Title: Getting the most out of your measurements: neural networks and active learning

Speakers: Annabelle Bohrdt

Series: Machine Learning Initiative

Date: February 18, 2022 - 11:00 AM

URL: https://pirsa.org/22020045

Abstract: Recent advances in quantum simulation experiments have paved the way for a new perspective on strongly correlated quantum many-body systems. Digital as well as analog quantum simulation platforms are capable of preparing desired quantum states, and various experiments are starting to explore non-equilibrium many-body dynamics in previously inaccessible regimes in terms of system sizes and time scales. State-of-the art quantum simulators provide single-site resolved quantum projective measurements of the state. Depending on the platform, measurements in different local bases are possible. The question emerges which observables are best suited to study such quantum many-body systems.

In this talk, I will cover two different approaches to make the most use of these possibilities. In the first part, I will discuss the use of machine learning techniques to study the thermalization behavior of an interacting quantum system. A neural network is trained to distinguish non-equilibrium from thermal equilibrium data, and the network performance serves as a probe for the thermalization behavior of the system. We apply this method to numerically simulated data, as well experimental snapshots of ultracold atoms taken with a quantum gas microscope.

In the second part of this talk, I will present a scheme to perform adaptive quantum state tomography using active learning. Based on an initial, small set of measurements, the active learning algorithm iteratively proposes the basis configurations which will yield the maximum information gain. We apply this scheme to GHZ states of a few qubits as well as ground states of one-dimensional lattice gauge theories and show an improvement in accuracy over random basis configurations.

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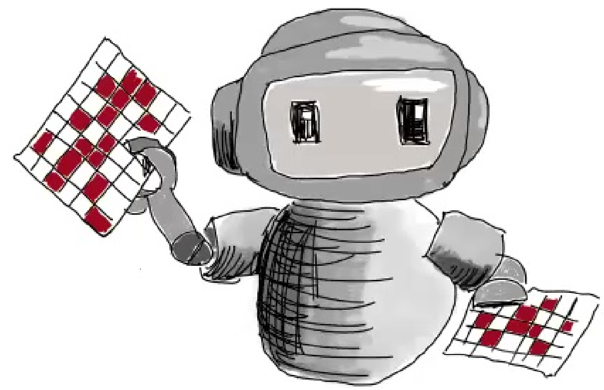
Getting the most out of your measurements: **neural networks & active learning**



Perimeter, 02/2022

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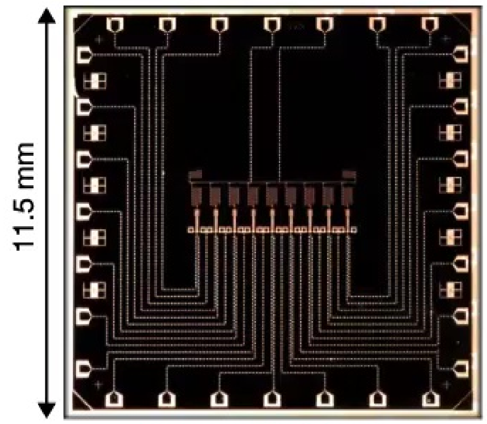
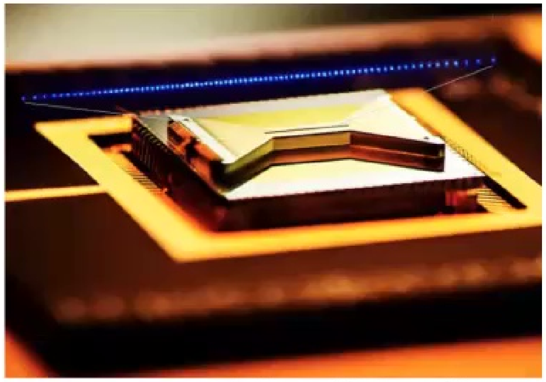
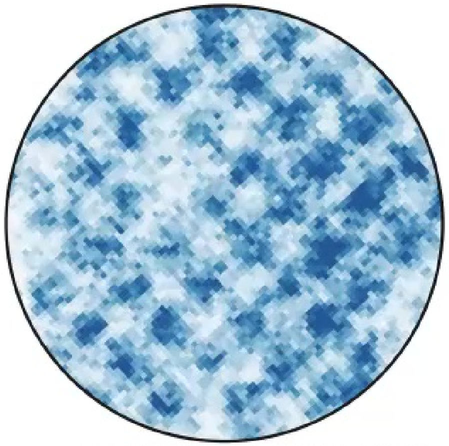
Quantum simulation



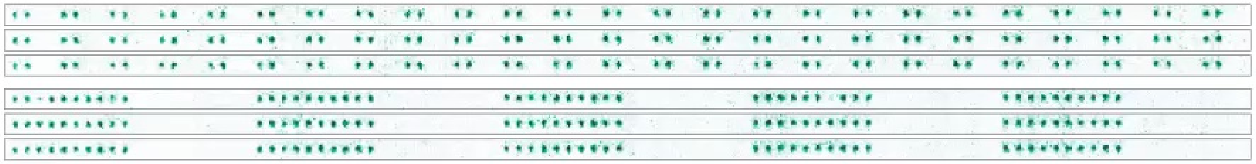
B. Chiaro et al., PRR (2021)



C. Monroe / Physicsworld



A. Mazurenko et al., Nature 545 (2017)



M. Endres et al., Science 354 (2016)

Perimeter, 02/2022

Sooshin Kim

Alex Lukin

Matthew Rispoli

Robert Schittko

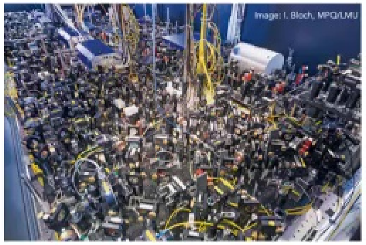
Michael Knap

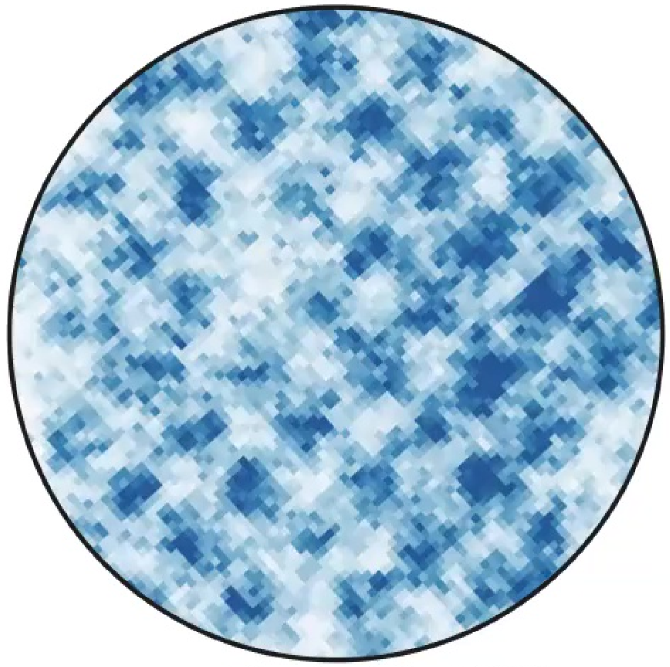
Markus Greiner

Julian Léonard

Annabelle Bohrdt

Quantum gas microscopy





A. Mazurenko et al., Nature 545 (2017)

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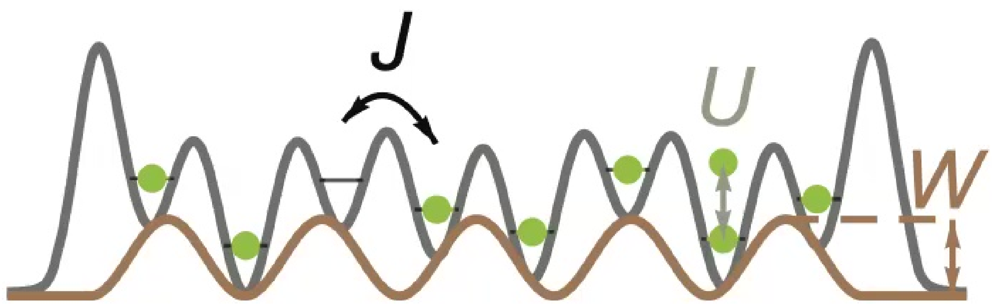
Interacting Aubry-André model

$$\hat{H} = -J\sum_i(\hat{a}_i^\dagger \hat{a}_{i+1} + h.c.) + \frac{U}{2}\sum_i \hat{n}_i(\hat{n}_i - 1) + W\sum_i h_i \hat{n}_i$$

