Photon losses create tension for Gaussian boson sampling

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Recent experimental claims of quantum advantage rely on the absence of classical algorithms that can reproduce the results. A tensor network algorithm can now challenge recent optical quantum advantage experiments.

The race to develop quantum computers has accelerated in recent years, with academic groups and companies alike presenting a series of so-called quantum advantage experiments. Such experiments aim to demonstrate that existing quantum devices can efficiently perform some tasks that would be intractable using the best classical supercomputers. However, current technical limitations of quantum devices can enable classical simulation methods to efficiently simulate the results. Writing in *Nature Physics*, Changhun Oh and colleagues[1] report on a classical algorithm that simulates a wide class of large-scale quantum advantage experiments, known as Gaussian boson sampling[2,3], using relatively modest computational resources.

In principle, quantum computers can outperform the best-known classical algorithms for very specific tasks, such as integer factorization. In practice, existing quantum computers are far from ideal: over time they accumulate uncorrected noise that can suppress the advantage of quantum algorithms. At present, quantum technologies are not mature enough to correct for this noise, and its effect can only be partially mitigated. The cumulative effect of noise can reach a level that makes it possible to design efficient classical algorithms that successfully imitate the quantum device's imperfect behaviour, challenging recent claims of quantum advantage.

To realize a successful quantum advantage experiment with existing quantum computers, one needs to find a delicate balance between two factors. The system size must be large enough so that classical methods cannot compete, yet small enough to prevent the noise from rendering the quantum signal unintelligible.

Two good candidates for this task are random circuit sampling with superconducting qubits and Gaussian boson sampling[4] with photons. These involve sampling from a probability distribution that is very easy to generate experimentally but very hard to imitate otherwise. The tasks themselves are quite artificial, without an obvious practical use, but they can prove the existence of a quantum advantage using a minimal number of resources. There is strong theoretical evidence that replicating the probability distributions from these experiments, in the absence of noise, is computationally hard for classical computers.

In 2019, Google announced its first quantum advantage milestone[5] by sampling from a probability distribution that was very hard to spoof classically. Since then, researchers have pushed their classical simulation techniques beyond previous limits and, by exploiting the imperfections of the experimental realization[6], have attempted to efficiently sample from the same distribution.

Many theoretical physicists turn to tensor network methods to tackle this task, as they offer very efficient parameterizations of quantum states that have unusually low entanglement[7]. Although quantum computers, in principle, create highly entangled states, sufficient noise can quickly destroy entanglement, making a tensor network treatment feasible.

Oh and co-workers addressed the Gaussian boson sampling problem, which involves preparing non-classical, so-called squeezed states of light as inputs to a network of beam splitters with several output ports (see Fig. 1). The output distribution is determined by counting how many photons are detected on each output mode. It is estimated that simulating an experiment with just a few hundred photons would pose a substantial challenge to current supercomputers.

Unfortunately, any real optical physics experiment has to deal with photon loss. Oh and colleagues took advantage of the high losses in existing Gaussian boson sampling experiments to create a tensor-network-based classical algorithm that simulates current-size experiments. They based their approach on algorithms that sample from a thermal state[8,9]. Although such a task is computationally efficient, it would not work for current Gaussian boson sampling experiments, which do not produce outputs close to a thermal state distribution.

The Gaussian photon states used in the boson sampling experiments can be described using a covariance matrix. Existing algorithms split the covariance matrix of the thermal state into an identity matrix corresponding to the quantum vacuum, plus a random classical part, which is easy to simulate.

Oh and co-workers realized that the quantum part could be improved by changing the quantum contribution from an identity matrix to an ideal Gaussian boson sampling's output covariance matrix, but with a smaller photon number.

Their tensor network method could perform simulations of the so-called ground truth distribution, which is the ideal distribution obtained by the covariance matrix of the output state after taking photon losses into account. The result was ground truth predictions that were more accurate than the largest available Gaussian boson sampling experiments, which are affected by additional imperfections beyond photon losses.

The team's analysis shows that most of the output photons in Gaussian boson sampling experiments are actually classical and do not contribute to producing a quantum advantage. This indicates that the quantum part modelled by classical tensor networks is able to capture the computationally challenging part of the experiment. These findings suggest that a more promising path to pinpoint the regime for quantum advantage should focus on reducing the loss rate and increasing the number of different squeezed states used as inputs, rather than increasing output photon numbers.

