



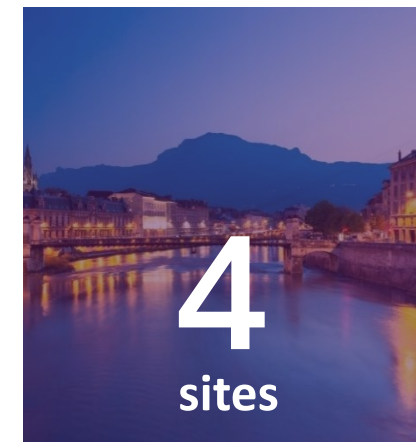
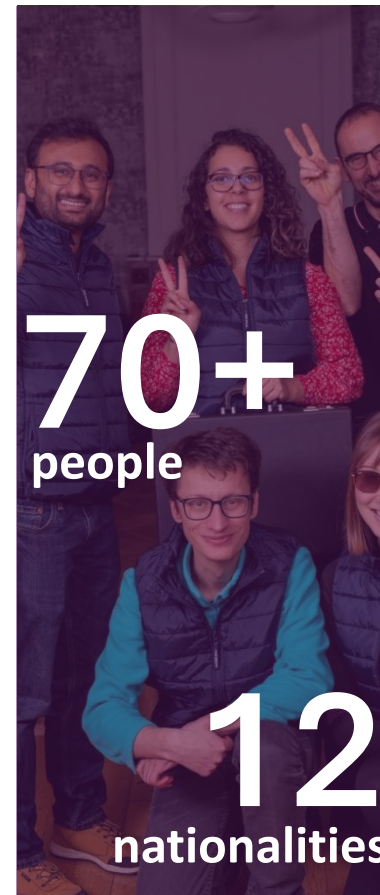
Randomized measurements for large-scale quantum experiments

Benoit Vermersch

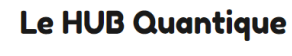
Quobly, and LPMMC Université Grenoble Alpes (on leave)

MIT Seminar

Quobly was launched in November 2022



Our networks:



Quantum Information Team @ Quobly

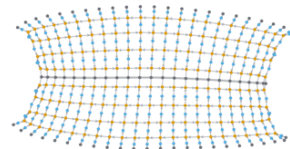
Measurements & Benchmarking



Tensor-Network Simulations
& quantum algorithms R&D
(open-source)

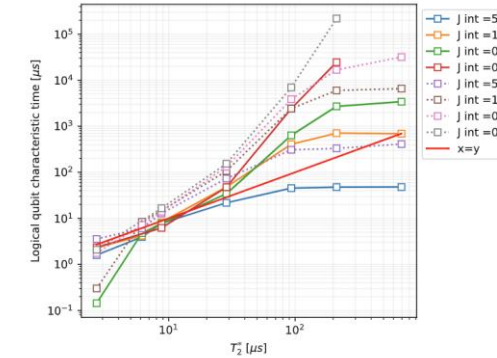
Classical preprocessing

Large scale compilation,
Tensor quantum programming,
Qubitization



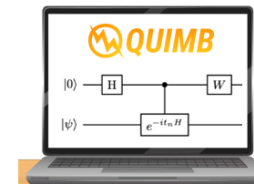
Architectures and quantum error correction

Surface-17 code



EVIDEN

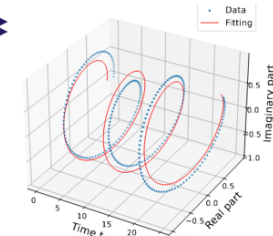
Internal Simulator



Classical postprocessing

Semi-Classical QFT
Time-series analysis
....

Benchmark with
tensor-networks



Today's menu

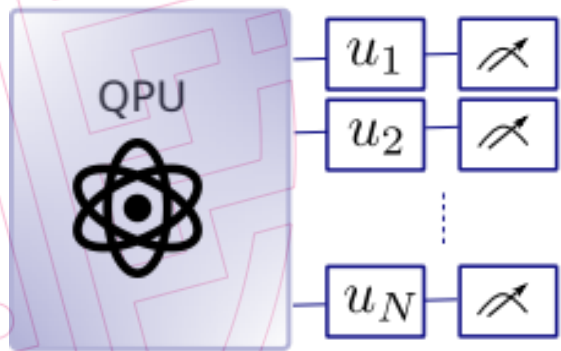
Moderate scale randomized measurements

- 1) Motivations
- 2) Measurements of entanglement entropies
- 3) More advanced usage and “statistical tricks”

Large scale learning via randomized measurements

Randomized measurements for large-scale experiments

Randomized measurements



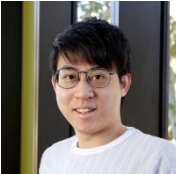
The randomized measurement toolbox A. Elben, S. T. Flammia, H.-Y. Huang, R. Kueng, J. Preskill, BV, P. Zoller, Nature Physics Review (2023).



P. Zoller (UIBK)



A. Elben (Psi)



J. Preskill, R. Huang (Caltech)



R. Kueng (Linz)



J.I.C Cirac (MPQ)



B. Kraus (TUM)



L. Piroli (Unibo)



M. Serbyn, M. Ljubotina (ISTA)



M. Votto, W. Lam (UGA)

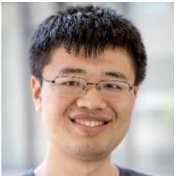


V. Vitale (Pasqal)



A. Rath (IQM)

Experiments



Xiao Mi (Google)



P. Jurcevic (IBM)



T. Brydges, M. Joshi,



C. Roos, R. Blatt (UIBK)

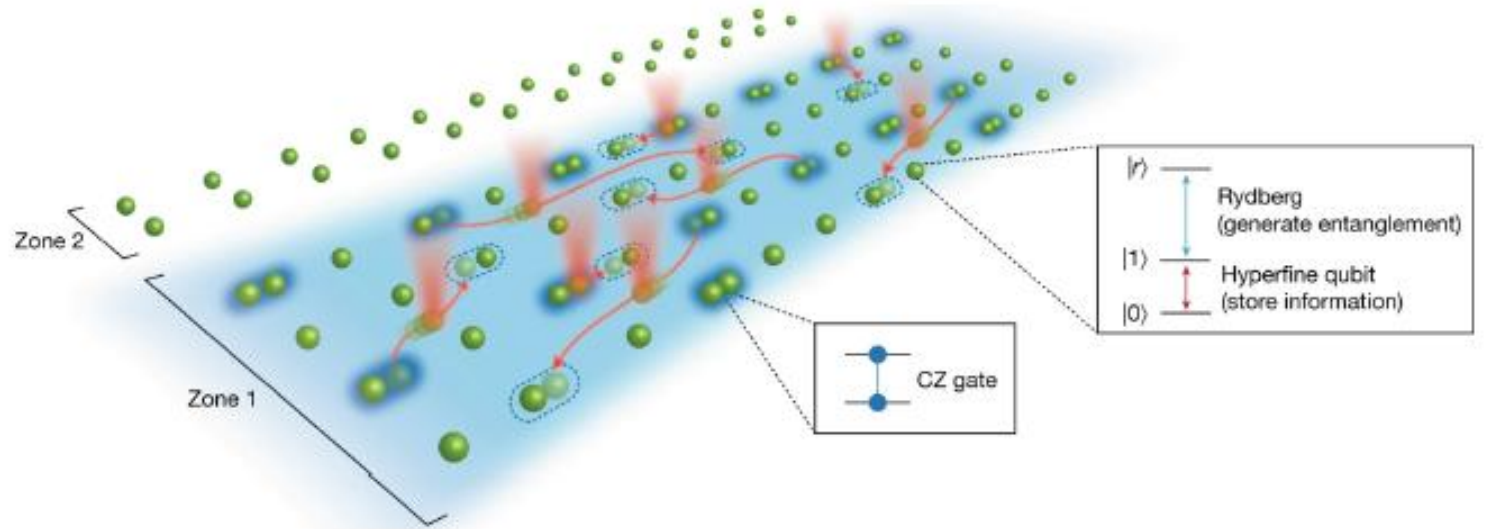
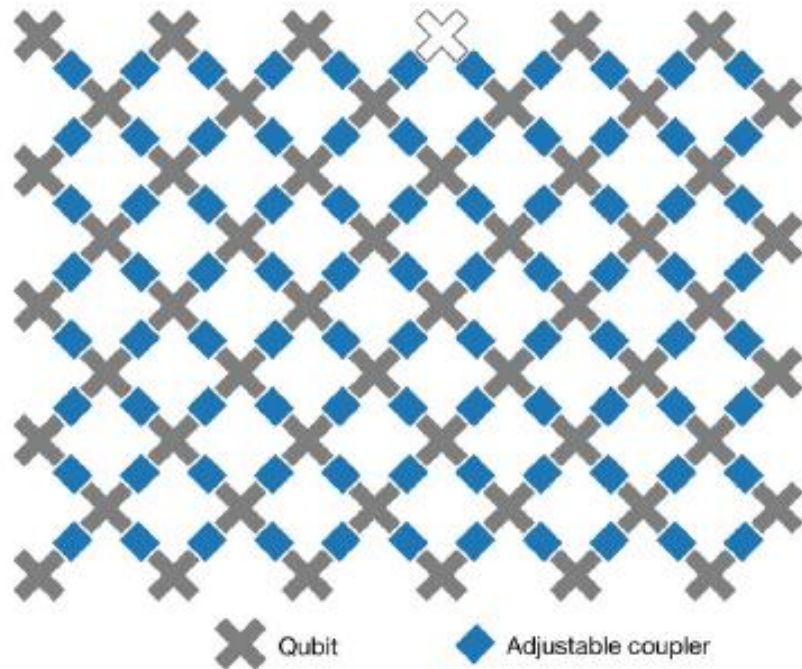


C. Lancien (UGA)

And many more...

LARGE-SCALE QUANTUM EXPERIMENTS

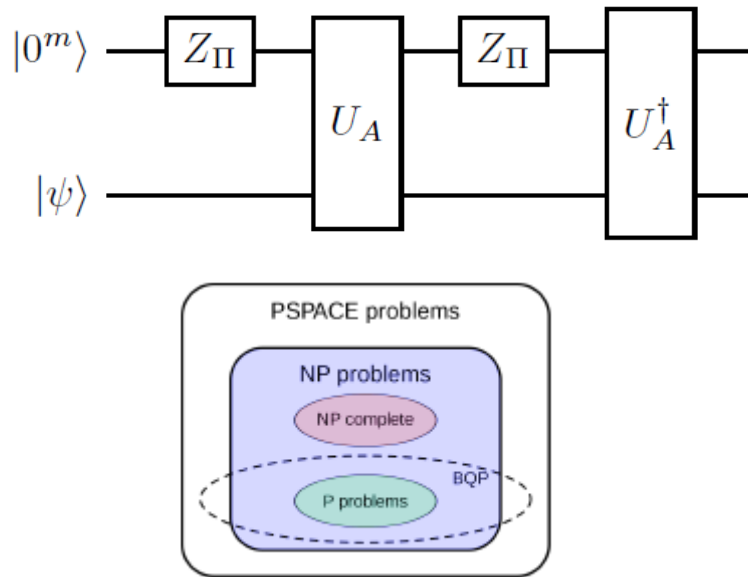
Nowadays several experiments realize large-scale programmable quantum many-body systems (~ 100 qubits) [Arute, Nature '19; Bluvstein, Nature '22]



