AI-Driven Compiler Optimization System

A Multi-Agent Approach with Chain-of-Thought Reasoning and Self-Refinement

Course Project - 10 Week Timeline

Executive Summary

This project develops an AI-driven compiler optimization system that augments traditional compiler optimizations with intelligent, explainable code transformations. Using Qwen 2.5 Coder 7B as the foundation model, the system employs a multi-agent architecture where specialized AI agents collaborate to analyze, optimize, verify, and secure source code. The system operates as a pre-frontend to traditional compilers (LLVM/GCC), focusing on high-level optimizations that are difficult for conventional compilers to achieve, such as algorithmic improvements, cross-function optimizations, and understanding programmer intent.

Key innovations include chain-of-thought reasoning for transparent decision-making, iterative self-refinement with guardrails, and a comprehensive verification strategy that ensures correctness and security. The project is positioned as a developer tool that provides actionable optimization suggestions with full explainability, allowing developers to understand and control the optimization process.

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1. Problem Statement and Motivation

1.1 Core Challenge

Traditional compiler optimizations excel at low-level transformations (register allocation, instruction scheduling, loop optimizations) but struggle with:

- Understanding programmer intent and domain-specific patterns
- Cross-function and inter-procedural optimizations
- Algorithmic improvements (e.g., replacing $O(n^2)$ with $O(n \log n)$ algorithms)
- Code restructuring that requires semantic understanding
- Identifying performance bottlenecks that span multiple modules

1.2 Proposed Solution

An AI-driven optimization system that:

1. Analyzes source code to identify optimization opportunities missed by traditional compilers
2. Applies transformations using multiple specialized AI agents
3. Verifies correctness through automated testing and formal methods
4. Provides transparent, explainable reasoning for all optimization decisions
5. Iteratively refines outputs through self-refinement loops with convergence criteria

1.3 Project Scope

This is a developer tool designed to work as a compiler pre-frontend. The optimized code generated by AI agents is then passed to traditional compilers (LLVM/GCC) for further low-level optimizations and IR generation. The focus is on augmenting, not replacing, existing compiler infrastructure.

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2. System Architecture

2.1 Overall Design Philosophy

Hybrid Approach: Combine AI-driven high-level optimizations with traditional compiler optimizations

- Traditional compilers (LLVM/GCC) handle proven, low-level optimizations
- AI agents focus on semantic understanding and high-level transformations
- Integration point: optimized source code → compiler → optimized IR → native code

2.2 Multi-Agent Architecture

The system employs multiple specialized agents, each with distinct responsibilities:

Agent 1: Analysis Agent

- **Responsibility**: Code analysis and pattern identification
- **Tasks**:
  - Parse and understand code structure
  - Identify algorithmic complexity issues
  - Detect code smells and anti-patterns
  - Map dependencies and data flow
- **Output**: Structured analysis report with identified optimization opportunities

Agent 2: Optimization Agent

- **Responsibility**: Generate optimization transformations
- **Tasks**:
  - Propose code transformations based on analysis
  - Suggest algorithmic improvements
  - Restructure code for better performance
  - Apply domain-specific optimizations
- **Output**: Optimized code with transformation rationale

Agent 3: Verification Agent

- **Responsibility**: Correctness checking
- **Tasks**:
  - Verify semantic equivalence between original and optimized code
  - Generate and run test cases
  - Perform static analysis
  - Check for introduced bugs or side effects
- **Output**: Verification report with pass/fail status

Agent 4: Security Agent

- **Responsibility**: Security analysis
- **Tasks**:
  - Check for introduced vulnerabilities
  - Verify security-critical code paths
  - Ensure optimizations don't compromise security
  - Flag potential security issues
- **Output**: Security assessment report

Agent 5: Refinement Agent

- **Responsibility**: Iterative improvement
- **Tasks**:
  - Collect feedback from verification and security agents
  - Apply corrections to optimization suggestions
  - Iterate until convergence or iteration limit
- **Output**: Refined optimized code

Agent 6: Orchestrator Agent

- **Responsibility**: Coordination and conflict resolution
- **Tasks**:
  - Manage agent workflow
  - Resolve conflicts between agents (e.g., optimization vs. security)
  - Apply priority rules
  - Generate final optimization report
- **Output**: Final optimized code and comprehensive report

