Generative modeling with Gaussian Boson Sampling: classically trainable Bosonic Born Machines

GPU Day 2026

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Outline

Photonic quantum computing

Born Machines in the photonic setting

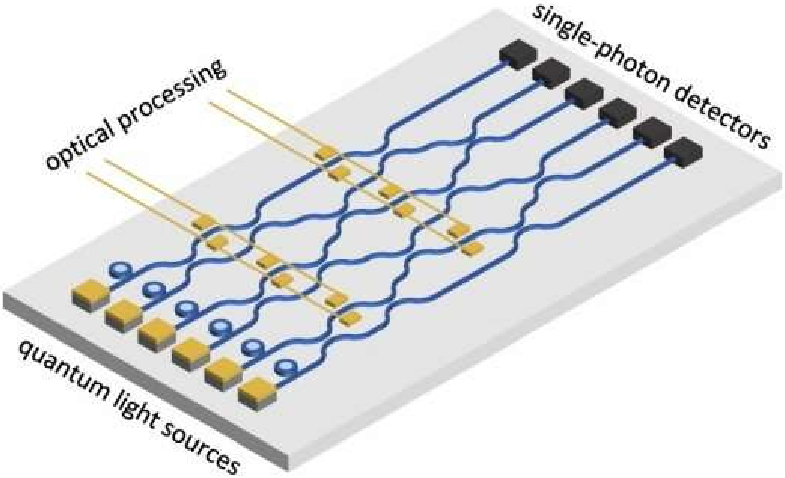
Gaussian Bosonic Born Machines

Numerical experiments

Photonic quantum computing

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:**

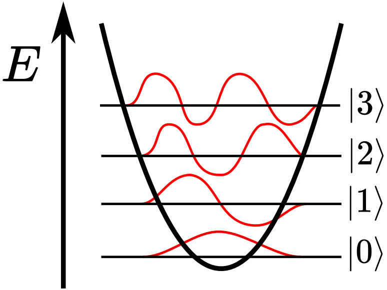
- Photon losses
- Nonlinearities are difficult to realize
- Single-photon sources are also difficult
- Timing (need to ensure indistinguishability)

Qubit-based vs. photonic quantum computing

	Qubit-based	Photonic
Information unit	Qubit	Qumode
Hilbert space dimension	Finite	Infinite
Basis states	$\lvert 0\rangle, \lvert 1\rangle$	$\lvert 0\rangle, \lvert 1\rangle, \lvert 2\rangle, \lvert 3\rangle, \ldots$
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 (modes) by quantum harmonic oscillators, and the states $|0\rangle$, $|1\rangle$, $|2\rangle$, $|3\rangle, \ldots$ correspond to excitations (**particles**).



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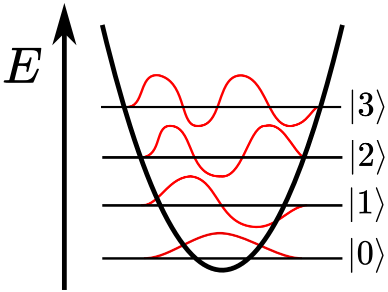
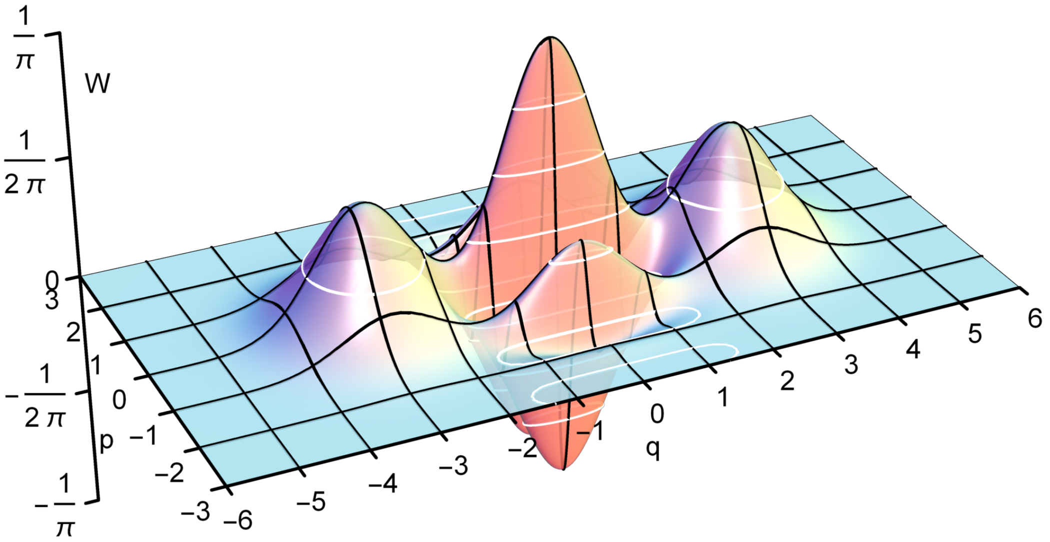


