

Neural Networks in Quantum Physics: An interdisciplinary perspective

Grenoble 2026

Thomas Spriggs, Vinicius Hernandez, Dima Oriekhov, Arash Ahmadi, Guliuxin Jin, Saqar Khaleefah, Marit Piek, Stan Bergkamp, Sibren van der Meer, Bokai Chen, Badr Zougari, Naoual El Yazidi, Cagan Karaca, Jonas Helsen, and Eliska Greplova

Quantum Matter and AI Lab



Automation
&
Control

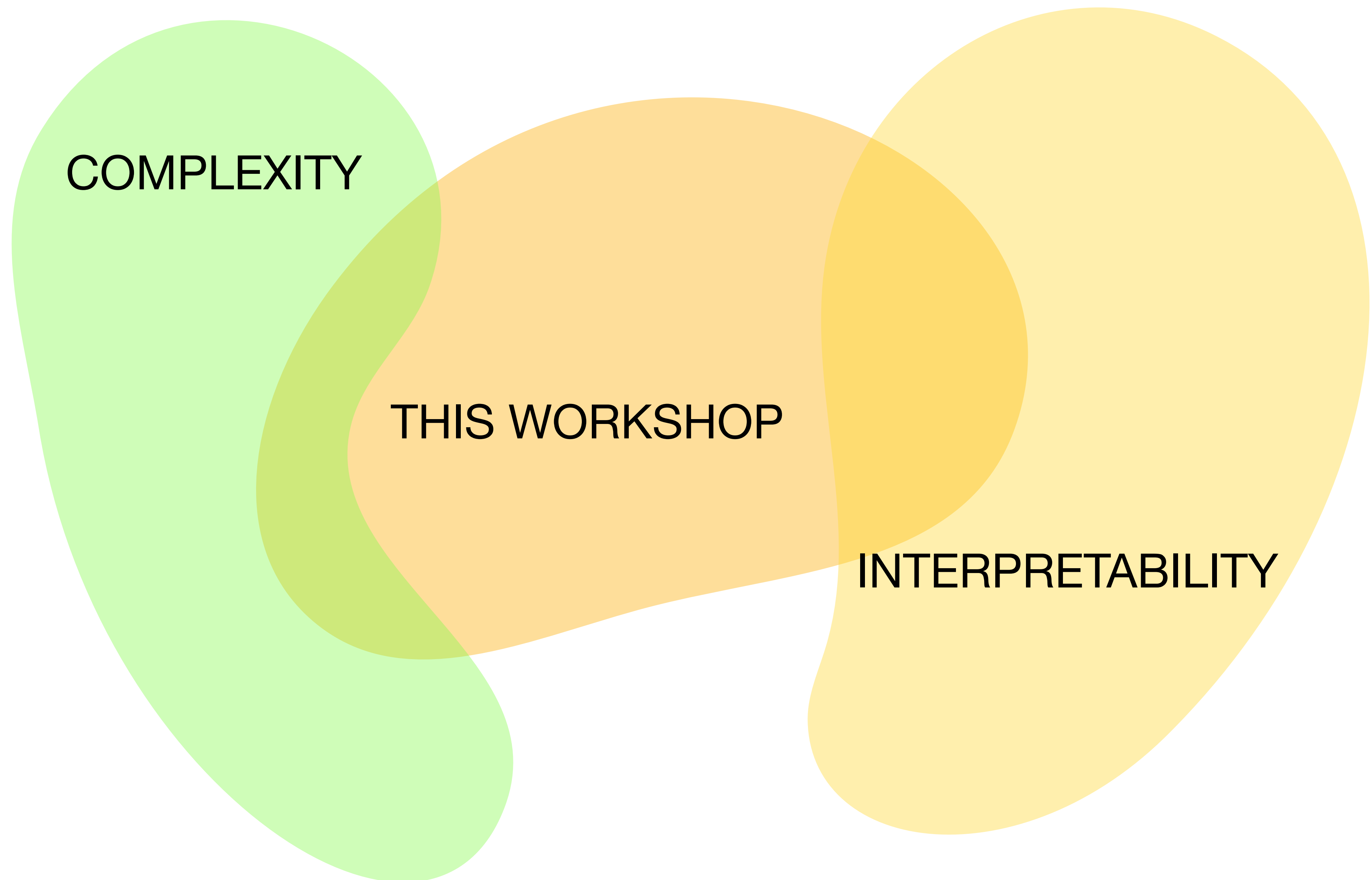
Verification
&
Validation



Simulation
&
Algorithms

Materials
&
Design

**How do we
make quantum
technologies
better?**



COMPLEXITY

THIS WORKSHOP

INTERPRETABILITY

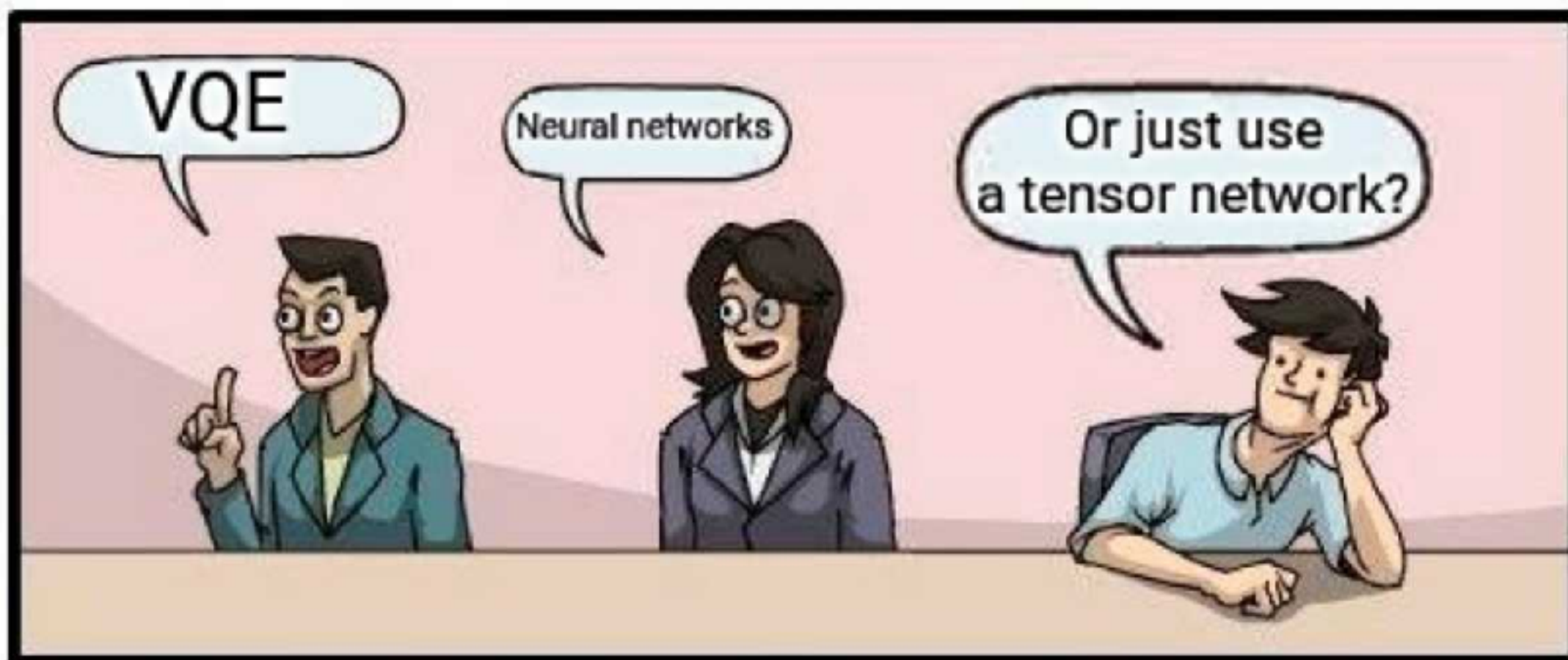
CAN WE INTERPRET WHAT
CONDMAT ML MODELS ARE
LEARNING TO ADVANCE
UNDERSTANDING?



WHAT DO QUANTUM COMPUTING
AND CONDMAT DESCRIPTIONS
OF HARD PROBLEMS
HAVE IN COMMON?

Part 1:

Can quantum information theory play a role in development of the next gen classical variational methods?



Article | [Published: 23 October 2019](#)

Quantum simulation using a programmable superconducting processor

[Frank Arute](#), [Kunal Arya](#), [Ryan Babbush](#), [Dave Bacon](#), [Joseph C. Bardin](#), [Rami Barends](#), [Rupak Biswas](#), [Sergio Boixo](#), [Fernando G. S. L. Brandao](#), [David A. Buell](#), [Brian Burkett](#), [Yu Chen](#), [Zijun Chen](#), [Ben Chiaro](#), [Roberto Collins](#), [William Courtney](#), [Andrew Dunsworth](#), [Edward Farhi](#), [Brooks Foxen](#), [Austin Fowler](#), [Craig Gidney](#), [Marissa Giustina](#), [Rob Graff](#), [Keith Guerin](#), ... [John M. Martinis](#)  [+ Show authors](#)

[Nature](#) **574**, 505–510 (2019) | [Cite this article](#)

Article | [Open access](#) | [Published: 14 June 2023](#)

Evidence for the utility of quantum computing before fault tolerance

[Youngseok Kim](#) , [Andrew Eddins](#) , [Sajant Anand](#), [Ken Xuan Wei](#), [Ewout van den Berg](#), [Sami Rosenblatt](#), [Hasan Nayfeh](#), [Yantao Wu](#), [Michael Zaletel](#), [Kristan Temme](#) & [Abhinav Kandala](#) 

[Nature](#) **618**, 500–505 (2023) | [Cite this article](#)

105k Accesses | **18** Citations | **947** Altmetric | [Metrics](#)

Computational simulation in quantum simulation

[Andrew D. King](#), [Alberto Nocera](#), [Marek M. Rams](#), [Jacek Dziarmaga](#), [Roeland Wiersema](#), [William Bernoudy](#), [Jack Raymond](#), [Nitin Kaushal](#), [Niclas Heinsdorf](#), [Richard Harris](#), [Kelly Boothby](#), [Fabio Altomare](#), [Andrew J. Berkley](#), [Martin Boschnak](#), [Kevin Chern](#), [Holly Christiani](#), [Samantha Cibere](#), [Jake Connor](#), [Martin H. Dehn](#), [Rahul Deshpande](#), [Sara Ejtemaee](#), [Pau Farré](#), [Kelsey Hamer](#), [Emile Hoskinson](#), [Shuiyuan Huang](#), [Mark W. Johnson](#), [Samuel Kortas](#), [Eric Ladizinsky](#), [Tony Lai](#), [Trevor Lanting](#), [Ryan Li](#), [Allison J.R. MacDonald](#), [Gaelen Marsden](#), [Catherine C. McGeoch](#), [Reza Molavi](#), [Richard Neufeld](#), [Mana Norouzpour](#), [Travis Oh](#), [Joel Pasvolsky](#), [Patrick Poltras](#), [Gabriel Poulin-Lamarre](#), [Thomas Prescott](#), [Mauricio Reis](#), [Chris Rich](#), [Mohammad Samani](#), [Benjamin Sheldan](#), [Anatoly Smirnov](#), [Edward Sterpka](#), [Berta Trullas Clavera](#), [Nicholas Tsai](#), [Mark Volkmann](#), [Alexander Whitaric](#), [Jed D. Whittaker](#), [Warren Wilkinson](#), [Jason Yao](#), [T.J. Yi](#), [Anders W. Sandvik](#), [Gonzalo Alvarez](#), [Roger G. Melko](#), [Juan Carrasquilla](#), [Marcel Franz](#), [Mohammad H. Amin](#)

Quantum computers hold the promise of solving certain problems that lie beyond the reach of conventional computers. Establishing this capability, especially for impactful and meaningful problems, remains a central challenge. One such problem is the simulation of nonequilibrium dynamics of a magnetic spin system quenched through a quantum phase transition. State-of-the-art classical simulations demand resources that grow exponentially with system size. Here we show that superconducting quantum annealing processors can rapidly generate samples in close agreement with solutions of the Schrödinger equation. We demonstrate area-law scaling of entanglement in the model quench in two-, three- and infinite-dimensional spin glasses, supporting the observed stretched-exponential scaling of effort for classical approaches. We assess approximate methods based on tensor networks and neural networks and conclude that no known approach can achieve the same accuracy as the quantum annealer within a reasonable timeframe. Thus quantum annealers can answer questions of practical importance that classical computers cannot.

Subjects: [Quantum Physics \(quant-ph\)](#); [Disordered Systems and Neural Networks \(cond-mat.dis-nn\)](#); [Statistical Mechanics \(cond-mat.stat-mech\)](#)
Cite as: [arXiv:2403.00910 \[quant-ph\]](#)
(or [arXiv:2403.00910v1 \[quant-ph\]](#) for this version)

Editors' Suggestion

Access by S

Solving the Sampling Problem of the Sycamore Quantum Circuits

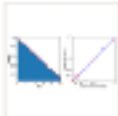
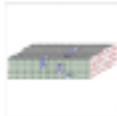
Feng Pan, Keyang Chen, and Pan Zhang
Phys. Rev. Lett. **129**, 090502 – Published 22 August 2022

ArticleReferencesCiting Articles (23)Supplemental MaterialPDFHTMLExport Citation

>

ABSTRACT

We study the problem of generating independent samples from the output distribution of Google's Sycamore quantum circuits with a target fidelity, which is believed to be beyond the reach of classical supercomputers and has been used to demonstrate quantum supremacy. We propose a method to classically solve this problem by contracting the corresponding tensor network just once, and is massively more efficient than existing methods in generating a large number of uncorrelated samples with a target fidelity. For the Sycamore quantum supremacy circuit with 53 qubits and 20 cycles, we have generated 1×10^6 uncorrelated bitstrings $\mathbf{x}$ which are sampled from a distribution $\hat{P}(\mathbf{x}) = |\hat{\psi}(\mathbf{x})|^2$, where the approximate state $\hat{\psi}$ has fidelity $F \approx 0.0037$. The whole computation has cost about 1.5 h on a computational cluster with 512 GPUs. The obtained 1×10^6 samples, the contraction code and contraction order are made public. If our algorithm could be implemented with high efficiency on a modern supercomputer with ExaFLOPS performance, we estimate that ideally, the simulation would cost a few dozens of seconds, which is faster than Google's quantum hardware.



Efficient tensor network simulation of IBM's Eagle kicked Ising experiment

[Joseph Tindall](#), [Matt Fishman](#), [Miles Stoudenmire](#), [Dries Sels](#)

We report an accurate and efficient classical simulation of a kicked Ising quantum system on the heavy-hexagon lattice. A simulation of this system was recently performed on a 127 qubit quantum processor using noise mitigation techniques to enhance accuracy (Nature volume 618, p.500–505 (2023)). Here we show that, by adopting a tensor network approach that reflects the geometry of the lattice and is approximately contracted using belief propagation, we can perform a classical simulation that is significantly more accurate and precise than the results obtained from the quantum processor and many other classical methods. We quantify the tree-like correlations of the wavefunction in order to explain the accuracy of our belief propagation-based approach. We also show how our method allows us to perform simulations of the system to long times in the thermodynamic limit, corresponding to a quantum computer with an infinite number of qubits. Our tensor network approach has broader applications for simulating the dynamics of quantum systems with tree-like correlations.

Comments: 18 Pages, 10 Figures. Updated to include improved BP-TNS data, simulation of the infinite system and improved error quantification

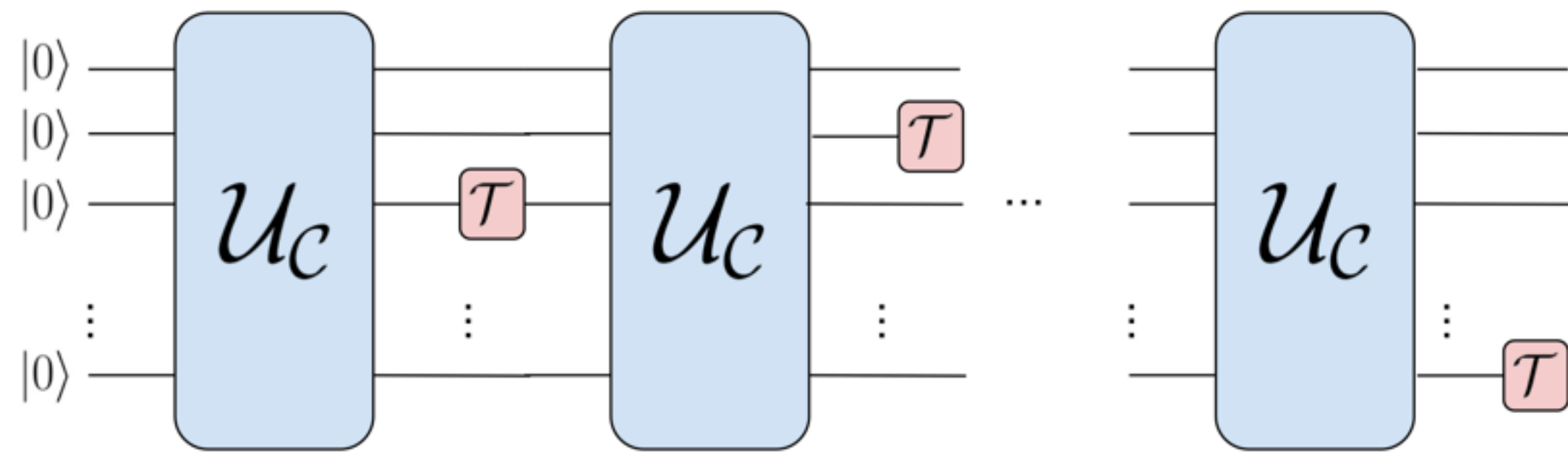
Subjects: [Quantum Physics \(quant-ph\)](#)

Cite as: [arXiv:2306.14887 \[quant-ph\]](#)

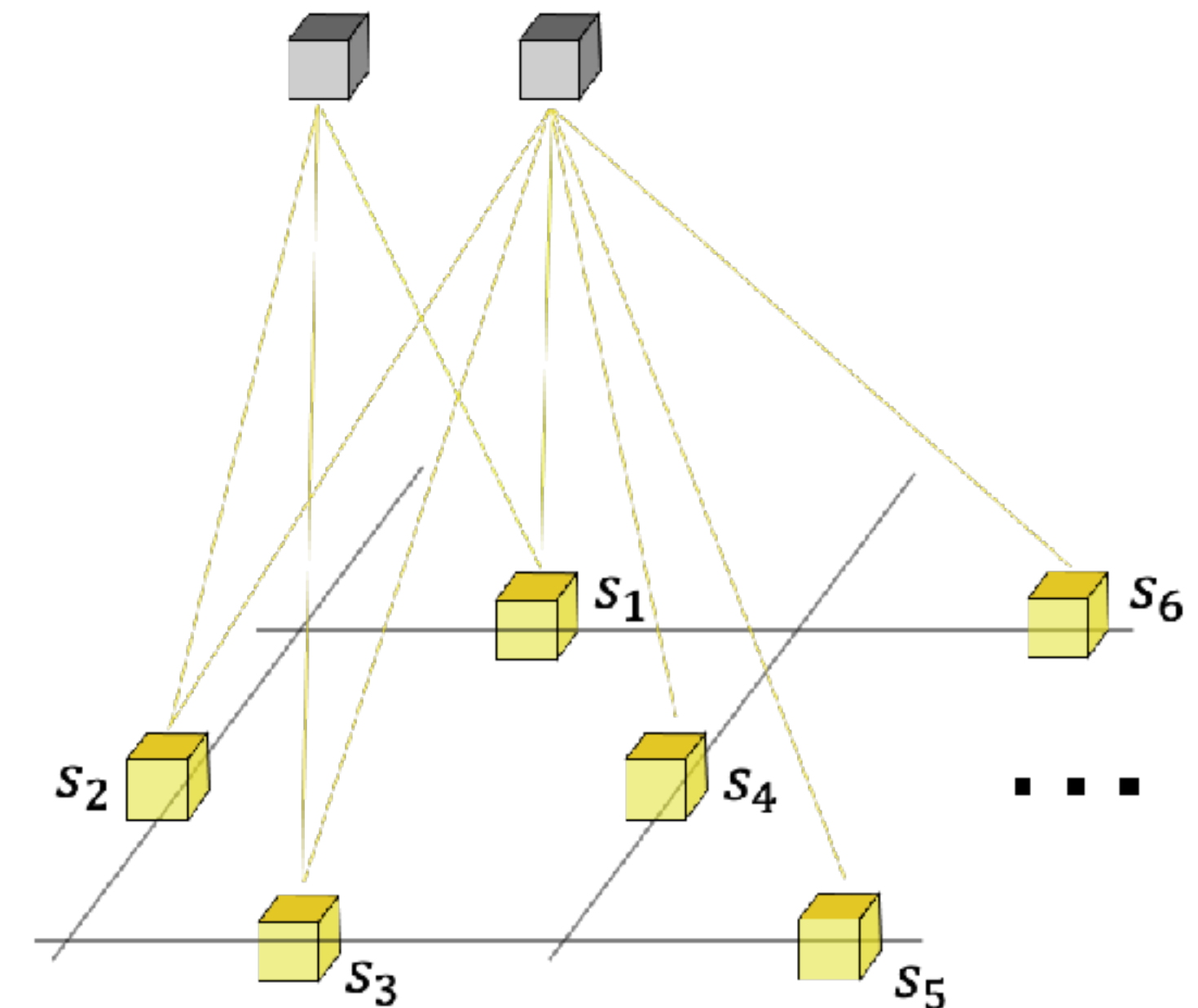
(or [arXiv:2305.14887v2 \[quant-ph\]](#) for this version)

<https://doi.org/10.48550/arXiv.2305.14887> 

Quantum Information vs. Condensed Matter



Gottesman-Knill Theorem



Variational Techniques

Classical Variational Methods

Find the ground state

$$\mathcal{H}|\Psi\rangle = E|\Psi\rangle$$

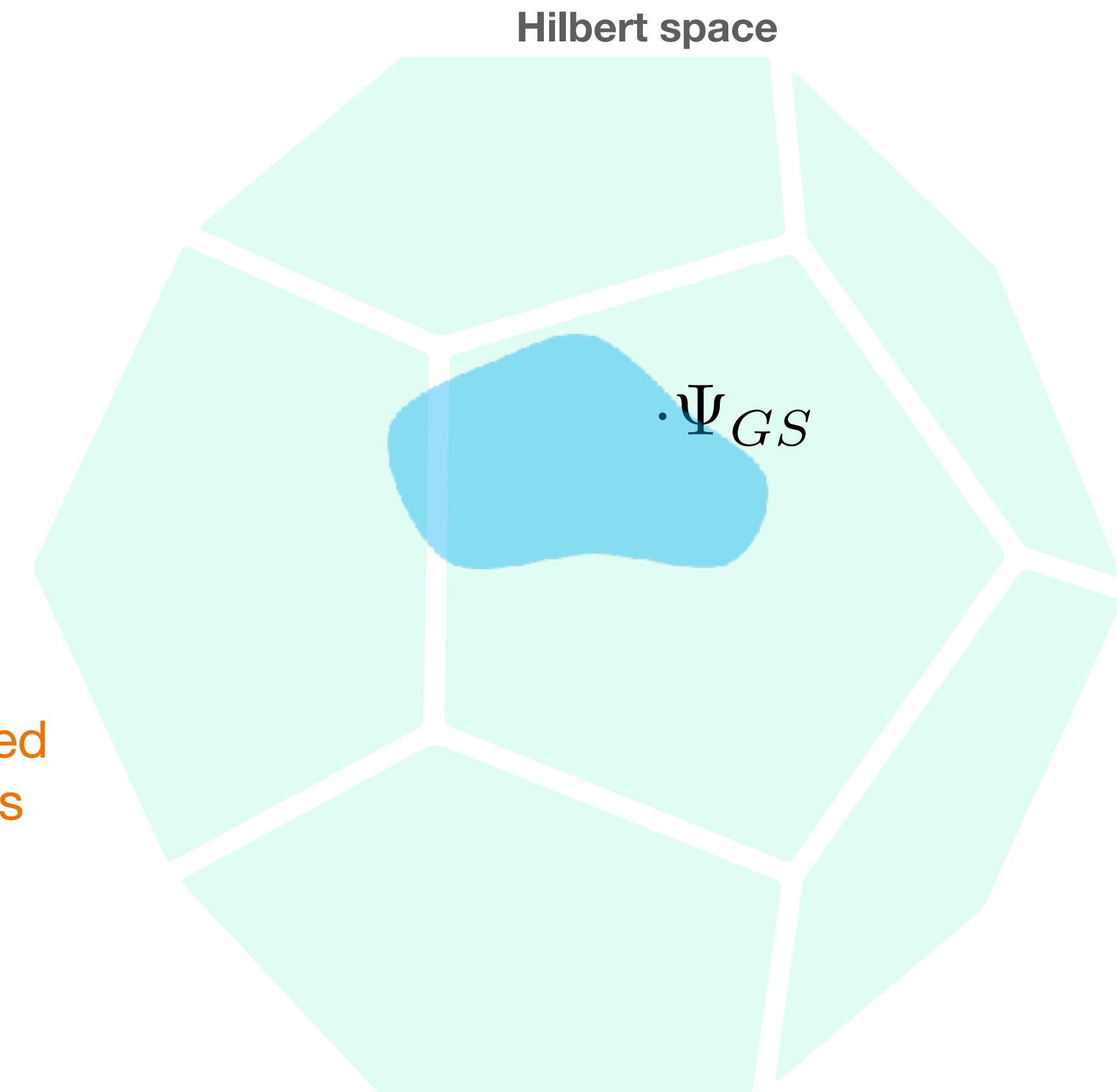
Parametrize $|\Psi\rangle$

$$|\Psi\rangle_{\theta} = \sum_{i=1}^{2^N} f_{\theta}(s_1^i, \dots, s_N^i) |s_1^i, \dots, s_N^i\rangle$$

parametrized
amplitudes

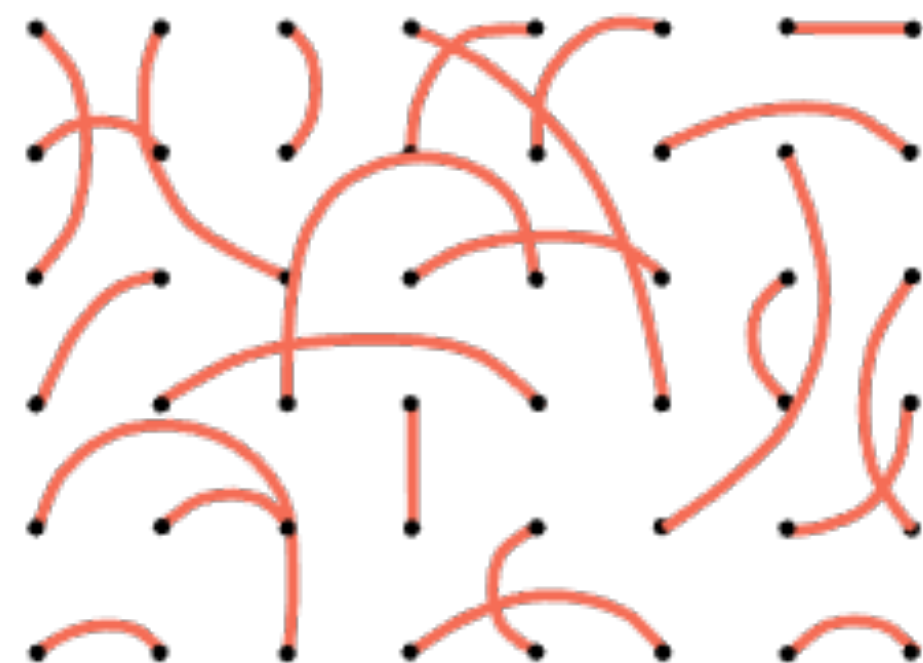
Variational principle

$$\frac{\langle \Psi_{\theta} | H | \Psi_{\theta} \rangle}{\langle \Psi_{\theta} | \Psi_{\theta} \rangle} \geq E_G$$



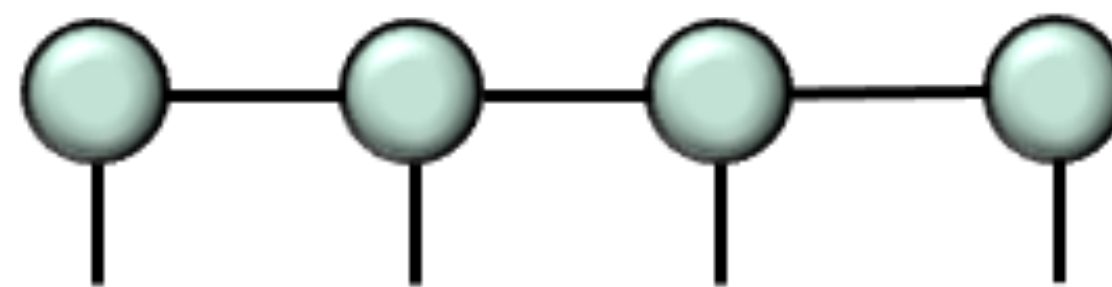
Classical Variational Methods

Motivated by physics of model:
RVB, Slater-Jastrow...