hopping

interaction

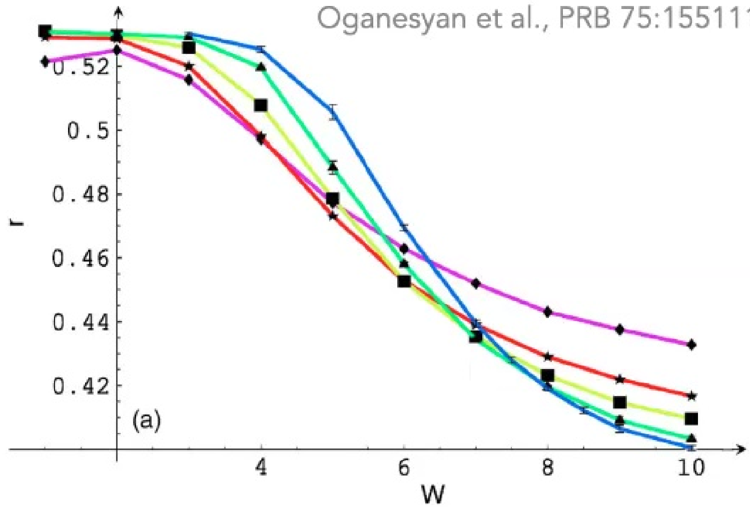
disorder potential

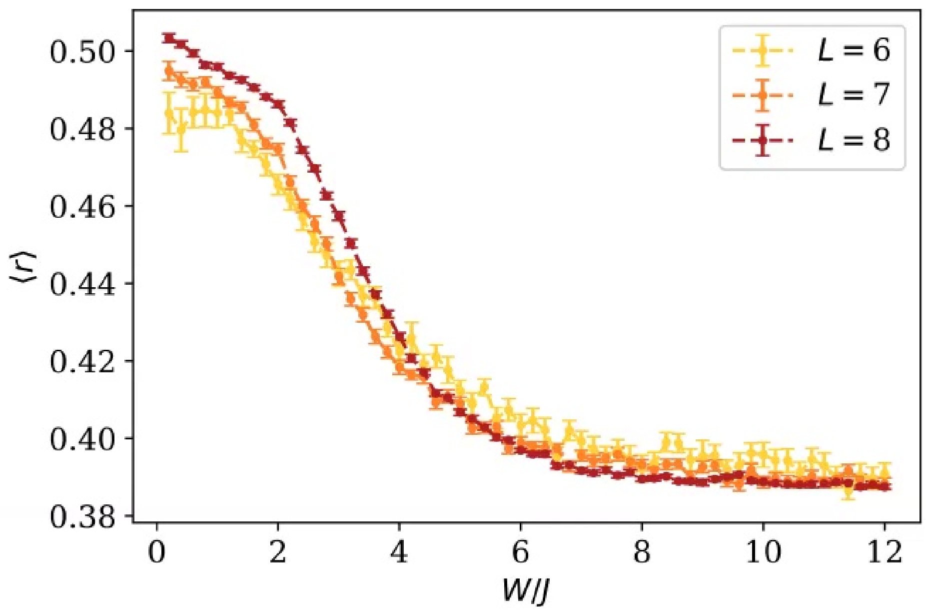


Spectral statistics

"To look for the diffusive-to-insulating phase transition in this model, we have chosen to use what appears to be numerically the most accessible quantity that shows a clear, well-understood difference between the two phases, namely, the spectral statistics of adjacent energy levels of the many-body Hamiltonian."

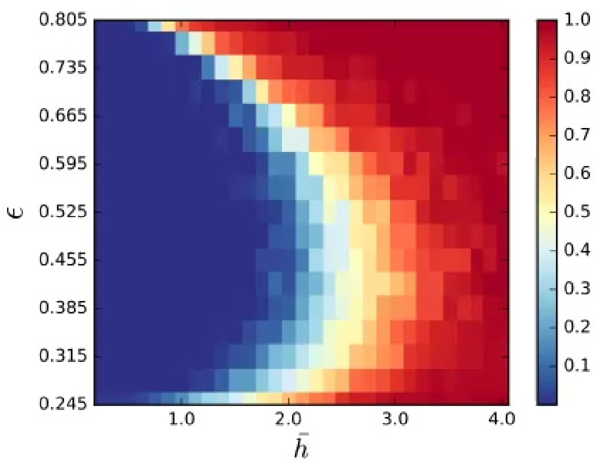
Oganesyan et al., PRB 75:155111 (2007)





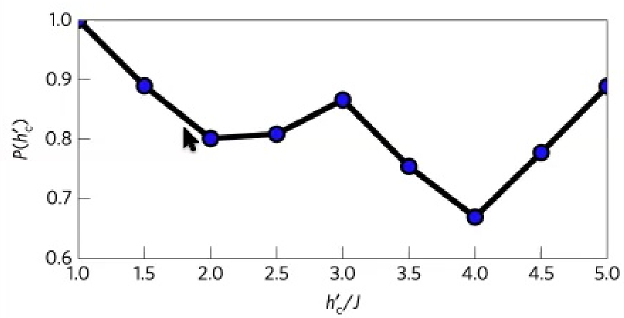
MBL and machine learning...

Entanglement spectra



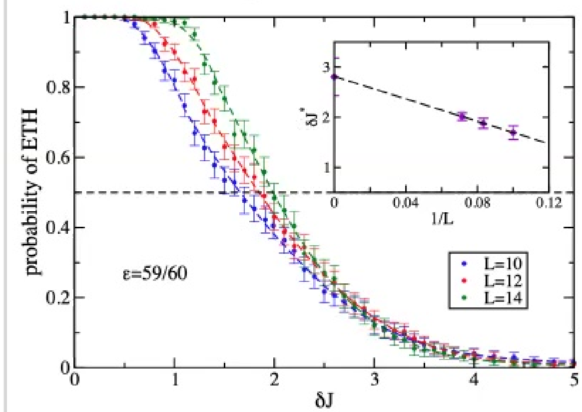
Schindler et al., Phys. Rev. B, 95:245134 (2017)

Entanglement spectra



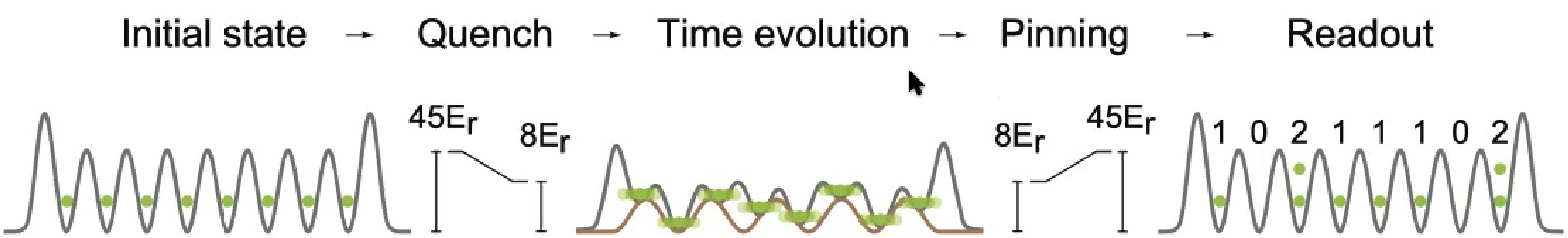
Van Nieuwenburg et al., Nature Physics, 13:435–439, 02 2017

Eigenstates



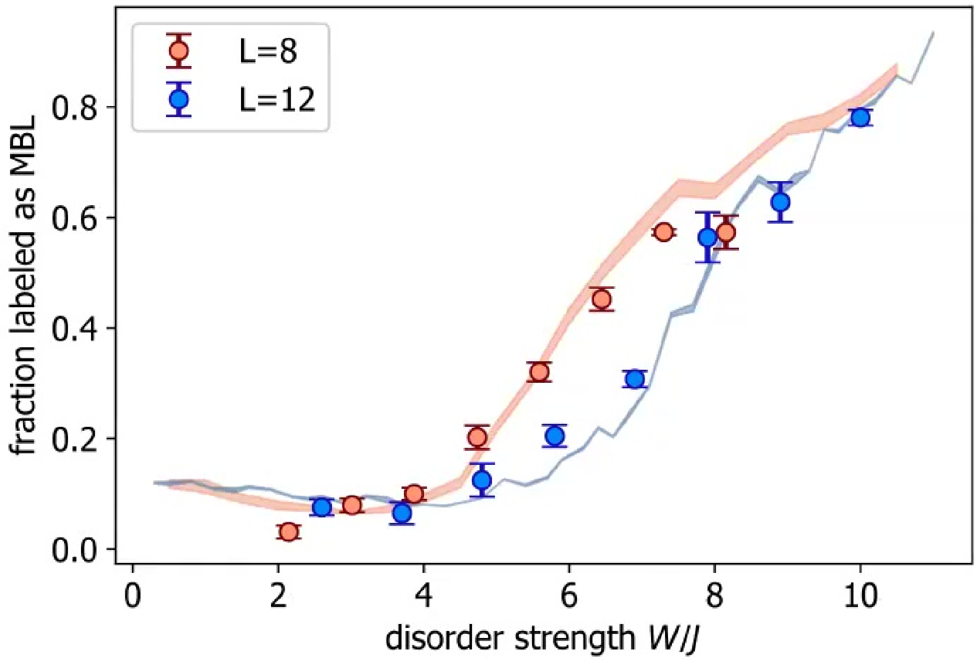
Zhang et al., Physical Review B, 99(5), Feb 2019

