## Representation of symmetric and anti－symmetric functions

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## Totally anti-symmetric functions

For a permutation $\sigma \in \Im_{N}$ (symmetric group on $n$ symbols):

$$
\Psi\left(x_{\sigma(1)}, x_{\sigma(2)}, \ldots, x_{\sigma(N)}\right)=(-1)^{\sigma} \Psi\left(x_{1}, x_{2}, \ldots, x_{N}\right)
$$

$\Psi \in \Lambda^{N} L^{2}\left(\mathbb{R}^{d}\right)$ (totally) anti-symmetric, in short:

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Why? Identical particles in quantum mechanics

- Bosonic particles: symmetric (also has applications besides quantum);
- Fermionic particles: antisymmetric (Pauli's exclusion principle)


## Variational principle for ground state

Given Hamiltonian operator $H$

$$
E_{0}=\inf _{\Psi \in \Lambda^{N} L^{2}\left(\mathbb{R}^{d}\right)} \frac{\langle\Psi| H|\Psi\rangle}{\langle\Psi \mid \Psi\rangle}
$$

For practical calculations, require to choose an ansatz for antisymmetric functions.

## Slater determinants (aka Quantum Chemistry 101)

Let $\left\{\varphi_{i}, i=1,2, \ldots, N\right\} \subset L^{2}\left(\mathbb{R}^{d}\right)$ be a set of orthonormal functions

$$
\Psi_{\mathrm{SD}}\left[\left\{\varphi_{i}\right\}\right](\boldsymbol{x})=\operatorname{det}\left[\begin{array}{cccc}
\varphi_{1}\left(x_{1}\right) & \varphi_{2}\left(x_{1}\right) & \cdots & \varphi_{N}\left(x_{1}\right) \\
\varphi_{1}\left(x_{2}\right) & \varphi_{2}\left(x_{2}\right) & \cdots & \varphi_{N}\left(x_{2}\right) \\
\vdots & \vdots & \ddots & \vdots \\
\varphi_{1}\left(x_{N}\right) & \varphi_{2}\left(x_{N}\right) & \cdots & \varphi_{N}\left(x_{N}\right)
\end{array}\right]
$$

This leads to the Hartree-Fock method, a cornerstone of quantum chemistry.

## Going beyond Hartree-Fock

However, for most systems, the ansatz of Slater determinant is too restrictive and leads to huge error (correlation energy).

Many generalizations have been proposed over the years

- Configuration interaction;
- (unitary) Coupled cluster;
- Multi-configurational self-consistent field;
- Slater-Jastrow wavefunctions;

Remark. An entirely different approach to address anti-symmetry is via second quantization.

## Backflow transformation ansatz

Proposed originally by [Feynman-Cohen, Phys Rev 1956] for liquid Helium.
Building blocks: $\varphi \in L^{2}\left(\mathbb{R}^{d} \times \mathbb{R}^{d(N-1)}\right)$ s.t.

$$
\varphi(x ; \boldsymbol{y})=\varphi(x ; \sigma \boldsymbol{y}), \quad \forall \sigma \in \mathbb{S}_{N-1}
$$

Backflow determinants:

$$
\Psi_{\mathrm{BF}}\left[\left\{\varphi_{i}\right\}\right](\boldsymbol{x})=\operatorname{det}\left[\begin{array}{cccc}
\varphi_{1}\left(x_{1} ; \overline{\boldsymbol{x}}_{-1}\right) & \varphi_{2}\left(x_{1} ; \overline{\boldsymbol{x}}_{-1}\right) & \cdots & \varphi_{N}\left(x_{1} ; \overline{\boldsymbol{x}}_{-1}\right) \\
\varphi_{1}\left(x_{2} ; \overline{\boldsymbol{x}}_{-2}\right) & \varphi_{2}\left(x_{2} ; \overline{\boldsymbol{x}}_{-2}\right) & \cdots & \varphi_{N}\left(x_{2} ; \overline{\boldsymbol{x}}_{-2}\right) \\
\vdots & \vdots & \ddots & \vdots \\
\varphi_{1}\left(x_{N} ; \overline{\boldsymbol{x}}_{-N}\right) & \varphi_{2}\left(x_{N} ; \overline{\boldsymbol{x}}_{-N}\right) & \cdots & \varphi_{N}\left(x_{N} ; \overline{\boldsymbol{x}}_{-N}\right)
\end{array}\right]
$$

with the shorthand $\overline{\boldsymbol{x}}_{-i}:=\left(x_{1}, \ldots, x_{i-1}, x_{i+1}, \ldots, x_{N}\right)$