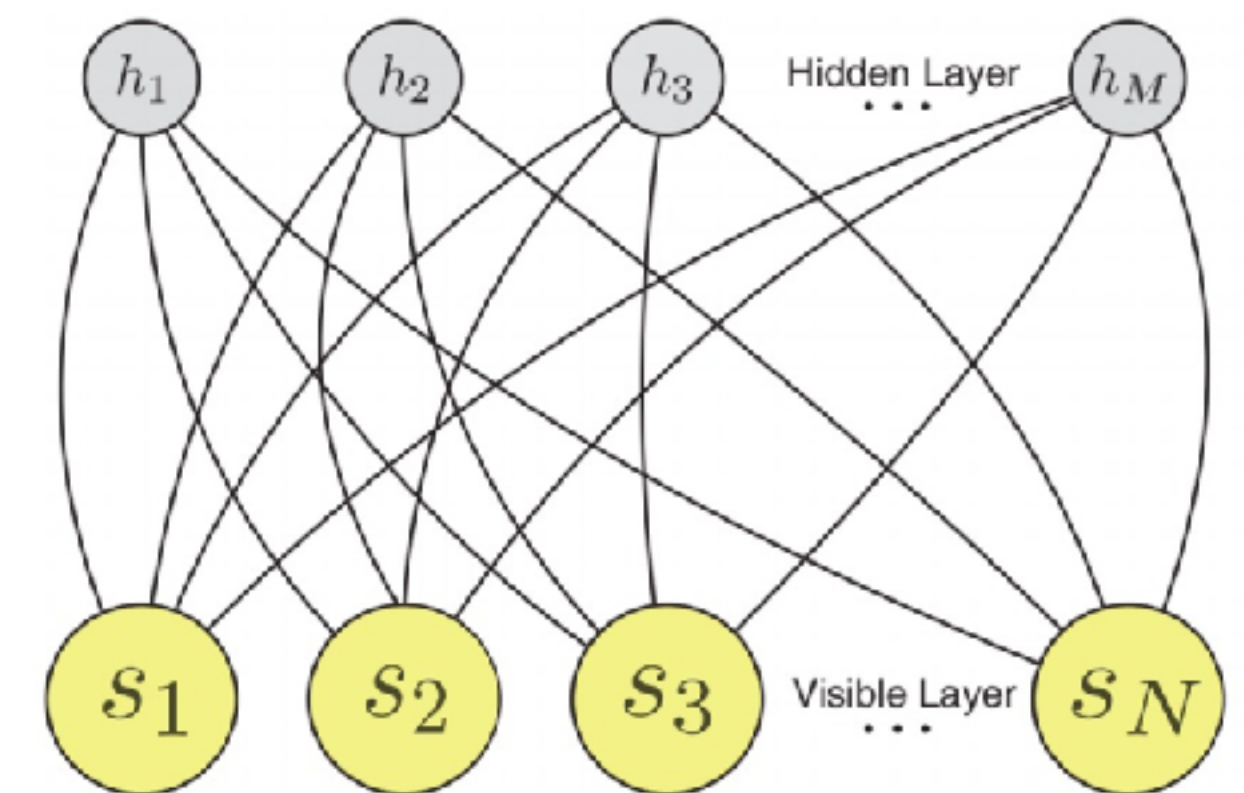
[P Anderson, Science (1987)]
[R Jastrow, PR (1955)]

Area law entanglement:
MPS, PEPS



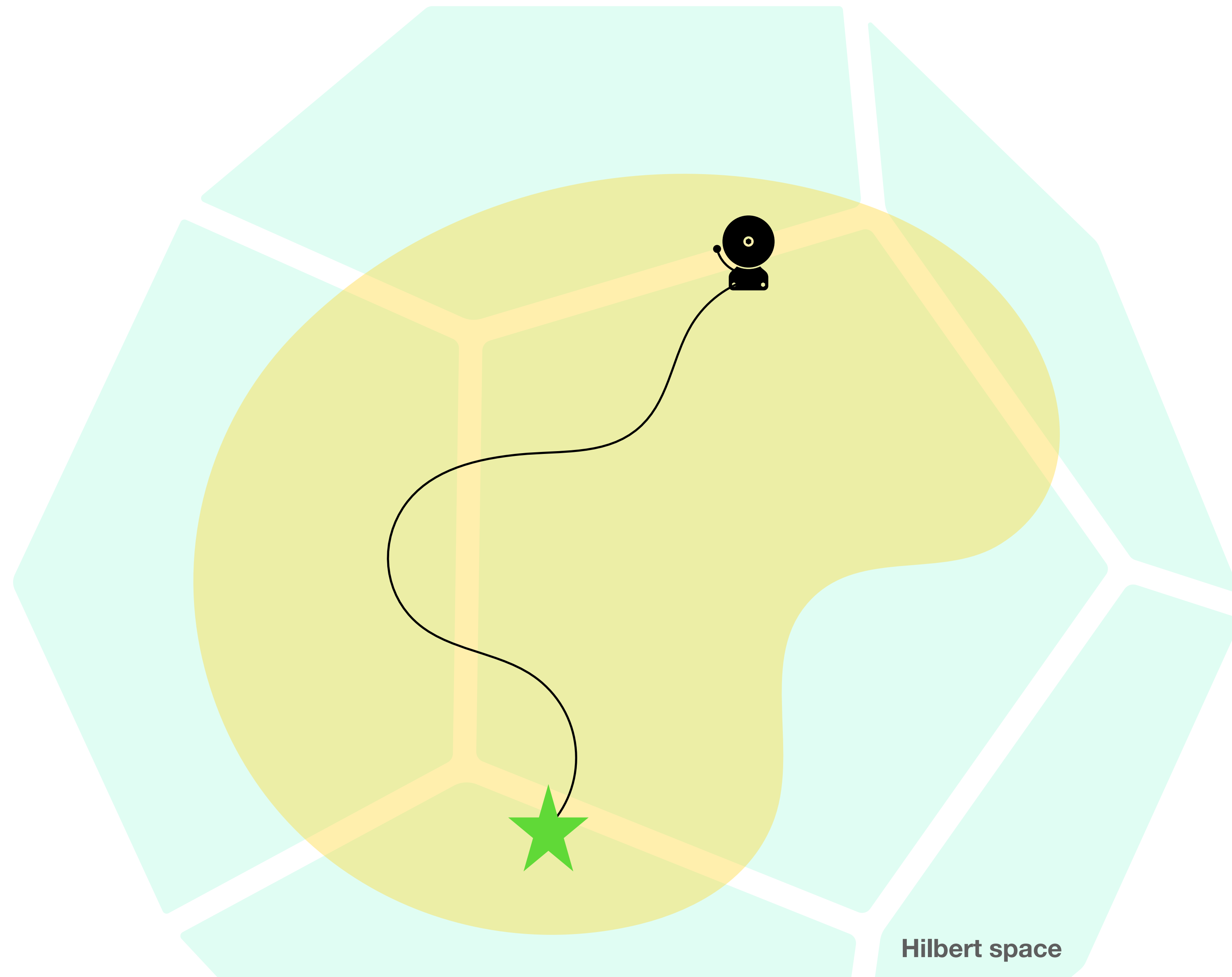
[A Klümper et al., J. Phys. A (1991)]
[S R White, PRL (1992)], [R Orus, AoP (2014)]

Generic:
Neural Networks

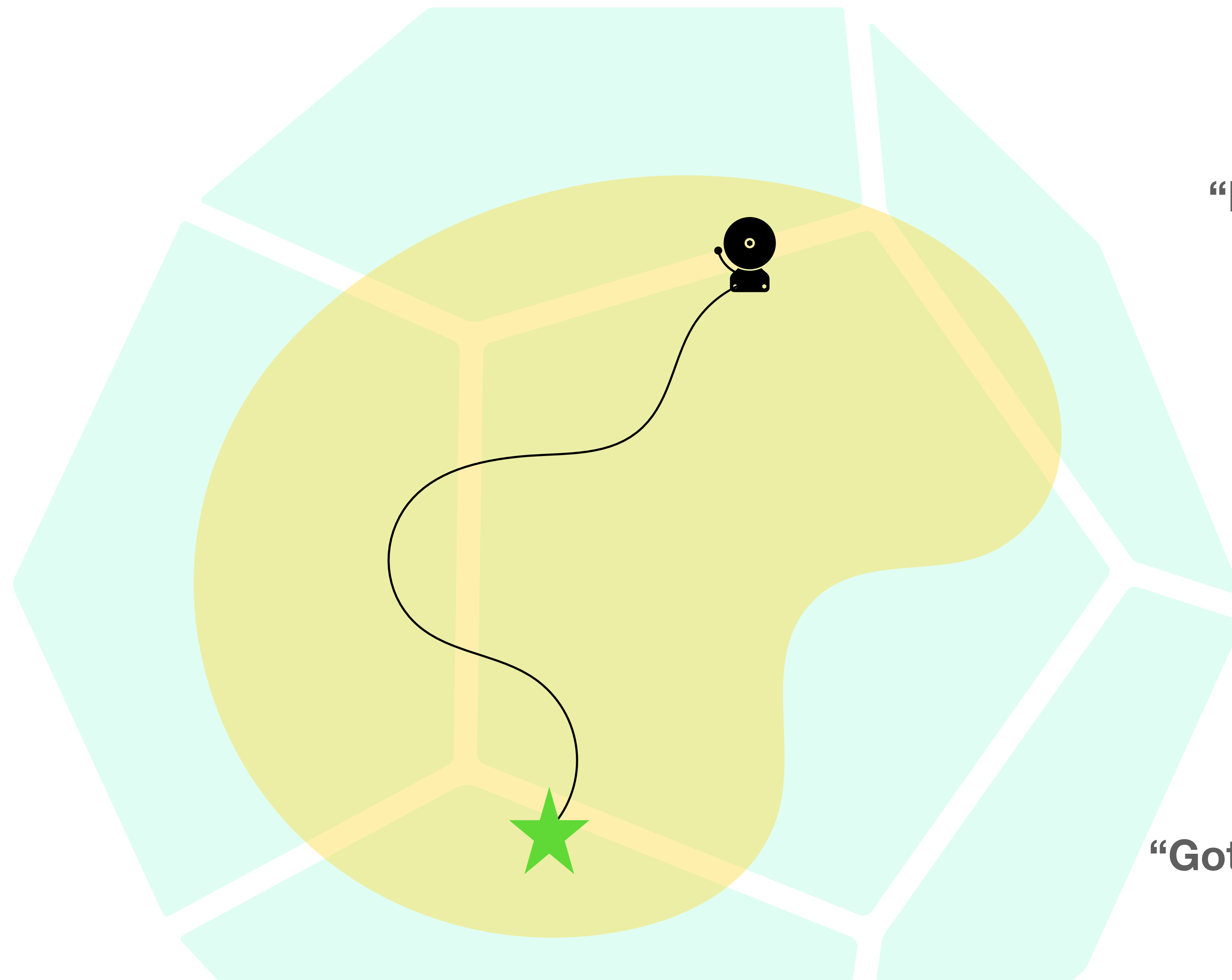


[G Carleo and M Troyer, Science (2017)]

Classical Variational Methods



Classical Variational Methods



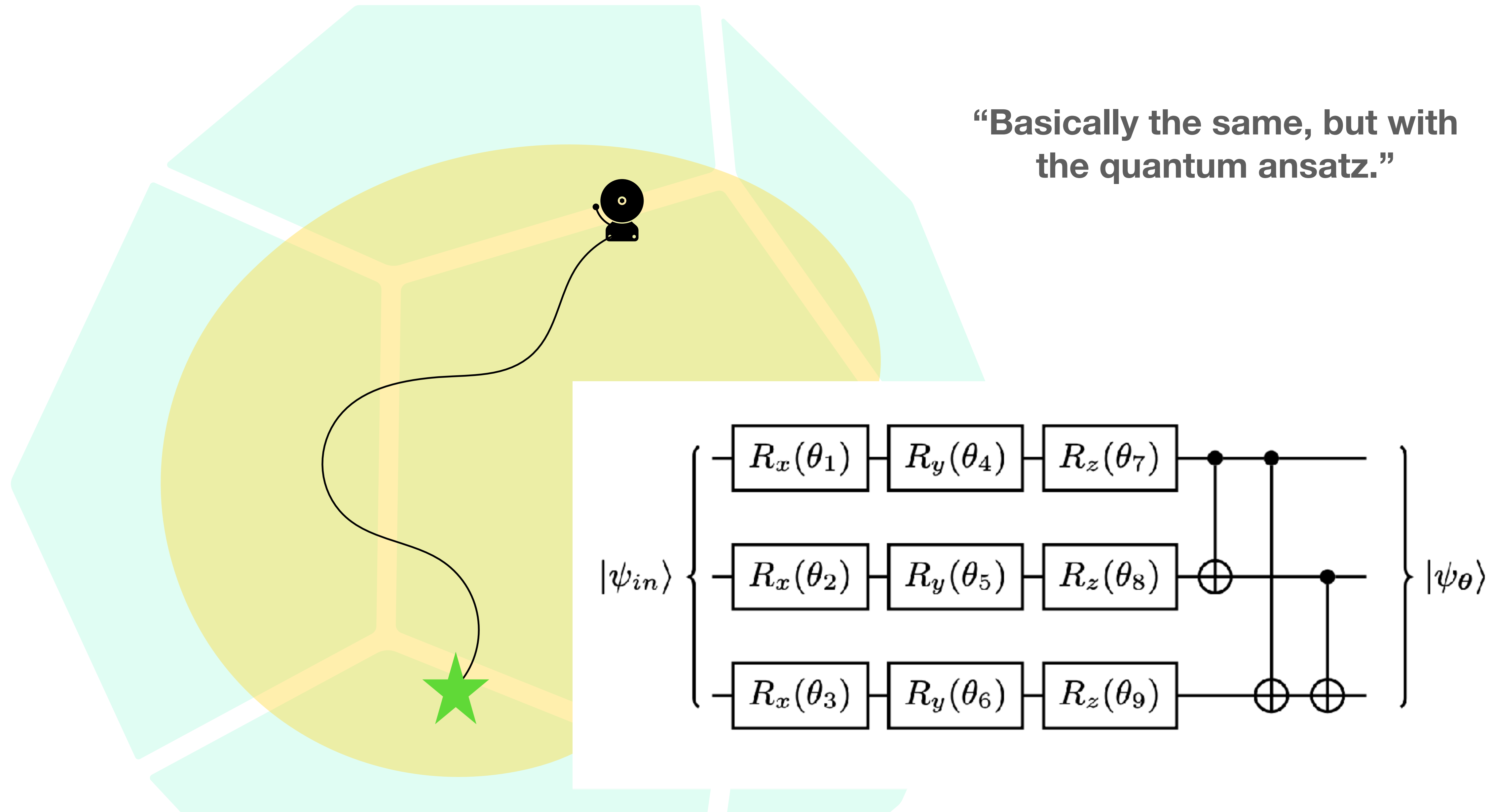
“Explore Hilbert space to minimize energy.”

$$E_{var}(W) = \frac{\langle \Psi_W | H | \Psi_W \rangle}{\langle \Psi_W | \Psi_W \rangle} \geq E_G$$

“Gottesman-Knill does not enter this equation.”

Quantum Variational Methods

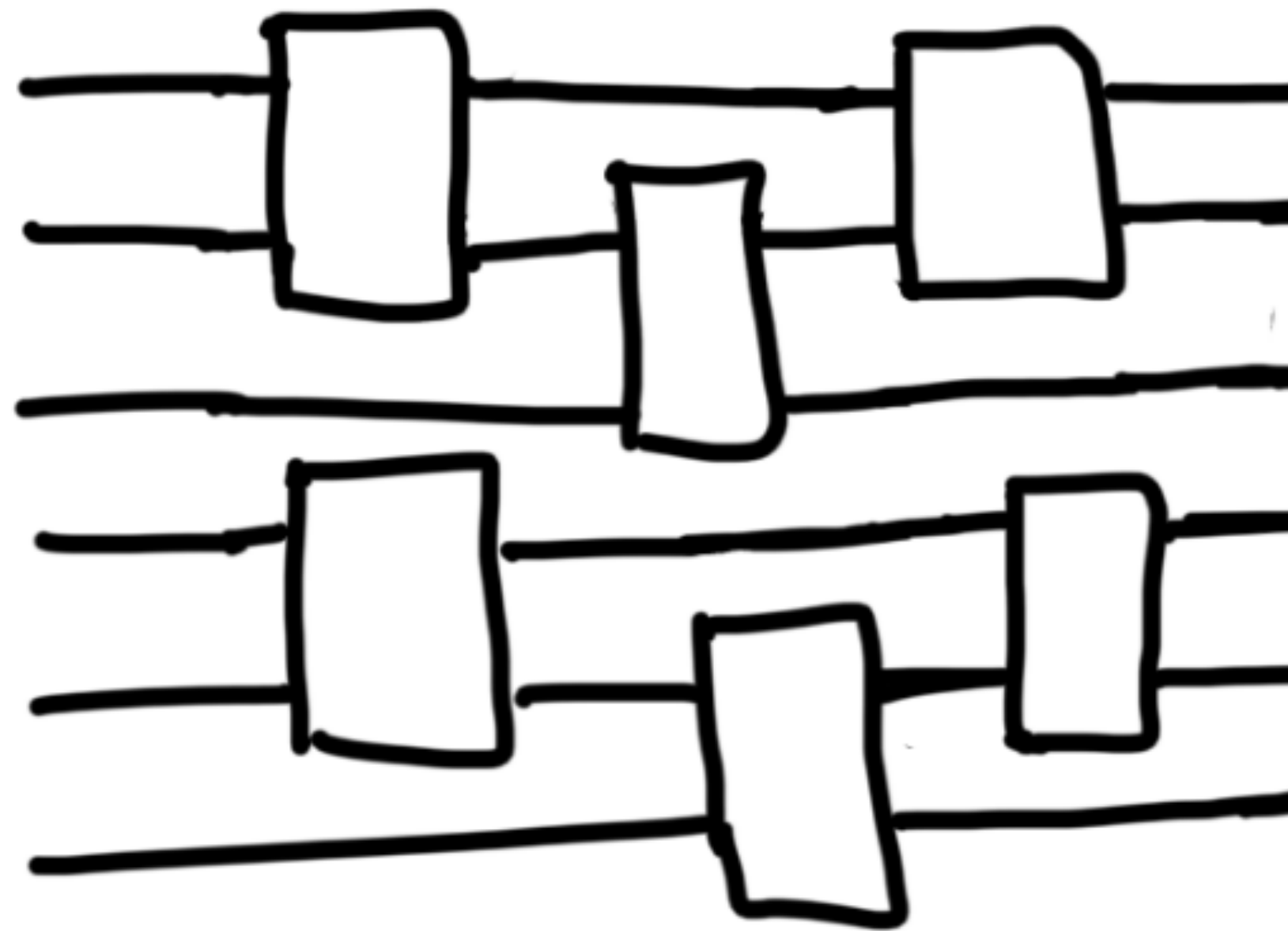
“Basically the same, but with the quantum ansatz.”



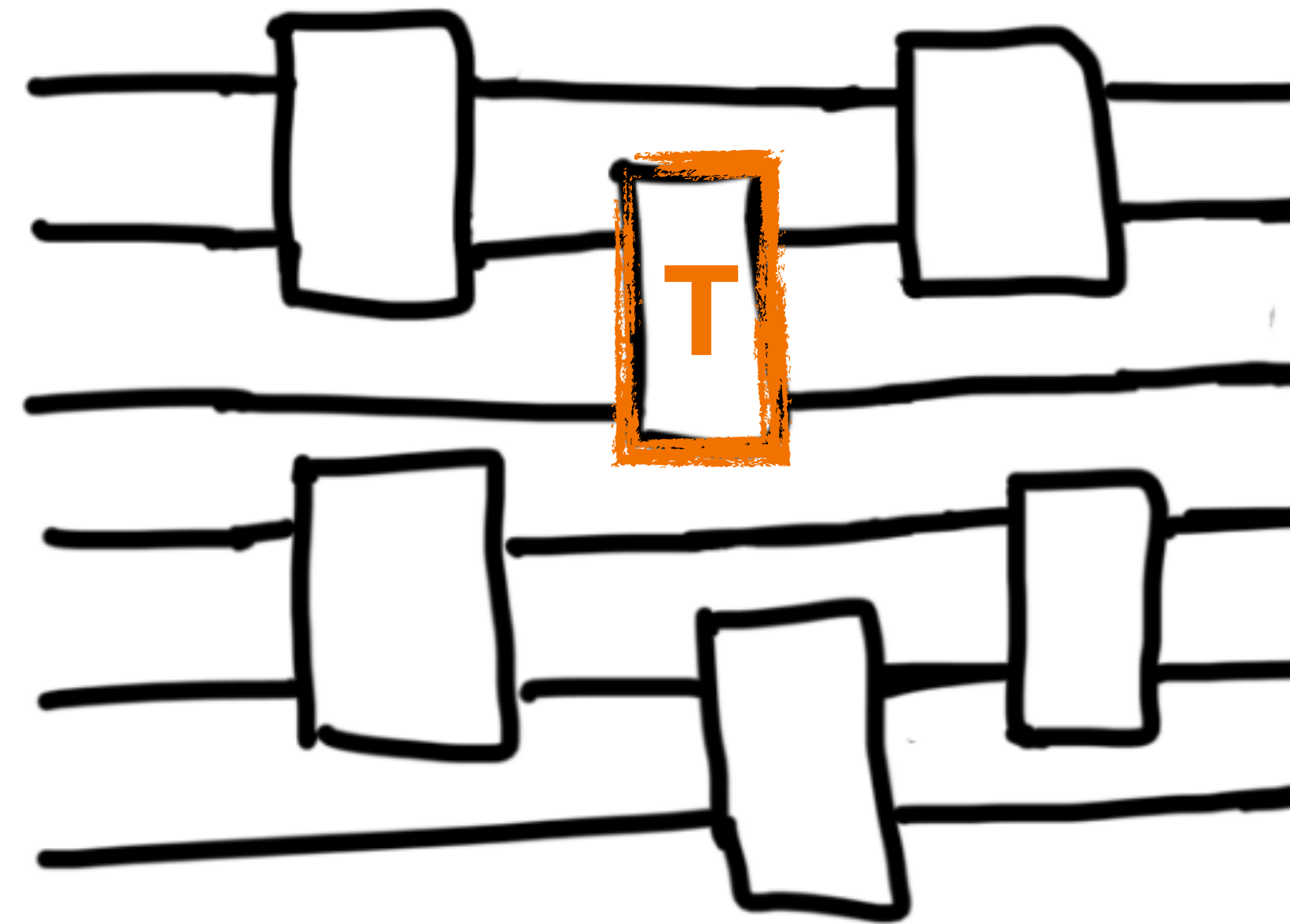
Simulatability in quantum info

Non-stabilizerness

Clifford group: Classically simulatable



Non-Clifford operations -> full Hilbert space



Non-stabilizerness

Stabilizer Renyi Entropy:

$$M_2(|\psi\rangle) = -\log \sum_{P \in \mathcal{P}_N} \frac{\langle \psi | P | \psi \rangle^4}{2^N}$$

Non-stabilizerness

Stabilizer Renyi Entropy:

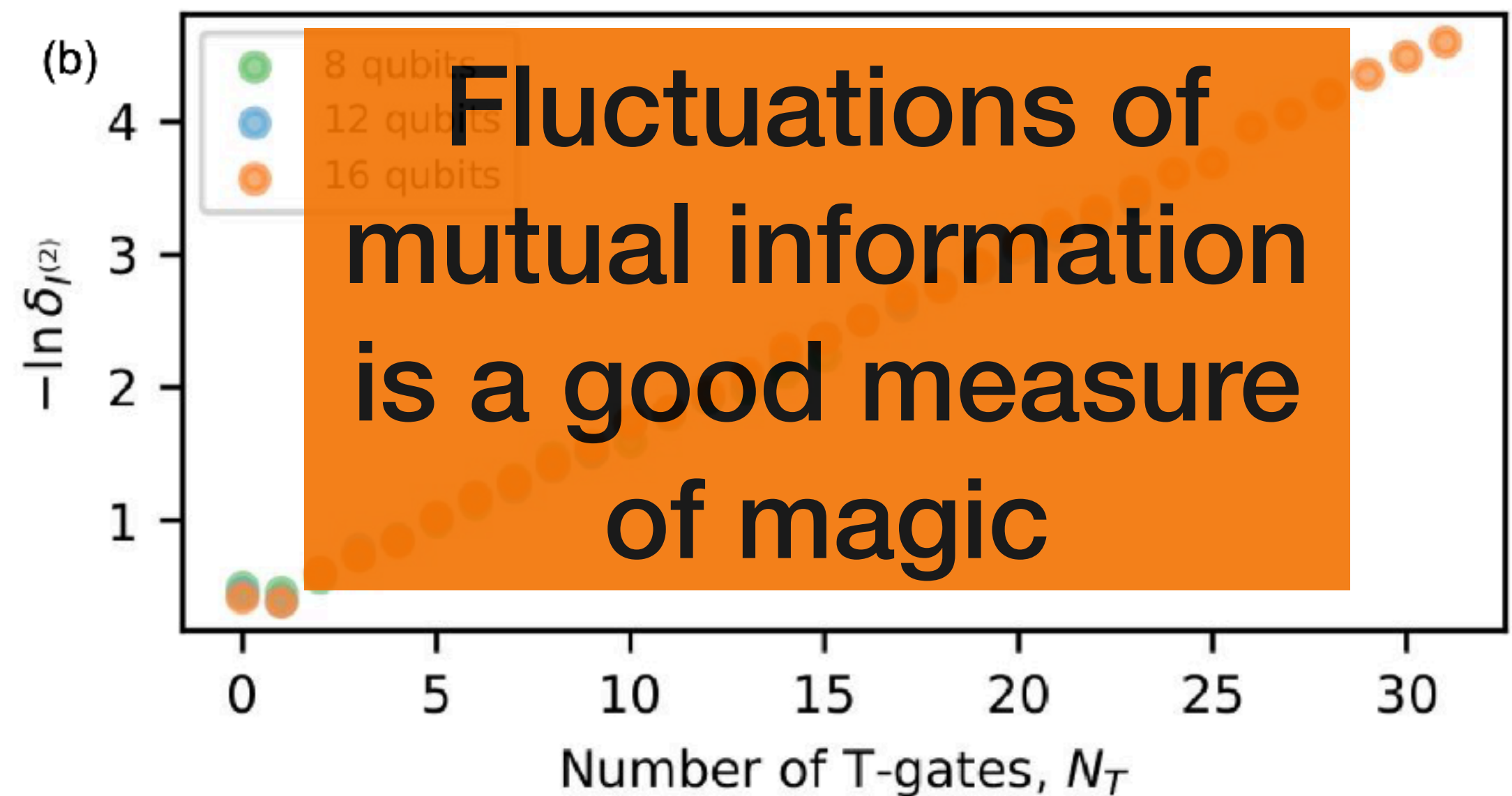
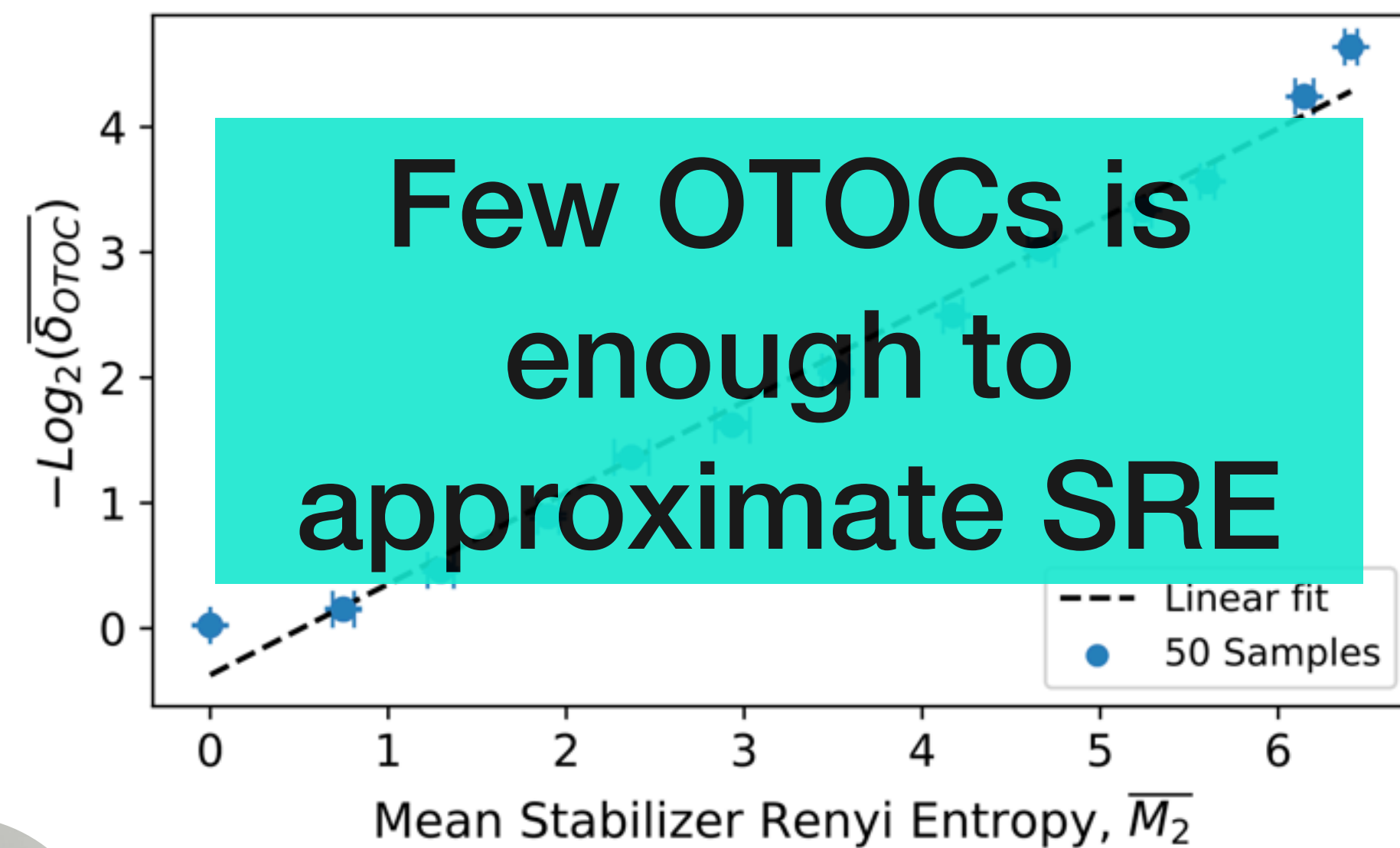
$$M_2(|\psi\rangle) = -\log \sum_{P \in \mathcal{P}_N} \frac{\langle \psi | P | \psi \rangle^4}{2^N}$$