WHAT'S THE POINT OF LARGE-SCALE QUANTUM EXPERIMENTS

Quantum computing

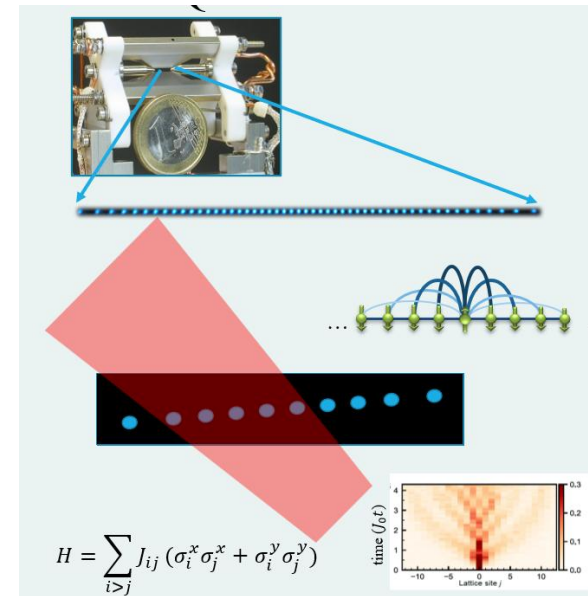
Solves a classical problem or quantum problem via a quantum algorithm



We hope to realize a computation that is not (easily) accessible to classical computers: **Quantum advantage**

Quantum simulation

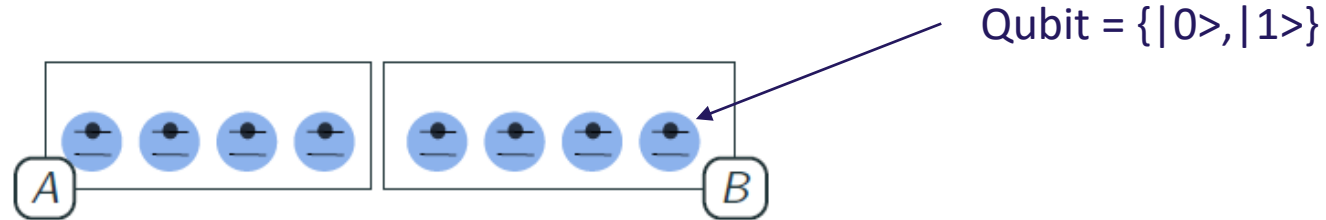
Emulates many-body physics via an artificial quantum material



Credit
Manoj Joshi (IQOQI)

We want to obtain meaningful **physical properties**

Entanglement: A central concept in quantum computing & quantum simulation



A and B are entangled iff $|\psi\rangle \neq |\psi_A\rangle \otimes |\psi_B\rangle$

Example with two qubits. The Bell state $|\psi\rangle = \frac{1}{\sqrt{2}}(|00\rangle + |11\rangle)$ is entangled

Entanglement is quantified via **Entropies**

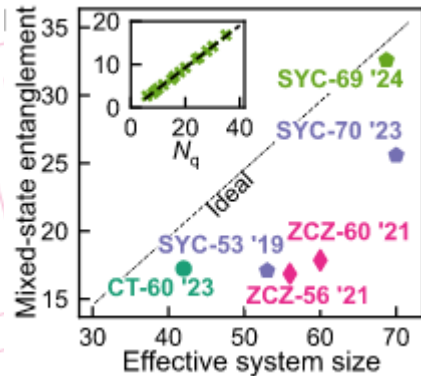
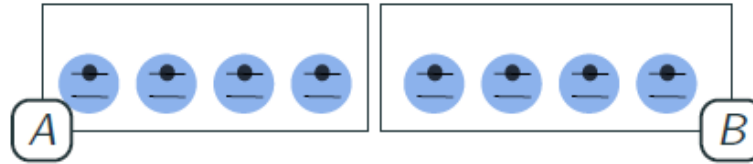
$$S_{\text{vN}} = -\text{Tr}[\rho_A \log(\rho_A)] \text{ von Neumann Entropies}$$
$$S_\alpha = \frac{1}{1-\alpha} \log[\text{Tr}(\rho_A^\alpha)] \text{ Rényi entropies}$$

Reduced Density Matrix

Purity

$$\text{Tr}(\rho_A^2)$$

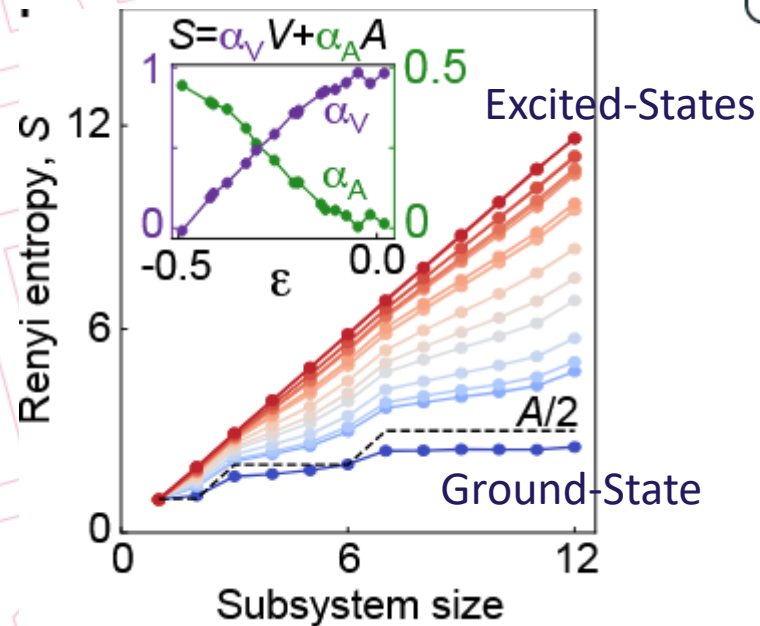
Entanglement: A central concept in quantum computing & quantum simulation



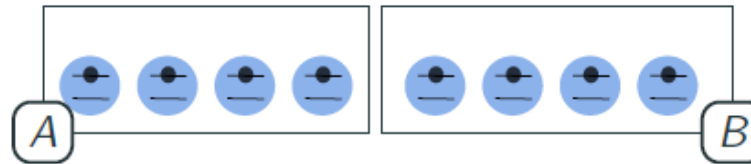
Andersen et al,
Nature 2025

- Most basic non-classical feature of **quantum computers**.
- All important quantum algorithms involve quantum operations that generate entanglement.
- Quantum algorithms with a low level of entanglement can be efficiently simulated with a classical computer (Eisert RMP 2010)
- Universal predictions for large-scale quantum computers (eg Nahum PRX 2017)

Entanglement: A central concept in quantum computing & quantum simulation

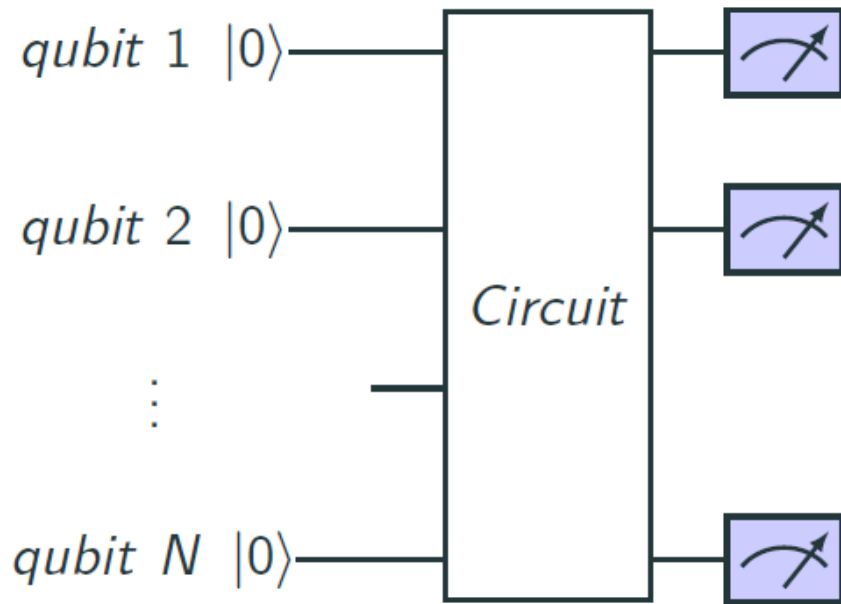


Andersen et al,
Nature 2025



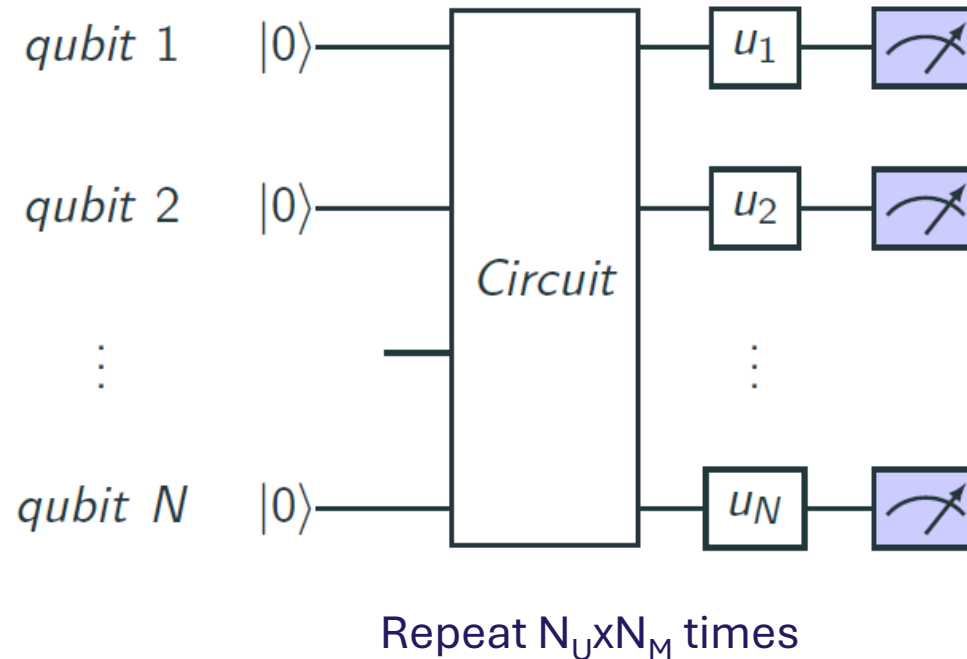
- Distinguish quantum phases in **quantum simulation**, spots quantum phase transitions (Eisert, RMP 2010)
- Describes many-body quantum dynamics, thermalization, disorder physics, etc

Measurements in quantum experiments



- Quantum measurements: the state $|s\rangle$ is measured with probability $\langle s|\rho|s\rangle$, in a certain measurement basis
- We have access to observables of the type $O|s\rangle = O(s)|s\rangle$.
- $$\langle O \rangle = \sum_s \langle s|\rho|s\rangle O(s) \quad (7)$$
- Measurement of 4^N observables: I can realize **state tomography**, i.e measure ρ .
- Can I measure the purity $\text{Tr}(\rho^2)$ more directly?

Randomized measurements: A single data acquisition procedure



- Randomized measurements: We measure $P_u(s) = \langle s | u \rho u^\dagger | s \rangle$, $u = u_1 \otimes \cdots \otimes u_N$.
- u_i chosen independently from the circular unitary ensemble (CUE)
- We extract quantities of interest from the statistics of $P_u(s)$, over random unitary transformations.

