

FeedbackEval: A Benchmark for Evaluating Large Language Models in Feedback-Driven Code Repair Tasks

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ABSTRACT

Code repair is a fundamental task in software development, facilitating efficient bug resolution and software maintenance. Although large language models (LLMs) have demonstrated considerable potential in automated code repair, their ability to comprehend and effectively leverage diverse types of feedback remains insufficiently understood.

To bridge this gap, we introduce FeedbackEval, a systematic benchmark for evaluating LLMs' feedback comprehension and performance in code repair tasks. We conduct a comprehensive empirical study on five state-of-the-art LLMs, including GPT-4o, Claude-3.5, Gemini-1.5, GLM-4, and Qwen2.5, to evaluate their behavior under both single-iteration and iterative code repair settings. Our results show that structured feedback, particularly in the form of test feedback, leads to the highest repair success rates, while unstructured feedback proves significantly less effective. Iterative feedback further enhances repair performance, though the marginal benefit diminishes after two or three rounds. Moreover, prompt structure is shown to be critical: incorporating docstrings, contextual information, and explicit guidelines substantially improves outcomes, whereas persona-based, chain-of-thought, and few-shot prompting strategies offer limited benefits in single-iteration scenarios. This work introduces a robust benchmark and delivers practical insights to advance the understanding and development of feedback-driven code repair using LLMs. All code and data are available at <https://github.com/SYSUSELab/FeedbackEval>.

KEYWORDS

Feedback-driven Code Repair, Large Language Models, Benchmark

1 INTRODUCTION

Code repair is a fundamental task in software development, enabling developers to efficiently identify and resolve errors [18, 25, 59]. With the rise of large language models (LLMs), there is increasing interest in leveraging their capabilities for automated code repair—not only for fixing human-written code but also for improving LLM-generated code by incorporating test feedback and compiler diagnostics [38, 41]. While LLMs have demonstrated promising performance in code generation [48, 52, 65, 74] and correction [18, 25, 59], their ability to interpret and effectively utilize feedback remains insufficiently explored, particularly in complex repair scenarios.

In practical software development, feedback-driven repair [17, 43, 50, 68] is essential. Developers iteratively refine their code based on test failures, compiler messages, and human reviews, relying on feedback to guide improvements. Understanding how LLMs process and act on such feedback is critical for improving their reliability in real-world development workflows. Moreover, enhancing LLMs' feedback comprehension is foundational for advancing autonomous multi-agent systems that support end-to-end software development [54, 55].

Existing research on LLM-based code repair primarily focused on evaluating repair accuracy or assessing LLMs under specific feedback conditions, such as test failures or compiler errors [5, 14, 63]. While some studies explore feedback-driven generation, they often limit their scope to single-iteration corrections and lack systematic comparisons across different feedback types [9, 39, 56, 69]. Additionally, although prompt engineering has been shown to improve LLM performance in various tasks, its role in enhancing feedback comprehension during code repair remains underexamined [27, 30, 32]. A significant gap exists in systematically benchmarking LLMs' ability to (1) process structured vs. unstructured feedback, (2) adapt to

iterative feedback, and (3) optimize repair success through different prompting strategies.

FeedbackEval. To bridge this gap, we introduce FeedbackEval, a benchmark designed to systematically evaluate LLMs' feedback comprehension and repair effectiveness across diverse conditions. Our benchmark consists of erroneous code segments derived from rule-based mutations, LLM-generated errors, and incorrect LLM-produced solutions, ensuring a broad representation of real-world failure cases. It encompasses multiple feedback scenarios, including structured (e.g., test and compiler feedback) and unstructured (e.g., human feedback), enabling a comprehensive assessment of LLMs' repair capabilities.

Empirical Study. Using FeedbackEval, we conduct an empirical study of five state-of-the-art (SOTA) LLMs (GPT-4o [2], Claude-3.5 [4], Gemini-1.5 [12], GLM-4 [72], and Qwen2.5 [11]) to understand how these LLMs process and utilize feedback in code repair. Specifically, we address the following research questions:

- **RQ1: How do different LLMs perform in single-iteration repair tasks utilizing feedback?** This question establishes a baseline for evaluating how well LLMs can resolve errors with a single feedback
- **RQ2: How do different types of feedback affect LLMs' performance in code repairs?** We analyze the effectiveness of different feedback types (e.g., compiler error message, human review comments) and their influence on LLM repair.
- **RQ3: How does the effectiveness of feedback evolve over multiple repair iterations for different LLMs?** This question investigates the iterative refinement capabilities of LLMs, emphasizing their adaptability across multiple iterations of feedback.
- **RQ4: To what extent do different prompting techniques impact the performance of LLMs in code repairs using feedback?** We explore how prompt engineering strategies affect feedback comprehension and repair success, evaluating techniques such as chain-of-thought reasoning, few-shot learning, and the inclusion of contextual information.

Main Findings. Based on our results, we summarize the following main findings: ① We observe that different LLMs exhibit significant performance gaps in feedback-driven code repair, with Claude-3.5 achieving an average repair accuracy of 60.8% and GPT-4o reaching 56.4%, outperforming Gemini-1.5 (55.6%), Qwen2.5 (54.8%), and GLM-4 (52.7%). ② Structured feedback types, particularly test feedback, yield superior results. Test feedback achieves the highest average success rate of 61.0%, suggesting that LLMs benefit more from clear, targeted guidance compared to unstructured feedback. Surprisingly, simple feedback, such as "The code is wrong. Please fix it," ranks second, suggesting LLMs can infer necessary corrections even without detailed error descriptions. ③ Iterative feedback improves LLM performance, with test and human feedback demonstrating the most significant gains. However, performance improvements diminish over successive iterations, typically stabilizing after two to three repair cycles, indicating that extended iterations yield diminishing returns. ④ Prompt structure significantly affects repair performance. Persona, chain-of-thought, and few-shot prompting exhibit minimal impact on single-iteration repair tasks. In contrast, docstrings, context, and guidelines yield

