Reinforcement learning architecture for automated quantum-adiabatic-algorithm design

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❖ Abstract

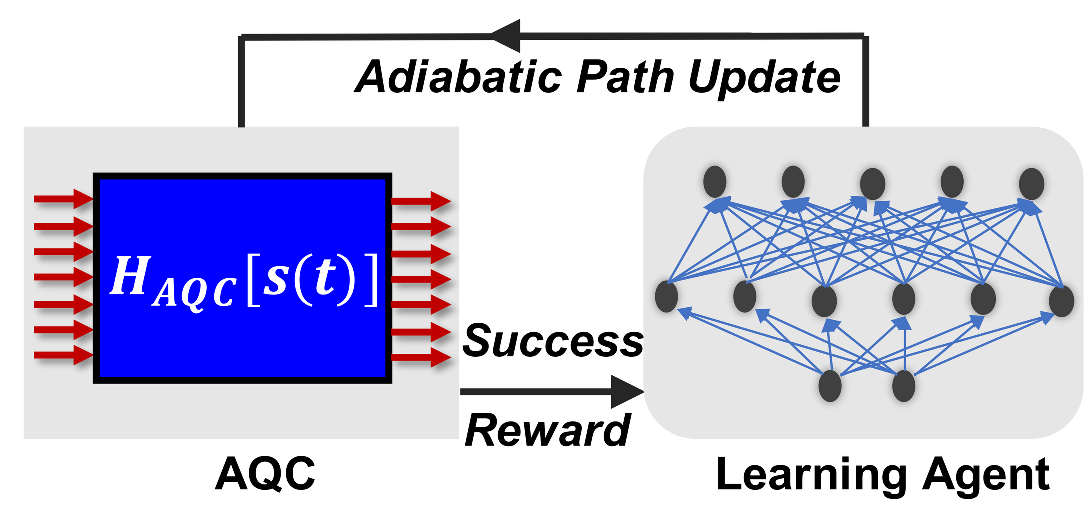
Quantum algorithm design lies in the hallmark of applications of quantum computation and simulation. Here we put forward a **deep reinforcement-learning** (RL) architecture for automated algorithm design in the framework of **quantum-adiabatic-algorithm**. Our approach is applicable to a class of problems with solution **hard-to-find but easy-to-verify.** We benchmark this approach in Grover-search and 3-SAT problems, and find that the adiabatic-algorithm obtained by our RL approach leads to significant improvement in the **success probability** and **computing speedups** to conventional algorithms.

We show that the RL approach is able to produce algorithms with **improved computation-complexity scaling automatically**, and that the algorithm by this approach has emergent **transferability**. Further considering the established complexity-equivalence of circuit and adiabatic quantum algorithms, we expect the RL-designed adiabatic algorithm to inspire novel circuit algorithms as well. Our approach is potentially applicable to different quantum hardwares from trapped-ions and optical-lattices to superconducting-qubit devices.