For example, the purity formula
(Elben, BV, et al, PRL 2018)

$$\text{Tr}(\rho^2) = 2^N E_u \left[\sum_{s, s'} (-2)^{-D(s, s')} P_u(s) P_u(s') \right]$$

Original protocol: van Enk-Beenakker (PRL 2012)

- Consider a single qubit



- We evaluate the statistics of

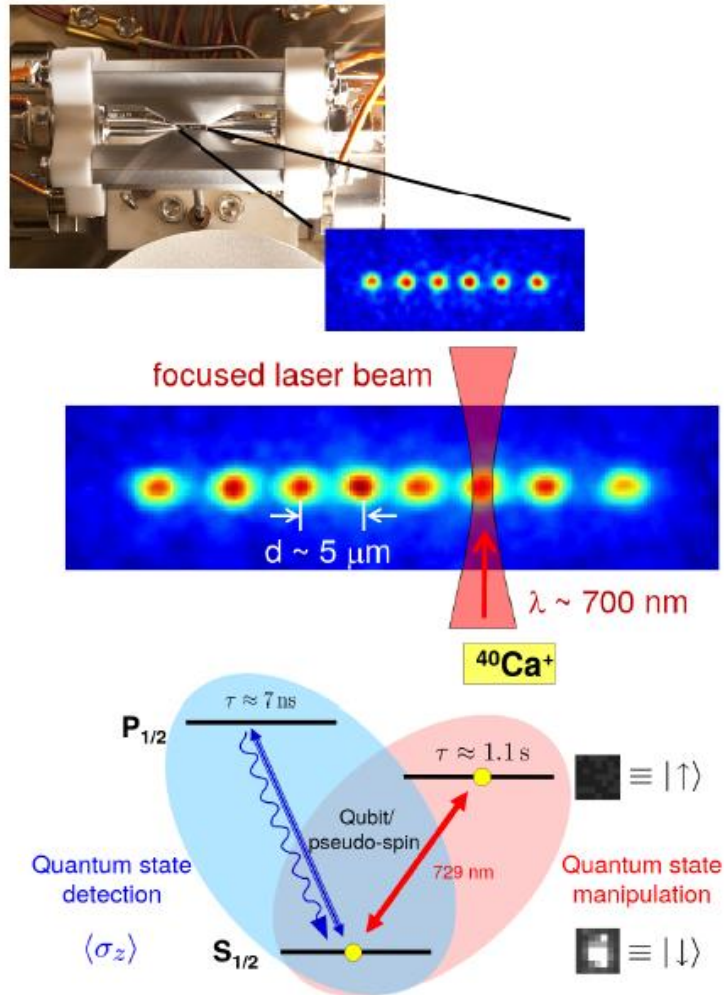
$$P_u(s) = \langle s | u \rho u^\dagger | s \rangle = \sum_{m,n} u_{s,m} \rho_{m,n} u_{s,n}^*$$

$$E[[P_u(s)]^2] = \sum_{m,n,m',n'} \rho_{m,n} \rho_{m',n'} E[u_{s,m} u_{s,n}^* u_{s,m'} u_{s,n'}^*] \quad (2)$$

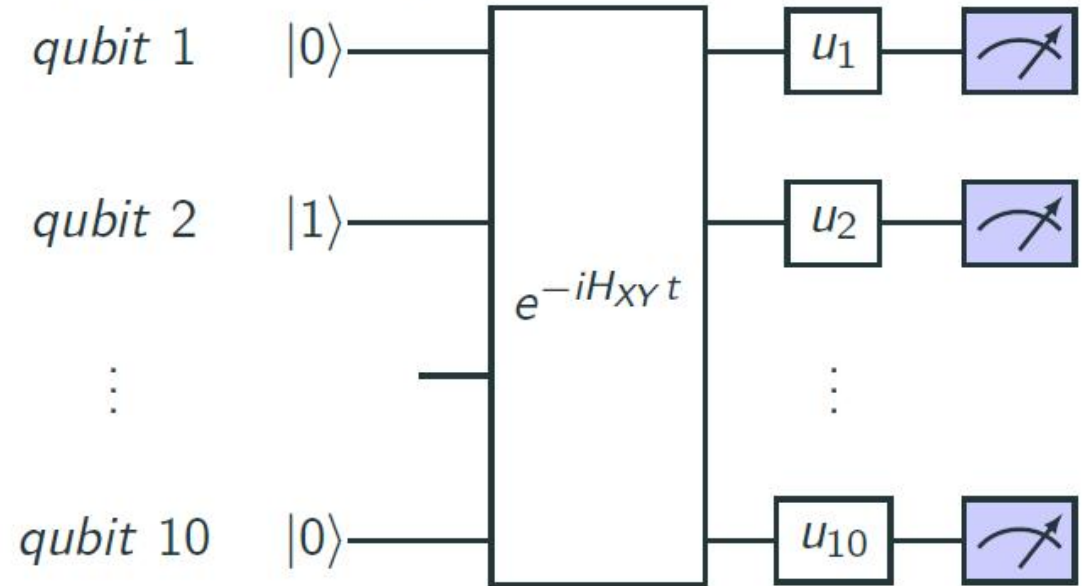
- Using Random Matrix Theory (2-design identities)

$$\begin{aligned} \overline{[P_u(s)]^2} &= \frac{1}{6} \sum_{m,n,m',n'} \rho_{m,n} \rho_{m',n'} (\delta_{m,n} \delta_{m',n'} + \delta_{m,n'} \delta_{m',n}) \\ &= \frac{1 + \text{Tr}(\rho^2)}{6} \end{aligned} \quad (3)$$

First demonstration: Brydges et al, Science 2019



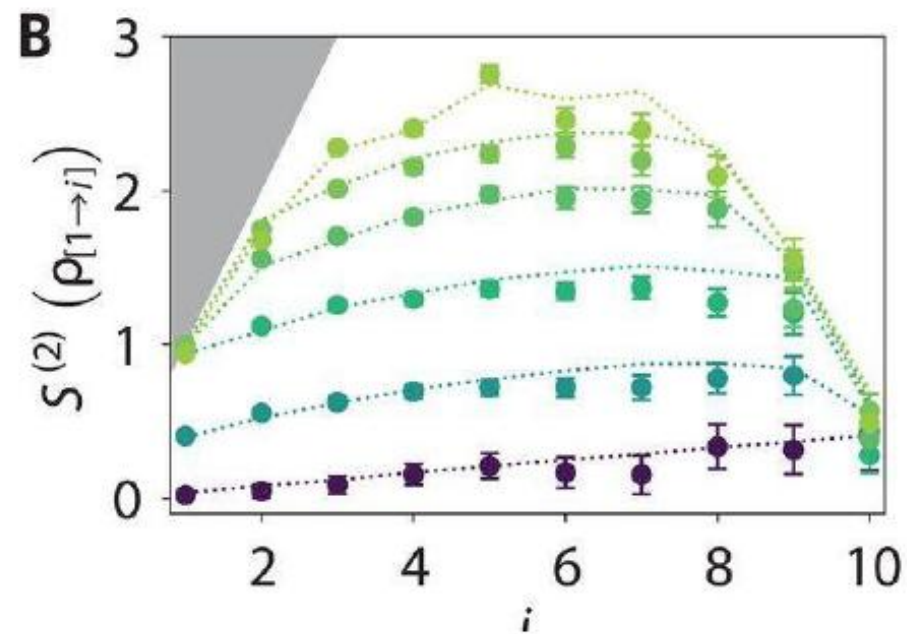
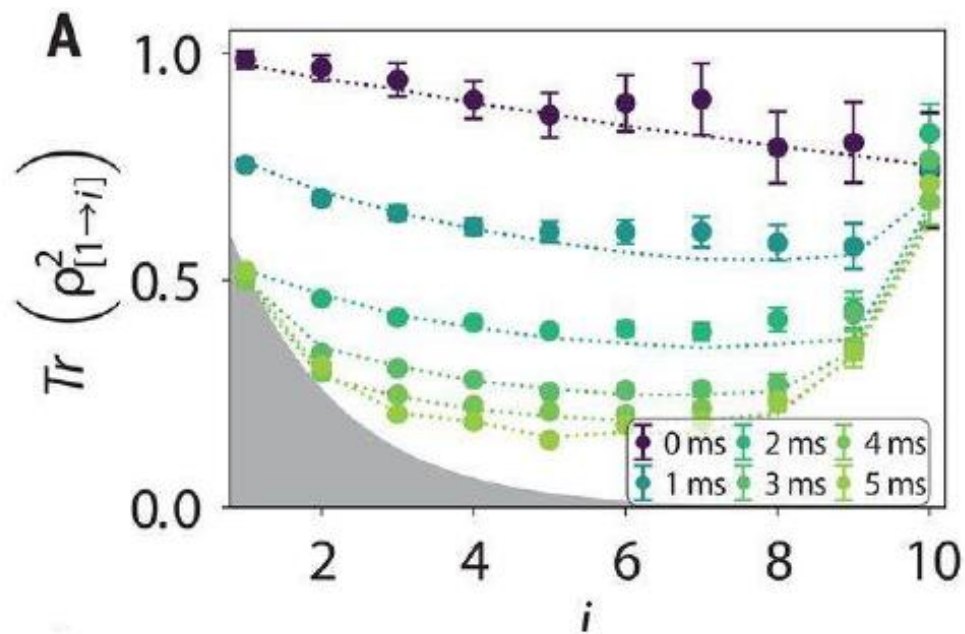
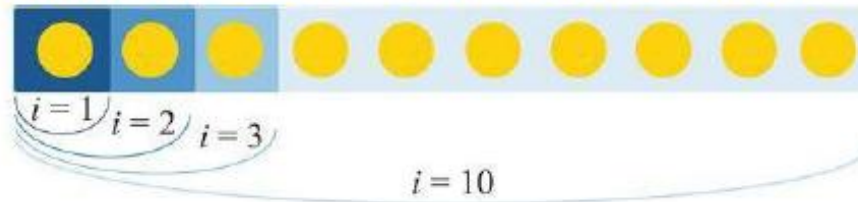
- A programmable quantum simulator



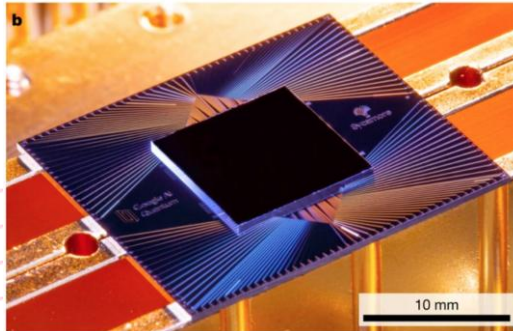
- Goal: Understand entanglement growth in a quantum system

First demonstration: Brydges et al, Science 2019

- Demonstration of randomized measurements with the measurement of the purity



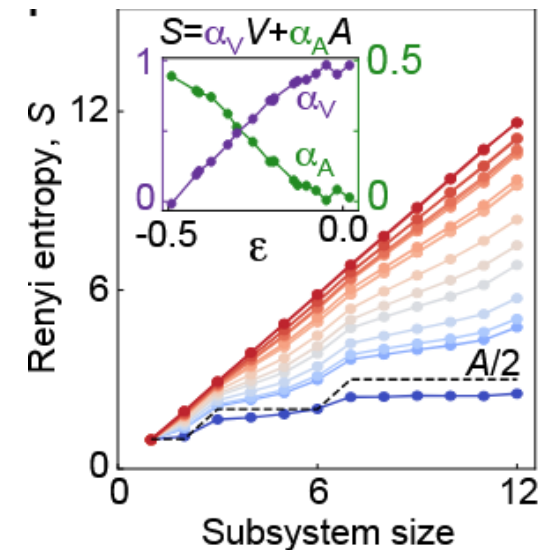
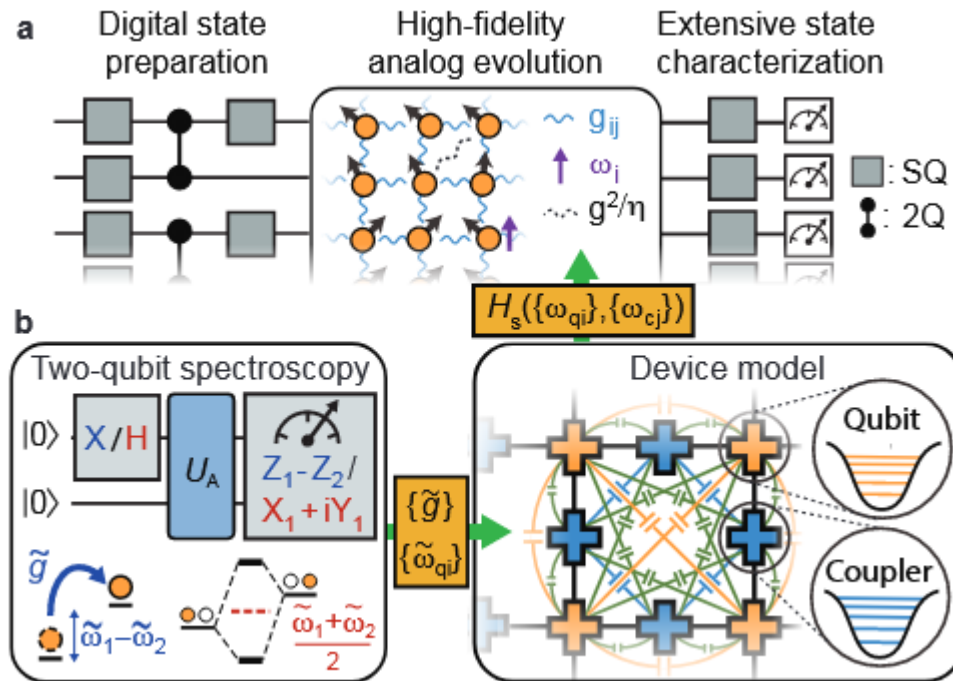
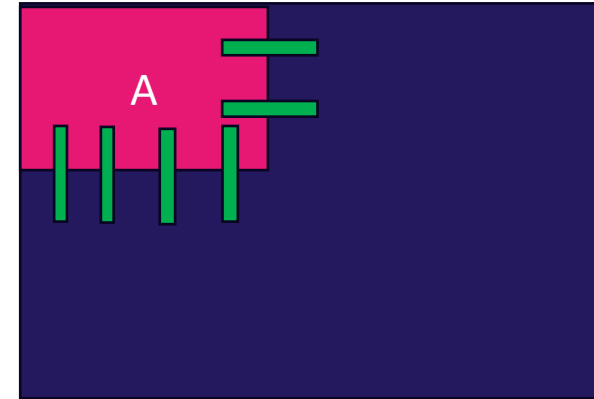
Recent use of RM: Andersen et al, Nature 2025



