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News & views

Quantum computing

Physics–AI collaboration quashes quantum errors

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A neural network has learnt to correct the errors that arise during quantum computation, outperforming algorithms that were designed by humans. The strategy sets out a promising path towards practical quantum computers.

Quantum computing is often touted as having the potential to solve problems that are beyond the capabilities of classical computers – from simulating molecules for drug development to optimizing complex logistics. Yet, a major obstacle stands in the way: quantum processors are prone to errors caused by disturbances from their environment and other sources. Overcoming this challenge is crucial to building a practical quantum computer. Writing in *Nature*, Bausch *et al.*[1] introduce AlphaQubit, an approach that uses artificial intelligence (AI) to make a huge leap in correcting these quantum errors, pushing researchers closer to achieving scalable quantum computing.

Quantum processors use quantum bits, or qubits, which are the basic units of quantum information. These processors can perform complex calculations by leveraging quantum properties, allowing the devices to process information in ways that classical computers cannot. However, the same features that make qubits powerful also make them fragile. Qubits are highly sensitive, meaning they are vulnerable to even the slightest disturbances, such as temperature changes, electromagnetic interference, or simply interactions with other qubits. These disturbances can cause qubits to lose their quantum state, leading to errors that accumulate and compromise computations.

To address this issue, researchers have developed strategies[2] that use redundancy to correct quantum errors. The idea is that information is encoded in a 'logical' qubit, which comprises many more physical qubits than are required to perform a computation. This redundancy allows some physical qubits (known as ancilla qubits) to detect and correct errors while other qubits are processing information. This enables quantum computers to perform longer and more reliable computations than they could otherwise. One of the most promising techniques in quantum error correction is known as the surface code[3], which organizes qubits into a 2D grid and uses frequent measurements to identify and correct errors. The surface code is popular because of its high tolerance for errors and its compatibility with existing quantum hardware.

A key challenge in implementing quantum error correction is how to decode the errors: information must be extracted from the qubits detecting the errors, and translated into corrective actions. This decoding process is crucial for determining how to fix errors without disturbing the remaining quantum information. Conventionally, human-designed algorithms have been used for decoding, including one known as minimum-weight perfect matching[4,5] (MWPM). This algorithm is effective for certain types of error but, as the number of qubits increases and noise becomes more complex, such methods often struggle. Real-world quantum errors can include cross-talk (unwanted interactions between qubits that are physically close to each other) and leakage (in which a qubit takes on states other than those required for a specific computation).

AlphaQubit is a quantum error decoder that uses machine learning to tackle quantum error correction in a way that differs fundamentally from human-led approaches. Instead of relying on predefined models of how errors occur, AlphaQubit uses data to learn directly from the quantum system, adapting to the complex and unpredictable noise found in real-world environments. By using machine learning, AlphaQubit can identify patterns and correlations in errors that conventional methods might overlook, making it a more versatile and powerful solution than existing approaches.

AlphaQubit is based on a transformer neural network architecture, a type of machine-learning model that has been used successfully in a range of applications, from natural language processing to image recognition. Bausch *et al.* trained AlphaQubit in two stages: first on synthetic data, which allowed the model to learn the basic structure of quantum errors, and then on real experimental data from Google's Sycamore quantum processor. The second stage enabled the model to adjust to the specific noise encountered in real hardware, improving its overall accuracy.

The authors' key innovation lies in their use of soft readout, which is a way of extracting

