By harnessing the power of the Google Sycamore processor (pictured here), Huang *et al*. showcase the exponential advantages offered by quantum computers for analyzing data from quantum experiments.

mere classical information. The quantum data can be used by the quantum computer to predict future results while requiring far fewer experiments.

One cannot input quantum data into a classical computer. Intuitively, one may think that this would give the quantum device a straightforward advantage. But the actual scenario is more nuanced. For a classical setup, the quantum state of an experiment can be measured and used as input, with each measurement freely chosen by the classical learning algorithm. Because the classical computer can arbitrarily choose when to measure each of the experiments, then at least in principle, all the information encoded in quantum states can be accessible. For a quantum setup, the quantum computer provides a minimal but key additional capacity: a small quantum memory that enables joint measurements on two copies of quantum data.

So in both cases, all the quantum data are converted to classical information before calculation, but in slightly different manners. Joint measurements—used in the quantum-enhanced scenario—unravel correlated properties of two separate quantum systems. This fundamentally exploits quantum entanglement (when the quantum states of two or more objects are intertwined with each other) and cannot be substituted by pairs of individual measurements. Since the early days of quantum information theory, it has been known that joint measurements can help distinguish quantum states, even when the states are uncorrelated (*3*). But until recently, it was not clear just how large an advantage this exploit can give quantum computers over their classical counterparts.

Building from the research line on so-called shadow tomography (*4*–*6*), Huang *et al.* argued that joint measurements lead to substantial advantages for learning about quantum systems. Namely, the quantum-enhanced strategy is exponentially more economical in terms of the number of quantum experiments needed for predicting the outcomes of just two measurements (*6*). The authors demonstrated the advantages of a quantum learning experiment using the Google Sycamore processor. The natural scenario of quantum data learning involves a "transducer" that transports the quantum state of results from an experiment into the quantum computer. Their experiment was simulated in the same quantum processor that analyzes the data, in a lab-on-a-chip setting. Once the quantum state is prepared, it is analyzed with classical and quantum-enhanced methods.

For the optimal predictions, the exact joint measurements may be known, at least in idealized settings. However, in the real experiment, the state preparation is imperfect, as is the measurement performed. To counteract this, the quantum processing is supplemented with classical machine learning to extract the strongest signals in the presence of experimental errors. This classical-quantum hybrid approach demonstrates advantages in our capacity to learn various fundamental properties of quantum systems—for example, predicting whether an unknown quantum process satisfies time-reversal symmetry. Their tests show that quantum computers can maintain their advantages in solving certain problems, even when errors specific to quantum computers are taken into account.

The work of Huang *et al.* intertwines the ability to characterize quantum systems (*4*–*6*) with machine learning, with implications for near-term quantum computers and perhaps even quantum sensing. The introduced generalization of classical machine learning to allow quantum data as inputs allows for certain benefits; namely, difficult proofs of advantages of quantum computers become easier. However, because of the hardware required to transfer quantum data in its unperturbed state from an experiment into the quantum computer, this method may be difficult to implement in certain settings, such as the high-energy physics experiments at the Large Hadron Collider. In smaller-scale experiments, however, transduction may be reasonable—for example, in quantum-optical experiments with nitrogen-vacancy centers in diamonds (*7*), which are often designed with transporting quantum information in mind. In a related vein, this work also opens a frontier for quantum sensing that involves quantum states and may lead to better advantages (*8*). Huang *et al.* proved in detail that for the data-driven prediction of properties of quantum experiments, no classical computer will ever pose a challenge to quantum ones—and that quantum computers may soon help expand human knowledge into new echelons. ■

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QUANTUM COMPUTATION

Solving a puzzle with atomic qubits

A quantum computer makes light work of the maximum independent set problem

By **Monika Schleier-Smith**

Imagine that you are asked to color a map of the world. Starting with your favorite color, you endeavor to fill in as many countries as possible without giving any neighboring countries the same color. This puzzle, despite its straightforward premise, is notorious for its computational complexity. On page 1209 of this issue, Ebadi *et al.* (*1*) report a quantum algorithm for solving the puzzle—known as the maximum independent set (MIS) problem—using individual atoms trapped in optical tweezers to represent the countries on the map. The demonstration is an important milestone in the broad effort to understand which computational problems stand to benefit from quantum computers.

To date, only a few quantum algorithms have been proven to offer clear advantages over classical computers. Moreover, even in cases where quantum computers theoretically provide a benefit—such as for factoring large numbers—practical applications will require major advances in quantum hardware beyond the current state of the art. By contrast, the coloring puzzle presented by Ebadi *et al.* belongs to a large class of optimization problems (*2*) that are potentially easier to solve using near-term quantum devices (*3*) but for which the attainable quantum speedup remains largely an open question (*4*–*6*). Such optimization problems, with technological relevance in areas such as supply chain logistics, can generically be framed as minimizing what is known as a cost function. The solution can be calculated by tasking the quantum computer to minimize the energy of a system of interacting particles or qubits, where the specific problem is encoded in the structure of the interactions.