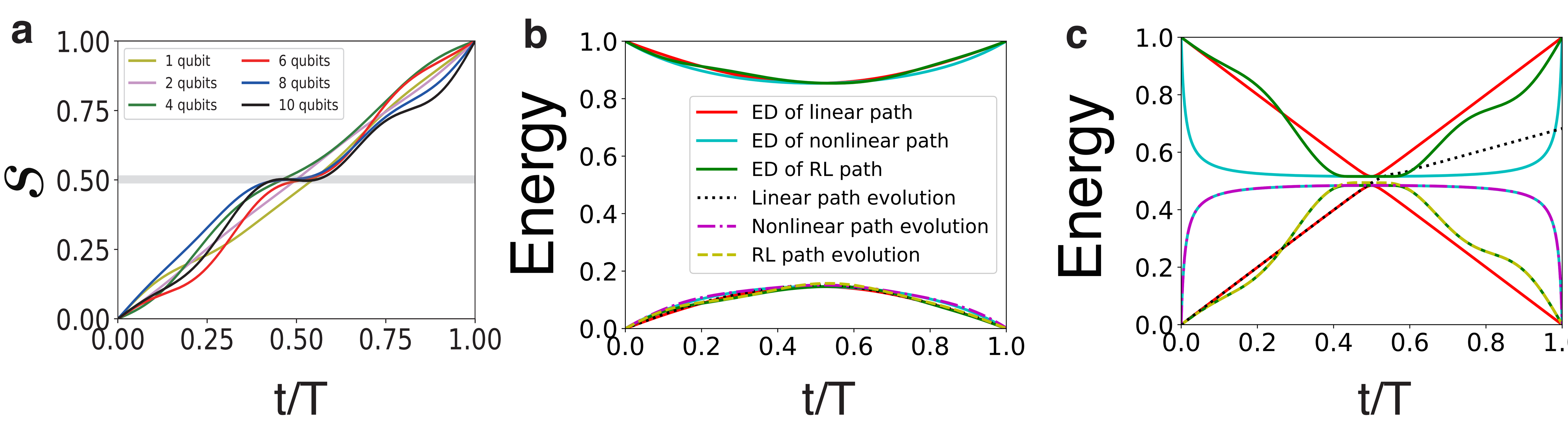
❖ Quantum adiabatic evolution

$$\hat{H} = s(t/T)\hat{H}_p + (1 - s(t/T))\hat{H}_b$$

❖ Basic framework

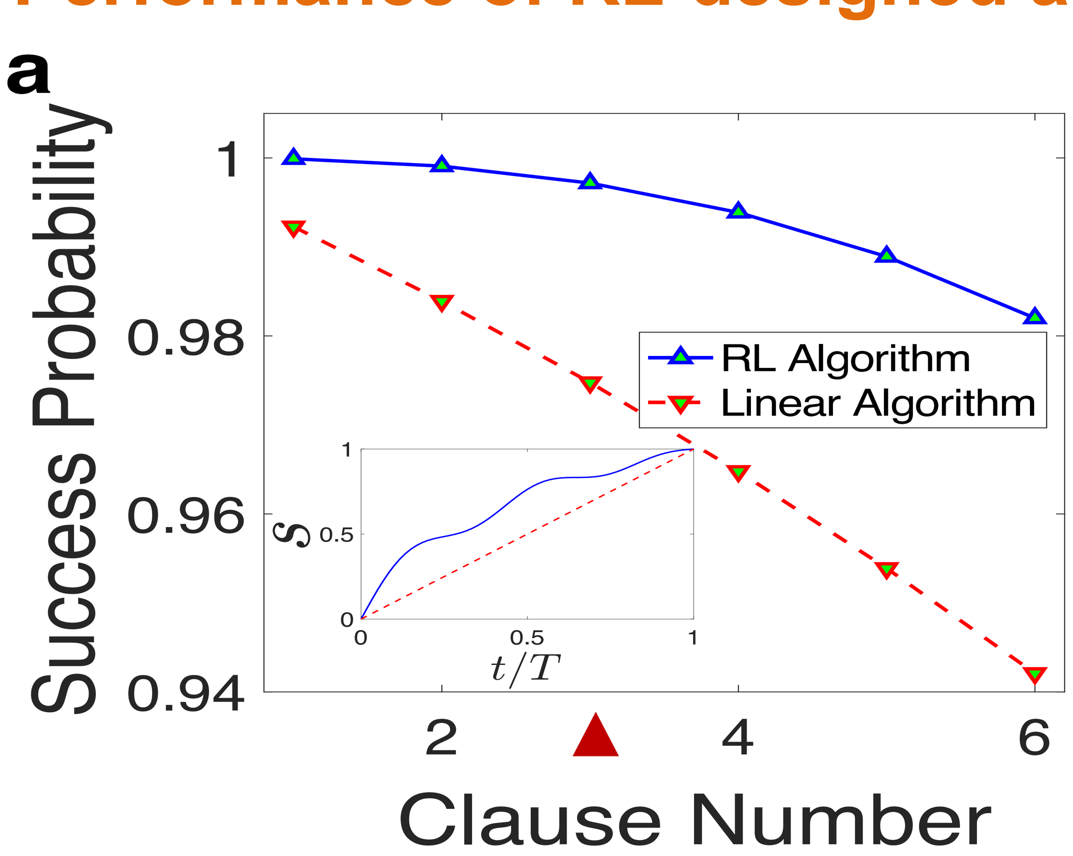


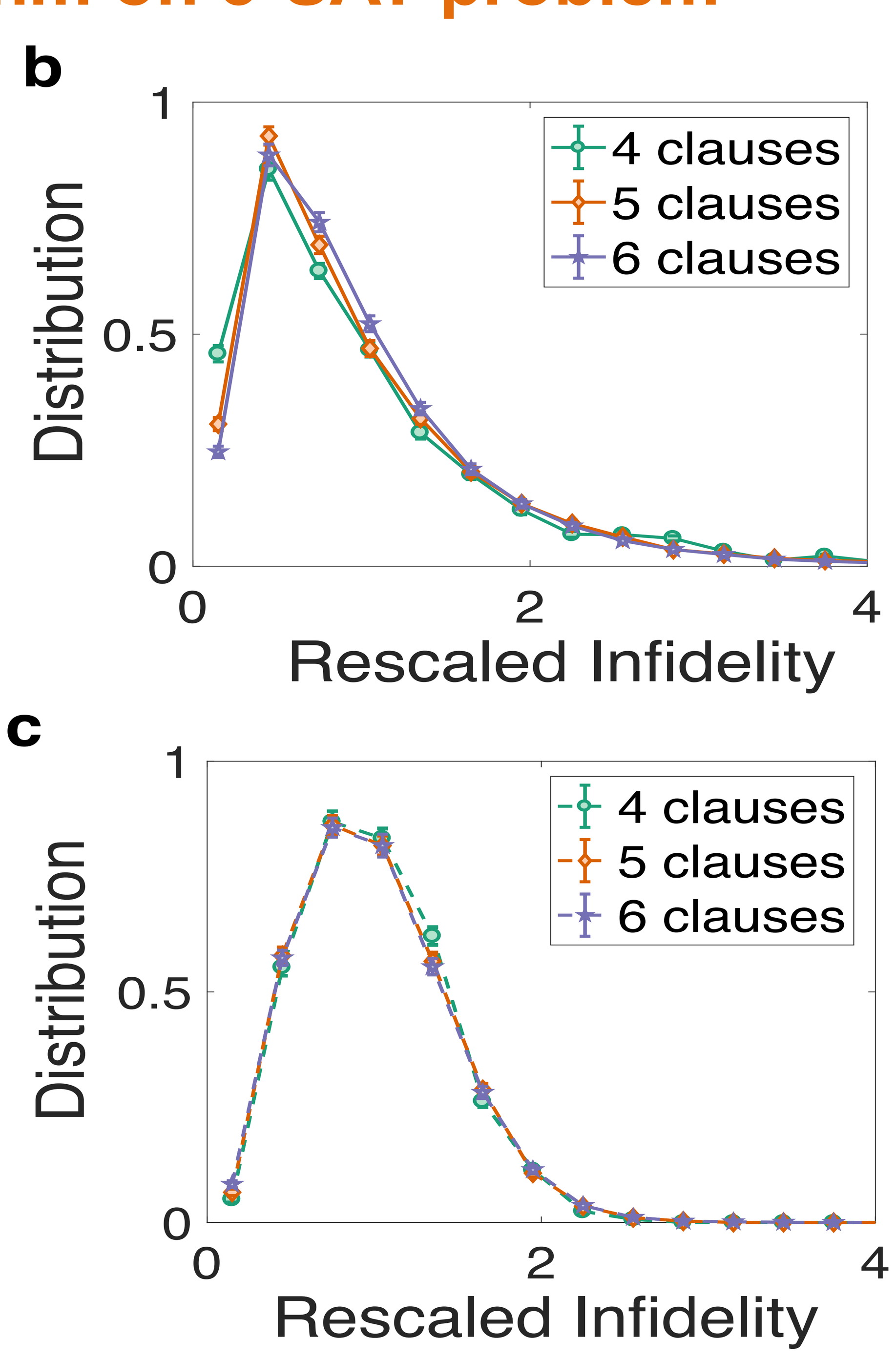
❖ Energy evolution from the RL-designed adiabatic path for Grover search problem



(a) shows the RL-designed path. (b) and (c) show the energy spectrum for the ground and first excited states with 1 and 10 qubits, respectively. The energy spectra of the instantaneous Hamiltonian are obtained by exact diagonalization (ED). The energy expectation values of the dynamical state following different Hamiltonian paths are shown by 'dashed' lines. It is evident from (c) that the RL-designed path is distinct from both of the linear and the nonlinear paths.

