

ESNT WORKSHOP

Emulation of PGCM calculations using the eigenvector continuation method



A. Roux

T. Duguet, J-P. Ebran, V. Somà, M. Frosini

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Outline

Part 1 : general considerations

- Introduction
- GCM formalism
- GCM workflow
- Emulator workflow
- Emulator quality
- Grassmannian distance

Part 2 : results

- The model
- Subspace distance
- Brute-force self-learning
- Fixed common space
- Under and over training
- Emulator quality vs subspace distance
- Computational cost

PGCM → Projected Generator Coordinate Method

- Beyond mean-field approximation of A-body nuclear problem (HFB)
- Static correlations & collective spectroscopy

EC → Eigenvector Continuation*

- Emulate eigensolutions of parametrized hamiltonian

PGCM-EC

- Same underlying formalism
- Taking advantage of

$$H^\mu = \sum_{k=1}^{n_p} \mu^k h_k$$

- Emulate PGCM for arbitrary μ with negligible cost
- Uncertainty propagation

* D.Frame et al, PRL 121, 032508 (2018)

A.Ekstrom, G.Hagen, arXiv:1910.02922v1 (2019)

T.Duguet et al, arXiv:2310.19419v1 (2023)

Part 1 : general considerations GCM formalism

PGCM state $\longrightarrow |\Psi\rangle = \sum_q f_q P |\Phi_q\rangle \longrightarrow$ Constrained HFB states

$\delta \frac{\langle \Psi | H | \Psi \rangle}{\langle \Psi | \Psi \rangle} = 0$ Symmetry restoring projection (N, Z, J)

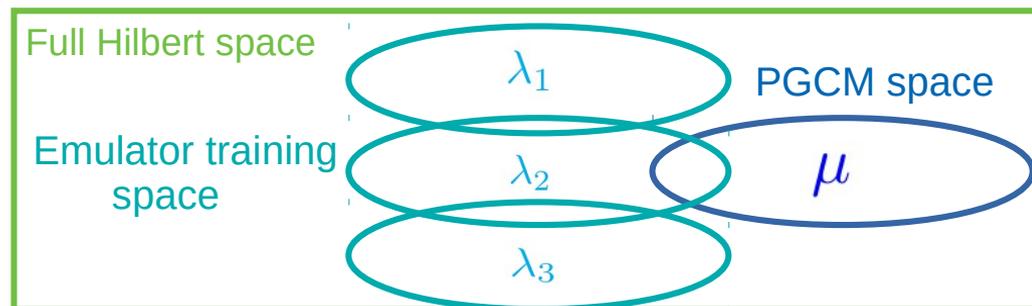
PGCM \longrightarrow f_q obtained by extremizing energy in physically-inspired small-dimensional subspace

\longrightarrow Ab initio collective spectroscopy

Strong point of PGCM

Emulator \longrightarrow needs to emulate both coefficients and subspace

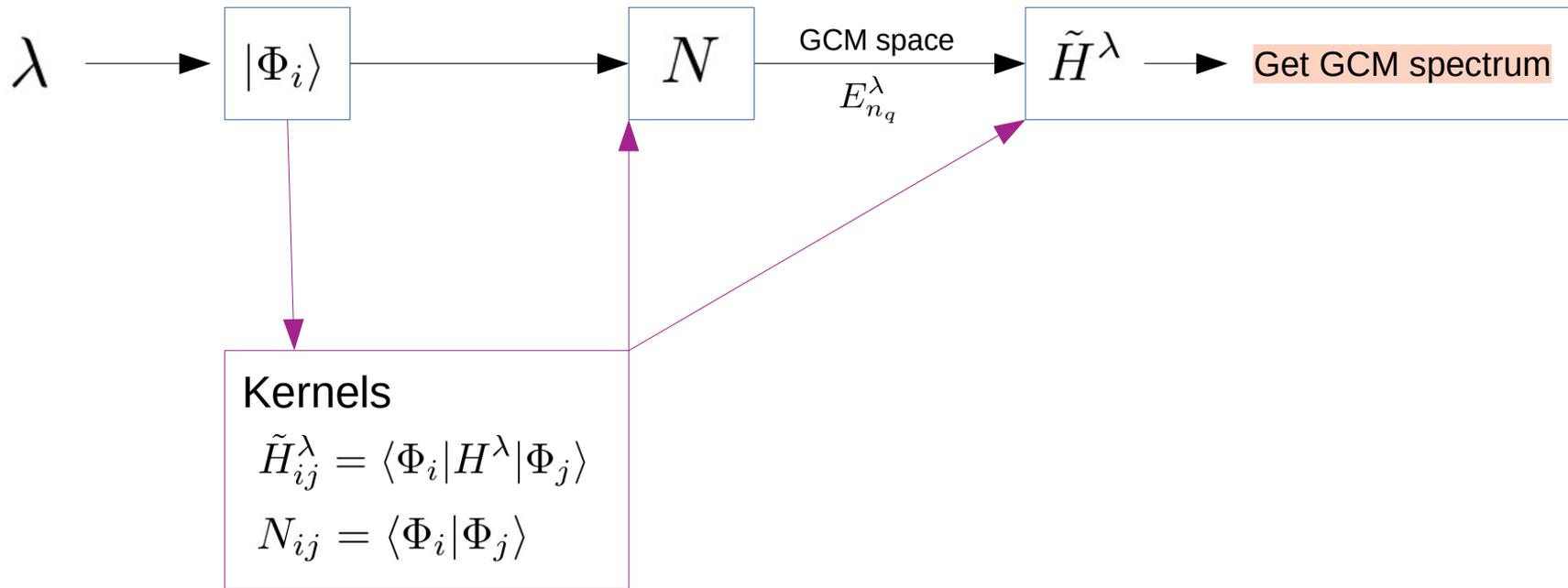
Challenging point for emulator



Part 1 : general considerations

GCM workflow

Interaction parameter λ HFB computations for H^λ $1 \leq i \leq n_q$ Diagonalise norm matrix N Keep eigenvalues $> \epsilon$ Diagonalise in N eigenbasis