scales $\sim 4^N$



Non-stabilizerness

We discovered some cool approximations



Simulatability in quantum info

Non-stabilizerness

RESEARCH

QUANTUM SIMULATION

Information scrambling in quantum circuits

Xiao Mi^{1,†}, Pedram Roushan^{1,†}, Chris Quintana^{1,†}, Salvatore Mandrà^{2,3}, Jeffrey Marshall^{2,4}, Charles Neill¹, Frank Arute¹, Kunal Arya¹, Juan Alalaya¹, Ryan Babbush¹, Joseph C. Bardin^{1,5}, Rami Barends¹, Joao Basso¹, Andreas Bengtsson¹, Sergio Boixo¹, Alexandre Bourassa^{1,6}, Michael Broughton¹, Bob B. Buckley¹, David A. Buell¹, Brian Burkett¹, Nicholas Bushnell¹, Zijun Chen¹, Benjamin Chiaro¹, Roberto Collins¹, William Courtney¹, Sean Demura¹, Alan R. Derk¹, Andrew Dunsworth¹, Daniel Eppens¹, Catherine Erickson¹, Edward Farhi¹, Austin G. Fowler¹, Brooks Foxen¹, Craig Gidney¹, Marissa Giustina¹, Jonathan A. Gross¹, Matthew P. Harrigan¹, Sean D. Harrington¹, Jeremy Hilton¹, Alan Ho¹, Sabrina Hong¹, Trent Huang¹, William J. Huggins¹, L. B. Ioffe¹, Sergei V. Isakov¹, Evan Jeffrey¹, Zhang Jiang¹, Cody Jones¹, Dvir Kafri¹, Julian Kelly¹, Seon Kim¹, Alexei Kitaev^{1,7}, Paul V. Klimov¹, Alexander N. Korotkov^{1,8}, Fedor Kostritsa¹, David Landhuis¹, Pavel Laptev¹, Erik Lucero¹, Orion Martin¹, Jarrod R. McClean¹, Trevor McCourt¹, Matt McEwen^{1,9}, Anthony Megrant¹, Kevin C. Miao¹, Masoud Mohseni¹, Shirin Montazeri¹, Wojciech Mruczkiewicz¹, Josh Mutus¹, Ofer Naaman¹, Matthew Neeley¹, Michael Newman¹, Murphy Yuezhen Niu¹, Thomas E. O'Brien¹, Alex Opremcak¹, Eric Ostby¹, Balint Pato¹, Andre Petukhov¹, Nicholas Redd¹, Nicholas C. Rubin¹, Daniel Sank¹, Kevin J. Satzinger¹, Vladimir Shvarts¹, Doug Strain¹, Marco Szalay¹, Matthew D. Trevithick¹, Benjamin Villalonga¹, Theodore White¹, Z. Jamie Yao¹, Ping Yeh¹, Adam Zalcman¹, Hartmut Neven¹, Igor Aleiner¹, Kostyantyn Kechedzhis^{1,*}, Vadim Smelyanskiy^{1,*}, Yu Chen^{1,*}

Interactions in quantum systems can spread initially localized quantum information into the exponentially many degrees of freedom of the entire system. Understanding this process, known as quantum scrambling, is key to resolving several open questions in physics. Here, by measuring the time-dependent evolution and fluctuation of out-of-time-order correlators, we experimentally investigate the dynamics of quantum scrambling on a 53-qubit quantum processor. We engineer quantum circuits that distinguish operator spreading and operator entanglement and experimentally observe their respective signatures. We show that whereas operator spreading is captured by an efficient classical model, operator entanglement in idealized circuits requires exponentially scaled computational resources to simulate. These results open the path to studying complex and practically relevant physical observables with near-term quantum processors.

Science 374, 1479–1483 (2021)

LETTER

Quantifying nonstabilizerness through entanglement spectrum flatness

Emanuele Tirrito^{1,2}, Poetri Sonya Tarabunga^{1,2,3}, Guglielmo Lami², Titas Chanda^{1,4}, Lorenzo Leone⁵, Salvatore F. E. Oliviero⁵, Marcello Dalmonte^{1,2}, Mario Collura^{2,3}, and Alioscia Hamma^{1,6,7}

Show more

Phys. Rev. A 109, L040401 – Published 24 April, 2024

Article

Phase transitions in random circuit sampling

<https://doi.org/10.1038/s41586-024-07998-6>

Received: 9 January 2024

Accepted: 26 August 2024

Published online: 9 October 2024

Open access

 Check for updates

Undesired coupling to the surrounding environment destroys long-range correlations in quantum processors and hinders coherent evolution in the nominally available computational space. This noise is an outstanding challenge when leveraging the computation power of near-term quantum processors¹. It has been shown that benchmarking random circuit sampling with cross-entropy benchmarking can provide an estimate of the effective size of the Hilbert space coherently available^{2–4}. Nevertheless, quantum algorithms' outputs can be trivialized by noise, making them susceptible to classical computation spoofing. Here, by implementing an algorithm for random circuit sampling, we demonstrate experimentally that two phase transitions are observable with cross-entropy benchmarking, which we explain theoretically with a statistical model. The first is a dynamical transition as a function of the number of cycles and is the continuation of the anti-concentration point in the noiseless case. The second is a quantum phase transition controlled by the error per cycle; to identify it analytically and model, which allows us to vary the strength of. Furthermore, by presenting a random circuit sampling phase with 67 qubits at 32 cycles, we demonstrate our experiment is beyond the capabilities of existing experimental and theoretical work establishes computationally complex phase that is reachable

Measuring nonstabilizerness via multifractal flatness

Xhek Turkeshi¹, Marco Schirò¹, and Piotr Śliemant^{1,2}

Show more

Phys. Rev. A 108, 042408 – Published 9 October, 2023

Phys. Rev. A 108, 042408 (2023)

Critical behaviors of non-stabilizerness in quantum spin chains

Poetri Sonya Tarabunga

The Abdus Salam International Centre for Theoretical Physics (ICTP), Strada Costiera 11, 34151 Trieste, Italy
International School for Advanced Studies (SISSA), via Bonomea 265, 34136 Trieste, Italy
INFN, Sezione di Trieste, Via Valerio 2, 34127 Trieste, Italy

Published: 2024-07-17, volume 8, page 1413
Eprint: arXiv:2309.00676v3
Doi: <https://doi.org/10.22331/q-2024-07-17-1413>
Citation: Quantum 8, 1413 (2024).

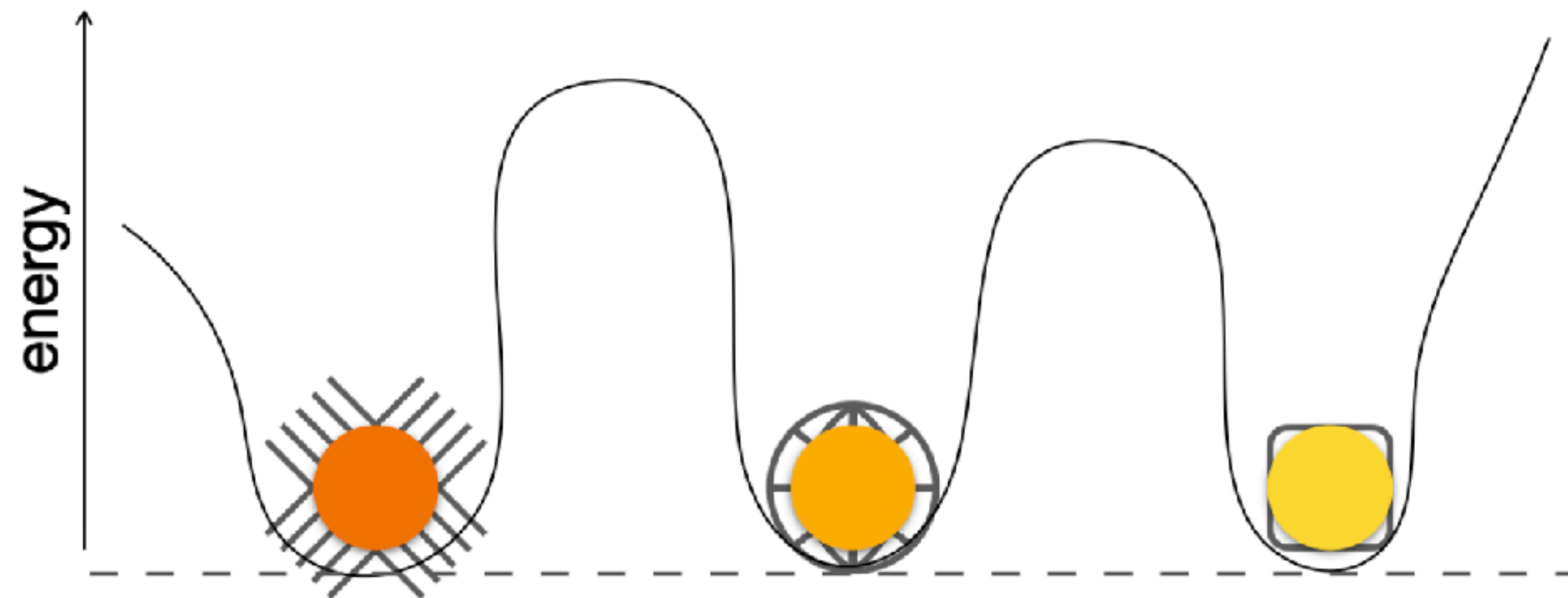
Quantum 8, 1413 (2024)

Phys. Rev. A 109, L040401 (2024)

“What is the non-stabilizerness of variational methods?”



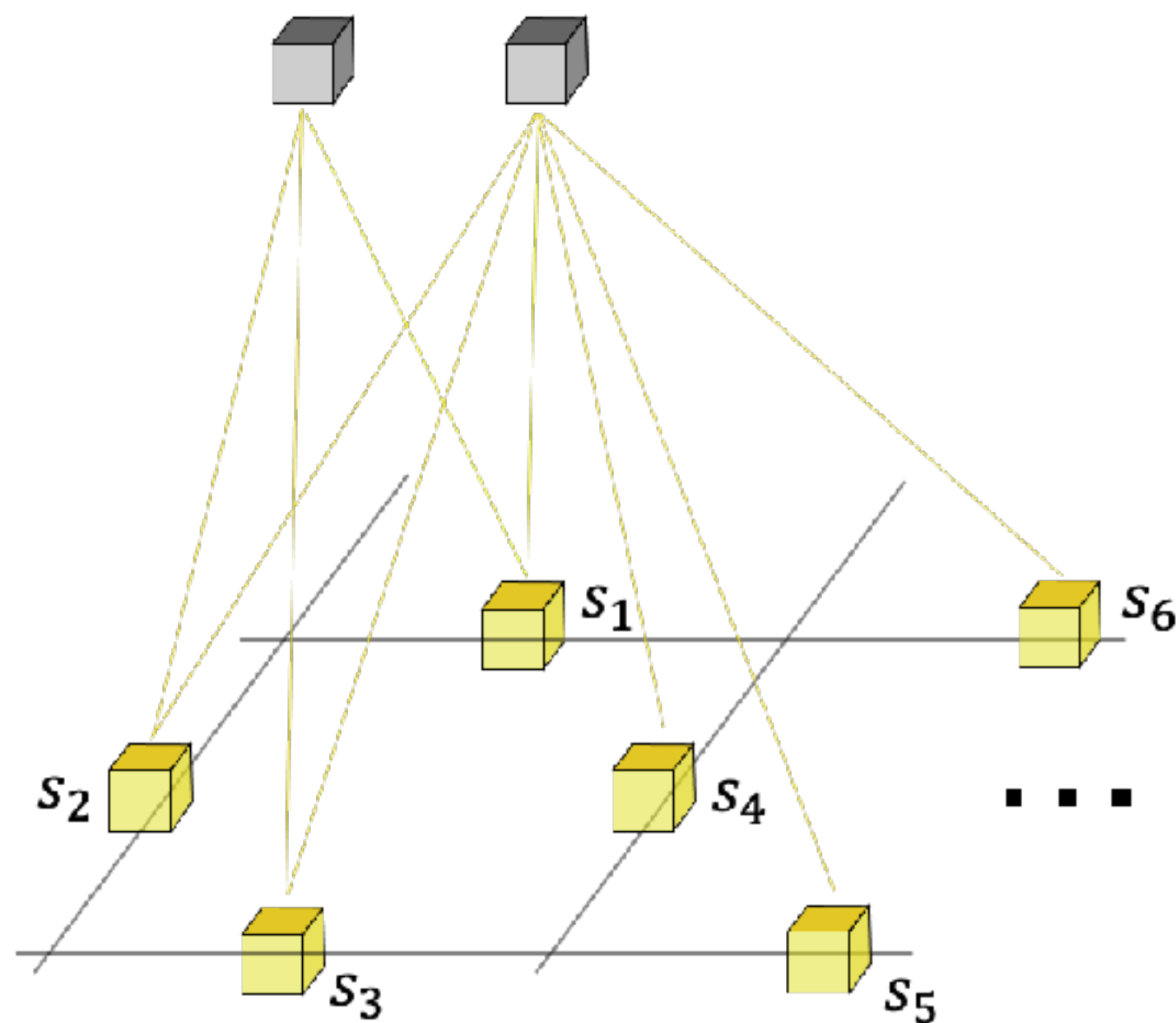
“What is the non-stabilizerness of variational methods?”



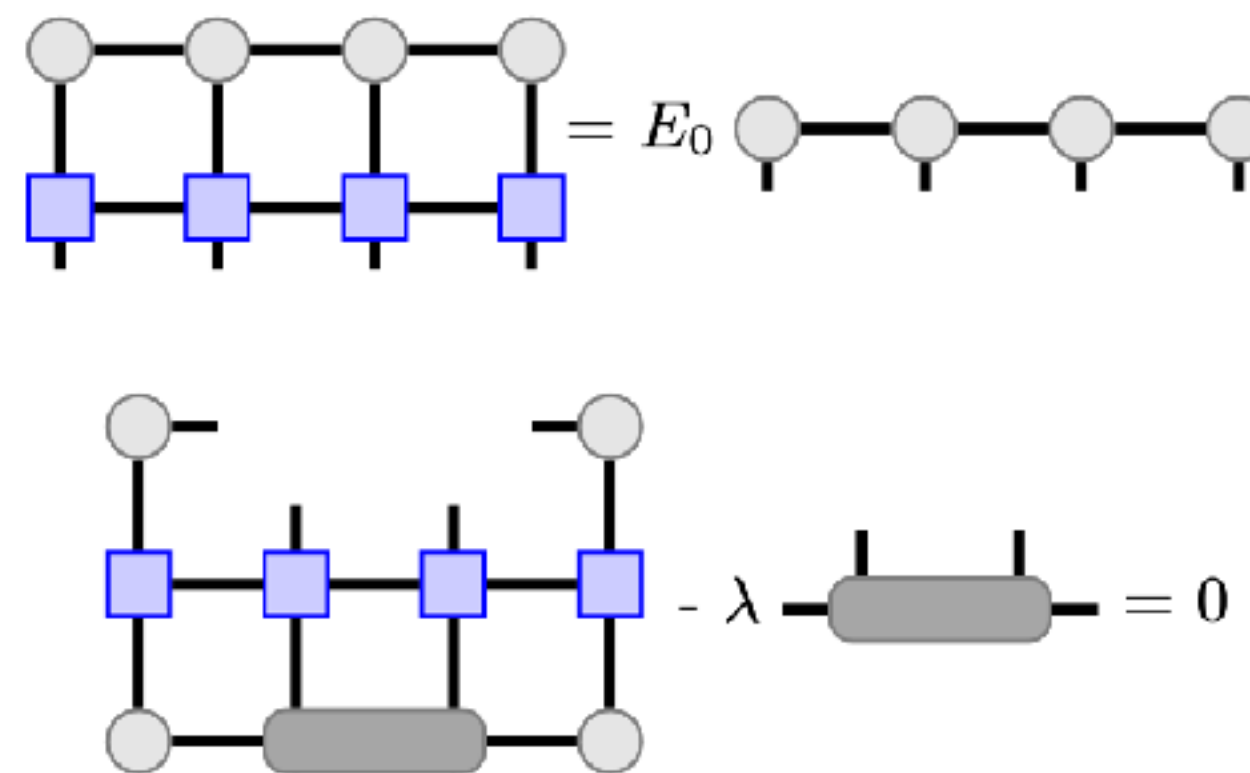
“Different minima can have the same energy but very different wave-function.”

Variational non-stabilizerness

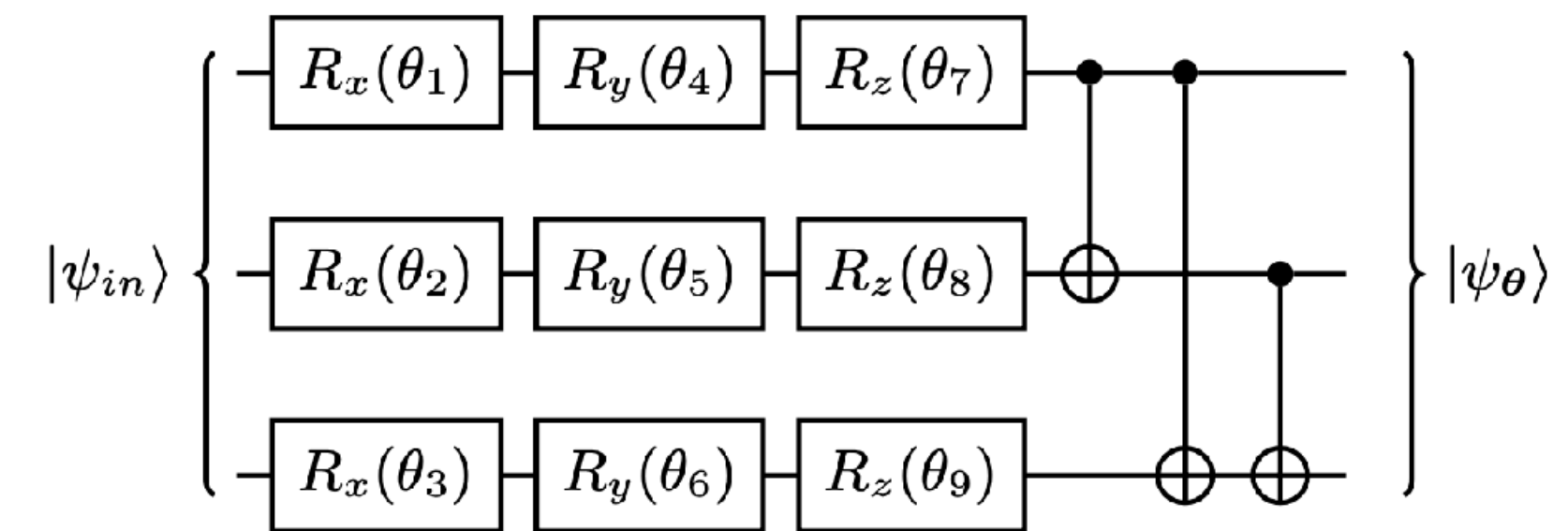
NQS



DMRG



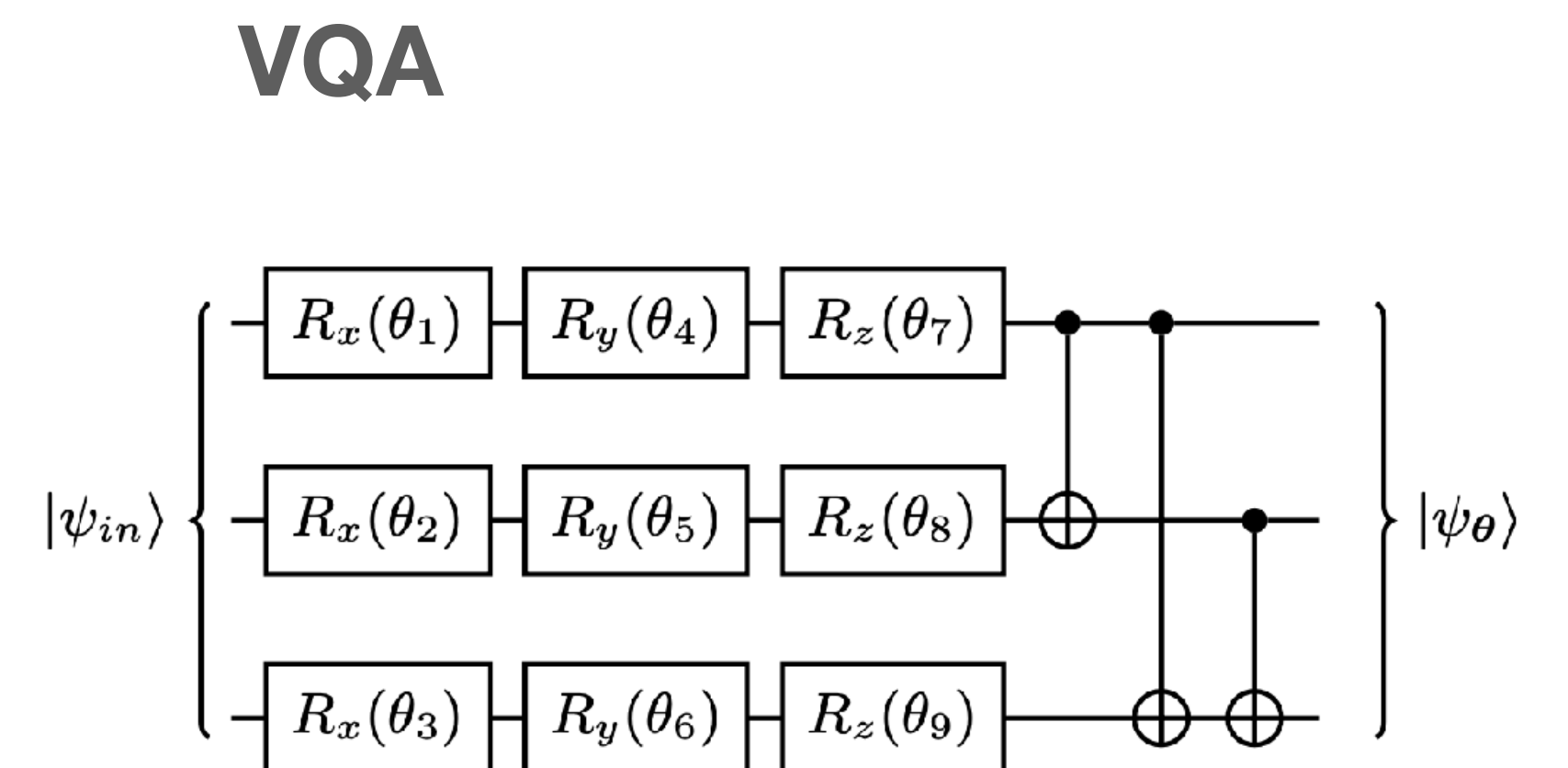
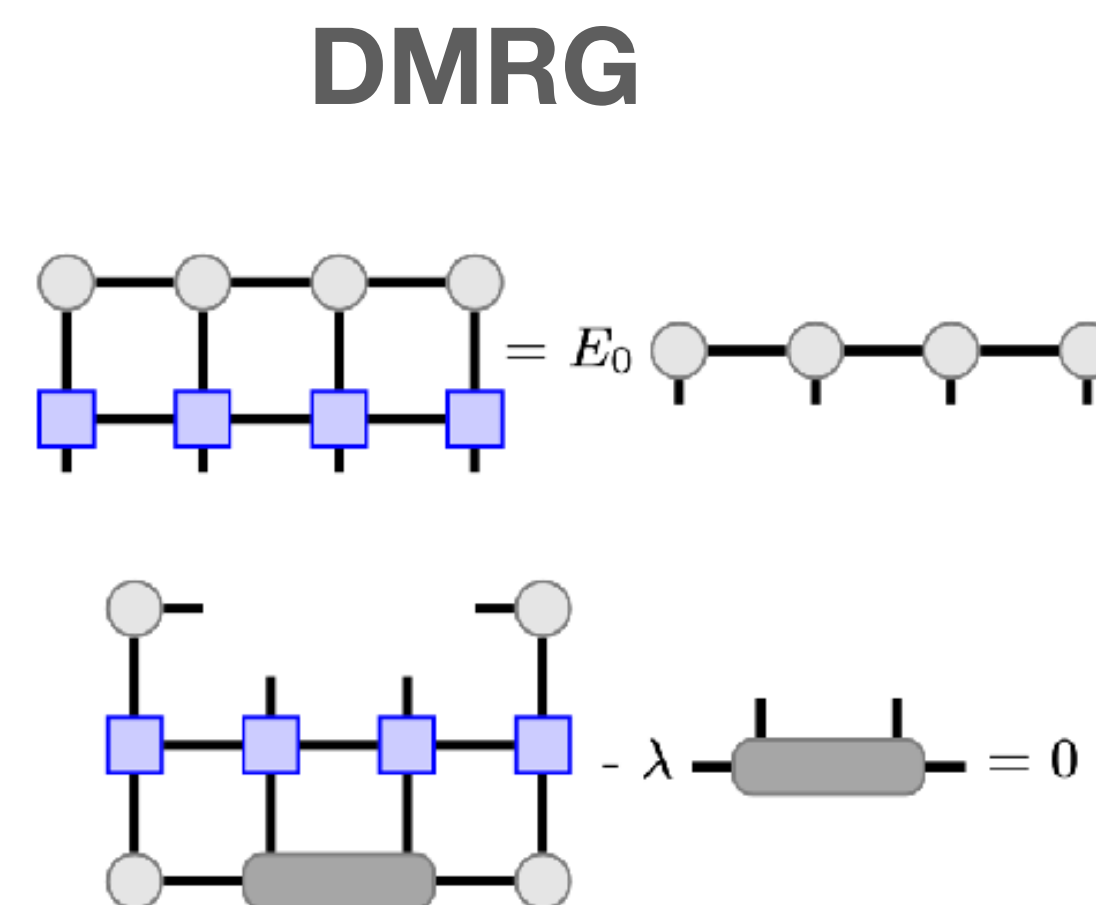
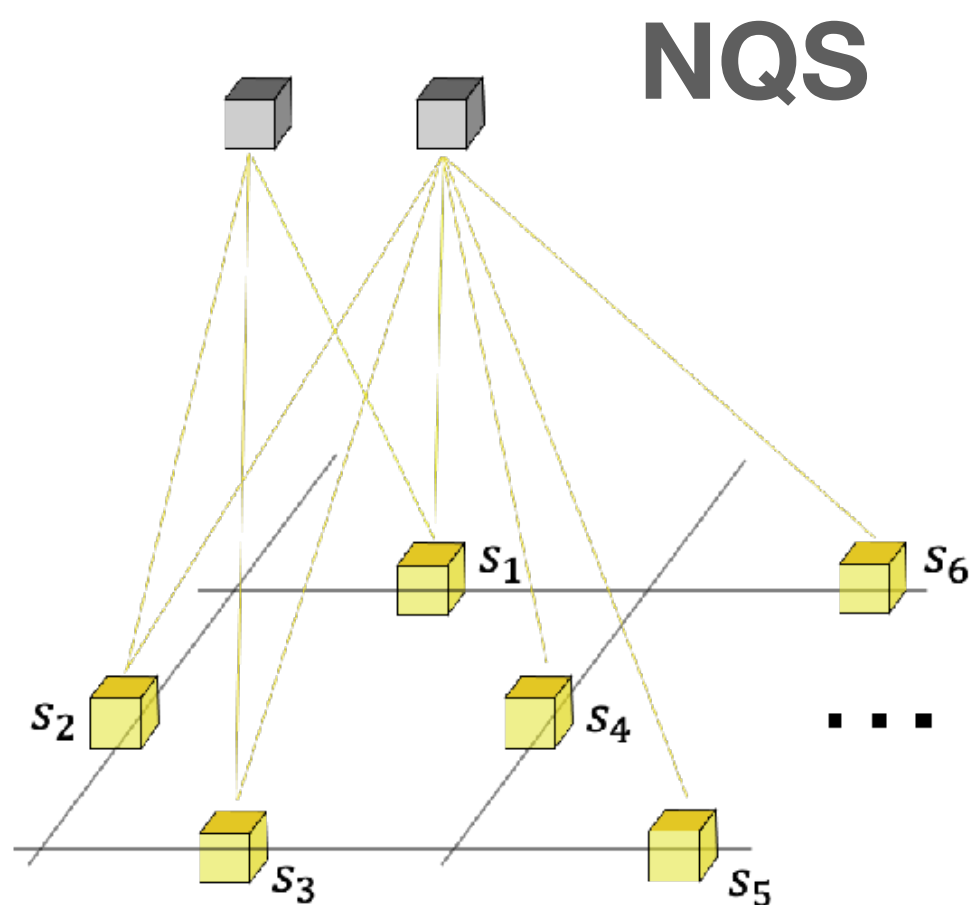
VQA



