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EDITORIAL

Recent progress and perspectives on quantum computing for finance

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1 Introduction

Quantum computing has attracted wide attention from both industry and academia for its promising perspective of surpassing classic computing in terms of efficiency and interpretability. In recent years, a lot of promising quantum algorithms have been proposed, leading to revolutionary theoretical and experimental results in many fields, especially in finance. In this article, we provide a broad overview of quantum computing for financial applications. Concretely, we review quantum optimization and show how quantum adiabatic computation can be adapted to solve financial problems. We also summarize the quantum stochastic modeling techniques, particularly the quantum Monte Carlo method, which is useful in derivative pricing and risk assessment. Additionally, we discuss that quantum machine learning is expected to boost financial big data analysis, where the training efficiency of the model is significantly better than that of the classical model, making it more suitable to meet the need for financial institutions to offer new big data- driven services aligning with diverse consumer behavior. Finally, we outlook directions for future trends and hope that it can inspire more in-depth research.

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2 Current techniques of quantum computing for finance

In this section, we provide the background and specific applications of quantum computing in finance.

2.1 Quantum optimization

Optimization problems, especially combinatorial optimization problems, are at the core of many financial problems [1]. For example, the portfolio optimization problem is to find the optimal asset investment allocation to maximize expected returns within bearable market risks [2]. There are many conventional optimizers designed to handle these problems. However, most financial optimization problems are NP-hard. As the number of variables (assets) to be optimized increases, the conventional optimizers will become impractical due to the longer optimization time and the increasing risk of falling into the local minima. Fortunately, quantum computing is expected to provide a new paradigm to handle combinatorial optimization problems, making it possible to find better solutions while reducing optimization time [3]. At the heart of quantum optimization is a method known as adiabatic quantum computation [4]. According to the adiabatic theorem [5], a quantum system can evolve to a different ground state that is dictated by the target Hamiltonian by starting it off with a simple low-energy ground state and gradually changing the Hamiltonian. Therefore, if we encode the original optimization problem into the target Hamiltonian and evolve the quantum system in an adiabatic way, the (approximate) solution of the problem will be encoded into the final quantum state. Quantum annealing is the physical process of implementing an adiabatic quantum computation [6]. This process is similar to classical or simulated annealing [7], where thermal fluctuations allow the system to accept worse solutions with a certain probability in order to expand the search space. The system tends to leave the local minima and move toward the global minima as the temperature slowly drops. It is demonstrated that the quantum annealing process explores the landscape of local minima more efficiently than thermal noise, especially when the energy barriers are tall and narrow [8]. Apart from quantum annealing, quantum approximate optimization algorithm (QAOA) [9] is another quantum algorithm that attempts to solve such combinatorial problems using a gate-model quantum computer. Recent work shows that QAOA is capable to solve financial optimization problems such as portfolio optimization [10], and crisis prediction [11] with reduced computational resources compared to classic algorithms.

2.2 Quantum stochastic modeling

Financial markets typically undergo unpredictable occurrences, which are usually difficult to characterize by determined models [12]. To effectively describe these uncertainties, stochastic modeling is explored to help make investment decisions, usually with a goal of maximizing return and minimizing risks. Monte Carlo is one of the numerical analysis-based techniques used in finance to estimate the impact of uncertainty on financial items [13]. In finance, the stochastic approach is typically used to simulate the effect of uncertainties affecting the financial object in question, which could be a stock, a portfolio, or an option. This makes Monte Carlo methods applicable to portfolio evaluation, personal finance planning, risk evaluation, and derivatives pricing [8]. However, if we want to obtain the expected value of an element from a complex distribution with high-dimensional variables with a small error, the number of simulations of Monte Carlo will become astronomical. To overcome this problem, Quantum Monte Carlo has been shown to offer up to a quadratic speedup over the performance of its classical counterpart [8]. Retrospecting quantum mechanics, measuring the quantum state can be viewed as a natural sampling process. By evolving the quantum system via an elaborately designed oracle, the distribution to be sampled is encoded into the amplitude of the quantum wave function, and then the expected value is directly obtained through the measurement. In practice, Quantum Monte Carlo has been successfully used in derivative pricing [14] and risk analysis [15], leading to the same prediction accuracy while reducing the sampling frequency.

2.3 Quantum machine learning

With the continuous expansion of financial historical data and the increasing requirements of consumers for personalized consumption and financial management, data-driven financial services have become the development trend of the financial service industry in the future [16]. Machine learning is a powerful tool that captures properties from data and use a set of general architectures to solve a variety of problems [17]. It is demonstrated that applying machine learning methods to financial problems can produce more useful results than standard methods [18]. As proof, it is now possible to train sophisticated models to identify patterns in stock markets, identify outliers and anomalies in financial transactions, automatically classify and categorize financial news, and optimize portfolios thanks to advances in machine learning and rich historical financial data [12]. However, the main obstacle is that traditional machine learning models are difficult to train. At the same time, as the amount of data and the complexity of the model increase, it will become more and more difficult to store data and models on a resource-limit classic system. Remarkably, quantum machine learning shines itself to tackle many financial problems while improving training efficiency and reducing storage space. For example, IBM presents experimental results of quantum risk analysis on a real quantum computer [15]. The authors of [19] propose to use quantum neural networks to process financial time series and make predictions for future stock prices. It is notable that while many quantum machine learning algorithms have the potential to surpass their classical counterparts, many of them require operations on a large-scale fault-tolerant quantum computer [20]. We believe that with the continuous improvement of the scale and reliability of quantum devices, quantum machine learning for finance will be truly implemented in practical applications soon.

3 Outlook of quantum computing for finance

Though quantum computing has proven its potential in handling various financial problems, challenges still exist due to the restricted scale of current quantum computational devices and the lack of a general design framework for quantum algorithms. We outlook two directions for future research.

3.1 Cooperation with classical computers

In the NISQ era, quantum-assisted classical computing is thought to be the most promising strategy [21]. However, the essential building blocks of quantum computing differ fundamentally from those of classical computing. A classical algorithm cannot be directly ported to work on a quantum computer. To reveal the computational benefits of quantum computing in finance, a bridge between classical and quantum algorithms must be built.

3.2 Computational efficiency

Most financial issues have tremendous computational complexity, such that many academics are hoping that quantum computing's acceleration capabilities would help. However, the computational complexity of a problem is not a guarantee that quantum computing can make a difference [12]. To better grasp the special benefits of quantum computing, more study is required to ascertain the true reasons for the acceleration impact of quantum computing and to identify the quantum algorithms that suitably fit financial applications.

4 Conclusion

In this paper, we review several applications where quantum computing has the potential to disrupt finance. We warn readers that while quantum computing offers significant computational benefits, these benefits would not be felt until large-scale quantum hardware is made available. It is also necessary to ingeniously transform financial problems into a form that can be solved by quantum computing. We would expect that the advancement of quantum hardware and quantum algorithms will result in more creative financial solutions.

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