

Fast & accurate emulation of two-body scattering

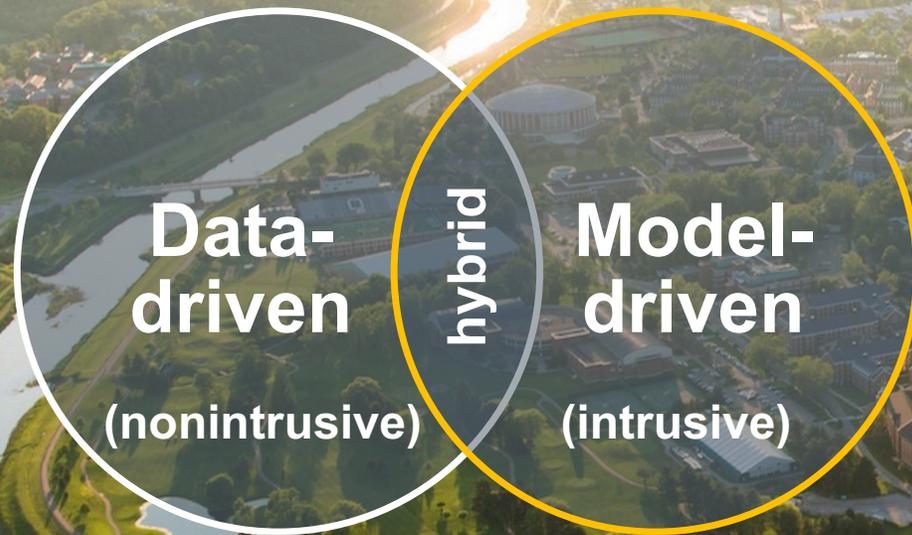
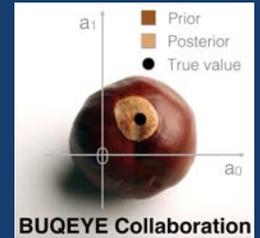


OHIO
UNIVERSITY

Christian Drischler (drischler@ohio.edu)

Eigenvector continuation & related techniques in nuclear structure & reaction theory

May 31, 2023 | Espace de Structure Nucléaire Théorique (CEA/DSM-DAM)



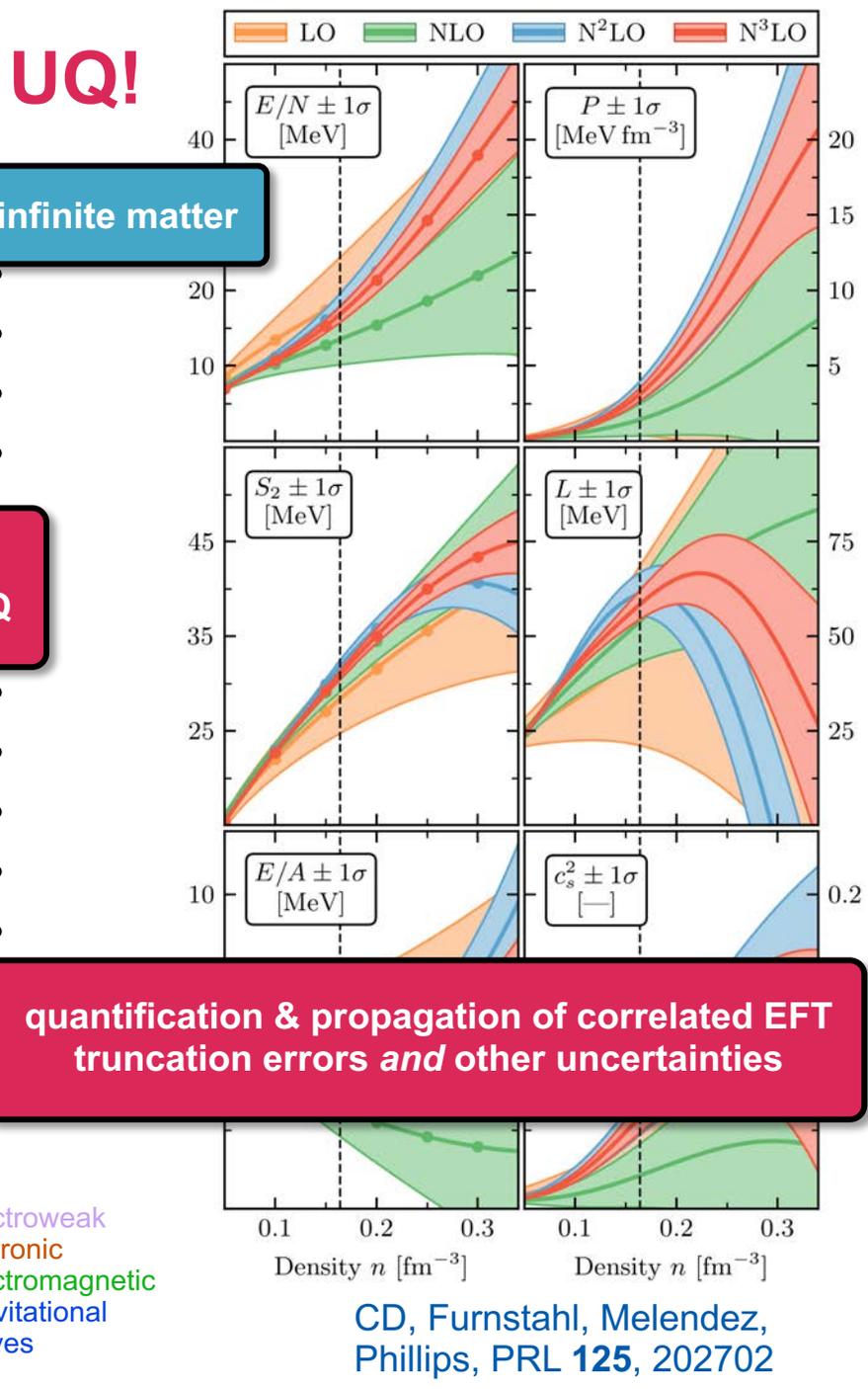
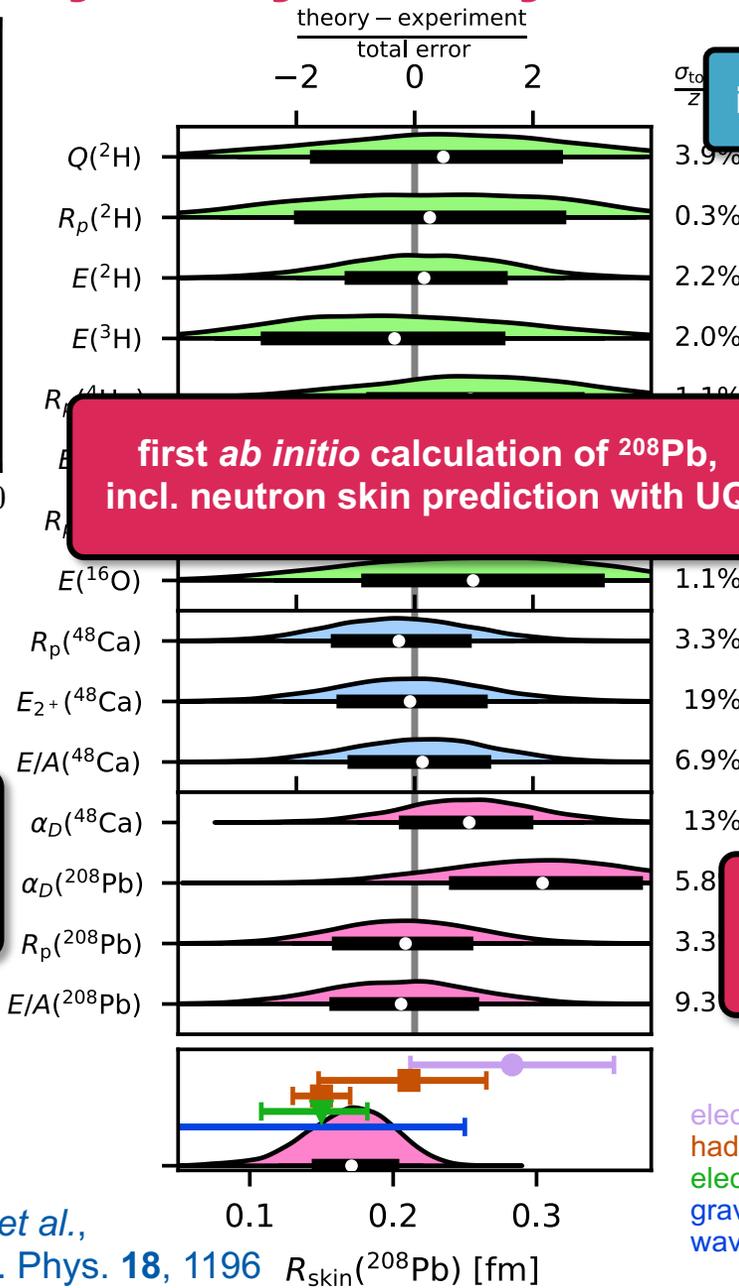
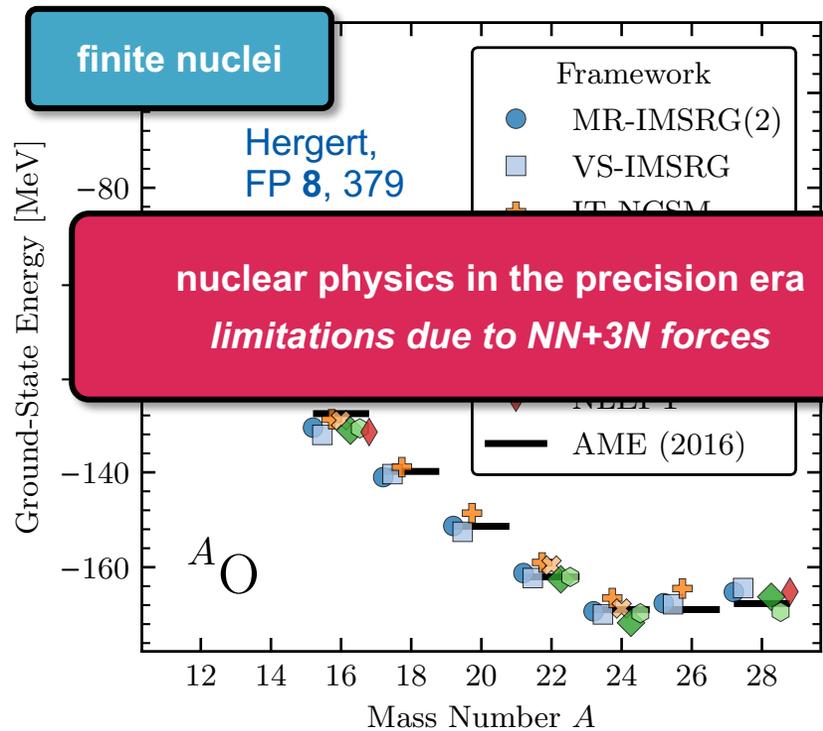
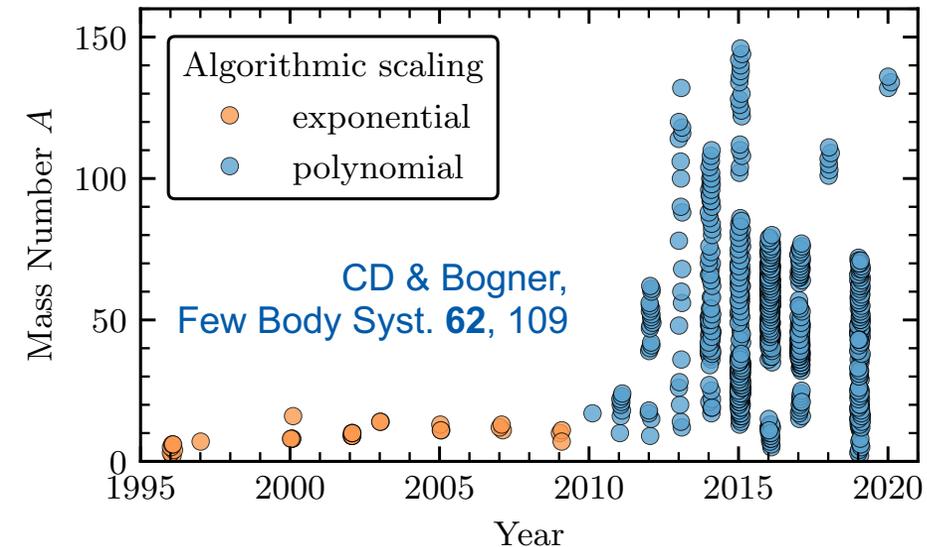
Reduced Order Model (ROM)
Classification

Ohio University Campus

Keywords:

- **Parametric Model Order Reduction**
- Reduced Basis Method
- **Galerkin Projection (Methods)**
- *Offline-Online* Decomposition
- Nuclear Scattering and Reactions
- Schwartz (or Kohn) Anomalies

Major process: CEFT, many-body theory, and UQ!



Motivation: mining scattering data

See also: talks at ISNET-9 last week at WUSTL: <https://physics.wustl.edu/isnet9>

Scattering experiments yield invaluable data for testing, validating, and improving chiral EFT (as well as reaction theory)

Competing formulations of chiral EFT with open questions on issues including

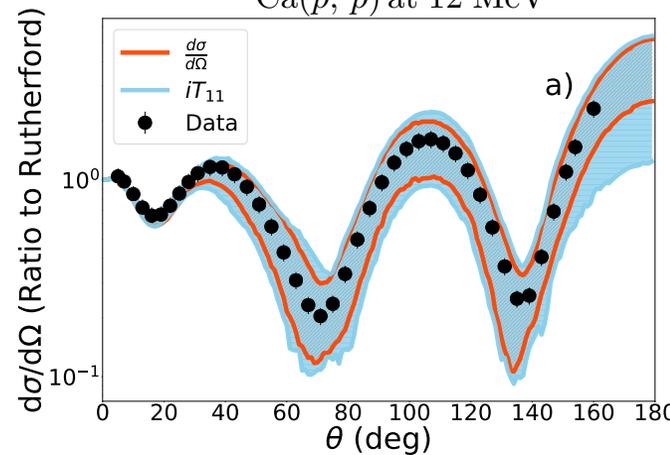
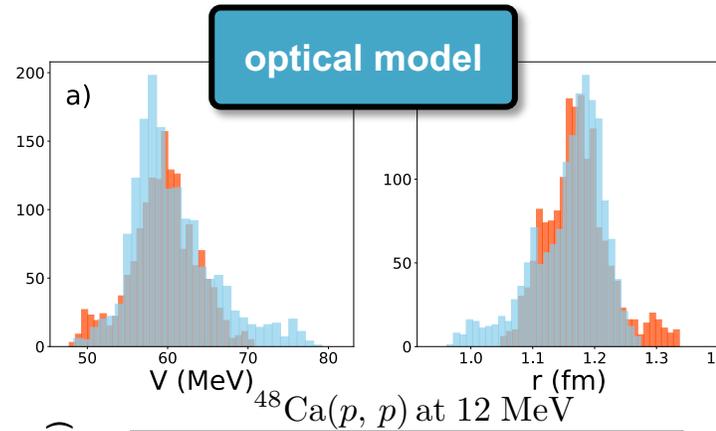
- EFT power counting
- sensitivity to regulator artifacts
- Differing predictions for medium-mass to heavy nuclei

see, e.g., Yang, Ekström *et al.*, *arXiv:2109.13303*
Furnstahl, Hammer, Schwenk, *Few Body Syst.* **62**, 72

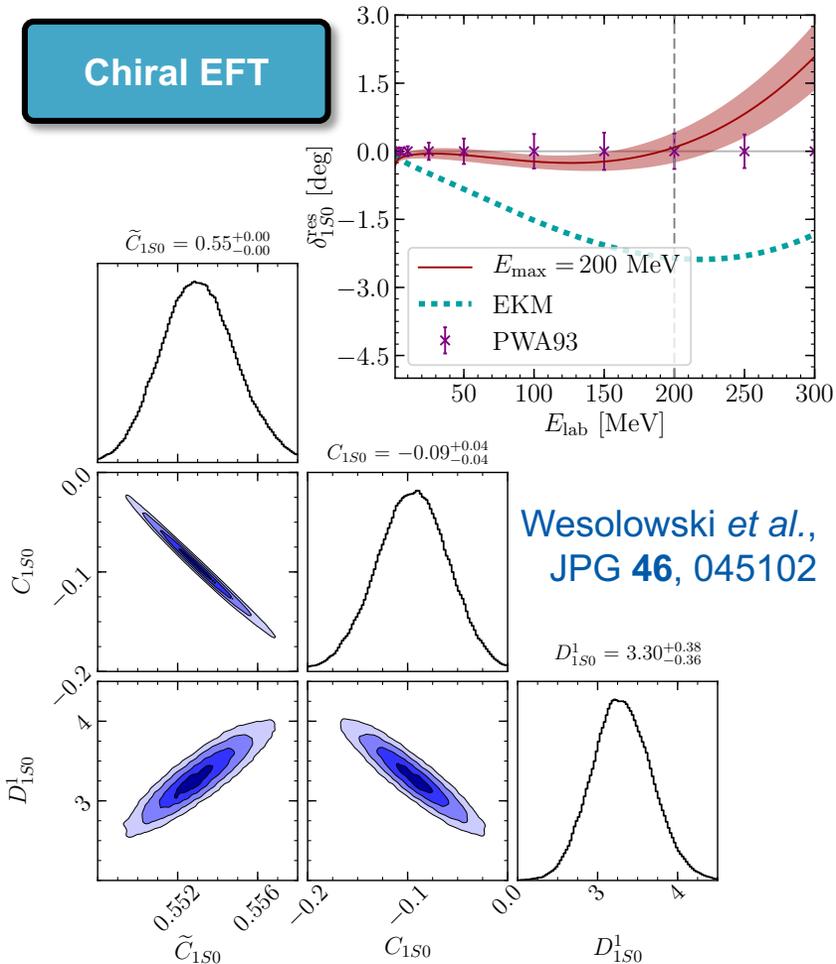
Bayesian methods can provide important insights into the issues of these potentials:

