

How to Understand Whole Software Repository?

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ABSTRACT

Recently, Large Language Model (LLM) based agents have advanced the significant development of Automatic Software Engineering (ASE). Although verified effectiveness, the designs of the existing methods mainly focus on the local information of codes, e.g., issues, classes, and functions, leading to limitations in capturing the global context and interdependencies within the software system. From the practical experiences of the human SE developers, we argue that an excellent understanding of the whole repository will be the critical path to ASE. However, understanding the whole repository raises various challenges, e.g., the extremely long code input, the noisy code information, the complex dependency relationships, etc. To this end, we develop a novel ASE method named RepoUnderstander by guiding agents to comprehensively understand the whole repositories. Specifically, we first condense the critical information of the whole repository into the repository knowledge graph in a top-to-down mode to decrease the complexity of repository. Subsequently, we empower the agents the ability of understanding whole repository by proposing a Monte Carlo tree search based repository exploration strategy. In addition, to better utilize the repository-level knowledge, we guide the agents to summarize, analyze, and plan. Then, they can manipulate the tools to dynamically acquire information and generate the patches to solve the real-world GitHub issues. Extensive experiments demonstrate the superiority and effectiveness of the proposed RepoUnderstander. It achieved 18.5% relative improvement on the SWE-bench Lite benchmark compared to SWE-agent.

CCS CONCEPTS

- Software and its engineering → Automatic programming;
- Computing methodologies → Multi-agent planning.

KEYWORDS

Automatic Software Engineering (ASE), Agents, Large Language Models (LLMs), Fault Localization, Program Repair, Monte Carlo Tree Search (MCTS)

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1 INTRODUCTION

Automating Software Engineering (ASE), which aims to automatically accomplish the Software Engineering (SE) tasks, is a promising and challenging research direction. Recent years, in the ASE domain, Large Language Models (LLMs), especially LLM-based agents, have demonstrated their strong general abilities, e.g., the environment awareness ability [15, 21, 37], planning & reasoning ability [6, 29, 32, 37], tool construction [48] ability, etc.

More recently, an exemplary milestone termed Devin [6] explores an end-to-end LLM-based agent system for complex real-world SE tasks (i.e., fix real-world Github issues). Specifically, it plans user requirements, utilizes editor, terminal, and search engine tools for independent decision-making and reasoning, and eventually generates code patches to meet the needs. This innovative approach has garnered considerable attention from the AI and SE communities, notably sparking interest in ASE [43, 49]. For instance, SWE-agent [43] strategically designs an Agent Computer Interface (ACI) to empower SE agents in creating & editing code files, navigating repositories, and executing programs. Additionally, AutoCodeRover [49] extracts abstract syntax trees in programs, iteratively searches for useful information based on requirements, and generates program patches.

Although the pioneers highlighted the road to advanced ASE and achieved promising performance, their designs, focusing on local information, failed to grasp the global context and intricate interdependencies among functions and classes. For example, SWE-agent [43] maintains a context window within a code file that allows the agent to scroll up and down. AutoCodeRover [49] searches functions or classes within the whole repository. Typically, the code comprising a full logic chain for a specific functionality is not arranged sequentially within a single file; rather, it is logically scattered across multiple folders and files. It is difficult to retrieve all relevant code files among maybe thousands of files in a repository, especially starting only from the text in user requirements. This paper argues that a comprehensive understanding of the whole repository becomes the most critical path to ASE.

Undoubtedly, it is challenging to utilize the vast information of an entire repository within LLM. Firstly, a GitHub repository may contain thousands of code files, making it impractical to include them all in the context windows of LLM. Even if it could, an LLM would struggle to accurately capture the code relevant to the objective within such an extensive context. Secondly, since user requirements are often described in natural language, identifying the relevant code within a repository presents a significant challenge. Thirdly, the intrinsic logic of how the code execution is distinctly different from the sequence of the code text in a file. For instance,

the location where a bug triggers an error message and the actual place that requires modification may not be in the same file, yet they are certainly logically connected.

To solve this problem, we propose a novel ASE method named RepoUnderstander by guiding the LLM-based agents to comprehensively understand the whole repository and take advantage of the learned repository-level knowledge. Imaging the human software engineers are solving project-level issues, they will first overview the repository to ensure a full understanding of the functional modules and dependencies that may be involved. Motivated by this practical insight, we first condense the complex repository-level information by constructing the repository knowledge graph in a top-down manner. Concretely, the repository is organized into a hierarchical structure tree, enabling a clear understanding of the code's context and scope. Besides, to facilitate comprehensive dependency and interaction analysis, the tree structure is further expanded into a reference graph that captures function call relationships.

Subsequently, we propose a Monte Carlo Tree Search (MCTS) based repository exploration strategy to empower the LLM-based agents the ability of collecting and learning repository-level knowledge. Specifically, the agents first collect the critical information regarding to the SE task on the repository knowledge graph by the explore-and-exploit strategy. Then, by simulating multiple trajectories and evaluating their reward score, our method iteratively narrows down the search space and guide the agents to focus on the most relevant areas. In addition, to better utilize the repository-level knowledge, we guide the agents to summarize, analyze, and plan for the repository information regarding to the SE targets. By these designs, it enables the agents to effectively and efficiently collect and learn task-relevant repository-level knowledge, therefore facilitating the precise fault localization and the informed patch generation. Finally, the agents are instructed to manipulate the API tools to dynamically acquire local information, and fix the real-world issues by generating patches. We demonstrate the superiority and effectiveness of RepoUnderstander via extensive experiments and comprehensive analyses. Besides, through carefully analyses during the experiments, we identify an important problem of the SWE-bench dataset, i.e., missing the necessary interface specification for new feature issues. We propose to fix it and achieve more reliable and effective evaluation for our method and the baseline. The main contributions of this paper are summarized as follows.

- We highlight the whole repository understanding as the crucial path to ASE and propose a novel agent-based method named RepoUnderstander to solve the challenges.
- We propose to condense the extensive codes and complex relations of the repository into the knowledge graph in a top-to-down mode, improving performance and efficiency.
- We design a Monte Carlo tree search based repository exploration strategy to assist the comprehensive understanding of the whole repository for the issue-solving agents.
- Extensive experiments and analyses demonstrate the superiority and effectiveness of RepoUnderstander¹.