Quantum AI

Demonstration of entanglement's **area law**
In the ground-state

Entanglement
"links"



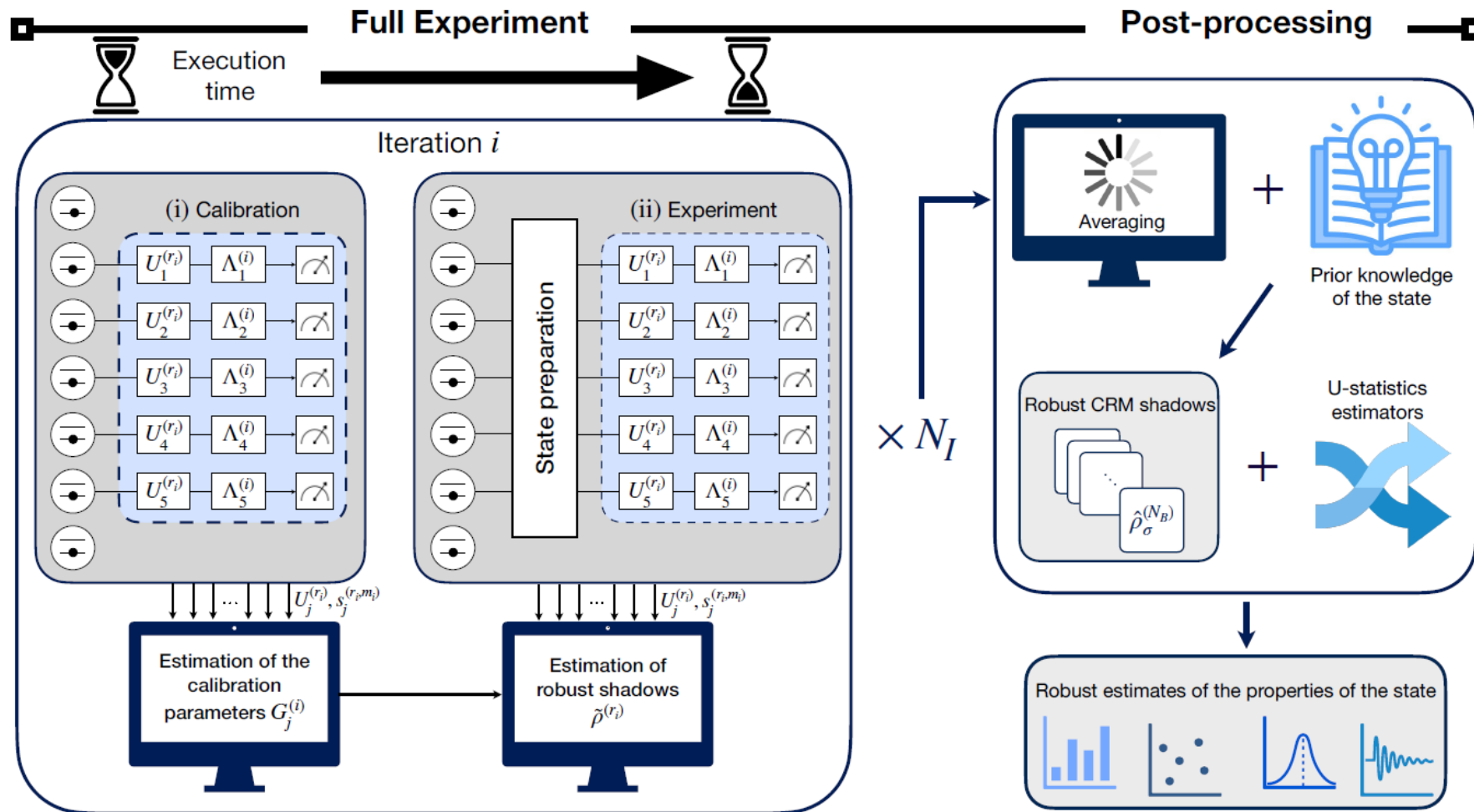
Today's menu

Moderate scale randomized measurements

- 1) Motivations
- 2) Measurements of entanglement entropies
- 3) More advanced usage and “statistical tricks”**

Large scale learning via randomized measurements

Experimental Robust Shadow Estimation and measurement of the quantum Fisher information (Vitale et al, PRX Q 2024)



Beyond the purity: Classical Shadows as the modern framework to postprocess randomized measurements

Data are processed 'robust classical shadows' (Chen et al, PRX 2021, improving the seminal Caltech paper: Nature Physics 2020)

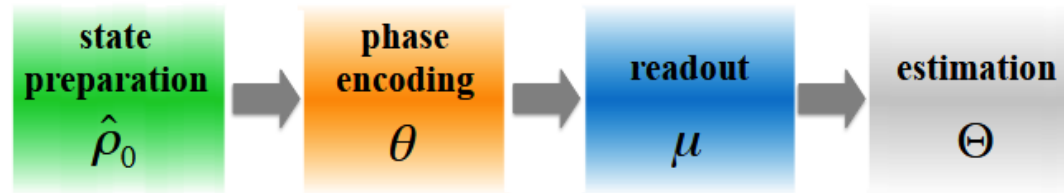
$$\tilde{\rho}^{(r,b)} = \bigotimes_{j=1}^N \left(\frac{3}{2F_b[j] - 1} U_j^{(r)\dagger} |s_j\rangle \langle s_j| U_j^{(r)} + \frac{F_z[j] - 2}{2F_b[j] - 1} \mathbf{1} \right), \quad (2)$$

where the calibration data of each batch b gives access to $F_b[j]$.

Estimations of functions of ρ are built based on the relation $E[\tilde{\rho}^{(r,b)}] = \rho$

$$\text{tr}[\rho O] \simeq \frac{1}{N_u} \sum_r \text{tr}[\hat{\rho}^{(r)} O], \quad \text{tr}[\rho^2] \simeq \frac{1}{N_u(N_u - 1)} \sum_{r_1 \neq r_2} \text{tr}[\hat{\rho}^{(r_1)} \hat{\rho}^{(r_2)}]$$

Quantum Fisher information measurements (Vitale et al, PRX Q 2024)



Quantum Cramer Rao bound on parameter estimation

$$(\Delta\theta)^2 \geq \frac{1}{mF_Q[\varrho, H]}, \quad \varrho(\theta) = \exp(-iH\theta)\varrho_0 \exp(+iH\theta),$$

The Quantum Fisher information (A=H, mixed state version, Braustein and Caves, PRL 1994)

$$F_Q = 2 \sum_{(i,j), \lambda_i + \lambda_j > 0} \frac{(\lambda_i - \lambda_j)^2}{\lambda_i + \lambda_j} |\langle i | A | j \rangle|^2 \text{ with } \rho = \sum_i \lambda_i |i\rangle \langle i|$$

Mapping the quantity to a measurable “shadow” quantity

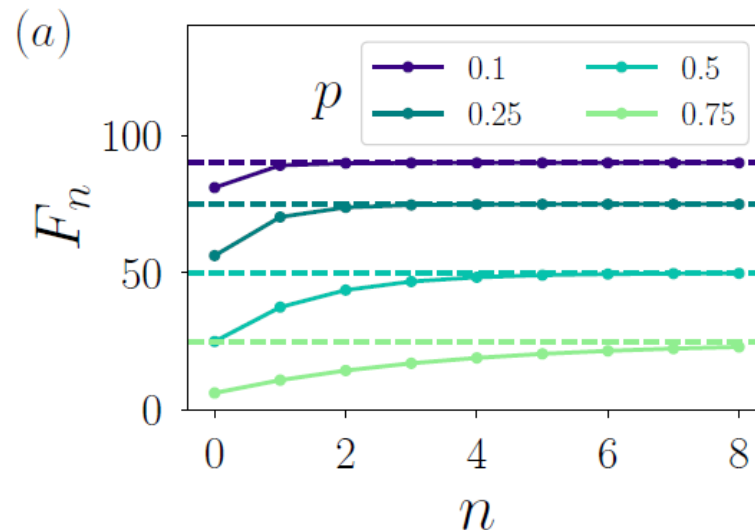
Multi-copy observable
MCO

$$\text{Tr}(O\rho^{\otimes n})$$

- Rath et al (PRL 2021): QFI is the limit of a series of MCO, i.e can be measured

$$F_n = 2 \text{Tr} \left(\sum_{\ell=0}^n (\rho \otimes \mathbf{1} - \mathbf{1} \otimes \rho)^2 (\mathbf{1} \otimes \mathbf{1} - \rho \otimes \mathbf{1} - \mathbf{1} \otimes \rho)^{\ell} \overset{\text{Swap operator}}{\mathbf{S}}(A \otimes A) \right) \quad (10)$$

- The series convergences exponentially faster to the QFI:
Example for noisy GHZ states ($N = 10$)



- The series of MCO F_n is estimated via randomized measurements

$$F_n = \text{Tr}(O\rho^{\otimes n}) = E[\text{Tr}(O\rho^{(r_1)} \otimes \dots \otimes \rho^{(r_n)})] \quad (11)$$

- We provide analytical variance bounds ('error bars')

$$\mathbb{V}[\hat{F}_n] \leq \sum_{k=1}^n \frac{n!^2 2^{kN}}{k!(n-k)!^2 (M-k+1)^k} \text{Tr}([O_k]^2)$$

$$O_k = \frac{1}{n!} \sum_{\pi} \text{Tr}_{\{k+1 \dots n\}} (\pi^\dagger O \pi [\mathbf{1}^{\otimes k} \otimes \rho^{\otimes (n-k)}]) \quad (12)$$

There will be a tradeoff in choosing n to control both systematic and statistical errors

We will probably need many measurements and postprocessing time, we will need some tricks to improve on that..