- parameter estimation
- model comparison
- sensitivity analysis

BUQEYE
Chalmers
ISNET



Catacora-Rios *et al.*,
PRC **104**, 064611



Wesolowski *et al.*,
JPG **46**, 045102

Scattering eqns. (FOM) can be solved accurately in few-body systems. **But:** prohibitively slow for statistical analyses of $A > 2$ scattering

Construct ROMs by removing superfluous information

Eigenvector Continuation vs Reduced Basis Method

PHYSICAL REVIEW LETTERS

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Featured in Physics

Eigenvector Continuation with Subspace Learning

Dillon Frame, Rongzheng He, Ilse Ipsen, Daniel Lee, Dean Lee, and Ermal Rrapaj
Phys. Rev. Lett. **121**, 032501 – Published 17 July 2018

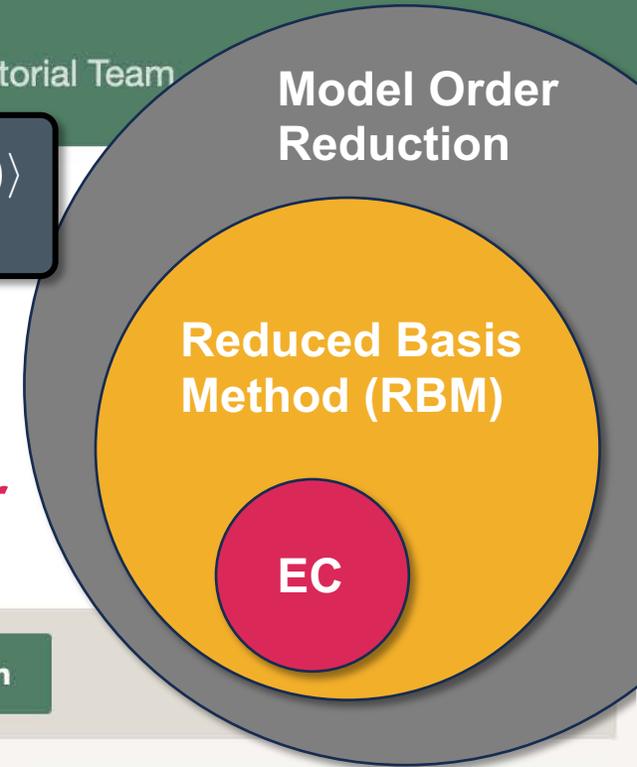
PhysICS See Synopsis: [Making Quantum Computations Behave](#)

EC has been a *game changer* for applying Bayesian methods in NP

Article References Citing Articles (59) Supplemental Material PDF HTML Export Citation

$$H(\theta) |\psi(\theta)\rangle = E(\theta) |\psi(\theta)\rangle$$

Schrödinger Equation



! Eigenvector continuation (EC) is a **specific implementation of the RBM** (which has been known for decades) for emulating parametric eigenvalue (and scattering) problems



Exciting opportunities to learn from the PMOR community, including language, algorithms, software, workflows error analysis, and many more

TABLE I. A sampling of recent MOR software libraries; see Ref. [13, Sec. 13.3] for an extensive listing.

Library	Language	Website	Remark
pyMOR ^a [86]	Python	pymor.org	focuses on RBMs for parameterized PDEs; integrates with external PDE solvers
libROM	C++	librom.net	library for efficient MOR techniques and physics-constrained data-driven methods; includes POD, DMD, projection-based ROM, hyper-reduction, greedy algorithm
MORLAB [87]	MATLAB	mpi-magdeburg.mpg.de/projects/morlab	MOR of dynamical systems based on the solution of matrix equations using spectral projection methods
modred [88]	Python	modred.readthedocs.io	library for computing modal decompositions and ROMs, including POD, DMD, and Petrov-Galerkin projection
pyROM [89]	Python	github.com/CurtinIC/pyROM	framework that employs Python visualisation tools; includes POD and DMD
pressio [90]	C++	pressio.github.io	minimally-intrusive interface for MOR routines, including Galerkin projections

^a See also the website of the Model Reduction for Parametrized Systems (MoRePaS) collaboration: morepas.org.

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A few remarks on projection-based ROMs (mainly for bound states)

Melendez, CD, Garcia, Furnstahl, and Zhang, J. Phys. G **49**, 102001
CD, Melendez, Garcia, Furnstahl, and Zhang, Front. Phys. **10**, 92931

1

(General) Kohn Variational Principle: *Toward emulating nuclear reactions using eigenvector continuation (with wave functions)*

CD, Quinonez, Giuliani, Lovell, and Nunes, Phys. Lett. B **823**, 136777
extends: Furnstahl, Garcia, Millican, and Zhang, Phys. Lett. B **809**, 135719

2

Newton Variational Principle: *Fast & accurate emulation of two-body scattering observables without wave functions*

Melendez, CD, Garcia, Furnstahl, and Zhang, Phys. Lett. B **821**, 136608

3

Wave-function-based emulation for nucleon-nucleon scattering in momentum space (*Kohn vs Newton VP*)

Garcia, CD, Furnstahl, Melendez, and Zhang, Phys. Rev. C **107**, 054001

See also Xilin Zhang's talk:
*Further developments on emulators
for quantum continuum states*

See also: CD & Zhang's contribution to Few Body Syst. **63**, 67



BUQEYE Guide to Projection-Based Emulators in Nuclear Physics

Front. Phys. **10**, 92931 (open access)

C. Drischler,^{1,2,*} J. A. Melendez,³ R. J. Furnstahl,³ A. J. Garcia,³ and Xilin Zhang²

ABSTRACT

The BUQEYE collaboration (Bayesian Uncertainty Quantification: Errors in Your EFT) presents a pedagogical introduction to projection-based, reduced-order emulators for applications in low-energy nuclear physics. The term *emulator* refers here to a fast surrogate model capable of reliably approximating high-fidelity models. As the general tools employed by these emulators are not yet well-known in the nuclear physics community, we discuss variational and Galerkin projection methods, emphasize the benefits of offline-online decompositions, and explore how these concepts lead to emulators for bound and scattering systems that enable fast & accurate calculations using many different model parameter sets. We also point to future extensions and applications of these emulators for nuclear physics, guided by the mature field of model (order) reduction. All examples discussed here and more are available as interactive, open-source Python code so that practitioners can readily adapt projection-based emulators for their own work.

Keywords: emulators, reduced-order models, model order reduction, nuclear scattering, uncertainty quantification, effective field theory, variational principles, Galerkin projection

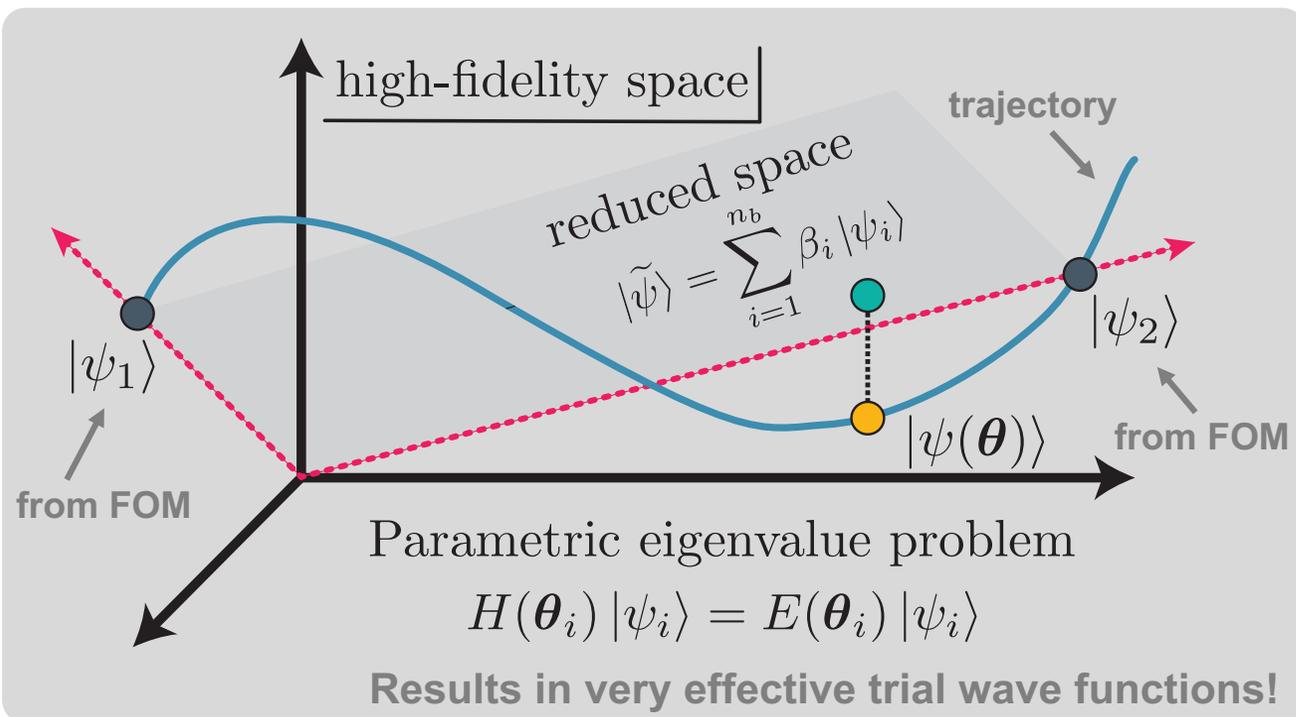
Pedagogical & interactive
Jupyter notebooks online!

see also
our Literature Guide
Melendez, CD *et al.*,
J. Phys. G **49**, 102001

Discusses:
eigen-emulators
(variational vs Galerkin)
Model Reduction
scattering emulators
open questions
future directions



Constructing ROMs: Variational & Galerkin Projection



Consider weak form: **Galerkin Projection**

$$\langle \zeta | H(\theta) - E(\theta) | \Psi \rangle = 0 \quad \forall \langle \zeta |$$

Reduce: $|\psi\rangle \rightarrow |\tilde{\psi}\rangle = \sum_{i=1}^{n_b} \beta_i |\psi_i\rangle \equiv \mathbf{X}\beta$

Choose n_b test functions $\langle \zeta_i | = \langle \psi_i | :$

$$\langle \zeta_i | H(\theta) - \tilde{E}(\theta) | \tilde{\Psi} \rangle = 0 \quad \forall i$$

Other choices possible \rightarrow Petrov-Galerkin ROM

Functional: **Variational Approach**

$$\mathcal{E}[\tilde{\psi}] = \langle \tilde{\psi} | H(\theta) | \tilde{\psi} \rangle - \tilde{E}(\theta) (\langle \tilde{\psi} | \tilde{\psi} \rangle - 1)$$

Trial wave function: $|\tilde{\psi}\rangle = \sum_{i=1}^{n_b} \beta_i |\psi_i\rangle \equiv \mathbf{X}\beta$

Find stationary point of the functional

Reduced Order Model

$$\tilde{H}(\theta)\beta = \tilde{E}(\theta)\tilde{N}\beta$$

generalized eigenvalue problem

$$\tilde{H}(\theta) = \mathbf{X}^\dagger H(\theta) \mathbf{X}$$

projected Hamiltonian

$$\tilde{N} = \mathbf{X}^\dagger \mathbf{X}$$

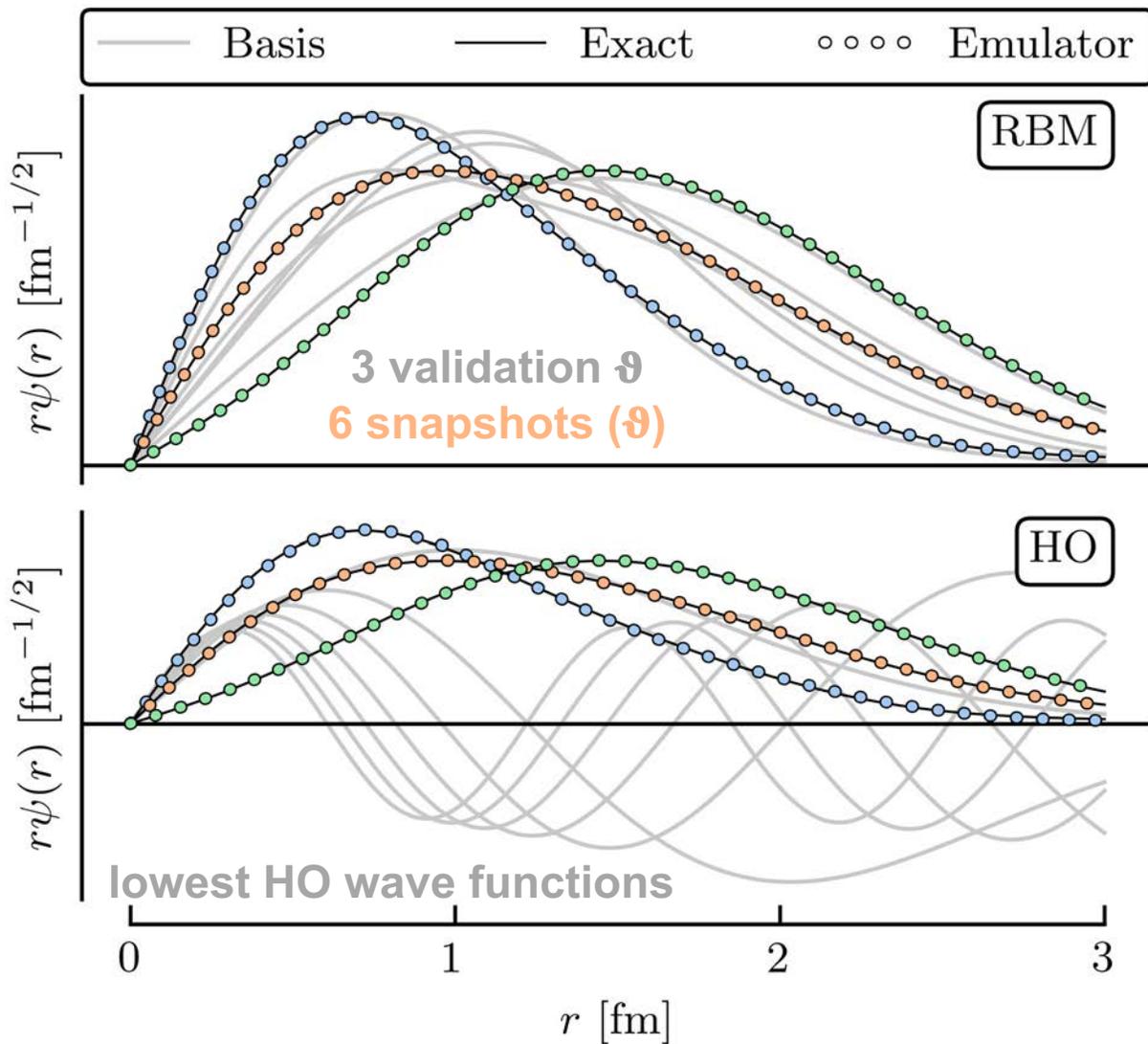
norm matrix

$$\mathbf{X} = [\psi_1 \ \psi_2 \ \dots \ \psi_{n_b}]$$

snapshots

Illustrative example: anharmonic oscillator

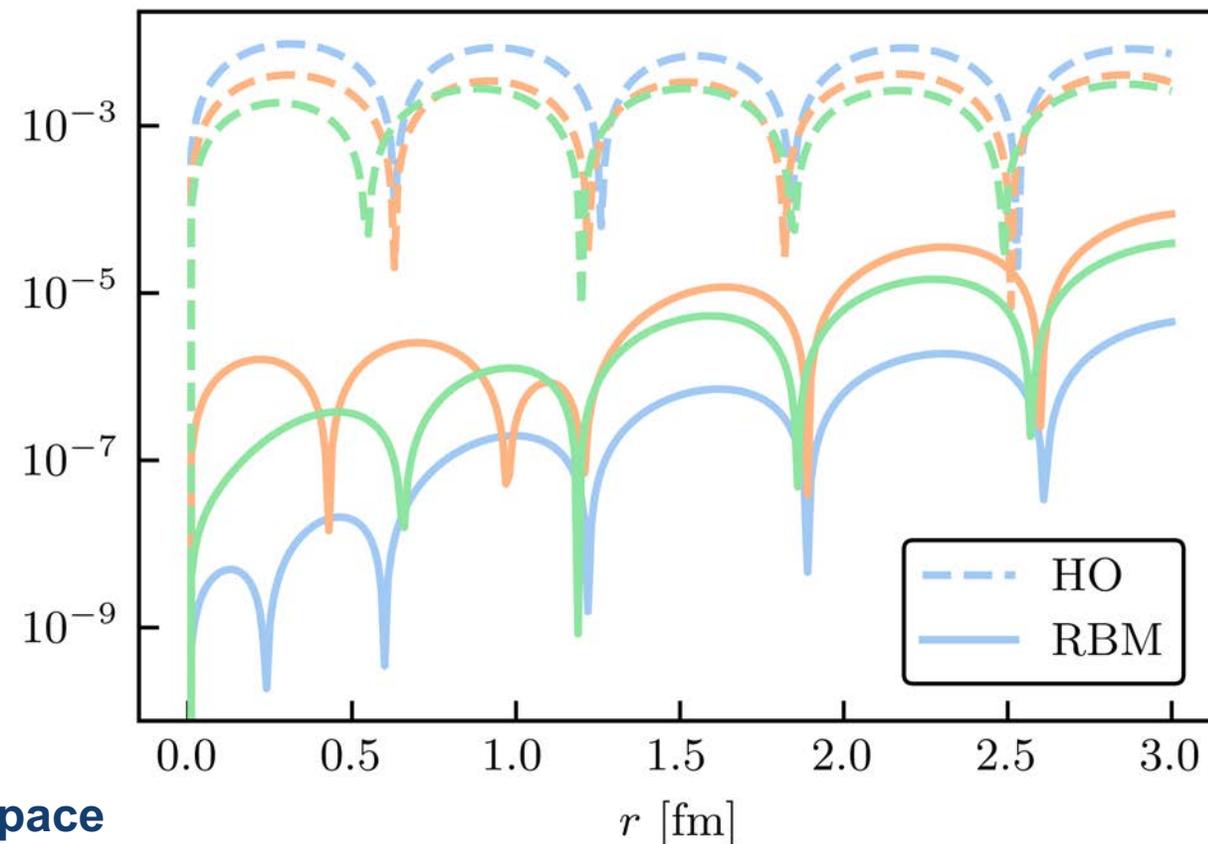
CD, Melendez, Garcia, Furnstahl,
and Zhang, Front. Phys. 10, 92931



$$V(r, \theta) = V_{\text{HO}} + \sum_{n=1}^3 \theta^{(n)} e^{-r^2/\sigma_n^2}$$

$\sigma_n = [0.5, 2, 4]$ fm (affine)

