

Hamiltonian learning via quantum Zeno effect

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(Dated: July 6, 2026)

EXTENDED ABSTRACT

A central challenge in quantum science is to understand and characterize the dynamics of closed quantum systems, which are entirely governed by their Hamiltonians. In realistic experimental settings, however, the effective Hamiltonian is often unknown and must be inferred from measurement data. This task is addressed by Hamiltonian learning (HL) [1], a fundamental problem in the broader landscape of learning quantum systems from experimental data. Closely related to quantum state and process tomography, Hamiltonian learning has become increasingly important not only for uncovering the fundamental structure of many-body quantum systems, but also for practical applications including device certification, error diagnosis, and quantum control optimization [2–5].

One particularly timely application of HL is the benchmarking and validation of quantum simulators, engineered quantum devices designed to mimic complex quantum dynamics and probe regimes beyond classical computation [6, 7]. As experimental platforms scale beyond one hundred qubits, validating that these devices faithfully implement their intended Hamiltonians becomes an increasingly urgent challenge [8]. This growing complexity motivates the development of Hamiltonian learning protocols that remain experimentally feasible even at large system sizes.

However, existing HL protocols typically face significant practical limitations and often lack experimental realization at comparable scales. Many approaches rely on demanding assumptions, such as the ability to prepare eigenstates or thermal (Gibbs) states of the unknown Hamiltonian [3, 4, 9–11]. Preparing such states is experimentally challenging on noisy intermediate-scale devices, limiting the applicability of these methods in practice. As a more experimentally accessible alternative, black-box unitary models treat the system as an unknown process accessible only through simple initial state preparation, black-box application of the Hamiltonian dynamics, and measurements [12]. While these approaches avoid complex state engineering, the learning task remains fundamentally challenging due to the exponential growth of the Hilbert space with system size. To mitigate this exponential complexity, one can exploit the intrinsic locality of many physically relevant systems. By reshaping the dynamics to isolate local interactions, the learning problem can be reduced to independent local reconstructions, potentially achieving optimal scaling. Nevertheless, such reshaping generally relies on enhanced quantum control, introducing additional operational overhead and experimental challenges.

In this work, we present a Hamiltonian learning protocol specifically tailored to geometrically local systems and designed to remain experimentally feasible at scale. The method enables scalable and parallel characterization of local Hamiltonian terms by exploiting the quantum Zeno effect (QZE), which refers to the confinement of a quantum system’s dynamics under frequent interventions [13]. While the QZE was originally discussed in the context of repeated projective or continuous measurements [14–16], it can also be realized through sequences of fast unitary operations [17, 18]. We adopt this unitary formulation, which avoids destructive measurements and is particularly well suited to quantum computing platforms. Importantly, in superconducting architectures the required Zeno kicks can be implemented using virtual Z gates [19], i.e., software-level frame updates that introduce essentially no additional time, noise, or calibration overhead. By applying frequent virtual Z gates to selected qubits, unwanted Hamiltonian couplings are suppressed and the dynamics is reshaped, effectively decoupling the system into non-interacting n -qubit patches. Each patch can then be independently characterized using quantum process tomography (QPT), turning the global Hamiltonian learning problem into a collection of local reconstructions of the Hamiltonian terms. Since non-overlapping patches evolve independently, they can be characterized in parallel [20–22], enabling efficient scaling with system size (Fig. 1(a)). The protocol requires only product-state preparation, short-time evolutions, and local Pauli measurements, and relies exclusively on virtual Z gates, which execute instantaneously and do not introduce additional decoherence.

Beyond its experimental simplicity, the protocol admits rigorous performance guarantees. By combining the Zeno-based reshaping error with the statistical error arising from QPT, we derive bounds on the overall reconstruction accuracy of the Hamiltonian coefficients. In particular, to achieve a target precision, the required number of channel uses scales logarithmically with the number of patches, while the number of unitary kicks required to implement