Trick 1: Common randomized measurements (BV et al, PRX Quantum 2023)

In some experiments we have a reference state in mind (eg GHZ state)

$$\tilde{\rho}_{\sigma}^{(ri)} = \tilde{\rho}^{(ri)} - \sigma^{(ri)} + \sigma$$

Reference state
↓

Robust classical shadow Reference state shadow

$$\sigma^{(r)} = \sum_{\mathbf{s}} P_{\sigma}(\mathbf{s} | U^{(ri)}) \bigotimes_{j=1}^N \left(3 U_j^{(r)\dagger} |s_j\rangle\langle s_j| U_j^{(ri)} - \mathbb{1} \right)$$

Such shifted shadow is still an unbiased estimator of the density matrix $\mathbb{E}[\hat{\rho}_{\sigma}^{(ri)}] = \rho - \sigma + \sigma = \rho$

But with improved variance properties

$$\mathbb{V}[\hat{O}] \leq \frac{n^2 \|O_A^{(1)}\|_2^2}{N_U} \left(3^{N_A} \|\rho_A - \sigma_A\|_2^2 + \frac{2^{N_A}}{N_M} \right) + \mathcal{O}\left(\frac{1}{N_U^2}\right)$$

n-copy observable

Functions of O and of the density matrix

Number of measurement settings

Number of shots per measurement settings 

Trick 1: Batching (Rath et al PRX Quantum 2023)

We group several shadows into $N_B > n$ batches to simplify postprocessing

$$\hat{\rho}_\sigma^{(b)} = \frac{N_B}{N_I} \sum_{i=(b-1)N_I/N_B+1}^{bN_I/N_B} \left(\sum_{r_i} \frac{\tilde{\rho}_\sigma^{(r_i)}}{N_U} \right)$$

U-statistics estimations (R. Huang et al, Nature Physics 2020)

$$\hat{F}_0 = \frac{4(N_B - 2)!}{N_B!} \sum_{b_1 \neq b_2} \text{Tr} \left(\hat{\rho}_\sigma^{(b_1)} [\hat{\rho}_\sigma^{(b_2)}, A] A \right),$$

$$\hat{F}_1 = 2\hat{F}_0 - \frac{4(N_B - 3)!}{N_B!} \sum_{b_1 \neq \dots \neq b_3} \text{Tr} \left(\hat{\rho}_\sigma^{(b_1)} \hat{\rho}_\sigma^{(b_2)} [\hat{\rho}_\sigma^{(b_3)}, A] A \right)$$

Postprocessing runtime: N_B^2, N_B^3 , etc

Barely affects statistical errors in the 'high accuracy regime'

Quantum Fisher information measurements (Vitale et al, PRX Q 2024)

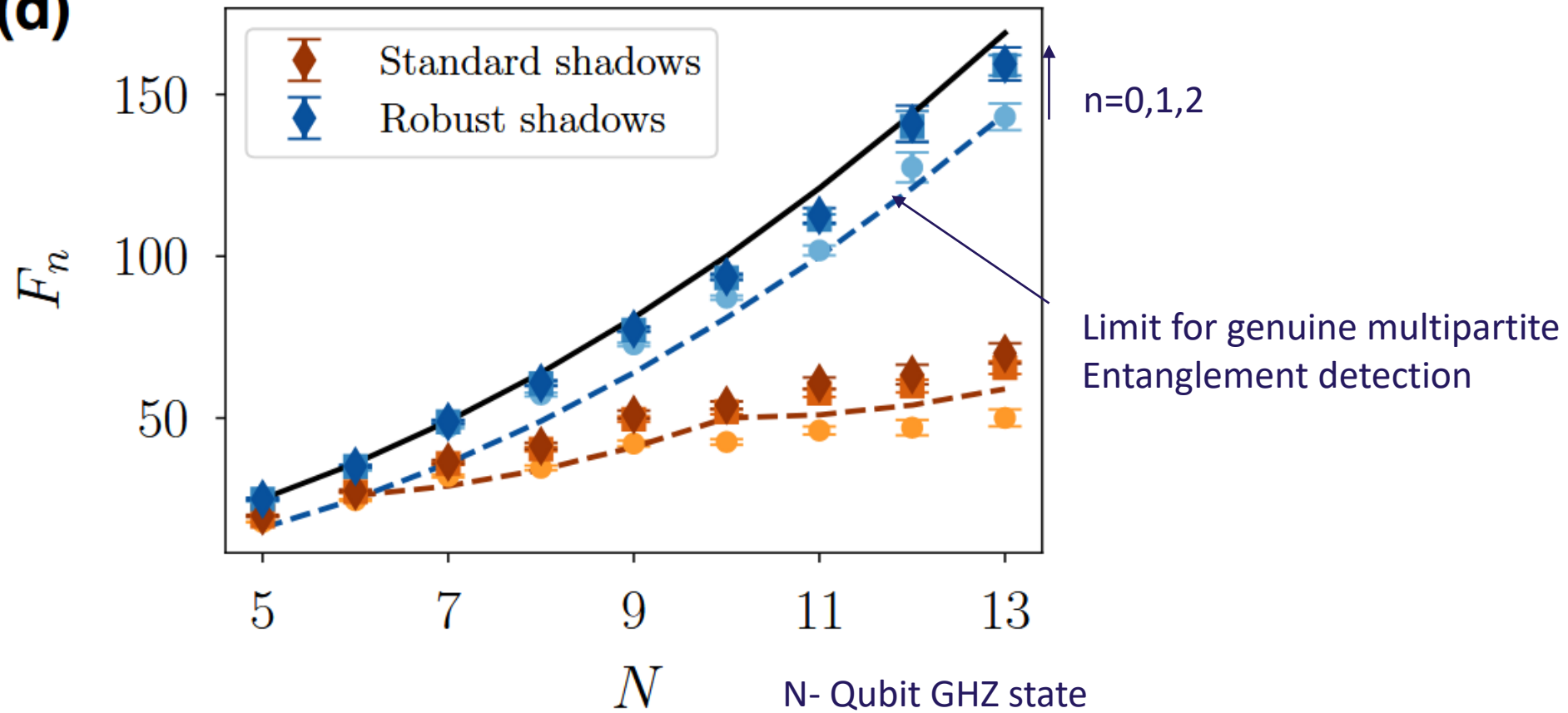


Petar Jurcevic
(IBM)



Vittorio Vitale

(d)



Some recent uses of randomized measurements to access entanglement

Quantities/Concepts	Platform	Reference
Entropies	Ions	Brydges et al Science 2019
OTOCs	Ions	Joshi et al, PRL 2020
Spectral Form Factors	Superconducting qubits	Dong et al, PRL 2025
Mixed-state entanglement*	Ions	Elben et al, PRL 2020
Cross-Platform verification*	Ions & superconducting qubits	Elben et al, PRL 2020 Zhu et al, Nature Comm 2022
Topological entropies	Superconducting qubits	Satzinger al, Science 2021
Symmetry resolved Entropies*	Ions	Vitale et al, Sci Post 2022
Entropies (live)	Ions	Stricker et al, PRX Q 2022
Operator entropies*	Ions	Rath et al, PRX Q 2023
Quantum Mpemba effect	Ions	Joshi et al, PRL 2024
Quantum Fisher information (Robust):	Superconducting qubits	Vitale et al, PRX Quantum 2024
Entropies (2D)	Superconducting qubits	Andersen et al, Nature 2025
Entropies (Robust)	Superconducting qubits	Hu et al, Nature Communications 16, 2943 (2025)
Entropies (large-scale) & tomography	Superconducting qubits	Votto et al, in preparation



RandomMeas.jl: Open-Source Package

RandomMeas: The randomized measurement toolbox in Julia

docs dev CI passing License Apache 2.0

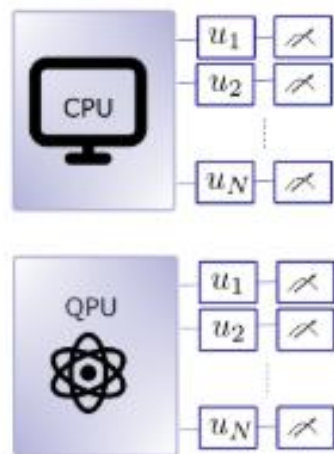
This package provides efficient routines for sampling, simulating, and post-processing randomized measurements, including classical shadows, to extract properties of many-body quantum states and processes. RandomMeas relies heavily on [ITensors.jl](#).



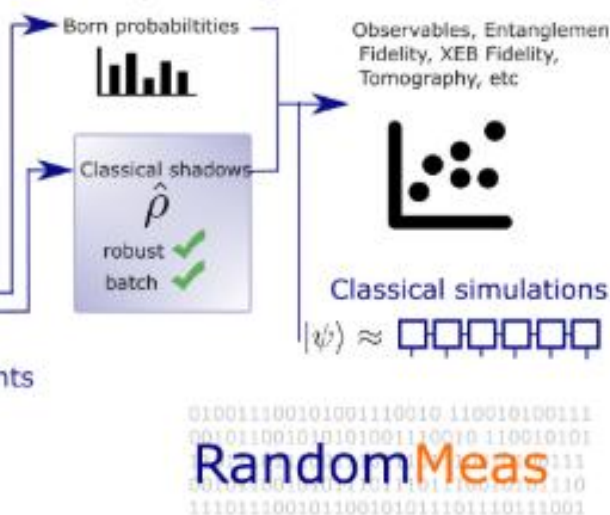
A. Elben (Psi)

Data acquisition

Simulation of randomized measurements



Postprocessing



Examples with Jupyter notebooks

Classical shadows

1. [Energy/Energy variance measurements with classical shadows](#)
2. [Robust Shadow tomography](#)
3. [Process Shadow tomography](#)
4. [Classical shadows with shallow circuits](#)
5. [Virtual distillation](#)

Quantum benchmark

6. [Cross-Entropy/Self-Cross entropy benchmarking](#)
7. [Fidelities from common randomized measurements](#)
8. [Cross-Platform verification](#)

Entanglement

9. [Entanglement entropy of pure states"](#)
10. [Analyzing the experimental data of Brydges et al, Science 2019](#)
11. [Surface code and the measurement of the topological entanglement entropy](#)
12. [Mixed-state entanglement: The p3-PPT condition and batch shadows](#)

Miscellaneous

13. [Noisy circuit simulations with tensor networks](#)

<https://github.com/bvermersch/RandomMeas.jl> & Julia's General Registry

Summary first part & transition

Many physical quantities have been recently measured with RM: Experimentally friendly acquisition, and numerically friendly “universal” postprocessing.

Robustness/Practical aspects well understood and experimentally demonstrated

For the purity and related quantities, number of measurements scales as 2^{aN} , $a \approx 1$, implies typically $N < 14$

More info in our review **“The randomized measurement toolbox”**
Elben, Flammia, Huang, Kueng, Preskill, BV, Zoller, Nat Rev Phys 2023

Let's expand this toolbox to large-scale systems reconstructions!