<pre>def verify_relayable_signature(public_key, doc, signature): sig_hash = .create_signature_hash(doc, 15) cipher = PKCS1_v1_5.new(RSA.ImportKey(), 28) return cipher.verify(sig_hash)</pre>	Erroneous Code
Verify the signed XML elements to have confidence that the claimed author did actually generate this message.	Docstring
<pre>{ "apis": "[b64decode', '.create_signature_hash', 'verify', 'new', 'importKey']", "classes": "[PKCS1_v1_5]", "vars": "[]" }</pre>	Context
<pre>Traceback (most recent call last): File ~/home/travis/builds/repos/jaywink-... federation/federation/protocols/diaspora/signatures_verify_relayable_signature_passk_validate0.py, line 79, in <module> assert verify_relayable_signature(PUBKEY, doc, SIGNATURE) File ~/home/travis/builds/repos/jaywink-... federation/federation/protocols/diaspora/signatures_verify_relayable_signature_passk_validate0.py, line 35, in verify_relayable_signature sig_hash = .create_signature_hash(doc, 15) TypeError: .create_signature_hash() takes 1 positional argument but 2 were given</pre>	Test Feedback
<pre>In line: def verify_relayable_signature(public_key, doc, signature): . Unused argument 'public_key', In line: def verify_relayable_signature(public_key, doc, signature): . Unused argument 'signature'</pre>	Compiler Feedback
The existing code contains a reference to 'RSA.ImportKey()' without passing the 'public_key' argument, which may lead to an error or unintended behavior since it currently lacks the required input for importing the public key. Additionally, you should ensure that the '.create_signature_hash' function is returning a hash compatible with the verification method used, and consider verifying if the signature verification process includes necessary exceptions handling for robustness. Lastly, it would be beneficial to confirm that 'verify()' properly checks against the expected signature format and value, enhancing the reliability of your verification process.	Human Feedback
The code is wrong. Please fix it.	Simple Feedback

Figure 1: An example of code repair task in FeedbackEval

substantial performance improvements, underscoring the importance of structured, context-rich input in enhancing LLM effectiveness for code repair tasks.

In summary, this paper makes the following contributions:

- A comprehensive benchmark for evaluating LLMs in feedback-driven code repair, covering diverse error types and feedback scenarios.
- A systematic empirical evaluation of state-of-the-art LLMs, providing insights into their strengths, limitations, and adaptability in iterative repair tasks.
- Actionable recommendations for improving LLMs' feedback comprehension and repair effectiveness, highlighting the role of structured feedback and optimized prompting techniques.

All data/code used in this study is provided in the package [1].

2 BENCHMARK CONSTRUCTION

In this section, we introduce our new benchmark FeedbackEval for feedback-driven code repair. We present the benchmark format (Section 2.1), the construction procedure (Section 2.2), and the resulting benchmark (Section 2.3).

2.1 Benchmark Format

Each task in the benchmark consists of an erroneous code segment, a descriptive docstring, contextual information, and multiple forms of feedback, simulating realistic software development scenarios where developers receive guidance from diverse sources. The key components of the benchmark are defined as follows:

- **Erroneous Code:** A faulty function or code snippet requiring correction serves as the initial state for the repair task.
- **Docstring:** A high-level description of the code's intended functionality, providing a semantic reference to help the LLM understand the goal of the code.

- **Context:** Supplementary information about the project or surrounding code environment, such as related APIs, class definitions, or global variables. This offers a broader understanding of the code's role within a larger system.
- **Test Feedback:** Derived from pytest [29] test cases, this feedback explicitly identifies failing tests and expected outcomes, providing clear, actionable guidance for code correction. This emulates real-world debugging, where developers rely on test results to diagnose issues.
- **Compiler Feedback:** Generated using pylint [36] static analysis, this feedback highlights syntax errors, code style violations, and potential bugs, offering technical insights into structural flaws in the code.
- **Human Feedback:** Simulated through GPT-4o-mini, this feedback mimics developer-generated suggestions in natural language, pointing out potential logic flaws and recommending best practices to improve code reliability and robustness.
- **Simple Feedback:** A minimalistic, generic form of feedback (e.g., "The code is wrong. Please fix it."). It evaluates whether the LLM can initiate repairs with only vague or insufficient guidance.

By incorporating multiple types of feedback, our benchmark challenges LLMs to demonstrate not only their code generation abilities but also their understanding of different feedback sources — from structured error outputs to nuanced human suggestions — reflecting the diverse forms of feedback encountered in real-world development.

2.2 Benchmark Construction

We follow three main steps to create FeedbackEval: (i) selecting code generation tasks, (ii) collecting erroneous code segments and (iii) generating diverse feedback types for each error instance.

2.2.1 Code Generation Task Selection. We select **HumanEval** [8] and **CoderEval** [64] as the sources for constructing FeedbackEval. **HumanEval** consists of 164 manually curated programming problems, each providing a function signature, a docstring, and corresponding unit tests, designed to evaluate the code generation capabilities of LLMs. The strength of this dataset lies in its high quality and diversity, covering a wide range of programming tasks, which helps assess LLMs' ability to generate code across different contexts.

However, recent studies indicate that existing LLM-based code generation methods struggle with generating code snippets that depend on project-specific contexts, such as private APIs, classes, data structures, or type constraints. **CoderEval** aims to address the limitations of **HumanEval** in evaluating code generation in real-world development scenarios. It selects code generation tasks from real open-source projects, covering multiple domains and considering common software development challenges such as complex data types, custom types, third-party libraries, and cross-procedural calls. Additionally, **CoderEval** categorizes tasks into six levels based on their dependency on external contexts and provides comprehensive test cases to assess LLMs' performance across various contextual settings.

In this study, we focus on the Python tasks of these two datasets, as the Python language is widely popular in both academia and industry. This approach not only aligns with the mainstream practices

Prompt for LLM-Driven Error Injection

You are an AI code editor and generator. Your goal is to analyze the @@Existing Code and generate mutants in it. You can generate one mutant by introducing a single, subtle alteration to the logic, structure, or syntax of the code. The mutation should impact the functionality in a meaningful way without completely changing the intent or purpose of the original code.

@@Existing Code {}

#Requirement:

1. Provide generated mutants directly.
2. Prohibit generating the exact same mutants.
3. Do not explain how the mutant was generated, only output the mutated code.
4. The output must be in the following format:

```
'''python
# Your codes here
'''
```

Figure 2: Prompt for LLM-driven error injection

in current research on LLMs but also enhances the comparability of our findings with existing literature. Consequently, it provides a reliable foundation for the comprehensive evaluation of LLMs' performance.

2.2.2 Erroneous Code Segments Collection. We employed three distinct methods to collect erroneous code segments, ensuring coverage of a wide range of error types and realistic coding challenges.

Rule-Based Error Injection. Building on previous mutation testing research [26, 33, 40], We introduce controlled errors into correct code implementations using predefined mutation operators. These operators systematically introduce common programming mistakes by modifying code elements such as arithmetic and logical operators, loop conditions, and function calls. By applying these rule-based transformations, we generate a structured set of erroneous code samples with well-defined error patterns, enabling precise error classification and controlled experimentation.

