

# ESNT WORKSHOP

**Fast emulation of large-scale ab-initio description of collective excitations**

**Rationale of the approach and (very) preliminary results**

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



01/06/2023



# Outline

## Introduction

Projected Generator Coordinate Method

Examples of recent PGCM computations

## PGCM-EC emulator project and goals

### PGCM-EC Algorithm

Brief review of PGCM

General idea of a PGCM-EC emulator

Presentation of simplified preliminary algorithm

## Model specifications

## Results

# PGCM

A whole new world of possibilities for ab initio studies

PGCM = zero-order of PGCM-PT

State-specific/multi-reference/symmetry-conserving perturbation theory

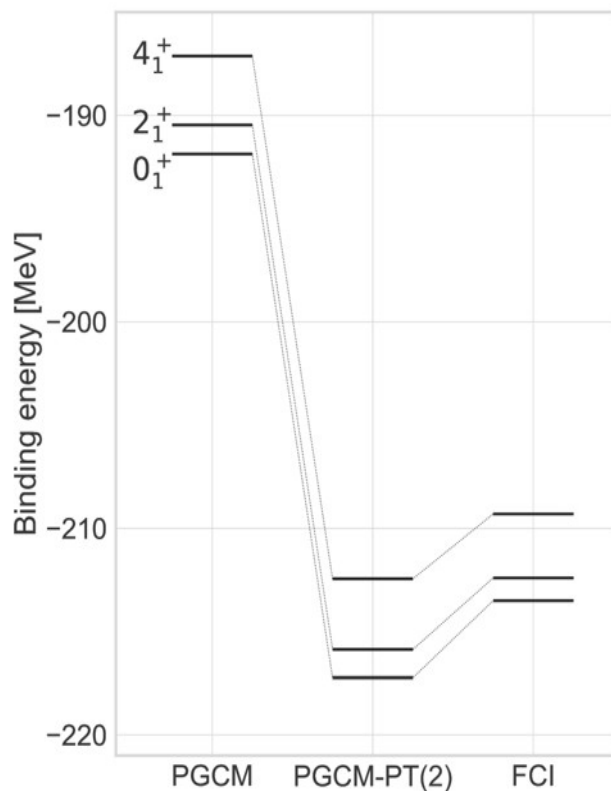
M. Frosini et al, EPJA (2022)

$$|\Psi_{\text{PGCM-PT}}\rangle = \Omega^{\text{PT}} |\Psi_{\text{PGCM}}\rangle$$



Dynamical collective correlations

Static collective correlations



- PGCM not converged for absolute energies

→ Large correction from dynamical correlations

$^{20}\text{Ne}$

$e_{\text{max}} = 4$

$\text{N}^3\text{LO NN interaction (Hüther et al 2020)}$

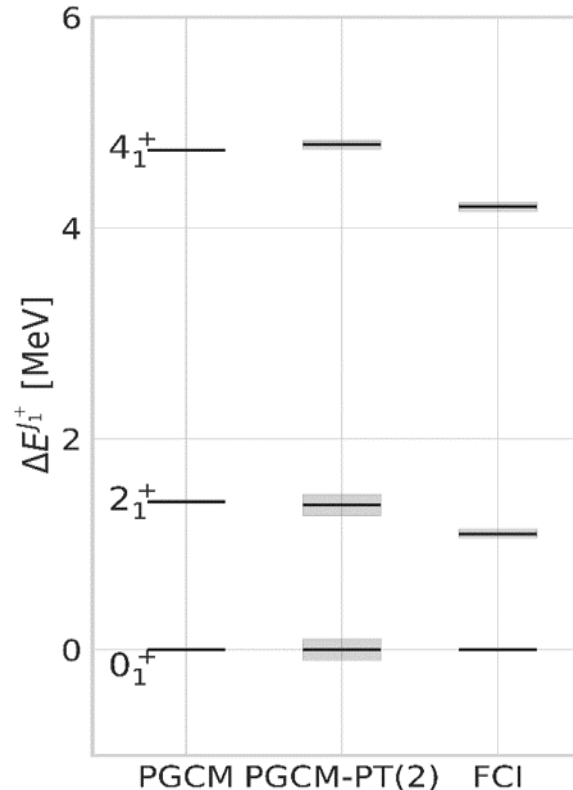
$l_{\text{srg}} = 1.88\text{fm}^{-1}$

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Static collective correlations

- PGCM not converged for absolute energies
  - Large correction from dynamical correlations
- PGCM is converged for excitation energies
  - Cancellation of dynamical correlations

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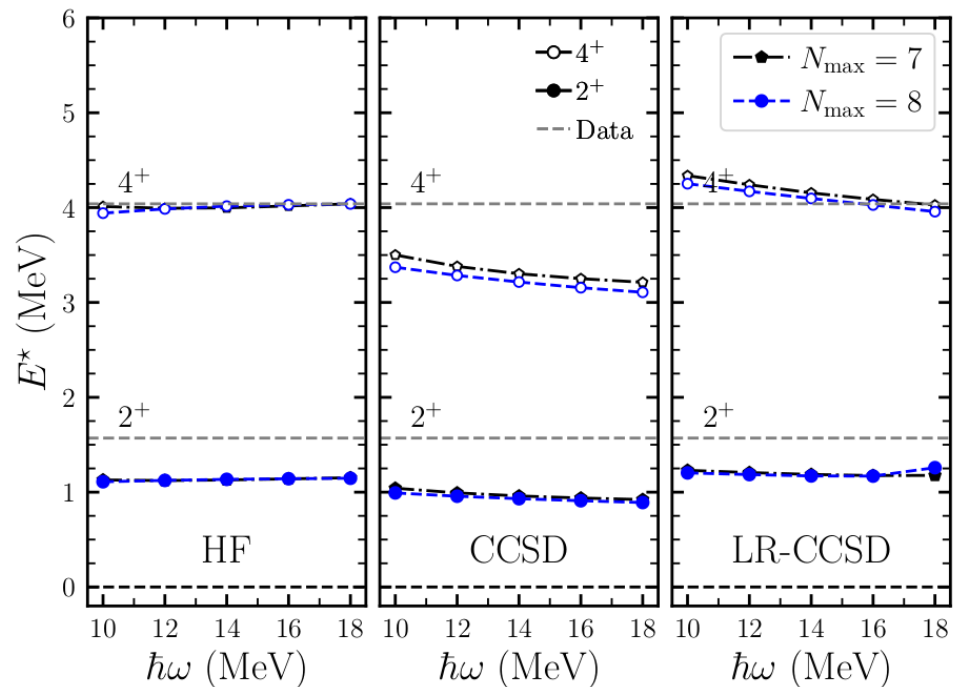
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$$|\Psi_{\text{PGCM-PT}}\rangle = \Omega^{\text{PT}} |\Psi_{\text{PGCM}}\rangle$$

Dynamical collective correlations

Static collective correlations

A. Ekström et al (2023)



- PGCM not converged for **absolute** energies

→ Large correction from dynamical correlations

- PGCM is converged for **excitation** energies

→ Cancellation of dynamical correlations

★ Confirmed by Projected Coupled Cluster approach

**PGCM appropriate for ab-initio spectroscopy**

# PGCM

A whole new world of possibilities for ab initio studies

- Low-lying collective spectroscopy

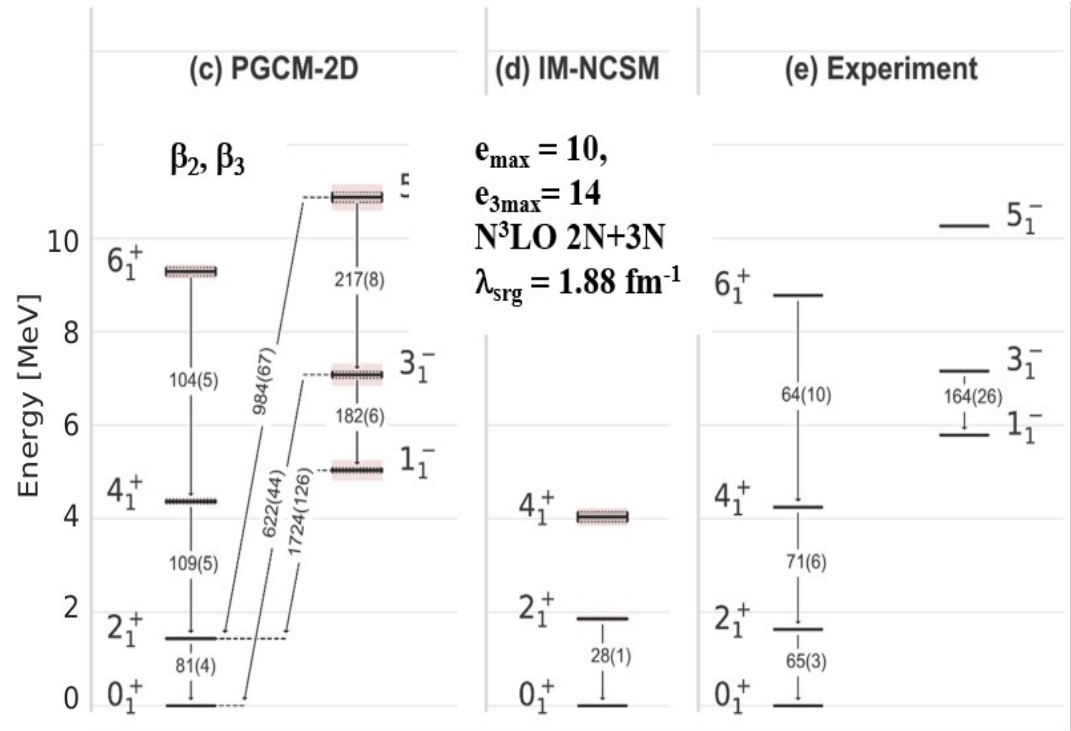
- ◆ PGCM  $^{20}\text{Ne}$

- ◆ Excellent account of exp. data

- Chiral order uncertainty  $\simeq 100$  KeV

- ◆ Good agreement of ground-state band with IM-NCSM

- Many-body uncertainty  $\simeq 100$  KeV

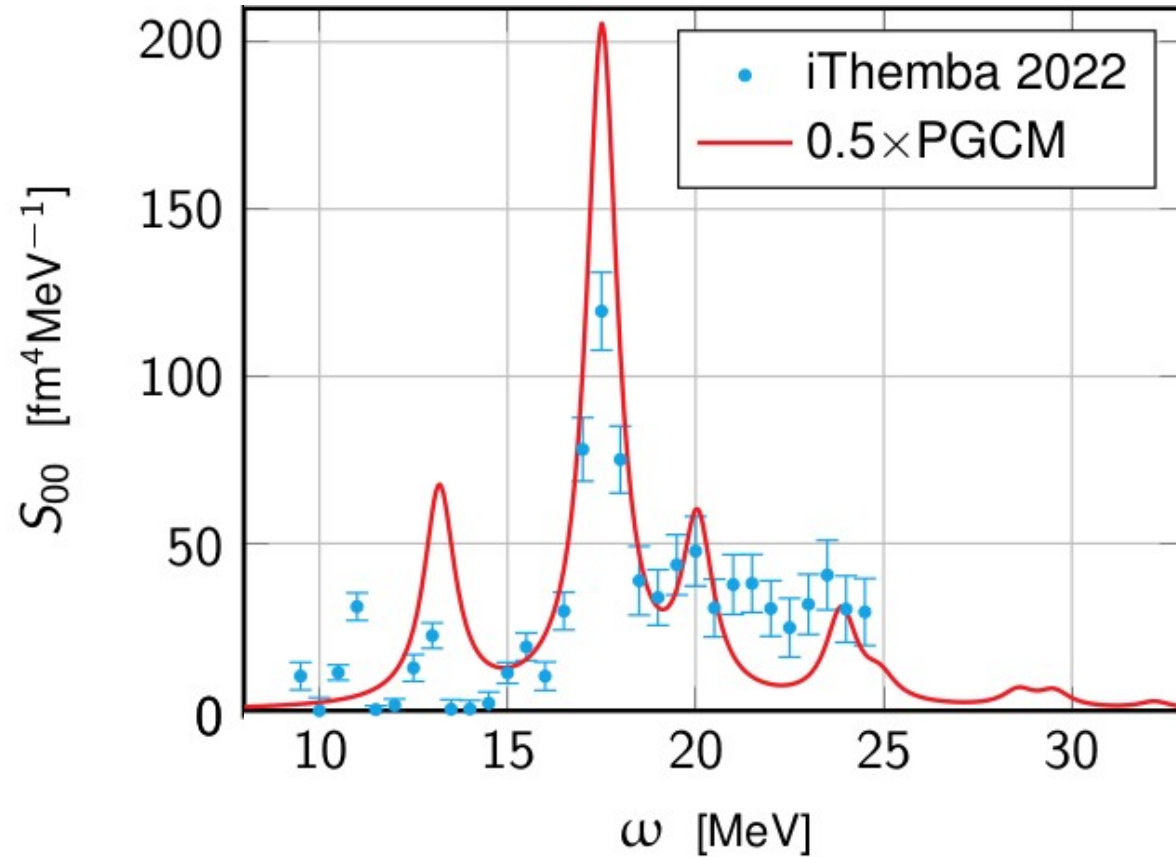


# PGCM

A whole new world of possibilities for ab initio studies

A. Porro, Saclay, thesis under writing (2023)

- Low-lying collective spectroscopy
- Giant resonances
- ◆  $^{28}\text{Si}$  monopole strength distribution vs exp. data



