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Quantum advantage without exponential concentration in kernel methods for learning data with group symmetries

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Quantum machine learning (QML) has the potential to outperform classical methods for certain structured data problems. For datasets with specific group structures, quantum kernels have been shown to learn more efficiently than classical approaches. These kernels use unitary representations of groups to construct feature maps that are covariant under group actions, enabling the algorithm to exploit symmetries in the data. They have been demonstrated, both theoretically and experimentally on a 27-qubit superconducting quantum processor, to effectively classify coset-structured data, which remains challenging for classical models unless the symmetry is explicitly encoded.

A significant challenge in QML is the occurrence of barren plateaus, where gradients vanish exponentially with system size, making training infeasible. We prove that kernel-based learning for the aforementioned group-structured problems avoids kernel concentration, ensuring trainability even as system size increases. Since kernel concentration is known to be equivalent to barren plateaus, our result connects to this broader challenge —showing that, contrary to growing skepticism, QML is not dead and trainable quantum models with performance advantages exist under the right conditions.

We introduce covariant quantum kernels tailored for data with an underlying group structure, enabling symmetry-aware quantum learning. Interpreting quantum kernels as variational quantum circuits provides a unifying perspective that connects kernel methods and parameterized quantum models for group-symmetric data. We extend the coset quantum kernel beyond two cosets and analytically show that the variance of the resulting kernels remains non-vanishing even as qubit number increases —our main result —demonstrating that the exponential advantage persists in the large-system limit. Finally, numerical simulations and analysis of bounded noise sources show that the kernels continue to separate data and avoid concentration, enabling symmetry-informed quantum learning on near-term hardware.

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