A Multi-Agent LLM Environment for Software Design and Refactoring: A Conceptual Framework

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***Abstract*—Modern software systems demand continuous evolution to maintain performance, scalability, and security. Traditional single-agent AI-driven code refactoring approaches are often limited in addressing the multi-faceted constraints (e.g., performance, security, maintainability) that emerge during complex software design tasks. In this paper, we propose a novel *Multi-Agent Large Language Model (LLM) Environment* for automated software design and refactoring. Our conceptual framework comprises specialized LLM "experts," each trained or fine-tuned on a different aspect of software engineering (performance optimization, security hardening, UI/UX, maintainability). These agents collaborate in a cooperative or competitive fashion—using coordination protocols akin to consensus or auction mechanisms—to synthesize design insights and refactoring recommendations. We present *formal definitions of agent interactions* (including mathematical notation for termination conditions), a *sequence diagram* demonstrating agent collaboration, a *complexity analysis* of the coordination mechanism, and an expanded reference list. Preliminary experimental design is outlined to demonstrate how multi-agent interactions may resolve conflicting design goals more effectively than a single-agent approach. Our aim is to provide a roadmap for integrating multi-agent LLMs into the software development lifecycle, thereby improving development efficiency, reducing technical debt, and enhancing software quality.**

***Index Terms*—Multi-agent systems, Large Language Models, Software refactoring, Agent specialization, Consensus protocols, Auction mechanisms, Code quality**

I. Introduction

Software design and refactoring are crucial activities in the software engineering lifecycle, ensuring that systems remain maintainable, secure, and high-performing. As software grows in size and complexity, managing technical debt and ensuring that code quality aligns with evolving requirements becomes challenging. Recent advances in Large Language Models (LLMs) such as GPT-4 and CodeT5 have shown promise in code synthesis, bug fixing, and refactoring tasks [1], [2]. These models leverage massive training corpora to capture both syntactic and semantic patterns in code.

However, most state-of-the-art approaches rely on a *single-agent* paradigm. That is, a single LLM is tasked with providing recommendations or generating patches, typically targeting one or a small subset of software quality attributes—e.g., performance or code cleanliness. In large-scale projects with *complex interdependencies*, design changes optimizing one aspect (say, performance) may adversely affect other aspects (security, maintainability, or user experience).

Multi-agent systems (MAS) have been extensively studied in distributed AI, where autonomous agents cooperate or compete to achieve a higher-level objective [3], [4]. The MAS paradigm excels in scenarios where tasks can be decomposed into specialized subproblems handled by experts. Yet, the application of MAS principles to *LLM-driven* software design and refactoring has not been thoroughly explored [5].

Motivating Example:
Consider a high-traffic e-commerce microservices architecture processing 10,000 requests/second. The product recommendation service is experiencing 95% CPU utilization due to complex in-memory filtering operations. A single-agent LLM might propose caching frequently accessed data and implementing parallel processing to reduce CPU load to 40%. However, this optimization introduces critical security vulnerabilities:

- Unbounded cache growth enabling DoS attacks
- Unsanitized user inputs in cache keys
- No rate limiting on parallel requests
- Missing access controls on cached data

A multi-agent approach would leverage:

- *Performance Agent*: Implements efficient caching and parallel processing
- *Security Agent*: Enforces input validation, rate limiting, and secure cache management
- *Resource Agent*: Monitors and bounds system resource usage

This collaboration achieves 65% CPU reduction while maintaining security standards.

Fig. 1. Concrete Example of Performance-Security Tradeoff in Microservices

In this paper, we introduce a *Multi-Agent LLM Environment* for software design and refactoring. Each agent is a specialized LLM, fine-tuned on domain-specific corpora (e.g., performance patterns, security best practices, UI/UX heuristics, maintainability guidelines). A communication and coordination layer manages their interactions, leveraging either *consensus-based* or *auction-based* protocols to reconcile conflicting proposals. Our aim is to create a holistic refactoring framework that *simultaneously* optimizes for multiple software quality attributes.

