



UNIVERSITÀ DEGLI STUDI DI MILANO
DIPARTIMENTO DI FISICA



On the lattice-based neural network quantum states

Carlo Barbieri



Next Generation Ab Initio Nuclear Theory — ECT*, July 14-18, 2025

Neural Network Quantum States (NQS):

$$\frac{\langle \Psi_V | H | \Psi_V \rangle}{\langle \Psi_V | \Psi_V \rangle} = E_V \geq E_0$$

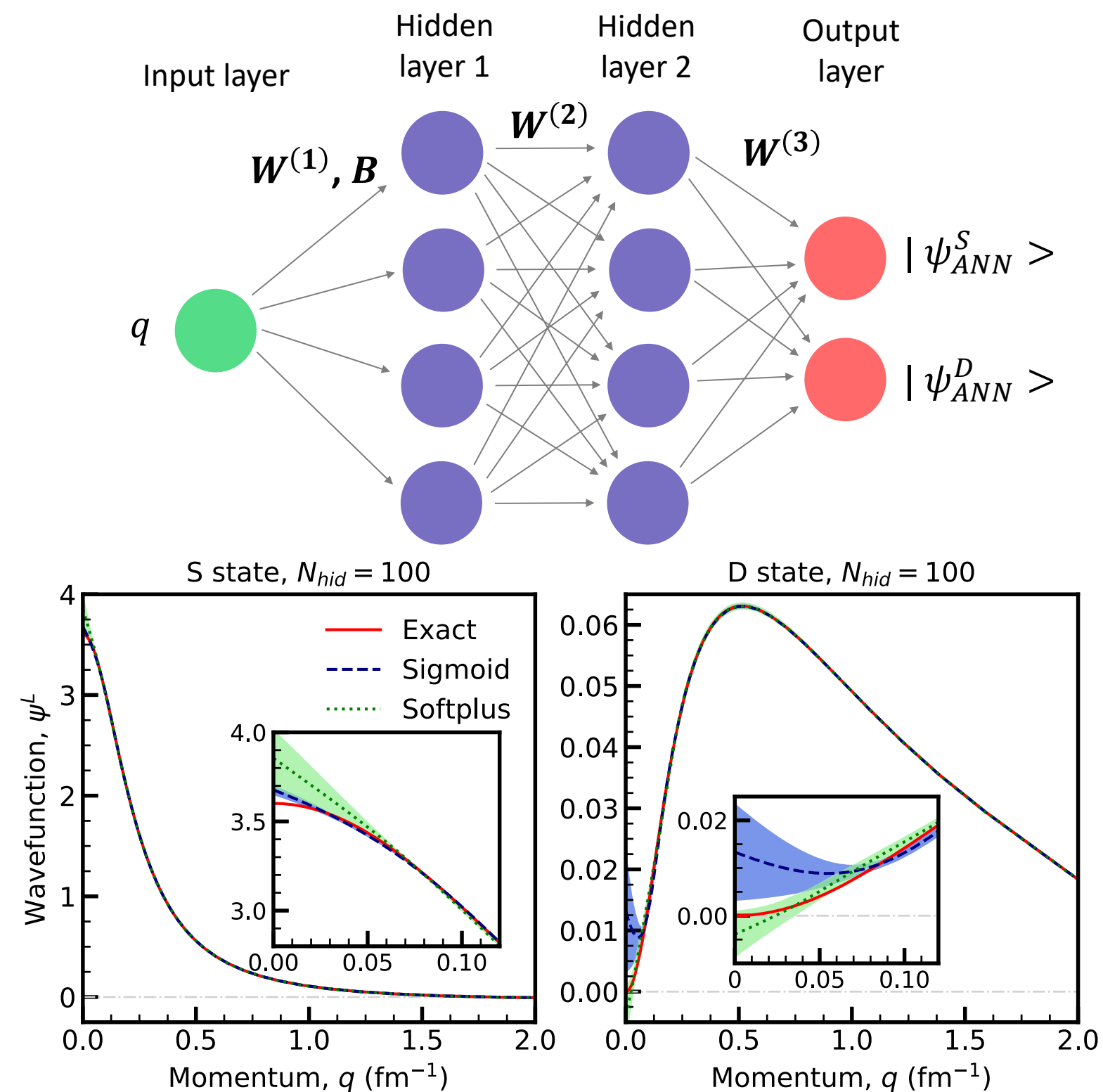
$$|\Psi_V^J\rangle = \prod_{i < j < k} \left(1 - \sum_{\text{cyc}} u(r_{ij}) u(r_{jk}) \right) \prod_{i < j} f(r_{ij}) |\Phi\rangle$$

neural networks

And the NQS is.... a VMC with a NN trial wave function!

Early NQS for nuclear physics

The deuteron:



Light nuclei:

	Λ	VMC-ANN	VMC-JS	GFMC	GFMC _c
^2H	4 fm^{-1}	$-2.224(1)$	$-2.223(1)$	$-2.224(1)$	-
	6 fm^{-1}	$-2.224(4)$	$-2.220(1)$	$-2.225(1)$	-
^3H	4 fm^{-1}	$-8.26(1)$	$-7.80(1)$	$-8.38(2)$	$-7.82(1)$
	6 fm^{-1}	$-8.27(1)$	$-7.74(1)$	$-8.38(2)$	$-7.81(1)$
^4He	4 fm^{-1}	$-23.30(2)$	$-22.54(1)$	$-23.62(3)$	$-22.77(2)$
	6 fm^{-1}	$-24.47(3)$	$-23.44(2)$	$-25.06(3)$	$-24.10(2)$

C. Adams, G. Carleo, A. Lovato, N. Rocco,
Phys. Rev. Lett. **127**, 022502 (2021)

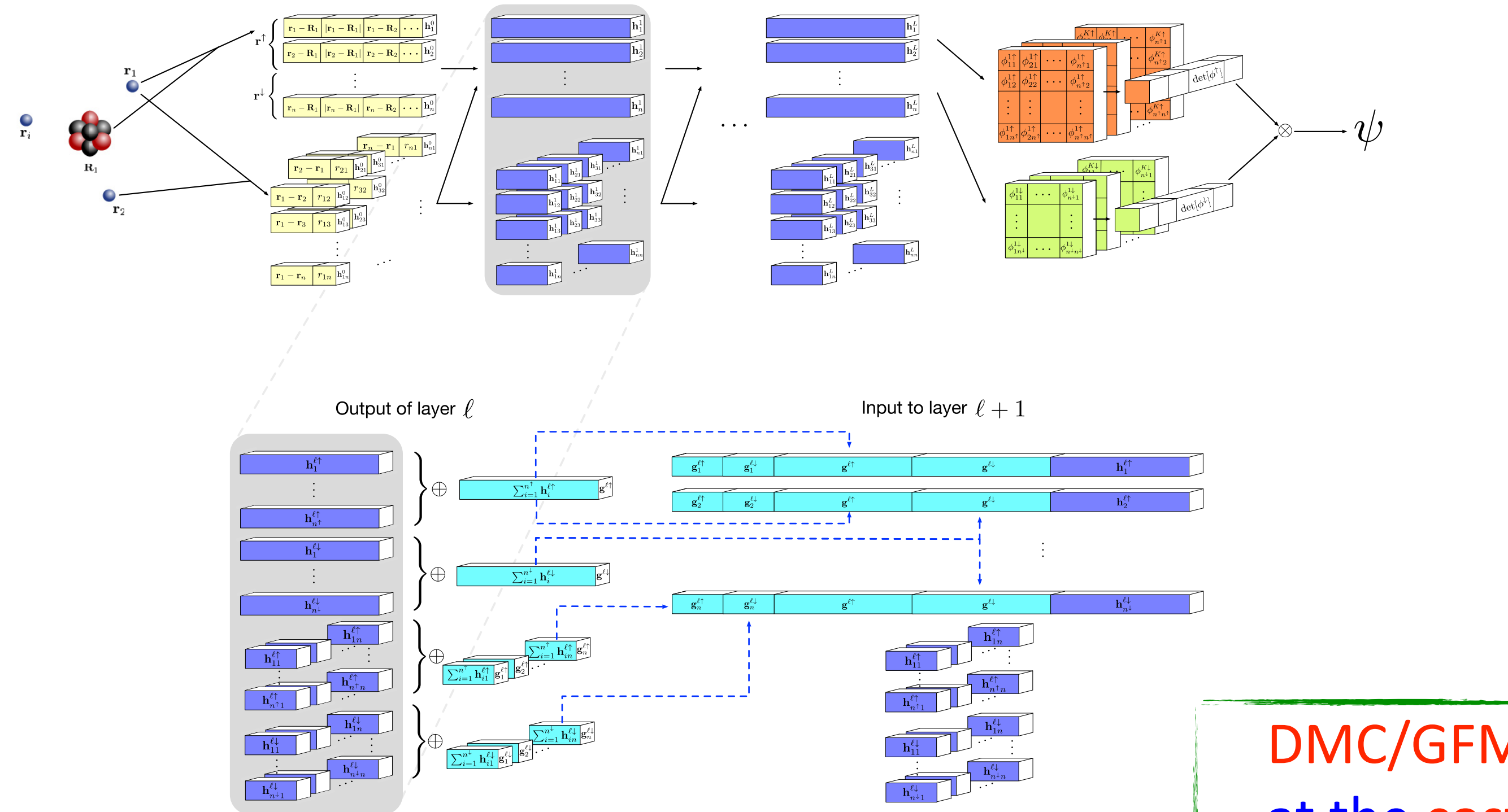
Keeble, Rios, Phys. Lett. B **809**, 135743 (2020)

Rozalén Sarmiento, Keeble, EPJ Plus **139**, 189 (2024)

Some example of NQS in quantum chemistry

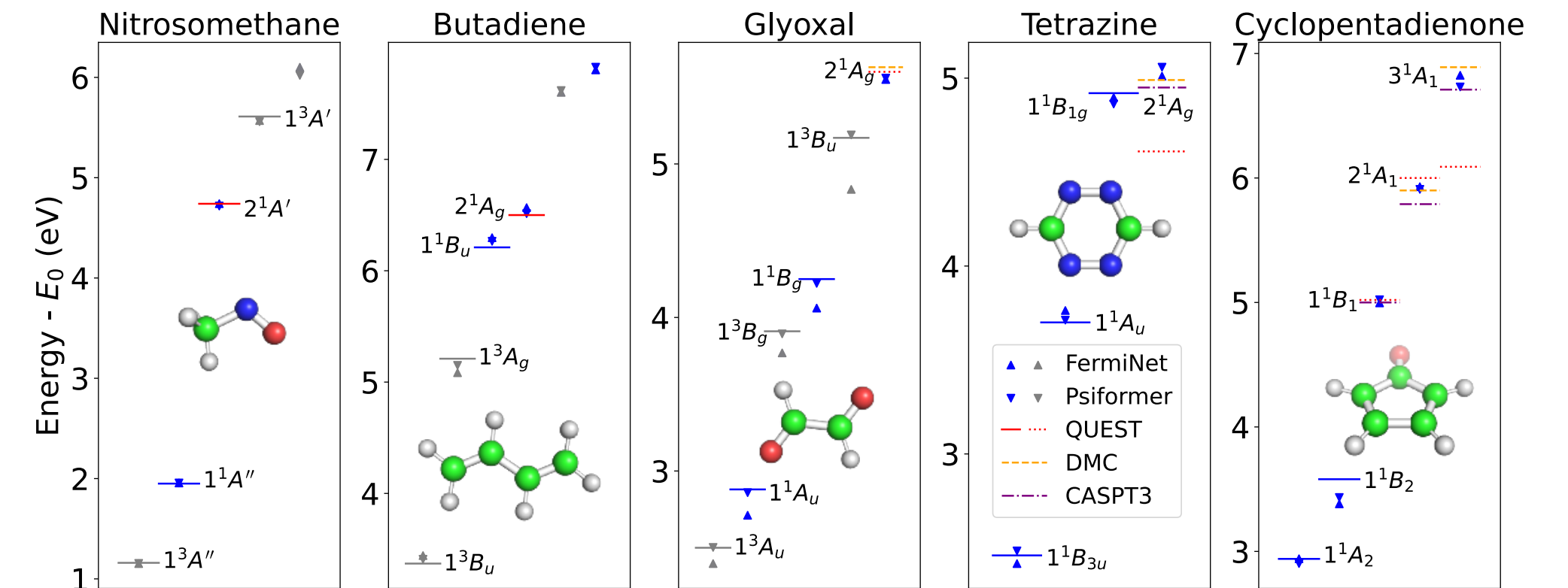
FermiNet NQS:

