Computational Science II

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Contents

Chapter 1

Introduction

Dequantization, the process of presenting classical counterparts to specific quantum machine learning (QML) algorithms while incurring only a polynomial slowdown, raises questions about the claimed exponential quantum advantage of QML algorithms. At the core of QML and its asserted advantages lies HHL algorithm, developed by Harrow, Hassidim and Lloyd [5]. It's noteworthy that Aaronson [1] critiqued the HHL algorithm for its intricate 'fine print' conditions, which also influence QML algorithms rooted in the HHL approach.

A few years later, Tang [8] dequantified the quantum recommendation algorithm initially proposed by Kerenidis and Prakash [7] with just a polynomial slowdown. This achievement was facilitated by the inherent similarities between quantum techniques, such as 'quantum phase estimation', and classical linear algebra methods, exemplified by techniques like 'ℓ^2-norm sampling through singular decomposition,' introduced several years ago [4].

The central implication of this outcome is that if quantum linear algebra algorithms can be efficiently dequantized, it prompts us to reevaluate the fundamental concept and applicability of the term "quantum" itself concerning algorithms. However, as Cotler, Huang, and McClean [3] assert, such skepticism loses its significance when dequantization is applied to data originating from quantum systems. In cases where classical computation cannot accurately capture experimental quantum data, QML undeniably offers large speedups. Therefore, such doubt may be resolved through the accumulation of an extensive amount of experimental quantum data, often referred as a matter of 'Quantum Random Access Memory' (QRAM). This is the direction of above three with Preskill and others [6] take.

Nevertheless, the uncharted territory at the intersection of quantum linear algebra and classical linear algebra remains an area ripe for exploration. This paper delves with clarity into the historical overview provided above and ultimately underscores its significance by addressing a recently suggested problem on 'classical and quantum singular value transformation' by Bakshi and Tang [2].

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