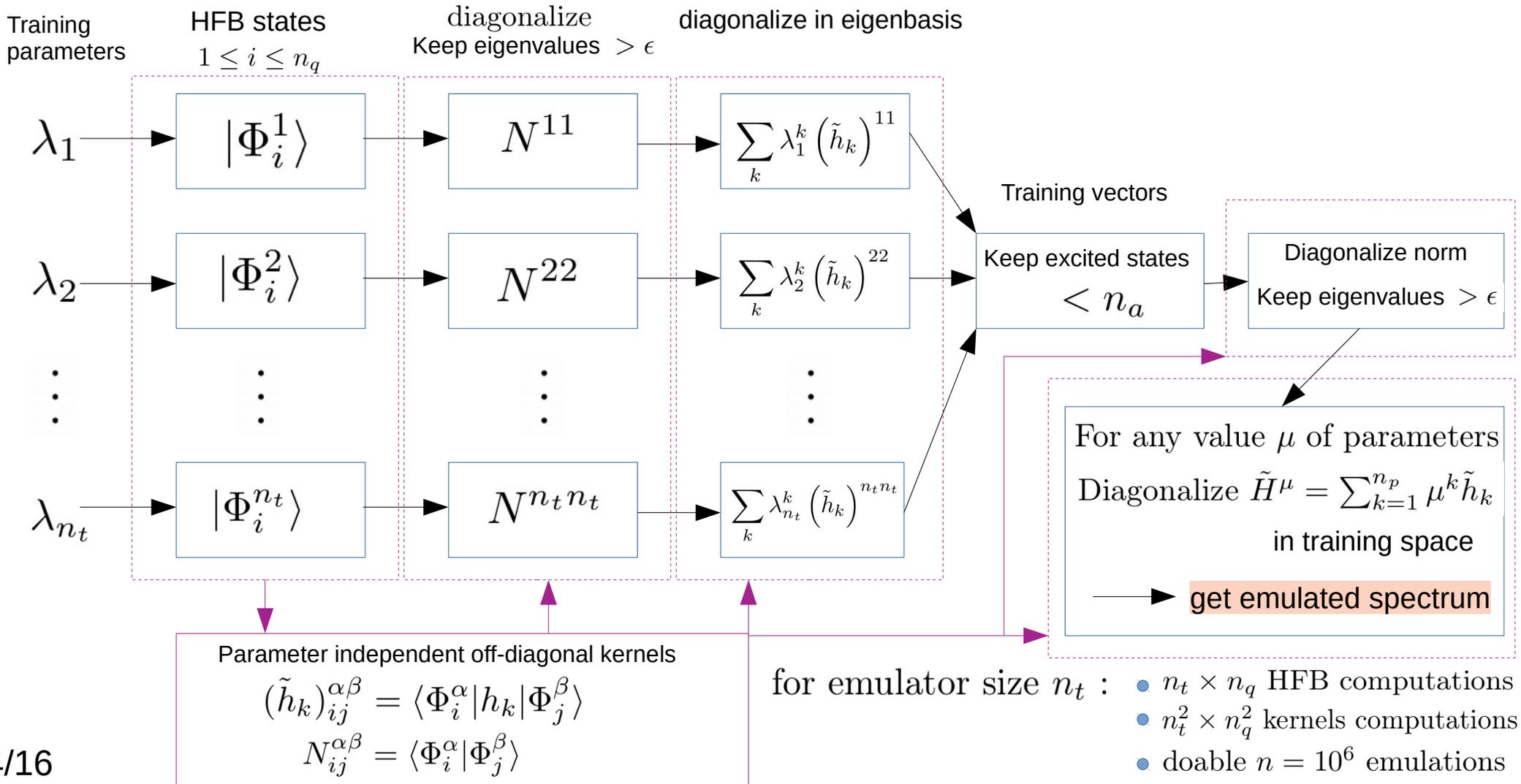


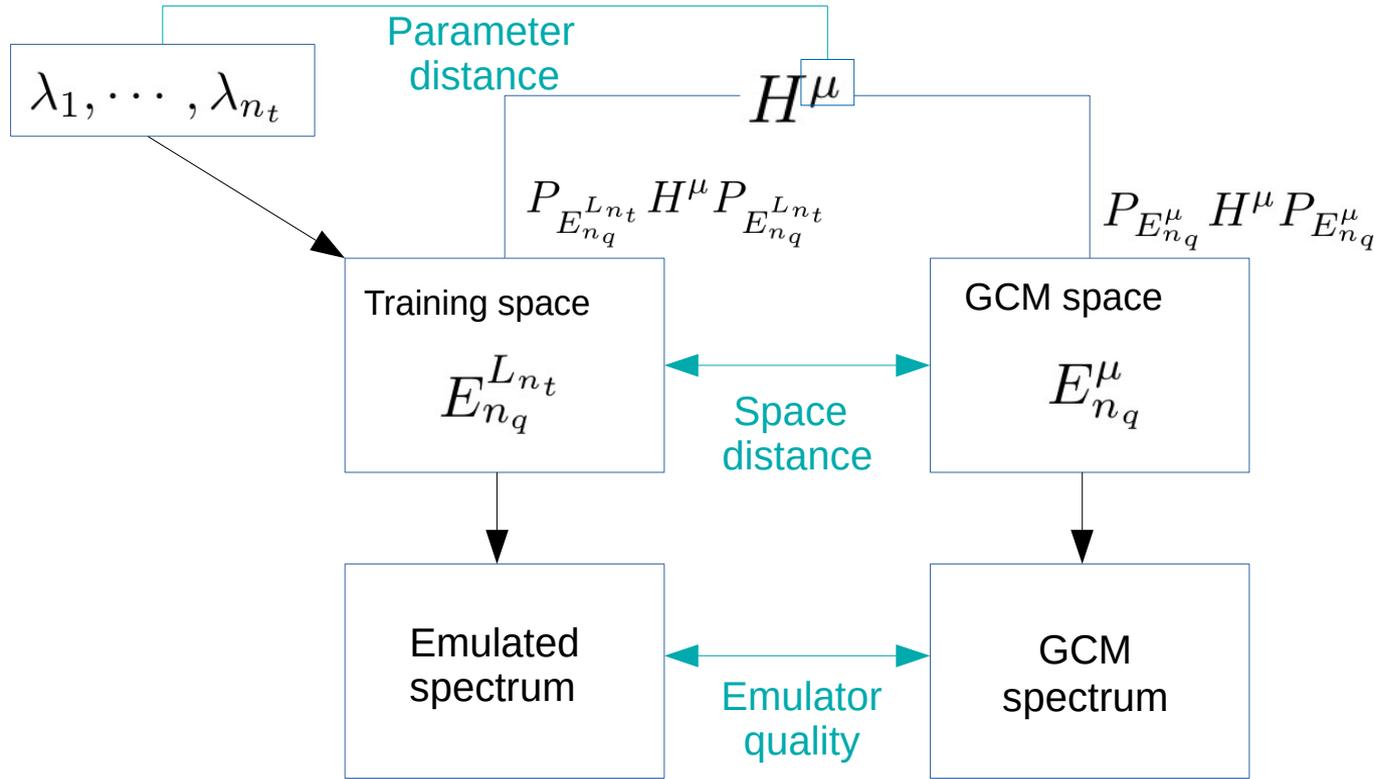
For n GCM computations :

- $n \times n_q$ HFB computations
- $n \times n_q^2$ kernels computations

} Numerically undoable
 $n \simeq 10^6$

Part 1 : general considerations Emulator workflow





- Parameter distance : Euclidean distance
- Space distance : Grassmannian distance
- Emulator quality : relative error

} Are they correlated ?

- \mathcal{H} , n -dimensional Hilbert space
- $\text{Gr}(k, \mathcal{H})$ set of k -dimensional linear subspace of \mathcal{H}
 - $= O(n) / (O(k) \times O(n - k))$
 - homogeneous space
 - riemannian manifold
 - ◆ geodesic distance
- For $V_1 \in \text{Gr}(k, \mathcal{H})$, $V_2 \in \text{Gr}(l, \mathcal{H})$, $k < l$ *
 - define $\Omega^-(V_2) = \{W \in \text{Gr}(k, \mathcal{H}) \mid W \subset V_2\} \subset \text{Gr}(k, \mathcal{H})$
- $\delta(V_1, V_2) =$ minimal geodesic distance from V_1 to $\Omega^-(V_2)$
- $\delta(V_1, V_2) = 0 \iff V_1 \subset V_2$ or $V_2 \subset V_1$
 - δ is a premetric

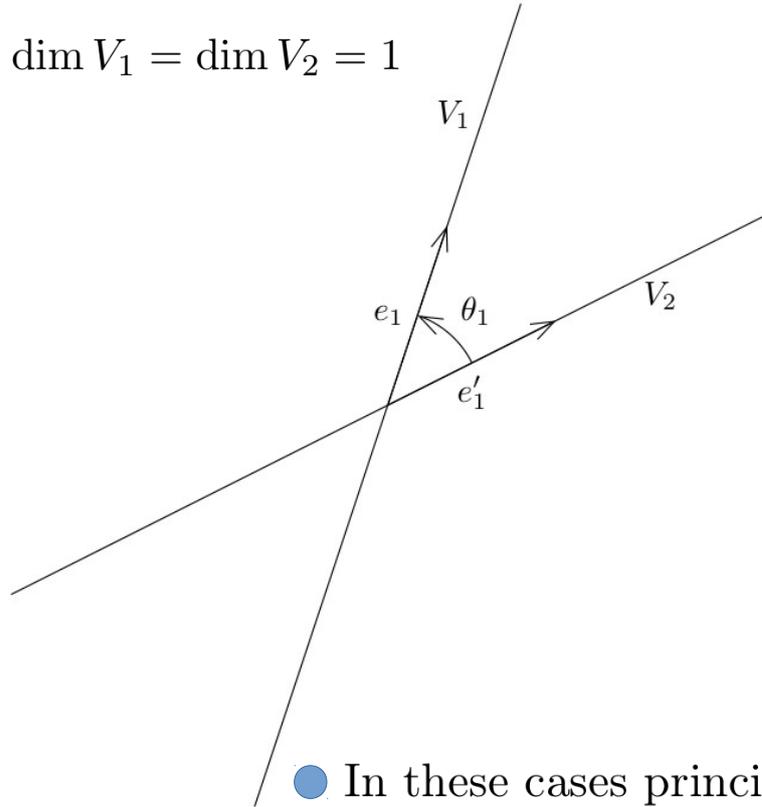
*Ye and Lim, SIAM (2016)

