

Learning and Diagnosing Quantum Many-Body Dynamics

Susanne Yelin (Harvard University)

Warwick, April 24, 2026

Outline

Act I Hamiltonian learning

Hu, Ma, Gon, Ye, Tong,
Flammia, Yelin
2502.11900
(PRXQ 2025)

Act II Lindbladian learning

Ivashkov, Romanov, Gong, Gu,
Hu, Yelin
2603.05492

Coda Chaos probe from learning

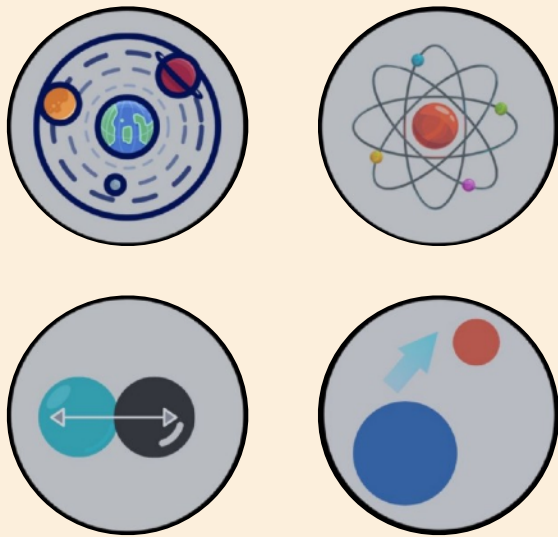
Gjonbalaj, Kokail, Yelin, Choi
2603.04486

Learning Hamiltonians

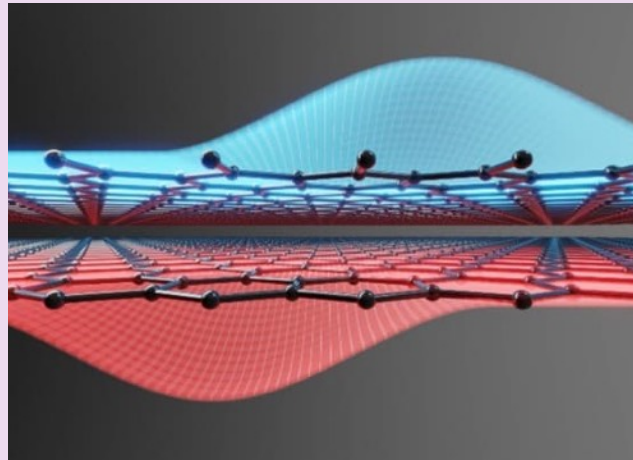
Motivation

- Understanding the interactions is one central theme in physics:

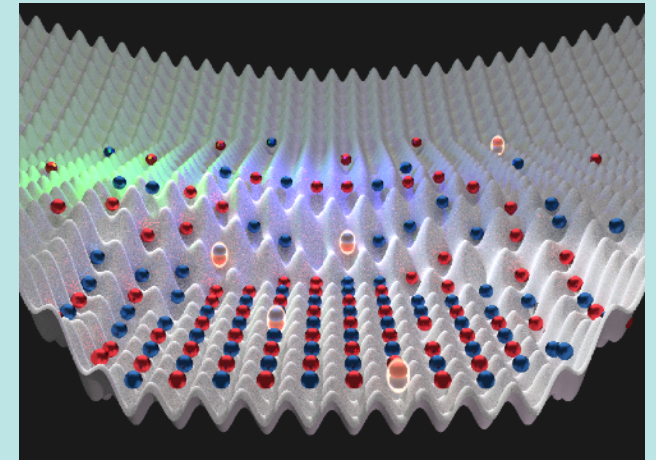
Four forces of Nature



Quantum materials



Programmable quantum devices



- What can we do if we have a programmable quantum computer? Does it help with learning the interactions?

Motivation

- Qubit Hamiltonian has the form $H = \sum_{s \in S} \mu_s P_s$, where $|\mu_s| \leq 1$ and $M = |S|$

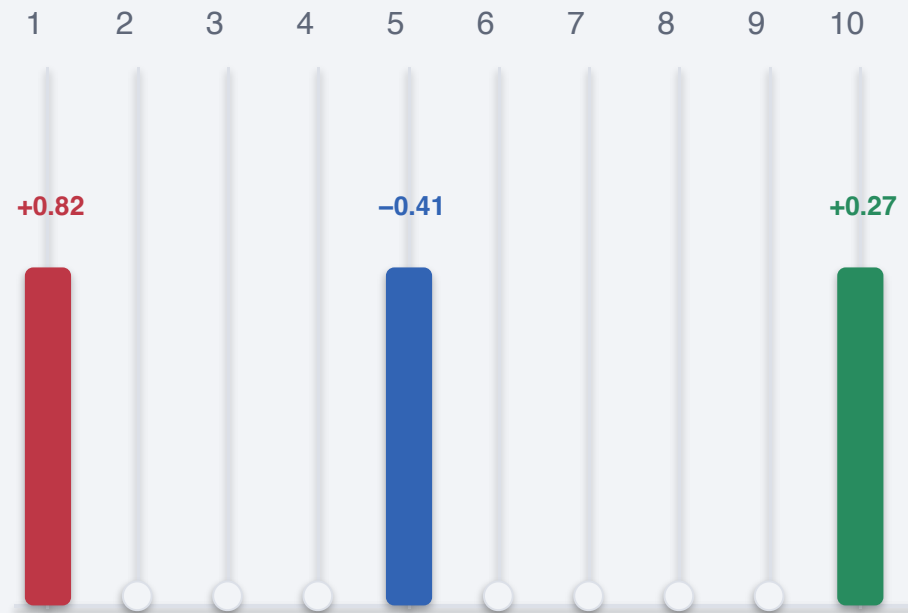
Sparse-support cartoon for ansatz-free learning

candidate dictionary

P₁	X	I	Z	I	I	Y
P ₂	I	X	X	I	Z	I
P ₃	Z	Z	I	I	I	I
P ₄	I	I	Y	X	I	I
P₅	X	X	X	X	I	I
P ₆	I	Z	I	I	Z	I
P ₇	Y	I	I	Y	I	X
P ₈	I	I	I	Z	Z	I
P ₉	Z	X	I	I	Y	I
P₁₀	I	I	Z	I	X	X

$\mu = (\mu_1, \dots, \mu_m)$ is sparse

support pattern



most entries = 0

learn support, then coefficients

Motivation

- Qubit Hamiltonian has the form $H = \sum_{s \in \mathcal{S}} \mu_s P_s$, where $|\mu_s| \leq 1$ and $M = |\mathcal{S}|$
- Goal: Learn each μ_s through experiments, such that the estimate $|\hat{\mu}_s - \mu_s| \leq \epsilon$
- Applications:

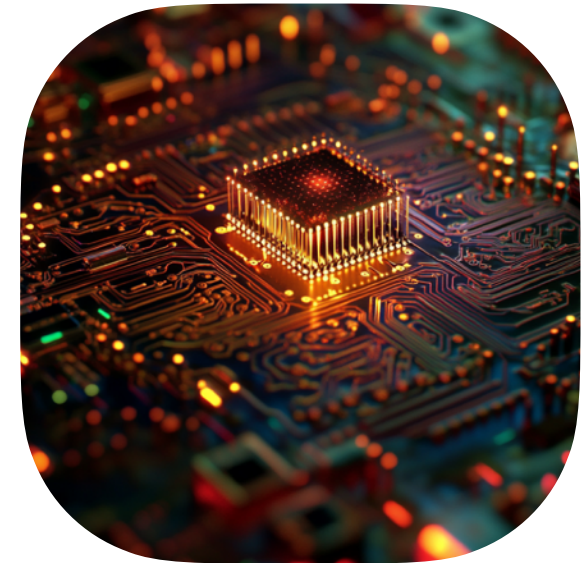
Quantum sensing



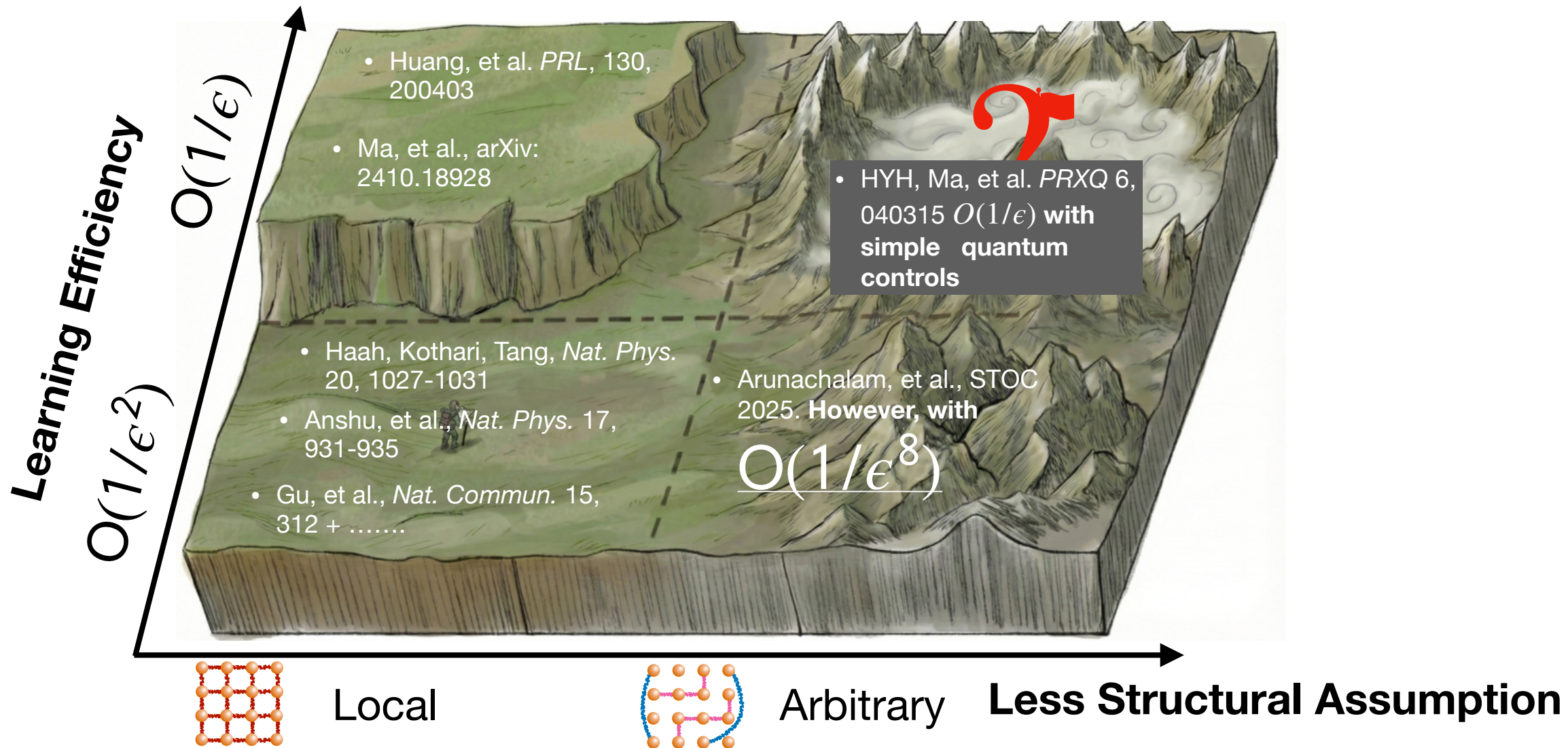
Many-body physics



Device benchmarking



The landscape of Hamiltonian learning



Main ideas

- Challenge 1: Extremely large search space $\sim 4^N$

Importance sampling using quantum process!

