Convergence to the fixed-node limit in deep variational Monte Carlo

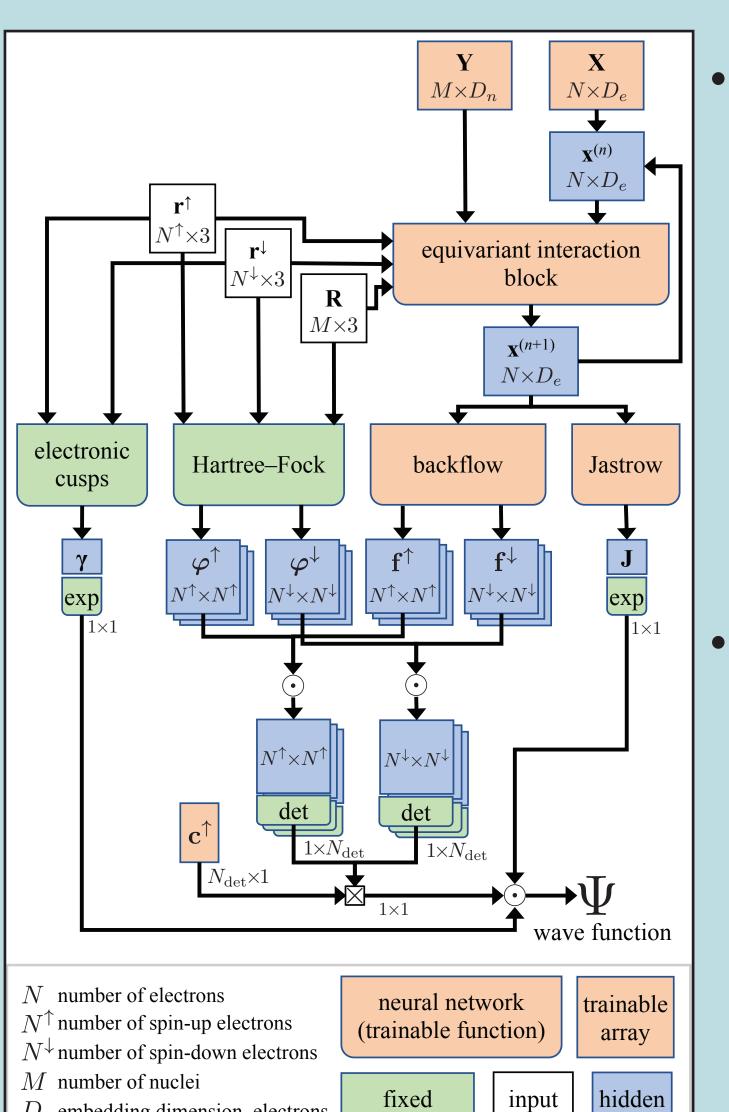
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PauliNet trial wavefunction ansatz [1]

highly expressive Slater-Jastrow-backflow type trial wavefunction

$$\psi_{\boldsymbol{\theta}}(\mathbf{r}) = e^{\gamma(\mathbf{r}) + J_{\boldsymbol{\theta}}(\mathbf{r})} \sum_{p} c_{p} \det[\tilde{\varphi}_{\boldsymbol{\theta}, \mu_{p}i}^{\uparrow}(\mathbf{r})] \det[\tilde{\varphi}_{\boldsymbol{\theta}, \mu_{p}i}^{\downarrow}(\mathbf{r})]$$
$$\tilde{\varphi}_{\boldsymbol{\theta}, \mu_{i}}(\mathbf{r}) = \varphi_{\mu}(\mathbf{r}_{i}) f_{\boldsymbol{\theta}, \mu_{i}}^{\otimes}(\mathbf{r}) + f_{\boldsymbol{\theta}, \mu_{i}}^{\oplus}(\mathbf{r})$$



• utilize expressiveness of DNNs permutation-invariant Jastrow factor

$$J_{\boldsymbol{\theta}}(\mathbf{r}) := \eta_{\boldsymbol{\theta}} \left(\sum_{i} \mathbf{x}_{i}^{(L)}(\mathbf{r}) \right)$$

permutation-equivariant backflow

$$\mathbf{f}_{oldsymbol{ heta},i}(\mathbf{r}) := \kappa_{oldsymbol{ heta}} ig(\mathbf{x}_i^{(L)}(\mathbf{r})ig)$$

