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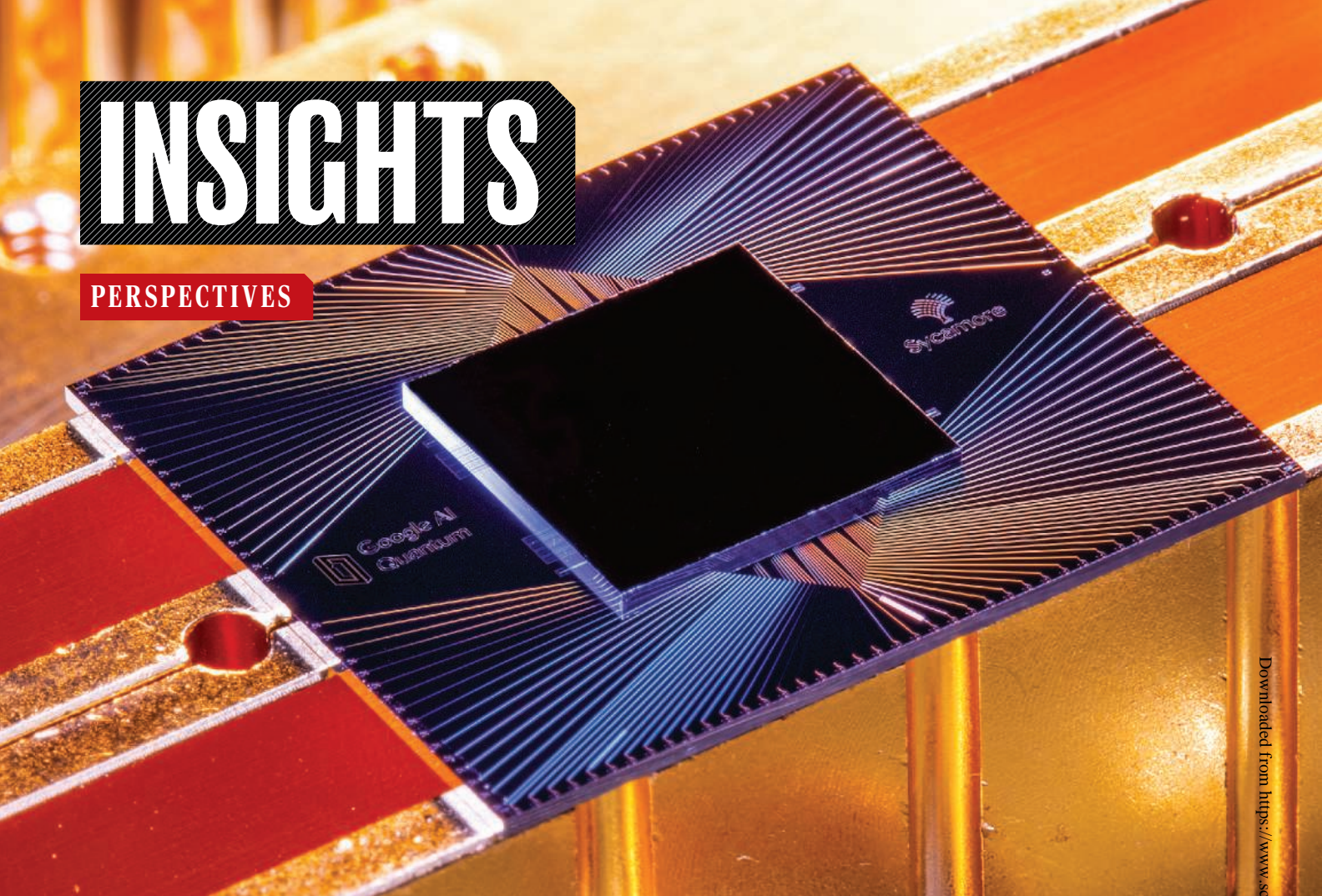
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# INSIGHTS

## PERSPECTIVES



### QUANTUM COMPUTERS

# Quantum learning unravels quantum system

A quantum computer has a decisive advantage in analyzing quantum experiment results

By **Vedran Dunjko**

In the early 1980s, American physicist Richard Feynman proposed that machines can exploit quantum phenomena to perform otherwise intractable computations. The kind of computation he envisioned was broadly about simulating the properties of a quantum system given its classical description. In the decades that followed, researchers have identified numerous other problems that in theory can only be solved within a reasonable time frame by using such a quantum computer. However, a quantum computer that can exercise this advantage over a classical computer does not exist yet. A recent hope is that near-term

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quantum computers may be used as a new type of machine learning device that offers an edge in analyzing data from quantum experiments. On page 1182 of this issue, Huang *et al.* (1) present an experimental realization of a quantum learning algorithm that has a provable advantage over its conventional counterpart while being within the reach of today's quantum computers.

The signature capacity of a quantum computer is the ability to predict the behavior of a many-particle quantum system when given its initial condition. With the development of machine learning methods, even more complex questions can be asked. Machine learning can enable such prediction even without full knowledge of the system, but with merely having access to previous experimental data. The task can be thought of as a two-stage process. The computer is fed a dataset that stems from some previ-

ous experiments over a quantum system. Then, the classical or quantum computer will have to predict the future of the system under slightly different settings. Intuitively, such data analysis may inherit the so-called quantum-classical performance gap, as described by Feynman: that the computation of the future state of the system, given its full description, is intractable for classical but feasible for quantum computers.

However, unexpectedly, the inclusion of training data could close this gap. Classical machine learning can sometimes predict properties of complex quantum systems (2), so it is unclear whether quantum computers hold an edge in this setup. Huang *et al.* propose an approach that will give quantum computers a decisive edge: by leveraging the quantum computer's ability to process "quantum data," raw quantum states that result from a quantum experiment and not

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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