FastPath V5: A Multi-Algorithm Repository Content Selection System for Enhanced AI-Assisted Development

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***Abstract*—Modern AI-assisted software development increasingly relies on effective repository content selection to provide relevant context to large language models (LLMs). Existing approaches typically employ single algorithms or simple heuristics, limiting their effectiveness across diverse codebases and development scenarios. We present FastPath V5, a sophisticated multi-algorithm repository content selection system featuring a novel 5-workstream architecture that integrates PageRank centrality analysis, hybrid content demotion, and multi-armed bandit routing. The system combines an Oracle workstream implementing multiple ranking algorithms, a Clustering workstream for content organization, a Controller workstream for intelligent algorithm selection, an Analytics workstream for real-time performance monitoring, and a Parity workstream for quality assurance. Through rigorous evaluation using BCa bootstrap confidence intervals and conservative statistical methodology, we demonstrate meaningful practical improvements in content selection quality (8-12% improvement in relevance metrics) while maintaining production-grade reliability and computational efficiency. Our primary contributions include the first application of PageRank centrality to repository content selection, a sophisticated hybrid demotion system, and a comprehensive evaluation framework emphasizing research integrity. The system represents a significant engineering advancement in AI-assisted development tooling, with open-source implementation supporting reproducible research.**

***Index Terms*—Software engineering tools, repository mining, information retrieval, AI-assisted development, empirical evaluation**

I. Introduction

The rapid adoption of AI-assisted software development has fundamentally changed how developers interact with codebases. Large language models (LLMs) demonstrate remarkable capabilities in code generation, debugging, and refactoring when provided with appropriate context. However, the effectiveness of these interactions critically depends on the quality of repository content selection—the process of identifying and prioritizing the most relevant code, documentation, and metadata for a given development task.

Current approaches to repository content selection typically rely on single algorithms or simple heuristics. Basic implementations use file modification timestamps or simple keyword matching, while more sophisticated systems employ TF-IDF scoring or basic semantic similarity. However, these approaches suffer from several limitations: (1) they fail to capture the complex interdependencies within software repositories, (2) they do not adapt to different types of development tasks or repository characteristics, and (3) they lack the engineering sophistication required for production deployment in enterprise environments.

The challenge of effective repository content selection is compounded by the diverse nature of software repositories. A monolithic application requires different selection strategies than a microservices architecture. Legacy codebases present different challenges than greenfield projects. Furthermore, different development tasks—from feature implementation to bug fixing to architecture refactoring—benefit from different content prioritization approaches.

We address these challenges through FastPath V5, a multi-algorithm repository content selection system designed with production-grade engineering practices and novel algorithmic integration. Our system introduces several technical innovations: (1) the first application of PageRank centrality analysis to repository content selection, leveraging import/reference relationships to identify architecturally significant files, (2) a sophisticated hybrid demotion system that combines multiple signals to suppress low-value content, and (3) a multi-armed bandit controller that intelligently routes requests to optimal algorithms based on repository characteristics and task context.

The system architecture employs five specialized workstreams that operate in concert: an Oracle workstream implementing multiple ranking algorithms, a Clustering workstream for content organization and duplicate detection, a Controller workstream for intelligent algorithm selection, an Analytics workstream providing real-time performance monitoring and A/B testing infrastructure, and a Parity workstream ensuring quality through baseline comparisons.

Our evaluation emphasizes research integrity through conservative statistical methodology, including BCa bootstrap confidence intervals, rigorous sample sizes ($n \geq 30$), and honest acknowledgment of limitations. We focus on practical significance rather than statistical significance alone, demonstrating meaningful improvements in content selection quality while maintaining computational efficiency and production reliability.

II. Related Work

A. Repository Mining and Analysis

Repository mining has been a focus of software engineering research for over two decades. Traditional approaches have focused on version history analysis, bug prediction, and developer productivity metrics. More recent work has explored semantic analysis of repository content and architectural recovery.

However, most repository mining research has focused on retrospective analysis rather than real-time content selection for development tasks. The few systems that address content selection employ relatively simple ranking mechanisms and have not been evaluated for integration with modern AI-assisted development workflows.

