

Ansatz-Free Learning of Lindbladian Dynamics In Situ

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In this work, we make substantial progress in open quantum system characterization by giving, to our knowledge, the first sample-efficient protocol for learning sparse Lindbladians *in situ* without any a priori knowledge of the interaction structure or locality.

Motivation. Open quantum systems are ubiquitous in quantum science, from molecular and condensed-matter settings to modern digital and analog multiqubit devices. Controlling such systems at the physical level requires a microscopic understanding of their dynamics and noise. The natural way to characterize an open quantum system is to identify its Lindbladian, which captures both the coherent (Hamiltonian) and dissipative components of the dynamics [1, 2]. In this work, we study Lindbladian learning in the *in situ* setting: one initializes the system in a simple input state, lets it evolve under its intrinsic Lindbladian, and measures the evolved state; the goal is then to identify the underlying unknown Lindbladian from the measurement data. Crucially, no quantum controls are applied during the evolution to avoid inadvertently modifying the underlying Lindbladian.

Gap in the literature. Despite recent progress on learning multiqubit Lindbladians, all prior *in situ* protocols with rigorous performance guarantees assume a known interaction graph, i.e., one knows in advance which qubits interact with which [3, 4]. Moreover, the assumed interaction model is typically geometrically local and restricted to single-qubit dissipation. These assumptions pose a crucial limitation: on realistic hardware, the relevant Hamiltonian and dissipator terms may be unknown and nonlocal [5], leading to an exponentially large candidate space. Whether generic Lindbladians can be efficiently learned without a known interaction model—i.e., *ansatz-free*—has remained a timely open problem in the quantum learning community.

Main advance. We resolve this open problem by giving the first end-to-end algorithm for learning a Lindbladian with polynomially-many terms in the experimentally minimal *in situ* setting. Our algorithm proceeds in two stages: *structure learning*, which identifies which interaction terms are present in the Hamiltonian and dissipator, and *coefficient learning*, which then estimates the strength of each identified term. The novelty of our work lies in performing the first stage without any prior structural input via a novel structure-learning routine, and in extending the second stage beyond the geometrically local, single-qubit-dissipation models via a newly introduced *Lindbladian patchwise Pauli tomography*. In addition, we identify short-time evolutions as a fundamental requirement for ansatz-free Lindbladian learning, rendering the time resolution of our protocol near-optimal.

Model and goal. We consider an unknown time-independent n -qubit Lindbladian $\mathcal{L}$ expressed in the Pauli basis as:

$$\mathcal{L}(\rho) = -i \sum_{P_i \in \mathcal{S}_H} h_i [P_i, \rho] + \sum_{P_i, P_j \in \mathcal{S}_D} a_{ij} (P_i \rho P_j - \frac{1}{2} \{P_j P_i, \rho\}), \quad (1)$$

where $\mathcal{S}_H$ and $\mathcal{S}_D$ are unknown Pauli supports of the Hamiltonian and dissipator. We denote by M an upper bound on the number of Pauli-basis coefficients that are nonzero. This upper bound is used only to set algorithmic parameters, and the algorithm does not require knowing the exact sparsity. Given query access to the generated evolution $\mathcal{E}_t = e^{t\mathcal{L}}$, the goal is to output estimates of all Lindbladian coefficients $\{h_i, a_{ij}\}$ to an additive error of ε with high success probability.