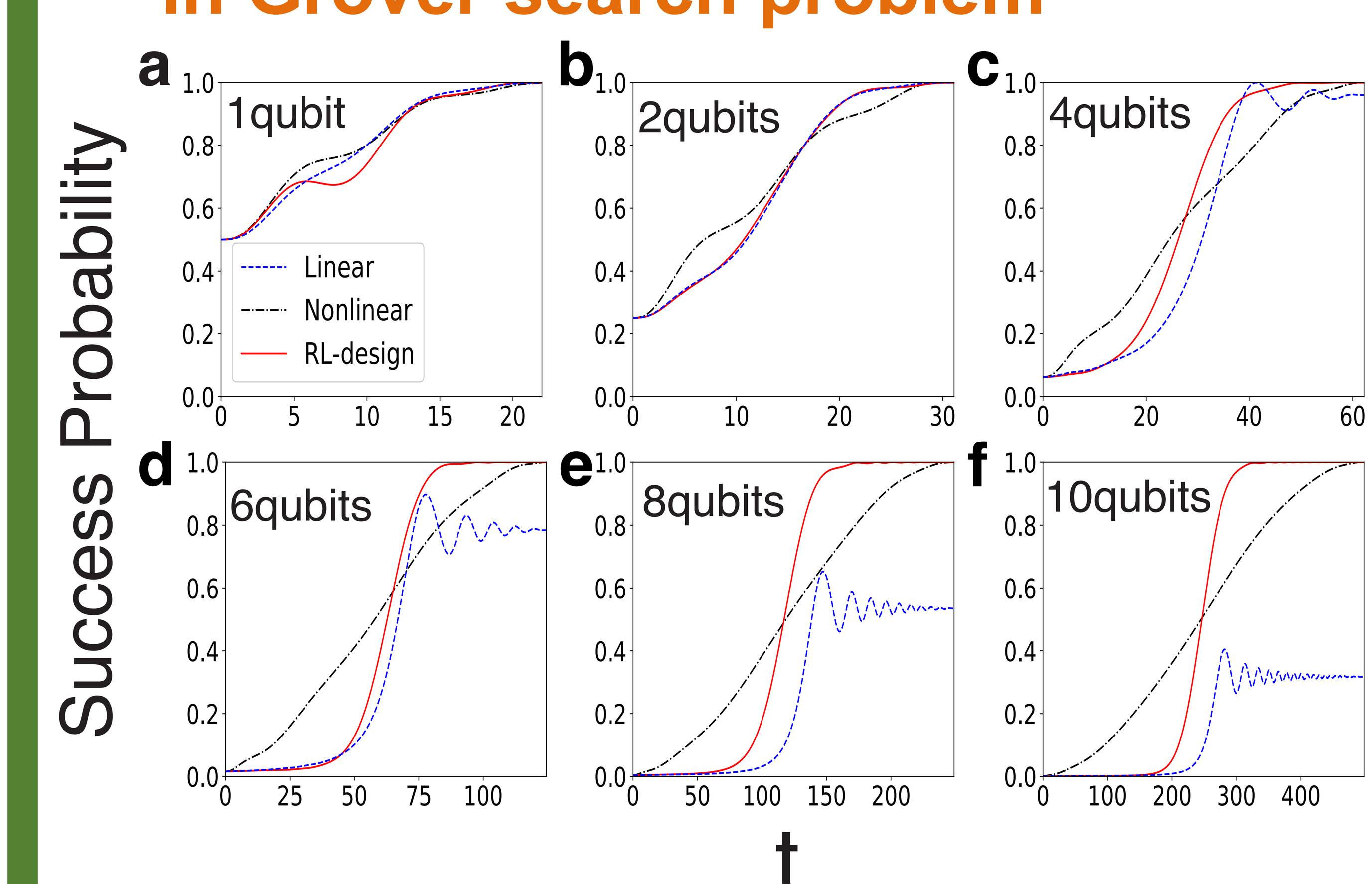
❖ Performance of RL-designed algorithm on 3-SAT problem





In (a), we show the comparison of the RL-designed and linear algorithms in the averaged success probability of solving random 3-SAT problems. (b) and (c) show the distribution of the infidelity for the RL-designed and linear algorithms, respectively. The infidelity distribution from the linear algorithm shown in (c) resembles a Wigner-Dyson type, whereas the distribution from the RL algorithm in (b) strongly deviates from that.

❖ Benchmark the different algorithms in Grover search problem



The success probability is obtained by taking the wave function overlap of the dynamical quantum state with search-target state. T follows the $\sqrt{N} = \sqrt{2^n}$ scaling where n is qubit number. The machinery adiabatic algorithm designed by RL shows significant improvement over the linear algorithm, and reveals the same computation-complexity scaling as the nonlinear algorithm.

❖ Summary :

In this work, we report a reinforcement-learning-based approach for automated quantum adiabatic algorithm design. Our devised approach is directly applicable to problems with solutions easy-to-verify such as searching, factorization, and NP-complete problems. Through numerically simulations, we show that the RL approach automatically finds an adiabatic algorithm for Grover search with quadratic speedup. In the application to the 3-SAT problems, we find surprising transferability of the RL-designed algorithm which suggests the algorithm trained on relatively-smaller size problems is applicable to larger sizes, which is both practically useful and theoretically inspiring in considering the complexity scaling. The performance of our approach can be further improved by introducing additional Hamiltonian terms, which would easily fit into the framework proposed here.

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