Towards Localized Surrogate models in Quantum Machine Learning for Cost Optimization and reduced Sample Complexity.

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Abstract:

Surrogate models in machine learning are designed to approximate the performance of a base model within defined tolerance limits, offering a more resource-efficient alternative to larger, more complex models. In quantum machine learning, where quantum advantages are anticipated primarily during the training stage rather than the inference stage, the development of surrogate models for inference tasks is particularly valuable [1]. Current research predominantly focuses on achieving global equivalence between surrogate models and their base counterparts [2][3]. However, our research proposes a shift towards localized surrogate learning, where the surrogate model replicates the performance of the base model on smaller, targeted subsets of data. This approach is expected to reduce resource consumption and sample complexity. We present a framework for Matrix Product State (MPS)-based surrogate models [4], demonstrating their utility in model interpretation [5], alongside a Fourier representation-based surrogate model in conjunction with classical windowing techniques that highlights reductions in resource costs and sample complexity [2]. Our ultimate objective is to analytically establish that localized surrogate models offer significant reductions in sample complexity and resource usage compared to both global surrogate models and the original base models.

Keywords: Quantum machine learning, Interpretability, Sample complexity, Windowing

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