VARIATIONAL LEARNING QUANTUM WAVE FUNCTIONS



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Intro to AI-driven Science on Supercomputers: A Student Training Series



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ATOMIC NUCLEI



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BROADER IMPACT



Credit: N. Rocco

V. Cirigliano, et al., J.Phys.G 49 (2022) 12, 120502



BROADER IMPACT





"AB-INITIO" NUCLEAR PHYSICS

In the low-energy regime, quark and gluons are confined within hadrons and the relevant degrees of freedoms are protons, neutrons, and pions



Effective field theories are the link between QCD and nuclear observables.

THE QUANTUM MANY-BODY PROBLEM

$$H = \sum_{i} \frac{p_i^2}{2m} + \sum_{i < j} v_{ij} + \sum_{i < j < k} V_{ijk}$$

$$H|\Psi_n\rangle = E_n|\Psi_n\rangle$$



THE QUANTUM MANY-BODY PROBLEM

• Nuclear forces are spin (and isospin) dependent

• Non relativistic many body theory aims at solving the many-body Schrödinger equation

$$H\Psi_n(x_1,\ldots,x_A) = E_n\Psi_n(x_1,\ldots,x_A) \quad \longleftrightarrow \quad x_i \equiv \{\mathbf{r}_i, s_i^z, t_i^z\}$$

• Nucleons are fermions, so the wave function must be anti-symmetric

$$\Psi_n(x_1,\ldots,x_i,\ldots,x_j,x_A) = -\Psi_n(x_1,\ldots,x_j,\ldots,x_i,x_A)$$

GREEN'S FUNCTION MONTE CARLO

The GFMC uses a many-body representation of the spin-isospin degrees of freedom



NEURAL NETWORK QUANTUM STATES



NEURAL SLATER-JASTROW ANSATZ

Product of mean-field state modulated by a flexible correlator factor

$$\Psi_{SJ}(X) = e^{J(X)}\Phi(X)$$

Mean-field: Slater determinant of single-particle orbitals

$$\det \begin{bmatrix} \phi_1(\mathbf{x}_1) & \phi_1(\mathbf{x}_2) & \cdots & \phi_1(\mathbf{x}_N) \\ \phi_2(\mathbf{x}_1) & \phi_2(\mathbf{x}_2) & \cdots & \phi_2(\mathbf{x}_N) \\ \vdots & \vdots & \ddots & \vdots \\ \phi_N(\mathbf{x}_1) & \phi_N(\mathbf{x}_2) & \cdots & \phi_N(\mathbf{x}_N) \end{bmatrix}$$

Each orbital is a FFNN that takes as input

$$\bar{\mathbf{r}}_i = \mathbf{r}_i - \mathbf{R}_{CM}$$



NEURAL SLATER-JASTROW ANSATZ

"Manually" imposing permutation-invariance scales factorially with A

 $J(X) = j(x_1, x_2, x_3) + j(x_1, x_3, x_2) + j(x_2, x_1, x_3) + j(x_2, x_3, x_1) + j(x_3, x_1, x_2) + j(x_3, x_2, x_1)$

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Solution: "deep-sets"
$$\longrightarrow J(X) = \rho_F \left[\sum_i \vec{\phi}_F(\bar{\mathbf{r}}_i, \mathbf{s}_i) \right]$$



Wagstaff et al., arXiv:1901.09006 (2019)

WAVE FUNCTION OPTIMIZATION

ANN trained by performing an imaginary-time evolution in the variational manifold

$$\begin{aligned} |\bar{\Psi}_{V}(\mathbf{p}_{\tau}) &\equiv (1 - H\delta\tau) |\Psi_{V}(\mathbf{p}_{\tau})\rangle \\ \mathbf{p}_{\tau+\delta\tau} &= \operatorname*{arg\,max}_{\mathbf{p}\in R^{d}} \left(\left| \langle \bar{\Psi}_{V}(\mathbf{p}_{\tau}) | \Psi_{V}(\mathbf{p}_{\tau+\delta\tau}) \rangle \right|^{2} \right) & \qquad |\bar{\Psi}_{V}(\mathbf{p}_{\tau})\rangle \\ |\Psi_{V}(\mathbf{p}_{\tau+\delta\tau})\rangle \end{aligned}$$

The parameters are updated as

$$\mathbf{p}_{\tau+\delta\tau} = \mathbf{p}_{\tau} - \delta\tau S^{-1}\mathbf{g}_{\tau}$$

J. Stokes, at al., Quantum 4, 269 (2020).

S. Sorella, Phys. Rev. B 64, 024512 (2001)

STOCHASTIC RECONFIGURATION



COMPARISON WITH GFMC

• The ANN Slater Jastrow ansatz outperforms conventional Jastrow correlations

	Λ	VMC-ANN	VMC-JS	GFMC	GFMC_{c}
² H	$4 {\rm fm}^{-1}$	-2.224(1)	-2.223(1)	-2.224(1)	-
	6 fm^{-1}	-2.224(4)	-2.220(1)	-2.225(1)	-
311	$4 {\rm fm}^{-1}$	-8.26(1)	-7.80(1)	-8.38(2)	-7.82(1)
11	6 fm^{-1}	-8.27(1)	-7.74(1)	-8.38(2)	-7.81(1)
⁴ He	4 fm^{-1}	-23.30(2)	-22.54(1)	-23.62(3)	-22.77(2)
	$6 \ {\rm fm}^{-1}$	-24.47(3)	-23.44(2)	-25.06(3)	-24.10(2)