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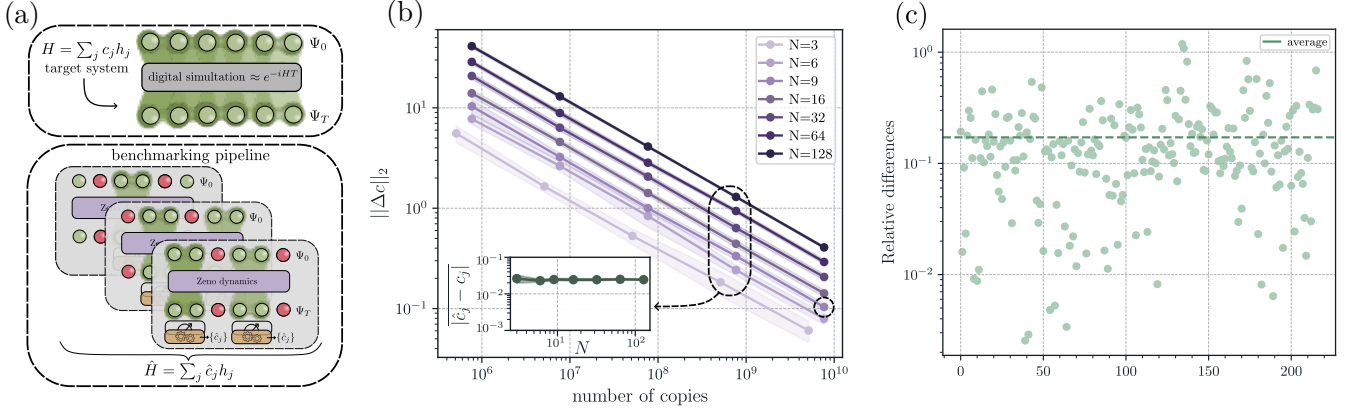


Figure 1: (a). Benchmarking digital quantum simulators via Hamiltonian learning. Top: a digital quantum simulator implements the target evolution. Bottom: our protocol uses Zeno-based reshaping to isolate local patches, enabling parallel quantum process tomography and accurate reconstruction of the simulated Hamiltonian. (b). Euclidean norm of the difference between reconstructed and true Hamiltonian coefficients as a function of the total number of copies used in the tomography, for system sizes up to $N = 128$ and fixed evolution time $T = 0.01$ and number of kicks $r = 10$. In the bottom right insert panel, we show the average absolute error for the coefficients at a fixed number of copies $\approx 10^9$. (c). Relative differences between real and reconstructed coefficients, the experiment was performed on the `ibm_brisbane` device.

the Zeno reshaping scales inversely with the desired Zeno accuracy. As a result, the protocol does not exhibit any exponential dependence on the system size, and the learning resources remain compatible with large-scale implementations. We support these analytical guarantees with numerical simulations on random one-dimensional, two-local Hamiltonians of increasing system size. By reconstructing systems of up to $N = 128$ qubits, we observe that the average absolute error on individual Hamiltonian coefficients remains essentially constant as the system grows. This behavior reflects the local nature of the protocol: each term is reconstructed independently from a fixed number of reshaping configurations, irrespective of the total system size (Figure 1 b.). These results confirm that the protocol maintains stable reconstruction performance in the large-system regime.

We experimentally validate the protocol on a superconducting quantum processor provided by IBM Quantum. We reconstruct a geometrically local Hamiltonian acting on a chain of 109 qubits, comprising single-qubit terms and nearest-neighbor two-qubit interactions. The implementation employs a fixed number of unitary Zeno kicks interleaved with the system dynamics and relies exclusively on product-state preparations and local Pauli measurements. The full experiment is completed within a few minutes of wall-clock time. The reconstructed Hamiltonian parameters exhibit an average relative error of approximately 10%, with absolute errors on individual coefficients of order 10^{-2} (Figure 1 c.). These results demonstrate that the protocol can be executed on current noisy quantum hardware and yields meaningful Hamiltonian estimates at system sizes beyond the reach of conventional characterization techniques.

Overall, our results establish a Hamiltonian learning protocol that combines theoretical guarantees with experimental feasibility on current quantum hardware. By leveraging Zeno-based reshaping to localize the dynamics and reduce the learning task to parallel local reconstructions, the protocol avoids the exponential overhead typical of black-box approaches while requiring only experimentally accessible operations. The combination of favorable scaling, numerical stability at increasing system sizes, and a large-scale hardware demonstration indicates that Hamiltonian learning can be performed in practice at system sizes where direct verification becomes nontrivial. We expect this approach to provide a practical tool for benchmarking and validating quantum simulators and processors, while also offering a scalable preprocessing framework that decomposes complex many-body dynamics into independent local reconstruction problems. Such a decomposition naturally complements learning-based approaches for quantum system characterization and dynamics, by reducing the complexity of the inference task and enabling parallel treatment of local subsystems.

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- [1] N. Wiebe, C. Granade, C. Ferrie, and D. Cory, Quantum hamiltonian learning using imperfect quantum resources, *Phys. Rev. A* **89**, 042314 (2014).
 - [2] C. Rouzé and D. S. França, Learning quantum many-body systems from a few copies, *Quantum* **8**, 1319 (2024).