D. Pfau et al., Phys. Rev. Res. **2**, 033429 (2020)

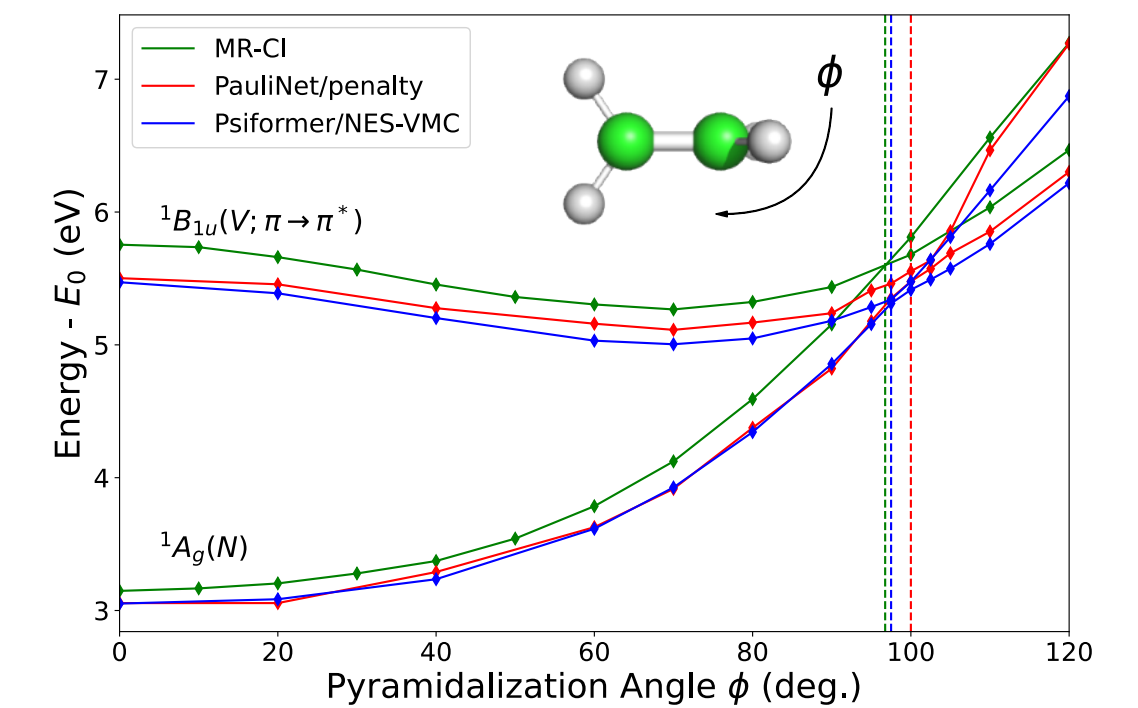


FermiNet for excited states:

D. Pfau et al., Science **385**, 6711 (2024)



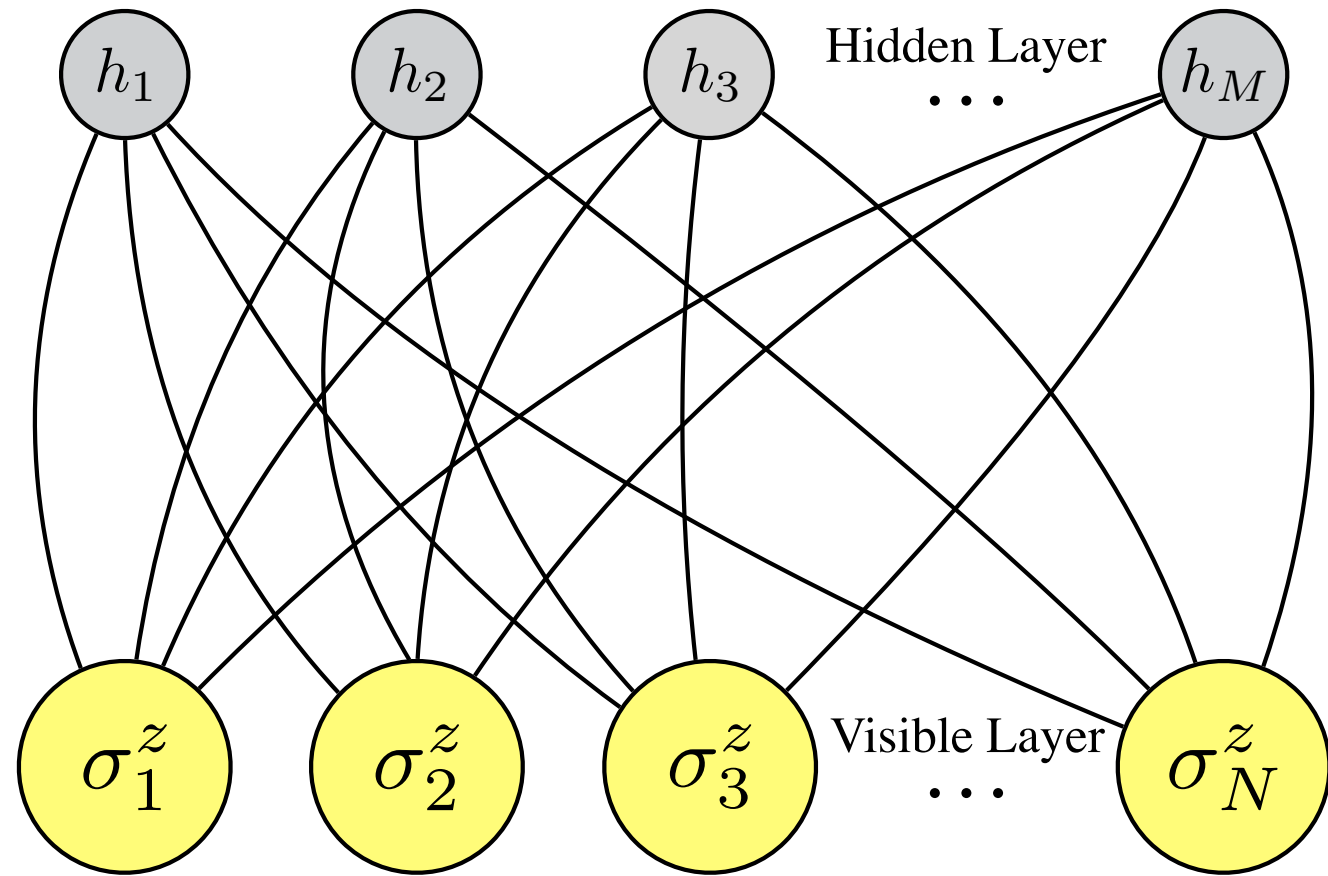
DMC/GFMC accuracy
at the cost of VMC !



And many other architectures for correlated fermions: see e.g., J. Hermann et al., Nature Reviews Chemistry **7**, 692–709 (2023)

NQS for spin lattices — RBMs

Restricted Boltzmann Machines:



$$E^{\mathcal{W}} = \frac{\langle \psi^{\mathcal{W}} | \hat{H} | \psi^{\mathcal{W}} \rangle}{\langle \psi^{\mathcal{W}} | \psi^{\mathcal{W}} \rangle}$$

$$\Psi_M(\mathcal{S}; \mathcal{W}) = \sum_{\{h_i\}} e^{\sum_j a_j \sigma_j^z + \sum_i b_i h_i + \sum_{ij} W_{ij} h_i \sigma_j^z}$$

[G. Carleo & M. Troyer, Science **355**, 602 \(2017\)](#)
[K. Choo, et al., Nature Comm., **11**, 2368, \(2020\).](#)

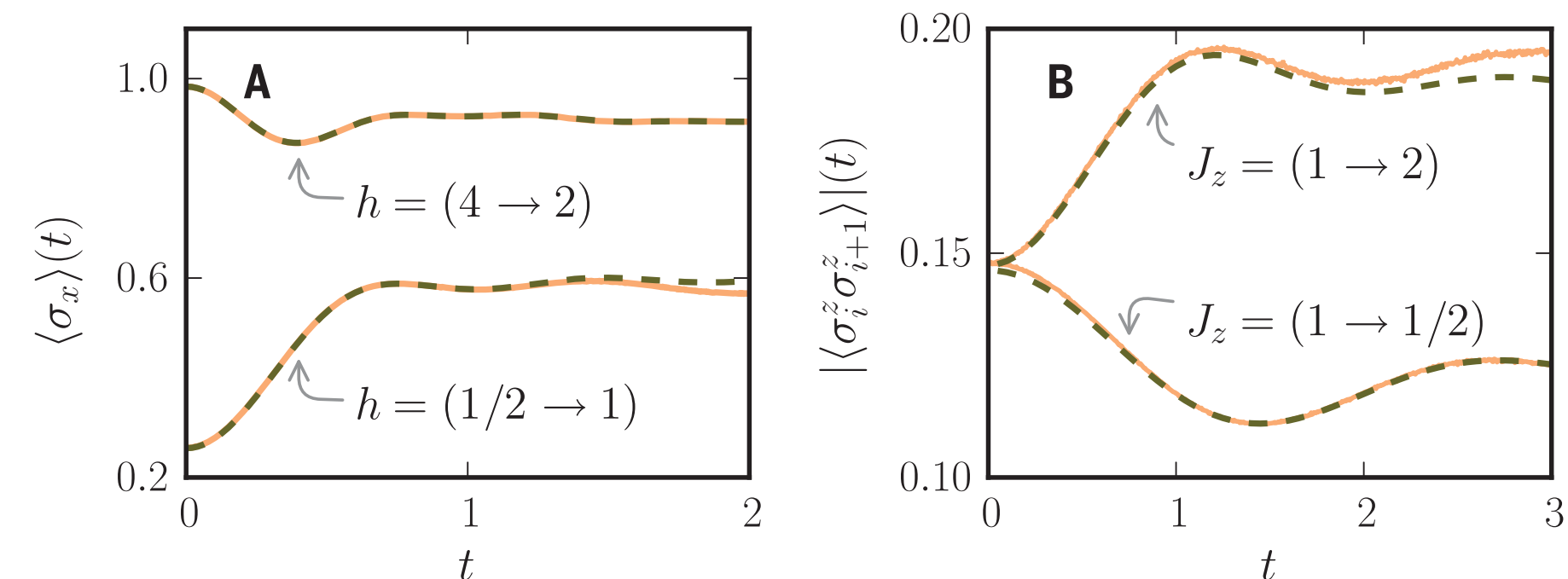
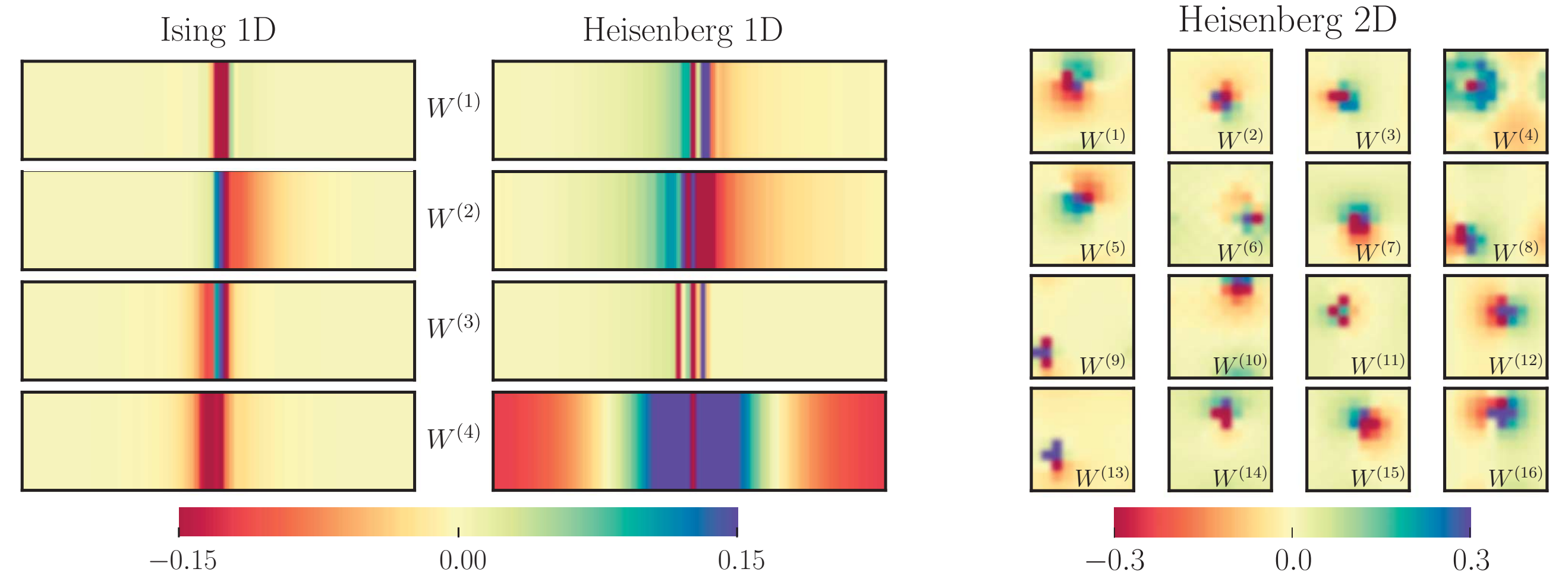
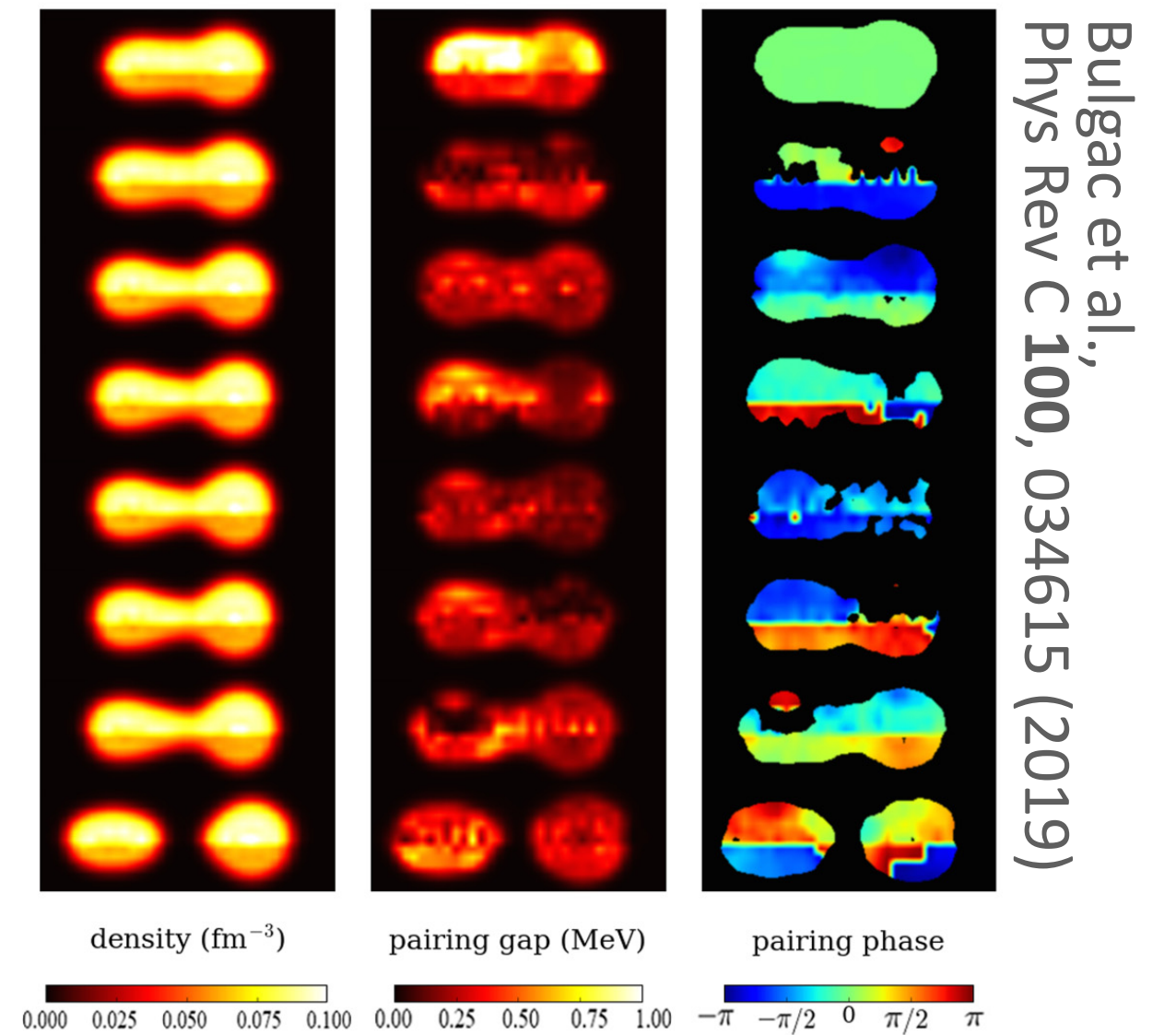