In the worst case, our algorithm recovers all nonzero coefficients to additive error ε with high success probability using

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

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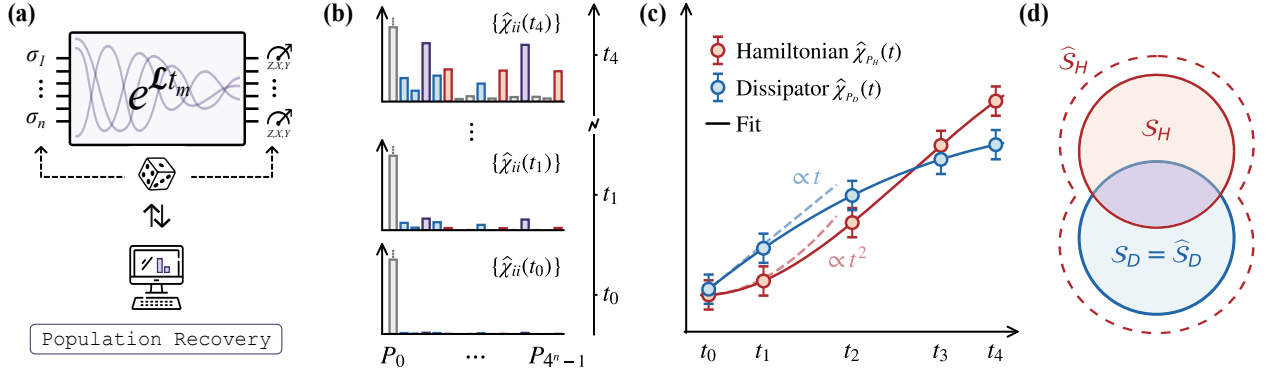


FIG. 1. **Structure learning from Pauli error rates at short times.** The protocol outputs sets $\hat{S}_D$ and $\hat{S}_H$ containing the true Hamiltonian and dissipator structures S_D and S_H , respectively. (a) We fix a set of short evolution times $\{t_m\}$ and, for each t_m , query the channel $e^{\mathcal{L}t_m}$ using the population-recovery protocol [6] to obtain a distribution of Pauli error rates $\{\hat{\chi}_{ii}(t_m)\}$. Each query consists of preparing a random Pauli product state, evolving for time t_m , and measuring in a random Pauli basis. (b) Collecting these estimated distributions over $\{t_m\}$ yields time traces of Pauli error rates. For very short times, only the identity component is appreciable. As t increases, the rates associated with Hamiltonian terms (red), dissipator terms (blue), and terms in the overlap $S_H \cap S_D$ (purple) begin to grow, spreading the rate distribution. (c) For each observed trace, we fit a low-degree Chebyshev interpolant and use the first and second derivatives of the fit at $t = 0$ to decide whether the Pauli enters through dissipation (first order) or through the Hamiltonian (second order): Pauli rates corresponding to dissipator terms $P_D \in S_D$ exhibit linear short-time growth, while purely Hamiltonian rates $P_H \in S_H \setminus S_D$ enter only at second order and exhibit quadratic short-time growth. (d) Finally, we threshold these derivative estimates to obtain candidate supports $\hat{S}_D$ and $\hat{S}_H$ that satisfy $\hat{S}_D = S_D$ and $\hat{S}_H \supseteq S_H$.

applications of $\mathcal{E}_t$, where ν governs the numerical stability of coefficient reconstruction. Our numerical evidence shows that the factor ν remains moderate for broad families of physically motivated Lindbladians. Finally, the protocol can be made robust to SPAM noise under independent single-qubit depolarizing errors with a quantified overhead.

I. CONTRIBUTIONS

Our results can be broken down into three parts.

(I) Ansatz-free structure learning from Pauli error rates. Our first contribution is a structure-learning procedure that identifies the dissipator support and a polynomial-size superset of the Hamiltonian support from short-time *Pauli error rates*. Writing $\mathcal{E}_t(\rho) = \sum_{i,j} \chi_{ij}(t) P_i \rho P_j$, the diagonal entries $\{\chi_{ii}(t)\}_i$ form the Pauli error rates. These can be estimated efficiently in our access model using the population recovery protocol [6]. The key structural observation is that the first two time derivatives at $t = 0$ separate dissipative and Hamiltonian contributions: dissipator-diagonal terms contribute at first order, while Hamiltonian-only terms are witnessed at second order. Consequently, by estimating $\chi_{ii}(t)$ at carefully chosen short times and extracting the first two derivatives $\chi_{ii}^{(1)}$ and $\chi_{ii}^{(2)}$, we recover candidate support sets

$$\hat{S}_D = S_D \quad \text{and} \quad \hat{S}_H \supseteq S_H$$

with $|\hat{S}_H|$ polynomially bounded in the problem parameters. This reduces the candidate space from $\Theta(4^n)$ Pauli terms to a polynomial-size list without any locality or structural assumptions.