LLM-Driven Error Injection. We follow previous studies on LLM-Driven Error Injection [51, 53] and utilize a specialized prompt to guide **GPT-4o-mini** in generating subtle and meaningful code mutations. The prompt, shown in figure 2, is designed to ensure that the generated mutants introduce single, impactful alterations to the logic, structure, or syntax of the original code while maintaining its overall intent.

LLM-Generated Incorrect Code. We extract erroneous code directly from LLM-generated outputs by running **GPT-4o-mini** on benchmark datasets (e.g., **HumanEval** and **CoderEval**) under a pass@10 evaluation setting. From these results, we filter out incorrect code segments that failed to pass the test cases or meet functional requirements. This approach captures naturally occurring errors generated by LLMs, providing insights into their typical failure modes and limitations in code generation tasks.

By integrating these three approaches, our benchmark captures a diverse range of coding errors, from syntactic and semantic mistakes to higher-level logical flaws.

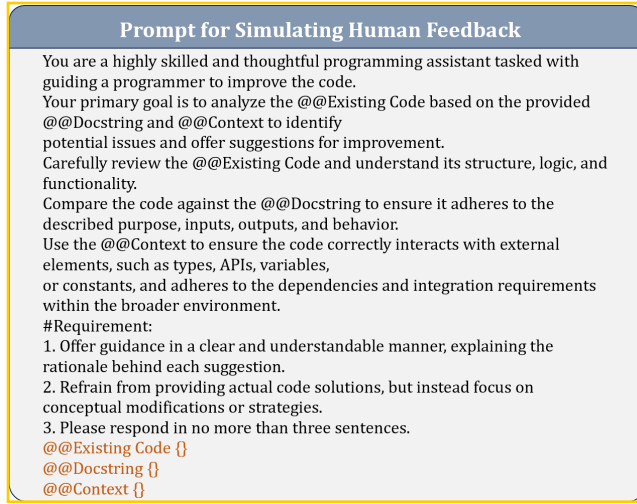


Figure 3: Prompt for simulating human feedback

2.2.3 Generating Diverse Feedback Information. For each erroneous code instance, we generate four types of feedback to simulate real-world debugging scenarios:

- **Test Feedback:** Extracted from pytest test cases, this feedback explicitly identifies failing tests and expected outcomes, providing clear and actionable guidance for code correction.
- **Compiler Feedback:** Generated using pylint static analysis, this feedback highlights syntax errors, code style violations, and potential bugs, offering technical and specific insights.
- **Human Feedback:** Simulated by GPT-4o-mini, this feedback mimics natural language input from a human reviewer, often containing unstructured and contextually rich suggestions [56, 69]. Figure 3 illustrates the prompt for simulating human feedback.
- **Simple Feedback:** A minimalistic form of feedback consisting of a single sentence: "The code is wrong. Please fix it." This feedback provides no specific guidance, evaluating the LLMs' ability to infer necessary repairs from minimal input.

Each erroneous code segment is paired with feedback from all four categories. By systematically analyzing how LLMs interpret and act upon different feedback types, the benchmark offers insights into their feedback comprehension, adaptability, and repair strategies across varying levels of complexity.

2.3 Resulting Benchmark

Following this methodology, we construct a new benchmark, FeedbackEval, to systematically evaluate LLMs' ability to interpret and utilize various feedback types in code repair. The benchmark is characterized by the following key features.

Scale. FeedbackEval consists of 394 coding tasks covering a diverse range of programming scenarios. In total, it includes 3,736 erroneous code instances, each paired with four distinct types of feedback.

Feedback Diversity. FeedbackEval systematically integrates multiple feedback types, distinguishing it from prior benchmarks that predominantly focus on compiler diagnostics or test-based

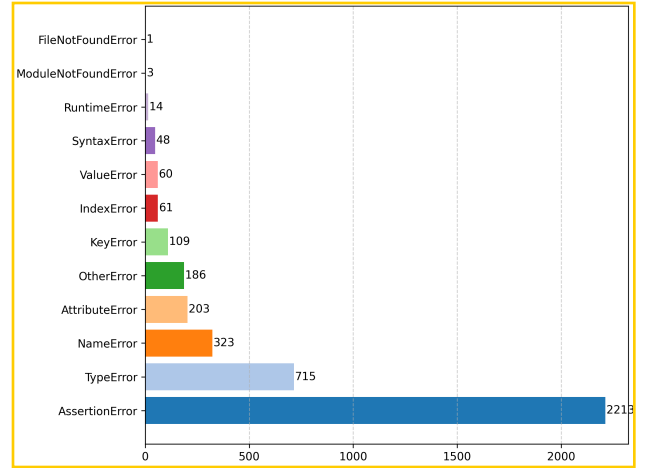


Figure 4: Distribution of Error Types in FeedbackEval

verification. By encompassing both structured (compiler messages, test failures) and unstructured (human reviews, simplified feedback) guidance, FeedbackEval enables a comprehensive analysis of how different LLMs interpret and utilize feedback. This makes it a valuable resource for studying iterative code refinement and enhancing feedback-driven LLM improvements.

Bug Diversity. Figure 4 illustrates the distribution of error types in FeedbackEval, categorized based on the exceptions encountered during execution or compilation. AssertionError is the most prevalent (2,213 instances), reflecting test failures caused by functional correctness issues, followed by TypeError (715 instances) and NameError (323 instances). The benchmark also includes a range of other error types, from AttributeError (203 instances) to rare cases such as ModuleNotFoundError (3 instances) and FileNotFoundError (1 instance). This diverse error distribution ensures that FeedbackEval provides a comprehensive evaluation of LLMs' ability to repair a wide spectrum of programming issues across different feedback modalities.

Overall, FeedbackEval features feedback diversity, incorporating both structured and unstructured feedback to simulate real-world debugging scenarios. Bug diversity ensures a broad representation of errors, enabling a thorough assessment of LLMs' performance across varied fault patterns. As FeedbackEval evolves, it can be expanded with more error types and complex repair tasks, further enhancing its ability to reflect realistic, large-scale debugging challenges.

3 EXPERIMENTAL SETUP

To answer the RQs, we conduct a study based on FeedbackEval. This section details the experimental setup, including LLM selection and implementation procedures.

LLM Selection. We select five mainstream LLMs with strong performance in code-related tasks, including both open-source and closed-source LLMs: GPT-4o (GPT-4o-2024-11-20) [2], Claude-3.5

(Claude-3-5-Sonnet-20241022) [4], Gemini-1.5 (Gemini-1.5-pro, released at 2024-9-24) [12], GLM-4 (GLM-4-Plus, released at 2024-8-29) [72], and Qwen2.5 (Qwen2.5-72B-Instruct, released at 2024-9-19) [11]. These LLMs are chosen for their advanced capabilities in code understanding, generation, and feedback adaptation, which are critical aspects of our study on feedback comprehension and evaluation.