Journal of Computational Physics

# Solving many-electron Schrödinger equation using deep neural networks 



# FermiNet: Quantum Physics and Chemistry from First Principles 

## Deep-neural-network solution of the electronic Schrödinger equation

Jan Hermann $\boxtimes$, Zeno Schätzle \& Frank Noé $\boxtimes$

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## No-go result for backflow ansatz?

## Theorem (Huang-Landsberg-L.)

For each fixed $N$, for all total degree $D$ sufficiently large, the algebraic ansatz map $\Psi_{B F}$ is not surjective.

$$
\operatorname{dim}(\text { target }) \approx N^{d N-d} \operatorname{dim}(\text { source }),
$$

i.e., in general, one needs a linear combination of roughly $N^{d N-d}$ backflow determinants to represent a general antisymmetric polynomial function.

## Symmetric functions

Deep Sets [Zaheer et al, NeurlPS 2017], an ansatz for (totally) symmetric function

$$
\Psi(\sigma \boldsymbol{x})=\Psi(\boldsymbol{x}), \quad \forall \sigma \in \mathbb{S}_{N}
$$

Choose a set of symmetric polynomials $\eta_{1}, \ldots, \eta_{m}$ and write

$$
f(\boldsymbol{x})=g\left(\eta_{1}(\boldsymbol{x}), \eta_{2}(\boldsymbol{x}), \ldots, \eta_{m}(\boldsymbol{x})\right)
$$

for a general function $g$.

## Deep Sets

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## Theorem (Chen-Chen-L.)

Given $d \geq 1, N \geq 1$, and a compact subset $\Omega \subset \mathbb{R}^{d}$. Let $\eta_{1}, \ldots, \eta_{m}$ generate $\mathcal{P}_{\text {sym }}^{d, N}(\mathbb{R})$ as $\mathbb{R}$-algebra.
For any $f: \Omega^{N} \rightarrow \mathbb{R}$ totally symmetric and continuous, there exists a unique continuous function $g: \boldsymbol{\eta}\left(\Omega^{N}\right) \rightarrow \mathbb{R}$ such that

$$
f(\boldsymbol{x})=g(\boldsymbol{\eta}(\boldsymbol{x}))
$$

where $\boldsymbol{\eta}=\left(\eta_{1}, \eta_{2}, \ldots, \eta_{m}\right)$.
The generation condition can be relaxed [Wang et al, ICLR 2024].
Orbit distinguishing property: Given $\boldsymbol{x}, \boldsymbol{x}^{\prime}$, if $\eta_{k}(\boldsymbol{x})=\eta_{k}\left(\boldsymbol{x}^{\prime}\right)$ for all $k=1, \ldots, m$, then $\exists \sigma \in \Im_{N}$, s.t., $\sigma \boldsymbol{x}=\boldsymbol{x}^{\prime}$.


Figure: Commutative diagram for the proof of Theorem.

## Symmetry to antisymmetry

Perhaps we can "borrow" results from symmetric case?
An old attempt:

$$
\Psi(\boldsymbol{x})=\Psi_{0}(\boldsymbol{x}) \Phi_{\text {sym }}(\boldsymbol{x})
$$

for a specific anti-symmetric function $\Psi_{0}$.

