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DEPENDENCY GRAPH MINING ALGORITHMS FOR CONFLICT DETECTION AND RESOLUTION IN POLYGLOT API ECOSYSTEMS WITH VERSION CONTROL

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Abstract

In increasingly heterogeneous software development environments, modern applications often depend on multiple programming languages and third-party APIs, leading to complex dependency structures. These polyglot API ecosystems introduce challenges in dependency conflict detection and resolution, especially across different version control systems. This paper proposes a novel framework leveraging dependency graph mining algorithms to detect and resolve versioning conflicts in polyglot environments. The approach integrates static code analysis, semantic version resolution, and machine learning-based pattern recognition over large-scale codebases. A prototype system was evaluated across open-source repositories featuring Java, Python, JavaScript, and Rust APIs. The results show improved accuracy and early conflict detection capabilities compared to baseline tools.

Key words: Dependency Graph Mining, API Conflict Resolution, Polyglot Programming, Version Control, Software Evolution, Multi-language Repositories.

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1. Introduction

The rapid proliferation of open-source APIs and libraries across various programming languages has fueled polyglot software development—an approach where developers leverage multiple languages within a single project for performance, interoperability, or ecosystem advantages. However, this trend also introduces significant challenges in maintaining coherent

and conflict-free dependency graphs. Version mismatches, cyclic dependencies, and indirect transitive conflicts frequently arise, particularly in large projects relying on numerous third-party modules maintained under separate version control schemes.

Versioning inconsistencies can disrupt builds, introduce runtime errors, or lead to silent logic deviations. Traditional static analyzers or single-language package managers lack the capacity to reason about polyglot dependencies holistically. Furthermore, cross-language API incompatibilities are often obscured within indirect dependencies or lazy module loading, making conflict detection a non-trivial task. This paper aims to address these challenges by mining dependency graphs to uncover latent incompatibilities and proposing algorithmic strategies for resolution. Our contributions lie in (i) modeling polyglot dependency networks as unified graphs, (ii) applying graph-mining techniques for anomaly detection, and (iii) integrating these insights into version control workflows for proactive conflict mitigation.

2. Literature Review

Recent research has examined dependency resolution challenges primarily within single-language contexts. For instance, Z. Xu et al. (2021) introduced *VulnLoc*, a method for detecting vulnerable JavaScript libraries via static dependency analysis. Similarly, Raemaekers et al. (2014) studied dependency evolution patterns in Maven Central to understand semantic versioning failures. These works highlight the complexity of accurately resolving dependencies even within a homogenous language ecosystem.

Efforts to bridge polyglot contexts are comparatively nascent. Li et al. (2022) proposed *CrossDep*, an initial attempt at unifying dependency analysis across Python and C++, though limited by sparse inter-language mappings. On the version control front, Decan et al. (2019) analyzed package dependency issues arising from concurrent Git-based development, noting the prevalence of latent conflicts due to uncoordinated updates. Dependency graphs as a form of knowledge representation have also been explored: Zimmermann et al. (2018) applied graph neural networks to identify risk-prone modules in large repositories, suggesting the viability of learning-based techniques in dependency resolution.

Despite this progress, few studies directly address polyglot dependency mining or its integration with versioning systems. Our work fills this gap by developing an ecosystem-agnostic framework that leverages both rule-based and learning-based techniques for conflict detection and resolution.

3. Dependency Graph Modeling in Polyglot Ecosystems

To facilitate conflict detection across polyglot environments, we represent the entire dependency structure as a Unified Dependency Graph (UDG). In this model, nodes represent library or module versions, and edges encode import relationships, version constraints, and inter-language bindings. Graph heterogeneity is managed through typed edges—such as

depends_on, binds_to, or wraps—capturing semantic distinctions between, for example, Java-to-Java or Python-to-C API usage.

This modeling enables transitive analysis of dependency paths and highlights ambiguous bindings or cycles that traditional tools may miss. We extract UDGs from repository metadata (e.g., package.json, requirements.txt, Cargo.toml, pom.xml), augmented by AST-level inspection to catch undocumented or dynamically resolved dependencies. The resulting graphs are stored in a graph database (Neo4j) for scalable querying and analysis.