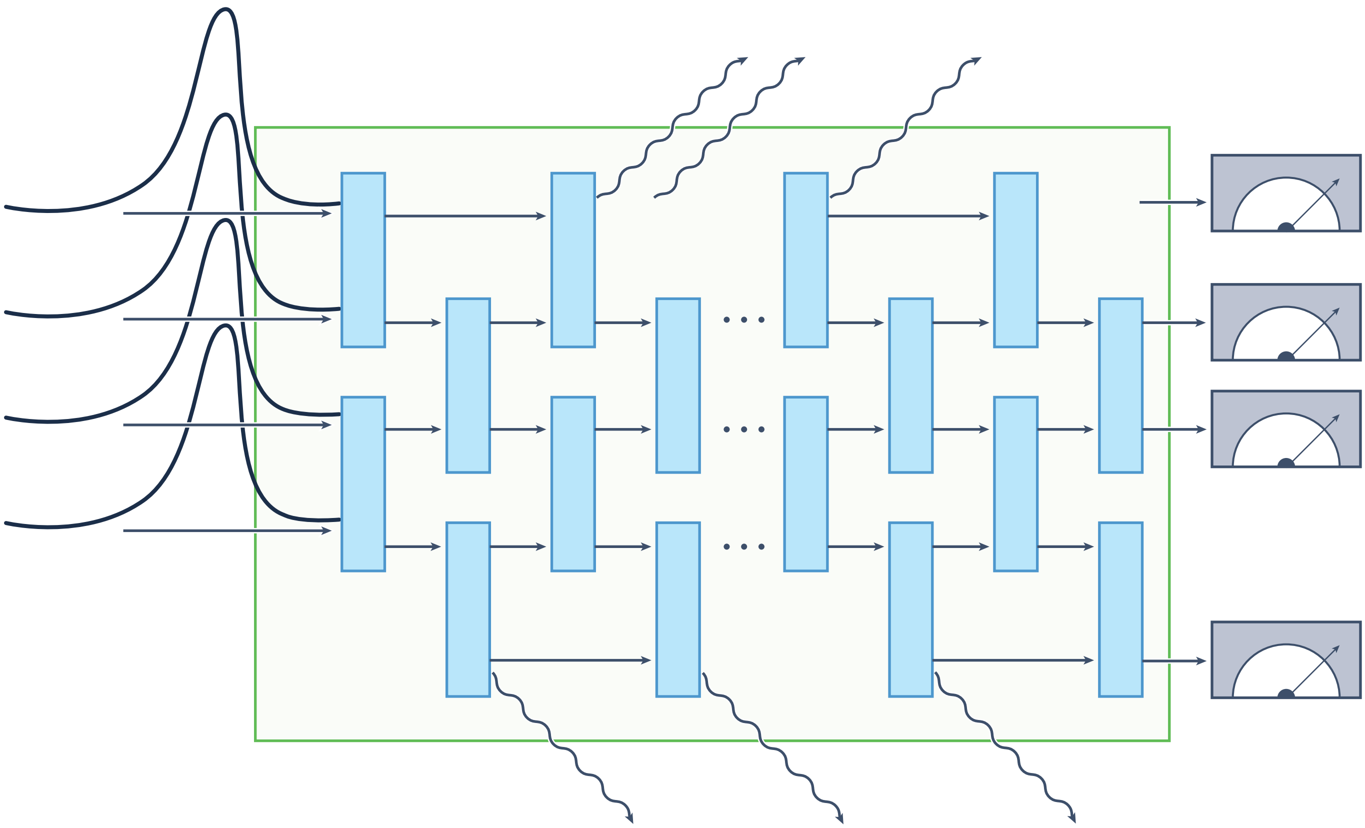

Fig. 1 | Gaussian boson sampling. Squeezed vacuum states (black curves) pass through a beam splitter network (blue rectangles) subject to photon losses (wavy arrows). At each output port of the network, the number of photons is measured. It is believed to be computationally hard for a classical computer to predict these potential measurement outcomes, which occur naturally in a boson sampling experiment.

Where does Oh and co-workers' work leave the boundary for quantum advantage[10]? This question requires a multifaceted answer. Architectures for future experiments and circuit connectivity will change, affecting the loss rate scaling as a function of the number of modes. Nevertheless, the team aimed to make a simple and consistent comparison in their work. Based on the computational capabilities of the current largest supercomputer, they provided parameter regimes that future experiments should aim to beat.

In the race towards quantum advantage, it can feel as though the finish line is constantly moving, as it cannot be defined using a single figure of merit. Oh and co-workers point out that their algorithm outperformed the experiment only with respect to certain benchmarks, which is different to claiming that their classical sampler surpasses the experiment. They have just ruled out all the evidence for quantum advantage that the experiments presented so far. Oh and co-workers' result is an advance that not only helps build better classical simulations but also challenges researchers to refine experiments, thereby bringing viable quantum computers closer.

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Competing interests

The author declares no competing interests.