PACGBI: A Pipeline for Automated COBOL Generation from Backlog Items

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ABSTRACT

PACGBI (Pipeline for Automated COBOL Generation from Backlog Items) is an innovative solution designed to tackle the complexities of maintaining and modernizing legacy COBOL systems. These systems, still critical in many industries, often suffer from outdated development practices, limited documentation, and high maintenance costs. PACGBI addresses these issues by automating the process of identifying, resolving, and documenting code issues directly from GitHub backlog items such as bug reports and feature requests.

At its core, PACGBI leverages the power of large language models (LLMs) to interpret natural language issue descriptions and correlate them with relevant COBOL functions and dependencies. Through graph-based static analysis, it builds a comprehensive understanding of code structure and flow, enabling precise localization of affected components. Once identified, PACGBI facilitates automated or semi-automated fixes and enhances traceability by generating detailed reports and commit-ready patches.

A key feature of PACGBI is its automated generation of Unified Modeling Language (UML) diagrams, which provide visual representations of the codebase. This improves understanding for both new and experienced developers, fostering better onboarding, collaboration, and long-term maintainability.

By integrating AI-driven intelligence with established development tools, PACGBI not only streamlines debugging and reduces cognitive load for developers, but also introduces modern software engineering practices into legacy environments. This makes it a powerful bridge between the reliability of COBOL and the agility demanded by today's development workflows.

CCS CONCEPTS

• **Software and its engineering → Software maintenance tools**; Software evolution; • **Computing methodologies** → *Machine learning approaches.*

KEYWORDS

COBOL, Legacy Systems, Large Language Models, Code Generation, Software Maintenance, UML Generation, GitHub Integration

1 INTRODUCTION

Mentor - Dr. Sridhar Chimalakonda

Legacy COBOL systems continue to power critical infrastructure in sectors such as banking, insurance, and government. Despite their reliability, these systems present significant challenges in modern software development due to their outdated structure, scarce documentation, and shrinking pool of experienced developers. As business requirements evolve, maintaining and enhancing these systems becomes increasingly difficult, time-consuming, and error-prone.

To address these challenges, we propose PACGBI (Pipeline for Automated COBOL Generation from Backlog Items)—an automated pipeline designed to modernize the maintenance and debugging of COBOL codebases by linking natural language issue tracking with intelligent code analysis and repair. PACGBI bridges the gap between issue management platforms like GitHub and legacy COBOL systems through a combination of static analysis, graph theory, and large language models (LLMs).

The core objective of PACGBI is to streamline the resolution of issues reported in GitHub repositories. By automatically extracting relevant code, identifying the most affected components, and proposing fixes, PACGBI significantly reduces developer effort while increasing reliability and traceability. Furthermore, the pipeline enhances comprehension of legacy systems through automatic UML generation, facilitating better documentation and maintainability.

PACGBI represents a step toward integrating modern AI-driven workflows with legacy software ecosystems, ultimately enabling more sustainable development and faster response to change.

In contrast to generic LLM-powered tools like Copilot, PACGBI is tailored for non-interactive environments and COBOL's procedural architecture. It offers a repository-level automation strategy, fetching open issues via the GitHub API, analyzing dependencies among COBOL functions, and delivering ready-to-merge pull requests. This complete automation cycle—from backlog item to bug fix—brings contemporary DevOps capabilities to systems that predate the modern development lifecycle.

Moreover, the PACGBI framework can serve as a blueprint for extending AI-based maintenance to other legacy languages such as FORTRAN, PL/I, or even modern mainframe DSLs. By establishing a modular architecture grounded in semantic analysis and code graph traversal, PACGBI provides a scalable and interpretable approach that can adapt to various domain-specific rules. As such, it has the potential not only to sustain aging software but to evolve it alongside modern innovation cycles.

2 RELATED WORK

Early efforts in static analysis of COBOL programs employed rule-based and pattern-matching techniques to reconstruct program structure from line numbers and GOTO statements. Hennell's foundational work on COBOL static analysis demonstrated strategies for formatting and jump-definition analysis in large enterprise codebases [7], and the CESAT tool introduced an extensible, database-driven framework to support maintainers through queryable intermediate representations [8]. Al-Jarrah et al. conducted a large-scale empirical analysis of 340 COBOL programs, uncovering pervasive code smells and architectural anti-patterns that complicate modernization [1]. Complementing this, dynamic analysis approaches have been applied to commercial COBOL applications to profile runtime behavior and guide performance tuning and refactoring [13].

