Photonic quantum computing and its applications to machine learning

AIME 2025

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November 27, 2025

Photonic quantum computing

Variational quantum algorithms

Photonic quantum machine learning

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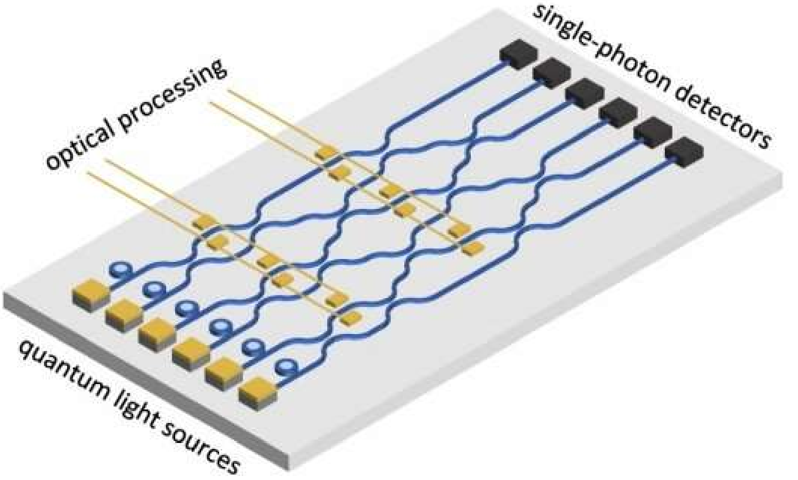
Photonic quantum computing

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



Why use photons?

✓ **Pros:**

- Stable coherence: photons interact weakly with the environment
- Fast: optical signals propagate at the speed of light
- Optical elements operate on room temperature
- Compatible with existing technologies

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✗ **Cons:**

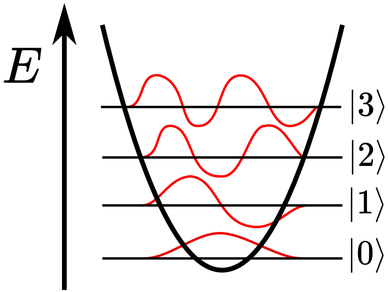
- Photon losses
- Nonlinearities are difficult to realize
- Single-photon sources are also difficult
- Timing (need to ensure indistinguishability)

Qubit-based vs. photonic quantum computing

	Qubit-based	Photonic
Information unit	Qubit	Qumode
Hilbert space dimension	Finite	Infinite
Basis states	$\|0\rangle, \|1\rangle$	$\|0\rangle, \|1\rangle, \|2\rangle, \|3\rangle, \ldots$
Elementary gates	Hadamard, CNOT, Pauli gates	Squeezing, Rotation, Displacement, (Kerr?)
Typical measurements	Computational/Hadamard basis measurements	Particle number detection Homodyne/heterodyne detection

Qumodes

We model qumodes by quantum harmonic oscillators, and the states $|0\rangle$, $|1\rangle$, $|2\rangle$, $|3\rangle, \ldots$ correspond to excitations (**particles**).



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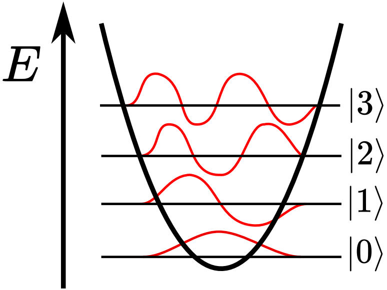
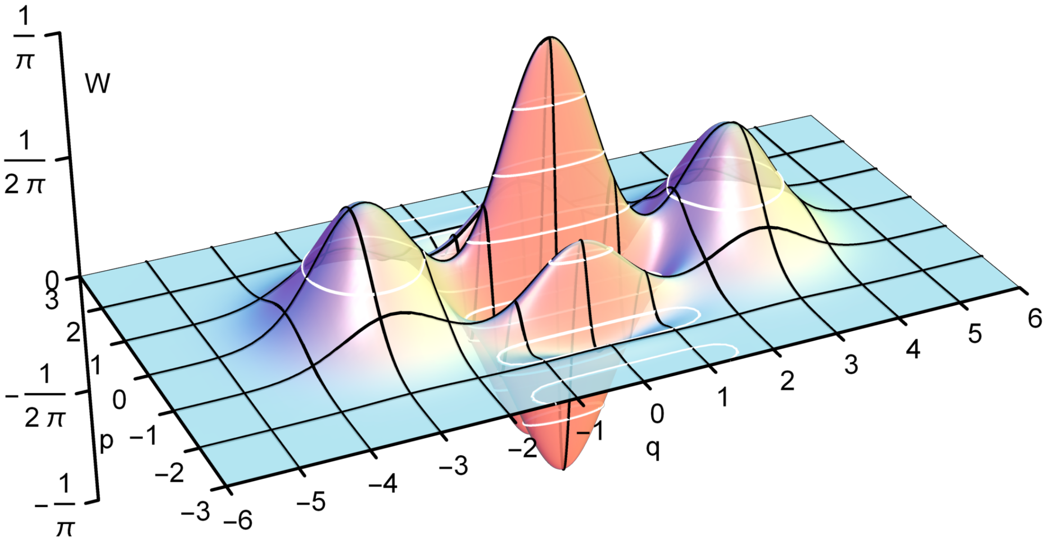