The Hamiltonian

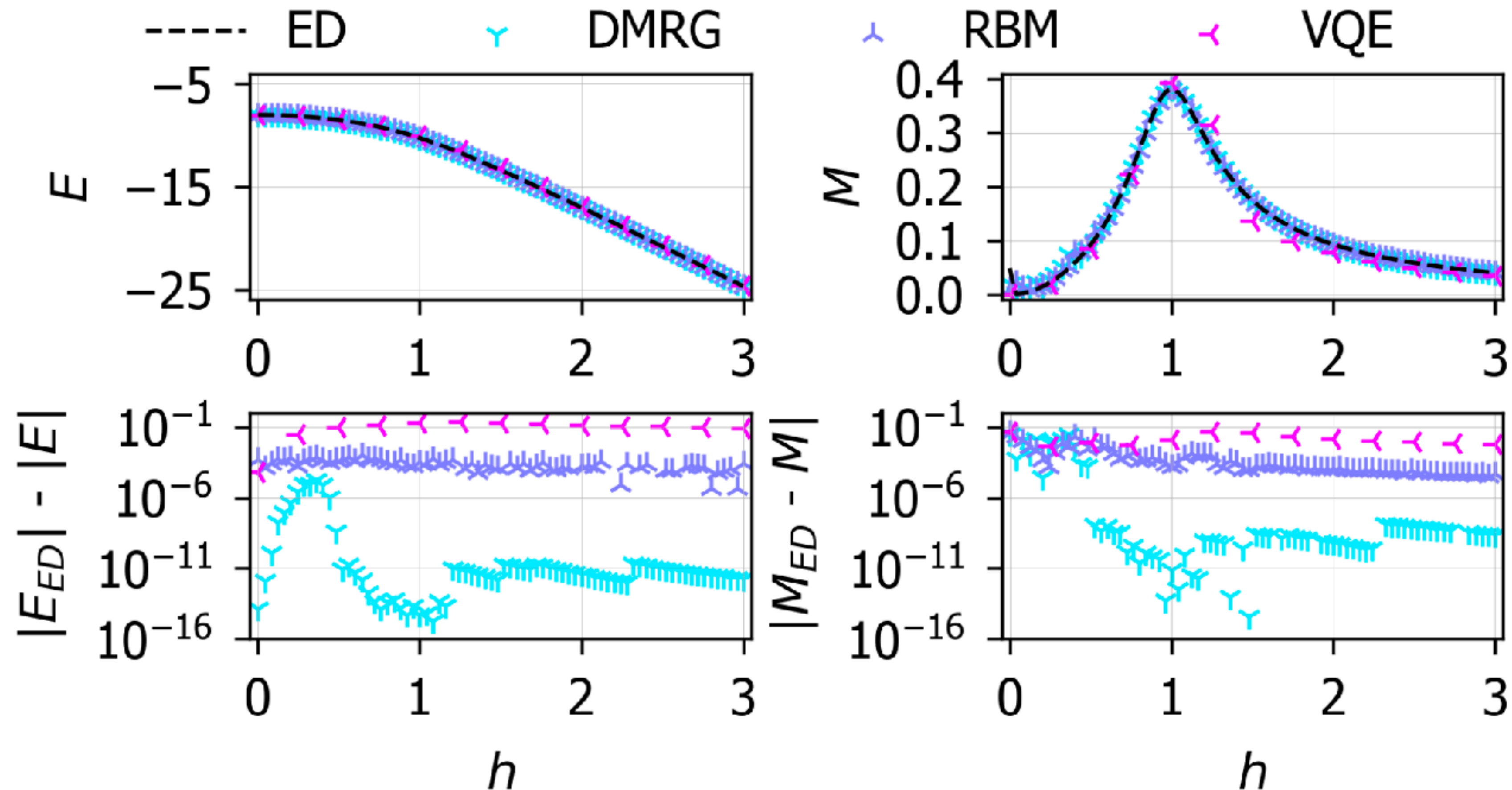
Transverse Field Ising Model

$$H = J \sum \sigma_i^z \sigma_{i+1}^z - h \sum \sigma_i^x$$



Variational non-stabilizerness

$$H = J \sum \sigma_i^z \sigma_{i+1}^z - h \sum \sigma_i^x$$



Better Energy = Better Magic?

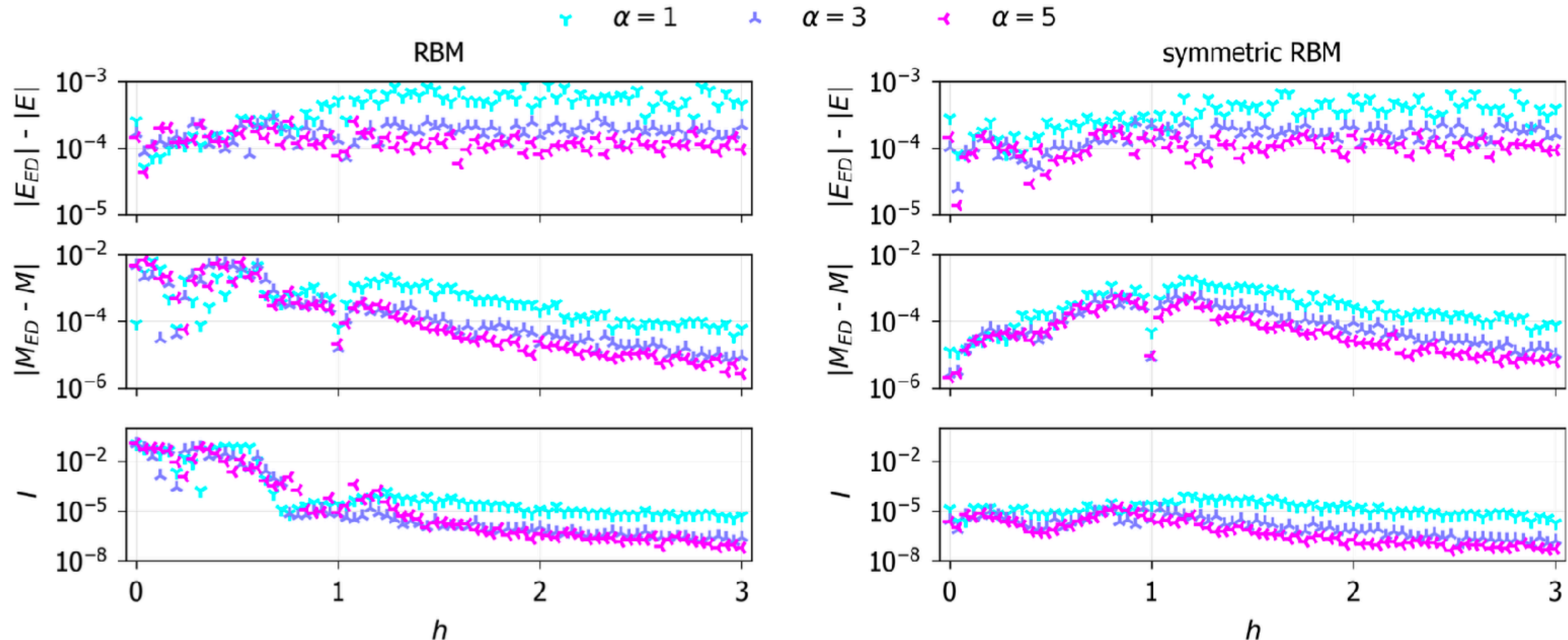
Spoiler: It's more complicated!

Better Energy = Better Magic?

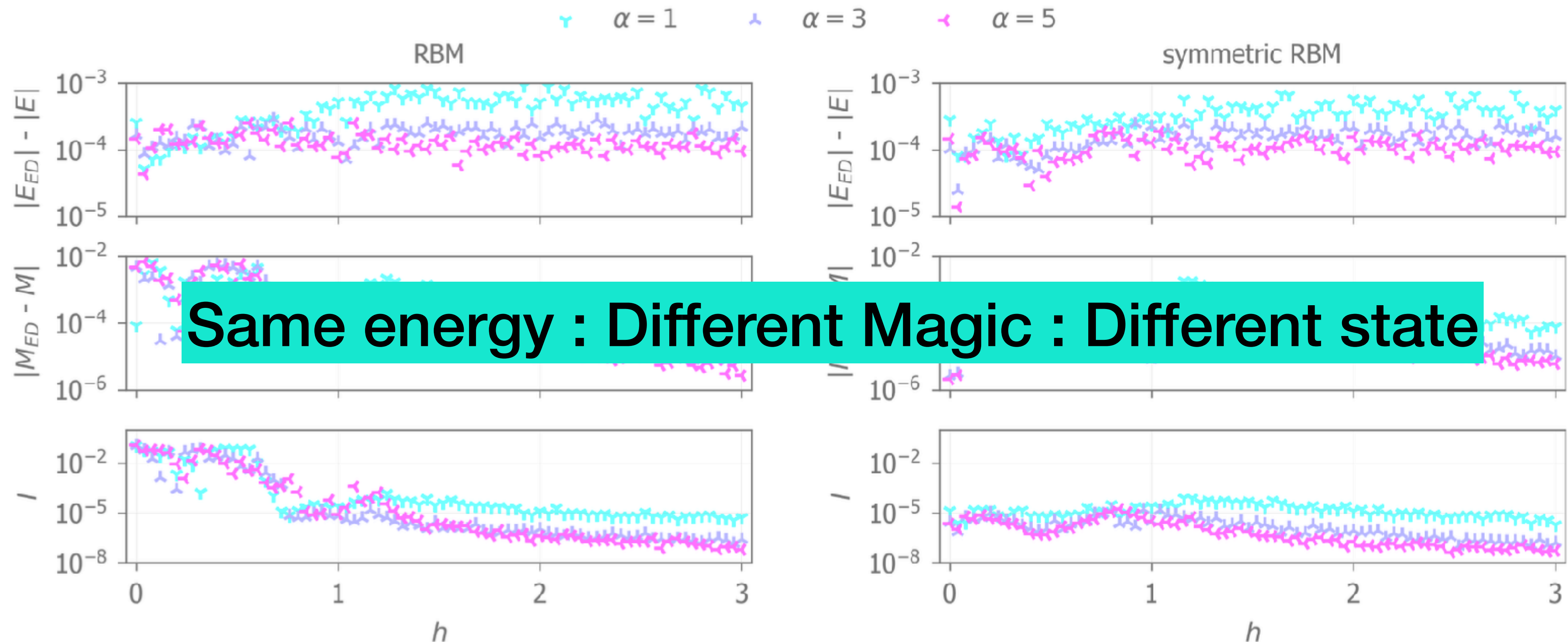
Spoiler: It's more complicated!

“Global Z_2 Symmetry: If I flip all spins, the state has the same energy.”

Better Energy = Better Magic ?



Better Energy = Better Magic ?



Non-stabilizerness of Neural Quantum States

Alessandro Sinibaldi,^{1,2,*} Antonio Francesco Mello,^{3,4,†} Mario Collura,^{3,5} and Giuseppe Carleo^{1,2}

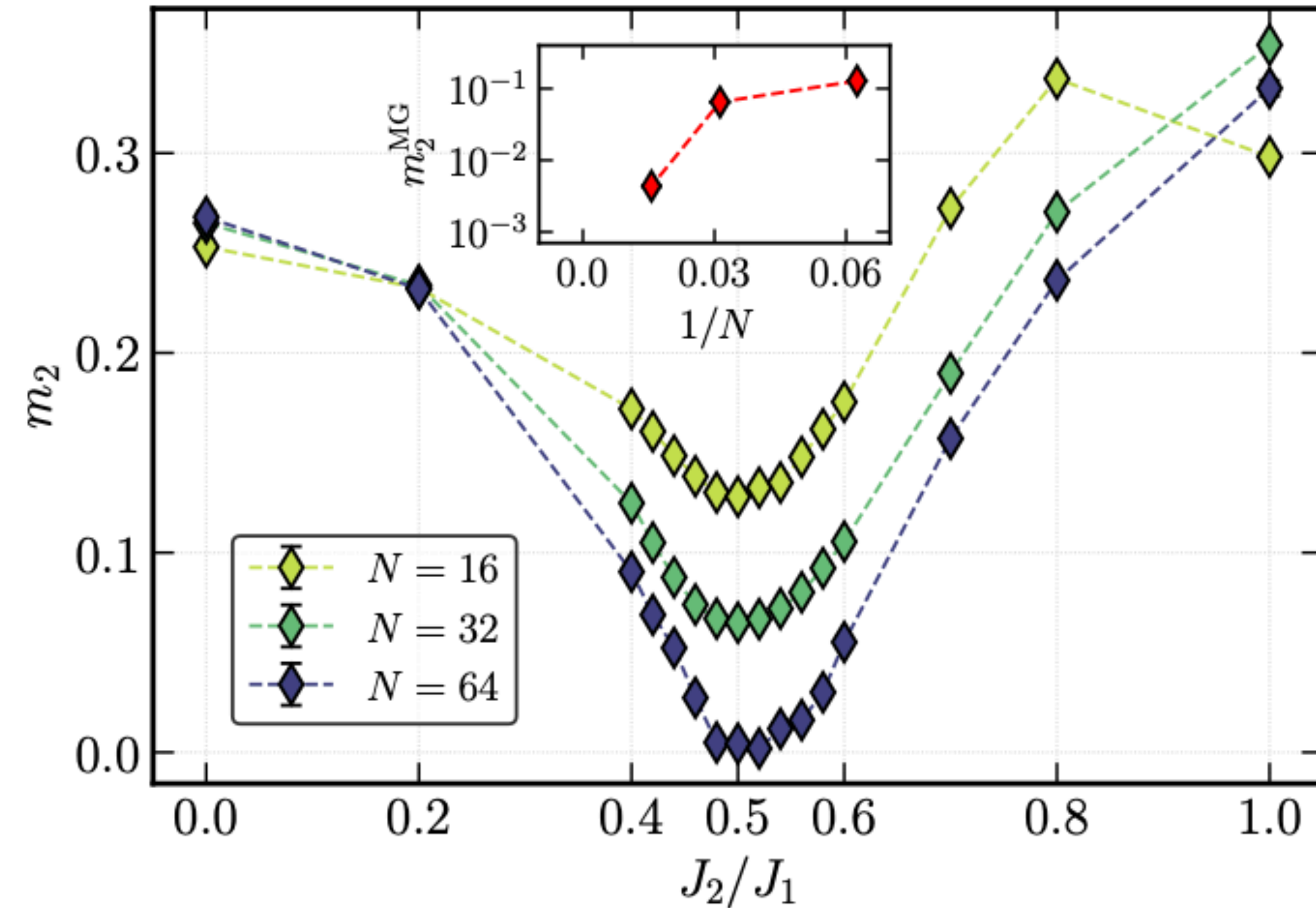
¹*Institute of Physics, École Polytechnique Fédérale de Lausanne (EPFL), CH-1015 Lausanne, Switzerland*

²*Center for Quantum Science and Engineering, EPFL, Lausanne, Switzerland*

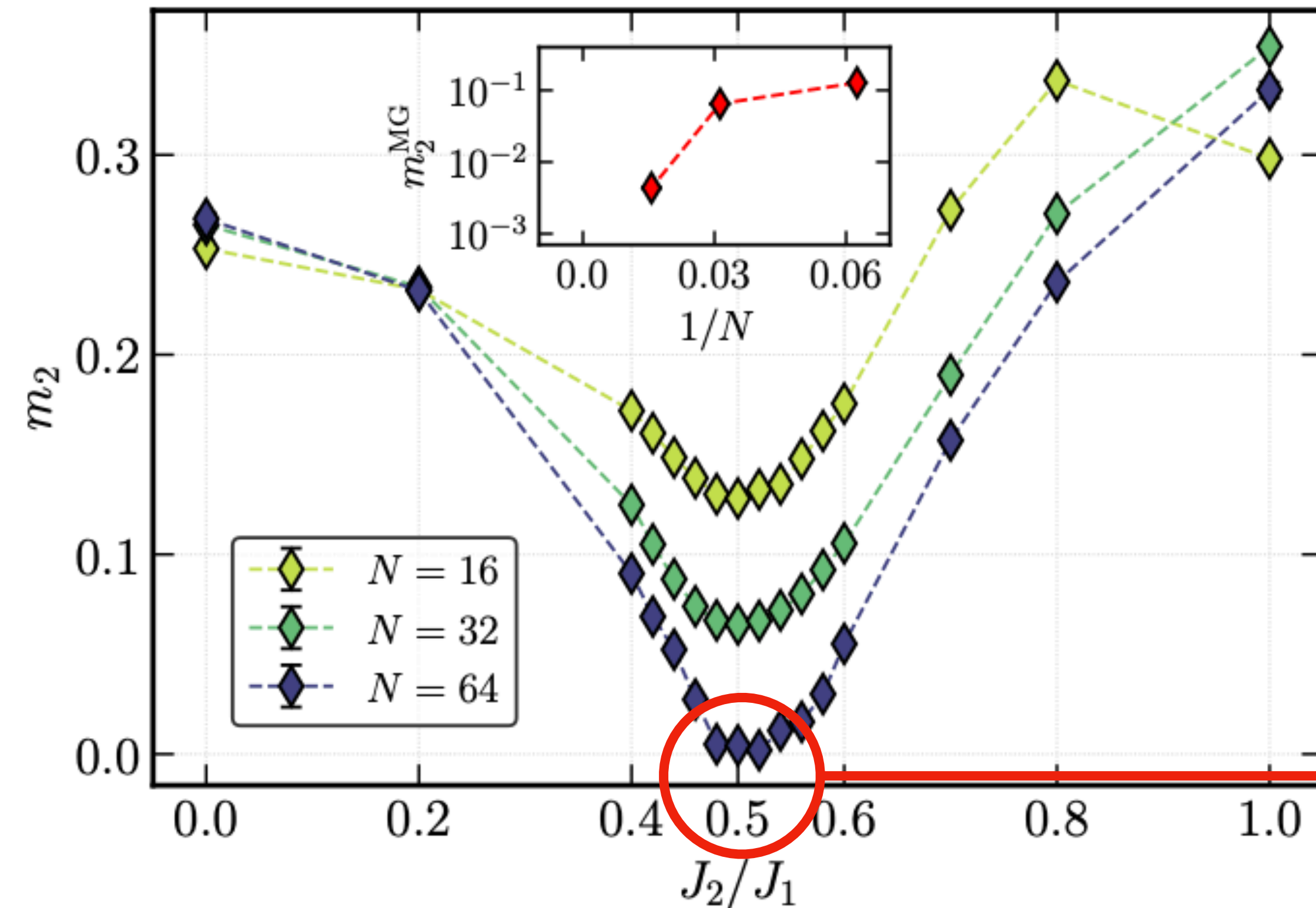
³*International School for Advanced Studies (SISSA), Via Bonomea 265, I-34136 Trieste, Italy*

⁴*Center for Computational Quantum Physics, Flatiron Institute, 162 5th Avenue, New York, NY 10010*

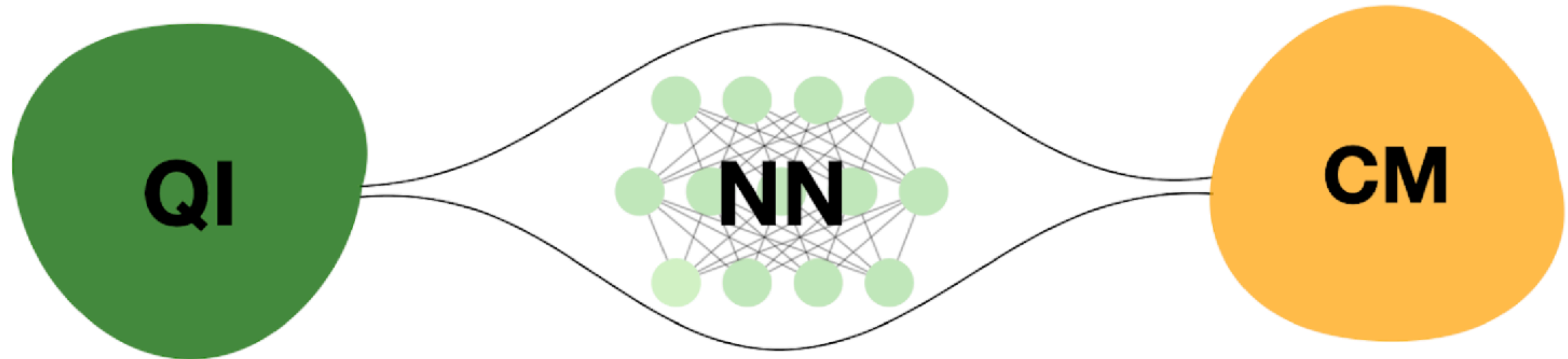
⁵*INFN, Sezione di Trieste, Via Valerio 2, 34127 Trieste, Italy*



Non-stabilizerness of Neural Quantum States

Alessandro Sinibaldi,^{1,2,*} Antonio Francesco Mello,^{3,4,†} Mario Collura,^{3,5} and Giuseppe Carleo^{1,2}¹*Institute of Physics, École Polytechnique Fédérale de Lausanne (EPFL), CH-1015 Lausanne, Switzerland*²*Center for Quantum Science and Engineering, EPFL, Lausanne, Switzerland*³*International School for Advanced Studies (SISSA), Via Bonomea 265, I-34136 Trieste, Italy*⁴*Center for Computational Quantum Physics, Flatiron Institute, 162 5th Avenue, New York, NY 10010*⁵*INFN, Sezione di Trieste, Via Valerio 2, 34127 Trieste, Italy*THIS IS IN A
STABILIZER GROUP!

The Message.



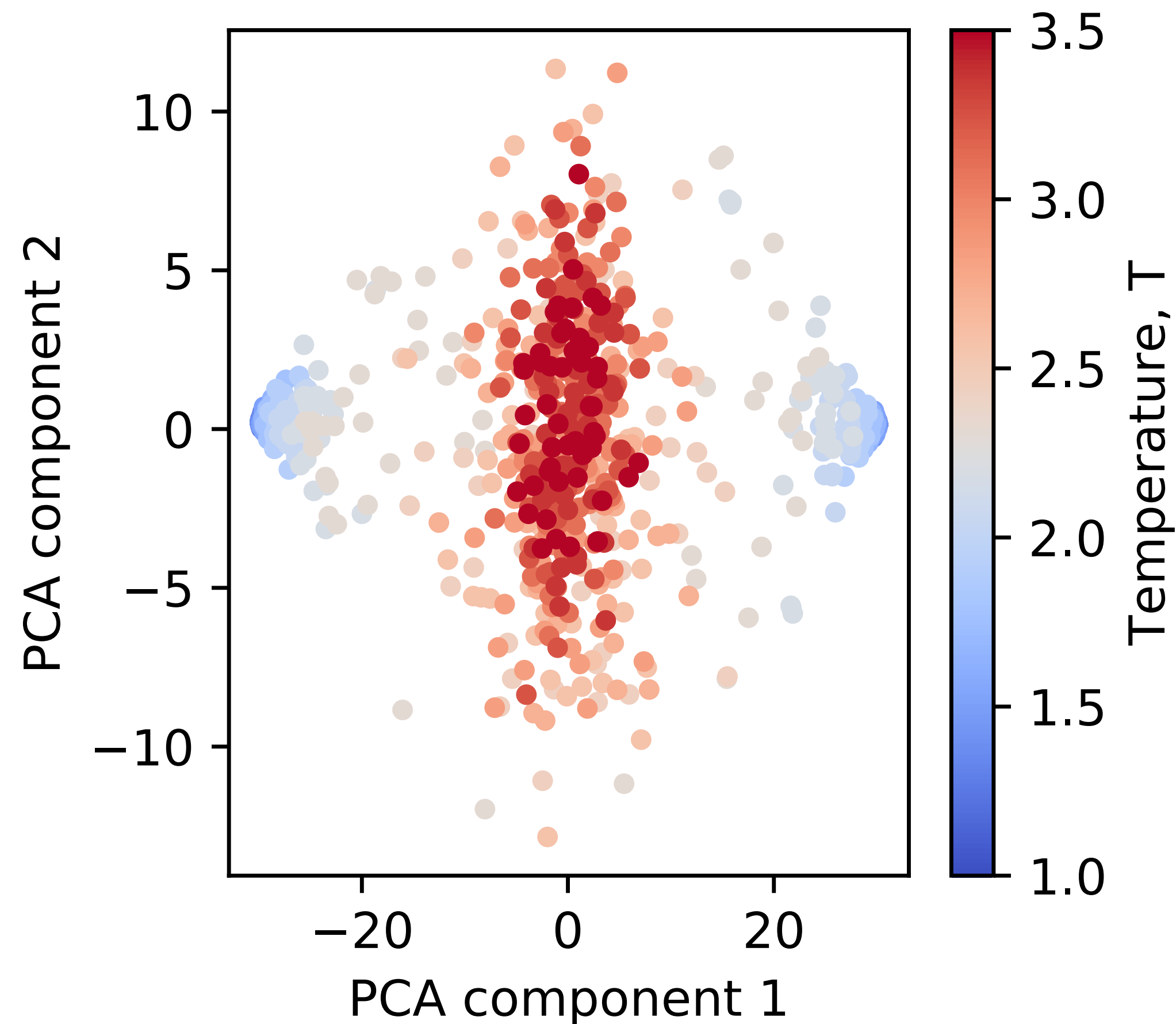
💡 Computational overlap of QI and CM is largely unexplored - let's discuss and think of new ideas! 💡

Part 2:

Can we train neural networks to learn useful interpretable quantities?