Large-scale entropies and tomography via randomized measurements

Probing many-body quantum states in large-scale experiments with randomized measurements, BV et al, Phys. Rev. X 2025

Learning mixed quantum states in large-scale experiments (to appear on arxiv)



P. Zoller (UIBK)



L. Piroli (Unibo)



M. Serbyn.



M. Ljubotina (ISTA)



J.I.C Cirac (MPQ)



M. Votto (UGA)



C. Lancien (UGA)

Connections to MPS/MPO
Gibbs State Tomography
Literature

Baumgratz et al, NJP 2013

Torlai et al, Nature Comm 2023

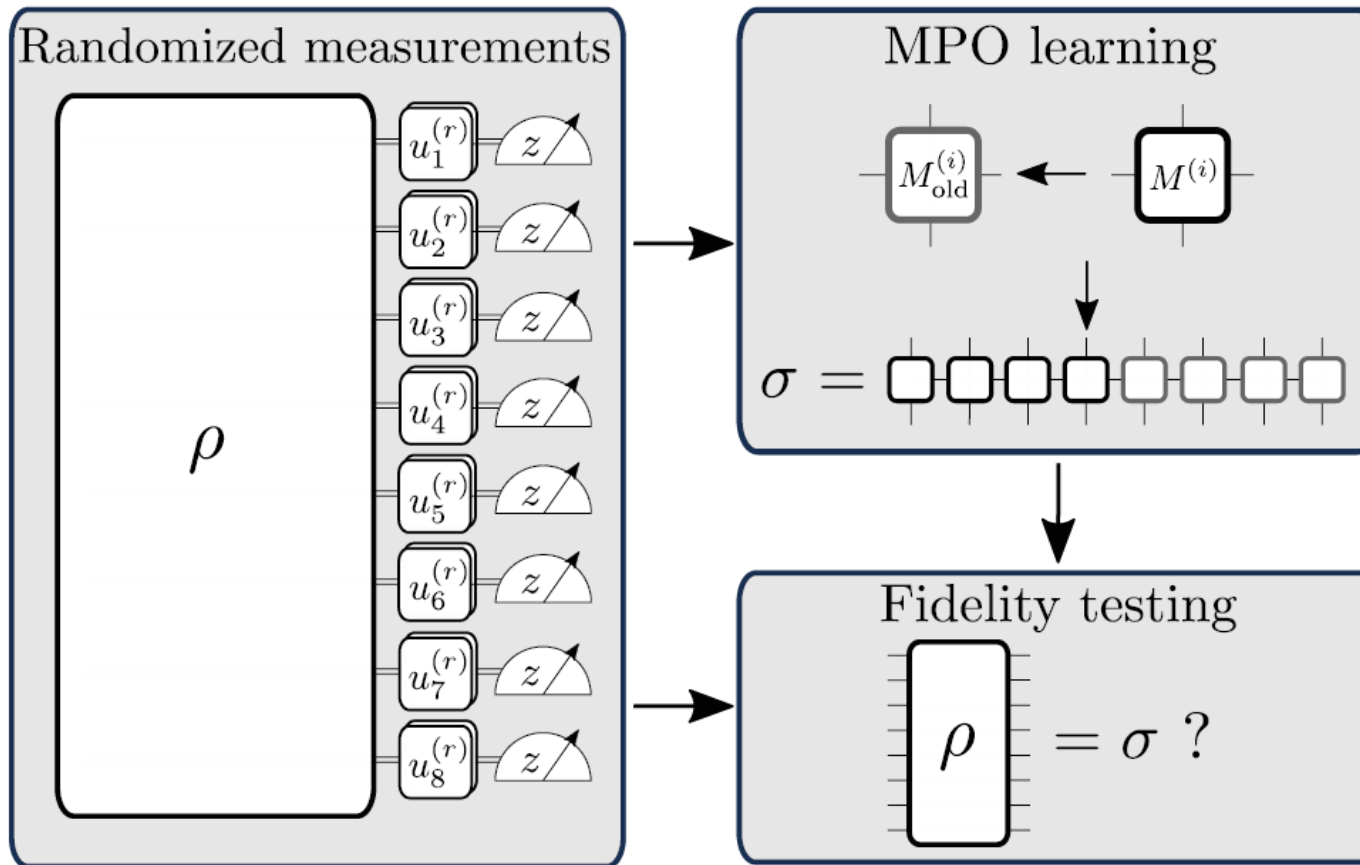
...

Anshu et al, Nature Physics 2021 (Review)

Joshi et al, Nature 2023

...

Goal a Tomography via randomized measurements



The learned state can be used to extract physical properties
Conveniently (no more batching, etc) and for error mitigation, etc

Matrix-Product-Operator (MPO)

Represents the quantum state as a 1D compressed object with linear cost in storage and manipulation

$$\sigma = \sum_{\{s_j\}, \{s'_j\}} M_{s_1, s'_1}^{(1)} M_{s_2, s'_2}^{(2)} \dots M_{s_N, s'_N}^{(N)} |\{s_j\}\rangle \langle \{s'_j\}|$$

describe output states of one-dimensional noisy/finite depth quantum circuits, as well as one-dimensional thermal states relevant to quantum simulation

K. Noh, L. Jiang, and B. Fefferman, [Quantum 4, 318 \(2020\)](#).

S. Cheng, C. Cao, C. Zhang, Y. Liu, S.-Y. Hou, P. Xu, and B. Zeng, [Phys. Rev. Res. 3, 023005 \(2021\)](#).

F. Verstraete, J. J. García-Ripoll, and J. I. Cirac, [Phys. Rev. Lett. 93, 207204 \(2004\)](#).

T. Kuwahara, A. M. Alhambra, and A. Anshu, [Phys. Rev. X 11, 011047 \(2021\)](#).

Learning mixed quantums in large-scale experiments: Technical statements

We assume the existence of a finite correlation length in the MPO framework.

This implies the approximate factorization condition (Vermersch al Phys. Rev. X 2024)

$$\left| \text{tr}[\rho_{ABC}^2]^{-1} \frac{\text{tr}[\rho_{AB}^2] \text{tr}[\rho_{BC}^2]}{\text{tr}[\rho_B^2]} - 1 \right| \leq \alpha e^{-|B|/\xi_\rho^{(2)}}$$

This assumption is satisfied in 1D quantum circuits, quantum Gibbs states (Capel et al, arxiv: 2024 in particular)

Learning mixed quantum states in large-scale experiments: Technical statements

Votto et al (arxiv:..) : In this case, one can learn the state using the inner product as cost function

$$\mathcal{F}_{\text{GM}}(\rho, \sigma) = \frac{\text{tr}[\rho\sigma]}{\sqrt{\text{tr}[\rho^2\sigma^2]}} \quad \text{With the MPO} \quad \sigma = \sum_{\{s_j\}, \{s'_j\}} M_{s_1, s'_1}^{(1)} M_{s_2, s'_2}^{(2)} \cdots M_{s_N, s'_N}^{(N)} |\{s_j\}\rangle \langle \{s'_j\}|$$

With arbitrary small total error and polynomially many measurements

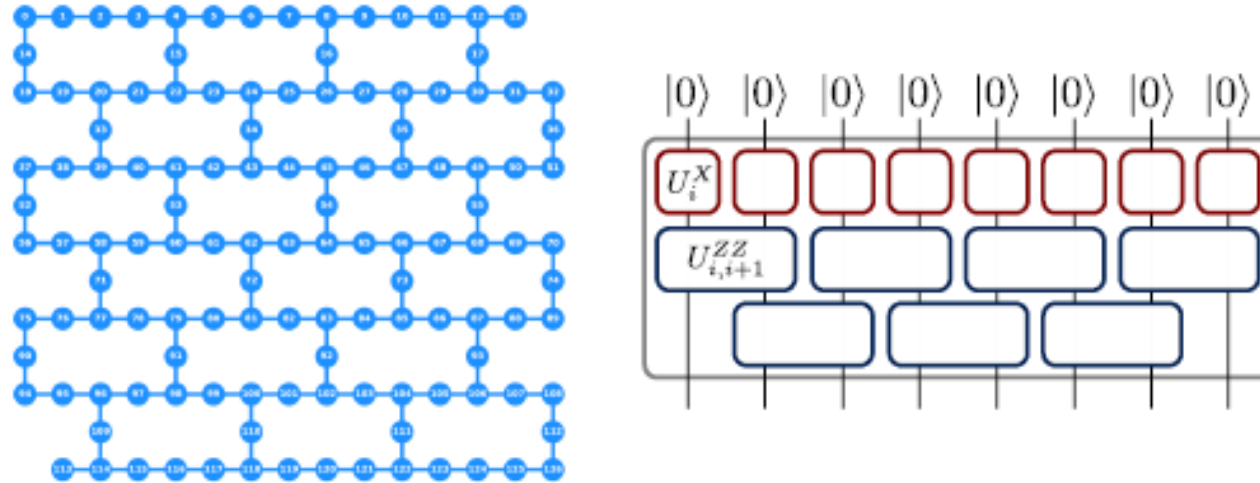
Proof idea: Gradient w.r.t local tensors can be set to zero using the rule

$$\text{tr}_{I_j \setminus \{j\}} [\sigma_{I_j} \partial_{M^{(j)}} \sigma_{I_j}] = \text{tr}_{I_j \setminus \{j\}} [\rho_{I_j} \partial_{M^{(j)}} \sigma_{I_j}]$$

↑
Classically computable

↑
Finite support “observable”, thus efficiently measurable

Learning mixed quantums in large-scale experiments: Demonstration

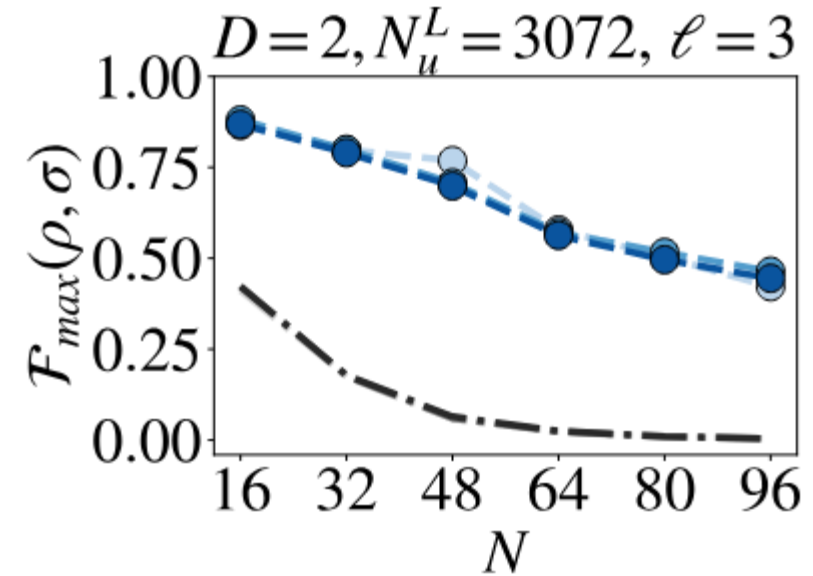
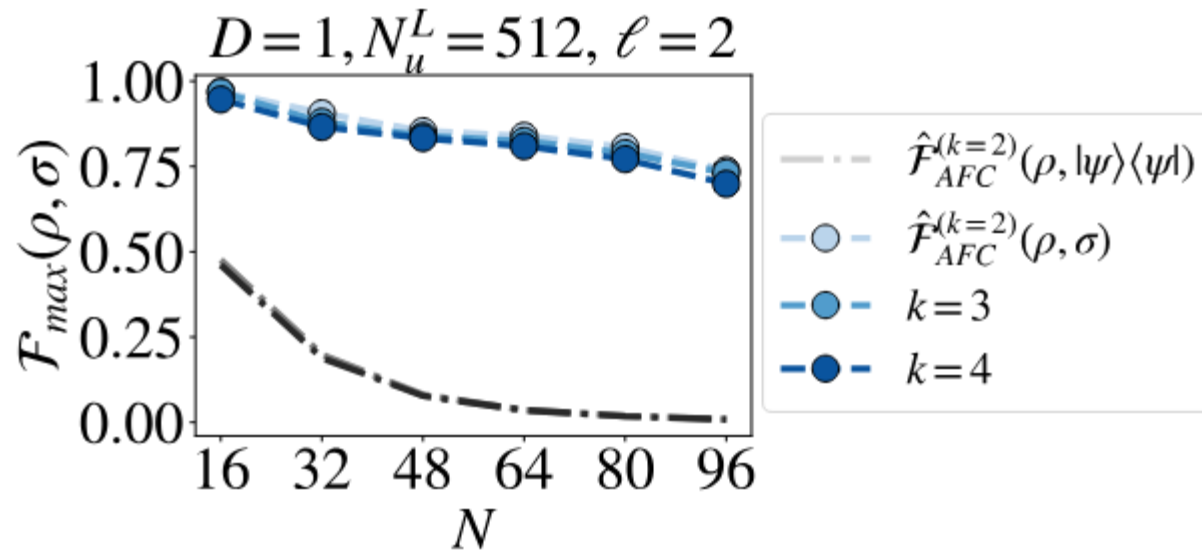


- Experimental setup: **superconducting quantum processor** (IBM Brisbane QPU), $N_{\text{tot}} = 96$ qubits, depth $D = 1, 2$ kicked Ising model

$$U_i^X = e^{-i\pi X_i/8}, \quad U_i^{ZZ} = e^{i\pi Z_i Z_{i+1}/4}$$

- We perform $M = N_u \times N_M = D \cdot 3072 \times 1024$ measurements

Learning mixed quantums in large-scale experiments: Demonstration

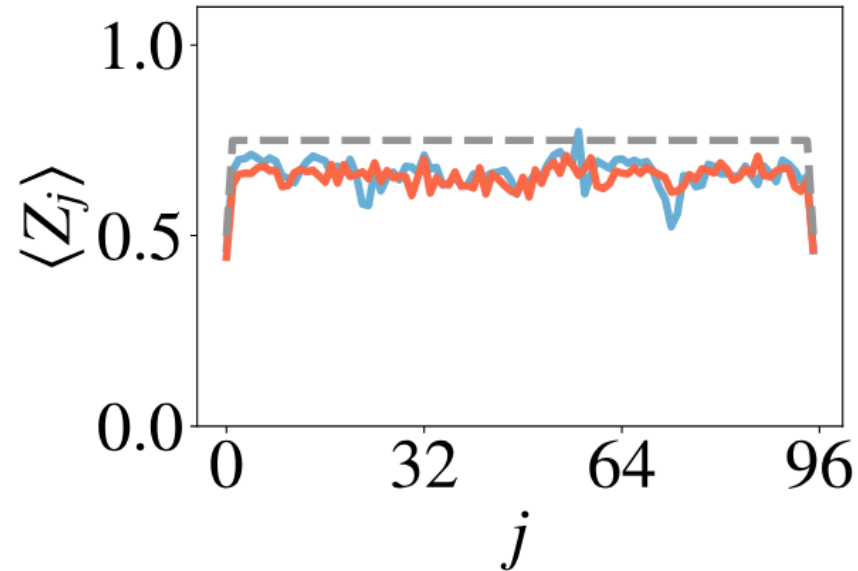


Experimental tomography of a $N = 96$ mixed qubit state (previous results: $N = 20$ qubits, MPS (Kurmapu et al PRXQ 2023) or Gibbs states (Joshi et al, Nature 2023))

The MPO σ captures the noisy features of the experiment.