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Works well for $d=1$ [Cauchy, J. Ecole Polytech. 1815] by choosing

$$
\Psi_{0}(\boldsymbol{x})=\operatorname{det}\left[\begin{array}{ccccc}
1 & x_{1} & x_{1}^{2} & \cdots & x_{1}^{N-1} \\
1 & x_{2} & x_{2}^{2} & \cdots & x_{2}^{N-1} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & x_{N} & x_{N}^{2} & \cdots & x_{N}^{N-1}
\end{array}\right]=\sum_{i<j}\left(x_{j}-x_{i}\right)
$$

Vandemonde determinant (aka Slater det. w/ $\varphi_{k}(x)=x^{k-1}$ ) However does not work in higher dimension (known in the physics / chemistry literature as the nodal surface difficulty)

## From symmetry to antisymmetry

A new attempt to change the ansatz, inspired by Deep Sets:

$$
\Psi(\boldsymbol{x})=g\left(\eta_{1}(\boldsymbol{x}), \eta_{2}(\boldsymbol{x}), \ldots, \eta_{m}(\boldsymbol{x})\right)
$$

where $\left(\eta_{1}, \ldots, \eta_{m}\right)$ sastify

- $\eta_{k}$ is anti-symmetric and continuous;
- $\eta_{k}(\boldsymbol{x})=0$ if and only if $x_{i}=x_{j}$ for some $i \neq j$;
- orbit distinguishing for $\mathfrak{S}_{N}$.

Take-home summary of ansatz:
Linear combination of dets $\rightarrow$ general odd function $g$ of dets

## Theorem (Chen-L.)

Given $d \geq 1, N \geq 1$, and a compact subset $\Omega \subset \mathbb{R}^{d}$, let $\left(\eta_{1}, \ldots, \eta_{m}\right): \Omega^{N} \rightarrow \mathbb{R}^{m}$ satisfy the assumption. For any $f: \Omega^{N} \rightarrow \mathbb{R}$ totally antisymmetric and continuous, there exits a unique continuous and odd function $g: \boldsymbol{\eta}\left(\Omega^{N}\right) \rightarrow \mathbb{R}$ such that

$$
f(\boldsymbol{x})=g(\boldsymbol{\eta}(\boldsymbol{x}))
$$

where $\boldsymbol{\eta}=\left(\eta_{1}, \eta_{2}, \ldots, \eta_{m}\right)$.

Question: How large $m$ needs to be?

Explicit construction for $\boldsymbol{\eta}$ (and an upper bound for $m$ ):
Key idea: Projecting points to $1 D$.

- Set $m=\frac{N(N-1)}{2} \cdot(d-1)+1$;
- Choose random vectors $\left\{w_{i}\right\}, i=1, \cdots, m \subset \mathbb{S}^{d-1}$;
- Take $\eta_{k}$ to be a Vandermonde determinant

$$
\eta_{k}(\boldsymbol{x})=\operatorname{det}\left[\begin{array}{ccccc}
1 & w_{k}^{\top} x_{1} & \left(w_{k}^{\top} x_{1}\right)^{2} & \cdots & \left(w_{k}^{\top} x_{1}\right)^{N-1} \\
1 & w_{k}^{\top} x_{2} & \left(w_{k}^{\top} x_{2}\right)^{2} & \cdots & \left(w_{k}^{\top} x_{2}\right)^{N-1} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
1 & w_{k}^{\top} x_{N} & \left(w_{k}^{\top} x_{N}\right)^{2} & \cdots & \left(w_{k}^{\top} x_{N}\right)^{N-1}
\end{array}\right]=\sum_{i<j} w_{k}^{\top}\left(x_{j}-x_{i}\right)
$$

$\left(\eta_{1}, \ldots, \eta_{m}\right)$ satisfy the assumption with high probability (suffices to make sure that the $1 D$ projections can distinguish points).

## Conclusion

$$
\Psi(\boldsymbol{x})=g\left(\eta_{1}(\boldsymbol{x}), \ldots, \eta_{m}(\boldsymbol{x})\right)
$$

- Ansatz for symmetric and antisymmetric functions;
- Exact representation for continuous functions;
- Efficiency: $m$ depends mildly on $d$ and $N$;

Some interesting directions:

- Regularity / singularity for wave-functions (in terms of $g$ and $\boldsymbol{\eta}$ );
- Training schemes for variational Monte Carlo;
- Applications to quantum systems.


## Thank you for your attention

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Reference:

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