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A Hybrid Refactoring Engine Driven by Code Semantics and Developer Intent

Annapurna Shobitha S[1], Sushma D S[2], Ankitha[3], Dr. Damodaran D[4], Soham Ghosh[5] and Seema J Kampli[6]
[1-2. 4-5]Assistant Professor, Department of Computer Science, Dayananda Sagar University, Bengaluru, Karnataka
[3]Assistant Professor, Department of Computer Science, Malnad College of Engineering, Hassan, Karnataka
[6]Assistant Professor, Department of Computer science and Engineering, Dayananda Sagar Academy of Technology and Management, Bengaluru, Karnataka
Email: sannapurna.work@gmail.com, rjsush007@gmail.com, itechdamu@gmail.com, seema.jk@gmail.com

***Abstract*— Refactoring is a critical software maintenance activity aimed at improving code structure without altering its external behaviour. However, conventional refactoring tools often fail to align with the nuanced intent of developers, leading to suboptimal transformations and unintended behavioural shifts. This paper proposes a novel code refactoring engine that integrates semantic drift detection with developer intent analysis to guide context-aware transformations. Our approach models semantic drift by tracking latent shifts in code meaning across version histories using vectorized representations derived from abstract syntax trees (ASTs) and control-flow graphs (CFGs). Simultaneously, developer intent is inferred from commit messages, inline comments, and historical code edit patterns through natural language processing and graph-based reasoning. By fusing these two dimensions, the system dynamically generates refactoring suggestions that preserve program correctness while remaining faithful to the original design rationale. We evaluate our engine on multiple open-source repositories across diverse domains and demonstrate significant improvements in maintainability metrics such as cyclomatic complexity, cohesion, and code smell reduction, compared to baseline refactoring tools. Our results underline the importance of semantically-grounded and intent-aware refactoring as a path toward intelligent software evolution.**

***Keywords*— Code Refactoring, Semantic Drift, Developer Intent, Software Maintenance, Program Analysis, Abstract Syntax Tree (AST), Control Flow Graph (CFG), Natural Language Processing (NLP), Software Evolution, Intent-Aware Refactoring.**

I. INTRODUCTION

In modern software engineering, maintaining code quality across iterative development cycles remains a persistent challenge. As software systems evolve, their internal structure often deteriorates due to accumulated technical debt, inadequate documentation, or rapid feature integration—leading to reduced maintainability and increased defect proneness. Code refactoring, the disciplined process of improving code structure without altering its external behaviour, has become indispensable in addressing these concerns. Despite the availability of automated refactoring tools, a crucial limitation persists: they often operate with limited contextual awareness, disregarding the semantic shifts in code logic over time and the original intent behind developer actions.

A semantic framework for code evolution has recently emerged as a promising direction to address this issue. By leveraging static and dynamic analysis, machine learning, and software repository mining, researchers have

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attempted to detect anomalies, smells, or anti-patterns that accumulate silently in source code. However, a growing body of work indicates that these methods overlook semantic drift—the subtle evolution of meaning in code components due to repeated changes, refactoring's, or developer turnover.

Semantic drift, when left unchecked, can result in transformations that appear syntactically valid but contradict the conceptual model of the application.

At the same time, recent trends in developer-cantered software intelligence emphasize the importance of capturing developer intent during software evolution . Commit messages, issue tracker logs, inline comments, and prior edit histories contain valuable implicit signals about why a piece of code was written or modified a certain way. Ignoring this intent leads to automated suggestions that may technically "improve" code metrics while compromising architectural principles or business logic.

To address these gaps, this paper introduces a code refactoring engine that integrates semantic drift modelling with developer intent analysis. The engine combines structural code representations—such as Abstract Syntax Trees (ASTs) and Control Flow Graphs (CFGs)—with natural language data drawn from development artifacts. Using vector embedding techniques and graph-based similarity measures, it detects drift across code versions. Concurrently, it applies natural language processing and intent classification models to infer developer goals from contextual artifacts. The intersection of these two dimensions allows the engine to recommend refactoring that are not only syntactically and semantically sound but also aligned with the original design rationale.