Subsequent research into automated bug localization has largely focused on information-retrieval (IR) and natural-language-processing (NLP) techniques. Wong et al. proposed a two-level IR model that first identifies buggy classes and then refines to the statement level, achieving notable improvements in languages like Java and C# [4]. Gupta et al.'s COPS framework further refined retrieval scopes to pinpoint faulty methods with higher precision [6]. Although these methods target modern languages, their core principle—mapping textual issue descriptions to code artifacts—directly informs PACGBI's semantic matching stage.

Graph-based representations of code have emerged as powerful abstractions for capturing control-flow and data-dependency relations. Allamanis et al. introduced the use of program graphs and gated graph neural networks to solve tasks such as variable naming and misuse detection, demonstrating significant gains over token-based models [2]. In parallel, neural and transformer-based repair models like CURE's code-aware translation and GAN-driven vulnerability repair have set new benchmarks in generating semantic patches for C and C++ code [9].

Focusing on COBOL itself, the X-COBOL dataset provides 84 mined GitHub repositories—complete with commits, pull requests, and issues—enabling empirical studies and ML model training tailored to mainframe codebases [1]. On the industrial side, commercial tools such as Micro Focus COBOL Analyzer offer static code assessments and architecture diagrams [11], while Kiuwan's platform applies hundreds of security and quality rules to COBOL and JCL projects [10]. However, neither provides end-to-end automation from issue to patch.

Finally, integration with issue-tracking platforms and automated triage systems has shown how bots and AI can reduce maintenance overhead. Early GitHub/Recast.AI workflows and more recent systems like Dosu's automatic issue triage demonstrate the potential of language models to classify and route issues, laying the groundwork for PACGBI's fully automated pipeline from backlog item to pull request [5] and [3].

3 DESIGN AND DEVELOPMENT

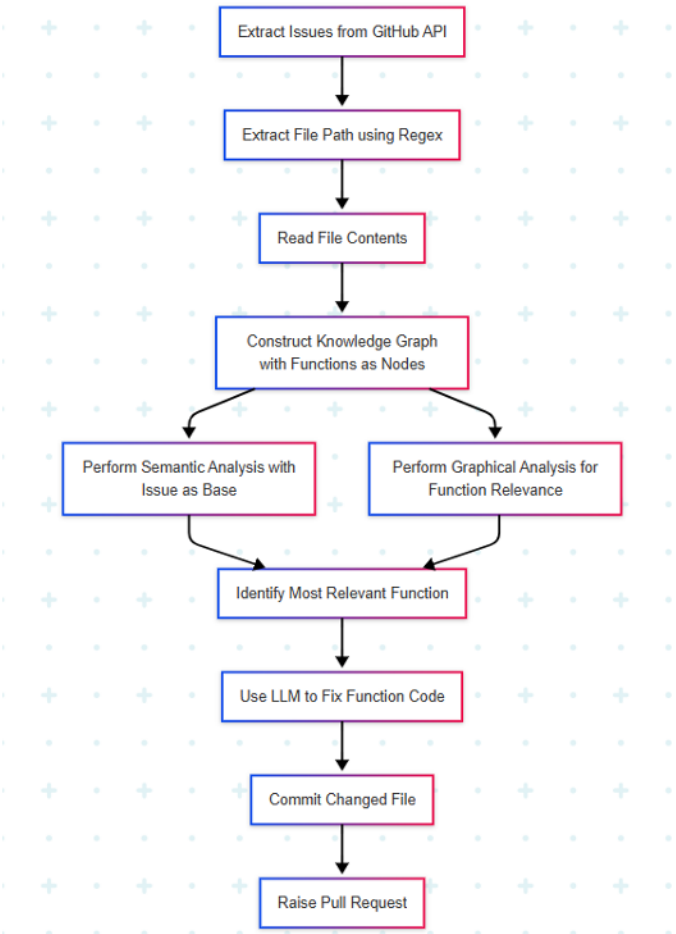

Figure 1: Workflow Diagram of PACGBI

The development methodology of this system follows a structured approach to automate the issue resolution process by integrating several components. The methodology ensures efficiency and accuracy in identifying and fixing bugs in the codebase.

