scalable quantum-classical interfaces & applications to quantum learning

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outline

- broad overview
- quantum readout problem
- classical shadows: new quantum-classical interfaces
- application: learning with quantum data
- synopsis

broad overview

what is quantum computing?

- quantum computers are **not** next generation of supercomputers
- we try to **re-invent the wheel of computing** itself

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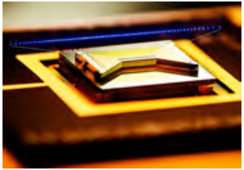

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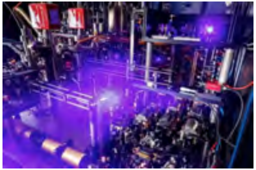

neutral atoms

photons

superconducting circuits

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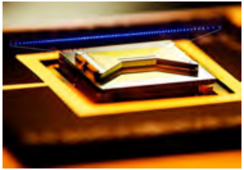

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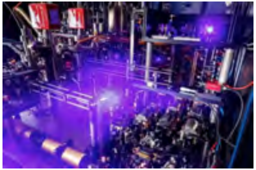

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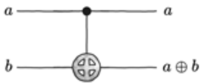

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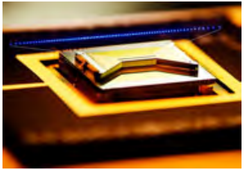
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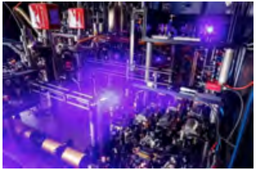
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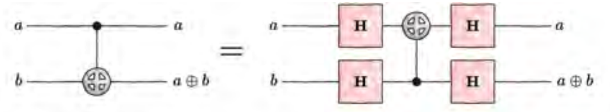

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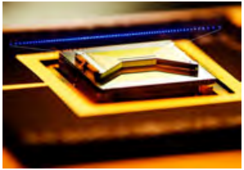

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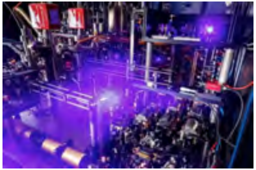

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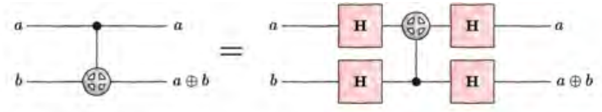

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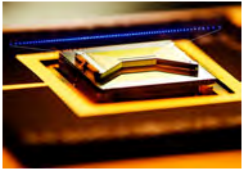
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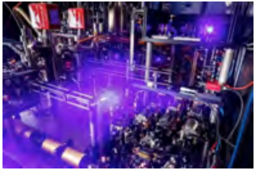
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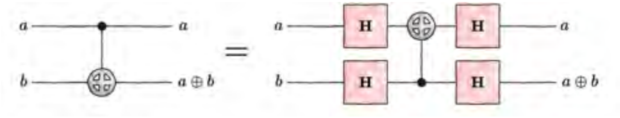

useful analogy:

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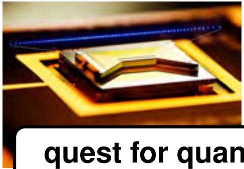


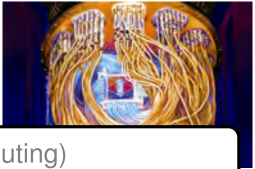

quest for quantum advantage (raison d’être for quantum computing)

identify tasks where quantum computers **justifiably** save **a lot of** resources:

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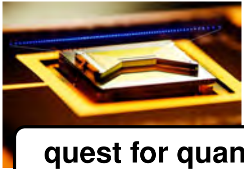


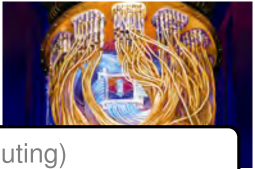

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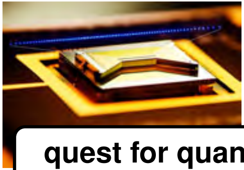


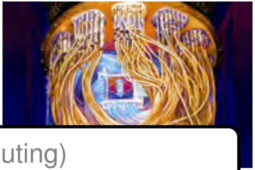

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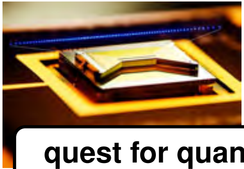


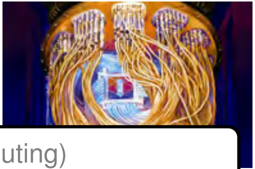

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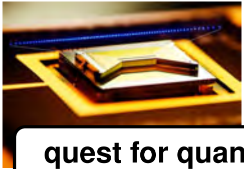


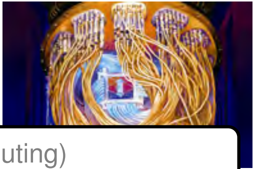

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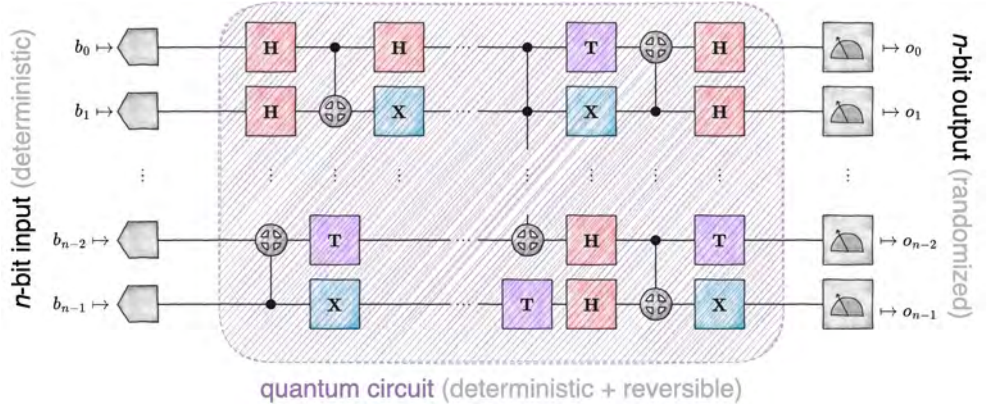
- **memory** (quantum compression) requires unfavorable compromises
- **training data size** (quantum-enhanced learning) window of opportunity