- Readily computable
 - $(u_i)_{1 \leq i \leq k}$ orthonormal basis of V_1
 - $(v_i)_{1 \leq i \leq l}$ orthonormal basis of V_2
- $X_{ij} = \langle u_i, v_j \rangle \rightarrow$ SVD
- $S = (s_1, \dots, s_m) = (\cos \theta_1, \dots, \cos \theta_m)$
 - $0 \leq \theta_i \leq \frac{\pi}{2}$ principal angles $m = \min(k, l)$
- $\delta(V_1, V_2) = \left(\sum_{i=1}^m \theta_i^2 \right)^{\frac{1}{2}} \leq \frac{\pi}{2} \sqrt{m}$
- upper bound attained iff V_1 and V_2 are orthogonal

Part 1 : general considerations

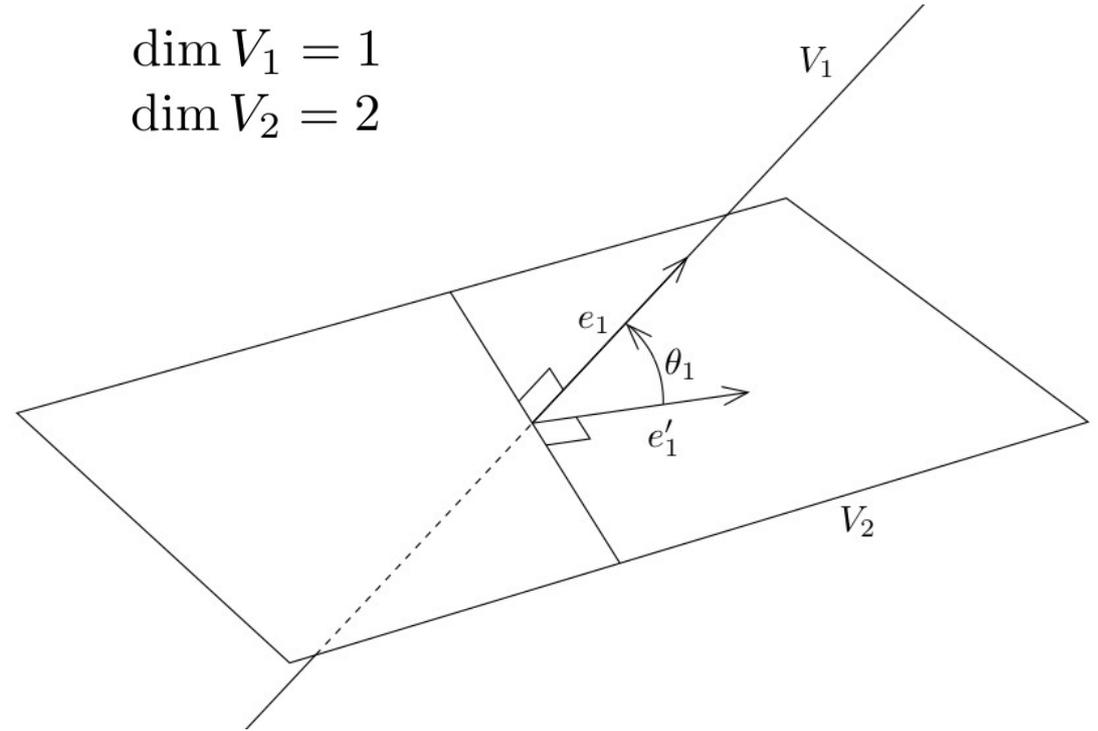
Grassmannian distance

$\dim V_1 = \dim V_2 = 1$



$\dim V_1 = 1$

$\dim V_2 = 2$



- In these cases principal angle θ_1 is the angle between subspace V_1 and V_2

—————► $\delta(V_1, V_2) = |\theta_1|$

- When $\dim V_1 = 1$ and $\dim V_2 = 2$

$\delta(V_1, V_2)$ is smallest distance between V_1 and all 1-dimensional subspaces of V_2

Part 2 : Results The model

- ^{20}Ne Nucleus
- No particle number & J^2 projections
- Brink & Boecker interaction (4 + 2 parameters)

$$V^{\text{BB}} = \sum_{i=0}^1 (w_i - m_i P_\sigma P_\tau) e^{-(r_1 - r_2)^2 / \mu_i^2}$$

+ kinetic & COM correction

→ $n_p = 4$

- mesh on β_2, β_3 with $n_q = 53$ points
- basis truncation : 8 oscillator shells
- Latin Hypercube Sampling in $[\lambda_0 - 10, \lambda_0 + 10]^4$
with $n_{\text{pes}} = 50$ points