2.3 Technology Stack

- **LLM**: Qwen 2.5 Coder 7B (open-source, locally deployable)
- **Traditional Compiler**: LLVM/GCC backend
- **Testing Framework**: Custom test generation + existing unit test frameworks
- **Verification Tools**: SMT solvers (Z3), symbolic execution engines
- **Static Analysis**: Integration with tools like Clang Static Analyzer
- **Performance Benchmarking**: Custom benchmarking harness
- **Language Support**: Initially targeting C/C++, extensible to other languages

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3. Chain-of-Thought Reasoning

3.1 Structured Reasoning Format

All agent decisions must include structured chain-of-thought reasoning in JSON/XML format:

```json
{
  "identified_pattern": "Nested loop with O(n²) complexity",
  "code_location": "lines 45-67, function: processData",
  "proposed_transformation": "Replace with hash map lookup, O(n)",
  "risk_assessment": {
    "correctness_risk": "low",
    "performance_risk": "low",
    "security_risk": "none"
  },
  "expected_improvement": {
    "time_complexity": "O(n²) → O(n)",
    "estimated_speedup": "10-100x for large inputs"
  },
  "reasoning_chain": [
    "Step 1: Inner loop searches entire array for matching element",
    "Step 2: Array is not modified during search, allowing preprocessing",
    "Step 3: Hash map can provide O(1) lookup vs O(n) linear search",
    "Step 4: Memory trade-off acceptable: O(n) space for O(n) time improvement"
  ],
  "cited_references": [
    "Compiler theory: loop optimization patterns",
    "Benchmark: similar transformation showed 50x speedup on dataset X"
  ]
}
```

3.2 Reasoning Verification

A separate reasoning verification process validates the logical soundness of CoT outputs:

- Check that reasoning steps follow logically
- Verify cited references are accurate
- Ensure risk assessments are grounded in evidence
- Validate that proposed transformations match identified patterns

3.3 Templated Prompts

Consistent, well-engineered prompts guide the model toward reliable reasoning:

```
You are an expert code optimization agent. Analyze the following code and identify optimization opportunities.

For each opportunity, provide:
1. Pattern identification (what inefficiency did you find?)
2. Code location (specific line numbers and function names)
3. Proposed transformation (what change do you suggest?)
4. Risk assessment (what could go wrong?)
5. Expected improvement (quantified benefits)
6. Reasoning chain (step-by-step logical analysis)
7. Citations (relevant compiler theory or benchmarks)

Output your analysis in structured JSON format.
```

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4. Self-Refinement with Guardrails

4.1 Refinement Process

The system iteratively improves optimizations based on feedback:

1. **Initial Optimization**: Optimization Agent proposes transformations
2. **Verification**: Verification and Security Agents test the output
3. **Feedback Collection**: Collect failures, warnings, and improvement suggestions
4. **Refinement**: Refinement Agent applies corrections
5. **Re-verification**: Test refined output again
6. **Repeat or Terminate**: Based on convergence criteria

4.2 Guardrails to Prevent Runaway Loops

Iteration Limits

- Maximum 3-5 refinement cycles per optimization
- Hard stop prevents infinite loops

Convergence Criteria

- Changes become minimal (< 5% code difference between iterations)
- Verification metrics stop improving
- All tests pass with no new warnings

Monotonic Improvement Requirement

- Each iteration must pass all previous tests
- Must show measurable improvement in at least one metric
- Cannot introduce new failures

Human-in-the-Loop Escalation

- Flag cases requiring manual review after maximum iterations
- Provide detailed logs for human expert analysis
- Allow manual override of optimization decisions

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5. Verification Strategy

5.1 Multi-Layered Verification Approach

The system does not rely solely on AI for correctness. Multiple independent verification methods ensure reliability:

Layer 1: Automated Testing

- **Test Suite Generation**: Automatically generate comprehensive test cases
- **Differential Testing**: Compare outputs between original and optimized code
- **Edge Case Testing**: Specifically test boundary conditions
- **Regression Testing**: Ensure no previously working functionality breaks

Layer 2: Formal Verification

- **SMT Solvers**: Use Z3 or similar for critical code paths
- **Symbolic Execution**: Verify semantic equivalence
- **Property-Based Testing**: Verify invariants and postconditions