Experimental protocol



Lukin et al., Science, 364(6437):256–260 (2019)

Learning the transition



Bohrdt et al., Phys. Rev. Lett. 127 (2021)

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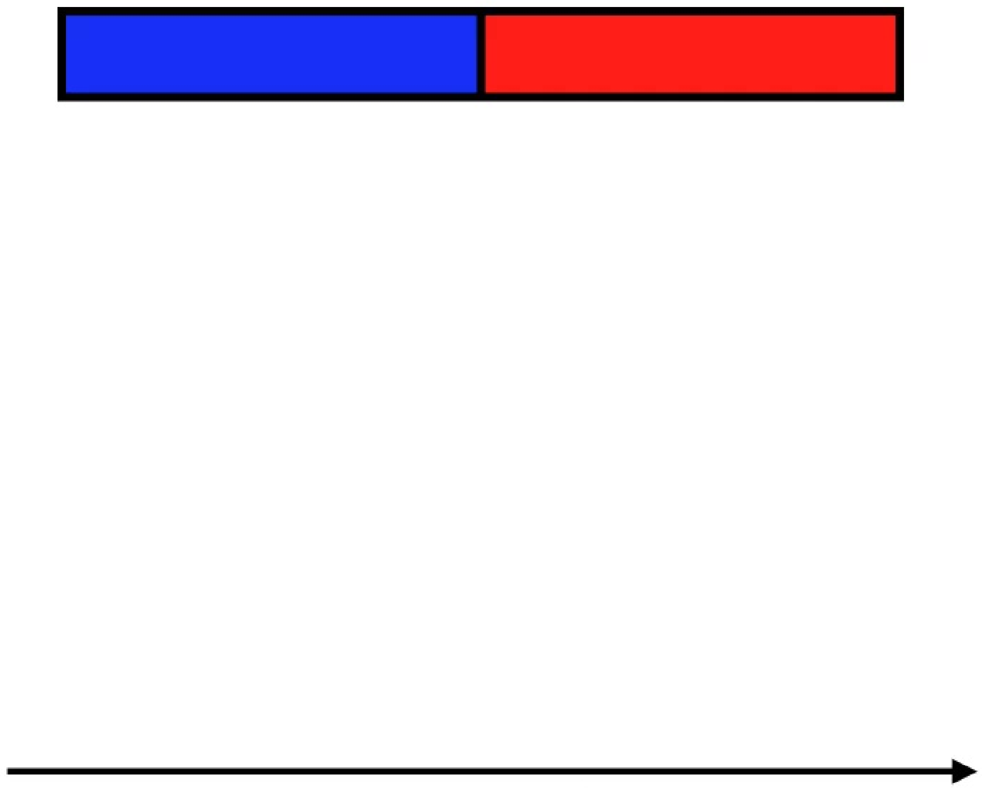
Confusion learning: general idea

Actual data:



Disorder strength

Introduced in van Nieuwenburg et al., Nature Physics, 13 (2017)

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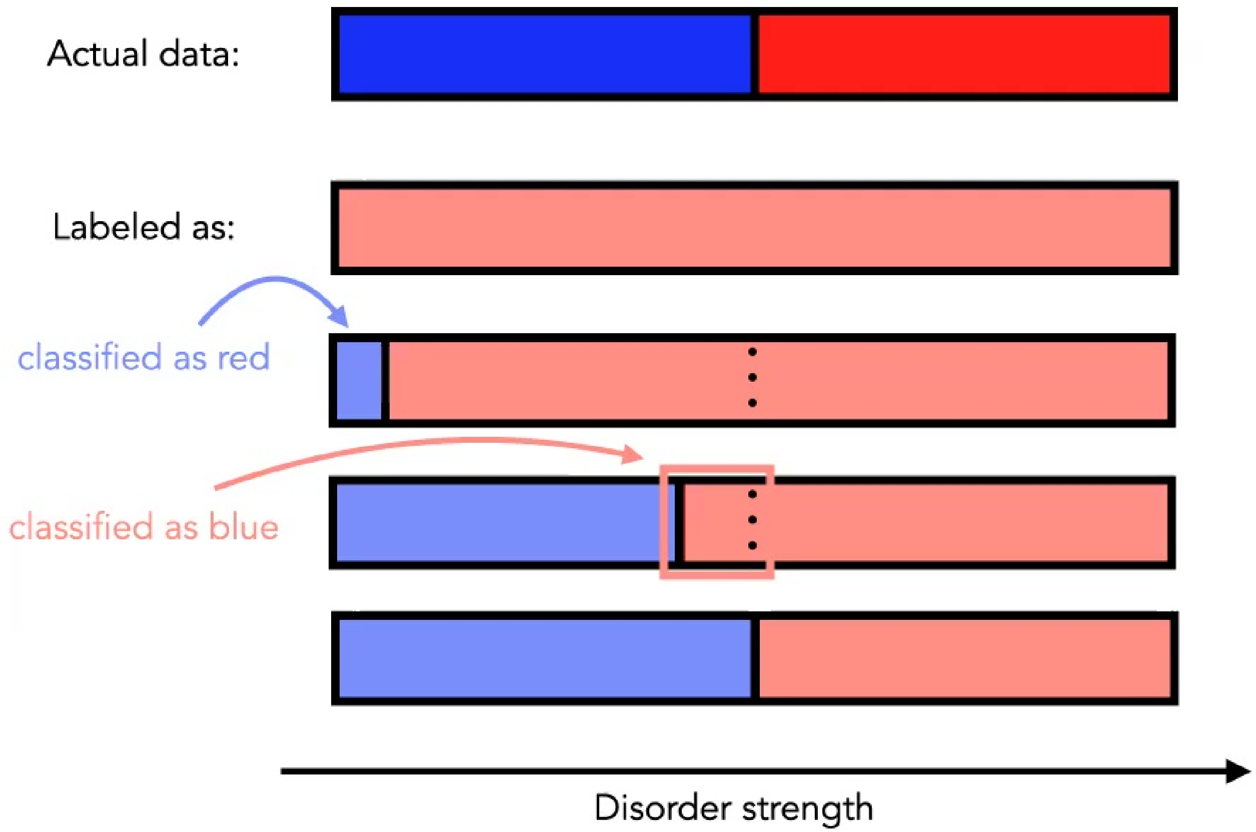
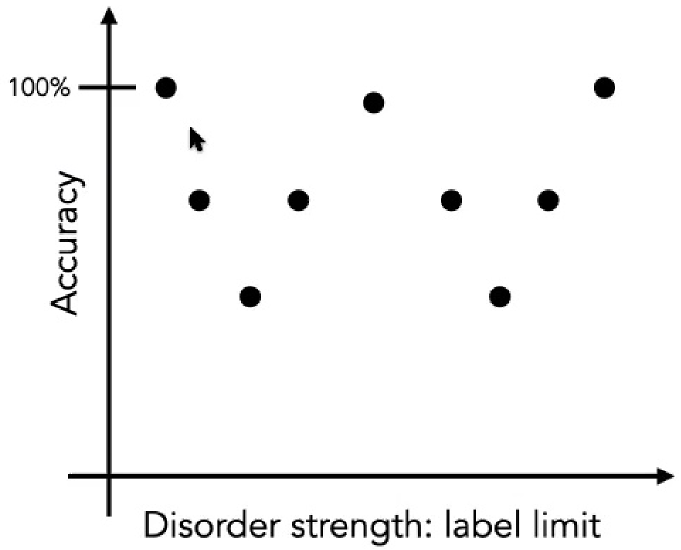
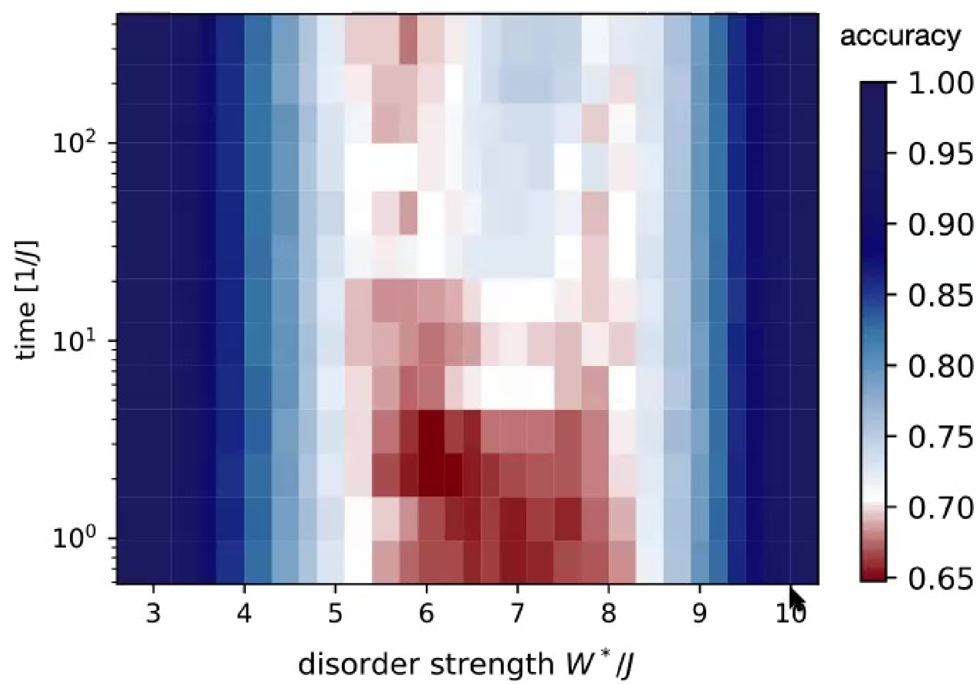
Confusion learning: general idea





