

Logic-Inspired Parameterised Quantum Circuits for Quantum Machine Learning

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Parameterized quantum circuits [1, 2] are among the leading candidates for implementing quantum machine learning models. However, it remains unclear under which conditions such models offer useful learning capabilities and how the choice of circuit architecture influences their expressibility, trainability and generalisation.

Motivated by ideas from interpretability [3, 4], NeuroSymbolic AI [5], and fuzzy logic [6, 7], we study a restricted parameterized quantum circuit inspired by logic-based computation. In particular, our model adopts the idea of continuously-valued truth assignments from fuzzy logic, rather than aiming to reproduce the full formal framework. Classical data are encoded using gates of the form $e^{-i \arcsin(\sqrt{x_i})X_i}$, where x_i denotes the i -th input feature and the rotation acts on the corresponding qubit. This encoding has the property that, when applied to the initial state $|0\rangle^{\otimes n}$, the probability of measuring the i -th qubit in the state $|1\rangle$ is exactly x_i . The trainable part of the circuit consists of gates of the form $e^{-i\theta X}$ and nearest-neighbour rotations generated by the CNOT operator, $e^{-i\theta \text{CNOT}}$. At Clifford angles, these operations reduce to classical Boolean logic operations on computational basis states, giving the model a natural logic-inspired structure while allowing continuous-valued inputs and trainable operations.

We investigate how the restrictions imposed by this architecture affect the expressive power, trainability and predictive performance of the resulting quantum machine learning model. In particular, we compare different circuit depths, data re-uploading strategies and entangling structures, and analyse when the trainable controlled operations contribute nontrivially to learning. Through numerical experiments on synthetic and tabular datasets, together with small-circuit analytical studies, we aim to understand which aspects of the circuit are responsible for its learning capabilities and where the limitations of this restricted logic-inspired ansatz arise.

References

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