Issue Localization via LLM-Driven Iterative Code Graph Searching

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***Abstract*—Issue solving aims to generate patches to fix reported issues in real-world code repositories according to issue descriptions. Issue localization forms the basis for accurate issue solving. Recently, large language model (LLM) based issue localization methods have demonstrated state-of-the-art performance. However, these methods either search from files mentioned in issue descriptions or in the whole repository and struggle to balance the breadth and depth of the search space to converge on the target efficiently. Moreover, they allow LLM to explore whole repositories freely, making it challenging to control the search direction to prevent the LLM from searching for incorrect targets. Meanwhile, because LLMs may not correctly produce the required interaction formats with the environment, they suffer from search failures.**

This paper introduces COSIL, an LLM-driven, powerful function-level issue localization method without training or indexing. To balance search breadth and depth, COSIL employs a two-phase code graph search strategy. It first conducts broad exploration at the file level using dynamically constructed module call graphs, and then performs in-depth analysis at the function level by expanding the module call graph into a function call graph and executing iterative searches. To precisely control the search direction, COSIL designs a pruner to filter unrelated directions and irrelevant contexts. To avoid incorrect interaction formats in long contexts, COSIL introduces a reflection mechanism that uses additional independent queries in short contexts to enhance formatted abilities. Experiment results demonstrate that COSIL achieves a Top-1 localization accuracy of 43.3% and 44.6% on SWE-bench Lite and SWE-bench Verified, respectively, with Qwen2.5-Coder-32B, average outperforming the state-of-the-art methods by 96.04%. When COSIL is integrated into an issue-solving method, Agentless, the issue resolution rate improves by 2.98%–30.5%.

I. Introduction

Recently, issue solving [1], [2] has become a crucial task as it directly addresses bugs [3]–[5] and feature requests [6], [7] in real-world code repositories, thereby improving software quality and ensuring the continuous evolution of repositories. Given an issue in a repository, issue-solving methods aim to generate a patch according to the issue description provided by users. Accurate localization is the foundation for successfully resolving issues [8]. It aims to search for a set of suspicious code snippets within a certain scope of code files (i.e., search space) of the code repository.

LLM-based methods [9]–[12] have become the main force in issue localization tasks. Existing LLM-based issue localization methods can be mainly divided into prompt-based methods and agent-based methods. They face the following common challenges. ❶ **They fail to balance the breadth and depth of the search space.** Prompt-based methods [9], [13] use the issue description and employ a hierarchical strategy to gradually converge to the target. However, issue description usually describes the symptoms rather than the essence of the problem [14], resulting in an overly narrow search space and causing relevant context to be ignored. Agent-based methods [10], [11], [15] leverage the code understanding capability of LLMs to freely explore the entire repository, which results in an overly broad search space and leads to the retrieval of irrelevant context. Irrelevant context interferes with useful information, leading to performance degradation. ❷ **They lack control of the search direction.** Prompt-based methods often use as much context as possible from the search space without verifying its relevance. This causes the LLM to explore some search directions yet unrelated to the issue, making it difficult to locate the correct target. Agent-based methods directly depend on agents to decide search direction, which often rely only on the current state and lack a global perspective [16]. As a result, the agent may repeatedly explore the same code segments, leading to chaotic search directions. Additionally, as the agent bases its subsequent decisions on historical feedback from the environment, chaotic search directions can propagate, resulting in redundant noise in the context and degrading the performance of issue localization. ❸ **They produce abnormal search processes due to incorrectly formatted interaction outputs.** LLM-based methods interact with the external environment (e.g., tool calling) via formatted outputs from the LLM [15], [17]. Prompt-based methods rely entirely on the LLM's inherent capabilities, which directly treat outputs with incorrectly formatted interactions as localization failures [9], [13], resulting in empty lists in the localization results. Agent-based methods typically add retry mechanisms, but the error messages produced by incorrectly formatted interactions are also included in the context [11]. As consecutive retries fill the context with error messages, they interfere with localization performance. Thus, the limited capability of LLMs to follow instructions for formatted output in long-context settings [18]

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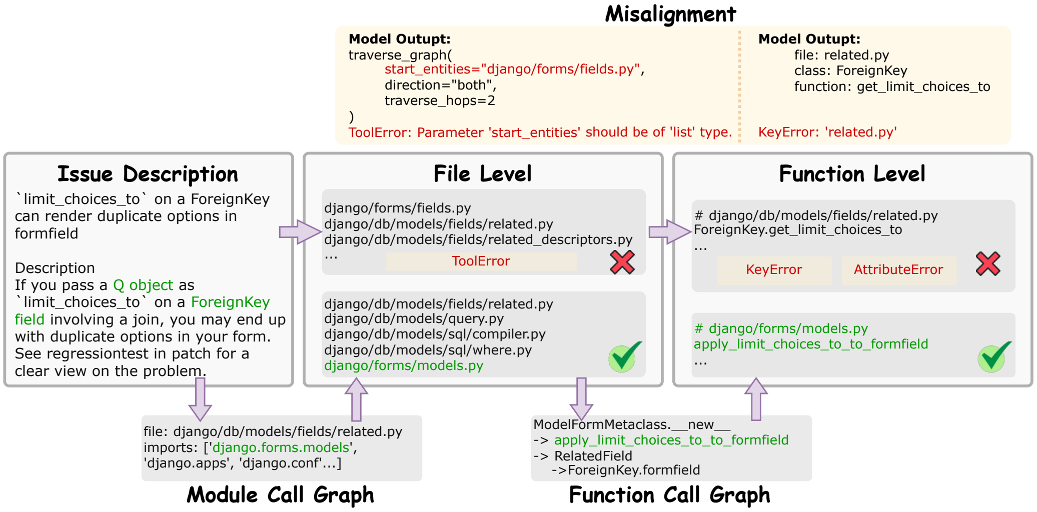

Misalignment
Model Outupt:
traverse_graph(
start_entities="django/forms/fields.py",
direction="both",
traverse_hops=2
)
ToolError: Parameter 'start_entities' should be of 'list' type.
Model Outupt:
file: related.py
class: ForeignKey
function: get_limit_choices_to
KeyError: 'related.py'
Issue Description
`limit_choices_to` on a ForeignKey can render duplicate options in formfield
Description
If you pass a Q object as `limit_choices_to` on a ForeignKey field involving a join, you may end up with duplicate options in your form.
See regressiontest in patch for a clear view on the problem.
File Level
django/forms/fields.py
django/db/models/fields/related.py
django/db/models/fields/related_descriptors.py
...
ToolError
django/db/models/fields/related.py
django/db/models/query.py
django/db/models/sql/compiler.py
django/db/models/sql/where.py
django/forms/models.py
Function Level
# django/db/models/fields/related.py
ForeignKey.get_limit_choices_to
...
KeyError
AttributeError
# django/forms/models.py
apply_limit_choices_to_to_formfield
...
file: django/db/models/fields/related.py
imports: ['django.forms.models', 'django.apps', 'django.conf'...]
Module Call Graph
ModelFormMetaclass.__new__
-> apply_limit_choices_to_to_formfield
-> RelatedField
->ForeignKey.formfield
Function Call Graph

Fig. 1. A motivating example of Django-13315.

becomes a performance bottleneck.

To overcome the challenges above, we propose CoSIL, an LLM-driven issue localization technique through iterative code graph searching. **To balance the breadth and depth of the search space**, we adopt a two-stage search strategy that performs broad exploration at the file level and in-depth analysis at the function level. Specifically, we provide the LLM with a module call graph to expand the search space beyond the files mentioned in the issue description, enabling the identification of additional suspicious modules. By further expanding the module call graph into a function call graph and performing an iterative search, we collect highly relevant contextual information in greater depth. **To control the search direction**, we design a pruner that rejects the LLM's exploration of irrelevant context. This ensures the effectiveness of the collected contextual information and filters out contextual noise. Given LLMs exhibit stronger instruction-following capabilities in short-context settings [18], we leverage a reflection mechanism [19] that summarizes decision information into a short context **to prevent the abnormal interaction format through enhancing LLM's formatted outputs**. It involves performing an additional, independent query at the end of each LLM interaction to double-check and format the final output.