Learning mixed quantum states in large-scale experiments: Extracting physical quantities

Magnetization

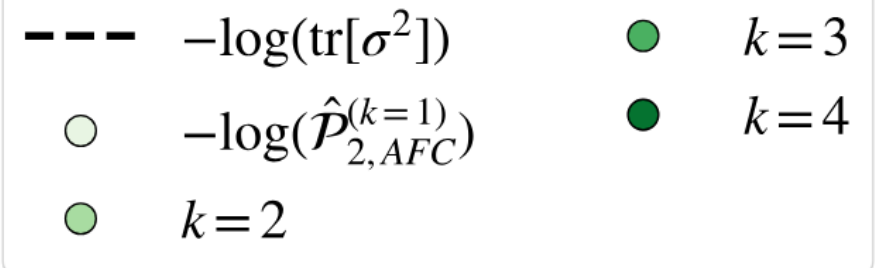
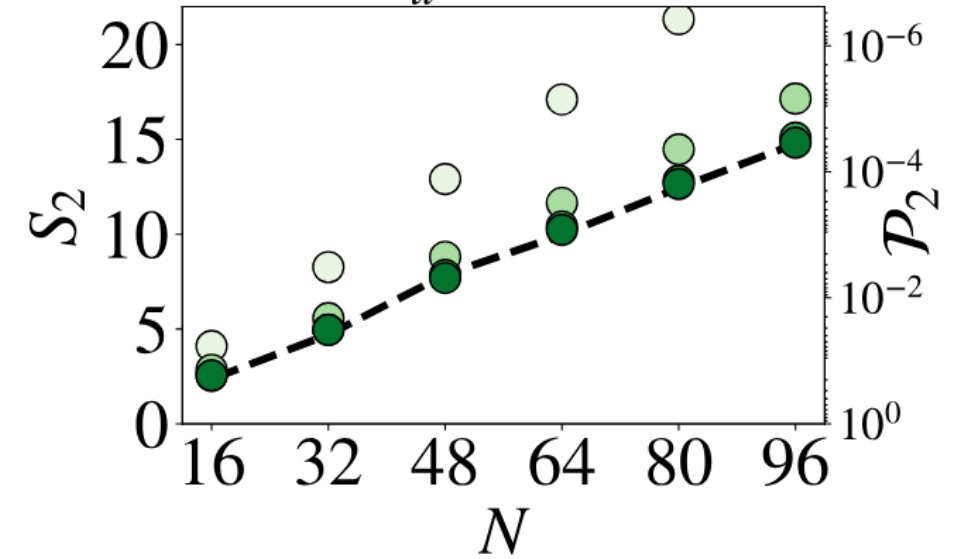


Direct contraction
Of the MPO

Estimation
through shadows
(lengthy calculation)

Estimation
of the ideal
Pure state

Entropy $D=2, N_u^L=3072, \ell=3$ Purity



Learning mixed quantums in large-scale experiments: Applications

Quantum Error Mitigation:

Based on a noisy experimental device, estimation of noiseless observable estimation values based on noise extrapolation, noise models & extra sampling, virtual distillation, etc (Cai et al, RMP 2023)

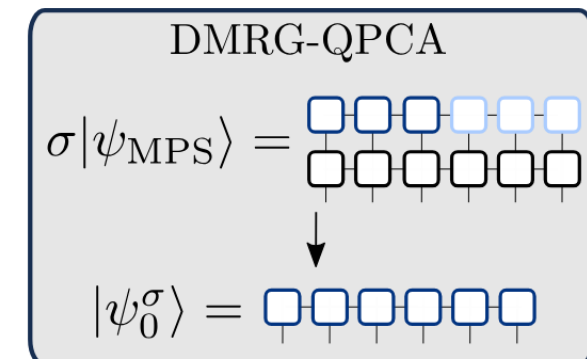
$$|\psi\rangle = U |\psi_0\rangle \longrightarrow \rho = \mathcal{U}(\gamma)\rho_0 \longrightarrow \langle O \rangle = \langle \psi | O | \psi \rangle$$

Here: Quantum Principal Component analysis (stronger version of virtual distillation) via the DMRG algorithm of tensor-networks (Review: Schollwoeck, Annals of Physics, 2011)

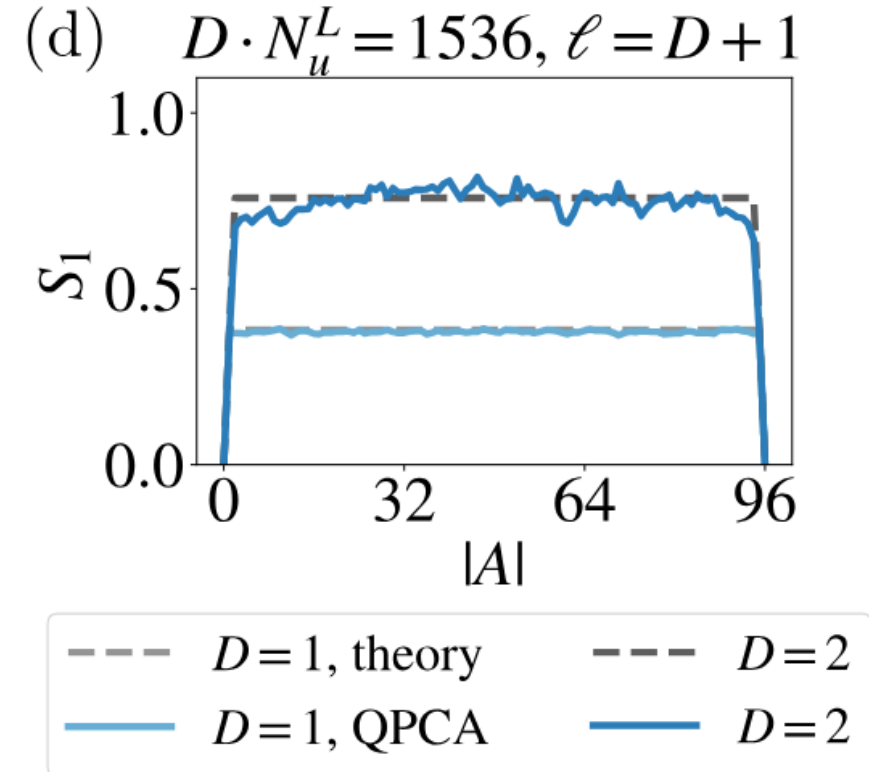
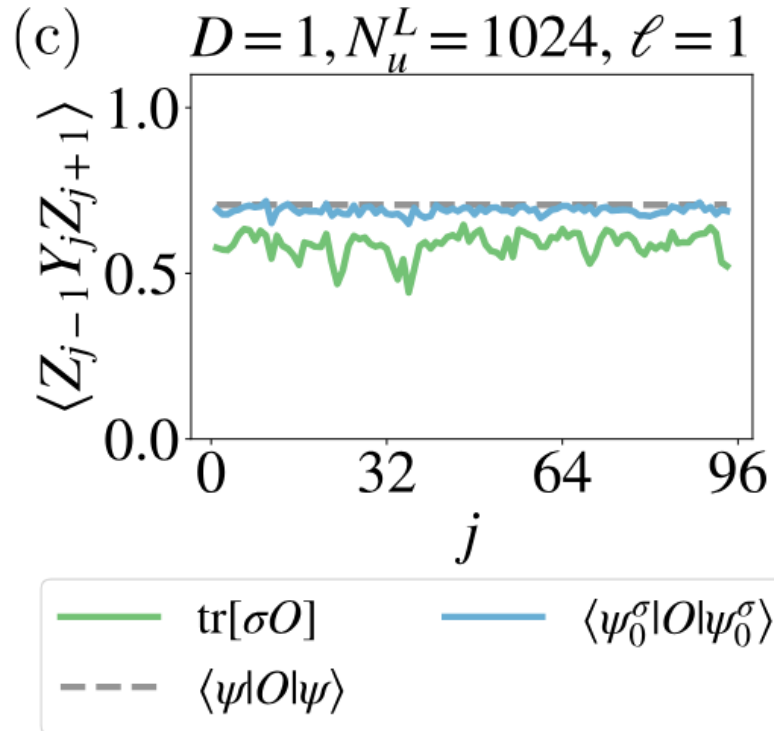
$$\rho = \sum_a \Lambda_a |\psi_a^\rho\rangle \langle \psi_a^\rho|, \text{ where } \Lambda_a > \Lambda_{a+1}$$

We search classically for the ground state of

$$H = -\sigma$$



Learning mixed quantums in large-scale experiments: Applications



Large-scale reconstruction of noiseless expectation values, and von Neumann entanglement entropies
(Despite the original exponentially small original mixed state)

Conclusions and Thank you

The Quantum Information Team at Quobly



Benoît Vermersch



Thibaud Louvet



Carlos Ramos-Marimón



Nathan Miscopein



Dimitri Lanier



Amara Keita

Contact me if you want to know
more, or join!