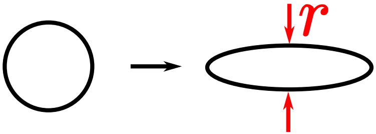
Photonic quantum states can also be described by continuous quasidistributions over the phase space.

Wigner function



Linear gates

- **Squeezing** $S(r)$:



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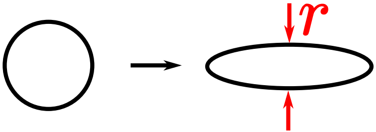
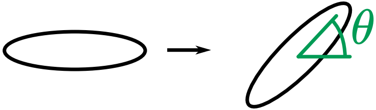


- **Rotation (or phaseshift)** $R(\theta)$ (passive, i.e., particle number preserving)



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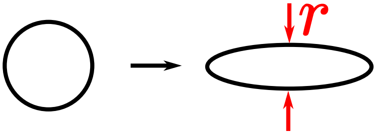

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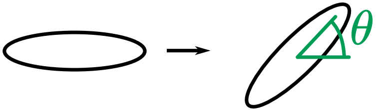
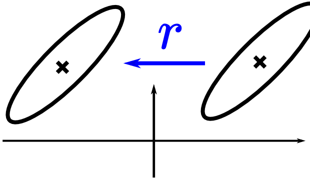


- **Displacement** $D(r)$



Encoding information in a photonic quantum computer

Discrete-variable encoding

Encoding qubits into photonic modes, e.g., into polarization.

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Quantum information is stored in quadratures ($\hat{x}$, $\hat{p}$) of the light field.

✓ **Pros:** deterministic Gaussian operations, scalable state preparation
✗ **Cons:** implementing non-Gaussian resources (e.g., Kerr gate) is expensive

Boson Sampling (BS) and Gaussian Boson Sampling (GBS)

Non-universal schemes aimed to demonstrate quantum advantage.

	BS	**GBS**
Input	Fock states (single photons)	Squeezed vacuum states
Circuit	Linear interferometer	Linear interferometer
Output distribution	$\propto$ **permanents** of matrices	$\propto$ **hafnians** of matrices
Classical hardness	✓	✓
Experimental scalability	?	✓
Applications	?	?

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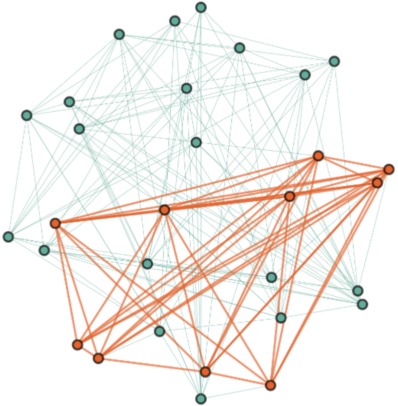
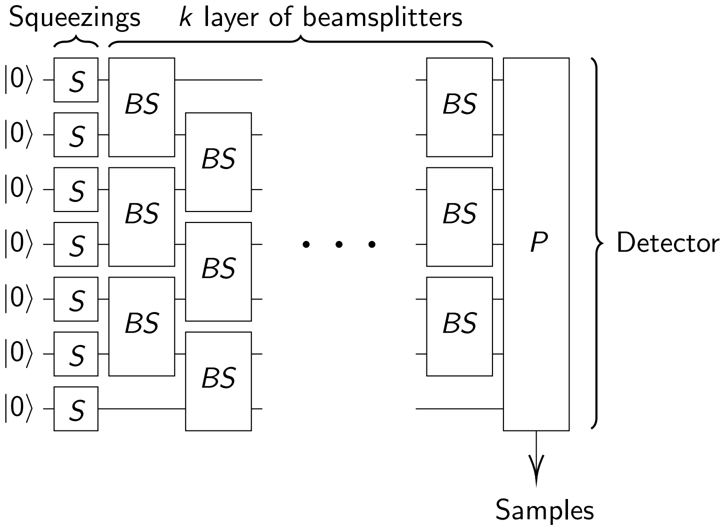
Potentially helpful for finding **dense subgraphs**, **maximum cliques** in graphs.

