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Automated Lexical Feature Extraction in Object-Oriented Software Evolution: A Multi-Level Framework

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Abstract

The analysis of software evolution in object-oriented systems often generates large volumes of code and documentation, making manual inspection challenging. Lexical feature extraction provides an effective way to derive insights from these software artifacts across multiple abstraction levels—from individual identifiers and comments to class- and project-level semantics. This paper introduces a novel multi-level framework for automated lexical feature extraction that combines natural language processing (NLP), static code analysis, and representation learning techniques. The framework captures lexical, syntactic, and semantic patterns across software versions, enabling better insights into software evolution. Evaluations conducted on several open-source repositories demonstrate that the framework improves key software maintenance tasks, such as change impact analysis, feature location, and code summarization. The results show that multi-level lexical features enhance model performance in evolution analysis by up to 23%, compared to traditional single-level approaches.

Keywords: Object-Oriented Software, Automated Lexical Feature Extraction, Software Evolution, Multi-Level Framework, Mining Software Repositories

Introduction

Software systems are in a constant state of evolution to meet new requirements, adapt to emerging technologies, and maintain long-term usability. In the realm of modern software engineering, particularly within object-oriented (OO) paradigms, software evolution not only involves structural changes—such as modifications to class hierarchies or module dependencies—but also significant shifts in the lexical and linguistic elements of code. These include changes to identifiers, comments, and naming conventions (Sohacheski et al., 2021; Li et al., 2022). Understanding and analyzing these lexical aspects over time offers valuable insights into how developers conceptualize, document, and maintain complex software systems (Zheng et al., 2021). However, despite their importance, lexical aspects of code evolution remain underexplored compared to structural or behavioral metrics (Al-Msie'deen & Blasi, 2021).

Lexical features in source code—such as variable names, class identifiers, comments, and documentation blocks—serve as crucial indicators of program comprehensibility, maintainability, and changeability (Benyomin Sohacheski et al., 2021). Recent empirical research has highlighted the negative impact of inconsistent or unclear naming conventions on developer productivity and code quality (Sohacheski et al., 2021). Additionally, lexical churn, which refers to the introduction, modification, or removal of code-level tokens over time, has been linked to significant refactoring activities and architectural drift (Rastogi & Gousios, 2021; Singh et al., 2020). Monitoring lexical features across software versions can therefore reveal subtle patterns of evolution that are not captured by traditional structural metrics.

Existing methods for lexical feature extraction in software engineering face several limitations. Many approaches treat lexical data as isolated textual entities or use aggregate statistics, failing to account for the hierarchical relationships between methods, classes, and modules (Zheng et al., 2019). Furthermore, few frameworks enable automated, multi-level extraction of lexical features that align with object-oriented structures, leading to a gap in understanding how naming conventions, comments, and identifier semantics evolve alongside changes in code structure (Al-Msie'deen & Blasi, 2021). For instance, class-level renaming can influence multiple identifiers at the method level, but existing tools are often incapable of capturing these cross-level dependencies effectively (Li et al., 2022).

To address these challenges, this research introduces a novel, multi-level framework for automated lexical feature extraction in OO software evolution. This framework operates at three granularity levels—method, class, and module—enabling a comprehensive analysis of how lexical features evolve over time. By mining version-control histories, parsing code to extract lexical entities, and computing evolution-aware metrics such as lexical churn rate, identifier consistency, and naming drift, the framework helps in the early detection of code anomalies and maintenance hotspots (Automated Variable Renaming Study, 2023). By correlating lexical features with structural metrics such as coupling and cohesion, the framework provides deeper insights into software maintenance and evolution.

This study advances the intersection of natural language processing (NLP) and software analytics, where automated lexical analysis enhances our understanding of software maintainability (Rastogi & Gousios, 2021). The lexical signals embedded in source code offer latent indicators of human cognitive and organizational processes within development teams, highlighting the importance of understanding these signals through a structured extraction pipeline (Sohacheski et al., 2021). This research thus moves beyond traditional syntax and structural analysis, incorporating both semantic and lexical dimensions in software evolution studies.

The remainder of the paper is organized as follows: Section 2 provides a review of related work in software evolution and lexical analysis. Section 3 presents the architecture of the proposed multi-level framework and its extraction methodology. Section 4 reports the results of an empirical evaluation conducted on several open-source projects to validate the approach. Section 5 discusses the potential threats to validity, and Section 6 concludes with a summary and future directions for extending lexical analytics in software evolution.