We implement CoSIL based on Qwen2.5-Coder-7B/14B/32B [20], and evaluate its effectiveness on SWE-bench Lite [1] and SWE-bench Verified [21]. Experimental results show that, compared to existing LLM-based issue localization methods, CoSIL average improves Top-1 localization accuracy by 6.61% at the file level and by 96.04% at the function level. Furthermore, when leveraging the localization results generated by CoSIL is integrated into an issue-solving method, Agentless [9], the issue resolution rate increases by 2.98%–30.5%, further demonstrating the usefulness in application scenarios. In addition, we conduct an ablation study on the key components of CoSIL, i.e., reflective alignment, module call graph, iterative search, and pruning. The results demonstrate the effectiveness of CoSIL's key components: iterative search as the core, call graphs for search space constraint, pruning for search direction management, and reflective alignment for ensuring interaction format. Finally, we evaluate CoSIL on different families of LLMs and compute its cost. Results show that it can generalize with a cost of 0.02$ and 0.34$ on DeepSeek-v3-0324 [22] and GPT-4o-2024-0806 [23].

In summary, our main contributions are as follows:

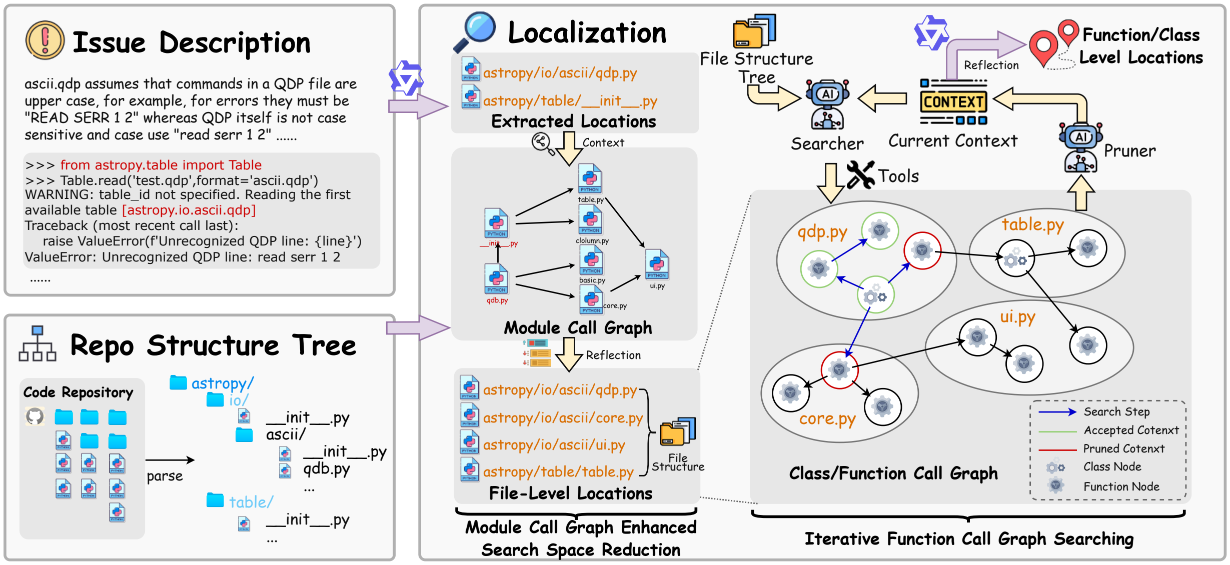
- We propose CoSIL, an LLM-driven function-level issue localization method without training or pre-indexing. It balances the breadth and depth of the search space while ensuring the accuracy of the search direction and the correct interaction formats.
- We conduct extensive and comprehensive experiments on SWE-bench Lite [1] and SWE-bench Verified [21]. Experiment results show that CoSIL achieves up to 48% Top-1 accuracy in function-level localization, nearly twice that of existing methods. It brings an average performance improvement of 14.90% on the issue-solving task.
- We open-source the replication package, including the source code and data of CoSIL, at https://github.com/ZJU-CTAG/CoSIL.

II. Motivation and Background

A. Motivating Example

Figure 1 presents a motivating example, which is an issue collected from the Django repository.

This example describes a phenomenon where passing a "*Q Object*" to the "*limit_choices_to*" parameter of a "*ForeignKey Field*" results in duplicate options appearing in the form. We inspect the results produced by three state-of-the-art issue localization methods, i.e., Agentless [9], OrcaLoca [10], and



ascii.qdp assumes that commands in a QDP file are upper case, for example, for errors they must be "READ SERR 1 2" whereas QDP itself is not case sensitive and case use "read serr 1 2" ......

```
>>> from astropy.table import Table
>>> Table.read('test.qdp',format='ascii.qdp')
WARNING: table_id not specified. Reading the first
available table [astropy.io.ascii.qdp]
Traceback (most recent call last):
    raise ValueError(f'Unrecognized QDP line: {line}')
ValueError: Unrecognized QDP line: read serr 1 2
 ......
```

Fig. 2. Overview of CoSIL.

LocAgent [11], using Qwen2.5-Coder-32B model. None of them successfully find the correct location to edit.

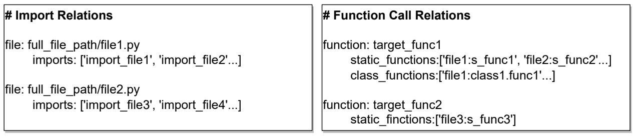
We analyze their trajectories when handling this case and summarize three major observations. ❶ The three methods are limited in search breadth or depth. Specifically, Agentless extracts targeted file names mentioned in the issue description [9], including "`django/forms/fields.py`" and "`django/db/models/fields/related.py`". While these files are related to the issue, they are not the ones that require modification. Conducting function-level localization within such a narrow search space makes it nearly impossible to identify the correct function to edit. In contrast, OrcaLoca searches by analyzing the frequency with which the LLM focuses on each function [10]. But the most frequently referenced function, "*ForeignKey.get_limit_choices_to*", may only be textually similar to the issue description but semantically irrelevant, searching in such an overly broad space as the entire repository is not feasible. ❷ These methods lack control of search directions. Specifically, when LocAgent uses the "*search_code_snippets*" tool to read code snippets, both the first and third actions inspect the source code of "*ForeignKey*", resulting not only in redundant context but also in an unordered search process. ❸ Incorrectly formatted outputs during interactions lead to the three methods crashing. Specifically, when LocAgent [11] calls the "*traverse_graph*" tool, where the LLM passes an argument with an incorrect type for the parameter "*start_entities*", it not only fails to retrieve context, but also includes detailed error messages of this "*ToolError*". Moreover, when these three methods feed back the decided locations, the localization may fail because unformatted output cannot be parsed. For example, Agentless [9] might output an incomplete file path, leading to a "*KeyError*" and ultimately a failed localization attempt.

From observation 1, we find that when the search space is too narrow, existing techniques cannot find the target within a space that excludes the correct one. When the search space is too broad, existing techniques may retrieve irrelevant targets that are only textually similar. This motivates a two-phase strategy to balance the search space, i.e., expanding the search breadth at the file level through the module call graph while maintaining search depth through function call graphs. From observation 2, we find that if the search direction is not restricted, the limited context window becomes populated with substantial redundant or unrelated content, leading to inefficiency. This motivates us to prune the irrelevant context to control the search directions. From observation 3, we find that incorrect output format during the LLM's interaction with the environment not only pollutes the context with irrelevant information but can even derail the localization process entirely. Motivated by the fact that LLM alignment degrades in long-context settings [18], [24], we integrate self-reflection [19] as a verifier to double-check and correct final decisions.