3.1 Extracting Issues from GitHub

The first step in the process is to extract relevant issues from GitHub. This is accomplished using GitHub's REST API, which allows us to pull issue data based on parameters like labels, state (open or closed), and other relevant filters. This step ensures that only the issues related to the specific project are retrieved.

Tools and Technologies:

- GitHub REST API
- HTTP requests for data retrieval

3.2 Extracting File Paths with Regex

Once the issue is extracted, the next task is to extract the file paths mentioned in the issue description. This is done using regular expressions (regex), which efficiently identify file paths from the text of the issue. Extracting the correct file path is crucial for the subsequent code analysis.

Tools and Technologies:

- Regular Expressions (Regex)

3.3 Constructing the Knowledge Graph

After extracting the file paths, the system proceeds to analyze the contents of the relevant files. The code is parsed, and functions are identified using regex patterns. Each function is treated as a node in the knowledge graph, with edges representing the function calls between them. This graph structure helps to visualize the relationships and dependencies between different functions in the codebase.

Tools and Technologies:

- Regular Expressions (Regex)
- Graph database or data structures (dictionary to maintain function calls)
- Graph visualization tools (NetworkX)

3.4 Semantic Analysis

The next step involves performing semantic analysis. The issue description is compared to the content of each function in the knowledge graph. This analysis helps to identify the functions most relevant to the issue at hand. The issue description serves as a base for matching with the function bodies.

Tools and Technologies:

- Natural Language Processing (NLP)
- Sentence embeddings

3.5 Graphical Analysis

In addition to semantic analysis, graphical analysis is conducted to further refine the relevance determination. The structure of the knowledge graph is analyzed using graph theory algorithms to evaluate the importance of each function. For instance, functions that are more central in the graph (i.e., those with more connections) may be considered more relevant to the issue.

Tools and Technologies:

- Graph theory algorithms (e.g., centrality measures, shortest path)
- Network analysis tools (NetworkX)

Let:

- $S(f)$ be the initial semantic score of function f
- $G = (V, E)$ be the directed graph of function dependencies
- α be the dependency propagation factor
- β be the centrality weighting factor
- $\text{Predecessors}(f)$ be the set of functions that call function f
- $C(f)$ be the betweenness centrality score of function f

We first adjust each function's score based on the semantic influence of its calling functions (dependency-based propagation):

$$S_\alpha(f) = S(f) + \alpha \sum_{g \in \text{Predecessors}(f)} S(g) \tag{1}$$

Then, we incorporate the structural centrality of each function to refine its importance:

$$S_{\text{final}}(f) = S_\alpha(f) + \beta \cdot C(f) \tag{2}$$

Combining both steps, the complete formula for the recalculated semantic score becomes:

$$S_{\text{final}}(f) = S(f) + \alpha \sum_{g \in \text{Predecessors}(f)} S(g) + \beta \cdot C(f) \tag{3}$$

This final score $S_{\text{final}}(f)$ more accurately reflects a function's relevance to the issue, accounting for both semantic similarity and graph-based importance.

3.6 LLM-Based Function Fix Generation

After identifying the most relevant function, the system inputs the function body and the issue description into a large language model (LLM), such as GPT-4. The LLM generates a fix based on its understanding of the issue and the code context. This approach allows for intelligent code modifications, reducing the need for manual intervention.

Tools and Technologies:

- Mistral LLM

3.7 Commit and Pull Request

Finally, the system commits the fixed code to the repository, creating a commit message and pushing the changes. A pull request is raised automatically for review and integration into the main codebase. This ensures that all changes are tracked, and the code is peer-reviewed before being merged.