Wave Function Absolute Residuals



Results obtained via diagonalization in the reduced space

Illustrative example: anharmonic oscillator

CD, Melendez, Garcia, Furnstahl,
and Zhang, Front. Phys. 10, 92931

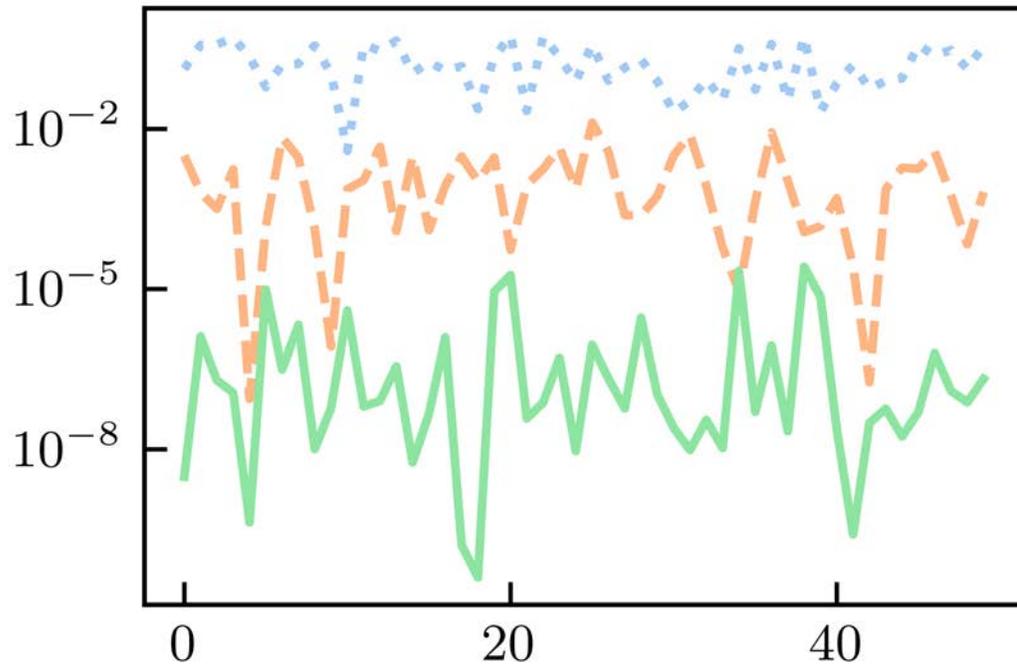
RBM combines the ideas from the other emulators:

- ✓ Uses **snapshot (wave) functions** rather than scalar (energies) for training (no nodes)
- ✓ Knows about the **underlying eigenvalue problem**

$$V(r, \theta) = V_{\text{HO}} + \sum_{n=1}^3 \theta^{(n)} e^{-r^2 / \sigma_n^2}$$

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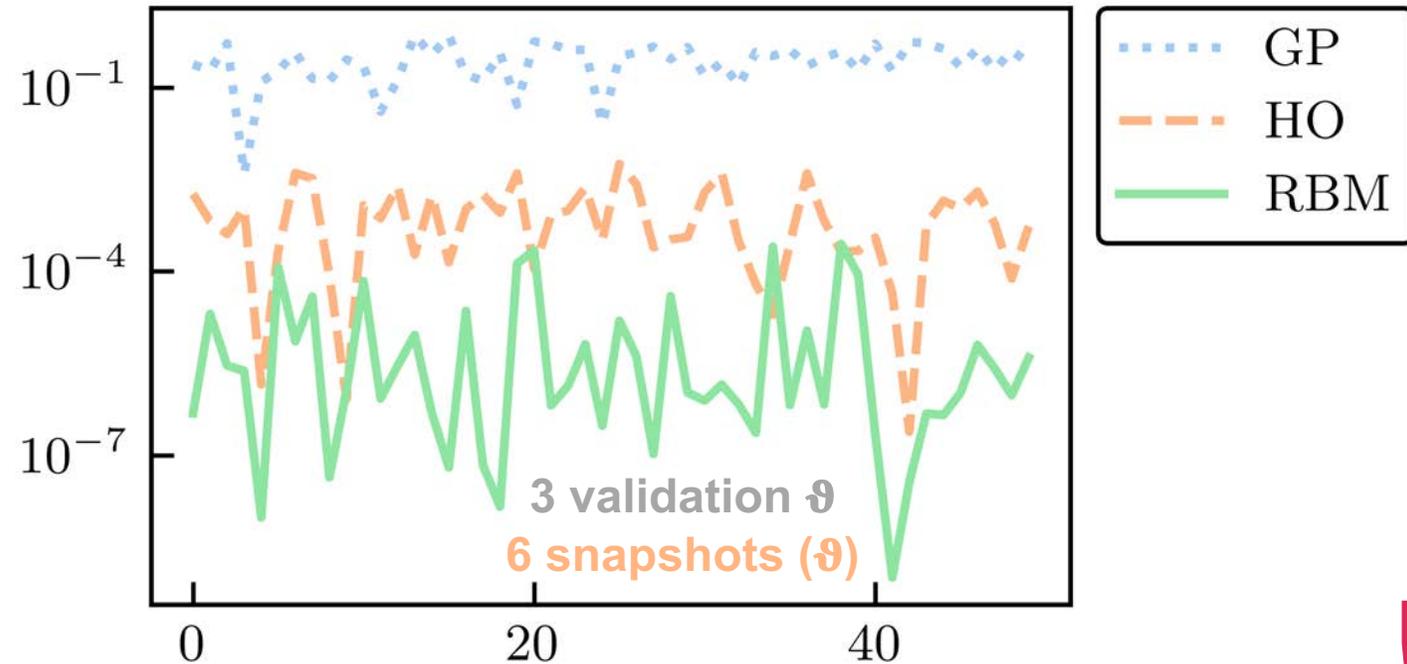
Ground-State Energy Residuals



Validation Index

OscillatorEmulator(...)
EigenEmulator(...)

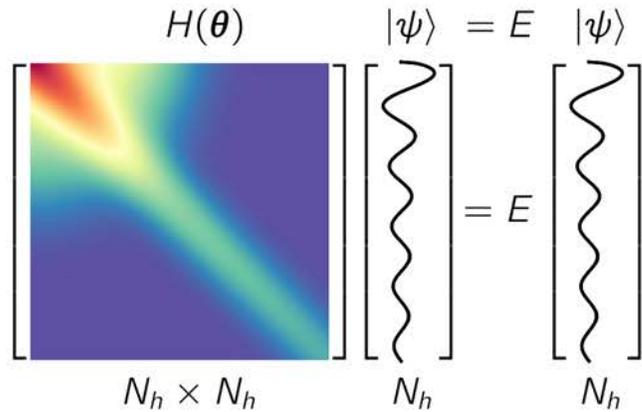
Ground-State Radius Residuals



Validation Index

**RBM (with snapshots)
outperforms GPs & HO**

High-fidelity system



Construct **(snapshot-based) ROMs** by systematically removing *superfluous* information in high-fidelity models

Time:  per θ sample

CPU time scales with the length of 

Offline-online decomposition:

Perform all demanding operations *once* upfront

(which is crucial for achieving high speed-ups)

Is *straightforward* for operators with an **affine**

parameter dependence

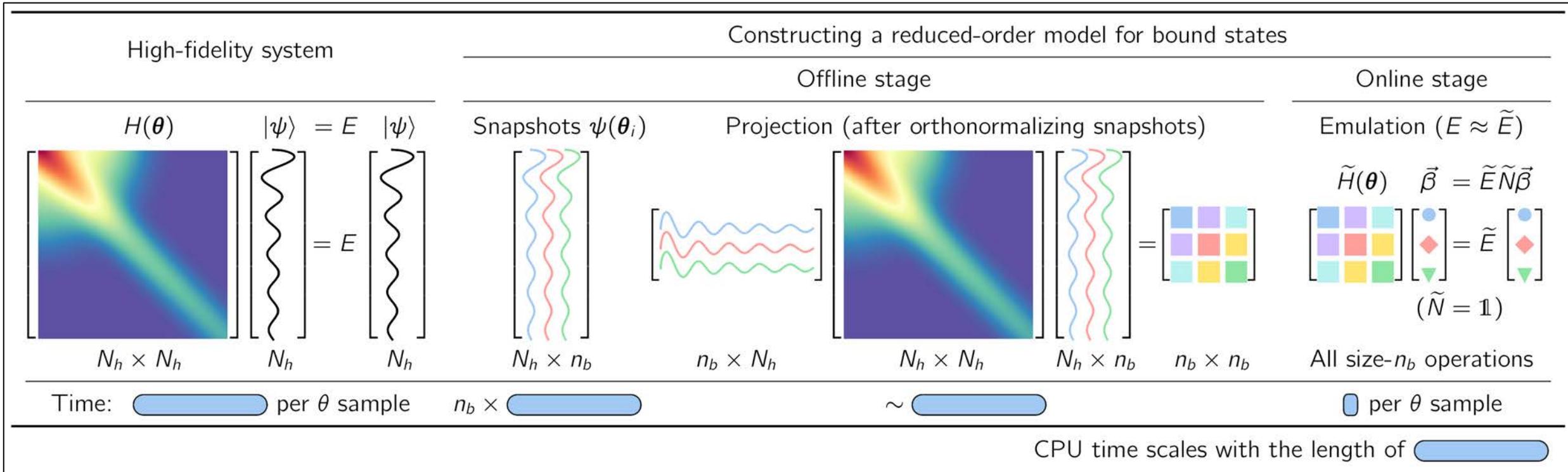
use **hyper-reduction methods** to handle non-linear systems and/or non-affine parameters

Offline stage (size- N_h operations):

- Solve high-fidelity system and construct snapshot basis
- Project high-fidelity system to reduced space

Online stage (size- n_b operations only):

- fast & accurate model predictions (e.g., for MC sampling)



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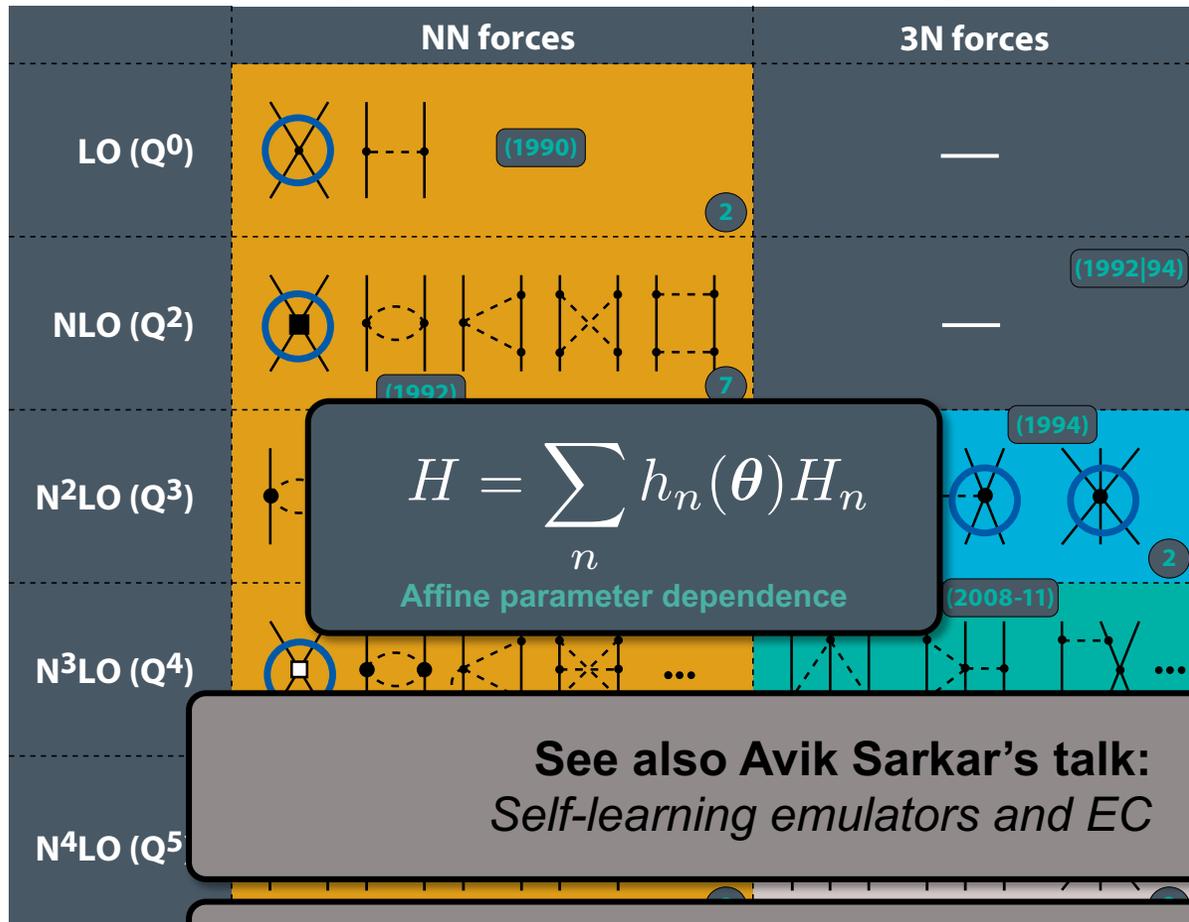
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Online stage (size- n_b operations only):

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Hierarchy of chiral forces (Weinberg PC)



$$H = \sum_n h_n(\theta) H_n$$

Affine parameter dependence

See also Avik Sarkar's talk:
Self-learning emulators and EC

See also Pablo Giuliani's talk:
Reduced basis methods for nuclear physics

with deltas, e.g., see Piarulli & Tews, Front Phys 7, 245

How to choose the snapshot basis?

Multiple approaches and their hybrids possible.
For instance:

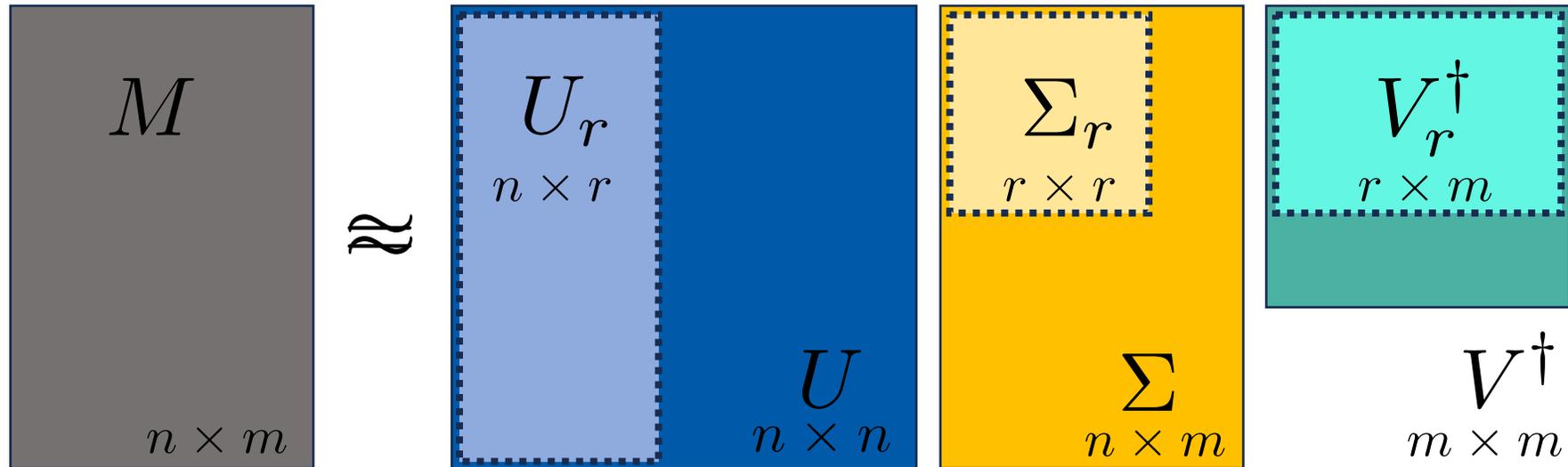
- obtain space-filling snapshots using **Latin hypercube** sampling (for small θ spaces)
- choose the snapshots near the to-be-emulated parameter ranges (ideally interpolation)
- Proper Orthogonal Decomposition (POD)
- **Greedy algorithms** and other active-learning methods to reduce the emulator's error iteratively

e.g., see Sarkar & Lee, PRR 4, 023214

The **POD** can be used to diagnose and (further) optimize the snapshot basis.