Implementation Procedure. For the experiments, we utilized a subset of FeedbackEval due to computational constraints and the need for focused analysis within a feasible runtime. We randomly selected one erroneous code instance per task, resulting a subset of 394 erroneous code instances, each paired with four distinct feedback types.

To ensure consistency and fairness in our evaluation, we apply the same experimental settings and evaluation metrics across all LLMs. Each LLM was evaluated using the same random sampling strategy with a temperature parameter set to 0.3, and all LLMs were accessed via their respective APIs. To measure performance, we introduced a new metric, **Repair@k**, which evaluates the pass rate of code after **k** rounds of iterative repair. This metric assesses the LLMs' ability to refine code based on feedback over multiple iterations, providing insights into their adaptability and robustness in feedback-driven scenarios.

4 RQ1: SINGLE-ITERATION CODE REPAIR

To understand how different LLMs handle code repair based on feedback, we evaluate their performance in single-iteration repair tasks.

4.1 Design

We design an experiment to evaluate the performance of five selected LLMs in single-iteration code repair tasks using feedback. For each of the 394 tasks in FeedbackEval, we randomly select an erroneous code segment and task the LLMs with repairing it in a single iteration based on one of four feedback types. To ensure a fair comparison, the same prompt templates are used across all LLMs and feedback types, as illustrated in Figure 5, adapted from prior studies [69]. The repair prompt in Figure 5 instructs the LLM to fix the given erroneous code based on specific feedback (e.g., compiler feedback, test feedback). Also, supplementary information, such as docstrings and contextual details, is provided to help the LLM better understand the task and the broader context of the code.

Performance is measured using the **Repair@1** metric, which quantifies the pass rate of repaired code after one feedback iteration. To mitigate randomness and enhance result reliability, each experiment is conducted twice under identical conditions, with the average performance reported as the final result. This setup systematically evaluates LLMs' ability to leverage feedback for code repair.

4.2 Results

Table 1 presents the average performance of different LLMs in feedback-driven single-iteration code repair on FeedbackEval.

Overall Performance. Table 1 presents the average performance of different LLMs in single-iteration code repair across various feedback types. Claude-3.5 achieves the highest overall score (60.8%)

Prompt for Code Repair Utilizing Feedback	
You are a professional code repair assistant skilled at fixing code errors based on the @@Feedback.	Persona
Your task is to correct the given erroneous code @@Existing Code.	Task
@@Feedback includes error messages, descriptions of logical issues, or deviations from expected functionality. @@Docstring provides a description of the function, its purpose, and details of its input and output parameters. @@Context refers to code elements such as types, APIs, variables, and consts defined outside the function under generation but within the dependent third-party libraries, current class, file, or project.	
Description	
@@Existing Code {} @@Docstring {} @@Context {} @@Feedback {}	
Information	
Based on the provided information, fix the erroneous code and ensure the following: 1.Resolve all errors to make the code functional. 2.Address the improvement points mentioned in the feedback. 3.Only need to fix the code; do not modify the function signature. 4.Please return the corrected code in the following format: ```python # Your codes here ...	
Guideline	

Figure 5: Prompt for Single-Iteration Code Repair Using Feedback

Table 1: Average Repair@1 on FeedbackEval for Selected LLMs

Feedback	GPT-4o	Claude-3.5	Gemini-1.5	GLM-4	Qwen2.5	Average
Test	61.7	65.0	60.4	57.6	60.6	61.0
Compiler	55.6	58.9	56.0	53.3	55.3	55.8
Human	50.1	55.8	51.6	46.6	48.5	50.5
Simple	58.2	63.4	54.4	53.5	54.9	56.9
Average	56.4	60.8	55.6	52.7	54.8	

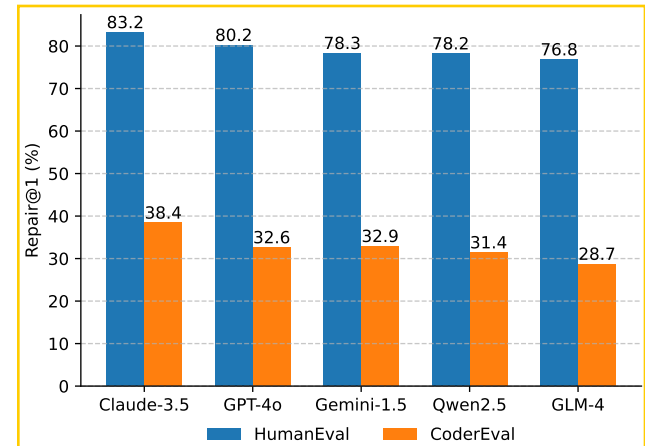


Figure 6: Repair@1 Results of Different LLMs across Two Datasets

and outperforms all LLMs across every feedback type, demonstrating its superior ability to leverage feedback for code repair. GPT-4o follows with a score of 56.4%, showing decent repair capability but performing noticeably worse than Claude-3.5, especially in handling human and simple feedback. Qwen2.5 (54.8%) and Gemini-1.5 (55.6%) perform comparably, exhibiting moderate feedback utilization, while GLM-4 (52.7%) consistently ranks the lowest across all feedback types.

Performance Comparison Across HumanEval and CoderEval. Figure 6 presents the Repair@1 comparison of different LLMs across HumanEval and CoderEval, highlighting how task complexity affects LLM performance.

For HumanEval, which consists of relatively simple function-level code generation tasks such as data structure operations and numerical computations, all LLMs achieve higher performance. Claude-3.5 leads with an average score of 83.2%, followed by GPT-4o (80.2%), Gemini-1.5 (78.3%), and Qwen2.5 (78.2%), while GLM-4 lags behind (76.8%).

In contrast, CoderEval introduces greater complexity, featuring repository-level tasks that require understanding broader code contexts and domain-specific logic. Challenges such as hallucinated method calls and incorrect API usage make repair tasks significantly harder. As a result, all LLMs experience a sharp performance drop (by 28.7% to 38.4%) compared to HumanEval, though their relative rankings remain largely unchanged. Claude-3.5 again achieves the highest score (38.4%), demonstrating the strongest adaptability to complex repairs, though still far from perfect. The other LLMs follow in the order of Gemini-1.5, GPT-4o, Qwen2.5, and GLM-4, with scores ranging from 32.9% to 28.7%.

The substantial performance gap between HumanEval and CoderEval underscores the increased difficulty of real-world software repair tasks. While LLMs perform well on function-level problems with limited scope, their effectiveness diminishes when handling complex, context-dependent errors. These results highlight the necessity of FeedbackEval in systematically evaluating LLMs under varying levels of complexity, providing a more comprehensive assessment of their real-world repair capabilities.