Differences with the GFMC due to deficiencies in the Slater-Jastrow ansatz

$$\Psi_{SJ}(X) = e^{J(X)}\Phi(X)$$

C. Adams, AL, et al, PRL 127, 022502 (2021)

$$\Phi(X) = \det \begin{bmatrix} \phi_1(x_1) & \phi_1(x_2) & \phi_1(x_3) & \phi_1(x_4) \\ \phi_2(x_1) & \phi_2(x_2) & \phi_2(x_3) & \phi_2(x_4) \\ \phi_3(x_1) & \phi_3(x_2) & \phi_3(x_3) & \phi_3(x_4) \\ \phi_4(x_1) & \phi_4(x_2) & \phi_4(x_3) & \phi_4(x_4) \end{bmatrix}$$

$$\Psi_{\rm HN}(X) = \det \begin{bmatrix} \phi_1(x_1) & \phi_1(x_2) & \phi_1(x_3) & \phi_1(x_4) \\ \phi_2(x_1) & \phi_2(x_2) & \phi_2(x_3) & \phi_2(x_4) \\ \phi_3(x_1) & \phi_3(x_2) & \phi_3(x_3) & \phi_3(x_4) \\ \phi_4(x_1) & \phi_4(x_2) & \phi_4(x_3) & \phi_4(x_4) \\ \chi_1(x_1) & \chi_1(x_2) & \chi_1(x_3) & \chi_1(x_4) \\ \chi_2(x_1) & \chi_2(x_2) & \chi_2(x_3) & \chi_2(x_4) \end{bmatrix} \begin{pmatrix} \phi_1(y_1) & \phi_1(y_2) \\ \phi_2(y_1) & \phi_1(y_2) \\ \phi_3(y_1) & \phi_1(y_2) \\ \phi_4(y_1) & \phi_1(y_2) \\ \chi_1(y_1) & \chi_2(y_2) \\ \chi_2(y_1) & \chi_2(y_2) \end{bmatrix}$$

Visible orbitals on visible coordinates	Visible orbitals on hidden coordinates
Hidden orbitals on visible coordinates	Hidden orbitals on hidden coordinates

J. R. Moreno, et al., PNAS 119, 2122059119(2022)



We extend the reach of neural quantum states to ¹⁶O

In addition to its ground-state energy, we evaluate the point-nucleon density of ¹⁶O with A_h=16



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DILUTE NEUTRON MATTER

 $7.0 \cdot$ NQS AFDMC (unconstrained) AFDMC (constrained) VMC 6.8 -Hartree-Fock . . Energy F 6.56.41000 2000 3000 4000 0 **Optimization Steps**

14 Neutrons @ ρ=0.04 fm-3

■ NQS: 100 hours on NVIDIA-A100

➡ AFDMC: 1.2 million Intel-KNL hours

B. Fore, AL et al., Phys. Rev. Res. 5, 033062 (2023)

CONDENSED-MATTER DETOUR



COLD FERMI GASES

Periodic-NQS to solve the two-components Fermi gas in the BCS- BEC crossover region



COLD FERMI GASES

We introduce a Pfaffian-Jastrow ansatz

$$\Phi_{PJ}(X) = pf \begin{bmatrix} 0 & \phi(x_1, x_2) & \cdots & \phi(x_1, x_N) \\ \phi(x_2, x_1) & 0 & \cdots & \phi(x_2, x_N) \\ \vdots & \vdots & \ddots & \vdots \\ \phi(x_N, x_1) & \phi(x_N, x_2) & \cdots & 0 \end{bmatrix}$$

In order for the above matrix to be skew-symmetric, the neural pairing orbitals are taken to be

$$\phi(x_i, x_j) = \eta(x_i, x_j) - \eta(x_j, x_i)$$

Example: pf
$$\begin{bmatrix} 0 & \phi_{12} & \phi_{13} & \phi_{14} \\ -\phi_{12} & 0 & \phi_{23} & \phi_{24} \\ -\phi_{13} & -\phi_{23} & 0 & \phi_{34} \\ -\phi_{14} & -\phi_{24} & -\phi_{34} & 0 \end{bmatrix} = \phi_{12}\phi_{34} - \phi_{13}\phi_{24} + \phi_{14}\phi_{23}$$

HOMOGENOUS ELECTRON GAS

The nodal structure is improved with neural back-flow transformations $\mathbf{x}_i \longrightarrow \phi(\mathbf{x}_i; \mathbf{x}_{j \neq i})$



COLD FERMI GASES



$$\left(\frac{E}{E_{FG}}\right)_{\rm exp} = \xi = 0.376(5)$$

BACK TO NUCLEAR PHYSICS







Liquid phase



²H clusters

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⁴He clusters



⁸Be clusters

24 Neutrons, 4 Protons @ ρ =0.01 fm⁻³



24 Neutrons, 4 Protons @ ρ =0.01 fm⁻³



OUTLOOK AND PERSPECTIVES

- **Neural network quantum states** can efficiently approximate quantum-many body wave functions across different energy scales
 - Atoms and molecules;
 - Cold atoms;
 - Atomic nuclei and neutron-star matter;

 Perspectives in real-time dynamics, relevant for fission, fusion and neutrino-oscillation experiments

THANK YOU