Quantum Diffusion Models for HEP

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00. Outline

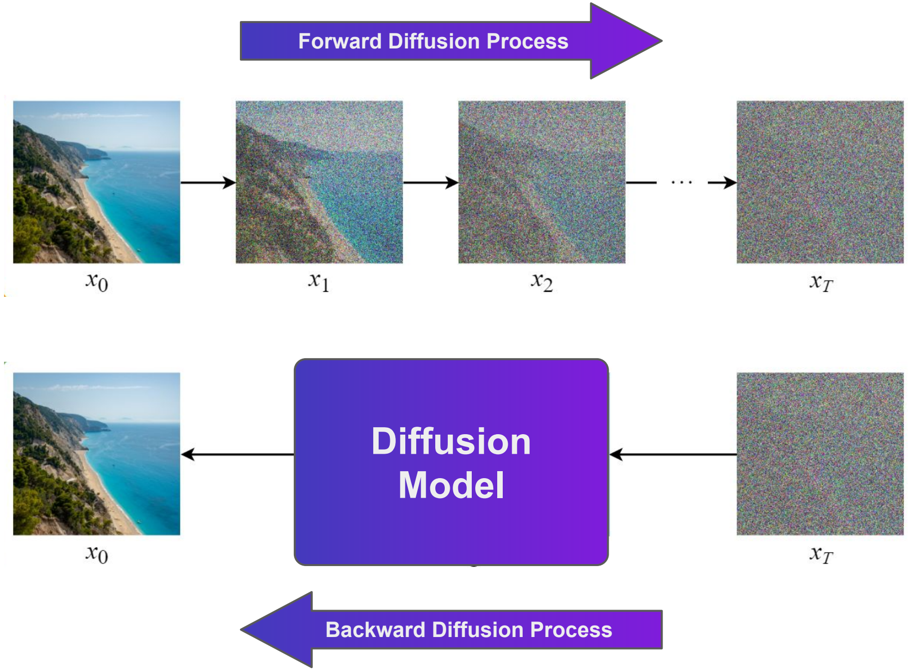
01. Introduction: What is a diffusion model?

- **Unfolding:**
  reconstructing the true particle-level signals from detector-smeared measurements.

- **Generative simulation:**
  Generate new events or shower data fast while consuming less energy.

- **Noise modeling:**
  find an accurate representation of the stochastic processes and uncertainties.

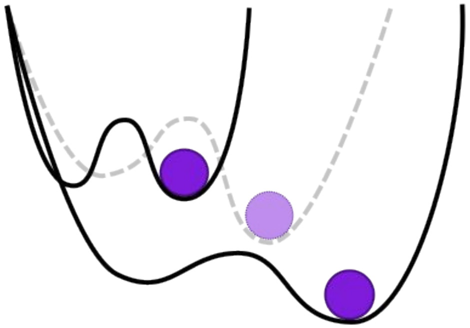
- **Model-to-data comparison:**
  Assessing how well the model reproduces real experimental measurements using robust statistical metrics and posterior analysis.



01. Introduction: Quantum Computing Paradigms

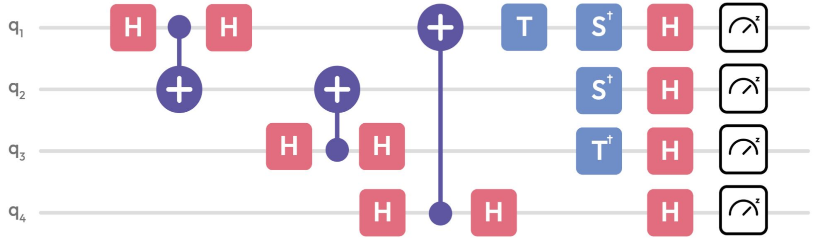
Analog Quantum Computing

- **Encoding**: Hamiltonian
- **Control**: Continuous
- Focuses on **Specific tasks** (could be universal)
- Bypasses Error-Correction needs



Digital Quantum Computing

- **Encoding**: Sequence of Gates
- **Control**: Discrete
- **Universal** General-Purpose Model
- Needs Error-Correction Codes.