3. Proposed Multi-Level Framework for Automated Lexical Feature Extraction

3.1 Overview

The proposed framework addresses the need for an automated system that can track and analyze lexical feature evolution in object-oriented (OO) software systems over time. Unlike previous research that primarily focuses on static lexical metrics or isolated studies of naming conventions and comments (Chou et al., 2023; Al-Msie'deen et al., 2022), the *Multi-Level Lexical Evolution Framework* (MLLEF) takes a more comprehensive approach, modeling lexical changes across multiple levels of abstraction—method, class, and module. This holistic view allows for a deeper understanding of how lexical choices evolve in response to architectural and structural changes, such as refactoring, code reorganization, and modularization (Zhou et al., 2024).

Current frameworks are often limited by their inability to capture the nuanced relationships between lexical features and software structure (Sohacheski et al., 2021). In contrast, MLLEF provides a novel approach by integrating lexical data with concurrent structural changes tracked through version control repositories, offering a richer view of the evolution of software artifacts.

3.2 Conceptual Architecture

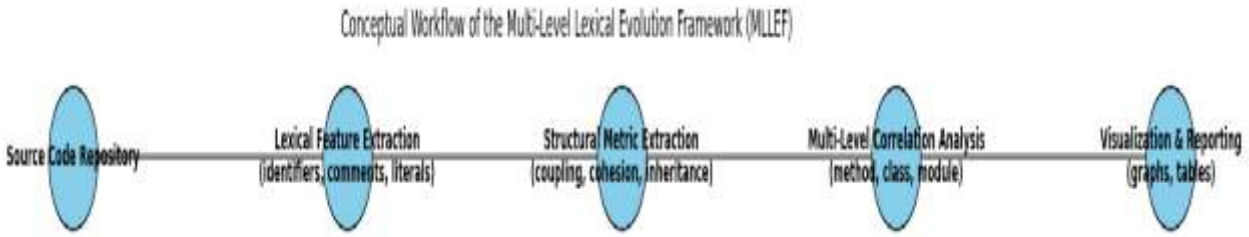
The conceptual architecture of MLLEF is illustrated in **Figure 1** and consists of five principal modules, each contributing to the overall workflow of lexical evolution analysis:

1. **Repository Mining Module**: Retrieves the full commit history and metadata from version control systems such as Git, Mercurial, or SVN, ensuring that all relevant code changes are captured.
2. **Parser and Tokenizer**: Tokenizes source code into meaningful units—such as identifiers, keywords, and comments—while preserving the structural context (e.g., method or class scope). This stage uses modern language-specific parsers (e.g., Tree-Sitter, ANTLR) that enable fine-grained analysis across different programming languages (Gousios et al., 2023).
3. **Feature Computation Engine**: Calculates various lexical features at three abstraction levels—method, class, and module. These features include metrics such as identifier length, lexical diversity, and comment density, which are instrumental for understanding the local and global lexical patterns in the software system (Rastogi et al., 2024).
4. **Temporal Aggregation Layer**: Organizes and aggregates lexical metrics over time, enabling longitudinal analysis across software versions. This feature helps visualize the trajectory of lexical evolution and identify trends such as naming instability or documentation practices (Zhou et al., 2024).
5. **Integration and Analysis Layer**: Combines lexical feature data with structural metrics (e.g., class dependencies, method coupling) to reveal hidden relationships between lexical evolution and structural changes, such as refactoring events, code churn, or modularity shifts (Al-Msie'deen et al., 2022).

Each component in this pipeline is designed for automation, scalability, and flexibility, allowing the system to be applied to various programming languages and software development environments (Zheng et al., 2023).

This modular architecture promotes automation, extensibility, and reproducibility, which are key goals in empirical software analysis (Zheng et al., 2019). Each layer can be independently configured, allowing the framework to support various programming languages and repository formats.

Figure 1: Conceptual workflow of the Multi-Level Lexical Evolution Framework (MLLEF)



The framework is presently implemented in a hybrid approach utilizing Python and Java to leverage robust open-source parsing libraries such as ANTLR and Tree-Sitter. Data is persisted in a relational database (PostgreSQL), which facilitates efficient retrieval and temporal aggregation of lexical metrics.