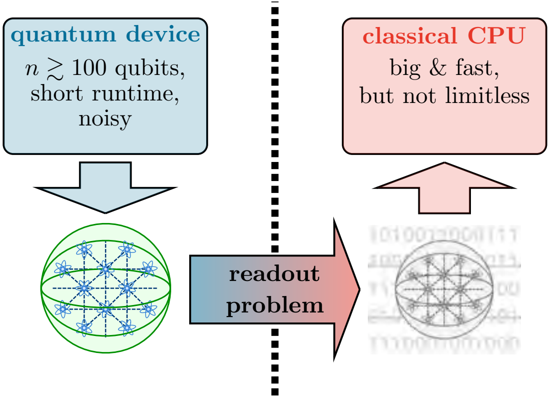
the quantum circuit model



produces a **distribution** over all 2^n bit strings; result often encoded in **statistical correlations**

quantum readout problem

quantum readout problem



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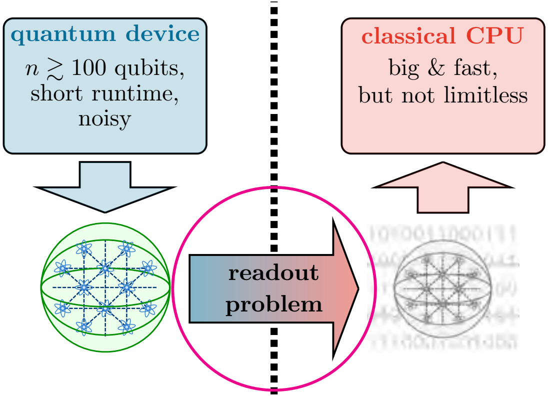

fundamental challenge

(often) exponential in qubit number

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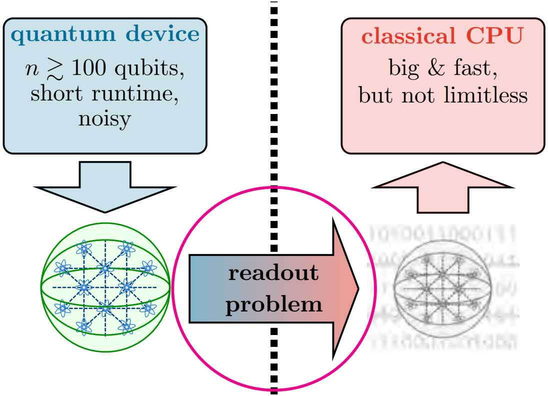

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100 qubits $\Rightarrow 2^{100} \approx 10^{30}$

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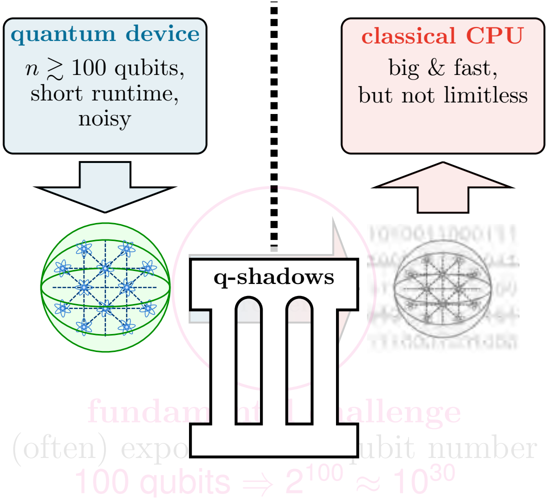


unified treatment of **all** computational resources

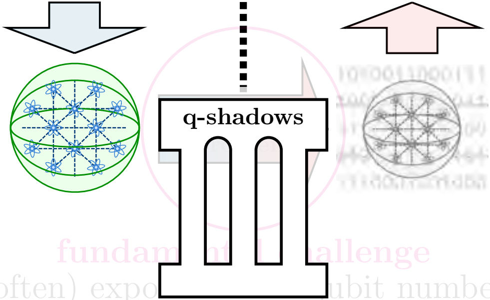
quantum readout problem

quantum device

$n \gtrsim 100$ qubits,
short runtime,
noisy

classical CPU

big & fast,
but not limitless



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enhanced readout (O1)

unified treatment of **all** computational resources

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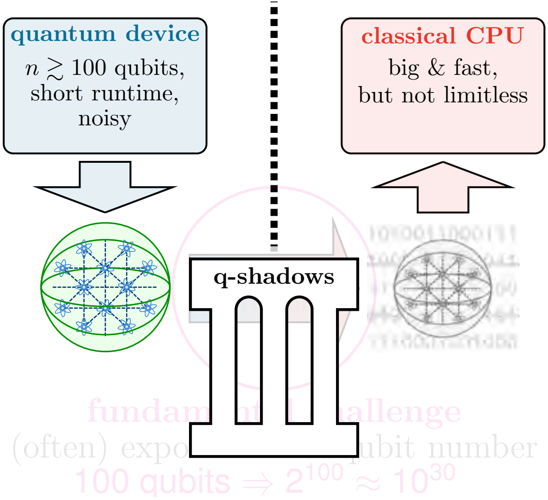

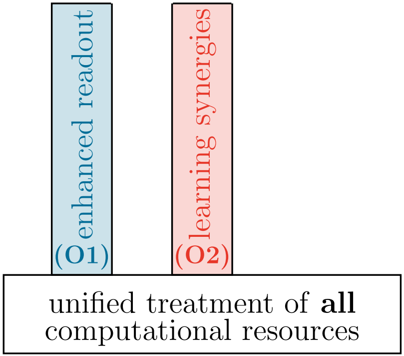

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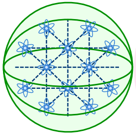

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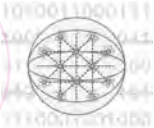