# PGCM

A whole new world of possibilities for ab initio studies

- Low-lying collective spectroscopy

- Giant resonances & multi-phonon

- ◆ Multi-phonon states on top of monopole resonance

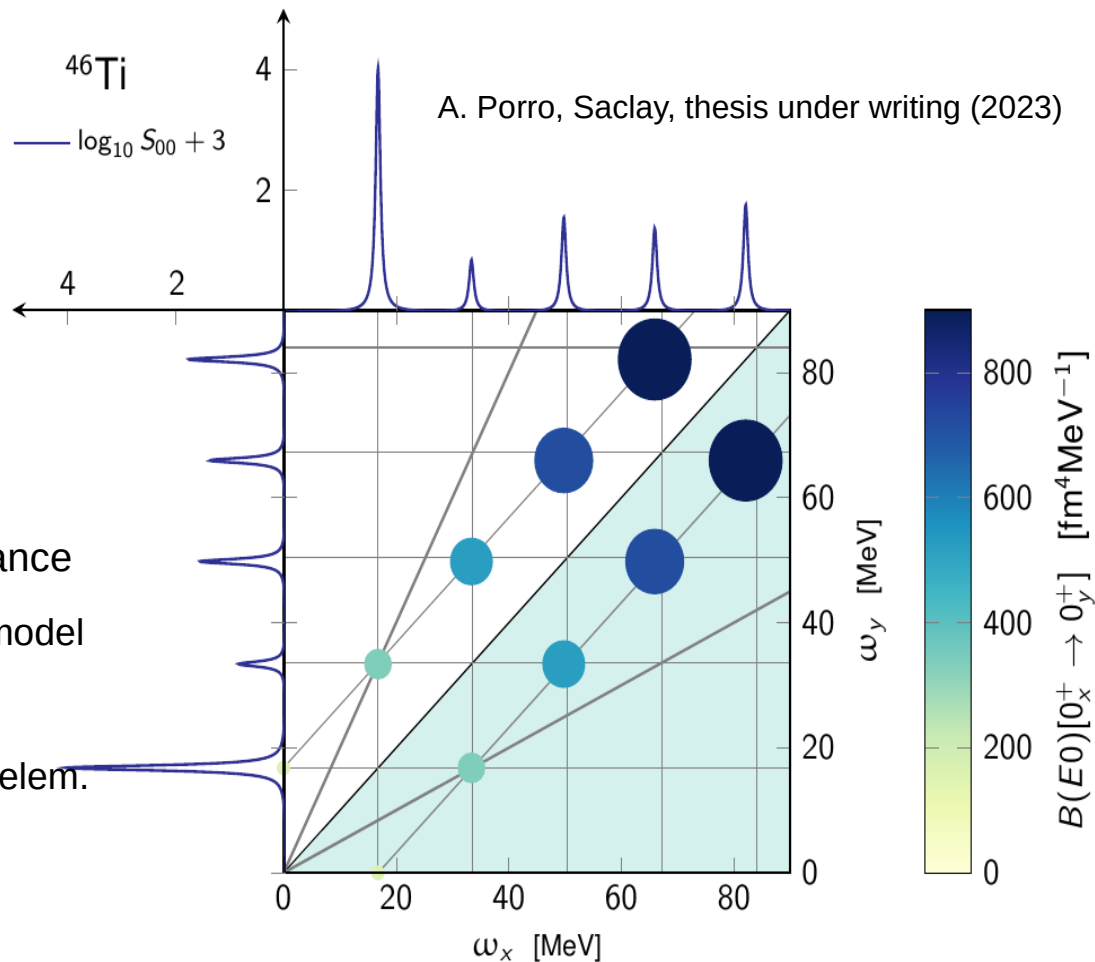
- Correspondance with harmonic oscillator model

- ★ HO spectrum

- ★ Linear growth of  $(n, n+1) B(E_0)$  matrix elem.

- Practically inaccessible in QRPA

- First ab initio prediction of this type



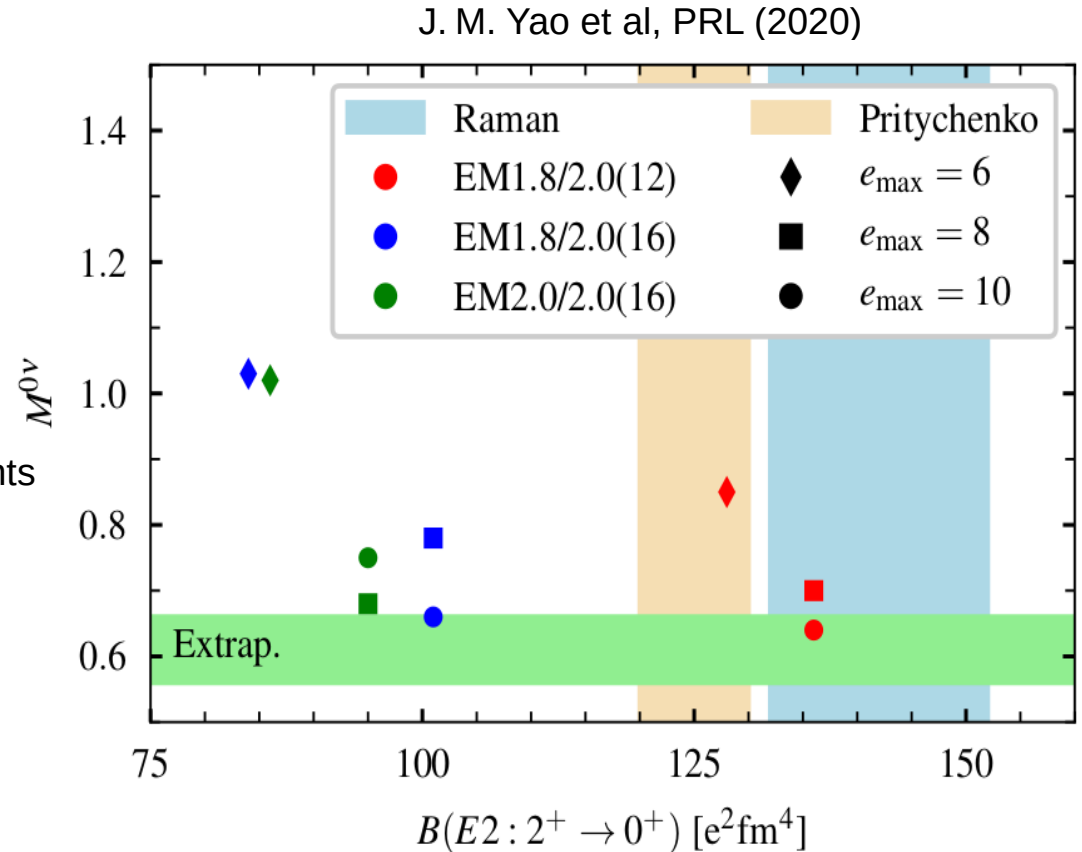


# PGCM

A whole new world of possibilities for ab initio studies

- Low-lying collective spectroscopy
- Giant resonances & multi-phonon
- Neutrinoless double-beta decay

◆ State of the art computation of matrix elements



# PGCM

A whole new world of possibilities for ab initio studies

- Low-lying collective spectroscopy

- Giant resonances & multi-phonon

- Neutrinoless double-beta decay

- Clustering

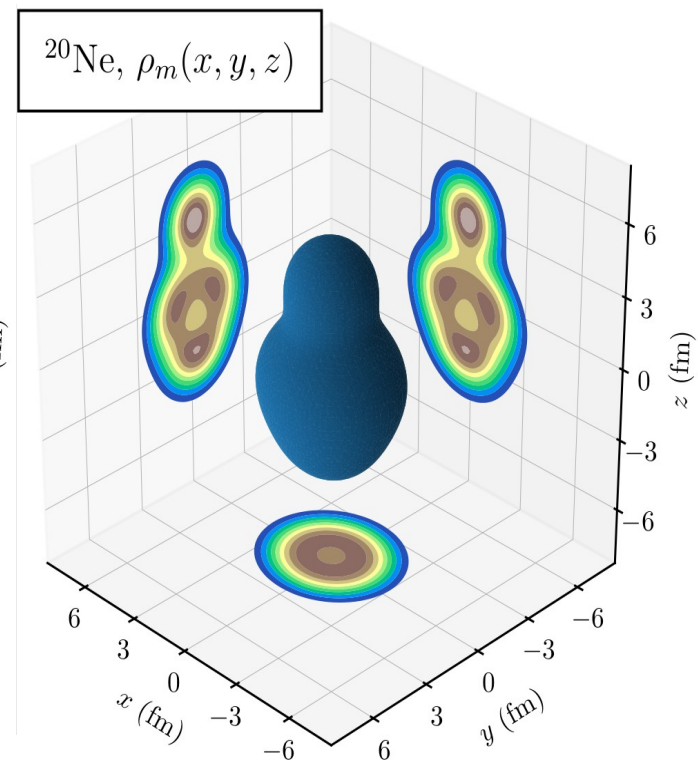
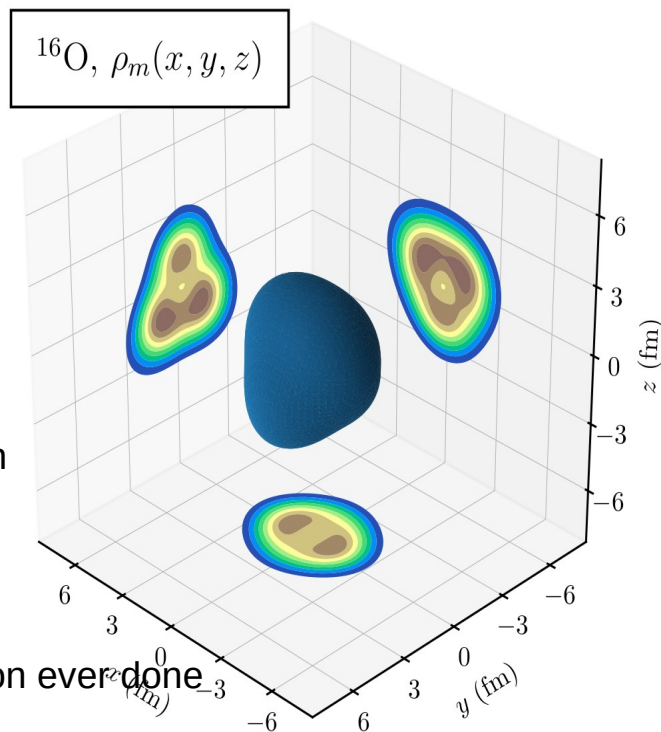
- ◆ Ground-state intrinsic density distribution

- $^{16}\text{O}$  : tetrahedral clustering

- $^{20}\text{Ne}$  :  $^{16}\text{O}$  clustering + alpha

- Most advanced PGCM computation ever done

B. Bally et al., in preparation (2023)



# PGCM

A whole new world of possibilities for ab initio studies

- Low-lying collective spectroscopy
- Giant resonances & multi-phonon
- Neutrinoless double-beta decay
- Clustering



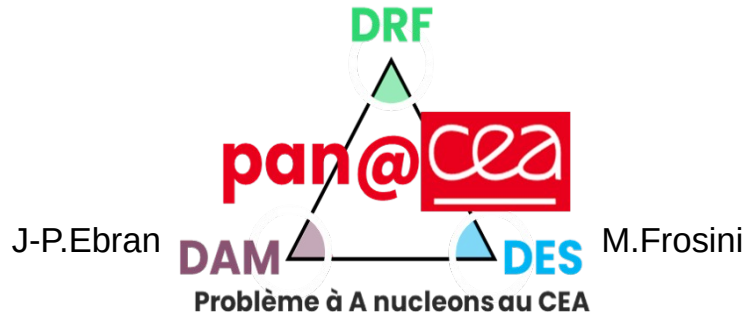
**PGCM-EC project**

**Combine all these aspects with EC**

# Numerical implementations of the collaboration

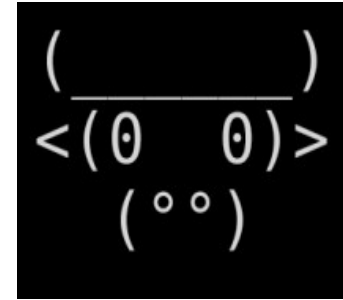
PAN@CEA

T. Duguet & V. Somà



TAURUS

B. Bally, A. Sanchez-Fernandez & T. Rodriguez



- Advanced multidimensional PGCM
- HFB states  $\longrightarrow$  Break  $N, Z, J^2, \Pi$  & time reversal  
 $\longrightarrow$  Constraints on  $Y_1^m, Y_2^m, Y_3^m, r^2$  &  $\Delta$
  - Symmetry restoration  $N, Z, J^2, \Pi$
  - Hamiltonian  $\longrightarrow$  Chiral Hamiltonian  
 $\longrightarrow$  Gogny effective interaction  
 $\longrightarrow$  Shell-model valence interaction

# PGCM-EC emulator project

## Goals

- Sensitivity analysis & error propagation for ab initio calculations of collective excitations
- Easy inclusion of collective excitations within fit of future chiral EFT interactions
- Large scale database of ab initio prediction of collective excitations with statistical analysis

## Preliminary tests

- One-dimensional GCM on  $\beta_{20} \leftrightarrow Y_2^0$
- No  $U(1)$  symmetry breaking = HF
- No  $J^2$  projection
- Brink & Boecker soft interaction (4 + 2 parameters)

## Necessary for full-fledged project

- Access to (SRG-evolved) splitted chiral Hamiltonian
- Access to state-of-the-art post-processing statistical tools