Photonic quantum states can also be described by continuous quasidistributions over the phase space.

Wigner function



Gaussian states

A **(pure) Gaussian state** is a photonic quantum state $|\psi\rangle$ completely characterized by its first and second moments, i.e., by the following quantities:

$$\boldsymbol{\mu} := \langle\psi| \boldsymbol{\xi}_i |\psi\rangle \,, \qquad \textbf{(Displacement vector)} \qquad (1)$$

$$\Sigma := \langle\psi| \{(\boldsymbol{\xi} - \boldsymbol{\mu})^\dagger, (\boldsymbol{\xi} - \boldsymbol{\mu})\} |\psi\rangle \,, \qquad \textbf{(Covariance matrix)} \qquad (2)$$

where $\boldsymbol{\xi} := (a_1, \ldots, a_d, a_1^\dagger, \ldots, a_d^\dagger)$, $\{A, B\} := AB + BA$, $d =$ number of photonic modes.

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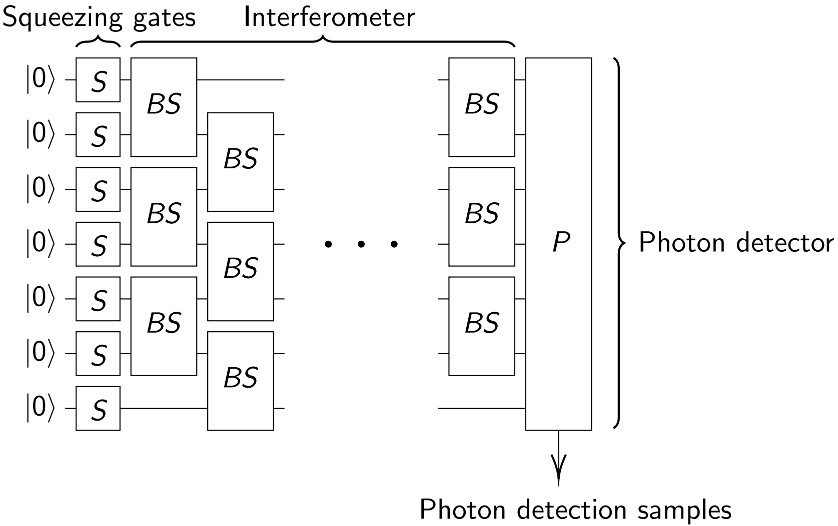
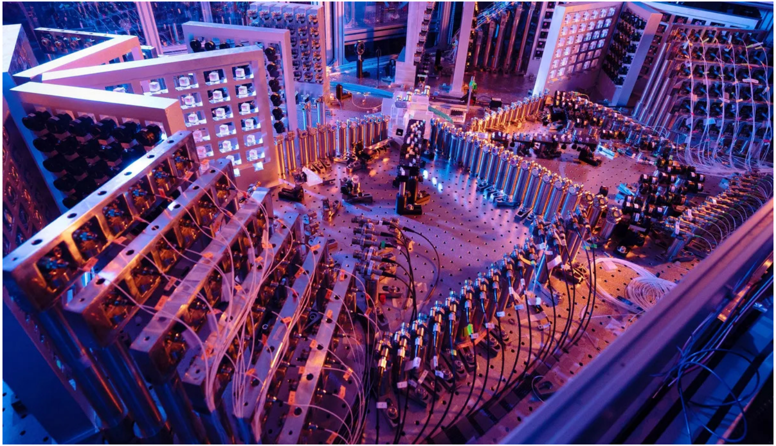
A photonic quantum state is Gaussian $\iff$ its Wigner function is a Gaussian distribution.