To generate the structure of interactions required to represent MIS problems, Ebadi

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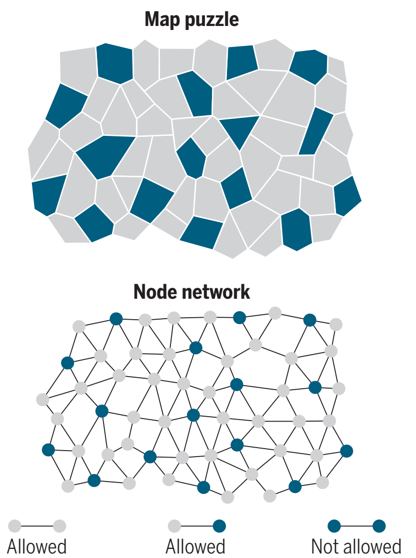
et al. used qubits encoded in the internal states of optically trapped atoms. Each atom can either be in the electronic ground state or a highly excited state known as a Rydberg state, where the electron cloud is thousands of times larger than in the ground state. An atom can be excited to the Rydberg state by a laser. However, any attempt to excite multiple neighboring atoms is constrained by strong interactions between atoms in the Rydberg state. Specifically, no more than a single atom can be excited within a minimum distance known as the blockade radius (*7–9*). Thus, atoms that are closer to one another than the blockade radius are equivalent to countries that share a border, where only one but not both can be colored blue, or in this case, be excited to the Rydberg state.

The method was put to test using a quantum processor with up to 289 atomic qubits, with each qubit trapped at the focus of a laser beam. By controlling the positions of the atoms, Ebadi *et al*. programmed specific instances of the MIS problem, each of which can be visualized as a graph with an atom at each node and with bonds between blockaded pairs (see the figure). They sought to solve the problem using an approach known as adiabatic quantum computation (*4, 10*). Here, the system parameters are ramped from an initial state in which the minimum-energy configuration is simple and known to a final state where the minimum-energy configuration provides a solution for the MIS problem. In the laser-driven atomic system, depending on whether the photon energy is lower or higher than the energy of a Rydberg excitation, the minimum-energy configuration can either have all atoms in the ground state or have as many atoms in the Rydberg state as possible without violating the blockade constraint. Thus, by ramping the frequency and intensity of the lasers, the atoms are driven from their initial ground states into a configuration of Rydberg excitations that, ideally, forms an MIS.

The key to this method is the maintenance of adiabaticity within the system—to ensure that the quantum system remains in its lowest-energy state throughout the ramping process. As an analogy, think of a waiter delivering an ice cream float to a diner. If the waiter moves too quickly, the drink may spill out, yet if he moves too slowly, the ice cream will melt—both of which are undesirable from the perspective of the diner. Similarly, in the quantum experiment, the system parameters must increase slowly enough for the atoms to settle into the MIS and yet fast enough for the quantum system to maintain its coherence, which is ultimately limited by the lifetime of the Rydberg states.

Coloring a map with a quantum computer

How many blue regions can this map have without any of them sharing a border? Instead of examining all the possibilities classically, Ebadi *et al*. solved the puzzle by using a quantum computer, composed of individual atoms that can only be excited (shown as ●) if all neighboring atoms are in their ground states (●). The map puzzle is encoded as a network of nodes, which represent the regions, and connections, which represent the shared borders.



A crucial question is whether this quantum algorithm provides a speedup over classical approaches. State-of-the-art classical algorithms employ a strategy known as simulated annealing, which mimics a physical process of preparing the interacting system at a high temperature and gradually reducing the temperature to reach the lowest-energy state. In practice, neither the quantum nor the classical algorithm always succeeds in finding the optimal solution. Thus, a figure of merit for the performance of the algorithm is the average number of times (*t*) that the algorithm would need to be run to succeed in finding the MIS. For the classical approach, this number of iterations t_{SA} is proportional to the ratio of the number of near-perfect solutions to the number of perfect solutions, where a near-perfect solution is defined as having one fewer "country" in its set than a perfect solution.

By contrast, the performance of the quantum algorithm not only depended on how many near-perfect solutions there are for every perfect one, it also depended on the gap in energy between the lowest-energy state and the first excited state. The smaller this gap, the slower a ramp one theoretically expects to require for the system to remain in its lowest-energy state to reach the perfect solutions. In cases where a sufficiently slow ramp could be performed within the time scale of the experiment, the quantum algorithm provided a speedup compared with the classical one. Specifically, the number of tries required by the quantum algorithm to solve the MIS problem scaled as the three-fifths power of the number of tries t_{SA} required classically, meaning that if the MIS problem is made more difficult such that the time required to solve it classically increases, for example, by a factor of 32, then the time required by the quantum computer will only increase by a factor of 8.

Although the experiment by Ebadi *et al*. is not the first to explore quantum optimization algorithms (*11–13*), it stands out for operating both with a large number of qubits and with sufficiently coherent interactions for quantum information to spread across the entire system within the time scale of the experiment (*14*). This combination appears to be crucial for the observed quantum speedup.

An important question for future work is whether the improved scaling of the quantum algorithm persists as the difficulty of the problems is increased, for example, by increasing the number of qubits. A potential challenge is that the gap in energy separating perfect from near-perfect solutions is expected to shrink as the number of qubits grows (*3, 11*), placing ever more stringent demands on how slowly the system parameters must be swept, and hence also on the coherence time of the experiment. One hope is to adopt the approach of an experienced waiter who moves so quickly that the drink begins to slosh, but ultimately executes just the right motions to bring it back to rest (*15*). Finding the right motions in a complex quantum system is bound to be a challenge, offering fertile ground for future research. ■

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10.1126/science.abq3754

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Science

Solving a puzzle with atomic qubits

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Science, 376 (6598), • DOI: 10.1126/science.abq3754

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