25-1 QIYA IBM Learning Course

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QIYA

Introduction

- This poster presents the results of the 2025-1 QIYA (Quantum Informatics at Yonsei Academy) IBM Learning Course team project.
- We explored quantum computing topics such as VQA, VQE, VQD, QML, and QSR, based on materials from the IBM Learning Course[3].
- This poster highlights our implementation of variational quantum algorithms (VQAs) and explores advanced techniques such as Quantum Fisher Information analysis, Quantum Sampling Regression using Gaussian Processes, and surrogate-based optimization.
- The full source code and results are available on our GitHub repository.

Variational Quantum Algorithm

- **Variational Quantum Algorithm (VQA)** is a hybrid approach that combines classical and quantum computing using variational methods.
- The typical workflow of a VQA includes the following steps:

step 1 **Initialize the problem**

step 2 **Prepare the ansatz**

$$\begin{aligned} |0\rangle \xrightarrow{U_R} U_R|0\rangle = |\rho\rangle &\xrightarrow{U_V(\vec{\theta})} U_A(\vec{\theta})|0\rangle \\ &= U_V(\vec{\theta})U_R|0\rangle \\ &= U_V(\vec{\theta})|\rho\rangle \\ &= |\psi(\vec{\theta})\rangle \end{aligned} \tag{1}$$

step 3 **Evaluate cost function**

$$\langle \hat{\mathcal{H}} \rangle_{\psi} := \sum_{\lambda} p_{\lambda}\lambda = \langle \psi | \hat{\mathcal{H}} | \psi \rangle \tag{2}$$

step 4 **Optimize the parameters to obtain results**

$$\vec{\theta}_{t+1} = \vec{\theta}_t - \eta \nabla \mathcal{C}(\vec{\theta}) \tag{3}$$

Quantum Fisher Information

- The **Quantum Fisher Information Matrix (QFIM)**[4] is the quantum counterpart of the classical Fisher information matrix. It quantifies how much information an observable random variable X carries about an unknown parameter θ in the distribution that models X.

$$\mathcal{F}_{ij} = 4\,\mathrm{Re}\Big[\langle \partial_i \psi(\boldsymbol{\theta}) | \partial_j \psi(\boldsymbol{\theta}) \rangle - \langle \partial_i \psi(\boldsymbol{\theta}) | \psi(\boldsymbol{\theta}) \rangle \langle \psi(\boldsymbol{\theta}) | \partial_j \psi(\boldsymbol{\theta}) \rangle \Big] \tag{4}$$

- **FAdam**[2] is an optimizer based on the Fisher information, often referred to as the natural gradient. In this project, we investigated a quantum version of FAdam.

$$\vec{\theta}_{t+1} = \vec{\theta}_t - \eta\, \mathbf{F}^{-1} \nabla \mathcal{L}(\theta) \tag{5}$$

Implementation

We implemented a variational eigensolver using the Quantum Sampling Regression (QSR) framework in combination with a Gaussian process-based surrogate model.

Ansatz `TwoLocal(ry, entanglement=cz)`
Observable Arbitrary Hermitian operator
Sampling Sobol sequence (quasi-random sampling)
Surrogate Gaussian process regression

Quantum Sampling Regression

- **Quantum Sampling Regression (QSR)**[5] is a variational algorithm that approximates a reference function using sampled parameter values.
- As the number of variational parameters increases, the number of required samples grows exponentially. Therefore, QSR is generally not efficient when used with high-dimensional ansätze.
- For sampling, we use **Sobol sequences**[6], which are a type of quasi-random low-discrepancy sequence.

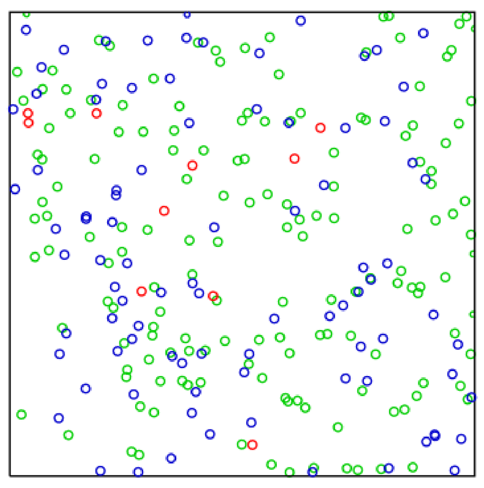

Fig. 1: Pseudorandom

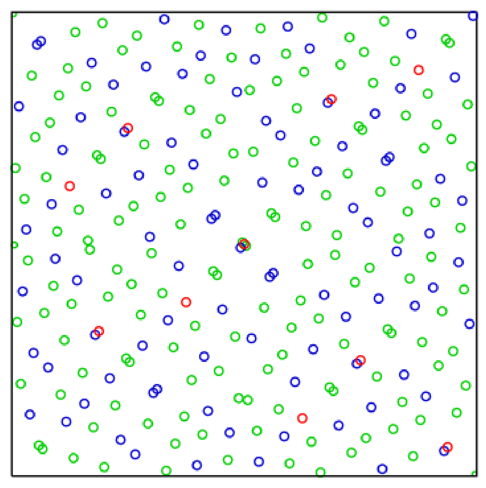

Fig. 2: Sobol sequence (quasi-random)