● 50×53 HF states → computation time : 736 hours

● $\frac{(50 \times 53)^2}{2} \times 6$ kernels → computation time : 2703 hours

Nominal parametrization

$$w_0 = -72.21 \text{ MeV}$$

$$m_0 = -68.39 \text{ MeV}$$

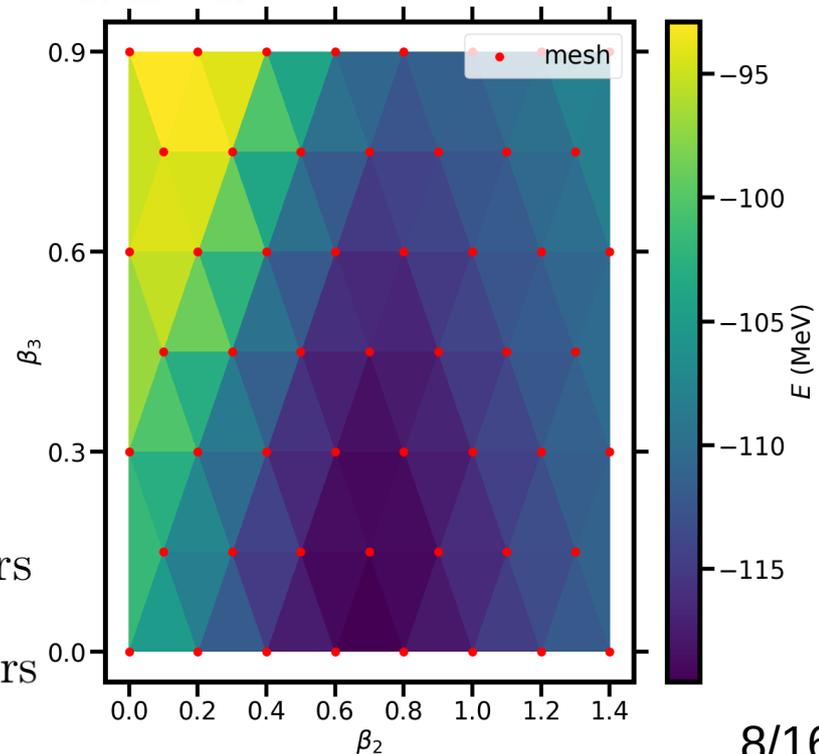
$$w_1 = -595.55 \text{ MeV}$$

$$m_1 = -206.05 \text{ MeV}$$

$$\mu_0 = 1.4 \text{ fm}$$

$$\mu_1 = 0.7 \text{ fm}$$

Fixed at nominal values



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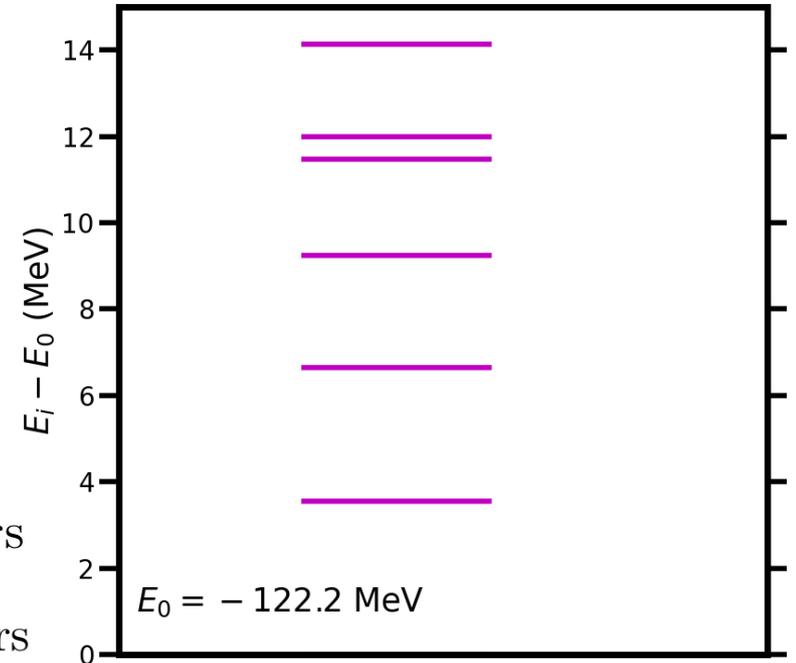
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Part 2 : Results Subspace distance

- for each $1 \leq i \leq 50$ compute $E_{53}^{\lambda_i}$ with $\epsilon = 10^{-6}$

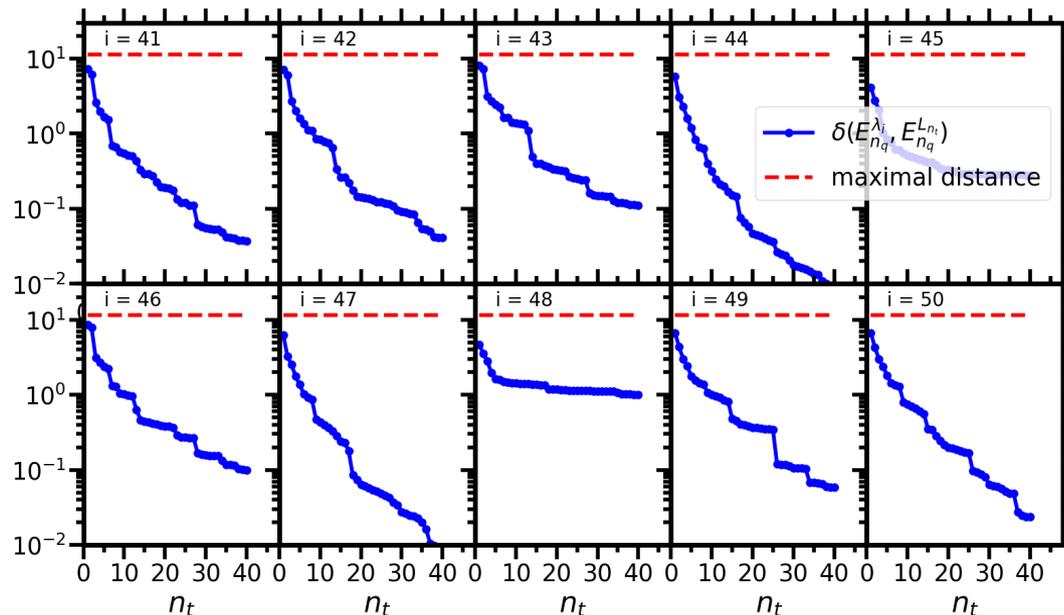
for $1 \leq i \leq n_t$ concatenate basis of $E_{53}^{\lambda_i}$

diagonalize norm matrix with $\epsilon^{L_{n_t}} = 10^{-8}$

get space $E_{53}^{L_{n_t}}$

compute $\delta(E_{53}^{\lambda_i}, E_{53}^{L_{n_t}})$ for $41 \leq i \leq 50$

n_t	1	10	40
mean d_{space}	6.546	0.825	0.168
dispersion d_{space}	1.322	0.367	0.290



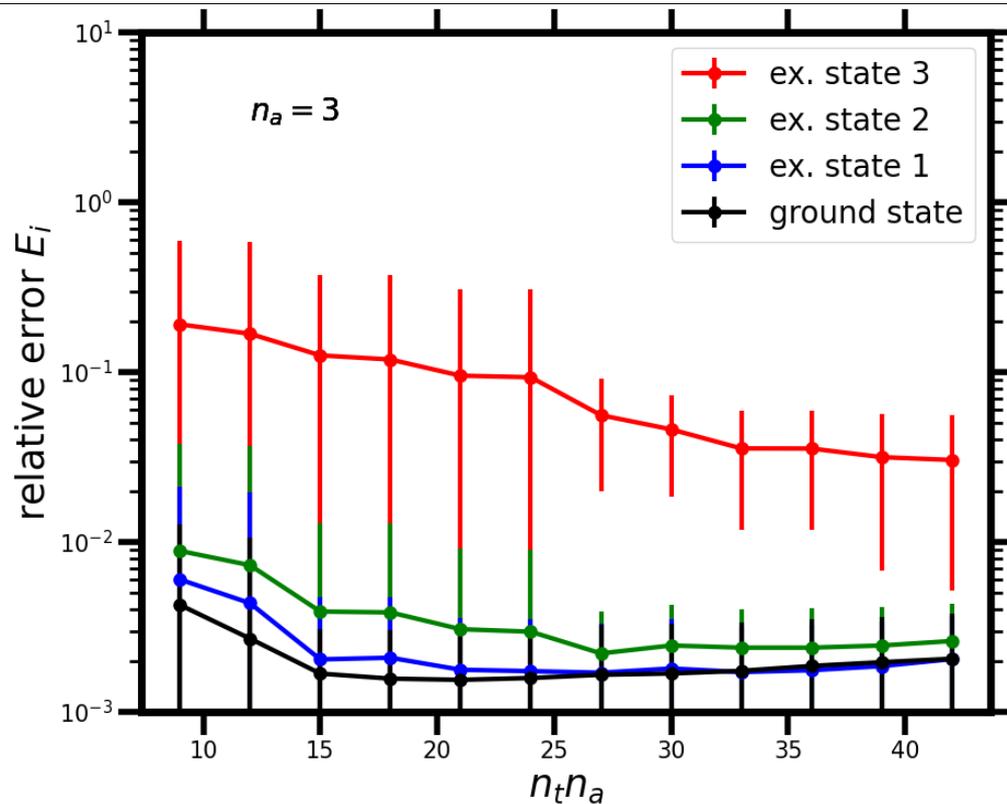
- Distance decrease quasi-exponentially for (essentially) all $41 \leq i \leq 50$

- $\delta(E_{53}^{\lambda_{43}}, E_{53}^{L_{40}}) \simeq \delta(E_{53}^{\lambda_{45}}, E_{53}^{L_{40}}) \simeq 0.1$ and $\delta(E_{53}^{\lambda_{48}}, E_{53}^{L_{40}}) \simeq 1$

—————► $E_{53}^{\lambda_{43}}, E_{53}^{\lambda_{45}}$ and $E_{53}^{\lambda_{48}}$ not fully emulated by training space