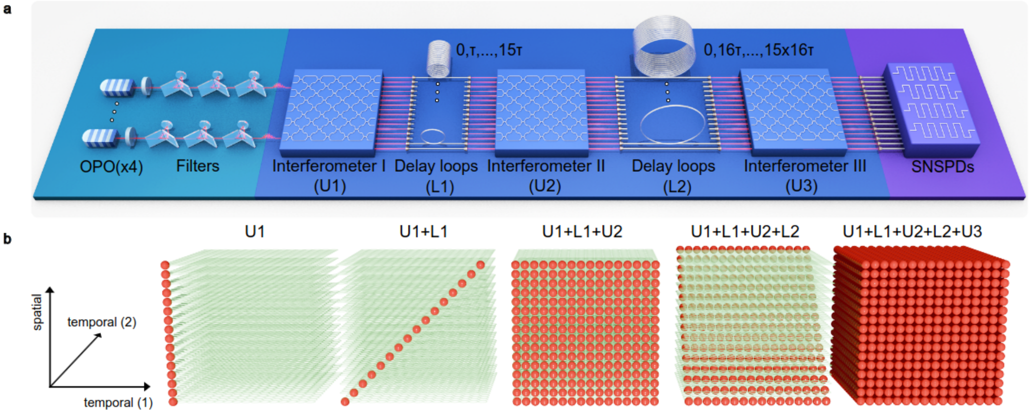
Gaussian Boson Sampling



Quantum advantage by USTC in 2019: 100 modes, up to 76 photons



New experiment in 2025: 8096 modes, 3050 photons



Born Machines in the photonic setting

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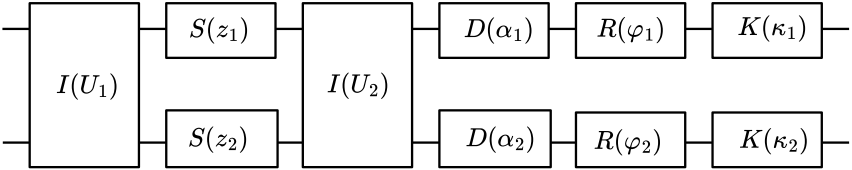
All the advantages of photonic quantum computing + additionally:

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

Continuous-variable quantum neural networks

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



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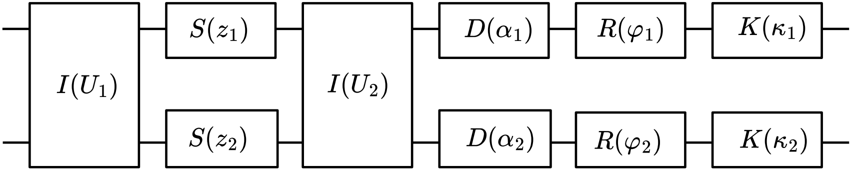

