Development of a Multi-Agent System Hedge Fund

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1 Motivation

Traditional hedge fund strategies, often reliant on human expertise and discretion, face challenges in managing vast amounts of data, identifying market patterns, and mitigating risks efficiently. The advent of artificial intelligence (AI) and multi-agent systems (MAS) offers a promising alternative by enabling autonomous, data-driven decision-making processes that can enhance both speed and accuracy in trading operations.

This thesis aims to explore the design and implementation of an automated hedge fund powered by a multi-agent system, where specialized agents collaborate to handle tasks such as market analysis, risk management, sentiment evaluation, and portfolio optimization. By implementing inter-agent oversight mechanisms, the likelihood of errors and adverse market behaviors can potentially be reduced and therefore contribute to a more robust decision-making process within the hedge fund. The proposed system will be evaluated against benchmarks to assess its performance.

2 Literature

Recent advancements in hierarchical reinforcement learning (HRL) have led to the development of agent-based systems that automate algorithmic trading and portfolio management strategies. R. Wang et al. (2021) proposed a hierarchical reinforcement learning framework for portfolio management, which addresses the challenge of optimizing investments while considering commission fees and price slippage. Their approach improved decision-making efficiency by organizing trading tasks into multiple layers, where high-level agents oversee overall portfolio allocation and while low-level agents execute specific trades. Han et al. (2023) extended HRL applications to pair trading, where they used hierarchical reinforcement learning to unify the sub-tasks of pair selection and pair trading. Their model enhanced trading performance by dynamically adjusting position sizes based on real-time market conditions. Finally, Qin et al. (2024) introduced a high-frequency trading system called EarnHFT that applies a three-stage hierarchical reinforcement learning framework to improve execution speed and market adaptability. It trained a diverse agent pool specialized for different market trends and dynamically picked the best one based on market conditions. Tests showed that it outperforms six high-frequency trading baseline models.

Large Language Models (LLMs) are rapidly advancing, with significant improvements in reasoning and decision-making, making them well-suited for agent-based systems in complex domains such as making investment decisions. In their paper, Yu, Yao, et al. (2024) proposed FinCon, a multi-agent system built on LLMs to enhance decision-making in financial tasks. The authors leveraged a hierarchical structure inspired by real-world investment firms like hedge funds, where "manager" agents oversee strategy and coordination, and "analyst" agents focus on task-specific insights. This hierarchical structure ensures effective cross-functional collaboration, allowing agents to work toward shared financial goals. At the same time, this approach lowers communication costs by ensuring that only relevant information reaches the necessary agents, reducing unnecessary peer-to-peer messaging. A key innovation in the paper is the introduction of a risk-control agent that implements a self-critiquing mechanism, which enables the system to refine its "investment beliefs" episodically. These beliefs, expressed as conceptual verbal reinforcements, improve the system's adaptability in volatile financial environments and ensure the timely propagation of updated knowledge to relevant agents.

In FinCon, analyst agents extract investment insights from large volumes of multi-source market data, where each agent focuses on a specific trading target. To enhance efficiency, each agent processes information from a single source using a uni-modal approach, filtering out noise and extracting relevant market signals. These insights are then consolidated to assist the manager agent. The system consists of seven analyst agents, each specializing in a different type of data processing. Some agents utilize LLMs for textual analysis, while others process audio from earnings call recordings or compute financial metrics for quantitative analysis. Additionally, a stock selection agent is responsible for portfolio diversification, applying quantitative finance principles to optimize investment strategies.

The manager agent serves as the sole decision-maker, responsible for executing trades and portfolio management. It determines portfolio weights using convex optimization techniques while considering trading constraints. Decision-making is supported by four key mechanisms: consolidating insights from analyst agents, incorporating timely risk alerts, refining investment beliefs based on diverse information sources, and conducting self-reflection on past trading actions to enhance future performance.

In their system, Yu, Yao, et al. (2024) employed a dual-level risk-control mechanism consisting of within-episode and over-episode risk management. The within-episode mechanism detects market risks in real-time, which enables the manager agent to adjust trading actions when significant losses occur, particularly when the Conditional Value at Risk (CVaR) drops. In contrast, the over-episode mechanism works across training episodes and compares past and present performance to refine investment strategies. This process is powered by Conceptual Verbal Reinforcement, which evaluates past decisions and provides structured guidance to improve future trading actions.