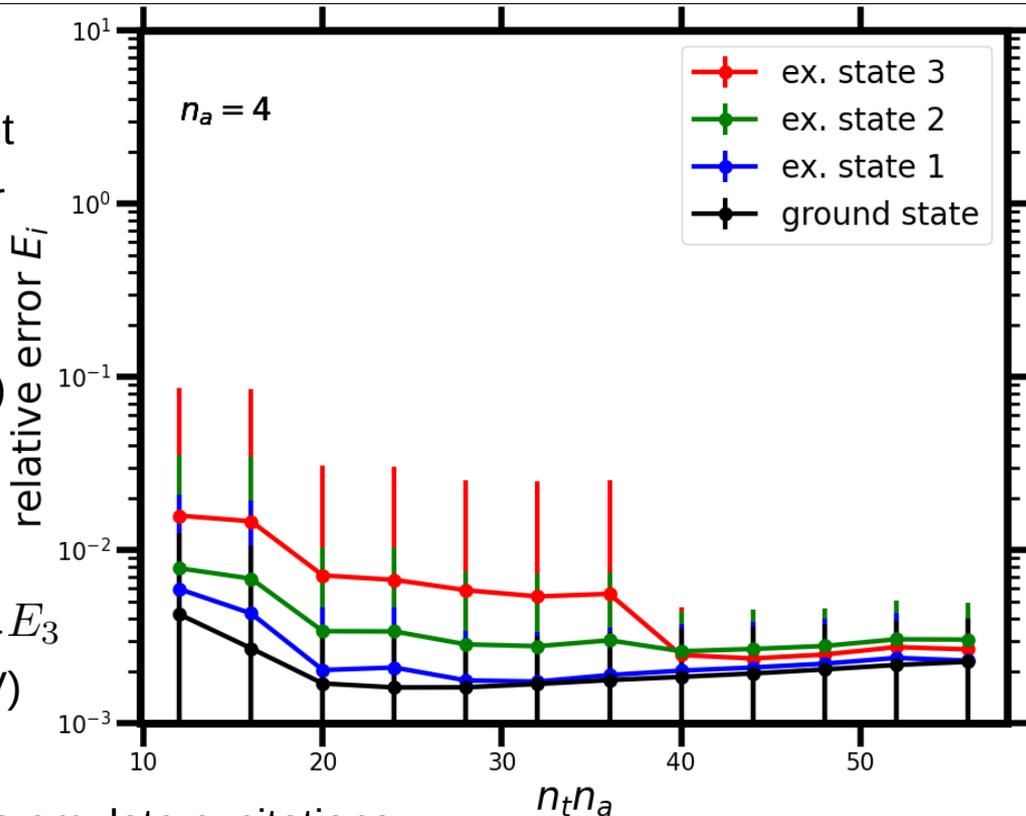
Part 2 : Results Brute-force self-learning

- For $1 \leq n_t < n_{t \max}$ take as $n_t + 1$ training point the one minimizing ground state relative error
- For $n_a = 3$ very good reproduction of $E_0 E_1 E_2$
 - Best relative error : 0.3 % (~ 0.4 MeV)
 - good reproduction of E_3
 - Best relative error : 3 % (~ 4 MeV)



Part 2 : Results Brute-force self-learning

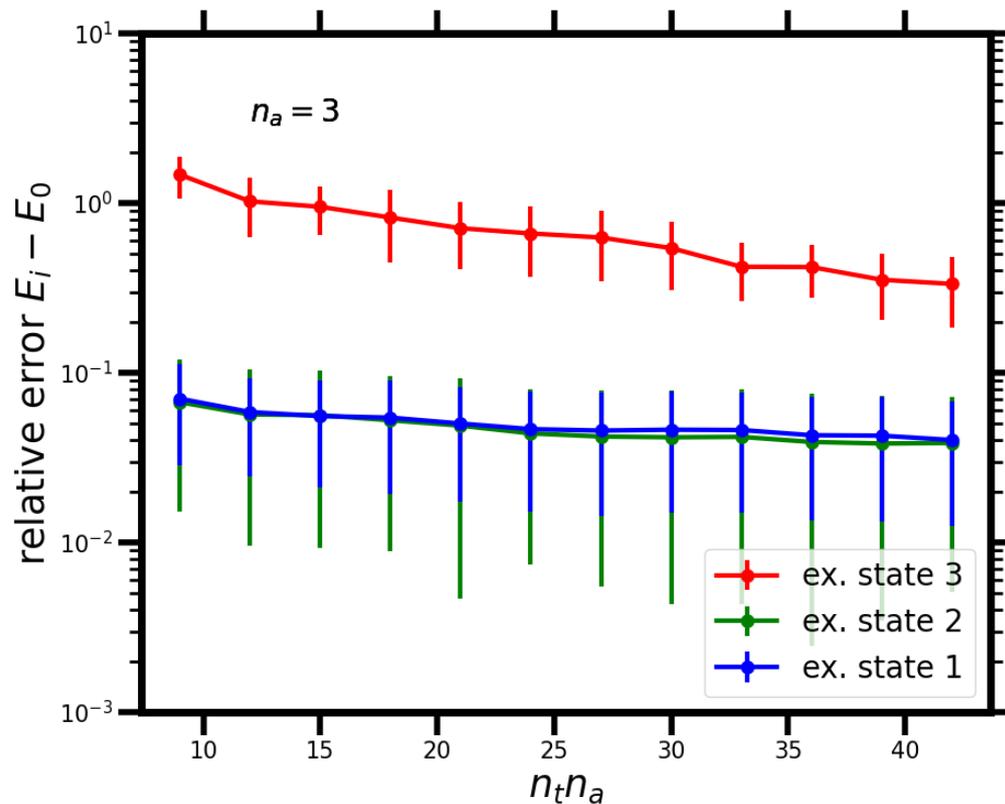
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 - good reproduction of E_3
 - Best relative error : 3 % (~ 4 MeV)
- For $n_a = 4$ very good reproduction of $E_0 E_1 E_2 \& E_3$
 - Best relative error : 0.3 % (~ 0.4 MeV)



- Training on excited states is necessary to emulate excitations
- Very good accuracy
- For $n_t \geq 6$ accuracy slowly degrades

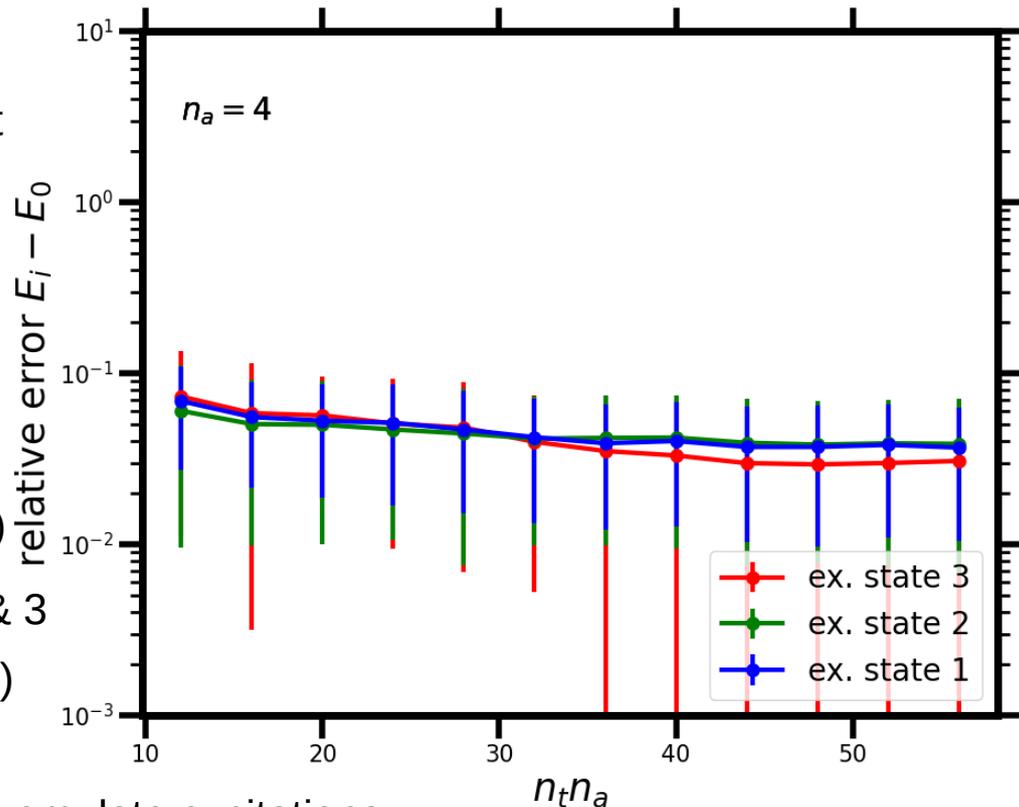
Part 2 : Results Brute-force self-learning