Tools and Technologies:

- Git version control
- GitHub API for creating pull requests

3.8 Release 2: GitHub Extension and UML Diagram Generation

In Release 2, the system was enhanced to function as a GitHub extension. This extension allows users to interact with the system directly within GitHub, simplifying the process of issue resolution. The GitHub extension can be installed directly from the repository using the following command:

`pip install git+` https://github.com/AnirudhArrepu/PACGBI-Tool-Dev.git

Before running the tool, ensure the following environment variables are set:

- `MISTRAL_API_KEY` – API key for the LLM (Mistral)

- `GITHUB_TOKEN` – Personal Access Token with repository and PR access

Once the environment is configured, run the extension using:

```
pacgbi
```

Additionally, the system was upgraded to include functionality for generating UML diagrams of the code. The UML diagrams provide a visual representation of the relationships between functions, offering developers a clearer understanding of the code's structure and interdependencies. This addition significantly improves the usability and effectiveness of the system.

Tools and Technologies:

- GitHub Extensions
- PACGBI-Tool-Dev repository
- UML Diagram generation tools

Figure 2: Generated UML Of functions within file. Since there are no edges, this means the file had no function relations.

4 USER SCENARIO

A developer working on a COBOL banking system finds a bug and raises a GitHub issue. PACGBI automatically:

(1) Extracts the file and function related to the issue.
(2) Uses an LLM (like Mistral or GPT-4 Turbo) to suggest a fix.
(3) Replaces the buggy code and integrates the changes.
(4) Commits the change and raises a PR (Pull Request) for developer review.

The developer simply reviews the changes instead of manually identifying and fixing the issue, dramatically reducing debugging time. Additionally, a UML diagram of the affected component is generated to assist with system understanding and documentation.

By enabling full integration into the Git-based development workflow, PACGBI supports not only experienced developers but also empowers non-technical stakeholders to see the progression from issue to resolution. The generated code can be used to train future LLMs for COBOL, creating a self-improving loop.

5 EVALUATION AND METRICS

The performance of the proposed tool was evaluated using two primary metrics, which focus on the accuracy of function detection and the relevance of the identified function to the issue at hand.

5.1 Function and Call Detection Accuracy

The first metric assesses the tool's ability to extract functions from the code and identify the interdependencies between them. The effectiveness of this component was measured as follows:

- **Function Extraction (100% accuracy):** The tool successfully identified and listed all functions within the given file.
- **Function Call Detection (80% accuracy):** The system correctly captured the function call relationships (edges) between the functions with an accuracy of 80%.

5.2 Semantic Relevance and Function Identification Accuracy

The second metric evaluates the tool's ability to determine the most relevant function for a given issue based on the propagated semantic scores. The accuracy of this component was assessed by analyzing the output of the graph-based analysis:

- **Graph-Based Analysis (75% accuracy):** When all function calls were correctly identified, the graph analysis accurately identified the function most relevant to the issue in 75% of the cases.

Therefore, the overall **system accuracy** was computed as the product of call detection accuracy and the correctness of the graph-based analysis:

$$\text{Overall Accuracy} = 75\% \times 80\% = 60\%$$

This final accuracy indicates that, on average, the tool correctly identifies the relevant function 60% of the time, suggesting a reasonable level of effectiveness in pinpointing functions related to specific issues.

6 DISCUSSION & LIMITATIONS

PACGBI offers substantial advancements in the automated debugging and documentation process for COBOL-based legacy systems. However, as with any novel tool, there are inherent limitations that must be acknowledged and addressed:

- **Dependence on LLM Training Data**: The performance of the large language model (LLM) integrated into PACGBI is heavily reliant on the training data used, which may not account for all edge cases in COBOL, particularly for highly domain-specific constructs or rare patterns in legacy systems. This could limit the model's ability to resolve issues in certain legacy environments where domain-specific jargon or unique business logic is prevalent.
- **Regex-based Parsing Challenges**: While regex is an efficient tool for extracting function definitions, it may struggle with highly irregular or deeply nested COBOL structures. In particularly large or non-standardized COBOL files, parsing errors or misclassifications may occur, leading to incomplete or inaccurate function extraction.
- **Graph-Matching and Scoring Algorithm Limitations**: The graph-matching and scoring mechanisms used to analyze function dependencies and semantic relevance can be further optimized. The current methodology primarily focuses on unsupervised learning, but the accuracy of the generated semantic scores could be improved with community

feedback and supervised fine-tuning on specialized COBOL datasets like X-COBOL [1]. Furthermore, the current scoring system is simplistic in nature and may overlook deeper structural relationships in complex codebases.