 $\eta_{m{\theta}}, \kappa_{m{\theta}}$ – fully-connected DNNs

 $\mathbf{x}_i(\mathbf{r})$ – latent-space many-body representation

• implement physical knowledge

Slater determinants

satisfy antisymmetry constraint of fermionic wavefunctions

cusp conditions

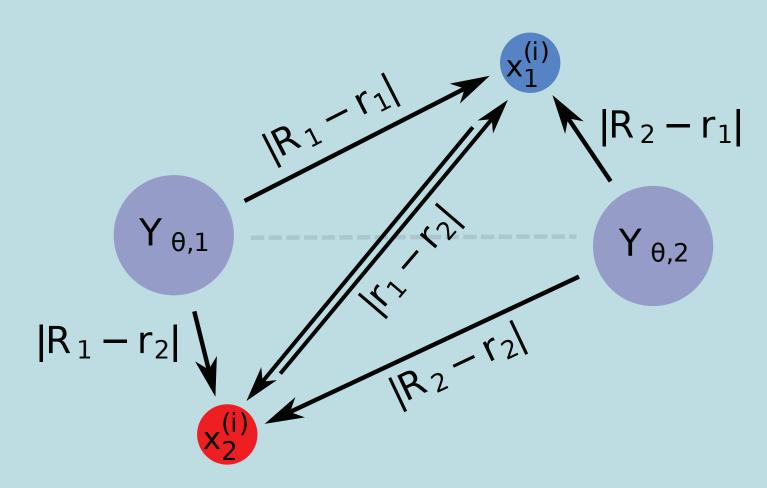
invoke analytically known asymptotics for short distances

quantum chemistry baseline

initialisation from Hartree Fock (HF) or MCSCF calculation

Graph-convolutional neural network [2]

 generating a permutation-equivariant latent-space many-body representation for the electrons



$$egin{aligned} \mathbf{x}_i^{(0)} &:= \mathbf{X}_{oldsymbol{ heta}, s_i} \ \mathbf{x}_i^{(n+1)} &:= \mathbf{x}_i^{(n)} + oldsymbol{\chi}_{oldsymbol{ heta}}^{(n)} ig(\{ \mathbf{x}_j^{(n)}, \{ | \mathbf{r}_j - \mathbf{r}_i | \} \} ig) \ &+ oldsymbol{\chi}_{oldsymbol{ heta}}^{\prime(n)} ig(\{ \mathbf{Y}_{oldsymbol{ heta}, j}, \{ | \mathbf{R}_j - \mathbf{r}_i | \} \} ig) \end{aligned}$$

 $\mathbf{X}_{oldsymbol{ heta},\pm},\mathbf{Y}_{oldsymbol{ heta},I}$ – electronic / nuclear embeddings continuous-filter convolution

Training procedure - VMC optimization

sample probability density associated with wavefunction

minimize energy on minibatches of electron configurations

$$\mathcal{L}(\boldsymbol{\theta}) = \mathbb{E}_{\mathbf{r} \sim \psi_{\boldsymbol{\theta}'}^2} \left[\frac{H \psi_{\boldsymbol{\theta}}(\mathbf{r})}{\psi_{\boldsymbol{\theta}}(\mathbf{r})} \right]$$

[1] J. Hermann, Z. Schätzle, and F. Noé, Deep-neural-network solution of the electronic Schrödinger equation, Nature Chemistry 12, 891 (2020)

[2] K. T. Schütt, et al, SchNet – A deep learning architecture for molecules and materials J. Chem. Phys.148, 241722 (2018)

Quantum chemistry background

The electronic structure problem

 D_e embedding dimension, electrons

Solve the Schrödinger equation for the electronic degrees of freedom

array

$$H\psi_n(\mathbf{r}) = E_n\psi_n(\mathbf{r}) \quad \psi_n \in \mathcal{H}^-$$

for the clamped-nucleus Coulomb Hamitlonian

$$H = \sum_{i=0}^{N} \Delta_i - \sum_{i=0}^{N} \sum_{j=0}^{M} \frac{1}{|\mathbf{r}_i - \mathbf{R}_j|} + \sum_{i=0}^{N} \sum_{j=0}^{i} \frac{1}{|\mathbf{r}_i - \mathbf{r}_j|}$$

The fermionic antisymmetry constraint

- Electronic wavefunctions must be antisymmetric under the exchange of two same-spin electrons

$$\psi(\ldots,\mathbf{r}_i,\ldots,\mathbf{r}_j,\ldots)=-\psi(\ldots,\mathbf{r}_j,\ldots,\mathbf{r}_i,\ldots)$$

entailing a nodal surface across which the wavefunction changes sign.