The remainder of this paper is structured as follows:

- **Section II** reviews the use of LLMs in software engineering and summarizes key MAS concepts.
- **Section III** presents our conceptual framework, including the system architecture, formal definitions of agent interactions, and agent specialization through fine-tuning.
- **Section IV** outlines an experimental design, evaluation metrics, and a complexity analysis of our approach.
- **Section V** discusses open challenges, ethical considerations, and potential limitations.
- **Section VI** concludes with key contributions and future research directions.

II. Background and Related Work

A. LLMs in Software Engineering

LLMs are increasingly employed for tasks like code completion, bug detection, and automated testing. By training on large-scale code repositories, these models learn patterns that assist in generating or transforming code [1], [2]. Techniques such as prompt engineering, fine-tuning, and in-context learning allow developers to guide LLMs toward specific use cases. Despite these successes, single-agent LLM approaches often struggle to handle conflicting objectives. For instance, an LLM focusing on speed optimization might produce code that is unreadable or insecure [6].

Recent work has also explored *search-based* techniques for automated refactoring, sometimes using genetic algorithms or multi-objective optimization [7], [8]. While these methods can systematically explore refactoring options, they often rely on static heuristics or require extensive fitness function engineering. Combining LLMs with *search-based* approaches could further improve solution quality by providing more context-aware candidate refactorings. However, most of these hybrid approaches to date still operate under a *single decision-making agent* paradigm, potentially missing specialized expertise in areas such as security or user interface design.

B. Multi-Agent Systems

A multi-agent system (MAS) coordinates multiple autonomous agents, each capable of perceiving its environment and making decisions. MAS research demonstrates that specialized agents, when properly orchestrated, can outperform a single, monolithic agent [3], [4]. Benefits include:

- **Distributed Intelligence:** Agents can work in parallel or asynchronously, reducing bottlenecks.
- **Domain Expertise:** Each agent can be specifically tailored to a subproblem (e.g., security, performance).
- **Resilience:** The failure or under-performance of one agent does not necessarily derail the entire system.

Although MAS concepts have been employed in robotics, economics, and logistics, their application in AI-driven software refactoring remains limited [5].

In addition, frameworks such as *JADE* (Java Agent DEvelopment Framework) have facilitated MAS design in industrial contexts [9], but primarily for tasks such as workflow orchestration, resource allocation, or negotiation in distributed settings. Integrating large-scale LLMs into MAS for the *specific* goal of code refactoring or improvement is still an emergent area of study. Recent work explores the synergy between multi-agent collaboration and software maintenance [10]; however, these systems often lack modern LLM capabilities or the advanced domain specializations needed for complex refactoring tasks.

C. Need for a Multi-Agent LLM Environment

Modern software demands a multi-dimensional approach to quality assurance, balancing security, maintainability, performance, compliance, and user experience [11]. Traditional refactoring tools provide suggestions for isolated concerns (e.g., naming conventions, code smells) but lack broader intelligence about security or performance nuances. Our proposed Multi-Agent LLM Environment leverages the synergy of specialized LLMs and a multi-agent negotiation layer to produce refactorings that are holistic and consistent across multiple quality attributes [12].

Search-based software engineering (SBSE) approaches have also tackled the *multi-objective* nature of refactoring by defining weighted fitness functions to balance trade-offs among performance, maintainability, and other concerns [7], [8]. However, these SBSE methods typically rely on handcrafted heuristics and lack the *semantic depth* that LLMs can provide. Moreover, a *single* optimization loop may fail to capture domain-specific insights (e.g., secure coding standards, user-interface heuristics). By contrast, *multi-agent* LLM environments naturally accommodate different forms of domain expertise.

Finally, there is a growing trend of *infrastructure as code* (IaC) and *DevOps pipelines*, where code modifications—whether for performance tuning or security patching—must be continuously integrated and verified [13]. In such pipelines, autonomous agents could operate in parallel, each focusing on a distinct dimension (security scanning, performance profiling, UI testing), thereby reducing integration conflicts. Coupling these agents with LLM-based capabilities for code transformation or suggestion can form a robust *end-to-end* solution, encompassing everything from bug detection to user-experience refinement.