Structure learning

$$H = \sum_{s \in S} \mu_s P_s$$

Coefficient learning

$$H = \sum_{s \in S} \mu_s P_s$$

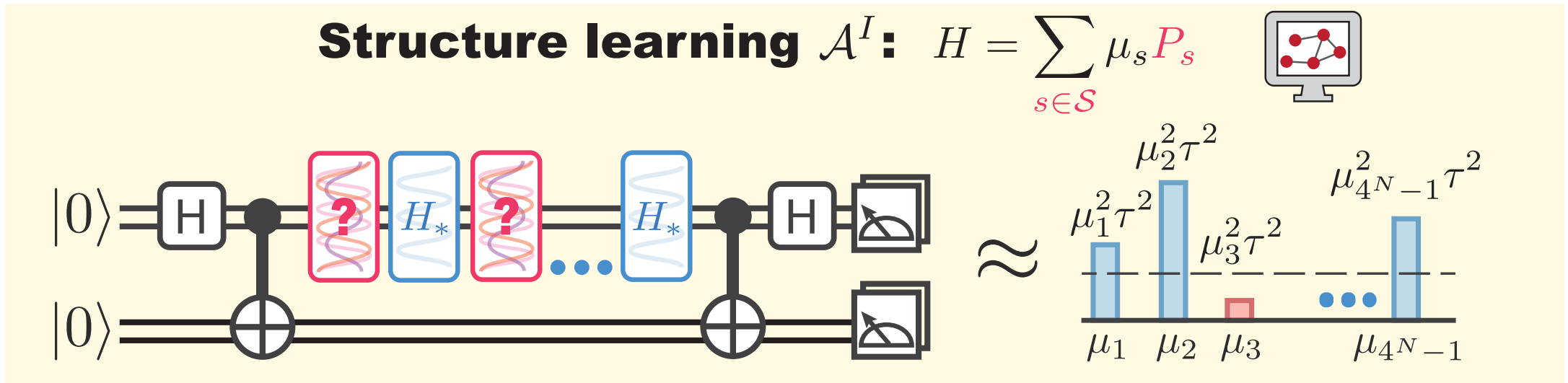
- Challenge 2: Getting to Heisenberg-limited scaling

Hierarchy

Main ideas

- Challenge 1: Extremely large search space $\sim 4^N$

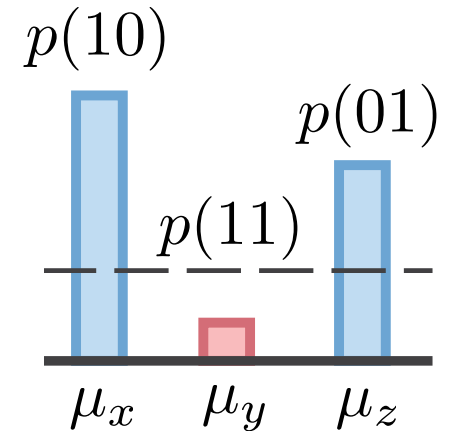
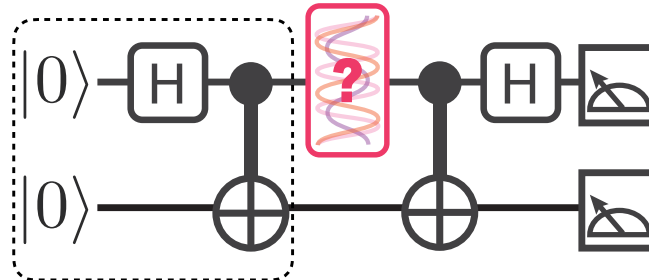
Importance sampling using quantum process!



Structure learning

- Single qubit problem: $H = \mu_x \sigma_x + \mu_y \sigma_y + \mu_z \sigma_z$

$$\sigma_x \rightarrow p(10) \quad \sigma_y \rightarrow p(11) \quad \sigma_z \rightarrow p(01)$$



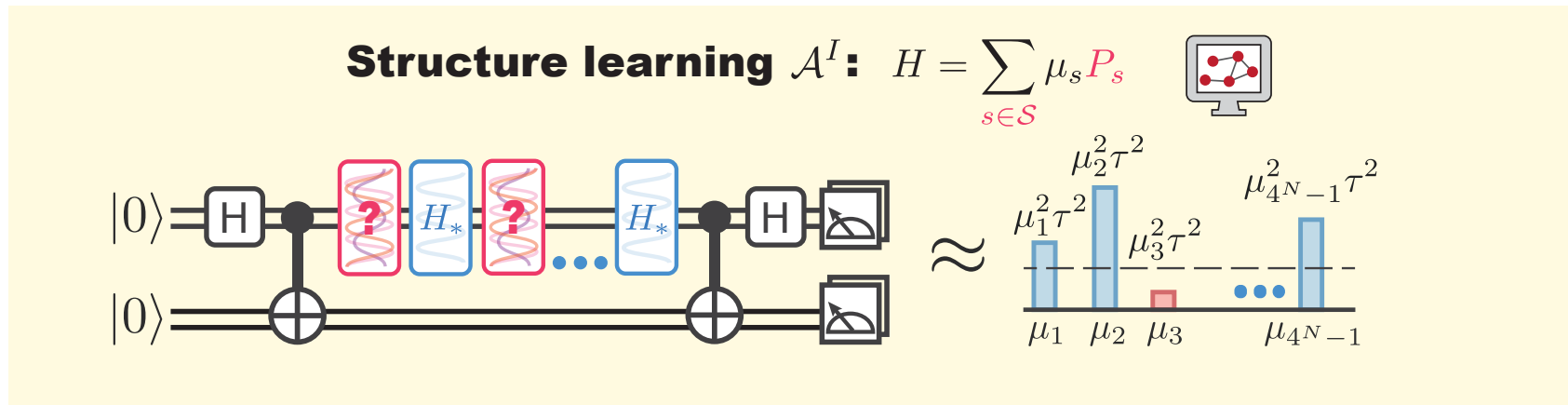
Idea from importance sampling!

$$|\Phi^+\rangle = \frac{|00\rangle + |11\rangle}{\sqrt{2}} \mapsto |\Phi^+\rangle - i\tau\mu_x|\Psi^+\rangle - i\tau\mu_y|\Psi^-\rangle - i\tau|\Phi^-\rangle + \mathcal{O}(\tau^2)$$

$$\mapsto p(01) \approx \tau^2 \mu_z^2 \quad p(10) \approx \tau^2 \mu_x^2 \quad p(11) \approx \tau^2 \mu_y^2$$

Structure learning

- Extending to many qubits:



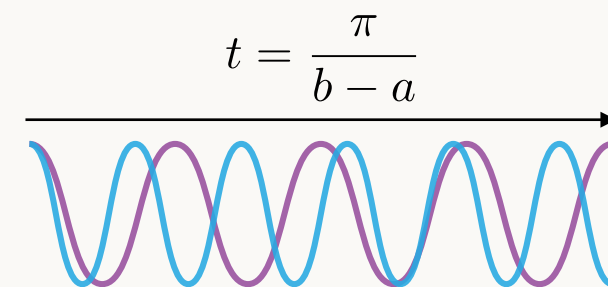
- Let $\mu_m = \min |\mu_s|$, if $\tau = \mathcal{O}(\mu_m/M)$, outcome probability is lower bounded by $\Omega(\mu_m^4/M^2)$.

Lemma: One can sample all support $\mathcal{S} = \{s : |\mu_s| > \mu_m\}$ **at lease once** with high probability by querying this quantum circuit $\mathcal{O}(M^2 \log M/\mu_m^4)$.

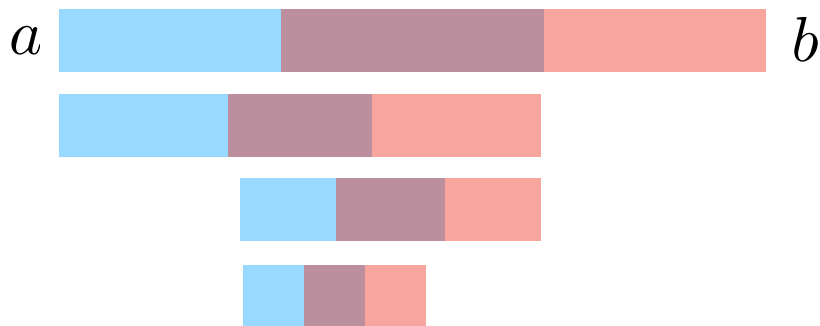
Coefficient learning

- Robust frequency estimation: Huang, Tong, Fang, Su. *PRL* Kimmel, Low, Yoder, *PRA*

Lemma: Let $\omega \in [a, b]$, and $Z(t)$ be an estimator of $e^{i\omega t}$ with constant precision, i.e. $|Z(t) - e^{i\omega t}| < 1/2$. One can decide whether $\omega \in [a, (a + 2b)/3]$ or $\omega \in [(2a + b)/3, b]$ with **one sample** at $t = \pi/(b - a)$.



- Single qubit problem: detect $H = \omega_z \sigma_z$ with unknown ω_z with single qubit at Heisenberg-limited scaling.