The variational approach of quantum mechanics

Apply the variational principle

$$E_0 = \min_{\psi} \langle \psi | H | \psi \rangle \leq \min_{\boldsymbol{\theta}} \langle \psi_{\boldsymbol{\theta}} | H | \psi_{\boldsymbol{\theta}} \rangle \quad \psi_{\boldsymbol{\theta}} \in \mathcal{H}^-$$

choose trial wavefunction and solve the optimization problem

$$\boldsymbol{\theta}^* = \underset{\boldsymbol{\theta}}{\operatorname{argmin}} \langle \psi_{\boldsymbol{\theta}} | H | \psi_{\boldsymbol{\theta}} \rangle$$

Variational quantum Monte Carlo (VMC)

Approximate the expectation value via Monte Carlo integration

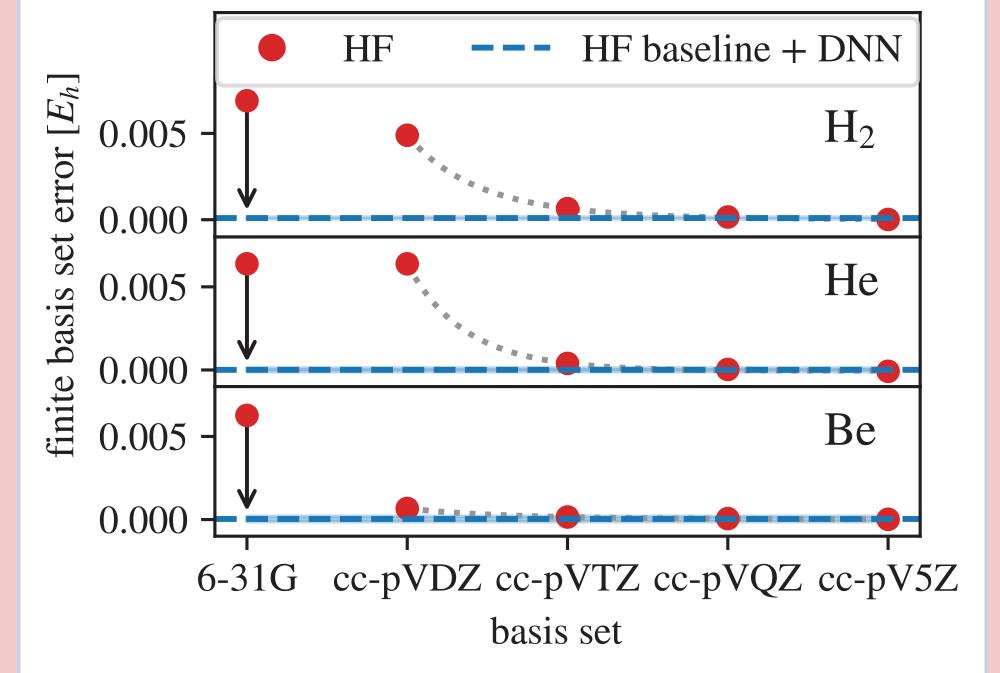
$$\langle \psi_{\boldsymbol{\theta}} | H | \psi_{\boldsymbol{\theta}} \rangle = \int \psi_{\boldsymbol{\theta}}(\mathbf{r}) H \psi_{\boldsymbol{\theta}}(\mathbf{r}) d\mathbf{r}$$

$$= \int \psi_{\boldsymbol{\theta}}(\mathbf{r})^2 \frac{1}{\psi_{\boldsymbol{\theta}}(\mathbf{r})} H \psi_{\boldsymbol{\theta}}(\mathbf{r}) d\mathbf{r} \approx \sum_{\mathbf{r} \sim \psi_{\boldsymbol{\theta}}^2} \frac{H \psi_{\boldsymbol{\theta}}(\mathbf{r})}{\psi_{\boldsymbol{\theta}}(\mathbf{r})}$$

Results – restricted variants of PauliNet for differnt levels of theroy

Deep orbital correction := single-particle version of PauliNet backflow correction Deep Jastrow := PauliNet without backflow correction