Fig. 4. Many-body unitary time evolution with NQS. NQS results (solid lines) for the time evolution induced by a quantum quench in the microscopic parameters of the models we study (the transverse

Why a NQS on the Lattice?

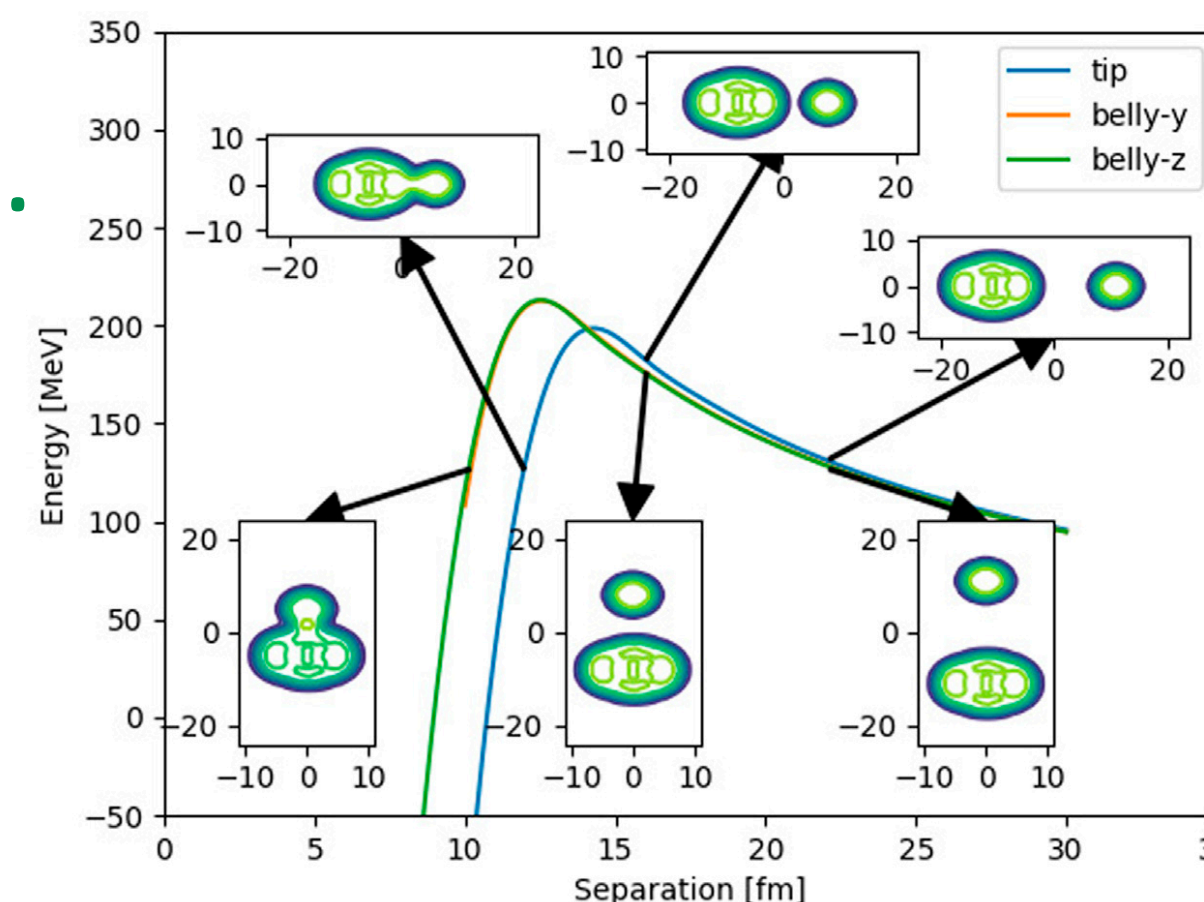
Advantages of a lattice-NQS for nuclei:

- It is hopeless — too costly to work in practice.
- Fermi-Pauli statistics comes for free (Fock space).
- Not tied to spherical or partially deformed ansätze (full deformation, etc...).
- Transfer learning (train few-nucleon first).
- Many-body dynamics.



Fission of ^{240}Pu :

- time dependent DFT inspired, in 3D
- $30 \times 30 \times 60 \text{ fm}^3$ box
- $24 \times 24 \times 48 = 27,000$ pts mesh



Mean-field simulations of Es-254
+ Ca-48 heavy-ion reactions

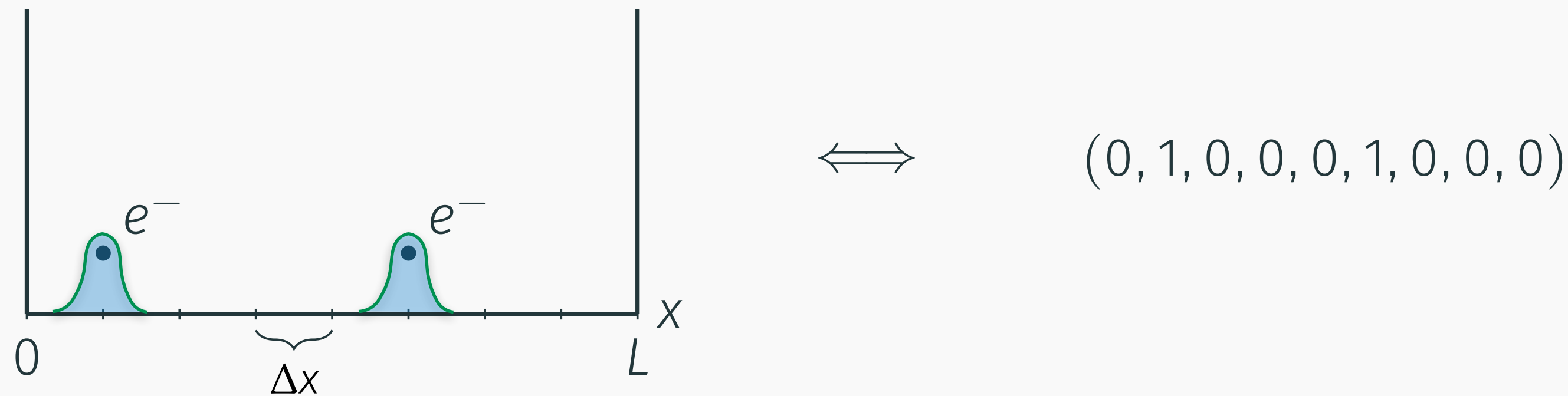
P. Stevenson et al.,
Frontiers **10**, 1019285 (2022)

NQS for fermions confined in a box



Confined fermions w/ a discrete coordinate space mesh

- Discretise coordinate space
- Use occupation number to locate particles



no need to worry about antisymmetrization!

- Use a Fock space basis to represent particle configurations:

$$|\psi\rangle = \prod_i \psi^\dagger(x_i) |0\rangle = |n_0=0, n_1=1, n_2=0, n_3=0, n_4=0, n_5=1, \dots, n_L=0\rangle$$

- Can be mapped into a system of spins (*with fixed magnetisation*):

$$\langle x|\psi\rangle \rightarrow \langle S|\psi\rangle \Leftrightarrow \begin{cases} c_{\uparrow\uparrow\uparrow\dots} \doteq \langle \uparrow\uparrow\uparrow\dots|\psi\rangle = \psi(\uparrow\uparrow\uparrow\dots) \\ c_{\downarrow\uparrow\uparrow\dots} \doteq \langle \downarrow\uparrow\uparrow\dots|\psi\rangle = \psi(\downarrow\uparrow\uparrow\dots) \\ \vdots \\ c_{\downarrow\downarrow\downarrow\dots} \doteq \langle \downarrow\downarrow\downarrow\dots|\psi\rangle = \psi(\downarrow\downarrow\downarrow\dots) \end{cases}$$

Can be solved as in
Carleo and Troyer,
Science **355**, 602 (2017)

NQS representation

- Use a Restricted Boltzmann Machine with complex parameter to represent the w.f.:

$$\mathcal{P}(\mathbf{v} \cap \mathbf{h}) = \frac{1}{\mathcal{Z}} \exp(\mathbf{a}^\top \mathbf{v} + \mathbf{b}^\top \mathbf{h} + \mathbf{h}^\top \underline{\underline{W}} \mathbf{v}) \quad \text{with:} \quad \begin{cases} \mathbf{v} \in \{-1, 1\}^{N_v} \\ \mathbf{h} \in \{-1, 1\}^{N_h} \end{cases} \quad \begin{cases} \mathbf{a} \in \mathbb{C}^{N_v} \\ \mathbf{b} \in \mathbb{C}^{N_h} \\ W \in \text{Mat}_{N_h \times N_v}(\mathbb{C}) \end{cases}$$

- Marginalize w.r.t. the hidden nodes:

$$\langle x | \psi \rangle \rightarrow \mathcal{P}(\mathbf{v}) = \sum_{\{\mathbf{h}\}} \mathcal{P}(\mathbf{v} \cap \mathbf{h})$$

$$\begin{cases} \mathbf{a} = \mathbf{a}^{(0)} + \Delta \mathbf{a} = \mathbf{a}^{(0)} + \sum_{i=1}^{N_h} \mathbf{a}^{(i)} \\ 1/\mathcal{Z} = \exp\left(\sum_{i=1}^{N_h} K^{(i)}\right) \\ \mathbf{w}^{(i)} = \begin{pmatrix} W_{1,i} \\ W_{2,i} \\ \vdots \\ W_{N_v,i} \end{pmatrix} \in \mathbb{C}^{N_v}, \\ \omega_i(\mathbf{v}) = \mathbf{w}^{(i)\top} \mathbf{v} + b_i = \sum_j W_{ji} v_j + b_i, \end{cases}$$

Restricted Boltzmann Machine

$$\psi(\mathbf{v}) = 2^{N_h} \exp(\mathbf{a}^{(0)\top} \mathbf{v}) \prod_{i=1}^{N_h} \left[\exp\left(K^{(i)} + \mathbf{a}^{(i)\top} \mathbf{v}\right) \cosh(\omega_i(\mathbf{v})) \right]$$

<— Note that $\mathbf{a}^{(i)}$ are site dependent and no hidden nodes are necessary for a single particle ($N_h=0$).