# PGCM-EC Algorithm review of PGCM

1

$$H(\lambda) = H^\lambda$$

Set of HFB states  $\{|\Phi^\lambda(q)\rangle\}_{q \in \{q_1, \dots, q_{n_q}\}}$

Constrained to  $\langle \Phi^\lambda(q) | Q | \Phi^\lambda(q) \rangle = q$

$q$  Deformation parameter

no  $\lambda$  dependence

$$P_M^\sigma$$

projection

$$P_M^\sigma |\Phi^\lambda(q)\rangle \equiv \frac{d_\sigma}{v_G} \sum_{\Theta=1}^{n_\Theta} D_{MM}^{\sigma*}(\Theta) U(\Theta) |\Phi^\lambda(q)\rangle$$

$$P_M^\sigma |\Phi^\lambda(q)\rangle$$

PGCM ansatz

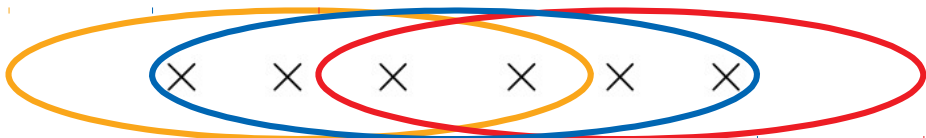
$$|\Psi_a^\lambda\rangle = \sum_{q=1}^{n_q} f_a^\lambda(q) P_M^\sigma |\Phi^\lambda(q)\rangle \text{ with } \delta \frac{\langle \Psi_a^\lambda | H^\lambda | \Psi_a^\lambda \rangle}{\langle \Psi_a^\lambda | \Psi_a^\lambda \rangle} = 0$$

Full Hilbert space

$$H^{\lambda_0}$$

$\lambda_0$  nominal param.

$$|\Psi_0^{\lambda_1}\rangle \quad |\Psi_1^{\lambda_1}\rangle \quad |\Psi_0^{\lambda_0}\rangle \quad |\Psi_1^{\lambda_0}\rangle \quad |\Psi_0^{\lambda_2}\rangle \quad |\Psi_1^{\lambda_2}\rangle$$



$$\text{Vect } \{|\Phi^{\lambda_1}(q)\rangle\}_q$$

$$\equiv V^{\lambda_1}$$

$$\text{Vect } \{|\Phi^{\lambda_0}(q)\rangle\}_q$$

$$\equiv V^{\lambda_0}$$

$$\text{Vect } \{|\Phi^{\lambda_2}(q)\rangle\}_q$$

$$\equiv V^{\lambda_2}$$

2

Hill-Wheeler-Griffin eq.

Solve Generalized Eigenvalue Problem

$$\longrightarrow \{f_a^\lambda(q)\}_{q \in \{q_1, \dots, q_{n_q}\}}$$

• Objective EC

Emulate

1

and

2

# PGCM-EC Algorithm review of PGCM

1

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$q$  Deformation parameter

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$$P_M^\sigma$$

projection

$$P_M^\sigma |\Phi^\lambda(q)\rangle \equiv \frac{d_\sigma}{v_G} \sum_{\Theta=1}^{n_\Theta} D_{MM}^{\sigma*}(\Theta) U(\Theta) |\Phi^\lambda(q)\rangle$$

2

$$P_M^\sigma |\Phi^\lambda(q)\rangle$$

PGCM ansatz

$$|\Psi_a^\lambda\rangle = \sum_{q=1}^{n_q} f_a^\lambda(q) P_M^\sigma |\Phi^\lambda(q)\rangle \text{ with } \delta \frac{\langle \Psi_a^\lambda | H^\lambda | \Psi_a^\lambda \rangle}{\langle \Psi_a^\lambda | \Psi_a^\lambda \rangle} = 0$$

$\sum_{q'=1}^{n_q} (\langle \Phi^\lambda(q) | H^\lambda P_M^\sigma | \Phi^\lambda(q') \rangle - E_a^\lambda \langle \Phi^\lambda(q) | P_M^\sigma | \Phi^\lambda(q') \rangle) f_a^\lambda(q') = 0 \rightarrow$  Off-diagonal projected **Hamiltonian** and **Norm** kernels  
 $\longrightarrow n_q \times n_q$  diagonalisation : negligible numerical cost

$$\langle \Phi^\lambda(q) | H^\lambda P_M^\sigma | \Phi^\lambda(q') \rangle = \frac{d_\sigma}{v_G} \sum_{\Theta=1}^{n_\Theta} D_{MM}^{\sigma*}(\Theta) \langle \Phi^\lambda(q) | H^\lambda U(\Theta) | \Phi^\lambda(q') \rangle$$

$\rightarrow$  Off-diagonal **Hamiltonian** and **Norm** kernels  
 $\longrightarrow n_q^2 n_\Theta$  kernels  $\mapsto$  PGCM cost  $n_q^2 n_\Theta \times N^4$

$$\langle \Phi^\lambda(q) | P_M^\sigma | \Phi^\lambda(q') \rangle = \frac{d_\sigma}{v_G} \sum_{\Theta=1}^{n_\Theta} D_{MM}^{\sigma*}(\Theta) \langle \Phi^\lambda(q) | U(\Theta) | \Phi^\lambda(q') \rangle$$

$\longrightarrow$  Computed via off-diagonal Wick Th./Pfaffian  
 Balian & Brezin (1969)    Robledo (2009)  
 Porro & Duguet (2022)    Bally & Duguet (2018)

# PGCM-EC Algorithm EC extrapolation

**Goal** •  $N_{\text{sim.}} \gg 1$  PGCM computations on  $H^\mu$  for  $\mu \in \{\mu_1, \dots, \mu_{N_{\text{sim.}}}\} \subset \mathbb{R}^{n_p}$

**Emulator** • Apply EC on  $H^\mu$  for training set  $\{|\Psi_a^{\lambda_i}\rangle\}_{\substack{0 \leq i < n_t \\ 0 \leq a < n_a}} \longrightarrow n_t \ll N_{\text{sim.}}$

$$\longrightarrow |\Psi_c^\mu\rangle_{\text{EC}} = \sum_{ia} g_{ac}^{\lambda_i \mu} |\Psi_a^{\lambda_i}\rangle$$

with  $g_{ac}^{\lambda_i \mu}$  solution of  $\sum_{ia} \left[ \langle \Psi_b^{\lambda_j} | H^\nu | \Psi_a^{\lambda_i} \rangle - E_c^\mu \langle \Psi_b^{\lambda_j} | \Psi_a^{\lambda_i} \rangle \right] g_{ac}^{\lambda_i \mu} = 0$  HWG-type equation

**Additional hypothesis** • Linear dependence of  $H^\mu$  on  $\mu \longrightarrow H^\mu = \sum_{k=1}^{n_p} \mu^k H_k$

$$\langle \Psi_b^{\lambda_j} | H^\mu | \Psi_a^{\lambda_i} \rangle = \sum_{k=1}^{n_p} \mu^k \langle \Psi_b^{\lambda_j} | H_k | \Psi_a^{\lambda_i} \rangle \longrightarrow \begin{matrix} \langle \Psi_a^{\lambda_i} | H_k | \Psi_b^{\lambda_j} \rangle \\ \langle \Psi_a^{\lambda_i} | \Psi_b^{\lambda_j} \rangle \end{matrix} \quad \begin{matrix} \text{Precompute} \\ \& \text{store} \end{matrix}$$

Removes  $\mu$  dependence complexity

Low dimensionality diagonalisation  $n_t n_a \simeq n_q \simeq \text{PGCM cost}$



# PGCM-EC Algorithm elementary kernels computation

Express  $\mu$ -independent kernels in terms of off-diagonal elementary kernels

$$\frac{\langle \Psi_a^{\lambda_i} | H_k | \Psi_b^{\lambda_j} \rangle}{\langle \Psi_a^{\lambda_i} | \Psi_b^{\lambda_j} \rangle} = \sum_{qq' \Theta} \underbrace{f_a^{\lambda_i*}(q) f_b^{\lambda_j}(q')}_{\lambda_{i,j}, a, b \text{ dependent}} D_{MM}^{\sigma*}(\Theta) \underbrace{\langle \Phi^{\lambda_i}(q) | H_k U(\Theta) | \Phi^{\lambda_j}(q') \rangle}_{\lambda_{i,j} \text{ dependent}, a, b \text{ independent}}$$

→ Costly part of the computation

→  $n_q^2 n_\Theta \times n_t^2 n_p \times n_{\text{nuclei}} n_{\text{interactions}}$

	$\lambda_0$	$\lambda_1$	$\lambda_2$
$\lambda_0$	$\langle \Phi_q^{\lambda_0}   H_k U_\Theta   \Phi_{q'}^{\lambda_0} \rangle$	$\langle \Phi_q^{\lambda_0}   H_k U_\Theta   \Phi_{q'}^{\lambda_1} \rangle$	$\langle \Phi_q^{\lambda_0}   H_k U_\Theta   \Phi_{q'}^{\lambda_2} \rangle$
$\lambda_1$	$\langle \Phi_q^{\lambda_1}   H_k U_\Theta   \Phi_{q'}^{\lambda_0} \rangle$	$\langle \Phi_q^{\lambda_1}   H_k U_\Theta   \Phi_{q'}^{\lambda_1} \rangle$	$\langle \Phi_q^{\lambda_1}   H_k U_\Theta   \Phi_{q'}^{\lambda_2} \rangle$
$\lambda_2$	$\langle \Phi_q^{\lambda_2}   H_k U_\Theta   \Phi_{q'}^{\lambda_0} \rangle$	$\langle \Phi_q^{\lambda_2}   H_k U_\Theta   \Phi_{q'}^{\lambda_1} \rangle$	$\langle \Phi_q^{\lambda_2}   H_k U_\Theta   \Phi_{q'}^{\lambda_2} \rangle$

→ massive computation of kernels

→ do this for all nuclei

→ Ab initio, Gogny, Skyrme

→ HPC challenge

→  $n_t$  training PGCM calculations

→ Computable with available technology

→ Training on excited states without additional cost

# PGCM-EC Algorithm preliminary simplification

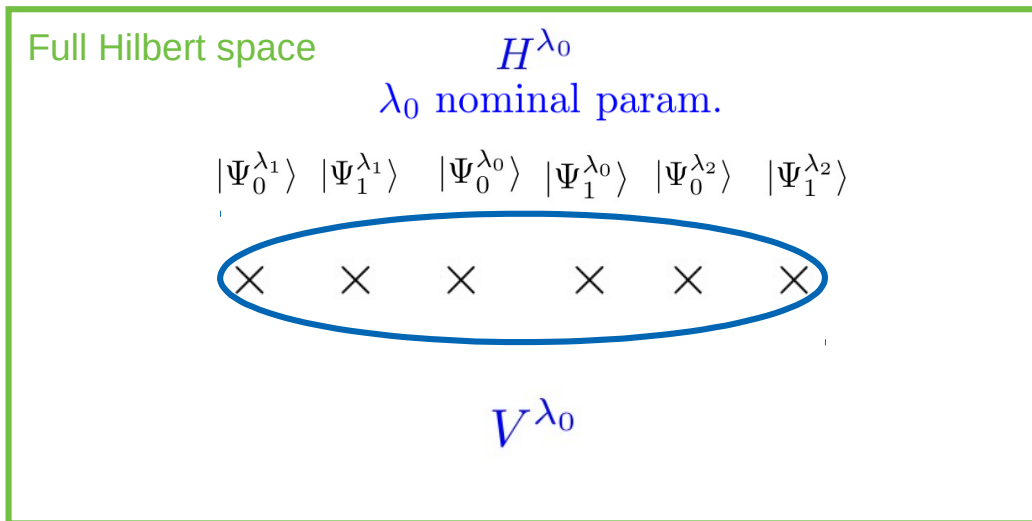
Costly part of the computation  $\longrightarrow \langle \Phi^{\lambda_i}(q) | H_k U(\Theta) | \Phi^{\lambda_j}(q') \rangle$

- First step  $|\Phi^\lambda(q)\rangle \xrightarrow[\lambda_0 \text{ nominal param.}]{\text{for all } \lambda} |\Phi^{\lambda_0}(q)\rangle$

◆ (Too ?) drastic complexity reduction

$$\langle \Phi^{\lambda_i}(q) | H_k U(\Theta) | \Phi^{\lambda_j}(q') \rangle \longrightarrow \langle \Phi^{\lambda_0}(q) | H_k U(\Theta) | \Phi^{\lambda_0}(q') \rangle$$