Additionally, Yu, Yao, et al. (2024) discussed other language agent systems for financial decision-making, such as those from Yang, X.-Y. Liu, and C. D. Wang (2023), Yu, Li, et al. (2023), and W. Zhang et al. (2024). While these models have demonstrated strong performances, some of them exhibit weaknesses. First, their reliance on short-term market fluctuations for risk assessment often overlooks long-term risk exposure, which is critical for sustainable investment strategies. Second, they are typically limited to single-asset trading, making them less effective for portfolio management. Third, these systems place excessive cognitive load on individual agents due to constrained context windows, leading to degraded decision quality. Multi-agent approaches, such as the one from C. Zhang et al. (2024), attempt to address this but suffer from high communication costs and slow decision-making due to frequent exchanges between LLM-based agents. Moreover, the lack of a clear optimization objective in these systems can compromise the effectiveness of their trading strategies.

This master's thesis will build upon the AI-Hedge-Fund project by Singh (2024), a proof of concept for an AI-powered hedge fund that explores the use of AI in trading decision-making and uses a multi-agent system to automate the actions within the hedge fund. The system employs multiple specialized agents working together to ultimately generate trading signals. The Valuation agent estimates stock values using discounted cash flow and owner earnings valuation. The Sentiment agent analyzes news sentiment to create trading signals, while the Technicals agent utilizes volatility, mean reversion, momentum, statistical arbitrage, and trend following to identify trading opportunities. Additionally, the Warren Buffett agent generates signals based on Buffett's investment principles and LLM-driven reasoning, and the Fundamentals agent evaluates profitability, growth, financial health, as well as several price ratios to assess investment potential. All trading signals from the various agents are processed by the Risk Management agent, which acts as a position-sizing controller to enforce predefined risk limits. It retrieves portfolio data and recent stock prices to determine the maximum allowable position size, applying a 20% per-stock allocation rule to prevent over-concentration. Rather than using traditional risk metrics like VaR, CVaR, or Sharpe Ratio, it focuses on position constraints to manage exposure effectively. Ultimately, the Portfolio Management agent makes final buy, sell, or hold decisions by integrating signals from the agents while considering position limits, available cash, and portfolio holdings. The Portfolio Management agent makes the trading decisions using an LLM that combines data into actionable trade recommendations with assigned confidence levels and reasoning. To maintain execution reliability, the agent applies retry logic and defaults to a hold position if errors occur.

3 Data

Table 1 shows where the data used for the thesis is obtained from. The data for this thesis will primarily be sourced from Yahoo Finance, accessed via the yfinance library. Yahoo Finance provides a comprehensive dataset, including stock prices, financial statements, fundamental metrics, and valuation indicators. For data not directly available through yfinance, such as certain technical indicators, these can be computed using historical prices.

Additionally, insider trading data and news sentiment are not accessible through yfinance and will be obtained by scraping the SEC's EDGAR database. While Alpha Vantage offers a free API for this data, its limitations on API requests make it less suitable for this study. Macroeconomic data, including interest rates, inflation, and GDP-related indicators, will be sourced from the Federal Reserve Economic Data (FRED) API, which provides free and reliable access to key economic metrics.

Agent	**Data**	**Source**
Portfolio Manager	Trading signals and confidence	from other agents
Risk Manager	Stock and bond prices, Portfolio holdings and position limits	yfinance from other agents
Fundamentals	RoE, net margin, operating margin, revenue, earnings, and book value growth, current ratio, debt to equity ratio, free cash flow per share, earnings per share, P/E-, P/B-, and P/S-ratios	provided by or calculated using yfinance
Sentiment	Insider trades and news sentiment	10-K scraper and Alpha Vantage
Technicals	EMA, RSI, ADX, ATR, bollinger bands, hurst exponent, volume, volatility, skewness, kurtosis	provided by or calculated using data yfinance
Valuation	free cash flow, net income, market cap, depreciation and amortization, CapEx, working capital, earnings growth rate	provided by or calculated using data yfinance
Warren Buffet	free cash flow, net income, market cap, total assets and liabilities, outstanding shares, CapEx, working capital, earnings growth rate	provided by or calculated using data yfinance
Macroeconomic	CPI, PCE, GDP growth, FFR	FRED
Fixed-Income	yield curve	FRED
Forward-looking	VIX	yfinance

Table 1: The table shows which agent needs what data and where that data can be obtained.

4 Methodology

4.1 Large Language Models

The Portfolio Manager receives trading signals and risk constraints in JSON format, necessitating the use of an LLM for processing. The specific LLM that will be employed in this thesis has yet to be determined, as the rapid pace of innovation in this field makes it challenging to identify the most suitable option in advance. In principle, preference will be given to LLMs specifically trained for investment decision-making or generally trained for financial tasks, such as FinBERT from Araci (2019) or FinMem from Yu, Li, et al. (2023). Additionally, Nie et al. (2024) provide a comprehensive review of LLMs in financial applications.