B. Call Graph Construction

As the call graphs in the repository typically describe the invocation and dependency relationships among modules at the class/function level, we can use them to expand the search space at a coarse granularity and to constrain the search space at a fine granularity.

In this work, we mainly use two types of call graphs: module call graphs and function call graphs. Given a code repository R, the module call graph is defined as $\mathcal{G}_M(R) = (\mathcal{V}_m, \mathcal{E}_m)$, where $\mathcal{V}_m$ consists of all modules in R, and $\mathcal{E}_m$ includes all "import" relationships between modules. Furthermore, each node in $\mathcal{V}_m$ can be expanded into multiple class/function nodes. Based on this, the function call graph can be defined as $\mathcal{G}_F(R) = (\mathcal{V}_f, \mathcal{E}_f)$, where $\mathcal{V}_f$ consists



```
# Import Relations

file: full_file_path/file1.py
        imports: ['import_file1', 'import_file2'...]

file: full_file_path/file2.py
        imports: ['import_file3', 'import_file4'...]
```

```
# Function Call Relations

function: target_func1
        static_functions:['file1:s_func1', 'file2:s_func2'...]
        class_functions:['file1:class1.func1'...]

function: target_func2
        static_finctions:['file3:s_func3']
```

Fig. 3. Textual representation of call graphs.

TABLE I
DESIGN OF SEARCH TOOLS.

Function Name	Description
search_class_node	Get the code snippet of a class node.
search_class_function_node	Get the code snippet of a class member function node.
search_file_function_node	Get the code snippet of a static function node.
exit	Terminate iteration search and go into summary phase.

of all the classes and functions defined in $\mathcal{V}_m$. $\mathcal{E}_f$ includes all "invoke" and "inherit" relationships between classes and functions. We use the LLM to construct the necessary call graph dynamically in a textual representation. Specifically, we provide the LLM with the code of the module/function and its import statements parsed from the files where they are located, prompting the LLM to analyze their outgoing dependency and generate a first-order subgraph centered on the target module/function. **An example of the call graph and the detailed construction algorithm through LLMs can be found in our online Appendix-A.**

III. Approach

In this section, we introduce CoSIL, an LLM-driven issue localization framework. As shown in Figure 2, CoSIL takes an issue description and a repository structure tree extracted from the original code repository as inputs and returns a recommendation list containing the signatures of the most suspicious functions. It consists of two stages, i.e., module call graph enhanced search space reduction at the file level and iterative function call graph searching at the function level.

To ensure that the search space is not limited and avoid an overly broad scope that includes the entire repository, CoSIL expands the search space from the modules mentioned in the issue description to imported modules by providing the LLM with the module call graph during the file-level stage (Section III-A1). To collect context and perform an in-depth search, CoSIL uses a specifically designed search tool to iteratively explore the function call graph at the function-level stage (Section III-A2). Additionally, to achieve a balance between context length and the density of relevant information, CoSIL utilizes a pruning mechanism to control the search direction and prevent irrelevant context from being retrieved (Section III-B). To enhance the LLM's ability to produce formatted outputs when interacting with the external environment, CoSIL leverages reflection at the end of each stage, thereby alleviating parsing errors in the final results (Section III-C).

A. Localization with Call Graph

1) Module Call Graph Enhanced Search Space Reduction: This stage takes the repository structure tree as input and returns a list of suspicious files as the search space. Because of the limited context window size of LLMs, directly providing the code in all files to the model is often infeasible. Inspired by previous studies [9], [13], we recursively traverse the entire repository and parse it into a hierarchical repository-structure tree representation. Considering that most issue reports contain information about candidate suspicious locations [25], we query LLM with the issue description to pre-select the related files The prompt template can be found in Appendix-E. Then, the "*import*" statements in the related files are parsed to construct a first-order subgraph of the module call graph, which starts from the related files. Such a subgraph is then converted into structured textual representations, as shown in Figure 3. Next, the pre-selected related files, along with the repository-structure tree and the module call graph, are fed into the LLM for search space expansion, enabling the reselection and reranking of the suspicious files. The rationale behind not utilizing the entire module call graph is that the repository-structure tree already provides a comprehensive view of the repository.

2) Iterative Function Call Graph Searching: This stage takes the file-level search space as input and returns a list of suspicious functions. Specifically, it consists of the following three steps. (**Detailed algorithm is in Appendix-B**)

Step I: Initialize the search state. This step aims to preliminarily determine one or several starting points for the search. Specifically, similar to the repository-structure tree described in Section III-A1, we construct a file-structure tree for all suspicious files, outlining all classes, member functions, and static functions within these files in a hierarchical format. Then we provide the issue description along with this file-structure tree as inputs to query the LLM to return selected points.

Step II: Iterative search contexts. This step aims to collect contextual information for locating suspicious functions. First, we construct a search agent by equipping the LLM with retrieval tools as shown in Table I and a pruner agent (detailed in Section III-B) by providing a function code snippet and asking for a boolean flag indicating if the code snippet should be used as context. Then, we set a maximum number of iterations to prevent the search agent from falling into an infinite loop. During each iteration step, the search agent first selects a target node from the set of accessible nodes (denoted as $visableNodes$) for exploration according to the issue description and the visited nodes (denoted as $contextNodes$). The target node could refer to a class, a class member function, or a static function. Depending on the type of the target node, the search agent invokes different search tools shown in Table I to retrieve node content. Next, the retrieved code will be verified by the pruner agent, which determines whether the target node is acceptable. Once the target node is confirmed and accepted by the pruner agent into $contextNodes$, its neighbor nodes within the function call graph become accessible and are added to the $visableNodes$

for selection in subsequent iterations. Notably, if the search agent returns an incorrect function-call parameter, i.e., the search agent would like to retrieve non-existent code elements, a post-processing procedure will prompt the search agent to reselect the node from the accessible nodes for exploration. Additionally, if the search agent invokes the "exit" tool, which means that sufficient information has been collected to support a decision, the iteration process will be terminated prematurely.

Step III: Summarize the suspicious functions. This step aims to select and rerank a set of the most suspicious functions or classes from the context nodes generated by Step II. Specifically, the search agent incorporates the retrieved code snippets from relevant context nodes into a summarization prompt as the background knowledge for in-context learning. Then, LLM returns a list of suspicious functions as localization results. The summarized function-level localization information can either be utilized for further fine-grained line-level localization or provided as contextual input to the LLM for subsequent program repair directly.

B. Context Management with Pruning

This component takes the issue description and code snippet to be explored by the search agent as input and returns a boolean flag indicating whether the node should be accepted. Specifically, when LLM selects a target node, the code snippet of the node is used as context to construct a prompt that instructs the LLM to analyze whether the node is related to the issue being addressed, and the LLM is asked to return a boolean value. If the pruner agent returns a "True" flag to accept this node as part of the context, its neighboring nodes will subsequently be expanded. Otherwise, the pruner directly rejects the expansion and excludes the node from the context, effectively pruning the search path.

By pruning the search path, CoSIL effectively guides the search direction, encouraging the LLM to explore suspicious functions to avoid getting stuck in local optima. Simultaneously, it enables efficient context management, preventing the agent from collecting excessive redundant information, which might lead to erroneous decision-making.

C. Reflective Alignment

This component takes the last returned response by the LLM in Section III-A1 and Section III-A2 to rerank and reformat the output. It acts as a verifier to guard against incorrect interaction formats in long-context scenarios [18].