q-shadows

100 qubits $\Rightarrow 2^{100} \approx 10^{30}$

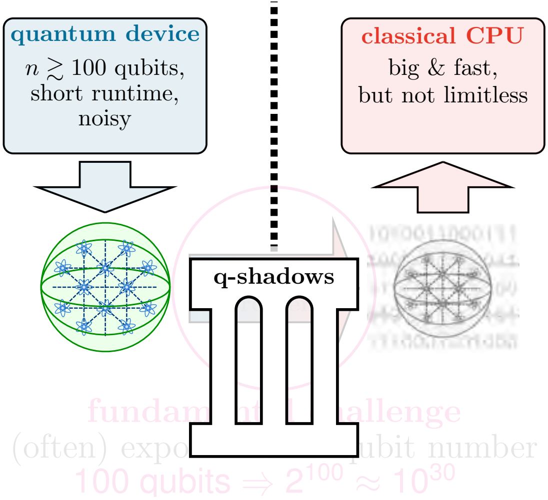
(O1) enhanced readout

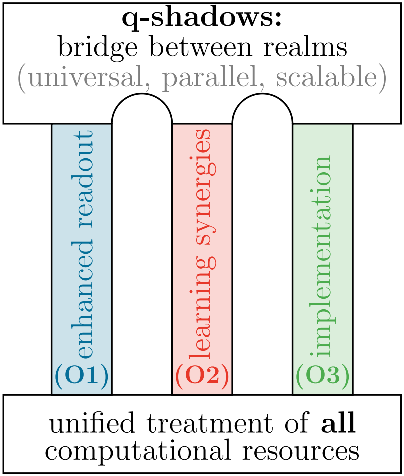
(O2) learning synergies

(O3) implementation

unified treatment of **all** computational resources

quantum readout problem

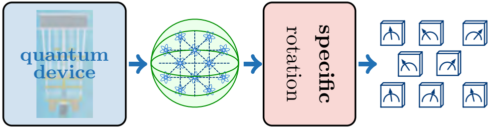




classical shadows: new quantum-classical interfaces

classical shadows: high-level overview

state of the art



special purpose, sequential

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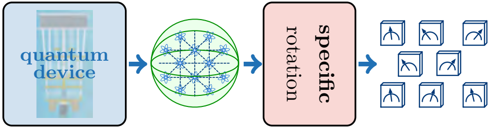

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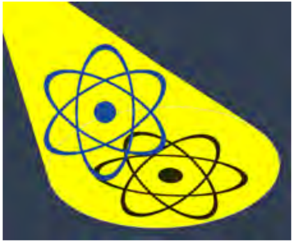

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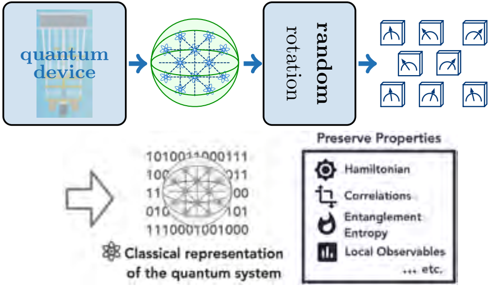

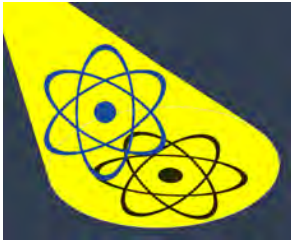

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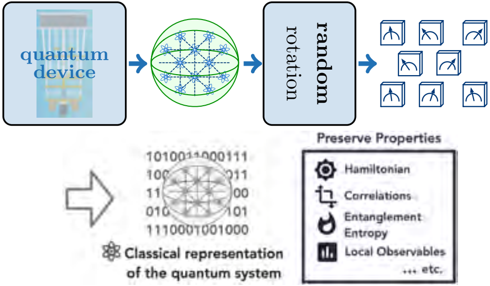
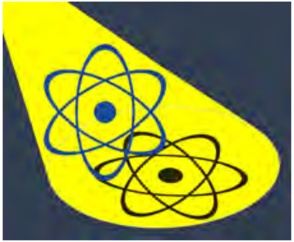
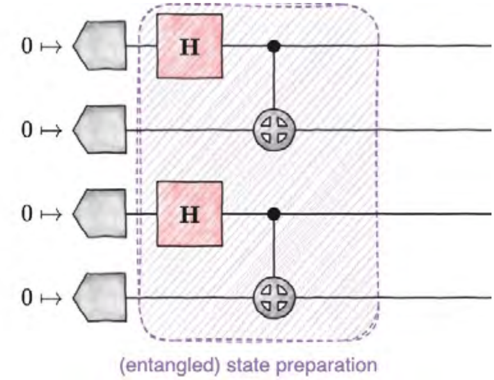




- classical shadows are new, universal & parallelizable (Huang, Kueng, Preskill, **Nature Physics** 2020)
- 2024 Bell prize for John Preskill

4 qubit case study: extracting properties directly

state preparation: two Bell states $\frac{1}{2}\left(|00\rangle + |11\rangle\right) \otimes \left(|00\rangle + |11\rangle\right)$



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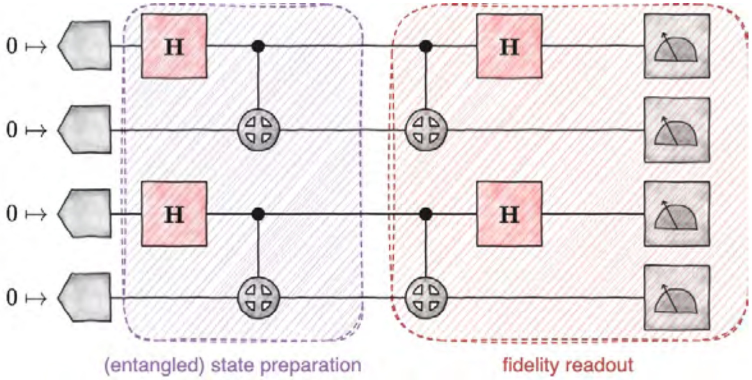
(T0) global fidelity with respect to target states



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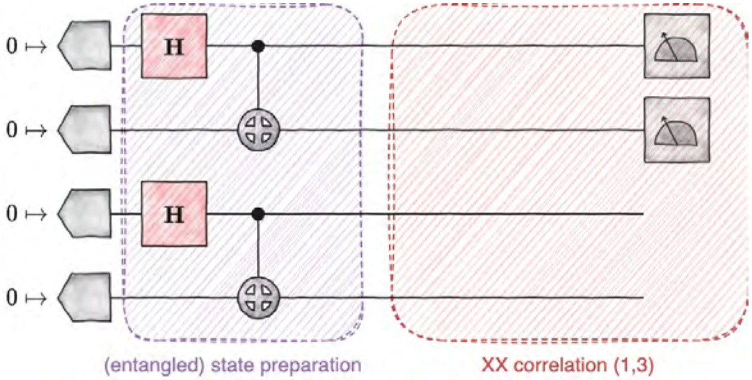
(T1a) ZZ correlations for qubits (0,1)