Phase Classification

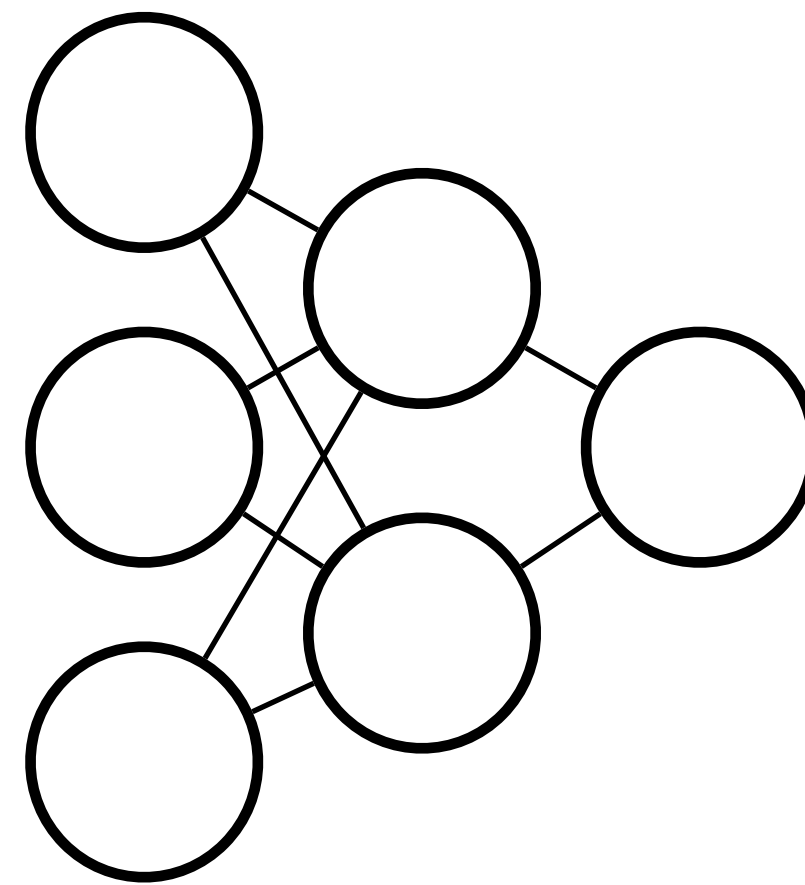


$$H = -J \sum_{\langle i,j \rangle} \sigma_i \sigma_j$$

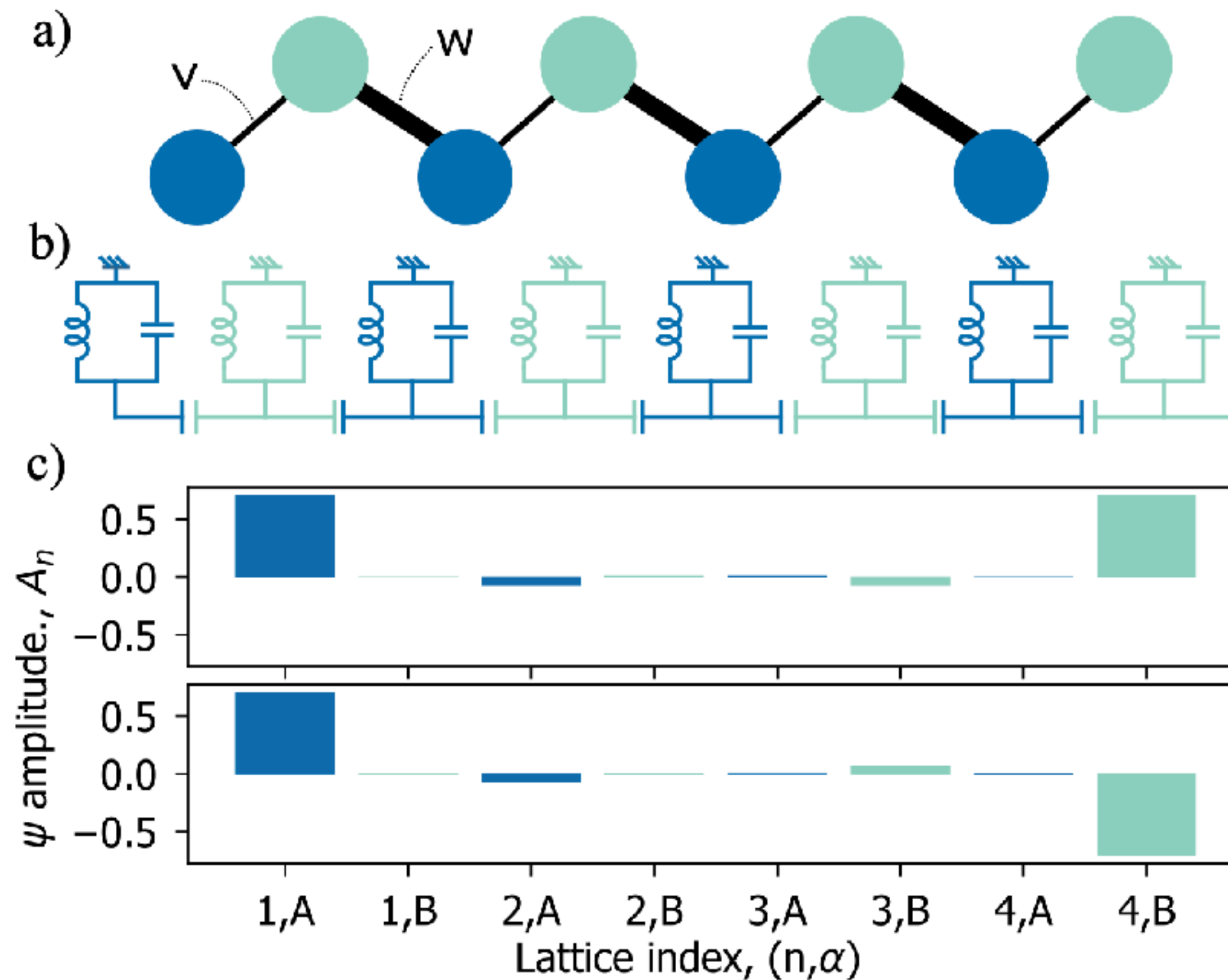
$$p(\sigma) = \frac{e^{-\beta H(\sigma)}}{Z}$$

$$T_c = \frac{2J}{k \ln(1 + \sqrt{2})} \sim 2.27$$

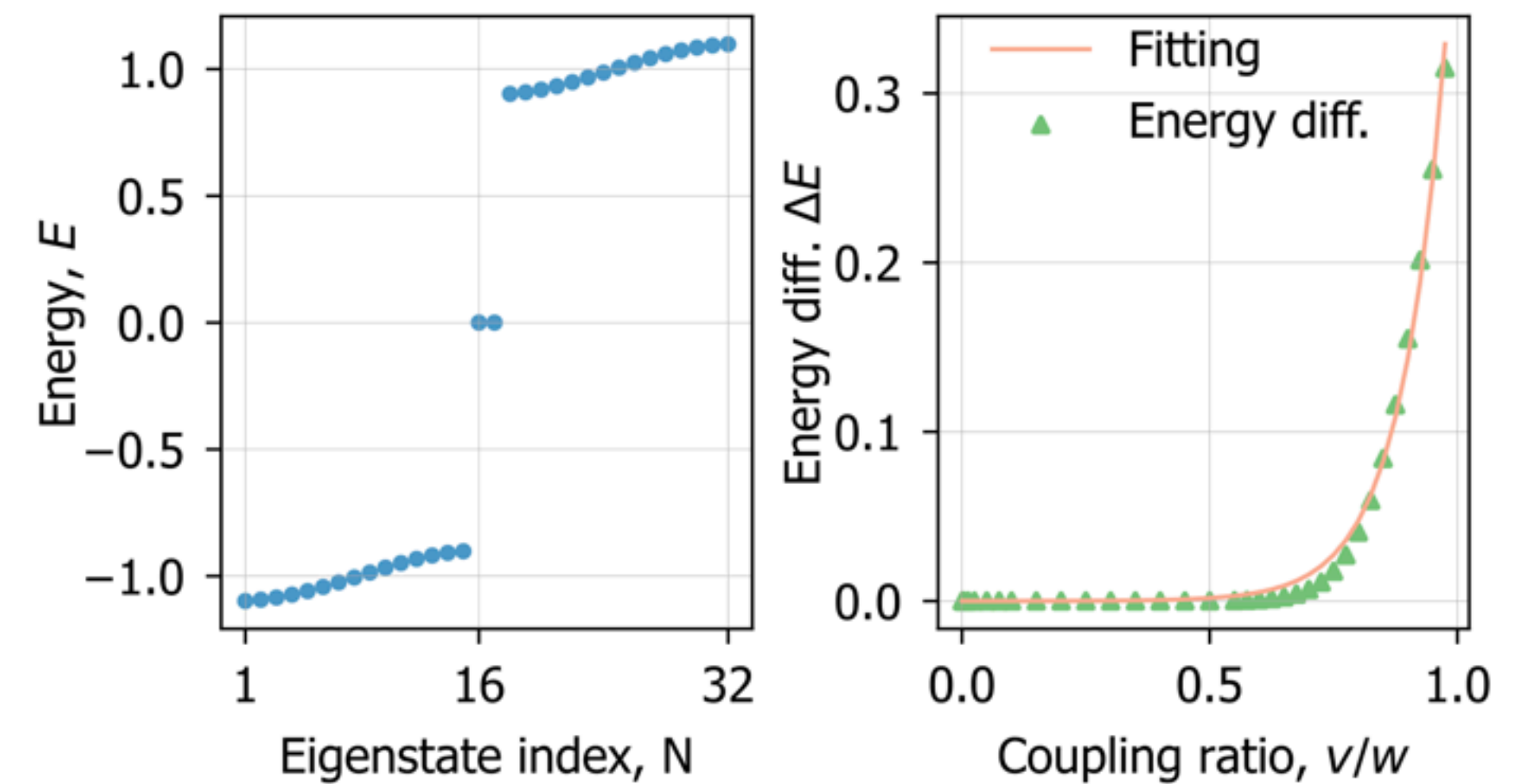
AI Image Classification



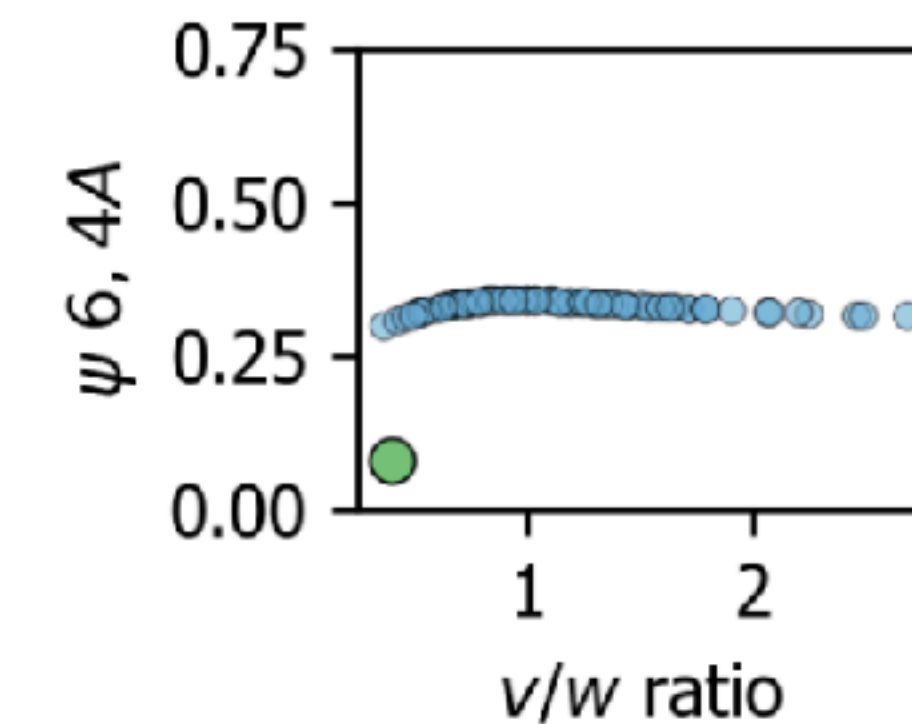
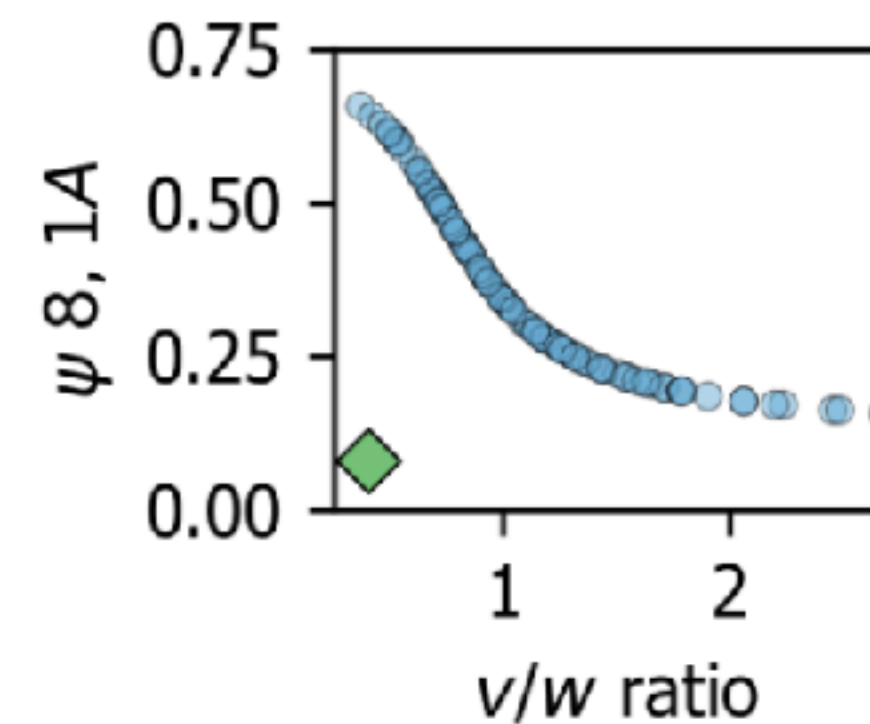
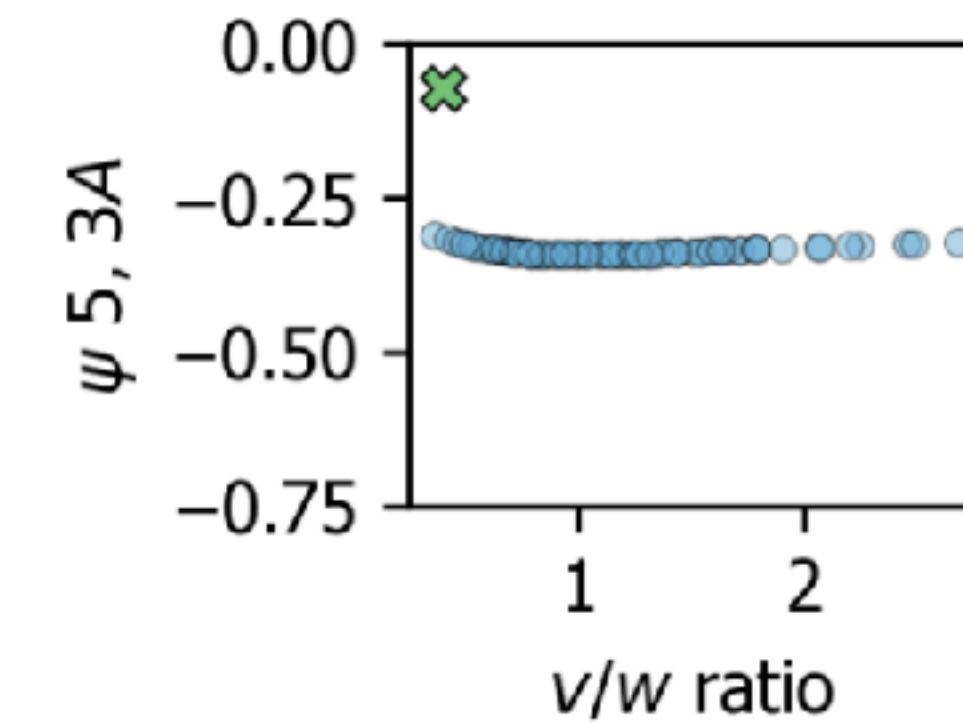
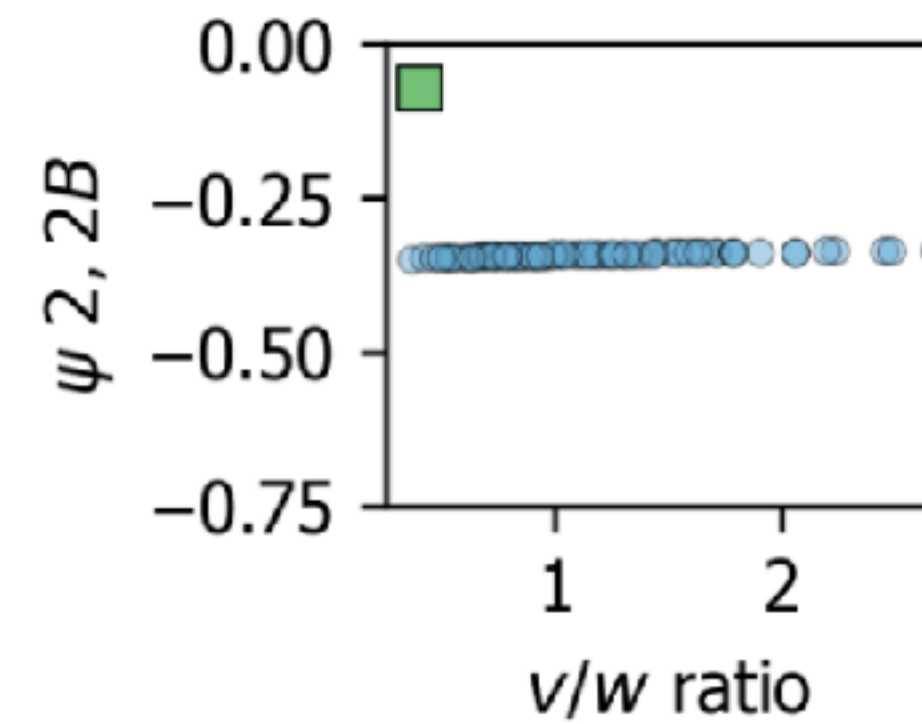
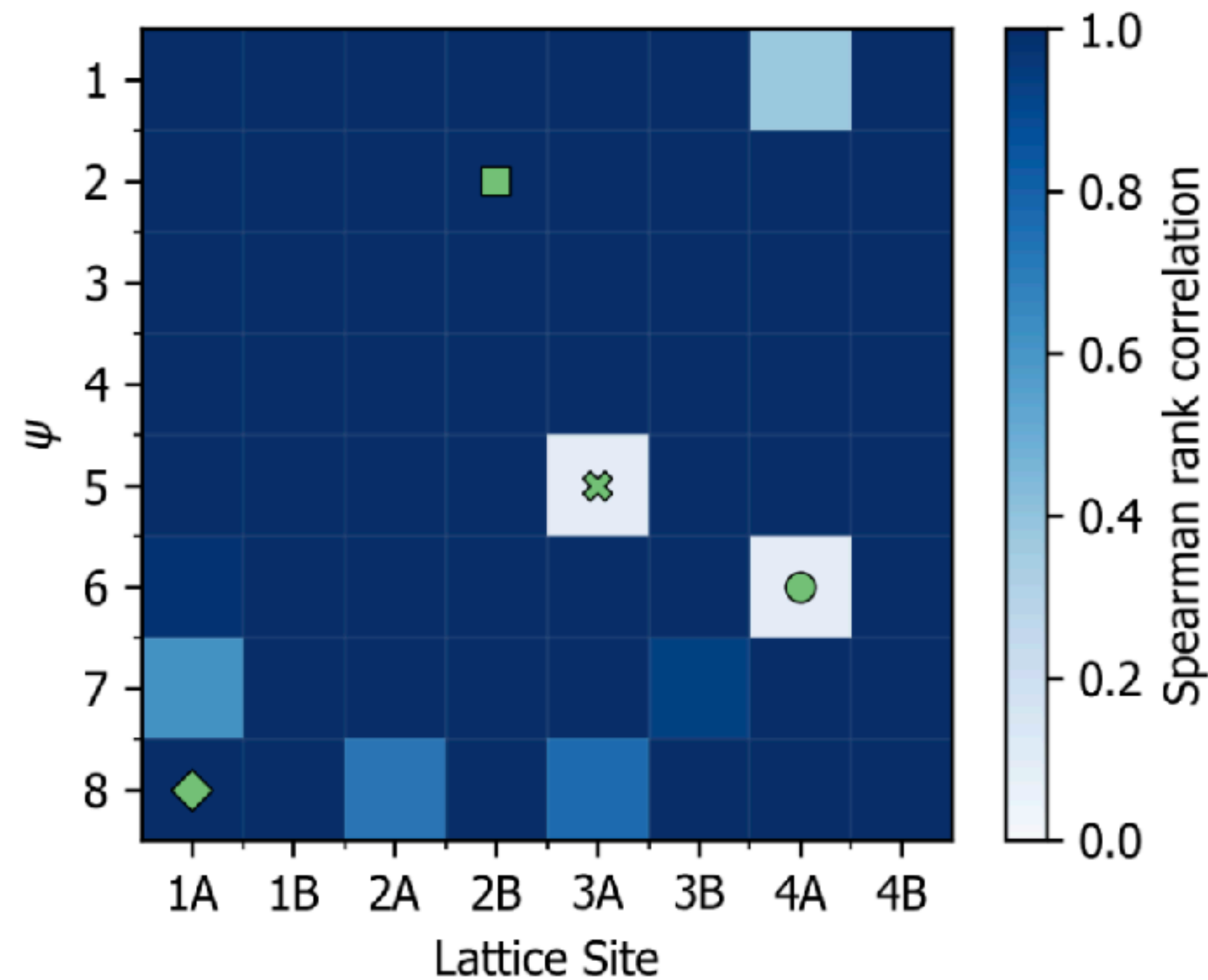
SSH: Adding topology into the mix



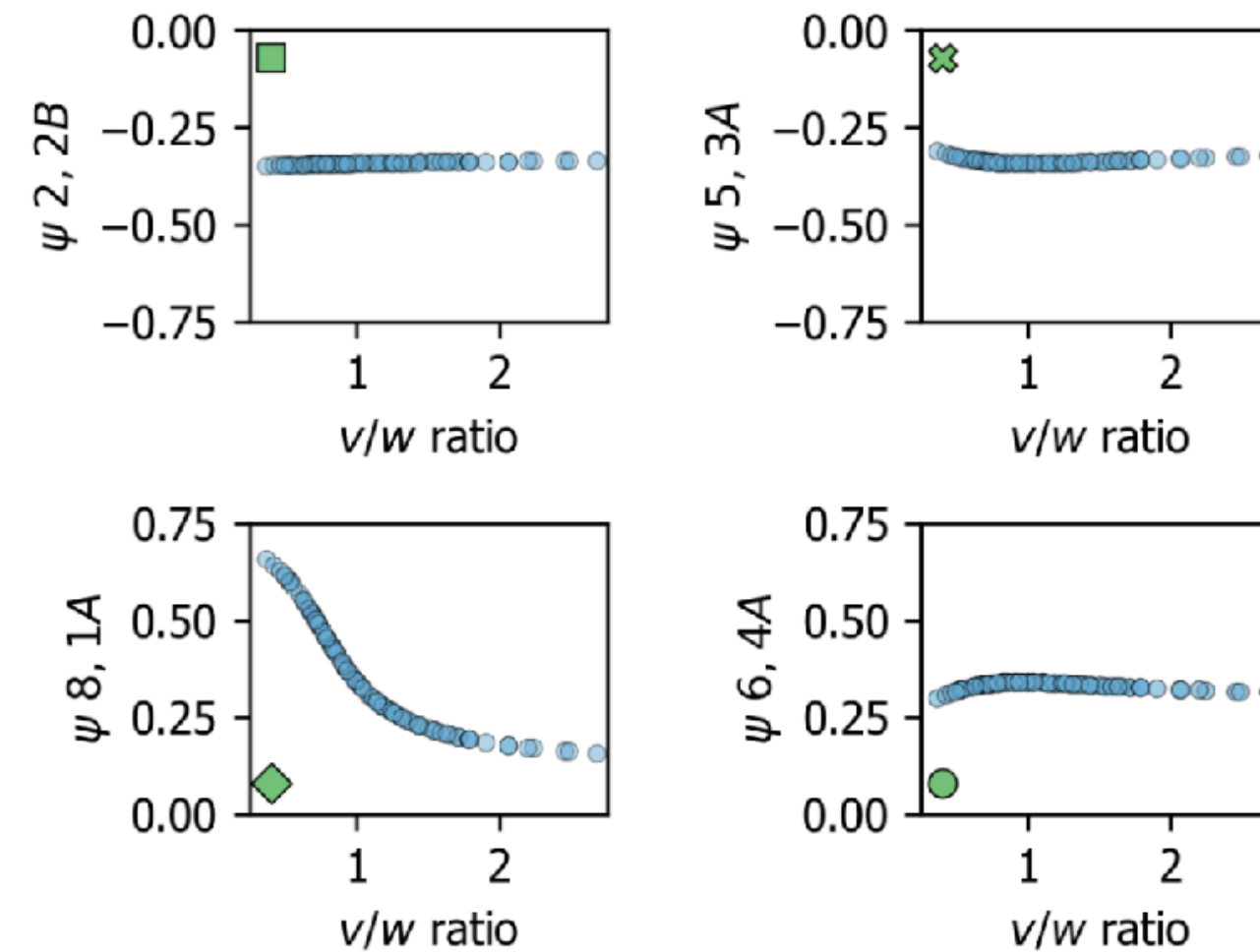
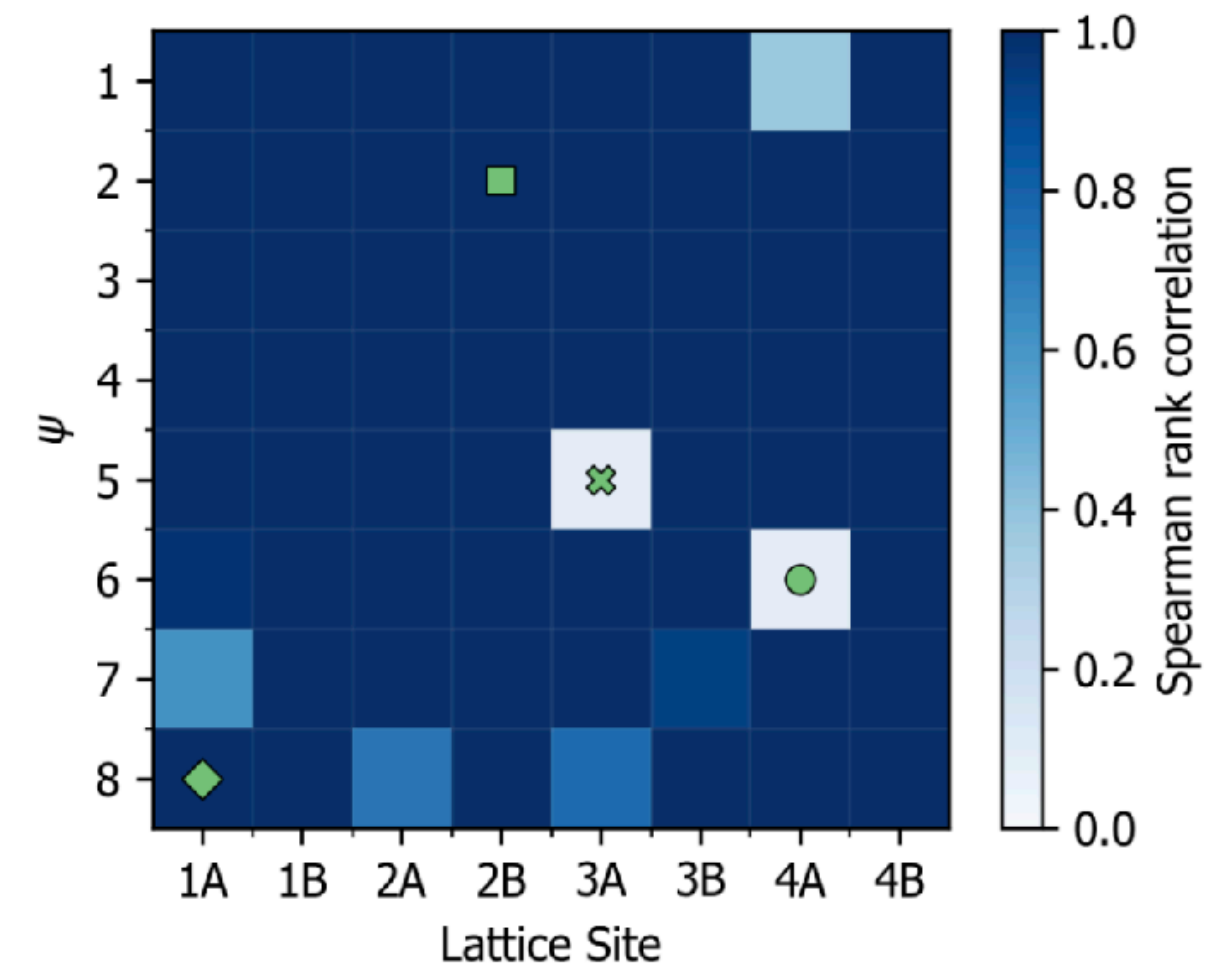
$$H = \sum_{n=1}^N (v_n c_{n,A}^\dagger c_{n,B} + w_n c_{n,B}^\dagger c_{n+1,A} + h.c.)$$