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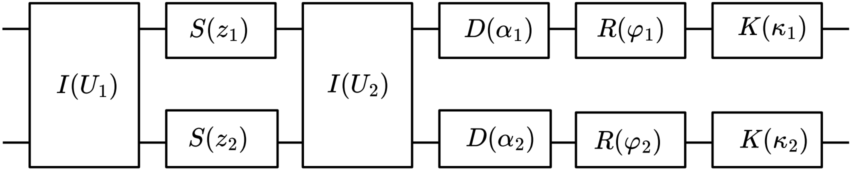

✓ **Pro:** High expressivity, universal

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

Example: Continuous-variable Born machines

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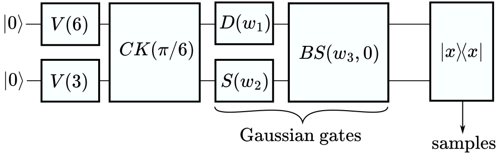
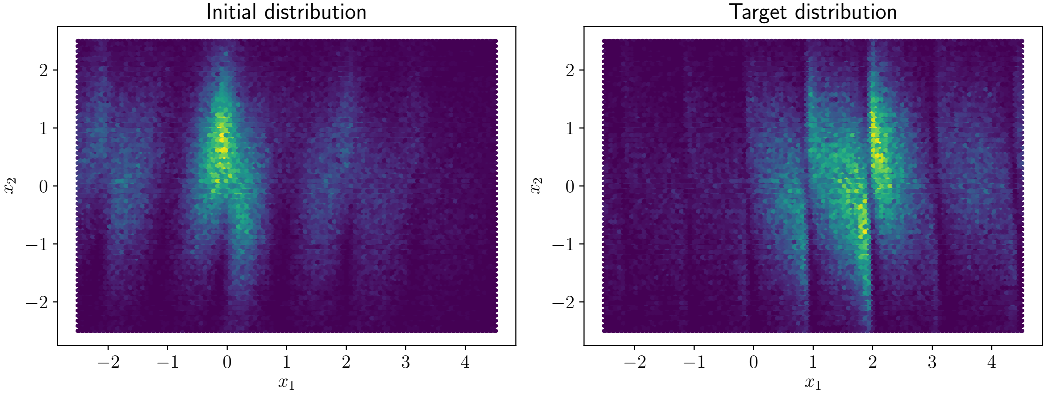
✓ **Pros**: Natural for continuous distributions

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

Example


$|0\rangle$
$|0\rangle$
$V(6)$
$V(3)$
$CK(\pi/6)$
$D(w_1)$
$S(w_2)$
$BS(w_3, 0)$
$|x\rangle\langle x|$
Gaussian gates
samples


Initial distribution
Target distribution
x_1
x_2
−2
−1
0
1
2
3
4

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Challenge: We need to find a "good" observable:

1. Easy to obtain its expectation values classically,
2. Has binary outcomes,
3. Correspond to experimentally feasible detection schemes.

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✓ More realistic experimentally than parity detection
✓ Higher expressivity in some cases

Parity expectation values

The expectation value of the parity operator $\Pi = (-1)^{\sum_i \hat{n}_i}$ can be written as

$$\mathrm{Tr}[\Pi\, \rho] = \left(\frac{\pi}{2}\right)^{d} W_{\rho}(\mathbf{0}) = \frac{\exp\left(-\boldsymbol{\mu}^{T}\Sigma^{-1}\boldsymbol{\mu}\right)}{\sqrt{\det \Sigma}}, \tag{5}$$