Proper Orthogonal Decomposition (POD)

POD is based on a (truncated) Singular Value Decomposition (SVD) of the snapshot basis:
See also Principal Component Analysis (PCA)



U and V are unitary matrices (e.g., $UU^\dagger = U^\dagger U = 1$) containing the singular vectors

Σ is a diagonal matrix with decreasing, nonnegative diagonal entries (singular values)

Truncating singular vectors corresponding to the r smallest singular values results in the best possible rank- r approximation (in Frobenius norm) to the original M (**low-rank approximation**)

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A few remarks on projection-based emulators in general

Melendez, CD, Garcia, Furnstahl, and Zhang, J. Phys. G **49**, 102001
CD, Melendez, Garcia, Furnstahl, and Zhang, Front. Phys. **10**, 92931

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See also Xilin Zhang's talk:
*Further developments on emulators
for quantum continuum states*

See also: CD & Zhang's contribution to Few Body Syst. **63**, 67

1

$$\beta [|\psi_{\text{trial}}\rangle] = \frac{K_\ell}{p} - 2\mu \langle \psi_{\text{trial}} | H(\theta) - E | \psi_{\text{trial}} \rangle \quad p = \sqrt{2\mu E}$$

2

stationary approximation to exact K_ℓ matrix [accurate up to $O(\delta u^2)$]

$$u_{\ell,E}^{\text{trial}}(r) \sim \frac{1}{p} \sin(\eta_\ell) + \frac{K_\ell}{p} \cos(\eta_\ell) \quad \eta_\ell = kr - \frac{\pi}{2}\ell \quad H(\theta) = T + V(\theta)$$

3

Training: solve RSE exactly for a set $\{\theta_i\}_{i=1}^{N_b}$ and construct the trial wave function:

$$|\psi_{\text{trial}}\rangle = \sum_{i=1}^{N_b} c_i |\psi_E(\theta_i)\rangle$$

4

5

Given $H(\theta)$, the stationary point is obtained by simple linear algebra:

$$\delta\beta[|\psi_{\text{trial}}\rangle] = 0 \quad \text{s.t.} \quad \sum_{i=1}^{N_b} c_i = 1$$

$$c_i = \sum_j (\Delta\tilde{U})_{ij}^{-1} \left(\frac{K_\ell^{(j)}(E)}{p} - \lambda \right) \quad \lambda = \frac{-1 + \sum_{ij} (\Delta\tilde{U})_{ij}^{-1} \frac{K_\ell^{(j)}(E)}{p}}{\sum_{ij} (\Delta\tilde{U})_{ij}^{-1}}$$

with matrix $\Delta\tilde{U}_{ij} = 2\mu \langle \psi_E(\theta_i) | 2V(\theta) - V(\theta_i) - V(\theta_j) | \psi_E(\theta_j) \rangle$

6

Approximate $K_\ell = \tan \delta_\ell$: $[K_\ell(E)]_{\text{exact}} \approx \sum_i c_i K_\ell^{(i)}(E) - \frac{p}{2} \sum_{ij} c_i \Delta\tilde{U}_{ij} c_j$

emulate

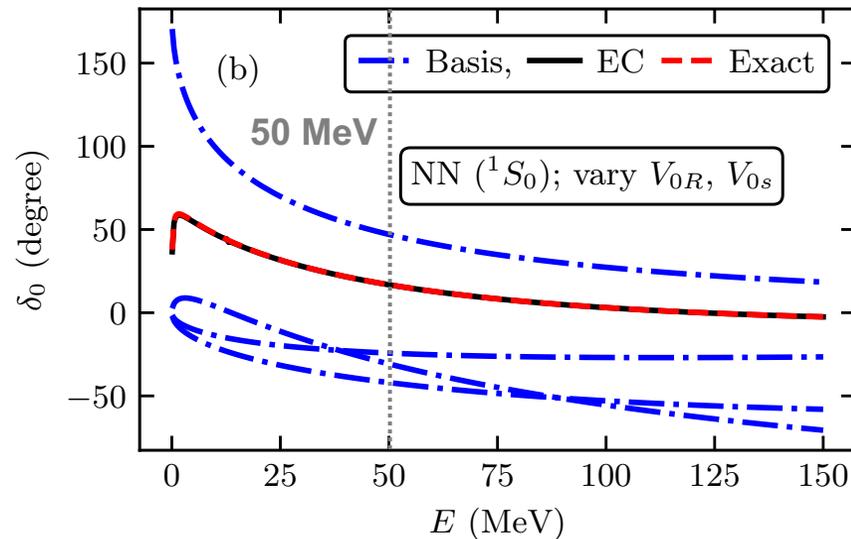
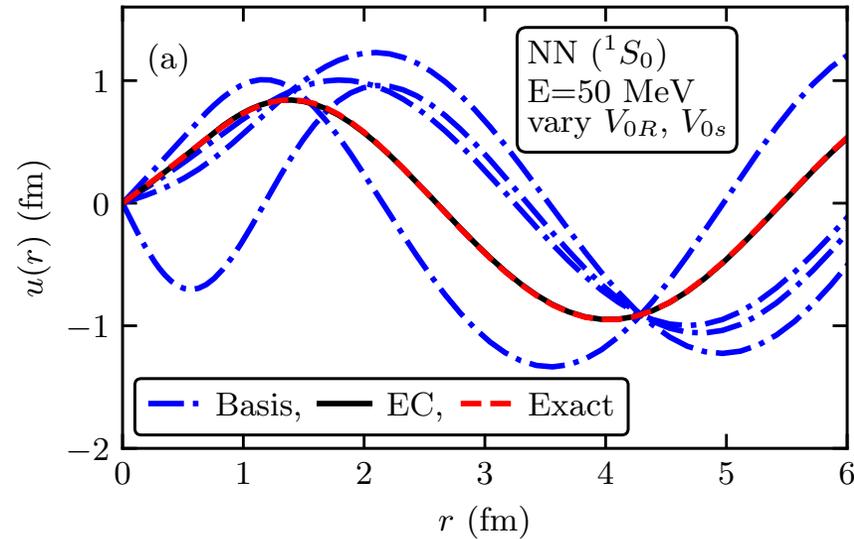
validate



for R matrix theory,
see Bai & Ren,
PRC 103, 014612

Wave functions and phase shifts

Furnstahl, Garcia, Millican, Zhang,
PLB 809, 10135719



Also studied:

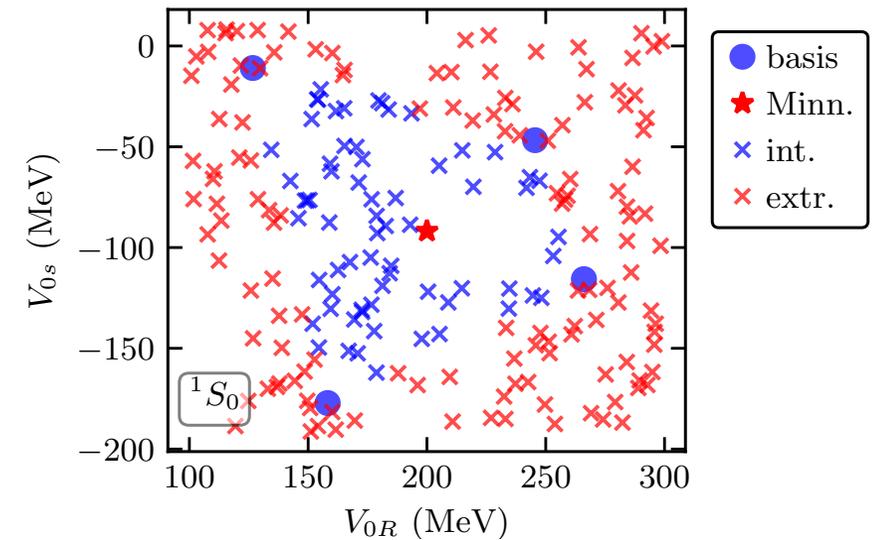
- local & nonlocal potentials
- incl. optical potentials
- higher partial waves

NN scattering

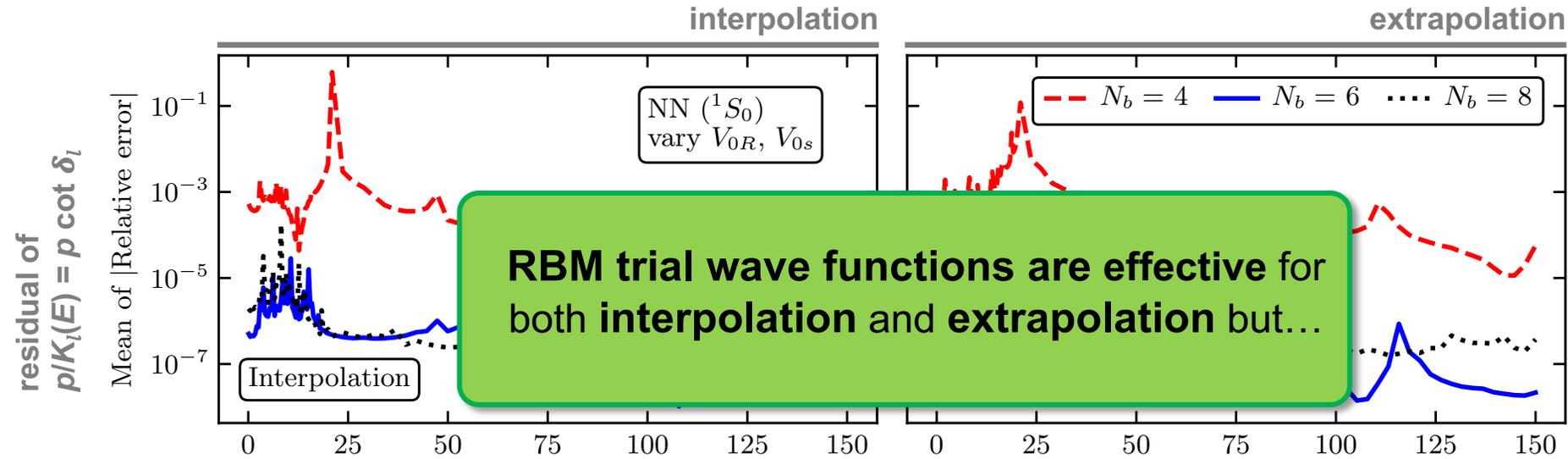
Minnesota potential

$$V(r) = V_{0R}e^{-\kappa_R r^2} + V_{0s}e^{-\kappa_s r^2}$$

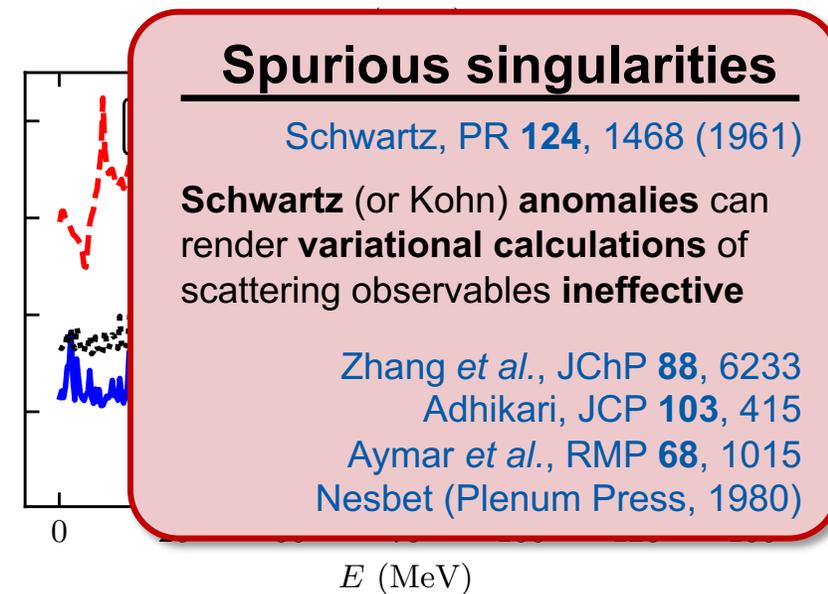
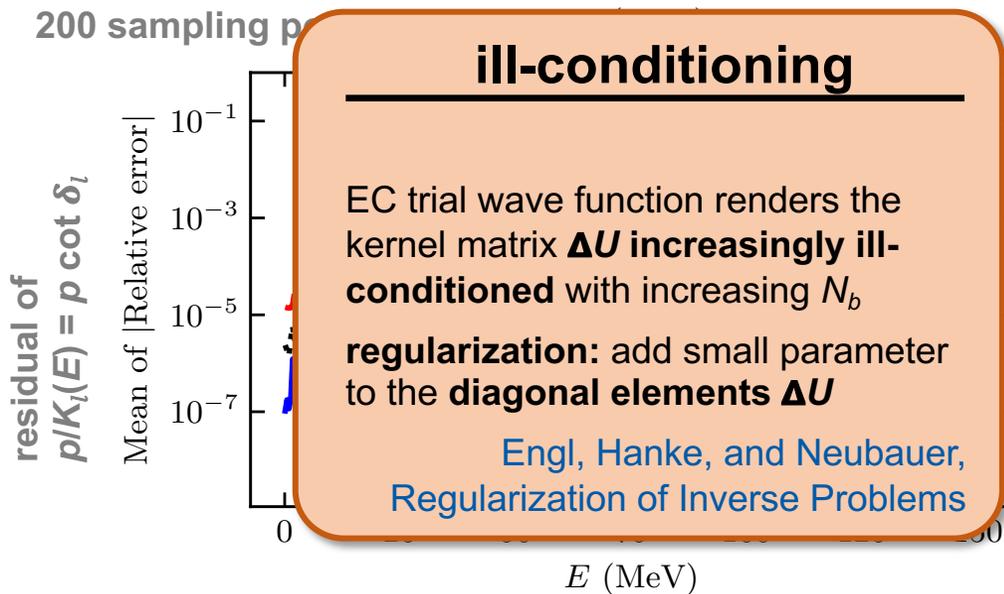
Training set: 4 Hamiltonians with different (V_{0R} , V_{0s}) and fixed (κ_R , κ_s)



Emulated wavefunctions and phase shifts reproduce well the exact results at the physical point (★)



linear parameters varied only
variation: ± 100 MeV



linear and nonlinear parameters varied
variation: ± 100 MeV; $\pm 50\%$

$$\beta_u [|\psi_{\text{trial}}\rangle] = \frac{L_\ell}{p} - \frac{2\mu}{\det u} \langle \psi_{\text{trial}} | H(\theta) - E | \psi_{\text{trial}} \rangle$$

stationary approximation to exact L_ℓ matrix [accurate up to $O(\delta u^2)$]

$$u_{\ell,E}^{\text{trial}}(r) \sim \frac{1}{p} \phi_\ell^{(0)}(r) + \frac{L_\ell}{p} \phi_\ell^{(1)}(r) \quad \begin{aligned} \phi_\ell^{(0)}(r) &\sim u_{00} \sin(\eta_\ell) + u_{01} \cos(\eta_\ell) \\ \phi_\ell^{(1)}(r) &\sim u_{10} \sin(\eta_\ell) + u_{11} \cos(\eta_\ell) \end{aligned} \quad \eta_\ell = kr - \frac{\pi}{2}\ell$$

Training: solve RSE exactly for a set $\{\theta_i\}_{i=1}^{N_b}$ and constrain $|\psi_{\text{trial}}\rangle = \sum_{i=1}^{N_b} c_i |\psi_E(\theta_i)\rangle$

$$L = K \text{ for } u = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$L = S \text{ for } u = \begin{bmatrix} i & -1 \\ i & 1 \end{bmatrix}$$

$$L = T \text{ for } u = \begin{bmatrix} 1 & 0 \\ i & 1 \end{bmatrix}$$

... any nonsingular matrix



$$K = \frac{u_{01} + u_{11}L}{u_{00} + u_{10}L} \quad c_i = 1$$

$$\lambda = \frac{-1 + \sum_{ij} (\Delta U)_{ij} L_\ell}{\sum_{ij} (\Delta \tilde{U})_{ij}^{-1}}(E)$$

with matrix $\Delta U_{ij} = \frac{\langle \psi_E(\theta_i) | 2V(\theta) - V(\theta_i) - V(\theta_j) | \psi_E(\theta_j) \rangle}{\det u}$

