Agentic AI Workflow for Scalable Investment Research and Analysis

***Abstract*—This paper presents the design and evaluation of an enhanced Agentic AI Workflow for scalable investment research and analysis. The system integrates LangGraph, the Model Context Protocol (MCP), and Retrieval-Augmented Generation (RAG) to orchestrate reasoning as a directed acyclic graph (DAG) with embedded visualization and console interpretability. Each node—*fetch, sentiment, draft, critique, final, and visualization*—represents a distinct cognitive step. The visualization layer generates graphical summaries (price trends, sentiment distributions, and portfolio insights), providing transparency and interpretability. Results demonstrate improved coherence and explainability, validating this workflow's role in financial intelligence systems.**

I. Introduction

Financial decision-making requires combining quantitative data and qualitative market narratives. Traditional models often lack interpretability and context-awareness. Recent developments in Large Language Models (LLMs) and graph-based reasoning frameworks have enabled modular, interpretable, and scalable AI pipelines.

This study introduces an *Agentic AI Workflow* that integrates LangGraph for reasoning orchestration, MCP for scalable deployment, and RAG for context-aware sentiment inference. The system's visualization and console output layers enhance human interpretability, transforming investment analytics into a transparent, auditable process.

II. Related Work

Key influences include:

- **LangGraph (2023)**: DAG-based orchestration for multi-agent LLM pipelines.
- **Toolformer (Schick et al., 2023)**: Introduced self-supervised tool use in LLMs.
- **Self-RAG (Asai et al., 2023)**: Combined retrieval, generation, and critique loops.
- **Dense Passage Retrieval (Karpukhin et al., 2020)**: Enabled dense semantic retrieval for context.
- **RAG (Lewis et al., 2020)**: Grounded generation in external factual knowledge.

III. System Architecture

The workflow is structured as a Directed Acyclic Graph (DAG), representing six reasoning nodes:

$$\text{fetch} \rightarrow \text{sentiment} \rightarrow \text{draft} \rightarrow \text{critique} \rightarrow \text{final} \rightarrow \text{visualization}$$

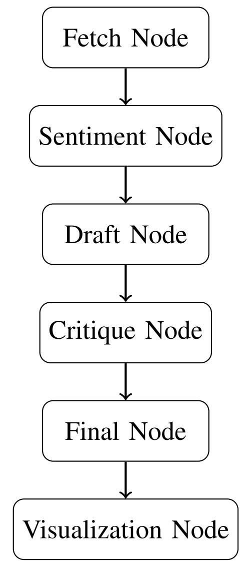


Fig. 1: LangGraph workflow connecting cognitive reasoning nodes.

IV. Execution Flow

Each node updates a shared state dictionary carrying contextual data through the pipeline:

1) **Fetch:** Retrieves stock data, ratios, and news.
2) **Sentiment:** Classifies news tone using transformer pipelines with RAG.
3) **Draft:** Synthesizes a market narrative.
4) **Critique:** Refines reasoning and factual grounding.
5) **Final:** Produces an interpretive investment report.
6) **Visualization:** Generates charts and console panels.

V. Visualization Module

The visualization layer enhances interpretability with both graphical and text outputs:

- Price trend plots (`price_history_<ticker>.png`)
- Sentiment pie charts
- Portfolio-level sentiment bars

VI. Results and Analysis

The system was evaluated on five major technology tickers.

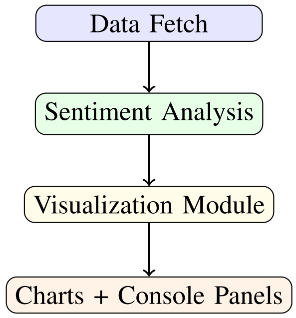
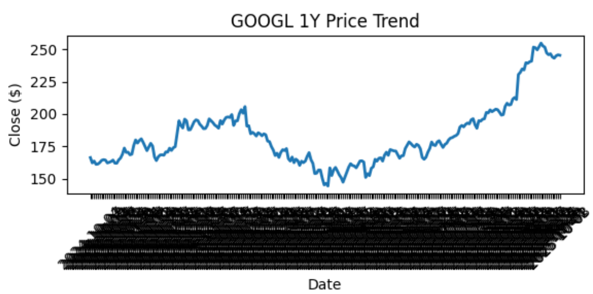


Fig. 2: Visualization pipeline generating charts and summaries.