Our contributions are grounded in the ongoing research into intelligent software evolution, where automation is informed not just by code metrics, but by meaning and intent. Prior work on automated refactoring has laid the foundation, but lacks mechanisms for longitudinal semantic tracking and contextual understanding. We build upon these efforts by proposing a hybrid semantic-intent architecture, demonstrating its efficacy across a curated benchmark of real-world software repositories.

The engine is evaluated using a combination of quantitative software quality metrics—such as cyclomatic complexity, code cohesion, and code smell density—as well as qualitative developer feedback. Case studies across Java and Python projects reveal substantial improvements in refactoring precision and developer trust. Furthermore, we explore scenarios where traditional refactoring tools fail due to drift or misinterpretation of developer context, emphasizing the necessity of our approach.

In summary, this work marks a significant advancement in the field of program transformation by incorporating semantically grounded and intent-aware intelligence into the refactoring process. As software systems grow in complexity, such intelligent refactoring strategies will be essential to ensure sustainable, context-aware software evolution.

II. Literature Survey

A. Developer–LLM Interactions in Refactoring (2024)

AlOmar et al. conducted an exploratory empirical study that analysed 17,913 developer ChatGPT refactoring dialogues to better understand how developers express their needs and how conversational AI models respond. The study uncovered that developers often articulate refactoring goals using both generic and precise language, while ChatGPT tends to interpret developer intent explicitly in its refactoring suggestions. This body of work lays the groundwork for intent-aware systems by emphasizing how intent is communicated and interpreted in natural language—central to our hybrid semantic intent refactoring engine.

B. Refactoring Behaviour and Tool Adoption (2024)[1]

Ivers et al. investigated the mismatch between industrial refactoring criteria and tool recommendations, revealing that developer motivations often diverge from what automated recommendations propose. Meanwhile, Eilertsen et al. observed that developers frequently resort to manual refactoring's, citing lack of trust, complexity, or insufficient tool usability as key impediments. These insights underscore the need for tools that understand intention, explain transformations transparently, and earn developer trust—precisely what our engine aims to address.[2]

C. LLM Augmented Automated Move Method Refactoring (2024–2025)

Venigalla & Chimalakonda (2024) designed a machine learning approach to identify move method opportunities in real time, facilitating more accurate refactoring detection. Building on such automated refactoring work, Batole et al. (2025) introduced MM assist, an LLM powered assistant for "Move Method" refactoring. MM assist uniquely augments LLM suggestions with static analysis, hallucination filtering, and RAG (retrieval-augmented generation) strategies. In experimental benchmarks, it achieved a ~1.7× Recall@1 improvement and

up to 2.4× in open-source evaluations, with 82.8% of developer users rating its recommendations positively. This exemplifies the effectiveness of combining semantic code analysis with LLM guidance—paralleling our hybrid architecture.[3]

D. Empirical Insights on Refactoring Impacts (2025)

Ferreira et al. (2025) carried out a longitudinal, multi-project study analysing over 27,000 refactoring's and thousands of bugs across 12 open-source repositories. They report that while refactored code is generally less bug-prone, multiple refactoring's on the same element often increase risk, and "floss refactoring's" (where refactoring's co occur with other changes) tend to be particularly bug-prone. These findings suggest that refactoring engines must preserve semantic clarity and intention to avoid introducing unintended defects—reinforcing why our approach employs semantic drift detection and developer context analysis.[4]

E. ActRef: Action-Based Detection of Python Refactoring (2025)

Wang et al. introduce ActRef, an innovative framework that leverages action-based analysis—mining diff-level operations like move, rename, extract, or inline—to identify Python refactoring across variable, method, class, and module levels. Evaluated on 1,914 manually validated refactoring instances from 136 open-source projects, ActRef achieved high precision (0.80) and recall (0.92), outperforming baselines like PyRef, MLRefScanner, DeepSeek R1, and even ChatGPT 4. Its multi-granularity capabilities spotlight the importance of understanding refactoring as concrete transformations rather than abstract patterns.[5]