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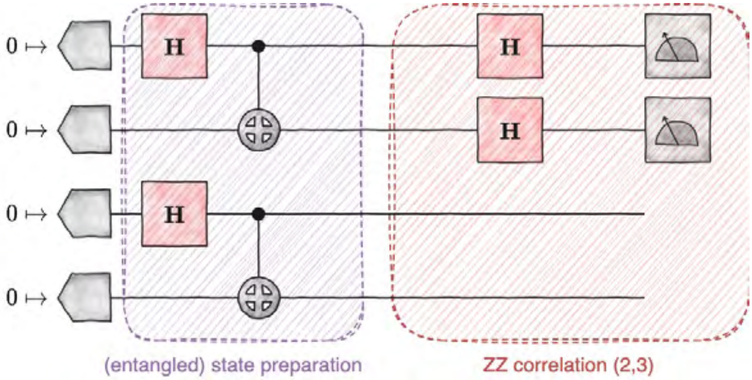
(T1b) XX correlations for qubits (0,1)



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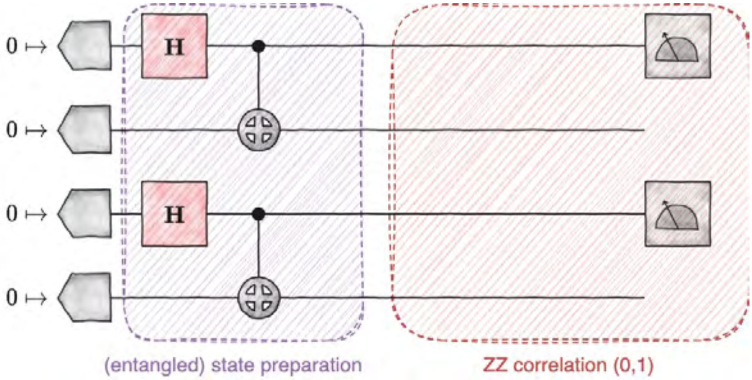
(T2a) ZZ correlations for qubits (0,2)



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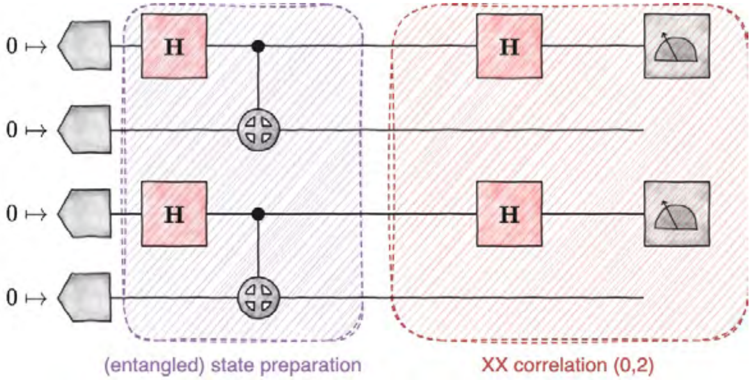

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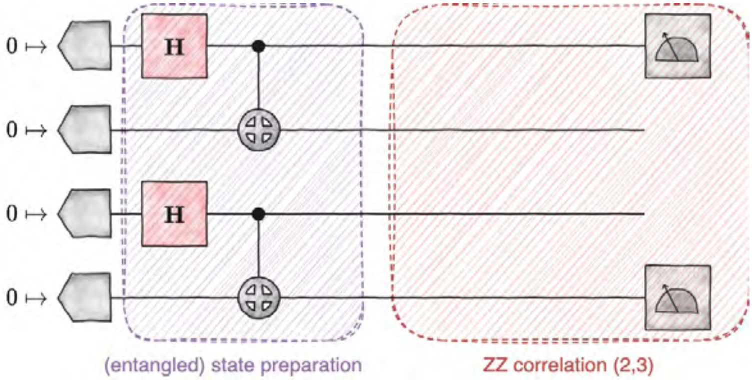
(T3a) ZZ correlations for qubits (0,3)



strategies to determine

- global fidelity
- two-bit correlations (Z)
- two-bit correlations (X)

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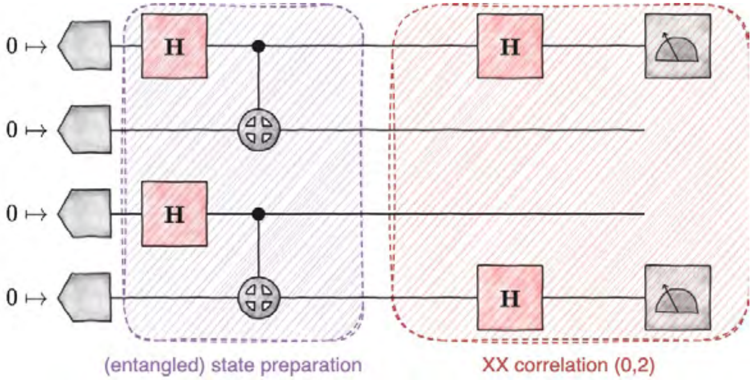

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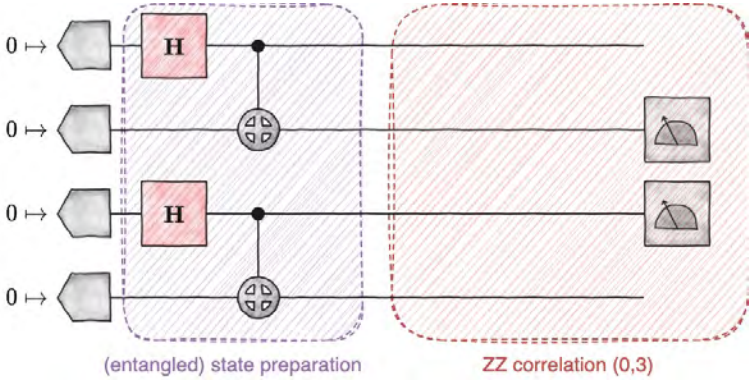
(T4a) ZZ correlations for qubits (1,2)



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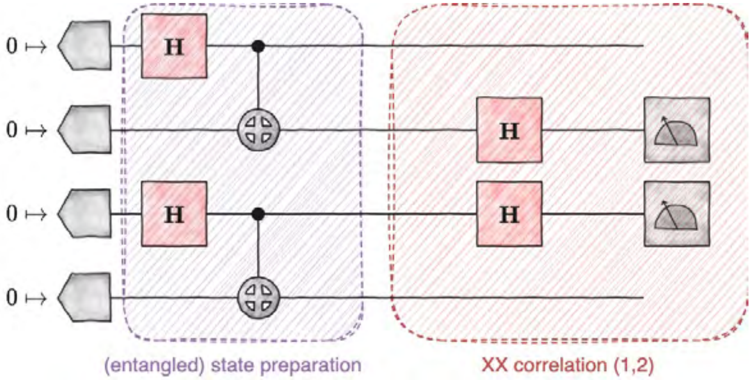