◆ Only  $f_a^\lambda(q)$  carry training parameters dependence



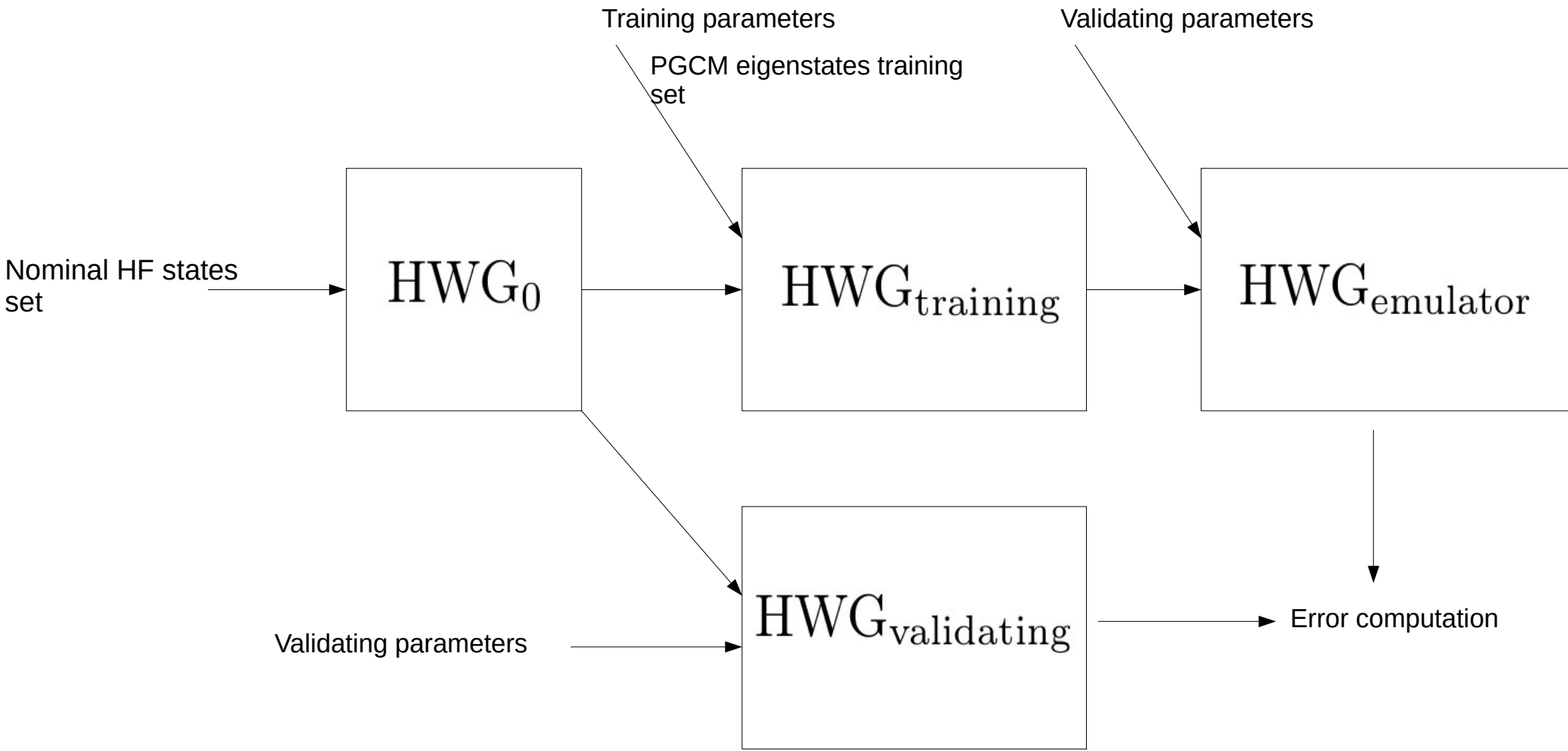
Ⓐ First step (today)

$$V^{\lambda_1} \simeq V^{\lambda_2} \simeq \dots \simeq V^{\lambda_{n_t}} \simeq V^{\lambda_0}$$

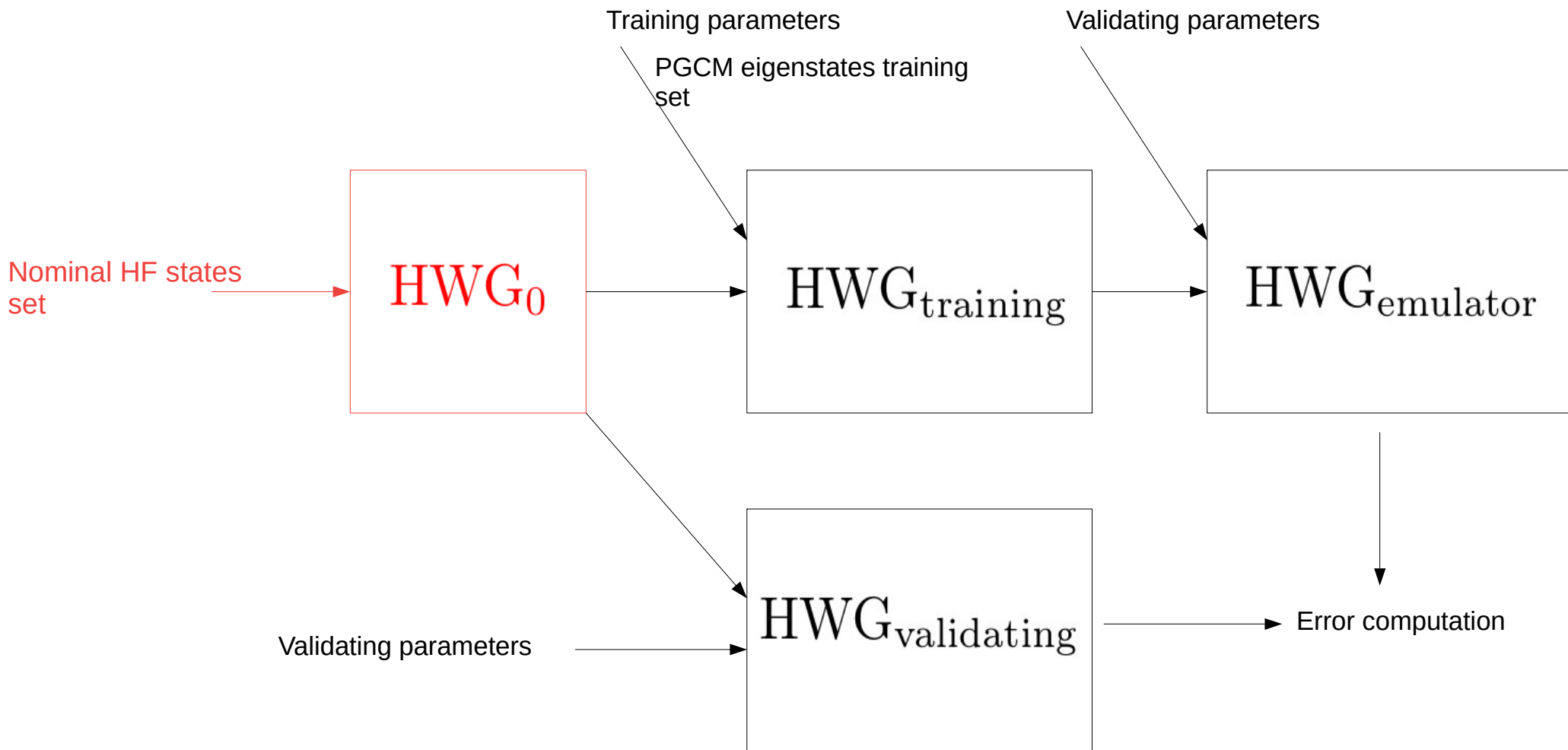
Ⓑ Next step : emulate  $V^\lambda$

$\longrightarrow$  To be investigated next

# PGCM-EC Algorithm Preliminary implementation



# PGCM-EC Algorithm Preliminary implementation



# PGCM-EC Algorithm Preliminary implementation

Set of HF states  $\{|\Phi^{\lambda_0}(q_i)\rangle\}_{1 \leq i \leq n_q}$

Generating  $V^{\lambda_0}$



HWG<sub>0</sub>

$$\langle \Phi^{\lambda_0}(q_i) | H_k | \Phi^{\lambda_0}(q_j) \rangle \quad 1 \leq i, j \leq n_q$$
$$\langle \Phi^{\lambda_0}(q_i) | \Phi^{\lambda_0}(q_j) \rangle$$

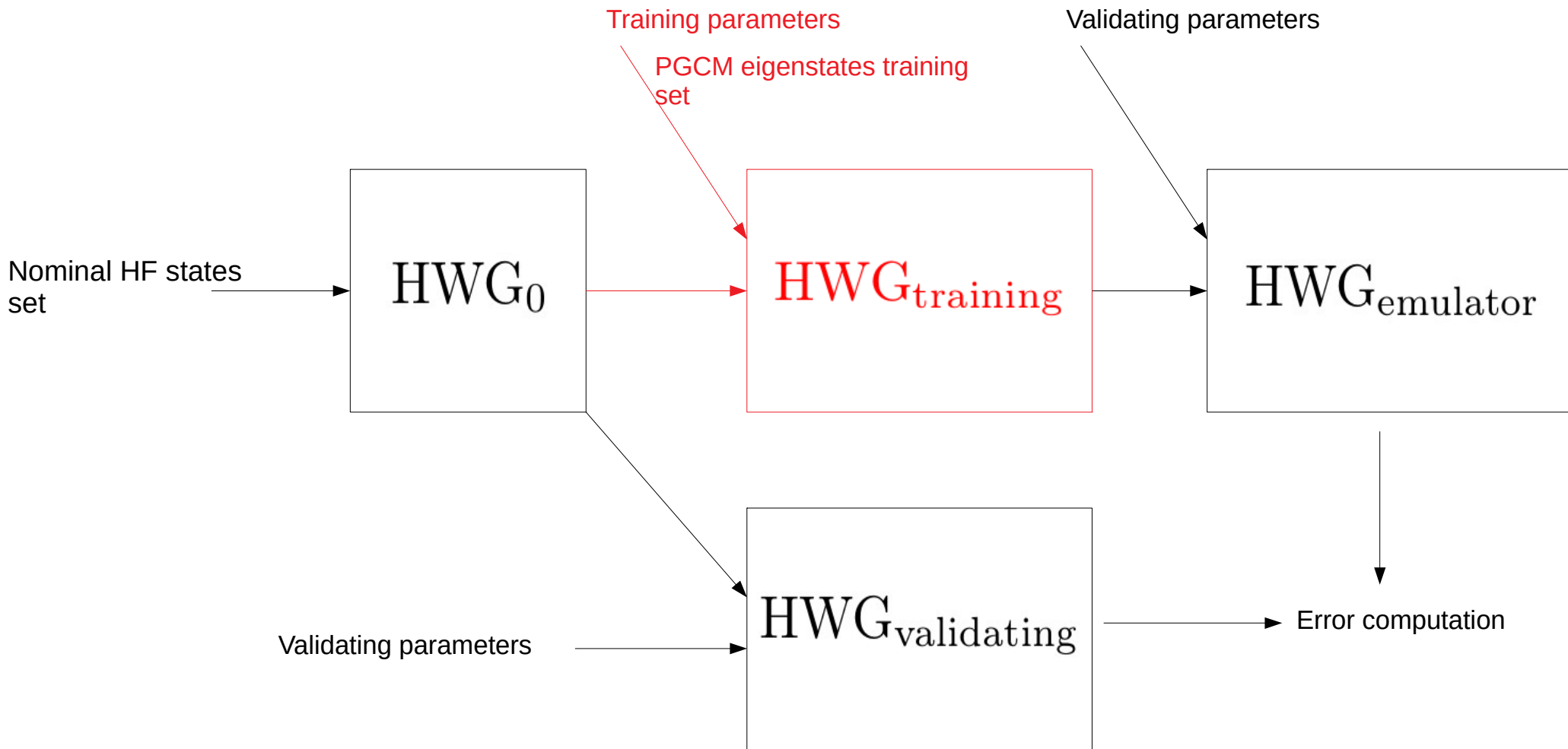
Diagonalize norm matrix

$$\{|\Theta_i^0\rangle\}_{1 \leq i \leq \dim V^{\lambda_0}} \subset V^{\lambda_0}$$

$$\langle \Theta_i^0 | H_k | \Theta_j^0 \rangle \quad 0 \leq i, j \leq \dim V^{\lambda_0}$$

$$\langle \Theta_i^0 | \Theta_j^0 \rangle = \delta_{ij}$$

# PGCM-EC Algorithm Preliminary implementation



# PGCM-EC Algorithm Preliminary implementation

HWG<sub>0</sub>

$$\{\mu_n\}_{1 \leq n \leq n_t} \subset \mathbb{R}^{n_p}$$

$$\{a_m\}_{1 \leq m \leq n_a} \subset \mathbb{N}$$



HWG<sub>training</sub>  $0 \leq i, j \leq \dim V^{\lambda_0}$

$$H_{ij}^{\mu_n} = \langle \Theta_i^0 | H^{\mu_n} | \Theta_j^0 \rangle = \sum_k \langle \Theta_i^0 | H_k | \Theta_j^0 \rangle \mu_n^k$$