Approximate L_ℓ : $[L_\ell(E)]_{\text{exact}} \approx \sum_i c_i L_\ell^{(i)}(E) - \frac{1}{2} \sum_{ij} c_i \Delta \tilde{U}_{ij} c_j$

emulate

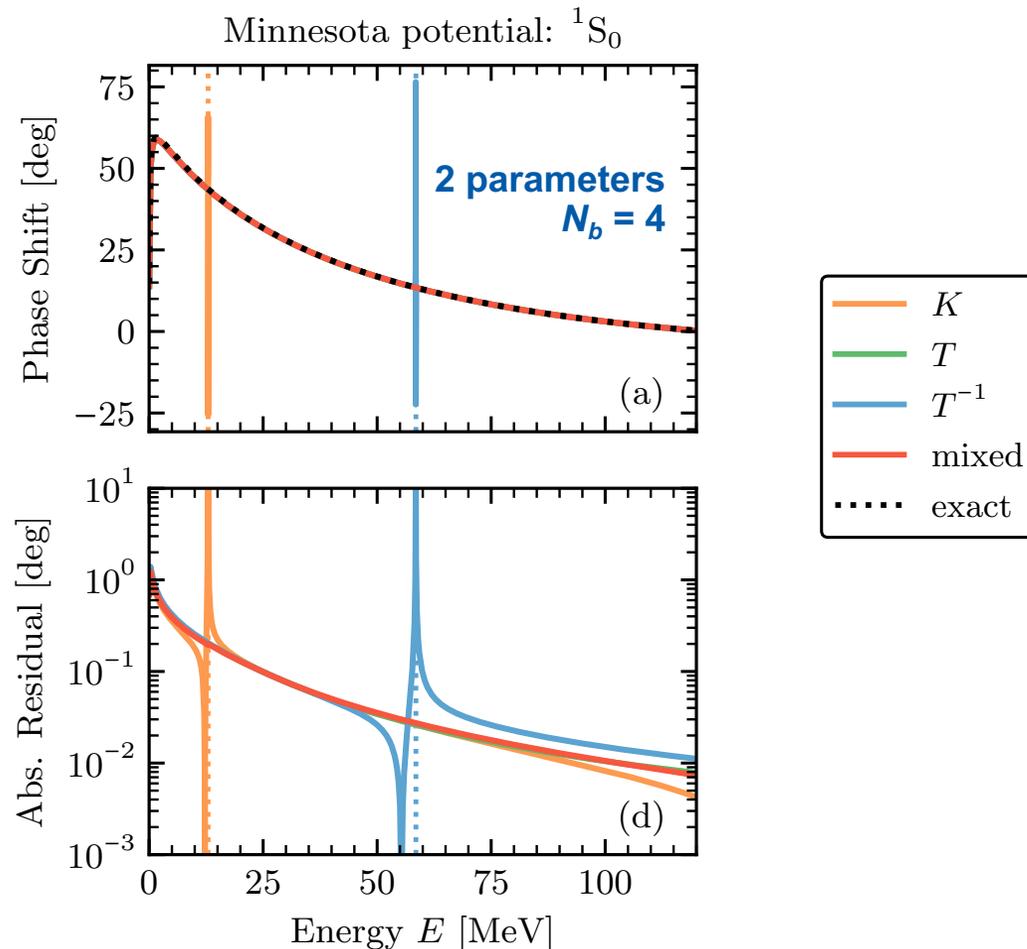
validate



for applications to N-d scattering, see:

Viviani, Kievsky, and Rosati, FBS 30, 3
Kievsky, NPA 624, 125

Kievsky, Viviani, and Rosati, NPA 577, 511



Minnesota potential

$$V(r) = V_{0R}e^{-\kappa_R r^2} + V_{0s}e^{-\kappa_s r^2}$$

Spurious singularities occur when there is no (unique) stationary approximation due to the functional; *i.e.*,

$$\det \Delta \tilde{\mathbf{U}}^{(\mathbf{u})} = 0$$

$$\sum_{ij} (\Delta \tilde{\mathbf{U}}^{(\mathbf{u})})_{ij}^{-1} = 0$$

No guarantee: all KVPs are prone to Schwartz anomalies, and we found anomalies for all potentials studied

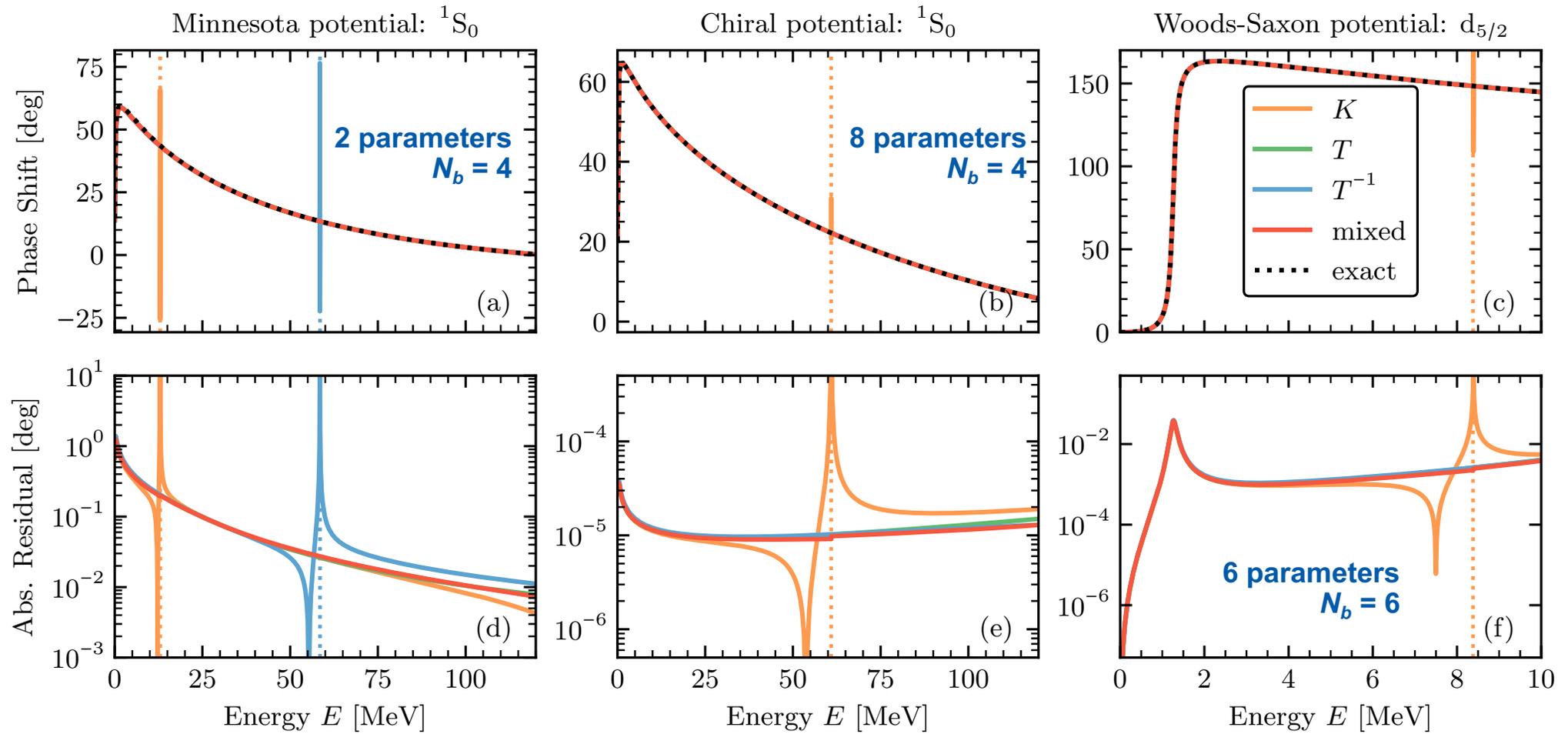
Advantage: for complex KVPs and/or optical potentials both, the real *and* imaginary part, need to cross zero

see also: Lucchese, Phys. Rev. A **40**, 112

Schwartz, Phys. Rev. **124**, 1468

Nesbet, *Variational methods in electron-atom scattering theory*

realistic real potentials



Basic idea: emulate a variety of matrices associated with different boundary conditions and **check for consistency**

$$\Delta^{(L)}(L_1, L_2) = \frac{L(L_1)}{L(L_2)} - 1$$

relative error

Viviani, Kievsky, and Rosati, FBS **30**, 3
Kievsky, Viviani, and Rosati, NPA **577**, 511

Filter out all inconsistent pairs $\{L_i, L_j\}_{ij}$ and **average over** (“mix”) the **remaining pairs** with weight $\Delta^{(L)}(L_i, L_j)$

Vary the size of the training set to shift the Schwartz anomalies and repeat

general case (via Möbius transform)

$$L'(L) \equiv \mathcal{L}_{u'}^{-1}(K(L)) = \frac{-u'_{01} + u'_{00}K(L)}{u'_{11} - u'_{10}K(L)}$$

How can Kohn anomalies be detected and removed? 

		$L_1 =$	$L_2 =$	
Using:	δ	K	T	S
$\chi(R) =$	$e^{i\delta}[F \cos \delta + G \sin \delta]$	$\frac{1}{1 - iK} [F + KG]$	$F + TH^+$	$\frac{1}{2}[H^- - SH^+]$
$\delta =$	δ	$\arctan K$	$\arctan \frac{T}{1 + iT}$	$\frac{1}{2i} \ln S$
K =	$\tan \delta$	K	$\frac{T}{1 + iT}$	$\frac{1 - S}{1 + S}$
T =	$e^{i\delta} \frac{L}{\sin \delta}$	$\frac{K}{1 - iK}$	T	$\frac{1}{2}(1 - S)$
S =	$e^{2i\delta}$	$\frac{1 + iK}{1 - iK}$	$1 + 2iT$	S
$V = 0$	$\delta = 0$	K = 0	T = 0	S = 1
V real	δ real	K real	$ 1 + 2iT = 1$	$ S = 1$

But: **not all KVPs are complementary.**
We derived a simple analytic condition
to identify redundant KVPs.

Redundant (canonical) pairs:

$$\begin{aligned} & (S, T) \\ & (K^{-1}, T^{-1}) \\ & (S, S^{-1})^* \end{aligned}$$

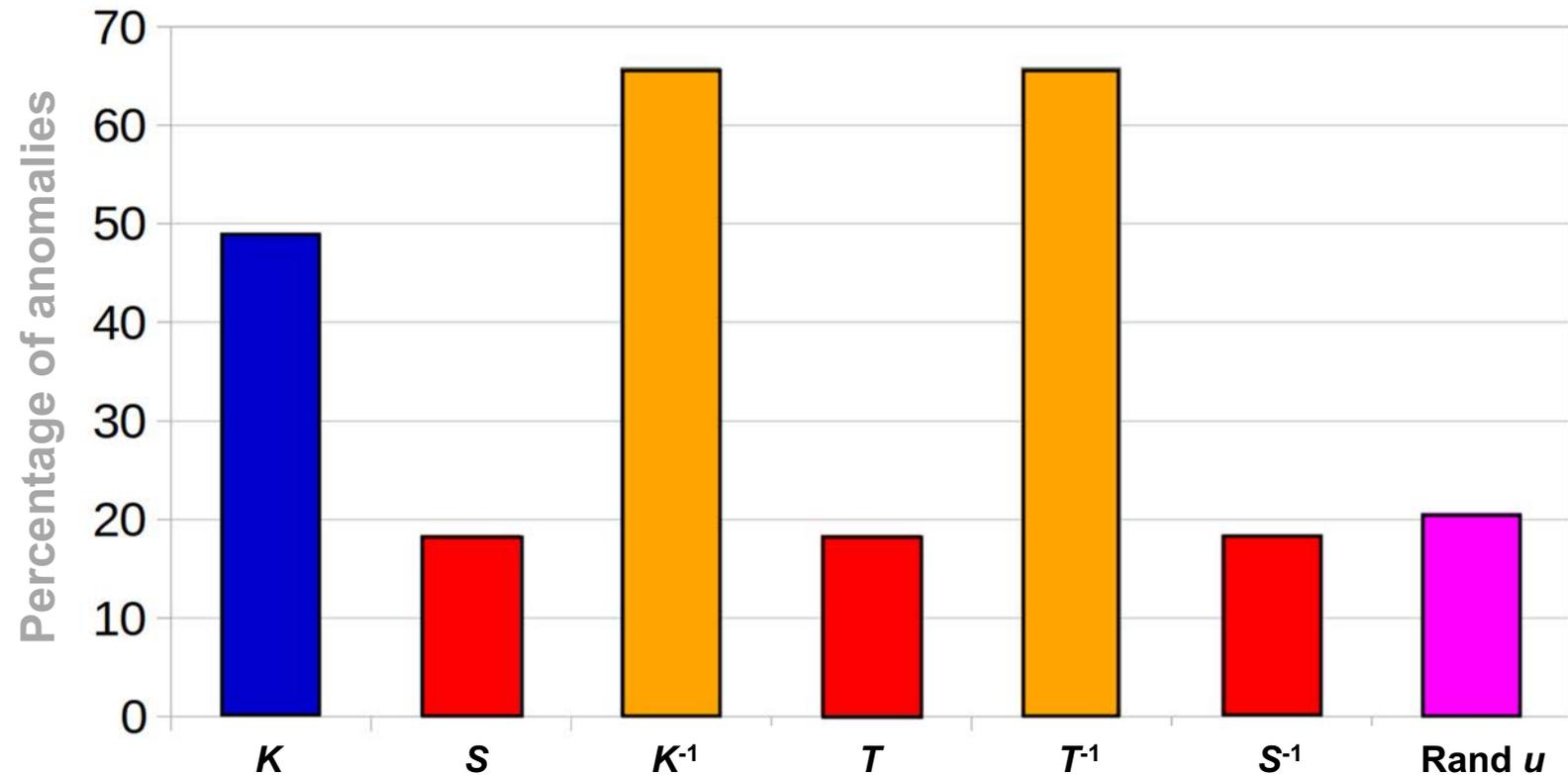
generalized S- & T-matrix KVP

*complex conjugated if V is real

We showed analytically that
KVPs are redundant if the *cross-
kernel matrix* is singular:

$$\mathbf{c} = \begin{pmatrix} u_{11} & u'_{11} \\ -u_{10} & -u'_{10} \end{pmatrix}$$

How can Kohn anomalies
be detected and removed ?



$L = 0$ | $A = 40$ | $E = 5-20$ MeV
Woods-Saxon potential
5 training points

5 random matrices covering a
wide range in $|\det(u)|$
sample size: 500

Condition number increases with increasing number of training points !

$$c_i = \sum_j (\Delta \tilde{U})_{ij}^{-1} \left(L_\ell^{(j)}(E) - \lambda \right) \quad \lambda = \frac{-1 + \sum_{ij} (\Delta \tilde{U})_{ij}^{-1} L_\ell^{(j)}(E)}{\sum_{ij} (\Delta \tilde{U})_{ij}^{-1}}$$

Methods to control the noise in matrix inversions include:

- nugget regularization
- Moore-Penrose inverse
- Tikhonov regularization

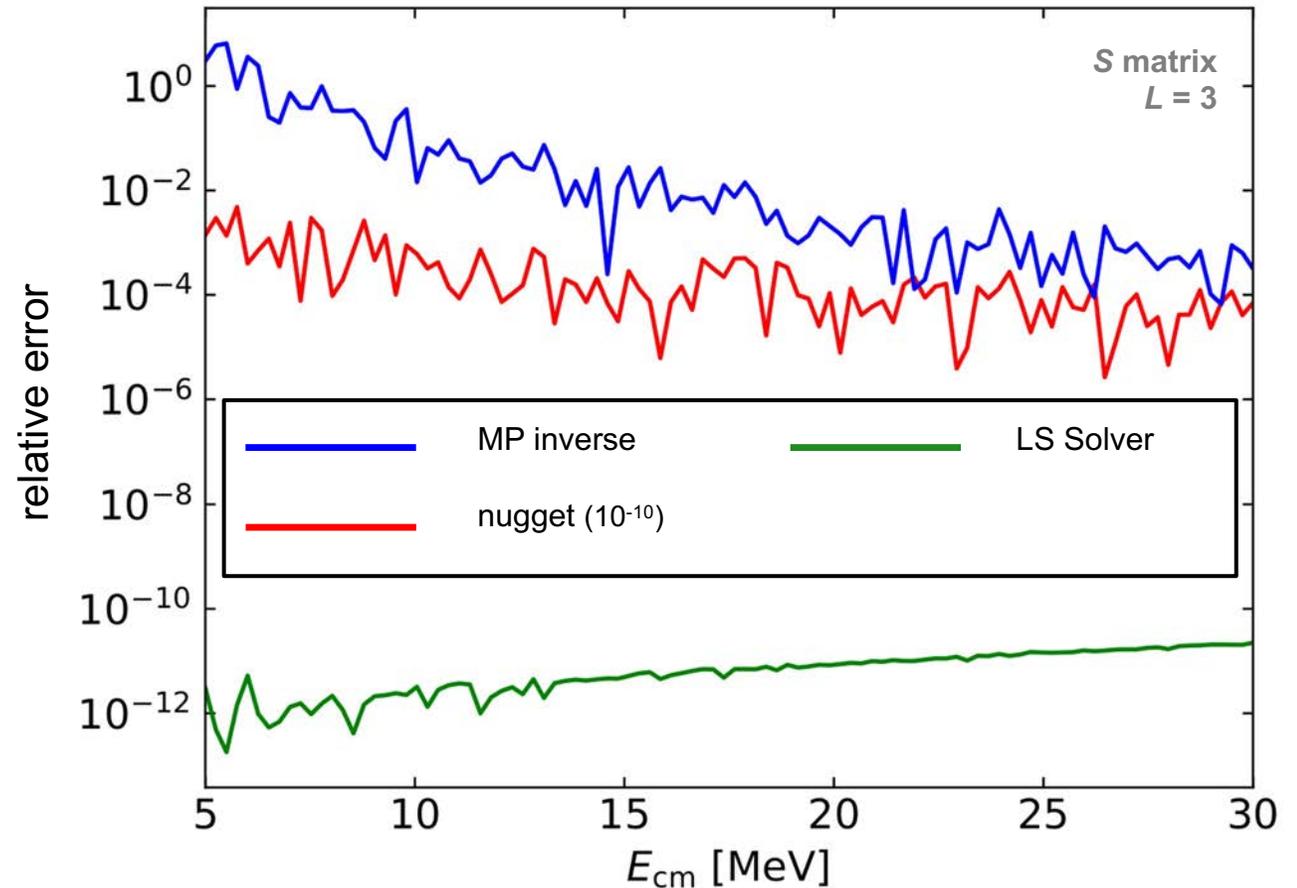
Golden Rule of numerical linear algebra:
Don't compute a matrix inverse unless you must.