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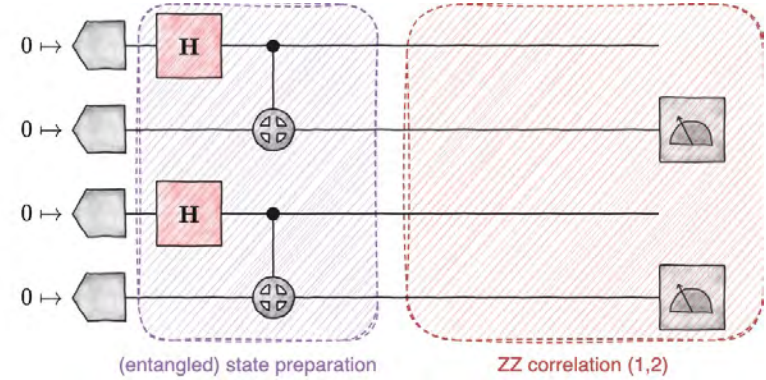
(T5a) ZZ correlations for qubits (1,3)



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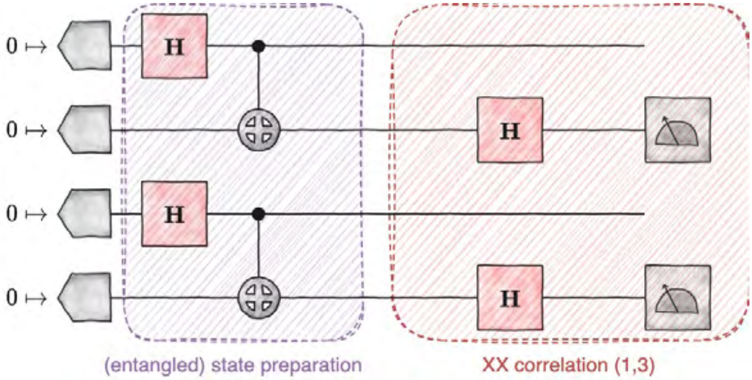
4 qubit case study: extracting properties directly

state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$

(T5b) XX correlations for qubits (1,3)



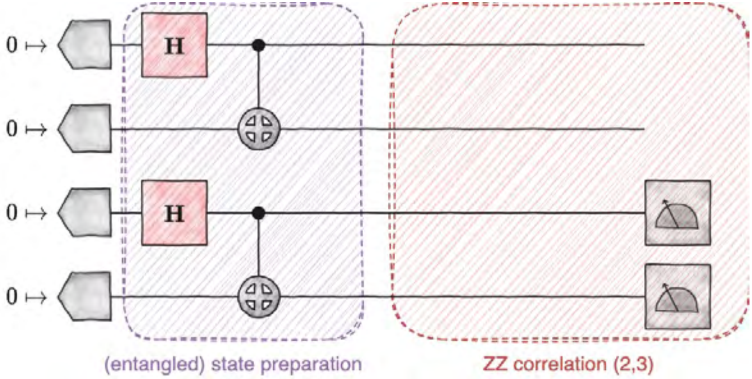
strategies to determine

- ○ global fidelity
- ○ two-bit correlations (Z)
- ○ two-bit correlations (X)

4 qubit case study: extracting properties directly

state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$

(T6a) ZZ correlations for qubits (2,3)



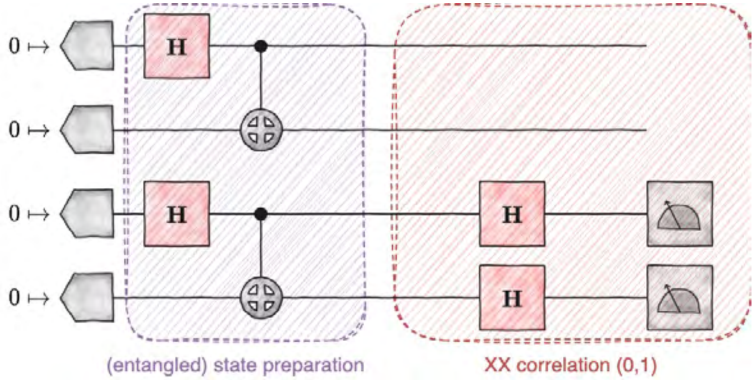
strategies to determine

- ○ global fidelity
- ○ two-bit correlations (Z)
- ○ two-bit correlations (X)

4 qubit case study: extracting properties directly

state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$

(T6b) XX correlations for qubits (2,3)



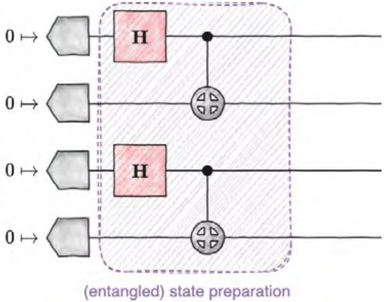
$13 = 1 + 2 \times 6$

strategies to determine

- ○ global fidelity
- ○ two-bit correlations (Z)
- ○ two-bit correlations (X)

4 qubit case study: classical shadows

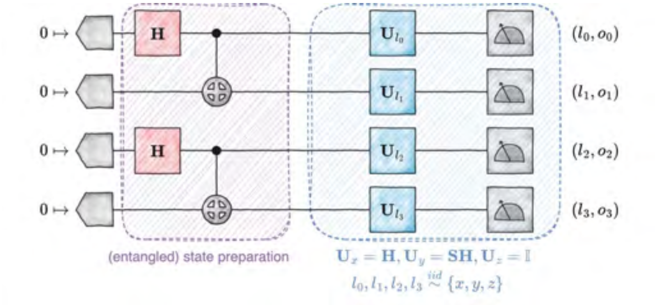
state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$



4 qubit case study: classical shadows

state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$

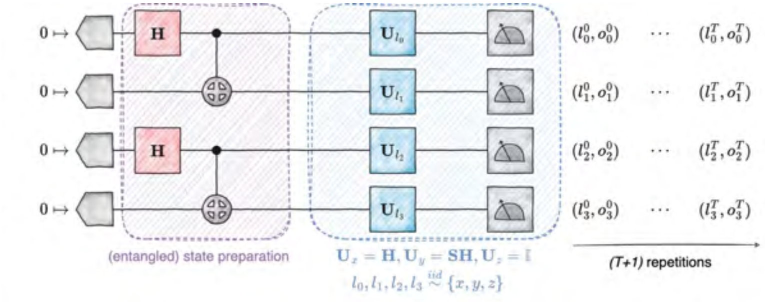
step 1: randomized readout (single-shot)