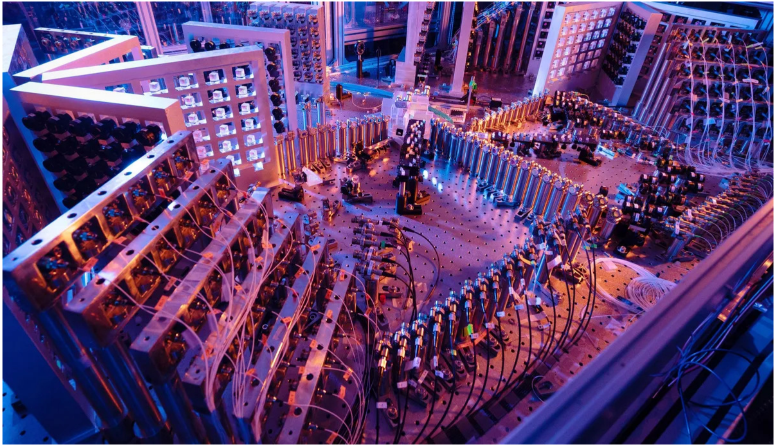


Typical setup of Gaussian Boson Sampling



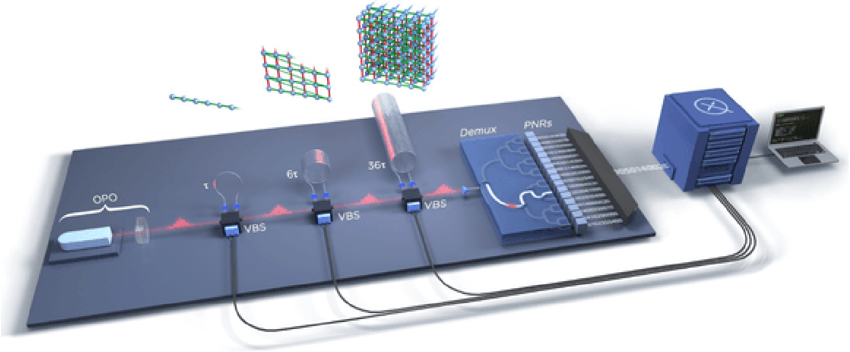
First quantum advantage by USTC (76 photons, 100 modes)

The Quantum Information Group of USTC in Hefei (led by Jian-Wei Pan) demonstrated an advantage over classical computation in 2020.

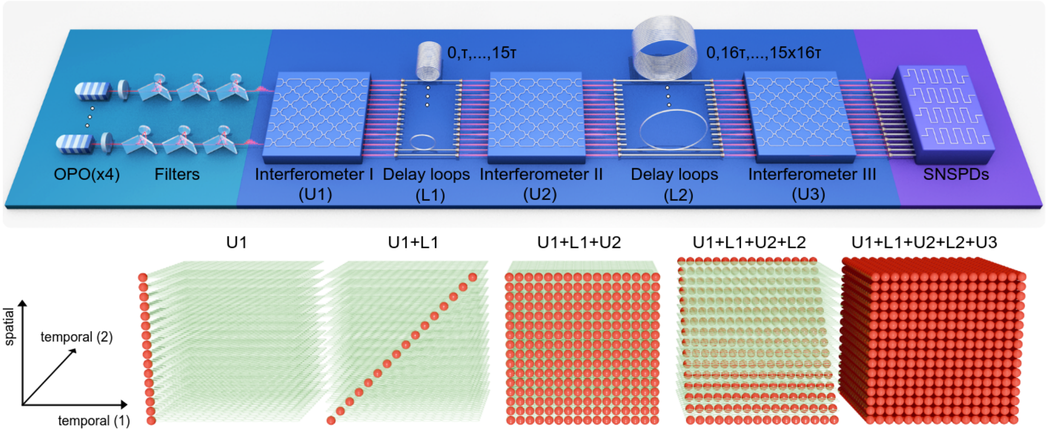


Quantum advantage by Xanadu (219 photons, 216 modes)