Deep orbital correction – postion-space correction of Hartree Fock (HF) orbitals

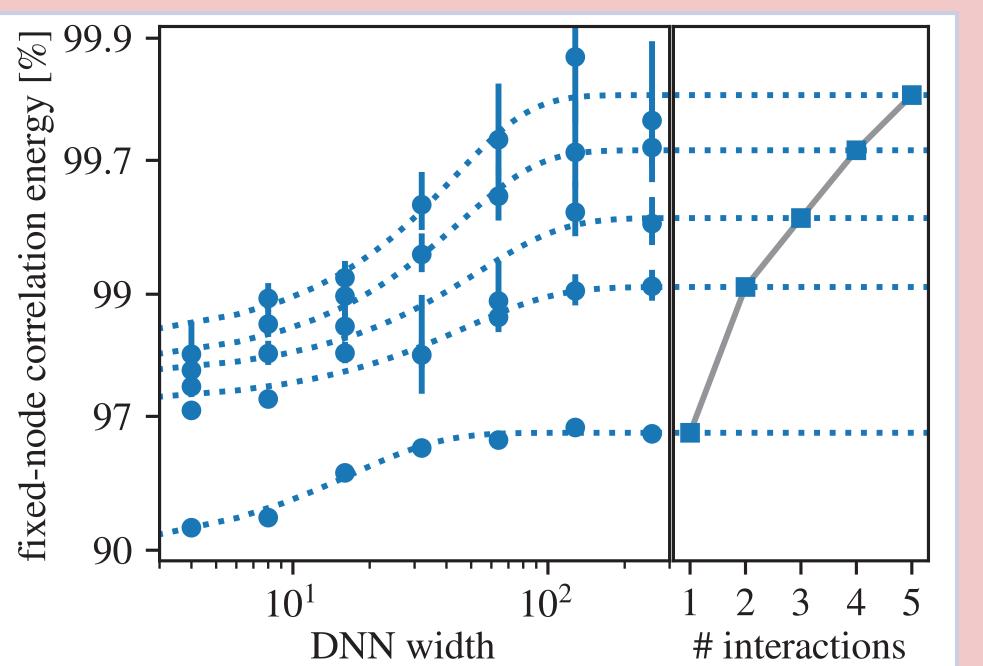


deep orbital correction reducing the finite-basis-set error of an imprecise HF baseline for H₂, He, and Be below 0.1 mH

"finite-basis-set error"

Error arising due to the projection on a finite single particle basis set.

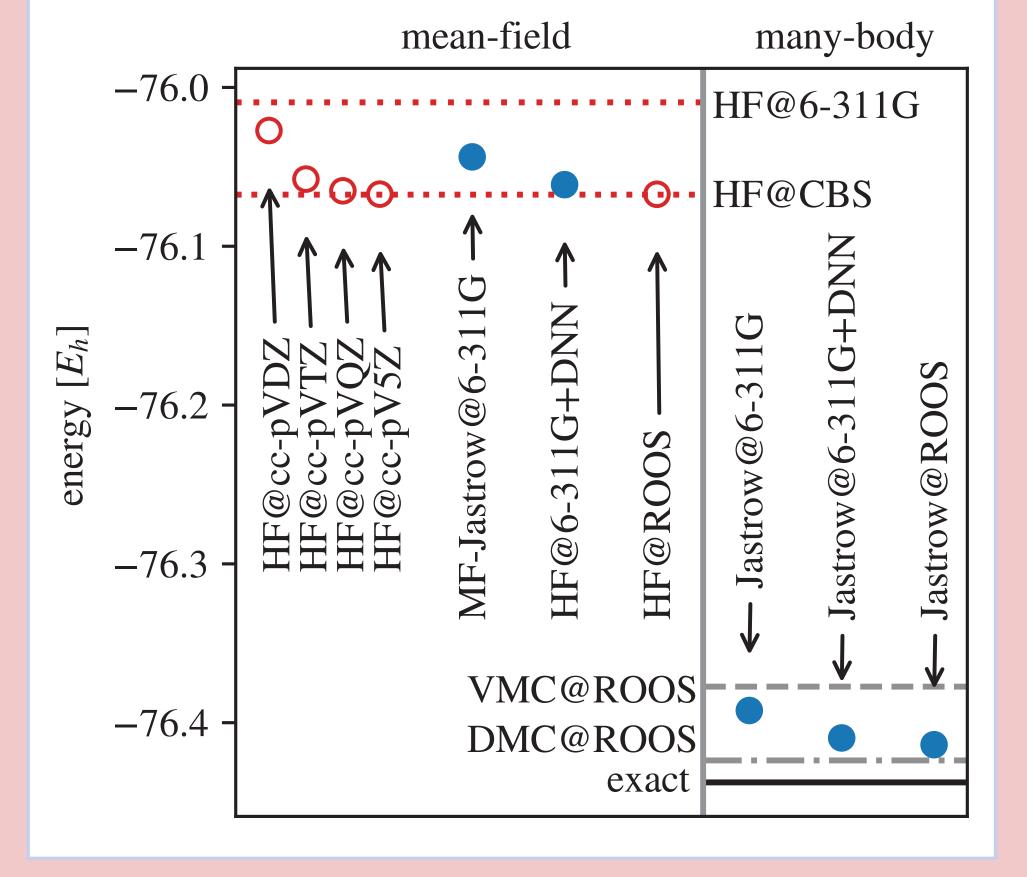
Deep Jastrow – systematic approach to the fixed-node limit



hyperparameter scan for LiH, showing a convergence to the fixed-node limit with increasing network size

"fixed-node correlation energy" Energy difference between mean-field energy and exact energy up to the error due to fixing the nodal surface of the trial wavefunction.

Deep Jastrow & orbital correction – application to the water molecule



fixed-node correlation energy for deep Jastrow factor with HF determinant

- in ROOS basis: 97.2(1)%
- with otbial correction: 96.0(2)%

surpassing the accuracy of reference single determinant VMC calculations from even a minimal baseline