# PIQUASSO

#### A Photonic Quantum Computer Simulation Software Platform

<u>Zoltán Kolarovszki</u>, Tomasz Rybotycki, Péter Rakyta, Ágoston Kaposi, Boldizsár Poór, Szabolcs Jóczik, Dániel T. R. Nagy, Henrik Varga, Kareem H. El-Safty, Gregory Morse, Michał Oszmaniec, Tamás Kozsik, Zoltán Zimborás

> HUN-REN Wigner Research Centre for Physics Eötvös Loránd University

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#### Photonic Quantum Computing

A photonic quantum computer stores information in independent optical modes called **qumodes**.





#### Quantum advantage by USTC

The Quantum Information Group of USTC in Hefei (led by Jian-Wei Pan) demonstrated an advantage over classical computation in 2020 (with improvements in 2021 and 2023, with the latter mentioning our method as a classical benchmark).





#### Quantum advantage by Xanadu

Xanadu also demonstrated an advantage over classical computation in 2022 on the Borealis chip, which is also publicly available.





# Classical simulation of photonic quantum computers



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#### Simulating photonic quantum circuits

We need to **simulate** photonic quantum computers, because:

- Photonic quantum computers are still **not widely available**, but we want to execute photonic quantum algorithms for research.
- It can aid circuit design.
- > Trying to simulate quantum computing may inspire **better classical algorithms**.
- It can be used to certify hardware.
- It helps photonic quantum machine learning research via automatic differentiation.



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However: Simulating photonic quantum circuits is classically hard in general!



## **PIQUASSO**: PhotonIc **QUA**ntum computer Simulator SOftware

We are developing and maintaining a new simulator framework written in Python called  $\mathbf{Piquasso}^1$ .

We wanted to have a simulator we could experiment with and we could extend and improve by ourselves.

#### Main goals:

- Extensibility (e.g., TensorFlow, JAX)
- ► High performance (e.g., via C++ PiquassoBoost plugin)
- Reproducibility
- Clean code

Piquasso is open source, available on  $GitHub^2$  and can be installed with:

pip install piquasso

<sup>2</sup>https://github.com/Budapest-Quantum-Computing-Group/piquasso



<sup>&</sup>lt;sup>1</sup>ZK et al., arXiv:2403.04006

#### Available simulators in **PIQUASSO**

Different state representations are useful depending on the scenario.

In Piquasso, you can choose from the following:

- GaussianSimulator: Simulates Gaussian states
- SamplingSimulator: Simulates the Boson Sampling scheme
- FockSimulator: Simulates Fock states
- PureFockSimulator: Simulates pure Fock states



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#### Available simulators in **PiquassoBoost**:

- BoostedGaussianSimulator: Same as GaussianSimulator, but reimplemented in C++ with improved hafnian and torontonian calculations.
- BoostedSamplingSimulator: Same as SamplingSimulator, where sampling algorithm is reimplemented and parallelized in C++ with improved permanent calculation algorithms.



#### Usage example

```
1 simulator = pg.GaussianSimulator(d=5)
2
3 with pq.Program() as program:
      pq.Q(all) | pq.Vacuum()
4
5
      for i in range(5):
6
           pq.Q(i) \mid pq.Squeezing(r=0.1) \mid pq.Displacement(r=1.0)
7
8
9
      pq.Q(0,1) | pq.Beamsplitter(theta=np.pi / 3)
      pg.Q(2,3) | pg.Beamsplitter(theta=np.pi / 4)
10
11
      pq.Q(3,4) | pq.Beamsplitter(theta=np.pi / 5)
      pq.Q(all) | pq.ParticleNumberMeasurement()
13
14
15 result = simulator.execute(program, shots=1000)
16 print(result.samples)
17 \# [(0, 1, 1, 2, 2), (1, 3, 0, 0, 1), (0, 1, 0, 0, 3), \ldots
```

Choose your framework!

- NumpyCalculator: Default calculator, uses NumPy, SciPy and Numba.
- TensorflowCalculator: Uses TensorFlow for calculations (with graph compilation and OpenXLA support).
- ► JaxCalculator: Uses \_\_\_\_\_\_\_ for calculations (with 🐼 OpenXLA support).





#### Fock space truncation

The Fock simulation is an **approximation**, due to the ubiquitous cutoff.

STRAWBERRY FIELDS: Local cutoff Constraint on the particle number by mode. State vector size:

 $c^d$ , c: **local** cutoff, d: number of modes. (1)

#### **PIQUASSO:** Global cutoff

Constraint on particle number on the whole system. State vector size:

 $\binom{d+c-1}{c-1}$ , c: global cutoff, d: number of modes. (2)

Contributions that are left out by using a global cutoff instead of a local one have small coefficients in most cases.

#### Photon losses<sup>3</sup>: PIQUASSO vs. STRAWBERRY FIELDS





<sup>3</sup>In a circuit using 4 continuous-variable quantum neural network (CVQNN) layers on 8 modes.

#### Automatic differentiation<sup>4</sup>: **PIQUASSO** vs. STRAWBERRY FIELDS



<sup>4</sup>In a circuit using 4 CVQNN layers with cutoff 10.



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#### Hafnian calculation speedup in PiquassoBoost



## PIQUASSO Composer

#### A web-based circuit composer is made available at https://piquasso.com.













## Applications



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#### I. Training continuous-variable Born machines (CVBMs)<sup>5</sup>

- Born machine: Parametrized quantum circuit producing probability distributions via Born's rule => generative quantum machine learning
- **CVBM:** Photonic quantum circuits can generate **position distribution**



<sup>5</sup>ZK, D. T. R. Nagy, Z. Zimborás, 2024, "On the learning abilities of photonic continuous-variable Born machines" [submitted]

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However, classically simulation is demanding, even for a single mode!

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# **PIQUASSO** uses a new classical algorithm for homodyne measurement tailored for **multimode systems**.

 $\sim~1000\times$  speedup over previous solutions!

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## I. Efficient training of multimode CVBMs with **PIQUASSO**







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#### II. Optimizing non-deterministic gates with imperfect detections<sup>6</sup>

Nondeterministic gates can implement **qubit** gates on a photonic quantum computer.



<sup>6</sup>C. Czabán, ZK, M. Karácsony, Z. Zimborás, 2024, "Suppressing photon detection errors in nondeterministic state preparation", ReAQCT'24



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Problem: Photon detectors have biases.

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#### II. Fidelity vs. success rate of conditional sign flip gate





III. Gate synthesis with adaptive circuit compression<sup>8</sup>

**Gate synthesis problem:** Given a unitary matrix, find a corresponding circuit implementing it!

**Existing solution:** Gradient-based optimization with universal layers.

Using  $\checkmark$  +  $\circledast$  OpenXLA  $\implies \sim 600 \times \text{speedup!}^7$ 

<sup>7</sup>With 25 CVQNN layers and Fock space cutoff 20, averaged from 1000 iterations. <sup>8</sup>H. Varga, 2024, "Decomposition of unitary matrices based on bosonic Hamiltonian operators into elementary photonic quantum gates" [unpublished] III. Gate synthesis with adaptive circuit compression<sup>8</sup>

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This speedup allows us to **compress** the circuit adaptively, by "throwing" out gates close to identity.

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