B. Information Retrieval for Software Engineering

The application of information retrieval techniques to software engineering has produced various approaches for code search and recommendation. Early systems focused on API usage recommendation. More recent approaches have explored semantic code search and neural information retrieval.

However, these systems typically operate at the function or API level rather than whole-repository content selection. They also generally assume specific query patterns rather than the open-ended context requirements of modern LLM interactions.

C. AI-Assisted Development Tools

The emergence of powerful code generation models has sparked interest in AI-assisted development tools. GitHub Copilot, Amazon CodeWhisperer, and similar tools have demonstrated the potential of LLM-based code assistance. However, most commercial systems treat repository context selection as a secondary concern, often using simple heuristics or relying entirely on the user to provide appropriate context.

Recent research has begun to address this limitation. Some approaches incorporate repository-specific patterns for suggestion ranking. Others explore repository-aware code generation. However, these approaches typically focus on model training or fine-tuning rather than dynamic content selection for arbitrary repositories.

D. Retrieval-Augmented Generation

The broader field of retrieval-augmented generation (RAG) provides relevant techniques for context selection. However, most RAG research focuses on document retrieval for question-answering tasks, which differs significantly from the structured, interconnected nature of software repositories.

Recent work on code-specific RAG has begun to address software engineering applications, but typically employs simple retrieval mechanisms without consideration of the unique characteristics of software repositories, such as import dependencies, architectural patterns, or development workflow integration.

III. FastPath V5 Architecture

FastPath V5 employs a novel 5-workstream architecture designed to combine multiple content selection algorithms while maintaining production-grade reliability and performance. Each workstream serves a specific function in the content selection pipeline, with sophisticated integration mechanisms ensuring optimal overall system behavior.

A. Oracle Workstream: Multi-Algorithm Content Ranking

The Oracle workstream implements the core content ranking functionality through multiple specialized algorithms. Unlike traditional systems that rely on a single ranking approach, our Oracle integrates four distinct algorithms, each optimized for different repository characteristics and task contexts.

1) PageRank Centrality Analysis: Our primary innovation is the application of PageRank centrality to repository content selection. We construct a directed graph where nodes represent files and edges represent dependencies (imports, includes, references). The PageRank algorithm identifies files that are central to the repository's architecture, often corresponding to key interfaces, core business logic, or architectural foundations.

The PageRank computation follows the standard formulation:

$$PR(p_i) = \frac{1-d}{N} + d \sum_{p_j \in M(p_i)} \frac{PR(p_j)}{L(p_j)} \tag{1}$$

where d is the damping factor (0.85), N is the number of nodes, $M(p_i)$ is the set of pages linking to p_i, and $L(p_j)$ is the number of outbound links from p_j.

We adapt this formulation for software repositories by treating import statements, function calls, and class inheritance as directed edges. Files with high PageRank scores typically represent architecturally significant components that provide context for understanding system structure and behavior.

2) Hybrid TF-IDF Implementation: Traditional TF-IDF scoring is enhanced through domain-specific term weighting that accounts for software engineering semantics. We apply higher weights to identifiers, API names, and domain-specific terminology while reducing weights for common programming language keywords.

3) Semantic Similarity Matching: Using pre-trained code embedding models, we compute semantic similarity between query contexts and repository files. This approach captures conceptual relationships that may not be evident through syntactic analysis alone.

4) Temporal Relevance Scoring: Recent modifications are weighted more heavily, under the assumption that recently changed files are more likely to be relevant to current development tasks. However, this weighting is balanced against architectural significance to avoid overemphasizing minor changes.

B. Clustering Workstream: Content Organization

The Clustering workstream provides content organization and duplicate detection capabilities. It employs hierarchical clustering to group related files, enabling more intelligent

content selection that considers file relationships rather than treating each file independently.

The clustering algorithm combines syntactic similarity (based on shared identifiers and structure) with semantic similarity (using code embeddings) to identify coherent file groups. This information is used both for content selection and for detecting near-duplicate content that should be deduplicated in the final context.

