Learning Algebraic Models of Quantum Entanglement [1]

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Quantum Information and Quantum Computing are two emerging areas of research, and are on their way to revolutionize our conception and implementation of computations. Recently, many efforts were deployed to unite Quantum Information, Quantum Computing and Machine Learning. They have largely been centered on integrating quantum algorithms and quantum information processing into machine learning architectures [2].

Our approach is quite the opposite. We use Machine Learning techniques to study and classify Quantum Entanglement, a key ressource in Quantum Computing. In our work, we train Artificial Neural Networks to learn algebraic varieties, defined by polynomial equations, that characterize and describe different entanglement classes for pure states [3].

Inspired by the work of Breiding *et al.* [4], we focus on determining the membership of a state to an algebraic variety, instead of determining the defining intrinsic equations. By sampling tensors living inside and outside a given algebraic variety, we are able to train ReLU networks to classify such tensors. In the case of varieties defined by homogeneous polynomials, we also design and train hybrid polynomial networks [5].

We give examples for detecting separable states, degenerate states, as well as border rank classification for up to 5 qubits and 3 qutrits.

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