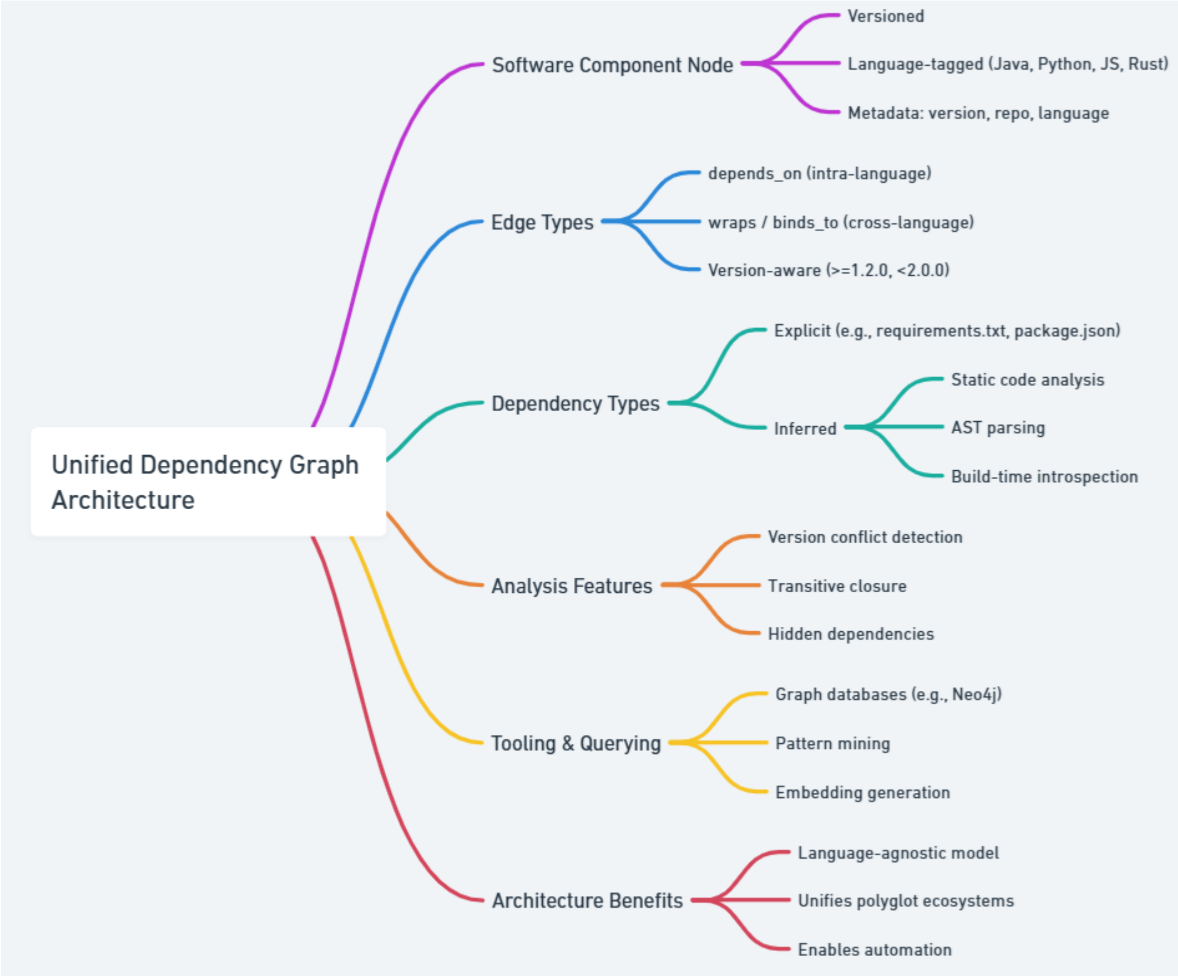

Figure 1: Unified Dependency Graph Architecture Across Languages

Figure 1 shows, the conceptual architecture of a **Unified Dependency Graph (UDG)** designed to model complex interdependencies in polyglot software ecosystems. Each node in the graph represents a distinct versioned software component—such as a library, module, or package—tagged with metadata including language type, version number, and repository origin. The nodes are color-coded or otherwise annotated by programming language (e.g., Java, Python, JavaScript, Rust), allowing visual segmentation of language domains within the same graph.