Finding 1: Claude-3.5 achieves the best performance in feedback-driven code repair, but all LLMs experience significant drops in repair success rates on tasks from CoderEval (28.7%-38.4%) compared to HumanEval, highlighting the challenges of complex, context-dependent errors in task-specific code repair and the need for improvement in real-world scenarios.

5 RQ2: IMPACT OF FEEDBACK TYPES

To evaluate the impact of different feedback types on LLM-based code repair, we analyze their effect on LLM performance and identify which type provides the most effective guidance for improving repair accuracy.

5.1 Design

We extend our analysis from RQ1 by assessing how different feedback types influence LLM repair performance. Specifically, we measure repair@1 across various LLMs and feedback categories to determine their relative effectiveness. Additionally, we examine the

relationship between task complexity and feedback utility, exploring whether more complex errors benefit from specific feedback types.

5.2 Results

Overall Impact. As shown in Table 1, test feedback achieves the highest repair success rate (61.0%), followed by simple feedback (56.9%), compiler (55.8%), and human feedback (50.5%). Test feedback is the most effective for all LLMs, likely due to its explicit and structured nature, which directly pinpoints errors.

Surprisingly, simple feedback, such as “The code is wrong. Please fix it” ranks second, suggesting LLMs can infer necessary corrections even without detailed error descriptions. Compiler feedback performs slightly worse, possibly because, while precise, it requires correct interpretation of technical details. Human feedback is the least effective, likely due to its unstructured and ambiguous nature.

Figure 7 shows an example of a code repair task with different feedback. The initial erroneous code fails due to excessive arguments in the `_create_signature_hash` function. Each feedback type yields a distinct repair outcome. Test feedback provides a trace-back identifying the argument mismatch, effectively guiding the LLM to remove the redundant argument, resulting in a successful fix. Compiler feedback detects unused arguments but lacks deeper reasoning, leading to a partial correction that retains the original argument error, ultimately failing the test suite. Human feedback offers detailed, structured suggestions, addressing multiple aspects such as `RSA.importKey()` usage and hash compatibility. However, LLMs misinterpret parts of the feedback, producing an overly complex revision that introduces exception handling but fails to resolve the core argument issue, leading to an unsuccessful repair. In contrast, simple feedback offers only a vague directive, resulting in a superficial modification that fails due to the unresolved argument error.

Overall, structured feedback proves most helpful, while simple feedback highlights LLMs’ strong inferential abilities, and human feedback remains the most challenging.

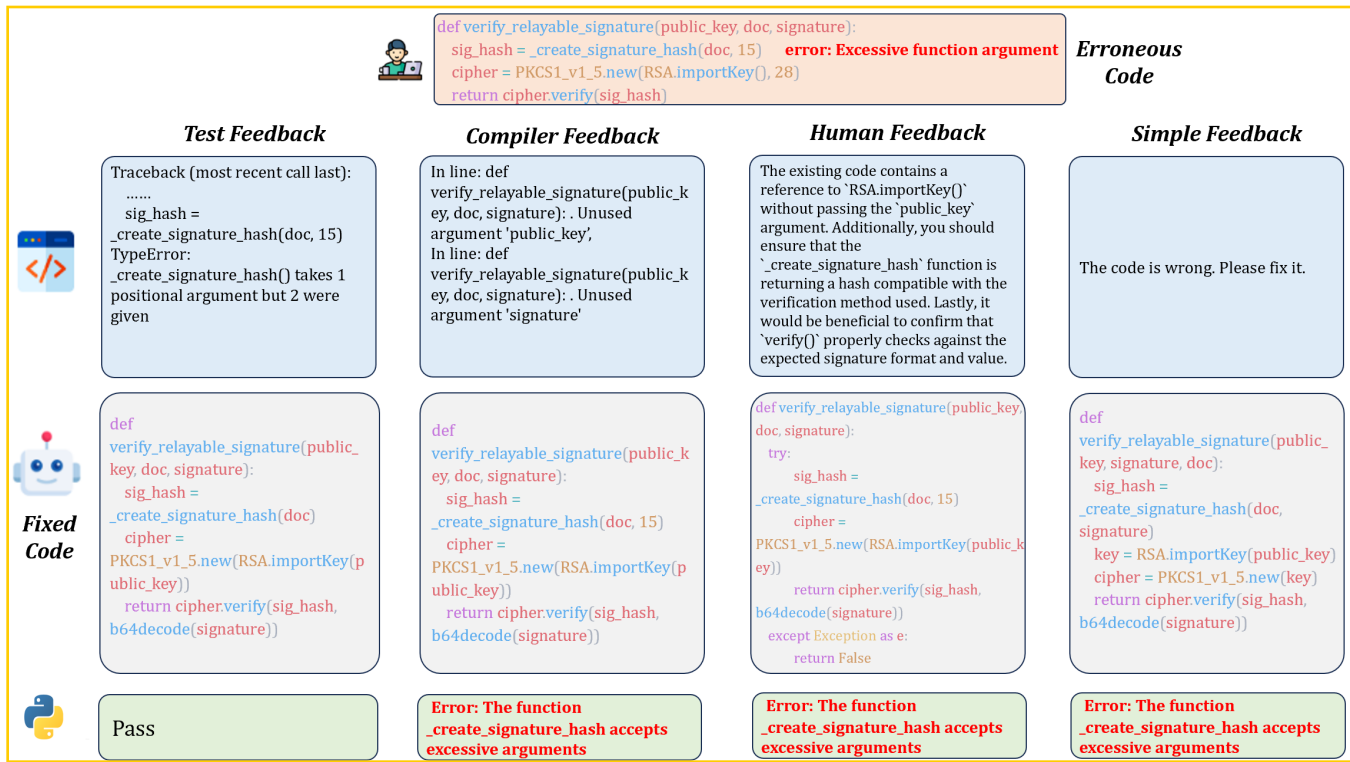
Performance on HumanEval Vs. CoderEval Table 2 compares the effectiveness of different feedback types on repair tasks from HumanEval and CoderEval. Across both datasets, Claude-3.5 consistently outperforms other LLMs, except when test feedback is used for HumanEval tasks.

For HumanEval, test feedback leads to the highest repair success rates for most LLMs (except Gemini-1.5), with GPT-4o at 85.6% and Claude-3.5 at 84.1%. This indicates that structured, test-based guidance is the most interpretable for LLMs. Compiler feedback is also effective, as seen in Claude-3.5’s 84.1%, demonstrating the value of error-specific feedback for accurate code repairs. In contrast, human feedback challenges all LLMs, resulting in lower performance (GPT-4o at 71.6%, GLM-4 at 67.7%) due to its unstructured nature and implicit reasoning demands. Simple feedback, while minimal, is beneficial, with Claude-3.5 scoring 85.3% highlighting the LLM’s strong inferential abilities.