Simple yet robust: find *stationary point* numerically (e.g., using an LS solver)

$$\begin{pmatrix} \Delta \tilde{U} & 1 \\ 1^T & 0 \end{pmatrix} \begin{pmatrix} c \\ \lambda \end{pmatrix} = \begin{pmatrix} L \\ 1 \end{pmatrix}$$

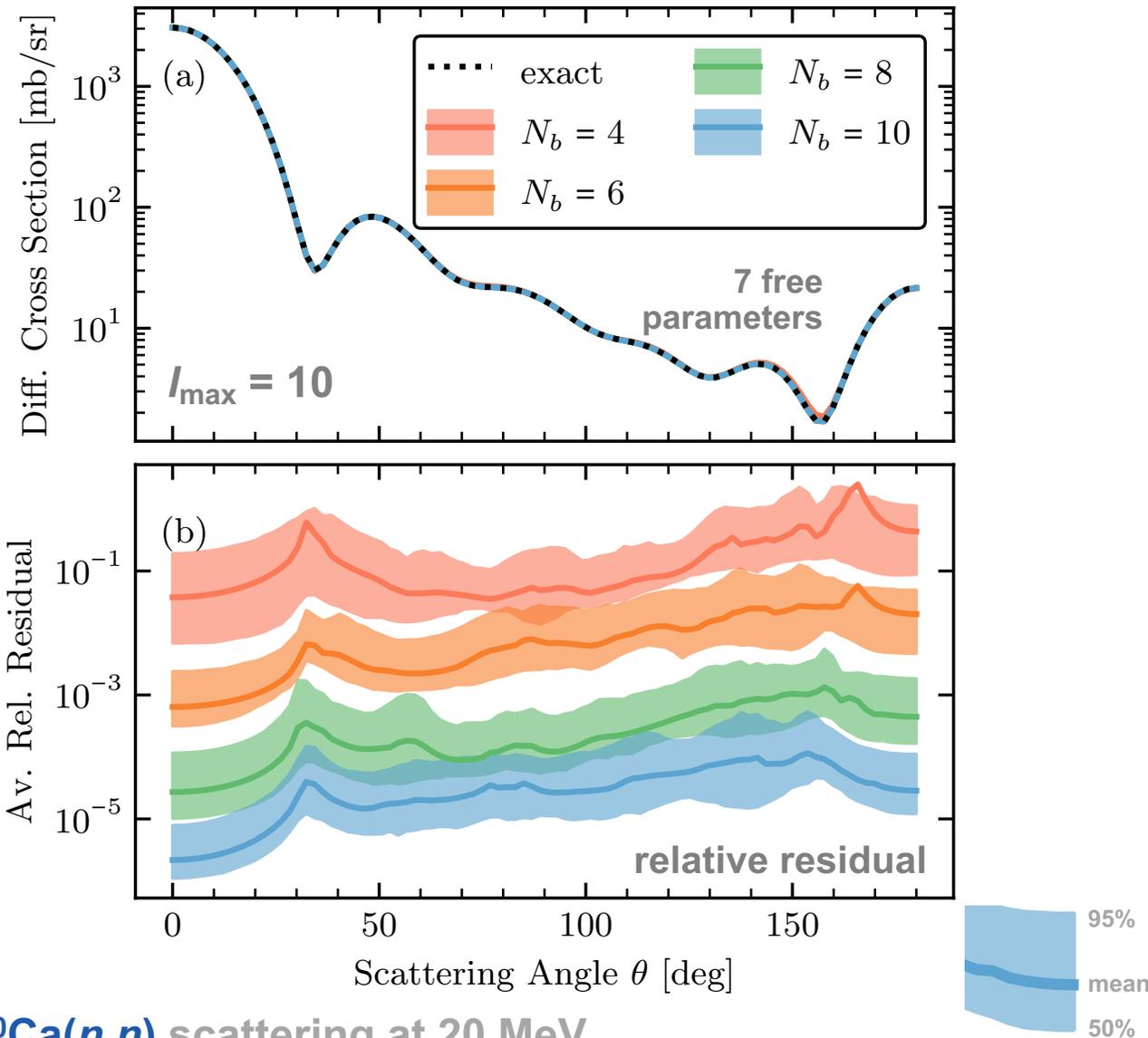
inverse-free, if possible

(Most methods will apply some sort of regularization)



Emulated differential cross sections

CD, Quinonez, Giuliani, Lovell, and Nunes, Phys. Lett. B **823**, 136777



$^{40}\text{Ca}(n,n)$ scattering at 20 MeV

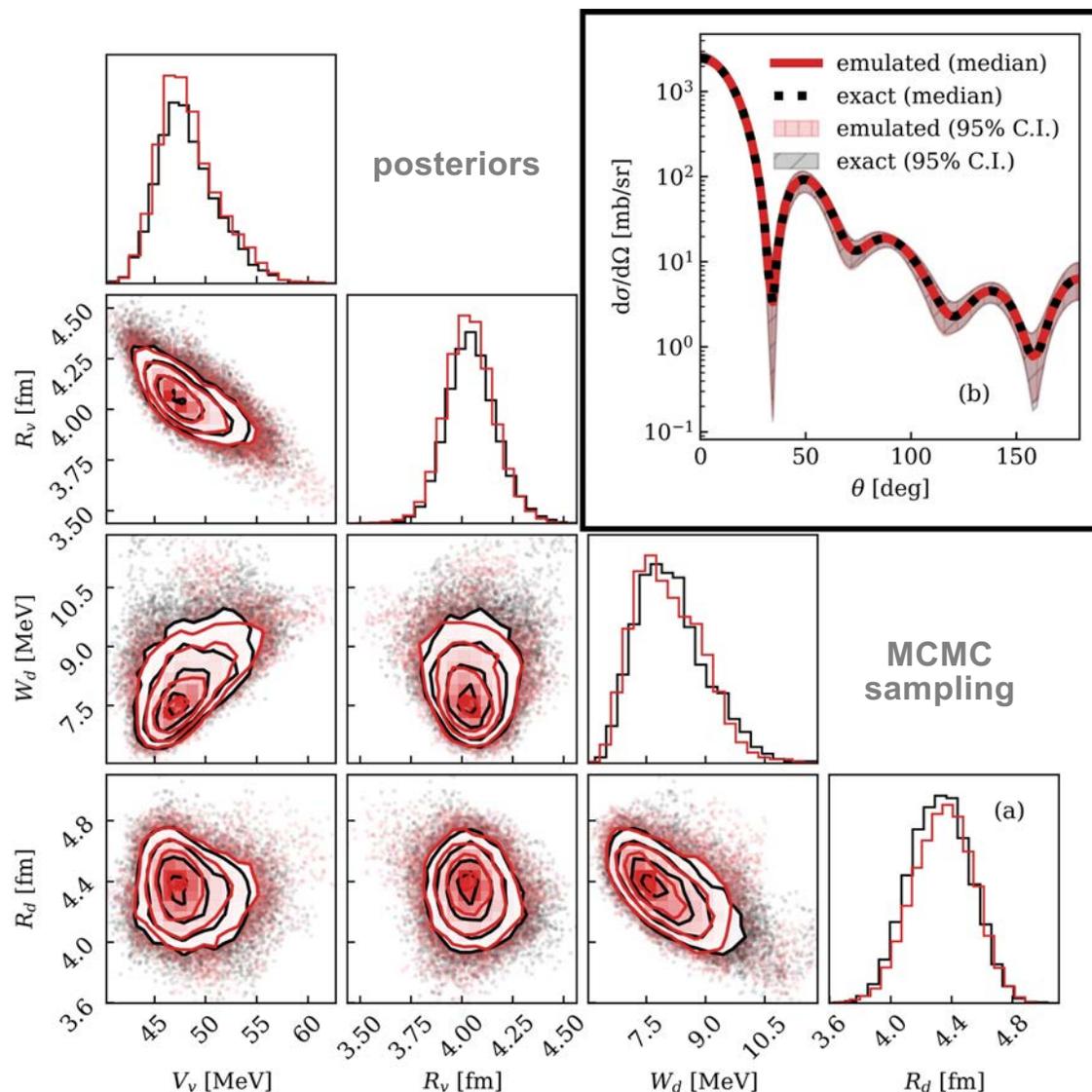
Realistic optical potential
$$V(r) = -V_v f_{\text{WS}}(r; R_v, a_v) - iW_v f_{\text{WS}}(r; R_w, a_w)$$

(Woods-Saxon form)

Training set: N_b random points within a $\pm 20\%$ interval centered around the Koning–Delaroche values to probe a **realistic region of the parameter space**

Sample again 500 random points: resulting bands are spanned by the *median* and *95% limit* of the residuals

For $N_b > 6$, the emulator **residuals do not exceed the experimental uncertainty**, typically $\approx 10\%$



$$\frac{d\sigma}{d\Omega} = \left| \frac{1}{2ik} \sum_{l=0}^{\infty} (2l+1) P_l(\cos\theta) (S_l - 1) \right|^2$$

Koning–Delaroche (optical) potential

Train emulators across partial-wave channels up to $l = 10$, with $N_b = 8$

Proof of principle: fast & accurate emulation of scattering observables for parameter estimation (using mock data)

excellent agreement between emulator (**red**) and exact scattering solution (**black**)

Mixed approach obtains **anomaly-free results** without adapting the training set

Goal: improving next-generation optical models & chiral interactions in the FRIB era

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A few remarks on projection-based emulators (mainly for bound states)

Melendez, CD, Garcia, Furnstahl, and Zhang, J. Phys. G **49**, 102001
CD, Melendez, Garcia, Furnstahl, and Zhang, Front. Phys. **10**, 92931

1

(General) Kohn Variational Principle: *Toward emulating nuclear reactions using eigenvector continuation (with wave functions)*

CD, Quinonez, Giuliani, Lovell, and Nunes, Phys. Lett. B **823**, 136777
extends: Furnstahl, Garcia, Millican, and Zhang, Phys. Lett. B **809**, 135719

2

Newton Variational Principle: *Fast & accurate emulation of two-body scattering observables without wave functions*

Melendez, CD, Garcia, Furnstahl, and Zhang, Phys. Lett. B **821**, 136608

3

Wave-function-based emulation for nucleon-nucleon scattering in momentum space

Garcia, CD, Furnstahl, Melendez, and Zhang, Phys. Rev. C **107**, 054001

See also Xilin Zhang's talk:
*Further developments on emulators
for quantum continuum states*

See also: CD & Zhang's contribution to Few Body Syst. **63**, 67

Newton variational principle

R. G. Newton,
scattering theory of
waves and particles

Melendez, CD, Garcia, Furnstahl,
and Zhang, PLB 821, 136608

$$\mathcal{K}[\tilde{K}] = V + VG_0\tilde{K} + \tilde{K}G_0V - \tilde{K}G_0\tilde{K} + \tilde{K}G_0VG_0\tilde{K},$$

with the free-space Green's function $G_0(E_q = q^2 / (2\mu))$

stationary approximation to exact K (or T) matrix [accurate up to $O(\delta K^2)$]

1

Training: solve LSE exactly for a set $\{\theta_i\}_{i=1}^{N_b}$ and construct the trial K (or T) matrix:

$$\tilde{K}(\vec{\beta}) = \sum_{i=1}^{N_b} \beta_i K_i$$

2

Given $H(\theta)$, the stationary point is obtained by simple linear algebra: $\frac{d\mathcal{K}}{d\vec{\beta}} \Big|_{\vec{\beta}_*} = 0$ $M\vec{\beta}_*(\theta) = \vec{m}$

with matrices $m_i(\theta) = \langle \phi' | [K_i G_0 V(\theta) + V(\theta) G_0 K_i] | \phi \rangle$

4

$$M_{ij}(\theta) = \langle \phi' | [K_i G_0 K_j - K_i G_0 V(\theta) G_0 K_j + K_j G_0 K_i - K_j G_0 V(\theta) G_0 K_i] | \phi \rangle$$

3

Approximate K : $\langle \phi' | K | \phi \rangle \approx \langle \phi' | \mathcal{K}_* | \phi \rangle = \langle \phi' | V | \phi \rangle + \frac{1}{2} \vec{m}^\top M^{-1} \vec{m}$.

5

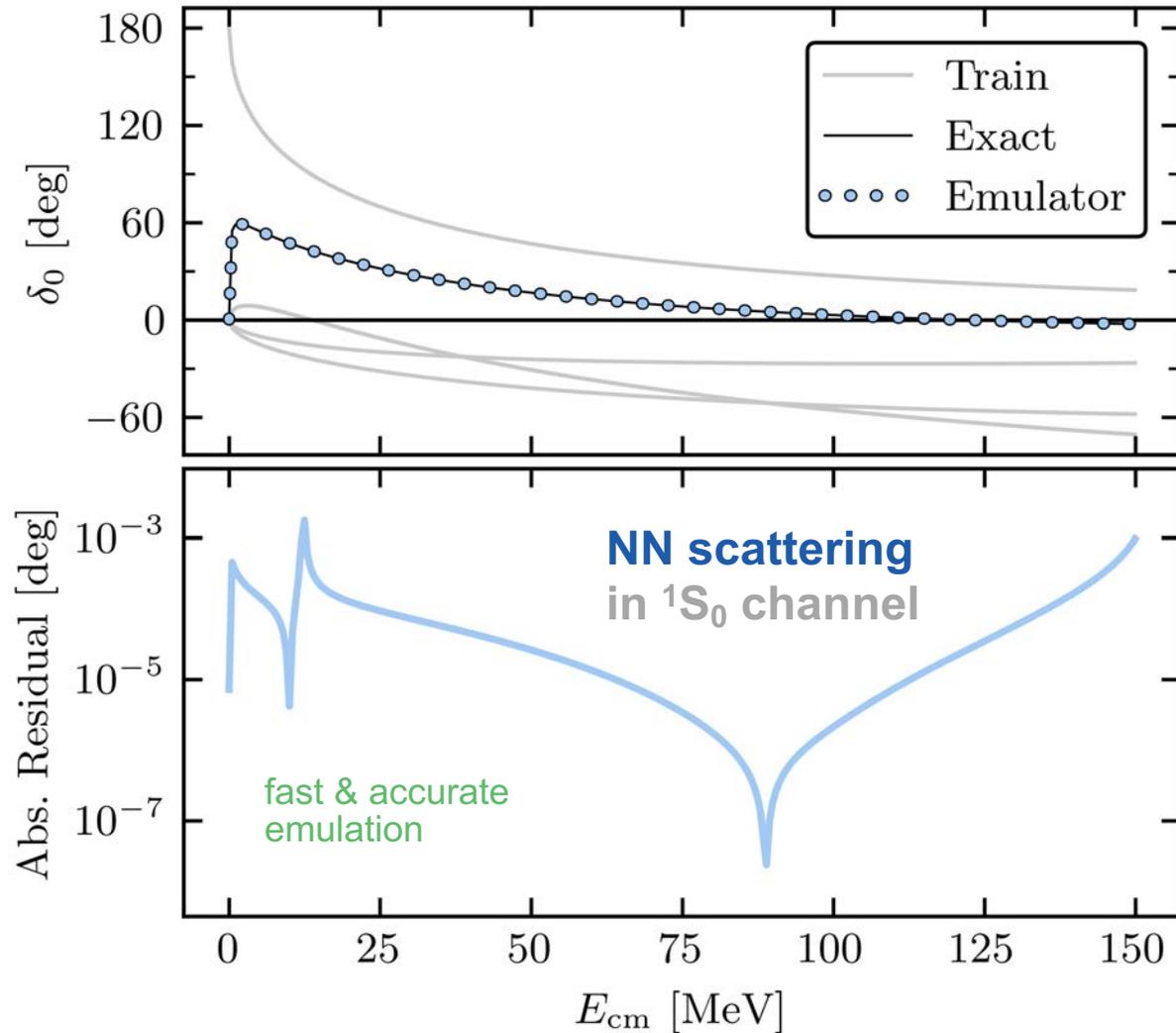
emulate

validate



Emulating phase shifts

Melendez, CD, Garcia, Furnstahl,
and Zhang, PLB 821, 136608

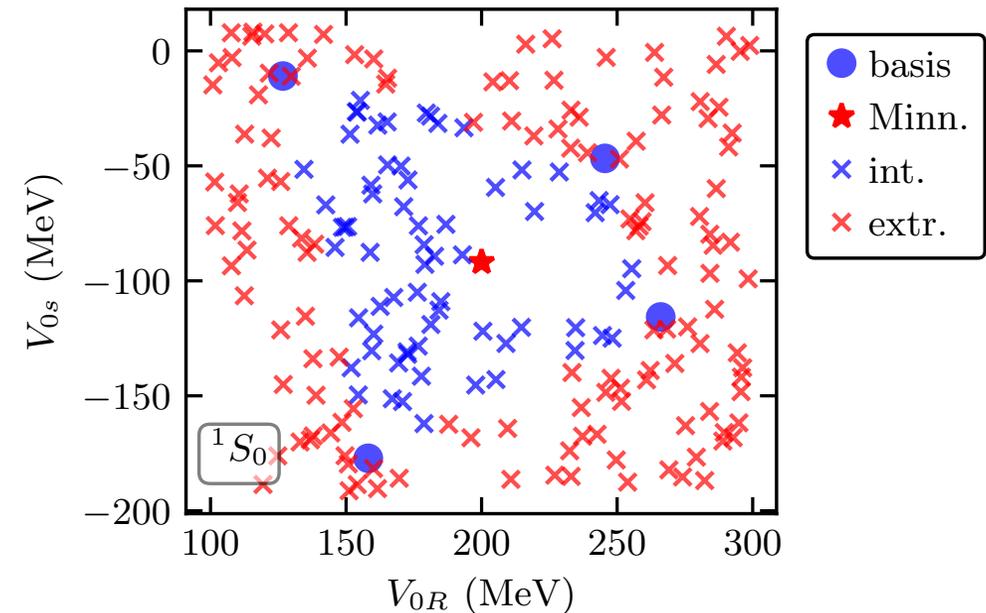


Newton Variational Principle

Minnesota potential

$$V(r) = V_{0R}e^{-\kappa_R r^2} + V_{0s}e^{-\kappa_s r^2}$$

Training set: 4 Hamiltonians with different (V_{0R}, V_{0s}) and fixed (κ_R, κ_s)