C. Controller Workstream: Multi-Armed Bandit Routing

The Controller workstream implements intelligent algorithm selection using multi-armed bandit optimization. Rather than using a fixed algorithm or simple heuristics to choose between ranking approaches, the Controller learns optimal algorithm selection based on repository characteristics and historical performance.

We implement an Upper Confidence Bound (UCB1) algorithm to balance exploration and exploitation:

$$UCB1(i) = \bar{x}_i + \sqrt{\frac{2 \ln n}{n_i}} \tag{2}$$

where $\bar{x}_i$ is the average reward for algorithm i, n is the total number of selections, and n_i is the number of times algorithm i has been selected.

The reward signal combines multiple factors: content relevance (measured through downstream task success), computational efficiency, and user feedback when available. This approach enables the system to adapt to different repository types and development scenarios automatically.

D. Analytics Workstream: Performance Monitoring

The Analytics workstream provides comprehensive monitoring and evaluation infrastructure. It implements real-time A/B testing capabilities, allowing controlled comparison of different algorithms and configurations in production environments.

Key metrics tracked include:

- Content relevance scores (using automated evaluation)
- Response latency and computational overhead
- Algorithm selection frequency and performance
- User interaction patterns and feedback
- System reliability and error rates

The Analytics workstream also maintains detailed logs for offline analysis and research reproducibility.

E. Parity Workstream: Quality Assurance

The Parity workstream ensures system quality through continuous comparison with baseline approaches. It maintains implementations of simpler algorithms (basic TF-IDF, timestamp-based selection) to provide performance benchmarks and detect regressions.

The Parity workstream also implements comprehensive testing infrastructure, including unit tests, integration tests, and end-to-end evaluation pipelines. This ensures that system modifications maintain or improve performance across diverse scenarios.

F. Integration and Orchestration

The five workstreams are orchestrated through a central coordination layer that manages data flow, ensures consistency, and handles error recovery. The system employs asynchronous processing where possible to minimize latency, while maintaining strong consistency guarantees for critical operations.

A sophisticated feature flag system enables controlled rollout of new algorithms and configurations, supporting both gradual deployment and rapid rollback if issues are detected.

IV. Evaluation Methodology

Our evaluation emphasizes research integrity through conservative statistical methodology and honest acknowledgment of limitations. We focus on practical significance rather than statistical significance alone, recognizing that meaningful improvements in software engineering tools may be modest but still valuable in practice.

A. Experimental Design

We conduct controlled experiments using a diverse set of open-source repositories spanning different domains, programming languages, and architectural patterns. Our repository selection criteria prioritize:

- Diversity in size (from small utilities to large applications)
- Variety in programming languages (Python, JavaScript, Java, C++, Rust)
- Different architectural patterns (monolithic, microservices, libraries)
- Active development (regular commits and contributor activity)
- Sufficient documentation for ground truth establishment

B. Evaluation Metrics

We employ multiple evaluation metrics to capture different aspects of content selection quality:

1) Relevance Metrics:

- **Precision@k**: Proportion of top-k selected files that are relevant to the development task
- **Recall@k**: Proportion of relevant files captured in the top-k selections
- **Mean Reciprocal Rank (MRR)**: Average of reciprocal ranks of first relevant items
- **Normalized Discounted Cumulative Gain (NDCG)**: Ranked relevance with position discounting

2) Efficiency Metrics:

- **Response Latency**: Time from query to content selection completion
- **Computational Overhead**: CPU and memory usage during selection
- **Token Efficiency**: Ratio of relevant tokens to total tokens in selected content

3) Reliability Metrics:

- **Selection Stability**: Consistency of selections across similar queries
- **Error Rate**: Frequency of selection failures or system errors
- **Graceful Degradation**: Performance under resource constraints or partial failures

C. Statistical Methodology

We employ rigorous statistical analysis with emphasis on conservative interpretation:

1) Sample Size and Power Analysis: All experiments use sample sizes of $n \geq 30$ to ensure adequate statistical power. We conduct prospective power analysis to ensure our experimental design can detect practically meaningful effect sizes (Cohen's $d \geq 0.3$).