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



Recent demonstration by USTC (3050 photons, 8196 modes)



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Where quantum advantage may arise:

- More efficient representation of high-dimensional distributions.
- Sampling from distributions that are classically intractable to sample from.
- Compact encoding of correlations (entanglement) difficult for classical models.

Variational quantum circuits

Variational quantum circuits (VQCs) constist of:

1. An initial state $|\psi(\boldsymbol{x})\rangle$ (optionally) depending on some data $\boldsymbol{x}$.

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$$f_j(\boldsymbol{\theta}) := \langle\psi(\boldsymbol{x})|\,\hat{U}^\dagger(\boldsymbol{\theta})\hat{O}_j\hat{U}(\boldsymbol{\theta})\,|\psi(\boldsymbol{x})\rangle\,. \tag{1}$$

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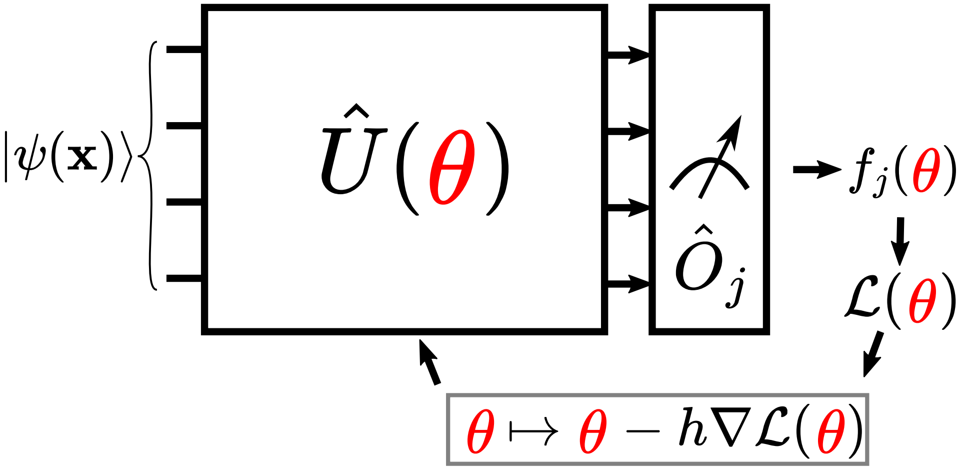
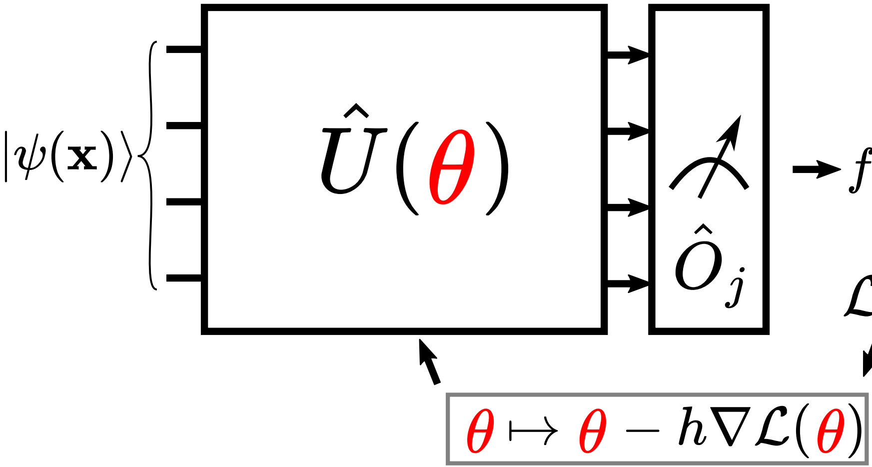
Goal: minimize $\mathcal{L}$ by tuning $\boldsymbol{\theta}$.