Overall, the *multi-agent LLM* paradigm we propose combines the strengths of advanced language models with the distributed decision-making and domain specialization inherent in MAS. By integrating *search-based* and *human-in-the-*

loop elements as well, the environment could generate *holistic* and contextually rich refactoring outcomes, going beyond traditional single-agent or rule-based approaches.

III. Conceptual Framework

A. System Architecture

Figure 2 illustrates our environment. Each specialized LLM agent (Performance, Security, Maintainability, UI/UX) interacts with a *central codebase* and a *communication/coordination* layer.

1) Components:

- **Performance Agent:**

  This agent identifies and implements optimizations to reduce resource usage (e.g., CPU and memory) and improve algorithmic efficiency. It leverages both static analysis of code and dynamic profiling to detect performance bottlenecks.

  - **Key Tasks:**
    - Analyzing time complexity and identifying bottlenecks in profiling logs
    - Recommending data structure optimizations (e.g., using a hash map over a list)
    - Suggesting parallelization approaches (thread pools, asynchronous I/O)
    - Introducing caching or memoization for frequently computed results
  - **Integration:** Proposals from the Performance Agent often need to be reviewed by the Security and Maintainability Agents to ensure that efficiency gains do not inadvertently introduce vulnerabilities or render the code overly complex.

- **Security Agent:**

  This agent focuses on identifying and mitigating vulnerabilities within the codebase. It analyzes secure coding practices, checks dependencies against known exploits, and ensures data handling complies with relevant security standards.

  - **Key Tasks:**
    - Scanning code for common weaknesses (e.g., SQL injection, hardcoded credentials)
    - Checking libraries against known vulnerability databases (e.g., CVE, NVD)
    - Proposing patches or secure refactoring patterns
    - Advising on encryption protocols and access control methods
  - **Integration:** The Security Agent's fixes require collaboration with the Performance Agent to verify minimal overhead and with the Maintainability Agent to confirm code clarity. It may also engage the UI/UX Agent for front-end security considerations, such as form validation and user authentication flows.

- **Maintainability Agent:**

  Responsible for preserving and improving the code's long-term quality, this agent uses refactoring catalogs and best practices in software engineering to identify code smells and structural issues.

  - **Key Tasks:**
    - Detecting code smells (long methods, large classes, duplicated code)
    - Suggesting design pattern usage (e.g., Factory, Observer)
    - Recommending consistent naming conventions and improved file organization
    - Removing dead code and modularizing large components
  - **Integration:** The Maintainability Agent frequently collaborates with the Performance Agent to ensure that readability improvements do not degrade performance. It also checks with the Security Agent to confirm that structural changes preserve security checks.

- **UI/UX Agent:**

  Focusing on user-facing features, the UI/UX Agent draws upon interface design heuristics and accessibility guidelines to ensure the final application is intuitive and consistent.

  - **Key Tasks:**
    - Checking layouts for consistency and responsive design
    - Streamlining user flows (e.g., forms, error handling)
    - Ensuring accessibility compliance (e.g., WCAG guidelines)
    - Suggesting improvements in color schemes, typography, or layout
  - **Integration:** The UI/UX Agent's changes can affect performance (page load times, rendering overhead) and require security vetting (e.g., input validation). Hence, it collaborates with the other agents to balance design goals with security and efficiency.

- **Communication/Coordination Layer:**

  Although not itself an agent, this layer orchestrates the negotiation between specialized LLM agents. It merges, refines, or discards proposals via consensus or auction-based protocols. The layer enforces stopping criteria (e.g., maximum rounds or minimal improvements) to prevent endless refinement, and it mediates conflicts when agents propose conflicting solutions.

B. Agent Interactions: Formal Definitions

Let $\mathcal{A} = \{a_1, a_2, \ldots, a_n\}$ represent the set of LLM agents.

