

The Cross-Kernel Margin: A Robustness Measure for Quantum Kernel Methods *

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Quantum devices in the current Noisy Intermediate-Scale Quantum (NISQ) era are inherently affected by noise [1], which degrades the predictive performance of quantum machine learning models [2]. This motivates the development of theoretical tools for analysing robustness under realistic noise. In this work, motivated by the established links between robustness and generalisation theory [3], we introduce the *cross-kernel margin*, a novel margin-based measure of robustness for Quantum Kernel-Assisted Support Vector Machines (QSVMs). The cross-kernel margin quantifies the alignment between the learned solution of a classifier under noise and the solution obtained in the ideal noiseless setting. We derive analytical upper and lower bounds for the cross-kernel margin, thereby characterising noise-induced margin degradation. These bounds are validated through numerical simulations across multiple datasets and experiments performed on real quantum hardware. We further present empirical results linking margin-based quantities with the generalisation performance of QSVMs, providing additional motivation for our margin-based robustness analysis. Finally, we empirically compare the degradation of the test accuracy obtained under the local depolarising noise model with the widely used global depolarising noise model. Together, these results provide a theoretical framework for analysing the robustness of quantum kernel methods in the NISQ era.

References:

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