Specifically, we maintain a message list to record each query and response during interactions with the LLM, and collect context through multiple queries. Since CoSIL requires the LLM to summarize the suspicious locations in the final query round (Section III-A1 and III-A2), the last response in the message list should contain the LLM's decision information. Reflective Alignment takes the issue description together with the last response containing decision information as context, and prompts the LLM to rerank and reformat the candidate locations given in the decision information to obtain the final localization result. The detailed prompt can be found in Appendix-E. Reflective Alignment is applied at the end of both file-level and function-level localization, significantly reducing localization failures caused by unstructured or improperly formatted outputs. It also retains the advantages of the reflection reasoning strategy [19], and thus can correct and rerank the localization results.

IV. Experiment Setup

A. Dataset

SWE-bench [1] is the most widely used dataset for evaluating large language models' capabilities in solving real-world software issues. It extracts 2,294 tasks from 12 Python code repositories, where each task requires submitting a patch to solve an issue in the corresponding repository. To control experimental costs, we conduct experiments on two popular subsets of SWE-bench:

- **SWE-bench Lite** [1] is a 300-instance subset selected using heuristic methods. It removes tasks where the issue description contains images, external hyperlinks, and other non-textual elements.
- **SWE-bench Verified** [21] is a subset of 500 instances developed by OpenAI. It is selected from 1,699 manually annotated instances by professional developers and removes instances with underspecified descriptions or overly specific test cases.

B. Baselines

We mainly compare CoSIL with open-source localization methods that focus on SWE-bench, including Agentless [9], Orcaloca [10], and LocAgent [11].

- **Agentless** is the current state-of-the-art open-source issue solving pipeline. It is designed based on human prior knowledge and performs issue localization by hierarchically querying the LLM for suspicious files, functions, and code lines. We use the localization component in Agentless as the baseline, denoted as **Agentless-FL**.
- **Orcaloca** designs an LLM agent framework, which searches on a unique code graph based on priority scheduling, action decomposition, and relevance scoring. In addition, it employs distance-aware pruning on the retrieved context, enhancing the accuracy of fault localization.
- **LocAgent** parses all dependency relationships within the code repository and constructs a large graph index, enabling the LLM to locate relevant entities through multi-hop reasoning using retrieval tools.

Additionally, we consider the fine-tuning-based approach BugCerberus [12], but fail in conducting the comparison because its implementation is not released.

C. Research Questions (RQs)

To evaluate the performance of CoSIL under issue localization tasks, we consider the following research questions.

- **RQ1. Effectiveness**: How effective is CoSIL in localizing buggy code snippets in the code repository?

TABLE II

Localization results under different LLMs on SWE-bench Lite. ER indicates *empty rate*.

Method	File-level					Function-level					
	Top-1	Top-3	Top-5	MAP	MRR	Top-1	Top-3	Top-5	MAP	MRR	ER
Qwen2.5-Coder-7B											
Agentless-FL	0.333 ↑23.1%	0.537 ↑7.4%	0.577 ↑10.4%	0.437 ↑20.6%	0.437 ↑14.4%	0.173 ↑23.1%	0.260 ↑12.7%	0.270 ↑13.7%	0.218 ↑10.6%	0.218 ↑14.7%	5.33%
OrcaLoca	**0.467** ↓12.2%	0.490 ↑17.7%	0.490 ↑30.0%	0.478 ↑10.3%	0.478 ↑4.6%	0.157 ↑35.7%	0.273 ↑7.3%	0.293 ↑4.8%	0.209 ↑15.3%	0.214 ↑16.8%	8.33%
LocAgent	0.400 ↑2.5%	0.507 ↑15.8%	0.533 ↑19.5%	0.458 ↑15.1%	0.458 ↑9.2%	0.047 ↑353.2%	0.140 ↑109.3%	0.160 ↑91.9%	0.091 ↑164.8%	0.092 ↑171.7%	21.00%
CoSIL	0.410	**0.577**	**0.637**	**0.527**	**0.500**	**0.213**	**0.293**	**0.307**	**0.241**	**0.250**	**1.00%**
Qwen2.5-Coder-14B											
Agentless-FL	0.537 ↑8.6%	0.687 ↑6.7%	0.723 ↑6.1%	0.618 ↑8.1%	0.611 ↑7.7%	0.187 ↑8.6%	0.253 ↑29.2%	0.280 ↑26.1%	0.219 ↑16.4%	0.224 ↑19.2%	1.00%
OrcaLoca	0.433 ↑34.6%	0.477 ↑53.7%	0.477 ↑60.8%	0.455 ↑46.8%	0.455 ↑44.6%	0.170 ↑19.4%	0.303 ↑7.9%	0.313 ↑12.8%	0.229 ↑11.4%	0.233 ↑14.6%	6.33%
LocAgent	0.510 ↑14.3%	0.633 ↑15.8%	0.650 ↑18.0%	0.572 ↑16.8%	0.572 ↑15.0%	0.090 ↑125.6%	0.283 ↑15.5%	0.317 ↑11.3%	0.192 ↑32.8%	0.190 ↑40.5%	22.33%
CoSIL	**0.583**	**0.733**	**0.767**	**0.668**	**0.658**	**0.203**	**0.327**	**0.353**	**0.255**	**0.267**	**0.33%**
Qwen2.5-Coder-32B											
Agenltess-FL	0.583 ↑5.1%	0.730 ↑6.8%	0.773 ↑8.3%	0.669 ↑5.4%	0.659 ↑6.4%	0.247 ↑75.3%	0.397 ↑37.8%	0.427 ↑35.8%	0.308 ↑51.0%	0.325 ↑51.7%	2.00%
OrcaLoca	0.590 ↑3.9%	0.640 ↑21.9%	0.640 ↑30.8%	0.615 ↑14.6%	0.615 ↑14.0%	0.217 ↑99.5%	0.417 ↑31.2%	0.447 ↑29.8%	0.302 ↑54.0%	0.317 ↑55.5%	2.67%
LocAgent	**0.647** ↓5.3%	0.727 ↑7.2%	0.740 ↑13.1%	0.683 ↑3.2%	0.683 ↑2.6%	0.103 ↑320.4%	0.377 ↑45.1%	0.447 ↑29.8%	0.231 ↑101.3%	0.244 ↑102.0%	13.67%
CoSIL	0.613	**0.780**	**0.837**	**0.705**	**0.701**	**0.433**	**0.547**	**0.580**	**0.465**	**0.493**	**0.00%**

- **RQ2. Ablation**: How do the key components of CoSIL contribute to its effectiveness?
- **RQ3. Application**: Can the buggy locations identified by CoSIL lead to better performance in issue solving?
- **RQ4. Generalizability**: How well does CoSIL generalize across different families of LLMs?

D. Evaluation Metrics

For RQ1 and RQ2, we mainly use the three evaluation metrics, i.e., *Top-N*, *MAP*, and *MRR*. They are widely used to evaluate the performance of fault location methods [12], [26]–[28]. Additionally, we measure the *empty rate* across the localization results. For RQ3, we use Applied% and Resolved% following prior works [10], [12], [17], [25].

Top-N: This metric counts how often at least one bug location appears within the top N recommendations. To measure the localization success rate, we normalize this count by the number of instances. We set N = {1, 3, 5}, as approximately 73.58% of developers consider only the top 5 results [29].

MAP: Mean Average Precision (MAP) evaluates the ranking quality of buggy elements identified by a technology [26]–[28].

MRR: Mean Reciprocal Rank (MRR) measures the ranking performance of a technology by evaluating the position of the first identified buggy element within the recommendation list [26]–[28].

Empty Rate: The empty rate refers to the proportion of cases where the suspicious location recommendation list generated by a technique is empty, indicating the technique fails to identify any candidate locations for a given issue.