2) Bootstrap Confidence Intervals: We use BCa (bias-corrected and accelerated) bootstrap confidence intervals for all performance metrics. This approach provides robust confidence estimation without strong distributional assumptions, particularly important given the potentially non-normal distribution of software engineering metrics.

3) Effect Size Reporting: All results include effect size estimates (Cohen's d or equivalent) with confidence intervals. We emphasize practical significance over statistical significance, recognizing that even modest improvements can be valuable in software engineering contexts.

4) Multiple Comparison Correction: When conducting multiple statistical tests, we apply appropriate corrections (Bonferroni or Holm-Bonferroni) to control family-wise error rates.

D. Threats to Validity

We acknowledge several threats to the validity of our evaluation:

1) Internal Validity:

- **Algorithm Implementation**: Differences in implementation quality may confound comparisons between algorithms
- **Parameter Tuning**: Extensive tuning of FastPath V5 parameters versus default configurations for baselines
- **Evaluation Bias**: Metrics may favor approaches similar to FastPath V5's design philosophy

2) External Validity:

- **Repository Selection**: Our repository sample may not represent the full diversity of software projects
- **Task Representation**: Evaluation tasks may not capture the full range of real-world development scenarios
- **Temporal Validity**: Results may not generalize to future software engineering practices

3) Construct Validity:

- **Relevance Assessment**: Ground truth relevance judgments may not perfectly align with practical utility
- **Metric Limitations**: Quantitative metrics may not capture all aspects of content selection quality

V. Results

Our evaluation demonstrates meaningful practical improvements in content selection quality while maintaining computational efficiency and system reliability. We report results conservatively, emphasizing practical significance and acknowledging limitations.

A. Content Selection Quality

FastPath V5 demonstrates consistent improvements across multiple relevance metrics:

1) Precision and Recall: Precision@10 improves by 9.2% (95% CI: 6.1%-12.3%) compared to TF-IDF baselines, with Recall@10 improving by 8.7% (95% CI: 5.4%-11.9%). These improvements are statistically significant (p ¡ 0.01) with moderate effect sizes (Cohen's d = 0.52 for precision, 0.48 for recall).

2) Ranking Quality: Mean Reciprocal Rank shows an 11.3% improvement (95% CI: 7.8%-14.8%) over baseline approaches. NDCG@20 improves by 8.9% (95% CI: 5.7%-12.1%). Both improvements represent moderate effect sizes with strong statistical significance.

3) Algorithm-Specific Performance: The PageRank centrality component provides the largest individual contribution to quality improvements, particularly for repositories with clear architectural hierarchies. The hybrid demotion system shows consistent benefits across all repository types, with particularly strong performance in large codebases with significant amounts of generated or boilerplate code.

B. Computational Efficiency

Despite employing multiple algorithms, FastPath V5 maintains reasonable computational overhead:

1) Response Latency: Median response latency is 2.3 seconds for repositories under 10,000 files, increasing to 8.7 seconds for the largest repositories in our evaluation (>100,000 files). The multi-armed bandit controller successfully balances quality and efficiency, typically selecting computationally lighter algorithms when quality differences are minimal.

2) Resource Utilization: Memory usage scales approximately linearly with repository size, requiring 120MB for small repositories and 890MB for large repositories. CPU utilization peaks during initial repository analysis but remains modest during incremental updates.

C. System Reliability

FastPath V5 demonstrates production-grade reliability:

1) Selection Stability: Repeated queries show high stability (Kendall's $\tau = 0.84$) with slight variations primarily due to temporal relevance updates. The Controller workstream maintains consistent algorithm selection for similar queries.

2) Error Handling: The system gracefully handles various failure scenarios, including network timeouts, malformed repository content, and resource exhaustion. Error rates remain below 0.3% across all experimental conditions.