More accurate than equivalent KVP calculation: KVP residuals: $O(10^{-3})$

Using the emulator for extrapolation

Melendez, CD, Garcia, Furnstahl,
and Zhang, PLB 821, 136608

Minnesota potential

$$V(r) = V_{0R}e^{-\kappa_R r^2} + V_{0s}e^{-\kappa_s r^2}$$

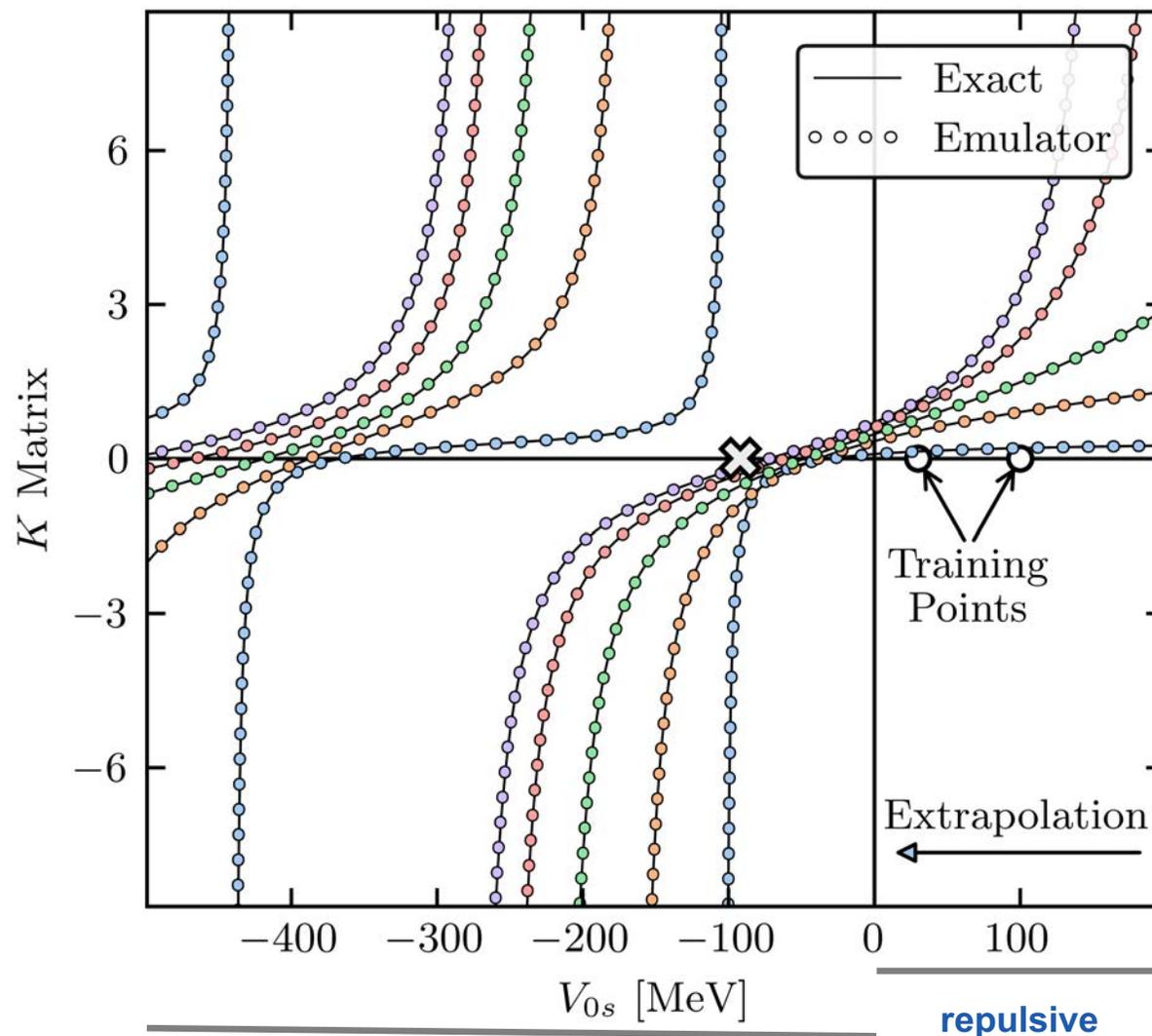
emulator as a **robust tool for extrapolations** (even from the repulsive to attractive regime)

Training set: two parameter sets with different $V_{0s} > 0$ (purely repulsive) and $(V_{0R}, \kappa_R, \kappa_s)$ fixed at the physical point

Colors correspond to different c.m. energies in the range 1–70 MeV.

Remarkable extrapolation far from the support of data and **across singularities in the K and K^{-1} matrix**

on-shell 1S_0 K matrix



Adding the Coulomb potential

Melendez, CD, Garcia, Furnstahl,
and Zhang, PLB 821, 136608

nonlocal potential

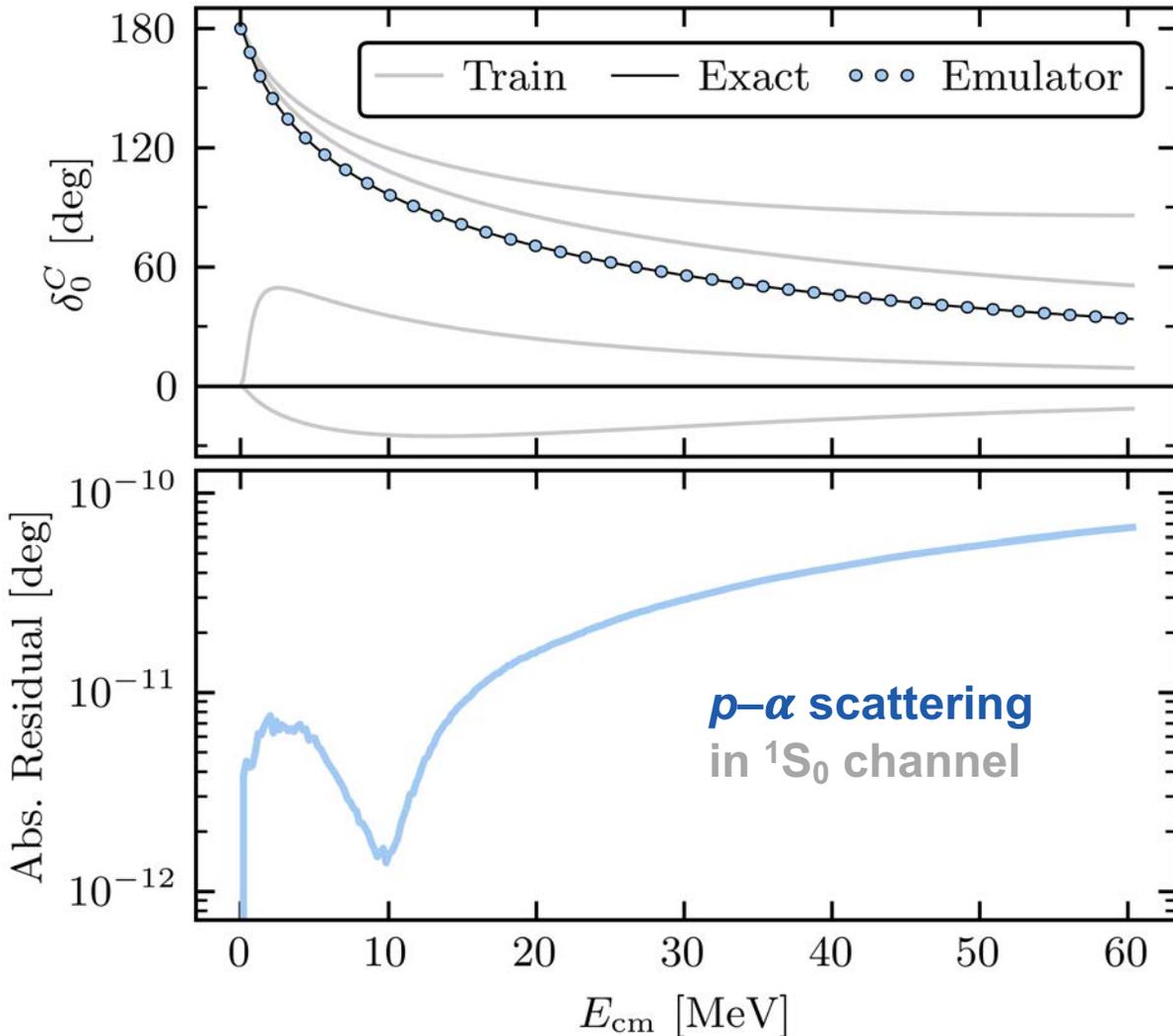
$$V_\ell(r, r') = V_{p\alpha, \ell}^{(0)} r'^\ell r^\ell e^{-\beta_\ell(r+r')}$$

Long range potentials: problematic for any LS equation (whether an emulator is used)

Vincent-Phatak method: cut off the Coulomb potential at a finite radius and then restore this physics using a matching procedure

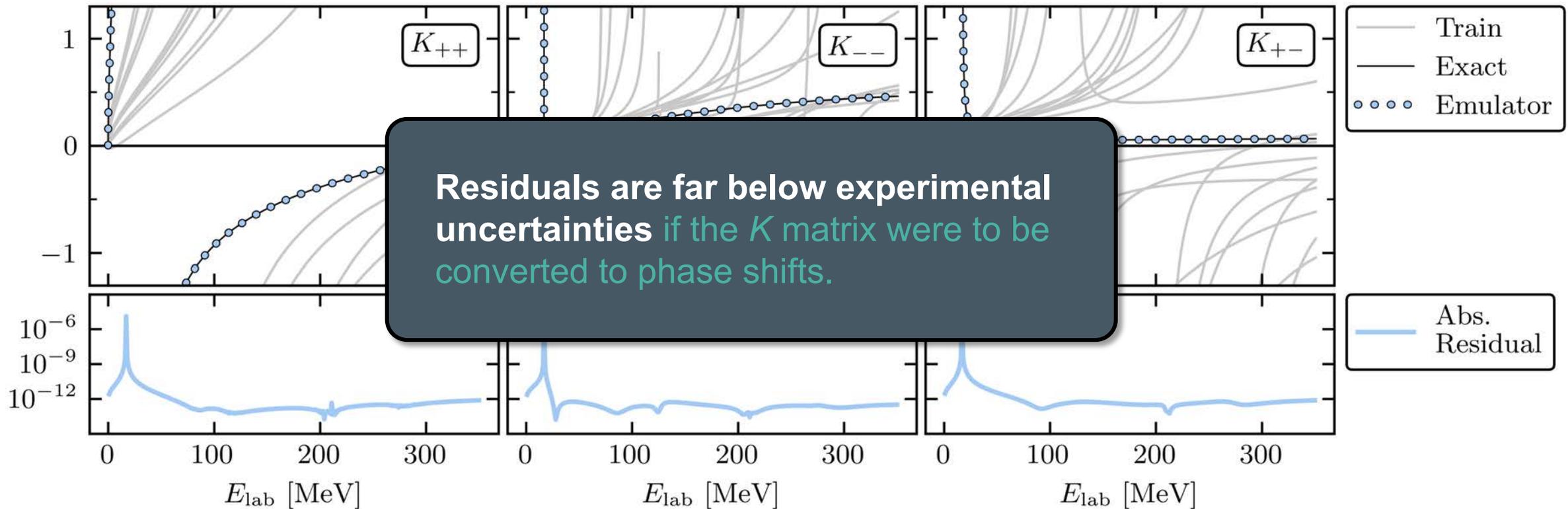
Training set: 4 Hamiltonians with different *linear* parameters $V_{p\alpha}$ and *nonlinear* β_0 fixed at the physical point.

Residuals are negligible in this range



Straightforwardly extended to coupled channel scattering

3S_1 - 3D_1 channel with
6 free parameters (LECs)



SMS chiral NN potential at N^4LO+ with
momentum cutoff $\Lambda = 450$ MeV

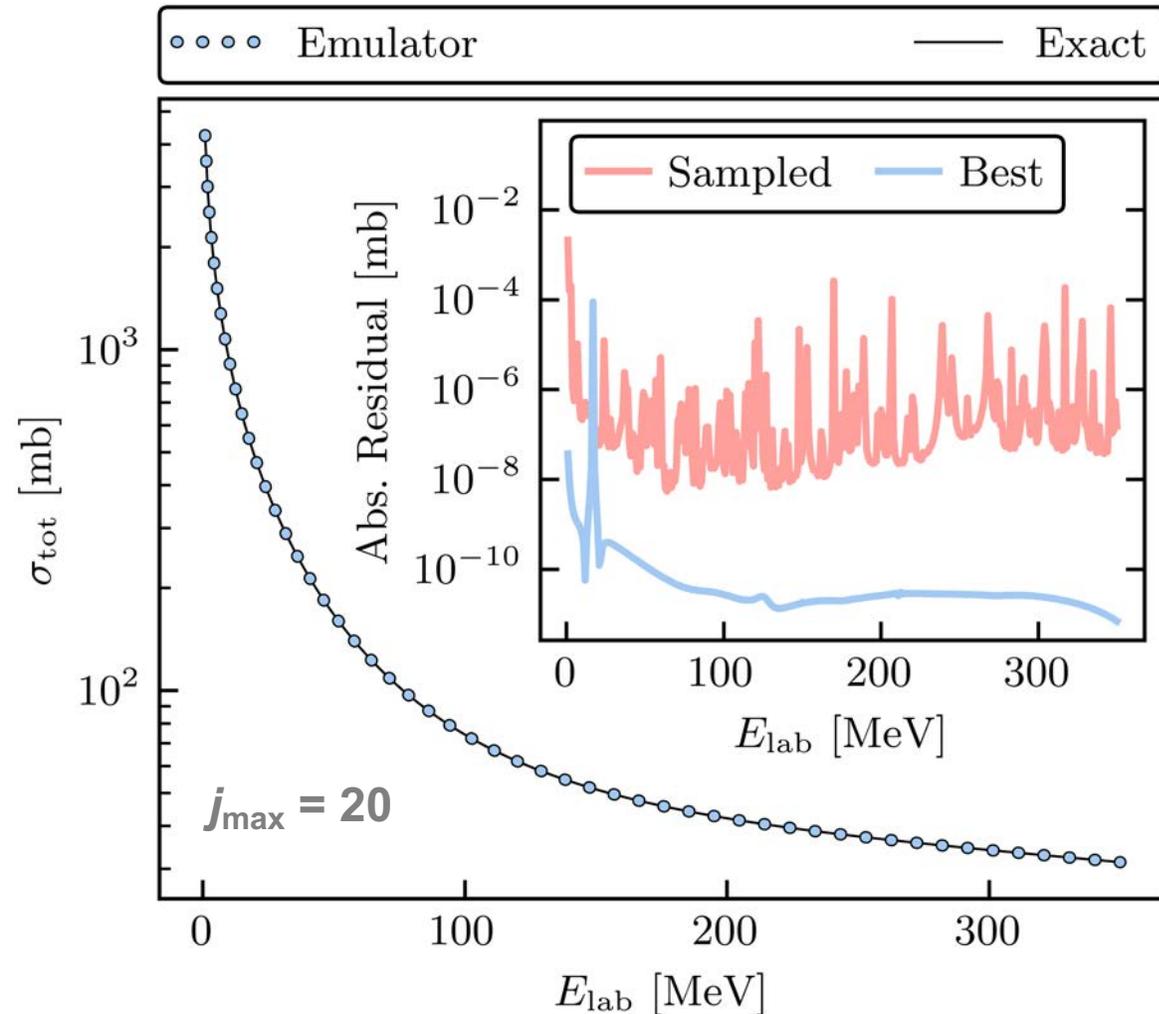
Reinert, Krebs, and Epelbaum, EPJ A 54, 86

12 training points randomly
chosen in the range $[-5, +5]$ in
the units used in the potential

Emulating total cross sections

Melendez, CD, Garcia, Furnstahl,
and Zhang, PLB 821, 136608

SMS chiral NN potential at N⁴LO+ with
momentum cutoff $\Lambda = 450$ MeV



Newton Variational Principle

$$\sigma_{\text{tot}}(q) = -\frac{\pi}{2q^2} \sum_{j=0}^{j_{\max}} (2j+1) \text{Re}\{\text{Tr}[S_j(q) - 1]\}$$

Train emulators across partial-wave channels up to $j = 4$ (while the remaining channels are fixed)

26 free parameters (LECs) varied

Residuals are vanishingly small compared to the cross section and its experimental uncertainty

Randomly sample 500 values: extrapolation of ± 10 [unit] beyond the range of the training data