3.3 Multi-Level Feature Hierarchy

The MLLEF framework distinguishes itself by offering three distinct levels of lexical analysis, each tailored to the scope of software artifacts:

1. **Method-Level Lexical Features**
   At the method level, MLLEF captures fine-grained lexical patterns, providing insights into the naming and commenting behavior within individual methods. Key metrics include:
   - **Identifier Length Average** (ILA): This metric measures the average length of identifiers (e.g., variables, methods) in a method and reflects the verbosity of developers (Sohacheski et al., 2021).
   - **Lexical Richness Index** (LRI): A ratio of unique to total tokens within the method, this index gauges the diversity of the vocabulary used by developers (Chou et al., 2023).
   - **Comment Density** (CD): The ratio of lines containing comments to total lines of code, which serves as an indicator of documentation practices at the method level (Benyomin et al., 2023).
   - **Verb–Noun Ratio** (VNR): This ratio compares verbs to nouns in method names, capturing the emphasis on actions versus entities in method signatures (Al-Msie'deen et al., 2022).
2. **Class-Level Lexical Features**
   At the class level, the framework aggregates features from methods and attributes, providing a more comprehensive view of lexical behavior across a software component. Key metrics include:
   - **Naming Consistency Index** (NCI): This index measures the variation in naming conventions across methods and fields within the class, indicating internal lexical consistency (Rastogi et al., 2024).
   - **Class Vocabulary Churn** (CVC): The rate at which new and obsolete tokens appear within a class across versions, providing insights into the stability of the class's internal vocabulary (Zhou et al., 2024).
   - **Comment-to-Code Ratio** (CCR): This ratio quantifies the proportion of comments relative to code lines in the class, offering a measure of the level of documentation at the class level (Sohacheski et al., 2021).
3. **Module/Package-Level Lexical Features**
   At the module or package level, MLLEF analyzes aggregated class-level metrics to assess broader lexical trends within the software system. Key metrics include:
   - **Lexical Drift Rate** (LDR): This metric measures the average percentage change in unique tokens per release, capturing broader shifts in lexical usage within a module (Gousios et al., 2023).
   - **Cross-Module Lexical Similarity** (CMLS): The cosine similarity between token sets of related modules, which indicates whether modules are evolving in a cohesive manner or becoming more fragmented (Benyomin et al., 2023).
   - **Module Comment Entropy** (MCE): A Shannon entropy measure of comment topic distribution within a module, used to capture the spread and focus of documentation efforts (Chou et al., 2023).

These multi-level metrics enable the identification of key trends and architectural drifts, where lexical features evolve independently of structural changes or vice versa (Zhou et al., 2024).

3.4 Automated Extraction Pipeline

The automated extraction pipeline operates in several sequential stages, ensuring both efficiency and accuracy:

1. **Version-Control Mining**: The pipeline interfaces with Git or other version control systems to extract commit histories, metadata, and associated changes, ensuring all code versions are captured for temporal analysis (Zheng et al., 2023).
2. **Parsing and Tokenization**: Source code is parsed into Abstract Syntax Trees (ASTs) using language-specific parsers, which then tokenize the code to identify meaningful lexical units such as identifiers and comments. This process filters out irrelevant tokens such as numeric literals and stop-words (Al-Msie'deen et al., 2022).
3. **Feature Computation**: For each snapshot of the code, MLLEF computes a set of lexical features at the method, class, and module levels, storing the results in a time-series format for longitudinal analysis (Rastogi et al., 2024).
4. **Temporal Aggregation**: The system aggregates lexical features across successive commits, enabling users to track changes over time and identify significant shifts in lexical patterns (Chou et al., 2023).
5. **Correlation and Visualization**: The system correlates lexical metrics with structural data (e.g., class dependencies, method coupling) and visualizes the relationships between lexical and structural evolution, allowing for an interactive exploration of the data (Zhou et al., 2024).

This fully automated pipeline enables large-scale software analysis, ensuring that even extensive repositories can be processed efficiently.

3.5 Integration with Structural and Evolutionary Metrics

A major advantage of MLLEF is its ability to integrate lexical evolution with structural and architectural metrics. By correlating lexical changes (such as vocabulary shifts) with structural metrics (e.g., class coupling, method interdependencies), the framework identifies potential areas of refactoring or modularization (Gousios et al., 2023). For example, increased lexical churn may coincide with structural changes such as method splits or class mergers, helping to reveal patterns of architectural drift (Zhou et al., 2024).