A similar trend is observed in CoderEval, where test feedback remains the most effective, with Claude-3.5 scoring the highest (45.9%) followed by Gemini-1.5 (40.4%). Compiler and simple feedback show moderate effectiveness, while human feedback is again

Table 2: Repair@1 Results of Different LLMs on Code Repair Tasks with Various Feedback

Feedback	GPT-4o		Claude-3.5		Gemini-1.5		GLM-4		Qwen2.5	
	HumanEval	CoderEval	HumanEval	CoderEval	HumanEval	CoderEval	HumanEval	CoderEval	HumanEval	CoderEval
Test	85.6	37.8	84.1	45.9	80.4	40.4	83.5	31.6	84.1	37.0
Compiler	82.7	28.5	84.1	33.7	82.6	29.4	80.7	25.8	80.8	29.8
Human	71.6	28.5	79.1	32.4	72.9	30.3	67.7	25.6	70.7	26.2
Simple	81.0	35.4	85.3	41.6	77.4	31.4	75.3	31.7	77.1	32.7
Average	80.2	32.6	83.2	38.4	78.3	32.9	76.8	28.7	78.2	31.4

**Figure 7: Example of Code Repair Task with Different Feedback**

the most challenging, particularly for GLM-4, which scores only 25.6%.

Finding 2: Test feedback consistently leads to the highest repair success rates across LLMs, with Claude-3.5 performing the best in both HumanEval and CoderEval. While compiler and simple feedback show moderate effectiveness, human feedback remains the most challenging due to its unstructured nature, and task complexity further impacts the utilization of different feedback types.

6 RQ3: MULTIPLE-ITERATION REPAIR

In this RQ, we investigate the effectiveness of feedback-driven code repair with iterative feedback, evaluating how LLMs adapt and improve their performance across multiple iterations of feedback.

6.1 Design

From our benchmark, we selected a subset of tasks for multi-iteration repair experiments, considering the higher time and computational costs, especially for repair tasks from CoderEval. Ultimately, we used all 164 HumanEval problems and randomly sampled 100 from the original 230 CoderEval problems. For each task,

an erroneous code segment was selected, ensuring diversity in error types and repair challenges. To maintain consistency, all LLMs were evaluated on the same erroneous code set, with each task paired with one of four feedback types: test feedback, compiler feedback, human feedback, or simple feedback.

For each task, the LLMs were provided with the initial erroneous code and corresponding feedback, after which they performed a repair iteration. The repaired code was subsequently re-evaluated, and new feedback (of the same type) was generated based on any remaining errors or issues. This iterative repair process continued for three iterations, allowing the LLMs to progressively refine the code based on feedback. To assess performance, we introduced the **Repair@k** metric, which measures the pass rate of the code after k repair iterations (where $k=3$ in this study).

6.2 Results

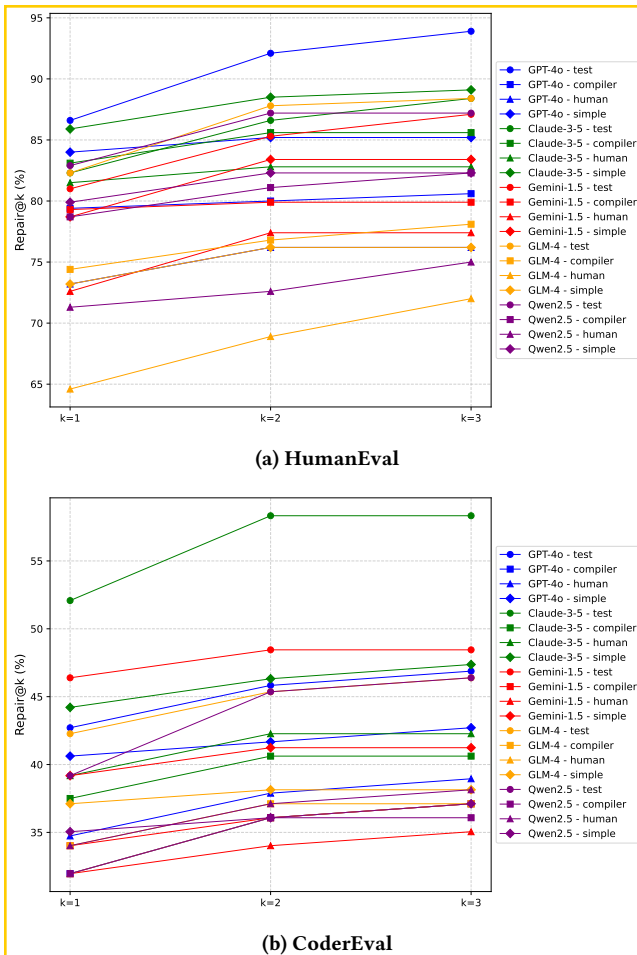


Figure 8: Performance changes across repair iterations

Table 3 presents a comprehensive analysis of how different LLMs respond to various types of feedback over multiple repair iterations.

Cross-LLM Performance Comparison. GPT-4o leads on HumanEval, especially with test feedback, achieving 93.9% at repair@3. This suggests strong adaptability to structured problem-solving tasks. Claude-3.5 demonstrates balanced performance across datasets and feedback types. It performs competitively under test and simple feedback (e.g., 89.1% on HumanEval), reflecting versatility in handling both datasets' characteristics. Gemini-1.5 achieves solid improvements on HumanEval with test feedback but lags on CoderEval, particularly under compiler and human feedback. This indicates a potential sensitivity to CoderEval's more complex code contexts. GLM-4 and Qwen2.5 generally underperform on both datasets, particularly with compiler and human feedback. However, Qwen2.5 shows late-stage recovery on CoderEval under human feedback (38.1%), indicating adaptation potential in later repair stages.

Comparative Effectiveness of Feedback Types. Test feedback remains the most effective and consistent, driving the highest performance gains for all LLMs across both datasets. Its structured, pass/fail nature appears well-suited to guiding LLMs toward correct outputs. Compiler feedback lags behind, showing only marginal improvements. This suggests that syntax-level feedback lacks sufficient information to guide higher-level code corrections effectively. Human feedback demonstrates dataset-dependent behavior. It plateaus early on HumanEval but shows late-stage gains on CoderEval, implying that human instructions may excel in complex, diverse tasks where LLM understanding needs deeper refinement. Simple feedback provides modest but stable improvements. While less effective than test feedback, its consistent performance across LLMs and datasets highlights its potential as a lightweight, general-purpose feedback mechanism.