$|\psi(\mathbf{x})\rangle$
$\hat{U}(\boldsymbol{\theta})$
$\hat{O}_j$
$f_j(\boldsymbol{\theta})$
$\mathcal{L}(\boldsymbol{\theta})$
$\boldsymbol{\theta} \mapsto \boldsymbol{\theta} - h\nabla\mathcal{L}(\boldsymbol{\theta})$



Question: How to determine $\nabla\mathcal{L}(\theta)$ efficiently?

Determining gradients on a quantum computer

Parameter shift rules help us to estimate gradients better.

$$\partial_i f(\boldsymbol{\theta}) = c\left[f(\boldsymbol{\theta} + s\,\boldsymbol{e}_i) - f(\boldsymbol{\theta} - s\,\boldsymbol{e}_i)\right], \tag{3}$$

where

- c is some constant,
- s is the parameter shift, **can be large**.

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Rough analogy: For

$$f(x) = \sin(x) \tag{4}$$

we can write

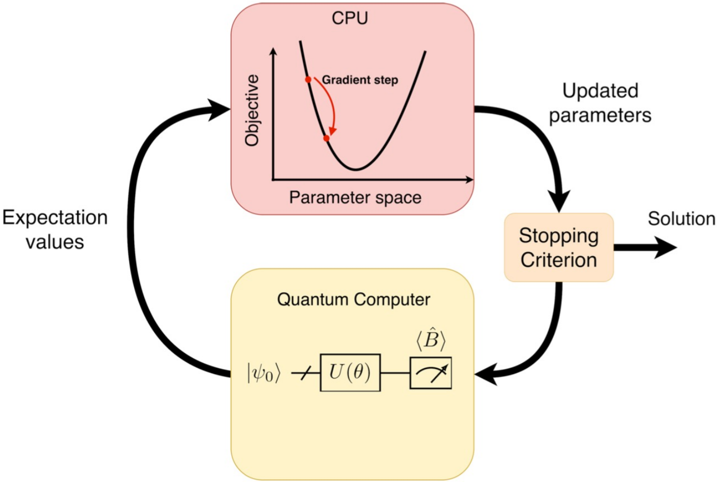
$$\frac{\mathrm{d}}{\mathrm{d}x} f(x) = \frac{1}{2}\,[\sin(x + \pi/2) + \sin(x - \pi/2)]\,.$$

A simple variational quantum algorithm

Variational quantum circuits: $U(\vec{\theta})$.

Optimization: gradient descent.

Gradients: parameter shift rules.



Challenges in quantum machine learning

- Encoding classical data in a quantum computer is generally difficult
- Poor local minima
- Barren plateaus (exponentially vanishing gradients)
- Costly gradient computation

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In general, there is a tradeoff between **expressibility** and **trainability**.

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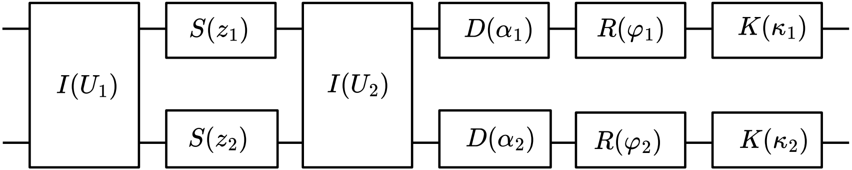
Promises:
All the advantages of photonic quantum computing + additionally:

- High-dimensional Hilbert space $\approx$ high expressivity?
- Interesting distributions for generative tasks

Continuous-variable quantum neural networks

Single layer = Linear gates (interferometer I, squeezing S, displacement D) + non-linear gates (Kerr K).



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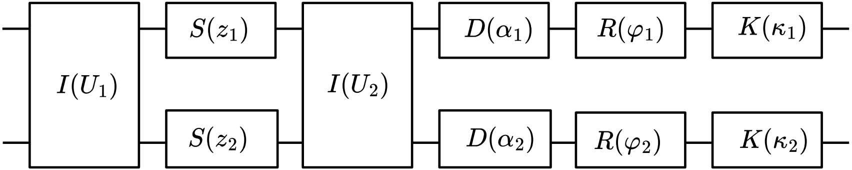

✓ **Pro:** High expressivity, universal

✗ **Con:** Trainability issues (no parameter shift rules, vanishing gradients?), Kerr gate is difficult experimentally