- For $1 \leq n_t < n_{t \text{ max}}$ take as $n_t + 1$ training point the one minimizing ground state relative error
- For $n_a = 3$ good reproduction of excitations 1 & 2
 - Best relative error : 4 % (~ 160 keV)
 - bad reproduction of excitation 3
 - Best relative error : 20 % (~ 800 keV)



Part 2 : Results Brute-force self-learning

- For $1 \leq n_t < n_{t \max}$ take as $n_t + 1$ training point the one minimizing ground state relative error
- For $n_a = 3$ good reproduction of excitations 1 & 2
 - Best relative error : 4 % (~ 0.16 MeV)
 - bad reproduction of excitation 3
 - Best relative error : 20 % (~ 0.8 MeV)
- For $n_a = 4$ good reproduction of excitations 1, 2 & 3
 - Best relative error : 4 % (~ 0.16 MeV)



- Training on excited states is necessary to emulate excitations
- Good accuracy but not fantastic
- For large n_t accuracy keeps improving slowly

Part 2 : Results

Emulator vs simulator in fixed common space

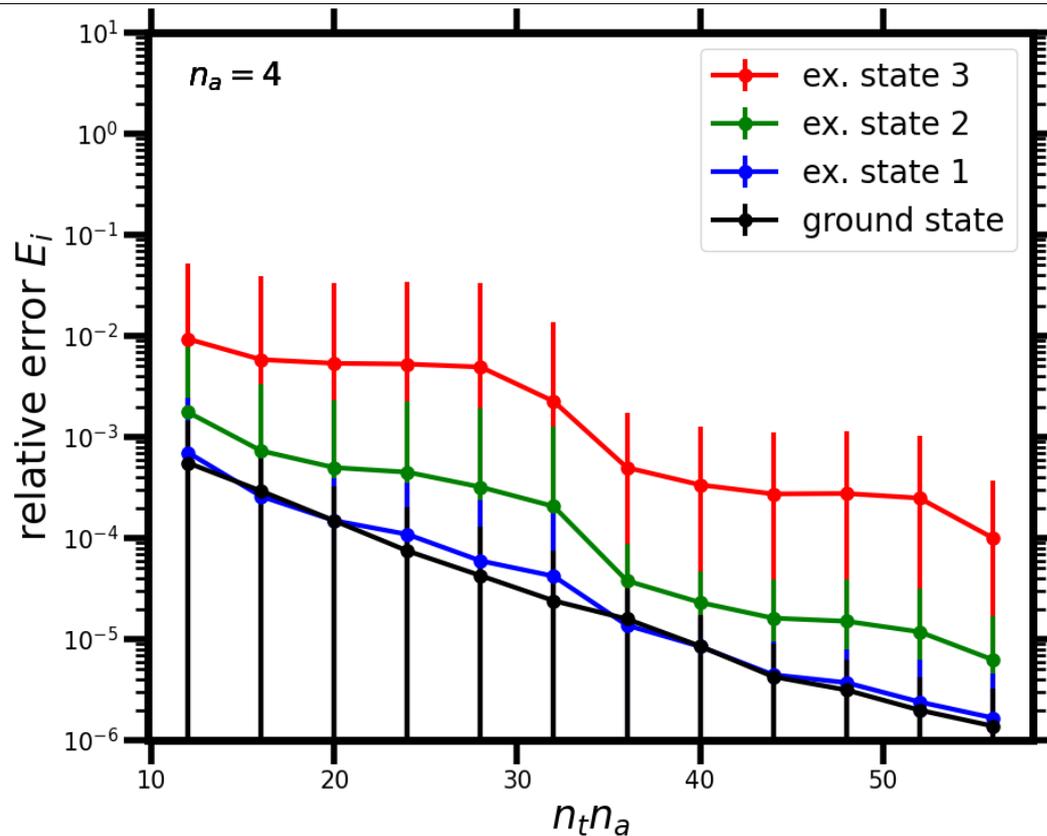
● Do emulation & GCM in a fixed common space

◆ Emulation of GCM coefficients

◆ No need to emulate GCM space

● Best relative errors

$E_0 \& E_1$	0.0002 %
E_2	0.001 %
E_3	0.01 %



Part 2 : Results Emulator vs simulator in fixed common space

- Do emulation & GCM in a fixed common space

- Emulation of GCM coefficients

- No need to emulate GCM space

- Best relative errors

$E_0 \& E_1$	0.0002 %
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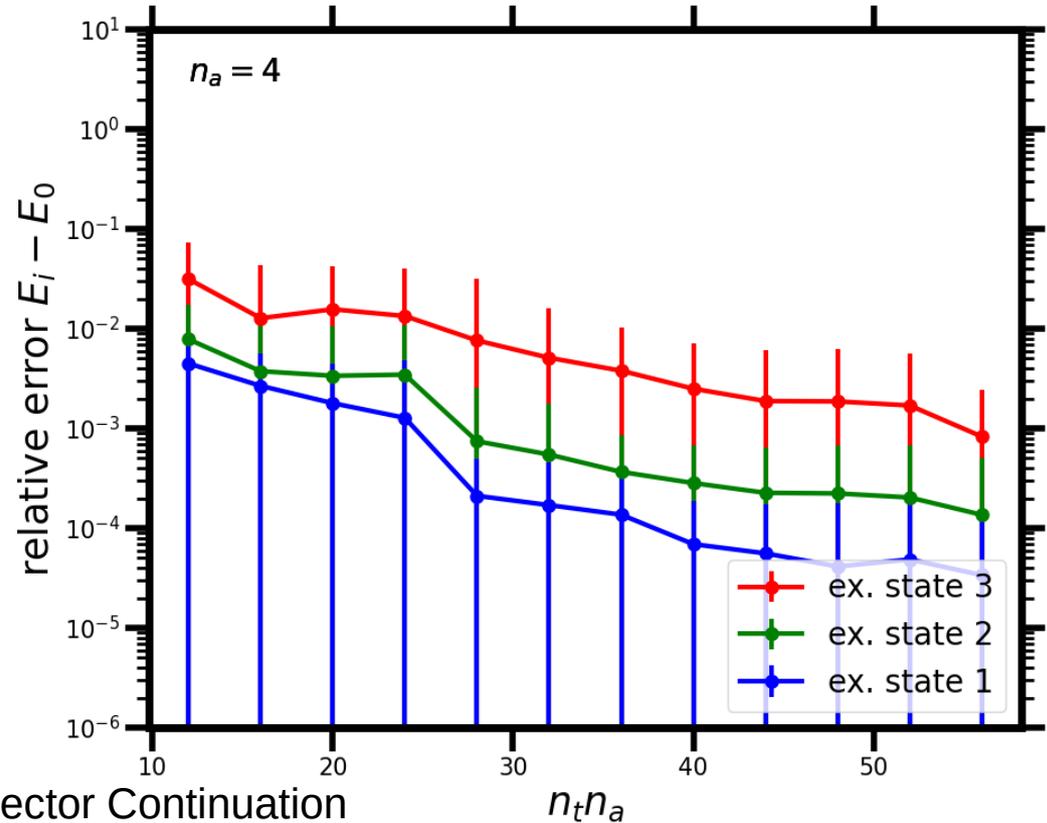
E_2	0.001 %
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E_3	0.01 %
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$E_1 - E_0$	0.003 %
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$E_2 - E_0$	0.01 %
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$E_3 - E_0$	0.1 %
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- Agrees with previous work on Eigenvector Continuation

