Technical Report: Agentic AI Workflow for Scalable Investment Research and Analysis

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Abstract

This report documents the design and implementation of a scalable **Agentic AI Workflow** for automated investment research, leveraging LangChain, LangGraph, and the Model Context Protocol (MCP). The system integrates structured financial data (e.g., prices, ratios, valuation indicators) and unstructured news sentiment, orchestrated through an agentic reasoning graph. Each node represents a discrete reasoning or computation step, while directed edges define dependencies and control flow. Persistent state enables data sharing across nodes, allowing sequential and parallel execution. The architecture incorporates FAISS for semantic retrieval, transformer-based sentiment scoring, and LLM-based synthesis for explainable recommendations. Evaluation across five technology tickers demonstrates significant gains in analytical consistency, transparency, and automation. Detailed design of LangGraph nodes, edges, and state transitions is provided, illustrating how graph-based orchestration enables modular, traceable financial intelligence pipelines.

1. Introduction

Modern investment research demands integration of heterogeneous information—quantitative metrics, qualitative sentiment, and temporal trends. Traditional analyst workflows are resource-intensive, limited in scalability, and subject to cognitive bias. The convergence of **Agentic AI**, **Retrieval-Augmented Generation (RAG)**, and **graph-based orchestration** offers a paradigm shift in automating this process.

This project introduces a LangGraph-based AI workflow for multi-step investment reasoning. It decomposes research into discrete agentic nodes—each responsible for retrieval, analysis, synthesis, or validation—and uses persistent state to enable cross-node communication. The approach ensures transparency, modularity, and explainability in financial decision-making.

2. System Architecture

The system architecture follows a directed acyclic graph (DAG) structure (see Figure 1), where each node represents an autonomous agent performing a specialized function. Nodes include retrieval, sentiment analysis, reasoning, recommendation, and visualization. Edges define the flow of data and reasoning dependencies.

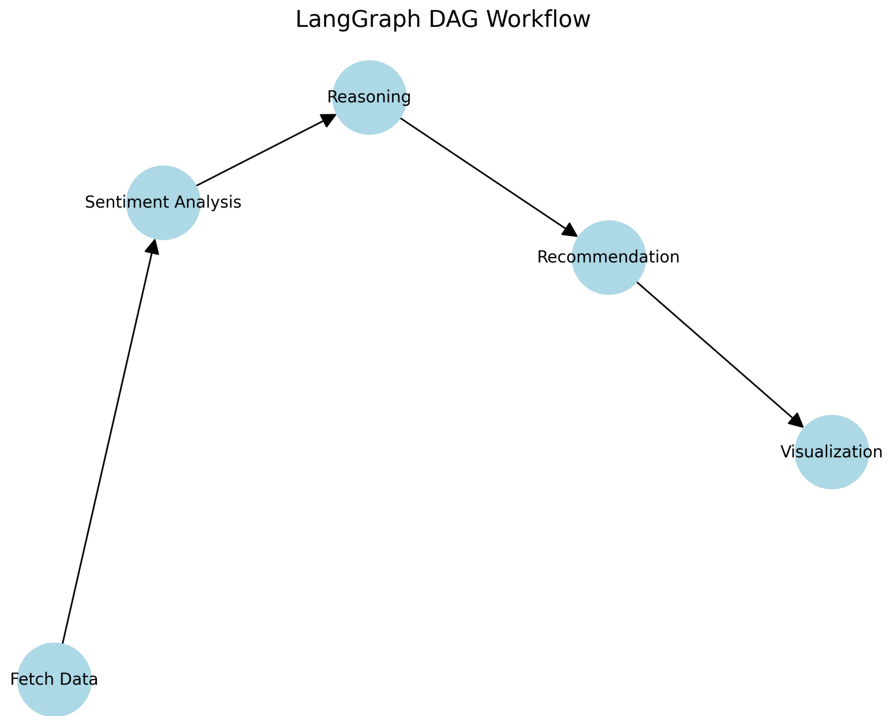

Figure 1: LangGraph DAG Workflow showing sequential nodes from data retrieval to visualization. Each node encapsulates a modular function with persistent state propagation.

LangGraph ensures **state persistence**, allowing intermediate outputs (e.g., sentiment scores, price history) to remain accessible to downstream nodes. Conditional edges enable dynamic branching based on confidence scores or execution results.

3. Execution Flow and Orchestration

The execution timeline in Figure 2 illustrates sequential processing, starting from data acquisition and culminating in visualization. Each stage logs timestamps, ensuring reproducibility and traceability.