Energy minimization

- The Hamiltonian for N_v fermions will be:

$$\mathcal{H} = T + V = \sum_i \frac{-\hbar^2}{2m_i(\Delta x)^2} \sum_j \left[\psi_{j+1}^\dagger \psi_j - 2\psi_j^\dagger \psi_j + \psi_{j-1}^\dagger \psi_j \right] + V \quad + \text{appropriate conditions at the walls.}$$

- Sample E_{loc} from $|\psi(x)|^2 \sim \text{RBM}^2$ using MCMC:

$$E_{loc}(\mathbf{x}) = \int d\mathbf{x}' \mathcal{H}_{\mathbf{x}\mathbf{x}'} \frac{\psi(\mathbf{x}')}{\psi(\mathbf{x})}$$

$$\frac{\langle \psi | \mathcal{H} | \psi \rangle}{\langle \psi | \psi \rangle} = \langle E_{loc} \rangle_{|\psi(\mathbf{x})|^2}$$

Use gradient descent w/ SR:

$$D_k(\mathbf{x}; \theta) = \frac{\partial_{\theta_k} \psi^\theta(\mathbf{x})}{\psi^\theta(\mathbf{x})}$$

$$\partial_{\theta_k} \langle \mathcal{H} \rangle_\psi = \langle G_k \rangle_{|\psi(\mathbf{x})|^2}$$

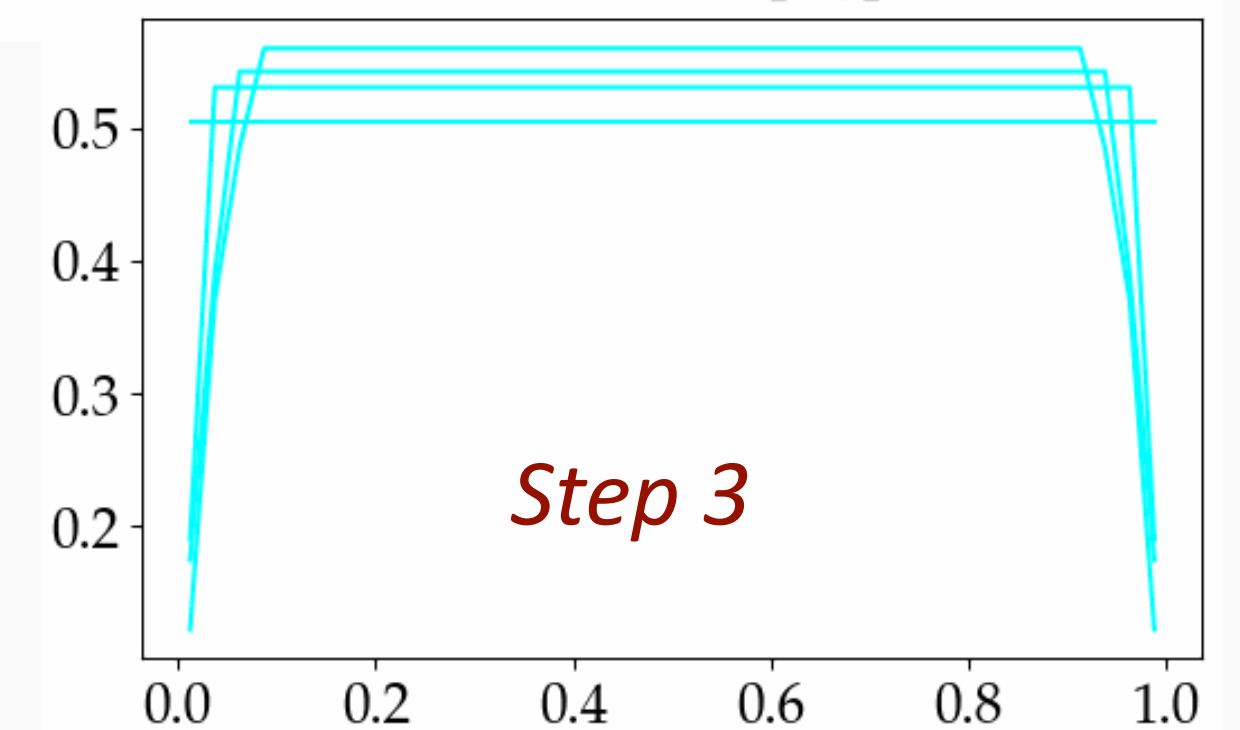
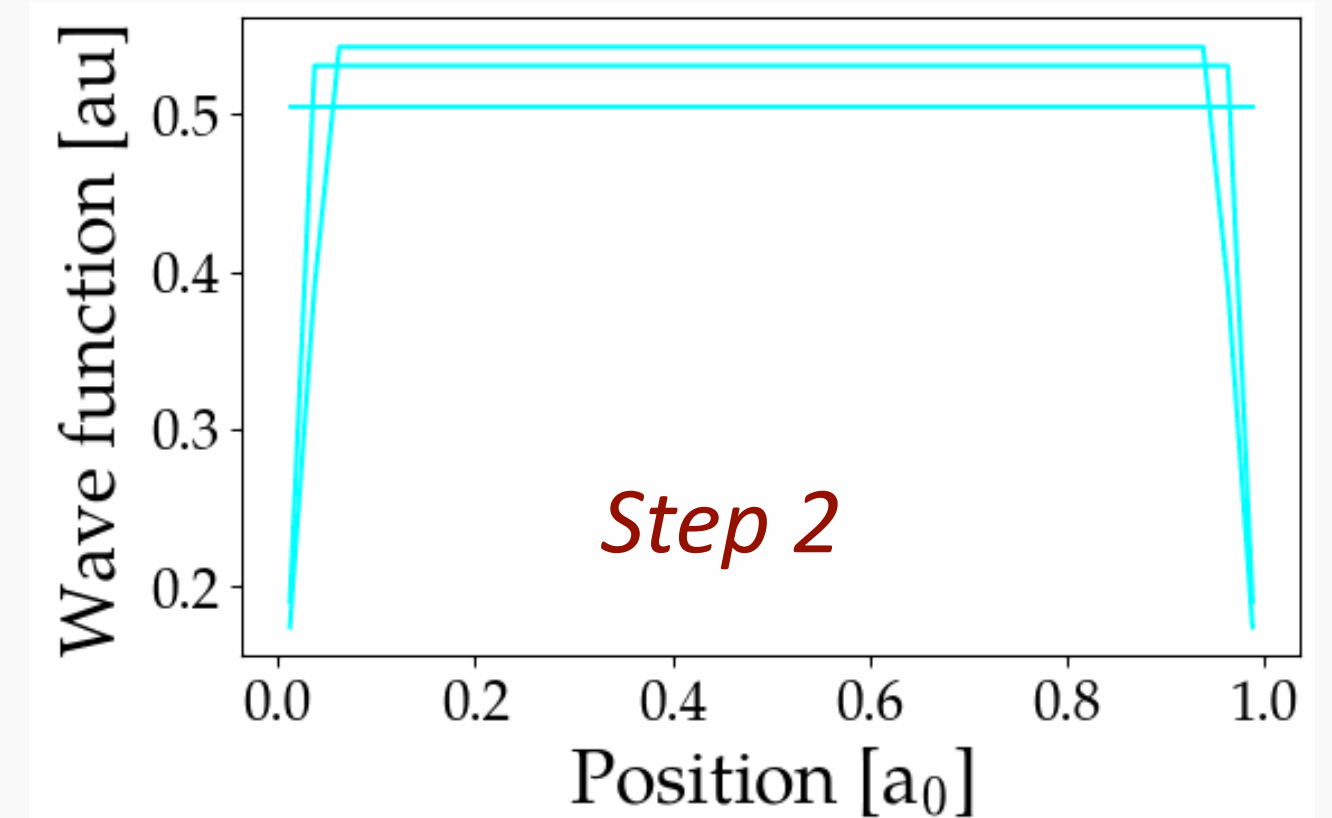
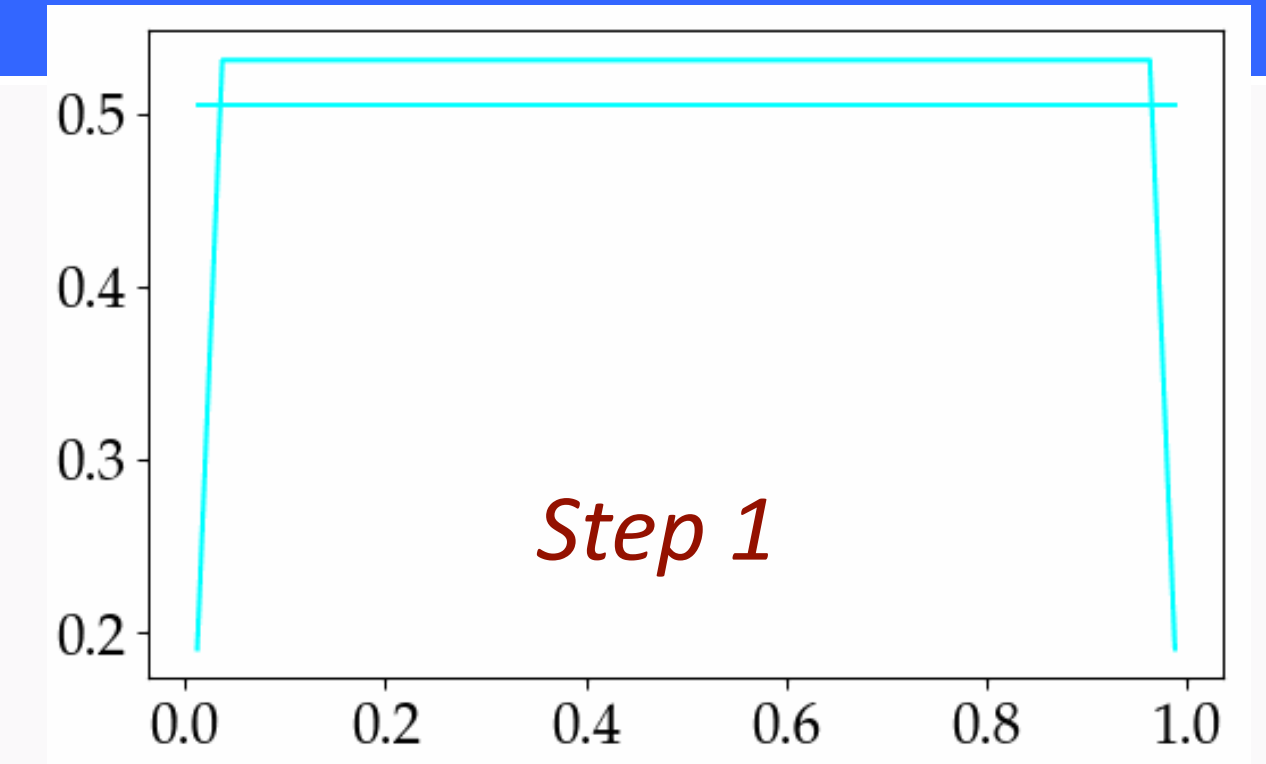
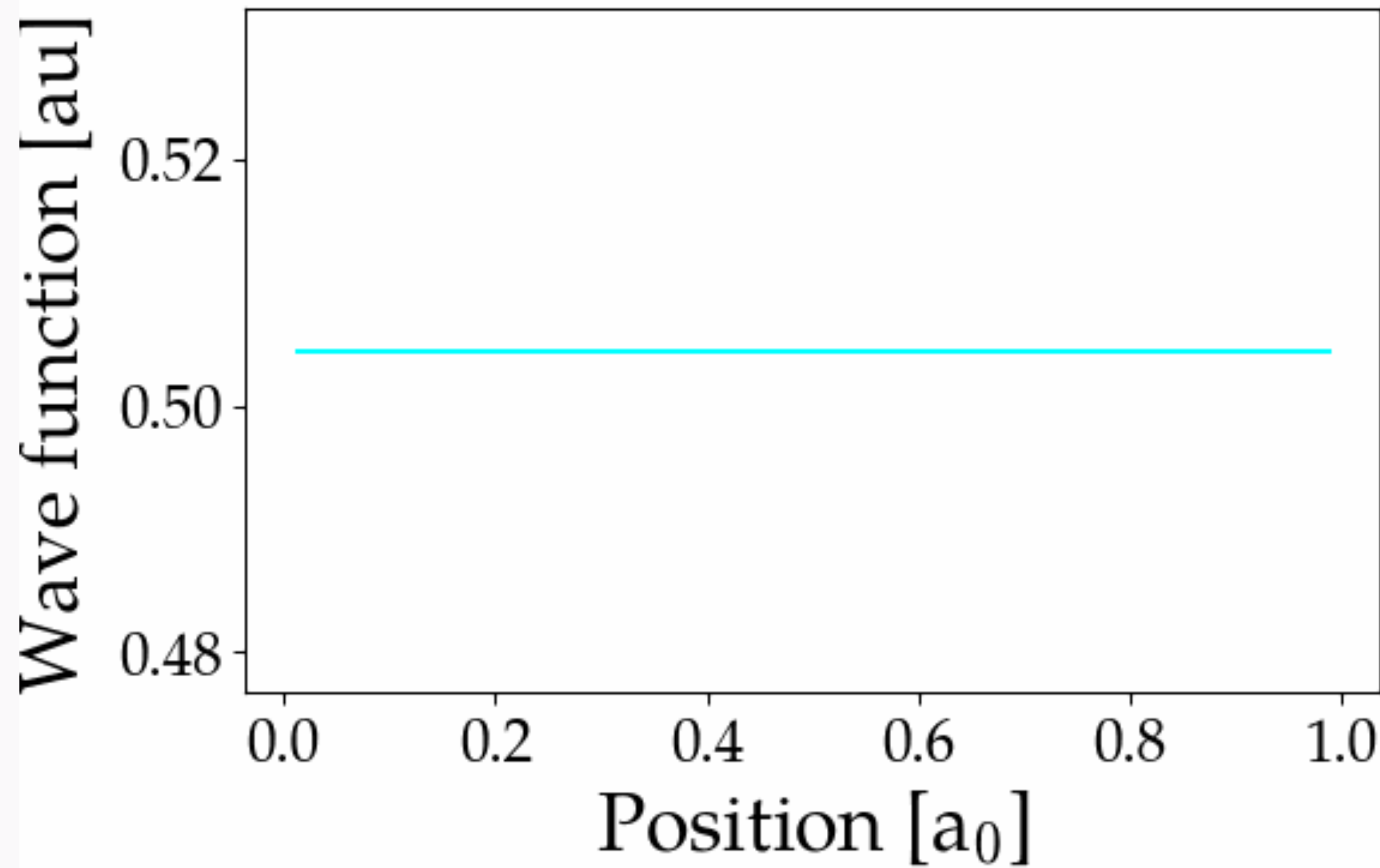
$$G_k(\mathbf{x}; \theta) = 2\text{Re} \left[D_k^*(\mathbf{x}; \theta) \left(E_{loc}(\mathbf{x}) - \langle E_{loc} \rangle_{|\psi(\mathbf{x})|^2} \right) \right]$$