¹<https://github.com/RepoUnderstander/RepoUnderstander>

2 RELATED WORK

2.1 LLM-based Software Engineering Agents

In recent years, Large Language Model (LLM) based AI agents have advanced the development of automatic software engineering. AI agents improve the capabilities of project-level software engineering (SE) tasks through running environment awareness [15, 21, 37], planning & reasoning [6, 29, 32, 37], and tool construction [23, 48]. Surprisingly, Devin [6] is a milestone that explores an end-to-end LLM-based agent system to handle complex SE tasks. Concretely, it first plans the requirements of users, then adopts the editor, terminal and search engine tools to make independent decisions and reasoning, and finally generates codes to satisfy the needs of users in an end-to-end manner. Its promising designs and performance swiftly ignited unprecedented attention from the AI community and SE community to Automatic Software Engineering (ASE) [43, 49]. For example, SWE-agent [43] carefully designs an Agent Computer Interface (ACI) to empower the SE agents capabilities of creating & editing code files, navigating repositories, and executing programs. Besides, AutoCodeRover [49] extracts the abstract syntax trees in programs, then iteratively searches the useful information according to requirements, and eventually generates program patches. Their designs mainly focus on the local information in the repository, e.g., code files, classes, or functions themselves. Although achieving promising performance, from the insights of the human SE developers, the excellent understanding of the whole repository is a critical path to ASE.

2.2 Evaluation of LLM-based Software Engineering Agents

Benefiting from the strong general capability of LLMs, LLM-based software engineering agents can handle many important SE tasks, e.g., repository navigation [37, 48], code generation [8, 15, 18, 34, 36], debugging [15, 43, 49], program repair [33, 43, 49]. The existing methods usually regard code generation as a core ability and mainly conduct evaluations on it. Precisely, the code generation test set [2, 5, 25, 28, 50] consists of the short problem description, the solution, and the corresponding unit test data. However, with the fast development of LLMs and agents, these datasets are no longer able to comprehensively evaluate their capabilities in the real-world SE tasks. To this end, the repository-level code completion and generation tasks [9, 12, 26] are presented to evaluate the repository understanding and generation capabilities of LLMs and agents. More recently, SWE team[19, 43] develop a unified dataset named SWE-bench to evaluate the capability of the agent system to solve real-world GitHub issues automatically. Specifically, it collects the task instances from real-world GitHub issues from twelve repositories. Consistent with previous evaluation methods, SWE-bench is based on the automatic execution of the unit tests. Differently, the presented test set is challenging and requires the agents to have multiple capabilities, including repository navigation, fault locating, debugging, code generation and program repairing. Besides, SWE-bench Lite [4] is a subset of SWE-bench, and it has a similar diversity and distribution of repositories as the original version. Due to the smaller test cost and more detailed filtering, SWE-bench Lite is officially recommended as the benchmark of LLM-based SE

agents. Therefore, consistent with previous methods [32, 43, 49], we report our performance on SWE-bench Lite.

2.3 Repository-level Code Intelligence

With the development of AI technology, the field of code intelligence has gradually transitioned from solving single function-level or code snippet-level problems to real-world software development at the repository level. In the repository-level code intelligence task, there are many works [3, 10, 13, 24, 27, 35, 45, 47] that aim to leverage the large amount of code available in current repositories to help code models generate better, more accurate code. Among them, StarCoder2 [27] and Deepseek-Coder [13] model repository knowledge in the pre-training stage, sort repository files according to reference dependencies, and guide the model to learn the global dependencies of repository information. RepoCoder [47] continuously retrieves relevant content by iterating RAG, while methods such as CoCoMIC [10] and RepoFuse [24] jointly use the RAG module and the current file's dependency relationship module to introduce it into the context of LLM. Although the above methods enhance the model's understanding of the repository context to a certain extent, the repository-level code often contains complex contextual call relationships, and the RAG method alone may not be able to recall all semantically relevant content. In addition, there may be a large amount of complex irrelevant information in the RAG results, which interferes with the model's accurate fault location. Therefore, starting from the practical experience of software engineering, we simulated people's global experience in understanding the repository and experience-guided exploration and location to achieve more effective repository understanding.

3 METHODOLOGY

3.1 Overview

We first describe the overall operating process of RepoUnderstander, and introduce the stages in detail in the subsequent parts of this section. Given a workspace, RepoUnderstander can automatically solve real-world GitHub issues. Among them, RepoUnderstander involves three key steps, repository knowledge graph construction stage, MCTS-enhanced repository understanding stage, information utilization & patch generation stage. The overall workflow is shown in Figure 1.

In **Repository Knowledge Graph Construction** phase, RepoUnderstander first builds a repository knowledge graph to represent the entire repository and describe the relationships between entities. This is achieved by parsing the software structure and analyzing it in a top-down manner. The repository is first organized into a hierarchical tree that allows a clear understanding of the context and scope of the code. To facilitate comprehensive dependency and interaction analysis, the tree structure is further extended into a reference graph that captures function call relationships.

Due to the large scale and information complexity of the repository knowledge graph, during the **MCTS-Enhanced Repository Understanding** phase, RepoUnderstander uses the Monte Carlo tree search algorithm to dynamically explore the entire graph. This method focus on discovering key information (i.e., repository functionality and dependency structure) that has a significant impact

on issue solving. Through correlation expansion and reference expansion, MCTS simulates multiple trajectories and evaluates their importance, dynamically narrowing the search space and allocating computing resources to the most relevant regions. This targeted navigation enables the model to efficiently access and process important information in the repository, thereby facilitating precise fault localization and informed patch generation.

Inspired by the actual development experience of human programmers, it is necessary to have certain global prior knowledge of the repository before solving specific tasks. Therefore, in **Information Utilization & Patch Generation** phase, RepoUnderstander first summarizes the important information collected in the repository understanding phase to form an experience of the entire repository. Then, in order for RepoUnderstander to use the global experience to obtain dynamic information during the problem solving process, we follow AutoCodeRover[49]'s information retrieval method and use API tools to extract information in the repository knowledge graph. This includes specific classes and functions and code snippets, etc., to maintain local dynamic knowledge during the task. After collecting enough context, RepoUnderstander uses global experience to summarize the currently acquired information to locate faults, generate modified code and return patches that try to resolve the issue.

3.2 Repository Knowledge Graph Construction

For human programmers, when solving project-level issues, developers first need to carefully review and understand the project's software repository to ensure that they have a full understanding of the functional modules and dependencies that may be involved. This includes building the hierarchical tree structure and call graph of the software repository. Through the hierarchical tree structure, developers can clearly see the overall architecture of the project and the relationship between each module; through the call graph, developers can understand the calling relationships and dependency paths between functions to identify the root causes of problems and the potential impact of changes.