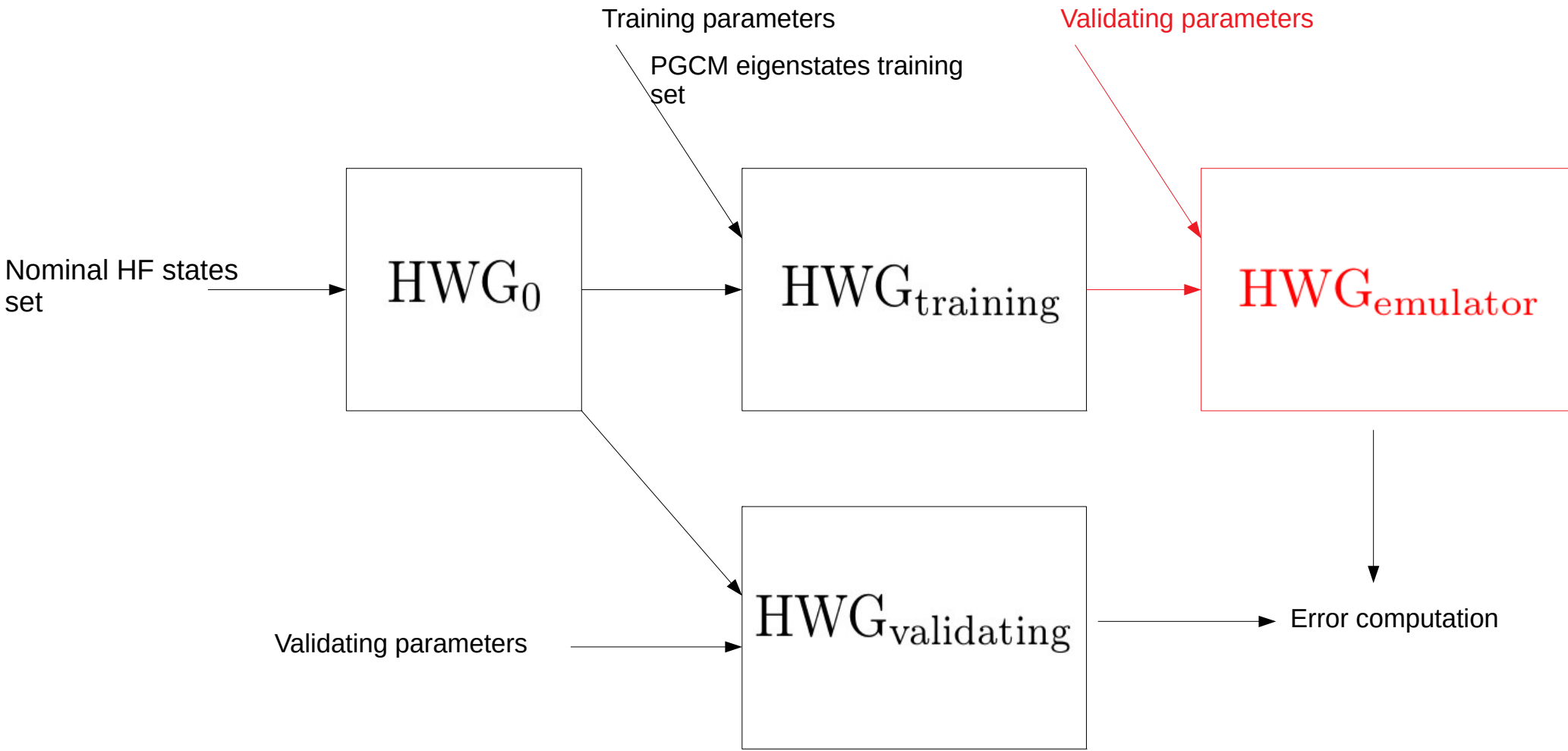
$$H^{\mu_n} | \Psi_{a_m}^{\mu_n} \rangle = E_{a_m}^{\mu_n} | \Psi_{a_m}^{\mu_n} \rangle$$

$$\begin{aligned} & \langle \Psi_{a_m}^{\mu_n} | H_k | \Psi_{a_{m'}}^{\mu_{n'}} \rangle \\ & \langle \Psi_{a_m}^{\mu_n} | \Psi_{a_{m'}}^{\mu_{n'}} \rangle \end{aligned}$$

Diagonalize norm matrix  
 $0 \leq i, j \leq \dim V^{\text{train.}}$

$$\begin{aligned} & \langle \Theta_i^{\text{train.}} | H_k | \Theta_j^{\text{train.}} \rangle \\ & \langle \Theta_i^{\text{train.}} | \Theta_j^{\text{train.}} \rangle = \delta_{ij} \end{aligned}$$

# PGCM-EC Algorithm Preliminary implementation





# PGCM-EC Algorithm Preliminary implementation

HWG<sub>training</sub>

$$\{\lambda_n\}_{1 \leq n \leq n_{\text{val}}} \subset \mathbb{R}^{n_p}$$



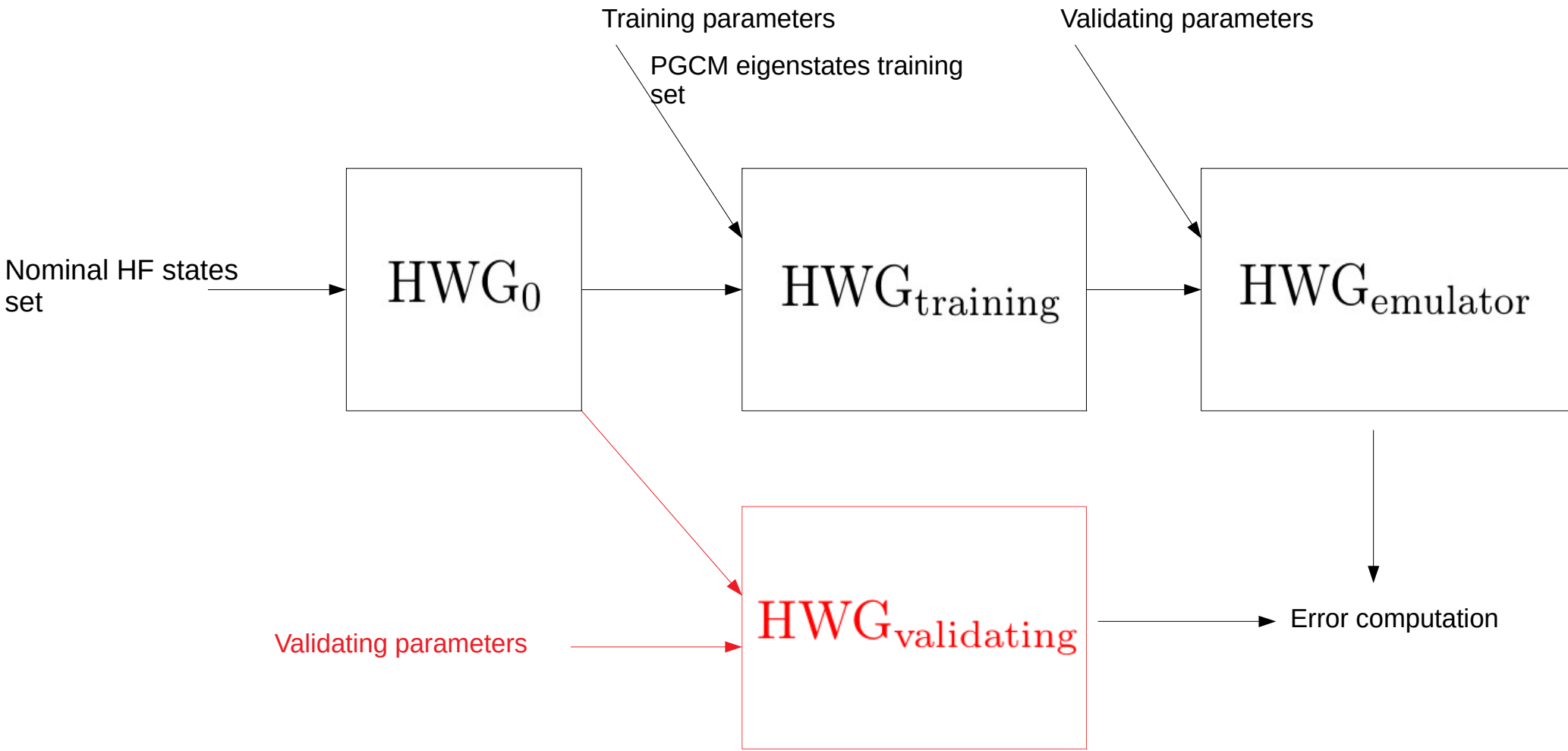
HWG<sub>emulator</sub>

$$0 \leq i, j \leq \dim V^{\text{train.}}$$

$$H_{ij}^{\lambda_n} = \langle \Theta_i^{\text{train.}} | H^{\lambda_n} | \Theta_j^{\text{train.}} \rangle = \sum_k \langle \Theta_i^{\text{train.}} | H_k | \Theta_j^{\text{train.}} \rangle \lambda_n^k$$

$$H^{\lambda_n} | \Psi_a^{\lambda_n} \rangle_{\text{emul.}} = E_a^{\lambda_n} | \Psi_a^{\lambda_n} \rangle_{\text{emul.}}$$

# PGCM-EC Algorithm Preliminary implementation



# PGCM-EC Algorithm Preliminary implementation

HWG<sub>0</sub>

$$\{\lambda_n\}_{1 \leq n \leq n_{\text{val}}} \subset \mathbb{R}^{n_p}$$

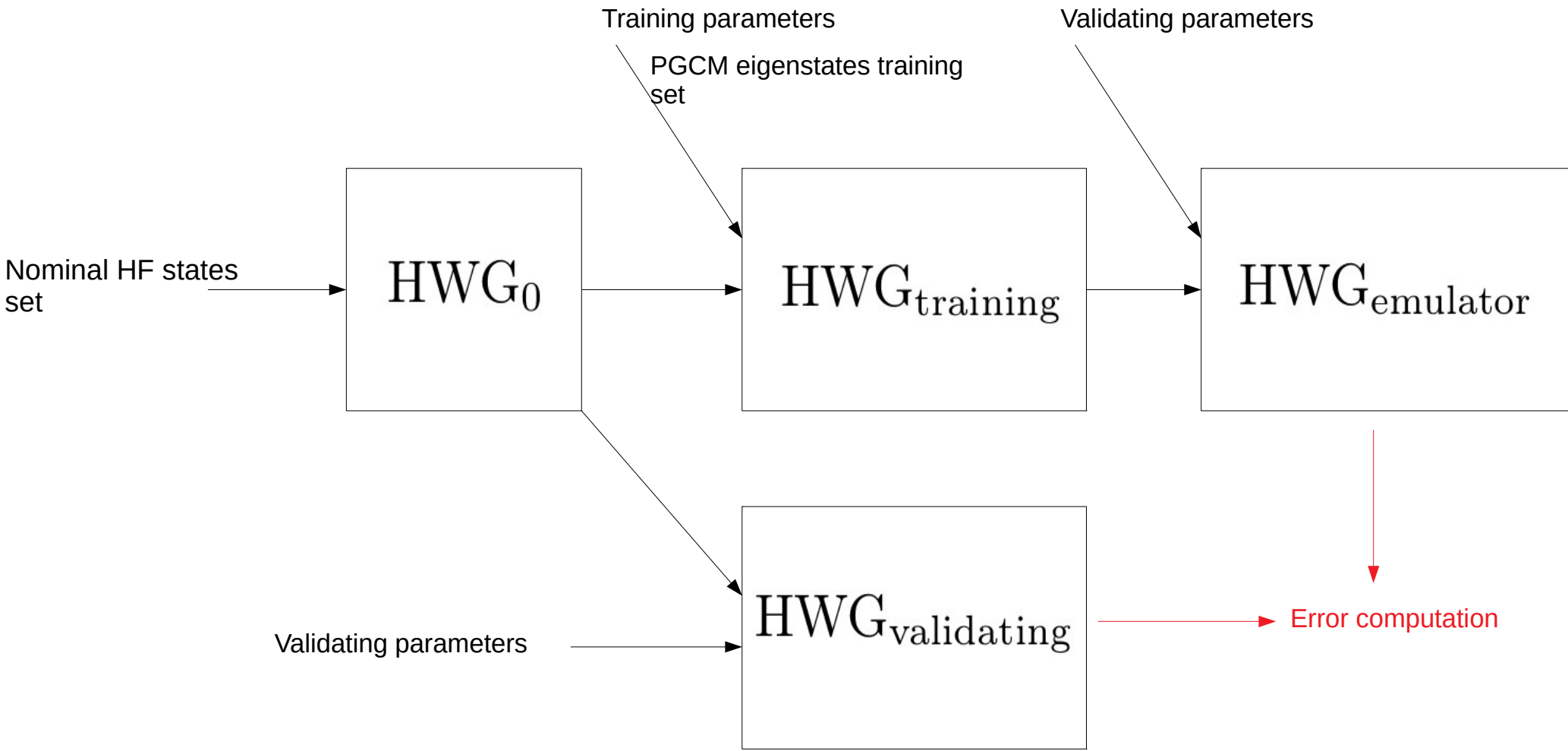


HWG<sub>validating</sub>  $0 \leq i, j \leq \dim V^{\lambda_0}$

$$H_{ij}^{\lambda_n} = \langle \Theta_i^0 | H^{\lambda_n} | \Theta_j^0 \rangle = \sum_k \langle \Theta_i^0 | H_k | \Theta_j^0 \rangle \lambda_n^k$$

$$H^{\lambda_n} | \Psi_a^{\lambda_n} \rangle = E_a^{\lambda_n} | \Psi_a^{\lambda_n} \rangle$$

# PGCM-EC Algorithm Preliminary implementation



# PGCM-EC Algorithm Preliminary implementation

Error computations

- Absolute energies
- Excitation energies
- Radii
- States distance → To be implemented soon

# Preliminary computation model definition

- $^{20}\text{Ne}$  Nucleus
- 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

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

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

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

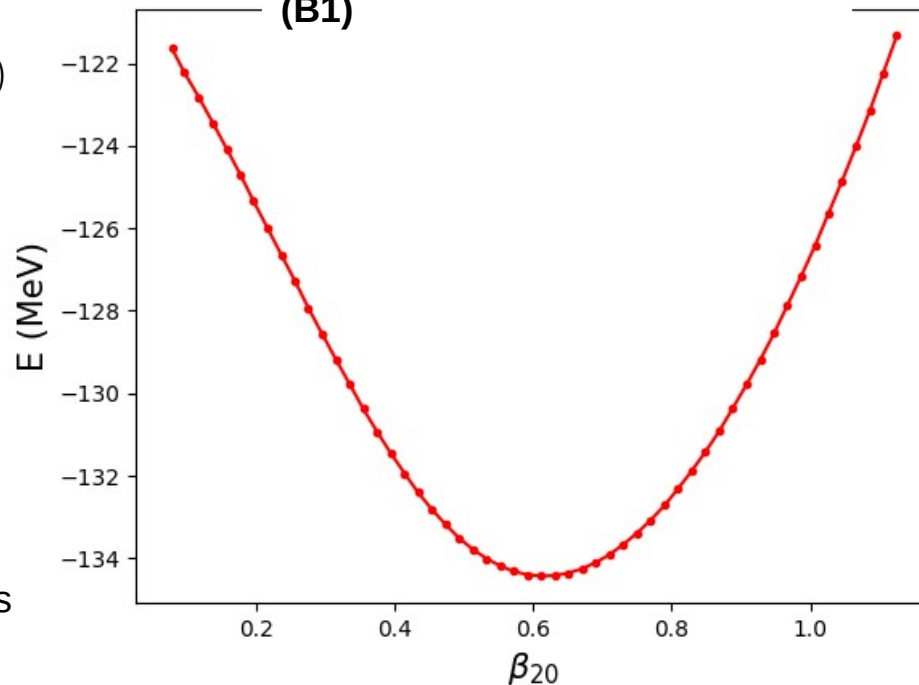
$$m_1 = -206.05 \text{ MeV}$$

Fix at nominal values

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

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

PES for nominal parameters  
(B1)