Performance Evolution Across Iterations. As illustrated in figure 8, the performance trajectory over iterations reveals two key trends: ① Most LLMs, particularly GPT-4o and Claude-3.5, exhibit sharp performance gains between repair@1 and repair@2, driven predominantly by test feedback. ② By repair@3, gains tend to plateau, especially for compiler and simple feedback types. This suggests diminishing returns from repetitive feedback when key semantic misunderstandings remain unaddressed.

Finding 3: Iterative feedback enhances LLM code repair, with test and human feedback yielding the highest gains. However, performance gains diminish over iterations, typically stabilizing after two to three iterations of repair.

7 RQ4: PROMPTING TECHNIQUES IMPACT

To investigate the impact of different prompting techniques on feedback-driven code repair, we evaluate how various prompting strategies affect LLMs' ability to interpret and apply feedback effectively during the code repair process.

7.1 Design

In this section, we explore the impact of various prompting techniques on feedback-driven code repair. Specifically, we investigate three key techniques: chain-of-thought reasoning [67], few-shot learning [6], and the inclusion of additional context information. As shown in Figure 9, we enhance the baseline prompt used in RQ1

Table 3: Repair@3 results of different LLMs on code repair tasks using various feedback.

Feedback	GPT-4o		Claude-3.5		Gemini-1.5		GLM-4		Qwen2.5	
	HumanEval	CoderEval	HumanEval	CoderEval	HumanEval	CoderEval	HumanEval	CoderEval	HumanEval	CoderEval
Test	86.6	42.7	82.3	52.1	81.0	46.4	82.3	42.2	82.9	39.2
	92.1 ↑	45.8 ↑	86.6 ↑	58.3 ↑	85.3 ↑	48.5 ↑	87.8 ↑	45.3 ↑	87.2 ↑	45.4 ↑
	93.9 ↑	46.9 ↑	88.4 ↑	58.3	87.1 ↑	48.5	88.1 ↑	46.4 ↑	88.2 ↑	46.4 ↑
Compiler	79.4	32.0	83.1	37.5	79.3	34.0	74.4	34.0	78.7	32.0
	80.0 ↑	36.1 ↑	85.6 ↑	40.6 ↑	79.9 ↑	37.1 ↑	76.8 ↑	37.1 ↑	81.1 ↑	36.1 ↑
	80.6 ↑	37.1 ↑	85.6	40.6	79.9	37.1	78.1 ↑	38.1 ↑	82.3 ↑	37.1 ↑
Human	73.2	34.7	81.5	39.2	72.6	32.0	64.6	32.0	71.3	34.0
	76.2 ↑	37.9 ↑	82.8 ↑	42.3 ↑	77.4 ↑	34.0 ↑	68.9 ↑	36.1 ↑	72.6 ↑	37.1 ↑
	76.2	39.0 ↑	82.8	42.3	77.4	35.1 ↑	72.0 ↑	37.1 ↑	75.0 ↑	38.1 ↑
Simple	84.0	40.6	85.9	44.2	78.7	39.2	73.2	37.1	79.9	35.1
	85.2 ↑	41.7 ↑	88.5 ↑	46.3 ↑	83.4 ↑	41.2 ↑	76.2 ↑	38.1 ↑	82.3 ↑	36.1 ↑
	85.2	42.7 ↑	89.1 ↑	47.4 ↑	83.4	41.2	76.2	38.1	82.3	37.1 ↑

Chain-of-Thought

You should follow the reasoning process below to fix the code:

- Carefully read the feedback and understand the essence of the problem.
- Check the parts of the code that might be causing these issues.
- Consider edge cases and special condition handling.
- Apply appropriate fixes while maintaining code style consistency.
- Verify whether the fix addresses all the issues mentioned in the feedback.

For example:

Erroneous Code:

```
def calculate_average(numbers):
    total = 0
    for num in numbers:
        total += num
    return total / len(numbers)
```

Feedback:
Consider adding error handling to manage potential issues, such as division by zero when the input list is empty. Additionally, using built-in functions like 'sum()' can simplify the code and improve readability, making it more pythonic. Finally, ensure that the function can handle non-numeric inputs to prevent runtime errors.

Fixed Code:

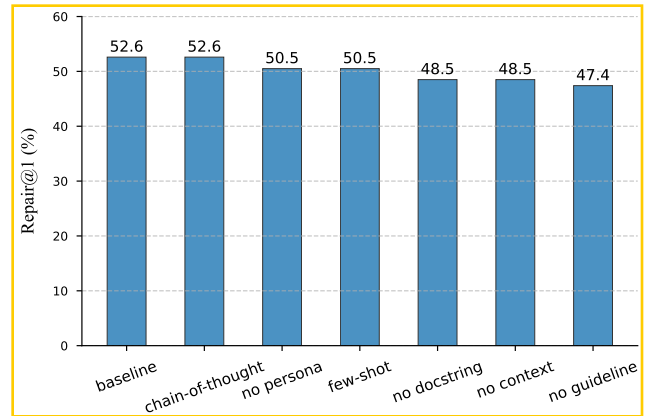
```
def calculate_average(numbers):
    if not numbers:
        raise ValueError("Input list is empty. Cannot calculate average.")
    return sum(numbers) / len(numbers)
```

Few-shot Example

Figure 9: Example of chain-of-thought and few-shot

by incorporating a chain-of-thought step for the chain-of-thought reasoning technique and adding a repair example for the few-shot learning approach. Furthermore, we examine the effect of providing extra context, such as docstrings, project-level context, and guidelines, by modifying the baseline prompt to remove these elements. Due to space constraints, the full details of the prompt are not included in the paper but are available in our release package [1].

For our experiments, we select the Claude-3.5 as the base LLM due to its strong performance in previous RQs. We evaluate the impact of different prompting techniques on its performance in a single-iteration code repair task. All experiments are conducted using the CoderEval dataset, with 100 randomly sampled erroneous

**Figure 10: Performances of different prompt techniques.**

code segments. Each experimental condition is systematically tested to assess how variations in prompting affect the LLM’s ability to interpret and apply feedback. The baseline prompt, as described in RQ1 (Figure 5), serves as the starting point, with specific modifications introduced for each experimental condition.