Introduced in van Nieuwenburg et al., Nature Physics, 13 (2017)

Confusion learning: results



Bohrdt et al., Phys. Rev. Lett. 127 (2021)

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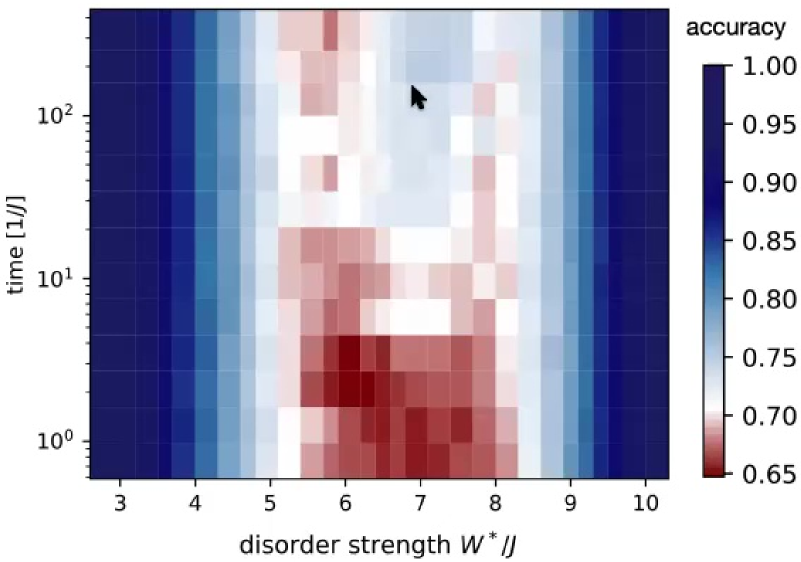
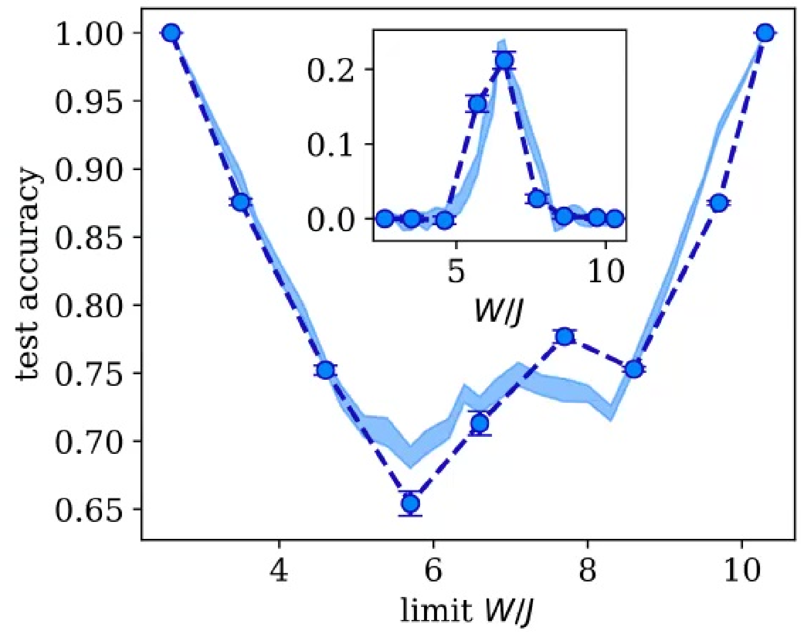
Confusion learning: results





Bohrdt et al., Phys. Rev. Lett. 127 (2021)

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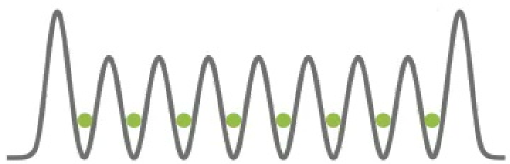
Learning thermalization

Initial state:

$$E_i = \langle\psi_0|\hat{H}|\psi_0\rangle$$



Thermal density matrix:

$$\hat{\rho}_\beta = \frac{1}{Z}\exp(-\beta_{\text{eff}}\hat{H})$$

$$\beta_{\text{eff}} = 1/T_{\text{eff}}$$

$$E_i = \text{tr}\left(\hat{H}\hat{\rho}_\beta\right)$$

Learning thermalization

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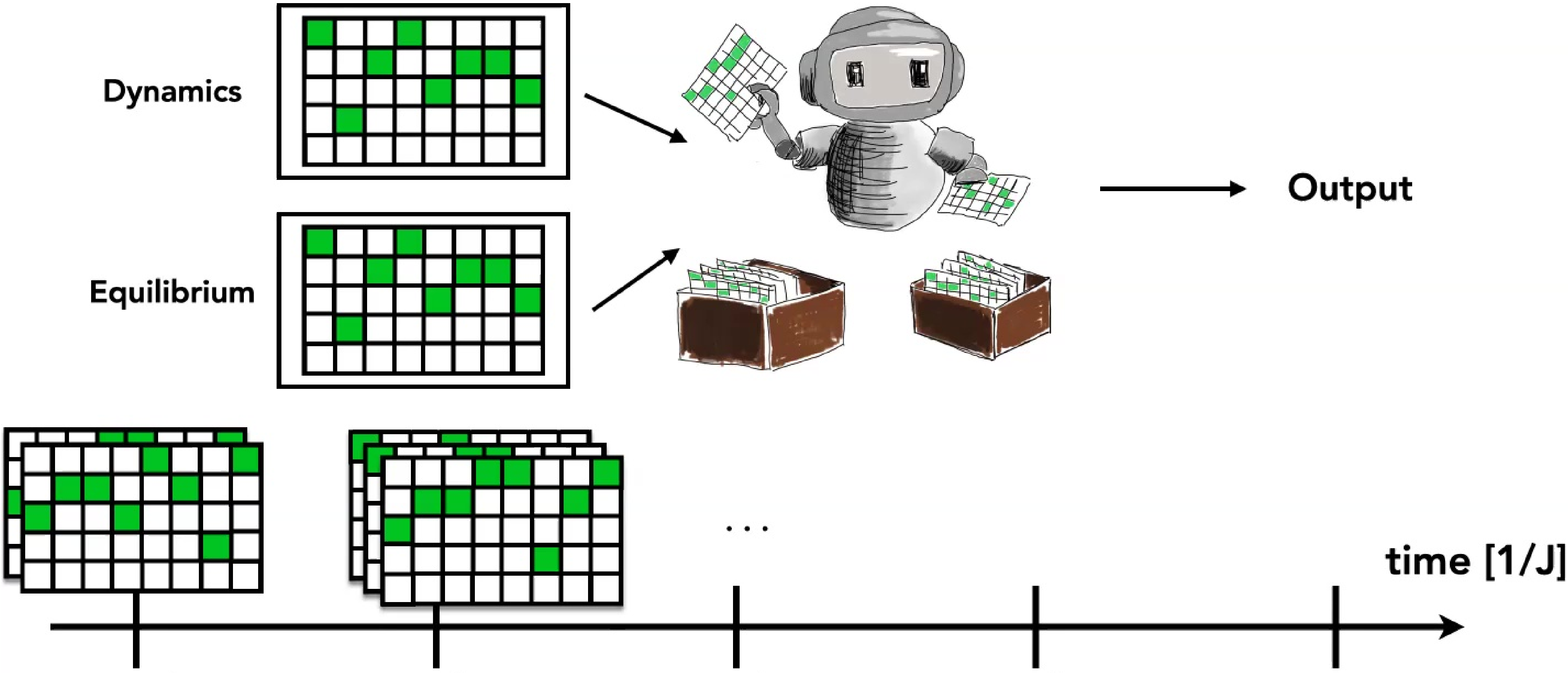