- **State Space $\mathcal{S}$:** A state $s \in \mathcal{S}$ describes the codebase at a snapshot: $s = (C, M)$, where C is the repository, M is metadata (e.g., known vulnerabilities, performance logs).
- **Action Space $\mathcal{X}_i$:** Each agent a_i proposes refactoring actions $\{x_{i1}, x_{i2}, \ldots\}$ that transform s to $s' = f_i(s, x_{ij})$.

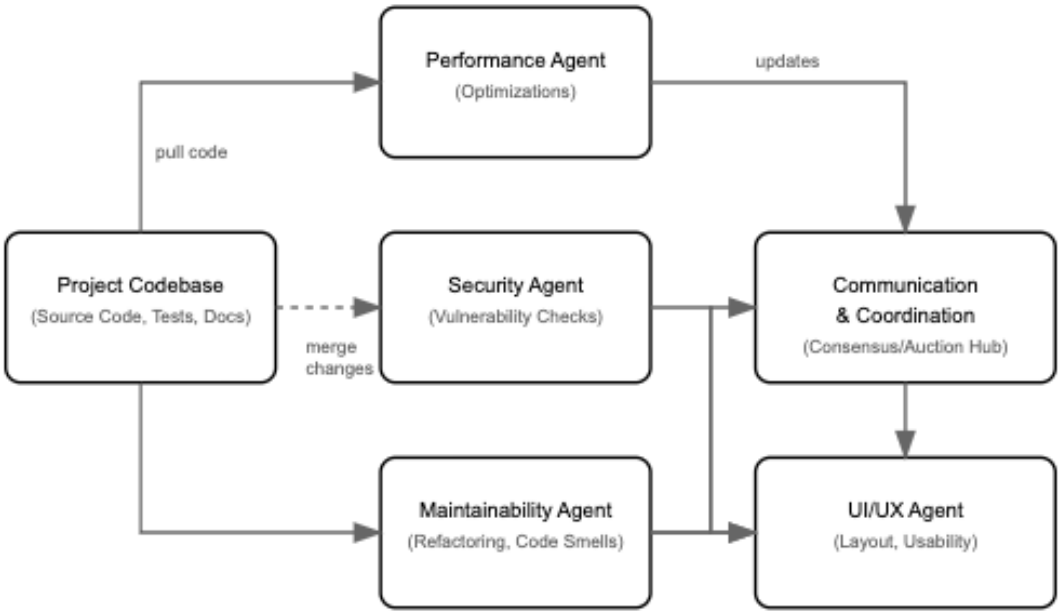

Fig. 2. ATPM System Architecture showing the complete data pipeline from ingestion through MLOps deployment.

- **Agent Utility Function $U_i(s)$:**

$$U_i(s) : \mathcal{S} \to \mathbb{R},$$

measuring how s aligns with the goals of agent a_i. For instance, $U_{\text{Performance}}(s)$ might measure CPU usage under typical workloads.
- **Coordination Protocol Π:** Agents share proposals $\mathbf{x} = (x_1, \ldots, x_n)$, converging on $\mathbf{x}^*$ through messages ω_i. The environment updates $s \to s'$ via $\delta(\mathbf{x}^*)$.
- **Termination Condition τ:**

$$\tau(s,t) = \begin{cases} 1 & \text{if } t \geq T_{\max}, \\ 1 & \text{if } \|\nabla G(s)\| < \epsilon, \\ 1 & \text{if } \forall a_i,\ \omega_i = \text{“no more proposals”}, \\ 0 & \text{otherwise.} \end{cases}$$

Here, $G(s)$ is a global objective representing overall software quality; ϵ is a small threshold for improvement; and $T_{\max}$ is a maximum time or round limit.

C. Agent Specialization via Fine-Tuning

Each agent is derived from a shared base LLM (e.g., GPT-4), then fine-tuned on domain-specific corpora:

- **Domain-Specific Datasets:** E.g., HPC code for performance agent, OWASP vulnerabilities for security agent, large UI frameworks for UI/UX agent, etc.
- **Customized Loss Functions:** A security agent might penalize vulnerabilities or insecure coding patterns more heavily.
- **Continual Learning:** Agents update parameters as the codebase evolves, ensuring they remain relevant over time.