7.2 Results

Figure 10 illustrates the impact of different prompting techniques on the performance of Claude-3.5 in single-iteration code repair tasks. Under the baseline setting depicted in figure 5, Claude-3.5 achieves a performance score of 52.6%. Notably, integrating chain-of-thought reasoning does not yield measurable improvements, as performance remains unchanged at 52.6%. This suggests that in single-iteration code repair using test feedback, explicitly guiding the LLM through reasoning steps may be redundant, as the feedback itself already provides a structured source of reasoning. The few-shot setup,

which provides example repairs before the main task, results in a performance score of 50.5%. This suggests that, unlike in other tasks where few-shot examples typically improve performance, the LLM in this code repair scenario may already extract sufficient understanding from the provided feedback and task description, reducing the necessity for additional demonstrations.

The ablation study further examines the effects of removing individual prompt components. Excluding the persona prompt results in a slight performance decline to 50.5%, indicating that while persona-based instructions may influence response formulation, their absence does not substantially impact repair accuracy. One possible explanation is that persona-based instructions primarily introduce stylistic preferences or redundant information that do not significantly enhance the LLM's understanding of the repair task.

In contrast, the removal of docstrings, context, and guidelines leads to more pronounced performance degradation. The absence of guidelines and contextual information reduces the score to 48.5, highlighting the importance of structured task instructions and surrounding code context in LLM comprehension. The most substantial decline occurs when docstrings are removed, lowering performance to 47.4%. This underscores the critical role of docstrings in project-level code repair, as they provide high-level semantic descriptions that help the LLM infer function behavior and intended functionality. Without docstrings, the LLM may struggle to determine the expected output and apply appropriate corrections based solely on local code structure and test feedback.

Finding 4: Persona, chain-of-thought, and few-shot learning exhibit minimal effect, suggesting they are less essential for single-iteration repair tasks. In contrast, docstrings, context, and guidelines demonstrate substantial performance improvements, underscoring the critical role of structured, context-rich input in enhancing the LLM's ability to perform effective code repairs.

8 THREATS TO VALIDITY

We have identified the following threats to our study.

Threats in Benchmark Construction. One potential threat lies in the limited size and scope of our benchmark, which currently focuses on Python and a subset of tasks from **HumanEval** and **CoderEval**. This may limit the generalizability of our findings to other programming languages or more diverse coding scenarios. To address this, we plan to extend the benchmark in the future to include more tasks, languages, and error types.

Threats in Erroneous Code. The quality of the erroneous code segments used in our benchmark is another potential threat. To ensure that the introduced errors are realistic and representative of common coding mistakes, we employ three distinct methods for generating erroneous code. This approach ensures the errors reflect common programming mistakes and support robust performance analysis.

Threats in Feedback Types. The diversity and representativeness of the feedback types used in this study present another potential threat to validity. While we incorporate four distinct feedback types, there may be additional forms of feedback not covered in our analysis. Future research could explore a broader range of

feedback mechanisms to further assess the generalizability of our findings.

Threats in Empirical Study. A potential threat to validity arises from the inherent randomness in LLM responses. Due to computational and time constraints, multi-iteration repair experiments were conducted only once. While this approach allowed us to explore iterative repair scenarios, the absence of repeated trials introduces a potential risk of result variability. Future work could address this limitation by performing multiple runs of multi-iteration experiments to further validate the consistency of the findings.

9 RELATED WORK

In this section, we mainly introduce related work on LLM-based code generation, LLM-based code repair and code benchmark.

9.1 LLM-based Code Generation

Recent advances in LLMs have significantly improved code generation capabilities. Code LLMs are designed specifically for code-centric tasks. For instance, models such as StarCoder [31], CodeLlama [42], and DeepSeek-Coder [19] benefit from extensive code-specific corpora and specialized training instructions [70, 71]. Recent studies have explored various applications of Code LLMs. These applications include vulnerability detection [10, 49, 58] unit test generation [44, 45, 61], code search [22, 28, 57], code summarization [3, 46, 47], and code generation [24, 34, 35].

9.2 LLM-based Code Repair

Recent research explores LLMs for Automated Program Repair (APR). AlphaRepair [59] pioneers a cloze-style approach, replacing buggy lines with masked tokens for LLMs to fill in. Alternative approaches typically focus on locating the fault and supplying the model with the buggy code along with its context, enabling it to generate suitable patches. For example, InferFix [25] combines static analysis with retrieval-augmented LLMs, using historical bug-fix pairs for patch generation. VulRepair [18] integrates CodeT5 with BPE tokenization and a T5 architecture, improving vulnerability repair accuracy. Further advancements include NTR [23], a two-stage template-guided framework enhancing LLM fine-tuning, and ChatRepair [60], a conversation-driven approach that iteratively refines patches, resolving 162 of 337 bugs cost-effectively.

9.3 Code Benchmark for LLMs

Researchers have introduced several high-quality code benchmarks to evaluate the performance of Code LLMs on code-related tasks. These benchmarks cover a wide range of tasks, including code generation [7, 15, 20], program translation [62, 73], code summarization [21, 37], code completion [13, 16, 32], etc. Some benchmarks focus on the code repair task, such as CoderUJB [66] constructed Zeng et al. which evaluate LLMs across diverse Java programming tasks, including test generation and defect detection. Ouyang et al. presented [40] MuBench. This dataset includes 1,700 artificial bugs generated by various mutators to evaluate the capability of automated program repair (APR) for LLMs. Existing benchmarks mainly focus on single-iteration repairs with limited feedback types, overlooking the iterative, multi-feedback nature of real-world code

repair. To address this, FeedbackEval introduces diverse error types, supports four feedback modalities, and evaluates iterative repair performance, enabling a more comprehensive assessment of LLMs' feedback comprehension and adaptability.

10 CONCLUSION

In this paper, we construct a comprehensive benchmark, FeedbackEval, to systematically evaluate LLMs' performance in feedback-driven code repair task. Our study highlights the strengths and limitations of LLMs in processing structured and unstructured feedback, adapting to iterative refinement, and leveraging prompting techniques. We find that structured feedback, particularly test feedback, yields the highest repair success rates by providing clear, actionable error localization. Surprisingly, simple feedback ranks as the second most effective type. Despite its lack of detail, it encourages LLMs to rely on their internal understanding of code and errors, leading to more generalized fixes. In contrast, compiler feedback offers technical insights but struggles with logic errors, while human feedback, despite its contextual richness, often leads to over-complicated or misinterpreted solutions. Iterative feedback improves performance, though gains plateau after two to three iterations. Additionally, prompt structure plays a critical role: docstrings, context, and guidelines significantly enhance repair accuracy, whereas persona, chain-of-thought, and few-shot prompting provide minimal improvement in single-iteration repairs. FeedbackEval advances the field by integrating diverse error types and feedback modalities, providing actionable insights for optimizing feedback utilization. In future work, we plan to explore hybrid feedback strategies and extend the benchmark to other programming languages and broader error categories.

ACKNOWLEDGMENTS

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