

A Universal Training Algorithm for Quantum Deep Learning

Friday, September 14, 2018 12:05 PM (40 minutes)

In recent months, the field of Quantum Machine Learning (QML) has had numerous advances and a rapid growth of interest from academia and industry alike. Recent works have focused on a particular class of QML algorithms, the so-called quantum variational algorithms (often called quantum neural networks), where an optimization over a set of parametrized quantum circuit ansatzes is performed in order to learn certain quantum states or quantum transformations. The explicit connection between these quantum parametric circuits and neural networks from classical deep learning had so far remained elusive. In this talk, we will establish how to port over classical neural networks as quantum parametric circuits, and we will further introduce a quantum-native backpropagation principle which can be leveraged to train any quantum parametric network. We will present two main quantum optimizers leveraging this quantum backpropagation principle: Quantum Dynamical Descent (QDD), which uses quantum-coherent dynamics to optimize network parameters, and Momentum Measurement Gradient Descent (MoMGrad), which is a quantum-classical analogue of QDD. We will briefly cover multiple applications of QDD/MoMGrad to various problems of quantum information learning, and how to use these optimizers to train classical neural networks in a quantum fashion. Furthermore, we will show how to efficiently train hybrid networks comprised of classical neural networks and quantum parametric circuits, running on classical and quantum processing units, respectively.

Talk based on [arXiv{1806.09729}].

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Session Classification: Session 6