Stochastic Reconfiguration

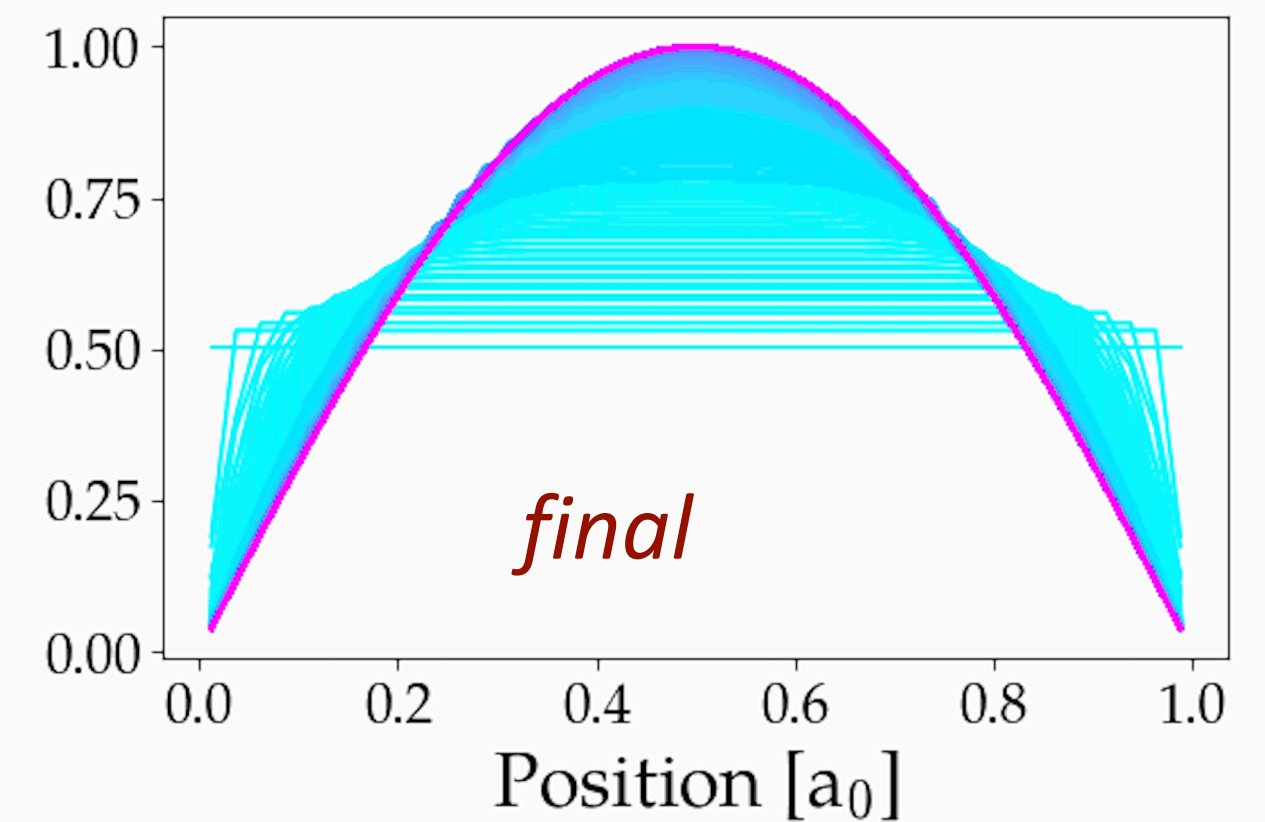
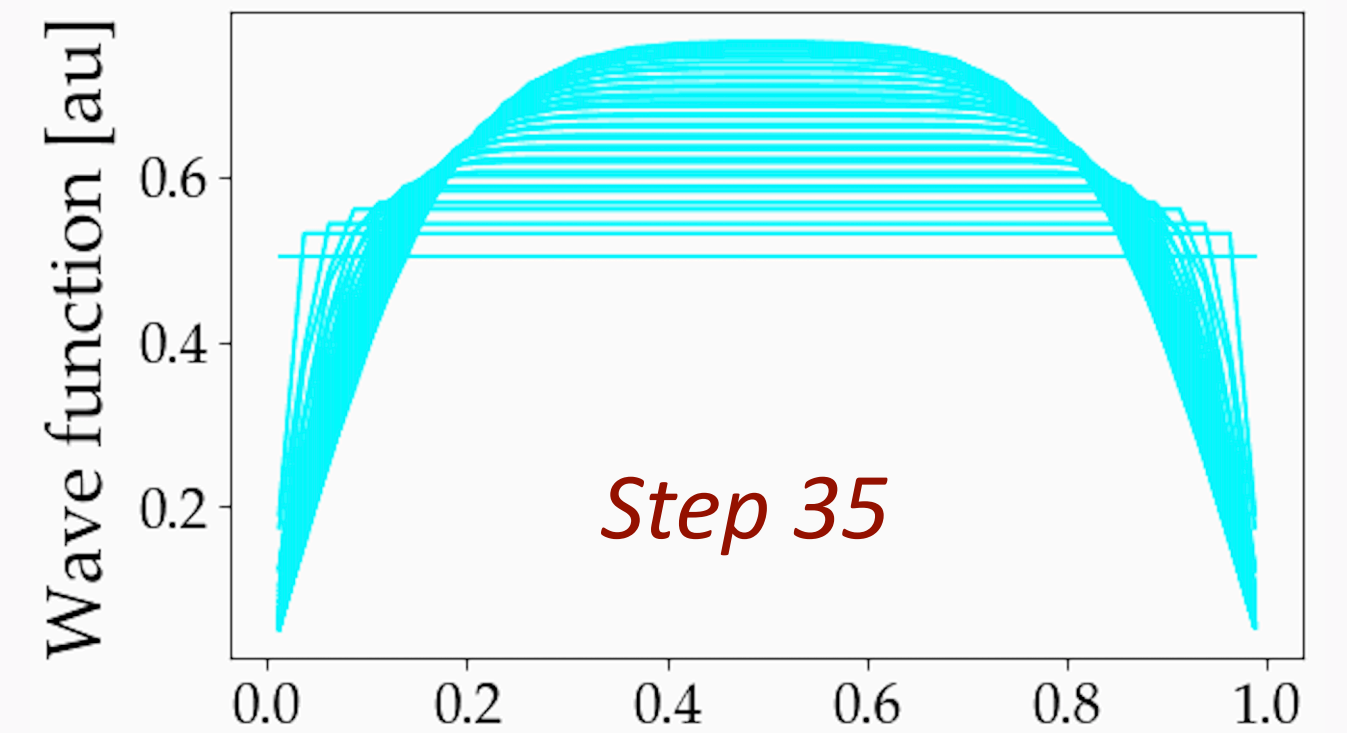
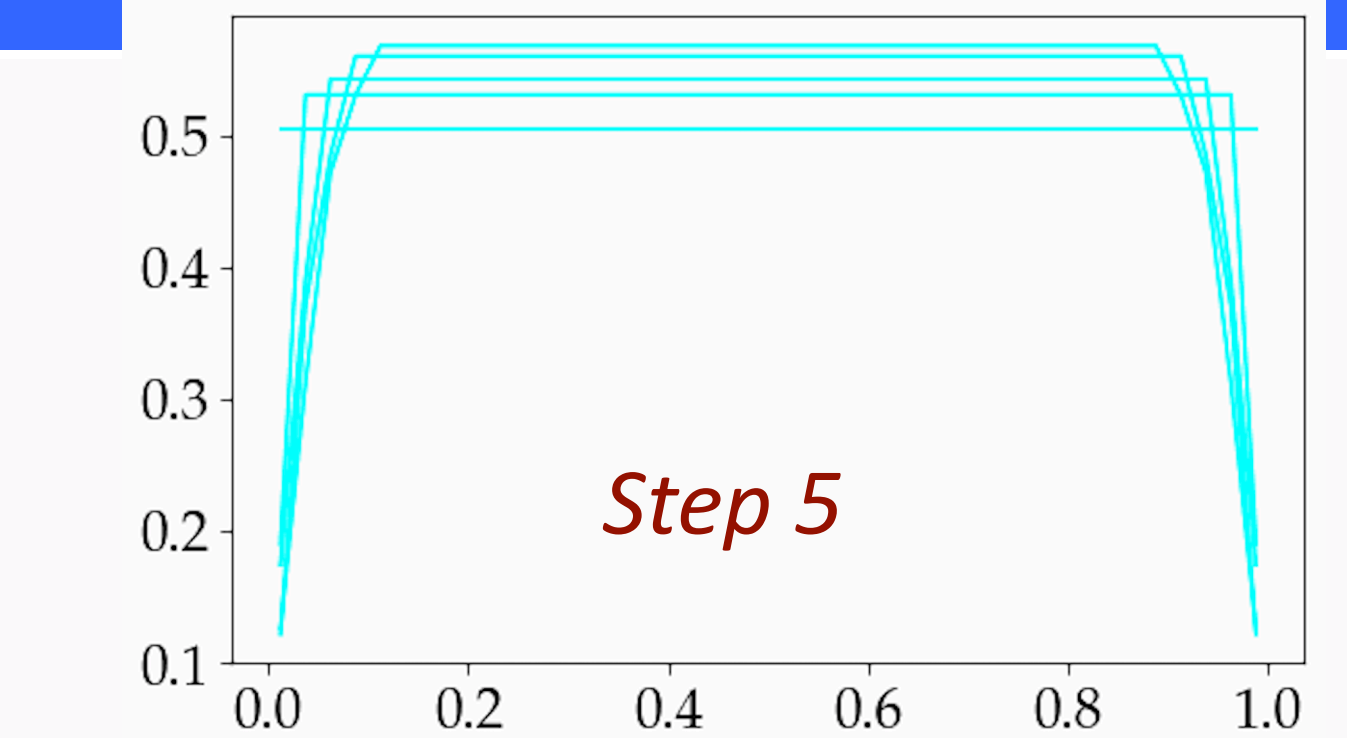
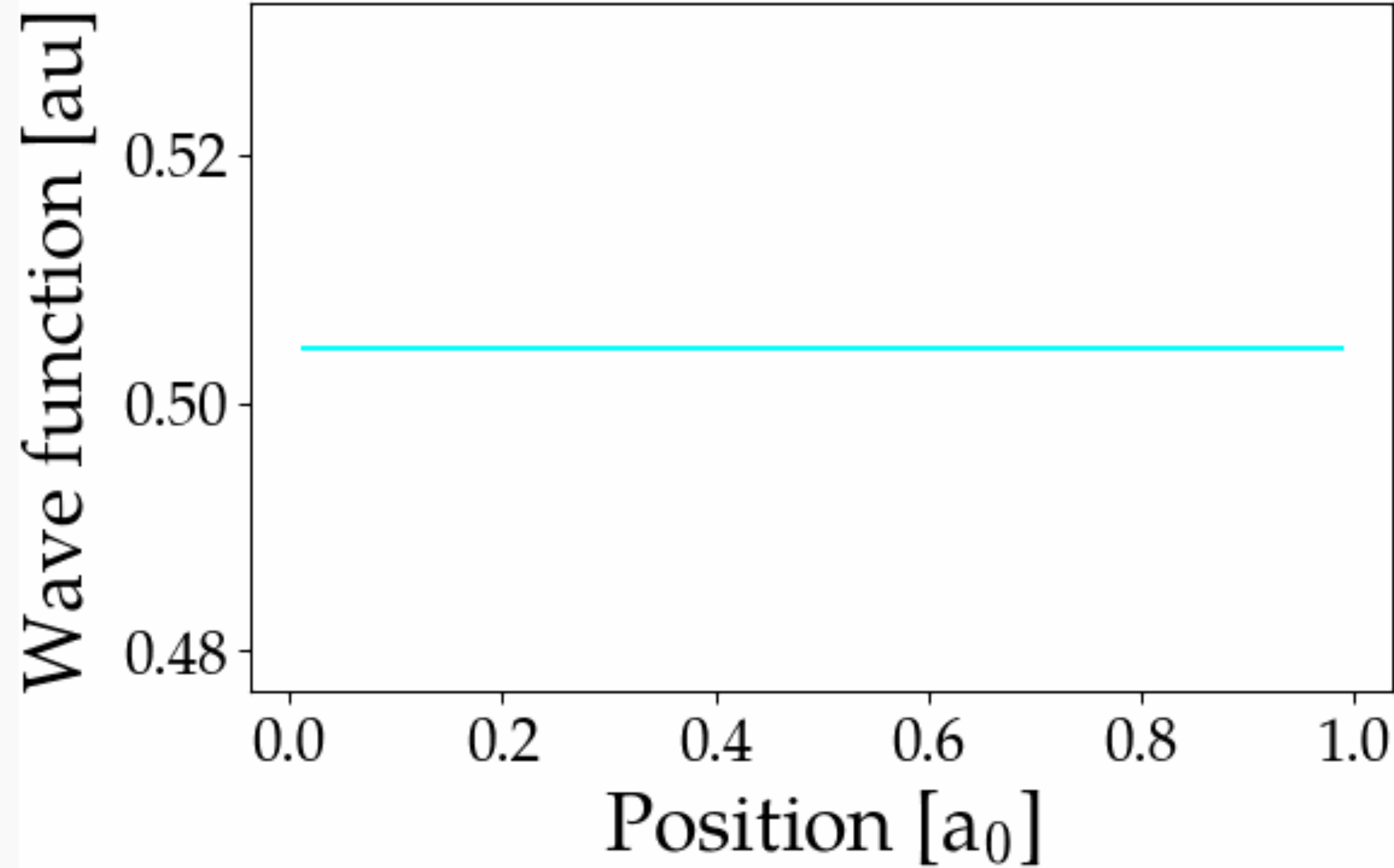
$$\theta^{(t+1)} = \theta^{(t)} - \eta^{(t)} S^{-1} \nabla_\theta \langle \mathcal{H} \rangle_\psi,$$