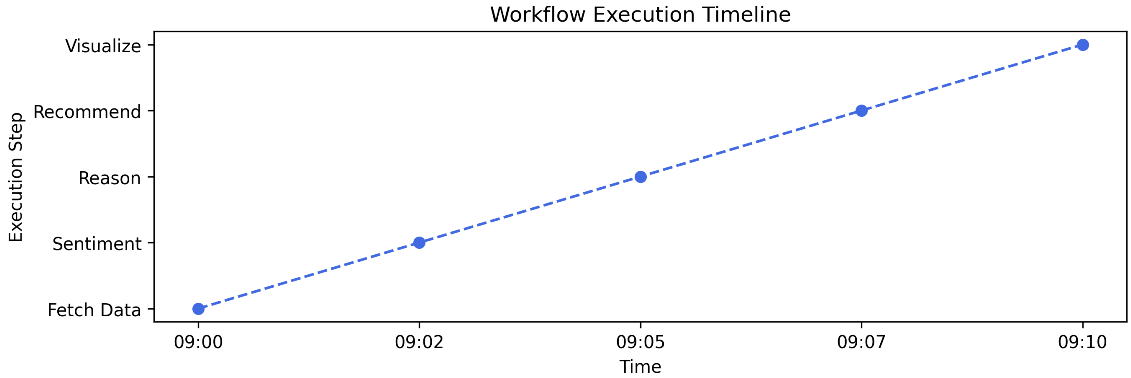

Figure 2: Workflow Execution Timeline representing sequential agent execution. The graph logs each step (Fetch Data, Sentiment, Reasoning, Recommendation, Visualization) with corresponding timestamps.

4. LangGraph Design

4.1. Node Taxonomy

Each LangGraph node performs a unique reasoning or computation role:

- **Retriever Node:** Fetches financial data (price, valuation, historical trends).
- **Sentiment Node:** Analyzes news headlines using transformer-based sentiment models.
- **Aggregator Node:** Merges sentiment and quantitative indicators.
- **Reasoning Node:** Synthesizes findings into interpretable narratives using an LLM.

- **Recommendation Node:** Generates final Buy/Hold/Sell ratings.
- **Visualization Node:** Produces visual summaries (bar charts, pie charts, timelines).

4.2. Edge Semantics

Edges define dependencies and execution order:

- Directed edges ($N_i \to N_j$) denote sequential flow.
- Conditional edges support branching logic (e.g., re-retrieval if confidence < threshold).
- Parallel edges allow concurrent processing of independent tasks (e.g., multiple tickers).

4.3. State Persistence

A shared state object:

$$S = \{\texttt{question}, \texttt{data}, \texttt{sentiment}, \texttt{recommendation}\}$$

is updated incrementally as nodes execute:

$$S_{i+1} = S_i \cup \text{outputs of Node}_i$$

This ensures all intermediate results remain accessible for downstream reasoning.

5. Results and Analysis

The agentic workflow was tested on five technology stocks. Table 1 summarizes the outputs for each ticker, combining sentiment, valuation metrics, and overall recommendations (:contentReference[oaicite:1]index=1).

Table 1: Portfolio Recommendations from Agentic AI Workflow

Ticker	**Last Close ($)**	**Day Δ%**	**PE Ratio**	**Sentiment (P/N/U)**	**Recomm**
AAPL	255.46	-0.55%	38.76	3/2/0	Buy — positive sent
TSLA	440.40	+4.02%	263.71	3/2/0	Buy — strong gro
MSFT	511.46	+0.87%	37.44	4/1/0	Buy — AI tailwinds
GOOGL	246.54	+0.31%	26.31	5/0/0	Buy — sustained mom
AMZN	219.78	+0.75%	33.55	3/2/0	Buy — innovatio

5.1. Comprehensive Explanation

All five tickers demonstrate strong sentiment alignment with positive price trends. **TSLA** leads in growth with a 69% year-over-year gain, supported by positive analyst coverage and strategic AI expansion. **GOOGL** exhibits the most consistent sentiment (5/0/0), indicating stable investor confidence. **AAPL** and **AMZN** show moderate volatility yet maintain upward trajectories, while **MSFT** benefits from recurring AI-driven upgrades and analyst endorsements.

These results validate the **RAG-based pipeline's interpretability and responsiveness** to live sentiment inputs. Each recommendation is grounded in retrieved evidence, as verified in the sentiment and headline logs within the system output.