Resolved% & Applied%: Resolved% refers issue resolution rate [1], which measures the percentage of problems that are successfully solved by a technique. Applied% denotes the application rate, which evaluates the percentage of patches that are generated by a technique and can be successfully applied to the corresponding repositories without syntax errors.

E. Implementation Details

In our experiments, we deploy the Qwen2.5-coder models (7B, 14B, and 32B) locally using the vLLM framework [30] following prior studies [11]. Additionally, we employ the official GPT-4o-2024-08-06 and DeepSeek-v3-0324 API to perform supplementary experiments to validate generalizability [9].

To ensure a fair comparison, we adopt greedy decoding (i.e., sampling with temperature=0) during the localization stage. Moreover, for each instance, we set the maximum number of iterations to 10 during the graph search process. For agent-based methods (i.e., OrcaLoca and LocAgent), we set the maximum number of retries per instance to 3 and the maximum search time to 15 minutes, following their default configurations. When comparing the effectiveness of various localization methods in enhancing issue solving, we uniformly utilized the repair component of Agentless-1.5 [9] to generate 10 candidate patches per instance using the predicted top-3 locations. One candidate patch is obtained through greedy decoding, and nine are generated with temperature=0.8. Moreover, we use regression tests selected by LLM and LLM-generated reproduction tests to validate the patches following the practice of Agentless-1.5 [9].

V. Experiment Result

A. RQ1: Effectiveness

To validate the effectiveness of CoSIL in issue localization, we conduct experiments based on the Qwen2.5-coder 7B/14B/32B models. Table II and Table III present the experimental results on SWE-bench Lite and SWE-Bench Verified, respectively.

Experimental results show that on SWE-bench Lite, CoSIL relatively improves file-level Top-1 localization accuracy by 8.28% on average and function-level Top-1 accuracy by 117.87%. On SWE-bench Verified, the average improvements are 4.94% and 74.21%, respectively. This demonstrates that CoSIL can localize issues more effectively, especially at the

TABLE III
LOCALIZATION RESULTS UNDER DIFFERENT LLMS ON SWE-BENCH VERIFIED. ER INDICATES *empty rate*.

Method	**File-level**					**Function-level**					
	Top-1	**Top-3**	**Top-5**	**MAP**	**MRR**	**Top-1**	**Top-3**	**Top-5**	**MAP**	**MRR**	**ER**
Qwen2.5-Coder-7B											
Agentless-FL	0.514 ↑5.8%	0.650 ↑7.1%	0.670 ↑10.7%	0.551 ↑11.1%	0.577 ↑8.1%	0.256 ↑10.2%	0.306 ↑17.0%	0.320 ↑15.0%	0.245 ↑15.9%	0.282 ↑13.1%	8.00%
OrcaLoca	0.510 ↑6.7%	0.534 ↑30.3%	0.534 ↑39.0%	0.490 ↑24.9%	0.522 ↑19.5%	0.206 ↑36.9%	0.322 ↑11.2%	0.340 ↑8.2%	0.227 ↑25.1%	0.266 ↑19.9%	7.20%
LocAgent	0.504 ↑7.9%	0.630 ↑10.5%	0.640 ↑15.9%	0.535 ↑14.4%	0.566 ↑10.2%	0.120 ↑135.0%	0.186 ↑92.5%	0.196 ↑87.8%	0.135 ↑110.4%	0.154 ↑107.1%	27.20%
CoSIL	**0.544**	**0.696**	**0.742**	**0.612**	**0.624**	**0.282**	**0.358**	**0.368**	**0.284**	**0.319**	**0.00%**
Qwen2.5-Coder-14B											
Agentless-FL	0.578 ↑4.2%	0.760 ↑0.3%	0.814 ↑0.5%	0.637 ↑3.1%	0.671 ↑2.7%	0.260 ↑65.4%	0.336 ↑64.3%	0.350 ↑68.0%	0.245 ↑73.9%	0.301 ↑63.8%	3.00%
OrcaLoca	0.542 ↑11.1%	0.574 ↑32.8%	0.574 ↑42.5%	0.524 ↑25.4%	0.557 ↑23.7%	0.232 ↑85.3%	0.366 ↑50.8%	0.378 ↑55.6%	0.258 ↑65.1%	0.300 ↑64.3%	5.40%
LocAgent	0.556 ↑8.3%	0.718 ↑6.1%	0.732 ↑11.7%	0.607 ↑8.2%	0.633 ↑8.8%	0.176 ↑144.3%	0.370 ↑49.2%	0.396 ↑48.5%	0.242 ↑76.0%	0.271 ↑81.9%	14.40%
CoSIL	**0.602**	**0.762**	**0.818**	**0.657**	**0.689**	**0.430**	**0.552**	**0.588**	**0.426**	**0.493**	**0.20%**
Qwen2.5-Coder-32B											
Agentless-FL	0.624 ↑2.6%	0.784 ↑4.8%	0.834 ↑3.6%	0.688 ↑2.5%	0.709 ↑3.0%	0.326 ↑36.8%	0.460 ↑31.7%	0.484 ↑34.3%	0.339 ↑35.4%	0.394 ↑34.8%	3.00%
OrcaLoca	0.612 ↑4.6%	0.654 ↑25.7%	0.654 ↑32.1%	0.590 ↑19.5%	0.633 ↑15.3%	0.254 ↑75.6%	0.468 ↑29.5%	0.486 ↑33.7%	0.308 ↑49.0%	0.359 ↑47.9%	4.00%
LocAgent	**0.686** ↓6.7%	0.806 ↑2.0%	0.816 ↑5.9%	**0.716** ↓1.5%	**0.743** ↓1.7%	0.250 ↑78.4%	0.464 ↑30.6%	0.530 ↑22.6%	0.325 ↑41.2%	0.367 ↑44.7%	12.80%
CoSIL	0.640	**0.822**	**0.864**	0.705	0.730	**0.446**	**0.606**	**0.650**	**0.459**	**0.531**	**1.00%**

function level, than the baselines. Besides, although OrcaLoca achieves the highest file-level Top-1 accuracy on SWE-bench Lite using Qwen2.5-coder-7B, and LocAgent achieves the highest file-level Top-1 accuracy on the two benchmarks using Qwen2.5-coder-32B, CoSIL still achieves the highest Top-5 file-level accuracy and the best function-level performance. This is because during file-level localization, CoSIL guides the LLM to explore files beyond those mentioned in the issue description to expand the breadth of the search space, which may lead to a decrease in Top-1 accuracy at file-level. At the function level, CoSIL guides the LLM in examining source code to make a deeper search and employs a pruner agent to filter out irrelevant locations to control search direction, which decreases the noise introduced from the file level, resulting in stronger performance. Since downstream tasks like issue solving typically rely on finer-grained localization and consider multiple candidate locations, CoSIL is still able to perform best in downstream tasks.

We also examine the *empty rate* of different methods at the function level. CoSIL successfully produces a recommendation list for almost all bugs, while agent-based methods, especially LocAgent, fail to localize by about 20%. We further inspect the frequency of error messages appearing in the context of CoSIL, and find that the frequency of "ToolError" and "KeyError" occurrences is significantly reduced. This is because the reflective alignment of CoSIL verifies the structure of the model's output, increasing the success rate of output parsing.