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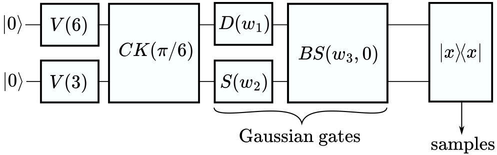
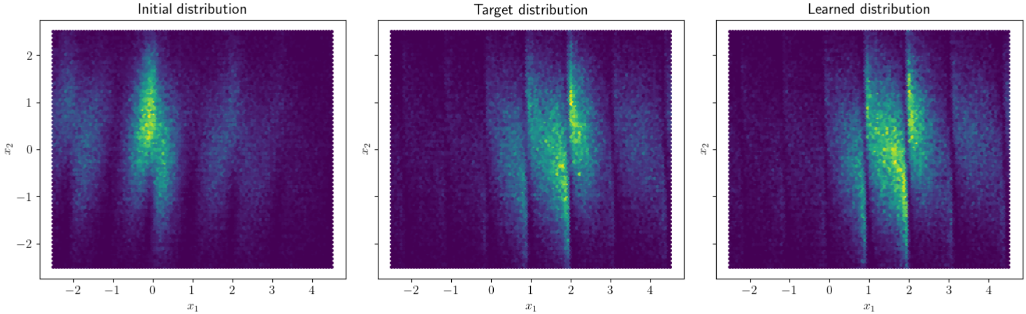
Continuous-variable Born machines: Train variational quantum circuit to learn probability distribution through **homodyne measurements** ($\hat{x}$ measurement)!

✓ **Pros**: More natural for continuous distributions

✗ **Cons**: Expensive gradients, no parameter shift rule, Kerr gate nonlinearity, only quantum distribution learning has been demonstrated

Two-mode CVBM training





New direction: training on classical computers?

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[Submitted on 4 Mar 2025]

Train on classical, deploy on quantum: scaling generative quantum machine learning to a thousand qubits

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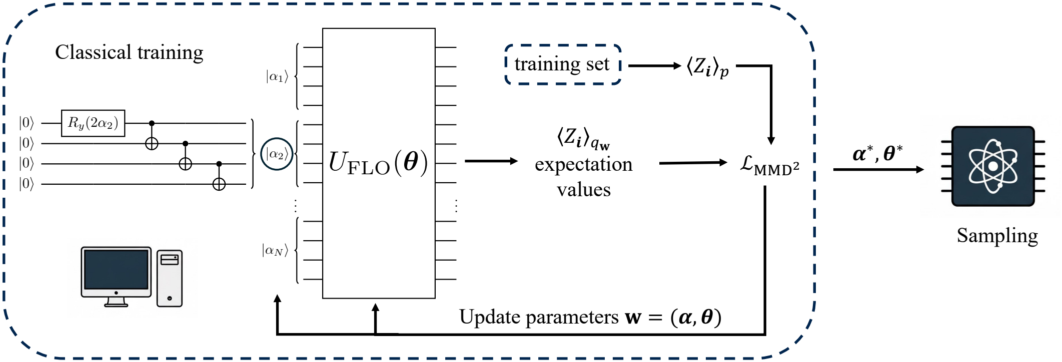
✗ **Cons:** Barren plateaus can still appear, potentially lower expressibility


Classical training
$|0\rangle$
$|0\rangle$
$|0\rangle$
$|0\rangle$
$R_y(2\alpha_2)$
$|\alpha_1\rangle$
$|\alpha_2\rangle$
$|\alpha_N\rangle$
$U_{\text{FLO}}(\boldsymbol{\theta})$
training set
$\langle Z_{\boldsymbol{i}}\rangle_p$
$\langle Z_{\boldsymbol{i}}\rangle_{q_{\mathbf{w}}}$
expectation values
$\mathcal{L}_{\text{MMD}^2}$
Update parameters $\mathbf{w} = (\boldsymbol{\alpha}, \boldsymbol{\theta})$
$\boldsymbol{\alpha}^*, \boldsymbol{\theta}^*$
Sampling

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Can we do similar with bosons?

Classically trainable Born machines based on Gaussian Boson Sampling

Idea:

- Parity-string (analog of Z-string) expectation values can be **efficiently** calculated for Gaussian states.
- Classically simulating the corresponding sampling is believed to be **intractable**.

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Question: Are Gaussian states expressive enough for generative tasks?