

Institut de Ciències del Cosmos UNIVERSITAT DE BARCELONA





Ab Initio Nuclear Structure with Machine Learning

Javi Rozalén Sarmiento



[1] H. Hergert, A Guided Tour of ab initio Nuclear Many-Body Theory, 2020



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The Quantum Many-Body Problem: NQS

• **Goal**: Solve for the wave function of an atomic nucleus, ψ



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• How? Rayleigh-Ritz variational principle

$$\frac{\langle \psi_{\theta} | \hat{H} | \psi_{\theta} \rangle}{\langle \psi_{\theta} | \psi_{\theta} \rangle} \ge E_{\text{GS}} \qquad \qquad |\psi_{\theta} \rangle = \int |p\rangle \,\psi_{\theta}(p_1, p_2, \dots, p_N) d^{3N}p$$

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• NQS Ansatz: $\psi_{NQS}(p_1, p_2, ..., p_A; \theta)$



Why Neural Networks?

NNs have "∞ power": a neural network can approximate any continuous function [2], [3].

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^[3] K. Hornik M. Stinchcombe, H. White, *Multilayer feedforward networks are universal approximators,* 1989

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• **Space complexity:** polynomial scaling of memory resources... possibly!



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[3] K. Hornik M. Stinchcombe, H. White, *Multilayer feedforward networks are universal approximators*, 1989

Live Neural-Network Training



J. Keeble & A. Rios, *Machine Learning the Deuteron, 2020*

J. Keeble & A. Rios & J. Rozalén Sarmiento, 2024

Live Neural-Network Training







Particle exchange symmetry

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- Spherical symmetry
 - $\psi(\vec{x}) = \psi(R\vec{x})$
- Time-reversal symmetry

$$\psi(\vec{x},\sigma)=\psi(T(\vec{x},\sigma))$$

Symmetries in Quantum Mechanics

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• Irreducible Representation (irrep) $D(g) = d_1(g) \oplus d_2(g) \oplus \cdots \oplus d_n(g)$ $= \begin{pmatrix} d_1(g) & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & d_n(g) \end{pmatrix}$ $D(r_{\theta}) = \begin{pmatrix} \sin \theta & \cos \theta \\ -\sin \theta & \cos \theta \end{pmatrix} \rightarrow \begin{pmatrix} e^{i\phi} & 0 \\ 0 & e^{-i\phi} \end{pmatrix}$



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Schur's Lemma
$d_1(g)$ irrep, H operator, $d_1(g)H = Hd_1(g)$
$\Rightarrow H = EI, E \text{ number} \qquad H = \begin{pmatrix} E_1 I & \cdots & 0\\ \vdots & \ddots & \vdots\\ 0 & \cdots & E_n I \end{pmatrix}$









^[4] T S Cohen and M Welling, Group Equivariant Convolutional Networks (2016)

^[5] T S Cohen and M Welling, Steerable CNNs (2016)

^[6] R Kondor and S Trivedi, On the Generalization of Equivariance and Convolution in Neural Networks to the Action of Compact Groups (2018)



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Re-thinking previous work...

Fermionic particle exchange, S_N Parity, $\mathbb{Z}/2\mathbb{Z} = \{e, a\}$ Intuition Intuition $\psi_{\text{NOS}}(x) \coloneqq \psi_{\text{NN}}(x) \pm \psi_{\text{NN}}(-x)$ $\psi_{\text{NQS}}(x_1, x_2, x_3) = \begin{vmatrix} \psi_1(x_1) & \psi_2(x_1) & \psi_3(x_1) \\ \psi_1(x_2) & \psi_2(x_2) & \psi_3(x_2) \\ \psi_1(x_3) & \psi_2(x_3) & \psi_3(x_3) \end{vmatrix}$ Group convolution Irreps of $\mathbb{Z}/2\mathbb{Z}$: Group convolution $D^{t}(e) = (1), \quad D^{t}(a) = (1)$ (Trivial rep) $\psi_{\text{NQS}}(x_1, x_2, x_3) = \sum_{\sigma \in S} (-1)^{\pi(\sigma)} \sigma(\psi_1(x_1)\psi_2(x_2)\psi_3(x_3))$ $D^{s}(e) = (1), \quad D^{s}(a) = (-1)$ (Sign rep) $\sigma \rightarrow$ "Alternating representation of S_N " $\begin{cases} \psi_+(x) \coloneqq \psi(x) + \psi(-x) \\ \psi_-(x) \coloneqq \psi(x) - \psi(-x) \end{cases}$

Toy exemple: $G = S_N$



Conclusions and future outlook

• What about continuous groups (SU(2))?

• What is the computational cost?

• Compute whole nuclear spectrum "at once"





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Thank you