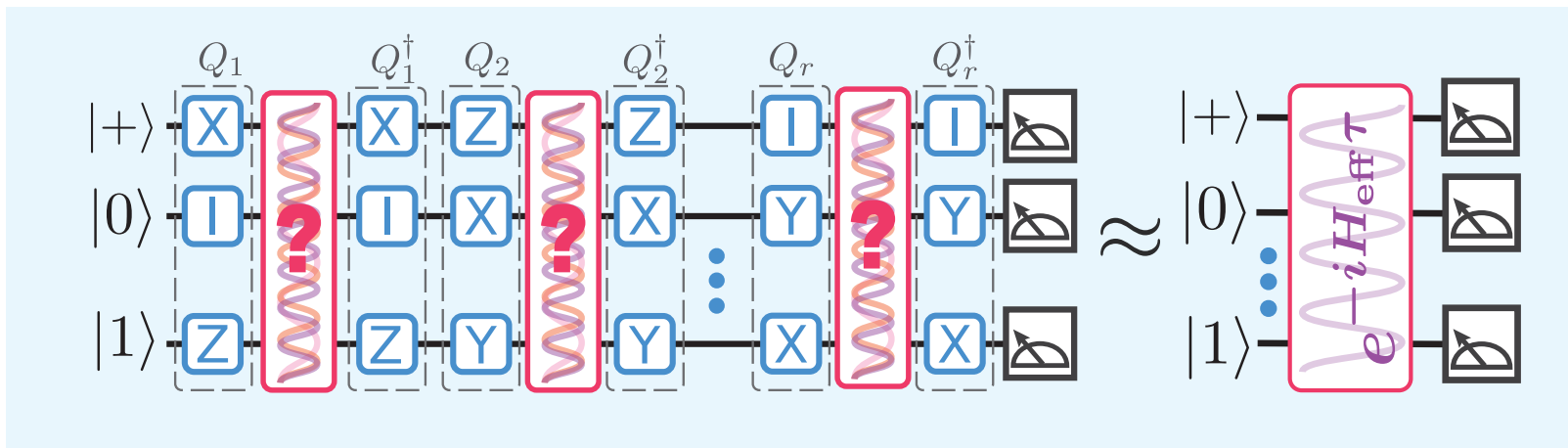
Total experiments

$$L \sim \log_{\frac{3}{2}} \left(\frac{b - a}{\epsilon} \right) \mapsto T \sim \sum_{l=1}^L t_l \sim \frac{1}{\epsilon}$$

Heisenberg scaling with single qubit!

Coefficient learning

- From single qubit to many qubits:



Suppose we want to isolate the dynamics from a single P_s , we insert random single qubit gates Q_i such that $[Q_i, P_s] = 0$. For each circuit, we are applying

$$Q_{r_2} e^{-iH\tau} Q_{r_2} \cdots Q_2 e^{-iH\tau} Q_2 Q_1 e^{-iH\tau} Q_1 \mapsto \mathbb{E}_Q [Q e^{-iH\tau} Q] = e^{-iP_s\tau} + \mathcal{O}(\tau^2)$$

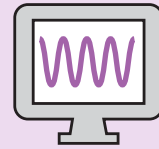
- Let $\mathcal{U}(\rho) = \mathbb{E}[U\rho U^\dagger]$ and $\mathcal{V}(\rho) = e^{-iP_s t} \rho e^{iP_s t}$, then $||\mathcal{U} - \mathcal{V}||_\diamond \leq 4M^2 t^2 / r_2$

Hierarchical learning



Structure learning $H = \sum_{s \in \mathcal{S}} \mu_s P_s$

$$T \sim \tilde{O}(1/\mu_m^3)$$

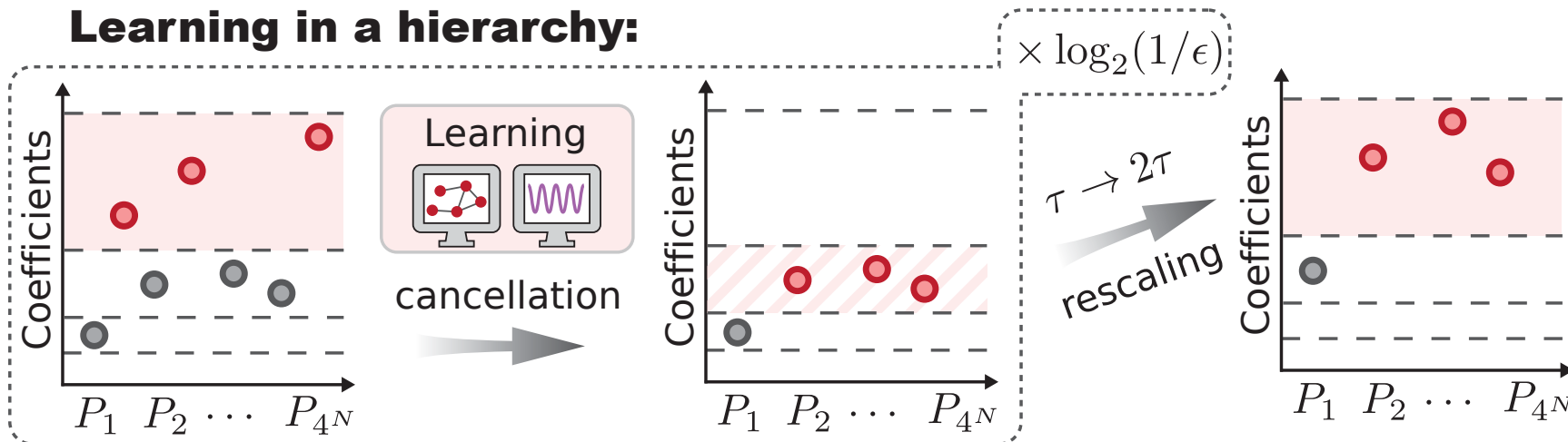


Coefficient learning $H = \sum_{s \in \mathcal{S}} \mu_s P_s$

$$T \sim \tilde{O}(1/\epsilon)$$

$$\Rightarrow \mu_m = \epsilon \Rightarrow T \sim \tilde{O}(1/\epsilon^3) \text{ 😞}$$

Learning in a hierarchy:

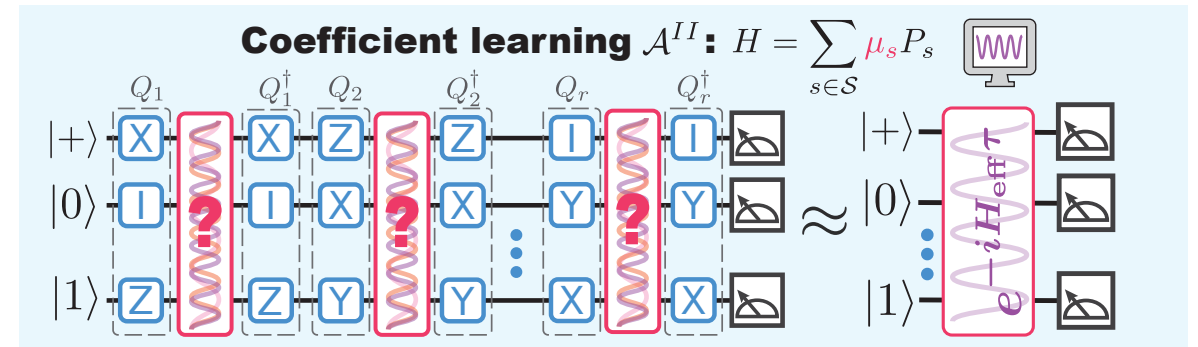
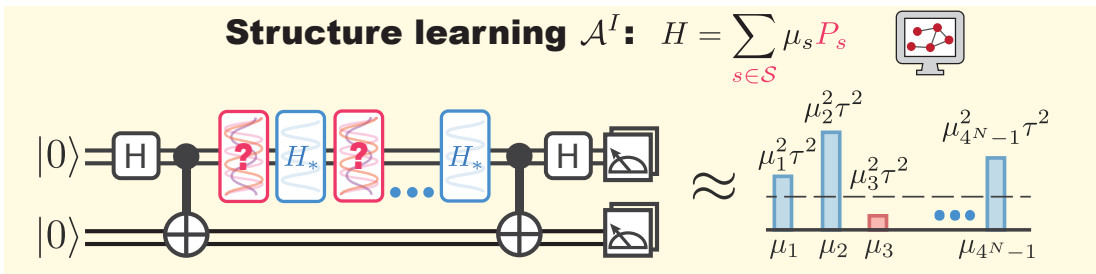


Divide terms into $J = \lceil \log_2(1/\epsilon) \rceil$ levels.
Each time, we learn $2^{-(j+1)} < |\mu_s| \leq 2^{-j}$ to ϵ precision.

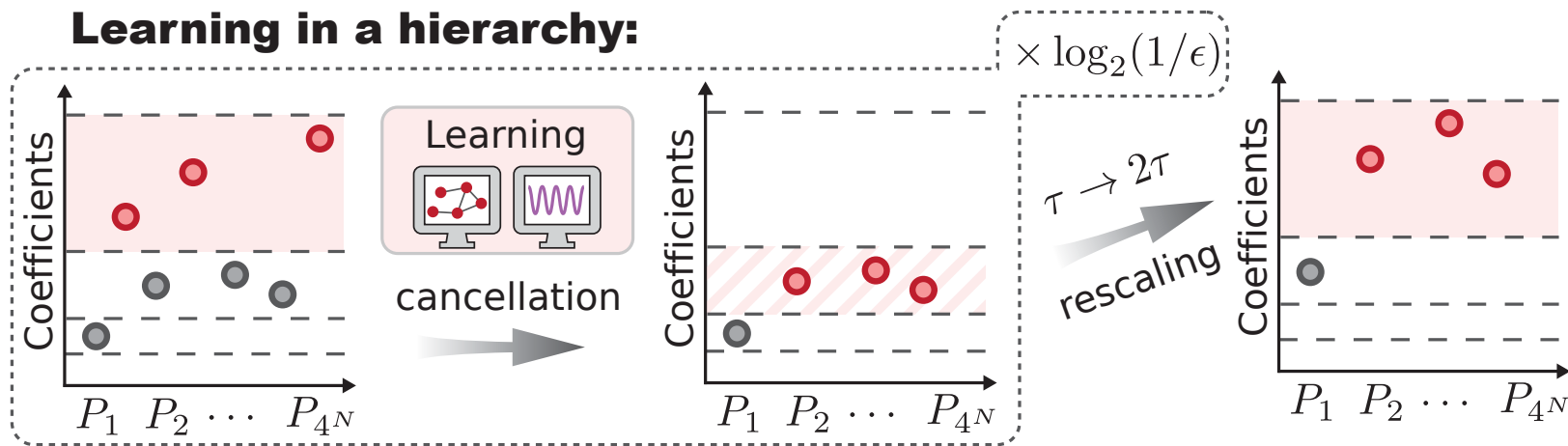
Main ideas

- Challenge 1: Extremely large search space $\sim 4^N$

Importance sampling using quantum process!