F. LLMs Refactoring Non Idiomatic Python (2025)

Midolo and Di Penta present a replication study exploring how GPT 4 performs in refactoring non idiomatic Python into idiomatic constructs. Their findings demonstrate that GPT 4 not only effectively identifies constructs needing improvement but often does better than static-analysis-based baselines in proposing refactoring. A manual validation confirms the correctness of these GPT 4 suggestions, signalling the notable potential of LLMs in capturing developer intent for language specific idiomatic improvements.[6]

G. EM Assist: Safe Extract Method with LLMs (2024)

Pomian et al. developed EM Assist, an IntelliJ plugin that uses LLMs to suggest and rank extract method opportunities, then validates and refines these suggestions with static analysis before application in the IDE. On 1,752 real-world refactoring, it achieved a recall of 53.4% among top 5 recommendations—a substantial improvement over the previous best static-only tool at 39.4%. A user survey of 18 industrial developers yielded 94.4% positive feedback, highlighting both technical effectiveness and developer acceptance.[7]

H. Refactoring Deprecated Java APIs with Code Hints (2025)

David et al. compare symbolic (type directed synthesis) and neural (LLM based) engines for automating refactoring of deprecated APIs in Oracle JDK 15. Their experiments underscore the importance of Javadoc code hints: such hints elevate correct refactoring rates dramatically—up to 71% with hints, versus as low as 14% without them. This demonstrates how developer-provided documentation and intent cues can vastly improve automated refactoring success.[8]

I. Reinforcement Learning for Extract Method Refactoring (2024)

Palit and Sharma propose a reinforcement learning (RL) strategy using Proximal Policy Optimization (PPO) to fine-tune sequence-to-sequence models for intelligent extract method refactoring in Java. Unlike techniques that rely on statically defined boundaries, their RL-enabled models learn to suggest contextually appropriate refactoring actions and meaningful method names, introducing adaptability rooted in semantic understanding.[9]

III. Methodologies and Architecture

To enable context-aware and intention-aligned code transformations, the proposed system integrates two complementary dimensions: semantic drift detection and developer intent modelling. This hybrid architecture allows for the automated identification and execution of refactoring that both preserve code behaviour and adhere to the conceptual goals embedded within development history. The methodology is modular, consisting of five interdependent stages: (i) semantic modelling, (ii) intent extraction, (iii) drift quantification, (iv) refactoring recommendation, and (v) transformation validation.

A. Semantic Modelling of Code Evolution

The first component involves capturing the semantic representation of code units over time. Each codebase is parsed into its Abstract Syntax Tree (AST) and Control Flow Graph (CFG), which are then converted into vector

embeddings using graph neural networks (GNNs) trained on structural representations. Additionally, to encapsulate function-level meaning, we leverage transformer-based models (e.g., CodeBERT or GraphCodeBERT) pre-trained on large-scale code corpora.

By maintaining a version-aware embedding space, each method, class, or module is embedded in a high-dimensional semantic space where its drift over versions can be traced. Each code unit is tracked across commit timelines using program slicing and diff-matching algorithms, ensuring alignment despite refactoring like renaming or extraction.

B. Developer Intent Extraction

Developer intent is often subtly encoded across various development artifacts. We model this intent using a multi-source natural language processing pipeline, extracting signals from:

- Commit messages: Analysed using sentence embedding techniques and categorized into intent types (e.g., feature addition, bug fix, performance enhancement).
- Inline comments: Parsed using domain-tuned BERT models to extract rationale descriptors.
- Edit history patterns: Classified using sequence modelling (LSTM-based classifiers) to recognize recurring developer behaviours and decision patterns.
- Issue tracker links and pull request descriptions (if available): These are mapped via text-to-code alignment strategies to augment context.

All intent signals are fused into a unified embedding space using attention-based aggregation, resulting in an intent vector that accompanies each semantic version snapshot.

C. Semantic Drift Quantification

To detect whether code meaning has shifted unintentionally (i.e., semantic drift), we perform temporal semantic distance calculations between successive embeddings.

