Automatic differentiation of photonic circuits

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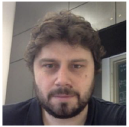
PIQUASSO

Piquasso team



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Outline

Photonic Quantum Computing

Photonic circuits as neural networks

Why simulate a photonic quantum computer?

Piquasso simulator framework

Tensorflow integration

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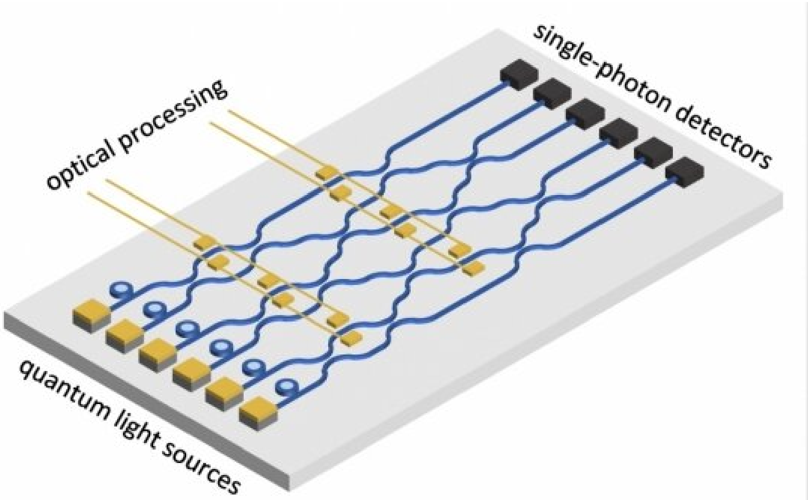
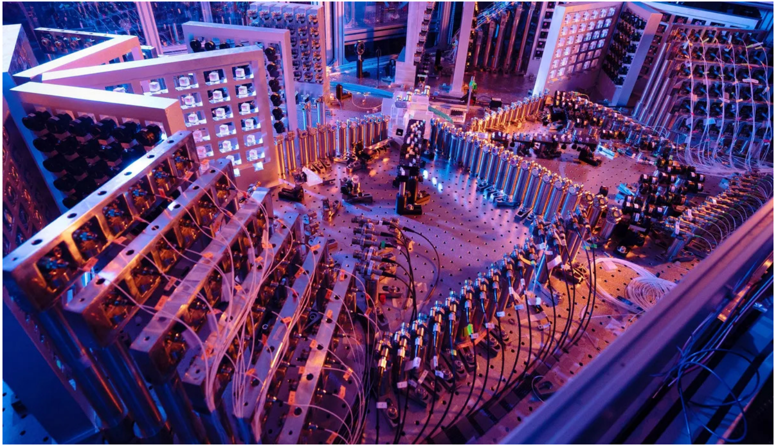
Photonic Quantum Computing

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



Quantum advantage

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



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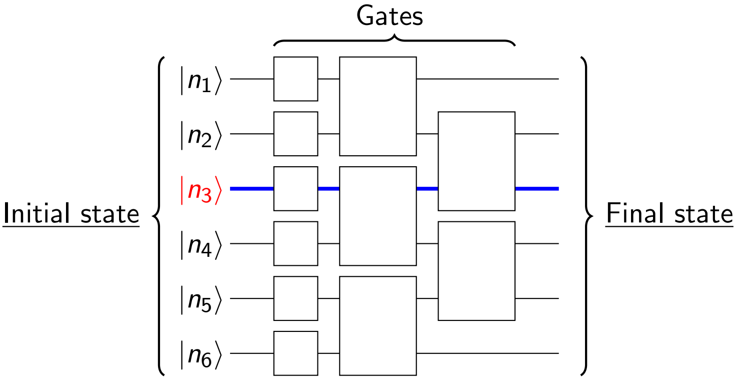
Modeling an optical circuit



States can be written as:

$$|\psi\rangle := \sum_{n_1,\dots,n_d \in \mathbb{Z}^d_{\geq 0}} c_{n_1,\dots,n_d} |n_1 \ \dots \ n_d\rangle \,. \tag{1}$$

Example state: $|\psi\rangle = \frac{1}{\sqrt{2}} |01\rangle + \frac{1}{\sqrt{2}} |10\rangle \,.$

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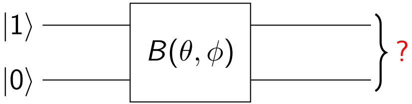
Simple example

Circuit with a single beamsplitter gate:



Output state:

$$? = B(\theta, \phi)\,|10\rangle = \cos\theta|10\rangle + e^{i\phi}\sin\theta|01\rangle. \tag{2}$$

Probability distribution: (using Born's rule)

$$\begin{aligned} p(\text{output} = 10) &= \cos^2\theta, \\ p(\text{output} = 01) &= \sin^2\theta. \end{aligned} \tag{3}$$

Idea: Photonic circuits as neural networks?

Qubit-based quantum computing $\implies$ measurement outputs are generally **discrete**.