Probing many-body quantum states in large-scale experiments with randomized measurements, Phys. Rev. X 2025



P. Zoller (UIBK)



L. Piroli (Unibo)



M. Serbyn. M. Ljubotina (ISTA)



J.I.C Cirac (MPQ)

Learning mixed quantum states in large-scale experiments (to appear on arxiv)



M. Votto (UGA)



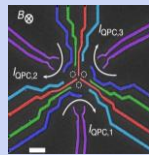
C. Lancien (UGA)

Quobly was born from the combined expertise of CEA and CNRS at Grenoble

ACADEMIC

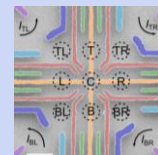
READY

2017



Coherent long-distance displacement of individual electron spins

2020

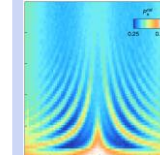


Coherent control of individual electron spins in a 2D array (9 quantum dots)

nature
nanotechnology

2021

nature
nanotechnology



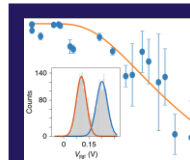
Distant spin entanglement via fast and coherent electron shuttling

DEVELOPING THE KNOW-HOW FOR CONTROLLING MULTIPLE SPIN QUBITS

INDUSTRY

READY

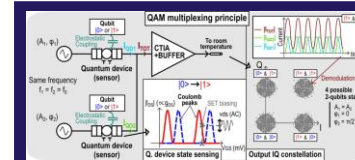
MANUFACTURING SPIN QUBITS IN INDUSTRIAL ENVIRONMENTS



2019

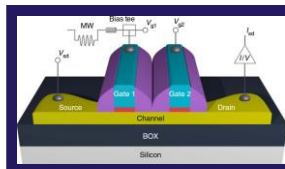
Gate-based high fidelity spin readout in a CMOS device

nature
nanotechnology



2025

Demonstrating QAM Multiplexing for Spin Qubits



A CMOS silicon spin qubit

2016

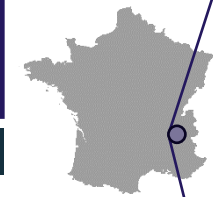


2022

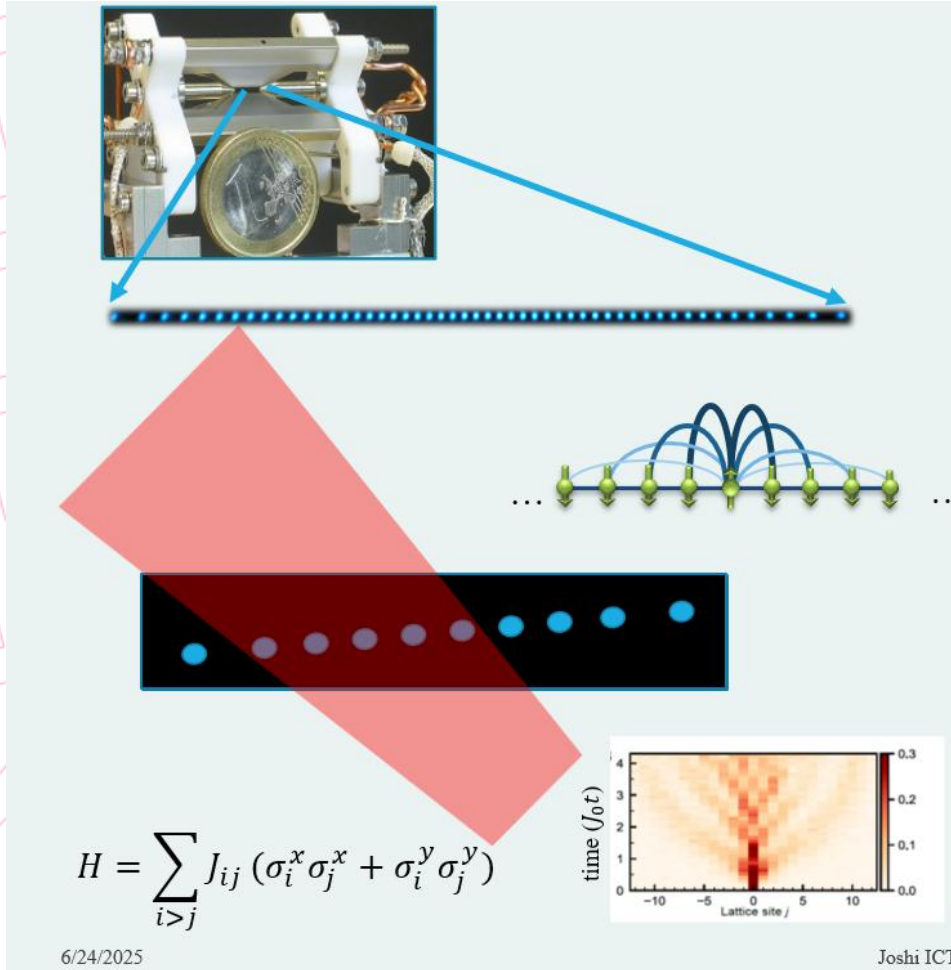
A single hole spin with enhanced coherence in natural silicon

nature
nanotechnology

We leverage the semicon. industry's 60+ years of experience, **fabless approach using commercial FD SOI technologies**



Back to ions: Experimental liouvillian learning with process shadows



Manoj
Joshi



Florian
Kranzl



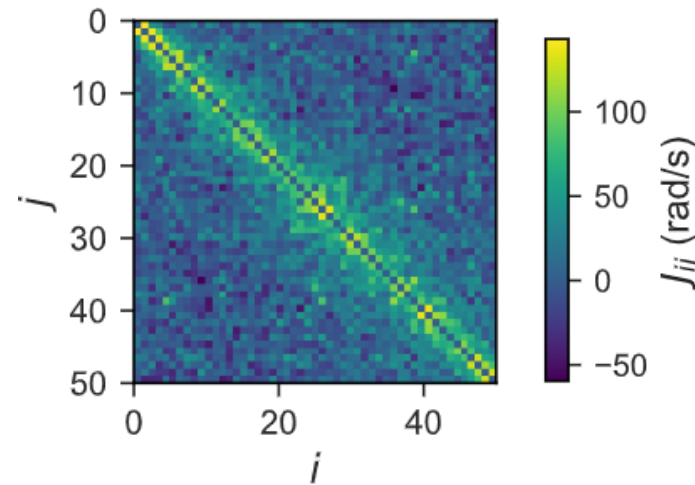
Johannes
Franke



Rainer
Blatt



Christian
Roos



William
Lam



Daniel Stilck
Franca



Barbara
Kraus



Peter
Zoller



Tristan
Kraft



Tobias
Olsacher



Lata Kh
Joshi

Back to ions: Experimental liouvillian learning with process shadows

$$\frac{d}{dt}\rho(t) = -i [H, \rho(t)] + D[\rho(t)]$$

$$H_{ij} = \sum_{\sigma_i, \sigma_j} h_{\sigma_i, \sigma_j} \sigma_i \sigma_j$$

$$D[\rho] = \sum_{i=1}^N D_i[\rho] \quad D_i[\rho] = \sum_{\sigma_i, \sigma'_i} d_{\sigma_i, \sigma'_i} \left(\sigma_i \rho \sigma'_i - \frac{1}{2} \{ \sigma'_i \sigma_i, \rho \} \right)$$

Goal: Learn the coefficients

- Wiebe et al. "Hamiltonian learning and certification using quantum resources." *PRL* (2014).
- Holzäpfel et al. "Scalable reconstruction of unitary processes and Hamiltonians." *Phys Rev A* (2015).
- Bairey, Arad, and Lindner. "Learning a local Hamiltonian from local measurements", *PRL* (2019).
- Evans, Harper, Flamia, "Scalable Bayesian Hamiltonian learning", arXiv:1912.07636 (2019)
- Li, Zou, and Hsieh. "Hamiltonian tomography via quantum quench", *PRL* (2020).
- Hu et al. "Ansatz-free Hamiltonian learning with Heisenberg-limited scaling." arXiv preprint arXiv:2502.11900 (2025).
- Olsacher et al. "Hamiltonian and Liouvillian learning in weakly-dissipative quantum many-body systems." *Quantum Science and Technology* (2025).
- Many more

One key application: Verified quantum simulation: Cai et al, arxiv:2311.14818, Trivedi et al, Nature Comm. 2025

Back to ions: Experimental liouvillian learning with process shadows

Theory: Stilck França, Daniel et al « Efficient and robust estimation of many-qubit {Hamiltonians », Nature. Comm. 2024

A closed linear system of equations, pair-wise

$$\begin{aligned} \left. \frac{d}{dt} \text{tr}(\rho_{ij}(t)) O_{ij} \right|_{t=0} = & \\ & -i \sum_{\sigma_i, \sigma_j} \text{tr}([\sigma_i \sigma_j, \rho_i \rho_j] O_i O_j) h_{\sigma_i, \sigma_j} \\ & + \sum_{\sigma_i, \sigma'_i} \text{tr} \left(\sigma_i \rho_i \sigma'_i O_i - \frac{1}{2} \{ \sigma'_i \sigma_i, \rho_i \} O_i \right) d_{\sigma_i, \sigma'_i} \\ & + \sum_{\sigma_j, \sigma'_j} \text{tr} \left(\sigma_j \rho_j \sigma'_j O_j - \frac{1}{2} \{ \sigma'_j \sigma_j, \rho_j \} O_j \right) d_{\sigma_j, \sigma'_j} \end{aligned}$$

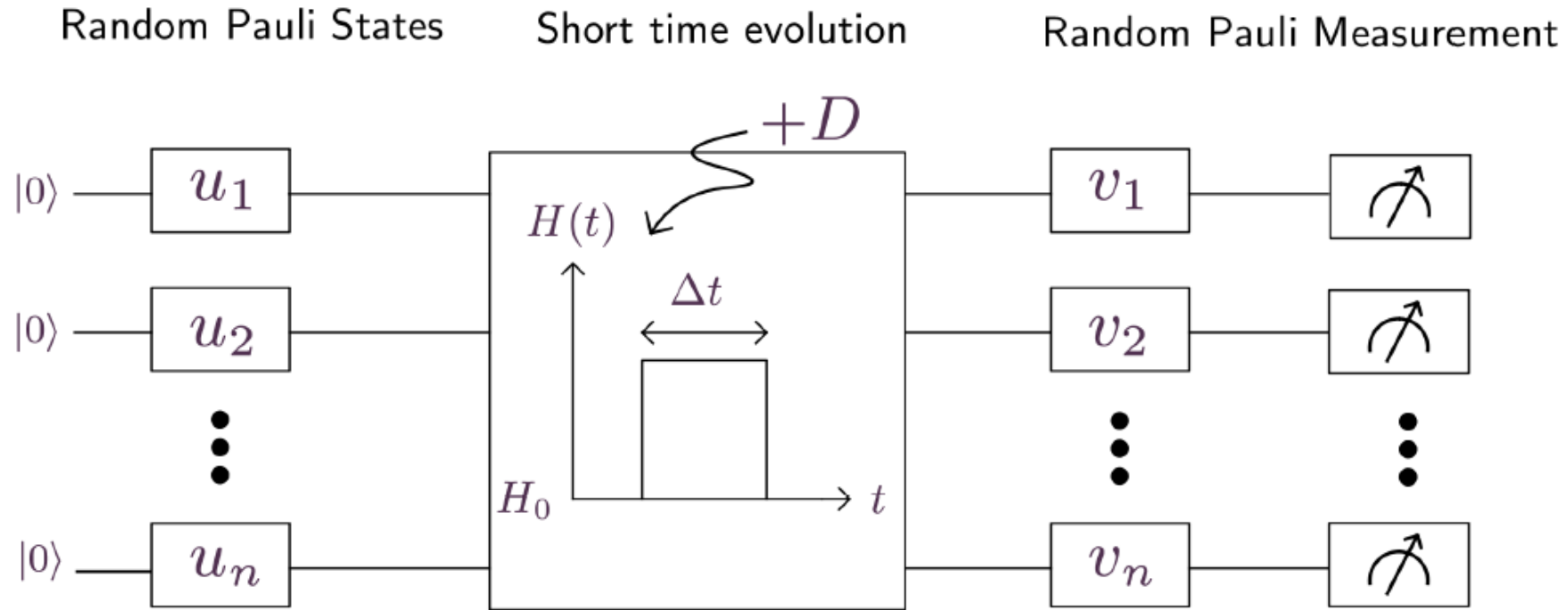
$$\rho_{ij} = \rho_i \otimes \rho_j \bigotimes_{n \neq i, j} \frac{\mathbb{I}_n}{2}$$

$$O_{ij} = \sigma_i \sigma_j$$

Unique Pseudo-inverse for enough initial states and measurement observables

Postprocessing for each pair independtly gives a N^2 runtime postprocessing algorithm

Back to ions: Experimental liouvillian learning with process shadows



$$\frac{\sum_r \langle O_{ij}^{(r)} \rangle}{N_c} \text{ is an unbiased estimation of } \text{Tr}(\rho_{ij} O_{ij})$$

Where the sum runs over the N_c “compatible” settings r defined such as and such that the rotation v maps O_{ij} to the computational basis

The probability to have a compatible setting is independent of system sizes

Back to ions: Experimental liouvillian learning with process shadows

a) 51 ion H&L learning

