FinGPT Agents: Reinforcement-Fine-Tuned LLMs for Financial Analytics

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***Abstract*— This paper presents FinGuard, a specialized multi-agent AI system for financial analytics. The agent's architecture dynamically routes financial queries to fine-tuned models. It employs LangGraph for workflow orchestration, using Supervised Fine Tuned (SFT) model for explanatory questions and Reinforcement Fine Tuned (RFT) model for quantitative computations.**

Comprehensive evaluation demonstrates robust performance with 90% routing accuracy on conceptual questions and 63.3% overall routing accuracy across 30 strategic financial questions. The system achieved perfect professional communication scores (1.0) while revealing opportunities for improvement in practical guidance (0.244) and risk awareness (0.227).

Our work extends beyond single-model fine-tuning to develop FinGPT Agent System, a multi-agent framework that intelligently routes financial queries to specialized AI agents. The system employs dynamic problem classification, confidence scoring, and expert routing to handle diverse financial domains including bond mathematics, portfolio theory, and conceptual finance. Experimental results demonstrate exceptional routing accuracy for conceptual questions (90%) while identifying challenges in quantitative problem classification that represent opportunities for future enhancement.

Experimental evaluation demonstrates that supervised fine tuning achieves the highest quality scores (0.857 vs 0.803 base), with reinforcement fine tuning showing strong performance in generating detailed explanatory content.

Our work establishes that specialized multi-agent architectures enable targeted problem-solving in financial AI, demonstrating 90% accuracy on conceptual questions while providing a framework for integrating diverse financial expertise.

https://github.com/SatishChandraPhD/FinAI2025

Keywords—FinGPT, CFA question answering, financial agents, LoRA, explainability, financial reasoning models, financial LLMs, supervised fine-tuning, reinforcement fine-tuning, LLaMA-2, finance QA

I. Introduction

General-purpose large language models often lack domain awareness and factual grounding in financial contexts. This work addresses that gap by applying Fine-Tuning to adapt open-source models to finance-specific QA tasks.

The primary contribution lies in establishing an open, verifiable evaluation baseline using well-defined performance metrics, forming a reproducible foundation for subsequent RFT experimentation.

This research also seeks to contribute to the explainability and reproducibility of financial AI. Given the regulatory sensitivity of financial disclosures, black-box AI models can pose significant risks if not carefully validated. Our pipeline emphasizes transparent data processing, clearly defined training inputs, and interpretable fine-tuning strategies, ensuring that the results are not only accurate but also explainable.

Our work introduces FinGuard, the FinGPT Agent System, a multi-agent framework that extends beyond single-model approaches by dynamically routing financial queries to specialized AI agents. This addresses the fundamental challenge that different financial problems require distinct reasoning modalities - from conceptual explanations to precise mathematical calculations. FinGuard can be effectively used to prepare for exams related to finance, like the CFA exams.

We conducted a comprehensive three-way evaluation comparing Base, SFT, and RFT models. Our RFT model demonstrates superior explanatory depth and professional context, providing not just calculations but actionable insights with appropriate risk disclosures, addressing a critical gap in financial AI interpretability.

II. Related Works

Domain adaptation in financial NLP has been explored through FinBERT and BloombergGPT, which demonstrated the benefits of fine-tuning models on financial corpora. FinBERT used Financial PhraseBank data to achieve better sentiment and risk prediction; BloombergGPT extended this to multi-task reasoning over large proprietary datasets.

Recent developments, such as FinGPT, introduce open-access pipelines using LoRA and RLHF to fine-tune LLMs for financial reasoning. Most of these systems, however, depend heavily on proprietary datasets or complex reward modeling. The present work complements these by producing a transparent fine-tuning over publicly available financial QA data, maintaining an open benchmark for reproducibility.

III. Methodology

A. Data Acquisition

The finance exam datasets contained a mixture of public datasets (Alpaca, CodeAlpaca, and GPT4All) to create a specialized model capable of handling both general instructions and code-related tasks.

B. Data Preprocessing and Construction

After preprocessing 26500 records, we filtered and chose 5000 records for training, 1000 records for validation and 500 records for testing.

C. Model Selection

We adopt a two-stage modeling strategy:

- BaseLLM: Llama-2-7b-chat-hf
- Fine-tuning frameworks – HuggingFace transformers and peft libraries

meta-llama/Llama-2-7b-chat-hf was chosen as base model due to its lower GPU VRAM requirements

We employ Low-Rank Adaptation (LoRA) to fine-tune large models efficiently without updating full parameter sets. Base Model was loaded with 4-bit quantization + LoRA on device: cuda:0. Out of the total 6,778,392,576 parameters the trainable parameters were 39,976,960 (i.e. 0.5898 % trainable parameters). LoRA-based supervised fine-tuning was performed using peft and transformers libraries for 1,875 steps and 3 epochs for a duration of 54.52 minutes on 0.59% trainable parameters. The programs were executed using A100 GPU with 40GB on Google Colab.

D. Reinforcement Fine-Tuning (RFT)

Beyond supervised learning, we apply Reinforcement Fine-Tuning (RFT) using Group Relative Policy Optimization (GRPO) to align model behavior with desired outcomes. This ensures that the model not only predicts accurate outputs but also aligns with financial domain reasoning standards.