Time resolution is a key obstacle: finite-difference differentiation would require time steps that shrink with the coefficient resolution, making the protocol experimentally impractical. We sidestep this by performing Chebyshev interpolation on a short-time window $\tau_{\max} = \Theta(1/M)$, obtaining derivative estimates whose required time resolution depends only polylogarithmically on the target precision. Figure 1 summarizes the structure-learning stage.

(II) Coefficient learning via Lindbladian patchwise Pauli tomography. Given $\hat{S}_H$ and $\hat{S}_D$, our second contribution is an ancilla-free coefficient-learning procedure that estimates all associated coefficients to accuracy ε using short-time derivatives of carefully chosen Pauli observables. Similar to other derivative-based approaches [3, 7, 8],

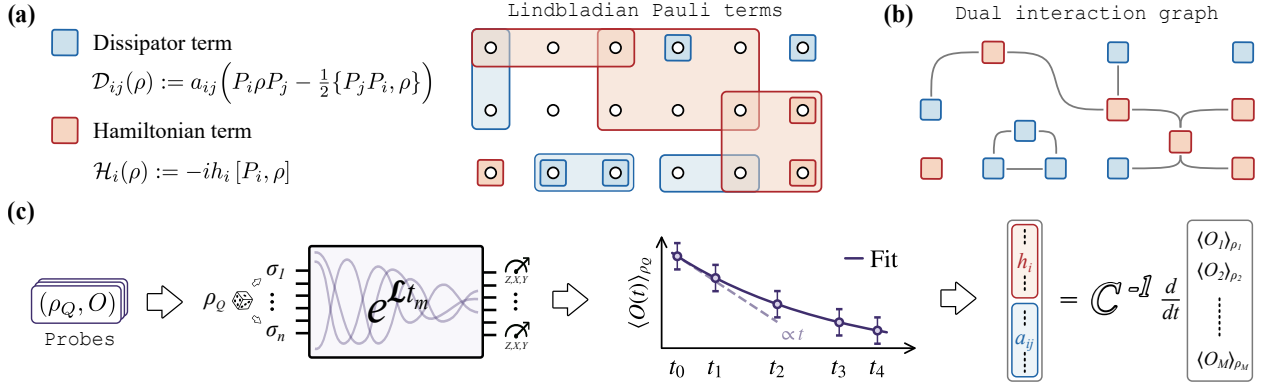


FIG. 2. **Coefficient learning from Pauli observables at short-times.** (a) The (unknown) Lindbladian is a sparse sum of Pauli terms: coherent Hamiltonian terms (red) and dissipative terms (blue), each acting nontrivially on some subset of qubits, represented by white circles. (b) In the dual picture, we define an interaction graph whose vertices are the nonzero Lindbladian Pauli terms and whose edges connect terms with overlapping qubit support. The maximum degree $\mathfrak{d}$ of the dual graph upper bounds how rapidly Heisenberg-evolved Pauli observables can spread. If $\mathfrak{d}$ is not known in advance, it can be upper bounded from the terms induced by the candidate structures $\hat{\mathcal{S}}_H, \hat{\mathcal{S}}_D$. (c) To learn the coefficients, we use the candidate supports $\hat{\mathcal{S}}_H$ and $\hat{\mathcal{S}}_D$ returned by structure learning to select a sufficient set of Pauli probes (ρ_Q, O) so that the resulting design matrix C is full rank. For each chosen probe, we sample $f(t) = \text{tr}\{\rho e^{t\mathcal{L}^\dagger}(O)\}$ at short Gauss-Chebyshev times $\{t_m\}$, fit a low-degree interpolant, and extract $\frac{d}{dt}f(t)|_{t=0}$. Stacking these derivative estimates yields a linear system $\mathbf{d} = C\mathbf{x}$ for the Lindbladian coefficients, which we solve classically.