# Nominal GCM computation Convergence

- Convergence of GCM energies & radii vs GCM truncation

→ Nominal parametrization (B1)

→ Energy cut on HF set

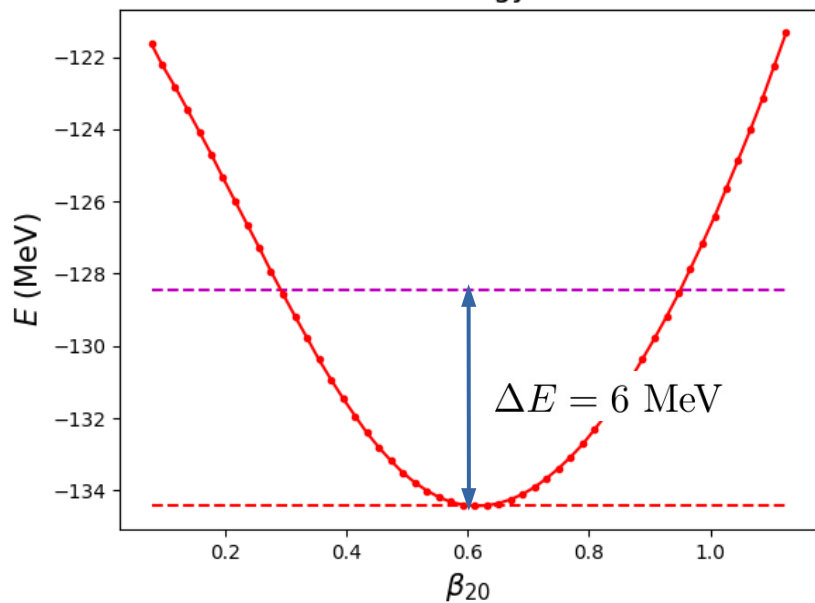
→ Energies converged for  $E_0$  + vibrational excitations  $E_1$  &  $E_2$

→ Radii converged for R0 & R1

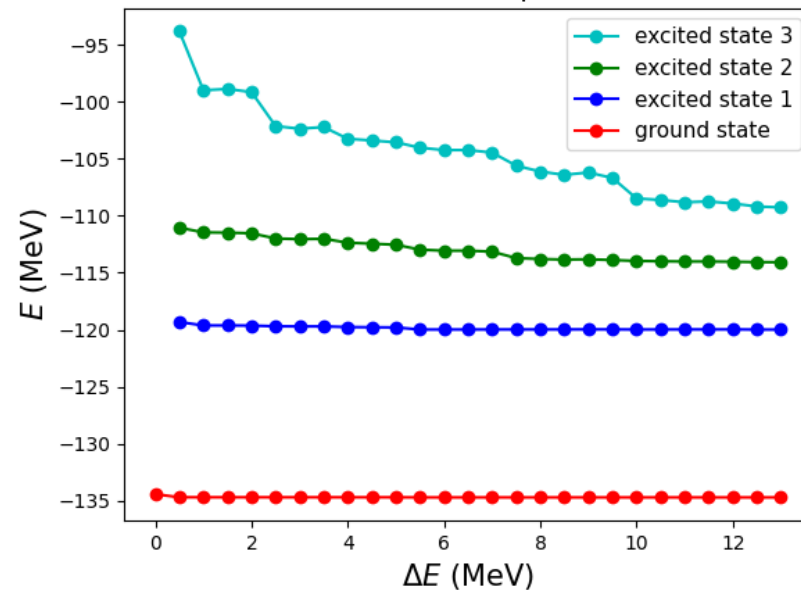
→ Evaluation of GCM truncation error

◆  $E_{n+1} - E_n$     ◆  $R_{n+1} - R_n$

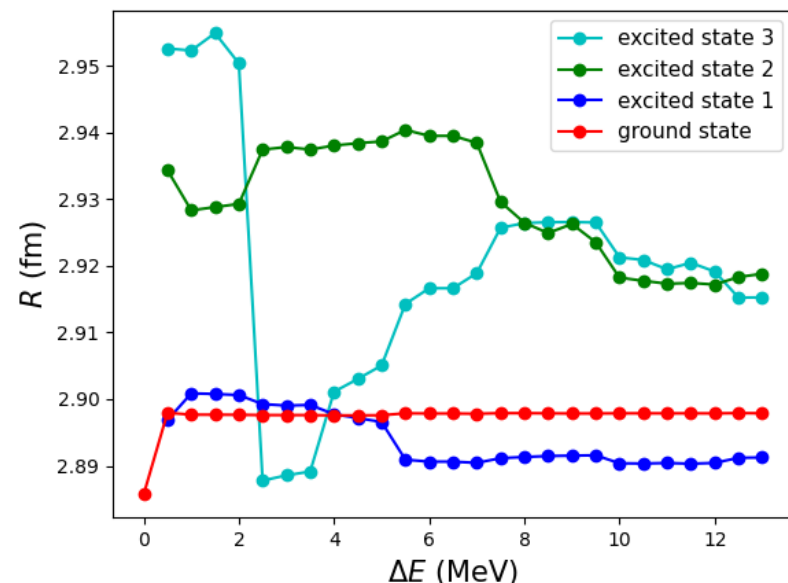
Potential Energy Surface



GCM absolute spectrum



GCM radii



# Nominal GCM computation Effective dimension

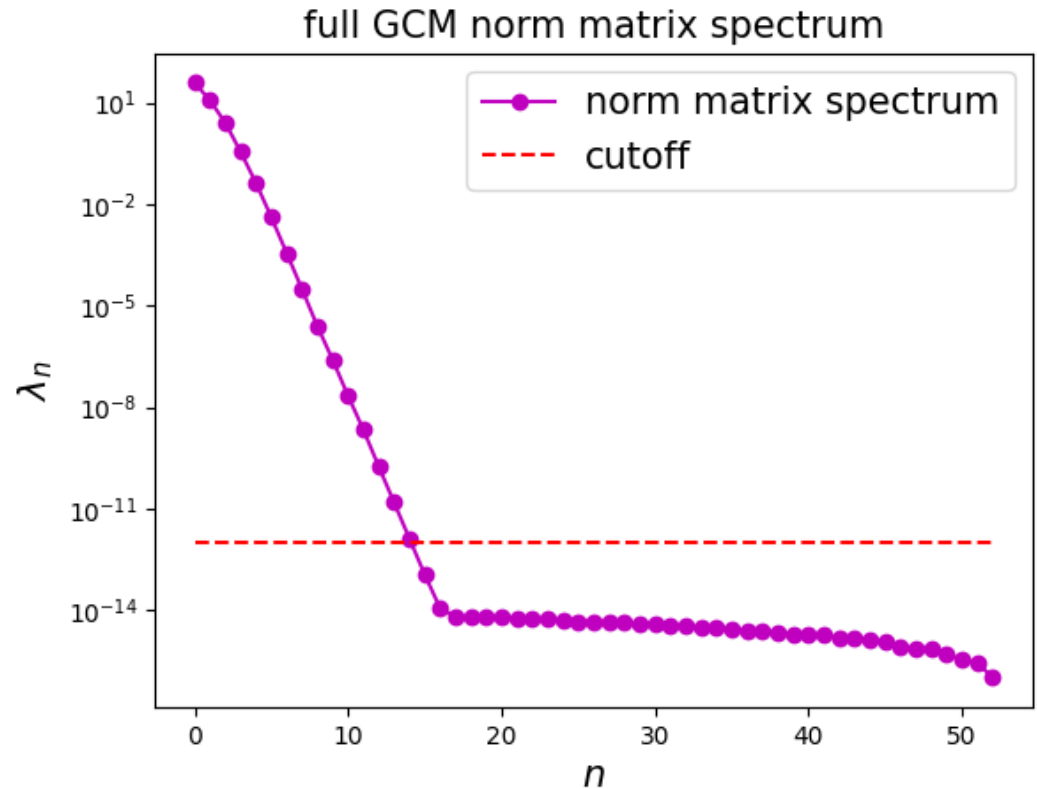
- Norm matrix spectrum

→ cutoff =  $10^{-12}$

→ Number of eigenvalues above cutoff

◆ Effective dimension of  $V^{\lambda_0}$

	Size	Dimension
GCM set	53	15





# 1 parameter GCM-EC Ground-state training

- One-dimensional emulator ( $w_0$ )

→ Ground-state training  $TS_0^{\text{ex.}} = \{0\}$

→ Training set of parameters

$$TS_1^{\text{par.}} = \{-80.21\}$$

$$TS_2^{\text{par.}} = \{-80.21, -78.21\}$$

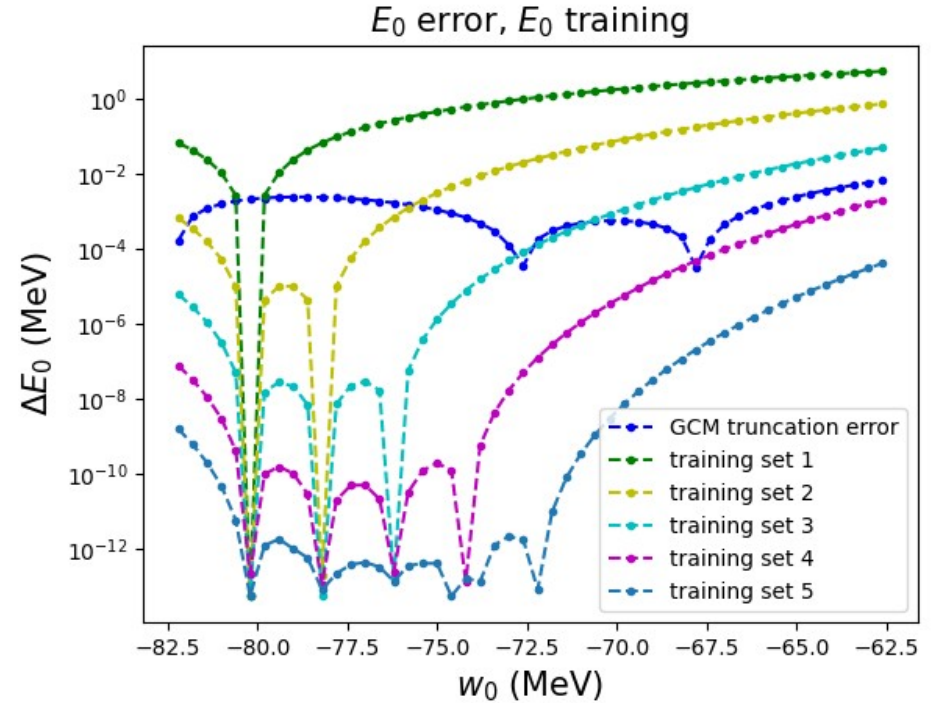
$$TS_3^{\text{par.}} = \{-80.21, -78.21, -76.21\}$$

$$TS_4^{\text{par.}} = \{-80.21, -78.21, -76.21, -74.21\}$$

$$TS_5^{\text{par.}} = \{-80.21, -78.21, -76.21, -74.21, -72.21\}$$

→ Excellent (good) interpolation (extrapolation) of ground-state energy

→ Excellent (good) interpolation (extrapolation) of ground-state radii



	Size	Dimension
GCM set	53	15
$TS_1^{\text{par.}}$	1	1
$TS_2^{\text{par.}}$	2	2
$TS_3^{\text{par.}}$	3	3
$TS_4^{\text{par.}}$	4	4
$TS_5^{\text{par.}}$	5	5

# 1 parameter GCM-EC Ground-state training

- One-dimensional emulator ( $w_0$ )

