FinPos: A Position-Aware Trading Agent System for Real Financial Markets

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Abstract

The exceptional potential of large language models (LLMs) in handling text information has garnered significant attention in the field of financial trading. However, most existing trading agents operate under intraday, independent unit-based trading tasks, where decisions are made as isolated directional actions, and thus lack awareness of continuous position management. Therefore, we propose a position-aware trading task designed to simulate a more realistic market. To address this task, we propose FinPos, a position-aware trading agent system designed to explicitly model and manage continuous positions. FinPos enhances position awareness through three key mechanisms: (1) professional-level interpretation of heterogeneous market information; (2) a dual-agent decision structure that separates directional reasoning from risk-aware position adjustment; and (3) multi-timescale reward signals, allowing the agent to internalize position awareness through experiential feedback rather than static instructions alone. Extensive experiments demonstrate that FinPos surpasses state-of-the-art trading agents in the position-aware trading task, which closely mirrors real market conditions. More importantly, our findings reveal that LLM-centered agent systems exhibit a vast, largely unexplored potential in long-term market decision-making.

1 Introduction

An explosion of market information, facilitated by evolving communication technologies, highlights the growing significance of automated trading systems. In the past decade, deep reinforcement learning (DRL) agents (Fischer, 2018; Shakya et al., 2023) gained considerable attention due to their ability to handle large financial datasets. However, their inherent difficulty in integrating unstructured text information (Benk, 2022) limits their applicability primarily to technical analysis and compromises their interpretability (Balhara et al., 2022).

Recently, large language models (LLMs) (Hurst et al., 2024; Liu et al., 2024) have demonstrated remarkable potential in handling text-modal information and solving complex tasks, such as reasoning and decision-making (Zhai et al., 2025). This suggests that LLM-centered agent systems have the potential to transcend the inherent capability boundaries of traditional DRL trading models. Specialized LLM agents designed for financial trading, like TradingAgents (Xiao et al., 2024), FINMEM (Yu et al., 2024a), and FinAgent (Zhang et al., 2024), have already achieved groundbreaking results. However, as shown in the left panel of Fig. 1, most existing LLM-based trading agents are formulated under *single-step trading tasks*: each day is treated as an isolated decision episode, with discrete actions and fixed unit sizes. Although some studies mention "position" in prompts, the *single-step trading tasks* fundamentally undermines continuous position management. In contrast, real-world trading is inherently multi-step and stateful: a trader's current holdings directly shape future risk, opportunity, and decision logic. To bridge this gap, we propose a **position-aware trading task**, which more closely aligns with real-world trading markets than previous setups.

As shown in the right panel of Fig. 1, existing agent architectures struggle to sustain high yield rates when tasked with position management. This is mainly because they lack three essential capabilities: **(1) Explicit position representation and exposure control:** Without a continuous position state, existing agents cannot perform risk-aware, dynamic exposure control. **(2) Long-term planning capability:** Trading tasks that are re-initialized daily are prone to developing agents with a myopic trading perspective. **(3) In-depth market analysis ability:** Short-term trends are often identifiable through market sentiment, yet a much deeper analysis is essential for understanding long-term growth potential.

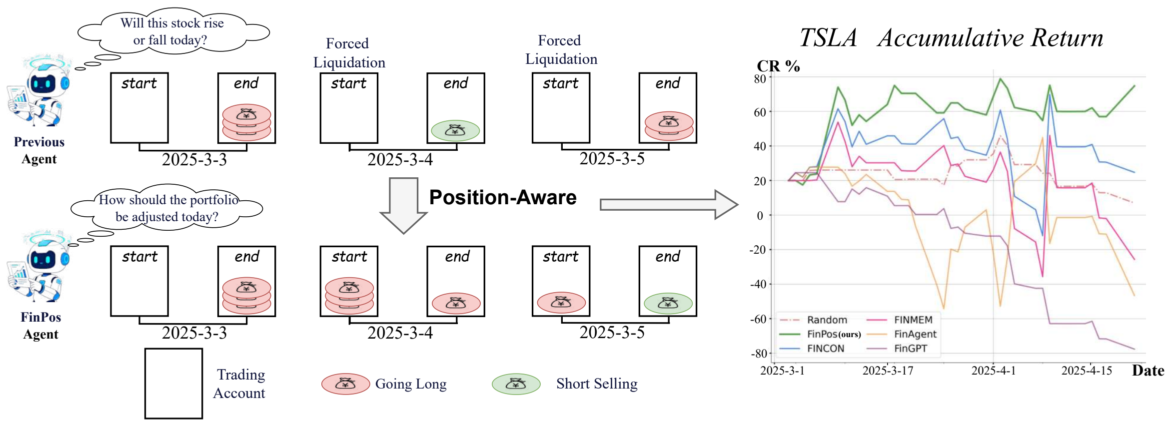

Figure 1: With the introduction of position awareness, the agent must not only predict current market trends but also manage the remaining positions in the account. Agents developed for tasks without position awareness are inadequate for addressing the new challenges posed by position-aware trading tasks.

To address these challenges, we propose **FinPos**, a position-aware trading agent designed to manage portfolio positions in realistic financial markets. FinPos integrates a dual-agent decision architecture with multi-timescale reward mechanism, where a Direction Decision Agent selects discrete actions (`buy`/`sell`/`hold`) and a Quantity and Risk Decision Agent determines transaction volumes.

