QuantAgents: Towards Multi-agent Financial System via Simulated Trading

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Abstract

In this paper, our objective is to develop a multi-agent financial system that incorporates **simulated trading**, a technique extensively utilized by financial professionals. While current LLM-based agent models demonstrate competitive performance, they still exhibit significant deviations from real-world fund companies. A critical distinction lies in the agents' reliance on "post-reflection", particularly in response to adverse outcomes, but lack a distinctly human capability: long-term prediction of future trends. Therefore, we introduce **QuantAgents**, a multi-agent system integrating simulated trading, to comprehensively evaluate various investment strategies and market scenarios without assuming actual risks. Specifically, QuantAgents comprises four agents: a simulated trading analyst, a risk control analyst, a market news analyst, and a manager, who collaborate through several meetings. Moreover, our system incentivizes agents to receive feedback on two fronts: performance in real-world markets and predictive accuracy in simulated trading. Extensive experiments demonstrate that our framework excels across all metrics, yielding an overall return of nearly 300% over the three years (`https://quantagents.github.io/`).

1 Introduction

In the data-driven era, the ascendancy of artificial intelligence has sparked transformative changes within the financial area (Kou et al., 2019). Advancements in large language models (LLMs), notably exemplified by systems like FinGPT (Yang et al., 2023a) and FinReport (Li et al., 2024), are significantly elevating the automation and intelligence levels in financial analysis and decision-making. These frameworks not only enhance the scope and profundity of financial analysis but also facilitate the generation of comprehensive financial reports. Particularly noteworthy are LLM-based agent systems such as FinAgent (Zhang et al., 2024), which possess the capacity to emulate human decision-making processes. These systems demonstrate prowess in iterative self-improvement via tools, memory, and reflection capabilities, thereby enabling them to execute intricate financial operations adeptly (Yang et al., 2023b).

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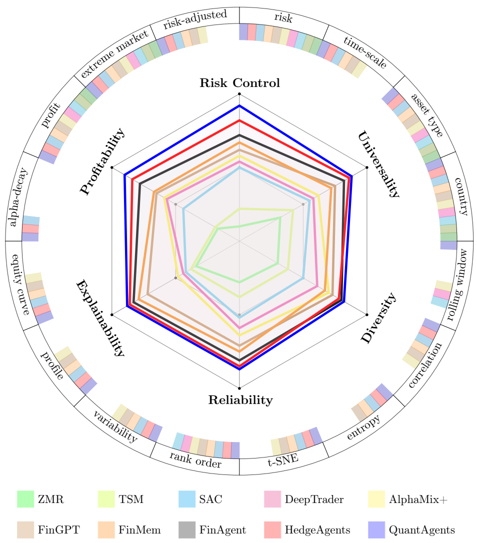

Figure 1: Our method has surpassed all baselines on the PRUDEX (Sun et al., 2023a) benchmark.

However, despite the strong performance of these agent-based systems in evaluations, significant disparities persist between their operational pipeline and those of real-world fund companies. A critical distinction lies in the agents' reliance on "post-reflection", where thinking and learning occur after events, particularly in response to adverse outcomes (Yang et al., 2023b; Park et al., 2023). While this approach aids in learning from past errors, it overlooks a distinct human capability: *long-term prediction of future trends*. This prediction and response to future events are pivotal in financial markets (Buz and de Melo, 2023). Financial practitioners recognize that while