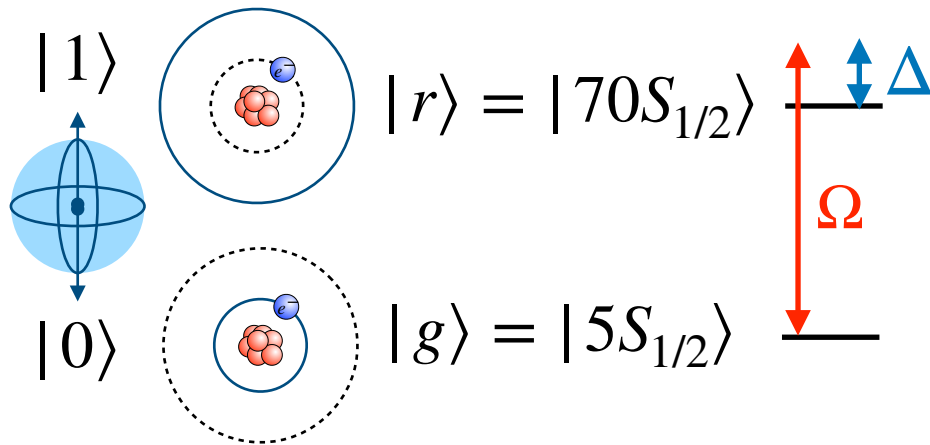
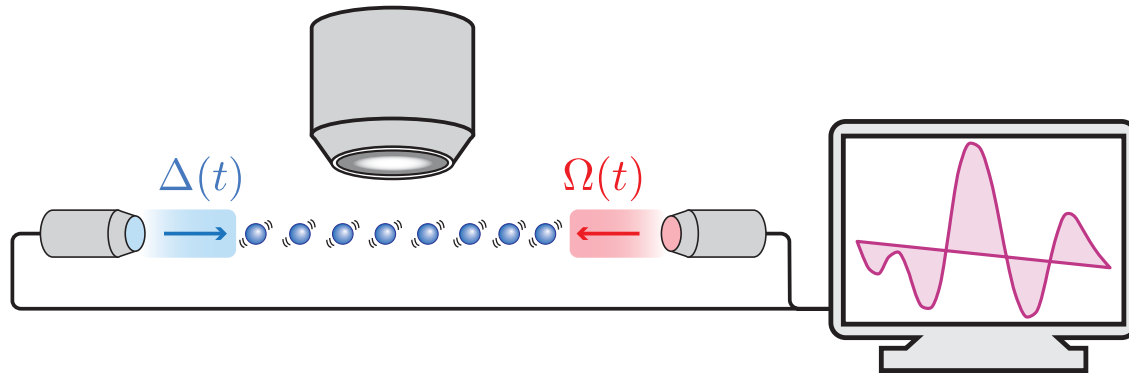


- Challenge 2: Getting to Heisenberg-limited scaling

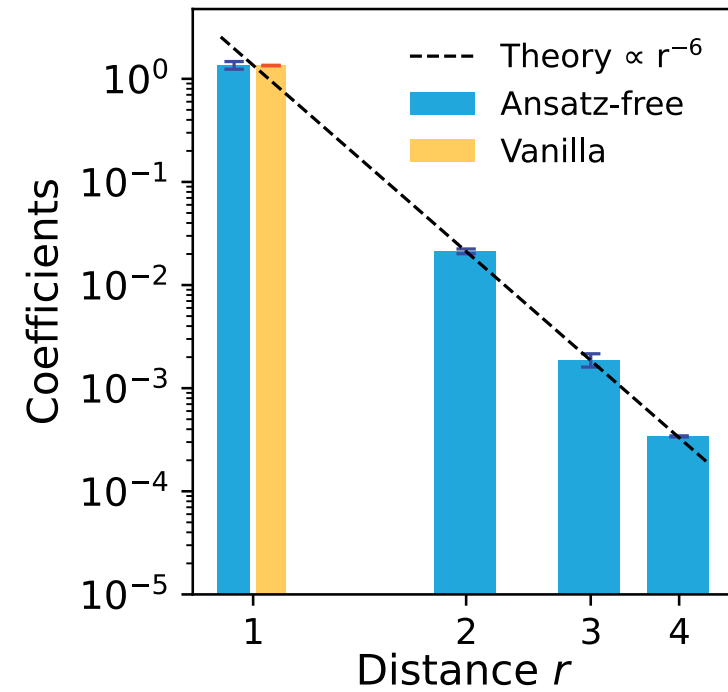
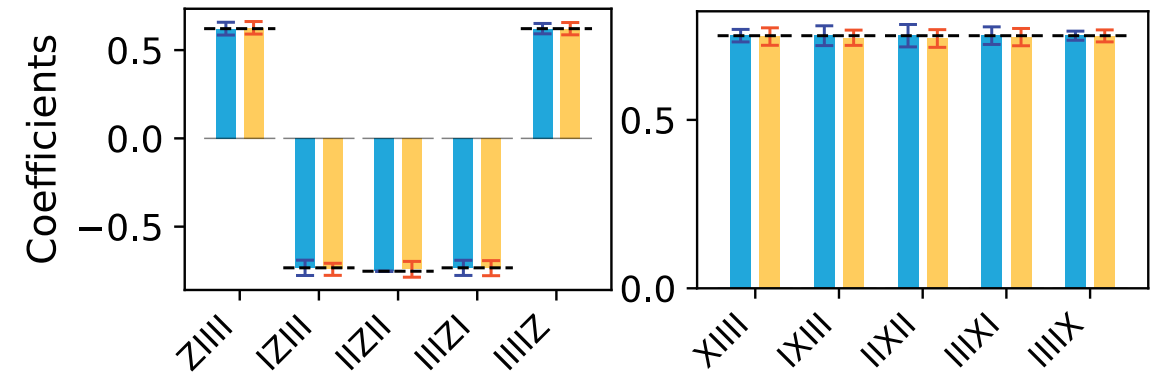


Applications

- Learning long-range interactions:

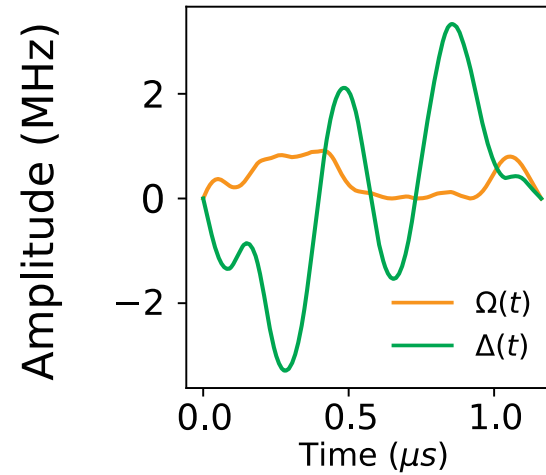


Analog Hamiltonian of Rydberg atom chains

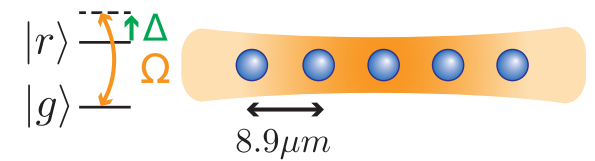


Applications

- Learning effective Hamiltonian, where one doesn't have good ansatz:
Find pulse to simulate ZXZ

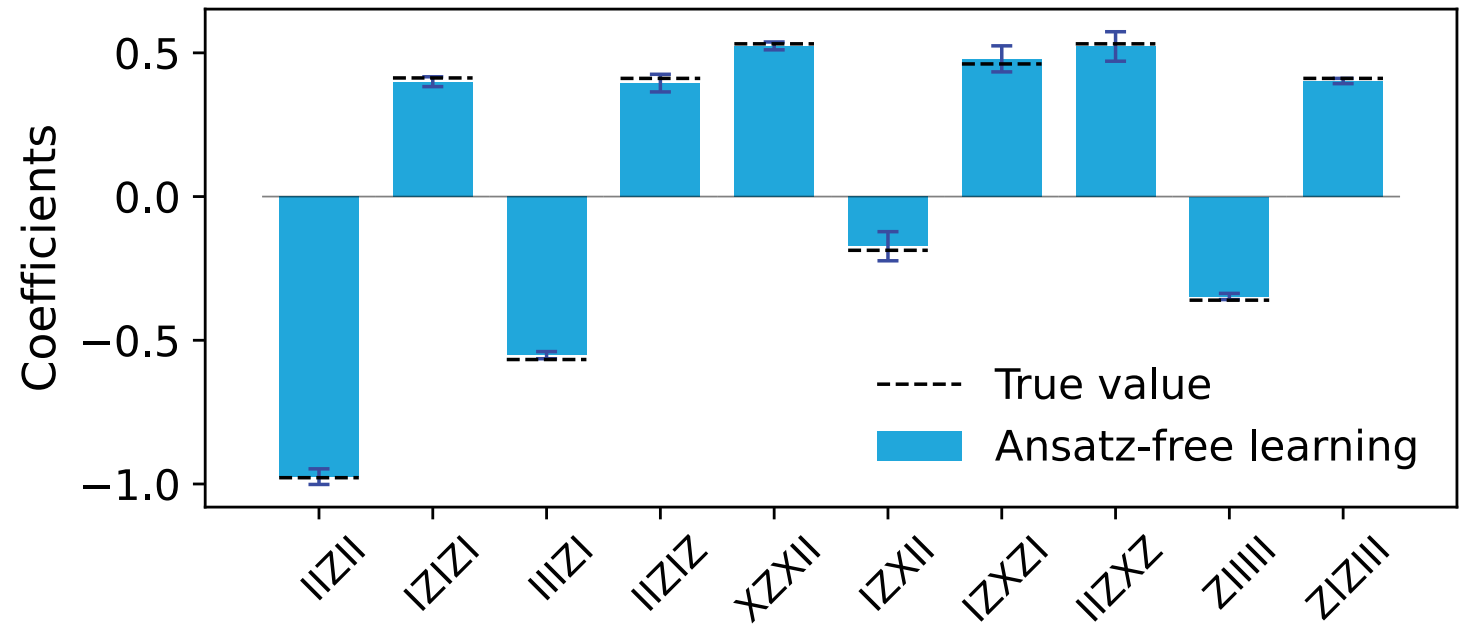
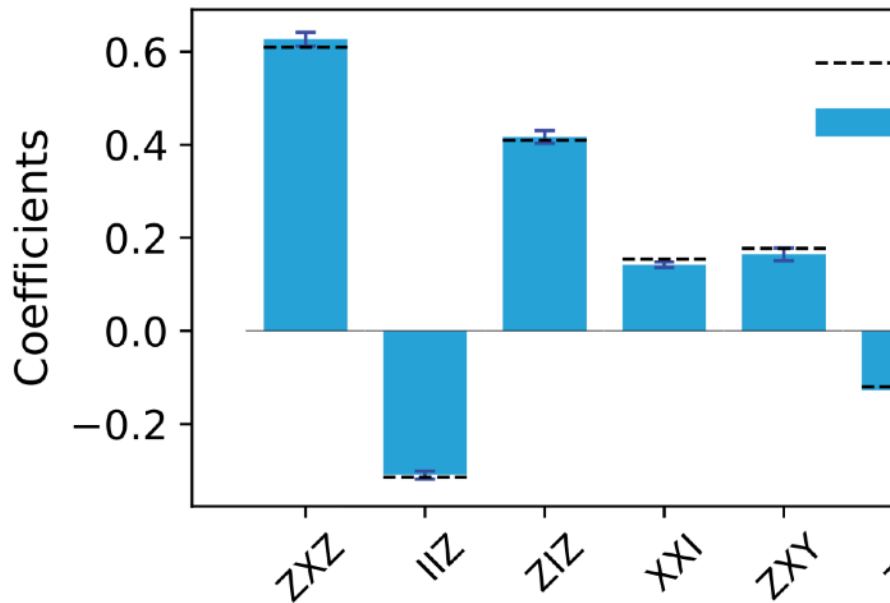