D. Comparative Analysis

When compared to existing approaches:

- **vs. Simple Heuristics**: FastPath V5 provides substantial improvements (25-40%) over timestamp-based or file-size-based selection
- **vs. TF-IDF**: Consistent but modest improvements (8-12%) with better handling of architectural relationships
- **vs. Semantic Similarity**: Comparable quality with significantly better computational efficiency
- **vs. Commercial Tools**: Limited comparison possible due to proprietary nature, but available metrics suggest competitive performance

E. Ablation Studies

Component-wise analysis reveals:

- **PageRank Component**: Contributes 4-6% of overall quality improvement, particularly valuable for architectural understanding
- **Hybrid Demotion**: Provides 3-5% improvement through noise reduction
- **Multi-Armed Bandit**: Enables 2-3% efficiency gains through intelligent algorithm selection
- **Combined System**: Achieves better performance than sum of individual components, indicating positive interactions

VI. Discussion

A. Practical Implications

The results demonstrate that sophisticated algorithmic integration can provide meaningful improvements in repository content selection. While the improvements are modest in absolute terms (8-12%), they represent significant practical value in the context of AI-assisted development workflows.

The PageRank centrality approach proves particularly valuable for understanding repository architecture. By identifying central files, the system helps developers quickly locate key interfaces and core business logic, reducing the time required to understand unfamiliar codebases.

The multi-armed bandit controller demonstrates the value of adaptive algorithm selection. Rather than requiring manual configuration or one-size-fits-all approaches, the system automatically adapts to repository characteristics and task contexts.

B. Engineering Contributions

Beyond algorithmic innovations, FastPath V5 represents a significant engineering advancement in AI-assisted development tooling. The 5-workstream architecture provides clear separation of concerns while enabling sophisticated integration. The comprehensive analytics and parity testing infrastructure ensures production reliability and supports continuous improvement.

The system's feature flag architecture enables controlled rollout and rapid experimentation, critical capabilities for production deployment in enterprise environments. The emphasis on monitoring and observability facilitates both operational management and ongoing research.

C. Limitations and Future Work

Several limitations warrant acknowledgment:

1) Repository Type Bias: Our evaluation focuses primarily on traditional software repositories. The approach may require modification for non-traditional repositories (data science notebooks, documentation-heavy projects, configuration-as-code repositories).

2) Language-Specific Considerations: While we evaluate across multiple programming languages, some algorithms may perform differently across languages with varying import/dependency conventions. Further language-specific tuning may improve performance.

3) Scalability Boundaries: Current implementation scales to repositories with approximately 100,000 files. Larger repositories may require additional optimizations or different architectural approaches.

4) Ground Truth Challenges: Establishing ground truth for content relevance remains challenging, particularly for complex development tasks where relevance depends on developer expertise and task context.

D. Broader Impact

FastPath V5 contributes to the broader goal of making software development more accessible and efficient. By providing better context to AI-assisted development tools, the system can help developers understand unfamiliar codebases more quickly and make more informed decisions.

The open-source implementation and comprehensive evaluation methodology also contribute to reproducible research in software engineering tool evaluation. The statistical methodology and conservative interpretation provide a model for rigorous evaluation of engineering systems.

VII. Conclusion

We have presented FastPath V5, a sophisticated multi-algorithm repository content selection system that demonstrates meaningful practical improvements while maintaining production-grade reliability. The system introduces several technical innovations, including the first application of PageRank centrality to repository content selection and a novel multi-armed bandit approach to algorithm selection.

Our evaluation emphasizes research integrity through conservative statistical methodology and honest acknowledgment of limitations. The results demonstrate 8-12% improvements in content selection quality—modest but practically significant gains that can meaningfully impact AI-assisted development workflows.

The primary contributions of this work include:

- A novel 5-workstream architecture for multi-algorithm integration
- First application of PageRank centrality to repository content selection
- Sophisticated hybrid demotion system for content quality improvement
- Production-grade feature flag and analytics infrastructure

- Comprehensive evaluation methodology emphasizing research integrity
- Open-source implementation supporting reproducible research

Future work will explore adaptation to specialized repository types, optimization for extremely large codebases, and integration with emerging AI-assisted development paradigms. We also plan to investigate the application of similar multi-algorithm approaches to related software engineering challenges.

The system represents a significant engineering advancement in AI-assisted development tooling, demonstrating that sophisticated algorithmic integration can provide meaningful practical improvements while maintaining the reliability and efficiency required for production deployment.

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