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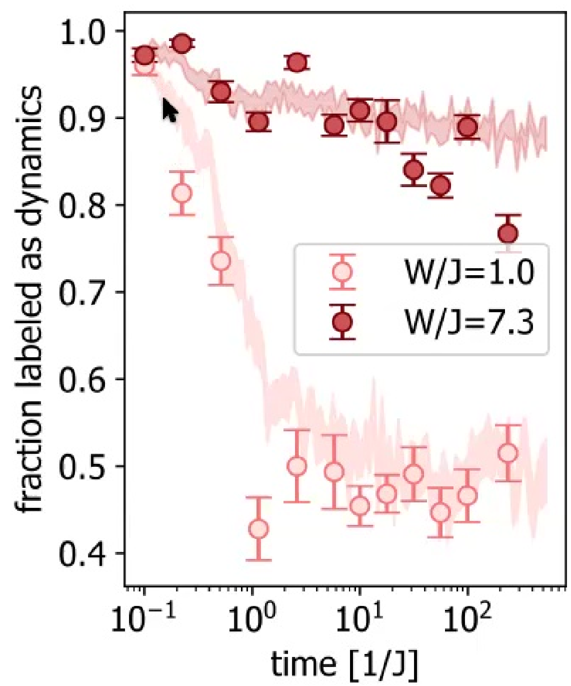
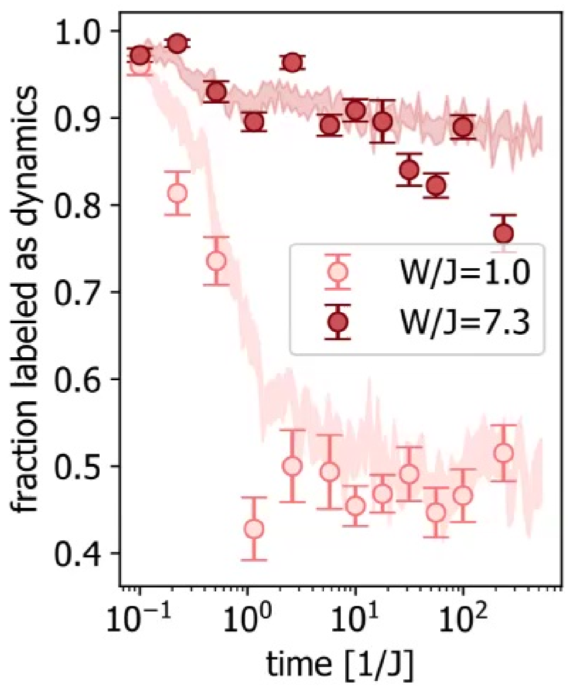
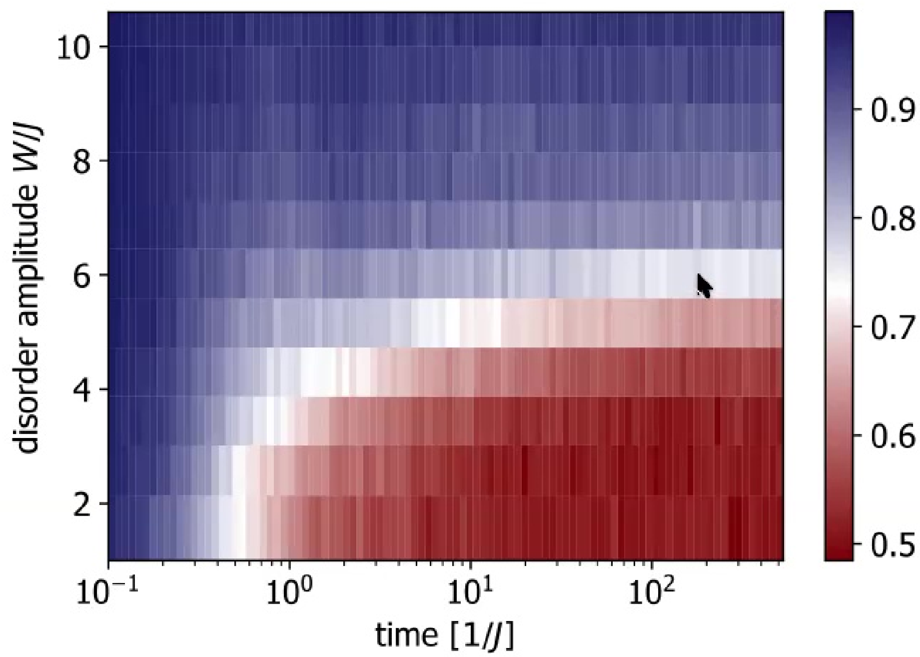
Learning thermalization



Bohrdt et al., Phys. Rev. Lett. 127 (2021)

Learning thermalization





Bohrdt et al., Phys. Rev. Lett. 127 (2021)

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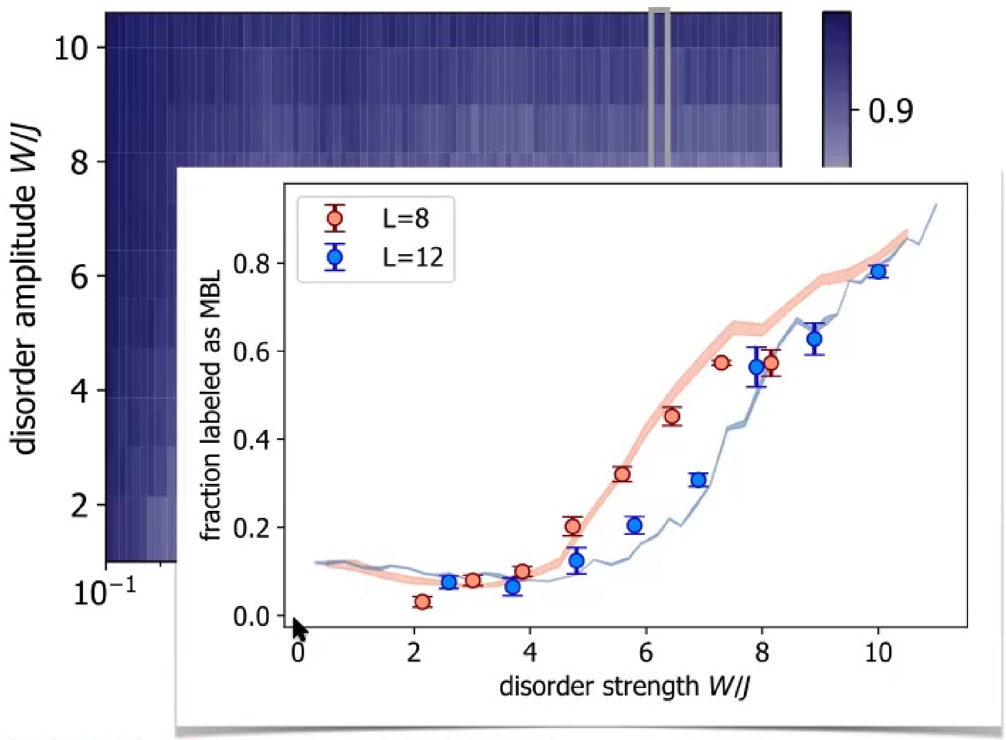
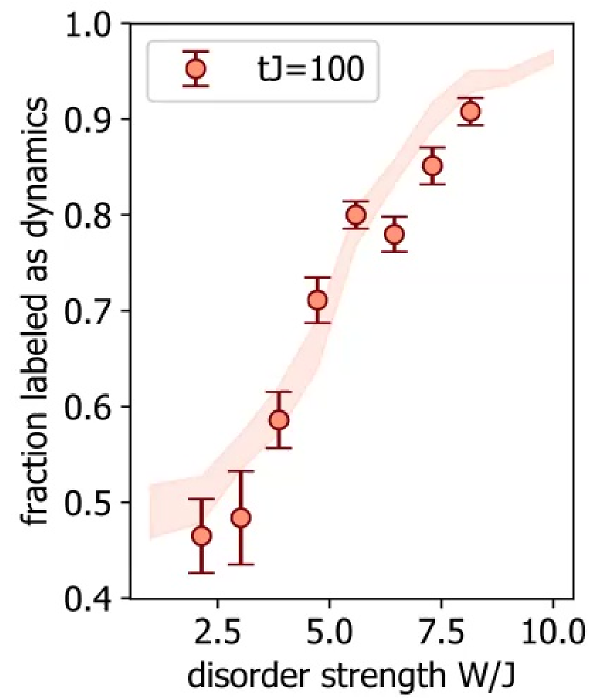
Learning thermalization





Bohrdt et al., Phys. Rev. Lett. 127 (2021)