We manually inspect the results to understand CoSIL's better performance, and summarize two main reasons. First, CoSIL expands the breadth of the search space through the module call graph, whereas other baselines are limited to the space defined by the issue description. For example, for the case shown in Figure 1, Agentless asks LLM to return suspicious files from the issue description, resulting in "`django/forms/fields.py`". In contrast, CoSIL provides the module call graph to the LLM so that the correct module ("`django/forms/models.py`") gets incorporated into the search space at the file level. Second, CoSIL performs localization by providing source code within the search space and pruning irrelevant code to control direction, whereas Agentless does not provide source code to the LLM, and OrcaLoca and LocAgent allow the LLM to explore freely without constraints. For the case shown in Figure 1, Agentless prompt LLM by a file skeleton format, which does not contain any implementation source code of functions in the file. LocAgent allows agents to explore code files themselves, leading to repeatedly calling the "*traverse_graph*" tool to examine the structure of "`django/forms/fields.py`" twice, and to use the "*search_code_snippets*" tool to retrieve all context related to "ForeignKey field" in files such as "`django/forms/fields.py`" and "`django/db/models/fields/related.py`", introducing a large amount of noise. In contrast, CoSIL uses a pruner agent to control direction to prevent irrelevant exploration. The pruner filters out unrelated paths (e.g., through "*RelatedField*"), guiding the search toward the correct function.

> **Answer to RQ1:** Compared to other baselines, CoSIL achieves 2.5%-34.6% improvement at Top-1 file level and 8.6%-353.2% at Top-1 function level with the lowest empty rate of recommendation list, which demonstrates its effectiveness.

B. RQ2: Ablation

CoSIL consists of four key components, i.e., reflective alignment, module call graph, function call graph, and pruning. To investigate their contributions to CoSIL's effectiveness, we separately eliminate each of them and evaluate the effectiveness of the obtained variant. To more clearly observe the performance differences between variants, we select the best-performing setting from RQ1 and conduct this ablation study using Qwen2.5-Coder-32B on SWE-bench Lite. We only evaluate the function-level localization performance for iterative

TABLE IV
ABLATION STUDY RESULTS OF COSIL ON SWE-BENCH LITE.

Method	File-level			Function-level		
	Top-1	MAP	MRR	Top-1	MAP	MRR
CoSIL	0.613	0.705	0.701	0.433	0.465	0.493
w/o Reflective Alignment	0.577 ↓5.9%	0.662 ↓6.1%	0.660↓5.8%	0.390 ↓9.9%	0.424 ↓8.8%	0.456 ↓7.5%
w/o Module Call Graph	0.540 ↓11.9%	0.630 ↓10.6%	0.630 ↓10.1%	0.383 ↓11.5%	0.421 ↓9.5%	0.448 ↓9.1%
w/o Iterative Search	-	-	-	0.320 ↓27.8%	0.372 ↓20.0%	0.390 ↓20.2%
w/o Pruning	-	-	-	0.413 ↓4.6%	0.445 ↓4.3%	0.482 ↓2.2%

TABLE V
THE IMPACT OF ITERATION ON COSIL'S PERFORMANCE.

Method	Function-level		
	Top-1	MAP	MRR
CoSIL@1	0.383	0.418	0.442
CoSIL@3	0.347	0.406	0.425
CoSIL@5	0.370	0.415	0.441
CoSIL@7	0.407	0.450	0.475
CoSIL@10	**0.430**	**0.461**	**0.489**

search and pruning, as these two components exclusively affect function-level localization. The results are shown in Table IV.

- **Module Call Graph (Section III-A1):** Eliminating the module call graph essentially removes the file dependency information provided to the LLM, and leads to a 10% performance loss. The reason may be that the LLM is misled by the repository-structure tree and causes the function-level search space to be altered, leading to the incorrect identification of suspicious files.
- **Iterative Search (Section III-A2):** Eliminating iterative search results in approximately a 20% performance drop. It may deprive CoSIL of the ability to obtain context from the function call graph, reducing it to make direct judgments based solely on the repository structure tree. Since the repository structure tree lacks concrete code segment information, it no longer provides the full context necessary to support decision-making.
- **Pruning (Section III-B):** Eliminating pruning contributes approximately 3% loss to the overall performance. It may increase CoSIL's tendency to explore multiple directions, leading to the inclusion of irrelevant and redundant information in the context. This may introduce noise into the context, making it harder for the LLM to focus on the most relevant code segments.
- **Reflective Alignment (Section III-C):** Eliminating reflective alignment leads to a performance drop of approximately 6–10%. This may be because it reduces the LLM's instruction-following capability and self-correction ability, resulting in outputs that cannot be properly parsed and ultimately leading to localization failure.

We provide two representative examples, i.e., Django-13315 and Django-12908, to demonstrate the contribution of each component. **The detailed description can be found in Appendix-C.** These results indicate that all these components are useful and effective for this task.

Furthermore, we explore the impact of the maximum search iterations (denoted as $maxIter$) on overall performance in the iterative search process. We repeat the function-level localization phase for $maxIter = \{1, 3, 5, 7, 10\}$ and record the Top-1, MAP, and MRR metrics. The results are presented in Table V, which shows that as the number of iterations increases, CoSIL's localization performance first decreases and then increases. This may be because, in CoSIL, the search process is conducted step by step, meaning the LLM can only access the next adjacent node in the function call graph at each iteration. As a result, the LLM requires a certain number of iterations to gather sufficient context about suspicious nodes. While a small amount of relevant context can aid decision-making to some extent, obtaining the full context of a suspicious node proves to be more effective.

TABLE VI
THE RESOLUTION RATE OF PATCHES GENERATED BY DIFFERENT LOCALIZATION METHODS ON SWE-BENCH.

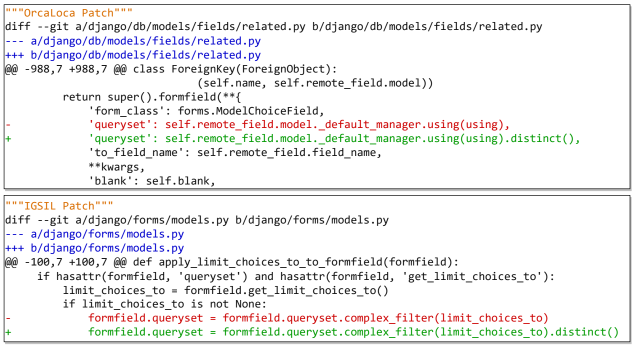
Method	SWE-bench Lite			SWE-bench Verified		
	Applied%	Resovled%	imp.	Applied%	Resovled%	imp.
Qwen2.5-Coder-32B						
Agentless	79.33	17.33	↑25.00%	84.80	27.40	↑9.49%
Orcaloca + Agentless	73.67	17.00	↑27.47%	71.80	27.20	↑10.29%
LocAgent + Agentless	77.33	19.00	↑14.05%	79.80	29.40	↑2.04%
CoSIL+ Agentless	**84.67**	**21.67**	-	**88.00**	**30.00**	-
GPT-4o						
Agentless	84.67	22.33	↑14.96%	90.80	32.00	↑8.13%
Orcaloca + Agentless	79.67	19.67	↑30.50%	77.40	31.00	↑11.6%
LocAgent + Agentless	81.33	21.00	↑22.24%	82.00	33.60	↑2.98%
CoSIL+ Agentless	**92.00**	**25.67**	-	**95.40**	**34.60**	-

> **Answer to RQ2:** All the key components of CoSIL contribute to its localization performance, with iterative search contributing most, accounting for approximately 20% of the overall performance impact. The number of iterations also influences CoSIL's effectiveness. Within the range of [1,10], localization performance first decreases and then increases, reaching its peak performance at 10 iterations.

C. RQ3: Application

To explore whether the improved localization results produced by CoSIL can help existing software engineering agents improve bug fixing, we use the function-level localization results obtained in RQ1 with Qwen2.5-coder-32B and apply the repair and patch validation phases of Agentless-1.5 for bug fixing. We separately generate patches using Qwen2.5-coder-32B and GPT-4o-0806. Table VI presents the results.