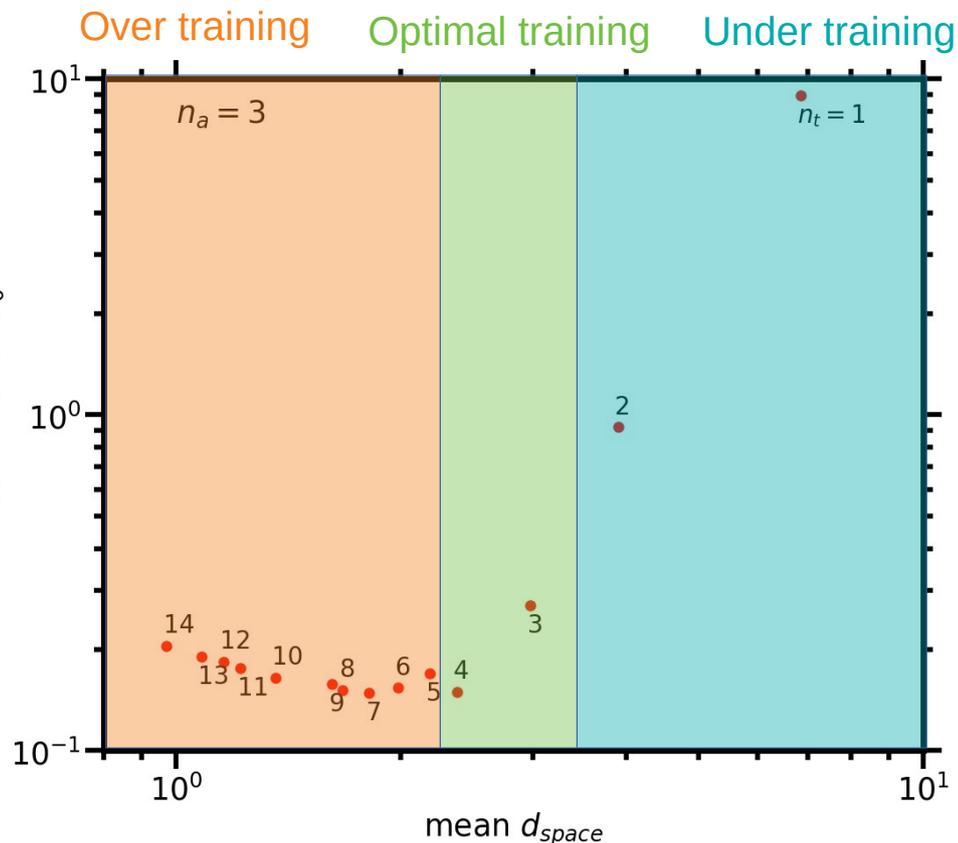
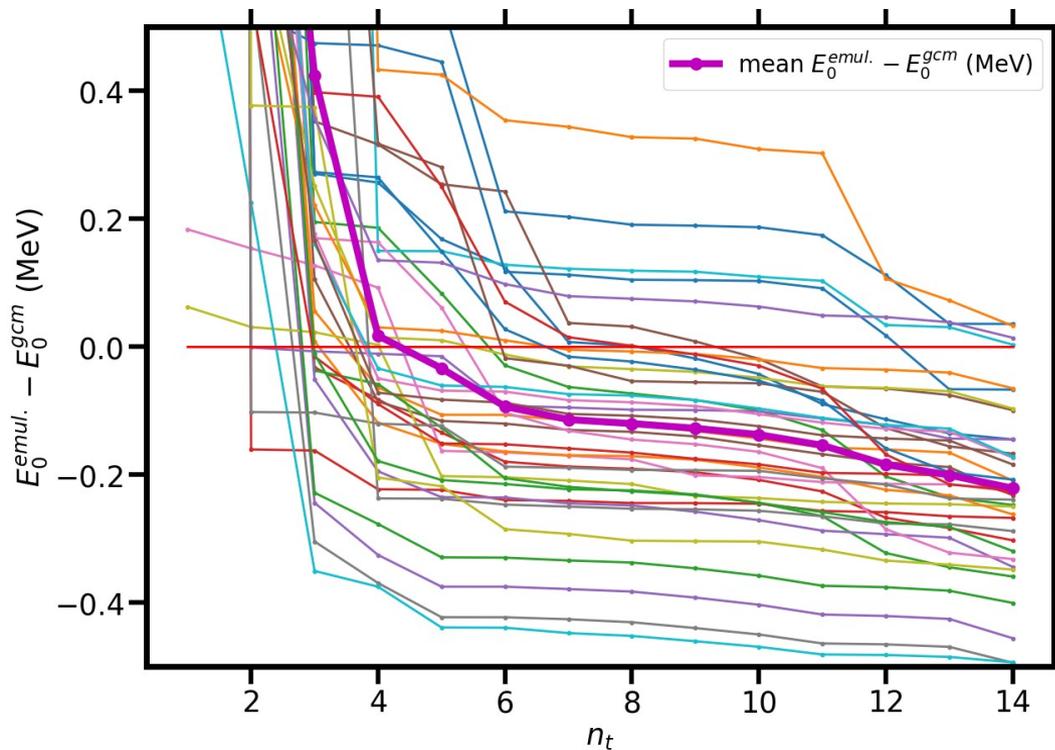
- Lee, Frame & Sarkar

- Hergert

- GCM subspace emulation is the limiting factor

- Need to investigate subspace distance

Part 2 : Results Under-training and over-training



● Variational principle

—▶ for $n_t \geq 5$ emulator is better than GCM

—▶ Emulator becomes a super GCM with additional coordinate μ **Over training**



Part 2 : Results

Correlation of emulator quality with subspace distance

- Mean ground-state energy error strongly correlated with mean distance

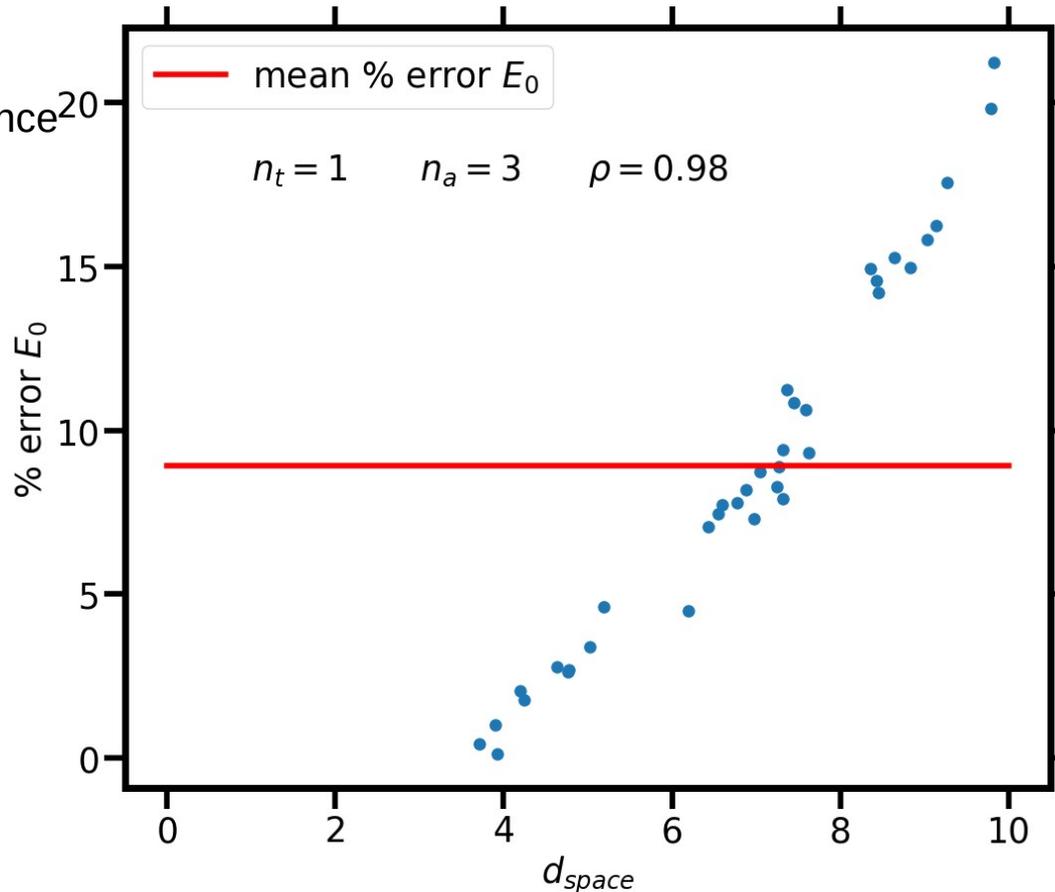
For $n_a = 3$ and $n_t = 1$

Distance from 4 to 10

Mean error around 10%

Strong correlation between error and distance to training

→ (Large) error dominated by GCM space too distant from training space



Part 2 : Results

Correlation of emulator quality with subspace distance

- Mean ground-state energy error strongly correlated with mean distance

For $n_a = 3$ and $n_t = 1$

Distance from 4 to 10

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Strong correlation between error and distance to training