- [3] E. Bairey, I. Arad, and N. H. Lindner, Learning a local hamiltonian from local measurements, *Physical Review Letters* **122**, 10.1103/physrevlett.122.020504 (2019).
- [4] J. Haah, R. Kothari, and E. Tang, Learning quantum hamiltonians from high-temperature gibbs states and real-time evolutions, *Nature Physics* **20**, 1027–1031 (2024).
- [5] W. Yu, J. Sun, Z. Han, and X. Yuan, Robust and efficient hamiltonian learning, *Quantum* **7**, 1045 (2023).
- [6] I. Georgescu, S. Ashhab, and F. Nori, Quantum simulation, *Reviews of Modern Physics* **86**, 153–185 (2014).
- [7] E. Altman, K. R. Brown, G. Carleo, L. D. Carr, E. Demler, C. Chin, B. DeMarco, S. E. Economou, M. A. Eriksson, K.-M. C. Fu, M. Greiner, K. R. Hazzard, R. G. Hulet, A. J. Kollár, B. L. Lev, M. D. Lukin, R. Ma, X. Mi, S. Misra, C. Monroe, K. Murch, Z. Nazario, K.-K. Ni, A. C. Potter, P. Roushan, M. Saffman, M. Schleier-Smith, I. Siddiqi, R. Simmonds, M. Singh, I. Spielman, K. Temme, D. S. Weiss, J. Vučković, V. Vuletić, J. Ye, and M. Zwierlein, Quantum simulators: Architectures and opportunities, *PRX Quantum* **2**, 017003 (2021).
- [8] J. Eisert, D. Hangleiter, N. Walk, I. Roth, D. Markham, R. Parekh, U. Chabaud, and E. Kashefi, Quantum certification and benchmarking, *Nature Reviews Physics* **2**, 382–390 (2020).
- [9] D. Burgarth, K. Maruyama, and F. Nori, Coupling strength estimation for spin chains despite restricted access, *Phys. Rev. A* **79**, 020305 (2009).
- [10] A. Anshu, S. Arunachalam, T. Kuwahara, and M. Soleimanifar, Sample-efficient learning of interacting quantum systems, *Nature Physics* **17**, 931–935 (2021).
- [11] X.-L. Qi and D. Ranard, Determining a local hamiltonian from a single eigenstate, *Quantum* **3**, 159 (2019).
- [12] A. Gu, L. Cincio, and P. J. Coles, Practical hamiltonian learning with unitary dynamics and gibbs states, *Nature Communications* **15**, 312 (2024).
- [13] P. Facchi and S. Pascazio, Quantum zeno subspaces, *Physical Review Letters* **89**, 080401 (2002).
- [14] K. Kakuyanagi, T. Baba, Y. Matsuzaki, H. Nakano, S. Saito, and K. Semba, Observation of quantum zeno effect in a superconducting flux qubit, *New Journal of Physics* **17**, 063035 (2015).
- [15] N. Kalb, J. Cramer, D. J. Twitchen, M. Markham, R. Hanson, and T. H. Taminiau, Experimental creation of quantum zeno subspaces by repeated multi-spin projections in diamond, *Nature Communications* **7**, 13111 (2016).
- [16] D. H. Slichter, C. Müller, R. Vijay, S. J. Weber, A. Blais, and I. Siddiqi, Quantum zeno effect in the strong measurement regime of circuit quantum electrodynamics, *New Journal of Physics* **18**, 053031 (2016).
- [17] P. Facchi, D. A. Lidar, and S. Pascazio, Unification of dynamical decoupling and the quantum zeno effect, *Physical Review A* **69**, 032314 (2004).
- [18] P. Facchi and S. Pascazio, Quantum zeno dynamics: mathematical and physical aspects, *Journal of Physics A: Mathematical and Theoretical* **41**, 493001 (2008).
- [19] D. C. McKay, C. J. Wood, S. Sheldon, J. M. Chow, and J. M. Gambetta, Efficient z gates for quantum computing, *Physical Review A* **96**, 022330 (2017).
- [20] J. Cotler and F. Wilczek, Quantum overlapping tomography, *Physical Review Letters* **124**, 100401 (2020).
- [21] B. G. M. Araújo, M. M. Taddei, D. Cavalcanti, and A. Acín, Local quantum overlapping tomography, *Physical Review A* **106**, 062441 (2022).
- [22] L. Pereira, J. J. García-Ripoll, and T. Ramos, Parallel tomography of quantum non-demolition measurements in multi-qubit devices, *npj Quantum Information* **9**, 22 (2023).