$$S_{ij} = \langle D_i^* \rangle \langle D_j \rangle - \langle D_i^* D_j \rangle,$$

One fermion — optimization



One fermion — optimization



Two fermions — optimization

Convergence with $N_v=10$

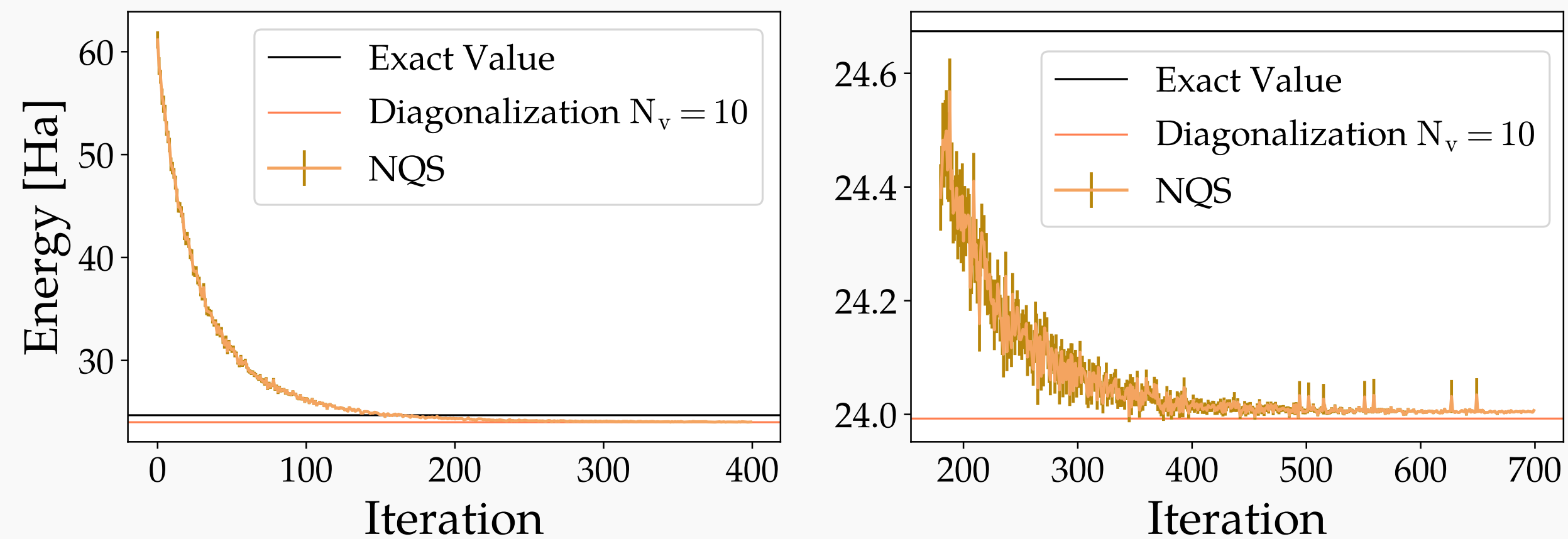


Figure 1: Solution for the two particles non-interacting problem with an RBM built with only 10 hidden nodes. This simulation proves that it is possible to have a satisfying approximation also with relatively few hyper parameters.

Hyperparameter optimization

N_h	$\langle t \rangle$ / iteration	$\Delta E / E$
40	2.75 min	2%
30	1.8 min	2.6%
20	1 min	0.03%
10	16.2 s	0.05%
5	4 s	60%

Table 1: Efficiency and quality of convergence of RBMs with various N_h to model the two non-interacting fermions in a box. N_v is set to 10 for every simulation.

Two fermions — NQS wave function

Neural network ground state

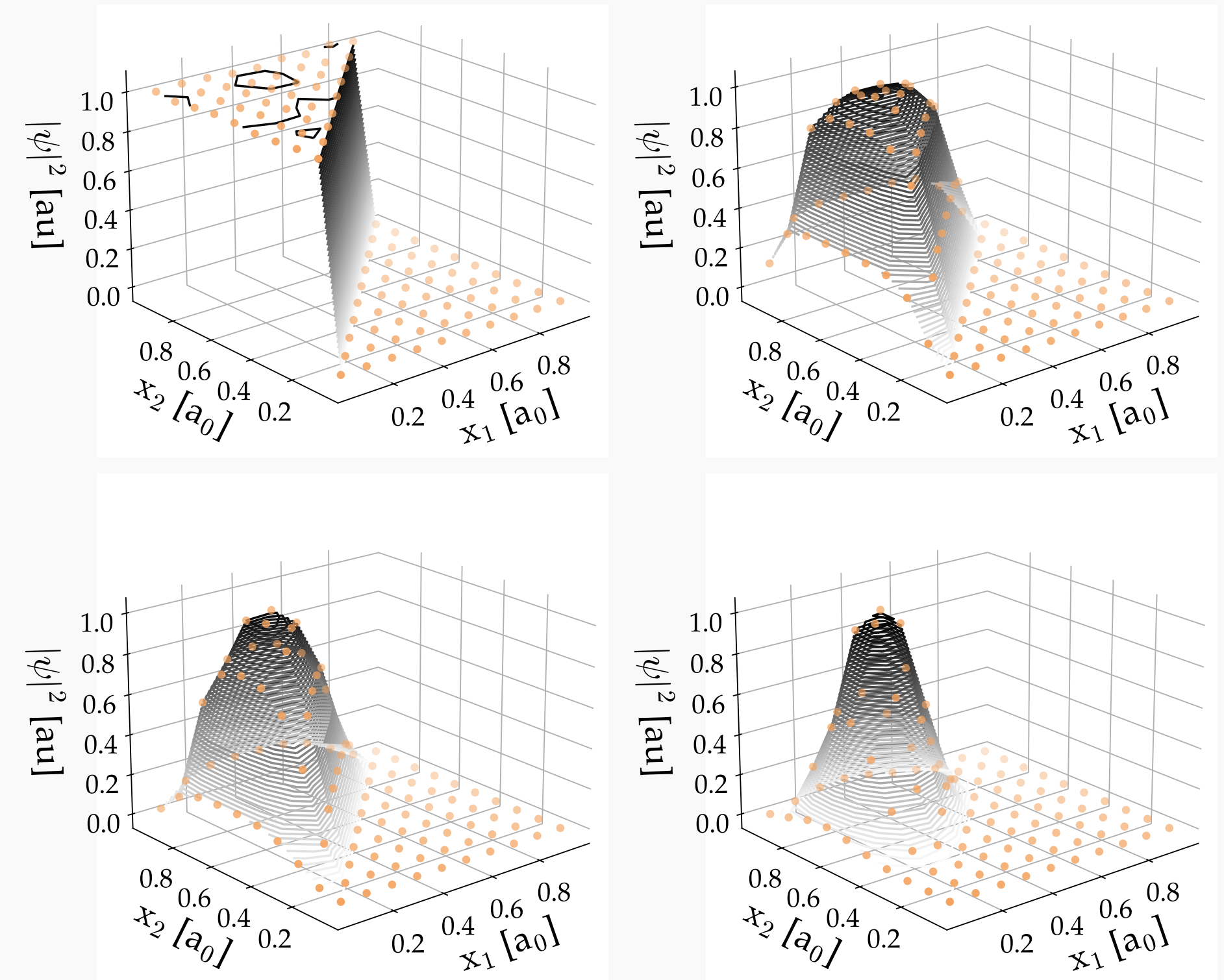
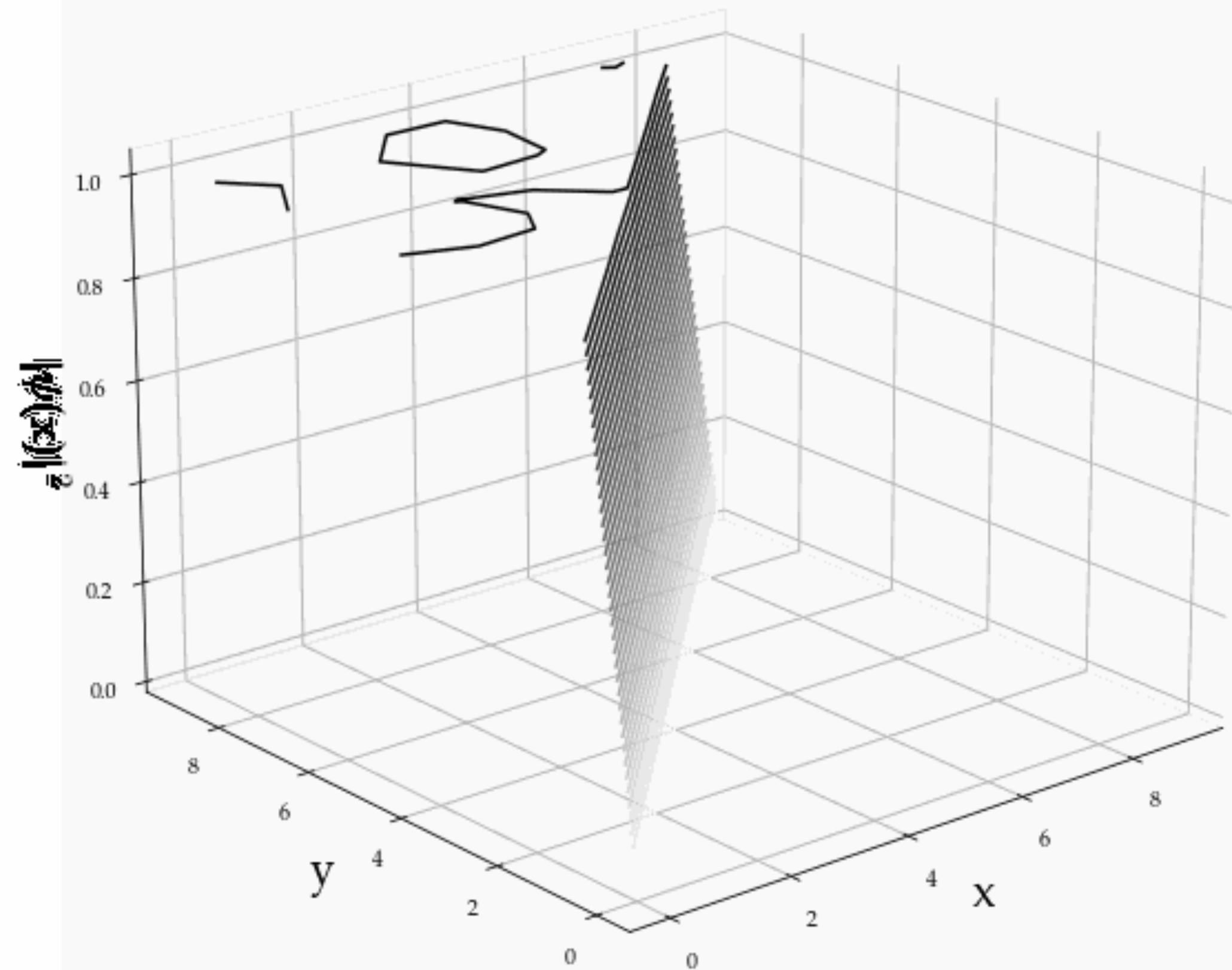