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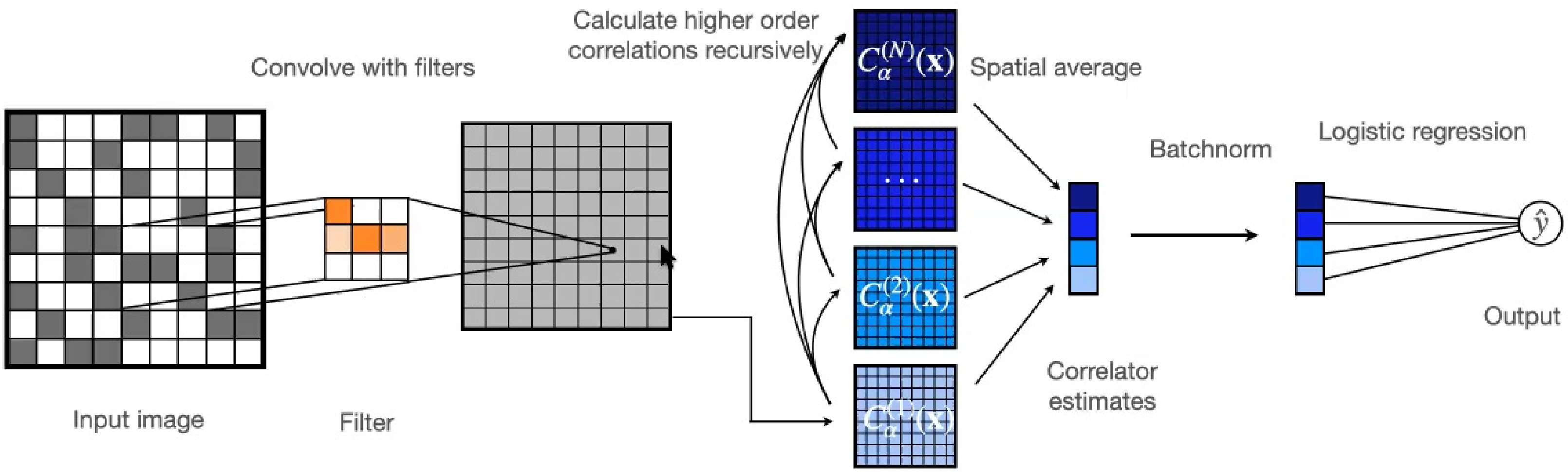
Interpretability: the CCNN



C. Miles, A. Bohrdt et al., Nature Communications 12, 3905 (2021) 18

Perimeter, 02/2022

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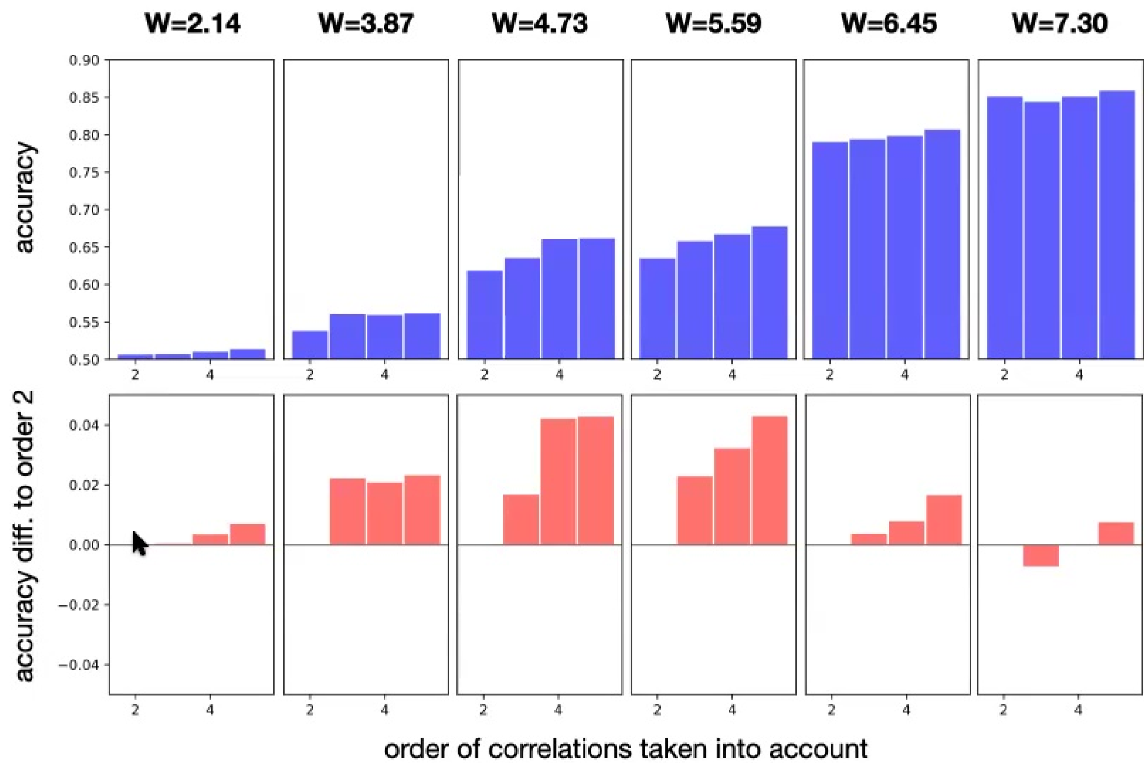
Learning thermalization



Bohrdt et al., Phys. Rev. Lett. 127 (2021)

Thermalization with conserved quantities

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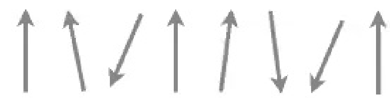
Transverse field Ising model: $\hat{H} = -\sum_i \left(J \hat{\sigma}_i^z \hat{\sigma}_{i+1}^z + h \hat{\sigma}_i^x\right)$ 

Conserved quantities: $I^{(1,+)} = H$

$$I^{(n,+)} = -J \sum_j (S^{xx}_{j,j+n} + S^{yy}_{j,j+n+2}) + h(S^{xx}_{j,j+n-1} + S^{yy}_{j,j+n-1})$$

$$S^{\alpha\beta}_{j,j+l} = \sigma_j^\alpha \left[\prod_{k=1}^{l-1} \sigma^z_{j+k}\right] \sigma^\beta_{j+l} \qquad S^{yy}_{j,j} = -\sigma^z_j$$

Grady, Phys. Rev. D, 25 (1982), Prosen, Journal of Physics A, 31 (1998)

Generalized Gibbs ensemble

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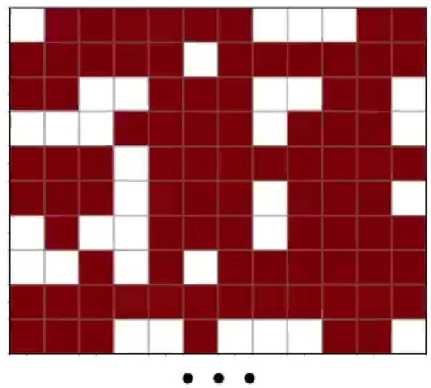
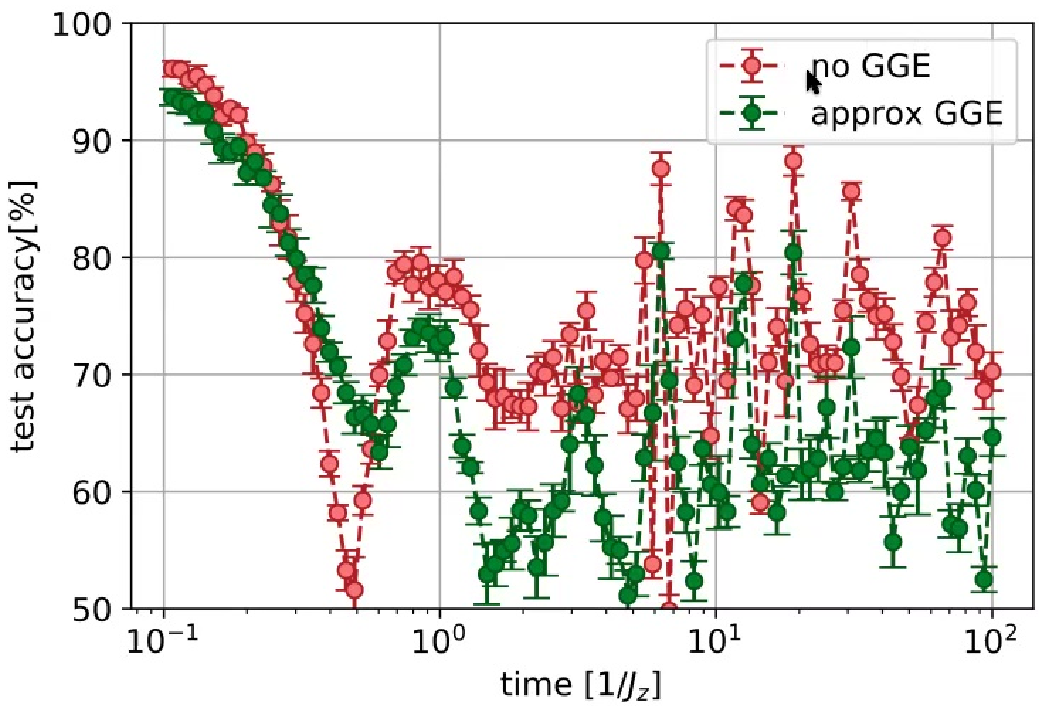
Initial state: $$|\psi_0\rangle = \prod_i \left(\sin\theta/2\,|\uparrow\rangle_i + \cos\theta/2\,|\downarrow\rangle_i\right)$$