Globally-driven atom arrays



$$U = \mathcal{T}[\exp(-i \int H(t) dt)] = \exp(-i\theta H_{\text{eff}})$$

What is effective Hamiltonian?



Learning Lindbladians

Modeling Noise - Lindblad Master Eq.

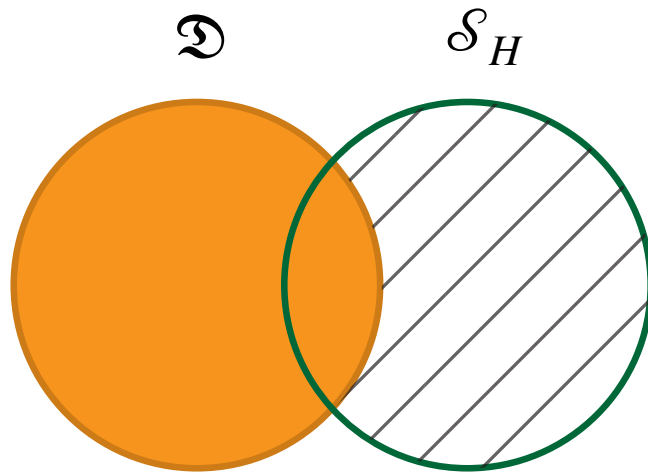
$$\frac{d\rho_s}{dt} = \mathcal{L}(\rho_s) = \underbrace{-i \sum_{P_k \in \mathcal{S}_H} h_k [P_k, \rho_s]}_{\text{Hamiltonian}} + \underbrace{\sum_{P_k, P_j \in \mathcal{S}_D} a_{kj} \left(P_k \rho_s P_j - \frac{1}{2} \{P_j P_k, \rho_s\} \right)}_{\text{Dissipator}}$$

P_k, P_j – n-qubit Pauli operators

ρ_s – system density matrix

h_k – real coefficients

$a \geq 0$ – Kossakowski matrix



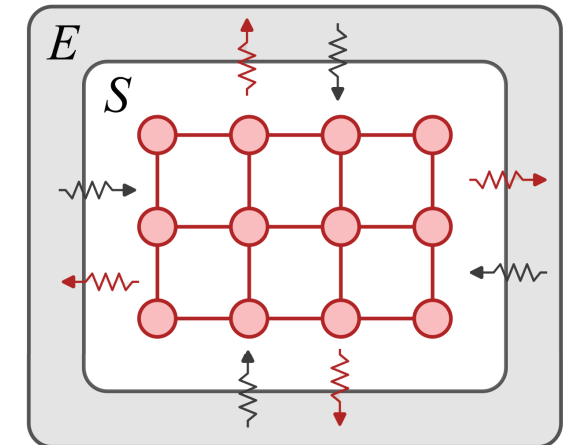
$\mathcal{S}_H$ Hamiltonian Structure

$\mathfrak{D}$ Dissipator Structure

$\mathcal{S}_H \setminus \mathfrak{D}$ Hamiltonian-
not-in-Dissipator (HNID)

$$\mathcal{S}_D \cdot \mathcal{S}_D \equiv \{PQ : P, Q \in \mathcal{S}_D\}$$

$$\mathfrak{D} \equiv (\mathcal{S}_D \cdot \mathcal{S}_D) \cup \mathcal{S}_D$$



Open-system Setup

$$\dot{\rho} = \mathcal{L}(\rho) = -i \underbrace{\sum_{P_i \in S_H} h_i [P_i, \rho]}_{\text{Hamiltonian}} + \underbrace{\sum_{P_i, P_j \in S_D} a_{ij} \left(P_i \rho P_j - \frac{1}{2} \{P_j P_i, \rho\} \right)}_{\text{Dissipator}}$$

Query model

Prepare
Pauli state



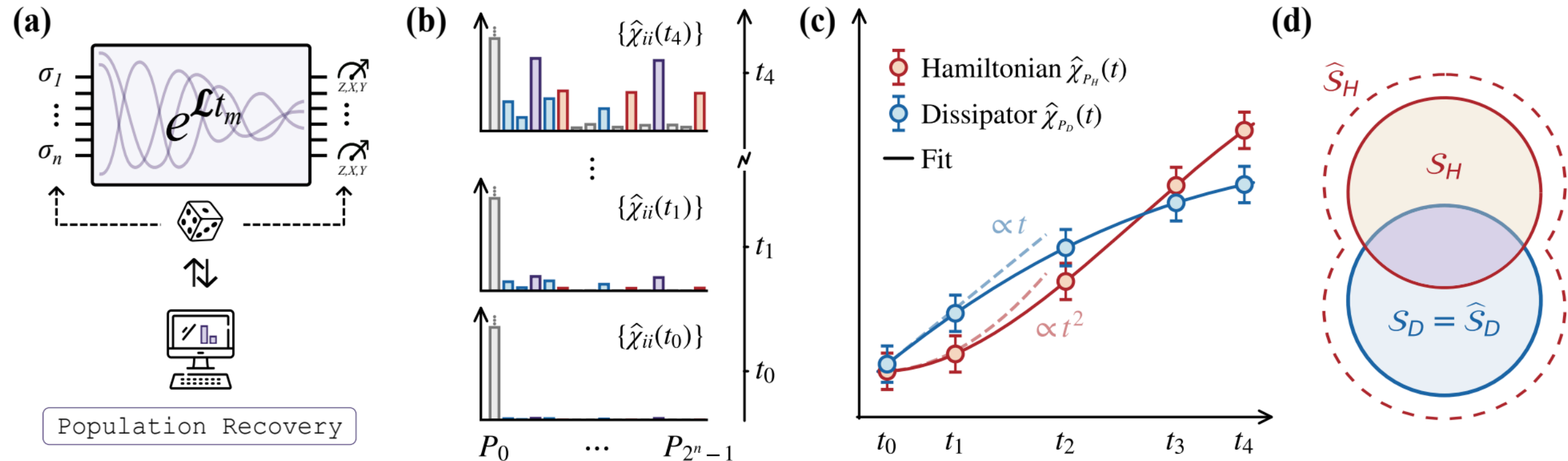
Evolve
native operators
for short t



Measure
single-qubit Pauli
basis

No interleaved control during the unknown evolution; otherwise you learn a control-dressed effective generator.

Lindbladian Structure Learning



Flammia and O'Donnell, [Quantum 5, 549 \(2021\)](#).

Lindbladian coefficient learning

(a)



Dissipator term

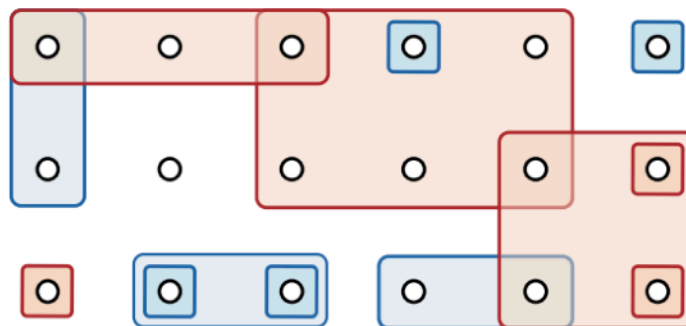
$$\mathcal{D}_{ij}(\rho) := a_{ij} \left(P_i \rho P_j - \frac{1}{2} \{P_j P_i, \rho\} \right)$$



Hamiltonian term

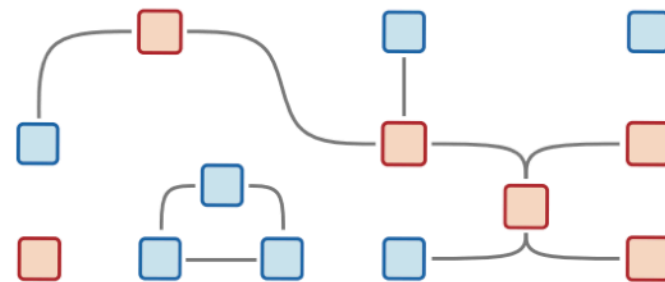
$$\mathcal{H}_i(\rho) := -i h_i [P_i, \rho]$$

