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Experimental Quantum Hamiltonian Learning using a silicon photonic chip and a nitrogen-vacancy electron spin in diamond

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The efficient characterization and validation of the underlying model of a quantum physical system is a central challenge in the development of quantum devices and for our understanding of foundational quantum physics. However, the impossibility to efficiently predict the behaviour of complex quantum models on classical machines makes this challenge to be intractable to classical approaches. Quantum Hamiltonian Learning (QHL) [1,2] combines the capabilities of quantum information processing and classical machine learning to allow the efficient characterisation of the model of quantum systems. In QHL the behaviour of a quantum Hamiltonian model is efficiently predicted by a quantum simulator, and the predictions are contrasted with the data obtained from the quantum system to infer the system Hamiltonian via Bayesian methods.

In our experimental implementation of QHL we use a quantum simulator in a silicon quantum photonic chip (Fig.1a), to learn the Hamiltonian of an electron spin in a diamond nitrogen-vacancy center (Fig.1b). The spin is optically addressed and read-out using a 532 nm continuous wave laser, while the spin manipulation is driven by microwave signals, as shown in Fig.1c. The dynamics under study are between the $m_s = 0$ and $m_s = -1$ states of the ground-state triplet (Fig.1d), which can be described using a Hamiltonian model $\widehat{H}(f) = f\hat{\sigma}_x/2$. In the silicon quantum photonics device a pair of entangled photons is generated on-chip by spontaneous four-wave mixing spiral sources. An integrated reconfigurable scheme allows to simulate the quantum dynamics of the spin system and the likelihoods required for the QHL protocol are calculated via projective measurements $\widehat{M}$.

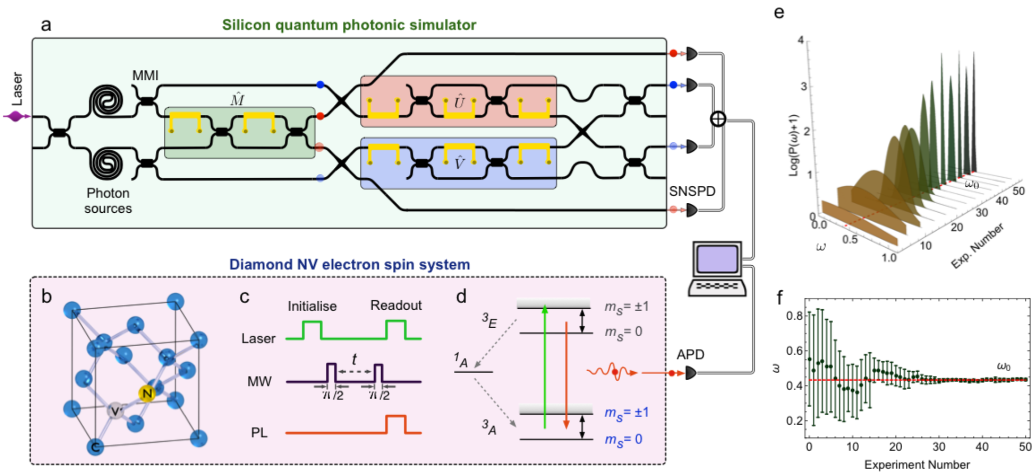

Fig. 1. The Silicon photonics quantum simulator in **a)** is used to learn the Hamiltonian dynamics of the diamond NV electron spin in **b)**. The two different systems are interfaced classically, allowing the implementation of the quantum Hamiltonian learning protocol using classical machine learning techniques. **c)** Initialization, manipulation and read-out of the electron spin system, and **d)** its energy-level diagram. **e)** and **f)** show the results of the QHL protocol. The distribution of the model parameter converges to the correct value ω_0 of the electron spin's Hamiltonian.

The two different quantum systems are interfaced through a classical processor that operates the inference process and drives the QHL protocol. The goal here is to learn the model parameter f, i.e. the Rabi frequency of the spin system. Fig.1e and Fig.1f show the successful convergence of the QHL algorithm, where the distribution over a normalized parameter $\omega = f/\Delta f$ converges to the correct value ω_0. The corresponding model parameter learned is $f = 6.93 \pm 0.09$ MHz, which is consistent with the Rabi frequency of the NV spin $f_0 = 6.90$ MHz obtained from a full fit, showing the successful implementation of QHL.

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