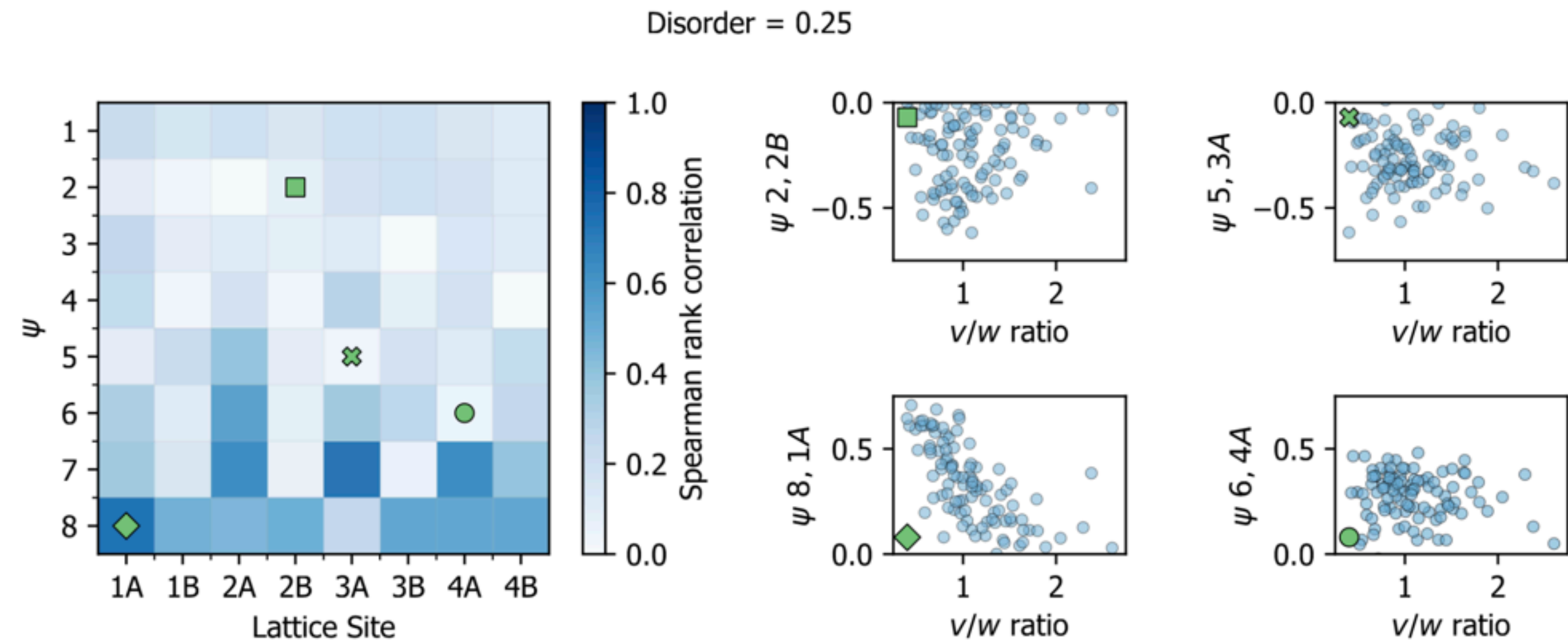
SSH: Learning the PT is **super** easy



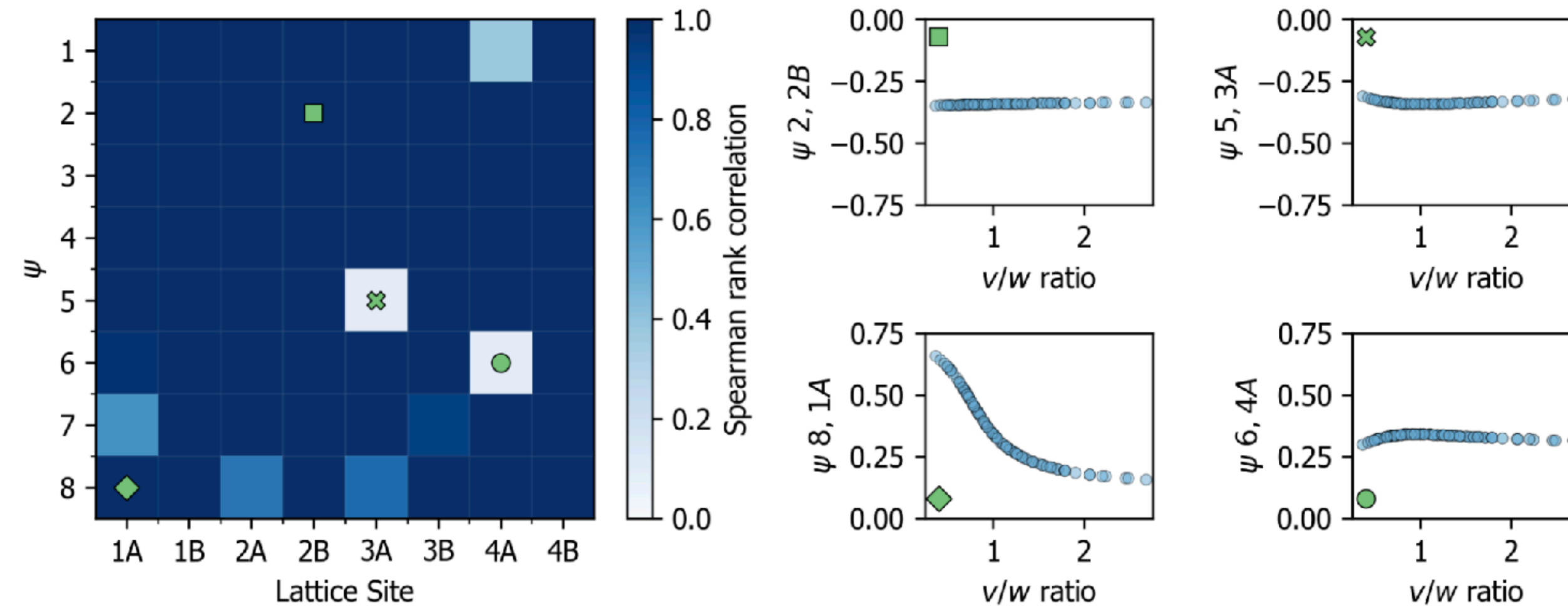
But the easy classification method



does not
generalize
well



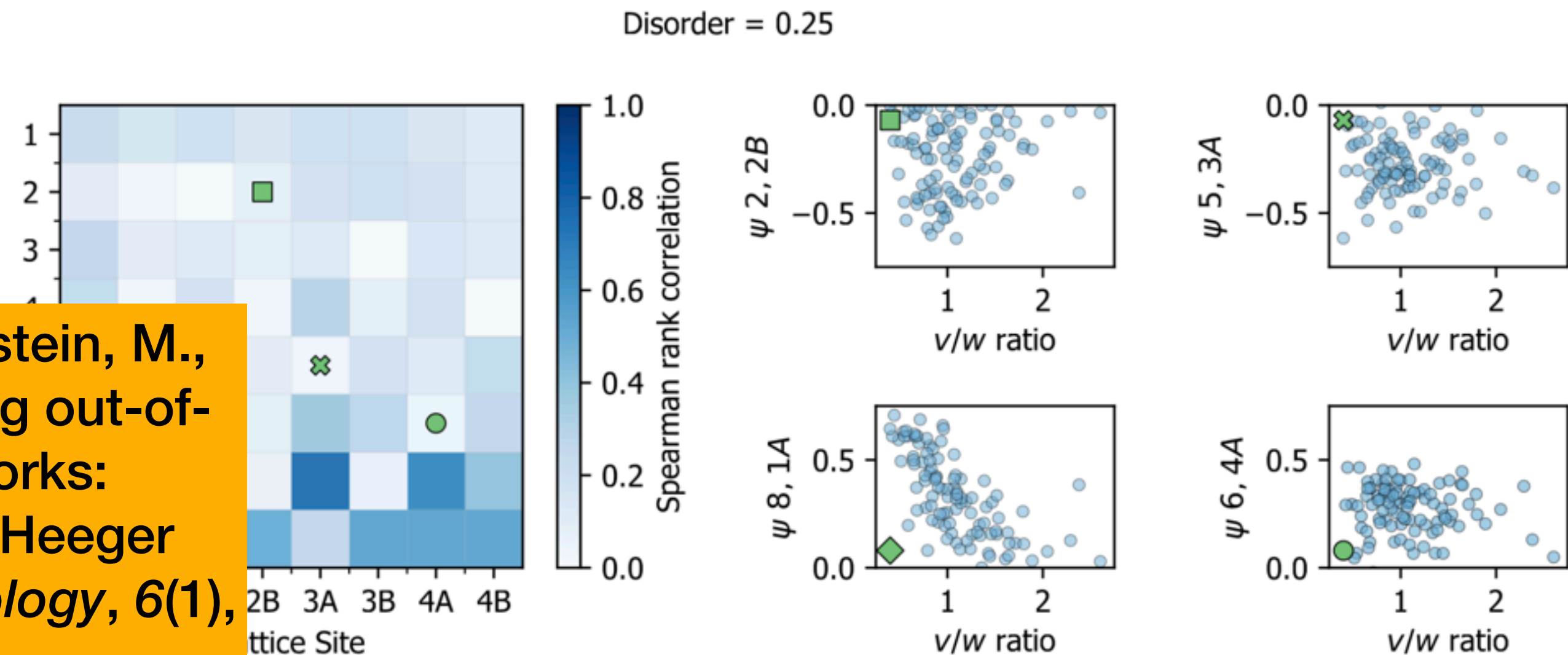
But the easy classification method



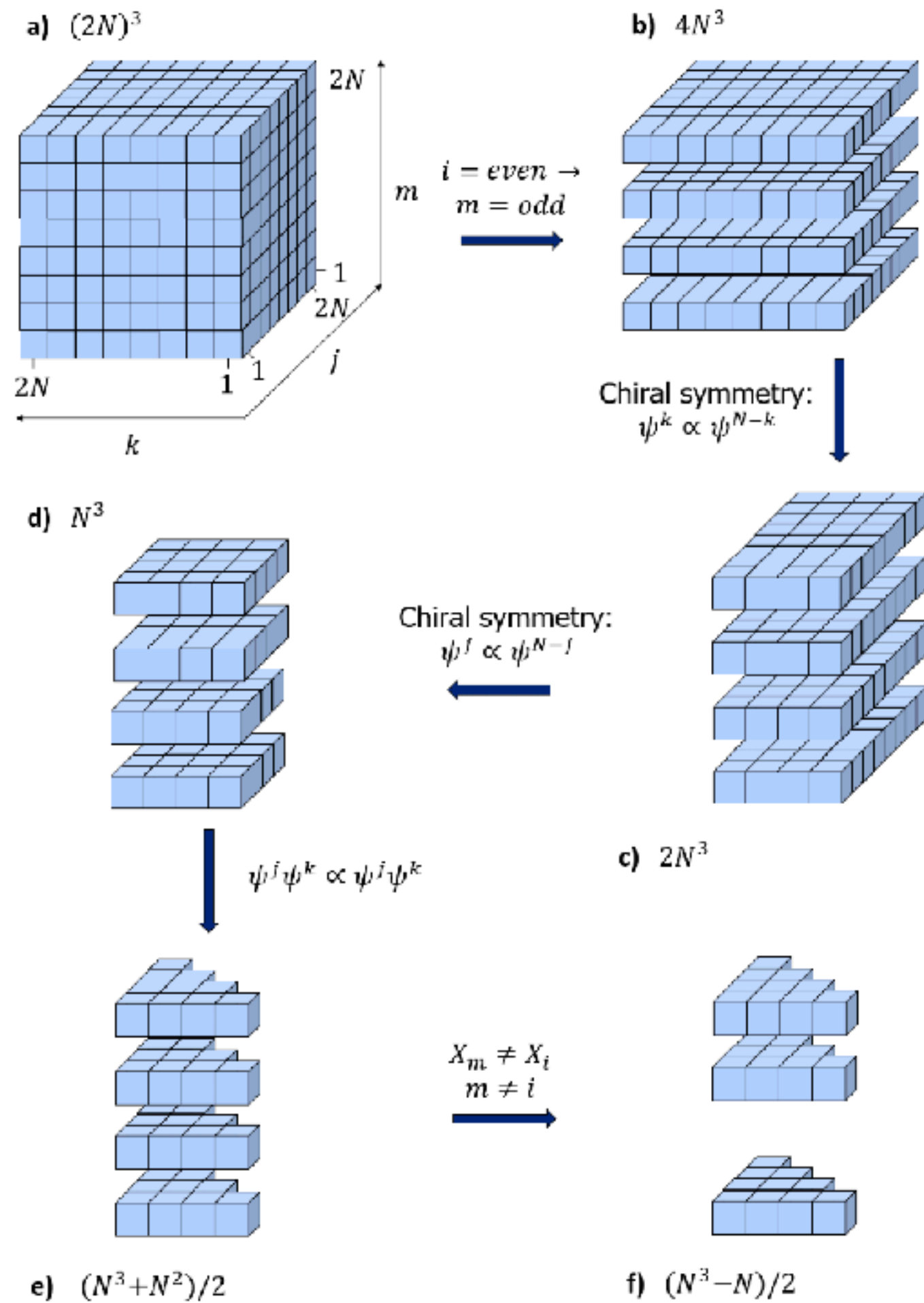
does not
generalize
well

For detailed explanation of SSH learning read this:

Cybiński, K., Płodzień, M., Tomza, M., Lewenstein, M., Dauphin, A., & Dawid, A. (2025). Characterizing out-of-distribution generalization of neural networks: application to the disordered Su–Schrieffer–Heeger model. *Machine Learning: Science and Technology*, 6(1), 015014.



Can we persuade the NN to learn topology? QMAI |



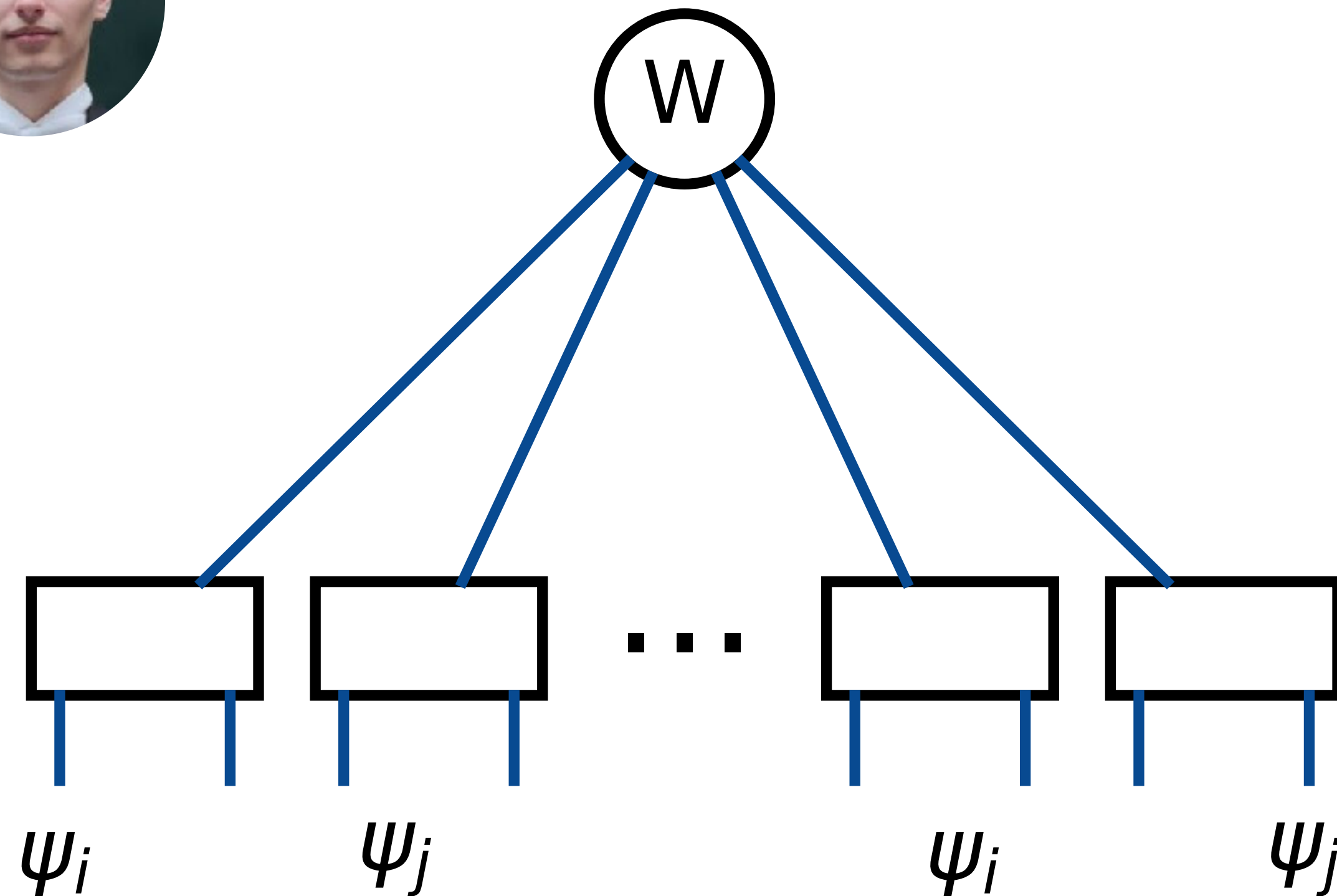
real space winding number (RSWN)

$$\nu = -\frac{1}{L} \text{Tr} \{ P_B Q P_A [X, P_A Q P_B] \}$$

Can we persuade the NN to learn topology? QMAI |

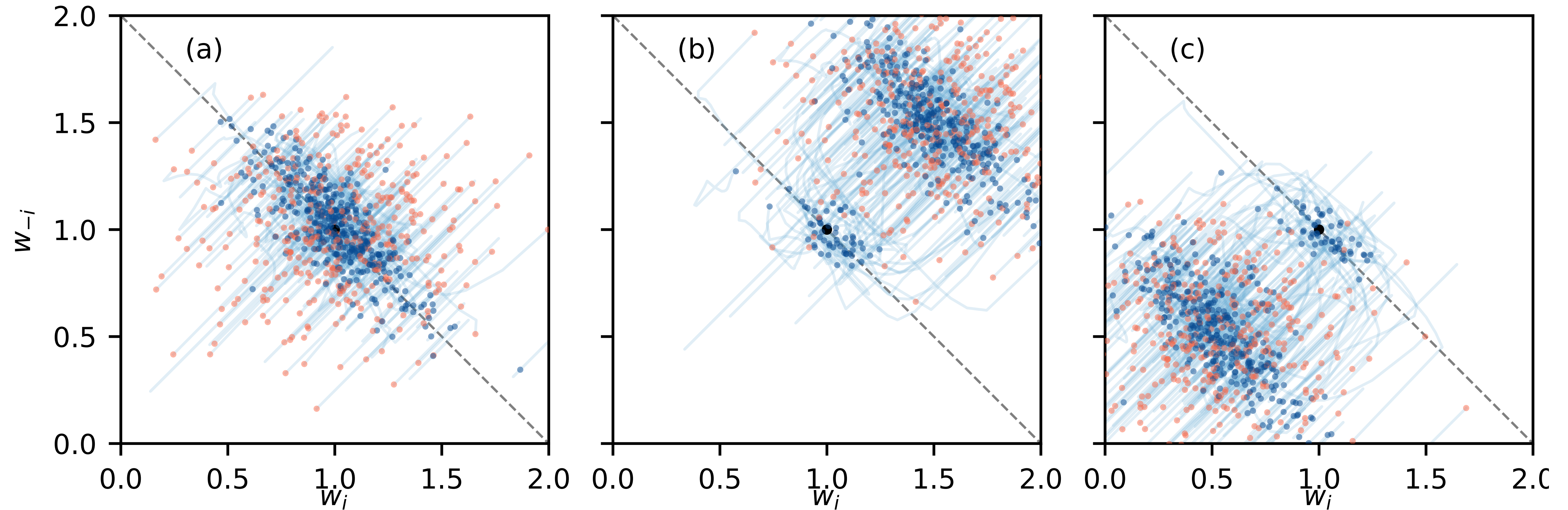


**real space winding number
(RSWN)**



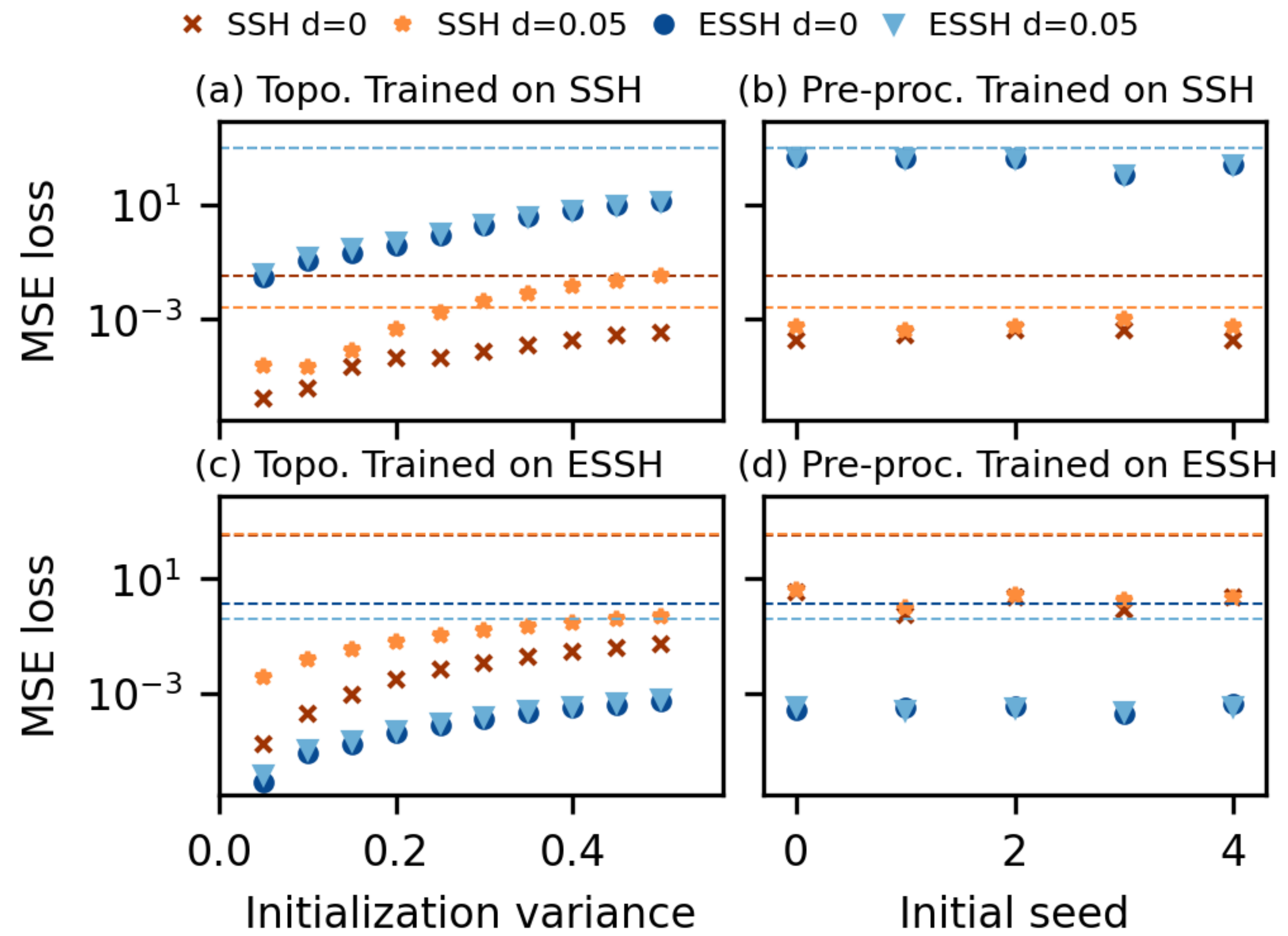
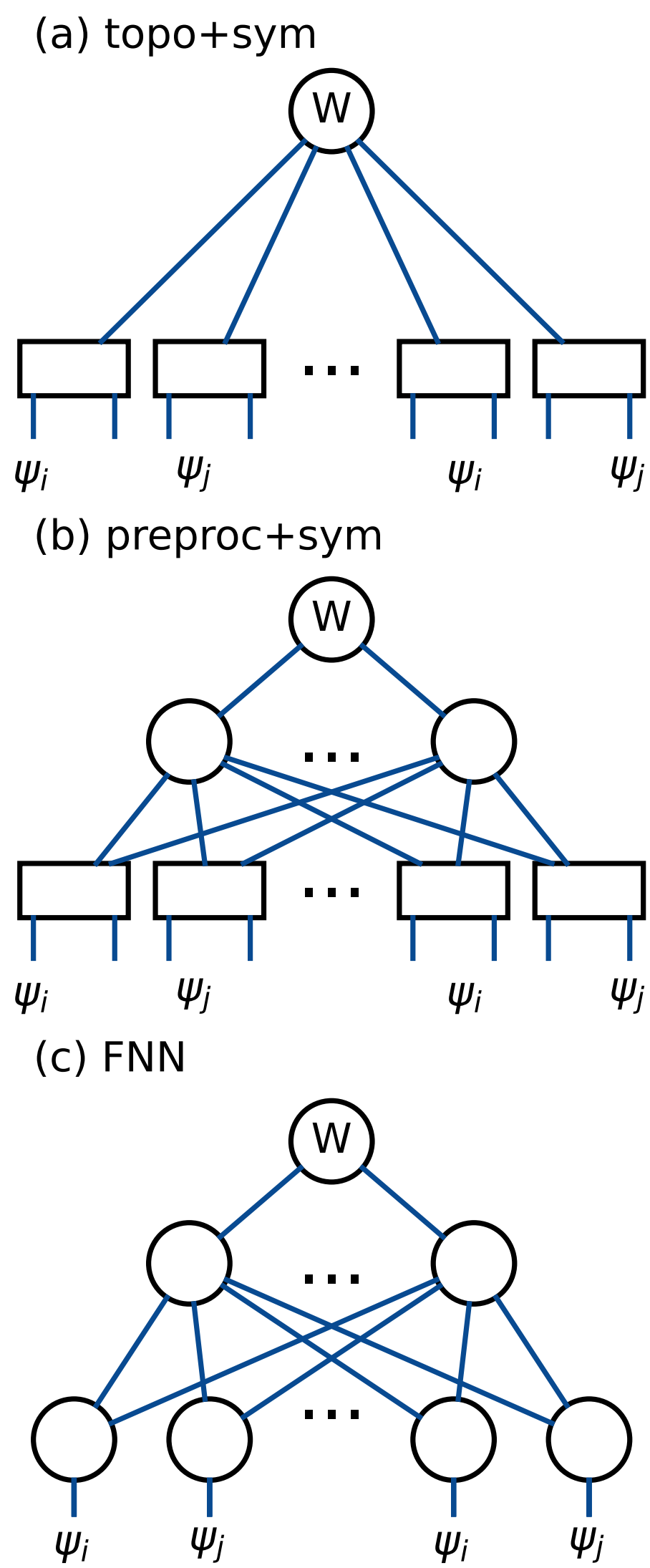
**Single layer neural
network that takes
pairs of
amplitudes and
returns RSWN**

Can we persuade the NN to learn topology? QMAI |



YES! (-ish)

Can we persuade the NN to learn topology? QMAI | TU Delft

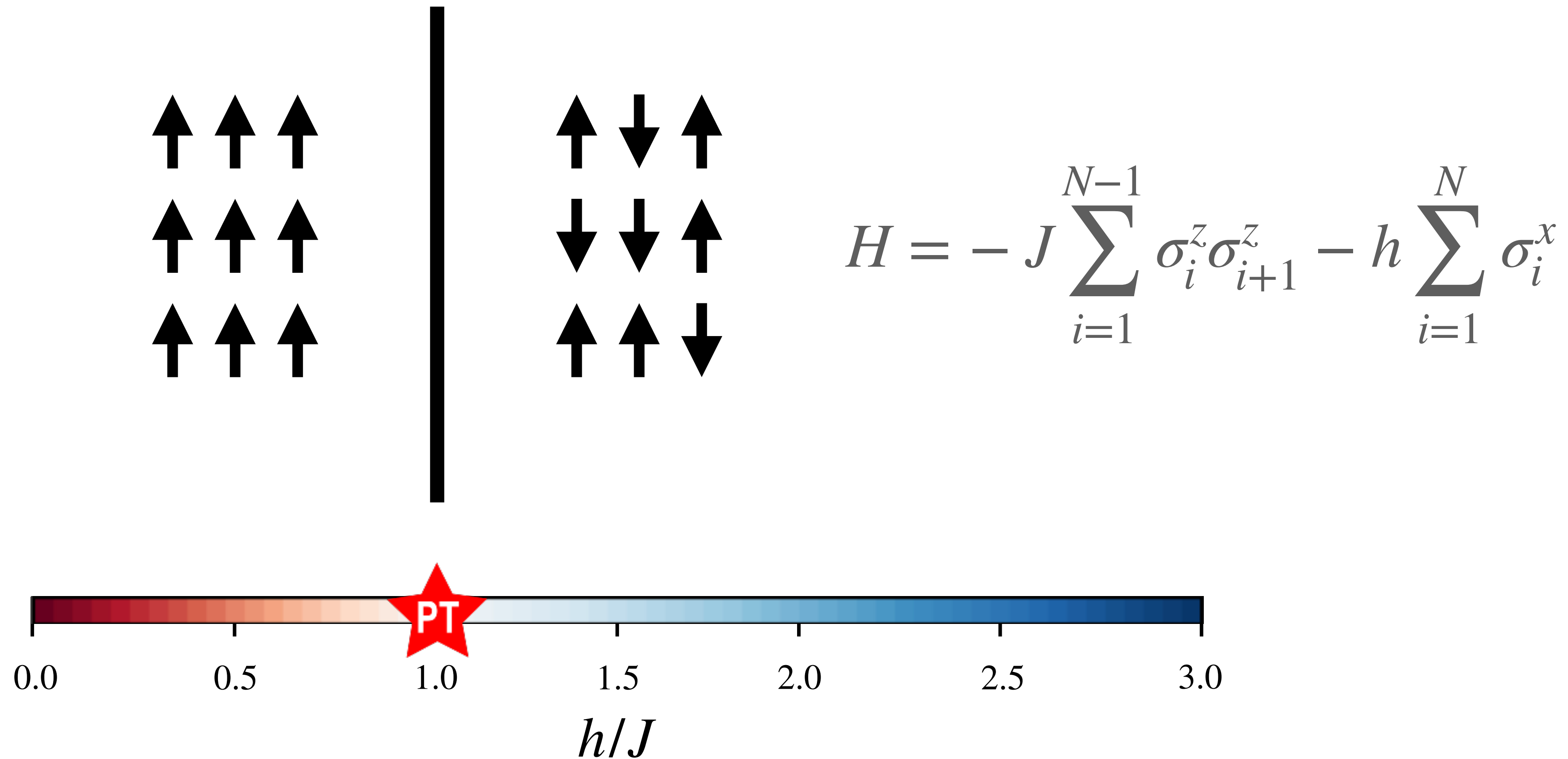


YES! (-ish)

BACK TO NQS!