Lindbladian Pauli terms

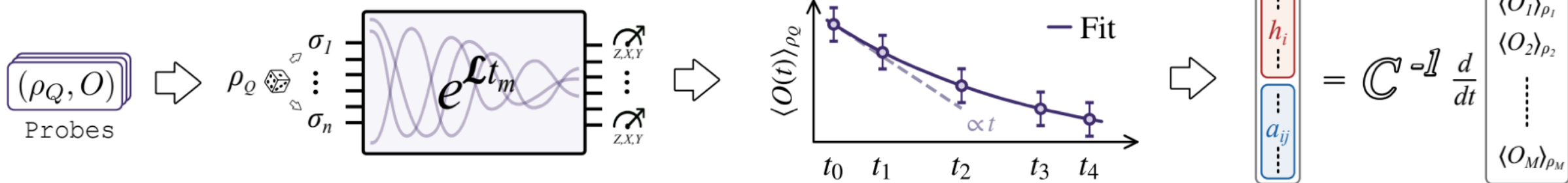


(b)

Dual interaction graph



(c)



Learning Complexity

End-to-end complexity of Lindbladian Learning

$$m_{\text{tot}} = \tilde{\mathcal{O}} \left(\frac{M^4 \nu^2}{\epsilon^4} \right)$$

Hamiltonian vs Lindbladian

same backbone, different access model

Ansatz-free Hamiltonian learning

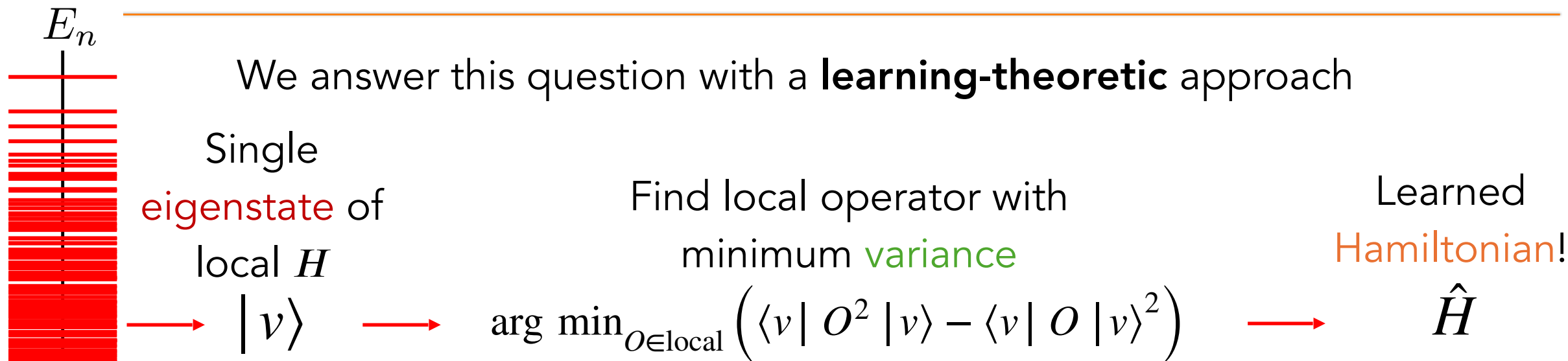
Ansatz-free Lindbladian learning

Target	Sparse Hamiltonian H	Full generator $H + D$
Access model	Controlled real-time evolution	In situ real-time evolution
Structure signal	Bell outcomes / twirled terms	Short-time Pauli error-rate derivatives
Coefficient step	Reshaping + robust frequency estimation	Patchwise derivative estimation + linear inversion
Best headline	Heisenberg-limited total evolution time	Native open-system characterization with near-optimal time resolution
Role of control	Helpful and, in general, information-theoretically important	Intentionally avoided during the unknown evolution

Learning Chaos

Hamiltonian learning

Qi and Ranard 2019



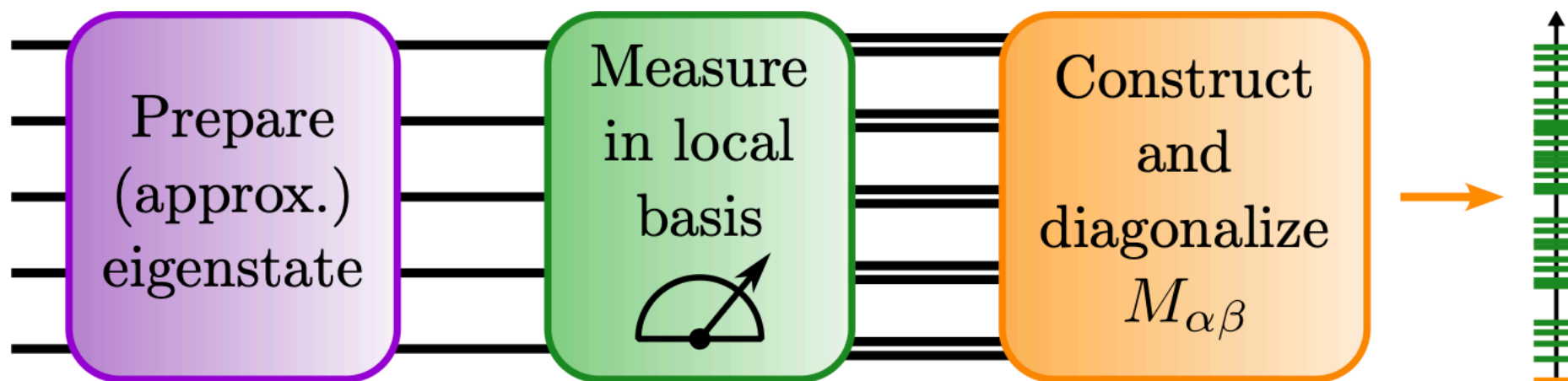
How sensitive is this process to noise?

Error in measuring variance $\longrightarrow$ Error in learned Hamiltonian

Does quantum **ergodicity** make this procedure more or less sensitive to noise?

Learning a Hamiltonian from one eigenstate

Algorithmic skeleton

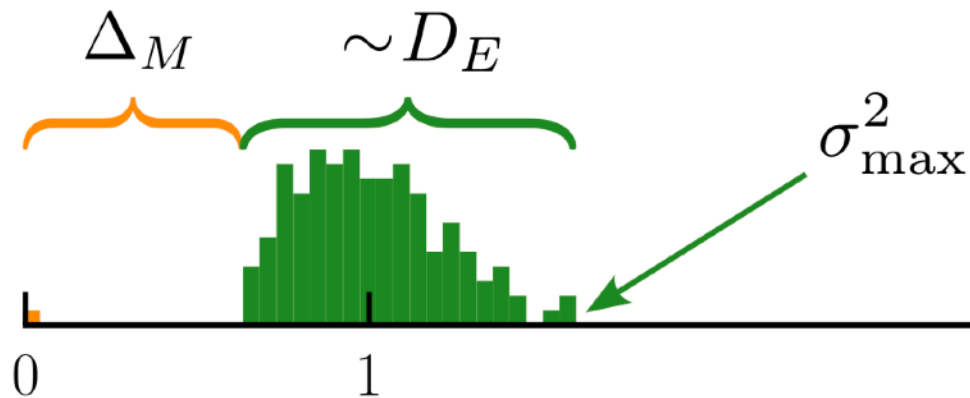
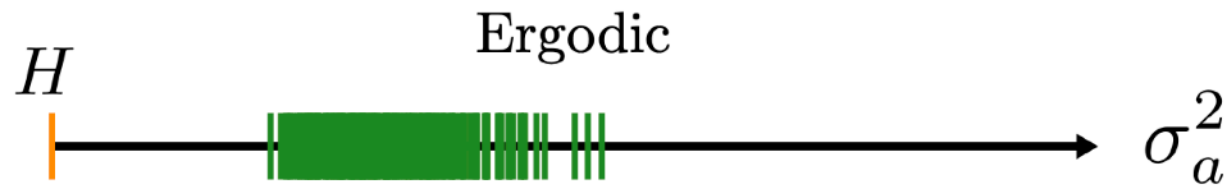
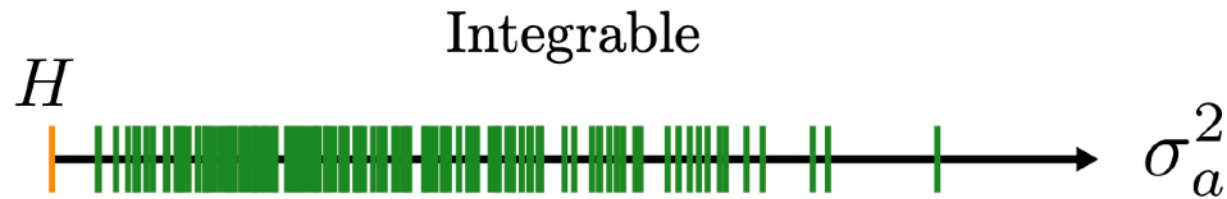


- Choose a local operator basis $\{L_\alpha\}$.
- Construct the covariance matrix M from one eigenstate.
- The Hamiltonian is the operator in the kernel (or approximate kernel) of M .
- So robustness of learning is encoded in the surrounding variance spectrum.

$$M_{\alpha\beta} = \frac{1}{2} \langle \{L_\alpha, L_\beta\} \rangle - \langle L_\alpha \rangle \langle L_\beta \rangle$$