01. Introduction: Why Quantum computing for ML?

- Larger Embedding Space:
  - Quantum states live in a 2^n-dimensional Hilbert space with just n qubits.
  - Quantum feature maps act like kernel methods, embedding data in a high-dimensional space.This enhances linearly separating complex patterns, much like SVMs in huge feature spaces.

- Non-Linearities:
  - The quantum system can process the non-linearities of the data, making it easier for classical framework to process this information.

02. Quantum Diffusion Models: State-of-the-Art

Quantum approaches[1,2]:

- Start with a set of quantum states sampled from an unknown distribution.
- Add quantum noise.
- Remove quantum noise using Parameterized Quantum Circuits (PQCs).
- Generate new quantum states that follow the initial distribution.

Hybrid Classical-Quantum approaches[3,4]:

- Embed a quantum layer (PQC) into an existing classical machine learning framework.
- Using quantum layer to improve performance of existing ML algorithms or reduce their number of parameters.

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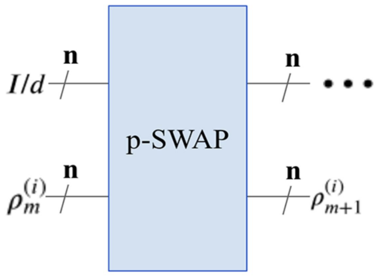
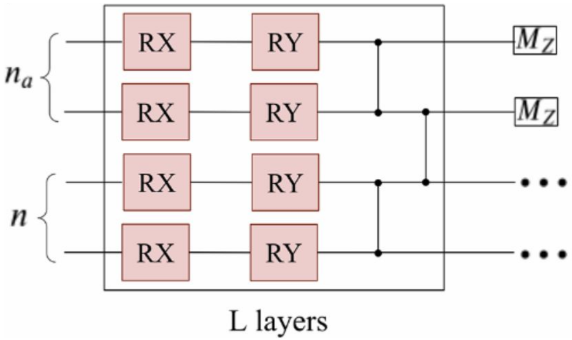
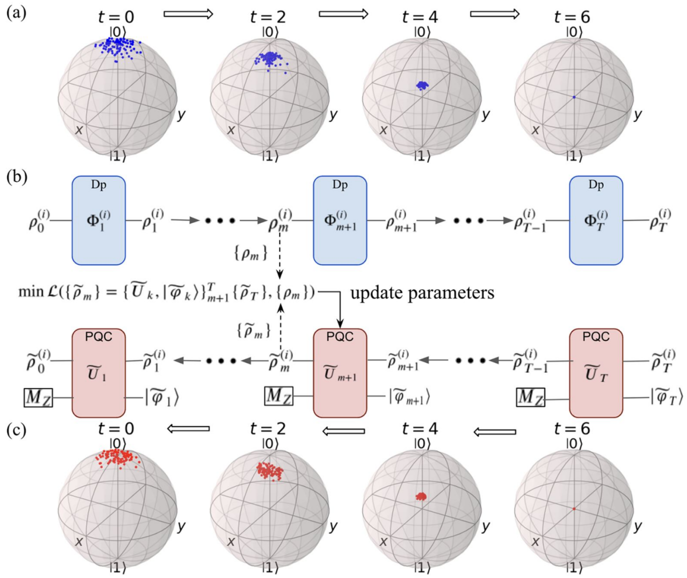
(1) Zhang, Bingzhi, et al. "**Generative quantum machine learning via denoising diffusion probabilistic models.**" Physical Review Letters 132.10 (2024): 100602.
(2) Kwun, Gino, Bingzhi Zhang, and Quntao Zhuang. "**Mixed-state quantum denoising diffusion probabilistic model**." Physical Review A 111.3 (2025): 032610.
(3) Wang, Yunfei, et al. "**Towards efficient quantum algorithms for diffusion probability models.**" arXiv preprint arXiv:2502.14252 (2025).
(4) Kölle, Michael, et al. "**Quantum denoising diffusion models.**" 2024 IEEE International Conference on Quantum Software (QSW). IEEE, 2024.