On SWE-bench Lite, CoSIL+Agentless increases the resolution rate by 14.05%–30.5%, while on SWE-bench Verified, the improvement is 2.04%–11.6%. This indicates that under the same repair conditions, more accurate localization information not only enhances a model's ability to generate patches that can be successfully applied but also improves the overall bug-fixing performance. Compared to Qwen2.5-coder-32B, GPT-4o-0806 demonstrates stronger patch gener-



```
"""OrcaLoca Patch"""
diff --git a/django/db/models/fields/related.py b/django/db/models/fields/related.py
--- a/django/db/models/fields/related.py
+++ b/django/db/models/fields/related.py
@@ -988,7 +988,7 @@ class ForeignKey(ForeignObject):
                              (self.name, self.remote_field.model))
         return super().formfield(**{
             'form_class': forms.ModelChoiceField,
-            'queryset': self.remote_field.model._default_manager.using(using),
+            'queryset': self.remote_field.model._default_manager.using(using).distinct(),
             'to_field_name': self.remote_field.field_name,
             **kwargs,
             'blank': self.blank,
```

```
"""IGSIL Patch"""
diff --git a/django/forms/models.py b/django/forms/models.py
--- a/django/forms/models.py
+++ b/django/forms/models.py
@@ -100,7 +100,7 @@ def apply_limit_choices_to_to_formfield(formfield):
     if hasattr(formfield, 'queryset') and hasattr(formfield, 'get_limit_choices_to'):
         limit_choices_to = formfield.get_limit_choices_to()
         if limit_choices_to is not None:
-            formfield.queryset = formfield.queryset.complex_filter(limit_choices_to)
+            formfield.queryset = formfield.queryset.complex_filter(limit_choices_to).distinct()
```

Fig. 4. Patch generated by OrcaLoca+Agentless and CoSIL+Agentless for Django-13315.

ation capabilities, highlighting the differences in how models inherently understand and utilize localization information.

Figure 4 presents an example where incorrect localization information directly leads to incorrect patch generation. In this example, CoSIL+Agentless and OrcaLoca+Agentless generate different patches for the issue Django-13315, where Agentless fails to generate. Although the LLM correctly identifies that function `distinct` should be used to address the form duplication problem described in the issue, an incorrect modification location causes the patch to fail the test suite.

> **Answer to RQ3:** CoSIL enhances issue solving by providing more accurate localization information. Compared to other baselines, CoSIL+Agentless achieves a 2.04%–30.5% improvement in the resolution rate.

D. RQ4: Generalizability

TABLE VII
THE LOCALIZATION RESULTS AND COSTS OF COSIL AND BASELINES UNDER DIFFERENT FAMILIES OF LLM.

Method	**SWE-bench Lite mini**					**SWE-bench Verified mini**				
	File@5	**Func@1**	**MAP**	**Token**	**$Cost**	**File@5**	**Func@1**	**MAP**	**Token**	**$Cost**
DeepSeek-v3-0324										
Agentless-FL	0.86	0.28	0.331	10.0k	0.003	**0.92**	0.46	0.494	10.1k	0.003
OrcaLoca	0.76	0.44	0.527	0.12M	0.026	0.80	0.40	0.507	0.10M	0.022
LocAgent	0.78	0.14	0.276	0.53M	0.055	0.80	0.30	0.390	0.64M	0.062
CoSIL	**0.90**	**0.64**	**0.659**	0.07M	0.022	**0.92**	**0.66**	**0.636**	0.07M	0.022
GPT-4o-2024-0806										
Agentless-FL	**0.92**	0.30	0.453	10.6k	0.026	0.86	0.58	0.599	10.4k	0.030
OrcaLoca	0.70	0.28	0.387	0.14M	0.370	0.76	0.36	0.459	0.10M	0.270
LocAgent	0.76	0.44	0.218	2.07M	4.004	0.56	0.24	0.290	2.04M	3.938
CoSIL	0.90	**0.56**	**0.604**	0.14M	0.341	**0.90**	**0.60**	**0.620**	0.12M	0.304

To investigate the generalizability of CoSIL across different families of LLMs, we additionally evaluate the effectiveness of CoSIL with two state-of-the-art models, i.e., DeepSeek-v3-0324 and GPT-4o-2024-0806, which are representatives of open-source and closed-source models, respectively. We independently sample 50 instances each from SWE-bench Lite and SWE-bench Verified, referred to as SWE-bench Lite mini and SWE-bench Verified mini, to control experimental costs. The instances selected have been released in the replication package. We report the Top-5 file-level accuracy, Top-1 function-level accuracy, and function-level MAP in Table VII. **The remaining metrics are provided in Appendix-D**.

On each dataset, CoSIL achieved the best function-level Top-5 localization accuracy and MAP, which demonstrates its generalization ability across different LLMs. We further evaluate the execution costs of different methods. Although Agentless shows the lowest token consumption and cost, we notice that this method is highly unstable: its function localization performance on SWE-bench Lite mini is only half that of CoSIL, but when using GPT-4o on SWE-bench Verified mini, it nearly matches CoSIL. In addition, we observed that OrcaLoca underperforms compared to CoSIL, while LocAgent is both less effective and significantly more expensive. These results indicate that CoSIL is the most cost-efficient method apart from Agentless.

> **Answer to RQ4:** CoSIL can generalize across both open-source and closed-source models, and it is also one of the most cost-efficient methods, requiring only $0.32 per instance with GPT-4o and $0.02 per instance with DeepSeek-v3.

VI. DISCUSSION

A. Evaluating Localization Based on Generated Patches

Some studies [9], [10], [31] evaluate issue localization performance together with issue solving by examining the percentage that the modification locations in the submitted patch match the corresponding ground truth patch. They typically use *file match rate* and *function match rate* as the evaluation metrics, which measure the probabilities that the modified file and function align with the ground truth, respectively. To facilitate comparison, we leverage CoSIL with GPT-4o-0513 for localization and generate four sets of candidate patches using the repair phase of Agentless-1.5 [9] on SWE-bench Lite, following prior studies [9], [13], [32]–[34]. Each set contains one greedy decoding sample and nine samples with temperature=0.8. We use the patch validation phase of Agentless-1.5 to select and rerank patches. We denote this result as **CoSIL@40**, and the results in Section V-C obtained with Qwen2.5-Coder-32B + GPT-4o are denoted as CoSIL@10, Agentless@10, Orcaloca@10, and LocAgent@10, as they only generate 10 patches for selection.

We compare CoSIL@40 with existing issue-solving methods that are also based on GPT-4o-0513, including OpenCSG Starship Agentic Coder [35], Agentless1.5 [9], AutoCodeRover-v2 [32], Infant Coder [34], RepoGraph [13], Moatless Tools [33], and SWE-Agent [17], in terms of file match rate and function match rate. Please note that these methods use different pipelines to generate and validate patches.

We observe that as localization accuracy improves, CoSIL@10, Agentless@10, OrcaLoca@10, and LocAgent@10, which use the same patch generation and validation pipeline, exhibit a positive correlation between file match rate, function match rate, and resolved%. However, some

TABLE VIII
PERFORMANCE OF METHODS USING GPT-4O ON SUBMISSIONS OF SWE-BENCH LITE. * INDICATES THE AGENT USES GPT-4O-0806 MODEL. † INDICATES THE RESULT IS REPRODUCED BY US.