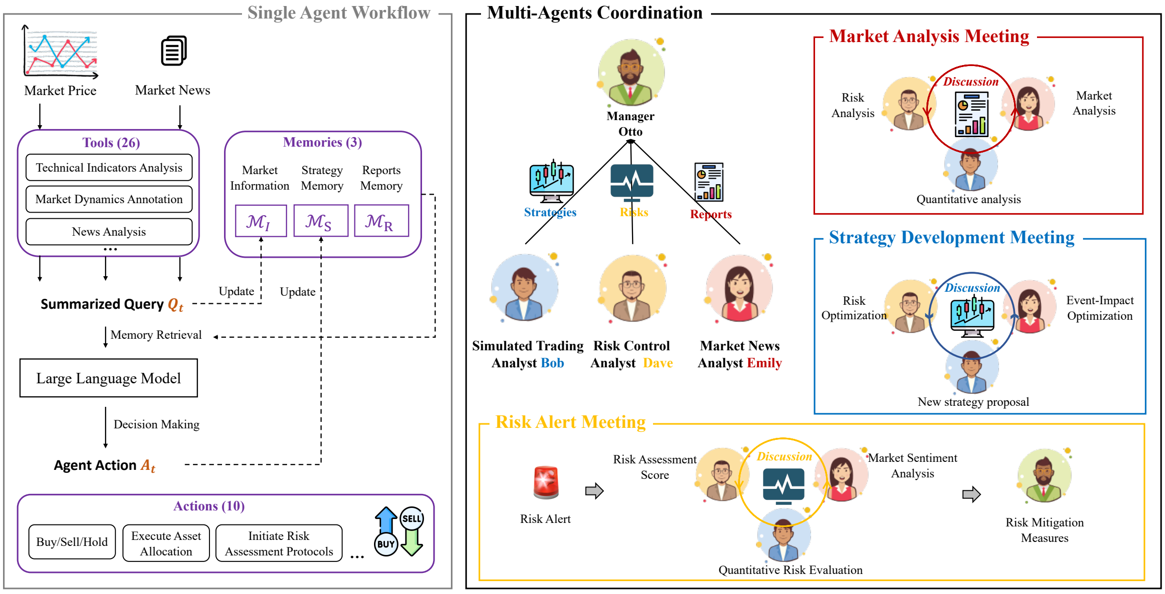

Figure 2: The workflow of QuantAgents, which is equipped with 26 tools, 3 types of memory to execute 10 actions. Furthermore, three meetings, i.e., market analysis, strategy development, risk alert meeting will assist in decision-making (e.g., buy).

market fluctuations are frequently unpredictable, sound investment decisions hinge on forward-looking market analysis. Consequently, **simulated trading** serves as an invaluable predictive instrument widely embraced by financial experts, augmenting their daily operations. This tool enables practitioners to experiment with diverse investment strategies devoid of actual risks, thereby enhancing their comprehension to market dynamics.

Therefore, this paper introduces an innovative multi-agent financial system named **QuantAgents**, designed to achieve long-term forecasting by simulated trading. This system not only learns from actual market but also anticipates and adjusts to market fluctuations through virtual trading environments. Specifically, QuantAgents comprises four agents: a simulated trading analyst, a risk control analyst, a market news analyst, and a manager, who collaborate through several meetings. Moreover, this system incentivizes agents to receive feedback on two fronts: performance in real markets and predictive accuracy in simulated trading. This dual reward mechanism aims to encourage agents to make more precise and forward-thinking decisions in intricate and dynamic financial markets. Through this approach, we hope narrow the gap between LLM-based agents and human financial experts, offering fresh perspectives and tools for advancing the financial industry in the future.

- To the best of our knowledge, this paper represents the first endeavor in developing a multi-agent financial trading system integrated with simulated trading, configured similarly to that of human quant traders.

- We design a dual reward mechanism to coordinate agent behaviors, i.e., rewards from the real market and rewards from simulated trading. In this way, agents are encouraged to make more forward-looking decisions within the complex and dynamic financial markets.

- Extensive experiments demonstrate that our framework excels across all metrics, yielding an overall return of nearly 300%. Meanwhile, we will release all datasets and codes for the convenience of the research community[1].

2 Related Work

2.1 LLM-based financial system

Quantitative finance is an interdisciplinary field that integrates finance with mathematical and statistical methods to address complex financial challenges (Kou et al., 2019; Kanamura et al., 2021). With the advent of large language models (LLMs), an increasing number of researchers are leveraging cutting-edge technologies in finance. Yang et al. (2023a) proposed FinGPT, which enables a thorough understanding of financial events and facilitates news analysis. Li et al. (2024) introduced FinRport, a framework that

[1]https://quantagents.github.io/

amalgamates diverse information to generate comprehensive financial reports on a regular basis. Compared to conventional models (Yu and Yuan, 2011; Wang et al., 2021a), these LLM-based approaches improve the accuracy and efficiency of market forecasting. However, these methods have yet to be fully learn from real-world fund companies, and essential components such as simulated trading have not been included.