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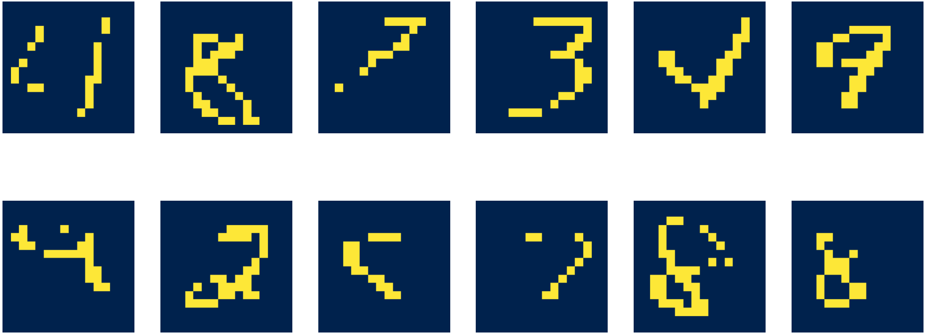
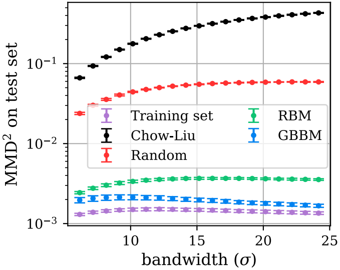
Importantly, expectation values are just the values of the Wigner functions evaluated at the origin $\implies$ **displacements are important!**

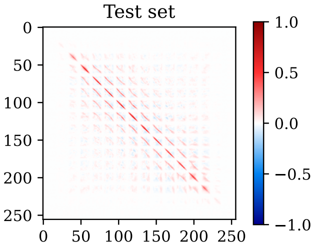
Numerical experiments

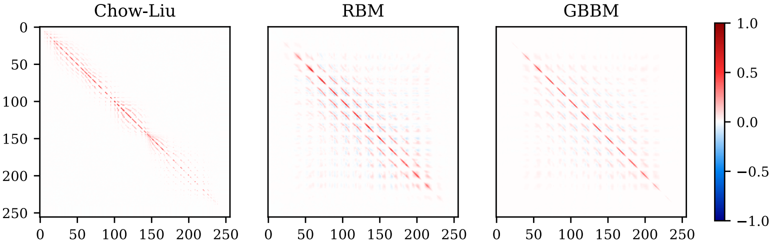
USPS dataset (handwritten digits)



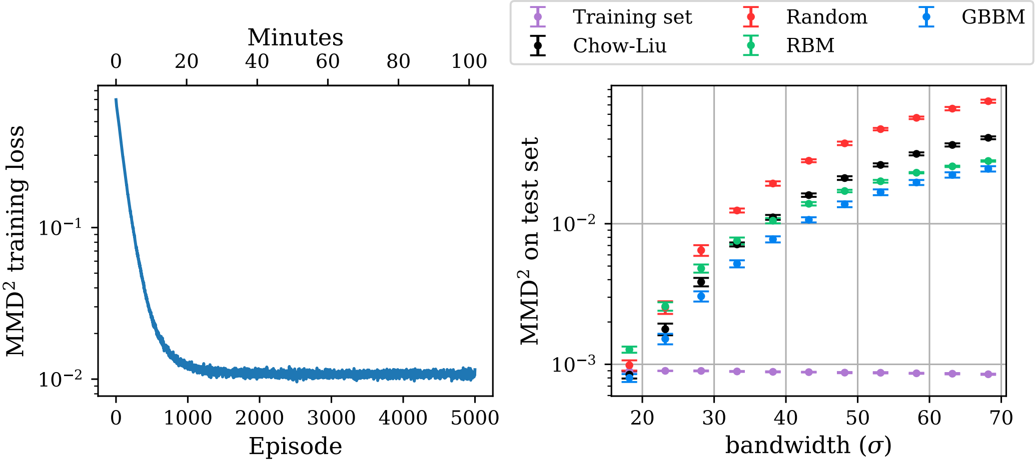
USPS training (256 modes)