Therefore, in order to learn from the practices of human programmers in understanding and maintaining code, we represent the entire repository as a repository knowledge graph and describe the relationships between entities by parsing the software structure (see Repo. Knowledge Graph Construction in Figure 1). First, we top-down analyze the structure of the software repository, organizing the repository into a hierarchical structure tree (including files, classes, and functions) to clearly understand the context and scope of the code. We then extend the tree structure into a reference graph containing function call relationships, allowing the model to perform comprehensive dependency and interaction analysis. Different from existing methods[10, 29], our reference relationship only involves functions, because functions are the basic unit of program execution, and the calling relationship between functions directly affects the behavior and execution logic of the program. Excessive reference relationships may increase the complexity of the graph structure and affect the analysis efficiency and accuracy of the model. This structured repository knowledge graph not only improves the efficiency of the model in retrieving relevant

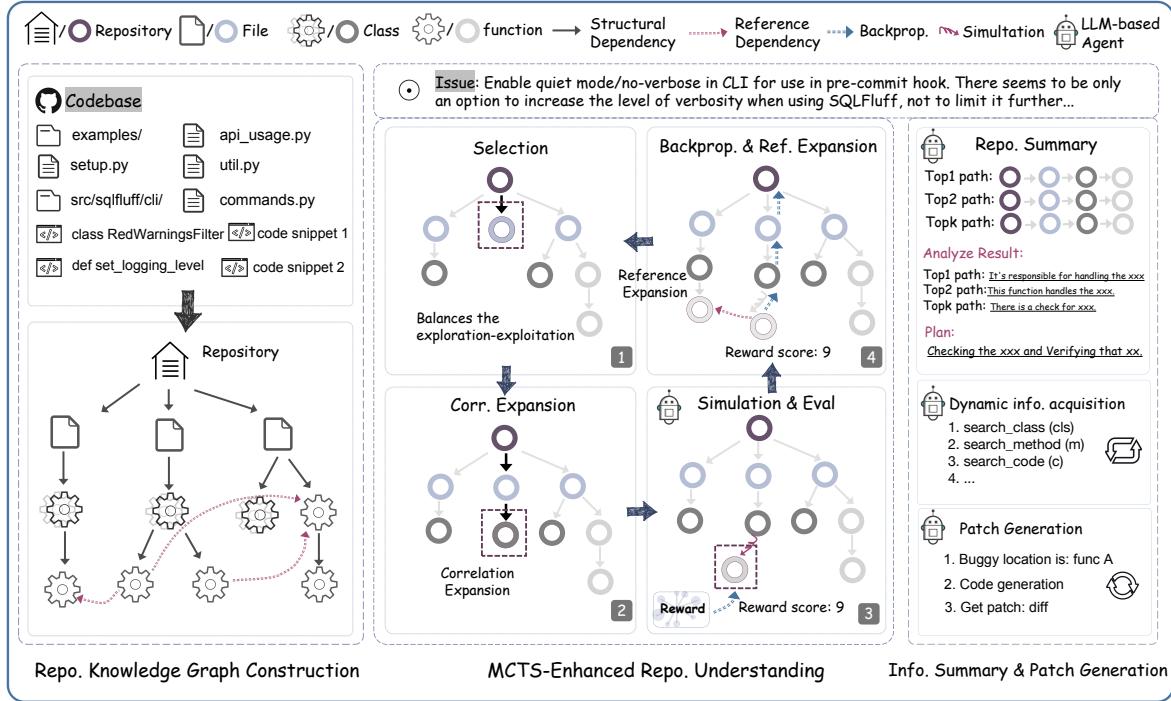


Figure 1: The overview of our proposed RepoUnderstander. Firstly, we construct the repository knowledge graph is constructed to efficiently represent the code and the dependency in the repository. Subsequently, we empower the agents with the ability of repository understanding by designing the Monte Carlo tree search based repository explore strategy. In addition, we guide the agents to summarize, analyze, and plan to better utilize the repository-level knowledge. Then, they can manipulate the tools to dynamically acquire issue-relevant code information and generate the patches to solve the real-world GitHub issues

information, but also ensures the consistency and reliability of the automated process.

Specifically, we recursively traverse each code file in the repository, use abstract syntax trees to parse the corresponding files respectively, and obtain basic units such as classes and functions, including their names, code snippets, paths, and locations in the files. We then add these elements to the structure tree from top to bottom. Finally, we analyze the calling relationship between functions and add corresponding directed edges to the graph. This in-depth understanding provides LLM agents with the necessary background knowledge and contextual information, allowing them to more accurately locate the problem and come up with effective solutions.

3.3 MCTS-Enhanced Repository Understanding

After building a repository knowledge graph, a comprehensive understanding of the information in the graph is critical to effectively solving problems. However, given the complexity and size of modern software systems, often containing hundreds of files and thousands of functions. The vast magnitude of the search space in large software repositories makes exhaustive analysis impractical. Furthermore, context length limitations of language models limit the amount of information that can be efficiently processed at given conversation. Therefore, without targeted methods to identify

highly relevant nodes and edges in graphs, models may struggle to perform accurate and efficient analysis, hampering their ability to solve real-world software engineering problems.

To address these challenges, we propose an repository exploration approach that leverages Monte Carlo Tree Search (MCTS) to enhance LLM and agents' understanding of software repositories (see MCTS-Enhanced Repo. Understanding in Figure 1). This method systematically explores the repository knowledge graph and prioritizes the discovery of critical information such as repository functions and dependency structures that have a greater impact on resolving issues. By simulating multiple trajectories and evaluating their importance, MCTS dynamically narrows the search space and focuses computational resources on the most relevant areas. This targeted navigation enables models to access and process important information more efficiently, thus facilitating precise fault localization and informed patch generation. The MCTS process begins from a root node, representing the repository node, and unfolds in four iterative stages: selection, correlation expansion, simulation&evaluation and backpropagation&reference expansion. Below we describe each stage in further detail.