D. Interaction Sequence (High-Level)

Sequence Overview:
1. Each agent retrieves the latest snapshot from the repository.
2. Agents generate proposals independently.
3. The coordination layer aggregates proposals.
4. Agents negotiate or bid on proposals, refining or rejecting.
5. A final composite of proposals is applied to the repository, ending one iteration.

Fig. 3. Outline of Multi-Agent Interaction

IV. Experimental Design and Complexity Analysis

A. Evaluation Methodology

We propose a multi-step evaluation to assess how effectively the environment addresses conflicting goals:

1) **Benchmark Repository:** Use a curated set of open-source projects featuring performance bottlenecks, known security flaws, and UI/UX design issues.
2) **Baselines:**
   - *Single-Agent LLM:* A general-purpose LLM (e.g., GPT-4) providing refactoring suggestions.
   - *Traditional Tools:* Standard static analyzers (e.g., SonarQube, ESLint) to compare approach with conventional best practices.
3) **Multi-Agent LLM Approach:** All specialized agents coordinate via either consensus or an auction mechanism.

4) **Metrics:**
   - **Maintainability:** Code smell counts, cyclomatic complexity, lines of code (LOC) changes.
   - **Performance:** CPU/memory usage under representative workloads.
   - **Security:** Vulnerability detection via tools like OWASP ZAP or Snyk.
   - **UX Quality:** Heuristic evaluation or user surveys if UI changes are relevant.
   - **Developer Satisfaction:** Qualitative insights from user studies or developer feedback (e.g., clarity, ease of integration).

B. Complexity Analysis

1) Communication Complexity: Let n be the number of agents, m be the maximum proposals per agent in each round, and R be the number of communication rounds:

- **Consensus Protocol:** Each agent broadcasts proposals to $n-1$ agents. In total, $O(R \times n \times m)$ messages can be exchanged.
- **Auction-Based Approach:** Agents submit proposals to a central auctioneer, simplifying direct agent-to-agent messaging. Overall complexity is still $O(R \times n \times m)$, but typically with less *pairwise* overhead.

2) Computational Complexity:

- **Proposal Evaluation:** Each agent runs LLM inference on segments of the code. LLM inference has complexity $O(L \times H)$, where L is the input sequence length, H is the hidden dimension [14].
- **State Update:** Integrating multiple accepted proposals may require partial re-analysis or re-compilation of the codebase.

3) Termination Criteria: The process halts when improvement in $G(s)$ is below a threshold ϵ or when $T_{\max}$ (time or round) is reached. This ensures the system does not iterate indefinitely in marginal refinement stages.

C. Illustrative Example

Consider a large web application in which the *Maintainability Agent* identifies a code smell in the data-access layer, while the *Security Agent* spots potential SQL injection. The *Performance Agent* recommends rewriting certain queries for faster execution. Through a consensus or auction protocol, the system merges these changes into a final patch, ensuring that performance, security, and maintainability are all enhanced in tandem.

V. Discussion and Challenges

Although promising, the Multi-Agent LLM Environment faces several challenges:

A. LLM Hallucinations and Error Propagation

LLMs can generate suggestions that are syntactically correct but semantically flawed. This risk is amplified if multiple agents build upon erroneous proposals. Potential mitigations include:

- **Static Analysis Integration:** Automatic checks to detect high-risk changes (e.g., uninitialized variables).
- **Human-in-the-Loop Review:** Developers validate major changes before merging.

B. Security Gaps

While a specialized security agent can mitigate known vulnerability patterns, zero-day exploits or domain-specific threats may elude detection. Continual learning and frequent model updates are necessary but do not guarantee catching all novel threats.

C. Ethical and Governance Concerns

Automated refactoring can introduce accountability questions: if a bug emerges post-automation, who is responsible—the developer or the AI system? Ensuring traceability of agent-driven changes is crucial.