2.2 Multi-Agent Framewrok

LLM-based agent systems, leveraging their cognitive and generative capabilities, have the ability to perform a range of complex tasks, including knowledge integration, information retention, logical reasoning, and strategic planning (Sumers et al., 2023; Pan and Zeng, 2023; Chen et al., 2025; Gu et al., 2025). Furthermore, initiatives based on multi-agent systems, such as "The Sims" from Stanford University (Park et al., 2023), have demonstrated the formidable power of collective intelligence. Through the collaboration of multiple agents, multi-agent systems are expected to make significant contributions in fields such as finance (Zhang et al., 2024), offering innovative approaches and sophisticated solutions for complex challenges (Hong et al., 2023; Wu et al., 2023).

3 Proposed Method

3.1 Preliminaries

QuantAgents is a multi-agent system designed to manage a fund company operating with NASDAQ-100 index components[2]. The inputs for this system include financial data such as stock prices, financial news, and company financial reports, which guide the execution of trading actions in both simulated and real-world environments.

3.2 Overall Framework

QuantAgents comprises four specialized agents, each contributing to different aspects of fund management, as presented in Table 1. These agents collaborate by participating in various meetings to assist manager Otto in decision-making. Among these meetings, market analysis meetings are held weekly to produce market reports, while strategy analysis meetings also occur weekly, focusing on enhancing investment strategies through simulated trading. Additionally, risk alert meetings are convened are triggered as needed.

[2]https://www.nasdaq.com/solutions/nasdaq-100

Table 1: QuantAgents comprises four agents.

Agent	Profession	Responsibility
Otto	Manager	Executes Decisions
Bob	Simulated Trading Analyst	Testing Strategies
Dave	Risk Control Analyst	Evaluates Risks
Emily	Market News Analyst	Provides Reports

3.3 Definitions of Single Agent

3.3.1 Tools.

Each agent in QuantAgents is equipped with a set of financial analysis tools $\mathcal{T}$, comprising 26 distinct tools such as Technical Indicator Analysis, News Event Extraction, and Portfolio Stress Testing[3].

3.3.2 Actions.

Each agent is defined by a detailed profile that specifies its description and permissions, ensuring a well-defined operational scope. The actions $\mathcal{A}$ include 10 types, such as Buy, Sell, and Hold. Each agent's profile specifies its description and permissions, defining its operational scope.

3.3.3 Memories.

The memory system $\mathcal{M}$ of each agent consists of three types: Market Information Memory ($\mathcal{M}_I$), which stores historical data including stock prices, financial news, and economic indicators; Strategy Memory ($\mathcal{M}_S$), which contains analysis of strategies in both simulated trading and real-world trading; and Report Memory ($\mathcal{M}_R$), which comprise in-depth analyses of markets, industries, and companies.

3.3.4 Single Agent Workflow.

Our QuantAgents employs a reflection-driven decision-making process, integrating LLM-based agents into a reinforcement learning framework. This workflow includes memory retrieval, decision making, and reflection update.

Firstly, we retrieve reliable experiential memories to augment decision-making. At time step t, a summarized query Q_t is compiled from inputs (e.g., stock prices, financial news) and used to retrieve $K = 10$ similar cases $\mathcal{M}_{ret}$ from the memory set $\mathcal{M} = \{\mathcal{M}_I, \mathcal{M}_S, \mathcal{M}_R\}$.

Based on the retrieved experiences $\mathcal{M}_{ret}$, we redefine a reinforcement learning framework to pursue the optimal investment strategy μ_t.

[3]For a detailed introduction to each component of agents, please refer to our Appendix.