$$\rho = \frac{1}{Z}\exp(-\beta H)$$

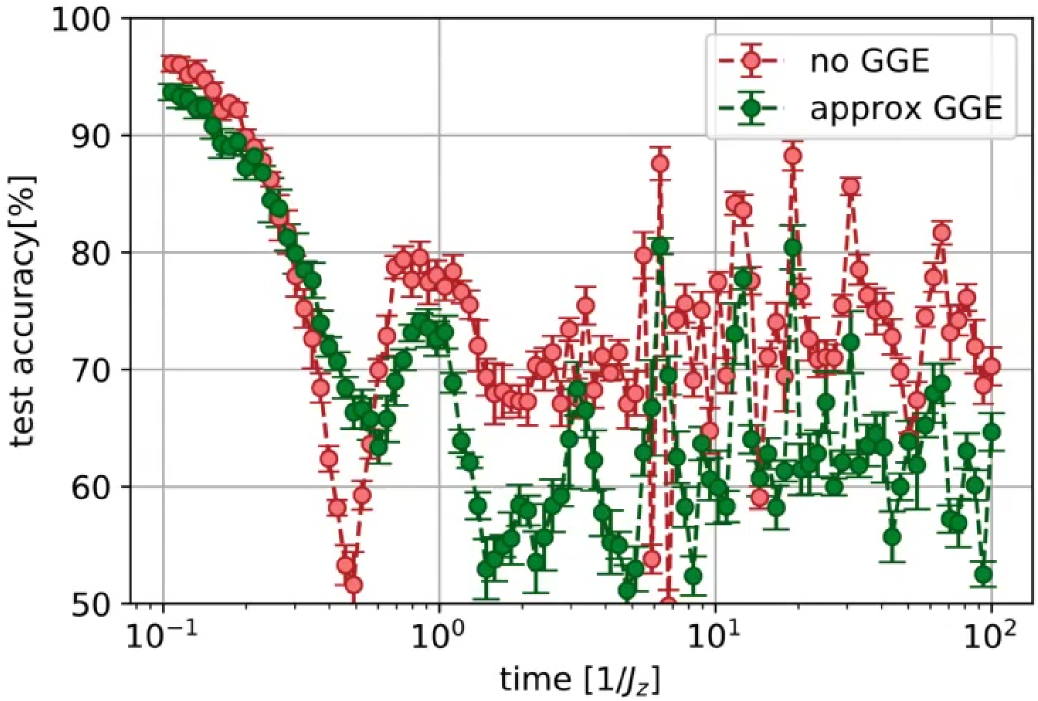
$$\rho_{\mathrm{GGE}} = \frac{1}{Z_{\mathrm{GGE}}}\exp(-\beta H - \lambda_2 I^{(2,+)} - \lambda_3 I^{(3,+)})$$

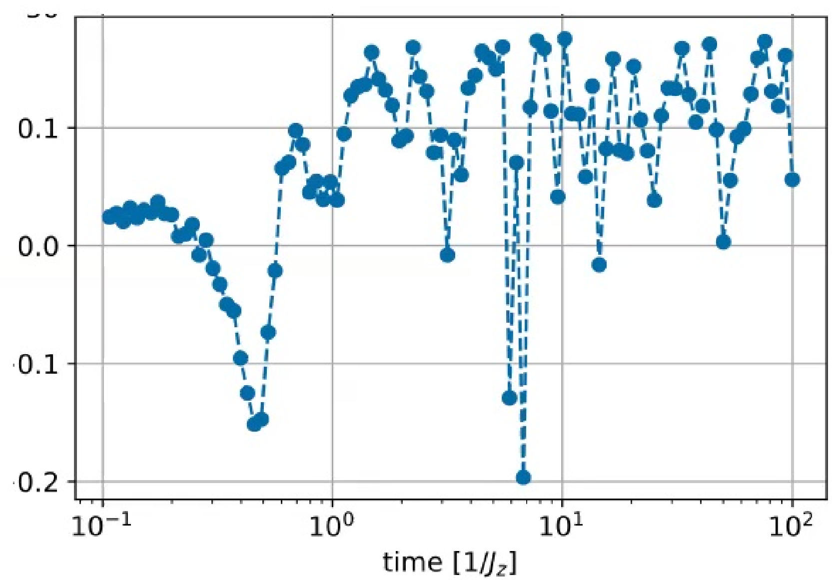
Thermalization with conserved quantities



Bohrdt et al., Phys. Rev. Lett. 127 (2021)

Thermalization with conserved quantities





Bohrdt et al., Phys. Rev. Lett. 127 (2021)

Active Learning

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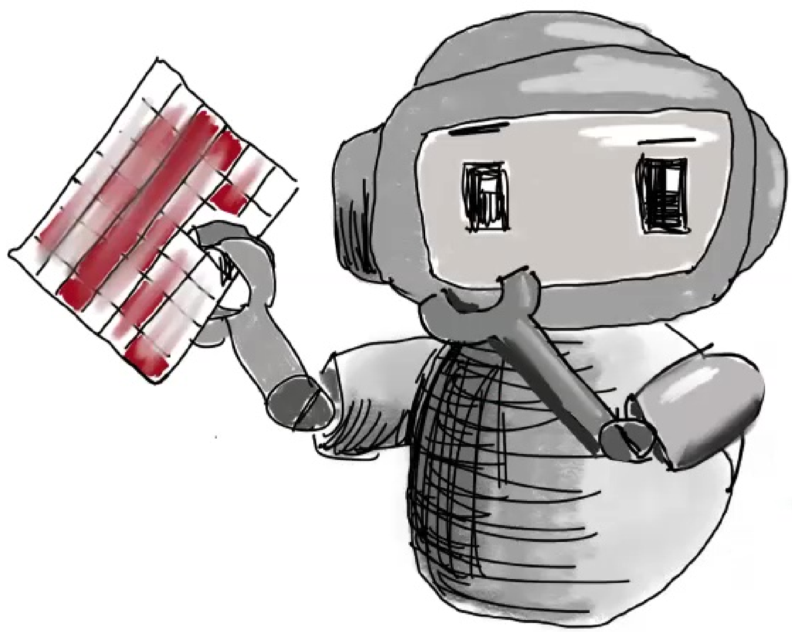

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State reconstruction with RBMs

- Given some reference basis (say z-basis), we want to reconstruct a target wave-function $\Psi(x) = \langle x|\Psi\rangle$

Torlai et al., Nature Physics (2018), Beach et al., SciPost (2019), Torlai et al., PRL (2019), Torlai&Melko, Ann. Rev. of CMP (2020), …

Active Learning

Hannah Lange

Matjaz Kebric

Fabian Grusdt

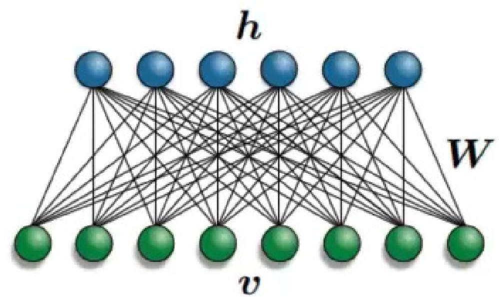
Annabelle Bohrdt

State reconstruction with RBMs

- Given some reference basis (say z-basis), we want to reconstruct a target wave-function $\Psi(x) = \langle x|\Psi\rangle$

- Use RBM wave-function:

$$\psi_{\lambda,\mu}(x) = \sqrt{\frac{p_\lambda(x)}{Z_\lambda}} e^{i\phi_\mu(x)/2}$$



Torlai et al., Nature Physics (2018), Beach et al., SciPost (2019), Torlai et al., PRL (2019), Torlai&Melko, Ann. Rev. of CMP (2020), ...