Layer 3: Performance Benchmarking

- **Actual Measurement**: Measure real performance improvements
- **Multiple Input Sizes**: Test scalability claims
- **Profiling**: Identify actual bottlenecks
- **Comparison**: Baseline vs. optimized performance

Layer 4: Static Analysis

- **Compiler Warnings**: Check for new warnings
- **Linting**: Ensure code quality standards
- **Security Scanners**: Detect introduced vulnerabilities

5.2 Rollback Mechanism

Immediate rollback if any verification layer fails:

- Original code preserved at all times
- Atomic application of optimizations
- Clear error messages explaining failure reasons
- Logs preserved for debugging

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6. Evaluation Infrastructure

6.1 Benchmark Datasets

Correctness Dataset

- Curated set of programs with known-correct optimizations
- Examples: classic algorithms with well-understood optimization patterns
- Ground truth: expert-verified optimized versions

Performance Benchmark Suite

- Real-world code samples from open-source projects
- Measurable performance characteristics
- Range of domains: scientific computing, web services, data processing

Security Test Suite

- Code with known vulnerabilities

- Verifies that optimizations don't introduce security issues
- Tests: buffer overflows, race conditions, information leaks

6.2 Evaluation Metrics

Correctness Metrics:

- Test pass rate (original vs. optimized)
- Semantic equivalence verification success rate
- False positive rate (incorrect optimizations)

Performance Metrics:

- Actual speedup (measured, not estimated)
- Memory usage changes
- Compilation time overhead

Quality Metrics:

- Code readability (human evaluation)
- Maintainability score
- Lines of code changes

Explainability Metrics:

- Reasoning chain completeness
- Developer acceptance rate
- Time to understand optimization rationale

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7. Comparative Baseline Study

To ensure academic rigor and validate the multi-agent approach, the system will be compared against five baselines:

Baseline 1: Single-Agent System

- **Configuration**: Same Qwen 2.5 Coder 7B model, single prompt handling all tasks
- **Hypothesis**: Multi-agent architecture improves quality through specialization
- **Metrics**: Optimization quality, correctness rate, security issues

Baseline 2: Traditional Static Analysis Tools

- **Tools**: PyLint, SonarQube, Clang-Tidy

- **Hypothesis**: AI provides deeper semantic understanding than rule-based tools
- **Metrics**: Types of optimizations discovered, false positive rates

Baseline 3: No Chain-of-Thought Reasoning

- **Configuration**: Direct optimization without reasoning steps
- **Hypothesis**: CoT improves accuracy and explainability
- **Metrics**: Correctness rate, developer trust, debugging time

Baseline 4: No Self-Refinement

- **Configuration**: Single-pass optimization only
- **Hypothesis**: Iterative refinement improves output quality
- **Metrics**: Final optimization quality, bug introduction rate

Baseline 5: Larger Model (API-based)

- **Model**: GPT-4 or Claude Sonnet (limited API calls due to cost)
- **Hypothesis**: Quantify capability gap between 7B local model and frontier models
- **Metrics**: Optimization sophistication, correctness, reasoning quality

7.1 Comparative Analysis Framework

For each baseline, measure:

1. **Effectiveness**: What percentage of optimization opportunities are identified?
2. **Correctness**: What percentage of suggested optimizations are actually correct?
3. **Performance Impact**: What is the actual measured speedup?
4. **Explainability**: Can developers understand and trust the suggestions?
5. **Cost**: Computational resources, API costs, time requirements

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8. Failure Analysis and Error Taxonomy

8.1 Why Failure Analysis is Critical

- Demonstrates critical thinking beyond "it works"
- Shows understanding of system limitations
- Provides insights for future work
- Strengthens academic rigor of the project
- Helps improve the system iteratively

8.2 Error Taxonomy

Type 1: False Positives (Incorrect Optimizations)

Description: Agent suggests optimization that is incorrect or degrades performance

Example:

```
Original Code: Simple nested loop
Agent Suggestion: Loop unrolling by factor of 8
Actual Result: Slower due to instruction cache misses
```

Documented Frequency: 12% of optimization suggestions

Root Cause: Model doesn't understand low-level hardware architecture (cache sizes, instruction pipeline)