>300x
faster than the exact calculation



Minnesota potential

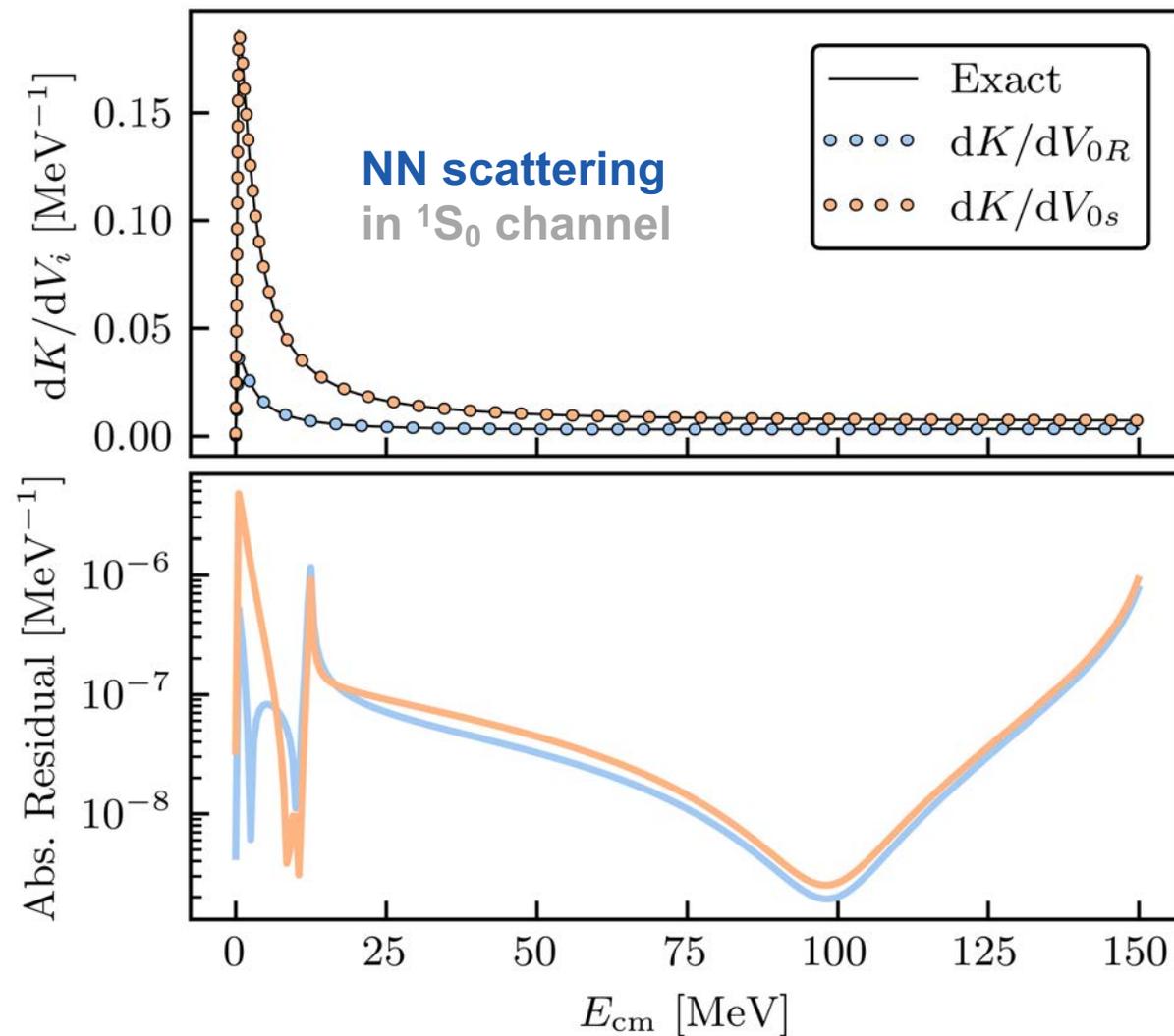
$$V(r) = V_{0R}e^{-\kappa_R r^2} + V_{0s}e^{-\kappa_s r^2}$$

Gradients w.r.t. the input parameters are useful for various optimization and Monte Carlo sampling algorithms.

Proof of principle:

We find that **emulated gradients**

- have **negligible residuals** at the physical point and
- can be incorporated in optimizers with **little computational overhead**



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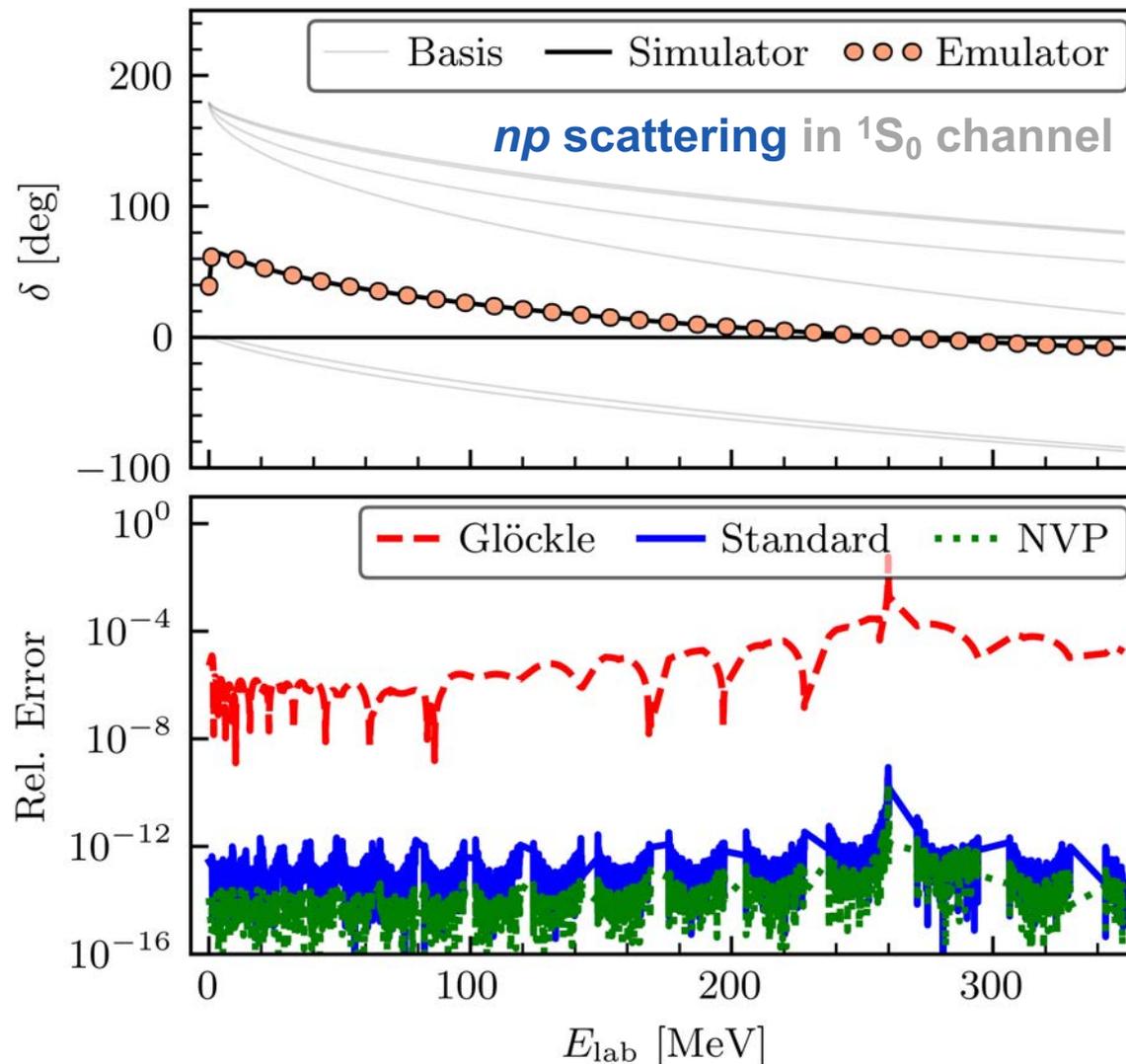
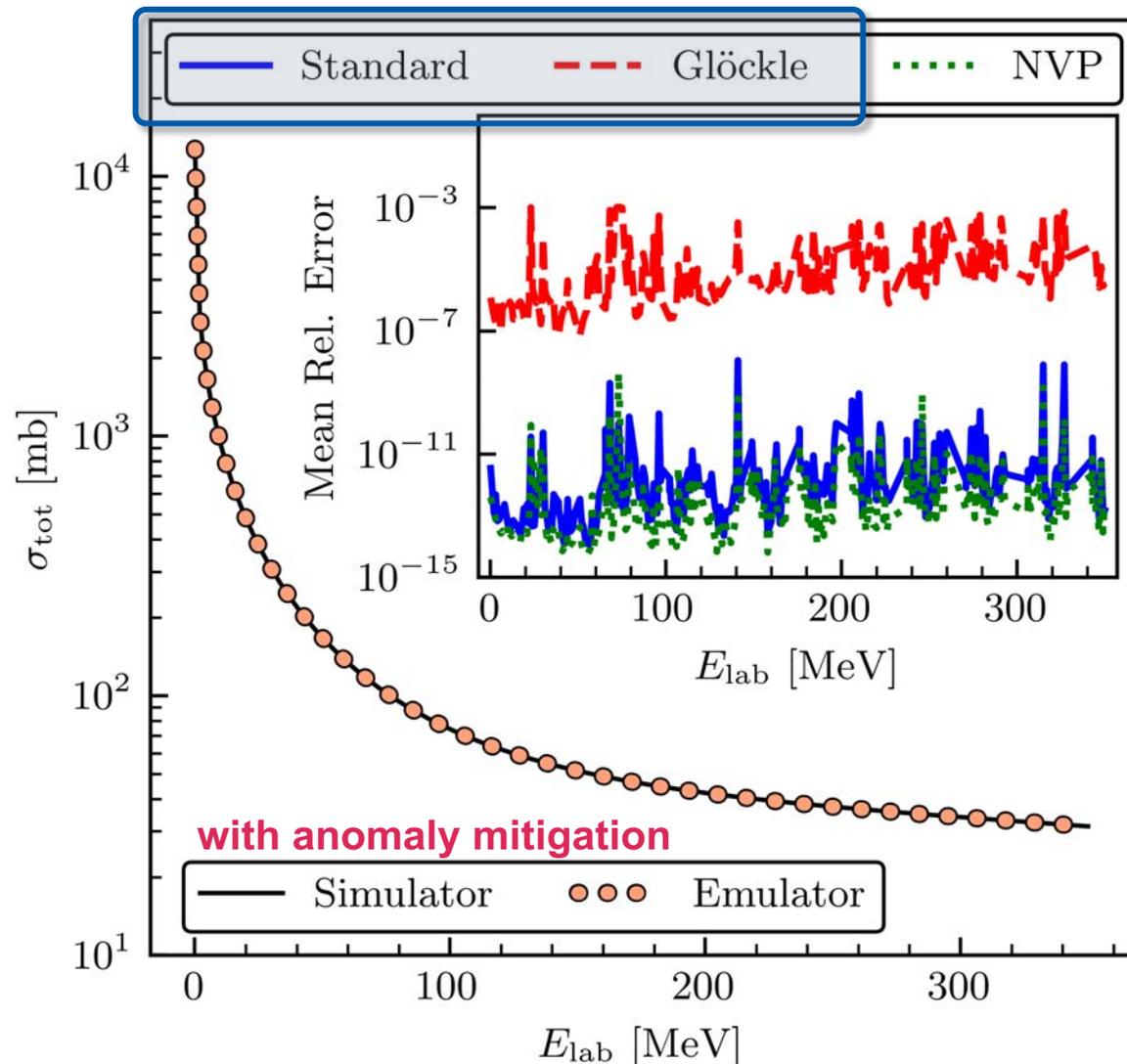
See also Xilin Zhang's talk:
*Further developments on emulators
for quantum continuum states*

See also: CD & Zhang's contribution to Few Body Syst. **63**, 67

Kohn vs Newton Variational Principle

Garcia, CD, Furnstahl, Melendez,
and Zhang, PRC 107, 054001

two implementations of the KVP



Complementary approaches

Variational Principle		Galerkin Projection Information			
Name	Functional for K	Strong Form	Trial Basis	Test Basis	Constrained?
Kohn (λ)	$\tilde{K}_E + \langle \tilde{\psi} H - E \tilde{\psi} \rangle$	$H \psi \rangle = E \psi \rangle$	$ \psi_i\rangle$	$\langle \psi_i $	Yes
Kohn (No λ)	$\langle \tilde{\chi} H - E \tilde{\chi} \rangle + \langle \phi V \tilde{\chi} \rangle + \langle \phi H - E \phi \rangle + \langle \tilde{\chi} V \phi \rangle$	$[E - H] \chi \rangle = V \phi \rangle$	$ \chi_i\rangle$	$\langle \chi_i $	No
Schwinger	$\langle \tilde{\psi} V \phi \rangle + \langle \phi V \tilde{\psi} \rangle - \langle \tilde{\psi} V - V G_0 V \tilde{\psi} \rangle$	$ \psi\rangle = \phi\rangle + G_0 V \psi\rangle$	$ \psi_i\rangle$	$\langle \psi_i $	No
Newton	$V + V G_0 \tilde{K} + \tilde{K} G_0 V - \tilde{K} G_0 \tilde{K} + \tilde{K} G_0 V G_0 \tilde{K}$	$K = V + V G_0 K$	K_i	K_i	No

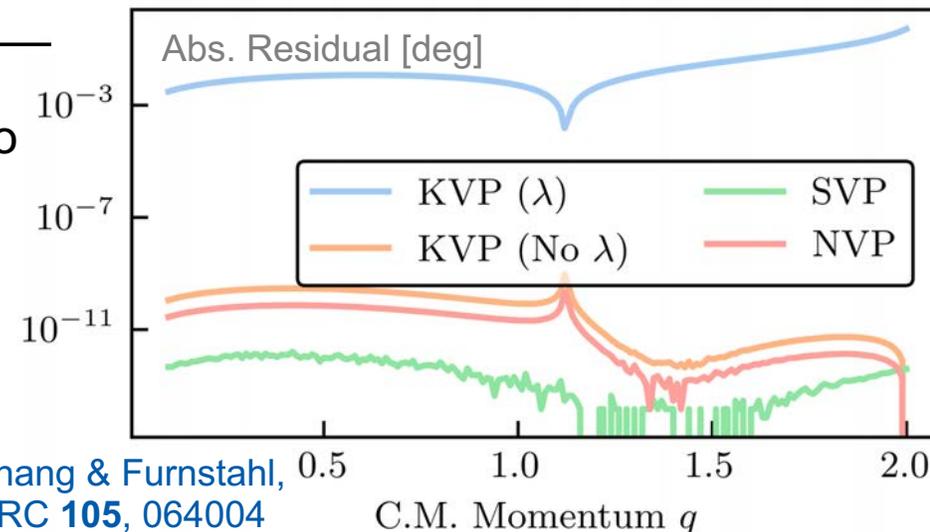
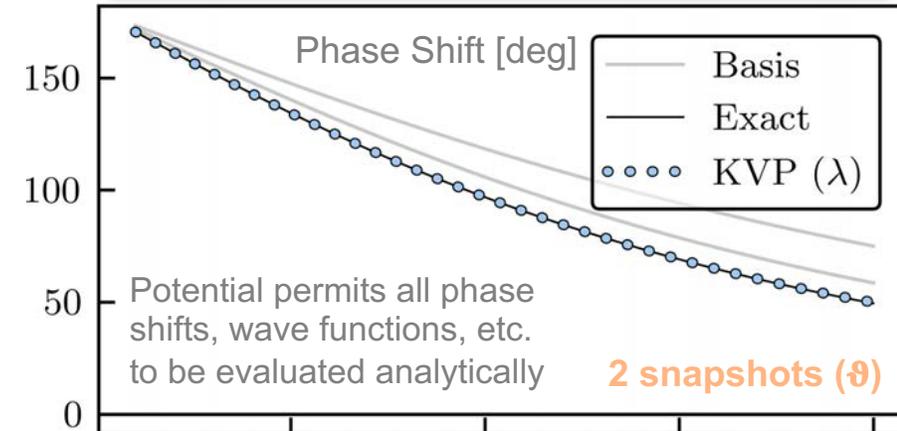
These variational emulators have G-ROM counterparts. But there are also **non-variational, e.g., “origin” ROMs** with $(r\psi)(0) = 0$, $(r\psi)'(0) = 1$

Complementary approaches to construct (two-body) ROMs: coordinate vs momentum space; variational vs Galerkin methods; ...

How do we construct *reliable* three-body scattering ROMs?

Yamaguchi potential

$$V_\ell = \sum_{ij}^{n=2} |v_i^\ell\rangle \Lambda_{ij} \langle v_j^\ell|$$



How large are emulator errors? When are they non-negligible? Are simple implementations of ROMs *good enough* for NP?

- convergence analyses are needed (for inter- and extrapolation)
- Understand their limitations and investigate potential improvements

How can we construct efficient greedy algorithms? POD-based and hybrid methods should be further investigated.

How can we leverage ROMs' remarkable extrapolation capabilities? For continuous *and* discrete problems?



G-ROMs for two-body scattering

**various implementations available (BUQEYE website)
approximate but highly accurate and inexpensive
offline-online decompositions important
hyper-reduction methods for non-affine/-linear problems**

What are the best practices for implementing ROMs efficiently? What can we learn from MOR software libraries like pyMOR or libROM?

Can we construct improved ROMs via Petrov-Galerkin projection? These ROMs are more general than G-ROMs (and variational ROMs).

What are the limits of hyper-reduction methods (in terms of accuracy and speed) applied to non-linear problems in NP?

How can we leverage ROMs as collaboration tools and open-source mini-apps accessible to non-experts?

Extensive MOR/RBM literature can (and should) provide guidance.