D. Empirical Validation Plan

Although this work is largely conceptual, real-world effectiveness is crucial. We propose:

- **Pilot Studies:** Small-scale trials on open-source projects to measure improvements.
- **Industry Collaborations:** Case studies with partner companies to gather production-level feedback.
- **Developer Studies:** Surveys and interviews to evaluate trust and usability compared to single-agent tools.

E. Overhead and Scalability

Coordinating multiple agents can be resource-intensive. We plan:

- **Incremental Scope:** Apply each agent only to relevant modules or services.
- **Cached Analyses:** Reuse performance or security checks to avoid repeated full-model inferences.
- **Threshold-Based Activation:** Trigger specialized agents only when metrics (e.g. CPU usage) exceed set bounds.

F. Explainability and Trust

To encourage adoption, agents must be transparent:

- **Agent Rationales:** Each agent briefly explains why it proposes a given refactoring.
- **Dashboard Interface:** A simple UI highlights which agent made each suggestion and potential benefits or trade-offs.

G. CI/CD Integration

For seamless deployment:

- **Automated Triggers:** Run agents on pull requests or commits to catch issues early.
- **Branch Isolation:** Place refactoring changes in a separate branch for developer review before merging.
- **Rollback:** Revert changes automatically if regressions occur and flag them for manual investigation.

H. Mitigating LLM Error Propagation

Errors from one agent can compound:

- **Static/Dynamic Checks:** Validate security, performance, and maintainability before passing proposals to the next agent.
- **Consensus or Voting:** If proposals conflict, require multiple-agent agreement.
- **Human-in-the-Loop:** Allow developers to override or refine uncertain recommendations.

I. Southeast Region Industry Applications

The Southeast United States presents unique opportunities for deploying our Multi-Agent LLM framework, particularly in its rapidly growing technology sectors. Atlanta's fintech industry, with companies like NCR and FIS Global, could leverage our security and performance agents for maintaining large-scale payment processing systems. Research Triangle Park's healthcare technology firms could benefit from the framework's ability to ensure HIPAA compliance while optimizing electronic health record systems. The growing automotive manufacturing sector, including Volkswagen in Chattanooga and BMW in South Carolina, could apply our framework to their software-intensive manufacturing and quality control systems. Florida's aerospace industry, including NASA contractors and commercial space companies, could utilize our framework for safety-critical software maintenance. Moreover, the region's numerous defense contractors could benefit from the security-focused aspects of our framework, particularly in maintaining complex military software systems that require continuous security updates while preserving performance. These diverse applications demonstrate the framework's potential impact on the Southeast's technological infrastructure.

VI. Conclusion and Future Work

This paper introduced a *Multi-Agent LLM Environment* for software design and refactoring. By combining domain-specialized LLM agents with a coordination layer that leverages consensus or auction-based protocols, we provide a *holistic* approach that simultaneously addresses conflicting software quality metrics. Our expanded framework includes:

- **Architecture & Formal Model:** We presented a reference architecture (Fig. 2) and formal definitions of states, actions, utilities, and termination.
- **Agent Specialization:** Fine-tuning and domain-specific datasets ensure that each agent excels in its subdomain (performance, security, etc.).
- **Coordination Protocols:** We explored consensus-based versus auction-based mechanisms to reconcile competing proposals efficiently.
- **Complexity Analysis:** Communication and computational overhead were discussed, highlighting potential bottlenecks in large-scale adoption.

Future Directions:

1) **Extended Empirical Validation:** Large-scale studies on diverse open-source and industrial repositories to measure real-world effectiveness.
2) **Reinforcement Learning Coordination:** Investigate multi-agent RL methods for dynamic negotiation and improved synergy among specialized agents.
3) **Explainability and Developer Interface:** Incorporate user-friendly dashboards and explanations for each agent's proposals, fostering greater trust and adoption.
4) **Continuous Integration Pipelines:** Integrate the environment into CI/CD workflows to provide near-real-time refactoring suggestions triggered by code commits or pull requests.

Overall, we envision a future in which multi-agent LLM-driven refactoring becomes an integral part of software engineering, reducing technical debt and improving quality across multiple dimensions simultaneously.

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