Ising model

CAN WE FIND PT's IN THE WEIGHT SPACE?

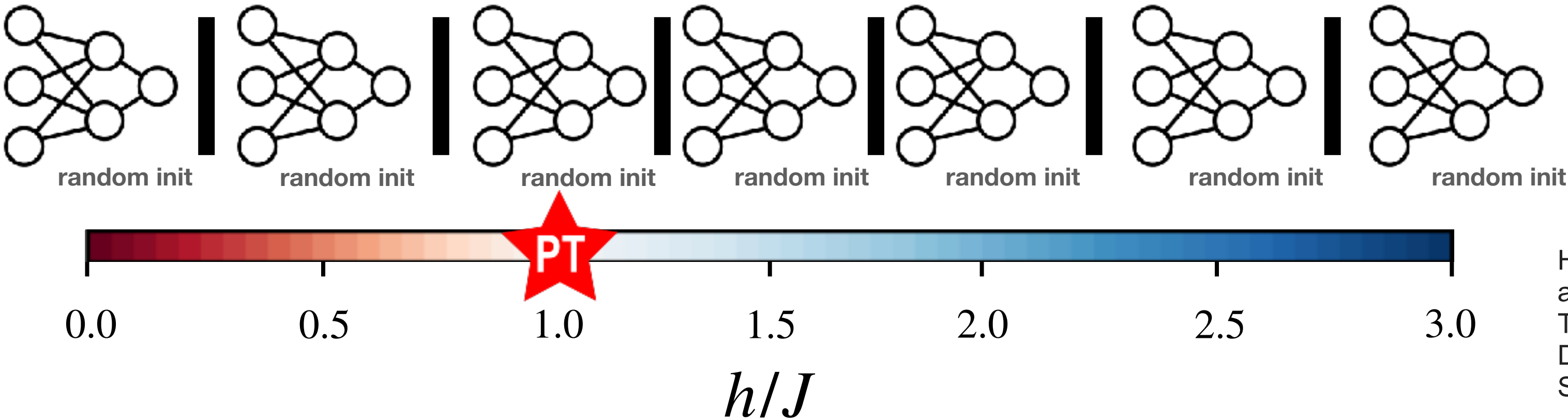


FINDING PT IN WEIGHTS OF NQS

Ising model

$$H = -J \sum_{i=1}^{N-1} \sigma_i^z \sigma_{i+1}^z - h \sum_{i=1}^N \sigma_i^x$$

Independent training



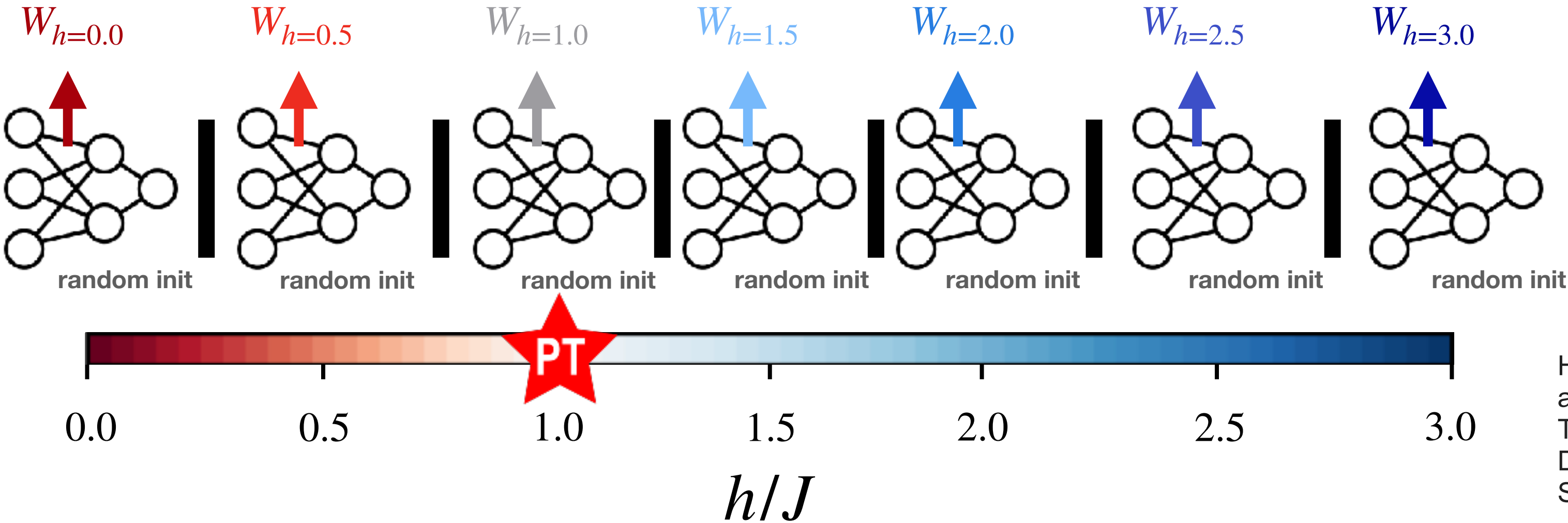
Hernandes, V., Spriggs, T., Khaleefah, S. and Greplova, E., 2025. Adiabatic Fine-Tuning of Neural Quantum States Enables Detection of Phase Transitions in Weight Space. *arXiv preprint arXiv:2503.17140*.

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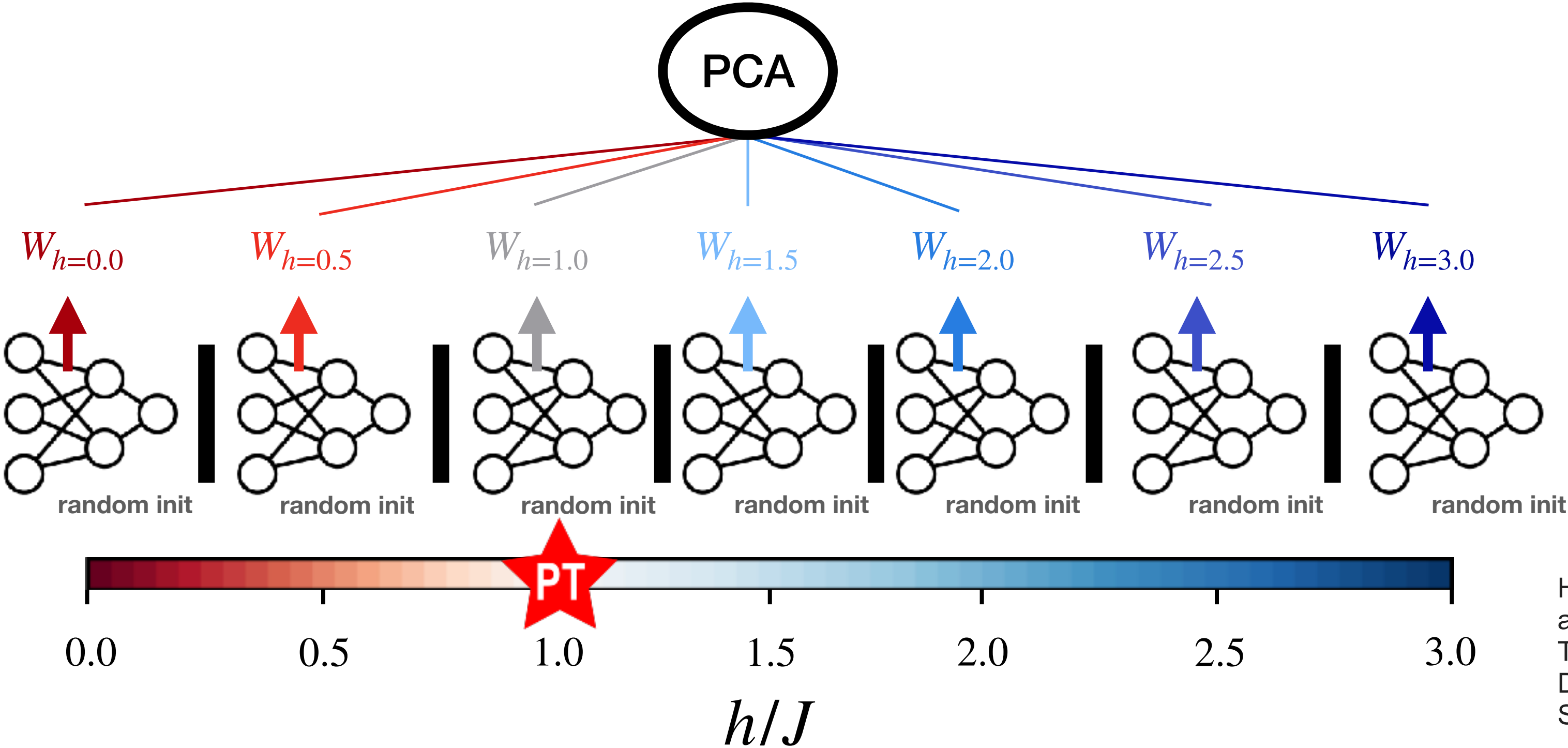
Hernandes, V., Spriggs, T., Khaleefah, S. and Greplova, E., 2025. Adiabatic Fine-Tuning of Neural Quantum States Enables Detection of Phase Transitions in Weight Space. *arXiv preprint arXiv:2503.17140*.

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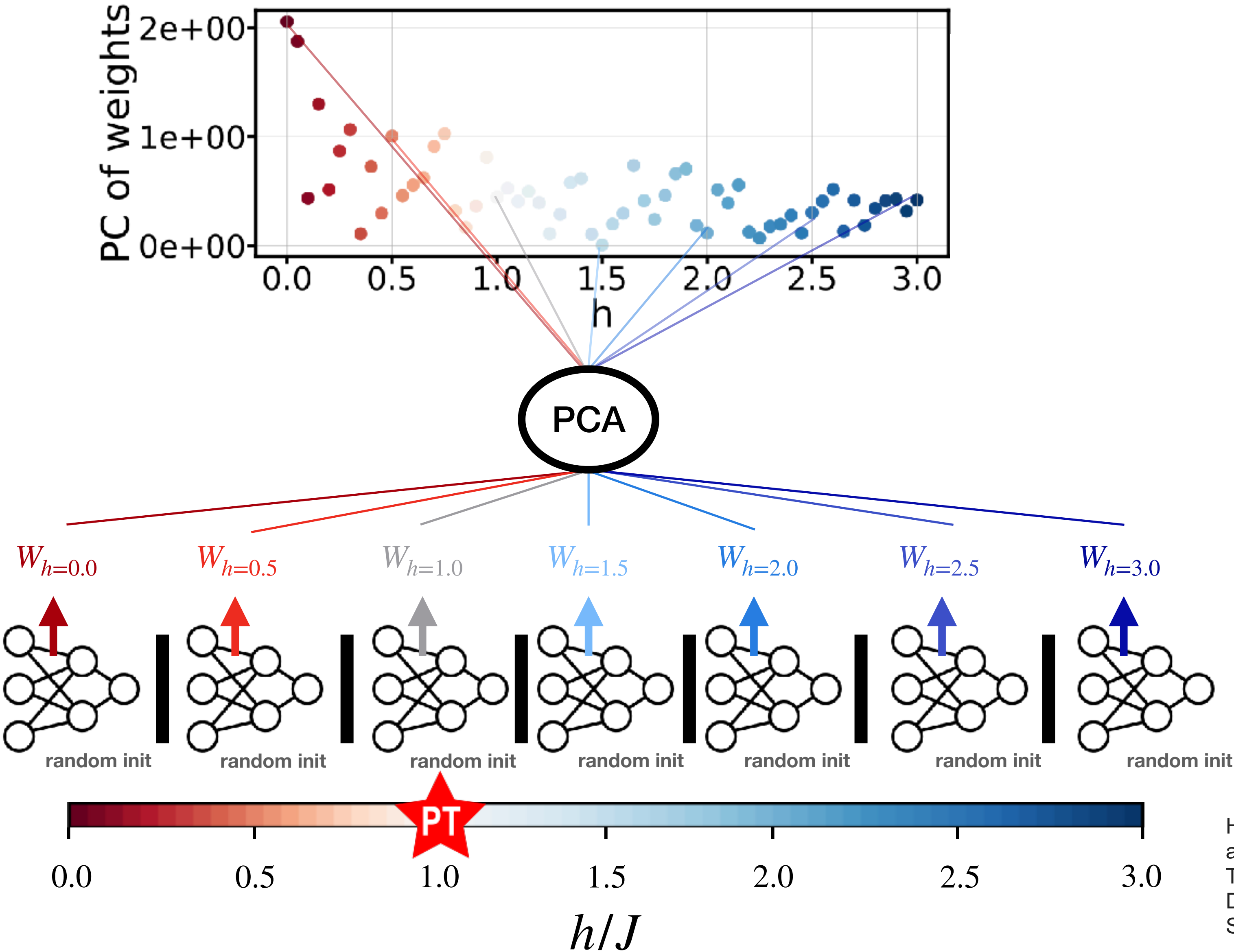
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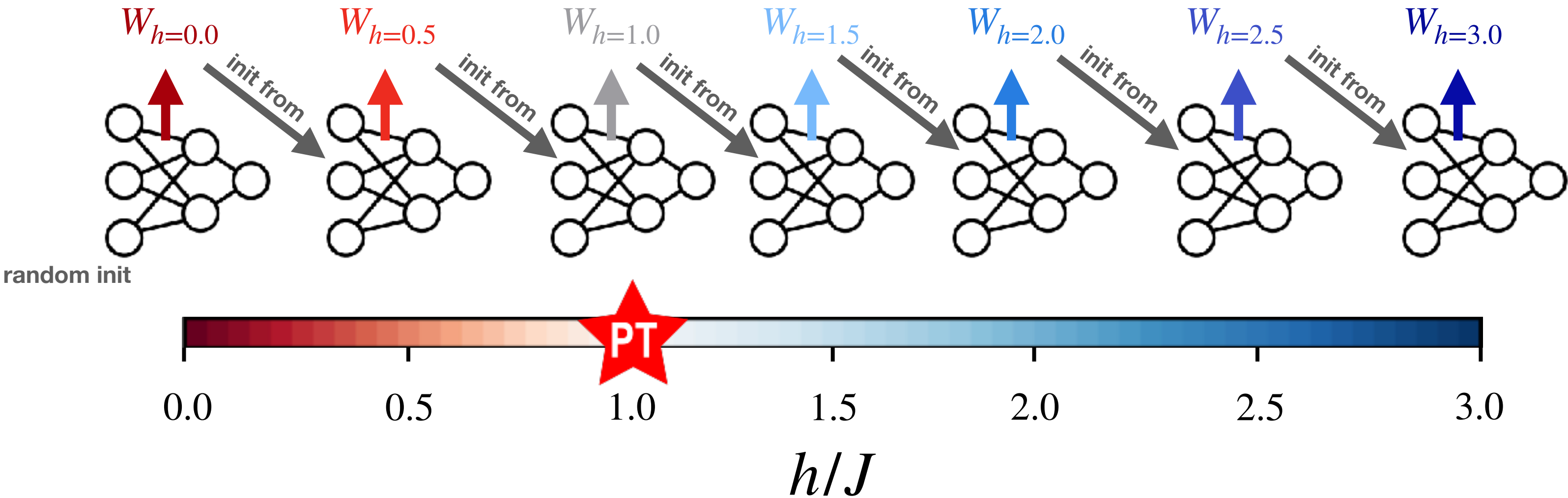
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Adiabatic fine tuning



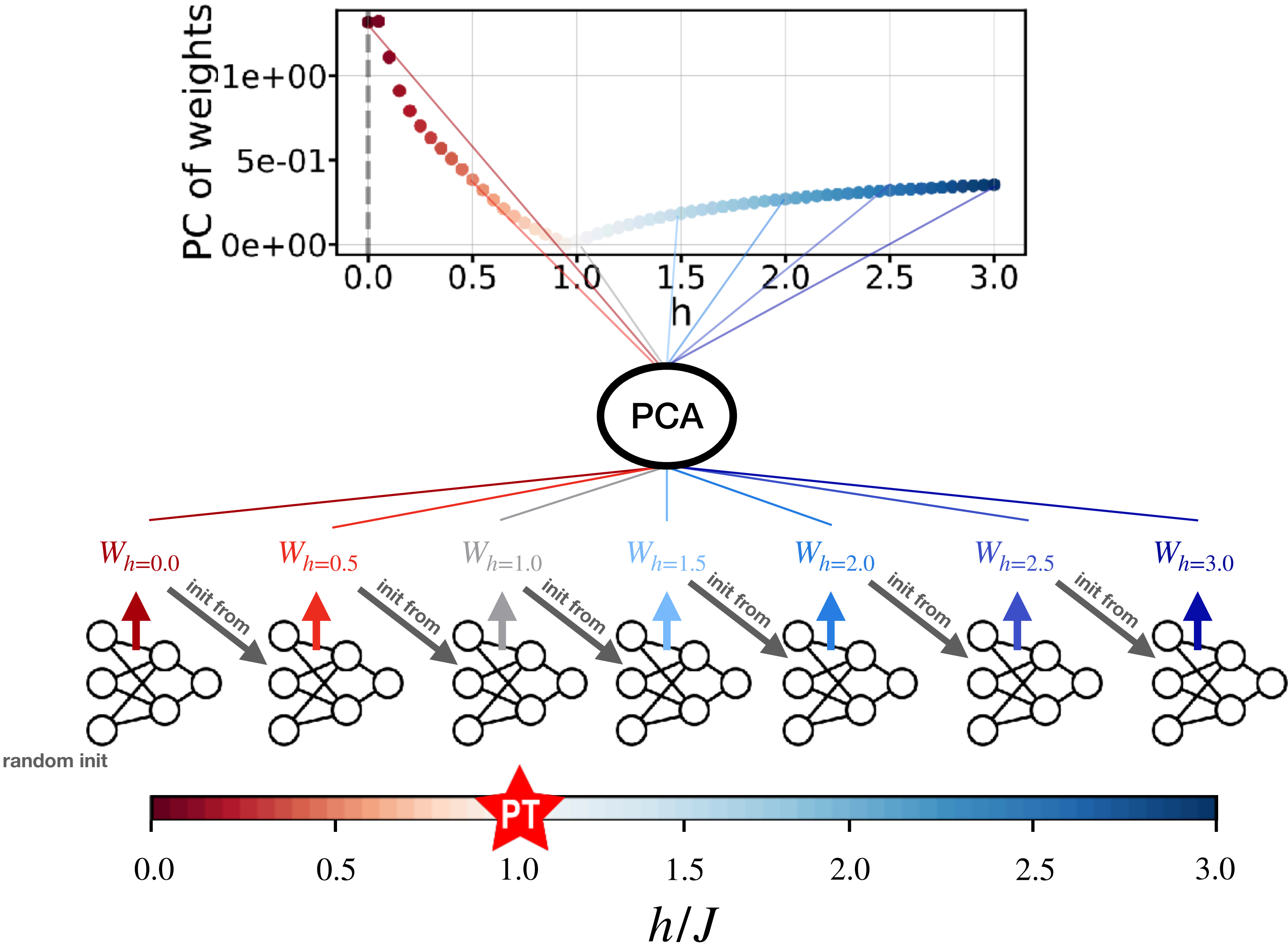
Hernandes, V., Spriggs, T., Khaleefah, S. and Greplova, E., 2025. Adiabatic Fine-Tuning of Neural Quantum States Enables Detection of Phase Transitions in Weight Space. *arXiv preprint arXiv:2503.17140*.

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Adiabatic fine tuning



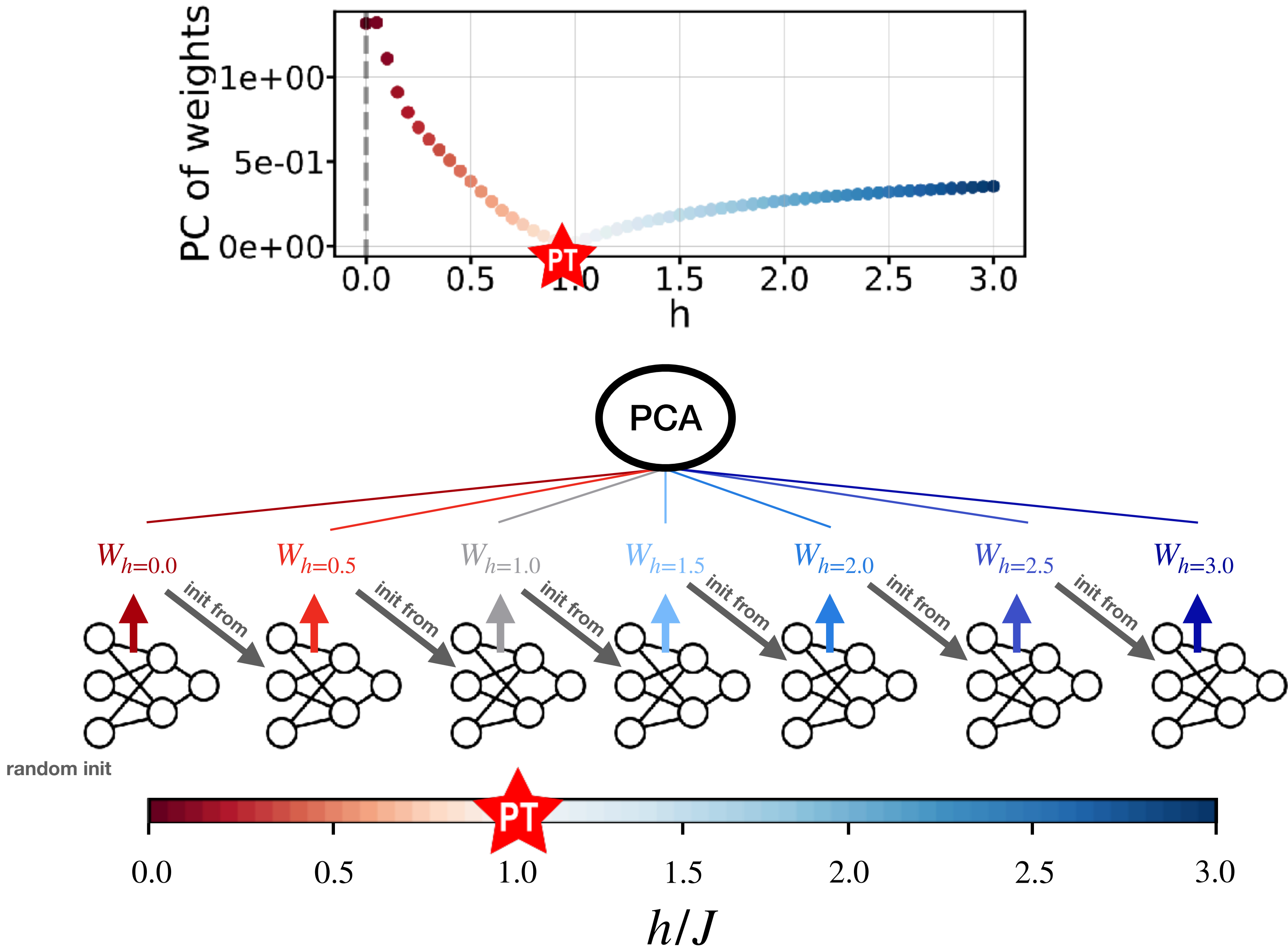
Hernandes, V., Spriggs, T., Khaleefah, S. and Greplova, E., 2025. Adiabatic Fine-Tuning of Neural Quantum States Enables Detection of Phase Transitions in Weight Space. *arXiv preprint arXiv:2503.17140*.

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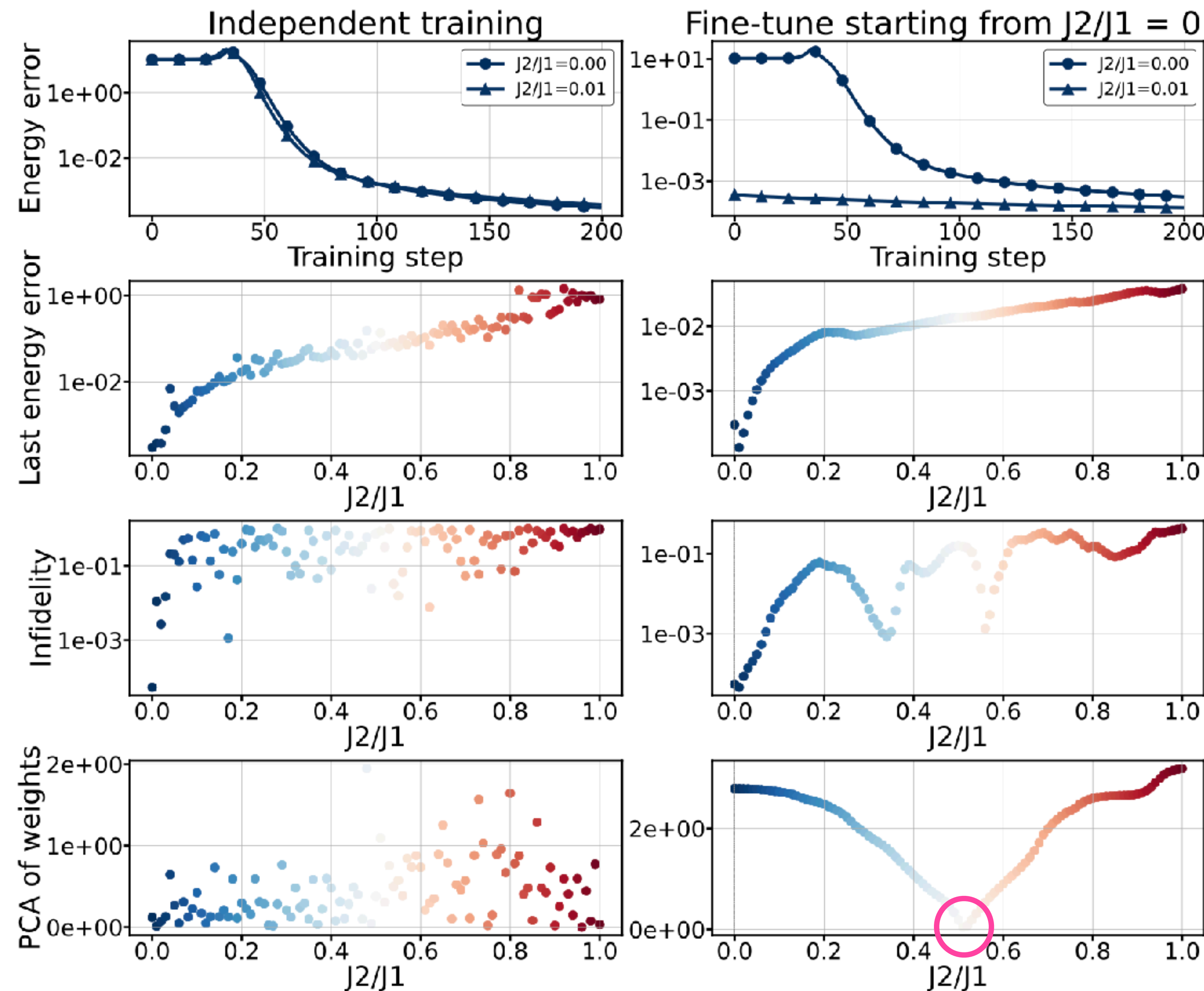
Adiabatic fine tuning



Hernandes, V., Spriggs, T., Khaleefah, S. and Greplova, E., 2025. Adiabatic Fine-Tuning of Neural Quantum States Enables Detection of Phase Transitions in Weight Space. *arXiv preprint arXiv:2503.17140*.