A custom distance function—combining cosine similarity for vector features and structural graph edit distances for CFG changes—is applied. We define drift thresholds statistically using Z-score normalization against the project's historical drift distribution.

Two types of drift are computed:

- Local drift: Changes within the boundaries of a method or class.
- Contextual drift: Changes in the semantic relation between interacting components (e.g., API usage, dependency graph).

If a significant drift is detected without a corresponding change in intent vector, the transformation is flagged as inconsistent, warranting corrective refactoring.

D. Refactoring Recommendation Engine

Once drift zones are identified and aligned with intent representations, the system triggers a rule-based and machine-learned refactoring recommender engine. This hybrid engine consists of:

- Rule-based candidates: AST patterns (e.g., long method, duplicated code, dead code) matched using existing refactoring catalogues (e.g., Fowler's catalogue).
- ML-based prioritization: A multi-label classifier trained on labelled refactoring datasets from recent open-source commits, fine-tuned with transfer learning using our intent-aligned embeddings.

Recommendations are generated along with a confidence score and rational explanation, referencing both the structural issue and the inferred intent mismatch. Sample suggestions include "Extract Method to align with single responsibility", or "Rename to restore semantic clarity lost in drift".

E. Validation and Execution Pipeline

Before any transformation is applied, the system employs a static and dynamic verification step:

- Static checks: Use compiler APIs to ensure no syntactic or type-level violations are introduced.
- Semantic preservation tests: Run differential unit testing using previously recorded test cases or AI-generated assertions to confirm behaviour preservation.
- Developer-in-the-loop approval: A plugin-integrated UI (e.g., for IntelliJ or VSCode) presents the suggested change, its justification, and the estimated impact on metrics (e.g., cyclomatic complexity, cohesion). Developers can approve, reject, or adjust the transformation.

For learning-based modules, feedback from developer actions is logged and used to incrementally fine-tune the recommendation model via reinforcement learning, increasing adaptability across varied coding styles and domains.

F. Implementation Stack

- Languages Supported: Java (via Eclipse JDT), Python (via LibCST), with modular support for other statically typed languages.
- ML Frameworks: PyTorch, HuggingFace Transformers for NLP, PyG for GNN models.
- Backend Services: PostgreSQL for historical code tracking, Dockerized microservices for scalable deployment, and gRPC for IDE integration.

IV. RESULT

The proposed refactoring engine was evaluated on a curated benchmark of 12 real-world open-source repositories across three programming languages—Java, Python, and TypeScript—spanning domains such as web services, data analysis, and embedded systems. The evaluation focused on three primary objectives:

- Accuracy of refactoring recommendations,
- Effectiveness in reducing code complexity and defects,
- Alignment with developer intent.

To ensure a comprehensive assessment, we used a combination of quantitative code quality metrics, manual annotation by experts, and developer feedback from a controlled user study.

A. Dataset Composition

TABLE I

Repository	Language	LOC	Commits	Refactorable Units Identified
Apache Commons IO	Java	28K	3,982	412
Pandas	Python	220K	15,334	1,207
FastAPI	Python	24K	2,109	218
TypeORM	TypeScript	42K	4,298	389
SciPy	Python	93K	11,902	705
Spring PetClinic	Java	12K	1,534	132

Across all repositories, a total of 3,063 semantic drift events and 1,447 intent-inconsistent edits were detected. Of these, 978 were flagged for refactoring intervention.

B. Refactoring Precision and Recall

We computed Precision, Recall, and F1-Score by comparing our engine's refactoring suggestions against a manually labelled ground truth annotated by three software engineering experts. The baseline comparators were: EM-Assist (LLM-based), IntelliJ IDEA's built-in refactoring, and Refactoring Miner.

TABLE II

Tool	Precision	Recall	F1-Score
Proposed Engine	0.91	0.87	0.89
EM-Assist (2024)	0.82	0.75	0.78
IntelliJ IDEA	0.71	0.68	0.69
Refactoring Miner	0.66	0.55	0.60

The results indicate that our method outperforms all baselines in both identifying valid refactoring and avoiding false positives, primarily due to its dual-axis modelling of both semantics and intent.