Photonic quantum computing $\implies$ measurement outputs are **continuous**.

photonic circuit $\sim$ **neural network**

gate parameters $\sim$ **weights**

Circuits are differentiable, e.g.

$$\partial_\theta B(\theta, \phi) |01\rangle = - \sin\theta |01\rangle + e^{i\phi} \cos\theta |10\rangle .$$

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Neural network model in photonic quantum computing

A classical neural network model is

$$\vec{y} = \mathcal{L}_n \dots \mathcal{L}_1(\vec{x}), \tag{4}$$

- $\vec{x}$ input, $\vec{y}$ output,
- $\mathcal{L}_i$ **neural network layer**,

$$\mathcal{L}_i = \varphi(W\vec{x} + \vec{b}) \tag{5}$$

- $W\vec{x} + \vec{b}$ is **linear** transformation,
- φ **nonlinear** "activation" function.

How can we adapt this contruction to photonic quantum computing?

Photonic Analogue

$$\left|\psi'\right\rangle = \mathcal{L}_n \dots \mathcal{L}_1 \left|\psi\right\rangle , \tag{6}$$

- $|\psi\rangle$ input, $|\psi'\rangle$ output state,
- $\mathcal{L}_i := \mathcal{L}_i(\vec{\theta})$: **continuous-variable quantum neural network layers** (CVNN),
- $\vec{\theta}$: **set of parameters** $\iff$ **weights**.

$\mathcal{L}_i$ should be the composition of a **linear** and a **non-linear** transformation.

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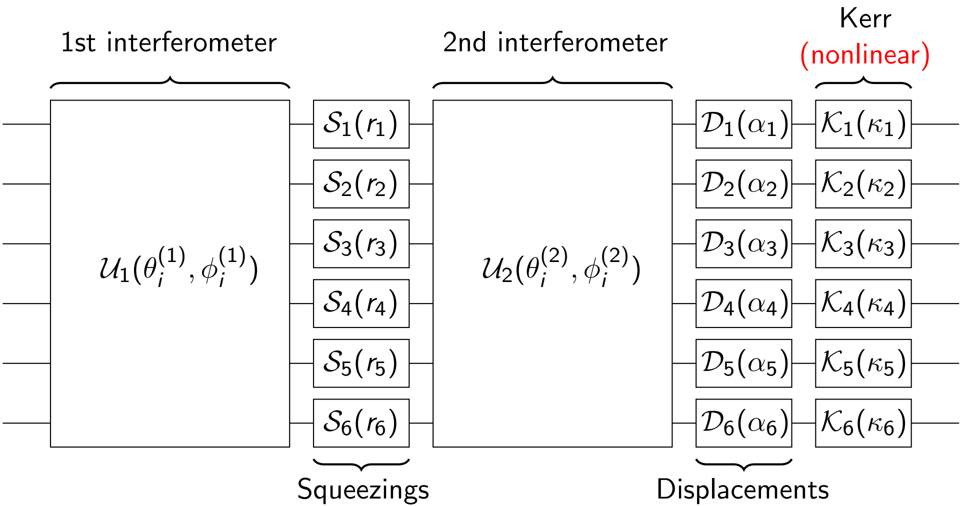
Continuous-Variable Neural Network layer



$$\mathcal{L} := \mathcal{K} \circ \mathcal{D} \circ \mathcal{U}_2 \circ \mathcal{S} \circ \mathcal{U}_1$$

Simulating photonic quantum circuits is needed!

- Photonic quantum computers are still **not widely available**,
- Trying to approximate quantum computing may inspire **better classical algorithms**,
- Can be used to **test hardware**,
- **Aids implementation** of quantum circuits (state learning, gate synthesis).

However: Simulating photonic quantum circuts is classically hard!

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Example problem: State learning

Given a photonic quantum state $|\psi\rangle$, **how can we prepare it using a photonic quantum computer?**

Solution: CVNN layers!

Cost function:

$$J(|\psi\rangle) = \| |\psi\rangle - |\psi^*\rangle \|_1 \tag{7}$$

$$|\psi^*\rangle = \mathcal{L}_n \circ \cdots \circ \mathcal{L}_1 |0\rangle , \qquad \mathcal{L}_i \textbf{ CVNN layers}. \tag{8}$$

Differentiating CVNN layers $\implies$ **backpropagation**.

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Photonic Quantum Computing

Photonic circuits as neural networks

Why simulate a photonic quantum computer?

Piquasso simulator framework

Tensorflow integration

Simulating a photonic quantum computer with Piquasso

We are developing a new simulator framework written in Python called **Piquasso**.

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

It is also beneficial to have multiple simulators for testing hardware.

Main goals:

- Extensibility (ability to write plugins),
- High performance (via C++ PiquassoBoost plugin),
- Reproducibility,
- Clean code.

Piquasso is open source, available on PyPI:

```
pip install piquasso
```

Simulation of nonlinear gates

Nonlinear gates (the Kerr gate) can only be simulated using the **Fock simulator**, where states are stored with their coefficients in the Fock basis.