→ Ground-state training  $TS_0^{\text{ex.}} = \{0\}$

→ Training set of parameters

$$TS_1^{\text{par.}} = \{-80.21\}$$

$$TS_2^{\text{par.}} = \{-80.21, -78.21\}$$

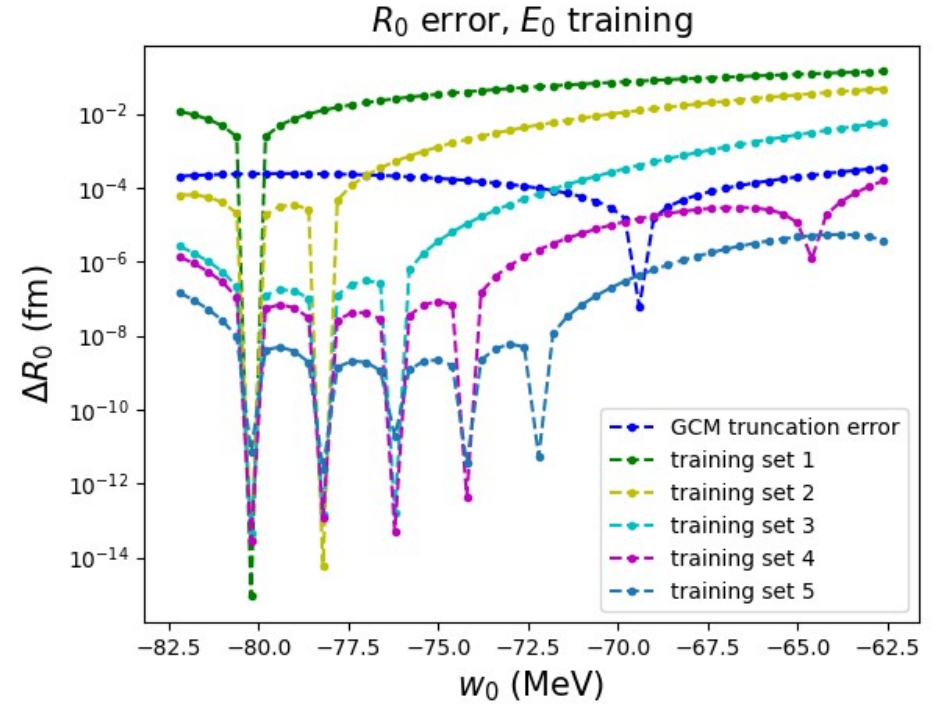
$$TS_3^{\text{par.}} = \{-80.21, -78.21, -76.21\}$$

$$TS_4^{\text{par.}} = \{-80.21, -78.21, -76.21, -74.21\}$$

$$TS_5^{\text{par.}} = \{-80.21, -78.21, -76.21, -74.21, -72.21\}$$

→ Excellent (good) interpolation (extrapolation) of ground-state energy

→ Excellent (good) interpolation (extrapolation) of ground-state radii



	Size	Dimension
GCM set	53	15
$TS_1^{\text{par.}}$	1	1
$TS_2^{\text{par.}}$	2	2
$TS_3^{\text{par.}}$	3	3
$TS_4^{\text{par.}}$	4	4
$TS_5^{\text{par.}}$	5	5

# 1 parameter GCM-EC Separate training for excited states

- Separate training for excited states

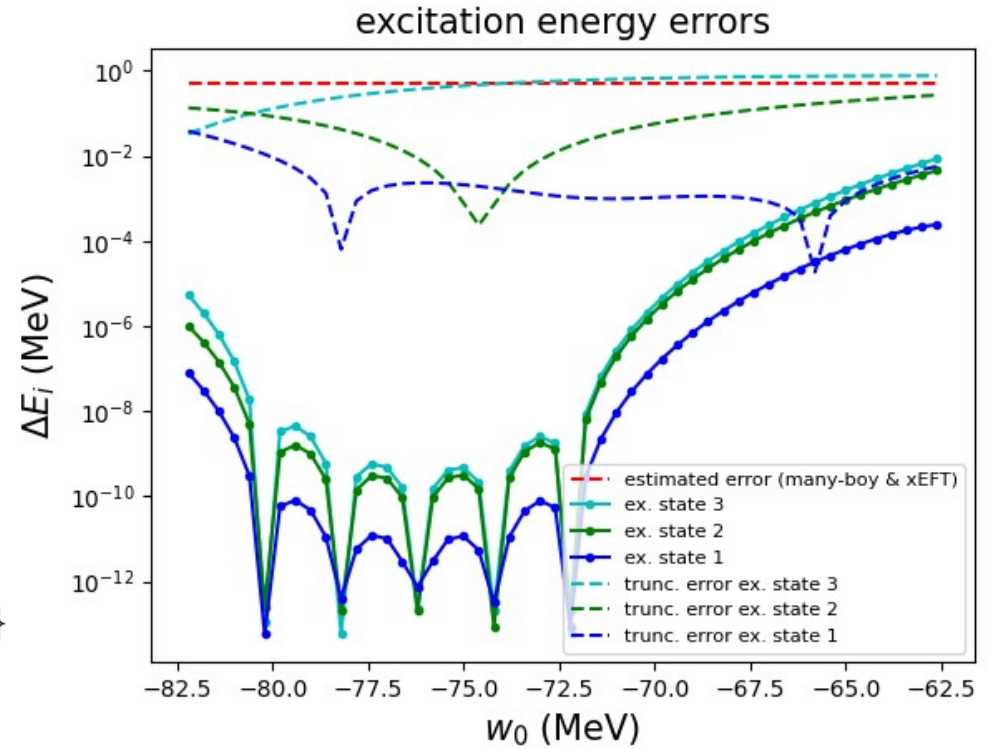
$$\text{TS}_1^{\text{ex.}} = \{1\}$$

$$\text{TS}_2^{\text{ex.}} = \{2\}$$

$$\text{TS}_3^{\text{ex.}} = \{3\}$$

- Common training for parameters

$$\text{TS}_5^{\text{par.}} = \{-80.21, -78.21, -76.21, -74.21, -72.21\}$$



→ Excellent (good) interpolation (extrapolation) of excitation energies

	Size	Dimension
GCM set	53	15
$\text{TS}_1^{\text{ex.}}$	5	5
$\text{TS}_2^{\text{ex.}}$	5	5
$\text{TS}_3^{\text{ex.}}$	5	5

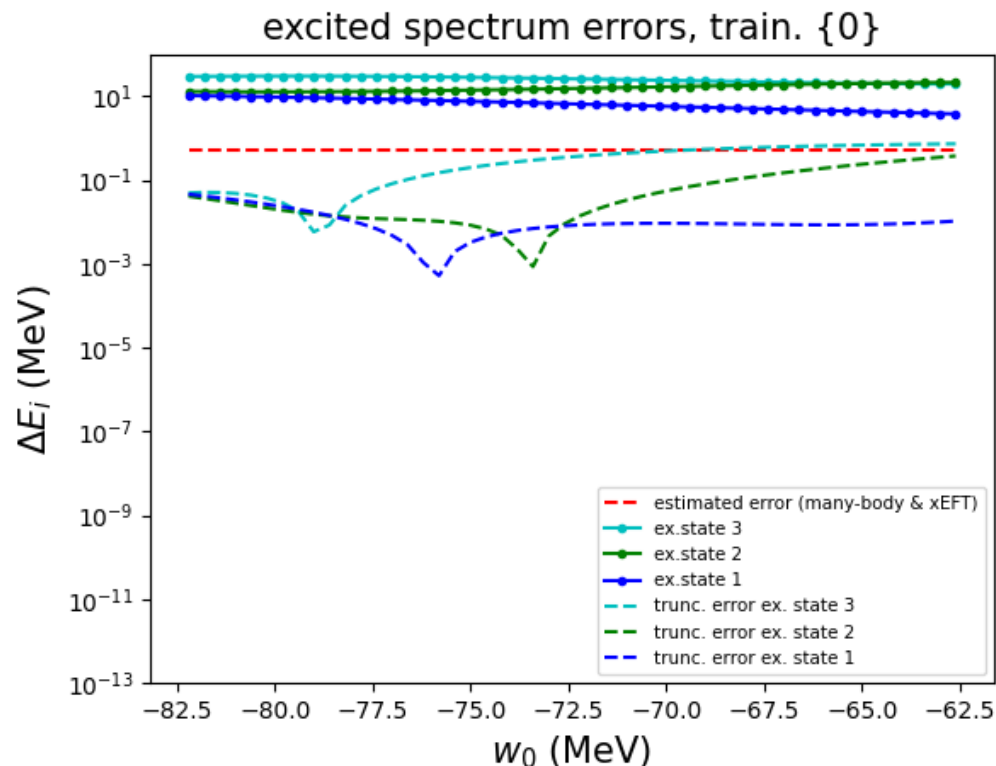
# 1 parameter GCM-EC Ground-state training for excited states

- Training on ground state

$$TS_0^{\text{ex.}} = \{0\}$$

$$TS_5^{\text{par.}}$$

→ Cannot reproduce excited states



	Size	Dimension
GCM set	53	15
$TS_0^{\text{ex.}}$	5	5

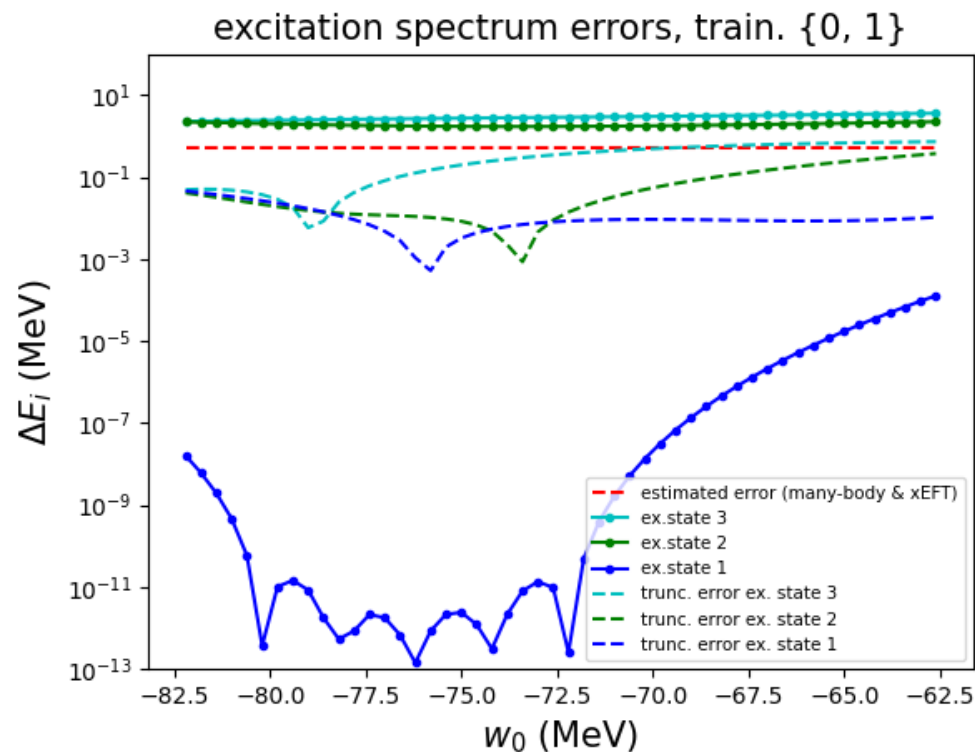
# 1 parameter GCM-EC Excited-state training for excited states

- Adding first excited state to training

$$TS_{01}^{\text{ex.}} = \{0, 1\}$$

$$TS_5^{\text{par.}}$$

→ First excitation energy immediately ok



	Size	Dimension
GCM set	53	15
$TS_{01}^{\text{ex.}}$	10	10

# 1 parameter GCM-EC Excited-state training for excited states

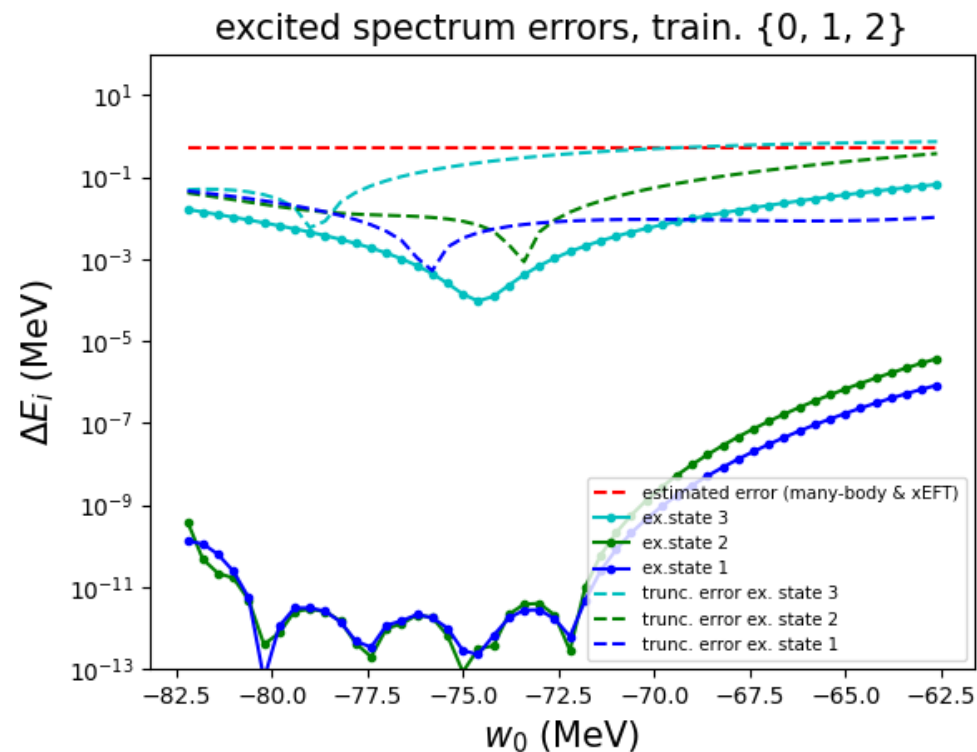
- Adding second excited state to training