Selection. The selection phase aims to balance exploration and exploitation problems in the node selection process. The main challenge in this phase is to maintain a balance between in-depth analysis of highly relevant content in the repository and a broad search

for potentially important information throughout the repository. Delving excessively into high-correlation modules can cause the model within a local optimal solution, ignoring that other critical paths or dependencies may exist. Extensive search may lead to the dispersion of computing resources and the processing of a large amount of irrelevant information, which increases the burden on the model and reduces search efficiency. To balance the needs of the above two aspects, we use the UCT algorithm [20] for node selection, following the formula: $UCT = \frac{w_i}{n_i} + c\sqrt{\frac{2\ln n_p}{n_i}}$, where w_i is the total reward of child node i . The calculation of specific rewards will be introduced in detail in Simulation & Evaluation section. n_i is the number of visits to child node i and n_p is the number of visits to the parent node. c is the exploration parameter used to adjust the balance between exploration and exploitation. In this work, we set c to $\sqrt{2}/2$.

Correlation Expansion. During the expansion process, leaf nodes are expanded to incorporate new nodes. If the current leaf node has a child node in the repository knowledge graph, the most likely child node is selected instead of random expansion. In this stage, we designed two methods: Correlation expansion and Reference relationship expansion. In this section, we mainly introduce correlation expansion, and reference relationship expansion will be introduced in the Backpropagation & Reference Expansion section. Similar code is most likely to be code related to user requirements. User requirements or issues usually contain some keywords that may add new or modified functions. Therefore, we use the bm25 score to calculate the relevance [9, 17, 42], and give priority to codes with higher relevance for expansion. Correlation expansion can effectively match user requirements with relevant nodes in the software knowledge graph, thereby improving the accuracy and efficiency of node expansion.

Simulation & Evaluation. After completing the expansion, we enter the simulation process. During the simulation, we start from the newly expanded node and simulate along possible paths to evaluate the effectiveness of these paths in solving the current issue. Consistent with the correlation expansion method, we continuously and recursively select the child nodes with the highest correlation scores in the software knowledge graph until leaf nodes, and then reward the nodes.

In the evaluation phase, we need to evaluate the relevance of the selected leaf nodes to the issue, including classes, top-level functions, class methods or sub-functions, etc. However, traditional evaluation methods usually rely on keyword matching and semantic matching algorithms, which perform poorly when dealing with complex software systems and diverse problem descriptions.

Inspired by the success of large language models in in-context learning (ICL) [11, 40] and Chain-of-Thought (CoT) [38] methods, we propose a reward method based on ICL and CoT, aiming to provide a more accurate and reliable solution for relevance evaluation in software repository. Our approach leverages the advanced ability of large language models to learn and optimize reward functions from limited examples of programming practice to accurately assess the correlation between leaf nodes and problem descriptions. Specifically, we first use ICL to let the language model learn to understand the core functions and operating modes of the reward function in a given context. Then, the CoT is used to enable the

You are a programming assistant who helps users solve issue regarding their workspace code.

Your main responsibilities include examining issue information to analyze possible causes of the issue and determine the code that needs to be fixed.

Please refer to the above responsibilities and provide detailed reasoning and analysis. Then at the last line conclude "Thus the probability score that this code needs to be modified to solve this issue is s ", where s is an integer between 1 and 10.

Examples

Issue: ModelChain.prepare_inputs error, ...

Code:

...

def prepare_inputs_from_poa(self, data): ...

...



Thought: To solve the problem in the prepare_inputs(), ...

Result: Thus the probability score that this code needs to be modified to solve this issue is 1.

Now the issue is:

{issue}

Code:

...

{method_type} method {method_name} in {rel_file_path} file.
{code_content}

Thought:

Result:

Thought: The provided code snippet is the `database_forwards` method of the `RenameModel` class. This method handles the ...



Consequently, to address the issue, modifications to the `database_forwards` method are needed to introduce checks ...

Given the direct correlation between the issue and the location of the behavior within the `database_forwards` method of the `RenameModel` operation, it's clear that changes to this code are required to resolve the raised concern.

Result: Thus the probability score that this code needs to be modified to solve this issue is 9.

Figure 2: Reward agent's input prompt template and output results, with some details omitted.

model to conduct in-depth reasoning based on the specific information in the question and code snippets to evaluate the correlation of leaf nodes. The reward function prompt template we designed (see Figure 2) starts with a guided system prompt that clearly points out the goals and responsibilities of the reward function. Then, through a series of example combinations of \langle issue description, code snippets, thinking process, results \rangle , the input, output and reasoning chain in the scoring process are demonstrated. Finally, the prompt ends with a new set of issue descriptions and code snippets, at which point the model is expected to learn the intermediate reasoning steps from the given examples and output corresponding reward scores. Finally, we only keep the nodes with a reward score of no less than 6 and return their content and structural dependencies.

Compared with traditional methods, our method reduces the dependence on large amounts of labeled data. This is critical to cope with diverse and evolving situations in software repository, as traditional approaches may suffer from the limitations of labeled data. Therefore, our method has better adaptability and accuracy when resolving real-world software development environments.

Backpropagation & Reference Expansion. After the evaluation ends, we perform a bottom-up update from the terminal node back to the root node. During this process, we update the visit count n and the reward value w . In addition, we also introduced reference relationship expansion in the backpropagation phase. Different from the conventional expansion method, we not only expand when we encounter leaf nodes, but also when we encounter those nodes with higher reward scores (set the threshold to a reward score of not less than 6 here), we will expand their reference modules and objects based on the repository knowledge graph. And then integrate them into new nodes. The insight is that in actual development, the node called by the current node is often the key node for function implementation, and the called node is usually the use of the current node and depends on the implementation and changes of the current node. Therefore, if a node has a higher reward score, the nodes with calling relationships may also be relevant. By expanding these calling relationship nodes, code snippets related to the current issue can be captured more comprehensively.

3.4 Information Utilization & Patch Generation

At this stage, RepoUnderstander first summarizes the whole repository experience, then obtains code snippet information dynamically on this basis, and finally generates patches that try to solve the problem. The three steps are detailed below.

Repository Summary. To more effectively utilize the global repository information collected during the repository understanding phase, we introduce a summary agent. The agent aims to systematically analyze and summarize the code snippets collected in the repository knowledge graph and submitted issues, and then plan how to solve the problem, thereby forming an experience of the entire repository. Specifically, the summary agent takes the issue and the collected relevant code fragments as input, and then outputs a summary of the relevant fragments in sequence and plans a solution. The specific prompt template is shown in Figure 3. Since the collected global repository information may be complex and contain a large number of code fragments and annotation descriptions, we only use the location description of the relevant code fragments (i.e., structural dependencies in the repository) and the output of the Summary Agent (i.e., summary and planning) as RepoUnderstander’s experience to guide subsequent actions. This experience does not include specific function implementation, but only focuses on overall repository experience guidance. The location description is formalized as `<file>a.py</file><class>Class A</class><func>func a</func>`, and the summary agent output is as shown in Figure 3.