→ (Large) error dominated by GCM space too distant from training space

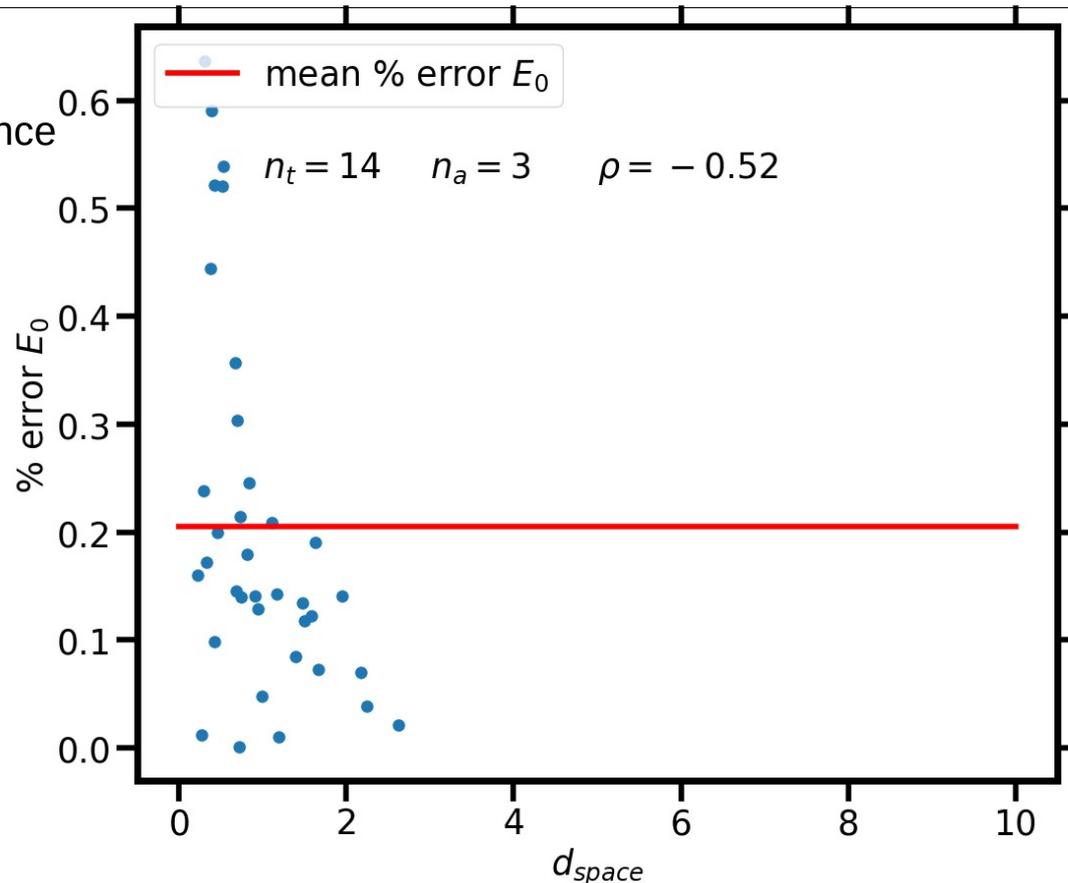
- For $n_a = 3$ and $n_t = 14$

All distances to training space reduced to ~ 1

Mean error down to 0.2 %

Residual error dispersion not correlated with residual distance

→ Due to over-training



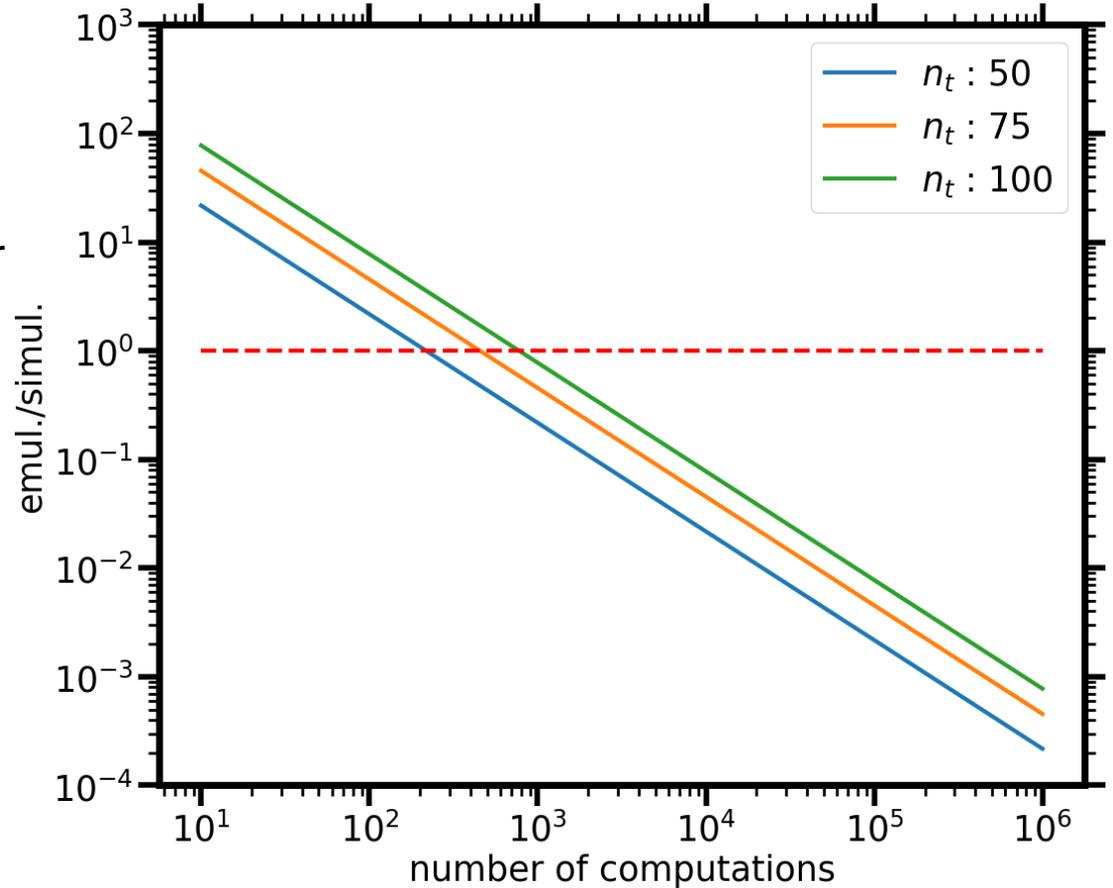
Part 2 : Results Computational cost

● For large emulators :

—▶ Gain for large computation number

◆ For 10^6 computations : gain of 10^4

◆ To be compared with
 10^5 from Erkstrom et al. (2019)



Conclusion & perspectives

Conclusion

- Good reproduction of absolute and excitation energies
- Large computational speedup
- Emulation limited by lack of common space

Perspectives

- Emulation of charge radii (already done but not shown)
- Including projection on J and emulation of electromagnetic transitions
- Moving to Chiral EFT Hamiltonians
- Large scale applications and sensitivity analysis