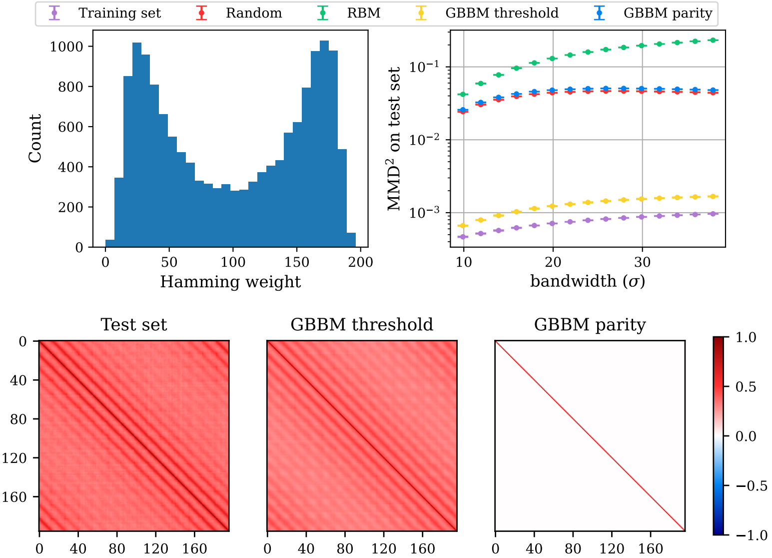




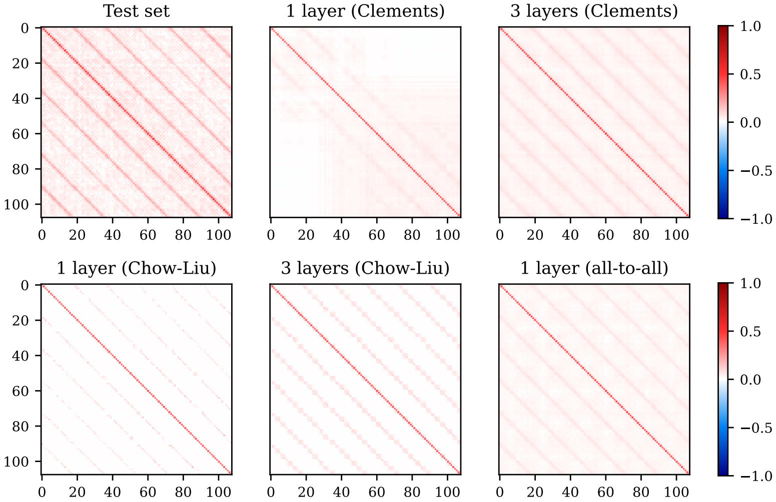
Genomic training (805 modes, over a million trainable parameters)



Training on the Ising dataset using threshold GBBMs



Effect of overparametrization



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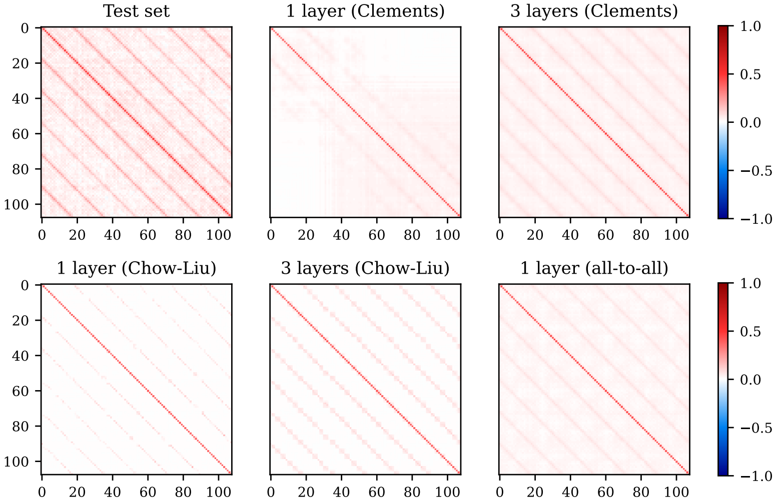

Importantly, we can compress the layers before deployment!

Conclusion and outlook

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- hard classical sampling,
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Further directions:

- non-binary outcomes,
- more expressive observables,
- the addition of non-Gaussianity,
- identifying the boundary between enhanced expressivity and classical intractability.