Arbitrary Polynomial Separations in Trainable Quantum Machine Learning

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Quantum mechanical systems naturally exhibit quantum correlations which are difficult to capture classically. Due to this property, there have been many proposals for using quantum systems to construct generative machine learning models capable of sampling from distributions beyond the reach of (efficient) classical models. Unfortunately, recent theoretical results have demonstrated that the resulting models typically take a time to train that is exponential in the associated model size; a corollary of these results is that practical exponential separations in expressive power over classical machine learning models are believed to be infeasible. We here circumvent these negative results by constructing a hierarchy of efficiently trainable QNNs that exhibit unconditionally provable, polynomial memory separations of arbitrary constant degree over classical neural networks in performing a classical sequence modeling task. The classical networks we prove a separation over include well-known examples such as recurrent neural networks and Transformers. We show that quantum contextuality is the source of the expressivity separation, suggesting that other sequence learning problems with similar long-time correlations may be a regime where achievable separations in quantum machine learning may exist. (arXiv:2402.08606).