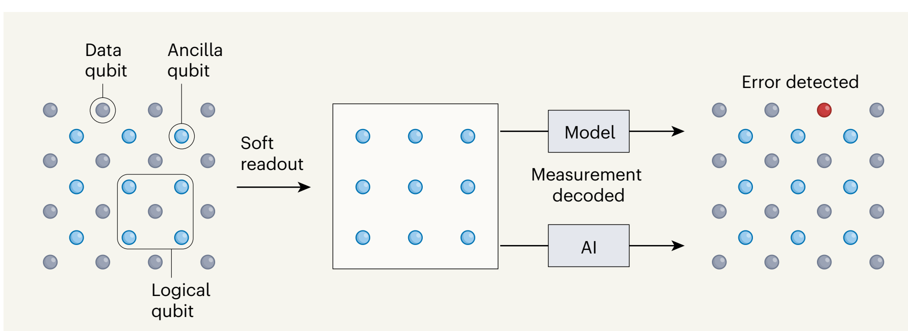

Figure 1 | Detecting errors in a quantum computer. Quantum bits (qubits) are the basic units of quantum information and are highly sensitive to disturbances that can cause them to lose their quantum state, compromising the effectiveness of quantum computers. To mitigate this problem, information can be encoded in a cluster of qubits called a logical qubit, which comprises qubits that store data, as well as 'ancilla' qubits that can be measured (through a process known as soft readout) to detect and correct errors. However, decoding these measurements is challenging, and is usually undertaken using models. Bausch *et al.*[1] showed that an AI-driven decoding strategy can facilitate quantum error correction in a way that is more accurate and adaptable than that offered by human-designed models.

analogue information from a quantum system without disturbing it too much. Whereas in conventional decoders, a measurement is either a 0 or a 1, soft readouts offer more nuanced information about the state of the qubit, which allows AlphaQubit to make more informed decisions about whether an error has occurred and how to correct it (Fig. 1).

When tested on both real-world and simulated data, AlphaQubit demonstrated a clear advantage over existing methods. The model was evaluated using the Sycamore processor, and decoded errors in surface codes with distances (the minimum number of simultaneously occurring errors that are needed to make a logical qubit fail) of three and five. This makes it more accurate than existing decoders, such as MWPM. The larger the distance, the more complex the error correction, because there are more physical qubits involved in each logical qubit — and this provides better protection against errors.

Bausch *et al.* also showed that AlphaQubit could be effective in larger quantum systems, maintaining accuracy for code distances of up to 11 — scalability that is crucial for future quantum computers. Even when faced with a lot of noise, including crosstalk and leakage, AlphaQubit outperformed the existing state-of-the-art methods. This result suggests that machine learning can handle the complexities of real-world quantum noise better than conventional human-designed algorithms can.

AlphaQubit's success is a milestone on the path towards fault-tolerant quantum computing. Fault tolerance means that a quantum computer can continue to operate correctly even when some of its components fail or produce errors. By using machine learning to enhance error correction, AlphaQubit paves the way for quantum processors that can correct their own errors efficiently, making large-scale quantum computations more feasible. AlphaQubit's ability to adapt to new data and improve over time is particularly promising for the evolving landscape of quantum hardware.

However, despite these impressive results, logical error rates need to be reduced still further. Ideally, to run complex quantum algorithms comprising thousands or millions of operations — a requirement for practical quantum computing — there should be no more than one error for every one trillion logical operations. AlphaQubit managed to limit error to around one in every 35 logical operations, so further improvements will be necessary to meet the demands of real-time quantum computations.

One of AlphaQubit's strengths is its ability to learn from data, making it highly adaptable to various types of quantum hardware. This adaptability is important because quantum hardware is still in its early stages of development, and different quantum processors might have different noise characteristics. By learning directly from experimental data, AlphaQubit can optimize its performance for each device, providing a tailored solution for error correction.

Bausch and colleagues' feat is not just about correcting errors; it represents a shift towards adaptive learning having a key role in managing quantum systems. The approach allows the model to learn from the nuances of each quantum device — a feature that will be crucial as quantum hardware continues to evolve. This adaptability could help to bridge the gap between today's noisy, error-prone quantum devices and the fault-tolerant quantum computers of the future by improving the way that errors are controlled, and by helping quantum computers to function correctly as they grow in size and complexity.

Moreover, the use of transformer neural networks for quantum error correction highlights the versatility of machine-learning models that were originally developed for entirely different applications. The success of AlphaQubit suggests that other types of machine-learning model could also be adapted to address specific challenges in quantum computing, from optimizing quantum circuits to developing quantum algorithms. This underlines the enormous potential for breakthroughs when ideas from different domains come together.

Although there is still much to be done, Bausch and colleagues' work is a step towards the ultimate goal: developing quantum computers that can perform reliable, large-scale computations free from errors. The study not only shows the power of AI to enhance quantum technologies, but also opens fresh research avenues. By combining quantum physics and machine learning, these innovations could unlock the true potential of the quantum realm.

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