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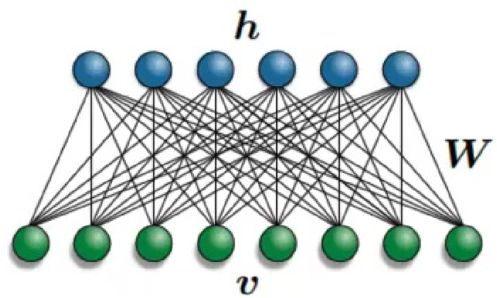
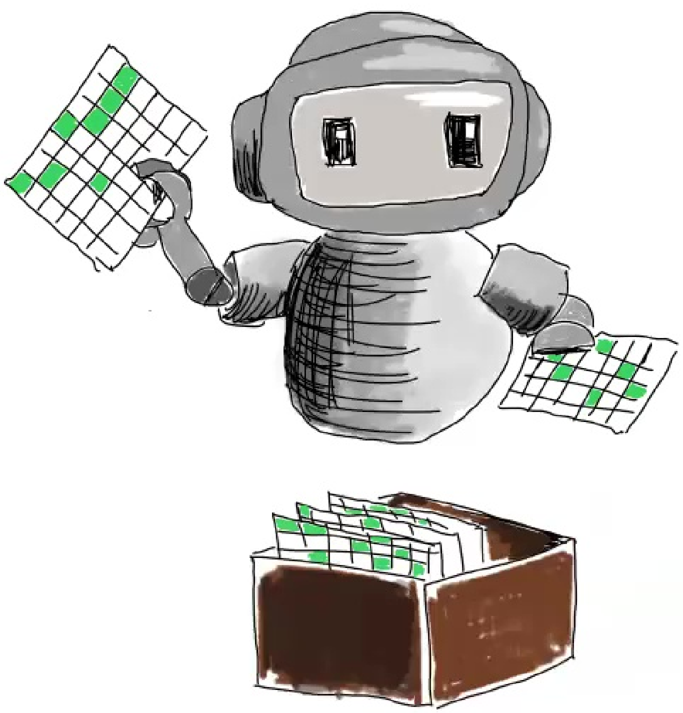
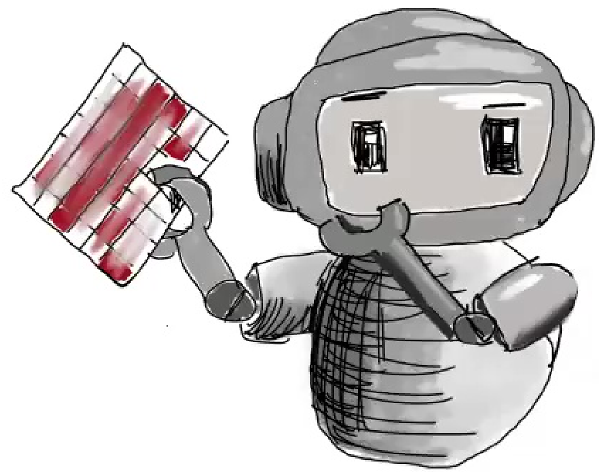


- Train RBM on a dataset of measurements $\left|\Psi(x^{[b]})\right|^2$ realized in a collection of bases $\{x^{[b]}\}$

Torlai et al., Nature Physics (2018), Beach et al., SciPost (2019), Torlai et al., PRL (2019), Torlai&Melko, Ann. Rev. of CMP (2020), …

Active Learning





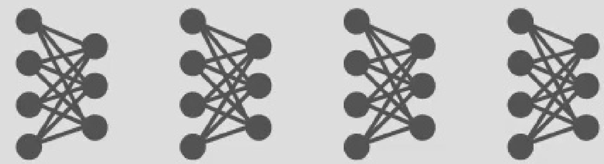
Cohn et al., Machine Learning (1994),
Tur et al., Speech Communication (2005), ...

Active Learning: First Stage

Choose reference basis $$\psi_{\lambda,\mu}(x) = \sqrt{\frac{p_\lambda(x)}{Z_\lambda}} e^{i\phi_\mu(x)/2}$$

Repeat for a (small) set of global bases:

- get a few samples in one (global) basis
- train n RBMs to learn the state



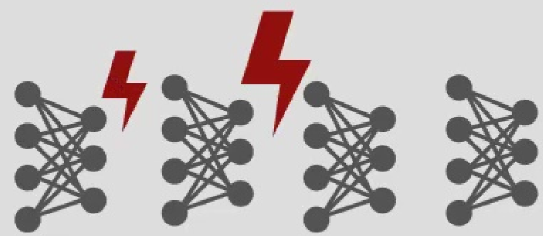
Query by committee: choose basis with smallest variance

Active Learning: Second Stage

Learn details of the state

Repeat until pre-set accuracy/max. number of measurements reached:

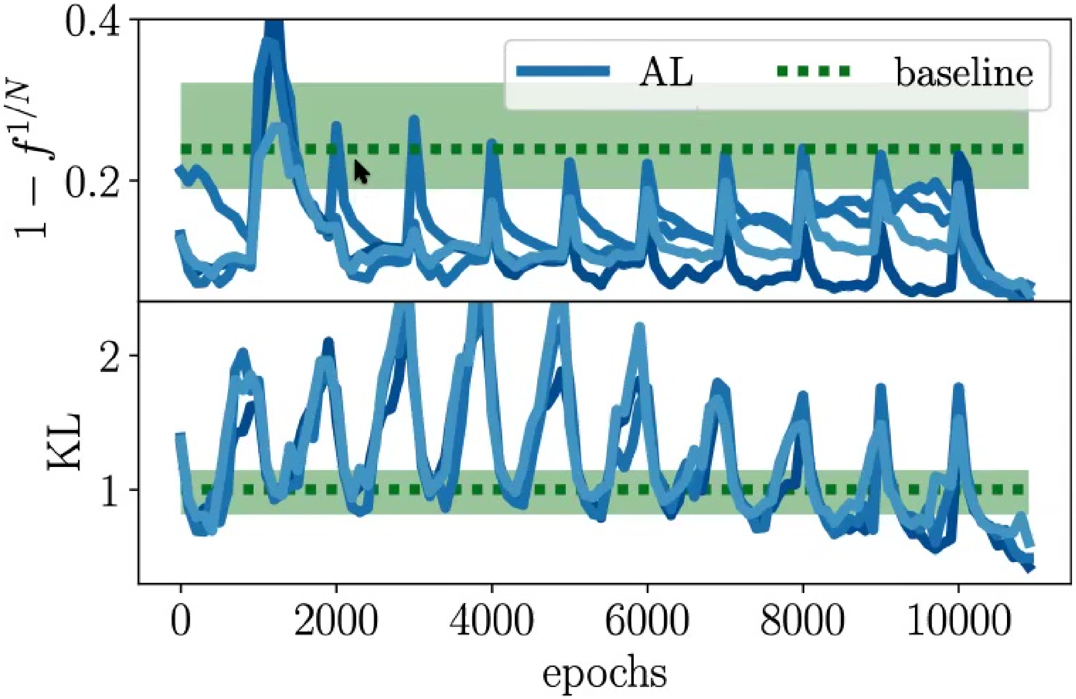
- sample in chosen basis
- train n RBMs to learn the state
- query by committee: choose basis where RBMs disagree most



Lange et al., in preparation

Learning Cycle

Learning a GHZ state with 9 qubits



Lange et al., in preparation

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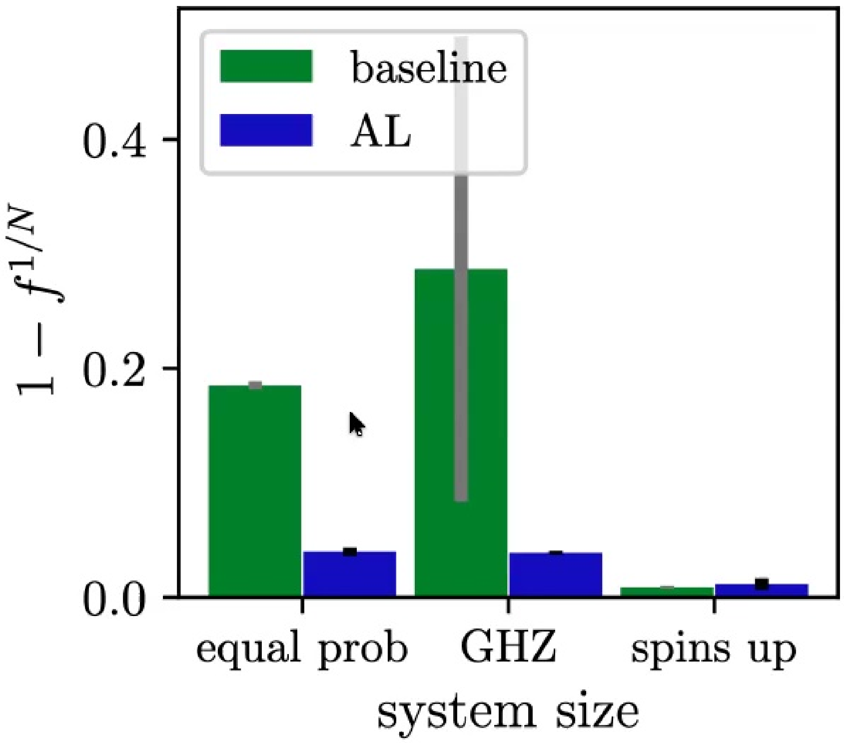
Active Learning: Results

Learning different 5 qubit states



Lange et al., in preparation

Thanks for your attention!