We need to differentiate the **Fock simulator**.

Example: Coherent state

$$|\alpha\rangle := e^{-\frac{|\alpha|^2}{2}} \sum_{n=0}^{\infty} \frac{\alpha^n}{\sqrt{n!}} |n\rangle , \tag{9}$$

but we cannot store every coefficients, we need a truncation:

$$|\alpha\rangle := e^{-\frac{|\alpha|^2}{2}} \sum_{n=0}^{c} \frac{\alpha^n}{\sqrt{n!}} |n\rangle . \tag{10}$$

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2 ways of truncating Fock space

The Fock simulation is an **approximation**.

One has to make a choice which occupation numbers are considered. When imposed, makes the dimension of the space of the system finite.

Strawberry Fields: Local cutoff
Constraint on the particle number **by mode**. State vector size:

$$c^d, \qquad c: \ \textbf{local}\text{ cutoff}, \ d: \ \text{number of modes.} \tag{11}$$

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

$$\binom{d+c-1}{c-1}, \qquad c: \ \textbf{global}\text{ cutoff}, \ d: \ \text{number of modes.} \tag{12}$$

Cutoff results in photon loss.

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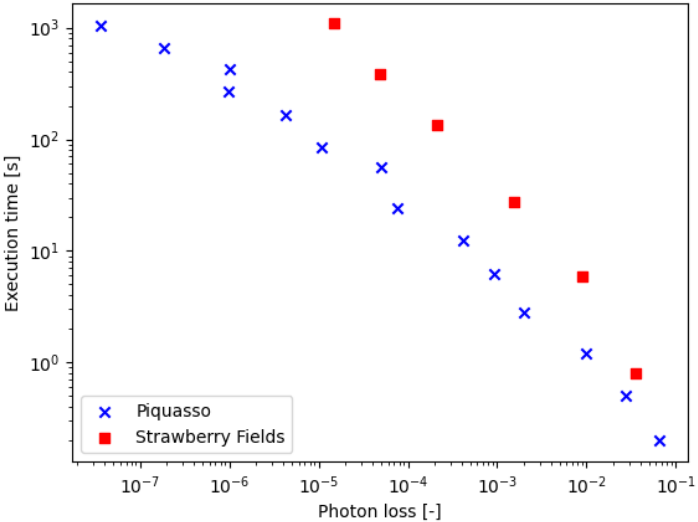
Photon loss in Piquasso vs. Strawberry Fields



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Simulation using Tensorflow

Piquasso now supports the Tensorflow machine learning platform.

Automatic differentiation of optical circuits

```
config = pq.Config(cutoff=4)
simulator = pq.TensorflowPureFockSimulator(d=3)
theta_1, theta_2 = tf.Variable(1.0), tf.Variable(2.0)
xi = tf.Variable(3.0)

with pq.Program() as program:
    pq.Q() | pq.Vacuum() | pq.Displacement(alpha=[0.1, 0.2, 0.3])
    pq.Q(0, 1) | pq.Beamsplitter(theta=theta_1)
    pq.Q(1, 2) | pq.Beamsplitter(theta=theta_2)
    pq.Q() | pq.Kerr(xi=xi)

with tf.GradientTape() as tape:
    probabilities = simulator.execute(program).state.fock_probabilities

tape.jacobian(probabilities, [theta_1, theta_2, xi])
# [<tf.Tensor: shape=(20,), dtype=float32, numpy=array(
# [ 0.        ,  0.03394834, -0.02936802, -0.00458031,  0.00062407, ...
```

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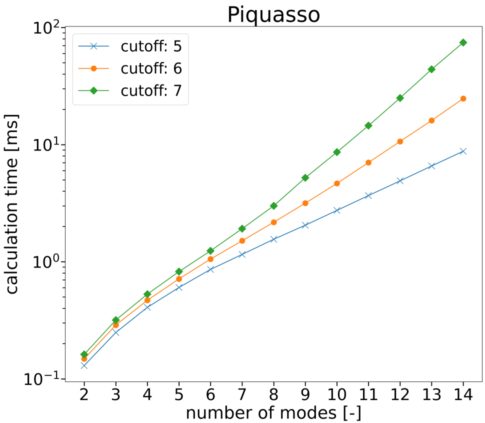
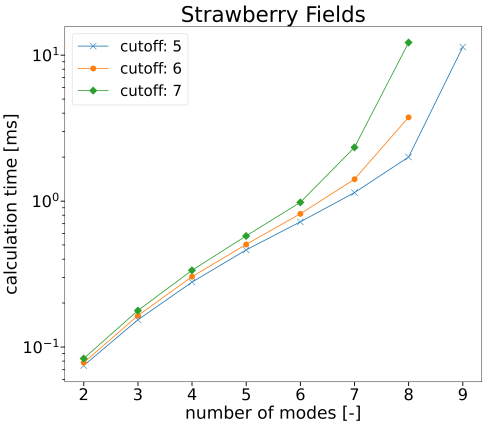
Benchmarking single CVNN layers





Thank you for your attention!