we use the identity:

$$\left. \frac{d}{dt} \langle O(t) \rangle \right|_{t=0} = \text{tr}(\rho \mathcal{L}^\dagger(O)),$$

which is linear in the unknown coefficients $\{h_i\}_{P_i \in \hat{\mathcal{S}}_H}$ and $\{a_{ij}\}_{P_i, P_j \in \hat{\mathcal{S}}_D}$. Varying probes (ρ, Q) yields a square linear system $\mathbf{d} = C\mathbf{x}$, where $\mathbf{x}$ collects all the unknown coefficients, and $\mathbf{d}$ collects the estimated (via Chebyshev interpolation) observable derivatives. The numerical stability of this system is governed by a conditioning factor $\nu = \|C^{-1}\|_{\infty \rightarrow \infty}$.

We advance prior derivative-based coefficient-learning approaches in two directions. First, we introduce *Pauli patchwise tomography*, a classical probe-selection routine that leverages $\hat{\mathcal{S}}_H$ and $\hat{\mathcal{S}}_D$ to construct an invertible design matrix without brute-force enumeration of all Pauli probes. We take advantage of the observed locality k of the supersets $\hat{\mathcal{S}}_H$ and $\hat{\mathcal{S}}_D$ in the computations that follow. By restricting probes to qubit supports of candidate terms (patches), we reduce the classical preprocessing time to $\mathcal{O}(16^k \bar{M})$ (versus $\mathcal{O}(16^k n^k)$ for naive enumeration), where $\bar{M}$ is the number of unknown coefficients supported on $\hat{\mathcal{S}}_H$ and $\hat{\mathcal{S}}_D$. Importantly, for highly non-local $k = \Theta(n)$, our Lindbladian learning algorithm remains efficient in terms of quantum sample complexity. At the same time, bounded locality k could substantially accelerate classical pre-processing. Second, to control the time resolution and query complexity of the derivative-estimation step, we generalize the Hamiltonian dual interaction graph [7, 8] to the Lindbladian setting. Concretely, we associate a vertex to each Pauli-basis summand of $\mathcal{L}^\dagger$ and connect vertices whose supports overlap; the maximum degree $\mathfrak{d}$ then controls the smoothness of time traces and leads to improved coefficient-learning guarantees with evolution times $t_{\min} = \tilde{\Theta}(1/\mathfrak{d})$. Figure 2 summarizes the coefficient-learning stage.

(III) Optimality of short-time resolution. Our third contribution is a lower bound showing that the short-time regime is not merely convenient but information-theoretically necessary for ansatz-free structure identification. Specifically, we prove that if a protocol is restricted to a time resolution coarser than $\tilde{\Theta}(1/M)$ (even allowing arbitrary single-copy input states and measurements), then there exist $M = \text{poly}(n)$ -sparse Lindbladians for which identifying the structure requires exponentially many channel queries. Intuitively, at such coarse time resolution, the evolution can drive all inputs close to a steady state, and since steady states generally do not identify generators, structure learning becomes hard. Thus, the time resolution $\tilde{\Theta}(1/M)$ achieved by our algorithm is nearly optimal for ansatz-free learning.

Overall, our work establishes that complete generator-level characterization of sparse Lindbladian dynamics is possible without an ansatz, using only experimentally minimal primitives. This provides a principled route to diagnosing unknown coherent and dissipative mechanisms in noisy quantum devices and opens the door to deploying generator learning as a standard diagnostic tool in calibration and control workflows.

The full manuscript is available on arxiv [9].

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