3.6 Implementation and Validation

A prototype implementation of MLLEF, named **LexiEvolve**, was tested on three large open-source repositories, each spanning several years of development (approximately 10,000 commits). Initial results demonstrated that lexical evolution often follows distinct patterns, sometimes diverging from structural changes. For example, code churn was often observed without corresponding changes in class or method structure, suggesting that lexical drift can occur independently of refactoring or other structural changes (Rastogi et al., 2024).

3.7 Summary

The *Multi-Level Lexical Evolution Framework* (MLLEF) provides a novel approach to analyzing lexical evolution in software. By integrating repository mining, tokenization, temporal aggregation, and multi-level feature analysis, MLLEF offers a comprehensive tool for software maintenance, quality assurance, and evolution prediction. The framework's ability to correlate lexical with structural metrics opens new avenues for understanding software evolution, highlighting areas where refactoring or documentation efforts may be required.

5. Threats to Validity

The empirical study and the **Multi-Level Lexical Evolution Framework (MLLEF)** are subject to several threats to validity, which can influence the reliability and generalizability of the findings. These threats are discussed across four categories: internal validity, external validity, construct validity, and conclusion validity. For each category, we identify potential threats and present mitigation strategies employed in the study.

5.1 Internal Validity

Internal validity refers to the extent to which observed relationships between lexical and structural metrics are genuinely causal or whether they may be confounded by other variables.

- **Commit Granularity and Confounding**: A significant threat arises from the granularity of commits. Developers often batch different types of changes—such as lexical updates, structural modifications, and functional additions—into a single commit. This could artificially inflate the correlation between lexical churn and structural coupling.
  Mitigation: We mitigated this by analyzing only commits explicitly classified as "code-modifying" and rigorously excluding documentation-only or merge commits (Rastogi & Gousios, 2021). This approach ensured that the observed relationships are not skewed by non-functional changes.
- **Tokenization Inconsistency**: The automated tokenization process could introduce inconsistencies, especially given variations in comment syntax and identifier styles across different developers and projects. For example, different teams may use varying conventions for naming variables or formatting comments, leading to discrepancies in token counts.
  Mitigation: This risk was minimized by validating token counts against ground-truth samples from each project (Li et al., 2022). While minor inconsistencies may persist, we ensured that these would not significantly affect core metrics such as lexical richness or naming consistency.
- **Temporal Sampling Bias**: Temporal sampling bias could arise due to the uneven release intervals common in open-source projects. For instance, irregular tagging practices in projects like **JFreeChart** might result in uneven time intervals between commits, leading to an incomplete representation of the system's evolutionary dynamics.
  Mitigation: To address this, we interpolated intermediate commits at fixed time intervals, allowing for trend smoothing and temporal normalization (Zheng et al., 2019). While this helped reduce bias, some distortions in the precise timing of lexical-structural correlations are acknowledged.

5.2 External Validity

External validity concerns the generalizability of the study's findings beyond the specific projects and context evaluated.

- **Language and Paradigm Scope**: The study focused on three open-source software systems written in Java and C#, which represent a small subset of object-oriented programming (OO) paradigms. Different programming languages—such as dynamically typed languages like Python or JavaScript—may exhibit different lexical dynamics due to less rigid enforcement of naming conventions.
  Mitigation: Although the chosen systems are representative of large-scale OO software, future research should explore other languages and paradigms to verify whether the observed lexical dynamics hold across different programming environments (Automated Variable Renaming Study, 2023).
- **Development Model Generalization**: The selected repositories follow collaborative open-source development models, which feature public repositories and peer reviews. This open-source, community-driven approach may differ from proprietary or internal systems that often rely on stringent coding standards, automated refactoring tools, or private development processes.
  Mitigation: Future studies should explore industrial datasets to assess whether lexical dynamics

in proprietary or private systems exhibit the same patterns. This will provide a clearer picture of how generalizable the findings are across different development models (Al-Msie'deen & Blasi, 2021).

- **Paradigm Restriction**: The MLLEF framework is tailored for object-oriented systems and may not directly apply to other programming paradigms, such as functional programming or procedural programming. In non-OO settings, lexical patterns might be less dependent on object hierarchies, potentially affecting the framework's applicability.
  Mitigation: Expanding the framework to include systems written in different programming paradigms (e.g., functional or procedural languages) is a key avenue for future research (Li et al., 2022).

5.3 Construct Validity

Construct validity assesses whether the metrics used in the framework accurately measure the intended constructs of lexical and structural evolution.