Dynamic information acquisition. Global experience information is RepoUnderstander’s experience summary of relevant information in the current workspace, which can help the language model understand issues and find solutions more quickly. In the process of solving problems, in order to make full use of

You are a senior software developer maintaining a large project. You are working on an issue submitted to your project. The issue contains a description marked between `<issue>` and `</issue>`.

We’ve collected some code snippets from the code repository that may be relevant.

To help diagnose and fix issues in repositories, let’s systematically analyze the collected context step by step.

```
<issue>
{issue_content}
</issue>

<collected_content>
{collected_content}
</collected_content>
```

Analyze results:

Based on the collected code snippets, here’s the analysis of the migration process that’s intended to update proxy model permissions:



1. The migration was introduced to update the `content_type` ...
2. The `update_proxy_model_permissions` function is designed ...
3. The `revert_proxy_model_permissions` function calls ...
4. The `Migration` class sets dependencies for this ...

Based on the description of the issue, it seems that so far:

- The error persists despite attempts to delete the ...
- The error has been encountered when updating from Django ...
- Clearing the virtual environment did not resolve the issue.

There are a few possible steps to fix the issue further:

- **Ensure the `content_type_id` and `codename` ...**
- **Examine the Proxy Models**.
- *** ... ***

Figure 3: Summary agent’s input prompt template and output results, with some details omitted.

this global experience information, RepoUnderstander further needs to dynamically extract local information from the current repository, including specific classes, functions and code snippets in the repository.

The ReAct [44] framework (i.e., Reson then Act) guides the model to generate inference trajectories and task-specific actions in a staggered manner, allowing the model to interact with the code repository and collect information. Specifically, the ReAct framework first generates reasoning paths through the Chain-of-Thought [38], and then outputs actual actions based on the reasoning results. Therefore, by using ReAct method, RepoUnderstander can call the corresponding search API according to task requirements and dynamically extract local information from the current repository to collect relevant context. We follow AutoCodeRover’s search API method [49], using the three-layer search method of `search_class`, `search_method`, and `search_code`. Specifically, RepoUnderstander first independently determines the API that needs to be called. Then the retrieval API will search for classes, methods and code

snippets in the repository knowledge graph, and finally return the results to the agent.

Patch Generation. In the patch generation step, RepoUnderstander first locates faults based on the summary of global experience and dynamic information, extracts the context of code snippets that may need to be modified, and then generates modified code snippets. Finally, a diff is generated based on the code snippet before modification and the code snippet after modification, and is returned as the final result. If a diff is incorrect due to syntax, we will retry until an applicable patch with correct syntax is generated. We follow AutoCodeRover [49] and set the maximum number of retries to 3 to ensure that the generated patch can be applied as much as possible.

4 EXPERIMENT

To validate the performance of RepoUnderstander, we conduct experiments and compare it with other LLMs and agents to demonstrate its superiority (§4.2, §4.4). In addition, we found that there is an information asymmetry problem in SWE-bench [19] caused by new added function names and variable names in the test patch (§4.3). We proposed issue patches to new feature types issues to solve this problem and test agents on the new *FIX* version test set. Finally, we systematically analyzed the problem-solving capabilities of RepoUnderstander at different stages (§4.5).

4.1 Experimental Setup

Datasets. We evaluate on the SWE-bench Lite dataset [19] which are constructed due to the high cost of evaluating in the complete SWE-bench. SWE-bench Lite includes 300 task instances sampled from SWE-bench, following a similar repository distribution. SWE-bench team recommend future systems evaluating on SWE-bench to report numbers on SWE-bench Lite in lieu of the full SWE-bench set if necessary. SWE-bench Lite aims to provide a diverse set of code base issues that can be verified using in-repository unit tests. It requires LLM systems to generate corresponding patches based on the actual issues in the repository, and then pass the tests.

Baselines. We compare RepoUnderstander with two types of baselines. The first category is the RAG baselines [19]. This type of baseline uses the BM25 method to retrieve code base files related to the issue and inputs them into LLM to directly generate patch files that solve the problem. The second type of baseline is the agents baseline (i.e., AutoCodeRover [49] and SWE-agent [43]), which locates the problem through complex multiple rounds of interaction and execution feedback, and finally generates a patch to solve the problem through iterative verification.

Metrics. Following the SWE-bench [19], We evaluate the effectiveness of RepoUnderstander, using the percentage of resolved instances and the patch application rate. Among them, the patch application rate refers to the proportion of instances where code changes are successfully generated and can be applied to existing code bases using Git tools. Resolved ratio represents the overall effectiveness of solving actual GitHub issues, and application ratio reflects the intermediate results of patch availability.

Method	Resolved	Apply
<i>RAG-based</i>		
SWE-Llama 7B	1.33% (4)	38.00%
SWE-Llama 13B	1.00% (3)	38.00%
ChatGPT-3.5	0.33% (1)	10.33%
GPT-4	2.67% (8)	29.67%
Claude-2	3.00% (9)	33.00%
Claude-3 Opus	4.33% (13)	51.67%
<i>Agent-based</i>		
AutoCodeRover	16.11% (48)	83.00%
SWE-agent	18.00% (54)	93.00%
RepoUnderstander	21.33% (64)	85.67%

Table 1: Main results for RepoUnderstander performance on the SWE-bench-lite test set. The numbers in brackets indicate the number of issues solved.

Configurations. All results, ablations, and result analyzes of RepoUnderstander use the GPT4-Turbo model (i.e., gpt-4-1106-preview [1], the same model with SWE-agent [43]). We use ast² and Jedi³ library to parse repository and obtain syntax structures and dependencies of repository. In MCTS-Enhanced Repository Understanding stage, we set the number of search iterations to 600 and maximum search time to 300 seconds. In Information Utilization & Patch Generation stage, we set the maximum number of summary code snippets to 10. SWE-bench has a relatively complex environment configuration. Thanks to the development of the open source community, we use the well-build open source docker of the AutoCodeRover [49] team for experiments.