- **Scaling to Large Codebases**: Although PACGBI performs well with moderately-sized COBOL codebases, its performance may degrade when scaling to extremely large systems with millions of lines of code. This is especially evident in scenarios where COBOL files are not modularized effectively, causing longer analysis times and potential resource bottlenecks.
- **Contextual Limitations**: Unlike modern programming paradigms that support high-level abstractions and agile development cycles, COBOL is a procedural language deeply tied to legacy business logic. Parsing paragraph-style functions and maintaining the correct order of execution in the context of legacy systems introduces unique constraints that are not easily addressed by general-purpose debugging tools.

Furthermore, while PACGBI's functionality is similar in some ways to modern IDE-based assistants like GitHub Copilot and AWS CodeWhisperer, our tool offers significant advantages tailored to the needs of legacy enterprise environments. Unlike these in-IDE tools, PACGBI operates within a Git-based workflow, allowing for autonomous issue detection, resolution, and documentation generation without requiring active developer intervention in the coding process. This creates a distinct value proposition for teams managing aging systems that need continual maintenance and rapid issue resolution without overhauling their entire workflow.

7 CONCLUSION AND FUTURE WORK

PACGBI demonstrates the transformative potential of AI-assisted automation for legacy software maintenance, particularly in COBOL-based systems. By automating common yet complex tasks such as bug detection, function identification, and code refactoring, PACGBI offers a more efficient and scalable solution for maintaining and enhancing legacy enterprise applications. This tool significantly improves the speed and reliability of debugging processes and provides accurate, automated documentation, which is a critical need for aging systems that often lack up-to-date documentation.

Unlike traditional in-IDE tools like Copilot or CodeWhisperer, which are designed primarily for modern web technologies, PACGBI operates as a standalone pipeline integrated into Git-based workflows. This enables PACGBI to better support legacy systems and avoid the pitfalls of IDE-based solutions that may struggle with COBOL or other older languages. The tool's ability to integrate into GitHub-based workflows and automatically create pull requests has proven to be a major advantage, with internal tests and external case studies demonstrating its effectiveness in rapidly addressing common issues. For instance, the PACGBI tool integrated with GitLab showed an impressive average issue resolution time of under 9 minutes per issue, with a merge request acceptance rate of 37.5% [12].

A key feature of PACGBI is its use of the **X-COBOL dataset** [1], which is invaluable for training the model to understand real-world COBOL code. This dataset, containing metadata and source code from 84 different COBOL repositories, has provided the foundation for developing an accurate semantic similarity model, which enables PACGBI to generate function-level fixes based on real-world code examples. The inclusion of this dataset has significantly enhanced the tool's ability to understand the nuances of legacy COBOL code and create more reliable, context-aware solutions.

In the future, we plan to expand PACGBI's capabilities and address some of the current limitations. Future work will focus on:

- **Refining the Scoring Mechanism**: Leveraging supervised learning techniques and incorporating more real-world COBOL issues will help refine the scoring mechanism for function relevance. Additionally, we will explore advanced graph algorithms to better capture the structural complexity of legacy systems.
- **Multi-file and Multi-module Support**: The next phase of development will enable PACGBI to handle multi-file changes and support larger, more sophisticated code refactoring tasks. This will be particularly important for enterprise-scale systems with complex codebases spanning multiple files.
- **Extended UML Generation**: We plan to enhance the UML generation feature to support state diagrams, sequence diagrams, and inter-file dependency visualizations. This will make it easier for developers to visualize complex legacy systems and understand the relationships between various modules.
- **Integration of Unit Test Generation**: We aim to integrate the generation of unit tests into the LLM pipeline, which will enable PACGBI to not only suggest code fixes but also propose appropriate tests to verify the changes. This integration will be crucial in improving code quality and confidence during the fix implementation phase.

Long-term, PACGBI's architecture is designed to be extensible for other legacy languages like FORTRAN and PL/I. As organizations continue to modernize their mainframe systems, PACGBI can bridge the gap by offering AI-augmented pipelines for refactoring, debugging, and maintaining these critical systems. We believe that the future of legacy system maintenance lies in AI-powered tools that help enterprises move towards modernization without losing the value embedded in their older systems.

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