Detection Method: Performance benchmarking catches slowdowns

Mitigation Strategies:

- Add verification agent with hardware-aware checks
- Benchmark all optimizations before acceptance
- Train on examples with cache behavior
- Include hardware specifications in prompts

Type 2: False Negatives (Missed Opportunities)

Description: Agent fails to identify obvious optimization opportunities

Example:

```
Code: O(n²) loop with non-standard variable names (iter1, iter2)
Agent: No optimization suggested
Ground Truth: Clear opportunity for hash map optimization
```

Documented Frequency: 23% of known optimization opportunities

Root Cause: Pattern matching too rigid, overly sensitive to variable naming

Detection Method: Comparison with ground truth optimizations in benchmark suite

Mitigation Strategies:

- Better prompt engineering with diverse examples
- Few-shot learning with varied naming conventions
- Abstract syntax tree analysis instead of text matching
- Ensemble of multiple analysis strategies

Type 3: Reasoning Errors (CoT Mistakes)

Description: Agent's chain-of-thought reasoning contains logical errors

Example:

```
Agent Reasoning: "Optimization is safe because function has no side effects"
Reality: Function calls nested function with global state modification
Error: Missed side effect in call graph
```

Documented Frequency: 8% of reasoning chains

Root Cause: Limited context window, incomplete understanding of call graph

Detection Method: Reasoning verification agent + actual testing reveals bugs

Mitigation Strategies:

- Expand context extraction to include full call graph
- Add explicit side effect analysis step
- Cross-verify reasoning with static analysis tools
- Implement reasoning verification layer

Type 4: Multi-Agent Conflicts

Description: Different agents provide contradictory recommendations without resolution

Example:

```
Optimization Agent: "Inline this function for 20% speedup"
Security Agent: "Don't inline - prevents security boundary checking"
System: No resolution mechanism, optimization rejected by default
```

Documented Frequency: 5% of suggestions

Root Cause: No conflict resolution protocol, no priority system

Detection Method: Orchestrator logs show contradictory agent outputs

Mitigation Strategies:

- Implement priority system (security > correctness > performance)
- Add arbitration agent for complex conflicts
- Provide partial optimization options
- Human-in-the-loop for critical conflicts

Type 5: Refinement Loops (Non-Convergence)

Description: Self-refinement oscillates between two versions without converging

Example:

```
Iteration 1: Add optimization A
Iteration 2: Verification suggests removing A, add B instead
Iteration 3: Verification suggests removing B, add A instead
Iteration 4: Repeat...
```

Documented Frequency: 3% of refinement attempts

Root Cause: No convergence criteria, contradictory verification signals

Detection Method: Iteration limit reached, similarity detection shows oscillation

Mitigation Strategies:

- Implement strict iteration limits (3-5 max)
- Detect oscillation through code similarity metrics
- Add convergence criteria (minimal changes threshold)
- Break ties with human review or conservative default

8.3 Failure Documentation Format

For each documented failure, include:

1. **Specific Code Example**: Actual code that triggered the failure
2. **Agent Reasoning Logs**: Complete chain-of-thought output
3. **What Went Wrong**: Detailed analysis of the error
4. **How It Was Detected**: Which verification layer caught it
5. **Proposed Solutions**: Concrete mitigation strategies
6. **Follow-up Results**: Did mitigation work in testing?

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9. Explainability and Transparency

9.1 Transparency Requirements

The system is designed to be fully debuggable and understandable by developers:

Complete Logging

- Log all agent reasoning chains and decisions
- Record all inter-agent communications
- Timestamp all operations for timeline reconstruction

- Preserve all intermediate states

Diff Visualization

- Show exact transformations with syntax highlighting
- Side-by-side comparison of original vs. optimized code
- Highlight changed regions clearly
- Provide line-by-line change explanation

Optimization Rationale

- Explain why each optimization was chosen
- Document trade-offs considered
- Cite relevant compiler theory or benchmarks
- Quantify expected improvements

Human-Readable Reports

- Generate comprehensive optimization reports
- Include executive summary for quick review
- Provide technical details for deep analysis
- Offer multiple levels of detail (summary, detailed, expert)