4.2 Comparison Experiment

We first evaluate the effectiveness of RepoUnderstander in SWE-bench Lite (300 instances). The performance comparison analysis between RepoUnderstander and other methods is shown in Table 1. In each instance, we provide a natural language description from a real-world software engineering problem and a local code repository of corresponding versions, asking the model to solve the problem and generate patches that can pass local automated testing. Resolved reflects the end-to-end ability of the current RAG LLM system and Agent system to solve software engineering problems. The results show that RepoUnderstander is significantly better than other RAG and Agent systems, achieving SOTA performance on the test set. Compared with the RAG system, our method improves performance by nearly 5 times. Compared with the state-of-the-art Agent system, **we improve the accuracy of SWE-agent by 18.5%**. These excellent performances demonstrate the advancement of our approach. In addition, the Apply application rate indicates the availability of generated patches. We found that Agent-based systems all achieved high availability, while RAG-based systems have lower availability, which proves that agent systems may be

²<https://docs.python.org/3/library/ast.html>

³<https://github.com/davidhalter/jedi>

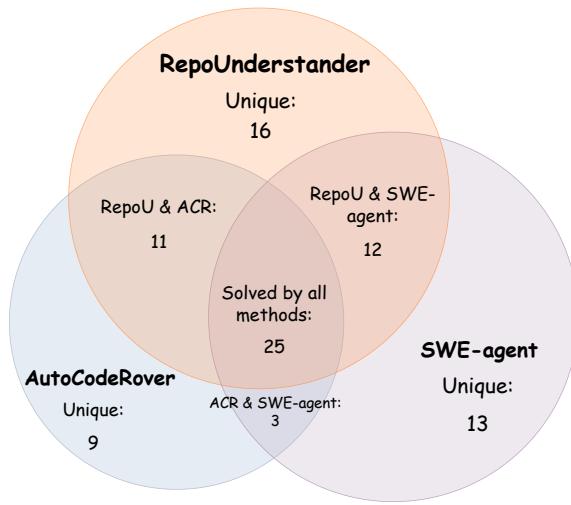


Figure 4: Venn diagrams of resolved cases of RepoUnderstander, SWE-agent and AutoCodeRover.

Method	Resolved	Apply
ACR & SWE-agent	24.33% (73)	98.00%
RepoU & ACR	25.33% (76)	94.67%
RepoU & SWE-agent	26.67% (80)	99.67%

Table 2: Venn diagram analysis of our method and baselines.

an important means to automatically solve software engineering tasks. SWE-agent has the highest Apply application rate due to the introduction of its running feedback capability, which shows that running feedback is an effective way. This paper focuses more on the understanding of the entire repository information. We will integrate running feedback in future work.

In addition, we also compared the issue-solving distribution diagrams of three Agent-based methods, and the results are shown in Figure 4. We found that our method is very complementary to the SWE-agent method. The two methods **jointly solved 80 examples, achieving a task resolved rate of 26.67%** (see Table 2), which further illustrates the complementarity of our method and the execution feedback method. We will provide a detail discussion and combination of the two methods in future work.

4.3 Dataset Analysis & Fix

User issues usually include *bug reports*, *feature requests*, and *enhancements*, etc [22, 30, 31, 39]. In SWE-bench dataset [19], we found that there is information asymmetry for issues of the feature request type, such as adding functions or adding parameter definitions. Specifically, since the test patch contains the signature information of the new features, and the LLM Agents input lacks this interface specification information, the agent model may not be able to correctly understand the full context of the problem. Even if the logic of the generated patch is correct, errors may occur

Method	Resolved	Apply
<i>SWE-bench-Lite</i>		
AutoCodeRover	16.11% (48)	83.00%
RepoUnderstander	21.33% (64)	85.67%
<i>SWE-bench-Lite-FIX</i>		
AutoCodeRover	18.00% (54)	84.00%
RepoUnderstander	23.00% (69)	88.00%

Table 3: Results for RepoUnderstander performance on the SWE-bench-Lite-FIX test set.

during testing. This information asymmetry may affect the performance evaluation and practical application of the LLM agents. From the perspective of software engineering practice, new features are usually defined and specified in the system design document. In actual development, the information of these new features should be specified rather than inferred by the agent model. Therefore, merging the new feature interface specification in the test patch into the problem description can enable the agent model to better understand the problem and reduce the impact of information asymmetry.

We made a fix for the SWE-bench Lite dataset and proposed a *FIX* version. Specifically, we integrated the new feature interface specifications in the test patch into the problem description through manual analysis, and guided the agent model to generate patches based on the complete problem description. In total, we fixed 45/300 instances in SWE-bench Lite. This method can better reflect the reality in practice, reduce the problems caused by information asymmetry, and thus improve the credibility and effectiveness of automatic software engineering technology in practical applications. As shown in Table 3, our experimental results show that on the *FIX* version test set, the methods RepoUnderstander and AutoCodeRover [49] have all improved, among which RepoUnderstander performs best, further demonstrating the superior performance of RepoUnderstander. We look forward to subsequent agent system work reporting their performance on the *FIX* version.

4.4 Ablation Study

4.4.1 Module Analysis. This ablation experiment aims to study the effectiveness of RepoUnderstander's global repository understanding component. (1) Remove MCTS & summary modules: RepoUnderstander has no prior knowledge of the repository structure and functions, that is, it lacks empirical information about the whole repository and can only locate relevant code snippets by searching through limited information in the issue. (2) Remove only the summary module: Only the signature and dependency structure of relevant information in the repository obtained by MCTS are used as global experience, and the summary and planning of information are removed. This experiment aims to verify the effectiveness of the summary agent, i.e., the importance of comprehensive summary of repository information. (3) Add a review agent module: After RepoUnderstander generates a patch that can be applied, in order to simulate the code review process in the development process, a static review of the patch by the review agent is added to discover

Method	Resolved	Apply
RepoUnderstander	21.33% (64)	85.67%
- w/o. summary	17.67% (53)	85.33%
- w/o. mcts & summary	16.00% (48)	80.33%
- w. review	18.33% (55)	87.67%

Table 4: Ablation results of RepoUnderstander.

possible defects in the newly generated code. If there is a defect, the patch is regenerated according to the review reason until a patch that passes the review is generated. This process is repeated up to three times.

