Agentic AI Workflow for Scalable Investment Research and Analysis

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***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, reasoning, 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 seven reasoning nodes:

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

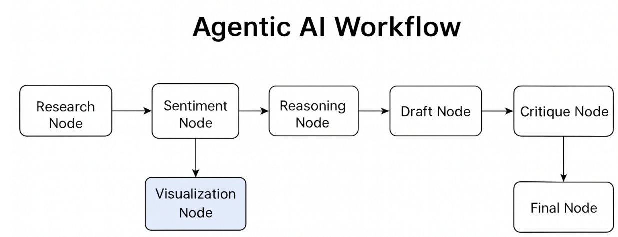

Fig. 1: LangGraph workflow connecting cognitive reasoning nodes.

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) **Reasoning**: Validates decision logic using entity-structured prompts.
6) **Final**: Produces an interpretive investment report.
7) **Visualization**: Generates charts and console panels.

V. Visualization Module

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

- Price trend plots (e.g., `price_history_AAPL.png`)
- Sentiment pie charts
- Portfolio-level summary (e.g., `portfolio_summary.png`)

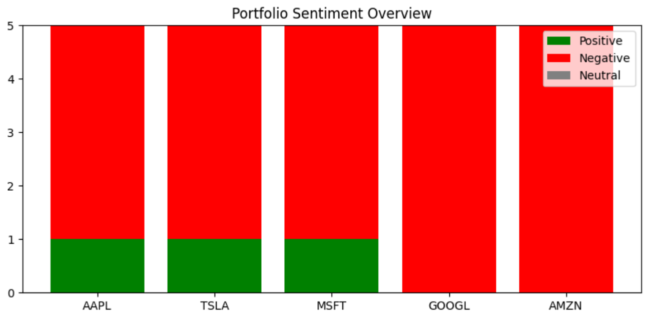

Fig. 2: Portfolio Summary Sentiment Distribution

VI. Results and Analysis

The system was evaluated on five major technology tickers: AAPL, TSLA, MSFT, GOOGL, and AMZN.

A. Recommendation Overview

Ticker	Close	% Change	P/E	Rec.
AAPL	245.27	-3.45%	37.16	Sell
TSLA	413.49	-5.06%	243.23	Sell
MSFT	510.96	-2.19%	37.46	Sell
GOOGL	236.57	-2.05%	25.25	Sell
AMZN	216.37	-4.99%	32.98	Sell

TABLE I: Real-time Recommendation Output

B. AAPL Snapshot

- Reasoning: **YES**
- Sentiment: *4 Negative, 1 Positive*
- Critique Highlight: *Apple stock down 3.5%, Prompt AI acquisition rumors*
- System Recommendation: **SELL**

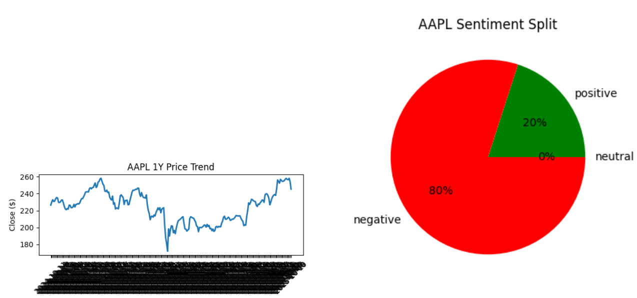

Fig. 3: Apple Price History and Sentiment Split

C. GOOGL Snapshot

- Reasoning: **YES**
- Sentiment: *5 Negative, 0 Positive*
- Critique Highlight: *Regulatory crackdown in UK, Alphabet share dip*
- System Recommendation: **SELL**

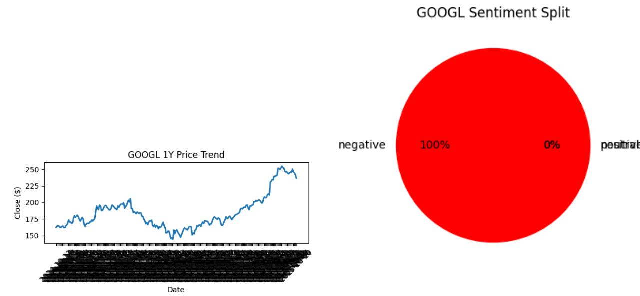

Fig. 4: GOOGL Price History and Sentiment Split

VII. Insights

- The reasoning node validates logic in real-time before final generation.
- The draft–critique–final loop improves factual grounding.
- RAG reduces hallucinations by providing context.
- Visual and console outputs increase transparency.

VIII. Future Work

- Integrate live market streams (e.g., Yahoo API)
- Add user-in-the-loop critique feedback
- Incorporate multi-sector portfolio filters
- Quantitative benchmark of decision accuracy

IX. Conclusion

This enhanced Agentic AI Workflow shows how LangGraph and MCP structure modular, interpretable reasoning pipelines for financial research. The reasoning node improves decision quality while visual and sentiment outputs bridge human-AI interpretability.

References

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