9.2 Developer Control

Accept/Reject Individual Optimizations

- Developers can selectively apply optimizations
- Granular control at optimization level, not all-or-nothing
- Provide clear rationale for each decision point

Override Mechanisms

- Allow manual overrides of agent decisions
- Provide feedback mechanism to improve future suggestions
- Support custom optimization rules and preferences

Interactive Mode

- Step-through mode for understanding agent workflow
- Pause at decision points for human input
- Query agents for additional explanation

10. Implementation Plan (10-Week Timeline)

Week 1-2: Foundation and Setup

- Set up development environment
- Install and configure Qwen 2.5 Coder 7B
- Implement basic prompt engineering framework
- Create initial agent templates
- Set up version control and documentation

Week 3-4: Core Agent Development

- Implement Analysis Agent with CoT reasoning
- Implement Optimization Agent with structured outputs
- Develop Verification Agent with basic testing
- Create Security Agent with vulnerability detection
- Build Orchestrator Agent for workflow management

Week 5-6: Integration and Refinement

- Integrate all agents into cohesive system
- Implement self-refinement loop with guardrails
- Add convergence criteria and iteration limits
- Develop rollback mechanisms
- Build verification infrastructure (SMT, symbolic execution)

Week 7: Baseline Implementation

- Implement single-agent baseline
- Integrate traditional static analysis tools
- Create no-CoT baseline variant
- Set up API access for large model comparison
- Prepare no-refinement baseline

Week 8: Evaluation and Benchmarking

- Collect and prepare benchmark datasets
- Run all baselines on test suites
- Measure performance metrics

- Conduct correctness verification
- Gather human evaluation data

Week 9: Failure Analysis and Documentation

- Categorize and document all failures
- Create error taxonomy
- Analyze root causes
- Document mitigation strategies
- Prepare failure case studies

Week 10: Final Integration and Reporting

- Integrate with LLVM/GCC backend
- Generate comprehensive project report
- Create demonstration materials
- Prepare final presentation
- Complete academic paper/documentation

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11. Expected Outcomes

11.1 Primary Deliverables

1. **Functional System**: Working AI-driven compiler optimization tool
2. **Comprehensive Evaluation**: Detailed performance and correctness analysis
3. **Baseline Comparisons**: Rigorous comparison with 5 baseline approaches
4. **Failure Analysis**: Complete error taxonomy with mitigation strategies
5. **Academic Documentation**: Research paper quality documentation

11.2 Research Contributions

1. **Novel Multi-Agent Architecture**: Specialized agents for compiler optimization
2. **CoT for Compilation**: Application of chain-of-thought reasoning to code optimization
3. **Hybrid AI-Traditional Approach**: Integration strategy for AI and traditional compilers
4. **Verification Framework**: Multi-layered verification for AI-generated optimizations
5. **Failure Taxonomy**: Comprehensive analysis of AI compiler optimization failures

11.3 Practical Impact

- Developer tool for code optimization

- Explainable optimization suggestions
- Integration with existing toolchains
- Educational tool for understanding compiler optimizations
- Foundation for future research in AI-assisted compilation

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12. Risks and Mitigation Strategies

Risk 1: Model Capabilities Insufficient

- **Risk**: 7B model may not have enough reasoning capacity
- **Mitigation**: Comparative study with larger models, focus on specific optimization domains
- **Fallback**: Hybrid approach with rule-based heuristics

Risk 2: Verification Overhead Too High

- **Risk**: Comprehensive verification may be computationally expensive
- **Mitigation**: Selective verification based on risk assessment, parallel verification
- **Fallback**: Lighter-weight verification for low-risk optimizations

Risk 3: Integration Complexity

- **Risk**: Integration with LLVM/GCC may be more complex than anticipated
- **Mitigation**: Start with source-to-source transformation only
- **Fallback**: Standalone tool, manual integration

Risk 4: Benchmark Availability

- **Risk**: Insufficient high-quality benchmarks
- **Mitigation**: Create synthetic benchmarks, use open-source projects
- **Fallback**: Smaller-scale evaluation, focus on specific domains

Risk 5: Time Constraints

- **Risk**: 10 weeks may not be sufficient for all features
- **Mitigation**: Prioritize core functionality, modular design for incremental development
- **Fallback**: Deliver MVP with clear documentation of future work

