



A Self-Attention Ansatz for *Ab-initio* Quantum Chemistry

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Quantum Chemistry

The behaviour of molecules and materials at the quantum scale is governed by how electrons and nuclei interact.

The (time-independent) **Schrödinger equation** describes this interaction:

$$\hat{H}\Psi = E\Psi \quad \hat{H} = -\frac{1}{2}\nabla^2 + \sum_{i>j} \frac{1}{r_{ij}} - \sum_{iI} \frac{Z_I}{r_{iI}} + \sum_{I>J} \frac{Z_I Z_J}{r_{IJ}}$$

\hat{H} **Hamiltonian** – kinetic energy of electrons, potential due to electrons and nuclei

Ψ **wavefunction** – function all of electron positions, Ψ^2 is joint probability

E **energy** – energy of the molecule

Problem Many-electron Schrödinger equation is NP hard [1]

Goal find accurate approximate solutions

Idea Use a neural network as a function approximator for the wavefunction [2]

This work explores attention-based network architecture for quantum wavefunctions we call the **Psiformer**: the **most accurate** ansatz for large molecular systems.

Optimization

Variational Monte Carlo (VMC) training loop [3]:

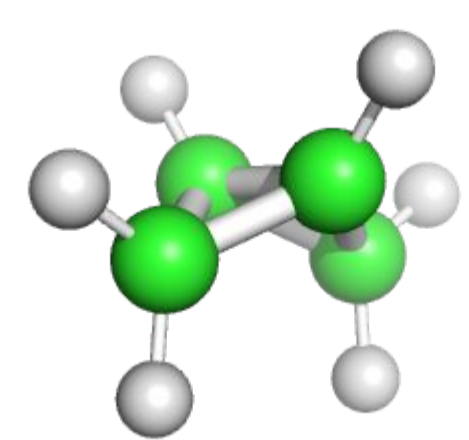
$$E = \frac{\langle \Psi \hat{H} \Psi \rangle}{\langle \Psi^2 \rangle} = \mathbb{E}_{\mathbf{r} \sim \Psi^2} [\Psi^{-1}(\mathbf{r}) \hat{H} \Psi(\mathbf{r})] = \mathbb{E}_{\mathbf{r} \sim \Psi^2} [E_L(\mathbf{r})]$$

Monte Carlo estimate of energy

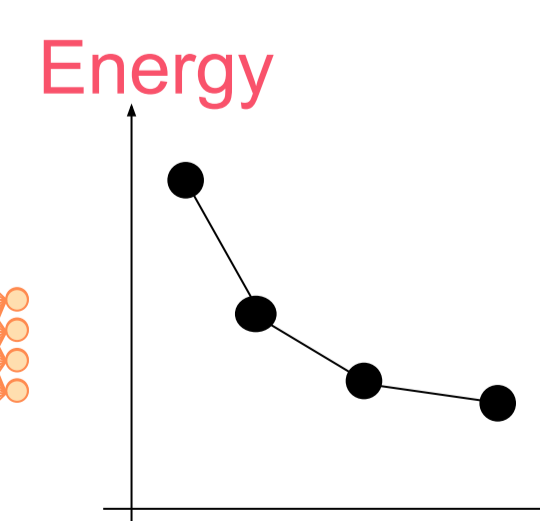
$$\nabla E = \mathbb{E}_{\mathbf{r} \sim \Psi^2} [(E_L(\mathbf{r}) - \langle E_L \rangle) \nabla \Psi(\mathbf{r})]$$