From covariance matrix to robustness

Qualitative spectrum picture



Δ_M
smallest nonzero
variance gap

worst-case
robustness

D_E
spread of nonzero
variances

uniformity of
robustness
across errors

$\sigma_{\max}^2$
largest variance

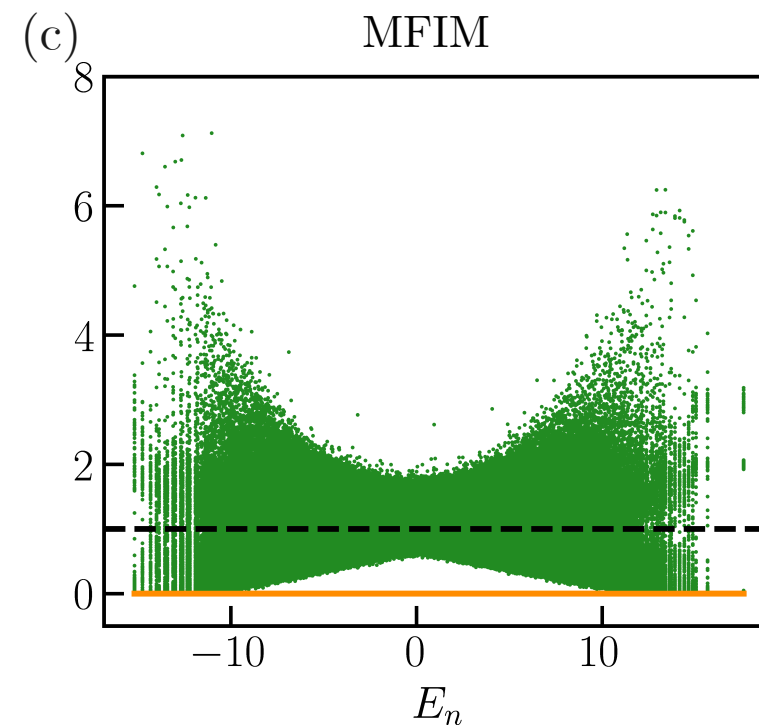
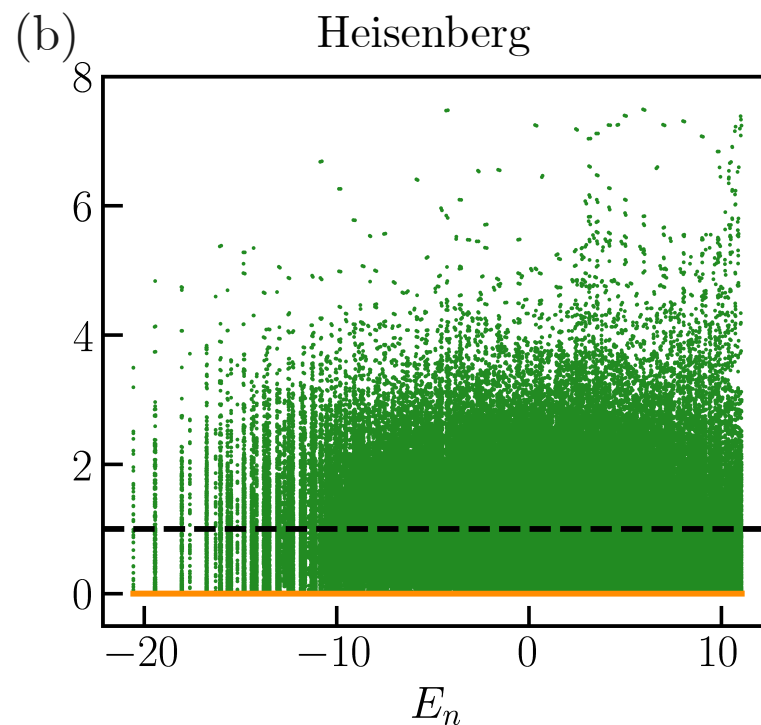
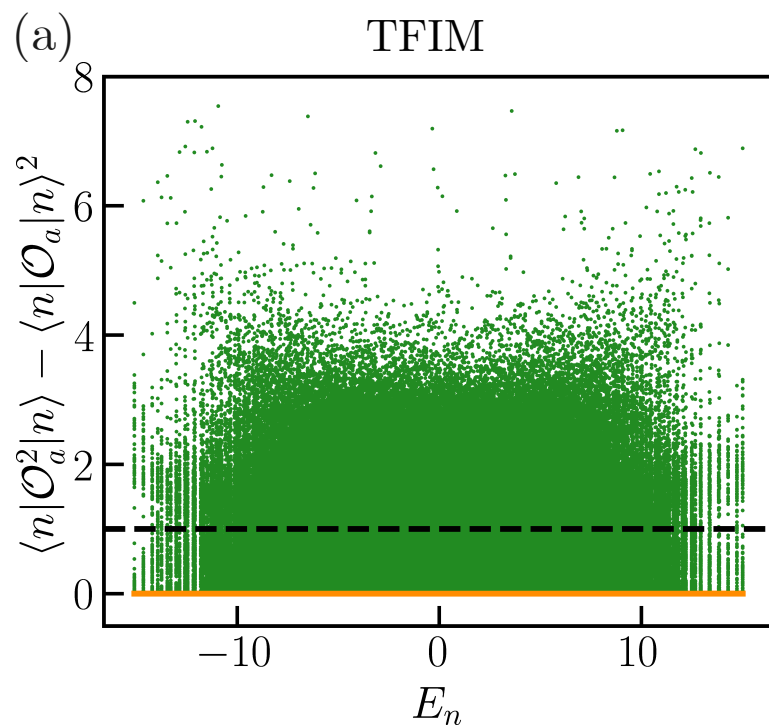
sensitivity to
local
perturbations

Hamiltonian learning in 1D spin chains

TFIM
(free fermion)

Heisenberg
(Bethe integrable)

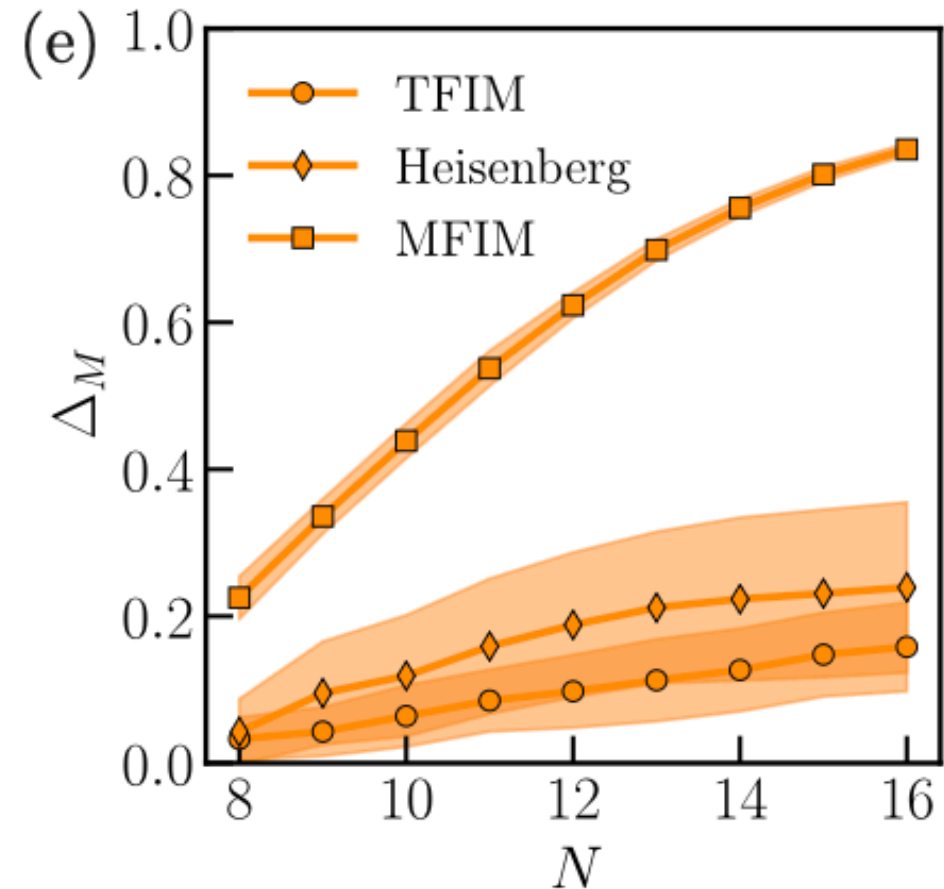
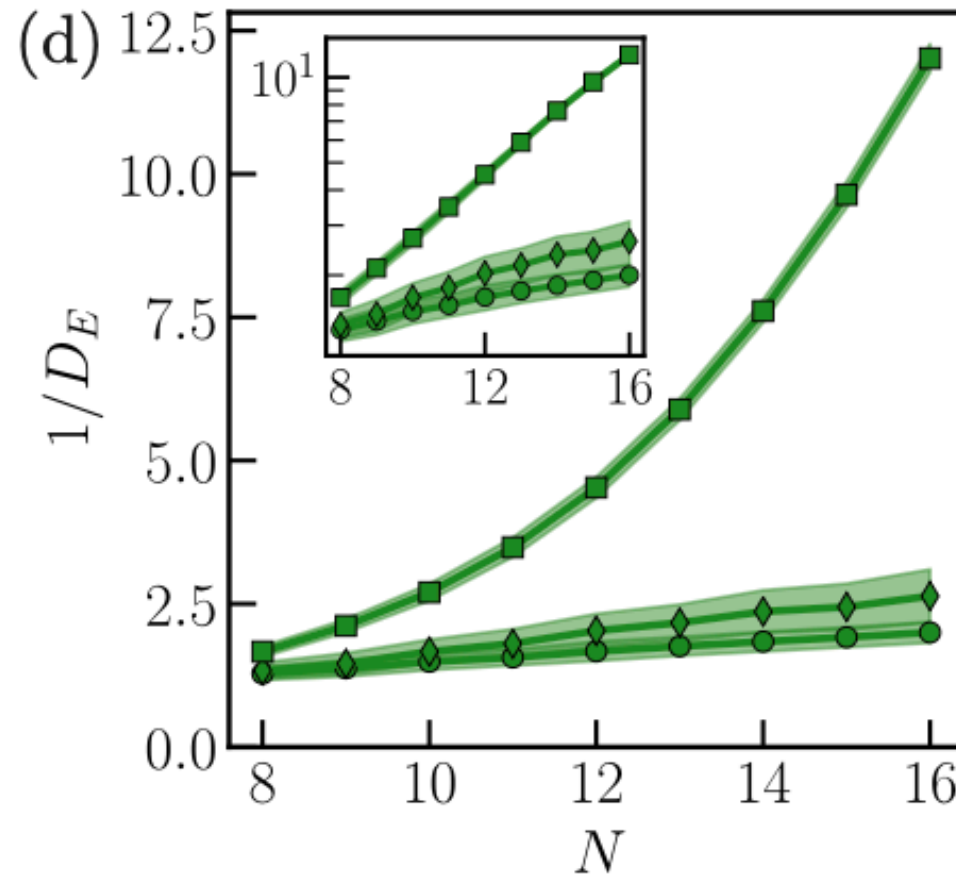
MFIM
(non-integrable)



Clear qualitative difference in spectra and robustness!