$$\text{TS}_{012}^{\text{ex.}} = \{0, 1, 2\}$$

$$\text{TS}_5^{\text{par.}}$$

→ First excitation energy ok

→ Second excitation energy now also ok



	Size	Dimension
GCM set	53	15
$\text{TS}_{012}^{\text{ex.}}$	15	14

# 1 parameter GCM-EC Excited-state training for excited states

- Adding third excited state to training

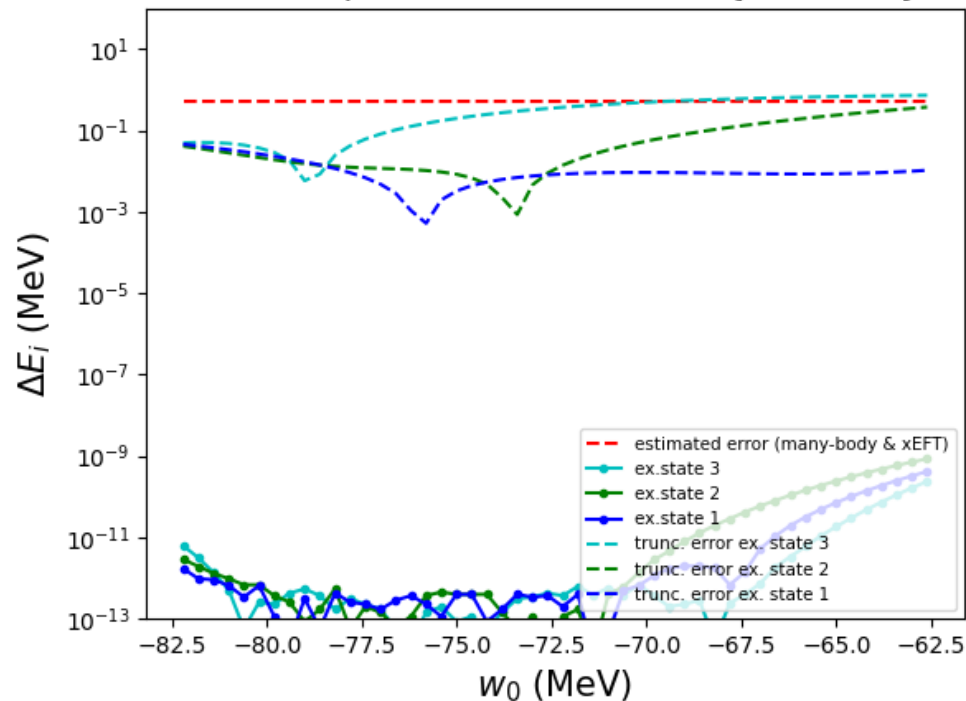
$$\text{TS}_{0123}^{\text{ex.}} = \{0, 1, 2, 3\}$$

$$\text{TS}_5^{\text{par.}}$$

→ First three excitation energies ok

- Training set span full GCM space

excited spectrum errors, train. {0, 1, 2, 3}



	Size	Dimension
GCM set	53	15
$\text{TS}_{0123}^{\text{ex.}}$	20	15

# 4 parameter GCM-EC random parameter training

- Regular rectangular mesh of  $[\lambda_0 - 10, \lambda_0 + 10]^4$  with  $4^4 = 256$  points  
→ sketchy, should use **latin hypercube sampling**

- Random mesh partition into  $\text{TS}_{\text{train.}}^{\text{param.}}$  and  $\text{TS}_{\text{val.}}^{\text{param.}}$   
→  $|\text{TS}_{\text{train.}}^{\text{param.}}| = n_t$

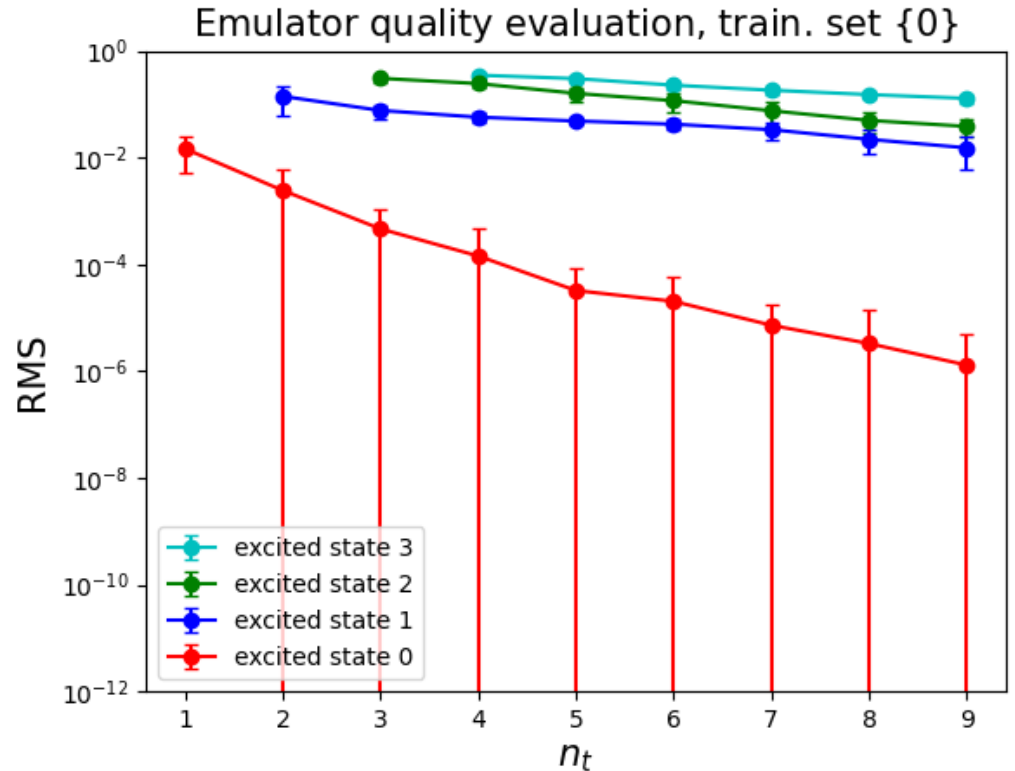
- Emulator cost function

$$\text{RMS}_a = \left( \sum_{\lambda \in \text{TS}_{\text{val.}}^{\text{param.}}} \left( \frac{E_a^{\text{emul.}}(\lambda) - E_a^{\text{val.}}(\lambda)}{E_a^{\text{val.}}(\lambda)} \right)^2 \right)^{1/2}$$

- Repeat  $N = 100$  times  
→ Mean RMS, deviation

- Emulator trained on ground state

$$\text{TS}_0^{\text{ex.}} = \{0\}$$



Good overall reproduction of ground state

Not true for excited states



# 4 parameter GCM-EC random parameter training

- Regular rectangular mesh of  $[\lambda_0 - 10, \lambda_0 + 10]^4$  with  $4^4 = 256$  points  
→ sketchy, should use **latin hypercube sampling**

- Random mesh partition into  $\text{TS}_{\text{train.}}^{\text{param.}}$  and  $\text{TS}_{\text{val.}}^{\text{param.}}$   
→  $|\text{TS}_{\text{train.}}^{\text{param.}}| = n_t$

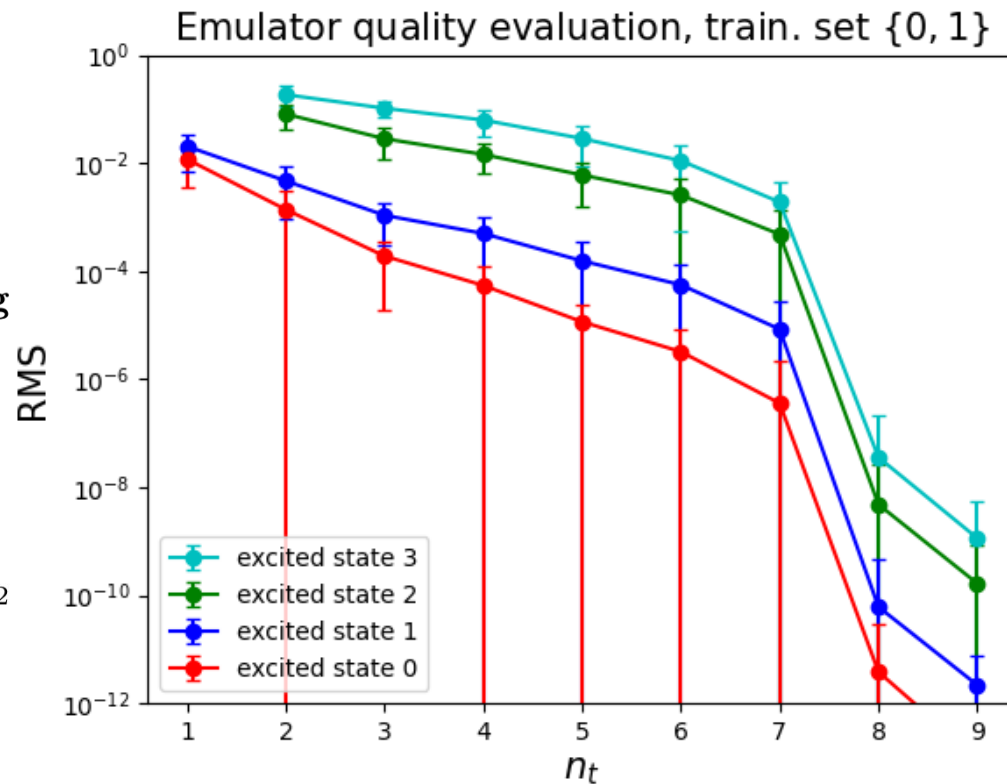
- Emulator cost function

$$\text{RMS}_a = \left( \sum_{\lambda \in \text{TS}_{\text{val.}}^{\text{param.}}} \left( \frac{E_a^{\text{emul.}}(\lambda) - E_a^{\text{val.}}(\lambda)}{E_a^{\text{val.}}(\lambda)} \right)^2 \right)^{1/2}$$

- Repeat  $N = 100$  times  
→ Mean RMS, deviation

- Emulator trained on ground state + excited state 1

$$\text{TS}_{01}^{\text{ex.}} = \{0, 1\}$$



Good overall reproduction of ground state

And first excited state

# 4 parameter GCM-EC random parameter training

- Regular rectangular mesh of  $[\lambda_0 - 10, \lambda_0 + 10]^4$  with  $4^4 = 256$  points  
 → sketchy, should use **latin hypercube sampling**

- Random mesh partition into  $TS_{\text{train.}}^{\text{param.}}$  and  $TS_{\text{val.}}^{\text{param.}}$   
 →  $|TS_{\text{train.}}^{\text{param.}}| = n_t$

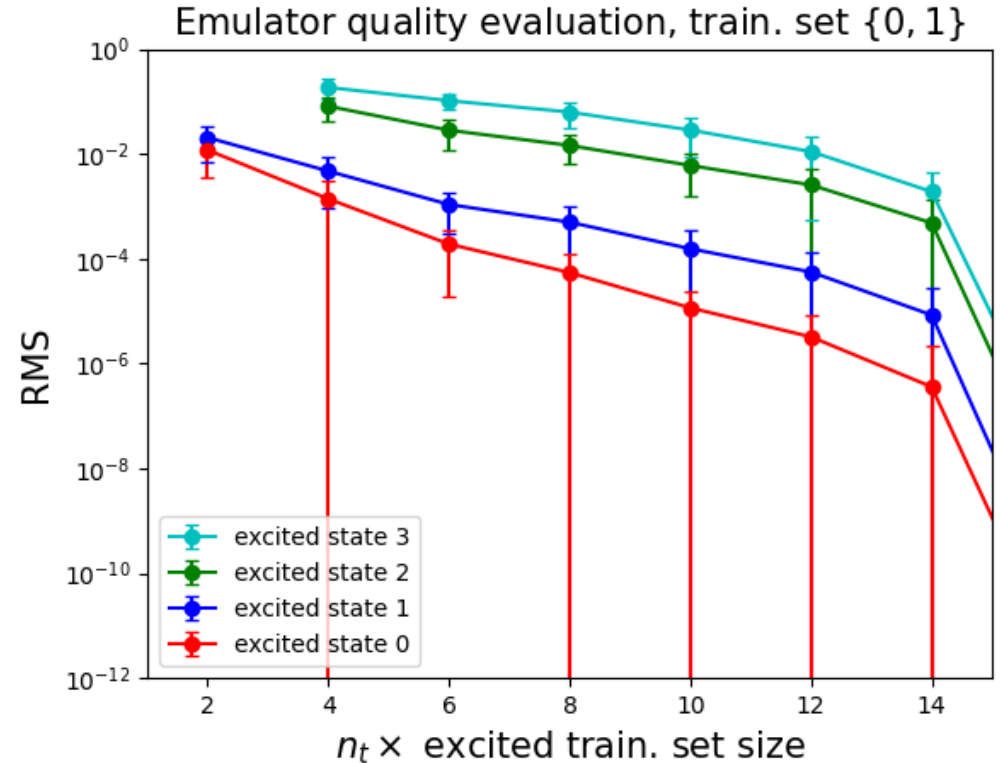
- Emulator cost function

$$RMS_a = \left( \sum_{\lambda \in TS_{\text{val.}}^{\text{param.}}} \left( \frac{E_a^{\text{emul.}}(\lambda) - E_a^{\text{val.}}(\lambda)}{E_a^{\text{val.}}(\lambda)} \right)^2 \right)^{1/2}$$

- Repeat  $N = 100$  times  
 → Mean RMS, deviation

- Emulator trained on ground state + excited state 1

$$TS_{01}^{\text{ex.}} = \{0, 1\}$$



Good overall reproduction of ground state

And first excited state

Taking into account effective dimension

# Conclusion & perspectives

- **Encouraging preliminary result**
  - Absolute energies
  - Excitation energies
  - Radii
- **Quick generalisation to less trivial model**
  - Ab initio
  - More observables
- **Time complexity reduction**
  - EC game-changing
  - Application to sensitivity analysis and interaction fits in nuclear theory