4 qubit case study: classical shadows

state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$

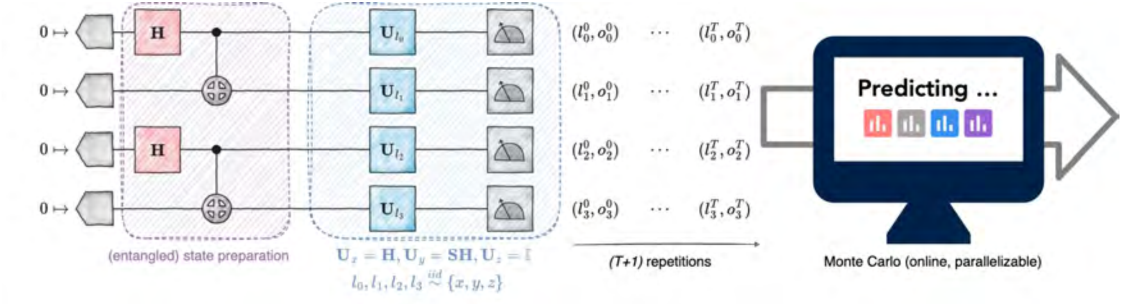
step 2: repeat T times with different random rotations



4 qubit case study: classical shadows

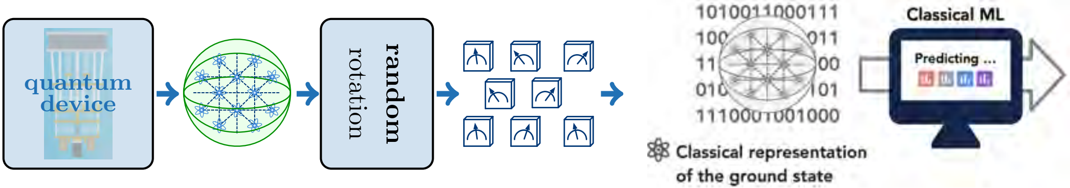
state preparation: two Bell states $\frac{1}{2}(|00\rangle + |11\rangle) \otimes (|00\rangle + |11\rangle)$

step 3: use classical data analysis to predict whatever you want **in parallel**



application: learning with quantum data

high-level vision



full quantum-classical learning pipeline:

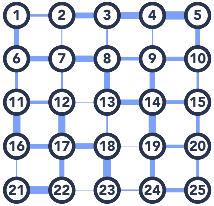
- a quantum architecture prepares *interesting* quantum states
- convert them into a classical shadow (new classical data format)
- use these classical shadows as training data for a classical ML model

$\Rightarrow$ *classical machine learning with quantum data*

vignette application: many-body ground state properties

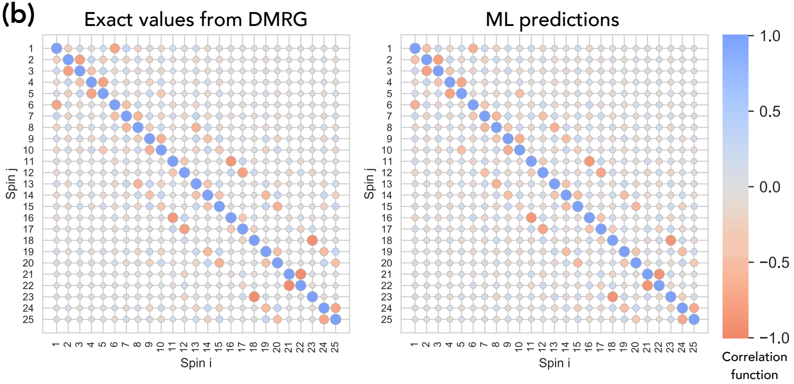
(a) 2D anti-ferromagnetic random Heisenberg model

$$H = \sum_{\langle ij \rangle} J_{ij}(X_i X_j + Y_i Y_j + Z_i Z_j)$$



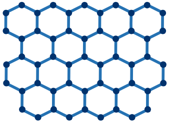
*The random J considered in (c)

(b)



vignette application: many-body ground state properties

$\mathbf{H}_{\text{tot}} = \sum_j \boldsymbol{H}$



Parameters describing a physical Hamiltonian

$\Rightarrow$

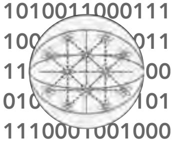
direct computation

$\rho(x) = \boldsymbol{v}_{\min}(x)\boldsymbol{v}_{\min}(x)^\dagger$

(expensive: $D = 2^n$)

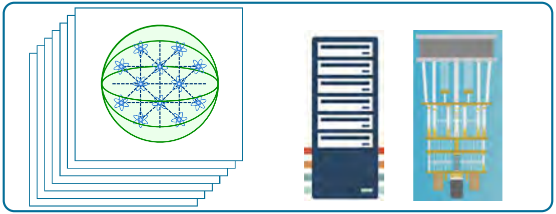
$\Rightarrow$

$\operatorname{tr}\left(\boldsymbol{O}\rho(x)\right)$



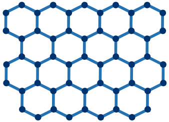
Classical representation of the ground state

vignette application: many-body ground state properties



$x \in [-1, 1]^m$

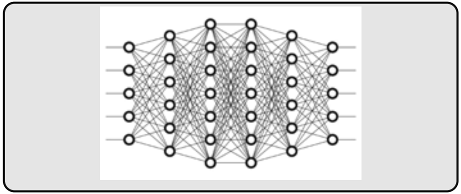
$\mathbf{H}_{\text{tot}}(x) = \sum_j \boldsymbol{H}(x)$



Parameters describing a physical Hamiltonian

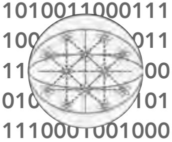
$\Rightarrow$

$(x_\ell, \rho(x_\ell)) \Downarrow x_\ell \overset{unif}{\sim} [-1, 1]^m$



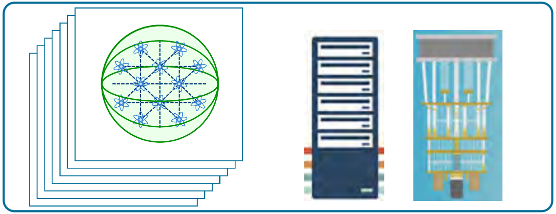
$\Rightarrow$

$\operatorname{tr}(\boldsymbol{O}\rho_{\text{train}}(x))$



Classical representation of the ground state

vignette application: many-body ground state properties



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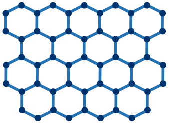