Our experimental results demonstrate the importance of global experience and the effectiveness of the summary agent. As shown in Table 4, removing these modules all resulted in a drop in the performance of RepoUnderstander, especially after removing the MCTS & summary agent; the number of problem instances solved decreased from 64 to 48, which highlights the importance of global experience for automatically solving repository-level issues. In addition, we found that after adding the review agent, the performance of RepoUnderstander dropped, suggesting the limitations of static review. We speculate that the LLM-based static review may only rely on the surface grammatical information of the code and cannot fully understand the semantic meaning of the code. Therefore, the static review may ignore some hidden logical errors or illogical situations in the code. Therefore, we suggest that subsequent work can combine dynamic program analysis [7, 41, 46] such as program instrumentation [14, 16] to improve the reliability of the LLM Agent.

4.4.2 Hyper Parameter Analysis. We further analyzed the impact of the iterations number in MCTS. We set the maximum number of iterations to 50, 200, and 600, and limited the maximum iteration time to 300 seconds. The results are shown in Table 5. We found that: (1) As the number of iterations increases, RepoUnderstander solves more actual issues. This shows that as the number of iterations rounds increases, agents will collect more repository information, i.e., they will have more experience with the repository, resulting in a higher problem solving rate; (2) As the number of iterations increases, we found that the relative improvement in problem solving gradually decreases. Specifically, the improvement of 50 iterations is significant compared to no iterations, but the relative improvement of the subsequent 200 and 600 iterations decreases. This may be because in the early stage, agents can quickly search and summarize relevant experience, but as the number of iterations increases, the convergence speed of the model gradually slows down, and the contribution of new information to performance improvement becomes smaller; (3) We observed that as the number of iterations increases from 200 to 600, the apply rate decreases. This phenomenon indicates that as the number of iterations increases, the model may be affected by some interference information when generating results, resulting in a decrease in the quality of the generated results. Therefore, when selecting the number of iterations, it is necessary to consider avoiding the influence of excessive interference information.

Iters	Resolved	Apply
0	16.00% (48)	80.33%
50	19.67% (59)	86.67%
200	20.67% (62)	88.00%
600	21.33% (64)	85.67%

Table 5: Hyperparameter results of RepoUnderstander.

4.5 Case Study

4.5.1 Wrong Reason. Although RepoUnderstander achieved better results than other methods in the ASE task, the task is still challenging (even when RepoUnderstander and SWE-agent worked together, only 80/300 instances were fully automatically solved). To guide the optimization of subsequent work, we analyzed the specific reasons for the unsolved issues and divided the failure types into three categories: *wrong location*, *apply patch failed*, and *wrong patch*. Wrong location means that the agent did not locate the root cause of the problem and mistakenly modified the code in other correct locations. Apply patch failed means that the agent did not generate a syntactically correct patch and could not be directly applied to the existing version of the repository. Wrong patch means that when the bug location and patch syntax are correct, the repaired code cannot completely solve the problem, i.e., the test case does not pass completely.

We compared the results of RepoUnderstander and the current SOTA agent SWE-agent on SWE-bench Lite, as shown in the figure. The results show that: (1) In terms of bug location, our method generated patches in the wrong location in 45.0% of the tasks, while SWE-agent generated patches in 62.0%. This shows that our method performs better in correctly locating bugs, and the global experience at the repository level plays a key role in fault location. (2) In terms of patch applicability, our method did not generate patches in 13.7% of the tasks, while SWE-agent generated 5.0%. (3) In terms of patch correctness, our method generated incorrect patches in 20.0% of the tasks, while SWE-agent generated 15.0%. These indicators show that our method is more accurate in locating bug locations, but has certain weaknesses in generating correct patches and ensuring patch applicability. This may be because the execution feedback module of SWE-agent allows the agent to iteratively generate and verify the correctness of patches. This also shows the importance of execution feedback for solving practical problems. Therefore, by combining the global experience at the repository level and an effective execution feedback mechanism, we can further optimize the effect of automated software repair.

4.5.2 Resolved Tasks Study. To further analyze the performance of RepoUnderstander in real-world problems, we selected two examples from SWE-bench (as shown in Figures 6 and 7) and compared them with the SOTA solution, SWE-agent. By analyzing the oracle patch, we determined the actual fault location that needs to be modified. Among them, the green highlight indicates that the agents correctly tracked the target that needs to be modified, and the yellow highlight indicates that the agents incorrectly identified the target that is not to be modified.

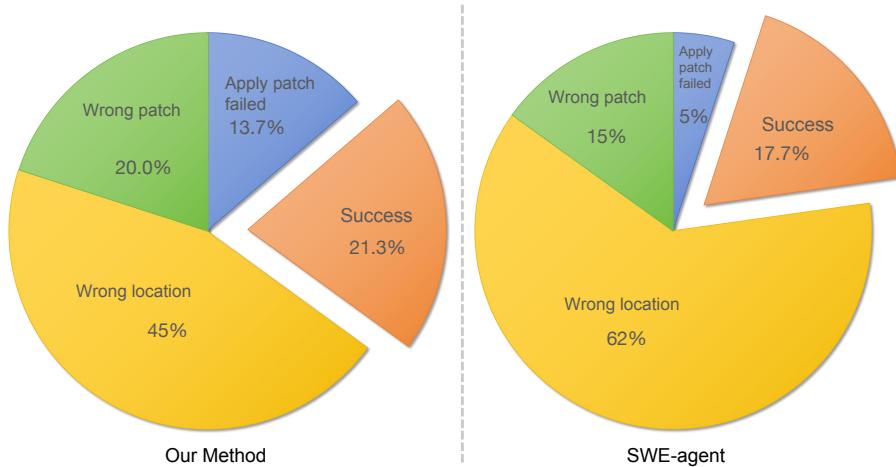


Figure 5: Distribution of results in SWE-bench Lite.

As shown in Figure 6, RepoUnderstander correctly explored the issue-related function to be modified `was_modified_since` in the MCTS-based Repository Exploration stage; in the subsequent summary stage, it clearly pointed out that the function needed to be updated; finally, under the guidance of global experience, the agents accurately searched and located the `was_modified_since` function in the dynamic information acquisition stage and the patch generation stage, and successfully implemented the correct modification. In contrast, in SWE-agent, agents can search for files and view file contents in a fixed window size through computer interface operations. However, due to the lack of guidance from repository experience knowledge, SWE-agent mistakenly located the function `get_conditional_response` in the local search. Although this function has a certain relevance to solving the issue, it is not directly related. Therefore, modifying the wrong place resulted in the failure to solve the task.