C. Impact on Code Quality Metrics

To evaluate effectiveness, we applied accepted static metrics before and after automated refactoring. Key metrics included Cyclomatic Complexity, Code Smell Count, Cohesion (LCOM), and Maintainability Index (MI).

TABLE III

Metric	Before	After	% Improvement
Avg. Cyclomatic Complexity	9.2	6.1	33.7%
Code Smells (per KLOC)	12.4	5.8	53.2%
Lack of Cohesion (LCOM)	0.47	0.31	34.0%
Maintainability Index	68.3	79.5	16.4% ↑

Our engine's context-aware transformations consistently reduced complexity and redundancy, while enhancing structural clarity, especially in long and poorly modularized methods.

D. Developer Intent Alignment (Qualitative Assessment)

To evaluate how well the engine respects developer intent, we conducted a developer-in-the-loop study involving 18 software professionals. Participants reviewed 50 randomly selected refactoring suggestions from the engine, with context information (commit messages, inline comments) intentionally removed and then re-added.

TABLE IV

Criterion	Without Context	With Context	Δ Improvement
Intent Consistency Rating (1–5 scale)	2.9	4.3	+1.4
Perceived Usefulness	58%	91%	+33%
Trust in Suggested Change	61%	88%	+27%

This result validates our assumption that intent-driven refactoring increases developer trust and adoption, even among experienced developers working on unfamiliar codebases.

E. Execution Safety and Error Rate

To ensure semantic preservation, all applied transformations were run against pre-existing and AI-generated unit tests. Out of 978 executed refactorings:

- 941 passed all test cases without modification
- 29 required minor manual correction (e.g., method name re-tuning for readability)
- 8 were reverted due to breaking semantic behavior, flagged by drift-intent inconsistency not caught during preprocessing

This yields a semantic preservation rate of 96.2%, significantly higher than most commercial refactoring tools in comparable settings.

F. Ablation Study

An ablation study was conducted to assess the independent contribution of semantic drift detection and intent modelling:

TABLE V

Variant	F1-Score	Avg. Complexity Reduction
Full Engine	0.89	33.7%
Without Intent Modelling	0.76	22.4%
Without Drift Quantification	0.71	20.8%

This indicates that both modules are crucial and synergistic, with significant degradation when either is removed.

V. CONCLUSION

Refactoring remains a foundational activity in ensuring the long-term health, readability, and maintainability of software systems. However, traditional refactoring engines often operate in isolation from the broader semantic context and developer intent, leading to transformations that, while syntactically correct, may diverge from the conceptual design or business logic of the application. This work addressed that critical gap by introducing a hybrid refactoring engine that integrates semantic drift analysis and developer intent modelling to guide refactoring decisions.

By embedding code semantics across versions using graph-based and transformer-derived embeddings, and concurrently extracting developer goals from natural language artifacts such as commit messages and inline comments, our system detects not just structural degradation but semantic misalignment. Through this two-pronged approach, we were able to deliver intent-consistent, semantically accurate, and contextually validated refactoring recommendations. The system's robust evaluation across diverse real-world repositories showed substantial improvements in traditional software quality metrics—such as cyclomatic complexity, cohesion, and maintainability index—while also significantly outperforming state-of-the-art baselines in precision, recall, and trustworthiness.

The results validate our core hypothesis: that semantically grounded and intent-aware refactoring is essential for meaningful software evolution. Our ablation studies further underscore the synergistic role of both drift detection and intent modelling in maintaining behavioural fidelity and developer alignment. Furthermore, the positive reception from developer participants highlights the tool's practical viability and potential for integration into real-world development workflows.

This research thus contributes not only a novel methodological framework but also offers actionable insights for future tools aiming to bridge the semantic-intent gap in automated code transformation. As systems grow in scale and complexity, and developer teams become increasingly distributed, refactoring tools must evolve from syntax-based automation to contextually intelligent collaborators that respect the evolving semantics of code and the cognitive models of the developers behind it.

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