Method	File Matched	Function Matched	Resolved%
*OpenCSG Starship [35]	0.720	0.523	**39.7**
Agentless-1.5 [9]	0.697	0.517	32.0
CoSIL@40	0.707	0.520	31.3
AutoCodeRover-v2 [32]	0.693	0.500	30.7
Infant-Coder [34]	**0.740**	**0.547**	30.0
RepoGraph [13]	0.710	0.493	29.7
†Agentless-1.5 [9]	0.690	0.480	28.3
Moatless-Tools [33]	0.730	0.507	24.7
SWE-Agent [17]	0.580	0.427	18.3
*Orcaloca@10	0.573	0.413	19.7
*LocAgent@10	0.603	0.447	21.0
*Agentless@10	0.650	0.450	22.3
*CoSIL@10	0.683	0.483	25.7

TABLE IX
A FURTHER COMPARISON BETWEEN COSIL AND AGENTLESS-1.5 ON LOCALIZATION AND PATCH GENERATION PHASES. † INDICATES THE RESULT IS REPRODUCED BY US. S-N INDICATES THE N-TH SET OF PATCHES.

Method	File-level			Function-level		
	Top-1	Top-3	Top-5	Top-1	Top-3	Top-5
Agentless-1.5	0.630	0.810	0.850	0.250	0.450	0.490
†Agentless-1.5	0.630	0.817	0.847	0.250	0.407	0.437
CoSIL@40	0.650	0.817	0.883	0.480	0.617	0.640
Resolution Rate of Each Set of Patches						
	S-1	S-2	S-3	S-4	All	Resolved%
Agentless-1.5	81/300	82/300	85/300	78/300	96/300	32.0
†Agentless-1.5	72/300	72/300	70/300	70/300	86/300	28.3
CoSIL@40	76/300	75/300	77/300	77/300	94/300	31.3

counterexamples emerge when different patch generation and validation processes are used. One example is that Infant-Coder, which has the highest function match rate, has a resolved% that is 9.7% lower than OpenCSG, which has the second-highest function match rate. A similar discrepancy occurs between CoSIL@10 and Moatless-Tools, as shown in Table VIII. These results may imply that when using different patch generation and validation pipelines, file and function match rates may not accurately reflect the localization performance. For example, poor generation and validation methods may fail to select the correct locations and generate unreasonable patches even when correct locations are provided in the candidate locations, leading to a decrease in file and function match rate.

Another interesting result is that CoSIL@40 performs closely to Agentless1.5, despite CoSIL demonstrating stronger localization capabilities (c.f. Table II). To understand this result, we fully reproduce Agentless-1.5 with its replication package, and conduct a detailed comparison among the intermediate results, including localization results and each set of generated patches, provided by the authors, generated by our reproduced Agentless, and produced by CoSIL+Agentless, as shown in Table IX. Although the reproduced localization performance is close to the official results, the correct patches generated by the official results of Agentless are consistently higher than our reproduced Agentless. The Top-5 function-level accuracy of CoSIL is higher than Agentless by 15%, the resolution rate of CoSIL+Agentless is slightly lower than Agentless. One possible reason behind the performance variations is the randomness caused by high-temperature sampling during patch generation.

B. Threats to Validity

Internal Validity. *Hyperparameter settings.* We set a maximum iteration count to control when the search terminates. Since the performance of CoSIL varies with different maximum iteration counts, it remains uncertain whether the chosen hyperparameters are optimal. We have conducted extensive experiments on hyperparameter settings to ensure that the chosen values are optimal within a reasonable range. *Data Leakage.* We conduct experiments using LLMs released after the publication of SWE-bench. Since SWE-bench is constructed from real-world GitHub projects, and GitHub also serves as a source of training data for such models, there is a potential risk of data leakage. Meanwhile, we observe that the baseline methods also use the latest LLMs, and CoSIL outperforms them under the same model settings. This relative comparison helps mitigate the threat to some extent.

External Validity. *Datasets.* We evaluate the effectiveness only on SWE-bench Lite and SWE-bench Verified. It remains uncertain whether CoSIL can generalize to other programming languages or datasets. However, SWE-bench is currently the most widely adopted benchmark. In future work, we plan to assess the effectiveness of CoSIL using additional benchmarks.

VII. RELATED WORK

A. LLM-Based Fault Localization

LLMs have demonstrated remarkable proficiency in localizing the code snippets according to the failure test cases and error messages. Wu et al. [36] demonstrate the applicability of LLMs in fault localization by directly providing erroneous code and logs to ChatGPT, prompting it to identify defective code lines. Kang et al. [27] leverage LLMs' function-calling capabilities and equip them with multiple retrieval tools to enhance their ability to explore code repositories. Xu et al. Qin et al. [28] propose AgentFL, which integrates LLMs with static analysis tools to enable repository-level fault localization. [26] and Wang et al. [37] combine static analysis and code retrieval tools to construct an LLM Agent that supports decision-making in fault localization. These methods often take failed test cases and fault information as input, rather than natural language requirement descriptions.

Recent studies [9]–[12] have also focused on the ability to identify specific code segments based on GitHub issue reports [1], [2]. Xia et al. [9] propose Agentless, which separates issue localization from issue fixing and employs hierarchical localization by directly prompting LLMs. Based on this, Chang et al. [12] introduce a method that refines the three levels of localization differently based on file structures, function call chains, and program dependency graphs, achieving multi-granularity localization performance improvements. Yu et al. [10] propose OrcaLoca, which utilizes an LLM-based agent to dynamically schedule attention across different locations and prunes the context based on distance. Chen et al. [11] propose LocAgent, which integrates multiple repository graphs to construct indexes, enabling search through various tools.

Unlike existing works [9]–[11], CoSIL neither expands the search space by building a complete repository index nor restricts it to the issue description. Instead, it adopts a two-stage search strategy: at the file level, it broadens the search space using the module call graph; at the function level, it performs an iterative search based on the function call graph, achieving a balance between the breadth and depth of the search space.

B. Agentic Methods for Issue Solving

Exploring solutions for software issues in real-world code repositories has become a widely studied problem among researchers. Existing issue-solving methods can be categorized into three main approaches. *LLM agent-based methods*, such as SWE-Agent [17], AutoCodeRover [25], [32], Openhands CodeAct [15], and Moatless Tools [33], equip agents with various tools for accessing and modifying repositories (e.g., bash, LSP), enabling them to autonomously explore and edit code files for bug fixing. For example, SWE-Search [38] builds upon this by introducing Monte Carlo Tree Search to explore the solution space for optimal fixes, mitigating the uncertainty caused by LLM sampling. *Pipeline-based methods*, represented by Agentless [9], incorporate human prior knowledge by manually identifying and providing predefined contextual information to assist in fixing issues. Methods such as RepoGraph [13] and PatchPilot [39] follow this approach. Additionally, researchers explore *fine-tuning open-source models* for issue-solving tasks. SWE-SynInfer [40] and SWE-Gym [41] demonstrate the effectiveness of fine-tuning and establish a paradigm for evaluating fine-tuned models on this task. SWE-Fixer [42] extends this work by introducing a simpler and more robust method for constructing training data. Furthermore, SWE-RL [43] and SoRFT [44] explore the potential of reinforcement learning for fine-tuning in the patch generation stage following DeepSeek-R1 [22] and make a great improvement.

VIII. Conclusion and Future Work

We propose CoSIL, an LLM-driven open-source solution for issue localization without training. CoSIL performs dynamic graph construction through prompt-based analysis of target code segments. It constrains the potential search space using a module call graph and conducts step-by-step iterative search over a function call graph. A pruning mechanism is introduced to control the search direction and manage context effectively. Using reflective alignment to ensure the interaction with the environment is in the correct format. On SWE-bench Lite, CoSIL achieves a 65% success rate in function-level localization. In addition, we integrate CoSIL with other open-source issue-solving methods, resulting in a 2.04%–30.5% improvement in resolution rate. This demonstrates that more accurate localization results in a higher issue resolution rate. In the future, we plan to extend CoSIL to support more programming languages and evaluation benchmarks. We also aim to enhance issue-solving agents' ability to utilize localization results more effectively.

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