J1-J2 MODEL

$$H = J_1 \sum_i \mathbf{S}_i \cdot \mathbf{S}_{i+1} + J_2 \sum_i \mathbf{S}_i \cdot \mathbf{S}_{i+2}$$

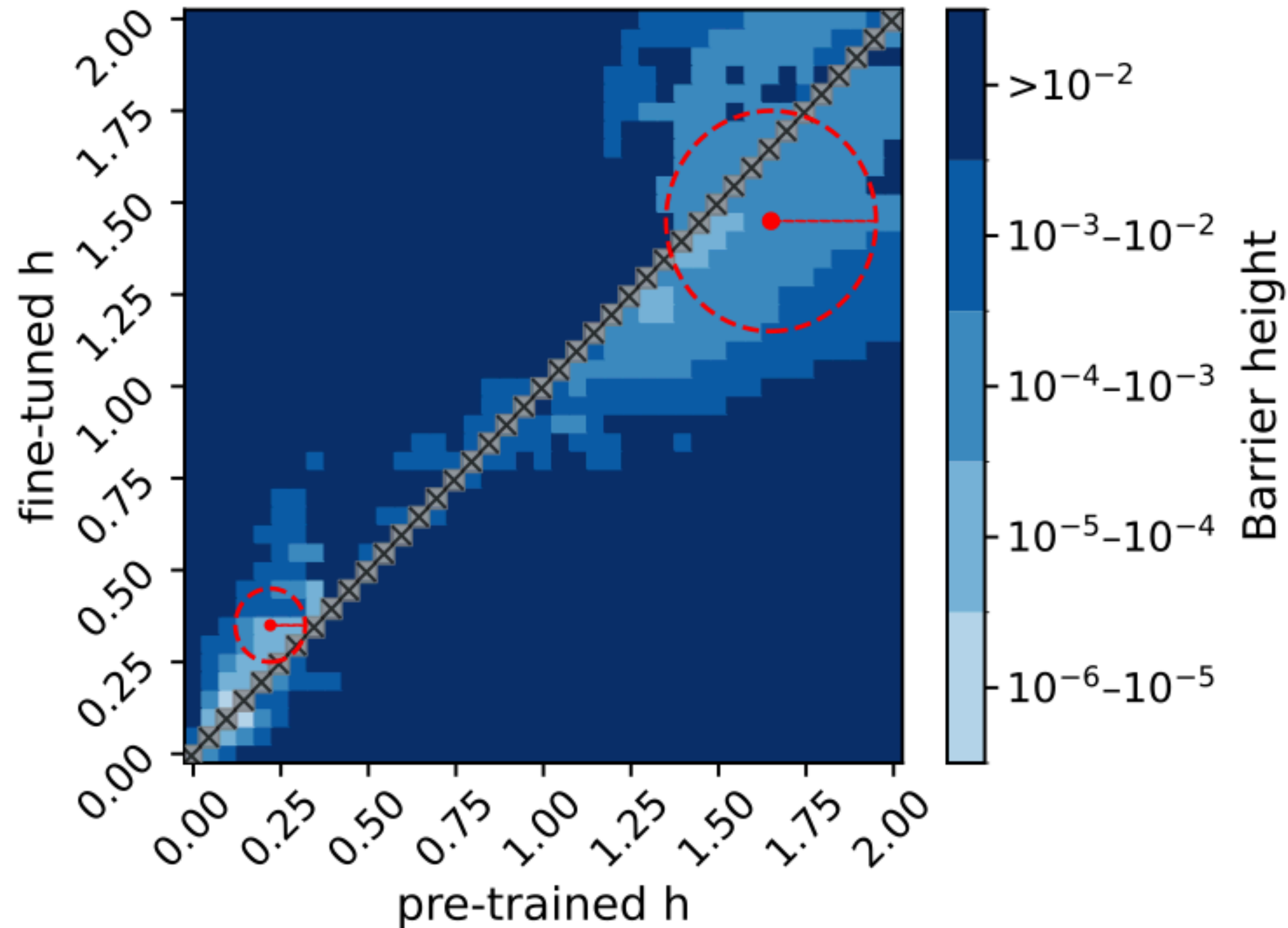


Hernandes, V., Spriggs, T., Khaleefah, S. and Greplova, E., 2025. Adiabatic Fine-Tuning of Neural Quantum States Enables Detection of Phase Transitions in Weight Space. *arXiv preprint arXiv:2503.17140*.

J2/J1 = 1/2 -> maximum frustration

MODE CONNECTIVITY

$$H = -J \sum_{i=1}^{N-1} \sigma_i^z \sigma_{i+1}^z - h \sum_{i=1}^N \sigma_i^x$$

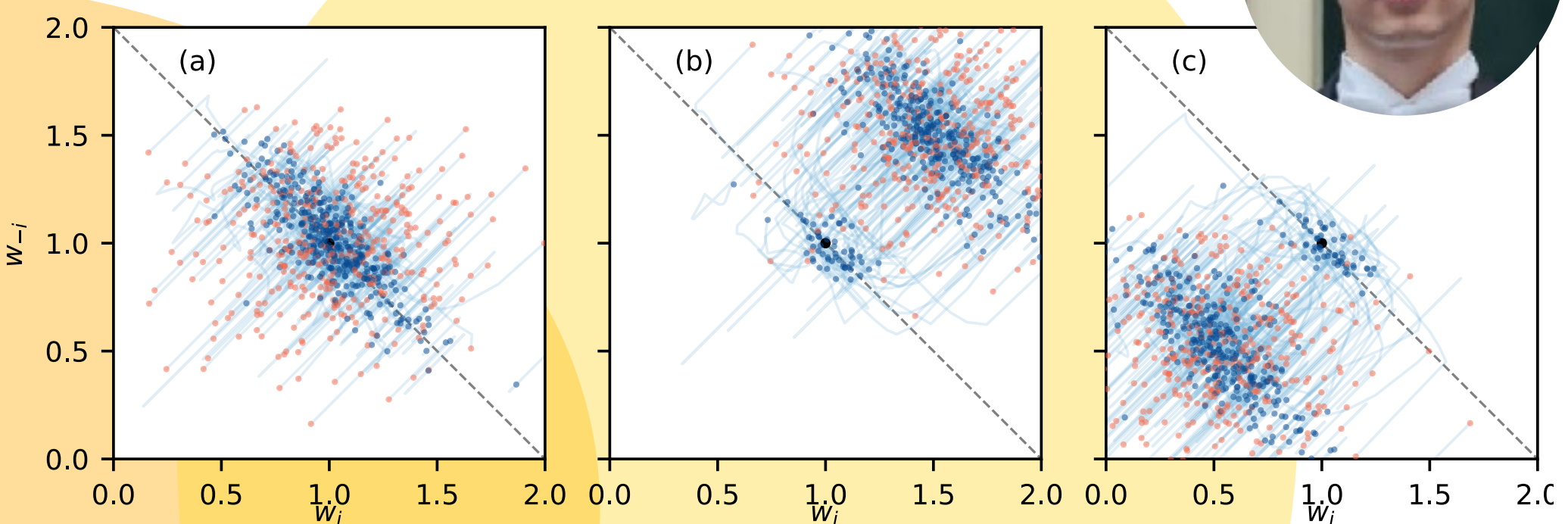
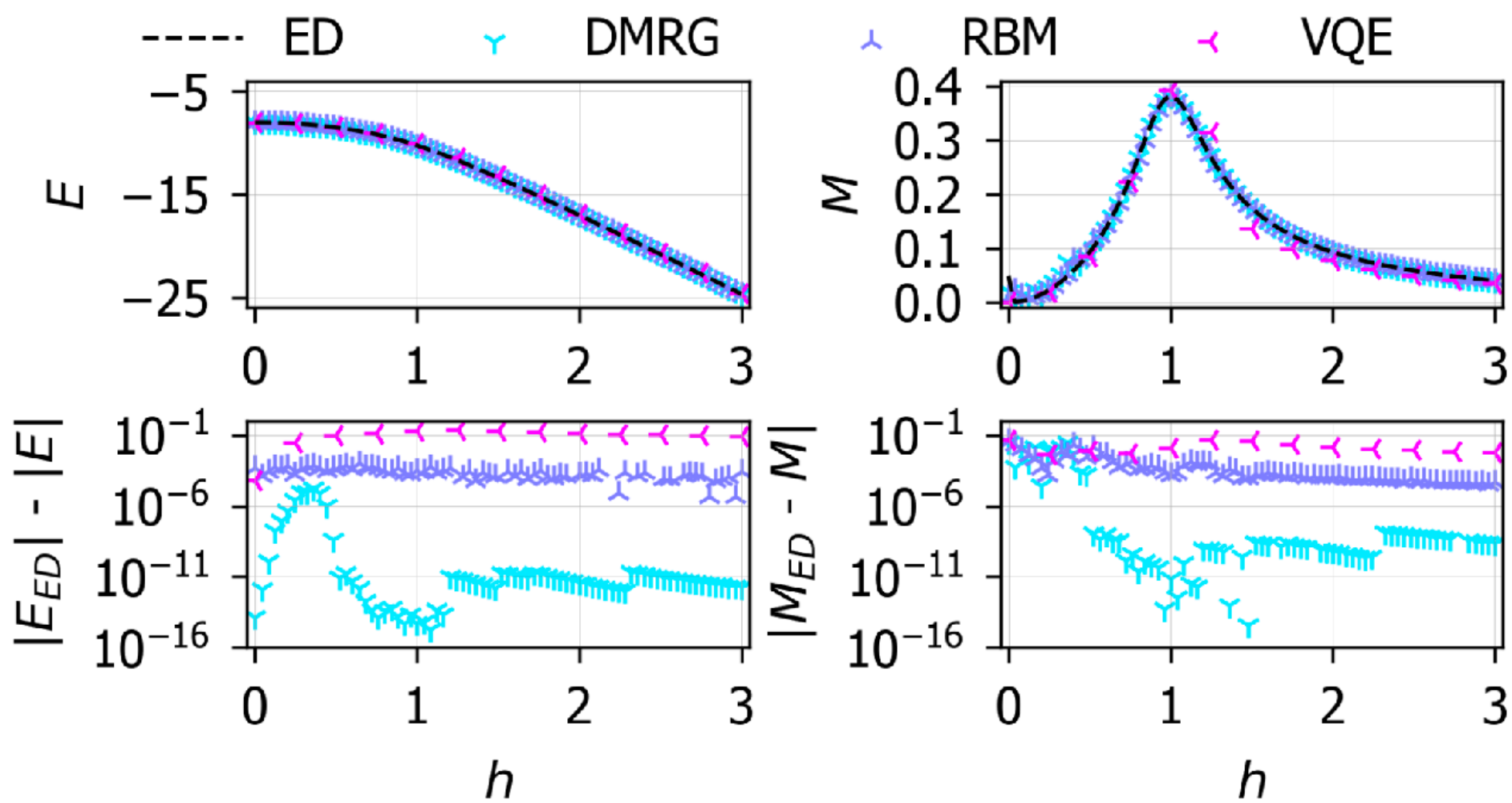


Hernandes, V., Spriggs, T., & Greplova, E.
(2026). Mode Connectivity in Neural Quantum
States. In *Northern Lights Deep Learning
Conference Abstracts 2026*.

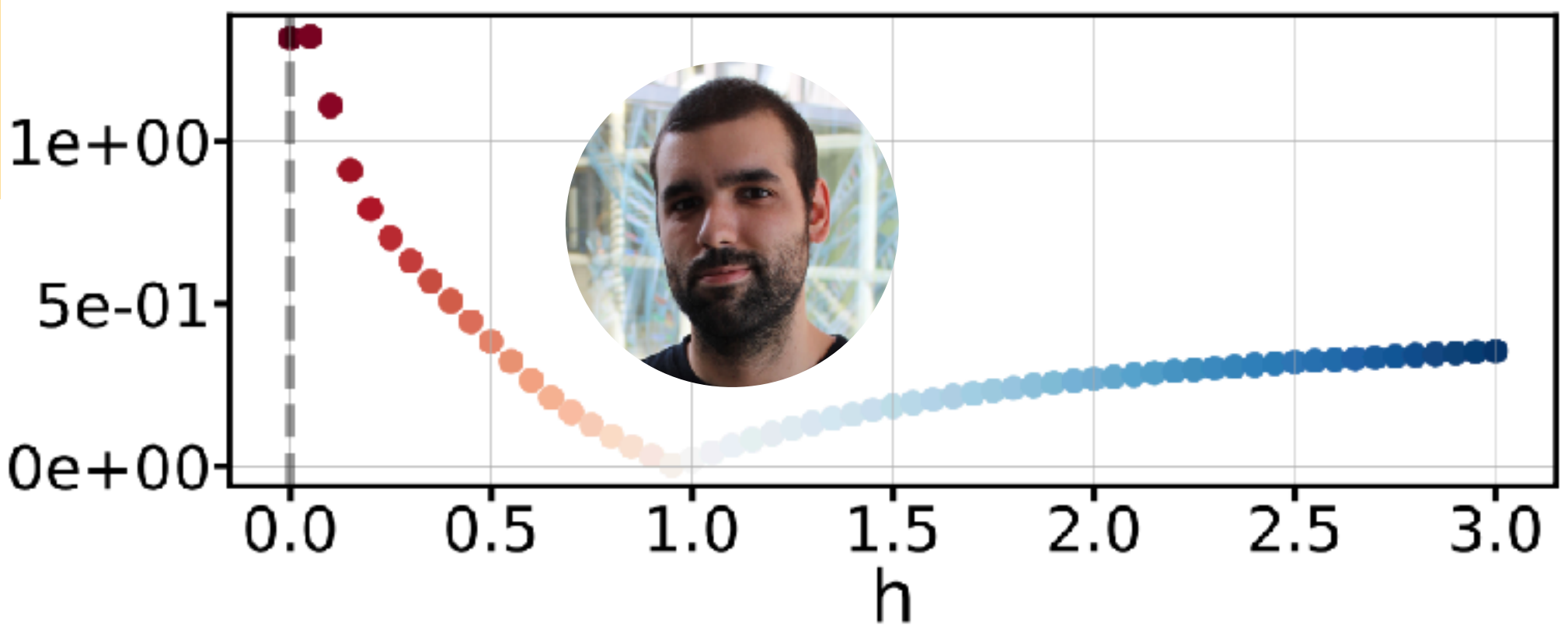


COMPLEXITY

QUANTUM INFORMATION MEASURES HAVE USEFUL INFORMATION ABOUT THE STRUCTURE OF THE STATE!

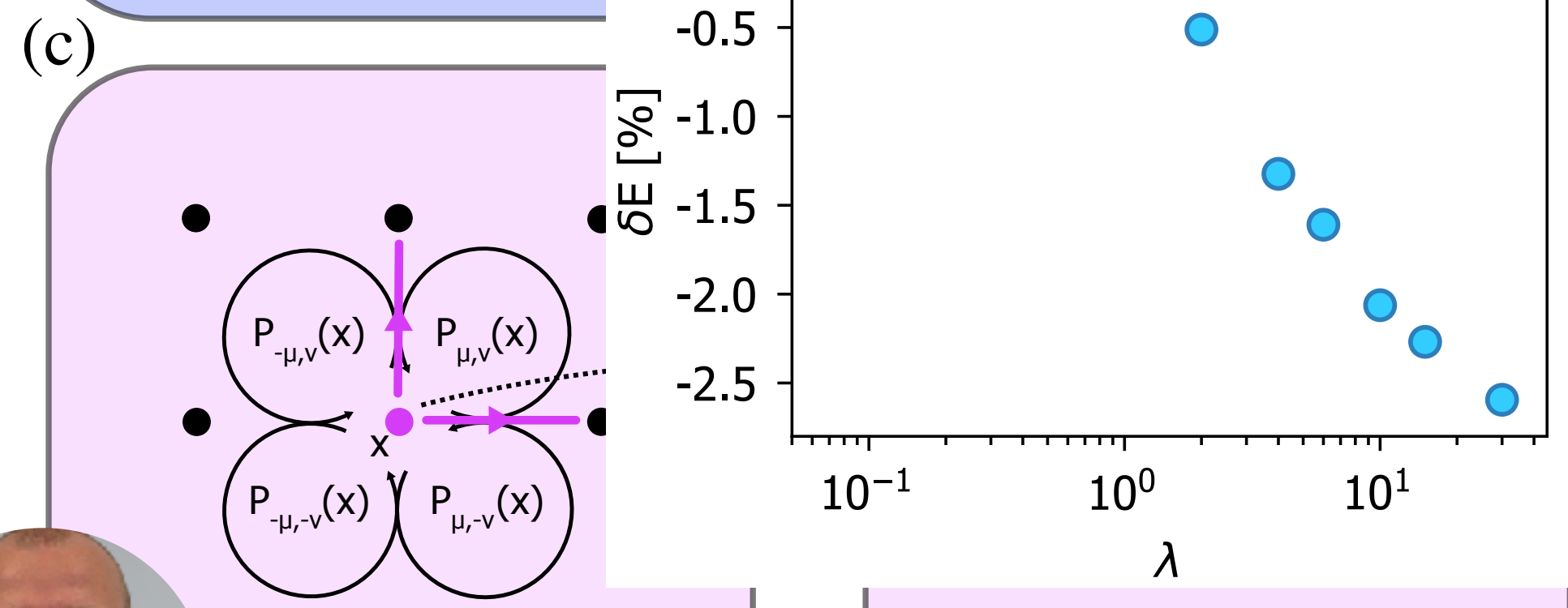
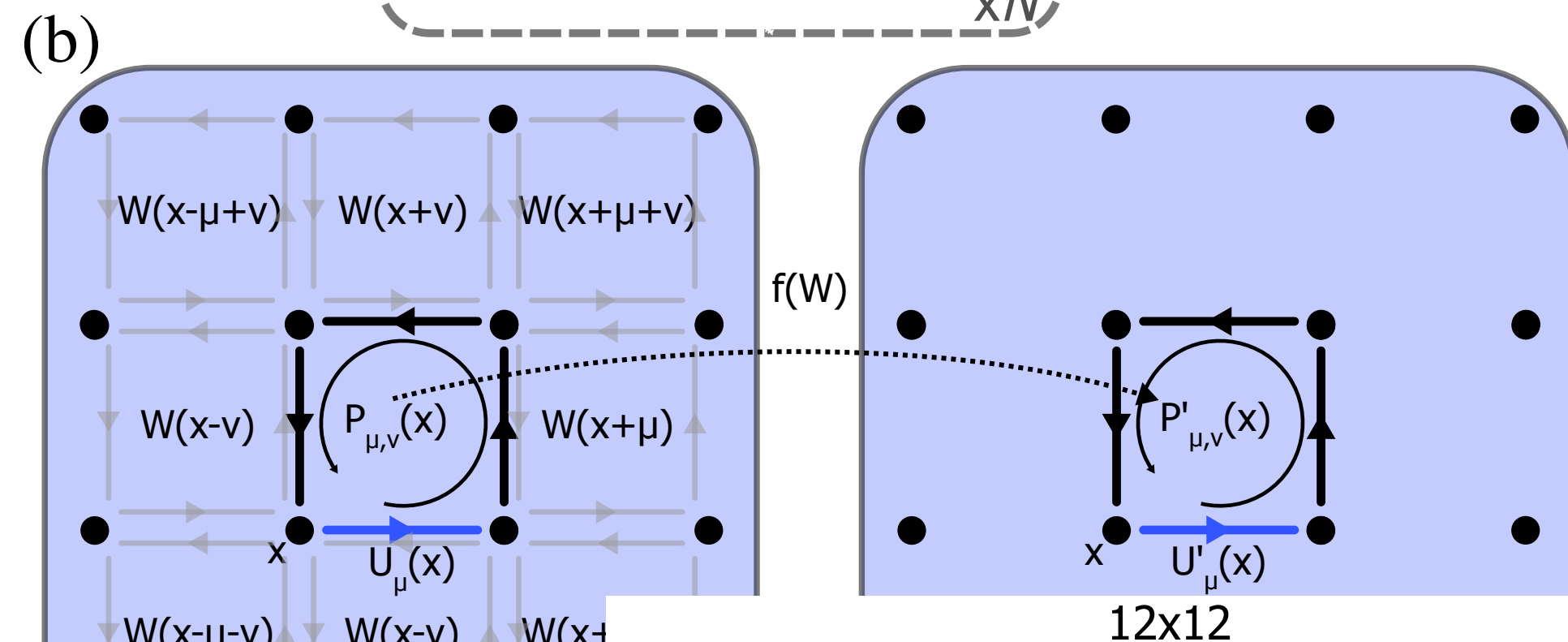
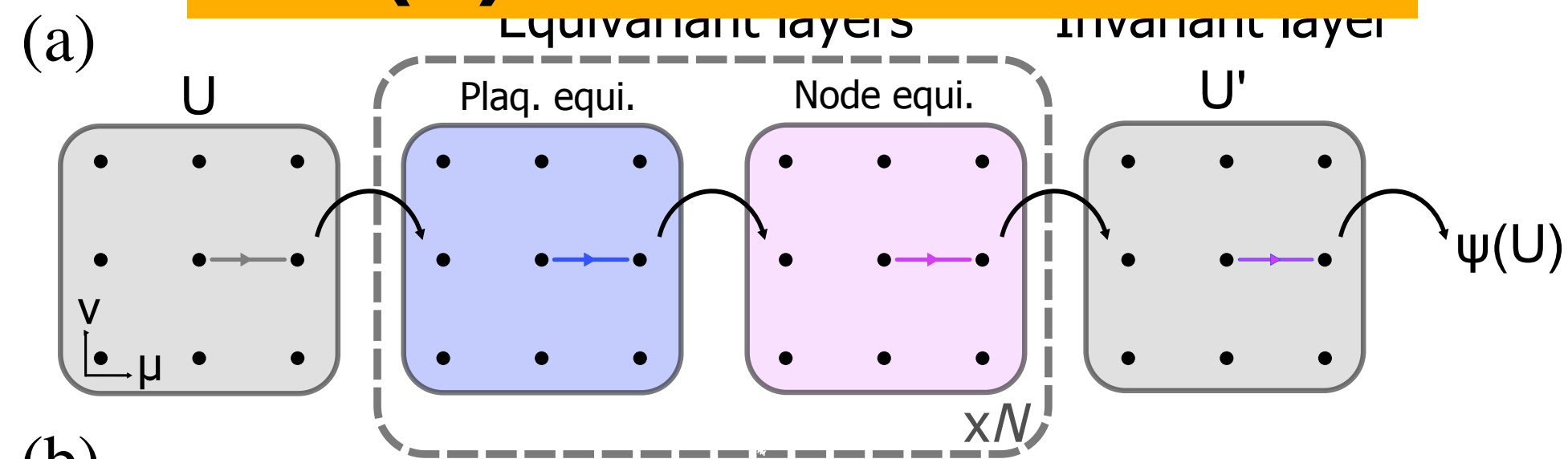


WEIGHT SPACES CAN HAVE USEFUL INTERPRETABLE PHYSICAL INFORMATION!

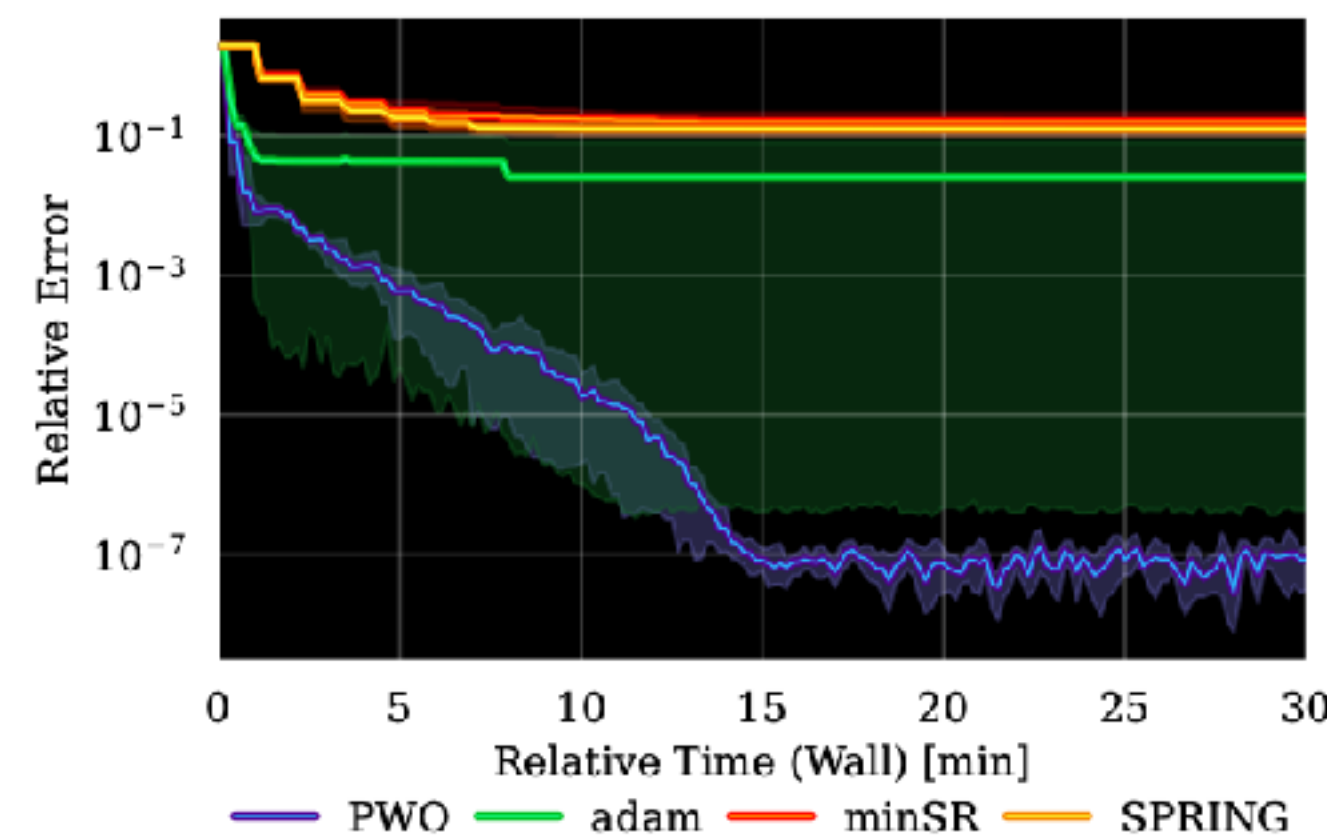
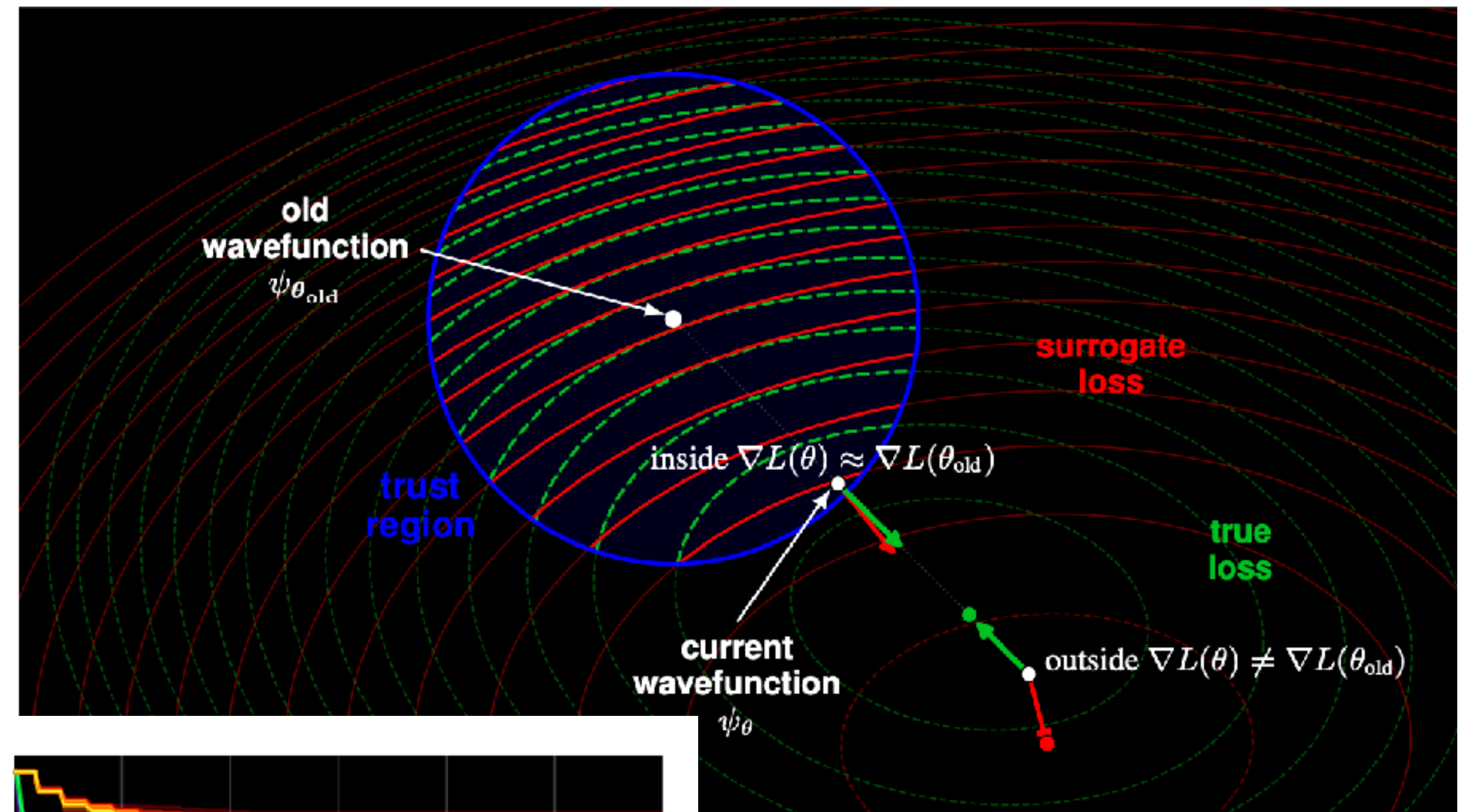


SU(2) Ground States

RL+NQS



Spriggs, T., Greplova, E., Carrasquilla, J. and Nys, J., 2026. Accurate Ground States of SU(2) Lattice Gauge Theory in 2+ 1 D and 3+ 1 D. *Physical review letters*, 136(10), p.101902.



Duque, J.A., Heredia, S.G., Hernandez, V., Greplová, E., Spriggs, T., Courville, A. and Dawid, A., 2026. One More Time: Revisiting Neural Quantum States from a Reinforcement Learning Perspective. *arXiv preprint arXiv:2607.02292*.

Quantum Matter and AI Lab

