NEURAL NETWORK AGENT PLAYING SPIN HAMILTONIAN GAMES ON A QUANTUM COMPUTER

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We develop an autonomous agent effectively interacting with noisy quantum computer to solve magnetism problems. By using the reinforcement learning the agent is trained to find the best-possible approximation of a spin Hamiltonian ground state from self-conducted experiments on quantum devices.

Within a reinforcement learning approach an agent taking some actions interacts with environment, receives feedback, estimates rewards and corrects its actions to increase a future reward. Reinforcement learning techniques have been actively developed and implemented in such a new field of research as quantum computing, in particular for quantum-error-correction systems [1]. It is important to note that only a few of these algorithms were tested on real quantum devices.

Motivated by recent results of Google DeepMind team [2] obtained for classic Atari games in this work we develop and practically implement a reinforcement learning scheme for approximating the ground states of spin Hamiltonians on quantum computers. We follow a distinct logic and consider a spin Hamiltonian problem as a game with the following rules. Starting with a random quantum state a player performs several quantum actions and measurements to get the best score that means the lowest energy and, as a result, the best approximation of the spin Hamiltonian ground state. To play this game we develop a multi-neural-network agent that determines a sequence of quantum gates for a short quantum circuit. In contrast to previous approaches [3, 4], which faced problems originating from the decoherence and gate errors, we do not use a fixed sequence of quantum gates, and at each iteration the agent chooses a new gate for quantum circuit depending on the current state of a quantum device on the basis of the calculated correlation functions. During the training process the agent writes short quantum programs and runs them on a simulator with noise. Having trained the agent on the quantum simulator by using the developed reinforcement learning technique we demonstrate its performance on real IBM Quantum Experience devices.

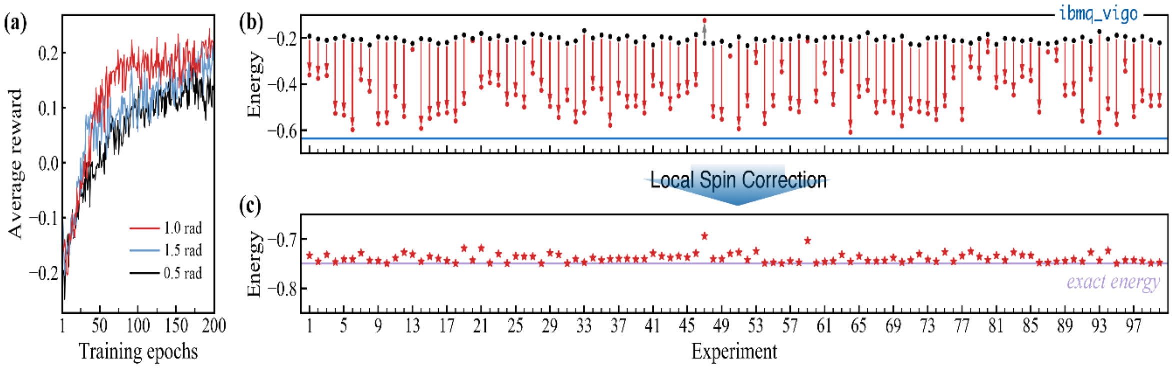

Fig. 1. (a) The average reward achieved per circuit on the quantum simulator with noise for different elementary rotation angles. (b) Performance of the trained agent demonstrated in experiments on the IBM Q Vigo device. (c) Ground state energies obtained on the real device after local moment correction.

Figure 1 (a) shows that the average reward during training process achieve saturation value within 100 epochs for reasonably chosen training parameters in case of antiferromagnetic Heisenberg dimer. Using trained agent, we performed a number of experiments on real quantum device (IBM Q Vigo) which are presented in Fig. 1 (b). Each red arrow denotes the lowering of energy with the circuits built by the agent in a particular experiment. Blue line indicates the average energy obtained with known singlet state quantum circuit on the real device showing the best possible ground state energy approximation on this device. To compensate the decoherence we use local spin correction procedure derived from a general sum rule for spin-spin correlation functions of a quantum system with even number of antiferromagnetically-coupled spins in the ground state. The resulting ground state energies for each experiment are shown in Fig. 1 (c) which are close to exact solution of the problem.

We also made qualitative comparison of the developed method with quantum variational approach which is available in full text of the research [5].

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