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Adaptive Polynomial Chaos As Quantum Born Machines for High-Fidelity Generative Modeling

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We present a quantum generative model that extends Quantum Born Machines (QBMs) by incorporating a parametric Polynomial Chaos Expansion (PCE) to encode classical data distributions. Unlike standard QBMs relying on fixed heuristic data-loading strategies, our approach employs a trainable Hermite polynomial basis to amplitude-encode classical data into quantum states. These states are subsequently transformed by a parameterized quantum circuit (PQC), producing quantum measurement outcomes that approximate the target distribution. By using an adaptive polynomial basis and a deeper variational Ansatz, the model maintains the key advantage of QBMs—efficient sampling from quantum-generated distributions—while enhancing expressivity for complex data. We validate this method on electromagnetic shower data from calorimeters, and our results demonstrate its efficacy and potential for broader applications.

Significance

Standard Quantum Born Machines (QBMs) rely on either direct or heuristic data-loading strategies that are fixed in advance. This work introduces a trainable Polynomial Chaos Expansion (PCE) (specifically with Hermite polynomials) to encode classical data into quantum amplitudes.

Typically, polynomial expansions are used classically for uncertainty quantification or dimensionality reduction. Merging them with a quantum circuit to form a generative model is a novel framework. This synthesis of polynomial expansions and quantum transformations provides a pathway to capture non-Gaussian, high-dimensional data more flexibly than existing QBM variants can. While QBMs have been studied on synthetic or low-dimensional data, this work applies the approach to realistic, high-energy-physics data (electromagnetic shower data from calorimeters).Demonstrating non-trivial performance on a domain-specific task strengthens confidence that the proposed model can handle real-world, complex distributions—an important step beyond proof-of-concept toy examples.

The model incorporates a deeper entangling variational circuit, going beyond superficial or low-depth designs. This addresses well-known limitations such as insufficient expressivity and the difficulty of capturing correlations. The synergy between adaptive polynomial encoding and a deeper quantum circuit pushes the boundary on representational power while retaining the hallmark benefit of QBMs: efficient sampling from a quantum-generated distribution.

By generalizing the encoding and the circuit design, the method can be extended to other complex data sets, not just calorimeter simulations. A major criticism of quantum generative approaches is that they often work in narrowly defined settings. Demonstrating a route to broader use—through a systematic polynomial encoding—shows genuine progress rather than a simple iteration.
Taken together, these points illustrate how the project advances beyond a standard QBM or a typical progress report. It introduces new theoretical underpinnings (adaptive polynomial encoding), delves into deeper circuit design, and validates the method on realistic high-energy-physics data, paving the way for broader quantum generative modeling applications.

References

Experiment context, if any

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