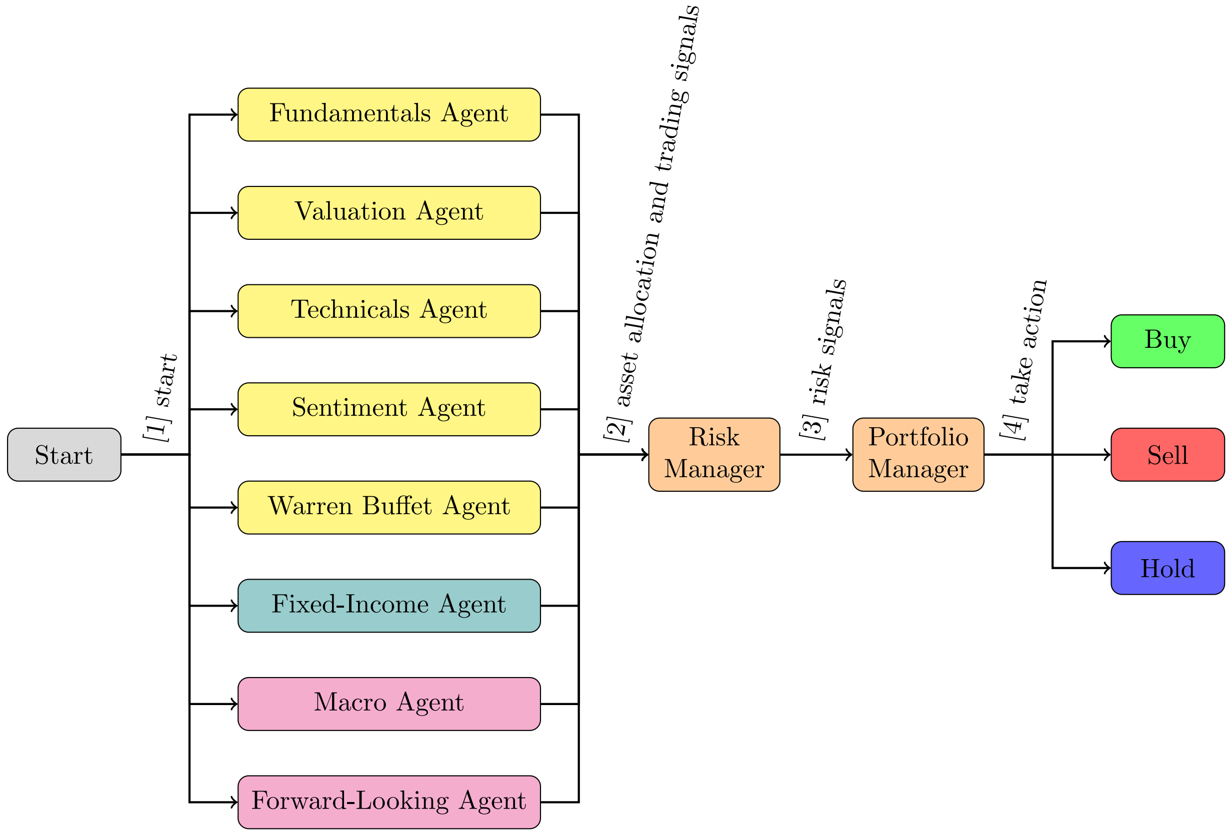

Figure 1: This figure shows the structure of the multi-agent system. The Fundamentals, Valuation, Technicals, Sentiment, and Warren Buffet agents, coloured yellow, create stock trading signals. The Fixed-Income agent, coloured blue, creates trading signals for investing in either short-term or long-term bonds. The Macro and Forward-looking agents, coloured pink, are responsible for the asset allocation and generate signals to either hold more or less equities or bonds. The risk manager consolidates the signals from the preceding agents and ensures that the limits for the positions in the portfolio are adhered to and that the risk measures are not exceeded. The trading signals and the risk manager's recommendation are then communicated to the portfolio manager, who then makes the final investment decision.

4.2 Autonomous Market Screening

In the current framework by Singh (2024), the agents operate solely on user-selected tickers and therefore the hedge fund is not fully automated. To achieve full autonomy, a regular market-wide screening process, e.g. at the end of each trading day, will be implemented to assess all available tickers and generate investment decisions based on the agents' trading signals and confidence. To mitigate excessive transaction costs, constraints should be introduced on both the total number of trades executed and the number of tickers held within the portfolio. Additionally, each executed trade will incur transaction costs, which will be modelled as a fixed percentage of the trade value, accounting for broker commissions and bid-ask spreads. Screening the entire financial market would be computationally expensive. Therefore, the hedge fund will be limited to U.S. stocks. Furthermore, mechanisms should be introduced to avoid unnecessary computations, such as caching of data, ending the research process early if agents provide contradictory signals, and not scraping EDGAR data if it is not up-to-date