02. Quantum Diffusion Models: State-of-the-Art



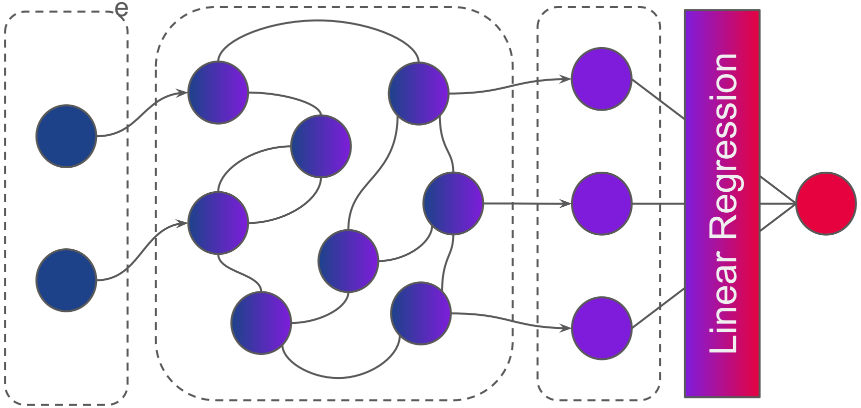




source: Kwun, Gino, Bingzhi Zhang, and Quntao Zhuang. "**Mixed-state quantum denoising diffusion probabilistic model**." Physical Review A 111.3 (2025): 032610.

03. Contributions: Quantum Reservoirs

- Can be used for data embedding (similar to kernel methods).
- Can be used for temporal-series processing (similar to RNNs).
- Uses the quantum system's natural dynamics as a reservoir.
- Captures and processes Complex nonlinear relationships between input information.
- Doesn't require gradient-based training (no barren plateaus)



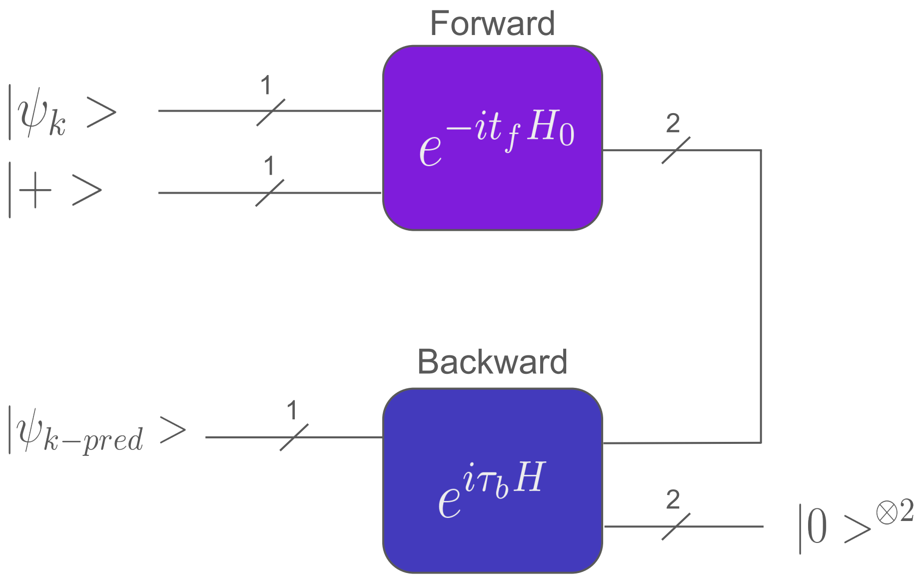
03. Contributions: Reverse Time Evolution

$$H_0 = \sum_{i}^{n} \sigma_i^x \sigma_{i+1}^x + \sigma_i^y \sigma_{i+1}^y + \Delta \sigma_i^z \sigma_{i+1}^z$$

$$\hat{H} = H_0 \otimes I^{\otimes m} + I^{\otimes n} \otimes H_0 + \lambda H_{int}$$

$$\hat{H}_{int} = \sigma_n^x \sigma_{n+1}^x + \sigma_n^y \sigma_{n+1}^y + \Delta \sigma_n^z \sigma_{n+1}^z$$

- **t_f**: forward time evolution.
- **τ_b**: backward time evolution.
- **λ**: coupling strength.
- **m**: number of ancilla qubits.
- **n**: number of input qubits.
- **$|\psi_k>$**: input state encoding the data.
- **$|\psi_{k\text{-pred}}>$**: final state.