Figure 2: Physical learning process of an RBM with $N_h = 20$ from the starting wave function (upper left). The NN seems to be learning boundaries and antisymmetry in the following iterations (number 15, 30 and 300 are reported).

3D lattice 1 and 2 electrons — finite size (FS) tests

Soft-shoulder interactions (Ryberg atoms):

$$\mathcal{V}(r) = \frac{\mathcal{V}_0}{\left(\frac{r}{R}\right)^6 + 1}$$

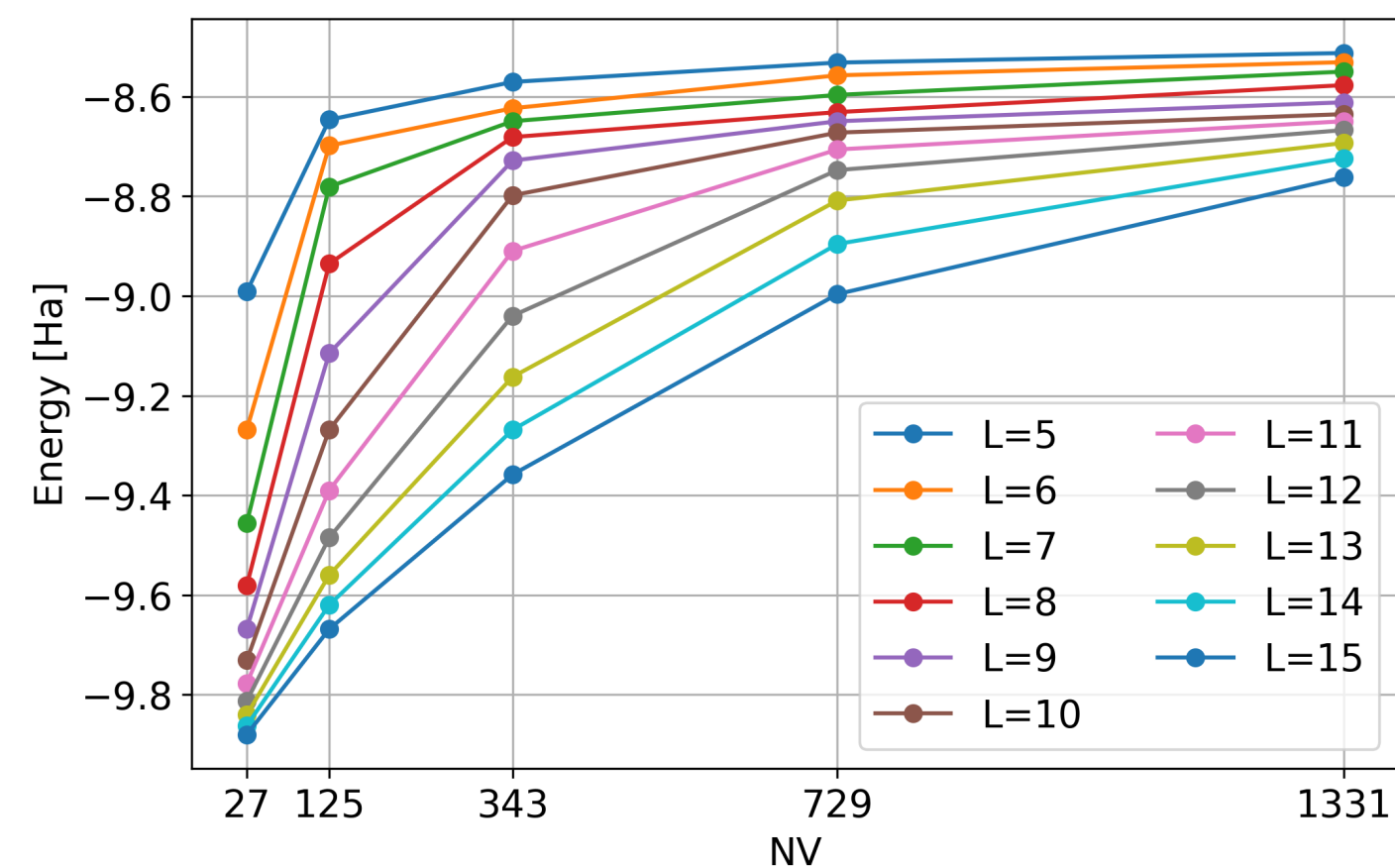


Figure 7.3: Energy as a function of NV, with different trap length values and with $\mathcal{V}_0 = -10$.

Good cusp and 1-body wave function in spite of finite size (FS) effects !!

Hydrogen atom (Coulomb force):

Long range interaction and cusps...

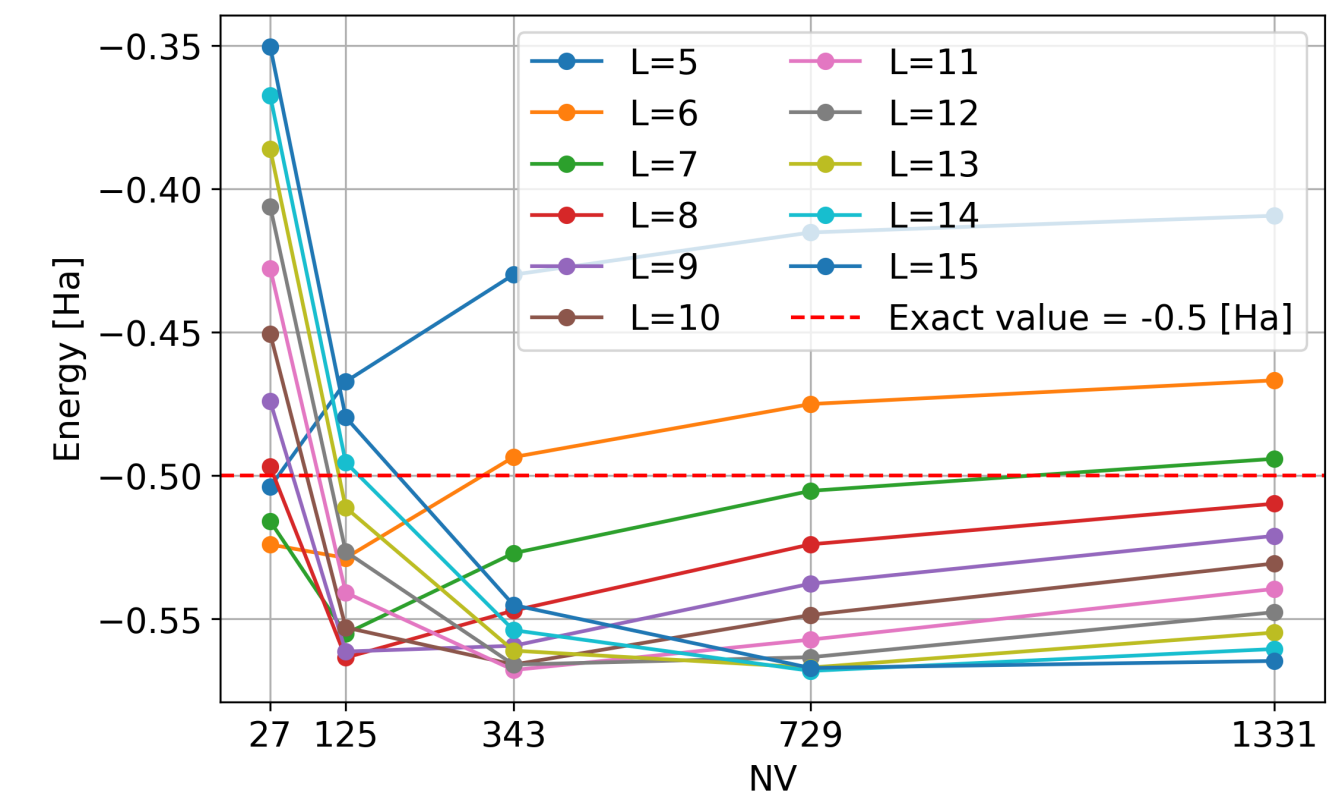
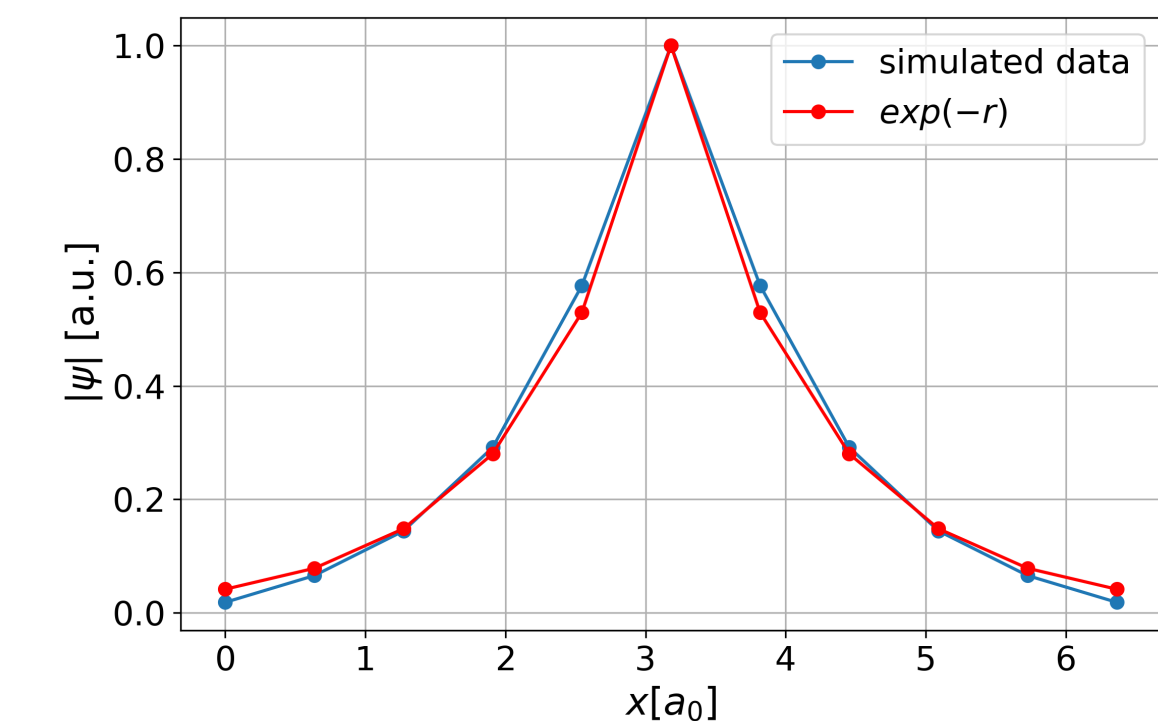
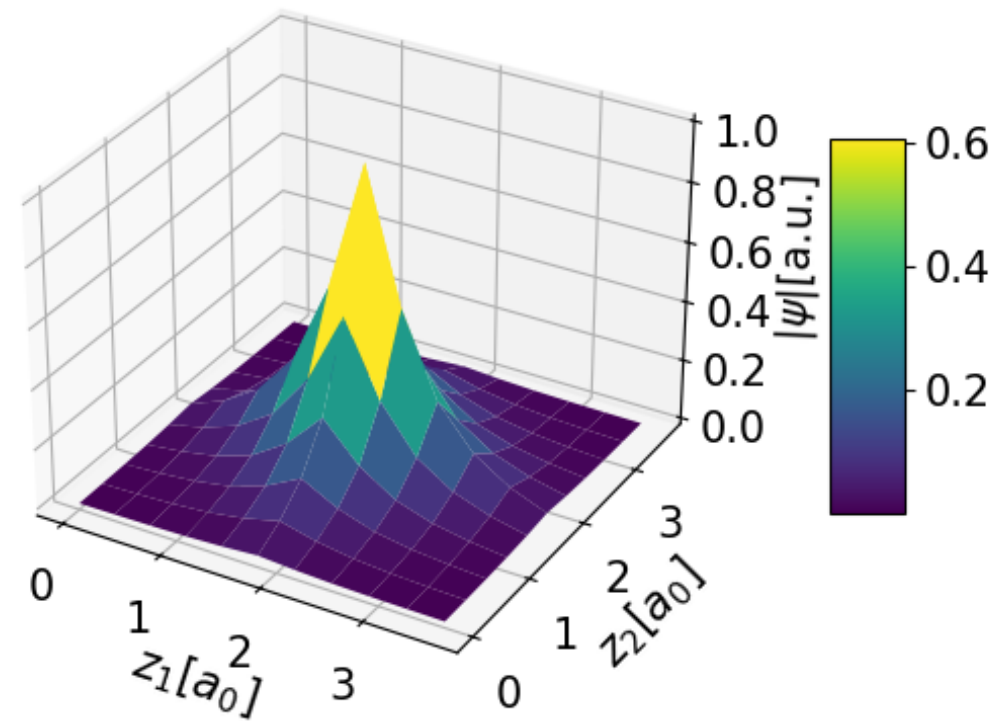