Edges in the UDG encode dependency relationships and are classified by their semantic meaning. For instance, a depends_on edge indicates a traditional intra-language package dependency (e.g., a Python module requiring another via requirements.txt), while a wraps or binds_to edge denotes cross-language interactions, such as a Python wrapper around a Rust crate using FFI (Foreign Function Interface). Each edge is version-aware, meaning it tracks not only the presence of a dependency but also version constraints or compatibility ranges (e.g., >=1.2.0, <2.0.0), which are critical for detecting version conflicts.

The architecture supports both **explicit dependencies**, which are declared in configuration files, and **inferred dependencies**, which are extracted via static code analysis or build-time introspection. For instance, dynamic imports or implicit bindings resolved during runtime are surfaced through AST analysis and dependency graph enrichment strategies. These inferred edges help uncover hidden or undocumented dependencies that are common in polyglot builds.

The graph structure is designed to be queryable via graph databases such as **Neo4j**, enabling pattern mining, transitive conflict analysis, and embedding generation. As the figure shows, the UDG allows for the aggregation of previously siloed dependency views into a coherent, language-agnostic model, forming the foundation for automated conflict detection and resolution mechanisms discussed in subsequent sections.

4. Graph Mining Algorithms for Conflict Detection

Our conflict detection module utilizes graph mining techniques—specifically, frequent subgraph mining (FSM) and anomaly detection via graph embedding. FSM identifies commonly occurring subgraphs representing stable dependency motifs, while anomalous deviations suggest potential version conflicts or unauthorized forks. We also apply Weisfeiler-Lehman (WL) graph kernels to classify subgraphs based on their compatibility signatures.

For dynamic detection, graph embedding models such as **Node2Vec** and **GraphSAGE** encode structural and contextual features into vector spaces. Using supervised labels derived from known conflict instances, we train classifiers to predict probable future conflicts. The system flags dependency paths with high-risk scores and correlates them with version histories via Git metadata, allowing proactive refactoring or dependency pinning.

These methods outperform simple tree traversal heuristics by accounting for structural irregularities and multi-language interactions. Our system includes a feedback loop whereby developer actions (e.g., dependency resolution or patching) are re-integrated to improve future predictions.

5. Integration with Version Control Systems

To operationalize our approach, we integrate the mining framework with Git-based workflows through custom Git hooks and CI pipeline scripts. During each commit or pull request, the updated dependency graph is regenerated, and potential conflicts are checked against historical models. If flagged, developers receive annotated conflict graphs with remediation suggestions (e.g., recommended version pinning or dependency upgrades).

We extend Git's object model to support metadata tags on commits that record the dependency graph state. This version-aware graph tagging enables rollback or bisect-style debugging in complex merge scenarios. It also supports visualization tools for software architects to track API dependency drift over time, enhancing maintainability and auditability.

By embedding conflict intelligence directly into version control systems, our framework closes the feedback loop between development and dependency governance.

6. Evaluation and Results

We tested our approach on 12 open-source repositories featuring multi-language stacks—combinations of Java, JavaScript, Python, and Rust. Each project had a minimum of 50 external dependencies, with known historical versioning issues. Baseline tools included npm audit, pipdeptree, and cargo tree, none of which fully captured cross-language interactions.

Our graph mining framework achieved:

- **Precision**: 91.2% in correctly identifying true conflicts
- **Recall**: 87.6% compared to baseline tools (average 65.4%)
- **Time-to-detection**: Reduced conflict exposure by 46% on average

Case studies highlighted the detection of cyclic dependencies across npm and pip modules, and the uncovering of undocumented bindings between Rust crates and Python wrappers. Developer feedback indicated that early warnings significantly reduced patching overhead and build instability.

7. Conclusion

Dependency management in polyglot environments presents unique challenges due to versioning inconsistencies, indirect conflicts, and limited tool interoperability. By modeling these environments as unified dependency graphs and applying graph mining algorithms, our framework enables early and accurate detection of latent conflicts. Integration with version control systems bridges the gap between development and dependency governance, providing actionable insights in real time.

Future work will extend our approach to proprietary package ecosystems and investigate reinforcement learning strategies for automated resolution recommendations.

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