistics** we assess the hypotheses by calculating their probabilities  $p(H_i|...)$  conditional on known and/or presumed information using the rules of probability theory.
- Parameter estimation: Assume that the model M<sub>i</sub> is true; Compute: p(α<sub>i</sub> | D<sub>obs</sub>, M<sub>i</sub>, I)
- Model comparison: Compute ratio:  $p(M_i | D_{obs}, I) / p(M_j | D_{obs}, I)$

**Bayes' theorem** (follows from probability product rule):

$$\begin{array}{ll} \textbf{posterior} & \textbf{likelihood} & \textbf{prior} \\ p(\pmb{\alpha}|D,I) = \frac{p(D|\pmb{\alpha},I)p(\pmb{\alpha}|I)}{p(D|I)} \\ \textbf{normalization} \end{array}$$

**Marginalization:**  $p(\alpha_1|D, I) = \int d\alpha_2 \dots d\alpha_k p(\boldsymbol{\alpha}|D, I)$ 

- For many lessons and suggestions on the use of Bayesian methods in Effective Field Theories, see work by the BUQEYE collaboration (and talks by Daniel and Sarah).
- Here we report on progress in implementing Bayesian methods for parameter estimation in Chiral EFT (up to N3LO) using NN scattering data (phase shifts).



N2LO: deuteron channel







#### **Expectation integrals, error propagation**

Expectation integrals for observables can be performed using the posterior pdf

$$\langle O(\boldsymbol{\alpha}) \rangle = \int d\boldsymbol{\alpha} p(\boldsymbol{\alpha} | D, I) O(\boldsymbol{\alpha})$$
$$\approx \frac{1}{N} \sum_{j=1}^{N} O(\boldsymbol{\alpha}_j)$$
The MCMC elements

The MCMC algorithm generates N samples  $\{\alpha_j\}$  according to the posterior pdf

#### **Deuteron observables**





#### **Deuteron observables**



## **STATISTICAL ERROR ANALYSIS**

In a minimum there will be an uncertainty in the optimal parameter values p<sub>0</sub> given by the χ<sup>2</sup> surface.<sup>1</sup>



- Approximate the objective function with a quadratic form in the vicinity of the optimum. Compute the hessian matrix.
- Expand observables similarly, to second order

$$\mathcal{O}(\mathbf{p_0} + \Delta \mathbf{p}) - \mathcal{O}(\mathbf{p_0}) \approx (\Delta \mathbf{p}^T) \mathbf{J}_{\mathcal{O}} + \frac{1}{2} (\Delta \mathbf{p}^T) \mathbf{H}_{\mathcal{O}} (\Delta \mathbf{p})$$

> The covariance between two observables is then

 $\operatorname{Cov}(\mathcal{O}_A, \mathcal{O}_B) \approx \mathbf{J}_{\mathcal{O}_A}^T \operatorname{Cov}(\mathbf{p_0}) \mathbf{J}_{\mathcal{O}_B} + \operatorname{second} \operatorname{order}$ 



#### **Deuteron observables**



#### **Redundant parameters**



(see also Sarah's talk)

# Conclusion

## CONCLUSION

#### **Quantum many-body systems in finite oscillator spaces**

- Demonstration how to profitably perform IR extrapolations in practice.
- Large-scale exact diagonalization reveals the relevant low-momentum scale of finite nuclei related to the threshold energy for the first open decay channel.

#### **Bayesian methods for uncertainty quantification**

- Demonstrated successful sampling of Bayesian posterior pdfs in the nucleon-nucleon sector and the subsequent error propagation.
- Bayesian analysis will allow:
  - the incorporation of truncation errors using marginalisation
  - model validation
  - model checking.

see Daniels's and Sarah's talks

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