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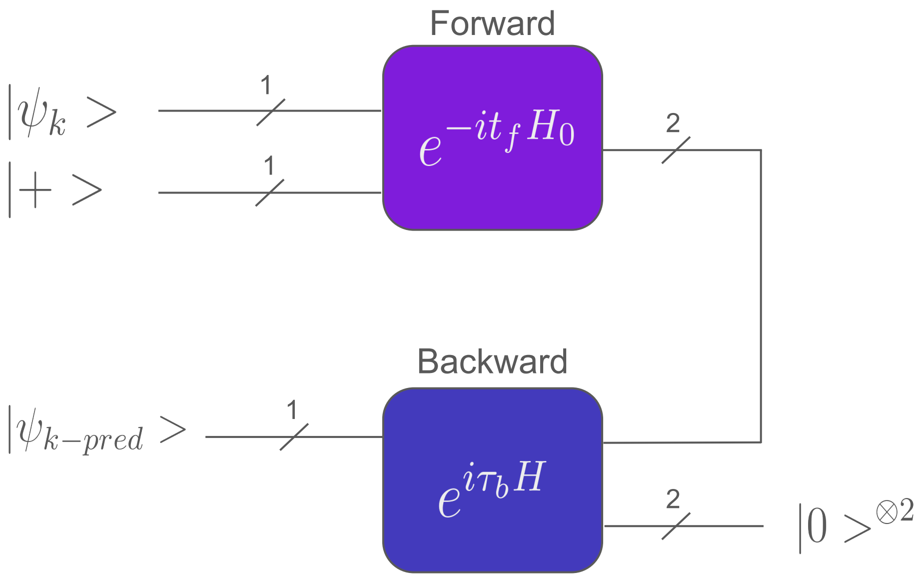
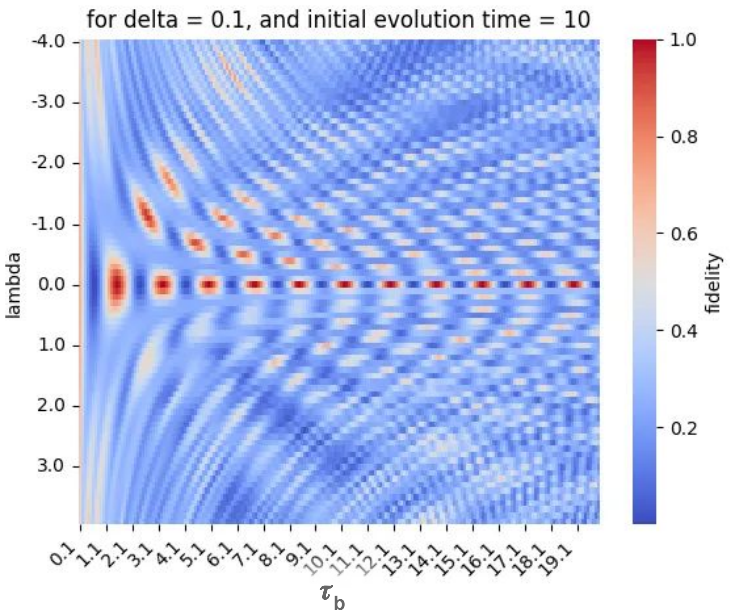
The trivial case:

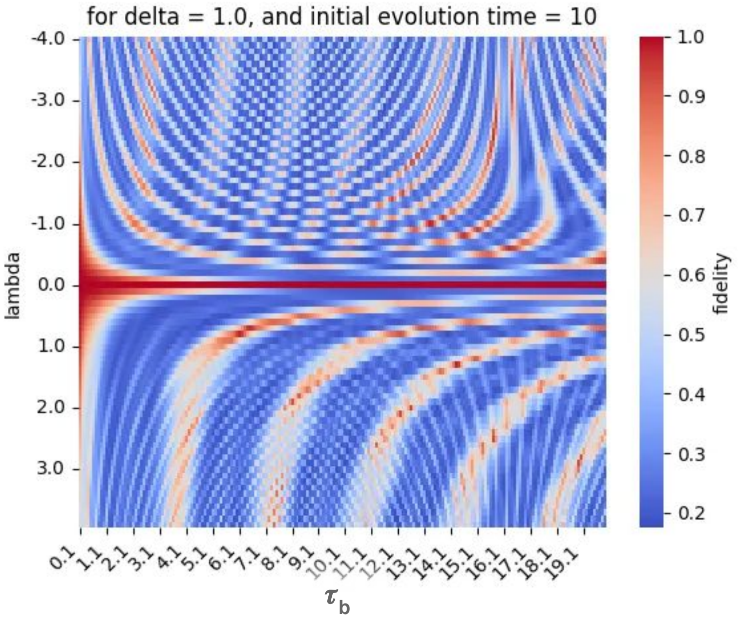
if: $\lambda = 0$ and $\tau_b = t_f$

Then: $|\psi_k> = |\psi_{k\text{-pred}}>$



03. Contributions: Results





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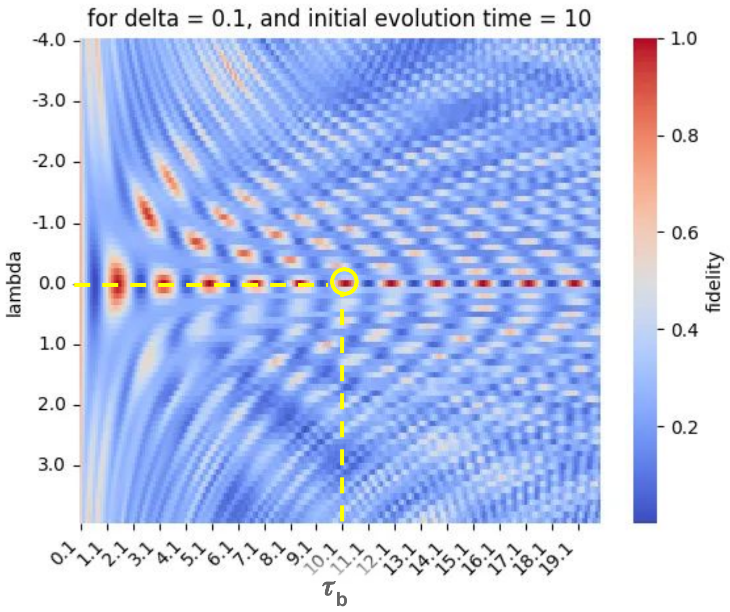
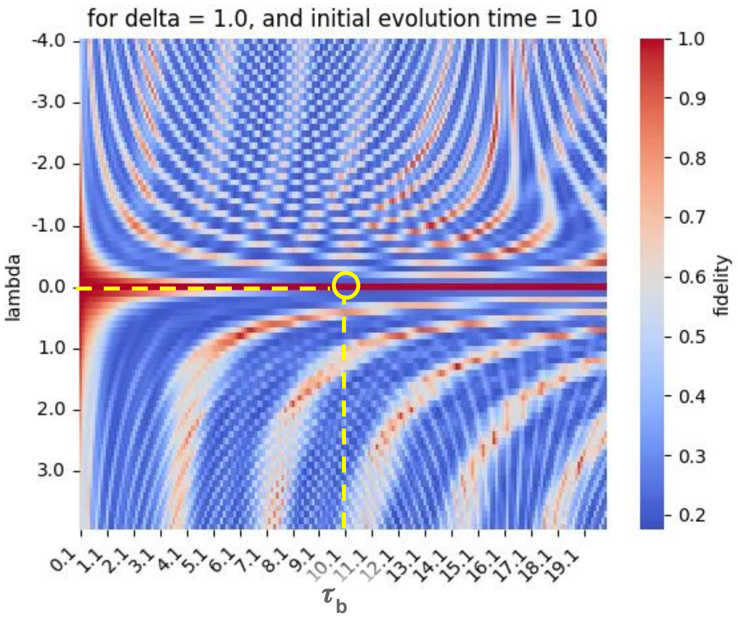
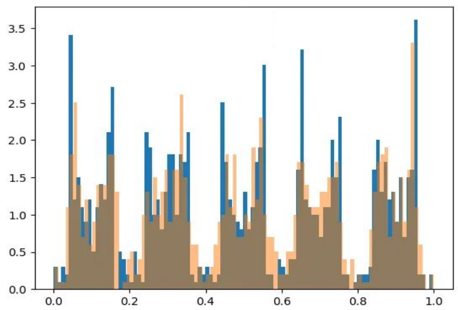