Gaussian Process

- A **Gaussian Process (GP)**[1] is a nonparametric supervised learning method commonly used for regression and probabilistic classification tasks.
- A GP defines a distribution over functions, assuming that any finite set of function values follows a multivariate normal distribution. This makes GPs useful for modeling uncertainty and performing function approximation, especially with limited data.

$$\mathbb{E}\left[e^{i\mathbf{s}^T(\mathbf{X}-\boldsymbol{\mu})}\right] = e^{-\frac{1}{2}\mathbf{s}^T\boldsymbol{\Sigma}\mathbf{s}} \tag{6}$$

$\mathbf{X} \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$ Multivariate normal distribution (vector form)
$\boldsymbol{\Sigma}$ Covariance matrix
$\mathbf{s} \in \mathbb{R}^n$ Coefficient vector

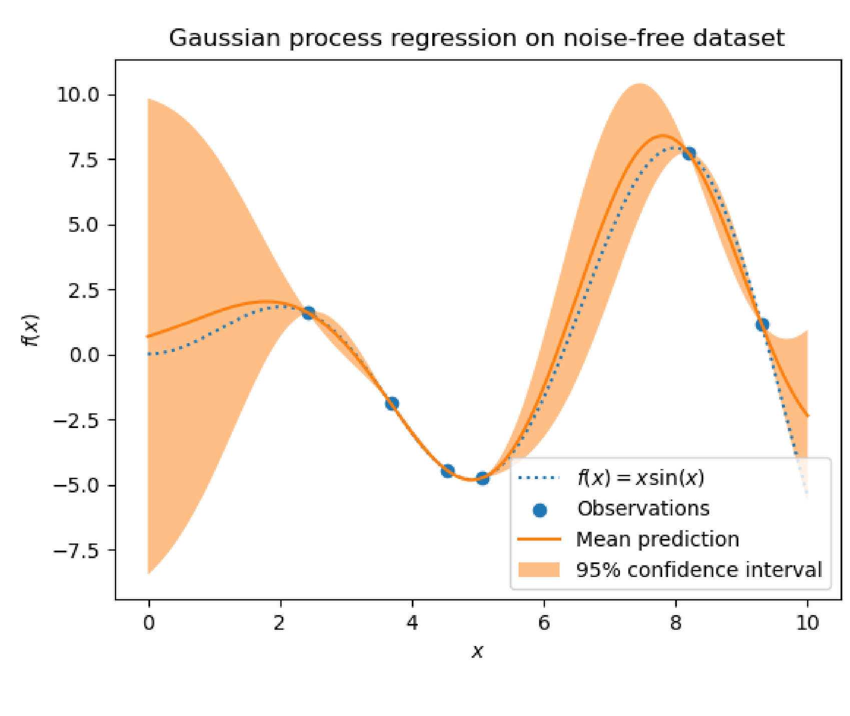

Fig. 3: Gaussian process

Result

- In terms of computational cost, the surrogate model is significantly cheaper than direct quantum evaluations in the NISQ era. Only a single quantum computation of steady-state observables is required, after which the surrogate model can be reused.
- The number of required samples when using Sobol sequences is a power of 2, i.e., 2^{param}, where *param* denotes the number of parameters. However, achieving higher resolution may require even more samples.

Post Project

QFIM-based sensitivity analysis, natural gradient optimization. Diffusion-inspired error-aware learning using inherent NISQ noise. Toward noise-leveraged quantum error mitigation.

References

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[3] *IBM Quantum Learning: Variational Algorithm Design*. URL: https://learning.quantum.ibm.com/ (visited on 06/12/2025).

[4] Johannes Jakob Meyer. "Fisher Information in Noisy Intermediate-Scale Quantum Applications". In: *Quantum* (2021). URL: https://quantum-journal.org/papers/q-2021-09-09-539/.

[5] Pedro Rivero, I. Cloet, and Z. Sullivan. "An optimal quantum sampling regression algorithm for variational eigensolving in the low qubit number regime". In: 2020. DOI: 10.26226/morressier.5fa409874d4e91fe5c54b993.

[6] *Sobol sequence*. URL: https://en.wikipedia.org/wiki/Sobol_sequence (visited on 06/12/2025).

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