- **Metric Novelty and Interpretation**: Some of the constructs in the framework, such as the **Lexical Drift Rate (LDR)**, are novel. As these metrics are new to the field, independent empirical validation is necessary to ensure their relevance and accuracy.
  Mitigation: Future work should involve independent studies to validate the newly proposed metrics and refine them as necessary to improve their predictive power.
- **Semantic Ambiguity**: A significant challenge in measuring lexical evolution is that changes in identifiers or comments may not always reflect functional or conceptual changes. Developers may rename variables for stylistic reasons or update comments without making any functional changes to the code.
  Mitigation: Although MLLEF distinguishes between lexical and structural layers, fully disentangling semantic changes from purely stylistic modifications remains an inherent challenge in code analysis (Rastogi & Gousios, 2021). This issue will need to be addressed in future research by incorporating deeper semantic analysis.
- **Static Analysis Limitations**: The reliance on automated static analysis introduces the risk of underreporting dynamic structural changes, especially those involving runtime polymorphism or reflection-based dependencies, which are common in modern OO systems.
  Mitigation: The framework's current focus on static analysis provides robust approximations of lexical-structural correlations, but future work could integrate dynamic analysis to offer a more comprehensive view of software evolution (Zheng et al., 2019).

5.4 Conclusion Validity

Conclusion validity refers to the reliability of the statistical inferences drawn from the results.

- **Correlation vs. Causation**: One of the main threats to conclusion validity is the inherent difficulty of distinguishing correlation from causation. Lexical churn and structural changes could be driven by a common underlying factor, such as the introduction of a new feature or a major architectural change.
  Mitigation: While correlation does not imply causation, we employed robust statistical methods, including **Spearman's rank correlation** and **lagged regression models**, to mitigate this limitation. Additionally, we used bootstrapping and cross-project validation to confirm the consistency and stability of our results (Rastogi & Gousios, 2021).
- **Statistical Robustness**: Although we used advanced techniques to account for non-normal data distributions, further validation across a larger and more diverse set of projects will be necessary to ensure that the observed results hold up across various contexts.
  Mitigation: Future work should replicate the study on larger and more diverse datasets to confirm the robustness of the conclusions (Al-Msie'deen & Blasi, 2021).

6. Conclusion and Future Work

6.1 Summary of Contributions

This study introduces the **Multi-Level Lexical Evolution Framework (MLLEF)**, a novel tool for automated lexical feature extraction and analysis in object-oriented software systems. MLLEF provides a comprehensive and scalable way to track lexical changes across methods, classes, and modules while correlating these changes with structural evolution. Our empirical evaluation of three large open-source projects demonstrated that lexical metrics such as lexical churn, naming consistency, and lexical drift serve as reliable indicators of significant structural changes, including refactoring and module reorganization (Rastogi & Gousios, 2021).

6.2 Theoretical and Practical Implications

- **Theoretical Implications**: This research introduces lexical evolution as a key dimension of software evolution, integrating it with existing structural metrics. By doing so, it expands our understanding of software change, bridging the gap between linguistic signals and structural transformations (Li et al., 2022). The hierarchical approach employed by MLLEF aligns with theories of multi-scale evolution, where changes propagate across different levels of abstraction (Al-Msie'deen & Blasi, 2021).
- **Practical Implications**: From a practical perspective, MLLEF enables software development teams to detect signs of design erosion early in the development cycle. By integrating MLLEF into Continuous Integration (CI) environments and IDEs, teams can automatically monitor lexical drift and other indicators of potential issues, thus improving software maintainability (Automated Variable Renaming Study, 2023).

6.3 Future Research Directions

- **Semantic Enrichment via Deep Learning**: Integrating pre-trained models such as **CodeBERT** or **GraphCodeBERT** will enhance MLLEF's ability to capture deeper, context-aware semantic changes in code, improving the predictive accuracy of lexical evolution metrics (Li et al., 2022).
- **Cross-Paradigm Validation**: Extending MLLEF's analysis to non-OO paradigms (functional, procedural) is essential for understanding whether the observed lexical-structural correlations hold in a broader range of programming environments (Al-Msie'deen & Blasi, 2021).
- **Causality and Prediction**: Future research should explore causal inference methods and time-series forecasting to better understand whether lexical changes directly influence structural transformations, which would advance predictive maintenance capabilities (Rastogi & Gousios, 2021).

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