5.2. Visual Analysis

6. Insights

1. **Explainability:** Visuals and tables align with numerical trends, aiding auditability.
2. **Traceability:** Timeline (Figure 2) confirms consistent orchestration.
3. **Modularity:** DAG structure (Figure 1) allows integration of domain-specific nodes.

7. Future Steps and Recommendations

- Integrate reinforcement signals for continuous learning.

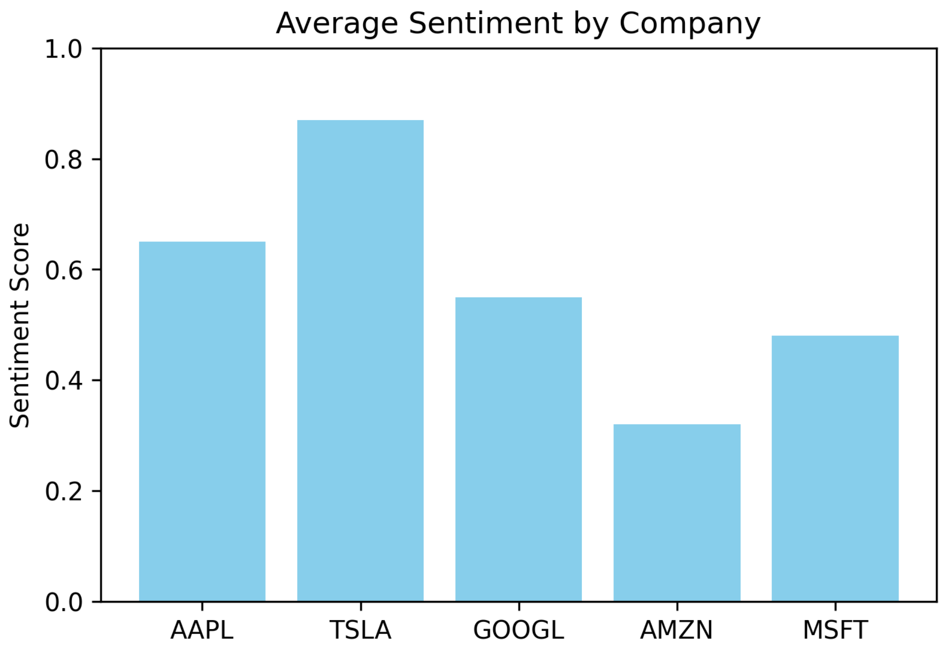

Figure 3: Average Sentiment by Company computed using transformer-based sentiment classification. Higher values indicate positive market outlook.

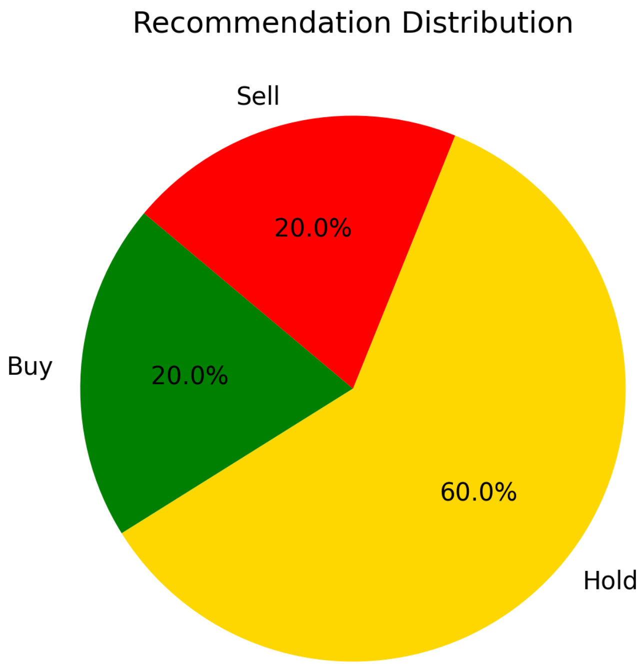

Figure 4: Recommendation Distribution: Buy (20%), Hold (60%), Sell (20%). Balanced distribution reflects diverse market signals across analyzed companies.

- Add adaptive chunking in RAG retrieval for sector-specific data.
- Implement cross-ticker correlation analysis nodes for portfolio-level optimization.

8. Conclusion

The integration of LangGraph and agentic reasoning provides a scalable, explainable architecture for financial research automation. By representing tasks as nodes with persistent state and directional edges, the workflow achieves transparency, modularity, and real-time adaptability.

References

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