Figure 7.1: Energy as a function of the number of visible nodes for the hydrogen atom, with different trap length values.

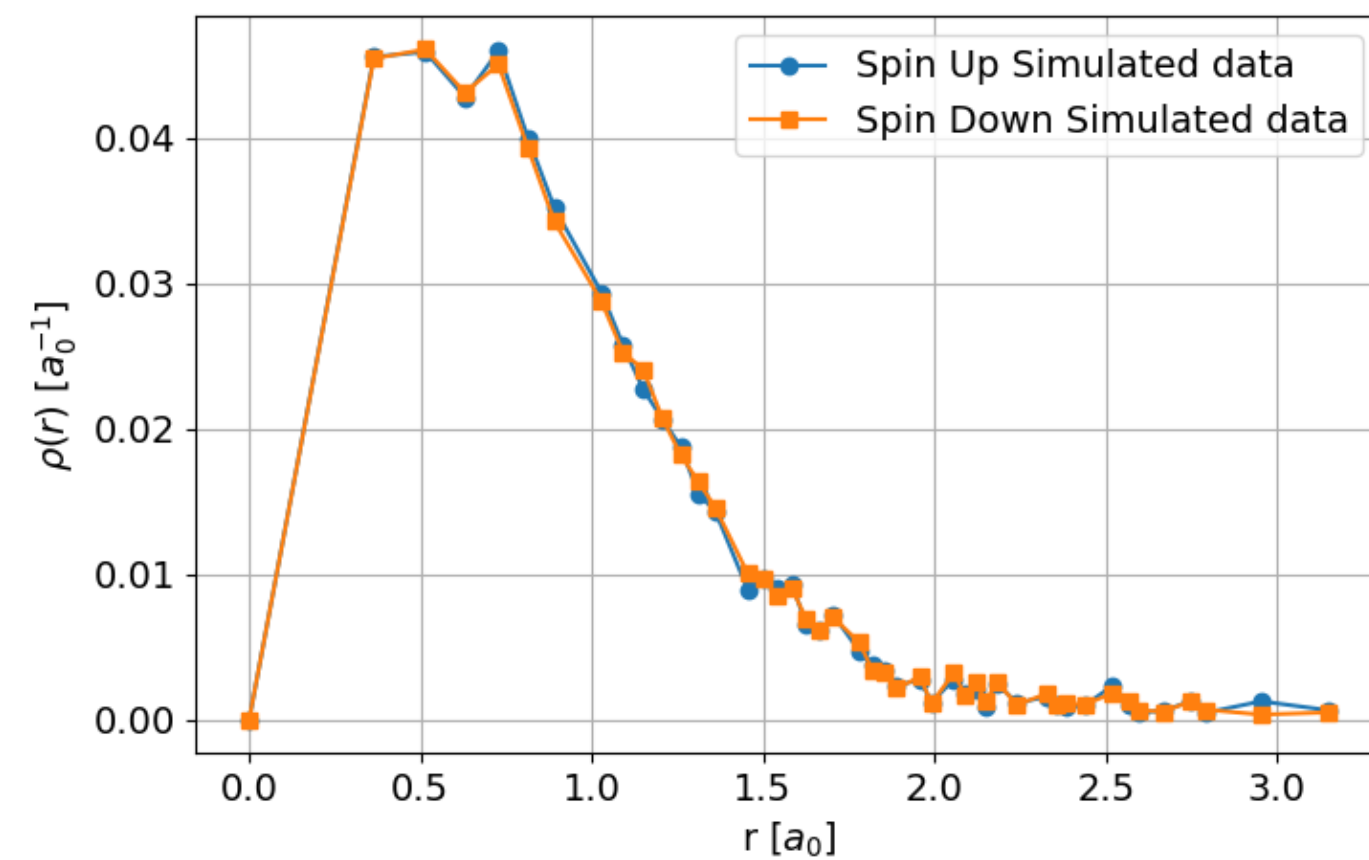


Examples with 2 electrons (Helium atoms)

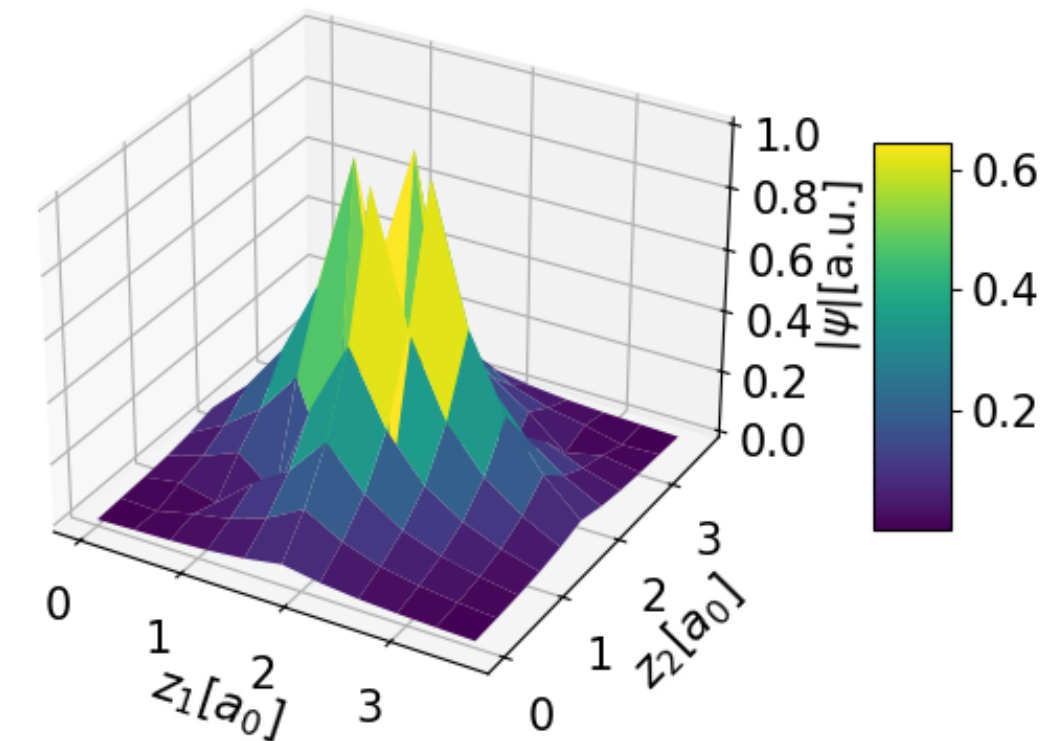
Inverted spins (He g.s.):



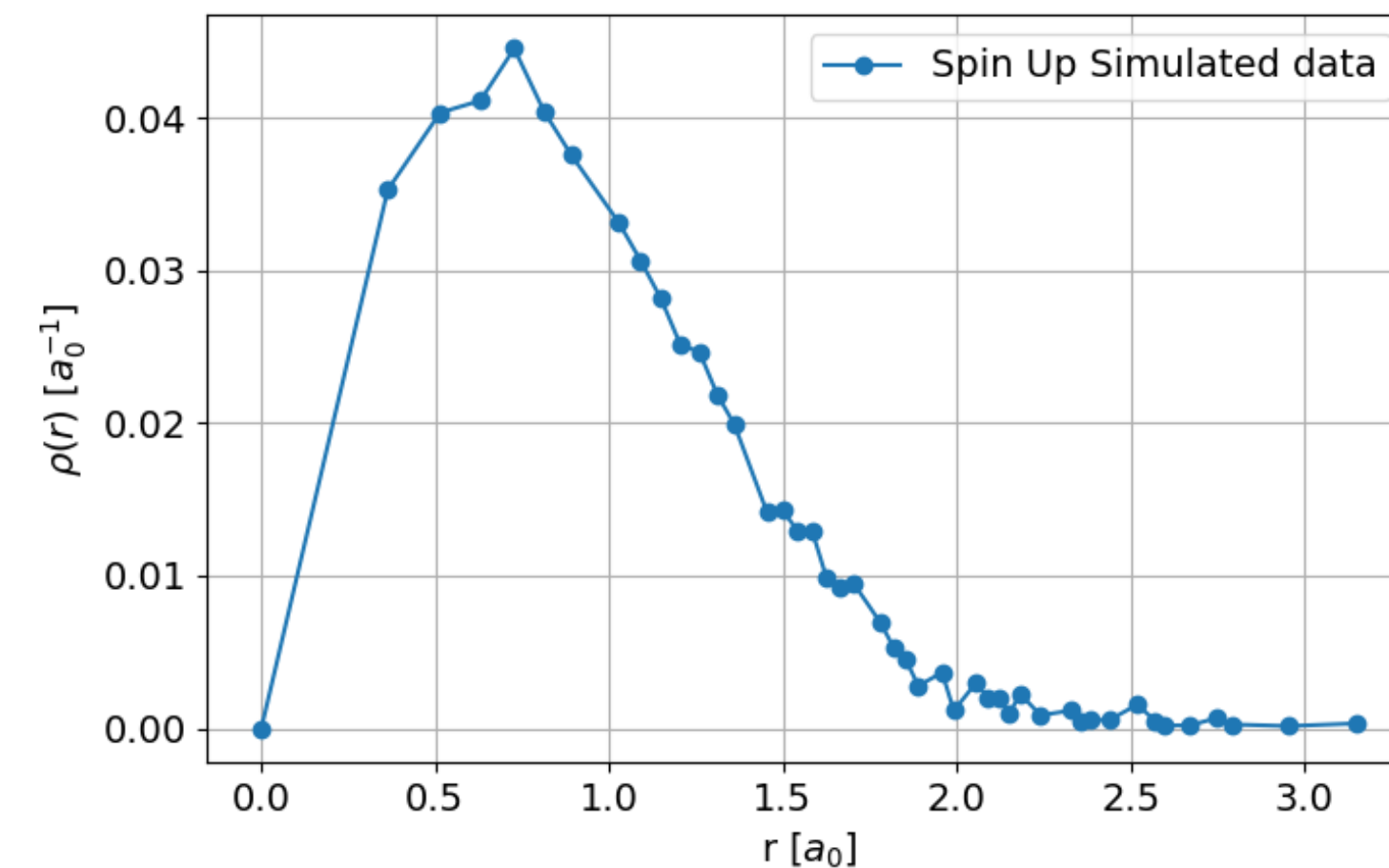
(d) Motion of two electrons along the z -axis with $x_1 = y_1 = x_2 = y_2 = 5$.



Two spins up (He g.s.):



(d) Motion of two electrons along the z -axis with $x_1 = y_1 = x_2 = y_2 = 5$.



Take home messages

- NQS on a lattice are highly challenging. And still at the infancy stage, anyway.
- BUT: they have great potentials (exotic structures, dynamics, etc.)
- Few fermions on small lattices are under reach—proof of principle.
- Transfer learning to heavy systems?? Maybe...
- NQS based VMC only exploits the variational principle (...but see PINN, next talk).

All merits goes to:
L. Lazzarino, G. Paravizzini, E. Redaelli, G. Borroni
(all BSc thesis projects...)

Thank you for your attention!!!