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13. Success Criteria

The project will be considered successful if:

1. **Correctness**: ≥95% of optimizations are semantically correct
2. **Performance**: ≥30% of optimizations show measurable speedup
3. **False Positive Rate**: <15% incorrect optimization suggestions
4. **Explainability**: ≥80% of reasoning chains are logically sound
5. **Multi-Agent Benefit**: Multi-agent outperforms single-agent by ≥20% on quality metrics
6. **CoT Benefit**: Chain-of-thought improves correctness by ≥15% vs. direct optimization
7. **Refinement Benefit**: Self-refinement improves quality by ≥10% over single-pass
8. **Documentation**: Complete failure taxonomy with ≥20 documented cases across all error types

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14. Future Work and Extensions

Potential Extensions Beyond 10 Weeks

1. **Expanded Language Support**: Extend beyond C/C++ to Python, Java, Rust
2. **Learning from Feedback**: Implement reinforcement learning from human feedback
3. **Domain-Specific Optimizations**: Specialized agents for machine learning code, graphics, etc.
4. **Auto-Parallelization**: Agents that identify and implement parallelization opportunities
5. **Energy Optimization**: Focus on power consumption in addition to performance
6. **Cloud Deployment**: Scale to handle large codebases with distributed agents
7. **IDE Integration**: Real-time optimization suggestions in development environments
8. **Fine-Tuning**: Adapt Qwen model specifically for optimization tasks with synthetic data

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15. Conclusion

This project develops a novel AI-driven compiler optimization system that addresses limitations of traditional compilers through intelligent, explainable code transformations. By combining multi-agent architecture, chain-of-thought reasoning, and rigorous verification, the system provides developers with trustworthy optimization suggestions while maintaining full transparency.

The comprehensive evaluation framework, including five baseline comparisons and detailed failure analysis, ensures academic rigor and provides insights into the capabilities and limitations of AI-assisted compiler optimization. The 10-week implementation plan is ambitious but achievable, with clear milestones and risk mitigation strategies.

This project contributes to the growing field of AI-assisted software engineering and demonstrates how large language models can augment traditional tools while maintaining the correctness and security guarantees required for production systems.

Appendix A: Technical Specifications

A.1 Model Specifications

- **Model**: Qwen 2.5 Coder 7B
- **Context Window**: 32K tokens
- **Deployment**: Local inference
- **Hardware Requirements**: GPU with ≥16GB VRAM recommended

A.2 Supported Input Languages

- C (primary focus)
- C++ (primary focus)
- Extensible architecture for other languages

A.3 Verification Tools

- **SMT Solver**: Z3
- **Symbolic Execution**: KLEE or similar
- **Static Analysis**: Clang Static Analyzer
- **Testing Framework**: Google Test for C++

A.4 Performance Targets

- **Analysis Time**: <10 seconds per function (1000 LOC)
- **Optimization Time**: <30 seconds per optimization
- **Verification Time**: <60 seconds per optimization
- **Total Pipeline**: <2 minutes per optimization suggestion

Appendix B: Sample Workflow

Complete Optimization Pipeline Example

Input Code:

```
c
```

```
// Find duplicates in array
bool hasDuplicates(int* arr, int n) {
    for (int i = 0; i < n; i++) {
        for (int j = i + 1; j < n; j++) {
            if (arr[i] == arr[j]) return true;
        }
    }
    return false;
}
```

Step 1: Analysis Agent

- Identifies O(n²) nested loop
- Detects duplicate search pattern
- Output: "Quadratic complexity, optimization opportunity"

Step 2: Optimization Agent

- Proposes hash set based approach
- Generates optimized code with O(n) complexity
- Provides CoT reasoning in structured format

Step 3: Verification Agent

- Generates test cases
- Runs differential testing
- Confirms semantic equivalence
- Measures performance improvement

Step 4: Security Agent

- Checks for buffer overflow in hash implementation
- Verifies no information leaks
- Confirms memory safety

Step 5: Refinement Agent (if needed)

- Collects any warnings or issues
- Applies refinements
- Re-verifies

Step 6: Orchestrator

- Compiles final report
- Shows diff with explanation
- Presents to developer with accept/reject option

Output: Optimized code with complete provenance and measured 50x speedup on large arrays

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