Efficient protocol for solving combinatorial graph problems on neutral-atom quantum processors

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1 Introduction

Neutral atom quantum processors are well suited to solving combinatorial graph problems. In fact, the Ising Hamiltonian describing the dynamics of the qubits is closely related to the cost function to be minimized. Solving the problems is then equivalent to finding the ground state of the system, which can be achieved by adiabatic annealing, as it has been shown in the case of the Maximum Independent Set (MIS) problem [1]. Although most QAOA applications focus on gate-based models of quantum computing, a promising avenue for noisy devices is represented by analog variational algorithms. The analog mode of operation involves the evolution of a quantum system under a continuously controllable resource Hamiltonian rather than the discrete application of a fixed set of quantum gates.

Whereas the successful implementation of a gate-based algorithm is limited by the absence of error correction on current devices, an analog algorithm is intrinsically more resilient to noise [1]. In this framework, the role of Rydberg atom arrays is recognized as a prominent example of how the ground state of a quantum Hamiltonian directly maps to the solution of a hard combinatorial graph problem, MIS on unit-disk graphs for instance.

On neutral atom platforms, preparing specific quantum states is usually achieved by pulse shaping, *i.e.*, by optimizing the time-dependence of the Hamiltonian related to the system. This process can be extremely costly, as it requires sampling the final state in the quantum processor many times. Hence, determining a *good* pulse is one of the most important bottlenecks of the analog approach. In this work, we propose a novel protocol for solving hard combinatorial graph problems that combines variational analog quantum computing and machine learning. Our numerical simulations show that the proposed protocol can reduce dramatically the number of iterations to be run on the quantum device. Finally, we assess the quality of the our approach by estimating the related Q-score, a recently proposed metric aimed at benchmarking QPUs.

2 Methodotogy

In this work, we focus on the Maximum Cut (MaxCut) and Maximum Independent Set (MIS) problems. While the MaxCut problem is equivalent to minimizing the Hamiltonian of a spin glass, the solutions of the MIS problem on unit-disk graphs can be encoded as the ground state of the Hamiltonian describing neutral-atoms devices [1].

2.1 Pulse prediction

The way combinatorial graph problems are usually solved with quantum hardware involves the optimal tuning of a set of parameters. This is usually done via an optimization loop that is applied to each instance of the problem, which is time and resource-consuming. To overcome both time and resource limitations, we propose a new supervised machine learning-based approach that automates the parameter choices and creates pulse sequences for analog quantum processes. Our model is based on the Chained Multi-Target Regression Algorithm (CMTRA) [2], which is generally used to predict multiple target values that are dependent upon the input and upon each other.

By predicting essential pulse parameters, one can considerably scale up quantum algorithms and, hence, solve bigger instances of complex combinatorial problems without dedicated optimization loops. The main objective of our supervised machine learning-based approach is to automatically provide : i) the Rabi frequency and detuning values on different instants of the pulse, and ii) the total duration of the pulse. Hence, the out-coming pulse is specifically tailored to evolve the system to states that represent (near-)optimal solutions for a given combinatorial graph problem instance.

2.2 Q-score metric

The Q-score metric [3] was developed to benchmark Quantum Processing Units at a time when commercially viable NISQ applications are becoming a reality. It is application-centric, hardware-agnostic, and can be applied equally effectively on current machines as well as future large-scale devices. For these reasons, the Q-score represents to date one of the best attempts at establishing a practical standardized benchmark that can be monitored over time to assess the evolution of quantum computers in solving real problems. Essentially, the Q-score is the largest number of qubits for which a solution to the problem is at least 20% better than the average random solution.

3 Results and concluding remarks

In our results, the score obtained stayed above the 20%, even in the presence of noise, up to the largest graphs we were able to simulate with noise in a reasonable amount of time. In order to determine the Q-score of the method and platform we need to extrapolate the results to larger problem sizes. To this end, we fit an exponential decay on the tail of the size dependence of the score $\beta(n) = \beta_0 e^{-n/n_0}$. The Q-score is then given by $Q_{score} = n_0 \log(5\beta_0)$. The results are summarized in 1. For both problems, the Q-score is of the order of 80 (except for MIS of non-UD graphs on noisy devices), to be compared with the Q-score determined in [3] for QAOA on state-of-the-art gate-based QC platforms. In particular, the presence of noise does not seem to lower significantly the score. Indeed, this specific behavior of analog quantum computing is very different from what was observed in the digital quantum circuits [3], where the score degrades faster for larger circuit depths. The comparison between the two approaches is not easy, as there is no equivalent to the circuit depth here. However, this example highlights the resilience to noises of the analog approach. For an in-deph overview of our work, one may refer to [4].

		Noiseless	Noisy
MIS	UD graphs	74 ± 5	86 ± 7
	Non-UD graphs	80 ± 10	63 ± 4
MaxCut	UD graphs	79 ± 11	75 ± 7
	Non-UD graphs	80 ± 6	91 ± 16

TAB. 1 – Estimated Q-scores for MIS and MaxCut problems on Unit-Disk and non-UD graphs and in a noisy and noiseless settings.

Références

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