Parameters describing a physical Hamiltonian

$\Rightarrow$

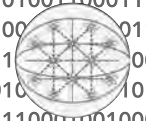
$(x_\ell, \rho(x_\ell)) \Downarrow x_\ell \overset{unif}{\sim} [-1, 1]^m$

$\rho_{\text{train}}(x) = \sum_{\ell=1}^{N} \kappa(x, x_\ell)\, \rho(x_\ell)$

κ : neural tangent kernel

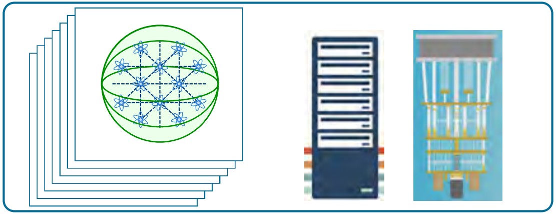
$\Rightarrow$

$\text{tr}\,(\boldsymbol{O}\rho_{\text{train}}(x))$



Classical representation of the ground state

vignette application: many-body ground state properties



$x \in [-1, 1]^m$

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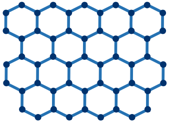

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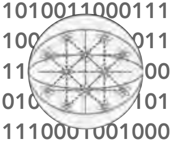
~~κ : neural tangent kernel~~

κ : ℓ_2-Dirichlet kernel

$\Rightarrow$

$\text{tr}(\boldsymbol{O}\rho_{\text{train}}(x))$



Classical representation of the ground state

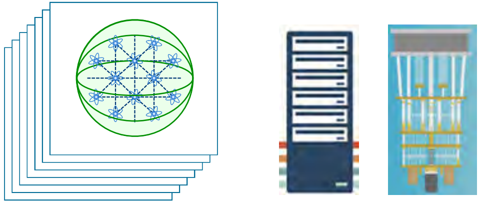
vignette application: many-body ground state properties

Theorem: assumptions on $\boldsymbol{H}(x)$, $\boldsymbol{O}$ ensure

$$\mathbb{E}_{x \overset{unif}{\sim} [-1,1]^m} \left| \mathrm{tr}\left(\boldsymbol{O}\rho_{\mathrm{train}}(x)\right) - \mathrm{tr}\left(\boldsymbol{O}\rho(x)\right) \right|^2 \leq \epsilon$$

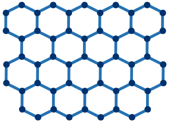
(MSE $\leq \epsilon$) with poly(m) = poly(n) scaling in

- training data size
- runtime + memory



$x \in [-1,1]^m$

$\mathbf{H}_{\mathrm{tot}}(x) = \sum_j \boldsymbol{H}(x)$



Parameters describing a physical Hamiltonian

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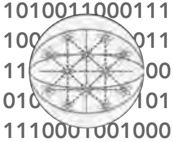
$$\rho_{\mathrm{train}}(x) = \sum_{\ell=1}^{N} \kappa(x, x_\ell)\, \rho(x_\ell)$$

~~κ : neural tangent kernel~~

κ : ℓ_2-Dirichlet kernel

$\Rightarrow$

$\mathrm{tr}\left(\boldsymbol{O}\rho_{\mathrm{train}}(x)\right)$



Classical representation of the ground state

main result

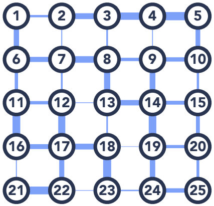
Theorem 1 (Learning to predict ground state representations; informal). *For any smooth family of Hamiltonians $\{H(x) : x \in [-1,1]^m\}$ in a finite spatial dimension with a constant spectral gap, the classical machine learning algorithm can learn to predict a classical representation of the ground state $\rho(x)$ of $H(x)$ that approximates few-body reduced density matrices up to a constant error ϵ when averaged over x. The required training data size N and computation time are polynomial in m and linear in the system size n.*

- H.Y. Huang, R. Kueng, G. Torlai, V.A. Albert, J. Preskill. *Provably efficient ML for many-body problems*. **Science 377**, eabk3333 (2022)
- L. Lewis, H.Y, Huang, V.T. Tran, S. Lehner, R. Kueng, J. Preskill. *Improved machine learning algorithm for predicting ground state properties*. **Nature Communications 15**, 895 (2024)

numerics: 2D Heisenberg model with $n = 25$ spins

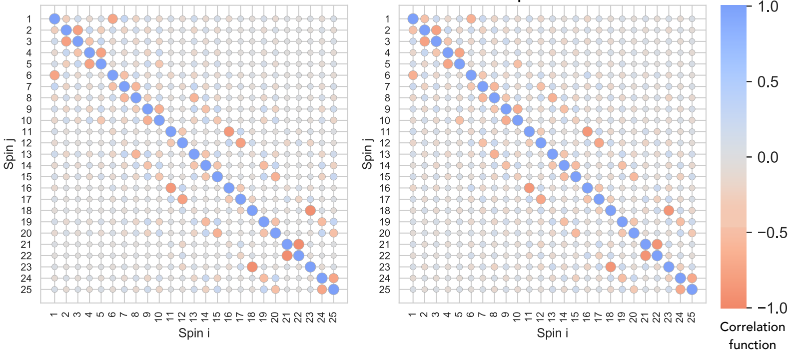
(a) 2D anti-ferromagnetic random Heisenberg model

$$H = \sum_{\langle ij \rangle} J_{ij}(X_i X_j + Y_i Y_j + Z_i Z_j)$$

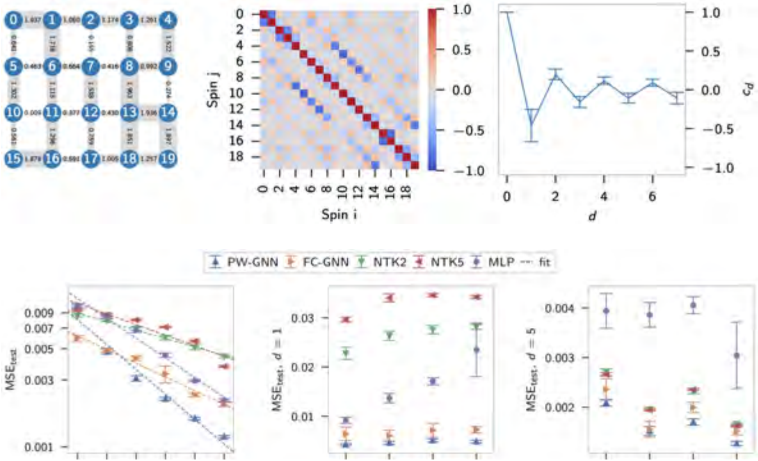


*The random J considered in (c)