Scaling in 1D spin chains

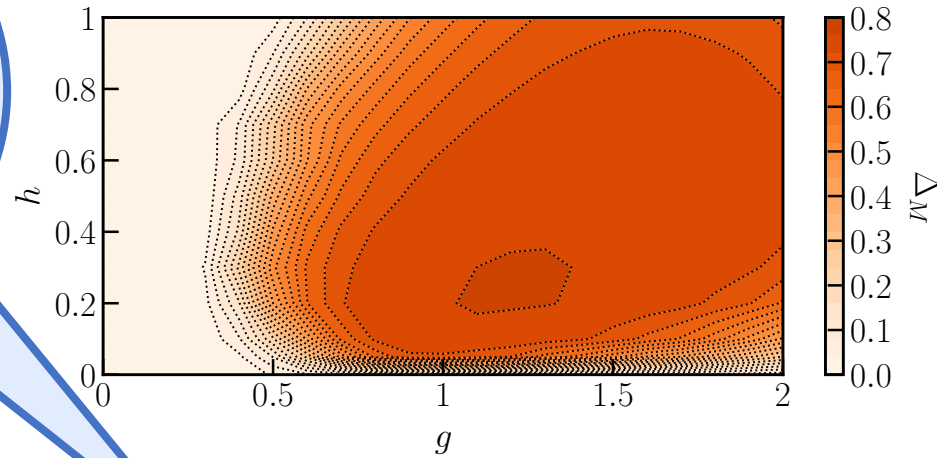
How does this change with N ?



Difference amplified as system grows!

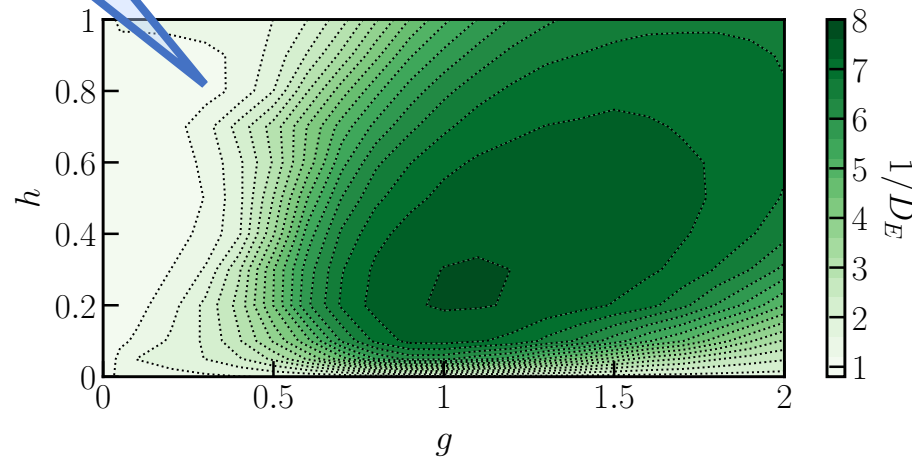
Where is the system most ergodic?

fits with
earlier measures
for the maximally
ergodic point



Worst-case
robustness of
learning

is more
differentiated than
most earlier



Uniformity of
robustness

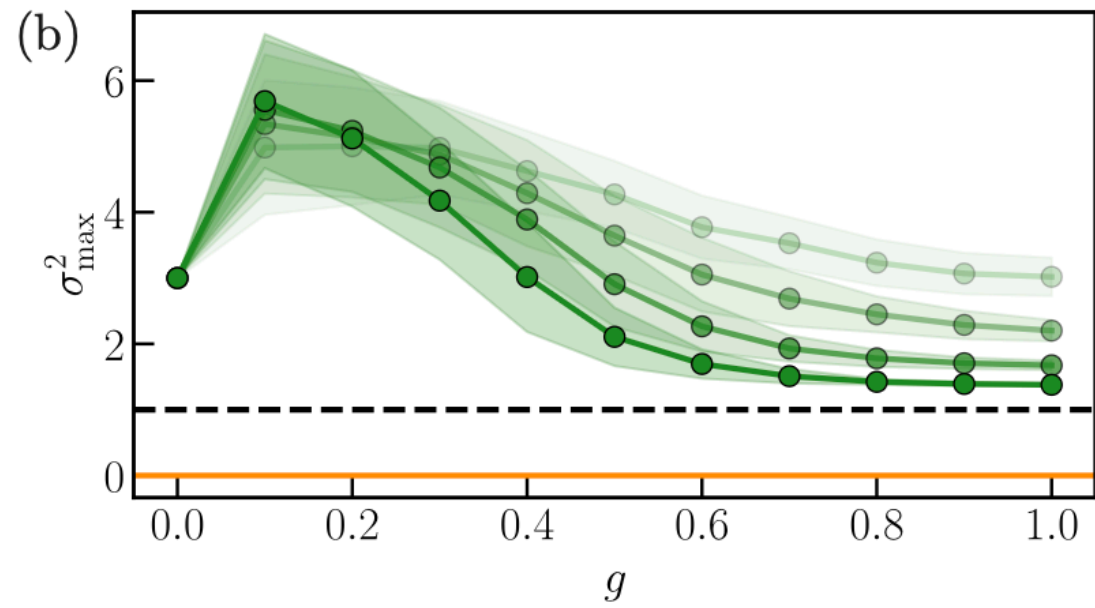
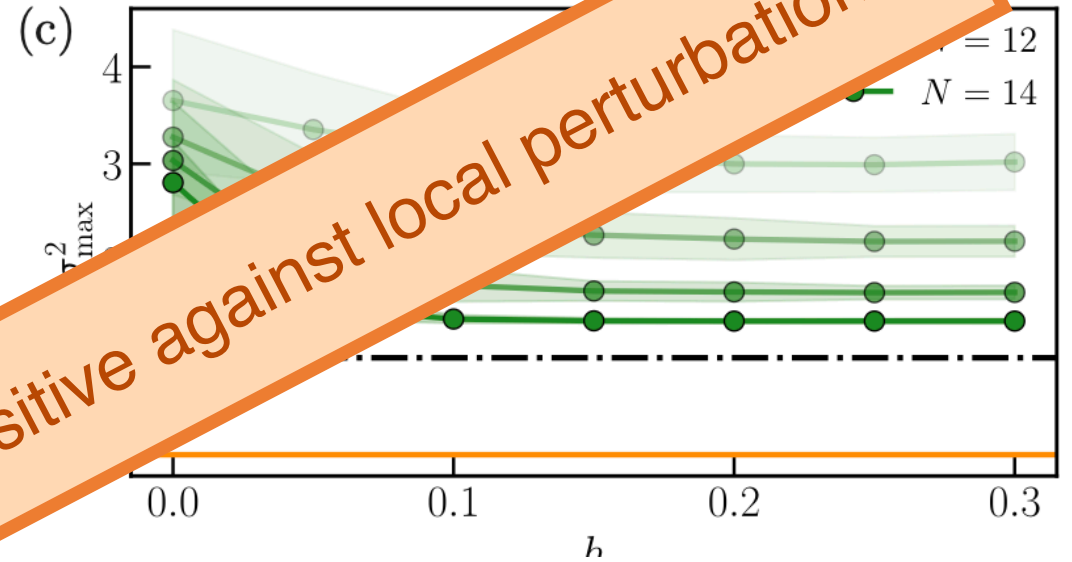
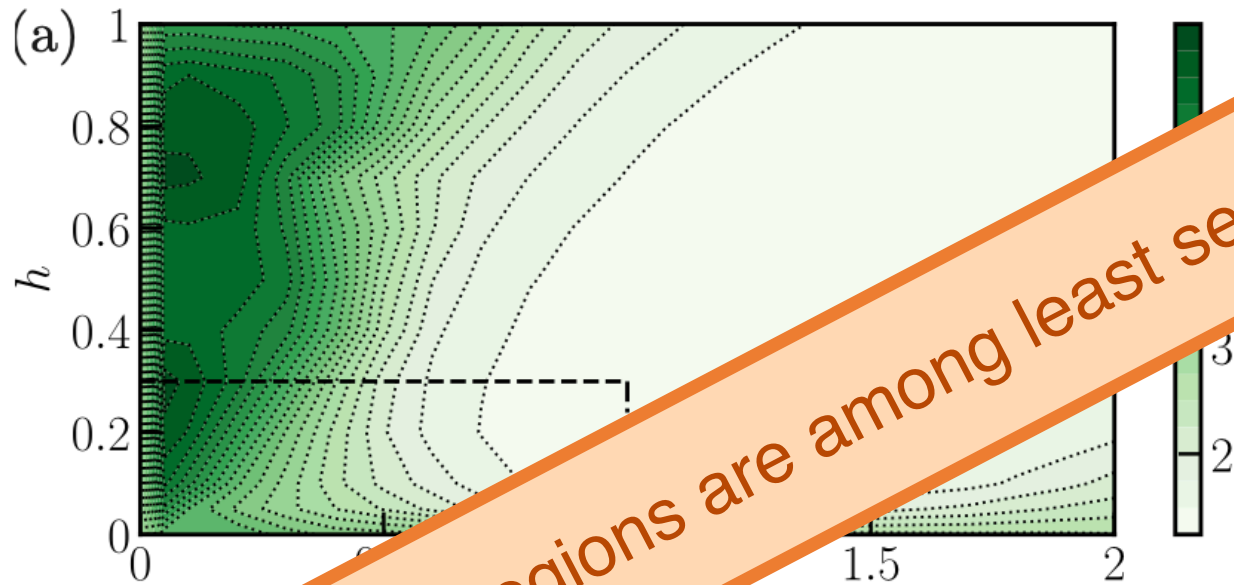
(Is learning robust
against **all** errors)

Is much
easier to learn

Local sensitivity is a different axis than ergodicity

Ergodic regions are among least sensitive against local perturbations!

$\sigma_{\max}^2$ probes local sensitivity



Experimental plausibility

State preparation

- Exact eigenstates are not required; approximate eigenstates with small energy width can still separate integrable and ergodic behavior.
- Coda does not rely on an unrealistic idealization of perfect state preparation.
- Approximate-state behavior can be non-monotonic in integrable models, but the diagnostic still distinguishes the regimes.

You can target experimentally reachable approximate eigenstates!

Measurement

- Because the metric is built from local operator data, local / randomized measurements are enough in principle.
- That is a practical advantage over diagnostics that require explicitly nonlocal observables or deeper circuits.
- Coda points toward accessible many-body diagnostics, not just a formal reinterpretation of learning theory.

Procedure not just purely formal.

Thank you!