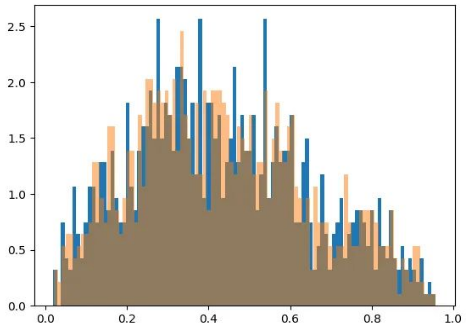


03. Contributions: Results

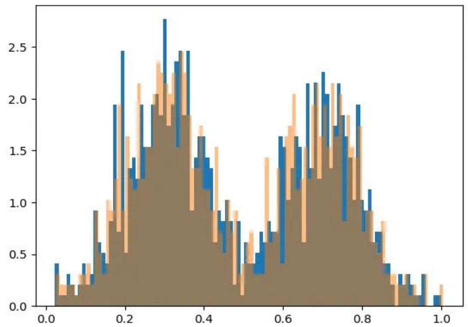
Wootters distance = 0.0142



Wootters distance = 0.0164



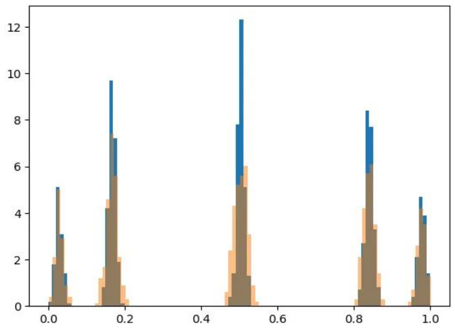
Wootters distance = 0.0154



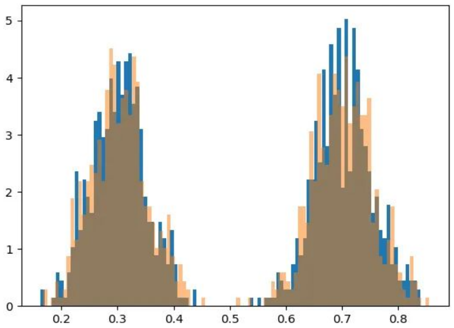
Original Distribution
Reconstructed Distribution

t_f=15 | τ_b=0.1
Δ = 1 | λ=0.7

Wootters distance = 0.0147



Wootters distance = 0.0146



04. Conclusions: Where to go from here?

- We discuss the possibility of using quantum reservoir computing to reconstruct initial data distribution.
  - we show that there are multiple non-trivial cases where the backward time evolution can successfully reconstruct the initial state.

- Current Limitation of the approach is that it requires access to original training samples.

- We are currently working on improving the approach to generate new data without relying on existing training samples.

05. Collaborators

- Qilimanjaro Quantum Tech, Barcelona, Spain:
  - Arnau Riera
  - Marcin Plodzien
- CERN Quantum Technology Initiative, Geneva, Switzerland:
  - Sofia Vallecorsa
  - Michele Grossi
- High-Energy Physics Institute (IFAE) and Universitat Autònoma de Barcelona, Barcelona, Spain:
  - M. Pilar Casado

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Thanks for listening!

06. References for Quantum Reservoir Computing

- Mujal, Pere, et al. "Opportunities in quantum reservoir computing and extreme learning machines." Advanced Quantum Technologies 4.8 (2021): 2100027.
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- Palacios, Ana, et al. "Role of coherence in many-body Quantum Reservoir Computing." Communications Physics 7.1 (2024): 369.
- Mujal, Pere, et al. "Time-series quantum reservoir computing with weak and projective measurements." npj Quantum Information 9.1 (2023): 16.