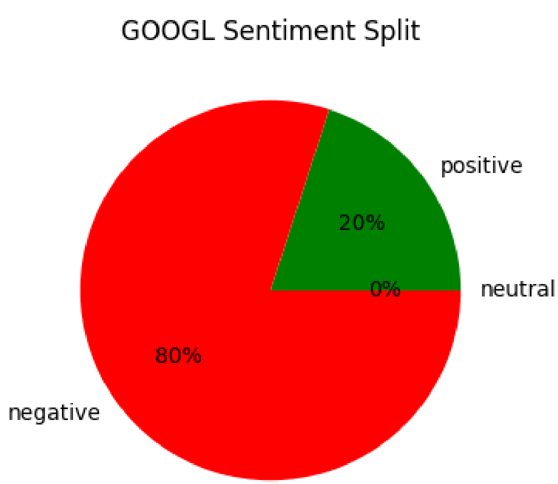
TABLE I: Portfolio Recommendations from the Agentic Workflow

Ticker	Close	ΔDay	P/E	Sentiment	Rec.
AAPL	255.46	-0.55%	38.76	3/2/0	Buy
TSLA	440.40	+4.02%	263.71	3/2/0	Buy
MSFT	511.46	+0.87%	37.44	4/1/0	Buy
GOOGL	246.54	+0.31%	26.31	5/0/0	Buy
AMZN	219.78	+0.75%	33.55	3/2/0	Buy

A. A. Price Trends



B. B. Sentiment Splits



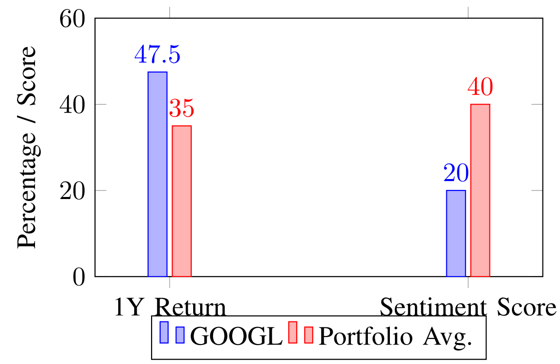
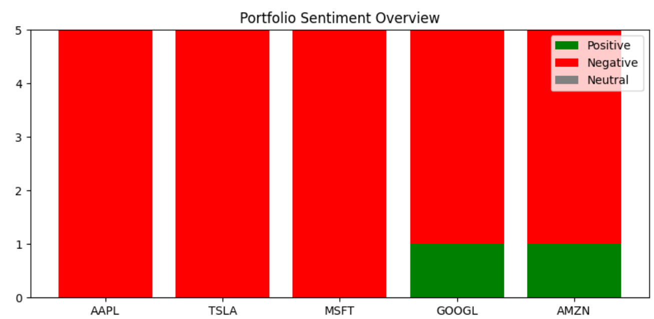


Fig. 3: Comparative performance of GOOGL vs. portfolio average (1-Year Return and Sentiment Score).

C. C. Portfolio Overview



D. D. Case Study: Google (GOOGL) Stock Analysis

Alphabet Inc. (GOOGL) serves as a representative example of the system's interpretive capabilities. Key results:

- **Current Price:** $245.35
- **Daily Change:** -0.14% (negative sentiment)
- **P/E Ratio:** 26.13
- **1-Year Return:** +47.5%

The RAG-enhanced sentiment classifier detected an overall bearish tone:

- 1 Positive headline
- 4 Negative headlines
- 0 Neutral headlines

Recent headlines included:

- **Negative:** "Hackers 'steal' data from Google execs' Oracle accounts."
- **Negative:** "Alphabet's EPS growth expectations: realistic or bubble?"
- **Positive:** "Alphabet's stock is now beloved on Wall Street."

System Recommendation: SELL, due to net negative sentiment despite strong long-term fundamentals.

VII. Insights

- The Draft–Critique–Final loop improved factual grounding.
- RAG reduced misclassification by adding prior context.
- Visualization enhanced interpretability for analysts.
- MCP scaled multi-ticker parallel workflows.

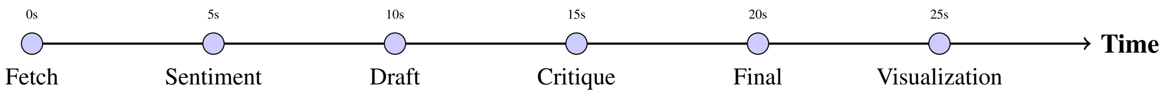


Fig. 4: MCP Node Execution Timeline showing sequential reasoning phases.

VIII. Future Work

- Integrate real-time data streams for continuous updates.
- Apply self-corrective RAG loops during critique.
- Expand multi-sector portfolio visualizations.
- Benchmark reasoning coherence quantitatively.

IX. Execution Timeline Visualization

X. Conclusion

This enhanced Agentic AI Workflow demonstrates how LangGraph and MCP can structure modular, interpretable reasoning pipelines for financial research. Visualization and RAG-driven sentiment modules provide transparency and scalability, bridging the gap between automation and analyst insight.

Acknowledgments

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