Four-Qubit Variational Algorithms in Silicon Photonics with Integrated Entangled Photon Sources

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Contents

Optimization Techniques

1. The paper uses both **Gradient Descent**and **Bayesian optimization**
2. But limitations in gradient descent due to **statistical errors and measurement time**
3. The paper could delve deeper into how the hybrid optimization approach

several optimization methods have been explored to enhance performance beyond traditional gradient descent and Bayesian optimization

Quantum Natural Gradient Optimization[1]

It accounts for the intrinsic curvature of the quantum state space. Unlike standard gradient descentwhich treats the parameter space. It can achieve faster convergence and avoid local minima more effectively.
steepest descent in the curved manifold:

$$\theta_{t+1} = \theta_t - \eta G^{+}(\theta_t) \nabla f(\theta_t) \tag{1}$$

$G^{+}(\theta_t)$: the pseudoinverse of the QGT at the current parameters θ_t,

[1] Stokes et al. 2020.

Conditional Value-at-Risk (CVaR) Optimization[2]

It modifies the aggregation function in optimization to focus on the tail of the distribution, potentially leading to faster convergence in variational quantum optimization.
Studies have shown that CVaR optimization can outperform traditional methods in certain combinatorial optimization problems.

[2] Uryasev 2000.

Scalability

1. The complexity of increasing qubit dimensions and the associated challenges could be better elaborated
2. For instance, how do the experimental setups scale for larger quantum problems?

Wang et al. have integrated more than 550 quantum optical components and 16 photon sources on a state-of-the-art single silicon chip[3]

[3] Wang et al. 2018.

Error Mitigation

We can work deeper on statistical errors and quantum projection noise a new solution known as parameter shift rule . Very recently, this technique has been reported also for VQAs implemented on PICs[4]

In the NISQ scenario, the system noise and the sample error forbid the acquisition of the analytic gradients.
Instead, the classical optimizer can only collect the estimated gradients. More precisely, suppose that the depolarization noise channel $\mathscr{N}_p(\cdot)$ is injected to each quantum circuit depth, i.e.

$$\mathscr{N}_p(\rho) = (1-p)\rho + p\frac{\mathbb{I}}{2^N} \tag{2}$$

[4] Li et al. 2017.

Distribution Technique

We can use distribution technique on quantum computing, which can reduce the cost time.[5]
Marry the distributed techniques with VQAs, could substantially contribute to use NISQ machines to accomplish real-world problems with quantum advantages

[5] Du, Qian, and Tao 2021.

Loss

Paper discusses insertion losses and their impact on photon pair generation and computational time. It might be useful to provide suggestions on how to mitigate these losses

- Here are some ways

Zero-Noise Extrapolation (ZNE)[6]

ZNE involves amplifying the noise in quantum circuits and then extrapolating the results to estimate the ideal, noise-free outcome. This method is particularly useful for mitigating errors in estimating expectation values of observables.

[6] Giurgica-Tiron et al. 2020.

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