Unbiased estimate of energy gradients

Evaluate energy for a molecule



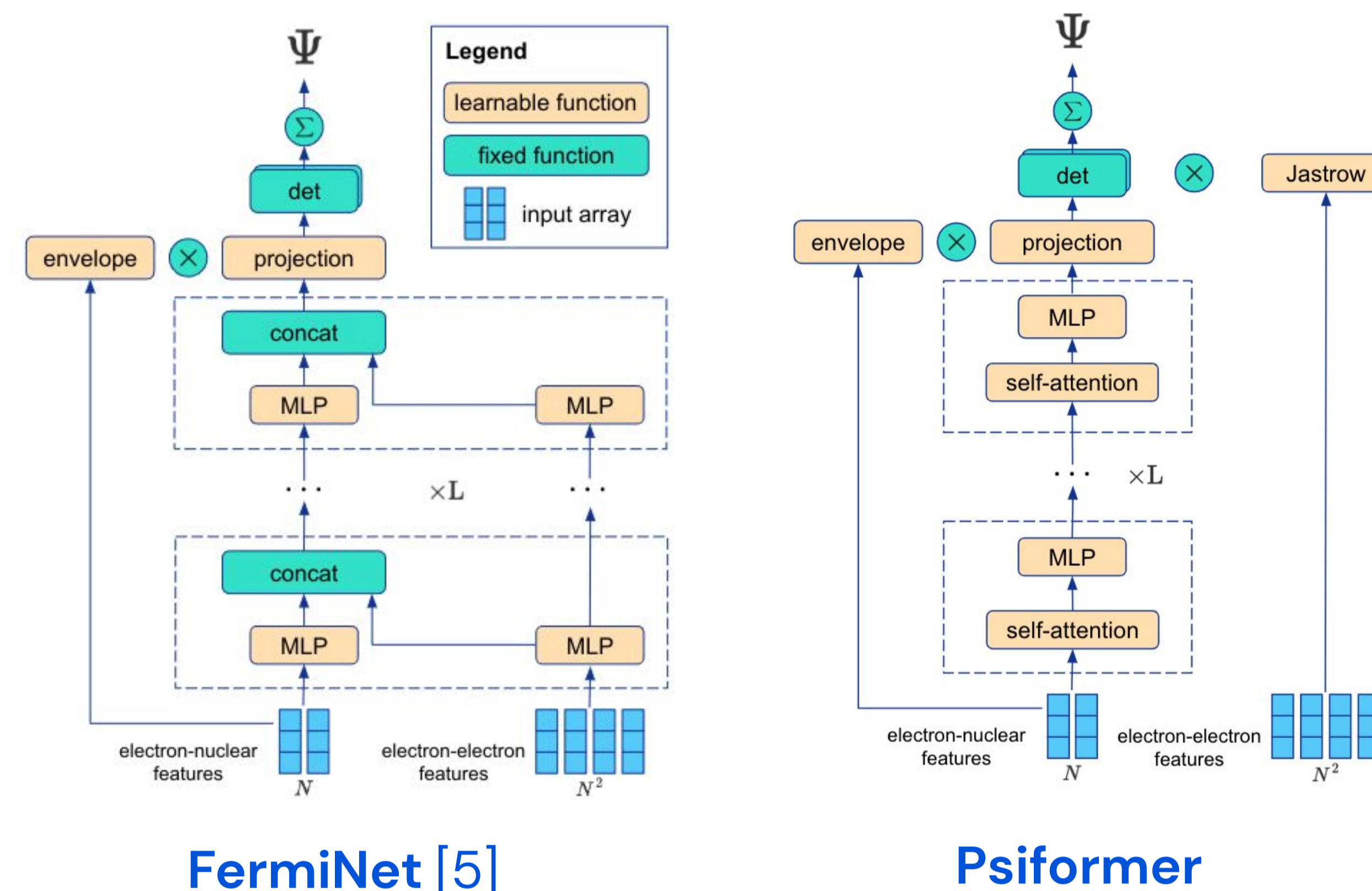
Variational: Minimize upper bound on the energy. Lower is strictly better. We use K-FAC as the optimizer [4].