In Figure 7, we analyzed and found that solving the matplotlib-26011 task can be achieved by modifying the `_set_lim` or `set_xlim` function. Both RepoUnderstander and SWE-agent correctly located the position to be modified. However, due to the running feedback and iteration capabilities of SWE-agent, the agents finally generated the correct patch through feedback information. This shows the importance of execution feedback for solving practical problems. Since RepoUnderstander and SWE-agent have certain complementarity, in the future we will combine global experience and effective execution feedback mechanism to further optimize the effect of automated software repair.

5 LIMITATION

5.1 Resource Overhead.

Although RepoUnderstander aims to guide large language models to fully understand the whole software repository to effectively solve the challenges in automatic software engineering (ASE), the Monte Carlo Tree Search (MCTS) process does require a certain amount of resource consumption. Specifically, we set the maximum number of iterations to 600 and the maximum search time to 300

seconds to ensure that the model can fully explore the search space and accurately evaluate the rewards of different paths. However, such settings are controllable and adjustable to adapt to different application scenarios and resource constraints. Through reasonable parameter adjustment, the best balance between resource consumption and result accuracy can be found. In addition, as shown in Table 5, only 50 iterations can also achieve results that are superior to other agents. Further research may discover more efficient strategies to reduce resource requirements while maintaining or improving agents performance.

5.2 Runtime feedback.

RepoUnderstander aims to study how to understand the entire software repository, and has emerged effective ASE capabilities through modules such as software knowledge graph construction and MCTS-enhanced repository understanding, especially in tasks such as fault location that rely on effective understanding of the entire repository knowledge. SWE-agent [43] uses information such as execution feedback to assist in verifying the correctness of generated patches, and iteratively repairs patches to pass tests, which has a certain effect on improving the correctness of patch generation. In Table 2, we analyze the distribution of problem solving by RepoUnderstander and SWE-agent, and find that the two methods have a certain complementarity, jointly solving **26.67%** of the problems on SWE-bench Lite. Inspired by this, in the future, further combining RepoUnderstander with runtime feedback is an effective way to enhance ASE capabilities.

6 CONCLUSION

This paper highlights the significance of understanding the whole software repository as a critical path to achieving automatic software engineering (ASE). To this end, we present a novel LLM-based agent method named RepoUnderstander, which guides agents to comprehensively understand entire repositories. Concretely, RepoUnderstander first constructs a repository knowledge graph to condense extensive and complex repository-level information into a

Issue: Fix handling empty string for If-Modified-Since header.

RepoUnderstander 

MCTS-based Repository Exploration:

```
<file>http.py</file><function>parse_http_date</function>
<file>static.py</file><function>was_modified_since</function>
<file>cache.py</file><function>get_conditional_response</function>
.....
```

Summary:

Analyze:

- In the code from 'http.py', the function 'parse_http_date' is xxx.
- The 'was_modified_since' function in 'static.py' checks if ...
-

Plan:

- Determine what commit "d6aff369ad3" changed related to xxx.
- If the decision to raise an exception for an empty string ...
- Implement a check for empty strings before calling xxx
- Update the 'was_modified_since' function to explicitly handle ...
-

Dynamic info. & Patch generation:

Search tool:

- search_code("d6aff369ad3")
- search_method_in_file("was_modified_since", "static.py")
-

Patch generation:

- Buggy location is: func **was_modified_since** 
- Updated code: xxx
- git diff & return diff. 

SWE-agent: 

- create reproduce_bug.py
- search_dir "d6aff369ad3"
- search_dir "If-Modified-Since"
- open django/middleware/http.py
- open django/utils/cache.py
- search_file "get_conditional_response" 
- edit (<file>cache.py</file><func>get_conditional_response</func>)
- python reproduce_bug.py
- submit 

Issue: xlim_changed not emitted on shared axis.

RepoUnderstander 

MCTS-based Repository Exploration:

```
<file>_base.py</file><class>_AxesBase</class><class_function>set_xlim</class_function>
<file>axis.py</file><class>Axis</class><class_function>_set_lim</class_function> .....
```

Summary:

Analyze:

- In `set_xlim()`: It sets the limits of the x-axis and has an 'emit' parameter ...
- In `__set_lim()`: It similarly sets view limits and notifies observers ...
- ...

Plan:

- Changing the hardcoded `emit=False` to `emit=True` would ...
- The recursion problem occurs because setting `emit=True` makes every shared axis call back into `__set_lim()` for all other shared axes, creating an endless loop.

Dynamic info. & Patch generation:

Search tool:

- search_class("_AxesBase")
- search_method_in_class("set_xlim", "_AxesBase")
- search_method_in_class("set_lim", "Axis")

Patch generation:

- Buggy location is: **set_lim** 
- Updated code: xxx 
- git diff & return diff. 

SWE-agent: 

- create reproduce_bug.py
- find_file "_base.py"
- open lib/matplotlib/axes/_base.py
- search_file "def set_xlim" 
- edit (<class>_AxesBase</class><class_function>set_xlim</class_function>)
- python reproduce_bug.py
- open lib/matplotlib/axes/_base.py
- edit (<file>lib/matplotlib/axes/_base.py</file>)
- python reproduce_bug.py
- submit 

Figure 6: Case of django-15498. (Partial workflow of RepoUnderstander and SWE-agent)

hierarchical structure. Subsequently, we enhance the agents' repository understanding through a Monte Carlo Tree Search (MCTS) enhanced repository exploration strategy. Finally, we guide the agents to summarize, analyze, and plan according to global experiences. Then, they can manipulate the tools to dynamically acquire information and generate patches to solve real-world GitHub issues.

We demonstrate the superior performance of RepoUnderstander through extensive experiments and comprehensive analyses. Our method achieves state-of-the-art performance on the SWE-bench Lite benchmark, outperforming existing RAG-based and agent-based systems. Furthermore, we address the issue of information asymmetry in the SWE-bench Lite dataset by proposing a FIX version that integrates new feature interface specifications into the problem description. Additionally, we conduct ablation studies to

Figure 7: Case of matplotlib-26011. (Partial workflow of RepoUnderstander and SWE-agent)

analyze the effectiveness of various components of RepoUnderstander and identify areas for further improvement. Our findings emphasize the importance of global repository experiences and the potential benefits of integrating runtime feedback mechanisms. Future work will focus on combining global experiences with runtime feedback mechanisms to further enhance the capabilities of LLM-based agents in solving complex software engineering tasks.

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