(b)



numerics: 2D Heisenberg model with different ML models



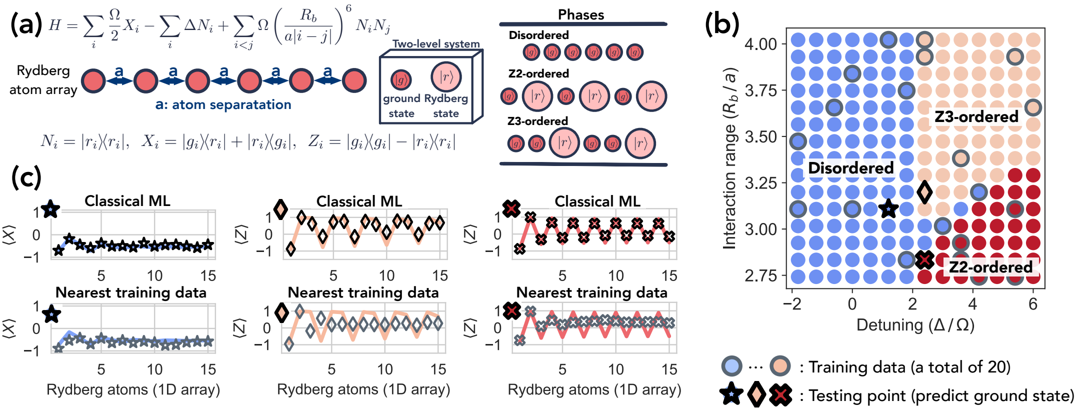
comparison between

- ○ NKT (green,red)
- ○ MLP (purple)
- ○ GNN (blue, orange)

collaboration with Caltech and Hochreiter group (JKU)

[Tran *et al*, NeurIPS workshop 22]

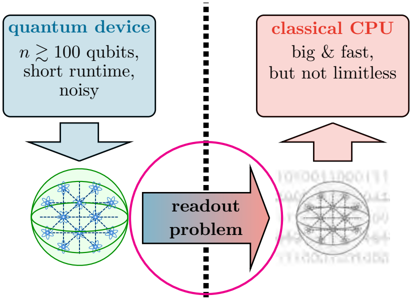
numerics: 1D chain of $n = 51$ Rydberg atoms



*Solid lines in the six line plots indicate exact values from DMRG

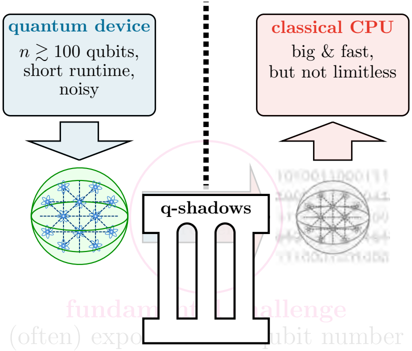
synopsis

synopsis

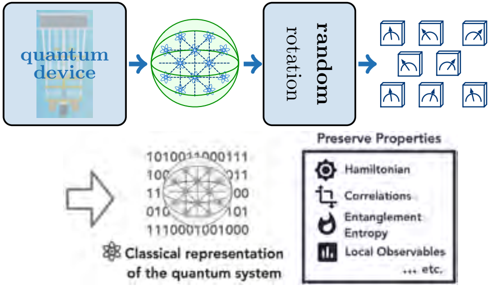


fundamental challenge
(often) exponential in qubit number

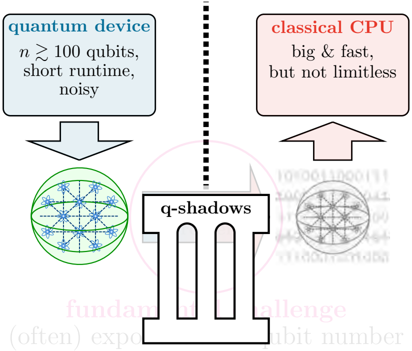
synopsis



classical shadows (quantum-classical interfaces)



synopsis



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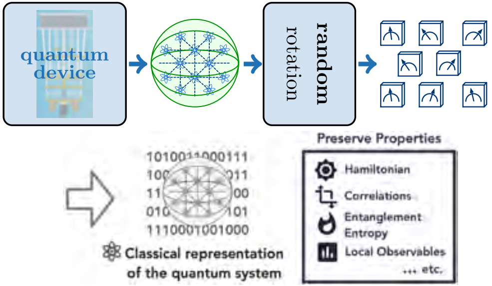
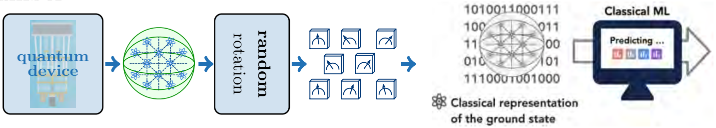


rigorous+efficient synergies with ML



QUICK department at Johannes Kepler University Linz
Quantum Information & Computation at Kepler

Johannes Kofler
- ➔ quantum information
- ➔ quantum foundations

Richard Kueng (chair)
- ➔ quantum computing
- ➔ (convex) optimization
- ➔ math of data science

"Don't mind your make-up, you'd better make your mind up." Frank Zappa

Team


Nina Brandl


Michaela Eder-Jahn


Sebastian Egginger


Kristina Kirova

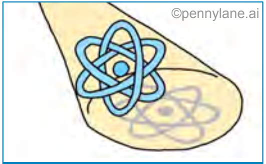

Elisabeth Peheim


Alexander Ploier

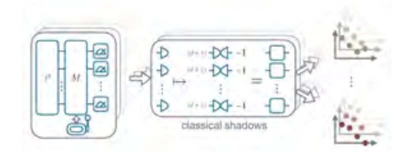

Viet Tran


Jadwiga Wilkens

JKU



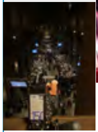
Classical shadow formalism

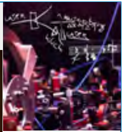


Hybrid quantum-classical algorithms

Join our team:
- ➔ PhD student
- ➔ Postdoc

BruQner
The Sound Of Entanglement





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