Sample points $\mathbf{r} \sim |\Psi^2|$
 Data is **self-generative**

Compute gradients.
 Optimize parameters to minimize the energy

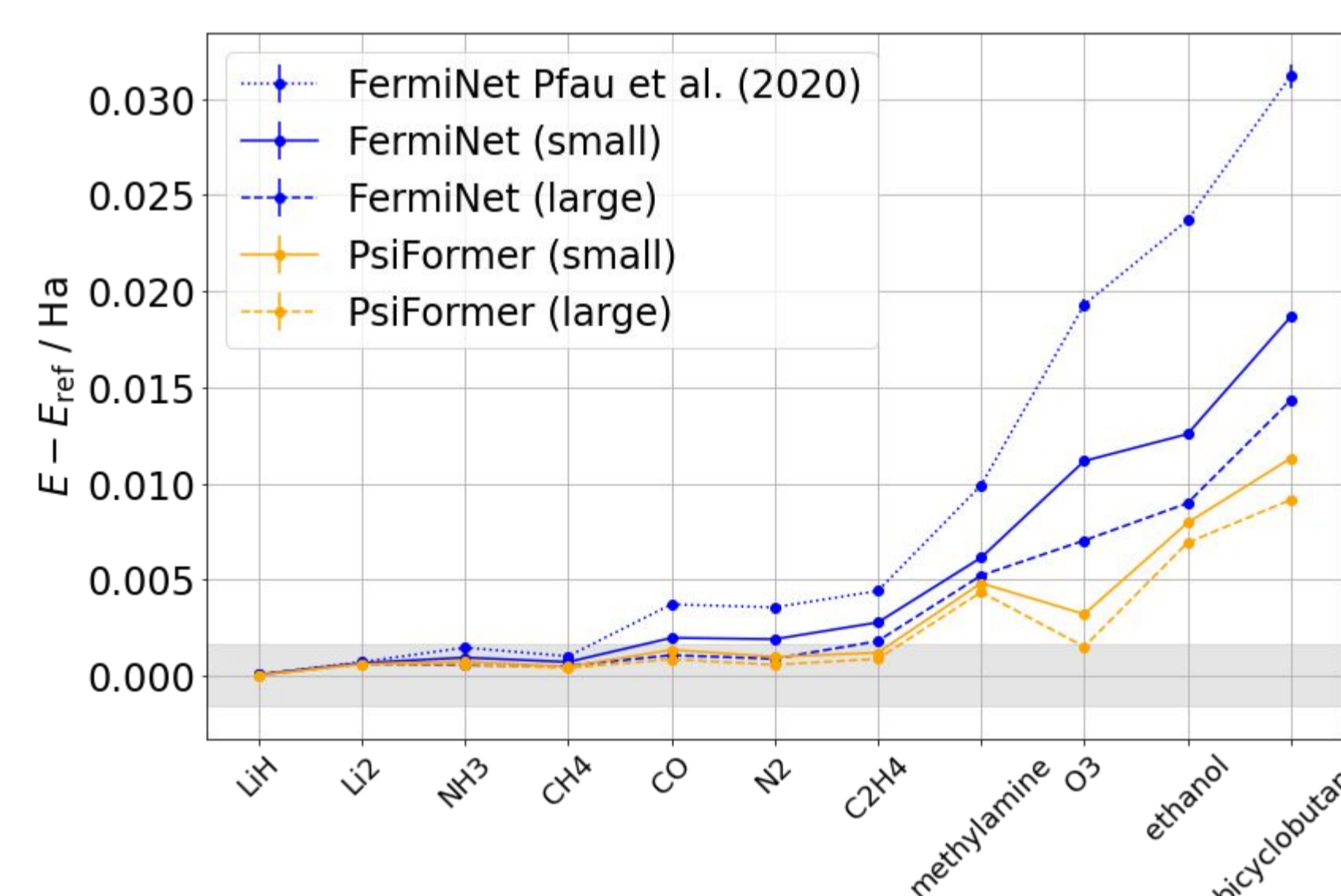
Architectures



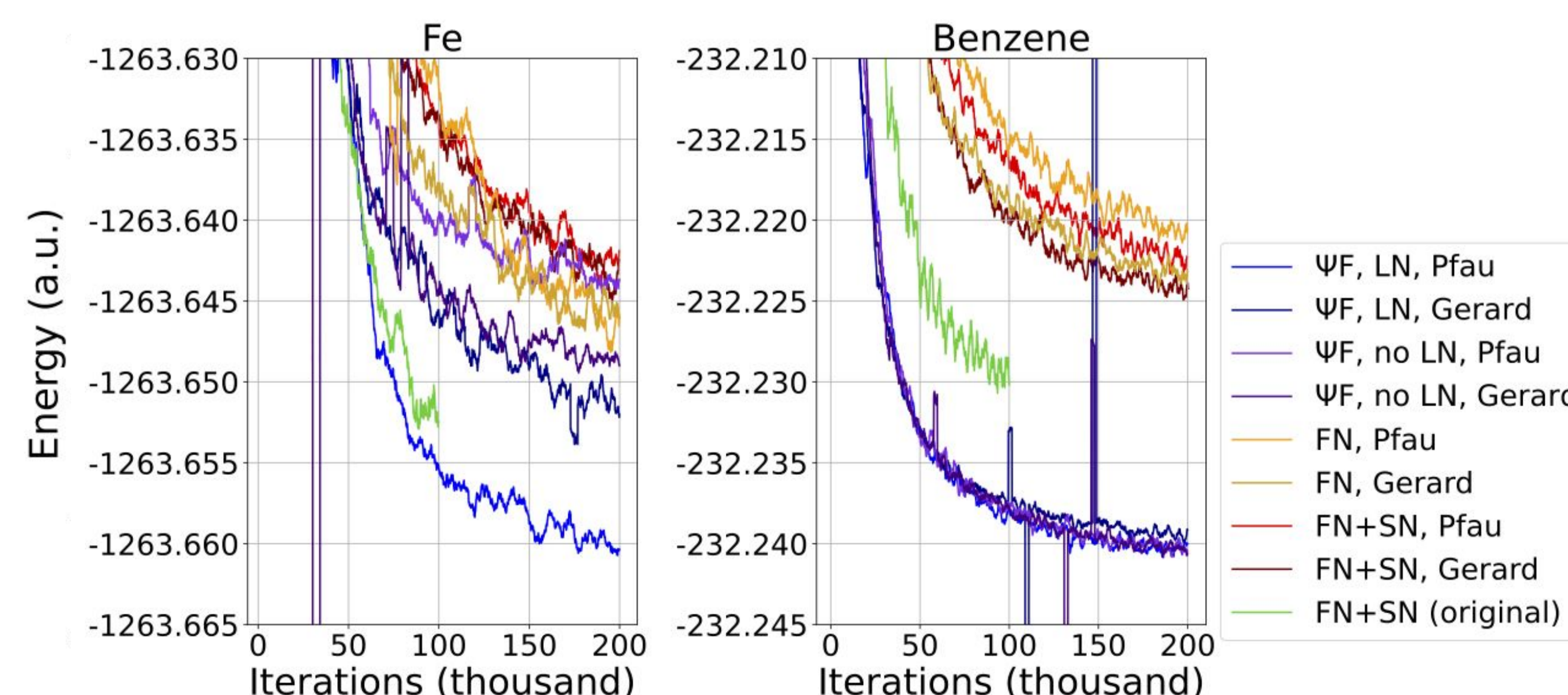
FermiNet [5]

