

Tighter Error Bounds for the qDRIFT Algorithm

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Recent work in quantum simulation has seen the development of several promising randomised algorithms. The qDRIFT algorithm has some beneficial properties, most notably, its favourable scaling as the number of steps required scales independently of the complexity of the system. However, existing error bounds for qDRIFT scale quadratically with the norm of the generator, limiting their efficiency for large-scale closed or open quantum system simulation. In this work [1], we refine the qDRIFT error bound by incorporating Jensen’s inequality and a careful treatment of the integral form of the error. This yields an improved scaling that significantly reduces the number of steps required to reach a fixed simulation accuracy. Our result applies to both closed and open quantum systems. For open systems, it removes the dependence on the maximum diamond norm of the generator terms; for the Hamiltonian (closed-system) case, we further sharpen the bound by evaluating the exact diamond norm of each commutator generator – the spectral spread of the corresponding Hamiltonian term – and by retaining, rather than further bounding, the Jensen mean term, which yields a strictly smaller coefficient in the resulting gate count. To demonstrate the practical impact of this refinement, we apply it to three settings: quantum chemistry simulations, dissipative transverse field Ising models, and Hamiltonian encoding of classical data for quantum machine learning. In each case, our bound leads to a reduction in gate counts, highlighting its broad utility in enhancing randomized simulation techniques.

References

- [1] I. David, I. Sinayskiy, and F. Petruccione, “Tighter error bounds for the qdrift algorithm,” *arXiv preprint arXiv:2506.17199*, 2025.