

Title

Quantum-Enhanced Topological Data Analysis for Robust Recovery of Cyclic Manifolds

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Abstract

High-dimensional, sparse datasets capturing continuous biological processes, such as the cell cycle, are important for studying cancer progression [1]. However, recovering these cyclic structures from highly stochastic data is a major challenge for classical machine learning. Commonly used metrics, such as Euclidean distance, measure linear paths between data points; what in presence of noise typical for high-dimensional biological data fails to capture the true underlying manifold [2]. Consequently, classical approaches often fail to distinguish genuine periodic signals from structural technical errors.

To address this, we introduce "Q-Cycle," a hybrid quantum-classical pipeline that uses the expressivity of quantum spaces for robust shape recovery. Q-Cycle maps classical features into a quantum space by encoding data into a parameterised quantum circuit via Chebyshev polynomials. Rather than mapping points linearly, this encoding using data re-uploading architecture to unroll data through a non-linear frequency spectrum. This quantum feature space acts as a geometric filter, using the high expressive power of quantum neural networks [4] to stretch the intrinsic cyclic structure while naturally suppressing isotropic background noise.

Unlike standard quantum kernel methods reliant on supervised classification, Q-Cycle is fully unsupervised. To mitigate barren plateaus, it evaluates local Pauli observables to construct a stable, projected quantum similarity matrix. These noise-resilient affinities pass directly into a computational topology pipeline [5], explicitly extracting the global continuous loops of the underlying system.

Benchmarked against empirical single-cell transcriptomic datasets, Q-Cycle successfully isolates sequential states and preserves macro-scale cyclic structures across severe noise thresholds where classical metrics degrade. This research explores a pathway towards demonstrating quantum advantage in high-dimensional representation learning.

References

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