4.3 Long-Short Trading and Custom Constraints

This thesis will introduce long-short trading strategies and incorporate customizable constraints to expand the hedge fund's investment capabilities. Currently, the hedge fund framework by Singh (2024) operates with long-only positions, where the maximum allocation per asset is capped at 20% of the total portfolio balance. By enabling short-selling, the hedge fund can profit from declining assets and implement market-neutral strategies, improving overall risk-adjusted returns. However, short-selling requires borrowing stocks, which incurs a borrowing fee that varies based on stock liquidity and availability. This cost will be modelled as an annualized percentage deducted daily from short positions. Additionally, the framework will be upgraded to support user-defined constraints. These constraints will be enforced by the Risk Manager agent, as is also done in the framework of Singh (2024).

4.4 Partially Observable Markov Decision Process

Because real-world market conditions are not fully observable, factors like hidden liquidity, undisclosed order flow, and macroeconomic uncertainty are only partially reflected in available signals. To address this issue, the automated hedge fund can benefit from implementing a partially observable Markov decision process (POMDP) framework, which models these uncertainties more effectively. POMDPs are often implemented using recurrent reinforcement learning methods, such as long short-term memory (LSTM), allowing the system to maintain a hidden internal state while integrating partial observations from the agents. In this setup, the LLM within the Portfolio Management Agent acts as an expert system, which makes the initial trading decisions, while a reinforcement learning (RL) model further refines and finalizes them. The RL model analyzes the LLM's textual outputs and recommendations, using historical performance data to identify beneficial patterns and enhance decision-making. This structure ensures that the LLM remains unchanged, preserving its reasoning capabilities, while the RL model optimizes the final investment decision.

4.5 Fixed Income Agent and Macro-Informed Portfolio Management

To enhance the hedge fund's investment strategy, this thesis will introduce a Macro agent to determine the asset allocation and a Fixed Income agent to manage the bond investments. The Macro agent will decide how much capital should be allocated to stocks versus bonds based on macroeconomic indicators, such as inflation (CPI, PCE), GDP growth, and the federal funds rate (EFFR). Given the rather short-term nature of the stock investments that this hedge fund makes, it's reasonable to invest relatively more in bonds than in equities when inflation, as measured by the CPI and PCE, and interest rates, as measured by the FFR, are high. Strong economic growth supports higher corporate earnings, making stocks more appealing, whereas weak growth increases demand for safe-haven assets like treasury bonds. Once the Macro agent determines the stock-bond allocation, the Fixed Income agent will determine the bond selection based on the yield spread. A steep yield curve signals higher expected returns on long-term bonds, whereas a flat or inverted curve suggests economic uncertainty, favouring shorter-duration bonds.

4.6 Forward-Looking Agent

In addition to the Macro agent, this thesis will introduce a Forward-Looking agent that adjusts the allocation between stocks and bonds based on implied market volatility, as measured by the VIX. The VIX, often referred to as the "fear gauge," reflects investors' expectations of future market volatility. When the VIX is low, market conditions are perceived as stable, encouraging a higher allocation to equities. Conversely, a high VIX indicates heightened uncertainty and potential market downturns, making bonds more attractive due to their lower risk profile. This agent therefore reduces risk during turbulent periods while taking advantage of equity growth during calmer market conditions, which in theory improves the risk-adjusted returns of the hedge fund.

4.7 Improved Risk Management

Building on the approach of Yu, Yao, et al. (2024), this thesis will implement a dual-level risk-control mechanism to strengthen the hedge fund's risk management framework. The existing Risk Management agent will be upgraded to incorporate proper risk measures, such as Conditional Value at Risk (CVaR), to provide a robust assessment of downside risk instead of just complying with the portfolio allocation constraints. The within-episode risk management component will monitor market conditions, allowing the system to adjust trading actions if significant losses occur, particularly when CVaR breaches predefined thresholds. Meanwhile, the over-episode risk management component will be implemented using a reinforcement learning model as described in section 4.4, which will refine investment decisions by evaluating past performance and adjusting risk-control policies accordingly.

4.8 Benchmarks

In order to assess the performance of the proposed AI-driven hedge fund, comparisons will be made against three benchmarks representing different market exposures and investment philosophies. First, the S&P 500 will be employed to provide a widely recognized measure of U.S. equity market returns. Second, the HFRI, e.g. a hedge fund index, will be utilized to position results within the alternative investment spectrum, though it is acknowledged that such indexes may exhibit biases arising from survivorship and self-reporting. Finally, a 60/40 portfolio, composed of 60% equities and 40% bonds, will be used as a traditional balanced benchmark to evaluate whether superior risk-adjusted returns are generated relative to a conventional allocation strategy.

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