Psiformer

Psiformer vs FermiNet



Lower energy on small benchmark molecules.



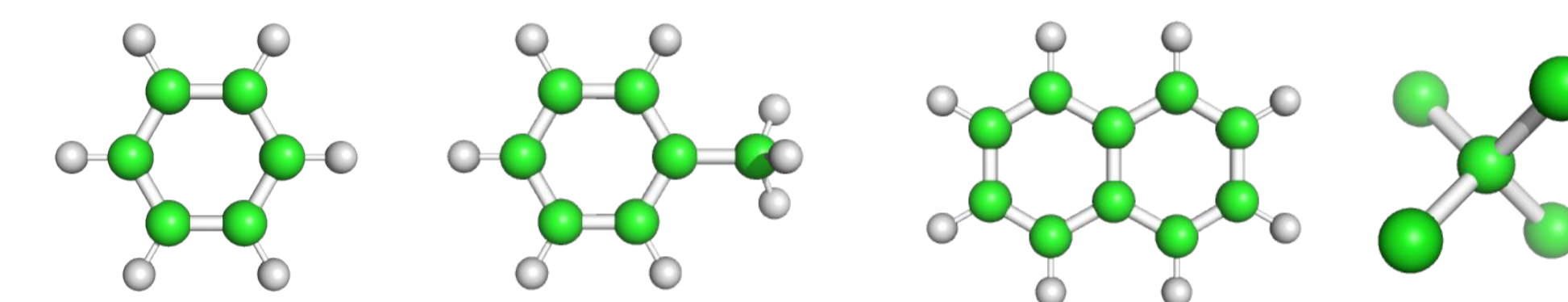
Psiformer performance gap grows for larger systems, even compared to newer FermiNet extensions [6]

The Pauli exclusion principle requires that the network is antisymmetric with respect of the electrons

This is achieved using a permutation-equivariant network, with a final determinant.

Code available at
<https://github.com/deepmind/ferminet>

Large molecules



System	FermiNet	No LayerNorm	LayerNorm
Benzene	-232.2205(2)	-232.2400(1)	-232.2393(1)
Toluene	-271.5274(2)	-271.5494(1)	-271.5538(1)
Naphthalene	-385.8147(4)	-385.8679(2)	-385.8685(2)
CCl ₄	-1878.684(1)	-1878.734(1)	-1878.804(1)

Ground-state energy of large molecules (lower is better). The Psiformer also outperforms external SotA results.

System	FermiNet	Psiformer	
		No LayerNorm	LayerNorm
Equilibrium	-464.3770(5)	-464.4624(2)	-464.4667(2)
Dissociated	-464.3724(6)	-464.4674(2)	-464.4660(2)
ΔE_{mono}	-0.0640(6)	-0.0176(2)	-0.0119(2)
$\Delta E_{10\text{\AA}}$	0.0046(8)	-0.0050(3)	0.0007(3)

DMC-level accuracy on the benzene dimer.

Future Work and References

Architecture exploration: how to beat the $O(n^2)$ scaling of self-attention and $O(n^3)$ scaling of determinants without sacrificing accuracy?

Materials: how to handle finite size effects?

- [1] M. Troyer and U.-J. Wiese, *Phys. Rev. Lett.* (2005)
- [2] J. Hermann *et al.*, arXiv:2208.12590 (2022)
- [3] W. M. C. Foulkes *et al.*, *Rev. Mod. Phys.* (2001)
- [4] J. Martens, R. Grosse, *ICML* (2015)
- [5] D. Pfau, J. S. Spencer *et al.*, *Phys. Rev. Research* (2020)
- [6] L. Gerard, M. Scherbela *et al.*, *NeurIPS* (2022)