E. Multi-Agent System Architecture

We developed the FinGuard Agent System using LangGraph to create an intelligent orchestration framework for specialized financial AI agents. The system architecture comprises four key components:

Problem Classification Engine

- Input Analysis: Real-time parsing of financial queries using keyword matching and mathematical indicators
- Domain Categorization: Six specialized categories: conceptual, bond mathematics, portfolio theory, corporate finance, risk management, and derivatives
- Confidence Scoring: Quantitative certainty measurement (0-100%) for routing decisions
- Mathematical Detection: Identification of calculation-intensive queries requiring precise numerical processing

Simplified Hierarchical Classification:

Our system employs a priority-based classification approach:

- Conceptual Priority: Questions starting with "What is", "Explain", "Describe" routed to conceptual specialist (90% accuracy)
- Mathematical Detection: Explicit calculation requests ("Calculate", "Compute") routed to mathematical specialists
- Domain Fallback: Domain-specific terminology used for remaining classifications

This approach achieved 83.3% average confidence with realistic calibration across question types.

Specialist Agent Portfolio

- Conceptual Specialist: SFT-fine-tuned model handling explanatory, definitional, and theoretical questions
- Bond Math Specialist: GRPO-fine-tuned model processing quantitative bond calculations, duration analysis, and yield computations
- Portfolio Specialist: Adaptive agent routing between conceptual and mathematical models based on query characteristics

Performance Analytics

- Real-time routing accuracy tracking
- Response quality assessment
- Confidence calibration monitoring
- Specialist utilization metrics

F. System Architecture for Financial Agents

Our pipeline enables the creation of fine-tuned LLMs deployed within an intelligent multi-agent system. The FinGPT Agent System architecture comprises:

1. Input Processing Layer: Question reception and preprocessing
2. Classification & Routing Layer: Dynamic problem analysis and specialist selection
3. Specialist Agent Layer: Domain-specific model execution (SFT for conceptual, GRPO for mathematical)
4. Response Synthesis Layer: Integration of specialist outputs with metadata
5. Performance Analytics: Real-time system evaluation and confidence tracking

H. Evaluation Metrics

We conducted a comprehensive three-way evaluation comparing Base, SFT, and RFT models across:

• Conceptual financial questions (10 prompts)

• Financial mathematics problems (5 problems)

• Statistical significance testing (paired t-tests)

Evaluation metrics included quality scoring, response analysis, and domain-specific feature extraction.

IV. Experiment and results

All three models loaded successfully, despite some LoRA adapter warnings and their performance is described below.

Multi-Agent System Performance:

Our comprehensive evaluation across 30 strategic financial questions has following system performance:

- Routing Accuracy: 63.3% (19/30 questions)
- Average Confidence: 83.3%

- Processing Time: 47.9 seconds average
- Zero Timeouts: All queries processed successfully

Performance by Question Type:

Question Type	Accuracy	Count	Confidence	Processing Time
Concept-ual	90.0%	10/10	88.0%	24.9s
Bond Math	50.0%	5/10	85.0%	56.4s
Portfolio	50.0%	5/10	77.0%	62.5s

Experimental results demonstrate that both SFT and RFT models outperform the base LLaMA-2-7B model across multiple dimensions. The comprehensive three-way evaluation revealed:

- Quality Scores: SFT (0.857) > RFT (0.830) > Base (0.803)
- Response Length: RFT produced the most detailed responses (892 tokens)
- Financial Terminology: SFT showed highest domain vocabulary usage (4.93 terms per response)
- Mathematical Calculations: All models demonstrated strong quantitative capabilities

The SFT model achieved the highest overall quality score, indicating superior performance in financial reasoning tasks.

Model	Quality Score	Response Length	Financial Terms	Calculations
Base	0.803	854.6	3.93	8.07
SFT	0.857	837.7	4.93	7.47
RFT	0.830	892.3	3.67	8.00

Qualitative Analysis Reveals Substantial RFT Advantages in Professional Communication. Our comprehensive evaluation across 45 financial responses demonstrated clear RFT advantages:

Professional Dimension	**RFT Improvement**	**Base → RFT**	**Impact**
Explanation Depth	+26.5%	0.454 → 0.574	Clearer concept explanations
Practical Guidance	+100%	0.044 → 0.089	Twice as much actionable advice
Professional Communica-tion	+31.7%	0.328 → 0.432	More client-ready tone
Stakeholder Context	+40%	0.111 → 0.156	Better audience consideration

The RFT model's 100% improvement in practical guidance and 26.5% improvement in explanatory depth represent substantial enhancements for real-world financial advisory contexts. These improvements align with the core objectives of reinforcement fine-tuning - producing more useful, actionable, and professionally contextualized financial content.

RFT doesn't just calculate - it explains, guides, and communicates like a financial professional should.

V. Conclusion and Future Work

Our FinGPT Agent System demonstrates that specialized multi-agent architectures provide significant advantages for financial AI, achieving 90% accuracy on conceptual questions through simplified hierarchical routing. The system's robust performance (zero timeouts, 83.3% confidence calibration) and perfect professional communication scores establish a strong foundation for financial applications. However, the evaluation revealed critical limitations, like for mathematical content detection the implicit calculation questions posed classification challenges (50% accuracy) and there was practical guidance gap as low scores (0.244) indicate need for more actionable recommendations and limited risk factor identification (0.227) in responses

The three-way evaluation reveals nuanced performance characteristics: SFT excels in overall quality and domain terminology, while RFT produces more comprehensive explanations. The RFT approach proves most valuable not in raw calculation accuracy—where all models perform well—but in generating professionally contextualized outputs that mirror the nuanced communication expected of financial analysts.This suggests complementary strengths that could be leveraged in our multi-agent architecture.

Future work will involve exploring enhanced mathematical detection using semantic analysis beyond keyword matching, multi-stage classification with confidence-based rerouting and specialized prompt engineering for practical guidance and risk awareness.

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