A defining challenge in **long-term planning capability** is that the risk and return consequences of an exposure decision are inherently delayed and cumulative—they unfold over multiple trading days rather than within a single step. To explicitly encode this temporal dependency into the agent's reasoning, FinPos adopts a multi-timescale reward market signal during training, which jointly considers daily immediate profit-and-loss (PnL) and medium- to long-term cumulative returns. This guides the Direction Agent to make non-myopic action choices that balance short-term responsiveness with strategic consistency.

To address **explicit position representation and exposure control**, the multi-timescale reward framework also feeds long-horizon performance signals into the reflection process of the Quantity and Risk Decision Agent. This enables the agent to internalize the concept of continuous position and understand how its sizing decisions impact portfolio dynamics. Consequently, the Quantity and Risk Decision Agent dynamically determines the specific transaction volume to buy or sell—subject to a CVaR-based upper bound on single-transaction exposure to ensure capital safety.

By observing the reasoning chain of trading agents, we observe that current trading agents often analyze market information superficially and lack causal reasoning abilities. For instance, when trading Tesla stock, the agent may overestimate the relevance of news such as "Musk invests in company A" while dismissing significant news like "major changes in U.S. tariff policy" as irrelevant to trading decisions. This issue arises because the information analysis agent lacks fundamental common sense about the specific forms of information. To enhance **in-depth market analysis ability**, we build upon the multi-agent information processing paradigm, go further by by injecting domain-specific financial knowledge and causal principles through tailored prompting. This enables FinPos to interpret market signals not just by sentiment, but by fundamental relevance and risk implications.

We conduct extensive experiments using data from multiple real stocks to demonstrate the effectiveness of the FinPos agent in authentic market environments. FinPos outperforms several state-of-the-art (SOTA) financial agents and is the first agent equipped with investment position management capabilities. Moreover, a series of ablation studies underscored the critical importance of risk management, long-term planning, and in-depth market analysis for the agent's ability to manage investment positions effectively.

2 Related Works

2.1 LLM-Based AI Agents

The evolution of LLMs capabilities has led to a growing interest in LLM-based agents. Recently, the LLM agents have expanded into various domains, including music (Yu et al., 2023), healthcare (Wang et al., 2025), and research (Li et al., 2024). These applications illustrate the vast potential of LLM agents in multiple facets of human society. We aim to bring this potential to the financial markets, making LLM agents key players in investment activities.

2.2 Financial LLM-Based Agents

The evolution of financial agent architectures has exhibited significant progress through successive innovations and expansions in cognitive modeling and system integration. FINMEM (Yu et al., 2024a) was the first to establish a fundamental trading agent architecture centered around analysis, memory, and decision modules. Building upon this foundation, FinAgent (Zhang et al., 2024) integrate multimodal input to enrich their information sources. FINCON (Yu et al., 2024b) and TradingAgents (Xiao et al., 2024) introduced the concept of investment group architectures into agent systems to enhance decision-making reliability. Fundamentally, these agents primarily address a simplified financial game focused on predicting next-day price movement. In real markets, however, agents must not only needs to determine the investment direction, but also decide when to adjust exposure and how much to allocate. Therefore, this paper adopts a position-aware trading task that more closely approximates real market environments.

3 Task Definition

3.1 Single-Step Trading Task

We define a baseline environment as a *Single-Step Trading Task*, where the agent's position is automatically liquidated at each timestep, and no position is carried over. Within this framework, the agent makes a trading decision $a_t \in \{-1, 0, 1\}$ at each timestep t, corresponding to selling, holding, or buying, respectively. Each decision assumes immediate liquidation at the next timestep, thereby making each action independent, with no continuation of position states. The cumulative return R is the sum of the logarithmic returns at each step:

$$R = \sum_{t=1}^{N} r_t, \quad r_t = a_t \times \log \frac{\text{price}[t+1]}{\text{price}[t]} \tag{1}$$

This setup is widely adopted in studies such as FINMEM (Yu et al., 2024a) due to its simplification of trading processes, which stabilizes the training environment and allows more straightforward model evaluation. However, this simplification comes with significant limitations: it completely ignores the continuity of holding positions and the gains and losses arising from holding positions in real trading, thus cannot capture the associated compound returns or the risk exposure carried across periods. Without modeling positions, the agent has no basis for risk control or for detecting market trends, both of which are central to real trading. More critically, by reducing trading to short-term, step-by-step predictions, such a setup underutilizes the natural strengths of LLMs in reasoning over longer horizons. Consequently, advancing financial trading agents towards practical application requires a task more closely mirrors real market conditions.

3.2 Position-Aware Trading Task

Compared to the aforementioned simplified setup, this paper proposes a trading task configuration that aligns more closely with real market behavior, *Position-Aware Trading Task*. In this environment, the agent makes a trading decision on each trading day (each timestep t based on the closing price) and explicitly maintains its position state. The agent's decisions no longer involve automatic liquidation; rather, it must consider the continuation and adjustment of current positions in future timesteps. Returns R are calculated from the cumulative logarithmic returns based on position:

$$R = \sum_{t=1}^{N} r_t, \quad r_t = \text{pos}_t \times \log \frac{\text{price}[t+1]}{\text{price}[t]} \tag{2}$$

Where pos_t represents the agent's current position state, dynamically updated based on past trading decisions. This setup not only more accurately models the continuity and trend dynamics of holding positions in trading but also allows the agent to naturally incorporate key capabilities in strategy learning, such as position control, risk exposure management, and entry-exit timing. The *Position-Aware Trading Task* provides the agent with a more challenging and practically meaningful learning objective, offering stronger potential for strategy generalization and real-world applicability.

Additionally, this task better aligns with the capability characteristics of trading LLM agents. Compared to traditional quantitative models, LLMs excel at extracting long-term trends and underlying